Application of Advanced Remote Sensing Data in Mineral Exploration in the Vicinity of Heavy Dense Forest Cover Area of Jharkhand and Odisha State Mining Area

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Abstract—The study has been carried out on the Saranda in Jharkhand and a part of Odisha state. Geospatial data of Hyperion, a remote sensing satellite, have been used. This study has used a wide variety of patterns related to image processing to enhance and extract the mining class of Fe and Mn ores.Landsat-8, OLI sensor data have also been used to correctly explore related minerals. In this way, various processes have been applied to increase the mineralogy class and comparative evaluation with related frequency done. The Hyperion dataset for hyperspectral remote sensing has been specifically verified as an effective tool for mineral or rock information extraction within the band range of shortwave infrared used. The abundant spatial and spectral information contained in hyperspectral images enables the differentiation of different objects of any object into targeted applications for exploration such as exploration detection, mining.

Keywords—Hyperion, hyperspectral, sensor, Landsat-8.

I. BACKGROUND

THIS study addressed the mining area in southern Jharkhand and the northern states of Odisha in India. The open mining of the presses and related minerals are explored here. The frequency associated with the mineral absorption scale is the key factor in determining the mining department. Acquired data set of Hyperion and Landsat-8 profile are used here to target the specific mineral class. It was profound to extract the Minerals Department to locate the Mining Department on its absorption scale. The dataset run in both versions is examined very closely in each subprofile.

I. OBJECTIVE

(1) This research has a number of objectives, a range of micro-M and nano-M analysis levels, which represent conditions and measures consistent with the structural use and search for new minerals. (2) These studies range from primary remote sensing studies to the effects of human impact on mineral exploration and the differentiation of whole minerals. (3) The integration of mining engineering by the hyperspectral analysis method is also a part of the objective considered for commercial purposes.

This study has the following goals: (1) Using the hyperspectral remote sensing method and analyzing its

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accuracy. (2) Thermal effect of minerals through comparison and contrast (3). Developing a large-scale mineral classification in the study area that can be used by other pioneers.

II. MATERIALS AND METHOD

Remotely sensed images are subject to degradation due to atmospheric effects and sensor physical obstructions. The important objective of image restoration is to give as much relief from such effects as possible. It is difficult to obtain hyperspectral (HS) (Fig. 2) or multispectral (MS) (Fig. 1) images with both high spatial and spectral resolution. Image enhancement is designed to enhance the content of the image signal; this includes contrast enhancement, slice density, edge enhancement. Extracting information, the presentation pattern of other spectral characteristics of the scene are not noticeable because they reproduce and enhance images of key elements, including images relative to bands, MS classification, change detection images [1], [2].

Various supervised classifications have been performed to identify the mineral class under the SAIL GUA mining range on Hyperion data. Also, NDVI is used to extract open cast mining. The FLAASH operation has been performed on both types of the strip to remove atmospheric aerosols. Minimum Noise Fraction and Pixel Purity Index are obtained to perform the corresponding removal of noise and to identify the clearest pixel [3].

The application is made to obtain the final member spectra to create signature classes in further N-dimensional visualization schemes for auto clusters. After comparison with the ground-truthing data, the signature class has to be validated and overlay it using the SAM band maximization method [4].

Analysis: (1) Raw data Hyperion and Landsat used here. The pre-processing includes preparing the data set to classification stage. Spectral Angle Mapper is used here to classify the mineral class and further, mapping by using ENVI Software.

III. RESULT

The regression (R = 1, approx) achieved shows the high accuracy of the train data with respect to the in-situ sampled data which shows the high accuracy of the abundance of the

mineral class at mining sites. This is the inbuilt spectral lib. The purpose is to explore and further differentiation from the USGS Spectral Library on iron ores and Mn ores. In-built spectra have been used for a number of processes for the purpose of differentiation and exploration, especially for ores, and applied on the number of times for both types of images i.e., Hyperion (Fig. 2) and L-8 (Fig. 1) [4], [5].

The HS & MS analysis is performed on imagery taken from the Earth's exploration site for different ore. As seen in classified figures (Figs. 1, 2) this, this study gives us true differentiation after a descriptive comparative analysis has been carried out on both types of images.

Landsat-8 (Data work out): This is one of the best methods for studying their mineral composition in global iron ore, showing a wide absorption band centered at 1250 nm due to the electronic transition of small amounts of Fe. The Multiband Imager is designed to detect an absorption band. The Multiband Imager includes both visible and near-infrared coverage, with spectral bands at 0.4 to 0.7 and 1.0 to 1.55 NIR. The instrumental spatial resolution is 30 m or 62 m NIR per pixel at a nominal altitude of 100 km.

Step-wise procedure:

Spectral resembling=>input-band=>Thor. ATM. correction_QUAC=>De-Striping=>sp-smoothing=>thor anomaly detection=>QUAC_Gain & Offset calibration=>a.det_QUAC

Several different sampling schemes can be used to assign the appropriate DN to an output cell or pixel. We refer to the shaded output pixels as a reference for further calibration and focus on them. The DN for this pixel is divided based on the DN of the closest pixel to the received input matrix, offset received is negligible. The marked input pixel DN switches to the shielded output pixel. This approach is called nearest neighbor resampling. Bilinear interpolation resampling takes the four most neighboring pixels as a distance-weighted average. It also improvises as a bubble resampling that takes 16 pixels into a matrix that surrounds each output pixel.

Spectral Angle Method Profile for Mineral Extraction: The spectral angle mapper matches the Hyperion and L-8 spectra with the built-in USGSs in n-dimensions. And each pixel is a vector in an n-dimensional space. For rigid targets, the smaller angles fall closer to the reference spectrum.

Step-wise procedure:

Input/Output File Selection=>Target-Selection=>Background Selection=>Bands Selection tho' BandMax=>Spectral Mapping uses Spectral Angle Mapper (SAM) =>Mapped Result Investigation.

In this experiment, the Band-Max algorithm was chosen to reduce the order errors (false positives) that automatically occur during a SAM analysis. In this particular step, we usually select background pixel spectra, which, moreover, are incorrectly identified as targets. The SAM angle is 0.1c. Now, in the SAM procedure, the image spectra were taken as reference in n-dimensions, n was taken as bands. Therefore, SAM separates the angle between the target spectrum and each pixel, not the vector.
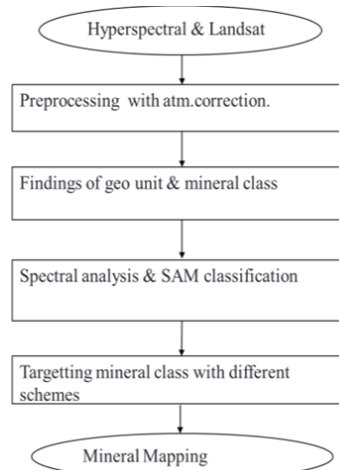

Fig. 1 (a) Flow chart depicting the methodology adopted for the preparation of mining mapping of minerals, by using remote sensing methods. The prime Method and job work for mapping of both types of images shown below as a block diagram
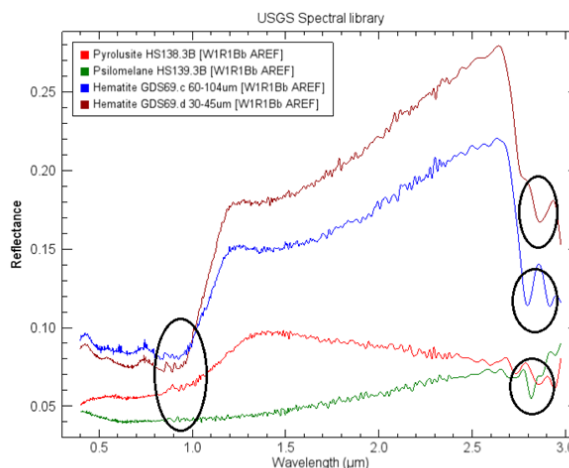

Fig. 1 (b) Inbuilt spectral library (Source: USGS Spectral lib., it has only taken as reference spectra under absorption scale, "shown in the black circle" of respective ore class) of Fe-ore and Mn-ore also used for extraction of Fe-ore and Mn-ore concerning with CIF lib. spectra. [Data Source: [1], [2] Additional data analyses were done using ENVI version 5.1 (Exelis Visual Information Solutions, Boulder, Colorado)]

Continuum Removal-profile: To determine the band depth, we define a continuum that is determined by fitting a cubic spline to the reflection peaks between the absorption characteristics. The wavelengths of the peak were generally $\lambda 1$, $\lambda 2$, $\lambda 3$, $\lambda 4$, and $\lambda 5$…, although this varied slightly for the properties of the weak adsorbed water near these peaks. Once a continuum fits the reflection spectrum, we divide the spectrum by sequence. The band depth D is $D = 1 - R / dR$, where R is the reflectance at the center of the absorption band and dR is the reflection of the continuum at the center of the band. This profile is advantageous to create the index and

signature class according to the mining area. Data file continuity is defined as the personal deletion spectrum or plot window. Step-wise procedure:

Spectral => Mapping Methods(Fig.1)=> Continuum Removal=>OK=> Save in File or Memory
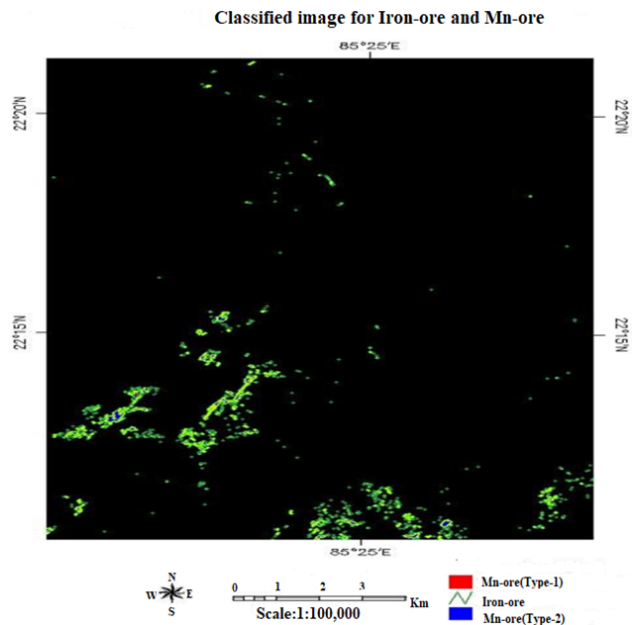
Classified image for Iron-ore and Mn-ore

Fig. 1 (c) Ground truth library spectra & the abundance of mn-ore validated by CIF Lib. Spectra from BIT Mesra, it is considered as One of the results for the mn-ore type from the open cast mining area. MTL File=>Spectral analysis =>no.of input-band=>ATM. correction=>Radiometric correction by using subset file=>Decorelation stretch=> Filtering=>Topographic modular used to detect mineral class. [Data Source: [1], [2] Additional data analyses were done using ENVI version 5.1 (Exelis Visual Information Solutions, Boulder, Colorado)]

Continuity removal analysis has improved the standard derivative analysis for such applications. HS data of any class that is more complex than many and much more complex spectra than the spectra of a similar class are presented there. In this particular study, the continuum removal profile became an additional topic in the standard derivative analysis. The goal is to estimate the biomass concentration based on remote sensing data.

IV. DISCUSSION

The secondary objective has been full-fledged by creating a mineral-index by the method of creating spectral signatures with different coordinate positions on the Hyperion data-set. Finally, the fluctuations between the two bands remove the level of continuity B_{x1} and B_{x2} of any useful shortwave. In this way, a mineral-index for the Hyperion scale was created to extract the mining class for open cast mining. This then makes it very easy to detect open cast mining on the Hyperion HS data-set (Fig. 2 (a)).
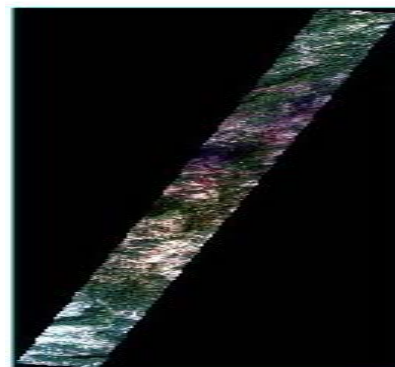

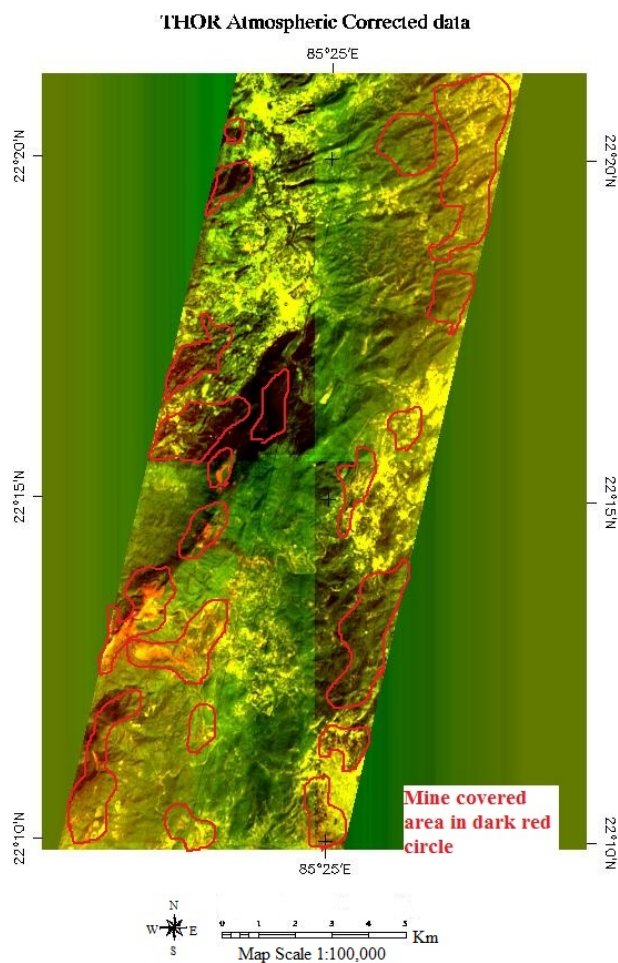Fig. 2 (a) Hyperion-class: (a) preprocessed data detecting ore class

THOR Atmospheric Corrected data

Fig. 2 (b) Digitized data [6]

V. CONCLUSIONS

In this study mineral targeting is accomplished by spectral investigation among data-sets for the study area on Hyperion. Also, the main objective is to discriminate in minerals. This has to be done using the SAM Band Max method. The OLI sensor data are used here according to the requirements; the

band maximum method has also been used to discriminate the minerals, to pick up the surrounding areas. Comparative analysis between the Hyperion, OLI, and CIF (BIT Mesra) data-sets has been performed to obtain extremely correct information between them. The verification is done by ground-truthing data. After successful testing between them, the mineral map is done.

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