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**GEOLOGICAL SURVEY OF CANADA
OPEN FILE 9311e**

**Expanded models of Canadian critical mineral prospectivity
maps for magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE), Mississippi–Valley
Type Pb–Zn and clast-dominated Pb–Zn**

S.E. Zhang and M. Parsa

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Expanded Models of Canadian Critical Mineral Prospectivity Maps for Magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$), Mississippi-Valley Type Pb-Zn and Clast-Dominated Pb-Zn

Abstract

This report provides expanded pan-Canadian prospectivity models for magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$), Mississippi-Valley Type Pb-Zn and clast-dominated Pb-Zn mineral systems. The key difference is that the models presented herein are aggregations of deep ensembles, which by design provides both a range of model complexity due to typical inter-practitioner differences in data-driven mineral prospectivity mapping and workflow-induced uncertainty analysis. The expanded models do not rely on any one specific workflow or its resulting model and instead, rely on the statistical properties of large de-correlated ensembles. Compared to the inaugural prospectivity models, there is an expansion in greenfield target area, providing additional targeting insight. In addition, for the magmatic Ni target, the covariates have been updated to be higher in spatial resolution and the spatial indexing system is now standardized. Datasets containing prediction results for magmatic Ni is offered for Canada, while for the MVT and CD Pb-Zn targets, the results are offered for all of North America and Oceania. Furthermore, positive samples for magmatic Ni that are re-indexed into the H3 system are provided as part of the data release.

1 Introduction

This report presents expanded prospectivity models for magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$), Mississippi-Valley Type (MVT) Pb-Zn and clast-dominated (CD) Pb-Zn mineral systems. The inaugural mineral prospectivity modelling (MPM) for these systems were conducted by [Lawley et al. \(2021\)](#) and [Lawley et al. \(2022\)](#). The key difference between models contained in this report and the inaugural ones are: (1) an expansion of target area through the use of a deep ensemble method; (2) increased spatial resolution of indexing for the covariates used for magmatic Ni; and (3) the inclusion of an uncertainty analysis. This report summarizes major methodological and outcome changes, and provides a data release of prospectivity predictions.

The main benefit of the expanded models is their additional target area and uncertainty analysis, which results from the use of a deep ensemble method that purposely creates a diversity of individual machine learning (ML) models. In single-model MPM, only a single model out of a few candidates are published. However, many models are possible depending on the heuristic implementation of the geodata science workflow. The deep ensemble method address two key issues associated with the scientific and statistical validity of MPM models ([Nwaila et al., 2024](#); [Zhang et al., 2024, 2025a](#)): (1) a lack of post-hoc validation coupled with rapid changes in methodology; and (2) deficiencies in the geodata science framework.

In (1), because many ML algorithms are designed to create models that can be unlimited in expressivity (e.g., universal function approximators), models can become overfitted and capture statistically spurious information or noise. The typical model life cycle in data science conducts validation using feedback during deployment, because during this stage, models make the most voluminous inferences and therefore, performance observed is the most robust statistically. This is the expectation in big data domains. Like any statistical model, ML models are of no intrinsic value but only practical value during deployment, where inferences on incoming streams of data can be tested. The value of ML models is therefore only known during deployment (e.g., model lift or gain). For MPM, this is impossible. The identical problem exists in weather or climate forecasting, because forecasts of the future cannot be validated in advance of forecasted time. The solution

is to create many de-correlated models and aggregate the result, which is similar to repeated measurements in metrology. The deep ensemble method modulates model complexity, which exists along a spectrum of model overfitting to underfitting, depending on workflow choices (e.g., feature dimensionality). Overfitted models provide minimal additional targeting information, because they score highly but spatially only depict targets around the vicinity of positive samples, which is equivalent to brownfield areas. Relatively underfitted models provide increased greenfield targets, with the obvious caveat that they may be more speculative. The nature of the deep ensemble ensures that a sub-population of models within each ensemble for each mineral system targeted are comparable to the inaugural models. These models do not contribute to new target areas. The remainder adds novel targeting information.

In (2), there is a severe deficiency in the geodata science framework that results from a post-hoc spatial extension of the data science framework with additional components that scrutinize spatial performance of models after deployment (Zhang et al., 2024). The geodata science framework is a nascent spatial extension of the data science framework, which is necessary because the data science framework is entirely aspatial. Statistical concepts such as out-of-sample testing in data science do not have well-defined or unique geostatistical equivalents (Hoffmann et al., 2021). The main issue is that geological systems such as mineral deposits are formed through thermodynamic disequilibrium, which makes their state (e.g., mineralization or not) a complex dynamical system, whose proxies are fractally distributed (Zuo, 2016). This means that two areas with differing geological complexity cannot be statistically compared rigorously (e.g., they have different spatial correlation ranges or equivalently spatially-varying feature diversity), which means that out-of-sample testing, such as cross-validation, cannot be statistically robust without levelling the complexity of the in-sample and out-of-sample populations. A main consequence of a post-hoc spatially-extended geodata science framework is that models are sequentially tuned in the variable domain (e.g., by maximizing aspatial metrics, such as the F1 score), then the spatial domain (e.g., by assessing the fraction of sites deemed positive and selecting models). However, the MPM objective is distinctly joint domain, which requires a simultaneous maximization of model performance in both the spatial and aspatial domains. This is a result of idiosyncratic task formulation in geodata science, because mineral exploration cannot be formulated into pure ML tasks, since it is conducted and budgeted spatially as opposed to on a basis of the ML covariates used for modelling. Consequently, client-specified criterion cannot be pre-hoc integrated into a pure ML task, which would otherwise dictate workflow design and experimentation. For example, an accurate model is irrelevant to targeting, if it does not sufficiently reduce the target area to make exploration feasible or yield new target areas (e.g., extract genuine greenfield targets from data that are not already known). Conversely, a model that reduces a target area to an acceptable extent is not useful if it is insufficiently accurate. Since models are optimized sequentially in data-driven MPM, there always exists equiprobable models – those performing similarly according to data science metrics (e.g., F1 score) but featuring a range of spatial characteristics.

The interaction of (1) and (2) together makes the notion of a unique best MPM model undefined. Furthermore, attempting to achieve any threshold of model performance in the ML sense only creates an equiprobable ensemble of spatially dissimilar models. This type of uncertainty has been named “workflow-induced” uncertainty. This is worsened by a lack of acceptance criterion in MPM, which is required of typical data-driven products. In published MPM products, there is no such criterion because end-users of MPM products are usually unknown or assumed and targets are mainly published as academic products (e.g., papers). If the exploration budget and the risk tolerance of end-users is unknown, then there are no design constraints to non-commercial MPM products.

This update provides a diversity of equiprobable models for a range of performance thresholds in a joint-domain manner. The inaugural models published can be considered to be within the right tail-end of the performance distribution of models with the exception of the magmatic Ni target, which uses higher resolution covariates in the model presented herein. Consequently, the inaugural magmatic Ni model cannot be strictly compared to the expanded one. The purpose of the models presented herein is to capture the entire performance

distribution, specifically capturing less complex models (e.g., those resulting from logistic regression), which perform more similarly to traditional knowledge-based models based on comparisons of knowledge- and data-driven MPM models (e.g., [Lawley et al. 2021](#)). The additional target areas offered by this update should be considered as alternative realizations of MPM targets, similar to, but broader than conditional simulations in geostatistics or knowledge-driven (e.g., weights of evidence) MPM models. The additional targeting areas are intended to promote greenfield exploration.

2 Data

The covariate data used for magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$) originates from [Bourdeau and Lawley \(2025\)](#). The datacube was originally built for prospectivity modelling of graphite in Canada, but it is identical in information content to the datacube for the magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$) mineral system ([Lawley et al., 2021](#)), because of substantial overlap in their mineral-system components. The data lineage of the graphite datacube traces to the same origins as for the magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$), but the spatial indexing has been improved in resolution. The original spatial indexing in the inaugural study was arbitrary, which has been superseded by the H3 Discrete Global Grid System (DGGS). The H3 DGGS is an open-source software developed by [Uber Technologies Inc. \(2020\)](#), featuring almost entirely hexagonal grid cells, which are also hierarchical (e.g., spatial amalgamation is integer based). Each cell is indexed by its unique H3 address. It offers a complete global coverage at multiple resolutions. The datacube presented in this report uses resolution 7 of the H3 DGGS, resulting in 98,825,162 unique H3 addresses worldwide. At this resolution, the average hexagon covers an area of 5.16 km², with average edge length of 1.22 km. This resolution is sufficient for both national and regional purposes, for the purpose of guiding mineral exploration. The H3 DGGS is benefitted by its broad adoption in navigation and mapping, primarily because it is maximally isotropic. This removes the spatial distortion associated with anisotropic grid systems and facilitates visual comprehension of cell-to-cell distances and object continuity. Optimizing the depiction of spatial continuity and connectivity is beneficial for the mapping of geoscientific objects, such as faults, rivers, cratonic boundaries and irregularly shaped swaths of prospective areas.

For the MVT and CD Pb-Zn mineral systems, the evidence layers are unchanged. The resolution of some of the evidence layers used in the inaugural MVT and CD studies are not the highest resolution available at the time of this writing; the datacube was chosen to provide cross-continental coverage given the scope of the study and the source of the annotated data. A significant portion of training data for the MVT and CD systems are located outside of Canada, which makes high-resolution evidence layers that are specific to Canada unusable. In this iterative update, we preserve the datacube as it was published to continue to provide updates for the MVT and CD mineral systems for Canada and its strategic partners (the United States and Australia).

The spatially indexed results (prospectivity scores and uncertainty as measured using the standard deviation) are released as part of this Open File. The entries in the data release are indexed using the H3 address (an alphanumeric hash value), which is the master key. No other new datasets are released as part of this report and readers are directed to the original data releases to access the original datacubes for additional datasets (e.g., covariates). The data archives are zipped together. Once unzipped, there are two files in csv format (comma-separated-values). The first file is “Ni_v1_2025.csv” and contains the prediction results for magmatic Ni in Canada and the spatially indexed positive samples. The second file is “Pb_Zn_v1_2025.csv” and contains the prediction results for MVT and CD Pb-Zn systems across North America and Oceania. The “v1” portion of the file names denotes dataset version one and facilitates data traceability.

3 Method

The method used in this study is the main source of difference between models herein and the inaugural models. It was first developed to understand uncertainty in [Zhang et al. \(2024\)](#), engineered into an applicative one in [Nwaila et al. \(2024\)](#) and subsequently revised and deployed for graphite exploration in Canada in [Zhang et al. \(2025b\)](#). The technical details and lineage of revisions are substantial and are beyond the scope of this report. Readers interested in details of the workflow and rationale are referred to the original publications. We herein provide a brief summary. The workflow was designed to propagate uncertainty due to implementation differences that are encountered in MPM. Sources of uncertainty due to choices in workflow components that are well-studied to date include: (1) negative annotation; (2) feature space dimensionality; (3) ML algorithm; and (4) hyperparameter tuning metric. For each component, modulation is intended to produce model diversity. The modulation of key workflow components creates different models, whose statistical dispersion allows workflow-induced uncertainty to be propagated.

Since prospectivity models cannot be reasonably validated using feedback unlike typical big data models, because drilling is expensive, risky and time-consuming, feed-forward validation was proposed by [Zhang et al. \(2024\)](#) as a work-around solution. To date, feed-forward validation has two components: (1) capture the central tendency of many de-correlated models, which is similar to improving measurements using repeated attempts and averaging the result; and (2) pre-hoc validation targets, named “certified reference targets” (CRTs), whose effect on workflows or methods is similar to calibration of instruments using certified reference materials. Treating the modulation of workflow components in the propagation of workflow-induced uncertainty as a model de-correlator, the resulting models constitute an ensemble and can be aggregated. This type of ensemble is called a deep ensemble because multiple workflow components are varied. The deep ensemble mimics the outcome of a group of MPM practitioners, similar to the use of ensembles to capture initial condition and heuristic variability in weather or climate forecasting ([Krishnamuri et al., 2000](#); [Maqsood et al., 2004](#); [Gneiting and Raftery, 2005](#)). The ensemble’s statistical moments are much more robust than individual models. The mean of the ensemble depicts the scientific consensus and the standard deviation the dissent. CRTs are unmistakable, well-studied and extensively explored mineral systems, whose footprints can be best compared with existing knowledge. CRTs enable MPM methods to be objectively inter-compared, as well as validated to the extent possible (e.g., methods producing physically unrealistic models are rejected). The deep ensemble workflow was validated in [Nwaila et al. \(2024\)](#) using two CRTs, the magmatic system of the Bushveld Complex and the modified sedimentary system of the Witwatersrand Basin (South Africa). For models presented herein, all workflow components, including hyperparameter grids are purposefully chosen to be identical to those used in [Zhang et al. \(2025b\)](#), because the method is an experimental control at the model deployment stage.

As part of the deployment formulation, a spatial acceptance criterion was created in [Nwaila et al. \(2024\)](#) – models that do not adequately distinguish between exploration and reconnaissance scales are considered excessively overfitted. The distinction is based on an order-of-magnitude heuristic that reconnaissance must occur at a spatial scale that is at least an order of magnitude larger than exploration, which makes MPM products meaningful. Models within any deep ensemble that fail this criterion are rejected during aggregation. Furthermore, in order to jointly measure the performance of models in both variable and spatial domains, a new performance metric was created – the variable-spatial (VS) metric. It is technically a composite metric that consists of two independent metrics, similar to normalized density. The two independent metrics are the F1 score and the spatial selectivity, which is one minus the fraction of all sites deemed prospective. The product form of the VS metric is range-bounded, which allows it to be used as a weight to perform model merging (ensemble aggregation). The weighted aggregation of de-correlated workflows (each of which produces a model) using a joint-domain metric is statistically related to bagging and boosting, which are concepts typically restricted to the ML algorithm. The deep ensemble method is therefore similar to bagging and reminiscent of boosting but at the workflow level and in a joint-domain manner (e.g., models performing better spatially are

given more weight).

Positive samples for magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$) were re-indexed into the H3 DGGS using the centroid of the original cells. For the other mineral systems, positive samples consisted of a combination of deposits and occurrences, following the inaugural studies. Performance assessment was conducted in both variable and spatial domains using the F1 score (weighted), the area-under-the-curve of the receiver-operating-characteristic (AUC-ROC), the fraction of sites prospective and the VS metric.

4 Results

4.1 Magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$)

The magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$) prospectivity map was created from a total of 2000 models. No models were discarded due to excessive overfitting. The AUC-ROC score of the models in the ensemble are generally higher than the F1 score (Fig. 1a). The spatial to variable domain coupling is noisy, although statistically, higher variable domain scores of models are correlated with better spatial performance (Fig. 1b). In comparison to the inaugural model, the prospectivity map shows that the contrast between non-prospective and prospective regions is sharpened and additional target areas have become available (Figs. 2, 3). The increase favours Canadian exploration of magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$). The prospectivity map (Fig. 3) is a companion map to the uncertainty map (Fig. 4). It depicts the degree of dissent between all models.

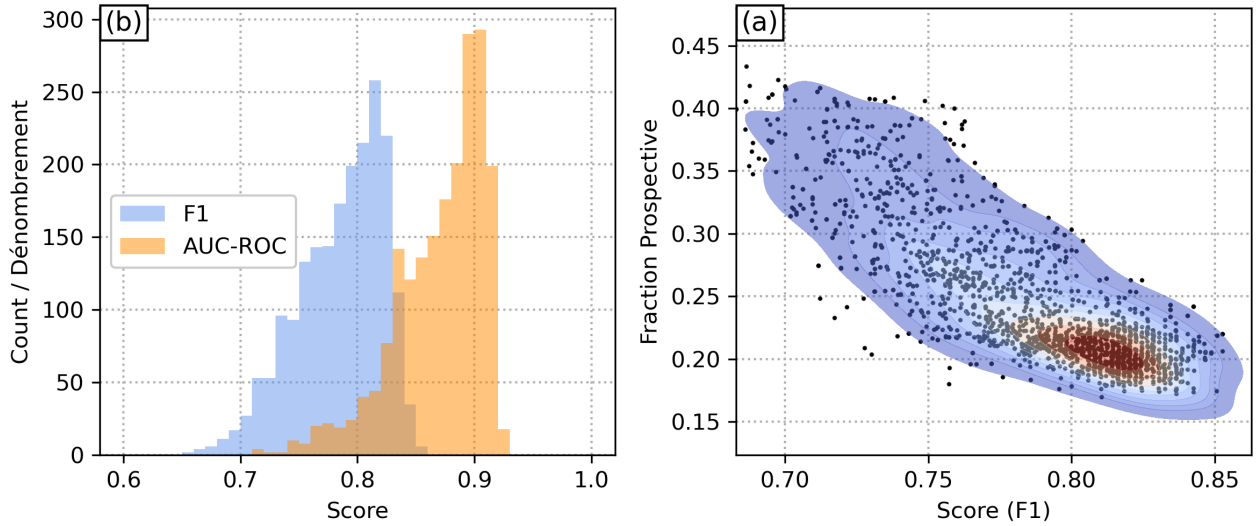


Figure 1. Variable and spatial domain performance of the deep ensemble for magmatic Ni ($\pm\text{Cu} \pm\text{Co} \pm\text{PGE}$). Performance of the ensemble is shown as a histogram (a) and as a scatter (b).

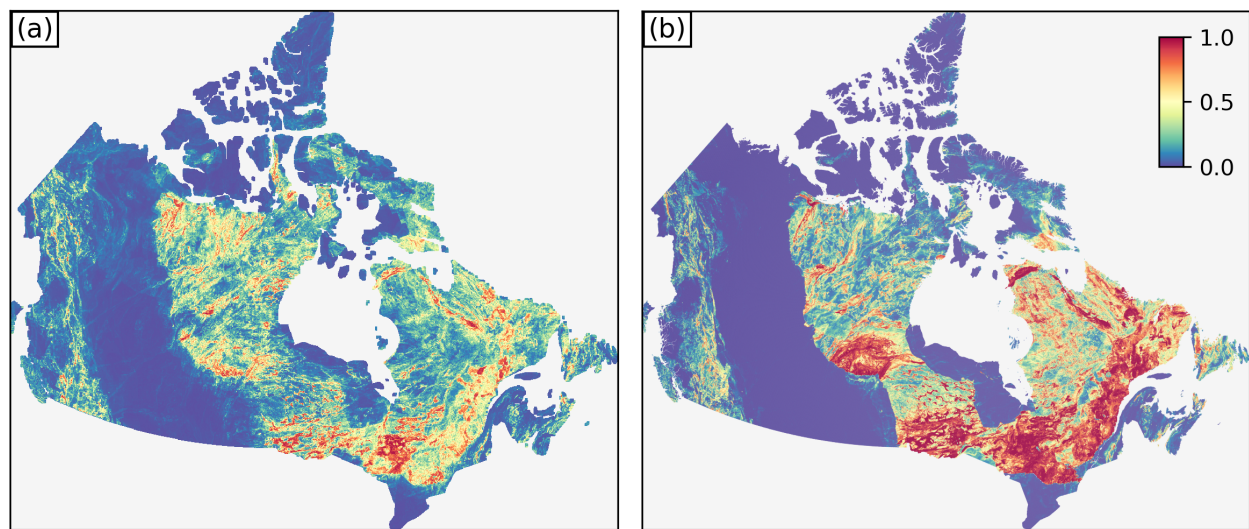


Figure 2. Comparison of original targeting information provided by a single model (a) and a deep ensemble of models (b) for the magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE) mineral system in Canada. The projection used is the Canada Atlas Lambert system.

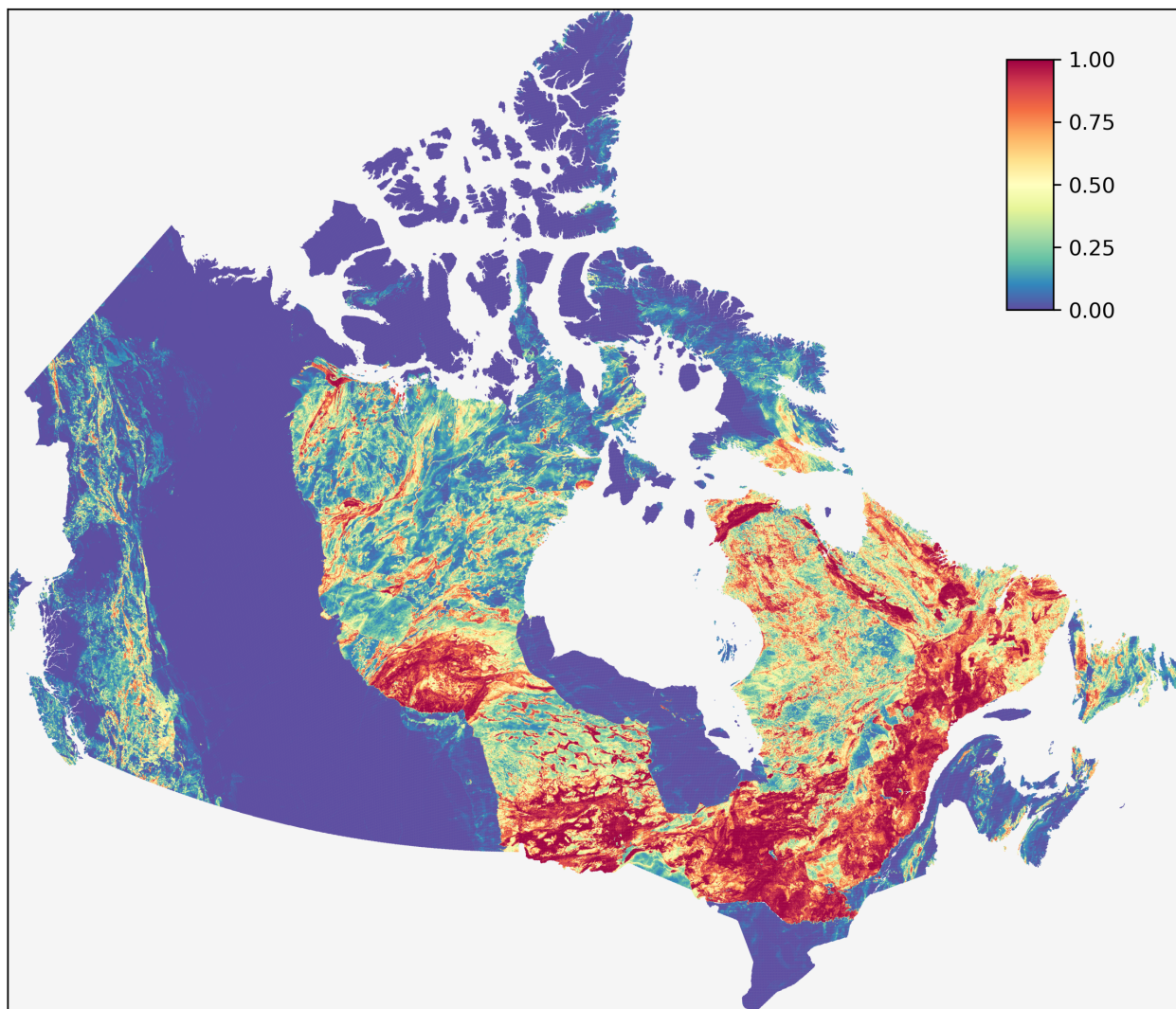


Figure 3. A high-resolution version prospectivity map of the magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE) mineral system. The projection used is the Canada Atlas Lambert system.

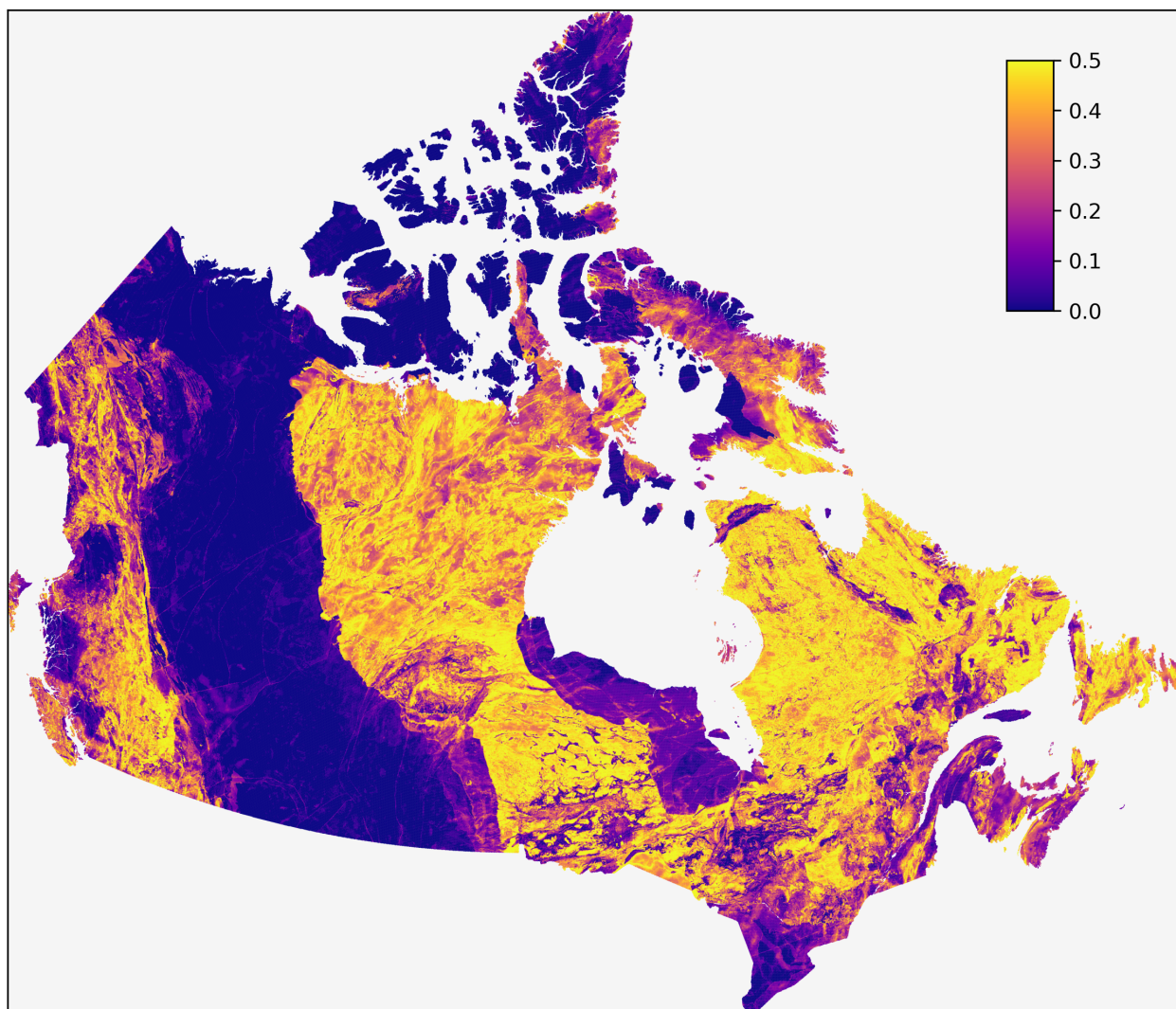


Figure 4. Uncertainty of the targeting information for the magmatic Ni ($\pm$ Cu $\pm$ Co $\pm$ PGE) mineral system in Canada. The standard deviation of the ensemble is used as the measure of dispersion. The projection used is the Canada Atlas Lambert system.

4.2 MVT Pb-Zn

The MVT Pb-Zn prospectivity map was created from a total of 2000 models. No models were discarded due to excessive overfitting. The AUC-ROC score of the models in the ensemble are generally higher than the F1 score (Fig. 5a). The spatial to variable domain coupling is noisy, although statistically, higher variable domain scores of models are correlated with better spatial performance (Fig. 5b). In comparison to the inaugural model, the prospectivity map shows that a substantial area of greenfield targets has become available (Figs. 6, 7). The increase favours Canadian exploration of MVT Pb-Zn, since the inaugural model did not reveal high potential for mineralization in Canada. The comparison also holds for Australia (Figs. 8, 9). The prospectivity maps (Figs. 7, 9) are companion maps to uncertainty maps (Figs. 10, 11). They depict the degree of dissent between all models.

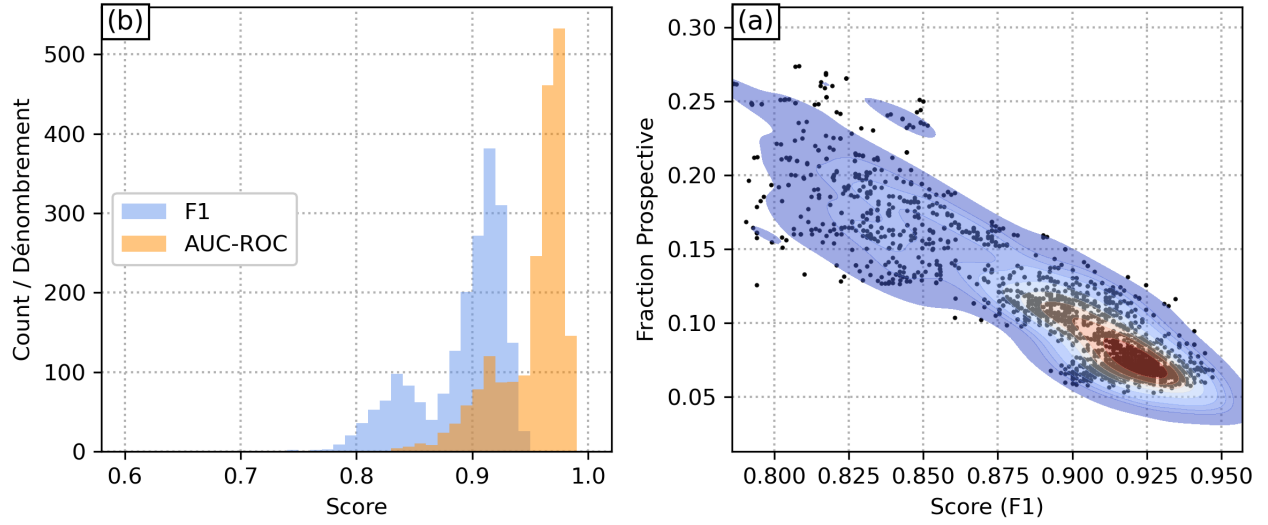


Figure 5. Variable and spatial domain performance of the deep ensemble for MVT Pb-Zn. Performance of the ensemble is shown as a histogram (a) and as a scatter (b).

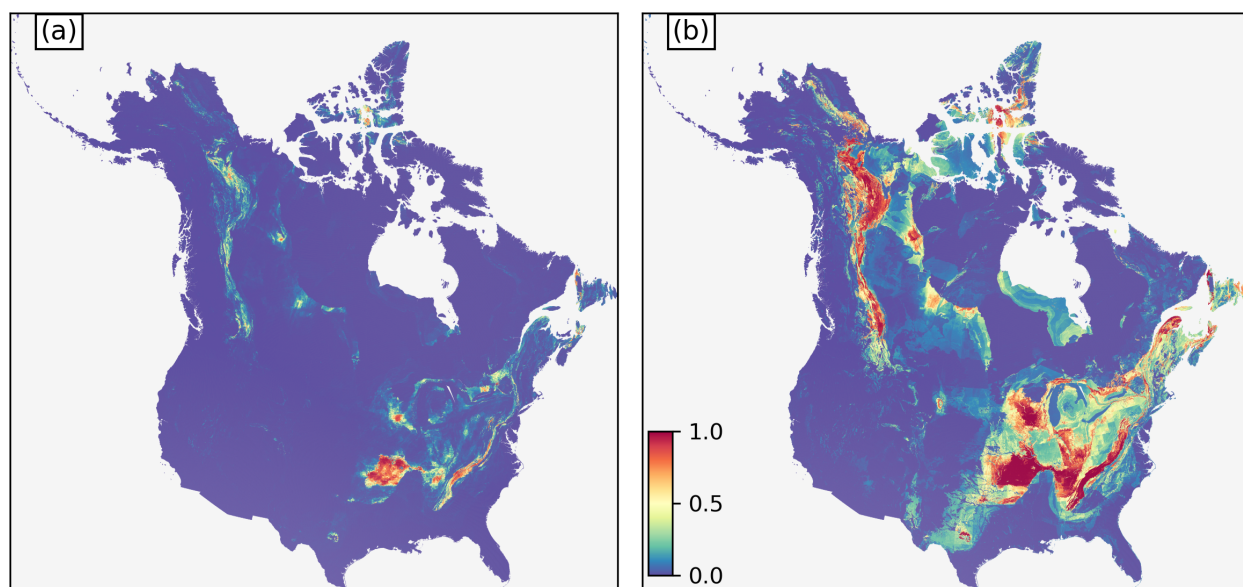


Figure 6. Comparison of original targeting information provided by a single model (a) and a deep ensemble of models (b) for the MVT Pb-Zn mineral system in North America. The projection used is the Canada Atlas Lambert system.

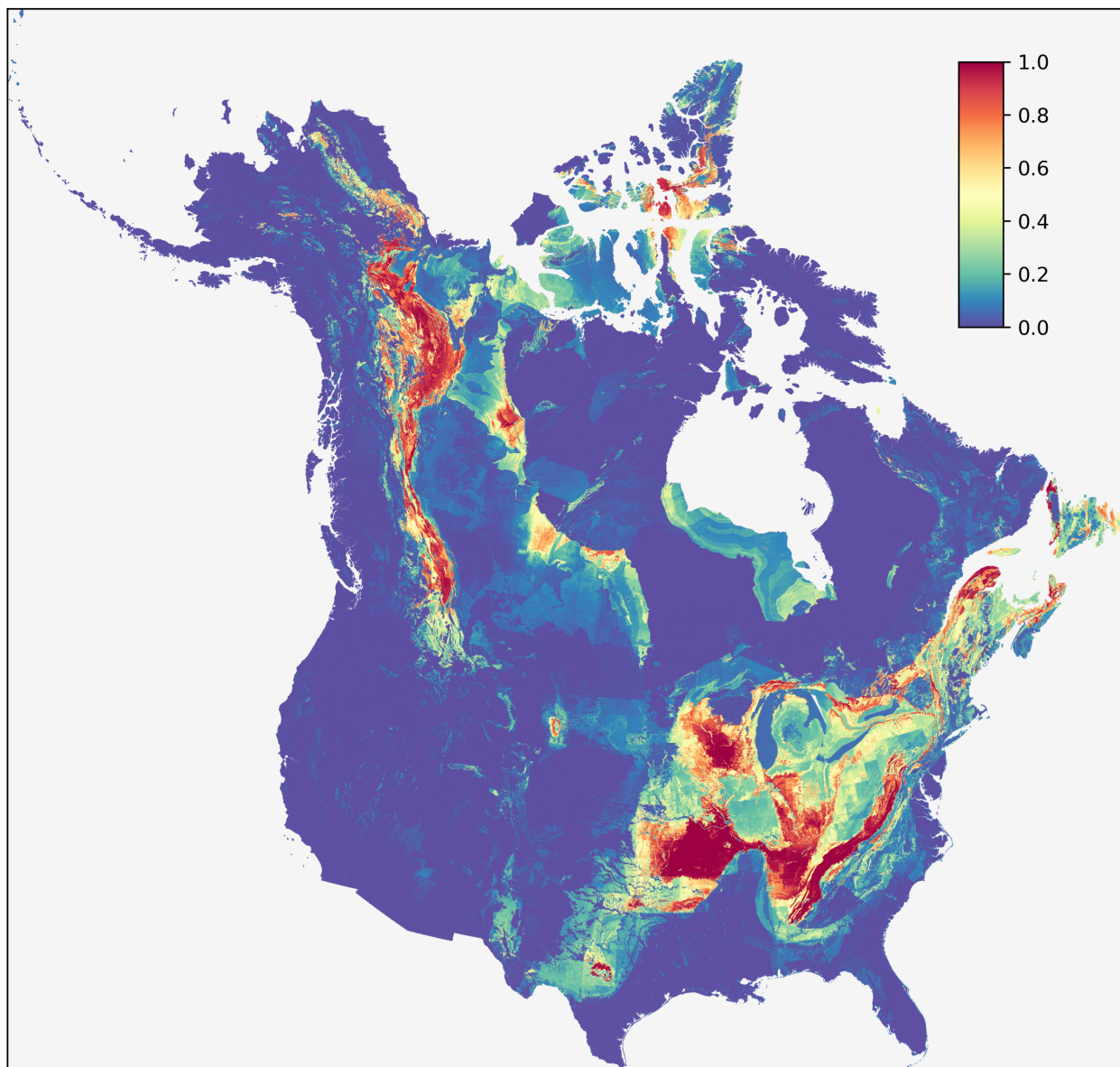


Figure 7. A high-resolution version of the alternate prospectivity map of MVT Pb-Zn mineral system. The projection used is the Canada Atlas Lambert system.

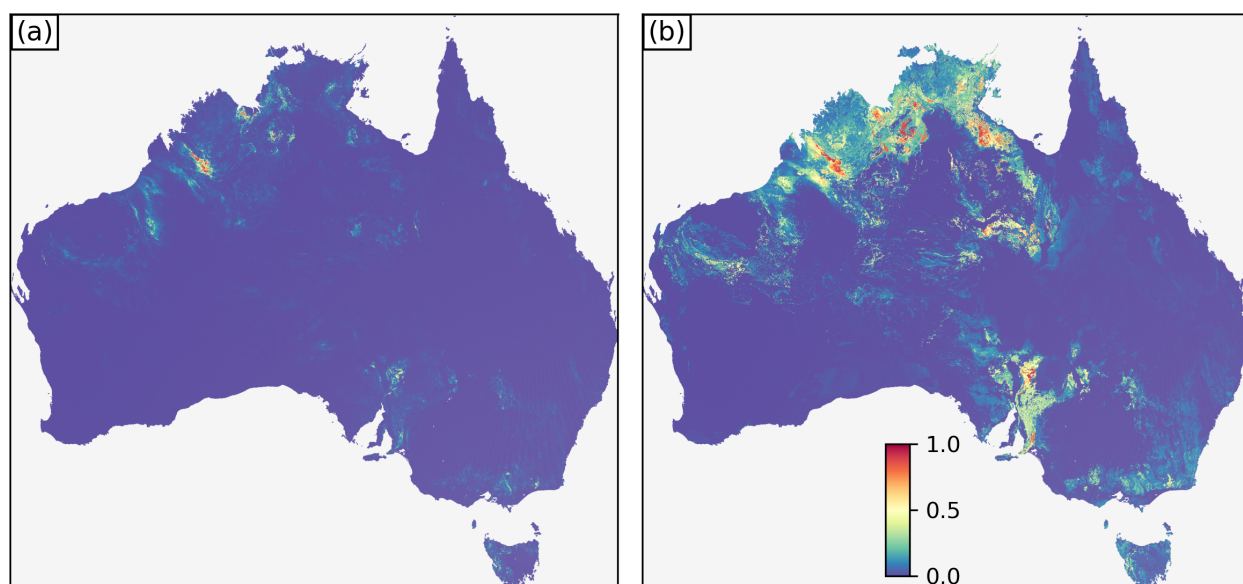


Figure 8. Comparison of original targeting information provided by a single model (a) and the expanded model (b) for the MVT Pb-Zn mineral system in Australia. Coordinates are displayed in WGS84 without projection.

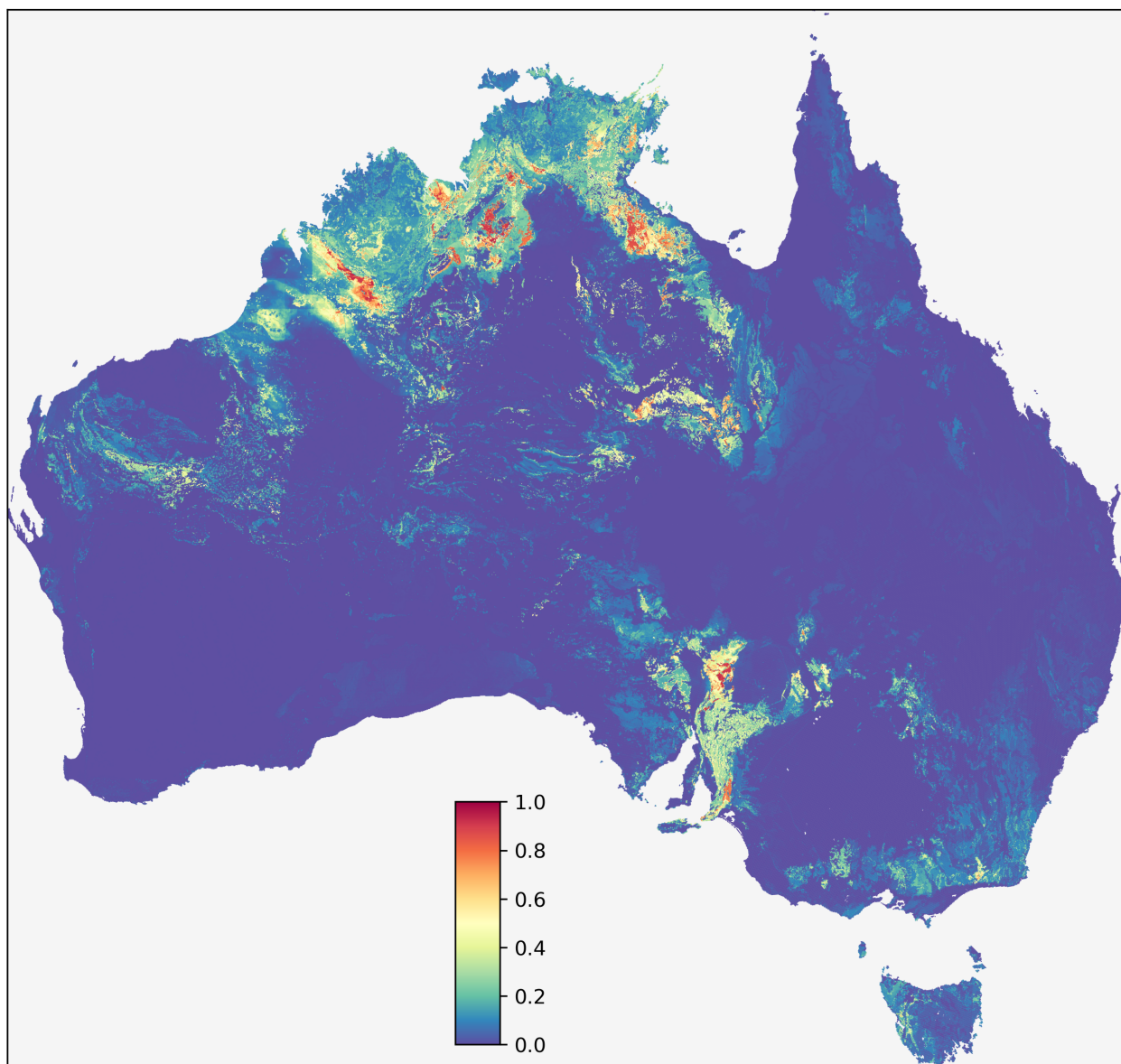


Figure 9. A high-resolution version of the alternate prospectivity map of MVT Pb-Zn mineral system in Australia. Coordinates are displayed in WGS84 without projection.

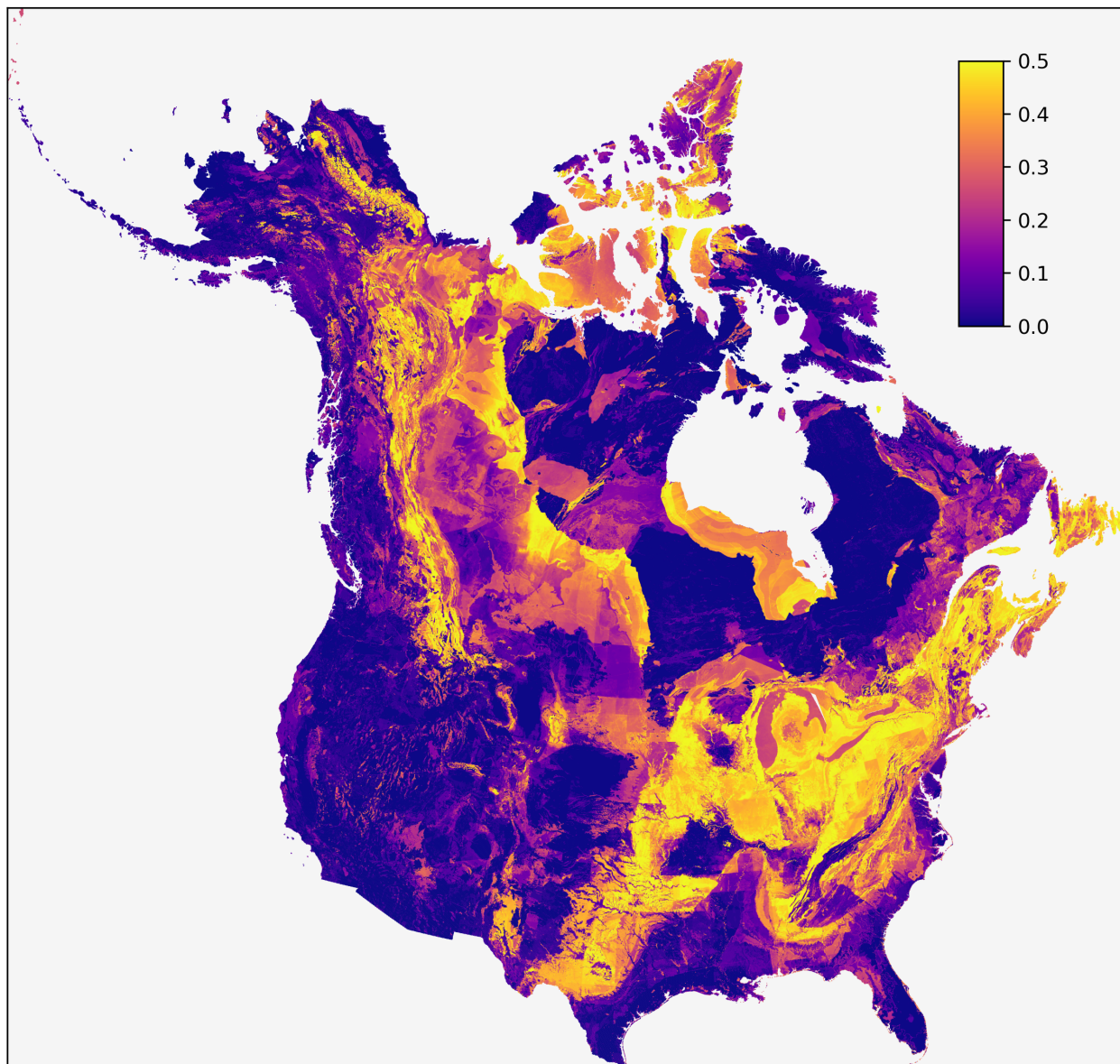


Figure 10. Uncertainty of the targeting information for the MVT Pb-Zn mineral system in Canada. The standard deviation of the ensemble is used as the measure of dispersion. The projection used is the Canada Atlas Lambert system.

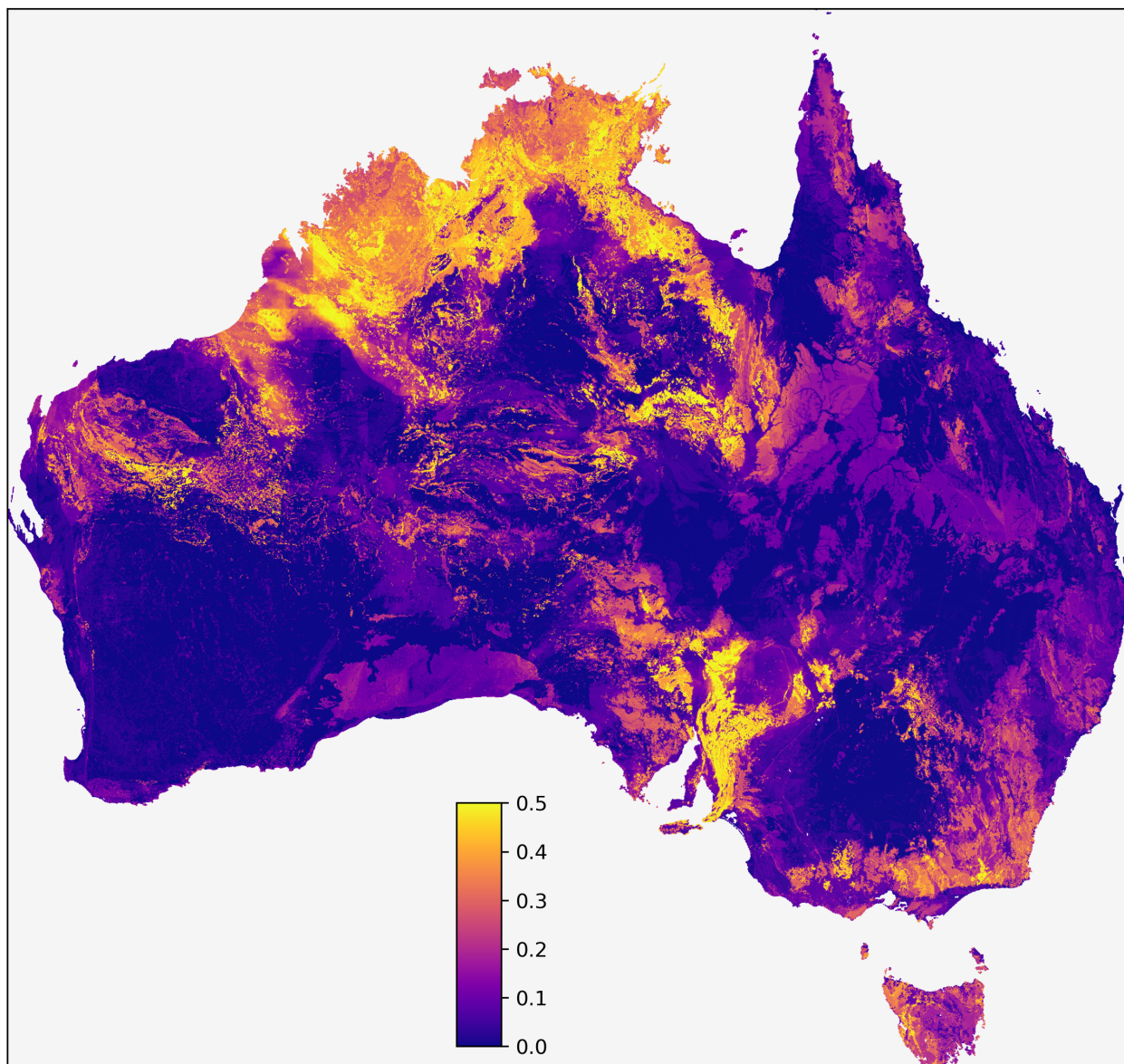


Figure 11. Uncertainty of the targeting information for the MVT Pb-Zn mineral system in Australia. The standard deviation of the ensemble is used as the measure of dispersion. Coordinates are displayed in WGS84 without projection.

4.3 CD Pb-Zn

The CD Pb-Zn prospectivity map was created from a total of 2000 models. No models were discarded due to excessive overfitting. The AUC-ROC score of the models in the ensemble are generally higher than the F1 score (Fig. 12a). The spatial to variable domain coupling is noisy, although statistically, higher variable domain scores of models are correlated with better spatial performance (Fig. 12b). In comparison to the inaugural model, the prospectivity map shows that a substantial area of greenfield targets has become available (Figs. 13, 14). The increase favours Canadian exploration of CD Pb-Zn, since the inaugural model did not reveal high potential for mineralization in Canada. The comparison also holds for Australia (Figs. 15, 16). Uncertainty maps (Figs. 17, 18) are companion maps to the prospectivity maps (Figs. 14, 16, respectively). They depict the degree of dissent between all models.

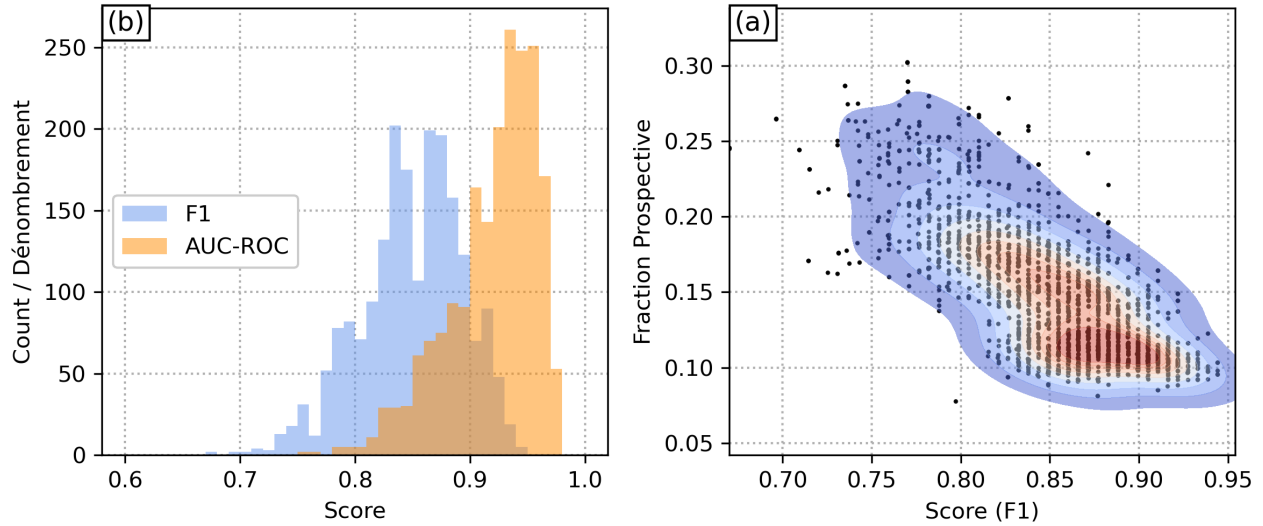


Figure 12. Variable and spatial domain performance of the deep ensemble for CD Pb-Zn. Performance of the ensemble is shown as a histogram (a) and as a scatter (b).

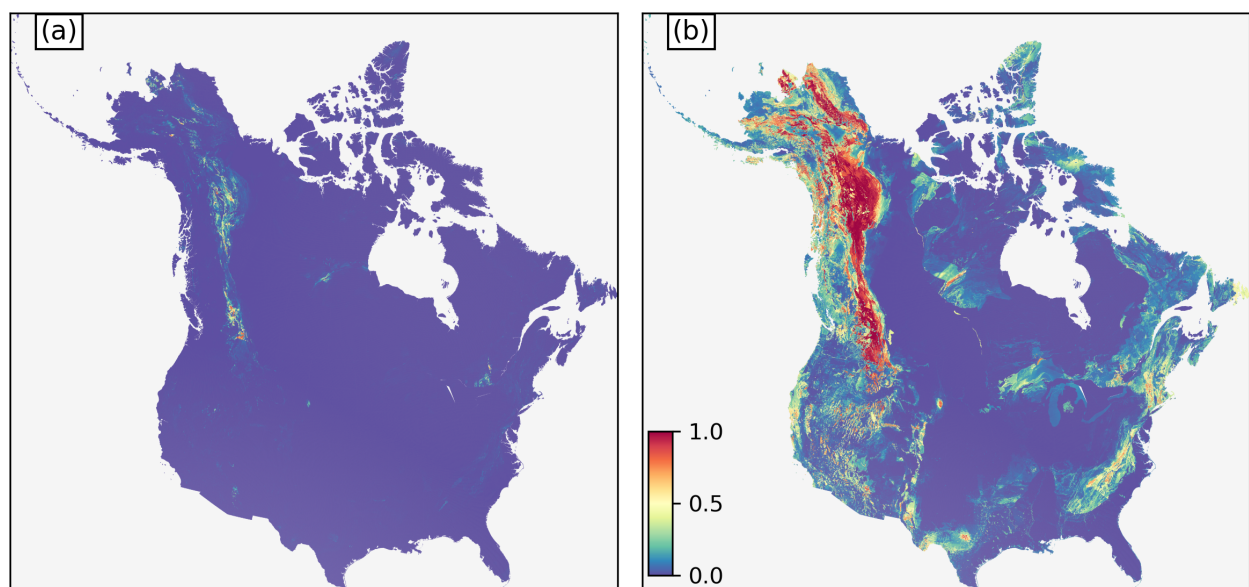


Figure 13. Comparison of original targeting information provided by a single model (a) and a deep ensemble of models (b) for the CD Pb-Zn mineral system in North America. The projection used is the Canada Atlas Lambert system.

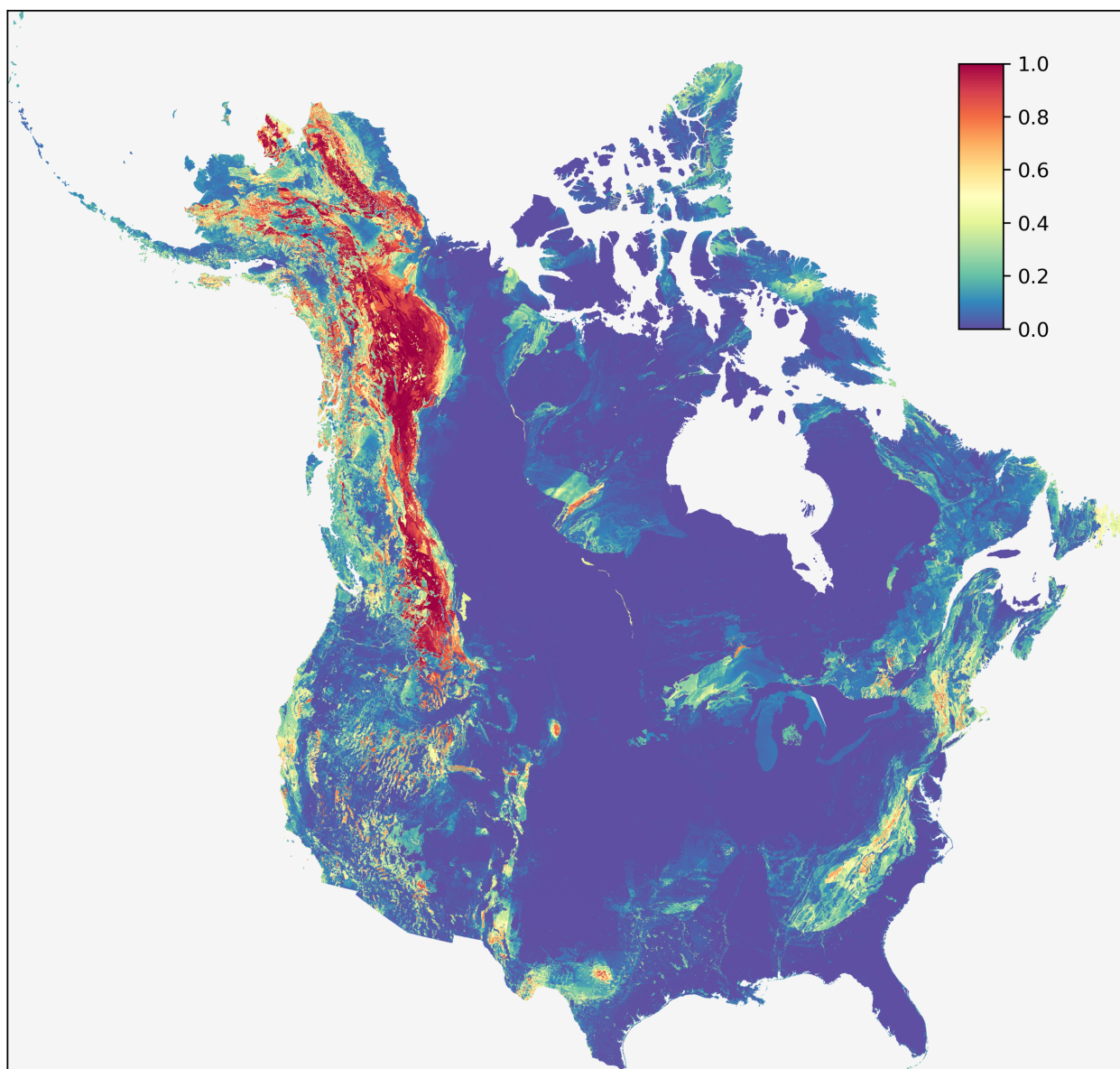


Figure 14. High-resolution version of the prospectivity map of CD Pb-Zn mineral system in North America. The projection used is the Canada Atlas Lambert system.

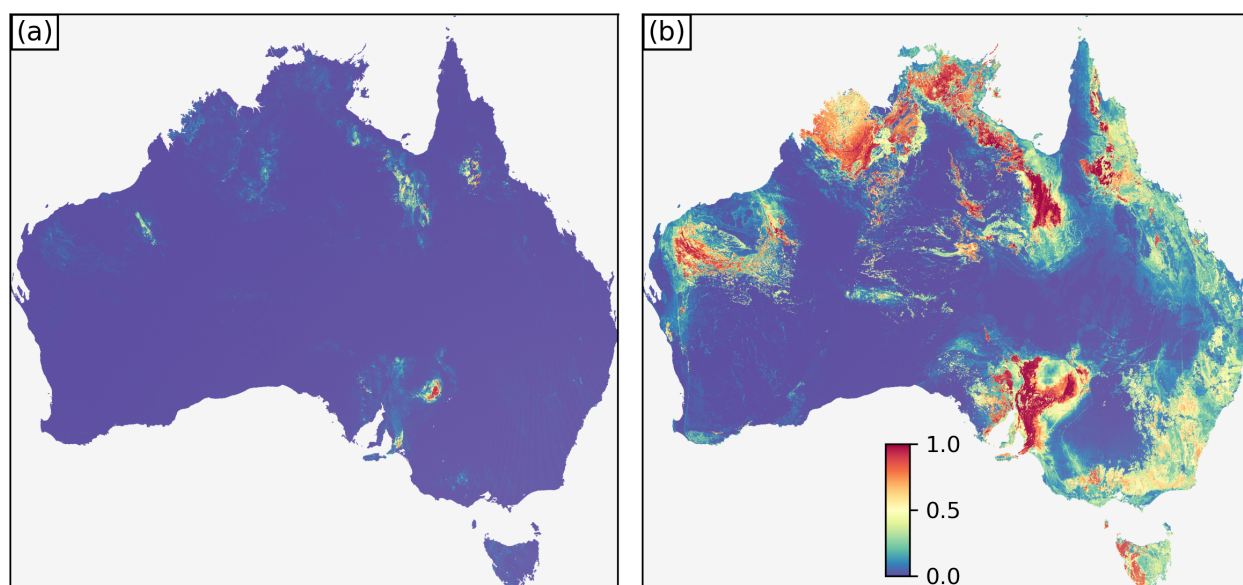


Figure 15. Comparison of original targeting information provided by a single model (a) and the expanded model (b) for the CD Pb-Zn mineral system in Australia. Coordinates are displayed in WGS84 without projection.

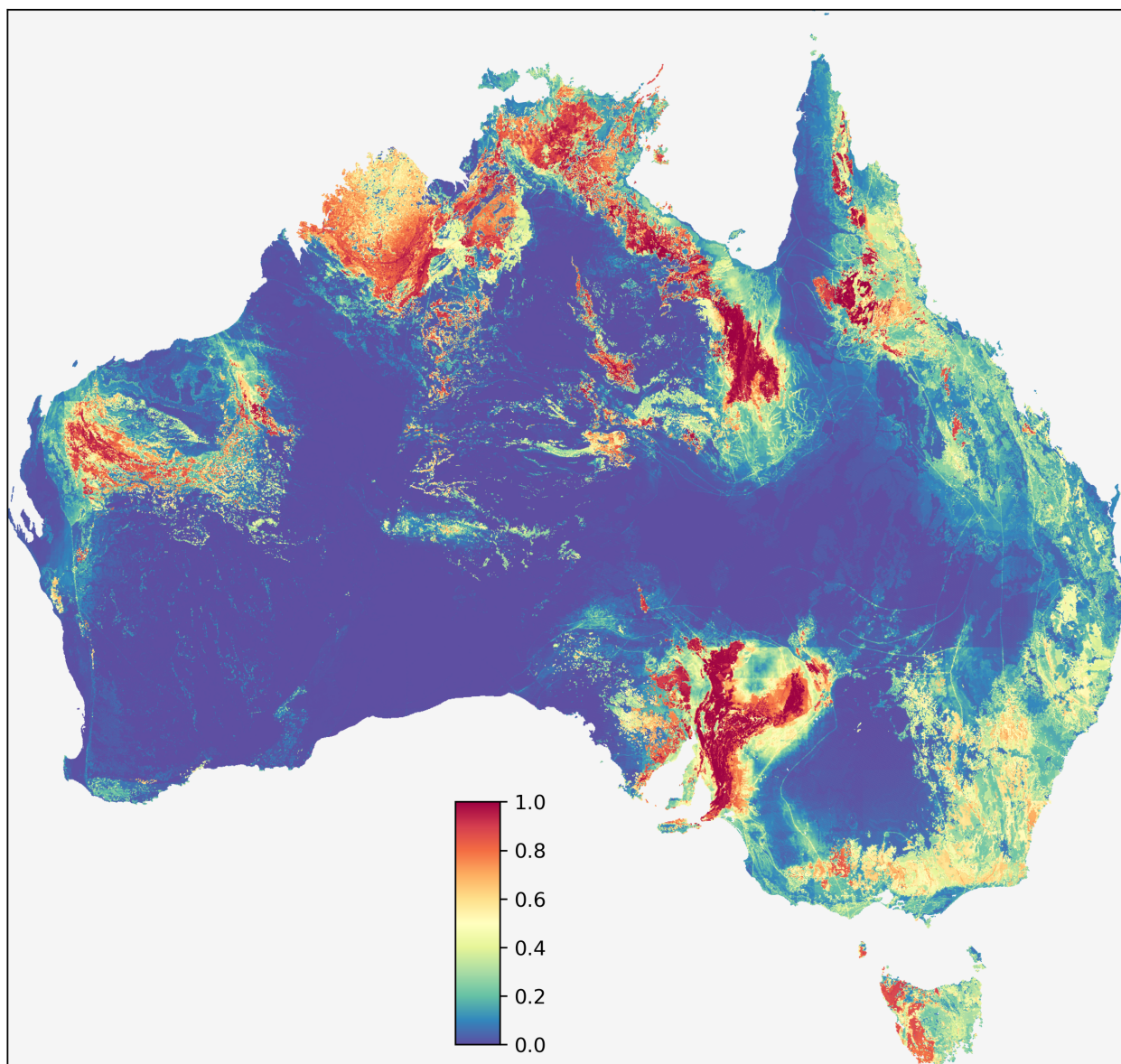


Figure 16. High-resolution version of the prospectivity map for the CD Pb-Zn mineral system in Australia. Coordinates are displayed in WGS84 without projection.

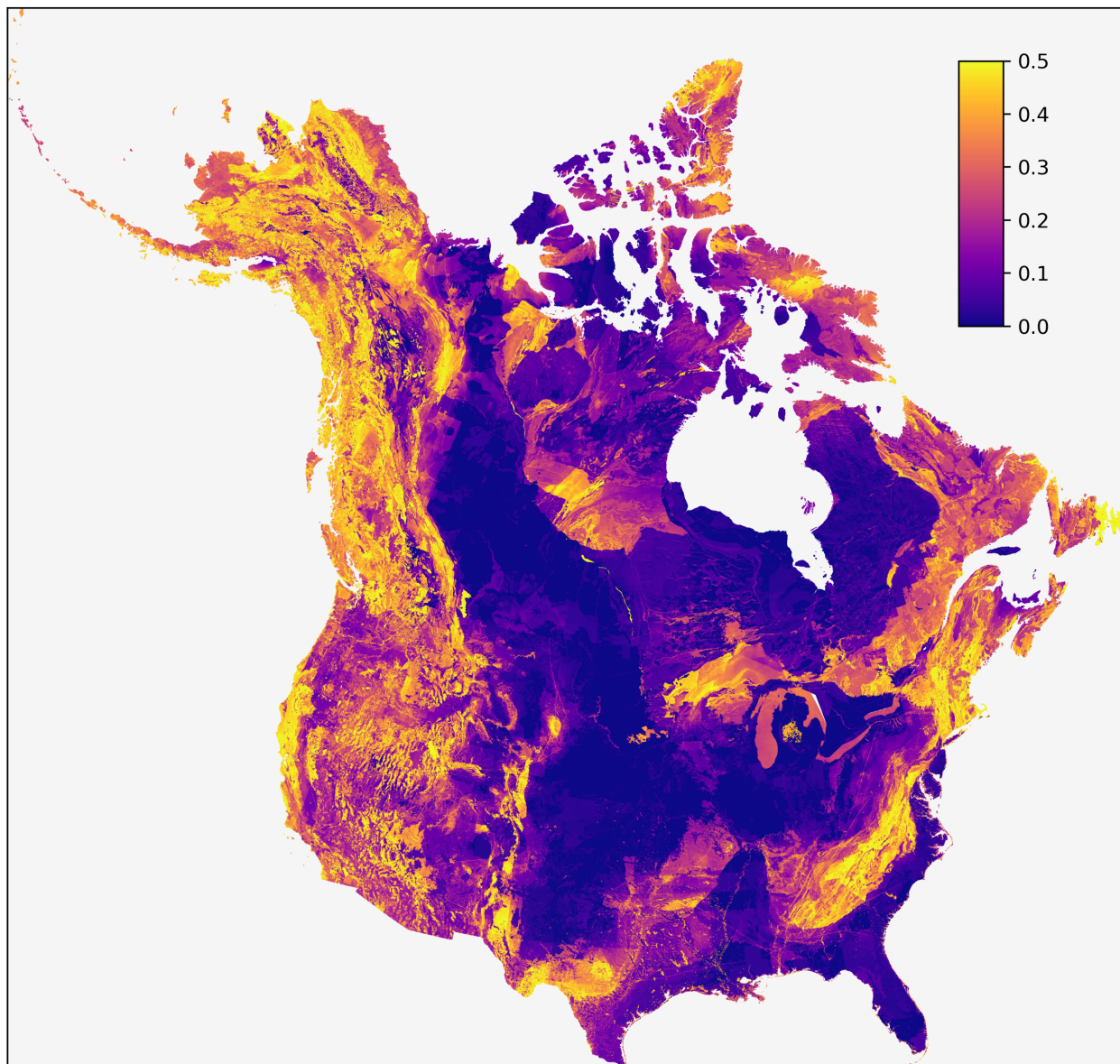


Figure 17. Uncertainty of the targeting information for the CD Pb-Zn mineral system in North America. The standard deviation of the ensemble is used as the measure of dispersion. The projection used is the Canada Atlas Lambert system.

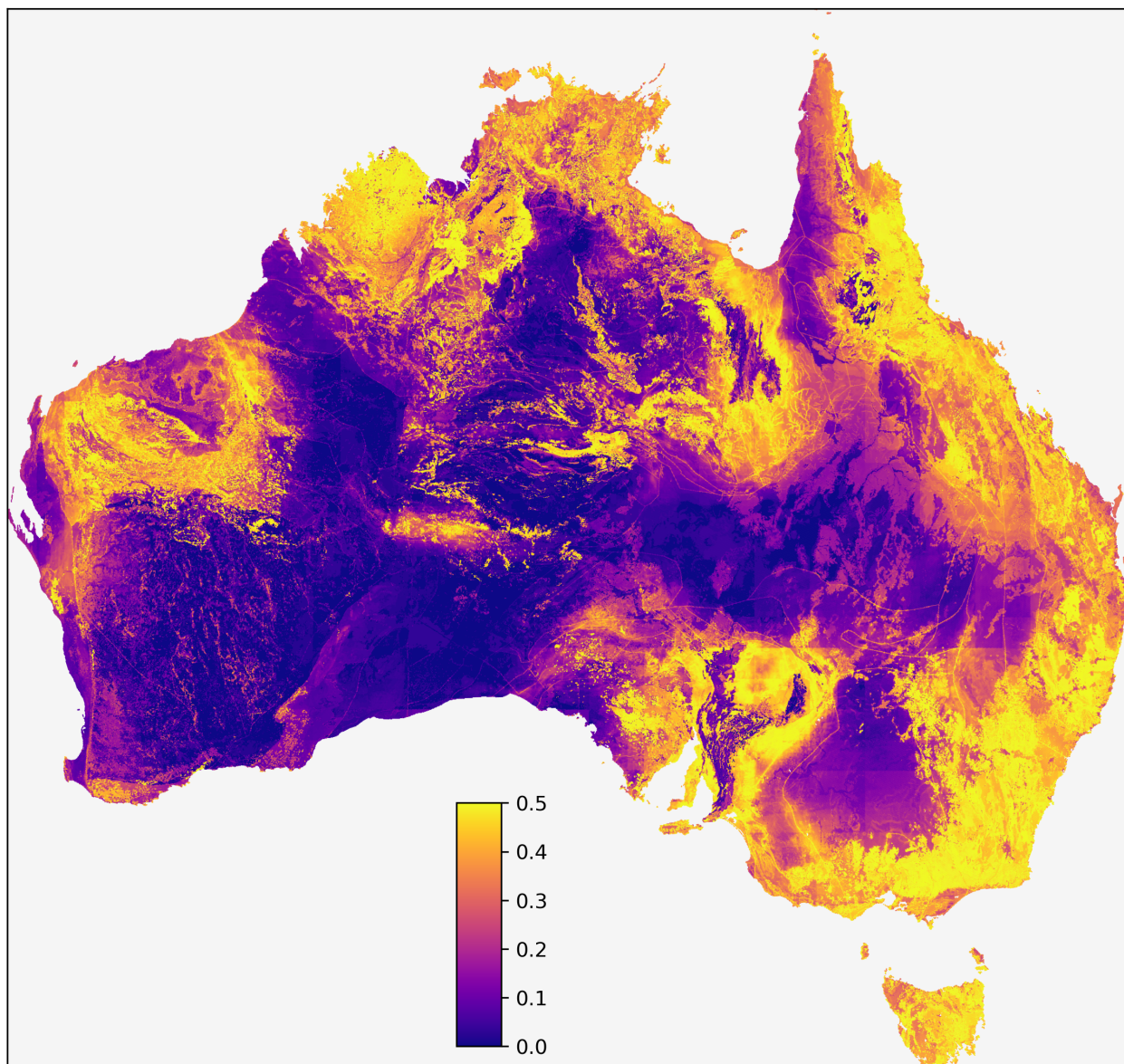


Figure 18. Uncertainty of the targeting information for the CD Pb-Zn mineral system in Australia. The standard deviation of the ensemble is used as the measure of dispersion. Coordinates are displayed in WGS84 without projection.

5 Summary

This report provides expanded prospectivity models for several critical minerals in Canada. The models are both applicative in support of pan-Canadian mineral exploration in a timely and agile manner and intended for scientific baseline purposes. Improved models in the future could make use of the models herein for statistically robust comparisons. The expanded models were produced using a deep ensemble method that propagated inter-practitioner or workflow-induced uncertainty.

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