The Magondi Belt, Zimbabwe - Mineral potential modeling using favourability functions

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The paper aims at illustrating a case study in mineral potential mapping through the favourability functions approach of Chung and Fabbri (1993). A sub-area in the Magondi Belt, Zimbabwe has been chosen to test the capability of an existing database comprising of an old geological map, a detailed airborne total magnetic field survey, and geochemical samples at the nodes of an exploration grid to represent the actual knowledge of the area for mineralized deposit prediction. These datasets were integrated using five different techniques using the joint probability function and the conditional independence hypothesis (Chung and Fabbri, 1999). A geological conceptual model was adopted for the representation of the mineralization occurrence, while existing mines in the area have been used as training set for the model.

In this specific study area, three types of factors were considered to be of importance for mineralization:

1. The geological unit
2. The distance from the basement rock, which is considered to be the source of copper mineralization, and
3. The presence of geological lineaments, in particular the faults and joints, through which mineralized solutions migrate

1 and 3 make use of the existing available geological map. The distance to the basement rock (second factor) was derived from the detailed processed magnetic map of the area. In addition, an extensive geochemical exploration database exists which was subsequently used to map the geochemical anomalies. The geochemical data representing the concentration of nine elements (Cu, Zn, Pb, Co, Fe, Ni, Ag, Au, As) were taken from core samples approximately 4 m below the surface. These were interpolated for exploratory purposes using the simple nearest neighbor interpolator. A correlation analysis done on the data shows that the concentration of the elements does not follow a clear association pattern.

The computed correlation matrix representing the different geochemical elements is shown in Table 1. From the latter, it is evident that most of these elements are uncorrelated. From the exploratory interpolation knowledge of the area also, it is possible to conclude that Pb, Ni and Co do not show any particular spatial pattern, their highest and lowest values being scattered randomly over the study area. For this reason, these elements were considered not relevant as spatial indicators and have been discarded in subsequent analyses. In addition, Ag, Au and As show extremely low concentrations, and have no physical relation with the occurrence of copper deposits. This has led to them not being considered in modeling. Eventually, only Cu, Fe and Zn have been retained as somehow meaningful geological indicators and together with the other causal factors: airborne total magnetic field, geological units, geological lineaments and the location of mining sites in the area were successively processed for the modeling analysis. Five known mines namely Avondale, Shackleton, Alaska, Angwa, and Hans are present in the area (see Figures 1 and 2). In order to have an appropriate representation of the mines, and also because the shape and dimension of the mineralized deposits were not known, a square window of NxN pixels around each mine location point was used. The pixels in the window received the value 1 (presence of mineralization) while the other pixels received 0 (absence of mineralization). This allows to produce a binary map with 5 1 valued windows and the rest equal to 0. The number of pixels N was chosen by subsequent trials (representation which maximizes the prediction performance) and using N=5 proved satisfactory.

Once the data have been prepared, a first modeling study has been performed. This involves the use of four out of five existing mines as the evidence layers, while some of the causal factors discussed above were designated as input for the prediction. The fifth mine was used for cross-validating the prediction. In order to test the prediction performance, the prediction score classes assigned to the pixels containing the discarded mine were recorded. It has been argued that if the prediction model works, then the "validation mines" should always be found in the highest scoring percentage of the area. For simplicity, the prediction maps were divided into 20 classes of favourability, each covering approximately 5% of the study area sorted in increasing favourability order. Thus, for instance, class 20 covers the 5% area with the highest prediction score, class 19 the 5% with second highest score and so on. According to this criterion, the scores of the area used as the "validation mine" should always keep in a range of high favourability scores. In this study, all the predictions that assign the "validation mines" with a score class ϒ⇑15 were chosen, and accordingly all the "validation mines" were in the 25% highest favourability score area. Following this criterion, different combinations of the causal factors were tested, and a sensitivity analysis of the model has been done. As expected, different predictors behaved differently, and only two of the seven made an acceptable prediction of all the "validation mines", namely the *fuzzy or* operation and the *fuzzy sum* operation.

Making a prediction using in turn only five of the six causal factors tested the sensitivity of the predictors. Moreover, the predictions using all six layers were compared with those obtained without using Zn and Fe. After many trials using different combinations of the causal factors, it appeared to be evident that the best prediction was possible when using the factors representing copper anomaly, distance from lineaments, geological units, and total field. These factors gave the prediction pattern with highest favourability score values in all the "validation mines". Although this holds in relative terms, the same cannot be said in absolute terms: also using the optimal pool of factors, some predictors fail badly in some cases. Figure 1 shows that only the fuzzy sum and fuzzy or operations keep in the acceptability range in all mines. In the same graph the prediction performance of the six factors is shown.

All predictors were sensitive to the most complete and detailed data, i.e. airborne total magnetic field. In addition, badly performing predictors were also significantly sensitive to the distance to lineaments. It can be argued that an improved representation of lineaments might thus increase the prediction rate of such behaving predictors. In the case in which data about lineaments are not satisfactory, these predictors should not be used. The geological units used in this first modeling attempt are not meaningful, since all mines occur in the same geological unit. Other factors, such as zinc and iron, sometimes produce favourability increases, which can be deemed spurious since it has been stated that no physical or geological link exists between the anomaly of such elements and copper mineralization. Due to the limited data set, in some cases it also appears that excluding a causal factor, such as distance to lineaments, improves the prediction. It must be recalled, on the other hand, that data in themselves give a first sketch of the conditional probability of mineralization, given a factor, by using observed conditional frequencies. It is a task of the expert's evaluation to modify these probabilities in order to achieve a good representation of the prediction pattern, by adjusting the conditional probabilities for the different factor classes according to his or her experience of the problem. For illustration purposes, two sensitivity analysis diagrams are reported in Figure 2.

In summary, from the exploratory analysis and modeling it has been possible:

- To validate the geological conceptual model adopted for mineralization, by stating that a prediction can be drawn by integrating these factors.
- To calibrate the predictors tested in this case study.
- To validate the prediction of each one, and to choose the best performing predictors on the basis of their capability to predict the "validation mines".

The final favourability maps produced define the most promising target areas to concentrate the exploration and detailed mapping efforts for mineral exploitation.

References:

Chung, C.F. & Fabbri, A.G., 1993. The representation of geoscience information for data integration, *Non Renewable Resource*s, Vol.2 n.2, Oxford, pp.122-139.

Chung, C.F. and FABBRI, A.G., 1999, Probabilistic prediction models for landslide hazard mapping. *Photogrammetric Engineering & Remote Sensing PE&R*S. v. 65, n. 12, p. 1389-1399.

CU	1								
PB	0.217514	1							
ZN	0.127237	0.230512	1						
FE	**0.399333**	**0.422935**	0.205321	1					
CO	**0.33941**	**0.328598**	0.188015	**0.703861**	1				
NI	0.088643	0.159756	0.050928	0.175653	0.374099	1			
AS	0.054031	0.023898	0.297403	0.110737	0.101505	0.05664	1		
AU	0.105329	0.020772	0.009198	0.020203	0.040742	0.042179	-0.00843	1	
AG	0.118025	0.045308	0.025826	0.060796	0.003236	0.002897	0.01292	0.071024	1
	CU	*PB*	*ZN*	*FE*	*CO*	*NI*	*AS*	*AU*	*AG*

Table 1- correlation matrix of geochemical data (correlations >0.3 highlighted)

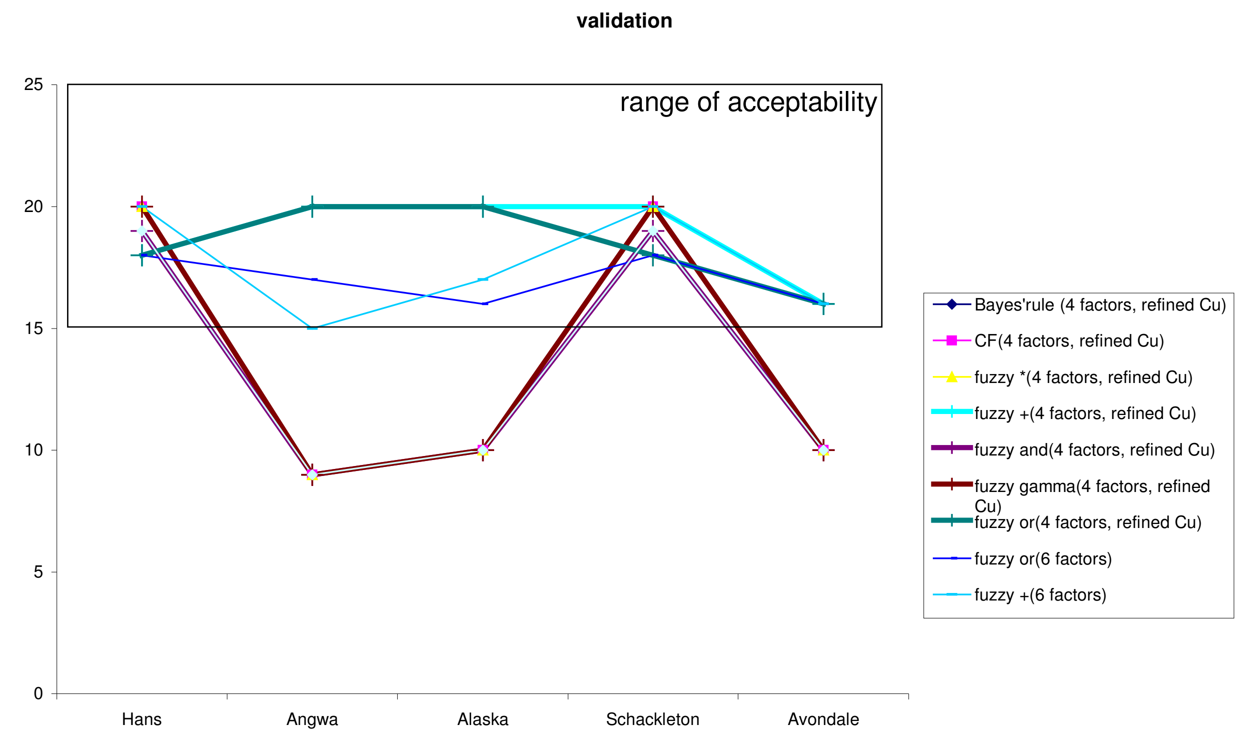
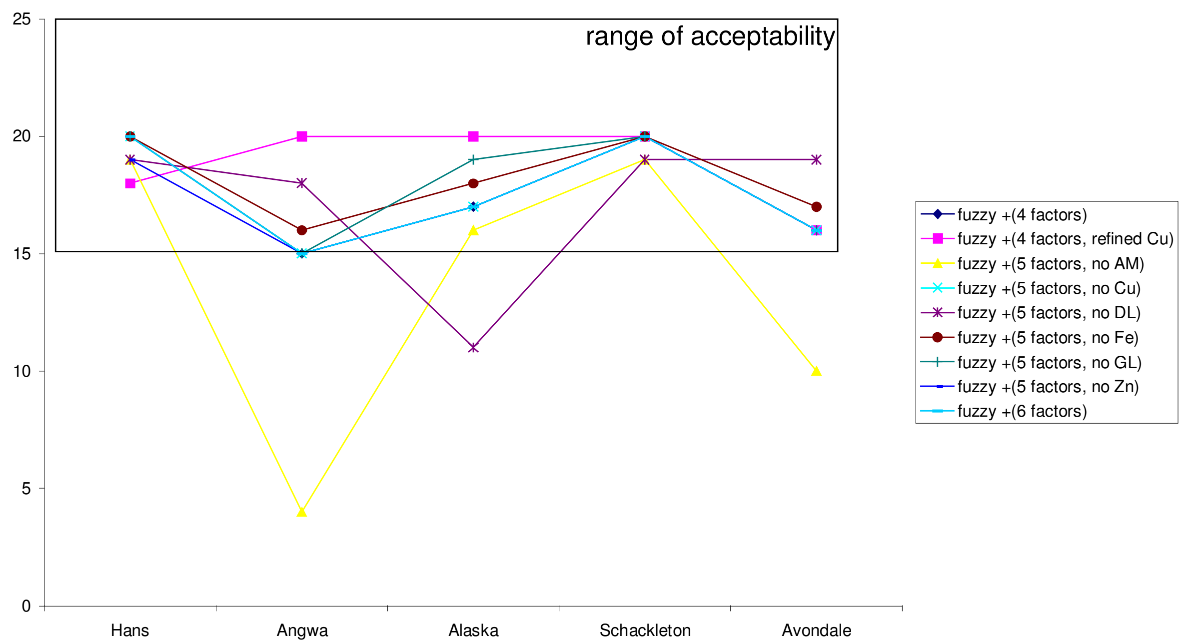


Figure 1 – validation of the prediction using four and six causal factors.

fuzzy sum



fuzzy product

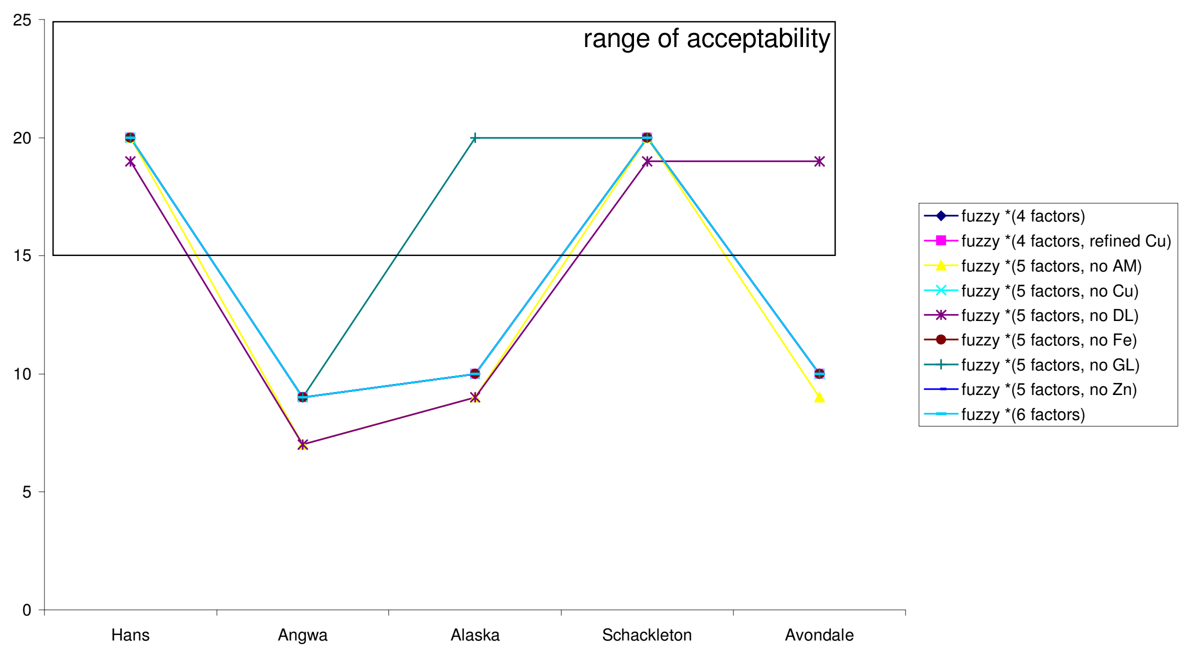


Figure 2 – Sensitivity analysis in two cases.