Geological Survey of Finland

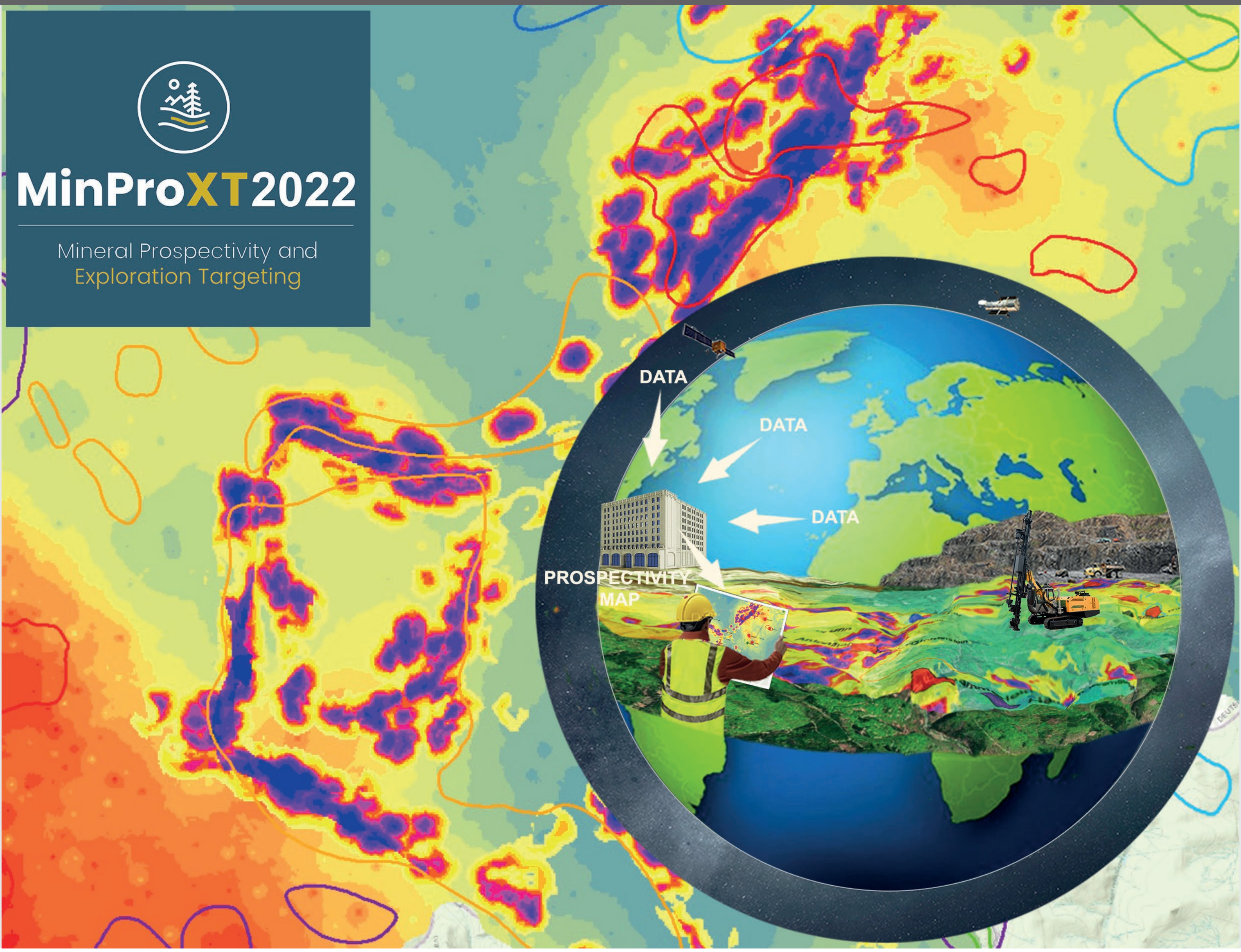
2023

MinProXT 2022
Mineral Prospectivity and Exploration Targeting

November 1–3, 2022

Andreas Knobloch, Johanna Torppa and Bijal Chudasama (eds)

GTK Open File Research Report 29/2023



GEOLOGICAL SURVEY OF FINLAND

Open File Research Report 29/2023

MinProXT 2022
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Abstract proceedings

Edited by Andreas Knobloch, Johanna Torppa and Bijal Chudasama

Figures in each abstract are prepared by the author(s) of that specific abstract.

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The Mineral Prospectivity and Exploration Targeting – MinProXT 2022 joined together prospectivity analysis experts from academia, governmental research institutes and the business sector. There were 2 scientific sessions, including 4 key-note 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 at MinProXT 2022.

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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TOPIC 2: 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

INTRODUCTION

In October 2021, the Geological Survey of Finland, in co-operation with the United States Geological Survey, the Indian Institute of Technology Bombay and the Centre for Exploration Targeting, University of Western Australia, successfully organized and conducted the first Mineral Prospectivity and Exploration Targeting (MinProXT 2021) webinar.

In 2022, the second edition of the event, MinProXT 2022, was organized by Beak Consultants GmbH, in co-operation with the Technical Research Centre of Finland (VTT) and the Geological Survey of Finland (GTK). MinProXT 2022 was held in the first week of November 2022 as a two-day hybrid event. Overall, following more than 270 registrations, more than 200 experts participated online and on-site. Taking place directly after the lifting of COVID-19 restrictions in Germany, it was also nice to welcome international participants in-person from Finland, Bulgaria and the USA to the on-site venue at Beak Consultants GmbH office in Freiberg, Germany. On the third day of MinProXT 2022, the on-site participants visited the “Terra Mineralia” minerals collection in Freiberg and went on a field trip to the “Zinnkammern” underground mine near Pöhla in the famous Erzgebirge mining region.

The event featured invited and non-invited talks by eminent scientists from the mineral exploration industry, research organizations and academic institutions. The following two topics were addressed in the MinProXT webinar:

Theme 1: Advances and recent development in the methods of 2D and 3D prospectivity mapping and geoscientific data analyses, and the associated limitations, uncertainties and challenges.

Theme 2: Real-world utilization of prospectivity maps in varied fields such as land-use assignments, infrastructure planning and others, in addition to mineral deposit exploration.

The primary objective of MinProXT was to present ideas on varied topics related to mineral prospectivity analyses and exploration targeting. The webinar aimed to be a confluence point to foster open discussion and interaction between predictive mapping research experts, public sector organization executives and experienced professionals from the mining and mineral exploration industry.

This proceedings publication is a compilation of the extended abstracts of the research presented in MinProXT 2022.

Organizing committee

Andreas Knobloch, Managing Director, Beak Consultants GmbH

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Proceedings preparation: Päivi Kuikka-Niemi, Geological Survey of Finland

Proceedings language check: Roy Siddall

Key-note speakers

Graham Lederer, Physical Scientist, United States Geological Survey

Title of the talk:
Automated georeferencing and feature extraction of geological maps and mineral sites

Dr. Graham Lederer investigates the supply of mineral commodities critical for societal needs. His current projects focus on developing methods for mineral resource assessment and the application of machine learning techniques. Prior to the USGS, Graham earned a PhD at the University of California Santa Barbara while studying granites in Himalaya and was a post-doc at MIT.

Christopher Lawley, Gold Metallogenist, Geoscience Australia

Title of the talk:
Applications of artificial intelligence for balancing conservation and biodiversity values with critical mineral exploration

Christopher Lawley's research experience blends analytical method development with field studies to investigate the sources and drivers of mineral systems. More recently, he has become interested in the application of machine learning to sustainable development issues. His research results have been applied across Canada, the United States, and Australia as part of an international effort to strengthen the supply chains of critical raw materials.

Mark Lindsay, Science Leader, CSIRO Mineral Resources

Title of the talk:
Propagating Uncertainty through the Minerals Pipeline: from regional prospectivity to the (conveyor) belt.

Mark Lindsay is a geoscientist whose research interests include understanding the complexities of uncertainty in 2/3D geoscientific modelling throughout the various scales and phases of mining and exploration. He is working toward a stochastic approach to modelling that attempts to understand the importance of different data types in answering interdisciplinary questions and providing support for decision-making. Mark has extensive experience integrating diverse data sets for interpretation, mineral systems and prospectivity studies while working with a number of geological surveys, leading mining organisations and various academic institutions around the world. Mark participates in many national and international research initiatives such as the Data Analytics for Resources and Environment (DARE) Training Centre, Loop Consortium and MinEx CRC. In his role as Science Leader in Mineral Resources – “Minerals 4D”, Mark will work across capability boundaries to bring deeper understanding of the links between the data we collect and the geological phenomena they represent.

Patrice de Caritat, Senior Principal Research Scientist, Geoscience Australia

Title of the talk:
The Heavy Mineral Map of Australia project: Vision, pilot and first data release

Patrice de Caritat’s university training is in geology, mineralogy and geochemistry, and his research interests include environmental, exploration and isotope geochemistry, hydrogeochemistry, low-density geochemical mapping, and soil forensic provenance. He is a Visiting Fellow at the Research School of Earth Sciences, Australian National University (ANU), and Adjunct Professor at the University of Canberra. In 2017-2018, Patrice was seconded to the Australian Federal Police. He holds a Lic Sci (BSc Hons) degree from the University of Louvain (Belgium), and PhD from the ANU. He has published over 160 scientific papers, reports, chapters, and books.

AUTOMATED GEOREFERENCING AND FEATURE EXTRACTION OF GEOLOGICAL MAPS AND MINERAL SITES

by

Lederer, G.[1], Rosera, J.[1], Goldman, M.[2], Graham, G.[2], Mishra, A.[3], Towler, A.[3], Wilson, B.[3], Graf, D.[3], Milano, M.[3], Roberts, E.[4], Hedrick, G.[4], Oertel, C.[4], Dardas, A.[4] and McEntee, T.[4]

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The predictive power of mineral prospectivity analysis depends on high quality, spatially accurate, analysis-ready datasets. Of paramount importance are geological maps and mineral site data, but the state of readiness for utilizing these datasets remains sub-optimal for advanced computational techniques. As the U.S. Geological Survey (USGS) fulfils its mission to map the distribution of critical mineral commodities, non-georeferenced maps held within historical collections represent rich sources of input data. Through a series of machine learning challenges organized by the Defense Advanced Research Projects Agency (DARPA) in collaboration with the USGS, significant progress has been made in accelerating data ingestion, processing and preparation tasks that enable mineral prospectivity mapping and mineral resource assessment workflows. Specifically, two tasks that previously required time-intensive human effort are discussed: 1) georeferencing map images and 2) legend-based feature extraction from map images.

INTRODUCTION

Mineral prospectivity mapping involves the use of advanced computational approaches to make predictions from evidence layers. Whereas several tools and methods have been developed to produce mineral prospectivity maps from analysis-ready data, many datasets and legacy sources of information require numerous data preparation steps for use as input layers. These data preparation tasks often represent the most time-intensive bottleneck within mineral prospectivity mapping workflows.

Geological maps and mineral sites (a term used broadly to encompass mineral occurrences, prospects, deposits and mines) represent two of the most fundamental data types used as inputs for mineral resource assessment, whether by quantitative methods or mineral prospectivity modelling. However, several factors inhibit the use of geologic maps in mineral prospectivity analyses. The scale of mineral sites, as opposed to larger mineral systems, is often smaller than the resolution of available digital maps. While higher resolution maps may exist, they may not be georeferenced or in a digital form suitable for geospatial analysis. For example, more than 100,000 geological maps within the United States have been indexed as part of the National Geologic Map Database (NGMDB), but only ~10% are currently available as digital map layers (Fig. 1).

The USGS conducts assessments of critical mineral commodities, a task requiring precise locations of known mineral sites, as well as high-resolution geological data to generate prospectivity models. To streamline the processing of geological and mineral occurrence data at scale, the USGS and DARPA have established two machine-learning (ML) competitions aimed towards efficiently 1) georeferencing historical maps and 2) extracting features from these maps.

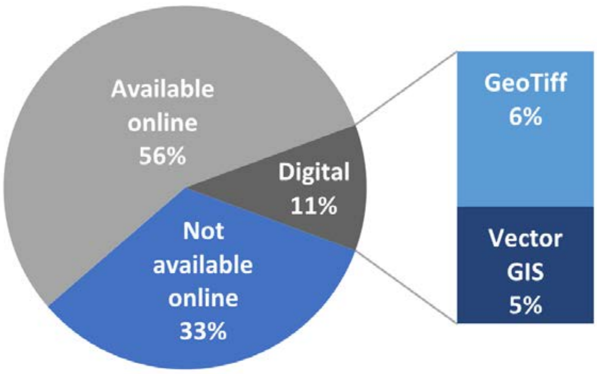

Fig. 1. Inventory of maps in the National Geologic Map Database (NGMDB).

DATA AND METHODS

Challenge 1: georeferencing

The first challenge tasks competitors with developing ML tools to semi-automatically georeference maps with a wide variety of basemap elements (Fig. 2). Whereas a human can seamlessly integrate several layers of information presented visually in a map image and conceptually relate each colour or pattern to a different observable feature on the landscape, a computer must be trained to do this using rich digital datasets and pattern matching. We supplied competitors with ~700 training maps and ~300 validation maps. Training maps contained between 10 to 20 randomly located control points that matched raster coordinates (i.e., rows/ columns) to projected coordinates. In practice, georeferencing images begins with an approximate location based on some *a priori* context. To replicate this, we supplied competitors with a location clue—a single latitude-longitude coordinate pair from within the image extent. Competitors had to identify coordinate information (grids, tick marks, etc.) and/or suitable baseline features for georeferencing the map. Subsets of the validation maps were periodically scored based on accuracy in comparison to manually georeferenced results. This provides competitors with an opportunity to fine-tune their model prior to the release of ~100 evaluation maps for final scoring.

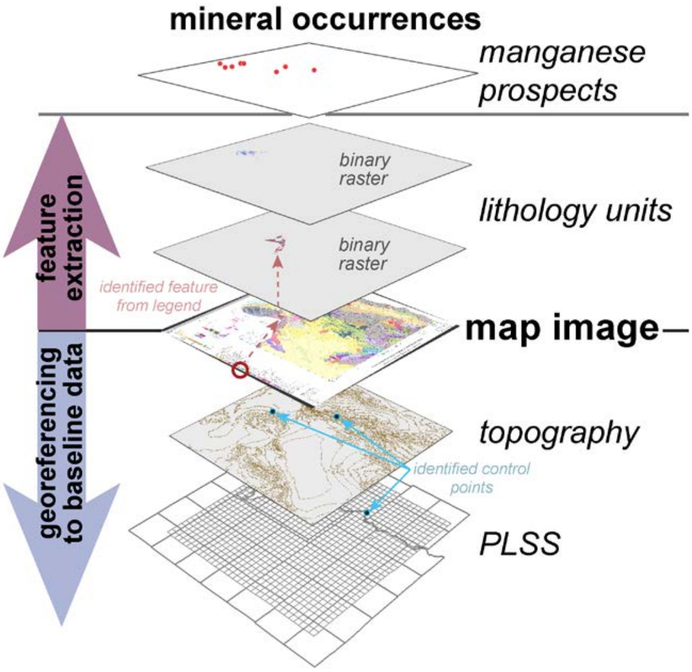

Fig. 2. Diagram relating a map to the two challenges.

Challenge 2: legend-based feature extraction

Fully digitizing and vectorizing a geological map can take many hours and cost thousands of dollars per map. Automating the process of map digitization is crucial to efficiently unlocking the information contained in map images as machine readable data. Despite recent advances in image segmentation and pattern recognition, automated extraction of features from geological maps remains challenging. Geological maps typically contain confounding elements, such as basemap topography, hydrology, culture or complex patterns. The second challenge requires competitors to use map legends to recognize colours and patterns of different features, and to extract these features from the map image. The training set consisted of ~200 maps with >4000 individual features, and the validation set contained 120 maps with ~2000 map features. Each training map was provided with a corresponding .json file labelling the legend features to be extracted as a binary raster. Competitors were given scores on their validation results by comparing their binary raster submissions to those created from vector files. The validation rounds provided an opportunity for competitors to fine-tune their model prior to final scoring against a separate set of evaluation maps.

RESULTS AND DISCUSSION

Digital extraction and accurate geolocation of geological and mine-related features from map images represents a critical step in mineral prospectivity and assessment workflows. The ability to automate parts of this process and combine the output with rich metadata attribution has potential to greatly increase the rate and comprehensiveness with which mineral resource assessments for critical mineral commodities can be completed. Integrating mineral sites and geological maps with geochemistry, geophysics and remote sensing datasets is expected to reveal new insights into the distribution and probability of occurrence of mineral deposits.

APPLICATIONS OF ARTIFICIAL INTELLIGENCE FOR BALANCING CONSERVATION AND BIODIVERSITY VALUES WITH CRITICAL MINERAL EXPLORATION

by

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Meeting the demand for electric vehicles over the next few decades will require a stable supply of the critical raw materials used in the manufacturing process, including nickel, copper and cobalt. The search for additional sources of these critical raw materials will likely accelerate environmental pressures on natural ecosystems, and new conservation areas are urgently needed to protect the most vulnerable habitats and species. However, very few, if any, research studies have evaluated whether area-based conservation targets can be balanced with increased exploration and development of critical raw materials across Canada, due in part to the difficulty of accurately predicting where these new mineral deposits are most likely to occur. Herein, we address this knowledge gap and overlay new national prospectivity model results for a major source of Canada’s battery minerals (i.e., magmatic mineral systems) with gaps in the protected-area network and five ecosystem services (i.e., freshwater, carbon, nature-based recreation, species at risk, climate-change refugia). The combined results are used to identify areas of high geological potential with lower ecological risk and to predict hotspots with the highest potential for conflicting land-use priorities in the future. Managing hotspots with multiple land-use priorities would necessarily involve partnerships with Indigenous people and other impacted communities to balance new natural resources development with conservation and biodiversity values.

INTRODUCTION

Magmatic mineral systems are the primary source of nickel (Ni) and cobalt (Co) in Canada, which are essential critical raw materials to increase the energy density and lower the cost of batteries for electric vehicles. Significant amounts of copper (Cu) and platinum group-elements (PGE) are produced as by-products of these Ni mining activities. Examples of this mineral system occur across Canada, and the search to find new sources of Ni, Cu and Co has the potential to negatively impact natural environments that are already threatened by natural resource extraction and processing. To protect the most vulnerable ecosystems, Canada has set national conservation targets as part of its commitments under the Convention on Biodiversity and the post-2020 Global Biodiversity Framework (i.e., 25% of land conserved by 2025 and 30% by 2030). Rapid expansion of this protected area network is required to meet these targets, as Canada is estimated to have conserved just 12.5% of its terrestrial area and inland water as of 2020. The application of artificial intelligence to lower the ecological and environmental risks of the natural resources sector could ultimately form part of the strategy towards the sustainable development of critical raw materials.

PROSPECTIVITY DATA AND METHODS

Magmatic Ni mineral systems form as ultramafic to mafic melts originating in the mantle are focused into the overlying crust by zones of pre-existing lithospheric weakness. National geological and geophysical survey compilations can be used to predict the most likely source regions and pathways for transporting these mantle melts to their depositional trap in the crust, as described in Lawley et al. (2021, 2022). Each of these input datasets were processed in R (R Core Team 2021) and spatially indexed using the H3 discrete global grid system (N.B. each hexagonal H3 cell is 1.22 km per side). Model training and spatial cross-validation were completed in R using the Gradient Boosting Machines (GBM) function in H2O (https://www.h2o.ai/). Model tuning included multiple random grid searches to find the best combination of hyperparameters, with the best GBM model identified using the area under the curve (AUC) for the receiver operating characteristics (ROC) plot.

ECOLOGICAL REPRESENTATION

Protected areas and other effective area-based conservation measures were taken from the 2021 Canadian Protected and Conserved Areas database. The percentage overlap between the protected area network and each ecoregion included within the National Ecological Framework provides a measure of the ecological representation of conserved areas. Ecoregions were then classified as having no protection (<1% overlap), poor protection (1–15%), moderate protection (15–30%) or good protection (>30%) in order to compare with the post-2020 Global Biodiversity Framework targets.

CONSERVATION DATA AND METHODS

Prioritizing high-capacity ecosystems that provide essential benefits to people represents an important component of conservation and land-use planning. Herein, we focus on some of the few previously published national assessments of ecosystem services in Canada, including (1) carbon storage (Mitchell et al. 2021), (2) freshwater (Mitchell et al. 2021), (3) nature-based recreation (Mitchell et al. 2021), (4) species at risk and (5) climate-change refugia and climate corridors (Stralberg et al. 2020). Ecosystem services and the results of the protected area gap analysis were combined using fuzzy logic with prospectivity results in Figure 1.

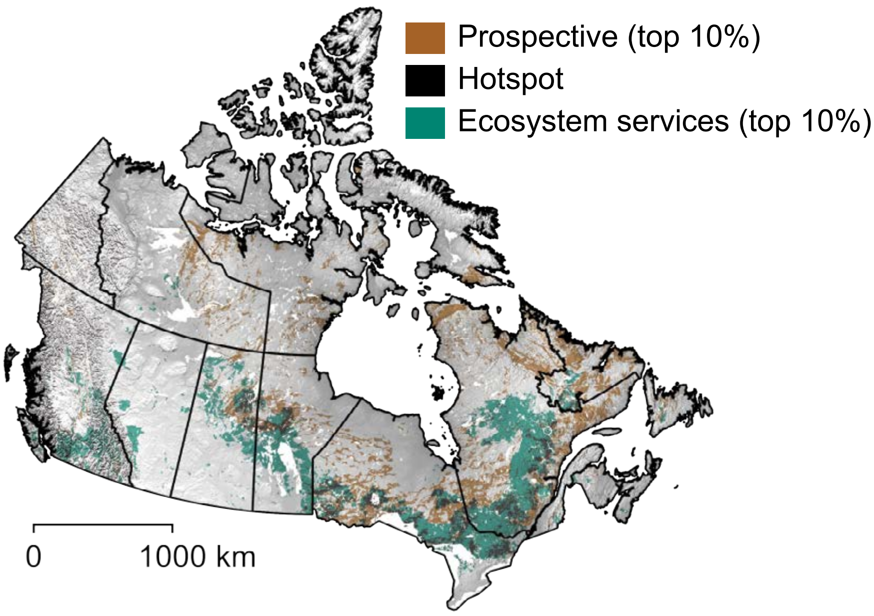

Fig.1. Prospectivity model results for magmatic mineral systems combined with five ecosystems services and the protected-area gap analysis. The results can be used as part of land-use planning to predict the potential for multiple priorities, i.e., “hotspots”.

RESULTS AND DISCUSSION

The AUC for the preferred GBM magmatic model is 0.972, reducing the search space for 90% of magmatic Ni deposits in the training and test set by 94% and 89%, respectively. The high AUC (0.955) for the test set, which was not used during training, suggests that the preferred GBM model can predict magmatic mineral systems “unknown” areas in Canada with good to excellent performance. Using the inflection point on the ROC plot as a threshold, we demonstrate that 16% of the most prospective model cells partially overlap with the current network of protected and other conserved areas, further reducing the search space for new critical mineral deposits. The vast majority of the remaining high prospectivity and unprotected cells correspond to ecoregions with less than half of the protected areas required to meet post-2020 Global Biodiversity Framework targets. Poorly protected ecoregions with one or more of the five ecosystem services are interpreted as hotspots with the highest potential for conflicting land-use priorities within the context of Canada’s battery minerals, including parts of southern Ontario and Québec, western Labrador, and northern Manitoba and Saskatchewan (Fig. 1). New development in these poorly protected ecoregions would need to be carefully managed, guided by Environmental, Social, Governance (ESG) best practises, and would necessarily include Indigenous people whose traditional lands are affected. In contrast, the statutory obligations and other conservation measures within the most protected ecoregions have the potential to lower the ecological and environmental risk of new critical mineral development. The results and the public data underlying these models can be used as input into land-use planning by Indigenous people and other impacted communities to assess economic opportunities, while examining the possibility of new or expanded conservation areas.

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PROPAGATING UNCERTAINTY THROUGH THE MINERALS PIPELINE: FROM REGIONAL PROSPECTIVITY TO THE (CONVEYOR) BELT

by

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Conceptual models of ore formation, or 'mineral systems' models, are the earliest manifestation of the metals liberated from the mining process. Mineral systems models are a holistic description of multi-scale aspects of ore formation that guide explorers in locating economic mineralisation. These models are holistic by recognising similarities between what may otherwise be distinct orebody genetic models. Trans-crustal shear and fault networks that transport hydrothermal fluids and magmas are conspicuous examples that have been used to explain the spatiotemporal position of various Au, Ni, Cu and other base metal camps. Likewise, mafic and ultramafic rocks have been labelled as source rocks for the commodities listed above but as important host rocks at smaller scales. Likewise, fault networks have been considered damage zones that potentially host mineralisation rather than serve as fluid pathways at smaller scales.

As the explorer descends in scale from regional exploration to a camp and prospect focus, the importance of datasets changes. Regional-scale geophysics is less useful due to data resolution, and geochemistry increases in importance as data are collected at resolutions appropriate to camp and prospect scales. The example of geophysics and geochemistry is instructive, as geophysics is very useful to image the Earth at depth, sometimes offering a 3D view if modelling and inversion are used. Still, petrophysics offers only a single property distribution to describe a rock (Fig. 1).

Geochemistry provides a more comprehensive view of Earth's properties through major and trace element analyses. While the formation depth can be loosely inferred using geochemistry, it is mostly used through classification diagrams to track the range of geological environments a rock has endured and represents near-surface rock distributions.

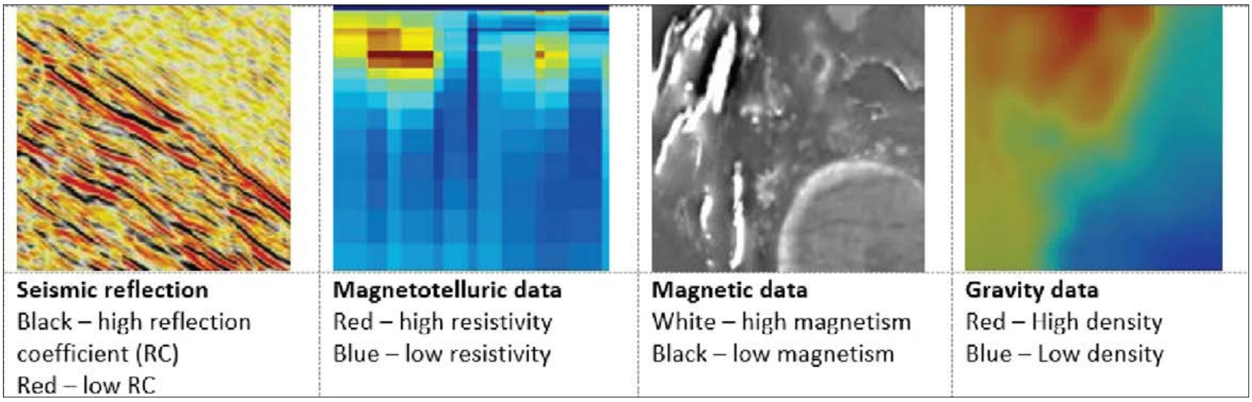

Fig. 1. Geophysical fields and their respective petrophysical properties (from Lindsay et al. 2020).

Any comprehensive study of the Earth to identify a mineral system requires the integration of multiple datasets that respond to different properties and scales. Individual geophysical datasets can be integrated through manual interpretation with petrophysics and geological information to produce a combined representation that acknowledges multiple physical fields. Still, these are convolved into a single knowledge-based representation where each dataset's contribution to the final result is usually unclear. Similarly, once geochemical classification labels have been assigned to various rocks in the study area, the source data are considered surplus to requirements and not retained.

Prospectivity methods provide a repeatable and systematic way to record various data processing and modelling steps taken during mineral systems analysis. They provoke discussion regarding where exploration should take place and provide a representation of our knowledge and data holdings in a spatially relevant and instructive form. If all goes well, the prospectivity analysis will support exploration activity to identify regions worth exploring while simultaneously exposing which datasets provide utility for the geological context. Smaller-scale targeting will take place, with drilling becoming the primary data acquisition method at smaller scales. Still, higher sampling rate datasets (ground magnetics, induced polarisation or surface geochemistry) take precedence to define an orebody before mining takes place.

A significant transition occurs when exploration changes to mining. Domains transition from science to engineering, and different uncertainties take hold. Datasets are acquired relevant to engineering concerns and conform to the strict requirements of the JORC code. Thus, data collection is performed to answer different questions from people with different backgrounds. The natural tendency of humans to optimise their activities according to their domain means that some datasets are ignored, as they are considered irrelevant, too uncertain, or inapplicable.

The risk is that useful insight from datasets collected earlier in the minerals value chain is not used when it could be to inform decisions. This scenario also plays in reverse when sampling campaigns conducted during exploration could collect data that informs decisions relevant to activities later in the minerals value chain. An obvious opportunity exists to take advantage of datasets typically used for prospective analyses in various minerals value chain activities.

Less obvious, but potentially more impactful, is to leverage insights for mining from our conceptual mineral system models. Conceptual models give a geometrical expectation. For example, Cu can be formed via various geological processes, from magmatic porphyry to sedimentary- and vein-hosted styles. The expected spatial and statistical distributions are quite different (Fig. 2). Fe is formed through supergene processes affecting banded iron formations or sedimentary processes in channel Fe deposits. Cu and Fe also form accessory commodities in other mineral systems models (e.g., Ni–Cu–PGE, Fe–oxide–Cu–Au deposits), which display their own particular spatial and statistical distributions.

Each of the example models has their own proponents, and conjecture exists over which processes and sequences lead to deposit formation. Uncertainty thus ensues. Epistemic uncertainty that is related to knowledge 'gaps', typically confronts us first. Still, aleatory uncertainty, related to measurement error, also impacts modelling once we start attributing datasets to the various components of a mineral system. Uncertainty analyses are now a welcome addition to prospectivity modelling, and useful gains have been made. Similar to how potentially useful datasets used in regional scale modelling can be used in mining activities, uncertainty can also be propagated through the minerals value chain to better inform decision makers.

A legitimate question is once a deposit has been defined and mining operations initiated, surely uncertainty related to its location is reduced to zero? At least in the context and spatial resolution of MPM studies, a cautious 'yes' may be the answer. But this is a multiscale issue, and uncertainty does not disappear, but merely changes according to the activity. Resource models are subject to uncertainties around the spatial and statistical distribution of high-grade and gangue material. Perhaps the uncertainty around distributions is lower, but the consequence, and hence risk, is higher. This is not just economic risk, but social (worker safety) and environmental (acid leakage into groundwater resources).

This presentation explores how the MPM community can increase the relevance of regional-scale predictions and uncertainty quantification to activities in the minerals value chain. Opportunities also exist to provide an 'early warning' to mine planners concerning how their mine may operate if the appropriate data are collected during the exploration phase. We can start to produce additional metrics from predictions, in addition to the mineral 'potential' or 'prospectivity', for a more comprehensive assessment of the ground for sustainable metal liberation.

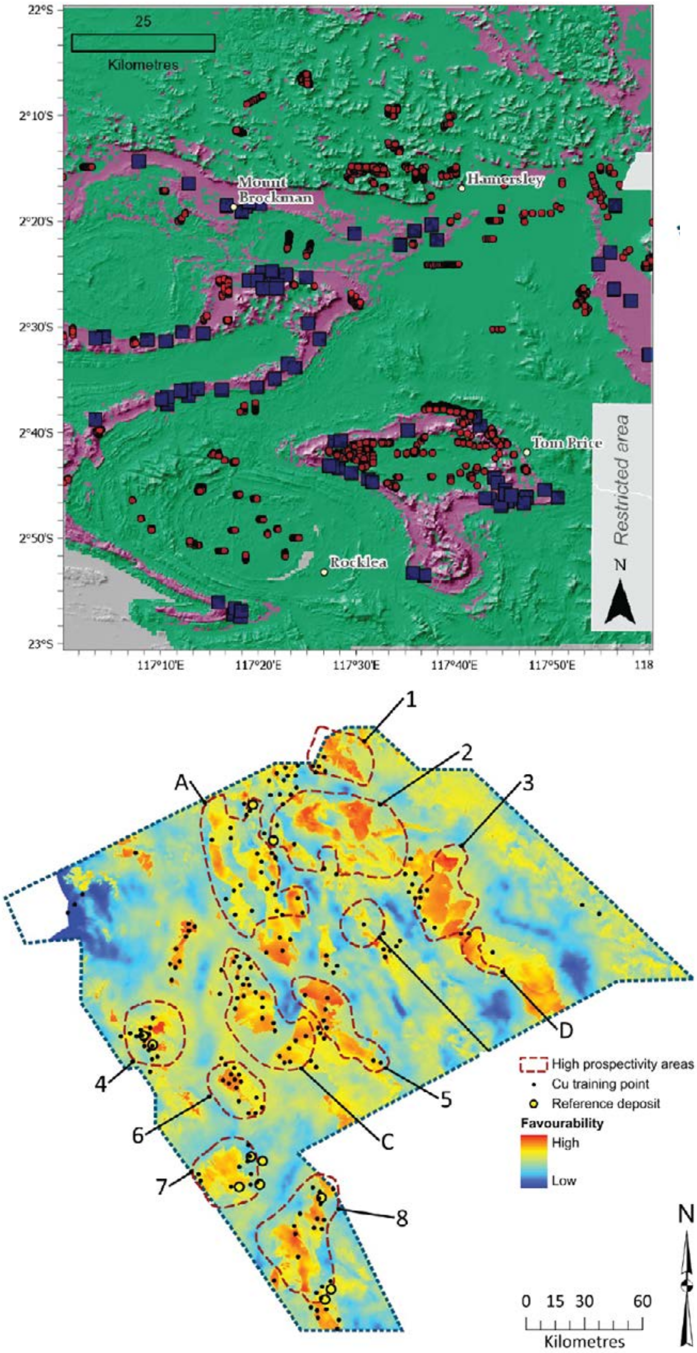

Fig. 2. Examples of spatial representations of mineral systems: on the left, a banded iron formation Fe model (adapted from Lindsay et al. 2022), and on the right, a porphyry Cu model (from Lindsay et al. 2014).

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THE HEAVY MINERAL MAP OF AUSTRALIA PROJECT: VISION, PILOT AND FIRST DATA RELEASE

by

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We describe a vision for a national-scale heavy mineral (HM) map generated through automated mineralogical identification and quantification of the HMs contained in archived floodplain sediments from large catchments covering most of Australia. The composition of the sediments reflects the dominant rock types in each catchment, with the generally resistant HMs largely preserving the mineralogical fingerprint of their host protoliths through the weathering–transport–deposition cycle. Heavy mineral presence/absence, absolute and relative abundance, and co-occurrence are metrics potentially useful to map, discover and interpret catchment lithotype(s), the geodynamic setting, magmatism, metamorphic grade, weathering, alteration and/or mineralization. Underpinning this vision was a pilot project, based on 10 samples from the national sediment sample archive, which demonstrated the feasibility of the larger, national-scale project. A first tranche of the national HM dataset, focusing on a nearly one million km^2 region centred on Broken Hill in southeastern Australia, was released in 2022. In that phase of the project, over 29 million mineral grains were analysed in 223 samples, identifying over 140 HM species. We also preview a bespoke, cloud-based mineral network analysis (MNA) tool to visualize, explore and discover relationships between HMs as well as between them and geological settings or mineral deposits. We envisage that the Heavy Mineral Map of Australia and MNA tool will contribute significantly to mineral prospectivity analysis and modelling, particularly for technology critical elements and their host minerals, which are central to the global economy transitioning to a more sustainable, lower carbon energy model.

INTRODUCTION

Heavy minerals (HMs) are those with a specific gravity greater than 2.9 g/cm^3 (e.g., anatase, zircon). They have been used successfully in mineral exploration programmes outside Australia for decades (de Caritat et al. 2022). Individual HMs and combinations, or co-occurrence, of HMs can be characteristic of lithology, the degree of metamorphism, alteration, weathering or even mineralisation. These are termed indicator minerals, and have been used in exploration for gold, diamonds, mineral sands, nickel–copper, platinum group elements, volcanogenic massive sulphides, non-sulphide zinc, porphyry copper–molybdenum, uranium, tin-tungsten, and rare earth elements mineralization. Although there are proprietary HM sample assets held by industry in Australia, no extensive public-domain dataset of the natural distribution of HMs across the continent currently exists.

DATA

In this project, we used floodplain sediment samples collected during the National Geochemical Survey of Australia (NGSA; www.ga.gov.au/ngsa; de Caritat 2022) from large catchments covering most of Australia and archived in Geoscience Australia's rock store.

VISION

We describe a vision for a national-scale Heavy Mineral Map of Australia (HMMA) generated through automated mineralogical identification and quantification of HMs contained in floodplain sediments (de Caritat et al. 2022). The composition of the sediments can be assumed to reflect the dominant rock and soil types within each catchment (and potentially those upstream), with the generally resistant HMs largely preserving the mineralogical fingerprint of their host protoliths through the weathering–transport–deposition cycle.

METHOD

The sediment samples were taken from both the surface (0 to 10 cm depth) and at depth (on average from 60 to 80 cm) in floodplain landforms, dried and sieved to a 75–430 µm grain-size fraction. The contained HMs were separated by dense fluids and mounted on cylindrical epoxy mounts. After polishing and carbon coating, the mounts were subjected to automated, quantitative mineralogical analysis on a TESCAN® Integrated Mineral Analyzer (TIMA) at the John de Laeter Centre, Curtin University. Using scanning electron microscopy and backscatter electron imaging integrated with energy dispersive X-ray analysis, the TIMA identifies minerals by comparing energy dispersive spectra with a customized library. Output data include the mineral identified, number of observations, weight and volume percent abundance, and median grain size.

PILOT PROJECT

Underpinning this vision is a pilot project, focusing on a subset of NGSA to demonstrate the feasibility of the larger, national-scale project (de Caritat et al. 2022). Ten NGSA sediment samples were selected and both their bulk and HM fractions were analysed (Fig. 1). The pilot project demonstrated that (1) the NGSA samples contained HMs, (2) the method developed yields quantitative HMs data and (3) the HM makeup of the NGSA sediments varies across the continent. The pilot project affirmed our expectations that a rich and diverse mineralogical ecosystem will be revealed by expanding HM mapping to the continental scale.

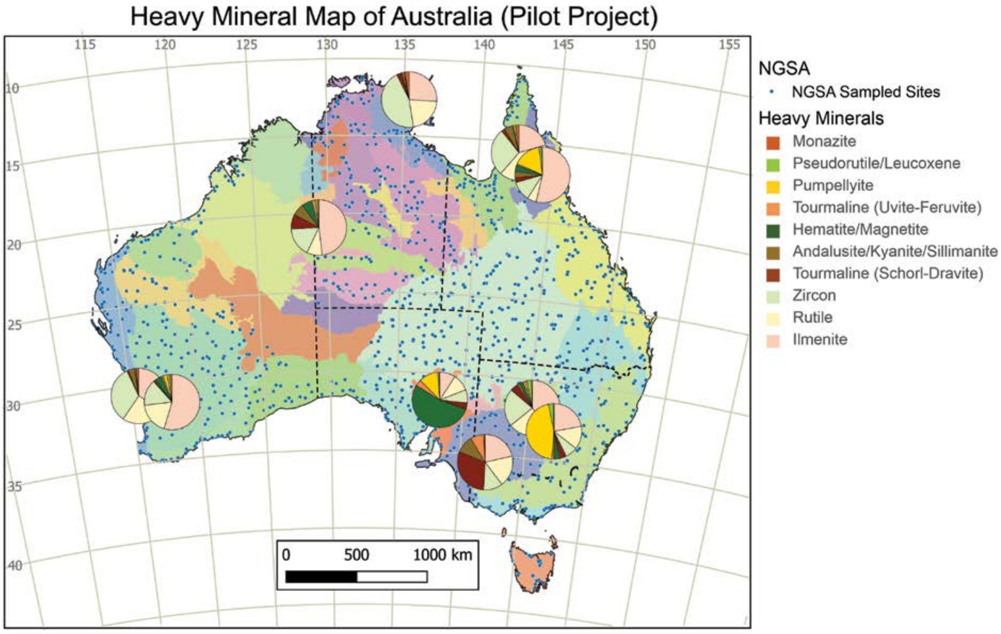

Fig. 1. Distribution map of 10 selected heavy minerals in the heavy mineral fractions of the 10 NGSA pilot samples (pie charts), overlain on Australia's geological regions (variable colours; Blake & Kilgour 1998). Map projection: Albers equal area.

FIRST DATA RELEASE

An initial partial data release in 2022 was the first milestone of the HMMA project. The selected area covers 965,000 km^2 centred on the Darling–Curnamona–Delamerian (DCD) region of south-eastern Australia, where the richly endowed Broken Hill mineral province lies. Here, we identified over 140 heavy minerals from 29 million individual mineral observations in 223 sediment samples.

MINERAL NETWORK ANALYSIS

Given the large and complex nature of the HM datasets generated in this project, we built a bespoke, cloud-based mineral network analysis (MNA) tool to visualise, explore and discover relationships between HMs, as well as between them and the geological setting or mineral deposits. Using the MNA tool on the DCD dataset, for instance, one can quickly identify interesting base metal mineral associations and their spatial distributions (Fig. 2).

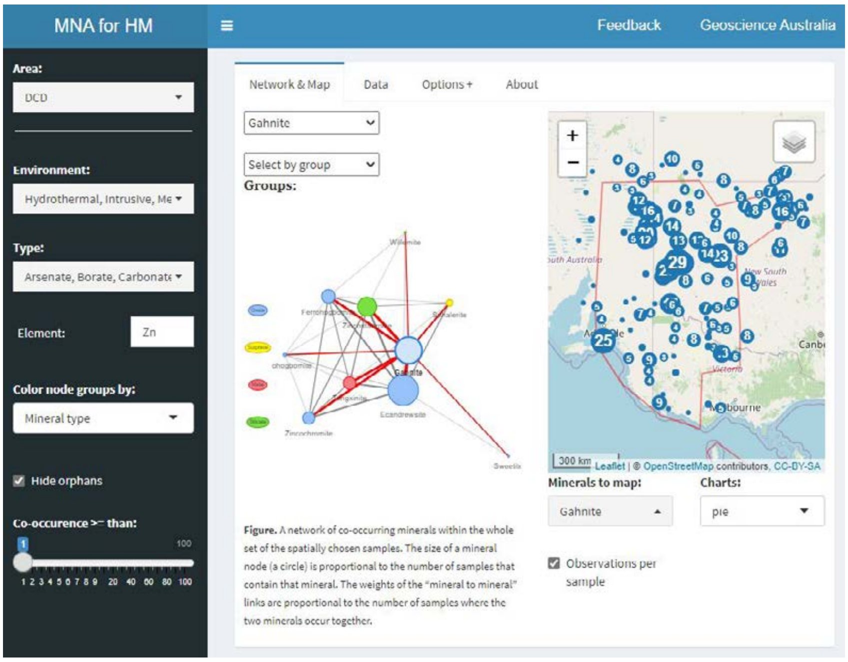

Fig. 2. Graphical user interface for Geoscience Australia's MNA cloud-based visualization tool for the DCD project (https://geoscienceaustralia.shinyapps.io/mna4hm/) showing the network for zinc minerals with the gahnite subnetwork highlighted in red (left) and the map of gahnite observations (right).

CONCLUSIONS

We envisage that the Heavy Mineral Map of Australia and the MNA tool will contribute significantly to mineral prospectivity analysis and modelling in Australia, particularly for technology critical elements and their host minerals, which are central to the global economy transitioning to a more sustainable, decarbonized paradigm.

ACKNOWLEDGMENTS

The NGSA and HMMA projects were funded by the Australian Government's 'Onshore Energy Security' and 'Exploring for the Future' programmes, respectively. The TIMA instrument was funded by a grant from the Australian Research Council (LE140100150). We acknowledge all stakeholders, including traditional owners, land holders and landowners for granting access to the NGSA sampling sites. PdC and EB publish with permission from the Chief Executive Officer, Geoscience Australia.

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PREDICTIVE MODELLING OF GEOCHEMICAL DATA AND GENERALIZED ANOMALY DETECTION

by

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Machine learning algorithms can be used to predict trace element concentrations from major and minor element concentration data. Since the models provide a way to reconstruct concentration data, they can be used to identify geochemical anomalies through reconstruction error. Here, we present the results from two studies, each demonstrating that the use of machine learning algorithms can be combined with domain-specific knowledge to facilitate the detection of mineral deposits.

INTRODUCTION

A wide range of geochemical elements have high-dimensional relationships that can be modelled using machine learning algorithms. In the variable domain, this can be used to predict the concentration of unknown samples. Using elemental relationship models, anomalous elemental concentrations can be detected through data reconstruction error. This can serve as a basis for unsupervised mineral prospectivity methods. The purpose of this presentation is to highlight two studies that effectively applied this concept. The first study used a secondary dataset with unknown data coherence (e.g., levelling) with a wide range of volcanic and plutonic rock samples from the Karoo large igneous province (Zhang et al. 2021). The second study used a high-quality regional sediment geochemical survey dataset from the Southeastern Churchill Province of Canada that was intended for mapping (Zhang et al. 2022).

DATA

Geochemical data from the Karoo large igneous province were compiled over many years from other primary publications and databases. The dataset is included in Zhang et al. (2021). The lake sediment geochemical dataset from the Southeastern Churchill Province of Canada can be found at the Geological Survey of Canada's Canadian Database for Geochemical Surveys (https://geochem.nrcan.gc.ca/).

RESULTS AND DISCUSSION

For the first study, trace elemental concentrations over various rock types were predicted using the major and minor elemental concentrations. Although the database is essentially in a state of quality that is the opposite of typical databases used for prospectivity mapping (e.g., primary and internally coherent), the performance of the models was excellent. A variety of elements (Hf, Tb, La, Y, Ce, Nd, Rb, Sm, Eu, Co, Sr, Lu, Pr, Ni, Cr and Zr) were predicted with a coefficient of determination (CoD) of more than 0.8 using multiple machine learning algorithms (Fig. 1a). Key findings in Zhang et al. (2021) include that the predictive models performed very well over many types of rocks (e.g., andesite, basalt and gabbro) and that raw and centred log-ratio-transformed data performed similarly for this task (Fig. 1b).

The second proof-of-concept study demonstrated that the main anticipated geochemical anomalies in the area in the form of rare earth element-bearing dispersal trains were easily detected and were the largest anomalies in the area in a multivariate sense (Fig. 1c). Two dispersal trains with non-identical elemental compositions emanate from two known locations. In the past, only the Strange Lake dispersal train (north in Fig. 1c) was documented. In comparison, the southern dispersal train originating from the Mistastin Batholith was a new, entirely data-driven and unsupervised learning-based discovery. As a result, Zhang et al. (2022) demonstrated that the anomaly detection method essentially automates the process discovery and data processing that was previously carried out through a geographical information system and principal component analysis-based approach (e.g., Grunsky & de Caritat 2019). Additional findings of Zhang et al. (2022) were that raw data generally had a comparable or higher performance than log-ratio-transformed data for this task, and a variety of algorithms, ranging from the highly explainable to the highly complex, were suitable for this task with small performance differences.

As a result of applying domain-specific knowledge (e.g., the role of major/minor and trace elements and the nature of desirable geochemical anomalies) and a machine learning framework (data processing and predictive modelling workflows), clear benefits were realized in both studies. These benefits include: simplified data processing that no longer requires considerations of data closure properties (where selected algorithms are not spatially aware in the feature space), and, as a result, no need for data imputation; automated process discovery that is guided by knowledge (of the geological relationships between features and targets); expanded applicability (no assumptions on sample type or mineral-based stoichiometry); and preserved integration in down-stream applications (e.g., as evidence layers for perspectivity maps or as guides to further manual exploration). This method may serve as a simple and practical first-order method for detecting geochemical anomalies in bulk geochemical data and facilitating the timely detection of mineral deposits.

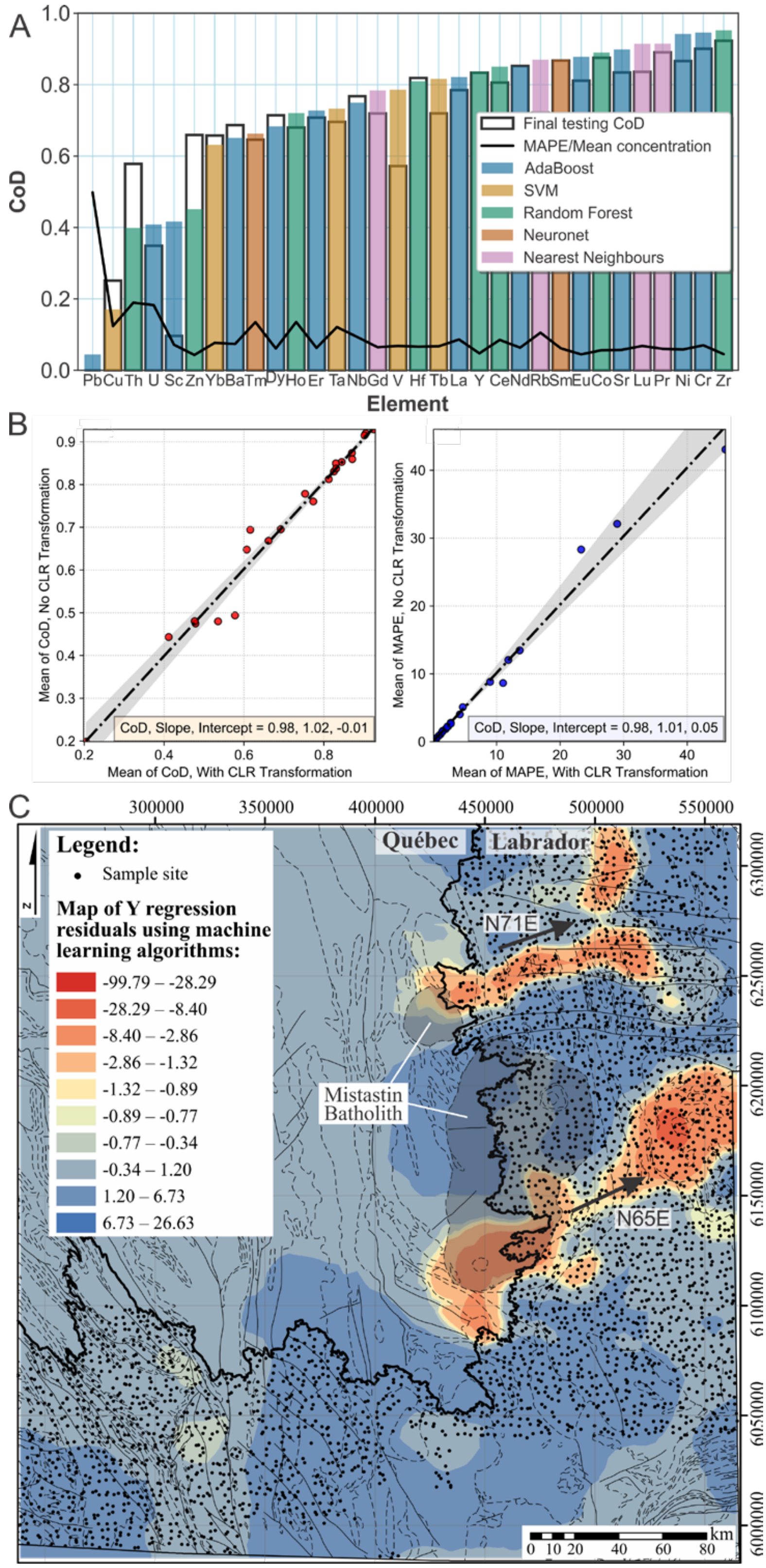

Fig. 1. Predictive modelling of geochemical anomalies. a) Algorithm selection and performance assessment, as measured using the coefficient of determination (CoD) of all trace elements with the median absolute prediction error (MAPE) divided by mean concentrations also shown. The best machine learning algorithms are shown for each element. b) Mean of the CoD (left) and MAPE (right) compared between training data that employed the CLR transformation and without CLR transformation. c) Regional anomaly map of Y using the machine learning-based geochemical anomaly method. Two valid ENE-trending glacial dispersal trains emanating from the southern and northern portion of the batholith are visible.

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EXPLORATION INFORMATION SYSTEM: COMBINING MINERAL SYSTEMS MODELLING WITH MINERAL PROSPECTIVITY MODELLING

by

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The project "Exploration Information System" (EIS) is a European Union (EU)-funded research and innovation initiative aiming to combine mineral systems modelling with mineral prospectivity analysis methods aimed at finding new sources for critical domestic primary raw materials within the EU. With the emerging exploration data, the need for efficient data analysis has become essential. The data are expensive and there is a need to get the most out of them. Recent advances in the use of artificial intelligence, including various machine learning algorithms within GIS platforms, have made it possible to combine geological knowledge and exploration data in complex mathematical models that can be used to make predictions about the existence of new mineral occurrences.

INTRODUCTION

The European project "Exploration Information System" (EIS) is operated by a consortium consisting of 17 partners from leading research institutes (4), academia (5), service providers (4) and the mining industry (4). The consortium member organizations come from six European Union (EU) member states (Finland, France, Germany, Spain, the Czech Republic and Sweden) and South Africa. One associate member of the consortium comes from Brazil. The project has received funding from the Horizon Europe research and innovation funding programme of the EU under Grant Agreement no. 101057357. The main objective of the EIS project is to develop innovative exploration concepts and data analysis tools to enhance the probability of finding new sources of critical raw materials for the EU's economy.

The rapid deployment of clean energy technologies as part of the energy transition implies a significant increase in demand for minerals. Global demand by the automotive industry for raw materials is likely to continue and is predicted to grow 5 to 10 times the current demand, due to increasing request from the EV sector (IEA 2021). This is a great motivation for developing new methods to find new sources of critical domestic primary raw materials within the EU.

TARGET AREAS

This consortium represents the main metal producing regions of Europe, including the Fennoscandian Shield and the Iberian and Central European Belts (Fig. 1).

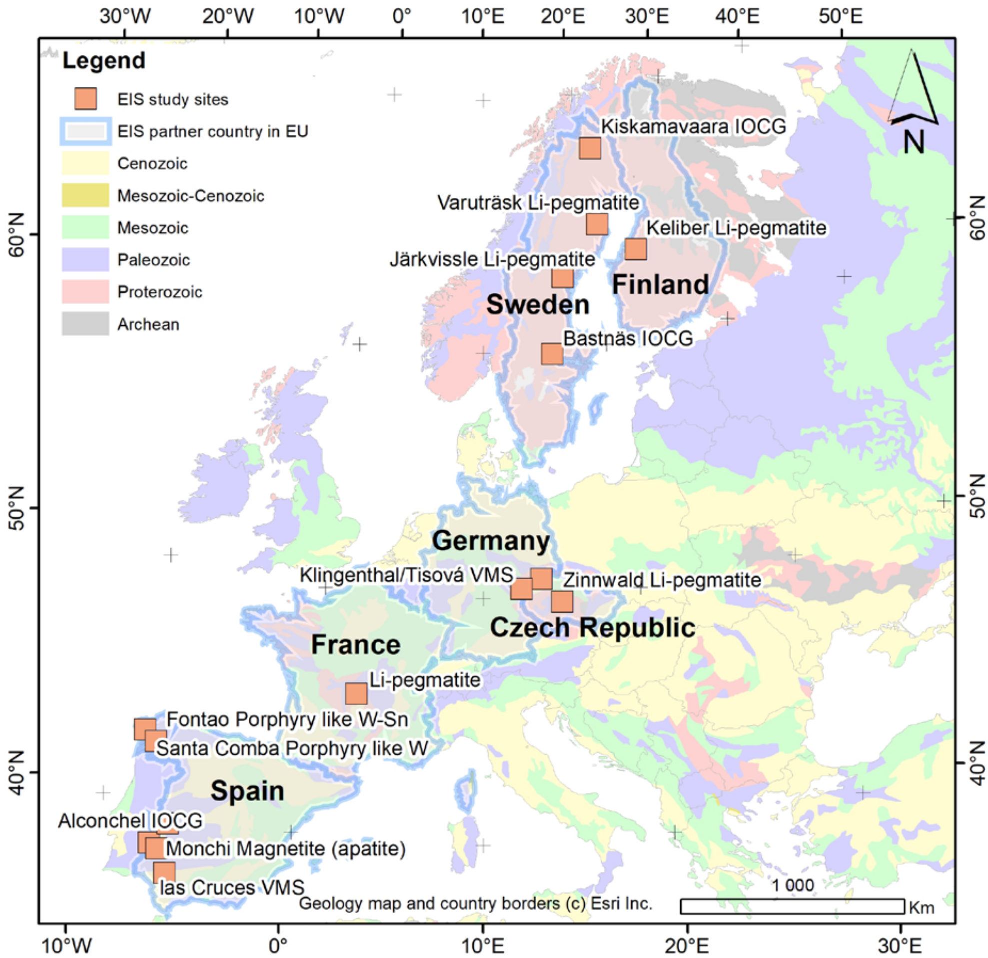

Fig. 1. EIS project study sites. Project partner countries within the EU are Finland, Sweden, Germany, the Czech Republic, France and Spain. Outside the EU, the project has two partner countries, South Africa and Brazil (associate partner).

The economically most important metallogenic belts of the EU show diverse geological contexts with evident potential for various mineral resources. The mineral deposits in the belts are the most feasible sources of critical, high-tech, and other economically important metals in the EU. In the EIS project, we are promoting the utilization of a hybrid approach using mineral systems modelling as a basis for mineral prospectivity modelling (Fig. 2).

MINERAL SYSTEMS

A critical part of EIS is a library of geological fingerprints of diverse types of mineral systems. These fingerprints are used for choosing the most relevant mappable geoscientific features which are essential for successful prospectivity analysis. In this project, we are using selected mineral deposits as study sites or test sites, and we have three different mineral systems as a case study in the project:

1. Cobalt minerals in VMS systems.
2. Lithium–tin–tantalum–tungsten minerals in granite/pegmatite-related systems.
3. Rare earths–cobalt minerals in IOCG systems.

The study and test sites are situated within the partner countries shown in Figure 1. Furthermore, the project has reference sites in South Africa and Brazil. These reference sites are Li-bearing pegmatites situated in the 450-km-long Orange River Pegmatite Belt in South Africa and the world class Carajás IOCG province in Brazil.

This project will increase access to critical raw materials in Europe by providing new information on critical mineral systems and new efficient data-analyst tools leading to an extension of the knowledge of existing deposits in Europe. The development of the new digital exploration tools will lead to faster new discoveries of mineral deposits (Li, W, Ta, Co and REE) within the EU.

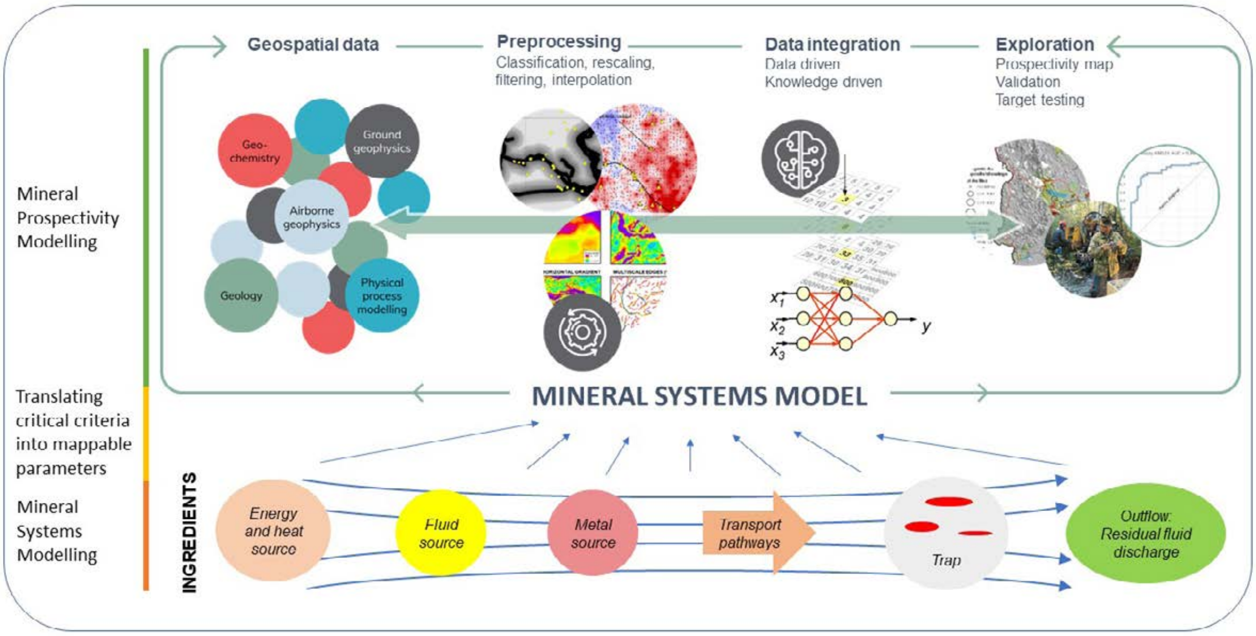

Fig. 2. Exploration Information System (EIS) combines mineral systems models (Knox-Robinson & Wyborn 1997) and mineral prospectivity modelling (Bonham-Carter 1994).

EIS METHODOLOGY

The ideal exploration information system consists of components for different steps of prospectivity analysis (Fig. 2). In the data pre-processing step, data are transformed to represent proxies for critical parameters of the mineral systems. Pre-processed data are then used as input to predictive modelling or other data analysis methods. In the final step of prospectivity analysis, model validation is performed to test how well the modelling and prospectivity mapping have performed. The EIS project will develop new data analysis methods by applying artificial intelligence, machine learning and deep learning in mineral prospectivity mapping together with new geo-models and mineral systems modelling (Yousefi et al. 2019, 2021). The methods developed will reduce the current high exploration costs and improve the accuracy of targeting in early phase exploration. This will make mineral exploration responsible in terms of energy efficiency and minimizing the footprint of mineral exploration in nature, as the aim is to make the most of the already existing exploration data. The project will apply UNFC code to harmonize the diverse population of mineral deposits and occurrences that will be used as training sites and validation data sets in prospectivity mapping for critical raw materials within the EU. In addition, tools will be tested for critical secondary raw materials prospectivity. The project will also raise the awareness of the general public about the importance of critical raw materials to the EU's economy and welfare.

After the completion of this project, the EIS will be a collection of software tools for semi-automated exploration targeting. Building all these components as modules in an open-source community-based platform will allow for contributions from numerous developers globally, outside the project consortium, boosting the development and maintenance of the product.

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UNCERTAINTIES IN MINERAL PROSPECTIVITY MODELS: A REVIEW OF SOURCES, QUANTIFICATION SCHEMES AND APPLICATIONS

by

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Mineral prospectivity mapping (MPM) is a multi-staged process developed to reduce the search space for the mineral exploration industry. The four main components of MPM include: (1) a rigorous conceptual understanding of the geological processes leading to the formation of mineral deposits; (2) geoscientific databases; (3) the applicability of these geoscientific datasets as mappable proxies for the ore-forming processes of interest; and (4) computer-based algorithms for processing and combining geoscientific datasets to estimate the mineral potential. Each of these four components is associated with multiple sources of error and uncertainty that will ultimately propagate into the final predictive models, potentially undermining their reliability. Herein, we start by defining the concepts of uncertainty in MPM, delve into the main sources of uncertainty underpinning MPM, summarize the quantification of schemes of uncertainty in MPM, and present an uncertainty-aided approach to delineating low-risk exploration targets.

INTRODUCTION

The renewable energy technologies needed to meet carbon neutrality and sustainability goals tend to be more material intensive, stressing the importance of exploration and discovery of new critical mineral deposits. However, the ever-rising cost of exploration surveys and the dwindling number of new mineral deposit discoveries may delay or increase the cost of the renewable energy transition. It is, therefore, of utmost importance to account for risk and uncertainty in various steps of the mineral exploration process to improve discovery rates. In national- and regional-scale exploration programmes, target generation is typically one of the initial steps of mineral exploration. Predictive modelling for mineral potential assessment, also known as mineral prospectivity modelling (MPM), is a multi-staged process to focus exploration efforts on the most prospective targets. MPM starts by distilling geoscientific datasets into a suite of vectors (evidence layers) that directly or indirectly describe ore-forming processes, as guided by experts and fundamental knowledge of the geological processes that transport and concentrate critical minerals from a source to a depositional trap (Fig. 1). These vectors are then exploited in computer-based frameworks for estimating the probability of discovering the spatial convergence of one or more ore-forming processes that are needed to form a mineral deposit. The above description highlights the four required steps to MPM, including: (1) conceptual models and geological frameworks that describe how critical mineral deposits form; (2) geoscientific databases; (3) the interpretation of geoscientific data for mapping ore-forming processes; and (4) computer-based algorithms for combining geoscientific data to estimate the mineral potential. Each component is associated with its own sources of error and uncertainty, which eventually propagate into the final predictive model, undermining its predictive ability (Fig. 1). Herein, we summarize the sources of uncertainty in MPM and review the quantification schemes available in the literature.

SOURCES OF UNCERTAINTY IN MPM

According to Brady (2014), uncertainty is "The lack of certainty, a state of limited knowledge where it is impossible to exactly describe the existing state, a future outcome, or more than one possible outcome." According to the above definition, mineral prospectivity mapping (MPM) is subject to uncertainty, as multiple outcomes (predictions) are possible for a given unit cell, potentially undermining the reliability of predictive models. Data- and model-related uncertainty are the two primary sources of uncertainty in the context of MPM (Zuo et al. 2021). The former, referred to as aleatoric or stochastic uncertainty, is linked to the acquisition and processing of data that are ultimately used as the input evidence layers in MPM. However, model-related uncertainty, also called epistemic or systemic uncertainty, chiefly arises from the choice of labelled samples and other training methods in machine-learning-based MPM (Fig. 2), the algorithms employed and parameter tuning. Knowledge-driven methods do not require labelled samples for model training but are still associated with subjectivity during data fusion and other forms of systemic uncertainty (Fig. 2). The outputs of MPM are prospectivity scores that can be used to rank exploration targets according to their mineral potential. Each prospectivity score (P) is a function of evidence layers (E_i), known mineralized zones (D), and non-mineralized zones (N) used for generating the predictive model, or $P_j = f\,(E_1^j, E_2^j, \ldots, E_n^j, D, N)$, where P_j is the prospectivity score of the j^{th} model cell and E_i^j is the value of the i^{th} evidence layer in the j^{th} model cell. Given the above definition, any imperfection in E_1^j, D, or N eventually affects P_j. These are, therefore, the main sources of uncertainty in MPM discussed below.

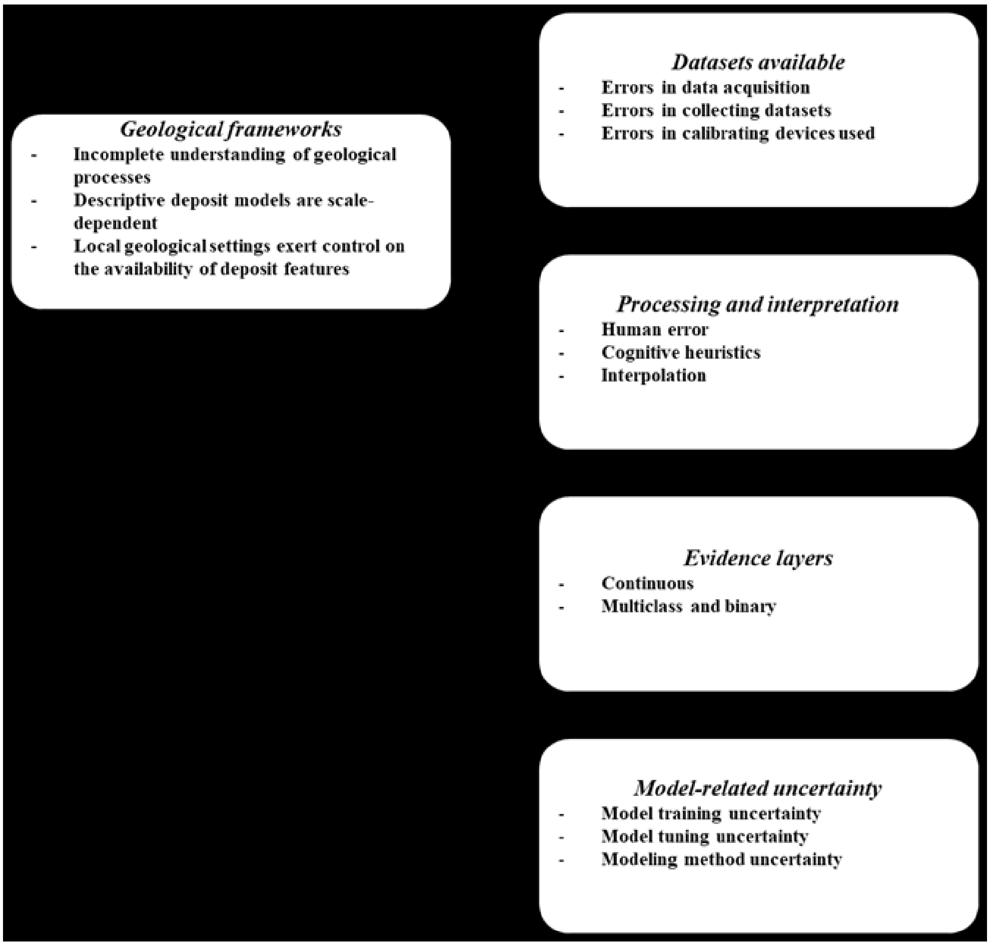

Fig.1. Multiple sources of uncertainty affecting evidence layers in MPM.

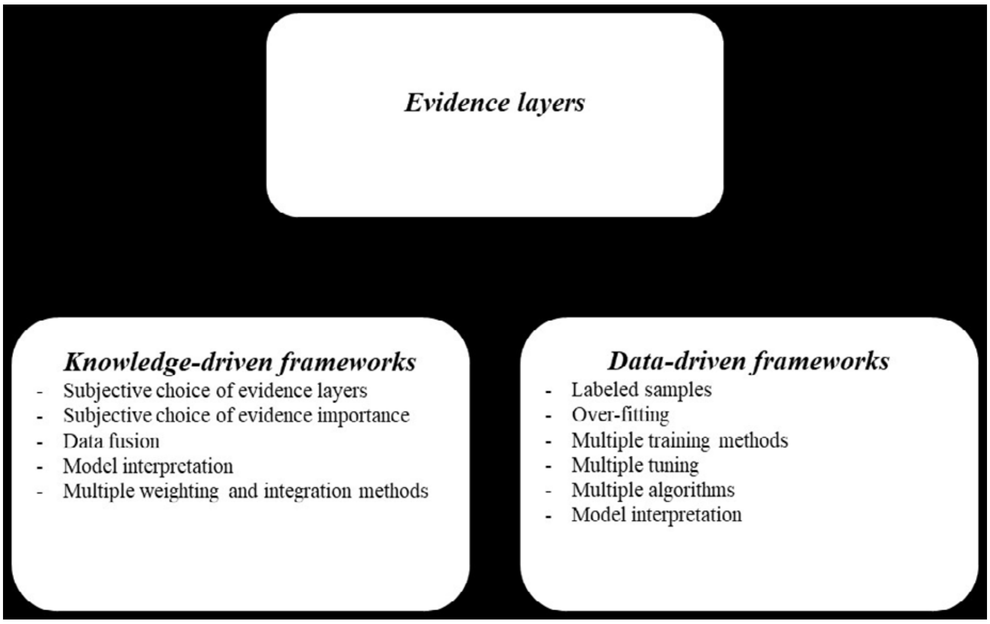

Fig. 2. Sources of uncertainty affecting the two main mathematical frameworks in MPM.

QUANTIFICATION OF UNCERTAINTY IN MPM

Uncertainty in MPM could be further defined by the status where the generation of multiple predictive outcomes, P_i^j, is possible for a given unit cell, j, or $P_i^j = (P_1^j, P_2^j, \ldots, P_n^j)$. Obviously, the predictive outcomes vary in a range R = [Min P_i^j, Max P_i^j]. A large R pertains to unreliable prediction and high uncertainty in this scenario. In contrast, a small R indicates that predictive outcomes are relatively uniform and that the predictions are more reliable and less uncertain. Therefore, the standard deviation of prospectivity scores can be used to quantify the uncertainty of model predictions (Jurado et al. 2015), or $U_i = \mathrm{SD}_{i=1}^{i=n}(P_i^j)$. In addition, the mean value of P_i^j has usually been considered a modulated predictive value, MP_j, for the j^{th} cell. The modulated predictive value can further be divided by the standard deviation to estimate the confidence of each model as an exploration target (i.e., confidence = U_j/MP_j). Generating multiple predictive outcomes is a prerequisite to using the above formulas. Different methods have been used for developing various models in MPM and geochemical anomaly mapping, ranging from Monte Carlo simulation to bootstrapping.

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EVALUATING PROSPECTIVITY MAPPING METHODS

by

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We discuss the evaluation of machine learning algorithms using both prospectivity and computer vision data sets. Computer vision data sets offer distinct advantages for benchmarking, but care must be taken when adapting them to the conditions encountered in prospectivity mapping.

INTRODUCTION AND SETUP

With the development and success of artificial intelligence (AI) and machine learning techniques in solving complex problems, particularly in computer vision, there has been a recent push to adopt such techniques for prospectivity mapping. Prospectivity mapping is a challenging problem in mineral exploration. It aims to identify prospective areas, typically for a particular mineral such as copper or lithium, given a range of geo-spatial data that may include geophysical data layers, geological maps, remote-sensing data and more.

The hope is that by fusing the data, hidden connections can be discovered and new prospective areas identified. Machine learning is a field that allows a computer algorithm to learn a relationship between some sets of input and output data without understanding the underlying causal mechanism that links them. As such, given known prospective areas and known geo-spatial data, such techniques can, at least in principle, be used to learn the connection between geo-spatial data and prospectivity, thus predicting new prospective regions where minerals can be discovered.

Machine learning methods such as support vector machines (SVM), random forests and deep neural networks have been widely applied in the field of computer vision. Excellent software libraries implementing such techniques are widely available, and geoscientists may try them out with minimal effort. It is thus tempting to use such codes on geo-spatial input data and to naively predict prospective areas. As we show in this work, such simplistic approaches tend to fail or mislead the user and can actually lead to the wrong conclusions. There are a few reasons why such failures occur. First, there is a fundamental difference between problems in computer vision and in prospectivity mapping. While most problems in vision admit an obvious solution, this is not the case with prospectivity mapping. A person does not need to be a domain expert to identify a cat in a photograph. However, many expert geoscientists disagree on the most prospective area given a set of geo-spatial data. In fact, in many cases, it is not obvious that there is a learnable relationship between data and prospectivity. To this end, the goals in this work are first to suggest simple testing for machine learning methods that one may want use for prospectivity mapping. This involves testing algorithms on simple to understand yet difficult to solve problems from computer vision that can serve as indicators of the possible success of the AI algorithm when applied to geo-spatial data. Secondly, we show how a novel method we have developed that combines convolutional neural networks with semi-supervised clustering using the graph Laplacian operator can be used to improve prospectivity mapping results.

TESTING ALGORITHMS

Although a number of publicly available geo-spatial data sets contain mineral content in some discrete places, it is difficult to use such data sets to assess different machine learning algorithms. There are two main issues. First, while many geo-spatial data types may have coverage almost everywhere in a region of interest, there are typically very few locations where mineral deposits are found (and thus prospective areas). At most locations, we do not know whether there is no mineralization or whether mineralization exists but has simply never been found. Furthermore, interpreting the results is difficult and there are no widely agreed upon evaluation metrics.

To this end, we suggest a simple benchmark that is significantly simpler than prospectivity mapping,yet appears to be challenging for most algorithms we have experimented with.

We consider the problem of image segmentation in the CamVid data set. This is a widely used computer vision benchmark data set that consists of 701 fully segmented images taken from dash-cam footage in Cambridge, UK. Each pixel in each of the images has been assigned a class, e.g., vehicle, road, signpost. In our experiments, we have attempted to identify vehicles from single CamVid images. The main difference between classical segmentation and our case is that we assume only a small number of points in each image that are labelled. For example, assuming our goal is to segment cars, we assume that we are given at most 100 pixels each from the vehicles and the background in each image. This is similar to prospectivity mapping in that only a small number of locations are labelled. A key difference is that we know the answer to this problem and can thus test the performance of each algorithm. When picking the sample points, we differentiate between two types of targets. The first are targets that are sampled and the second are targets that have no sampling points in them. This is demonstrated in Figure 1, which presents a sample CamVid image along with segmentation results from our novel method and two traditional machine learning algorithms, XGBoost and support vector machines with a radial basis function kernel. The perfect algorithm should be able to determine the boundaries of the sampled targets and find targets that have no samples. We see that our novel method achieves both of these goals, while the traditional methods do not. Both the XGBoost and SVM models give many false positive predictions and fail to accurately identify the unlabelled car.

We have also applied our novel method to publicly available data in Queensland, Australia. We used gravity, magnetics, topography, radiometrics and ASTER remote sensing data as input and assayed Cu values from publicly available RC drilling data as labels. We spatially smoothed the labels before running our algorithm, as we did not expect to be able to predict at the spatial resolution provided by the drillhole data. The results are presented in Figure 2. Our results fit the labelled data and suggest some other areas of elevated prospectivity. Evaluation of our method is ongoing, but our initial tests on the CamVid data set provide confidence in the ability of our method to work well given very limited training data. We hope that such evaluations may be performed as a matter of course when considering applying novel machine learning methods to prospectivity mapping.

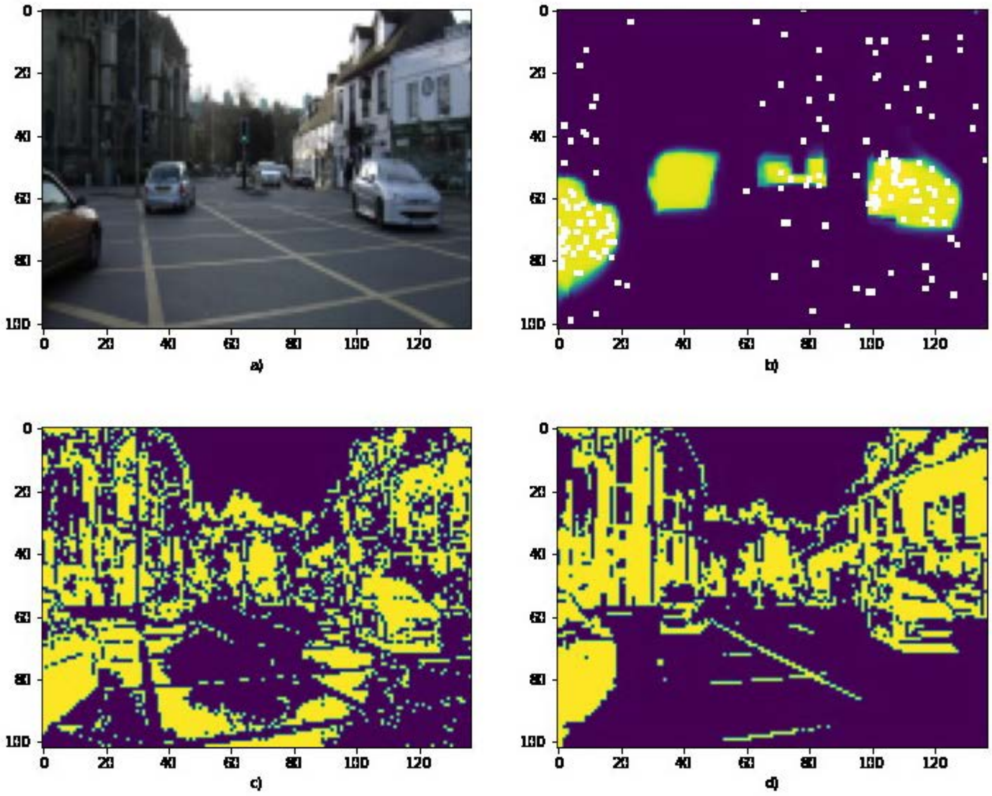

Fig. 1. a) Input image. b) Novel graph Laplacian-based segmentation result. White dots indicate labelled pixels. c) XGBoost segmentation result. d) Support vector machine classifier segmentation result.

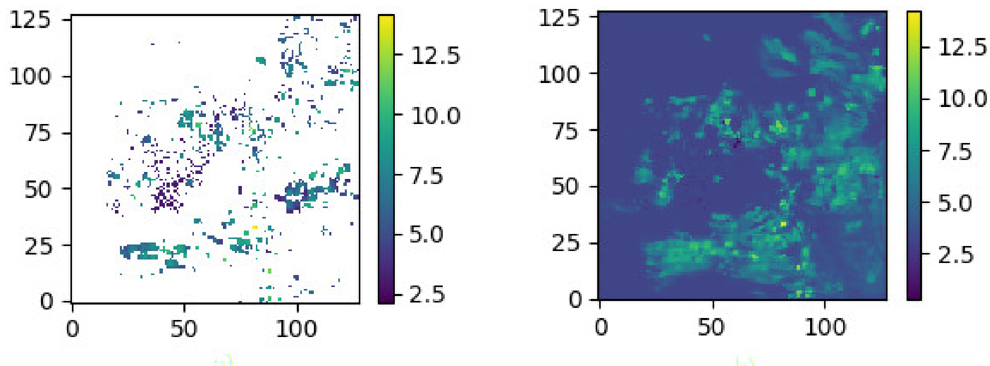

Fig. 2. Results of our novel algorithm applied to public geoscience data in Queensland, Australia. a) Labels. We use assayed Cu values from publicly available historical drilling data as labels. Units are log(ppm). b) Predicted Cu values in log(ppm).

CHALLENGES IN EXPLORATION TARGETING OF BLIND MINERAL DEPOSITS

by

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Blind mineral deposits occur at greater depths and generally display fewer and poorer signals in the earth's surface. For these reasons, finding their depositional sites is a challenging undertaking. The needs of industries will steer future exploration strategies and developments towards mineral exploration at depth.

INTRODUCTION

Given that the search space for finding mineralization is moving from near-surface environments to greater depths, exploration geologists are attempting to develop methods for improving the performance of mineral exploration targeting (MET) approaches (Yousefi et al. 2019, 2021). Consequently, the search for deeper deposits is a progressing field. According to the available literature, it appears that after rapid progress, we are in a short period of stability in MET performance without much improvement in terms of finding blind mineral deposits. This is probably the reason why researchers have pointed out that there has been a decline in mineral exploration success (Davies et al. 2021).

PROBLEMS AND CHALLENGES

Mineral deposits at greater depths may be different from well-known types (Wood 2018) and might also be undefined types (Davies et al. 2021). In my opinion, the poorer performance of MET approaches in terms of recognizing bind deposits principally results from the extra attention to and specific focus on known deposit locations, mostly easily discovered in near-surface environments. However, the purpose of MET is not to find known deposit sites, but to recognize new exploration targets leading to new discoveries. Data-driven and supervised MET approaches focus on finding the best fit between the exploration data and known deposit locations. In knowledge-driven and unsupervised approaches, a model's effectiveness is usually evaluated using known deposit locations. Furthermore, well-known mineralization features, which are elicited from known deposit models, are used to select exploration criteria in the MET procedure. It appears that to explore bind mineral deposits in deeper areas, we should focus on new search spaces that may be distant from the known deposit locations. MET in new search spaces involves greater uncertainty, and in contrast, has a greater possibility of finding new mineralization (Davies et al. 2021). Searching for mineral deposits in new spaces faces the challenges and problems of less or a lack of exploration data, unknown or incompletely known complex ore forming processes, and a lack of visible features. Consequently, imagination and its ensuing innovative ideas are needed to mitigate the problems.

FUTURE RESEACRH DIRECTIONS

To explore blind mineralization and to jump to a higher level of exploration success, we need to bring geology and better understanding of ore-forming processes into the MET procedure. Ideas for improving MET performance for these deeper deposit sites could be initiated by further focusing on understanding the components of ore-forming processes at depth and converting them into maps of features and proxies, i.e., mineral system-based approaches rather than analogue deposit models (McCuaig et al. 2010). There are mineralization subsystems that have not so far been translated into evidence maps. Two questions (as examples of many inquisitive and crucial matters dealing with ore formation) for possible solutions in future are 1) how can fluid mixture sites be modelled and converted into evidence maps? and 2) how can an evidence map representing multi-phase intrusions be modelled and used in the MET procedure?

Artificial intelligence (AI) techniques are highly likely to facilitate MET of deeper deposits, but with some changes to the viewpoint of explorers and through making improvements in the way they are going. To ensure the upmost performance of AI techniques and to increase their learning agility towards blind deposit sites, geology and knowledge of ore-forming processes should be incorporated into the selection of exploration criteria, weighting, and integration stages of MET much more than the existing practices of focusing on known deposit locations. Using known deposit locations as training sites may exacerbate the problem of searching for blind deposits in new search spaces. To mitigate the problem, AI, including deep and machine learning, could instead be applied to reveal patterns and understand the complex and non-linear ore-forming processes of deeper mineral deposits. In the future, non-traditional features and proxies may emerge to find signs of mineralization. The study of Levinson (1974) gave me the idea of preparing Figure 1 to illustrate what I have in my mind.

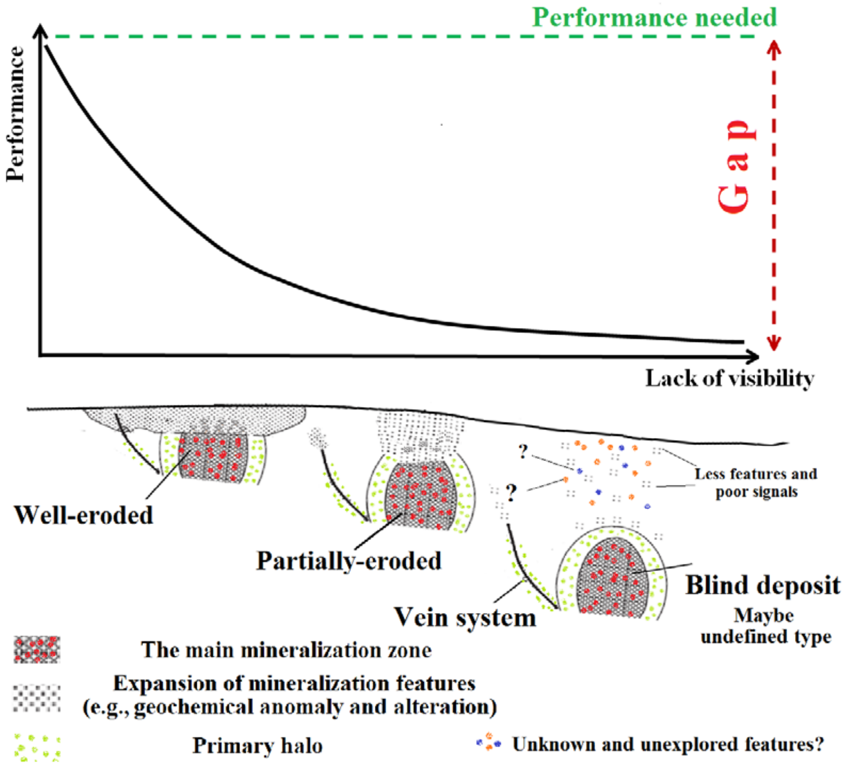

Fig. 1. Lack of visibility versus MET performance as search spaces move to greater depths.

CONCLUSION

Innovative ideas are needed to develop methods for exploring blind mineral deposits in the future.

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DISCRIMINATION OF GEOCHEMICAL ANOMALIES USING GEOLOGICAL CONSTRAINTS AND GEOCHEMICAL LANDSCAPE MODELLING

by

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A stream sediment survey is one of the most effective methods for mineral prospecting, reflecting the mineralization characteristics at regional scales. The complex geological environment and geochemical landscape bring difficulty to geochemical anomaly mapping. In this research, the geochemical landscape and geological constraints were considered using a Bayesian Maximum Entropy (BME) model to identify the Mo polymetallic mineralization in Jining, Inner Mongolia, China. The influences of the geological constraints and geochemical landscape factors were considered to make up the shortage of missing and incomplete observations in the regional geochemical dataset, and consequently the uncertainty of the defined geochemical anomaly definition was highly reduced.

INTRODUCTION

Geochemical anomaly mapping is a significant part of mineral exploration projects. With acknowledgement of the importance of geochemical maps, the challenge is how to generate a reliable geochemical map. The geochemical anomalies related to mineralization are the outcome of the interaction between various geological processes, such as structures, formations and rocks. While stream sediment is the best sampling medium, stream sediment samples are vulnerable to the geochemical landscape and various geological processes. Therefore, the geological environment is crucial for the formation and distribution of geochemical anomalies, and even play a critical role at the regional scale. Many researchers have proposed integrated frameworks for incorporating different types of geological information into the process of mineral prediction (Wang et al. 2022a, 2022b). However, few studies have been reported in which the integration of geological constraints acted as secondary data for acquiring enhanced geochemical anomaly maps.

DATA AND METHODS

In this research, approximately 1,630 geochemical samples at a 1:200,000 scale were collected from an area covering 6,500 km^2. Each sample was analysed for 39 elements. Approximately four stream sediment samples were mixed as a single sample in each 2 × 2 km^2 grid. The discovered Quanzigou, Caosiyao and Dasuji molybdenum deposits are large and superlarge deposits in this area, which are closely related to the fault structures (i.e., NE direction). In this study, geochemical landscape factors, including slope, aspect and the drainage catchment basin, were extracted using ASTGTM2 DEM data, which have minimal cloud cover. Based on the previous geological literatures, mid-acidic magmatic rock of Yanshanian, NE linear structures, Archaean metamorphic rock and the intersection of faults are the primary influences on the formation and distribution of geochemical anomalies in this area.

The BME framework is a spatiotemporal mapping method based on spatiotemporal random fields. Hence, the framework can be considered for complex non-Gaussian and non-linear stochastic relationships between the observed values and the model predictions. All the available data with uncertainty were transformed into quantitative mathematical constraints. The BME was implemented in two stages: 1) calculation of the *a priori* probability density function for unsampled points using geographically weighted regression (GWR), and 2) geochemical mapping and spatial uncertainty assessment. More details regarding the BME model can be found in Christakos and Kolovos (1999) and Wang et al. (2015).

RESULTS AND DISCUSSION

Stream sediment data that can directly provide mineralization information were considered as hard data. The Mo concentrations suffered from closure effects. Thus, the approach of constructing single isometric logratio transformation (ILR) variables was employed to transform Mo concentrations, which allowed the relative information for all remaining parts to be taken into consideration (see Egozcue et al. 2003). Geochemical landscape conditions (i.e., slope, aspect, drainage catchment basin and average precipitation) and geological constraints (i.e., faults, rocks, formation and fault intersections) were used to construct probabilistic soft data based on GWR (Fig. 1). The BME model integrated the transformed Mo element and the probability soft data model using GWR during the spatial estimation of unsampled locations. Afterwards, to map the Mo-polymetallic mineralization anomalies in stream sediments at a scale of 1: 200,000 (hard data), the stream sediment data were integrated with the soft data. The impacts of the geochemical landscape, in addition to geological constraints, on sediment dispersion halos were studied.

a)

b)

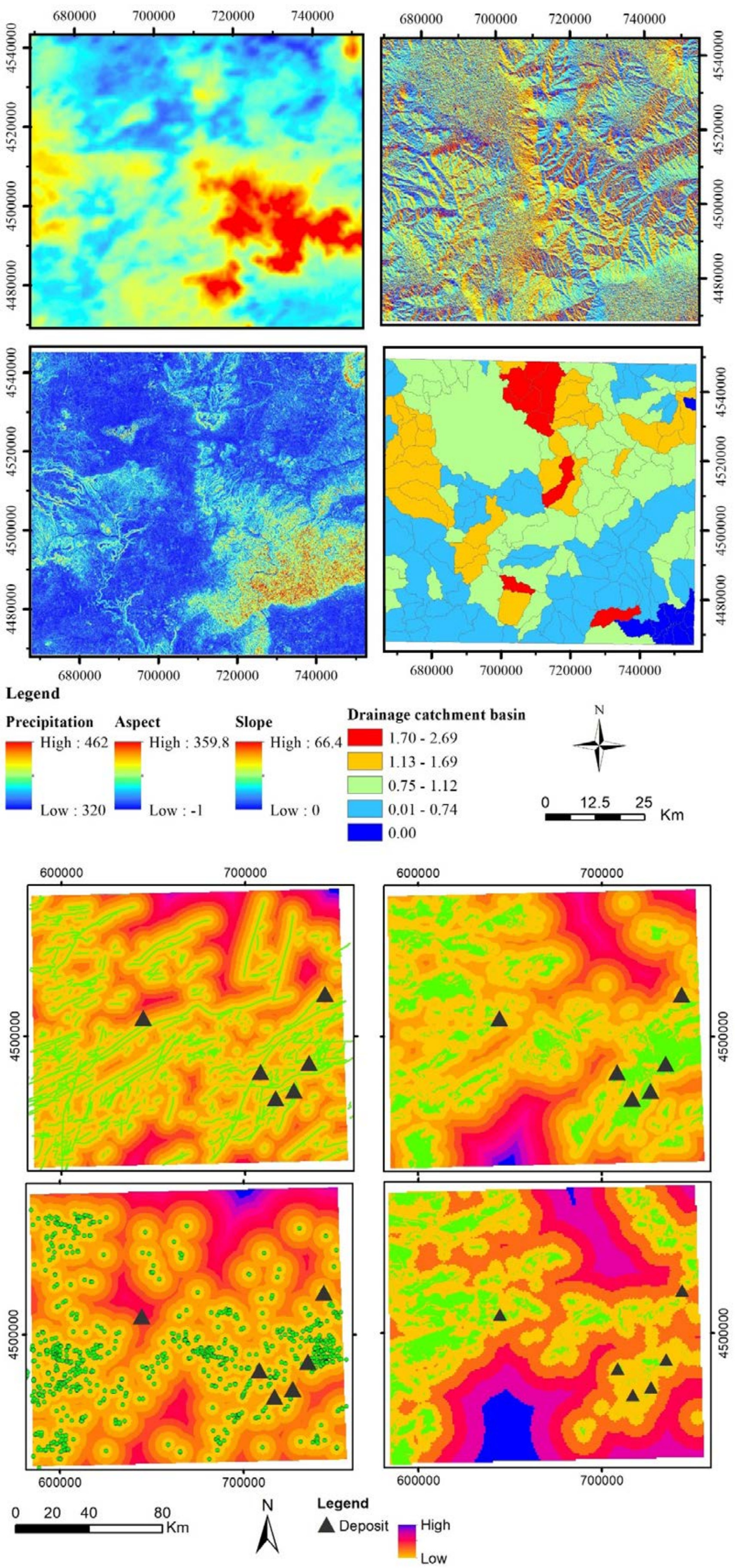

Fig. 1. Spatial distribution of a) geochemical landscape factors and b) geological constraints.

The cross-validation was implemented on the prediction results integrated with the geochemical landscape factors, suggesting that the values estimated by the BME model were significantly correlated with the ILR-transformed Mo concentrations, and indicating that the BME model provides an accurate prediction (Fig. 2a). The results obtained from BME highlighted weak anomalies attributed to topographical changes. Anomalous regions related to mineralization may be associated with undiscovered deposits that should be considered in future geological prospecting work. The prediction results based on the constructed geological constraints were compared with the prediction results of GWR. The spatial relationships between the discovered deposits and cumulative area demonstrated better prediction results for BME (Fig. 2b), proving that BME is more suitable for the definition of deposits in different periods. There are mainly three periods of molybdenum polymetallic mineralization occurrence in this study area, which take Caosiyao, Dasuji and Quanzigou as representatives. The results of BME delineated the deposits with different mineralization backgrounds more effectively compared to other methods, which is consistent with the geological setting. Consequently, the combination of BME and GWR is a valuable model for considering various constraints for geochemical anomaly identification.

a)

b)

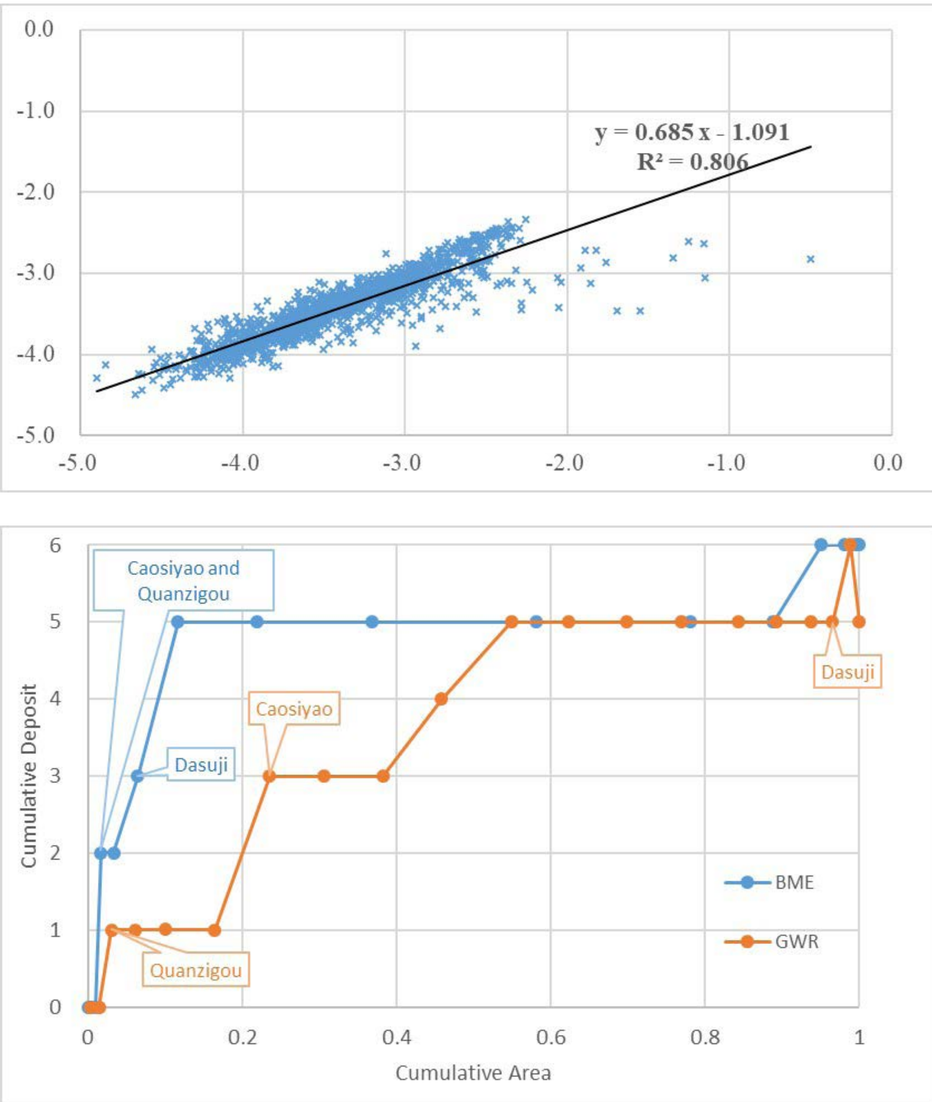

Fig. 2. a) Scatter plots of Mo observed concentrations and the values predicted by BME estimations, and b) the spatial relationships between cumulative deposits and the cumulative area.

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A PRELIMINARY APPROACH TO TARGET GENERATION FOR BASTNÄS-TYPE REE MINERALISATION IN BERGSLAGEN, SWEDEN

by

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In this study, we performed preliminary potential mapping for targeting of Bastnäs-type REE mineralisation in Bergslagen, Sweden. At the regional scale, spatial analysis of mappable criteria was verified and carried out. Available geological, structural, geochemical and geophysical data, including REE mineralisation, were optimised and have been used to generate a potential map for REE mineralisation using the mineral systems approach and hybrid weighted fuzzy method. The results demonstrate that areas with the presence of BIFs, skarn and limestone and where airborne magnetic anomaly patterns are openly S-folded, suggesting sinistral shearing in relation to the D2 deformational event, are important exploration targets for REE mineralisation.

INTRODUCTION

The Bastnäs-type REE deposits are skarn-hosted, magnetitedominated and are locally associated with polymetallic (Cu, Au, Co, Bi, Mo) mineralisation (cf. Geijer 1961, Holtstam & Andersson 2007). This deposit type occurs in the central part of the Palaeoproterozoic Bergslagen ore province, forming a discontinuous narrow belt, the so-called "REE line" (Jonsson & Högdahl 2013). This mineralisation type occurs within strongly altered, c. 1.90–1.87 Ga felsic metavolcanic and metasedimentary rocks in the Nora–Riddarhyttan–Norberg region (Fig. 1). The REE silicate-bearing mineralisation generally occurs as seemingly epigenetic, massive to disseminated magnetite-skarn replacements in marbles. Based on slight local differences in the chemistry and mineralogy of the Bastnäs-type deposits in Bergslagen, Holtstam and Andersson (2007) suggested a division into two subtypes: those mainly enriched in LREE and Fe-rich silicates, and those enriched in LREE and HREE+Y together with Mg, Ca and F (Holtstam & Andersson 2007).

We present a mineral systems approach data analysis for the Bastnäs-type REE mineralisation at the regional scale, based on present knowledge and available data at the Geological Survey of Sweden (SGU), and apply the concept to target generation. This work will be continued, expanded and completed during the on-going Horizon Europe funded Exploration Information System (EIS) project.

DATA AND METHODS

A suite of data, including surface geological and structural maps, airborne magnetic and lithogeochemical data (all from SGU databases), have been used for interpretation, spatial analysis and modelling. Firstly, the data were harmonised, and we then used the mineral systems approach (McCuaig et al. 2010, Sadeghi et al. 2021) for the targeting of Bastnäs-type REE mineralisation at the regional scale. The present approach demonstrates a hybrid fuzzy weighted overlay technique, in which the favourable mappable criteria have been chosen according to a conceptual model focusing on mineral system on REE mineralisation (Sadeghi & Ripa 2019).

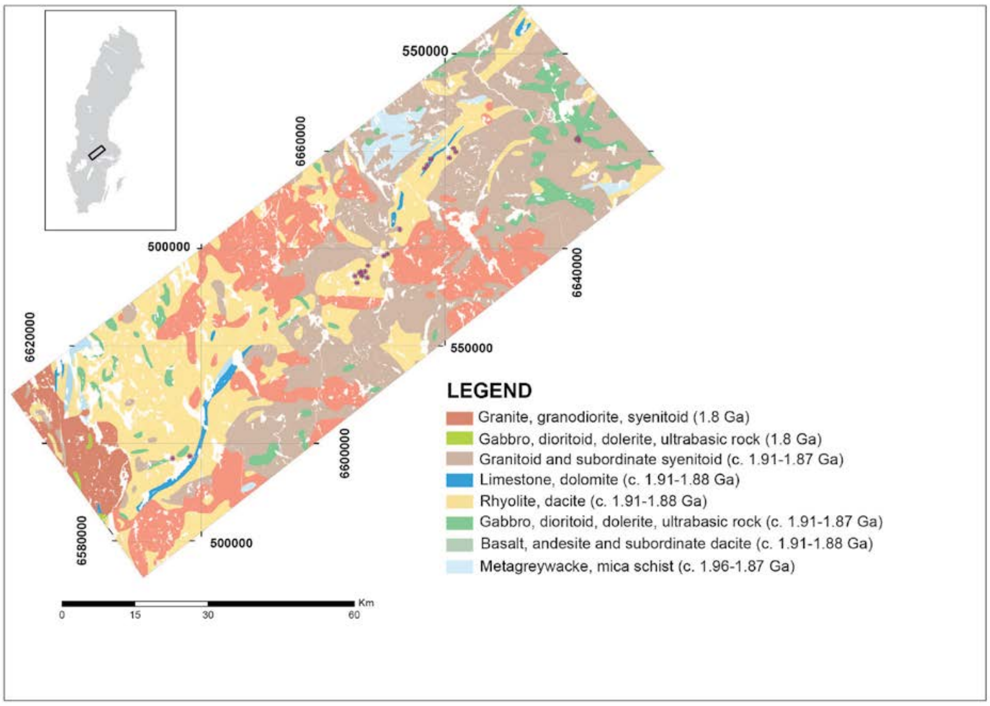

Fig. 1. Simplified geological map of the study area (the REE line) showing known REE deposits (red stars). (Source: geological map and mineral resource databases at SGU). Coordinate system: SWEREF99_TM.

RESULTS AND DISCUSSION

A part of the EU-funded EIS project is focused on defining components associated with the mineral system for different mineralisation types (e.g., IOCG, REE), but at this stage, we are applying our existing knowledge and presently available data. The following criteria could be used in defining the Bastnäs-type mineral system and then translated to a map.

Source: The presence of alkaline magmatic activity, including granitoids and rhyolite–dacite with calc-alkaline affinity, geochemistry of rocks and probably the presence of mafic subvolcanic and intrusive rocks may be important for the metal and heat sources.

Active pathway: Shear zones, faults and the orientation of regional-scale structures, together with alteration pathways, in country rocks may present the active pathways related to REE mineralisation.

Trap: Structures such as faults and folds may act as physical traps, and the presence of limestone, marble and dolomite may represent potential chemical traps.

Modification: The presence of iron-rich rocks and mineralisation linked with emplacement of volcanic- subvolcanic rocks may be considered in target generation.

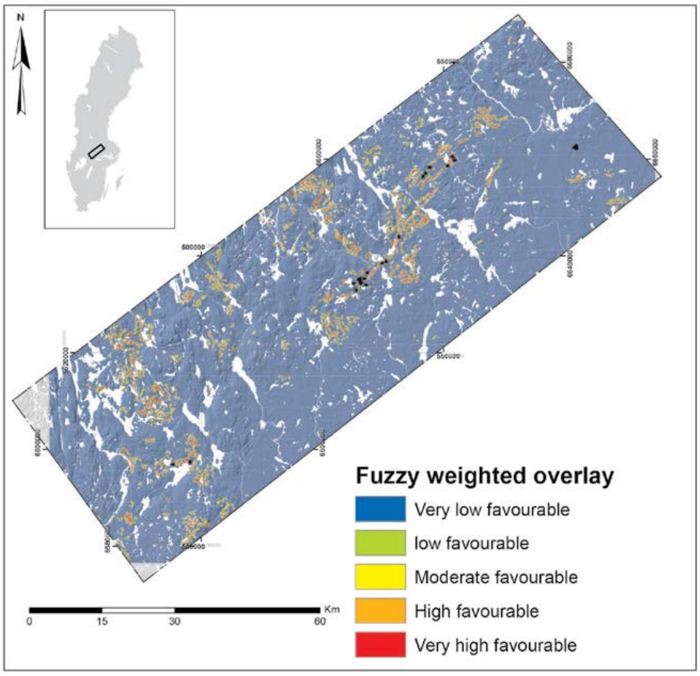

Fig. 2. Preliminary regional target generation map for Bastnäs-type REE mineralisation (black stars) in Bergslagen.

According to Stephens et al. (2009), southwest–northeast is the general trend of S2 foliation in this part of Bergslagen. Previous studies (Sadeghi & Ripa 2019, Sadeghi et al. 2017), have documented that sinistral shearing in relation to the D2 deformational event are closely related to the location of REE mineralisation. The magnetic anomaly pattern is openly S-folded, suggesting sinistral shearing in relation to the D2 deformational event. Some of the known REE-bearing deposits appear to be located at specific points along these S-shaped kinks, namely close to where the pattern turns more northerly, going from southwest to northeast. On the other hand, the spatial distribution of the REE deposits in relation to structures revealed by the aeromagnetic data suggests that their formation was somehow related to the phase of D2 deformation, or to processes coeval with it, and was thus probably later than the phase of intense and semi-regional hydrothermal alteration. The preliminary regional target generation for Bastnäs-type REE mineralisation in Bergslagen is illustrated in Figure 2.

In summary, since most skarn-associated REE deposits in Bergslagen are found in this area, and less so elsewhere, it seems likely that 1) the presence of BIFs, skarn and limestone, 2) the phase of intense and widespread hydrothermal alteration and 3) processes synchronous with D2 were somehow crucial to the environment and process associated with the formation of the REE deposits. The carbonate rocks may have served as trap rocks during any stage of high-temperature hydrothermal process following their formation. However, as the early stage of REE mineralisation pre-dates major regional metamorphism, it cannot have post-dated this. The phase of hydrothermal alteration may locally have led to initial LREE enrichment of the country rocks. Metamorphic to metasomatic processes during M2/D2 may have formed fluids that released the REEs from the country rocks and then precipitated them in trap rocks at certain structurally favourable sites, or partially remobilised REEs from the early stage of mainly carbonate-hosted mineralisation.

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MACHINE LEARNING APPLICATION FOR MINERAL ABUNDANCE PREDICTION FROM DRILL-CORE HYPERSPECTRAL DATA AT THE DEPOSIT SCALE

by

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In order to properly assess and characterize potential mineral deposits, it is essential to extract and analyse drill-core samples. However, the traditional logging process is often inaccurate and inconsistent. Hyperspectral (HS) drill-core scanning can supplement traditional logging techniques by providing high-resolution mineralogical data that cover the entire length of the boreholes. This process is also fast, reproducible, non-destructive and cost-effective. Nonetheless, when applied at the deposit scale, including several kilometres of drill core, it results in large datasets that are challenging to interpret, validate and incorporate into traditional workflows. In this contribution, we showcase the increased value of hyperspectral imaging to an exploration campaign by incorporating machine learning techniques. A supervised dictionary learning algorithm that exploits the complementary information from scanning electron microscopy-based automated mineralogy (SEM-MLA) and HS imaging techniques is applied for estimating mineral quantities along all boreholes. The approach is showcased on data acquired from Elvira, one of the test sites of the NEXT project funded by the EU Horizon 2020 research and innovation programme. Elvira is a shale-hosted volcanogenic massive sulphide (VMS) deposit located in the Iberian Pyrite Belt (IPB), where 7000 m of drill cores were acquired along 80 boreholes. The results provide insights into the controls on the mineral assemblages and chemical composition of specific minerals across the whole volume at several spatial scales, from large-scale variations within apparently homogeneous black shales to small-scale mineral composition variation, of potential use as vectors towards mineralization. This approach based on machine learning can easily be transposed to different ore deposits with limited input from a geologist.

INTRODUCTION

To improve the speed and accuracy of big data analysis, the use of machine learning (ML) techniques has been suggested in different scientific fields. ML techniques offer automatic approaches to discover underlying relations within a large data set (Acosta et al. 2019, Paoletti, et al. 2019). The application of these methods in the geological remote sensing community is growing. Nonetheless, there is no clear implementation of these techniques for the analysis of drill-core hyperspectral (HS) data at the deposit scale. In this contribution, we showcase the increased value of HS imaging to an exploration campaign by incorporating unsupervised ML techniques in the sampling selection strategy and a supervised ML technique for mineral abundance prediction using high-resolution mineralogical analysis as training data.

DATA AND METHODS

To illustrate the proposed workflow, the Elvira deposit was selected. This is a shale-hosted polymetallic (Cu–Zn–Pb) pyrite–chalcopyrite-rich massive sulphide deposit located in southwest Spain, one of the test sites for the European NEXT project. Altogether, 7 km of drill cores were scanned from 80 different boreholes from the Elvira site. The drill-core HS data were acquired using a SisuROCK drill-core scanner workstation from Specim, Spectral Imaging Ltd, equipped with an Asia Fenix sensor with 450 spectral bands between 380 and 2500 nm along the electromagnetic spectrum and a spatial resolution of 1.5 mm per pixel.

A data-driven approach was implemented for sample selection, applying an unsupervised classification analysis of the HS data based on a combination of principal component analysis, K-means and end-member extraction to ensure that all representative spectral groups of the deposit were included. From the unsupervised analysis, 24 samples were selected for SEM-MLA.

A dictionary learning method (Khodadadzadeh & Gloaguen 2019, De La Rosa et al. 2021, 2022) based on a supervised learning algorithm for estimating mineral quantities in drill core HS data was applied (Fig. 1). The method links the high-resolution mineralogical analyses from the SEM-MLA sections and HS data to learn a dictionary, conceptually a linear mapping relating mineral proportions to a HS signal. The method results in the propagation of the mineralogical quantification learned from the co-registered dataset to entire boreholes.

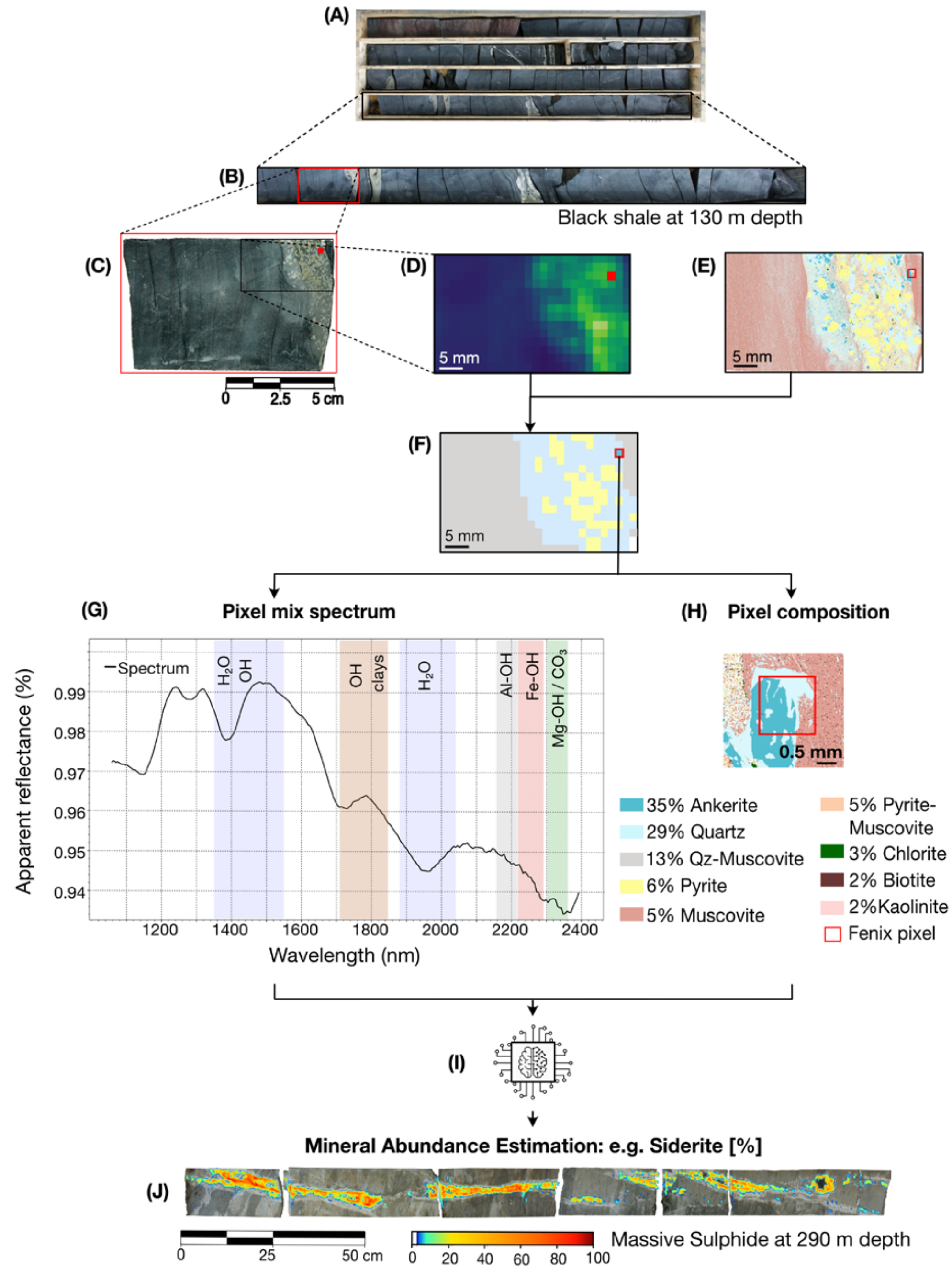

Fig. 1. Graphical description of the proposed workflow. a) Hyperspectral drill-core data scanning. b) Data pre-processing. c) Sample selection. d) Hyperspectral data. e) SEM-MLA mineral map. f) Multi-sensor, multi-scale co-registration g) Pixel spectrum. h) Pixel mineral composition. i) Dictionary learning algorithm. j) An example of siderite abundance estimation (zoom in core section) with zero values set to transparent for clarity.

RESULTS AND CONCLUSSIONS

The results are condensed in the mineral abundance prediction along the boreholes, where significant variations in composition and mineral abundance estimations are observed. For specific minerals and mineral groups, there is a clear relationship between their abundances, chemical composition (in the case of chlorite) and proximity to the massive sulphide mineralization. We demonstrated that machine learning can be used to automatically process large amounts of hyperspectral data from drill cores, making exploration campaigns more efficient.

Several benefits are brought from the prediction of mineral quantification along boreholes. Mineral assemblages formed by white mica and chlorite were recognized, allowing the differentiation between shale packages. Changes in shale composition towards the massive sulphide were identified, allowing the definition of proxies for mineralization based on iron oxides and the ratio between iron-rich and magnesium-rich chlorites. This approach based on machine learning adds value to the drill-core data, allowing for a better understanding of the geological setting of the Elvira deposit and providing valuable insights for future exploration targeting in the region. Furthermore, the method can easily be implemented in different ore deposits.

ACKNOWLEDGEMENTS

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APPLICATION OF ADVANGEO® 2D PREDICTION SOFTWARE IN BURKINA FASO: A FIRST WEST AFRICAN NATIONAL MINERAL PLAN WITH FAVOURABILITY MAPS BASED ON ARTIFICIAL NEURAL NETWORKS

by

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INTRODUCTION

Burkina Faso, due to its geological context and the multiple prospecting and mining research activities carried out in its territory, has a high potential for mining exploration and discovery of mineral deposits. In recent decades, the country has experienced significant mining development focused on industrial gold and zinc production. In spite of the important geological diversity, mining production in Burkina Faso remains mostly focused on gold (17 industrial gold mines and 1 zinc mine). In order to take stock of the country's mining potential and to increase and diversify mining development, the Government, via the Ministry of Mines and Quarries, has commissioned the development of a new Mineral Plan of Burkina Faso through the Bureau of Mines and Geology (BUMIGEB). Gold, copper, aluminium, iron, manganese, titanium, vanadium, phosphate, lead, zinc, uranium and other mineralization is known throughout the country. Today, mining is the country's main source of revenue. The challenge is to diversify this production by continuing prospecting and research. The Mineral Plan (Barth et al. 2022) will support the Ministry in promoting and implementing research and mining of the country's versatile mineral resources.

DATA AND METHODS

This new Mineral Plan, realized by Beak Consultants GmbH in cooperation with BUMIGEB, is a bilingual document integrating an overview of the geology and mining activities of Burkina Faso, a national inventory of mineral resources, a metallogenic model and favourability models. Using the knowledge and available geological, geochemical and geophysical data, predictive models based on artificial neural network (ANN) algorithms have been created to identify future target areas for Au, Ni, Mn, sulphides (Cu, Zn, Pb, Sb), Fe–Ti–V and bauxite.

The models are generated using ®advangeo 2D Prediction software, developed by Beak Consultants GmbH (Barth et al. 2014).

The following activities have been carried out:
1. The collection, review and correction of existing data; 2. Digitization of mining sites and their spatial extension from high-resolution satellite images and available literature; 3. Data harmonization; 4. Metallogenic analysis and identification of ore-controlling parameters; 5. Preparation of data for input to the predictive mapping algorithms; 6. Modelling and predictive mineral mapping; 7. Definition of mineral zones to be proposed as targets for further investigation.

RESULTS AND DISCUSSION

The resulting data reflecting the state of knowledge have been transferred to BUMIGEB in ArcGIS formats. They were integrated, in addition to all cartographic data, in a harmonized database of mineral occurrences containing data from previous projects, combined with more than 2,000 artisanal mining sites detected from satellite images.

To further clarify the overall potential for other strategic metals, a metallogenic model has been elaborated and priority exploration targets were generated for Li, U and sulphides. These models provide a brand-new comprehensive prospecting tool. Using them together with all available information, mineral substances in Burkina Faso have been evaluated in the current economic context. Promotion charts have been created to attract investment for selected commodities.

Information on commodities such as Cu, Zn, Pb, Sb, Fe, Ti, Mn, Al and Ni is available and accessible. Important deposits of metals other than gold, such as Perkoa (Zn, Pb, Ag) or Tambao (Mn), have been explored and mined. Some information exists on PGEs, rare metals (Sn, Mo, Ta, Nb, W) and REEs. Knowledge of uranium is limited to airborne geophysical, geochemical and local ground-truthing data. High-quality geochemical maps only exist for the southwestern part of Burkina Faso.

Mineral favourability maps and metallogenic considerations indicate potential for the following types of ore mineralization: 1. Gold in various geological environments, with and without sulphides, mainly as primary mineralization, but also in placers; 2. Base metals (massive and disseminated sulphide ores) related to Birimian volcano-sedimentary belts; 3. Mn in oxidation caps above Mn-carbonate layers in metasediments of volcano-sedimentary belts; 4. Ferrous and related metals (Cr, Fe, Ti, V, Ni, (Co)), Cu and potentially PGEs related to segregations in ultramafic and mafic intrusives; 5. Ni (Co) and Al in laterites on top of potential source rocks.

The following substances require special attention to clarify their mineralization types and presence in potentially industrial grades and tonnages: 1. Li identified in post-tectonic leucogranite and pegmatite zones, 2. PGEs, 3. U identified by spectrometric surveys located on top of granitoids and pegmatites, but having been studied in the field on the surface only, 4. U known in the Kodjari phosphorites in south-eastern Burkina Faso, but average grades are not known.

The findings obtained using data-driven (ANN-based) favourability models in combination with knowledge-based mineralization models were used to compile an action plan consisting of a 10-year exploration programme and a communication plan for disclosure of results and interaction with investors and scientists accompanying the proposed activities.

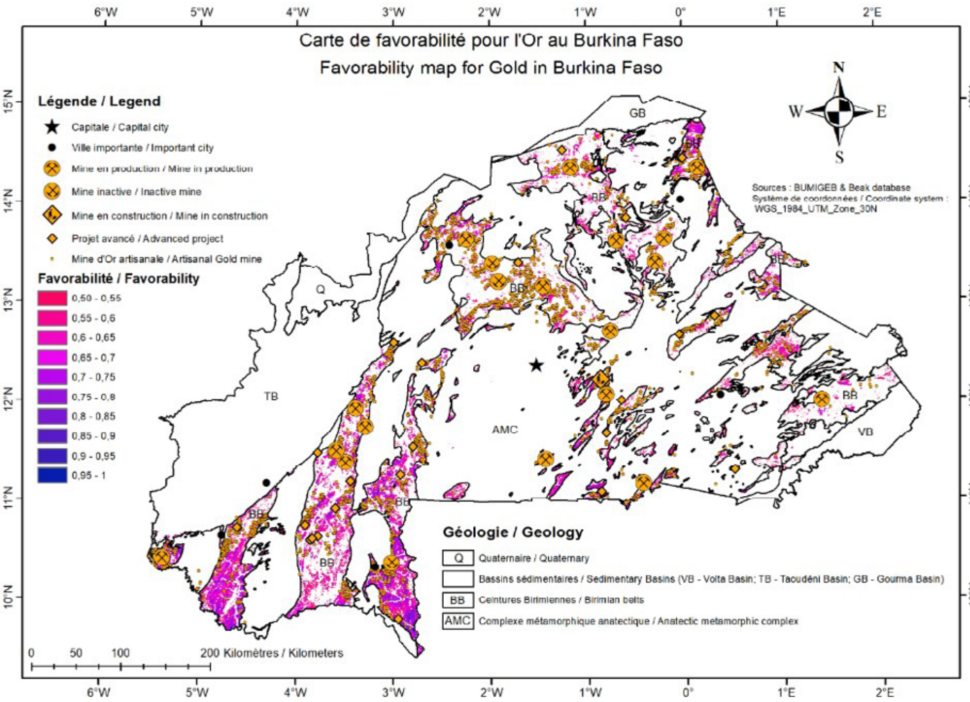

Fig. 1. Example of an AI-generated mineral favourability map: Gold in Burkina Faso, produced with ®advangeo 2D Prediction software developed by Beak Consultants GmbH and ArcGIS (Barth et al. 2022).

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USE OF PASSIVE SEISMIC TECHNOLOGIES IN MINERAL EXPLORATION

by

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INTRODUCTION

As mineral exploration seeks deeper targets and targets buried under cover, the need for low-cost and low-impact subsurface imaging is increasing. A recent addition to the toolbox of geophysical methods is ambient noise surface wave tomography (ANSWT), which produces 3-D V_s models of the subsurface using naturally occurring seismic signals. Here, we provide a brief introduction to the ANSWT method and review several recent applications.

Seismic signals for ANSWT imaging come from natural and anthropogenic sources, including ocean swell, earthquakes, wind and traffic. ANSWT uses cross-correlation between receiver pairs to extract the Green's function of the ground between the sensors; the dispersion of the surface waves from the cross-correlated data is used to generate a near-surface velocity model (typically from a few hundred metres to ~2 km depth), a proxy for the structure or changes in sub-surface rock types or properties. ANSWT results can be used as standalone, jointly inverted with geophysical or geological data, or used to improve the imaging of active source data.

The key technology for the ANSWT method is the development of autonomous seismic recorders ("nodes") that enable reliable, low-cost, continuous recording of seismic data for weeks or months. Nodes facilitate the low-cost collection of dense passive seismic data and provide other types of subsurface imaging. Nodes are also used to collect active-source seismic data. A complementary method employs optic fibres to capture the seismic signals.

SALLY, CANADA

The Sally platinum-group metal prospect in Ontario, Canada, is located at the northern margin of the Proterozoic Coldwell Complex, a ring-shaped series of gabbros overlain by syenites. The goal of the seismic survey was to determine the structure and geometry of the Eastern Gabbros, the high-density, seismically fast gabbros that host the mineralization. Altogether, 200 3-component nodes were deployed with a 300 m nominal distance; data were recorded for 33 days. The surface wave velocity model traced the lower margin of the Eastern Gabbros and identified a strong velocity anomaly in Archaean footwall metasediments to the north and underlying the main intrusion. The anomaly is interpreted as a pyroxenite intrusion of the type that hosts PGM mineralization.

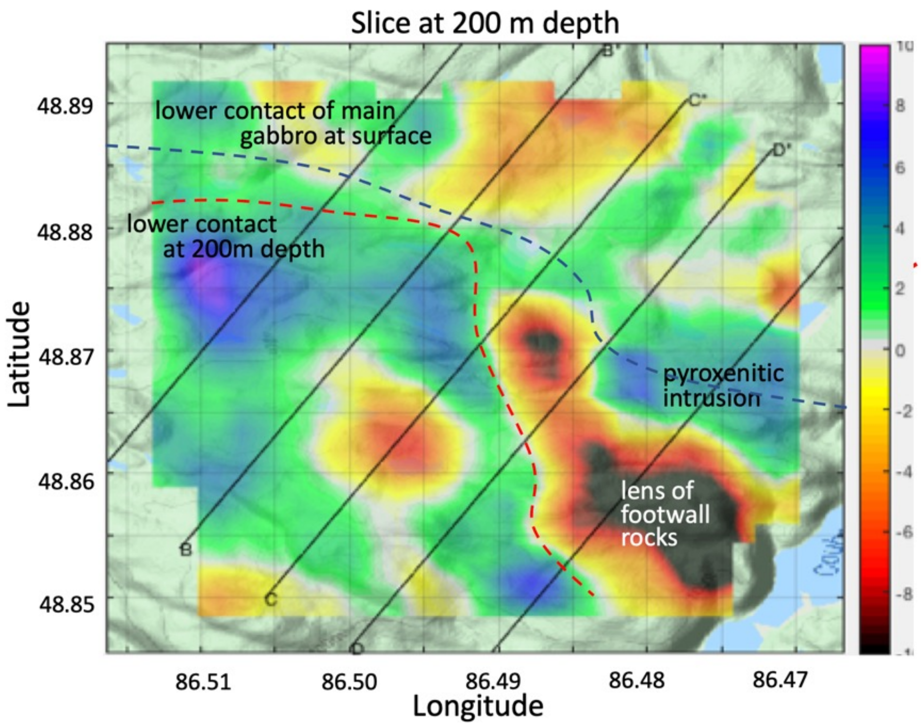

Fig. 1. Sally, Canada. A slice through the velocity model at 200 m depth with the matching surface geological observation by Good et al. (2015). The lower contact dips steeply and is found farther to the south in the seismic model. A possible pyroxenitic intrusion is imaged to the north of a lens of footwall metasediments.

HOTAZEL, SOUTH AFRICA

An ANSWT survey was conducted at the Hotazel manganese prospect in South Africa. The goals were to determine the thickness and geometry of the younger sedimentary units and to image the units containing manganese ore. In total, 120 seismic stations were deployed along two linear arrays (20 m spacing, 1.2 km total length) and ambient seismic noise was recorded for 9 days. This less-than-optimal array was used to produce the velocity model in Figure 2. The sharp increase in velocity at depths of about 100 m in the west to about 75 m in the east is interpreted to image the base of the cover, and the high velocities in the underlying unit map the mineralized formation. These interpretations are confirmed by the positions of the units in the core logs.

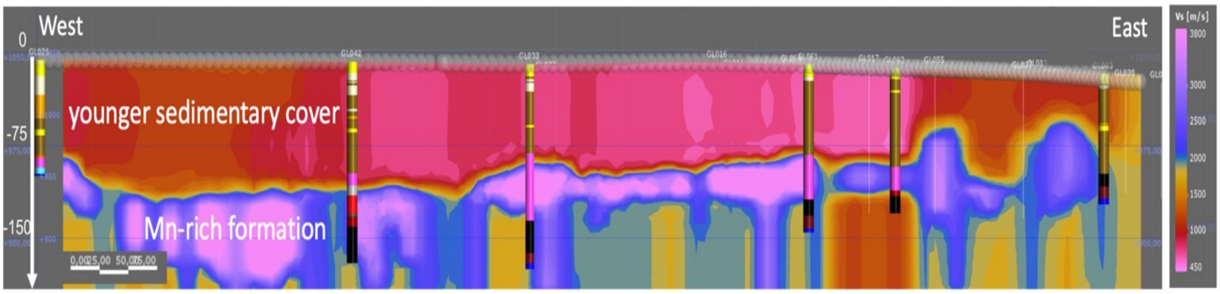

Fig. 2. Vertical section through the velocity model obtained at the Hotazel Mn deposit.

KALLAK, SWEDEN

This survey formed part of the PACIFIC project, which was financed by the European Union’s Horizon 2020 program (www.pacific-h2020.eu). The targets were iron deposits near Kallak in northern Sweden. Figure 3 presents a velocity model obtained in a preliminary ANSWT survey. The main objective of the project is to demonstrate the feasibility of a multi-array approach using seismometers deployed in a surface array and within drill holes. This survey was conducted in the summer of 2021 and the data are currently being processed.

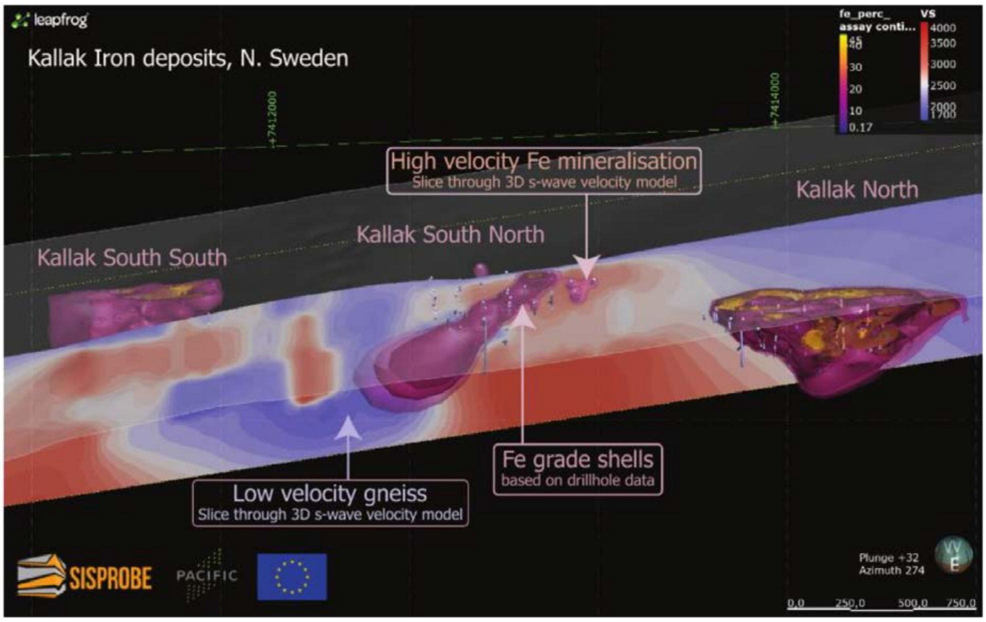

Fig. 3. Kallak, Sweden. Comparison between the locations of ore deposits inferred from geological models and drilling, and a velocity model obtained during a preliminary ANSWT survey.

COVER MAPPING AT BOULIA, AUSTRALIA

Ambient noise surface wave tomography and the horizontal-to-vertical spectral ratio (HVSR) method were applied to image the cover/basement contact on a prospect near Boulia, 200 km south of Mt Isa in Queensland, Australia. The method was also applied to the continuous seismic dataset for comparison. The data were collected using 100 triaxial self-contained nodes deployed along a 30-km section of rural road for a period of 19 days in December 2019.

The S-wave velocity tomogram obtained using the ANSWT method down to 2 km below the surface shows a clear subhorizontal interface at about 700 m depth, where the velocity increases from roughly 2500 m/s to 3500 m/s. This contact can be compared with the results from an expensive active reflection seismic survey previously conducted along this road, and with (qualitative) results from a magnetotelluric survey in this area. At a few locations, core data from drilling produced high-confidence depth-of-cover data. Generally, these data sets agreed quite well. The ANSWT cover thickness matched borehole data to within 50–70 m, which is not much worse than the reflection data estimates (30 m error).

The HVSR data indicated a much shallower layer interface, even using fairly accurate S-wave velocity values. This interface probably corresponds to superficial layers of alluvium or altered rock within the cover. Nonetheless, the HVSR data provided useful constraints for the ANSWT depth inversion.

The passive seismic data were also reprocessed assuming a sensor spacing of 3000 m using data from only 13 nodes. Manual data processing and quality control produced 75 useful dispersion curves in the frequency range 0.33–4 Hz. The depth inversions produced a low-resolution tomogram with very a similar cover/basement method for prospecting and targeting at local to regional scales.

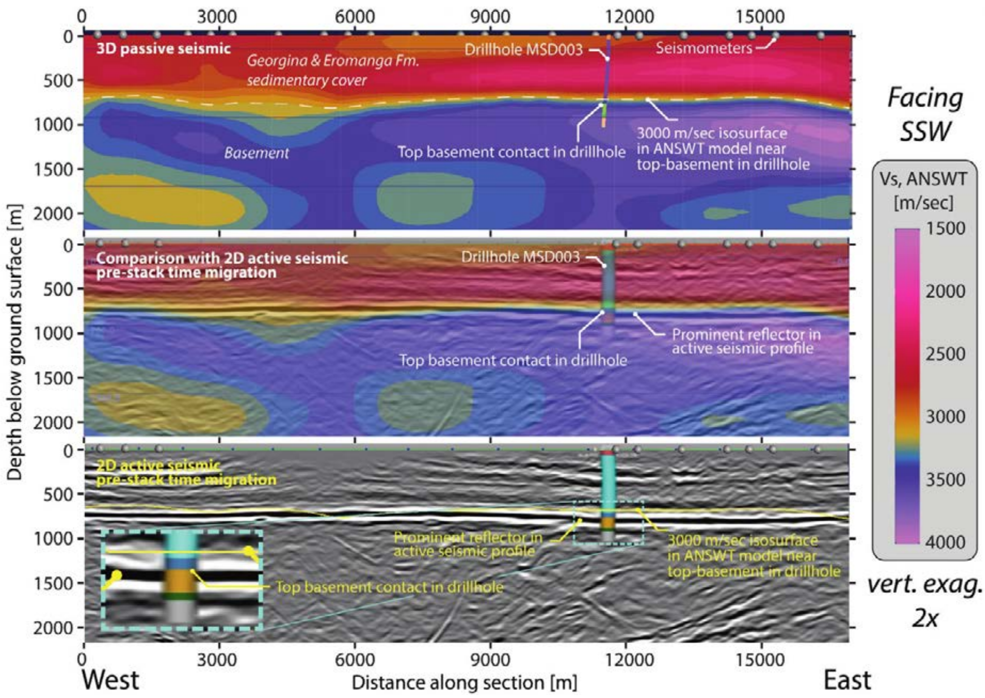

Fig. 4. Vertical cross-sections showing the ANSWT passive seismic model (top), the 2D active seismic pre-stack time migration (bottom in greyscale), and in the middle panel, the two techniques superimposed. Inset shows the top basement position in drillhole MSD-003 compared with the ANSWT model and the active seismic profile.

OTHER ONGOING PROJECTS

Past and ongoing projects include greenfield exploration for magmatic nickel, porphyry copper and VMS deposits and the use of fibre-optic based systems (DAS) to image and monitor tailings facilities. Figure 5 shows the locations where passive seismic technology has been used to target mineral deposits, as well as several other applications of the method.

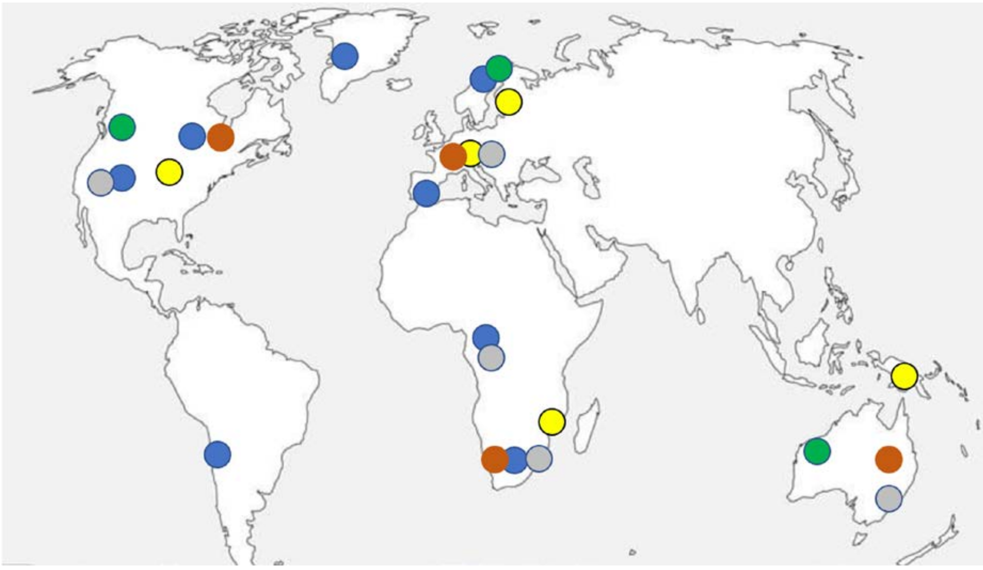

Fig. 5. Locations where passive seismic methods have been used. Blue circles – mineral exploration; brown circles – cover mapping; yellow circles – energy resources; green circles – tailings facilities monitoring; grey circles – civil engineering.

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LITHIUM POTENTIAL MAPPING USING ARTIFICIAL NEURAL NETWORKS: A CASE STUDY FROM CENTRAL PORTUGAL

by

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The growing importance of and demand for lithium (Li) for industrial applications, in particular rechargeable Li-ion batteries, have led to a significant increase in exploration efforts for Li-bearing minerals. To ensure and expand a stable Li supply to the global economy, extensive research and exploration are necessary. Artificial neural networks (ANNs) provide powerful tools for exploration target identification that can be cost-effectively applied in various geological settings. We present an integrated approach to Li exploration targeting using ANNs for data interpretation, based on Köhler et al. (2021). The Li potential was calculated for an area of approximately 1200 km2 in the surroundings of Bajoca Mine (Northeast Portugal), based on medium-resolution geological maps (1:50,000) and stream sediment geochemical data (1 sample per 0.25 km2). Extensive knowledge of geological processes leading to Li mineralisation (such as weathering conditions and diverse Li minerals) proved to be a determining factor in the exploration model. The proposed approach reveals that using ANNs, geological and geochemical data can be used to delineate and rank exploration targets of almost any deposit type.

INTRODUCTION

Lithium (Li) is on the European Union's (EU) list of critical raw materials, is an important element in modern technological applications, and plays a key role in the realisation of electromobility and effective energy storage. The supply of Li to the global industry depends on expanding the supply of resources Portugal hosts considerable Li resources and is the first Li-producing European country, but represents only 1.3% of world production. Recent exploration by different mining companies has increased the Portuguese reserves by multiple times, and significant research has been performed to enhance understanding of Li mineralisation types and deposits.

Artificial neural networks (ANNs) are powerful in the early stages of resource exploration. In recent years, several studies have demonstrated the potential of ANNs and their uses in geological contexts. Neural networks have several advantages over existing methods, including the ability to respond to critical combinations of parameters, the combination of datasets without the loss of information inherent in existing methods, and results that are relatively unaffected by redundant data, spurious data and data containing multiple populations. A geographic information system (GIS), in concert with ANN software, offers great potential by providing a range of tools to query, manipulate, visualise and analyse geological, geochemical and geophysical data in mineral exploration applications. This study aimed to use ANNs to process classical geological data (maps and geochemical analyses) reliably and cost-effectively to enhance exploration targeting, ultimately leading to a new exploration process chain at the target scale. Similar approaches could be extended to other areas of the Iberian Peninsula or even the European Variscides, allowing increased knowledge of Li pegmatite distribution.

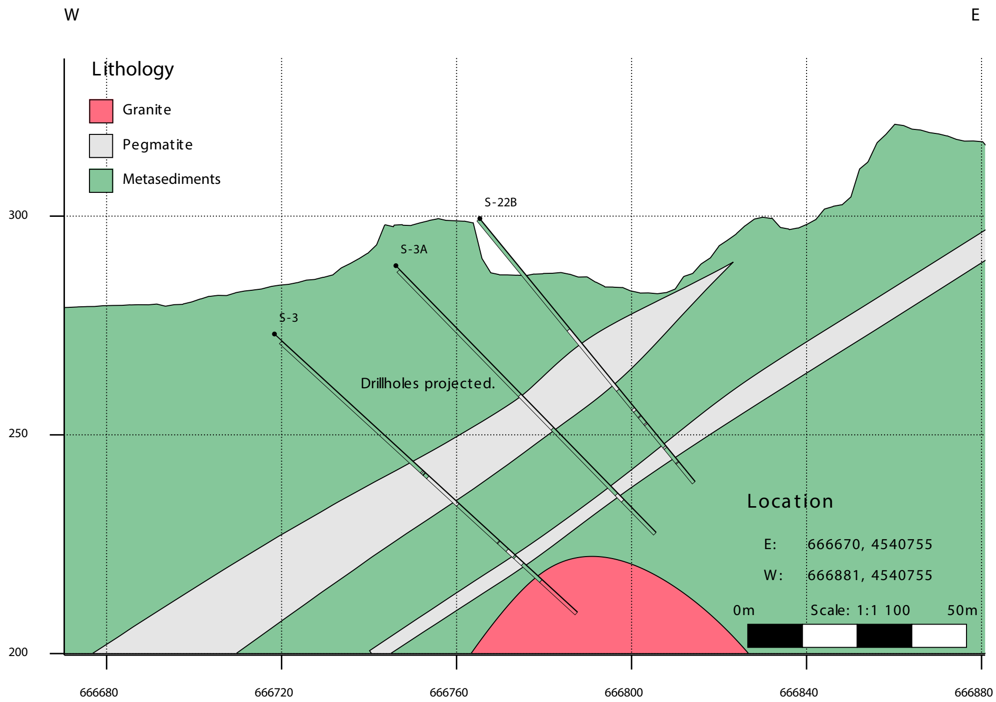

Fig.1. Geological profile of Bajoca Mine, featuring Li-bearing pegmatite dykes with a spatial relation to a granitic body hosted within metasedimentary rocks.

DATA AND/OR METHODS

Geological maps of the study area provided the geological framework for this study and were used to identify and digitise pegmatite and other individual geological units for further use in the prediction software.

Stream sediment geochemical data (survey spot position and geochemical analysis) were obtained from earlier studies.

The catchment creation was based on digital elevation model (DEM) data and the flow direction network.

Li mineralisations in the study area principally occur in aplite–pegmatite bodies and hydrothermal veins, all with a spatial relation to a granitic body (Fig. 1). Regionally, Li mineralisation occurs in highly evolved aplite–pegmatite dykes hosted within metasedimentary rocks, with an increasing fractionation degree as the distance to the granite increases. However, the regional granites are enriched in elements such as Li, P or Rb when compared with the metasediments. It is therefore important to separate these two lithologies, since Li signals could occur both in granites from their initial Li content (low Li content but huge volume) or Li pegmatites (high Li content but low volume), but cannot be clearly distinguished in the stream sediment data. Hence, we excluded stream sediment data from granite areas, since pegmatitic Li mineralisations (in the study area) are commonly only hosted by metasedimentary rocks and apical or marginal areas of granitic intrusions hosted by metasediments.

Unclassified factor analyses of the stream sediment data were conducted to obtain a preliminary overview of the elements related to local Li mineralisation and to reduce the overall input data for the prediction software. Seven factor classes (with eigenvalues > 1) could be identified and attributed: (1) metamorphic signature, (2) granitoid signature, (3) polymetallic signature, (4) siliceous signature, (5) Li-emphasised, (6) Sn(–Nb)-emphasised, and (7) W–Ti-emphasised. The Li-emphasised class has relatively high Li contents and shows coherent enrichments in Sn, As, Mo, Cu and Ag. The data from these elements were subsequently used in the ANN model.

ANNs of the multilayer perceptron type were implemented in advangeo® Prediction. In this study, the prediction software was used to perform artificial neural networks of the multilayer perceptron type to identify Li mineralisation over the given study area. Controlling parameters included digitised geological units (1:50,000), digitised pegmatites (1:50,000) and selected stream sediment data.

RESULTS AND DISCUSSION

The prediction software delivered a distribution probability map in the value range of 0–1, illustrating the Li potential over the study area (Fig. 2). Areas depicted with 1 or close to 1 are the areas with the highest probability of Li-bearing rocks. Within the study area (approximately 1200 km^2), 50 km^2 were mapped with a Li potential between 0.1 and 1 (Fig. 2). These areas were mainly located in regions of metamorphic rocks in the vicinity of granite intrusions, compatible with possible greisen cupolas or pegmatites and their host rocks. High predictive areas (>0.5 Li probability) extend over 6.4 km^2 and are mainly located directly to the south/southwest of Bajoca Mine (5.6 km^2) and to a lesser extent north of the town of Meda (0.47 km^2), as well as southwest of Santa Comba village (0.35 km^2).

The spatial distribution of Li-predictive areas in the transition of metasediments and granites could be a result of possible (hidden) greisen cupolas or pegmatites (Fig. 2). As a result of the strong generalisation of geological units (metamorphics, intrusives, etc.), the areas with Li potential are mainly related to stream sediment geochemistry. Particularly straight area borders are caused by the boundaries of the main geological formations. Comparing the distribution of different elements across the study area (Sn, W, Li, Mo, As), several areas could be ruled out regarding Li mineralisation sensu stricto (pegmatites). As a result, only Bajoca Mine was used to validate the ANN model. However, the model was also able to predict the Li mineral deposits located near the border of Portugal and Spain in the northeast part of the study area. The presence of Li mineralisation in this area was confirmed from the mining activities in the Riba D'Alva mine. Further research is needed to validate the proposed approach in other areas, i.e., to check the high-potential areas identified through the mineral prospectivity mapping for the occurrence of unknown mineralisation. Ultimately, the resultant Li mineralisation prediction map (Fig. 2) could be a useful tool for future exploration campaigns for exploration and mining companies, since it can help to delineate smaller interest areas in a large geographic area (>1,250 km^2). We recommend focusing future exploration activities on the following locations with a high predicted Li potential: areas surrounding Bajoca Mine, Li anomalies in the west of Meda, possible greisen cupolas in the south of the study area, and areas north of Feli Mine.

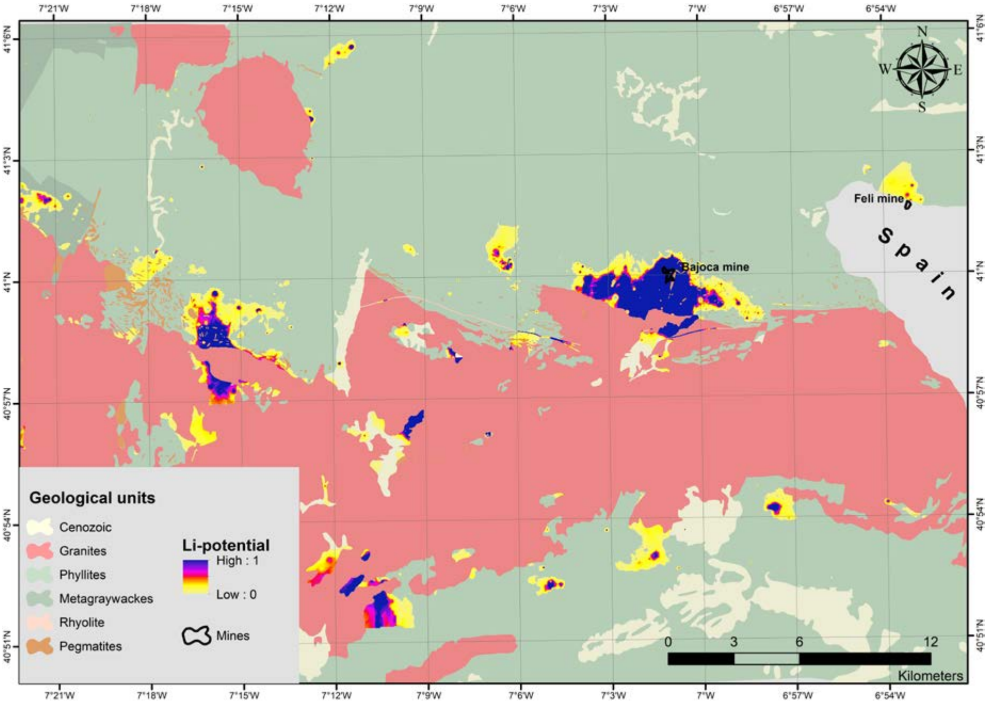

Fig. 2. Predicted Li mineralisation based on geological data.

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2D MINERAL PREDICTIVE MAPPING WITH MACHINE LEARNING ALGORITHMS IN COLOMBIA

by

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The combination of machine learning (ML) algorithms and GIS-based approaches has allowed the development of new methods in mineral exploration, such as the integration of artificial intelligence modelling and mineral predictive mapping as a tool to support mineral deposit targeting. In this study, feed-forward back-propagating artificial neural networks (ANN), under a hybrid approach, were implemented in conjunction with the mineral systems method in order to identify the most favourable areas for selected mineral deposit types (porphyry, orogenic, epithermal and intrusion-related Au deposits) at a regional scale. This process was based on the workflow knowledge discovery in databases (KDD), as defined by Fayyad et al. (1996), and the mineral systems approach of McCuaig (2010). The study was conducted in Colombia in a region of approximately 21,867 km^2 and aimed to improve knowledge of mineral deposits from the data of the Servicio Geológico Colombiano (SGC). The general selected ANN attributes were a sigmoid activation function, a balancing ratio of 50% and a slope-dependent mean square error (MSE) algorithm for weight adjustment. The best performance was obtained for an ANN with a single hidden layer and for a maximum number of iterations between 250 and 500. Further iterations overfitted the training data, whereas the use of a second hidden layer did not provide any acceptable outcomes. The overall performance was assessed and verification of the models was performed through the examination of receiver operator (ROC) and mean square error (MSE) curves, with values over 0.9 and below 0.02, respectively. Validation of the same models was carried out using different ANN configurations, as well as with the available geochemical data. The obtained models displayed a good visual fit to the training data and even properly identified wrongly labelled deposits. Target areas of interest were selected for future exploration campaigns in order to identify the respective mineralization indicators.

INTRODUCTION

Mineralizations are ubiquitous from north to south of the south American Andean Cordillera, with a number of well-known cases. Recognized by Sillitoe (2008) as a fertile metallogenetic area, Colombia is home to numerous deposits, such as La

Colosa, Marmato and Jericó. New data processing techniques, along with recent data mining techniques, such as machine learning algorithms, have opened a new possibility to understand the local and regional mineral genesis by correlating mineral occurrences with regional geological settings (e.g., fault systems), thus allowing the identification of potential areas where certain commodities are more likely to be found. In this project, a particular region within Colombia was studied through machine learning algorithms (in particular, artificial neural networks) to create a mineral predictive map for certain mineral deposits (porphyry, orogenic, epithermal and intrusion-related Au deposits). The ML models were constructed with reference to the tectonic evolution and metallogenetic understanding of the region. Algorithms were built through the software advangeo® (Beak Consultants GmbH) and prediction maps were constructed, supported by analysis of their accuracy. Finally, the project specified targets for future exploration campaigns by the geological survey.

DATA AND/OR METHODS

Mineral Systems Approach

To determine the relationship between mineral occurrences and the geological setting of the area being analysed, it is necessary to construct a general overview of the type of process that controlled the known deposits in the area. As defined by Walshe et al. (2005), the approach must use a "genuine mineral system [model] that [is] independent of types/classes and [is] constrained by data at all scales, spatial as well as temporal". Consequently, the mineral systems approach takes the general outline described by McCuaig et al. (2010) to transform a conceptual model into a targeting model by defining, in turn, the critical systems, constituent processes and targeting elements, and finally identifying mappable criteria.

Machine Learning: Artificial Neural Networks

An artificial neural network (ANN) is the machine learning algorithm that was used in this project. This type of model simulates the behaviour of the human brain, where a set of neurons are responsible for the interpretation of an input signal, according to Hajian and Styles (2018). When the complete network has been executed, the output can be compared with true values (training values) and an error can be calculated. The aim is consequently to reduce the calculated error to obtain a prediction that is as close to reality as possible. The model selected for this study was a feed-forward back-propagation neural network that updates the weights assigned to each attribute through learning.

Knowledge Discovery in Databases

Mining for information and extracting knowledge has become not only highly relevant to retrieve significant results, but also requires a new generation of computational techniques under the name of knowledge discovery in databases (KDD). KDD is "the process of extracting interesting, non-trivial, implicit, previously unknown and potentially useful information or patterns from data in large databases" (Fayyad et al. 1996). The first step is pre-processing using Oasis montaj, ArcGIS Pro, Python and Excel. This is followed by transformation, data mining and evaluation steps conducted using advangeo®, concluded with the visualization of the results in ArcGIS Pro (or any other special data management tool).

Equations

For the learning process of the neural network selected for this project, the minimum squared error was used:

$$MSE \equiv \frac{1}{n}\sum_{i=1}^{n}\left(y_i - (\overline{y_i}\,)\right)^2$$

RESULTS AND DISCUSSION

A predictive map for porphyry deposits was attained with a 1000-iteration model, with an overall area under the curve (AUC) score of 0.979, indicating good precision when identifying true positives over false positives, and marking the analytical signal of the magnetics as the most important attribute for this deposit type. Circular to semi-circular features produced by the model can be correlated with Cu anomalies, an element that usually accompanies these mineralizations. Potential exploration targets were selected according to these results, as shown on Figure 1.

Regarding epithermal deposits, a 500-epoch model was found to produce the best results for delimiting areas with higher favourability, identifying sub-volcanic rocks as the most important influence on the findings. Although all deposits are located to the west of the central cordillera, the algorithm identified prospective areas towards the eastern side. A total AUC of 0.985 was attained. The shape of the deposits does not have a defined form and depends on the country rock, and matches well with the findings from Marmato, a well-known deposit used within the training set. The model was validated based on the association with Pb anomalies.

On the other hand, the resulting intrusion-related plutonic Au model revealed that the slope of the magnetic response is the most relevant input parameter for defining favourable areas. With an AUC of 0.97 and 100 learning epochs, the largest areas (centre and northeast) correspond with the two major plutonic intrusions of the area, the Sonsón and Antioquia Batholiths, and a smaller one, the Mariquita Batholith. Histogram results indicate that the algorithm correctly labelled the known occurrences within the high-probability regions of the map. Additionally, the error curve for the model displayed a smooth behaviour throughout the learning phase, as well as the repetition runs checking for stability. Validation was performed, with a clear correlation with arsenic anomalies.

Finally, orogenic deposits were modelled, and the radiometric response, associated with alterations, and specifically with the change in the values (slope), was the most relevant attribute. The best AUC value was 0.977 with 250 iterations. The relevant type of mineralization being modelled is that in the area marked as intrusion-hosted, where tensional zones and veins exist, explained by the timing of such intrusions related to the "Bolivar aulacogen" and emplaced into the greenschist- to amphibolite-grade sedimentary sequences.

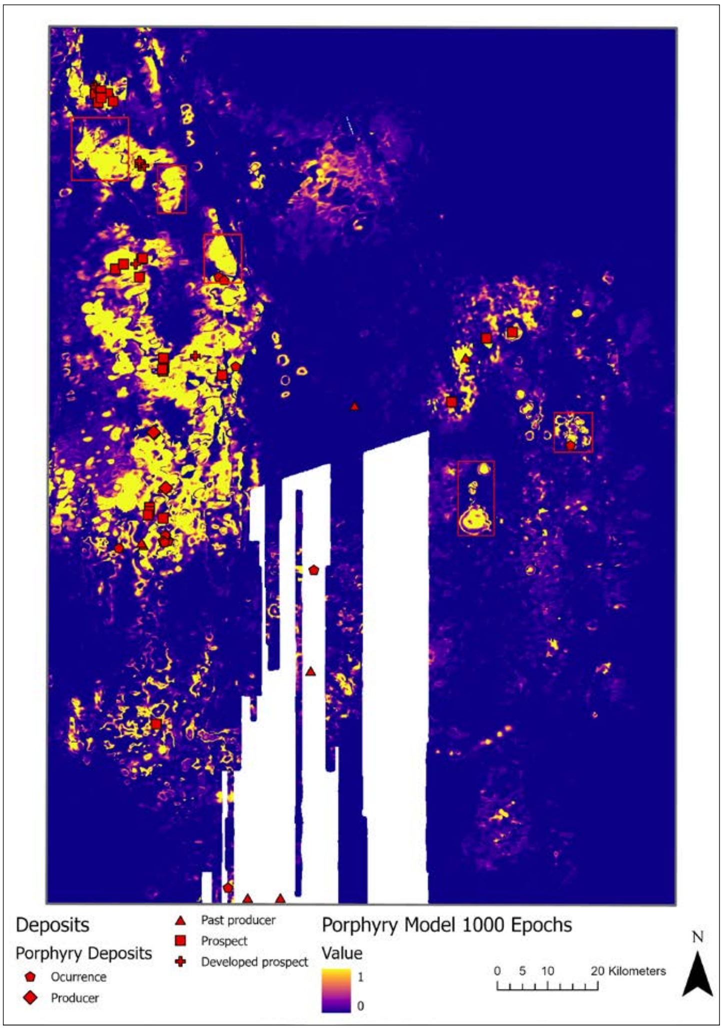

Fig. 1. Prediction map for porphyry deposits, with red squares marking the exploration targets suggested by the findings of the project.

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EXPLORATION TARGETING OF LITHIUM–SPODUMENE PEGMATITES IN THE KAUSTINEN REGION OF FINLAND

by

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This study describes prospectivity mapping of lithium-bearing spodumene pegmatites in the Kaustinen area of Finland using till geochemical and LiDAR-based glacial geomorphological data. The Li-pathfinder elements from till geochemistry data were used as input explanatory variables. Three prospectivity methods, weights-of-evidence, logistic regression and fuzzy logic-based overlay, were implemented for mapping the potential of Li-enrichment in the study area. The results from the weights-of-evidence and the logistic regression models show high capture efficiencies, with area under the curve values of 0.909 and 0.917, respectively. The fuzzy model, however, has a relatively low area under the curve value, i.e., 0.708. Nevertheless, the collective results from this study could be used to locate areas for detailed ground exploration and identification of new Li-rich pegmatites in the Kaustinen area.

INTRODUCTION

To facilitate the transition towards a low-carbon economy, the global demand for critical raw materials comprising metals and minerals needed for the development of green-technological products has been increasing rapidly. These include, for example, metals and minerals used in battery production such as lithium, cobalt and graphite. Lithium, in particular, is one of the most important battery metals because of the extensive use of lithium-ion batteries in modern technology.

Finland is one of the few EU countries with a high potential for lithium mineral resources. The main source of lithium is the spodumene mineral in LCT (Li, Cs, Ta) pegmatites. In Finland, such pegmatites occur in southern Ostrobothnia around Kaustinen, Somero-Tammela, Kitee-Tohmajärvi, Haapaluoma-Kaatiala, Eräjärvi, Seinäjoki, Heinola, Kisko, Kemiö and Kalajoki (Alviola 2012). The Kaustinen lithium area is one of the important provinces that contains several albite–spodumene pegmatite deposits, such as at Länttä, Emmes, Outovesi, Syväjärvi, Leviäkangas and Rapasaaret, for which mineral resource estimates have also been calculated. However, a systematic GIS-based mineral prospectivity analysis for Li resources does not exist for the Kaustinen area. This study therefore focused on data analysis and regional scale prospectivity mapping for the lithium potential in the Kaustinen area (Fig. 1) using different geostatistical methods.

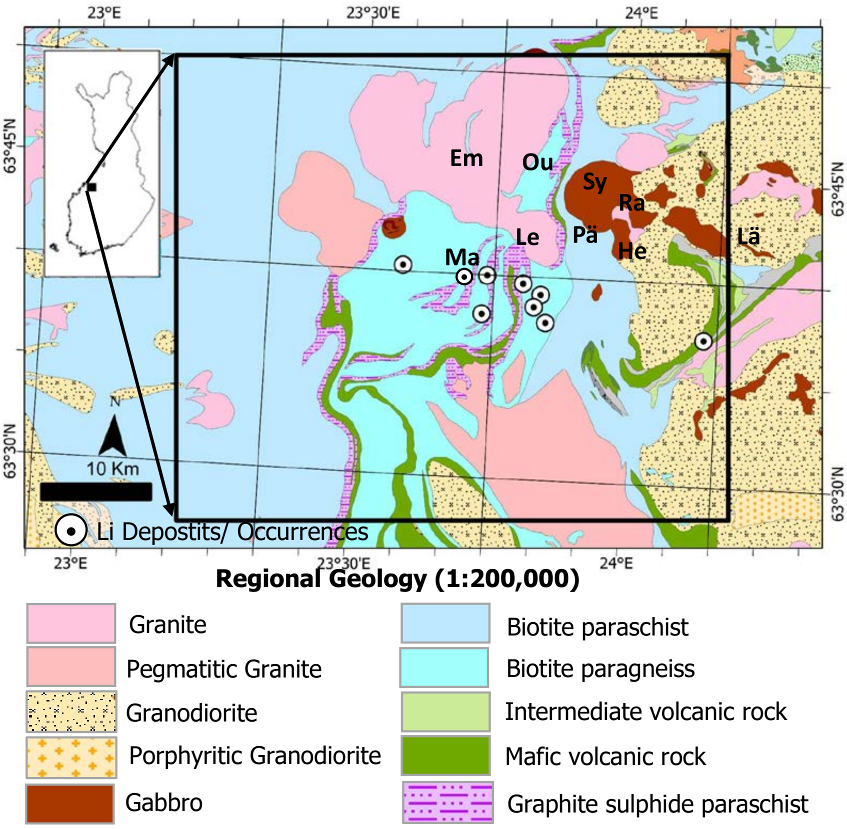

Fig. 1. The study area and a regional geological map of the study area with an overlay of known deposits and occurrences in the Kaustinen region. These are labelled as Sy: SyvŠjŠrvi, Ra: Rapasaaret, PŠ: PŠivŠnevŠ, He: Heikinkangas, Le: LeviŠkangas, Ma: Matoneva, Ou: Outovesi, Em: Emmes and LŠ: LŠnttŠ. (Chudasama & Sarala 2022)

DATA AND METHODOLOGY

This task was implemented using the Geological Survey of Finland's targeting till and bedrock geochemical data. In the Kaustinen area, the targeting till data comprise about 22,420 data points, sampled every 100–400 m along each sampling line; the inter-line spacing ranges between 500–2000 m (Gustavsson et al. 1979). This dataset has analytical data for 45 elements (major, minor and trace elements) measured across 14 measurement channels. For the current study, the Li-pegmatite pathfinder elements selected for spatial data analysis were As, Be, Bi, K, Li, Sb and Zr. The bedrock drilling data in this area around the known deposits were used to generate training points for Li-potential mapping. The workflow involved spatial data analyses, geostatistical data processing and prospectivity modelling using geological and geochemical datasets, integrated with estimated glacial transport directions and distances based on regional geomorphological interpretation (LiDAR DEM) models. GIS-based prospectivity mapping was implemented using three prospectivity methods, viz., fuzzy logic, weights-of-evidence (WofE) and logistic regression (LR). The multi-method modelling approach was implemented to account for subjective and statistical biases induced in each model because of inherent modelling assumptions. The results can hence complement each other and facilitate comparative analysis of exploration targets.

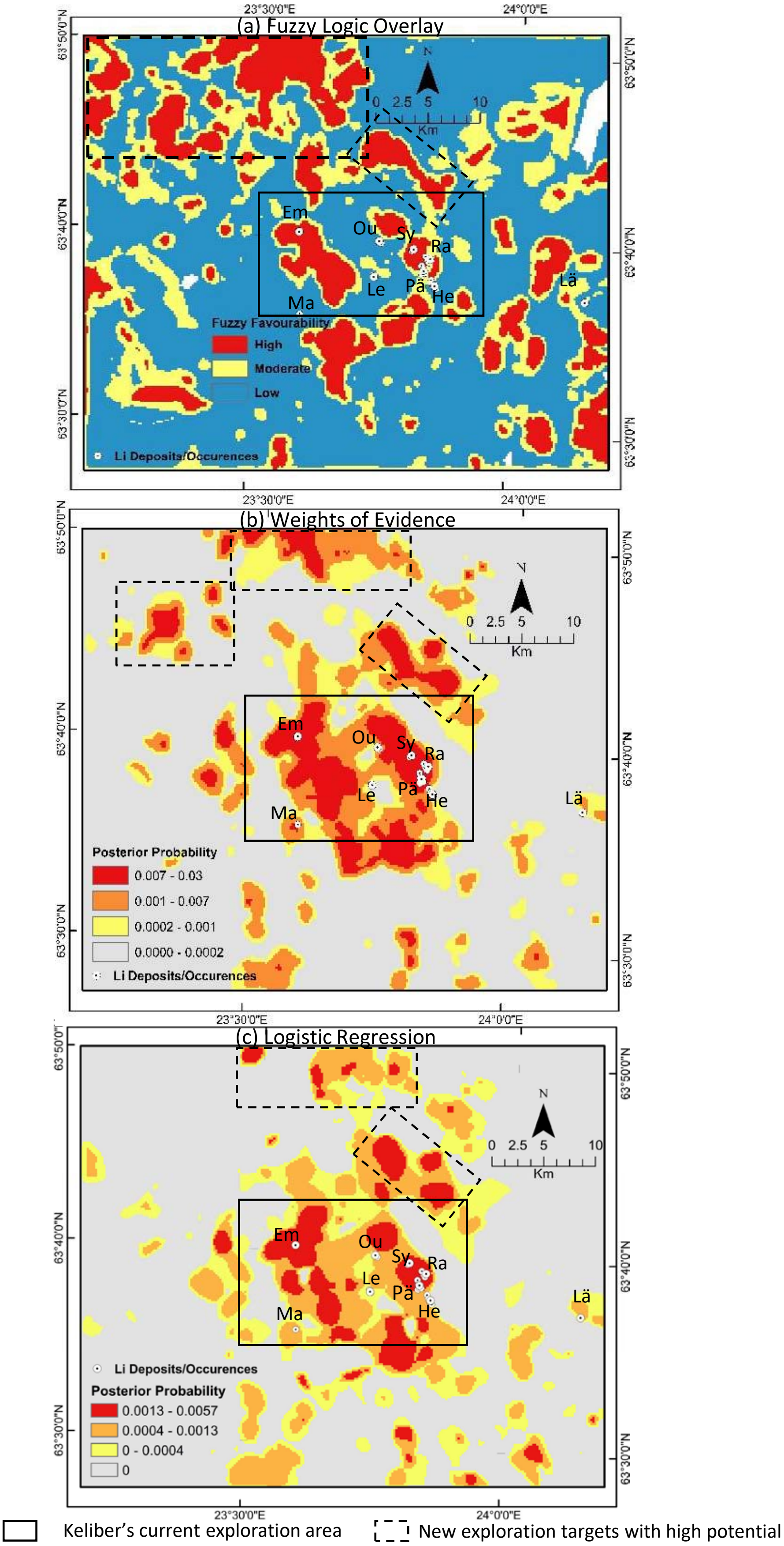

Fig. 2. Li-pegmatite potential maps for the study area in the Kaustinen region based in a) the fuzzy logic method, b) weights-of-evidence method and c) logistic regression method. For labelling of the deposits and occurrences, refer to the caption of Figure 1. Reproduced from Chudasama and Sarala 2022.

RESULTS AND CONCLUSIONS

Three prospectivity maps were created for mapping the potential of Li-enriched pegmatite in the Kaustinen area (Fig. 2). These maps capture the well-explored central region as highly prospective. The weights-of-evidence and logistic regression models show high capture efficiencies, with area under the curve values of 0.909 and 0.917, respectively. The fuzzy model has a relatively low area under curve value, i.e., 0.708. The Kaustinen area in Finland is a well-known Li province. A cluster of prospects (deposits and occurrences) exist in the central part of the study area (Figs. 1 and 2). All the prospectivity maps identify the central part hosting this cluster as a high potential area (Fig. 2). The results from this study additionally identify the unrecognized potential of lithium pegmatites outside the main central exploration area. The results from this study could hence be used to locate areas for detailed ground exploration activities and the identification of new Li-rich pegmatites in the Kaustinen area.

ACKNOWLEDGMENT

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ARTIFICIAL INTELLIGENCE (AI)-BASED EXPLORATION TARGETING FOR SMALL-SCALE GOLD MINING OPERATIONS IN THE DUNKWA AREA, GHANA

by

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The objective of the investigation programme in Ghana was to develop new exploitation targets suitable for artisanal and small-scale mining. The method used – AI-based evaluation of legacy data and closely focused field work – can help drive similar small-scale mining enterprises in Ghana and other countries.

INTRODUCTION

About 35% of Ghana's annual 142 t gold production (Ghana Chamber of Mines 2019) is produced by artisanal and small-scale mining (ASM) operations. Thus, they contribute substantially to Ghana's mining industry-generated national income and are an important factor in poverty reduction and national development. Because of declining production figures, exhausting resources and enormous ASM-related environmental damage, the Government of Ghana established the World Bank-financed programme "Ghana Artisanal and Small-Scale Mining Formalisation Project (GASMFP)" executed under the management of the National Ministry of Lands and Natural Resources and accompanied by the Ghana Geological Survey Authority. Among others, the generation of new exploitation targets suitable for ASM activities was one of the key tasks of this programme. The project aimed to develop, implement and test the integration of artificial intelligence (AI) methods into all steps of exploration targeting, from regional mapping using exclusively existing datasets to local scales by adding, where necessary, geochemical stream sediment and soil data, pitting and hard rock sampling (see Fig. 1).

DATA AND/OR METHODS

Artificial neural networks (ANN) are an excellent instrument for the identification of exploration targets. The approach was implemented in Beak's advangeo® 2D Prediction Ssoftware (Barth et al. 2014). The respective data processing workflow is presented in Figure 1. Using known mineral occurrences as training features and pre-existing geoscientific data as controlling parameters, exploration target maps were compiled in an iterative process using the steadily growing knowledge during the project as follows:

- at the beginning: using regional geophysical and geological data for identification of the general survey area;
- after legacy data collection: for detailed planning of the field survey programme; and
- at the end: consideration of all field data for final exploration targeting, follow-up work and programme design.

The interim target map was verified independently using the results of stream sediment sampling: the stream sediment Au anomalies matched very well with the main ANN-generated target areas. The results of ANN-based exploration targeting and stream sediment, auger and soil sampling confirmed each other.

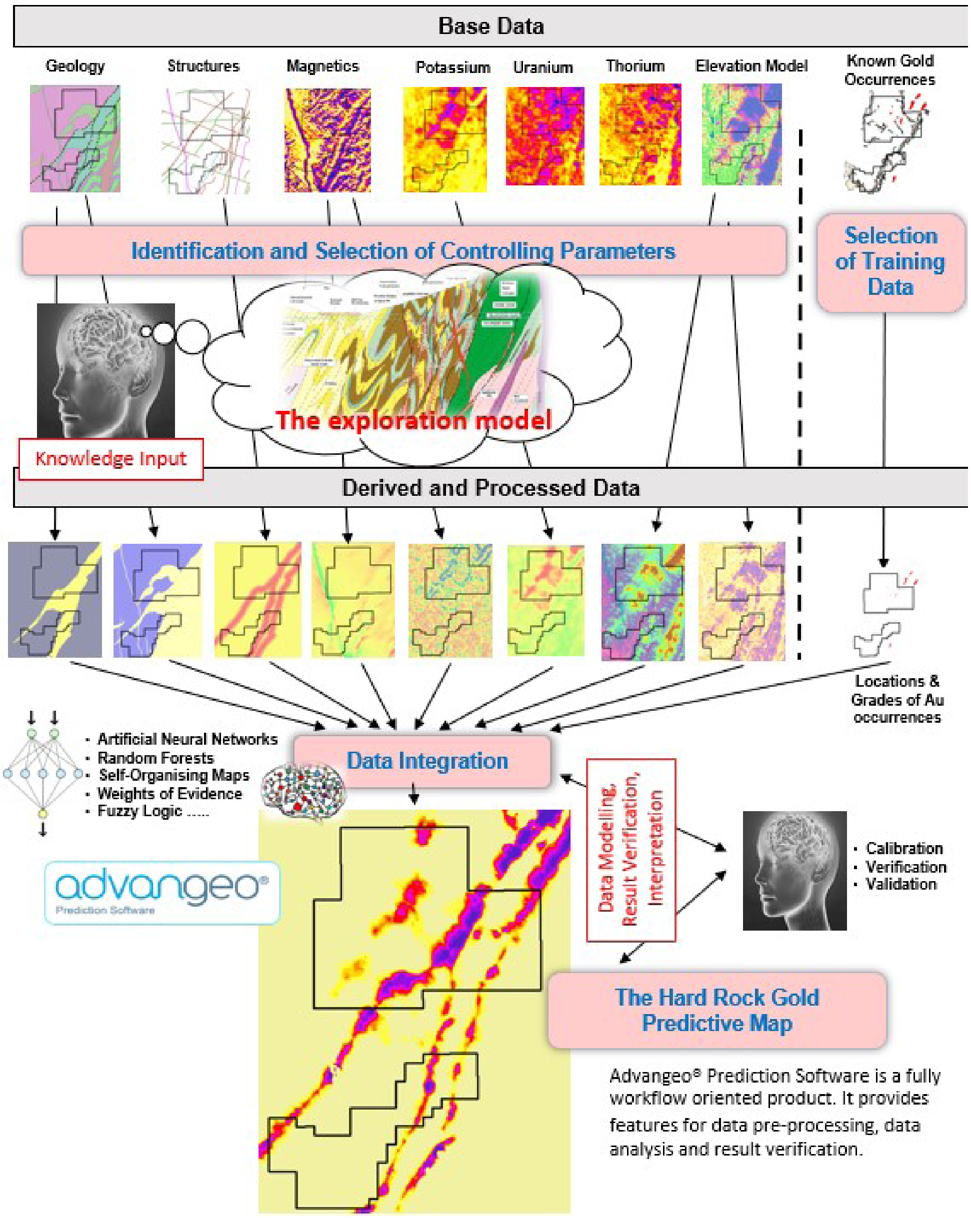

Fig. 1. ANN-based exploration targeting workflow implemented in advangeo® 2D Prediction software.

RESULTS AND DISCUSSION

The approach provided excellent technical results, leading to the identification of low-thickness high-grade quartz veins as potential ASM targets, and allowed exploration expenses and the project execution time to be minimized. Drilling targets are recommended for further detailed exploration activities (Fig. 2). The identified mineralisation type is considered to be suitable for traditional underground mining of low thickness veins using a combination of adits, drifts and overhead cuttings (Fig. 3). Compared with land-consuming low-grade placer mining, this mining method is much less land consuming but requires more technology and investment. The exploration targeting methodology tested in this case study could be applied in further similar activities throughout Ghana and in other countries as well.

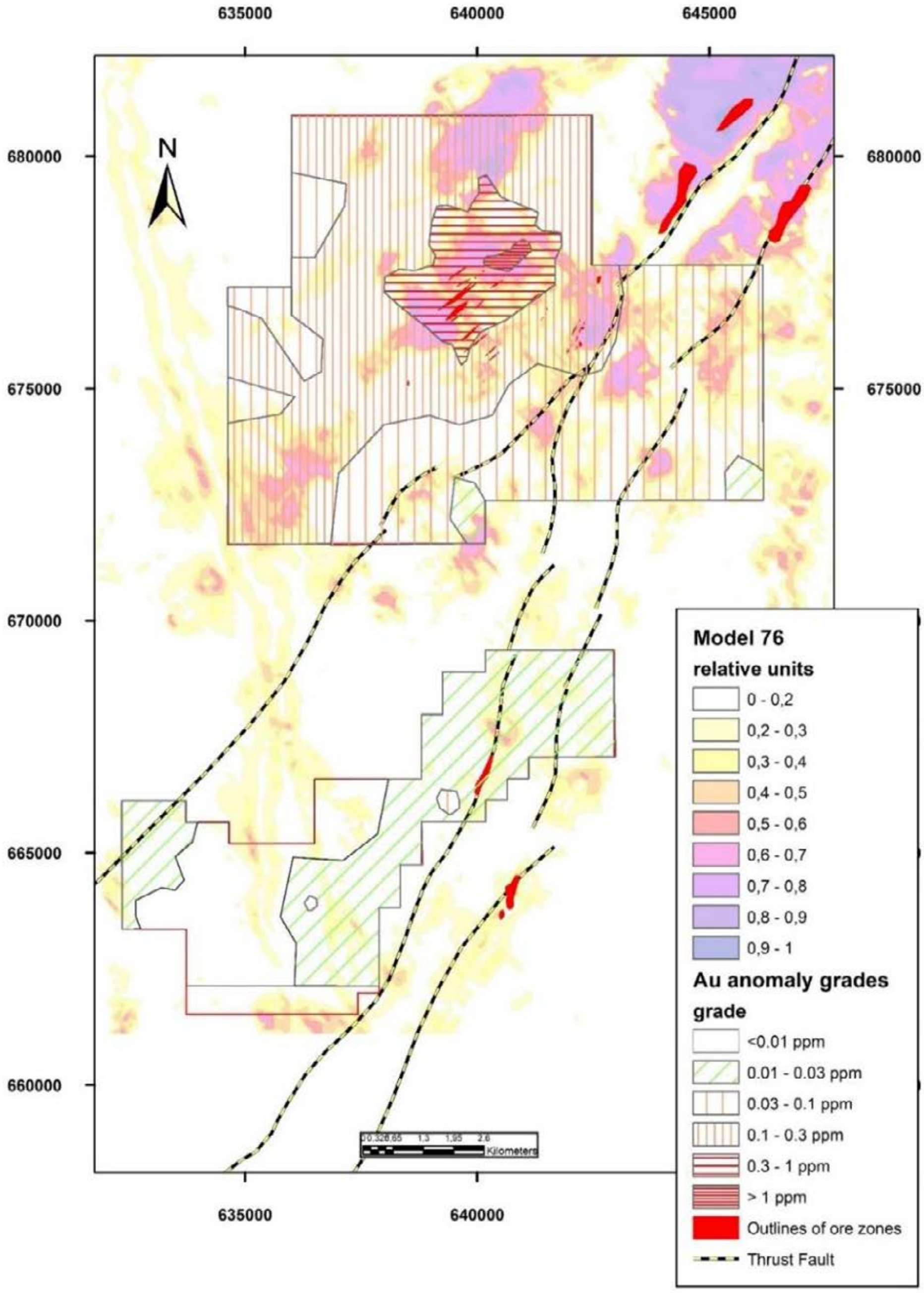

Fig. 2. The final target map, consisting of a combination of two independent datasets: stream sediment Au anomalies and ANN-based targeting using remote sensing data (radiometry and magnetics).

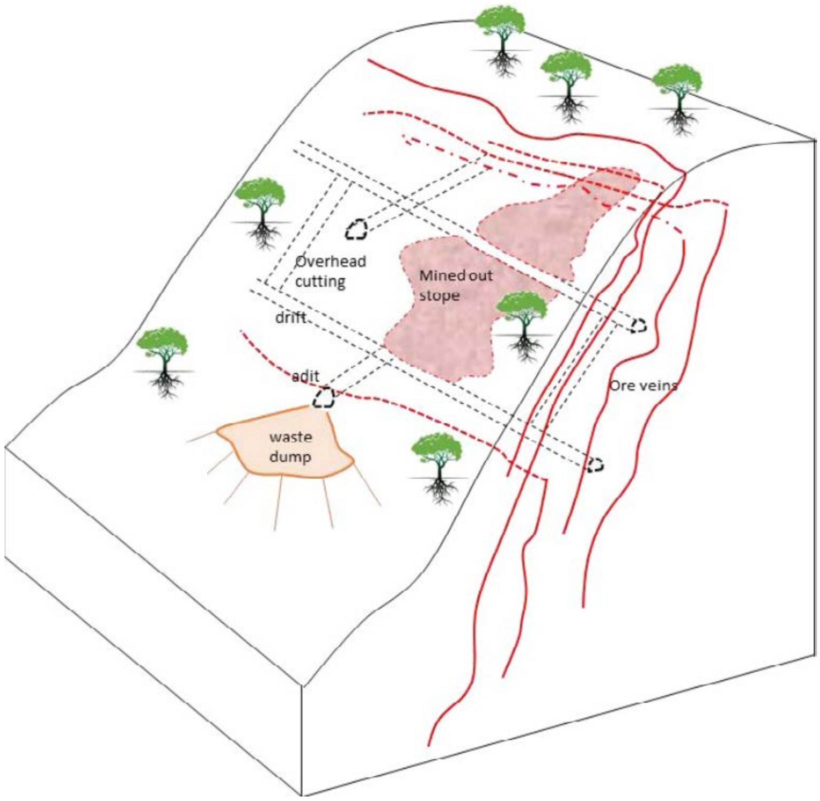

Fig. 3. The proposed mining technology consists of traditional vein mining using a system of adits, drifts, overcuttings and steep stopes.

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SNOW CHEMISTRY FOR EXPLORATION IN FINLAND: A WORKFLOW FOR RELIABLE RESULTS

by

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INTRODUCTION

Snow as an environmental sampling medium is mostly known only in relation to substances from the air, such as dust or pollen, in ice sheets or glaciers. However, earlier studies, from Russia and Canada, suggest that snow could also act as a catchment medium for metal ions migrating through the soil layers (Taivalkoski et al. 2019). Hence, could snow even possibly be used as a medium for capturing signals from bedrock? This would require that elements, as well as hydrocarbons, are released from the bedrock and migrate through the overlying transported cover, often glacial sediments, as ions or gases and are eventually captured by the snow. Naturally, the expected element concentrations in snow are very low, especially for snow that exists for only one winter season. However, snow as a sampling material would have the great advantage that the sampling and analytical methods have almost no impact on the environment.

In order to investigate whether snow could be used as a sampling medium in relation to the geological subsurface, and thus also for the detection of mineralization, snow was sampled within the framework of the EU project NEXT (New Exploration Technologies, Grant Agreement 776804) with regard to two questions: 1) Are the measured concentrations evaluable with regard to environmental properties, i.e., can they be measured reliably enough?, and 2) Does the element composition in the snow change significantly with changes in the bedrock lithology, independent of soil properties?

DATA AND METHODS

The test area is located in northern Finland, about 35 km west of the city of Rovaniemi. It is an Au-Co prospect, discovered by Mawson Gold Limited, within the northern part of the Peräpohja belt, between the Central Lapland Ggranitoid Ccomplex (CLGC) to the N and the Pudasjärvi complex to the SE (Vanhanen et al. 2015, Nironen 2017). The test area is approximately 7.5 km^2 in size, and is located in an ecologically diverse area with lakes, peatland, and mineral soils. Cook and Hudson (2018) described the major lithologies as reduced metasedimentary units with oxidized siliciclastic, albitized and carbonatized units, together with mafic rocks that are distributed within the oxidized and reduced sequences (lava flows, dykes and volcanoclastic sediments). These units are isoclinally folded and are host to the high-grade, strata-bound Au--Co mineralization, which is associated with hydrothermal alteration in reactive host rocks.

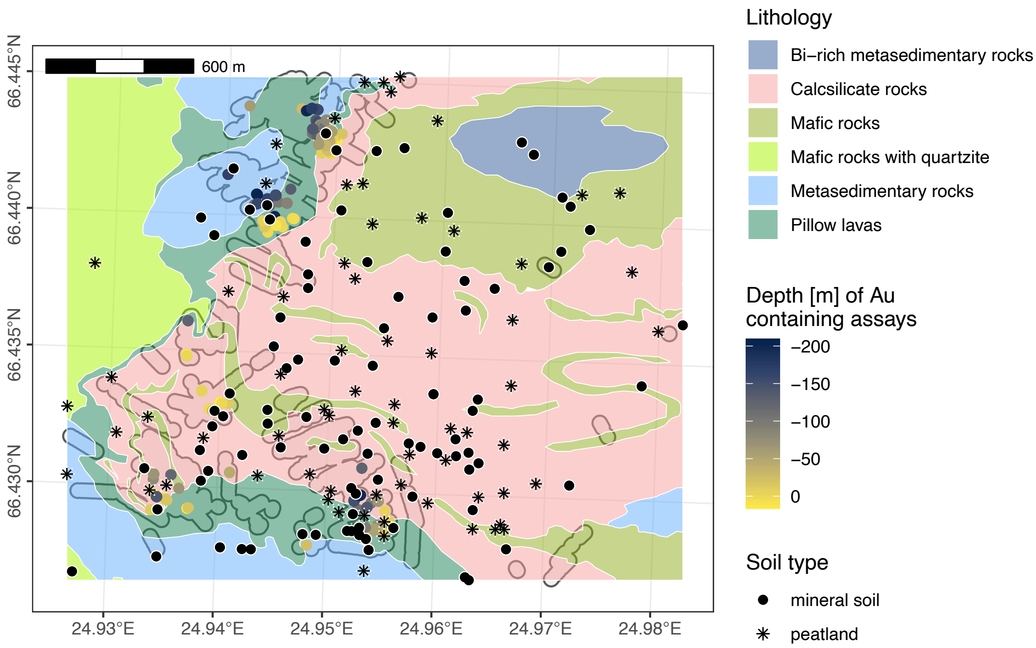

Fig. 1. Rajapalot geological map (modified from Mawson). Five prospects are indicated by known Au -mineralizations in the upper 200 m. Soil type indicates the surface property of the snow sampling location.

At 160 sampling locations, as shown in Figure 1, snow samples were collected for chemical analysis and pH measurements in March/April 2019 within a period of 14 days. The sampling design followed a stratified simple random sampling scheme (de Gruijter et al. 2006), where the strata were calculated by intersection of the map for soil type (peatland, mineral soil) and categorised geophysical measurements, the total magnetic intensity (TMI) and the electromagnetic response (VTEM). Each of the 18 strata had been sampled with 8 to 9 snow samples. For quality control, field replicate samples had been collected at 18 randomly chosen sampling locations.

Analytical methods and QAQC

All samples were analysed at the Geological Survey of Finland (GTK), using a Nu AttoM SC-ICPMS (Nu Instruments Ltd., Wrexham, UK). To ensure that the measured concentrations are not simply data noise, a three-part QAQC procedure was applied: 1) the measurement uncertainty from the counting statistics of the

ICP-MS software was not allowed to exceed 20% on average per element, 2) 40 lab replicate measurements were used to estimate the measurement uncertainty for the measurement procedure, which should be less than 50% on average per element, and 3) the field replicate samples were used to estimate which elements show very small-scale (<2 m) strong fluctuations, and are thus unsuitable for the detection of geologies. The elements B, Ba, Ca, Cs, Li, Mg, Rb, Sr, Tl, and V all met these conditions.

Data handling and statistical methods

The concentrations can depend strongly on how mobile ions are produced and transported from bedrock and soil and how effectively the snow has retained the ions, i.e. how much "pure" snow material dilutes the concentrations. To evaluate the elemental pattern, it is therefore important to look not at the concentrations, but at the ratios of the concentrations. This can be achieved, for example, by applying log-ratio transformations, such as those formalized in the compositional data analysis approach, CoDa (Aitchison 1986, van den Boogaart & Tolosana-Delgado 2013).

Whether the elemental patterns in the snow depends on soil properties and/or lithological characteristics was tested using statistical tests (MANOVA for categorical variables and a linear model for continuous data), where the response variable was the measured elemental composition, represented as scores of an isometric log-ratio transformation (Egozgue et al. 2003), and the explanatory variables were soil type, various soil properties, and the aforementioned geophysical and lithological categories. For tests that were statistically significant, the test was repeated, this time using pairwise log-ratios of the snow data, one by one, as the response variable. This allowed the determination of which element subcompositions were influenced by the respective surface or subsurface property.

RESULTS AND DISCUSSION

Element concentrations in snow ranged from 1 ng/L to 6000 ng/L, depending on the element. Despite the sometimes very low concentrations, the elements selected by the QAQC procedure have shown resilient data. The most important influence on the geochemistry of snow is the soil type, i.e., whether snow is sampled on mineral soil or on peatland. For example, Rb is relatively more concentrated on mineral soil, while Li and Ca tend to be more concentrated on peatland. All the other tested properties, i.e., soil pH, soil pore water conductivity, soil conductivity, soil dielectric permittivity, organic matter thickness and overburden thickness, showed no influence.

With respect to subsurface properties, the signals are much weaker, as expected, but the statistical tests were still significant. For the geological units, especially B and V show distinct features, e.g., B is particularly highly concentrated over units consisting mainly of pillow lavas, while V is depleted over the calcsilicate units, among others (see Fig. 2). Since these two elements are certainly not influenced by known surface properties, and especially not by soil type, it can be assumed with some certainty that the occurrence of the elements in snow is indeed influenced by the lithologies in the subsurface.

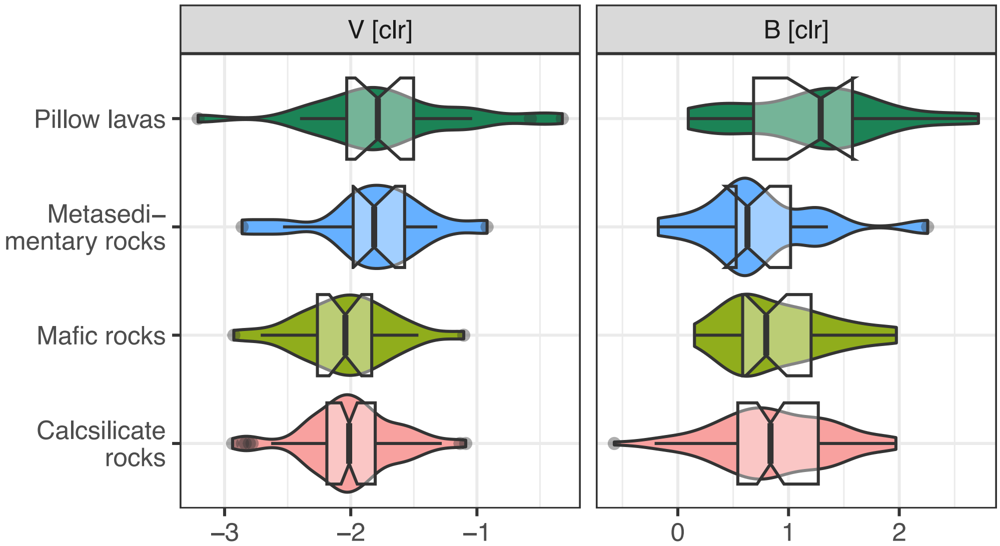

Fig. 2. Element centred log-ratio (clr) scores for V and B with respect to the lithological map, shown in Figure 1. Clr scores show the log-ratio of concentrations to the geometric mean of the measured composition. This allows for visualization in plots to reduce the effect of concentration dilutions, to better show positive results of the log-ratio tests.

Samples above the mineralization, however, were not statistically significantly different from samples in background areas. Nevertheless, a discrimination function between an "on" deposit and an "off" deposit could be calculated using linear discriminant analysis (LDA). This LDA uses the ilr-transformed concentration data (ilr-LDA) and also includes the individual measurement data uncertainties of the samples and elements (Pospiech et al. 2021). It was important here not to include elements that were particularly strongly influenced by surface properties and lithologies. Using ilr-LDA, this allowed a good separation of the two groups of "on" and "off" deposits. Thus, it could be shown that it is possible to calculate predictive models for mineralization on the basis of snow data, taking into account the influence of surface and subsurface properties.

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UAV-SUPPORTED ALTERATION AND STRUCTURAL MAPPING OF CU–PORPHYRY AND AU EPITHERMAL SYSTEMS FOR EXPLORATION TARGETING

by

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´A UAV-based survey with a combined RGB and TIR camera was utilized and tested for hydrothermal alteration mapping and targeting for copper and gold mineral exploration in the Vlaykov Vruh Cu–porphyry deposit and Pesovets and Petelovo Cu–Au epithermal systems, Panagyurishte ore district, Bulgaria.

INTRODUCTION

The Panagyurishte ore district, Bulgaria, is situated in the Srednogorie zone in the western part of the global Cu-Au-dominant Tethyan-Eurasian Cu–Au metallogenic belt (Bogdanov 1987, Popov et al. 2012, Richards 2015). The belt extends eastwards from Europe through Turkey, Asia and Malaysia. The Cu–Au epithermal ore deposits (Elshitsa Radka, Krassen) and closely associated Cu–porphyry deposits (Vlaykov Vruh, Tsar Assen, Pepelovo) were an enticing target for geological studies and exploration during the last century. The Panagyurishte area is typified by thick volcanic sequences and relatively shallow intrusions. Coeval Cu–Au epithermal ore deposits occur in andesite–dacite volcanic sequences (91.5–85Ma U/Pb age; von Quadt et al. 2005) closely associated with Cu–porphyry deposits

Targets for further prospecting are porphyry–copper and epithermal gold occurrences associated with silica caps around the explored old mines, which need reassessment as possible targets for Cu and Au exploration.

DATA AND METHODS

Field geological mapping of alteration minerals, tectonic structures and breccias, combined with remote sensing satellite data (Sabine 1999, Amin & Mazlam 2012) and UAV-supported mapping (Bogdanov et al. 2021), is an important and efficient approach for mineral deposit prospecting, target evaluation and decision-making for mineral exploration of Cu–porphyry and Au–epithermal systems. When distal sensing is combined with field mapping and proximal modern mineral detection methods such as SWIR (1300–2500 nm) and Raman spectroscopy, XRD and ore petrography is a more efficient tool for the detection of hydrothermally altered minerals and zones based on their diagnostic spectral signatures.

The examples below present UAV-based survey results by means of a DJI Matrice 300 RTK Combo with a Zenmuse H20T combined RGB and TIR camera that was utilized and tested for hydrothermal alteration mapping and targeting for copper and gold mineral exploration in the Vlaykov Vruh Cu–porphyry deposit and Pesovets and Petelovo Cu–Au epithermal systems.

RESULTS AND DISCUSSION

Vlaykov Vruh Cu–porphyry deposit

UAV-supported TIR mapping of the Vlaykov Vruh porphyry copper deposit with alteration mineral assemblages detected by XRD outlined phyllic (Qz-sericite) alterations hosted in the dacitic and andesitic volcanic rocks and propylitic (quartz–albite–chlorite) alteration zones in the granodiorite porphyry intrusion. The latter could also be discriminated by a higher thermal response (lighter colour) as compared with the subvolcanic dacitic rocks (Fig. 1).

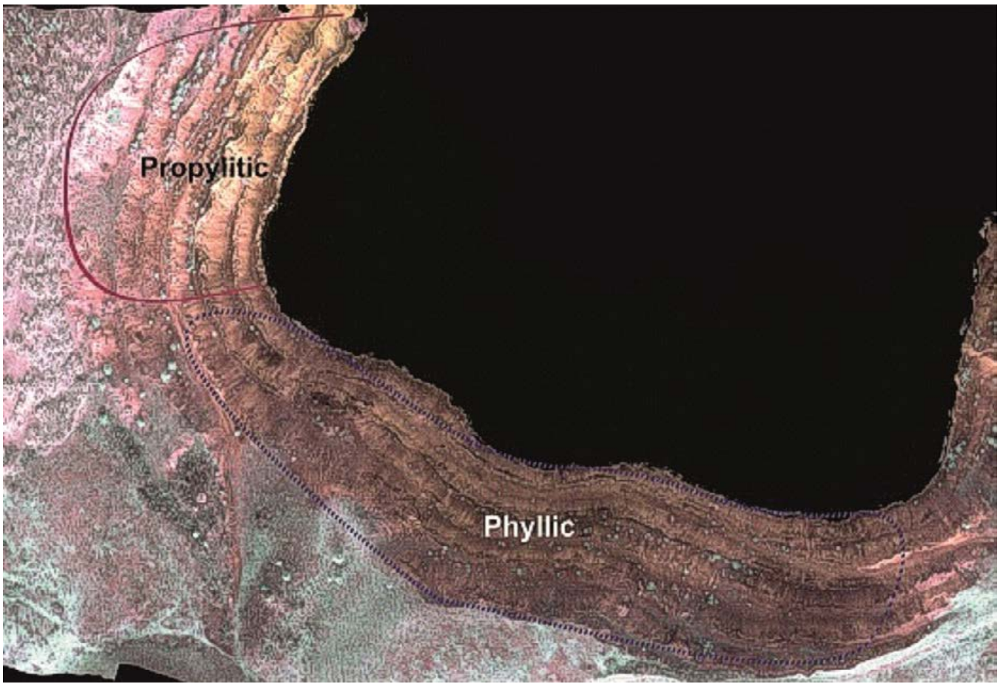

Fig. 1. Propylitic and phyllic alteration domains in the Vlaykov Vruh porphyry–copper deposit as outlined by TIR and XRD mapping.

Pesovets epithermal gold deposit

The Pesovets volcanic neck with radial and concentric fault structures in addition to some regional fault zones were clearly outlined during the UAV-supported survey. Mineral alteration mapping of the Pesovets silica cap outlined overlapping advanced argillic and argillic fault-controlled proximal and more distal propylitic domains (Fig. 2a) as potential high-sulphidation gold mineral exploration targets for further evaluation. Alunite, Na-alunite-1c, APS minerals (svanbergite), dickite, kaolinite, topaz and rutile, in addition to albite, analcime, muscovite, phlogopite, montmorillonite, magnetite, pyrolusite, hematite, goethite and anatase were detected by their spectral signature by means of XRD, Raman and SWIR spectroscopy in the argillic and advanced argillic zones around Pesovets peak in the pervasively silicified andesitic lavas, tuffs and breccias. The Cu in the Qz–topaz-rich zone, as indicated by the field Skyray Explorer 7000 XRF study, varies from 6.48 to 11.82 ppm in the argillic domain, while in the advanced argillic part it varies from 17.38 to 50.03 ppm in a good correlation with As, which may assist in defining the geochemical signature of different alterations and mineralized zones.

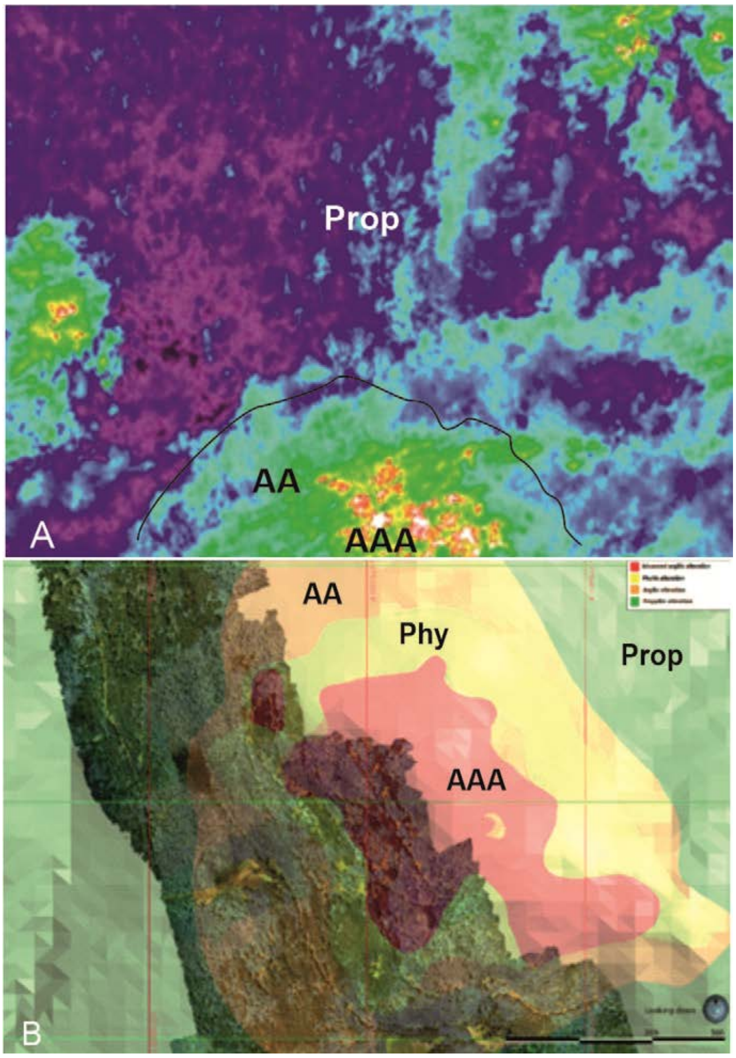

Fig. 2. a) TIR mapping of advanced argillic, argillic and propylitic domains in the Pesovets silica cap; b) UAV-supported alteration mapping with a 3D Leapfrog Geo model of the Petelovo volcanic cone.

Petelovo epithermal gold deposit

The Petelovo epithermal high sulphidation gold deposit is situated about 8 km E–SE of the town of Panagyurishte. The deposit is genetically related to the Petelovo volcanic structure, which consists of pyroxene-bearing andesitic lavas, breccias and tuffs. Quartz-diorite and granodiorite porphyrites were developed at depth in a volcano-plutonic structure. The UAV-based survey combined with 3D alteration modelling with Leapfrog Geo in the Petelovo silica cap outlined well-defined advanced argillic and argillic zones with 3–20 g/t Au around the central part of the pervasively silicified andesitic lavas and breccias, with massive and vuggy silica and a more distal propylitic zone (Fig. 2b). Concentric and radial fault zones of the Petelovo volcanic cone, in addition to NW- and NE-trending faults, have also been outlined during the UAV -supported mapping. The recent study examples demonstrate new applications based on UAV-supported alteration mapping for mineral prospecting as a cost-efficient tool for quick exploration targeting and evaluation of porphyry and epithermal systems.

ACKNOWLEDGEMENTS

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SCHEELITE AS AN INDICATOR MINERAL: INSIGHTS FROM THE RAJAPALOT AU–CO DEPOSIT, NORTHERN FINLAND

by

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As a part of a regional heavy mineral study, scheelite textures and compositions were characterized from the Rajapalot Au–Co deposit in northern Finland. The petrographic observations, CL textures and LAICP-MS trace element analyses revealed eight distinct types of scheelite in the deposit, and the overall trace element contents in these scheelite grains differed from the reported scheelite compositions from orogenic gold deposits. We interpret that this reflects the redox conditions and atypical fluid chemistry related to the formation of Rajapalot scheelite and the Au–Co mineralization. The compositional distinctiveness of Rajapalot scheelite suggests potential for its successful use in heavy mineral studies.

INTRODUCTION

Scheelite has traditionally been used as an indicator mineral in the exploration of W and Au deposits (McClenaghan & Paulen 2018). The EIT Raw Materials-funded MinExTarget project is probing the limits of scheelite indicator mineral potential by testing whether glacial till-hosted scheelite compositions can be used as an indicator of adjacent bedrock mineralization. The prototype study location of the MinExTarget project is the till-covered area around the Rajapalot Au–Co deposit in northern Finland. As a crucial first phase of the study, we have characterized the compositional range of scheelite in this deposit. Our analysis revealed eight distinct textural and compositional types of scheelite, with overall compositional ranges differing from the typically reported values from orogenic gold deposits.

The Rajapalot Au-Co deposit is one of the orogenic gold mineralizations of Finland with an atypical metal association (e.g., Cu, Co, Ni and U), located near the northern edge of the Palaeoproterozoic (2.4–1.9 Ga) Peräpohja Belt (PB) in Finnish Lapland (Ranta et al. 2018). PB is a 170-km-long, 80-km-wide and 5-km-thick supracrustal belt of deformed and metamorphosed volcanic and sedimentary rocks deposited in both continental and marine environments, and later metamorphosed up to greenschist facies in the south and amphibolite facies in the north. The Rajapalot deposit is the most significant finding from PB, with an inferred mineral resource of 10.9 million tonnes at a grade of 2.5 g/t gold and 443 ppm cobalt by

Mawson Oy in 2021 (Rantala et al. 2021). The Rajapalot Au–Co resource is hosted within six separate ore bodies: Raja, Rumajärvi, the Hut, Palokas, South Palokas and Joki-East. The elevated Au–Co contents at Rajapalot are associated with 1–10% sulphides: pyrrhotite, pyrite and minor chalcopyrite, cobaltite, Au, Bi–Te-rich phases, molybdenite, scheelite, wolframite, monazite and traces of uraninite and thorite. The mineralized sections typically occur in two litho-tectonic domains: 1) brittle deformed albitite and albitite breccia and 2) ductile sheared micaceous metasediments and foliated muscovite–biotite schists. At Palokas, the host rock is an altered chlorite–Mg–Fe amphibole–pyrrhotite rock, inferred to have a mafic or ultramafic igneous protolith.

METHODS

Scheelite has been extensively studied based on the cathodoluminescence (CL) texture, trace elements and REE patterns from a large number of various deposits (e.g., Poulin et al. 2018, Sciuba et al. 2020). Recently, multivariate exploratory analysis has been successful in discriminating between mineral deposit types and characterizing ore-forming processes (Sciuba et al. 2020). In this study, we characterized scheelite with petrographic observations, SEM-CL imaging and LA-ICPMS trace element analysis from 21 Rajapalot drill core samples from Raja, Rumajärvi, the Hut and South Palokas ore bodies, and compared the results with available literature data on worldwide scheelite compositions using multivariate data reduction techniques.

RESULTS AND DISCUSSION

Detailed petrographic observations led to the identification of eight textural scheelite varieties: 1) fracture, 2) disseminated, 3) vein, 4) disseminated foliation, 5) foliation, 6) sulphide foliation, 7) scheelite–wolframite lenses and 8) wolframite replacement (Fig. 1). In scheelite–wolframite lenses and in fracture fillings, scheelite occurs together with wolframite in equilibrium, whereas in muscovite–biotite schist, primary wolframite is replaced by scheelite.

Most scheelite texture types have bright and homogeneous CL typical for orogenic deposits, but the disseminated, foliation, and fracture-type scheelites showed weak CL zoning and sector zoning (Fig. 1), which are more commonly observed from magmatic-hydrothermal deposits (Poulin et al. 2018).

Scheelite LA-ICPMS trace element results revealed 11 trace elements (Na, Mg, Si, P, S, Mn, As, Sr, Y, Nb and Mo) and REEs with a mean concentration above 5 ppm, with large variation in the contents of these elements between scheelite texture types. The contents of Sr, Mo, and As, elements used for discrimination of ore-forming processes and deposit types, vary greatly within the deposit and are atypical for most orogenic gold deposits. Molybdenum contents in scheelite, with a mean of 65 ppm, are higher in all but three textural types compared to the typical orogenic gold values (<10 ppm). In addition, the average As content (39 ppm) in Rajapalot scheelite is higher than typical orogenic gold (9 ppm) but lower than magmatic (312 ppm) or hydrothermal vein (76 ppm) scheelite. The most striking compositional feature in Rajapalot scheelite is the low average Sr compared to literature data on orogenic (987 ppm) or magmatic (387 ppm) mineralization.

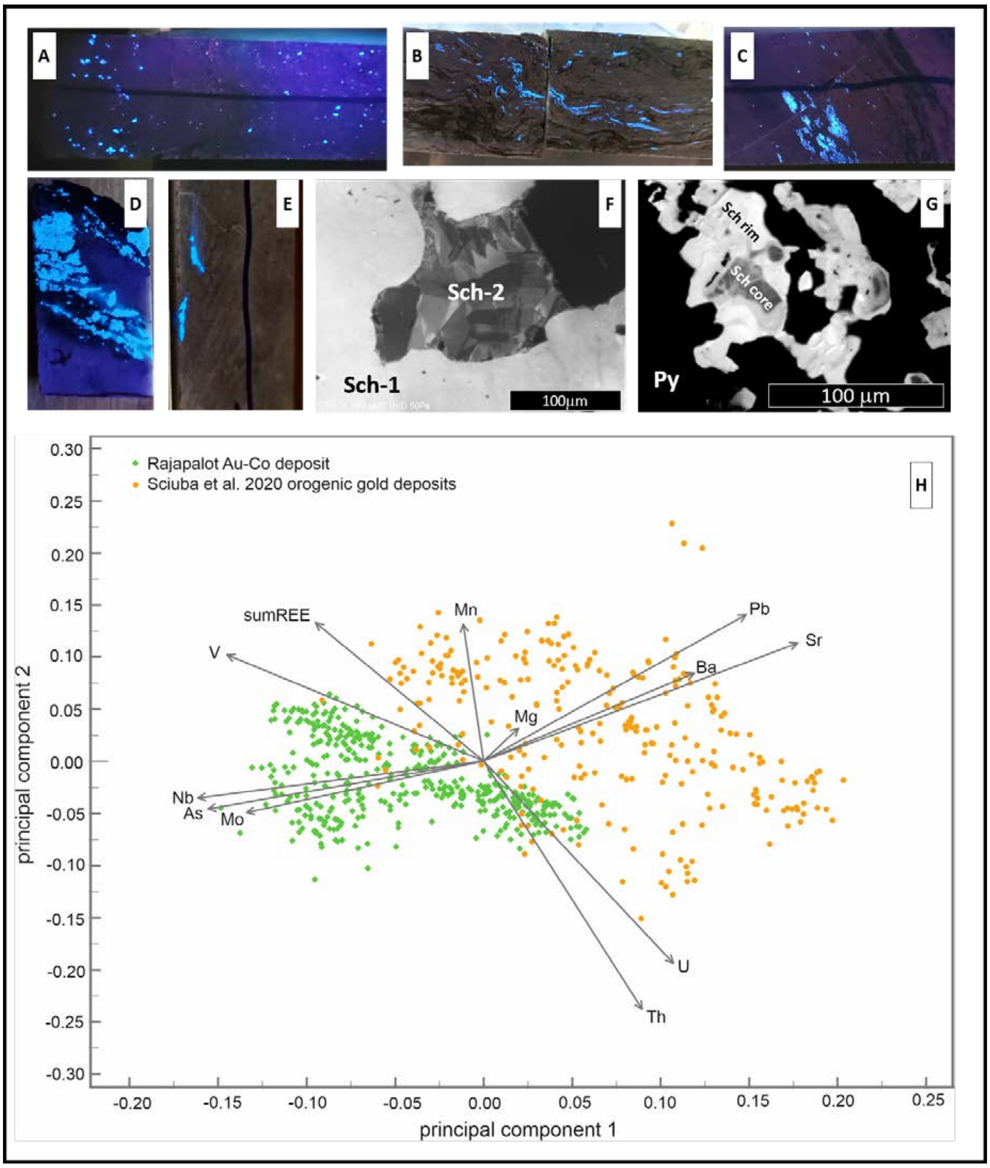

Fig. 1. Rajapalot scheelite. 1) UV-light core macrophotographs, scale: halved HQ core (A–E): A, disseminated scheelite; B, foliation-parallel scheelite; C, scheelite-wolframite lenses; D, quartz-apatite-scheelite veins; E, fracture-filling wolframite-scheelite. 2) SEM-CL images: F, bright homogeneous (Sch-1) and dark sector-zoned scheelite (Sch-2); G, image of strongly zoned, dark-cored scheelite. 3) H. PC1 vs PC2 plot of PCA discrimination projection, showing separation from a typical orogenic gold– scheelite composition.

The SREE content of Rajapalot scheelite ranges from 28 ppm (vein type) to 2527 ppm (disseminated type), with a mean of 665 ppm for all grains analysed. SREE varies greatly between samples and textural types. Even within individual grains, SREE, the shape of the CN-REE profile and Eu_A vary significantly. Concave bell-shaped CN-REE profiles are typical, with the highest SREE contents and largest negative Eu_A, whereas flat or convex CN-REE profiles are common, with low SREE contents and the most positive Eu_A. The complex and highly variable SREE, CN-REE profiles and Eu_A observed imply that numerous factors, such as redox, pH, lithology buffer by extensive albitization, co-precipitating minerals and wolframite-scheelite equilibrium, may control these values.

Exploratory data analysis indicates that several trace element and REE substitution mechanisms may control the observed trace variation in Rajapalot scheelite, including the direct and coupled substitution with the 8-coordinated Ca^{2+} and tetrahedral W^{6+} sites. In bivariate trace element discriminatory diagrams for scheelite (Poulin et al. 2018), the Rajapalot scheelite compositions plot inconclusively between metamorphic and magmatic–hydrothermal fields. Supervised (discriminant projection analysis) and unsupervised (principal component analysis) multivariate discrimination methods further imply compositional independence of Rajapalot scheelite. Overall, the compositions of Rajapalot scheelite appear distinct but more affiliated to orogenic gold deposit scheelite than scheelite from other deposit types.

We interpret that elevated Mo and As values in Rajapalot scheelite indicate slightly more oxidizing conditions than is typical for most orogenic fluids. This finding is supported by mineralogical observations: rutilated ilmenite and the occurrence of magnetite in some samples. In addition, the very low Sr content and the compositional distinctiveness of Rajapalot scheelite implied by the multivariate analysis are signs of a somewhat atypical fluid chemistry. These identified compositional characteristics may be useful in identifying "Rajapalot deposit-type" scheelite grains in heavy mineral studies.

CONCLUSION

The fluids in the Rajapalot Au–Co deposit that crystallized scheelite were different from typical metamorphic mineralizing fluids. Trace element results and mineralogical observations suggest more oxidizing conditions than are typical for orogenic gold deposits. Understanding these atypical orogenic fluids better could lead to improved exploration models and greater success in discovering these valuable gold deposits with critical/battery metal by-products.

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