Mineral Prospectivity and Exploration Targeting – MinProXT 2021 Webinar

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Johanna Torppa and Bijal Chudasama (eds)

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The Mineral Prospectivity and Exploration Targeting – MinProXT 2021 Webinar joined together prospectivity analysis experts from academia, governmental research institutes and the business sector. There were 29 invited talks that covered different aspects of prospectivity analysis from method development to the practical use of prospectivity models and maps. This proceedings publication is a compilation of extended abstracts of the presentations given MinProXT 2021 webinar.

Keywords: mineral exploration, machine learning, mathematical models, webinar, geosciences, data integration, geoinformatics, mathematical geology, prospectivity analysis, target generation, geoscientific data analysis, MinProXT

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INTRODUCTION

Mineral prospectivity analysis aims at generating models and maps that can be used to distinguish regions with high mineral potential from those with low potential. The purpose of prospectivity maps depends on their spatial resolution. Regional maps in the low-resolution end are used to narrow down the area where more detailed geophysical and geochemical mapping should be carried out. Thus, such maps are not meant for discovering deposits, but they can direct exploration activities to the reasonable geological settings and domains. If exploration activities are taking place in a geologically unfeasible area, even best exploration strategy wouldn’t lead to discovery of deposits. Using the detailed geophysical and geochemical data from areas marked as prospective on the regional maps, high resolution target-scale maps can be generated to point out specific drilling targets.

Each prospectivity map is a result of tedious work, and methods for prospectivity analysis are still evolving. Since the mineral prospectivity community is a very small group even globally, discussions and sharing of information among those involved is crucial for further development in this field of research. Also feedback from the mineral exploration industry is of utmost importance for enhancing the practical applications of prospectivity analysis. Inspired by this need of interaction, the first move towards arranging MinProXT 2021 was made in spring 2021 at the Geological Survey of Finland, after a year-long travel ban had prevented the arrangement of physical meetings and a new era of online communication had started. Subsequently the MinProXT webinar was arranged as a joint effort of the Geological Survey of Finland, the United States Geological Survey, the Indian Institute of Technology Bombay and the Centre for Exploration Targeting, University of Western Australia. The webinar brought together the researchers involved in mineral prospectivity analysis and professionals involved in mineral exploration related decision making. Invited talks were delivered by delegates from geological surveys, academia and mining companies on the current state of prospectivity analysis related research and its applications.

The webinar was arranged in two parts to enable participation from all over the globe. Each part was arranged on two subsequent days lasting a little more than 3 hours per day. There were 15 invited talks in Part 1 webinar for the Eastern hemisphere and 14 in Part 2 for the Western hemisphere. 35-40 participants attended each of the four sessions on the respective days. Each day additionally had an interactive discussion session to facilitate free-form conversations between the invited speakers and the attendees. The two themes that the webinar addressed were:

- Advances and recent development in the methods of prospectivity mapping and geoscientific data analyses, and the associated uncertainties, limitations, and challenges.
- Real-world utilization of the prospectivity maps in varied fields such as land-use assignments, infrastructure planning and others in addition to mineral deposit exploration.
The improvement of the technical resources for arranging online events, such as internet connection and software, has been enormous during the past one and a half years. Also, the ability of people to act correctly in online events hosting tens or even hundreds of participants has gone a huge step forward. These facts enabled the fluent flow from one presentation to another and lively exchange of ideas during the discussion sessions.

This proceedings publication of the MinProXT 2021 webinar is a compilation of the extended abstracts of the research presented in MinProXT 2021. Based on the outcomes of the webinar, it is evident that, although mineral exploration industry started early on with the application of mathematical models and machine learning for exploration, machine learning aided prospectivity analysis has yet not been able to develop even close to its full potential. However, considering the intensity of current research on machine learning and artificial intelligence, mineral prospectivity analysis has great potential to become one of the most important tools to manage exploration and mining in the future. The key challenges that must be tackled to be able to take full advantage of machine learning in prospectivity analysis are (i) the need for diverse expertise and skills beyond fundamental geosciences, (ii) the lack of adequate datasets and (iii) uncertainty assessments.

The fields of expertise required to select, process and analyse data, and to perform the actual prospectivity modelling, include mineral–systems related geophysical, geochemical and geological knowhow as well as computational data analysis capabilities. This means that the work must be carried out as teams consisting of experts in these various fields of research. Academia should also adapt to the increasing use of computational methods in geological research by urging students to participate in courses of applied mathematics and computational data analysis. A strong link must also exist between the research teams and the end-users. Currently, on the one hand, the industry is sometimes unable to understand and properly utilize the prospectivity maps. On the other hand, researchers are not producing prospectivity maps that would be optimal for the needs of exploration and mining companies. By bridging the gap between the prospectivity modelling researchers and the industry, the needs of the end-users and the capabilities of prospectivity analysis would meet in an optimal way. Overall, machine learning aided prospectivity analysis is not used to make the decisions about where to go drilling or where to establish the mine, but it provides support for decision making. Hence, one objective that the mineral prospectivity group should aim to pursue is to shift focus from experimenting with different methods to creating practical results that can be used routinely by exploration managers for making business-related decisions.

As machine learning requires much more data than expert driven prospectivity modelling, the amount of available data often becomes the restricting factor when selecting a suitable data analysis method. Data augmentation using machine learning methods such as self-organizing maps can contribute towards creation of training points similar in feature space to the existing training points. Another approach that still has lots of unused potential for increasing the amount of training data in regional-scale prospectivity analysis tasks, is to define the training regions based on the geological settings only, without considering political and cultural boundaries. Challenges in this approach are, for instance, the heterogeneity of the data from different countries as well as organizing the international co-operation and funding. In the data-rich areas, the research currently concentrates on data integration and testing the performance of the large number of different variants of machine learning methods. One central aspect that is rarely addressed in the published research is the generation of reliable performance tests and evaluation of the uncertainty of the prospectivity maps. The ultimate test of performance of
prospectivity maps is drilling the prospective areas, but this might not be practically feasible. Hence, development of adequate performance indices is imperative for ranking and prioritization of drilling targets, and to add confidence to the results. Additionally, interpreted datasets contribute significantly towards stochastic uncertainties in the resulting prospectivity maps. Therefore, the application of machine learning methods for feature engineering and pattern recognition from the available exploration datasets also offers tremendous possibilities for reduction of subjective bias from geological interpretations.

One remarkable new extension in prospectivity analysis methodology is 3D prospectivity modelling. This is only natural because the modelled feature (i.e., the mineralization) varies in all three spatial dimensions. Especially in target scale, implementation of 2D prospectivity modelling becomes increasingly difficult, since the site is already known to be prospective. Even considering the higher spatial resolution of the target-scale models, the search-area reduction capacity of 2D prospectivity maps may not be greatly appreciable. In practice, 3D prospectivity modelling means incorporating the 3D framework of the structural complexities and mineralization horizons into the prospectivity models. The approach could facilitate identification of subsurface mineralized horizons, and has already started to shape up with several studies implementing weights of evidence-based 3D prospectivity mapping. The major limitation to 3D prospectivity analysis is the lack of exploration datasets. While the mineral prospectivity community is still struggling with the availability of training datasets for 2D prospectivity analysis.

Fig. 1. A three-way synergy between the national geological surveys, the academia and research institutions and the mining and exploration industry to identify and address the issues pertaining mineral prospectivity analysis.
and related uncertainties, it is not a surprise that a jump into 3D world is bound to pose challenges. However, these challenges with both 2D and 3D prospectivity analysis can be overcome by fostering collaborative research between the national level geological surveys, the academia and research institutions and the mineral exploration and mining industry (Fig. 1). MinProXT 2021 efficiently boosted this collaboration, and it has the potential to offer and develop into an equally inspiring venue for exchange of ideas in the coming years as well.

Organizing committee

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**Key-note speakers**

**Dr Gregor Partington**, Managing Director, Kenex; Operations Manager, Duke Exploration

**Title of the talk:**

*Outcomes from using mineral potential modelling as a tool to support decision making in mineral exploration and resource development*

Dr Gregor Partington has been involved in mining and exploration in Australasia for 40 years and has experience in discovery and development of projects for gold, copper, silver, tin, tungsten, tantalum, lithium and PGE metals. The businesses he has created are focused on creating business opportunities through the application of spatial and predictive modelling. Dr Partington is the Managing Director of Kenex and the Operations Manager at Duke Exploration.

**Dr Jon Hronsky**, Principal of Western Mining Services; Adjunct Professor, Centre for Exploration Targeting, the University of Western Australia

**Title of the talk:**

*Mineral exploration targeting and prospectivity analysis – A practitioner’s perspective*

Dr Jon Hronsky has more than 35 years’ experience in the mining and exploration industry. He is currently a Principal of Western Mining Services, a consultancy group that provides strategic–level services across the global mineral exploration industry. Previous roles included Manager of Strategy and Project Generation for BHP’s global mineral exploration group and Chief Geoscientist for WMC Resources. Jon is an Adjunct Professor at the Centre for Exploration Targeting at the University of Western Australia. He is a Director of several ASX mining companies, and also a partner in Ibaera Capital, a mining–focused private–equity fund. In 2019, he was awarded the Order of Australia medal for services to the Mining Industry.

**Dr Andreas Barth**, Managing Director, Beak Consultants GmbH

**Title of the talk:**

*Mineral predictive mapping (MPM) – From intuition to quantitative hybrid 3D modelling*

Dr Andreas Barth is an exploration geologist and geochemist. His passion is the understanding of mineral–forming processes and metallogeny as preconditions for effective exploration strategies. After cumbersome, mostly manual work in the 1980s, the fast development of information technology has made statistics, GIS processing and artificial intelligence available for big data analysis. Since 2000, Dr Barth has focused on the development of effective data management systems and on the application of artificial intelligence methods for analysing geological data. Consequently, since 2008, this led to the development of Beak Consultant’s work–flow oriented advangeo® prediction software for easy access to AI technologies in a common GIS environment. Since 1994, Dr Barth has been the Managing Director of Beak Consultants GmbH.
Dr Nicole Januszczak, Global Practice Lead Mineral Systems, BHP

Title of the talk:
Beyond prospectivity maps: Tackling the growth challenge facing the mining industry with the application of mineral systems

Dr Nicole Januszczak joined BHP in 2020 as Global Practice Lead Mineral Systems for the Resource Centre of Excellence, based in Toronto, Canada. Prior to this she held a number of senior positions at De Beers Group including Senior Exploration Manager for the Americas. She has a Ph.D. degree in geology from the University of Toronto. She has over 20 years of experience in predicting, targeting and exploring minerals and metals in diverse cultural and geographical regions around the world.
OUTCOMES FROM USING MINERAL POTENTIAL MODELLING AS A TOOL TO SUPPORT DECISION MAKING IN MINERAL EXPLORATION AND RESOURCE DEVELOPMENT

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INTRODUCTION

The science, techniques, tools and data availability for mineral potential modelling (MPM) have come a long way since the publication of the book by Bonham-Carter in 1994. The advent of modern data collection and storage technologies and a global effort by national geological surveys to provide precompetitive digital data has resulted in a huge increase in data volume. This means exploration decision-making has become much more complex. However, the opportunity for making new discoveries has improved at the same time. Current exploration targeting usually fails to incorporate recent advances in MPM and mineral system research, and the mineral exploration industry rarely uses MPM techniques in exploration, particularly in the decisions that lead to discovery and the development of new economic orebodies.

Government geological surveys are more comfortable using MPM to aid their business objectives, with examples including the Geological Survey of NSW recently completing a project mapping the main mineral systems in NSW using MPM (e.g., Ford et al. 2019) and the Geological Survey of Finland, GTK (e.g., Nykänen 2020). Both geological surveys have not only used MPM to help market the prospectivity of their jurisdiction to encourage investment in mineral exploration, but they also recognise the power of MPM to support resource and land management decisions. This supports the ideas presented by Yousefi et al. (2019) regarding the need to develop decision support systems that can be used by the mineral exploration industry and other stakeholders. Here, two case studies are provided in which the results of MPM have been used to support investment decisions in the discovery, development and mining of new orebodies.
USING MPM AT THE REGIONAL SCALE

The mineral exploration industry and researchers are more accepting of the use of MPM for regional targeting, as it tends to better match the resolution of data available for these types of studies. In this case study, the initial aim of the project was to map the potential for porphyry–style mineralisation in central Queensland in any age of rocks, in contrast to the usual exploration models that focus on Permo–Carboniferous systems. The case study is also a good example of the power of using MPM with regional–scale data, which uses bedrock geology as the main targeting map data source with support from datasets such as geophysics and geochemical data.

The study started with a review of available literature, compiling publicly available data mainly from the Queensland Geological Survey, testing of predictor maps, and generating a prospectivity map using the weights of evidence technique. Details of the study and the resultant exploration of the Bundarra project, with maps, sections, diagrams and photographs, are available from kenex.com.au/Projects/bundarra.asp (Kenex 2021b) and duke–exploration.com.au/ (Duke Exploration 2021).

The Bundarra Project area was mapped as being one of the most prospective targets, confirming that many of the required geological features for porphyry–style mineralisation were present. A follow-up review of publicly available databases confirmed that the area mapped by the regional–scale MPM had the potential for immediate exploration and resource development for copper, silver and gold from a porphyry system related to the intrusion of the Bundarra pluton. Follow-up field geological mapping and geochemical analysis suggested that the mineralisation around the Bundarra pluton was potentially part of a lode–style porphyry mineral system, consistent with an Andean–style convergent margin model.

The results from the regional MPM provided the confidence to invest in making tenement applications over the target area, which was freely available, and the subsequent raising of capital to support follow-up exploration. This culminated in mapping of the local–scale prospectivity of the Bundarra pluton using MPM, which successfully mapped the mineral potential of the Bundarra tenement for porphyry copper–silver–gold mineralisation. A 64–km² area surrounding the perimeter of the Bundarra pluton was mapped as prospective. Targets were generated from the MPM, which represented the areas with the greatest geological potential for hosting porphyry copper–silver–gold mineralisation. The MPM targeting reduced the prospective exploration search space from 466 km² (size of the study area) to 63.6 km² (area of the prospective area), 10.86 km² (area of the targets), and finally to 3.44 km² (area of highly prospective targets).

The results were used to plan diamond and resource drilling at the Mt Flora prospect, which was mapped as the highest priority target. The first phase of drilling was successful and an Inferred JORC Code (2012) resource of 16 Mt at an average grade of 0.5% Cu and 6.9 ppm Ag at a 0.2% Cu cut–off grade, which equates to 78,000 tonnes of copper and 3.6 million ounces of silver, was reported six months after listing Duke Exploration on the ASX. There are currently five other target areas with similar development potential on the Bundarra project as mapped by MPM.

The use of MPM has helped provide confidence in the decisions and investment in the exploration that discovered a new resource of copper and silver in an area that is considered as primarily prospective for coal resources. The workflow, techniques and targeting methodologies used are clearly an example of the type of decision support system described by Yousefi et al. (2019) but applied using a variety of software tools in a relatively manual way rather than in a centralised system.

Is this really a new discovery, given that copper was mined from the area in the 1880s? Maybe not, but the rediscovery of a new modern resource of copper and silver would not have occurred without the use of MPM and the associated
targeting systems developed. The Bundarra pluton case study is an example of the rediscovery of an opportunity that to some extent has been hidden in clear sight and how MPM-supported decision making can speed up discovery.

**USING MPM FOR RESOURCE DEVELOPMENT AT THE MINE SCALE**

This case study is from an opportunity at the other end of the exploration value chain to the Bundarra pluton case study and is an example that is less well understood by the industry of how MPM can aid decision making in the resource development stage. This work was carried out to support resource development at the Tampa Gold Project in Western Australia (Nielsen et al. 2019). The aims of the study were to help constrain resource estimation, understand the distribution of gold grades from the resource estimation techniques with respect to geological and physiochemical continuity, and predict the location of new gold mineralisation for future exploration drilling to expand the gold resource at the Tampa gold deposit. Details of the study and the resultant resource development and mining, with maps, sections, diagrams and photographs, are available at [http://kenex.com.au/Projects/tampa.asp](http://kenex.com.au/Projects/tampa.asp) (Kenex 2021a).

Because the target is at the mine scale, the resolution required to map the mineral system requires MPM to be performed in 3D using data from detailed pattern drilling and mine-scale geophysical 3D inversions and constrained by a local-scale granulite-facies orogenic gold mineral system model. The data included lithology, structure, rock property data and geochemical data. Altogether, 44 individual maps were created in 3D and tested for their spatial correlation with training data from high-grade gold drill intersections, using the weights of evidence technique. Of these, 11 were chosen for the MPM that had the highest spatial correlation with the training data and did not duplicate map patterns.

Drilling on a 10-m square grid was subsequently undertaken over the area where the post-probability results mapped a high and continuous probability for gold mineralisation, while the resource model estimated less continuous and lower grade gold mineralisation. The drilling aimed to compare the gold continuity with the resource estimate gold grades and post-probability values from the 40 m by 40 m spaced resource drilling. The results were used to test the performance of both the resource and MPM and assess the use of MPM to help map geological domains for resource estimation. Results from the infill drilling confirm the gold continuity compared to the post-probability values and that MPM predicted the location and distribution of gold mineralisation within the area drilled. The gold results were also better and more continuous than predicted by the resource estimate. Importantly, these results confirm that geological and physiochemical controls on gold mineralisation at the mine scale can be numerically measured and mapped at the scale of an orebody. This allows MPM to be considered as an option to constrain and help inform the results of geostatistical techniques used in resource estimation.

**FUTURE OF MPM IN MINERAL EXPLORATION AND DEVELOPMENT**

It is clear from the advances now being made in machine learning systems that these will become important tools to help exploration and mining into the future. Current research has advanced the techniques needed, and the quality of available
data is rapidly improving. The availability and quality of data remains critical, as made clear by Ford (2019). No matter how good our MPM techniques are, they have to use quality data and maps to work successfully. More importantly for industry to start routinely using MPM, access is needed to the type of systems described by Yousefi et al. (2019), with the main algorithms and tools available in one software system, including decision support workflows. The final piece of the jigsaw is the availability of trained professionals to manage, maintain and run these systems, which needs to be considered as part of university degrees in geology, particularly in those institutions that teach economic geology.

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ANALYSING MINERAL SYSTEMS USING GEO-CONSTRAINED NON-EUCLIDEAN DISTANCES

by

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Mineral system analysis demands a combination of the understanding of fundamental geological processes and the multiscale structural, stratigraphic, and tectonic setting at the time of mineral deposit formation. In many complexly deformed terranes, our understanding of the former far outweighs our understanding of the latter. Analysing the spatial relationships between known mineralisation and geological ‘features’ such as faults, intrusions and specific stratigraphic units has traditionally used a Euclidean metric to describe distance. Developing alternate distance metrics that better represent geological processes may allow us to better constrain which processes, and which features, define a specific mineral system. This study demonstrates the potential for using non-Euclidean approaches to estimating distance in regions of complex geology.

INTRODUCTION

The use of Euclidean (straight-line) distances in classical geostatistics is an understandable short cut, but limits our ability to unravel mineral systems, as it weakens the links between geological features, such as faults, and the underlying processes, such as fluid flow, that underpin minerals systems. Recent work involving geological models (von Harten et al. 2021) has demonstrated the utility of using implicit 3D modelling codes to allow folding to be taken into account during geostatistical analysis. The use of more complete non-Euclidean graph-based analyses has been demonstrated in fields as diverse as house prices (Lu et al. 2011) to hydrology (Curriero 2006). In this study, we explored a new graph-based methodology for analysing geological topology that permits a range of non-Euclidean distance metrics to be explored.
METHODS

We have modified the map2loop/map2model codes (Jessell et al. 2021) to deconstruct a part of the 1:500 K Interpreted Bedrock Geology Map of the Hamersley Region of Western Australia (Fig. 1a), (Thorne & Trendall 2001). First, we decompose the map into individual fault or stratigraphic contact bounded polygons, which we colour using an arbitrary colour scheme (Fig. 1b). The geological map is then converted into a graph data structure storing the spatial relationships and types of contact between all the geological polygons and faults in the map. Specifically, fault–fault, fault–stratigraphy and stratigraphy–stratigraphy relationships are extracted from the map. In Figure 2, we only show the graph of the original map, not the deconstructed polygons, to make the graph easier to interpret. Each fault (circle) and stratigraphic polygon (square or triangle) represents a node in the graph, and each contact an edge.

To provide a baseline, we can calculate the centroids of each polygon and compare its distance to a reference polygon, here the Turee Creek Group, which we

![Fig. 1. Geological map and derived maps showing various metrics for calculating distance; see text for details.](image-url)
could imagine contains a mineral deposit of interest (Fig. 1c), and we can think of this map as showing the classical view of the deposit’s ‘neighbourhood’. There are many possible methods for calculating distance in a graph. Here, we highlight two methods, the resistance distance (a proxy for fluid flux) and the Dijkstra shortest path (Hagberg et al. 2008). The resistance distance (Fig. 1d) represents the distance between two nodes of a graph akin to treating the graph as a grid of resistors with each resistance equal to the provided weight of a contact. In the example shown here, the resistor weightings are arbitrarily assigned as: fault = 1; fault–formation contact = 5 and formation–formation contact = 9, where higher numbers mean less favoured pathways. The shortest paths are thus weighted towards geological polygons that are connected to the Turee Creek Group by multiple faults, such as the Hardy Formation.

If we are more interested in the shortest pathways between two features, we can use Dijkstra’s algorithm, which calculates the shortest weighted path, and in this example, we can include two additional node weights as well, and we used fault–fault intersection = 3; formation = 7. In Figure 1e, we highlight one example

Fig. 2. Graph of spatial relationships between faults and stratigraphic units for the area shown in Figure 1. Black lines are fault–fault relationships, orange lines are formation–formation relationships and olive-green lines are fault–stratigraphic group relationships.
of the shortest path with black arrows, which traverses both stratigraphic polygons and contacts according to the assigned weights. We can compare this distance map with the same calculation where four of the faults (thicker lines) have been assigned much higher weights, which reduces their likelihood of providing the shortest path (Fig. 1f).

**DISCUSSION**

The graph-based analysis used in this study demonstrates the potential for incorporating additional geological information to define non-Euclidean distances in a mineral systems context. For clarity, distances here were calculated between stratigraphic units, but could also be between faults and units, or mineral deposits and faults. In the example here, we have used electrical resistivity as a proxy for fluid flow, as the mathematical descriptions are similar, and in the future we could also add capacitance/storage capacity for elements.

A closer coupling to geological processes and age relationships is also possible using this method, as different faults, or generations of faults, can be weighted according to their relevance during the activation stages of mineralisation. We could also draw upon empirical relationships between the width of damage zones (and hence permeability) and fault length to modify graph element weighting.

The complexity of graph descriptions of 3D models scales with the number of geological features, not the number of dimensions, so this approach can be equally well be used if 3D geological models are available. Finally, we should emphasise that these calculations are not intended to replace fully coupled fluid–mechanical modelling. However, they may provide a pathway to rapid analysis of mineral systems in an exploration setting, and highlight regions worthy of the effort required for more complete numerical modelling.

**ACKNOWLEDGEMENTS**

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HYBRID MINERAL PREDICTIVE MAPPING WITH SELF-ORGANIZING MAPS AND A MULTILAYER PERCEPTRON

by


Self-organizing maps (SOM) are a versatile tool to analyse and interpret gridded datasets such as remote sensing or potential field data. The data are transformed from geographic space to SOM space, where they can be clustered according to overall similarity. For geological interpretation, the clustered data are transformed back to geographical space. We enhance the utility by applying a multilayer perceptron (MLP) in SOM space to produce mineral predictive maps. The reduced number of grid cells in SOM space improves the performance of the MLP and the tolerance to imperfections in the model input data compared to an application of the MLP to the original data. The resulting mineral prediction map allows the definition of exploration zones for detailed studies.

INTRODUCTION

In the case of mineral prospectivity mapping, numerical methods are used to analyse large amounts of data to find patterns typical for certain types of mineral deposits. The critical factors for the formation of mineral deposits are typically known from mineral systems modelling. However, the processes involved in deposit formation are usually far too complex for deterministic models. Moreover, the input data for any type of deterministic model are necessarily incomplete due to the highly localized nature of sampling and the impossibility of observing the starting conditions of the mineralisation process. Often, only parts of the mineral system are accessible to investigation, because other parts are too deep in the subsurface, cut off by later tectonic deformation or removed by erosion.

Mineral prospectivity mapping attempts to deal with these limitations by finding relevant patterns in the available data, often coupled with a self-learning process that utilizes known mineral occurrences. The presented method combines two types of artificial neural networks (Fig. 1): self-organizing maps (SOM) and a multilayer perceptron (MLP). We apply it to the prediction of tin skarn deposits in the German Erzgebirge area.

DATA AND METHODS
Self-organizing Maps

A self-organizing map (Kohonen 2001) is an unsupervised artificial neural network that projects a set of n-dimensional vectors, referred to as data vectors, to a two-dimensional SOM lattice. The lattice consists of cells, each of which is represented by an n-dimensional vector referred to as a codebook vector. Each data vector is assigned to the cell whose codebook vector is closest to the data vector itself. The SOM cell that a data vector is assigned to is referred to as the best matching unit (BMU) for that data vector. The usability of SOM for mineral predictive mapping is based on the algorithm’s topology-preserving properties: similar data vectors are assigned to SOM cells in close proximity to each other. This is because each time a data vector is assigned to its BMU, not only is the BMU codebook vector modified to more closely resemble the data vector, but the codebook vectors of the neighbouring cells in the SOM lattice are also similarly modified.

![Diagram of the data flow in the SOM-MLP mineral prospectivity mapping approach. The MLP operates solely on SOM-clustered data (light blue). The MLP output is then transformed back to geographical space, giving the final map.](image)

The Multilayer Perceptron

The multilayer perceptron (MLP) is a simple type of artificial neural network. A neuron can receive input information from other connected neurons, and every connection has a weight assigned to guide the flow of information. If the incoming information exceeds a certain threshold of the activation function, the information is propagated to other connected neurons. The training of the MLP consists of adjusting the connection weights from an initial state by comparing the predicted values at the training points with the actual values of the training points. The learning algorithm optimizes the connection weights in each iteration until the residual error falls below a defined threshold or until a defined number of iterations is completed. The result is a prospectivity map of the dimensionless parameter favourability (Knobloch et al. 2017).

By running the MLP in SOM space, the calculation is much faster, as the number of grid cells is strongly reduced. Additionally, problems with overfitting are mitigated, because the training data localities are clustered with highly similar localities in common SOM cells. To obtain the mineral prospectivity map, the data are transformed back to geographical space (Fig. 1).
Model Input Data

The generalized geological map units were transformed into a set of binary grids where a value of 1 indicates the presence of the respective unit and a value of 0 its absence. The tectonic dataset was separated into four sets, which correspond to different phases of tectonic activity in the region. Additionally, intersections of faults were extracted and the faults were separated into four size categories. For each of the nine faults datasets, a grid with distances to the nearest fault was calculated.

From a 50-element stream sediment survey (0.94 samples per km²), grids were interpolated for each of the analysed elements. The sampling point is shifted to the centre of the catchment area and the measured concentrations are log-transformed for the interpolation. The shifting improves the delineation of anomalies, and the log-transformation is chosen to preserve weaker anomalies in the gridded data.

Geophysical data (gravity, magnetics) were reprocessed and various derivatives were calculated as model input data.

The outcrops of the known tin skarn occurrences in the map area were digitised for use as training and validation data for the MLP.

RESULTS AND DISCUSSION

The final mineral prospectivity map uses 26 model input data layers. For comparison, the MLP was applied to the same model input data and training data in geographical space. A section of the resulting maps is presented in Figure 2.

A visual comparison of the maps shows the tiled appearance of the SOM–MLP map, in which each tile represents the data vectors that were assigned to one codebook vector and therefore return the same favourability.

Despite careful tuning of the algorithm’s parameters, the problem of overfitting is evident in some areas of the MLP-only map, where the prospective area is segmented into disconnected spots separated by corridors of near-zero prospectivity. This is a geologically implausible result, which is largely avoided in the SOM–MLP map.

Fig 2. Comparison of corresponding fragments of the mineral prospectivity maps obtained with SOM–MLP and MLP only.
The most interesting result of the SOM–MLP is a linear NW–SE-striking zone of high prospectivity to the north of the Schwarzenberg gneiss cupola, which is not well resolved in the MLP-only map. A parallel zone to the south of the cupola corresponds to the Rittersgrün–Plavno fault system, a complex fault zone along which several skarn occurrences are lined up (Ondruš et al. 2003, Hösel 1997). The northern zone does not correspond to any mapped fault system of comparable size and contains only one known skarn deposit at Bernsbach (Hösel 1997). The possibility of a so far unrecognised tectonic zone, which may have provided pathways for the fluids from the underlying tin-specialised granite and promoted the formation of tin skarns, is a result that merits further exploration activities.

REFERENCES


The increased use of machine learning methods for mineral potential mapping has resulted in a number of challenges being raised in relation to how to handle big data. Proposed solutions to these challenges frequently make assumptions relating to the nature of the input data, which can be invalid for some mineral systems and/or input data types. This paper briefly addresses some of these input data challenges and presents some possible solutions.

INTRODUCTION

There has been a recent proliferation of studies utilising machine learning–based techniques for mineral potential mapping. Methods such as random forests (e.g., Carranza & Laborte 2015) and neural networks (e.g., Nykänen 2008) are most commonly applied in mineral potential mapping studies. However, very few of the case studies presented have utilised big data.

In the few published studies that have realistically attempted to use big data for mineral potential mapping, a number of challenges have been identified. For example, Xiong et al. (2018) implemented a case study using a deep autoencoder network that took 42 pre-classified input maps. However, the authors noted challenges when more input variables were included in the model. The method implemented is also considered less accurate than supervised learning methods. Ford (2020) implemented a random forest–based case study that utilised up to 197 input maps, but found that the use of input maps that had not been pre-classified produced much weaker results than using binary input maps.

Most of the challenges that relate to the use of big data in mineral potential mapping arise from two issues: (1) the lack of sufficient known deposits that can be used to train the model and (2) the large number of unique conditions that the model is required to generalise. This paper briefly discusses how these challenges arise in practice and suggests some hypothetical solutions.
DATA AND METHODS

To highlight the aforementioned challenges, data from the Macquarie Arc in central NSW, Australia, were used to produce mineral potential maps for a porphyry Cu–Au mineral system. The comprehensive list of predictive variables used to represent spatial proxies for the mineral system processes are provided in Ford et al. (2019). Both random forests (RF) and neural networks (NN) were used to generate mineral potential maps for the porphyry Cu–Au mineral system. Both binary maps (thresholds or other classifications determined using weights of evidence statistics) as well as unclassified maps (with no favourability criteria applied) were used as input to the models. There were 164 binary input maps and 197 unclassified input maps generated that relate to the mineral system. Fourteen known porphyry Cu–Au deposits were used in training the model, with an additional 14 non-deposit locations being generated (Ford 2020). A separate subset of 211 porphyry Cu–Au occurrences was used for validation. This resulted in four mineral potential maps being generated: (1) RF with binary input maps (RF164), (2) RF with unclassified input maps (RF197), (3) NN with binary input maps (NN164) and (4) NN with unclassified input maps (NN197).

RESULTS AND DISCUSSION

Three criteria were used for assessing the results of the mineral potential maps generated using RF and NN: (1) training accuracy, (2) prediction of validation occurrences within the prospective area and (3) reduction of the exploration search space. Both RF models had the same training accuracy of 89.3%, as evaluated from the confusion matrix. However, the NN models had vastly different training accuracies (defined by the loss function), with the binary input maps producing a training error of 0.000072, while the unclassified input maps produced a training error of 1.00075. Model RF164 predicted 88.1% of the validation occurrences within the prospective area (93.5% search space reduction), RF197 predicted 97% (52.3% search space reduction), NN164 predicted 91% (84.7% search space reduction) and NN197 82.5% (62.9% search space reduction).

Although the RF and NN models typically showed a reasonable training accuracy, the output mineral potential maps using NN show clear overfitting of the training data (Fig. 1). Overfitting is a consequence of the few known porphyry Cu–Au deposits used to train the model, combined with the large number of unique conditions present. For example, in the models that utilised the 197 unclassified input maps, each pixel represents a different unique condition. With only 28 training points to learn from (14 known deposits, 14 non-deposit locations), the models have difficulty learning how to generalise the remainder of the unique conditions.

A number of studies have been undertaken that aimed to address the limited availability of training data for machine learning through data augmentation. Methods such as SMOTE (Chawla et al. 2002) or the addition of noise (e.g., Brandmeier et al. 2020) are commonly used to increase the size of the “deposit” training class for mineral potential mapping. However, the methods assume that neighbouring classes share similar characteristics to the class that contains the original known deposit.

While this may be a sensible assumption to make for many mineral systems and input maps (i.e., a buffer of 300 m around a fault is reasonably similar to a 400–m buffer), it is not necessarily a valid assumption when categorical or discontinuous numeric input maps are used. For example, in the porphyry Cu–Au case study, one
of the key targeting criteria is magma fertility, which is constrained to the host rocks. These host rocks are not buffered, so the neighbouring class in this case would result in the augmented “deposit” data points being placed in geologically non-permissive units. When a number of these categorical or discontinuous maps are included in the model, the issue is exacerbated. These cases tend to arise most often when the host rock (or some characteristic thereof) is critical for targeting the mineral system.

One possible solution to this problem is to use these data augmentation methods as is, and then manually remove any new “deposit” training sites that fall in non-permissive geological units. The pitfall of this approach is that in doing so, a location that has all of the other targeting criteria but may represent a location of incomplete geological mapping may then fail to be highlighted as prospective.

Fig. 1. Output mineral potential map for model NN197 showing a lack of variation in the prospectivity values (inset shows prospectivity over Gidginbung, where some intermediate values are observed in a few pixels to the west).
Further to this, while these data augmentation methods represent a way to increase the size of the training dataset, they also have limitations when too many unique conditions are present. Machine learning methods still end up learning too much from the small number of known occurrences that are used as the basis for the oversampling or augmentation, which can lead to further overfitting.

Overfitting can also be addressed by reducing the complexity of the model through a reduction in the number of unique conditions. For the porphyry Cu–Au models, this was implemented through the use of binary input maps (reclassified based on weights of evidence statistics). Other methods can be used to reduce the number of classes in each input map and/or the number of input maps could be reduced. While this may represent the most practical solution, the simplification of the input maps risks losing critical detailed information that can help with characterising the mineral system.

The challenges related to the lack of known deposits with which to train the model and the complexity of the input maps are related. Future research avenues should consider both of these challenges together, as solutions published to date are not suitable for mineral potential mapping with very large numbers of unique conditions and little (training) data.

REFERENCES


APPLICATION OF C–C FRACTAL MODELLING TO SEPARATE ANTHROPOGENIC FROM GEOGENIC PATTERNS

by

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Most of the classification models applied in exploration and urban geochemical studies typically consider the relationship between geochemical concentration values and mathematical, statistical or geometrical properties. Therefore, geological interpretations take place passively after model characterisation. The concentration–concentration (C–C) fractal model was developed to actively improve such procedures by integrating concentrations and geology. It mutually classifies the target element concentrations based on the other elements that are highly correlated with the target element. This model was developed further in this study to separate anthropogenic from geogenic patterns in urban and environmental geochemical studies.

INTRODUCTION

One of the significant aims in geochemical data analysis projects is the application of highly efficient classification models to distinguish mineralisation signals from other processes or sources, as well as controls on variation in background geochemical distributions (Grunsky & de Caritat 2019). In environmental or urban geochemistry, the objective is generally the separation of geochemical patterns related to anthropogenic contamination from those derived from natural or geogenic processes (Zissimos et al. 2021). The data addressed in these cases are commonly presented in the form of geochemical maps at various scales, sampling densities and sampling geometries (Sadeghi 2020).

Various mathematical and statistical models have been applied to regional geochemical data to reveal subtle geochemical patterns related to the effects of different styles of mineralisation or variations in parent lithologies. Fractal/multifractal modelling is amongst the most robust models for this purpose. In this research, a newly developed concentration–concentration (C–C) fractal model (Sadeghi 2020, 2021) was applied to the soil data of Lemesos, Cyprus, to separate anthropogenic from geogenic patterns. Here, the C–C model results are compared with those of the conventional concentration–area (C–A) fractal model (Cheng et al. 1994), applied to centred log–ratio (clr) transformed data (called tF data), and interpreted further.
DATA AND METHODS

In Lemesos, the study focused on the raw and tF data. The C–A model was applied to all factors of tF, including tF1, tF2 and tF3, among the whole eight factors obtained by clr-transformation of the data (Fig. 1). The C–C fractal model was also applied to the raw data (with outliers removed) of Cr–Ni, in addition to Pb–Ag and Ni–Cr (Fig. 2).

Equations

Sadeghi (2020, 2021) developed the C–C fractal model based on the equation:

\[ C_2 (\geq C_1) = F C_1^{-D} \]  

(1)

where \( C_1 \) represents the target element concentration required to create the anomaly map, \( C_2 (\geq C_1) \) is the cumulative concentration of the element classified in the same factor with the main element with concentration values higher than or equal to \( C_1 \), \( F \) is a constant and \( D \) is the fractal dimension of the spatial distribution of element concentrations.

RESULTS AND DISCUSSION

The factor scores of C–A fractal models and the two-element pairing C–C fractals display distinct population ranges, although the boundary between populations 1 and 2 (background to marginally anomalous) is somewhat arbitrary, as there is curvature in the fractal plots. The main geological controls on the multivariate geochemistry are very clear. The C–A fractal populations for tF1 scores defining the boundary between the carbonates (mainly the Pakhna Formation) to the north of Lemesos and the alluvium–colluvium-dominated areas that contain a mixture of CTSS and TO-derived materials. In Factor 3, dominated by Cr–Ni, the higher fractal populations follow the outwash areas to the alluvial plains from the main streams that drain south from the TO across the coastal plain that contains Lemesos. This is largely replicated by the Ni–Cr C–C fractal model, which shows almost identical patterns to the Factor 3 C–A fractal distribution patterns.

The upper populations in the Factor 2 C–A fractals are largely restricted to a zone that runs in an E–W band across the southern limits of the Lemesos urban area (Fig. 1). Most of the modern Lemesos urban area, however, sits within the main background population. It is again noted that the Pb–Ag–Sn–Zn association has been previously identified as relating to anthropogenic contamination (Zissimos et al. 2018). The Pb–Ag C–C fractal plot provides a different perspective on this association, with the same E–W high concentration zone defined by the higher two populations (Fig. 2), but most of the modern Lemesos urban zone and surrounding the main region of contamination.

In the case of the Ni–Cr C–C fractals, this provided little additional information to that obtained by the plots of the Factor 3 scores, as Ni and Cr are dominant (or in fact just the raw Ni or Cr data). The Pb–Ag C–C plot did, however, identify low-level contamination across the Lemesos urban area, which the Factor 2 scores and Pb, Ag, Sn or Zn individually did not (Fig. 2).
Fig. 1. IDW-interpolated map of the scores of the first three factors of the clr-transformed data classified based on the C–A fractal model (from Sadeghi 2020).
Fig. 2. IDW-interpolated map of fractal populations for the C–C fractal models of Pb-on-Ag and Ni-on-Cr (from Sadeghi 2020).

REFERENCES


PROSPECTIVITY MODELLING TO PRACTICAL EXPLORATION TARGETING: BRIDGING THE GAP?

by

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Mineral prospectivity modelling, increasingly discussed in research publications, is yet to significantly improve the effectiveness of practical exploration targeting, particularly in under-explored regions at the deposit to camp scale. This situation is unlikely to be changed by simply increasing the number of case studies, or through the introduction of new computational algorithms. The significant theoretical and practical challenges of predictive prospectivity modelling impose limitations on achievable modelling outcomes. Challenges that can be addressed in the medium term include the following: more effective translation of mineral system concepts into mappable targeting criteria; aligning the spatial scale and resolution of output models with those of the available critical input datasets; the identification of subtle yet fundamental metallogenic controls operating at district to camp scales; and adequately modelling the uncertainty of prospectivity models. Prospectivity modelling can be a valuable intermediate tool for decision support, but cannot ultimately replace expert decision making in exploration targeting.

INTRODUCTION

Case studies of mineral prospectivity modelling commonly use one of several established approaches and methods and measure the effectiveness of an output prospectivity map based on its relative success in correctly identifying the locations of known deposits and confirmed unmineralized locations. A growing number of studies also invoke the mineral system conceptual framework (Wyborn et al. 1994, McCuaig & Hronsky 2014), aiming to better link mathematical data aggregation models with essential geological processes leading to the formation of mineral deposits (McCuaig et al. 2010). However, the rapid proliferation of published case studies has failed to significantly improve the effectiveness of mineral exploration targeting (Hronsky & Kreuzer 2019). This paper highlights several critical challenges and limitations of the current approaches to prospectivity modelling, particularly in their practical application to exploration targeting.
METHODS

Practical limitations of prospectivity modelling

Mineral prospectivity modelling aims to assess the relative favourability, or probability of occurrence of a mineral deposit, $P_D$, in each cell within a study area, given a combination of other observed or interpreted features and properties of $n$ types within the same cell

$$P_D = F(x_{1k}, x_{2m}, ..., x_{nj})$$

Prospectivity modelling analysts typically focus on: (i) the construction of $n$ evidential data layers/maps from the available geological datasets, and (ii) the selection of an ‘optimal’ data integration algorithm $F$.

For practical exploration targeting under-explored or even unexplored areas, the effectiveness of prospectivity modelling outputs is inevitably limited by several key factors, including: (i) the availability of critical geological information (of the required types, volumes, scale, consistent coverage, spatial resolution and variety); (ii) understanding of critical and constituent mineral system processes and the ability to identify their expressions in the available geological data; (iii) uncertainty (of the available data, knowledge, processing and aggregation algorithms and models) and its effects on spatial predictions; (iv) the intrinsic predictability of specific locations of undiscovered mineral deposits, both theoretically and given the practically achievable levels of data and knowledge.

Prospectivity models integrating input data with an inconsistent scale, coverage and spatial resolution produce outputs strongly biased towards better explored areas (typically in outcropping areas and/or areas proximal to known mineralisation). This risk of bias can be addressed by either limiting the spatial extent of modelling to those areas with consistent data coverage and resolution or by excluding datasets with highly variable coverage and resolution. However, the former would limit modelling to restricted areas of intensive historic exploration, and the latter to models applicable at the regional to district scale.

While successfully ‘finding’ known mineralisation in a small proportion of the study area is commonly interpreted as evidence of the effectiveness of a prospectivity model, it is more often a manifestation of the tendency of models to over-fit known mineral deposits. It is difficult to demonstrate the real predictive capability of prospectivity models with respect to undiscovered deposits.

Cryptic metallogenic controls

Fundamentally different geological factors act as critical controls on mineral systems at different scales. Province-scale metallogenic factors (such as the role of tectonic settings and geodynamics) and deposit-scale controls and indicators (intrusive source and conduit rocks, permeable structures, direct evidence of mineralisation) are best understood and effectively used (within the limitations of the available data) in regional–scale conceptual targeting and empirical direct detection. However, fundamental metallogenic controls are often ‘invisible’ in the input datasets, being too conceptual, too large or too small for the scale and resolution of the data. Such cryptic controls operating at scales of tens of kilometres are often manifested by richly endowed metallogenic zones (districts or belts) and smaller clusters of mineral deposits (camps) within much larger mineral provinces.

Metallogenic zones and belts are often spatially associated with deep crustal domain boundaries (and other major inherited basement structures; McCuaig & Hronsky 2014), which could have only subtle expressions in the datasets commonly...
used to generate evidential layers for prospectivity modelling. The identification of such cryptic metallogenic controls generally requires careful analysis of several complementary lines of evidence (including the spatial distribution of known deposits; Lisitsin 2015) and remains a major challenge in poorly explored regions.

**Uncertainty of prospectivity models**

Every step in prospectivity modelling, from the collection of the original geological data to the selection of an ‘optimal’ prospectivity map, introduces and compounds uncertainty, which inevitably propagates into final modelling outputs. Uncertainties of error (imprecision, data processing), fuzziness (of concepts and boundaries) and ambiguity (non-specificity of interpretation or contradictory interpretations) are ubiquitous and inevitable, but rarely identified, let alone modelled and assessed in prospectivity modelling.

There are multiple valid choices of a conceptual model, input datasets, ways to transform the input data into a collection of evidential layers and methods of data integration, and many more sets of their combinations, each leading to a specific prospectivity map. This multitude of valid options defines a prospectivity model space, comprising multiple realistic combinations of concepts, inputs, processing and aggregation models (each within its own space), and the resultant output space of multiple valid prospectivity maps. The variability of outputs can be represented in a probabilistic form, numerically and graphically (e.g., as maps of percentiles of prospectivity; Lisitsin et al. 2014), providing explicit assessment of the effects of uncertainty on prospectivity modelling outputs.

**DISCUSSION**

Prospectivity modelling outputs are always practically limited by the available data and knowledge, are susceptible to bias and carry significant (and mostly undefined) uncertainty. Unbiased predictions of the specific locations of undiscovered deposits (deposit-scale outputs) in a relatively large region, given commonly available geological data, will probably remain impractical in the foreseeable future. This can render prospectivity maps unsuitable for their intended use in practical exploration targeting, if an ‘optimal’ prospectivity map is considered as a final product in exploration targeting at the deposit to camp scale.

However, the most significant potential value of prospectivity modelling is as an integrated input in decision making regarding exploration targeting, rather than its output. Prospectivity modelling can provide valuable information about the relative importance of different input datasets, identify critical missing data types and areas with insufficient data coverage and resolution, identify potential problems with original conceptual models and methods of data processing and integration. Methods of machine learning and broader artificial intelligence can be used for more effective feature engineering to derive evidence of the manifestations of a mineral system from the input datasets. However, evaluation of the adequacy of modelling inputs and outputs and effective decisions on a way forward will require the direct involvement of a team of experts in mineral system analysis, data acquisition, modelling and exploration, and their ability to effectively communicate across their subject matter domain boundaries. This is a paradigm of using technology for expert intelligence augmentation/amplification (Hronsky & Kreuzer 2019) rather than replacement.
In many cases, additional systematic data acquisition will be required to effectively map (rather than predict) actual manifestations of the critical and constituent elements of a mineral system in a study area, which are often invisible in the available data, regardless of the choice of methods for feature engineering and data integration.

Prospectivity modelling can be a valuable intermediate tool for decision support, but cannot ultimately replace expert decision making in exploration targeting.

REFERENCES


GISSOM SOFTWARE FOR MULTIVARIATE CLUSTERING OF GEOSCIENTIFIC DATA

by

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We present the GisSOM software tool, which was developed to perform analysis with self-organizing maps (SOM), especially considering the needs of applications using spatially referenced data. GisSOM was developed in the NEXT project, funded by the European Union’s Horizon 2020 research and innovation programme. GisSOM was applied in the framework of NEXT to the processing of two real-life geoscientific datasets in order to distinguish minerals based on their spectra and to find and visualize structures in a complex multivariate dataset used in prospectivity analysis.

INTRODUCTION

When an unknown feature needs to be modelled, there are essentially two ways to generate the model. In those cases where the functional dependence of the modelled feature on a set of explanatory variables is known, an analytical model with physically meaningful parameters can be generated. In other cases, where there are unknown dependencies that an expert-defined analytical model would miss and unknown phenomena affecting the measurable explanatory variables, an empirical model may perform better. Empirical modelling commonly requires more data than analytical modelling, since the number of model parameters tends to be larger. In geoscientific studies, an extensive set of explanatory geophysical, geochemical and geological data is often available that could be used to model the unknown feature. However, the amount of training data for generating the model, i.e., locations or samples where the modelled feature is known, may be small. In such cases, it may be useful to first explore and simplify the explanatory dataset before incorporating training data. Self-organizing maps (SOM) method is a powerful tool for revealing the structure of data and for simplifying large multivariate datasets using vector quantization, which adapts to the distribution of the variables. While simplifying data is the common use case of SOM, it also has potential in performing data augmentation. In this contribution, we present a new SOM software tool, GisSOM, which was developed in the NEXT project funded by the Horizon 2020 programme. GisSOM was developed considering especially geospatial data analysis tasks.
SOM AND GISOM

SOM computation is based on adaptive learning of interconnected neurons that are organized on a SOM grid. The connections between neurons are predefined, commonly with a 2-dimensional rectangular or hexagonal layout. When a neuron is fed with information from the dataset, it teaches the neighbouring neurons as well, gradually forming a map (the SOM) with a set of neurons that represent the input data space, and that are organized so as to facilitate exploration of the structure of the data. A SOM is completely independent of the possible geospatial coordinates of the original data (unless they are included in the SOM analysis along with other variables, but this is rarely reasonable). Although SOM itself is not a spatial analysis method, GisSOM was developed to consider the needs of spatial data applications. When spatial data are provided to GisSOM, it registers the geospatial coordinates in the data input phase, performs SOM computations without considering the coordinates, and maps the results back to the geographical reference frame.

Overall, GisSOM offers a multitude of ways to represent the results as images and plots to facilitate investigating the patterns in and structure of the data. In addition to showing results as static maps on a SOM grid and a geographic frame, GisSOM has the option to perform k-means clustering of the SOM result and to interactively examine the link between the SOM grid and geographic reference frame. In addition, boxplots and scatterplots displaying the distribution of variables within the k-means clusters are generated.

Interpretation of the SOM result depends on the size of the SOM grid and on the properties of the input dataset. The size of the SOM, i.e., the number of neurons, is in many applications significantly smaller than the number of data points. This setup allows the data vectors to be quantitized and, thus, the size and complexity of the dataset to be reduced. Labelled data points with a known class can be shown on the SOM. When applying SOM to vector quantization, the distribution of labels on the SOM provides information on the similarity of the classes and the distribution of the dataset within the framework of the classification scheme.

The number of neurons can also be larger than the number of data points. In this setup, only some of the neurons in the final SOM represent observations. The rest of the neurons represent values that do not appear in the dataset but could be observed if additional observations or measurements were carried out. This feature can have potential in data augmentation applications.

RESULTS AND DISCUSSION

In NEXT, GisSOM was used for two very different types of applications: data clustering for prospectivity analysis of orogenic gold deposits in Finnish Lapland (Chudasama et al. 2021a, Chudasama et al. 2021b) and clustering of spectroscopic data from mineral samples. The prospectivity analysis case study directly relates to the topics of MinProXT webinar, and some properties in the mineral spectra SOM could also be applied in predictive mapping. Details of the input data and use of the SOM results in prospectivity analysis are presented in another abstract of this volume (Chudasama et al. 2021a), while here we present some examples of how to use GisSOM to explore such datasets.

The idea of using GisSOM in prospectivity analysis was to quantize the large and complex dataset, compute k-means clusters on the SOM and investigate the data structure and distribution of variables on the SOM grid. Since the number of
variables in the dataset was only fifteen, it was feasible to investigate the distribution of each variable separately on the SOM grid. The distributions of two variables are presented as an example (Fig. 2). Using the variable SOMs together with the cluster-wise boxplot distributions of the variables and the image showing the clusters on SOM, it is easy to visually investigate the spread of variable values within a cluster and differences between clusters. Clusters are also presented in a geographic frame for this spatially referenced dataset to relate the clusters to other spatial features (e.g., drill core data) not included in SOM computations.

In the other test case of the NEXT project, the clustering of spectral mineral data, there were eleven mineral samples with a known composition, each of which was characterized by more than 150 variables derived from four different analysis methods. The size of the SOM was 10 x 10, which means that only about 1/10 of the SOM neurons represent measured samples. However, all the neurons have learned from the data. When the data points are shown on the SOM coloured according
to the k-means cluster (Fig. 2), it can be seen that for each mineral, the sample spectral data are different, but similar enough to be clustered together. If the “empty” neurons in each cluster are assumed to represent as yet unobserved data, this type of SOM application could be used as a data augmentation method. Thinking of prospectivity modelling, could the training data be augmented using SOM?

Fig. 2. Spectral mineral data SOM with sample labels. SOM nodes are coloured based on the k-means cluster they belong to.

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INTRODUCING THE DATABASE OF GLOBAL LAYERED INTRUSIONS

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We have compiled data on 565 layered and differentiated igneous intrusions globally, documenting their (i) location, (ii) age, (iii) size, (iv) geotectonic setting, (v) putative parent magma(s), (vi) crystallisation sequence, and (vii) mineral deposits. Most intrusions occur in Russia (98), Australia (72), Canada (52), Finland (37), South Africa (38), China (33), and Brazil (31). Notable clusters of: (i) Archean intrusions (~15%) include those of the McFaulds Lake Area (commonly known as the Ring of Fire, Canada), Pilbara craton (Australia) and Barberton greenstone belt (South Africa); (ii) Proterozoic intrusions (~56%) include those of the Giles Event and Halls Creek Orogen (Australia), Kaapvaal craton and its margin (South Africa and Botswana), Kola and Karelia cratons (Finland and Russia), and Midcontinent Rift (Canada and USA); and (iii) Phanerozoic intrusions (~29%) include those of eastern Greenland, the Central Asian Orogenic Belt (China and Mongolia) and the Emeishan large igneous province (China). Throughout geological time, the occurrence of many layered intrusions correlates broadly with the amalgamation (and somewhat less so with the break-up) of supercontinents, yet the size and mineral inventory of intrusions show no obvious secular changes. In our compilation, 337 intrusions possess one or more types of mineral occurrences, including: (i) 107 with stratiform PGE reef-style mineralisation, (ii) 138 with Ni–Cu–(PGE) contact-style mineralisation, (iii) 74 with stratiform Fe–Ti–V–(P) horizons, and (iv) 35 with chromitite seams. Sill-like or chonolithic differentiated intrusions in extensional tectonic settings and spanning geological time are most prospective for Ni–Cu–(PGE) mineralisation. In contrast, PGE reef-style deposits are most prevalent in larger, commonly lopolithic intrusions that are generally >1 Ga in age (~75%). Stratiform Fe–Ti–V–(P) horizons are most common in the central and upper portions of larger layered intrusions, occurring in the Archaean and Phanerozoic. Approximately 80% of intrusions with chromitite seams are older than 1 Ga and >50% of them also contain PGE reefs. Based on the distribution of layered intrusions in relatively well-explored terranes (e.g., Finland, South Africa, Western Australia), we propose that 100s of layered intrusions remain to be discovered on Earth, particularly in poorly explored and relatively inaccessible regions of Africa, Australia, Russia, Greenland, Antarctica, South America, and northern Canada.
INTRODUCTION

In addition to being natural laboratories for studies on igneous processes, layered intrusions host a wide range of important mineral deposits, notably PGE reefs, disseminated or massive Ni–Cu–PGE deposits, stratiform massive or disseminated Fe–Ti–V–(P) layers, and chromite seams. Additional mineral deposits include REE, Nb, P, Au, building stone, andalusite, asbestos, magnesite, and, in associated felsic intrusives, tin and fluorite. Among the most studied are PGE reef-style deposits (e.g., UG2 and Merensky reefs of the Bushveld Complex, JM reef of the Stillwater Complex, Main sulphide zone of the Great Dyke), commonly with Ni and Cu as significant by-products. Additional important ore types include chrome and (Ti-) magnetite layers. The Cr seams usually occur in the lower portions of the intrusions, whereas Fe–Ti–V oxide deposits typically occur in the evolved portions of layered intrusions. Both tend to show remarkable lateral consistency and common knife-sharp contacts with the silicate host rocks. We have compiled data on ~600 layered intrusions and sills (Smith & Maier 2021). Based on our data, we review the distribution of the intrusions in space and time and evaluate concepts of igneous layering and ore genesis.

RESULTS AND DISCUSSION

Layered igneous intrusions (LI) occur across the globe and geological time, with a clustering in Archean cratons and during supercontinent amalgamation. While the scientific advances in understanding the petrogenesis of the intrusions have been considerable, many questions remain. The following may be highlighted:

(i) Tectonic setting: many notable LI correlate with episodes of voluminous magmatism associated with inter- or intra- continental rifting, possibly involving slab delamination or mantle plume impingement at the base of the lithosphere. Many others occur in magmatic arc environments (e.g., Ural–Alaskan–type intrusions). Post-collisional intrusions (e.g., Variscan and CAOB intrusions) appear to commonly host Ni–Cu mineralisation, seldom Fe–Ti–V (e.g., Bjerkreim–Sokndal, a few CAOB intrusions), and no Cr occurrences. Intrusions located in synorogenic/ convergent settings appear to be rare.

(ii) Mantle sources: Are the parent magmas generated in the asthenosphere, the SCLM, or both? In view of the high PGE budget of some intrusions, could there be mantle domains that are relatively PGE enriched, perhaps representing incompletely dissolved late veneer material, and if so, how can this be tested? Is the plume model universally applicable or is there evidence for plate-driven magmatism in some provinces (e.g., Musgrave/Giles Complex; Maier et al. 2015).

(iii) Composition of magmas: Examination of fine-grained sills and dykes in the floor of intrusions and chilled margins at their basal contact, as well as the trace element content of cumulate rocks and minerals indicates that there are 2 types of magma (SHMB and Al-tholeiite) in several of the most prominent intrusions (e.g., Bushveld, Stillwater, Finnish 2.45 Ga intrusions). Does this reflect contamination of komatiitic parent magmas with progressively more refractory crust or melting of different mantle sources?

(iv) Magma emplacement: Do the magmas intrude as crystal mushes, crystal-poor melts, or both? What is the key evidence, and which factors control the mode of emplacement (e.g., could upper crustal subsidence, induced by magma...
emplacement, trigger magma ascent from mid-crustal staging chambers? Could this control the size of intrusions, in addition to the size of the thermal mantle anomaly? How common is out-of-sequence sill emplacement, and what is the precision and accuracy of the geochronological methods on which this idea is largely based?

(v) Origin of layering: To what degree is the layering of primary magmatic origin, i.e., resulting from granular flow and sill emplacement? If it is largely secondary, as argued by Boudreau (2017), why are there relatively few hydrous phases such as magmatic mica and hornblende?

(vi) Origin of sulphide and oxide reefs: While most authors argue that the reefs are of magmatic origin, the mechanism of sulphide melt saturation and the mode of sulphide concentration remain debated. The most controversial question is probably whether sulphides and oxides were concentrated within the intrusions (e.g., via phase settling, or granular flow and kinetic sieving/percolation), or in a staging chamber or feeder conduit, from where they were entrained by the ascending magma.

(vii) Broader implications: Mafic–ultramafic intrusions volumetrically comprise a significant proportion of Earth’s crust and, as such, their emplacement may have a significant impact on Earth’s atmosphere. Many layered igneous intrusions are associated with the emplacement of large igneous provinces, which in turn correlate with mass extinction events (Bond & Wignall 2014). The emplacement of LIPs may be most devastating when emplaced amongst carbonate host rocks (e.g., Bushveld LIP, Siberian Traps; Ganino & Arndt 2009, Stordal et al. 2017, Le Vaillant et al. 2017).

Fig. 1. Global distribution of layered igneous intrusions coloured by their age and sized by their aerial extent (km$^2$). The spatial distribution of cratons is that of Bleeker (2003), which have been buffered to 500 km. The map was produced in ArcMap 10.7.1. Giant > 10,000 km$^2$, large > 1,000 km$^2$, medium > 100 km$^2$, and small < 100 km$^2$. 
REFERENCES

MAPPING PORPHYRY MINERAL SYSTEM ELEMENTS AT THE TERRANE SCALE

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The practical application of a prospectivity analysis to porphyry copper exploration at the terrane scale.

INTRODUCTION

Strategic exploration decisions at global and terrane scales are a critically important first step in determining where to focus many years of effort and exploration investment. Success in this regard requires a fundamental understanding of the regional controls on ore formation and the ability to map them accurately.

The mineral system concept described by McCuaig (2014) and others has been of much utility in providing a conceptual foundation to the task of prospectivity assessment at the terrane scale. The existence or otherwise of mineral system elements reliably observed at the regional scale is an important means of focusing exploration beyond a retrospective assessment of known endowment. In this context, prospectivity analysis is a useful means of mapping, semi-quantitatively, the strength of evidence in support of the presence of regional ore formation controls. However, in practical application, prospectivity analysis at the terrane scale is generally a data-‘challenged’ exercise, particularly where there is a paucity of government-sponsored precompetitive datasets available. For this situation, the methodology employed must both accommodate and map the uncertainties inherent in variable data environments.

The following outlines one such scheme, a fuzzy logic workflow practically applied in porphyry copper exploration.

MINERAL SYSTEM

McCuaig (2014) describes the four critical mineral system elements as fertility, architecture, geodynamic trigger and preservation, where ore deposition is an emergent outcome of their temporal and spatial interaction. The elements of relevance at the terrane or continental scale are generally the first three in the list, with fertility and architecture being the ones most readily mapped in the spatial domain. The geodynamic trigger, in this context, represents events corresponding
with short transitions out of sustained periods of compressional tectonics (Hronsky 2011). For this purpose, the geodynamic trigger determines the mineralising epochs of interest, a temporal condition rather than a spatial one. Consequently, the workflow reduces to the mapping of fertility and architecture for a given time window.

**FERTILITY**

Fertility, in the porphyry copper context, equates to the propensity of a magmatic suite to produce ore-forming variants, the controls on which are generally accepted (Rohrlach & Loucks 2005, Rosenbaum et al. 2005) as being the geodynamic mechanisms that keep arc magmas pooled at the base of the crust for extended periods of time (typically 7–20 Myr). The following fertility workflow aims to synthesise a set of proxy data that maps this condition. These may include the following:

- Lithogeochemical trace element data;
- A range of geological evidence that informs the prevailing stress regime (e.g., cessation of volcanism, structural evidence etc.);
- Geophysical evidence that maps crustal thickness and the geometry of the subduction environment;
- Plate modelling.

Given the eclectic and highly contextualised nature of the inputs and the inevitable lack of uniformity in the data coverage, a set of synthesis maps is used to assimilate the aforementioned proxy data into a uniform representation. Depending on the input data available, the synthesis maps constructed may include any or all of the following:

- Lithogeochemical point data (points);
- Lithogeochemical detrital data (polygons);
- Geodynamic domains (polygons).

In all cases, the GIS vector elements (inferred above) have a standardised set of attributes.

For the geochemical data, these include several proxies that quantify the petrogenetic processes controlling magmatic fertility (Loucks 2014), derived from major, minor and trace element concentrations in whole rock data. These take the form of a class weight representation (Bonham-Carter 1994). Analogously, class weights pertaining to the favourability, or otherwise, of the subduction environment at the time of interest are drawn from a combination of both qualitative and quantitative geological observations and modelling.

In all cases, the final class weight for each vector element is a measure of the central tendency of the individual class weight estimates (the actual statistic used is dependent on the type of data). Importantly, this formulation allows for a confidence or uncertainty estimate based on the variance and the number of the aforementioned inputs available.

Each synthesis map forms the basis of a corresponding predictor map, i.e., a raster representation of fuzzy membership. The workflow used in the predictor production is dependent on the type of vector elements in question.

For polygon–based synthesis maps, i.e., detrital geochemistry and geodynamic domains, a simple vector-to-raster conversion using a linear fuzzy membership function, i.e., class weight multiplied by map weight divided by 100, is applied. Where class weight is not defined (outside polygons), null values are assigned.
Similarly, confidence values are directly assigned to the cells inside polygons and zero confidence assigned outside.

For point data, which are generally sparse, non-uniformly located and variable, the method used is more involved. Commonly used numerical means of interpolation and extrapolation, e.g., polynomial splining, polygonal estimations and kriging, are not optimal given the aforementioned sampling issues and the underlying processes giving rise to the data in question. Consequently, the approach here defines an ‘area of influence’ of the in situ geochemical data, which is an area pertaining to each sample or group of samples, which are reasonably informed by their collective class weight. For this application, the selected lithogeochemical data are proxies for low and mid-crustal magmatic processes, and so the workflow links the fuzzy membership and confidence defined at the sample sites to co-located surface projections (polygons) of the interpreted causal magmatic complex. This is interpreted from broad wavelength potential field data (airborne magnetics primarily) using the methodology described by Behn (2001). Fuzzy membership and confidences are then assigned using the aforementioned polygon-based process.

The final fertility predictor and the corresponding confidence estimate is the combination of all the available fertility predictors. This is either a weighted average by confidence or via the application of a fuzzy ‘OR’ or ‘AND’ logic.

ARCHITECTURE

Analogously, the architecture workflow follows a similar synthesis followed by a predictor sequence. In this case, the architecture synthesis uses polyline elements, with attributes pertaining to the interpreted geometry, kinematics and factors relating to the strength of the data evidence supporting the existence of the structural element in question. The latter is used as a basis for a confidence estimate. The Architecture predictor workflow allows for any one of the geometric or kinematic attributes, or combinations thereof, to be used as a means of determining a hierarchy of fuzzy membership. In this case, the fuzzy set is all architectural elements and/or their intersections that are conduits of ore-forming magmas. This process results in a predictor and confidence map pair for each of the nominated architectural groups of interest. The final architectural predictor is the fuzzy OR combination of the individual inputs.

REGIONAL PROSPECTIVITY

The final ‘Regional Prospectivity’ is simply a fuzzy gamma combination of the aforementioned final predictors smoothed by a nine-point averaging convolution filter (example provided in Fig. 1). The smoothing is a practical means of representing boundary and positional uncertainty, commensurate with the regional inputs used in map construction.
Fig. 1. Example of regional prospectivity.

REFERENCES


IOCG PROSPECTIVITY MODELLING FOR GAWLER GREENFIELD REGIONS – SECOND PLACE SUBMISSION IN THE EXPLORESA COMPETITION

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For the ExploreSA competition, Caldera Analytics created a machine learning model that predicted the prospectivity of basement-hosted iron oxide–copper–gold (IOCG) deposits in the Gawler Craton of South Australia, focusing on challenging the existing beliefs and pushing the known extent of the Gawler IOCG province into new areas. The model was developed in a conservative spatial cross-validation framework to ensure that it could generalise to new and unexpected geological regions. The highly variable cover thickness of the Gawler Craton and its impact on the geophysical predictors was mitigated through a novel way of applying upward continuation filters based on the local depth to basement. The best-performing model was a simple logistic regression model, with the final IOCG prospectivity predictions showing a broad alignment in explored areas with the expert-driven mineral systems approach. Predictions in underexplored areas of the Gawler Craton show highly prospective areas correlating with gravity anomalies, crustal-scale faults and magnetotelluric conductor anomalies.

INTRODUCTION

In 2020, the open innovation platform Unearthed, in partnership with the South Australia government, hosted the ExploreSA online crowd-sourced competition for applying new and innovative techniques to help find mineral deposits. For this competition, Caldera Analytics submitted an approach to using machine learning to generate prospectivity maps for iron oxide–copper–gold (IOCG) deposits in the Gawler Craton. This submission, the focus of this extended abstract, was ultimately awarded 2nd place and a $50,000 prize.

IOCG deposits are large copper deposits that the Gawler Craton is famous for. While the eastern Gawler area is the main area for hosting massive hematite IOCG deposits, there is no conclusive evidence that the northern extent ends at the Mount Woods Domain or that it does not extend west into the Gawler Range Volcanics.

There were two goals of this machine learning approach for IOCG prospectivity. The first goal was to replicate the mineral systems approach employed by Skirrow et al. (2019) in modelling IOCG prospectivity of the Mt Isa Region, and Wise (2019)
in modelling IOCG prospectivity of the eastern Gawler Craton. However, instead of an expert-driven weights-of-evidence model, a data-driven machine learning model was used. This data-driven approach could then be used to generate one possible answer to how far the IOCG province might extend beyond the known areas.

The second goal was to be able to apply the approach to greenfield areas with limited data availability. As the first goal was to assess the northern and western extents of the IOCG province, this naturally goes into areas with very little basement drilling. If the machine learning model prospectivity maps were to be of business value to exploration companies, the model needed to be trained on data that are available in these greenfield areas.

**DATA AND/OR METHODS**

The specific goal of the model was to predict IOCG and IOCG-related mineralisation that displayed positive gravity responses.

The exact model prediction was a binary classification setup where a positive (1) label was a drillhole containing at least one metre of >0.5% Cu basement mineralisation, calculated from downhole assays. Copper mineralisation from younger cover was not included, so intersections from prospects such as Mt Gunson and Myall Creek were excluded from the dataset.

**Training Dataset**

Data used for creating the training dataset were sourced from public drilling in the IOCG regions of South Australia (Gawler Craton) and Queensland (Mt Isa Inlier & surrounds). The regions that contain IOCG mineralisation in the Northern Territory could not be included due to the lack of coverage in the AUSLAMP magnetotelluric surveys.

For each drillhole, the depth to basement was manually recorded from exploration reports and logging. This was important for both ensuring that copper mineralisation from younger cover was not included when calculating the binary labels, and also for exploring the impact of depth to basement on geophysics-based predictors.

**Predictors and Features**

The choice of datasets largely followed the mineral systems approach employed by Skirrow et al. (2019). The four main sources of predictors were gravity surveys, aero-magnetic surveys, AUSLAMP magnetotelluric models and interpreted crustal-scale faults. Hiltaba suite granites, an important predictor for mineral systems, were not used as a potential source of features due to the unreliable nature of the solid geology interpretations in the underexplored regions of the Gawler Craton.

Datasets that mostly captured surface information (e.g., ASTER Hyperspectral Imaging) were not used due to the pervasive younger cover.

The non-uniform nature of the ground gravity surveys that are the source of the state-wide gravity grids must be accounted for to create reliable models. Any area where the spacing between gravity surveys was not close enough to produce meaningful anomalies was excluded from this model. Thus, training points were not taken from these regions, and model predictions were not generated for these regions. Regions generally needed to have spacing between ground survey points of 1 km or less.
The highly variable cover thickness throughout the Gawler Craton provides a constraint in that the magnitude of magnetic and gravity anomalies cannot be numerically compared without accounting for the depth to basement (technically the depth to source). This was accomplished by applying upward continuation (UC) filters to level out the magnetic and gravity geophysics to a pseudo depth to basement level of 500 m. Labels where the depth to basement was 10 m would have a UC filter of 490 m applied to the geophysical features, while labels where the depth to basement was 450 m would only have a UC filter of 50 m applied.

Validation

A spatial cross-validation framework was used to perform model selection and hyperparameter tuning. Six different validation zones were created, each designed to have unique characteristics. Each zone was roughly based on regional geological provinces (e.g., the Mt Isa region was its own validation zone), ensuring that the validation zones were large enough that no training information would leak into the validation points, and also ensuring that each validation zone was different enough from the corresponding training data. This ensured that the best-performing model would be one that could generalise to different geological regions, both in terms of cover thickness and host lithology.

RESULTS AND DISCUSSION

The final model selected was a simple logistic regression model. Other models such as random forest were tested but did not perform as well in the cross-validation performance metrics. Considering the tough cross-validation framework, where the validation fold distribution could be radically different from the training fold distributions, it makes sense that the simplest algorithm generalised the best.

The impact of applying ‘upward continuation normalisation’ to account for the depth to basement variation in the dataset resulted in the validation AUPRC increasing from 0.64 (None) to 0.74 (UC normalisation to 500 m).

Visual inspection of the model predictions, as illustrated in Figure 1, for the known IOCG province showed broad alignment with the existing mineral systems approach employed by Wise (2019).

Analysis of the feature importance also aligned with the assumptions of mineral systems IOCG prospectivity modelling, with gravity anomalies, some magnetic anomalies, crustal-scale faults and crustal magneto-telluric conductors scoring high on the feature importance.

When analysing the IOCG prospectivity in regions beyond the known extents of the Gawler IOCG province, several broad areas of elevated prospectivity correspond with the Mabel Creek Ridge and the Peake & Denison Inlier. It is hoped that mineral explorers will use these prospectivity models along with traditional exploration techniques to further lower the risk of exploring in these greenfield areas.
Fig. 1. Model generated IOCG prospectivity for the Gawler IOCG region.

REFERENCES


This study developed a GIS-based prospectivity model for delineating target areas for follow-up exploration of REE deposits associated with carbonatite–alkaline complexes in NW India. A generalised mineral systems model was used to identify the mappable exploration criteria. Predictor maps were generated from public-domain geological, geophysical and satellite data to represent the components of the mineral system and then combined in a fuzzy inference system (FIS) to obtain an REE prospectivity map. High prospectivity is noted around Mundwara, Sarnu-Dandeli and Kamthai. High-resolution airborne and ground geophysical surveys, followed by scout drilling, are recommended in these areas.

**INTRODUCTION**

REEs are a group of 17 metallic elements that are critical for technological development (González-Álvarez et al. 2021 and references therein). No primary economic-grade deposit of REE has been discovered so far in India, despite the presence of various enriched source rocks such as carbonatites, pegmatites and alkaline complexes. In this contribution, we developed a GIS-based prospectivity model for exploration targeting of REEs associated with carbonatite–alkaline complexes in Western Rajasthan, India.

The study area falls in the state of Rajasthan in northwest India (Fig. 1a). This area was chosen because it is a known major carbonatite province of India, and well-integrated public domain datasets are available. Geologically, the study area comprises the Neoproterozoic Malani Igneous Suite, which is mostly covered under a thick horizon of Holocene wind–blown sand. Sedimentary sequences (Marwar Supergroup, Jaisalmer–Sarnu–Barmer–Uttarlai Formations) ranging in age from Late Neoproterozoic to Eocene occur in the western part of the study area around the Barmer area (Ramakrishnan & Vaidyanadhan 2008, Fig. 1a). Several major well-preserved Cretaceous carbonatite–alkaline complexes occur in the study area, including Mer–Mundwara and Sarnu–Dandeli (Fig. 1a). The Mer–Mundwara
complex displays a characteristic ring structure, with the alkaline–mafic rock suites occurring in the form of two ring structures and a dome (Pande et al. 2017). The Sarnu–Dandeli occurrence extends over a large area and includes the smaller occurrences of Danta–Langera–Mahabar and Kamthai. Kamthai is considered to be potentially a world–class REE deposit (Bhushan & Kumar 2013). These carbonatite–alkaline complexes represent a younger carbonatite magmatism episode related to the post–Gondwana breakup and northward drifting of India over the reunion mantle plume (Ray & Pande 1999).

**DATA AND METHODS**

This study used openly available public domain geophysical datasets distributed by the Geological Survey of India (Geological Survey of India 2021: [http://bhukosh.gsi.gov.in/Bhukosh/Public](http://bhukosh.gsi.gov.in/Bhukosh/Public)). The datasets used were (1) ground–based gravity anomaly data (10–km sample interval); (2) mosaiced airborne magnetic data (75–m grid cell size); (3) Shuttle Radar Topography Mission (SRTM) DEM data (90–m resolution), (4) geological and structural maps (1:50,000 scale); and (5) a lineament map (1:250,000 scale). In addition to the above, 1.6–km–resolution satellite–based topography and gravity data (EGM2008, ICGEM 2021: [http://igem.gfz-potsdam.de](http://igem.gfz-potsdam.de)) were also used to supplement the SRTM topography and the coarse ground gravity data.

This research was implemented in the following sequential steps. (1) A generalised conceptual model of REE mineral systems was developed based on the approach described by McCuaig and Hronsky (2014). (2) An exploration targeting model for REE mineral systems in the study area was developed, which was used to identify targeting criteria at the district scale. (3) Spatial data processing and analysis tools were used to process primary geoscience data to map the targeting criteria in the form of predictor GIS layers. (4) The predictor maps were integrated using a fuzzy inference system (FIS; Porwal et al. 2015, Chudasama et al. 2016) to generate an REE prospectivity map of the study area. A multi–stage FIS was used to generate the REE prospectivity map. In the first stage, a series of FIS were used to generate fuzzy prospectivity maps for individual components of REE mineral systems, namely fertility, geodynamic settings and architecture, by combining their respective fuzzy predictor maps. In the second stage, the fuzzy prospectivity maps of the individual components were combined using the product operator to generate the REE prospectivity map of the study area (Fig. 1b).

**RESULTS AND DISCUSSION**

The main components of the carbonatite–alkaline complex–hosted REE mineral systems are: (1) pockets of metasomatised sub–continental lithospheric mantle (SCLM), which form fertile source regions for REE–bearing fluids; (2) extensional geodynamic settings associated with mantle plumes, mainly intra–continental rifts and large igneous provinces (LIP); and (3) favourable structural architecture comprising networks of (a) trans–lithospheric faults and reactivated zones of structural weakness for tapping REE–enriched fluids from SCLM, and (b) shallow–level faults and joints for focusing the REE–enriched fluids to near–surface levels.

A series of predictor maps were generated from public–domain geological, geophysical and satellite data to represent the above components. These included: distance to the (1) Deccan LIP, (2) Réunion mantle plume trace and (3) Barmer
rift, lineaments derived from (4) magnetic data, (5) gravity data and (6) satellite imagery data, (7) post-Cambrian non-felsic intrusions, (8) circular features derived from geophysical and topographic data, (9) surficial lineaments derived from geophysical data, (10) points of intersection of the surficial lineaments and (11) a magnetic anomaly map.

Geophysical data were used for subsurface geological interpretations, as most of the study area is under a thick sand cover. Near-surface faults were extracted from the first vertical derivatives of the total magnetic field and gravitational-field intensity data. Deeply penetrating structures were extracted from the
upward-continued total magnetic field and gravitational-field intensity data. The general trend of both gravity- and magnetic-derived lineaments is NNW–SSE, which is consistent with the trends of the northern Cambay–Barmer basin (Bladon et al. 2015). Circular features were automatically mapped from the gravity, magnetic and topographic datasets using the algorithm and software described by Holden et al. (2011).

Several exploration target areas for further follow-up were identified based on the analysis of the output prospectivity map (Fig. 1b), wherein a strong structural control is clearly evident. The known carbonatite occurrences at Mundwara, Sarnu-Dandeli and Kamthai show high prospectivity. Detailed deposit scale exploration and geochemical analysis are recommended for these regions. High prospectivity is also noted to the east of Sarnu-Dandeli, where it exhibits a circular outline and possibly indicates a circular intrusion. Scattered high prospectivity patches are noticed around Sarnu-Dandeli and Mundwara. These could be fragments of the main complex, like Kamthai. Radiometric surveys are recommended for these regions.

This GIS-based prospectivity model workflow for exploration targeting of REEs associated with carbonatite–alkaline complexes can be further tuned and applied globally.

REFERENCES


THREE-DIMENSIONAL WEIGHTS OF EVIDENCE
MODELING OF CONCEALED ORE DEPOSITS USING
THE 3DWOFE SOFTWARE PACKAGE

by

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The shortage of outcropping ore deposits and the inefficiency of traditional methods for discovering deep-seated deposits have increased the necessity for developing three-dimensional modeling methods for in-depth exploration. 3DWofE, a Python-based open-source software package, provides the tools required for three-dimensional modeling of concealed ore bodies by developing a data-driven prospectivity modeling method called weights of evidence. This package is able to provide three types of models, including posterior probability, uncertainty, and Studentized posterior probability, that guide exploration geologists through identifying potential regions of target mineralization at depth.

INTRODUCTION

The development of three-dimensional modeling methods can improve our understanding of ore deposits concealed at depth from various aspects. The main challenges in three-dimensional modeling are extracting exploration criteria from diverse datasets and integrating available information to guide future blind exploration. In recent years, mineral prospectivity mapping methods, known as efficient methods in integrating multiple exploratory datasets, have been developed in three-dimensional space (Mao et al. 2019). Among these methods, the weights of evidence (WofE) method, a data-driven method based on the Bayes rule, can provide a fully quantitative and informative prospectivity model and fuse all available constraints in a probabilistically rigorous fashion. In general, the WofE method represents the degree of correlation between a specific type of mineralization and a particular model under specific conditions known as evidence (Bonham–Carter 1994).

In this contribution, in addition to a brief description of the WofE method, we discuss the abilities of 3DWofE. This Python-based open-source software package enables the user to implement ordinary and fuzzy WofE methods for mineral prospectivity modeling of deep-seated ore deposits in three-dimensional space.
This package comprises several subroutines with different functions leading to the determination of positive and negative WofE for continuous and discrete evidential models and integrating selected evidential models to create posterior and Studentized posterior probability models. The resultant probability models are used to identify potential regions of mineralization in the modeling space.

DATA AND/OR METHODS

WofE are determined based on Bayesian probabilistic inference and used for estimating the posterior probability of target mineralization with the assumption of conditional independence between input evidential models (Xiao et al. 2015) China. The assessment was achieved through a sequential implementation of metallogegenic modelling and 3D modelling of geology, geochemistry and prospectivity. A metallogenic model for the Jiama deposit and 3D modelling workflow were used to construct multiple 3D layers of volumetric and triangular mesh models to represent geology, geochemistry and ore-controlling features in the study area. A GIS-based 3D weights-of-evidence analysis was then used to estimate the subsurface prospectivity for Cu (Mo). The prior probability of target mineralization is updated using WofE in the light of input evidential models. These input models can be of any data type, such as geological, geochemical, or geophysical, which are associated with target mineralization.

The WofE method is applicable for prospectivity mapping when a number of mineral occurrences are known, which can then be extended to known mineralization voxels in a 3D space. The degree of correlation between a particular model and target mineralization is determined using calculated positive or negative weights (Tao et al. 2019) northwestern China. A 3D geological model was constructed using geological maps, geological plans, cross sections, and boreholes. The geological model and metallogenic model of the Honghai deposit were used to generate 3D predictor maps. The weights of evidence method and fuzzy logic were then used to integrate the various predictor maps to create prospectivity maps. Capture efficiency curves were subsequently used to delineate high-prospectivity areas in the prospectivity maps. The weights of evidence method and fuzzy logic delineated 96.13% and 90.60%, respectively, of the known mineralization in the high-prospectivity areas, which occupied about 5.89% and 6.33% of the study area. Receiver operating characteristic (ROC) WofE can be interpreted in geological terms, intuitively, indicating the association between evidential models and the presence/absence of target mineralization. Therefore, an evidential model can be used to assess the contribution of a geological process in the creation and prospectivity of a specific type of mineralization.

The 2D WofE method can be readily implemented using available GIS packages; however, implementing this method in a 3D space is challenging, and the 3DWofE package can be considered as a tool to overcome this challenge. A variety of geoscientific data are used for creating evidential models in the early stage of mineral prospectivity modeling. In general, evidential models are categorized into continuous and discrete models. Discrete models are usually created using qualitative data such as lithological and alteration data, and each unit of these models can be considered as an individual binary model for calculating ordinary WofE. Continuous models are created using quantitative data such as geochemical and geophysical data, and there are two ways to deal with models of this type. First, we can consider a specific threshold for each continuous model and convert it into a binary model for calculating the ordinary WofE that causes the loss of information. Second, we
can classify each model and determine fuzzy WofE for each class separately, which increases the reliability of the final probability models. The proposed software package can work with both types of models and determine ordinary and fuzzy WofE for a variety of evidential models. The posterior probability model is created by integrating input evidential models based on Bayes' equation in a log-linear form while assuming conditional independence holds (Bonham-Carter et al. 1989).

It is challenging and vital to identify and quantify the uncertainty associated with geological or prospectivity models. The effects of uncertainty due to missing information can be calculated using the WofE method. 3DWofE is able to create the uncertainty model by adapting the approach described before (Bonham-Carter 1994, Cheng & Agterberg 1999), and the variance of the posterior probability is determined using the variance of the weights at each voxel. The Studentized posterior probability refers to the posterior probability ratio to the corresponding standard deviation, which equals the square root of total variance at each voxel. The Studentized posterior probability acts as a measure of the relative certainty of the posterior probability. Due to a lack of confidence in results, the voxels where the Studentized value falls below some threshold can be masked out to provide a reliable estimation of target mineralization at depth.

Fig. 1. a) Posterior probability and b) Studentized posterior probability models of a deep-seated porphyry Cu deposit created using 3DWofE (Farahbakhsh et al. 2020).
RESULTS AND DISCUSSION

The 3DWofE package has been developed for three-dimensional WofE modeling of concealed ore deposits and detecting potential regions of mineralization at depth. In a recent study, this package was used for modeling a deep-seated porphyry Cu deposit in SW Iran (Farahbakhsh et al. 2020). Based on the results, the posterior and Studentized posterior probability models shown in Figure 1 predicted more than 60% of the target mineralization in less than 40% of the modeling space, although the prediction rate relies significantly on the input evidential models and the extent of the modeling space. The results demonstrate the efficiency of 3DWofE in modeling the target ore body, which implies that using the posterior probability and Studentized posterior probability models, we can minimize the risk of further exploration and optimize the process of selecting new locations for drilling.

We usually remove some of the evidential models from the modeling process due to the low correlation with target mineralization or violating conditional independence and choose the integration method based on the selected evidential models. 3DWofE provides a normal and a hybrid solution for integrating input models. If selected evidential models are all binary, the user can select a normal solution, and if they are a combination of both binary and classified models, a hybrid solution can be selected. The latter is able to minimize the loss of information and provides a more reasonable model by integrating ordinary and fuzzy WofE.

REFERENCES


MINERAL PREDICTIVE MAPPING: FROM INTUITION TO QUANTITATIVE HYBRID 3D MODELLING

by

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For many years, mineral predictive mapping was guided by knowledge and intuition using exploration models and later paper maps. In the 2000s, powerful information technology together with the ever-rising amount of data created the basis for the broad development of computer-based mineral predictive mapping technologies. Finally, the availability of easy-to-use software products (e.g., Beak’s advangeo® Prediction Software) is enhancing the introduction of AI technologies into the daily practical work of geoscientists.

HISTORY

Mineral predictive mapping is as old as mining. Over thousands of years, the right places for mineral exploitation were identified simply by the application of accumulated knowledge and intuition. In 1556, mineral exploration models were first drawn on paper by the famous Georgius Agricola in Freiberg (Georgius 1556). 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 a background 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, knowledge-based (intuitive) methods were broadly used to compile various mineral potential, metallogenic and similar maps, representing the spatial expression of expert knowledge and its interpretation.

KNOWLEDGE-BASED, DATA-DRIVEN AND HYBRID APPROACHES

Consequently, the first mathematical approaches in analysing geological data sets followed certain rules: for example, a granite intrusion in carbonate rock sequences forms skarns.

In the 1980s and 1990s, the implementation of fuzzy logic knowledge-based mineral predictive mapping approaches started (Ping et al. 1991).
Simultaneously, understanding grew 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, the fold axis and rock contacts (e.g., Carranza & Laborte 2015). Because of its ease and plausibility, the weights of evidence method became widely used (e.g., Agterberg et al. 1993). In the 1990s, artificial neural networks were successfully applied to predict Carlin-type gold deposits (The Northern Miner 1997) in the U.S. and massive sulphide deposits in Japan (Singer & Kouda 1996).

With the increasing amounts of data and computer capabilities, more data-driven approaches became common, such as random forests (Carranza & Laborte 2015) and logistic regression.

The recently developed hybrid models combine both knowledge/intuition and data-driven approaches. In these models, the geologist’s knowledge/intuition is incorporated via data preparation describing the spatial relationships between the dependent variable and its controlling parameters. Hybrid models provide the best results, as they combine the advantages of both knowledge-based and data-driven methods (e.g., Porwal et al. 2011, Brosig et al. 2020). Data-driven approaches are an excellent tool to verify/develop our knowledge.

![Fig. 1. The general applicability of data-driven, knowledge-based and hybrid systems.](image)

**CREATING USER-FRIENDLY APPLICATION SOFTWARE**

Since 2008, Beak Consultants has developed its advangeo® Prediction Software integrating several data-driven and knowledge-based methods into the widely used ESRI ArcGIS software (Brosig et al. 2020). Advangeo® supports the entire workflow of data preparation, model calibration, results evaluation (cross-validation, statistical analysis (histograms, correlation), network errors, network connection weights) and results presentation. Many useful functions especially ease the data pre-processing of multispectral, geophysical and other raster data.

In cases where high-quality data are available, quantitative predictive models can be created (Brosig et al. 2020). In this case, the dependent variable is not the “favourability” of the presence of a mineral occurrence at a certain location, but instead, one of its quantitative parameters, e.g., grade or tonnage.
3D PREDICTIVE MODELLING

In 2016, the 2D version of advangeo® software was successfully transformed into a 3D version, capable of interacting with any 3D voxel model. This advancement allowed further integration with inverse modelling data from 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 (Brosig et al. 2020, Rohstoffe Erzgebirge 2021 https://rohstoffe-erzgebirge.de/).

PREDICTIVE MODELS AS VALUE ADDED PRODUCTS

Mineral predictivity maps are important products with added value compared to simple datasets. They provide new understanding and ideas for both private and public bodies, which do not usually have the capabilities for this type of research. Mineral predictivity maps/models are directly usable in mineral exploration targeting (https://rohstoffe-erzgebirge.de/, Rohstoffe Erzgebirge 2021) and investment attraction.

Fig. 2. The workflow of advangeo® mineral predictivity mapping.
WHAT DOES THE FUTURE LOOK LIKE?

In the future, hybrid mineral predictive mapping approaches will become a standard. Terrestrial data will be integrated with multitemporal remote sensing data and directly interact with ongoing prospecting/exploration field work (Barth et al. 2021).

CONCLUSION

In the last two decades, computer-based mineral predictive mapping has developed from “niche” methods toward well-established approaches to qualitative and quantitative data analysis. The most accurate results are provided by hybrid methods combining both knowledge-based and data-driven approaches. The availability of easy-to-use software products integrating data pre-processing, data analysis, evaluation of the reliability of results and results visualization strongly supports this development.

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MAPPING MULTIVARIATE ORE OCCURRENCE DATA WITH CORRESPONDENCE ANALYSIS

by

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Correspondence analysis is a multivariate method that can be applied to mineral abundance data. Ore mineral assemblages from broadly underutilized prospect and occurrence data can be treated as geochemical anomalies, projected to low-dimensional space, and returned as a map. This approach could have applications for mineral prospectivity mapping and delineation of permissive areas during mineral assessments.

INTRODUCTION

Point locations of mineral deposits are necessary components of mineral prospectivity mapping (MPM) and assessment studies. These points are used to validate and train models used in MPM. Deposit points of the type sought are often extracted from large datasets, such as the Mineral Resources Data System (MRDS 2005), that also contain a wealth of qualitative information. However, qualitative data attached to mineral deposit records other than those being targeted are often not utilized in MPM studies. The historical data stored in unused records of uneconomic mines and prospects potentially contain mappable information that can be used to aid in MPM.

This study demonstrates that the ore mineral assemblages of uneconomic deposits can be treated as multivariate geochemical anomalies and that correspondence analysis (CA) can be used to compress ore abundance data into low-dimensional space. The technique is similar to how principal component analysis (PCA) is used to reduce the dimensionality of soil geochemistry for MPM (Carranza 2009). Ore minerals are counted within quadrats and the abundance data are analyzed with CA. Principal correspondence axes are extracted, and the scores for each quadrat are returned to the map. These spatial CA layers characterize mineral assemblage variations in uneconomic deposits and can be incorporated into traditional MPM models. A case study of these techniques from the well-characterized southern Basin and Range province in the southwestern United States is presented.
DATA AND METHODS

Locations and attribute data of inactive mines and prospects in the southern Basin and Range province were extracted from MRDS. Records listed as “low quality” and those with poor spatial precision were removed. Minerals listed as “ore” in each record were extracted, and a point file for each type of mineral in the entire dataset was created. To minimize duplicate entries or oversampling, each point file was filtered such that only one of each mineral species could occur every 500 m (Rosera & Coleman, in press).

The filtered data for each ore mineral point file were tabulated within quadrats (USGS 1:24,000 quadrangle outlines). The result of the quadrat counting is an $i \times j$ contingency table, $N$, where the rows, $i$, represent individual quadrangles, and the columns, $j$, represent ore minerals. Element $n_{ij}$ therefore represents the abundance of ore mineral $j$ within quadrangle $i$.

Correspondence Analysis

Correspondence analysis is a multivariate technique that is similar to PCA, but for count-based data. It is commonly applied to species abundance data in ecological studies, or categorical survey results in social sciences (Greenacre 2017). Unlike other interval-based multivariate methods, all the input data for CA are scaled to the same number: the grand total of the contingency table, $N$. This preserves the relationships between the row and column variables and makes CA a powerful tool for visualizing relationships. The normalized column and row totals (“profiles”) yield point clouds that are projected into low-dimensional space and scaled to the same correspondence axis (which are analogous to principal components).

A contingency table representing ore mineral abundances in each quadrangle was analyzed with CA. Rare ore minerals with fewer than 15 occurrences in the study area were aggregated into classes and divisions according to their Nickel–Strunz codes (Rosera & Coleman, in press). Row scores for each CA principal dimension were extracted and returned to map view. To aid in visualization, these data were interpolated with ordinary kriging. Biplots were constructed to aid in interpretation of the row scores.

RESULTS AND DISCUSSION

More than 6,300 points from 187 unique mineral species were counted. However, 144 mineral types had fewer than 15 total occurrences (8.3% of the total). Most of the variability lies within 43 ore minerals that make up 91.7% of the data.

Variations in mineral assemblages for each quadrangle can be visualized with biplots (Fig. 1). The location of the point for each quadrangle (the rows; gray points) plots in the direction determined by the loadings of the columns (ore minerals; red text and triangles). For example, the first CA dimension captures the correlation of manganese oxides/hydroxides (i.e., similar angle with respect to the origin), and the second dimension captures variation between fluorite–barite and cinnabar and rare native metals (e.g., mercury).

A powerful aspect of this approach is that the row scores can be returned to map view and interpolated with traditional techniques (Fig. 2). The spatial variations along CA dimension 1 highlight differences between regions with elevated occurrences of manganese oxides/hydroxides (highly positive scores) and those that plot near the origin, or with slightly negative values (Fig. 1). Hence, near-zero and
negative values for CA dimension 1 correspond to regions with known porphyry Cu deposits and spatially related systems (Mars et al. 2019, Fig. 2b). Correlations of Mn oxides/hydroxides, as well as fluorite and barite are captured on positive scores along CA dimension 1 (Fig. 2b). These regions follow a broad arc that begins near the NV–CA–AZ juncture in the west that continues towards southern NM.

Fig. 1. CA biplot for dimensions 1 and 2. Only the ore minerals with the greatest contributions to CA axes are shown.

Future Opportunities

This preliminary study highlights how historically underutilized mineralogy data from uneconomic prospects and inactive mines can be transformed and returned to a map. The method can be further improved by investigating: 1) the effect of other types of scaling to CA; 2) the sensitivity to quadrat sizes; 3) the correlation of CA layers with regional geological features, and 4) the strength, or importance, of CA layers as predictors in a specific MPM exercise.
Fig. 2. CA dimension 1 results for 1:24,000 quadrangles. a) Results showing row scores for each quadrangle. The scores plot in weighted locations based on ore mineral loadings (red points, Fig. 1). b) Same as panel a, but after interpolating data with ordinary kriging.

REFERENCES


DATA-DRIVEN PROSPECTIVITY MODELLING OF SEDIMENT-HOSTED MINERAL SYSTEMS

by


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Mississippi Valley-type (MVT) and clastic-dominated (CD) deposits are important sources for Zn, Pb, Ag, and Cd, as well as the critical elements Ga, Ge, In and Sb. However, mapping the drivers, sources, pathways and traps of MVT and CD deposits within the much larger and mostly unmineralized sedimentary basins remain some of the least understood aspects of these mineral systems. Herein, we address these knowledge gaps by integrating public geoscience datasets from Canada, the United States of America and Australia using a discrete global grid system to map the continent-scale footprints of MVT and CD deposits.

INTRODUCTION

Demand for critical raw materials is expected to accelerate over the next few decades due to continued population growth and the shifting consumption patterns of the global economy. Sedimentary basins are highly prospective for a wide variety of critical raw materials, and improved mineral exploration targeting in these settings has the potential to mitigate future supply chain vulnerabilities. However, the vast size of the sedimentary basins that host Mississippi Valley-type (MVT), clastic-dominated (CD; also known as sedimentary exhalative or SEDEX) and other sedimentary-hosted deposits (i.e., 100s to 100,000s of km²) continues to present problems for mineral exploration targeting, which has historically depended on high-resolution, commonly propriety, deposit- and districtscale datasets. The continentscale footprints of MVT and CD deposits, which are likely to be important for understanding the drivers, sources and metal endowment of the largest deposits in any given district, are the least understood aspect of these mineral systems. New national data compilations and the increasing diversity, resolution
and availability of regional geophysical datasets from geological survey organizations have the potential to address these knowledge gaps.

**DATA AND METHODS**

Herein, we map the footprints of MVT and CD deposits using public geoscience datasets and an open-source workflow in R (R Core Team 2021). First, national geological and geophysical datasets from Canada, the United States of America and Australia are used to map mineral systems at the largest spatial scales. Second, geological, geochronological, geophysical and other supporting datasets from all three countries are spatially indexed and combined using the H3 discrete global grid system (DGGS; Uber Technologies Inc. 2020).

**Fig. 1.** Preliminary weights-of-evidence (WOE) model results for Mississippi Valley-type (MVT) and clastic-dominated (CD) deposits across the U.S. and Canada. Bivariate colours are based on quantile scaling of the sum WOE for each deposit model and H3 cell. High prospectivity scores for MVT deposits tend to be associated with carbonate platforms and foreland basins inboard of orogenic belts, whereas high prospectivity scores for CD deposits tend to be associated with rift basins and/or passive margins at the edges of cratonic lithosphere. The interiors of old cratons are the least prospective for both deposit types.

Third, prospectivity model training (e.g., weights-of-evidence, neural networks, decision trees and stacked ensemble methods) and validation (i.e., spatial, K-fold crossvalidation) are performed on the complete data cube of all three countries for the first time. Finally, statistical analysis of the data inputs and prospectivity modelling results provide new insights into the multivariate signatures of MVT
and CD deposits, which, in turn, have the potential to advance mineral systems models for critical raw materials.

**RESULTS AND DISCUSSION**

The information value from the weights–of–evidence (WOE) method provides clues to the importance of each dataset to the model results (Agterberg 1992, Bonham–Carter 1994, Lawley et al. 2021). Maximum and minimum geological ages from the reinterpreted bedrock maps yield two of the highest information values for the preferred MVT and CD prospectivity models. Geological ages, coupled with Phanerozoic paleo–geographic reconstructions, can be used to map the availability of brinegenerating source regions (e.g., low– to midlatitude carbonate platforms and evaporites) and oxidized fluids that are essential for metal transport. For example, the virtual absence of MVT and CD deposits in the Archean likely reflects the limited availability of oxidized, basinal brines prior to the oxygenation of the atmosphere at ca. 2.4 Ga (Leach et al. 2010, Figs. 1 and 2).

![Preliminary weightsofevidence (WOE) model results for Mississippi Valleytype (MVT) and clasticdominated (CD) deposits in Australia. Bivariate colours are based on quantile scaling of the sum WOE for each deposit model and H3 cell.](image)

Statistical analysis of the model results further demonstrates that the edges of cratonic lithosphere (Hoggard et al. 2020) and shape index calculated from satellite gravity anomalies (Ebbing et al. 2018) within and inboard of orogenic belts are effective at mapping the most favourable paleo–tectonic settings and deepest
pathways of MVT and CD deposits. The relative importance of pre-existing structures in the deep crust for focusing ore-forming fluids is further supported by the high information value of other national magnetic and gravity datasets that are preprocessed to emphasize longwavelength anomalies. We demonstrate that the combined geological, geochronological and geophysical datasets have the potential to significantly reduce the search space for mineral exploration targeting. For example, the preliminary WOE models (Figs. 1 and 2) yield “area under the curve” (AUC) values for the successrate plot of 0.863 and 0.774, respectively, based on the spatially independent test set. More advanced modelling methods, which are trained and validated during a series of machine learning competitions in H2O (H2O.ai 2021: www.h2O.ai), have the potential to significantly improve model performance. The winner of these competitions, such as the preliminary gradient boosting machine (GBM) model results for MVT and CD deposits, yield AUC values of 0.954 and 0.933, respectively, based on the same test set. These preliminary GBM models reduce the search space by over 96%. Overall, prospectivity modelling highlights the potential benefits of mapping mineral systems at the largest spatial scales to improve mineral exploration targeting for critical raw materials.

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RESOURCE ASSESSMENT USING ADVANCED DATA ANALYTICS APPLIED TO MULTI-ELEMENT GEOCHEMICAL SURVEY DATA

by

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Resource assessment was carried out using advanced data analytics and machine learning-based prediction methods from stream sediment geochemical survey data in British Columbia, Canada. The geochemical data were transformed to centred log-ratio coordinates, after which principal component analysis, independent component analysis and t-distributed stochastic neighbour embedding were applied to render coordinates that show inter-element relationships and coherent geospatial patterns. Non-co-located mineral occurrence data from the MINFILE database, including mineral deposit model type, were tagged to the closest stream sediment site. Stream sediment sites with a distance of less than 3000 m to the closest MINFILE site were assigned the mineral deposit type and used as the training set. Stream sediment sites greater than 3000 m were assigned as “unknown” and formed the “test” set. Methods of classification and prediction were used to determine the accuracy of the training set and subsequent prediction of the test data. The resulting predicted classes and geospatial maps of posterior probabilities show the likelihood of mineral deposit types occurring across the area. For some mineral deposit types, the predictions have high accuracy and also highlight areas of increased mineral prospectivity. Some mineral deposit types are not well predicted, mainly because of compositional overlap and the lack of a suitable number of sites to define the training set.

INTRODUCTION

Resource assessment for the prediction of known and undiscovered mineral resources has a long history with the development of applied research in industry and government. Mineral prospectivity methodology has developed during the past 40 years and has recently been summarized by Yousefi et al. (2021). Resource assessment methodologies incorporate qualitative, quantitative and hybrid information from which mineral resources can be predicted. This study presents a methodology for mineral resource prediction using advanced data analytics applied to stream sediment geochemical survey data from British Columbia (BC), Canada.
Previously, the approach taken by the British Columbia Geological Survey (BCGS) for resource assessment involved a three-part resource assessment, including the use of expert opinion, and is summarized in Kilby (2004).

This study is based on the work of a previous resource assessment of the area (Grunsky & Arne 2020a, 2020b). Resource assessment requires information on the existence of past mineral resource discoveries that are typically recorded in mineral information databases compiled by government or industry. These databases typically describe mineral occurrences, developed prospects, past and current producers, past production, resource estimates and expenditures, along with information on an assigned mineral system. Assigning a mineral system model to occurrences and prospects may be inaccurate due to a lack of information. These parameters define the potential significance of the resource.

![Location map of stream sediment sampling sites (black dots) overlying a map of the regional geology.](image)

**METHODS**

The method used in this study employed the British Columbia MINFILE database and stream sediment multi-element geochemical survey data over selected areas in BC. Each MINFILE site was assigned a proposed mineral deposit model as documented in the BCGS Mineral Deposit Model catalogue. A measure of the distance from each mineral occurrence/prospect/producer to each stream sediment sampling site was determined. A threshold of 3000 m was chosen, from which a MINFILE occurrence was “tagged” to a stream sediment sampling site. The resulting dataset was then partitioned according to the mineral deposit model that was assigned in the MINFILE database. This dataset defined the “training” set for resource prediction. All other sites were tagged as “unknown” and assigned to the “test” dataset. In several cases, the number of sites for each deposit model was <10. Depending on
the model, these sites were merged with similar mineral deposit models or were dropped from further consideration.

As geochemical data are compositional, a centred logratio transform was applied to the data to overcome the potential problem of closure. The processes of rock formation, weathering, mass wasting, glaciation, alteration and mineralization may occur as either linear or non-linear processes. The use of different metrics can assist in discovering patterns and geochemical structure in the data. Metrics were derived from the application of principal component analysis (PCA), independent component analysis (ICA) and t-distributed stochastic neighbour embedding (t-SNE), the first reflecting linear processes and the latter two reflecting non-linear processes. The resulting metrics were then used to characterize, classify and predict mineral deposit types.

Classification and prediction of the mineral deposit types was carried out using analysis of variance, linear discriminant analysis, quadratic discriminant analysis and random forests. Cross-validation methods were applied to avoid the effects of over-fitting the data. The results of the mineral deposit predictions using the training sets provided measures of class prediction. Maps of class prediction and maps of prediction based on kriged images of posterior probability were created and evaluated with a comparison of the known MINFILE occurrences. Figure 2 presents a kriged image map of posterior probability for porphyry Cu deposit prediction using random forests applied to PCA coordinates.

**RESULTS AND DISCUSSION**

For some mineral deposit types, the match of predicted classes was geospatially close to the known MINFILE occurrences (Fig. 2). For other types of mineral deposit, the number of predicted class locations appeared to be excessive, which may be due to significant compositional overlap of a given site with several mineral deposit models. Maps of the posterior probabilities reflect “geospatial coherence” and assist in defining areas that are known to contain specific mineral deposit types, as well as areas that may be untested, potentially fertile mineral deposit sites.

In this type of study, there are several assumptions and caveats that need to be considered:

1. The geochemical composition of the stream sediment associated with individual mineral deposit models is uniquely distinct. In some cases, this assumption is not warranted.
2. The stream sediment samples represent a suitable medium from which the geochemical characteristics of mineral systems can be identified. Not all mineral deposit types can be best represented by stream sediment geochemistry.
3. The MINFILE model identification is accurate. This may not be the case for some types of mineral systems and, as a result, there will be an increase in uncertainty of prediction.
4. The location of a MINFILE site and the associated stream sediment site may not be within the same catchment area.
5. Because the corresponding MINFILE site and the stream sediment sample site are not co-located, there is always the likelihood that the stream sediment composition does not reflect the observed mineralization at the MINFILE site. The distance threshold of 3 km appears to work for some mineral deposit types, but not necessarily for others.
Although this study only involved the use of geochemical data, such an approach when combined with other geospatial data, including geology, geophysics, geological structure and digital elevation models, and analysed using advanced data analytics and machine learning methods, will assist in a more robust, consistent and defensible way of predicting additional mineral resources through “process discovery” and “process validation”.

Fig. 2. Kriged image map of posterior probability for porphyry Cu deposits (BCGS Model Lo4).

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MODELLING OF CU–AU PROSPECTIVITY IN THE CARAJÁS MINERAL PROVINCE (BRAZIL) THROUGH MACHINE LEARNING: DEALING WITH IMBALANCED TRAINING DATA

by

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Mineral prospectivity mapping (MPM) models naturally have imbalanced training data, as the number of known mineral deposit occurrences (as a proxy of the mineralized or positive class) is naturally much smaller than the number of non-mineralized locations (the negative class). The use of imbalanced data leads to difficulties in the training of machine learning models for MPM due to a bias in learning towards the features of the predominant (i.e., negative) class. In the present study, we evaluate the effects of the synthetic minority over-sampling technique (SMOTE) on Cu–Au prospectivity modelling using support vector machines in the Carajás Mineral Province (Brazil). SMOTE addresses the issue of imbalanced training data by generating synthetic samples that have similar features to known mineral occurrences. The results demonstrate that SMOTE can significantly increase the performance and spatial efficiency of MPM.

INTRODUCTION

Machine learning (ML) algorithms are increasingly being used in various fields of geosciences, especially for mineral prospectivity mapping (MPM). However, due to the unbalanced nature of prospectivity modelling problems, care must be taken when using these algorithms. The huge imbalance between known mineralized locations (i.e., the minority and positive class) and known non-mineralized locations (i.e., the majority and negative class) makes it difficult for ML algorithms to learn the classification rules between the majority and minority classes during training (i.e., learning). This leads to biased estimation of the decision boundaries towards the majority (i.e., non-mineralized) class and a higher misclassification (false negative) rate of the minority (i.e., mineralized) class based on testing locations (Japkowicz & Stephen 2002, Sun et al. 2009).
Reported solutions for handling the learning difficulties of ML algorithms when trained with imbalanced data regarding the majority and minority classes have previously been proposed at data and algorithm levels (e.g., Chawla et al. 2002, Sun et al. 2009). Recently, some authors have demonstrated that the use of the synthetic minority over-sampling technique (SMOTE) for synthetic over-sampling of the non–mineralized class (Hariharan et al. 2017, Li et al. 2019) can improve the performance of mineral prospectivity models trained with unbalanced data. In this context, here the effects of SMOTE on MPM are explored. We aim to demonstrate that SMOTE can significantly improve the performance of ML algorithms in MPM. To achieve this goal, a systematic approach was developed where 400 training datasets were produced with different ratios of mineralized-to-non-mineralized samples ranging from 20:1 to 1:20. This strategy was used to evaluate the performance of an SVM algorithm under different ratios of mineralized-to-non-mineralized samples for modelling the prospectivity of Cu–Au deposits in the Carajás Mineral Province (CMP), Brazil.

**DATA AND/OR METHODS**

The spatial recognition criteria for prospectivity modelling of Cu–Au deposits in the CMP were defined based on the mineral system approach to exploration targeting (McCuaig et al. 2010). Based on current knowledge of CMP geology and the similarities of the Cu–Au mineralization with the class of iron oxide–copper–gold (IOCG) deposits, the spatial datasets used to produce the model input features include a geological map, proximity to geological contacts, a geological complexity map derived from the map of faults/fractures, proximity to gravimetric worms, a map of magnetic analytic signal amplitude, proximity to magnetic worms, eTh/K and eU derived from radiometric data, and the locations of known Cu–Au deposits.

The original training dataset (30 mineralized locations and 600 non-mineralized locations) was interactively re-sampled using SMOTE. The class of mineralized locations was over-sampled at a rate N varying from 100% to 2000% at increments of 100 to generate synthetic samples. The class of non-mineralized locations was randomly under-sampled at a rate N varying from 100% to 5% at steps of 5. The total number of samples generated at each re-sampling interaction was calculated as , where is either the over-sampling or under-sampling rate and is the corresponding total number of mineralized or non-mineralized locations in the original training dataset. In this way, 400 training datasets with different ratios of mineralized to non-mineralized samples were obtained, one per over-sampling/under-sampling rate pair, including the original dataset, which corresponds to the 100%/100% pair.

To assess the changes in model performance produced by re-sampling the original dataset, an SVM model was trained for each one of the 400 training datasets, and the performance for each model was then compared. A flowchart of the model construction process is presented in Figure 1. Some of the algorithms developed in this study are available online (Prado 2020).
RESULTS AND DISCUSSION

The synthetic generation of mineralized samples using the SMOTE algorithm can significantly increase the classification performance and the spatial efficiency of data–driven MPM through ML. However, care should be taken when increasing the number of mineralized samples without changing the number of non–mineralized samples. According to the results, prospectivity models derived using balanced training datasets are more stable on training and have better spatial efficiency. Therefore, the performance of prospectivity models derived by an ML method can be increased using SMOTE only if the model is trained with the same or nearly the same number of mineralized and non–mineralized samples. Nevertheless, this result needs further verification by testing this approach using other ML methods, and in other regions with different numbers of known deposits. Also, other sampling techniques need to be trialled and compared with SMOTE.

The advantage of using spatial sampling techniques to deal with the imbalanced training data problem in MPM is that they are easy to implement and do not require in–depth knowledge of ML architectures, which is necessary when implementing algorithm level solutions. The use of these techniques can lower the risk in mineral exploration and should allow exploration geologists to make spatially–informed decisions.

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BEYOND THE PROSPECTIVITY MAP: TACKLING THE GROWTH CHALLENGE FACING THE MINERAL INDUSTRY WITH THE APPLICATION OF MINERAL SYSTEMS

by

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To aid the development of renewable technologies and distribution of new charging infrastructure, copper production will have to double over the next 30 years. Powering the next generation of battery technology and the forecast demand for electric and hybrid vehicle will require nickel production to increase nearly four-fold. Net zero emissions targets cannot be achieved without the mining industry and many of the essential minerals we produce. Picking the right ground to explore is key to successful exploration. A mineral systems approach provides critical grounding for predictive models, links directly to business decisions, translates directly into exploration work programs and identifies gaps to direct research and technology roadmaps.

INTRODUCTION

In the future, the most significant discoveries will be under cover in technically challenging environments that render them blind to our current exploration toolkit for predicting and detecting ore deposits. To help address this gap, we will increasingly rely on insights from predictive prospectivity analyses and machine learning. An integral part of this approach will be to identify and test datasets we do not routinely use, and to apply datasets in new and innovative ways depending on scale.

Picking the right ground to explore is key to successful exploration. If we choose the wrong spots on the globe, we allocate limited people, time, and money to areas with a relatively low probability of value creation through the discovery of world-class mineral resources. Considerable value therefore lies in front–end loading predictive modelling at global and regional scales to ensure that we are exploring for world-class deposits in the best mineral belts in the world and not exploring for the best deposit in a mediocre belt.

Individual ore deposits are part of larger mineral systems that are the expression of a number of geological processes enabling ore accumulation and concentration. A mineral systems approach to exploration is therefore predicated on an understanding of the critical processes that need to align in space and time for
an ore deposit to form. Mineral systems therefore provide critical grounding for predictive models that use either knowledge–driven or data–driven approaches to assess the prospectivity of a given area.

The opportunity in this space is truly extraordinary. At BHP we have learned from our success in petroleum. The petroleum industry was forced to look in remote and deeply buried (or in this case deep underwater) environments decades ago. With the application of systems thinking and technology development needed to image the petroleum system, they can now take an area the size of London and with the light from eight lampposts they can essentially draw a map of the city. We are being similarly challenged in minerals. We currently use brute-force sampling and drilling to connect the dots, but in time we will use more remote sensing data and geophysics to calibrate fewer samples and drillholes (essentially isolated points and pencils in space) to characterize entire volumes of rock and image mineral systems in their entirety. Earth observatory information combined with deep probing information that looks deep into the Earth’s lithosphere will be used to quantify the elements that contribute to big mineral systems.

**MOUNTAINS OF DATA**

Our search is greatly enhanced by the proliferation of open–source, pre–competitive data. What was once considered top–secret data is now material for student projects. Our phones have the same quality of information that the CIA and the Pentagon used to go to a secure facility to access. But it is not just about having access to terabytes of data; we now have access to a variety of open–source and commercially available tools that have evolved to help us visualize and interrogate these data.

The challenge in dealing with mountains of data is knowing what you are looking for. Prospectively analyses enable us to interrogate datasets in a variety of ways, but we may not know what we are looking for in that mountain of data or what it may look like. Machine learning algorithms help to see patterns that humans might not pick out or even think to look for, taking empirical observations to the next level. We must seek to understand what these patterns represent and the underlying processes or we risk chasing false positives in our exploration programmes, or worse, exploring in the wrong area because our models have been trained on datasets that yield misleading outputs. This runs the risk of introducing selection or survivorship bias into our predictive models (Fig. 1).

The example in Figure 1 highlights the critical importance of effectively combining geoscientist–powered and machine–learning–driven predictive modelling. Using machine learning to interrogate large volumes of data and extracting meaningful knowledge will require geoscientists to transition from being data gatherers to knowledge workers. We know that artificial intelligence cannot provide the solution on its own. We need skilled data architects to organize datasets at different scales and resolutions. We need inquisitive and experimental data scientists to sample data and recognize meaningful patterns. We need domain experts to ask the right questions of the data and understand what the computer is seeing and what it means.
Fig. 1. An example of selection or survivorship bias in aircraft from World War II. By analysing where planes had suffered the most damage, it was suggested that wingtips and the central body required better armour. Statistician Abraham Wald countered that the Navy should reinforce the armour on the nose, engines, and mid-body. Planes shot in these regions were not making it back to be analysed (Ellenburg 2014).

USING A MINERAL SYSTEM LENS

Mineral systems equip geoscientists with the right questions to ask as we seek to understand the critical processes reflected in data-driven predictive models. An understanding of the system and the geological factors that control the generation of an ore deposit can be used to expand the mappable footprint of a deposit and explain correlations uncovered with the inclusion of machine learning (Wyborn et al. 1994, McCuaig & Hronsky 2014).

Importantly, mineral systems link to specific business decisions at different scales in the exploration process, such as regional terrane selection, camp-scale targeting and prospect delineation (Fig. 2). Mineral systems operate across scales and span the gap between prediction and detection, and therefore place prospectivity outputs in the business context and clearly demonstrate how they inform exploration decisions. Mineral systems play a critical role, effectively grounding the application of prospectivity analyses to business decisions and using our understanding to postulate what datasets or integrated knowledge products are needed at a given scale to effectively map a mineral system.

In this way, the work begins when a prospectivity map is made. It is critically important to iterate, validate and conduct sensitivity analyses to understand the impact of different input and training datasets and expose any assumptions or bias. Initially, workflows cannot be overly rigid or prescriptive; playing with data should become routine. Data scientists should be nested with geoscientists who have expert knowledge of the underlying processes so an effective and efficient iterative approach can be adopted. Prospectivity workflows considerably improve when an iterative approach is used, and a learning loop is established. This learning loop extends beyond the confines of a prospectivity mapping exercise. It is equally important to incorporate insights from teams on the ground who are conducting detailed technical reviews and field exploration programmes whose learnings improve our knowledge of the mineral system and our ability to predict, detect and extract our resources more effectively.
Fig. 2. An example of the application of mineral systems to business decisions across three scales of exploration decisions: regional terrane selection, camp-scale targeting and prospect delineation. From McCuaig et al. 2019.

Prospectivity analyses conducted with a mineral systems lens also help highlight what we may not have quite right. These analyses shine a spotlight on missing datasets or integrated knowledge products, gaps in our understanding of the mineral system, or technology needed to enhance our exploration toolkit. This provides razor-sharp focus for research programmes and technology development. We need the best global datasets and knowledge products that align with the critical elements of our mineral systems back in time. The competitive advantage that we hope to realize from research partnerships is no less than a superior understanding of the Earth System and why world-class deposits form in some areas in space and time and not in others. A key differentiating capability is that mineral systems operate across all scales, spatially and temporally, enabling adaptation from two-dimensional prospectivity maps that focus largely on the shallow parts of a mineral system to holistic predictive modelling, which informs a comprehensive understanding of mineral systems in four dimensions, deep into the Earth system and further back in time.

REFERENCES

MINERAL PROSPECTIVITY MAPPING FOR CRITICAL RAW MATERIALS AT THE EUROCPEAN SCALE WITH THE CBA METHOD

by

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This contribution presents pan-European prospectivity maps for lithium, cobalt, natural graphite, niobium, tantalum, phosphates and rare earth elements that were produced by the GeoERA FRAME project. These maps are based on the cell-based association (CBA) method, which was specifically developed for mineral prospectivity mapping at regional to continental scales. The purpose of this method is to address issues such as uncertainties in the location of cartographic objects and the need to consider geological contexts. Several options to calculate favourability scores were statistically tested and compared to improve the accuracy of the method and produce the final maps.

INTRODUCTION

Lithium (Li), cobalt (Co) and natural graphite are essential for energy storage technologies and electric transportation. Niobium (Nb) is essentially used to produce high-strength low-alloy (HSLA) steels for construction, the automotive industry and pipelines. Tantalum (Ta) is needed for applications in electronics (capacitors), metallurgy (crucibles, heat exchangers, etc.), chemistry, superalloys or carbides (e.g., cutting tools). Phosphates are largely used across the world for the production of fertilizers, and rare earth elements (REE) are used in a wide range of equipment for green energy and digital technologies. All these commodities are considered critical raw materials (CRM) for the EU (2020). As these elements are mostly produced outside Europe, their supply for European industry is potentially a threat. Moreover, primary resources should be exploited as a priority in Europe
to reduce CO₂ emissions resulting from their shipping. To address these issues, the GeoERA FRAME project (“Forecasting and Assessing Europe’s Strategic Raw Materials Needs”) studied CRM in Europe that are essential for “green” technologies and the energy transition. An objective in the FRAME project was to produce prospectivity maps of CRM at the continental scale. The purpose of mineral prospectivity mapping (MPM) is to identify a priori areas with a high probability of discovering new deposits.

METHODOLOGY

In this contribution, we present mineral prospectivity maps of Europe for primary Li, Co, graphite, Nb, Ta, phosphate and REE, calculated with the cell-based association (CBA) approach (Tourlière et al. 2015), which is an alternative to GIS-supported prospectivity methods. It has been developed by BRGM to better manage uncertainties related to cartographic data. The basic principle of CBA is to circumvent the one-to-one point–feature relationship, which can be a source of significant errors in prospectivity mapping (e.g., uncertainties in point location or polygon contours, inappropriate generalization of favourability to a whole polygon, etc.). To do so, CBA considers the environment of the points (e.g., all lithologies in the vicinity of a deposit). This is done by superimposing a regular grid on the area of study and identifying the association in each of its cells. In parallel, lithological associations are also defined around each known deposit. These are considered favourable. All cells of the grid are then ranked based on their similarity with the favourable associations. A cell is ranked by combining frequency ratios (FR, or the frequency of a given lithology in all standard buffers versus the frequency of the same lithology in all cells of the grid) of all lithologies it contains.

In this study, several techniques for combining FR were tested: the sum of FR, product of FR, sum of “favourable” (i.e., >1) FR and product of “favourable” (i.e., >1) FR. In addition, ranking by simply summing the lithology frequencies in standards was tested. The compilations of deposits for Li, Co, graphite, phosphate, Nb and Ta were provided by the FRAME project (e.g., Gautneb et al. 2019), while the REE dataset was derived from the EURARE project (Bertrand et al. 2017). The data were organized so that each of the seven commodities had a distinct dataset. We performed statistical tests to measure and compare the reliability of results from the different ranking approaches. For each ranking technique, an average AUC (area under the curve) value and standard deviation were calculated, which allowed us to measure its performance per dataset. Based on these results, a prospectivity map was calculated for each complete dataset with the 1:1.5 million geological map of Europe (Billa et al. 2008), a regular grid of 10 by 10 km cells covering the whole of Europe and the best-performing ranking technique per dataset (Fig. 1). The 10 by 10 km resolution is rather coarse, but it was a good compromise between computing constraints and exploration significance.

RESULTS AND CONCLUSION

The prospectivity maps presented here highlight prospective areas that are known by exploration geologists, including the Variscan or Alpine belts for Li. More importantly, however, these maps also highlight, at the continental scale, areas that are favourable for the discovery of new CRM mineralizations in Europe that are less known and not as intensively studied. As such, they are valuable outputs of the
FRAME project that, in addition to confirming the capacity of CBA to produce MPM at the continental scale, can help in assessing (and possibly safeguarding) prospective areas where mineral exploration should focus in the coming years. In this regard, and to facilitate their exploitation, the seven prospectivity maps presented here will be made available in the coming weeks on the EDGI online platform (EDGI 2021), available at https://data.geus.dk/egdi/?mapname=egdi_geoera_frame.

Fig. 1. CBA prospectivity maps for Co, Li, graphite, phosphate, Nb, Ta and REE in Europe, and a map illustrating the datasets (top) that were used.
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MINERAL PROSPECTIVITY USING A VNET FRAMEWORK

by

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We developed a mineral prospectivity method using a VNET architecture, which uses deep learning and convolutional neural networks designed specifically for geoscience data. The framework is flexible for raster and point data layers with the option for sparse labels, i.e., drill hole locations, which do not exist everywhere in the survey area. The method is tested on an orogenic gold project in the Canadian Arctic, where a prospectivity map of gold grade was predicted across the whole survey region using gold values from existing drill holes as training. A set of recently completed drill holes is used for post-prediction validation.

INTRODUCTION

Mineral prospectivity is becoming increasingly common as the years progress, and the goal is to capitalize on the latest advancements in machine learning to create the best prospectivity product possible. Over the years, this progression has transitioned from weights of evidence (Agterberg et al. 1990) to logistic regression (Harris & Pan 1999) and, more recently, to deep neural networks (Cracknell & Reading 2014). From a geoscience perspective, a huge benefit of deep neural networks is the ability to treat data layers as an image with the ability to use convolutions to analyse patterns in the image at various spatial scales. This advancement from previous methods allows the prospectivity map to incorporate not only a data value at a particular point, but also the spatial patterns around the data point. To this end, we have developed a VNet deep learning framework (Peters et al. 2019) and tested it on a field data set.

The Committee Bay Greenstone Belt is located in Nunavut, Canada, and has many known mineralized gold locations. However, the size of the area of interest is quite large (40 km x 30 km), meaning that there is a strong demand for a prospectivity map that can help to focus exploration efforts. By inputting all available geoscience data layers into the VNet framework, we are able to achieve this task, and the accuracy of the prediction is subsequently examined with a new set of drill holes.
DATA AND METHODS

A frequency-domain airborne electromagnetic and magnetic dataset provides many of the data layers used in this field example, and the labels are composed of gold grades from many decades of drilling. The nature of the airborne survey meant that there were no gaps in data, which is a common problem with many prospectivity studies. In the case of missing data, one can use the VNet framework to predict the missing data and then input the full data layers into the algorithm again to predict gold grades. However, full data layers are always preferred if possible.

The VNet was trained using gold values from sparse drill holes from 1997–2018, where during the training, drill holes were left out of the training set for validation purposes. An additional validation occurred when drill hole results from 2019 were provided after the prospectivity map had been completed, so this allowed an opportunity to check and assess the predictions.

The actual predictions are formed by learning the mapping function $f$, such that

$$f(\Theta; X) = Y$$

(1)

for all pairs of geoscience data $X$ with corresponding labels $Y$, with trainable parameters $\Theta$. The training is completed by minimizing the loss function shown in Eq. (2) to obtain the optimum training parameters $\Theta$.

$$\min \ell (f(\Theta; X); Y)$$

(2)

RESULTS AND DISCUSSION

The VNet framework was run, and the top panel of Figure 1 shows the prospectivity prediction in the region with the highest density of labels, i.e., gold grades in drill holes. The predictions are plotted as circles while the label values are plotted as plus symbols. Both are overlaid on the reduced-to-pole magnetic data layer. This top panel shows the good spatial correlation between the labels and the trained prediction as would be expected in a region with a high label density. After the prospectivity process had been completed we received additional drill holes that were used for further validation. Four of the seven additional holes are shown in the bottom panel of Figure 1.

Here there is a good correlation with the three eastern drill holes, but sadly, the westernmost drill hole did not hit gold in the AI-predicted area in the southern part of the well. This drill hole did encounter a 1.4 g/t Au intercept at the northern end of the drill hole, but this was offset from the AI target. The additional three drill holes not presented in Figure 1 were spread across the survey area and were planned based on geological targets. These drill holes did not encounter significant gold intercepts, and the AI predicted low gold values in these locations. One of these drill holes is shown in Figure 2 where no gold was intercepted in the drill hole and no gold was predicted by the prospectivity map. These are technical successes and are important data points to help validate the predictions. However, there needs to be more testing of the AI high gold grade targets to truly evaluate how well the predictions are doing.
Fig. 1. Top) Training the VNet. Drilling results over 0.5 g/t Au shown as red plus symbols. Prospectivity predictions over 0.1 g/t Au shown as coloured circles. Overlaid on reduced-to-pole magnetics. Bottom) Validating the VNet. Drill hole gold values from 2019 not used in training, with gold values over 0.1 g/t Au shown as plus symbols. Prospectivity predictions over 0.1 g/t Au shown as circles. Overlaid on reduced-to-pole magnetics. Gold grade colour scale: dark blue = 0–0.1 g/t Au, light blue = 0.1–0.2 g/t Au, white = 0.2–0.3 g/t Au, orange = 0.3–0.5 g/t Au, red = 0.5+ g/t Au.
There is still a lot of work left to do to make prospectivity mapping a more robust and reliable exercise for targeting, but as with all prospectivity products, it is an iterative process. New drilling results will be input into the Vnet to produce a new round of predictions. We are also researching data augmentation methods to increase the number of data layers to improve the whole workflow. This can be in the form of simple data augmentation, where each data layer can be rotated or flipped, or it can be a more complex process such as multiple point statistics (MPS). In MPS, many new data layers are simulated based on the properties of the original image, and in theory should improve the ability to train the network to find gold.

Fig. 2. Validating the VNet. Drill results shown in blue, meaning all values are below 0.1 g/t Au. Prospectivity predictions over 0.1 g/t Au shown as coloured circles. Overlaid on reduced-to-pole magnetics.

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MINERAL SYSTEM APPROACH FOR THREE-DIMENTIONAL TARGET GENERATION OF IRON OXIDE (±APATITE) MINERALISATION IN THE BLÖTBERGET MINING AREA, BERGSLAGEN, SWEDEN

by

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In this study, prospectivity mapping at the Blötberget mining site in Bergslagen, Sweden, was carried out in 2D and 3D according to the mineral system concept and via a fully integrated dataset. At the regional scale, spatial analysis on mappable criteria was verified and carried out in 2D. Legacy and new data collected in the framework of the EU-funded Smart Exploration project were optimised and used to develop multiscale 3D geological models, including iron mineralisation, and a susceptibility model from the constrained 3D inversion of magnetic data. Subsequently, new mineralisation targets were generated using the mineral system approach by integrating various data and models. This included airborne magnetic, gravity, seismic and petrophysical data, as well as the proximities to structures and contacts with felsic volcanic and granitic rocks.

INTRODUCTION

The study area is situated in the historical mineral district of Bergslagen in south-central Sweden. Felsic volcanic rocks (c. 1.91–1.89 Ga) and interlayered limestone characterize the Bergslagen lithotectonic unit. Siliciclastic sedimentary rocks stratigraphically envelop this volcanic succession, and all the rocks are intruded by a dominant calc–alkaline, c. 1.91–1.87 Ga plutonic suite. More alkali–calcic magmatic activity, combined with the emplacement of anatectic granite and pegmatite, overlapped and succeeded the polyphase metamorphism and migmatization events at c. 1.87–1.83 Ga and c. 1.82–1.75 Ga, respectively (Stephens & Jonsson 2020).

The iron oxide mineralization in Bergslagen is comprised of skarn–type iron oxide deposits, Kiruna–type deposits and banded–iron formations (BIFs). The area of interest, the Blötberget area, is known for its iron oxide–apatite–bearing deposits. The mineralization in Blöteberget is known from boreholes to extend down to at least 800–850 m depth (Malehmir et al. 2017). The origin of the apatite–rich iron
oxide deposits is considered to be synvolcanic, although this is disputed, with a study favouring a magmatic–to–high–temperature hydrothermal origin (Jonsson et al. 2013).

McCuaig et al. (2010) described linking of the mineral system with available data for practical exploration targeting, translating data to mappable criteria. We present a mineral system model for iron oxide–apatite mineralization in Bergslagen at the mining camp scale and apply the concept to the deposit scale in the Blötberget mining area in the form of 3D models. This effort, including the collection of new data, re–interpretation and multiscale modelling, was carried out within the framework of the H2020–funded Smart Exploration project.

**DATA AND/OR METHODS**

A series of data, including borehole logs and an ore block model, as well as surface geological and structural, LiDAR, 2D and 3D seismic, and airborne magnetic data, were used for the modelling and interpretation of new target areas.

Firstly, a 3D geological model was created using existing data in the following order.

a) Borehole data were visualized and simplified in 3D. b) Geological and geophysical models, as well as topographic data, were used to generate fault surfaces. c) Surfaces were derived from ore block models. d) Structural data on planar and linear geological features were used to guide surface interpolations. e) 3D reflection seismic data were used to automatically extract a high–amplitude signal that may be associated with mineralization. f) Borehole data were used to match the high–amplitude shells with those of the mineralization intersected in the boreholes. g) An ore shell and fault block model were created and used as constraints (Bastani et al. 2019, 2020). h) The updated 3D deposit model was then exported for 3D constrained inversion of the airborne magnetic data to verify its reliability and generate a well–constrained susceptibility model.

Secondly, we used a mineral system approach (MacCuaig et al. 2010) for 3D prospectivity mapping in Blötberget. A mineral system model of the iron oxide–apatite type in this area at the regional scale has been presented by Sadeghi et al. (2019, and references therein), which was partly used for identifying mappable criteria at the mining scale. For the 3D prospectivity mapping, we considered a) proximity to syn–volcanic granite and proximity to the rhyolite–dacite representing the sources, b) proximity to the structure density considered as a transport factor in the mineral system approach, c) the iron ore shell and the modelled faults using different datasets have been considered as trap factors and d) magnetic susceptibility (constrained model) greater than 0.1 (SI) and magnetic anomalies are considered as representing deposition.

**RESULTS AND DISCUSSION**

Using the above–mentioned datasets, the evidential layers were translated into maps and extracted in 3D using GoCAD software based on the mineral system approach model. The MPM for potential undiscovered iron oxide in the Blötberget was carried out using a knowledge–based multi–class index–weighted overlay method. Accordingly, their proximity has been modelled in 3D to be integrated for target generation. The results of the previous data integration (Malehmir et
al. 2020) were utilized in the targeting of iron oxide in Blötberget by including a 3D magnetic susceptibility model (Bastani et al. 2019, 2020; Fig. 1).

Previous multidisciplinary research aimed at building a 3D model of Blötberget using seismic data, as well as magnetic (unpublished work) and geological data, supported with downhole measurements and drill hole data, suggested new evidence of the lateral and deep extension of the ore deposit. In addition to the previous achievements, applying a mineral system approach to the available existing data provides additional information on the formation of the ore deposit and the role of structural influence in the present location of the mineralization. The applicability of the mineral system approach and the achieved results suggest a downwards extension of the favourable area and the lateral extension of mineralization not only towards the west, but also towards the NE, where a cross-cutting fault extending NNW–SSE was suggested by previous 3D model building in Blötberget.

Fig. 1. 3D geological and geophysical models were constructed on a semi-regional scale around the Blötberget iron deposit. A 3D prospectivity map was generated according to the mineral system and shows the extension of the favourable area of mineralization both in depth and towards the NE and SE.
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MACHINE LEARNING METHODS FOR ASSISTING IN THE IDENTIFICATION OF DRILLING TARGETS WITHIN THE RAJAPALOT PROJECT AREA IN FINLAND

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This contribution presents the results of prospectivity modeling for gold in the Rajapalot project area in the northern Fennoscandian Shield in Finland. Different statistical and machine learning methods were implemented for detailed prospectivity modeling of the Rajapalot study area. The methods used were unsupervised self-organizing maps and supervised artificial neural networks, fuzzy inference systems and adaptive neuro-fuzzy inference systems. The results indicate that with the help of unsupervised and supervised knowledge- and data-driven methods, it is possible to (i) identify mineralization-related patterns in feature space from the input data without the use of training data, (ii) delineate prospective areas based on conceptual understanding of mineralization processes by implementing the knowledge-driven approach, and (iii) recognize mineralization features represented in the training data and facilitate learning of these by data-driven models.

INTRODUCTION

The Rajapalot project area in the Peräpohja Belt (PB) in northern Finland (Fig. 1) contains important high-grade gold–cobalt resources. Exploration for ore-body delineation, expansion of known prospect areas and resource estimation is ongoing in the Rajapalot area by Mawson Gold (the company that holds exploration permits in this area). The regional- and belt-scale prospectivity maps of the PB by Niiranen et al. (2019) and Nykänen et al. (2017) highlight the smaller camp-scale Rompas–Rajapalot area with high prospectivity, but these do not provide enough detail to target the actual mineralization. Hence, to produce a more detailed prospectivity map of the project area, this work focused on the target-scale prospectivity modeling of gold mineralization in Rajapalot using advanced statistical and machine learning methods to identify drilling areas with high mineral potential.
METHODS

The workflow implemented in this study comprised (1) mineral system modeling, (3) the formulation of geological hypotheses and creation of corresponding evidence layers, (3) statistical testing of each geological hypothesis, and (4) mineral prospectivity modeling. We used knowledge derived from the existing literature and from discussions with Mawson’s exploration geologists about the Rajapalot mineral system’s genetic model to identify the localized pathways and trap-related favorable settings. We then formulated geological hypotheses for the mineralization processes and derived the corresponding evidence layers. The next step involved statistical testing of each geological hypothesis to check whether the evidence layers representing the mineralization process can resolve the mineralized from the non-mineralized drill-core sections. This helped us to identify the most representative evidence layers that served as inputs to the advanced statistical and machine learning algorithms for prospectivity modeling. Finally, we used both unsupervised and supervised (knowledge- and data-driven) machine learning methods for mineral prospectivity modeling.

The unsupervised machine learning method used was self-organizing maps (SOMs). This is an effective method for generating a low-dimensional (usually 1D to 3D) representation of n-dimensional input data. From a SOM, patterns related to the mapped mineralization-related processes can be identified in the input data space. K-means clustering of the SOM results further identified distinct populations in the dataset. The geospatial domains corresponding to specific populations could, by means of visual interpretations and statistical evaluations, be related to the mineralized drill-core sections, thus representing the prospective mineralization area. Finally, we implemented supervised classification of the SOM codebook vectors using an artificial neural network (ANN). Fuzzy inference systems (FISs) and a hybrid adaptive neuro-fuzzy inference system (ANFIS) were also implemented.
for knowledge-based prospectivity modeling. Model uncertainties related to parameterization of the membership functions of the FIS were quantified by running Monte Carlo simulations (MCS). 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.

RESULTS AND DISCUSSION

The clusters identified from the unsupervised SOM indicated geospatial domains of prospective mineralization zones in the proto-prospectivity map (e.g., Cluster 0, Fig. 2a). The data-driven approaches identified a localized high-prospectivity area near the underexplored prospects (e.g., Hut Prospect, H, Fig. 2b), thereby imparting further confidence in the exploration of these underexplored prospects. In the results from the knowledge-driven approach (FIS), the general NE–SW trend of mineralization along the high prospectivity zones becomes evident (Fig. 2c). These trends conform to the structural settings that exercise strong control on mineralization. For instance, the known prospects are located near the hinge of a kilometer-scale open fold with a NE–SW-trending axial trace. These trends are also mapped in the prospectivity results along the hinge and limbs of this fold.

Mawson is continuing to actively explore these existing prospects to identify new mineralized areas. Several exploration targets were identified in our study. Recent news releases by Mawson (https://mawsongold.com/news/news-releases/2021, Mawson 2021) indicate promising drilling results at these
locations. This includes the Joki East area and the area around the less explored Hut prospect, both of which have yielded mineralized horizons from drilling. All the above findings from the drilling activities in a way have helped us validate our results and improve our understanding of the mathematical modeling of mineralization processes for prospectivity mapping.

To summarize, prospectivity maps do indicate areas for ground exploration, but they are not the sole guiding elements in the selection of drilling areas. Most importantly, we conclude that mineral prospectivity studies can be transformed from predictive tools at the regional scale to supporting decision-making systems at the target scale.

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MINERAL RESOURCE ASSESSMENT AND MAPPING 
OF PROSPECTIVITY BY THE GEOLOGICAL SURVEY 
OF BRAZIL: A WORK IN PROGRESS

by

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The Geological Survey of Brazil is developing several projects involving mineral 
potential modelling in order to promote and guide mineral exploration of precious/ 
base metals and critical minerals. The current targeted raw materials are copper, 
gold, uranium, lithium and graphite. The techniques used mostly depend on the 
availability of information and scale of the final maps to be presented (continental, 
craton, province and district scale), each one related to specific methodological 
approaches. The techniques may be either manual/specialist-dependant (con-
tinental scale) or knowledge/data-driven (craton, province and district scales), 
including the use of machine learning algorithms. The mapping of prospectivity 
may help decision makers in prioritizing areas for mineral exploration and thus 
be a powerful tool to reduce the geological risk in mineral exploration. The main 
challenge in working with mineral potential modelling in Brazil is the heteroge-
neity of available datasets, while future challenges include the cross-checking of 
geologically favourable targets with ESG drivers to help in targeting exploration 
investments to areas with lower social and environmental risks.

INTRODUCTION

Brazil is a continental-scale mining country with a diverse geological setting, pre-
senting a remarkable potential for mineral exploration of precious and base metals, 
as well as critical minerals. The country has several mineral provinces and mining 
districts that are still underdeveloped. In addition, world-class mineral provinces 
with a long history of mineral exploration and numerous deposits under exploita-
tion still have considerable potential for new discoveries (e.g., Costa et al. 2019).
The Geological Survey of Brazil (CPRM) manages a permanent programme of mineral resource assessment and mapping of prospectivity in order to evaluate the undiscovered mineral potential of the country, to subsidise the formulation of public policies, such as investments in infrastructure in potential areas still underexplored, and to promote mineral exploration. In this paper, we describe the critical aspects of CPRM’s quantitative resource assessment approach, especially the mineral potential modelling projects and techniques under development.

**METHODS**

The first efforts by CPRM to assess the mineral potential of a given area through spatial data modelling are described in Bizzi et al. (2003). However, the publication of favourability maps started with Campos et al. (2017), based on exploration targeting techniques under a mineral system approach (Wyborn et al. 1994, McCuaig & Hronsky 2014). Mineral potential modelling (MPM) has been applied in recent years by CPRM to map the prospectivity of different metals, especially gold and copper (e.g. Tavares et al. 2020), although the current projects cover a broader variety of raw materials, including critical minerals such as lithium and graphite, as well as uranium, copper and gold.

The MPM techniques used by CPRM mostly depend on the availability of information and scale of the final maps to be presented. We are currently developing projects that will result in maps at four different scales:

1. **Continental-scale mineral potential maps** are targeted at raw materials that have been barely explored in the country and for which we forecast a future growth in demand by the mineral industry, or that are strategic for the Brazilian State. Currently, continental-scale maps are under development for uranium mineral systems and are also planned to be developed in the near future for selected critical minerals. This class of maps is entirely based on expert estimates (e.g., Kreuzer et al. 2010) and is intended to identify and rank current and potential production regions (mineral provinces and/or districts), presented at the 1:2,500,000 scale. The country has been divided into around 120 geological clusters, for which key geological factors are evaluated and ranked regarding the known or potential occurrence of the targeted substance.

2. **Craton-scale mineral potential maps** are used to evaluate the regional extension of recently discovered mineral systems in emerging provinces and are under development to assess the Proterozoic porphyry copper potential of the south-eastern Amazonian Craton (northern Brazil) at the 1:1,000,000 scale. The MPM is knowledge-driven, using both multiclass overlay and fuzzy logic techniques (e.g., Silva & Souza-Gaia 2020, Souza-Gaia et al. 2020), with datasets strongly supported by airborne and satellite geophysics (magnetometry, gamma spectrometry, gravimetry).

3. **Province-scale favourability maps** are used to assess and target known mineral systems in the major and emerging mining areas, currently being developed to assess copper, gold, lithium, uranium and graphite at the 1:250,000 scale. The MPM in these areas is oriented to occur in two stages, first in a knowledge-driven approach (multiclass overlay, fuzzy logic), in order to help the designing of the conceptual model and evidence maps, and then in a data-driven approach, using machine learning algorithms (MLA), especially random forest (RF). Usually, the dataset includes airborne geophysics and...
geochemistry (stream sediments, pan concentrates) and regional geological information, although the heterogeneity of the distribution of available information may be challenging.

4. District-scale favourability maps are the most detailed products of our portfolio (1:100,000 to 1:50,000 scales) and are under development for copper, gold and uranium. They are usually coupled with regional metallogenic studies that result in comprehensive datasets that allow high-quality mapping of prospectivity. The MPM at this scale can be either knowledge- or data-driven, depending on the availability of mineral occurrences in the studied area.

As a general rule, modelling at more regional scales may be used to identify and rank areas that should be addressed at more detailed scales, although areas well known for their mineral potential may be developed regardless of a previous ranking.

**DISCUSSION**

The mapping of prospectivity through different MPM techniques may help decision makers in prioritizing areas for mineral exploration and thus be a powerful tool to reduce exploration risk. Furthermore, aligning the development of favourability maps with comprehensive assessment and geo-economic studies may be useful as a showcase to promote potential areas that are still underexplored and to help the formulation of public policies.

The main challenge of performing systematic MPM in Brazil is the lack of homogeneous and consistent datasets, especially concerning geological mapping, which covers in detail only a fraction of the country, while large emerging areas for the mineral industry are still deficient in basic geological knowledge. The data that have a broader distribution include airborne geophysics and remote sensing imagery. Thus, several strategies using MLA and python-based programming solutions are under development in order to enhance the data processing, such as the calculation of uranium anomalies through RF regression (Costa et al. 2020) and the estimation of structural complexity based on gamma spectrometry data variance.

Moreover, CPRM is mostly focused in 2D MPM, while the main potential in mature areas is buried and would be better addressed through 3D modelling. Joint magnetometry-gravimetry inversion has been attempted at selected sites, but Brazil still lacks coverage with other potential geophysical methods that would allow such an approach with more assertiveness.

Finally, CPRM intends to deal in the near future with the alignment between mineral resource assessment and ESG drivers, in order to rank possible targets in terms of social and environmental impacts/risks. Spatial data modelling can be a powerful tool to guide this issue.
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