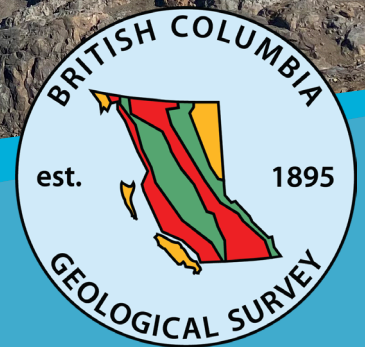




Pan-Canadian workshop on mineral potential modelling, September 23, 2025, program with extended abstracts



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Pan-Canadian workshop on mineral potential modelling, September 23, 2025, program with extended abstracts

Workshop steering committee

Marc-André Brideau, British Columbia Geological Survey
Virginie Daubois, Géologie Québec
Adrian Hickin, British Columbia Geological Survey
Christopher Lawley, Carleton University
Curran Wearmouth, British Columbia Geological Survey

Ministry of Mining and Critical Minerals
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Program (Pacific Standard Time; * speaker)

- 08:00-08:15 **Acknowledgement of traditional lands and opening remarks**
Marc-André Brideau, British Columbia Geological Survey, British Columbia Ministry of Mining and Critical Minerals
- 08:15- 08:30 **Adrian S. Hickin***, Marc-André Brideau, British Columbia Geological Survey
Introduction to the Mineral Potential Modelling Workshop and its connection to the Pan-Canadian Geoscience Strategy
- 08:30- 08:45 **Guilherme Ferreira**, Brazil Geological Survey
Mineral potential modeling in Brazil: previous experiences and new challenges
- 08:45- 09:00 **Andreas Knobloch**, Beak Consultants, Freiberg, Germany
Mineral predictive mapping using machine learning: Selected case studies and lessons learned from work over 20 years
- 09:00- 09:15 Emily Barner, Policy Legislation and Competitiveness Branch, British Columbia Ministry of Mining and Critical Minerals
Bryan Mitchell*, Strategic Indigenous Partnerships Division, British Columbia Ministry of Mining and Critical Minerals
Mineral potential mapping: A planner's perspective
- 09:15- 09:30 **Break**
- 09:30- 09:45 **Christopher Lawley***, (Carleton University) Steven Zhang, Mohammad Parsa (Geological Survey of Canada)
Mineral potential modelling past, present, and future
- 09:45- 10:00 **Mohammad Parsa***, (Geological Survey of Canada), Christopher Lawley (Carlton University), Steven Zhang, and Renato Cumani (Geological Survey of Canada)
Interpretable pan-Canadian mineral potential models
- 10:00- 10:15 **Steven Zhang***, Christopher Lawley (Carleton University), and Mohammad Parsa (Geological Survey of Canada)
Uncertainty in data-driven mineral prospectivity mapping with an emphasis on sources idiosyncratic to mineral exploration
- 10:15- 10:30 **David Diekrup***, John Hinchey, Geological Survey of Newfoundland and Labrador
Mineral potential modelling in Newfoundland and Labrador: Applications, challenges, and future directions
- 10:30- 10:45 **Donald Burden***, Angie Barras, Nova Scotia Department of Natural Resources, Geological Survey Division
Holistically modelling the critical mineral potential of Nova Scotia
- 10:45- 11:00 **Amirabbas Karbalaieiramezanali***, Serge Allard, Aaron Bustard, Kay Thorne, Geological Surveys Branch, New Brunswick Department of Natural Resources
Mineral potential modelling in New Brunswick, Canada: Recent advances and key projects
- 11:00- 11:15 **Virginie Daubois***, Fabien Solgadi, Géologie Québec, Ministère des Ressources naturelles et des Forêts, Gouvernement du Québec
Two decades of mineral potential modelling in Québec: Geoscientific knowledge at the core of Géologie Québec's work
- 11:15- 11:30 **Break**
- 11:30- 11:45 **Marc L. Rinne**, Manitoba Geological Survey
Mineral potential assessments and related updates to mineral occurrence data in Manitoba
- 11:45- 12:00 **Michael Raiwet**, Saskatchewan Geological Survey
Mineral potential in Saskatchewan: Background, method, and recent developments
- 12:00- 12:15 Curran Wearmouth, **Marc-André Brideau***, British Columbia Geological Survey
Evolution of mineral potential modelling at the British Columbia Geological Survey: Historical foundations, current practices, and future directions
- 12:15- 12:30 **Tyler Acorn**, Northwest Territories Geological Survey
Northwest Territories Geological Survey mineral and energy potential modelling overview
- 12:30- 12:45 Alex Brubacher, Patrick Sack, **Jan Dettmer***, Yukon Geological Survey
Territory-scale mineral potential mapping for Yukon
- 12:45-13:45 **Group discussion**
- 13:45-13:50 **Closing remarks**
Marc-André Brideau, British Columbia Geological Survey, British Columbia Ministry of Mining and Critical Minerals

Introduction to the Mineral Potential Modelling Workshop and its connection to the Pan-Canadian Geoscience Strategy

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The Pan-Canadian Geoscience Strategy (PGS) is a federal, provincial, and territorial initiative aimed at enhancing the coordination, accessibility, and impact of geoscience across Canada (NGSCC, 2022). Developed in response to calls from governments, industry, and stakeholders, the strategy seeks to align public geoscience efforts that support priorities such as the Canadian Minerals and Metals Plan and the various federal, provincial, and territorial critical mineral and mining strategies. It emphasizes the essential role that geoscience contributes to Canada's economic competitiveness, investment attractiveness, and innovation through digital technologies.

The PGS is structured into five priority areas: 1) advancing framework geoscience; 2) enhancing mineral and energy potential modelling; 3) improving access to geoscience data; 4) supporting geoscientist training; and 5) increasing public literacy in geoscience. Priority area 2 focusses on enhancing Canada's ability to assess and predict mineral and energy resources through advanced modelling, integrated geoscience data, and cross-jurisdictional collaboration. Mineral potential modelling supports land-use decisions by identifying areas with high potential for undiscovered mineral deposits, helping planners balance development with environmental and community values (e.g., Brown, 2012; Bullen, 2020; British Columbia Geological Survey, 2025). It guides responsible exploration and conservation efforts to protect sensitive areas and highlights prospective areas for critical minerals vital for clean technologies. Mineral potential information encourages the consideration of mineral exploration and mining interests while fostering transparency and building public trust.

Mineral deposits are not randomly distributed and form in specific geological environments during distinct periods in Earth history. This spatial and chronological predictability underpins the rationale for mineral potential modelling, enabling the identification of prospective areas through systematic analysis of geoscience patterns. Mineral potential modelling is used to characterize the likelihood of an undiscovered mineral deposit at a given location. It integrates geological knowledge of mineral systems with data such as geological maps, geophysical and geochemical surveys, and known mineral occurrences. These datasets are analyzed using Geographic Information Systems (GIS) or, increasingly, programming languages such as Python, to identify patterns and relationships between known mineral deposits that can be extrapolated to identify other prospective regions. The modelling process can be a continuum ranging from 'expert-driven' (or knowledge-driven) which relies on geologist decisions, to 'data-driven', which uses machine

learning and statistical methods (Bonham-Carter, 1994, p. 269). The primary output is typically a mineral potential map that shows the relative prospectivity of a given area. To assess overall prospectivity of a region, multiple mineral system models may be combined, yielding a more comprehensive estimation of an area's mineral potential.

Mineral potential modelling faces challenges that can affect its accuracy and reliability. These challenges include data limitations such as incomplete or uneven coverage and inconsistent quality across an area. Geological complexity further complicates modelling efforts and near-surface geology provides only a limited view of 3D mineral systems that may have been significantly altered by tectonic processes. Direct observation of subsurface geology typically relies on drilling, which provides detailed information but is spatially restricted and costly. The modelling method also presents challenges. Expert-based models can be biased by subjective decisions related to the selection and importance of input data. Data-driven approaches address this limitation during the model training process using known areas of mineralization but also require human interventions and can lack predictive capability in new areas. Furthermore, integrating diverse datasets can be technically demanding and technological barriers, including the need for high-performance computing and access to expertise, further complicate the modelling process. Moreover, how mineral potential modelling is understood by different clients is an under-addressed issue. For example, land-use experts, Indigenous groups, government organizations, and explorationists are likely to have different levels of geoscience knowledge. Tailoring communication and visualization of results to suit different audiences is essential for ensuring the data are accessible and actionable. Correctly identifying the target audience can also assist with choosing an appropriate modelling method.

Geological surveys across Canada are well-positioned to tackle these challenges. With expertise, extensive data, and digital infrastructure, they can lead efforts to produce the accessible, high-quality geoscience data needed for modelling, particularly in underexplored regions. Geological surveys can also improve data integration by developing interoperable platforms, making their data discoverable, and advancing GIS and modelling tools. Geological complexity is best addressed through ongoing investment in mapping and research to better understand mineral systems enabling the recognition of the key elements that are essential in forming a mineral deposit. Geological surveys are continuing to deploy computing

technology and foster partnerships with data scientists and artificial intelligence and machine learning specialists to advance modelling, while working towards opportunities to incorporate traditional Indigenous knowledge.

Given the complexity and importance of mineral potential modelling, this workshop is a first step in fostering and coordinating innovation across federal, provincial, and territorial jurisdictions in Canada. This national forum brings together geological surveys and researchers to share knowledge, discuss methods, and begin addressing shared challenges such as data integration, gaps in data coverage, model uncertainty, and model interpretation. Participants explore emerging tools in AI, machine learning, and geospatial analysis along with sharing their experience on how to best deliver this information to interested parties. Ultimately, the workshop supports cross-jurisdictional collaboration and ensures that mineral potential modelling efforts are transparent and scientifically robust, and that products are not only accessible but also appropriate for decision making.

References cited

- British Columbia Geological Survey, 2025. Mineral potential modelling at the British Columbia Geological Survey. British Columbia Ministry of Mining and Critical Minerals, British Columbia Geological Survey Information Circular 2025-07, 4p.
- Brown, T J., 2012. Mineral potential mapping – a new spatial decision support tool for industry and planners. In: Hunger, E., and Walton, G. (Eds.) Proceedings of the 16th Extractive Industry Geology Conference, pp. 76-87.
<https://static1.squarespace.com/static/54199a46e4b05afa19b4e68c/t/545776e4b06ff246527907/1415018220218/Brown+76-87.pdf>
- Bonham-Carter, G.F., 1994. Geographic information systems for geoscientists: modelling with GIS, Pergamon, 398 p.
<https://doi.org/10.1016/C2013-0-03864-9>
- Bullen, W., 2020. New mineral potential mapping methodology for Yukon: Case studies from the Beaver River and Dawson regional land use planning areas. In: MacFarlane, K.E., Ed.), Yukon Exploration and Geology 2019. Yukon Geological Survey, pp. 23-42.
- NGSCC, 2022, (National Geological Surveys Committee of Canada). Pan-Canadian Geoscience Strategy: Enhancing geoscience data, knowledge and access for a stronger future. Natural Resources Canada, 24p.
https://www.geologicalsurveys.ca/sites/ngsc/files/2022-02/pgs-accessible_0_0.pdf

Mineral potential mapping: A planner's perspective

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Land-use planning in British Columbia guides sustainable resource stewardship and management of public land and waters to meet economic, environmental, social, and cultural objectives. In 2018, following a period of limited planning activity, a provincial initiative began emphasizing multi-agency collaboration and meaningful engagement with Indigenous Nations and with local governments, communities, and the mineral exploration industry as part of its commitments to advance reconciliation, support a strong economy, and protect ecosystem health and biodiversity. Prompted by the global search for critical minerals and by the need to better inform land-use planning discussions, the British Columbia Geological Survey (BCGS) revitalized its mineral potential modelling after a period of relative inactivity lasting about 30 years (Wearmouth et al., 2024a, b). This new modelling is a key component to guide land-use and investment decisions and to ensure that mineral resources are adequately represented alongside surface resource interests such as forestry.

Although mineral potential mapping plays a key role in land-use planning, particularly in geologically diverse and resource-rich jurisdictions like British Columbia, the use of the models faces challenges. First, planners and rights holders commonly lack familiarity with the technical aspects of geology, mineral exploration, and mining. This knowledge gap can lead to misinterpretation or underuse of mineral potential data. For example, modelling maps may be perceived as having a level of finality, but geological knowledge, tools, and exploration priorities evolve through time. Or it may not be recognized that the maps are based on different levels of interpretation and thus have inherent uncertainties, which are difficult to convey. Second, relative to other natural resource-focussed planning frameworks, it is difficult to assign a financial value to a non-renewable resource that is potentially present below surface in an area. Third, technical and logistical complexities also arise in assembling high-quality datasets and managing long lead times for modelling. These issues are compounded by the need to overlay mineral potential with other land values such as cultural heritage, ecological sensitivity, and existing land use to support balanced and informed planning outcomes.

Despite these challenges, opportunities exist in using geology as a neutral and constructive entry point in land-use discussions because traditional knowledge and Western science intersections can serve as a foundation for dialogue to build a common understanding of the natural history and geological resources in the province, unlike potentially polarizing project-specific proposals. Indigenous Nations have shown strong interest in accessing and understanding mineral potential information within their territories, recognizing its value for self-determination and informed decision making. The BCGS role as a science agency has proven instrumental in building trust and facilitating knowledge exchange. Through its engagement program, the Survey works with Indigenous

Nations to raise awareness of research projects on their lands, identify opportunities and challenges, and explore partnerships. The Survey also provides Indigenous Nations with geoscience knowledge and tools to guide resource management and land-use decisions. In addition, significant coordination is being made within the Ministry of Mining and Critical Minerals and with the other ministries involved in the land-use planning process (e.g., Ministry of Water, Land and Resource Stewardship, Ministry of Environment, Ministry of Indigenous Relations and Reconciliation) to incorporate mineral potential information in the considerations reviewed as part of the engagement and negotiation discussions.

Key considerations include the necessity of plain language communication, the value of direct engagement between geoscientists and land-use planning team members, and the importance of early and proactive preparation. The value of mineral potential mapping is in identifying areas of overlapping interests such as including high-potential areas and sensitive surface values like cultural heritage resources. Identifying such intersections helps the planning team prioritize negotiation and allocate appropriate discussion time. Mineral potential mapping is not just a technical exercise, it is a strategic tool that, when thoughtfully applied, can enhance transparency, reduce uncertainty, and support inclusive, evidence-based land-use planning across British Columbia.

References cited

- Wearmouth, C.D., Peters, K.J., Czertowicz, T.A., and Orovan, E.A., 2024a. Mineral potential modelling results for northwestern British Columbia, a comparison between past and current work at the British Columbia Geological Survey. In: Geological Fieldwork 2023, British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-01, pp. 79-95.
- Wearmouth, C., Czertowicz, T., Peters, K.J., and Orovan, E., 2024b. Mineral potential modelling at the British Columbia Geological Survey: Renewed methods with application to northwestern British Columbia. British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-02, 28 p

Mineral potential modelling past, present, and future

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Mineral potential modelling (MPM) is a type of multi-criteria decision-making technique used to identify areas with high potential for undiscovered mineral deposits and to support land-use planning. Before the widespread adoption of computers, MPM was completed manually by overlaying transparent geological, geochemical, and geophysical maps on light tables. Advances in more automated and digital forms of mapping started in the 1960s driven by significant improvements to hardware and software, including the development of the first Geographic Information Systems (GIS) by Roger Tomlinson in 1963. While working as the head of the Canada Land Inventory for the Canadian Federal Government, Tomlinson (1974) developed the Canada Geographic Information System to combine physical geography, biological, social, and economic data for land-use planning and natural resources management. Quantitative MPM based on probabilistic modelling started with early work by Deverle Harris and Donald Singer at Pennsylvania State University and later by Fritz Agterberg at the Geological Survey of Canada during the 1960s and 1970s. These early MPM studies made the remarkable conceptual leap from simply documenting the locations of known mineral occurrences to estimating the probability of undiscovered mineral occurrences based on the available geoscientific information (Harris, 1965; Agterberg et al., 1972; Singer et al., 1972).

Between the 1970s and the 1990s, further advances in computer hardware and software allowed greater access to GIS and ultimately led to MPM emerging as a distinct sub-field in the mathematical geosciences and to steadily increasing interest by the mineral exploration industry (Singer and Mosier, 1981; Sangster 1983). The development of dedicated plugins that expanded the capabilities of traditional GIS software (e.g., weights of evidence (WOE), logistic regression, and others) played a critical role in increasing the accessibility of MPM tools beyond pure research applications. Examples include the Spatial Data Modeller (SDM) for the ArcGIS software developed by the United States Geological Survey and the Geological Survey of Canada (now available through the Geological Survey of Finland; <https://github.com/gtkfi/ArcSDM>) and the more recent Exploration Information Systems (EIS) toolkit and plugin for the QGIS software developed as a Horizon Europe project coordinated by the Geological Survey of Finland (<https://eis-he.eu>). For most of the 20th century, advances in MPM were closely coupled to the development of GIS software and the technological capabilities of computer hardware. However, beginning in the 2000s, renewed interest

in data science and the surge in development of open-source software, created new pathways to advance MPM as reviewed in Porwal et al. (2015) and Liu et al. (2022).

Today, traditional desktop GIS software is inherently limited by the local hardware resources of a single machine and is not designed for the iterative, experimental nature of modern data science workflows, which are driven by continuous model performance evaluation and refinement (Liu et al., 2022; Zhang et al., 2025). Implementing these more complex and non-linear workflows, is difficult or impossible with traditional GIS software (e.g., iterative tuning of hyperparameters). Instead, these more complicated data science workflows tend to require precise control, internal or end-to-end execution automation, collaborative coding (e.g., workflow, library, and algorithm sharing), and careful management using high-level and general-purpose programming language such as python (Liu et al. 2022). Simultaneously, the data used in MPM has become much bigger and higher dimensional, making the data modelling primarily focussed on data attributes or machine learning features, as opposed to spatial distribution (Zuo et al., 2019). The shift to code-driven workflows also enables automation and access to distributed computing environments for Big Data applications, and comprehensive documentation that ensure reproducibility and transparency. Application Programming Interfaces (API) and libraries developed for these programming languages provide access to the current state-of-the-art tools in deep learning and geospatial analysis (Soliman and Terstriep, 2019; Stewart et al., 2022). Code-centric modelling has also enabled aspatial visualizations that are atypical of GIS, such as of decision boundaries, model explainability, and latent spaces. Critically, many of these technologies are available for free. Whilst traditional desktop GIS users can still access these tools through plugins and packages like ArcPy, the key pieces of data science infrastructure and library development supporting modern MPM will likely be decoupled from GIS software development for the foreseeable future.

The future of MPM will also likely involve further automation. Historically, significant time was spent on preparing data for modelling and/or feature engineering. In the future, these types of data engineering tasks will likely be automated by deep learning to unlock the potential for end-to-end learning on raw and unstructured data (Parsa et al., 2024, 2025). The expected shift to pure data-driven workflows will have important impacts on the role that geoscientists have on the final MPM product going forward given that feature engineering was the one part of the MPM workflow that benefitted the most from domain

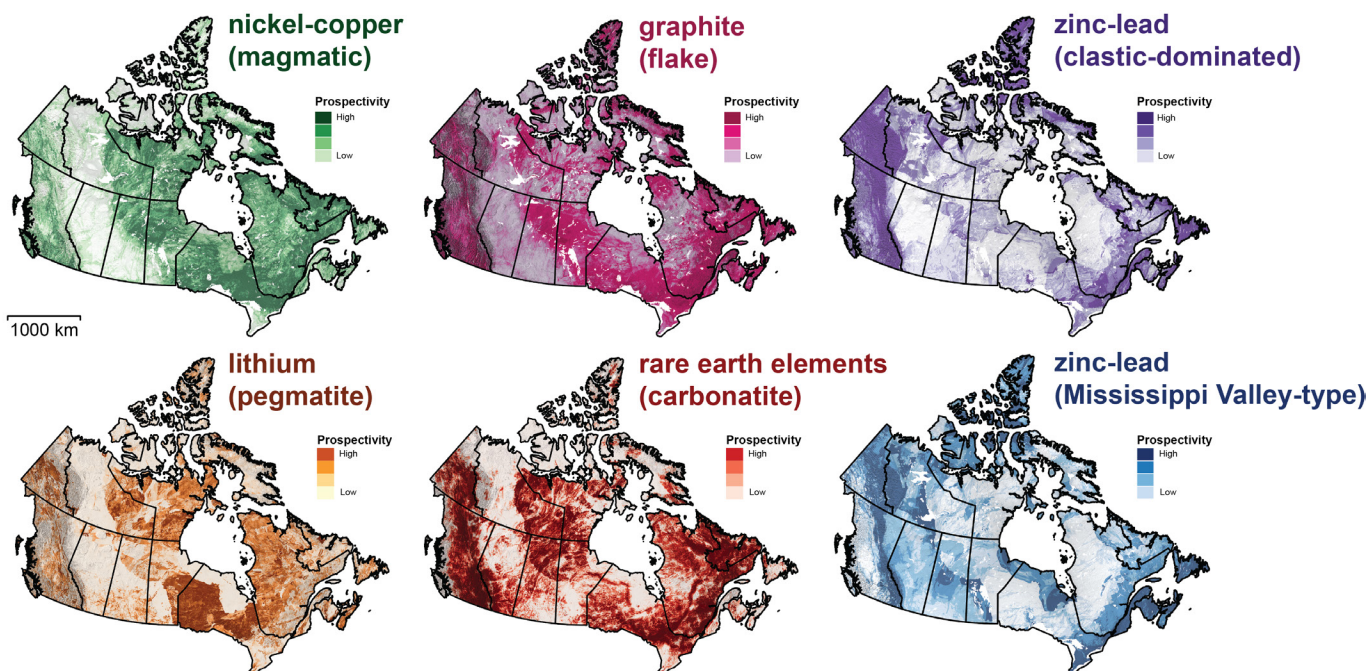


Fig. 1. Family of MPM developed by Lawley (2022a, b), Parsa (2024, 2025), and Zhang (2025).

expertise. Future MPM will also require increased focus on uncertainty analysis, model validation, and better integration of MPM products into other decision support systems (Parsa et al., 2024, 2025). The conventional approach of basing exploration decisions on the best-performing model will soon be superseded by pure data science workflows that treat each model as a single experiment within an ensemble (Lawley et al., 2022a, b; Zhang et al., 2025). Consensus models based on these ensembles modulate the uncertainty related to arbitrary choices made in most previous MPM workflow designs and provide decision makers with a stable and more reliable product (Zhang et al., 2025). As geological surveys, industry, and academia continue to collect more high quality data, and through new sensor-based methods of data acquisition, it may become possible in the future to validate and then update MPM closer to real-time. If successful, real-time testing would allow MPM products to be falsifiable (Zhang et al., 2025), which is a key requirement for all scientific disciplines. Improving the reliability and trust in MPM products is essential as research results are now being used by governments to develop policies and make land-use decisions (Fig. 1; Lawley et al., 2022a). These applications go beyond the pure commercial interests of the mineral exploration industry that MPM was originally proposed for. Indeed, the expanded role of MPM as input into broader land-use planning now mirrors the original motivation for the development of GIS more than 60 years ago. The proposition that MPM, if done effectively, can reduce operational costs by focussing exploration on areas with the greatest potential and minimize environmental impact by limiting unnecessary exploration in low-potential areas is more relevant today than ever.

References cited

- Agterberg, F.P., Chung, C.F., Fabbri, A.G., Kelly, A.M., and Springer, J.S., 1972. Geomathematical evaluation of copper and zinc potential of the Abitibi area, Ontario and Quebec. Geological Survey of Canada, Paper, 71-41, 55 p.
<https://doi.org/10.4095/102407>
- Harris, D.P., 1965. An application of multivariate statistical analysis to mineral exploration. Unpublished Ph.D. thesis, Pennsylvania State University, 965 p.
- Lawley, C.J.M., McCafferty, A.E., Graham, G.E., Huston, D.L., Kelley, K.D., Czarnota, K., Paradis, S., Peter, J.M., Hayward, N., Barlow, M., Emsbo, P., Coyan, J., San Juan, C.A., and Gadd, M.G., 2022a. Data-driven prospectivity modelling of sediment-hosted Zn-Pb mineral systems and their critical raw materials. *Ore Geology Reviews*, 141, 1-23.
<https://doi.org/10.1016/j.oregeorev.2021.104635>
- Lawley, C.J.M., Mitchell, M.G.E., Stralberg, D., Schuster, R., McIntire, E., Bennett, J.R., 2022b. Mapping Canada's green economic pathways for battery minerals: Balancing prospectivity modelling with conservation and biodiversity values. *Earth Science, Systems and Society*, 2, 1-20.
<https://doi.org/10.3389/esss.2022.10064>
- Liu, Y., Carranza, E.J.M. and Xia, Q., 2022. Developments in quantitative assessment and modeling of mineral resource potential: An overview. *Natural Resources Research*, 31, 1825-1840.
<https://doi.org/10.1007/s11053-022-10075-2>
- Parsa M., Lawley, C.J.M., Cumani, R., Schetselaar, E., Harris, J., Lentz, D.R., Zhang, S.E., and Bourdeau, J.E., 2024. Predictive modeling of Canadian carbonatite-hosted REE +/- Nb deposits. *Natural Resources Research*, 33, 1941-1965.
<https://doi.org/10.1007/s11053-024-10369-7>

- Parsa, M., Lawley, C.J.M., Cawood, T., Martins, T., Cumani, R., Zhang, S.E., Thompson, A., Schetselaar, E., Beyer, S., Lentz, D.R., Harris, J., Jodeiri Akbari Fam, H., and Voinot, A., 2025. Pan-Canadian predictive modeling of lithium-cesium-tantalum pegmatites with deep learning and natural language processing. *Natural Resources Research*, 34, 639-668.
<https://doi.org/10.1007/s11053-024-10438-x>
- Porwal, A., and Carranza, J.M., 2015. Introduction to the Special Issue: GIS-based mineral potential modelling and geological data analyses for mineral exploration. *Ore Geology Reviews*, 33, 477-483. <https://doi.org/10.1016/j.oregeorev.2015.04.017>
- Sangster, 1983. The Canadian experience in mineral potential assessment. *Geoscience Canada*, 10, 70-76.
- Singer, D.A., 1972. Multivariate statistical analysis of the unit regional value of mineral resources. Unpublished Ph.D. thesis, Pennsylvania State University, 211 p.
- Singer, D.A., and Mosier, 1981. A review of regional mineral resource assessment methods. *Economic Geology*, 76, 1006–1015.
<https://doi.org/10.2113/gsecongeo.76.5.1006>
- Soliman A., and Terstriep, J., 2019. Keras Spatial: Extending deep learning frameworks for preprocessing and on-the-fly augmentation of geospatial data. *GeoAI '19: Proceedings of the 3rd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*, 69-76.
<https://doi.org/10.1145/3356471.3365240>
- Stewart, A.J., Robinson, C., Corley, I.A., Ortiz, A., Lavista Ferres, J.M., Banerjee, A., 2022. TorchGeo: deep learning with geospatial data. *SIGSPATIAL '22: Proceedings of the 30th International Conference on Advances in Geographic Information Systems*, 1-12.
<https://doi.org/10.1145/3557915.356095>
- Tomlinson, R.F., 1974. *Geographical Information Systems, Spatial Data Analysis and Decision Making in Government*. Unpublished Ph.D. thesis, University of London, 444 p.
- Zhang, S.E., Lawley, C.J.M., Bourdeau, J.E. Parsa, M., Cumani, R., and Thompson, A., 2025. Mineral prospectivity modeling of graphite deposits and occurrences in Canada. *Natural Resources Research*, 34, 1243-1270.
<https://doi.org/10.1007/s11053-024-10451-0>
- Zuo, R., Xiong, Y., Wang, J., and Carranza, E.J.M., 2019. Deep learning and its application in geochemical mapping. *Earth Science Reviews*, 192, 1-14.
<https://doi.org/10.1016/j.earscirev.2019.02.023>

Interpretable pan-Canadian mineral potential models

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Mineral Prospectivity Mapping (MPM) is the process of identifying geoscientific data trends that are associated with mineral deposits and extending trends across a study area to identify additional areas with high potential for future discoveries. This approach supports decision making and land management by highlighting regions likely to host the next generation of mineral resources. However, prospectivity models are continuous probability models that are not directly interpretable. This caveat adversely affects the downstream use of these models.

The concept of interpretability in Mineral Prospectivity Mapping (MPM) is twofold. First, prospectivity models commonly lack clarity on how to define an area as prospective, primarily because these models typically represent continuous probability distributions. To address this, researchers have proposed using subjective or objective threshold values to delineate prospective areas. However, these thresholds are usually based solely on prospectivity scores, without considering underlying model uncertainties. Yet, MPM is inherently influenced by both data-related and knowledge-based uncertainties. Therefore, these uncertainties should be accounted for when interpreting prospectivity models to ensure more reliable and meaningful outcomes. Second, MPM requires interpretation to explain what drives a given prediction. For example, if the model classifies 10% of an area as prospective, it is important to understand which evidence layers (features) contributed to that outcome.

Our approach to addressing the above challenges consists of three steps: 1) quantifying workflow-induced uncertainties, as outlined by Zhang et al. (2024); 2) applying a risk-return analysis to prioritize areas that exhibit both low risk (i.e., low uncertainty) and high return (i.e., high prospectivity) as demonstrated in Parsa et al. (2024, 2025); and 3) employing post-hoc interpretability methods, such as SHAP (SHapley Additive exPlanations; Lundberg and Lee, 2017), to rank the importance of input features in the prospectivity mapping process.

Herein, we present the results of a pan-Canadian prospectivity model of lithium-cesium-tantalum (LCT) pegmatites using a deep-learning-based approach, in which 2D Convolutional Neural Networks (CNNs) have been used for predictive modelling (see Parsa et al., 2025 for details about the evidence layers).

The presence of multiple alternatives at each step of a typical prospectivity modelling workflow leads to an immense number of possible model results (Zhang et al. 2024). For this case study, the major sources of uncertainty in MPM were recognized

as input convolutional image sizes, training data labels, regularization strength, and the drop out rate of CNNs. This choice was motivated by the premise that even slight changes in these parameters can lead to variations in prospectivity models. Such parameters were, therefore, considered dynamic for quantifying uncertainties and risk-return modelling, leading to an ensemble of 1,000 models. In this case study, besides conventional model parameters, the convolutional image size was also regarded as a hyperparameter due to its impact on prospectivity models. As per our experience, larger convolutional image sizes tend to capture more regional anomalies, whereas smaller convolutional image sizes tend to be more effective in capturing local structures. Modelling was also facilitated with a spatial attention mechanism, detailed in Parsa et al. (2025), which significantly improved the performance of models in the ensemble. This mechanism helps the model concentrate on the most pertinent feature, thereby enhancing the overall performance of a neural network-based model. In other words, this mechanism allows the neural network to emphasize the regions within a convolutional window that are more representative of LCT pegmatites.

The ensemble was then used for a risk-return modelling (Fig. 1). The threshold values determined, derived from the 33rd and 66th values of risk and return (Fig. 1), were used to derive the interpretable predictive model (Fig. 2). That is, risk and return were transformed into three-class categorical variables, the combination of which led to a nine-fold classification scheme ranging from ‘low-risk, low-return’ to ‘high-risk, high-return’. High-return values indicate the areas with consistently high prospectivity across the ensemble of prospectivity models and should be given priority. Similarly, low-return values should be given priority because they point to the areas that have low uncertainty across most models within the ensemble. In other words, low-risk areas are the cells that show minimal variability regardless of the changes in model parameters. Exploration efforts, therefore, should be focused in low-risk, high-return areas of the model.

The risk-return predictive model (Fig. 2) also offers local and global interpretability because, by using SHAP analysis (Fig. 3), it may help determine the features that control the classification model. SHAP is used to interpret and explain the decisions made by a machine learning model after training. It highlights the most impactful features that influence the model’s predictions. This form of interpretability is especially valuable for complex deep neural networks, which are commonly considered ‘black boxes’ because of their intricate architecture.

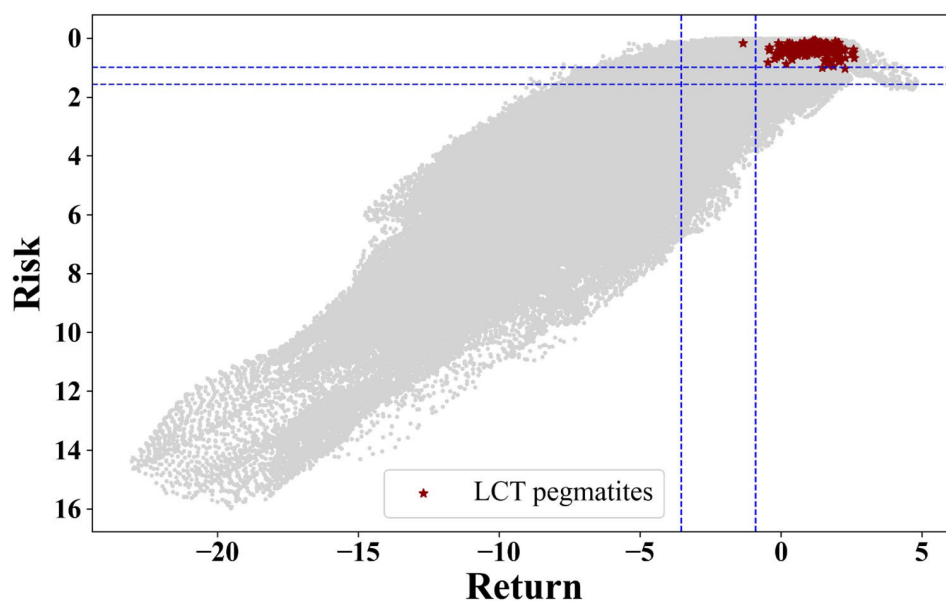


Fig. 1. The risk-return analysis applied to the MPM of Canadian LCT pegmatites. Dashed lines are the 33% and 66% percentile values of risk and return, leading to a none-fold classification scheme.

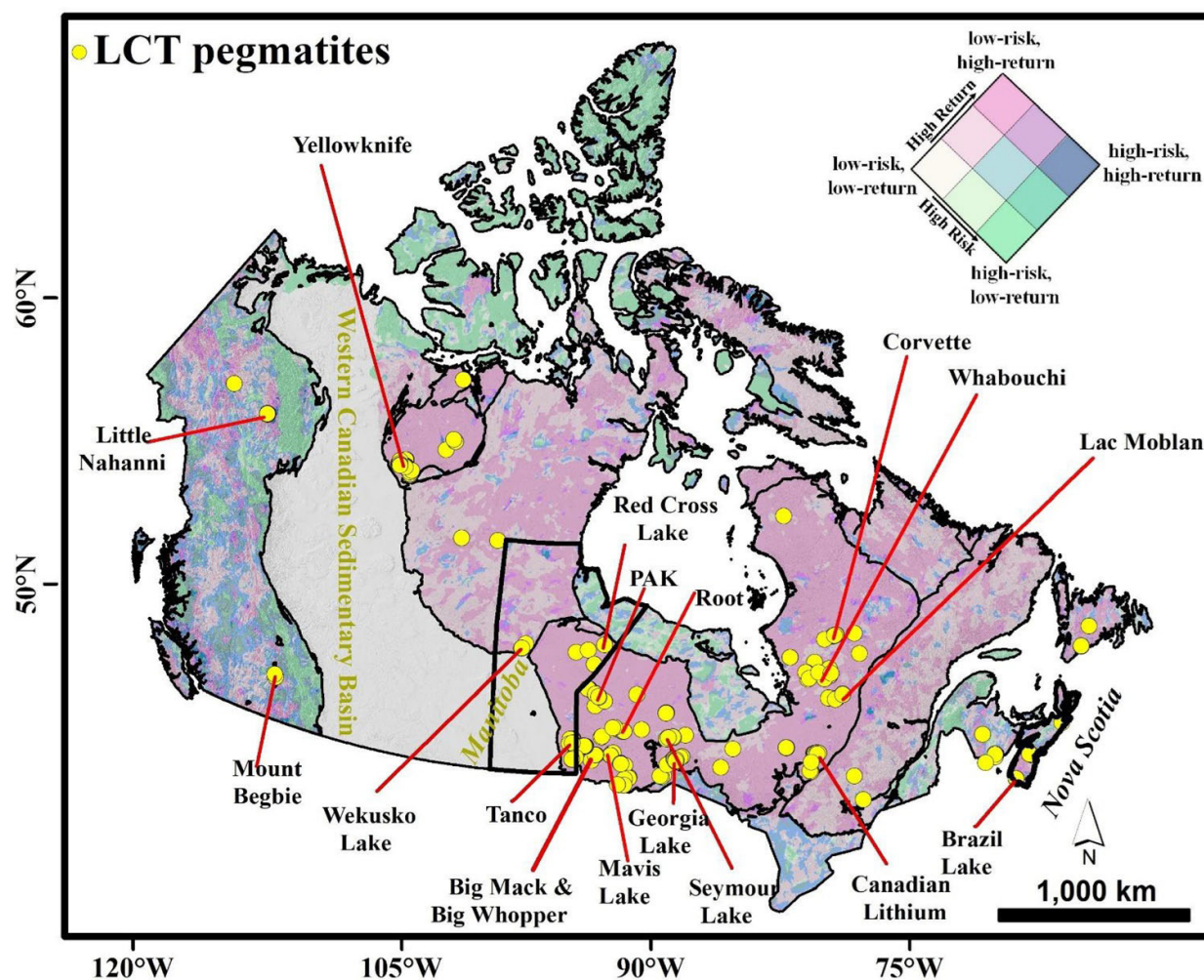


Fig. 2. The risk-return prospectivity model of Canadian LCT pegmatites.

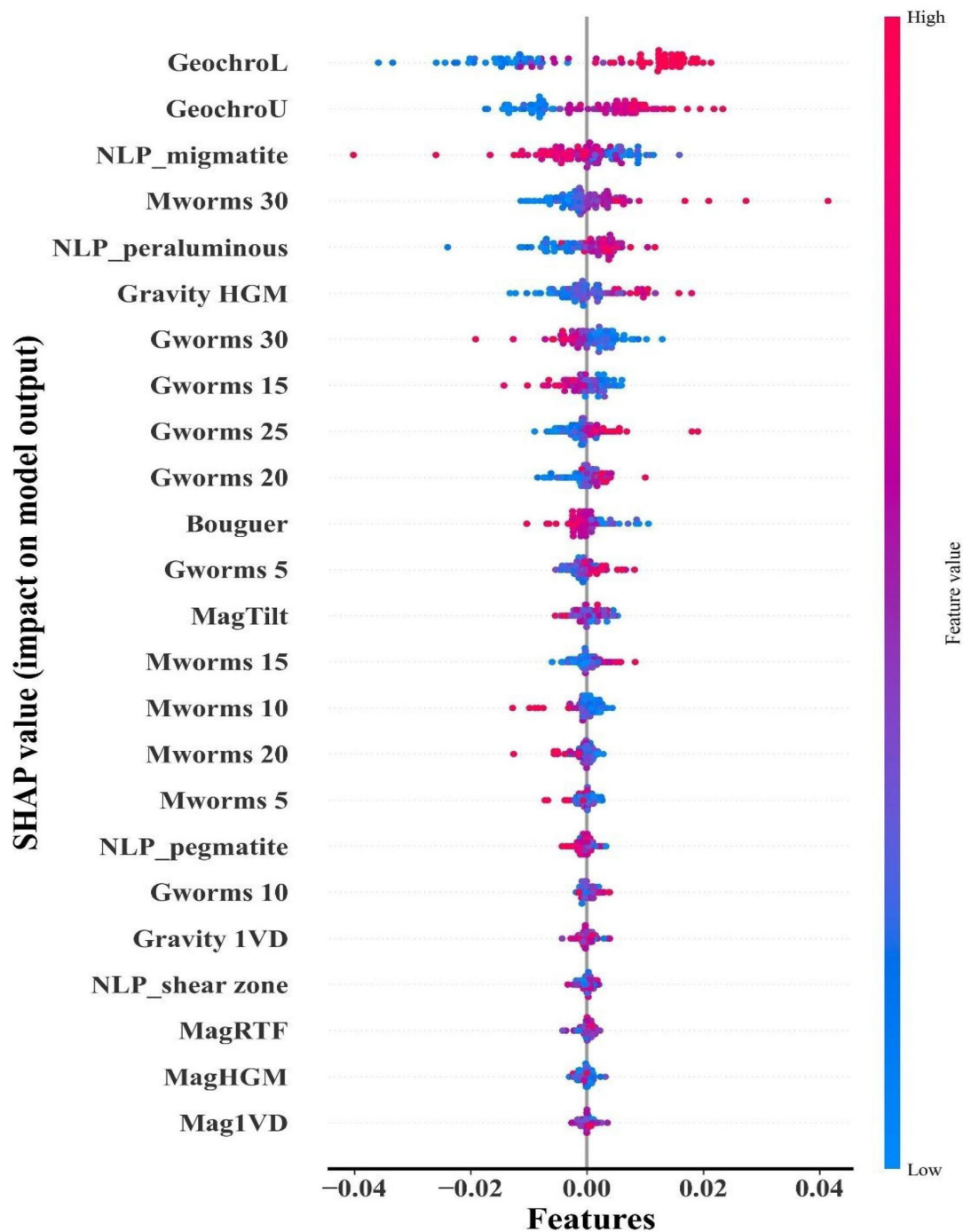


Fig. 3. SHAP analysis of the predictive model in Figure. 2. See Parsa et al. (2025) for details on evidence layers used in this model.

References cited

- Lundberg, S.M. and Lee, S.I., 2017. A unified approach to interpreting model predictions. 31st Conference on Neural Information Processing Systems.
<https://proceedings.neurips.cc/paper/2017/file/8a20a8621978632d76c43dfd28b67767-Paper.pdf>
- Parsa, M., Lawley, C.J., Cumani, R., Schetselaar, E., Harris, J., Lentz, D.R., Zhang, S.E. and Bourdeau, J.E., 2024. Predictive modeling of Canadian carbonatite-hosted REE+/- Nb deposits. *Natural Resources Research*, 33, 1941-1965.
<https://link.springer.com/article/10.1007/s11053-024-10369-7>

- Parsa, M., Lawley, C.J., Cawood, T., Martins, T., Cumani, R., Zhang, S.E., Thompson, A., Schetselaar, E., Beyer, S., Lentz, D.R., and Harris, J., 2025. Pan-Canadian predictive modeling of lithium–cesium–tantalum pegmatites with deep learning and natural language processing. *Natural Resources Research*, 34, 639-668.
<https://link.springer.com/article/10.1007/s11053-024-10438-x>
- Zhang, S.E., Lawley, C.J., Bourdeau, J.E., Nwaila, G.T., and Ghorbani, Y., 2024. Workflow-induced uncertainty in data-driven mineral prospectivity mapping. *Natural Resources Research*, 33, 995-1023.
<https://link.springer.com/article/10.1007/s11053-024-10322-8>

Uncertainty in data-driven mineral prospectivity mapping with an emphasis on sources idiosyncratic to mineral exploration

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Mineral prospectivity mapping (MPM) began as a form of geospatial analysis and statistics (e.g., Harris, 1965; Agterberg et al., 1972; Singer et al., 1972). Modern MPM is increasingly data-driven (e.g., Lawley et al., 2022a, b; Parsa et al., 2024; 2025), which is a scientific philosophy that eschews prior hypotheses in exchange for objective data modelling. Data-driven MPM (DDMPM) is increasingly practiced by formally trained geodata scientists. Geodata science is a nascent discipline that integrates data science, geoscientific inquiry, geostatistics and geospatial analysis. Uncertainty in DDMPM is important because: 1) DDMPM is becoming a scientific inquiry as opposed to a deterministic methods used in geospatial analysis; and 2) the mineral industry is typically adverse to risk because of high costs and long timescales from exploration to extraction (IEA, 2023), which makes the progression and outcome of the mineral value chain captive to early decisions (Bartos, 2007). The investment interest in any prediction (e.g., a DDMPM product) depends on its trustworthiness, or equivalently, certainty. Uncertainty analysis relates change in outcome to change in input or process, such as data, modelling workflow, and validation. Known uncertainty types in DDMPM are workflow-induced, aleatoric or epistemic.

Workflow-induced uncertainty is a framework-level uncertainty that results from limitations of the geodata science framework (Zhang et al., 2024b). One of these limitations is that the conventional data science framework is mostly aspatial (e.g., out-of-sample testing or imputation). So far, spatial considerations are sequential additions to the data science framework rather than systemic integration. For example, executing the data science framework to train a model, then evaluating spatial characteristics during deployment makes DDMPM optimization sequential. Typically, the data science practice is to select higher performing models. However, it was empirically shown that high performing models in the data science framework are not necessarily high performing models in the spatial domain, which means that the geodata science framework cannot fully solve the DDMPM problem (Zhang et al., 2024b). Sequential optimization of model performance in the variable domain (e.g., an acceptable F1 score) produces equiprobable models with differing spatial characteristics (e.g., spatial selectivity). This makes subjective decisions made during modelling a major source of uncertainty in DDMPM. It also modulates both aleatoric and epistemic uncertainties (Zhang et al., 2024b). The use of aspatial frameworks also inflates model performance, by uncertain margins (Hoffmann et al., 2021). Of the explored sources, data annotation (Fig. 1) and machine learning (ML) algorithm are the biggest contributors, about an order of magnitude bigger than feature space dimensionality, hyperparameter tuning metric or random subsets of negative samples (Nwaila et al., 2024; Zhang et al.,

2024b, 2025a; 2025b).

Aleatoric uncertainty is inherent randomness within data that cannot be reduced by collecting more data (Hüllermeier and Waegeman, 2021). In DDMPM, its origin is broader than in typical ML tasks. Sources of aleatoric uncertainty related to DDMPM are mainly the nugget effect and annotation non-uniformity. Mineralization is a disequilibrium process. Its state across space and time is a complex dynamical system (a dynamical system is a deterministic mathematical system that exhibits behavior that could be complex, e.g., chaotic or difficult to predict), typically modelled as fractal systems (Zuo, 2016). However, because some of the critical ore-forming processes in these complex systems are also scale-dependent, spatial correlations are only locally consistent (e.g., the range in a variogram). The degree of disequilibrium is captured geostatistically as the nugget, which describes the roughness of the underlying distribution or equivalently, short-distance correlation of samples (Zhang et al., 2024a). The nugget is irreducible using repeated measurements and is thus a persistent source of uncertainty for DDMPM. A similar type of aleatoric uncertainty is levelling. Geodata surveys at large spatial scales are seldom levelled or capable of being levelled due to overlapping timescales of survey implementation and evolution (Bourdeau et al., 2024). As a result, the spatial distribution of aleatoric uncertainty can be highly variable. One consequence can be seen as rectangular patches in large-scale DDMPM products, which result from fitted models confusing aleatoric uncertainty with mineralization (Figs. 1c, d).

Annotation non-uniformity is the second major source of aleatoric uncertainty related to DDMPM. The probabilistic gap (He et al., 2018) is a critical concept in supervised and positive-and-unlabelled tasks. It is the theoretical separability between the least positive sample and similar true negatives. In DDMPM, the probabilistic gap is the geoscientific distinction between fertile and barren samples. However, it is ill-defined due to annotation non-uniformity, even ignoring complex system effects. Sample labelling depends on non-stationary (i.e., inconsistent definition of “deposit” across space and time) and typically undetermined factors extrinsic to DDMPM, such as: economic condition (e.g., commodity pricing); geological complexity (e.g., refractory phases); mineral engineering capability (e.g., ability to remove refractories); resource modelling and sampling (e.g., replicability of resource models, Owusu and Dagdelen, 2024); and political and geopolitical conditions (e.g., material criticality; Zhang et al., 2025b). Both complex dynamics and annotation non-uniformity make the probabilistic gap between positives and negatives non-unique (because its nature depends on the definition of positivity), noisy (because definition is not solely determined by mineralization proxies) and non-smooth (nearby or similar

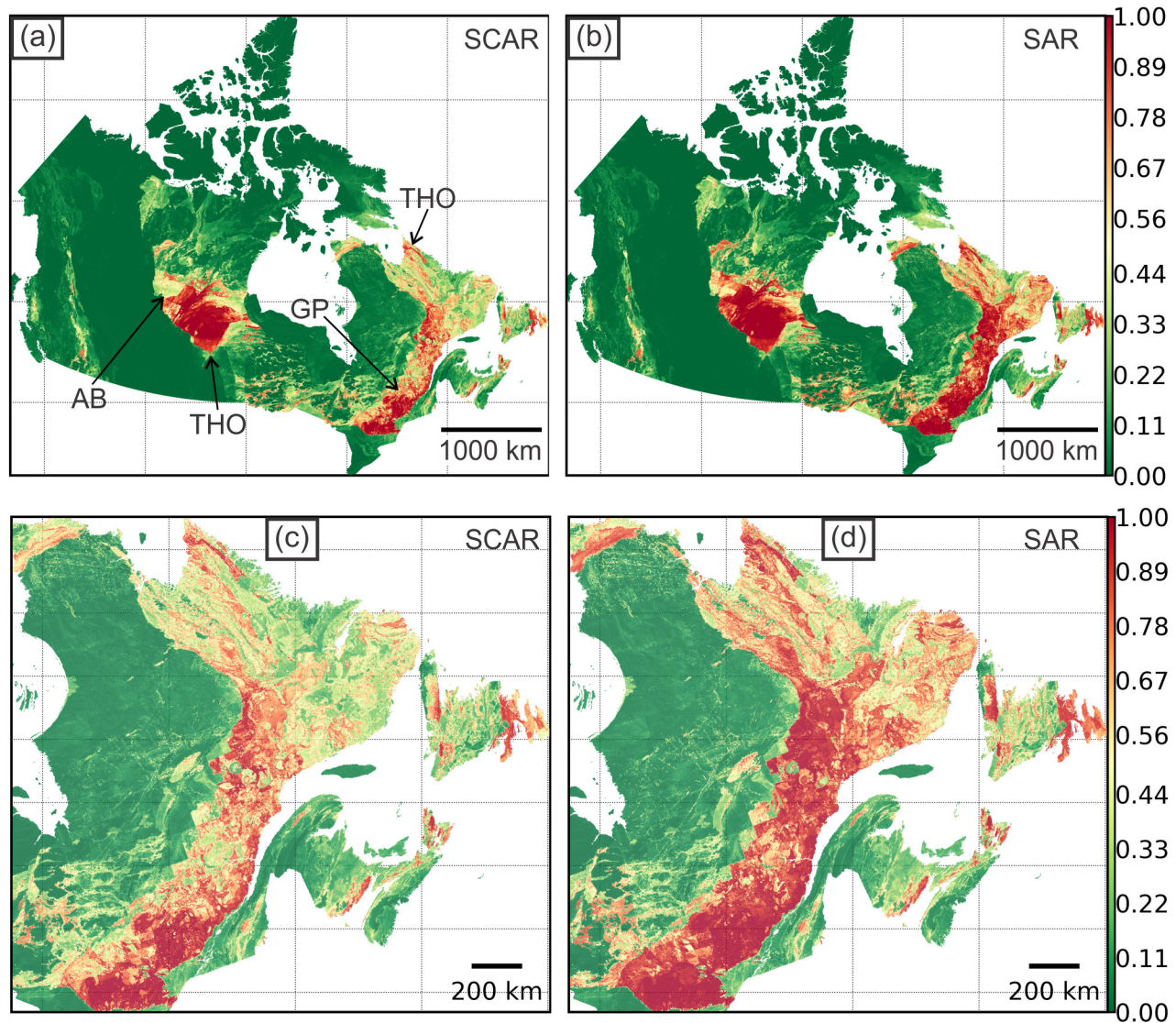


Fig. 1. Effect of data annotation of negative samples on flake graphite MPM outcome. Two labelling mechanisms are shown: selected completely at random (SCAR) **a**) and of the Grenville Province in **c**); and selected at random (SAR) using a recursive annotation method in **b**) and of the Grenville Province in **d**). Labelled geological locations include: Athabasca Basin (AB); Trans-Hudson Orogen (THO); and Grenville Province (GP).

samples can be either fertile or barren) (Zhang et al., 2025b). An ill-defined probabilistic gap manifests as equiprobable decision boundaries. For example, for DDMPM using historically annotated data, the target area is biased towards larger and geologically simpler targets (Zhang et al., 2025b). Therefore, the transitional area on prospectivity maps between positive and negative prospectivity is uncertain, depending on the nature of the probabilistic gap and its treatise during modelling.

Epistemic uncertainty in DDMPM, aside from the common model expressivity limitations, originates from the lack of information, which is a combination of sample abundance and quality. Samples labelled and unlabelled should capture sufficient information about the fertility of a target. However, the behavior of mineralization is complex relative to observable proxies and sampling density, which makes MPM a generally under-constrained problem. For example, comparable mineral

systems on any basis of their proxies may or may not host target mineralization (e.g., magmatic sulfide deposits being variably fertile for precious metals). Theoretically, this is because the state of complex systems is exponentially sensitive to initial or boundary conditions (e.g., subtle differences in transport mechanism and driving force in mineral systems can lead to fertile or barren systems). Consensus has not been reached on the types of data necessary to optimally assess each component of a mineral system in relation to system fertility (e.g., Park et al., 2021). Complexity also affects the meaning of data and MPM expectations. For example, if a random subset of samples were drawn from all positives originating from a complex system, then assuming a distribution obeying the Pareto principle, about 20% of the cleanest of such samples (most resembling distinct mineral systems) contain about 80% of the relevant targeting information (Fig. 2). A lack of information

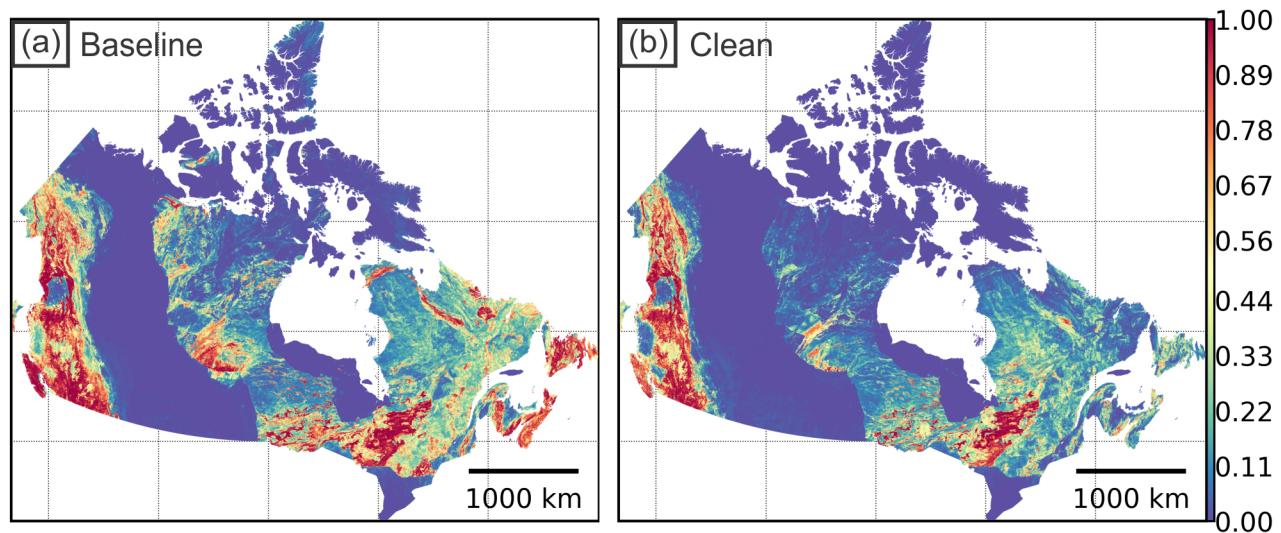


Fig. 2. Pan-Canadian copper prospectivity maps made using the entire collection of positive samples ($n = 20848$) in **a**) and using only the cleanest samples ($n = 2996$ or 14.4% of all positives) in **b**). About 71% of the target area overlap across all thresholds between **a**) and **b**).

relative to noisy behavior of systems at disequilibrium means that DDMPM models trained on such data only learn low-order statistics of mineralization, which is generally where the geology could host a target mineral system and not the system's fertility (Zhang et al., 2025b). Sensitivity to initial conditions limits the realism of DDMPM outcome. For example, ML algorithms that interpolate between fertile to barren samples to make inferences on unknown samples often makes no rigorous sense geoscientifically. Addressing these types of issues will likely require more complex models. However, the available geodata is currently limited (e.g., abundance of annotated samples), which means that most DDMPM models are at high risk of overfitting, where complexity is unrelated to the task and statistically spurious.

Uncertainty in DDMPM is a rich subdomain, which exists at the intersection of experimental science, geodata science, and geoscience. Understanding uncertainty in DDMPM paves the way towards more informed and investable MPM products. Many challenges face uncertainty analysis in DDMPM including: 1) a lack of validation; 2) geodata science-framework immaturity; and 3) idiosyncratic sources that are extrinsic to both geospatial analysis and pure data science. Addressing such challenges requires an integrated expertise of geodata science and geoscience.

References cited

- Agterberg, F.P., Chung, C.F., Fabbri, A.G., Kelly, A.M., and Springer, J.S., 1972. Geomathematical evaluation of copper and zinc potential of the Abitibi area, Ontario and Quebec. Geological Survey of Canada, Paper 71-41, 55 p.
<https://doi.org/10.4095/102407>
- Bartos, P. J., 2007. Is mining a high-tech industry?: Investigations into innovation and productivity advance. *Resources Policy*, 32, 149-158.
<https://doi.org/10.1016/j.resourpol.2007.07.001>
- Bourdeau, J. E., Zhang, S. E., Nwaila, G. T., and Ghorbani, Y. 2024. Data generation for exploration geochemistry: Past, present and future. *Applied Geochemistry*, article 106124.
<https://doi.org/10.1016/j.apgeochem.2024.106124>
- Harris, D.P., 1965. An application of multivariate statistical analysis to mineral exploration. Unpublished Ph.D. thesis, Pennsylvania State University, 965 p.
- Hoffmann, J., Zortea, M., de Carvalho, B., and Zadrozny, B. 2021. Geostatistical learning: Challenges and opportunities. *Frontiers in Applied Mathematics and Statistics*, 7, article 689393.
<https://doi.org/10.3389/fams.2021.689393>
- Hüllermeier, E., and Waegeman, W. 2021. Aleatoric and epistemic uncertainty in machine learning: An introduction to concepts and methods. *Machine learning*, 110, 457-506.
<https://doi.org/10.1007/s10994-021-05946-3>
- IEA, 2023. Energy Technology Perspectives 2023. International Energy Agency (IEA), 463 p.
<https://www.iea.org/reports/energy-technology-perspectives-2023>
- Lawley, C.J.M., McCafferty, A.E., Graham, G.E., Huston, D.L., Kelley, K.D., Czarnota, K., Paradis, S., Peter, J.M., Hayward, N., Barlow, M., Emsbo, P., Coyan, J., San Juan, C.A., and Gadd, M.G., 2022a. Data-driven prospectivity modelling of sediment-hosted Zn-Pb mineral systems and their critical raw materials. *Ore Geology Reviews*, 141, 1-23. <https://doi.org/10.1016/j.oregeorev.2021.104635>
- Lawley, C.J.M., Mitchell, M.G.E., Stralberg, D., Schuster, R., McIntire, E., Bennett, J.R., 2022b. Mapping Canada's green economic pathways for battery minerals: Balancing prospectivity modelling with conservation and biodiversity values. *Earth Science, Systems and Society*, 2, 1-20.
<https://doi.org/10.3389/esss.2022.10064>
- Nwaila, G. T., Zhang, S. E., Bourdeau, J. E., Carranza, E. J. M., Enslin, S., Manzi, M. S. D., Andriampenanana, F., and Ghorbani, Y. 2024. Mineral reconnaissance through scientific consensus: First national prospectivity maps for PGE–Ni–Cu–Cr and Witwatersrand-type Au deposits in South Africa. *Natural Resources Research*, 33, 2357-2384.
<https://doi.org/10.1007/s11053-024-10390-w>
- Owusu, S. K. A. and Dagdelen, K., 2024. Impact of competent persons' judgements in mineral resources classification. *Journal of the Southern African Institute of Mining and Metallurgy*, 124, 371-382.
<http://doi.org/10.17159/2411-9717/1538/2024>
- Park, J. W., Campbell, I. H., Chiaradia, M., Hao, H., and Lee, C. T. 2021. Crustal magmatic controls on the formation of porphyry copper deposits. *Nature Reviews Earth & Environment*, 2, 542-557.
<https://doi.org/10.1038/s43017-021-00182-8>

- Parsa M., Lawley, C.J.M., Cumani, R., Schetselaar, E., Harris, J., Lentz, D.R., Zhang, S.E., and Bourdeau, J.E., 2024. Predictive modeling of Canadian carbonatite-hosted REE +/- Nb deposits. *Natural Resources Research*, 33, 1941-1965.
<https://doi.org/10.1007/s11053-024-10369-7>
- Parsa, M., Lawley, C.J.M., Cawood, T., Martins, T., Cumani, R., Zhang, S.E., Thompson, A., Schetselaar, E., Beyer, S., Lentz, D.R., Harris, J., Jodeiri Akbari Fam, H., and Voinot, A., 2025. Pan-Canadian predictive modeling of lithium–cesium–tantalum pegmatites with deep learning and natural language processing. *Natural Resources Research*, 34, 639-668.
<https://doi.org/10.1007/s11053-024-10438-x>
- Singer, D.A., 1972, Multivariate statistical analysis of the unit regional value of mineral resources. Unpublished Ph.D. thesis, Pennsylvania State University, 211 p.
- Zhang, S. E., Bourdeau, J. E., Nwaila, G. T., Parsa, M., and Ghorbani, Y. 2024a. Denoising of geochemical data using deep learning—implications for regional surveys. *Natural Resources Research*, 33, 495-520.
<https://doi.org/10.1007/s11053-024-10317-5>
- Zhang, S. E., Lawley, C. J. M., Bourdeau, J. E., Nwaila, G. T., and Ghorbani, Y. 2024b. Workflow-induced uncertainty in data-driven mineral prospectivity mapping. *Natural Resources Research*, 33, 995-1023.
<https://doi.org/10.1007/s11053-024-10322-8>
- Zhang, S. E., Lawley, C. J. M., Bourdeau, J. E., Parsa, M., and Cumani, R., 2025a. Mineral prospectivity modeling of graphite deposit and occurrences in Canada. *Natural Resources Research* 34, 1243-1270.
<https://doi.org/10.1007/s11053-024-10451-0>
- Zhang, S. E., Coutts, D., Parsa, M., Cumani, R., and Thompson, A., 2025b. Recursive annotation for negative labeling in data-driven mineral prospectivity mapping. *Natural Resources Research*.
<https://doi.org/10.1007/s11053-025-10510-0>
- Zuo, R. 2016. A nonlinear controlling function of geological features on magmatic–hydrothermal mineralization. *Scientific Reports*, 6, article 27127.
<https://doi.org/10.1038/srep27127>

Mineral potential modelling in Newfoundland and Labrador: Applications, challenges, and future directions

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The Geological Survey of Newfoundland and Labrador (GSNL) has used mineral potential modelling as a tool to visualize the relative prospectivity of selected areas of the province to support land-use decisions and mineral exploration. Unlike forests and other natural resources, mineral deposits are not readily discernible and require indirect evaluation. In remote areas with poor access, geoscience data coverage is sparse, yet competing land-use demands necessitate timely assessments of mineral potential. To date, GSNL has applied mineral potential modelling on a project-by-project basis rather than through a province-wide program. No organized efforts are currently ongoing, largely due to limited staff capacity, uneven data coverage in remote regions, and uncertainty around how end users may apply the resulting products.

Past work at GSNL followed a semi-quantitative GIS-based workflow adapted from Ryan et al. (2010). Input features were grouped into three categories: 1) exploration data, including records of historic and modern mining and exploration activity; 2) geological and structural data, reflecting current understanding of mineral deposit formation and preservation; and 3) surficial data, such as lake sediment geochemical indices. These data were combined into relative prospectivity scores for individual map areas. The resulting maps provided a visual representation of mineral potential.

This work demonstrated that mineral potential modelling can provide timely, transparent evaluations of relative prospectivity, even in data-limited regions. However, significant challenges remain for broader application in Newfoundland and Labrador. Remote areas are often under-represented because prospecting and exploration data are sparse. Uncertainties arise from every stage of the process, including data availability, data quality, modelling choices, and assumptions about deposit models. As emphasized in recent studies (e.g., Lawley et al., 2022; Wearmouth et al., 2024), mineral potential maps should not be interpreted as economic valuations, but rather as relative indicators to be used in consultation with geoscience experts. End users with limited experience may misinterpret low-prospectivity rankings as definitive, potentially diverting attention from areas with genuine, but under-recognized, potential, or leading to the premature allocation of lands for other developments. Conversely, areas identified as relatively prospective could also be overstated if based on incomplete data.

At present, GSNL does not maintain an active mineral potential modelling program. The main limitations are lack of dedicated human resources, uneven data coverage, and concerns around consistent scientific standards and stakeholder use. Future implementation will likely depend on the establishment of national best practices and further work to improve both

the quality of input data and the communication of modelling uncertainty.

References cited

- Lawley, C.J.M., Gadd, M.G., Parsa, M., Lederer, G.W., Graham, G.E., and Ford, A., 2023. Applications of natural language processing to geoscience text data and prospectivity modeling. *Natural Resources Research*, 32,1503-1517. <https://link.springer.com/article/10.1007/s11053-023-10216-1>
- Ryan, R.J., Fisher, B.E., MacHattie, T.G., Prime, G., O'Reilly, G.A., and Calder, J.H., 2010. Guide to accompany the Geological Resource Atlas of Nova Scotia (Open File Maps ME 2010-1, -2, -3 and -4). Nova Scotia Department of Natural Resources, Mineral Resources Branch, Open File Report ME 2010-2, 38 p.
- Wearmouth, C.D., Peters, K.J., Czertowicz, T.A., and Orovan, E.A., 2024. Mineral potential modelling results for northwestern British Columbia, a comparison between past and current work at the British Columbia Geological Survey. In: *Geological Fieldwork 2023*, British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-01, pp. 79-95.

Holistically modelling the critical mineral potential of Nova Scotia

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Since late 2023, Nova Scotia has been undertaking a modernization of its mineral potential modelling. The objective of this project is to create a model of critical mineral potential in Nova Scotia, integrating a robust geological framework with spatial analyses of environmental, social and governance (ESG) considerations and economic feasibility. This model will provide factual insights to better understand emerging commodity inventories, encourage development, de-risk investment, and inform land-management decisions while training a new generation of highly qualified personnel. Support for this work has been provided to the Nova Scotia Geological Survey Division under the Geological Survey of Canada–led CMGD Initiative. Modernizing mineral potential modelling across the province aims to help strengthen the supply chains of critical minerals in Canada needed for a sustainable, modern world.

The modernization of mineral potential modelling in Nova Scotia was identified as a priority because the current models are about fifteen years out of date. Many of the methods and software that were used and mineral potential models that were developed have changed with time, necessitating that this work be reconstructed and updated. The original mineral potential assessment was completed in 2010 with a series of four mineral potential models (Nova Scotia Department of Natural Resources, Mineral Resources Branch, 2010a, 2010b, 2010c, 2010d) and an accompanying guide (Ryan et al., 2010). These thematic maps illustrate historically important mining and quarry resource areas in Nova Scotia. They were created to highlight historical staking and exploration trends, mineral domains, aggregate domains and maps indicating overall prospectivity. Using ArcGIS Pro and Model Builder, a relative ranking of mineral potential was calculated using a combination of spatial analysis and expert-driven inputs. Data sources included a variety of geoscience inputs and industry activity indicators, such as historical staking, exploration and mining activity (Nova Scotia Department of Natural Resources, Mineral Resources Branch, 2010b). Rankings were further upgraded for properties containing current or past-producing mines, exploration drillholes, and abandoned openings (AMO) such as shafts or adits.

The NovaROC database provides a partial digital record of exploration licenses, though its reliability diminishes for older data. The 2010 model incorporated 360,000 claims and licensing data only from 1940 to 2009. As part of the current update, we aim to integrate post-2009 data and may revise how staking information is used in future models.

Existing expert-driven models also define various mineral

domains in Nova Scotia. These domains were historically identified using the Mineral Occurrence Database and were ranked ‘low’, ‘medium’ and ‘high’ potential for hosting different styles of mineralization. Rankings were determined by a number of subject matter experts (Nova Scotia Department of Natural Resources, Mineral Resources Branch, 2010c). In 2010, thematic maps were published for a range of commodities, including antimony, barite and beryllium, carbonate and zeolite, coal, copper, granophile elements, gold, IOCG, manganese, potash, titanium, uranium, and zinc (Ryan et al., 2010). Rankings criteria included the presence of active or past-producing mines, associated mineral occurrences, significant standalone occurrences, and the presence of key rock units historically known to host economic mineralization.

Aggregate resource maps were created through expert knowledge to identify areas of the province with moderate and high potential for domestic aggregate production and shipping of aggregate products (Nova Scotia Department of Natural Resources, Mineral Resources Branch, 2010a). These maps highlighted areas with bedrock that was suitable for crushing into aggregate, and areas that held good potential to be used as sand and gravel resources including glaciomarine and glaciofluvial features such as eskers, kames and outwash plains. The maps also highlighted major operating aggregate producers, current and past-producing quarries and areas located close to the coast where export markets could be served from.

In all, more than 400,000 records were evaluated to produce the 2010 Mineral Resource Potential map series (Fig. 1), amalgamating calculations used to create the three other map series based on models of exploration and mining activity, mineral occurrences and deposits, and aggregate resource (Nova Scotia Department of Natural Resources, Mineral Resources Branch, 2010d). The map series ranks areas based on their overall mineral potential (Fig. 1). Moderate to high mineral potential areas mostly cluster where past mining activities occurred, for example the gold districts of Meguma, near Walton (barite and base metals), over historical coal mining areas, over Windsor Group rocks, and over the southwestern Nova Scotia tin domain. All the historical mining districts are shown as having moderate to high mineral potential.

Current work to update mineral potential models has chiefly focused on imparting new, long-term robustness and maintaining data freshness using ArcGIS Pro and Model Builder. These tools are being levered to minimize manual data entry and automate key components of the workflow, resulting in streamlined, parameter-driven tools that can be easily re-

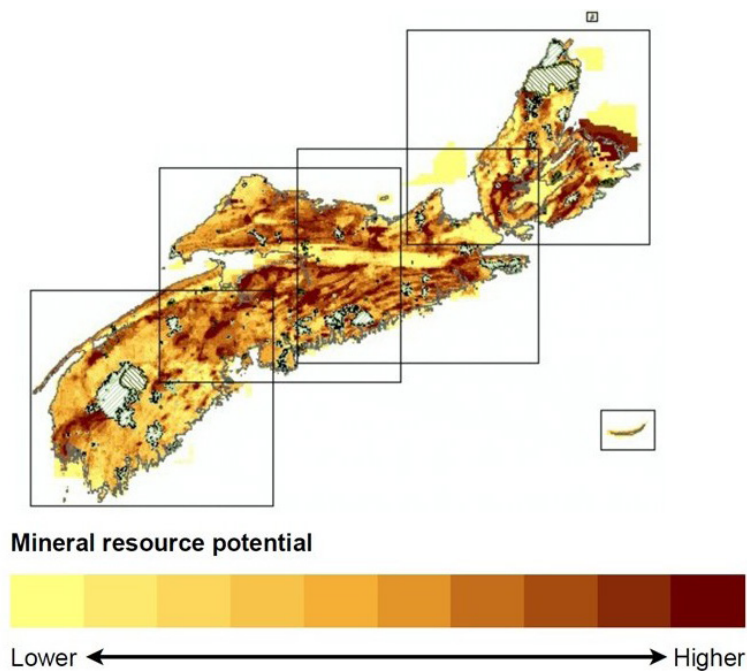


Fig. 1. Mineral resource potential in four sheets extending across all of Nova Scotia. Colours represent a ten-fold mineral resource potential score based on modelling. Darker colours having a higher mineral resource potential. This map is the amalgamation of calculations used to create three other map series based on models of exploration and mining activity, mineral occurrences and deposits, and aggregate resources.

run and adapted as needed. Model Builder's geoprocessing capabilities allow for cascading effects in subsequent steps that reduces the repetition of work required to maintain these models over time. Models can be easily fine-tuned and troubleshoot in ways that keep records of intermediate steps for examination and optimization. Additionally, the software provides intuitive visualizations of inputs and outputs that have proven valuable for technical staff during model development and review.

Ideally, a new approach will allow us to keep models current, making updates as new data are added into mineral occurrence, drillhole, and exploration licence databases. We aim to produce dynamic prospectivity models that allow for flexible weightings of rankings criteria, making it easier to adjust the influence of specific parameters as new insights emerge, particularly in comparison to the static framework used in the 2010 models.

Historically in Nova Scotia, significant importance has been placed on gold, coal, gypsum, barite and aggregate resources. Understanding the modern potential for critical minerals will help Nova Scotians better understand their resources, grow their economy and protect their environment for generations to come.

In addition to creating a mineral resource potential model, we plan to incorporate ESG and economic factors into the final models. This should provide additional context to potential investors and those considering exploring in Nova Scotia. We plan to publish model results primarily as an interactive GIS map to allow engagement with as broad an audience as possible. A new version of the mineral potential model is planned to be completed by early 2027.

References cited

- Nova Scotia Department of Natural Resources, Mineral Resources Branch (compiler) 2010a. Geological resource atlas, aggregate resources, southwestern area of Nova Scotia. Nova Scotia Department of Natural Resources, Mineral Resources Branch Open File Map ME 2010-3 (sheets 1-4), 1:250,000 scale. <https://novascotia.ca/natr/meb/geoscience-online/interactive-map-mra3.asp>
- Nova Scotia Department of Natural Resources, Mineral Resources Branch (compiler) 2010b. Geological resource atlas, exploration and mining activity, northeastern area of Nova Scotia. Nova Scotia Department of Natural Resources, Mineral Resources Branch Open File Map ME 2010-1 (sheets 1-4), 1:250,000 scale. <https://novascotia.ca/natr/meb/geoscience-online/interactive-map-mra1.asp>
- Nova Scotia Department of Natural Resources, Mineral Resources Branch (compiler) 2010c. Geological resource atlas, mineral occurrences and deposits, southwestern area of Nova Scotia. Nova Scotia Department of Natural Resources, Mineral Resources Branch Open File Map ME 2010-2 (sheets 1-4), 1:250,000 scale. <https://novascotia.ca/natr/meb/geoscience-online/interactive-map-mra2.asp>
- Nova Scotia Department of Natural Resources, Mineral Resources Branch (compiler) 2010d. Geological resource atlas, mineral resource potential, southwestern area of Nova Scotia. Nova Scotia Department of Natural Resources, Mineral Resources Branch Open File Map ME 2010-4 (sheets 1-4), 1:250,000 scale. <https://novascotia.ca/natr/meb/geoscience-online/interactive-map-mra4.asp>
- Ryan, R.J., Fisher, B.E., MacHattie, T.G., Prime, G., O'Reilly G.A., and Calder, J.H., 2010. Guide to accompany the Geological Resource Atlas of Nova Scotia (Open File Maps ME 2010-1, -2, -3, -4). Nova Scotia Department of Natural Resources, Mineral Resources Branch Open File Report ME 2010-2, 42 p.. <https://novascotia.ca/natr/meb/data/pubs/10ofr02/10ofr02.pdf>

Mineral potential modelling in New Brunswick: Recent advances and key projects

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New Brunswick hosts a diverse and significant endowment of mineral resources, including metallic minerals (e.g., zinc, lead, copper, silver, gold, tungsten, molybdenum, tin, indium, antimony, bismuth, cadmium, nickel, manganese, and rare earth elements), industrial minerals (e.g., potash, salt, limestone, gypsum, silica, gravel, sand, peat, clay, and crushed rock), as well as hydrocarbons and fossil fuels (e.g., conventional oil and natural gas, oil shale, shale gas, and coal). Despite this broad resource base, mineral potential modelling (MPM) efforts in New Brunswick have to date primarily focussed on occurrences of metallic minerals. This mineral endowment has long played a vital role in the province's economy and includes several major deposits. For instance, the Bathurst mining camp in northeastern New Brunswick hosts 46 volcanic-hosted massive sulfide deposits with a combined pre-mining resource exceeding 500 million tons (Goodfellow and McCutcheon, 2003; McCutcheon and Walker, 2020). This endowment, which accounts for a significant portion of Canada's historical Zn, Pb, Cu, and Ag production, ranks the Bathurst camp among the few mining districts globally with such large volumes of known base-metal sulfide mineralization. The Mount Pleasant mine, south of Fredericton, is among the world's largest known indium-bearing deposits and hosts Canada's most significant undeveloped indium resource (Sinclair et al., 2006). Furthermore, four gold districts have been delineated, one in northern New Brunswick, which includes multiple gold zones in the Chaleur Bay synclinorium (e.g., Sánchez-Mora et al., 2021; Bustard and Dahn, 2024) and three in the southwest, comprising the Clarence Stream deposits and the Annidale and New River gold belts (e.g., Thorne et al., 2008). In addition, manganese deposits near Woodstock (e.g., Way, 2014) represent some of the largest undeveloped resources of their kind in North America.

One of the essential prerequisites for conducting MPM is access to a wide range of geospatial datasets. In recent decades, the New Brunswick Geological Surveys Branch (NBGSB) has made efforts to compile and publicly disseminate such data (Government of New Brunswick, 2025a), including geological (Government of New Brunswick, 2025b), geochemical (e.g., till; Government of New Brunswick, 2025c), airborne geophysical (Government of New Brunswick, 2025d), and mineral occurrences databases (Rose and Johnson, 1990; Government of New Brunswick, 2025e), thereby facilitating MPM studies by researchers, exploration companies, and prospectors. Additionally, the NBGSB adopted an element-specific approach to delineate metallogenic zones and belts through a series of thematic reports and geological zonation maps. These reports consider both significant non-metallic and metallic minerals in New Brunswick, with examples

of the latter including manganese (Webb, 2008), uranium (McLeod & Smith 2010), tungsten (Stewart et al., 2011), gold (Thorne, 2011), lead (Walker, 2013a), zinc (Walker, 2013b), and antimony (Branscombe et al., 2018). They document mineral occurrences, deposit types, and exploration guidelines. These compilations provide valuable insights that support the application of the mineral systems approach to MPM (McCuaig et al., 2010).

Mineral prospectivity in New Brunswick is assessed using both knowledge-driven and data-driven methods, depending on the scale, data availability, and objective of each project. Key geoscience datasets, including geology, geochemistry, geophysics, and mineral occurrences, are systematically compiled and integrated into multi-criteria decision analysis frameworks or machine learning models to generate mineral potential maps. All prospectivity maps and methods are published through peer-reviewed journals, with a preference for open access (e.g., Karbalaieiramezanali et al., 2025), or released as open file reports (e.g., Karbalaieiramezanali et al., 2024a,b), ensuring transparency and accessibility. These products are regularly presented at the annual Exploration, Mining and Petroleum (EMP) conference, which has been hosted in Fredericton for more than 50 years and is a key venue for engaging with industry stakeholders. Through this forum, direct communication with prospectors and exploration companies is maintained, allowing for feedback and supporting the practical use of the maps in ongoing exploration activities.

Recent MPM projects in New Brunswick (Fig. 1) have been primarily funded and supported by the NBGSB and carried out either independently or in collaboration with the University of New Brunswick (UNB) and the Geological Survey of Canada (GSC). A postdoctoral project funded by the McCain Foundation and conducted at UNB, in collaboration with the NBGSB, focussed on predictive modeling of volcanic-hosted massive sulfide prospectivity in northeastern Bathurst mining camp. Parsa et al. (2023) applied machine learning-based mineral prospectivity mapping to delineate promising Zn, Pb, Cu, and Ag zones. They addressed three key challenges: weak geophysical and geochemical signals, a limited number of known deposits, and high geological variability. To improve robustness, an ensemble regularized regression approach (LASSO, Ridge, Elastic Net) was employed, effectively reducing overfitting and uncertainty.

A PhD project funded by NBGSB and UNB focuses on gold mineralization in northern New Brunswick (Mami Khalifani et al., 2024). It integrates GIS data with portable and micro-XRF analyses of core samples from Williams Brook, McIntyre Brook, Mulligan Gulch, and Simpsons Field, representing both orogenic and epithermal systems in

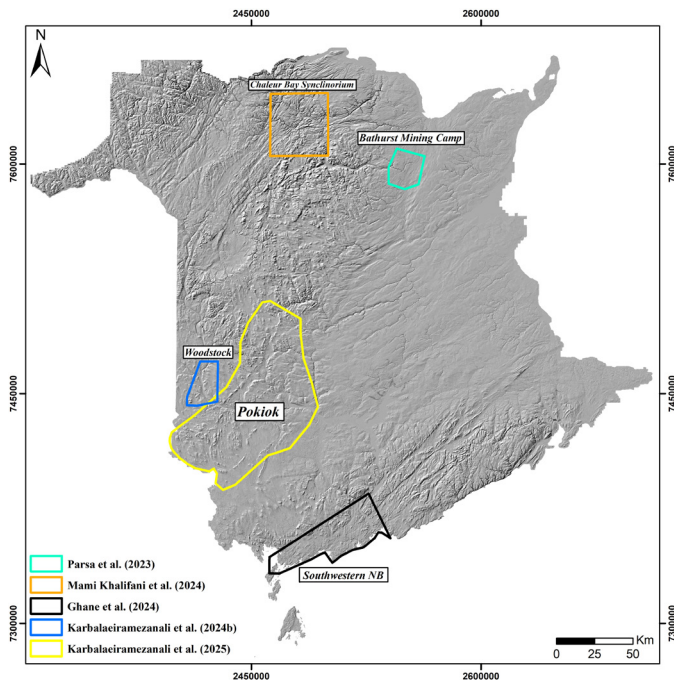


Fig. 1. Areas in New Brunswick where MPM projects have been conducted in recent years or are ongoing.

the Chaleur Bay synclinorium. Another PhD project funded by NBGSB and UNB integrates geological, geochemical, and geophysical datasets to identify gold and polymetallic targets in southwestern New Brunswick (Ghane et al., 2024). The study employs ML with expert interpretation, μ XRF/pXRF, geophysical measurements, and mineralogical analyses across multiple terranes and structures. It aims to generate predictive maps based on spatial proxies and petrophysical–geochemical data. A related study by Ghane et al. (2025) focusses on orogenic gold, applying ensemble ML methods (RF, XGBoost, XGBRF) to calibrate geophysical and geological layers. Structural complexity emerged as the most important predictor, and model uncertainty was quantified via bootstrap variance to develop confidence-weighted prospectivity maps. Together, these studies demonstrate a robust, data-driven approach to targeting gold in complex terranes.

Since 2021, the ‘Evaluation and Characterization of the Mineralizing Systems within the Western and Northern Pokiok Batholith’ project has focussed on Devonian intrusion-related systems such as Sisson Brook (W-Mo) and Lake George (Sb). The study includes geological mapping (Gebru, 2024), till geochemistry (Gilmore, 2024), aeromagnetic interpretation (Ugalde et al., 2024), and MPM (Karbalaieiramezanali et al., 2024a). Karbalaieiramezanali et al. (2025) applied a Monte Carlo-based knowledge-driven MPM framework targeting W–Mo–Sb–Au systems. The MCS–LBWA–MARCOS model, integrating the mineral systems approach with parsimonious weighting and risk–return analysis, achieved the highest accuracy, reducing the search area by ~15% while capturing ~73% of known occurrences. The ‘Mineral Prospectivity Mapping of Porphyry–Low Sulfidation Epithermal Systems in the Woodstock Area’ project (2024–ongoing) targets porphyry and epithermal mineralization in a historically Mn-rich district. Karbalaieiramezanali et al. (2024b) used a mineral systems approach and Random Forest modelling, transforming key

geoscience layers into spatial vectors, evaluated by ROC–AUC, to delineate prospective zones.

A Critical Minerals Geoscience and Data (CMGD) initiative project, approved in 2025, is investigating the geochronology and petrogenesis of granitoids and related critical mineral systems in New Brunswick. It aims to generate precise geochronological and petrochemical datasets for felsic magmatism-related systems (e.g., stockwork and greisen, pegmatites, polymetallic veins). A complementary MPM project will target Sn–W–Li–Cs–Ta mineralization linked to granitic plutons. Additionally, NBGSB is currently developing methods for a provincial-scale MPM to support land-use planning. The study uses 31 GIS layers grouped under five main criteria: mineral occurrences, bedrock geology, faults, till geochemistry, and distinct geological areas. Sub-criteria are weighted using expert knowledge and integrated via an Index Overlay model to generate a composite prospectivity map highlighting high-potential zones.

References cited

- Branscombe, L., Charnley, B., and Thorne, K., 2018. Antimony. New Brunswick Department of Energy and Resource Development, Energy and Mines Division. Mineral Commodity Profile 12, 7 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/mcp_12-e.pdf
- Bustard, A.L., and Dahn, D.R.L., 2024. Characteristics and structural setting of vein-hosted Au–Ag–Pb–Zn mineralization associated with the Mulligan Gulch Porphyry, north-central New Brunswick. New Brunswick Department of Natural Resources. Geoscience Report 2024-1, 33 p. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx>
- Gebru, A., 2024. Petrological assessment of granitoids in the Pokiok region and vanadium potential of the Benton area, New Brunswick, NTS 21 G/11, 12, 13, 14, and 21 J/03. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 81–87. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Ghane, B., Lentz, D.R., Thorne, K.G., Parsasadr, M., and Hughson, K., 2024. Mineral potential mapping in southwestern New Brunswick: Integration of geochemical, geophysical, and geological datasets in predictive modelling. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 92–96. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Ghane, B., Lentz, D.R., and Thorne, K., 2025. Mineral prospectivity mapping of orogenic gold mineralization in southwestern New Brunswick, Canada (poster). GAC-MAC 2025 Conference, Fredericton, NB, Canada. <https://doi.org/10.13140/RG.2.2.18055.51362>
- Gilmore, W.F., 2024. Pokiok plutonic suite till sampling project: A focus on critical minerals. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 88–91. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Goodfellow, W.D., and McCutcheon, S.R., 2003. Geologic and genetic attributes of volcanic sediment-hosted massive sulfide deposits of the Bathurst Mining Camp, northern New Brunswick: a synthesis. In: Goodfellow, W.D., McCutcheon, S.R., and Peter, J.M. (Eds.), Massive Sulphide Deposits of the Bathurst Mining Camp, New Brunswick, and Northern Maine. Economic Geology Monograph 11, pp. 245–302.

- Government of New Brunswick, 2025a. Data Catalogue-GeoNB, New Brunswick Department of Natural Resources. <https://www.snb.ca/geonb1/e/dc/catalogue-E.asp>
- Government of New Brunswick, 2025b. Bedrock geology. New Brunswick Department of Natural Resources. https://www2.gnb.ca/content/gnb/en/departments/erd/energy/content/minerals/content/bedrock_mapping.html
- Government of New Brunswick, 2025c. Till geochemistry. New Brunswick Department of Natural Resources. <https://www2.gnb.ca/content/gnb/en/departments/erd/open-data/geochemistry.html>
- Government of New Brunswick, 2025d. Airborne Magnetic, Gravity, EM and Multiparameter Surveys of New Brunswick. New Brunswick Department of Natural Resources. <https://www2.gnb.ca/content/gnb/en/departments/erd/energy/content/minerals/content/Geophysics/AirborneMagneticGravityEMMultiparameterSurveys.html>
- Government of New Brunswick, 2025e. Metallic Minerals, New Brunswick Department of Natural Resources. <https://www2.gnb.ca/content/gnb/en/departments/erd/open-data/metallic-minerals.html>
- Karbalaeiramezanali, A., Parsasadr, M., Lentz, D.R., Gebru, A., Thorne, K.G., and Gilmore, W.F., 2024a. Mineral prospectivity mapping of the Devonian intrusion-related mineralization, the Pokiok plutonic suite. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 39-43. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Karbalaeiramezanali, A., Parsasadr, M., Lentz, D.R., Thorne, K.G., and Gebru, A., 2024b. Machine learning-based prospectivity mapping for porphyry–low sulphidation deposits in Woodstock. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 34-38. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Karbalaeiramezanali, A., Parsa, M., Lentz, D.R., and Thorne, K.G., 2025. Prospectivity modeling of Devonian intrusion-related W–Mo–Sb–Au deposits in the Pokiok plutonic suite, west-central New Brunswick, Canada, using a Monte Carlo-based framework. *Natural Resources Research*, 34, 669-702. <https://doi.org/10.1007/s11053-024-10437-y>
- Mami Khalifani, F., Lentz, D.R., and Walker, J.A., 2024. Predictive modelling of gold mineralized systems in northern New Brunswick: Insights from the analysis of multiple geoscience datasets. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 97-102. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- McCuaig, T.C., Beresford, S., and Hronsky, J., 2010. Translating the mineral systems approach into an effective exploration targeting system. *Ore Geology Reviews*, 38, 128-138. <https://doi.org/10.1016/j.oregeorev.2010.05.008>
- McCutcheon, S.R., and Walker, J.A., 2020. Great mining camps of Canada 8. The Bathurst mining camp, New Brunswick, Part 2: Mining history and contributions to society. *Geoscience Canada*, 47, 143-166. <https://doi.org/10.12789/geocanj.2020.47.163>
- McLeod, M.J., and Smith, E.A., 2010. Uranium. New Brunswick Department of Natural Resources, Lands, Minerals and Petroleum Division, Mineral Commodity Profile No. 6, 7 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_6-e.pdf
- Parsa, M., Lentz, D.R., and Walker, J.A., 2023. Predictive modeling of prospectivity for VHMS mineral deposits, northeastern Bathurst mining camp, NB, Canada, using an ensemble regularization technique. *Natural Resources Research*, 32, 19-36. <https://doi.org/10.1007/s11053-022-10133-9>
- Rose, D.G., and Johnson, S.C., 1990. New Brunswick computerized mineral occurrence database. New Brunswick Department of Natural Resources, Minerals and Energy Division, Mineral Resource Report 3, 69 p.
- Sánchez-Mora, D., McFarlane, C.R., Walker, J.A., and Lentz, D.R., 2021. Geochemistry and U–Pb geochronology of the Williams Brook area, Tobique–Chaleur zone, New Brunswick: Stratigraphic and geotectonic setting of gold mineralization. *Canadian Journal of Earth Sciences*, 58, 1040-1058. <https://doi.org/10.1139/cjes-2020-0094>
- Sinclair, W.D., Kooiman, G.J.A., Martin, D.A., and Kjarsgaard, I.M., 2006. Geology, geochemistry and mineralogy of indium resources at Mount Pleasant, New Brunswick, Canada. *Ore Geology Reviews*, 28, 123-145. <https://doi.org/10.1016/j.oregeorev.2003.03.001>
- Stewart, H.J., McLeod, M.J., and Thorne, K.G., 2011. Tungsten. New Brunswick Department of Natural Resources, Lands, Minerals and Petroleum Division, Mineral Commodity Profile No. 7, 7 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_7-e.pdf
- Thorne, K.G., 2011. Gold. New Brunswick Department of Natural Resources, Lands, Minerals and Petroleum Division, Mineral Commodity Profile No. 8, 8 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_8-e.pdf
- Thorne, K.G., Lentz, D.R., Hoy, D., Fyffe, L.R., and Cabri, L.J., 2008. Characteristics of mineralization at the main zone of the Clarence Stream gold deposit, southwestern New Brunswick, Canada: Evidence for an intrusion-related gold system in the northern Appalachian orogen. *Exploration and Mining Geology*, 17, 13-49.
- Ugalde, H., Morris, W.A., and Dahn, D.R.L., 2024. High-resolution aeromagnetic compilations, New Brunswick: Updating the data for the New Brunswick Open Data Portal. In: Smith, E.A. (Ed.), Geoscience project summaries and other activities 2024. New Brunswick Department of Natural Resources, Information Circular 2024-1, pp. 14-17. <https://dnr-mrn.gnb.ca/ParisWeb/PublicationDetails.aspx?Num=IC%202024-1&lang=e>
- Walker, J.A., 2013a. Lead. New Brunswick Department of Energy and Mines, Minerals and Petroleum Division, Mineral Commodity Profile No. 10, 6 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_10-e.pdf
- Walker, J.A., 2013b. Zinc. New Brunswick Department of Energy and Mines, Minerals and Petroleum Division, Mineral Commodity Profile No. 9, 6 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_9-e.pdf
- Way, B., 2014. Stratigraphic and paleoenvironmental setting of the Woodstock Fe–Mn deposits in west-central New Brunswick. Geological Association of Canada–Mineralogical Association of Canada Joint Annual Meeting Fredericton, NB, Field Trip B10.
- Webb, T.C., 2008. Manganese. New Brunswick Department of Natural Resources, Lands, Minerals and Petroleum Division, Mineral Commodity Profile No. 1, 8 p. https://www2.gnb.ca/content/dam/gnb/Departments/en/pdf/Minerals-Minerales/MCP_1-e.pdf

Two decades of mineral potential modelling in Québec: Geoscientific knowledge at the core of Géologie Québec's work

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The mission of Québec's Ministère des Ressources naturelles et des Forêts (MRNF) is to manage and support the sustainable development of the province's natural resources and territory. This mission is being carried out by Géologie Québec through the acquisition, compilation, and dissemination of geoscientific knowledge. Since the early 2000s, Géologie Québec has also been actively involved in mineral potential modelling to assess the likelihood of discovering specific deposit types in areas of interest. These studies help address various land-use planning challenges, inform strategic decision making, and promote Québec's mineral potential more effectively.

The establishment of SIGÉOM, Québec's Geomining Information System, in 1995 played a pivotal role in facilitating mineral potential assessments across the province. SIGÉOM is Géologie Québec's spatially referenced information system, which provides centralized access to a repository of geoscientific data collected in the past 150 years. Continuously updated with geological data from government surveys, industry exploration, and academic research, it serves as a critical tool for mineral potential assessments, exploration guidance, scientific research, and resource management.

The rise of digital platforms and algorithms in recent decades has driven the adoption of increasingly sophisticated assessment methods. Conceptual mineral prospectivity maps based on SIGÉOM data were first produced for various deposit types, including volcanogenic massive sulfides (Dion and Lamothe, 2002), IOCG (Lamothe and Beaumier, 2001; 2002), and kimberlites (Labbé, 2002). The 'hybrid fuzzy logic' approach (Brown et al., 2003; Porwal et al., 2003) quickly gained traction at Géologie Québec, because it offered a compromise between the flexibility of conceptual approaches and the rigour of empirical methods. It has since been applied to model volcanogenic massive sulfides (Lamothe et al., 2005; Lamothe, 2011; 2013), porphyry Cu-Au-Mo (Labbé et al., 2006; Lamothe, 2009), and orogenic gold deposits (Lamothe and Harris, 2006; Lamothe, 2008; 2014; Allard et al., 2015).

In the last decade, Géologie Québec has continued to monitor technological advances in artificial intelligence (AI) applied to mineral prospectivity mapping, though a formal integration framework is still under development. As noted by Zuo (2020), these methods allow for more objective analysis and facilitate the discovery of complex spatial patterns and statistical relationships in geoscientific datasets. Despite these technological advances, geological expertise remains essential. Géologie Québec emphasizes that regional-scale mineral potential assessments must integrate data-driven approaches with sound geological interpretations, within a framework of sustainable development and balanced land use.

Most metallogenic models developed by Géologie Québec since 2005 follow a semi-empirical approach inspired by

Porwal et al. (2003), which integrates data-driven fuzzy logic by combining the empirical weights-of-evidence (WoE) method with conceptual fuzzy reasoning. The method uses known deposit locations from the SIGÉOM database, with about 85% of the deposits forming the training set and the remaining 15% withheld as a validation set to test the final predictive map. Geological, geophysical, and geochemical parameters relevant to the model are first tested using the WoE method to quantify their spatial association with the deposit set. The ArcSDM extension (Bonham-Carter et al., 1989; Kemp et al., 2001) is used to calculate contrast values for each parameter. These model layers are then combined using fuzzy overlay operators to produce a composite fuzzy favourability value in the final prospectivity map.

The fuzzy OR operator is employed to combine parameters that may represent the same geological phenomenon and highlights areas where any individual factor is high. The fuzzy GAMMA operator provides a compromise between union and intersection, allowing the modeller to modulate the influence of overlapping favorable parameters. Data processing is conducted using ArcGIS Model Builder (v.10.1) with SIGÉOM data, allowing for rapid model updates as the database evolves. Géologie Québec currently uses ArcGIS 10.7 and is gradually transitioning to ArcGIS Pro and QGIS.

Because mineral potential modelling relies on integrated geoscientific data, the centralized SIGÉOM database represents an essential resource (Fig. 1). Users can download all available geoscientific data for a study area in various formats (FGDB, Shapefile, CSV, or GPKG; Ministère des Ressources naturelles et des Forêts du Québec, 2025). The database is continuously updated with MRNF's annual geoscientific acquisition efforts, academic research, and mandatory industry reporting.

To further enhance the geochemical database, Géologie Québec has, for the past two years, applied AI models to extract static geochemical data from PDF-format company reports. This technique (Blondelle, 2022) is expected to double the number of analyses in the geochemical database and improve future modelling efforts. Additionally, mineral potential at Géologie Québec is assessed using geochemical data from secondary environments (lakes, streams, till, soil) through natural thresholding and multiple spatial regression techniques, particularly in Québec's northern regions, where geoscientific coverage is limited (Fig. 1). The multiple spatial regression method used is based on Trépanier's (2006) adaptation of the Geographically Weighted Regression concept by Fotheringham et al. (2002). First applied to the entire lake sediment database by Lamothe (2010), it has more recently been used in localized surveys in Eeyou Istchee Baie-James (e.g., Lamarche, 2024). The goal is to predict elemental concentrations in samples based on lithological contributions while minimizing local

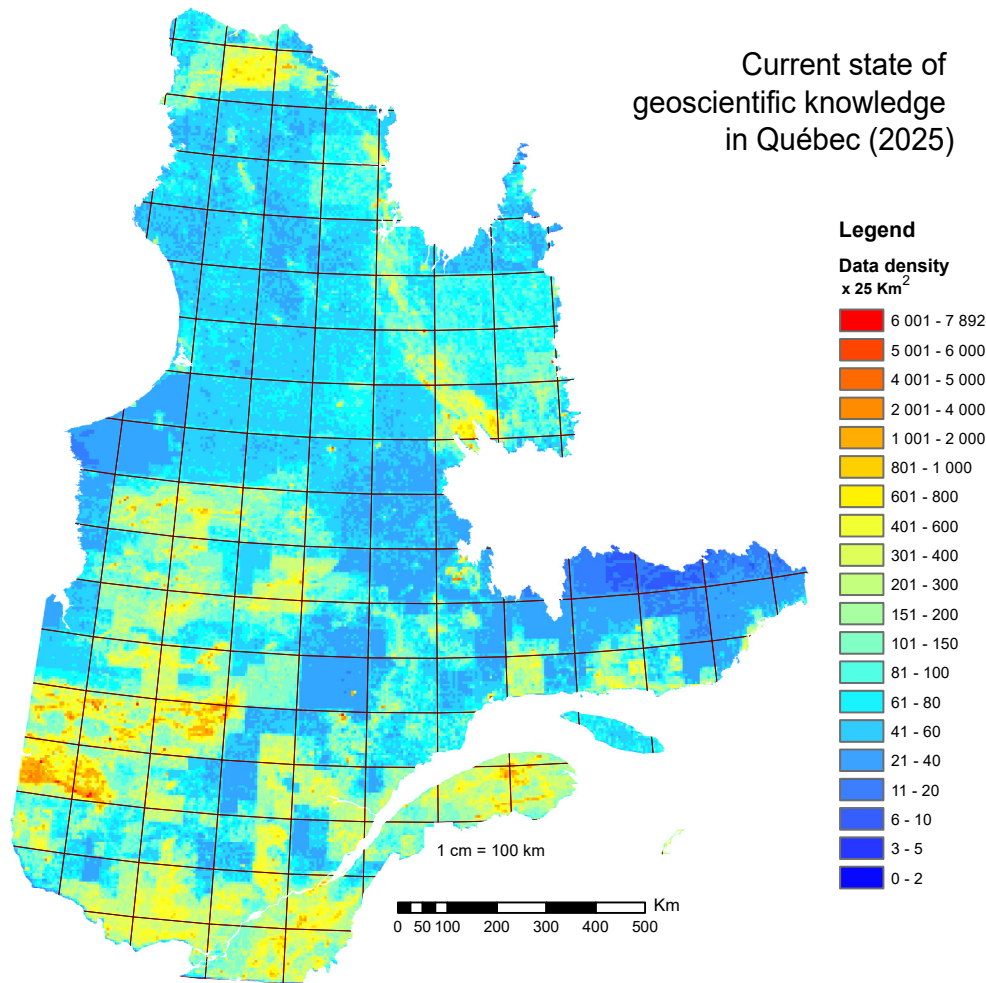


Fig. 1. Map of Québec's state of geoscientific knowledge illustrating the distribution and density of available data in the SIGÉOM database as of 2025 (Ministère des Ressources naturelles et des Forêts du Québec, 2025). The map was produced by performing a spatial intersection of all georeferenced documents and data using 25 km² grid cells extending across the entire province. More than 91,000 documents, 3 million point features, 700,000 linear features, and 800,000 polygons were used to generate the density map. Density represents the number of occurrences per cell (e.g., geological reports, mapped faults, lithological units, drill holes), with a color gradient from blue (low density) to red (high density).

background noise. If a measured concentration significantly exceeds the predicted value, the residual value may indicate nearby mineralization. Each prediction is calculated from neighboring sample compositions using a multiple spatial regression equation. This method helps prioritize geoscientific data acquisition in underexplored areas that show unexplained geochemical anomalies.

The most recent mineral potential study using the hybrid WoE/fuzzy logic approach focussed on orogenic gold in the Eeyou Istchee James Bay region (Allard et al., 2015; Fig. 2a). It updated a previous assessment by Lamothe (2008; Fig. 2b) by integrating new geological, geochemical, and geophysical data, along with recent discoveries by mining companies. This led to more precisely defined high-favourability zones, particularly associated with volcano-sedimentary rocks.

To explore AI-based approaches, a university partnership applied the HyperCube® predictive algorithm to develop a parallel orogenic gold potential model in the same area

(Larouche et al., 2018). The resulting map closely aligned with the previous work, while also better identifying the most influential variables in the model. Since then, further advanced algorithm studies have been conducted with industry and academic partners to lever the SIGÉOM database, including AI-based geoscientific data analysis (Blouin, 2020), deep learning for preliminary geological mapping from airborne magnetic data (Cedou et al., 2022), and 2D curvilinear lineament extraction (Abbassi and Cheng, 2025).

Recent and past studies alike highlight the importance of a robust geoscientific database—both in terms of quality and quantity—for reliable mineral potential modelling. To provide a harmonized database, a compilation of several lake sediment geochemical surveys was recently completed, producing leveled maps for various metallic elements (As, Cu, Ni, Zn) across much of the Canadian Shield in Québec (Solgadi, 2024). These maps, available via SIGÉOM's interactive portal, support rapid visualization of areas of interest, and further

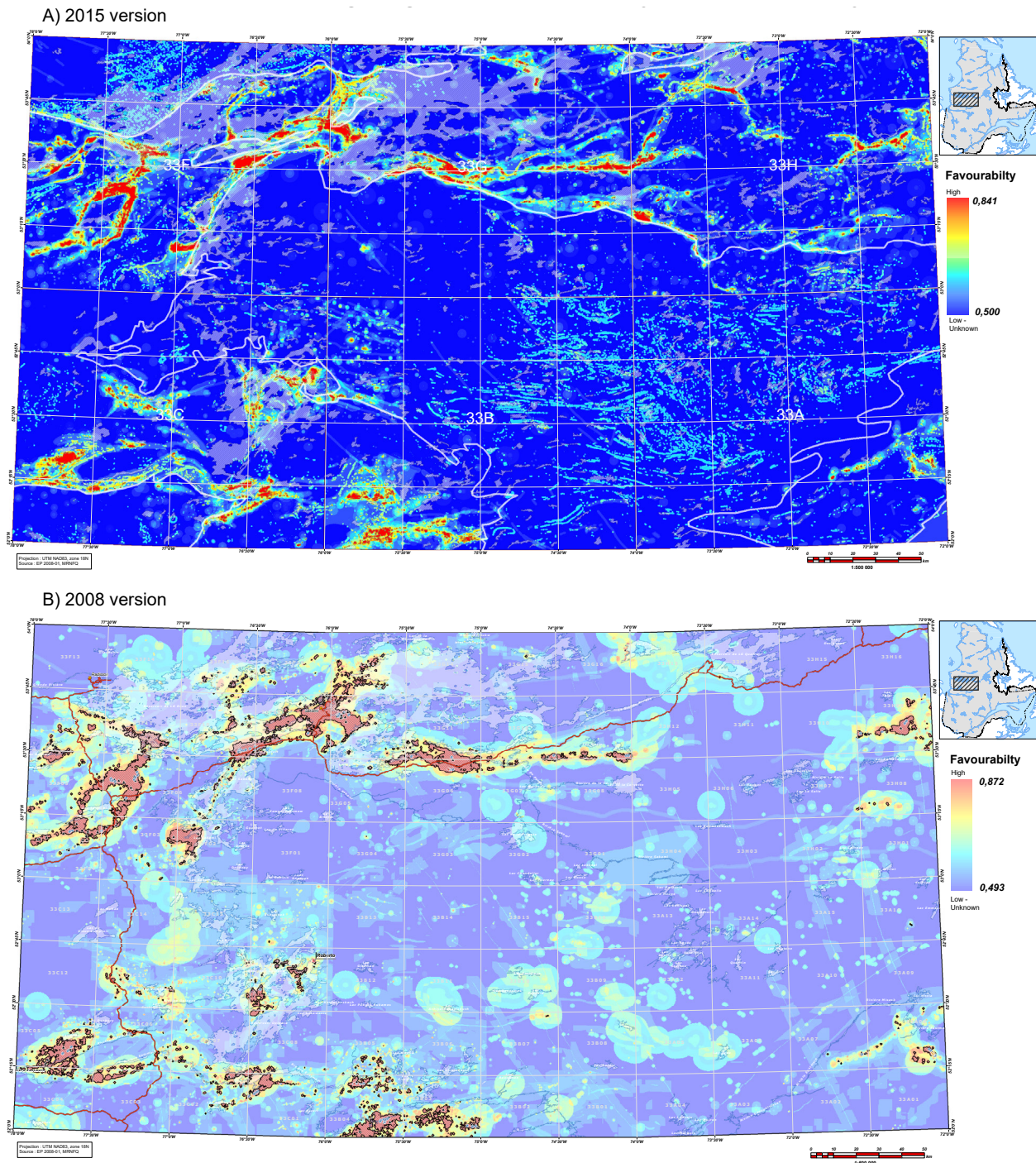


Fig. 2. Evolution of the orogenic gold potential assessment model for the Eeyou Istchee James Bay region. **a)** The updated 2015 version, based on a more robust database that includes updated geological mapping by Géologie Québec and exploration work by mining companies (Allard et al., 2015). **b)** The original 2008 version (Lamothe, 2008). The updated model highlights new and better-constrained high-favourability zones, shown in red

statistical treatments such as spatial regression could help detect anomalous signals.

Mineral potential modelling is a dynamic and evolving process that must adapt to new metallogenic models, integration of new data, and technological innovation. Géologie Québec is working to modernize its modelling practices by incorporating machine learning techniques into regional-scale potential

mapping, while keeping geoscientific expertise at the core of its approach, pursuing a hybrid knowledge- and data-driven strategy. Concurrently, the organization must continue to address environmental and social considerations in mineral development by enhancing both the communication and accessibility of geoscientific data in a manner that respects community rights, notably those of Indigenous communities,

and promotes equitable regional benefits. Despite the increasing use of advanced tools, the modelling methods developed in the past two decades remain valuable tools for land-use planning and for prioritizing geoscientific data acquisition across Québec's vast and geologically diverse territory.

References cited

- Abbassi, B., and Cheng, L. Z., 2025. ELC2D : une interface graphique pour l'extraction de linéaments curvilignes en 2D. URSTM, Ministère des Ressources naturelles et des Forêts, Québec; MB 2025-03, 52 p.
- Allard, G., Goutier, J., and Lamothe, D., 2015. Évaluation du potentiel en minéralisations d'or de type orogénique, municipalité d'Eeyou Istchee Baie-James (version 2014). Ministère de l'Énergie et des Ressources naturelles, Québec; EP 2015-01, 42 p., 1 plan.
- Blondelle, H., 2022. Capturing tabular data in documents related to the mining domain. Second EAGE Digitalization Conference and Exhibition, March 2022, Vol. 2022, pp. 1–9. European Association of Geoscientists & Engineers.
<https://doi.org/10.3997/2214-4609.202239049>
- Blouin, M., 2020. Traitement statistique et analyse avancée de données géoscientifiques par intelligence artificielle. GEOLEARN, Ministère de l'Énergie et des Ressources naturelles, Québec; MB 2020-13, 49 p.
- Bonham-Carter, G. F., Agterberg, F. P., and Wright, D. F., 1989. Weights of evidence modelling: a new approach to mapping mineral potential. In: Agterberg F.P., and Bonham-Carter G.F., (Eds.), Statistical Applications in the Earth Sciences. Geological Survey of Canada, Paper 89-09, pp. 171-183.
- Brown, W., Groves, D., and Gedeon, T., 2003. Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral-potential mapping. Natural Resources Research, 12, 183-200.
<https://doi.org/10.1023/A:1025175904545>
- Cedou, M., Gloaguen, E., Blouin, M., Caté, A., Paiement, J.-P., and Tirad, S., 2022. Cartographie géologique préliminaire des données magnétiques aéroportées par apprentissage automatique profond. INRS, Ministère de l'Énergie et des Ressources naturelles, Québec; MB 2022-08, 51 p.
- Dion, C., and Lamothe, D., 2002. Évaluation du potentiel en minéralisations de type sulfures massifs volcanogènes de la région de Chibougamau (32G) – intégration de géodonnées par la technologie d'analyse spatiale. Ministère des Ressources naturelles, Québec; EP 2002-04, 43 p., 40 plans.
- Fotheringham, A. S., Brundson, C., and Charlton, M., 2002. Geographically weighted regression: the analysis of spatially varying relationships. John Wiley & Sons Ltd., 282 p.
- Kemp, L. D., Bonham-Carter, G. F., Raines, G. L., and Looney, C. G., 2001. Arc-SDM: ArcView extension for spatial data modelling using weights of evidence, logistic regression, fuzzy logic and neural network analysis. Retrieved from <http://www.ige.unicamp.br/sdm/>
- Labbé, J.-Y., 2002. Évaluation du potentiel de découverte de kimberlites dans la région du grand-nord du Québec – intégration de géodonnées par la technologie d'analyse spatiale. Ministère des Ressources naturelles, Québec; EP 2002-05, 29 p., 1 plan.
- Labbé, J.-Y., Pilote, P., and Lamothe, D., 2006. Évaluation du potentiel minéral pour les gîtes porphyriques de Cu-Au-Mo de l'Abitibi. Ministère des Ressources naturelles et de la Faune, Québec; EP 2006-03, 47 p., 1 plan.
- Lamarche, O., 2024. Levé géochimique de sédiments de fond de lac dans le secteur de la rivière au Castor, Province du Supérieur. Ministère des Ressources naturelles et des Forêts, Québec, Geo Data Solutions GDS Inc.; RP 2024-02, 56 p.
- Lamothe, D., 2008. Évaluation du potentiel en minéralisations de type orogénique de la Baie-James. Ministère des Ressources naturelles et de la Faune, Québec; EP 2008-01, 54 p., 33 plans.
- Lamothe, D., 2009. Évaluation du potentiel minéral pour les gîtes porphyriques de Cu-Au ± Mo de la Baie-James. Ministère des Ressources naturelles et de la Faune, Québec; EP 2009-01, 54 p., 1 plan.
- Lamothe, D., 2010. Modélisation de cibles de l'environnement secondaire par des techniques de seuils naturels et de régression spatiale multiple. Ministère des Ressources naturelles et de la Faune, Québec; EP 2010-01, 28 p.
- Lamothe, D., 2011. Potentiel en minéralisations de sulfures massifs volcanogènes de l'Abitibi – version 2011. Ministère des Ressources naturelles et de la Faune, Québec; EP 2011-01, 18 p., 1 plan.
- Lamothe, D., 2013. Évaluation du potentiel en minéralisations de sulfures massifs volcanogènes de type pélitique-mafique pour la Fosse du Labrador. Ministère des Ressources naturelles, Québec; EP 2012-01, 43 p., 1 plan.
- Lamothe, D., 2014. Évaluation du potentiel pour les minéralisations de type orogénique dans le Domaine Nord de l'Orogène de l'Ungava. Ministère de l'Énergie et des Ressources naturelles, Québec; EP 2013-01, 36 p., 1 plan.
- Lamothe, D., 2015. Évaluation du potentiel pour les minéralisations de type orogénique dans le domaine Nord de l'Orogène de l'Ungava. Ministère de l'Énergie et des Ressources naturelles, Québec; EP 2013-01, 36 p., 1 plan.
- Lamothe, D., and Beaumier, M., 2001. Évaluation du potentiel en minéralisations de type Olympic Dam-Kiruna de la région du lac Manitou (SNRC 22I). Ministère des Ressources naturelles, Québec; EP 2001-01, 36 p., 58 plans.
- Lamothe, D., and Beaumier, M., 2002. Évaluation du potentiel en minéralisations de type Olympic Dam-Kiruna de la région du lac Fournier (22P) – intégration de géodonnées par la technologie d'analyse spatiale. Ministère des Ressources naturelles, Québec; EP 2002-01, 45 p., 57 plans.
- Lamothe, D., and Harris, J. R., 2006. Évaluation du potentiel en minéralisations de type orogénique des roches archéennes de l'Abitibi. Ministère des Ressources naturelles et de la Faune, Québec; EP 2006-01, 64 p., 1 plan.
- Lamothe, D., Harris, J. R., Labbé, J.-Y., Doucet, P., Houle, P., Moorhead, J., Dion, C., Savard, R., and Melancon, M., 2005. Évaluation du potentiel en minéralisations de type sulfures massifs volcanogènes (SMV) pour l'Abitibi. Ministère des Ressources naturelles, Faune et Parcs, Québec; EP 2005-01, 99 p., 1 plan.
- Larouche, E., Allard, G., Girard, R., Dombrowski, C., and Daigneault, R., 2018. Étude prédictive du potentiel minéral pour les gîtes d'or orogénique du secteur de la Baie-James en utilisant le classificateur binaire HyperCube®. UQAC, Ministère de l'Énergie et des Ressources naturelles, Québec; MB 2018-20, 108 p.
- Ministère des Ressources naturelles et des Forêts du Québec, 2025. SIGÉOM – Système d'information géomine. [Online] https://sigeom.mines.gouv.qc.ca/signet/classes/11102_indexAccueil?l=a
- Porwal, A., Carranza, E. J. M., and Hale, M., 2003. Knowledge-driven and data driven fuzzy models for predictive mineral potential mapping. Natural Resources Research, 12, 1-25.
- Solgadi, F., 2024. Cartes géochimiques nivelées des sédiments de fond de lac du Québec. Ministère des Ressources naturelles et des Forêts, Québec; RP 2024-04, 19 p.
- Trépanier, S., 2006. Identification de domaines géochimiques à partir des levés régionaux de sédiments de fond de lacs – Phase 2. CONSOREM; projet 2005-03. Ministère des Ressources naturelles et de la Faune, Québec; MB 2006-07, 82 p.
- Zuo, R., 2020. Geodata science-based mineral prospectivity mapping: a review. Natural Resources Research, 29, 3415-3424.
<https://doi.org/10.1007/s11053-020-09700-9>

Mineral potential assessments and related updates to mineral occurrence data in Manitoba

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Since 1928, the Manitoba Geological Survey (MGS) has collected, compiled, and shared the geoscience data needed to inform mineral potential assessments in the province. The MGS publishes these data in publications such as the annual MGS Report of Activities, which highlights new survey findings relating to mineral potential.

Systematic assessments of mineral potential by the MGS have been mostly limited to smaller project areas. Examples include a VMS deposit potential model for part of the Flin Flon - Snow Lake area (Wright and Carter, 1996) and a set of maps showing modeled VMS and shear-hosted gold potential in part of the Lynn Lake greenstone belt produced using a combination of aeromagnetic data, regional geology including structures, and bedrock geochemistry (Rogge et al., 2000). The MGS also publishes annual brochures for selected commodities or commodity groups, containing a brief province-scale overview of important known deposits, key geological processes or host rocks, or major developments (e.g., new mineral resource estimates, mine closures).

Based on informal group discussions within MGS, a straightforward series of distance buffers around weighted mineral occurrence points and selected geological units (e.g., ultramafic units, syenite complexes, graphite-rich sedimentary units) was used and adjusted for recent cases that required constructing polygons of higher mineral potential within a given map extent. In the area of interest, weighting of each mineral occurrence point was determined by expert consensus (accounting for differences between e.g., a bedrock sample with 1000 ppm Ni and another with 1% Ni, or between an isolated bedrock sample and a larger prospect with published resource estimates). To better communicate possible limitations due to bias in sample locations or other data, the internal maps produced by this rough method include a cautionary note that “Gaps in geoscience data [in the map area] prevent thorough assessments of mineral potential; zones in beige and grey may indicate a lack of data (such as in large zones of buried bedrock) rather than a lack of potential. The gaps in data vary both by region and by commodity; this map is a simplification that may change based on future work or understanding.”

The MGS has not published any province-wide mineral potential maps. Since 2020, related efforts have instead been focused on expanding the provincial database of mineral occurrences in bedrock, with immediate impacts on mineral potential assessments. Previous versions of Manitoba’s Mineral Deposits Database (MDD; Conley et al., 2009) omitted large regions of Manitoba and lacked clear criteria for occurrence classification, resulting in hundreds of ‘mineral occurrences’ later deemed to be unimportant or irrelevant with respect to mineral potential. After establishing criteria for mineral occurrence classification – now expanded to include a wider range of commodity types – new mineral occurrence data

were and are being gathered from a range of sources including provincial assessment reports.

The compilation of new mineral occurrence data in Manitoba is being achieved mostly through: 1) collection of bedrock geochemistry results, assisted with a table extraction tool (tabula-py), to identify any results exceeding defined occurrence minimum values; 2) keyword / phrase searches that allow for natural language variations and typos or OCR errors (282 phrases relating to Manitoba commodities, using dtSearch); and 3) collection of other occurrence data including location information, which typically involves georeferencing of sample or drill collar location maps. Compared to the MDD version last published in 2009 (Conley et al., 2009), the current version (Rinne, 2024), which is updated annually, provides a more comprehensive view of the spatial distribution of various mineral commodities in Manitoba (Fig. 1).

MDD updates have enabled producing new mineral occurrence maps and plain-language summaries of mineral potential in selected regions, many provided at the request of First Nations communities. Presented examples include the regions surrounding Red Sucker Lake, Wuskwi Sipihk First Nation, and the Lynn Lake greenstone belt.

In these plain-language mineral potential reports, a glossary is included to define terms or features included on the maps (e.g., rare-earth elements, greenstone belt, G10 garnet, Superior boundary zone, shear zone), which can vary significantly by region or by report. Along with the glossary definitions, introductory text is included to better communicate some of the nuances surrounding sampling biases, spatial limitations of some data, or the overall low likelihood of finding new economic mineral deposits even in an area deemed to be of relatively high potential. Example statements include: “Very few mineral occurrences are (or lead to) mines, but clusters of occurrences – in combination with other information like bedrock geology maps – could indicate a higher chance of finding a mineral deposit that can be mined,” and “In some areas that appear to lack mineral occurrences, that may be due to a lack of information, rather than a lack of mineral potential. For example, there are many areas where we are only able to guess at the type of bedrock buried below thick layers of sediment.”

As the mineral occurrence database continues to expand, the MGS plans to generate province-wide mineral potential maps by machine learning methods such as those presented by Lawley et al. (2021), incorporating the new mineral occurrence data in addition to other layers such as aeromagnetic data and geological ages.

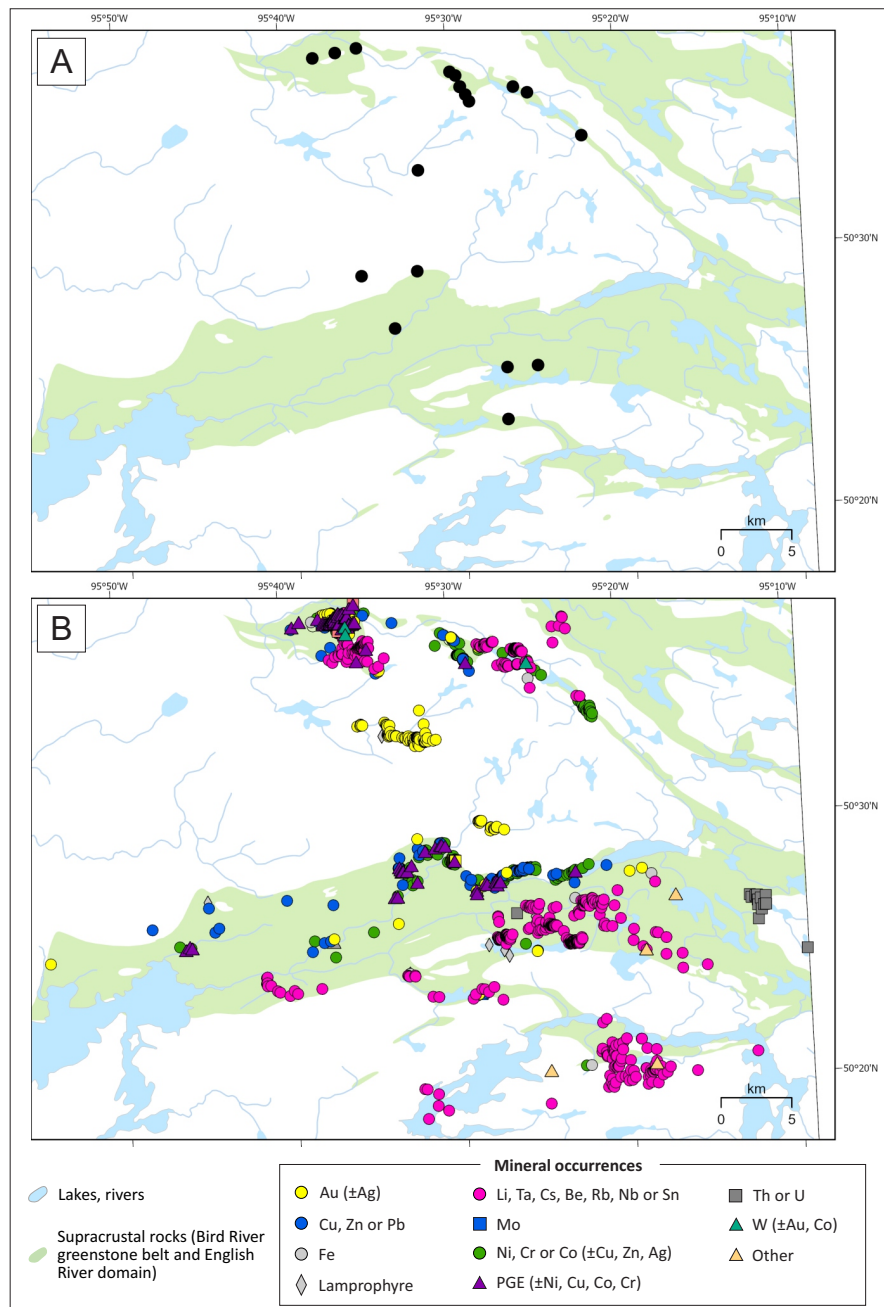


Fig. 1. Mineral occurrence maps in the Bird River belt of southeastern Manitoba, demonstrating improvements in mineral occurrence point data from **a)** occurrences indicated by black dots in a 2009 version of the MDD, to **b)** occurrences in a 2024 version of the MDD (available in Rinne, 2024), compiled mostly from assessment reports.

References cited

- Conley, G.G., Heine, T.H., Prouse, D.E., and Leskiw, P.D., 2009. Mineral Deposits Database. Manitoba Science, Technology, Energy and Mines, Manitoba Geological Survey. <https://www.manitoba.ca/iem/geo/gis/databases.html>
- Lawley, C.J.M., Tschirhart, V., Smith, J.W., Pehrsson, S.J., Schetselaar, E.M., Schaeffer, A.J., Houle, M.G., and Eglington, B.M., 2021. Prospectivity modelling of Canadian magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE) sulphide mineral systems. *Ore Geology Reviews*, 132, article 103985. <https://doi.org/10.1016/j.oregeorev.2021.103985>
- Rinne, M.L., 2024. Updates to the Manitoba Mineral Deposits Database; Manitoba Economic Development, Investment, Trade and Natural Resources, Manitoba Geological Survey, GeoFile 5-2024.
- Rogge, D.M., Halden, N.M., and Beaumont-Smith, C.J., 2000. Mineralization-potential mapping: a data-fusion analysis. In: Report of Activities 2000, Manitoba Industry, Trade and Mines, Manitoba Geological Survey, pp. 82-90.
- Wright, D.F. and Bonham-Carter, G.F., 1996. VHMS favourability mapping with GIS-based integration models, Chisel Lake-Anderson Lake area. In: Bonham-Carter G.F., Galley A.G., and Hall G.E.M., (Eds.) EXTECH I: A Multidisciplinary Approach to Massive Sulphide Research in the Rusty Lake-Snow Lake Greenstone Belts, Manitoba. Geological Survey of Canada, Bulletin 426, pp. 339-401.

Mineral potential in Saskatchewan: background, method, and recent developments

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The province of Saskatchewan contains mineral occurrences for 27 of the 34 minerals identified by the Government of Canada (Government of Canada, 2025) as being critical to the national economy and security (Fig. 1a; Saskatchewan Ministry of Energy and Resources, 2024). Currently, the province produces three of these critical minerals; Saskatchewan is the world's largest producer of potash, the second-largest producer of uranium, and produces approximately 2% of the world's helium (Saskatchewan Ministry of Energy and Resources, 2024).

In 2023, the Government of Saskatchewan released *Securing the Future: Saskatchewan's Critical Mineral Strategy*, which outlines policies, incentives, and investments to strengthen the province's resource sector (Government of Saskatchewan, 2023). Key objectives are to increase production of potash, uranium and helium, and to double the critical minerals produced by 2030. Early results are encouraging. Supported by the 2021 Helium Action Plan: From Exploration to Exports, helium production rose from 2.1 million m³ in 2021 to 4.4 million m³ in 2024 (Government of Saskatchewan, 2021; Saskatchewan Ministry of Energy and Resources, 2023b, 2024). Furthermore, Foran Mining Corporation's McIlvenna Bay mine is expected to begin commercial copper and zinc production in 2026 (Foran Mining Corporation, 2025). These advances build upon decades of research, exploration work, and mineral potential assessments (Yurkowski, 2021; Hatton et al., 2025). As companies explore deeper for new deposits, innovative techniques will be essential. Integrating modern data analyses with existing mineral potential assessments will help meet the province's targets.

Mineral potential in Saskatchewan (Fig. 1b) is evaluated using the classification system developed by MacLaren (1990), which was later formalized into procedural guidelines by Rogers and Hart (1995). These guidelines are applied alongside mineral deposit models developed by Rogers et al. (1995) and Rogers (2014). Mineral potential assessments are completed by evaluators competent in ore deposit geology, geophysics, and geochemistry and who understand the jurisdictions being assessed. Evaluation for metallic and gem deposits uses up to four criteria: geology, mineralization, and geochemistry and/or geophysics. For evaluations of industrial minerals, economic criteria—including distance to infrastructure, market access, and surface access—replace geochemistry and geophysics criteria. Available datasets for each criterion are subjectively reviewed and ranked on a scale from 1 to 3, based on the strength of evidence for a given mineral deposit type. In evaluation areas associated with more than one mineral deposit type, only

the deposit type with the highest individual rankings is used for the final mineral potential determination. The combined score for all criteria produces an overall mineral potential ranking, from low (1) to high (4). Two additional rankings, very high (5) and extremely high (6), are reserved for areas near identified or inferred resources, typically close to producing or past-producing mines. Areas with insufficient data are assigned to 'unknown' categories: U, U-2 (moderate), or U-3 (moderate to high). U-2 and U-3 indicate regions with limited or outdated information but with geological environments that are favourable for specific mineral deposits.

The Government of Saskatchewan provides several publicly available online tools to aid in mineral potential assessments. The Saskatchewan Publications Centre serves as a repository for research and data compiled by the Saskatchewan Geological Survey (SGS), including reports, geological and geophysical maps, 3D models, and cross-sections (Saskatchewan Ministry of Energy and Resources, n.d.-g). The Saskatchewan Mineral Deposit Index (SMDI) is a searchable database that inventories known mineral showings across the province and the Saskatchewan Mineral Assessment Database (SMAD) allows users to access non-confidential mineral assessment reports (Saskatchewan Ministry of Energy and Resources, n.d.-e, n.d.-d). Finally, the Saskatchewan Mining and Petroleum GeoAtlas (GeoAtlas) is an ESRI® ArcGIS based interactive online mapping platform. It integrates data from Publications Centre, SMDI, SMAD, and includes layers for mineral resources, land tenure, and assessed mineral potential (Fig. 1; Saskatchewan Ministry of Energy and Resources, n.d.-b).

Mineral potential assessments are enhanced by adopting a mineral systems approach that leverages advanced mathematical models, machine learning, and artificial intelligence (e.g., Wise, 2019). Working in east-central Saskatchewan, Mahmoodi et al. (2021) generated mineral prospectivity maps for base metals and gold in the Reindeer zone of Trans-Hudson orogen (Fig. 2). Their study employed Random Forest (RF) and Support Vector Machine (SVM) supervised machine learning algorithms, which classify data based on patterns learned from training datasets. Mahmoodi et al. (2021) trained their models using publicly available 1:250,000 scale bedrock geology maps, 1:1,000,000 scale faults and shear zones maps, metamorphic facies map, lake sediment data analyses, Bouguer gravity anomaly, residual magnetic intensity, and SMDI locations and metadata downloaded from GeoAtlas. The trained models successfully predicted 77% of known base metal occurrences and 84% of known gold occurrences.

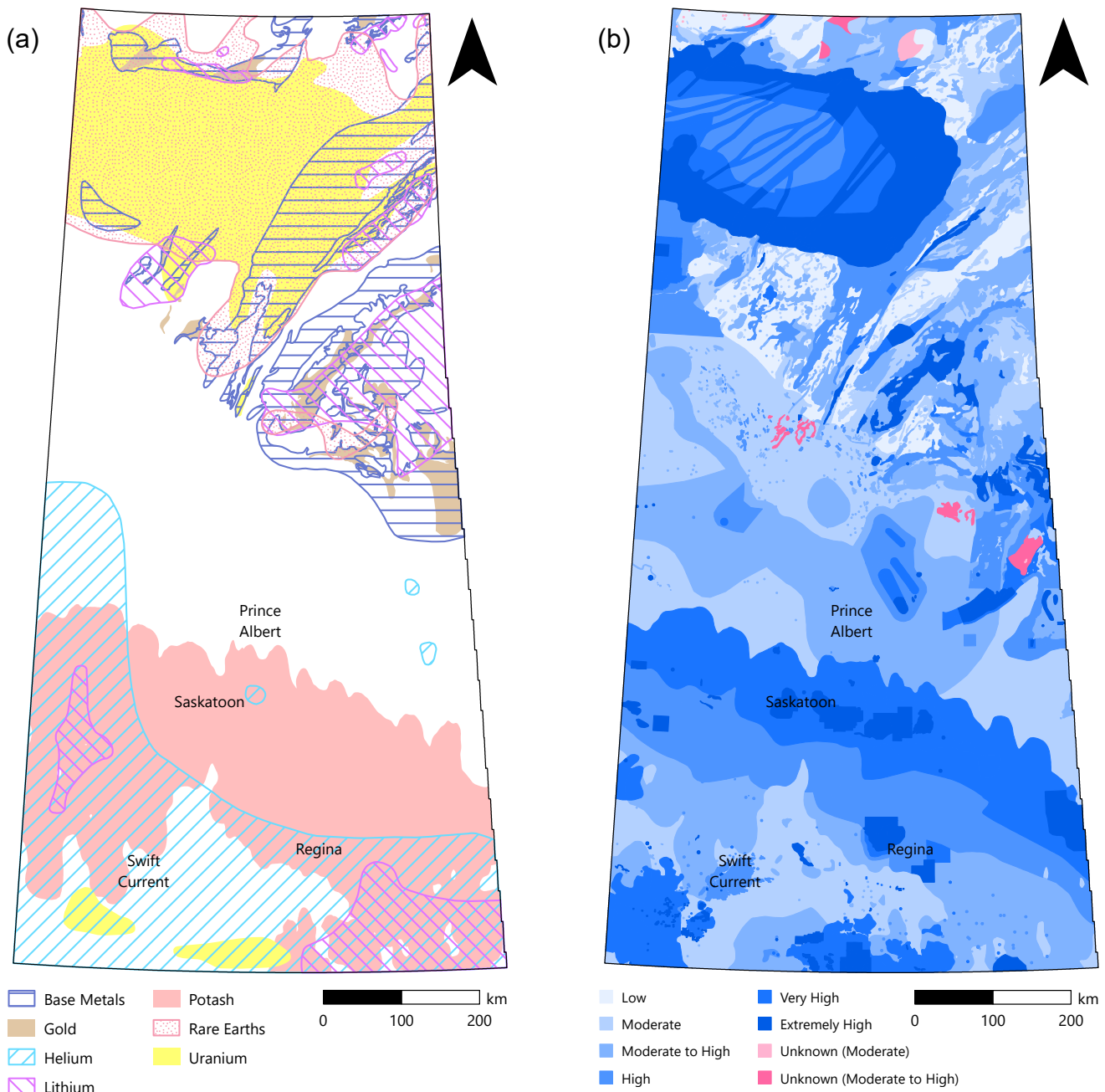


Fig. 1. a). Resource map of Saskatchewan detailing regions of mineral potential for base metals, gold, helium, lithium, potash, rare earth elements, and uranium. Datasets downloaded from the Saskatchewan Mining and Petroleum GeoAtlas (Saskatchewan Ministry of Energy and Resources, 2018b, 2018c, 2023a, n.d.-a). **b).** Mineral potential resource assessment map of Saskatchewan using classification systems and procedures of MacLaren (1990) and Rogers and Hart (1995). Dataset downloaded from the Saskatchewan Mining and Petroleum GeoAtlas (Saskatchewan Ministry of Energy and Resources, 2018a).

The adoption of advanced techniques will be strengthened by the Saskatchewan Geoscience Data Management Project (SGDMP), which is anticipated to launch in late 2025 (Saskatchewan Ministry of Energy and Resources, n.d.-c). This multi-year initiative will modernize and integrate its databases and datasets into a new unified system. The new system streamlines data collection for field geoscientists by allowing them to collect and upload data at the time of

entry. Regulatory mineral tenure assessment reporting will be enhanced by implementing digital report submissions, management, and review. Non-confidential assessment reports will be more readily accessible, including options for bulk downloads. Data integration and relational structuring may help provide new insights between datasets and will reduce manual data preparation, cleaning, and normalization tasks. This will improve workflows, reduce human error,

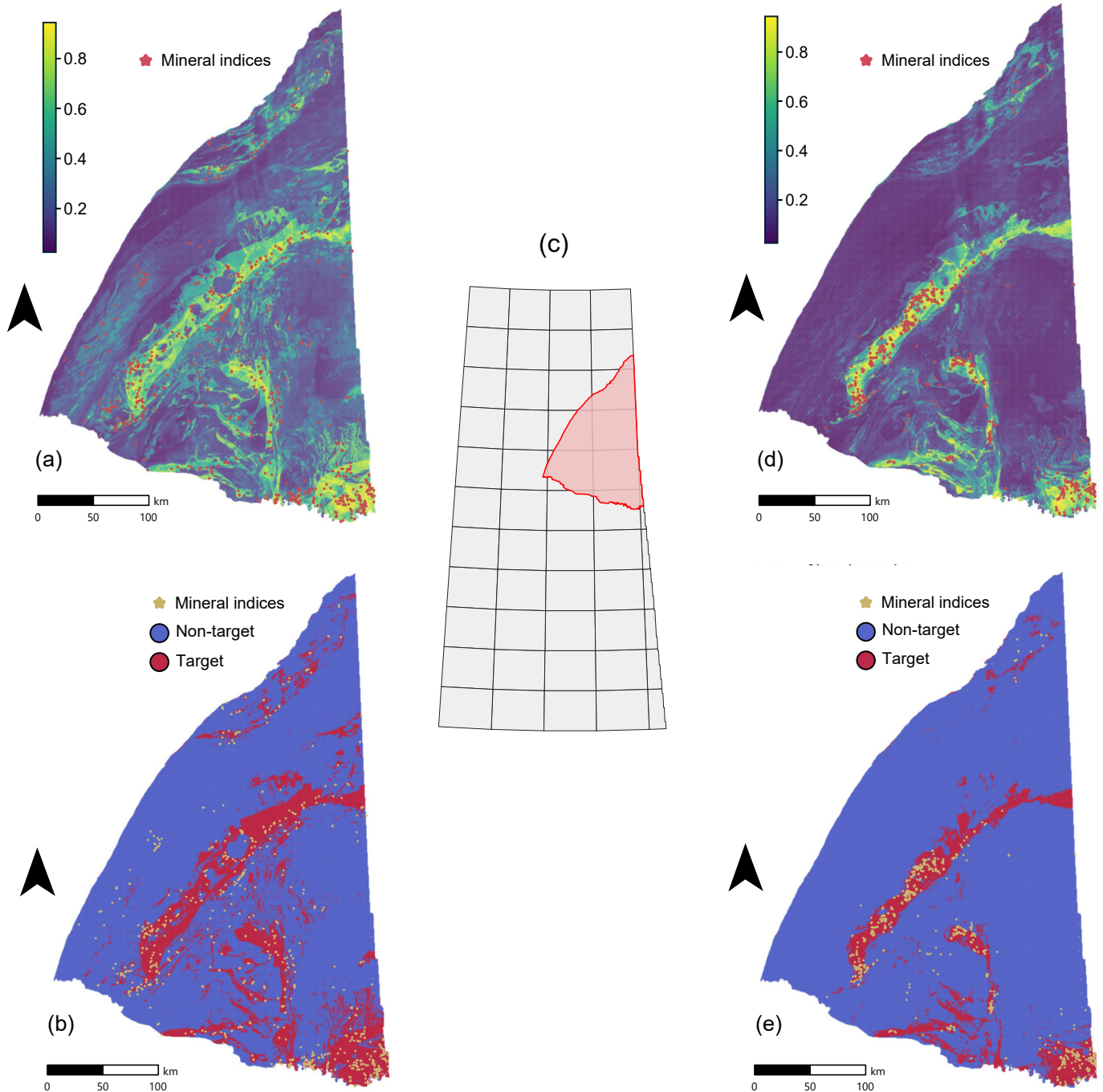


Fig. 2. Mineral prospectivity maps for base metals and gold in the Reindeer zone of Trans-Hudson orogen (modified from Mahmoodi et al., 2021). **a).** Map using a colour scale to represent base metal potential based on Random Forest and Support Vector Machine predictive algorithms. Higher probability is represented by warmer colours. **b).** Map representing binary values indicating target values with high base metal potential. Dots on a) and b) represent known base metal showings from the Saskatchewan Mineral Deposit Index. **c).** National Topographic System 250 Grid map of Saskatchewan with project area highlighted in red. **d).** Map using a colour scale to represent gold potential based on Random Forest and Support Vector Machine predictive algorithms. Higher probability is represented by warmer colours. **e).** Map representing binary values indicating target values with high gold potential. Dots on d) and e) represent known gold showings from the Saskatchewan Mineral Deposit Index.

and ultimately produce higher-quality products. For mineral potential assessments, the SGDMP will enable enhanced historical analyses and the creation of new assessments by leveraging a fully integrated system. Furthermore, it will unlock the potential to implement advanced analytical models using machine learning and artificial intelligence.

References cited

- Foran Mining Corporation, 2025. Foran Reports Q2/25 Construction Progress at McIlvenna Bay. Foran Mining Corporation, 14p.
<https://foranmining.com/wp-content/uploads/2025/07/News-Release-Q2-2025-Operations-Update-vFinal.pdf> (Accessed August 11, 2025)
- Government of Canada, 2025. Canada's critical minerals.
<https://www.canada.ca/en/campaign/critical-minerals-in-canada/critical-minerals-an-opportunity-for-canada.html> (Accessed July 29, 2025)
- Government of Saskatchewan, 2021. Helium Action Plan: From Exploration to Exports. Government of Saskatchewan, 7p.
<https://publications.saskatchewan.ca/#/products/115246>
- Government of Saskatchewan, 2023. Securing the future: Saskatchewan's critical minerals strategy. Government of Saskatchewan, 34p.
<https://publications.saskatchewan.ca/#/products/120502>
- Hatton, M., Lewis, W., Howery, J., Howery, J., Moreau-Verlaan, J., Lincoln, N., Muir, W., Binette, L., 2025. 2025 Technical report on the McIlvenna Bay Project, Saskatchewan, Canada. Foran Mining Corporation, File 169524701, 77p.
https://foranmining.com/wp-content/uploads/2025/03/Foran_-_Technical_Report_-_RPT-24701-0001_1_final.pdf (Accessed August 11, 2025)
- Mahmoodi, O., Card, C.D., and Morelli, R.M., 2021. Mineral prospectivity mapping using supervised classification: gold and base metal potential in the Reindeer Zone of the Trans-Hudson Orogen. Saskatchewan Ministry of Energy and Resources, Saskatchewan Geological Survey, Summary of Investigations 2021, Volume 2, Miscellaneous Report 2021-4.2, Paper A-3, 15p.
- McLaren, G.P., 1990. A mineral resource assessment of the Chilko Lake Planning Area. British Columbia Ministry of Energy, Mines and Petroleum Resources, British Columbia Geological Survey Bulletin 81, 130 p.
- Rogers, M.C., 2014. Saskatchewan descriptive mineral deposit models. Saskatchewan Ministry of Energy and Resources, Saskatchewan Geological Survey, Open File Report 2014-2, 169p.
- Rogers, M.C., and Hart, C.N., 1995. Procedural guidelines for qualitative mineral potential evaluations by the Ontario Geological Survey. Ontario Geological Survey, Open File Report 5929, 37p.
- Rogers, M.C., Breaks, F.W., Fyon, F.A., and Kelly, R.I., 1995. Descriptive mineral deposit models of metallic and industrial deposit types and related mineral potential assessment criteria. Ontario Geological Survey, Open File Report 5916, 241p.
- Saskatchewan Ministry of Energy and Resources, 2018a. Mineral Resource Assessment, CSRS NAD83 Zone 13, Saskatchewan Geological Survey 2018 [Dataset]. Saskatchewan GeoAtlas.
<https://geoatlas.saskatchewan.ca> (Accessed July 29, 2025)
- Saskatchewan Ministry of Energy and Resources, 2018b. Resource Map - Potash for the Province of Saskatchewan, CSRS NAD83 Zone 13, Saskatchewan Geological Survey 2018 [Dataset]. Saskatchewan GeoAtlas.
<https://geoatlas.saskatchewan.ca> (Accessed July 29, 2025)
- Saskatchewan Ministry of Energy and Resources, 2018c. Resource Map - Uranium for the Province of Saskatchewan, CSRS NAD83 Zone 13, Saskatchewan Geological Survey 2018 [Dataset]. Saskatchewan GeoAtlas.
<https://geoatlas.saskatchewan.ca> (Accessed July 29, 2025)
- Saskatchewan Ministry of Energy and Resources, 2023a. Resource Map - Rare Earth Elements Potential for the Province of Saskatchewan, CSRS NAD83 Zone 13, Saskatchewan Geological Survey 2023 [Dataset]. Saskatchewan GeoAtlas.
<https://geoatlas.saskatchewan.ca> (Accessed July 29, 2025)
- Saskatchewan Ministry of Energy and Resources, 2023b. Saskatchewan exploration and development highlights 2024. Saskatchewan Geological Survey, Ministry of Energy and Resources, Miscellaneous Report 2023-3, 19p.
- Saskatchewan Ministry of Energy and Resources, 2024. Saskatchewan exploration and development highlights 2024. Saskatchewan Geological Survey, Ministry of Energy and Resources, Miscellaneous Report 2024-3, 20 p.
<https://publications.saskatchewan.ca/#/products/125070>
- Saskatchewan Ministry of Energy and Resources, n.d.-a Resource Map - Lithium Potential for the Province of Saskatchewan, CSRS NAD83 Zone 13, Saskatchewan Geological Survey [Dataset]. Saskatchewan GeoAtlas.
<https://geoatlas.saskatchewan.ca> (Accessed July 29, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-b. Saskatchewan Mining and Petroleum GeoAtlas. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<https://gisappl.saskatchewan.ca/geoatlas> (Accessed July 27, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-c. Saskatchewan Geoscience Data Management Project. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<https://www.saskatchewan.ca/business/agriculture-natural-resources-and-industry/mineral-exploration-and-mining/saskatchewan-geological-survey/saskatchewan-geoscience-data-management-project> (Accessed July 27, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-d. Saskatchewan Mineral Assessment Database. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<http://mineral-assessment.saskatchewan.ca> (Accessed July 27, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-e. Saskatchewan Mineral Deposit Index. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<https://mineraldeposits.saskatchewan.ca/> (Accessed July 27, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-f. Saskatchewan Mining and Petroleum GeoAtlas. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<https://gisappl.saskatchewan.ca/geoatlas> (Accessed July 27, 2025)
- Saskatchewan Ministry of Energy and Resources, n.d.-g. Saskatchewan Publications Centre. Ministry of Energy and Resources, Saskatchewan Geological Survey.
<https://publications.saskatchewan.ca/> (Accessed July 27, 2025)
- Wise, T., 2019. Prospectivity modelling of the Olympic Cu-Au Province. MESA Journal 90, 36-41.
- Yurkowski, M. M., 2021. Helium in southern Saskatchewan: geological setting and prospectivity. Saskatchewan Ministry of Energy and Resources, Saskatchewan Geological Survey, Open File Report 2021-2, 77p.

Evolution of mineral potential modelling at the British Columbia Geological Survey: Historical foundations, current practices, and future directions

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For the first time in about 30 years, the British Columbia Geological Survey (BCGS) is revitalizing its mineral potential mapping efforts. These efforts are being driven by the need for the critical minerals required for a green economy and, together with information from other natural resource sectors such as forestry, to support Indigenous Nations, provincial government, and rights holders, in making land-use decisions.

The British Columbia Geological Survey has a long history of producing mineral potential maps, dating back to the 1970s (McCarney 1972, Matheson 1973; Forester 1981). However, these maps were limited to areas that had demonstrated exploration or mining activity. Systematic analysis across the province was not initiated until the early 1990s (Kilby 1995, 2004; MacIntyre, and Kilby 2009). Applying approaches developed by the United States Geological Survey (Brew, 1992; Singer, 1993) but modified for British Columbia, the 1990s work was the first organized province-wide mineral potential mapping program of its kind. Experts from government, industry, and academia assessed all available geological, geochemical and geophysical data to determine probabilistic estimates using fuzzy logic to estimate the likely number of undiscovered deposits (Kilby, 2004). The ranking of the provincial land base for metallic deposits was based on the gross in-place value of the commodities for both known and estimated undiscovered deposits. The dollar value calculated was used only as a relative ranking measure across various mineral deposit types. The final products included province-wide maps, showing the relative ranking of the land from 'highest' to 'lowest' based on metallic and industrial mineral potential (Fig. 1). Although this 1990s work remains of value, it was costly, time consuming, and challenging to update.

The revitalized mineral potential mapping program at the BCGS takes advantage of information gained from bedrock mapping since the 1990s, improved exploration techniques, new exploration discoveries, and a better understanding of the geologic processes leading to mineralization. Furthermore, the exponential growth in computing power, along with advancements in general-purpose programming languages, has greatly enhanced the application of statistical techniques and machine learning methods for modelling mineral potential (Partington, 2010; Porwal and Kreuzer, 2010; Harris et al., 2015; Kreuzer et al., 2015; Ford et al., 2019; Yousefi et al., 2019, 2021; Ford, 2020; Lawley et al., 2021, 2022). The updated modeling efforts at the BCGS have integrated these advancements, leading to mineral potential products that are less capital and labour-intensive, more objective, easier to update, and quicker to develop compared to previous province-scale maps (Wearmouth et al., 2024a; Wearmouth et al., 2024b).

Current work at BCGS applies a mineral systems framework in combination with the probabilistic weights-of-evidence method (Harris, 1965; Agterberg et al., 1972; Singer et al.,

1972; Agterberg et al., 1990) to evaluate the mineral potential of a given area. The mineral systems approach emphasizes similarities between deposits and takes a large-scale view of all the components that control generating deposits (source, transport, and trap). This approach integrates multiple geological features as mappable proxies for a complete mineral system, represented as series of binary predictive maps.

Data used in the current modelling program draws on a range of BCGS datasets, including MINFILE, British Columbia Digital Geology (Cui et al., 2017), and geochemical databases (e.g., Lett and Rukhlov, 2017). Regional-scale gravity (NRCAN, 2020a) and aeromagnetic data (NRCAN, 2020b) are also incorporated.

Using ArcGIS (Esri, 2025) and Arc-SDM (Geological Survey of Finland, 2024), the weights-of-evidence technique is applied to calculate relative prospectivity scores based on the range of geological, geochemical, and geophysical input data. Combining predictive maps for a range of mineral systems yields a ranked assessment of overall mineral potential (Agterberg et al., 1990; Agterberg, 1992; Bonham-Carter, 1994). To ensure objective assessment of model performance, validation datasets are held blind, and area-frequency plots are employed to further refine the modelling process and validate model results.

Recent work has modelled mineral systems across northern British Columbia (Fig. 2) including porphyry, volcanogenic massive sulphide (VMS), magmatic mafic to ultramafic sulphide, sedimentary exhalative (SEDEX), and Mississippi Valley-type (Wearmouth et al., 2024c; 2024d). Model results for porphyries in northwestern British Columbia reveal strong spatial associations between known deposits and several geological features, such as proximity to volcanic rocks ($\leq 2,350$ m), distance to intermediate to felsic intrusive rocks ($\leq 1,000$ m) within areas of high total residual magnetic intensity (>160 nT/m), proximity to mapped faults (≤ 850 m), and stream-sediment geochemical anomalies, specifically elevated concentrations of silver ($\text{Ag} > 0.33$ ppm), gold ($\text{Au} > 0.01$ ppm), and copper ($\text{Cu} > 106$ ppm) (Wearmouth et al., 2024b).

Building on this foundation, the BCGS plans to expand the scope and scale of modelled mineral systems and integrate advanced machine learning techniques to support greater automation and develop a broader suite of models. Advanced machine learning algorithms such as artificial neural networks promise enhanced predictive performance, and additional validation techniques such as cross-validation and confusion matrixes offer greater objective validation metrics (Lawley et al., 2021). Additional future work includes the development of a comprehensive, data-driven mineral potential map for the entire province, complemented by targeted commodity-specific maps.

Wearmouth

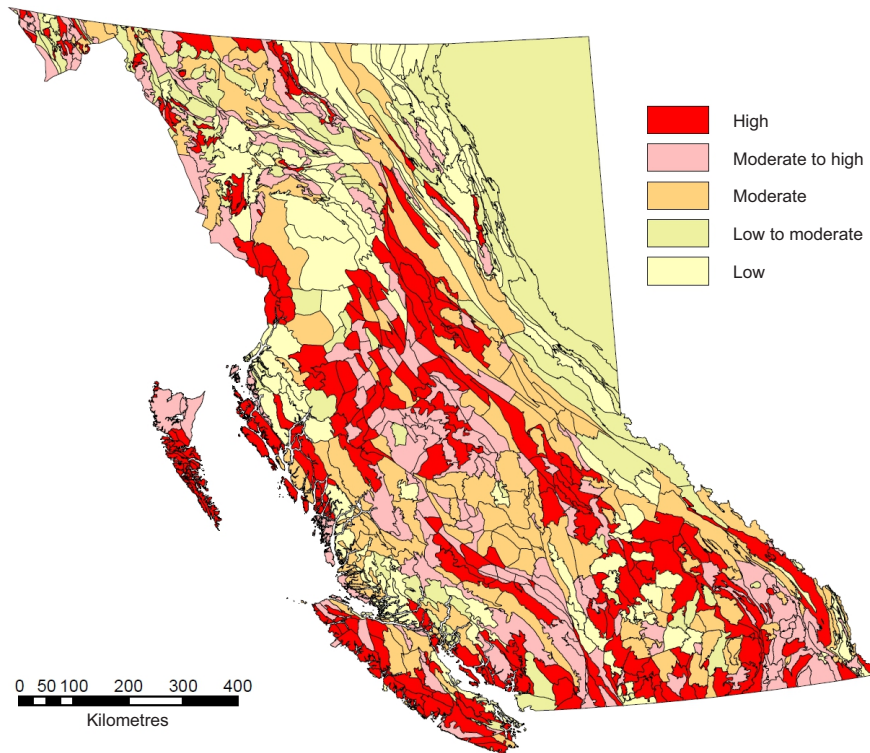


Fig. 1. Metallic mineral potential map for British Columbia completed in 1997. Total number of tracts is 794. From MacIntyre (2004).

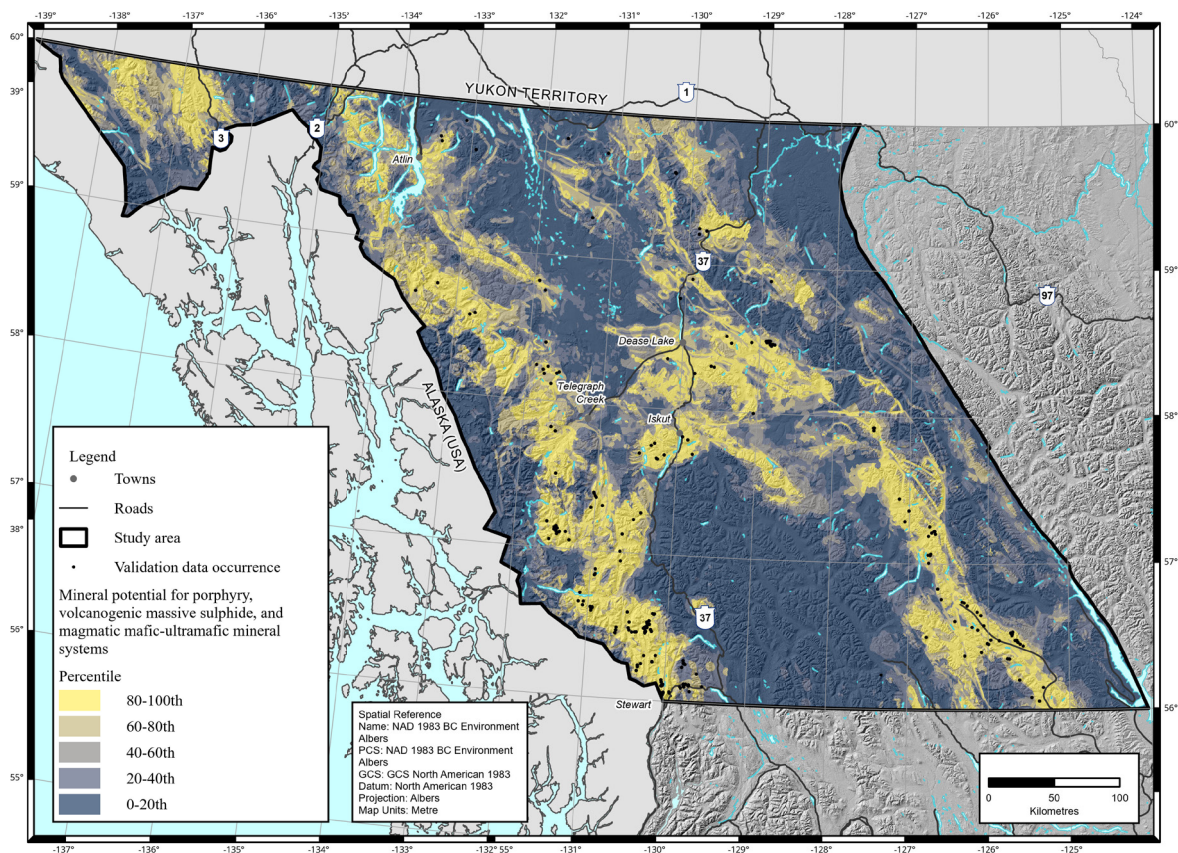


Fig. 2. Combined metallic mineral potential map for parts of northern British Columbia for porphyry, VMS, and magmatic mafic-ultramafic mineral systems. From Wearmouth et al. (2024a).

As machine learning becomes increasingly applied to mineral potential modelling, and as the demand for modernized land-use planning and sources of critical minerals intensify, there is a growing need for up-to-date, accessible mineral potential products. Mineral potential products designed by the BCGS will continue to support a wide range of users, including Indigenous Nations pursuing self-determination, nontechnical decision-makers and explorationists. By providing essential geoscientific context, mineral potential models help ensure that decisions are informed by an understanding of the province's mineral potential.

References cited

- Agterberg, F.P., 1992. Combining indicator patterns in weights of evidence modeling for resource evaluation. *Nonrenewable Resources*, 1, 39-50.
- Agterberg, F.P., Bonham-Carter, G.F., and Wright, D.F., 1990. Statistical pattern integration for mineral exploration. In: GAÁL, G. and Merriam, D.F., (Eds.) *Computer Applications in Resource Estimates, Computers and Geology special volume*, pp. 1-21.
- Bonham-Carter, G., 1994. *Geographic information systems for geoscientists: Modelling with GIS*. Pergamon, 398 p.
- Brew, D.A., 1992. Decision points and strategies in quantitative probabilistic assessment of undiscovered mineral resources. US Geological Survey, Open File 92-308, 23 p.
<https://doi.org/10.3133/of92307>
- Cui, Y., Miller, D., Schiarizza, P., and Diakow, L.J., 2017. British Columbia digital geology. British Columbia Ministry of Energy, Mines and Petroleum Resources, British Columbia Geological Survey, Open File 2017-8, 9 p. Data version 2019-12-19.
- Esri, 2025. ArcGIS.
<https://www.esri.com/en-us/arcgis/geospatial-platform/overview>
- Ford, A., 2020. Practical implementation of random forest-based mineral potential mapping for porphyry Cu-Au mineralization in the Eastern Lachlan Orogen, NSW, Australia. *Natural Resources Research*, 29, 267-283
<https://doi.org/10.1007/s11053-019-09598-y>
- Ford, A., Peters, K.J., Partington, G.A., Blevin, P.L., Downes, P.M., Fitzherbert, J.A., and Greenfield, J.E., 2019. Translating expressions of intrusion-related mineral systems into mappable spatial proxies for mineral potential mapping: Case studies from the Southern New England Orogen, Australia. *Ore Geology Reviews*, 111, article 102943.
<https://doi.org/10.1016/j.oregeorev.2019.102943>
- Forester, J., 1981. Mineral Inventory - Land Use Map of Ashcroft (NTS 0921). British Columbia Department of Mines and Petroleum Resources, British Columbia Geological Survey Mineral Deposit Land Use Map, MD921, 1:250,000 scale.
- Geological Survey of Finland, 2024. *Spatial Data Modeler 6 for ArcGIS Pro 3.0+*.
<https://github.com/gtkf/ArcSDM> Last accessed August 8th, 2025
- Harris, J.R., Grunsky, E., Behnia, P., and Corrigan, D., 2015. Data and knowledge-driven mineral prospectivity maps for Canada's north. *Ore Geology Reviews*, 71, 788-803.
<https://doi.org/10.1016/j.oregeorev.2015.01.004>
- Kilby, W.E., 1995. Mineral potential project-overview. In: *Geological Fieldwork 1994*, British Columbia Ministry of Energy, Mines and Petroleum Resources, British Columbia Geological Survey, Paper 1995-1, pp. 411-416.
- Kilby, W.E., 2004. The British Columbia mineral potential project 1992-1997 – methodology and results. Ministry of Energy and Mines, British Columbia Geological Survey, GeoFile 2004-2, 324 p.
- Kreuzer, O.P., Miller, A.V.M., Peters, K.J., Payne, C., Wildman, C., Partington, G.A., Puccioni, E., McMahon, M.E., and Etheridge, M.A., 2015. Comparing prospectivity modelling results and past exploration data: A case study of porphyry Cu-Au mineral systems in the Macquarie Arc, Lachlan Fold Belt, New South Wales. *Ore Geology Reviews*, 71, 516-544.
- Lawley, C.J.M., Tschirhart, V., Smith, J.W., Pehrsson, S.J., Schetselaar, E.M., Schaeffer, A.J., Houle, M.G., and Eglington, B.M., 2021. Prospectivity modelling of Canadian magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE) sulphide mineral systems. *Ore Geology Reviews*, 132.
<https://doi.org/10.1016/j.oregeorev.2014.09.001>
- Lett, R., and Rukhlov, A.S., 2017. A review of analytical methods for regional geochemical survey (RGS) programs in the Canadian Cordillera. In: Ferbey, T., Plouffe, A., and Hickin, A.S., (Eds.), *Indicator Minerals in Till and Stream Sediments of the Canadian Cordillera*. Geological Association of Canada Special Paper Volume 50, and Mineralogical Association of Canada Topics in Mineral Sciences Volume 47, pp. 53-108.
- MacIntyre, D.G. and Kilby, W.E. 2009. Atlin-Taku Mineral Resource Assessment, northwestern British Columbia (NTS 104F, J, K, L, M, N): methodology and results. In: *Geological Fieldwork 2008*, British Columbia Ministry of Energy Mines and Petroleum Resources, British Columbia Geological Survey Paper 2009-1, pp. 45-53.
- Matheson, A.H., 1973. Mineral Inventory - Land Use Map of Fernie (NTS 082G). British Columbia Department of Mines and Petroleum Resources, British Columbia Geological Survey Mineral Deposit Land Use Map, MD82G, 1:250,000 scale.
- NRCAN, 2020a. Canada-gravity compilation.
<https://open.canada.ca/data/en/dataset/5a4e46fe-3e52-57ce-9335-832b5e79fecc>. Last accessed December 16, 2023.
- NRCAN, 2020b. Canada-aeromagnetic survey data compilation.
<https://open.canada.ca/data/en/dataset/752fe3fc-d871-5ae1-9bd9-2b6f65880a8d> Last accessed December 16, 2023.
- Partington, G., 2010. Developing models using GIS to assess geological and economic risk: an example from VMS copper gold mineral exploration in Oman. *Ore Geology Reviews*, 38-3, 197-207.
<https://doi.org/10.1016/j.oregeorev.2010.02.002>
- Porwal, K., and Kreuzer, O., 2010. Introduction to the special issue: mineral prospectivity analysis and quantitative resource estimation. *Ore Geology Reviews*, 38-3, 121-127.
- Singer, D.A., 1993. Basic concepts in three-part quantitative assessments of undiscovered mineral resources. *Natural Resources Research*, 2, 69-81.
<https://doi.org/10.1007/BF02272804>
- Wearmouth, C.D., Peters, K.J., Czertowicz, T.A., and Orovan, E.A., 2024a. Mineral potential modelling results for northwestern British Columbia, a comparison between past and current work at the British Columbia Geological Survey. In: *Geological Fieldwork 2023*, British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-01, pp. 79-95.
- Wearmouth, C., Czertowicz, T., Peters, K.J., and Orovan, E., 2024b. Mineral potential modelling at the British Columbia Geological Survey: Renewed methods with application to northwestern British Columbia. British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-02, 28p.
- Wearmouth, C.D., Peters, K.J., Czertowicz, T.A., and Orovan, E.A., 2024c. Preliminary mineral potential maps for the porphyry, volcanic massive sulphide, and magmatic mafic-ultramafic mineral systems, northwestern British Columbia. British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Open File 2024-05, 1:800,000 scale.

- Wearmouth, C.D., Czertowicz, T.A., and Peters, K.J., 2024d. Preliminary mineral potential maps for the SEDEX and MVT mineral systems, northeastern British Columbia. British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Open File 2024-11, 1:500,000 scale.
- Yousefi, M., Kreuzer, O.P., Nykänen, V., and Hronsky, J.M.A., 2019. Exploration information systems – A proposal for the future use of GIS in mineral exploration targeting. *Ore Geology Reviews*, 111, article 103005.
<https://doi.org/10.1016/j.oregeorev.2019.103005>
- Yousefi, M., Carranza, E.J.M., Kreuzer, O.P., Nykänen, V., Hronsky, J.M.A., and Mihalasky, M.J., 2021. Data analysis methods for prospectivity modelling as applied to mineral exploration targeting: State-of-the-art and outlook. *Journal of Geochemical Exploration*, 229, article 106839.
<https://doi.org/10.1016/j.gexplo.2021.106839>

Northwest Territories Geological Survey mineral and energy potential modelling overview

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The Northwest Territories Geological Survey (NTGS) has completed 29 mineral potential modelling projects. Initial work was completed in 1989, with the bulk of the projects conducted between 2002 and 2013, and additional work in 2019. These projects have largely supported land-use planning, including evaluations for candidate protected areas under the Protected Areas Act, and have provided input to federal, territorial, and Indigenous governments and other decision-making bodies. In addition to these projects, NTGS Staff have collaborated with other interested parties, including the Geological Survey of Canada and academic research groups.

The workflows used by the NTGS were primarily based on the MERA (Mineral and Energy Resources Assessment) approach (Scoates et al., 1986). This is a knowledge-driven, GIS-based framework that integrates geophysical, geochemical, geological, structural, and mineral occurrence data into mineral potential categorizations and maps. The effectiveness of this method heavily depends on the availability of sufficient datasets. In the Northwest Territories, the combination of vast geographic scale and uneven areal data coverage means that many datasets are sparse, fragmented, or only available at regional resolutions. NTGS projects have necessarily relied on expert-driven interpretation, with fewer opportunities to apply large-scale, data-driven approaches such as machine learning. Efforts are underway to combine fragmented datasets into unified, accessible resources. As new datasets are generated and integrated, the potential to expand into more data-intensive methods will increase.

Reference

Scoates, R.F.J., Jefferson, C.W., and Findlay, D.C., 1986. Northern Canada mineral resource assessment. In: Cargill S.M. and Green S.B. (Eds.), *Prospects for Mineral Resource Assessment on Public Lands: Proceedings of the Leesburg Workshop*. U.S. Geological Survey, Circular 980, pp. 111-139.
<https://doi.org/10.3133/cir980>

Territory-scale mineral potential mapping for Yukon

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Predictive modelling techniques for assessing mineral potential, widely used in economic geology (e.g., Agterberg et al. 1972; Agterberg 1989; Carranza, 2009), are currently being used by the Yukon Geological Survey to provide territory-wide mineral potential maps for land-use planning that will replace those created in the early 2000s and are now considered obsolete. In recent years, land-use plans have used mineral potential maps that were generated for individual planning areas. These maps were created using inconsistent methods and data types making it difficult to make comparisons between land-use areas. In our current work, we are using a mineral systems approach that relies on current geological, geophysical and geochemical data. When complete, Yukon, south of 66°N, will have consistent mineral potential maps for mineral systems including: silicilastic-dominated massive sulfide, carbonate-dominated massive sulfide, volcanogenic massive sulfide, reduced intrusion related, oxidized intrusion related, mafic-ultramafic related, orogenic.

Territory-scale mineral potential maps created using a mineral systems approach will be carried out with Kenex, a consulting company based in New Zealand. The anticipated project completion is in 2026. This approach was chosen to provide high-level consistency with neighboring British Columbia. Mineral systems are associated with specific commodities, including critical minerals, thus the individual mineral system maps can be combined to produce commodity-specific maps. This approach enables interpretation of regional mineral potential for commodities such as copper, zinc, lead, nickel, tungsten, gold, and silver. The anticipated useful life span of the maps is approximately 10 years.

Yukon is underlain by two major tectonic domains: Ancestral North America and the Intermontane and Insular superterrane, which were accreted to its western flank (e.g., Colpron et al., 2007; Yukon Geological Survey, 2020). Each geologic domain hosts specific mineral systems, which are considered in eight mineral potential maps. We consider rocks of Ancestral North America for sediment-hosted massive sulfide, reduced intrusion-related gold, volcanic-hosted massive sulfide, and carbonate-hosted massive sulfide systems. Rocks of the Intermontane and Insular superterrane are considered for magmatic mafic-ultramafic, orogenic, volcanogenic massive sulfide, and oxidized intrusion-related systems.

The mineral systems approach to mineral potential envisages three components: source of metals, fluid transport pathways, and metal trap. The highest potential is associated with the best sources (e.g., deep-water basin sedimentary rocks), mapped fluid pathways (e.g., synsedimentary faults) and known traps (e.g., redox changing rock types). The modelling of mineral potential can be achieved with a variety of data-driven approaches that rely on statistical analysis of geospatial data (e.g., Bonham-Carter et al., 1990) or machine-learning

based analysis of geospatial data (e.g., Zu et al., 2011). Both deterministic and probabilistic methods (e.g., Bonham-Carter et al., 1990; Leite and de Souza Filho, 2009) are common, where probabilistic methods can provide more comprehensive uncertainty propagation for the predictive models. The method applied here is weights-of-evidence modelling (WoE; e.g., Bonham-Carter et al., 1990) which produces probabilistic estimates of mineral potential based on binary data input maps and training points. The approach computes posterior probabilities of mineral potential by updating a prior probability (knowledge about the potential before data are considered) with binary predictor data. Predictors used in initial WoE studies were limited to a few geologic and geophysical datasets that were converted to binary predictors (e.g., Agterberg et al., 1993). With many advances in GIS software, extensive data are now commonly applied, including polygon types, line types, and point types (e.g., Wearmouth et al., 2024).

The data sources used for mineral potential estimates here include 22 datasets, including many of the products produced and hosted by the Yukon Geological Survey. The data types include areal, linear and point data. Yukon bedrock geology data include bedrock map units (polygons), bedrock contacts (lines), bedrock faults (lines), bedrock unit ages (polygons), and bedrock terrane groups (polygons). The surficial geology data include the limits of known glacial events (polygons), surficial geology units (polygons), and placer creek potential (lines). Geophysical raster data include the Bouguer anomaly, the total magnetic intensity, and the first vertical magnetic derivative. Geochemical data include stream-sediment geochemistry (polygon and point), catchment analysis for deposit type and quality (polygon), and lithogeochemistry (point). Point data also include ~3000 mineral occurrences, 100 deposits (with grades, tonnage, and mineral types).

An important aspect of weights of evidence modelling is to determine data weights based on correlation of the various data types with correctly predicting control or training points. Training points are known deposits contained in MINFILE, where the mineral system is known with a high level of confidence. We defined more than 70 training points predominantly in Yukon but supplemented with points from British Columbia. The training points are distributed across the eight mineral systems considered for potential maps.

To date, the map for the sediment-hosted massive sulfide mineral system has been completed (Fig. 1). The mineral potential for the Ancestral North America portion of Yukon is based on 19 training points, of which 9 lie in Yukon and 10 in British Columbia. In Yukon, areas of high (>80th percentile) mineral potential are predominantly north of the Tintina fault in Cambrian, Silurian, and Devonian-Mississippian shales; correlative rocks southwest of the Tintina fault also have high potential. At the 19 training points, the best data for predicting

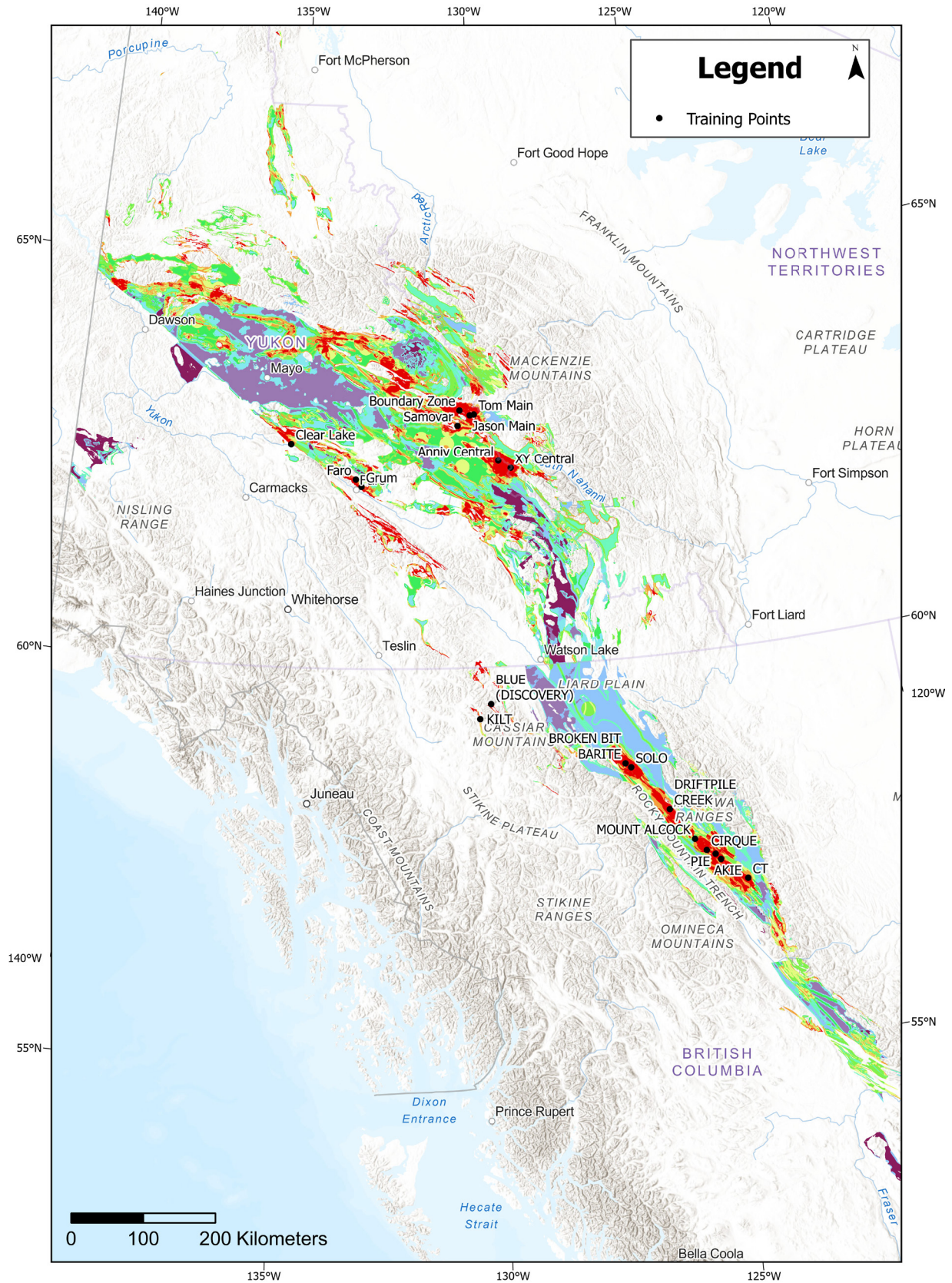


Fig. 1. Mineral potential map for the sediment-hosted massive sulfide mineral system in Yukon. The colour scale represents quantiles of probability, with red and orange being high probability (>80th percentile). The map extends into British Columbia to provide more complete training data. Training data are shown as black dots.

metal source are distance to fine-grained siliciclastic rocks and host lithology. The best data for predicting fluid pathways are distance to faults and the best data for predicting metal traps are bedrock competency contrast from lithology, stratigraphic unit, density of faults, distance to >200 ppm Zn stream sediment samples, distance to related mineral occurrences, and distance to folds. Using these criteria and data, 8.1 % (19,000 km²) of the Ancestral North American domain has high sediment-hosted massive sulfide potential.

References cited

- Agterberg, F. P., 1989. Computer programs for mineral exploration. *Science*, 245, 76-81.
- Agterberg, F. P., Chung, C.F., Fabbri, A.G., Kelly, A.M., and Springer, J.S., 1972. Geomathematical evaluation of copper and zinc potential of the Abitibi area, Ontario and Quebec. *Geological Survey of Canada Paper*, 71-41, 55 p.
- Agterberg, F. P., Bonham-Carter, G.F., Cheng, Q., and Wright, D.F., 1993. Weights of evidence modeling and weighted logistic regression for mineral potential mapping. In: Davis, J.C., and Herzfeld, U.C. (Eds.) *Computers in Geology 25 Years of Progress*. International Association for Mathematical Geology Studies in Mathematical Geology 5, pp. 13-32.
- Bonham-Carter, G.F., Agterberg, F.P., and Wright, D.F., 1990. Weights of evidence modelling: a new approach to mapping mineral potential. In: Agterberg F.P., and Bonham-Carter G.F., (Eds.), *Statistical Applications in the Earth Sciences*. Geological Survey of Canada, Paper 89-09, pp. 171-183.
- Carranza, E. J. M. 2009. Geochemical anomaly and mineral prospectivity mapping in GIS. *Handbook of Exploration and Environmental Geochemistry Volume 11*, Elsevier, Amsterdam, 351 p.
- Colpron, M., Nelson, J.L., and Murphy, D.C., 2007. Northern Cordilleran terranes and their interactions through time. *GSA Today*, 17, 4-10.
- Knox-Robinson, C.M. and Wyborn, L.A.I., 1997. Towards a holistic exploration strategy: Using geographic information systems as a tool to enhance exploration. *Australian Journal of Earth Scientists* 44, 453-463.
- Leite, E.P., and de Souza Filho, C. R., 2009. Probabilistic neural networks applied to mineral potential mapping for platinum group elements in the Serra Leste region, Carajás Mineral Province, Brazil. *Computers & Geosciences* 35, 675-687.
- Wearmouth, C. D., Peters, K.J., Czertowicz, T.A., and Orovan, E.A., 2024. Mineral potential modelling results for northwestern British Columbia, a comparison between past and current work at the British Columbia Geological Survey. In: *Geological Fieldwork 2023*, British Columbia Ministry of Energy, Mines and Low Carbon Innovation, British Columbia Geological Survey Paper 2024-01, pp. 79-95.
- Yukon Geological Survey, 2020. A digital atlas of terranes for the northern Cordillera. Yukon Geological Survey. <https://data.geology.gov.yk.ca/Compilation/2> [accessed August 26, 2025].
- Zuo, R., and Carranza, E.J.M., 2011. Support vector machine: A tool for mapping mineral prospectivity. *Computers & Geosciences* 37, 1967-1975.



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