

# Mineral mapping of the chitradurga schist belt



## Mineral mapping of the Chitradurga Schist Belt: A remote sensing approach to delineate potential resources

### Introduction:

The Optimum utilization of natural resources is major and important objective of a Country. However the Policy makers making decisions about allocating land use to reach the competing demands sources the reliable information of these natural resources very important prerequisite as it enables decision- making agencies to estimate prospective benefits from different uses of the land and prioritize them based on social and economic needs of the society. It is easy to map the surface exposed spatial data such as water body, soil, forests etc where as other natural resources such mineral deposits occur below the land surface and cannot map directly, but it possible to map mineral potential zones.

For many developing countries, however, there is a general lack of geoexploration data required for a reliable and comprehensive nationwide mineral potential assessment and classification. This lack of geoexploration data and nationwide comprehensive mineral potential assessment and classification have brought about conflicts and competing demands between land-uses that permit mineral resources development and those that promote protection of ecosystems (Domingo, 1993). The mineral potential assessment and classification of an area is critical for land-use policymaking so that prospective land is not alienated from mineral resources development in the future (McCammon and Briskey, 1992; McLaren, 1992). In order to achieve mineral potential assessment and classification despite

the lack or incompleteness of systematic and comprehensive geoexploration datasets alternative methodologies are needed.

The term ‘ mineralization’ refers to the collective geological processes that lead to the formation of mineral deposits (Bateman, 1951b) The term ‘ mineral potential’ describes the possibility of the presence of mineral deposits or mineralization. Mineral potential assessment or classification is a multi-stage activity with the ultimate objective of delineating mineralised zones that can be exploited under prevailing economic conditions (Reeves et al., 1990).

Mineral potential assessment or classification is a multi-stage activity with the ultimate objective of delineating mineralized zones that can be exploited under prevailing economic conditions (Reeves *et al.*, 1990). Ideally, during each stage, multivariate and multi-source geoexploration datasets are used to guide the succeeding stages of mineral potential assessment and classification. At the small and medium-scale stage (i. e., regional to district scale ranging from 1: 50, 000 to 1: 100, 000), for example, the geoexploration datasets required should be derived from geological, geophysical and geochemical surveys. The increasing need to integrate geoexploration datasets arises from the fact that the easily-recognized mineral deposits have long been known and that more evidences and advanced methods are necessary to accurately assess and classify the mineral potential of a particular area (Bonham-Carter, 1997; Chinn and Ascough, 1997; Raines, 1997; Pan and Harris, 2000).

Mineral potential, as used in this research, is the set of characteristics attributed to a particular area that describes the probability for the presence of mineral deposits or existence of mineralization. Factors affecting economic viability of mineral deposits are not considered in this definition because the geological and mineral deposit data that are available are insufficient to determine sizes and grades of mineral deposits. Mineral potential is determined by how well the

geological and mineral deposit data fit established mineral deposit models and existing knowledge about the mineralization of a particular area. Mineral potential statements that arise from this research are estimates, rather than facts, because of the dynamic and variable nature of geological knowledge and the mineral exploration environment. It is, however, of prime importance that these statements establish the potential for the discovery of mineral deposits.

The geologically-constrained predictive mineral potential maps generated in this research are based on two factors: favourability and validity.

Favourability is determined by integration of geological variables that are considered essential for mineral occurrence. Validity is determined by how well the predictive models delineate correctly known mineral deposits that were not used to generate the models. These two factors are important for assessing the efficacy of the methodologies developed for geologically-constrained predictive mapping of mineral potential. Mineral deposits, whether metalliferous or non-metalliferous, are accumulations or concentrations of one or more useful substances that are for the most part sparsely distributed in the Earth's crust (Bateman, 1951a). The geological

processes that lead to the formation of mineral deposits are collectively called mineralization (Bateman, 1951b).

The term ' mineral potential' describes the possibility of the presence of mineral deposits or mineralization. Mineral potential does not take into account economic factors such as deposit grade, tonnage, physical, chemical and mineralogical characteristics, nature and thickness of overburden, availability of man power and technology, market demand, etc., as these are typically unknown during mineral potential mapping. Mineral potential mapping of an area involves demarcation of potentially mineralized zones based on geologic features that exhibit significant spatial association with target mineral deposits. These features, which are termed recognition criteria, are spatial features indicative of various genetic earth processes that acted conjunctively to form the deposits in the area. Recognition criteria are sometimes directly observable; more often, their presence is inferred from their responses in various spatial datasets, which are appropriately processed to enhance and extract the recognition criteria to obtain evidential or predictor maps.

Remote sensing, as a direct adjunct to field, lithologic and structural mapping, and more recently, GIS have played an important role in the study of mineralized areas. A review on the application of remote sensing in mineral resource mapping is attempted here. It involves understanding the application of remote sensing in lithologic, structural and alteration mapping. Remote sensing becomes an important tool for locating mineral deposits, in its own right, when the primary and secondary processes of mineralization result in the formation of spectral anomalies. Reconnaissance lithologic

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mapping is usually the first step of mineral resource mapping. This is complimented with structural mapping, as mineral deposits usually occur along or adjacent to geologic structures, and alteration mapping, as mineral deposits are commonly associated with hydrothermal alteration of the surrounding rocks. In addition to these, understanding the use of hyperspectral remote sensing is crucial as hyperspectral data can help identify and thematically map regions of exploration interest by using the distinct absorption features of most minerals. Finally coming to the exploration stage, GIS forms the perfect tool in integrating and analyzing various georeferenced geoscience data in selecting the best sites of mineral deposits or rather good candidates for further exploration.

Spectral identification of potential areas of hydrothermal alteration minerals is a common application of remote sensing to mineral exploration. The extraction of spectral information related to this type of target from Landsat Thematic Mapper (TM) imagery has been achieved through the use of image processing techniques such as band ratioing and principal component analysis (PCA) (Sabine 1999). With the limited spectral resolution provided by Landsat TM, alteration mapping has been restricted to the detection of areas where alteration processes are likely to have occurred—the TM visible and near-infrared (VNIR) and shortwave infrared (SWIR) bands are only able to discriminate areas rich in iron oxides/hydroxides and clay and carbonate minerals, respectively.

When one collects multivariate data in some field of application a redundancy effect often arises because of covariation between variables. An interesting issue in reduction of dimensionality of the data is the desire to

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obtain simplicity for better understanding, visualizing and interpreting the data on the one hand, and the desire to retain sufficient detail for adequate representation on the other hand. E. g. a remote sensing device typically measures the emitted intensity at a number of discrete wavelengths or wavelength intervals for each element in a regular grid. This “repetition” of the measurement at different wavelengths induces a high degree of redundancy in the dataset. This can be used for noise reduction and data compression. A traditional method used in this context is the celebrated principal components transformation. This is a pixel-wise operation that does not take the spatial nature of image data into account. Also, principal components will not always produce components that show decreasing image quality with increasing component number. It is perfectly imaginable that certain types of noise have higher variance than certain types of signal components.

Principal Component Analysis (PCA) is a mathematical technique for reducing the dimensionality of a data set (Jackson, 1983). Because digital remote sensing images are numeric, their dimensionality can be reduced using this technique. In multi-band remote sensing images, the bands are the original variables. Some of the original bands may be highly correlated and, to save on data storage space and computing time, such bands could be combined into new, less correlated eigen images by PCA. In addition to its use in this way, PCA can be used as a change detection technique in remote sensing (Jensen, 1986; Fung and LeDrew, 1987; Muchoney and Haack, 1994).

Principally, there are two ways in which PCA can be used in change detection (Jensen, 1986; Muchoney and Haack, 1994):

1. Independent data transformation analysis - in which multitemporal image data sets are spectrally enhanced separately using PCA. Each image is then separately classified for use in post classification change detection.
2. Merged data transformation - in which all the bands from the  $n$  - dimensional multitemporal image data set are registered and treated as a single  $N$  - dimensional data set as input to the PCA (where  $n$  is the number of bands per image,  $N = n \times$  the number of image dates). Approach two is applied in this work, which assessed wetland change on the Kafue Flats in Zambia. The aim was to assess the potentials and limitations of using PCA for change detection on this heterogeneous land cover scene. Whereas the methodology is not new and has been demonstrated elsewhere (e. g. Fung and LeDrew, 1987), this is yet another example demonstrating its use. Computationally, three steps are involved in the principal component transformation (Eklundh and Singh, 1993). The first is the calculation of a covariance or correlation matrix using the input data sets, the second is the calculation of eigen values and eigen vectors, and the third is the calculation of principal components. The principal components calculated using the covariance matrix are referred to as unstandardized principal components, and those calculated using the correlation matrix are referred to as standardized principal components (Eklundh and Singh, 1993; ERDAS Inc., 1994). The use of a correlation matrix, in calculating principal components, implies scaling of the axes so that each feature has unit variance. This normalisation process prevents certain features from dominating the analysis because of their large numerical values. Because unstandardized



PCA preserves the dynamic range of the original data in the analysis, it was employed in this work in preference over standardized PCA.

Broad band remote sensing systems, such as the Landsat Multispectral Scanner (MSS, 4 bands) and Landsat Thematic Mapper (TM, 7 bands), drastically under sample the information content available from a reflectance spectrum by making only a few measurements in spectral bands up to several hundred nanometers wide. Imaging spectrometers, on the other hand, sample at close intervals (bands on the order of tens of nanometers wide) and have a sufficient number of spectral bands to allow construction of spectra that closely resemble those measured on the laboratory instruments. Imaging spectrometry is defined as ' the simultaneous acquisition of images in many narrow, contiguous spectral bands' ( Goetz et al., 1985). Analysis of imaging spectrometer data allows data allows extraction of detailed spectrum for each picture element (pixel) of the image. High spectral resolution reflectance spectra collected by imaging spectrometers allow direct identification ( and in some instances. Abundance determinations) of individual materials based upon their reflectance characteristics including minerals( Goetz et al., 1985: Lang et al., 1987: Pieters 1994: Clark et al., 1996: Board man and Huntington, 1996: Crowley and Zimbelman, 1996),