Mineral potential modelling results for northwestern British Columbia, a comparison between past and current work at the British Columbia Geological Survey

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Abstract

Nearly thirty years ago, the British Columbia Geological Survey (BCGS) initiated a project to assess the mineral potential of the entire province, the first assessment of its kind. This project combined data about known mineral occurrences and the geology of the province, and what was then understood about which rocks favour mineral deposition to develop a relative ranking of mineral potential for a broad range of deposit types. To aid in the search for the critical minerals needed for a low-carbon future, the BCGS has revitalized its mineral potential mapping efforts, taking advantage of about 30 years of new data, knowledge, advances in GIS applications, and computer power to enable statistical analysis of spatial data using weights of evidence modelling. A comparison of results between work done in the 1990s and the current modelling for a large region of northern British Columbia indicates that the new work largely corroborates the old. Both are of value for assisting land-use decisions and for mineral exploration. The 1990s work ranks certain areas as having a significantly higher relative prospectivity because the original work focused on deposit profiles that classified occurrences into about 120 deposit types for a wide range of metals whereas the new work adopted a mineral systems approach to examine critical mineral potential, considering only the porphyry, volcanogenic massive sulphide, and magmatic mafic-ultramafic systems. The recent work ranks some areas as having a significantly higher relative prospectivity mainly because it uses new data and knowledge accumulated in the last 30 years. The revitalized modelling is far less labour intensive than the work done in the 1990s. Automated manipulation of spatial data and statistical analysis will ease making updates and making future iterations more comprehensive by including other mineral systems.

Keywords: Mineral potential modelling, mineral potential map, land-use planning, mineral systems, statistical methods, geospatial data treatment, predictive maps, weights of evidence, data-driven modelling, porphyry deposits, volcanogenic massive sulphide deposits, magmatic mafic-ultramafic deposits

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1. Introduction

Nearly 30 years ago, the British Columbia Geological Survey (BCGS) initiated a project to assess the mineral potential of the entire province in support of land-use decisions. Applying approaches developed by the United States Geological Survey (Brew, 1992; Singer, 1993) but modified for British Columbia, this work was the first state- or province-wide assessment of its kind. The project combined data about known mineral occurrences and the geology of the province, and what was then understood about which rocks favour mineral deposition to develop a relative ranking of mineral potential, with defined 'tracts' of lower to higher potential (Kilby, 1995, 1996, 2004). Prompted by the global search for the critical minerals needed for a low-carbon future, the BCGS started a program to inventory the critical minerals that are produced or could be produced in the province (Hickin et al., 2023) and renew mineral potential studies with a focus on these minerals. Since the original assessment was carried out, bedrock mapping projects have increased our knowledge of the rocks underlying the province. Additionally, exploration techniques have improved, many new mineral occurrences have been discovered and the geologic processes leading to mineralization have been intensively investigated. Furthermore, exponential increases in computing power have led to significant advances in applying geographic information system (GIS) platforms and using computerized statistical methods to model 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). These advances have been adopted by geoscientists in industry, government, and academia for appraising mineral potential (Knox-Robinson and Wyborn, 1997; Harris et al., 2015; Kreuzer et al., 2015; Lawley et al., 2021; Nykanen et al., 2023).

The rejuvenated modelling at the BCGS also applies these advances (for details see Wearmouth et al., in press). Like the original program of the 1990s, the new modelling will assist land-use conversations between multiple parties with diverse interests. Also, the new work will be used to evaluate the provincial endowment of the critical minerals needed to support the low-carbon transition, grow the economy, diversify global supply chains, and continue as a preferred supplier for partner nations (Hickin et al., 2023). In this paper we describe the methods used in the work done in the 1990s and the work currently being done, then compare the results for a large area of northwest British Columbia, which includes the traditional lands of the Gitanyow, Kaska Dena, Kwadacha, Metlakatla, Nisga'a, Tahltan, Takla Lake, Taku River Tlingit, Tsay Keh Dene, and Tsetsaut Skii Km Lax Ha First Nations (Fig. 1).

2. Geologic context

The study area spans a large segment in the northwestern part of the Canadian Cordillera (Fig. 1). This 2000 km long northwest-trending accretionary orogen consists of several long, narrow, far-travelled terranes (in some cases, 1000s of km) that welded to the western margin of Ancestral North America in the last 180 million years (e.g., Nelson et al., 2013; Colpron and Nelson, 2021). The Cordillera records a history of supercontinent rifting and a succession of island arc volcanosedimentary and intrusive assemblages (terranes) developed outboard of Ancestral North America and accreted to each other and to the proto-continental margin with final amalgamation produced by collisions driven by the westward motion of the North American continental plate. The amalgamated Cordillera then became the site of Cretaceous and Cenozoic arc and post-arc magmatism. Terrane evolution continues today as the Juan de Fuca plate slides beneath Vancouver Island. As reviewed by Nelson et al. (2013), Hickin et al. (2017) and Colpron and Nelson (2021), the diverse tectonic processes, from supercontinent breakup through development of long-lived arc terranes, to terrane accretion and post-accretion magmatism, metamorphism, deformation, and sedimentation, have generated diverse mineral systems across the province.

West of Ancestral North America, Cordilleran terranes are commonly grouped into superterranes and terranes (Fig. 1). Ancestral North America (including Cassiar terrane) consists of predominantly sedimentary rocks that were deposited on cratonic basement during the Paleoproterozoic and Mesoproterozoic and during and after the Neoproterozoic to Cambrian breakup of the supercontinent Rodinia, which created the western margin of Laurentia, the nucleus of what is now North America. The Intermontane superterrane consists of a diverse group of Late Paleozoic to Mesozoic volcano-sedimentary assemblages and kindred intrusive bodies that formed mainly in and adjacent to island arcs outboard of Ancestral North America in the proto-Pacific Ocean. The Insular superterrane consists of similar island arc terranes; the Intermontane-Insular terrane boundary lies within the syn- to post-accretionary Coast Plutonic complex, a linear arc-axial belt that extends the length of the Cordillera. The Outboard terranes are mostly late Mesozoic to Cenozoic forearc siliciclastic assemblages, bounded to the west by the present-day Cascadia subduction zone and Queen Charlotte fault. Modern-day volcanic complexes related to Cascadia subduction are distributed along the length of the western Cordillera, and many of the terranes are partially covered by sedimentary rocks that were deposited during terrane accretion and collision, when older rocks were deformed, uplifted, eroded, and redeposited in newly created sedimentary basins. The variety of tectonic settings and paleogeographic environments recorded by these terranes and superterranes since the Mesoproterozoic generated conditions favourable for a variety of mineral systems.

Current exploration in the study area, which includes parts of the Northwest and North Central mining regions, focuses on a diverse suite of deposits (see summary in Clarke et al., 2024). The study area includes two active mines (Brucejack and Red Chris) and one mine (Premier Gold) is on track to have its first gold pour in 2024. All three are in the 'Golden Triangle', the popular name for a loosely defined area in the Northwest Region containing significant gold, silver, copper, and molybdenum deposits (British Columbia Geological Survey, 2023).

3. Mineral potential modelling methods in British Columbia, past and present

Depending on the purpose and the data available for a given area, different methods can be used to assess the prospectivity of an area of interest. These methods are commonly expressed in terms of being 'knowledge-driven' ('expert-driven') or 'data-driven' (e.g., Bonham-Carter, 1994, p. 269). However, these terms are pure end-members of a continuum and are unlikely to fully apply to any given case. For example, even though the early BCGS modelling relied heavily on geoscience experts to make key decisions, it was fundamentally based on mineral occurrence (MINFILE), bedrock geology, geochronologic, geochemical, aeromagnetic, and industry assessment report (ARIS) data and the knowledge gained from these data. Similarly, even though the current modelling uses computer algorithms instead of geoscience experts, human interventions and expert knowledge are still required at different stages. Furthermore, both the old and new modelling use similar data sources; although the new modelling accesses more up-to-date data, much of the data in both cases are not entirely 'raw' but based on human interpretations. For example, all geological maps are inherently interpretive and rock unit boundaries, or the existence, positioning, or relative age of faults are made by mappers. Or knowledge experts make decisions about what deposit type or mineral system a given mineral occurrence should be assigned to in the MINFILE or ARIS databases. The fundamental difference between knowledge-driven and data-driven modelling is in how weights are assigned to the data (Bonham-Carter, 1994, p. 269). In knowledge-driven methods, data are reviewed and subjectively weighted by experts, relying on their level of expertise and knowledge and are thus considered more subjective (Bonham-Carter, 1994). Examples of knowledge-driven techniques include index overlay

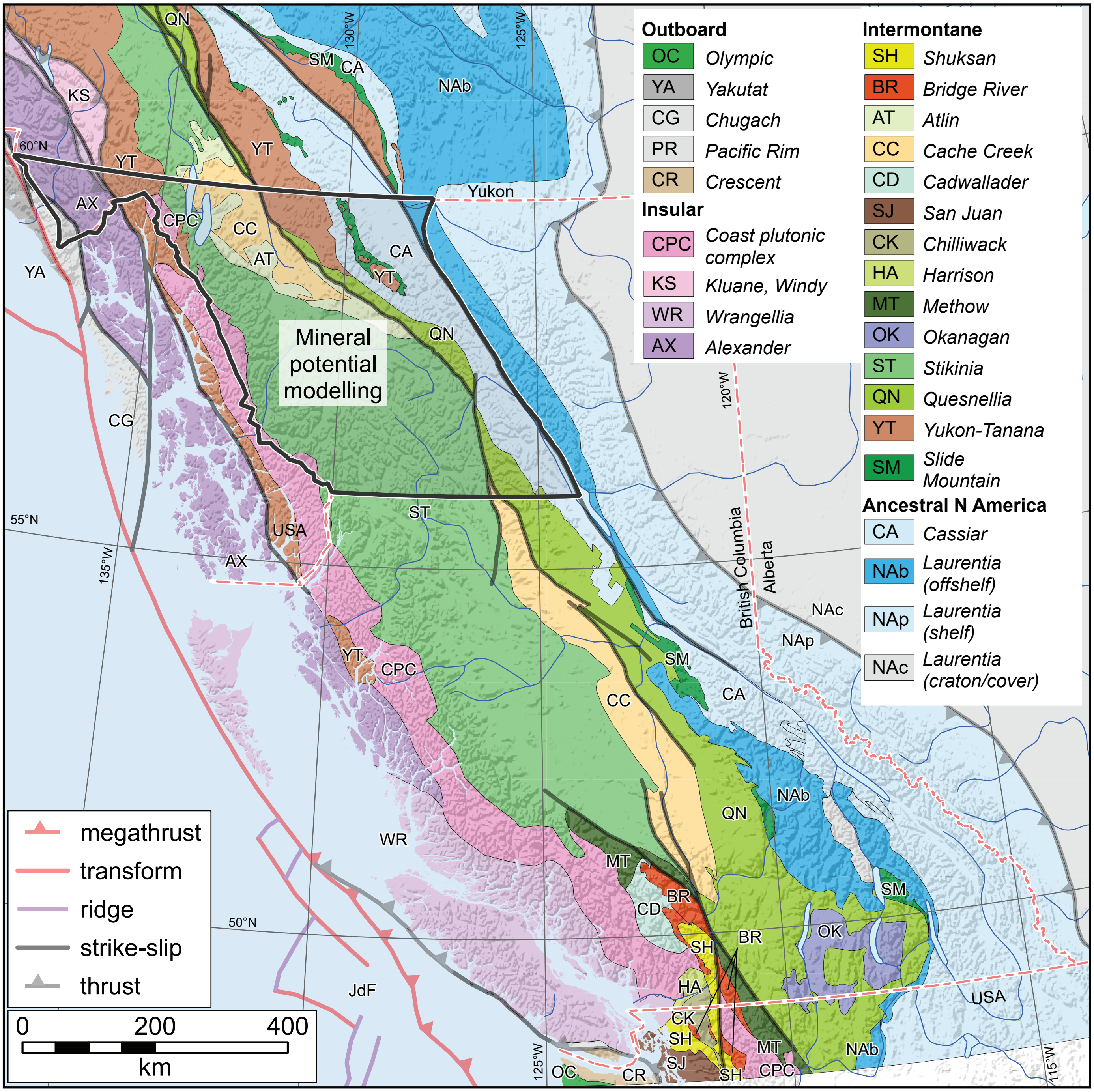

Fig. 1. Mineral potential modelling study area, 2023. Terranes after Colpron (2020).

(Yousefi and Carranza, 2016) and fuzzy logic (e.g., Porwal et al., 2003). In data-driven methods, computer algorithms seek statistical associations or patterns within data to determine relevance to known training data and are thus considered more objective. Examples of data-driven methods include weights of evidence (e.g., Bohnam-Carter et al., 1990), random forest (Ford, 2020), and neural networks (Singer and Kouda, 1999).

3.1. 1990s mineral potential project

The British Columbia Geological Survey has mapped and inventoried the mineral deposits of the province for more than 130 years (Sutherland Brown, 1998). The Mineral Potential project, later referred to as the Level 1 Mineral Resource Assessment (MacIntyre et al., 2004, 2009), was initiated in 1992 by the British Columbia Geological Survey to assist land-use decisions. The project objectives were to: 1) rank the land base of the province by its ability to support economic activity through mineral exploration and extraction, 2) produce credible and understandable evaluations by all users; and 3) incorporate the expertise of the mining and exploration communities (Kilby, 2004). Level 2 mineral resource assessments were developed for smaller areas in northwest (MacIntyre and Kilby, 2009; MacIntyre et al., 2009) and coastal British Columbia (MacIntyre et al., 2003, 2004).

The 1990s work combined known mineral occurrences, what was then understood about which rocks favour mineral deposition, and the geology of a given area to develop a relative ranking of mineral potential (Kilby, 1995, 2004; MacIntyre and Kilby, 2009). Emphasizing the differences between deposit types, mineral potential assessments focused on deposit profiles that classified occurrences into about 120 deposit types based mainly on genetic models (see Lefebure and Jones, 2022). The profiles included descriptions of geological characteristics, mineral exploration techniques, resource data, age of mineralization, tectonic setting, and concepts about deposit origins. The approach used built on work by the United States Geological Survey (Brew, 1992; Singer, 1993) but modified for British Columbia (Kilby, 2004). Tracts of land of similar geological character were defined and experts from government, industry, and academia assessed all available data to determine probabilistic estimates for the expected number of undiscovered deposits. The ranking of the 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 of each tract was determined using expert input, commodity prices, and a Monte Carlo simulation to determine probable tonnage and grade information for each deposit type. Importantly, the dollar scores were intended as a ranking tool and not intended to imply a particular dollar value to the ground being ranked.

Mineral potential regions were defined and divided further into tracts, which contain similar geological characteristics, but separated from other tracts by faults or major contacts (Kilby, 2004). The final products included regional maps, showing the relative ranking of tracts based on metallic mineral potential. Additional attribute information such as tract area, number of mineral occurrences, value of know resources, value of past production, and value of exploration expenditures were provided. Mineral resource assessment data were also provided for each tract and included the number of potential new deposit discoveries by type, dollar value of commodities in potential discoveries, types of commodities expected to be discovered, and the relative ranking of a tract out of 794 tracts in the province (Fig. 2).

3.2. 2023 mineral potential modelling

To support current land-use decisions and to evaluate critical mineral opportunities, the Survey is now reviving provincial mineral potential assessment. Like the work done in the 1990s, the data used in the current work comes from MINFILE, BC Digital Geology, and geochemical databases curated by the British Columbia Geological Survey and integrated with MapPlace, the BCGS open access geospatial web service (Cui et al., 2018). We also used regional-scale gravity (Natural Resources Canada, 2020a) and aeromagnetic data (Natural Resources Canada, 2020b).

The current work adopts mineral systems concepts that can be used to focus on specific commodities such as critical minerals in contrast to the 1990s work, which does not provide commodity-specific information. The current work also uses a data-driven weights of evidence approach.

3.2.1. Mineral systems

In contrast to the 1990s work, which emphasized the differences between deposits split into about 120 types (Lefebure and Jones, 2022), the current assessment adopts a mineral system approach, which emphasizes similarities between deposits and uses a large-scale view of all the factors that control generating and preserving deposits (e.g., Knox-Robinson and Wyborn, 1997; Hronsky and Groves, 2008; McCuaig et al., 2010; Ford et al., 2019; Groves et al., 2022). Originally proposed by Wyborn et al. (1994) and drawing on ideas from the petroleum industry (e.g., Magoon and Dow, 1994), the geological components that have been traditionally used to define a single mineral system include energy to drive the system, source of ligands, source of metals, transport pathways, traps, and outflow zones (Knox-Robinson and Wyborn, 1997). Adapting the traditional use, the mineral system concept we adopt uses source, transport, trap and direct detection of ore deposits as a proxy for the presence of a complete mineral system. The approach recognizes that the ore deposit, which is relatively small (<km in plan view), is the central feature of a larger system that may be detectable at a regional scale (>10 km in plan view). The mineral systems approach focuses on processes that are common across mineral systems, which enables the simultaneous assessment of many deposit types at a variety of scales (McCuaig et al., 2010). An economic deposit is unlikely if any one of source, transport, and trap are lacking; areas that bear evidence for all components will be evaluated as being favorable for mineralization. Being process-based, the mineral systems approach is neither restricted to a geological setting nor limited to a specific ore deposit type. To date, the new modelling has focused on the porphyry, volcanogenic massive sulphide, and magmatic mafic to ultramafic sulphide mineral systems.

3.2.2. Weights of evidence modelling

The current work uses weights of evidence modelling to rank the mineral potential of the study area (see Wearmouth et al., in press for details). Weights of evidence is a Bayesian statistical approach that allows the analysis and combination of various datasets to predict the location of the feature in question (Bonham-Carter, 1994). This technique calculates the relationship of the feature being tested for a given area and the number of training data points (sites of known mineralization; Tables 1-3) that fall within that area. The statistical spatial analysis allows for a non-biased assessment of a large

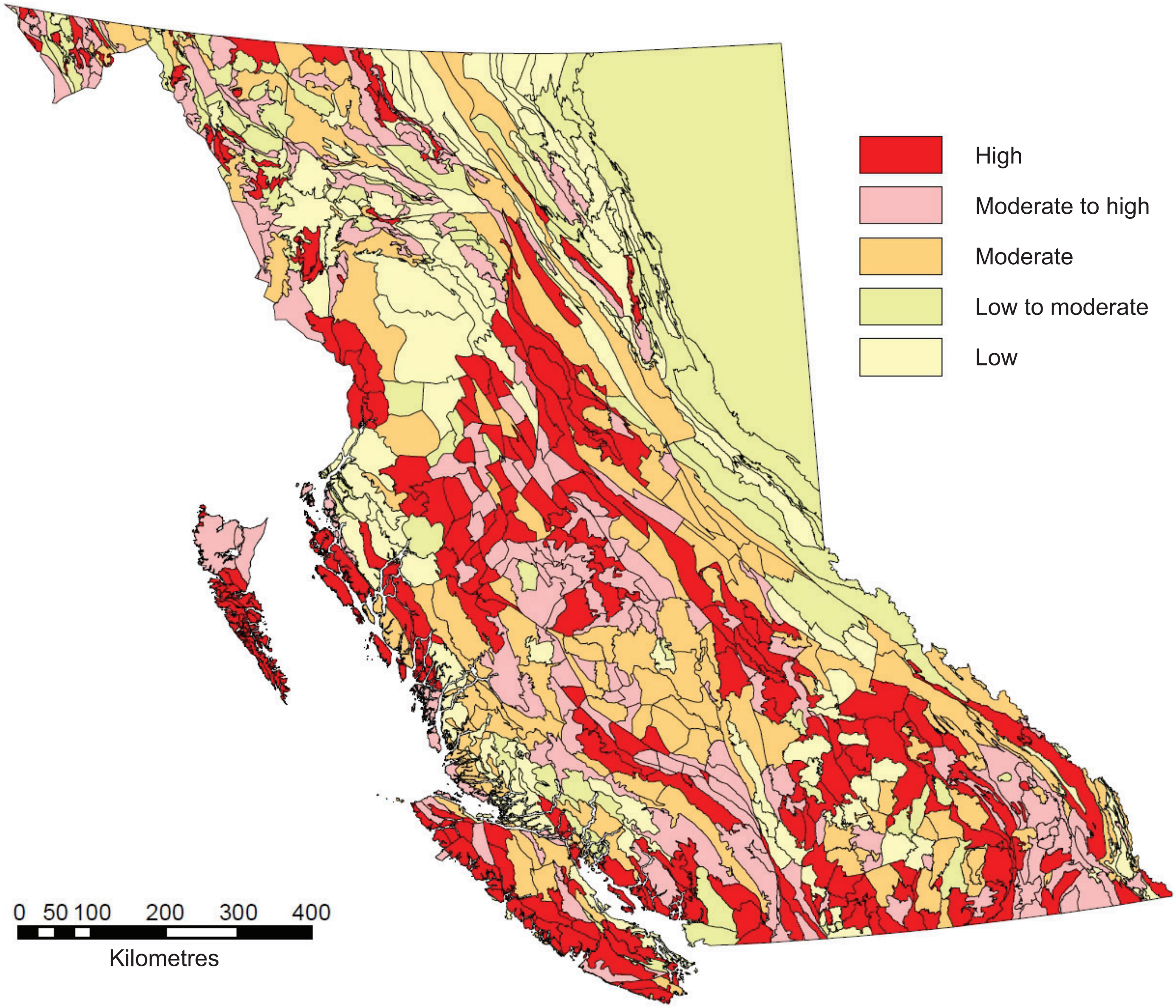

Fig. 2. Metallic mineral potential map for British Columbia based on the Mineral Potential project completed in 1997. Total number of tracts is 794. From MacIntyre (2004).

Table 1. Porphyry model training points.

Name	Status	Mineralization style	Belt	Terrane
Galore Creek	Developed prospect	Alkalic porphyry Cu-Au	Intermontane	Stikine
Kemess South	Past producer	Porphyry Cu +/- Mo +/- Au	Intermontane	Stikine
Schaft Creek	Developed prospect	Porphyry Cu +/- Mo +/- Au	Intermontane	Stikine
Saddle North	Prospect	Porphyry Cu +/- Mo +/- Au,	Intermontane	Stikine
KSM	Developed prospect	Porphyry Cu +/- Mo +/- Au	Intermontane	Stikine
Red Chris	Producer	Porphyry Cu +/- Mo +/- Au	Intermontane	Stikine
Thorn	Prospect	Subvolcanic Cu-Ag-Au	Insular	Stikine
Eaglehead	Developed prospect	Porphyry Cu +/- Mo +/- Au	Intermontane	Cache Creek
Bronson Slope	Developed prospect	Porphyry Cu +/- Mo +/- Au	Insular	Stikine
Gnat Pass	Developed prospect	Porphyry Cu +/- Mo +/- Au	Intermontane	Stikine
Hat	Prospect	Alkalic porphyry Cu-Au	Intermontane	Stikine
Ruby Creek	Developed prospect	Porphyry Mo (Low F- type)	Intermontane	Cache Creek

Table 2. Volcanogenic massive sulphide model training points.

Name	Status	Mineralization style	Belt	Terrane
Eskay Creek	Past producer	Noranda/Kuroko	Intermontane	Stikine
Dago	Past producer	Noranda/Kuroko	Intermontane	Stikine
Tulsequah Chief	Past producer	Noranda/Kuroko	Coast Plutonic	Nisling
Kutcho	Developed prospect	Noranda/Kuroko	Intermontane	Cache Creek
Granduc	Past producer	Besshi	Intermontane	Stikine
Rock and Roll	Developed prospect	Besshi	Intermontane	Stikine
Joss’alun	Prospect	Cyprus	Intermontane	Stikine
Windy Craggy	Developed prospect	Besshi	Insular	Alexander
Mount Henry	Prospect	None attributed	Insular	Alexander

Table 3. Magmatic mafic-ultramafic model training points.

Name	Status	Mineralization style	Belt	Terrane
E&L	Developed prospect	Tholeiitic intrusion-hosted	Intermontane	Stikine
Turnagain Nickel	Developed prospect	Alaskan-type	Intermontane	Quesnel
Orca	Showing	Alaskan-type	Intermontane	Cache Creek
Nixon	Showing	Alaskan-type	Intermontane	Quesnel
Mandible	Prospect	Alaskan-type	Intermontane	Cache Creek
Queen	Prospect	Alaskan-type	Intermontane	Quesnel
HC	Prospect	Alaskan-type	Intermontane	Quesnel
Anyox-Rodeo	Showing	Flood basalt-associated	Coast Plutonic	Nisling
Taurus	Showing	Alaskan-type	Intermontane	Quesnel
TNS12	Showing	Tholeiitic intrusion-hosted	Intermontane	Stikine

number of mappable proxies (e.g., distance to intrusive rock contacts, density of fault intersections, presence of anomalous geochemical stream-sediment sample, and occurrence of magnetic high anomalies) for ore-forming processes to determine their relevance to the mineral system (Bonham-Carter, 1994). We used the Arc-SDM extension for ArcGIS to carry out this analysis and the mineral potential modelling.

Using input parameters (area being examined, unit cell area, number of training points) a ‘prior probability’ was calculated for each mineral system. The prior probability represents the chance of randomly discovering a deposit in the study area before any additional evidence for mineralization is applied. The aim of weights of evidence modelling is to add evidence in support of hypotheses to increase or decrease the prior probability of each grid cell in the study area. The probability of finding a new occurrence after adding layers of evidence is referred to as the ‘posterior probability’. Layers of evidence, or predictive maps, that reduce the search space while capturing the most training points will have the best spatial correlations and their combination will result in highest posterior probabilities when combined into the model (Bonham-Carter, 1994; Bonham-Carter et al., 1990). The spatial correlation, or the contrast value (C), of a mappable feature (e.g., distance to faults) was calculated by using the relationship between the area with the feature being tested and the number of training data points that fall within that area compared with the number of points that fall in the remainder of the study area. The studentized contrast (StudC) value is also calculated during the weights of evidence process and indicates the uncertainty in the C value (Tables 4-6).

The predictive maps derived from the spatial correlation analysis are typically binary, distinguishing areas favourable or unfavourable for capturing training points (Figs. 3-5). These predictive maps were input into the final mineral potential model for each mineral system. The output of the mineral potential modelling is a grid that maps the geological potential for mineralization for each grid cell (Fig. 6). The output grid values range from 0 to 1 and map the posterior probability, which has either increased or decreased from the prior probability, depending on the combination of weighted predictive map variables. The final grid represents the relative prospectivity ranking of cells rather than an absolute measure of the probability of finding a deposit (Agterberg and Bonham-Carter, 1990; Bonham-Carter, 1994; Ford et al., 2019). This is because ore-forming geological processes are commonly interconnected and not strictly independent. Therefore, weights of evidence assumes conditional independence, which leads to posterior probabilities being overestimated in the final mineral potential model (Bonham-Carter, 1994; Bonham-Carter et al., 1990).

Table 4. Statistical spatial analysis results for predictive maps used in the porphyry model.

Mineral system component	Spatial variable	Variable ID	# TP	C	StudC
Source	Distance to 237-170 Ma rocks	200 m	11	3.7	3.6
	Distance to volcanic rocks	2350 m	11	3.0	2.9
Transport	Distance to contacts of intermediate and felsic intrusives (+ high total residual total field magnetic areas)	Class 9-10 (>160 nT/m), felsic intrusive, 1000 m	11	4.0	3.8
	Distance to all faults	850 m	10	3.0	3.8
Trap	Fault intersection density	Class 4-10 (moderate to high density)	12	2.7	2.6
Deposition	Ag stream anomalies	Ag > 0.33 ppm	11	2.0	1.9
	Au stream anomalies	Au > 0.01 ppm	12	1.9	1.8
	Cu stream anomalies	Cu > 106.05 ppm	10	1.9	2.5

Table 5. Statistical spatial analysis results for predictive maps used in the volcanogenic massive sulphide model.

Mineral system component	Spatial variable	Variable ID	# TP	C	StudC
Source	Distance to volcanic and volcaniclastic rocks (and metamorphic equivalents)	300 m	9	3.2	4.1
Transport	Distance to minor faults	3100 m	10	3.0	2.8
Trap	Fault intersection density	Class 5-10 (moderate to high density)	9	2.2	2.8
Deposition	Stream sediment Ag anomaly (mean, reclassified)	Class 10 (>0.27 ppm)	5	2.3	3.6
	Stream sediment Cu anomaly (mean of each catchment)	Class 8-10 (>50.4 ppm Cu)	10	3.1	2.9
	Rock chip Au anomaly	66.75 ppb Au, 2000 m buffer	3	2.2	1.9

Table 6. Statistical spatial analysis results for predictive maps used in the magmatic mafic-ultramafic model.

Mineral system component	Spatial variable	Variable ID	# TP	C	StudC
Source	Distance to ultramafic or mafic intrusives	300 m	6	5.0	6.1
Transport	Distance to minor faults	2700 m	7	2.8	2.6
Trap	Magnetics 1st vertical derivative	Class 8 – 10 (>0.0085 nT/m)	7	3.0	2.8
	Fault density	Class 7-10 (high density)	8	2.4	2.2
Deposition	Gravity isostatic residual	Class 7 – 10 (>9.50 mGal)	7	2.4	2.2
	Stream sediment Co anomaly	33.05 ppm	7	2.4	2.2

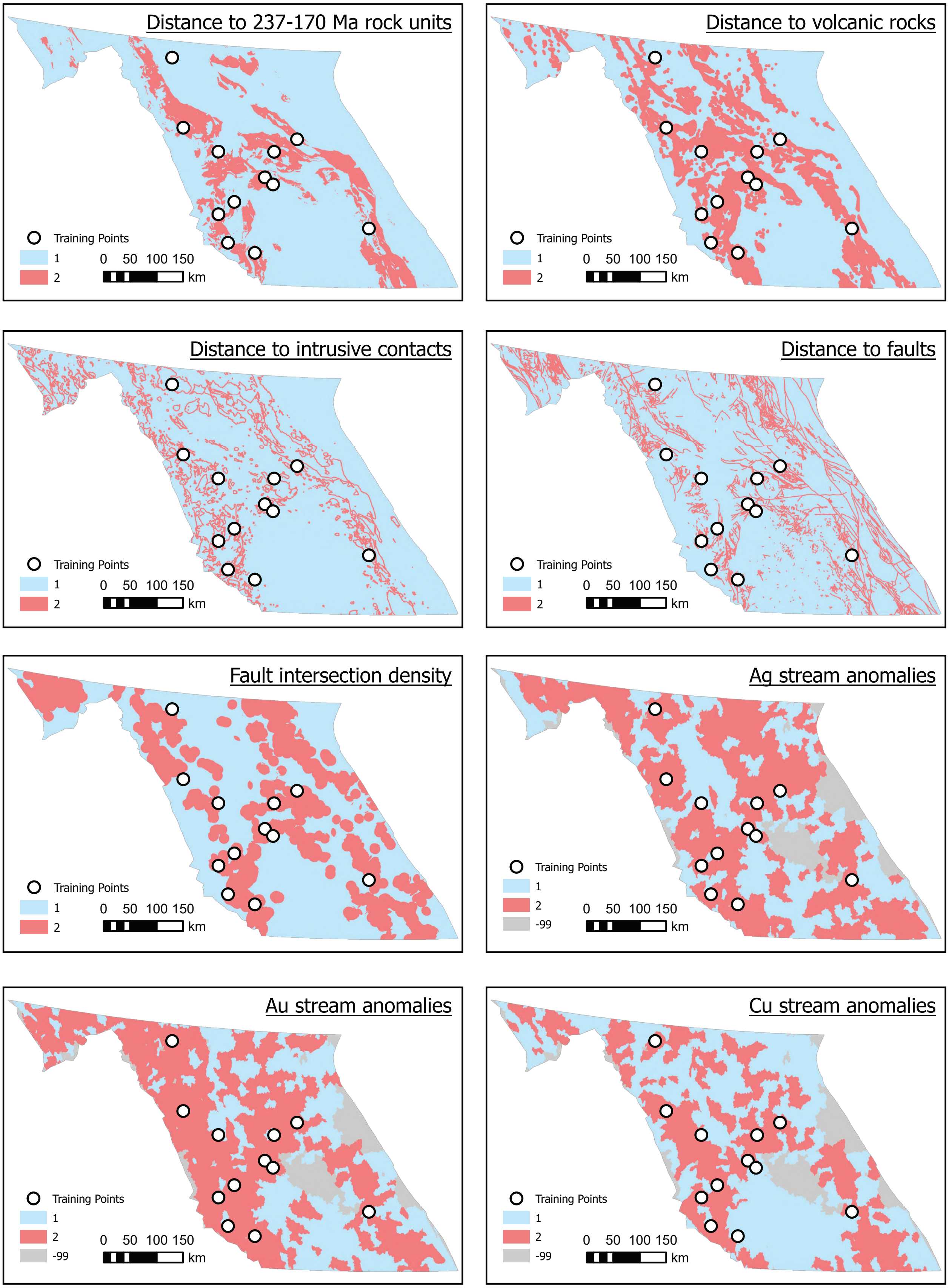

Fig. 3. Predictive maps used in the porphyry model. Red indicates areas that are favourable for capturing training data, blue are areas that are less favourable, and grey (-99 in the legend) areas indicate data gaps.

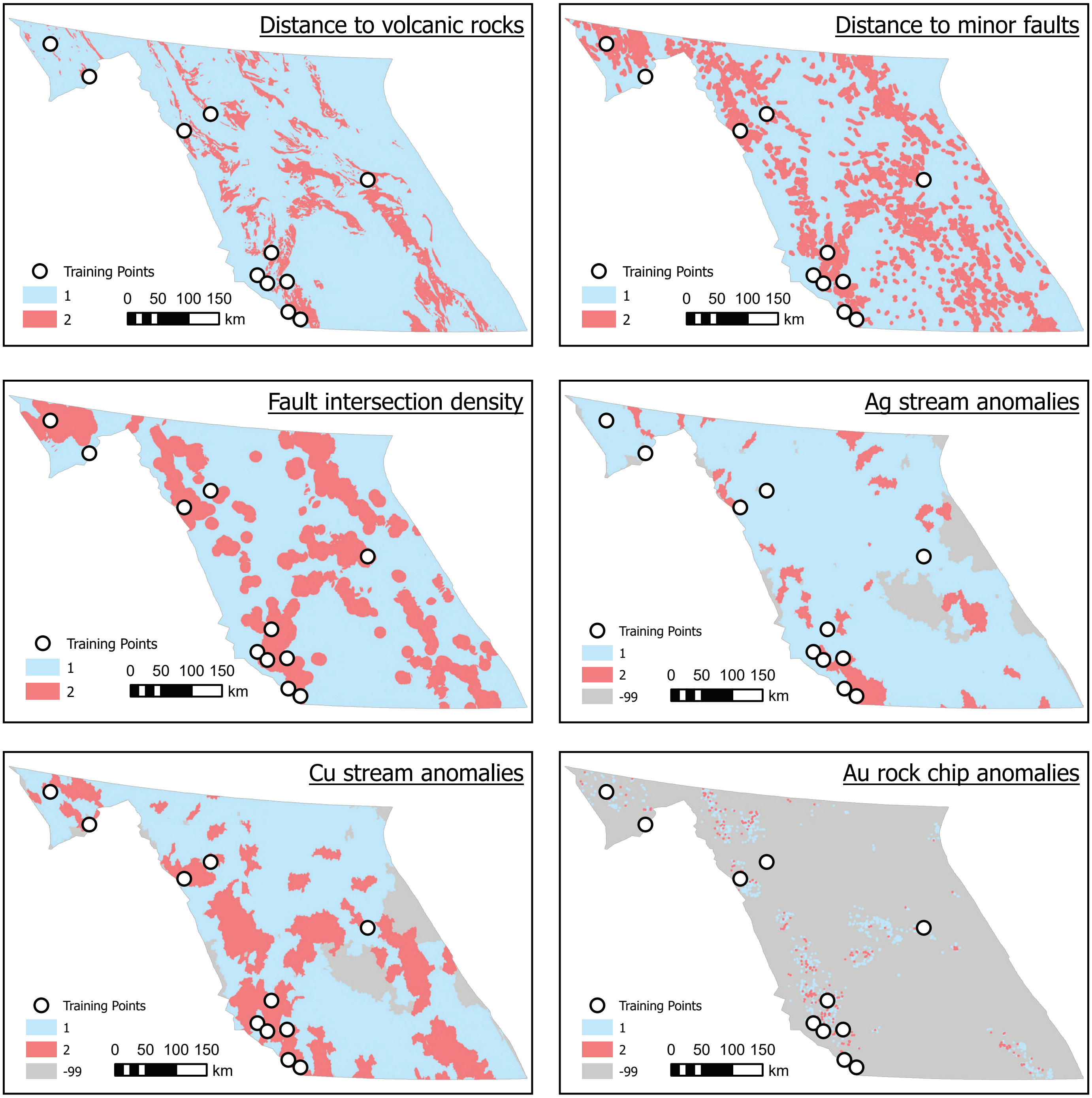

Fig. 4. Predictive maps used in the volcanogenic massive sulphide model. Red indicates areas that are favourable for capturing training data, blue are areas that are less favourable, and grey (-99 in the legend) areas indicate data gaps.

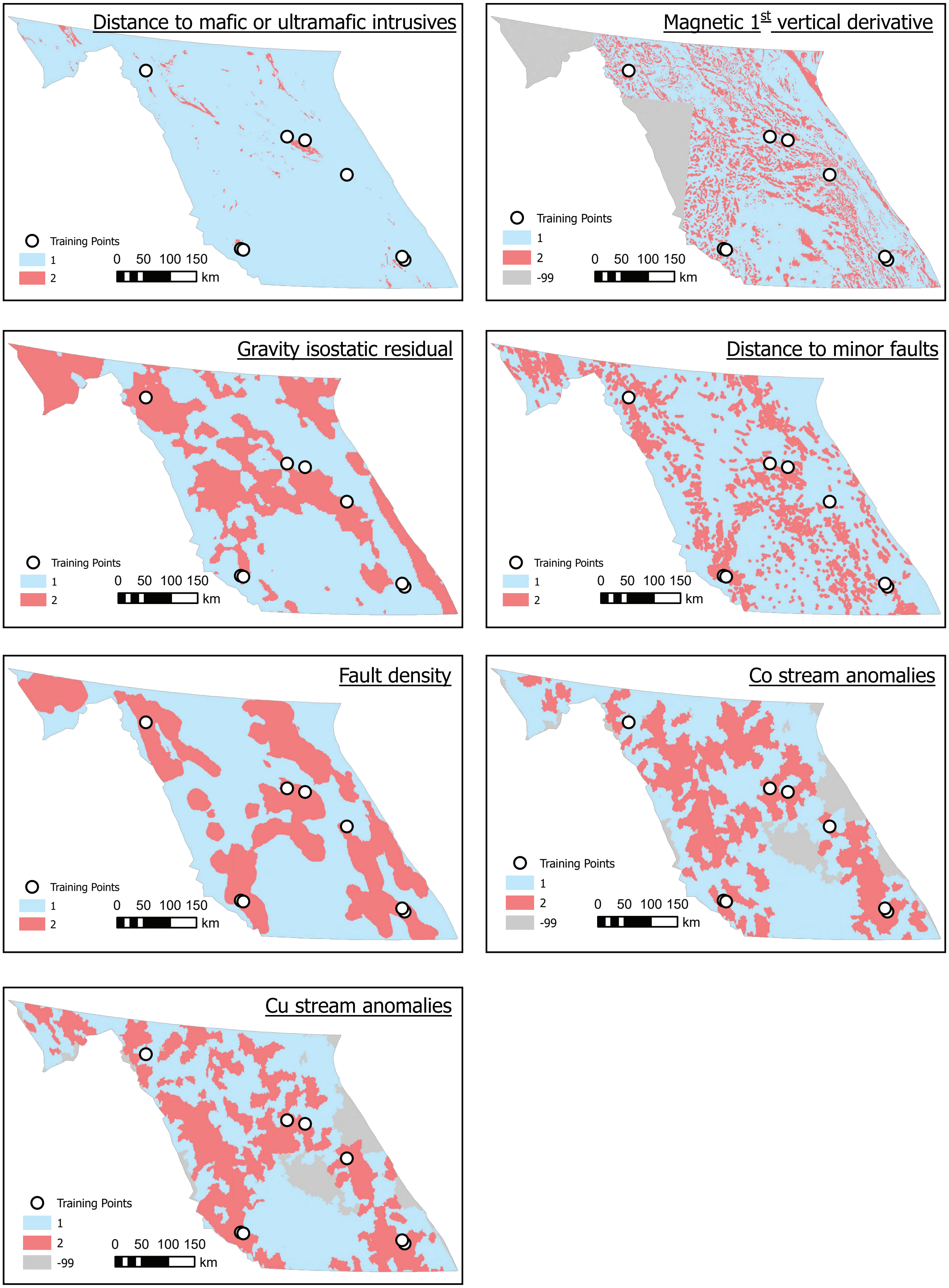

Fig. 5. Predictive maps used in the magmatic mafic to ultramafic model. Red (1 in the legend) indicates areas that are favourable at capturing training data, blue (2 in the legend) is less favourable, and grey (-99 in the legend) areas indicate data gaps.

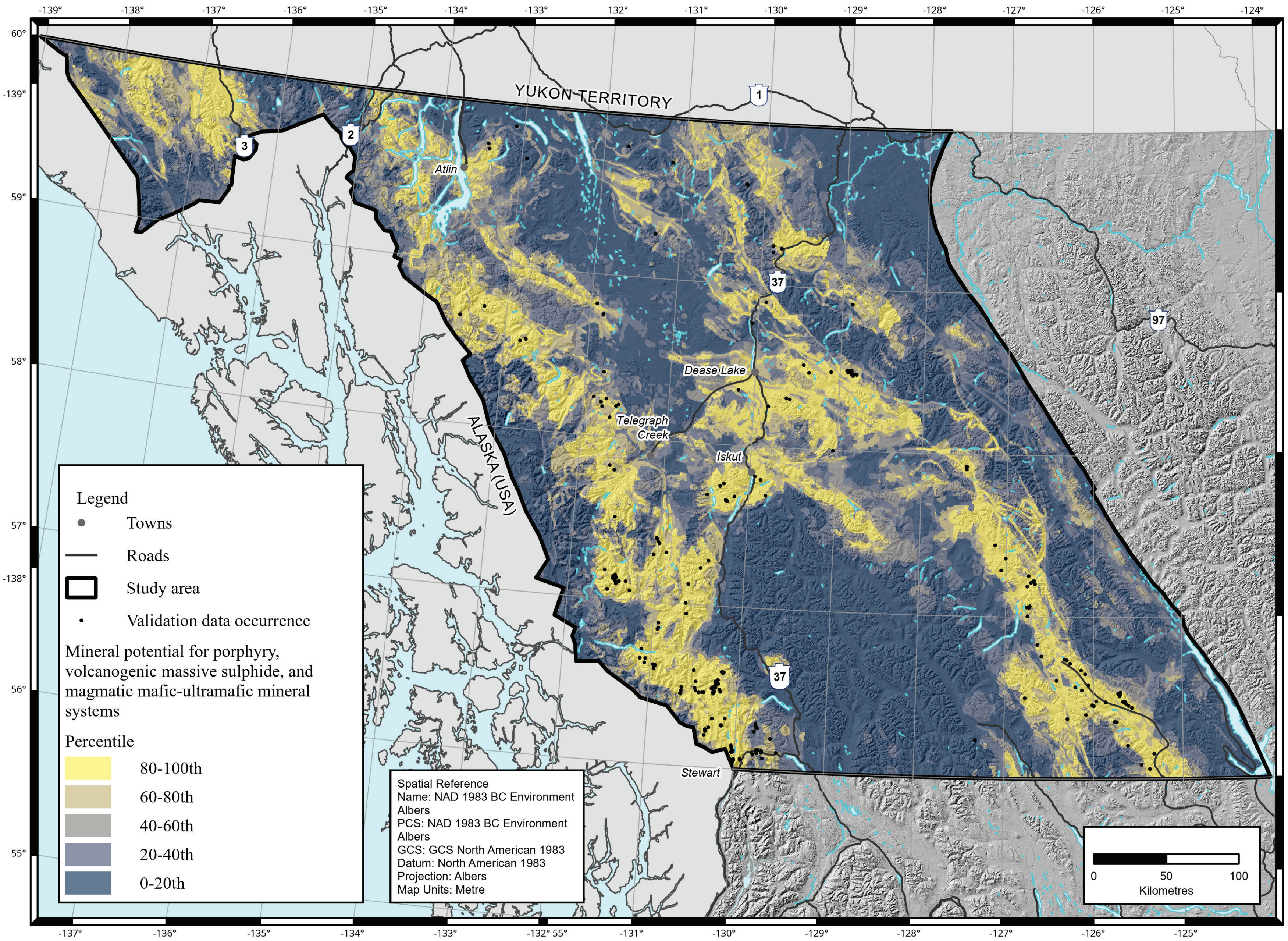

Fig. 6. Combined mineral potential map for porphyry, volcanogenic massive sulphide and magmatic mafic-ultramafic deposits from current modelling.

We used a subset of mineral occurrences not used as training points to validate the mineral potential model (Fig. 6). To ensure the validation data set was independent of the modelling process, it was excluded in the production of the final mineral potential map. We divided the final mineral potential maps into ten equal percentile divisions based on the posterior probability values (Table 7; Fig. 6). Of note, all three mineral systems capture approximately 70% of all the validation data in the 70th percentile or greater.

4. Comparing results from past and current modelling

To compare the results, the land-based rankings from Kilby (2004; Fig. 7) and the current work were converted to percentile or quantile values. These values were subtracted in a GIS to illustrate and quantify the difference of rankings for the same area. Areas with the highest percentile difference have the greatest difference in ranking; areas with the lowest percentile difference indicate general agreement between the two results.

Five equal percentile divisions were used to compare the results from the past and current work (Fig. 8; Table 8).

For 33% of the study area the studies are in broad agreement (±0-20% percentile difference, Table 8). The area surrounding the Kerr deposit (Fig. 8, location C) is ranked as the 100th percentile by the current work and as the 99th percentile in the past work. Current work recognizes that all the statistically significant mappable features used to model porphyries capture the Kerr deposit. Historical work calculated that the tract containing the Kerr deposit has close to the highest dollar values in region, based on variables such as know resources and future undiscovered deposits. The area mainly underlain by Bowser basin rocks (Fig. 8, location D) also yielded close results, receiving a ranking in the <10th percentile in the current work and the 16th percentile in the past work. The 1990s work suggested that Bowser basin is devoid of metallic economic mineral deposits and predicted few to no future deposits to be discovered within it. Current modelling suggests the Bowser basin contains few of the statistically significant mappable features used for any of the mineral systems modelled.

For 2% of the study area (Table 8; Fig. 8, highlighted in purple) the two studies yielded markedly different results. For example, in the general Atlin area (Fig. 8, location A) Kilby et al. (2004) assigned a relative ranking 80-100% higher than in the present work. This is primarily because Kilby et al. (2004) examined all metallic minerals and all deposit types whereas the current work focused only on the porphyry, volcanogenic massive sulphide, and magmatic mafic-ultramafic sulphide systems and did not model for placer gold. An area in the southeastern part of the study yielded similarly different results (Fig. 8, location E). This area was indicated to have a low relative prospectivity ranking (<12th percentile) in the current work but a high ranking (88th percentile) by Kilby et al. (2004). This difference may highlight gaps in fault data used in the present work.

Table 7. Distribution of validation data for each mineral system within each tenth percentile division.

Hierarchy	Percentile	Porphyry	VMS	Mafic-ultramafic
Highest	90-100	62%	51%	51%
	80-90	13%	15%	16%
Moderate to high	70-80	4%	2%	7%
	60-70	11%	14%	4%
Moderate	50-60	1%	2%	6%
	40-50	0%	3%	0%
Moderate to low	30-40	2%	1%	5%
	20-30	1%	1%	8%
Lowest	10-20	5%	8%	3%
	0-10	2%	1%	1%
		n = 121	n = 86	n = 106

Table 8. Percentile difference between the Level 1 Mineral Assessment of Kilby (2004) and current work. Negative percentile difference indicates Kilby (2004) provided a higher assessment than the current work for the same area. Positive values represent areas ranked higher in the current work than in Kilby (2004).

Percentile difference	Area (km^2)	Percentage of study area
+100-80	5,619	3%
+80-60	12,023	6%
+60-40	17,553	9%
+40-20	31,492	16%
(+/-) 20-0	63,688	33%
(-) 40-20	38,012	20%
(-) 60-40	15,005	8%
(-) 80-60	7,019	4%
(-) 100-80	3,295	2%

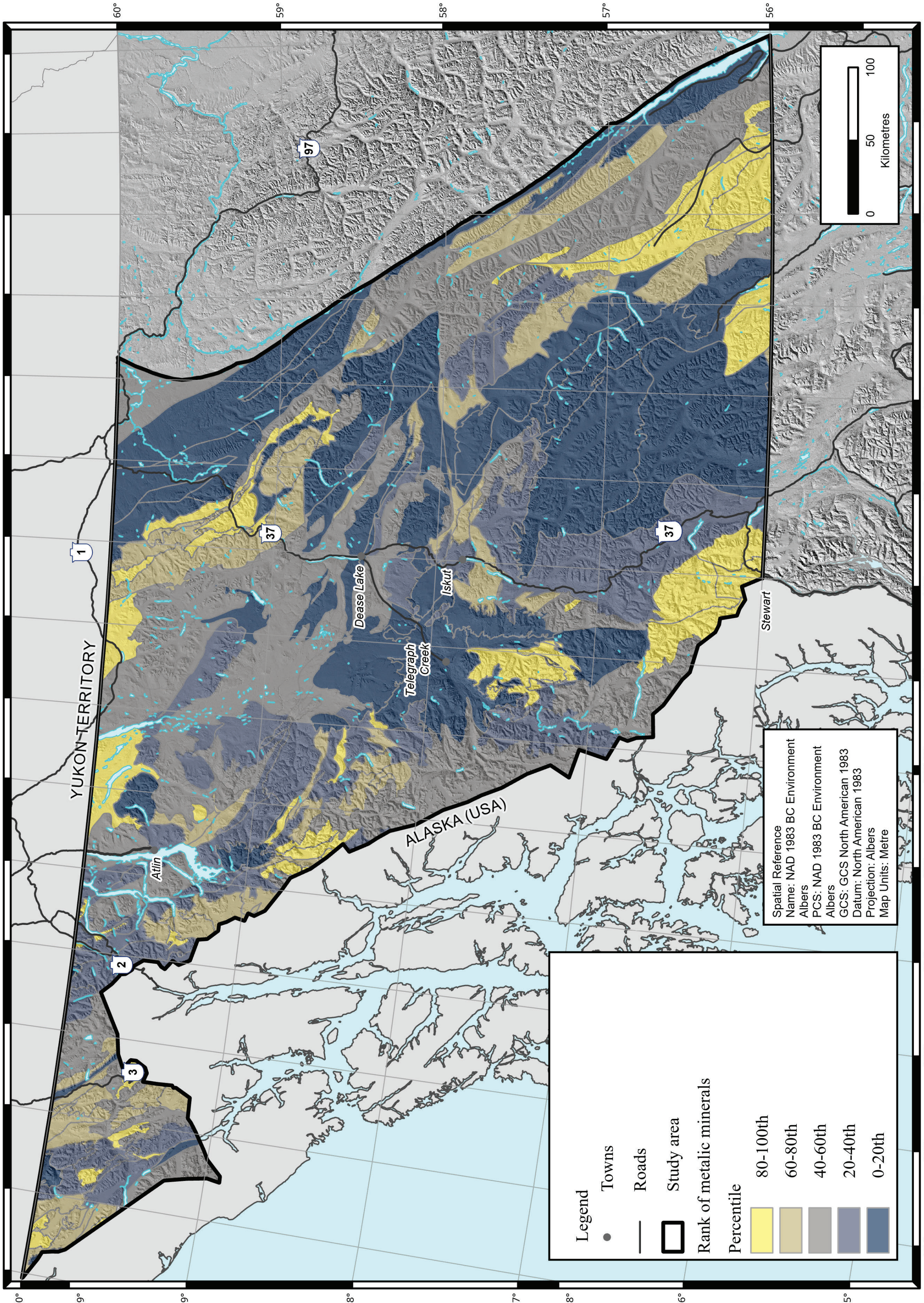

Fig. 7. Metallic mineral potential evaluation from 1990s (after Kilby, 2004).

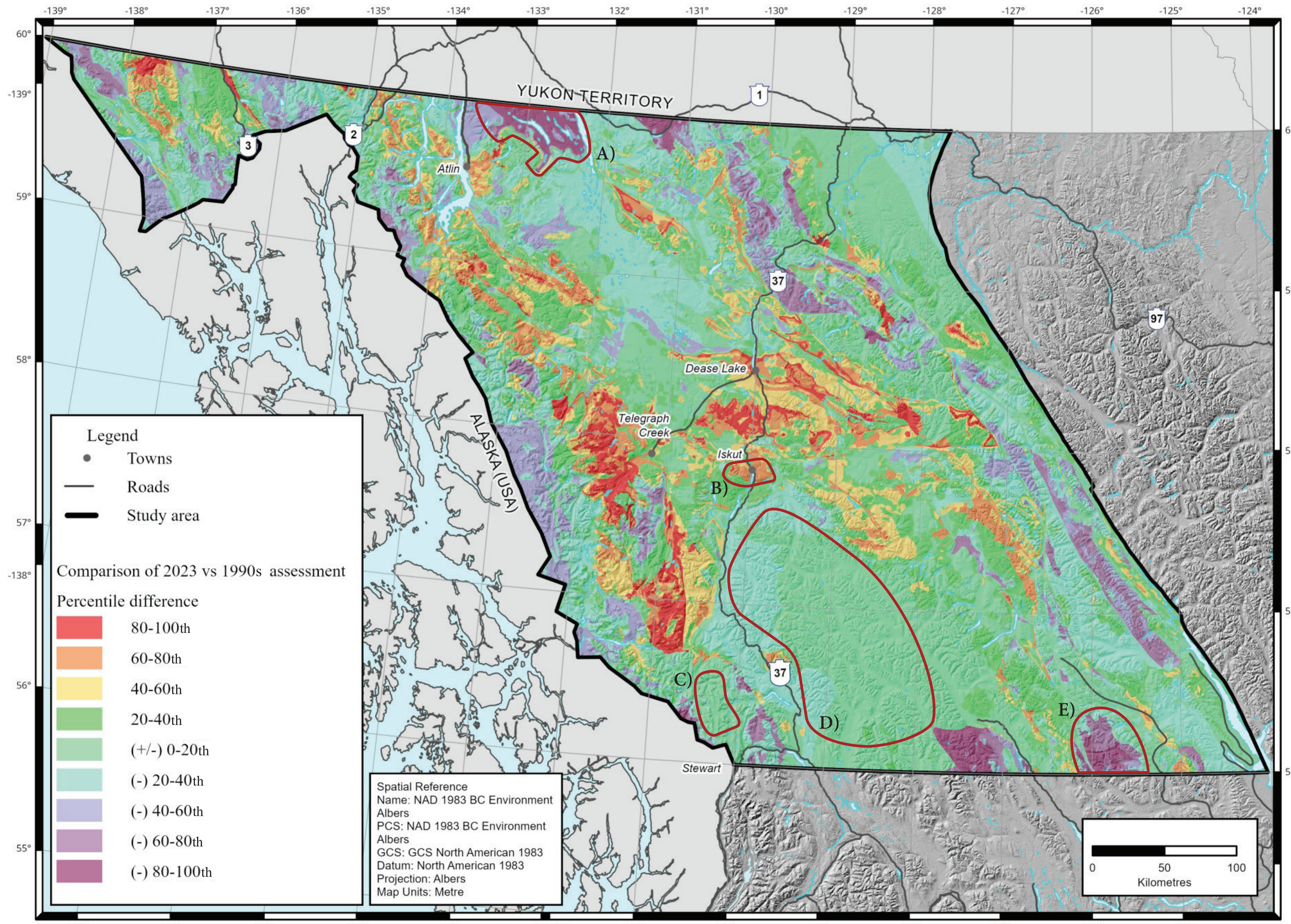

Fig. 8. Difference in relative prospectivity ranking between current and past modelling. Positive percentile differences indicate areas where the current work assigned greater relative prospectivity values than Kilby et al., 2004; greatest differences in red. Negative percentile differences indicate areas where Kilby (2004) assigned greater relative prospectivity values than the current work; greatest differences in purple. Areas of close similarity (±0-20%) are indicated in light green. Areas discussed in text: A- Atlin area; B- Iskut area; C- area surrounding Kerr deposit; D- Bowser basin; E- Oslinka River area.

For 3% of the study area (Table 8; Fig. 8, highlighted in red), the current work ranked relative prospectivity significantly higher than Kilby et al. (2004), likely because the current work has the advantage of new data. For example, the Iskut area (Fig. 8, location B) has seen significant mapping and exploration work in the last ten years and includes the Saddle North deposit, originally discovered as a soil geochemistry anomaly between 2013-14 (Flynn, 2020).

In general, the mineral potential maps produced by the current modelling resolve prospectivity at a finer scale compared to the broader 'tract' areas of historical results. Current modelling was completed on 50 m^2 grid. As a result, the study area consisted of 77,523,332 cells, each being tested for the absence or presence of a predictive map and given a relative ranking. The tract approach by Kilbry (2004) was completed on a much broader scale with an average tract area of 1000 km^2.

5. Conclusion

Both the work done in the 1990s and the current work are of value for modelling mineral potential in support of land-use decisions, and the new work largely corroborates the old. In large part, differences arise because the recent work has the benefit of about 30 more years of data, the knowledge derived from these data, and the knowledge derived from investigations into the processes that generate deposits. The original work focused on deposit profiles that classified occurrences into about 120 deposit types for a wide range of metals. In contrast, the new work adopted a mineral systems approach to examine critical mineral potential, considering only the porphyry, volcanogenic massive sulphide, and magmatic mafic-ultramafic systems. Future iterations that include other mineral systems will make updates of new modelling more comprehensive.

Mineral potential evaluations have uncertainties related to data availability, data quality, the level of relationship between mineral occurrences and the input data, the estimation method, and the deposit model. Because of these uncertainties neither the past nor present mineral potential assessments can be used to indicate the size or economics of a potential mineral deposit and cannot be used to make valuations on any resource. Any approach to modelling is limited by available data, and results represent a time-specific evaluation (Ford et al., 2019). Because of advances in GIS applications and computer power, statistical analysis of spatial data in the new modelling is far less labour intensive than the 1990s work, can be readily updated, and is more easily reproducible. As more data and knowledge become available, past evaluations may be updated to keep understanding the mineral potential of the study area current.

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