INTERPRETATION OF AIRBORNE GEOPHYSICAL DATA BY USING ARTIFICIAL NEURAL NETWORKS: APPROACH AND CASE STUDIES

A. Barth, A. Knobloch, S. Noack

Beak Consultants GmbH, 09599 Freiberg, Germany - (silke.noack, andreas.knobloch, sven.etzold, andreas.barth)@beak.de

KEY WORDS: artificial neural network, geophysical data analysis, GIS, mineral potential mapping, geological mapping

ABSTRACT:

Because of its complex nature and the wide variety of controlling factors, the geological and mineral resource interpretation of remote sensing data requires sophisticated interpretation methods. Artificial neural networks (ANN) offer an unbiased data driven approach, as they are able to “learn” from "examples" (e.g. known sites of mineral occurrences, known geological formations) and subsequently transfer this “knowledge” into a larger area with similar data sets.
In the past, the application of the technology in geo-science was difficult due to its low awareness level and problems to integrate it into geo-data processing algorithms. In this situation, the software advangeo® was created to provide a normal GIS user with a powerful tool to use ANNs for predictive mapping within a standard ESRI ArcGIS environment. Besides this, the approach provides useful data-processing and data-analysis tools that are adjusted to the solution of special problems: geo-hazards and mineral deposits. Among others, there are algorithms for preparation of vector data, vector/raster data transformation, analysis of raster data (incl. geophysical grids) and data processing reliability analysis. The approach is able to add considerable value to existing data. In different case studies ANN’s have shown their capabilities in modelling and prediction of a wide variety of geological, environmental and geo-economic issues: mineral potential mapping, geological mapping, environmental geology, geo-hazard potential mapping. The application of ANN technologies for data interpretation offers important advantages, as they are applicable even if the relationships between the depending variable (e.g. the rock type) and the controlling factors (e.g. remote sensing data) are not really known, they consider many influencing factors, they work with available data, they are comparable quick and easy to use, and they offer both qualitative (where?) and quantitative (where and how many?) predictive features.

1. METHOD: ARTIFICIAL NEURAL NETWORKS

The ANN data interpretation approach is based on the functionality of a biological nervous system being composed of many interconnected neurons (nerve cells), which receive process and transfer information. After reaching a certain threshold, nerve cells are activated and forward information to other connected neurons. During a learning process the inter-connections are adapted. The simulation of these biochemical processes in an ANN is realized by artificial neurons and the weights of the connections (Backhaus et al. (2003) and Kriesel (2009)).

ANN are usually organized in layers. The network topology describes the number of layers (Figure 1), the number of neurons in layers and the way of their interconnection: Important parameters are the direction of signal propagation (forward / backward) and the type and level of connection (completely connected / with shortcuts).

The used paradigm of ANN is the Multilayer Perceptron (MLP). It consists of 3 or more layers: The input layer receives the values of the controlling parameters. The neurons of the hidden layer(s) and the output layer process the weighted signals from the neurons of its previous layer and calculate an output value applying an activating function. The output layer, typically consisting of only one neuron, represents the dependent variable to be modelled.

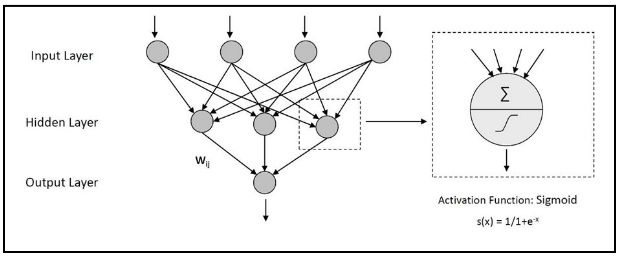

Figure 1: Scheme of a feed-forward artificial neural network

During the learning process the weights are adapted in an iterative process. In this process, the mean squared error (MSE) between the expected outputs and the actual situation (between modelled and training data) is minimised. The training is stopped after reaching a defined count of iterations (epochs) or if the error falls below a defined minimum.

2. INTEGRATION OF THE METHOD INTO GIS: SOFTWARE ADVANGEO®

The software advangeo® is implementing the ANN Multilayer perceptron (MLP) approach into the standard ESRI GIS environment. The software is working with raster datasets.

2.1 Graphical User Interfaces and Functionality

Main components of the software are the Data & Model Explorer and the GIS-Extension (see Figure 2).

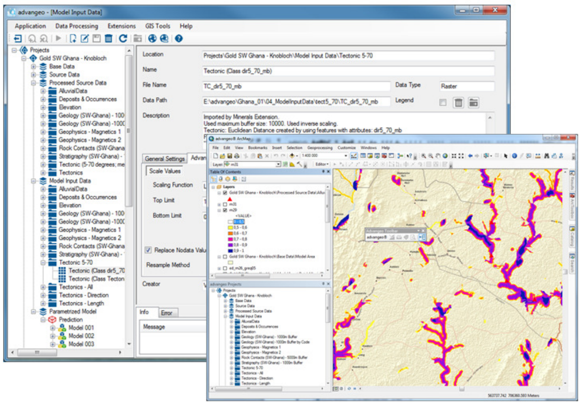

Figure 2: Software advangeo® graphical user interfaces: Data & Model Explorer (left) and GIS Extension (right)

The Explorer allows the creation and administration of projects including the organization and processing of geo-data and the parameterization and calculation of the ANN models. In a step by step process it guides the user through the various steps of model environment definition, data preparation, ANN training and model verification. In the Explorer, the project and its data are organized in a Windows like tree structure.

The project, the recorded working steps and all model data and metadata are stored. The database and the physical data is located in a closed file structure allowing the simple copy and paste of projects from user to user or to another storage medium. An overview of the architecture of advangeo® is shown in Figure 3.

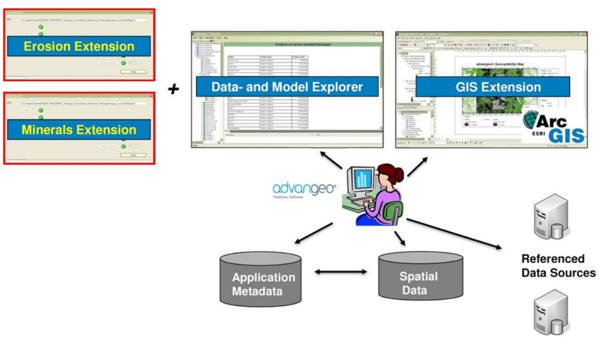

Figure 3: The advangeo® software architecture

2.2 Workflow

Advangeo® consists of different modules, offering an integrated workflow which guides the user through the different work steps of data pre-processing and model creation:

- Module “Base Data”: Definition of model base parameters i.e. origin, grid cell size, extent, outline and spatial reference of the model area (Base raster and Project Area) and the creation of different areas for training, testing and application,
- Module “Source Data”: Organization of Source Data, i.e. any kind of input data in different raster and vector format, such as digital elevation models, geophysical raw data, sample points, geological maps or land use maps.
- Module “Processed Source Data”: Creation of derived data sets as raster or vector data, e.g. interpreting spatial relationships, derivatives; such as distance maps, slope direction maps, lithological maps, interpolated geochemical data maps.
- Module “Model Input Data”: Generation of consistent raster data based on existing Processed Source Data for its use in models with different user options, e.g. options for scaling, creation of binary rasters from nominal data or fill NoData values automatically with a defined value.
- Module “Parameterized Models”: Parameterizing and training of ANN-models and application of trained models.

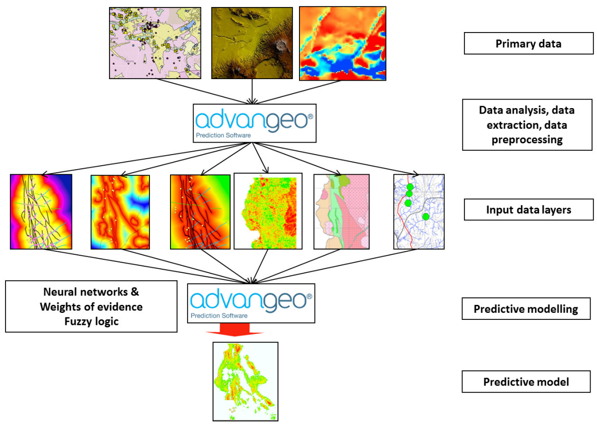

Figure 4: The predictive modelling workflow

2.3 Software extensions

Considering that the data modelling is carried out as a raster analysis, the neighbourhood of a pixel is not interpreted. Therefore, all spatial information like the distance of a point to a fault or a certain geological contact must be derived from source data information. This data processing requires an extensive knowledge of data manipulation techniques as well as a lot of time. To support the user in complex and often repeated steps of data preparation, two extensions for automated data processing were implemented:

- Erosion Extension: processing of digital elevation models, soil maps and land use maps and the combination of geological data with elevation model data
- Minerals Extension: automated processing of geological maps, classification of linear elements and rock contact zones, processing of geophysical data and geochemical data, interpolation of point data.

Both extensions consist of graphical user interfaces for data selection, execution of processing operations and create ready to use model input data.

3. CASE STUDIES: GOLD POTENTIAL MAPPING IN GHANA

Artificial neural networks (advangeo®) have been used to create mineral predictive maps for two areas in Ghana: the Lawra belt in the NW of the country, and the Ashanti, Sefwi and Kibi belts in SW Ghana (Figure 5).

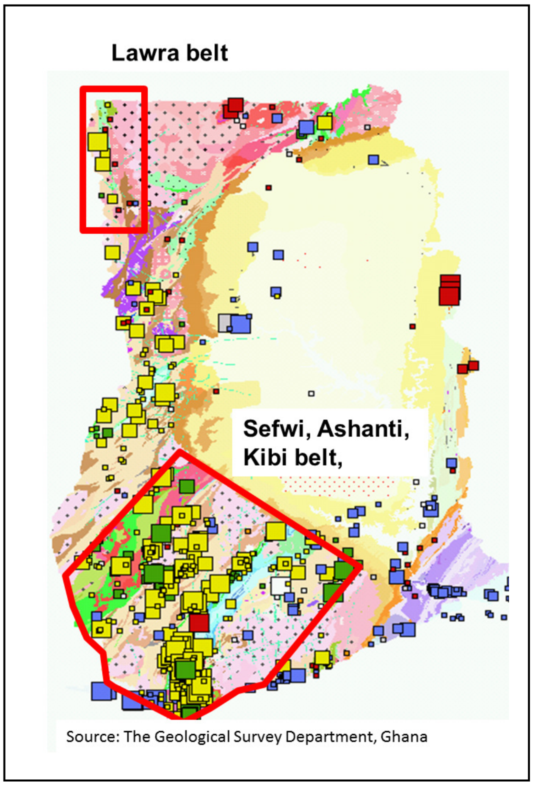

Figure 5: The study areas in Ghana

Gold potential mapping in the Lawra belt

The Lawra belt in NW Ghana stretches N-S over a distance of approx. 120 km. In this area several gold occurrences are known, but the level of knowledge is still low and not comparable with the famous gold belts in SW Ghana. Using the available airborne geophysical data (magnetics, electro-magnetics, radiometric data), the mineral deposit database and the 1:1M Geological Map, a series of gold potential maps was compiled. Best results have been computed by using a combination of geological and geophysical data. The electromagnetics have shown the best sensitivity compared with radiometric and magnetic data.

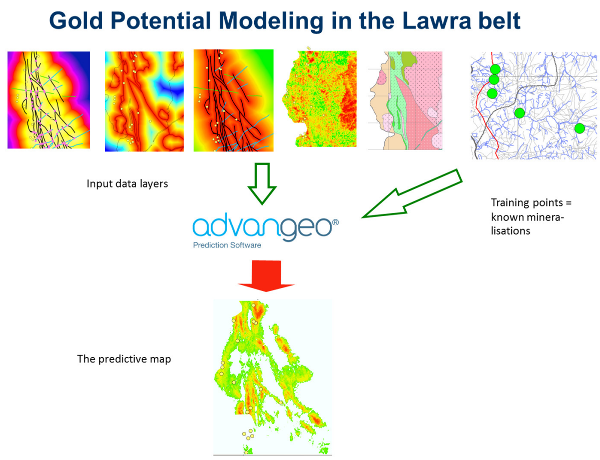

Figure 6: Gold Potential Mapping in the Lawra Belt

The study area in **SW Ghana** comprises about 60,000 km². Using the mineral occurrence database, the geological map 1:1M, airborne magnetic data, and the SRTM elevation model, various derived datasets (see Figure 7, Figure 8) have been created and used for both quantitative and qualitative mineral predictive mapping.

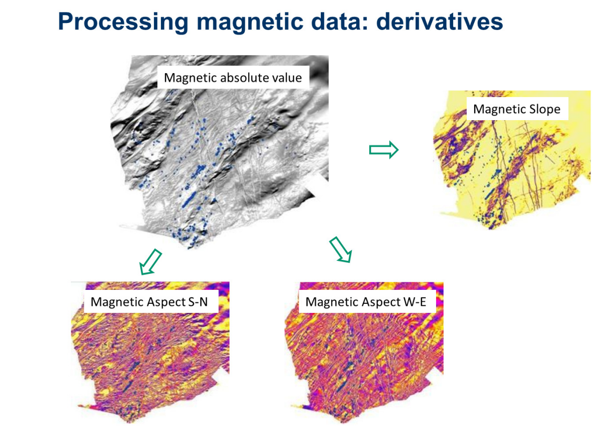

Figure 7: Pre-processing of magnetic data

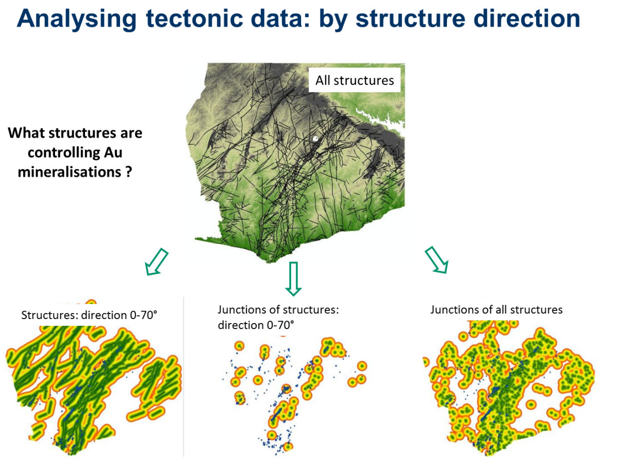

Figure 8: Pre-processing of tectonic data

Modelling results have been used for the evaluation of single prospects (see Figure 9).

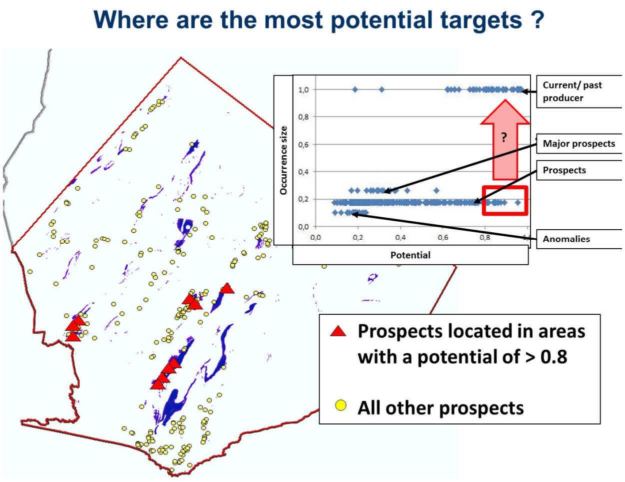

Figure 9: Evaluation of prospects with regard to their potential

By using the quantitative modelling results, high potential prospects can clearly be separated from prospects with less potential. The model can easily be upgraded with new exploration data.

As a result of the extensive data analysis and modelling, a gold potential map in a scale of 1: 1,000,000 (see Figure 10) was created. This map provides an excellent base for exploration targeting, investment promotion and small scale mining guidance.

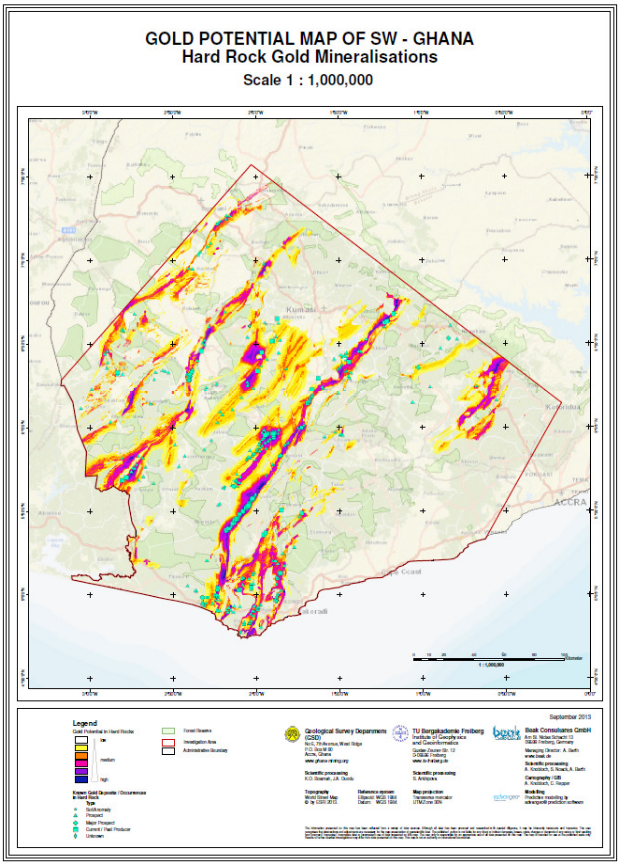

Figure 10: Hard Rock Gold Potential Map 1.1,000,000

4. CONCLUSIONS

Artificial neural networks are an efficient instrument to model the relationships between a depending geoscientific parameter (e.g. the mineral potential, a geological unit) and the controlling factors (e.g. airborne geophysical data, geological maps).

The approach is a consequently data driven, avoiding the biased influence of a scientist. The knowledge of the expert is essential for the selection and preparation of input data and for the validation of the results.

Advangeo® provides an effective software environment for data pre-processing, model generation, and result visualisation. It is a tool to build up structured and comprehensible models within the widely used ESRI GIS environment.

ACKNOWLEDGEMENTS

The authors sincerely thank the Geological Survey of Ghana for their excellent support and the authorization to present proprietary project results in this article. The advangeo research project was supported by the German Federal Ministry of Economy and Technology (project identification numbers: IW072061, EP09260, EP101247, EP121295).

REFERENCES

Arkhipova, S., 2013: Prognose von Goldexplorationszielen in Südwest-Ghana mittels künstlicher neuronaler Netze und logistischer Regression. Unpublished master thesis. TU Bergakademie Freiberg

Backhaus, K., Erichson, B., Plinke, W., & Weiber, R., 2003. Multivariate Analysemethoden – eine anwendungsorientierte Einführung. Berlin: Springer-Verlag.

Barth, A., Berger, A., 2010: Probability of Erosion Gully Formation - Limpopo Region. Map created in project AEGOS – Phase 1 (African European Georesources Observation System). Beak Consultants GmbH, Freiberg.

Barth, A. , Noack, S., Legler, C., Seib, N., Rexhaj, A., 2010: Rohstoffprognosekarten mit Verfahren der künstlichen Intelligenz – Fortschrittliche Identifizierung von Rohstoffpotentialen in Entwicklungs- und Schwellenländern. Glück Auf 146, (2010), Nr. 4

Drebenstedt, C., Knobloch, A., Gusat, O., Fischer, C., Barth, A., 2010: Risk Assessment of Coal Fires in the P.R. China Using Artificial Neural Networks and GIS. In: Latest Developments on Coal Fire Research. Bridging the Science, Economics, and Politics of a Global Disaster. Proceedings of "ICCFR2 – Second International Conference on Coal Fire Research". 19 – 21 May 2010, Berlin, Germany.

Kallmeier, E., Roscher, M., Böhnke, R., Barth, A., Drebenstedt, C.: Modellierung und Bewertung der Stabilität von Tagebaukippen mit künstlichen neuronalen Netzen. 15. Geokinematischer Tag, TU Bergakademie Freiberg. 2014.

Knobloch, A., Gusat, O., 2010: Development of a Coal Fire Prognosis Map for China Using Artificial Neural Networks and GIS. In: IUR "Scientific Reports on Resource Issues" Volume 3, 2010.

Knobloch, A., Barth, A., 2010: Analyse der räumlichen Verteilung von Manganknollen mit Verfahren der künstlichen Intelligenz. Unveröffentlicht. Beak Consultants GmbH im Auftrag der Bundesanstalt für Geowissenschaften und Rohstoffe. Freiberg, 12.11.2010.

Knobloch, A., Zeidler, M.: Risikoanalyse des Hochwasser-rückhaltebeckens Glashütte. Unveröffentlicht. Beak Consultants GmbH im Auftrag der Landestalsperrenverwaltung Sachsen. 2010.

Kriesel, D., 2009. A Brief Introduction to Neural Networks. Retrieved December 30, 2009, from http://www.dkriesel.com.

Noack, S., & Otto, L.-F., 2010. Erste Ergebnisse einer Prognose der Befallswahrscheinlichkeit von Waldbeständen durch den Buchdrucker (Ips typographus L.) mittels eines künstlichen neuronalen Netzes. Poster presented at Forstwissenschaften: Grundlage nachhaltiger Waldbewirtschaftung, Göttingen, Germany. Retrieved October 24, 2010, from http://www.beak.de/advangeo/advangeo_prediction/news/fowi_2010

Noack, S., Barth, A., Irkhin, A., Bennewitz, E., Schmidt, F., 2012: Spatial Modeling of Natural Phenomena and Events with Artificial Neural Networks and GIS. International Journal of Applied Geospatial Research (IJAGR), Volume 3 (1), p. 1-20.

Nuspl, A., 2012: The application of artificial intelligence for metallic mineral exploration targeting of Sn and W skarns in the Erzgebirge/Vogtland area. Unpublished master thesis. TU Bergakademie Freiberg

PETERS, R., SCHMITZ, G., CULLMANN, J. 2006. Flood routing modelling with Artificial Neural Networks. Advances in Geosciences, 9/2006, 131-136.

Römer, T., 2012: GIS-gestützte Analyse der Beziehungen zwischen Biotop- und Land-nutzungstypen sowie Brutvorkommen ausgewählter Vogelarten. Unpublished master thesis. Hochschule für Technik und Wirtschaft (University of Applied Sciences for Engineering and Economy) Dresden/Germany.