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

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Abstract — **The central Erzgebirge is well known for its tin and tungsten deposits. A combination of knowledge and data driven approaches was used to create qualitative and quantitative prediction maps for both vein-hosted and skarn-hosted Sn and W deposits. The advangeo® Prediction Software uses Artificial Neural Networks (ANN) to create 2D, 2.5D and 3D predictive models for these and other commodities.**

I. 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 in 1950 to 1990. Recently, exploration activities in the vicinity of historical mining areas have resumed. The ROHSA project (raw materials of Saxony) of the Saxon State Office for Environment, Agriculture and Geology (LfULG) aims to improve access to data regarding to the economic geology and mining history of the area. Phase 3.1 of the ROHSA project includes the creation of qualitative and quantitative predictive maps of Sn, W, fluorite and baryte for a test area in the central Erzgebirge with an up-to-date approach using ANN. The test area includes approx. 740 km² in the vicinity of the historic mining centers of Geyer – Ehrenfriedersdorf, Annaberg-Buchholz and Aue – Schwarzenberg.

This area is characterized by the Annaberg gneiss dome in the south-east and the Aue – Schwarzenberg gneiss dome in the south-west. The gneiss is overlain by a several km thick sequence of mica schists, phyllites and shales of cambro-ordovician age, which drape around the gneiss domes in the southern part and dip with approx. 40° to the NW in the northern part of the test area. 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 mica schist – phyllite sequence.

For the 3D predictive model, 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.

II. Methodology

2D case. To facilitate computation, all datasets must be converted to a common grid, in this case of 50 m resolution. A database was compiled of known deposits, and the location, size and category of resource blocks within them. The corresponding grid cells were then assigned the property of deposit for Sn resp. W of the vein resp. skarn type. For quantitative predictions, the metal content of the resource blocks was divided evenly across their corresponding grid cells. These are the training data which the ANN will attempt to recover 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 from published sources and the archives of LfULG. Geophysical and geochemical data were processed and interpolated to the common grid. Gradients and curvatures of the field were calculated in advangeo® Prediction Software 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 sets of faults may be relevant to the formation of the 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 advangeo®, eight types of models were calculated (combinations of commodity: Sn or W, type: vein or skarn, qualitative or qualitative), each with the appropriate training data and different combinations of MID. The resulting predictions were assessed by the smoothness of the error curves, the residual error and by their power to recover the training data. For each MID, connection weights and the weight according to Garsons´ algorithm [1] [2] were calculated to assess the importance of various geologic factors. In successive models, the MID are refined to test different combinations and obtain progressively better predictions. The prediction grids are then converted to prediction maps for each type of deposit.

2.5D case. The 2D predictions are limited to the near surface area. While they can predict some concealed deposits by incorporating the distance grids discussed above, it is not possible to resolve the variability with depth. In the case of the skarn deposits, some depth discrimination is possible because the 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 assess the level of erosion of the overall ore district and of individual deposits. We created separate 2D models as described above for each of the three horizons and projected each prediction grid to its position in

3D space (Fig. 1). The result is a differentiated picture of the skarn deposits in the test area and with improved detection and accurate depth estimates of predicted concealed deposits. Unlike a full 3D approach, this model is still limited to calculating only vertical distances to the granites, and to calculating only horizontal distances to faults that are assumed to be uniformly vertical.

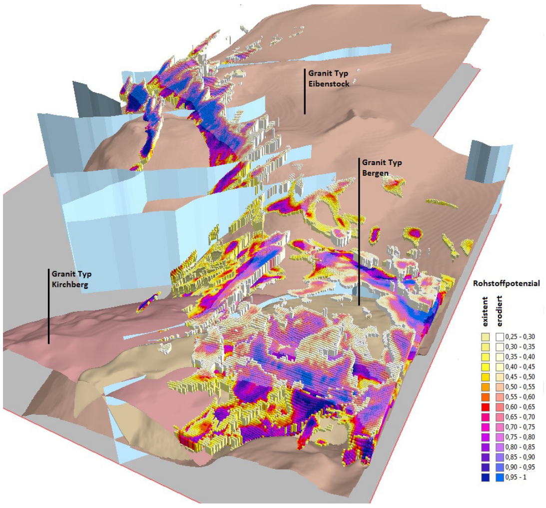

Figure 1 – 3D view of the 2.5D skarn prediction color-coded with the predicted favourability. The paler color scale represents the eroded parts of the deposits. View is from the SW across the Aue – Schwarzenberg gneiss dome.

3D case. To overcome these limitations and to fully analyze the 3D geometry of known deposits relative to controlling faults or contacts, a transition from a grid-based model to a voxet-based model is necessary. A 3D model of the extended test area was constructed and converted to a voxet model in Paradigm Gocad®. Inversion modeling via Intrepid GeoModeller® was employed 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 (100x100x50 m, corresponding to 12.8 Mio. voxels in the 80x20x4 km model space) 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 advangeo3D® Prediction Software. Model creation, assessment and refinement proceeded in analogy with the 2D case. The prediction is returned as another voxet and can be viewed and manipulated in Gocad®, or free viewers like Geocando or Mira Geoscience Analyst®.

III. Results & Discussion

Prediction maps of the model area were generated for the different types of commodities and deposits. The maps contain charts that help the user to asses the model quality and a table of the MID and their relative weights. Of note is the potential for tin reserves and resources in vein-type deposits in the model area predicted as slightly in excess of 200 kt, mostly in the known deposits and their periphery. Tin in skarn-type deposits is predicted to amount to 700 kt, mostly in so far poorly explored areas. For tungsten, the amount in vein-type deposits is negligible (few kilotons), however 120 kt are predicted to be hosted in skarns. For the comparatively better explored areas the predictions are similar to earlier predictions using other techniques. For less explored areas, no previous quantitative predictions are available. The erosional level of the district is intermediate, with about 50% of the skarn deposits eroded.

For the extended model area in the 3D case, currently only qualitative predictions (the likelihood of a deposit irrespective of its commodity content) are available. At this point, it is likely that concealed skarn deposits exist in the roof of some concealed granites.

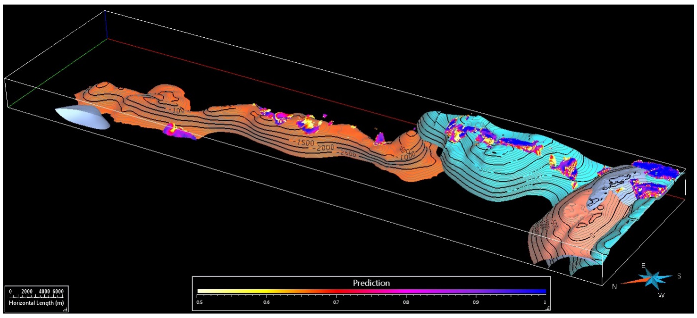

Figure 2 – View of the 3D prediction for skarn-type tin deposits. Individual voxels are 100x100x50 m and color-coded for the predicted favourability for this deposit type. View is from the West.

IV. Conclusion

A wide array of qualitative and quantitative geological data can be evaluated via Artificial Neural Networks. We have demonstrated an application to a traditional mining area and the prediction of as-yet unexplored concealed deposits in this area. Quantitative estimates are in line with estimates from other techniques. The progress from 2D to 3D modeling has greatly improved the numerical representation of deposit-controlling geological factors and enables us to define drilling targets and locate them in3D space.

Acknowledgment

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