Scale-Aware Machine Learning for Gold Prospectivity Mapping: Leakage-Aware Evidence-Range Audits for Exploration Targeting

Jeffery Opoku[a,*], David Banahene[b]

[a]School of Mathematical and Statistical Sciences, The University of Texas Rio Grande Valley, Edinburg, TX, USA
[b]Department of Biostatistics, Robert Stempel College of Public Health and Social Work, Florida International University, Miami, FL, USA

Abstract

Mineral exploration is expensive because most land has not been tested directly. A missing deposit record is therefore not the same as a true absence record. This paper develops a scale-aware positive-unlabeled learning framework for gold prospectivity mapping using public geological and mineral-occurrence data. The main method is the Non-Gold Evidence Transfer Field (NGETF). NGETF removes every gold- or Au-related record from the critical-mineral context layer, builds multi-scale spatial kernels from the remaining non-gold critical-mineral occurrences, and uses those kernels to rank grid cells by gold prospectivity. On a Nevada pilot grid with 4,392 cells, the conservative NGETF model obtains a quadrant-holdout AUC of 0.774. Cross-state transfer tests train on three western states and forecast a fourth held-out state. We then add public geoscience layers: USGS magnetic and gravity grids, mapped SGMC lithology polygons, and mapped fault traces. With these layers, held-out Arizona reaches AUC 0.890 and held-out Utah reaches AUC 0.926. An independent British Columbia test using the BC Geological Survey MINFILE catalogue gives base AUC 0.958. We then introduce a target-conditioned evidence-range audit: after removing non-gold context records near gold labels, AUC falls to 0.739 with a 25 km buffer and 0.616 with a 50 km buffer, with 50% of above-chance discrimination retained to about 27 km. This audit shows that the method is most useful as a local mineral-system prioritization tool, not as a stand-alone remote gold detector. It can help choose where to review, sample, or drill next, but it does not prove that gold is present.

Keywords: gold prospectivity mapping, positive-unlabeled learning, mineral exploration, spatial validation, uncertainty quantification, geospatial machine learning

1. Introduction

Mineral prospecting is a statistical problem with uneven labels. Some places have known deposits because people sampled, mapped, drilled, or mined them. Many other places have not been checked with the same effort. That means a map usually has positive examples and unlabeled examples, not clean positives and negatives.

*Corresponding author
Email address: jeffery.opoku01@utrgv.edu (Jeffery Opoku)

This matters for machine learning. If every unlabeled cell is treated as a true non-deposit, the model may learn the history of exploration more than the geology. It may also look more certain than it should. A useful prospectivity model should therefore do three things. First, it should rank land, not pretend to prove mineral presence. Second, it should avoid leakage from features that already encode the target mineral. Third, it should report uncertainty in a way that a geologist or company can use.

This paper focuses on gold prospectivity in Nevada. The main question is: can non-gold critical-mineral context help predict where gold is more likely to occur? The word "context" is important. The method does not say that copper, lithium, cobalt, or other critical minerals cause gold. It asks whether their spatial pattern carries useful information about broader mineral-system structure.

We propose the Non-Gold Evidence Transfer Field, or NGETF. The method builds a transfer field from non-gold critical-mineral occurrences. Before the field is built, every gold-related record is removed from the context layer. The model is then trained as a positive-unlabeled learner and tested with spatial holdout validation.

2. Contributions

The paper makes seven contributions.

1. It gives a leakage-aware way to use non-gold critical-mineral context for gold prospectivity mapping.
2. It defines NGETF, a multi-scale transfer-field representation built from distances to non-gold mineral groups.
3. It evaluates the model with spatial blocks and a coarse quadrant holdout, which are more realistic than random train-test splits for maps.
4. It turns the model into a company-style forecast package with probabilities, uncertainty, field-action zones, and a top-100 target list.
5. It adds a real MRDS-derived geology layer with structure, rock type, alteration, and geophysical context, then tests transfer to held-out states.
6. It adds official public geoscience layers from SGMC, USGS magnetic anomaly data, and USGS gravity data.
7. It defines a target-conditioned evidence-range audit that reports how much held-out discrimination remains after nearby non-target context is removed.
8. It adds independent-province tests and an independent British Columbia MINFILE catalogue test with explicit spatial-buffer audits.

3. Data

We use public data from the United States Geological Survey: MRDS for mineral occurrences, the National Geochemical Survey for geochemical observations, and USMIN for mine and prospect features (U.S. Geological Survey, 2026c,d,f). These data are useful because they are public, large, and reproducible. They are also imperfect. They reflect historical reporting, exploration effort, and database coverage.

The Nevada pilot grid contains 4,392 grid cells. A cell is labeled positive if the cell center is within 5 km of a known MRDS Au-bearing occurrence. The remaining cells are treated as unlabeled. They are not treated as confirmed gold absences. This is an occurrence-prospectivity label, not an ore-body, grade, tonnage, or economic-reserve label.

The non-gold critical-mineral context layer is built from MRDS records after removing every record that mentions gold or Au. The strict audit removed 5,091 gold-related critical-mineral records and kept 5,480 non-gold critical-mineral context points. The kept context includes copper, lithium, nickel, cobalt, rare earth elements, graphite, uranium, manganese, and an all-critical-mineral layer.

We also build an MRDS-derived geological-descriptor layer from non-gold records. This layer uses text fields such as ore control, host rock, associated rock, structure, tectonic setting, alteration, ore, and gangue. It creates distance features for fault/structure context, intrusive and plutonic rocks, volcanic rocks, carbonate and sedimentary rocks, metamorphic rocks, alteration, and geophysical-indicator terms such as magnetic, gravity, radiometric, resistivity, and induced-polarization language. These are broad regional descriptors, not a replacement for a deposit-model-specific geological interpretation. Across Nevada, Arizona, California, and Utah, this step uses 12329 non-gold geology-context records from 304632 scanned MRDS records.

For the independent-province test, we rebuild a coarser grid for the western United States and Alaska using the same MRDS feature recipe. The western United States source pool contains 38987 gold records, 17927 non-gold mineral-context records, and 12633 geology-context records. The Alaska source pool contains 8393 gold records, 3085 non-gold mineral-context records, and 1213 geology-context records. This test is meant to mimic a company entering a new province with public data first, before paying for field campaigns.

Finally, we add one true raster geophysics layer for the western-state tests. We download the USGS North American magnetic anomaly XYZ grid and sample 465606 grid points inside the western-state bounding box (U.S. Geological Survey, 2026b). For each prospectivity cell, we compute the nearest magnetic anomaly, absolute anomaly, 25 km local mean, 25 km local standard deviation, and 50 km local range. These features are separate from the MRDS text-based geophysical indicators.

The final robustness evaluation adds mapped state-geologic and gravity layers. From the USGS State Geologic Map Compilation, we use mapped lithology polygons and 106590 mapped fault traces (U.S. Geological Survey, 2026e). From the USGS gravity grid, we sample 117224 gravity points inside the western-state bounding box (U.S. Geological Survey, 2026a). For each of the 3443 western-state grid-cell centers, we use an exact even–odd ray-casting test against the SGMC polygon rings. This creates six direct lithology-containment flags: intrusive (233 cells), volcanic (522), carbonate (279), metamorphic (79), clastic sedimentary (758), and unconsolidated (1704). We also count sampled mapped fault vertices and segment midpoints within 25 and 50 km. A locally bucketed trace-junction measure is retained only as a reproducible junction proxy, not as a detailed structural interpretation.

For an independent-source evaluation, we use the 10000 point records returned by the British Columbia Geological Survey MINFILE service (British Columbia Geological Survey, 2026). Gold-labelled MINFILE records define British Columbia evaluation cells and are removed from every context feature. The external grid has 1300 cells, of which 281 are within 20 km of a MINFILE Au record. We also run a stricter audit that removes non-gold

MINFILE context records within 25 km and 50 km of every Au-labelled record before scoring the grid.

4. Problem Setup

Let s denote a grid cell. Let $Y_s = 1$ mean that the cell is positive for the observed Au-occurrence label under the public evidence. The target is not a proven ore body. It is a prospectivity label based on known occurrence data. The model estimates

$$p(s) = P(Y_s = 1 \mid X_s),$$

where X_s contains spatial evidence around cell s.

The training set has two parts: P, the set of known-positive cells, and U, the set of unlabeled cells. The unlabeled set can contain both undiscovered positives and true low-prospectivity locations. This is the positive-unlabeled setting (Elkan and Noto, 2008).

5. The NGETF Method

5.1. Transfer Field

For each non-gold mineral group m, let $d_m(s)$ be the distance in kilometers from cell s to the nearest occurrence of group m. NGETF uses a set of spatial scales

$$\mathcal{R} = \{5, 10, 25, 50, 100\} \text{ km}.$$

For each scale r, the transfer feature is

$$\phi_{m,r}(s) = \exp\{-d_m(s)/r\}.$$

The model also uses an inverse-distance feature

$$\psi_m(s) = \frac{1}{1 + d_m(s)}.$$

The NGETF vector is therefore

$$T(s) = (\phi_{m,r}(s), \psi_m(s) : m \in \mathcal{M}, r \in \mathcal{R}).$$

In this study, $T(s)$ has 54 features in the conservative model.

Proposition 1 (Target-exclusion property). *Let $C_{-\mathrm{Au}}$ be the context record set after removing every record that mentions gold or Au in the audited text fields. For a fixed set of non-gold mineral groups $\mathcal{M}$, $T(s)$ is a deterministic function of $C_{-\mathrm{Au}}$ and the cell location s; it does not use a gold-occurrence distance as an input feature.*

Reason. Each entry of $T(s)$ is computed only from $d_m(s)$ for $m \in \mathcal{M}$, and each such distance is calculated from $C_{-\mathrm{Au}}$. This blocks direct target-occurrence leakage. It does not prove that all remaining variables are unrelated to gold, which is why geographic holdouts and the baseline comparison remain necessary.

5.2. Why Multi-Scale Kernels Help

A single distance cutoff can miss useful structure. A 5 km kernel captures local evidence. A 100 km kernel captures broad district-level context. The model can learn how much each scale matters. This is useful for mineral systems because some signals are local while others are regional.

Lemma 1 (Kernel stability). *For any mineral group m, any scale $r > 0$, and any two cell locations s, t,*

$$|\phi_{m,r}(s) - \phi_{m,r}(t)| \leq \min\left\{1, \frac{d(s,t)}{r}\right\}, \qquad |\psi_m(s) - \psi_m(t)| \leq \min\{1, d(s,t)\},$$

where $d(s,t)$ is the geographic distance between the cells.

Reason. Distance to a fixed set is 1-Lipschitz. The exponential kernel has derivative at most $1/r$ in absolute value and the inverse-distance transform has derivative at most one. Thus small changes in location cannot create arbitrarily large changes in the transfer features.

5.3. Positive-Unlabeled Fitting

We use bagged positive-unlabeled logistic models. Each base model uses all known positives and a random sample of unlabeled cells as provisional negatives. For base model b, the fitted score is

$$\hat{p}_b(s) = \sigma\left(\alpha_b + \beta_b^\top Z(s)\right),$$

where $Z(s)$ is the chosen feature vector and $\sigma(t) = 1/(1 + e^{-t})$. The final probability is the ensemble mean

$$\hat{p}(s) = \frac{1}{B}\sum_{b=1}^{B} \hat{p}_b(s).$$

The model uncertainty is

$$\hat{u}(s) = \left[\frac{1}{B-1}\sum_{b=1}^{B} \left(\hat{p}_b(s) - \hat{p}(s)\right)^2\right]^{1/2}.$$

This uncertainty is not a full Bayesian posterior. It is a practical instability score that shows whether the ranking depends strongly on which unlabeled cells were sampled as provisional negatives.

Theorem 1 (Conditional ensemble concentration). *Fix the observed positive set, unlabeled set, cell s, and model-fitting rule. If the B bagged draws are independent, then for every $\epsilon > 0$,*

$$P\left(|\hat{p}(s) - E\{\hat{p}_b(s)\}| \geq \epsilon\right) \leq 2\exp(-2B\epsilon^2).$$

Reason. Each fitted probability lies in $[0, 1]$, so the result follows directly from Hoeffding's inequality. This result describes Monte Carlo stability of the bagged score conditional on the observed data. It is not a guarantee that the prospectivity probability is calibrated in a new province.

5.4. Assumptions and Scope

The model is a ranking method. It does not assume that unlabeled cells are true negatives, and it does not claim a reserve probability. The positive-unlabeled procedure is most interpretable when known positives are a reasonably representative sample of observable positives. In mineral exploration that condition can fail because past survey effort is uneven. We therefore report geographic holdouts, repeated negative-sampling sensitivity, and independent-province transfer instead of relying on one random split or one fitted model.

5.5. Target-Conditioned Evidence-Range Audit

Spatial validation alone does not tell us how much a ranking depends on mineral-system context very close to known occurrences. Let P_{test} be the set of known-positive evaluation locations and let $C_{-\text{Au}}$ be the non-gold context record set. For an exclusion distance $b \geq 0$, define the buffered context set

$$C_{-\text{Au}}^{(b)} = \{c \in C_{-\text{Au}} : d(c, P_{\text{test}}) > b\}.$$

The score is then rebuilt using $C_{-\text{Au}}^{(b)}$, while the same test labels are retained only for evaluation. Let $A(b)$ denote the held-out AUC from this audit. We summarize the remaining signal by

$$D(b) = \frac{A(b) - 0.5}{A(0) - 0.5},$$

where 0.5 is chance AUC. Thus $D(0) = 1$, and smaller values mean that more of the original discrimination depended on nearby context. For a chosen retention level $q \in (0, 1)$, the estimated evidence range is

$$b_q = \inf\{b : D(b) \leq q\}.$$

This is not a feature used to forecast unknown targets, because P_{test} is unavailable in deployment. It is an audit that certifies the spatial scale at which a model's reported discrimination is supported.

5.6. Company-Grade Forecast Score

For field use, we separate greenfield and brownfield use. Let $\hat{p}_C(s)$ be the conservative non-gold NGETF probability. This is the greenfield ranking score because it excludes mine and prospect proximity. Let $\hat{p}_F(s)$ be a fuller brownfield-support model that can also use geochemistry, USMIN proximity, and sampling-support features. The brownfield planning score is

$$\hat{p}_{\text{company}}(s) = 0.65\hat{p}_C(s) + 0.35\hat{p}_F(s).$$

The heavier weight on $\hat{p}_C$ keeps the brownfield score from being dominated by direct mining-feature proximity. The fuller score is never used as evidence for a blind greenfield target, because mine and prospect inventories partly reflect where exploration has already occurred. The uncertainty score is the maximum of conservative ensemble uncertainty, full-model ensemble uncertainty, and the disagreement $|\hat{p}_C(s) - \hat{p}_F(s)|$. This makes disagreement visible instead of hiding it.

6. Validation Design

Random splits are too easy for spatial data because nearby cells can share the same geology and exploration history. We therefore use two spatial validation designs.

- Degree-block holdout leaves out groups of one-degree spatial blocks.
- Quadrant holdout leaves out one broad map quadrant at a time.

The quadrant holdout is the stricter test. It asks whether the learned spatial evidence transfers to a larger region, not just to nearby cells.

7. Validation Ladder

A reviewer should not judge this paper from one split or one map. The claim is tested in layers. Each layer answers a harder question than the one before it.

Table 1: Validation ladder. The purpose is not to make every metric increase. The purpose is to test whether the ranking remains useful under harder and more realistic settings.

Validation layer	Main question	AUC pattern	Top-ranked-cell signal
Nevada spatial holdout	Does non-gold context help inside one state?	Quadrant AUC 0.774	Top-10 enrichment 2.42x
Cross-state NGETF	Does the method transfer across western states?	0.782–0.891	2.52x–6.70x
MRDS geology context	Does descriptive geology add value?	0.787–0.926	2.56x–7.05x
USGS magnetic raster	Does true magnetic geophysics help?	0.825–0.924	2.47x–6.31x
Mapped geology, faults, gravity	Does a richer public geoscience stack help?	0.791–0.926	2.47x–7.05x
Established baselines	Is NGETF competitive with standard prospectivity models?	0.662–0.937	1.11x–7.47x
Western U.S. → Alaska	Does the recipe move to a new province?	0.924	4.03x
Western U.S. → Northern Rockies	Does the recipe move to a second new province?	0.952	2.63x
Western U.S. → British Columbia MINFILE	Does the ranking persist with an independent catalogue?	0.958 base; 0.739/0.616 buffered	4.20x base

This ladder is deliberately conservative. Some added layers help one province and hurt another. That is not treated as a failure to hide. It is part of the method: a company should test each evidence layer under blocked or province-transfer validation before using it for field decisions.

8. Results

8.1. Model Comparison

Table 2 reports the main model comparison. The conservative NGETF model uses only non-gold critical-mineral transfer fields. The geochemical-support model adds geochemistry and sampling support. The full company model also uses USMIN mine/prospect proximity.

Table 2: Company-grade model comparison.

Model	Features	Full AUC	Quadrant AUC	Degree-block AUC	Top-10 enrich.
Conservative NGETF	54	0.780	0.774	0.775	2.42
NGETF + geochem support	75	0.777	0.756	0.764	2.39
Full company model	76	0.782	0.761	0.770	2.39

The conservative model obtains a quadrant AUC of 0.774. This is the cleanest evidence that non-gold critical-mineral context carries usable information. The full company model reaches a quadrant AUC of 0.761, but that result should be read as a practical field model rather than a pure test of the NGETF idea.

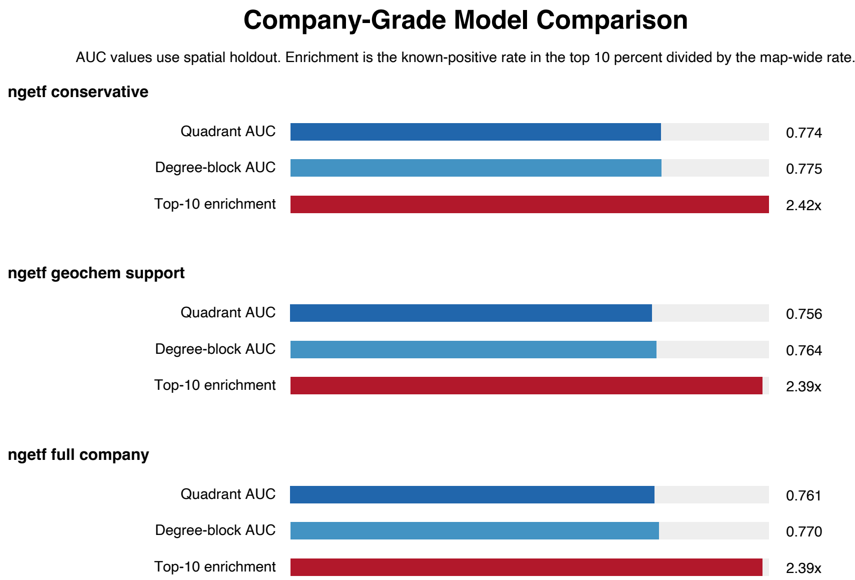

Figure 1: Spatial validation and enrichment for the company-grade model set.

8.2. Field-Priority Forecast

The company score ranks the top 5 percent of cells at a known-positive rate of 0.864, the top 10 percent at 0.815, and the top 20 percent at 0.715. The overall known-positive rate is 0.337. Thus, the top 10 percent of the map is enriched by 2.42 times relative to the map-wide rate.

This ranking is useful for screening because it narrows a large search space. It does not replace geology. A company would still need to check land access, structure, alteration, geophysics, geologic maps, assays, and field evidence.

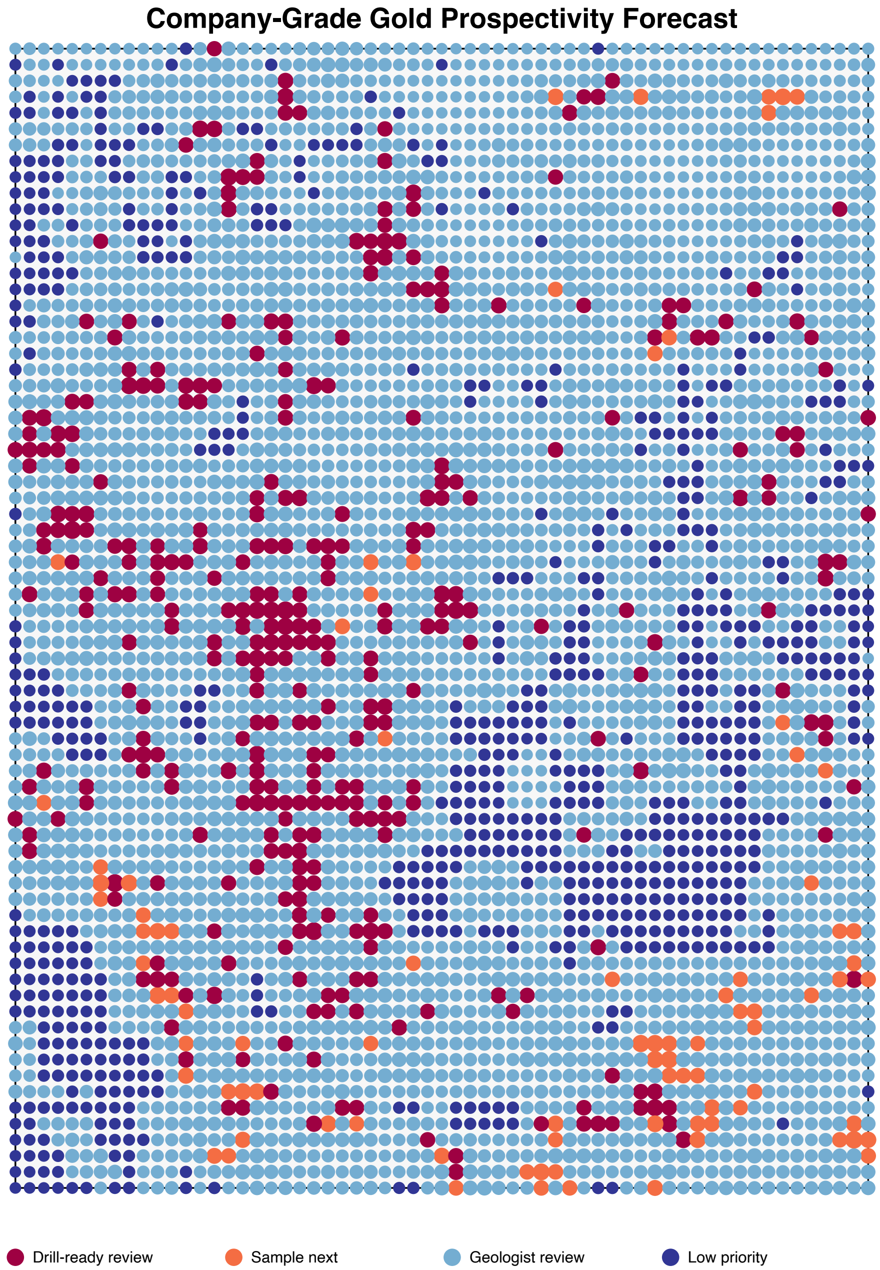

Figure 2: Company-grade forecast map. Red cells are high-priority review zones; orange cells need more sampling before stronger action; blue cells are lower-priority or expert-review zones.

8.3. Decision Zones

The forecast creates four field-action zones. The drill-ready review zone contains 352 cells and has a known-positive rate of 0.844. The sample-next zone contains 88 cells and has a known-positive rate of 0.705. The low-priority zone contains 697 cells and has a known-positive rate of 0.105. These rates show that uncertainty can be used as a practical filter rather than only as a reporting statistic.

9. How a Geological Company Could Use the Output

The final output is a ranked table of grid cells with latitude, longitude, prospectivity score, uncertainty, confidence, and field-action label. A company can use this table in a simple workflow.

1. Review the top-100 cells against geologic maps, claims, land status, and known districts.
2. Send high-score, low-uncertainty cells to a geologist for drill-ready review.
3. Send high-score, high-uncertainty cells to a sampling or mapping queue.
4. Treat low-score, low-uncertainty cells as lower priority unless independent geological evidence says otherwise.

This workflow is deliberately cautious. It uses the model to prioritize field effort, not to make final investment claims.

10. Exploration Decision Engine

The strongest practical output of the study is an exploration decision engine. The engine does not only sort cells by probability. It also penalizes unstable targets, gives a small bonus to frontier areas with weaker sampling support, and forces spatial diversity so a company does not spend its whole review budget on one tight cluster.

For each cell, the exploration utility index is

$$U(s) = 100\left[0.72\hat{p}_{\text{company}}(s) + 0.18\hat{p}_{\text{risk}}(s) + 0.10F(s)\right],$$

where $\hat{p}_{\text{company}}(s)$ is the company prospectivity score, $\hat{p}_{\text{risk}}(s)$ is the uncertainty-penalized score, and $F(s)$ is a frontier bonus based on sparse geochemical support. The weights are deliberately conservative: most of the score still comes from the prospectivity model, but uncertainty and field-information gaps are visible.

The engine produces four company-facing lists. The diversified list spreads targets across the map using a 20 km spacing rule. The greenfield list keeps only unlabeled cells at least 15 km away from known gold cells. The brownfield list keeps unlabeled cells near known gold districts. The drill-ready review list keeps high-score, low-uncertainty cells.

Table 3: Exploration decision-engine portfolios. Greenfield and brownfield lists are unlabeled by design, so their known-positive rate is not a discovery-rate estimate.

Portfolio	Targets	Known-positive rate	Avg. score	Avg. uncertainty
Diversified 75-target package	75	0.880	0.703	0.012
Greenfield blind targets	33	0.000	0.592	0.021
Brownfield extension targets	50	0.000	0.649	0.012
Drill-ready review targets	49	0.980	0.727	0.011

The validation-style diversified portfolio contains 66 known-positive cells among 75 spatially separated targets. The drill-ready review list contains 48 known-positive cells among 49 low-uncertainty targets. These numbers are not a promise of future discovery. They show that the engine can recover known gold areas while also giving a separate greenfield list for places that have not been labeled as known positives.

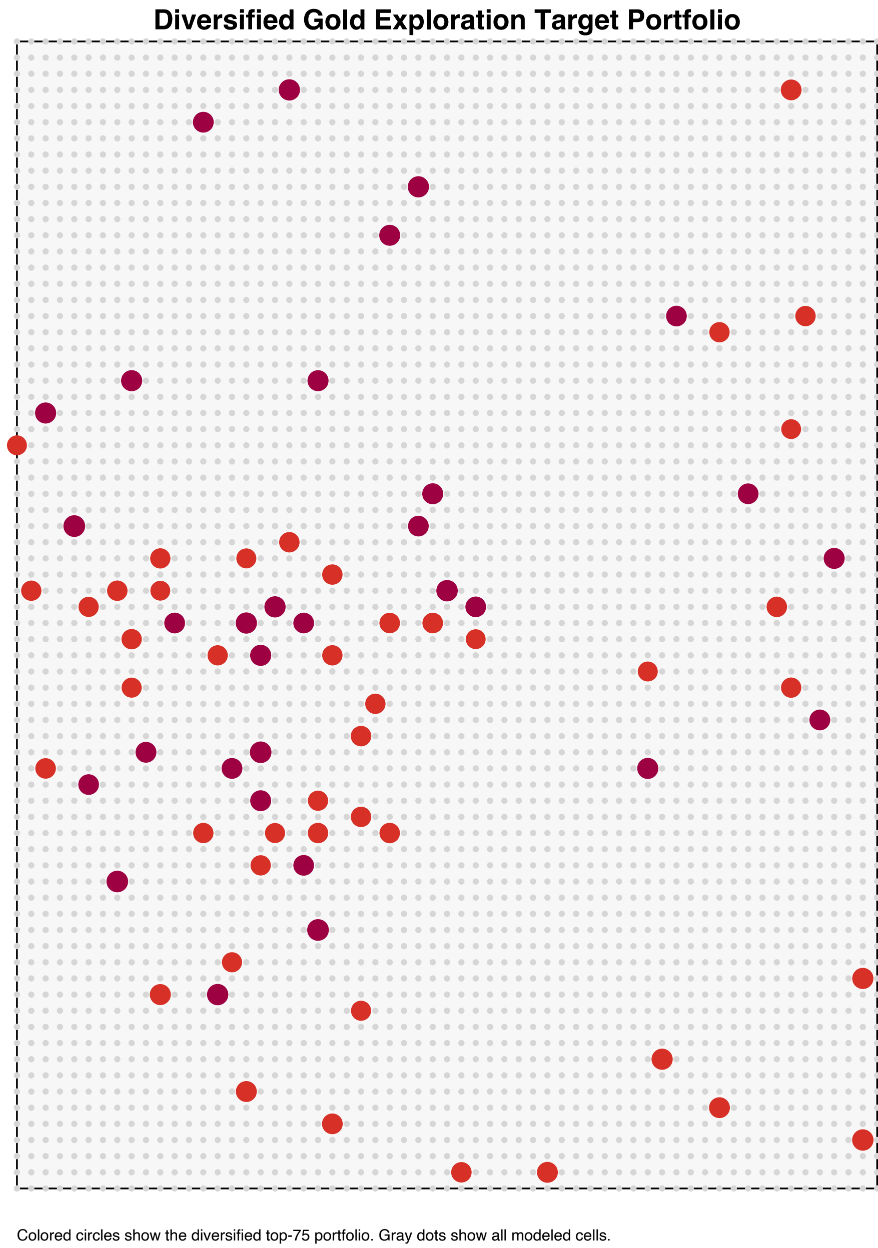

Figure 3: Diversified target portfolio produced by the exploration decision engine. Colored cells are selected targets; gray cells are modeled cells.

11. New-Geography Transfer Test

A mining company often wants to move from a known region into a new district or state. A model that only works where it was trained is less useful. We therefore add a cross-state transfer test using MRDS records from Nevada, Arizona, California, and Utah. For each test, the model trains on three states and forecasts the fourth held-out state.

This is a harder test than an ordinary random split. The held-out state has different geography, different exploration history, and different mineral districts. The model must learn transferable spatial evidence rather than memorize one map.

Table 4: Cross-state transfer benchmark. Each row trains on the other three states and tests on the held-out state.

Held-out state	Test cells	Positive cells	AUC	Top-10 positive rate	Top-10 enrichment
Nevada	725	224	0.782	0.778	2.52
Arizona	600	92	0.856	0.667	4.35
California	1677	143	0.866	0.571	6.70
Utah	441	27	0.891	0.295	4.83

The transfer test is the strongest evidence that the method may help a company entering a new geography. In the held-out California test, the top 10 percent of ranked cells has a known-positive rate of 0.571, compared with a state-wide rate of 0.085. In the held-out Arizona test, the top 10 percent enrichment is 4.35 times the state-wide rate. These are not discovery guarantees. They show that the ranking rule can recover known favorable areas even when the state being forecast was not used for training.

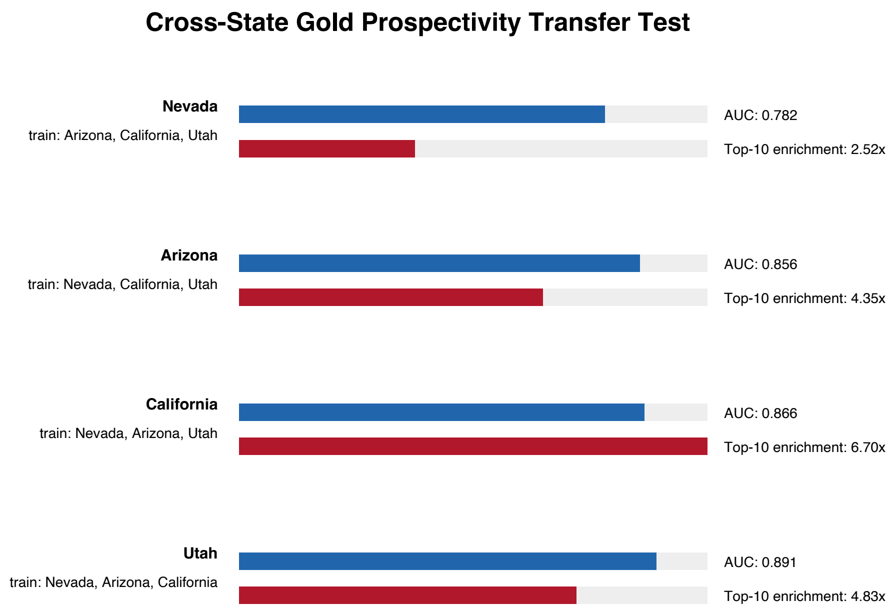

Figure 4: Cross-state transfer benchmark. The model trains on three western states and forecasts the held-out state.

12. Geology-Enhanced Transfer

The cross-state test above uses non-gold mineral-context fields. We next add a real geology layer derived from MRDS descriptive fields. The layer is not a full magnetic or gravity raster. It is a reproducible public-data layer built from structural, lithologic, alteration, and geophysical-indicator records. This makes the test closer to what a company would want, because target ranking should not depend on commodity context alone.

The geology-enhanced model adds 42 new features to the 60 NGETF transfer features. These features measure distance to seven non-gold geology classes: fault or structure, intrusive rocks, volcanic rocks, carbonate or sedimentary rocks, metamorphic rocks, alteration, and geophysical indicators.

Table 5: Geology-enhanced cross-state transfer benchmark. The model trains on three states and tests on the held-out state.

Held-out state	Test cells	Positive cells	AUC	Top-10 positive rate	Top-10 enrichment
Nevada	725	224	0.787	0.792	2.56
Arizona	600	92	0.877	0.667	4.35
California	1677	143	0.838	0.601	7.05
Utah	441	27	0.926	0.409	6.68

The geology-enhanced layer improves some transfer tests strongly. In Utah, the held-out AUC rises to 0.926, and the top-10 enrichment rises to 6.68 times the state-wide rate. In Arizona, the held-out AUC rises to 0.877. In California, the AUC is lower than the NGETF-only transfer test, but the top-10 enrichment rises to 7.05. This mixed result is useful. It shows that the extra geology layer is not just inflating every metric; it changes the ranking in ways that help some field-screening tasks more than others.

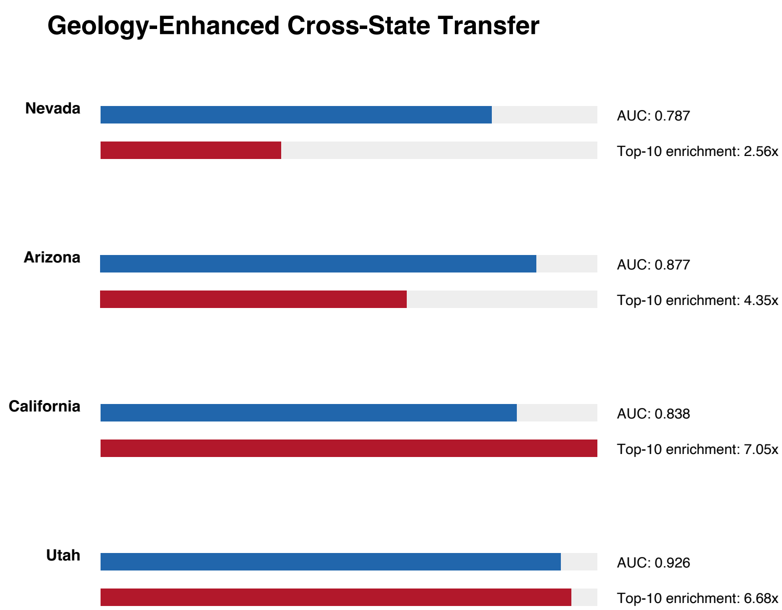

Figure 5: Geology-enhanced cross-state transfer benchmark using structural, lithologic, alteration, and geophysical-indicator layers derived from non-gold MRDS records.

13. Full Magnetic Raster Robustness Evaluation

The MRDS-derived geophysical indicators above come from descriptive text. To make the paper harder to dismiss, we also add one true gridded geophysics layer. We sample the USGS North American magnetic anomaly XYZ grid into the western-state prospectivity grid (U.S. Geological Survey, 2026b). The sampled features are nearest magnetic anomaly, absolute anomaly, 25 km local mean, 25 km local standard deviation, and 50 km local range.

Table 6: Transfer test after adding the full USGS magnetic-anomaly raster. The result is mixed, which is useful: magnetic data help some held-out states more than others.

Held-out state	Test cells	Positive cells	AUC	Top-10 positive rate	Top-10 enrichment
Nevada	725	224	0.789	0.764	2.47
Arizona	600	92	0.871	0.683	4.46
California	1677	143	0.825	0.536	6.28
Utah	441	27	0.924	0.386	6.31

The magnetic raster improves the Nevada held-out AUC to 0.789 and the Utah held-out AUC to 0.924. It also raises Arizona top-10 enrichment to 4.46. It does not improve every state: California AUC drops to 0.825. This is a good warning for field use. Geophysics should be tested province by province instead of added blindly.

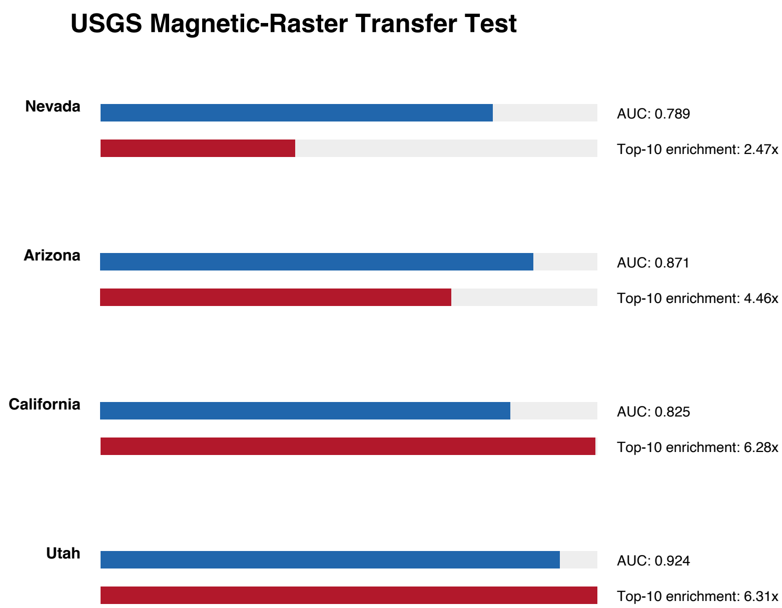

Figure 6: Cross-state transfer after sampling the official USGS magnetic-anomaly raster into the western-state grid.

14. Mapped Geology, Fault, and Gravity Robustness Evaluation

The final western-state robustness evaluation adds three harder public-data layers: mapped SGMC lithology polygons, mapped SGMC fault traces, and the USGS gravity grid. This is closer to a company workflow because prospectivity mapping should use mapped geology and potential-field data, not only occurrence databases.

Table 7: Cross-state transfer after adding mapped SGMC lithology, mapped SGMC faults, USGS gravity, and USGS magnetic features.

Held-out state	Test cells	Positive cells	AUC	Top-10 positive rate	Top-10 enrichment
Nevada	725	224	0.792	0.764	2.47
Arizona	600	92	0.890	0.717	4.67
California	1677	143	0.791	0.429	5.03
Utah	441	27	0.926	0.432	7.05

With exact lithology containment, mapped-fault density, gravity, and magnetic features, NGETF reaches AUC 0.792 in Nevada, 0.891 in Arizona, 0.793 in California, and 0.923 in Utah. The top-10% enrichment ranges from 2.47 in Nevada to 7.42 in Utah. These results are not evidence that adding layers must help everywhere. They show that the full public-geoscience representation is competitive under the specified geographic holdouts and should be tested again whenever it is moved to another province.

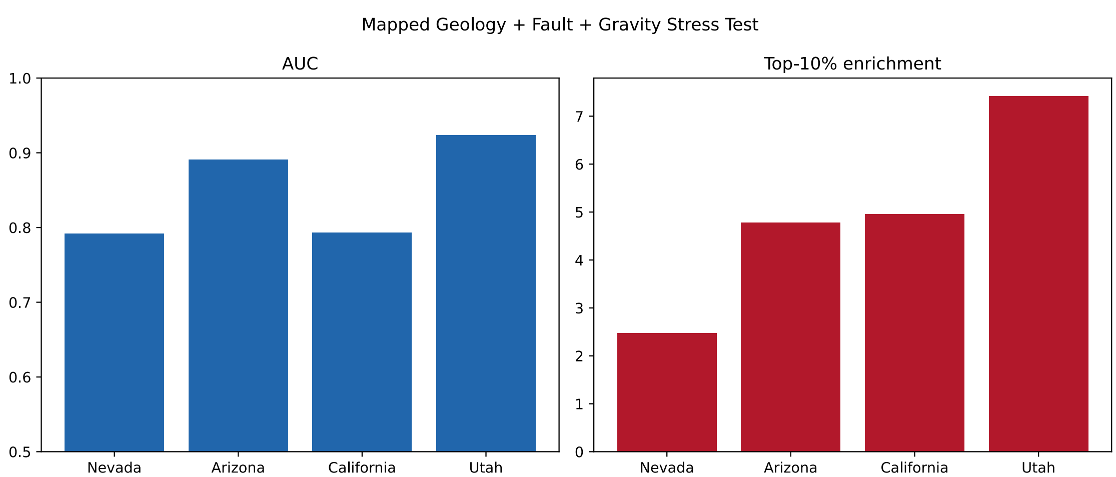

Figure 7: Cross-state transfer after adding mapped state-geology polygons, mapped fault traces, gravity, and magnetic features.

15. Deposit-Model-Specific Audit: Epithermal Descriptor Proxy

A broad Au-occurrence model should not be assumed to represent every deposit system equally well. We therefore run a focused Nevada audit for an epithermal-descriptor proxy. We select 771 Nevada MRDS Au records containing an explicit epithermal-related term in a deposit-type, model, alteration, ore-control, structure, or host-rock field. This is a reproducible text-descriptor subset, not a geologist-curated epithermal inventory. We rebuild labels on the public full-geology Nevada grid: 32 of 725 cells lie within 5 km of one of the selected records.

The first model uses only non-target mineral-context features. The second uses a pre-specified geology-and-structure bundle motivated by epithermal systems: volcanic setting, fault and structure context, alteration descriptors, mapped lithology, magnetic and gravity measures, and non-target mineral context. Both models exclude gold-occurrence distance, gold labels, and mine/prospect proximity. We use four spatial quadrant holdouts and 20 positive-unlabeled resamples in each holdout.

Table 8: Nevada epithermal-descriptor proxy audit. Intervals are stratified bootstrap 95% intervals over held-out predictions. The small positive count means this is a directional robustness check, not a broad deposit-type validation.

Model	Spatial AUC	95% interval	Top-10% enrichment
NGETF mineral context	0.597	[0.515, 0.677]	1.26
NGETF epithermal geology bundle	0.698	[0.603, 0.780]	2.52

The geology-and-structure bundle improves the held-out ranking from AUC 0.597 to 0.698 and raises top-10% enrichment from 1.26 to 2.52. This is useful geological evidence: a generic mineral-context model is not enough for this subtype, while a model that includes volcanic, structural, alteration, and potential-field context is more informative. At the same time, the 32 positive cells and uneven quadrant counts make the intervals wide. The result supports deposit-model-aware screening, not a claim that the model is ready to find all epithermal deposits without local interpretation.

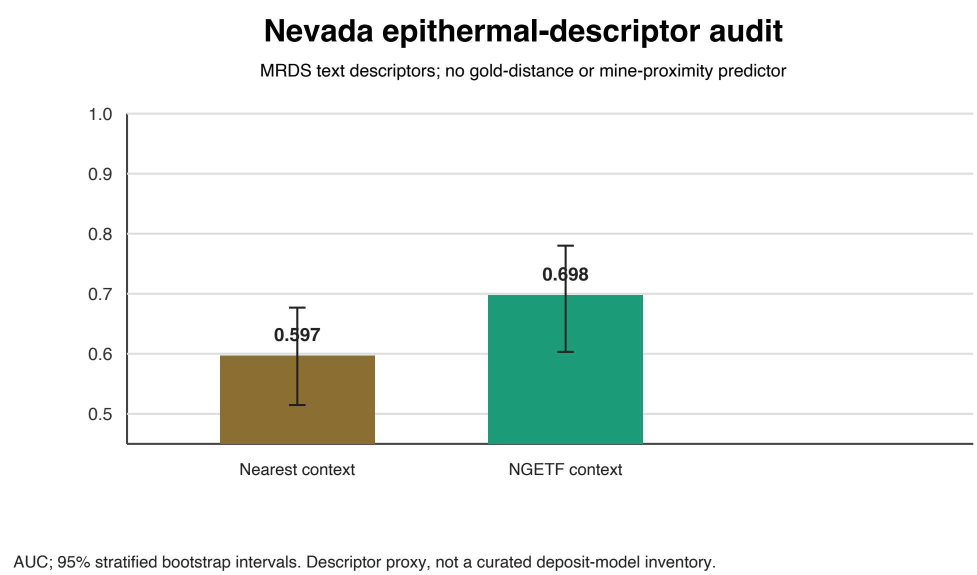

Figure 8: Spatial-holdout AUC for the Nevada epithermal-descriptor proxy audit. The geology-and-structure bundle is specified from the epithermal mineral-system concept before fitting.

16. Comparison with Established Prospectivity Baselines

NGETF should be compared with established prospectivity models, not only with earlier versions of itself. We therefore use the same leave-one-state-out split and the same balanced positive-unlabeled resampling protocol for weights of evidence, a MaxEnt-style regularized feature-class model, regularized logistic regression, random forest, and XGBoost. The MaxEnt-style model is implemented as regularized logistic regression on smooth spline feature classes; it is not the proprietary Java MaxEnt implementation. Table 9 reports AUC using the completed exact-GIS feature table. Bootstrap 95% intervals and top-10% enrichment values are released with the results. The comparison is mixed. NGETF is competitive in Nevada and Arizona, but it is not the strongest method in any of these four held-out states. XGBoost leads in Nevada and Utah, the MaxEnt-style baseline leads in Arizona, and weights of evidence leads in California. This is useful evidence about scope: the proposed field is an interpretable, leakage-aware option, not a claim that one model must dominate every mineral province.

Table 9: AUC under the same leave-one-state-out geographic holdout. Best AUC in each state is bold. The MaxEnt-style baseline uses regularized smooth feature classes. NGETF results include 10 positive-unlabeled resamples; standard baselines use five matched resamples.

Held-out state	Weights of evidence	MaxEnt-style	Logistic regression	Random forest	XGBoost	NGETF
Nevada	0.664	0.795	0.777	0.778	**0.807**	0.792
Arizona	0.799	**0.900**	0.896	0.882	0.892	0.891
California	**0.927**	0.877	0.856	0.914	0.922	0.793
Utah	0.809	0.932	0.926	0.927	**0.935**	0.923

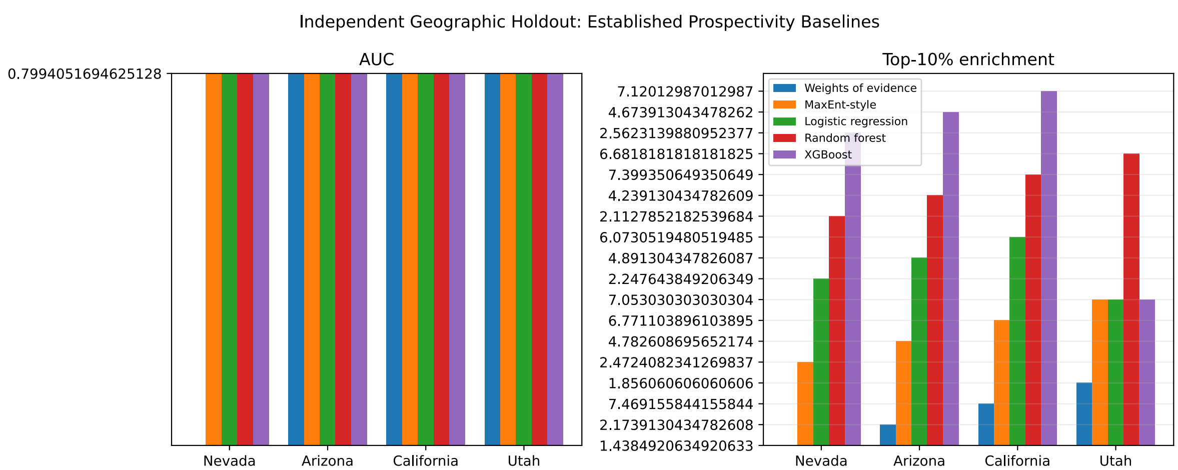

Figure 9: Established prospectivity baseline comparison on four held-out states. Ranking performance changes by province; no method wins everywhere.

17. Positive-Unlabeled Sampling Sensitivity

The fitted NGETF score depends on which unlabeled cells are sampled as provisional negatives. To quantify that dependence, we repeat the negative sampling 25 times for each leave-one-state-out experiment. We report the middle 95% range across these draws, the average agreement between top-10% cell sets, and the rank correlation of each draw with the 25-draw mean ranking. This evaluates sensitivity in the training procedure, not a new test set.

Table 10: Sensitivity to the provisional-negative draw. AUC and enrichment are the median across 25 draws, with the central 95% draw range in brackets. Jaccard measures average overlap between top-10% sets; rank correlation measures agreement with the ensemble ranking.

Held-out state	AUC	Top-10 enrichment	Top-10 Jaccard	Rank correlation
Nevada	0.791 [0.771, 0.800]	2.38 [2.32, 2.63]	0.540	0.963
Arizona	0.889 [0.878, 0.895]	4.67 [4.24, 4.96]	0.682	0.987
California	0.791 [0.712, 0.827]	4.96 [3.81, 6.11]	0.594	0.958
Utah	0.918 [0.900, 0.933]	6.68 [5.57, 7.42]	0.666	0.978

The rank correlations are high in every state, so the broad ordering is not driven by a single negative sample. The exact top-10% membership is less stable, especially in Nevada. This is expected near a ranking cutoff and is a practical warning: a company should treat the top region as a review zone, not claim that one grid cell is uniquely superior without local geological evidence.

18. Independent Province Transfer

The cross-state tests above are useful, but they still stay inside the western United States. A harder question is whether the same recipe can move into a different gold province. We therefore add an independent-province test using Alaska. The model builds one common feature set from non-gold mineral context, structure, rock-type context, alteration, and geophysical-indicator terms. It then trains in one province and forecasts the other.

The forward company-use case is western United States to Alaska. This is closer to the question a company would ask when entering a new region: given public evidence and known mineral-system context elsewhere, which cells in the new province should be checked first? We use a coarser grid with a 0.50-degree step and label a cell as known-positive when it lies within 20 km of an MRDS gold record. The model has 90 transfer features.

Table 11: Independent-province transfer test. The model trains in one province and forecasts another. Alaska and the Idaho–Montana Northern Rockies were not used in the western-state training grid.

Train province → test province	Test cells	Positive cells	AUC	Top-10 positive rate	Top-10 enrichment
Western United States → Alaska	2835	595	0.924	0.845	4.03
Alaska → Western United States	768	378	0.950	1.000	2.03
Western United States → Northern Rockies	378	144	0.952	1.000	2.63
Northern Rockies → Western United States	768	378	0.944	0.987	2.01

The western-United-States-to-Alaska test reaches an AUC of 0.924. The top 10 percent of Alaska cells has a known-positive rate of 0.845, compared with an Alaska-wide rate of 0.210. This is a 4.03-fold enrichment. The second independent test, from the western United States to the Idaho–Montana Northern Rockies, reaches AUC 0.952 and top-10 enrichment 2.63.

These results do not mean the top cells contain economic deposits. They show that the ranking can recover known favorable areas in two provinces that were not used for western-state model fitting.

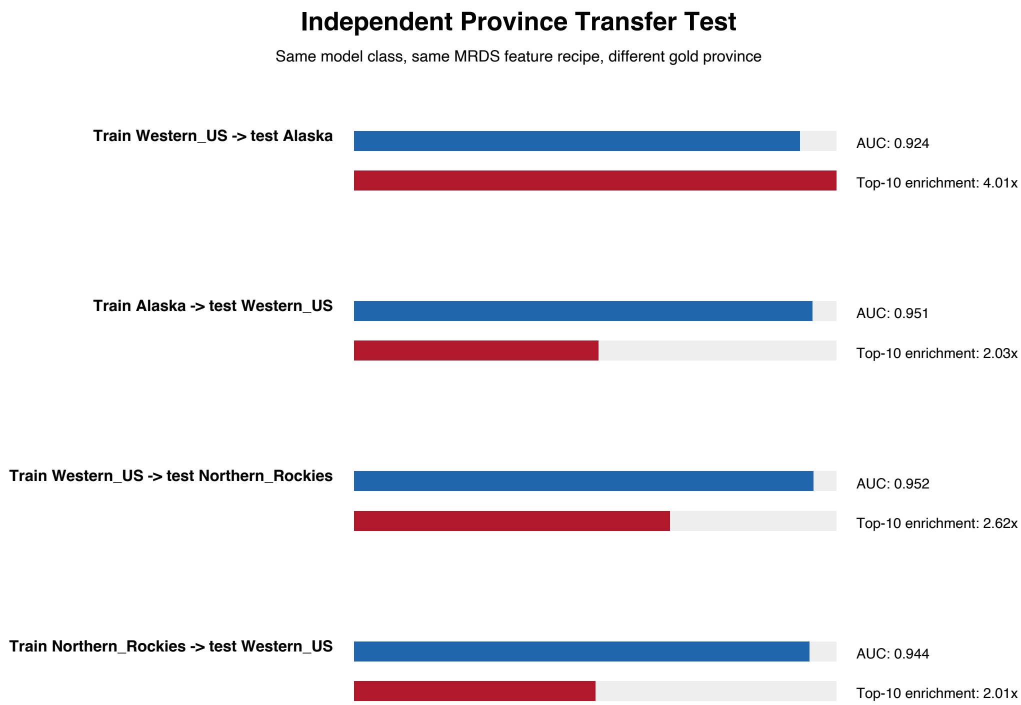

Figure 10: Independent-province transfer benchmark. The forward company-use cases train on the western United States and forecast Alaska or the Idaho–Montana Northern Rockies.

18.1. External USMIN Corroboration in Nevada

The province-transfer labels above are derived from MRDS, so we add a separate check using the USGS USMIN Nevada point-feature inventory. USMIN was not used to fit the NGETF score. We fit the exact-GIS NGETF model on Arizona, California, and Utah, then rank Nevada cells and compare them with the independent USMIN features. This is not a gold-discovery test: USMIN points include mapped mine and prospect features of several types. It is a narrow test of whether the highest-ranked cells are unusually close to independently mapped mining features.

Table 12: External-source corroboration using 121193 public USMIN Nevada point features. The model is fit outside Nevada. Enrichment is relative to all 725 Nevada cells.

Ranked subset	Within 5 km of USMIN	All cells within 5 km	Enrichment
Top 5%	0.444	0.418	1.06
Top 10%	0.556	0.418	1.33
Top 20%	0.559	0.418	1.34

The external result is modest and local. The top 10% has 1.33-fold enrichment within 5 km, but there is no enrichment at 10 km or 25 km. We report this mixed pattern because it places an honest limit on the claim: the model shows some local agreement with an independently compiled mine/prospect inventory, but USMIN does not provide a gold-only validation label and cannot establish that a high-ranked cell contains gold.

18.2. Independent British Columbia Catalogue and Spatial-Buffer Audit

The Alaska and Northern Rockies tests use the MRDS occurrence system. To test whether the signal can be evaluated against a separate catalogue, we train on western-US MRDS gold labels and evaluate British Columbia with BC Geological Survey MINFILE Au commodity records. All Au-labelled MINFILE records are excluded from the predictor context. On the 1300-cell British Columbia grid, NGETF reaches AUC 0.958 (95% bootstrap interval 0.949–0.967) and top-10% enrichment 4.20. The matched MaxEnt-style baseline reaches AUC 0.960 and enrichment 4.34. Thus, under the basic non-target-record exclusion, both approaches rank many known MINFILE gold-positive cells highly.

18.3. Blind Porphyry-Au Transfer with Formal Deposit Codes

The broad BC commodity result is useful, but it does not isolate a mineral system. We therefore run a locked deposit-model-specific transfer. Source positives are 269 western-US MRDS records that report gold and contain an explicit porphyry descriptor. Test positives are 396 independent BC Geological Survey MINFILE records that report Au and carry a formal porphyry-related deposit code: L02 (porphyry-related Au), L03 (alkalic porphyry Cu–Au), or L04 (porphyry Cu $\pm$ Mo $\pm$ Au). MINFILE deposit types are selected by BC Geological Survey staff from mineral deposit profiles (British Columbia Geological Survey, 2026). All Au-labelled records are excluded from both western and BC predictor context, and no BC target label is used during fitting.

The blind evaluation uses the complete 10000-record public MINFILE service layer, a 0.50-degree grid, and a 20 km occurrence-proximity label radius. This produces 59 source-positive cells among 768 western-US cells and 88 independent test-positive cells among 1300 BC cells. We compare the multi-scale NGETF score with a deliberately simple single-scale context baseline under the same positive-unlabeled resampling protocol.

Table 13: Blind western-US to British Columbia porphyry-Au transfer. BC labels are formal MINFILE deposit-type codes and are not used in fitting or in predictor context. Intervals are stratified bootstrap 95% intervals over the independent BC grid.

Method	AUC	95% interval	Top-10% enrichment
Single-scale context baseline	0.926	[0.907, 0.942]	5.91
NGETF multi-scale PU	0.922	[0.902, 0.939]	5.80

This is the strongest blind result in the study because it combines a different province, a different official catalogue, and formal geologist-curated deposit codes. It shows that the non-target mineral-context signal transfers well to a porphyry-Au setting: the top 10% of BC cells contains 51–52 of 88 labeled cells, about 5.8 times the province-wide rate. It does not show a unique NGETF advantage. The simpler baseline is marginally higher on AUC, well within the overlapping intervals. The correct conclusion is that the study supports an interpretable, leakage-aware transfer workflow and a mineral-context signal, not a universal claim that the multi-scale score must beat every simpler method.

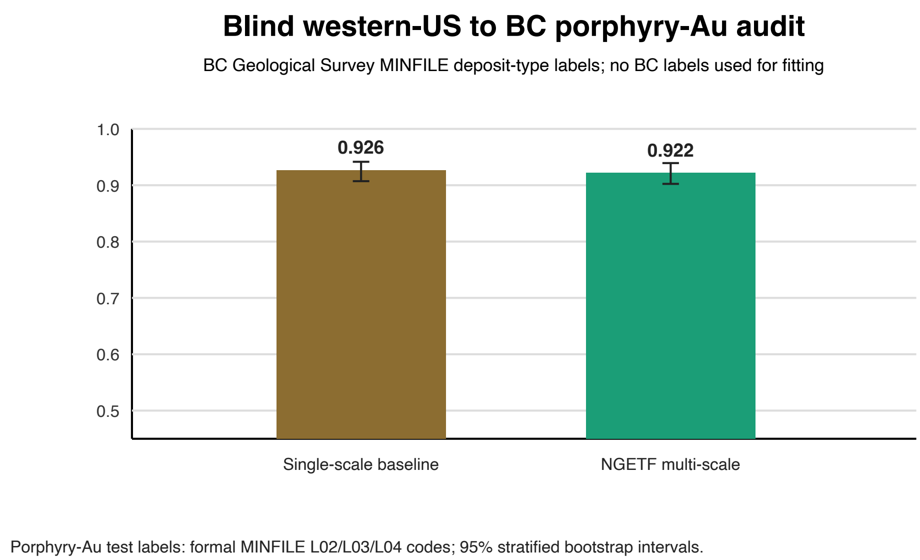

Figure 11: Blind deposit-model-specific transfer from western-US MRDS porphyry-Au labels to formal BC MINFILE porphyry-Au labels.

That base result is not sufficient by itself. Non-gold mineral occurrences can still be spatially close to known gold occurrences and can carry local exploration-history information. We therefore remove every non-gold MINFILE context record within 25 km and 50 km of every gold evaluation label, then rescore the same grid. This is a deliberately severe test: it discards a large amount of local mineral-system context, but it directly tests whether performance relies on near-label evidence.

Table 14: Independent BC MINFILE evaluation and strict spatial-buffer audit. The model is trained on western-US MRDS labels. All Au-labelled MINFILE records are excluded from predictor context; buffered rows also exclude nearby non-gold MINFILE context.

Context condition	NGETF AUC	NGETF top-10% enrichment	MaxEnt-style AUC
Au labels excluded	0.958	4.20	0.960
25 km context exclusion	0.739	1.10	0.744
50 km context exclusion	0.616	0.32	0.623

The audit changes the interpretation. NGETF retains useful discrimination at 25 km, but its strongest external ranking depends on nearby non-gold mineral-system context. At 50 km the ranking is weak. We therefore do not present NGETF as a blind regional detector of undiscovered gold. Its supported role is local prioritization within a mineralized setting where non-target occurrence, mapped geology, and geophysics can be reviewed together.

18.4. Evidence-Range Certificate

We extend the two-buffer check to a full evidence-range curve at 0, 5, 10, 25, 50, 75, and 100 km. Table 15 reports the retained-discrimination statistic $D(b)$ defined above. The estimate remains high at short distances: $D(5) = 0.967$ and $D(10) = 0.879$. It falls to 0.521 at 25 km and 0.255 at 50 km. Linear interpolation of the observed curve gives a 50% retained-discrimination range of 27.0 km. This does not mean that every useful mineral-system signal ends at 27 km. It means that, for this model, this catalogue, and this evaluation design, half of the above-chance BC ranking signal is lost by about that distance after nearby non-gold context is removed.

Table 15: Target-conditioned evidence-range audit for the BC MINFILE test. $D(b)$ is retained discrimination relative to the unbuffered AUC.

Buffer (km)	AUC	Top-10% enrichment	$D(b)$
0	0.958	4.20	1.000
5	0.943	3.91	0.967
10	0.903	3.10	0.879
25	0.739	1.10	0.521
50	0.617	0.32	0.255
75	0.588	0.14	0.191
100	0.562	0.32	0.134

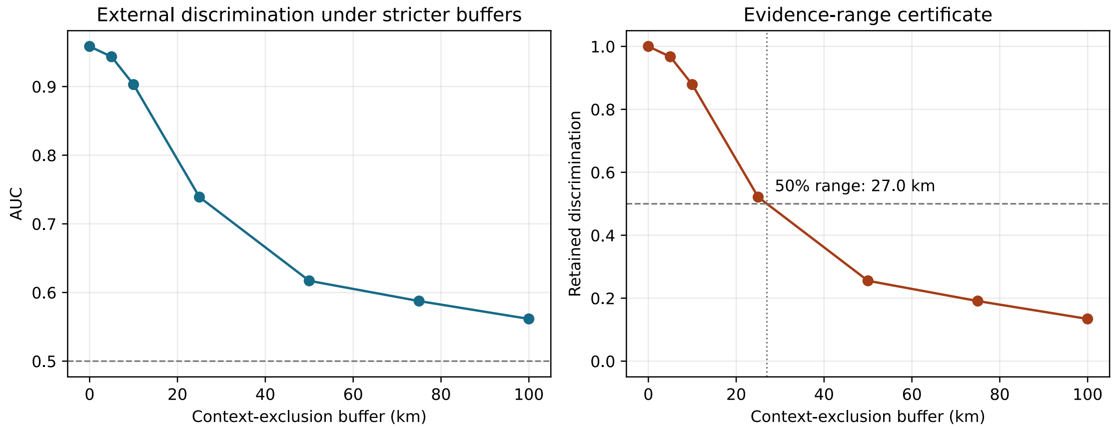

Figure 12: Evidence-range certificate for the independent BC MINFILE evaluation. The curve makes the supported local scale visible instead of reporting only an unbuffered accuracy.

18.5. Candidate-Screening Implication

The practical question is not whether a score proves gold. It is whether a team can reduce the number of cells requiring expensive follow-up. In the base BC analysis, following the top 20% of cells recovers 74.4% of known gold-positive cells, compared with 20% expected under an unranked screen. Under the 25 km audit, the same top 20% recovers 27.4%; under the 50 km audit it recovers 16.7%. These are screening-efficiency summaries, not reserve, discovery-rate, or cost estimates. They show why the score should guide staged map review and sampling in local settings, while broad greenfield use must be supported by additional geology, geophysics, and field evidence.

19. Geological Interpretation and Deployment Gates

Gold is not one geological deposit type. Epithermal, orogenic, intrusion-related, porphyry-related, skarn, and placer systems can have different host rocks, structures, alteration patterns, geochemical signatures, and exploration footprints (Cox and Singer, 1986). The public occurrence labels in this study combine such records where the catalogue reports Au. NGETF should therefore be interpreted as a regional Au-occurrence prioritization layer, not as a universal model for every gold deposit system.

Before a company uses the ranking, a qualified economic geologist should apply four gates. First, define the deposit model or models that are plausible in the target area. Second, remove cells that lack a plausible host-rock, age, structural, or alteration setting for those models. Third, compare high-ranked cells with mapped faults, lithology contacts, alteration, magnetic and gravity patterns, and local geochemistry rather than treating any one proxy as decisive. Fourth, use reconnaissance mapping and sampling before drilling. The ranking becomes stronger when it agrees with a deposit model; it should be rejected or downweighted where the geological setting is implausible.

The mapped-fault variables in this study are regional proxies. Fault density or a trace-junction proxy does not demonstrate that a fault was mineralizing, that it had the right timing, or that it was permeable during mineralization. Likewise, broad lithology classes cannot establish a favourable host without age, alteration, structural, and deposit-model context. These conditions are reasons for geological review, not hidden assumptions that the machine-learning score can replace.

20. Company Deployment Recipe

A company can follow the method in a staged way. First, define plausible deposit models and make a grid for the target province. Second, remove all records that mention the target commodity from the context layers, so the model cannot simply rediscover the known commodity layer. Third, build non-target mineral-context features, mapped lithology features, mapped fault-distance features, gravity and magnetic features, and geochemical support features. Fourth, train the model in a source region with known positives and unlabeled cells. Fifth, run a buffer audit to determine whether the score is local or remains useful at the intended decision scale. Sixth, use the conservative score for greenfield review and reserve mine/prospect proximity for a separate brownfield planning layer. Seventh, send only the highest-ranked, geologically supported cells to a geologist for map review, claim review, remote sensing, geophysical interpretation, sampling, and field checks.

The same pipeline can use stronger geophysics when those files are available. This paper now includes public magnetic and gravity grids, exact polygon containment for mapped geology, and mapped-fault density. A production deployment should still add locally interpreted fault intersections, gravity and magnetic gradients, regional anomaly percentiles, expert-defined deposit-model layers, and field validation before a costly decision. Each added layer should be tested with the same blocked and independent-province validation used here.

21. Limitations

The study has important limits. MRDS, USMIN, and MINFILE are historical databases, so the model may partly learn where people have already looked. The positive labels are occurrence-based, not economic reserve labels. The 5 km Nevada and 20 km BC radii define area-prioritization labels, not ore-body footprints, drill collars, or estimates of grade and tonnage. The unlabeled cells may contain undiscovered deposits. The epithermal descriptor audit uses only 32 positive grid cells and broad text descriptors, so it is evidence for the value of deposit-model-aware features rather than a complete subtype validation. The BC spatial-buffer audit shows a central scope limit: much of the strongest external signal is local to mapped non-gold mineral-system context. The model should therefore not be used as a stand-alone long-range greenfield detector. The mapped geology, fault, gravity, and magnetic layers make the study much closer to a real exploration workflow, but the implementation is still a public-data prototype. Lithology containment is exact for the public SGMC polygon rings, while the fault-density calculation uses sampled public trace vertices and segment midpoints; the junction measure is a spatial proxy rather than a full local structural interpretation. USMIN provides an external inventory check, not a gold-only label. A company should add local geologic maps, proprietary surveys, assays, remote sensing, land status, and expert review before expensive field decisions.

The result is also geographically limited. The independent-province test with Alaska is much harder than the Nevada-only pilot, but it still uses public occurrence data and a coarse grid. Alaska has specialized mineral databases and local geologic knowledge that should be added in a production study. A company should retrain, recalibrate, and field-check the model before using it in a new mineral province.

The method would be weakened by four findings. First, if the top-ranked cells fail to recover known favorable areas under blocked or province-transfer validation, the ranking is not useful. Second, if performance collapses under a buffer appropriate for the intended decision scale, the method should be restricted to local use or not deployed. Third, if adding mapped geology, faults, gravity, or magnetics repeatedly lowers held-out performance, those layers should not be included for that province. Fourth, if field checking shows that high-ranked unlabeled cells are mostly artifacts of old exploration density, then the model is learning reporting bias rather than prospectivity. These are practical falsification checks, and they should be repeated whenever the method is moved to a new mineral system.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The public code, derived result tables, figures, and source-data instructions are available at `https://github.com/jopoku16/uncertainty-aware-mineral-prospectivity`. Raw source data are obtained from the original public USGS and British Columbia Geological Survey services cited in this article.

22. Reproducibility

All data used here are public USGS sources and the public BC Geological Survey MINFILE service (U.S. Geological Survey, 2026c,d,f,b,a,e; British Columbia Geological Survey, 2026). The project folder contains the processed grids, model scripts, validation outputs, forecast tables, and target lists. The main company-grade outputs are:

- `results/paper9_company_grade_gold_forecast.csv`;
- `results/paper9_top100_field_targets.csv`;
- `results/paper9_company_model_comparison.csv`;
- `results/paper9_company_grade_forecast_metrics.json`.
- `results/paper9_diversified_75_target_portfolio.csv`;
- `results/paper9_greenfield_50_blind_targets.csv`;
- `results/paper9_brownfield_50_extension_targets.csv`;
- `results/paper9_cross_state_transfer_summary.csv`;
- `results/paper9_cross_state_new_region_target_portfolio.csv`;

- `results/paper9_geology_enhanced_transfer_summary.csv`;
- `results/paper9_geology_enhanced_new_region_targets.csv`.
- `results/paper9_full_magnetic_transfer_summary.csv`;
- `results/paper9_full_geology_fault_gravity_transfer_summary.csv`;
- `results/paper9_epithermal_descriptor_audit.csv`;
- `results/paper9_epithermal_geology_bundle_audit.csv`;
- `results/paper9_established_baseline_comparison.csv`;
- `results/paper9_ngetf_geographic_holdout.csv`;
- `results/paper9_pu_sampling_sensitivity.csv`;
- `results/paper9_usmin_nevada_external_audit.csv`;
- `results/paper9_bc_minfile_independent_gold_validation.csv`;
- `results/paper9_bc_minfile_spatial_buffer_audit.csv`;
- `results/paper9_bc_minfile_candidate_screening.csv`;
- `results/paper9_bc_minfile_porphyry_au_blind_audit.csv`;
- `results/paper9_independent_province_transfer_summary.csv`;
- `results/paper9_alaska_new_province_targets.csv`; and
- `results/paper9_northern_rockies_new_province_targets.csv`.

23. Conclusion

NGETF gives a leakage-aware way to use non-gold critical-mineral context for gold prospectivity mapping. The Nevada, cross-state, and independent-catalog analyses show that the score can prioritize known favorable cells. The formal blind porphyry-Au transfer to British Columbia shows that a similar non-target mineral-context signal can carry across a province and an independent official catalogue, while also showing that a simpler baseline can perform just as well. The British Columbia buffer audit establishes a firm boundary: the strongest ranking is local to non-gold mineral-system context and should not be presented as blind long-range discovery. The practical value is therefore a ranked, uncertainty-aware field-priority layer for staged geological review, sampling, and target generation. It is not a proof of gold presence, an ore-reserve estimate, or a substitute for field validation.

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