Towards Australian Metallogenic Maps through Space and Time

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1. Introduction

The rapid growth in digital spatial geo-data is a key driver of frontier research for resource exploration. Computing methodologies and technologies are growing in importance in combining and relating the numerous spatial datasets to each other, through space and time. As available data increases both in resolution and modality, the opportunity for unlocking knowledge by cutting-edge high-performance computational means increases. In our approach we apply high-resolution data-mining and machine learning techniques across multiple datasets, extracting features and associations that achieve good separability based on known ground-truth locations. In this way, metallogenic maps can be developed that incorporate estimated associations from a collection of datasets through 3-dimensional space. Utilising this methodology, we approach iron ore in Western Australia as a case study in order to build, train and test a classifier that successfully predicts the location of an iron-ore deposit throughout two target areas, the Pilbara and Yeelirrie Blocks (Figure 1). The iron-ore deposits were acquired from the OZMIN database and represent past and present ore deposits. Economically viable iron-ore in Western Australia is typically either martite-goethite (M-G) or martite-microplaty hematite (M-mplH), both consisting of over 55% wt Fe (Morris, 1985). Though there is still some uncertainty over the exact process, it is generally accepted that supergene enrichment is the main driver for transforming a banded iron-formation to an economic iron-ore deposit (Morris, 1985).

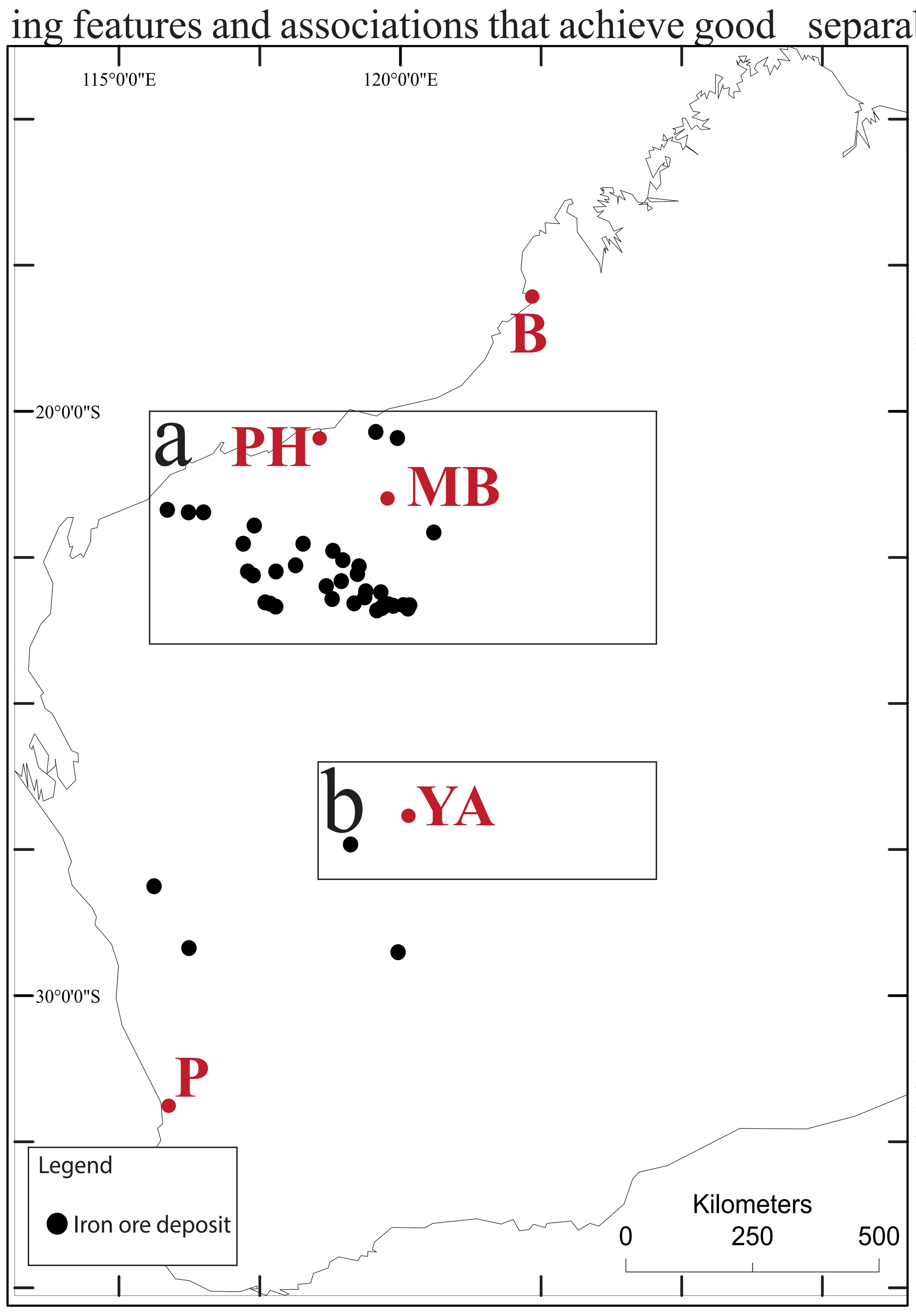


Figure 1 Map of Western Australia with the Pilbara (a) and Yeelirrie (b) blocks outlined by the black rectangles. The red circles highlight large townships and cities throughout Western Australia; B, Broome; MB, Marble Bar; P, Perth; PH, Port Headland; YA, Yeerillie Airport. The geographical extent of both rectangles (Pilbara: (-21ºS, 115ºE) (-24ºS, 123ºE); and Yeelirrie: (-26ºS, 118ºE) (-28ºS, 124ºE)) were used as case study areas due to their correlation with iron ore (Pilbara, iron rich; Yeelirrie, iron poor). By selecting smaller areas we minimised the computational time required for the generation of the trained algorithm. Integration of cloud computing would allow for larger spatial areas to be analysed. The solid black circles represent the iron ore deposits that were used in this study.

2. Methodology

Our approach involves the joint assessment of 6 geophysical datasets, namely Gravity anomaly, Magnetic anomaly, Topography, and K-, Th- and U- Radiometrics at a resolution of ~150 m. The location of known iron-ore deposits (acquired from the OZMIN database) are used to extract statistical features from the geophysical datasets (Figure 2). Using these extracted features, we utilised dimensionality reduction through principal component analysis (PCA) to minimise computational time and then tested multiple classification tools to determine a suitable model (Figure 2). Cross-validation (10 folds, 70% training, 30% testing) was used to validate the ability of each classifcation tool by separating the data into training and testing sets for the classifier to operate on. This procedure is repeated ten times, and the average classification success of each repetition is taken as a measure of the classifier's ability to distinguish iron-ore (Figure 2). The selected classifier, a linear discriminant classifier, successfully distinguished 87% of iron-ore deposits. Using this classifier, we then applied it to the two regions of interest, the iron rich Pilbara, and the iron poor Yeelirrie. Finally, the output of this application was converted to a probability heat map (Figure 3).

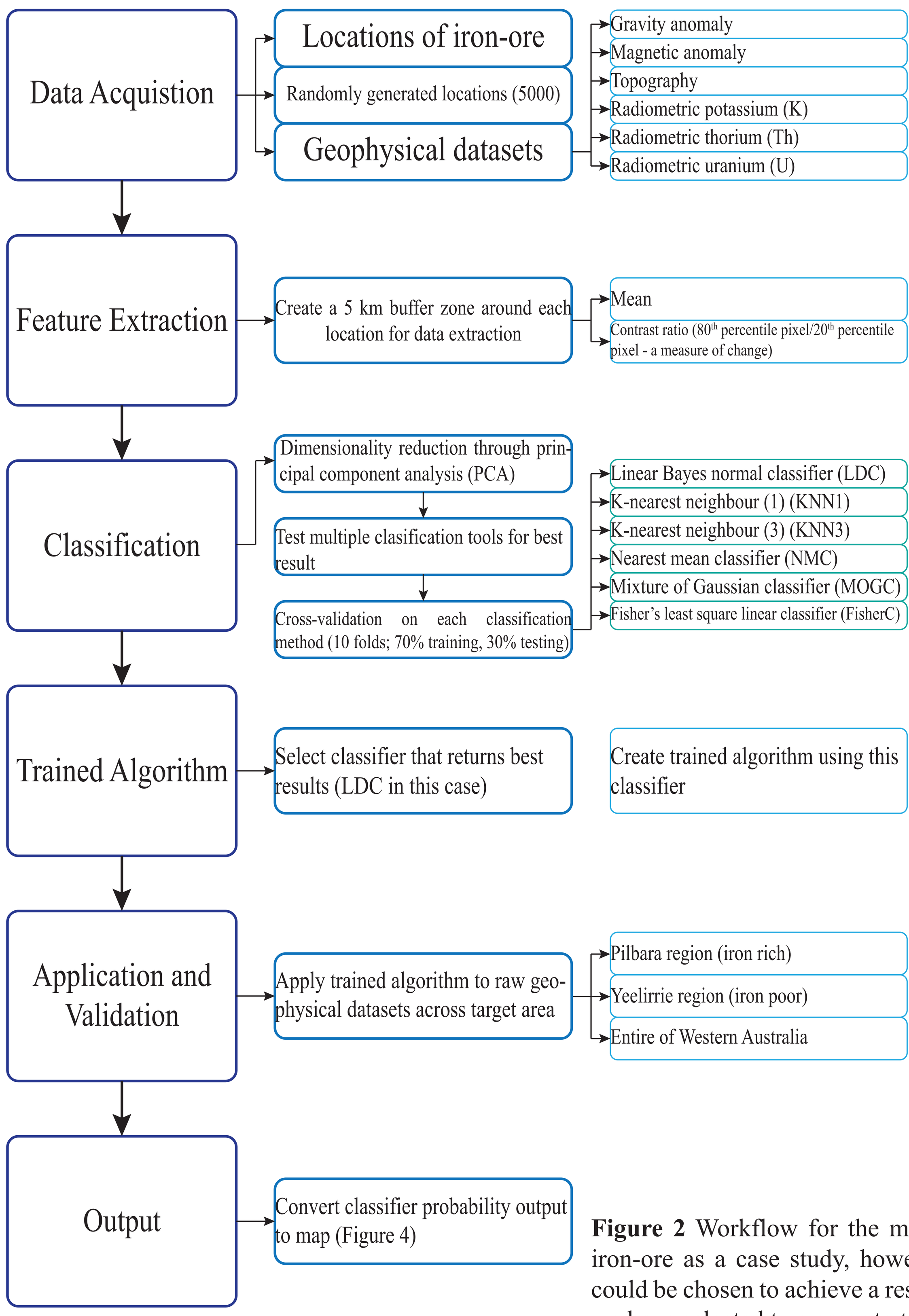
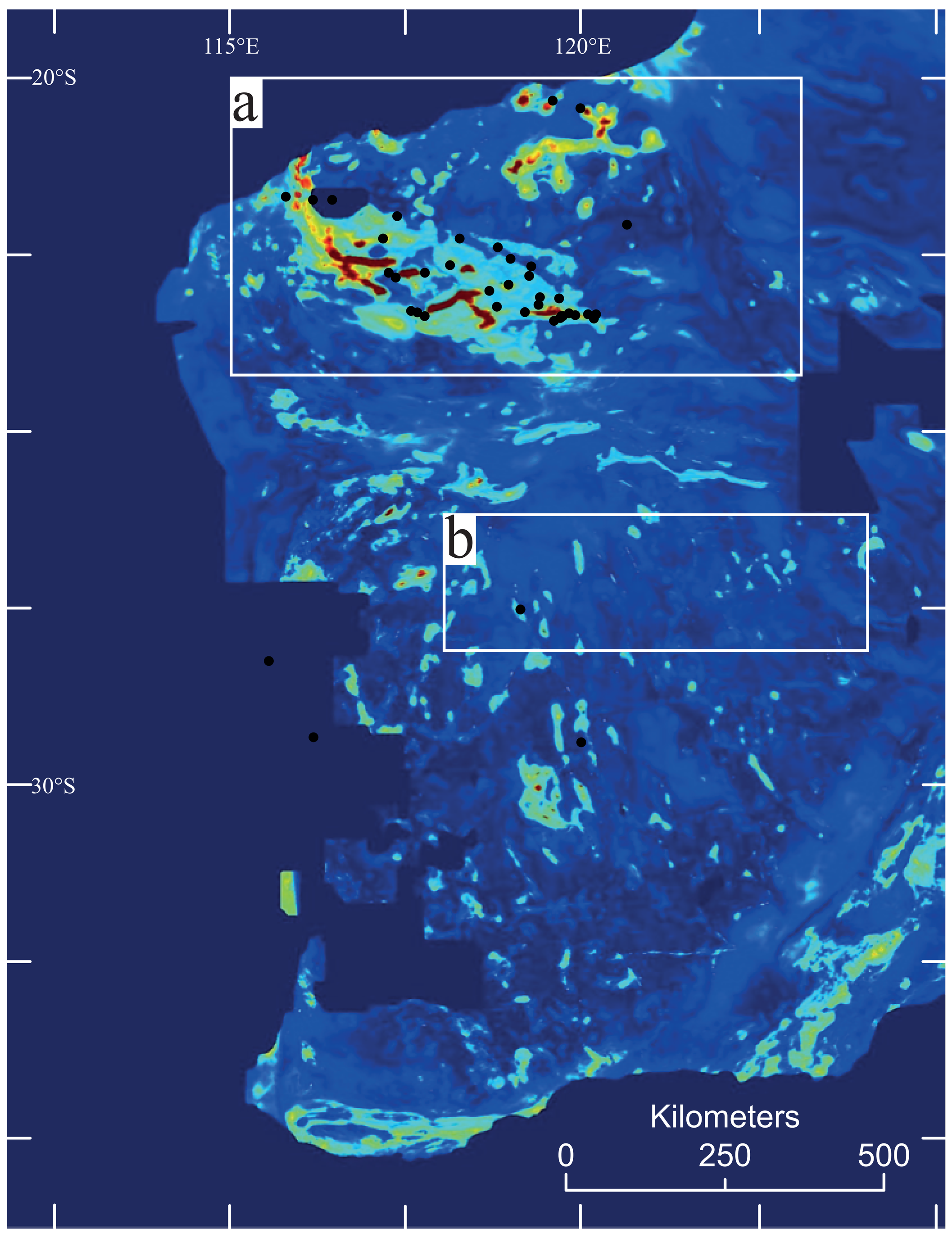


Figure 2 Workflow for the methodology that we have employed. We have used iron-ore as a case study, however any commodity and/or combination of datasets could be chosen to achieve a result. To ensure that our classification scheme is robust, we have selected two areas to test our methodology on, the iron rich Pilbara and iron poor Yeelirrie. We expect that the classifier should be able to distinguish between areas that are iron rich and iron poor, and so by testing in these areas we seek to validate the classifier and prevent over-training on our data.

3. Results

The final output of the methodology is a heat map depicting the probability of iron-ore occurring (Figure 3). The success of out methodology is based on satisfying the ground-truth predictions that the Pilbara would be iron rich (Figure 3a) and the Yeelirrie iron poor (Figure 3b). The heat map demonstrates this, showing a relatively bright Pilbara Block compared to a dim Yeelirrie Block. In the Pilbara region, the Hammersley Province is clearly visibly, and there is an additional area of prospectivity clustered around Marble Bar towards the north. Comparably, the Yeelirrie block is relatively barren with small islands of higher prospectivity.



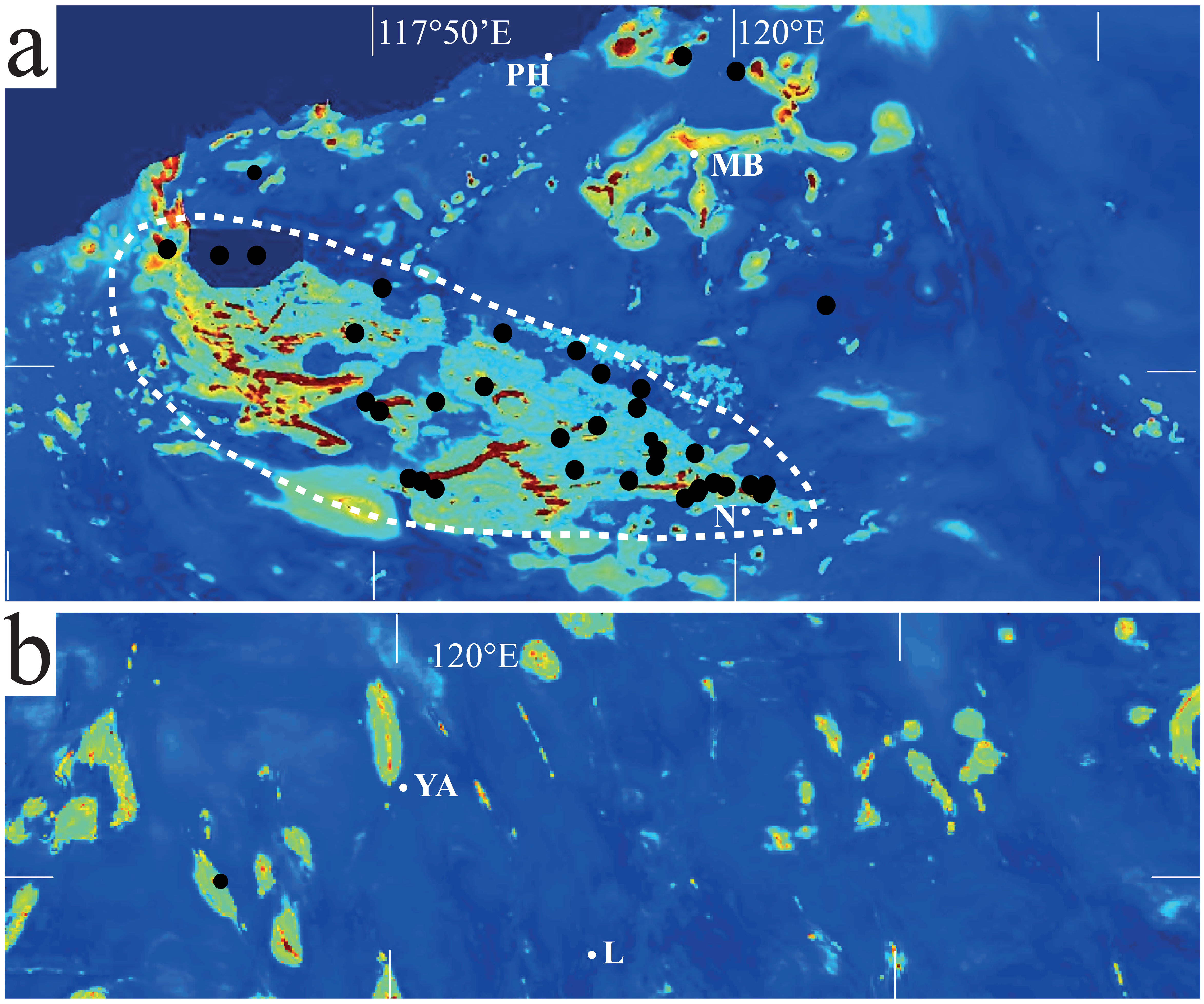


Figure 3 Map of Western Australia depciting the conversion from classifier output to heat map of the probability of iron-ore occuring. (a) shows the extent of the Pilbara bounding box, and (b) shows the extent of the Yeelirrie bounding box. The black cirlces represent known iron-ore deposits, the flat navy blue indicates areas of no data. White cirlces indicate townships in the area; L: Leinster; MB: Marble Bar; N: Newman; PH: Port Headland; YA: Yeelirrie Airport, and the white dashed line encloses the Hammersley Province. As predicted based on known ground-truths, the large swathes of the Pilbara region have a high probability of iron-ore forming, while the Yeelirrie is relatively barren.

4. Future Work and References

For the entire Australian continent (roughly 4100x3000 km), approximately 540 million calculations are required per association; therefore cloud computing will offer new pathways for parallelising these computations.. The next step will be a coupling of this approach to plate tectonic reconstructions to explore the regional kinematic and geodynamic environments associated with metallogenesis, as well as introducing temporal contraints for metallgenic events.

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