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CELL BASED ASSOCIATIONS, A PROCEDURE FOR CONSIDERING SCARCE AND MIXED MINERAL OCCURRENCES IN PREDICTIVE MAPPING

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Abstract

Cell Based Association is an innovative mineral favorability procedure designed to answer special needs of the mining industry in data wise critical situations where usual favorability methods may not yield satisfactory results. Those situations relate to input data quality (e.g.: clustered points, mixed and scarce data, approximate location) or some assumptions that are considered unreasonable (e.g.: map areas relevance, conditional independence).

The principle of CBA consists in replacing polygons of geological units with a square cell grid (hence the 'cell-based'). Each cell contains a range of units ('association') that are binary coded in terms of their presence (1) or absence (0) within study area. The loss of resolution inherent to this procedure is compensated by the enriched information contained in each cell owing to the notion of (lithological) association.

Lithological associations are considered as binary spectra and as such are classified using Ascendant Hierarchical Clustering (AHC) thus obtaining a synthetic map of lithological associations. The prospectivity map shows as favorable the cells of the same AHC classes that the ones including mineral occurrences.

It was observed that CBA can distinguish between different ore deposit varieties from a blended mineral occurrences data set. CBA can theoretically include any spatialized data (e.g.: geophysics,

36 structural data) as an extra variable to specify classification and narrow favourable areas. Doing so
37 would make it an independent favorability mapping procedure and is still under development.

38 Cell size in a grid is a critical parameter of the procedure; it must be compatible with the
39 looked-for phenomena and should have a sufficient lithological variability.

40 In addition to its use for producing favorability maps, a CBA-derived map could help in
41 understanding the background information contained in geological maps. CBA can also be applied
42 to other fields, such as agriculture and urban planning.

43

44 Key words: Favorability mapping, grid cell, classification, attribute association

45

46 1. Introduction

47 Mineral favorability is a branch of predictive analytics that focuses on designing statistical methods
48 to point out favourable zones in terms of mining potential.

49 From Carranza (2009) : *"The term mineral prospectivity (...) is similar to the terms mineral potential*
50 *and mineral favourability, both of which imply the chance or likelihood that mineral deposits of the*
51 *type sought are contained in a region or district under investigation. (...)*

52 *Modeling of mineral prospectivity is a regional- or district scale mapping activity, whether field*
53 *based or GIS based, which aims to delineate prospective areas for further exploration at the next*
54 *higher scales of mapping. Notwithstanding the scale of mapping, mineral prospectivity is related to*
55 *the degrees of presence and degrees of importance of individual pieces of spatial evidence of*
56 *occurrence of mineral deposits of the type sought. That is, in a region or district under*
57 *investigation, if there are more important pieces of spatial evidence in an area than in another*
58 *area, then the former is considered to have higher prospectivity than the latter".*

59 The most basic case relates to measuring the statistical link between a mineral occurrence (MO)
60 data set (points) and a geological map (polygons). This can roughly be translated as finding what
61 makes places where mineral occurrences were observed distinguishable and trying to target
62 similar locations.

63 End result is often a favorability map that displays the odds of finding something of interest.

64 Cell Based Association (CBA) is meant to be used during the strategic stages of exploration when
65 available data often does not meet the requirements (independence, representativeness of MO) of
66 usual favorability methods such as Weight of Evidence, Fuzzy Logic, Artificial Neural Networks to
67 be used effectively (Bonham-Carter, 1984, Carranza, 2011, Schaeben, 2011)).

68 Usually the requirements are not met due to poor quality of the mineral occurrence data set.

69 Indeed, the mineral occurrence data set is normally considered as a unique representative sample
70 of unique elements of a single population (or at least a known number of different populations).

71 This is not always the case as mineral occurrences data sets are most of the time classified
72 according to the (potential) resource observed (e.g.: zinc mineral occurrences) which can lead to
73 mixing different types of mineral occurrences that relate to different genesis processes (hence

74 different lithological environments) into a single mineral occurrence data set. Ultimately this means
75 the user will obtain a mixed favorability map that, at best, roughly ranks the different types of
76 mineral occurrences on a single scale that may make no sense because each type should be
77 analysed separately from the others or, at worst, a global fuzzy favorability map that makes even
78 less sense.

79 Also, when the mineral occurrences data set is too scarce it is impossible to assess if it is
80 representative which is one major assumption/requirement of most favorability methods.

81 Lastly, considering each mineral occurrence as individual leads to an overestimate of the
82 importance of clustered areas that in fact describe a single object geologically wise which is even
83 more critical in the case of mixed mineral occurrence data sets.

84 To address these problems, we propose a procedure called 'Cell-Based Associations' (CBA).
85 Using a square grid (of appropriate cell size fixed by user) in which each cell records the presence
86 or absence of lithological units from the geological map and a hybrid driven (combining data and
87 user driven approaches) classification of all cells, this procedure allows to generate a synthetic
88 map that can be coupled to the mineral occurrence data set. CBA thus allows better
89 characterization and sorting of a number of different complex environments associated with the
90 looked for phenomena.

91

92 A technique consisting in applying a grid with included attributes over a study area was
93 previously described by McCammon et al. (1983) for generating predictive maps, but rather than
94 using their Characteristic Analysis method of data processing of a logical type, CBA uses statistical
95 ranking of coded cells for identifying the different associations/environments contained in the map.

96

97 **2. The principles of CBA**

98 The case study presented here in for illustrating the principles of the CBA procedure is a mapping
99 of mineral favorability, where the points are mineralized occurrences (MO) and the polygons are
100 geological units (lithologies). The artificial map in Figure 1 shows the type of document used by
101 geologists when looking for prospective areas that are *a-priori* favourable to the presence of
102 mineralization. On this map, mineral occurrences are present in the B, D and E units. Occurrence

103 "OCC-4" is located in unit C, but its position very close to the limit between units E and D might be
104 imprecise.

105 The CBA procedure was applied to that dataset. First, the optimal cell size of the grid
106 had to be defined. This size relies on two main constraints: 1) it should be coherent with the size of
107 the studied phenomena (Carranza, 2009), and 2) it must allow a sufficient variability of the
108 geological units. Too small cells will contain only one unit, but too large ones will contain too many
109 (if not all) units.

110 The relationship between the variability inside the grid cell and its size has been studied in
111 the dataset in order to define the optimized size for a cell. Variability has been estimated using 2
112 parameters: the average number of geological units per cell and the number of lithological spectra
113 (or associations, see definition below) generated by the 'cut-out' of the map by grids with different
114 cell sizes (Table 1). The graphic representation (Figure 2) of this result shows that the optimal size
115 of a cell ranges from 7 to 12 km (side length of square cells), which corresponds to a number of
116 spectra comprised between 15 and 17 (for a theoretical maximum of 36 [i.e. 2^5] possible
117 combinations, 17 being the maximum number of combinations present in the map) and an average
118 number of lithologies per cell ranging from 1.8 to 2.2 (Table 1). In this example, the cell size was
119 arbitrarily set at 10 km that is between 7 and 12km.

120 Once the cell size has been defined by user, the grid is generated and superimposed on the
121 geological map (Figure 3). All cells have for attributes all the units represented in the map. The
122 geological information contained in each cell is coded as presence = 1 or absence = 0 of each
123 geological contained in the map (Figure 4 and Table 2). Each cell is then characterized by a
124 binary-type attribute spectrum showing the presence/absence of each unit within it. There is thus a
125 transition from a discrete categorical variable (rock type) to a set of binary variables describing a
126 lithological spectrum or – more generally - an attribute spectrum. This operation does not consider
127 the relative or absolute surface of the geological units, but only their presence or absence. This
128 reasoning is based on the idea that the projected surface of a unit on a geological map is irrelevant
129 for determining its real importance as a small area unit may be the critical factor that determines a
130 particular lithological environment (e.g.: dyke fields) or may be the end of a much larger body (e.g.:
131 plutonic intrusion) it also may be partially masked surficial deposits. It seems preferable to

emphasize the presence of poorly represented units than to lose that information because mining favorability is ultimately a 3D problem. The processing of each unit as an independent binary variable assumes that a geological map is a combination of exclusive events, in other words: at every location of the map a single lithology may be observed.

This technique avoids the loss of attribute information (Bai et al., 2011) and renders it directly usable for multivariate analysis. The maximum number of possible combinations is 2^n , where n is the number of attributes, here geological units. If the number of attributes is large, the individual processing of all present combinations becomes impossible, implying the need to use a method that allows grouping the attribute spectra into representative classes of existing combinations.

Same processing should have been possible in raster mode but that implies a multiplication of layers (one per unit) and a possible loss of information for small surface covering units. The creation of a single table containing all the attributes is less time consuming, makes it easier to treat and is coherent with the notion of spectrum created by concatenation of the attributes.

In the present work, the hybrid driven Ascendant Hierarchical Clustering (AHC) method has been used to classify the associations within the cells.

147

3. The principles of AHC

AHC uses a system of aggregation by pairs of elements according to: 1) their proximity based on a dissimilarity function that measures the multivariate statistical distance between the elements; and 2) an aggregation function that groups those that are iteratively the closest (Rolet and Seguin, 1986)

In the present case, the calculation relies on a dissimilarity index based on "percent disagreement" (Equation 1) and an aggregation function based on the reciprocal neighbours method (Rham, 1980) after centring and reduction of the data.

The dissimilarity index is as follows:

$$dP(I_i, I_j) = \frac{\text{number of } (x_{ik} \neq x_{jk})}{K} \quad (1)$$

Where i and j are the identifiers of the compared elements I, k is the variable (geological unit) identifier, x is the variable value, and K the number of variables (number of units). This type of

160 dissimilarity function is used for variables of the categorical/discrete type, and is the most suitable
161 for evaluating the distance between elements.

162 However, in our specific case it is also possible to use the usual Euclidean distance
163 (Equation 2) as it is easier to apply instead of the dissimilarity function.

$$164 \quad dE(I_i, I_j) = \sqrt{\sum_k (x_{ik} - x_{jk})^2} \quad (2)$$

165 For this, equations 3.1 to 3.2 are used. As x can only take the values 0 or 1, we have:

$$166 \quad \sqrt{\sum_k (x_{ik} - x_{jk})^2} = \text{number of } (x_{ik} \neq x_{jk}) \quad \forall x = \{0,1\} \quad (3.1)$$

168 Where

$$169 \quad dE(I_i, I_j) = dP(I_i, I_j) * K \quad \forall x = \{0,1\} \quad (3.2)$$

170 Where i and j are the identifiers of the compared elements I (cells), k the variable (unit) identifier, x
171 the value of the variable, and K the number of variables (units).

172 The choice of Euclidian distance is arbitrary as it is the most "intuitive" but other kind of distance
173 could be used as Manhattan distance for example. The aggregation factor for classes is minimum
174 in-class variance. Varying those parameters could lead to significantly different results in
175 classification that have not been tested.

176 AHC produces a binary hierarchical grouping of the attributes characterizing each element in
177 a class. The quality of such grouping progressively degrades with a diminishing number of classes
178 (Hastie et al., 2009). This is generally expressed as a dendrogram (Figure 5) showing intermediate
179 grouping results and their hierarchical relations, which allows to select the number of classes to
180 represent lithological environments. That number of classes is based on the morphology of the
181 dendrogram and has to be balanced by the user between a low level of aggregation (numerous
182 classes) that will give a fine description of lithological associations with the risk to describe very
183 local associations and a high level of aggregation (few classes) that will be too comprehensive and
184 thus not applicable to the searched result. Once the level of cutting chosen by the user, an attribute
185 is added to the table to store the AHC class attribute (Table 3) in order to mark the classes
186 attributed to each cell, each class corresponding to a group of associated units.

187 It is also possible to calculate classification quality for each cell and each level. This quality
188 criteria corresponds to the Euclidean distance between the cell and the barycentre of the class to
189 which the cell belongs. The quality value associated with each cell ('Qual' columns in Table 3) thus
190 shows the strength of the link between the cell and its attributed class. This parameter ideally
191 should be 0, but this is conceptually impossible when grouping the lithological associations by
192 using AHC. This quality parameter is useful for comparing different classification levels (number of
193 classes) of the same dataset.

194

195 **4. Results**

196 Figure 6 shows a cartographic plot of classes and thematic analysis for a 10 class cut-off of
197 the dendrogram.

198 Cells of the same class do not exactly present the same lithological spectrum. This is the
199 case, for instance, for the four cells of class 7 (no filling) from which 2 are of type 00110 and 2 of
200 type 00111. The grouping of class 7 was thus based on a common spectrum of type 0011x (x
201 being 1 or 0). Class 5 (horizontal and vertical cross-hatching) shows a similar case with a spectrum
202 of the 01x11 type and class 10 (left inclined wide-spaced hatching) with a spectrum of the 1x101
203 type. This clearly illustrates that classification quality decreases along with the number of classes.
204 Nevertheless, the fundamental characteristics of the associations forming the classes are
205 conserved.

206 Producing the favorability map (Figure 7) consists in (i) selecting the classes of the cells that
207 contain occurrences, and (ii) extracting all the cells showing one of the favourable classes. In this
208 example, cells of class 6 (association of units D and E), 7 (units C, D and E) and 8 (units C and D)
209 are associated to mineral occurrences and are, thus corresponding to geological environments
210 favourable for the presence of mineralisation. In this example, other classes do not contain any
211 occurrence and are thus considered as non-favourable

212

213 5. Discussion

214 The CBA procedure goes counter to the natural tendency of trying to obtain the finest
215 possible resolution. CBA, on the contrary, aims to define an **association** of elementary signatures
216 present in a larger area, rather than looking for the smallest elementary signature possible. This
217 led to the idea of considering a larger cell that integrates an environment defined as the presence
218 or absence of all lithological units in the study area.

219 Moreover, this type of approach mimics the thought process of geoscientists as it associates
220 phenomena with a multifactorial context rather than a single criterion. In mineral exploration, for
221 instance, the exploration geologist will favour a complex geological setting over a single unit (e.g.
222 Billa et al., 2004; Roy et al., 2006; Cassard et al., 2008).

223 Cell size is a critical parameter to the procedure and must comply with two major constraints:
224 coherence with the size of the phenomena of interest (Carranza, 2009), and sufficient variability of
225 the attributes per cell. For correct operation of the procedure, the cells should neither be too small
226 (mono-attribute cells that pixelate the map), nor too large (cells containing most or all attributes). It
227 also is the cell size parameter that allows CBA to deal with over and under sampling issues of the
228 mineral occurrence data set.

229 As discussed in section 2, given that the MO display minute to no clustering effect, a grid of
230 suitably-sized meshes can be calculated, based on the variability of the lithology parameter
231 estimated either on the average number of unit contained in grid cells or on the number of unique
232 lithological associations 'generated' by this grid. Conversely, statistics based on MO spatial
233 behaviour (i.e. "kernel density method for univariate data" (Silverman, 1986) or "pair correlation
234 function $g(r)$ " (Van Leeuwen et al, 1959)) may be used as indicators to optimize cell size
235 provided that they allow for sufficient variability of the units in the cells. As a last resort, the size of
236 the cells is a decision of the user who must reconcile a size compatible with the map(s) scale and
237 the searched for events. CBA, as described in this paper, is based on a regular grid, but it will
238 work just as well with cells of variable size adapted to the influence of the units, so as to limit the
239 number of mono-attribute cells.

240 The idea of 'specific surface' of a unit, whether by cell or within the study area, was
241 considered as irrelevant as this is a variable induced by the intersection between topography and
242 units that may be partly covered by overlapping units. It is supposed that the area of a mapped unit
243 is not a critical criterion and that mineral deposits are likely to be linked to "rare" units as much as
244 more frequent ones. This is why only existence is taken into account (0 or 1) which in return
245 favours presence over absence: it highlights details over global trends because we consider that
246 only the proximity to observed MO is important in this case.

247 CBA uses positive reasoning assuming that "non-links" are impossible to demonstrate. In reality, it
248 is impossible to conclude that the absence of a certain unit reduces the odds of finding a MO.
249 Geological maps and geologists observation are never perfect and, having no MO in a certain
250 lithological setting does not make it unfavourable, it makes it non-favourable. As such, positive
251 reasoning (observations lead to consider the environment in which they are found as favourable)
252 should be preferred over negative reasoning (environments in which no observation are found are
253 unfavourable). Ultimately, this relates to the way field geologists work, describing the environment
254 where the presence of MO proves that it is a favourable one, whatever are the respective surfaces
255 of the units on the geological map.

256 For other subjects, however, such as agricultural or town-planning studies, this surface factor may
257 be introduced as the respective percentage covered by each attribute in the cell, with 0 indicating
258 its absence. This type of approach has not yet been tested but could be an interesting
259 development of this work.

260 For cell ranking, the Ascendant Hierarchical Clustering (AHC) has been selected because, in
261 addition to being a hybrid driven classification function, it produces a hierarchical tree
262 (dendrogram) that shows the relations between the different classes. The number of classes is a
263 user decision helped by the shape of the branches of the dendrogram and the level of details he
264 requires. Based on the cut-off level (i.e., the number of classes) of the tree, the classes will be
265 more or less informative, thus more or less focused on relevant lithological spectrum. For rather
266 low cut-off levels (i.e., few classes), AHC commonly produces a "garbage" class that covers all
267 cells poorly classified for this level. In the case of several occurrences falling within this class, it is
268 however always possible to extract the related cells for an independent re-classification.

269 Other methods of multivariate classifications – as, for example, IsoData, K-means clustering - may
270 yield different results. They are still to be tried.

271 The result obtained from such data processing is a new synthetic map of the assemblage of
272 classified cells showing the different groups of associations in the study area.

273 Family of cells containing MO will be regarded as favourable and the capability of the procedure to
274 describe the contained association of lithologies is helpful for exploration teams to point out the
275 cells showing the same environment than the ones with MO. Even in that case, results must be
276 interpreted to check their relevance.

277 CBA can induce a bias for points located near a cell boundary that might correspond to a
278 different lithological spectrum from that effectively favourable. This drawback is limited if the
279 number of occurrences is sufficiently large. However, if too many showings lie close to cell
280 boundaries, it may be necessary to shift the grid origin or change the cell size (Pakyuz-Charrier,
281 2013).

282 According to points presented and discussed here above, predictive results of the CBA
283 procedure could possibly be further improved by:

- 284 - Ignoring specific units (such as alluvium) that clearly are irrelevant to the phenomenon
285 looked for. Classification will then be based on a partial lithological spectrum, which might
286 improve the quality of the result.
- 287 - Introducing relevant parameters into the cells that come from other thematic layers, such
288 as the presence/absence of faults or geophysical anomalies. Such additional attributes
289 enrich the information contained in the spectrum and can be used for classification, which
290 then becomes multi-thematic. The approach would then shift from a "bivariate-data driven"
291 to a "multivariate-data driven" method (Carranza, 2011) that resembles McCammon's
292 "characteristic analysis" (1983).
- 293 - Producing more relevant classes by using other classification methods.

294 In supervised mode, CBA can be used by processing only cells that contain occurrences,
295 provided they are sufficiently numerous for statistical processing. In this case, only the lithological
296 spectra associated to mineralization would be classified. A predictive map would then be produced
297 by selecting all cells with comparable spectra to those deriving from the classification. This

298 approach (Cassard et al., 2012; Tourlière et al., 2012) is not illustrated here. In simple cases, it
299 may allow dispensing with classification, becoming comparable to the "characteristic analysis"
300 approach (McCammon, 1983).

301

302 In addition the synthetic map produced by spectra classification with the CBA procedure can help
303 in (i) interpreting a thematic map and (ii) highlighting the presence of distant but similar association
304 areas.

305

306 **6. Conclusions**

307 The Cell-Based Associations (CBA) procedure was developed for overcoming the limitations
308 caused by low quality input data sets often used in early stages of mining exploration.

309 Application of a cell grid (*'cell based'*) of suitable size (fixed by the user) over a study area
310 and the coding of the units found in each cell as 1 (presence) or 0 (absence), allows obtaining a
311 binary attribute spectrum (*'association'*) that can be statistically classified.

312 Decrease in resolution of the original data induced by the procedure is compensated by the
313 concept of association that, after classification, allows the extraction and regrouping of more
314 complex environments and their cartography as a synthetic map.

315 This approach better considers the complexity of geological phenomena favouring the
316 presence of mineralization and is able to distinguish different types of favourable lithological
317 environments. It is also possible to integrate data from other thematic layers (e.g., tectonic
318 structures, geophysical properties...) into the cells which enriches the attribute spectrum, thus
319 opens the possibility of creating multi-thematic synthetic maps.

320 As presented in that paper, CBA can be a guide to mining exploration essentially at strategic scale
321 when the mining occurrences are scarce or clustered and units areas are irrelevant or small areas
322 are suspected to be important.

323 The hybrid driven statistical method (Ascendant Hierarchical Clustering) has been used in
324 this study for calculating the grouping of geological environments by cell but other methods of
325 classification can be relevant too. CBA can also be used as a dataset for predictive methods of the
326 supervised type by using cells containing showings as learning sets.

327

328 Apart from any search for predictions the CBA procedure produces a synthetic thematic
329 representation that may help in the interpretation of complex and/or very large scale maps.

330

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337

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Mis en forme : Anglais (États Unis)

Mis en forme : Espagnol
(International)

391 Figures :
 392 Figure 1: Geological map and mineral occurrences (theoretical example)
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 411 levels in the dendrogram. Whole numbers correspond to the lithological association for a given cell
 412 and for a set cut-off level (see Figure 5). 'Qual' measures the quality of each cell in terms of the
 413 dissimilarity between it and the multivariate centre of gravity of the class comprising the cell
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 416

**CELL BASED ASSOCIATIONS, A PROCEDURE FOR CONSIDERING SCARCE AND MIXED
MINERAL OCCURRENCES IN PREDICTIVE MAPPING**

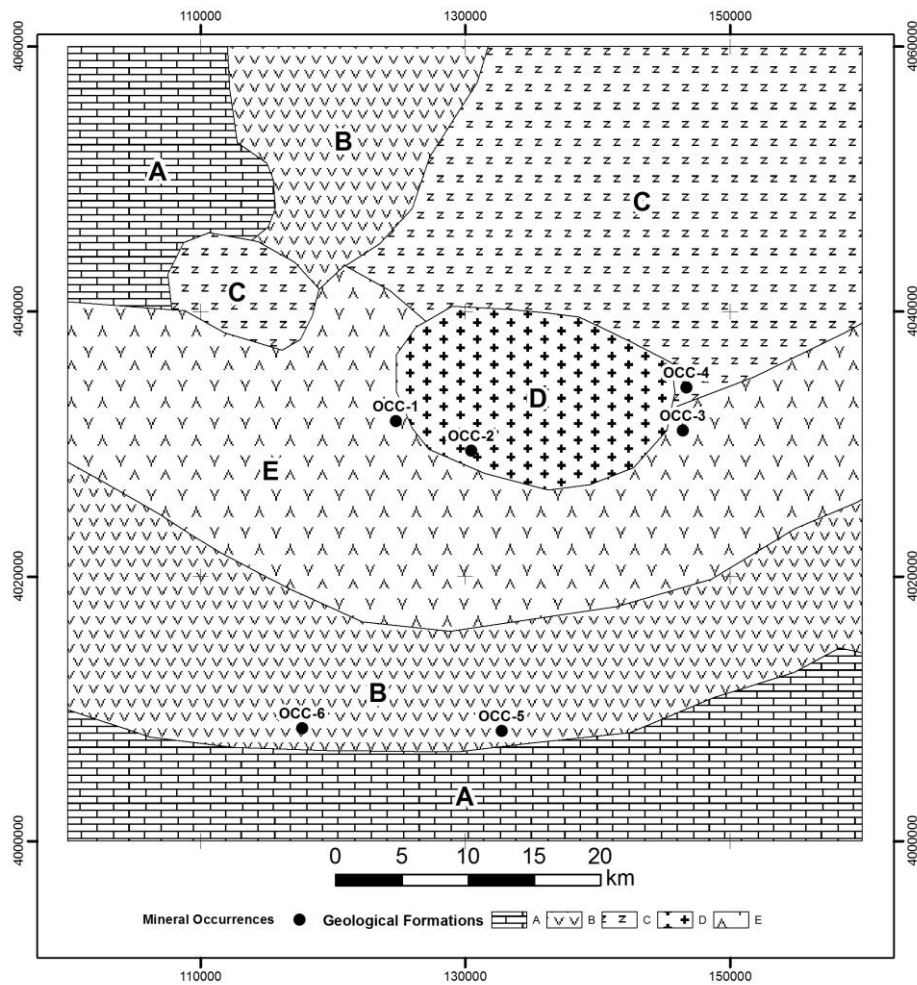


Figure 1: Geological map and mineral occurrences (theoretical example)

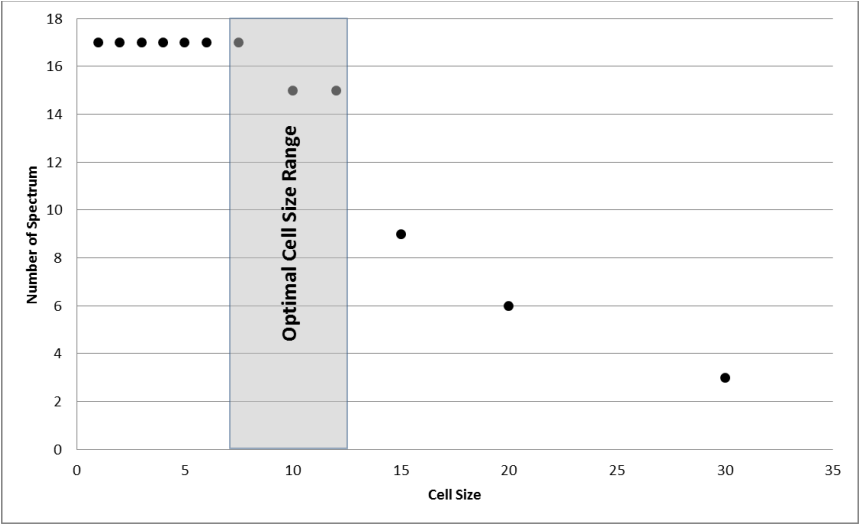
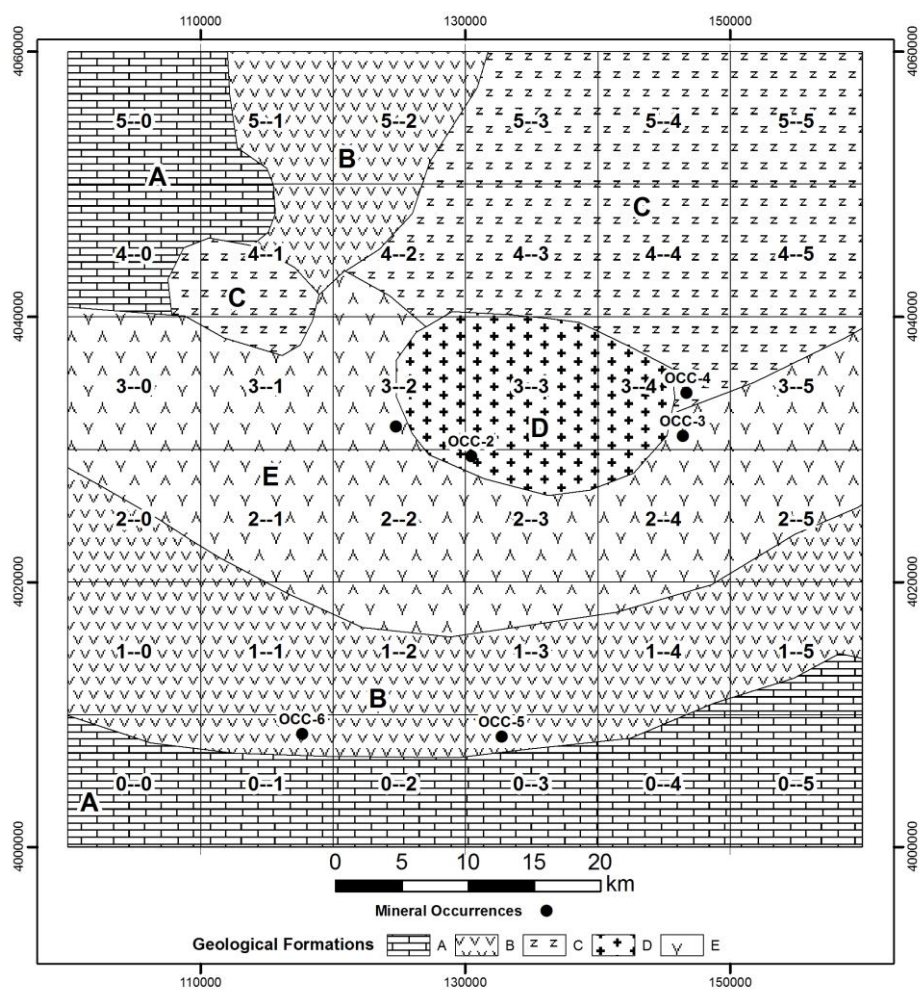
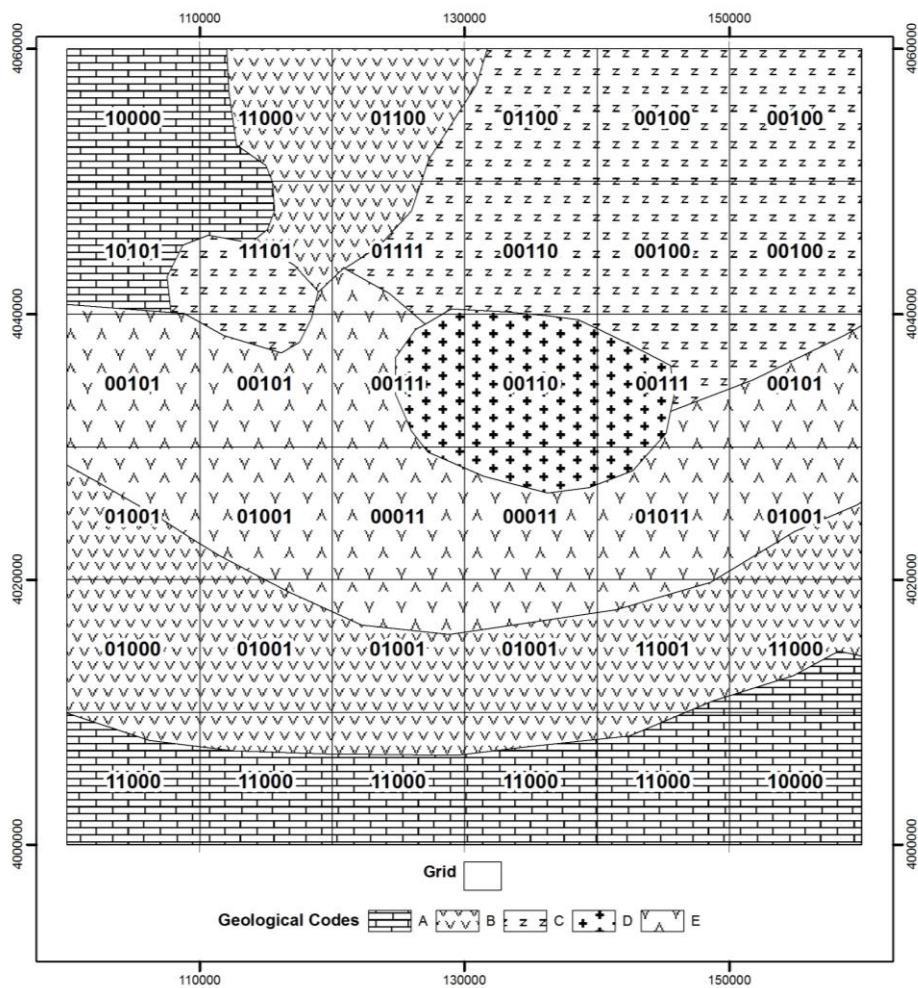


Figure 2: Optimal cell size range estimated by the number of different spectra generated by the gridding



430

431 Figure 3: Grid mesh of 10 km applied to the geological map of Figure 1 and numbering of cells



432
433 Figure 4: Grid applied to the geological map of Figure 1 and binary coding of the lithological spectra of cells

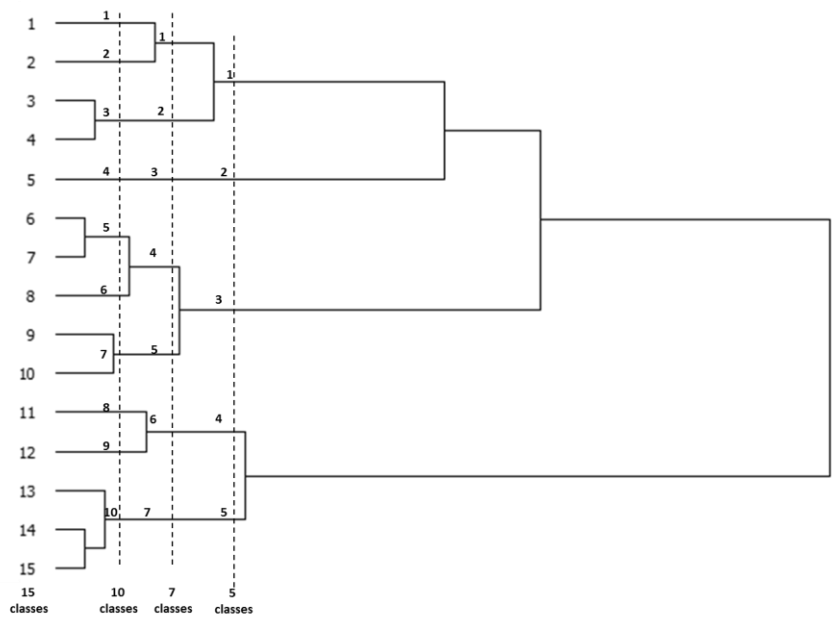
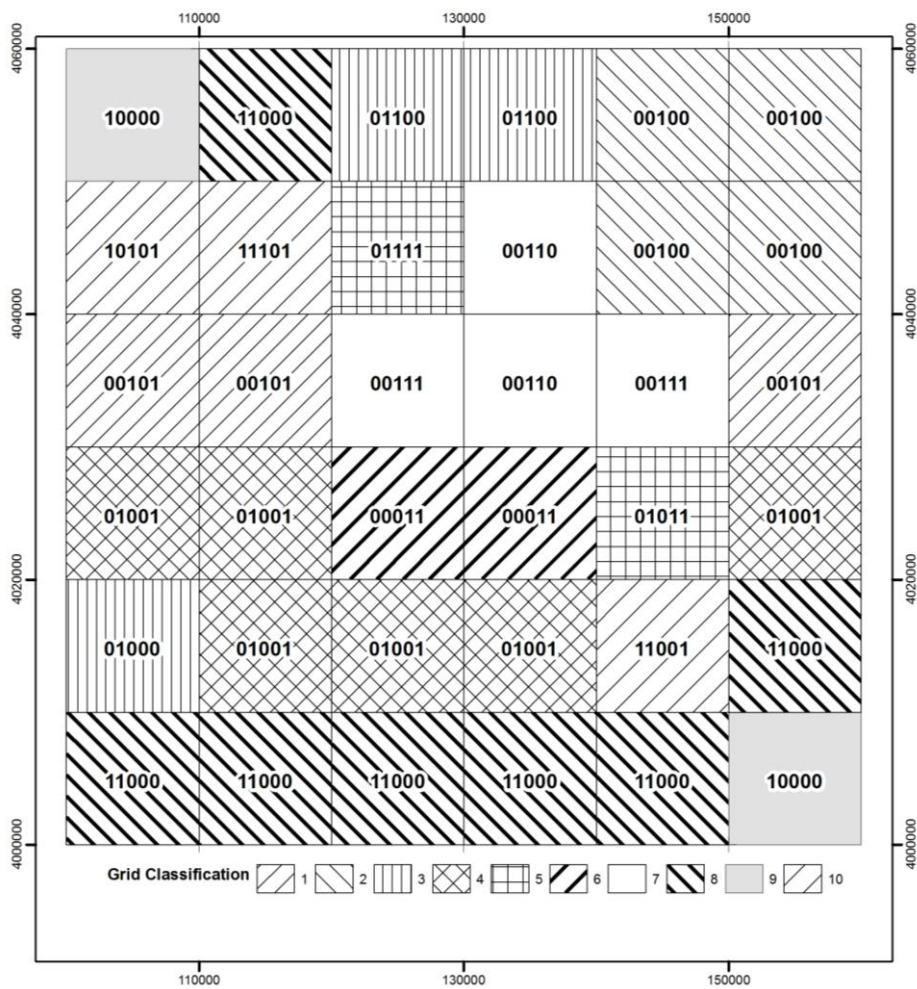


Figure 5: Dendrogram of lithological associations; data are those of Figure 4; dotted lines indicate cut-offs according to the desired number of classes (15, 10, 7 and 5 classes)



440
 441 Figure 6: Result of cell classification with AHC in the case of a cut-off at 10 classes. The binary series correspond to the
 442 lithological spectra of the different cells (Figure 4)

443

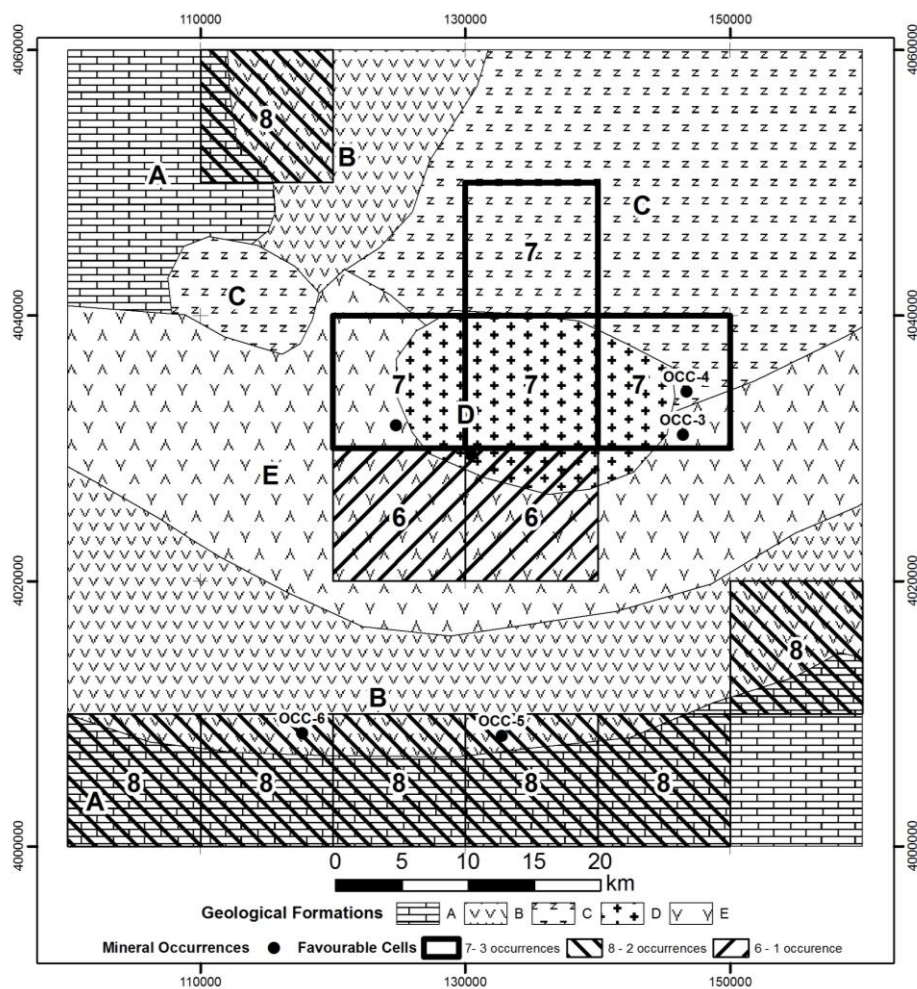


Figure 7: Favorability map: cells of the same class as those containing occurrences, bold numbers indicating the class of association.

Number of cells	Cell size (km)	Average number of lithologies by cell	Number of Specific lithologic spectra	Number of cells with occurrences
4	30	4.25	3	4
9	20	3.11	6	4
16	15	2.56	9	5
25	12	2.16	15	4
36	10	2.06	15	5
64	7.5	1.78	17	5
100	6	1.57	17	5
144	5	1.51	17	5
225	4	1.4	17	6
400	3	1.3	17	6
900	2	1.2	17	6
3600	1	1.1	17	6

Table 1: Relationships between the cell size and the lithological variability. Grey area = optimal cell size range.

Formations								Formations						
Cell#	A	B	C	D	E	Lithological Spectrum		Cell#	A	B	C	D	E	Lithological Spectrum
0--0	1	1	0	0	0	11000		3--0	0	0	1	0	1	00101
0--1	1	1	0	0	0	11000		3--1	0	0	1	0	1	00101
0--2	1	1	0	0	0	11000		3--2	0	0	1	1	1	00111
0--3	1	1	0	0	0	11000		3--3	0	0	1	1	0	00110
0--4	1	1	0	0	0	11000		3--4	0	0	1	1	1	00111
0--5	1	0	0	0	0	10000		3--5	0	0	1	0	1	00101
1--0	0	1	0	0	0	01000		4--0	1	0	1	0	1	10101
1--1	0	1	0	0	1	01001		4--1	1	1	1	0	1	11101
1--2	0	1	0	0	1	01001		4--2	0	1	1	1	1	01111
1--3	0	1	0	0	1	01001		4--3	0	0	1	1	0	00110
1--4	1	1	0	0	1	11001		4--4	0	0	1	0	0	00100
1--5	1	1	0	0	0	11000		4--5	0	0	1	0	0	00100
2--0	0	1	0	0	1	01001		5--0	1	0	0	0	0	10000
2--1	0	1	0	0	1	01001		5--1	1	1	0	0	0	11000
2--2	0	0	0	1	1	00011		5--2	0	1	1	0	0	01100
2--3	0	0	0	1	1	00011		5--3	0	1	1	0	0	01100
2--4	0	1	0	1	1	01011		5--4	0	0	1	0	0	00100
2--5	0	1	0	0	1	01001		5--5	0	0	1	0	0	00100

461 Table 2: Attributes of the grid after extracting the lithological information. For each cell (line)
 462 a lithological spectrum is defined by the presence/absence of each lithology on the map
 463 (columns)

464

Cell#	Lithological spectrum ABCDE	AHC15	Qual15	AHC10	Qual10	AHC7	Qual7	AHC5	Qual5
0--0	11000	11	0.00	8	0.00	6	0.44	4	0.44
0--1	11000	11	0.00	8	0.00	6	0.44	4	0.44
0--2	11000	11	0.00	8	0.00	6	0.44	4	0.44
0--3	11000	11	0.00	8	0.00	6	0.44	4	0.44
0--4	11000	11	0.00	8	0.00	6	0.44	4	0.44
0--5	10000	12	0.00	9	0.00	6	1.54	4	1.54
1--0	01000	3	0.00	3	1.32	2	1.32	1	2.34
1--1	01001	5	0.00	4	0.00	3	0.00	2	0.00
1--2	01001	5	0.00	4	0.00	3	0.00	2	0.00
1--3	01001	5	0.00	4	0.00	3	0.00	2	0.00
1--4	11001	13	0.00	10	1.48	7	1.48	5	1.48
1--5	11000	11	0.00	8	0.00	6	0.44	4	0.44
2--0	01001	5	0.00	4	0.00	3	0.00	2	0.00
2--1	01001	5	0.00	4	0.00	3	0.00	2	0.00
2--2	00011	8	0.00	6	0.00	4	1.11	3	1.42
2--3	00011	8	0.00	6	0.00	4	1.11	3	1.42
2--4	01011	7	0.00	5	0.99	4	1.11	3	2.00
2--5	01001	5	0.00	4	0.00	3	0.00	2	0.00
3--0	00101	1	0.00	1	0.00	1	1.13	1	1.52
3--1	00101	1	0.00	1	0.00	1	1.13	1	1.52
3--2	00111	10	0.00	7	0.99	5	0.99	3	1.02
3--3	00110	9	0.00	7	0.99	5	0.99	3	1.73
3--4	00111	10	0.00	7	0.99	5	0.99	3	1.02
3--5	00101	1	0.00	1	0.00	1	1.13	1	1.52
4--0	10101	14	0.00	10	1.48	7	1.48	5	1.48
4--1	11101	15	0.00	10	0.94	7	0.94	5	0.94
4--2	01111	6	0.00	5	0.99	4	1.79	3	1.74
4--3	00110	9	0.00	7	0.99	5	0.99	3	1.73
4--4	00100	2	0.00	2	0.00	1	0.85	1	0.86
4--5	00100	2	0.00	2	0.00	1	0.85	1	0.86
5--0	10000	12	0.00	9	0.00	6	1.54	4	1.54
5--1	11000	11	0.00	8	0.00	6	0.44	4	0.44
5--2	01100	4	0.00	3	0.66	2	0.66	1	1.52
5--3	01100	4	0.00	3	0.66	2	0.66	1	1.52
5--4	00100	2	0.00	2	0.00	1	0.85	1	0.86
5--5	00100	2	0.00	2	0.00	1	0.85	1	0.86

465 Table 3: Attributes of the grid after AHC. The different AHC columns correspond to different cut-off levels in the
 466 dendrogram. Whole numbers correspond to the lithological association for a given cell and for a set cut-off level (see
 467 Figure 5). 'Qual' measures the quality of each cell in terms of the dissimilarity between it and the multivariate centre of
 468 gravity of the class comprising the cell
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