Knowledge Driven GIS Modelling Techniques for Copper Prospectivity Mapping in Singhbhum Copper Belt – A Retrospection.

Basab Mukhopadhyay, Asit Saha and Niladri Hazra
Geodata and Database Division, Geological Survey of India, 27, J. Nehru Road,
Kolkata - 700016
mailto:gsi_chq@vsnl.com

Abstract:

Geographic Information System (GIS) provide an efficient analytical tool for generation of mineral prospectivity map by integrating large volume of exploration datasets of geological, geophysical and geochemical parameters. Over the past years, two contrasting analytical approaches have been tried in the field of GIS analysis: one is a conceptual knowledge driven approach, and the other is a data driven approach. The knowledge driven approach in exploration is carried out by extracting the spatial factors from exploration dataset on the basis of the exploration model, quantification of spatial factors and finally integration of these factors through map combination processes. There are several map combination processes in a knowledge driven approach, these are Boolean logic combination, algebraic combination, index overlay combination, fuzzy logic and vector fuzzy logic combinations, and so on.

The Singhbhum copper Belt – a narrow, arcuate, highly sheared linear zone in Singhbhum Precambrian Terrain has huge inventory of exploration dataset generated by Geological Survey of India (GSI) in course of multimetal exploration spanning over five decades. Several map combination methodologies and analytical techniques (Boolean logic, index overlay, fuzzy and vector fuzzy methodologies) were applied on the dataset comprising lithology, favourable contacts, wall rock alteration, aeromagnetic and ground geophysical anomaly, shear zone, lineaments, chemical anomaly for copper in bed rock and so on. The knowledge driven map combination approaches stated above have been employed to establish a relationship between the spatial dataset and the existing exploration model generated by GSI. In these approaches, individual basic layers of evidences are integrated in the map on the basis of selection criteria (Boolean logic), score assigned (index overlay) or fuzzy membership /

prospectivity values (fuzzy/vector fuzzy), according to their relationship in respect of mineralisation. These maps are integrated by map weights (index overlay), fuzzy gamma and other operators (fuzzy inference modeling), vectoral fuzzy combination relating to prospectivity and confidence (vector fuzzy method) to generate final GIS model in the Singhbhum Copper Belt around TS 73J.

It is interesting to note that prospective areas for further search for copper mineralisation spatially remains almost the same irrespective of map combination methodology adopted. This is because the assignment of relative importance of layers in terms of quantitative scoring and rule for map integration in a knowledge driven approach is strictly dependent on the exploration model, which remains the same for all the methodologies. In conclusion, this can be said that irrespective of subjectivity embedded in the methodology, the product of knowledge driven GIS analysis is dependent on the quality of dataset and genetic/exploration model of the area. It may be interesting to test the validity of this conclusion by employing knowledge driven analytical tools on the exploration dataset from other areas.

(I) Introduction:

Data generated from the modern day exploration campaign are not only diverse but voluminous also. Sophisticated geological, geochemical, remote sensing and geophysical techniques combined with high-resolution ground and air-borne geophysical surveys are not only make mineral exploration more laboratory oriented but also makes the task difficult for interpretation. Many sophisticated techniques like stable and radiometric isotope analysis, fluid inclusion study and litho-geochemistry are introduced in exploration campaign for proper understanding the process of mineralisation and in turn also used for generation of genetic/exploration model for that commodity. Hence, the positive result of modern day exploration lies in the effective analysis of the datasets, the extraction of only the exploration relevant factors and integration of these factors to a single prospectivity map (Knox-Robinson, 2000). Visualisation and integration of these high volume of data require an analytical system viz. GIS, which has been designed for effectively store, interrogate and integrate diverse spatial and non-spatial data to generate prospectivity map depending on a hypothesis. Over the past decade, a number of techniques have been evolved to make use of exploration dataset and construct maps that illustrate how mineralisation potential or prospectivity changes over an area (Knox-Robinson and Wyborn, 1997). The GIS modeling methodologies in prospectivity mapping of a commodity can be categorized either as knowledge driven or data driven. There are several knowledge driven modeling approaches are available and which can be effectively transformed into GIS analytical environment: some of which can be summarized as Boolean logic, Index Overlay, Fuzzy Inference analysis and Vector Fuzzy modeling. The main objective of this paper is threefold: i) application of above mentioned techniques on the exploration datasets of Singhbhum Copper Belt on the basis of proposed exploration model ii) generation of prospectivity maps by different methodologies iii) comparison of results of different methodologies for generation of equivocal conclusion.

(II) Singhbhum Copper Belt - Geology and Mineralisation:

GSI has carried out extensive survey work in the form of systematic geological mapping on 1:63,360; 1:50,000 & 1:25,000 scales followed by detailed geological mapping of prospective locales on 1:10,000, 1:5,000 and 1:2,000 scales. Mapping work is intimately followed by airborne magnetic, electromagnetic and scintillometric sensor surveys accompanied by geochemical and ground geophysical surveys in selected areas to access the mineral potential mainly for copper. Nearly 600 boreholes are drilled to access the nature of copper ore-body disposition and estimation of reserve (Anon, GSI, 1991).

The Singhbhum Copper Belt, located in Jharkhand, Eastern India forms an arcuate highly deformed linear zone in the Singhbhum Crustal Province and considered one of the most potential sulphide bearing stretch of the country. The Singhbhum Shear Zone marks the boundary between a southern platform and a northern mobile belt. The Singhbhum Shear Zone is developed along the southern fringe of the Proterozoic Fold Belt of North Singhbhum. This fold belt is sandwiched between the Early Archean Cratonic Nucleous represented by Singhbhum and Bonai Granite in the south and Proterozoic Chottanagpur Granite Complex to the north. A curvilinear belt of metasedimentaries belonging to Dhanjori and Singhbhum Group of Proteropzoic age occupies the intervening gap area between the Singhbhum and Chottanagpur crustal province. The Singhbhum shear zone, which has developed in this Proterozoic belt, is a northery dipping arcuate ductile shear zone (Ghosh and Sengupta, 1987) marked by lenticular mylonite zone. The width and trend of the shear zone is 10Km & SW-NE in the western part, gradually narrows down to 1 km & E-W in the central part and again widens to more than 5 Km & NW-SE in southeastern part. In the southeastern part the shear zone splits into a number of N-S trending narrow shear zones (Banerji, 1981). In the western part the shear zone branches out and follow the northern and southern boundary of Chakradharpur Granite Gneiss. The rocks within the Singhbhum shear zone form a tectonic mélange comprising of granite mylonite, quartz-mica phyllonite, quart-tourmaline rock and deformed volcanic & volcanoclastic rocks (Mukhopadhyay and Deb, 1995). The shear sense indicators suggest a thrust type of deformation (Mukhopadhyay and Deb, 1995). The copper mineralized zone runs parallel to Singhbhum Shear Zone.

The copper mineralisation along Singhbhum Copper Belt is located along the Dhanjori Group of rocks south of shear zone and Singhbhum Group of rocks north of shear zone. The copper sulphide mineralisation is considered to be associated mainly with the meta-volcanics and meta-tuff sequences of the above mentioned Groups (Anon, GSI, 1991). The predominant chalcopyrite – pyrite – pyrrhotite ore mineral assemblage is concentrated along massive to braided veins, stringers, dissemination, discordant to sheet like bodies.

Stratigraphic control of mineralisation is completely absent in the area: no stratigraphic horizon has been found to exclusively contain the ore bodies. Lithological control in chemical sense is not also obvious (Sarkar, 1966a). In Badia and Mosabani, the orebodies are concentrated in soda-granite rocks whereas in Surda, Turamdih, Bayanbil and Tamapahar, this is concentrated in chlorite schist, chlorite-biotite-quartz and quartz chlorite schist. In many other places, the ore body is concentrated along sheared basic volcanics of Dhanjori Group. It is found that in soda granite rocks the ore bodies are richer and thicker compared to ore bodies in other lithounits (Sarkar, 1966a). Thus, it can be summarized that all 'shear zone rocks' are mineralized to a varied extent, out of which the sheared granitoids and metabasics are more mineralized compared to metasediments and metaultrabasic rocks. The orebodies in the area are represented by both sulphide and oxide facies. Chalcopyrite is the predominant sulphide mineral and oxide is represented by magnetite, ilmenite and rutile. Ore bodies are primarily concentrated along the major dislocation surface – the 'Singhbhum Shear Zone' and lineaments adjacent and parallel to it. The ore shoots are emplaced along the dislocation planes parallel to the shear surfaces. Mobilisation of the ore body is mainly taken place along shear bands, thus parallel to subparallel discontinous ore bodies (i.e. parallel to prominent structural grains of the area) is controlled by local trend of slip planes (Anon, GSI, 1991). The ore shoots are emplaced along the synformal part of $B^{/}$ folds (reclined folds with down dip axis) and that too in their steeper southern limb. Axes of these $B^{/}$ folds are parallel to the transportation direction. The down dip orientation of the lineation / fold axis of these folds indicate the plunge of the ore shoot (Sarkar, 1966a). Sengupta (1972) indicated that pervasive foliation parallel to regional axial planar schistosity developed in the early history of shear movement, has remained a potential plane of weakness along which there have been successive movement of different nature resulting in shear cleavage/ slip planes dipping at a gentler angle along schistose shear zone rocks. Sulphide mineralization which are later to this fractures localized them as ore zone which are lensoid or tabular in shape, linear in strike running parallel to the schistosity. He also suggested that locally developed down dip cross warps have favoured the opening of foliation planes, also serves the locales of ore deposition. The entire shear zone is characterised by intense hydrothermal activity resulting in silicification, tourmalinisation, biotitisation, chloritisation and sericitisation in the rock. It is found that chloritisation is more characteristics for sulphide and uranium mineralisation (Dunn, 1937; Sengupta, 1972). Dunn (1937), opined that hydrotherms derived from the granitic magma at the later stage, gave rise to apatite-magnetite and sulphide mineralisation in two separate and sequential phases. As ore body with uniform ore mineralogical assemblage occurs along contrasted rock type, the contribution of shear zone rocks in ore formation may be considered as poor because of chemical incompatibility between the rock types. However, the shear zone rocks have generated favourable locales for ore bearing hydrotherms coming from deeper sources. Such ore bearing hydrothermal process can only generate uniform ore mineralogy in contrasting petrochemical assemblage (Sarkar, 1966b). P.R. Sengupta (1972) suggested that sulphide mineralisation is epigenetic and deposited from high temperature hydrothermal solution when deformation and metamorphism is well advanced. The favourable locales are generated by defomation and metamorphism; preceded and in part accompanied by iron-magnesis metasomatism giving rise to biotitisation in apatite-magnetite mineralization and chloritisation for sulphides. Banerjee(1962, 1981) opined that major concentration of ore deposit is in the central sector where metasomatism predominates over granitic activity, indicating that metasomatism was the dominant process of ore localization. Talapatra (1968), worked around Mosabani supported the view of Banerjee (1962) that copper sulphide and associated minerals are generated from a dual source – partly extraneous and partly indigenous, and metal bearing migmatic solution invading the shear planes dumped its load at suitable sites. It is to be mentioned here that soda-metasomatism and sulphide mineralisation are not spatially closely related except at Badia-Mosabani (Sarkar, 1984). Sarkar (1984) proposed a volcano-hydrothermal replacement +/ volcano – sedimentary precipitation taking place before regional folding and progressive dynamo-thermal matamorphism. He opined that the ore mineralisation is of Cuprous type of volcanic sulphide deposit which are proximal in nature and deposited by near surface replacement of earlier rock/sediment. The $d^{34}S$ data supports the view (Sarkar,1984). From the fluid inclusion and isotope study from the samples of Mosabani mines, Changkakoti et. al. (1987) suggested that the temperature of sulphide mineralization is in between 275 and 450^0 C, oxygen and hydrogen isotope studies indicate that ore fluids were evolved either from formation water with meteoric precursors or were deeply circulating meteoric water which equibrated with ^{18}O-rich rock at elevated temperature. From the above discussion, it appears that main process of localization of sulphide minerals is by hydrothermal process. Most of the workers from GSI supported this view.

It is also found that zones of high aeromagnetic and ground geophysical anomalies proved effective in hidden target zones. The high copper anomaly in bed rock is taken for targeting hidden copper mineral deposit (Anon, GSI, 1991).

(III) Exploration Model and GIS Datasets:

Keeping the above observations and genetic model into account, a conceptualized exploration model has been generated which is illustrated below (Anon, GSI, 1991):

?? Surface and subsurface investigations suggest that chlorite schist, quartz-chlorite schist, sericite-quartz chlorite schist, chlorite-quartz schist and its variants, altered basic rocks in most of the cases and soda-granite in Mosabani-Badia area belonging to Singhbhum and Dhanjori Groups acts as host rock for copper mineralisation.

?? Lithocontacts of above mentioned metasediments and basic volcanic rocks serve as easy channel for ore mobilization during shearing.

?? Structural fabric generated during folding episodes and shearing are the fundamental planes for ore localization. Shear zone itself and lineaments parallel and close to it also serves as general conduit for ore mobilization.

?? High aeromagnetic and ground geophysical anomalies are important signature for subsurface mineralisation.

?? Wall rock alteration in the form of chloritisation, sericitisation, biotitisation and tourmalinisation are important imprint caused by ore fluid and host rock interation

- ?? Presence of bed-rock geochemical anomaly is indicator of subsurface mineralisation.

The GIS dataset generated keeping the exploration model in view are as follows:

- ?? Lithology and favourable contacts: generated from existing compiled geological maps in different scales and attribute value updated.
- ?? Lineament, fault, fold and shear zone: generated from existing compiled maps.
- ?? Wall rock alteration layer: generated from reports and maps.
- ?? Geophysical Layer: Aeromagnetic, Ground geophysical anomaly (IP, SP, Magnetic and EM) axes are digitised and attribute value updated.
- ?? Geochemical layer: Interpreted bed rock copper geochemical anomaly digitized from compiled geochemical map and attribute value updated.

(IV) Knowledge Driven GIS Modelling Approaches:

In the knowledge driven approach, the model dissected the constituents for formation of mineral deposit into different genetic parts. These constituents are called as factors: those are possibly responsible for formation of mineral deposit. These factors are required because the physical and chemical principles governing the formation of mineral deposit are too complex for direct prediction from mathematically expressed theory. Thus, the prediction is mostly relying on the empirical relationship generated from deposit model (Bonham-Carter, 1994). It is also to be noted that presence of a suitable factor though increase the chance of finding the mineral deposit but absence of it not always ruled out the possibility. Once the conceptual model is conceived; the suitable factors are extracted from the geological, geophysical and geo-chemical dataset. These factors are overlain in GIS by different mathematical models to produce a single prospectivity map showing areas, which are conforming or jointly illustrating these factors or not. Areas, which satisfy all, or majority of the factors are turned to be the high suitable zones for further exploration.

There are several GIS models available for combining the exploration dataset on identified spatial relationship between the GIS dataset and conceptual model. These models are applied on the spatial factors generated from the exploration dataset on Singhbhum Copper Belt and are illustrated below.

a) Boolean Logic Method:

In this model, all identified spatial factors which are responsible for copper mineralisation can only have two states; favourable (True or 1) and nonfavourable (False or 0). Thus, by this process a traditional conditional operator can be applied on the dataset; the operator can be ‘Boolean and’ or ‘Boolean or’; for classifying the multi-thematic maps to a single prospectivity map. In other word, the areas, which is positive to the above criteria, is taken as true and reverse is false. Thus, the final product is a classified map that illustrates two states i.e. prospective or non-prospective. In case of Singhbhum Copper Exploration data a criteria (Prescriptive Boolean model, Bonham-Carter, 1994) is chosen as [(favourable lithology = ‘metasediment + metavolcanics’) and (within 1km of shear-zone) and (ground_geophysical_anomaly = ‘High_response’) and (airborne_magnetic = ‘moderately_magnetic’) and (geochemical_copper_anomaly_value > 200ppm)]: if this criteria is true then the area is prospective (value, 1) for copper mineralisation other wise not (value, 0) (Das et. al., 2002). The ‘and’ operator in the above statement is ‘Boolean and’. The GIS model is stated in Fig 1, stating two states, high probability and low probability, high probability is suitable for further detailed exploration.

Figure 1:

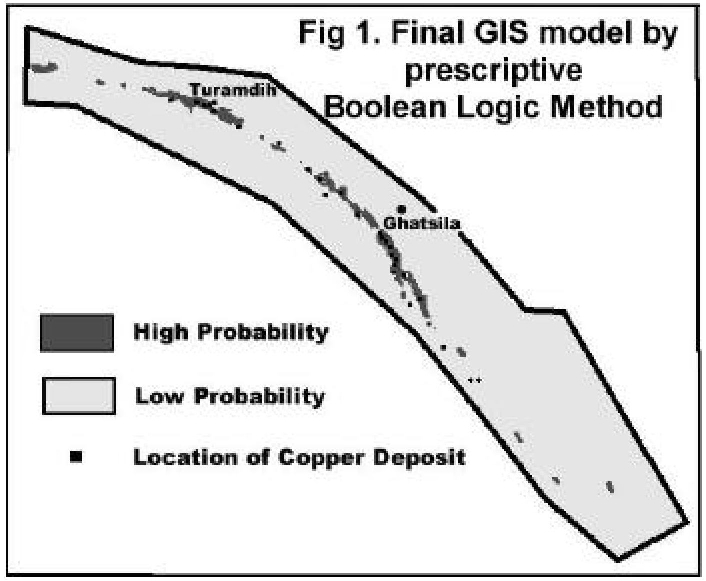

Fig 1. Final GIS model by prescriptive Boolean Logic Method

b) Index Overlay Method:

In this method, the evidence (factors) consists of a set of exploration dataset (maps) and weights are estimated from the measured association between known mineral occurrences and the exploration model for a particular terrain. The hypothesis then repeatedly evaluate all possible location of the maps using the weight and in turn produce a mineral potential map in which the evidences of several map layers are combined by this map combination rule.

In the *index overlay method*, each input map (layer of evidence) to be used as evidence is assigned a different score (weight), as well as the maps are receiving different weight (Bonham-carter, 1994) depending on the exploration model. An area that is geologically well explored with a relatively well-understood exploration model in hand (the present study area), assignment of weight on different themes or maps ought to be through knowledge driven approach. This not only help in developing a clear understanding of relationship between datasets (both geological, geophysical or geochemical) but this also give flexibility to an exploration geologist to manipulate weight on different elements or evidence maps through geological knowledge about the terrain in different stages of analysis. This is advantageous for developing perhaps a variety of scenarios for different weight schemes, reflecting differences in opinion amongst experts, and allows the evaluation of sensitivity of the mineral potential maps to such differences.

After defining the score by knowledge driven approach for elements or maps, the average score (index weight) is then defined by

$$S = \frac{\sum_{i}^{n} S_{ij} W_i}{\sum_{i}^{n} W_i}$$

Where S is the weighted score for an area object, W_i is the weight for the i-th input map, and S_{ij} is the score for the j-th class of the i-th map, the value of j depending on the class actually occurring at the current location (Bonham-carter, 1994).

The predictive model was generated by summing up the various derived maps (comprising of lithological, structural, geochemical, wall rock alteration and geophysical) that provide evidence for copper mineralisation into one or more mineral favourability maps. The overlap combination process of the images involves the weighing and union of evidences by a map combination rule i.e. *Index overlay method*. The intermediate factor maps are combined to generate maps resulted in the highest cumulative weights in the area where all the recognition criteria co-exist. As discussed earlier in the index overlay method each class of every map is given a different score as well as the maps themselves receiving different weights allowing for a more flexible weighting system. The individual score of the map elements have been discussed in the publication by

Mukhopadhyay et. al. (2002a). The map scores assigned to the individual layers of evidences and the inference model is also discussed in detail in the publication listed above. The process and assignment of weights are illustrated in detail in a paper by Mukhopadhyay et. al. (2002a) and the inference network & final result is summarized in Fig.2.

Fig 2

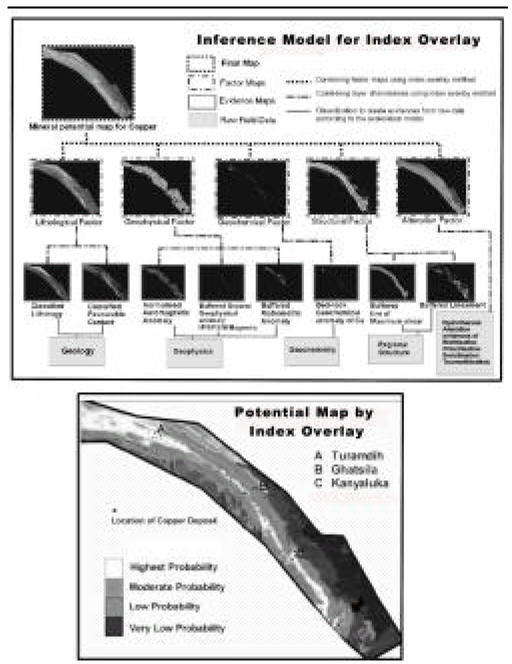

Fig 2. Diagram showing the flowchart and final GIS model of Singhbhum Copper Belt by Index Overlay Method

c) Fuzzy Inference Modelling:

In the classical GIS modeling, the process converts the multiclass maps into binary predictor pattern. The pattern assumes a boundary between favourable and unfavourable ground (Carranza and Hale, 2000). However, the boundary between these two classes is imprecise and thus fuzzy (Carranza and Hale, 2001). Hence, classifying predictor maps on the basis of their mineral favourability needs an imprecise concept that takes care the favourability zones on a gradational basis rather than simply classifying them into classes of membership or nonmembership. As fuzzy set is expressed on a continuous scale from 1 (full membership) to 0 (full nonmembership) (Bonham-Carter, 1994), the inference engine generates map on a gradational pattern depending on the fuzzy membership value, which also takes into consideration the probability and possibility of finding mineral potential in actual ground. In the fuzzy system, the extraction and combination of different evidences, is carried out by operators. An et. al. (1991) discussed five operators, which are found useful for combing the exploration dataset. These are fuzzy and, fuzzy or, fuzzy algebric product, fuzzy algebric sum and fuzzy gamma operators. Out of these five operators: the last four operators have been used in this analysis. The pricipal approaches taken for calculating fuzzy membership values are illustrated below.

?? Reclassification of complex geological, aero magnetic and geochemical map into smaller numbers of simplified units (classes).

?? Generation of proximity map by buffering operation showing classes of distance to linear features (such as favourable litho contact, lineaments, shear zone, ground geophysical anomaly axis etc.).

?? Assignment of fuzzy membership values to each element (class) of a map by intuitive subjective judgement in case of qualitative/discrete data or by defining a simple mathematical function in case of quantified/continuous data. The assignment of fuzzy values in this terrain is discussed in details by Mukhopadhyay et.al.(2002b) and details is given in the table1.

Map combination is an intuitive method where different primary and derived evidences are combined by a set of principles. For example, in this case, the evidence maps (comprising of lithology, favourable contacts, aeromagnetic, shear zone, lineaments and faults, ground geophysical, wall rock alteration and geochemical anomaly) can be combined in raster mode by a single or combination of fuzzy operators. A detailed inference diagram (fig. 3) is attempted to show how the different layers are combined and finally integrated by fuzzy operators. Here, the geological, geophysical and structural evidences are combined by fuzzy or operator to extract the maximum evidence from each layer. It also suggests that high value of any layer can be a useful evidence for copper mineralisation. Whereas, fuzzy algebric product operator is used in wall rock alteration layer to extract evidences for simultaneous occurrences of one or two alteration evidences. Finally fuzzy gamma operator combines all the evidence maps with gamma value as 0.95 to generate the final predictive map. Choosing of gamma value is subjective. As opined by Bonham-Carter (1994): to generate increasing effect of fuzzy membership values in the final map, gamma value need to be higher than 0.8. In this particular case, increasing gamma value higher than 0.95 bears very little effect on the final map (i.e. final GIS model). The final map grades the region into five subclasses in terms of suitability of finding copper occurrences i.e. highly suitable, fairly suitable, moderately suitable, lowly suitable and nonsuitable (Fig. 3). The process is discussed in great details in the publication by Mukhopadhyay et. al. (2002b)

d) Vector Fuzzy Modelling:

The fuzzy logic methodology discussed above is highly applicable where GIS modeling is based on a conceptual approach i.e. based on a conceptual deposit model. To overcome the deficiencies of gamma (‘?’) function in fuzzy inference modelling, a new and more powerful fuzzy logic method called ‘Vectorial Fuzzy Logic’ is introduced based on vector mathematics that allows a measure of confidence to be included in the prospectivity analysis (Knox-Robinson, 2000). This is probably a unique GIS analytical methodology that takes into consideration the confidence in predicting prospectivity besides grade the area into zones of prospectivity with relative confidence.

This method generates two values in each location, one for ‘prospectivity’ related to a particular spatial relationship and the other defining the ‘measure of confidence’. This also takes care of three needs simultaneously: i) particular spatial relationship is represented by confidence of a prospectivity value, ii) the confidence represents overall importance of each spatial relationship relative to other, iii) the confidence value allows the null data value to be used. The two quantities, prospectivity and confidence are treated as vectors, prospectivity as direction of the vector and confidence as magnitude of vector (Knox-Robinson, 2000). In vector fuzzy logic, each prospectivity value (ranging from 0 to 1) is multiplied by ?/2 and the resultant number is used to represent the direction, in radians, of the vector. Thus, mutually orthogonal vectors can represent the lowest and highest prospectivity. The length of the vector is used to represent the confidence of the prospectivity value, null value is represented as zero length vector i.e. zero prospectivity. The combination involves calculation of resultant vector for prospectivity (equation 1) and length of the resultant vector related to the confidence of prospectivity (equation 2) (Knox-Robinson, 2000).

$$?_c = (2/?) \arctan \left[\left(?_{i=1}^{n} l_i \text{ Sin } (? ?_i/2)\right) / \left(?_{i=1}^{n} l_i \text{ Cos } (? ?_i/2)\right) \right]$$

----- equation (1)

and

$$l_c = ? \left[\left(?_{i=1}^{n} l_i \text{ Sin } (? ?_i/2)\right) ** 2 + \left(?_{i=1}^{n} l_i \text{ Cos } (? ?_i/2)\right) ** 2 \right]$$

------- equation (2)

Where $?_i$ is the fuzzy prospectivity value for the i^{th} input layer (0= ? i = 1, i varies from 1 to n), li is the confidence value for i^{th} input layer, $?_c$ is the combined prospectivity value and l_c is combined confidence on prospectivity.

All the evidences or spatial relationship are treated equally and quantified as continuous surface defined by fuzzy prospectivity value. Initially, every data point in each input layer of evidence (comprising of lithology, favourable contacts, aeromagnetic,shear zone, lineaments and faults, ground geophysical, wall rock alteration and geochemical anomaly) is represented by vector of unit length i.e. confidence as unity for each point. The vectorial fuzzy combination employing equation 1 & 2, combines the above primary layer of evidences & intermediate evidence maps and generate two predictive maps, one representing the copper prospectivity map of the area and the other representing the measure of confidence in defining the prospectivity (fig. 4). The ideal combination of finding the locales of copper deposit will be those places where both confidence and prospectivity is high. Such a map is generated for this terrain by deploying a simple logical operator stated in fig. 4. This model (fig.4) is cross validated by plotting the known copper deposit/occurrences of this terrain, which fits well. The marked area defined by P in fig.4, can be treated as potential sites for further copper exploration (Mukhopadhyay, in press).

Fig 4

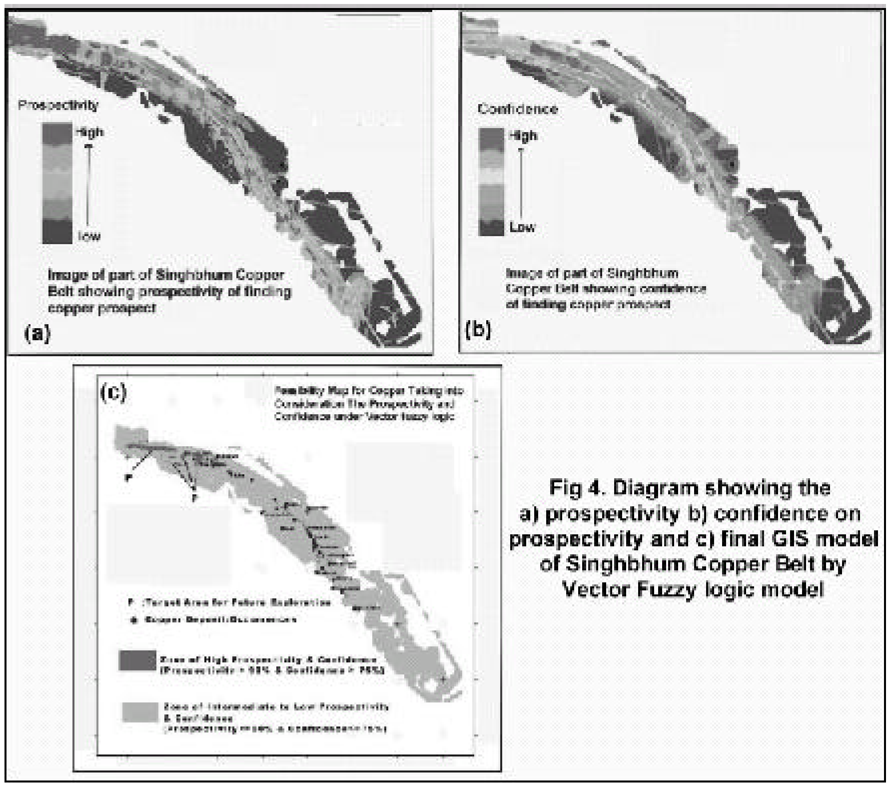

Fig 4. Diagram showing the a) prospectivity b) confidence on prospectivity and c) final GIS model of Singhbhum Copper Belt by Vector Fuzzy logic model

(V) Discussion and Conclusion:

The methods of combining multiple factorial maps in a knowledge driven GIS modeling encompass a wide variety of models. In the mineral exploration, map combination process is based on empirical to theoretical principles which is responsible for ore deposit formation in that tectono-stratigraphic domain. similarly, such principle varies from terrain to terrain and for different metallogenetic domains. Four basic map combination methodologies namely Boolean logic, Index overlay, fuzzy inference modeling and vector fuzzy modeling are applied on the causative factors generated from exploration dataset of Singhbhum Copper Belt on the basis of exploration model. The inferences that are drawn on the basis of these GIS models are summarized below:

?? The Boolean prescriptive model suggests a couple of locales west of Turamdih as the potential site for further exploration (Fig 1).

?? The GIS model generated by Index Overlay Method (Fig 2) unequivocally confirmed that the copper mineralization is magmatic and shear controlled which is the existing view regarding copper mineralization in Singhbhum. The model also identifies two broad localities; one E and SE of Kanyaluka area and a large area west of Turamdih.

?? The GIS model created by the fuzzy operators confirms coincidence between bed rock copper anomaly and high suitability zone predicted by the model (Fig 3). The final map (Fig 3) inferred two clusters (marked by P) located west of Turamdih is highly suitable for further copper exploration.

?? The predictive GIS model generated by vector fuzzy logic methodology created two maps; one regarding the prospectivity of copper and other representing the confidence regarding defining the prospectivity. The final GIS model (Fig 4) defined areas where both confidence and prospectivity is high. This model delineates couple of locales west of Turamdih as prospective sites for further exploration.

Now, from the above discussion it can be safely concluded that the product/result of the above four combination methodologies pointed to a more or less same place i.e. west of Turamdih as potential site for further exploration. It is also true that for all the above methodologies the exploration dataset and the genetic/exploration model remains the same. This is because the assignment of relative importance of layers in terms of quantified scoring and rule of map integration in a knowledge driven approach is strictly dependent on the exploration model, which remains the same for all the GIS models described earlier. In conclusion, this can be said that irrespective of subjectivity embedded in the methodology, the product of knowledge driven GIS analysis is dependent on the dataset, its spatial relationship and genetic/exploration model of the area. This is true for this terrain but for other tectono-stratigraphic domain it demands testing and consideration.

Acknowledgement:

The authors expressed their gratitude to all the officers worked on Project Singhbhum and Project Geoinformatics – Singhbhum Precambrian on 73J. They also remains grateful to Shri E. V. R. Parthasaradhi, Dy. D. G. (IT), Dr. M.K. Mukhopadhyay and Dr. J. Simhachalam, Director, Geodata and Database Division for encouragement and constructive criticism, and finally to Director General, GSI for giving permission to publish this paper.

?? An,P., Moon, W.M. and Rencz, A., 1991. Application of fuzzy set theory for integration of geological, geophysical and remote sensing data, Canadian Journal of Exploration Geophysics, V 27, pp 1-11

?? Anon, GSI, ER, 1991. Unpublished GSI report on Project Singhbhum – Synthesis of data of Singhbhum Copper Belt, Singhbhum District, Bihar: Part I & II., unpublished.

?? Banerji, A. K., 1962, Cross folding, migmatisation and ore localization along part of Singhbhum Shear Zone, Bihara, Economic Geology, Vol 57, pp 50-71.

?? Banerjee, A. K., 1981, Ore genesis and its relationship to volcanism, tectonism, granitic activity and metasomatism along Singhbhum Shear Zone, Eastern India, Economic Geology, Vol 76, pp 905-912.

?? Bonham-Carter, G. F.,1994, Geographic Information System for Geoscientists: Modelling with GIS, Pergamon.

?? Carranza ,E.J.M.. and Hale, M., 2001, Geologically-contrained fuzzy mapping of gold mineralisation potential, Baguio district, Phillipines, Natural Resource Research, V10, no 2 , pp 125-136.

?? Changkakoti, A.,Gray, A., Morton, R. D. and Sarkar, S. N., 1987, The Mosabani Copper Deposit, India – A preliminary study on the Nature and genesis of ore fluids, Economic Geology, Vol 82, pp 1619-1625.

?? Das, S.K., Mukhopadhyay, B., Laskar, T. and Roy, B.C., 2002, Abstract volume of National seminar on Role of Information Technology in Geosciences, February 19&20, 2002, Bhubaneshwar, pp 88-89.

?? Dunn, J. A., 1937. The mineral deposits of Eastern Singhbhum and sorrounding areas. Memoir Geological Survey of India, Vol 69, Part I.

?? Mukhopadhyay, Basab., Hazra, Niladri.,Das, Swapan Kumar.,and Sengupta, Sujit Ranjan., 2002a, Mineral potential map by a knowledge driven GIS modeling : an example from Singhbhum copper belt, Jharkhand, Proceedings of 5th annual international conference Map India 2002, New Delhi, pp 405-411.

?? Mukhopadhyay, Basab., Hazra, Niladri and Mukhopadhyay, M. K., 2002b, Integration of exploration dataset in GIS using fuzzy inference modeling: example from Singhbhum Copper Belt, Jharkhand, India, GIS Development, July Issue, Vol 6, Issue 7, pp 18-21.

?? Knox-Robinson, C. M. and Wyborn, L.A. I., 1997, Towards a holistic exploration strategy: using Geographic Information system as a tool to enhance exploration. Australian Journal of Earthsciences, Vol 44, pp 453-463.

?? Knox-Robinson, C. M., 2000, Vectoral fuzzy logic: a novel technique for enhanced mineral prospectivity mapping, with reference to orogenic gold mineralisation potential of the Kalgoorlie terrane, Western Australia. Australian Journal of Earthsciences, Vol 47, pp 929-941.

?? Sarkar, S.C., 1966a, Structures and their control of ore mineralisation in the Moinajharia-Mosabani-Surda section of the Singhbhum Copper Belt, Bihar. Contribution to the Geology of Singhbhum, edited by S. Deb, Jadavpur University, Calcutta, pp 75-83.

?? Sarkar, S.C., 1966b, Ore deposits along Singhbhum Shear Zone and their genesis. Contribution to the Geology of Singhbhum, edited by S. Deb, Jadavpur University, Calcutta, pp 91-101.

?? Sarkar, S.C., 1984, Geology and ore mineralisation of the Singhbhum Copper – Uranium Belt, Eastern India, Jadavpur University, Calcutta, p. 263.

?? Sengupta, P. R.,1972, Studies of mineralization in the South-Eastern part of the Singhbhum Copper Belt, Bihar, Memoirs Geological Survey of India, Vol 101, p 82.

?? Talapatra, A. K., 1968, Sulphide mineralization associated with migmatisation in the South Eastern part of the Singhbhum Shear Zone, Bihar, India, Economic Geology, Vol 63, pp 156-165.

Table 1: Fuzzy prospectivity value assigned to geological features of Singhbhum Copper Belt (After Mukhopadhyay et. al. 2002b).

Lithology		Favourable Contact		Shear Zone		Lineament and Fault		Wall Rock Alteration		Ground Geophysical (IP+SP+EM +Magnetic)	
Lithological Unit	***Fuzzy pros. Value***	***Contact between***	***Fuzzy pros. Value***	***Distance class in meters***	***Fuzzy pros. Value***	***Relationship with shear zone***	***Fuzzy pros. Value***	***Criteria***	***Fuzzy pros. Value***	***Charact e-ristics***	***Fuzzy pros. Value***
(I) Chlorite schist/ quartz chlorite schist/ sericite quartz chlorite schist/ chlorite quartz schist/ Talc chlorite schist / soda granite	0.9	(i) Units of Group (I) of column 1	0.9	<= 500	0.9	(i) Within 250m and parallel to sub-parallel to shear zone	0.5	(i) Two or more alteration type present	0.5	(i) Strong ground anomaly	0.9
(II) Hornblende schist and Epidiorite	0.8	(ii) Units of Group (II) and between Group (I) & (II)	0.8	>500 - <=1000	0.8	(ii) Within 250m and not parallel to shear zone	0.3	(ii) Only one alteration type present	0.3	(ii) Weak ground anomaly	0.2
(III) Ultrabasics and mica schist	0.6	(iii) Units of Group (III) and between Group (II) & (III)	0.6	>1000 - <=1500	0.7	(iii) Outside 250m of shear zone	0.1	(iii) No alteration present	0.01		
(IV) Other rock types	0.2	(iv) Other rock types	0.2	>1500 – <= 2000	0.6						
				>2000 – <= 2500	0.5						
				>2500 - 3000	0.4						

Table 1: Fuzzy prospectivity value assigned to geological features of Singhbhum Copper Belt (After Mukhopadhyay et. al. 2002b).