

INTRODUCTION

Regions covered by glacial till and vegetation are always challenging areas for geological mapping. Enormous datasets and innovative methods and techniques are utilized to increase confidence and extract more information for geological maps and exploration purposes. This project aims to clarify and to add more value to lithological information and bedrock geology of the Targeting Resources through Exploration and Knowledge (TREK) project. A lithological map was developed from geochemical basal till data by creating a geological classification scheme from existing regional geochemical datasets. After evaluation and quality control of datasets, the uni-variant data were considered to best define the elements and analytical methods of value from the existing datasets. Bi-variant and tri-variant diagrams were used to display and interpret improved geological information about the area of study. Classic data methods were utilized to provide a better understanding of statistical characteristics of major oxides, trace and rare earth elements for specific geological units. To extract the lithological information, data-driven and knowledge-driven methods were applied to raster and vector data.





Figure 2 : Distribution map of basal till in AOI, subdivided based on attributed geology unit from database.

OVERVIEW OF DATASETS

The datasets are till analysis results from the TREK geochemistry project. Two till survey results were processed include:

• Geochemical and Mineralogical Data, TREK Project, Interior Plateau, British Columbia; Geoscience BC, Report 2014-10 (Jackaman and Sacco, 2014).

• Geochemical Reanalysis of Archived Till Samples, TREK Project, Interior Plateau, central BC (parts of NTS 093C, 093B, 093F & 093K); Geoscience BC, Report 2015-09 (Jackaman and Sacco, 2015).

A total of 677 new samples, 1456 archived samples plus quality control samples were analyzed using different methods for minor, trace and oxide of elements. The samples used in the process are basal till which can provide primary information related to local bedrock (Figure 2).

METHODOLOGY

The main goal of this study is to extract as much (* Proportion of variance accounted) information as possible from geochemical datasets to add confidence to lithological interpretations of bedrock beneath till.

The visualisation and data interpretation is divided to two major groups:

The statistics-based interpretation and visualisation of geochemical DBs

 The spatial-based comparison and interpretation of information based on DBs processing



geochemistry dataset, Geoscience BC, 2014-10

Application of Geochemical Datasets for Geological Mapping TREK Mapping Project, Central British Columbia

The following methods were applied on the datasets:

• Principal Component Analysis (PCA) . The results of extracted information from each PC corresponds to the objects of interest in the AOI. Contribution of the data as vector points or pixels in this multivariate method is the basis of extracting the similarity from the dataset. The contribution can be as a crisp number or a fuzzy membership based on the data characteristics.

Weighted Sum Integration Model (WSIM). The knowledge-based lithology lines were extracted and spatialy evaluated to make a final lithology map. Then the map was interpreted to determine possible rock types and add information to the attribute table.

The brief steps of the model are shown in Flowchart 1.

SUMMARY OF RESULTS AND DISCUSSION

Correlation matrix as the foundation of geochemical studies (Table 1) provides positive correlation for TiO2 – CaO – MgO – Fe2O3 – Cr2O3 and a strong correlation between SiO2 and K2O where both have considerable negative correlation with other major element oxides.

The transformation in PCA is shown by scores and PCs derived from the classified score-based PC layers. PCA was applied on the dataset, but on its own cannot produce predictions of specific geology units. It can produce a visual estimate layer of calculated values that is essential to determine different rock types. Fuzzy-weights approach was used to cover the blind spots of Boolean operators for geological dataset. The lithological units were extracted in GIS fundamental format to predict knowledge-based geological layer.

Correlation	SiO2_pct	Al2O3_pc t	Fe2O3_pct	MgO_pct	CaO_pct	Na2O_pct	K2O_pct	TiO2_pct	P2O5_pct	MnO_pct	Cr2O3_pct
SiO2_pct	1.0	-0.3847	-0.9297	-0.7896	-0.6923	0.003563	0.607	-0.7585	-0.4765	-0.3486	-0.5015
Al2O3_pct	-0.3847	1.0	0.1627	-0.02415	0.1374	-0.05074	0.1406	0.08349	-0.1045	-0.1698	-0.1193
Fe2O3_pct	-0.9297	0.1627	1.0	0.7986	0.654	0.05312	-0.6977	0.8365	0.5539	0.4269	0.5567
MgO_pct	-0.7896	-0.02415	0.7986	1.0	0.8021	0.2003	-0.7486	0.7228	0.426	0.4341	0.7726
CaO_pct	-0.6923	0.1374	0.654	0.8021	1.0	0.5436	-0.6155	0.8408	0.341	0.151	0.7104
Na2O_pct	0.003563	-0.05074	0.05312	0.2003	0.5436	1.0	-0.1026	0.4295	0.2194	-0.06707	0.2527
K2O_pct	0.607	0.1406	-0.6977	-0.7486	-0.6155	-0.1026	1.0	-0.6415	-0.1531	-0.2264	-0.7349
TiO2_pct	-0.7585	0.08349	0.8365	0.7228	0.8408	0.4295	-0.6415	1.0	0.5331	0.2243	0.6723
P2O5_pct	-0.4765	-0.1045	0.5539	0.426	0.341	0.2194	-0.1531	0.5331	1.0	0.514	0.1907
MnO_pct	-0.3486	-0.1698	0.4269	0.4341	0.151	-0.06707	-0.2264	0.2243	0.514	1.0	0.1451
Cr2O3_pct	-0.5015	-0.1193	0.5567	0.7726	0.7104	0.2527	-0.7349	0.6723	0.1907	0.1451	1.0

Table 1: Classical (Pearson's) correlation matrix values



Figure 4: Weighted- Raster layers using kriging approach

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Flowchart 2: Knowledge Driven/Supervised Weighted Sum Integration Model (WSIM), applied on Till geochemistry dataset, Geoscience BC, 2014-10 and 2015-09



Figure 3: Bi-variant diagrams, SiO2 vs. element oxides



Figure 5: Spatial distribution of 7 PCs based on minor and trace elements analytical results, eastern TREK area central BC., The element loadings on the PCs from the target dataset are weighted using fuzzy function

The method enables PCs to associate to geological classification using geologic factors controlling the components. The results are interpreted using rock geochemical characteristics loading on each PC and geological information of the area. Correlation of results were evaluated using bedrock geology information of the area. An example is the extracted units which have spatial distribution in the north and has correlation with the Eocene Quanchus Suite granodiorite. The geochemical combination of this unit most likely confirms the granodioritic rocks.



CONCLUSION

• Knowledge- based integration methods were applied to geoscience datasets to produce new scientific information that gives the possibility of advanced understanding of geological setting of the area.

- The method strongly gives the possibility of sub-unit separation in bedrock units.
- As the nature of geochemical datasets are more qualitative than quantitative, fuzzy approach gives the flexibility to determine the most appropriate lithology boundaries.
- Hybrid statistical methods and Geospatial information system (GIS) allows:
- to model and interpret the data using the parameters of the real world.
- to attribute a set of information relevant to the specified geology domain.

Cheng, Q., Bohnam Carter, G., Wang. W., Zhang, Sh., Li, W. and Qinglin X., (2011) A spatially weighted principal component analysis for multi-element geochemical data for mapping cations of felsic intrusions in the Gejiu mineral district of Yunnan, China, Computers and Geosciences, V. 37, P 662-669. Grunsky, E.C., (2007) Advances in Regional-Scale Geochemical Methods, The Interpretation of Regional Geochemical Survey Data, Geological Survey of Canada, Natural Resources Jackaman, W. and Sacco, D. (2014, 2015), Geochemical Datasets, TREK Project, Interior Plateau, British Columbia; Geoscience BC data.





Figure 6: Lithological layer using KFPCA (a) and Preliminary bedrock geology map (b) (Angen et. al., 2015) eastern TREK area. B: Basalt, BA: Basaltic andesite, A: Andesite, AB: Andesite basalt, D: Dacite, GD: Granodiorite, RD: Rhyodacite

Lithology polygons vector layer, extracted from raster layers using Weighted Sum Integration Model (WSIM) is shown in figure 7 and attributed by chemical analyses information for different rock types from felsic to basic.

Attribute table re-processed and classified for volcanic/ plutonic/ sedimentary/ metamorphic rocks using database information and the latest bedrock geology map of TREK area. To evaluate the results, rock samples are plotted on the lithology layer.

Figure 7: Lithological layer using WSIM, attributed by chemical analyses information for different rock types. B: Basalt, BA: Basaltic andesite, A: Andesite, DI: Diorite, D: Dacite, GD: Granodiorite, MDI: Monzodiorite, MG: Monzogranite RD: Rhyodacite, QDi: Quartz diorite, QM: Quartz monzonite, R: Rhyolite, Sed: Sedimentary rock, Meta: metamorphic rock

to connect the results to geological characteristics and get the most substantive results from the DBs.

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