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Full length article

Machine learning framework for prospectivity mapping of Cu–Au porphyry mineralisation in the Lachlan Fold Belt, eastern Australia

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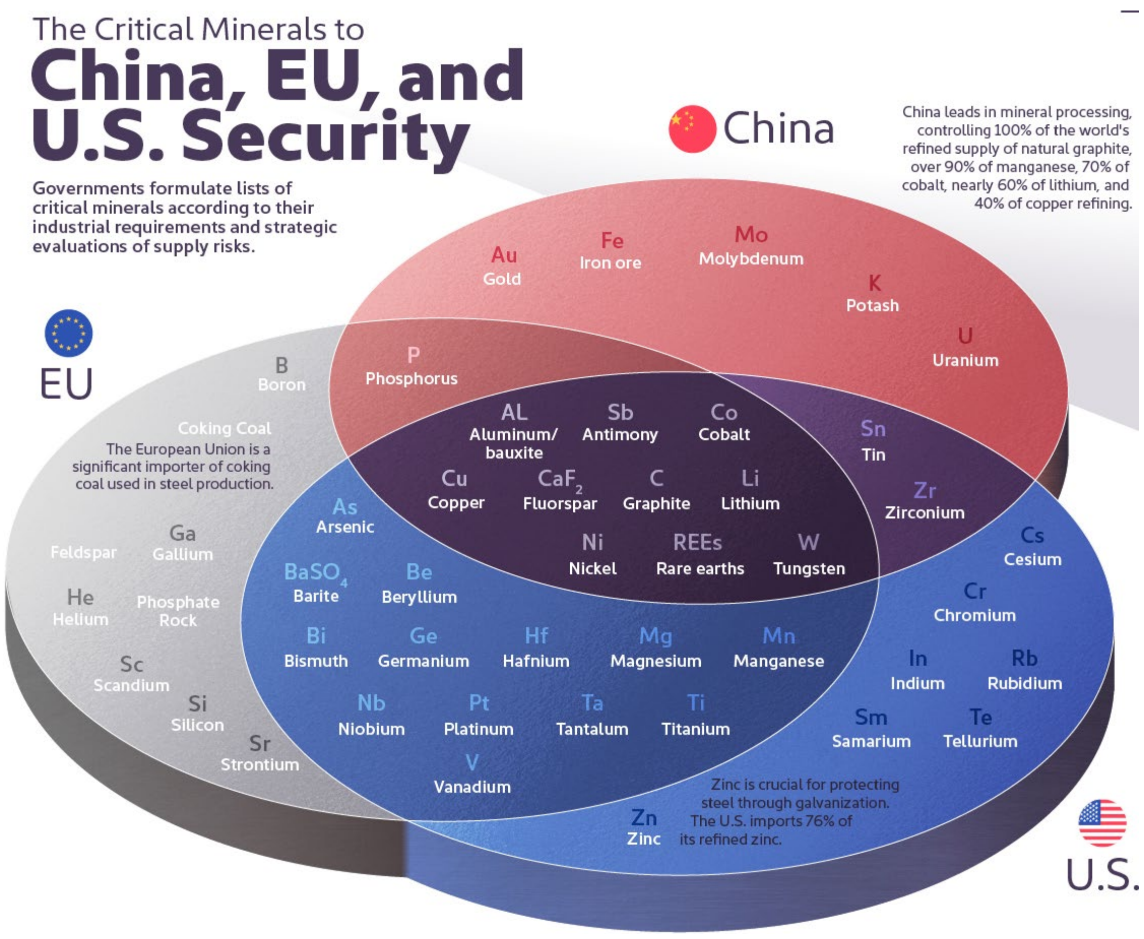
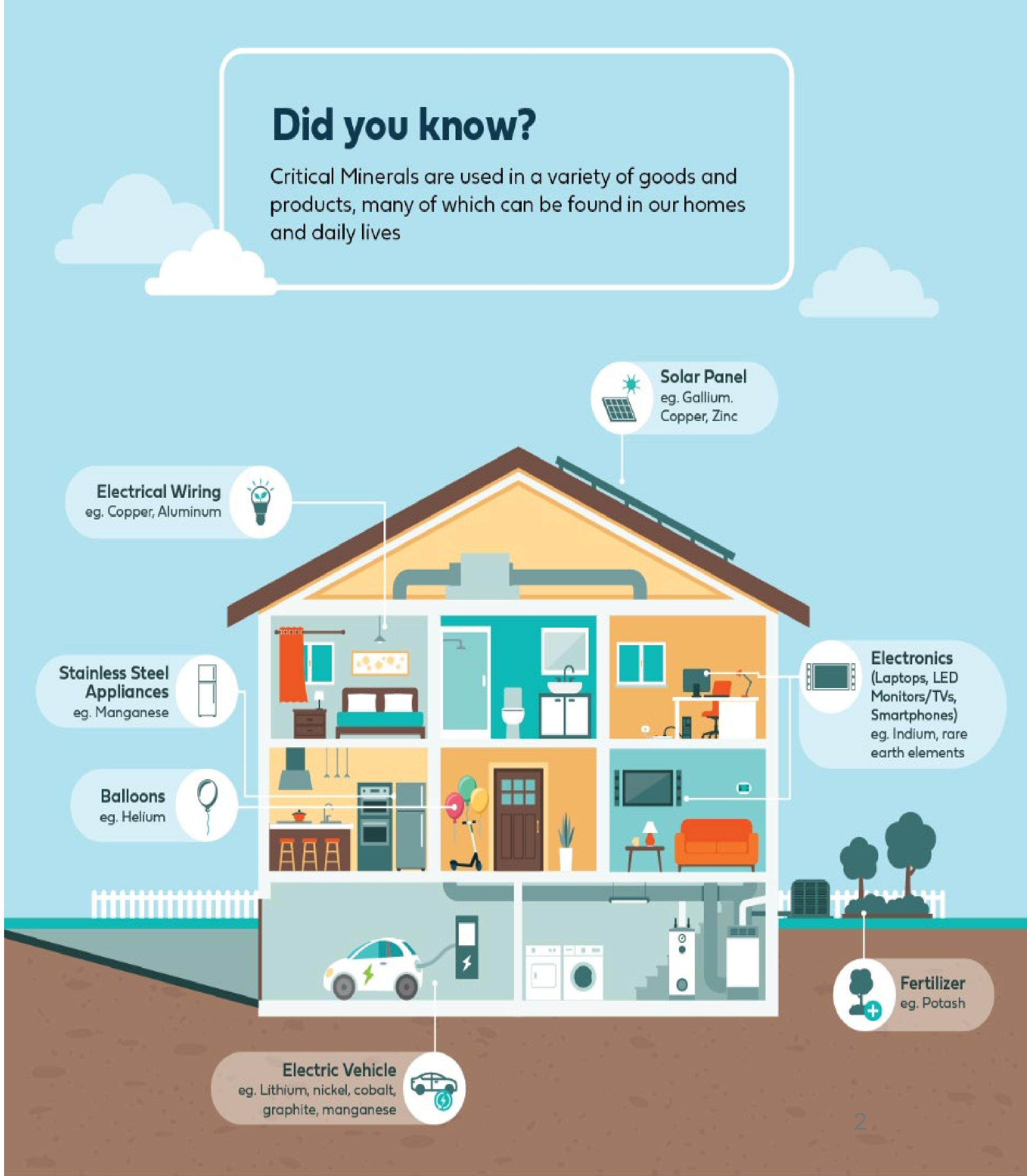
❑ Critical Minerals

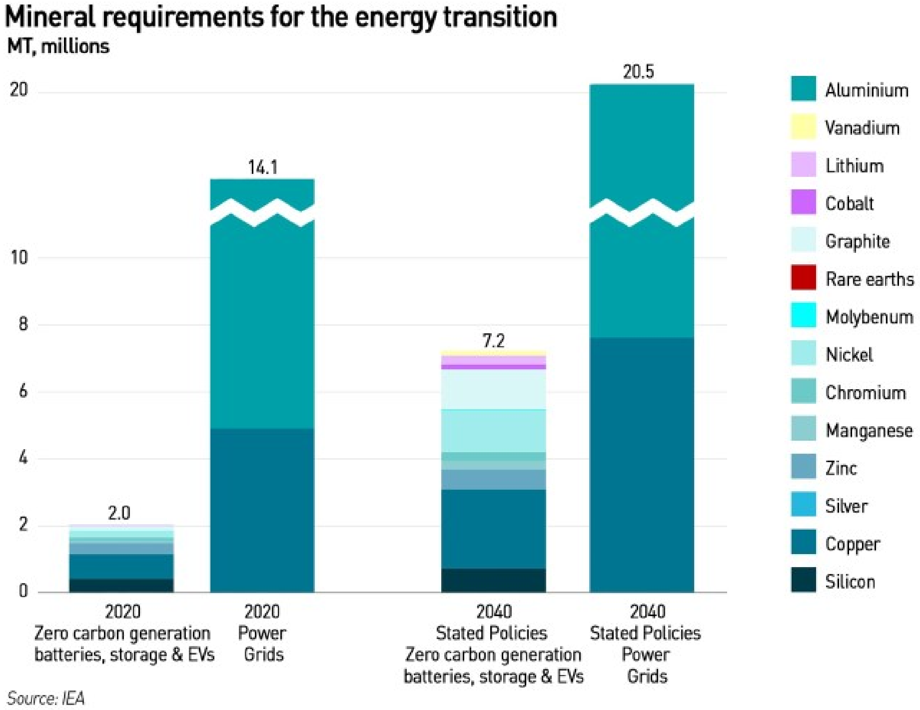
A metallic or non-metallic element can be considered critical if it meets criteria such as **Economic Importance / Supply Risk / Lack of Substitutes.**

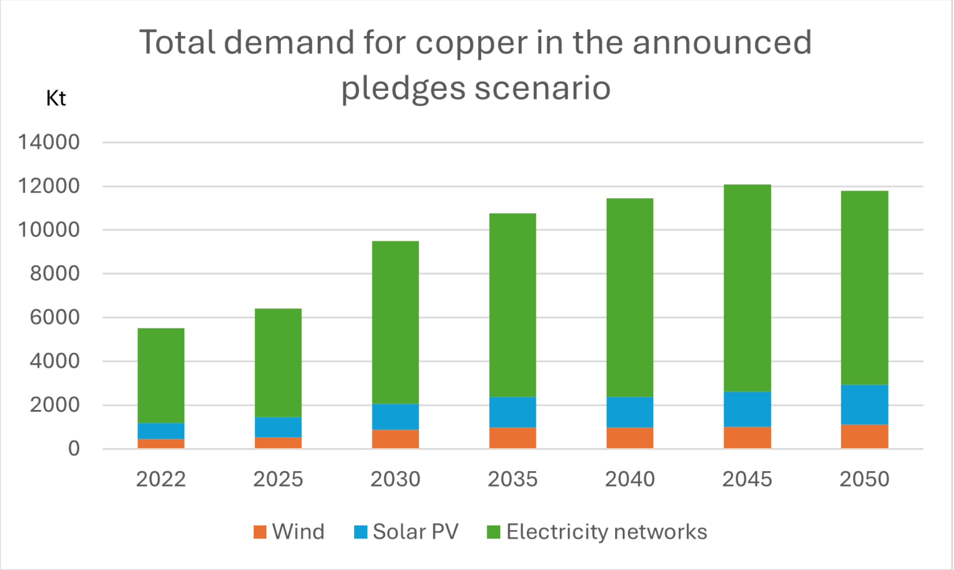


Source: IRENA, The U.S. Department of Energy

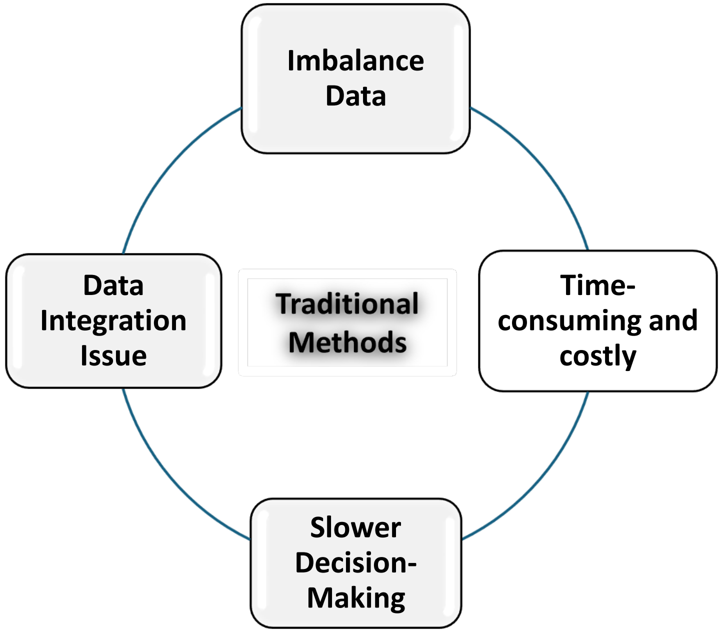


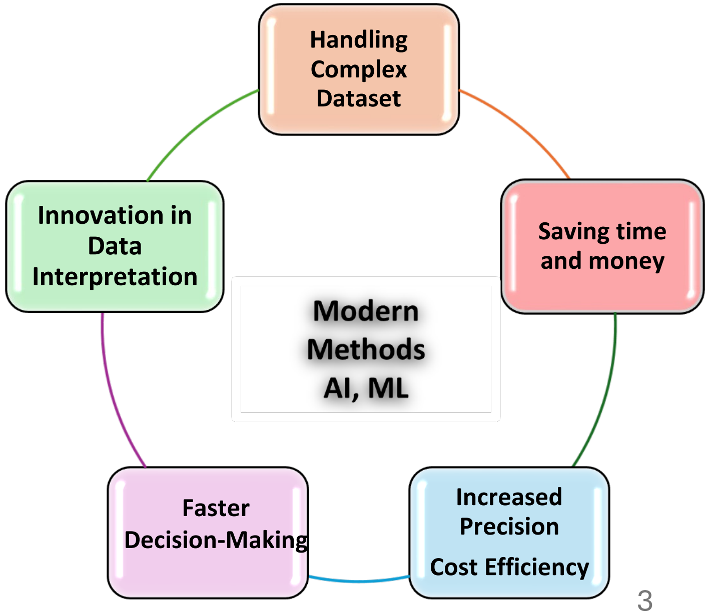
Introduction





Source: IEA Critical Minerals Market Review 2023





Geological Setting of NSW

❑The host rocks:

volcanic and intrusive rocks formed in tectonically active subduction zones, especially andesites, diorites, granodiorites, and tonalites

❑The age of formation:

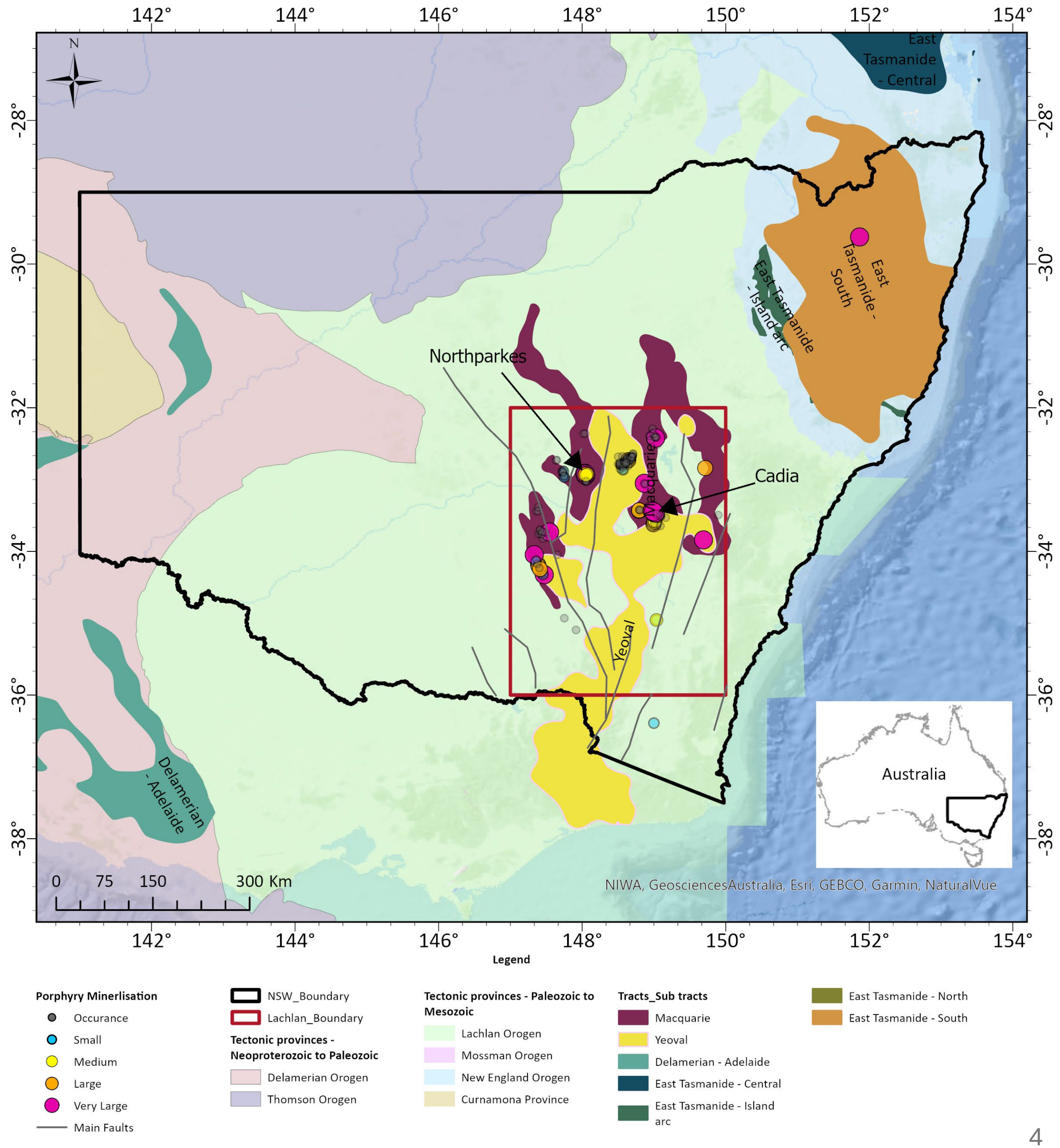
Ordovician to Early Silurian

❑Alteration :

Potassic alteration
Phyllic (sericitic) alteration
Argillic alteration
Propylitic alteration

❑Structure Control:

Fault zones
Fracture networks
Dilational zones



Materials and methods

- Data Layers and Features

- ❑ **Geological Maps**
- ❑ **Geophysical Data**
- ❑ **Satellite Images**
- ❑ **Digital Elevation Model**

a) Geological maps: Metamorphic faces (AF: Amphibolite facies, GlF: Granulite facies, SF: Subgreenschist facies, UG: Upper Greenschist);

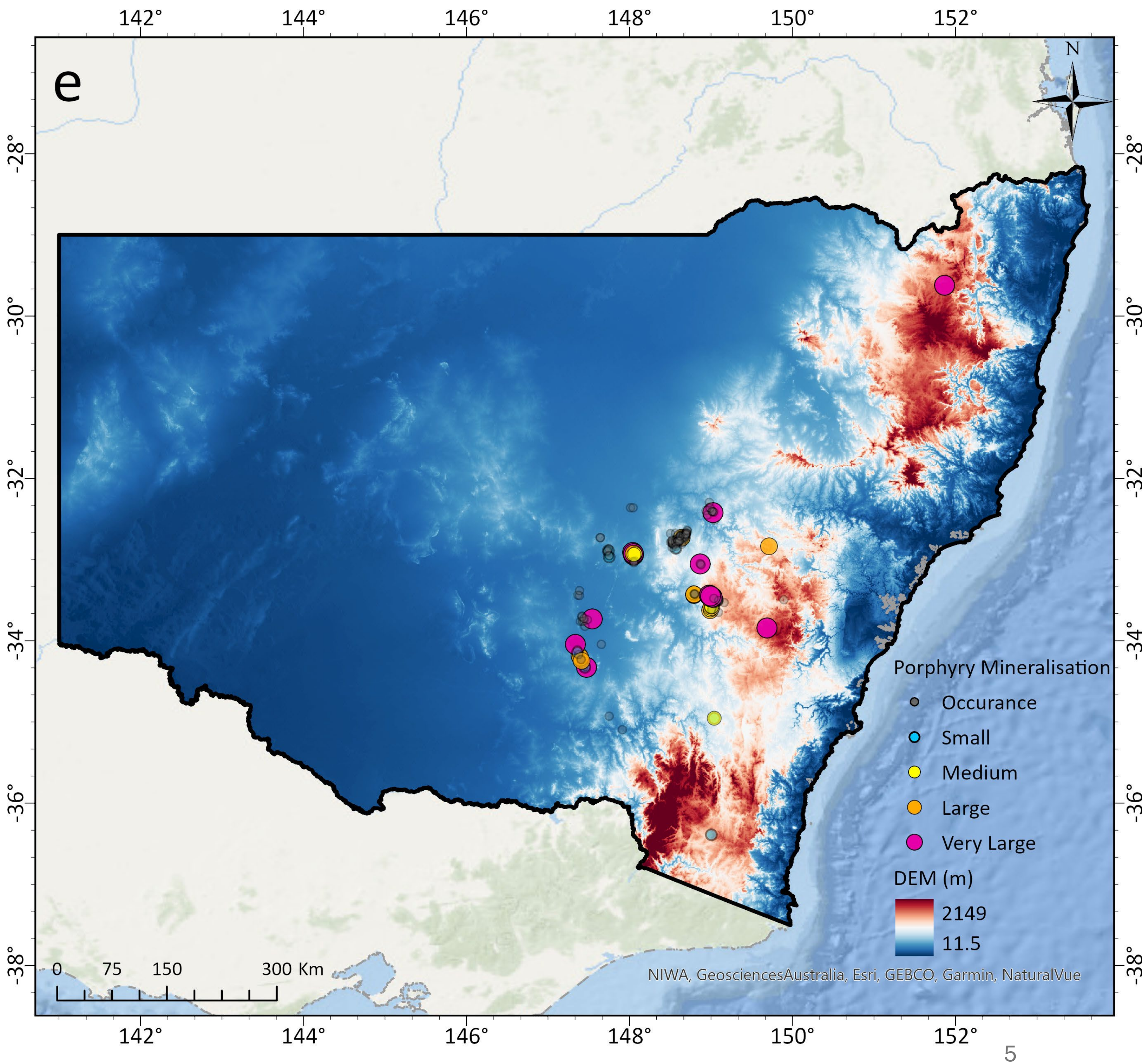
b) GVG: **Gravity** Vertical Gradient

c) Rad K Ratio: **Radiometric** potassium ratio

d) TMI-RTP: Total **Magnetic** Intensity Reduced to the Pole

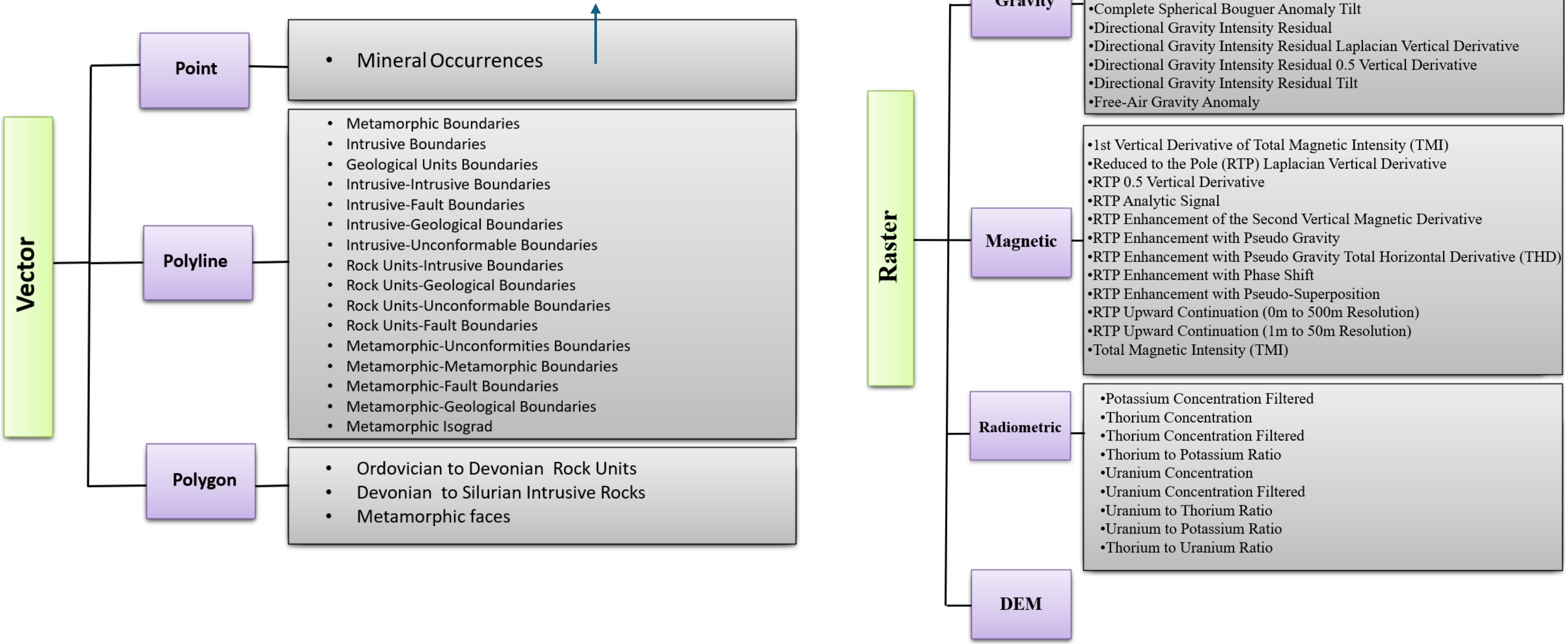
e) DEM: Digital Elevation Model.

Source: MinView Website /CSIRO Data Access Portal

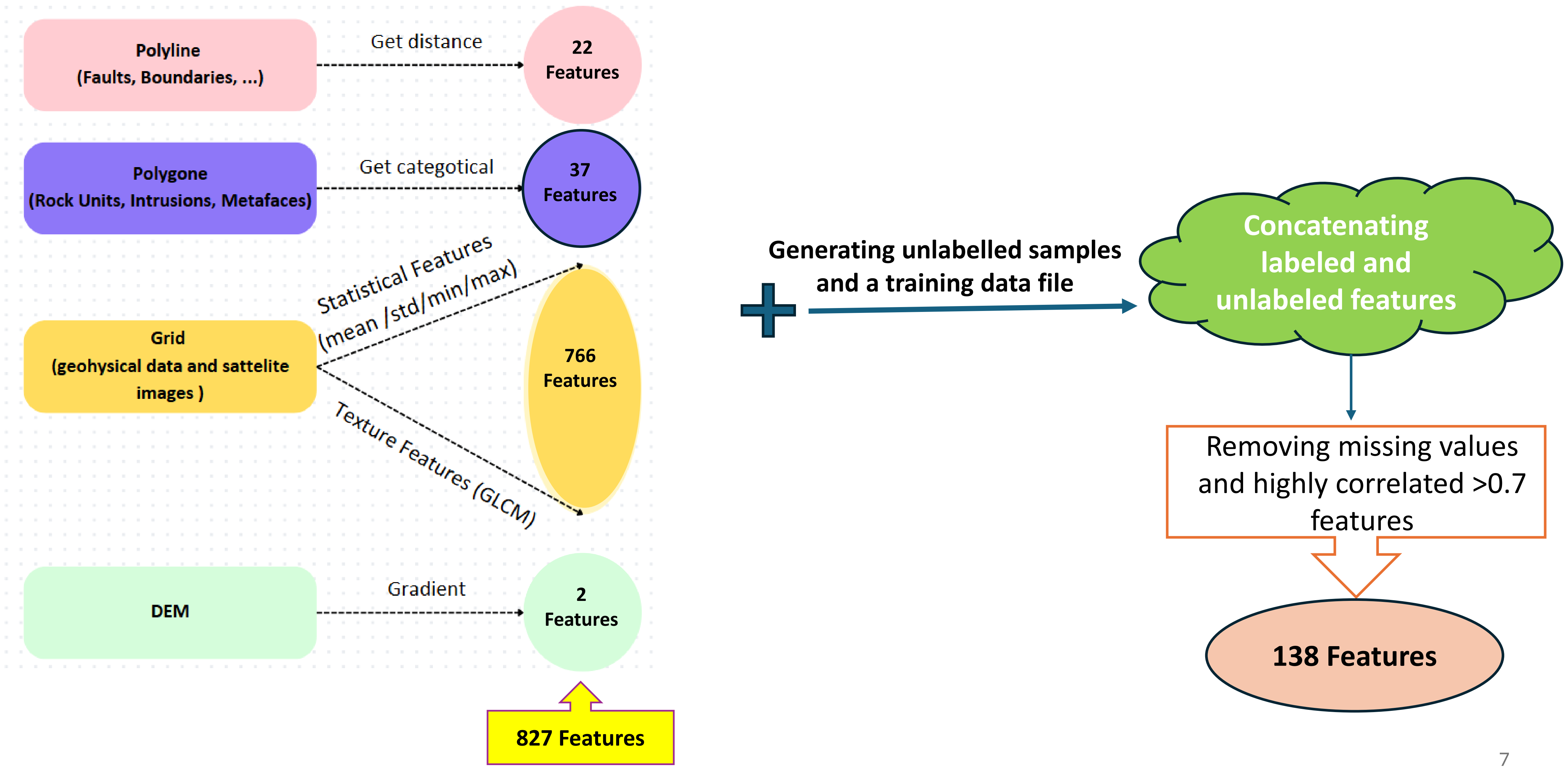


Step 1: Data Layers and Features

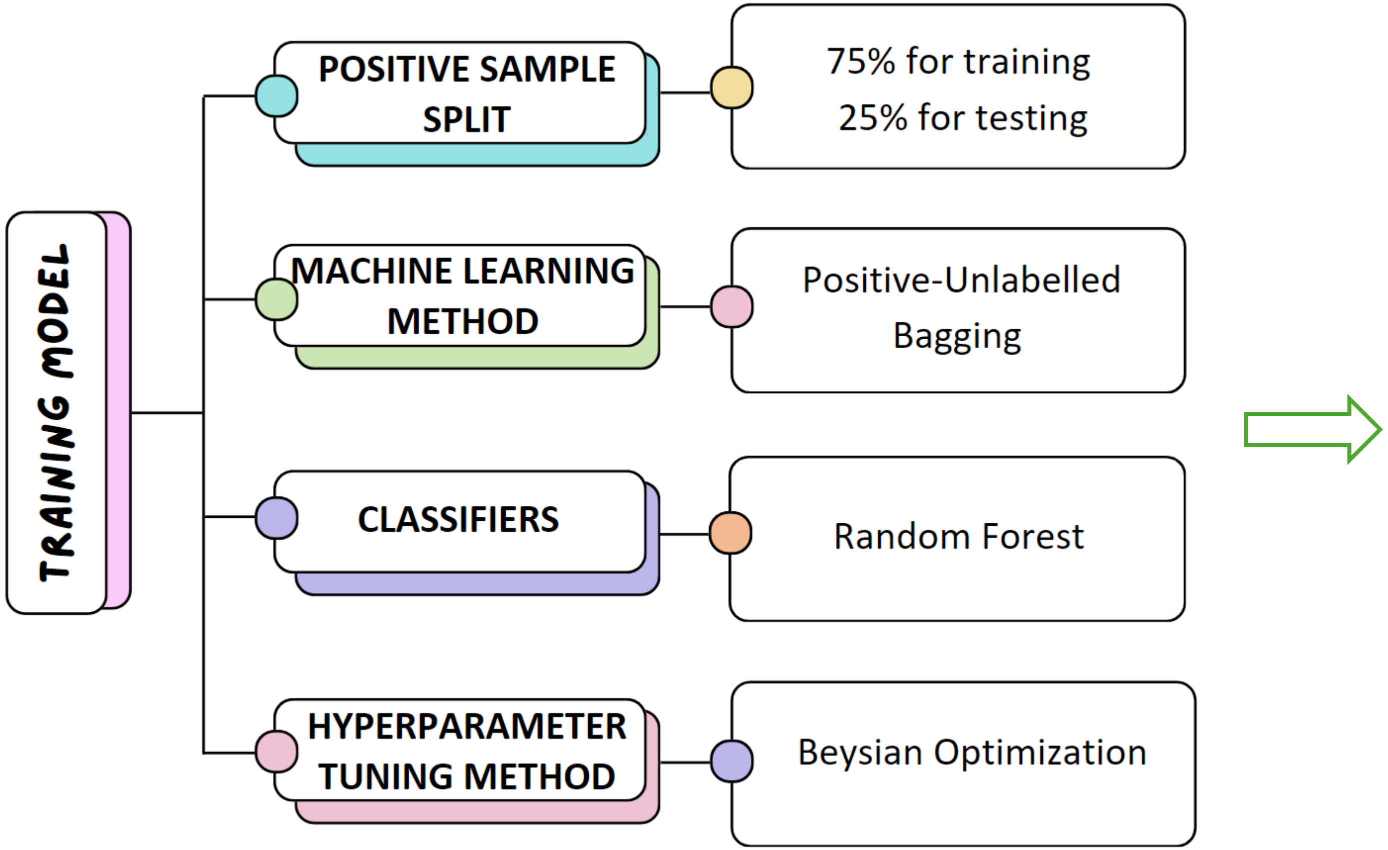
Deposit size	Weight
Occurrences	0.1
Small	0.2
Medium	0.3
Large	0.4
Very Large	0.5



Step 2: Training Data File



Step 3: Forecast and Assesment



Accuracy (138 features)	F1 Score	Accuracy (Positive Samples)
0.954	0.877	0.923

Accuracy (26 features)	F1 Score	Accuracy (Positive Samples)
0.957	0.884	0.923

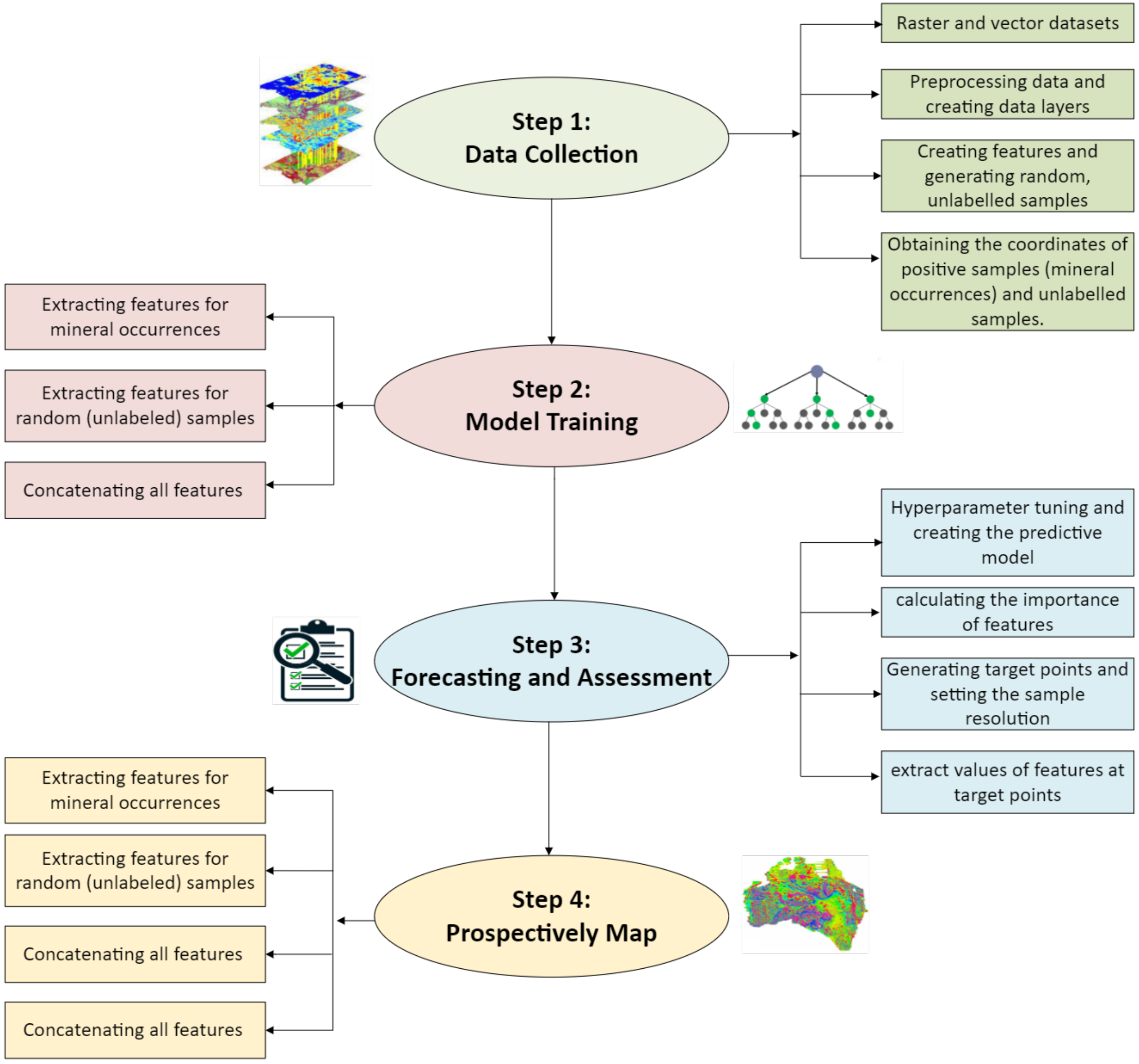
Our Framework

Innovations:

1) First-time implementation in NSW for the exploration of porphyry mineralisation.
2) Developed a database with over 800 features.
3) Applied a size-based weighting (case-sensitive learning) system to enhance the robustness of our exploration model.

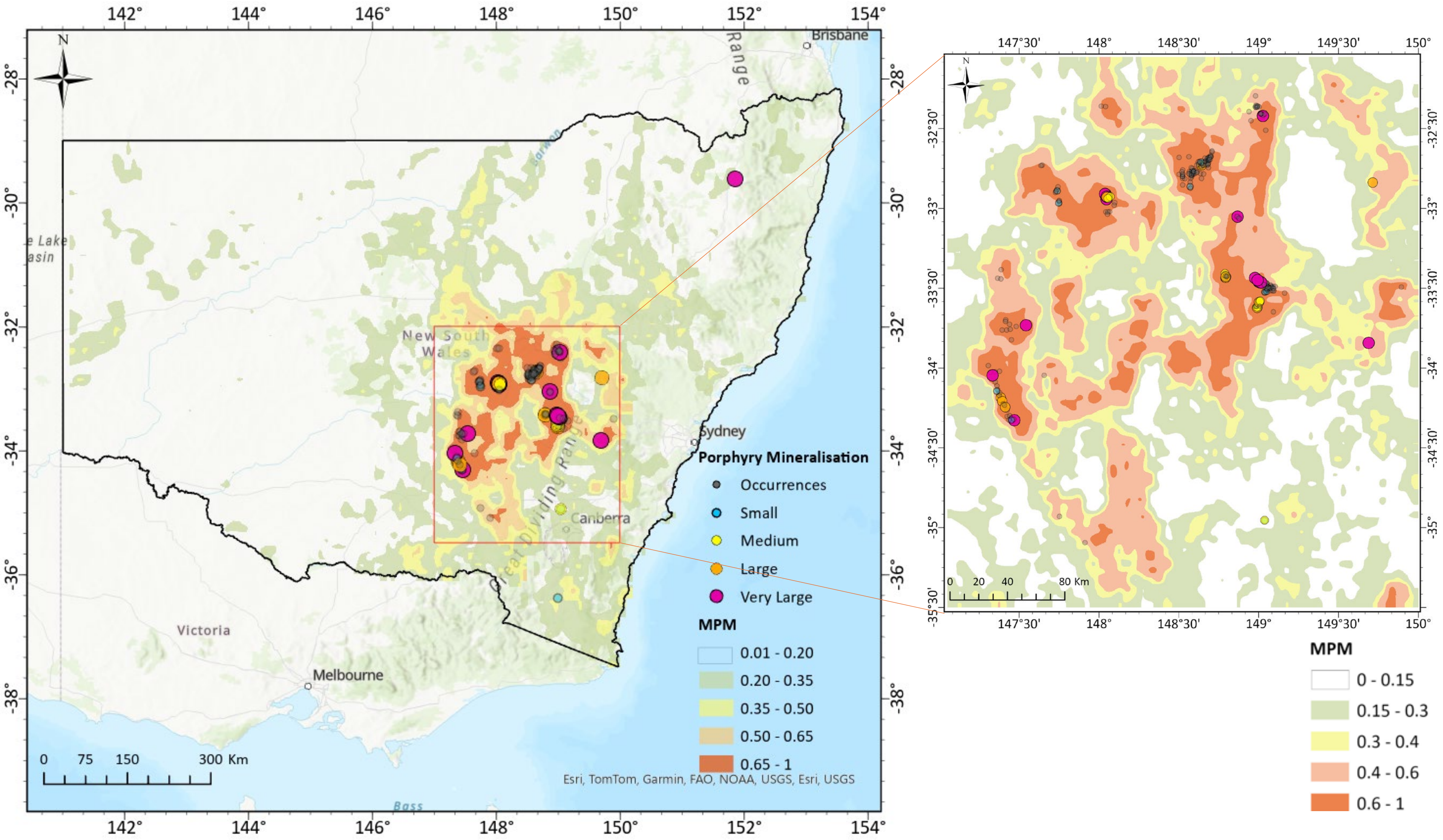
Strengths :

1) Used PU Bagging to improve reliability and accuracy in identifying porphyry mineralisation.
2) Employed Random forest classifier to handle data noise, list important features, train the model using a mixture of categorical and numerical features.

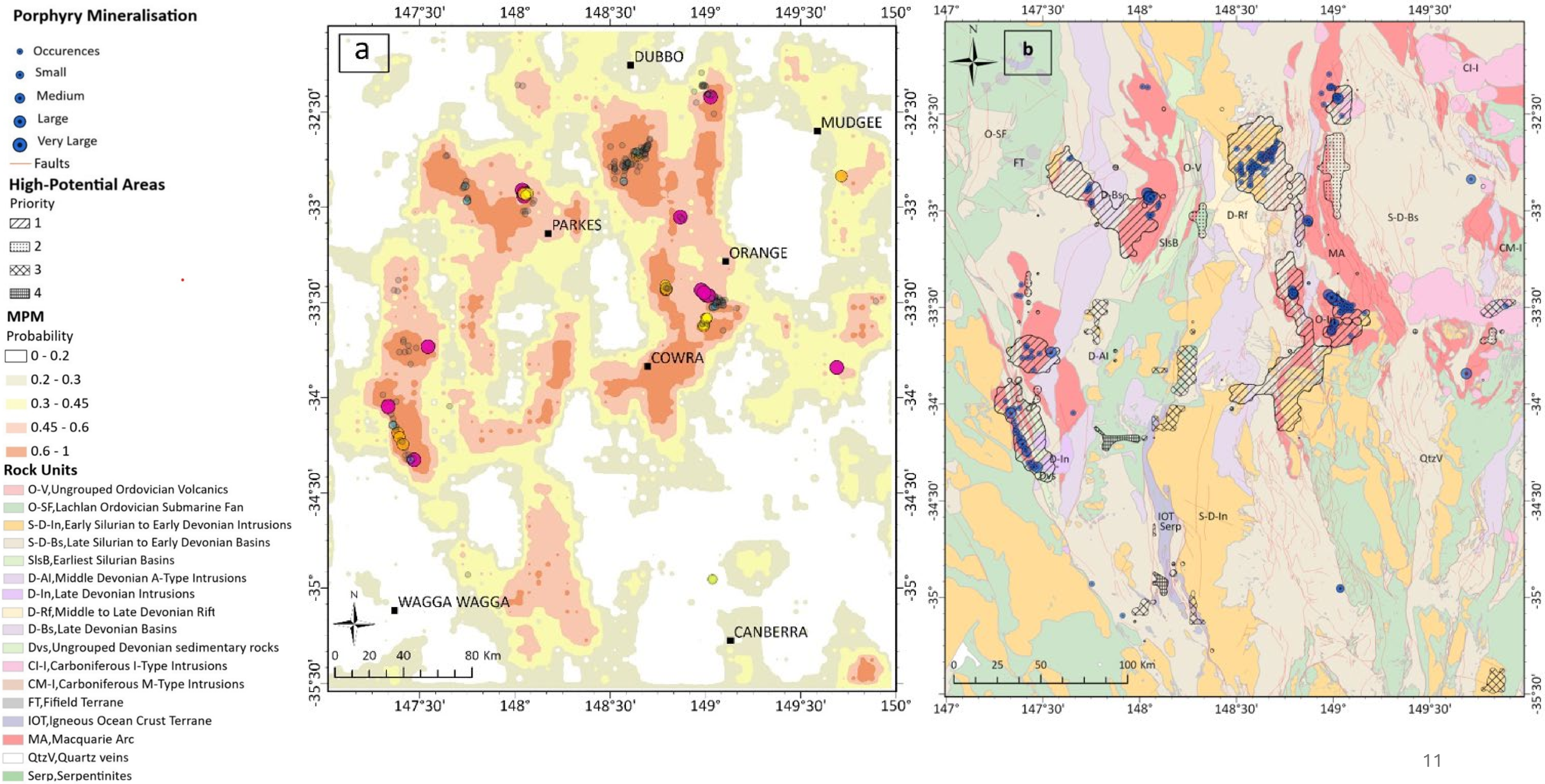


Step 4: Mineral Prospectivity Map (MPM)

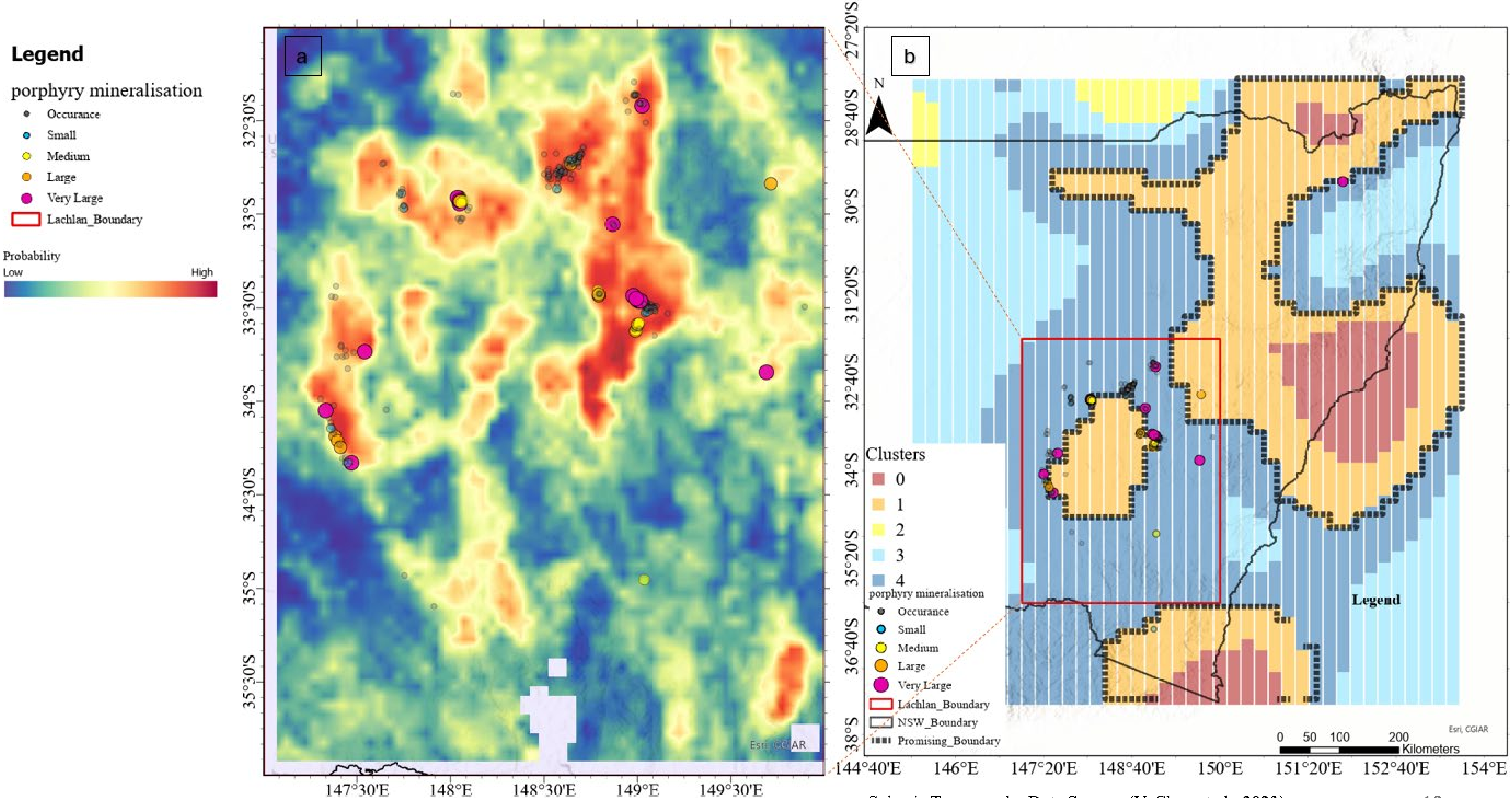
Feature	Importance
Standard deviation of the total magnetic intensity grid with the first vertical derivative applied	0.209
Mean of the total magnetic intensity grid with the first vertical derivative applied	0.087
Metamorphic Facies (Tabberabberan Greenshist facies)	0.087
Maximum of gravity grid of the Complete Spherical Cap Bouguer Anomaly with the tilt derivative enhancement	0.080
Correlation of AlOH_group_composition_	0.064
Distance to Unconformities in Metamorphic Boundaries	0.062
Distance to Faulted boundaries within the Lachlan Fold Belt	0.054
Standard deviation of grid illustrating the ratio of thorium to potassium concentrations from radiometric data	0.034
Mean of reduced-to-pole magnetic grid transformed into pseudo-gravity data	0.034
Distance to intrusive boundaries	0.031



Ranking of high-potential Zones in the Lachlan region



Seismic Tomography Investigation



Seismic Tomography Data Source: (Y. Chen et al., 2023).

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