Data-Driven Mineral Exploration and Geological Mapping in the North West Mineral Province

Data61 & CSIRO Mineral Resources

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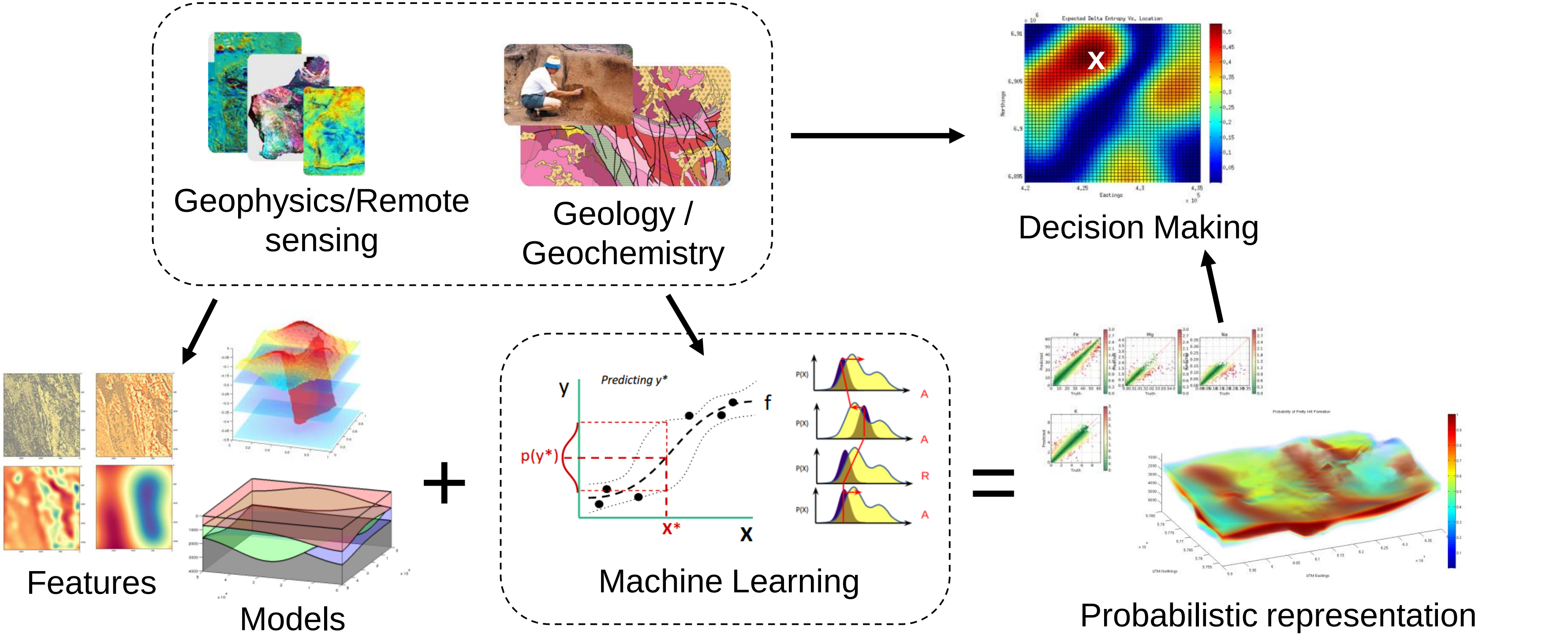
Machine learning for geoscience applications



Machine learning

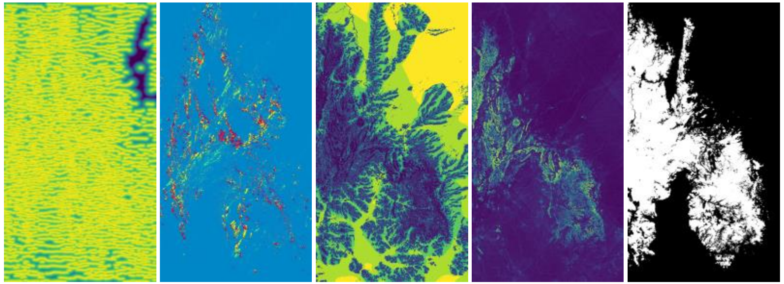
1. Data preparation
2. Feature extraction
3. Model selection
4. Train/test/validate
5. Prediction
6. Communication

- Gather, ingest, and clean data
- Data formats
- Missing data
- Detection limits
- Consistent units
- Measurement techniques
- Coordinate systems
- Consult experts

Machine learning

1. Data preparation
2. Feature extraction
3. Model selection
4. Train/test/validate
5. Prediction
6. Communication

- What secondary features or interpretations are relevant?
- Transforms (e.g. wavelets), textures, distances (e.g. to faults)
- Dimensionality reduction



Machine learning

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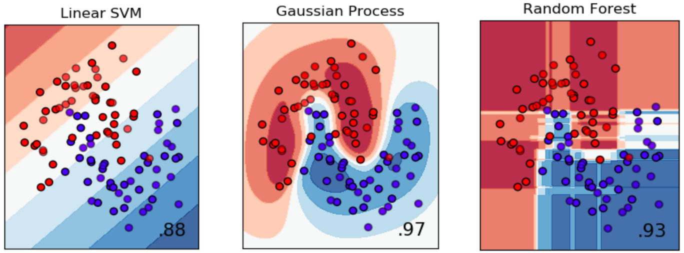
- Classification, regression, unsupervised?
- Model structure



- Probabilistic?
- Hyperparameters
- Iterate as part of validation

Machine learning

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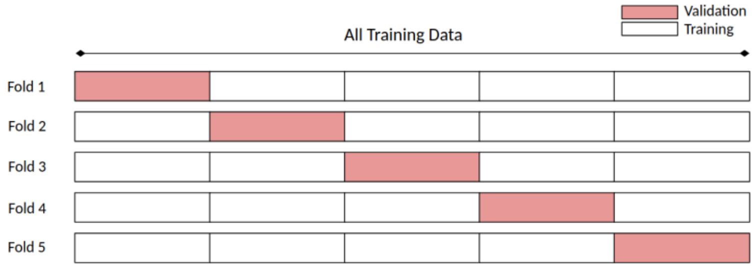
6. Communication

- Learn a generalisable model
- Split dataset into train and test/validation dataset



- Measure performance (e.g. MSE, R^2, precision, recall, f1, log loss)

Machine learning

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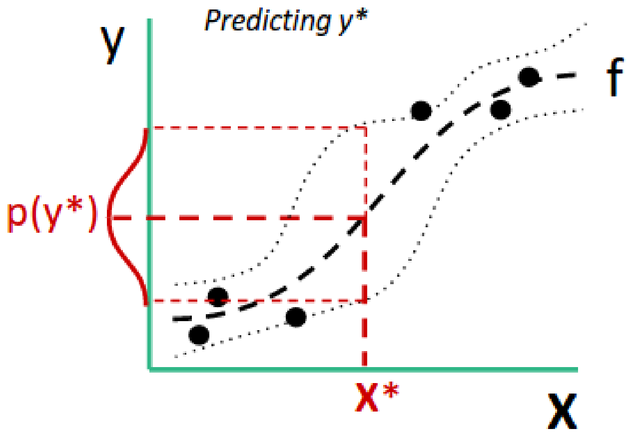
5. Prediction
6. Communication

- Process query data
- Run model on unseen data



- Covariate shift?

Machine learning

1. Data preparation
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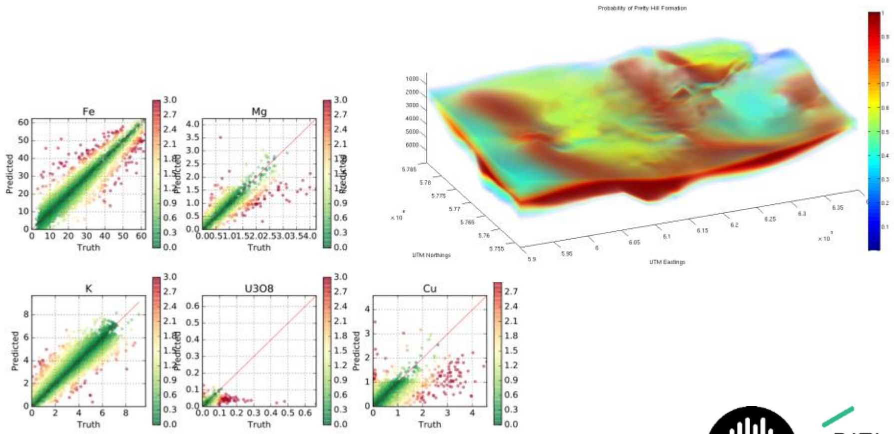
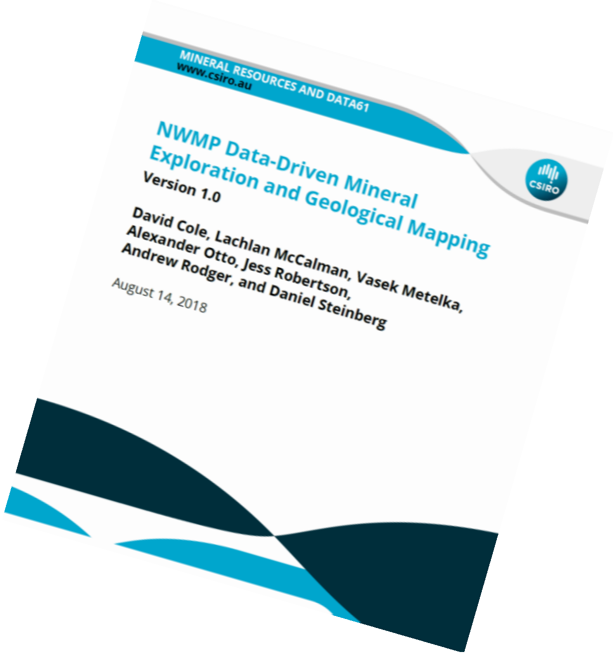
6. Communication

- Model assumptions and limitations
- Visualisation
- Interpretation/insights



Applications of data-driven modelling

1. Mineral occurrence mapping
2. Automated geological classification
3. Interpreted geology anomaly detection
4. Modelling geochemistry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NWMP Data-Driven Mineral Exploration and Geological Mapping

Version 1.0

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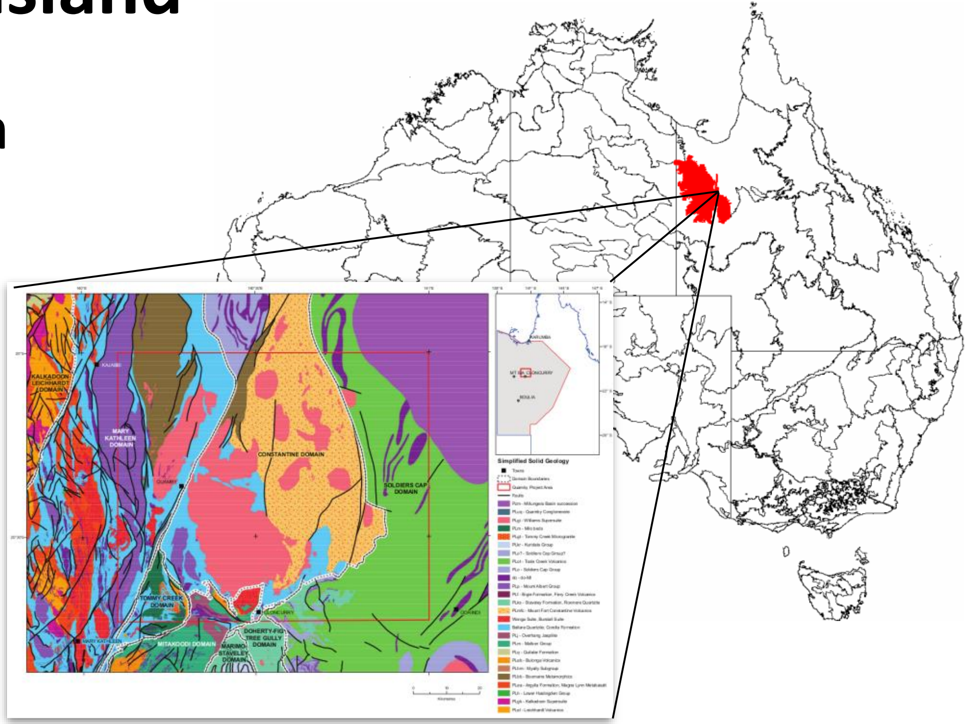
August 14, 2018

Mt Isa region of Queensland

- Existing mines and known mineral deposits
- E.g. Cu-Au, Ag-Pb-Zn, U

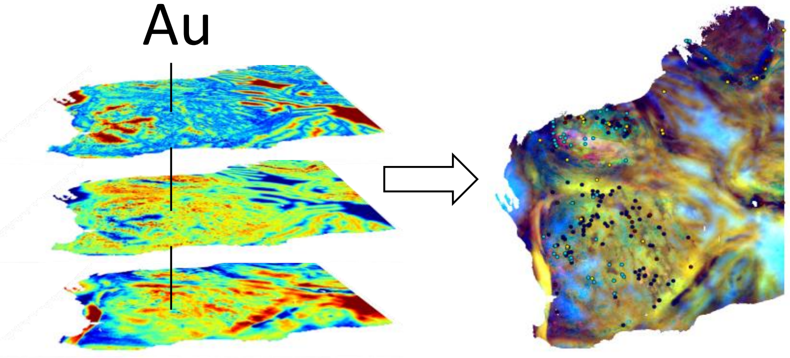
- Geochemical surveys
- Geophysics
- ASTER, DEM, etc.
- Interpreted geology



GREENWOOD, M.L. & DHNARAM, C.R., 2013: 3D mineral potential of the Quamby area. Queensland Minerals and Energy Review Series, Department of Natural Resources and Mines, Queensland.

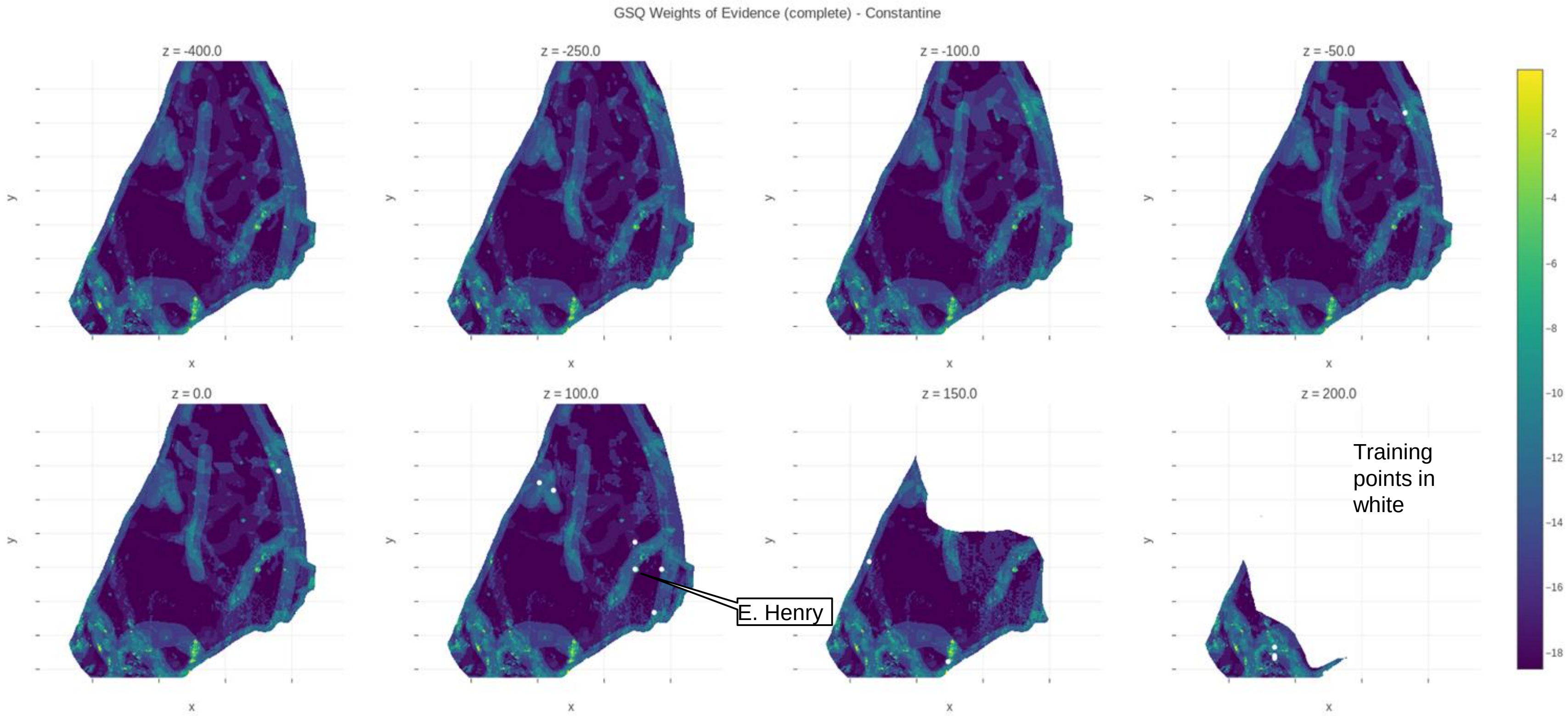
Mineral occurrence mapping

- Generate a map of mineral "prospectivity" using:
  - Geospatial feature data
  - Known deposit locations

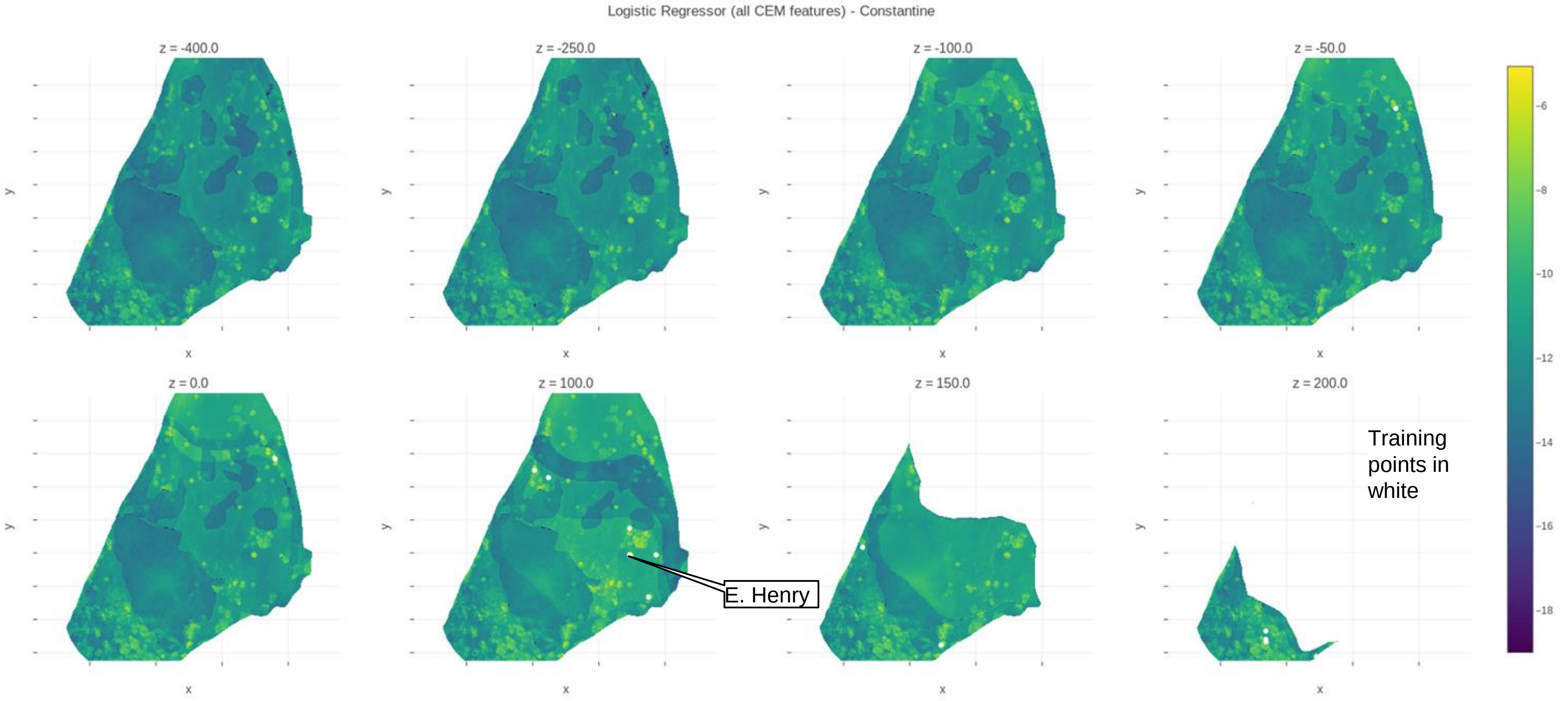


- *Weights of Evidence* vs *Machine learning*
  - Comparison with classic ML approach shows ML has less constraints, better cross-validation performance
  - Difficult problem - small and biased training data set

Mineral occurrence mapping



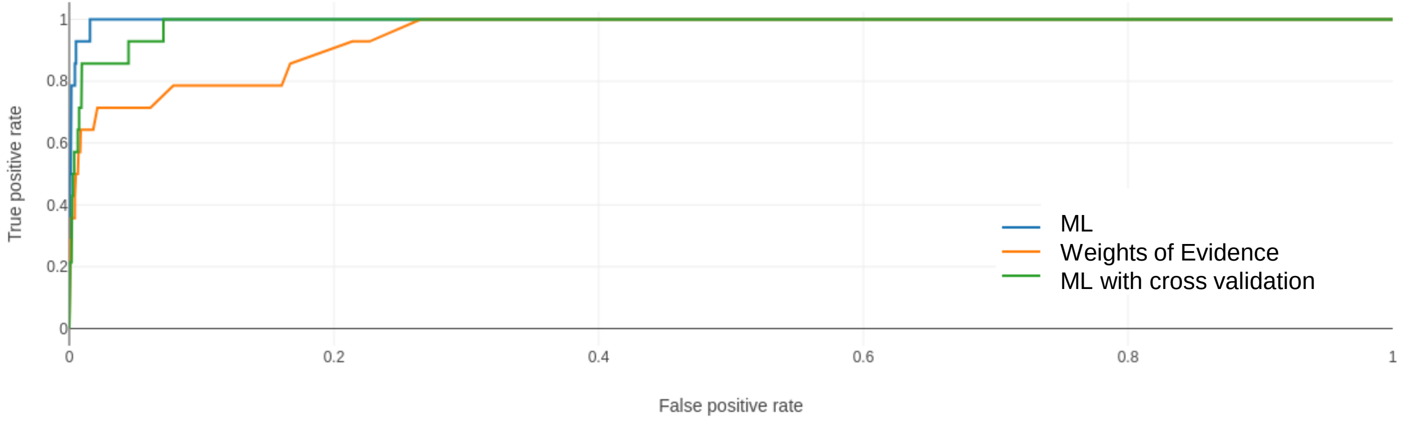
Mineral occurrence mapping



Mineral occurrence mapping

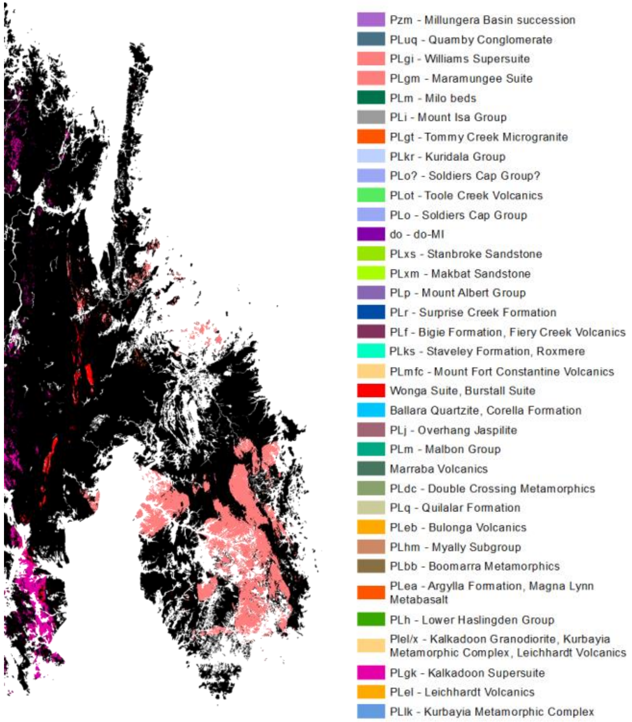
- Classifier performance
  - Log loss
  - ROC curve

classifier	log loss
logistic regressor (with CV)	0.000039
weights of evidence	0.000337

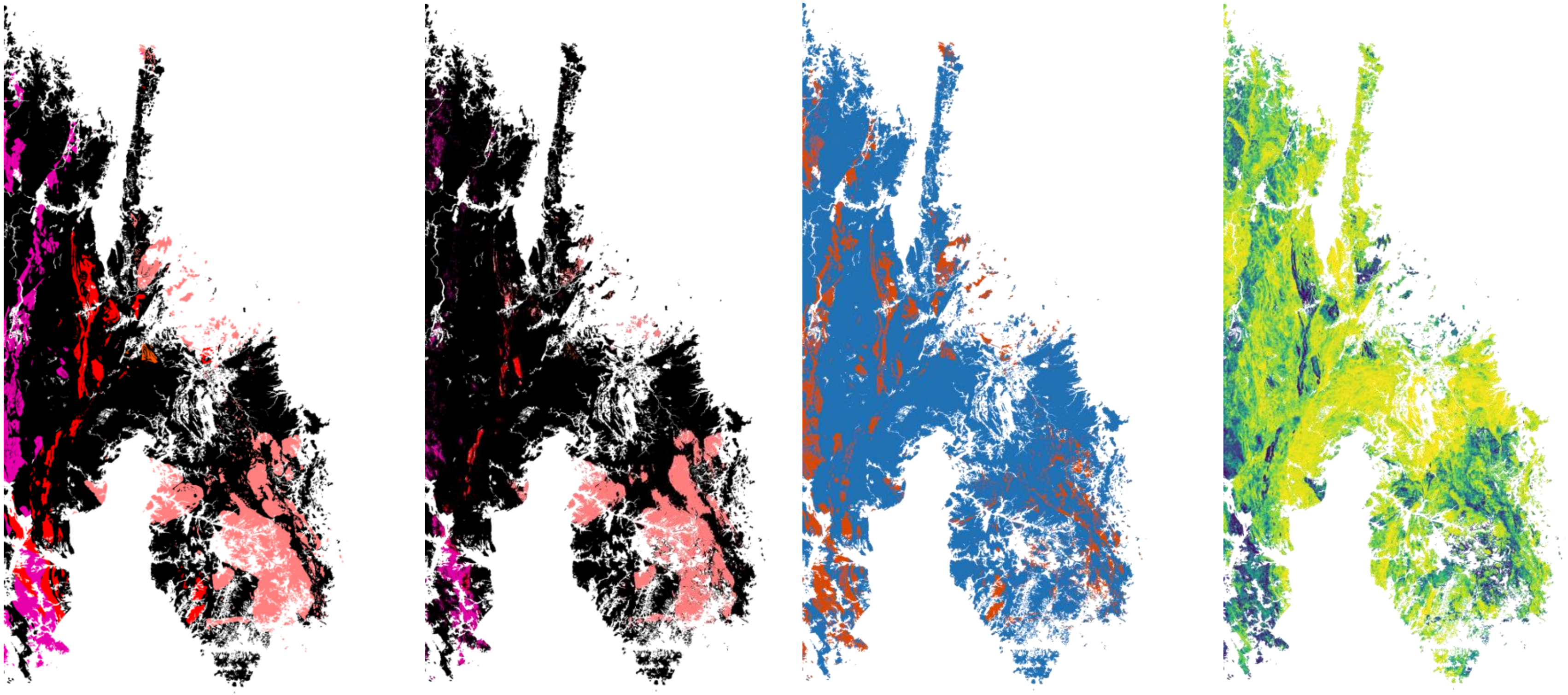


Classification of outcropping granite

- 6000 surface observations
  - 6 classes (5 granites + None)
- Surface + geophysical covariates
  - ASTER, DEM, MrVBF, Gamma, Gravity, Magnetics
- Random forest classifier



Classification of outcropping granite



Interpreted geology | Model prediction | Difference | Model probability

Classification of outcropping granite

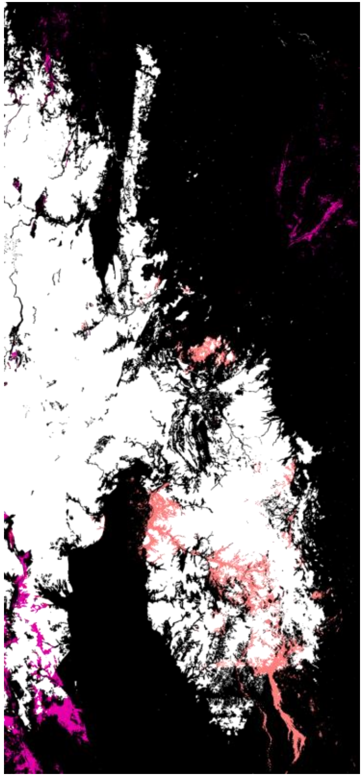
- Comparison to interpreted geology

label	precision	recall	f1-score	% of data points
None	0.86	0.98	0.92	76.6
PLgk – Kalkadoon Supersuite	0.69	0.21	0.32	6.9
PLgm – Maramungee Suite	1	0	0	0.2
PLgt – Tommy Creek Microgranite	0.91	0.08	0.14	0.1
Plgi – Williams Supersuite	0.86	0.74	0.8	11.5
PLgw – Wonga Suite, Burstal Suite	0.86	0.1	0.18	4.7

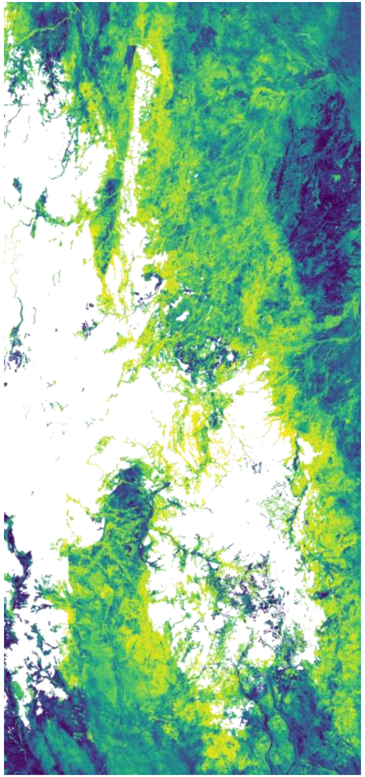
Classification of outcropping granite

- Predicting outcrops outside interpreted geology model

Interpreted geology



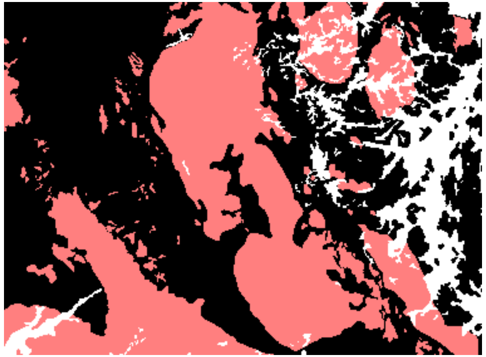
Model prediction



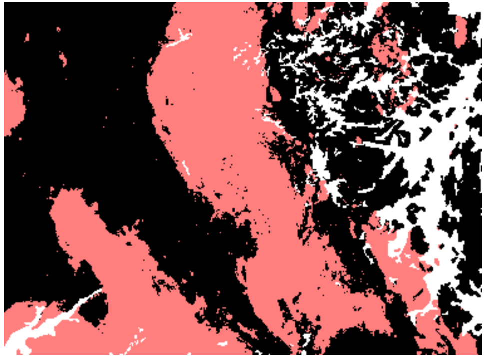
Model probability

Classification of outcropping granite

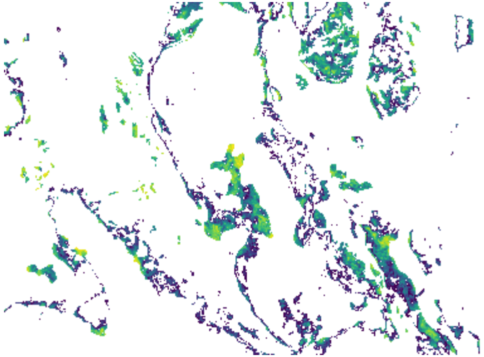
- Identify areas of disagreement with interpreted geology



Interpreted geology



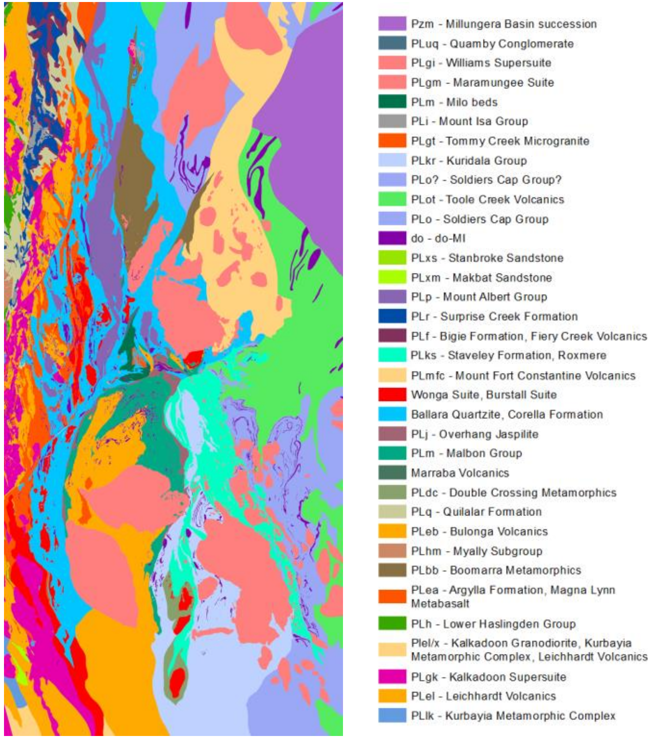
Model prediction



Model probability

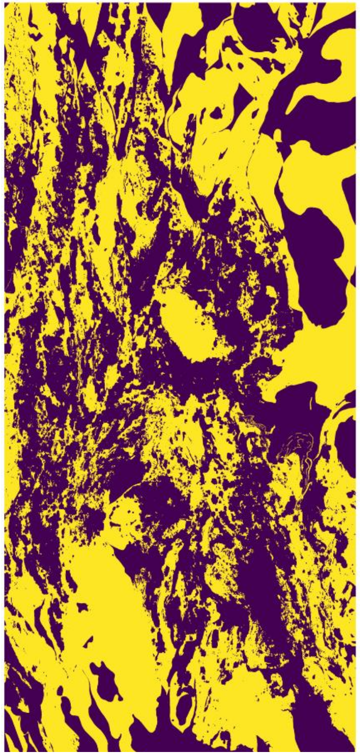
Anomaly detection of interpreted geology

- Interpreted geological mapping is an involved manual process
- Can we “audit” this by finding areas of potential disagreement
- Utilise anomaly detection algorithms such as ‘*One Class SVM*’
- Per-class model using geophysical datasets

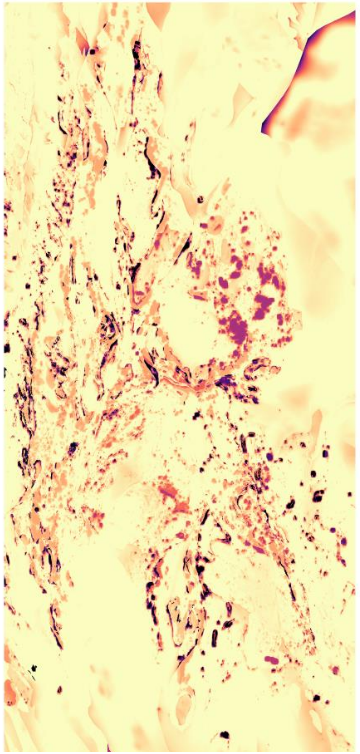


Anomaly detection of interpreted geology

- up to 50% anomalous (nu = 0.5)
- Anomalies (purple)
- Distance to hyperplane
- Mean anomalous distance per class



Anomalies



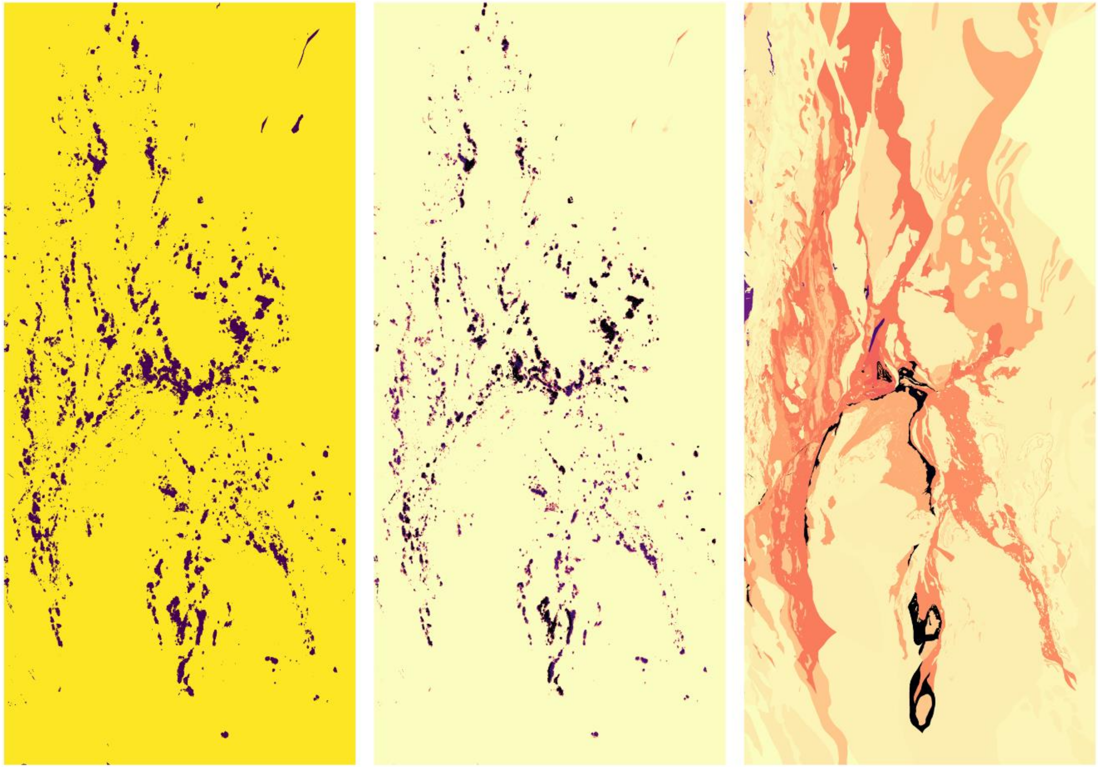
Anomalous distance

Mean anomalous distance

Anomaly detection of interpreted geology

- 5% anomalous

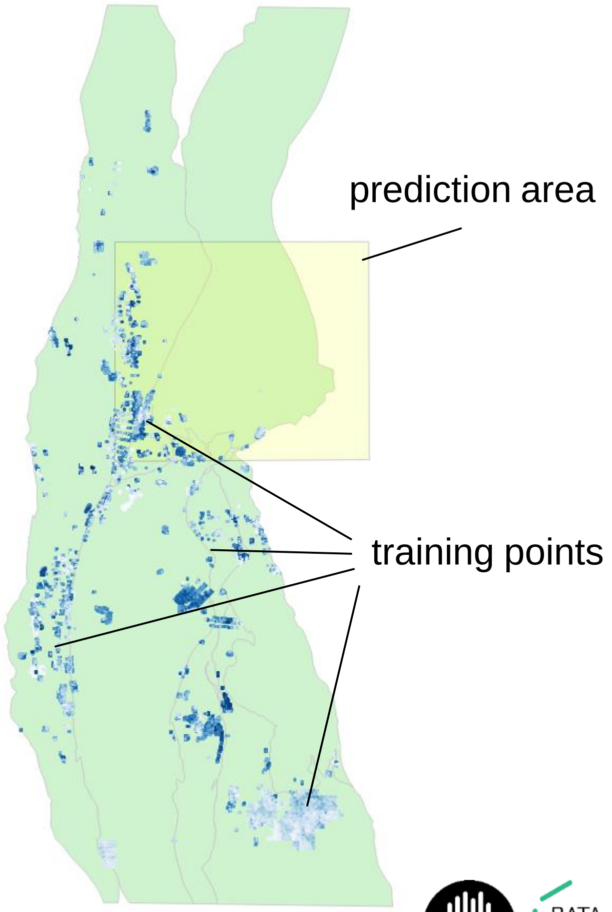
- Anomalies (purple)
- Distance to hyperplane
- Mean anomalous distance per class



Anomalies　Anomalous distance　Mean anomalous distance

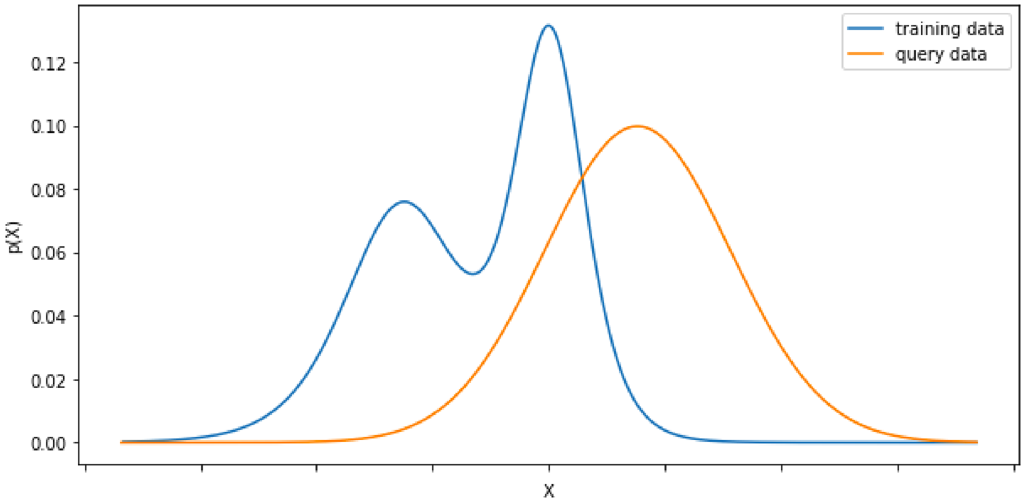
Modelling of geochemistry

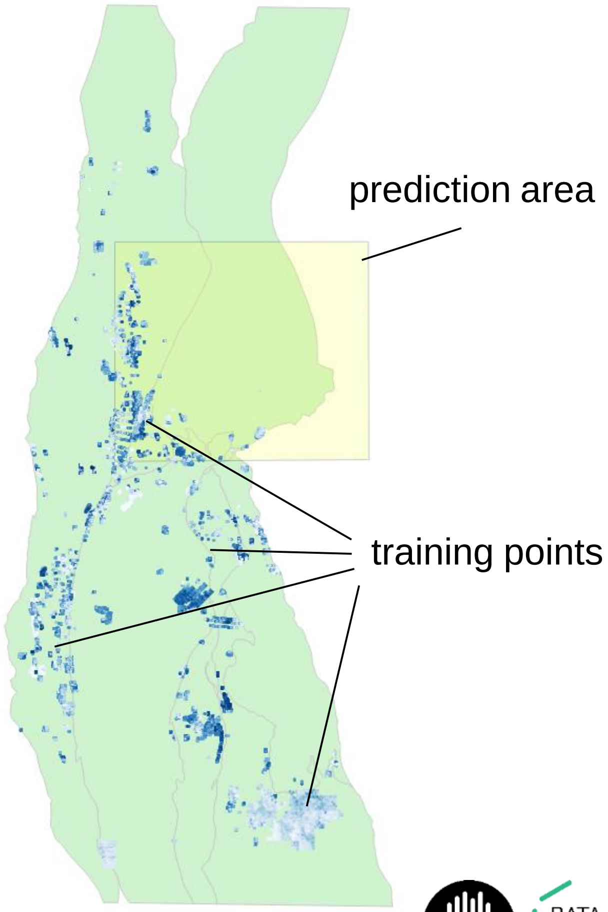
- Spatial model of soil geochemistry
- Covariates: geophysics
- Targets: chemical concentrations
- Training data: survey samples from out-cropping areas
- Model
  - Random forest regressor
  - Classifier to model covariate shift



Covariate shift

- Training data different from query data
- Biased sampling (e.g. fixed area, outcropping, known/expected properties)
- Train a classifier to distinguish between them





Modelling of geochemistry

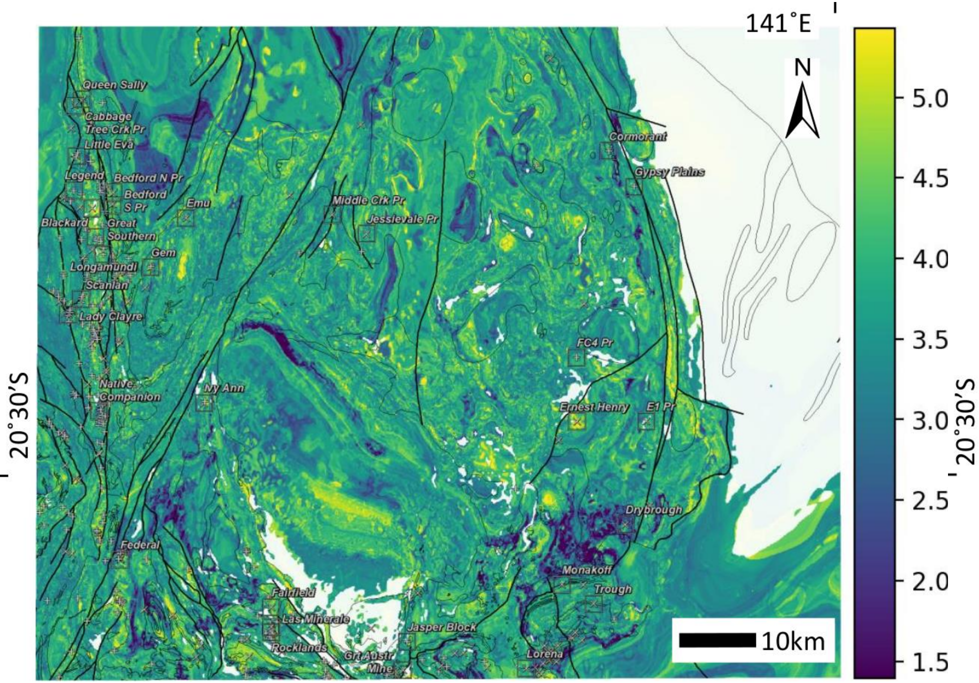
- Cross-validation results

Element	R^2 score (magnetics and gravity)	R^2 score (magnetics and gravity + wavelets)
Au	0.44	0.51
Cu	0.65	0.72
Pb	0.69	0.79
Zn	0.61	0.68

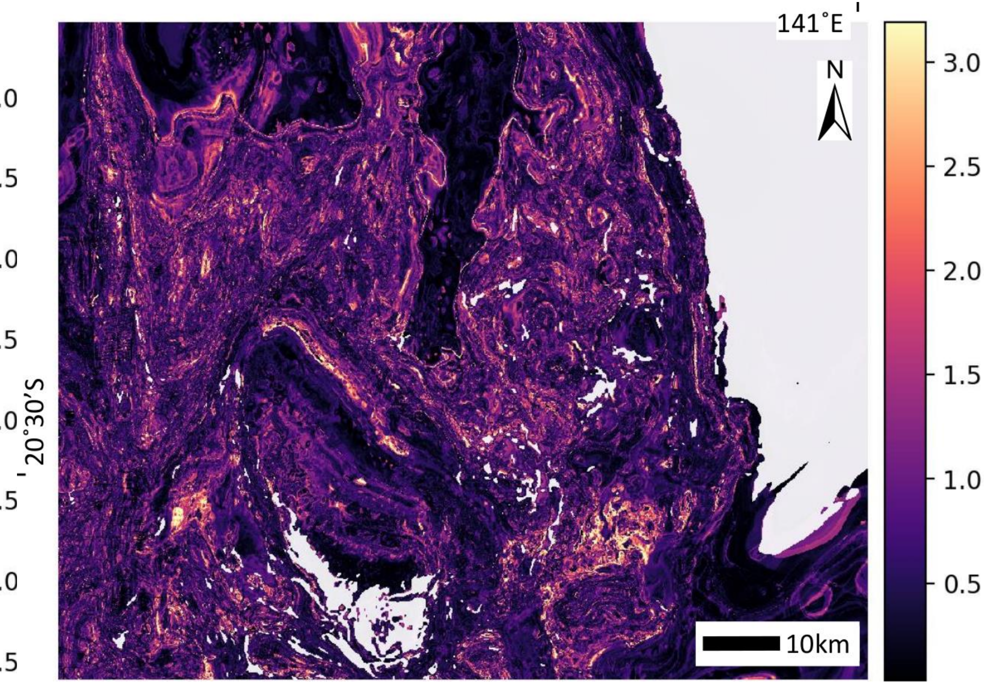
Covariate shift classifier accuracy	55%	95%

Modelling of geochemistry

- log(Cu) prediction - gravity and magnetics



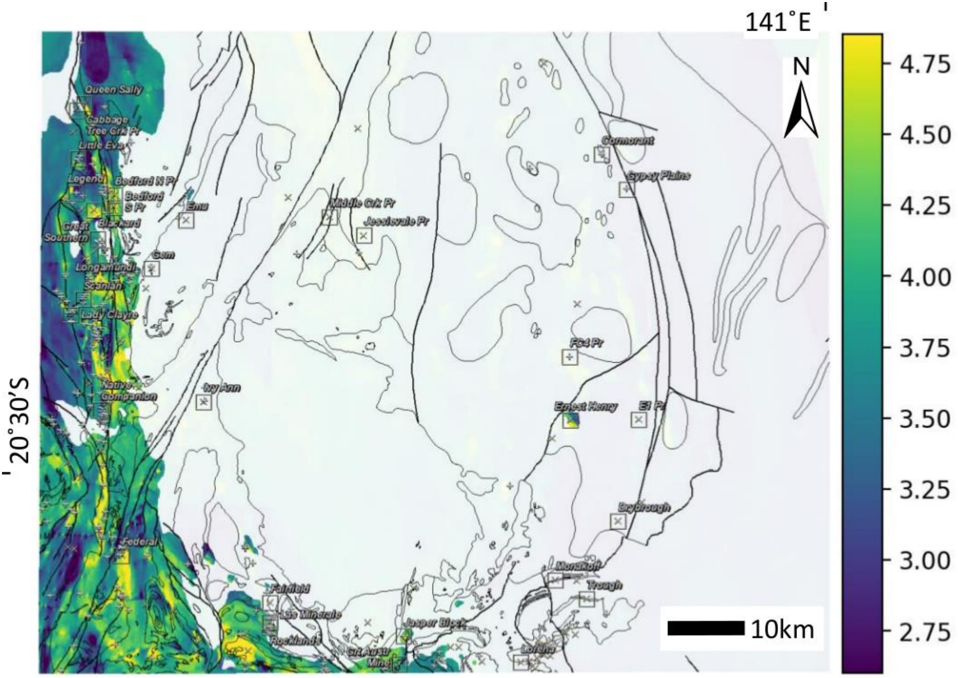
Model prediction



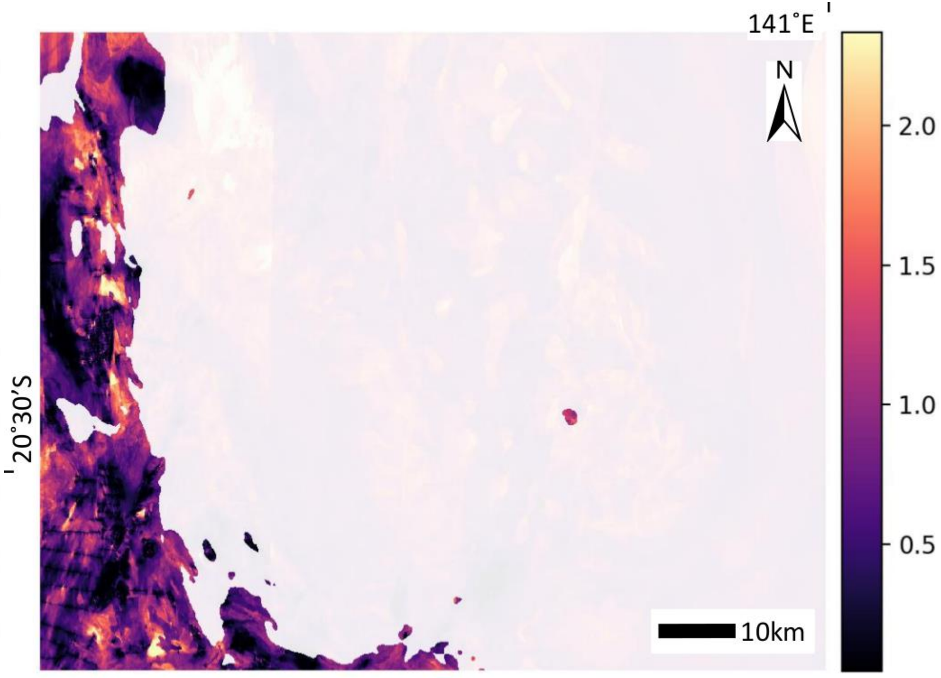
Model uncertainty

Modelling of geochemistry

- log(Cu) prediction - gravity and magnetics + wavelets



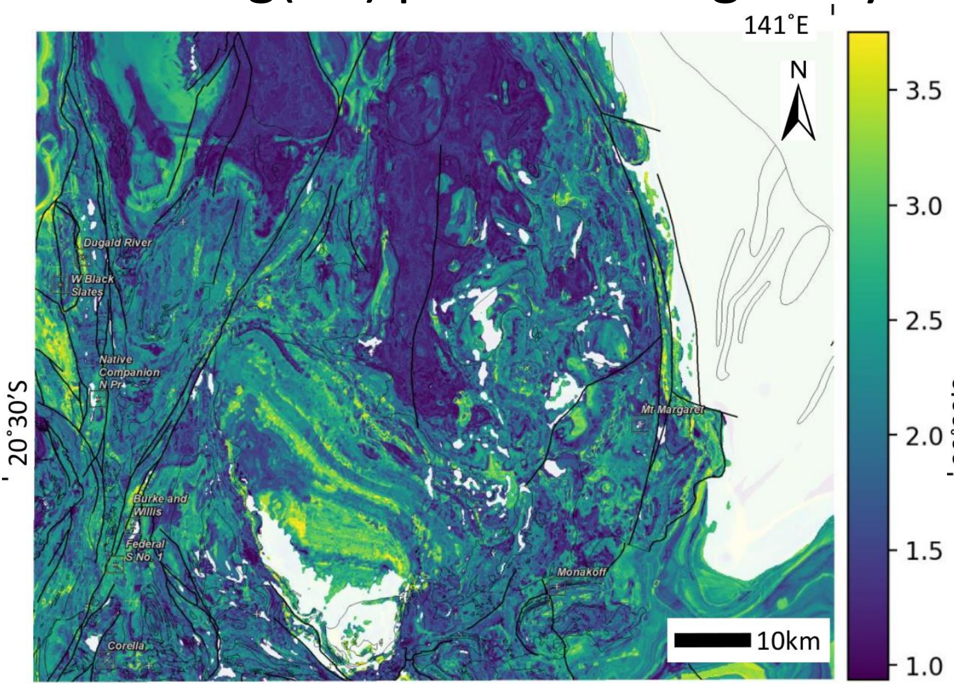
Model prediction



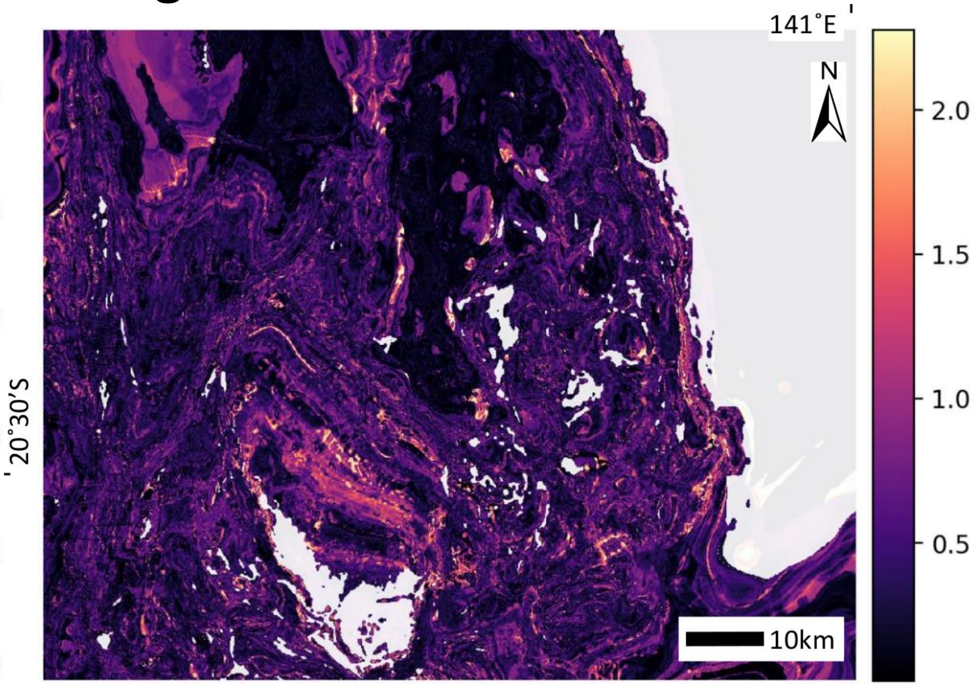
Model uncertainty

Geochemical modelling

- log(Pb) prediction - gravity and magnetics



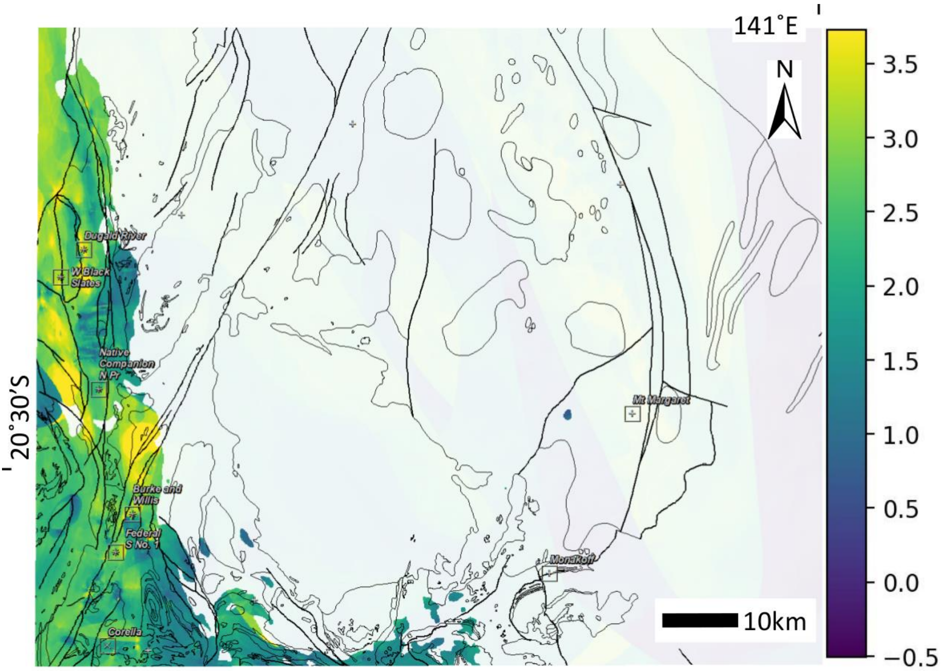
Model prediction



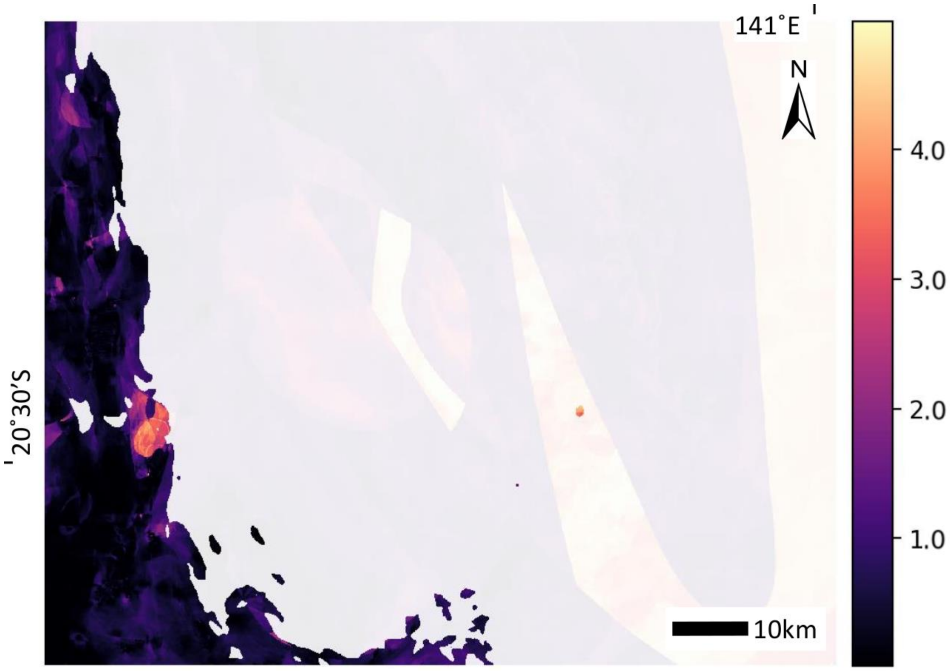
Model uncertainty

Modelling of geochemistry

- log(Pb) prediction - gravity and magnetics + wavelets



Model prediction



Model uncertainty

Conclusions & Recommendations

- Machine learning approaches in geological mapping and exploration targeting:
  - Augment existing mapping processes (e.g. geology classification, anomaly detection, outcrop prediction)
  - Provide geospatial predictions from point observations (e.g. geochemistry - better gridding/can serve as alternative to prospectivity mapping)
  - Maximise data use while estimating uncertainty in prediction
- Considerations for GSQ data practises:
  - Validate data-driven models with new/unseen data
  - Collect new datasets (based on model predictions / uncertainty)
  - Awareness of sampling bias (e.g. negative samples, unexplored regions)
  - Data management / integration to support data-driven modelling

THANK YOU

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