Hydrogeochemical Vectoring to Concealed Porphyry Copper Systems Using Unsupervised Machine Learning: A Case Study from Central British Columbia, Canada

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Abstract

Environments with thick cover present a challenge to surficial exploration efforts the Canadian Cordillera has extensive Quaternary glacial till and sediment cover, making it difficult to find hidden ore bodies. An alternative is using hydrogeochemistry as an exploration tool, to detect anomalies associated with mineralization. This study demonstrates the hydrogeochemical vectoring to porphyry copper deposit using unsupervised machine learning and a spatial workflow to explore beneath the cover of British Columbia, Canada. A framework of 3501 stream and groundwater data points was compiled, cleaned for string-censored limits of detection (LOD) and evaluated across 12 physicochemical variables simultaneously. An unsupervised K-Means algorithm successfully separated the groundwater into two clusters: "Fresh Baseline Water" (n=3314) and "Ore-Interacting Anomaly" water (n=187). The univariate evaluation achieved a clean separation of 90.67% dissolved Sulfate, confirming sulfate as an effective exploration vector; the multivariate pipeline resolved the 9.33% overlap zone between background and mineralized samples. A custom trail gradient index (Cu * Mo)/ (Zn) was deployed was deployed to segment the anomalies into three distinct trails: Proximal Hypogene Core (n=75) with mean Mo=16.81ppb, Zn=205.75ppb, a Secondary Reducing Zone (n=21) exhibiting peak copper precipitation; (mean Cu: 1.26ppb) and a Distal Exploration Halo (n=90) with mean Zn=51.04ppb and elevated Electrical Conductivity mean= 580.44µS/cm. QGIS mapping show these clusters align with the major regional fault networks, providing a non-invasive exploration tool.

- **Subject Keywords**: Exploration hydrogeochemistry; Porphyry copper systems; unsupervised machine learning; K-Means clustering; Structural fault zones; British Columbia Geological Survey.

Introduction

Environments with thick cover pose a challenge for exploration efforts in the sense that; the mineralization is invisible and geochemical datasets are complex, traditional exploration techniques are inefficient, require more time and are costly (Kidder & Jones, 2017; Kidder et al, 2022). A non-invasive alternative exploration tool that can detect anomalies associated with mineral occurrences buried deep under cover is hydrogeochemistry (Kidder & Jones, 2025; Kidder et al, 2020). Hydrogeochemistry is the chemical compositions water and how it interacts with rocks and minerals in the crust (Nordstrom, 2011). As groundwater migrates through fractures and buried bedrock, it actively interacts and weathers the surrounding rock (Koh et al, 2015), this process changes the chemistry of the water. The oxidation of sulfide minerals lowers the pH of water (Amoldago & Sunkari, 2026) and releases sulfate anomalies that can be detected at significant distances from the source of mineralization (Kidder et al, 2025; Leybourne & Cameroon, 2010), highlighting the relevance of hydrogeochemistry.

The Canadian Cordillera (British Columbia) lies beneath a thick layer of glacial till composed of crushed rock, clay, and sand that blankets much of south-central and central British Columbia, a region described to have discovered and undiscovered porphyry deposit buried beneath the glacial cover (Mihalasky et al 2011). Porphyry deposits are large mineralized networks formed by small intrusions (Briggs, 2014; Sinclair, 2007), the principal minerals of porphyry copper deposits are pyrite, chalcopyrite, and bornite embedded in silicate host rocks (Lan et al, 2024; Sinclair, 2007). Oxidized groundwater breakdown sulfide minerals into sulfates (SO_4^{2-}) and trace elements (Arroyo & Siebe 2007; Nordstrom et al, 2015), the acidic condition of the water make it easier for dissolved copper and mobile ions to be carried away by water (Kidder et al, 2020). Sulfates (Miller et al, 1982) and Molybdenum (Mo) are the most important pathfinders for regional hydrogeochemistry as they are stable and remain in solution for a long time under different environmental conditions, co-occurring elevated SO_4^{2-} and Mo may indicate a trail to the mineralized ore body.

Traditional analyses to geochemical and hydrogeochemical variables rely on univariate statistical thresholds such as the 95^{th} percentile, ±2 times the median absolute deviation (Kidder et al, 2025), or an arbitrary value. The advances in data science and machine learning provide an alternative to identify hydrogeochemical patterns in large datasets, unsupervised machine learning- K-Means clustering- evaluates chemical variables simultaneously (Troccoli et al, 2022), allowing for the separation of fresh background groundwater from ore interacting water. Groundwater that has interacted with a mineralized ore zones often migrate through crustal faults and shear zones, the Canadian Cordillera has these fracture networks that form the region's porphyry copper systems.

This study aims to integrate machine learning hydrogeochemistry with Geographic Information System (GIS) to map and visualize the framework of hydrogeochemical anomalies against the structural fault systems, ultimately proving vectors to mineralized porphyry copper deposits. The objectives are to: (1) compile the hydrogeochemical dataset of British Columbia from the Canadian Regional Geochemical Surveys (RGS), standardize Limit of Detection values and filling any missing data with averages for statistical analysis; (2) run an unsupervised K-Means clustering using (pH, EC, TDS, SO_4, Mg, Fe, Ca, Cu, Mo, Zn, As, Sb, Se) matrix, for fresh water and ore interacting anomaly water separation; (3) engineer copper trail index (Cu * Mo)/ (Zn), implement the conditional percentile filters to separate the anomalies into distinct porphyry sub zones; (4)

integrating the sub zones with British Columbia geology and faults in QGIS, execute spatial heatmap of ore fluid signatures.

Materials & Methods

2.1 Study area

British Columbia is located in the western part of Canada, situated between the Pacific Ocean and the Rocky Mountains. The research region of this study is across the province of British Columbia Canada, between latitudes 48°N and 60°N and Longitudes -132°W and -119°W. British Columbia lies on pre-Cretaceous metamorphic, metasedimentary and plutonic rocks, as well as buried Precambrian crystalline crust from the ancient North American craton and Canadian Shield,

The region is dominated by a series of accreted oceanic island arcs and continental terranes that collided with the west margin of North America throughout the Paleozoic and Mesozoic eras (Kuhn et al, 2020; Johnson, 2008 and Boggs, 2004).

The geology is defined by the Quesnellia and Stikinia terrains; Quesnellia is predominantly made up of high potassium, calc-alkaline to shoshonitic submarine volcanics and sediments of the Talca Group (Kuhn et al, 2020). These volcanic and plutonic assemblages host the largest porphyry copper-gold- molybdenum deposit in western Canada. The primary mineralization is hosted in the upper Triassic to Lower Jurassic alkali and calc- alkaline intrusive suite (Sinclair, 2007), the ore minerals consist of chalcopyrite, bornite, pyrite and accessory molybdenite.

A massive geographic bowl formed between the collided islands, where it collected massive runoff from eroding mountains. This sedimentary overburden consist of the Bowser Lake Group and the Nechaco Basin. During the Quaternary period, the region experienced repeated, intense continental glaciation, leaving behind a complex glacial till, glaciofluvial outwash sands, and thick lacustrine silts (Mosher & Moran, 2001). The topography ranges from deeply incised, organic-rich mountainous drainage basins to flat internal plateau terrains.

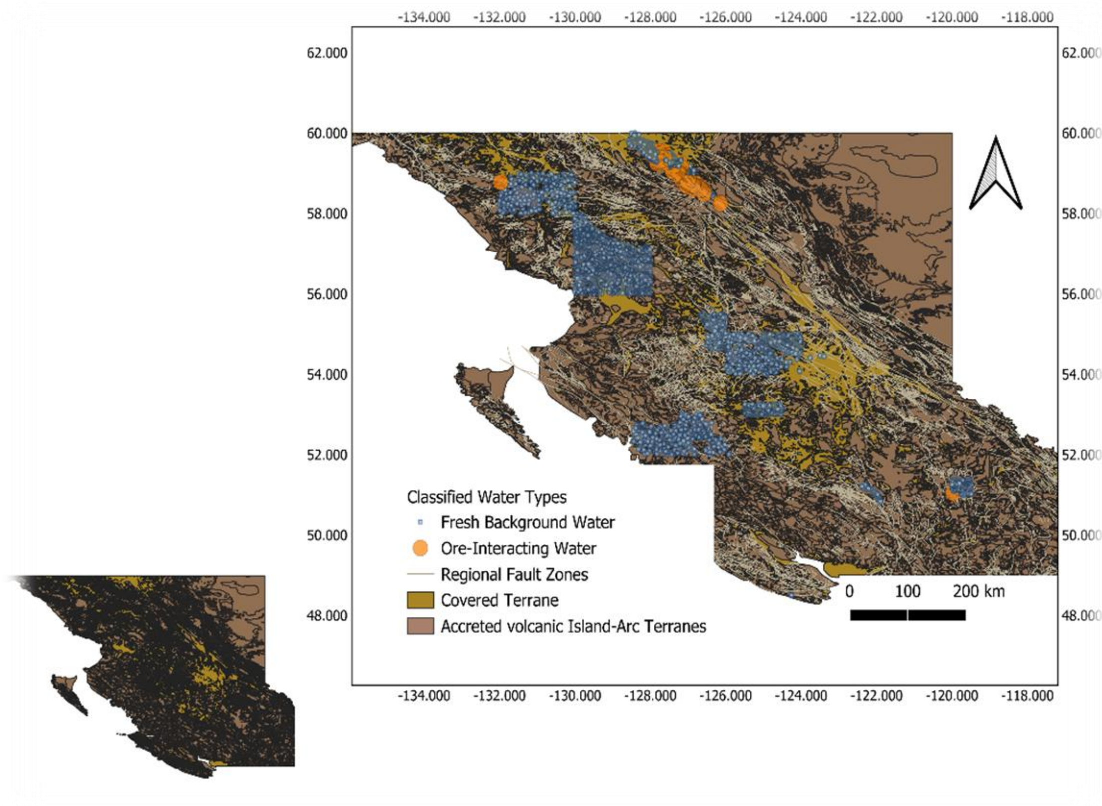

Figure 1. The hydrogeochemistry of British Columbia, Canada showing anomalous water flowing along regional fault systems.

2.2 Geochemical database and data compilation

The data was obtained from the Canadian Regional Geochemical Surveys (RGS) database, with analysis carried out using the hydro sheet dataset from the Excel file rgs_2020 xlsx, focusing on 13 physicochemical parameters: pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Sulfate (SO_4), Magnesium (Mg), Iron (Fe), Calcium (Ca), Copper (Cu), Molybdenum (Mo), Zinc (Zn), Arsenic (As), Antimony (Sb) and Selenium (Se).

2.3 Data cleaning and pre-processing pipeline

The raw data was imported into Python Pandas library, rows were filtered to focus on the exploration area of Central British Columbia. Data cleaning began by removing sample points missing pH and coordinates values, elements exhibiting censored values below the Limit of Detection were then standardized and the remaining numerical detection boundary were replaced by half the elements specific limit. The remaining cells with missing values were populated with the dynamic column median of the respective variable.

2.4 Vector Index engineering and multivariate standardization

The custom formula (Cu * Mo)/ (Zn + 1e-5) was used to create a trail index to the hidden porphyry copper deposit. The reason for this is; dissolved copper and molybdenum show sulfide inputs close to the main ore body, while the highly mobile Zinc defines the distal halo, the constant (1e-5) was added to avoid mathematical division by zero errors. Since the original input parameters have different orders of magnitudes and measurement (pH scales, EC in μS/cm and trace metals in ppb), the matrix was normalized by means of the StandardScaler from scikit-learn; this transformed the variables to a mean of 0 and variance of 1, ensuring high spikes of base ion did not mathematically overwhelm the subtle pathfinder anomalies

2.5 Unsupervised clustering and conditional zoning logic

An unsupervised K-Means algorithm analyzed the physicochemical variables, Sulfide oxidation indicators and porphyry pathfinder matrices simultaneously; separating the water into two clusters: Cluster 0 (Fresh Background Water) and Cluster 1 (Ore-Interacting Water).

A conditional zoning script was applied to the anomalous water population (n=187) into three exploration targets using relative internal percentiles:

1. Proximal (Hypogene Core): The samples show molybdenum concentrations that reached the $\geq 60^{th}$ percentile within the anomaly cloud, which indicates the primary ore indicator.
2. Medial (Secondary Reducing Zone): These are samples in which copper concentrations reached the $\geq 60^{th}$ percentile, showing the reducing zone where Mo decreases but Cu increases.
3. Distal (Outer Exploration Halo): The residual anomaly samples where mobile elements had traveled beyond the reduction zone, dominated chemically by elevated Zinc signatures.

2.6 The integration of spatial GIS and structural Modeling

The shape files for the fault systems, bedrock geology and Quaternary data were obtained from the British Columbia Geological Survey. The dataset and coordinates of cluster 1 were imported into QGIS for geographic plotting. A heatmap was generated using kernel density estimation using radius values of 0.30 to 0.50 degrees, generating heat clouds using the Cu vector index.

Results

3.1 Initial machine learning population delineation

The Python pipeline successfully loaded the data from the hydro sheet, renamed columns accordingly and isolated the array to Central British Columbia, establishing 3501 hydrogeochemical rows. The unsupervised K-Means clustering successfully segmented the elemental matrix into two cluster, Figure 2 below: Fresh Baseline Water (n=3314); characterized by slightly alkaline pH of 7.75, EC mean= 97.35μS/cm and baseline SO_4 mean=11.14, low trace metal indicators; Cu mean= 0.62ppb and Mo mean= 0.50ppb. The ore-interacting anomaly (n= 187) display elevated EC, dissolved SO_4 and distinct anomalies in mobile trace metals.

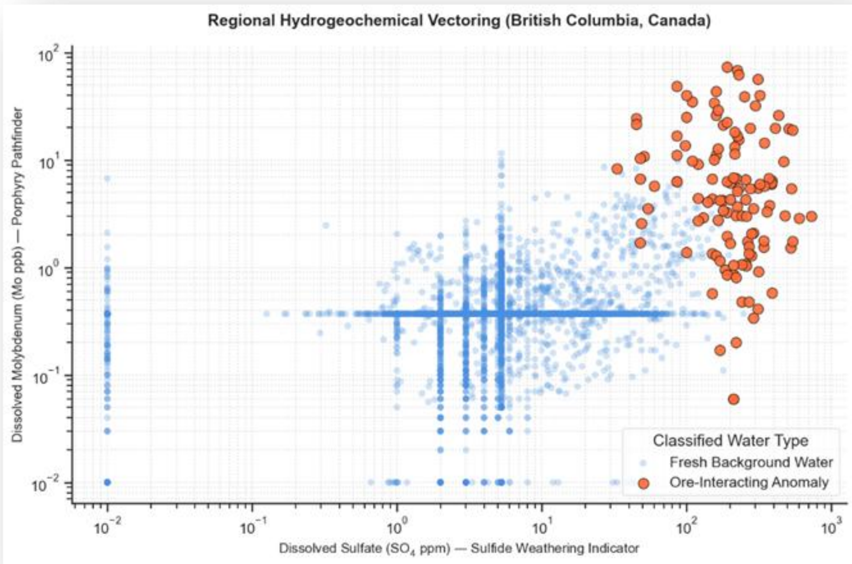

Figure 2: K-Means cluster showing Fresh Baseline water and Ore-Interacting Anomaly

3.2 Univariate vs. multivariate separation metrics

The univariate statistical evaluation achieved 90.67% SO_4^{2-} clean separation as an indicator between background and anomalous water. However there was an overlap zone of 315 false alarm background samples flow past the anomaly group's minimum threshold. This statistical overlap validates the need for the multivariate machine learning script, which dynamically resolves this noise by cross-evaluating the pathfinder matrices simultaneously.

The background meteoric exhibit a broad range of sulfate (-0.1 to 248.2ppm) though they cluster tightly around median of 5.28ppm. The delineated anomalous fluids range from 33.0 to 730.0ppm with a median value of 215.0ppm.

3.3 Geochemical characterization of vectoring sub-zones

By applying the conditional geochemical percentile filters to the 187 machine learning anomalies, the pipeline successfully traced a distinct ore-system chemical gradient. The distribution and exact geochemical signatures of these three sub-zones are documented in the grid below:

Table 1: Geochemical Vector Signatures and Core Average Target Matrix (Mean Values)

Classified Exploration Zone	Sample Size (n)	pH	EC (µS/cm)	SO_4 (ppm)	Cu (ppb)	Mo (ppb)	Zn (ppb)
Fresh Regional Baseline	3314	7.75	97.35	11.14	0.62	0.50	1.13
Proximal (Hypogene Core)	75	8.26	259.57	208.20	1.25	**16.81**	**205.75**
Medial (Secondary Reducing Zone)	21	8.26	396.38	**262.58**	**1.26**	1.90	7.71
Distal (Outer Exploration Halo	90	8.14	**580.44**	131.93	0.21	1.27	51.04

The Proximal Hypogene Core shows a spike in Mo (16.81ppb) and Zn (205.75ppb) values, indicating the primary mineralization zone. An increase in the Cu (1.26ppb) and Sulfate (262.58ppm) in the Medial Secondary Reducing Zone is indicative of a reducing zone where Cu precipitates, leaving elevated Sulfates in solution. The distal Outer Exploration in indicated by elevated EC (580.44µS/cm), Zn (51.04ppb) as well as low concentrations of Cu (0.21ppb) and Mo (1.27ppb) that have dropped out of solution.

3.4 Spatial clustering and structural alignment

Overlaying the British Columbia Geological Survey structural database with the proximal hypogene samples and medial secondary samples revealed a localized halo; the heatmap revealed an intense cloud along fault systems as shown in Figure 3 below, confirming the ore fluids are migrating through these fractures and the highly focused heat cloud directs to the mineralized zone.

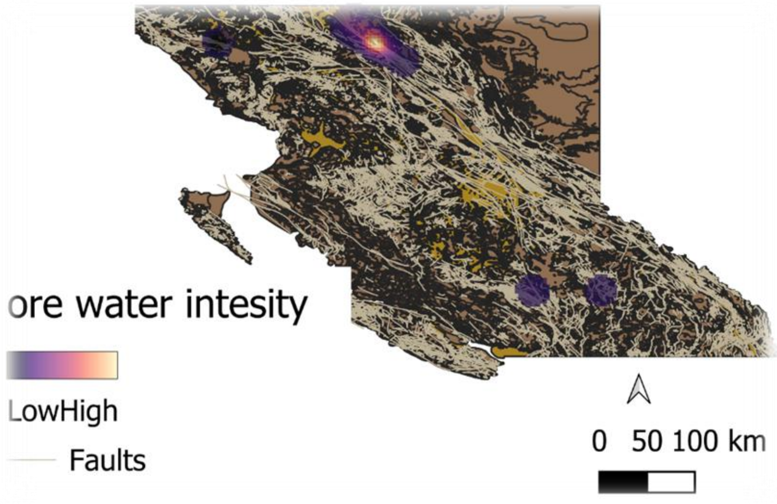

Figure 3: A heatmap showing ore interacting water intensity; high intensity at the proximal hypogene core, to the low intensity distal halo zone.

Discussion

4.1 Aqueous geochemical mechanics and the alkaline "cover effect"

Sulfide weathering processes are driven by oxidation of sulfide minerals when exposed to water and oxygen, releasing sulfates and hydrogen ions that lower the pH of the surrounding water. The 90.67% sulfate separation rate between background water and ore fluids indicates water has chewed through a sulfide ore. While primary sulfide oxidation is a strongly acid-generating reaction, the Proximal Hypogene Core and Medial Secondary Reducing zones display an increased, alkaline pH mean of 8.26. This is reflected by the carbon-bearing glaciofluvial sediments and cover unique to the Cordilleran terrains (Parbhakar-Fox & Lottermoser, 2016). This neutralizing effect forces dissolved copper to precipitate rapidly as secondary copper carbonates or adsorb onto iron-manganese oxyhydroxides; this chemical barrier explains why copper remains modest (1.26 ppb) and restricted to a narrow, high-priority window of just 21 medial samples. Co-occurring elevated sulfates (208.20) and molybdenum (16.81) with the moderate copper show the proximal hypogene core, where the ore body was chewed by water and the slight spike in Copper (1.26ppb) and drop in Molybdenum (1.90ppb) indicated the secondary deposit.

The K-Means model successfully isolated this subtle trap by evaluating the multi-element chemical matrix simultaneously, preventing these muted copper values from being dismissed as simple background noise.

4.2 Pathfinder dispersion models: Mo stability vs. Zn mobility

Because copper precipitates rapidly when encountering neutralizing cover networks, relying solely on raw copper concentrations to vector toward hidden porphyry deposits is a flawed exploration strategy. This limitation highlights the critical importance of multivariate pathfinder dispersion trends (Amoldago & Sunkari, 2026), specifically the Molybdenum (Mo) versus Zinc (Zn) decoupling observed across the sub-zones. Unlike copper, molybdenum is highly soluble and thermodynamically stable in alkaline, oxygenated groundwater; it acts as the premier indicator for the deep proximal hypogene core (Leybourne & Cameroon, 2010), yielding a concentration spike (16.81 ppb) over the regional baseline. In contrast, Zinc has a different dispersion mechanism: it is highly enriched in the proximal core (205.75 ppb) due to the zoning of the deposit; it retains high hydromorphic mobility across broad pH levels into the Distal Exploration Halo (51.04 ppb) alongside massive total dissolved solids (mean EC: 580.44 μS/cm). This chemical zonation creates a reliable vectoring gradient: a widespread distal Zn-EC anomaly points to an active, nearby mineralized system.

4.3 Spatial controls: fault conduits as migration pathways

The linear alignment between water-type clusters in Figure 1 and the mapped regional fault systems visually validates the study's structural framework. The permeability of the crustal fault networks and regional shear zones allowed fluids to migrate and deposit minerals. The heat clouds show that deep chemical anomalies travel horizontally along these fault margins, providing clear exploration vectors.

4.4 Integrating stable isotopes as a complementary exploration tool

Incorporating aqueous stable isotope systematics represents a powerful complementary tool to confirm these targets (Leybourne & Cameroon, 2010). Although this provincial database does not include isotopic data, integrating them would provide definitive physical evidence of fluid origins and sulfide weathering processes:

- Stable oxygen $\delta^{18}O$ and hydrogen $\delta^{2}H$ can determine the origin of water molecules, whether the anomalous fluid is shallow meteoric rainwater or deep magmatic fluid migrating through fault systems.
- Sulfur isotopes can help determine sulfate concentrations in groundwater (Kirste et al, 2003), distinguishing ore-interacting waters from false alarms caused by ordinary evaporites or agricultural fertilizers (Amoldago & Sunkari, 2026). Porphyry copper sulfide minerals have a narrow signature near 0‰. Measuring the $\delta^{34}S$ of dissolved sulfate can distinguish between background noise and an active oxidizing chalcopyrite ore body.

4.5 Limitations and future work

Although the unsupervised K-Means clustering algorithm and conditional zoning was successful in vectoring to mineralization, certain limitations within the data pipeline provide a framework for future use. First constraint is loading the standardized multivariate matrix into clustering engine without prior reduction pass, for instance, variables that are closely correlated to each other; dissolved iron and sulfate correlate because they are co-released during oxidation of pyrite. This correlation may lead to a double weight, biasing cluster calculations towards high abundance base components. Future work will integrate Principal Component Analysis (PCA) and K-Means, running a PCA will allow the system to compress the chemical variables into uncorrelated Principal Components. This will isolate the true anomalies from the water sample more sharply, stripping out geochemical variance caused by the surrounding bedrock. Furthermore sampling for stable isotope ($\delta^{18}O$, $\delta^{2}H$ and $\delta^{34}S$) will allow for distinguishing between true sulfide weathering pathways exhibiting sulfur isotope signature near 0‰ and false alarm anomalies.

Additionally the incorporation of ultra-trace gold (Au) and Rubidium (Rb) to the multivariate matrix can enhance the vectoring capability for future pipelines. Ultra-trace gold would provide an unequivocal vector to the high temperature proximal hypogene core where Au is tightly connected to the primary chalcopyrite mineralization. Analyzing Rb- which substitutes for potassium ultimately amplifying hydrothermal alteration signatures- would allow the unsupervised algorithm to map this central alteration zone. Integrating Au and Rb with Cu-Mo-Zn can provide the metal footprint and the underlying hydrothermal alteration for mineralized body.

Conclusion

This study successfully validates the integration of unsupervised multivariate hydrogeochemical clustering and structural spatial modeling as a powerful, non-invasive exploration tool for targeting blind porphyry copper systems under thick cover. By loading a preprocessing and data cleaning into Python, the project effectively standardized the regional hydrogeochemical samples of British Columbia.

The unsupervised K-Means clustering separated the dataset into 2 clusters of Fresh Baseline Water (n=3314) and Ore-Interacting Anomaly water (n= 187). While univariate evaluation achieved a clean separation of 90.67% dissolved Sulfate, confirming sulfate as an effective exploration vector; the multivariate pipeline resolved the 9.33% overlap zone between background and mineralized samples.

By engineering a copper vector index (Cu * Mo)/ (Zn) alongside percentile conditional filtering, this study successfully delineated the Proximal Hypogene core marked by a spike in molybdenum (16.81ppb), the Medial Secondary zone exhibiting alkaline, copper precipitating trap (mean Cu: 1.26ppb, Mean SO_4: 262.58ppm) and the Distal Exploration Halo dominated by elevated Zinc (51.04ppb) and high Electrical Conductivity (580.44µS/cm).

Spatial GIS validation within QGIS aligned these mathematical clusters with the regional fault networks. Weighted Kernel Density Estimation heatmaps visually mapped theses active pathways of structural heat clouds. Ultimately, this end-to-end data pipeline proves that advanced computing workflows can be combined with fundamental economic geology principles to drastically minimize active search footprints, reduce false-alarm targets and successfully locate deep metal resources hidden beneath cover environments.

Data Availability Statement

- The hydrogeochemical data utilized in this study are open source and publicly available through the Geological Survey of Canada (GSC) and the British Columbia Geological Survey (BGCS); the raw hydrogeochemical data stream matrix and associated metadata can be accessed via the official Canadian Open Government Portal under the Regional Survey (RGS) program archives (Database finder: RGS2020_data.xlsx).

- The supporting geoscience layers for British Columbia, including the province- wide bedrock geology polygons and regional structural fault lines database, are publicly accessible under the British Columbia Open Government License (https://gov.bc.ca).
- Zenodo link: https://doi.org/10.5281/zenodo.22903863

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Special recognition is extended to the developers and maintainers of the open-source software utilized throughout this data pipeline, including the Python Software Foundation libraries (pandas, numpy, and scikit-learn) and the QGIS Development Team for providing the advanced spatial mapping platform. Finally, the author acknowledges valuable feedback from peers and mentors who reviewed the structural geology layouts and geochemical zoning logic during preparation of this preprint manuscript.

Author Contributions

Kukudi B.F: Conceptualization, Data Curation, Software Architecture, Formal Statistical Analysis, GIS Spatial Modeling, Map Cartography, Writing – Original Draft Preparation, Review & Editing.

Conflicts of Interest

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Code Appendix: Multivariate data pipeline and hydrogeochemical sub-zoning engine

The following complete, self-contained Python script executes the data cleaning, preprocessing, unsupervised machine learning classification, and advanced exploration zoning workflow documented in this manuscript. The pipeline requires standard Python data science libraries (pandas, numpy, scikit-learn).

Hydrogeochemical Exploration Vectoring Engine

Author: Boago Felicity Kukudi

License: Open Source (MIT)

Description: Case- insensitive dynamic column mapping, LOD cleaning, K-means multivariate clustering, and ore system sub-zoning.

```
import os

import numpy as np

import pandas as pd

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans


# Define the explicit data paths based on your localized system layout

excel_path = "rgs2020_data.xlsx"

# Validate that the file is resting in the active folder matrix before loading

if not os.path.exists(excel_path):

    print(f" Error: Cannot find your data repository file at '{excel_path}'.")

    print("Please ensure 'rgs2020_data.xlsx' is sitting in your notebook project folder.")

else:

    print(f" Found file at target path. Reading data from the 'hydro' sheet...")

            # Load targeted exploration fields explicitly to save system memory
            columns_to_load = [
                'LAT', 'LONG', 'pH', 'Cnd_uS/cm', 'TDS_ppm', 'SO4_ppm',
                'Mg_ppm', 'Fe_ppm', 'Ca_ppm', 'Cu_ppb', 'Mo_ppb',
                'Zn_ppb', 'As_ppb', 'Sb_ppb', 'Se_ppb'
            ]
```

```
   df = pd.read_excel(excel_path, sheet_name="hydro", usecols=columns_to_load)
# 2. Rename coordinate and field properties to clean QGIS standards
   df = df.rename(columns={
      'LAT': 'Latitude',
      'LONG': 'Longitude',
      'Cnd_uS/cm': 'EC',
      'TDS_ppm': 'TDS'
   })

   # Drop empty baseline rows missing critical entries
   df = df.dropna(subset=['Latitude', 'Longitude', 'pH'])

   # 3. SPATIAL FILTER ACROSS REGIONAL BRITISH COLUMBIA COORDINATES
   df_bc = df[
      (df['Latitude'].between(48.0, 60.0)) &
      (df['Longitude'].between(-132.0, -119.0))
   ].copy()

   # 4. REMOVE TEXT FLAGS AND PROCESS CENSORED DETECTION LIMIT DATA (< LOD)
   def clean_detection_limits(val):
      if pd.isna(val):
         return np.nan
      if isinstance(val, str):
         val = val.strip()
         if val.startswith('<'):
            try:
               return float(val.replace('<', '')) / 2
            except ValueError:
               return np.nan
         elif val.upper() in ['N.D.', 'ND', 'N/A']:
            return np.nan
      try:
         return float(val)
      except ValueError:
         return np.nan

   target_chem_fields = [
      'pH', 'EC', 'TDS', 'SO4_ppm', 'Mg_ppm', 'Fe_ppm', 'Ca_ppm',
      'Cu_ppb', 'Mo_ppb', 'Zn_ppb', 'As_ppb', 'Sb_ppb', 'Se_ppb'
   ]

   for col in target_chem_fields:
      df_bc[col] = df_bc[col].apply(clean_detection_limits)
      df_bc[col] = df_bc[col].fillna(df_bc[col].median())
```

```
# 5. CONSTRUCT EXPLORATION TRAIL GRADIENT INDEX
df_bc['Cu_Vector_Index'] = (df_bc['Cu_ppb'] * df_bc['Mo_ppb']) / (df_bc['Zn_ppb'] + 1e-5)


# 6. RUN UN-SUPERVISED CLUSTERING (K=2)
ml_features = target_chem_fields + ['Cu_Vector_Index']
valid_features = [col for col in ml_features if df_bc[col].min() != df_bc[col].max()]

X = df_bc[valid_features].copy()
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

kmeans = KMeans(n_clusters=2, random_state=42, n_init=10)
df_bc['Cluster'] = kmeans.fit_predict(X_scaled)

# Identify water types based on metal concentrations
c0_cu = df_bc[df_bc['Cluster'] == 0]['Cu_ppb'].mean()
c1_cu = df_bc[df_bc['Cluster'] == 1]['Cu_ppb'].mean()

if c1_cu > c0_cu:
    df_bc['Water_Type'] = df_bc['Cluster'].map({0: 'Fresh Background Water', 1: 'Ore-
Interacting Anomaly'})
else:
    df_bc['Water_Type'] = df_bc['Cluster'].map({1: 'Fresh Background Water', 0: 'Ore-
Interacting Anomaly'})


# 7. EXECUTE GEOLOGICAL SUB-ZONING RULES FOR THE ANOMALIES
df_bg = df_bc[df_bc['Water_Type'] == 'Fresh Background Water'].copy()
df_anomaly = df_bc[df_bc['Water_Type'] == 'Ore-Interacting Anomaly'].copy()

df_bg['Ore_Zone'] = 'Fresh Regional Baseline'

# Establish internal thresholds inside the anomaly array using percentiles
mo_threshold = df_anomaly['Mo_ppb'].quantile(0.60)
cu_threshold = df_anomaly['Cu_ppb'].quantile(0.60)

def assign_ore_zone(row):
    if row['Mo_ppb'] >= mo_threshold:
        return 'Proximal (Hypogene Core)'
    elif row['Cu_ppb'] >= cu_threshold:
        return 'Medial (Secondary Reducing Zone)'
    else:
```

```
        return 'Distal (Outer Exploration Halo)'

    df_anomaly['Ore_Zone'] = df_anomaly.apply(assign_ore_zone, axis=1)

    # Re-combine full data frameworks and save to disk
    df_final_zoned = pd.concat([df_bg, df_anomaly], ignore_index=True)

    os.makedirs("processed_data", exist_ok=True)
    df_final_zoned.to_csv("processed_data/central_bc_zoned_vectors.csv", index=False)

    print(f"Pristine map layer successfully saved to:
'{os.path.abspath('processed_data/central_bc_zoned_vectors.csv')}'")
```

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