Critical minerals – prospectivity mapping using generative AI

Presented by

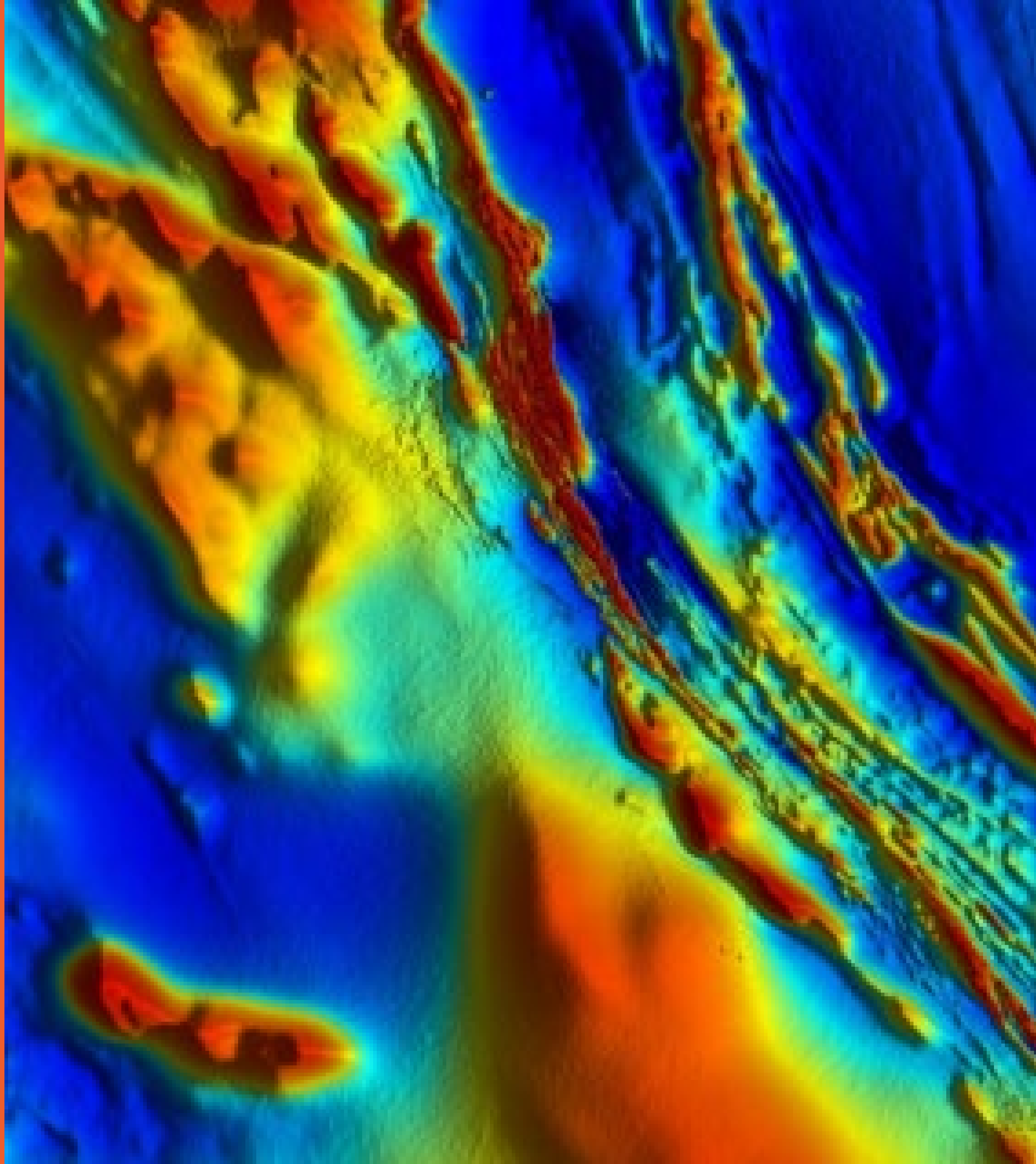
Dietmar Müller

The University of Sydney, School of Geosciences

THE UNIVERSITY OF SYDNEY

EarthBYTE

Building a Virtual Earth



EarthByte Group

- Geology and Geophysics Research Group at the University of Sydney
- established in 2002
- www.earthbyte.org
- Philosophy: Build an e-research community through shared open software and digital data
- Current focus on critical mineral exploration, e.g. copper, nickel, cobalt, REEs

Ehsan Farahbakhsh

Vera Nolte-Wilson

Nathan Wake

Critical minerals/metals

- Essential in a range of strategic sectors – renewable energy, modern technologies, …
- Strategic investment at federal and state level

Australian Mining

Powering the future of transportation

HOME | LATEST NEWS | ALL TOPICS | RESOURCES | EVENTS | CRITICAL MINERAL

Funding, News

NSW Mining enjoys spending boom

ALEXANDRA EASTWOOD
February 16, 2024, 8:30 am

Mining companies injected a record amount of $23.6 billion into the NSW economy in FY23, +41%

FINANCIAL REVIEW

Sophie was going to be a singer, instead she's digging up rocks

Students like Sophie Allen are choosing degrees based on the contribution they can make to slowing global warming.

Julie Hare
Education editor
Sep 15, 2023 – 12.49pm

Save | Share | Gift this article

Listen to this article
9 min

Sophie Allen's first great love – her first career choice – was always going to be music. But underwhelmed by her undergraduate study, she made an about-turn and enrolled in science.

It was when she took geology as an elective subject that her future suddenly took shape. She would play a role in addressing climate change in precisely the field that has been shunned by many of her generation because of its association with fossil fuels.

Earth Systems Research Project GEOL3888: using machine learning to prospect for minerals in the Lachlan fold belt

Cost of living crisis is unearthing more women who want to work in the mining industry

ABC Capricornia / By Scout Wallen
Posted Mon 22 Apr 2024 at 6:44am

ABC NEWS

Dietmar Müller • You
Professor of Geophysics at University of Sydney
6mo

The last day of class today in GEOL3888, the Earth Systems Research Project unit in the School of Geosciences University of Sydney! We used machine learning to prospect for copper, gold and lead mineral deposits in th ...see more

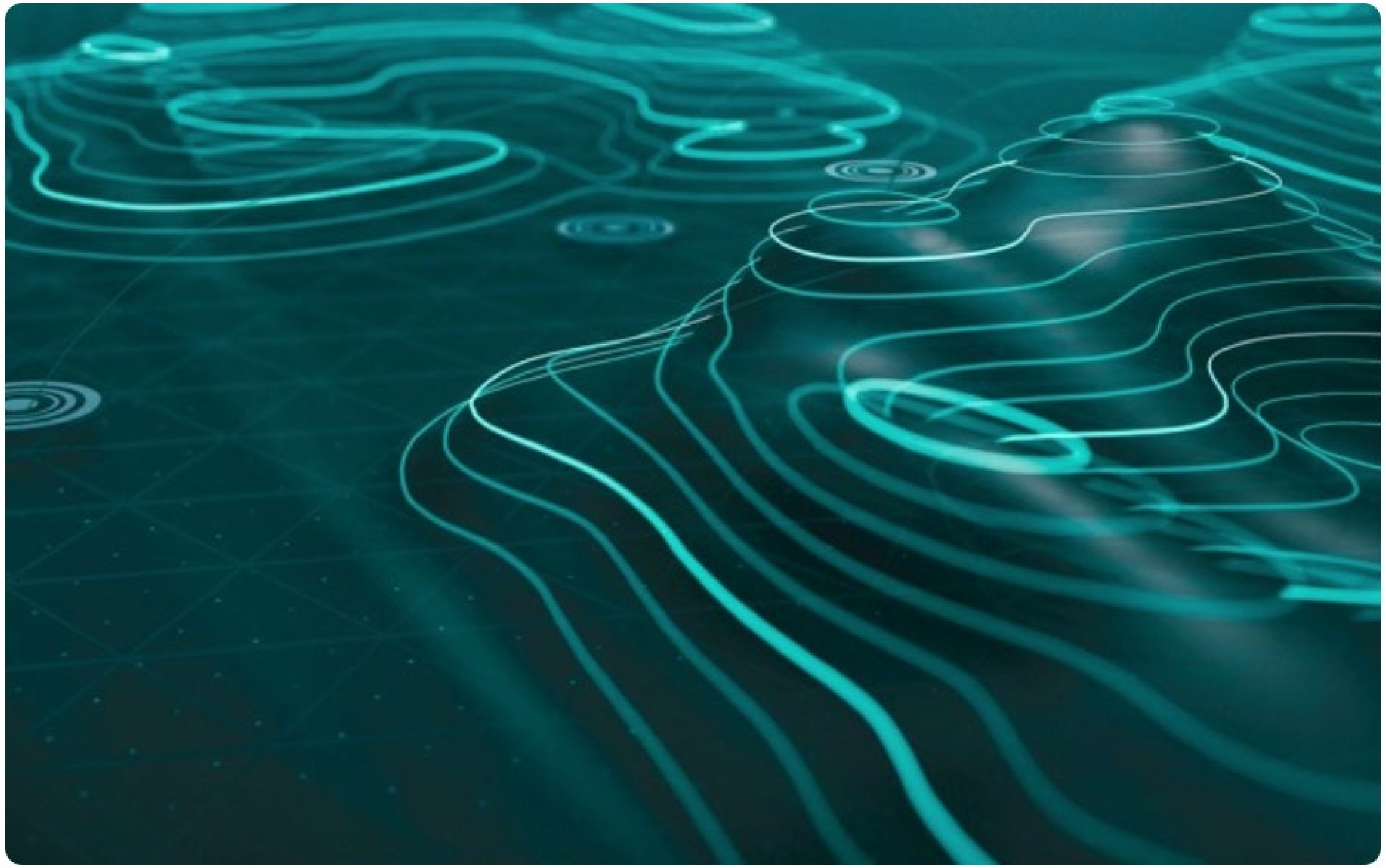
Why machine learning and AI in exploration?

SMALL CAPS

Hot Topics

AI and machine learning helping miners find new resources

By Colin Hay - June 1, 2023



Eos

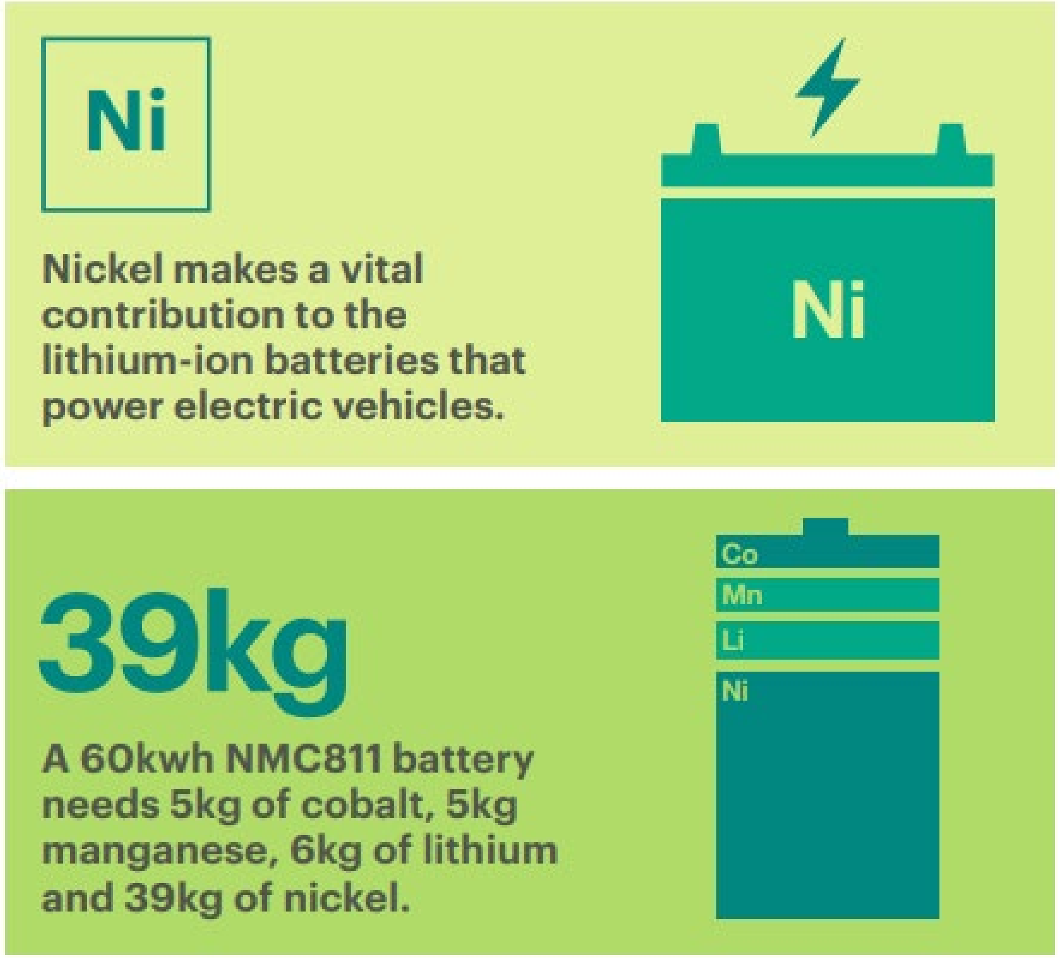
ABOUT SECTIONS TOPICS PROJECTS NEWSLETTER SUBMIT TO *EOS*

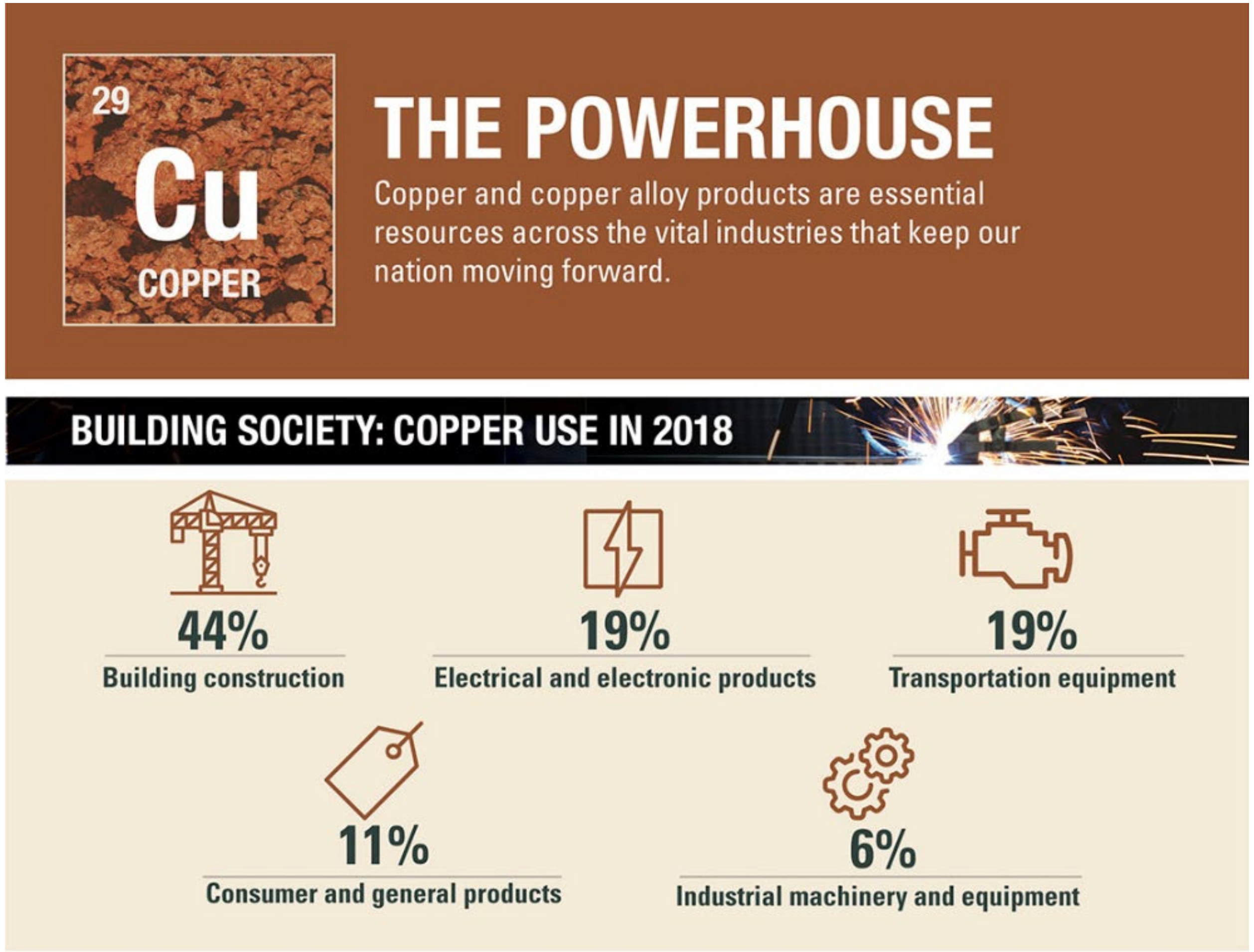
Machine Learning Could Revolutionize Mineral Exploration

Using a global data set of zircon trace elements, new research demonstrates the power of machine learning algorithms to accurately identify and locate porphyry copper deposits.

By Aaron Sidder 26 August 2022

Today’s focus: Nickel, cobalt and copper



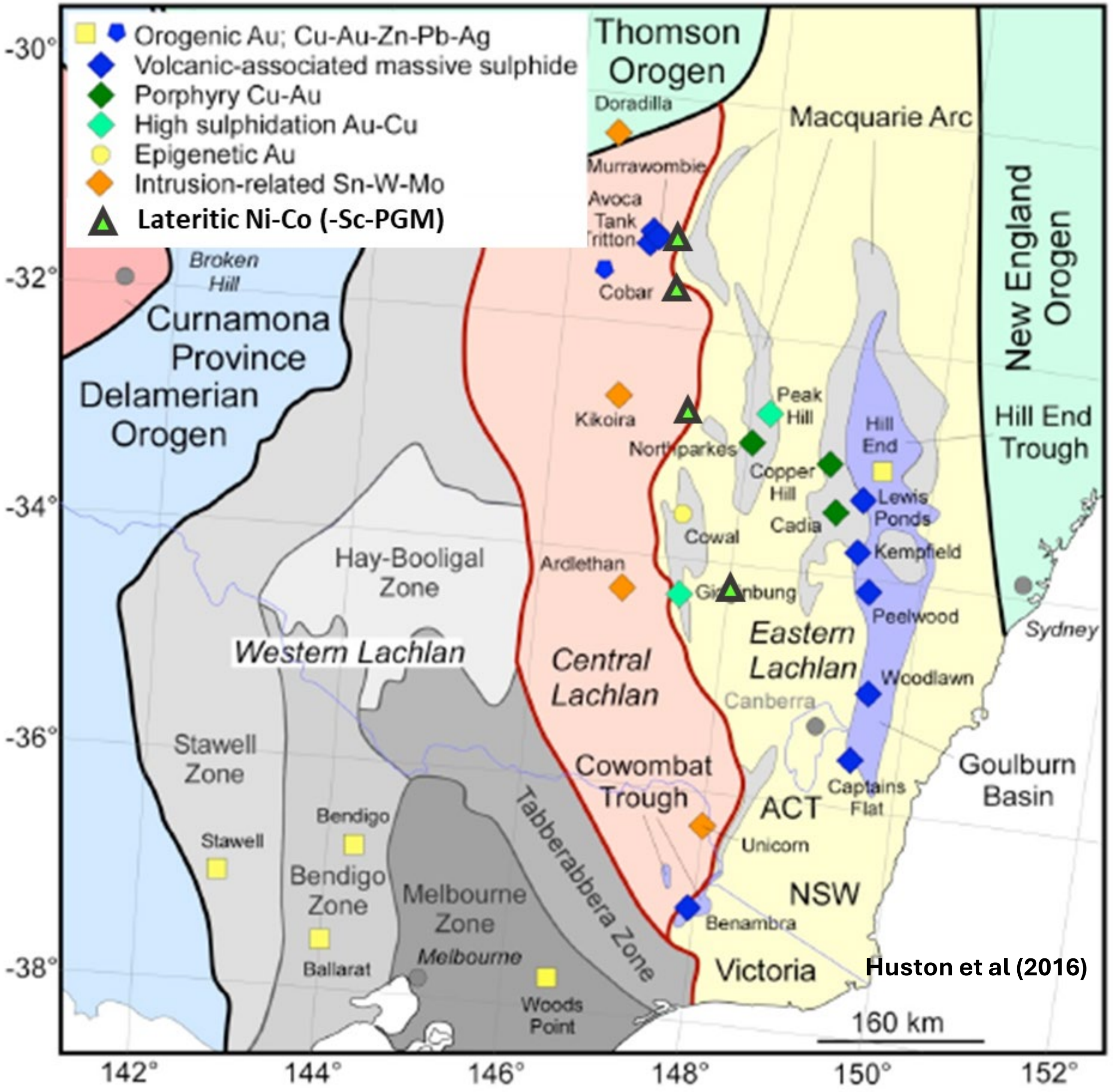


- **Ni and Co** – steel manufacture, specialty alloys, aviation, aerospace & chemical industries
- **Cu** – power generation, transport, …

Lachlan Orogen exploration potential

- **Rich metallogenic endowment** from discrete orogenic-magmatic events along active margin
- Lateritic **Ni-Co** deposits
- - Mafic-ultramafic source rocks
  - Serpentinised ophiolites (Camb-Ord)
  - Mafic-ultramafic intrusions (Ord-Sil)
- - Supergene enrichment Ni-Co
  - Cenozoic deep lateritic weathering
- Diverse range of **Cu**-rich deposits

- NSW remains underexplored
- Multi-dimensional datasets can be analysed using machine-learning to advance exploration



Lachlan Orogen Metallogenic Diversity

Lateritic Ni-Co Minerals System

- **Source**: Geodynamic setting and associated magmas and fluids required to extract ore components (melts or fluids) from mantle and/or crustal sources
- **Transport**: Lithospheric structural architecture that provides pathways for fertile magmas and fluids, transferring ore components from source to trap
- **Trap/Deposition**: Lateritisation concentrates ore components in the host rocks and/or structures
- **Preservation**: Low relief and tectonic stability best to preserve the ore components

	Ni	Co
Ferricrete	<0.6%	<0.1%
"Limonite"	0.8-1.5%	0.1-0.2%
Saprolite	1.5-3%	0.02-0.1%
Saprock		
Bedrock	0.3%	0.01%

- Different parts of the system can be mapped via specific combinations of geological and geophysical features

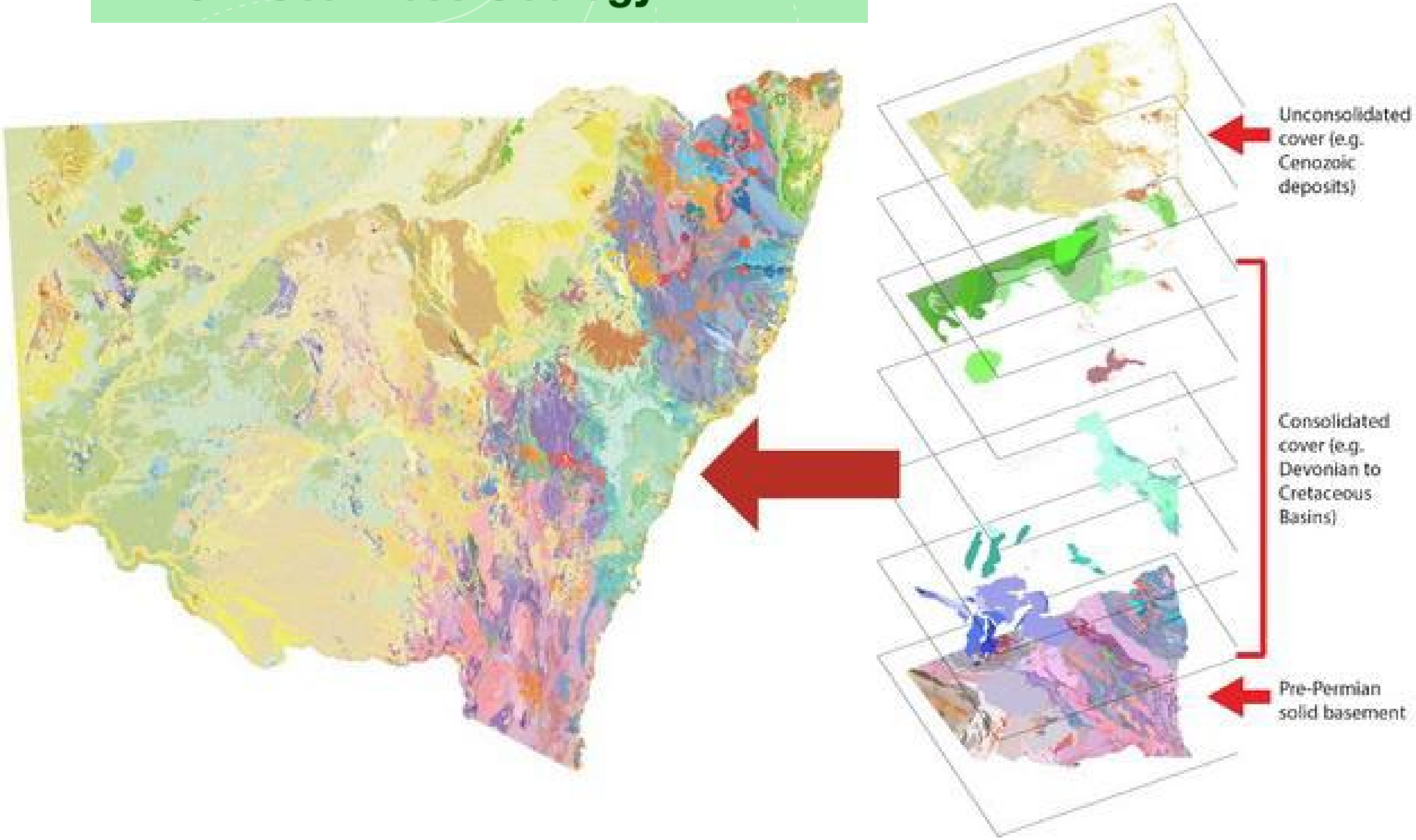
Landscapes of Ni-Co deposits

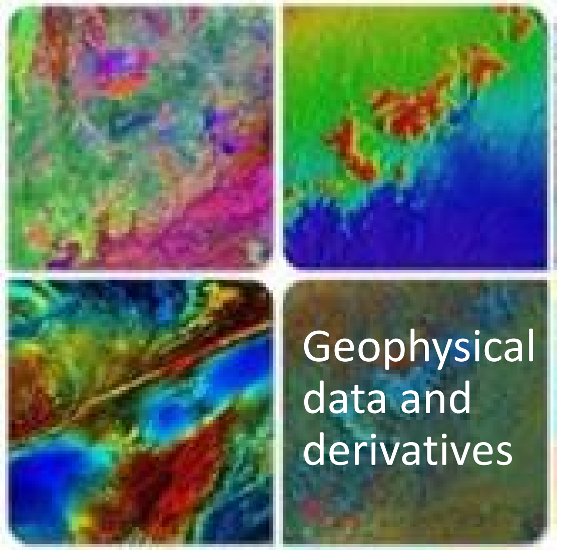
Thuddungra (Nico Young) lateritic Ni-Co (Jervois, 2018)

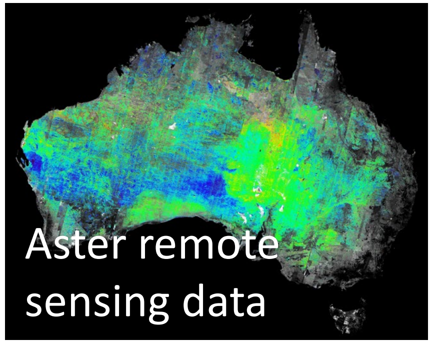
Syerston (Owendale) lateritic Ni-Co (CleanTeq, 2017)

Nyngan (West Lynn) lateritic Ni-Co (Alchemy, 2017)

Data: Known ore deposit sites, geology, geophysics





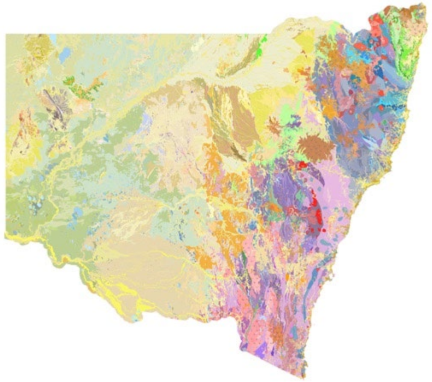


- 300 features derived from combined data,
- grids at 0.01° resolution (~1 km)

Data Layers and Features

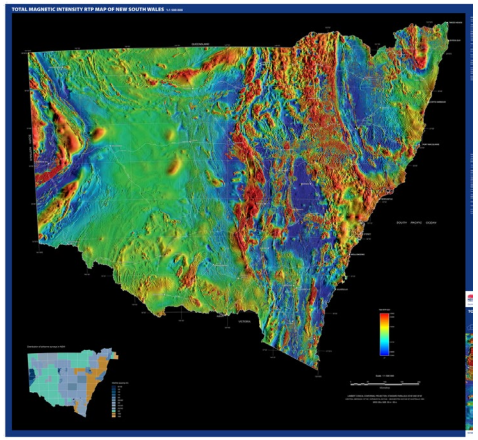
20 Geological Layers → 34 Features

- Geological boundaries
- Metamorphic facies and isograds
- Faults
- Intrusions
- Rock units



72 Geophysical Layers → 288 Features

- Magnetic
- Gravity
- Radiometric
- Remote sensing



Data: a more detailed look

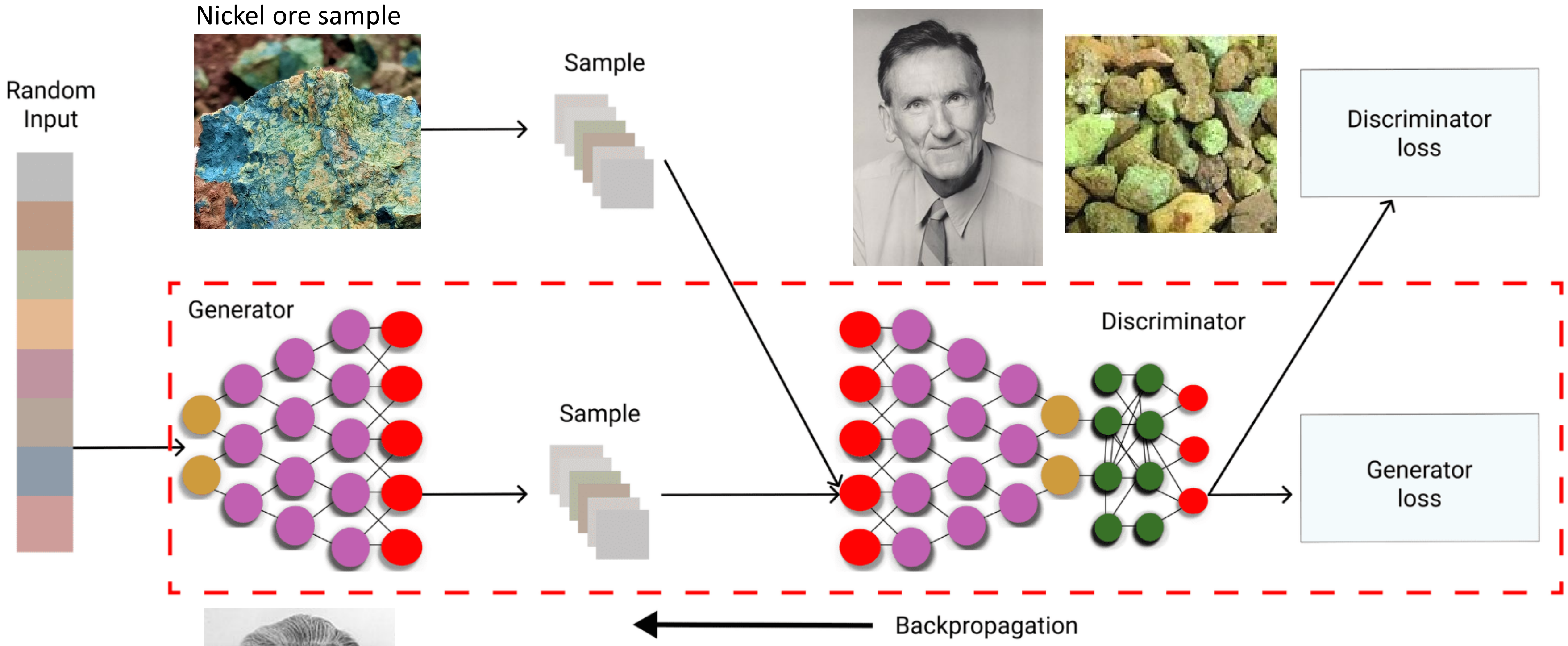
District	No. of Occurrences	Major Resources	Source rocks
Thuddungra	**8**	**Yes**	**Ophiolite**
Syerston	**5**	**Yes**	**Mafic-ultramafic Intrusion**
Homeville	**2**	**Yes**	**Mafic-ultramafic Intrusion**
Nyngan	**3**	**Yes**	**Mafic-ultramafic Intrusion**
Bungonia	**16**	**No**	**Unknown**

- Lateritic Ni-Co clusters listed from south to north
- Bungonia – exotic Co occurrences (source rock unknown)
- Examples of major resources:
  - Nico Young (Thuddungra) – 53.6 Mt @ 0.66% Ni & 0.05% Co
  - Sunrise (Syerston) – 160 Mt @ 0.56% Ni & 0.09% Co
  - Collerina (Homeville) – 17.9 Mt @ 0.89% Ni & 0.06% Co

Data Type	Data Layers
Geological	Rock units Faults Unconformities Metamorphic facies
Magnetics	RTP transformation + various filters
Gravity	Bouguer anomaly, derivatives
Radiometrics	K, Th, U Ratios
Remote sensing	ASTER multispectral
Terrain	DEM

Machine-learning: training

Problem 1: Shortage of training data (< 30 with > 300 features)! GAN to the rescue.



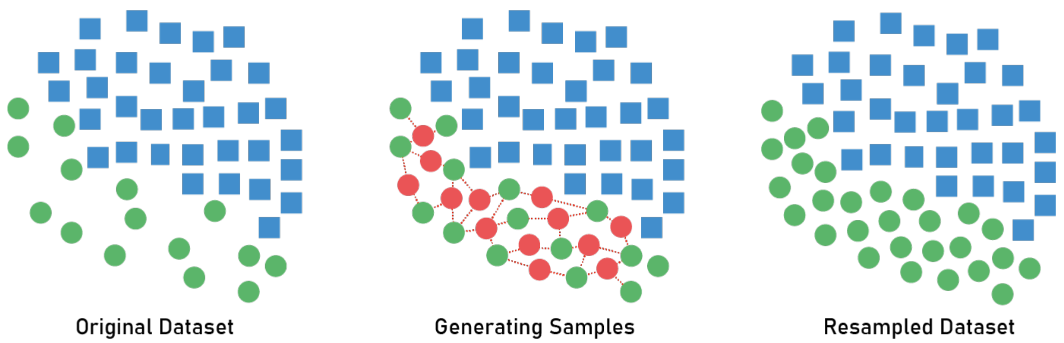
Modified from datenwissen.com

A generative adversarial network (GAN) is a deep learning architecture.
It trains two neural networks to compete against each other to generate new data from a given training dataset

Improved GAN: SMOTE-GAN

- **Synthetic Minority Oversampling Technique**
- Interpolates between the "minority class" nearest neighbours to suggest new training samples.
- Our minority class are known ore deposits
- SMOTE-GAN plays a 'game' between generator and discriminator to find realistic ore deposit samples

Synthetic Minority Oversampling Technique



Sharma et al. (2022)

Other SMOTE-GAN applications:

Financial fraud detection

Healthcare product development

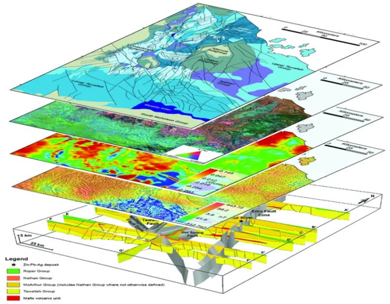
Insurance risk assessment

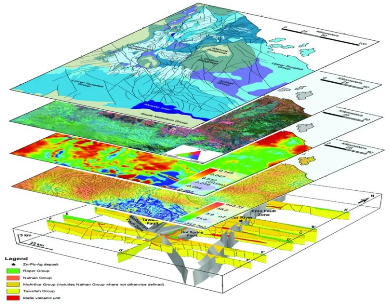
Marketing

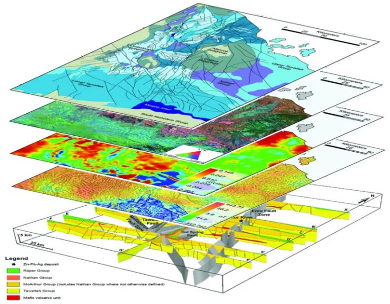
Problem 2: We don’t have a database of non-deposits (negative examples)

Positive examples (ore deposits)

Particular features



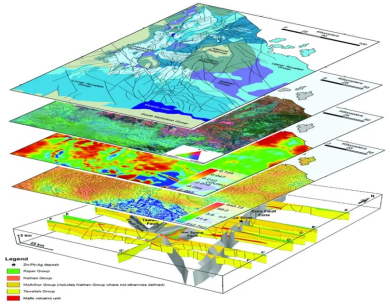




Blaikie and Kunzmann (2020)

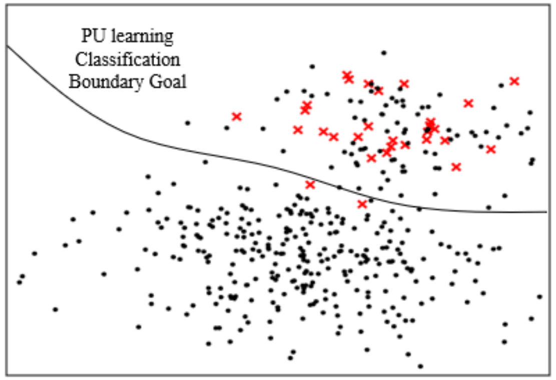
Unlabelled examples

Wide range of features



Positive and Unlabelled Bagging

- **Positive and unlabelled learning** is a semi-supervised binary classification approach that **recovers labels from unknown samples** by learning from positive samples and relabelling unknown samples
- The method is applied after SMOTE-GAN to separate unknown samples into positive and negative samples



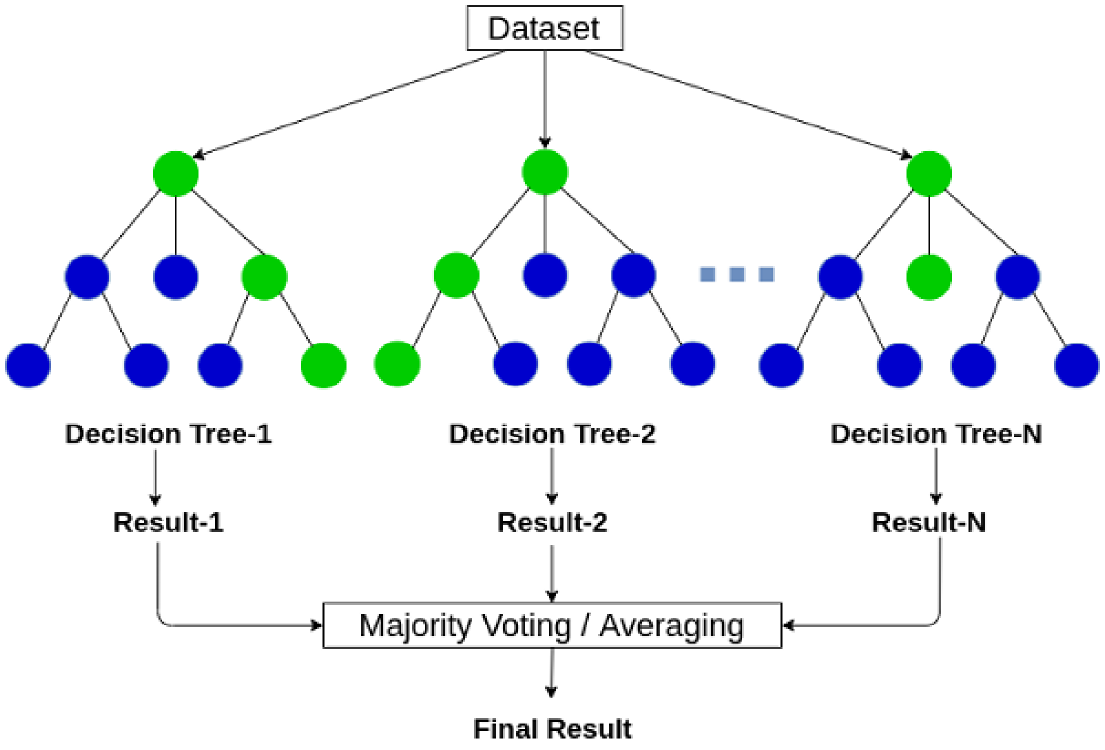
(b) Positive Unlabeled learning problem with only a percentage of positive labels known and all others unknown.

Distinguish positive and negative examples from characteristics of a growing positive set

Jaskie (2019)

Random Forest for algorithm training

- Random Forest is a popular ensemble learning technique that uses multiple decision trees for better accuracy and robustness.
- It is effective in handling missing and noisy data typical in geological datasets
- Its capability to process large datasets with many features without needing dimensionality reduction is crucial, as it ensures no potentially important features are omitted, maintaining the model's accuracy.

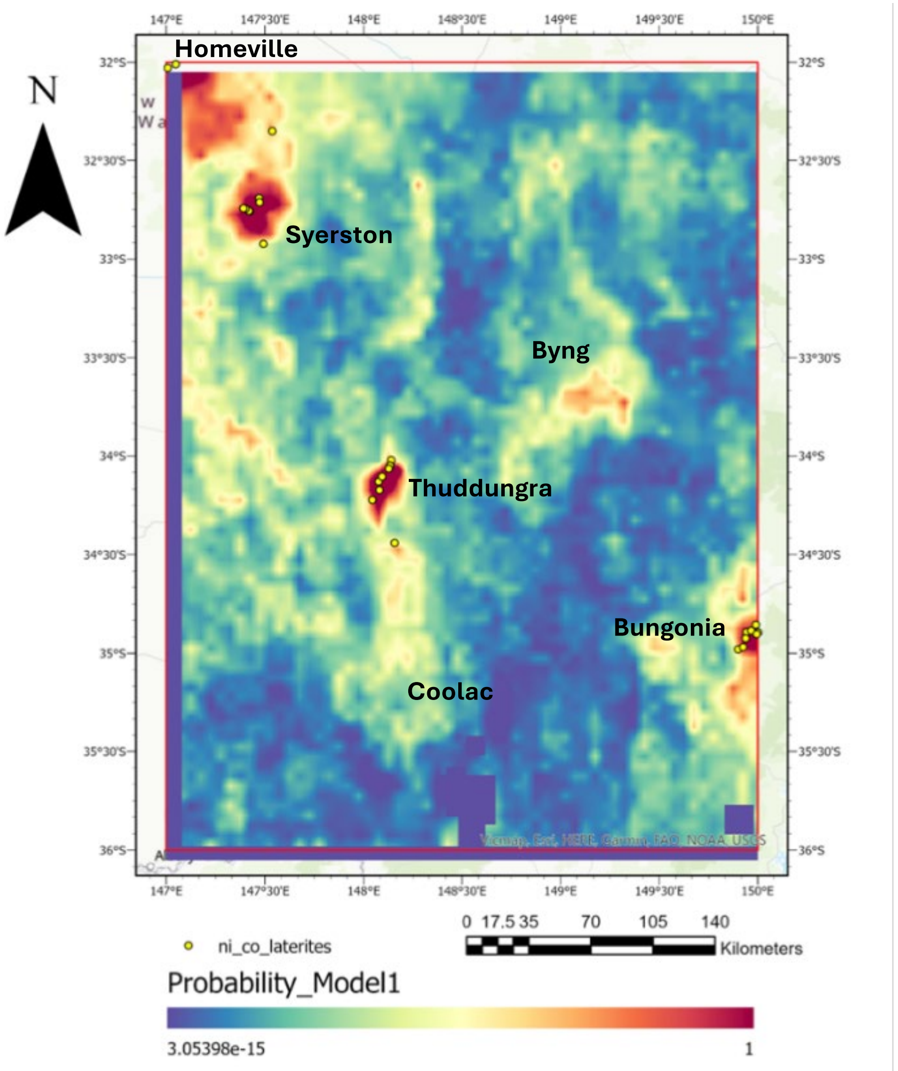


Model 1 Feature importance – all input data (>300 features)

Feature	Importance	Cumulative Sum
Correlation of AlOH group content	0.099	0.099
Mean of phase of TMI_RTP	0.084	0.183
Benambran subgreenschist facies	0.067	0.250
Standard deviation of CSCBA gravity 2016	0.055	0.305
CSP clastic sediments	0.041	0.346
LAO faulted boundary	0.039	0.385
CSP Null	0.038	0.423
Mean deviation of CSCBA gravity 2016	0.034	0.457
Unconformities of metamorphic boundaries	0.028	0.486
Dissimilarity of ferric oxide content	0.026	0.512
Mean of radiation dose rate	0.024	0.535
Mean of pseudo gravity of TMI_RTP	0.023	0.558
X horizontal derivative of ellipsoid DEM	0.022	0.580
Correlation of half vertical derivative of TMI_RTP	0.022	0.602
Mean of FeOH group content	0.021	0.623

All data layers

– Top 15 feature proxies for lateritic Ni-Co



Model 1 – Prospectivity map

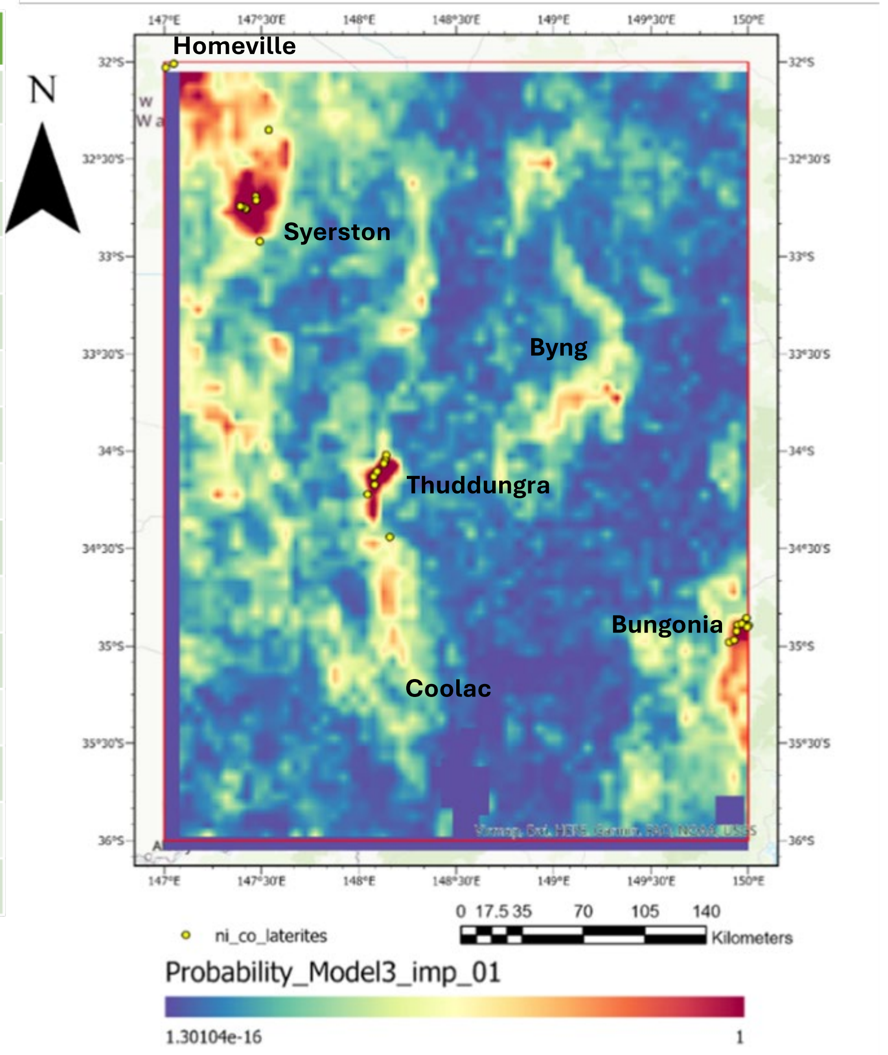
Lateritic Ni-Co mineralisation

Model 2 Feature importance – <10% of all features used

Feature	Importance	Cumulative Sum
Correlation of AlOH group content	0.134	0.134
Benambran subgreenschist facies	0.127	0.260
Mean of phase of TMI_RTP	0.115	0.375
CSP clastic sediment	0.080	0.456
Standard deviation of CSCBA gravity 2016	0.076	0.532
CSP Null	0.057	0.589
Unconformities of metamorphic boundaries	0.045	0.634
LAO faulted boundary	0.039	0.674
Mean of radiation dose rate	0.030	0.704
Mean deviation CSCBA gravity 2016	0.027	0.731
Standard deviation of 1VD of CSCBA gravity 2016	0.022	0.754
Mean of pseudo gravity of TMI RTP	0.021	0.775
Mean of ferrous hydroxide (FeOH) group content	0.021	0.796
Dissimilarity of silica index	0.021	0.817
Dissimilarity of 1VD of CSCBA gravity 2019	0.020	0.837

Data layers >0.01 Cut-off

– Top 15 feature proxies for lateritic Ni-Co



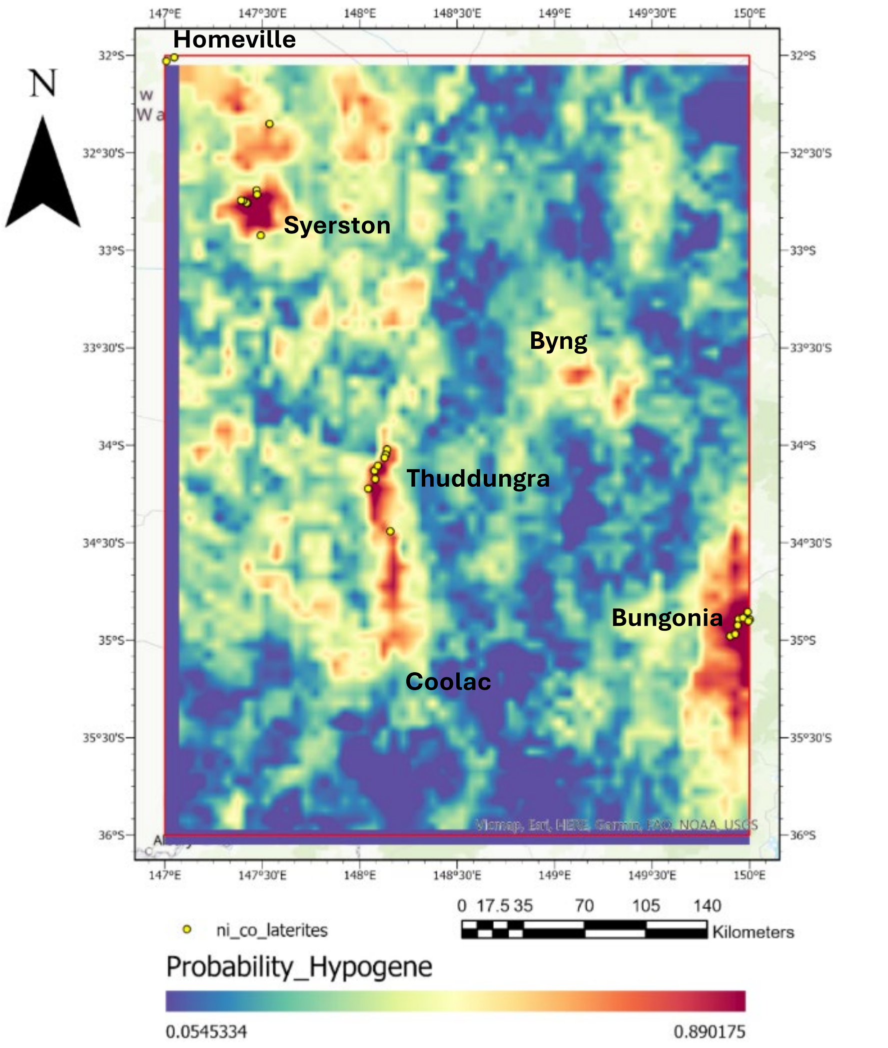
Model 2 – Prospectivity map

Lateritic Ni-Co mineralisation

Model 3 Hypogene (primary) feature selection

Feature
LAO_Serpentinite
LAO_Ultramafic igneous rocks
Mean of phase of TMI RTP
Benambran subgreenschist facies
LAO_unconformable boundaries
LAO_geological boundaries
Mean of CSCBA gravity 2016
Mean of isostatic residual gravity 2016
Unconformities of metamorphic boundaries
Faults of metamorphic boundaries
Unconformable boundaries of intrusion boundaries
Mean of pseudogravity of TMI_RTP
CSP geological boundaries
LAO_faulted boundaries
Correlation of AlOH group content
Correlation of opaque index
Benambran upper greenschist facies
Mean of MgOG group content

Data layers representing / proxies for source rocks

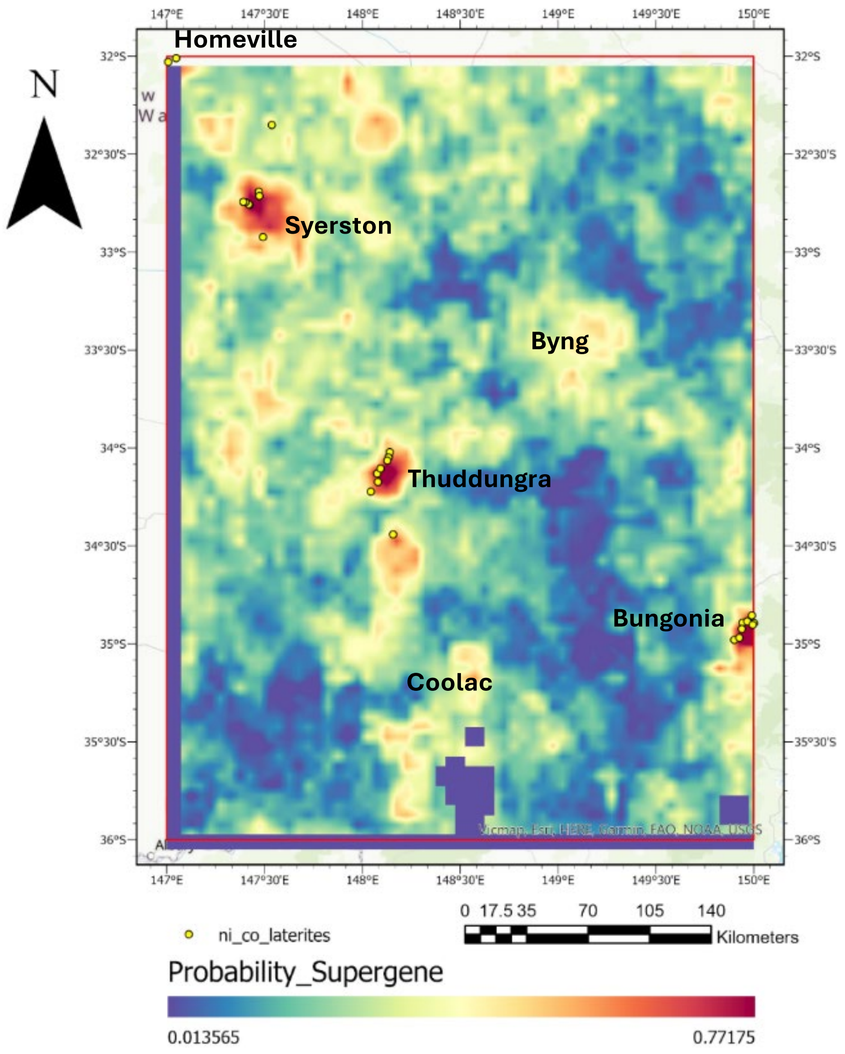


Model 3 – Prospectivity map
Lateritic Ni-Co mineralisation

Model 4 Supergene (secondary) feature selection

Feature
Correlation of 1VD TMI
X horizontal derivative of ellipsoid DEM
Correlation of AlOH group content
Correlation of half vertical derivative of TMI_RTP
Correlation of green vegetation content
Dissimilarity of ferric oxide content
CSP clastic sediment
Dissimilarity of uranium (U) concentration unfiltered
Standard deviation of ratio of Th to K
Dissimilarity of ratio of U to K
Mean of silica index
Correlation of ferric oxide composition
LAO_Serpentinite
LAO_Ultramafic igneous rock
Correlation of gypsum index
Mean of FeOH group,conten
Strandard deviation of radiation dose unfiltered
CSP geological boudaries
LAO_RockUnit_faulted boundaries

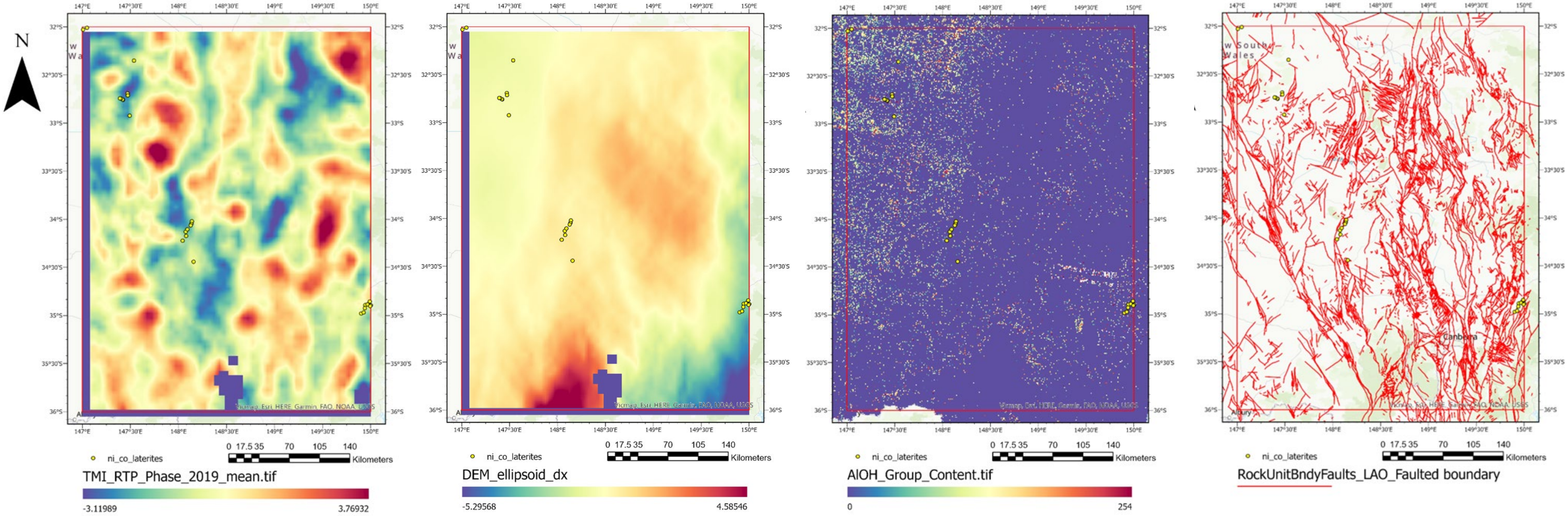
Data layers representing / proxies for weathering profiles



Model 4 – Prospectivity map
Lateritic Ni-Co mineralisation

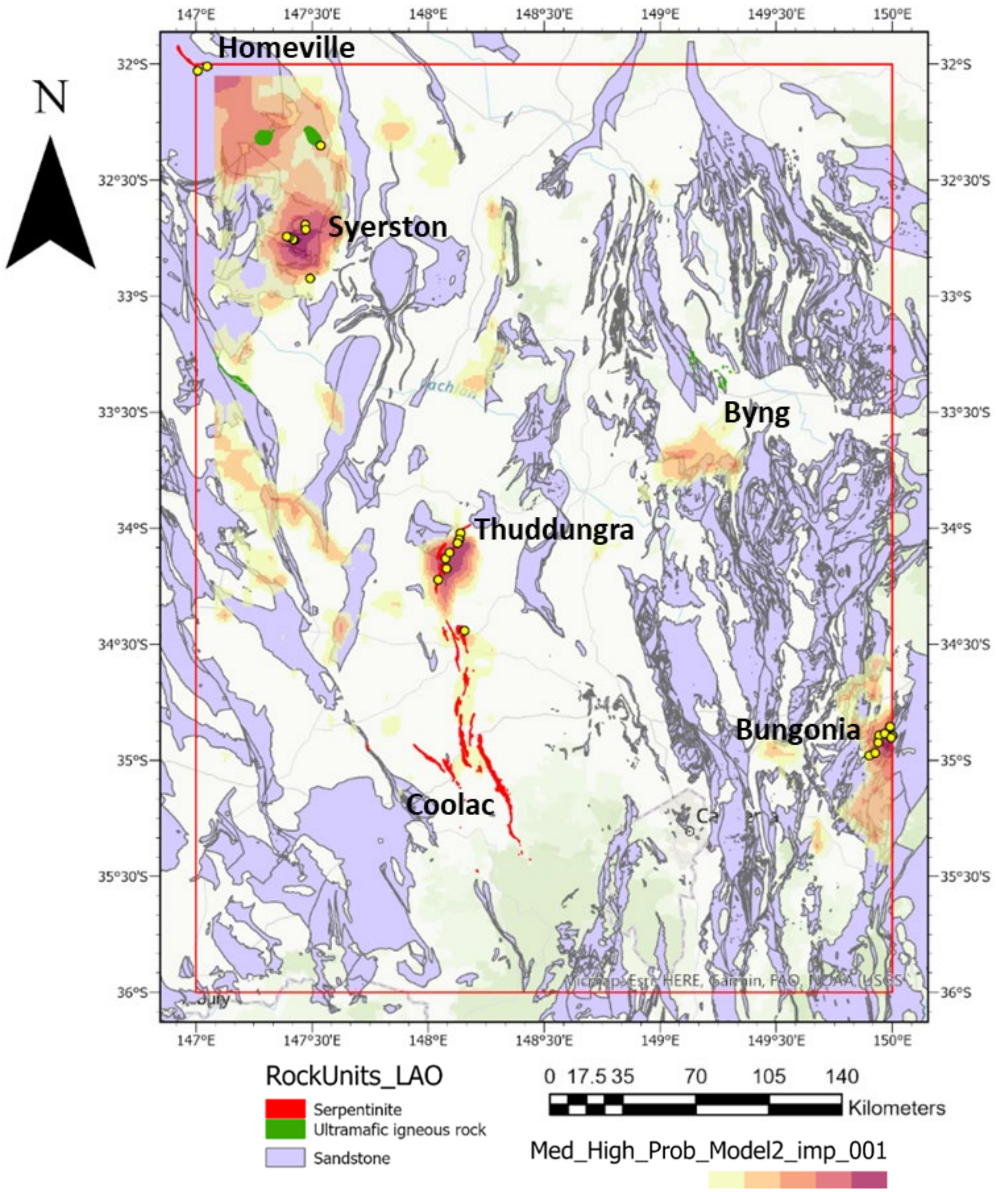
Top Features for successful training

a. Magnetics TMI RTP b. Digital Elevation c. AlOH Abundance d. Fault Boundaries



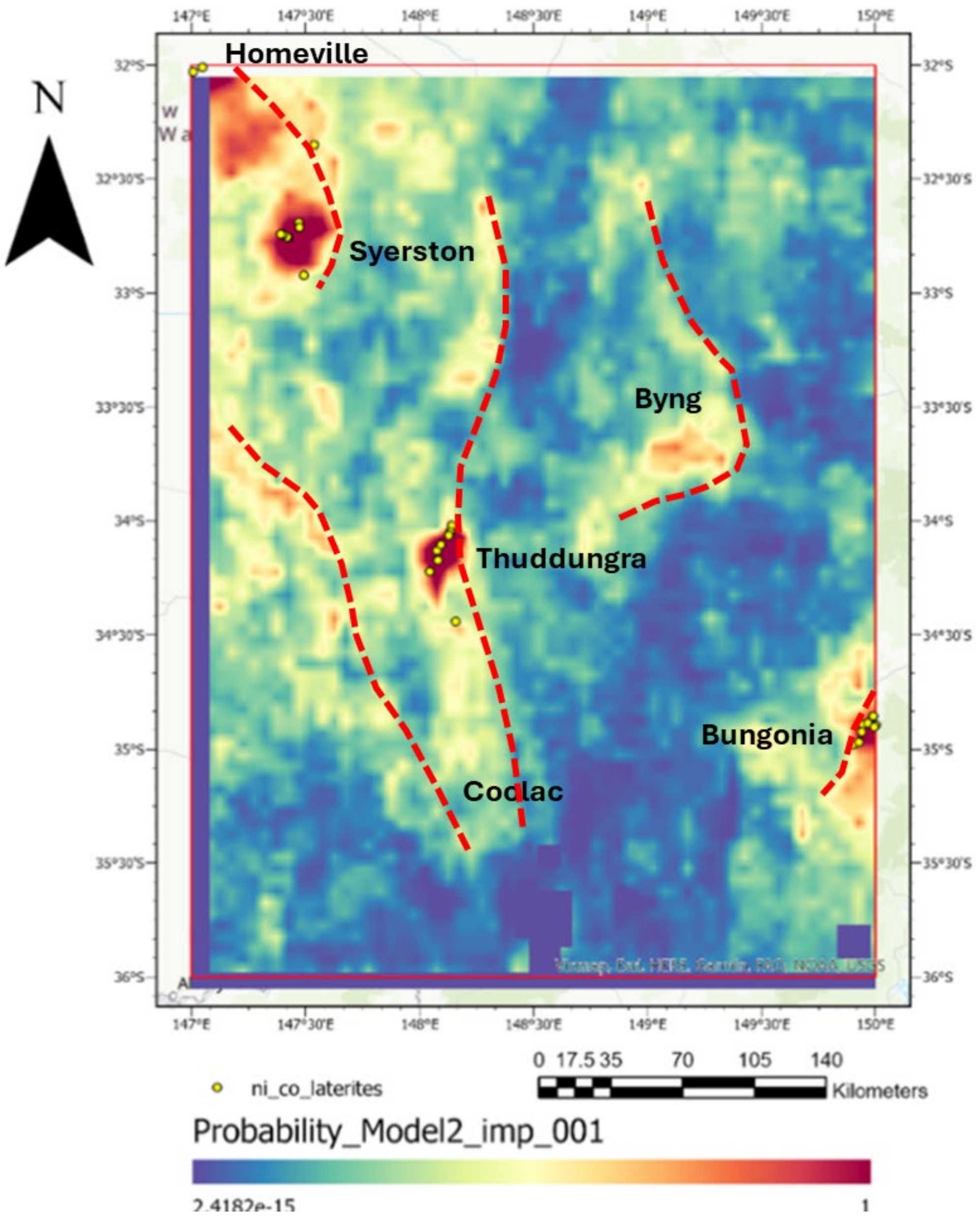
- Examples of four high ranking features:
  a) Mean TMI reduce-to-pole phase 2019; b) Horizontal derivative of DEM;
  c) ASTER multispectral AlOH group content; d) Lachlan Orogen_ Rock Unit fault boundaries.
- Training set mineral occurrences are plotted as circles.

Targeting



- Key geological features map, highlighting:
  - Distribution of Ni-Co source rock units
    - Ophiolites
    - Mafic-ultramafic intrusions
  - Distribution of other basement rocks
    - Metasedimentary rock units
- Overlain by:
  - Lateritic Ni-Co occurrences (training set)
  - Model 2 Lateritic Ni-Co prospectivity map
    - moderate to high probabilities (yellow-red)

Targeting



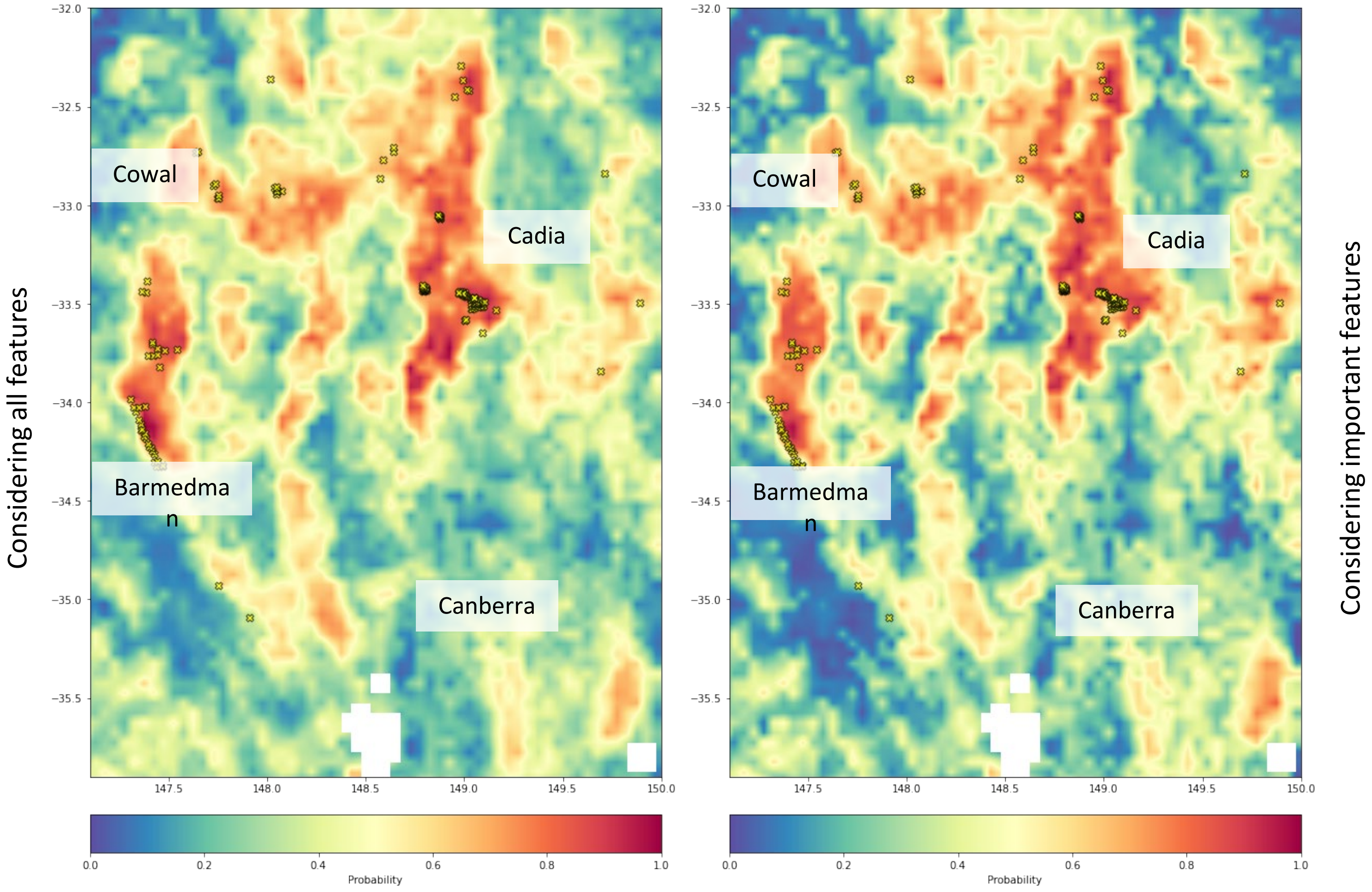
Potential new greenfield areas for future exploration:

- Coolac-Thuddungra serpentinite belts
  Two sub-parallel linear/curvilinear belts
  - each extending over +200-300 km
- Syerston-Homeville-Nyngan mafic-ultramafic intrusion field
  - lobate high-probability feature (~30 x 70 km)
- Byng Volcanics
  - 150 km long arcuate feature
- Bungonia region
  - Cobalt in manganiferous wads
  (Cenozoic grits/sandstone - source unknown)

Method can easily be scaled to higher resolution in target regions

Preliminary prospectivity maps for porphyry Cu

All features (>300) Most important features (<30)



Cu occurrences are weighted by tonnage and grade

- Magnetic grids and intrusive boundaries are the most important data layers.
- Important features include:
  - Standard deviation and mean of the first vertical derivative of magnetic data
  - Dissimilarity of the total horizontal gradient of the pseudo gravity of magnetic data
  - Proximity to faulted intrusive and rock boundaries

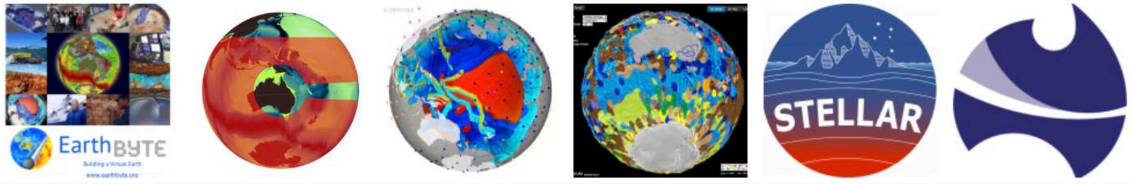
EarthByte

Building a Virtual Earth

Home | Research | People | Publications | Resources | Training & Outreach | News | Multimedia | Opportunities | Links

Conclusions

- Machine learning has an enormous potential for critical mineral exploration in NSW
- From general to detailed exploration: Easy scaling to finer local resolution
- Robust when faced with noisy data
- Additional features can easily be included
- Several ARC and CRC avenues for industry-government-university collaboration



Earthbyte | Deep Carbon | GPlates | GPlates Portal | STELLAR | AuScope

Search …

THE UNIVERSITY OF SYDNEY | School of Geosciences

EarthByte News

Space News: Surprising connections between Earth and Mars

1:36 pm 26 Apr 2024

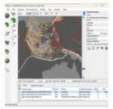
CBC LISTEN Live Radio

CBC Podcasts

Featured Podcasts

Quirks and Quarks: EarthByte on Canadian National Radio with a story on Earth, Mars and ocean mixing

1:24 pm 23 Apr 2024



GPlates 2.5 released

12:58 pm 15 Apr 2024

GPlates

GPlates 2.5 software and data sets

NSW industry partners wanted!

ARC Linkage

ARC Industry Fellowships

CRC-P

Contact:
dietmar.muller@sydney.edu.au

www.earthbyte.org