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Exploration information systems – A proposal for the future use of GIS in mineral exploration targeting

Mahyar Yousefi[a,*], Oliver P. Kreuzer[b,c], Vesa Nykänen[d], Jon M.A. Hronsky[e,f]

[a] Faculty of Engineering, Malayer University, Malayer, Iran
[b] Corporate Geoscience Group, PO Box 5128, Rockingham Beach, WA 6969, Australia
[c] Economic Geology Research Centre, School of Earth & Environmental Science, James Cook University, Townsville, QLD 4811, Australia
[d] Digital Products and Services, Geological Survey of Finland, PO Box 77, FI-96101 Rovaniemi, Finland
[e] Western Mining Services PL, Suite 26, 17 Prowse St, West Perth 6005, WA, Australia
[f] Centre for Exploration Targeting, School of Earth Science, University of WA, Crawley 6009, WA, Australia

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ABSTRACT

The advent of modern data collection and storage technologies has brought about a huge increase in data volumes with both traditional and machine learning tools struggling to effectively handle, manage and analyse the very large data quantities that are now available. The mineral exploration industry is by no means immune to this big data issue. Exploration decision-making has become much more complex in the wake of big data, in particular with respect to questions about how to best manage and use the *data* to obtain *information*, generate *knowledge* and gain *insight*. One of the ways in which the mineral exploration industry works with big data is by using a geographic information system (GIS). For example, GIS platforms are often used for integration, interrogation and interpretation of diverse geoscience and mineral exploration data with the goal of refining and prioritising known and identifying new targets. Here we (i) briefly discuss the importance of carefully translating conceptual ore deposit models into effective exploration targeting maps, (ii) propose and describe what we term exploration information systems (EIS): a new idea for an information system designed to better integrate the conceptual mineral deposit model (i.e., the critical and constituent processes of the targeted mineral system) with data available to support exploration targeting, and (iii) discuss how best to categorise mineral systems in an EIS as scale-dependent subsystems to form mineral deposits. Our vision for the future use of EIS in exploration targeting is one whereby the mappable ingredients of a targeted mineral system are translated and combined into a set of weighted evidence (or proxy) maps automatically, resulting in an auto-generated mineral prospectivity map and a series of ranked exploration targets. We do not envisage the EIS replacing human input and ingenuity; rather we envisage the EIS as an additional tool in the *exploration toolbox* and as an *intelligence amplifying system* in which humans are making use of machines to achieve the best possible results.

1. Introduction

Mineral exploration targeting requires the compilation, integration and interrogation of diverse, multi-disciplinary data (e.g., Hronsky and Groves, 2008). In today's world, this is commonly done using a geographic information system (GIS), the light table environment of our modern computer-age. A GIS is a powerful computer-based system designed to capture, store, manipulate, analyse, manage, and present spatial data (e.g., Groves et al., 2000) and their non-spatial attributes that can be stored in linked, interrogatable tables.

In mineral exploration targeting, as in many other fields of applied geoscience, GIS has surpassed the human ability to integrate and quantitatively analyse the ever-growing amount of geospatial data available, thereby progressively replacing the traditional working methods. Over the past two decades and driven by significant improvements in soft- and hardware capabilities, powerful GIS-based, algorithm-driven methods have been developed in support of exploration targeting. These methods fall under the umbrella term of mineral prospectivity mapping (MPM), also known as mineral prospectivity analysis, spatial predictive modelling or mineral potential modelling (e.g., Bonham-Carter, 1994; Pan and Harris, 2000; Carranza, 2008; Porwal and Kreuzer, 2010; Yousefi and Nykänen, 2017; Hronsky and Kreuzer, 2019). The resulting mineral prospectivity maps are typically generated through a combination of multiple evidential (or predictor)

* Corresponding author.
E-mail address: m.yousefi.eng@gmail.com (M. Yousefi).

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maps representing a set of targeting criteria (also referred to as mappable criteria or proxies), defined and combined based on measured spatial or genetic associations with the targeted mineral deposits and each other.

Despite significant methodological and computational advances over the past two decades, MPM is yet to prove effective in real world exploration (McCuaig and Hronsky, 2000, 2014; Porwal and Kreuzer, 2010; Joly et al., 2012; Hagemann et al., 2016a), particularly as regards helping to discover large, potentially economic mineral deposits. As discussed in Hronsky and Kreuzer (2019), whilst the concepts and technology behind MPM are sound, effective deployment is currently limited due to issues regarding the use of input data. The main implication of this thesis is that MPM will become an effective exploration tool once input data are processed and organised to more uniformly and objectively reflect the targeted search space and underlying targeting model.

The next important step-change required for MPM to become a more effective exploration tool is better integration of the conceptual mineral deposit model with data available to support exploration targeting. We believe this can be achieved by way of an exploration information system (EIS) that can address and handle complex natural phenomena such as mineral systems and, thereby, play a key role in exploration targeting and in the development of orebodies. Given the diversity and complexity of ore-forming processes and the tectonic environments of ore formation (e.g., McCuaig et al., 2010; Pirajno, 2016; Hagemann et al., 2016a), future implementation of an EIS would require (i) the generation of *information* from *data* (i.e., the collection and organisation of exploration and geoscience *data* in such a way that they become *information* that has additional value beyond the value of the original *data* themselves), (ii) *knowledge*-generation (e.g., from *information* about ore-forming processes), and (iii) the gaining of *insight* relevant to the development of mineral exploration targeting strategies. Hence, by converting the *data* to *information*, *information* to *knowledge*, and *knowledge* to *insight*, an EIS would facilitate problem-solving in mineral exploration targeting and provide a platform where mineral systems *insight* can be converted into mappable criteria and the prediction of undiscovered mineral deposits.

Here we introduce the conceptual framework for an EIS, a concept we view as the next logical step in the future development and adaption of GIS technology for use in mineral exploration targeting and MPM. In addition, we discuss how EIS would facilitate the more effective translation of conceptual ore deposit models into real-world exploration targeting models.

2. Exploration information systems (EIS)

Information systems help to organise, visualise and analyse *data* and to convert raw *data* into useful *information* with the overall goal of supporting and improving decision making (Grabowski et al., 2014; Laudon and Laudon, 2014) (Table 1). One such example most geoscientists would be familiar with is GIS, which is designed to support decision making in the geosciences. The proposed EIS we envisage as a type of executive level information system as illustrated in Fig. 1, designed to convert *data* to *insight* as illustrated in Fig. 2. The following sections provide a description of the underlying concepts of the EIS and propose a framework for its practical application in the future development and adaption of GIS technology for use in mineral exploration targeting.

2.1. Underlying concepts

2.1.1. From data to insight

The purpose of exploration targeting is to delineate and prioritise tectonic environments where ore deposits are more likely to form (e.g., magmatic arcs, calderas, intracratonic basins) across scales and over time. Exploration and geoscience *data* available for well-explored areas, as well as the target area, provide the initial stepping stone to compiling *information* about ore-forming processes. This *information* (e.g., about the timing and controls on the location of ore formations) can then be used to generate *knowledge* about the constituent processes (cf. McCuaig et al., 2010) involved in generating a diverse range of ore deposit systems. *Knowledge* is *information* selected, interpreted and used in a way that when taken together it forms a coherent representation of natural phenomena which is useful in understanding what is currently taking place in the real world (Grabowski et al., 2014). The *knowledge* gained helps answer questions such as, what are the signals coming from the *information*? And, what can be predicted from the *information*? Subsequently, the *knowledge*, obtained from the improved understanding of ore-forming processes, is used to gain *insight* into the process of exploration targeting analysis. These *insights* are concepts that have predictive capacity. In addition, *insight* gained from *knowledge* would be invaluable in developing a follow-up exploration strategy concerned with (i) recognising and understanding critical ore-forming processes, (ii) defining the constituent processes of the critical ore-forming processes, (iii) extracting targeting elements for each constituent process (the geological expressions of the constituent processes), and (iv) selecting mappable targeting criteria (cf. McCuaig et al., 2010). Fig. 3 provides an example of the procedure of converting *data* to exploration *insight*.

2.1.2. Mineral systems approach and taxonomy of ore-forming processes

A major challenge in mineral exploration targeting is to improve and map our knowledge of processes critical to the formation of mineral deposits (cf. McCuaig and Hronsky, 2000; Hronsky, 2004, 2011; McCuaig et al., 2010). The mineral systems approach (Knox-Robinson and Wyborn, 1997; Wyborn et al., 1994; McCuaig et al., 2010; Joly et al., 2015; Hagemann et al., 2016a) is ideally suited for this task because it considers the critical ore-forming processes that are required to produce mineral deposits of a particular type and divides them into subsystems (Porwal et al., 2015) to better understand the formation and gain exploration *insight* on the spatial localisation of mineral deposits. As schematically illustrated in Fig. 4, the critical processes are fundamental to and at the core of the mineral systems concept (cf. Wyborn et al., 1994; Pirajno, 2009, 2010, 2016; McCuaig and Hronsky, 2000; Partington and Mustard, 2005; Hronsky, 2004, 2011; Hedenquist et al., 2005; Kreuzer et al., 2007, 2008, 2010, 2015; McCuaig et al., 2010; Pirajno et al., 2011, 2015; Joly et al., 2013, 2014, 2015; Pirajno and Zhou, 2015; Hagemann et al., 2016a; Huston et al., 2016; Almasi et al., 2017; Ford et al., 2018). They are abstract processes and as such difficult to understand and comprehend. Whilst abstract at the critical process level a mineral system can typically however be broken down into several constituent processes which can, in turn, be translated into a series of targeting elements and their mappable criteria. These elements have the advantage of being easier to conceptualise and recognise in geoscience and exploration data. Consequently, the mappable criteria give us some idea of the possible *modus operandi* of the critical processes at the core of a mineral system.

For the adaption of the mineral systems terminologies (e.g., McCuaig et al., 2010; Hagemann et al., 2016a) in the context of the EIS, with regard to the fact that fundamentally different geological factors act as critical controls on mineral systems at different scales and times, we classify the mineral subsystems into three general categories for use in exploration targeting:

(i) *Pre-mineralisation subsystems* (i.e., those subsystems linked to mantle and/or crustal fertility and/or ground preparation, and that may have operated or existed for a long time prior to mineralisation):

- Broad regional- to continent-scale tectonic and geodynamic processes required to establish energy gradients promoting subsequent mineralizing events. These processes generate environments of broad fertility and set the scene for subsequent

Table 1
Different types of Information Systems and their summary description.

Type	Description
Database Management System	- Lowermost operational level system - Combines software and data - Provides and organizes basic data required in support of operational management
Management Information System	- Provides structured information facilitating support planning, controlling, and decision-making functions of middle managers - Reveals interaction of the data - Compiles data to produce "information" provided in a variety of output formats
Knowledge Work System	- Promotes knowledge creation and ensures that knowledge and technical skills are aligned with organizational purposes and strategy - Promotes knowledge dissemination by way of graphic, analytical, communications, and document management tools - Typically includes a user-friendly interface assisting users to obtain required information quickly and easily - Examples include CAD and virtual reality systems, and financial workstations
Decision Support System	- Commonly employed at senior management level of an organization - Helps analyze existing structured information and offers access to databases, analytical tools, "what if" simulation tools, and assists with interorganizational information exchange - Allows to project the potential effects of managerial decisions into the future - Employs a wide variety of decision models to analyze data or summarize vast amount of data into a form (e.g., tables, charts, and maps) that make the comparison and analysis of data easier for managers
Executive Information System	- Uppermost strategic-level system commonly employed at the executive and senior management level and without the need for intermediaries - Offers more general computing capabilities, better telecommunications and more efficient display options compared to Decision Support Systems - Helps analyze the environment in which an organization operates and assists with planning appropriate courses of action - Helps identify opportunities and long-term trends and provides forecast trends - Uses advanced graphics software facilitating display of critical information summarized in charts, graphs, and maps designed to assist problem solving

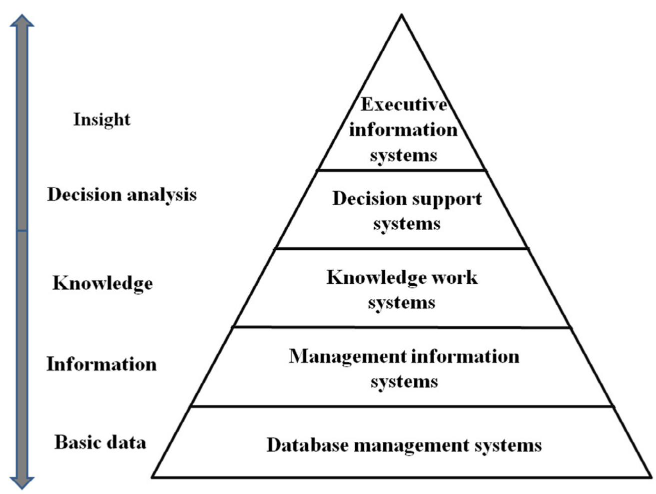

Fig. 1. Five level pyramid model based on the processing requirement for converting *data* into *insight* in an information system.

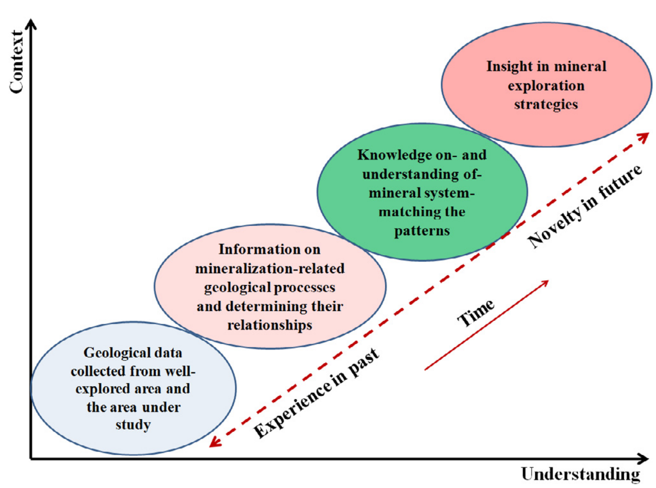

Fig. 2. Adaption of different levels of information system for the understanding of ore-forming processes.

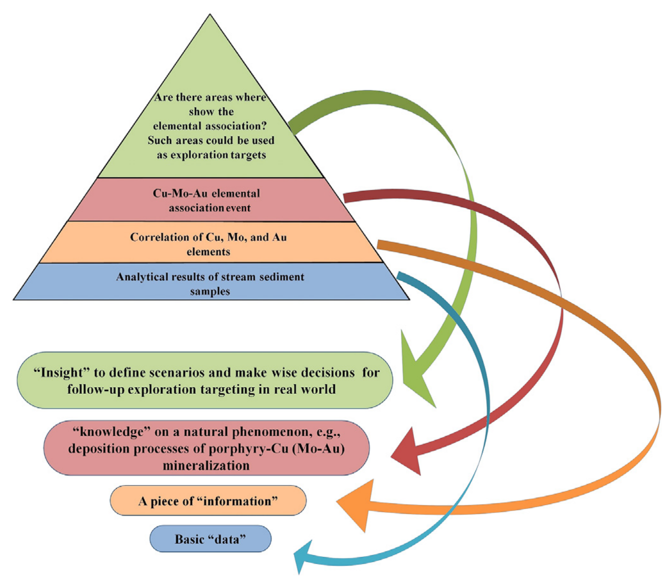

Fig. 3. An example of converting *data* into exploration *insight*.

transiently and spatially anomalous events promoting mineral deposit formation (i.e., ground preparation concept). Examples are subduction zones, which provide a fertile environment for generation of various mineral deposit styles but where a *trigger* event (e.g., a seismic ridge subduction) is required for mineral deposits to form.

- Crustal-scale tectonic and geochemical processes that produce *sources* of metals and chemical ligands.
- Processes that generate and drive metal-enriched fluid/magma flow, which could be termed *drivers*.
- Geological processes that build structural architecture facilitating migration of the hydrothermal and metalliferous fluids/ magma to the deposition zones. These processes operate at lithospheric, crustal, province and district scales and are termed *conduits* or *pathways*.

(ii) *Syn-mineralisation subsystems* (i.e., those subsystems relating to the dynamic processes controlling mineralisation):

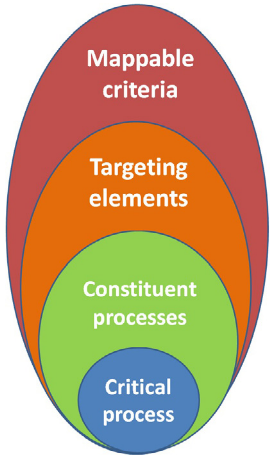

Fig. 4. Schematic illustration of the mineral system concept, showing an incompletely known critical process at the innermost part, the corresponding constituent processes and targeting elements at the intermediate parts, and their mappable criteria at the outermost part that are more easily understood.

- Transient tectonic and geodynamic events required to establish spatially anomalous regional settings at the time of mineralisation. For example, anomalous compression is a *trigger* event crucial in the formation of porphyry copper deposits.
- Physical and chemical mechanisms that modify the metalliferous fluid composition and act as a *throttle* to deposit the metal in *trap* sites. These processes operate in and close to the *trap* or ore *deposition* sites at the camp to deposit scales.
- Fluid/magma mixing, fractional crystallisation, phase immiscibility, fluid–rock interaction, decompression and density separation are other examples of chemical and physical processes causing metal *deposition* from a fluid/magma (Hagemann et al., 2016a). For example, lateral and/or vertical zonation patterns of mineralisation-related elements (Yousefi, 2017b) are targeting elements, i.e., geological expressions for the constituent processes (McCuaig et al., 2010) of primary geochemical dispersions (Yousefi, 2017a, b). Such targeting elements indicate the operation of a chemical scrubber as a syn-mineralisation subsystem of ore-forming critical processes. Wall rock alteration is also a targeting element that expresses the reaction of wall rock and fluid as a constituent process of a syn-mineralisation subsystem, i.e., a chemical scrubber. Similarly, elemental zoning patterns and wall rock alteration could be mapped using lithogeochemical surveys and remote sensing studies.
- There are other non-genetic subsystems, which act at the *trap* or ore *deposition* sites and show only spatial association with mineralization. For example, in the formation of podiform chromite deposits, there is no proven genetic role for faults or fractures, indicating our incomplete knowledge on the formation processes of this deposit type. However, these features are spatially associated with many chromite deposits possibly due to the diapiric formation of chromite-bearing serpentine masses, which results in faults or fractures (Roshanravan et al., 2018a). Thus, fault or fracture density is a potential targeting element, which could be mapped from solid geology interpretation, geophysical data or remote sensing studies.

(iii) *Post-mineralisation subsystems* (i.e., those subsystems relating to exhumation, preservation, upgrading and/or secondary dispersion processes):

- Several critical geological factors have been identified in terms of their functioning as post-mineralisation subsystems after deposition of the primary ore. For example, geochemical surveys work well in areas where tectonic processes aided in the *exhumation* of mineral deposits and climatic processes promoted their oxidation and secondary geochemical element dispersion. The effects of these subsystems are important to consider when aiming to vector into potential sites of mineral deposition (e.g., Spadoni, 2006; Yousefi et al., 2012, 2013).
- Time is an equally important factor (Hagemann et al., 2016a). For example, the complex interplay of post-mineralisation subsystems can sometimes result in the formation of more concentrated secondary mineral deposits, such as placer gold deposits and in uranium geology there are many examples of deposits that only became economic due to supergene upgrading (e.g., Itataia, Brazil: Veríssimo et al., 2016). Thus, the importance of post-mineralisation subsystems for the preservation of mineral deposits cannot be neglected.

In mineral system-based exploration targeting, commonly only pre- and syn-mineralisation subsystems are taken into account even though the effects of post-mineralisation subsystems could and should be considered and translated into mappable criteria at all scales of the targeting process. Post-mineralisation subsystems are diverse and can be further subdivided according to the types of processes involved and their scales and timing.

2.1.3. Exploration scales

Ore deposits are products of a variety of geological processes operating at various scales from micrometres to 1000 s of kilometres. Mineralisation-related geological processes can also cover extensive time periods and typically commence long before ore deposition (i.e., ground preparation) (e.g., Misra, 2000; Ford and McCuaig, 2010; Joly et al., 2012, 2015). Therefore, in mineral exploration targeting there is commonly a hierarchy of scale-dependent targeting parameters, from global to deposit scale, dependent upon the available datasets and the scale of the underlying causative processes leading to mineral deposit formation (McCuaig and Hronsky, 2000; Hronsky, 2004; McCuaig et al., 2007a,b; Hronsky and Groves, 2008). The relative importance of pre-, syn- and post-mineralisation subsystems varies depending on the scale at which critical ore-forming geological processes operate. Consequently, the scale dependency of exploration targeting criteria is a critical issue which must be taken into account in the application of mineral system concepts (Wyborn et al., 1994) in order to generate reliable exploration targets (e.g., Hronsky and Groves, 2008; Ford and McCuaig, 2010; McCuaig et al., 2010; Hagemann et al., 2016a; Joly et al., 2012). Ignoring this and inappropriately combining targeting criteria relevant at different scales would inevitably lead to biased and ineffective exploration targeting models. Fig. 5 shows the operation of various subsystems of ore-forming processes from regional to deposit scale exploration targeting for outcropping, partially outcropping, buried, and blind mineralisation.

2.2. Components of an EIS

2.2.1. Input data

Data resolution has a strong bearing on the type, quantity and quality of the targeting-relevant information that can be extracted from the data. For example, at the regional to district scale the available data are typically of low resolution whereas camp to deposit scale datasets commonly have a significantly higher spatial resolution providing a much clearer picture of the targeted geology and supporting delineation of direct drill targets (de Quadros et al. 2006; Ford and McCuaig, 2010).

For the purpose of this paper, mineral exploration data are categorised into six broad categories: (i) geophysical, (ii) geochemical, (iii) geological, (iv) remote sensing, (v) geoscientific, and (vi) drilling. Given the breadth of data types, appropriate data selection, preparation and presentation (Aitken et al., 2018) are important if any information is to be extracted from the data. Examples of exploration data acquired at the deposit scale include drillhole information (e.g., lithology, assay values), isotope geochemistry and fluid inclusion data, elemental

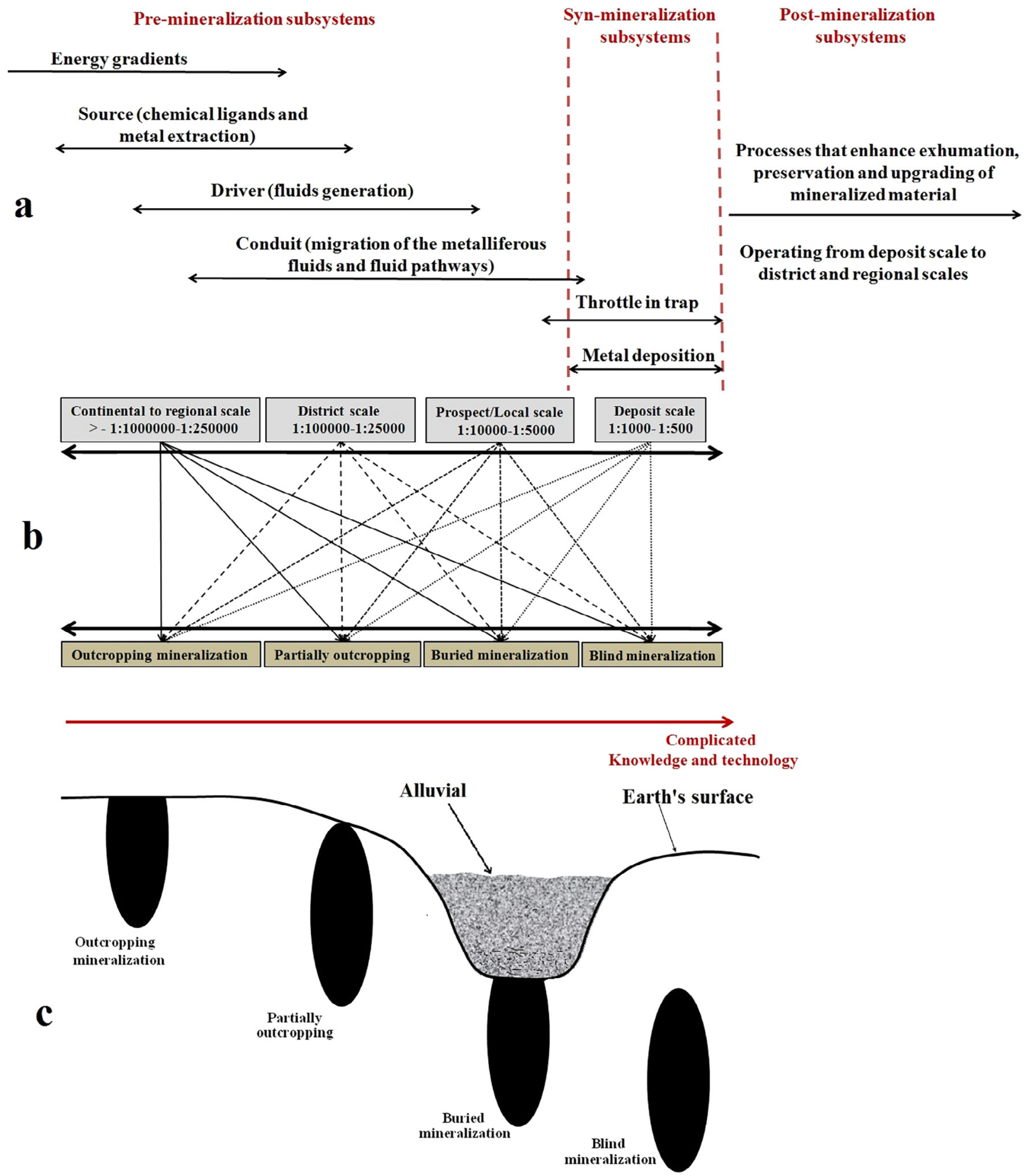

Fig.5. Various subsystems of ore-forming processes respecting the scale of the operations (a), intricacy in the understanding of the processes as the mineralisation occurs in greater depth, at every scale the mineralisation may occur at a different depth (b), and concept of mineralisation depth (c). Geological processes that produce energy and metal sources operate at continent to regional scales (thousands of square kilometres), the subsystems that construct the structural architecture for the migration of hydrothermal and metalliferous fluids operate mainly at regional to district scales (a few thousand square kilometres) while the physical and chemical processes related to wall rock alteration and ore deposition are deposit-scale subsystems mainly acting at ore trap sites (less than a few square kilometres and most intense at the deposit locales).

distribution patterns and primary geochemical halos, wall rock alterations and ground geophysical data. Local geological attributes of known mineral deposits (e.g., the presence of chemically or mechanically favourable rocks, structural dilation zones, or particular alteration assemblages) are critical to understanding the processes controlling mineral formation at deposit scale exploration. In this regard, relevant regional-scale factors, such as lithospheric architecture and tectonic trigger events should be mapped (Hagemann et al., 2016a). Geochronological data and constrains on the timing of ore formation are also very important here, in particular where the regional geology is complex and/or poorly known. Deeply penetrating geophysics (e.g., Korsch and Doublier, 2016), isotopic terrane mapping (Champion and Huston, 2016), sequence stratigraphy (e.g., Witt et al., 2013), regional (or deep) structural controls on the spatial distribution of mineral deposits (e.g., Lisitsin, 2015) and global gravity models interpreted from satellite data (Bettadpur et al. 2015; Ries et al. 2016) are examples of regional datasets (Hagemann et al., 2016a) which can be gridded and used to display regional-scale mappable targeting criteria. Regional and continental scale geochemical mapping (Buccianti, 2015; Lancianese and Dinelli, 2015) can be applied to model aspects critical to metal dispersion in geochemical provinces. Satellite and airborne remote sensing may serve as a source of scale-independent geological data but are most effective in hilly and mountainous arid environments where vegetation is largely absent and bedrock exposure is widespread. The regional criteria and datasets of mineral systems are effective for target generation at regional and continental scales, i.e., ground selection while at the deposit scale detailed exploration datasets are obtained using direct detection tools. In this regard, at the intermediate camp to district scales (tens of kilometres) criteria selection is a challenge in respect of exploration targeting (Hronsky and Groves, 2008; McCuaig et al., 2010; Yousefi and Carranza, 2015b; Hagemann et al., 2016a) for which the nature and operation of some controls has been widely recognised (e.g., major crustal to lithospheric-scale faults and their geometry, regional intrusive domes and anticlinoria: Neumayr and Hagemann, 2002; Goldfarb et al., 1997, 2005; Hagemann et al., 2016a). Mineral system controls operating at such intermediate scales are responsible for the formation of richly endowed metallogenic zones, districts, or belts (Hagemann et al., 2016a).

At the regional-scale (100s–1000s of kilometres), ore-forming geological processes are often similar even for different types of mineral systems (Wyborn et al., 1994; McCuaig et al., 2010; McCuaig and Hronsky, 2014). For example, according to Hagemann et al. (2016a), all hydrothermal mineral systems involve the mobilisation of metals from a source by fluids and the focused flow of mineralising fluids to metal deposition sites. Various researchers (e.g., Wyborn et al. 1994, Knox-Robinson and Wyborn, 1997, Hagemann and Cassidy, 2000) pointed out that the mineral systems approach allows for the investigation of multiple mineralisation styles within a single system. For example, chemically reactive rocks, indicating a possible ore *trap*, are a critical deposit scale factor, however the proportion of outcropping and concealed chemically reactive lithologies could be taken into consideration during regional scale exploration targeting as a proxy for depositional processes.

For the purpose of an EIS, the “data richness mapping” method (Aitken et al., 2018), a quantitative assessment of presence, quality and attributes of data, could be applied to better evaluate the data input to mineral exploration targeting.

2.2.2. Mineral systems library

In order to make GIS a more efficient environment (i.e., for the practical application of EIS), one of the key requirements is to provide the GIS in conjunction with an interrogatable library of mineral systems designed as a support tool to aid target generation in mineral exploration (Fig. 6). For example, a spectral library exists that contains the spectral properties of rocks and minerals supporting automated processing of remote sensing data (Baldridge et al., 2009). Other fields that already offer such reference libraries include, for example, geophysics (e.g., typical resistivity and conductivity values of geological and regolith materials providing crucial information for interpreting electromagnetic survey data), petrophysics (e.g., rock property data providing a vital link between observed geophysical data and interpreted geology) and geochemistry (e.g., geochemical data of average crustal element abundances providing important clues as to potential mineralisation-related element enrichment and depletion within a surveyed area).

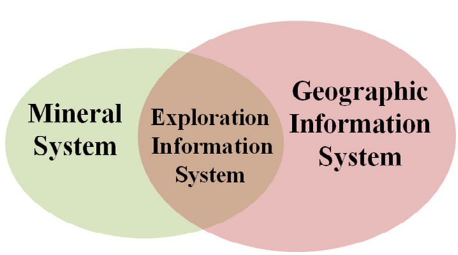

Fig. 6. A schematic sphere of influence for a mineral system in conjunction with GIS that makes EIS.

Many examples exist of variably complete mineral systems models covering various types of mineral deposits and geological regions (Table 2). Many of the existing mineral systems models are however too complex, incomplete, and/or inconsistent as they are commonly designed for a particular region and each author presents their model in a somewhat different format. As such, the existing mineral systems models are not readily useable in an EIS or applicable to targeting globally. Consequently, continuous updating and the improvement of existing models, the translation of traditional mineral deposit models into mineral systems and exploration targeting models (cf. McCuaig et al., 2010) will, over time, result in a more extensive library of universally applicable mineral system models for use in a future EIS. We believe that up-to-date mineral systems models are an essential element of any exploration targeting work flow, facilitating the integration of new data and information not only in a general sense but also of more detailed local subsystems compiled for particular districts, belts or regions. Building a library of mineral systems that can be updated with new *data*, *information* and *knowledge* should thus be an integral part of any EIS and something to be undertaken routinely by the geological survey organisations of this world.

2.2.3. Exploration and analytical toolbox

In addition to understanding mineral systems, a further major challenge in mineral exploration targeting is the translation of mineral subsystems into mappable criteria (proxies, exploration criteria, mappable features) (e.g., McCuaig et al., 2010). Progress in GIS technology has resulted in a more powerful and capable technology environment than was achievable in the past by way of conventional data analysis. In this regard, there are numerous analytical tools in GIS facilitating a variety of geoscience data analyses as well as mineral exploration-relevant data. Additionally, numerous computer tools and methods (codes and software) have and continue to be developed and applied in the analysis of mineral exploration data. These tools are designed to visualise exploration data and map evidence and patterns indicative of the targeted mineral subsystems. Subsequently, pattern recognition, image-processing, modelling and the visualisation of exploration data, structural analysis, geophysical interpretations, geochemical mapping, data mining, spatial and non-spatial statistical analyses, geostatistics, artificial neural networks, exploratory data analysis, subsurface data analyses, the three dimensional (3D) modelling of geological features, logging and borehole data analysis and geological processes modelling are examples of the tools (computer programs/software and codes) used to reveal and quantify the spatial and genetic associations between mineral deposits and geological features.

New forms of representation based on the object-oriented model (Goodchild, 2009) also increased the ability of GIS to represent the dynamic subsystems of the ore-forming processes as analysable or mappable features and consequently a better understanding of the ore-forming geological processes. GIS is an interpretive environment in which 3D spatial data can be interrogated, manipulated and represented in a meaningful manner, in order to provide insight into geological problems. In an effort to make the software environment ‘interrogation-friendly’, a set of components identified by project participants as crucial, convenient, or simply expected were developed for the GIS-3D plug-in (Sprague et al., 2006; Hagemann et al., 2016a).

The aim of the exploration analytical toolbox is to derive and recognise significant signatures and evidence from mineral exploration data at the scale of investigation. Exploration targeting analysis requires multiple data streams resulting from different exploration methods, so the proposed EIS should provide effective tools for the interpretation of various types of exploration data. The implementation of numerous analytical methods, mentioned above, relating to the analysis of exploration data is however difficult within the same toolbox. One solution could be to use already-developed computer algorithms from image processing, forecasting, estimation, and classification domains and implementing them using well-established software

Table 2
Examples of mineral systems and deposit models worldwide.

Mineral system and deposit model	Example of compiler
Ore systems of mineral deposits of Canada	Goodfellow (2007)
Ore deposits related to convergent plate margins	Pirajno (2016)
Orogenic and intrusion-related gold, volcanic sediment-hosted base-metal sulfides, magmatic nickel–copper and magmatic platinum group element sulfides, iron-oxide copper gold, tin-tungsten, igneous and metamorphic related rare earth elements, surficial uranium and unconformity related uranium	Joly et al. (2015)
Magmatic and hydrothermal mineral systems, such as magmatic ore deposits, porphyry deposits, skarns, granite-related ore deposits, precious metal deposits in metamorphic terranes, Carlin-style deposits, epithermal precious and base metals, sediment-hosted Pb–Zn, sediment-hosted stratiform deposits, iron-formations, and the hydrothermal model for the Witwatersrand Au–U deposits	Hedenquist et al. (2005)
Zinc	Huston et al. (2006)
Magmatic nickel sulfide	Markwitz et al. (2010)
Orogenic gold	Groves et al. (1998), Hagemann and Cassidy, (2000), Goldfarb et al. (2001), Groves et al. (2003), Kreuzer et al. (2007), Almasi et al. (2017), Downes and Fitzherbert (2018a)
Magmatic Ni–Cu-PGE	Beresford et al. (2007), McCuaig and Hronsky (2014), Barnes et al. (2016)
Iron ore	Hagemann et al. (2016b)
Basin-related uranium	Jaireth et al. (2016)
Porphyry copper	Kreuzer et al. (2015), USGS
Podiform chromite	Roshanravan et al. (2018a)
Mississippi valley-type fluorite deposits	Yousefi et al. (2014)
Granite Gold Mineral Systems	Partington and Mustard (2005)
Grasmere-type massive sulfide mineralisation	Downes and Fitzherbert (2018b)
Komatiite-hosted Ni sulfide and enriched iron-formation mineral systems	GSWA
Other types	GA, BC, USGS, NSWGS, GSWA, Ludington et al. (1985), Partington et al. (2007), Nielsen et al. (2015b), Pirajno et al. (2011, 2015), Pirajno and Zhou (2015), Peters et al. (2017), Ford et al. (2018)

GA; Geoscience Australia, BC; British Columbia, USGS; United State Geological Survey, NSWGS; New South Wales Geological Survey, GSWA; Geological Survey of Western Australia.

tools to generate targets.

2.2.4. Extraction of evidence features and proxies

The results of the MPM are dependent on the types of geological features used to represent the corresponding subsystems of ore deposition (Joly et al., 2012; Yousefi and Carranza, 2015b). The criteria indicating the operation of ore-forming subsystems, identifiable through exploration data analysis, should be mapped as evidence features and/or proxies to allow spatial analyses. It is notable that some of the criteria may not be portrayed directly in map form but could be modelled as spatial proxies (McCuaig et al., 2010). The evidence features and proxies are themselves evidence of the ore-forming processes that are directly (i.e., lithology extracted from a geological map) or indirectly (e.g., lithology interpreted from geophysical data) derived from the exploration datasets available (McCuaig et al., 2010). Most geological maps would however be based on at least some geophysical interpretation so, in reality, the split may not be as clear cut, leading to issues with conditional dependence when these maps are used for prospectivity mapping.

The evidence and proxies indicating the operation of ore-forming systems must be converted to GIS-readable features so that the features can be mapped and their relationships with mineralisation quantified. Interrogation engines, i.e., spatial and attribute-based questions about where and/or what features exist in 2D or 3D spaces (Sprague et al., 2006) could be applied for feature extraction. Symbology tools provide various kinds of vector and raster objects for the representation of exploration features. The evidence and proxies can be presented as vector- and raster-based GIS. A vector GIS is suitable for use in extracting and representing evidence features (e.g., Groves et al., 2000). Raster-based GIS are commonly used for the representation of numeric proxies (e.g., Yousefi 2017a,b). In the raster-based GIS, each cell has a value denoting the state of a particular evidence feature or proxy at that location and so can be used to model and quantify the relationships between individual subsystems of ore-forming processes and mineral deposits.

2.2.5. Quantification of relationships

There are various spatial and genetic relationships between exploration evidence data and mineral deposits (e.g., Groves et al., 2000; Almasi et al., 2017), each of which represents a certain exploration criterion of prospectivity for mineral deposits or a critical process of ore systems (Table 3). After developing an understanding of the type of relationship (i.e., proximity, association, abundance, and anomaly relationships) between mineral subsystems and the targeted deposit, the relationship must be mapped and quantified as a continuous surface (e.g., Groves et al., 2000; Carranza, 2008; Yousefi and Carranza, 2015a) to model exploration targets (Table 3). Several categories of methods exist for the quantification purpose (Bonham-Carter, 1994; Pan and Harris, 2000; Carranza, 2008; Porwal and Kreuzer, 2010; Yousefi and Nykänen, 2017), i.e., assigning weights to exploration spatial values, each of which has its advantages and disadvantages. All of the categories lie between two end members, knowledge- and data-driven methods with their categorisations based on the relative amount of expert judgments and training data in assigning weights.

The mineral systems approach has a probabilistic nature (Lord et al., 2001; Kreuzer et al., 2008) as it seeks the probability of operation of each of the subsystems of the ore-forming processes, so that when the probability is close to 0 or 1, respectively it indicates either the absence or the presence of mineral deposits (McCuaig et al., 2010; Yousefi and Carranza, 2015a,b,c). Different logistic functions exist, such as “large”, “small”, “near” (Tsoukalas and Uhrig, 1997; Almasi et al., 2017) and those which have been applied by Yousefi et al. (2012), Yousefi and Carranza (2015a,b,c, 2016, 2017) and Yousefi and Nykänen (2016) which can be used to assign weights to continuous exploration data representing the probability of operating subsystems of the ore-forming processes, or the amount of relationships between mineral deposits and exploration evidence data. The application of logistic functions in assigning weights is not bias-free because it is possible to use other mathematical functions, the choice of which require a judgment call from the individual analyst. Yousefi and Carranza (2015b, 2017), Yousefi and Nykänen (2016), Roshanravan et al. (2018a), and Mao

Table 3
Different kinds of relationships between mineral deposits and indicator features and their quantification ways.

Relationship type	Description	Example	Quantification way
Proximity	Deposits are hosted preferentially closer to a feature than distal	Mineral deposits typically exist in close proximity (i.e., short distances) to certain geological features or structures	Low values of proximity must be represented by high scores (weights) whereas high values of proximity low scores
Abundance	Deposits are more likely to occur in areas where there is a high spatial density of a particular feature	Faults density, silicified veins, and dykes	High abundance values must be given high scores whereas low abundance values low scores
Association	Deposits are preferentially hosted or controlled by a particular feature	A certain rock type	Such particular features must be given high scores in comparison with other features
Anomaly	Situations in which geochemical and/or geophysical-potential are used to derive spatial proxies for processes critical to ore systems	Mineral deposits may have spatial correlation with high values of geochemical anomalies, representing enrichment processes of ore systems	High values of geochemical anomalies must be given high scores
		Mineral deposits may have spatial correlation with low values of geochemical anomalies, representing depletion processes of ore systems	Low values of geochemical anomalies must be given high scores
		Mineral deposits have strong spatial associations with intermediate evidence values but not with lowest and highest evidence values*	Intermediate evidence values must be given high scores whereas the lowest and highest evidence values are given lowest scores

* In some geological settings mineral deposits occurred where aeromagnetic data have intermediate values resulting from low magnetic intensity of argillic alteration and high magnetic intensity of iron ores.

et al. (2019) all explicitly compared classified and continuous weighted evidence layers and demonstrated that the application of continuous quantification approaches result in more reliable exploration targeting models as the method does not require, known examples of mineralisation as training data, classified evidence values, user-defined functions and the direct judgment of analysts in assigning weights. It is important to note here that the slope, inflection point and midpoint of logistic functions can be defined through the method proposed by Yousefi and Nykänen (2016) without relying on the analyst's judgment and training sites.

2.2.6. Integration

A general consensus exists among mathematical geoscientists that areas with a higher number of mappable indicator features of higher statistical or conceptual importance (i.e., greater weights), display a higher priority for further exploration than areas with a lower number of indicator features of lower importance (e.g., Yousefi and Carranza, 2017). Thus, the best integration function is one that can apply each of these theses. Various integration functions (Table 4), have been developed and applied to combine maps of quantified relationships, i.e., weighted evidence layers and generate exploration targets. The effectiveness of integration functions is affected by the nature of the data input to prospectivity mapping (e.g., the quality of the predictive maps) and the weighting methods applied, therefore different integration functions should be examined to select the best and more reliable exploration targets. In this regard, EIS could be applied to generate exploration targets by using different integration functions quickly.

2.2.7. Validation and selection of the preferred model

Given our incomplete understanding of ore-forming processes and incomplete data, there is typically more than one exploration targeting model that fits the concepts and data. Therefore, selection of the most reliable models and targets is critical for time and cost-efficient exploration. The key criteria to be considered when testing prospectivity models include: (i) At every scale of exploration targeting, area reduction is one of the key aims because the probability of finding undiscovered ore deposits within smaller target areas is higher than that for a larger target area (Mihalasky and Bonham-Carter, 2001). (ii) In mineral prospectivity mapping, the location of known deposits, if present, can be used as a way to test the predictive capacity of prospectivity models. This can be done by overlaying mineral deposit locations, if any, on exploration targeting models (e.g., Stensgaard et al., 2006; Carranza and Laborte, 2016; Nykänen et al., 2015; Yousefi and Carranza, 2015a,b) to evaluate the reliability of the targets generated. For example, if a prospectivity model predicts a higher number of known deposit locations, the model will have performed better than a model that predicts less (cf. Bonham-Carter, 1994; Mihalasky and Bonham-Carter, 2001; Carranza, 2008; Yousefi and Carranza, 2015b). Considering the two criteria *i* and *ii*; if two different prospectivity models are used to map exploration targets of different sizes but with the same prediction rate, the probability of finding undiscovered deposits within the model that mapped the smaller target area will be higher (cf. Mihalasky and Bonham-Carter, 2001), meaning model effectiveness is closely linked to targeting precision which is related to area. (iii) There is another issue regarding the contribution of non-deposit locations in the evaluation of spatial evidence layers and prospectivity models (e.g., Nykänen, 2008; Nykänen et al., 2015; Chen, 2015). Valid target areas generated by a mineral prospectivity mapping method should have less coincidence with non-deposit locations where mineral deposits are predicted as unlikely to be present, due to locally unsuitable geological settings and lack of positive exploration indicators (Carranza, 2008; Nykänen et al., 2015; Chen and An, 2016). According to the three criteria discussed above, several evaluation methods (Table 5) have been developed each with a variety of

Table 4
Examples of the integration function.

Integration function		Reference, e.g.
Boolean logic		Bonham-Carter (1994), Carranza (2008)
Bayesian and posterior probability		Bonham-Carter (1994), Carranza (2008)
Fuzzy operators		An et al. (1991), Bonham-Carter (1994)
Weighted mean	Knowledge-driven index overlay	Bonham-Carter (1994), Carranza (2008)
	Data-driven index overlay	Yousefi and Carranza (2016)
Expected value		Yousefi and Carranza (2015a)
Geometric average		Yousefi and Carranza (2015c), Almasi et al. (2017), Roshanravan et al. (2018b)
Union score		Yousefi and Carranza (2017)

Table 5
Evaluation methods of exploration targeting models.

Evaluation method	Evaluation criteria	Proposed and applied by
Success-rate and prediction-rate curves	• Prediction rate of mineral deposit locations • Area of exploration targets	Chung and Fabbri (2003), Agterberg and Bonham-Carter (2005), Fabbri and Chung (2008), Harris et al. (2015), Parsa et al. (2016)
Receiver operating characteristics (ROC) curves	• Prediction rate of mineral deposit locations • Prediction rate of non-deposit locations	Chauhan et al. (2010), Nykänen et al. (2015), Chen (2015), Chen and Wu (2016, 2017)
Prediction-area (P-A) plot	• Prediction rate of mineral deposit locations • Area of exploration targets	Yousefi and Carranza (2015a,b, 2016)
Improved prediction-area (P-A) plot	• Prediction rate of mineral deposit locations • Prediction rate of non-deposit locations • Area of exploration targets	Roshanravan et al. (2018b)
Post probability values to the training data points	• Associating the training sites with the modeled posterior probability values in the final model • The sensitivity of the model to specific training sites can be tested by calculating successive models and leaving out one of the training sites in turn. This is a type a jack-knife test	Nykänen and Salmirinne (2007)

advantages and disadvantages in terms of how they applied deposit locations. As can be seen in Table 5, the improved P-A plot is a powerful method for validating and choosing the best exploration targeting models in areas where there are known deposits because it uses all three criteria discussed above simultaneously.

A problem nevertheless however remains with the evaluation of targeting models in areas where there are no known deposits to be used as testing sites, thus the most significant validation method here is field-testing (e.g., Nykänen and Salmirinne, 2007; Gholami et al., 2012; Yousefi and Carranza, 2015a). The highest ranked targets must however be selected for field-testing and observations even in areas where there are known deposits. The degree of success will therefore be defined when follow up exploration programs are evaluated in terms of results such as presence of mineralisation, small economic deposit, or large and world class economic deposits, related also to different companies and investors.

2.2.8. Target prioritisation

Exploration targeting models are generally continuous maps, which means an explorer would have to categorise and prioritise the target area with respect to favourable and unfavourable domains (e.g., Aitken et al., 2018; Yousefi and Carranza, 2015b, 2016). Classification of the prospectivity values in an exploration targeting model into a map of targets showing their priority for further exploration programs requires proper selection of threshold values (e.g., Porwal et al., 2003; Parsa et al., 2016). For this, the Student's t-value (Bonham-Carter et al., 1989), which measures the statistical significance of prospectivity values of exploration targeting models, with regard to known deposit sites, could be used as a data-driven method for objective definition of the thresholds. The concentration–area (C–A) fractal model proposed by Cheng et al., (1994) can be applied for objective selection of the threshold values in greenfield exploration without using known deposit locations (Yousefi and Carranza, 2015b). Exploration targeting generally identifies a number of targets by several orders of magnitude, for which field observations always help to better define and prioritise the targets.

Fig. 7 illustrates a schematic flow of the aforementioned EIS-based operations for mineral exploration targeting.

3. Discussion

3.1. Why is EIS-based exploration targeting urgently needed?

Eliciting *knowledge* of complicated ore-forming subsystems from the huge amount of *data* and *information* obtained from the heterogeneous and complex earth while addressing issues related to probability, similarity, vagueness, randomness, ambiguity, possibility and imprecision (e.g., Yousefi and Carranza, 2015a), is a tricky undertaking. Consequently, *knowledge* deficiency remains a problem especially where the search for undiscovered mineral deposits shifts from outcropping deposits to greater depths with a higher geological complexity (Fig. 8). Information systems are a methodological aspect of the real world enabling, describing its complexity (Grabowski et al., 2014), such that automatic understanding and perception of earth-related data could be possible. Grabowski et al. (2014) stated that new generations of computer systems, given the current stage of development of computer science, may be capable of generating at least a semblance of *knowledge* automatically and as the capabilities of information systems grow, the boundary between the range of activities available for computers and the area reserved for human activity will shift. It is claimed that knowledge management is fundamental to improving the capabilities of a particular technology and the successful adoption and implementation of such technology increasingly depends on the efficient use of these processes (Al-Emran et al., 2018). There are a number of knowledge management processes including knowledge identification, knowledge capture, knowledge development, knowledge sharing, knowledge dissemination, knowledge application, and knowledge storage (Al-Emran et al., 2018) which should be respected in the construction of EIS to modulate the knowledge deficiency on ore-forming processes.

Many different exploration analysis tools and methodologies are currently being used to target mineral deposits. Exploration companies and research centres occasionally also create their own proprietary format and methodologies. The non-formalised language produced by this variety of methods is one reason why making a particular, comprehensive system is required to produce a common language. Therefore, construction of a particular and specified ‘information system’, i.e., an EIS, results in a coherent and logically structured set of exploration data analysis procedures and targeting tools providing the mineral explorer with a better perception of natural phenomena, i.e., in terms of their understanding of ore-forming processes while making use of the interactive environment to build computer-generated targeting models in the real world.

As discussed by McCuaig and Hronsky (2000), McCuaig et al. (2007a,b) and Hagemann et al. (2016a) and further illustrated in this paper, ore deposit models have traditionally been focused (i) at the deposit-scale (which is at least in part driven by the relative ease of access and more abundant data availability at or near mineral deposit locations) with little or no consideration of the broader earth processes (i.e., pre-mineralisation subsystems) that must operate for ore deposition to occur, (ii) on resolving the “why” (i.e., the genetic) rather than “where” (i.e., the spatial predictive) aspects of mineral deposit formation, and (iii) identifying differences between, rather than commonalities in, the formation of particular types of mineral deposits (i.e.,

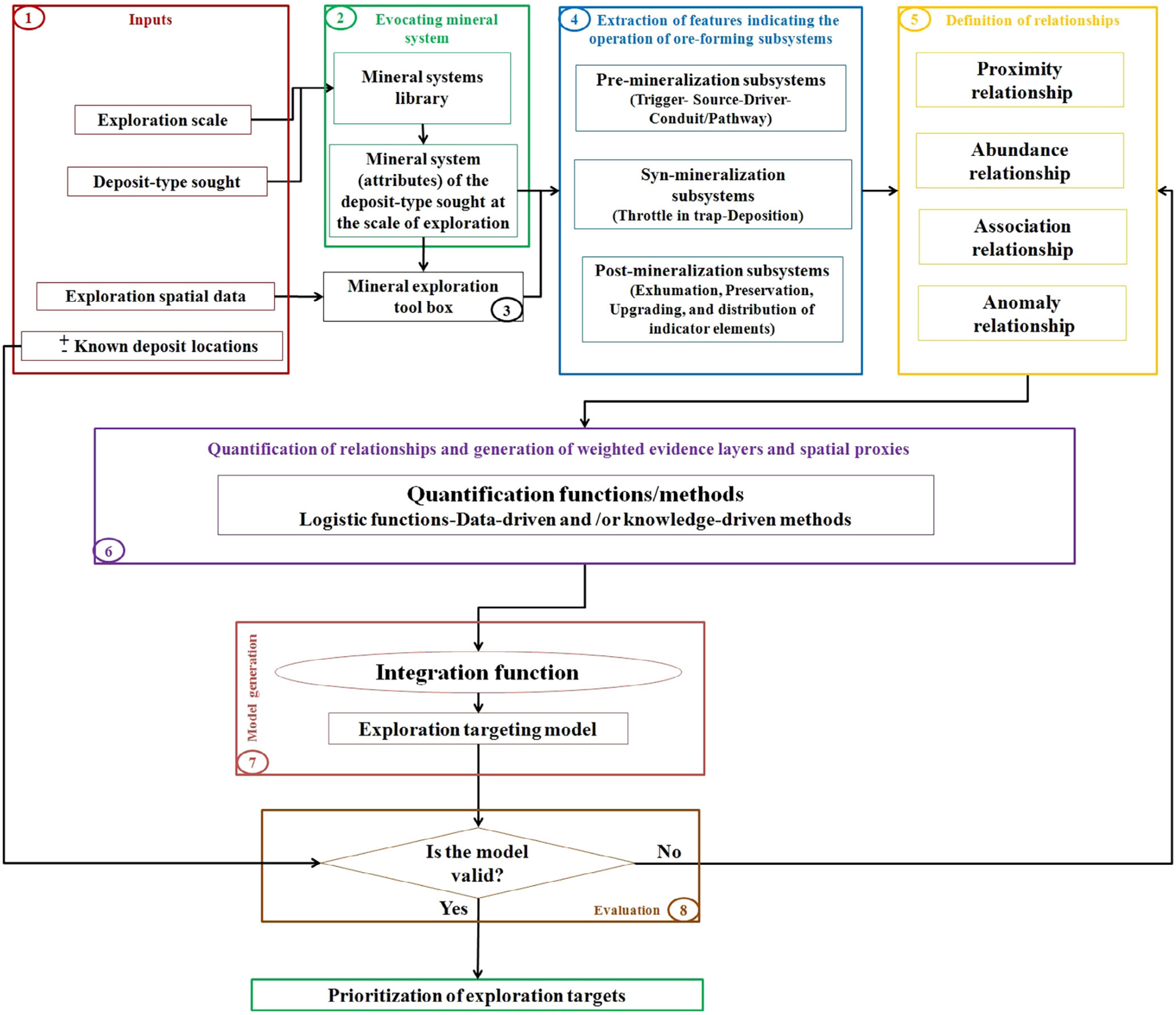

Fig. 7. A schematic flow showing the procedure of operations in an EIS for exploration targeting.

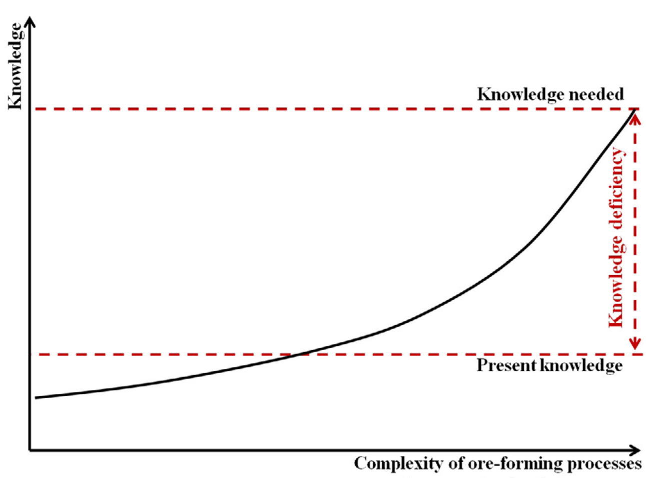

Fig. 8. Variation of knowledge deficiency with the amount of geological complexity.

stereotyped versus holistic thinking). Therefore, in the case of MPM adopting, a traditional deposit-centric approach (e.g., a data-driven MPM technique that uses the location of known mineral deposits as training data) will result in a prospectivity map that can find analogues of (i.e., areas that have the same characteristics as) the known deposits but may fail to identify areas that contain variations on the theme (cf. examples provided in McCuaig et al. (2007a,b). Therefore, it is imperative for MPM and mineral exploration targeting in general, to adopt a holistic, spatial predictive approach that incorporates scale-dependent data relating to the targeted mineral deposit type to serve robust and testable exploration models. Consequently, as discussed in this paper appending the mineral systems concepts, GIS technology and exploration analysis tools results in an ideally suited package, i.e. EIS for the purpose of mineral exploration targeting, through which a variety of models could be generated and compared in order to select the best.

3.2. Vision for an EIS

We envisage implementation of an EIS as a geoprocessing toolbox attached to a commercial GIS platform. For example, the EIS could be presented as a set of model builder functions in ArcGIS™ Spatial

Analyst. In addition, experienced modelers could develop tools in an open-source GIS platform such as the freely available QGIS software package, thereby promoting greater uptake. An operational EIS toolbox should include all the essential components discussed in this paper (Fig. 7). The fundamental basis of EIS is the mineral system library defining the critical parameters used for MPM in GIS. Therefore, a link between this database and a GIS is a necessity. Certain GIS tools necessary to create the proxies to critical parameters would also be required as this is a critical step in MPM. Depending on the scale and the data available there should also be a variety of MPM methods of different types as separate easily updatable modules and finally a set of model validation techniques would also be needed. Building all these components as modules in an open source community-based platform would potentially allow for contributions from numerous developers globally making the development, maintenance and updating of such a complex system possible. It is expected, given future advances in the 3D GIS space, that EIS could also operate effectively using 3D input data.

When fully implemented, an EIS would be a software package for semi-automated exploration targeting within an open GIS platform to maximise the scientific community's accessibility in terms of commercial use. The 'mineral system library' proposed is also expected to be able to be updated in a flexible manner. An EIS should include tools for pre-processing data, i.e. translating the critical parameters of the mineral systems into mappable features and proxies, which is the step where the pre-existing geoscientific knowledge of the exploration team is planted into the exploration data. The rapid generation of different exploration targeting models, in terms of using various new integration functions, is also expected to feature. Eventually, these models could be shared in a common database for other users. Furthermore, tools for validating and comparing the modelling results are essential to make modelling reliable. The ultimate aim of an EIS would be to assist exploration teams in their decision making throughout the different stages and across the different scales of an exploration project. Furthermore, an EIS could be used by geoscientists to explore and learn more about the mineral systems and ore forming processes by analysing and quantifying the spatial association between the mineral deposits and geoscience data derived from geophysical, geochemical and geological surveys during mineral exploration.

3.3. Challenging concerns and issues ahead

Lack of data – particularly 3D data – quality issues and ensuring the full coverage necessary to map mineral systems accurately, are some of the issues that continue to hold back the effective use of exploration targeting mapping. Lack of data attribution is also a problem here. For example, minimal or incomplete attribution may prevent easy extraction of key features from an input dataset (e.g., fault data are almost never attributed in terms of fault type and age). Building a well-organised mineral systems library covering all deposit types will be a difficult task but will, progressively, be established.

Much of the research to date, including the tools developed thus far has focused on surface or near surface exploration data, so in order to explore mineral deposits at progressively greater depths (Hagemann et al., 2016a), computational infrastructure must be developed to represent and capture data and mappable evidence for ore-forming processes in 3D environment.

As the types of data and information used in exploration targeting change with scale, conceptual predictive targeting is the most effective approach from continental to regional scale studies, whereas at the smaller district to deposit scales direct detection techniques become more important (Hronsky and Groves, 2008; McCuaig et al., 2010) because the deposit scale is defined as direct targeting of mineralisation that can be drill tested. At the deposit scales the mineralisation processes are best represented by 3D datasets (Joly et al., 2012), whereas geological insights on the regional scales can be represented and spatially interrogated in mainly 2D. Both, however, are best understood in a 4D space-time framework. Thus, 3D modelling tools for exploration targeting (e.g., Wang et al., 2011; Nielsen et al., 2015a, 2019; Payne et al., 2015; Li et al., 2018) must be developed further, especially for deposit scale studies. For this, as with 2D data, geological uncertainty in 3D models should be taken into account (Lindsay et al., 2012).

Uncertainty may be defined as the deviation of our observations from reality (Bárdossy and Fodor, 2001). Given our incomplete knowledge of complex mineralisation-related geological processes that cannot be observed directly, our measurements (e.g., data and information relating to these processes) and the ensuing interpretation of the results may diverge from what happened or what exists in the real world. Therefore, there are a variety of sources of uncertainty affecting the translation of mineral systems understanding into exploration targeting models and target prioritisation (cf., Singer and Kouda, 1999; Van Loon, 2002; Cheng, 2007; McCuaig et al., 2007a,2010; Kreuzer et al., 2008; Nykänen et al., 2008; Kreuzer and Etheridge, 2010; Partington, 2010; Joly et al., 2012; Lisitsin et al., 2013; Yousefi et al., 2013; Yousefi and Carranza, 2015a; Hagemann et al., 2016a; Yousefi and Nykänen, 2016; Almasi et al., 2017). Various methods of measuring uncertainty have been progressively developed (Bárdossy and Fodor, 2001; Partington and Sale, 2004; McCuaig et al., 2007a,b; Hronsky and Groves, 2008; Celikyilmaz and Burhan Türksen, 2009; Kreuzer and Etheridge, 2010; Partington, 2010; Lindsay et al., 2012; Lisitsin et al., 2014; Yousefi and Carranza, 2015a, 2017; Zuo et al., 2015), for example as demonstrated by Partington, (2010), highlighting the contribution of economic factors to the exploration targets recognised through MPM results in better understanding the exploration risk and uncertainty allowing prioritisation of the targets in terms of amounts of metal and economic factors. Uncertainties nevertheless remain resulting from complexity and dissimilarities in geological processes, complex mineralisation-related anomaly patterns and the heterogeneity of the earth that should be modulated. Furthermore, complicated relationships between evidence features and mineral deposits, the inaccurate and imprecise presentation of geological features in exploration datasets, subjective interpretation and selection of exploration data and the representativeness of the targeting criteria cause other types of uncertainties, which also need to be investigated.

4. Concluding remarks

- Exploration information systems (EIS) are defined here as a framework for systematic and consistent data collection, definition of targeting elements, generation of targeting proxies and integration of targeting criteria.
- Future establishment of EIS could be achieved by creating a mineral systems library for key deposit types and spatially enabling this library by linking it to the GIS environment.
- Generating EIS is a necessity for mineral exploration targeting in the GIS environment and mineral prospectivity mapping in particular. If adequately managed, the huge amounts of data and information relating to ore-forming processes can be converted into exploration *knowledge* and *insight*.
- Automated translation of ore-forming processes into spatial proxy maps and the ensuing targeting models would allow analysts to examine various weighting methods and integration functions, evaluate them and select the most applicable to generate exploration targets. As this paper emphasises however, the EIS includes a set of tools to help in the process of mineral exploration and development making this practice more effective, it does not completely replace human input.
- In any attempt at mineral exploration targeting, the exploration scale and the corresponding subsystems of ore-forming processes must be contributed. For this, the categorisation of ore-forming processes into pre-, syn-, and post-mineralisation subsystems facilitates a better understanding of how they operate in different scales.

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