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

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Abstract — **For many years, mineral predictive mapping was guided by intuition and knowledge based approaches using maps and exploration models. The development of powerful affordable computers, together with the broad availability of various large data sets has provided the base for development of various computer based mineral predictive mapping technologies. These advances when coupled with easy to use software products (e.g. Beak`s advangeo® Prediction Software) is enhancing the introduction of AI technologies into daily practical work making them available to GIS users and 3D modelers.**

I. History

Mineral predictive mapping is as old as mining is. Over thousands of years, determining the right places for mineral exploitation were identified simply by application of accumulated knowledge and intuition. Beginningin 1556, mineral exploration models and exploration activities were drawn on paper by the famous Georgius Agricola in Freiberg. Much later, in 1815, the first geological maps were published by William Smith in England. Starting in the early 20th century, maps of minerals were compiled, showing mineral occurrences on abackground of geological maps. In 1913, Lafitte established Metallogeny as a science describing how mineral formation is temporally and spatially controlled by geological history. These ideas were further developed by Russian (e.g. Bilibin and Smirnow, German (Tischendorf, Baumann) and other scientists. For decades, these knowledge based (intuitive) methods, were broadly used for compilation of various mineral potential, metallogenic and similar maps, representing the spatial expression of expert knowledge and their interpretation. The maps were broadly combined with impressive exploration models for various mineral deposit types expressing the growing understanding of mineral formation processes as a result of a variety of geological, geochemical, geophysical, and temporal interactions.

II. Knowledge based, data driven and hybrid approaches

Consequently, it is not surprising that first mathematical approaches in analysing geological data sets were knowledge based following certain rules: e.g. a granite intrusion in carbonate rock sequences forms skarns, and skarns may carry magnetite, sphalerite and many more commercially important minerals.

In the 1980s and 1990s, with the development of affordable powerful computers for daily use, the implementation of fuzzy logic knowledge based mineral predictive mapping approaches started [1]. The increasing amount of remote sensing data and geophysical datasets contributed considerably to the success of these methods.

Simultaneously, the understanding of the importance of data driven approaches in analysing dependencies between the event of mineral occurrence formation and various controlling parameters and its location, e.g. distances to structures, fold axis, rock contacts grew (e.g. [2]). Because of its ease and plausibility, the method weights of evidence became widely used for analysis of spatial dependencies of mineral deposits to structures and other geological features (e.g. [3]). Other methods, such as neural networks and logistic regression, were recognised, but their practical use was limited because of still missing calculation capacities and the problem on how to apply them to analyse spatial features. In the 1990ies, artificial neural networks were applied successfully to predict Carlin Type gold deposits [5] in the U.S. and massive sulfide deposits in Japan [4].

Since that time, a increasing number of computer based mineral predictivity mapping applications have been published mainly by university and governmental institution based researchers. With increasing amounts of data and computer capabilities more data driven approaches became common, e.g. random forests [2] or logistic regression. The general success of various methods was compared and respective recommendations were drawn [6].

Over the past decade it has become recognized that hybrid models that combine both accumulated knowledge and data driven approaches can provide a more nuanced approach. In these models the geologist’s knowledge is incorporated via data preparation, i.e. maps or 3D data representing spatial relationships between the independent and the dependent data variables. It is now recognized that hybrid models provide the best results, as they combine the advantages of both knowledge based and data driven methods (e.g. [7]).

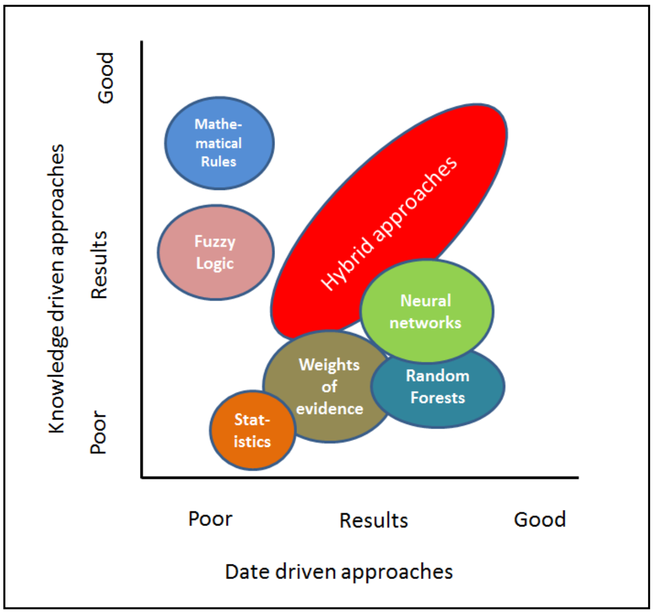

Figure 1 – The general applicability of data driven, knowledge driven and hybrid systems

III. Practical Limitations

The practical application of mineral predictivity methods is still limited because of a limited understanding of the methods, as well as because of missing user-friendly software. The use of data driven approaches is especially difficult, because of too many parameters and settings, issues arising during data preparation, and problems of integrating AI approaches into commercially available GIS software.

In case of neural networks, a number of parameters incl. network configurations, activation functions, number of iterations, etc. must be chosen. Data must be prepared according to the requirements of activation functions. On the other hand, calculation results have to be evaluated with regard to their correctness and plausibility. In practice, many data sets are created and used in models, producing a long list of files and settings. All these issues are limiting factors for practical application of advanced mineral predictivity methods in daily practice.

IV. Creating user friendly application software

It was in this environment that in 2008, Beak Consultants launched the development of its advangeo® Prediction Software integrating first data-driven and later knowledge-based methods into the widely used ESRI ArcGIS software [9] to overcome these limitations. Advangeo® was developed to use software structures not only for data analysis but also for storage of calculation parameters, guides to take the user through data preparation algorithms, and provide tools for prediction result evaluation. Important tools include those for data cross validation, statistical analysis (histograms, correlation), review of network errors, and analysis of network connection weights.

In cases where high quality data is available, quantitative predictive models can be created. In this case, the independent variable is not the “favorability” of the presence of a mineral occurrence at a certain location, but instead, one of its quantitative parameters, e.g. grade or tonnage.

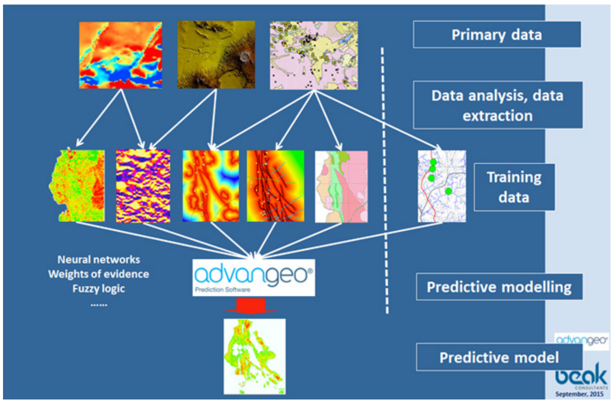

Figure 1 – The workflow of advangeo® mineral predictivity mapping

V. 3D predictive modelling

In 2016, another major advance was made when the 2D version of the advangeo® software was successfully transformed into a 3D version, capable of interacting with any 3D Voxel model. This advancement now allows the further integration with inverse modelling data of 2D geophysical fields, as magnetic and gravimetric data help to create reasonable geological 3D models as a requirement for 3D mineral prediction.For one of the first demonstrations of this technology, a detailed 3D model of the German Erzgebirge mineral region was built and populated with tin and tungsten (Sn-W) mineral occurrence data as training data for Sn-W prospectivity mapping [8].

VI. Predictive Models as value added products

Mineral predictivity maps are important value-added products compared to simple datasets. They provide new knowledge and ideas to both private and public bodies, which usually do not have the capabilities for this type of research. Mineral predictivity maps/ models are usable directly for mineral exploration targeting, attracting investment and land use planning. In this context mineral predictivity models and maps are becoming a valuable derived data set supporting normal planning instruments.

VII. What does the future look like

In the future, we envision using hybrid (combined knowledge based and data driven) mineral predictive mapping approaches widely in daily practice. This will involve using 2D and 3D models, and integrating them further with more data sets (e.g. remote sensing data) and ongoing exploration/ prospecting activities. This will help to directly guide field work. Another important importance advance is the quantitative mineral predictivity analysis for regions using grade – tonnage relationships. Using the existing advangeo® Prediction Software as a base more semi-automatic algorithms for data preparation and result evaluation, and integration of more data analysis features will be incorporated.

VIII. Conclusion

In the last two decades computer based mineral predictive mapping has developed from “niche” methods toward well-established approaches of qualitative and quantitative data analysis. The most accurate results have been shown to be provided by hybrid methods combining both knowledge based and data driven approaches. The practical usability of mineral predictive mapping depends on the availability of readily available and easy to use software products, integrating data pre-processing, data analysis, result reliability evaluation and visualization features.

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