NEXT
New Exploration Technologies

06 September 2021

Transforming Regional-Scale Predictions to Target-Scale Detections – Empowered by Advanced Statistical and Machine Learning Methods

For this latest write-up, we invited Bijal Chudasama, Postdoctoral Research Scientist and Johanna Torppa, Senior Scientist within the Information Solutions Unit at the Geological Survey of Finland (GTK) to guide us on the research they are performing in the framework of the EU funded Horizon 2020 New Exploration Technologies (NEXT) project. The area of specialization they discussed with us for this write-up deals with mineral prospectivity analysis.

Could you give us an introduction to the scope and purpose of mineral prospectivity analysis?

Mineral prospectivity analysis aims at distinguishing areas with high mineral potential from those with low potential. The resulting prospectivity maps show the variation of predicted mineral potential in a study area. These are used, for instance, in mineral exploration targeting by mining companies as well as in land-use planning by the public sector. The two essential parts of mineral prospectivity analysis are (1) conceptual mineral systems modeling and (2) mineral prospectivity modeling. Conceptual mineral systems modeling refers to gaining a geological understanding of the processes that form a mineral deposit of a certain type. Mineral prospectivity modeling involves generating a mathematical model based on the geoscientific variables representing mineralization processes and predicting prospectivity values based on this model. In addition, there are several phases of data processing and statistical analysis to support the analysis. Prospectivity analysis is commonly performed on a regional scale, as well as on shield- and belt-scales, depending on the intended use of the maps.

The Geological Survey of Finland (GTK) has, over the years, developed methods for prospectivity modeling and systematically implemented modeling of mineralization in Finland and abroad. These studies have been conducted at regional scales, belt scales and also at, smaller, camp-to-target-scales for various mineral systems. Through this effort, Finland has been at the forefront of country-wide mineral prospectivity modeling and mineral resources assessment, and particularly for modeling of gold mineralization. There are regional-scale studies covering, for instance, the entire Fennoscandian Shield in northern Finland (Figure 1a and 1b), followed by belt-scale studies for each of the important Palaeoproterozoic Belts such as the Central Lapland Belt (Figure 1c) and the Peräpohja Belt (Figure 1d) within the Fennoscandian Shield in Finland.

Aside from regional-, shield- and belt-scales, you also mentioned camp- and target-scales. Could you guide us on the motivation for this additional focus?

The regional scale prospectivity map of the Peräpohja Belt (Figure 1d) highlights the smaller camp-scale Rompas-Rajapalot area with high prospectivity but does not provide enough detail to target the actual mineralization. To produce a more detailed prospectivity map in camp or target scale, different aspects have to be considered as compared to when modeling at the regional scale. Regional scale studies are driven by the mineral systems approach. As a consequence, a strong emphasis is made on the identification of all the components associated with the formation (sources, pathways and traps) and preservation of mineralization.

To explain this in more detail, it is well-known in our field of expertise that for a region to be prospective for mineral deposits today, it must necessarily show evidence of all the critical ingredients that are required for the formation and preservation of those deposits. This means it requires (1) source(s) of ore components, transporting fluids, and energy to drive the system, (2) pathways or conduit(s) along which metals and fluids were transported from source to a sink, (3) traps signifying the physical and/or chemical mechanism(s) that deposited ore components at the sink and (4) preservation, i.e. processes permitting the preservation of mineralization in the crust up to the present time. If any of these ingredients are absent from a region, its mineral prospectivity will be low.

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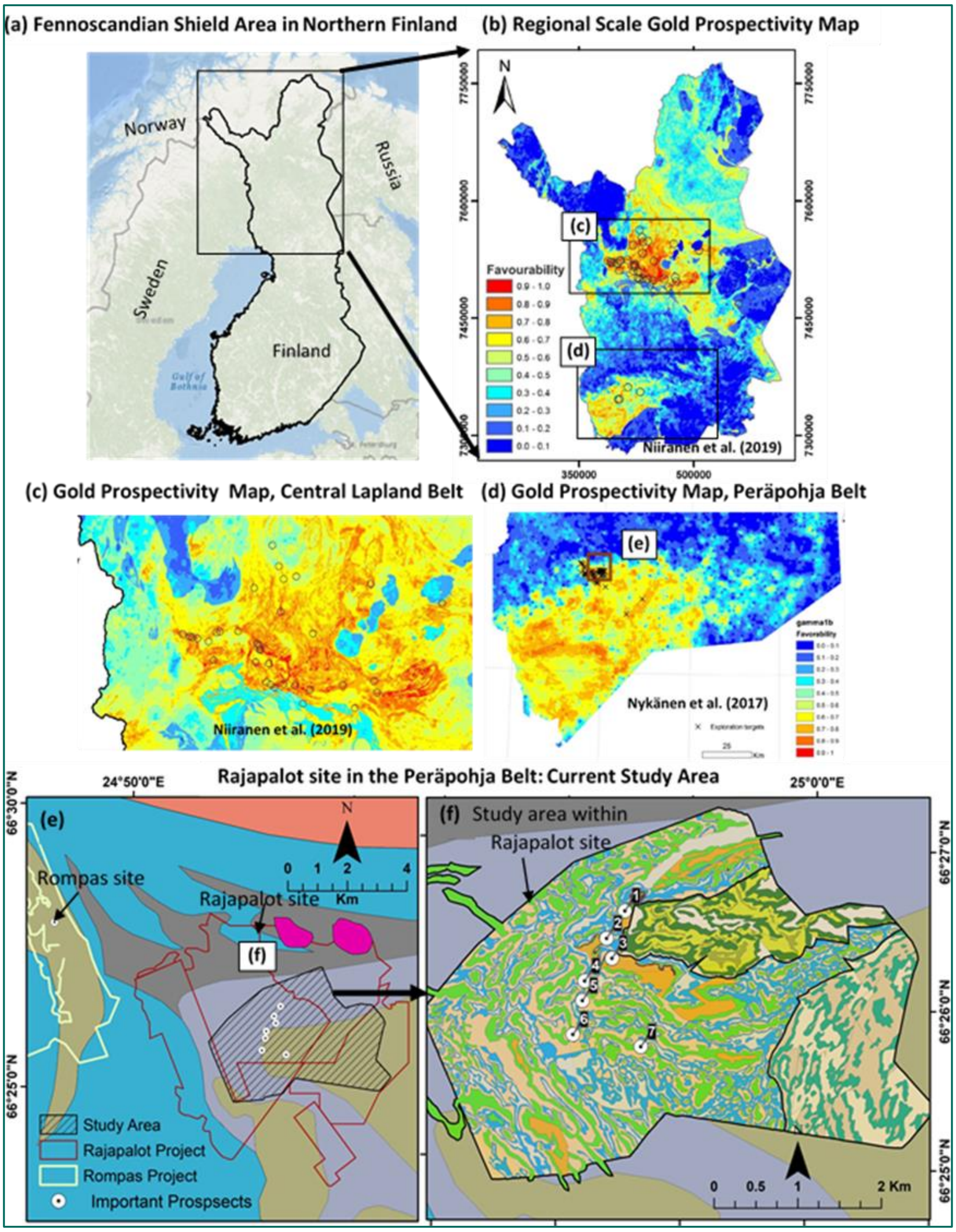

Figure 1: Prospectivity maps at different scales: Previous regional- and belt-scale studies for gold mineralization in Finland (frames a to d). The Rajapalot area (frames - e and f) within the Peräpohja Belt is the target-scale study area for identification of ground exploration targets in the NEXT project.

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All of these components associated with mineralization can be mapped at a regional and belt-scale. Once prospective regions have been identified from regional- and belt-scale studies, more detailed prospectivity analyses can be carried out in camp- or even smaller target-scale. In these smaller exploration areas, signal from the trap component only can mainly be observed because its significance outweighs that of the sources and pathways. Essentially, this difference in the significance of the mineral system components is what distinguishes a regional-scale study from a camp- or target-scale study.

In the NEXT project, our emphasis has been on identifying the trap regions and the associated geological processes. The Rompas-Rajapalot area actually comprises two different local subtypes of mineralization – the Rompas style and the Rajapalot style. In NEXT, we particularly focused on target-scale prospectivity modeling of gold mineralization in the Rajapalot project area (Figure 1e and 1f) to identify drilling areas with high mineral potential.

Could you share more details about the approaches and methods you employed for this research?

We approached our ambition to gain new insights about the geological processes operating in the trap components of a mineral system in a systematic and highly comprehensive manner. For this reason, we used several methods which generally fall under the umbrella of, respectively (1) mineral system modeling, (2) statistical testing of geological hypothesis and (3) mineral prospectivity modeling (see Figure 2).

For defining the mineral system model, we used the extensive knowledge derived from existing literature as well as the results obtained for the Rajapalot target area through field surveys conducted by research colleagues in the NEXT project to feed into a conceptual mineralization model. This enabled us to identify the trap-related favourable settings and the constituent geological processes leading to mineralization. Based on these insights, we formulated several geological hypotheses of the mineralization processes and derived the corresponding evidence layers from available geoscientific datasets.

Our second step involved the statistical testing of the geological hypotheses formulated on the basis of the conceptual mineralization model. We used both parametric and non-parametric statistical tests, such as the T-test, the Wilcox-test and the Kolmogorov-Smirnov test. This was aimed at checking if the evidence layers could distinguish the drill core sections with gold mineralization from those with very little or no gold. In turn, this helped us to identify the most representative evidence layers that then served as inputs to the advanced statistical and machine learning algorithms for prospectivity mapping. This second step was crucial because what the machine-learning algorithm 'learns' is very sensitive to what the

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input data represent. Hence, the main objective was to curate the input datasets in such a way that they paint a holistic picture of the mineralization settings to which the machine-learning algorithm was then applied.

In the final, third step, we used both unsupervised and supervised machine learning methods for mineral prospectivity modeling. The unsupervised method used was self-organizing maps (SOM). This was implemented using the open source GisSOM application (Releases · gtkfi/GisSOM · GitHub) developed by GTK in the framework of the NEXT project. SOM is an effective method for generating a low-dimensional (usually 1 up to 3 dimensional) representation of multi-dimensional/ multivariate input data. Through this conversion of the input data to the SOM-space, geological patterns can be identified, considering only the distribution of the geoscientific input variables and neglecting the spatial aspect. Additionally, distinct populations in the input dataset can be identified through the implementation of K-means clustering of the results obtained in the SOM-space. The reason for implementing this clustering is that the geospatial domains corresponding to specific populations can, by means of visual interpretations and statistical evaluations, be related to the mineralized drill-core sections, thus representing prospective mineralization areas. The transformation of the input data to the SOM-space itself does not require direct use of any training data. However, we can further apply supervised classification upon the SOM-space results using an artificial neural network (ANN). This approach of running an ANN on the SOM results was developed by the German company Beak Consultants GmbH in the NEXT partnership. More details about this further approach can be found in the write-up NEXT advances mineral predictive mapping with Self-Organizing Maps, by Andreas Brosig, who is the 3D Modeling Team Leader at BEAK.

For those more acquainted with this field of specialization, we wish to highlight that in addition to the above methods, we also implemented Fuzzy Inference Systems (FISs) and a hybrid Adaptive Neuro Fuzzy Inference System (ANFIS) for knowledge-based prospectivity modeling. Additionally, modeling uncertainties related to parametrization of the membership functions of the FIS were quantified by running Monte Carlo Simulations (MCS). The MCS-based FISs generated prospectivity maps at varying confidence levels. In the ANFIS approach, the parameters of the system were learnt by an artificial neural network in a hybrid learning environment using the gradient descent algorithm and least square estimators.

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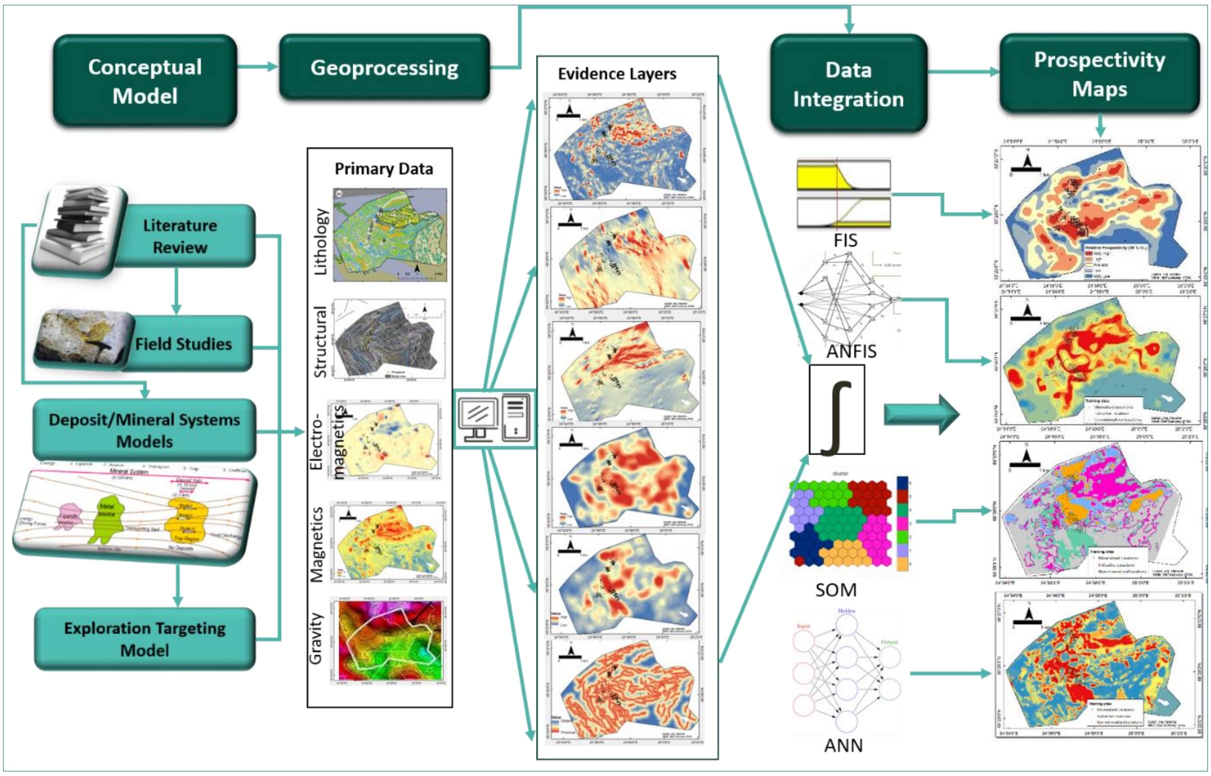

Figure 2: Prospectivity Modeling Workflow and Results

Clearly, the range of methods employed has been extensive. Based on the outcomes would you favour one method over another, or do you see the need to adopt a composite workflow in which you would essentially mix and match all of these distinct methodologies?

Usually, exploration models tend to get somewhat biased by existing discoveries. Especially data-driven machine learning based methods lead to discoveries similar to the ones already known, because the machine learning algorithm is caught up in learning only those features and patterns that are present in the training data. Hence, we are not able to identify new sub-types of mineralization or characterize the diverse controls on mineralization. Since mineral systems are formed as a consequence of tremendous interaction between different geological processes, the same mineral system can contain different types of mineralization. In such situations the knowledge-driven approaches become particularly useful, because they can target geological processes forming the deposit rather than geological features associated with the deposit. Machine learning can be applied in knowledge-based approaches as well but, in this instance, the machine is learning also from the knowledge of the geoscientist and not only from the data.

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Hence, the reasoning behind using unsupervised SOM together with supervised knowledge- and data-driven methods was to be able to:

- identify mineralization-related patterns in the input data without the use of training data
- delineate prospective areas based on the conceptual understanding of the mineralization processes by implementation of the knowledge driven approach, and
- recognize mineralization features represented in the training data and facilitate learning of these patterns by data-driven models.

Most importantly, we conclude from this study that mineral prospectivity studies can be transformed from predictive tools at the regional scale to an aid to detection tools at the target scale for identifying targeted drilling areas. The results presented here were submitted to the journal *Ore Geology Reviews* and the manuscripts are being processed.

"Geological science is full of ambiguities and uncertainties. Exploration of mineral deposits is a challenging yet an exciting task. Nevertheless, with most of the larger deposits already discovered and exploited, finding new deposits is the need of the hour. However, the complex interactions and overprinting of several geological processes since billions of years, have led to their manifestation as highly stochastic phenomena. The non-deterministic nature of earth system processes makes the fitting of mathematical models to geological data even more complicated. Yet, precisely these notions continue to stimulate my interest to gain a better understanding of these systems. Today's advanced modeling approaches come to the rescue to identify hitherto hidden patterns. Interpreting the outcomes of our modeling is like revealing the story the data have all along been trying to tell us! With my background in geology, and my expertise in geoscientific data analysis, data integration, machine learning and mathematical modeling, I try to unravel the enigmatic processes that may have contributed to the formation of mineral deposits on Earth."

Bijal Chudasama is a Postdoctoral Research Scientist in the geoinformatics and geoscientific data analyses team at the Geological Survey of Finland (GTK)

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"Like many others, I started from observing the surrounding environment on the surface of our little Earth. It was obvious that a lot is happening there that as humans we cannot directly observe. At the end, the answer to everything always seemed to be in physics and chemistry. Driven by my interest in physics, I took a tour a little further, to the Solar System and beyond. Among many things, it was exciting to model the physical properties of asteroids, seen only as tiny dots in images taken from Earth. It was also inspiring, in a few rare cases, to compare the model to the real shape and spin state of an asteroid imaged by a spacecraft. After landing back on Earth, I started digging below the Earth's surface. How can we know what is in there, below us, without actually going there? Although the target of study is really close compared to an asteroid or a distant galaxy, we just cannot easily get there. What we do is the same as in astronomical problems: find a model that describes the target with parameters that we can measure from the Earth's surface and above. This playground is where I feel at home; working with numbers and functions, and trying to get them organized with the help of physics and chemistry that have always been known to somehow be involved."

Johanna Torppa is a Senior Scientist in the geoinformatics and geoscientific data analyses team at the Geological Survey of Finland (GTK)

More about NEXT: www.new-exploration.tech

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