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Review Paper

Natural Resources Research Publications on Geochemical Anomaly and Mineral Potential Mapping, and Introduction to the Special Issue of Papers in These Fields

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In its 26 years of existence, the journal of Natural Resources Research (NRR) has published and continues to publish papers on geochemical anomaly and mineral potential mapping. This is consistent with its aims and scope to publish quantitative studies of natural (mainly but not limited to mineral) resources exploration, evaluation and exploitation, including environmental and risk-related aspects. Over the years, NRR has contributed significantly more to the publication of developments in mineral potential mapping and notably less to the publication of developments in geochemical anomaly mapping. In more detail, NRR has contributed significantly more to the publication of research on development of robust quantitative methods for analysis and synthesis of spatial evidence of mineral potential but notably less to the publication of research on development of geologically focused models of mineral potential. The editorship of NRR recognizes the latter as a challenge to promote further research on development of numerically robust as well as geologically focused mineral potential models, and this special issue is a major initiative in response to that challenge. The recent inclusion of Natural Resources Research for coverage by the Clarivate Analytics (formerly the Institute for Scientific Information) in the Science Citation Index Expanded™ and Journal Citation Reports® (JCR) Science Edition will help make Natural Resources Research meet that challenge.

KEY WORDS: Numerical methods, mineral systems, GIS, journal impact.

INTRODUCTION

The journal of Natural Resources Research (NRR) was founded in 1992 by Richard McCammon. Its original name, Nonrenewable Resources, was changed to the present one in 1999, but its objective remained the same: to promote quantitative approaches to mineral resource exploration, assessment, extraction and utilization. However, since its name was changed, the scope of the NRR has also broadened to publish quantitative studies of natural (mainly but not limited to mineral) resources exploration, evaluation and exploitation, including environmental and risk-related aspects. Thus, NRR covers a wide variety of resources including minerals, coal, hydrocarbon, geothermal, water and vegetation. Typical articles make use of geoscientific data or analyses to assess, test or compare resource-related aspects.

Finding new mineral deposits is becoming increasingly more and more difficult, as the most obvious ones have probably been all discovered al-

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ready. This requires, among others, sustained research and development of methods to facilitate mineral deposit discovery. Significant developments in the geographic information system (GIS) technology during the last four to five decades or so have been useful in the development of quantitative methods of geoscientific data analysis and integration, particularly for geochemical anomaly and mineral potential mapping (Bonham-Carter 1994; Pan and Harris 2000; Carranza 2008). In this article, we review the general developments of GIS-based mineral potential mapping by looking into the yearly variations of published papers in this field. Then, we review the publications of NRR on mineral potential mapping, which is one of the major fields within the scope of this journal. Although NRR is not exclusively dedicated geochemical anomaly mapping, it has published a few articles on this field and these are also reviewed briefly here. Finally, we introduce the papers in this special issue on GIS-based geochemical anomaly and mineral potential mapping.

The field of geochemical anomaly mapping has existed since the early 1970s, and detailed explanations of the science of this field can be found in Levinson (1974), Rose et al. (1979), Govett (1983), Butt and Zeegers (1992), Kauranne et al. (1992), Hale and Plant (1994) and Hale (2000). In very simple terms, this field involves separation of background and anomalous geochemical samples and using the latter group to delineate targets for further exploration of undiscovered deposits. Traditionally, the task of delineating exploration targets based on geochemical anomalies was achieved by stacking on a light table same-scale maps of anomalies of single elements or suites of elements in order to define exploration targets based on intersections of anomalies. Since about three to four decades ago, this task was facilitated by the use of an ‘‘electronic light table’’ (i.e., a GIS). Then, in the late 1980s, the field of geochemical anomaly mapping intuitively evolved into the field of mineral potential mapping, as geochemical anomaly maps need to be integrated with geological datasets in order to delineate geologically meaningful exploration targets (Bonham-Carter et al. 1988, 1989; Agterberg et al. 1990).

DEVELOPMENTS IN MINERAL POTENTIAL MAPPING

Mineral potential mapping is concerned with quantifying and mapping the likelihood that mineral deposits are present in a study area. It is synonymous to *mineral prospectivity mapping*, which is concerned with quantifying and mapping the likelihood that mineral deposits may be found by exploration in a study area. Indeed, these two terms—mineral potential mapping and mineral prospectivity mapping—have been used interchangeably in the literature and are hereafter both denoted as MPM.

Thus, MPM involves the collection, analysis and integration of geochemical, geological and geophysical data from multi-sources to quantify spatial relationships between anomalies (i.e., indicators of mineralization) and existing occurrences of mineral deposits of the type sought and use the quantified spatial relationships to map mineral potential or prospectivity. The integration of anomalies, derived from a variety of geo-exploration data, has been done traditionally with the aid of a light table, upon which maps of the same sizes and scale are stacked on top of each to outline potential or prospective areas defined by intersections of anomalies. However, in the last three to four decades or so, MPM has been made more efficient with the aid of a geographic information system (GIS).

The procedure of GIS-based MPM starts with definition of a conceptual model of mineral potential (Fig. 1), which describes theoretical relationships among various factors or controls of how and where certain types of mineral deposits form. The conceptual model guides the choice of spatial geoscience datasets to be used in MPM. Analyses of spatial geoscience datasets to define predictive model parameters can provide feedback to the definition and fine-tuning of the conceptual model of mineral potential (cf. Carranza and Hale 2002b; Carranza 2009a) and eventually to the creation of predictor maps. The integration of predictor maps, using a certain method, yields a map of mineral potential or prospectivity, which needs to be validated in order to judge its predictive ability and, thus, its usefulness for decision-making to guide mineral exploration.

In general, GIS-based MPM can be either *data-driven* or *knowledge-driven*. Methods of data-driven MPM, which involve quantitative analysis of spatial relationships between anomalies (i.e., indicators of mineralization) and existing occurrences of mineral deposits of the type sought, are suitable for ‘‘brownfields’’ or well-explored regions wherein the objective is to define additional targets for exploration. Methods of knowledge-driven MPM, which

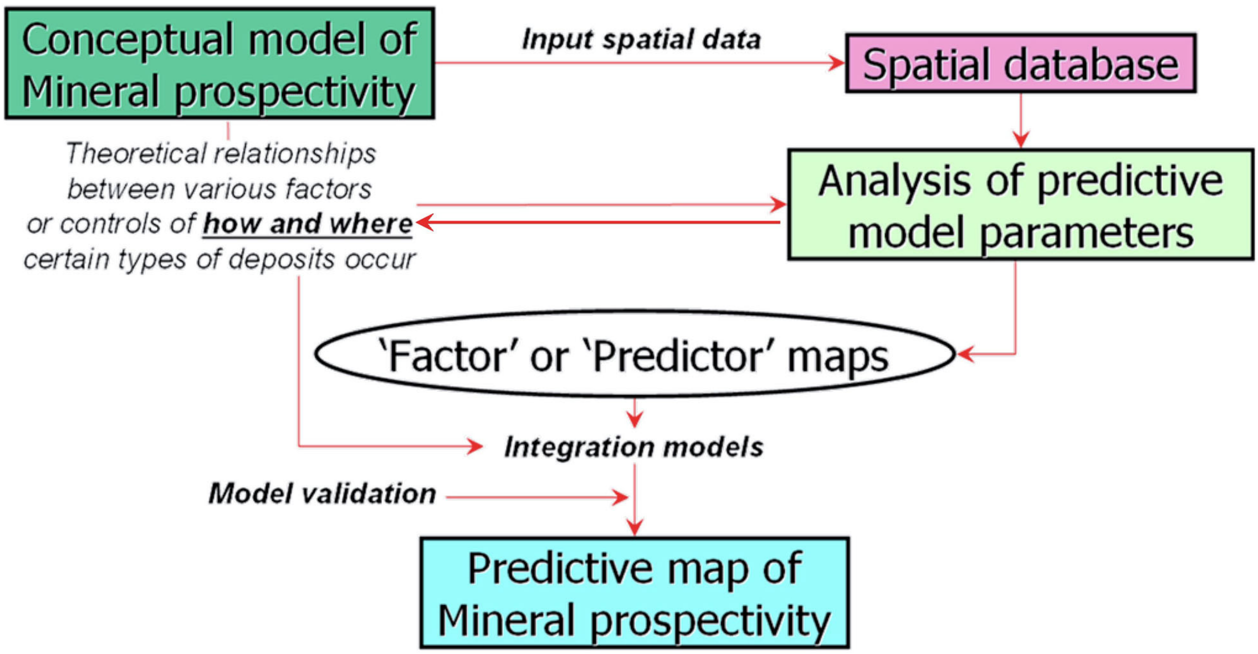

Figure 1. General flowchart of MPM (slightly modified from Carranza (2008)).

are based on expert judgment of spatial relationships between anomalies (i.e., indicators of mineralization) and existing occurrences of mineral deposits of the type sought, are suitable for "greenfields" or under-explored regions wherein the objective is to define new targets for exploration. The developments in MPM in the last three to four decades or so have involved testing and application of various methods, considering the assumptions as well as the strengths and limitations of each and every method. The different data- and knowledge-driven methods of GIS-based MPM are listed in Tables 1 and 2, respectively. The methods and references to these methods given in these tables are a representative sampling of the developments in GIS-based MPM as these are the most commonly used and are published mostly in peer-reviewed journals/books (see reference list).

Developments of methods for data-driven MPM preceded those for knowledge-driven MPM by at least 10 years (Fig. 2). This is largely because MPM is mainly a form of deductive modeling, which involves analysis of patterns from observations (data) in order to derive a model (hypothesis/theory) of mineral potential or prospectivity (cf. Fig. 1). Weights of evidence (WofE) is the most widely used data-driven method of MPM, whereas fuzzy logic (FL) is the most widely used knowledge-driven method of MPM (Fig. 2). The development of WofE has been pioneered by Bonham-Carter et al. (1988, 1989) and Agterberg et al. (1990), whereas the development of FL has been pioneered by An et al. (1991). An analysis of annual publications regarding MPM shows that there have been generally 2–4 papers on WofE modeling of MPM since the development of WofE for MPM in 1988 up to the present, whereas there has been a significant increase in papers on FL modeling of MPM since the development of FL for MPM in 1991 up to the present (Fig. 3). In particular, the significant increase in papers on FL modeling of MPM took place in the last 5–10 years. There is an underlying reason for the growth in research on conceptual (or knowledge-driven) modeling of MPM relative to the decline in research on empirical (or data-driven) modeling of MPM, as discussed below.

The development of GIS-based MPM has been influenced by the publication of three textbooks (Fig. 4), among which the textbook by Bonham-Carter (1994) has been the most influential as it has been cited at least 1500 times (according to Google Scholar). However, the later textbooks by Pan and Harris (2000) and Carranza (2008) certainly have also influenced the development of methods for MPM as, according to Google Scholar, these have been cited at least 100 times and at least 260 times,

Table 1. Methods commonly used for data-driven GIS-based MPM

Method	References to seminal work and succeeding innovative applications
Bivariate data-driven	
Weights of evidence analysis	Bonham-Carter et al. (1988, 1989), Agterberg and Bonham-Carter (1990, 2005), Agterberg et al. (1990, 1993), Bonham-Carter and Agterberg (1990, 1999), Bonham-Carter (1991, 1994), Agterberg (1992, 2011), Xu et al. (1992), Rostirolla et al. (1998), Cheng and Agterberg (1999), Raines (1999), Singer and Kouda (1999), Carranza and Hale (2000, 2002a,b), Pan and Harris (2000), Venkataraman et al. (2000), Asadi and Hale (2001), Harris et al. (2001, 2003), Mihalasky and Bonham-Carter (2001), Moreira et al. (2002), Porwal et al. (2001, 2006a, 2010a), Scott and Dimitrakopoulos (2001), Tangestani and Moore (2001), Agterberg and Cheng (2002), Paganelli et al. (2002), Raines and Mihalasky (2002), Carranza (2004, 2008, 2009b), Chen (2004), Chen et al. (2005), De Quadros et al. (2006), Daneshfar et al. (2006), Harris and Sanborn-Barrie (2006), Nykänen and Raines (2006), Nykänen and Ojala (2007), Nykänen and Salmirinne (2007), Raines et al. (2007), Feltrin (2008), Ford and Blenkinsop (2008), Oh and Lee (2008), Austin and Blenkinsop (2009), Debba et al. (2009), Deng (2009), Fallon et al. (2010), Partington (2010), Porwal et al. (2010a), Zuo (2011), Joly et al. (2012), Magalhães and Souza Filho (2012), Chen et al. (2014), Lindsay et al. (2014), Liu et al. (2014), Andrada de Palomera et al. (2015), Ford et al. (2015, 2016), Nielsen et al. (2015a), Payne et al. (2015), Zhang and Zhou (2015), Zuo et al. (2015), Gao et al. (2016), Zeghouane et al. (2016), Zhang et al. (2016)
Evidential belief analysis	Chung and Fabbri (1993), An et al. (1994b), Carranza and Hale (2003), Carranza et al. (2005, 2008a, b, c, 2009, 2015), Carranza (2008, 2009a, 2011, 2015), Carranza and Sadeghi (2010), Liu et al. (2015), Ford et al. (2016), Oskouei and Soltani (2016)
Multivariate data-driven:	
Discriminant analysis	Chung (1977), Prelat (1977), Bonham-Carter and Chung (1983), Harris and Pan (1999), Pan and Harris (2000), Harris et al. (2003), Carranza (2008), Geranian et al. (2016)
Characteristic analysis	Botbol et al. (1977, 1978), McCammon et al. (1983, 1984), Harris (1984), Pan and Harris (1992a, 2000)
Logistic regression analysis	Chung (1978, 1983), Chung and Agterberg (1980, 1988), Bonham-Carter and Chung (1983), Agterberg (1988, 1992, 1993), Agterberg et al. (1993), Harris and Pan (1991, 1999), Sahoo and Pandalai (1999), Pan and Harris (2000), Harris et al. (2001, 2003, 2006), Carranza and Hale (2001b), Raines and Mihalasky (2002), Agterberg and Bonham-Carter (2005), Daneshfar et al. (2006), Nykänen and Ojala (2007), Carranza (2008), Carranza et al. (2008a), Oh and Lee (2008), Fallon et al. (2010), Porwal et al. (2010a), Chen et al. (2011), Mejía-Herrera et al. (2015)
Favourability analysis	Pan (1993a,b,c), Pan and Porterfield (1995), Pan and Harris (1992b, 2000), Rostirolla et al. (1998), Chen (2004)
Likelihood ratio analysis	Chung and Fabbri (1993), Chung et al. (2002), Chung and Keating (2002), Chung (2003), Harris and Sanborn-Barrie (2006), Stensgaard et al. (2006), Oh and Lee (2008)
Artificial neural networks	Singer and Kouda (1996, 1997, 1999), Harris and Pan (1999), Pan and Harris (2000), Brown et al. (1999, 2000, 2003a, b), Bougrain et al. (2003), Harris et al. (2003), Porwal et al. (2003a, 2004), Rigol-Sanchez et al. (2003), Harris and Sanborn-Barrie (2006), Behnia (2007), Skabar (2005, 2007a,b), Nykänen (2008), Pereira Leite and De Souza Filho (2009a,b), Oh and Lee (2010), Abedi and Norouzi (2012), Magalhães and Souza Filho (2012), Asadi et al. (2015), Rodriguez-Galiano et al. (2015), Shabankareh and Hezarkhani (2016)
Bayesian network classifiers	Porwal et al. (2006b), Porwal and Carranza (2008)
Support vector machine	Porwal et al. (2010b), Zuo and Carranza (2011), Abedi et al. (2012), Rodriguez-Galiano et al. (2015), Geranian et al. (2016), Shabankareh and Hezarkhani (2017)
Random Forest	Rodriguez-Galiano et al. (2014, 2015), Carranza and Laborte (2015a, b, 2016), Harris et al. (2015), Gao et al. (2016), McKay and Harris (2016), Zhang et al. (2016)

Table 2. Methods commonly used for knowledge-driven GIS-based MPM

Method	References to seminal work and succeeding innovative applications
Boolean logic	Bonham-Carter (1994), Barnes et al. (1999), Thiart and De Wit (2000), Knox-Robinson (2000), Harris et al. (2001), Moreira et al. (2002), Carranza (2008)
Binary index overlay	Bonham-Carter (1994), Carranza et al. (1999), Thiart and De Wit (2000), Carranza (2008)
Multi-class index overlay	McLaren (1992), Bonham-Carter (1994), Barnes et al. (1999), Cooper et al. (2000), Knox-Robinson (2000), Harris et al. (2001, 2008, 2015), Chica-Olmo et al. (2002), De Araújo and Macedo (2002), Moreira et al. (2002), Billa et al. (2004), Roy et al. (2006), Carranza (2008), Cassard et al. (2008), Madani (2011), Herbert et al. (2014), Nielsen et al. (2015a), Payne et al. (2015), Yazdi et al. (2015), Yousefi and Carranza (2015b), Abedi et al. (2016, 2017), McKay and Harris (2016)
Fuzzy logic	An et al. (1991), Reddy et al. (1992), Chung and Fabbri (1993), Gettings and Bultman (1993), Bonham-Carter (1994), Cheng (1996), Choi et al. (2000), D'Ercole et al. (2000), Groves et al. (2000), Knox-Robinson (2000), Porwal and Sides (2000), Venkataraman et al. (2000), Rogge et al. (2000, 2003), Carranza and Hale (2001a), Moreira et al. (2002), Moon (1993), Porwal et al. (2003b, 2015), Tangestani and Moore (2003), Ranjbar and Honarmand (2004), De Quadros et al. (2006), Eddy et al. (2006), Harris and Sanborn-Barrie (2006), Rogge et al. (2006), Nykänen and Ojala (2007), Nykänen and Salmirinne (2007), Carranza (2008), Nykänen et al. (2008a, b, 2015), Lusty et al. (2009), Zuo et al. (2009), González-Álvarez et al. (2010), Costa e Silva et al. (2012), Ghanbari et al. (2012), Joly et al. (2012), Lusty et al. (2012), Magalhães and Souza Filho (2012), Abedi et al. (2013, 2015, 2016, 2017), Ford and Hart (2013), Lisitsin et al. (2013, 2014), Pazand et al. (2013), Barros de Andrade et al. (2014), Lindsay et al. (2014, 2016), Liu et al. (2014), Naghadehi et al. (2014), Najafi et al. (2014), Alaei Moghadam et al. (2015), Yousefi and Carranza (2015a, 2017), Asadi et al. (2015), Ford et al. (2015, 2016), Moradi et al. (2015), Nielsen et al. (2015b), Yazdi et al. (2015), Zhang and Zhou (2015), Du et al. (2016), Elliott et al. (2016), Farzamian et al. (2016), Leväniemi et al. (2017), McKay and Harris (2016), Mostafavi Kashani et al. (2016), Yousefi and Nykänen (2016), Zhang et al. (2017), Zhou and Zhang (2016)
Evidential belief	Moon (1990, 1993), Chung and Moon (1991), Moon et al. (1991), An et al. (1992, 1994a, b), Chung and Fabbri (1993), Wright and Bonham-Carter (1996), Tangestani and Moore (2002), Chen (2004), Rogge et al. (2003, 2006), Carranza (2008), Abedi et al. (2017)

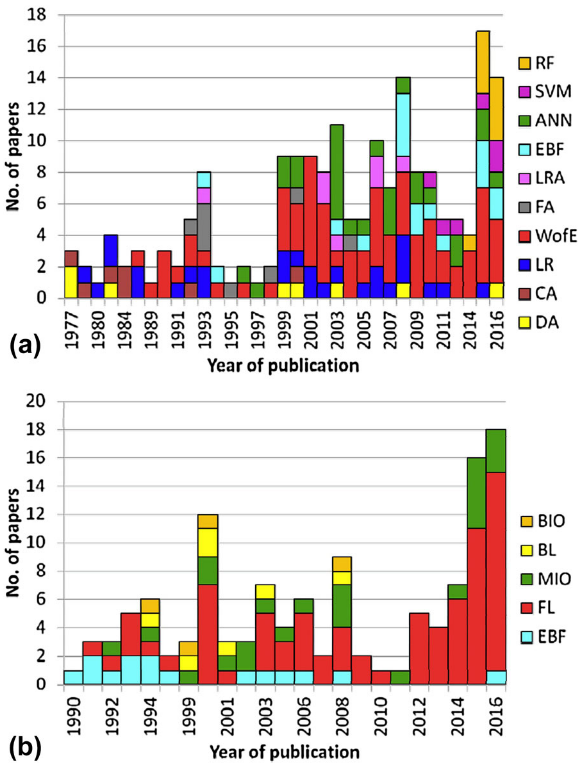

Figure 2. Years and numbers of publications of mostly journal papers on methods of (**a**) data-driven MPM and (**b**) knowledge-driven MPM. The publications included in these graphs are cited in Tables 1 and 2. DA = discriminant analysis. CA = characteristic analysis. LR = logistic regression. WofE = weights of evidence. FA = favorability analysis. LRA = likelihood ratio analysis. EBF = evidential belief functions. ANN = artificial neural network. SVM = support vector machine. RF = random forest. FL = fuzzy logic. MIO = multi-class index overlay. BL = Boolean logic. BIO = binary index overlay.

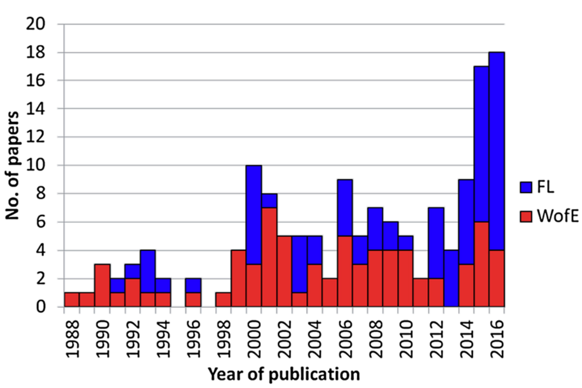

Figure 3. Years and numbers of publications of mostly journal papers on the applications of weights of evidence (WofE) and fuzzy logic (FL) to MPM. The publications included in the graphs are cited in Tables 1 and 2.

respectively. The influence of each of these three textbooks seems to be reflected by a decrease in number of journal/conference papers in the years after their respective publication year (Fig. 5), suggesting perhaps that researchers in the field of MPM were studying these textbooks after their publication and then published their findings later on. A similar pattern is associated with the publication of the first paper on WofE for MPM Bonham-Carter et al. (1988). However, it may be difficult to ascertain whether this supposition is true.

Nevertheless, on the one hand, the first publication on mineral potential mapping that can be found by a year-to-year search of the literature using the search terms "*mineral potential mapping*" AND "*GIS*" in Google Scholar in the Internet is a book chapter by Bonham-Carter and Agterberg (1990) about the application of microcomputer-based GIS to mineral potential mapping. Thus, it can be said that the Canadians, as Bonham-Carter and Agterberg worked then for the Geological Survey of Canada, introduced the term mineral potential mapping. And, on the other hand, the first publication on mineral prospectivity mapping that can be found by a year-to-year search of the literature using the search terms "*mineral prospectivity mapping*" AND "*GIS*" in Google Scholar in the Internet is a journal article by Brown et al. (1999) about the use of a multilayer feed-forward neural network for mineral prospectivity mapping. Thus, it can be said that the Australians, as Brown et al. worked then for academic institutions in Australia, introduced the term mineral prospectivity mapping. Indeed, a compilation of papers on MPM in peer-reviewed geoscience journals shows that the Canadians have pioneered the development of GIS-based MPM for three decades or so since the late 1970s, although development in GIS-based MPM has grown to a global scale in the last two decades (Fig. 6).

Developments in GIS-based MPM in the last four decades have been published in various journals (Fig. 7); however, about 45% of journal papers on this topic have been published in the journals owned by International Association for Mathematical Geosciences (IAMG), namely NRR, Mathematical Geosciences (MG) and Computers & Geosciences (C&G). This reflects that developments in GIS-based MPM significantly involved the development of robust mathematical methods for analysis and synthesis of spatial evidence of mineral potential. It is remarkable that 30% of journal papers on GIS-based MPM have been published in NRR. It is

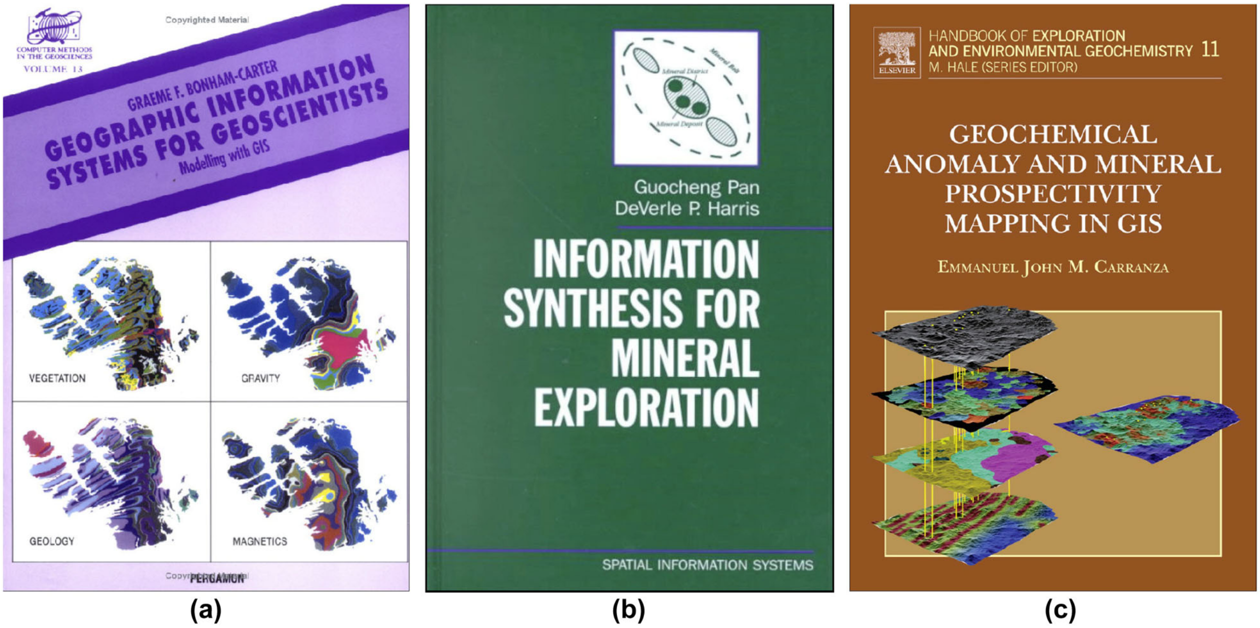

Figure 4. Front cover of textbooks relevant to MPM, authored by: (**a**) Bonham-Carter (1994); (**b**) Pan and Harris (2000); and (**c**) Carranza (2008).

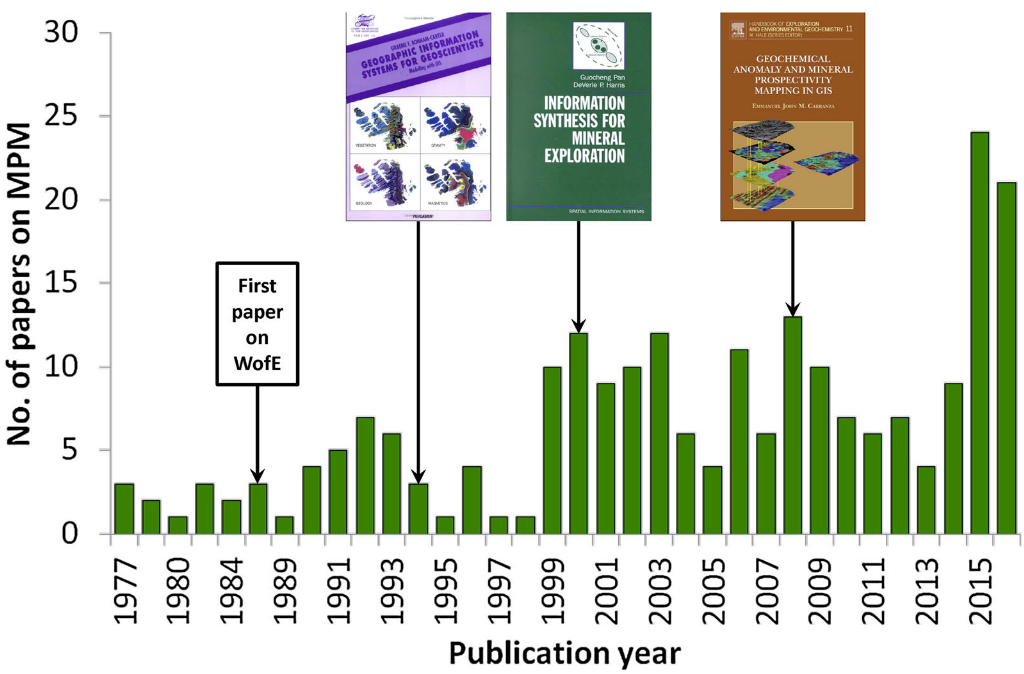

Figure 5. Numbers and years of publication of mostly journal papers regarding MPM, as well as years of publication of the first paper on weights of evidence (WofE) modeling of MPM and those of three textbooks relevant to MPM (see text for details). The publications included in the graph are cited in Tables 1 and 2.

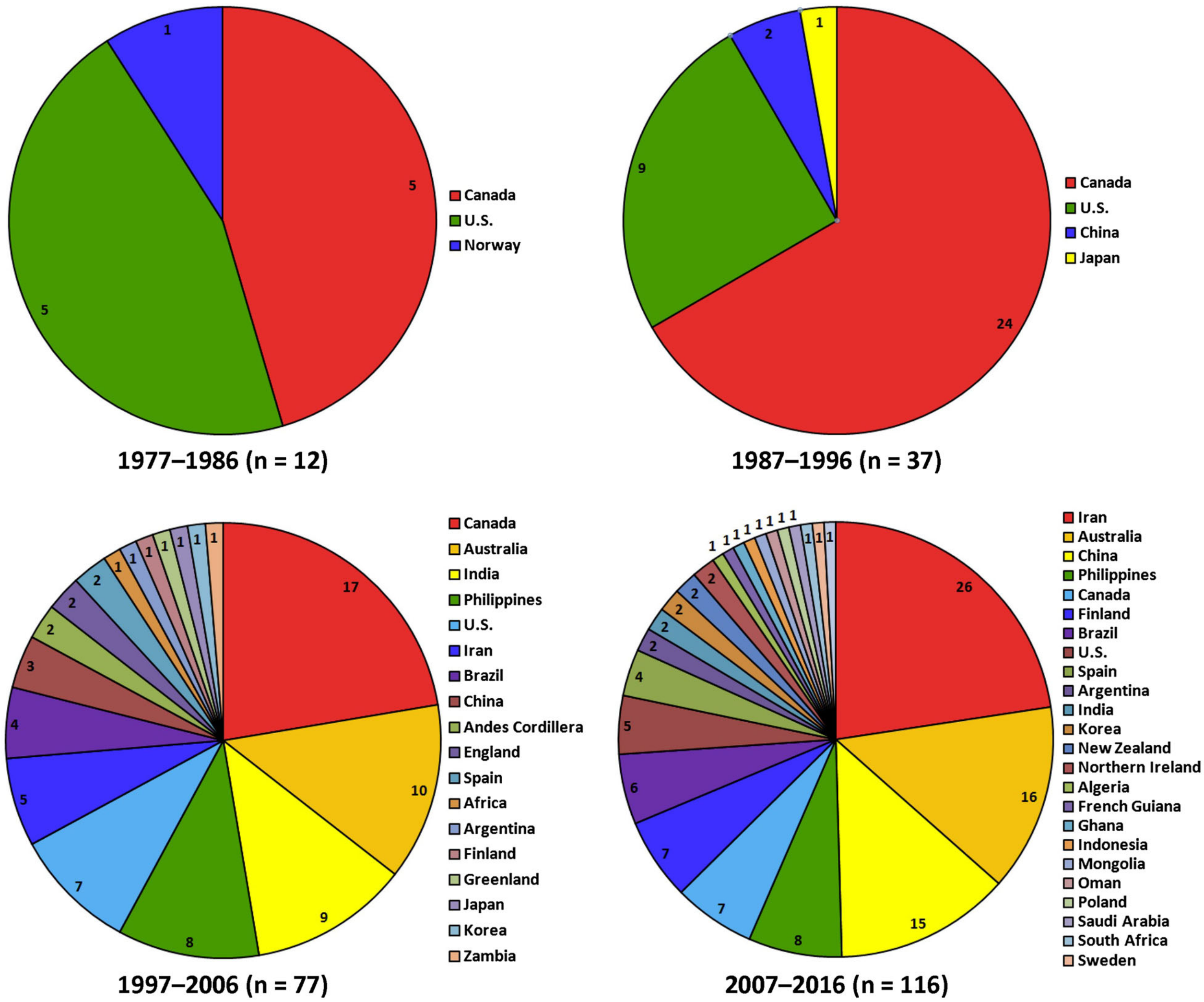

Figure 6. Source countries of studies on MPM published as articles in peer-reviewed geoscience journals during the last four decades divided into four 10-year slices. Number of articles is denoted by *n*. The publications included in these charts are cited in Tables 1 and 2.

remarkable as well that 18% of journal papers on this topic have been published in Ore Geology Reviewers (OGR), which is an economic geology journal. Intriguingly, the number of papers on GIS-based MPM published in NRR has decreased significantly during the last decade, whereas that in OGR has increased significantly during the last decade (Fig. 8). This reflects that developments in GIS-based MPM also significantly involved the development of geologically focused models of mineral potential. There is a common underlying reason for these observations and for the earlier observation regarding the growth in research on conceptual (or knowledge-driven) modeling of MPM relative to the decline in research on empirical (or data-driven) modeling of MPM. This common underlying reason is the adoption in GIS-based MPM of the *mineral systems* approach to exploration targeting.

The concept of ''mineral systems'' for exploration targeting, proposed by Wyborn et al. (1994), describes ''all geological factors that control the generation and preservation of mineral deposits, and stress the processes that are in involved in mobilising ore components from a source, transporting and accumulating them in more concentrated form and then preserving them throughout the subsequent geological history.'' The mineral systems approach to exploration targeting is, according to Walshe et al. (2005), a paradigm that requires answers to five

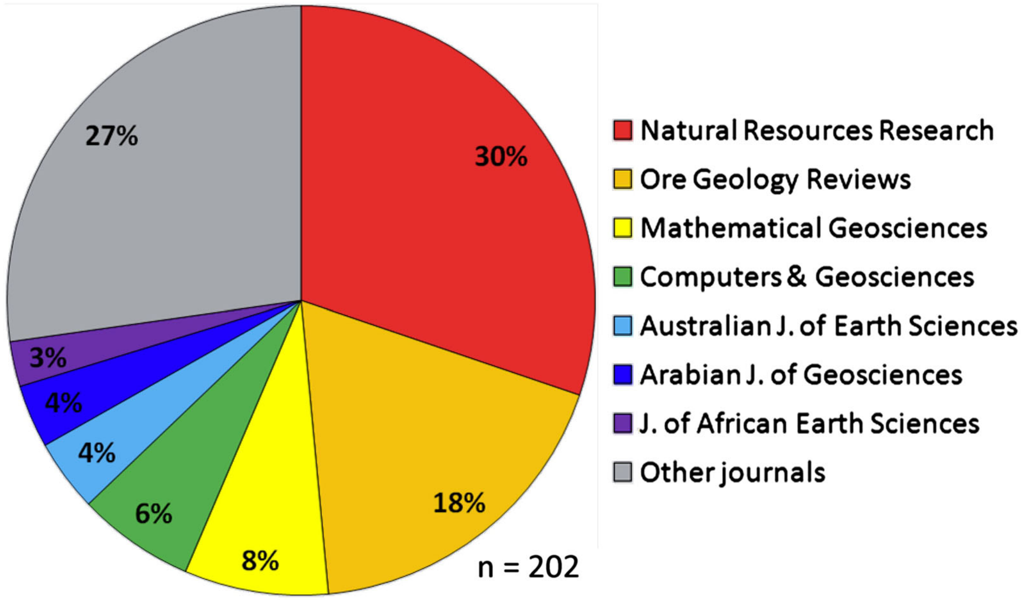

Figure 7. Distributions of papers on MPM published in peer-reviewed geoscience journals in the last four decades (1977–2016). The journal papers included in this chart are among those cited in Tables 1 and 2.

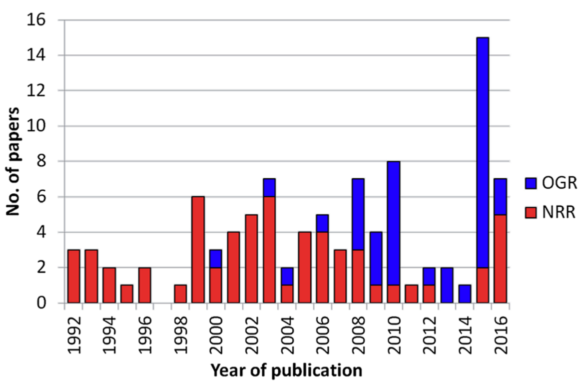

Figure 8. Numbers and years of publication of papers on GIS-based MPM published in Natural Resources Research (NRR) and Ore Geology Reviews (OGR). The journal papers included in this graph are among those cited in Tables 1 and 2.

questions in order to guide mineral exploration, namely: (1) What is the architecture/size of the system?; (2) What is pressure, temperature and geodynamic history of the system?; (3) What is the nature of the fluids and fluid reservoirs in the system?; (4) What are the fluid pathways and drivers of fluid flux?; and (5) What are the transport and depositional mechanisms? Therefore, the mineral systems approach to exploration targeting focuses on three geological elements (or processes) that are critical to the formation of mineral deposits, namely: source of metals, fluid pathways and traps. For GIS-

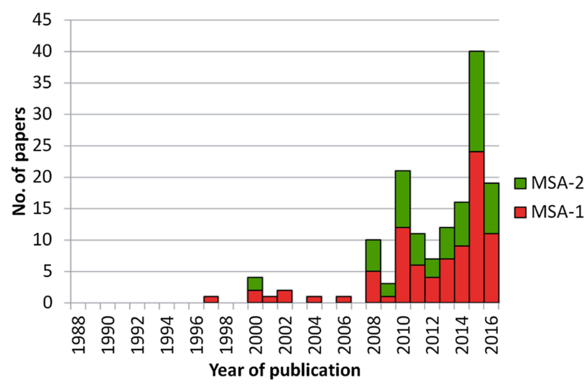

Figure 9. Numbers and years of publication of journal papers yielded by a document search (as of March 11, 2017) via Google Scholar using the terms (a) ‘‘*mineral systems*’’ AND ‘‘*mineral potential mapping*’’ AND ‘‘*GIS*’’ (denoted as MSA-1) and (b) ‘‘*mineral systems*’’ AND ‘‘*mineral prospectivity mapping*’’ AND ‘‘*GIS*’’ (denoted as MSA-2).

based MPM, these critical elements must be translated into mappable criteria (or spatial proxies) of mineral prospectivity (cf. McCuaig et al. 2010; Porwal and Kreuzer 2010; Porwal and Carranza 2015). Research on the adoption in GIS-based MPM of the mineral systems approach to exploration targeting has grown significantly in the last decade (2007–2016) (Fig. 9). Because the mineral systems approach to GIS-based MPM is intuitively a knowledge-driven approach and because FL is the mostly

Table 3. Top 15 most cited articles on geochemical anomaly mapping obtained by a document search in Scopus (https://www.scopus.com) using the search terms "*geochemical anomaly*" AND "*GIS*" (as of May 24, 2017)

Rank	Article title	Authors	Year	Source*	Citation
1	Mapping singularities with stream sediment geochemical data for prediction of undiscovered mineral deposits in Gejiu, Yunnan Province, China	Cheng, Q.	2007	OGR 32, 314-324	192
2	Spatial and scaling modelling for geochemical anomaly separation	Cheng, Q.	1999	JGE 65, 175-194	169
3	Integrated spatial and spectrum method for geochemical anomaly separation	Cheng, Q., Xu, Y., Grunsky, E.	2000	NRR 9, 43-51	140
4	Late-kinematic timing of orogenic gold deposits and significance for computer-based exploration techniques with emphasis on the Yilgarn Block, Western Australia	Groves, D.I., Goldfarb, R.J., Knox-Robinson, C.M., Ojala, J., Gardoll, S., Yun, G.Y., Holyland, P.	2000	OGR 17, 1-38	138
5	A spatial analysis method for geochemical anomaly separation	Cheng, Q., Agterberg, F.P., Bonham-Carter, G.F.	1996	JGE 56, 183-195	108
6	Controls on mineral deposit occurrence inferred from analysis of their spatial pattern and spatial association with geological features	Carranza, E.J.M.	2009	OGR 35, 383-400	98
7	Effective use and interpretation of lithogeochemical data in regional mineral exploration programs: Application of Geographic Information Systems (GIS) technology	Harris, J.R., Wilkinson, L., Grunsky, E.C.	2000	OGR 16, 107-143	67
8	Catchment basin modelling of stream sediment anomalies revisited: Incorporation of EDA and fractal analysis	Carranza, E.J.M.	2010	GEEA 10, 365-381	34
9	Fractal pattern integration for mineral potential estimation	Cheng, Q., Agterberg, F.P., Bonham-Carter, G.F.	1996	NRR 5, 117-130	24
10	Towards a quantitative model of downstream dilution of point source geochemical anomalies	Moon, C.J.	1999	JGE 65, 111-132	24
11	Application of geochemical anomaly identification methods in mapping of intermediate and felsic igneous rocks in eastern Tianshan, China	Zhao, J., Wang, W., Dong, L., Yang, W., Cheng, Q.	2012	JGE 122, 81-89	23
12	Geochemical mapping using a geomorphologic approach based on catchments	Spadoni, M.	2006	JGE 90, 183-196	18
13	Geochemical mapping in Georgia, USA: A tool for environmental studies, geologic mapping and mineral exploration	Cocker, M.D.	1999	JGE 67, 345-360	17
14	Usefulness of stream order to detect stream sediment geochemical anomalies	Carranza, E.J.M.	2004	GEEA 4, 341-352	17
15	Assessment of metal contamination in a small mining- and smelting-affected watershed: High resolution monitoring coupled with spatial analysis by GIS	Coynel, A., Blanc, G., Marache, A., Schäfer, J., Dabrin, A., Maneux, E., Bossy, C., Masson, M., Lavaux, G.	2009	JEM 11, 962-976	14

*Sources: GEEA = Geochemistry: Exploration, Environment, Analysis; JEM = Journal of Environmental Monitoring; JGE = Journal of Geochemical Exploration; NRR = Natural Resources Research; OGR = Ore Geology Reviews

Table 4. Top 15 most cited articles on mineral potential mapping obtained by a document search in Scopus (https://www.scopus.com) using the search terms "*mineral potential*" AND "*GIS*" (as of May 24, 2017)

Rank	Article title	Authors	Year	Sources*	Citation
1	Singularity analysis of ore-mineral and toxic trace elements in stream sediments	Cheng, Q., Agterberg, F.P.	2009	C&G 35, 234-244.	91
2	Artificial neural networks for mineral-potential mapping: a case study from Aravalli province, western India	Porwal, A., Carranza, E.J.M., Hale M.	2003	NRR 12, 155-171	90
3	Weights of evidence modeling of mineral potential: a case study using small number of prospects, Abra, Philippines	Carranza, E.J.M.	2004	NRR 13, 173-187	84
4	Non-linear theory and power-law models for information integration and mineral resources quantitative assessments	Cheng, Q.	2008	MG 40, 503-532	75
5	Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi district, Zambia	Carranza, E.J.M., Woldai, T., Chikambwe, E.M.	2005	NRR 14, 47-63	74
6	A hybrid neuro-fuzzy model for mineral potential mapping	Porwal, A., Carranza, E.J.M., Hale, M.	2004	MG 36, 803-826	67
7	A hybrid fuzzy weights of evidence model for mineral potential mapping	Porwal, A., Carranza, E.J.M., Hale, M.	2006	NRR 15, 1-14	58
8	Bayesian network classifiers for mineral potential mapping	Porwal, A., Carranza, E.J.M., Hale, M.	2006	C&G 32, 1-16	54
8	Measuring the performance of mineral-potential maps	Agterberg, F.P., Bonham-Carter, G.F.	2005	NRR 14, 1-17	48
10	Mineral deposits of Turkey in relation to Tethyan metallogeny: implications for future mineral exploration	Yigit, O.	2009	EG 104, 19-51	48
11	Spatial association of mineral occurrences and curvilinear geological features	Carranza, E.J.M., Hale, M.	2002	MG 34, 203-221	45
12	VHMS favourability mapping with GIS-based integration models, Chisel Lake-Anderson Lake area	Wright, D.F.	1996	BGSC 426, 339-371	43
13	Application of mineral exploration models and GIS to generate mineral potential maps as input for optimum land-use planning in the Philippines	Carranza, E.J.M., Mangaoang, J.C., Hale, M.	1999	NRR 8, 165-173	38
14	A predictive GIS model for mapping potential gold and base metal mineralization in Takab area, Iran	Asadi, H.H., Hale, M.	2001	C&G 27, 901-912	38
15	Weighting spatial information in GIS for copper mining exploration	Hosseinali, F., Alesheikh, A.A.	2008	AJAS 5, 1187-1198	35

*Sources: AJAS = American Journal of Applied Sciences; BGSC = Bulletin of the Geological Survey of Canada; C&G = Computers & Geosciences; EG = Economic Geology; MG = Mathematical Geosciences; NRR = Natural Resources Research

Table 5. Top 15 most cited articles on mineral prospectivity mapping obtained by a document search in Scopus (https://www.scopus.com) using the search terms "*mineral prospectivity*" AND "*GIS*" (as of May 24, 2017)

Rank	Article title	Authors	Year	Source*	Citation
1	Artificial neural networks: a new method for mineral prospectivity mapping	Brown, W.M., Gedeon, T.D., Groves, D.I., Barnes, R.G.	2000	AJES 47, 757-770	104
2	Controls on mineral deposit occurrence inferred from analysis of their spatial pattern and spatial association with geological features	Carranza, E.J.M.	2009	OGR 35, 383-400	98
3	Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi district, Zambia	Carranza, E.J.M., Woldai, T., Chikambwe, E.M.	2005	NRR 14, 47-63	74
4	Application of GIS processing techniques for producing mineral prospectivity maps – a case study: mesothermal Au in the Swayze greenstone belt, Ontario, Canada	Harris, J.R., Wilkinson, L., Heather, K., Fumerton, S., Bernier, M.A., Ayer, J., Dahn, R.	2001	NRR 10, 91-124	70
5	Knowledge-guided data-driven evidential belief modeling of mineral prospectivity in Cabo de Gata, SE Spain	Carranza, E.J.M., van Ruitenbeek, F.J.A., Hecker, C., van der Meijde, M., van der Meer, F.D.	2008	IJAEOG 10, 374-387	70
6	Predictive mapping of prospectivity and quantitative estimation of undiscovered VMS deposits in Skellefte district (Sweden)	Carranza, E.J.M., Sadeghi, M.	2010	OGR 38, 219-241	68
7	Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping	Carranza, E.J.M., Hale, M., Faassen, C.	2008	OGR 33, 536-558	58
8	Vectorial fuzzy logic: a novel technique for enhanced mineral prospectivity mapping, with reference to the orogenic gold mineralisation potential of the Kalgoorlie Terrane, Western Australia	Know-Robinson, C.M.	2000	AJES 47, 929-941	57
9	Reconnaissance-scale conceptual fuzzy-logic prospectivity modelling for iron oxide copper–gold deposits in the northern Fennoscandian shield, Finland	Nykänen, V., Groves, D.I., Ojala, V.J., Eilu, P., Gardoll, S.J.	2008	AJES 55, 25-38	42
10	Using fuzzy logic in a geographic information system environment to enhance conceptually based prospectivity analysis of Mississippi Valley-type mineralisation	D'Ercole, C., Groves, D.I., Knox-Robinson, C.M.	2000	AJES 47, 913-927	41
11	Objective selection of suitable unit cell size in data-driven modeling of mineral prospectivity	Carranza, E.J.M.	2009	C&G 35, 2032-2046	35
12	From Predictive Mapping of Mineral Prospectivity to Quantitative Estimation of Number of Undiscovered Prospects	Carranza, E.J.M.	2011	RG 61, 3051	31
13	Use of noise to augment training data: A neural network method of mineral-potential mapping in regions of limited known deposit examples	Brown, W.M., Gedeon, T.D., Groves, D.I.	2003	NRR 12, 141-152	30
14	Exploration targeting for orogenic gold deposits in the Granites-Tanami Orogen: Mineral system analysis, targeting model and prospectivity analysis	Joly, A., Porwal, A., McCuaig, T.C.	2012	OGR 48, 349-383	28
15	Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral-potential mapping	Brown, W., Groves, D., Gedeon, T.	2003	NRR 12, 183-200	26

*Sources: AJES = Australian Journal of Earth Sciences; C&G = Computers & Geosciences; IJAEOG = International Journal of Applied Earth Observation and Geoinformation; NRR = Natural Resources Research; OGR = Ore Geology Reviews; RG = Resource Geology widely used (and perhaps the most efficient) method for knowledge-driven MPM, there is a statistically significant positive correlation ($r = 0.6$, $p < 0.05$) between the number of papers on FL modeling of MPM (Fig. 3) and the number of papers on mineral systems approach to MPM (Fig. 9) during the last decade (2007–2016).

Prior to the development of the mineral systems approach to GIS-based MPM (i.e., mainly prior to 1997; Fig. 9), conceptual models of mineral prospectivity for GIS-based MPM (Fig. 1) were based mostly on mineral deposit models (e.g., Cox and Singer, 1986; Roberts et al., 1988), which describe the typical spatial attributes (e.g., geological characteristics) of certain types of mineral deposits as well as their regional geological environments. Because the typical spatial attributes of certain types of mineral deposits may not be relevant to particular deposit types in particular study areas (i.e., mineral deposits are unique even though they are grouped into types according to their similarities), focusing on mineral systems (i.e., using spatial proxies of metal source, fluid pathways and traps) instead makes GIS-based MPM more process based and more geologically focused. Therefore, it can be said that there have been mainly two stages in the development of GIS-based MPM, namely: (1) an earlier stage devoted mostly to the development of robust quantitative methods for analysis and synthesis of spatial evidence of mineral potential and (2) a later stage devoted mostly to the development of geologically focused models of mineral potential. Whereas the initial stage was motivated by the Canadians, the second stage was stimulated by the Australians. The boundary between these two stages is fuzzy, and in fact these two stages strongly overlap each other because undoubtedly researchers who have contributed to the development of GIS-based MPM have endeavored and continue to endeavor to develop numerically robust as well as geologically focused mineral potential models; however, the initial stage was mainly during 1977–2006, and the second stage is mainly during 2007–present.

Accordingly, although NRR has significantly contributed to the publication of developments of GIS-based MPM in general (Fig. 7), NRR has contributed more significantly to the promotion of the initial stage and less significantly to the second stage (Fig. 8). The editorship of NRR recognizes the latter as a challenge to promote further the development of numerically robust as well as geologically focused mineral potential models. In the following sections, NRR articles relevant to GIS-based geochemical anomaly mapping and MPM are reviewed briefly in chronological order of publication.

NRR PUBLICATIONS ON GEOCHEMICAL ANOMALY MAPPING

Only a few articles relevant to geochemical anomaly mapping have been published in NRR, as it is not exclusively dedicated to the field of exploration geochemistry.

Cheng et al. (1996) used the concepts of fractal/multi-fractal dimensions and fractal measure to estimate prior and posterior probabilities of a small unit cell in a study area to contain at least one mineral deposit occurrence. This resulted in a new version of the WofE method for MPM, which can also be used to map geochemical anomalies.

Chen and Zhao (1998) subjected multi-element lithogeochemical data to factor analysis to understand zonation in primary halos around a gold deposit in China and to use the results of the analysis for mapping multi-element anomalies to support mineral exploration.

Costa and Koppe (1999) subjected pedogeochemical data to geostatistical analysis to derive probability maps, indicating uncertainty of geochemical anomalies, to select areas for further exploration.

Cheng et al. (2000) proposed a novel method for mapping geochemical anomalies by integration of spatial and spectrum analysis. The proposed method was demonstrated using soil geochemical data from an area in Sumatra (Indonesia).

Singer and Kouda (2001) discussed unsupervised and supervised learning methods for extracting useful information from exploration geochemical data.

Twarakavi et al. (2006) presented supervised learning of geochemical anomalies under condition of sparse data and showed that support vector machines and robust least-square support vector machines perform better than neural networks and kriging techniques.

El-Makky and Sediek (2012) subjected multi-element stream sediment geochemical data from Egypt to Q-mode cluster and R-mode factor analyses as well as to enrichment factor analysis to map anomalies associated with gold–sulfide deposits and their associated hydrothermal alteration zones. They found that R-mode factor analysis, compared to Q-mode cluster analysis, provided easily and reasonably interpretable results, whereas the enrichment factor analysis produced results indicative of a promising area for further detailed exploration.

He et al. (2013) demonstrated that, using multifractal and frequency distribution analyses, geochemical exploration data of most elements from secondary media (e.g., soils, stream sediments) should be modeled with nonlinear mathematical methods or should be transformed to linear distributions before modeling with linear mathematical methods.

Luz et al. (2014) subjected Cu- and Zn-soil geochemical data from an area in Portugal in order to map anomalies using the concentration–area fractal model, which has been proposed by Cheng et al. (1994).

None of the foregoing articles have addressed the closure problem inherent in the statistical analysis of compositional data, such as exploration geochemical data (Aitchison 1984). As this is a significant aspect of geochemical anomaly mapping, we have, since the publication of the last article above, ensured that no articles involving geochemical anomaly mapping gets published in NRR without "opening" of exploration geochemical data by log-ratio transformation prior to any kind of statistical analysis.

The above-reviewed nine articles represent only ~1% of all (=740) articles NRR has published since 1992. However, two of the above-reviewed articles are among the most cited/applied in this field (Table 3). This information suggests that NRR can potentially make a strong impact to research on geochemical anomaly mapping.

NRR PUBLICATIONS ON MINERAL PROSPECTIVITY MAPPING

NRR Articles on Data-Driven MPM

Agterberg (1992) explained the WofE method, which was proposed by Bonham-Carter et al. (1988, 1989) and Agterberg et al. (1990), for integrating evidential layers for MPM with emphasis on undiscovered deposits' effect on the calculation of weights and posterior probabilities. He distinguished between statistics that are sensitive to unit cell size and statistics that are more-or-less independent of it. He concluded that positive weights of evidence in the WofE method can be compared with coefficients of evidence in the logistic regression (LR) method.

Goossens (1993) used remote sensing (Landsat TM, airborne magnetic and radiometric) datasets to assess potential for granite-related mineralization in a 20-km × 20-km area in Spain. The nature of pixels surrounding a pixel classified as having potential was considered when deciding whether classification is correct. Weights were assigned to uncertainty of interpretation. Interpreted and weighed data were integrated in supervised classification to derive a probability map highlighting zones with potential for granite-related mineralization that were confirmed by all datasets.

Pan (1993b) demonstrated the indicator favorability theory in a case study for data-driven MPM in order to account for spatial correlations of geophysical, geochemical and geological datasets with assumption that mineral potential can be modeled by a combination (Θ) of a set of response variables derived from the datasets. The indicator favorability theory estimates mineral prospectivity of every location in two stages: (1) estimation of a linear combination of response variables by maximizing variance var(Θ) and (2) estimation of favorability function (F) by minimizing variance var[$F - \Theta$]. The first stage is essentially a principal components analysis (PCA) of data at known deposit locations, and the coefficients of the target indicators are applied to the corresponding datasets covering the entire study area to map mineral potential.

Pan and Porterfield (1995) demonstrated a comprehensive methodology particularly for large-scale MPM in order to design optimal in-fill drilling (to check continuity of ore-grade and convert a part of geological resources into minable reserves) and select step-out drilling targets (for finding new orebodies around known ore deposits) in a gold-mining district. The central information synthesizer is canonical or indicator favorability analysis. The study resulted in delineation of several drilling targets.

Cheng et al. (1996) used the concepts of fractal/multi-fractal dimensions and fractal measure to estimate prior and posterior probabilities of a small unit cell in a study area to contain at least one mineral deposit occurrence. This resulted in a new version of the WofE method for MPM. The method was demonstrated in a case study to map potential for gold mineralization in the Iskut River area, northwestern British Columbia (Canada), where occurrences of gold deposits, which have fractal/multi-fractal properties, were integrated with several geochemical, geophysical and geological evidence layers.

Rostirolla et al. (1998) used WofE (Agterberg 1992) and PCA (Pan 1993b) in two case studies of MPM in Brazil. The results of both methods in either case study are fairly similar.

Cheng and Agterberg (1999) demonstrated a new approach of WofE modeling based on fuzzy sets and fuzzy probabilities in a MPM case study for gold deposits in Meguma Terrane, Nova Scotia (Canada). In this new hybrid method, fuzzy sets of subjective genetic elements are generated instead of converting data into binary or ternary evidence; fuzzy probabilities are then defined to derive posterior probability of a unit cell to contain mineral deposits based on fuzzy evidence. The hybrid method provides for objective or subjective definition of a fuzzy membership function of evidence as well as for objective definition of fuzzy or conditional probabilities. In a purely data-driven approach, derived posterior probabilities are completely dependent on existing data, but when the hybrid method is applied, they depend partly on expert knowledge.

Harris and Pan (1999) described a probabilistic neural network (PNN), which is a particular artificial neural network (ANN) architecture designed to compute the probability for membership in each of two or more classes (e.g., mineralized and barren), to classify mineralized and non-mineralized cells using geological, geochemical and geophysical variables. They have shown that the PNN outperforms two traditional multivariate supervised classification methodologies, namely LR and discriminant analysis (DA), for MPM.

Sahoo and Pandalai (1999) used LR to integrate indicator patterns for estimation of the probability of occurrence of gold deposits in a part of the auriferous Archaean Hutti–Maski schist belt. They used data consisting of categorical and continuous variables obtained from a coded lineament map and geochemical anomaly maps of the pathfinder elements of gold in soil and groundwater. Their study shows that LR is adequate for identifying mineralized areas with the type of data used.

Raines (1999) applied the WofE method to construct a prospectivity model for epithermal-Au deposits in the Great Basin (western USA). He concluded that the WofE MPM model is reasonable for the delineation permissive areas for epithermal deposits that are comparable to expert's delineation and that have objective, reproducible and well-defined characteristics, and provided a quantitative measure of confidence.

Singer and Kouda (1999) compared the WofE method to PNN using data from Chisel Lake–Anderson Lake, Manitoba (Canada). Despite the sparse deposits in the study area, the results demonstrate the PNN's ability to derive unbiased probability estimates and lower error rates compared to those derived by the WofE method. The WofE method resulted in strong bias, and errors are mostly known barren areas misclassified as prospective. Although the Chi-square test for independence indicated no significant correlations among the evidential layers, the test for expected number of deposits indicated that the results of the WofE method violated the assumption of conditional independence (CI). However, the PNN has no problem dealing with the CI assumption except that its performance strongly depends on having a completely representative training set.

Venkataraman et al. (2000) applied the WofE method and a FL algorithm to integrate information interpreted from remote sensing, geochemical, geological and ground-based datasets of Rajpura–Dariba, Rajasthan (India) to target potential base metal mineralized areas. Both their WofE and fuzzy MPM models showed four classes of potential zones of sulfide mineralization; however, their fuzzy model predicted more new potential areas.

Carranza and Hale (2000) applied the WofE method to integrate binary predictor patterns of geological features for prediction of gold potential using two sets—small-scale (n = 63) and large-scale (n = 19) occurrences—of gold deposits. The derived spatial associations between the binary predictor patterns and either set of gold occurrences, which indicate the geological features that are useful for mapping of prospectivity for gold in the Baguio District (Philippines), are consistent with the known geological controls on gold mineralization in the district. The resulting MPM maps based on the two sets of mineral occurrences data are similar, indicating that small-scale occurrences, which often outnumber large-scale occurrences, are important in MPM for economic deposits of the type sought.

Chen et al. (2001) introduced the concept of geo-anomaly unit (GU) as an area with distinct features that can be delineated by combining maps of ore-forming factors using computer techniques. The factor maps are binary (i.e., square cells coded with either 0 or 1 for absence or presence, respectively, of ore-forming features) and integrated by PCA to derive a score map of linear combination of ore-forming features. Cells with high scores are suggested as exploration targets.

Harris et al. (2001) used two data-driven methods (WofE, LR) and two knowledge-driven methods (weighted index and Boolean overlay) to produce gold prospectivity maps of the Swayze greenstone belt, Ontario (Canada), using geological, geochemical, geophysical and remotely sensed (Landsat) datasets assembled in a GIS. The derived gold prospectivity maps are more or less different as the evidential layers were purposely generated in different ways according to each modeling method. Some of the several areas classified by all modeling methods to have high gold potential coincide with known gold prospects. However, the data-driven prospectivity maps were better predictors of the known gold prospects.

Mihalasky and Bonham-Carter (2001) used the WofE method to quantify the spatial association of lithodiversity with metallic mineral sites in Nevada. They calculated lithodiversity by counting the number of unique geological map units within square-shaped sample neighborhoods of different sizes. They found that the spatial association between mineral sites and lithodiversity increased with increasing lithodiversity and that this relationship was consistent for (1) both basin-range and range-only regions, (2) four sizes of sample neighborhoods, (3) various mineral site subsets, (4) three scales of geological maps and (5) areas not covered by large-scale maps. They interpreted high lithodiversity to likely reflect the occurrence of complex structural, stratigraphic, and intrusive relationships that are thought to control, focus, localize, or expose mineralization. They proposed that lithodiversity measurements in areas that are not well explored may help delineate regional-scale exploration targets.

Carranza and Hale (2001a) used fuzzy sets of favorable distances to geological features and favorable lithologic formations, based upon qualitative and quantitative knowledge of spatial associations between known gold occurrences and geological features in the Baguio District (Philippines) and then combined the fuzzy predictor maps using FL as the inference engine. Their results, which are comparable to their previous work using WofE modeling (Carranza and Hale 2000), demonstrate the usefulness of fuzzy modeling of mineral potential.

Scott and Dimitrakopoulos (2001), in a case study in Australia, estimated mineral potential using the US Geological Survey three-part resource assessment process (Singer 1993) and data-driven GIS-based MPM by WofE. The results of their case study recognize that quantitative resource assessment and GIS-based MPM are complementary processes that support mineral resources development.

In a district-scale MPM case study for porphyry-Cu mineralization, Carranza and Hale (2002a) applied the WofE method to analyze the spatial association between known porphyry-Cu deposits and geologic features in Benguet, Philippines. They found that the porphyry-Cu occurrences are spatially associated with contacts of porphyry plutons, margins of batholithic plutons and strike-slip fault discontinuities and that the porphyry plutons are spatially associated with margins of batholithic plutons and strike-slip fault discontinuities. Based on these significant spatial associations, they further applied the WofE method to map zones favorable for porphyry-Cu mineralization and zones favorable for porphyry pluton emplacement in Benguet Province, Philippines. Validations of the predictive models show their usefulness for delineating targets for follow-up exploration.

Paganelli et al. (2002) applied the WofE method to determine the spatial associations of known kimberlite locations with variously trending lineaments at the Buffalo Head Hills area (Canada). They then used structural lineament maps, Bouguer gravity data, magnetic characteristics of the Buffalo High and Buffalo Utikuma terranes, and the boundary between those two terranes to derive a map of favorability for kimberlite emplacement. The results show highest favorability for kimberlite emplacement along the boundary between the Buffalo High and Utikuma terranes and correspondence with NNE-trending lineaments and their intersections with NE and ENE lineaments.

Raines and Mihalasky (2002) used a combination of WofE and weighted LR to generate pluton-related deposit tract maps and compared these maps with tract maps generated by US Geological Survey experts. They found that, in general, there is a very strong spatial correlation between the data- and knowledge-driven tract maps. This study suggests that, similar to the findings of Scott and Dimitrakopoulos (2001), data-driven MPM can be the first part of the 3-part quantitative mineral resource assessment proposed by Singer (1993).

Agterberg and Cheng (2002) revisited the requirement of the WofE that updating the prior probability of mineral deposit occurrence with two or more evidential map layers is allowed only if the evidential layers exhibit CI with respect to known mineral deposits. They provided formal proof that CI of evidential layers implies that the sum of posterior probabilities weighted by unit cell area equals the number of known mineral deposits. They then proposed the ‘‘omnibus test’’ for CI, which is exact and simpler to use than existing tests of CI adapted from discrete multivariate statistics.

As the performance of ANNs for MPM is undermined by the paucity of deposit training patterns relative to barren training patterns, Brown et al. (2003a) proposed to overcome this problem by adding random noise to the original training patterns in order to create additional synthetic deposit training data. In the Kalgoorlie Terrane study area, the number of deposit training patterns increased from approximately 50–1000 by adding noise to the original deposit training data, which resulted in significant increase in both the classification performance of a trained multilayer perceptron (MLP) neural network, a feed-forward ANN, and the quality of the resultant prospectivity map.

Porwal et al. (2003a) described a GIS-based application of a radial basis functional link net (RBFLN), another type of ANN, to map potential for sedimentary exhalative (SEDEX) base metal deposits in an area in the Aravalli metallogenic province (western India). They trained a series of RBFLNs to determine the network architecture and estimate parameters that mapped the maximum number of validation vectors correctly to their respective targets. The trained RBFLN with the best performance with respect to the validation dataset was used for processing all feature vectors to generate a predictive map that was further reclassified into a prospectivity map showing zones with high, moderate and low prospectivity for SEDEX base metal deposits in the study area. The usefulness of RBFLN for MPM is indicated by the consistency of the spatial distribution of mapped high prospectivity zones with the conceptual models of base metal metallogeny in the study area.

Bougrain et al. (2003) used ANN to extract from a GIS database knowledge about factors relevant to the formation of precious and base metal deposits in the Andes. Results of the analysis indicate as much as 25 attributes as known or potential factors relevant to the formation of gold deposits in the Andes Cordillera. They used the trained ANN to distinguish potentially mineralized sites from non-mineralized sites. Their study demonstrates how ANN can be applied efficiently to assist mineral exploration, where general domain knowledge alone is inadequate to satisfactorily model the plausible controls on mineralization from a continent-scale database.

Brown et al. (2003b) proposed that the use of evidential layers represented as fuzzy membership variables is a useful method for integrating subjective knowledge with empirical data in an ANN approach to MPM. They used a MLP neural network to integrate up to 17 variables to derive prospectivity maps for orogenic gold deposits in the Archean Kalgoorlie Terrane of Western Australia. They used two types of fuzzy membership variables. For the first type, the spatial associations of data with known gold deposits were used to determine fuzzy membership values. The second type of fuzzy membership variables represents rheological contrast at lithologic boundaries, in which fuzzy membership values, although based on geological field data, are subjective. The methods described can be applied to various subjective data (e.g., favorability of tectonic environment, reactivation along major faults or host stratigraphy) used in regional exploration programs, but which normally would not be used as inputs in an ANN approach.

Harris et al. (2003) compared the performance of WofE, PNN, LR and DA for data-driven MPM in three case studies with contrasting scale and geologic information, and using randomly selected cells for training and validation in every case study. The deposit-scale Carlin study reveals that the performances of the various methods from lowest to highest are: PNN, DA, LR and WofE. The district-scale Alamos study shows that the performances of the various methods from lowest to highest are: DA, PNN and WofE. Unlike findings from the Alamos and Carlin studies, the regional-scale Nevada study DA, LR, PNN and WofE. Their study also demonstrated that the inferior performance of WofE is the result of the loss of information when data of the variables are discretized into binary maps to satisfy procedure requirement by WofE.

Carranza (2004) applied the WofE method to map potential for porphyry-Cu prospects in an area measuring ~920 km^2 with 12 known porphyry-Cu prospects. Uncertainty due to missing geochemical evidence is shown to have an influence on tests of assumption of CI among predictor maps with respect to prospects. However, for the final predictive model, the assumption of CI, which was initially rejected based on the omnibus test, was accepted based on a new omnibus test (Agterberg and Cheng 2002). Validation of the final predictive model demonstrates the plausibility of the WofE method for MPM in large areas with few mineral prospects.

Agterberg and Bonham-Carter (2005) contended that the random cell selection procedure followed by Harris et al. (2003) for training and validation of MPM necessarily results in better performance for the more flexible methods (i.e., DA, LR and PNN), but this did not necessarily indicate that these methods are better than WofE. They showed, by comparison with LR modeling, which does not need discretization of data, that the discretization of data into binary evidence in the WofE method is usually advantageous as it prevents occurrences of extremely high posterior probabilities. They concluded further that mineral occurrences must not be randomly sampled together with their surrounding environments in small cells but must be modeled as discoveries at points.

Carranza et al. (2005) demonstrated the application of data-driven evidential belief functions (EBFs), initially proposed by Carranza and Hale (2003), to map prospectivity for aquamarine-bearing pegmatites in the Lundazi District (eastern Zambia). Data-driven EBFs not only represent spatial association of target deposits with an evidential layer but also take into account spatial relationships among classes of evidences in an evidential layer. Spatial data that provide positive or negative evidence of prospectivity can be determined by data-driven EBFs. Data-driven EBFs of only positive evidence of prospectivity must be integrated for MPM. Validation of the results illustrated the usefulness of data-driven EBFs for MPM.

Skabar (2005) presented a new approach whereby MLP neural networks can be trained to yield output values that can be interpreted strictly as posterior probabilities. This approach uses all data in the generation of a model, thereby eliminating dependence on the choice of training data. The approach was followed to map prospectivity for gold in the Castlemaine region of Victoria (Australia). Comparison of the results with those of a method for estimating probability density functions showed that the MLP approach and the density estimation-based approach performed roughly equally per validation with the bootstrap ''leave-one-out'' method.

Chen et al. (2005) applied WofE modeling for MPM in large areas with small number of mineral prospects. They used predictor layers derived from a digital database that includes 1:200,000 scale geological, geochemical, and geophysical maps, and remote sensing images in study area. Their results show four main metal ore belts occupying 29% of their study area in China, which delineate 81% of the known porphyry-Cu occurrences.

Porwal et al. (2006a) developed a hybrid fuzzy WofE model for MPM that uses as inputs knowledge-based fuzzy membership values and generates outputs of data-based conditional probabilities. A knowledge-driven logistic membership function is used to derive fuzzy membership values, thereby allowing treatment of systemic uncertainty and generation of multi-class evidential layers. The fuzzy evidential layers are then integrated using the WofE method. The hybrid fuzzy WofE model was applied to regional-scale mapping of prospectivity for base metal mineralization in the south-central part of the Aravalli metallogenic province (western India). Validation of the results demonstrated the usefulness of the hybrid fuzzy WofE model for MPM.

De Quadros et al. (2006) compared the performances of the WofE and fuzzy methods for MPM based on a conceptual model for structurally controlled lode gold–quartz vein deposits in an area in Brazil. The found that, compared to the FL method, the WofE method delineated smaller highly favorable zones and that the WofE method produced higher biased probability within favorable zones.

Daneshfar et al. (2006) used the WofE and LR methods separately for MPM to delineate areas with potential for Zn–Pb Mississippi valley-type mineralization using evidential layers derived from Landsat TM data and regional geological data. Their two sets of results did not exhibit remarkable differences from each another, and the validation of the results demonstrated the usefulness of either the WofE or LR method for MPM.

Nykänen and Ojala (2007) validated predictive WofE and LR models of mineral prospectivity by the bootstrap ''leave-one-out'' method, actual field testing and follow-up analysis of previously drilled core within predicted highly prospective areas. All these methods of validation indicate that the WofE and LR mineral prospectivity models have successfully delineated both known and new areas of gold mineralization.

Behnia (2007) used the GIS-based RBFLN method for predictive mapping in Central Iran to delineate areas with potential for Proterozoic mineralization characterized mainly by several iron, apatite and uranium deposits. The results showed that a successful classification depends on the existence of spatially well-distributed deposits and non-deposits throughout the study area.

Raines et al. (2007) applied WofE modeling to compare the use of geological maps of different scales as inputs to GIS-based MPM to delineate permissive tracts for porphyry deposits in the USA, as the first step of a mineral resource assessment. The results indicate that porphyry tracts delineated using input from 1:2,500,000-scale geologic maps are similar to porphyry tracts delineated using input from either 1:10,000,000 or 1:35,000,000-scale geological maps. This finding demonstrates that conceptual context from small-scale maps is more appropriate for porphyry tract definition than from larger scale maps. The study also demonstrates the usefulness of the WofE method for analysis of strengths of spatial associations between mineral potential maps and known mineral occurrences.

Nykänen (2008) also used the RBFLN method to produce a series of prospectivity maps for the under-explored Paleoproterozoic Central Lapland Greenstone Belt, Northern Fennoscandian Shield, Finland, which is thought to be highly prospective for orogenic gold mineralization. They found that, when applied to the same evidential layers that are proxies for conceptual geological controls, the RBFLN method performed similarly as the LR method but outperforms the WofE and the FL methods. They also found that the performance of the RBFLN method improved when the training feature vectors were weighted according to the size of the known gold deposits.

For situations of MPM where mineral deposit occurrences are known, Fabbri and Chung (2008) discussed strategies for blind testing of MPM. They also described how to create a prediction rate graph, for validation of predictive models, whereby the *X*-axis of the graph represents proportion of a study area predicted to be prospective and the *Y*-axis represents proportion of ''undiscovered'' occurrences within the predicted prospective area. Such prediction rate graph is similar to the occurrence–area plots described by Agterberg and Bonham-Carter (2005), but the prediction rate graph makes use of occurrences for blind testing (i.e., occurrences not used for generation of a predictive prospectivity model).

Deng (2009) had shown that, when the CI assumption in the WofE method is violated, bias in posterior probability estimates has an intuitive and convenient interpretation, and then, he derived a formal expression for the bias. Then, using the correlation structure of the predictor patterns, he developed a modified WofE model to correct for the bias. For validation of the proposed modified WofE model in a case study, he proposed to use the receiver operator characteristic (ROC) curve analysis as it is often employed for binary response models (e.g., mineral occurrence is a binary variable). Results of validation using ROC curves demonstrated the usefulness of the proposed modified WofE model.

Oh and Lee (2010) performed a GIS-based ANN for mapping prospectivity for hydrothermal Au–Ag mineralization in the Taebaeksan District (Korea) using four different training datasets, derived by likelihood ratio and WofE methods, to analyze the effect of training. The results of their study showed that ANN performed best, followed by likelihood ratio and WofE.

Because the application of the WofE method to MPM often results in violation of the CI assumption, Agterberg (2011) proposed a modified WofE method whereby WofE is performed first and then WLR is applied to the weights. The results of the proposed modified WofE method are similar to those when the modified WofE method proposed by Deng (2009) is applied to correct for bias due to violation of the CI assumption.

Integration of several spatial data relevant to MPM is advantageous. However, for methods that involve estimating densities (e.g., PNNs) a high-dimensional input is disadvantageous due to the so-called curse of dimensionality. In view of this, Skabar (2011) described a substitute approach to the estimation of densities, using similarity-based learning, whereby he showed how (a) to estimate, using the concept of eigenvector graph centrality, the density of a set of deposit training examples from a graphical model of such examples and (b) to estimate from these data the likelihood of a test example without creating a new graph. Testing the proposed approach to a case study for gold deposits showed that, in terms of predictive capability, it is superior to conventional density estimation methods and is a bit better than MLP neural networks.

Mejía-Herrera et al. (2015) used curvature and proximity to certain geological features as predictor variables in LR to predict Cu potentials in the

Kupferschiefer. Curvature is geometric attribute measurable in horizons of a surface structural model. Their LR models show positive correlation between curvature estimated on the surface depicting the mineralized layer and predicted probabilities of Cu potentials.

Carranza (2015) applied data-driven EBFs for MPM (cf. Carranza et al. 2005) to the same study area, measuring ~920 km^2 with 12 known porphyry-Cu prospects, where he applied the WofE method to map potential for porphyry-Cu prospects. The results indicate that method of data-driven EBFs is as efficient as the WofE method for MPM in areas where as few as 12 prospects are known and where evidential layers contain missing values.

Index overlay and Boolean logic are two methods traditionally used for knowledge-driven MPM. As the assignment of evidential weights based on expert opinion introduces bias that is difficult, if not impossible, to quantify, Yousefi and Carranza (2016) proposed a data-driven index overlay method for MPM, in which weights of evidential layers are estimated from data, and a data-driven Boolean logic method for MPM, in which thresholds for creating binary evidential layers are established based on data. The results of their MPM case study for porphyry-Cu deposits in an area in the Kerman Province in southeast Iran demonstrate the usefulness of the proposed methods.

Ford et al. (2016) examined the performances of the data-driven WofE and EBF methods and the knowledge-driven FL method of MPM to target for orogenic gold mineralization using incomplete data from the Carajás mineral province (Brazil). The results of their study demonstrate that the WofE method is the most effective, compared to the EBF and FL methods, for MPM with incomplete data. This paper by Ford et al. (2016) is the first to introduce in NRR the mineral systems approach to GIS-based MPM.

The random forests (RF) is a machine learning algorithm that has been shown recently as a viable method for data-driven MPM (Rodriguez-Galiano et al. 2014, 2015; Carranza and Laborte 2015a, b; Harris et al. 2015). Carranza and Laborte (2016) carried out a case study to map prospectivity for hydrothermal Au–Cu mineralization in Catanduanes Island (Philippines), where 17 prospects of hydrothermal Au–Cu deposits exist, in order to examine further the ability of RF modeling (a) for data-driven MPM in areas with few occurrences (i.e., <20) of mineral deposits and (b) for treatment of evidential layers with missing values. The results show that: (a) RF outperforms data-driven EBFs; (b) RF allows analysis of spatial associations between known prospects and each evidential layer, just as data-driven EBFs; and (c) and missing values in evidential layers can be treated in RF through RF-based imputation, whereas in data-driven EBFs, missing values are assigned maximum uncertainty. The case study demonstrates the usefulness of the RF algorithm for data-driven MPM in regions with few occurrences of the deposit type sought. This paper by Carranza and Laborte (2016) adapts a conceptual mineral systems model as framework for data-driven MPM.

In a MPM case study for gold deposits around the Huritz Group and Nueltin Suite, Nunavut (Canada), McKay and Harris (2016) compared the performance of the RF method to that of a knowledge-driven methodology involving weighted index overlay and FL methods. The results showed that the RF method outperformed knowledge-driven methodology and illustrated several advantages to the RF method, namely: (a) ability to take both categorical and/or continuous data as variable inputs, (b) ability to estimate importance of each input variable and (c) an unbiased internal estimation of mapping error, which makes cross-validation of final outputs to determine accuracy unnecessary.

Geranian et al. (2016) compared the performance of DA and support vector machine (SVM) for modeling subsurface gold mineralization by integrating surface soil geochemical anomalies and borehole data at the Sari Gunay gold deposit, NW Iran. The results of their study indicate that SVM outperforms DA in data-driven MPM.

Thus, NRR has several publications of research on novel methods for data-driven MPM as well as research on case-to-case innovation of existing methods for data-driven MPM.

NRR Articles on Knowledge-Driven MPM

McLaren (1992) described probably the first or one of the earliest applications of the weighted index overlay method for MPM. He classified mineral prospectivity of British Columbia (Canada) using three unique themes of field data (geological setting, geochemistry and mineral occurrences) and based on two factors (favorability and degree of confidence). He assessed prospectivity according to how well evidential data satisfy criteria defined from established mineral deposit models. He assessed degree of confidence depending on number of data themes determined to be favorable. Qualitative descriptions of each prospectivity class suggest the possibility for future exploration as an index of expected land use.

Reddy et al. (1992) proposed the use of GIS to develop an expert system for regional-scale MPM for volcanogenic massive sulfide (VMS) deposits in the Early Proterozoic Snow Lake greenstone belt of northwest Manitoba (Canada). Their expert system consisted of an inference network to model expert knowledge, to propagate evidence from input maps and to integrate information by FL and Bayesian updating to derive prospectivity maps depicting evaluation of hypotheses. A model's sensitivity to changes in the parameters was evaluated by validating areas with predicted high prospectivity against the spatial distribution of known VMS deposits.

Chung and Fabbri (1993) used an artificially constructed dataset to demonstrate three representation methods—probability measures, Dempster-Shafer EBFs, and fuzzy membership functions—and their corresponding estimation procedures with analyses of the implications and of the assumptions that are required in each method to thematic mapping. They also discussed difficulties associated with the construction of probability measures, EBFs and fuzzy membership functions and proposed alternative procedures to overcome those difficulties.

An et al. (1994b) demonstrated EBFs for managing uncertainties in the integration of evidential data for MPM. The EBFs provide the capability to distinguish between negative information and lack of information, which is desirable when integrating diverse datasets with different spatial resolutions and spatial extents. Their study demonstrated that EBFs can provide a realistic quantitative model of mineral potential.

Rehder (1994) demonstrated an expert system for MPM, which constructs an inference network for assessing prospectivity for epigenetic gold deposits. He described three different approaches for constructing an inference network, discussed aspects of human reasoning and compared it with machine reasoning for assessing data as evidence of mineral prospectivity, and discussed some actual problems concerning uncertainty, contradictory evidence and prior probabilities. Included in the exploration model are technical aspects like costs and schedule.

An et al. (1994a) formulated an object-oriented modeling framework and respective reasoning processes using EBFs for a knowledge-based approach to integration of evidential layers. The mechanism developed for uncertainty propagation also worked well for MPM using real mineral exploration datasets from the Snow Lake area, northern Manitoba (Canada).

Cheng (1996) proposed fuzzy relations to derive weights for qualitative variables according to their partial order relations. They proposed two asymmetric measure indexes (incidence coefficient and probability difference) for quantifying asymmetric associations between evidential layers, from which the partial order relations can be generated. The combination of the fuzzy relations method with the asymmetric measure indexes leads to new methods for map overlay and data integration for MPM. Two types of models were demonstrated by an artificial example for MPM.

Carranza et al. (1999) demonstrated the application of a conceptual mineral exploration model and GIS to classify prospectivity for nickeliferous laterite in an area in northeastern Philippines. They modeled and integrated evidence maps in a way similar to that described by McLaren (1992) to furnish a nickeliferous laterite potential map. They compared this map with present land-use classification and policy in the area and found that the potential zones are in areas where mineral resources development is prohibited. Their study illustrated that MPM is a critical support to land-use policymaking to ensure that prospective land is considered in future mineral resource development.

Carranza and Hale (2001a) applied the theory of fuzzy sets to map prospectivity for gold in the Baguio District (Philippines). Maps of lithologic units and proximity to geological features, transformed into fuzzy evidence maps based upon empirical and expert knowledge of spatial associations of geological features with known gold occurrences in the district, were combined using FL as the inference engine. The results demonstrate the usefulness of the fuzzy set approach for MPM.

De Araújo and Macedo (2002) assigned expert-driven weights to geological, geochemical and airborne geophysical layers of evidence and integrated these for MPM in an area in the Ribeira Valley, São Paulo and Paraná States (Brazil) using weighted linear combination (WLC) and order weighted average (OWA) methods, which are variants of the weighted index overlay method. The evidence layers chosen and expert-driven weights were based on two mineralization models: (1) Perau type, sedimentary exhalative, and (2) Panelas type, vein-type carbonate hosted. The OWA method yielded the better results, with prospectivity maps depicting several classes of prospectivity occupying relatively minor areas. The WLC method yielded more coherent results but lacking details for minor areas. Both methods are inexpensive and viable for MPM in regions similar to the studied one.

Porwal et al. (2003b) proposed new fuzzy models for MPM, namely: (1) a knowledge-driven fuzzy model, which transforms input evidential values into fuzzy membership values by using a logistic function, and (2) a data-driven model, which derives fuzzy membership values of input evidential maps by using a piecewise linear function based on quantified spatial associations of evidential layers with known mineral deposits. They also described a graphical procedure for defuzzification and classification of output fuzzy prospectivity maps. The two new fuzzy models were demonstrated for mapping prospectivity for base metal deposits in an area in south-central Aravalli metallogenic province, Rajasthan (western India). Cross-comparison of the prospectivity maps derived by the proposed models indicates their strong similarity. Validation of both models again known deposits indicated their usefulness for delineating prospective zones to guide future exploration work.

Harris et al. (2008) performed MPM for four different mineral deposit types (i.e., SEDEX Zn–Pb–Ag, carbonate-hosted Zn–Pb–Ag, intrusion-related skarn and gemstones, and Carlin-type gold) within the Greater Nahanni Ecosystem. They followed an expert-driven approach to weighting of evidence layers similar to the WLC method used by De Araújo and Macedo (2002). Their validation of the individual mineral potential maps, using plots of number of mineral occurrences as a function of area, which depict a validation method that is essentially the same as the one proposed by Agterberg and Bonham-Carter (2005), showed strong goodness of fit with known occurrences per deposit type. Finally, they derived a composite mineral potential map by combining the four potential maps using a maximum operator.

Pazand et al. (2011) proposed the analytic hierarchy process (AHP) to evaluate weights of evidence layers for GIS-based knowledge-driven evaluation of potential for porphyry-Cu mineralization in an area in Iran using evidence layers derived from geological, geochemical, and geophysical, and remote sensing data. The results demonstrated acceptable outcomes for porphyry-Cu exploration in the study area.

Lusty et al. (2012) applied knowledge-driven FL modeling to map prospectivity for Caledonian-age turbidite-hosted orogenic gold mineralization in the Southern Uplands–Down–Longford Terrane, using geochemical and geophysical data from in conjunction with other spatial geoscience datasets. They emphasized that, since FL modeling depends on subjective judgment, it is important to understand well the key controls on the mineralization being sought and their relative importance, limited to the components of the model that can be mapped from available data.

Elliott et al. (2016) applied weighted index overlay and FL methods to determine new prospective sites for natural sand resources in the Central Texas Frac Sand District. The results of their study showed that the distribution of weights in the FL method clearly identifies prospective locations with less ambiguity compared to weighted index overlay method.

Asadi et al. (2016) integrated the AHP and the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) algorithm, following Pazand and Hezarkhani (2015), to map prospectivity for porphyry-Cu in a district in central Iran with very few known porphyry-Cu occurrences. With mapped highly favorable to favorable areas covering roughly 2% of the study district and delineating most of the few known porphyry-Cu occurrences, several prospective areas with no known porphyry-Cu occurrences are now recognized as exploration targets.

Thus, NRR has quite a good number of publications of research on novel methods for knowledge-driven MPM as well as research on case-to-case innovation of existing methods for knowledge-driven MPM.

Impact of NRR Articles on Development of MPM

The above-reviewed 51 and 16 articles on, respectively, data- and knowledge-driven MPM represent only ~7 and ~2%, respectively, of all (=751) articles NRR has published from volume 1 in 1992 to volume 26 in 2017. However, some of the above-reviewed articles are among the most cited/applied in this field (Tables 4, 5). This information indicates that NRR has made and continues to make strong impact to research on GIS-based MPM.

ORGANIZATION OF THE SPECIAL ISSUE

There are 10 articles in this special issue. The first four articles are relevant to geochemical anomaly mapping and the last six to MPM.

Articles on Geochemical Anomaly Mapping

Carranza (2017) showed that anomalies of geochemical enrichment factors are no better than anomalies of log-ratio-transformed geochemical data. This study demonstrates further that exploration of geochemical data, being compositional data, should first be ''opened'' by log-ratio transformation in order to address the closure problem inherent in the statistical analysis of such data (cf. Aitchison 1984; Filzmoser et al. 2009a, b, Filzmoser et al. 2010).

Yousefi (2017) proposed and demonstrated a method of pixel-based modeling of geochemical landscape in order to avoid estimation errors resulting from interpolation of point lithogeochemical data. In this method, the square pixel covering each composite rock sample is considered its area of influence. By using this method together with the concept of multiplicative geochemical halos and the concentration–area fractal modeling, anomalies of multiplicative geochemical halos were delineated and then integrated to model metal zoning for vectoring into porphyry-Cu mineralization. Validation of the results against stockwork distribution and locations of Cu occurrences demonstrates that the proposed pixel-based method and the metal zoning concept is a powerful tool for targeting areas with potential for porphyry-Cu deposits.

Parsa et al. (2017) subjected log-ratio-transformed stream sediment geochemical data to robust principal components analysis to derive a multivariate geochemical signature of porphyry-Cu deposits in their area, and then, they subjected positively shifted values of multivariate mineralization-related geochemical signature to singularity mapping, as a filtering method, to enhance subtle but significant geochemical anomalies. The superiority of anomalies extracted from the filtered multivariate geochemical signature over anomalies extracted from the non-filtered geochemical signature was indicated by the higher success rate former compared to that of the latter.

Zuo (2017) reviewed the state of the art of applications of machine learning in identifying geochemical anomalies.

Articles on Mineral Potential Mapping

Hariharan et al. (2017) applied the synthetic minority over-sampling technique to modify the initial dataset and bring the deposit-to-non-deposit ratio closer to 50:50 in their RF-based gold prospectivity modeling of the Tanami Region, a greenfields terrain in Western Australia. They then objectively determined an optimal threshold prospectivity value by using statistical measures such as data sensitivity, specificity, kappa and percent correct classification. Their RF regression modeling with the modified dataset of close to 50:50 deposit-to non-deposit ratio delineated ~5% of the region as high prospectivity areas as compared to only ~1% by the original dataset, implying that the original ''sparse'' dataset led to underestimation of prospectivity.

Tessema (2017) discussed the chromite mineral system in the Bushveld Complex (BC) in South Africa as the framework for data-driven predictive mapping of prospectivity, using RBFLN, for chromite deposits in the Western Limb and the Nietverdiend layered mafic intrusion of the BC. The RBFLN model correctly classified 73% of the validation deposits into highly prospective areas, which cover 6.5% of the study area, and the RBFLN correctly classified all the non-deposit validation points into low prospectivity areas, which occupy 86.6% of the study area. Results of cross-validating the RBFLN model with a fuzzy WofE model show that the two models agree well on broad-scale targeting of high prospectivity areas for further exploration of chromite deposits.

Mutele et al. (2017) presented prospectivity mapping by FL modeling based on a mineral system model of critical processes responsible for the formation of polymetallic Sn–F–REE mineralization associated with the Bushveld granites of the Bushveld Igneous Complex, South Africa. They used spatial proxies of proximity to differentiated granites (representing heat and metal-rich fluid sources), Rb geochemical map (representing fluid-focusing mechanism), principal component maps (PC4 Y–Th and PC14 Sn–W, representing fluid pathways for high- and low-temperature mineralization, respectively) and proximity to roof rocks (representing traps). This study yielded encouraging results with delineation of 13 new exploration targets.

Duarte Campos et al. (2017) adopted the mineral systems approach to MPM in the Gurupi Orogenic Gold Belt, north–northeast Brazil. They used the knowledge-driven multi-class overlay method to weight and integrate spatial predictors of prospectivity derived from up-to-date regional-scale geological, geochemical and geophysical datasets compiled by the Geological Survey of Brazil. This study resulted in considerable reduction in the search area and delineation of new exploration targets.

Feizi et al. (2017) presented a novel hybrid AHP-Shannon Entropy approach for assigning weights to evidence for MPM in a case study for porphyry-Cu potential mapping in Iran. They evaluated their output mineral potential map by field checking and chemical analysis of rock samples. They found outcrops with evidence of a porphyry system in areas with high potential values, and they found good correlation between high potential values and Cu content of rock samples taken from the field.

Nykänen et al. (2017) combined a mineral deposit model and a mineral systems model into a conceptual model for MPM, which they tested in an active mineral exploration terrain within the Paleoproterozoic Peräpohja Belt (PB) in the Northern Fennoscandian Shield, Finland, where recent mineral exploration activities have indicated several gold-bearing mineral occurrences. They used the ROC spatial statistical technique to optimize rescaling of input datasets and integration of data using FL. Spatial coincidence of high prospectivity values with current exploration licenses and exploration drilling sites for gold indicates the validity of their conceptual mineral prospectivity model.

CONCLUDING REMARKS

The Natural Resources Research journal leads the promotion, through publication, of developments in research of methods for mineral potential mapping (Fig. 7). Since its foundation in 1992, the journal has contributed significantly to the publication of research on development of robust numerical methods for the analysis and integration of spatial datasets relevant to mineral potential mapping. It was only in recent years that the journal has started to publish research on development of geologically focused quantitative models of mineral potential. The reason for the latter is not that research on development of geologically focused models of mineral potential does not fall within the scope of the journal but because academics involved in this research field prefers to publish in peer-reviewed journals that are abstracted/indexed in the Science Citation Index Expanded™ (or SciSearch®) and Journal Citation Reports® (JCR) Science Edition. However, Natural Resources Research has just recently been selected for coverage in SciSearch and JCR as well as in Current Contents®/Physical Chemical and Earth Sciences (see editorial of the author at http://link.springer.com/article/10.1007/s11053-017-9328-5). This recognition from the Clarivate Analytics (formerly the Institute for Scientific Information) will make Natural Resources Research more attractive to researchers in the fields of geochemical anomaly and mineral potential mapping, and so we can foresee a raise in the number of submitted papers in these fields in the years to come.

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REFERENCES

FROM NRR

Agterberg, F. P. (1992). Combining indicator patterns in weights of evidence modeling for resource evaluation. *Nonrenewable Resources, 1,* 39–50.

Agterberg, F. P. (1993). Calculation of the variance of mean values for blocks in regional resource evaluation studies. *Nonrenewable Resources, 2,* 312–324.

Agterberg, F. (2011). A modified weights-of-evidence method for regional mineral resource estimation. *Natural Resources Research, 20,* 95–101.

Agterberg, F. P., & Bonham-Carter, G. F. (2005). Measuring the performance of mineral-potential maps. *Natural Resources Research, 14,* 1–17.

Agterberg, F. P., & Cheng, Q. (2002). Conditional independence test for weights-of-evidence modeling. *Natural Resources Research, 11,* 249–255.

An, P., Moon, W. M., & Bonham-Carter, G. F. (1994a). An object-oriented knowledge representation structure for exploration data integration. *Nonrenewable Resources, 3,* 132–145.

An, P., Moon, W. M., & Bonham-Carter, G. F. (1994b). Uncertainty management in integration of exploration data using the belief function. *Nonrenewable Resources, 3,* 60–71.

Asadi, H. H., Sansoleimani, A., Fatehi, M., & Carranza, E. J. M. (2016). An AHP–TOPSIS predictive model for district-scale mapping of porphyry Cu–Au potential: A case study from Salafchegan Area (Central Iran). *Natural Resources Research, 25,* 417–429.

Behnia, P. (2007). Application of radial basis functional link networks to exploration for Proterozoic mineral deposits in Central Iran. *Natural Resources Research, 16,* 147–155.

Bougrain, L., Gonzalez, M., Bouchot, V., Cassard, D., Lips, A. L. W., Alexandre, F., et al. (2003). Knowledge recovery for continental-scale mineral exploration by neural networks. *Natural Resources Research, 12,* 173–181.

Brown, W. M., Gedeon, T. D., & Groves, D. I. (2003a). Use of noise to augment training data: A neural network method of mineral–potential mapping in regions of limited known deposit examples. *Natural Resources Research, 12,* 141–152.

Brown, W. M., Groves, D. I., & Gedeon, T. D. (2003b). Use of fuzzy membership input layers to combine subjective geological knowledge and empirical data in a neural network method for mineral-potential mapping. *Natural Resources Research, 12,* 183–200.

Carranza, E. J. M. (2004). Weights of evidence modeling of mineral potential: A case study using small number of prospects, Abra, Philippines. *Natural Resources Research, 13,* 173–187.

Carranza, E. J. M. (2015). Data-driven evidential belief modeling of mineral potential using few prospects and evidence with missing values. *Natural Resources Research, 24,* 291–304.

Carranza, E. J. M. (2017). Geochemical mineral exploration: Should we use enrichment factors or log-ratios? *Natural Resources Research*. doi:10.1007/s11053-016-9318-z.

Carranza, E. J. M., & Hale, M. (2000). Geologically constrained probabilistic mapping of gold potential, Baguio District, Philippines. *Natural Resources Research, 9,* 237–253.

Carranza, E. J. M., & Hale, M. (2001a). Geologically constrained fuzzy mapping of gold mineralization potential, Baguio District, Philippines. *Natural Resources Research, 10,* 125–136.

Carranza, E. J. M., & Hale, M. (2002a). Where are porphyry copper deposits spatially localized? A case study in Benguet Province, Philippines. *Natural Resources Research, 11,* 45–59.

Carranza, E. J. M., & Laborte, A. G. (2016). Data-driven predictive modeling of mineral prospectivity using Random Forests: A case study in Catanduanes Island (Philippines). *Natural Resources Research, 25,* 35–50.

Carranza, E. J. M., Mangaoang, J. C., & Hale, M. (1999). Application of mineral exploration models and GIS to generate mineral potential maps as input for optimum land-use planning in the Philippines. *Natural Resources Research, 8,* 165–173.

Carranza, E. J. M., Woldai, T., & Chikambwe, E. M. (2005). Application of data-driven evidential belief functions to prospectivity mapping for aquamarine-bearing pegmatites, Lundazi District, Zambia. *Natural Resources Research, 14,* 47–63.

Chen, J., Wang, G., & Hou, C. (2005). Quantitative prediction and evaluation of mineral resources based on GIS: A case study in Sanjiang region, southwestern China. *Natural Resources Research, 15,* 285–294.

Chen, Y., Zhao, P., Chen, J., & Liu, J. (2001). Application of the geo-anomaly unit concept in quantitative delineation and assessment of gold ore targets in western Shandong uplift terrain, Eastern China. *Natural Resources Research, 10,* 35–49.

Cheng, Q. (1996). Asymmetric fuzzy relation analysis method for ranking geoscience variables. *Nonrenewable Resources, 5,* 169–180.

Cheng, Q., & Agterberg, F. P. (1999). Fuzzy weights of evidence method and its application in mineral potential mapping. *Natural Resources Research, 8,* 27–35.

Cheng, Q., Agterberg, F. P., & Bonham-Carter, G. F. (1996). Fractal pattern integration for mineral potential estimation. *Nonrenewable Resources, 5,* 117–130.

Cheng, Q., Xu, Y., & Grunsky, E. (2000). Integrated spatial and spectrum method for geochemical anomaly separation. *Natural Resources Research, 9,* 43–52.

Chung, C. J., & Fabbri, A. G. (1993). The representation of geoscience information for data integration. *Nonrenewable Resources, 2,* 122–139.

Costa, J. F., & Koppe, J. C. (1999). Assessing uncertainty associated with the delineation of geochemical anomalies. *Natural Resources Research, 8,* 59–67.

Daneshfar, B., Desrochers, A., & Budkewitsch, P. (2006). Mineral-potential mapping for MVT deposits with limited data sets using Landsat data and geological evidence in the Borden Basin, Northern Baffin Island, Nunavut, Canada. *Natural Resources Research, 15,* 129–149.

De Araújo, C. C., & Macedo, A. B. (2002). Multicriteria geologic data analysis for mineral favorability mapping: Application to a metal sulphide mineralized area, Ribeira Valley Metallogenic Province, Brazil. *Natural Resources Research, 11,* 29–43.

Deng, M. (2009). A conditional dependence adjusted weights of evidence model. *Natural Resources Research, 18,* 249–258.

De Quadros, T. F. P., Koppe, J. C., Strieder, A. J., & Costa, J. F. C. L. (2006). Mineral-potential mapping: A comparison of weights-of-evidence and fuzzy methods. *Natural Resources Research, 15,* 49–65.

Duarte Campos, L., Machado de Souza, S., Alves de Sordi, D., Tavares, F. M., Klein, E. L., & Dos Santos Lopes, E. C. (2017). Predictive mapping of prospectivity in the Gurupi Orogenic Gold Belt, north–northeast Brazil: An example of district-scale mineral system approach to exploration targeting. *Natural Resources Research*. doi:10.1007/s11053-016-9320-5.

Elliott, B. A., Verma, R., & Kyle, J. R. (2016). Prospectivity modeling for Cambrian-Ordovician hydraulic fracturing sand resources around the Llano Uplift, Central Texas. *Natural Resources Research, 25,* 389–415.

El-Makky, A. M., & Sediek, K. N. (2012). Stream sediments geochemical exploration in the northwestern part of Wadi Allaqi Area, South Eastern Desert, Egypt. *Natural Resources Research, 21,* 95–115.

Fabbri, A., & Chung, C. J. (2008). On blind tests and spatial prediction models. *Natural Resources Research, 17,* 107–118.

Feizi, F., Karbalaei-Ramezanali, A., & Tusi, H. (2017). Mineral potential mapping via TOPSIS with hybrid AHP-Shannon entropy weighting of evidence: A case study for porphyry-Cu, Farmahin area, Markazi Province, Iran. *Natural Resources Research*. doi:10.1007/s11053-017-9338-3.

Ford, A., Miller, J. M., & Mol, A. G. (2016). A comparative analysis of weights of evidence, evidential belief functions,

and fuzzy logic for mineral potential mapping using incomplete data at the scale of investigation. *Natural Resources Research, 25,* 19–33.
Geranian, H., Tabatabaei, S. H., Asadi, H. H., & Carranza, E. J. M. (2016). Application of discriminant analysis and support vector machine in mapping gold potential areas for further drilling in the Sari-Gunay gold deposit, NW Iran. *Natural Resources Research, 25,* 145–159.
Goossens, M. A. (1993). Integrated analysis of Landsat TM, airborne magnetic, and radiometric data, as an exploration tool for granite-related mineralization, Salamanca province, Western Spain. *Nonrenewable Resources, 2,* 14–30.
Hariharan, S., Tirodkar, S., Porwal, A., Bhattacharya, A., & Joly, A. (2017). Random forest-based prospectivity modelling of greenfield terrains using sparse deposit data: An example from the Tanami Region, Western Australia. *Natural Resources Research*. doi:10.1007/s11053-017-9335-6.
Harris, D., & Pan, G. (1999). Mineral favorability mapping: A comparison of artificial neural networks, logistic regression, and discriminant analysis. *Natural Resources Research, 8,* 93–109.
Harris, D., Zurcher, L., Stanley, M., Marlow, J., & Pan, G. (2003). A comparative analysis of favorability mappings by weights of evidence, probabilistic neural networks, discriminant analysis, and logistic regression. *Natural Resources Research, 12,* 241–255.
Harris, J. R., Lemkow, D., Jefferson, C., Wright, D., & Falck, H. (2008). Mineral potential modelling for the greater Nahanni ecosystem using GIS based analytical methods. *Natural Resources Research, 17,* 51–78.
Harris, J. R., Wilkinson, L., Heather, K., Fumerton, S., Bernier, M. A., Ayer, J., et al. (2001). Application of GIS processing techniques for producing mineral prospectivity maps—A case study: Mesothermal Au in the Swayze Greenstone Belt, Ontario, Canada. *Natural Resources Research, 10,* 91–124.
He, J., Yao, S., Zhang, Z., & You, G. (2013). Complexity and productivity differentiation models of metallogenic indicator elements in rocks and supergene media around Daijiazhuang Pb–Zn deposit in Dangchang County, Gansu Province. *Natural Resources Research, 22,* 19–36.
Lusty, P. A. J., Scheib, C., Gunn, A. G., & Walker, A. S. D. (2012). Reconnaissance-scale prospectivity analysis for gold mineralisation in the Southern Uplands-Down-Longford Terrane, Northern Ireland. *Natural Resources Research, 21,* 359–382.
Luz, F., Mateus, A., Matos, J. X., & Gonçalves, M. A. (2014). Cu- and Zn-soil anomalies in the NE border of the South Portuguese Zone (Iberian Variscides, Portugal) identified by multifractal and geostatistical analyses. *Natural Resources Research, 23,* 195–215.
McKay, G., & Harris, J. R. (2016). Comparison of the data-driven random forests model and a knowledge-driven method for mineral prospectivity mapping: A case study for gold deposits around the Huritz Group and Nueltin Suite, Nunavut, Canada. *Natural Resources Research, 25,* 125–143.
McLaren, G. P. (1992). Classifying mineral potential in support of land-use policy decisions in British Columbia, Canada. *Nonrenewable Resources, 1,* 85–96.
Mejía-Herrera, P., Royer, J. J., Caumon, G., & Cheilletz, A. (2015). Curvature attribute from surface-restoration as predictor variable in Kupferschiefer copper potentials. *Natural Resources Research, 24,* 275–290.
Mihalasky, M. J., & Bonham-Carter, G. F. (2001). Lithodiversity and its spatial association with metallic mineral sites, Great Basin of Nevada. *Natural Resources Research, 10,* 209–226.
Mutele, L., Billay, A., & Hunt, J. P. (2017). Knowledge-driven prospectivity mapping for granite-related polymetallic Sn–F–(REE) mineralization, Bushveld Igneous Complex, South Africa. *Natural Resources Research*. doi:10.1007/s11053-017-9325-8.
Nykänen, V. (2008). Radial basis functional link nets used as a prospectivity mapping tool for orogenic gold deposits within the Central Lapland Greenstone Belt, Northern Fennoscandian Shield. *Natural Resources Research, 17,* 29–48.
Nykänen, V., Niiranen, T., Molnár, F., Lahti, I., Korhonen, K., Cook, N., et al. (2017). Optimizing a knowledge-driven prospectivity model for gold deposits within Peräpohja Belt, northern Finland. *Natural Resources Research*. doi:10.1007/s11053-016-9321-4.
Nykänen, V., & Ojala, V. J. (2007). Spatial analysis techniques as successful mineral-potential mapping tools for orogenic gold deposits in the Northern Fennoscandian Shield, Finland. *Natural Resources Research, 16,* 85–92.
Nykänen, V., & Raines, G. L. (2006). Quantitative analysis of scale of aeromagnetic data raises questions about geologic-map scale. *Natural Resources Research, 15,* 213–222.
Oh, H. J., & Lee, S. (2010). Application of artificial neural network for gold–silver deposits potential mapping: A case study of Korea. *Natural Resources Research, 19,* 103–124.
Paganelli, F., Richards, J. P., & Grunsky, E. C. (2002). Integration of structural, gravity, and magnetic data using the weights of evidence method as a tool for kimberlite exploration in the Buffalo Head Hills, Northern Central Alberta, Canada. *Natural Resources Research, 11,* 219–236.
Pan, G. (1993a). Indicator favorability theory for mineral potential mapping. *Nonrenewable Resources, 2,* 292–311.
Pan, G., & Porterfield, B. (1995). Large-scale mineral potential estimation for blind precious metal ore bodies. *Nonrenewable Resources, 4,* 187–207.
Parsa, M., Maghsoudi, A., Carranza, E. J. M., & Yousefi, M. (2017). Enhancement and mapping of weak multivariate stream sediment geochemical anomalies in Ahar area, NW Iran. *Natural Resources Research.*.
Pazand, K., Hezarkhani, A., Ataei, M., & Ghanbari, Y. (2011). Combining AHP with GIS for predictive Cu porphyry potential mapping: A case study in Ahar Area (NW, Iran). *Natural Resources Research, 20,* 251–262.
Porwal, A., Carranza, E. J. M., & Hale, M. (2003a). Artificial neural networks for mineral-potential mapping: A case study from Aravalli Province, Western India. *Natural Resources Research, 12,* 155–171.
Porwal, A., Carranza, E. J. M., & Hale, M. (2003b). Knowledge-driven and data-driven fuzzy models for predictive mineral potential mapping. *Natural Resources Research, 12,* 1–25.
Porwal, A., Carranza, E. J. M., & Hale, M. (2006a). A hybrid fuzzy weights-of-evidence model for mineral potential mapping. *Natural Resources Research, 15,* 1–14.
Raines, G. L. (1999). Evaluation of weights of evidence to predict epithermal-gold deposits in the Great Basin of the Western United States. *Natural Resources Research, 8,* 257–276.
Raines, G. L., Connors, K. A., & Chorlton, L. B. (2007). Porphyry copper deposit tract definition—A global analysis comparing geologic map scales. *Natural Resources Research, 16,* 191–198.
Raines, G. L., & Mihalasky, M. J. (2002). A reconnaissance method for delineation of tracts for regional-scale mineral-resource assessment based on geologic-map data. *Natural Resources Research, 11,* 241–248.
Reddy, R. K. T., Bonham-Carter, G. F., & Galley, A. G. (1992). Developing a geographic expert system for regional mapping of volcanogenic massive sulfide (VMS) deposit potential. *Nonrenewable Resources, 1,* 112–124.
Rehder, S. (1994). Experiences with an expert system for gold exploration in Botswana. *Nonrenewable Resources, 3,* 123–131.
Rostirolla, S. P., Soares, P. C., & Chang, H. K. (1998). Bayesian and multivariate methods applied to favorability quantification in Recôncavo Basin and Ribeira Belt, Brazil. *Nonrenewable Resources, 7,* 7–24.

Sahoo, N. R., & Pandalai, H. S. (1999). Integration of sparse geologic information in gold targeting using logistic regression analysis in the Hutti-Maski Schist Belt, Raichur, Karnataka, India—A case study. *Natural Resources Research, 8,* 233–250.

Scott, M., & Dimitrakopoulos, R. (2001). Quantitative analysis of mineral resources for strategic planning: implications for Australian geological surveys. *Natural Resources Research, 10,* 159–177.

Singer, D. A. (1993). Basic concepts in three-part quantitative assessments of undiscovered mineral resources. *Nonrenewable Resources, 2,* 69–81.

Singer, D. A., & Kouda, R. (1999). A comparison of the weights-of-evidence method and probabilistic neural networks. *Natural Resources Research, 8,* 287–298.

Singer, D. A., & Kouda, R. (2001). Some simple guides to finding useful information in exploration geochemical data. *Natural Resources Research, 10,* 137–147.

Skabar, A. A. (2005). Mapping mineralization probabilities using multilayer perceptrons. *Natural Resources Research, 14,* 109–123.

Skabar, A. A. (2011). Mineral prospectivity prediction from high-dimensional geoscientific data using a similarity-based density estimation model. *Natural Resources Research, 20,* 143–155.

Tessema, A. (2017). Mineral systems analysis and artificial neural network modeling of chromite prospectivity in the Western Limb of the Bushveld Complex, South Africa. *Natural Resources Research*. doi:10.1007/s11053-017-9344-5.

Twarakavi, N. K. C., Misra, D., & Bandopadhyay, S. (2006). Prediction of arsenic in bedrock derived stream sediments at a gold mine site under conditions of sparse data. *Natural Resources Research, 15,* 15–26.

Venkataraman, G., Babu Madhavan, B., Ratha, D. S., Antony, J. P., Goyal, R. S., Banglani, S., et al. (2000). Spatial modeling for base-metal mineral exploration through integration of geological data sets. *Natural Resources Research, 9,* 27–42.

Yousefi, M. (2017). Analysis of zoning pattern of geochemical indicators for targeting of porphyry-Cu mineralization: A pixel-based mapping approach. *Natural Resources Research*. doi:10.1007/s11053-017-9334-7.

Yousefi, M., & Carranza, E. J. M. (2016). Data-driven index overlay and Boolean logic mineral prospectivity modeling in greenfields exploration. *Natural Resources Research, 25,* 3–18.

Zuo, R. (2017). Machine learning of mineralization-related geochemical anomalies: A review of potential methods. *Natural Resources Research*. doi:10.1007/s11053-017-9345-4.

FROM OTHER SOURCES

Abedi, M., Kashani, S. B. M., Norouzi, G. H., & Yousefi, M. (2017). A deposit scale mineral prospectivity analysis: A comparison of various knowledge-driven approaches for porphyry copper targeting in Seridune, Iran. *Journal of African Earth Sciences, 128,* 127–146.

Abedi, M., Mohammadi, R., Norouzi, G. H., & Mohammadi, M. S. M. (2016). A comprehensive VIKOR method for integration of various exploratory data in mineral potential mapping. *Arabian Journal of Geosciences, 9,* 1–21.

Abedi, M., & Norouzi, G. H. (2012). Integration of various geophysical data with geological and geochemical data to determine additional drilling for copper exploration. *Journal of Applied Geophysics, 83,* 35–45.

Abedi, M., Norouzi, G. H., & Bahroudi, A. (2012). Support vector machine for multi-classification of mineral prospectivity areas. *Computers & Geosciences, 46,* 272–283.

Abedi, M., Norouzi, G. H., & Fathianpour, N. (2013). Fuzzy outranking approach: A knowledge-driven method for mineral prospectivity mapping. *International Journal of Applied Earth Observation and Geoinformation, 21,* 556–567.

Abedi, M., Norouzi, G. H., & Fathianpour, N. (2015). Mineral potential mapping in Central Iran using fuzzy ordered weighted averaging method. *Geophysical Prospecting, 63,* 461–477.

Agterberg, F. P. (1988). Application of recent developments of regression analysis in regional mineral resource evaluation. In C. F. Chung, A. G. Fabbri, & R. Sinding-Larsen (Eds.), *Quantitative analysis of mineral and energy resources* (pp. 1–28). Dordrecht: D. Reidel Publishing Company.

Agterberg, F. P., Bonham-Carter, G. F., & Wright, D. F. (1990). Statistical pattern integration for mineral exploration. In G. Gaál & D. F. Merriam (Eds.), *Computer applications in resource estimation* (pp. 1–21). Oxford: Pergamon Press.

Agterberg, F. P., Bonham-Carter, G. F., Cheng, Q., & Wright, D. F. (1993). Weights of evidence modeling and weighted logistic regression in mineral potential mapping. In J. C. Davis & U. C. Herzfeld (Eds.), *Computers in geology* (pp. 13–32). New York: Oxford University Press.

Aitchison, J. (1984). The statistical analysis of geochemical compositions. *Mathematical Geology, 16,* 531–564.

Alaei Moghadam, S., Karimi, M., & Sadi Mesgari, M. (2015). Application of a fuzzy inference system to mapping prospectivity for the Chahfiroozeh copper deposit, Kerman, Iran. *Journal of Spatial Science, 60,* 233–255.

An, P., Moon, W. M., & Bonham-Carter, G. F. (1992). On knowledge-based approach on integrating remote sensing, geophysical and geological information. *Proceedings of the International Geoscience and Remote Sensing Symposium (IGARSS), 1992,* 34–38.

An, P., Moon, W. M., & Rencz, A. (1991). Application of fuzzy set theory for integration of geological, geophysical and remote sensing data. *Canadian Journal of Exploration Geophysics, 27,* 1–11.

Andrada de Palomera, P., van Ruitenbeek, F. J. A., & Carranza, E. J. M. (2015). Prospectivity for epithermal gold-silver deposits in the Deseado Massif, Argentina. *Ore Geology Reviews, 71,* 484–501.

Asadi, H. H., & Hale, M. (2001). A predictive GIS model for mapping potential gold and base metal mineralization in Takab area, Iran. *Computers & Geosciences, 27,* 901–912.

Asadi, H. H., Porwal, A., Fatehi, M., Kianpouryan, S., & Lu, Y. (2015). Exploration feature selection applied to hybrid data integration modeling: Targeting copper–gold potential in central Iran. *Ore Geology Reviews, 71,* 819–838.

Austin, J. R., & Blenkinsop, T. G. (2009). Local to regional scale structural controls on mineralisation and the importance of a major lineament in the eastern Mount Isa Inlier, Australia: Review and analysis with autocorrelation and weights of evidence. *Ore Geology Reviews, 35,* 298–316.

Barnes, R. G., Jaireth, S., Miezitis, Y., & Suppel, D. (1999). Mineral potential assessment of parts of the southern New England Orogen. In P. G. Flood (Ed.), *New England Orogen, proceedings of the NEO '99 conference*, 1–3 February 1999. University of New England, Armidale (pp. 373–382).

Barros de Andrade, L., Moreira Silva, A., & De Souza Filho, C. R. (2014). Nickel prospective modelling using fuzzy logic on Nova Brasilândia metasedimentary belt, Rondônia, Brazil. *Revista Brasileira de Geofísica, 32,* 419–431.

Billa, M., Cassard, D., Lips, A. L. W., Bouchot, V., Tourliére, B., Stein, G., et al. (2004). Predicting gold-rich epithermal and porphyry systems in the central Andes with a continental-scale metallogenic GIS. *Ore Geology Reviews, 25,* 39–67.

Bonham-Carter, G. F. (1991). Integration of geoscientific data using GIS. In D. J. Maguire, M. F. Goodchild, & D. W. Rhind

(Eds.), *Geographic information systems: Principles and applications* (Vol. 2, pp. 171–184). London: Longman.
Bonham-Carter, G. F. (1994). *Geographic information systems for geoscientists: Modelling with GIS* (p. 416p). Ontario: Pergamon.
Bonham-Carter, G. F., & Agterberg, F. P. (1990). Application of a microcomputer-based geographic information system to mineral-potential mapping. In J. T. Hanley & D. F. Merriam (Eds.), *Microcomputer applications in geology, II* (pp. 49–74). New York: Pergamon Press.
Bonham-Carter, G. F., & Agterberg, F. P. (1999). Arc-WofE: A GIS tool for statistical integration of mineral exploration datasets. In *Proceedings of the 52nd session of the International Statistical Institute*, Helsinki, August 10–18, 1999. http://www.stat.fi/isi99/proceedings.html.
Bonham-Carter, G. F., Agterberg, F. P., & Wright, D. F. (1988). Integration of geological datasets for gold exploration in Nova Scotia. *Photogrammetric Engineering and Remote Sensing, 54,* 1585–1592.
Bonham-Carter, G. F., Agterberg, F. P., & Wright, D. F. (1989). Weights of evidence modelling: A new approach to mapping mineral potential. In F. P. Agterberg & G .F. Bonham-Carter (Eds.), *Statistical applications in the earth sciences*. Geological Survey of Canada, Paper 89-9 (pp. 171–183).
Bonham-Carter, G. F., & Chung, C. F. (1983). Integration of mineral resource data for Kasmere Lake area, Northwest Manitoba, with emphasis on uranium. *Mathematical Geology, 15,* 25–45.
Botbol, J. M., Sinding-Larsen, R., McCammon, R. B., & Gott, G. B. (1977). Weighted characteristics analysis of spatially dependent mineral deposit data. *Mathematical Geology, 9,* 309–311.
Botbol, J. M., Sinding-Larsen, R., McCammon, R. B., & Gott, G. B. (1978). A regionalized multivariate approach to target area selection in geochemical exploration. *Economic Geology, 73,* 534–546.
Brown, W., Gedeon, T., & Barnes, R. (1999). The use of a multilayer feedforward neural network for mineral prospectivity mapping. In T. Gedeon, P. Wong, S. Halgamuge, N. Kasabov, D. Nauck, & K. Fukushima (Eds.), *ICONIP '99: ANZIIS'99 & ANNES'99 & ACNN'99: Proceedings of the 6th international conference on neural information processing* (Vol. 1, pp. 160–165), IEEE, Piscataway, U.S.A, Perth edn.
Brown, W. M., Gedeon, T. D., Groves, D. I., & Barnes, R. G. (2000). Artificial neural networks: A new method for mineral prospectivity mapping. *Australian Journal of Earth Sciences, 47,* 757–770.
Butt, C. R. M., & Zeegers, H. (Eds.). (1992). *Regolith exploration geochemistry in tropical and subtropical terrains. Handbook of exploration geochemistry* (Vol. 4). Amsterdam: Elsevier.
Carranza, E. J. M. (2008). *Geochemical anomaly and mineral prospectivity mapping in GIS. Handbook of exploration and environmental geochemistry* (Vol. 11). Amsterdam: Elsevier.
Carranza, E. J. M. (2009a). Controls on mineral deposit occurrence inferred from analysis of their spatial pattern and spatial association with geological features. *Ore Geology Reviews, 35,* 383–400.
Carranza, E. J. M. (2009b). Objective selection of suitable unit cell size in data-driven modeling of mineral prospectivity. *Computers & Geosciences, 35,* 2032–2046.
Carranza, E. J. M. (2011). From predictive mapping of mineral prospectivity to quantitative estimation of number of undiscovered prospects. *Resource Geology, 61,* 30–51.
Carranza, E. J. M., & Hale, M. (2001b). Logistic regression for geologically-constrained mapping of gold mineralization potential, Baguio district, Philippines. *Exploration and Mining Geology Journal, 10,* 165–175.
Carranza, E. J. M., & Hale, M. (2002b). Spatial association of mineral occurrences and curvilinear geological features. *Mathematical Geology, 34,* 203–221.
Carranza, E. J. M., & Hale, M. (2003). Evidential belief functions for data-driven geologically constrained mapping of gold potential, Baguio district, Philippines. *Ore Geology Reviews, 22,* 117–132.
Carranza, E. J. M., Hale, M., & Faassen, C. (2008a). Selection of coherent deposit-type locations and their application in data-driven mineral prospectivity mapping. *Ore Geology Reviews, 33,* 536–558.
Carranza, E. J. M., & Laborte, A. G. (2015a). Data-driven predictive mapping of gold prospectivity, Baguio district, Philippines: application of Random Forests algorithm. *Ore Geology Reviews, 71,* 777–787.
Carranza, E. J. M., & Laborte, A. G. (2015b). Random forest predictive modeling of mineral prospectivity with small number of prospects and data with missing values in Abra (Philippines). *Computers & Geosciences, 74,* 60–70.
Carranza, E. J. M., Owusu, E., & Hale, M. (2009). Mapping of prospectivity and estimation of number of undiscovered prospects for lode gold, southwestern Ashanti Belt, Ghana. *Mineralium Deposita, 44,* 915–938.
Carranza, E. J. M., & Sadeghi, M. (2010). Predictive mapping of prospectivity and quantitative estimation of undiscovered VMS deposits in Skellefte district (Sweden). *Ore Geology Reviews, 38,* 219–241.
Carranza, E. J. M., Sadeghi, M., & Billay, A. (2015). Predictive mapping of prospectivity for orogenic gold, Giyani greenstone belt (South Africa). *Ore Geology Reviews, 71,* 703–718.
Carranza, E. J. M., Van Ruitenbeek, F. J. A., Hecker, C., Van der Meijde, M., & Van der Meer, F. D. (2008b). Knowledge-guided data-driven evidential belief modeling of mineral prospectivity in Cabo de Gata, SE Spain. *International Journal of Applied Earth Observation and Geoinformation, 10,* 374–387.
Carranza, E. J. M., Wibowo, H., Barritt, S. D., & Sumintadireja, P. (2008c). Spatial data analysis and integration for regional-scale geothermal potential mapping, West Java, Indonesia. *Geothermics, 33,* 267–299.
Cassard, D., Billa, M., Lambert, A., Picot, J. C., Husson, Y., Lasserre, J. L., et al. (2008). Gold predictivity mapping in French Guiana using an expert-guided data-driven approach based on a regional-scale GIS. *Ore Geology Reviews, 34,* 471–500.
Chen, C., Dai, H., Liu, Y., & He, B. (2011). Mineral prospectivity mapping integrating multi-source geology spatial data sets and logistic regression modelling. In *Proceedings of the 2011 IEEE international conference on spatial data mining and geographic knowledge series (ICSDM)*, 29 June–01 July 2011, Fuzhou, China (pp. 214–217).
Chen, C., He, B., & Zeng, Z. (2014). A method for mineral prospectivity mapping integrating C4. 5 decision tree, weights-of-evidence and m-branch smoothing techniques: a case study in the eastern Kunlun Mountains, China. *Earth Science Informatics, 7,* 13–24.
Chen, Y. (2004). MRPM: Three visual basic programs for mineral resource potential mapping. *Computers & Geosciences, 30,* 969–983.
Chen, Y., & Zhao, P. (1998). Zonation in primary halos and geochemical prospecting pattern for the Guilaizhuang gold deposit, eastern China. *Nonrenewable Resources, 7,* 37–44.
Cheng, Q., Agterberg, F. P., & Bonham-Carter, G. F. (1994). The separation of geochemical anomalies from background by fractal methods. *Journal of Geochemical Exploration, 51,* 109–130.
Chica-Olmo, M., Abarca, F., & Rigol, J. P. (2002). Development of a decision support system based on remote sensing and GIS techniques for gold-rich area identification in SE Spain. *International Journal of Remote Sensing, 23,* 4801–4814.
Choi, S., Moon, W. M., & Choi, S. G. (2000). Fuzzy logic fusion of W-Mo exploration data from Seobyeog-ri, Korea. *Geosciences Journal, 4,* 43–52.

Chung, C. F. (1977). An application of discriminant analysis for the evaluation of mineral potential. In R. V. Ramani (Ed.), *Application of computer methods in the mineral industry, proceedings of the 14th APCOM symposium*. Society of Mining Engineers of American Institute of Mining, Metallurgical, and Petroleum Engineers, New York (pp. 299–311).

Chung, C. F. (1978). Computer program for the logistic model to estimate the probability of occurrence of discrete events. *Geological Survey of Canada Paper, 78–12,* 23p.

Chung, C. F. (1983). SIMSAG: Integrated computer system for use in evaluation of mineral and energy resources. *Mathematical Geology, 15,* 47–58.

Chung, C. F. (2003). Use of airborne geophysical surveys for constructing mineral potential maps. In W. D. Goodfellow, S. R. McCutcheon, & J. M. Peter (Eds.), *Massive sulfide deposits of the Bathurst mining camp, New Brunswick, and Northern Maine Economic Geology Monograph* (Vol. 11, pp. 879–891). Colorado: Society of Economic Geologists.

Chung, C. F., & Agterberg, F. P. (1980). Regression models for estimating mineral resources from geological map data. *Mathematical Geology, 12,* 472–488.

Chung, C. F., & Agterberg, F. P. (1988). Poisson regression analysis and its application. In C. F. Chung, A. G. Fabbri, & R. Sinding-Larsen (Eds.), *Quantitative analysis of mineral and energy resources* (pp. 29–36). Dordrecht: D. Reidel Publishing Company.

Chung, C. F., Fabbri, A. G., & Chi, K. H. (2002). A strategy for sustainable development of nonrenewable resources using spatial prediction models. In A. G. Fabbri, G. Gáal, & R. B. McCammon (Eds.), *Geoenvironmental deposit models for resource exploitation and environmental security* (pp. 101–118). Dordrecht: Kluwer.

Chung, C. F., & Keating, P. B. (2002). Mineral potential evaluation based on airborne geophysical data. *Exploration Geophysics, 33,* 28–34.

Chung, C. F., & Moon, W. M. (1991). Combination rules of spatial geoscience data for mineral exploration. *Geoinformatics, 2,* 159–169.

Cooper, D. C., Rollin, K. E., Colman, T. B., Davies, J. R., & Wilson, D. (2000). Potential for mesothermal gold and VMS Deposits in the Lower Palaeozoic Welsh Basin. BGS Research Report, RR/00/09. DTI Minerals Programme Publication No. 4. British Geological Suvery, Keyworth.

Costa e Silva, E., Silva, A. M., Bemfica Toldeo, C. I., Mol, A. G., Otterman, D. W., & Cortez de Souza, S. R. (2012). Mineral potential mapping for orogenic gold deposits in the Rio Maria granite greenstone terrane, Southeastern Pará State, Brazil. *Economic Geology, 107,* 1387–1402.

Cox, D. P., & Singer, D. A. (Eds.) (1986). Mineral deposit models. U.S. Geological Survey Bulletin 1693, United States Government Printing Office, Washington.

Debba, P., Carranza, E. J. M., Stein, A., & Van der Meer, F. D. (2009). Deriving optimal exploration target zones on mineral prospectivity maps. *Mathematical Geosciences, 41,* 421–446.

D'Ercole, C., Groves, D. I., & Knox-Robinson, C. M. (2000). Using fuzzy logic in a Geographic Information System environment to enhance conceptually based prospectivity analysis of Mississippi Valley-type mineralisation. *Australian Journal of Earth Sciences, 47,* 913–927.

Du, X., Zhou, K., Cui, Y., Wang, J., Zhang, N., & Sun, W. (2016). Application of fuzzy Analytical Hierarchy Process (AHP) and Prediction-Area (PA) plot for mineral prospectivity mapping: A case study from the Dananhu metallogenic belt, Xinjiang, NW China. *Arabian Journal of Geosciences, 9,* 1–15.

Eddy, B. G., Bonham-Carter, G. F., & Jefferson, C. W. (2006). Mineral potential analyzed and mapped at multiple scales—a modified fuzzy logic method using digital geology. In J. R. Harris (Ed.), *GIS for the earth sciences, Geological Association of Canada Special Publication 44* (pp. 143–162). St. John's: Geological Association of Canada.

Fallon, M., Porwal, A., & Guj, P. (2010). Prospectivity analysis of the Plutonic Marymia Greenstone Belt, Western Australia. *Ore Geology Reviews, 38,* 208–218.

Farzamian, M., Rouhani, A. K., Yarmohammadi, A., Shahi, H., Sabokbar, H. F., & Ziaiie, M. (2016). A weighted fuzzy aggregation GIS model in the integration of geophysical data with geochemical and geological data for Pb–Zn exploration in Takab area, NW Iran. *Arabian Journal of Geosciences, 9,* 1–17.

Feltrin, L. (2008). Predictive modelling of prospectivity for Pb–Zn deposits in the Lawn Hill Region, Queensland, Australia. *Ore Geology Reviews, 34,* 399–427.

Filzmoser, P., Hron, K., & Reimann, C. (2009a). Principal components analysis for compositional data with outliers. *Environmetrics, 20,* 621–632.

Filzmoser, P., Hron, K., & Reimann, C. (2009b). Univariate statistical analysis of environmental (compositional) data: Problems and possibilities. *Science of the Total Environment, 407,* 6100–6108.

Filzmoser, P., Hron, K., & Reimann, C. (2010). The bivariate statistical analysis of environmental (compositional) data. *Science of the Total Environment, 408,* 4230–4238.

Ford, A., & Blenkinsop, T. G. (2008). Combining fractal analysis of mineral deposit clustering with weights of evidence to evaluate patterns of mineralization: application to copper deposits of the Mount Isa Inlier, NW Queensland, Australia. *Ore Geology Reviews, 33,* 435–450.

Ford, A., Hagemann, S. G., Fogliata, A. S., Miller, J. M., Mol, A., & Doyle, P. J. (2015). Porphyry, epithermal, and orogenic gold prospectivity of Argentina. *Ore Geology Reviews, 71,* 655–672.

Ford, A., & Hart, C. J. (2013). Mineral potential mapping in frontier regions: A Mongolian case study. *Ore Geology Reviews, 51,* 15–26.

Gao, Y., Zhang, Z., Xiong, Y., & Zuo, R. (2016). Mapping mineral prospectivity for Cu polymetallic mineralization in southwest Fujian Province, China. *Ore Geology Reviews, 75,* 16–28.

Gettings, M.E., & Bultman, M. W. (1993). Quantifying favorableness for occurrence of a mineral deposit type using fuzzy logic—An example from Arizona. U.S. Geol. Survey Open-File Report 93-392.

Ghanbari, Y., Hezarkhani, A., Ataei, M., & Pazand, K. (2012). Mineral potential mapping with fuzzy models in the Kerman-Kashmar Tectonic Zone, Central Iran. *Applied Geomatics, 4,* 173–186.

González-Álvarez, I., Porwal, A., McCuaig, T. C., & Maier, W. D. (2010). Hydrothermal Ni prospectivity analysis of Tasmania, Australia. *Ore Geology Reviews, 38,* 168–183.

Govett, G. J. S. (1983). *Rock geochemistry in mineral exploration. Handbook of exploration geochemistry* (Vol. 3). Amsterdam: Elsevier.

Groves, D. I., Goldfarb, R. J., Knox-Robinson, C. M., Ojala, J., Gardoll, S., Yun, G. Y., et al. (2000). Late-kinematic timing of orogenic gold deposits and significance for computer-based exploration techniques with emphasis on the Yilgarn Block, Western Australia. *Ore Geology Reviews, 17,* 1–38.

Hale, M. (Ed.). (2000). *Geochemical remote sensing of the subsurface. Handbook of exploration geochemistry* (Vol. 7). Amsterdam: Elsevier.

Hale, M., & Plant, J. (Eds.). (1994). *Drainage geochemistry. Handbook of exploration geochemistry* (Vol. 6). Amsterdam: Elsevier.

Harris, D. P. (1984). *Mineral resources appraisal—Mineral endowment, resources, and potential supply—Concept, methods, and cases* (p. 445p). New York: Oxford University Press.

Harris, D. P., & Pan, G. (1991). Consistent geological areas for epithermal gold-silver deposits in the Walker Lake quad-

rangle of Nevada and California delineated by quantitative methods. *Economic Geology, 86,* 142–165.
Harris, J. R., Grunsky, E., Behnia, P., & Corrigan, D. (2015). Data- and knowledge-driven mineral prospectivity maps for Canada's North. *Ore Geology Reviews, 71*(788), 803.
Harris, J. R., & Sanborn-Barrie, M. (2006). Mineral potential mapping: examples from the Red Lake Greenstone Belt, Northwest Ontario. In J. R. Harris (Ed.), *GIS for the earth sciences, Geological Association of Canada Special Publication 44* (pp. 1–21). St. John's: Geological Association of Canada.
Harris, J. R., Sanborn-Barrie, M., Panagapko, D. A., Skulski, T., & Parker, J. R. (2006). Gold prospectivity maps of the Red Lake greenstone belt: Application of GIS technology. *Canadian Journal of Earth Sciences, 43,* 865–893.
Herbert, S., Woldai, T., Carranza, E. J. M., & Van Ruitenbeek, F. J. A. (2014). Predictive mapping of prospectivity for orogenic gold in Uganda. *Journal of African Earth Sciences, 99,* 666–693.
Joly, A., Porwal, A., & McCuaig, T. C. (2012). Exploration targeting for orogenic gold deposits in the Granites-Tanami Orogen: Mineral system analysis, targeting model and prospectivity analysis. *Ore Geology Reviews, 48,* 349–383.
Kauranne, L. K., Salminen, R., & Eriksson, K. (Eds.). (1992). *Regolith exploration geochemistry in arctic and temperate terrains. Handbook of exploration geochemistry* (Vol. 5). Amsterdam: Elsevier.
Knox-Robinson, C. M. (2000). Vectorial fuzzy logic: a novel technique for enhanced mineral prospectivity mapping with reference to the orogenic gold mineralisation potential of the Kalgoorlie Terrane, Western Australia. *Australian Journal of Earth Sciences, 47,* 929–942.
Levinson, A. A. (1974). *Introduction to exploration geochemistry* (p. 612p). Calgary: Applied Publishing Ltd.
Leväniemi, H., Hulkki, H., & Tiainen, M. (2017). SOM guided fuzzy logic prospectivity model for gold in the Häme Belt, southwestern Finland. *Journal of African Earth Sciences, 128,* 72–83.
Lindsay, M., Aitken, A., Ford, A., Dentith, M., Hollis, J., & Tyler, I. (2016). Reducing subjectivity in multi-commodity mineral prospectivity analyses: Modelling the west Kimberley, Australia. *Ore Geology Reviews, 76,* 395–413.
Lindsay, M. D., Betts, P. G., & Ailleres, L. (2014). Data fusion and porphyry copper prospectivity models, southeastern Arizona. *Ore Geology Reviews, 61,* 120–140.
Lisitsin, V. A., González-Álvarez, I., & Porwal, A. (2013). Regional prospectivity analysis for hydrothermal-remobilised nickel mineral systems in western Victoria, Australia. *Ore Geology Reviews, 52,* 100–112.
Lisitsin, V. A., Porwal, A., & McCuaig, T. C. (2014). Probabilistic fuzzy logic modeling: quantifying uncertainty of mineral prospectivity models using Monte Carlo simulations. *Mathematical Geosciences, 46,* 747–769.
Liu, Y., Cheng, Q., Xia, Q., & Wang, X. (2014). Mineral potential mapping for tungsten polymetallic deposits in the Nanling metallogenic belt, South China. *Journal of Earth Science, 25,* 689–700.
Liu, Y., Cheng, Q., Xia, Q., & Wang, X. (2015). The use of evidential belief functions for mineral potential mapping in the Nanling belt, South China. *Frontiers of Earth Science, 9,* 342–354.
Lusty, P. A. J., Gunn, A. G., McDonnell, P. M., Chacksfield, B. C., Cooper, M. R., & Earls, G. (2009). Gold potential of the Dalradian rocks of north-west Northern Ireland: Prospectivity analysis using Tellus data. *Applied Earth Science, 118,* 162–177.
Madani, A. A. (2011). Knowledge-driven GIS modeling technique for gold exploration, Bulghah gold mine area, Saudi Arabia. *The Egyptian Journal of Remote Sensing and Space Science, 14,* 91–97.
Magalhães, L. A., & Souza Filho, C. R. (2012). Targeting of gold deposits in Amazonian exploration frontiers using knowledge-and data-driven spatial modeling of geophysical, geochemical, and geological data. *Surveys In Geophysics, 33,* 211–241.
McCammon, R. B., Botbol, J. M., Sinding-Larsen, R., & Bowen, R. W. (1983). Characteristics analysis-1981: final program and a possible discovery. *Mathematical Geology, 15,* 59–83.
McCammon, R. B., Botbol, J. M., Sinding-Larsen, R., & Bowen, R. W. (1984). The New CHARaracteristic ANalysis (NCHARAN) Program. U.S. Geological Survey Bulletin 1621.
McCuaig, T. C., Beresford, S., & Hronsky, J. (2010). Translating the mineral systems approach into an effective exploration targeting system. *Ore Geology Reviews, 38,* 128–138.
Moon, W. M. (1990). Integration of geophysical and geological data using evidential belief function. *IEEE Transactions on Geoscience and Remote Sensing, 28,* 711–720.
Moon, W. M. (1993). On mathematical representation and integration of multiple geoscience data sets. *Canadian Journal of Remote Sensing, 19,* 663–667.
Moon, W. M., Chung, C. F., & An, P. (1991). Representation and integration of geological, geophysical and remote sensing data. *Geoinformatics, 2,* 177–188.
Moradi, M., Basiri, S., Kananian, A., & Kabiri, K. (2015). Fuzzy logic modeling for hydrothermal gold mineralization mapping using geochemical, geological, ASTER imageries and other geo-data, a case study in Central Alborz, Iran. *Earth Science Informatics, 8,* 197–205.
Moreira, F. R. S., Almeida-Filho, R., & Câmara, F. (2002). Spatial analysis techniques applied to mineral prospecting: An evaluation in the Poços de Caldas Plateau. *Revista Brasileira de Geosciêcias, 33*(2-Supplement), 183–190.
Mostafavi Kashani, S. B., Abedi, M., & Norouzi, G. H. (2016). Fuzzy logic mineral potential mapping for copper exploration using multi-disciplinary geo-datasets, a case study in seridune deposit, Iran. *Earth Science Informatics, 9,* 167–181.
Naghadehi, K. M., Hezarkhani, A., Honarpazhouh, J., & Shabani, K. S. (2014). Integration multisource data for mineral exploration by using fuzzy logic, case study: Taknar deposit, NE of Iran. *Arabian Journal of Geosciences, 7,* 3227–3241.
Najafi, A., Karimpour, M. H., & Ghaden, M. (2014). Application of fuzzy AHP method to IOCG prospectivity mapping: A case study in Taherabad prospecting area, eastern Iran. *International Journal of Applied Earth Observation and Geoinformation, 33,* 142–154.
Nielsen, S. H. H., Cunningham, F., Hay, R., Partington, G., & Stokes, M. (2015a). 3D prospectivity modelling of orogenic gold in the Marymia Inlier, Western Australia. *Ore Geology Reviews, 71,* 578–591.
Nielsen, S. H. H., McKenzie, C., Miller, A., Partington, G., Payne, C., Puccioni, E., et al. (2015b). Chatham Rise nodular phosphate—Modelling the prospectivity of a lag deposit (offshore New Zealand): A critical tool for use in resource development and deep sea mining. *Ore Geology Reviews, 71,* 545–557.
Nykänen, V., Groves, D. I., Ojala, V. J., Eilu, P., & Gardoll, S. J. (2008a). Reconnaissance scale conceptual fuzzy-logic prospectivity modelling for iron oxide copper–gold deposits in the northern Fennoscandian Shield, Finland. *Australian Journal of Earth Sciences, 55,* 25–38.
Nykänen, V., Groves, D. I., Ojala, V. J., Eilu, P., & Gardoll, S. J. (2008b). Combined conceptual/empirical prospectivity mapping for orogenic gold in the northern Fennoscandian Shield, Finland. *Australian Journal of Earth Sciences, 55,* 39–59.
Nykänen, V., Lahti, I., Niiranen, T., & Korhonen, K. (2015). Receiver operating characteristics (ROC) as validation tool for prospectivity models—A magmatic Ni–Cu case study from the Central Lapland Greenstone Belt, Northern Finland. *Ore Geology Reviews, 71,* 853–860.

Nykänen, V., & Salmirinne, H. (2007). Prospectivity analysis of gold using regional geophysical and geochemical data from the Central Lapland Greenstone Belt, Finland. In: Juhani Ojala, V. (Ed.), *Gold in the Central Lapland Greenstone Belt, Finland*. Geological Survey of Finland, Special Paper 44, pp. 251–269.

Oh, H.-J., & Lee, S. (2008). Regional probabilistic and statistical mineral potential mapping of gold-silver deposits using GIS in the Gangreung area, Korea. *Resource Geology, 58*, 171–187.

Oskouei, M. M., & Soltani, F. (2016). Mapping of potential Cu and Au mineralization using EBF method. *Applied Geomatics*. doi:10.1007/s12518-016-0178-3.

Pan, G. C. (1993b). Canonical favourability model for data integration and mineral potential mapping. *Computers & Geosciences, 19,* 1077–1100.

Pan, G. C. (1993c). Regionalized favorability theory for information synthesis in mineral exploration. *Mathematical Geology, 25,* 603–631.

Pan, G. C., & Harris, D. P. (1992a). Decomposed and weighted characteristic analysis for the quantitative estimation of mineral resources. *Mathematical Geology, 24,* 807–823.

Pan, G. C., & Harris, D. P. (1992b). Estimating a favourability equation for the integration of geodata and selection of mineral exploration targets. *Mathematical Geology, 24,* 177–202.

Pan, G. C., & Harris, D. P. (2000). *Information synthesis for mineral exploration*. New York: Oxford University Press Inc.

Partington, G. (2010). Developing models using GIS to assess geological and economic risk: An example from VMS copper gold mineral exploration in Oman. *Ore Geology Reviews, 38,* 197–207.

Payne, C. E., Cunningham, F., Peters, K. J., Nielsen, S., Puccioni, E., Wildman, C., et al. (2015). From 2D to 3D: Prospectivity modelling in the Taupo Volcanic Zone, New Zealand. *Ore Geology Reviews, 71,* 558–577.

Pazand, K., & Hezarkhani, A. (2015). Porphyry Cu potential area selection using the combine AHP-TOPSIS methods: A case study in Siahrud area (NW, Iran). *Earth Science Informatics, 8,* 207–220.

Pazand, K., Hezarkhani, A., & Pazand, K. (2013). Predictive mapping for porphyry copper mineralization: a comparison of knowledge-driven and data-driven fuzzy models in Siahrud area, Azarbaijan province, NW Iran. *Applied Geomatics, 5,* 215–224.

Pereira Leite, E., & De Souza Filho, C. R. (2009a). Artificial neural networks applied to mineral potential mapping for copper-gold mineralizations in the Carajás Mineral Province, Brazil. *Geophysical Prospecting, 57,* 1049–1065.

Pereira Leite, E., & De Souza Filho, C. R. (2009b). Probabilistic neural networks applied to mineral potential mapping for platinum group elements in the Serra Leste region, Carajás Mineral Province, Brazil. *Computers & Geosciences, 35,* 675–687.

Porwal, A., & Carranza, E. J. M. (2008). Classifiers for modelling of mineral potential. In O. Pourret, P. Naïm, & B. Marcot (Eds.), *Bayesian networks: A practical guide to applications* (pp. 149–171). Chichester: Wiley.

Porwal, A., & Carranza, E. J. M. (2015). Introduction to the special issue: GIS-based mineral potential modelling and geological data analyses for mineral exploration. *Ore Geology Reviews, 71,* 477–483.

Porwal, A., Carranza, E. J. M., & Hale, M. (2001). Extended weights-of-evidence modelling for predictive mapping of base metal deposit potential in Aravalli province, western India. *Exploration and Mining Geology Journal, 10,* 273–287.

Porwal, A., Carranza, E. J. M., & Hale, M. (2004). A hybrid neuro-fuzzy model for mineral potential mapping. *Mathematical Geology, 36,* 803–826.

Porwal, A., Carranza, E. J. M., & Hale, M. (2006b). Bayesian network classifiers for mineral potential mapping. *Computers & Geosciences, 32,* 1–16.

Porwal, A., Das, R. D., Chaudhary, B., Gonzalez-Alvarez, I., & Kreuzer, O. (2015). Fuzzy inference systems for prospectivity modeling of mineral systems and a case-study for prospectivity mapping of surficial Uranium in Yeelirrie Area, Western Australia. *Ore Geology Reviews, 71,* 839–852.

Porwal, A., González-Álvarez, I., Markwitz, V., McCuaig, T. C., & Mamuse, A. (2010a). Weights-of-evidence and logistic regression modeling of magmatic nickel sulfide prospectivity in the Yilgarn Craton, Western Australia. *Ore Geology Reviews, 38,* 184–196.

Porwal, A. K., & Kreuzer, O. P. (2010). Introduction to the special issue: Mineral prospectivity analysis and quantitative resource estimation. *Ore Geology Reviews, 38,* 121–127.

Porwal, A., & Sides, E. J. (2000). A predictive model for base metal exploration in a GIS environment. *International Archives of Photogrammetry and Remote Sensing, XXXIII,* 1178–1184.

Porwal, A., Yu, L., & Gessner, K. (2010b). SVM-based base-metal prospectivity modeling of the Aravalli Orogen, northwestern India. Geophysical Research Abstracts, 12 EGU2010-15171.

Prelat, A. E. (1977). Discriminant analysis as a method of predicting mineral occurrence potentials in central Norway. *Mathematical Geology, 9,* 343–367.

Ranjbar, H., & Honarmand, M. (2004). Integration and analysis of airborne geophysical and ETM+ data for exploration of porphyry type deposits in the Central Iranian Volcanic Belt using fuzzy classification. *International Journal of Remote Sensing, 25,* 4729–4741.

Rigol-Sanchez, J. P., Chica-Olmo, M., & Abarca-Hernandez, F. (2003). Artificial neural networks as a tool for mineral potential mapping with GIS. *International Journal of Remote Sensing, 24,* 1151–1156.

Roberts, R. G., Sheahan, P., & Cherry, M. E. (Eds.) (1988). *Ore deposit models. Geoscience Canada Reprint Series 3*, Geological Association of Canada, Newfoundland.

Rodriguez-Galiano, V. F., Chica-Olmo, M., & Chica-Rivas, M. (2014). Predictive modelling of gold potential with the integration of multisource information based on random forest: A case study on the Rodalquilar area, Southern Spain. *International Journal of Geographical Information Science, 28,* 1336–1354.

Rodriguez-Galiano, V., Sanchez-Castillo, M., Chica-Olmo, M., & Chica-Rivas, M. (2015). Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines. *Ore Geology Reviews, 71,* 804–818.

Rogge, D. M., Halden, N. M., & Beaumont-Smith, C. J. (2000). Mineralization-potential mapping: A data-fusion analysis. In: Report of activities 2000, Manitoba Industry, Trade and Mines, Manitoba Geological Survey, pp. 82–90.

Rogge, D. M., Halden, N. M., & Beaumont-Smith, C. J. (2003). Application of data integration for deformation potential mapping using remotely acquired data sets within the Lynn Lake Greenstone Belt, northwestern Manitoba, Canada. *Canadian Journal of Remote Sensing, 29,* 458–471.

Rogge, D. M., Halden, N. M., & Beaumont-Smith, C. (2006). Application of data integration for shear-hosted Au potential modelling: Lynn Lake Greenstone Belt, Northwestern Manitoba, Canada. In J. R. Harris (Ed.), *GIS for the earth sciences, Geological Association of Canada Special Publication 44* (pp. 191–210). John's: Geological Association of Canada, St.

Rose, A. W., Hawkes, H. E., & Webb, J. S. (1979). *Geochemistry in mineral exploration* (2nd ed., p. 657p). London: Academic Press.

Roy, R., Cassard, D., Cobbold, P. R., Rossello, E. A., Billa, M., Bailly, L., et al. (2006). Predictive mapping for copper–gold magmatic-hydrothermal systems in NW Argentina: Use of a regional-scale GIS, application of an expert-guided data-driven approach, and comparison with results from a continental-scale GIS. *Ore Geology Reviews, 29,* 260–286.

Shabankareh, M., & Hezarkhani, A. (2017). Application of support vector machines for copper potential mapping in Kerman region, Iran. *Journal of African Earth Sciences, 128,* 116–126.

Shabankareh, M., & Hezarkhani, A. (2016). Copper potential mapping in Kerman copper bearing belt by using ANFIS method and the input evidential layer analysis. *Arabian Journal of Geosciences, 9,* 1–12.

Singer, D. A., & Kouda, R. (1996). Application of a feedforward neural network in the search for Kuruko deposits in the Hokuroku district, Japan. *Mathematical Geology, 28,* 1017–1023.

Singer, D. A., & Kouda, R. (1997). Use of neural network to integrate geoscience information in the classification of mineral deposits and occurrences. In: Gubins, A. G. (Ed.), *Proceedings of exploration 97: 4th decennial international conference on mineral exploration* (pp. 127–134).

Skabar, A. A. (2007a). Mineral potential mapping using Bayesian learning for multilayer perceptrons. *Mathematical Geology, 39,* 439–451.

Skabar, A. (2007b). Modeling the spatial distribution of mineral deposits using neural networks. *Natural Resource Modeling, 20,* 435–450.

Stensgaard, B. M., Chung, C. J., Rasmussen, T. M., & Stendal, H. (2006). Assessment of mineral potential using cross-validation techniques and statistical analysis: A case study from the Paleoproterozoic of West Greenland. *Economic Geology, 101,* 1297–1413.

Tangestani, M. H., & Moore, F. (2001). Porphyry copper potential mapping using the weights-of-evidence model in a GIS, northern Shahr-e-Babak, Iran. *Australian Journal of Earth Sciences, 48,* 695–701.

Tangestani, M. H., & Moore, F. (2002). The use of Dempster-Shafer model and GIS in integration of geoscientific data for porphyry copper potential mapping, north of Shahr-e-Babak, Iran. *International Journal of Applied Earth Observation and Geoinformation, 4,* 65–74.

Tangestani, M. H., & Moore, F. (2003). Mapping porphyry copper potential with a fuzzy model, northern Shahr-e-Babak, Iran. *Australian Journal of Earth Sciences, 50,* 311–317.

Thiart, C., & De Wit, M. (2000). Linking spatial statistics to GIS: Exploring potential gold and tin models of Africa. *South African Journal of Geology, 103,* 215–230.

Walshe, J. L., Cooke, D. R., & Neumayr, P. (2005). Five questions for fun and profit: a mineral systems perspective on metallogenic epochs, provinces and magmatic hydrothermal Cu and Au deposits. In J. Mao & F. P. Bierlein (Eds.), *Mineral deposit research: Meeting the global challenge 1* (pp. 477–480). Heidelberg: Springer.

Wright, D. F., & Bonham-Carter, G. F. (1996). VHMS favourability mapping with GIS-based integration models, Chisel Lake–Anderson Lake area. In: Bonham-Carter, G.F., Galley, A.G., & Hall, G.E.M. (Eds.), *EXTECH I: A multidisciplinary approach to massive sulphide research in the Rusty Lake–Snow Lake Greenstone Belts, Manitoba*. Geological Survey of Canada Bulletin 426, pp. 339–376, 387–401.

Wyborn, L. A. I., Heinrich, C. A., & Jaques, A. L. (1994). Australian proterozoic mineral systems: Essential ingredients and mappable criteria. In: *Proceedings of Australian Institute of Mining and Metallurgy annual conference* (pp. 109–115), 5–9 August 1994.

Xu, S., Cui, Z., Yang, X., & Wang, G. (1992). A preliminary application of weights of evidence in gold exploration in Xiong-er Mountain Region, He-Nan province. *Mathematical Geology, 24,* 663–674.

Yazdi, Z., Rad, A. R. J., & Ajayebi, K. S. (2015). Analysis and modeling of geospatial datasets for porphyry copper prospectivity mapping in Chahargonbad area, Central Iran. *Arabian Journal of Geosciences, 8,* 8237–8248.

Yousefi, M., & Carranza, E. J. M. (2015a). Fuzzification of continuous-value spatial evidence for mineral prospectivity mapping. *Computers & Geosciences, 74,* 97–109.

Yousefi, M., & Carranza, E. J. M. (2015b). Geometric average of spatial evidence data layers: A GIS-based multi-criteria decision-making approach to mineral prospectivity mapping. *Computers & Geosciences, 83,* 72–79.

Yousefi, M., & Carranza, E. J. M. (2017). Union score and fuzzy logic mineral prospectivity mapping using discretized and continuous spatial evidence values. *Journal of African Earth Sciences, 128,* 47–60.

Yousefi, M., & Nykänen, V. (2016). Data-driven logistic-based weighting of geochemical and geological evidence layers in mineral prospectivity mapping. *Journal of Geochemical Exploration, 164,* 94–106.

Zeghouane, H., Allek, K., & Kesraoui, M. (2016). GIS-based weights of evidence modeling applied to mineral prospectivity mapping of Sn-W and rare metals in Laouni area, Central Hoggar, Algeria. *Arabian Journal of Geosciences, 9,* 1–13.

Zhang, N., & Zhou, K. (2015). Mineral prospectivity mapping with weights of evidence and fuzzy logic methods. *Journal of Intelligent & Fuzzy Systems, 29,* 2639–2651.

Zhang, N., Zhou, K., & Du, X. (2017). Application of fuzzy logic and fuzzy AHP to mineral prospectivity mapping of porphyry and hydrothermal vein copper deposits in the Dananhu-Tousuquan island arc, Xinjiang, NW China. *Journal of African Earth Sciences, 128,* 84–96.

Zhang, Z., Zuo, R., & Xiong, Y. (2016). A comparative study of fuzzy weights of evidence and random forests for mapping mineral prospectivity for skarn-type Fe deposits in the southwestern Fujian metallogenic belt, China. *Science China Earth Sciences, 59,* 556–572.

Zhou, K., & Zhang, N. (2016). Mineral prospectivity mapping for Porphyry-type and hydrothermal vein-type copper deposits using fuzzy analytical hierarchy process and geographic information system. *Journal of Intelligent & Fuzzy Systems, 31,* 3143–3153.

Zuo, R. (2011). Regional exploration targeting model for Gangdese porphyry copper deposits. *Resource Geology, 61,* 296–303.

Zuo, R., & Carranza, E. J. M. (2011). Support vector machine: a tool for mapping mineral prospectivity. *Computers & Geosciences, 37,* 1967–1975.

Zuo, R., Cheng, Q., & Agterberg, F. P. (2009). Application of a hybrid method combining multilevel fuzzy comprehensive evaluation with asymmetric fuzzy relation analysis to mapping prospectivity. *Ore Geology Reviews, 35,* 101–108.

Zuo, R., Zhang, Z., Zhang, D., Gao, Y., Carranza, E. J. M., & Wang, H. (2015). Evaluation of uncertainty in mineral prospectivity mapping due to missing evidence: a case study with skarn-type Fe deposits in Southwestern Fujian Province, China. *Ore Geology Reviews, 71,* 502–515.