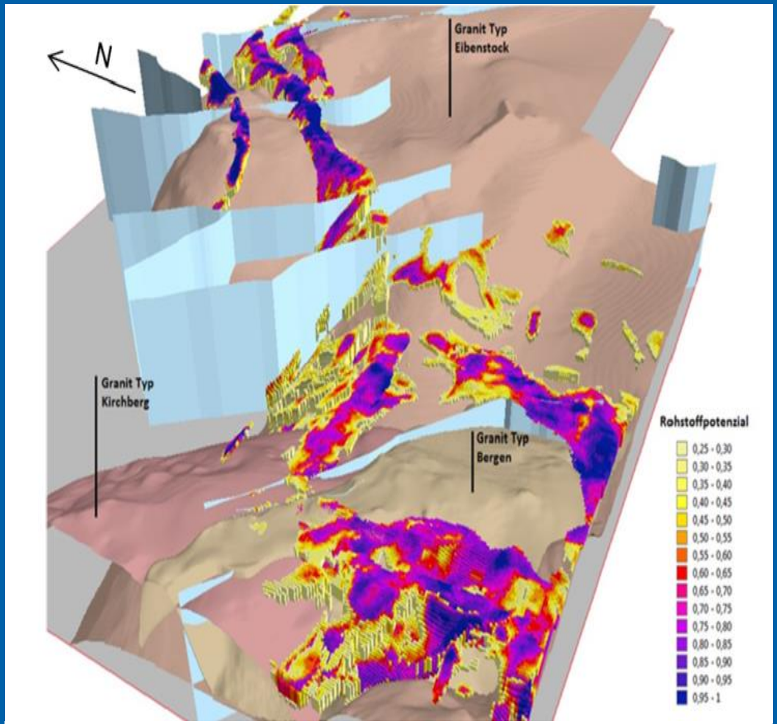
Mineral predictive mapping - from intuition to quantitative hybrid 3D modelling

De re Metallica ex libre. Georgius Agricola, 1556



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

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MINERAL PROSPECTIVITY current approaches and future innovations

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

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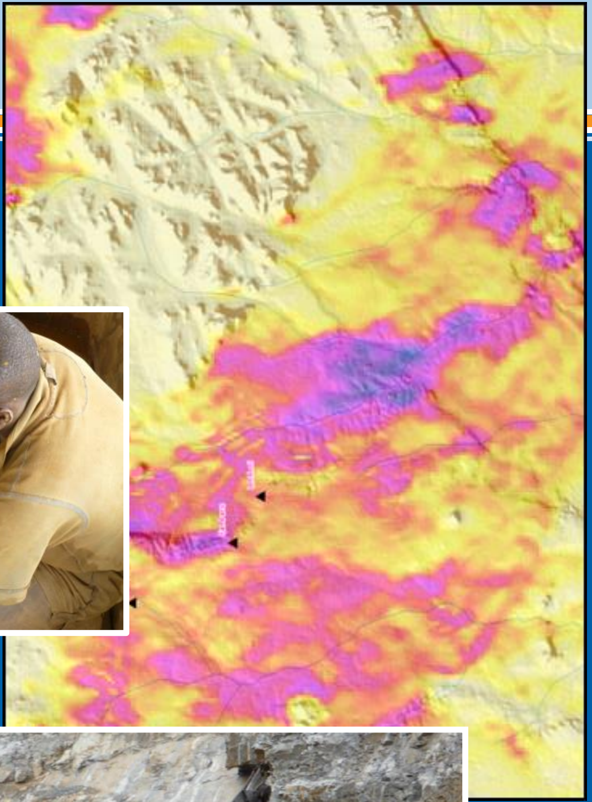
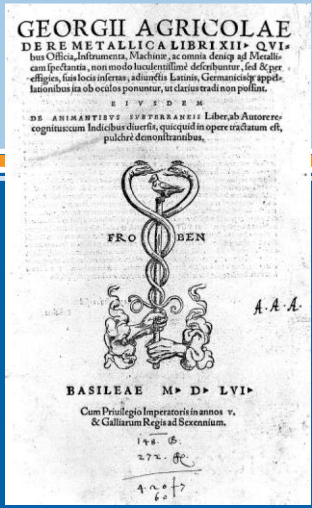
Agenda

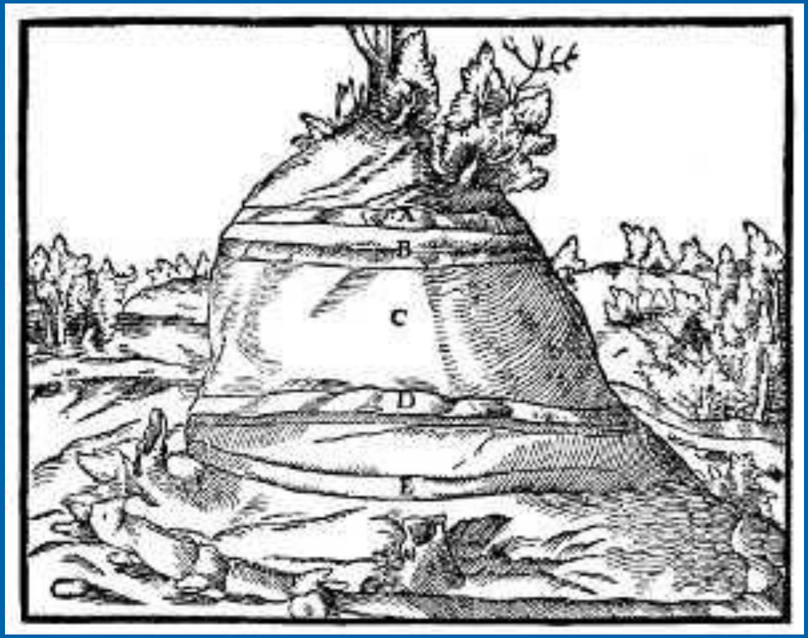
- History
- Maps and Metallogeny
- Exploration models
- Predictive mapping approaches
- Data issues
- Qualitative and quantitative methods
- 2D, 2.5D and 3D predictive mapping
- Result verification
- Value added products




GEORGII AGRICOLAE
DE RE METALLICA LIBRI XII. QVIbus Officia, Instrumenta, Machinæ, ac omnia deniq; ad Metallicam spectantia, non modo luculentissimè describuntur, sed & per effigies, suis locis insertas, adiunctis Latinis, Germanicisq; appellationibus ita ob oculos ponuntur, ut clarius tradi non possint.
EIVSDEM
DE ANIMANTIBVS SVBTERRANEIS Liber, ab Autore recognitus: cum Indicibus diuersis, quicquid in opere tractatum est, pulchrè demonstrantibus.
FRO BEN
A·A·A·
BASILEAE M. D. LVI.
Cum Priuilegio Imperatoris in annos v. & Galliarum Regis ad Sexennium.

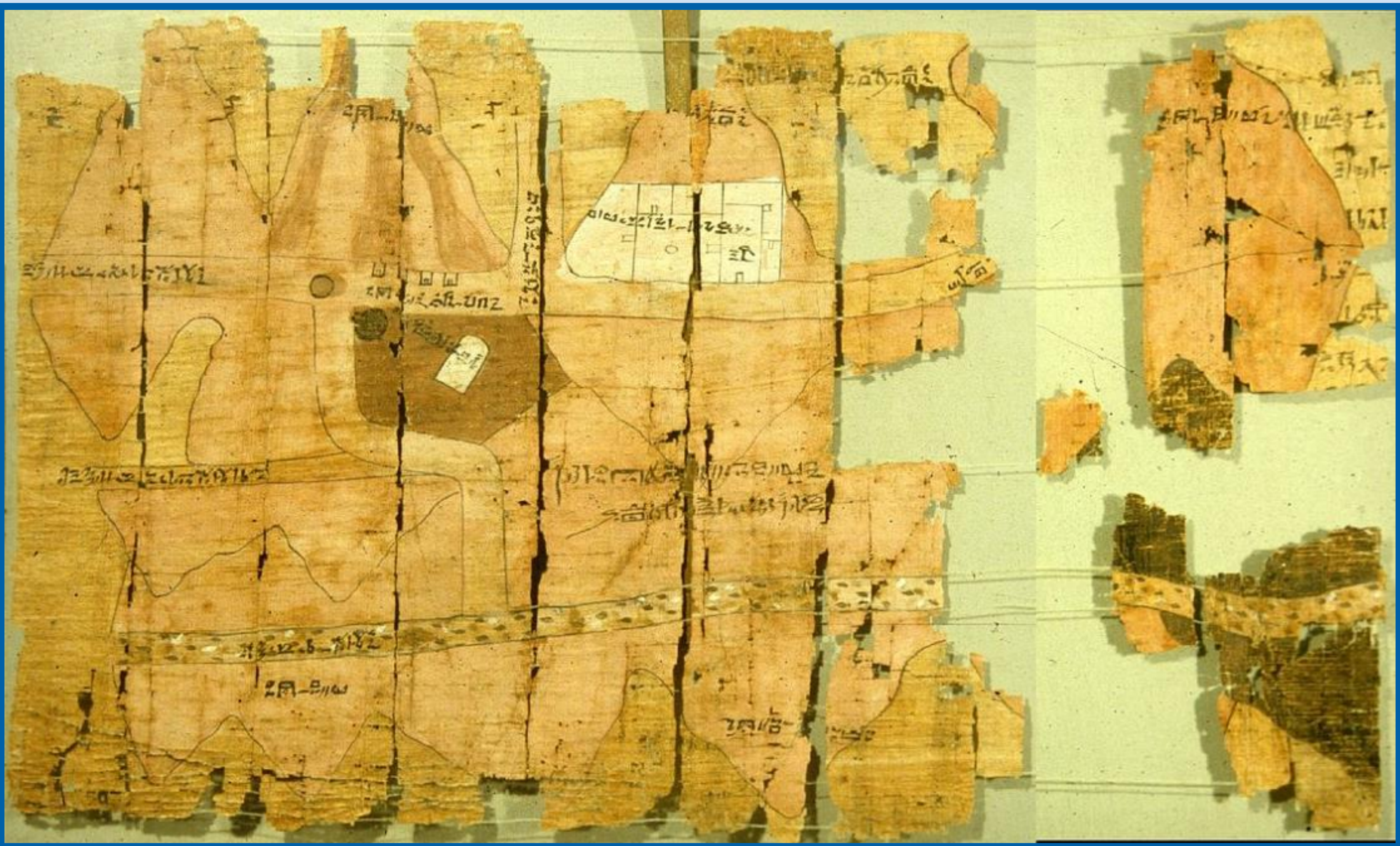
The first book about mineral predictive mapping

- 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.



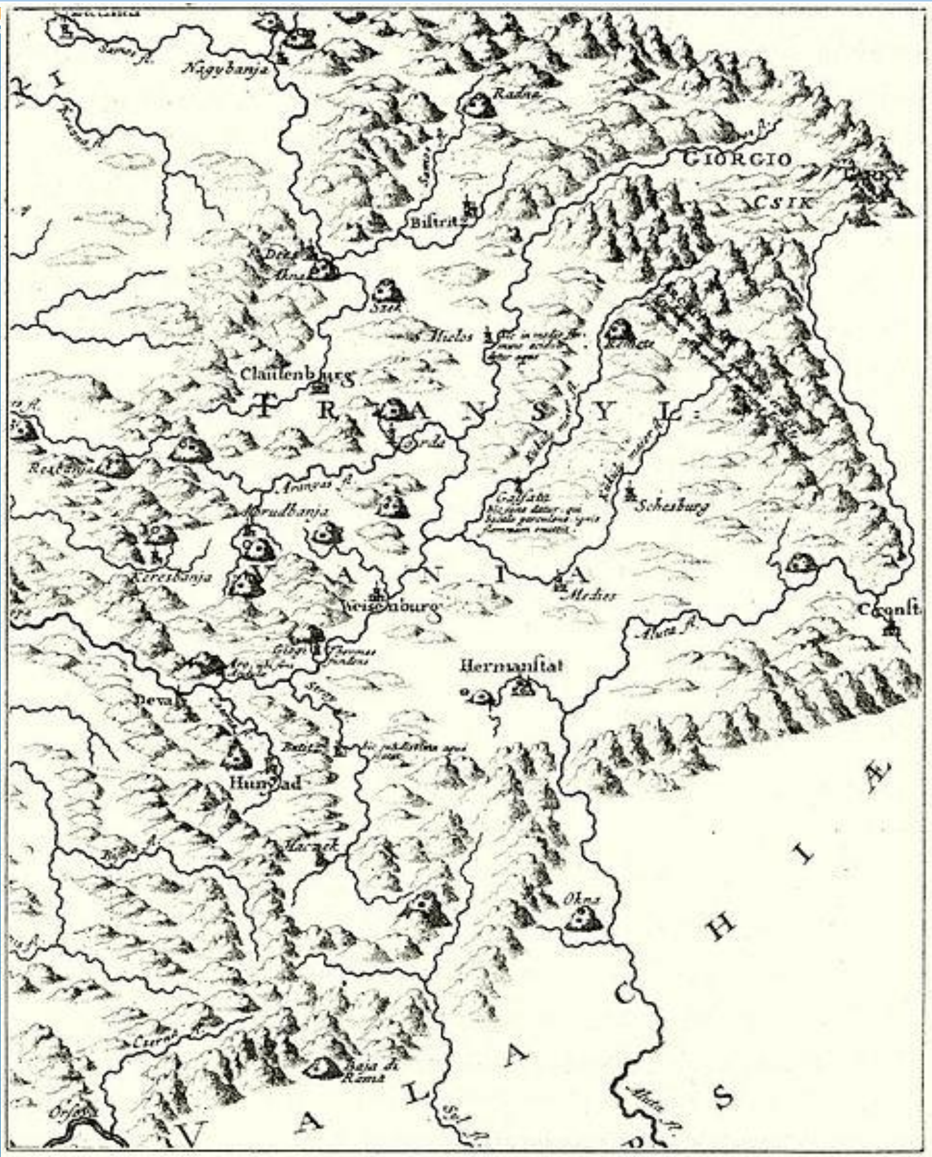
Georgius Agricola, 1556: De re Metallica ex libre

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)).

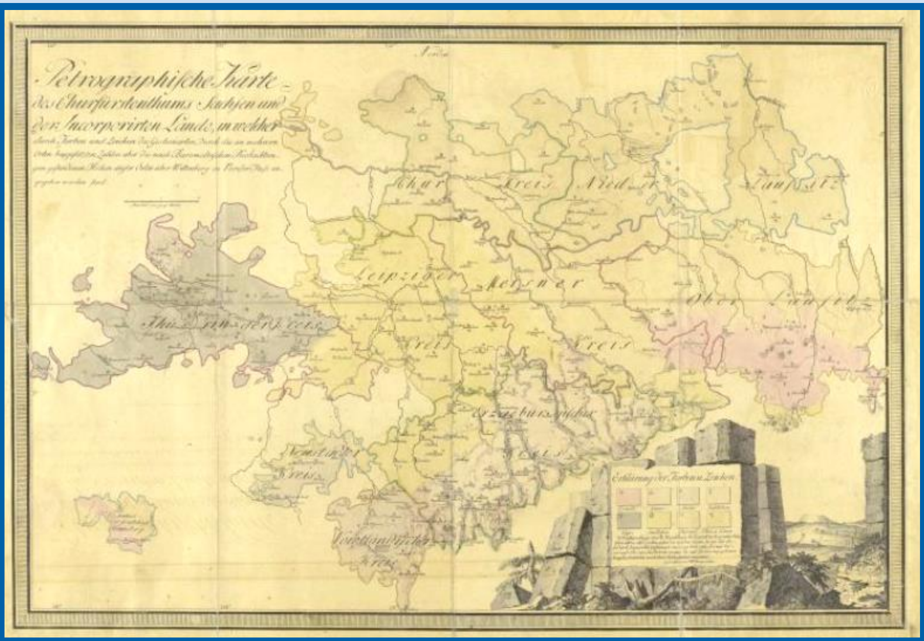
(https://commons.wikimedia.org/wiki/File:Mining_Map_of_Northern_Transylvania_in_Danubius_Pannonico-Mysicus_1726_by_Marsigli,_v2.jpg)

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

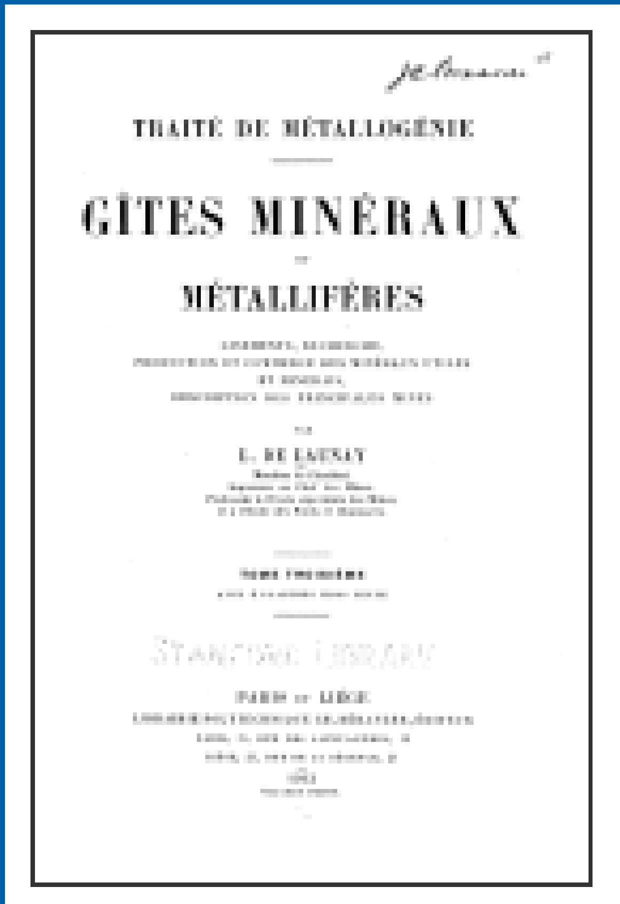
The Geological Map of England. William Smith, 1814



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


TRAITÉ DE MÉTALLOGÉNIE

GÎTES MINÉRAUX

MÉTALLIFÈRES

L. DE LAUNAY

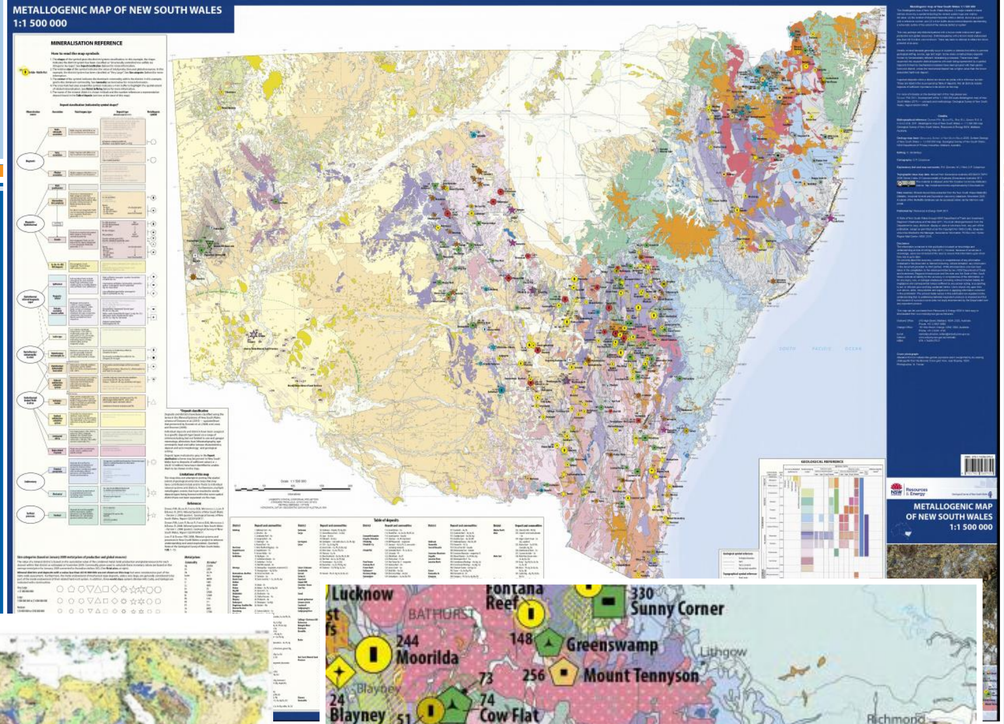
PARIS ET LIÈGE

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

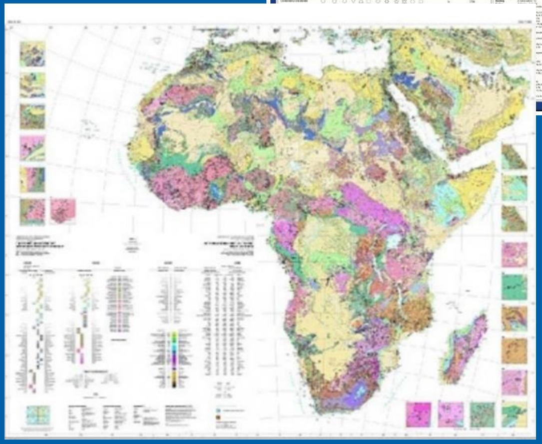
"Metallogeny studies mineral deposits … in order to determine the laws, ruling their predominant appearance in a particular geological zone….

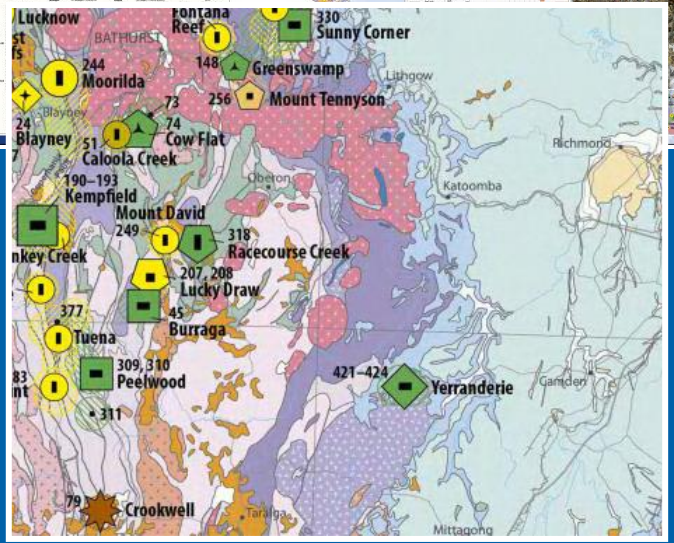
The mineral deposit is understood as a part of its geological environment

In the 20th century world-wide metallogenic maps were created



Demonstrate the dependencies between minerals and the geological environment.



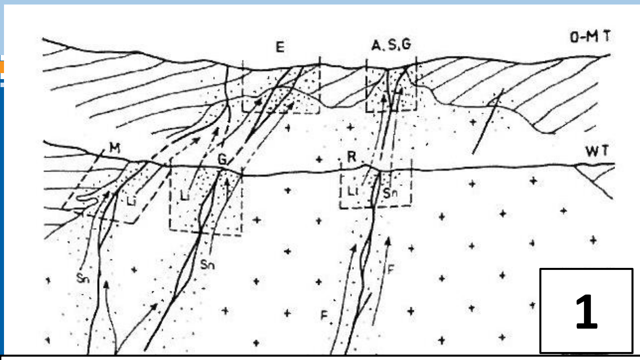


Synthesis of geology, tectonics, time, and minerals

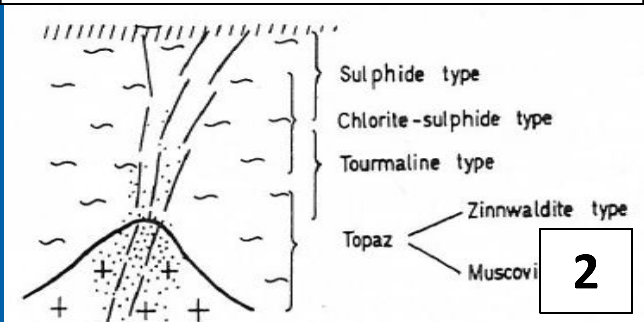
Lindgren, 1933; Turneaure, 1955; Petrascheck, 1965; Guild, 1971, 1972, 1974; Routhier, 1983; Guilbert and Park, 1986, S.S. Smirnow, J.A. Bilibin, E.T. Shatalov, D.V. Rundkvist, G. Tischendorf, ...

Exploration models: another abstraction of the reality.

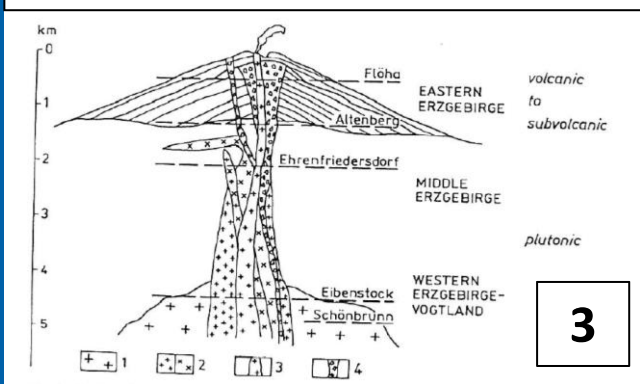
Example: Sn in the Erzgebirge



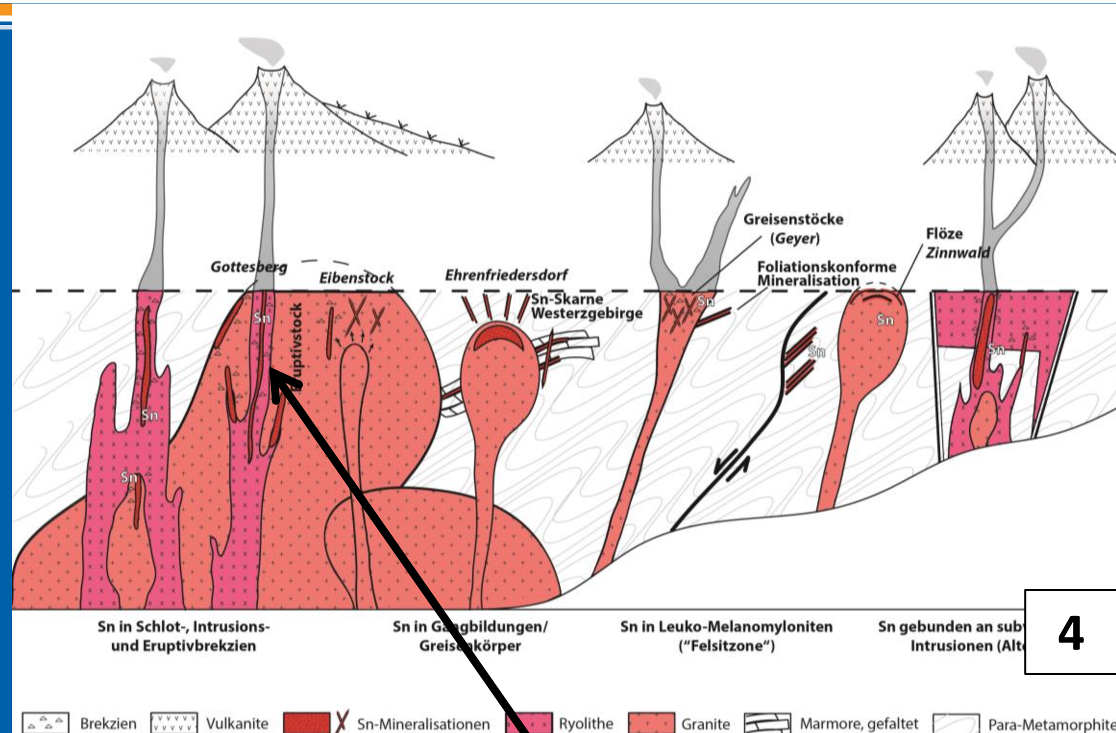
Tischendorf, 1969



Baumann & Tischendorf, 1978



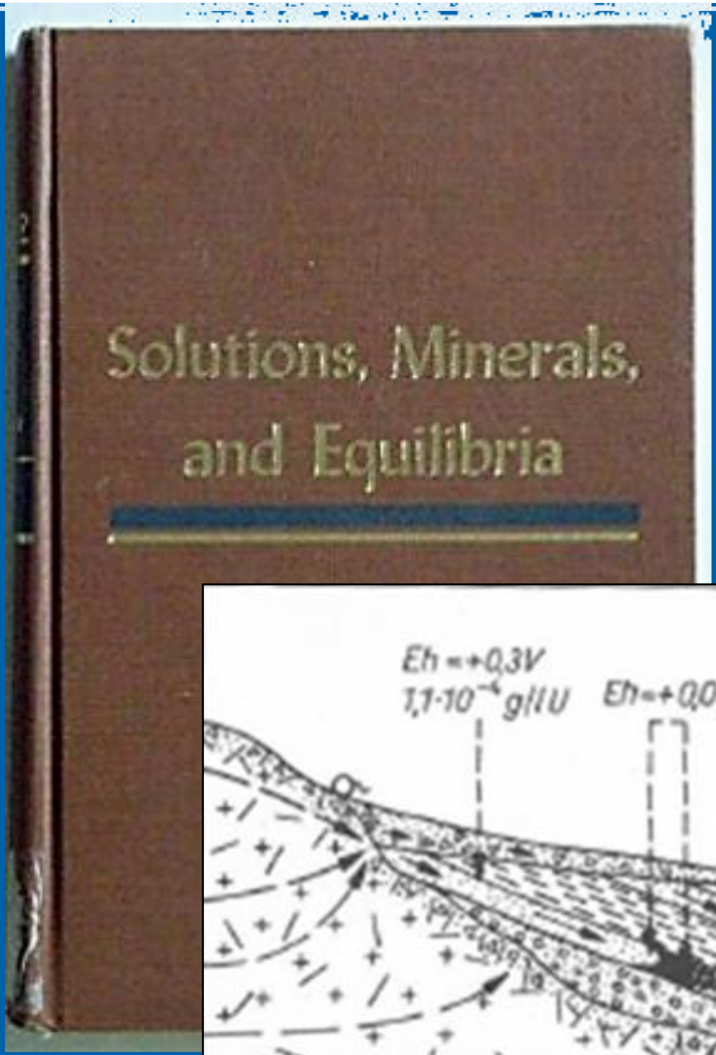
Seltmann, 1992



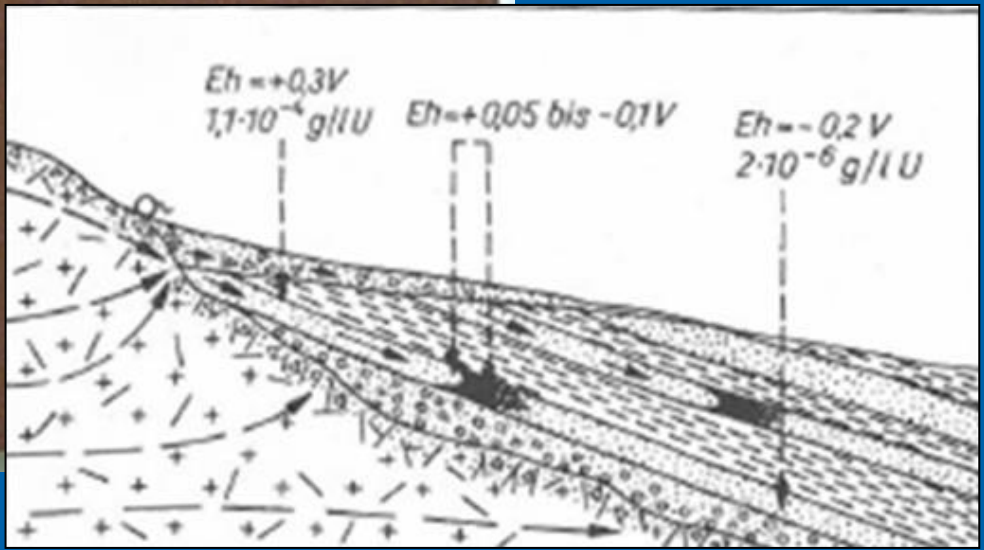
Beak, 2015

120 kt Sn in a breccia pipe on top of a subvolcanic stock

Physico-chemistry created the base for modern mineral deposit formation concepts



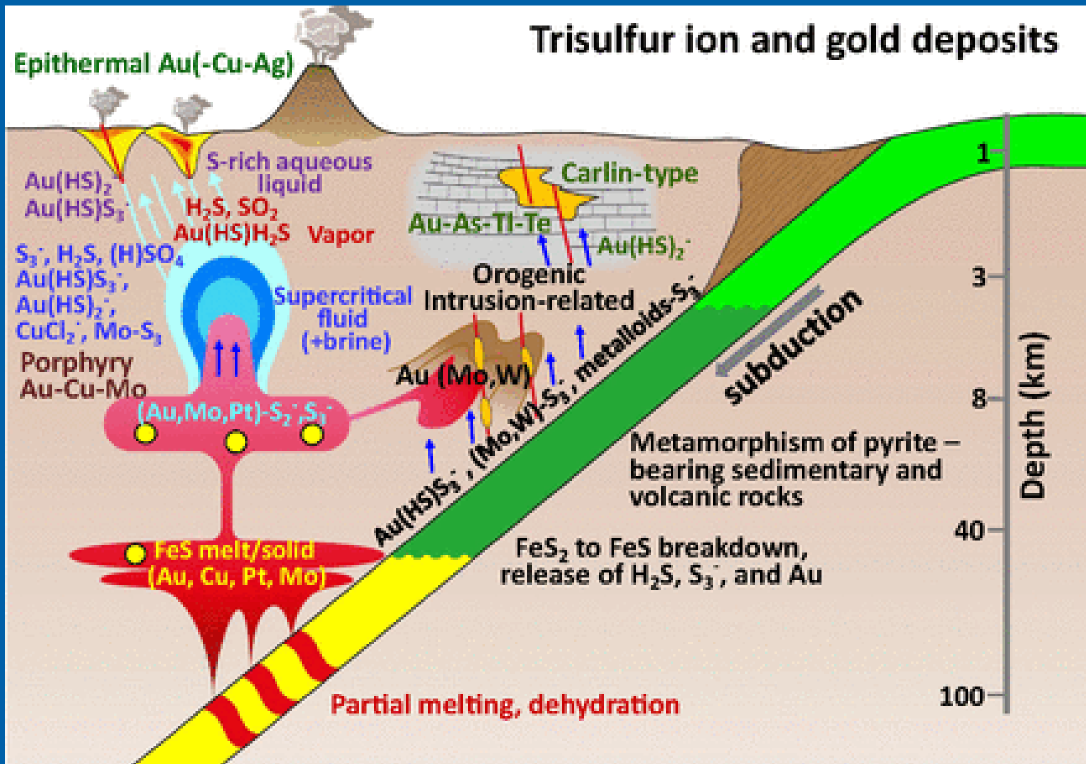
Garrels & Christ, 1965.
A milestone in understanding mineral occurrence formation processes, and consequently a key for identification of prospecting criteria.



Evseeva, Perelman, 1962

Formation of sandstone hosted U, controled by redox processes

Plate tectonics is the base for many mineral occurrence formation models



http://www.pnas.org/content/112/44/13484/F4.expansion.html

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.

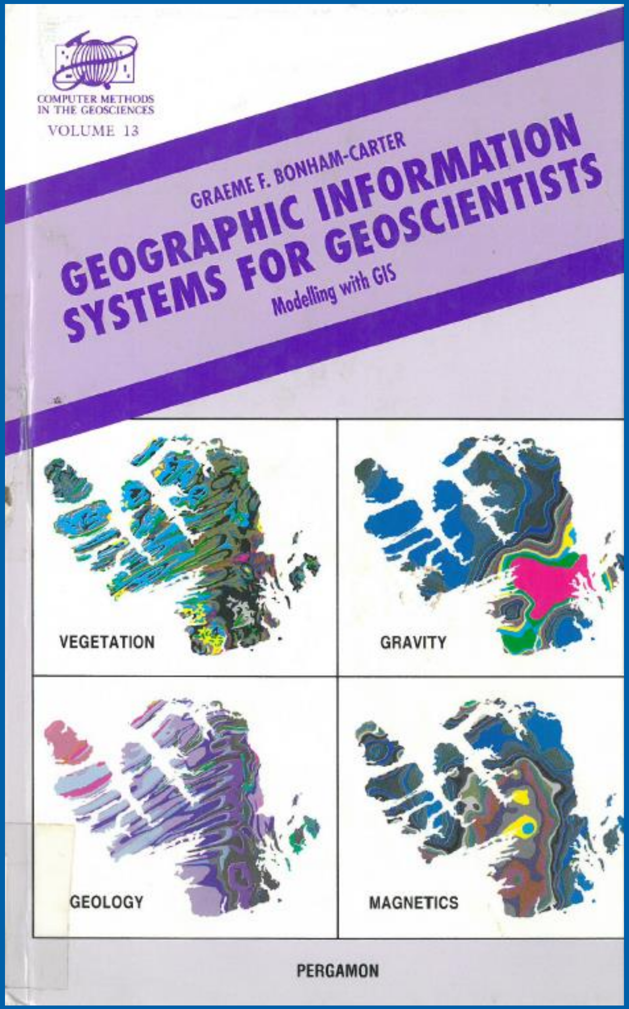
In the 1980ies, the ground was prepared …..

In the 80ies the preconditions were prepared for new approaches in mineral prediction:

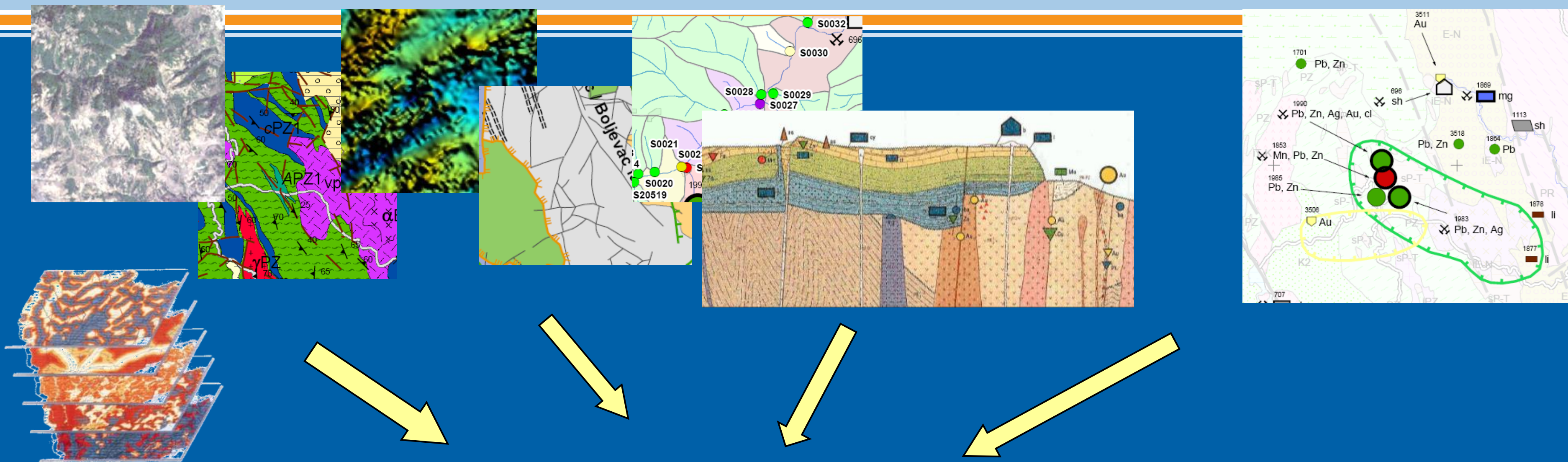
- Metallogenic concepts/ maps
- Exploration models
- Ever growing amount of data, incl. remote sensing
- Available and useable personal computers
- Software: GIS, statistics, the roots of AI

→ Computerization and processing of mass data started

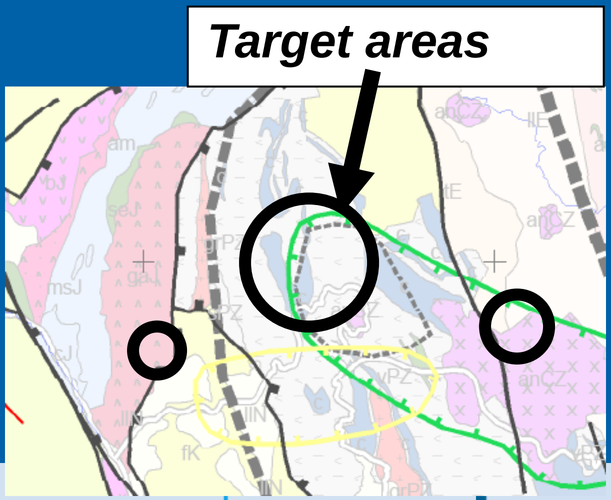
The first summarizing publications were released, e.g.: Bonham-Carter, 1994



We are lost in data and knowledge …



We are lost in data and knowledge

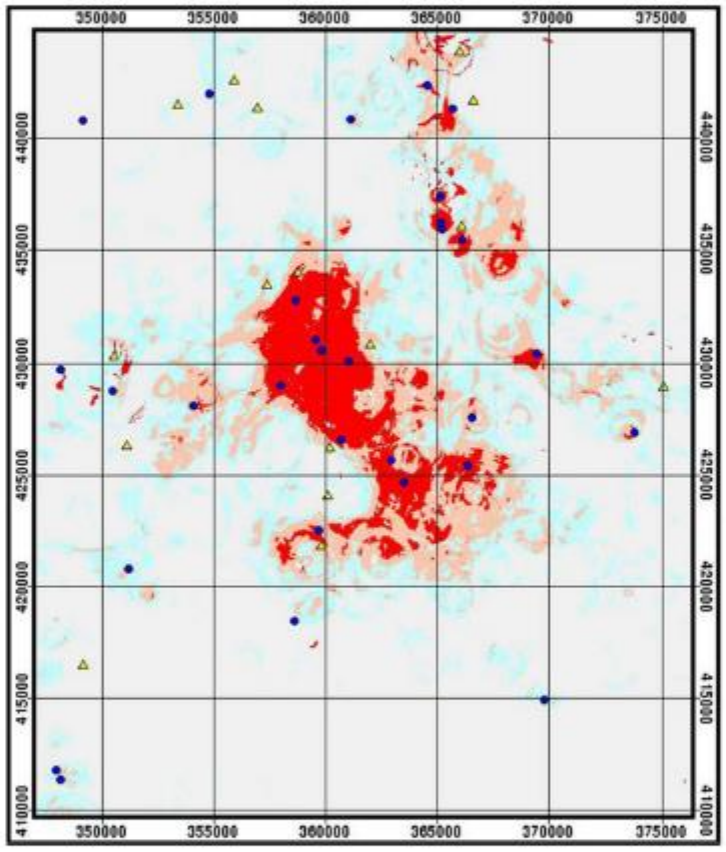


Expert´s knowledge / experience was increasingly supported by modern information technology

What is mineral prospectivity and how to model it ?

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

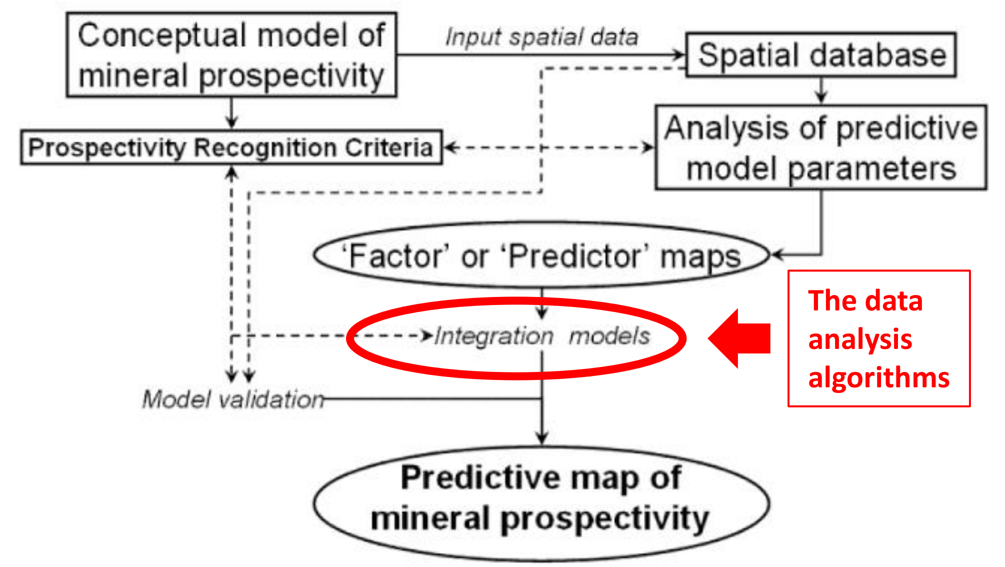
The General Approach of Mineral Predictive Analysis

The depending variable:

Likelihood of presence of a mineral occurrence of a certain type in a defined piece of land.

Controlling parameters:

Our datasets.



Carranza, 2009

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.

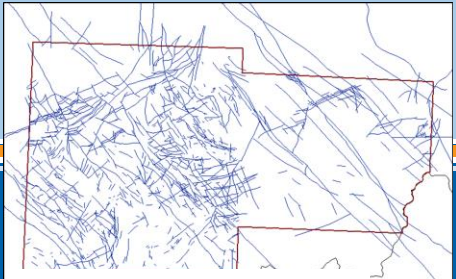
How to consider spatial dependencies ?

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

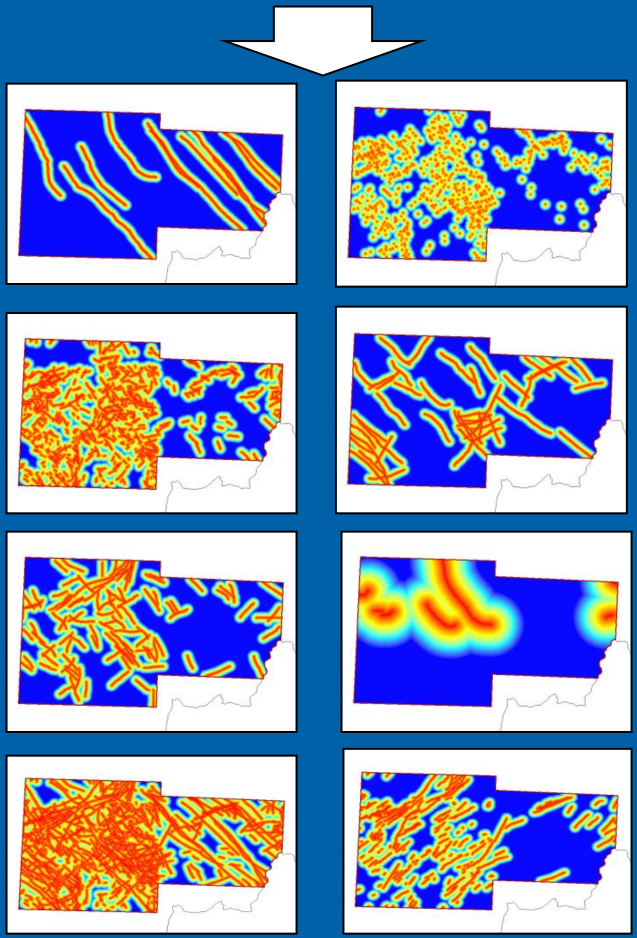
We need to “teach” the system:

- 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, ….

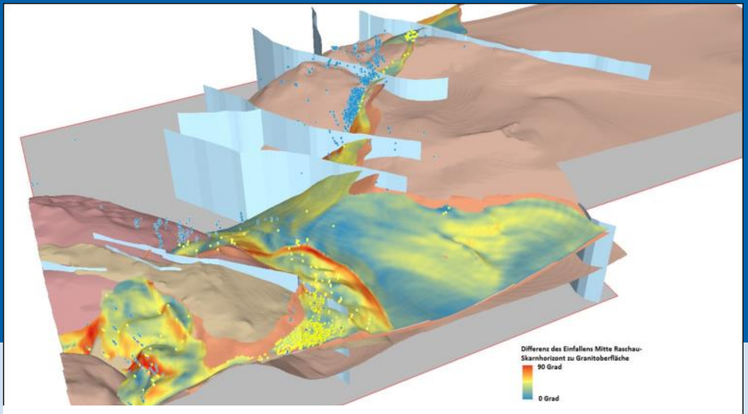
Tectonics is split into many derived datasets



ROHSA 3.1, Beak, LfULG



Differences between dipping angles of granite surface and host rock foliation



ROHSA 3.1, Beak, LfULG

Preconditions for successful mineral predictive mapping

Exploration models:

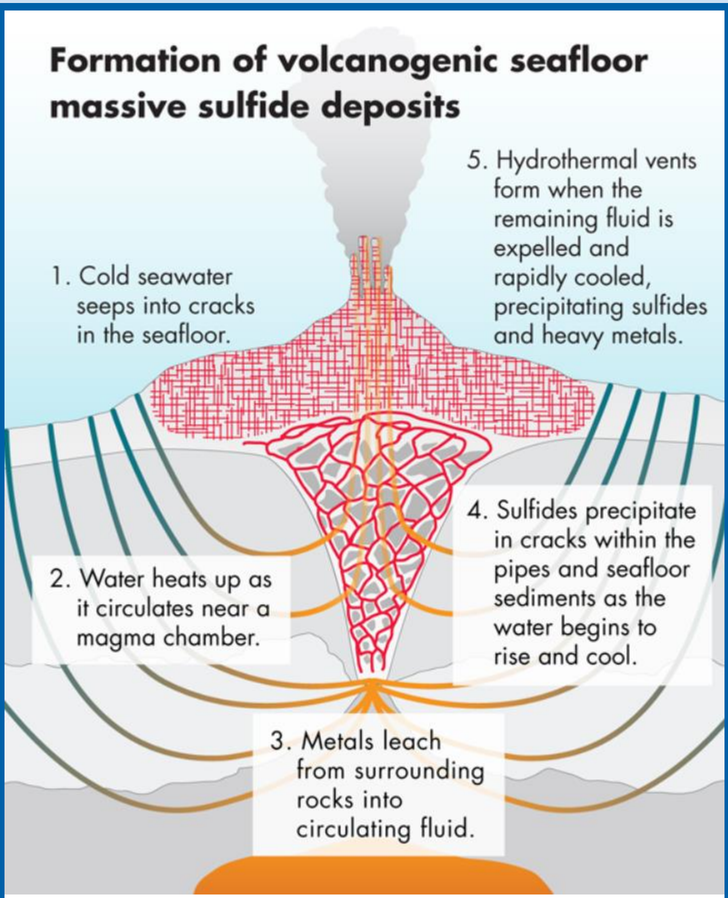
- Deep understanding of mineral occurrence formation processes

As much as possible relevant data:

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

Algorithms:

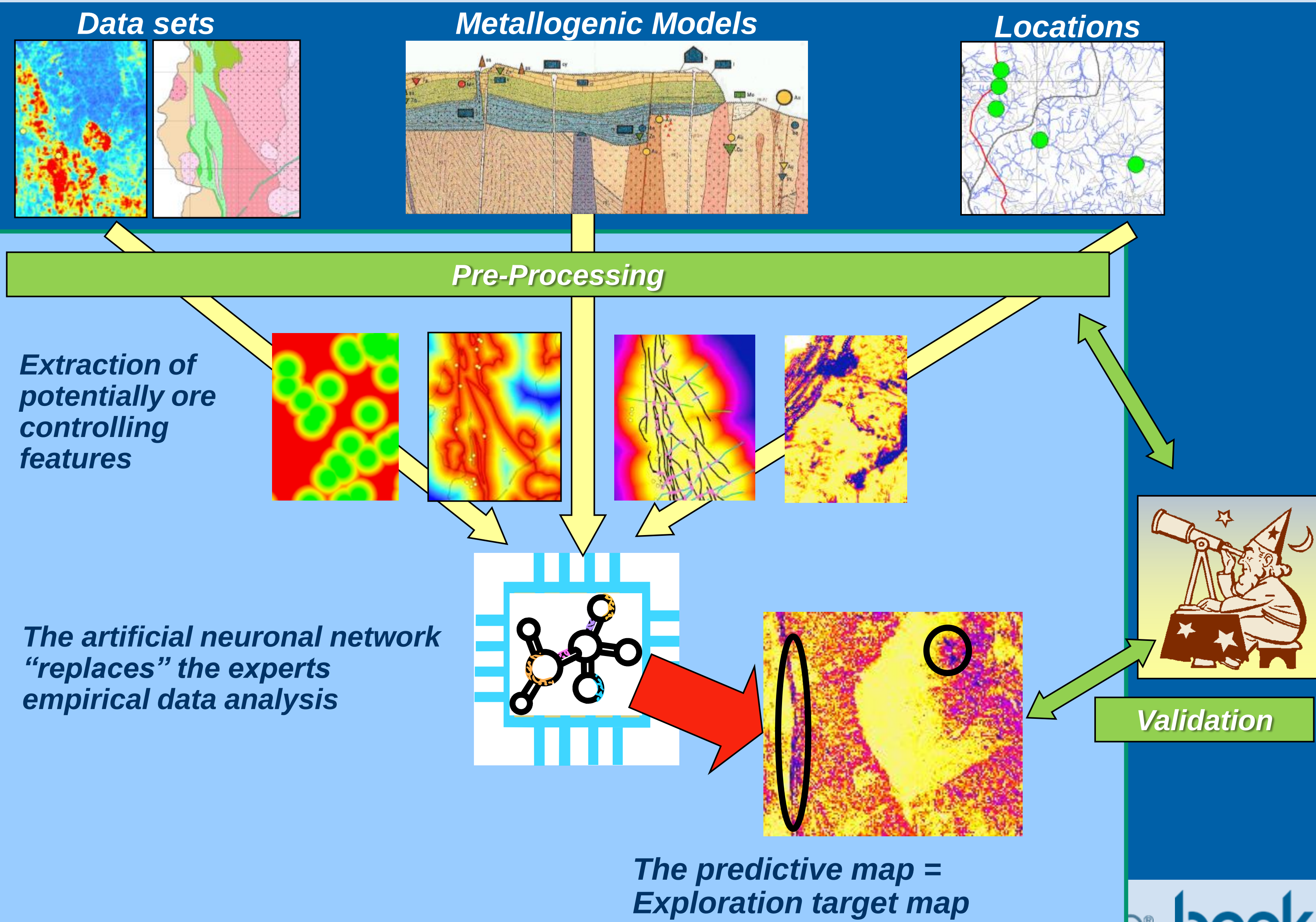
- Artificial Intelligence (AI)



Earth Science Australia, 2017

http://earthsci.org/mineral/energy/geomin/VMS_formation.png

AI algorithms supplement (replace?) the geologist's intuition



advangeo® Prediction Software

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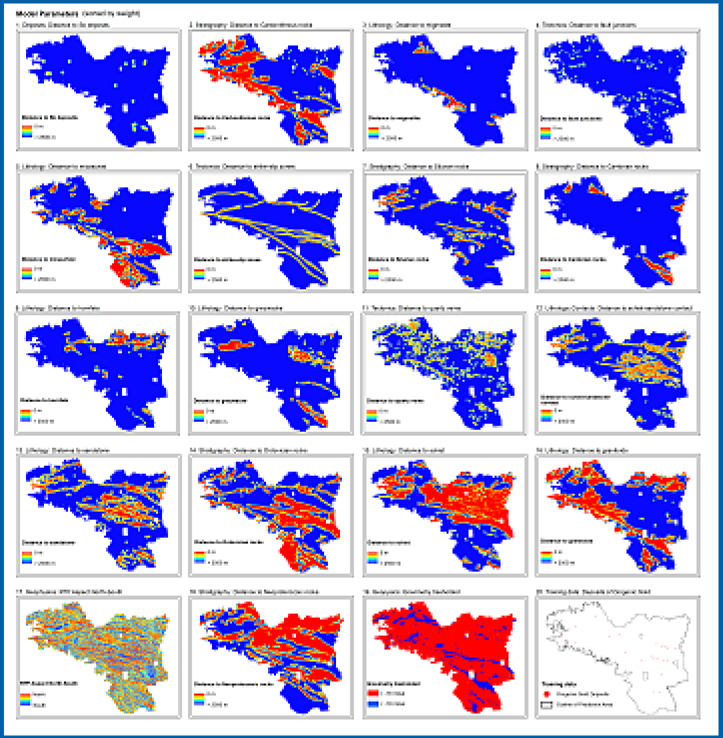
Different groups of data

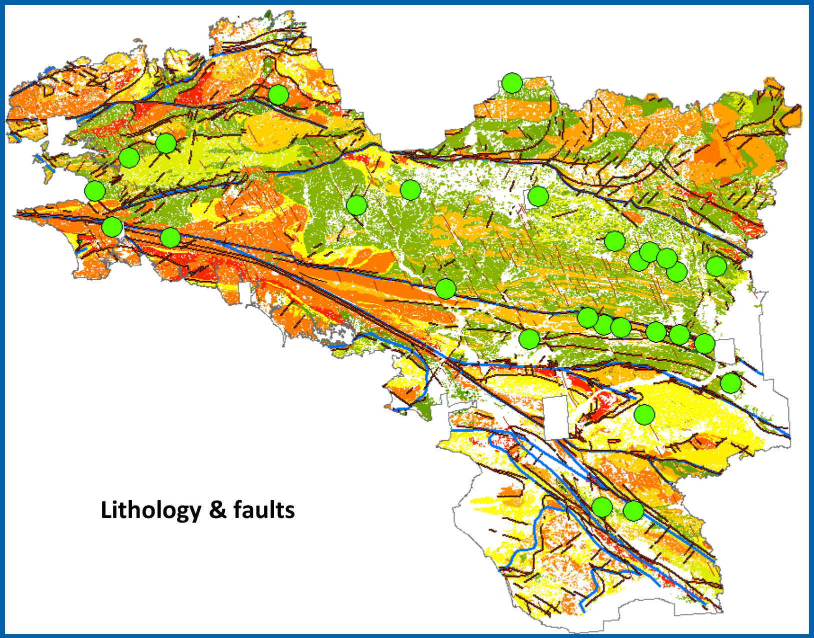
- Sharp data with clear relationships to the depending variable:
  - Granite cupola and greisen
  - Granite and limestone = skarn
  - High Au-anomaly = mineralisation outcrop

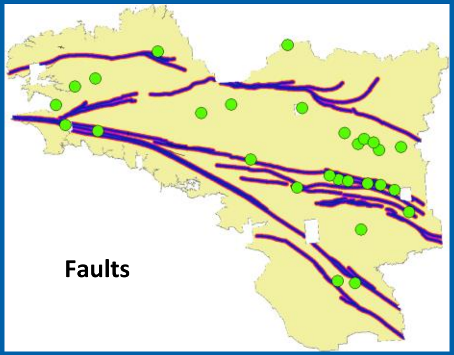
- Datasets with unclear relationships/ multiple sources:
  - Mo anomalies are the result of different sources (black shales, greisens, hydrothermal veins, porphyries,…)
  - Magnetic properties are the result of multiple lithologies in a complex geology

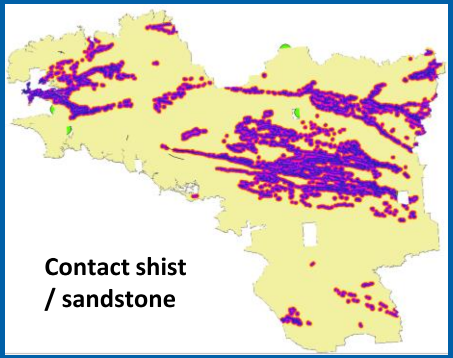


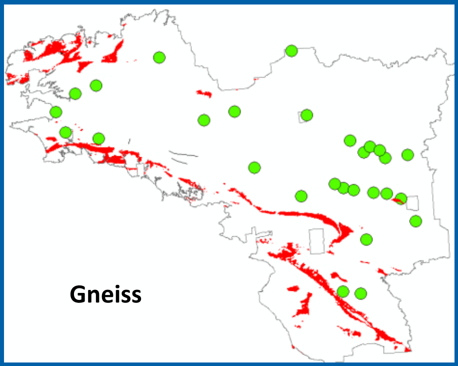
Geological Data

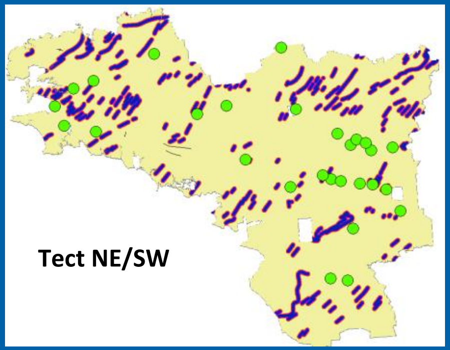
- Geological maps
- 3D models
- A tremendous amount of independent data can be derived
- Geochemical and geophysical properties can be derived



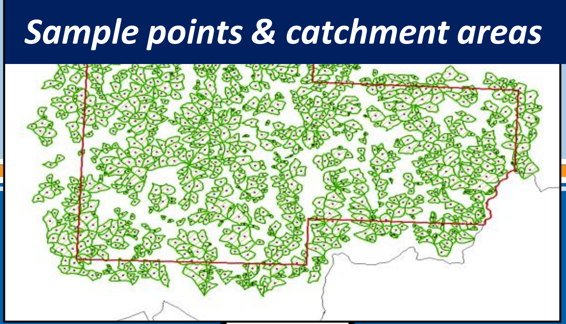


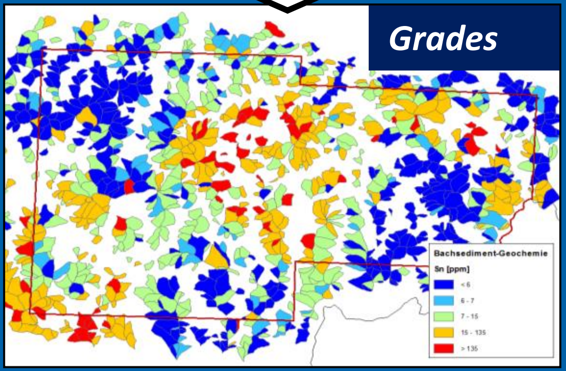


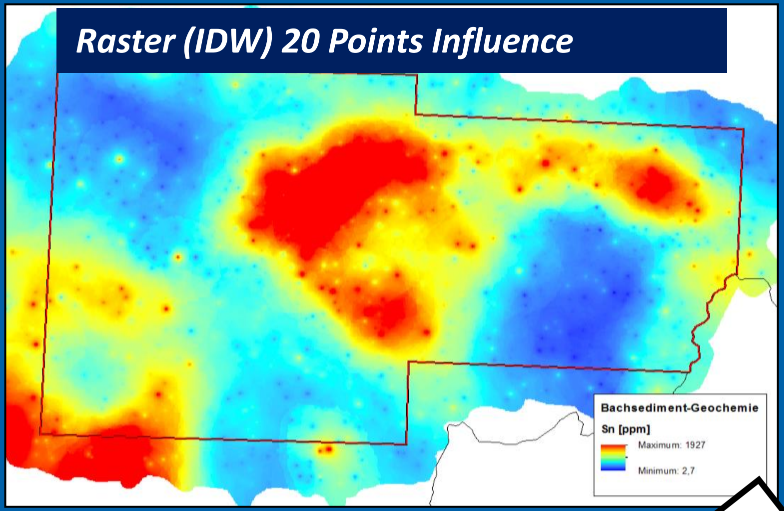


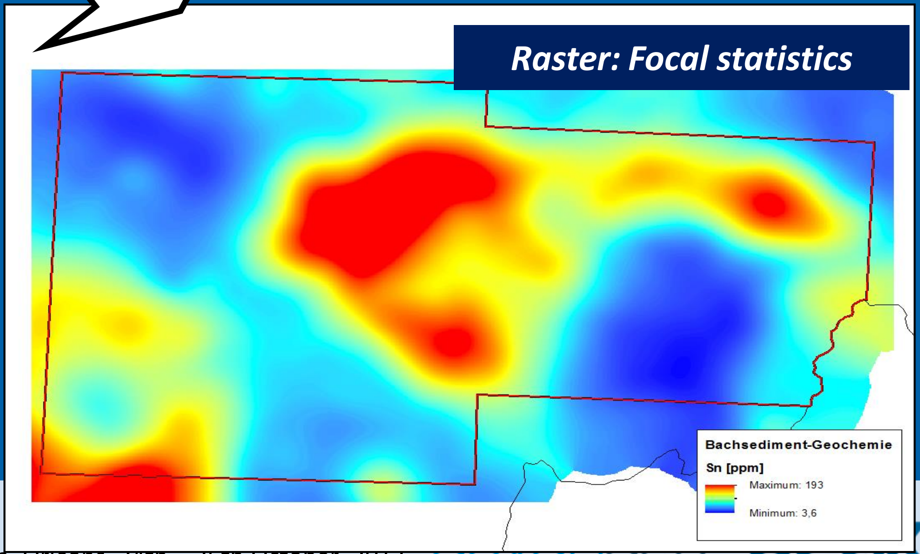


Geochemical Data



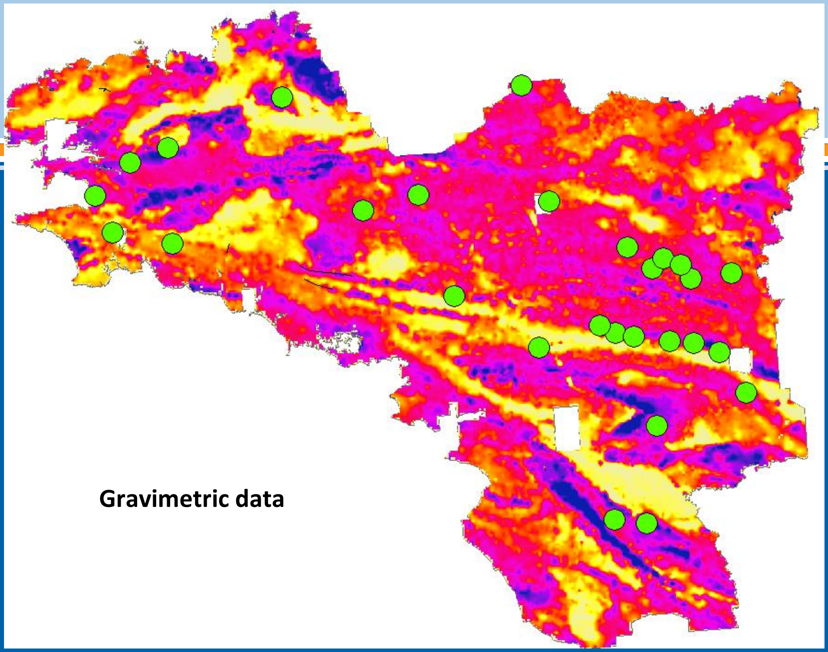


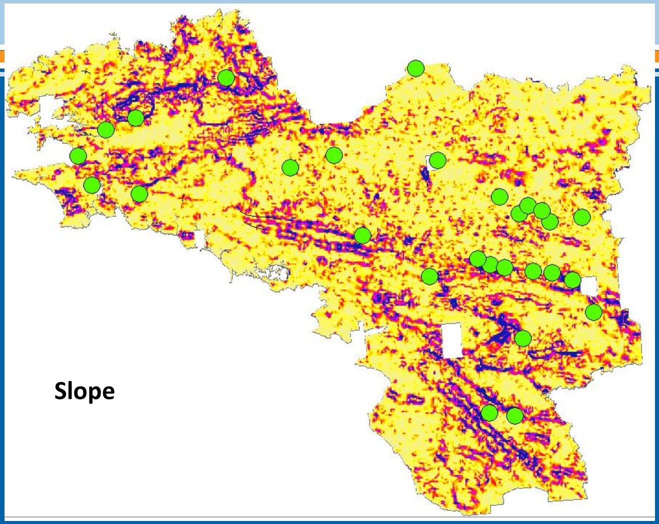


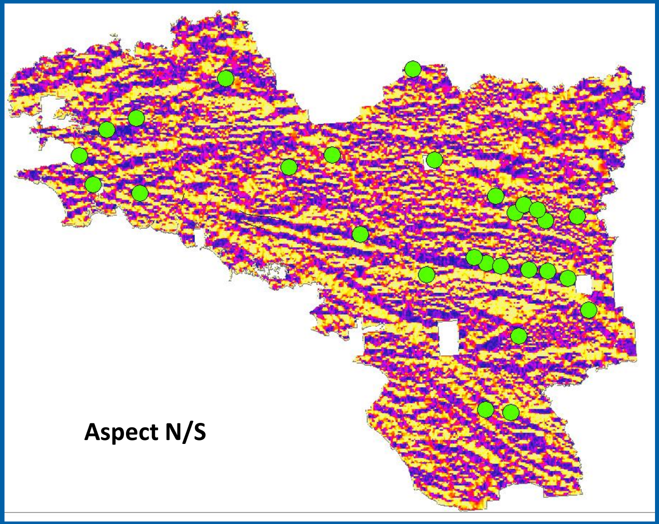


- Direct indication
- High information content
- Cumbersome to get
- Depending on the scale and accuracy:
  - Stream sediments
  - Soil
  - Rocks

Geophysical Data





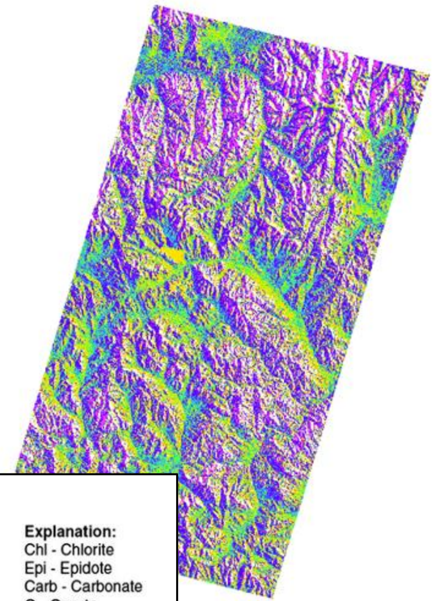


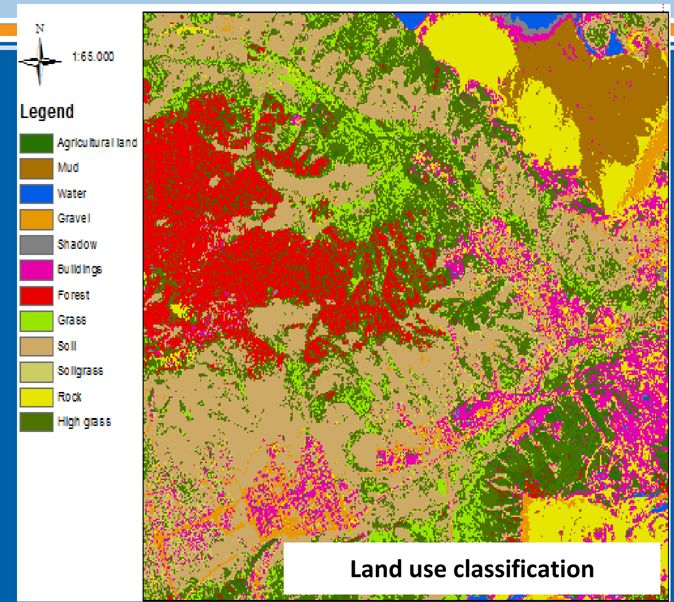
- Indirect indication
- High resolution is possible
- Various penetration depth
  - Radiometrics, spectrometry – surface
  - Magnetics, gravimetry – deeper structures
- Simple to get
- Expensive

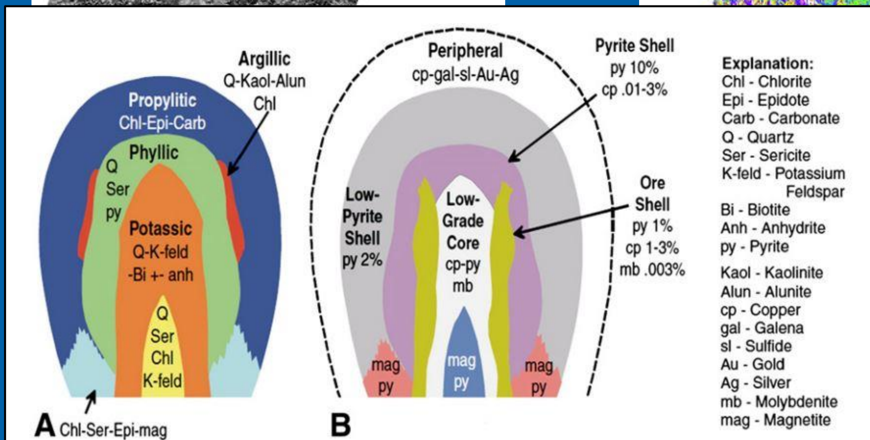
Spectral data

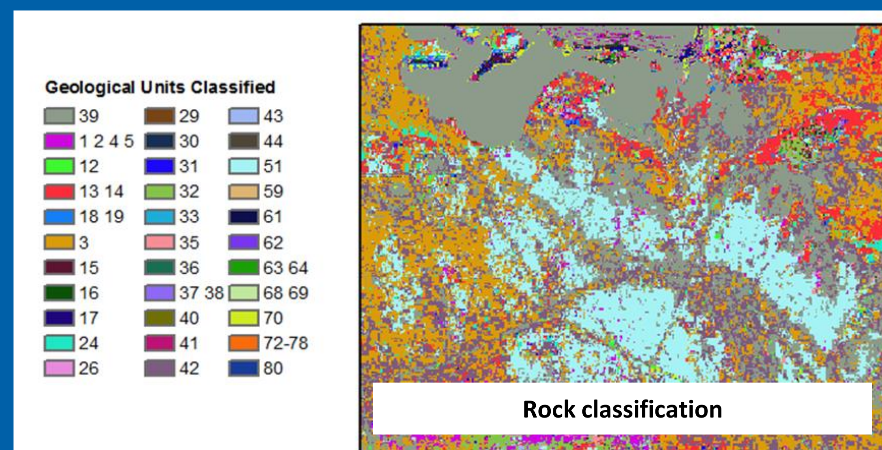
ASTER data, Band 1

Cosine correction of band 1



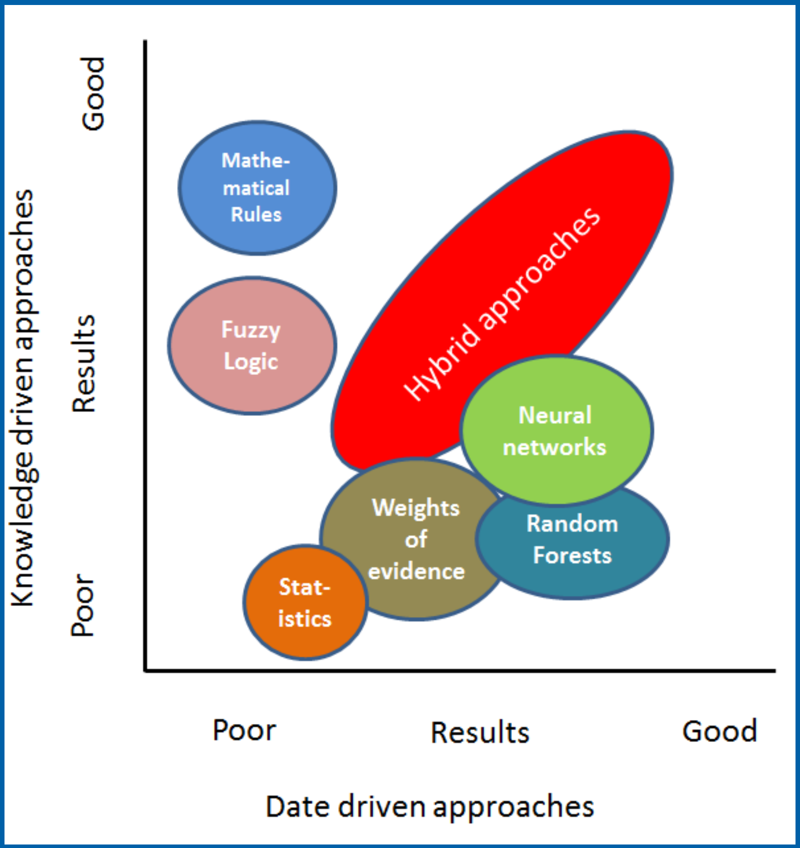






- Mapping of alteration minerals
- High resolution data possible
- Simple to get
- Not expensive
- Problematic in vegetated areas

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

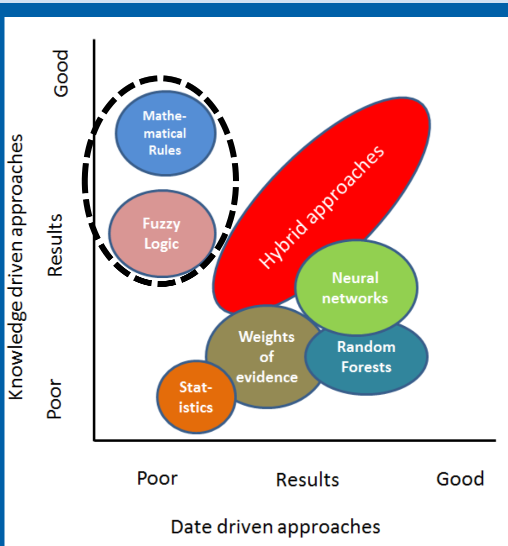
- The algorithm finds the dependencies by itself
- We need training points

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

Hybrid approaches

Combinations of the above

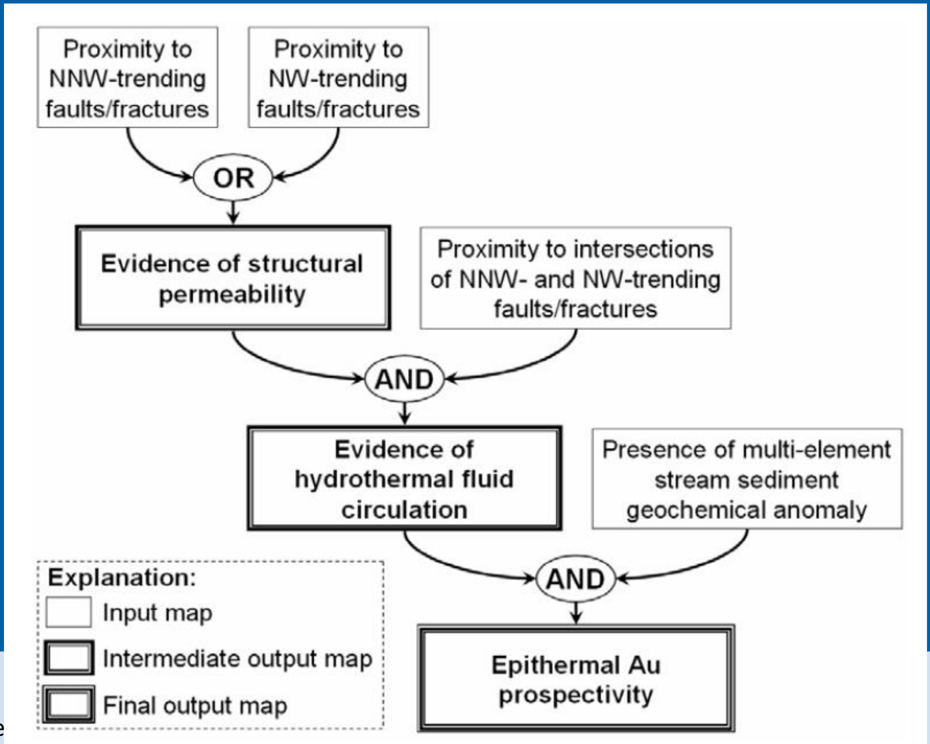
Knowledge based methods: aggregation of data by functions



Knowledge based methods

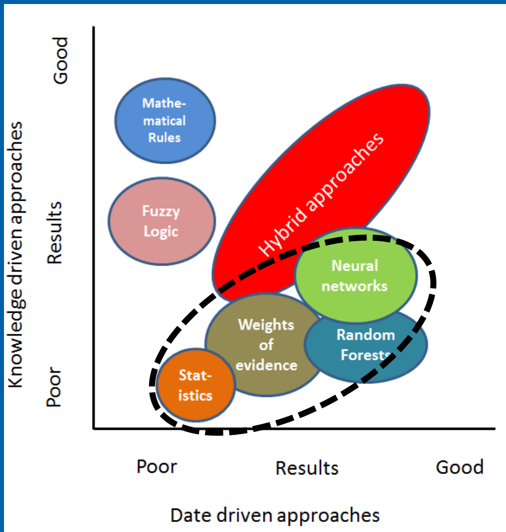
- We know dependencies and use that knowledge
- We can find only what we know
- We do not need training points
- Prospectivity map = f (evidential maps)
- Fuzzy logic modelling

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 predictive mapping methods



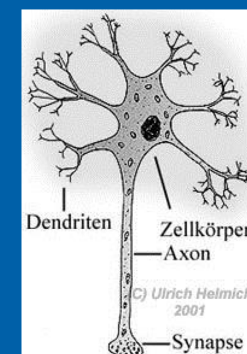
Data driven approaches

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

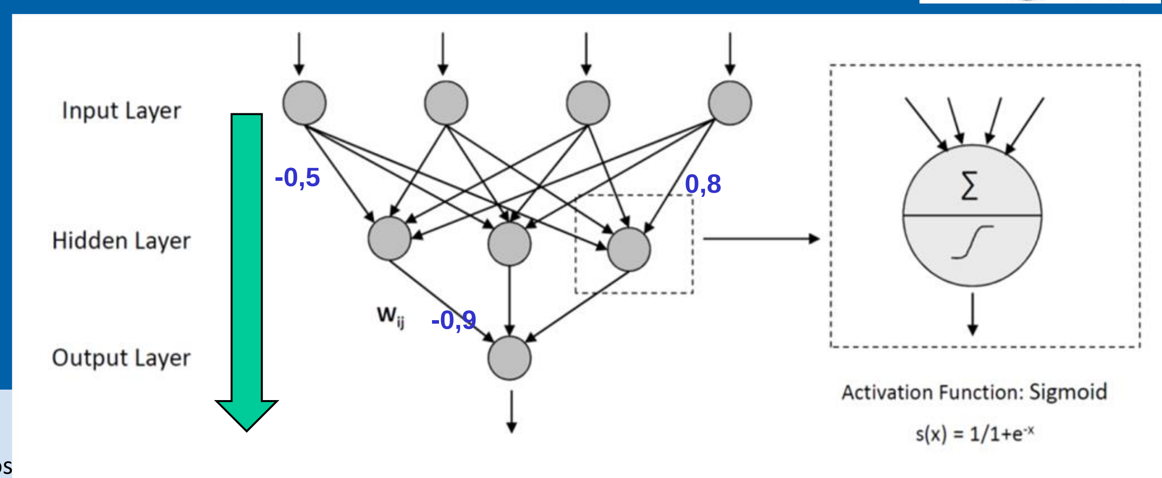
Statistics, Weights of evidence, Artificial neural networks, Random forests, Logistic regression, ….

- Functionality: simulate a biological neural system
- Consists of artificial neurons
- In most cases layer-like configuration
- Apply “knowledge” to unknown areas.

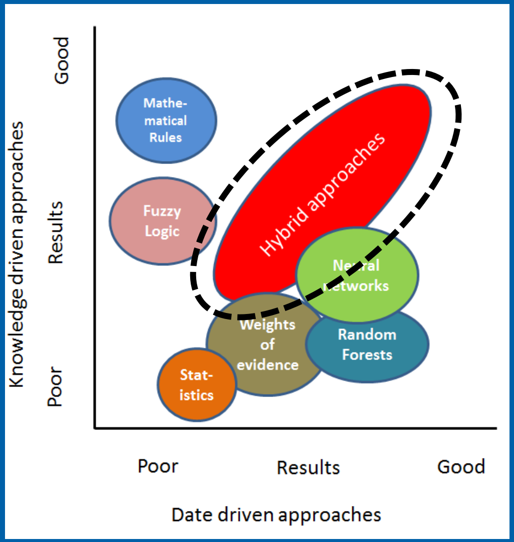
Artificial neural networks (ANN)



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 controling 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/ likelyhood) at a site (ranked between 0 and 1)?

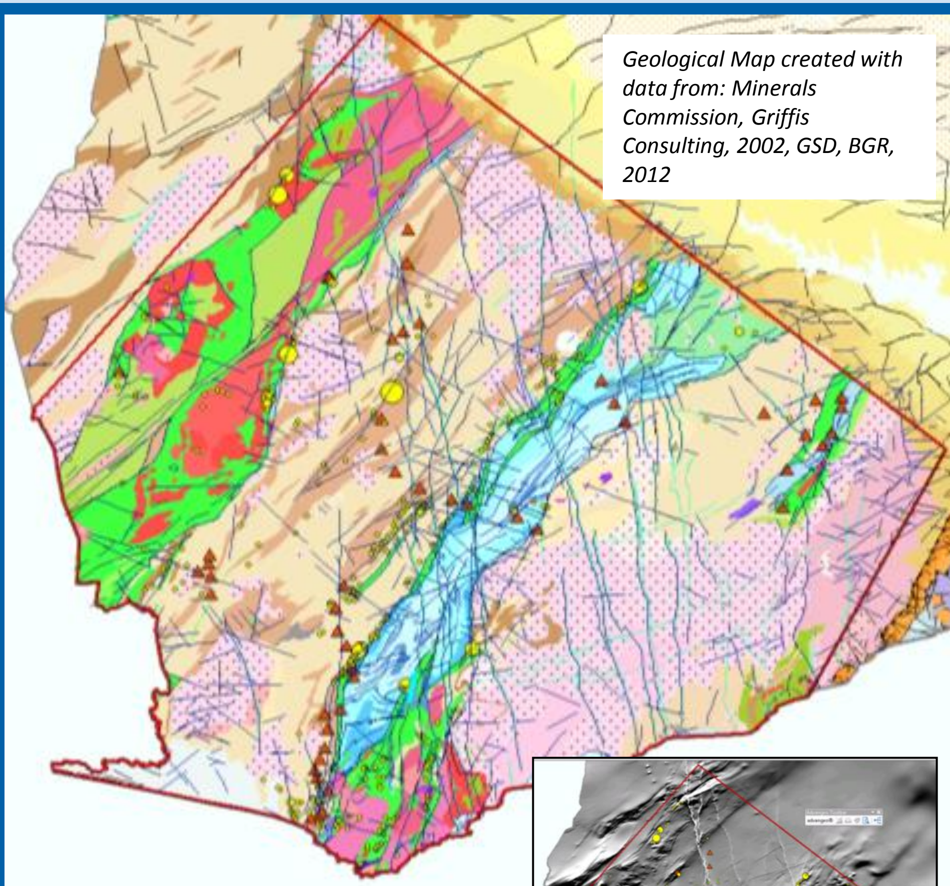
Quantitative Modelling answers the questions:

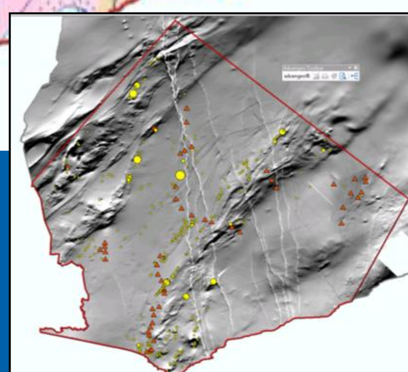
- Where ?
- How much at a site (grades, tonnages or similar)?

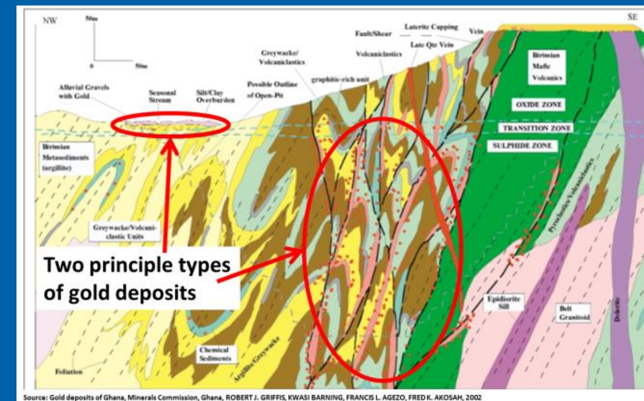
Quantitative modelling becomes possible if we use numbers, e.g. grades/ specific resources as input values, e.g. for neural network applications.

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



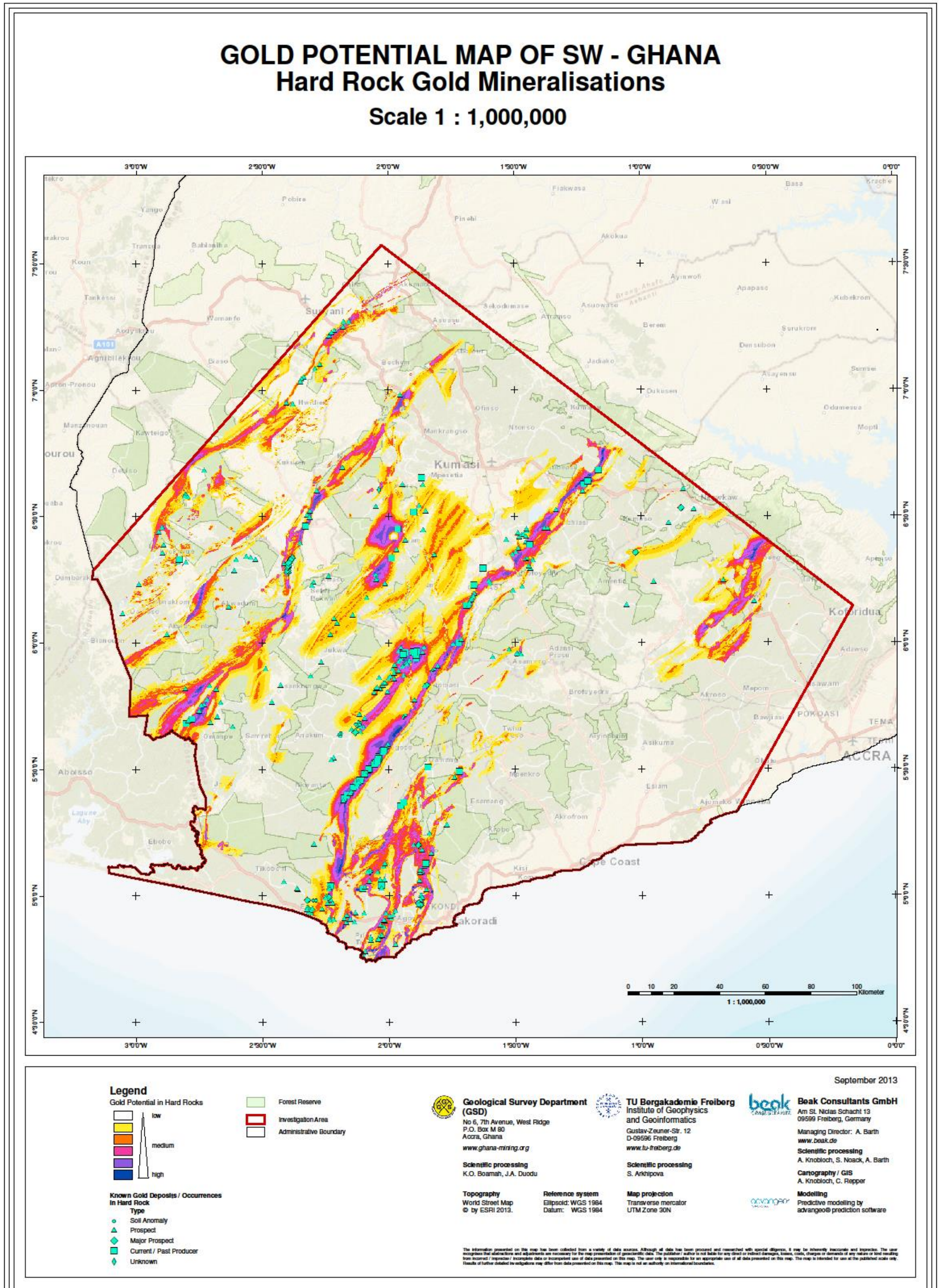




Source: Gold deposits of Ghana, Minerals Commission, Ghana, ROBERT J. GRIFFIS, KWASI BARNING, FRANCIS L. AGEZO, FRED K. AKOSAH, 2002

- 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

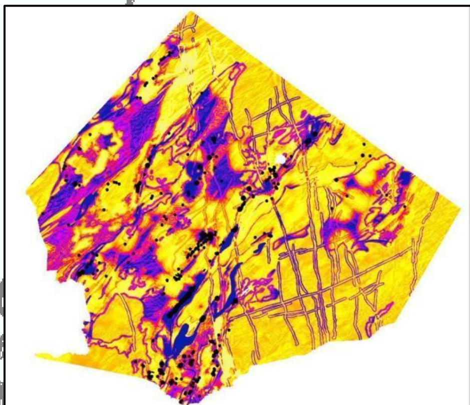
Qualitative modelling.

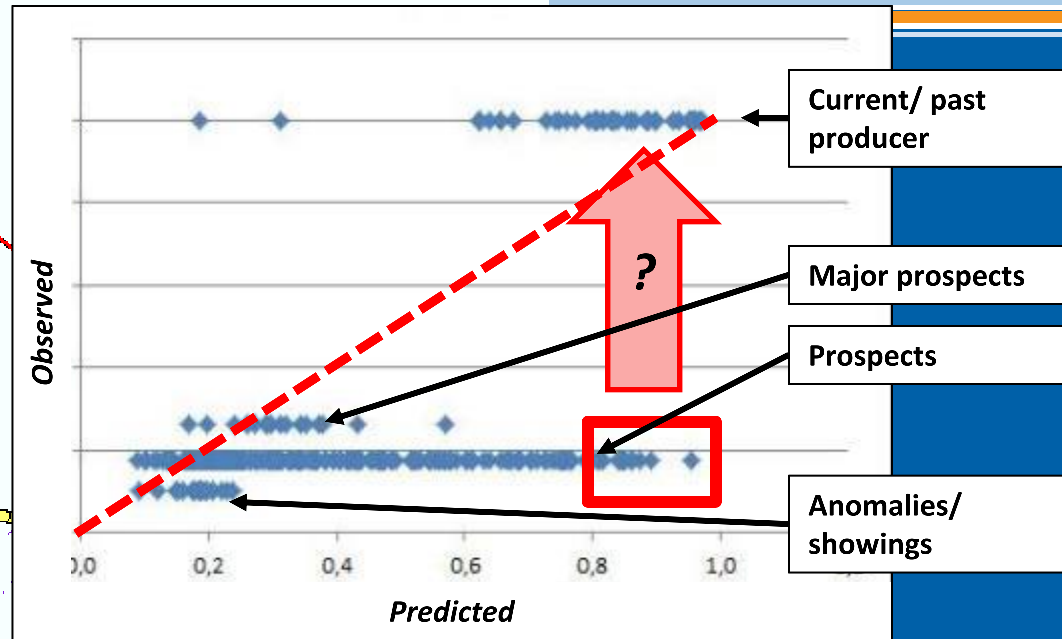
The ANN created predictive map is:

- 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.



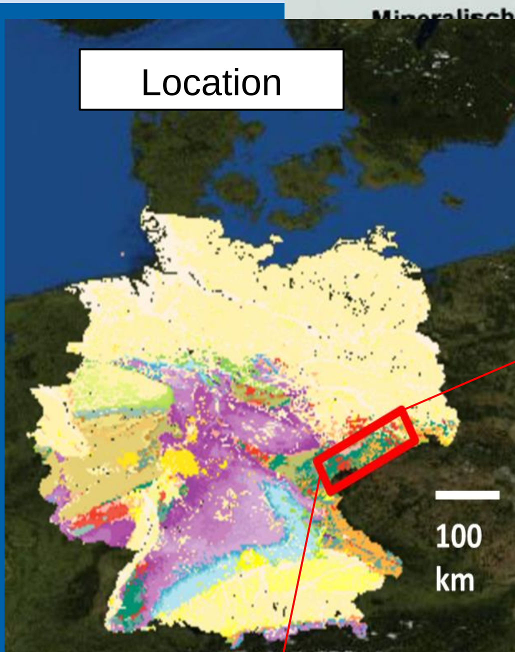


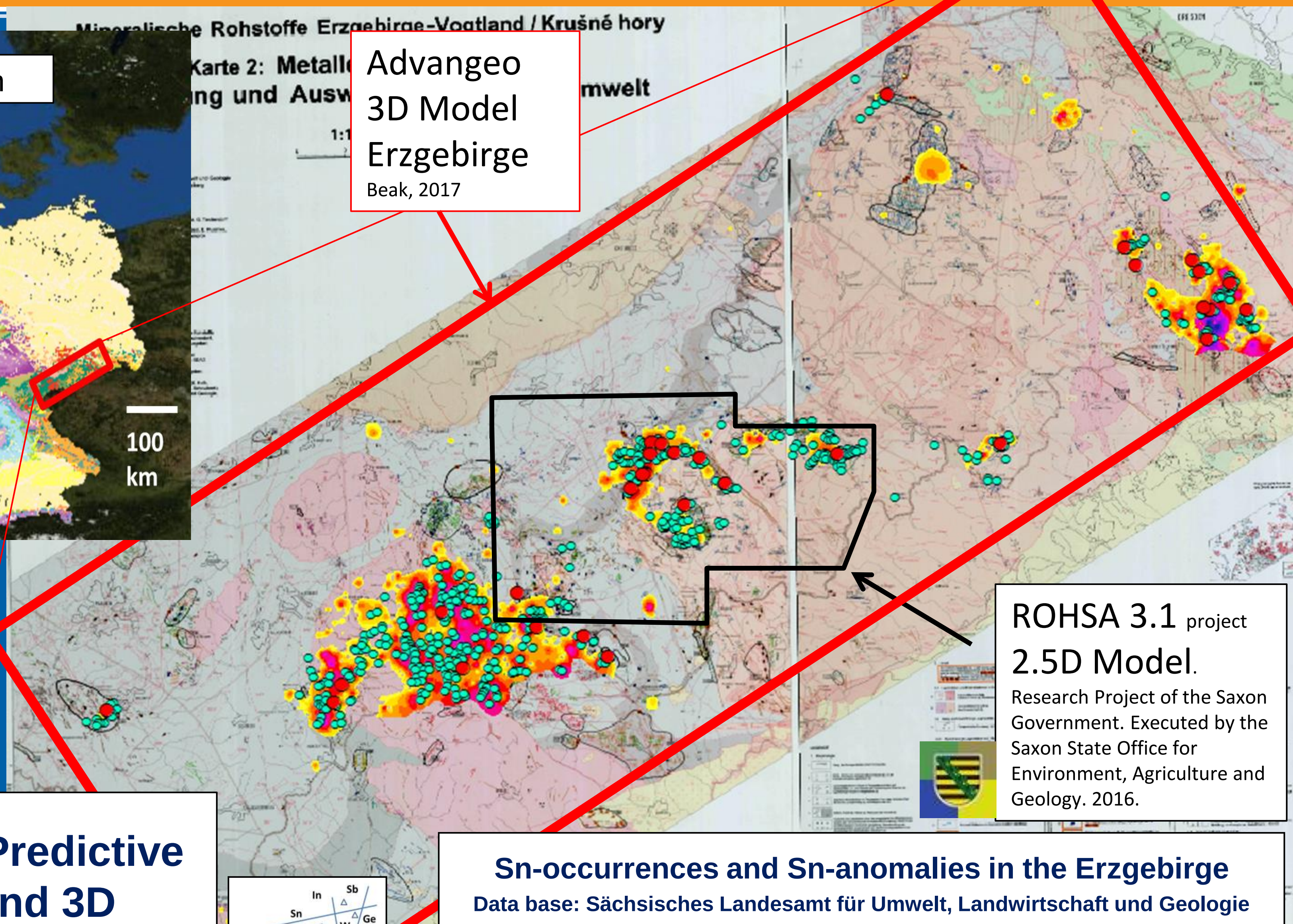
Prospects located in areas with a potential of > 0.8

All other prospects

Barth, Knobloch, Boamah, 2013

Identification of new opportunities in a traditional mining region





Advangeo
3D Model
Erzgebirge
Beak, 2017

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.

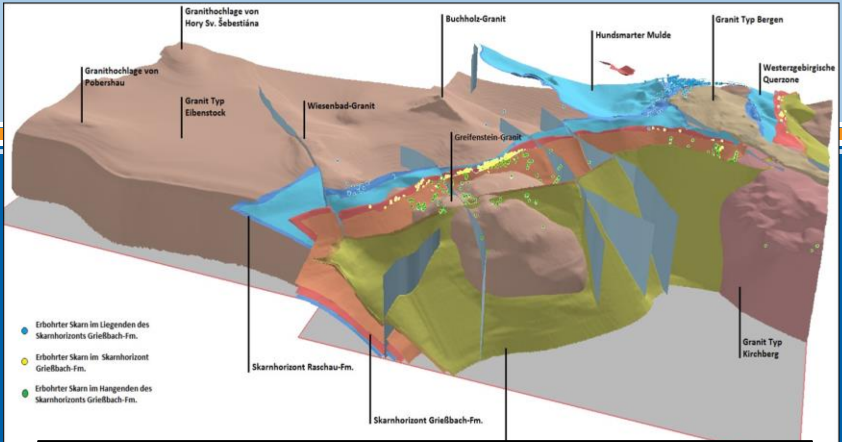
Sn-occurrences and Sn-anomalies in the Erzgebirge
Data base: Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie

Kartengrundlage: Hösel, G., u.a. (1990): Mineralische Rohstoffe Erzgebirge – Vogtland / Krusne Hory 1:100.000. Sächsisches Landesamt für Umwelt und Geologie, Bereich Boden und Geologie, Freiberg.

Method: Predictive 2,5D and 3D Modelling with ANN

WISTAMERZ

Predictive 2,5D and 3D Modelling: approaches and preconditions



Granites, main faults and carbonate layers

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

GIS is sufficient.

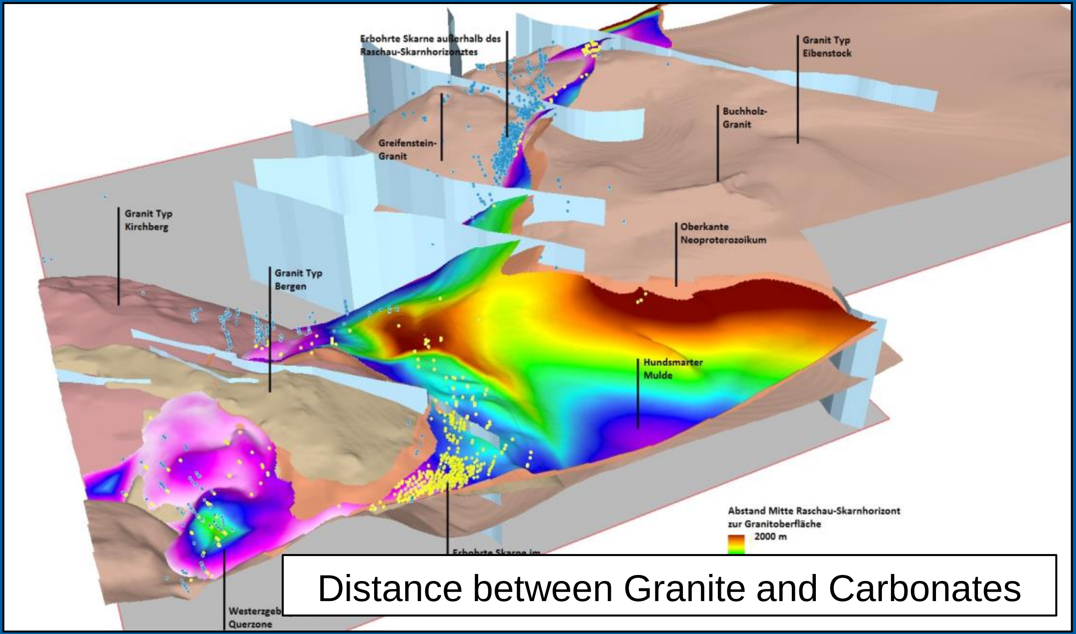
3 D Modelling: using Voxel models. Real 3D software required.

Algorithms:

- Similar to 2D: knowledge based, data driven, hybrid

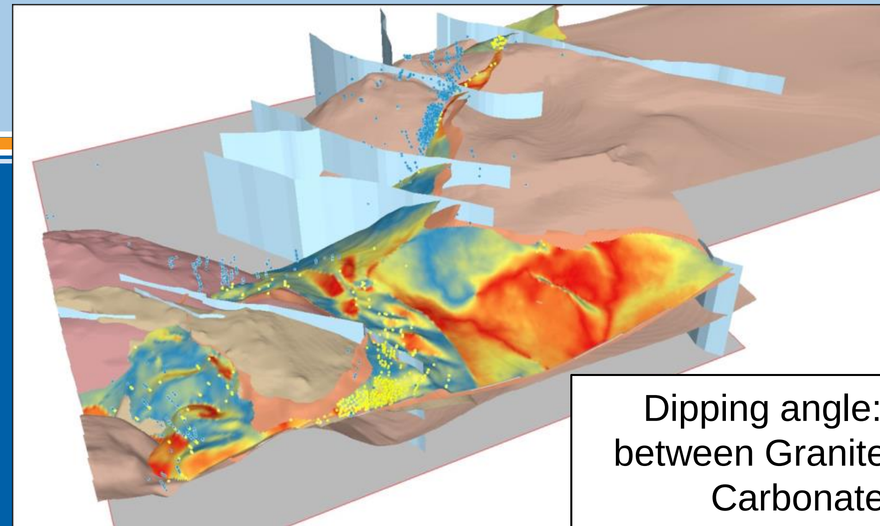
Preconditions:

- High quality 3D data: geology, geophysics, geochemistry, minerals
- Software



Distance between Granite and Carbonates

The 2,5D model of the Central Erzgebirge



Dipping angle: Difference between Granite surface and Carbonate layers

Algorithms:

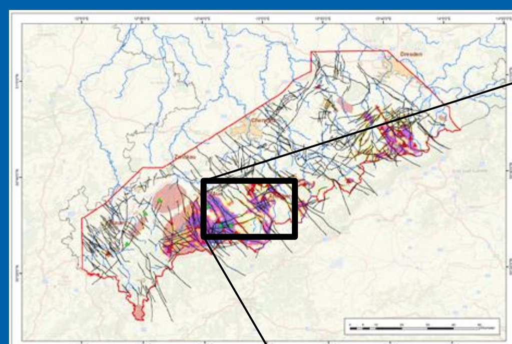
- ANN

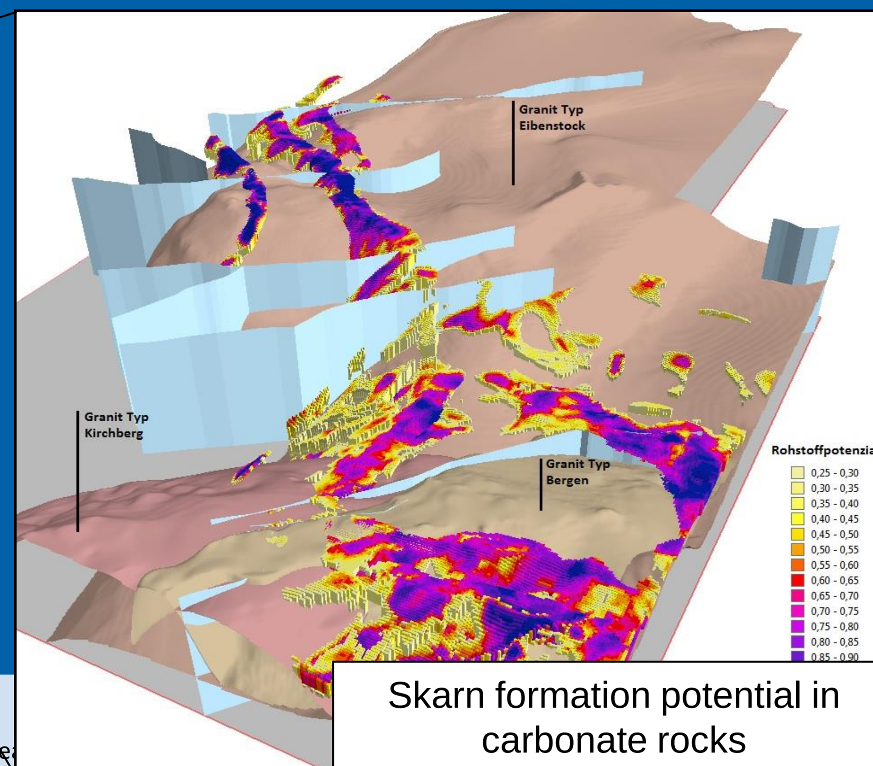
Software:

ESRI & advangeo®

Database:

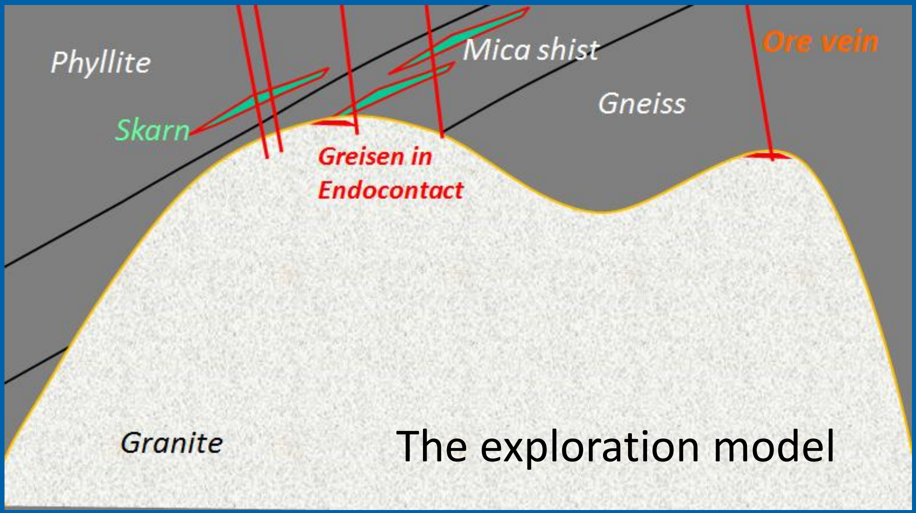
- 196 Reports
- 531 Maps
- 423 Sections
- 2014 Bore holes > 20m
- Geochemichal data
- Geophysical data





Skarn formation potential in carbonate rocks

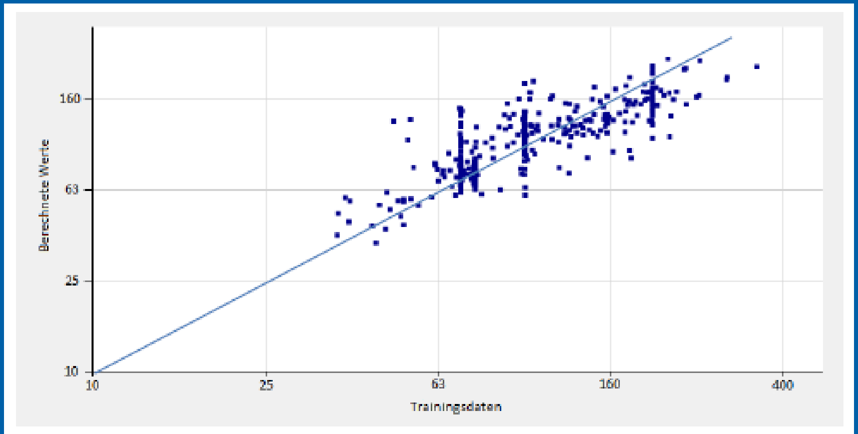
Estimated amount of Sn in skarns in the Central Erzgebirge

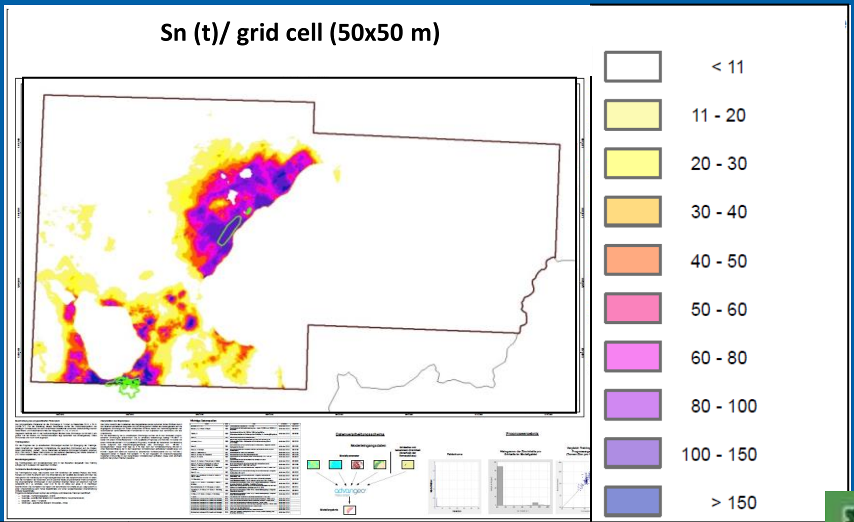


Tin content:

- Within the contour > 0,25: 775.888 t
- Within the contour > 0,5: 593.034 t

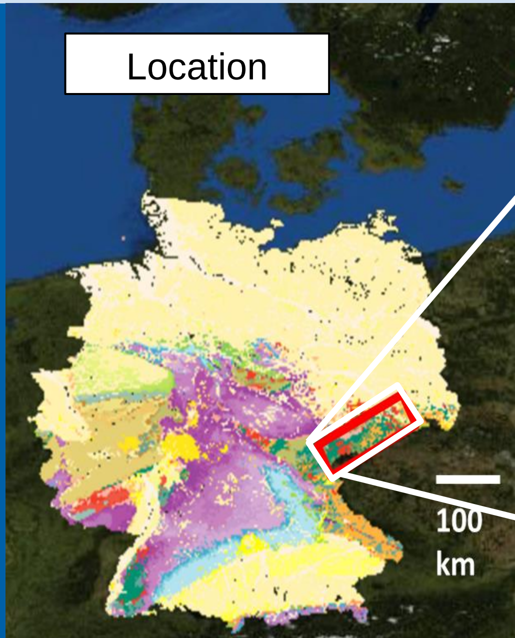
Known Tin Resources of all classes: 83.490 t
Estimated from model data within these blocks: 86.040 t
11 % of the estimated Sn potential are doscovered so far

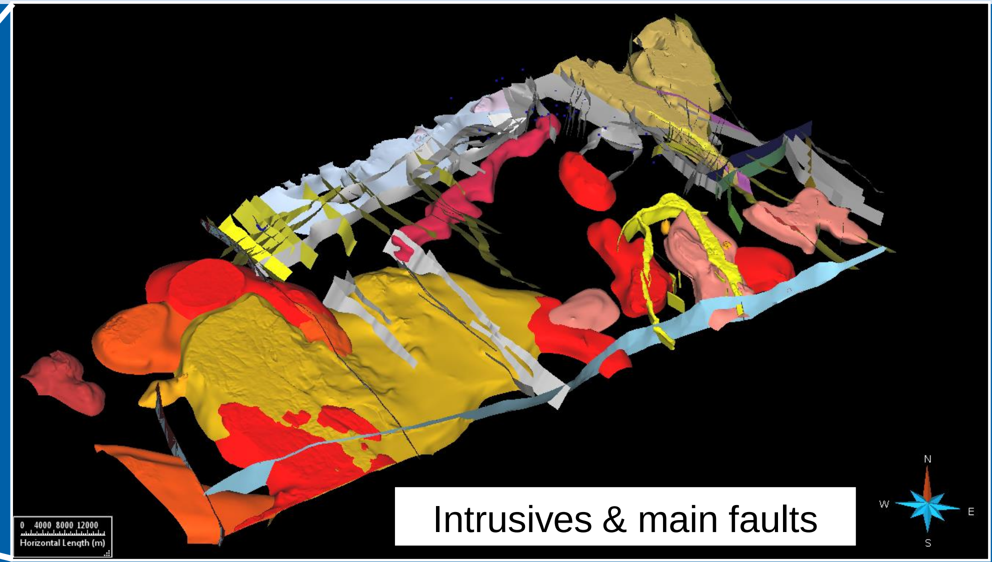




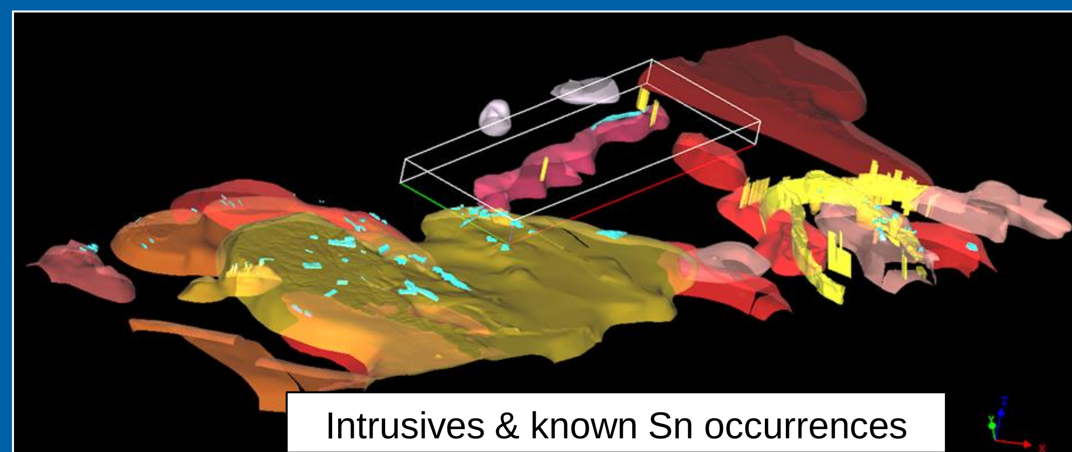
Data base: Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie	2.5D Model of the ROHSA 3.1 Project

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



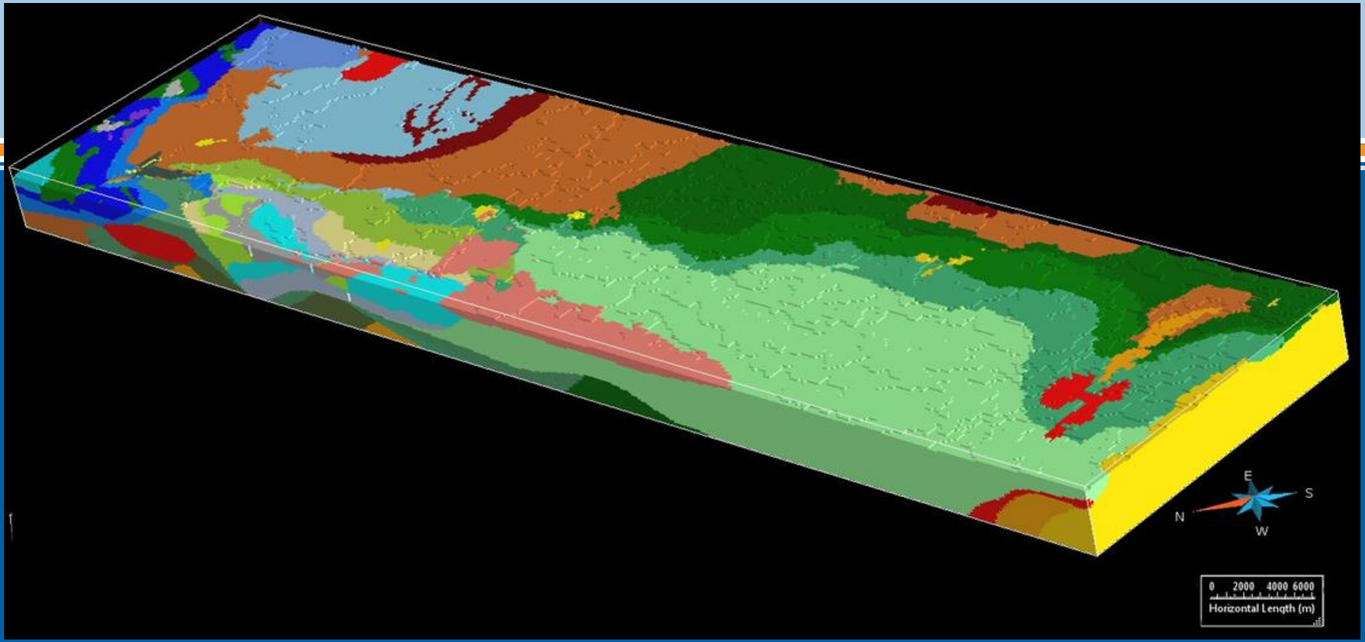
Base Data provided by Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie

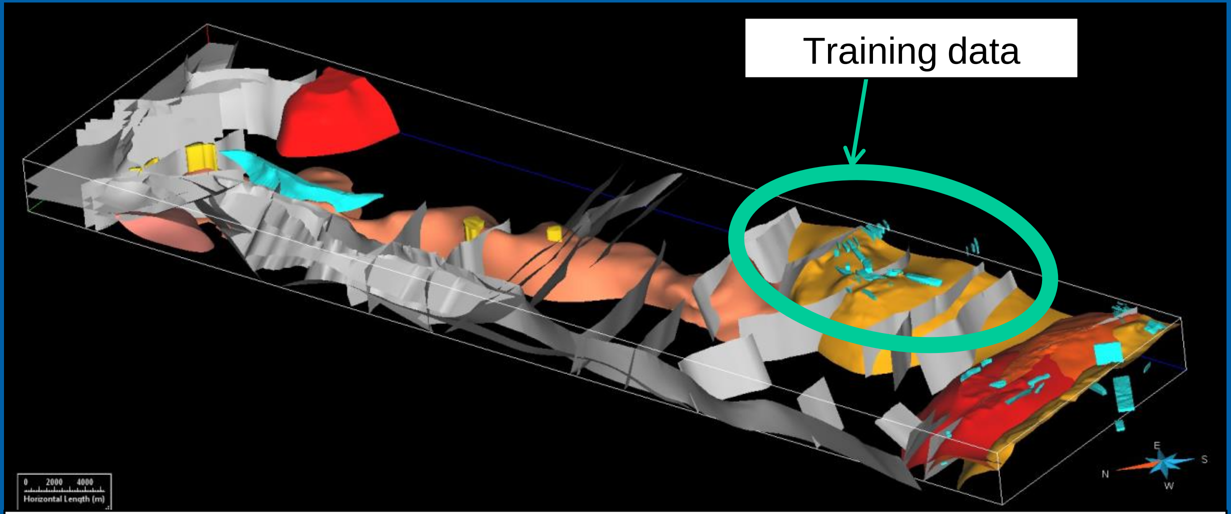
Modelling the Northern Rim

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®

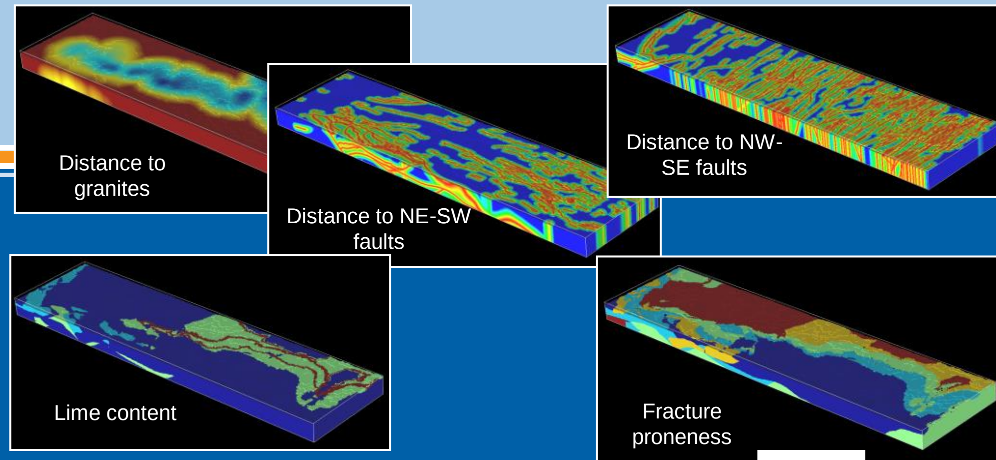


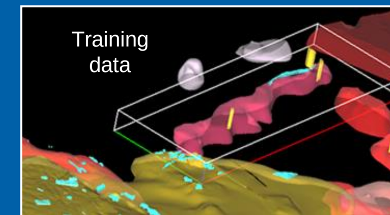


Base Data provided by Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie

Sn in the Northern Rim

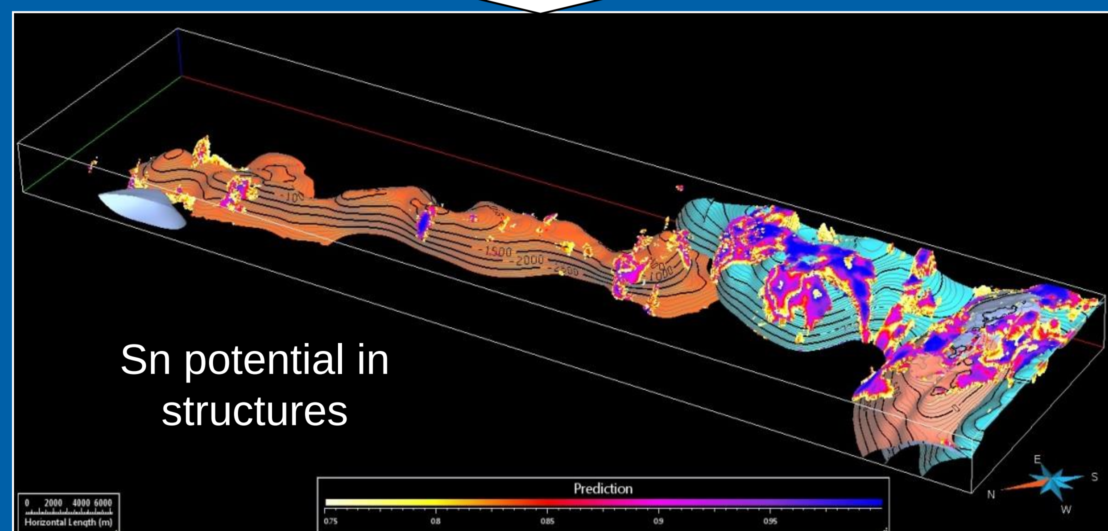
Consideration of real 3D properties derived from the geological model.





Sn skarn and Sn vein potential modelled by using ANN.

3D advangeo® Prediction Software

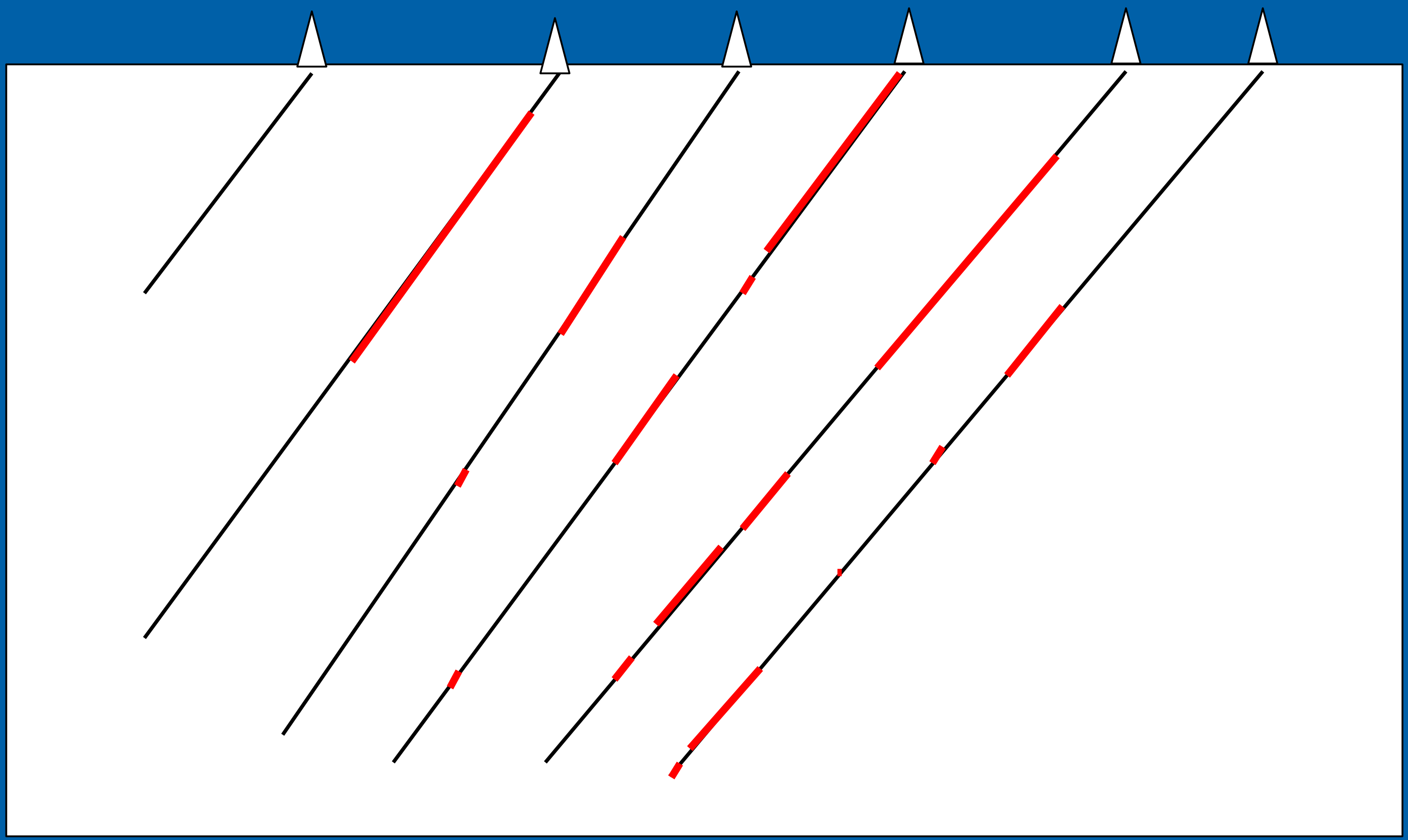


Base Data provided by Sächsisches Landesamt für Umwelt, Landwirtschaft und Geologie

Please see the poster session:

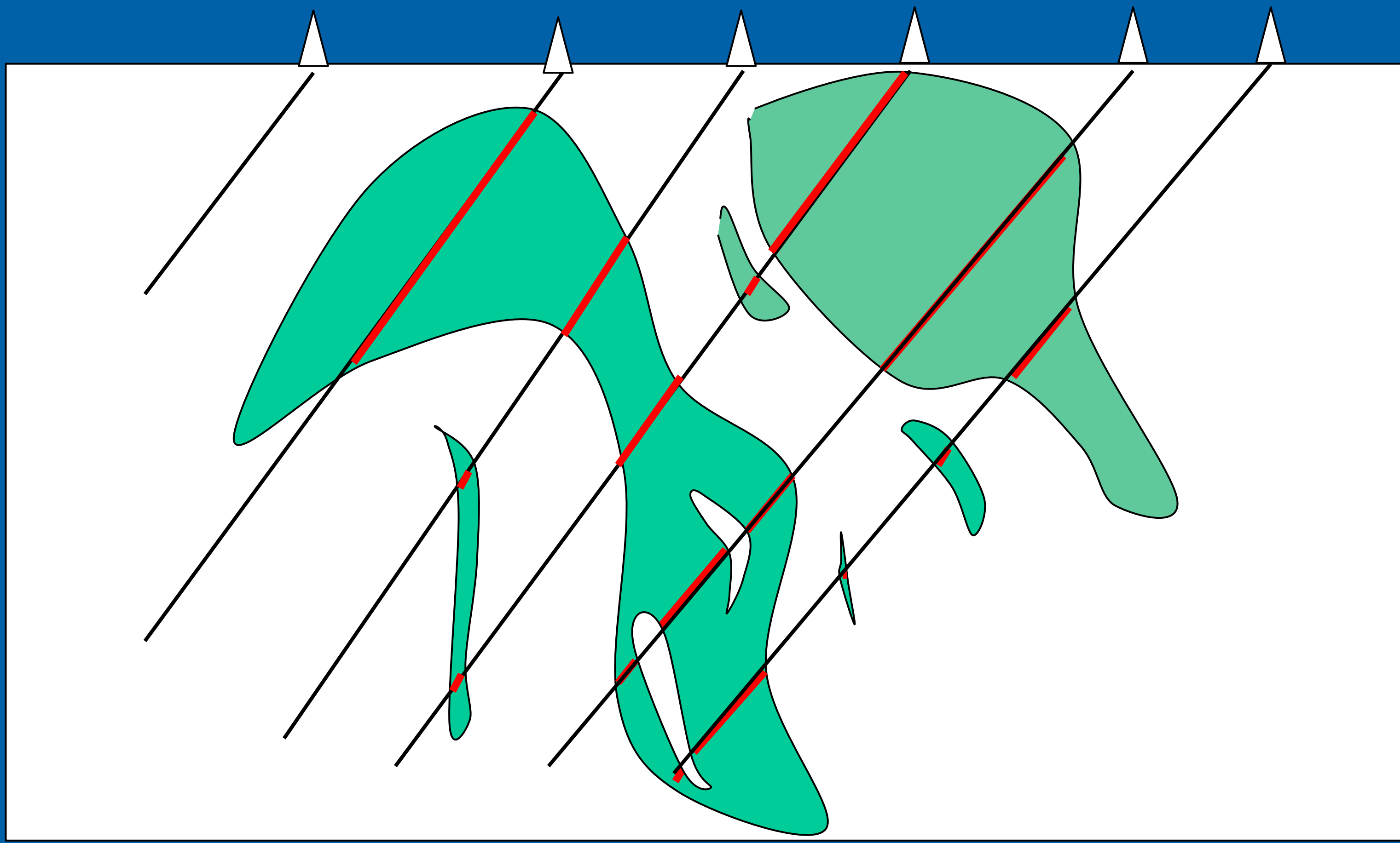
Brosig et. al: Mineral predictive mapping in 2D, 2.5D and 3D using Artificial Neural Networks – Case study of Sn and W deposits in the Erzgebirge, Germany

How reliable is the model ?

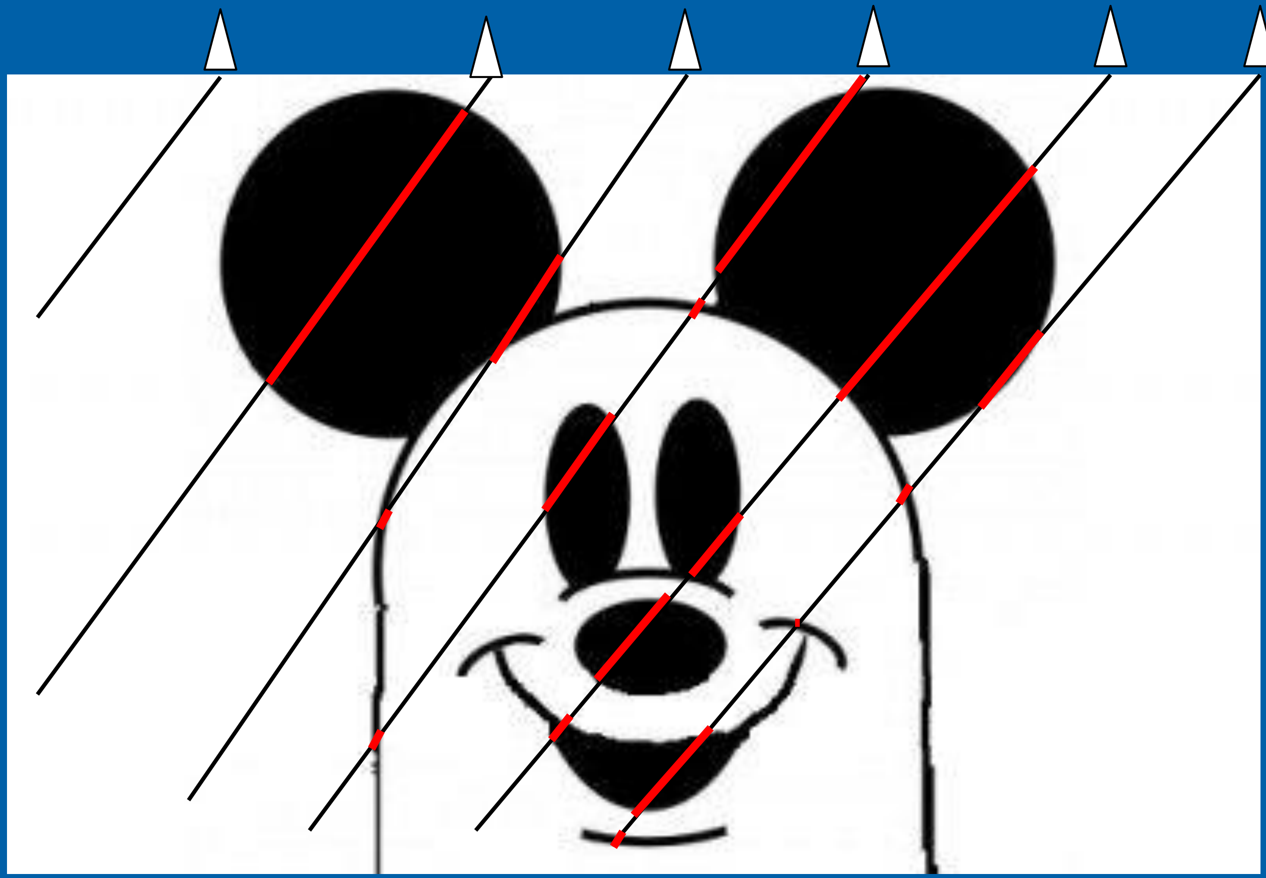


What kind of ore bodies are behind this drilled pattern?

This interpretation looks reasonable…….



But this is possible as well.

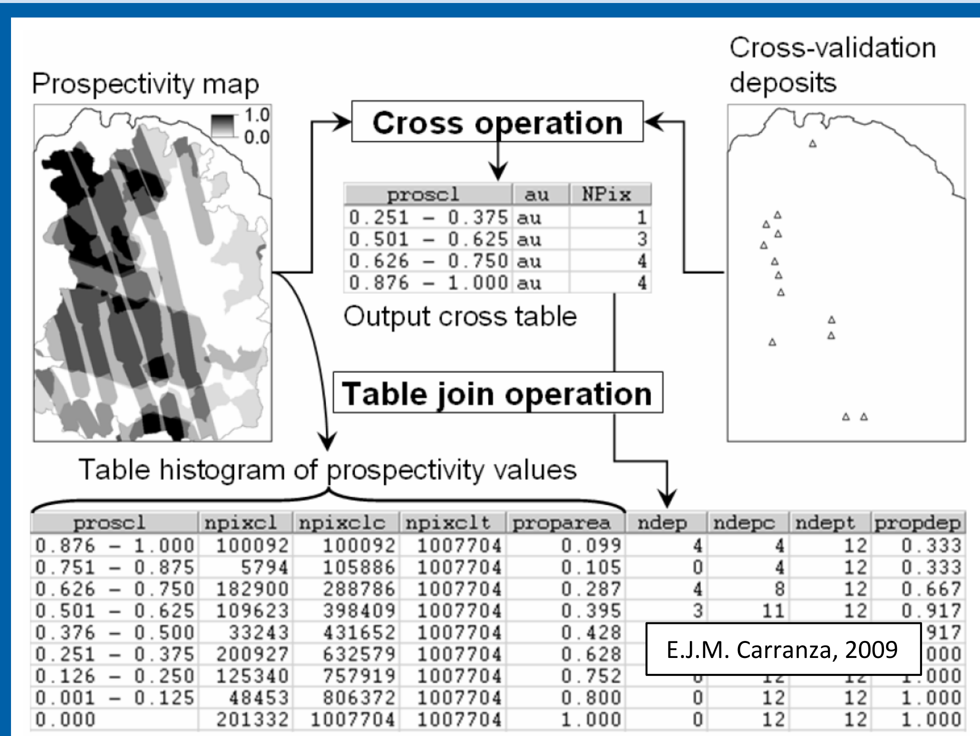


Model verification procedures

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

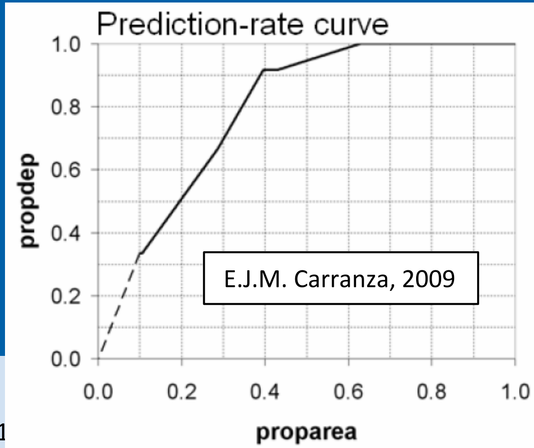
Important approaches:

- 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 plausibilty/ value of the weights (ANN)

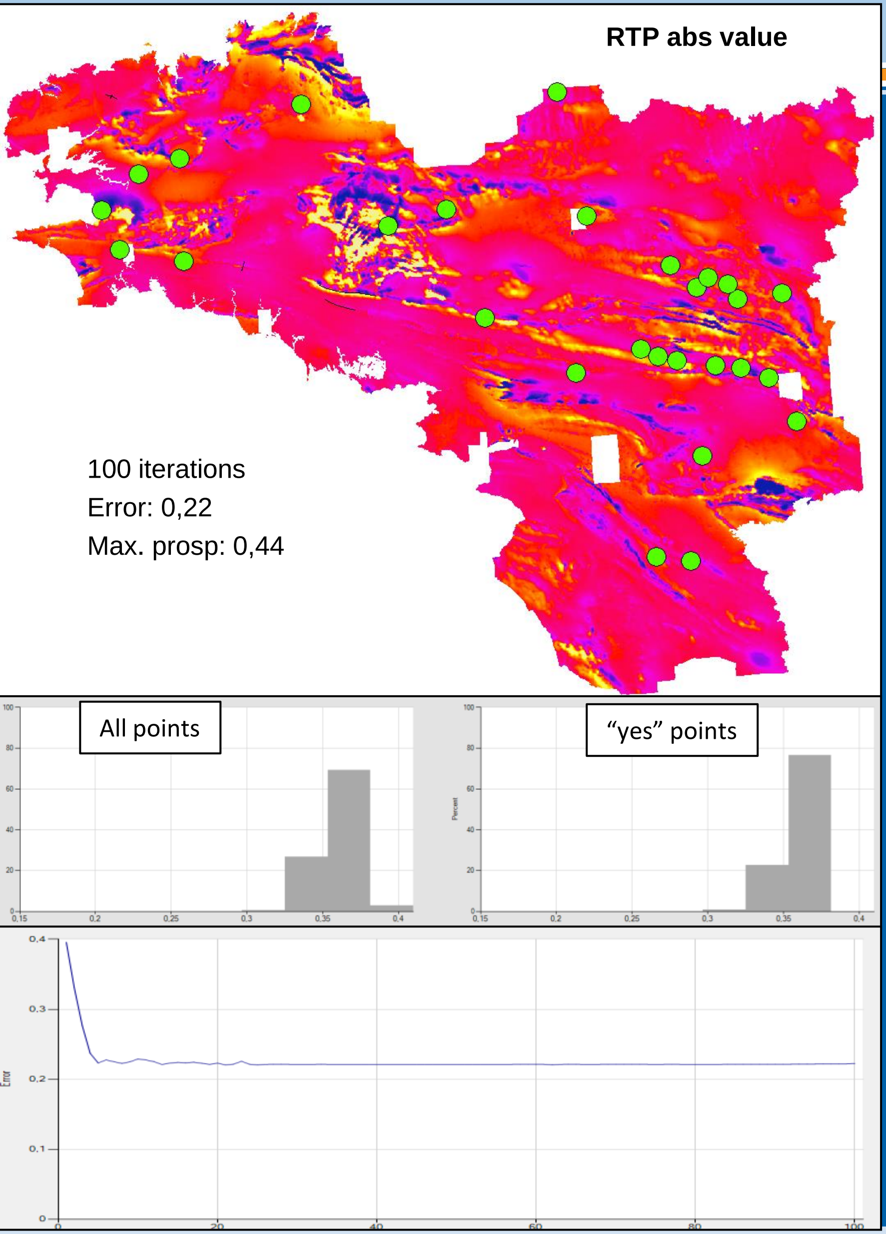


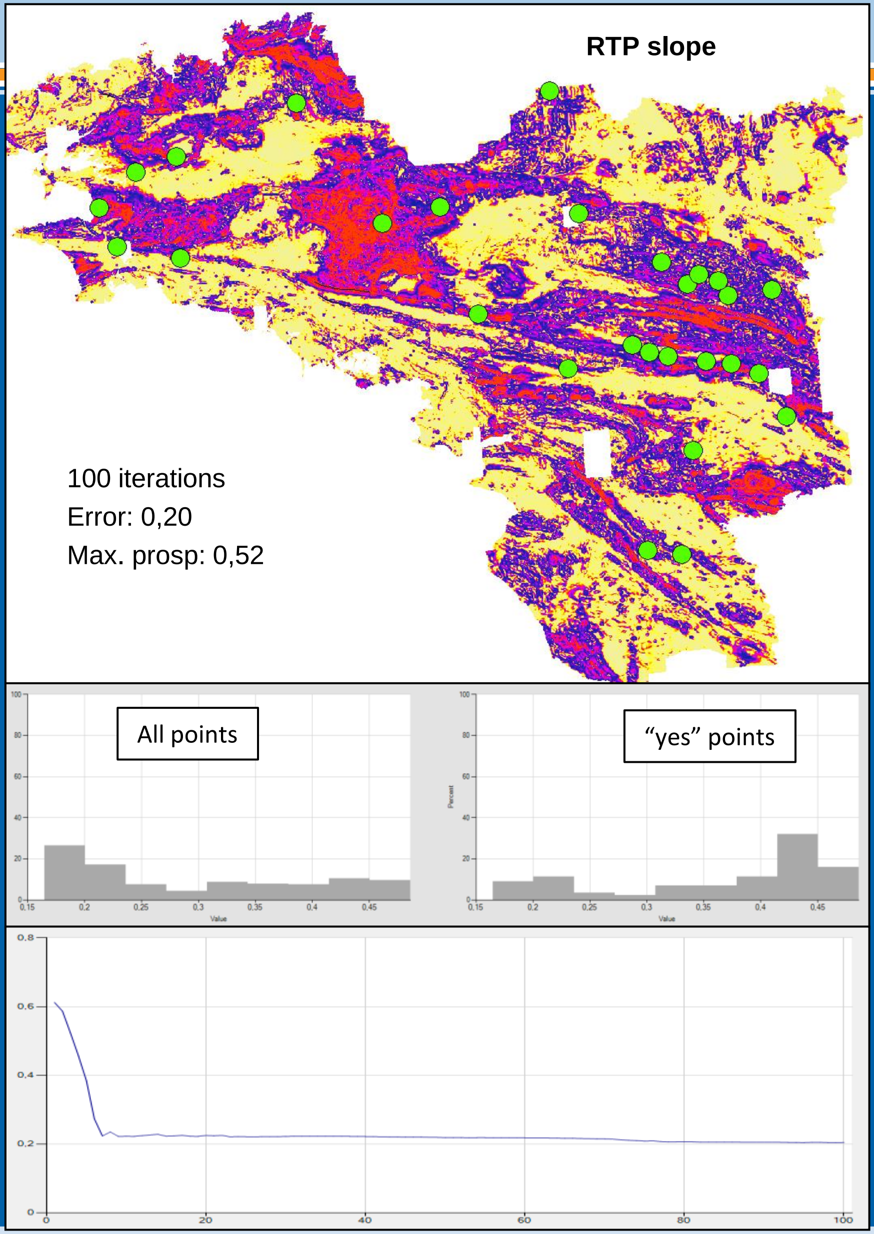
proscl	au	NPix
0.251 – 0.375	au	1
0.501 – 0.625	au	3
0.626 – 0.750	au	4
0.876 – 1.000	au	4

proscl	npixcl	npixclc	npixclt	proparea	ndep	ndepc	ndept	propdep
0.876 – 1.000	100092	100092	1007704	0.099	4	4	12	0.333
0.751 – 0.875	5794	105886	1007704	0.105	0	4	12	0.333
0.626 – 0.750	182900	288786	1007704	0.287	4	8	12	0.667
0.501 – 0.625	109623	398409	1007704	0.395	3	11	12	0.917
0.376 – 0.500	33243	431652	1007704	0.428	[illegible]	[illegible]	[illegible]	917
0.251 – 0.375	200927	632579	1007704	0.628	[illegible]	[illegible]	[illegible]	000
0.126 – 0.250	125340	757919	1007704	0.752	[illegible]	[illegible]	[illegible]	[illegible]
0.001 – 0.125	48453	806372	1007704	0.800	0	12	12	1.000
0.000	201332	1007704	1007704	1.000	0	12	12	1.000

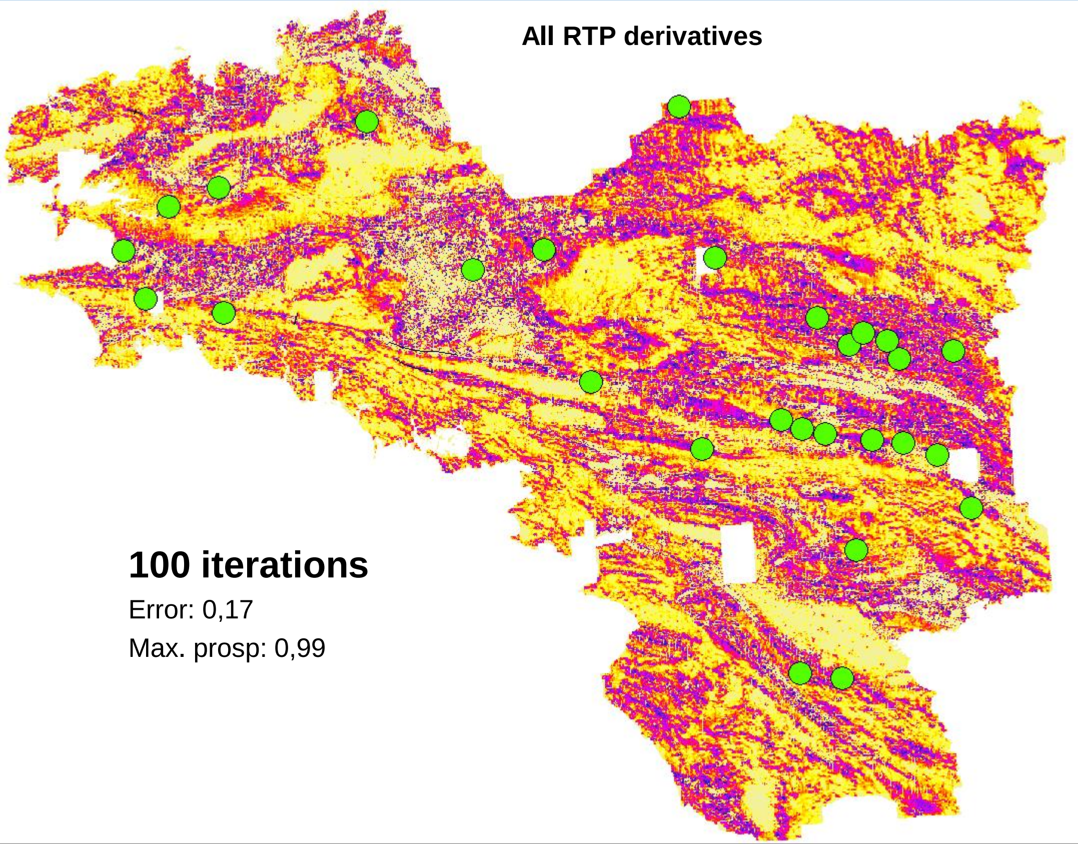


The Contest Data: ANN based Sensitivity Analysis





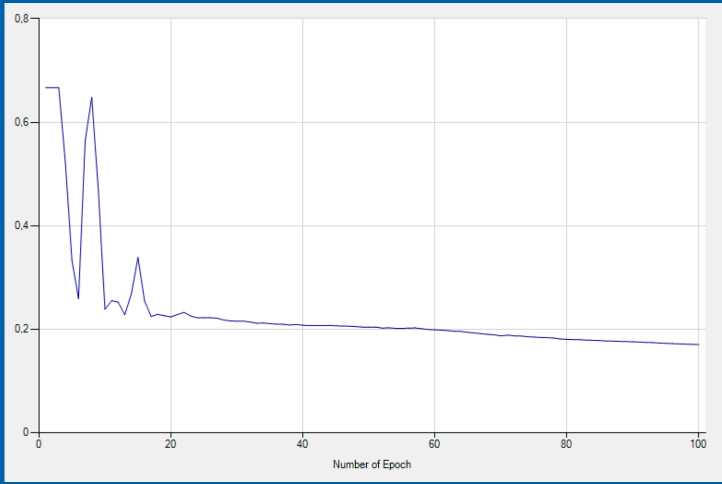
Using all RTP derivatives

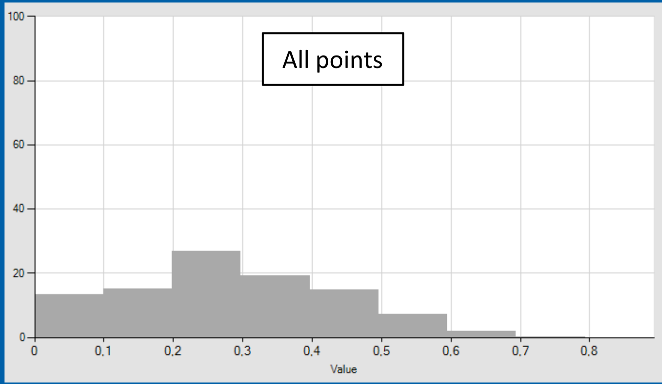


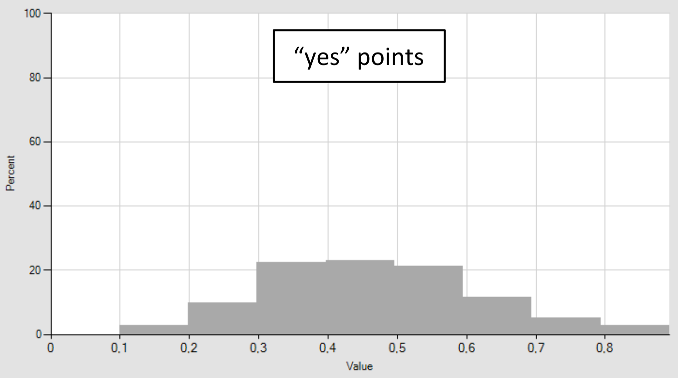
100 iterations

Error: 0,17

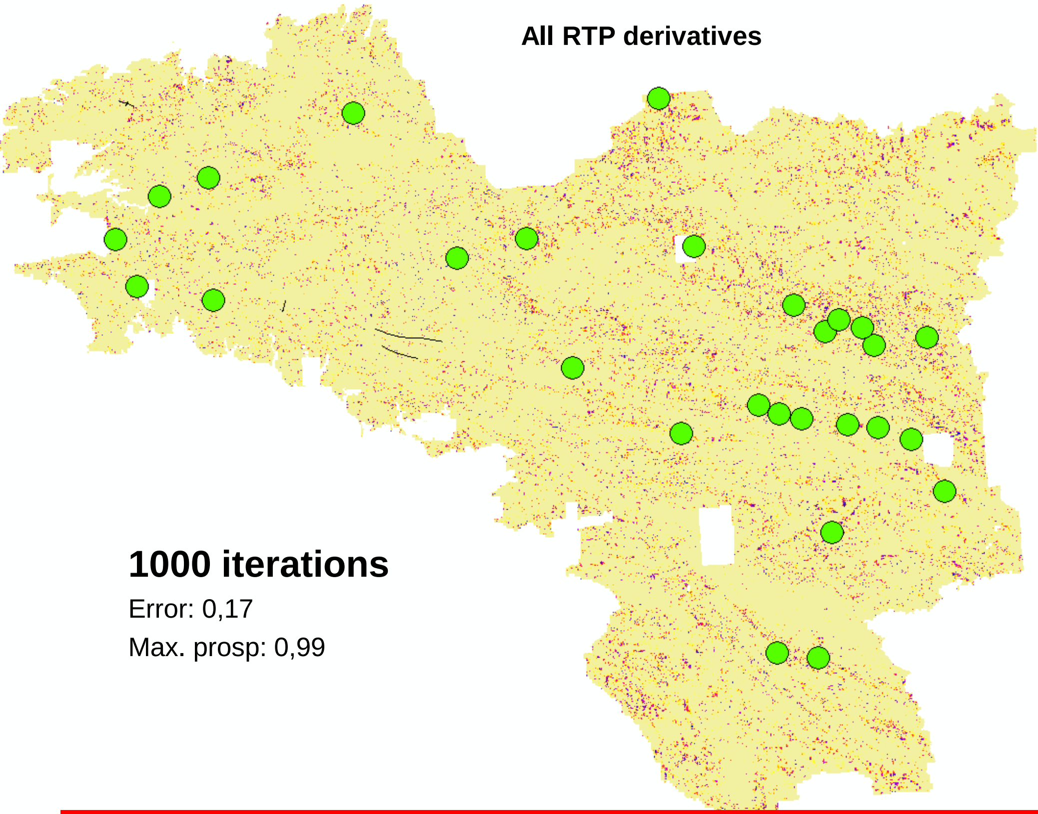
Max. prosp: 0,99







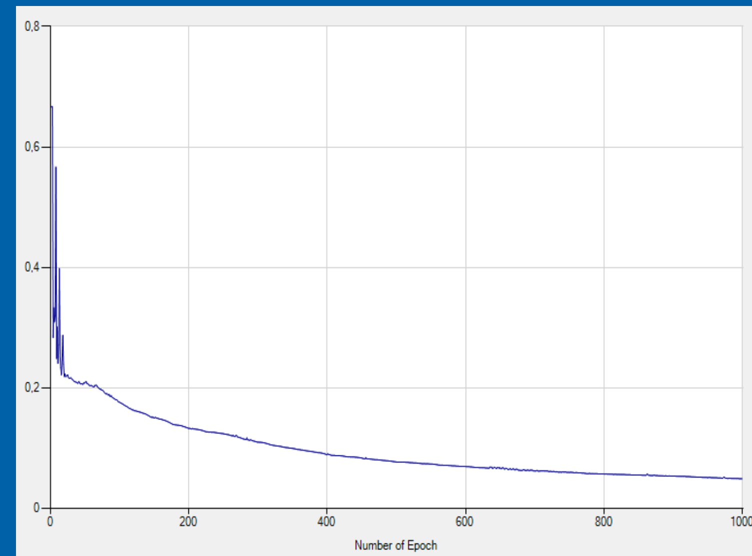
Using all RTP derivatives



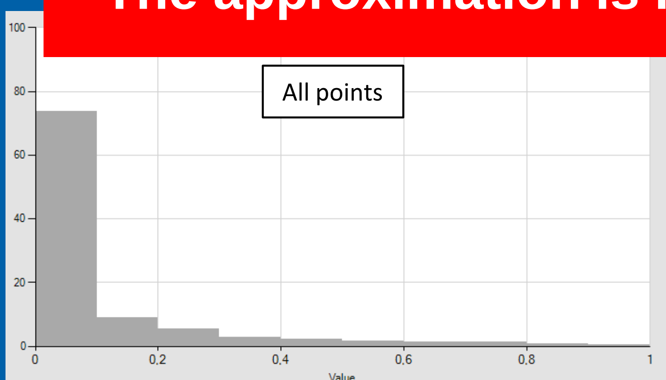
1000 iterations

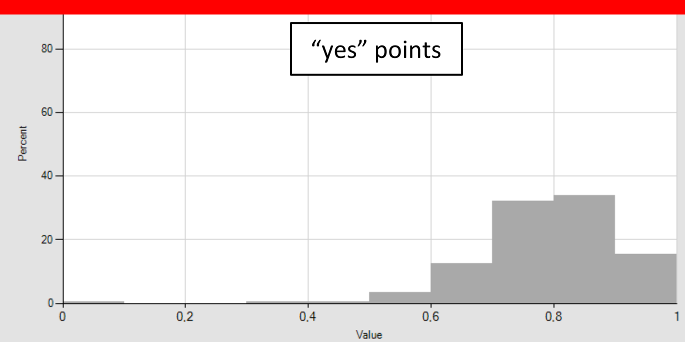
Error: 0,17

Max. prosp: 0,99

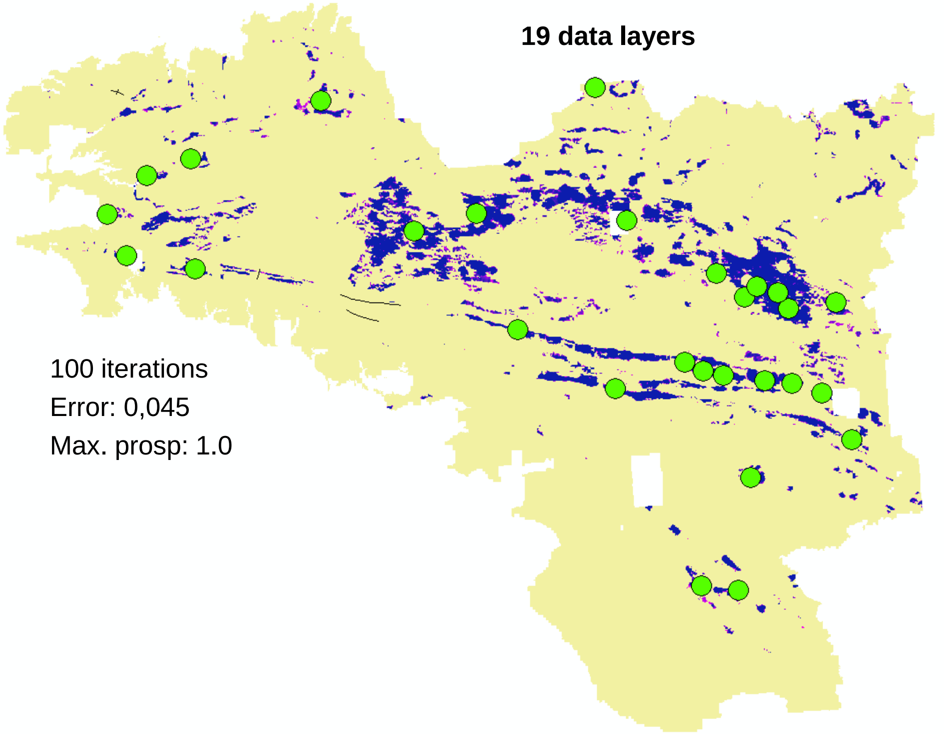


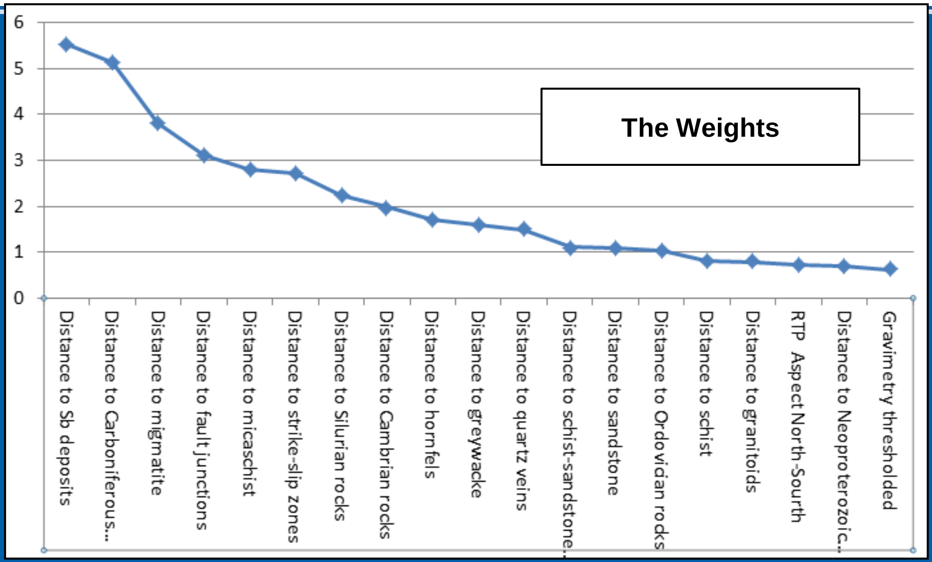
The approximation is much better, but the model is overfitted

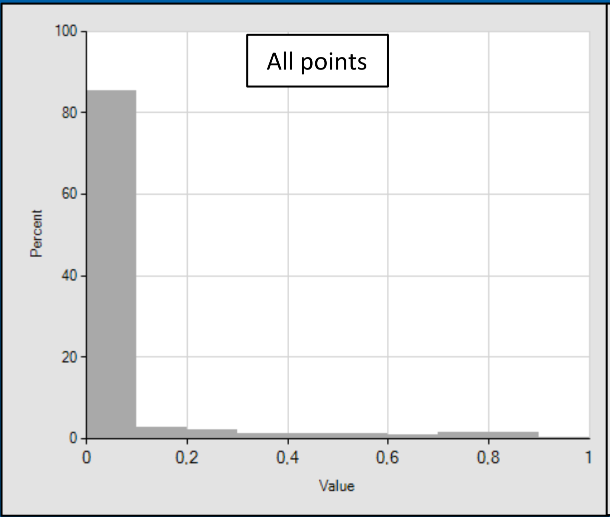


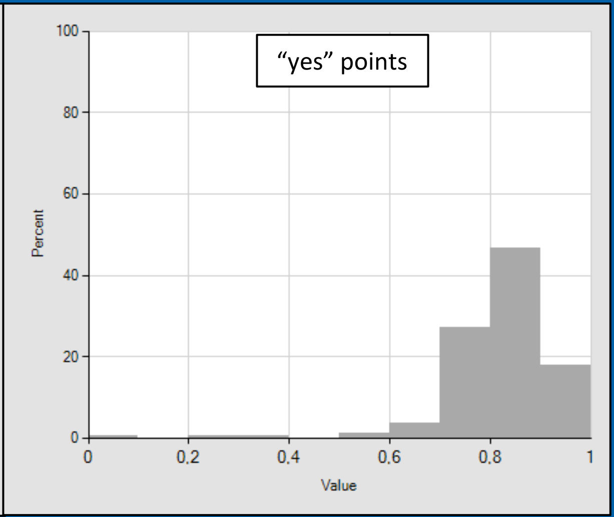


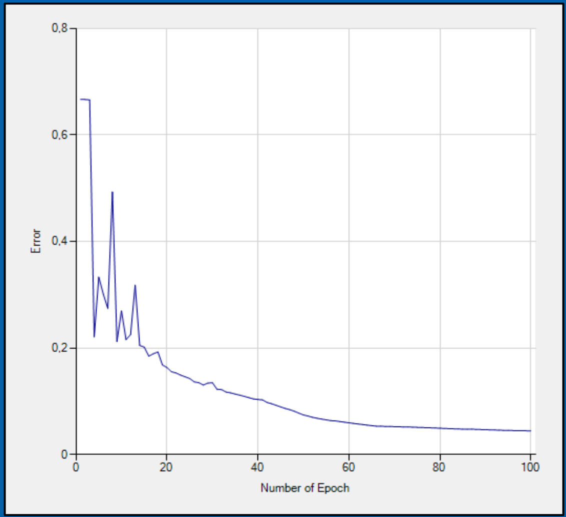
Our final model – mainly controlled by geological parameters



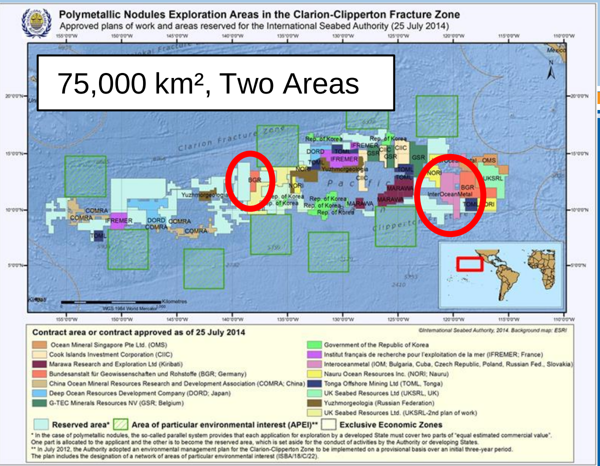




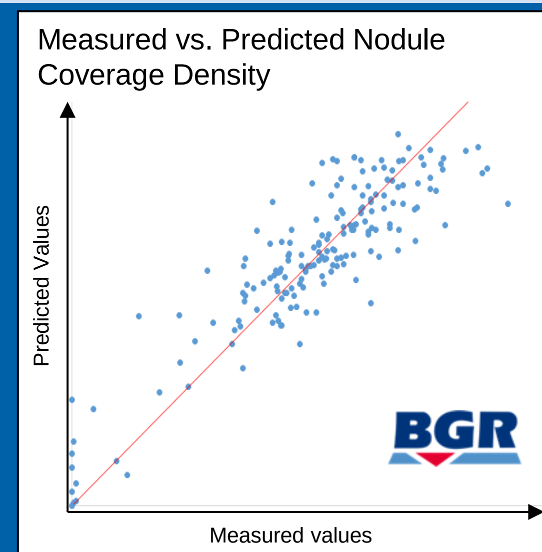


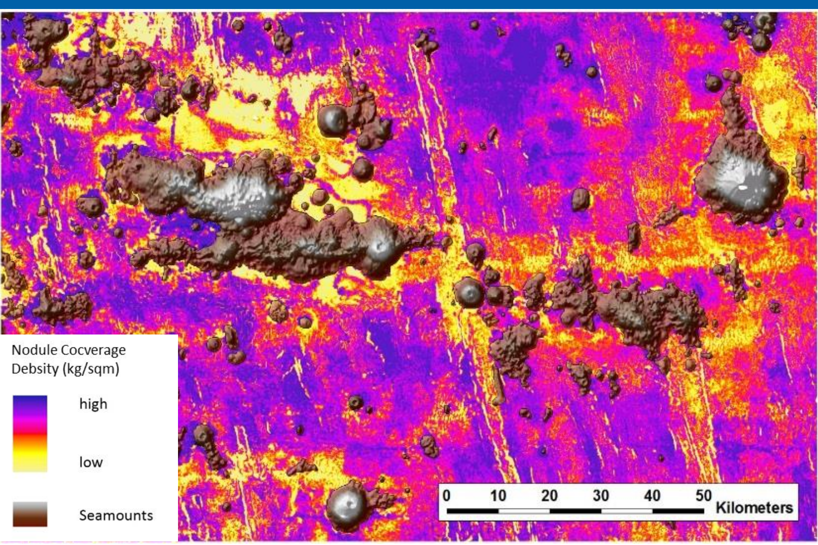


Example: Quantitative Modelling of Mn Nodule Ressources

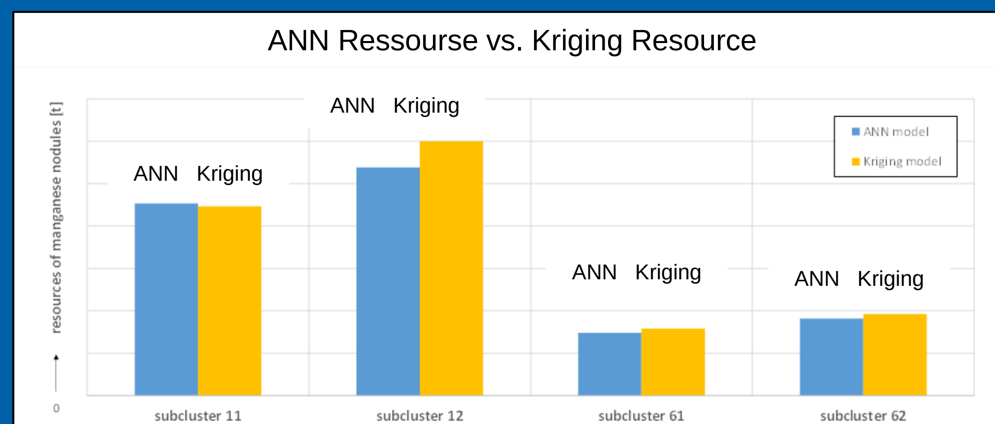


- 17 input layers
- 1000 iterations
- Excellent verification of ANN resources by classic statistics (Kriging Model)





Knobloch et al, 2015: Predictive mapping of the nodule abundance and mineral resource estimation in the Clarion-Clipperton Zone using artificial neural networks and classical geostatistical methods.

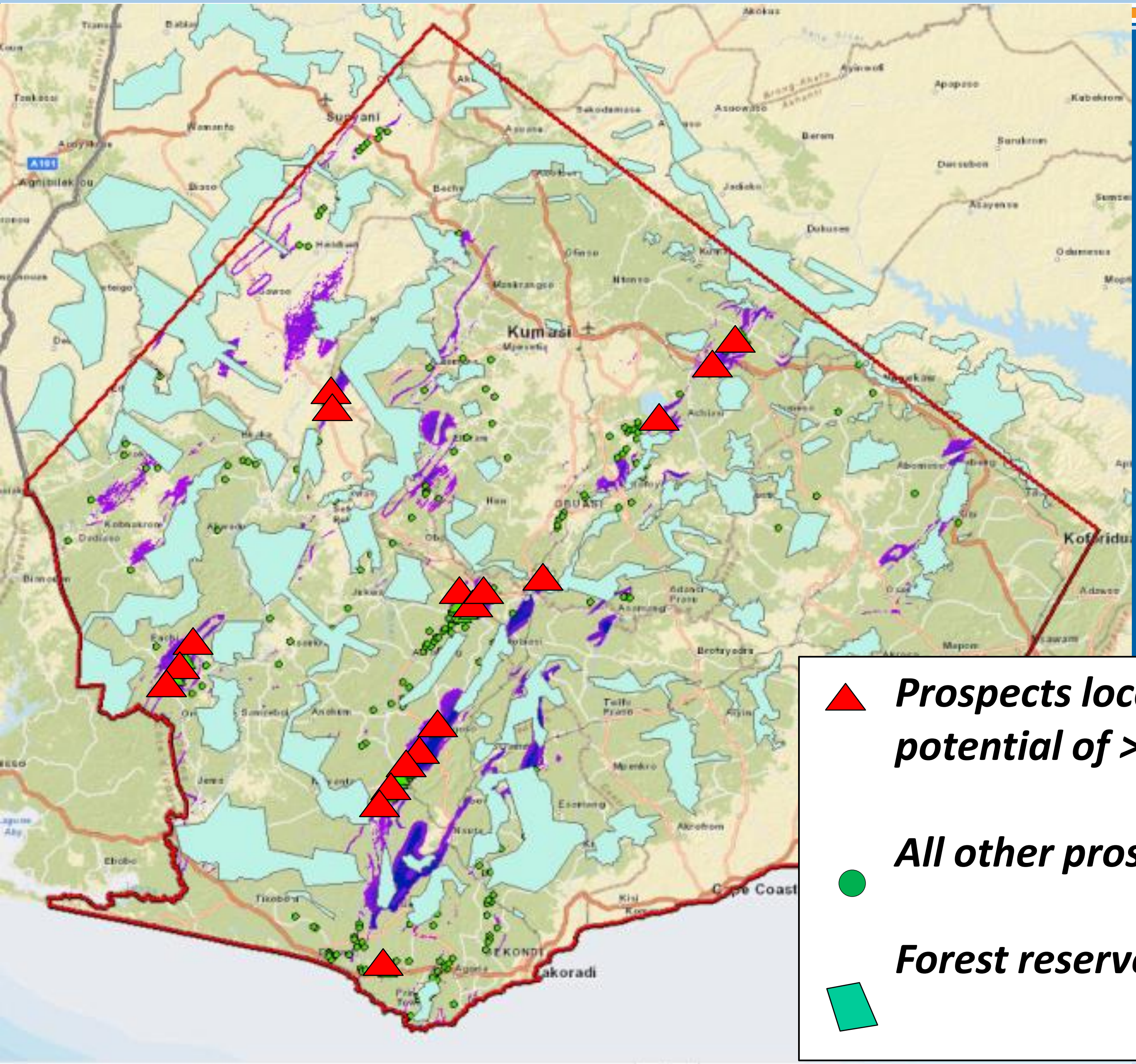


Predictive maps as value added products

- 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….

Tantalite Mining in Rwanda

Gold in SW Ghana: Conflict with forest reserves

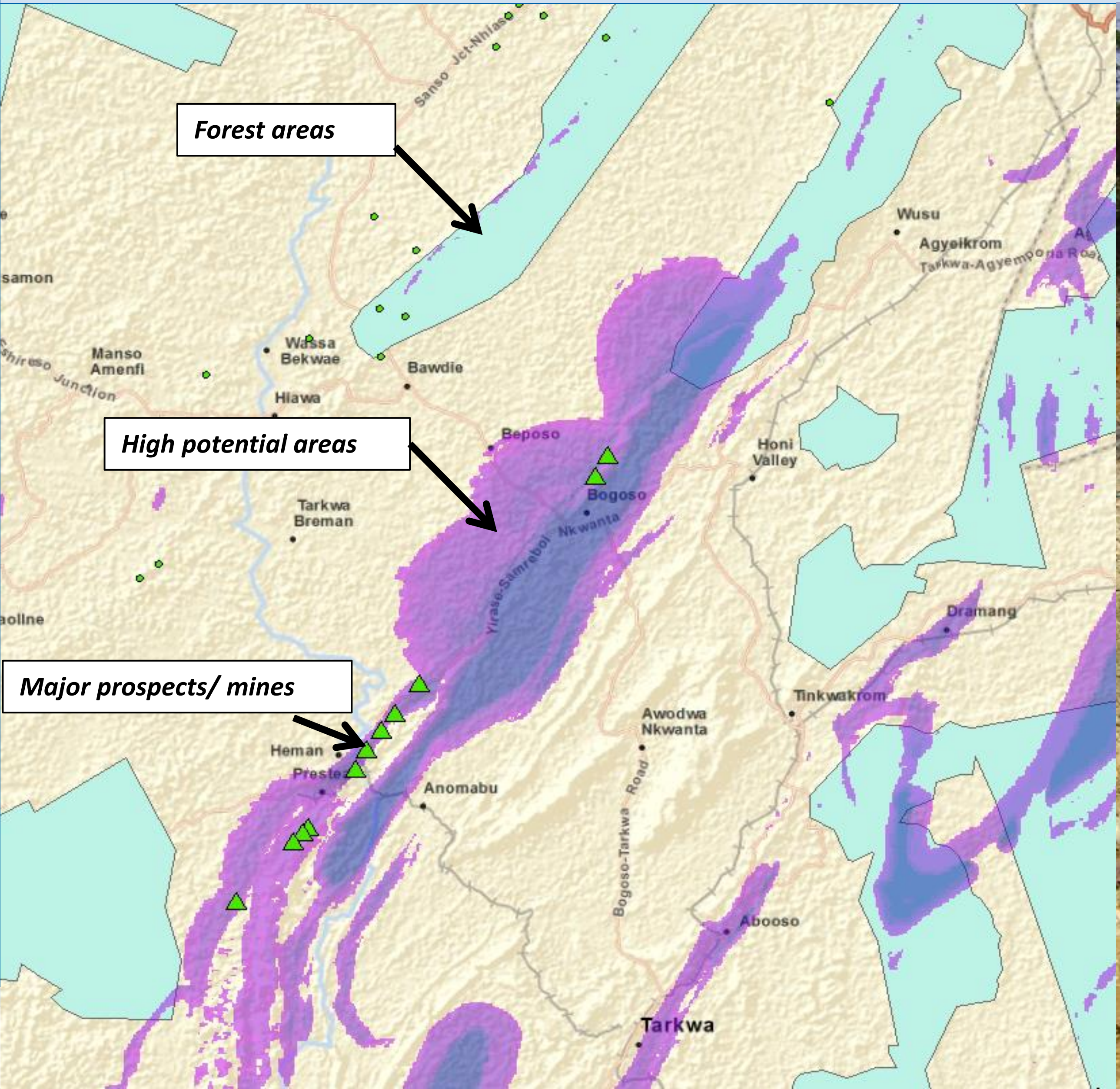


Prospects located in areas with a potential of > 0.7

All other prospects

Forest reserves

Detailed conflict map



Artisanal Placer Gold Mining in Ghana

The spatial planning process

Mineral deposits & mining preferences

forestry preferences

Infrastructure preferences

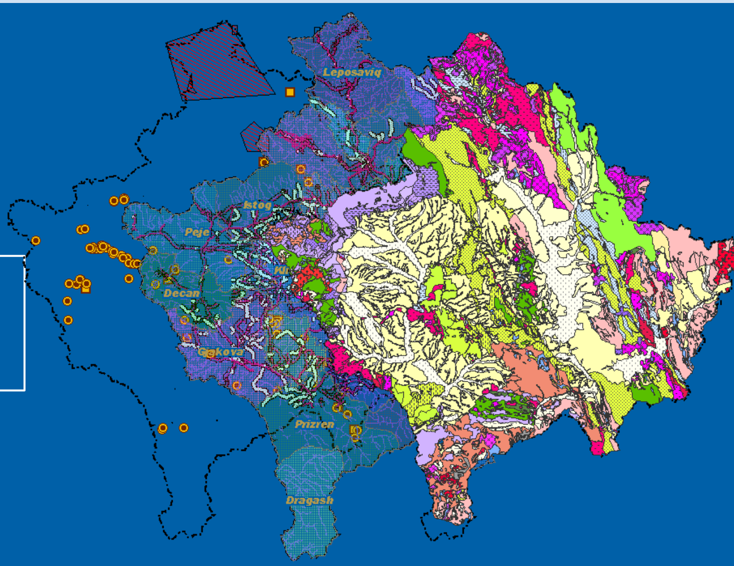
housing preferences

agriculture preferences

Nature conservancy preferences

other preferences
…..

Spatial planning decision process



National Development Plan

(covers 10 – 15 years)

Set of thematic maps and explanations

A few words about the future

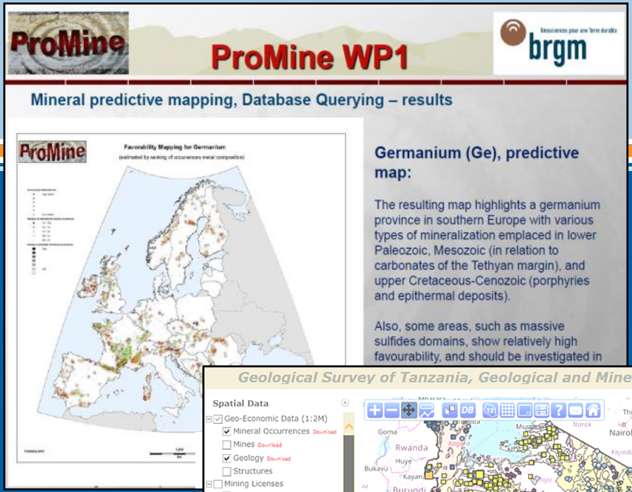
- Further development of technologies and approaches: AI, 3D, remote sensing data, verification procedures, interactive technologies

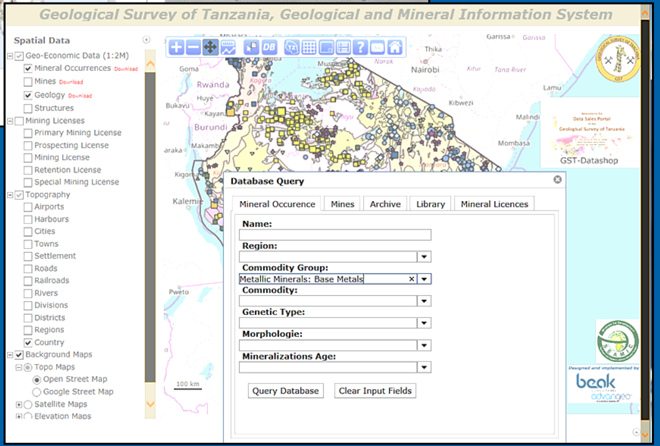
- We need user friendly application software.

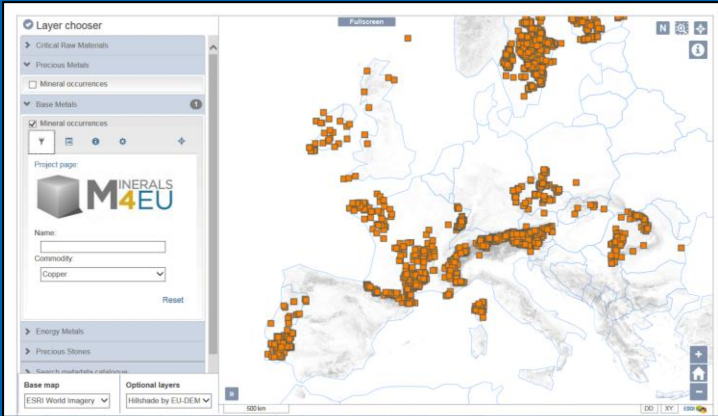
- Process more data: The problem is not missing data but missing data processing.

- 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/

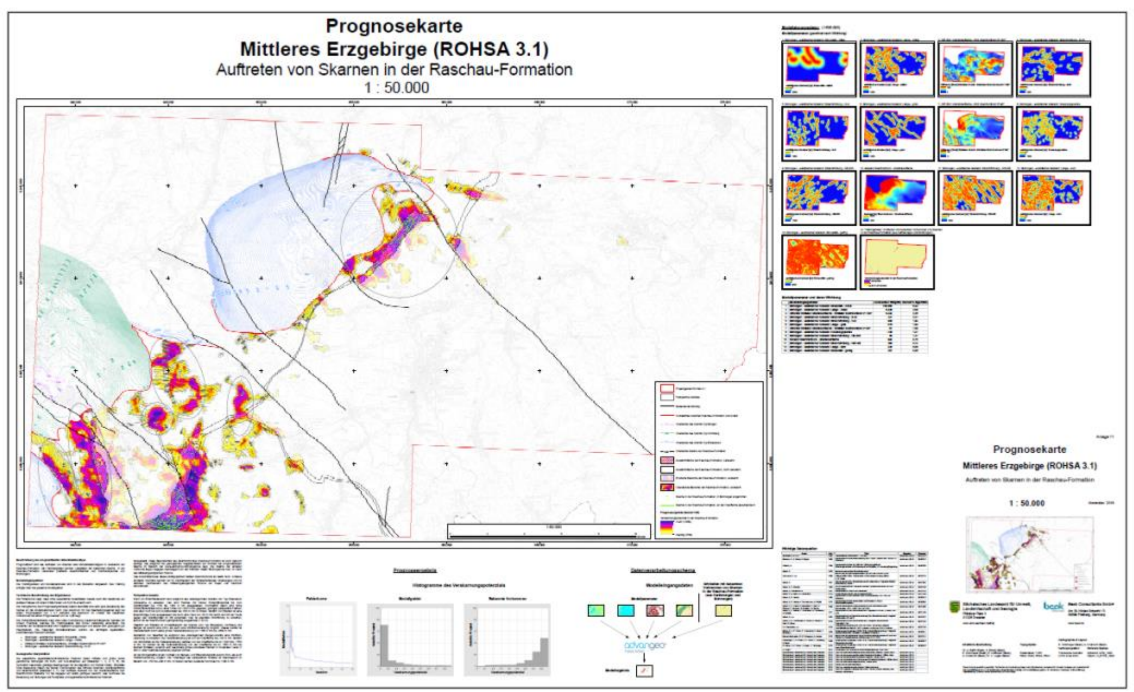
Conclusions

- 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

Prospecting in the Volta Region, Ghana

Thank You !

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



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