MICA
Minerals Intelligence Capacity Analysis

FACTSHEET

2D Predictivity Mapping

Predictivity (or prospectivity) mapping: a way to reduce the exploration phase, make it more efficient and less intrusive and to discover more rapidly mineral deposits. An overview based on E.J.M. Carranza'synthesis (2011).

Scope (conceptual model & main characteristics)

The following text is based on extracts (simplified) taken from the exhaustive synthesis made by E.J.M. Carranza (2011): 'Geocomputation of mineral exploration targets' (doi: 10.1016/jcageo.2011.11.009).

Mineral exploration endeavors to find ore deposits (i.e., economically viable concentrations of minerals or metals) for mining purposes. Delineation of targets for mineral exploration is the crucial initial stage in a series of mapping activities that may result in ore deposit discovery. The late 1980s through the 1990s saw rapid and far-reaching developments in geocomputational techniques for delineating exploration targets and several papers published in exploration-related literature have explained and documented various GIS-aided and/or GIS-based geocomputational methods for delineating exploration targets.

Mineral exploration target delineation

Delineation of mineral exploration targets is a multi-stage mapping activity from regional to local scales. Every scale of exploration target delineation involves collection, analysis and integration of various thematic geoscience data sets in order to extract spatial geo-information, namely (a) geological, geochemical and/or geophysical anomalies associated with mineral deposits of the type sought and (b) prospective exploration targets, which are areas defined by overlaps of such anomalies. Thus, delineation of exploration targets intrinsically assumes that (a) a target is characterized by evidential features, which are the same as or similar to those of the known locations of mineral deposits of the type sought and (b) if more important evidential features are present in one target than in another, then the former has higher mineral prospectivity than the latter. Therefore, delineation of exploration targets is equivalent to predictive modelling or mapping of mineral potential or mineral prospectivity. The term *mineral potential* refers to the chance or likelihood that mineral deposits of the type sought are contained in an area, whereas the term *mineral prospectivity* refers to the chance or likelihood that mineral deposits of the type sought can be found at every location. The terms mineral potential and mineral prospectivity are therefore synonymous and can be used interchangeably. However, geocomputational modelling of exploration targets must pertain to just one type of mineral deposit. Thus, a model of exploration targets for epithermal Au deposits is not applicable to guide exploration for porphyry Cu deposits, and vice versa.

Geocomputational modelling of exploration targets follows specific steps starting with the definition of a *conceptual model of exploration targets* for mineral deposits of the type sought (Fig. 1). Such a conceptual model is prescriptive rather than predictive, as it specifies in words and/or diagrams the theoretical relationships between various geologic processes or controls in terms of *how* and especially *where* mineral deposits of the type sought are likely to occur. Defining a conceptual model of exploration targets for the deposit-type sought requires knowledge of various geological processes relevant to the formation of the deposit-type sought. That knowledge allows defining key *targeting elements* (or exploration criteria). A conceptual model of mineral exploration targets and the targeting elements provide the framework for predictive mapping of exploration targets in terms of determining suitable (a) geoscience spatial data sets to be used, (b) evidential features to be enhanced and extracted from each data set, (c) method(s) of mapping evidential features from individual geoscience spatial data sets, (d) method(s) of creating predictor maps, and (e) method(s) of integrating predictor maps to create a predictive model or map of exploration targets. The preceding items (b), (c) and (d) constitute the geocomputational analysis of *predictive model parameters*.

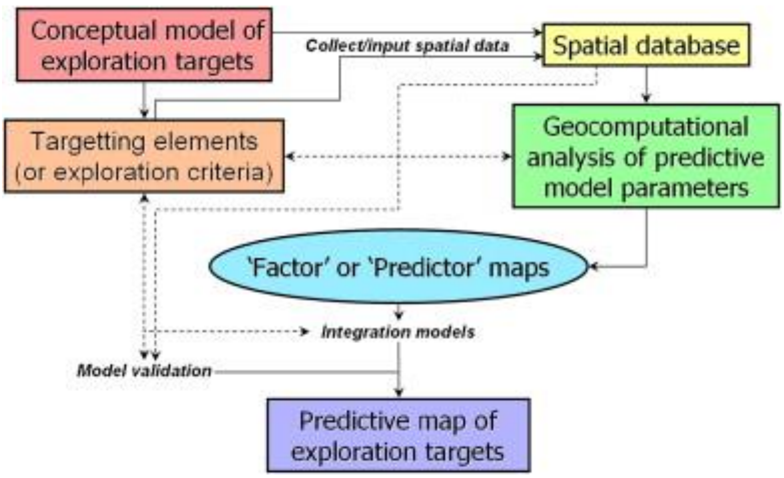

Fig. 1. Elements of predictive modeling of mineral exploration targets.

Creating predictor maps involves assigning weights to evidential features through either knowledge-driven analysis or data-driven geocomputation of their spatial associations with mineral deposits of the type sought (Bonham-Carter, 1994 and Carranza, 2008). Knowledge-driven analysis of spatial associations between evidential features and mineral deposits is appropriate in frontier or less-explored (or so-called 'greenfields') *geologically permissive areas*, where no or very few mineral deposits of the type sought are known to occur. By 'geologically permissive', it is meant that the present or past geological setting of an area represents processes that might have led to formation of certain type(s) of mineral deposits (Singer, 1993). Data-driven geocomputation of spatial associations between evidential features and known deposit-type locations is appropriate in areas representing moderately- to well-sampled (or so-called 'brownfields') *mineralized landscapes* in geologically permissive areas, where the objective is to delineate new targets for further exploration of undiscovered deposits. Methods for data-driven geocomputation of spatial associations between known deposit-type locations and spatial evidence can be either bivariate or multivariate (Table 1).

Model/method	**References to seminal works and recent applications**
Knowledge-driven	
Boolean logic	Bonham-Carter (1994), Thiart and De Wit (2000), Harris et al. (2001b)
Binary index overlay	Bonham-Carter (1994), Carranza et al. (1999), Thiart and De Wit (2000)
Multi-class index overlay	Bonham-Carter (1994), Harris et al. (2001b), Chica-Olmo et al. (2002), De Araújo and Macedo (2002), Billa et al. (2004), Harris et al. (2008)
Fuzzy logic	An et al. (1991), Gettings and Bultman (1993), Bonham-Carter (1994), D'Ercole et al. (2000), Groves et al. (2000), Knox-Robinson (2000), Porwal and Sides (2000), Venkataraman et al. (2000), Carranza and Hale (2001a), Porwal et al. (2003b), 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 et al., 2008a and Nykänen et al., 2008b, González-Álvarez et al. (2010)
Evidential belief	Moon, 1990 and Moon, 1993, Chung and Moon (1991), Moon et al. (1991), An et al., 1992, An et al., 1994a and An et al., 1994b, Chung and Fabbri (1993), Wright and Bonham-Carter (1996), Tangestani and Moore (2002), Chen (2004), Rogge et al. (2006)
Bivariate data-driven	
Weights-of-evidence analysis	Bonham-Carter et al., 1988 and Bonham-Carter et al., 1989, Agterberg and Bonham-Carter, 1990 and Agterberg and Bonham-Carter, 2005, Agterberg et al., 1990 and Agterberg et al., 1993a, Bonham-Carter and Agterberg, 1990 and Bonham-Carter and Agterberg, 1999, Bonham-Carter, 1991 and Bonham-Carter, 1994, Agterberg, 1992 and Agterberg, 2011, Xu et al. (1992), Pan (1996), Rostirolla et al. (1998), Cheng and Agterberg (1999), Raines (1999), Singer and Kouda (1999), Carranza and Hale, 2000, Carranza and Hale, 2002b and Carranza and Hale, 2002c, Pan and Harris (2000), Venkataraman et al. (2000), Asadi and Hale (2001), Mihalasky and Bonham-Carter (2001), Harris et al. (2001b), Porwal et al., 2001, Porwal et al., 2006a and Porwal et al., 2010a, Scott and Dimitrakopoulos (2001), Tangestani and Moore (2001), Agterberg and Cheng (2002), Paganelli et al. (2002), Raines and Mihalasky (2002), Harris et al. (2003), Carranza, 2004 and Carranza, 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), Raines et al. (2007), Feltrin (2008), Ford and Blenkinsop (2008a), Oh and Lee (2008), Austin and Blenkinsop (2009), Debba et al. (2009), Fallon et al. (2010)

Model/method	References to seminal works and recent applications
Evidential belief analysis	Chung and Fabbri (1993), An et al. (1994b), Carranza and Hale (2003), Carranza et al., 2005, Carranza et al., 2008a, Carranza et al., 2008b and Carranza et al., 2008c, Carranza, 2008, Carranza, 2009a and Carranza, 2011, Carranza and Sadeghi (2010)
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)
Characteristic analysis	Botbol et al., 1977 and Botbol et al., 1978, McCammon et al., 1983 and McCammon et al., 1984, Harris (1984), Pan and Harris, 1992a and Pan and Harris, 2000
Logistic regression analysis	Chung, 1978 and Chung, 1983, Chung and Agterberg, 1980 and Chung and Agterberg, 1988, Bonham-Carter and Chung (1983), Agterberg, 1988, Agterberg, 1992 and Agterberg, 1993, Agterberg et al. (1993a), Harris and Pan, 1991 and Harris and Pan, 1999, Sahoo and Pandalai (1999), Pan and Harris (2000), Harris et al., 2001b and Harris et al., 2006, Carranza and Hale (2001b), Raines and Mihalasky (2002), Harris et al. (2003), 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)
Favourability analysis	Pan, 1993a, Pan, 1993b and Pan, 1993c, Pan and Portefield (1995), Pan and Harris, 1992b and Pan and Harris, 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, Singer and Kouda, 1997 and Singer and Kouda, 1999, Harris and Pan (1999), Pan and Harris (2000), Brown et al., 2000, Brown et al., 2003a and Brown et al., 2003b, Bougrain et al. (2003), Harris et al. (2003), Porwal et al., 2003a and Porwal et al., 2004, Rigol-Sanchez et al. (2003), Harris and Sanborn-Barrie (2006), Behnia (2007), Skabar, 2005, Skabar, 2007a and Skabar, 2007b, Nykänen (2008), Pereira Leite and De Souza Filho, 2009a and Pereira Leite and De Souza Filho, 2009b, Oh and Lee (2010)
Bayesian network classifiers	Porwal et al. (2006b), Porwal and Carranza (2008)

Table 1. Models/methods of information/data integration used in geocomputational mapping of mineral exploration targets.

Every method for creating and/or integrating predictor maps has inherent *systemic* (or procedural) errors with respect to interactions of geological processes involved in mineral deposit formation. In addition, every input geoscience spatial data set or mapped evidential features used in geocomputational modelling of exploration targets invariably contains *parametric* (or data-related) errors with respect to distribution of discovered and undiscovered mineral deposits. These errors are inevitable in predictive modelling. However, because such errors are finally compounded into the predictive map of exploration targets, it is imperative to apply measures for *model calibration* and, if possible, to reduce errors through model validation in every step of the geocomputational analysis. Model calibration and model validation aim, of course, at deriving the best possible predictive map of exploration targets because its purpose is to provide opportunity for the discovery of undiscovered ore deposits of the type sought.

Geocomputational tools for understanding mineral systems

Traditionally, it was important in conceptual modelling of exploration targets to apply mineral deposit models (e.g., Cox and Singer, 1986), which describe the specific geological characteristics of certain types of mineral deposits and their regional geological environments. However, adoption of a mineral system approach to delineation of exploration targets (Wyborn et al., 1994) is nowadays advocated because of the recognition that mineral deposits are focal points of much larger systems of energy and mass flux (Hronsky and Groves, 2008). In contrast to the deposit model approach, which relies mainly on using specific geological features as evidence of mineral prospectivity, the mineral system approach to delineation of exploration targets relies on a 5-question paradigm (Price and Stoker, 2002). The five questions, which relate to processes of geologic controls on mineralization, are: (i) What is the architecture and size of the system?; (ii) What is the P-T and the geodynamic history of the system?; (iii) What is the nature of the fluids and fluid reservoirs in the system?; (iv) What is the nature of fluid pathways and processes driving fluid flow?; and (v) What is the chemistry of metal transport and deposition in space as well as time? Czarnota et al. (2010) recently described an application of the mineral system approach to define district-scale targets for orogenic gold in the eastern Yilgarn Craton in Western Australia. Using suitable spatial data, they interpreted and mapped expressions (or spatial evidence or proxies) of processes depicted by each of the five questions. Predictor maps, representing mappable mineral system process proxies (or targeting elements), were then created (by assigning weights to spatial evidence or proxies) and integrated through a multi-class index overlay knowledge-driven approach.

Process understanding of a mineral system is the key to identification of targeting elements. Such understanding can be either conceptual or empirical. Fuzzy logic methods have been used to represent conceptual process understanding of mineral systems. However, Porwal and Kreuzer (2010) argue that predictive modelling of exploration targets can only produce useful results if the spatial data sets used allow modelling of the critical geological processes and elements controlling mineralization. Inversion of geophysical data, which involve various geocomputing algorithms depending on type of data, can provide insights into the architectural elements and physical and chemical properties of a mineral system. Many recent developments in geocomputational techniques for geophysical data inversion are potentially useful for improving our understanding of mineral systems based on geophysical data.

Analyses of the spatial pattern of known mineral deposit occurrences and their spatial association with certain geological features provide empirical spatial geo-information that potentially improves our conceptual understanding of mineral systems (Carranza, 2008). Fry analysis, which is a graphical method of spatial autocorrelation analysis, can be used to infer structural controls on occurrence of certain types of mineral deposits and geothermal fields. Fractal analysis of the spatial distributions of certain types of mineral deposits has been used to infer geologic controls on mineralization. Arias et al. (2011). sought to establish and develop more sophisticated simulation models that incorporate both multifractal concepts and geologic controls on mineralization to derive spatial constraints for predictive mapping of exploration targets.

However, as mineral deposits were formed from fluids, geocomputational modelling of fluid flow has traditionally been important in understanding mineral deposit formation. Recent studies of fluid flow modelling for understanding mineral deposit formation include e.g., using a Lagrangian finite difference code to simulate deformation, fluid flow, and heat transport in porous media for obtaining insights into mineralization, the application of cellular nonlinear networks to simulate mineral zonation or using cellular nonlinear networks to mimic hydrothermal deposit-forming geochemical processes. Such simulation studies resulted in spatial patterns of geochemical components, which provide insights into hydrothermal deposit-forming systems and spatial patterns of expressions of the processes involved.

Geocomputational modelling of mineral exploration target evidence

Mapping (i.e., identifying, enhancing and extracting) of spatial features representing mineralization controls from appropriate spatial (geological, geochemical and geophysical) data is an objective of geocomputational analysis of predictive model parameters (Fig. 1). Methods of enhancing and extracting spatial evidence of mineral exploration targets are specific to evidential themes (i.e., geochemical, geological and geophysical) and types of geoscience spatial data. Various concepts of mapping significant geochemical anomalies (i.e., due to mineral deposits) are now mostly well-established and various GIS-aided and/or GIS-based geocomputational methods are well-documented in the literature (e.g., (Carranza, 2008). However, during the last two decades, methods for fractal/multifractal modelling of significant geochemical anomalies have been developed to consider not only the statistical distributions but also the spatial distributions of geochemical data (Geocomputational methods for mapping of hydrothermal alterations as evidence of mineral deposit occurrence, involve application of remotely-sensed spectral data as well as gamma-ray data (. However, remote sensing of hydrothermal alteration for mineral exploration in vegetated terrains is still problematic, although relative success can be achieved by integration of other suitable spatial data or application of spatial masking techniques Remote sensing using spectral and/or gamma-ray data sets can assist mapping of geological features such as faults and intrusive rocks representing, respectively, structural and heat-source controls on mineralization. However, detecting the presence of such geological features in the subsurface is also possible through geocomputational analysis of geophysical data sets.[2]

Geocomputational tools for integrating mineral exploration target evidence

Harris (1969), Sinclair and Woodsworth (1970) and Agterberg (1971) pioneered the data-driven geocomputational modelling of exploration targets through integration of evidential data by application of probabilistic statistical methods. About a decade later, Duda et al. (1978) and Campbell et al. (1982) proposed artificial intelligence (i.e., knowledge-driven) techniques for assessment and representation of evidential data to locate exploration targets. The period of development of those artificial intelligence techniques was roughly contemporaneous with the period of development of data-driven multivariate statistical techniques (e.g., discriminant analysis, characteristic analysis, and logistic regressionHowever, the proposed artificial intelligence techniques did not gain more popularity than the data-driven statistical methods, probably because the former were subjective and irreproducible compared to the latter. Although the list in Table 1 is not complete, it seems that the most popular GIS-based methods for representing and integrating spatial evidence to map exploration targets are fuzzy logic, weights-of-evidence, logistic regression and artificial neural networks. This is likely due to the freely-available ArcSDM geocomputing tools that implement those four methods in ArcView and in ArcGIS The weights-of-evidence became a popular tool since the late 1980s because it can easily be implemented in a GIS computing platform and, even before the ArcSDM geocomputing tools were developed, a user-friendly computer code – Arc-WofE – was developed as an 'extension' in ArcGIS (+ Spatial Analyst) GIS package - Bonham-Carter and Agterberg (1999). In contrast, logistic regression has been used even before the rapid developments in GIS technology in the late 1980s (Table 1). The most likely reason is that logistic regression is the most appropriate technique for modelling the relationship between a dichotomous variable (e.g., presence/absence of mineral deposits) and several independent variables that do not have to be normally distributed, linearly related or homoscedastic. In addition, the main advantage of logistic regression over weights-of-evidence is that, unlike the latter, the former is not subject to problems associated with lack of conditional independence among predictor maps. Since the late 1990s, artificial neural networks have also become popular for predictive mapping of exploration targets because they are not affected by the lack of conditional independence among predictor maps.

The performances of the most popular data-driven methods and some of the other methods in Table 1 (e.g., evidential belief, discriminant analysis, favorability analysis) are roughly similar. However, artificial neural networks usually outperform discriminant analysis, logistic regression, and weights-of-evidence (Harris and Pan, 1999, Singer and Kouda, 1999 and Harris et al., 2003). However, artificial neural networks, like all the other multivariate data-driven methods (Table 1), cannot cope with missing evidential data. In contrast, the two bivariate data-driven methods – weights-of-evidence and evidential belief – allow representation of missing evidential data (Carranza, 2008 and Agterberg, 2011). In addition, artificial neural networks, like all the other data-driven methods, require a large number of known occurrences of mineral deposits of the type sought for training and creating predictive models of exploration targets. More importantly, unlike the parameters of bivariate data-driven methods and the other multivariate data-driven methods (Table 1), the parameters of artificial neural networks are not interpretable in terms of relative importance of predictor maps. In other words, artificial neural networks do not supplement the mineral system approach to delineation of exploration targets with insights into the inter-play of geologic controls of mineralization. However, recent applications of genetic programming and support vector machines show that machine learning algorithms (like Random Forest algorithm) can help to overcome the 'black-box' limitations of artificial neural networks.

Contexts of use, application fields	-> contexts (e.g., environmental, economic, social assessment) -> which types of stakeholder questions are concerned? -> link to published studies that implement the method

For the last 30 years, predictivity mapping has become very popular as a decision-making tool. Hundred of studies are referenced, published or not and the domain is still developing.

Predictivity mapping is mainly used in target generation for mineral exploration as an answer to one or several question(s). These questions are asked by mining companies or state institutions in view to improve their knowledge in terms of potential ressources and/or their strategy for specific exploration.

Predictivity mapping can also be used for defining the safeguarded area around deposit of public importance (see the docSheet '**Mineral deposits of public importance: the MINATURA2020 Approach'**

Input parameters	-> which parameters are needed to run the method

Every kind of geosciences data is relevant for predictivity mapping. Obviously, the data content must be coherent with the kind of mineralzation searched.

At least, a geological map and a set of known occurrences are required. Additional information related to structural information (e.g., faults), geophysics, geochemistry… can be used to improve the final result.

The differents sets of data must be compatible with their use inside the GIS (Geographical Information System) software. Pre-treatments (i.e., change of coordinate system) might be necessary to guarantee the geographical coherency of data.

It is also assumed that the characteristics of the dataset(s) (e.g., number of data, location of data, data density, scale, data completeness, harmonization, i.e., same encoding rules…) are coherent with the searched phenomenon.

Type(s) of related input data or knowledge needed and their possible source(s)	-> which types of data are needed to run the method, from which sources could they come… -> could be qualitative data or quantitative data, and also tacit knowledge, hybrid, etc.

Two questions have to be answered first! Where, which area? What kind of mineralisations are to be prospected? If needed, an expert can possibly generate the parameters of a specifically sought metallogenic model.

From this, georeferenced geoscientific data is needed, from public domain or specifically surveyed as geological maps, occurrences databases, geophysical surveys as points or grids (and/or interpreted geophysical anomalies), geochemical surveys as pointsor grids (and/or interpreted geochemical anomalies), remote sensing data/interpretation… These data can be validated and/or pre-treated by experts.

Data can be qualitative (geological maps, anomalies) and/or quantitative (geophysical values or geochemical grades). Other data like protected areas can be added to improve the final result in targeting.

If a preliminary model is not mandatory (this depends on the kind of predictivity mapping approach envisaged) the resulting map should be interpreted by an expert who may possibly reject it if inferences drawn from such a map seem dubious and/or incoherent

Model used (if any, geological mathematical, heuristic…)	-> e.g., geological model for mapping -> e.g., mathematical model such as mass balancing, matrix inversion, can be stepwise such as agent -based models, dynamic including time or quasidynamic specifying time series… -> can also be a scenario

Expert driven predictive mapping involves metalogenic models associated with their favourable (and eventually unfavourable) parameters and the predictivity mapping will consist in the combination of these parameters to produce the best targets. (see for example Billa et al., 2004; Cassard et al., 2008)

Data driven predictive mapping involves mathematical calculations and/or analogical analysis to operate the data.

System and/or parameters considered	-> **the system can be described by its boundaries**. These can refer to a geographic location, like a country, or a city, the time period involved, products, materials, processes etc. involved, like flows and stocks of copper, or the cradle-to-grave chain of a cell phone, or the car fleet, or the construction sector, or the whole economy… -> **parameters** could possibly refer to geographic co-ordinates, scale, commodities considered, genesis of ore deposits and others…

Predictivity mapping is applied to a predetermined study area that can be a continent, a country, a province, a mountain range, a sedimentary basin… As a target generation tool, predictivity mapping is more dedicated to studies at regional scale, even if the methodologies involved can be used at a more local scale for specific needs.

Data must be made coherent in term of projection system, of harmonization through the different databases and, if possible, as comprehensive as possible. The opinion of an expert can be required to evaluate data/results relevancy.

Time / Space / Resolution /Accuracy / Plausibility…	-> to which spatio-temporal domain it applies, with which resolution and/or accuracy (e.g., near future, EU 28, 1 year, country/regional/local level…) -> for foresight methods can also be plausibility, legitimacy and credibility…

Predictivity mapping is dependant of data and, possibly of concepts, on which metallogenic models are built. Every addition or renewing of information (i.e., a new geological map or a new geophysical survey) or new concepts can lead to a new study. Calculations algorithms are also supposed to evolve, as concepts,, and predictivity mapping results can be improved with time.

Indicators / Outputs / Units	-> this refers to what the method is actually meant for. Units are an important part but that is most of the time not sufficient to express the meaning. For example, **the indicators used in LCA express the cradle-to-grave environmental impacts of a product or service**. This can be expressed in kg CO_2-equivalent. But also in €. Or in millipoints. Or in m^2year land use. -> for foresight methods the outputs are products or processes

The predictivity mapping study will be realized at a scale compatible with the size of the searched targets and taking into account the characteristics of the initial dataset such as the density of data, and its quality and completeness… .

Treatment of uncertainty, verification, validation	-> evaluation of the uncertainty related to this method, how it can be calculated/estimated

A clue to estimate the accuracy of a targeting map is to produce it with a part of the occurrences (learning dataset) et to check if the result is comparable when the study is performed with the second part of the dataset (control dataset) Some basisc statitistics like histograms and/or cumulative frequencies can also help in improving the results. The analysis of Receiver Operating Characteristic (ROC) curves is a standard method to estimate the accuracy of the results in predictivity mappaing.

The validation of the result maps must be done by expert(s). The ultimate proof will be the field controls.

Main publications / references	-> e.g., ILCD handbook on LCA, standards (e.g. , ISO) -> can include reference to websites/pages -> references to be entered with their DOI

Billa M., Cassard D., Lips A.L.W., Bouchot V., Tourlière B., Stein G., Guillou-Frottier L. (2004). Predicting gold-rich epithermal and porphyry systems in the central Andes with a continental-scale metallogenic GIS. Ore Geology Reviews 25 (2004) 39 – 67. **doi:10.1016/j.oregeorev.2004.01.002**

Bonham-Carter G.F. (1994). Geographic Information Systems for Geoscientists*:* Modelling with GIS. Pergamon, Oxford, 398 pp.
https://www.elsevier.com/books/geographic-information-systems-for-geoscientists/bonham-carter/978-0-08-041867-4

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Cassard D., Billa M., Lambert A., Picot J.-C., Husson Y., Lasserre J.-L., Delor C. (2008). Gold predictivity mapping in French Guiana using an expert-guided data-drivenapproach based on a regional-scale GIS. Ore Geology Reviews, 34, pp. 471-500. **DOI: 10.1016/j.oregeorev.2008.06.001**
http://www.academia.edu/29636336/Gold_predictivity_mapping_in_French_Guiana_using_an_expert-guided_data-driven_approach_based_on_a_regional-scale_GIS

Hastie T., Tibshirani R., Friedman J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer, Stanford (2009). **DOI: 10.1007/b94608**

Knox-Robinson, C.M. and Groves, B.I. (1997). Gold prospectivity mapping using a Geographic Information System (GIS) with examples from the Yilgarn Bolck of Western Australia. Chronique de la Recherche Minière, 529, pp. 127-138.

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https://pubs.er.usgs.gov/publication/70011613

Nykänen V. (2008). Spatial data analysis as a tool for mineral prospectivity mapping. GSF-2008

Schaeben H. (2011). Comparison of mathematical methods of potential modeling. Math. Geosci., 44, pp. 101–129. **DOI: 10.1007/s11004-011-9373-2**
https://link.springer.com/article/10.1007/s11004-011-9373-2

Silverman B.W. (1986). Density estimation for statistics and data analysis, Monographs on Statistics and Applied Probability. Chapman and Hall/CRC, London (1986), pp. 7–11
https://ned.ipac.caltech.edu/level5/March02/Silverman/paper.pdf

Tourlière B., Pakyuz-Charrier E., Cassard D., Barbanson L., Gumiaux C. (2015). Cell Based Associations: A procedure for considering scarce and mixed mineral occurrences in predictive mapping. Computers and Geosciences, Elsevier, 78, 53-62. **doi: 10.2016/j.cageo.2015.01.012**

Related methods	-> List of comparable methods, their particularities… -> link to one or several other existing fact sheet(s)

CBA is a new method developed in BRGM in view to address some problems of the methods described by Carranza by the use of:

- A regular gridding of the study area (Cells),
- A replacement of the relation point<->polygon by a relation point<->environment inside each cell of the grid (Association),
- A presence/absence coding (1/0) of all the events (i.e; geological formations) present on the study area in each cell of the grid,
- A classification or a ranking of the associations contained in the cells.

CBA involves a reduction of the resolution of the original data compensated by the consideration of the more complex environment coded in each cell.

- CBA can minimize the problem of location errors,
- CBA is coupled to a numerical approach of the association (HAC and/or ranking),
- CBA is able to distinguish different favourable environments and caracterize them,
- Non relevant formations can be eliminated form the calculations e.g., alluviums),
- CBA allows the combination of all types of spatialized data.

Caution:

- Size of the cells and grid positioning are critical parameters,
- Irrelevant formations can affect the results,
- Grids and classifications are not transposable,
- Scale coherency in data is preferable.

Some examples of operational tools (CAUTION, this list is not exhaustive)	-> e.g., software… Only give a listing and a reference (publication, website/page…) -> **should be provided only if ALL main actors are properly cited**

GIS tools:

- ArcMap (ESRI) and its extensions (Spatial Analyst, ArcSDM)
- QGis

Standard software for pre-treatments:

- Excel
- Access

Key relevant contacts	-> list of relevant **types** of organisations that could provide further expertise and help with the methods described above.

BRGM (http://www.brgm.fr/)

GTK (http://en.gtk.fi/))

GEUS (http://www.geus.dk/UK/Pages/default.aspx)

BEAK Consultants GmbH (http://www.beak.de/beak/de/home)

Glossary of acronyms /abbreviations	-> Definition
GIS	Geographic Information System