Mineral predictive mapping in 2D, 2.5D and 3D using Artificial Neural Networks

Case study of Sn and W deposits in the Erzgebirge, Germany

beak CONSULTANTS
advangeo® Prediction Software

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Introduction

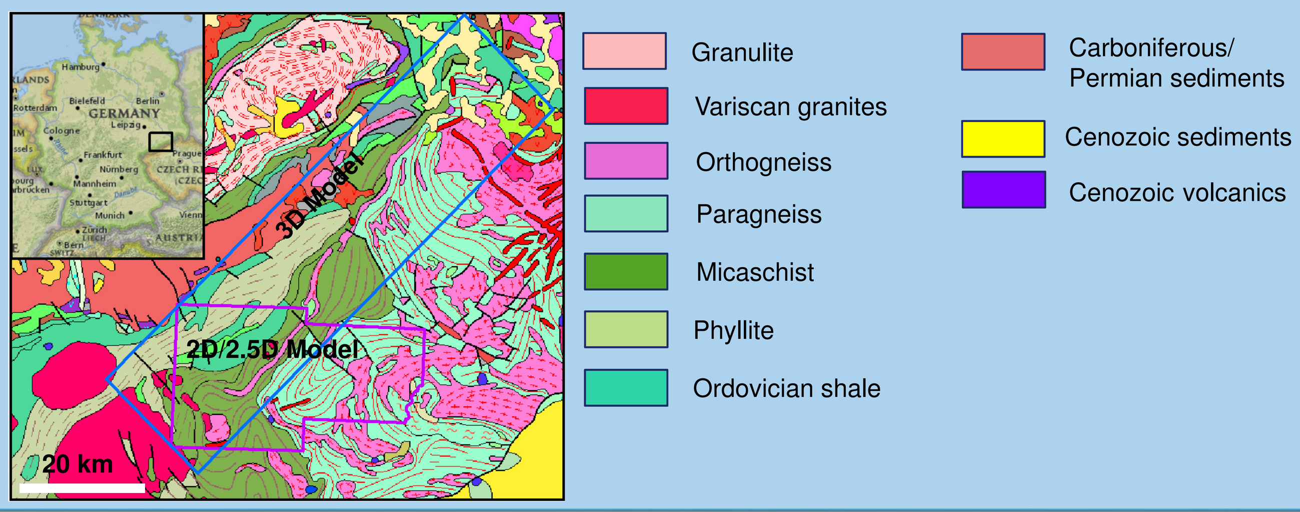
Tin and Tungsten mining in the Erzgebirge mountains (Saxony, Germany) has a history going back at least to the 14th century and reached its peak between 1950 to 1990.

Qualitative and quantitative predictive maps of Sn, W, fluorite and baryte for a 740 km² test area in the central Erzgebirge were created with an artificial neural network (ANN) based approach using advangeo®.

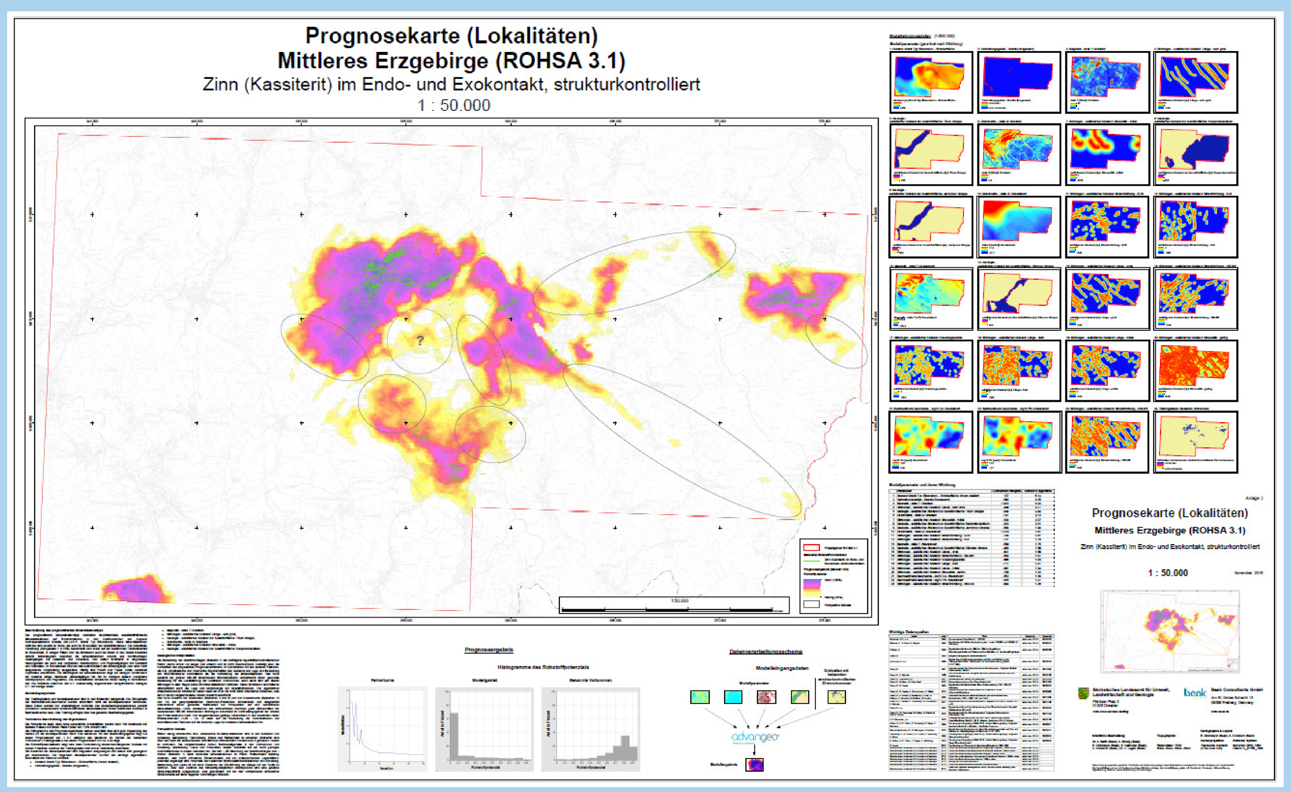
The area is characterized by gneiss domes overlain by a several km thick sequence of mica schists, phyllites and shales of Cambro-Ordovician age.

The gneiss domes are intruded by syn- to postorogenic Variscan granites of the Eibenstock (Sn-, W-, Li-enriched), Bergen (W-enriched) and Kirchberg (barren) types. Sn and W deposits occur as pneumatolytic quartz-cassiterite resp. quartz-wolframite veins and as magnetite-cassiterite-wolframite-scheelite skarns in three distinct levels of the micaschist – phyllite sequence.

For the 3D predictive models, the area was extended to the NW along the Central Saxon Lineament, an area with many fault-bounded blocks of various lithologies and an inferred covered intrusion of a Sn-enriched granite.



2D Models



Prediction map for vein-hosted Sn

ROHSA 3
Sachsen hebt seine Schätze

ROHSA 3 (Rohstoffe in Sachsen)

The 2D and 2.5D models were created in the frame of the ROHSA 3 project funded by the Saxon State Office for Environment, Agriculture and Geology.

All datasets were converted to a uniform grid, in this case of 50 m resolution. A **database of known deposits** was compiled with the location, size and category of resource blocks. For quantitative predictions, the metal content of the resource blocks was divided evenly across the corresponding grid cells. These datasets were used as the training data, which the ANN tried to remap from the model input data during the training phase of the modeling.

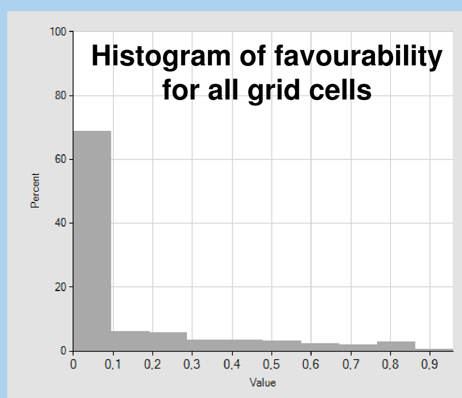
Geological, geochemical (stream sediment geochemistry) **and geophysical data** (aeromagnetics, surface gravity surveys, airborne gamma spectrometry) were collected, processed, and interpolated to the uniform grid. Gradients and curvatures of the field were calculated in advangeo® and used as additional optional model input data (MID).

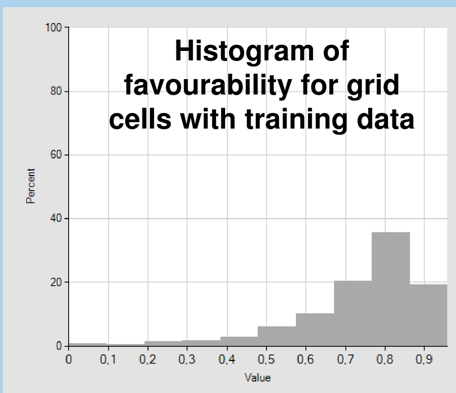
Faults were grouped by direction (N-S, NE-SW, E-W, NW-SE) and by length to assess which fault sets are relevant to the formation of different types of deposits. The grid cells were attributed with distances to the nearest fault of every type, and the distance to the nearest fault crossing.

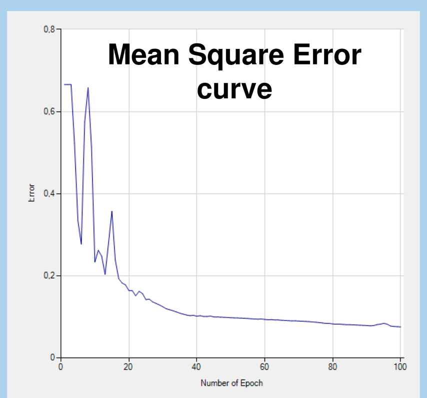
Finally, an isobath model of several geologic horizons and the surfaces of the different granite types was constructed. Distances were calculated between the granite and the horizons and the granites and the surface.

In the **advangeo® Prediction Software**, eight types of model were calculated (combinations of commodity: Sn or W; type: vein or skarn; data: qualitative or qualitative), each with the appropriate training data and different combinations of MID.

The resulting predictions were evaluated by the smoothness of the error curves, the residual error and by their accuracy to remodel the training data. For each MID, connection weights and the weight according to Garsons´ algorithm were calculated to interpret the importance of the various geologic factors. In successive models, the MID were refined to test different combinations and obtain progressively better prediction results.





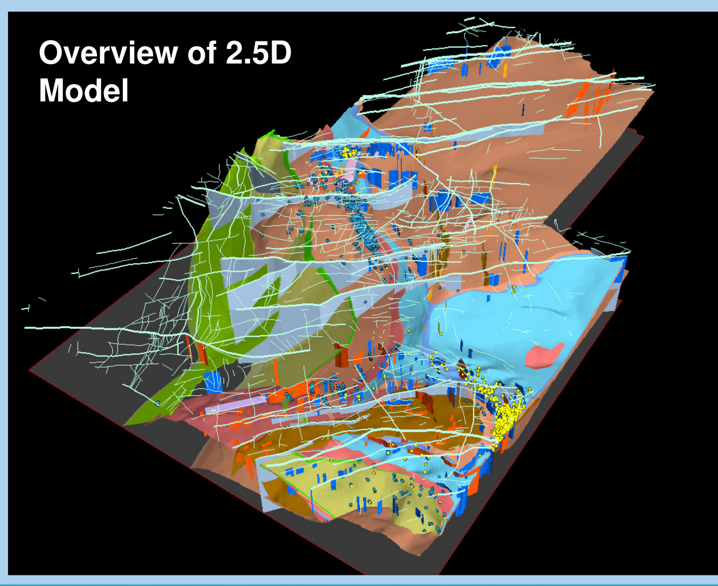


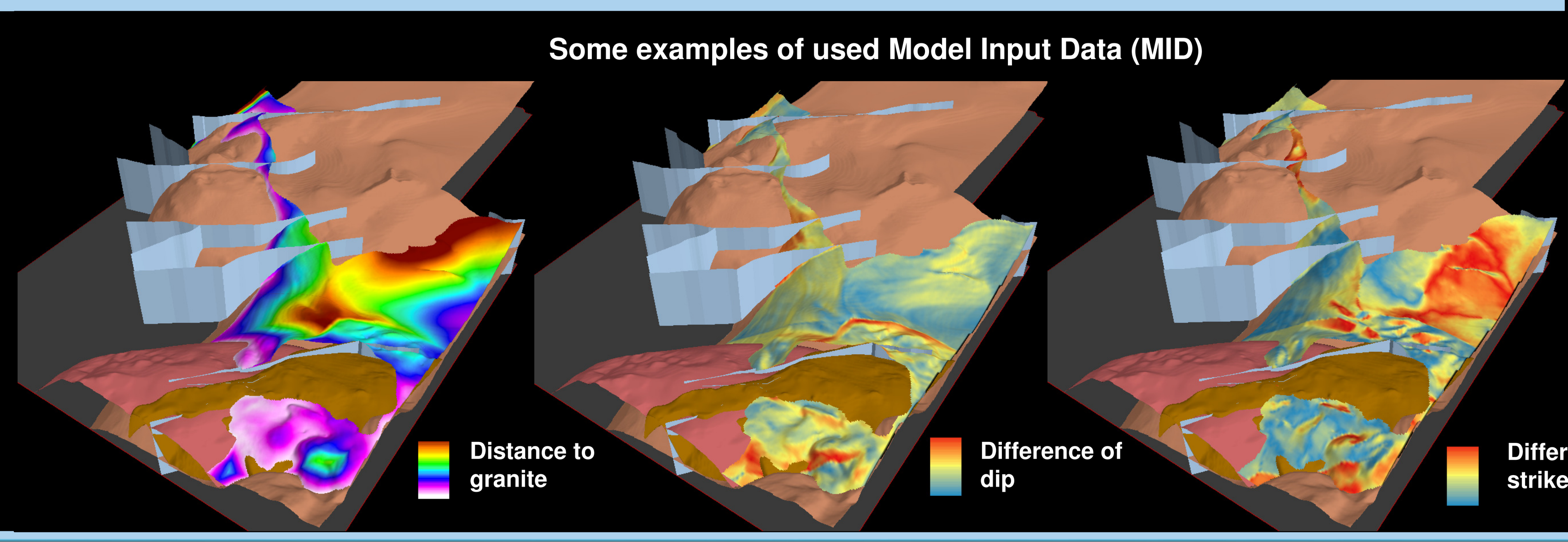
Weighting of Model Input Data for the vein-hosted Sn model

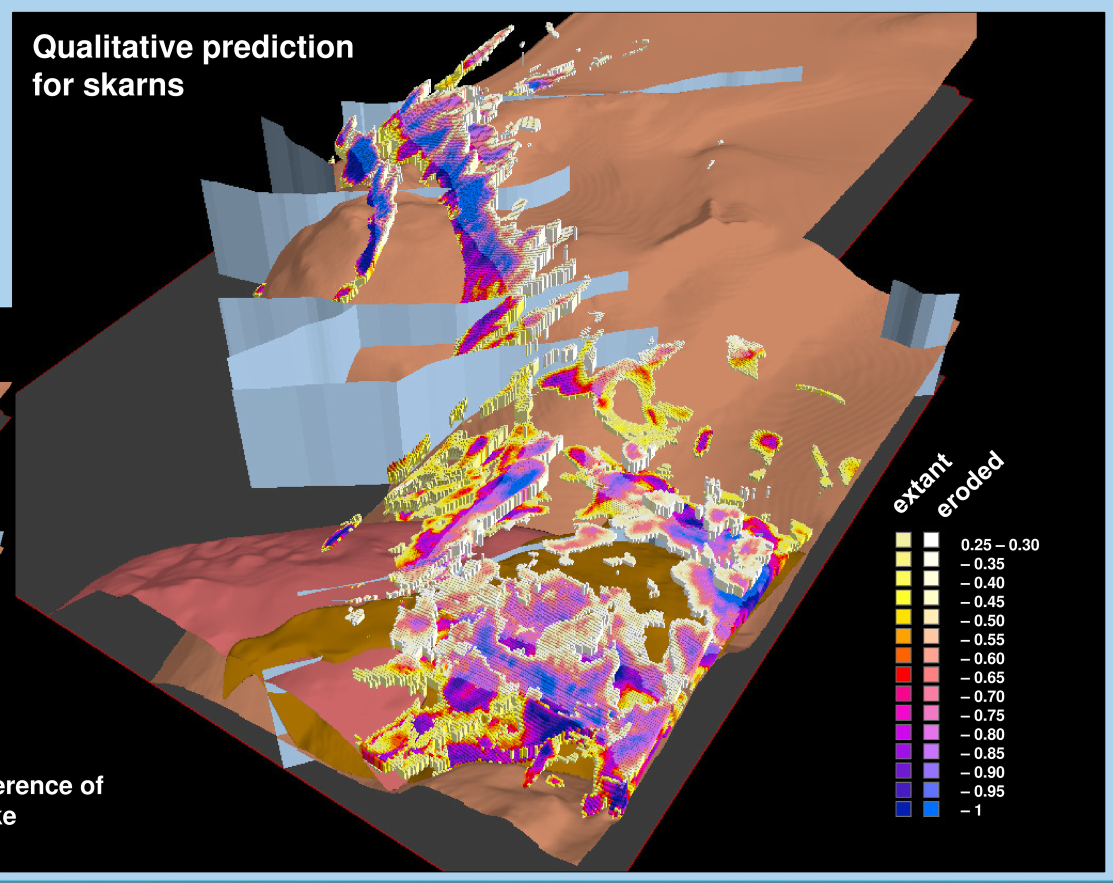
Model Input Data (MID)	Connection Weights	Garsons´ Algorithm
Distance to granite type Eibenstock	107,14	5,14
Extent of granite	-590,37	3,25
Aeromagnetics DeltaT Slope	-1922,43	3,24
Distance to very large faults	-498,07	3,17
Distance to Geological Units – Thum Group	-433,56	2,44
Gravimetry Gradient	-741,45	2,13
Distance to faults of high sinuosity	-324,36	2,07
…	…	…

2.5D Models

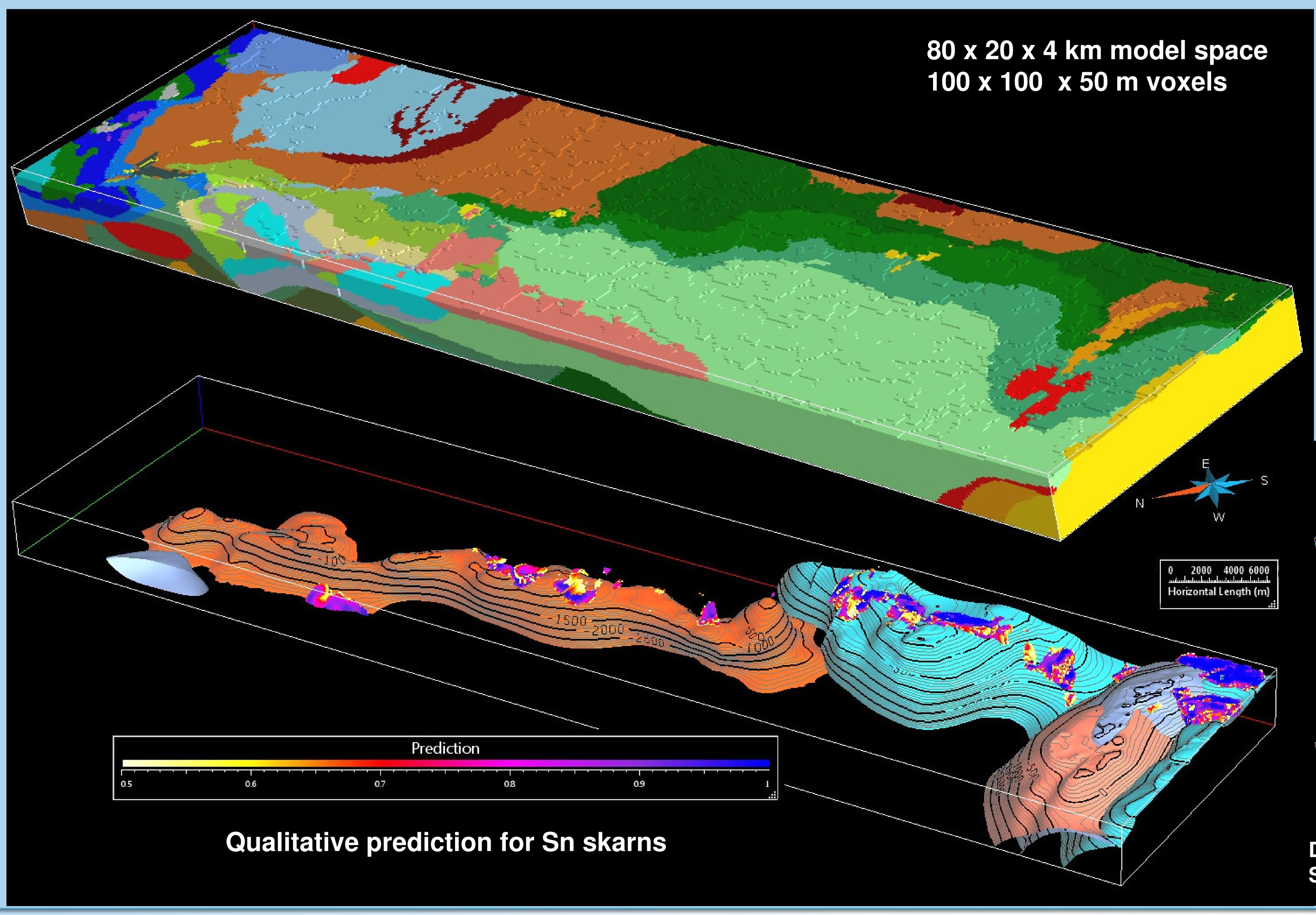
Skarns occur in three distinct calcareous horizons. Distances to granites and faults were calculated with respect to the median plane of these horizons. Furthermore, the 3D angles between these median planes and the underlying granite were calculated. By reconstructing the eroded parts of the skarn horizons as far as possible with the known structural data and thickness constraints it is possible to "predict" former skarn occurrences in the eroded part of the model and thereby to **assess the level of erosion** of the overall ore district and of individual deposits The result is a differentiated picture of the skarn deposits in the test area with improved detection and accurate depth estimates of predicted concealed deposits.



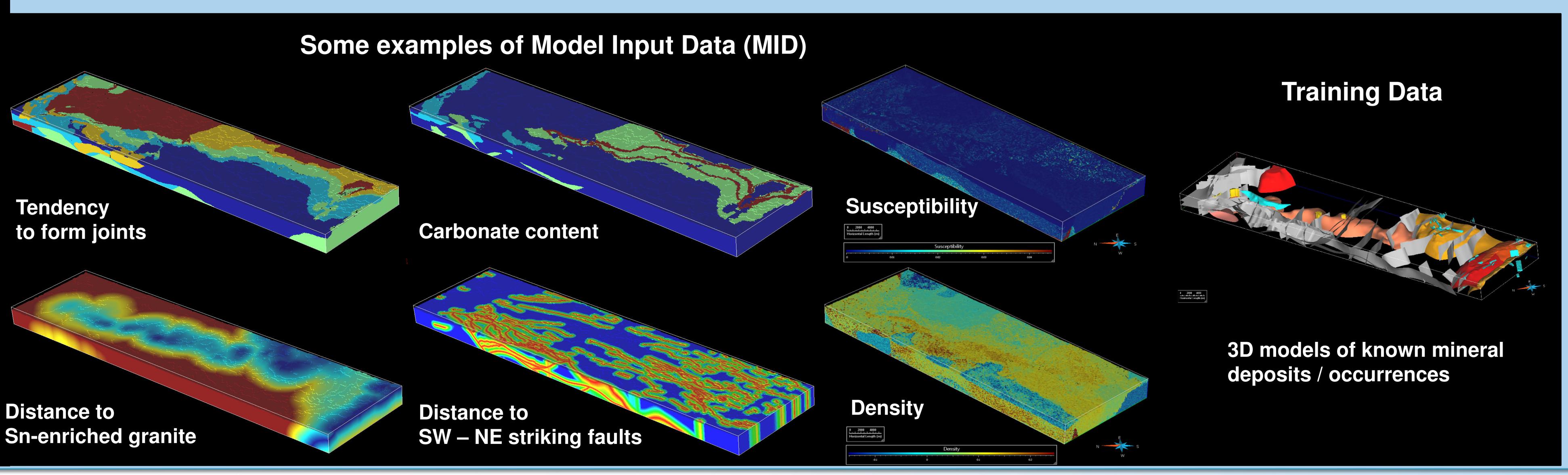




3D Models



A 3D model of the extended test area was constructed and converted to a Voxet model in Paradigm Gocad®. **3D Inversion modeling** via Intrepid GeoModeller® was applied both to convert gravity and magnetics data to 3D data (in the form of density and susceptibility models) and to refine the geometry of concealed granite intrusions. The individual voxels were attributed with geological unit, lithology, geochemical and geophysical properties, tendency to form joints, existence of calcareous layers and other properties. True 3D distances to the different categories of faults and to the granite surfaces were calculated with the tools available in Gocad®. The outer boundaries of known deposits were modeled and the voxels inside were assigned as training data for the corresponding type of deposit. The Voxet was imported into the **advangeo® 3D Prediction Software**. Model creation, assessment and refinement proceeded in analogy with the 2D case. The prediction voxet can be viewed and manipulated in Gocad®, or free viewers like Geocando or Mira Geoscience Analyst®.



Results

- **Prediction maps** for vein- and skarn-hosted Sn and W over a 740 km² area were created.
- The maps contain charts to asses the model quality and a table of the used MID and their relative **weights**.
- Predicted mineral reserves / resources:
  - **Sn** in vein-type deposits of 200 kt; Sn in skarn-type deposits is predicted to amount to 700 kt,
  - **W** hosted in skarns with 120 kt WO_3; W in vein-hosted deposits are negligible (< 2 kt).
- The **erosional level** of the district is intermediate, with about 50% of the skarn deposits eroded.

Conclusions

- A wide array of qualitative and quantitative geological data can be integrated and used with **Artificial Neural Networks.**
- Successful application of the approach to a traditional mining area and the **qualitative and quantitative prediction** of unexplored concealed deposits in this area as a result.
- Progress from 2D to 3D modeling has greatly improved the numerical representation of deposit-controlling geological factors and enables to **define drilling targets and locate them in 3D space.**

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Mineral Prospectivity Conference, 24th – 26th October 2017, Orléans, France

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