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Ranking mineral exploration targets in support of commercial decision making: A key component for inclusion in an exploration information system

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ABSTRACT

An exploration information system (EIS) is a way of creating, and managing exploration targets and should include the entire process from conceptual mineral system models to, modelling the mineral system using available data, to generation of targets or prospect areas. The main goal for any EIS is to help find new mineral deposits that are economic to mine and process at the financial conditions of the time. Prioritisation and management of exploration targets is a key to success in mineral exploration, particularly with the increasing use of mineral potential modelling techniques, including AI, which can generate a large number of targets in a study area for testing. In this paper, we present ideas for the components for an EIS designed to optimise the mineral exploration process and provide critical decision-making support. The Macquarie Arc porphyry copper-gold mineral system in New South Wales is used as an example to illustrate how such a system can be developed and implemented. Accepted mineral potential mapping workflows are used coupled with a targeting process that generates, attributes, and ranks prospect areas to produce exploration targets. The proposed front-end of the EIS is an Exploration Management Dashboard, which can be used by executives and managers to facilitate informed decision-making and optimal allocation of capital. We advocate for a standardised system capable of accommodating various commodities, input datasets, and diverse analytical techniques, including AI-driven methods and validation tools. Flexibility for user customisation, especially for non-technical users, and real-time data integration are seen as an essential part of any EIS. Furthermore, the system is designed to be dynamic, with continuous updates and improvements as new data are collected, ensuring that exploration is always focussed on the areas with the greatest potential prospectivity.

1. Introduction

The mining industry depends on mineral exploration to continue to provide the metals and minerals that society depend on. Exploration or prospecting, as it was known historically, depends on the recognition of geological features that can be used to find new economic deposits of metals and minerals in the Earth's crust (Böhmer and Kucera, 2013). Since the first recorded mining activities for flint to make tools in Neolithic times, to mining ochre at the 43,000 year old Ngwenya Mine in Eswatini (Swaziland), or the Ancient Egyptians who first mined malachite (copper) for ornaments but advanced to mine gold from the mines of Nubia, exploration has involved reconnaissance of selected areas for the required geological features, for example, green and blue coloured rocks suggest the presence of malachite or copper. The science of exploration has advanced since the days of prospecting on foot due to improved knowledge from research into the genesis of ore deposits, to the ability to collect regional-scale data consistently, extensively, and rapidly, and more importantly the ability to analyse the various data using computer techniques to allow the discovery of new metal and mineral deposits (Okada, 2021 and references therein). The power and speed of the new computer technologies and modelling techniques, including artificial intelligence (AI), means the management of mineral

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exploration and its outcomes (prospects) have become more critical. And as discovery rates decline it is ever more important to invest finite capital into the prospects that have the best chance of economic success.

Mineral exploration targeting is a scale-dependent process that starts at global to regional scales, with follow-up exploration used to vector into new discoveries at local and mine scales, down to the scale of planning the location of drill holes (Hronsky, 2004; Hronsky and Groves, 2008). Most exploration targeting in the last fifty years has been performed by searching prospect information from mineral occurrence databases and geological maps or subjectively choosing areas based on past experience or local prospecting knowledge. While these targeting methods, which largely rely on near surface exploration techniques, have been effective in the past, many areas have been subject to multiple cycles of exploration that have now either exhausted near surface potential, or simply failed to identify less well exposed mineral deposits. The advent of modern data collection and storage technologies and a global effort by national geological surveys to provide precompetitive digital data has resulted in a huge increase in data volume (Hill et al., 2020). This means exploration decision-making has become much more complex at a subjective level. Past exploration approaches also often fail to incorporate the recent advances that research has made in the understanding of mineral systems that provide the geological context for discovery.

The science of Mineral Potential Modelling (MPM) has now become an important technique for mapping exploration prospects. The tools and data available for MPM have come a long way since the publication of "Geographic Information Systems for geoscientists - Modelling with GIS" by Bonham-Carter in 1994 (Bonham-Carter, 1994), including advances in technology that allow prospectivity modelling based on machine learning techniques, using AI to help with exploration targeting (Xiong et al., 2018; Zuo et al., 2019; Liu et al., 2022 and references therein). There are a growing number of mineral exploration companies who now believe that by using such modern statistical techniques and mineral systems knowledge, it is possible to maximise the value of mineral assets and increase the probability of discovery of new mineral resources (Bonham-Carter et al., 1988; Partington et al., 2001; Partington and Sale, 2004; Partington and Mustard, 2005; Archibald and Holden, 2009; Porwal and Kreuzer, 2010; Kreuzer et al., 2015; Liu et al., 2022; Nykänen et al., 2023). The results from regional MPM can provide the confidence to invest in making tenement applications over the highly prospective areas that are freely available and the subsequent raising of capital to support follow-up exploration. MPM results can be used to plan diamond and resource drilling, allowing investment of capital in the highest priority prospect areas. The results from MPM also allow forgotten opportunities to be re-prioritised in a more objective way as the commodity market evolves, for example to increase discovery rates of critical minerals like copper, REEs, and lithium. MPM can also be used at the mine scale to better understand geological and financial risk to mining ore bodies (Nielsen et al., 2019).

Despite the recent advances, uptake in the use of MPM by the mineral exploration industry in real world exploration, in particular to help make the decisions that lead to discovery and the development of new economic mineral deposits, remains limited. Interestingly, government geological surveys are more comfortable using MPM to aid their business objectives, with examples including the Geological Survey of New South Wales (GSNSW) recently completing a project mapping the main mineral systems in NSW using MPM (e.g., Ford et al., 2019a), the Geological Survey of Finland GTK (e.g., Nykänen et al., 2017), and the British Columbia Geological Survey (e.g., Orovan et al., 2022). These geological surveys have not only used MPM to help market the prospectivity of their jurisdictions to encourage investment in mineral exploration, but they also recognise the power of MPM to support resource and land management decisions. The complexity of the mineral exploration targeting process and the variety of needs of stakeholders who are interested in mapping mineral prospectivity, including industry and government, highlights the importance of the development of a decision support system that can be used in conjunction with MPM as presented by Yousefi et al. (2019, 2021).

We started using MPM to aid exploration targeting, and subsequent exploration management of prospects mapped by MPM over twenty years ago. This has given us a perspective on how to use the large amounts of data now available at national and international scales, which MPM techniques to use, and how to apply mineral systems research to constrain and test the results of MPM. Our MPM workflows are well developed and consistent with other experts in the field (Ford et al., 2019b; Yousefi et al., 2019,2024; Nykänen et al., 2023). The processes involved in the MPM workflow and managing resulting exploration prospect areas, although largely database and GIS based, have been manual and time consuming to implement to date (Fig. 1).

The MPM workflow is well understood and documented in the literature (Ford et al., 2019b; Yousefi et al., 2019, 2021; Nykänen et al., 2023) and generally follows the steps below:

1. Research and development of a mineral systems model for the mineral system in question including local variations in the mineral system.
2. Compilation of data available that is relevant to the mineral system in question and processing of that data.
3. Creation of predictive maps from the compiled data that represent proxies for the critical parameters of the mineral system, either using spatial analysis or expert knowledge to define thresholds between favourable and unfavourable areas.
4. Data integration using the most appropriate modelling method (data-driven or knowledge-driven) based on the study area and data.
5. Model validation and analysis of outputs.
6. Prospect generation, attribution, and management.

There is general agreement that Steps 1–5 are important for a successful MPM project. However, Step 6 is often not the focus of academic studies or is left to the end user to work out what to do with the results. For mineral exploration, the goal of MPM is to create prospect areas from the outputs that represent areas of increased prospectivity based on the input data and knowledge. The processes for creating, attributing, and managing these prospect areas are an important part of the workflow that is often not described. We have developed a targeting system that can be applied at any scale from regional project generation to detailed drill targeting. However, the way we map and manage exploration prospects remains mainly manual, particularly integration of economic data that allow the most efficient prioritisation of the prospect areas produced. Our current focus is now on researching and developing techniques that can automate these processes so that they can be included in the MPM software system (EIS) stressing the need for it to be seen as a management tool for mineral exploration. The aims of this paper are to describe the workflows and systems that we have developed over the last twenty years that when combined represent a semi-automated version of a type of EIS proposed by Yousefi et al., (Fig. 1; 2019; 2021). We also present our ideas, which will be the focus for our research and development in the future, to better integrate and automate the various techniques, workflows, and technologies that we currently use to manage and prioritise our mineral exploration projects for follow up investment (e.g., Fig. 1).

2. Lachan fold belt porphyry copper-gold mineral potential case study

For this paper, we use data and results from studies of porphyry copper–gold mineralisation over the Macquarie Arc in Eastern Australia (Fig. 2) by the GSNSW (Ford et al., 2019) and the United States Geological Survey (USGS; Bookstrom et al., 2014) to illustrate the processes needed in an EIS, with a focus on prospect area development and management. The data and reports from both studies are publicly available from the GSNSW (search.geoscience.nsw.gov.au/produc

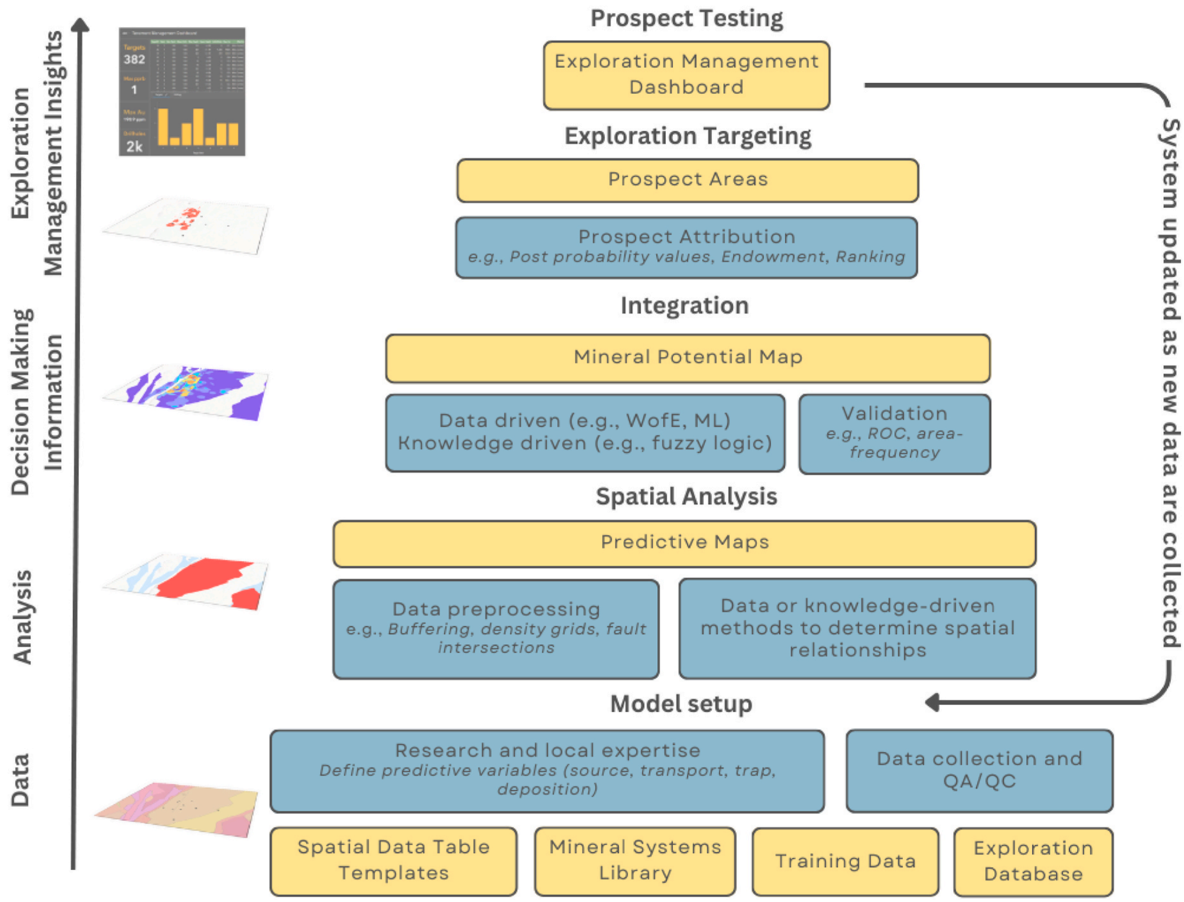

Fig. 1. Current EIS structure based on technology, software and workflows used to identify prospective areas.

t/9253) and the USGS (pubs.usgs.gov/publication/sir20105090L). The GSNSW study mapped the prospectivity for Ordovician-early Silurian porphyry copper-gold mineralisation, while the USGS study provides an endowment estimate for the same mineral system. The GSNSW study was chosen because the data and results are publicly available as pre-competitive data to support and advance mineral exploration in NSW, and research is continuing based on the results of the study (Ford et al., 2019a; Ford, 2020). The results from the mineral potential mapping are continuing to be used, for strategic land planning and decision making by the NSW government, as a technical resource for improved mineral system studies by the GSNSW, and for promoting mineral exploration in the Eastern Lachlan fold Belt through identification of key exploration criteria and the delineation of prospective ground.

2.1. Mineral systems research and the development of a mineral systems model

Mineral systems research, listing of key predictive variables, and the development of a spatial data table that lists all the predictive maps that can be developed as proxies of the mineral system are the important first steps of an EIS. An easy to access, organised, and standardised library of general mineral system descriptions needs to be available with local variations and lists of key predictive variables added as projects are completed over specific areas. Example spatial data tables for each mineral system should be included in the library so that knowledge from previous research can be utilised. In our system (Fig. 1), the mineral system descriptions and the spatial data table are stand-alone files, with descriptions manually updated as required for each project. However, the goal is to integrate the mineral descriptions and various mineral system spatial data tables into the EIS so that data entry and updates can be done automatically in the GIS environment during spatial analysis.

The mineral system concept is now well established and is now widely used to help exploration targeting (Wyborn et al., 1994; Kreuzer et al., 2008; Hronsky and Groves, 2008; McCuaig et al., 2010). Applied to mineral exploration, the mineral systems approach requires identification at various scales of the critical ore-forming processes and ingredients that can be mapped that characterise a particular mineral system. These diagnostic features can then be used as guides in area selection and exploration targeting. It is critical that all the factors involved in the processes being modelled are understood and replicated in the model for MPM techniques to be effective. This means the final map not only integrates all the digital data available but also the knowledge of the processes being modelled.

The porphyry mineral system description used for the Macquarie Arc study is generally well understood and has been successfully applied worldwide (Sillitoe, 1972, 1973, 2008; Cooke et al., 2005; Singer et al., 2008; Cox and Singer, 1986; Simpson et al., 2019; Forster and Blevin, 2019). Porphyry copper–gold deposits are typically low-grade deposits containing up to billions of tonnes of ore, associated with structurally controlled vein networks which are spatially and genetically related to intermediate to felsic porphyritic intrusions of Phanerozoic age. The depth of emplacement is 1.5–4 km. Plutons at depth (up to 8 km) comprise the source of heat, metals, and mineralising fluids.

The porphyry Cu–Au mineral system comprises the following geological processes:

- Magma fractionation: e.g., crystallising pyroxene–biotite > amphibole with hydrous melt fraction emplaced upwards (e.g., apophyses) prior to volatile saturation at 1.5–4 km.

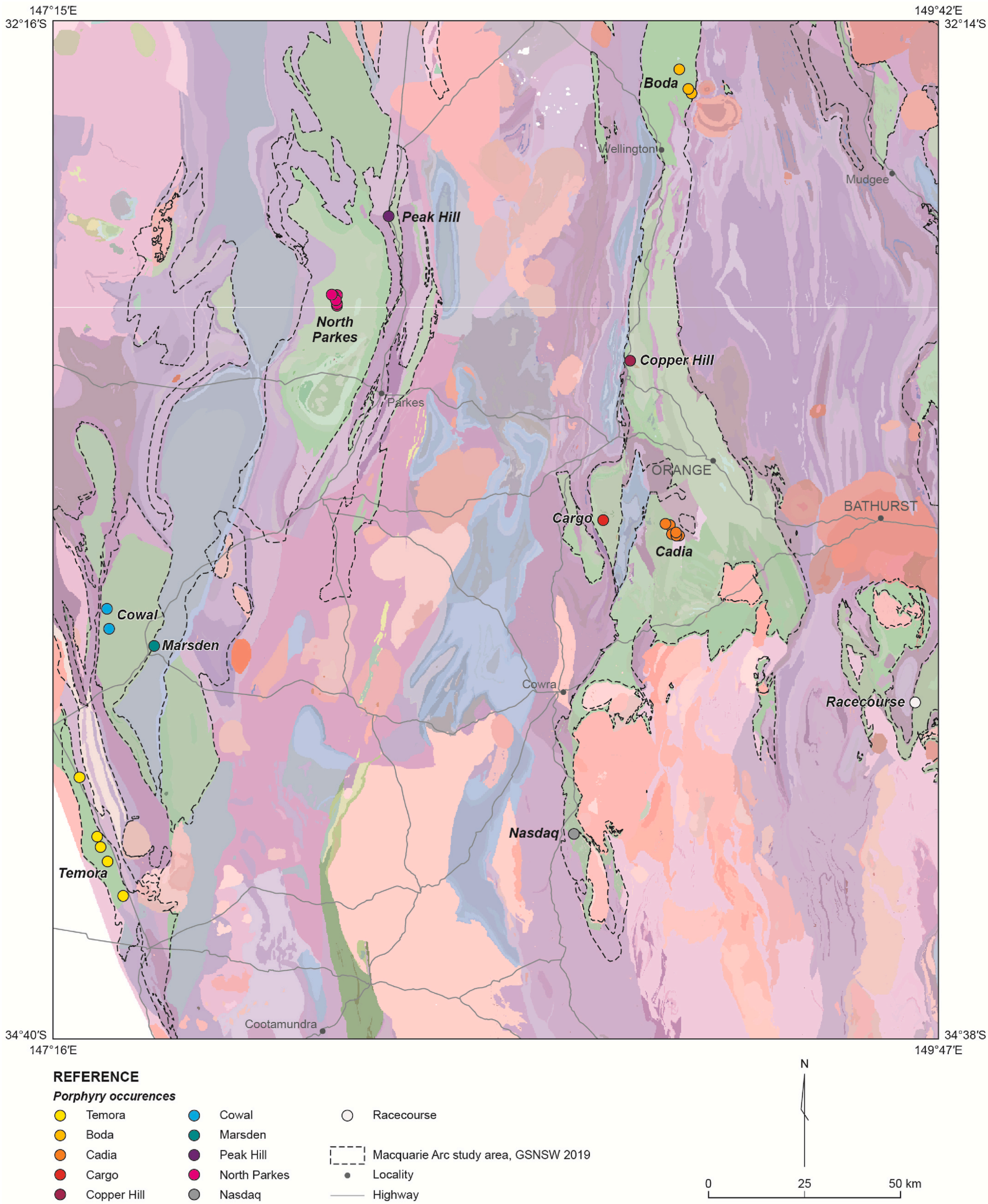

Fig. 2. Geology map over the central portion of the Macquarie Arc study area.

- Pre-, syn- and late-intrusions are common as melts and are progressively tapped from the main convecting magma. Precipitation of ore metals as magmatic sulphide phases can be caused by sulphide saturation or assimilation of carbon.
- Fluids at near-magmatic temperatures pond beneath roof rocks causing hydrostatic failure (second boiling), and fluid up-flow and decompression, forming steeply-dipping sheeted and stockwork veins.
- Cu is transported as an aqueous chloride complex ($CuCl^0$), whereas bisulfide Au complexes predominate at < 350 °C and near neutral to weakly acidic conditions.
- Hydrothermal precipitation mechanisms: Cu and Mo combination of depressurisation, cooling of aqueous ($CuCl^0$) complexes and wall-rock reaction. Destabilisation of Au–Bi-sulphide complexes due to fO2 increase and pH changes including on contact with Fe-oxides and sulphides (e.g., skarn).
- $\delta^{34}S$ data are typically +4 to −10‰ (though as low as −19‰ at Northparkes) with depletion towards the core of the system, due to partitioning of ^{34}S into the hydrothermal fluids under highly oxidised conditions.

The Macquarie Arc is the premier porphyry district in the Tasmanides of eastern Australia, hosting an endowment of over 15 Mt of Cu, about 70% of that in NSW, and more than 95% is hosted by porphyry deposits of any age. Porphyry and related skarn deposits of the Macquarie Arc also host over 65 Moz Au, which is more than 50% of the Au endowment in NSW. A local mineral system description was developed for the Macquarie Arc using current research and data and ideas provided by the GSNSW (Crawford et al., 2007; Glen et al., 2007, 2011; Blevin, 2002; Forster et al., 2011; Fox et al., 2015). This was used to constrain the mapping of the geological processes, or proxies for those processes, that are present in the mineral system to create a series of predictive maps to be used to create the mineral potential models. The key features that characterise the Macquarie Arc porphyry system are listed below under the relevant mineral system component.

Source

- Calc-alkaline magmas of Ordovician to early Silurian age
- Intrusions which are oxidised magnetite-series diorite to quartz monzonite–syenite and pegmatitic phases
- Shoshonitic (high-K) subaqueous volcanics
- Association with skarn and epithermal mineral occurrences
- Large elliptical magnetic highs (100×100 m to 2 km) and smaller anomalies (up to 500 × 200 m) with an inner "donut" low indicative of porphyry signatures at depth.

Transport

- Regional structures
- Cross-volcanic belt structures (NW or WNW trending).

Trap

- Graben structures
- Dilational fault bends
- Pipe-like, finger-like and dyke-like complexes emplaced near the base of K-rich volcanics
- Veining and propylitization.

Deposition

- Known Ag–Au-base metal epithermal mineralisation
- Mesothermal carbonate–Au–As–base-metal mineralisation
- Au–Zn bearing phyllic–pyrite zones
- High Au/Cu ratios in relatively restricted late phyllic and silicic (cap) alteration zones
- Cu, Au, Ag, and Mo geochemical anomalies with peripheral Pb and Zn
- Elevated Ti, V, P, F, Ba, Sr, Rb, Nb, Te, Pb, Zn, and PGE assays.

This list was used to create a comprehensive spatial data table in MS Excel that was used to record information about all the predictive maps that were developed including their relevance to the mineral system, GIS methods used to create them, data required, and statistical correlations of the various maps to a set of known porphyry copper–gold deposits (Download the full results here: search.geoscience.nsw.gov.au/product/9253).

2.2. Data compilation and processing

Tools for data compilation and processing are an important part of any EIS. These should include tools for concatenating fault data and creating derivative point datasets for intersections, jogs, bends, and splays, checking topology of geology data, processing of geochemistry and geophysical data, and creating stream catchment maps from a DTM. Tools to aid in the selection of training points for data-driven modelling methods should also be included. These could include training point thinning tools as well as tools to select random subsets of training data to use for validation.

The study area for the mineral potential model was masked to the Macquarie Arc, which includes the permissive host rocks for the Ordovician–early Silurian porphyry Cu–Au mineral system. The extent of the Macquarie Arc was defined from both the seamless geology and a geophysical interpretation undercover provided by the GSNSW (Fig. 3).

Data used to map the porphyry copper-gold mineral potential in the Macquarie Arc was provided by the GSNSW from their high-quality precompetitive datasets. Specific data were improved for the MPM project, including updated seamless basement geology, fault data attributed with ages, events, and fault order, geochemistry, geophysics, and mineral occurrence files with verified mineral system attributes. The data were analysed and reclassified in accordance with the mineral system features described above. Data processing included classifying and attributing rock units, creating derivative datasets from fault data, and statistical analysis of geochemical data relevant to the mineral system.

The Macquarie Arc Porphyry copper–gold MPM model used in this paper required training data for spatial analysis of the data, to create predictive maps and for the MPM modelling. These training data were chosen from the GSNSW MetIndEx database in collaboration with GSNSW geologists. The 14 training points that were selected have sufficient regional spread, are related to the same mineralisation event, and represent the range of deposit styles present in a porphyry copper–gold mineral system (Table 1; Figs. 2 and 3).

Mineral occurrence, resource endowment and mine data are also key datasets that are required in an EIS to constrain exploration targeting and help prioritise and manage the resulting prospect areas. Endowment data from the USGS resource assessment study were integrated with the MPM training data to create an example of the type of resource endowment database that needs to be included in an EIS (Table 1). Any EIS will have to be able to deal with multiple commodities and deposits that contain different combinations of metal like the deposits that form in a porphyry mineral system. The known mines and resources in the Macquarie Arc study area contain varying quantities of copper, gold, molybdenum, and silver. So, to be able to use the deposits for economic and spatial analysis, their total metal endowment needs to be standardised and aggregated. The EIS can do this by linking the various metal endowments and calculating the metal value of the endowment for each metal, using current or chosen historic metal prices. The advantage of using this approach is that the metal values provide immediate information on the potential economic opportunity of a deposit and allows the comparison of diverse deposit types and, if the metal price data are updated regularly, provides information on the commodities to be

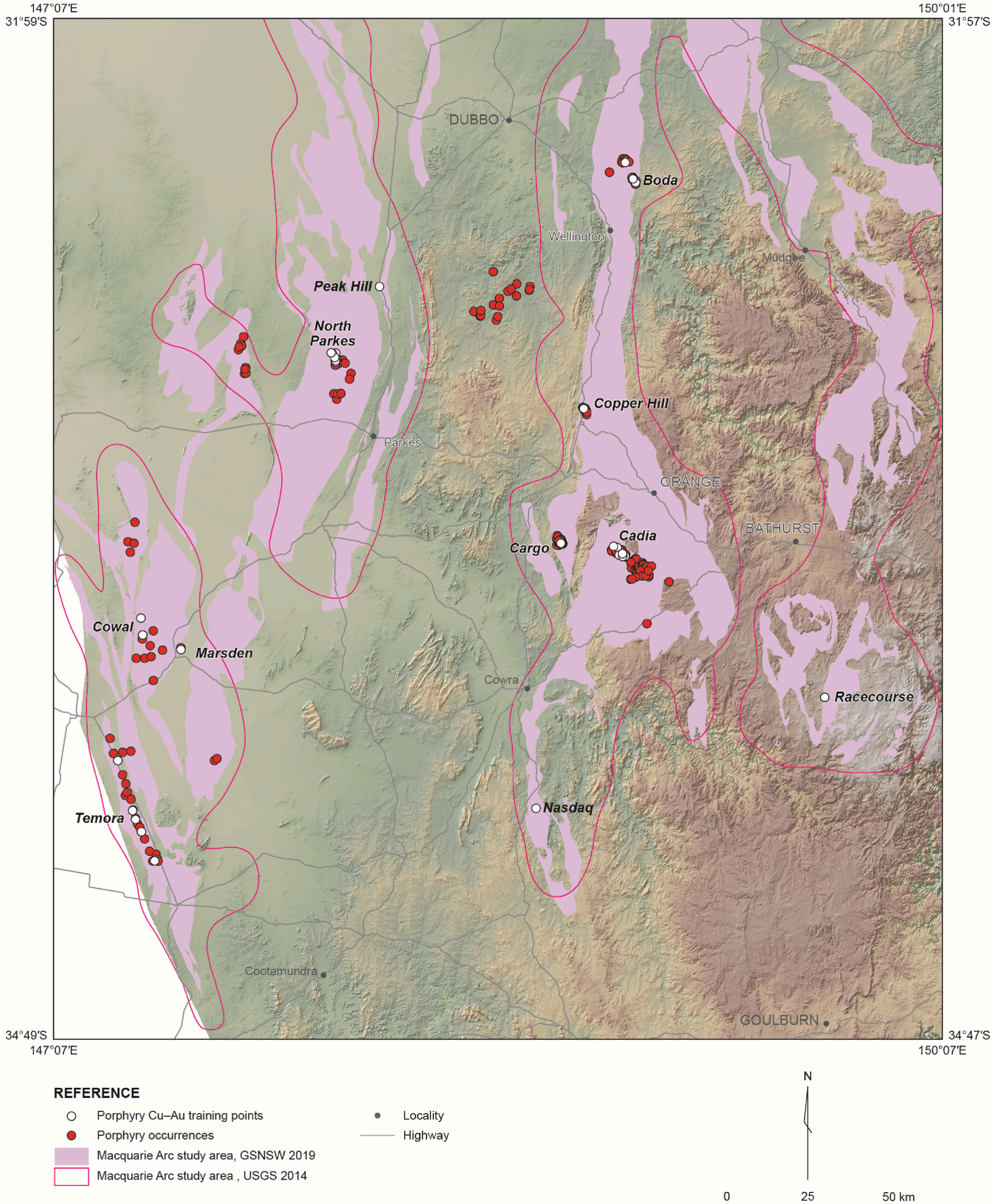

Fig. 3. Porphyry copper–gold training points in the central portion of the Macquarie Arc study area (Ford et al., 2019. USGS study areas shown as a red outline for comparison (Bookstrom et al., 2014).

Table 1
List of prospects and mine data used as training points for the porphyry copper–gold mineral potential model and USGS endowment study (Ford et al., 2019; Bookstrom et al., 2014). Note ES = USGS endowment study (Bookstrom et al., 2014), TP = training point from porphyry copper–gold mineral potential model, UG = underground mine, PPrb = post probability value at the data point from porphyry copper–gold mineral potential model, A$ = Australian dollars, and Cu Eq T = copper equivalent tonnes (see text above for method of calculation).

Name	Group	Easting	Northing	Study	Type	Cu Eq T	Metals A$M	PPrb
Cadia East	Cadia	686,451	6,296,476	ES	UG	14,470,741	$107,469	0.9599
Cadia East	Cadia	686,547	6,295,639	TP/ES	Pit	1,110,000	$1432	0.8493
Ridgeway	Cadia	683,693	6,298,742	TP/ES	UG	1,459,229	$11,772	0.763
Cadia Hill	Cadia	685,387	6,296,054	ES	Pit	688,651	$889	0.8493
Cadia Far East	Cadia	687,250	6,295,655	ES	Pit	302,400	$390	0.0223
Big and Little Cadia	Cadia	684,852	6,298,387	ES	Pit	168,354	$217	0.3159
E–26	North Parkes	596,602	6,358,550	TP/ES	Pit	988,377	$3738	0.0083
E–48	North Parkes	597,710	6,357,098	ES	UG	497,224	$2352	0.0083
E–22	North Parkes	597,066	6,358,213	ES	Pit	218,346	$1267	0.0083
E–27	North Parkes	598,004	6,358,425	ES	Pit	182,184	$1148	0.0083
E–37	North Parkes	597,980	6,356,097	ES	Pit	45,914	$71	0.0012
E–28	North Parkes	597,976	6,355,653	ES	Pit	30,814	$68	0.0012
E–31N	North Parkes	597,981	6,356,208	ES	Pit	42,675	$279	0.0083
Mandamah	Temora	535,400	6,217,100	ES	Resource	193,481	$1235	0.2972
Culingerai	Temora	536,295	6,214,378	ES	Resource	50,411	$344	0.0927
Estoril	Temora	538,122	6,210,601	ES	Resource	55,124	$418	0.0927
Yiddah	Temora	530,827	6,232,582	TP/ES	Resource	296,796	$1073	0.0459
Gidginbung	Temora	542,195	6,201,625	TP/ES	Pit	221,388	$1524	0.6422
E42	Cowal	537,962	6,276,583	TP	Pit/UG	999,584	$18,340	0.8525
E39	Cowal	538,513	6,271,355	TP	Prospect	728,313		0.2047
Kaiser	Boda	689,678	6,412,217	TP	Resource	129,336	$6888	0.0005
Boda	Boda	690,504	6,411,092	TP	Resource	54,000	$16,803	0.0001
Glen Hollow	Boda	687,303	6,417,299	TP	Prospect	978,803		0.2121
Marsden	Marsden	550,299	6,266,872	TP/ES	Resource	2,107,432	$4518	0.0813
Copper Hill	Copper Hill	674,502	6,341,285	TP/ES	Resource	3,086,235	$4413	0.763
Racecourse	Racecourse	748,817	6,252,109	ES	Resource	1,443,502	$221	0.0007
Cargo	Cargo	667,434	6,299,702	TP/ES	Resource		$70	0.0248
Peak Hill	Peak Hill	611,504	6,379,010	TP	Pit	191,547	$2226	0.2047
Nasdaq/Kiola	Nasdaq	659,792	6,217,812	TP	Prospect			0.004

focussed on as economic conditions change.

The total metal value and copper equivalent endowment in Tables 1 and 2 were calculated by adding the recorded resource estimate data for copper, gold, molybdenum, and silver together using the metal prices at September 27, 2023 of A$12,572 per tonne of copper, A$2974 per ounce of gold, A$113,450 per tonne of molybdenum and A$$35.66 per ounce of silver to give a total endowment metal value that converts to a total copper metal equivalent tonnage value, using the formula Metal Tonnes*Metal Grade*Metal Price = Metal Value aggregated for all metals divided by the copper metal price (Tables 1 and 2).

Some of the known porphyry copper-gold deposits listed in Table 1 tend to be clustered, which enhances their economic potential to be developed into profitable mines. These deposits were grouped in our example, according to the 2-km rule of Singer et al. (2005), with their resources aggregated for grade-tonnage and spatial-density modelling within the EIS (Table 2). The Cadia group of deposits, including at least five individual porphyry copper-gold deposits and two skarn copper-gold deposits, when combined qualifies the Cadia group of deposits as a world-class giant resource of both copper and gold, according to the criteria of Singer (1995), and amounts to about 71% of the copper and 89% of the gold in identified resources of known porphyry copper-gold deposits in the Macquarie Arc (Bookstrom et al., 2014). The Northparkes group of deposits includes at least four porphyry copper-gold deposits. Temora central group of porphyry copper sites includes three known deposits and several prospects. Two other deposits in the Temora area are grouped with nearby porphyry copper prospects (c.f., Table 1, and Table 2).

Table 2
List of mines and resource areas used in both studies, sorted by total metal value (Metals A$M), combined using the 2-km rule of Singer et al. (2005), with their resources aggregated for the purposes of grade-tonnage and spatial-density estimation in the EIS. See Table 1 for individual mine and resource data and for details on how the PPrb values and metal values were calculated. Type - if it is an operating mine or resource awaiting development. Metals A$M - the aggregated metal values based on the endowments reported by Bookstrom et al. (2014), Predicted MAMV A$M - the estimated metal value from the post probability Macquarie Arc MPM model using Macquarie Arc endowment data only, Predicted GbMV A$M - the estimated metal value from the post probability Macquarie Arc MPM model using the USGS global porphyry endowment data (Singer et al., 2008). Rank A$M - value after other economic cost factors are applied, which are used to rank the prospect areas to identify prospect targets.

Name	Type	Study	Easting	Northing	PPrb	Metals A$M	Predicted MAMV A$M	Predicted GbMV A$M	Rank Value A$M
Cadia	Mine	USGS	686,451	6,296,476	0.9599	$228,811	$164,758	$298,527	$85,529
Boda	Resource	MPM	687,303	6,417,299	0.2121	$2408	$8176	$27,425	$487
Northparkes	Mine	USGS	596,602	6,358,550	0.0083	$38,802	$8176	$27,425	$2
Cowal	Mine	MPM	537,962	6,276,583	0.8525	$1626	$569	$2242	$8186
Marsden	Resource	USGS	550,299	6,266,872	0.0813	$18,149	$28,957	$145,995	$27
Temora	Mine	USGS	543,144	6,201,375	0.6422	$25,214	$687	$4821	-$443
Copper Hill	Resource	USGS	674,502	6,341,285	0.7630	$12,567	$3731	$19,476	$81,749
Peak Hill	Mine	MPM	611,504	6,379,010	0.2047	$679	$2495	$13,630	$181
Racecourse	Resource	USGS	748,817	6,252,109	0.0007	$10,274	$12,378	$44,123	$0
Cargo	Resource	USGS	667,434	6,299,702	0.0248	$9157	$15,633	$76,828	$119

2.3. Creation of predictive maps

Tools for transforming the raw data into features that can be used to test for association with the training data and create the final predictive maps will be an important component of an EIS. These should include multi buffer distance tools to test for proximity relationships, raster classification tools to test for categorical relationships or relationships with reclassified continuous data, and density tools to create density grids from point and line data. The tools to calculate the spatial statistics needed to determine the spatial correlation of the data to the training points for data driven modelling methods will be included in the modelling tools.

The weights of evidence modelling technique was used in the GSNSW study to calculate spatial statistics, optimise the capacity of the various maps to predict the presence of porphyry copper–gold deposits and to create a mineral potential map for porphyry copper–gold mineralisation in the Macquarie Arc. Weights of evidence uses Bayesian statistics and allows the analysis and combination of various datasets to predict the location of the feature in question (Bonham-Carter et al., 1989; Agterberg et al., 1993; Bonham-Carter, 1994). The technique is based on the presence or absence of a characteristic or pattern (e.g., distance to fault) and the occurrence of an event (e.g., mineral occurrence). The spatial analysis process allows for a non-biased assessment of a large number of predictive variables derived from available data in order to determine their relevance to the mineral system. The technique is well understood and is an accepted data driven MPM technique. The spatial analysis and weights of evidence modelling was carried out using the Arc-SDM extension for ArcGIS.

The GSNSW study area for the porphyry Cu–Au model was converted into a 50 × 50m grid that represents the extent of the permissive geology and the grid cell distribution for all subsequent predictive map grids created for the model. The study area contains 9,239,756 cells for a total area of 23,100 km^2. The cell size of the grids was chosen to represent the minimum scale that the data should be viewed. A unit cell of 1 km^2 was used for the weights of evidence statistical calculations and represents the area assigned to each training point during the spatial analysis. Using the input parameters of the study area, unit cell, and number of training points, a prior probability was calculated (0.000606) that represents the chance of randomly finding a deposit within the study area before any additional evidence for mineralisation is applied. The aim of weights of evidence modelling is to add evidence in support of a hypothesis to increase or decrease the prior probability of each grid cell in the study area.

Before conducting the spatial analysis, GIS processing was carried out on the data. Polygon features such as geological units can be tested directly or a buffer may be applied to identify an area of influence (for example around an intrusion), or to account for shallow-dipping units. Point and line data were buffered before being tested. Alternatively, these data were gridded to determine the density of features or to show the interpolated distribution of elements for a geochemistry dataset. Continuous data, such as geophysics maps or density grids, were reclassified into a small number of classes to allow them to be tested for a correlation with the training data.

Spatial statistics were calculated using the weights of evidence tools in Arc-SDM and used to create the predictive maps, i.e., determining buffer distance thresholds, and to understand how well the map in question can predict the training data. This process creates a weights table for each predictive map that contains the spatial correlation results and weights that are used to calculate the final model values. The weights tables contain important statistics that we add to our spatial data tables, which can be used to understand the results and make decisions about the relevance of the predictive maps for mineral potential modelling (Bonham-Carter, 1994; Bonham-Carter et al., 1989). The spatial analysis resulted in the creation of 164 valid predictive maps for the porphyry copper–gold mineral system that have been tested for a spatial correlation with the corresponding training data. Forty eight percent of the valid maps correlated with the training data (C value ≥ 1). The full spatial correlation results for each predictive map are available for review (search.geoscience.nsw.gov.au/product/9253) and are an important exploration management resource for understanding the relevance of each dataset to porphyry copper–gold mineralisation in the Macquarie Arc.

2.4. Modelling and validation

Several methodologies are commonly used for mineral potential modelling including data-driven techniques such as the weights of evidence method we have used in our example. An EIS should include a comprehensive suite of methods so that the modeller can decide on the best method (or combination of methods) that best suits their study area. This should include other data-driven methods (including AI) such as logistic regression (e.g., Carranza and Hale, 2001; Nykänen et al., 2008; Porwal and Kreuzer, 2010), neural networks (e.g., Singer and Kouda, 1999; Porwal et al., 2003; Nykänen, 2008), random forests (e.g., Carranza and Laborte, 2016; Ford et al., 2015; Ford, 2020; Roshanravan et al., 2023), and knowledge-driven methods such as fuzzy logic (e.g., Tangestani and Moore, 2003; Porwal et al., 2003; González-Álvarez et al., 2010; Yousefi and Carranza, 2015; Nykänen et al., 2023). Validation techniques should also be available including the area-frequency tool used in this study (Behnia et al., 2023) and the receiver operating characteristics (ROC) technique (Obuchowski, 2003; Fawcett, 2006; Nykänen et al., 2017, 2023).

A mineral potential map was developed for the porphyry copper–gold mineral system using a selection of predictive maps that represent all stages of the mineral system model described above. The model was created using the weights of evidence tools in Arc-SDM. Predictive maps were chosen that have the best regional coverage, a significant spatial association with the training data, and minimal duplication of predictive map patterns. The mineral potential map was primarily created for the purpose of identifying broad-scale strategic areas to conserve important resource lands for the government rather than delineating exploration targets for industry. Tighter constraints on the predictive maps used in each mineral potential model may be required to target company exploration activity. Several predictive map combinations were tested before the final set of maps were chosen to optimise the final result with respect to predicting the location of the training data. The output mineral potential map based on the maps listed in Table 3 is a grid of values that map the geological potential for the presence of porphyry copper–gold mineralisation for each grid cell. The output grid values range from 0 to 1 and map the post probability, which has either increased or decreased from the prior probability, depending on the combination of weighted predictive map variables (Fig. 4).

The model was validated by calculating the efficiency of classification using the Area–Frequency tool in ArcSDM. This is a measure of how well the training sites were predicted by the model. The efficiency of classification increases (approaches 100%) as more training points are predicted within a smaller prospective area. The porphyry copper–gold mineral potential model has an efficiency of classification of 96.0%. The area considered to be prospective (where the post probability is greater than the prior probability) covers an area of 3707 km^2 compared to the study area of 23,100 km^2, which has reduced the exploration search space to 15.18% of the total study area (Fig. 4).

2.5. Analysis of the MPM post probability results

The results of the modelling for porphyry Cu–Au mineral potential in the Macquarie Arc highlight that moderately to very strongly oxidised magmas that are also K-enriched have the best correlation with the training data. This is in-line with the current understanding of the porphyry Cu–Au mineral system in the eastern Lachlan Orogen. Additionally, the regional-scale faults failed to show a very strong correlation

Table 3
List of predictive maps used for the Porphyry copper–gold mineral potential model (The full spatial correlation results for all predictive maps created are available for review at (search.geoscience.nsw.gov.au/product/9253). #TP: number of training points, C: contrast value, StudC: studentised contrast value.

Mineral System	Spatial Variable	Predictive Map	Variable ID	# TP	C	StudC
Source	Association with Ordovician–early Silurian intrusions (Benambran cycle)	d2intall2	800 m	9	2.59	4.64
	Association with fertile magma (oxidised and K-rich)	mf_redoxken	Moderately to very strongly oxidised AND med- to ultra-high-K	10	1.45	2.44
	Shoshonitic/high K subaqueous volcanics	d2vhighk2	4600 m	10	2.48	4.19
Transport	Fault age (Benambran Contraction)	d2fltbenc2	1400 m	8	2.01	3.71
Trap	Reactivity Contrast – All	d2reactcon2	850 m	8	1.42	2.63
	Fault Bends-Jogs-Splays	d2fltbjs2	1550 m	12	2.36	3.09
	Magnetics (high)	rtphi2	Class $\geq$ 6	9	1.94	3.48
Deposition	Drillhole–Rock–MinOcc Cu–Au anomaly	d2cuau	Combined drill hole–rock Au $\geq$ 0.04 ppm and Cu $\geq$ 1260 ppm	14	3.88	3.72
	Au, Cu, Ag, Zn occurrence density (constrain by age)	densaucuagzn2	Class $\geq$ 2	10	2.17	3.67

with the training points. However, fault bends, jogs, and splays are likely to be important to the localisation of fertile magmas in the study area.

The most prospective areas for porphyry Cu–Au mineralisation within the Macquarie Arc are located around the Cadia and Cowal districts (Fig. 4). The Cadia East, Copper Hill, Cowal, Endeavour 39, Gidginbung, and Ridgeway training points all lie in areas of high to very high potential; while Cargo, Combella, Peak Hill, Marsden, and Yiddah lie in areas of enhanced mineral potential (Fig. 4; Table 1). Northparkes and Nasdaq are located within the prospective area. Other highly prospective areas are located around the Gidginbung and Copper Hill districts, as well as near the Glendale deposit to the south of Cadia (Fig. 4) and the Milly Milly prospect to the south of Cowal. In addition, there are a number of areas away from the main mineralised trends that have moderate to high potential for hosting porphyry Cu–Au mineralisation, despite having no known occurrences of this type (Fig. 4). In particular, a north–south trending zone of relatively high prospectivity is located just to the west of the highly prospective area around the Glendale deposit. There are no known occurrences of any type located in this area. A northeast trending zone of moderate to high prospectivity is also highlighted approximately 2 km to the west-northwest of the Black Ridge Copper Mine. Another area of moderate prospectivity with no known mineral occurrences is located to the northwest of the Peak Hill deposit. These areas share the same key magma fertility characteristics as the highly endowed areas around the Cadia and Cowal districts (i.e., oxidised, and high-K magma, shoshonitic volcanics), as well as having favourable structures for the transport and trapping of mineralised fluids.

Although all the key magma fertility characteristics are present in the area, the Northparkes district was only highlighted as weakly prospective. A review of the remainder of the maps used for creating the porphyry Cu–Au mineral potential model highlights the lack of faults mapped in this poorly exposed part of the Macquarie Arc. Exploration for porphyry Cu–Au mineralisation in the Northparkes district has typically focussed on interpretation of high-resolution magnetic data, RAB drilling, and multi-element geochemistry. However, it is also possible that the faults may be mapped in company data that has not been incorporated into government datasets. As faults are the key dataset used to derive many of the transport and trap maps, the prospectivity of the Northparkes district may be upgraded with incorporation of better resolution structural mapping. This is an example of one of the key outputs from MPM that uses spatial analysis to generate predictive maps: the results provide a list of the important data that correlate spatially with the known deposits and provide a guide to follow up data to be collected over less prospective areas if the data are missing. The Boda-Kaiser project currently being explored with success is a good example of how the mapping of important predictive features can upgrade the prospectivity of an area. The Kaiser deposit was used as one of the porphyry Cu–Au training points but is located in an unprospective area in the model (although only 7 km south of a prospective region associated with the Glen Hollow prospect). This is due to the absence of mapped intrusions of the appropriate age (highly prospective), shoshonitic/high-K volcanics within the sequence (highly prospective), and the lack of mapped structures. However, recent company mapping has identified relevant intrusions in the area and the GSNSW seamless geology can now be updated to include these. If the MPM was rerun when these data are integrated the prospectivity of the Boda-Kaiser project would be improved. This highlights the importance of being able to use automated feedback loops in any EIS to assess the effects of integrating new data on the prospectivity (e.g., Fig. 1).

3. Mapping prospect areas

Prospect areas are a key input into any EIS. These can be mapped in various ways, including subjective mapping of areas based on local knowledge, mapping areas around known occurrences of minerals including historic mines, mapping areas of anomalous geochemistry, mapping areas of anomalous geophysical properties, or by using the results of knowledge- or data-driven MPM techniques, including AI. Our preference is to use the least subjective method available based on data availability constraints and to use a method that integrates all available data and knowledge. Multiple MPM methods can also be used with the results integrated to produce prospects with increased certainty (Yousefi et al., 2024). The results of the post probability values from the MPM model developed for the Macquarie Arc porphyry Cu–Au study is used as an example of how we map prospect areas from MPM model results that can then be used in an EIS.

Prospect areas can be mapped from a MPM model by reclassifying the resultant output map grid in a GIS into a classified grid, with prospective areas split into classes above a certain threshold of geological potential measured by post probability values and non-prospective areas below this threshold. Statistical methods, which are similar to those used to map geochemical or geophysical grid anomalies, can be used to reclassify the post probability values above the prior probability with equal interval, quantile, natural breaks, geometric deviation, and standard deviation techniques all useful and generally provided by current GIS software like ArcGIS or QGIS. Cut-offs can also be defined by specifying a percentage area of the study that is to be focussed on, which allows the exploration search space to be reduced to match the intended exploration investment.

The prior probability of any MPM model always defines the lower cut off threshold, as any grid cell with a value greater than the prior probability must have at least one required predictive geological feature present. In our example study the prior probability is 0.000606, so any grid post probability value greater than this is considered to be part of a potential prospect area. However, just using the prior probability often does not provide the best prospect area resolution, depending on how the output from the prospect area mapping is to be used. For example, the scale resolution required to identify areas for tenement acquisition is

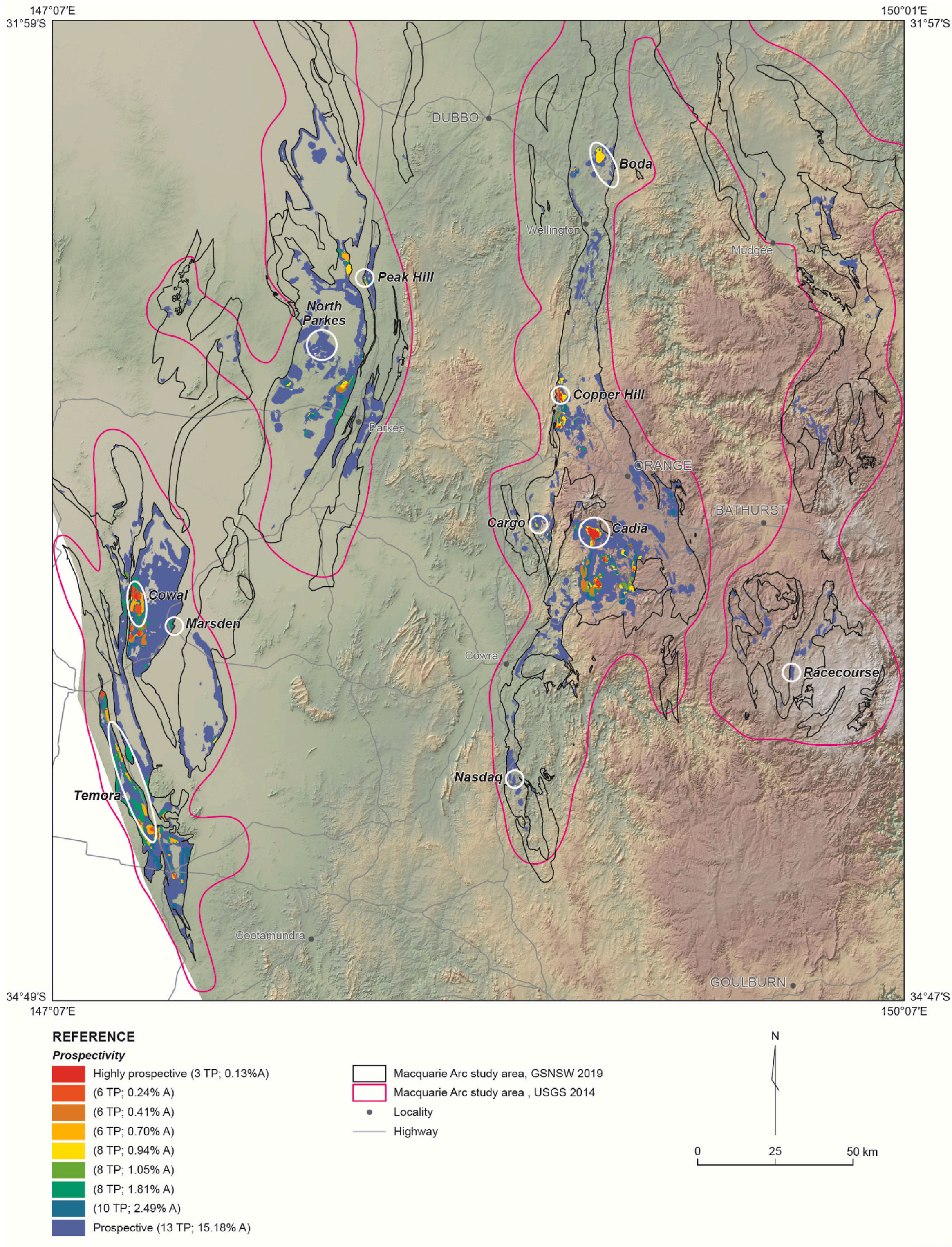

Fig. 4. Porphyry copper–gold mineral potential results in the central portion of the Macquarie Arc study area showing the cumulative number of training points (TP) and percentage of study area (A) captured by each class.

orders of magnitude different to the resolution required for drill hole planning.

An intuitive and effective way of reclassifying the results from a MPM model to map prospect areas is to attribute the prior probability values from the model to mine and mineral occurrence data in the study area (e.g., Table 2). The probability cut offs can then be chosen based on the range of post probability values of the known producing mines compared to the endowment of the mines and prospects. This method was used to map the example prospect areas in this paper with the mine endowment compared to the post probability value from the MPM model listed in Tables 1 and 2.

The detailed deposit metal value endowment data listed in Tables 1 and 2 were plotted against the PPrb values from the Macquarie Arc MPM model to assess the relationship between endowment and geological potential measured by the model post probability values. The distribution of post probability values against reported metal endowment using the total metal values for the mines and resources define four distinct classes (Fig. 5; Tables 1 and 2). Those below the prior probability, which are considered to be non-prospective. A group of deposits that sit between the prior probability and a post probability value of 0.0081, with generally low endowment values. A group between post probability values of 0.0081 and 0.63, which have potentially significant economic endowment values and a group above post probability values of 0.63 that have high post probability values and high economic endowment values. Interestingly, there is a gap between the two groups, which we interpret to suggest, like endowment estimates using Zipf's Law, these may be the likely range of metal value endowments for potential new discoveries in the Macquarie Arc area (e.g., Fallon et al., 2010; Howarth et al., 1980; Rowlands and Sampey, 1977). The prospect areas were split into two classes based on the distributions of post probability values and metal values with a lower order class between 0.0081 and 0.63 post probability values and a high order class between 0.63 and 0.9599.

This classification of the Macquarie Arc MPM model resulted in 566 prospect areas in total, of which 69 are highly prospective (primary) prospect areas and 497 are prospective (secondary) prospect areas. Nine of the prospect areas include training points used in the Macquarie Arc MPM model and five training points are not covered by prospective areas. The Cadia East porphyry deposit is 1.5 km^2 and the recently discovered Boda porphyry based on current drilling has an area of 0.4 km^2. It is therefore assumed in our example that a prospect area must be at least 0.4 km^2 in area to provide the scale for an economic deposit to be present. This reduces the number of primary prospect areas to 16 and the secondary prospect areas to 141.

The primary prospect areas have similar geological features that have been mapped at the Cadia, Temora and Cowal mines whereas the secondary prospect areas have similar geology to the Peak Hill and Northparkes mines. So, without taking economic or social licence to operate factors into account, the prospect areas can be prioritised into targets for exploration using the MPM model post probability values by ranking them using the order of the highest post probability values to the lowest.

4. Applying economic factors to prospect areas in an EIS

The main goal for any EIS is to help find new mineral deposits that are economic to mine and process at the financial conditions of the time. This applies to both exploration companies, who make the discoveries and develop them into profitable mining assets and governments at all levels, who need to manage and promote the efficient and socially responsible development of these mining assets. The discovery of profitable mines can only be successfully done if economic parameters are considered at the targeting stage (e.g., Henley, 1997; Partington and Sale, 2004; Kreuzer et al., 2008; Hronsky and Groves, 2008; Partington, 2010; Kreuzer et al., 2015).

The mineral system concept assumes that for efficient deposition of metal in the Earths' crust, all the required process have occurred (Wyborn et al., 1994; Kreuzer et al., 2008; Hronsky and Groves, 2008). This means from a MPM perspective that those areas where all the geological proxies for the mineral system process occur together are the prospect areas most likely to host larger and therefore economic deposits of metals (e.g., Partington, 2010; Yousefi and Carranza, 2017; Yousefi et al., 2019). The post probability values derived from any mineral potential model provide a numeric measure of this required spatial overlap. This means that if the assumption that only the largest metal

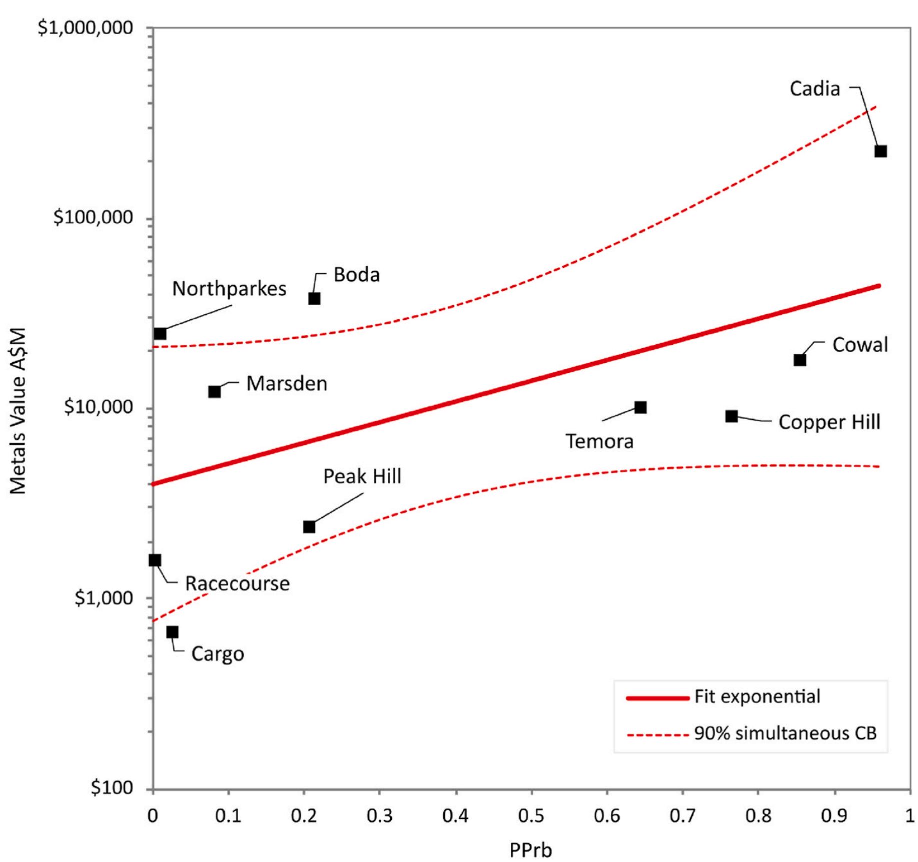

Fig. 5. Plot of aggregated copper equivalent tonnage endowment from Table 2 compared to post probability values with a statistical correlation test based on an exponential distribution. A Spearman's Rank correlation gives a strong statistically valid positive correlation coefficient of 0.54 using the Fit on the graph.

deposits occur where the required geological process overlap is valid there should be a positive statistical correlation between the post probability values and metal endowment in the study area. It is therefore important before ranking prospect areas from a MPM model that this assumption is tested statistically by attributing the MPM post probability values to all relevant metal occurrence data, particularly the training data (e.g., Tables 1 and 2). This allows metal endowment to be plotted against post probability values and any statistical relationship can then be tested (Fig. 5).

In the Macquarie Arc, the endowment metal data have a strongly skewed log normal distribution, which is typical of resource metal endowment distributions (e.g., Singer et al., 2008; Fallon et al., 2010; Howarth et al., 1980; Rowlands and Sampey, 1977). The post probability values from the MPM model have a similar strongly skewed log normal distribution that seems to compare with the endowment data distribution. A Spearman's Rank correlation coefficient was calculated to test the correlation between the metal endowment and post probability values as neither distribution are normally distributed. The Spearman's Rank correlation gave a strong statistically valid positive correlation coefficient of 0.54, confirming the observation from comparing the distributions that there is a positive statistical relationship between total metal value and the MPM post probability values (Fig. 5). The positive correlation suggests that even though the metal endowments of the training data were not taken into account by the MPM technique, the resulting post probability values have the potential to be used to estimate potential metal endowment directly. This also provides confidence in economic analyses using the assumption that there is a higher probability of discovering deposits with larger metal endowments in regions where the highest number of geological map variables (Table 3).

The positive correlation between the post probability values and recorded metal values allowed a statistical estimate of endowment to be made based on the average and maximum post probability value for the prospect area and the distribution of metal values for the local grade tonnage data listed in Tables 1 and 2, and also for the global grade tonnage data provided by Singer et al. (2008). Singer et al. (2008) confirmed statistically that the global porphyry copper-gold grade-tonnage model best represents the potential undiscovered porphyry copper-gold deposits of the Macquarie Arc. Our approach is similar to the second part of the three-part quantitative assessment technique used by the USGS but based on statistical relationships between the post probability data distribution and the grade tonnage data distribution rather than assigning the grade tonnage data to the prospect areas from the Macquarie Arc MPM subjectively (c.f., Singer 1993; Singer 2010; Singer and Menzie 2010). The advantage of using statistical distributions of the data is that it makes it possible to assign global grade tonnage data in a less subjective way than is currently used in resource endowment assessments (c.f., Bookstrom et al., 2014; Partington, 2010).

Total metal values in A$ were calculated for the local and global grade tonnage data as listed in Tables 1 and 2 and the percentile metal values calculated as listed in Table 4. It was assumed that the post probability percentile value is equivalent to the metal value percentile for either grade tonnage data set (Table 4). This assumed relationship allows global mineral system grade tonnage data like that provided by Singer et al. (2008) to be used in localised study areas where grade tonnage data may be limited or not available. There is sufficient local grade tonnage data available in the Macquarie Arc MPM example to use these metal values in preference to the global dataset to estimate prospect area metal values for use in our example EIS.

A GIS linked database of exploration prospect areas was developed for the study area that is based on the reclassified area polygons from the Mcquarie Arc MPM (e.g., Fig. 1). This database also lists the geological predictive factors that are present and the geological potential from the post probability values for each prospect area. An important outcome of the prospectivity modelling is to determine what data are missing from lower ranked prospects, especially those that are freely available or

Table 4
Percentile ranges of the Macquarie Arc MPM post probability values compared to the same percentile ranges for the Macquarie Arc metal values from the recorded copper equivalent endowments (Bookstrom et al., 2014) and the global porphyry grade tonnage copper equivalent endowments (Singer et al., 2008).

	PPrb Range	MA Metal Value	Global Metal Value
10 perc	0.0007–0.0054	$569	$2242
20 perc	0.0054–0.0083	$687	$4822
30 perc	0.0083–0.0228	$2186	$7893
40 perc	0.0228–0.0813	$2495	$13,630
50 perc	0.0813–0.1823	$3731	$19,476
60 perc	0.1823–0.3084	$8176	$27,425
70 perc	0.3084–0.7630	$12,378	$44,123
80 perc	0.7630–0.8499	$15,632	$76,829
90 perc	0.8499–0.9169	$28,956	$145,991
95 perc	0.9169–0.9470	$124,676	$253,519
96 perc	0.9470–0.9599	$164,751	$298,527

previously undiscovered, which would improve their prospectivity. Typically, such prospects may have geophysical and structural data available from regional mapping and remote sensing studies, but may lack detailed drilling, structural analysis, or geochemical sampling. To complete a detailed analysis of each prospect or prospect cluster, a unique conditions grid is created in association with each prospectivity model. This grid is a response map containing the intersection of all the input variables as a single integer, effectively combining the predictive maps while maintaining a record of the spatial distribution of each variable. The unique conditions grid allows prospects to be easily identified and grouped according to the data missing that could be collected to upgrade (or downgrade) the prospect and prioritised accordingly. This is a critical part of the post-modelling analysis carried out using GIS that can provide important exploration management insights but is often not used to its full potential.

The economic parameters as metal values were also attributed to each prospect area based on the documented tonnes and grade ranges of the various metals in the operating mines in the study area by using the percentiles listed in Table 4. This now allows the various prospect areas to be ranked using the predicted metal value, which provides a better understanding of the economic potential of the prospect and is one of the most important factors when making a decision to invest in follow up exploration expenditure.

5. Ranking prospect areas in a minerals exploration information and management system

From an organisations corporate perspective, there are a range of other factors that need to be considered when ranking prospect areas that potentially affect the economic potential of the target, particularly prospect value and the costs required to develop and mine the prospect if a new deposit is found. Consequently, any EIS has to be able to not only include the potential value of any prospect area but also any costs that may be associated with developing that prospect area into an economic mine. The potential values and costs can then be mapped and compared in a consistent way to produce ranked prospects for future investment. There also needs to be the flexibility to include additional cost data or social licence to operate information based on an organisation or company's operational or strategic requirements. Some of the additional data we use in our current system was added to the database of exploration prospect areas from the Macquarie Arc MPM as an example of the types of information that are required, how the prospect areas can be linked to other external data sources and how these can be used to better inform the target area ranking system used in our EIS.

Mine development and operating costs are fundamental costs that need to be included in an EIS to allow better ranking of prospect areas. Mine development costs include all the costs required to make the decision to start a mining operation based on an estimated reserve of metals. These include resource and reserve estimation costs, which are mainly drilling costs, process recovery costs, mainly related to metallurgy, process engineering costs, feasibility study costs and capital investment costs to fund the building and commencement of the mining operation. These costs can be provided in an EIS based on current detailed company budgeted costs or can come from the various global resource cost databases and reports that are widely available (e.g., Robinson and Menzie, 2012).

In the Macquarie Arc example, it is assumed that all prospect areas require standalone processing and mining from underground mines. A more sophisticated approach could attribute the type of mining required or map optimal trucking distances around processing facilities at operating mines in the area of interest and vary capital and operation costs accordingly. The average exploration cost is assumed to be A$105 per tonne of copper equivalent endowment to take a prospect area to a decision to mine. The exploration cost was applied to all prospect areas that had no reported endowment for the prospect area. This cost is based on reported global discovery rate costs for copper, but would be improved by using discovery costs that take account of national investment attractiveness (e.g., from the Fraser Institute Survey of Mining Companies www.fraserinstitute.org/), infrastructure (e.g., Wildman et al., 2015), access, and local costs of exploration. Mine operating costs were assumed from the All-in Sustaining Cost (AISC) that is reported on a quarterly basis by the companies that operate the Cadia and Northparkes underground mines for this example, which currently is around A $4500 per tonne of copper equivalent endowment. Both are considered to be highly profitable and low-cost underground operations and are used in this example as a best-case scenario for the primary prospect areas. SP Global Market intelligence reported an average AISC for all copper production globally to be US$2.12 per pound (shorturl.at/yABY1), which converts to A$7850 per tonne copper equivalent using an A$ price taking account of inflation to 2023. Smaller mines tend to have higher costs due to smaller economies of scale. So, the A$7850 per tonne copper equivalent was used for the secondary prospect areas, which are likely to have smaller endowments. A more comprehensive range of mine operation cost data from different mining scenarios need to be developed for inclusion in an EIS (e.g., Robinson and Menzie, 2012). Developing a global database of reported AISC from differing mine scenarios over time would be invaluable and would allow the user to input statistically derived cost data or actual distributions to be used in Monte Carlo Simulations of potential costs for input in an EIS.

Tenement and ownership data can be extracted from public government databases and integrated with the prospect maps, showing whether the area is already held for mineral extraction purposes, as well as who owns the land for access purposes. Prospect areas that are held by other parties therefore need to have an acquisition cost attributed to them. If the goal is to pick up new free ground, targets covered by tenements can be excluded before the target analysis is undertaken. Or in this example, an acquisition cost of A$350 per tonne of copper tonnes equivalent is assumed based the average copper equivalent endowment price paid for recent copper projects from our Australian deals database. Any future development of an EIS will have to be able to input these types of costs for various commodities from potentially external data sources or databases.

The prospect areas in this example have also been attributed with cadastral information on whether they lie within National Parks, populated areas and with the distance to nearest infrastructure (roads, rail, airstrip etc.). Consequently, the 11 prospect areas located within a National or State Park are considered to have no value. Alternatively, if mining is allowed in any environmentally sensitive area, it will incur additional development and operating costs, which will need to be taken account of in any financial analysis.

Any future EIS should also consider using net present value (NPV) calculations for the potential mines in the prospect areas based on mine lives estimated from the potential copper equivalent endowment (e.g., Partington, 2010), along with more sophisticated economic analysis including Monte Carlo simulations. This will mean future EISs will need to be able to access differing internal and external databases of economic data relating to mineral exploration and mining that are available internally in organisations or through the internet.

A total cost attribute was calculated for each prospect area by using the potential endowment from the prospect area metal values and adding all the costs together (e.g., Table 2). A final rank value was calculated by multiplying the prospect area potential metal value by the National Parks value to give those target areas with environmental issues no value and subtracting the total costs from the prospect area metal values. This was then multiplied by the prospect area average post probability value to emphasise those prospect areas where the required predictive variables occur most consistently in the prospect area the highest. The target areas can then be sorted and mapped according to their rankings to allow visualisation and further analysis to support decision making by the management of the company or organisation to more efficiently target investment into mineral exploration and the discovery of new mines.

The ranking of prospect areas in an EIS is one of the simplest and efficient ways of deriving insights into the understanding and potential for discovering new mineral deposits in a region. It immediately allows management to see where effort and investment should be focussed, which is critical for both government and industry. A summary of the ranking of the target areas for the resources and mine endowments listed in Table 2 is provided in Table 5 at various stages of the modelling and targeting workflow. The initial ranking based on the maximum post probability value in a prospect area is an effective way of ranking prospects for follow up work. The differences in ranking after the endowment values are added and the costs deducted generally improves the ranking of areas with known endowment but importantly provides insights into the economic potential if a discovery is made. It allows the user of the EIS to link geological potential measured by the MPM post probability values to economic potential. The prospect area analysis has reduced the number of prospect areas from 157 with a total area of 1157 km^2 to 152 prospect areas with a positive economic value with a total area of 993 km^2. There are 37 of these prospective areas that have no record of historic or modern exploration in government databases that have a total area of 83 km^2. One of these prospect areas is a primary target as classified from the MPM post probability values, which has a final rank of 6. None of these areas are covered by national or state parks and 15 of these prospect areas are partially covered by existing tenements but none are freely available.

Any future EIS needs to have the flexibility to be able to tailor the target ranking part of the system to the needs of the user. For example, the user may benefit from knowledge about historic exploration in the area of interest, which can be summarised by attributing the recorded historic mineral occurrences held in government databases to the

Table 5
Comparison of prospect area ranks for the main mines and resources at various stages of the target analysis in the Macquarie porphyry example. PPrb - ranks from MPM post probability values; PA - ranks of prospect areas greater than 0.4 km^2; MA MV - ranks based on Mcquarie Arc endowment statistics; GB MV - ranks based on global porphyry endowment statistics; Cost - ranks when costs are taken into account; Final - ranks when all factors are taken into account.

Name	PPrb Rank	PA Rank	MA MV Rank	GB MV Rank	Cost Rank	Final Rank
Cadia	1	1	1	1	9	1
Northparkes	170	112	8	9	1	110
Temora	13	10	3	4	5	11
Marsden	77	65	6	7	3	67
Copper Hill	3	3	1	1	9	2
Racecourse	NR	NR	NR	NR	NR	NR
Cargo	49	40	4	5	6	38
Boda Glen Hollow	45	37	4	5	6	18
Cowal	4	4	2	2	7	4
Peak Hill	52	43	4	5	6	33

prospect area. The number of drillholes, maximum drill depth, and maximum metal assays are also useful information that is not immediately available from the MPM results or used to develop the MPM.

As discussed by Yousefi et al. (2019 and 2021) any EIS will have to incorporate interlinking GIS and database technologies (Fig. 1) and technicians to manage the system. The system will also have to be able to pass on the information, knowledge, and insights to executive and corporate level management where the skills to use and interpret GIS data and information are usually lacking. It is therefore critical that an EIS has a frontend dashboard type system to allow other users at various levels to access and use the outputs from the system in their decision-making. An example of such a frontend dashboard using the attributes for the prospect areas is available at (https://eis-viewer.kenex.com.au/) for the reader to sort and query the results from the Macquarie Arc porphyry MPM example and ask their questions of the system to provide the insights they need.

6. Conclusions

As discussed by Yousefi et al. (2021) one of the important outcomes from an EIS are insights that are derived from the data and knowledge that are input into the system. The insights about the data, predictive maps and mineral system research for the Macquarie Arc porphyry copper and gold mineral system that we have gained from this work include:

- Tools for transforming the raw data into features that can be used to test for spatial association with training data and create the final predictive maps will be an important component of an EIS. This means GIS with links to internal and external databases will be an important component in any system. It is possible to use GIS as the front-end of an EIS that is complimented with additional plug-in features to manage, analyse, and report the inputs and outputs from the system. Development and research into the optimal approach is an important first step in the development of any EIS.
- Geological understanding based on mineral system research is a critical input to an EIS. This means any system must contain or have access to descriptions of the range of important mineral systems, summary lists of the key geological features of the mineral system, and detailed tabulations of the predictive maps that are required to be developed as proxies of those geological features. Being able to automate the use and input of results from spatial analysis done at this stage that constrains the making of the predictive maps is important and an area where future development needs to focus.
- Training data are an important input into any EIS, which means the system either needs to contain endowment databases or grade tonnage databases for the most common mineral system deposits. Or the system must be able to link through the internet to the various databases available from national and state governments (e.g., Singer et al., 2008).
- Given the user of the EIS may want to compare deposits with different commodity mixes and deposits of different commodities, the system must be standardised using a technique like metal equivalents. A standardised approach needs to be developed to do this or it can be based on metal prices as in our example. This means the EIS must include or have access through the internet to current and potentially historic metal price data.
- Spatial analysis of the predictive maps leads to important insights into the data that is available and being used in the EIS and provides ideas on data that are missing and data that need to be collected to improve the outputs from the EIS either by government as pre-competitive data or by Companies as follow-up exploration. Automated reporting of this type of analysis needs to be considered as an important future development for any EIS.
- The EIS will have to include a comprehensive suite of MPM methods so that the user can decide on the best method (or combination of methods) that best suits their project. This should include other data-driven methods (including AI) such as logistic regression, neural networks, random forests, and knowledge-driven methods such as fuzzy logic. Validation techniques should also be available including the Area-frequency tool.
- Research into using weighted training data based on endowment factors in data driven techniques will help better produce MPM outputs that can be used with endowment and economic data that are available. This potentially can lead to improving resource assessment studies by allowing them to be more objective and answer the “where” question as well as the “how much question”.
- The spatial analysis and MPM results provide important geological insights into the understanding of the Macquarie Arc porphyry mineral system. Better data coverage and mapping of the granites, particularly key magma fertility attributes and a consistent fault data set at regional scales is important. The lack of these data explains the anomalously low post probability values for the Northparkes and Boda areas. Improving these datasets have the potential to most effectively update the prospectivity in the Macquarie Arc porphyry study area and could lead to new discoveries.
- The main goal for any EIS is to provide the analysis that helps find new mineral deposits that are economic to mine and process at the financial conditions of the time.
- A single database of prospect areas will be the main output to be managed from the MPM. This means the variety of tools that allow the reclassification of a MPM to map prospect areas will need to be available to the user in an EIS. Particularly tools that can use endowment or economic factors to help with the classification. Research into developing tools that can optimise this task is important to improve the outputs from the system.
- The Macquarie Arc porphyry MPM PPrb values have a positive correlation with recorded endowment, which confirms the observation by Partington (2010). This is an important relationship for using MPM in an EIS as it allows endowment and economic data to be statistically attributed to prospect areas used in the system rather than subjectively (e.g., Bookstrom et al., 2014; Partington, 2010). More research into using more sophisticated techniques and approaches would be important, including integrating Monte Carlo Simulation into this stage of the workflow.
- The EIS must be able to not only include the potential value of any prospect area but also any costs that may be associated with developing that prospect area into an economic mine. The potential values and costs can then be mapped and compared in a consistent way to produce ranked targets for future investment. Thought needs to be given when designing the system to including internal databases of cost information or including external links to these databases through the internet.
- Research is needed on how to incorporate the various economic analytical techniques, like NPV calculations, into the EIS to optimise the ranking of the prospect areas in the system to produce target areas.
- Any future EIS needs to have the flexibility to be able to tailor the prospect ranking part of the system to the needs of the user. For example, the user may benefit from knowledge about historic exploration in the area of interest, which can be summarised by attributing the recorded historic mineral occurrences held in government databases to the prospect area. The number of drillholes, maximum drill depth and maximum metal assays are also useful information that is not immediately available from the MPM results or used to develop the MPM.
- Thought needs to be given into how the results from the EIS can be best viewed and used by nontechnical users of the system, particularly at an executive management and corporate level.
- The ultimate goal for the EIS of the future is for the system to rapidly apply automated feedback loops to the output of the system to assess the effects that collecting new data has on the prospectivity of the

target areas in the system or to understand the effects of changing economic conditions on the exploration targeting and investment decisions that are made both by government and industry.

In conclusion our vision for the future EIS is that when new data or information on a mineral system become available it will be possible to input the new data or information into the system and for the attributes that can be used to create the insights that better inform an organisation to be updated in real time. It is clear from the advances now being made in machine learning systems that these will become important tools to help exploration and mining into the future. Current research has advanced the techniques needed and quality of data available is improving rapidly. The availability and quality of data remains critical as made clear by Ford et al. (2019b): no matter how good our MPM techniques are they must use quality data and maps to work successfully. More importantly for industry to start routinely using MPM, access to the type of systems described by Yousefi et al. (2019,2024), with the main algorithms and tools available in one software system, including decision support workflows is needed. The final piece of the jigsaw is availability of trained professionals to manage, maintain and run these systems, which needs to be considered as part of university degrees in geology, particularly those institutions that teach economic geology.

CRediT authorship contribution statement

Greg A. Partington: Conceptualization, Methodology, Writing – original draft. **Katie J. Peters:** Project administration, Writing – original draft, Writing – review & editing. **Tom A. Czertowicz:** Visualization, Writing – original draft, Writing – review & editing. **Phil A. Greville:** Methodology. **Phillip L. Blevin:** Writing – review & editing. **Engdawork A. Bahiru:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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