HYPERSPECTRAL RADIOMETRY TO ESTIMATE THE GRADES OF IRON ORES OF NOAMUNDI, INDIA – A PRELIMINARY STUDY

T.Magendran[1], and S.Sanjeevi[2]

[1]Research Scholar, Department of Geology, Anna University, Chennai - 600 025; Tel: 044-22358443;
E-mail: magi.geoinfo@gmail.com

[2]Professor, Department of Geology, Anna University, Chennai - 600 025; Tel: 044-22358446;
E-mail: ssanjeevi@annauniv.edu

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ABSTRACT: This paper present the results of a study to assess the potential of the visible, NIR and SWIR energy of the EMR in differing iron ores of different grades in a rapid manner using hyperspectral radiometry. Using different iron ore samples from Noamundi mines, Jharkhand, India, certain spectro-radiometric measurements and geochemical analysis were carried out and the results have been presented. It was observed that the primary spectral characteristics of iron ores lie in the 850 to 900nm region. Various methods to evaluate the parameters for each curve such as: the radius of curvature of the maximum absorption trough, position of the trough with respect to wavelength in the NIR region and distance of the trough from a reference line, were adopted. Comparison of the spectral parameters and the geochemistry of the samples indicates that the depth of absorption (distance of trough from a reference line) in the NIR region for a sample has a strong positive correlation with the iron oxide content in the sample, while the radius of curvature of the absorption trough has a strong negative correlation with the iron oxide content. Such strong correlations indicate that hyperspectral radiometry in the visible and NIR regions can give a better estimate of the grade of iron ore. This study has demonstrated that generation of empirical models using hyperspectral radiometric techniques is helpful to quantify the grade of iron ores with limited geochemical analysis.

1. INTRODUCTION

Minerals do not occur uniformly on the earth surface and they are confined to small pockets. The conventional methods used for the mineral exploration are largely time and money consuming and need huge and skilled human effort. We also have to find new methods for the exploration of minerals other than the conventional methods, which will make the exploration comparatively easy and cost effective. It is believed that the remote sensing could possibly be a potential tool for mineral exploration and Ore-grade estimation (Sanjeevi 2008). This paper examines the potential of hyperspectral radiometry in predicting the grade of iron ores in a rapid manner. Iron ores are rocks and minerals from which metallic iron can be economically extracted. The iron itself is usually found in the form of magnetite (Fe_3O_4), hematite (Fe_2O_3), goethite (FeO (OH)), limonite ($FeO(OH){\cdot}nH_2O$) or siderite($FeCo_3$). The quality of iron ore estimation includes hyperspectral radiometry an offshoot of spectroscopy. Demand for iron ore has taken off in recent years, led by rising steel production in China, now the world's top importer. According to the report by Credit Suisse in 2009, high demand from steel mills will bring about a global iron ore supply deficit of between 20 million and 25 million tons in the forth coming years. All these facts indicate a rising demand for iron ores, there by necessitating the adoption of rapid and accurate approaches to iron ore exploration.

Table 1 Types of iron ores and their characteristics
(Source: http://www.mii.org/Minerals/photoiron.html)

S.No.	Name	Composition	Average % of Iron	Commercial Name
1	Hematite	Fe_2O_3	70%	Red Ore
2	Magnetite	Fe_3O_4	72.4%	Black Ore
3	Limonite	$FeO(OH).nH_2O$	59.63%	Brown Ore
4	Siderite	$FeCo_3$	48.2%	Spathic Ore

1.2 Spectroscopy

Spectroscopy is the study of light as a function of wavelength that has been emitted, reflected, or scattered from a solid, liquid, or gas. The principles of spectroscopy are applied to study many minerals and materials. Reflectance spectroscopy is a tool where electromagnetic radiation can be used to probe a surface and, through the absorption features in the spectrum of the scattered light, can be used to identify materials. Further, the sample needs no preparation, and with modern portable instruments, high quality reflectance spectra of a sample may be obtained in just a few seconds. Accurate abundances are usually difficult to determine with reflectance spectroscopy, but approximate thresholds can be determined (Clark and Roush, 1984; Clark 1999).

Field spectroscopy is a technique of fundamental importance in remote sensing that deals with interactions between energy and objects in the natural environment. Milton (1987) observes that field spectroscopy has a role to play in at least three areas of remote sensing, namely calibration, prediction and modelling. Field spectro-radiometric techniques have been successfully used to predict certain properties of water bodies, grasslands, minerals and rocks, forests, crops and several other surface features from their reflectance spectra (e.g., Tucker and Miller 1977, Thompson and Salisbury 1983, Card et al. 1988, Malthus and Madiera 1993). All these studies demonstrate that reflectance spectra generated by laboratory/field spectroscopy can be used: (i) to select the appropriate regions of the electromagnetic spectrum for a given application of remote sensing and (ii) to determine the spectral parameters for assessing the properties of various cover types/materials/minerals.

2. STUDY AREA

The Noamundi iron ore mines of TATA Steel limited forms the study area. Noamundi is a mining town in western Singhbhum district in the Indian state of Jharkhand. It lies about 125 km from Jamshedpur and 64 km from Chaibasa. The major product of this mine is iron ore (including blue dust).

2.1 Geology of Noamundi

High-grade hematite ores of the Iron Ore Group in the Noamundi area are hosted by a lateral extensive, 220 m thick Banded Iron Formation (BIF) in a folded greenstone belt succession of Paleoarchean age (Figure 1). Single ore bodies, which are up to 3 km long along the strike and several hundred meters wide, are strata bound.
(http://econgeol.geoscienceworld.org/cgi/content/abstract/103/2/365).

Dunn and Dey (1942) described the stratigraphic succession in these parts of Singhbhum as older Chaibasa stage overlain by younger iron ore stage and followed by the Dhanjori group over an unconformity.

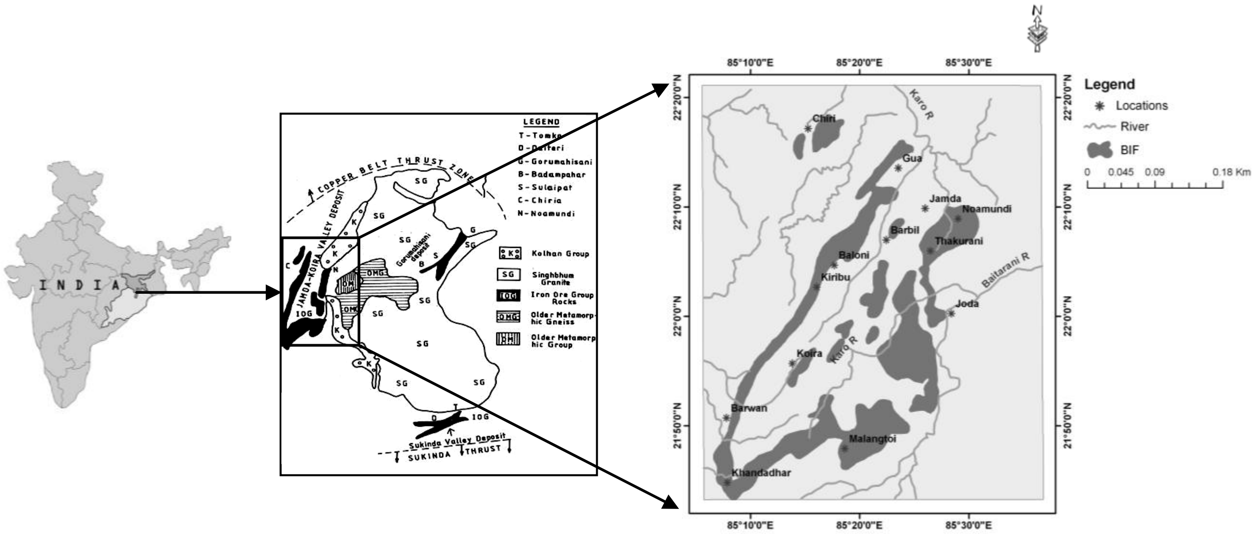


Figure 1 Geological map of Singhbhum and Noamundi Region
(Source: Directory of Indian Mines & Metals. Compiled by P K Gosh 1952)

2.2 Methodology

This study is an integrated approach that includes sample collection, sample preparation, spectro- radiometry, geochemical analysis, statistical analysis and empirical modeling. Accordingly, the methodology section describes each of these components. Figure 2 depicts the flow chart of the methodology adopted in this study.

2.3 Sample collection, Preparation and Analysis

Samples of hematite were collected from the TATA Steel mines at Noamundi, in such a way that they represent the high grade, average grade and low grade variation. For each of the grade, hard, friable and soft samples were collected. Care was taken to collect samples of three different size fractions. Large blocks and the fine blue dust were also collected. Since this study aims to relate the chemical composition of the ores to the spectral response, geochemical analysis is an essential step. Standard procedure adopted for ore samples were used to determine iron oxide content in the iron ore samples. To simulate/fabricate ore samples of different grades, the three basic grades: high, average and low were powdered to 100 mesh size and mixed at different proportions. The different proportions are 1:1(50-50%), 1:2(33-66%), 2:1(66-33%), 1:3(25-75%), 3:1(75-25%). The sample mixtures with proportions 1:1, 1:3, 3:1 are used for spectral studies and generation of empirical models, while, the sample with proportions 1:2, 2:1 are used for validation of empirical models.

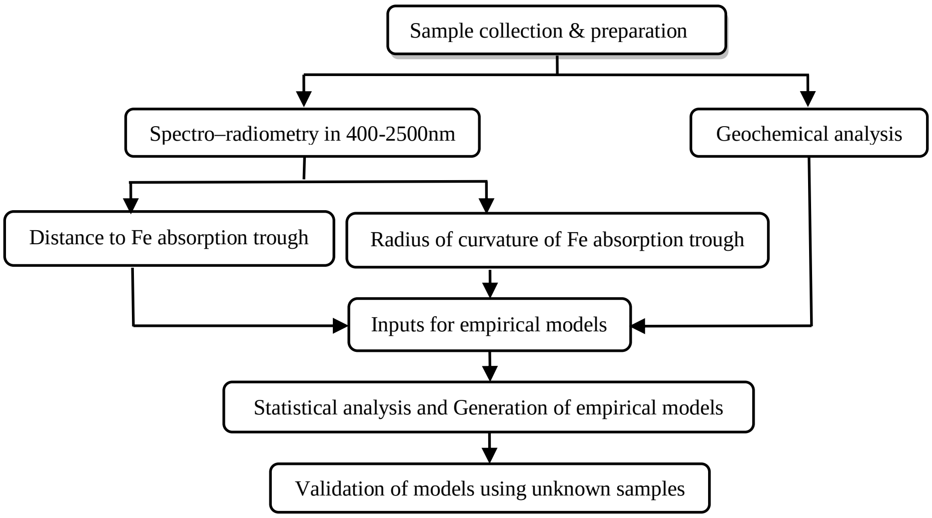


Figure 2 Flow chart showing the methodology adopted in this study

2.4 Estimating Spectral Parameters for the Empirical Model

Radius of Curvature Method

Spectro-radiometer is used to generate the spectral curves and these curves are plotted. Spectral curves (C) are exported in AutoCAD to draw a tangent to the maximum depth point of 850-950nm wavelength region. Therefore Fe α1/R. where R, is the Radius of the curvature.

Depth as a Parameter - Absorption Ratio

Absorption ratio indicates the percentage of absorption for particular curves. For this a common relative reflectance percentage value is taken as a benchmark (100 % reflectance) from this benchmark value, the distance is calculated by drawing perpendicular lines to the maximum depth point (maximum absorption point).

3. RESULTS AND DISCUSSION

3.1. Spectral Curves

The results of spectral reflectance measurement done with the Spectroradiometer are varied. The samples collected shows maximum absorption from 850nm-900nm. In figure 3 the sample D1 has maximum absorption in 850-900nm has more iron content, than the other samples. Sample B1 has least absorption and has less iron and more alumina content, because the absorption of this curve is more in 2200nm than for the other curves. Thus, the absorption of the curves depends on the chemical composition of the sample.

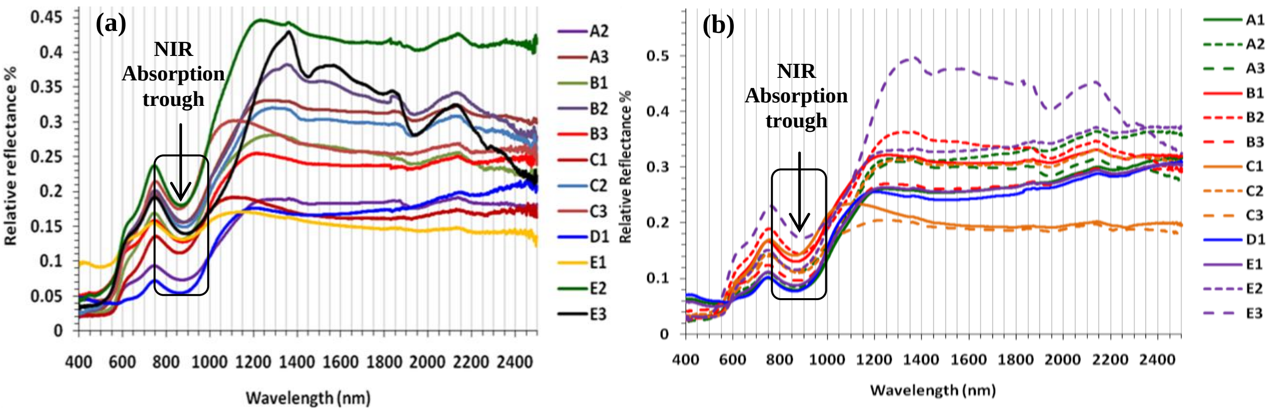
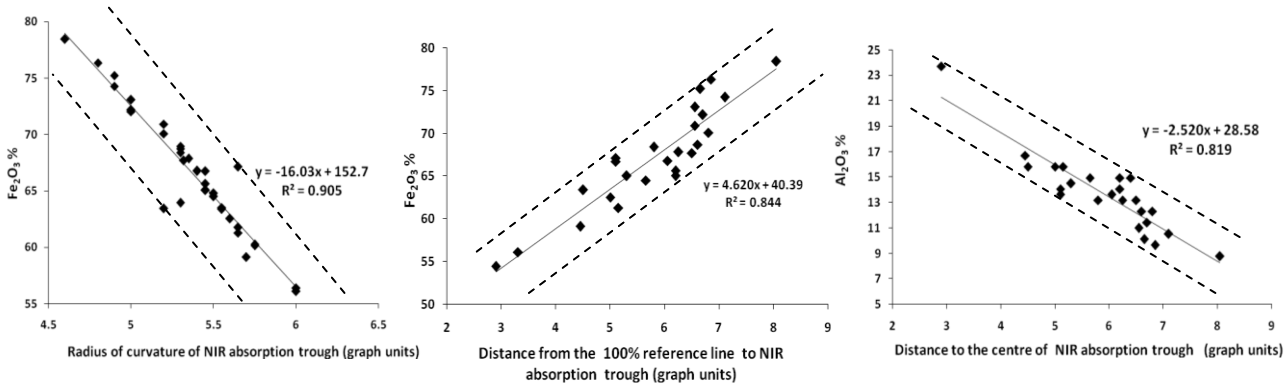


Figure 3 Spectral curves (400-2500 nm) of (a) Massive and (b) powder Hematite samples

3.2 Generation of Empirical Models

From an analysis of spectral curves in the VNIR region, it is evident that there is an increasing absorption in the NIR region with increasing iron content. The absorption features can be characterized in terms of the radius of curvature of the absorption trough and the depth of absorption with respect to the maximum reflectance line (100%).

A correlation study between the Radius of Curvature of the absorption trough and the iron oxide content of the corresponding sample reveals that the 2 parameters have a strong negative correlation (figure 4a) with an R value of -0.951. Similarly a correlation study between the depth of absorption with respect to the maximum reflectance line (100%) and the iron oxide content reveals that these parameters have a strong positive correlation (figure 4b) with an R value of
0.918. The alumina content reveals a strong negative correlation with the distance of the trough (figure 4c) with an R value of -0.904. Such strong correlations suggest that an empirical model can be generated relating the radius of curvature in the VNIR region and iron oxide content of iron ores. Such an empirical model can be used to predict the iron oxide abundance or grade of iron ore, not by geochemical analysis but by taking the spectral measurement and by computing the radius of curvature. Accordingly, the empirical model (regression equation) to predict the iron oxide content is given as y=-16.30x + 152.7, y = 4.620x+40.39, -2.520x+28.58 for Fe_2O_3 Vs Radius of curvature and Fe_2O_3, Al_2O_3 Vs depth respectively.



(a) (b) (c)

Figure 4 (a) Empirical model relating Fe_2O_3 in iron ore samples and radius of curvature of maximum absorption trough at NIR.
(b) Empirical model relating Fe_2O_3 and distance from the reference line and
(c) Empirical model relating Al_2O_3 and distance from the reference line

3.3 Validation of Empirical Models

Having generated the empirical models, the next step is to evaluate the accuracy of the model. This was done by carrying out spectro-radiometric studies of 20 samples whose iron oxide content was not estimated by geochemical analysis (at this stage). The radius of curvature of the absorption trough at 850 to 900 nm and the depth of absorption with respect to the reference line were measured and these values were input into the empirical/ regression model. When the model was run, the result was the iron oxide content of 20 samples. The next step was the estimation of actual iron oxide content of these 20 samples by geochemical analysis. The predicted iron oxide content of these 20 samples was compared with the actual iron oxide content (figure 5a & 5b). From the figure, it can be seen that there is almost perfect match between the predicted and actual values of iron oxide content (R^2=0.920). The mismatch between predicted and actual values for samples 7, 10, 11, 18, 19 and 20 is perhaps due to the other components (Al_2O_3, SiO_2 etc.) which can alter the degree of absorption and hence the radius of curvature values.

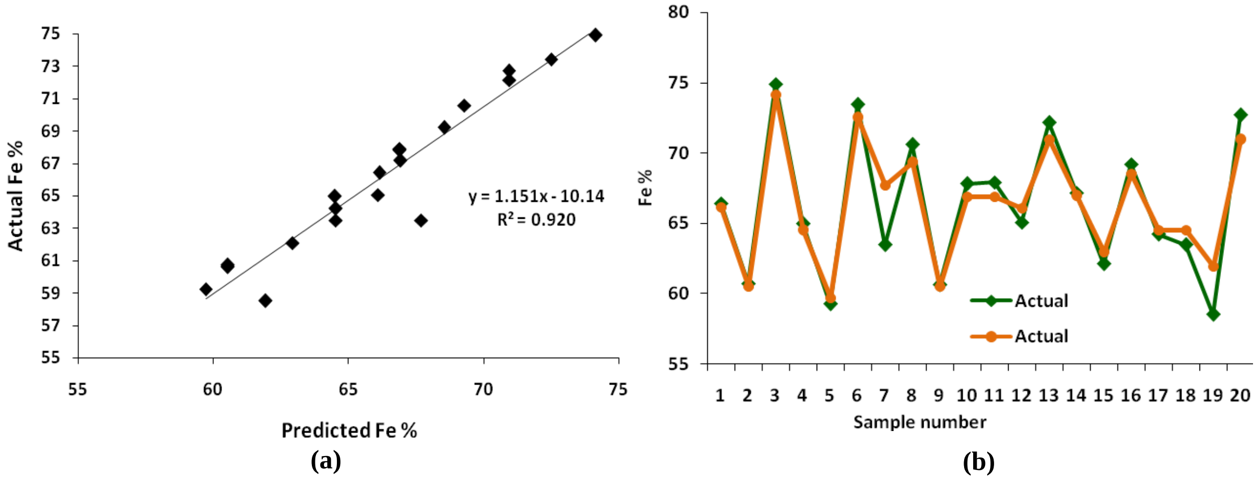


Figure 5 (a) Relation between actual and predicted values of iron oxide in the iron ore samples

(b) Match between the actual and predicted values of iron oxides in iron ore samples

4. CONCLUSIONS

This work describes the potential of hyperspectral radiometry in identifying the well defined absorption features of iron oxide in the 0.85-0.90µm region. It is seen that in categorizing iron ore grades, the spectral curves express the total iron content of the samples through two parameters, radius of curvature of the NIR trough and distance of the absorption trough. A strong correlation (R^2=0.905) is seen between the radius of curvature of NIR absorption trough and the iron oxide content, while a moderate to strong correlation (R^2=0.844) is seen between the depth of the curve from the 100% reflectance line and the iron oxide content. R^2 value of 0.819 is observed as the correlation value between depth of the curve from the 100% reflectance line and the Al_2O_3 content in iron ore samples. Thus the spectra based empirical models that make use of the R^2 values can be used to predict the iron oxide and alumina content in the iron ores. Hence, it may be mentioned that hyperspectral radiometric techniques may be used in the visible and VNIR regions for estimating different iron ore grades in a rapid manner, than the traditional methods.

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