Characterization and mapping of hematite ore mineral classes using hyperspectral remote sensing technique: a case study from Bailadila iron ore mining region

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Abstract

The study demonstrates a methodology for mapping various hematite ore classes based on their reflectance and absorption spectra, using Hyperion satellite imagery. Substantial validation is carried out, using the spectral feature fitting technique, with the field spectra measured over the Bailadila hill range in Chhattisgarh State in India. The results of the study showed a good correlation between the concentration of iron oxide with the depth of the near-infrared absorption feature ($R^2 = 0.843$) and the width of the near-infrared absorption feature ($R^2 = 0.812$) through different empirical models, with a root-mean-square error (RMSE) between < 0.317 and < 0.409 . The overall accuracy of the study is 88.2% with a Kappa coefficient value of 0.81. Geochemical analysis and X-ray fluorescence (XRF) of field ore samples are performed to ensure different classes of hematite ore minerals. Results showed a high content of Fe > 60 wt% in most of the hematite ore samples, except banded hematite quartzite (BHQ) (< 47 wt%).

Keywords Hyperspectral remote sensing · Spectral feature fitting · Spectral angle mapper · XRF

1 Introduction

Developments in hyperspectral remote sensing technology enable mapping of various geological and lithological structures and identification of different minerals [1, 2], including altered minerals like kaolinite, montmorillonite, illite, dickite, alunite, feldspar, etc., and different types of iron ores like hematite, magnetite, and goethite [3]. Each mineral exhibits unique absorption and spectral reflectance pattern in the electromagnetic spectrum, which allows the identification of every element, and relative abundance in the rock sample for any given location. For instance, spectral absorption in the visible and near-infrared (VNIR) region gives essential information about iron oxides [4]. Fe^{2+} ion contained in rocks is accountable for absorption at a wavelength of nearly 900 to 1100 nm, and Fe^{3+} ion sources for absorption at 750 nm–870 nm

wavelength regions. Material having an utmost quantity of iron content shows higher reflectance phenomena at a wavelength portion of 870 nm [5]. VNIR and shortwave infrared (SWIR) wavelength bands are very useful for lithological mapping, identifying hydrothermally altered minerals, and differentiating oxide and hydroxide minerals in high-terrain regions, differentiating various types of carbonate lithologies such as limestone karst and hydrothermal dolomites [6]. The transition of electrons between different transition metals like iron (Fe), manganese (Mn), and chromium (Cr) is associated with the reflectivity of multiple minerals in VNIR and SWIR spectral bands [7]. In this background, the present study is taken up to map different types of hematite ore minerals in the Bailadila mines situated in the southernmost part of Chhattisgarh State, India, using EO-1 Hyperion data.

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2 Study area

Bailadila mining area is the first enormous open-cast iron ore mine in India, located in Dantewada District, Chhattisgarh State, between $18^{\circ}35'48''$ and $18^{\circ}38'30''$ N latitude and $81^{\circ}13'22''$ and $81^{\circ}16'00''$ E longitude, covering in Survey of India (SOI) toposheet no. 65F/1, F/2, F/5, and F/6. Bailadila hill range extends 40 km in length and 4 km in width, and this range is the highest point (1276 m MSL) within Chhattisgarh State (Fig. 1).

The generalized geological succession in the Bailadila hill range after [8] as mentioned in [9] and [10] is shown in Table 1. The Bailadila meta-sedimentary sequence unconformable overlies the older metamorphic of Bengal Group with intervening post-Bailadila granites [10, 11]. This meta-sedimentary in the area forms two approximately parallel N-S trending ridges, extending

about 30 km from Kirundul in the south to Jhirka in the north, where they confluence and extend further northward [8]. The sequence exposed on the eastern flank of the east ridge forms as an east-dipping overturned limb of an isoclinal syncline. The western ridge is also a synclinal ridge, with near-vertical to steeply eastward dipping beds. The phyllites and conglomerates occupying the intervening valley are the sequences in the area that form a northerly plunging synclinorium [8, 11]. The regional strike of the main Bailadila range is N-S with steep easterly dips. The Bailadila range consists of two high ranges separated by a valley. Crookshank H. [8] identified two lightly folded overturned synclines for the two ridges and as eroded anticline occupying the valley in between. The main fold has been superimposed by two sets of easterly and northwesterly cross-folds. The geological map of the study area is shown in Fig. 2.

Fig. 1 Location of the study area: **a** India, **b** Chhattisgarh State, **c** Dantewada District, and **d** Bailadila iron ore mining region covered in Hyperion imagery

Table 1 Geological succession of the study area [10]

Proterozoic Archean	
Recent	Soils and alluvium laterite
<i>Unconformity</i>	
Cuddapah (Purana)	Lime stone, shales, slate Sandstone and slates, quartzite, grits, conglomerates
<i>Unconformity</i>	
Igneous rocks	Dolerite, pegmatite Charnockite series Granite Greenstones Granitic gneisses and pegmatite
Bailadila iron ore series	Banded hematite quartzites and iron ores Grunerite quartzites, chloritic ferruginous Phyllites, carbonaceous shales White quartzites
<i>Unconformity</i>	
Bengpal series	Ferruginous schists, schistose conglomerates Basalt and tuffs Andalusite phyllites, schists, gneisses, and quartzites Grunerite–garnet schists, BHQ, garnet–andalusite quartzites Sericitic quartzites and sandstones
<i>Not distinct unconformity</i>	
Sukma series	Sillimanite quartzite Magnetite quartzite, grunerite schists Diopside gneiss Hornblende schists Cordierite–biotite gneisses, cordierite–anthophyllite rocks
Basement not exposed

Fig. 2 Geological map of the study area

3 Methods of study

For this study, Hyperion (EO-1) satellite imagery with a spatial resolution of 30 m dated December 9, 2009, covering Bailadila hill range was used to map the hematite ore minerals, substantial with spectral signatures of ore samples collected using ASD field spectroradiometer. Hyperion level-1R satellite data product with 242 spectral bands was downloaded from the USGS official Web site (<https://earthexplorer.usgs.gov/>), and the data were processed using Digital Image Processing software (Fig. 3). Initially, Hyperion data were preprocessed to remove the bad bands, vertical lines, and other lightening effects. The resized and processed data are atmospherically corrected to minimize the atmospheric influence caused by aerosols and other constituents present in the atmosphere. Spectra of various hematite ore classes extracted from the satellite imagery were analyzed using field-based spectra collected at appropriate locations with the help of the Global Positioning System (GPS). Field spectra of various hematite ore samples have been collected at different locations and processed to eliminate the temperature drift and water

Fig. 3 Flowchart of the methodology adopted in the study

vapor absorption effects before using them for analysis. Spectral analyst techniques were used to correlate the similarity between image and field spectrum after continuum removal. Significantly matched image spectra were used as endmembers for mapping various hematite ore classes using the SAM algorithm. Geochemical and XRF analyses have been performed to ensure the amount of iron content present in the ore samples at respective locations. The accuracy of the map is assessed using the confusion matrix method and also through spectral similarity between image and field spectra using statistical spectral feature fitting techniques.

4 Results and discussion

4.1 Data processing

The foremost aim of preprocessing is to minimize geometric distortions, atmospheric, and solar flux effects of the data. This task is achieved through digital image processing techniques to convert spatial data into meaningful information. The most crucial step involves the removal of bands with no information from the data. The list of bands which are removed from the dataset is (1–7 and 225–242) non-illuminated, (58–78) for overlap region, (120–132, and 165–182 and 221–224) for water vapor absorption band, and (185–187) identified noise band. Therefore, 86

spectral bands are eliminated, and only 156 spectral bands are processed for utilization. The geometric correction of datasets is achieved through a suitable geo-referencing process. A cross-track illumination correction tool is used to rectify vegetation effects, device effects, scanning, and other lightening effects of imagery [12]. While processing, it is observed that data contain vertical black strip lines due to inaccurate standardization of discrete sensors on the raiment. This unresolved striping effect in the data can lead to a poor understanding of the result. The striping effect is removed after applying wavelet Fourier adaptive filtering directly in the image domain [13] (Fig. 4).

4.2 Atmospheric correction

The significant and critical step of processing hyperspectral data is to convert the radiance to reflectance called an atmospheric correction. Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) tool is an effective meteorological physics-based model, and this correction model is utilized for atmospheric correction [14]. The following parameters are used in the atmospheric correction module: atmospheric model: (selected based on seasonal latitude surface temperature model) tropical model is used for this purpose; water retrieval technique: for retrieving water amount for each pixel at 1135 nm water absorption feature. 2-band (K-T) as an aerosol retrieval model; rural as an aerosol model; and DISORT

Fig. 4 Hyperion imagery **a** before and **b** after removal of stripping effect

as moderate-resolution transmittance multi-scatter model at a resolution of 15 cm^{-1} [15]. Accurate wavelength calibration is critical for atmospherically correcting Hyperion (EO-1) data. Spectral radiance at a sensor is calculated with the use of the following arithmetic equation (Eq. (1)) [16]:

$$L = \left(\frac{AP}{1 - peS} \right) + \left(\frac{Bpe}{1 - peS} \right) + La \quad (1)$$

where L is the device spectral radiance; P —surface reflectance of the pixel; Pe —mean of average surface reflectance for the pixel and an adjacent part; S —spherical albedo of the atmosphere; La —radiance backscattered by

the atmosphere; and A and B —coefficients which depend on atmospheric and geometric condition. An atmospherically corrected spectrum is shown in Fig. 5.

4.3 Comparison of image spectra and ground truth data

Hyperspectral data consist of noise in the form of spikes and artifacts, and these are removed from the imagery during preprocessing, before the extraction of information of features in the form of spectra. Based on field spectral signatures collected at different sites, the corresponding pixel locations are recognized using ground coordinates (Table 2). The obtained iron ore samples are uniformly distributed to represent the entire mining area in the image. It is observed that the sample locations cover all the types of hematite iron ores (gray hematite, blue hematite, laminated ore, lateritic ore, and banded hematite quartzite). The sampling sites are identified in such a way that the buffering area equal to spatial resolution ($30 \text{ m} \times 30 \text{ m}$) is enclosed by a single type of ore in the targeted mining locations. The spectra extracted from Hyperion imagery for recognized sites are representing various classes of hematite iron ores within the research area (Fig. 1).

4.4 Spectral response of hematite ore samples

Hyperion reflectance spectra of five different hematite ores are shown in Fig. 6. To distinguish the variations in the depth of major absorption bands present in hematite ore spectra on a per-pixel basis, to normalize the curves continuum removal method was applied, to isolate the features, and to allow their comparison from a common baseline. A complete explanation of the continuum removal method is given by [17]. It is observed that different hematite ore samples have absorption between 750 and 1100 nm due to the presence of iron oxide; the depth of absorption spectrum increases with the increasing

Fig. 5 Image spectra **a** before and **b** after atmospheric correction

Table 2 The locations of field samples collected

Sample no.	Description	Location	
		Latitude (N)	Longitude (E)
1	Gray hematite	18° 36' 57.3"	81° 13' 52.9"
2	Blue hematite	18° 36' 57.29"	81° 14' 0.03"
3	Laminated ore	18° 36' 38.84"	81° 14' 2.87"
4	Lateritic ore	18° 37' 0.47"	81° 14' 2.08"
5	BHQ	18° 36' 47.93"	81° 13' 51.83"
6	BHQ	18° 38' 17.7"	81° 14' 14.64"
7	Gray hematite	18° 37' 56.84"	81° 14' 22.29"
8	Blue hematite	18° 37' 39.68"	81° 14' 27.66"
9	Laminated ore	18° 37' 32.67"	81° 14' 16.66"
10	Lateritic ore	18° 37' 36.64"	81° 14' 12.61"
11	BHQ	18° 38' 48.77"	81° 14' 14.35"
12	Gray hematite	18° 39' 30.14"	81° 13' 40.4"
13	Blue hematite	18° 39' 29.71"	81° 13' 45.8"
14	Laminated ore	18° 38' 45.34"	81° 14' 5.13"
15	Lateritic ore	18° 39' 36.25"	81° 13' 41.98"

Fig. 6 Image reflectance spectra of **a** gray hematite, **b** blue hematite, **c** laminated ore, **d** lateritic ore, and **e** banded hematite quartzite (BHQ)

amount of iron content in the ore sample; the width of absorption spectrum increases with decreasing the concentration of iron oxide. Gray hematite has shown a strong absorption depth at 905.25 nm and width 0.334146, whereas BHQ showed absorption depth at 872.53 nm and width 0.453543. Spectral parameters of various hematite ore classes and their iron content values are presented in Table 3.

4.5 Field spectra

The utmost significant step in this study is to collect the spectra in the field as the study area was hilly terrain and inaccessible due to other local conditions. Field spectroscopy measures the reflectance properties of rocks, vegetation, soil, and other objects under natural environmental

Table 3 Geochemistry and respective spectral parameters of various hematite ore samples

Sample no.	Sample name	Spectral parameters		Geochemical analysis	
		Iron absorption features		Fe %	
		Depth	Width	Geochemistry	XRF
1	Gray hematite	905.25	0.334146	68.5	68.4
2	Blue hematite	895.44	0.361492	67.2	67.3
3	Laminated ore	892.32	0.381354	64.5	64.6
4	Lateritic ore	865.35	0.395421	62.2	62.3
5	BHQ	872.53	0.453543	32.6	32.5
6	BHQ	872.53	0.443543	31.9	32.1
7	Gray hematite	905.25	0.332142	68.2	68.2
8	Blue hematite	895.44	0.365492	67.5	67.1
9	Laminated ore	892.32	0.392354	63.8	63.7
10	Lateritic ore	865.35	0.398421	61.2	61.4
11	BHQ	872.53	0.443253	33.1	32.8
12	Gray hematite	905.25	0.324152	67.9	67.5
13	Blue hematite	895.44	0.372382	66.8	66.7
14	Laminated ore	892.32	0.384321	64.2	64.5
15	Lateritic ore	865.35	0.378432	62.1	62.3

conditions. Spectral signatures of different types of hematite ores are collected using the spectroradiometer (SVC HR1024) model in visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum at a bandwidth of 10 nm at 15-degree angular fields of view (FOV). Field spectra are processed to improve the signal-to-noise ratio and resampled with an interval of 5 nm. Since field spectra are collected in the natural environment, it is crucial to remove some of the bands which belong to temperature drift and water vapor absorption before further analysis. The spectroradiometer is structured with different characteristic variations in sensor sensibility, which is utilized in diverse temperature environments. The temperature drift correction is applied at 1001 nm wavelength because of field spectra collected at different temperature conditions [18]. During the collection of field spectra, water vapor absorption bands arise at wavelength regions of 1350–1460 nm, 1790–1960 nm, and 2350–2500 nm due to atmospheric effects [15]; a correction is applied to eliminate these bands. Field signature

contains self-generated noise; hence, appropriate filter is applied to smoothen the spectra. Savitzky–Golay smoothing filter has generated high-accuracy output [19]. Field spectra and photographs of various hematite ore minerals are shown in Fig. 7.

4.6 Spectral analysis

Matching of image spectra and field spectra is done using an absorption feature-based method known as the spectral feature fitting method. This technique is established by Clark [20]. These techniques work on continuum-removed reflectance spectra. Continuum removal is a mathematical function applied to isolate the authentic absorption features of iron ore mineral pixels from hyperspectral imagery [21]. Spectral feature fitting uses a continuum-removed unknown spectra which are compared with continuum reference spectra of known mineralogy and also produced RMS error image for each endmember to calculate RMS error. A least-square fit is calculated band by band between every reference spectra and the continuum-removed unknown spectra. Low RMS error indicates a high similarity between the field spectrum and the shape of the image spectrum. The similarity between the image spectra and reference spectra is shown by the fit image which is generated by measuring a ratio between scale image and RMS error image. Prominent absorption features are identified between the wavelengths of 750 nm and 1100 nm for oxide minerals (hematite) [22] (Fig. 8). Correlation and comparison of image spectra with field spectra of various hematite ores are also done using spectral feature fitting, SAM, and binary encoding (BE). These techniques are robust and most frequently used spectral matching techniques. All the techniques show acceptable matching scores (Table 4), and it is observed that image spectra are ideally matched with field spectra (Fig. 9). Therefore, it can be believed that there is a possibility to map the different types of hematite ores after deriving appropriate spectral parameters from the imagery. The image spectra extracted through spectral analysis techniques are used as endmembers for the classification of the data. A statistical spectral feature fitting technique was also applied to measure the similarity between image and field spectra in the form of RMS error. The resultant RMS errors of gray hematite, blue hematite, laminated ore, lateritic ore, and banded hematite quartzite are < 0.317 , < 0.358 , < 0.393 , < 0.401 , and < 0.409 , respectively. The sample, which is having a high percentage of iron content, showed a significant match with field spectra. With an increase in the percentage of impurities in the sample, RMSE also increased slightly (Fig. 10). The result of this is used to assess the mapping correctness of hyperspectral imagery.

4.7 Geochemical analysis

4.7.1 Wet chemical analysis

The purpose of the geochemical analysis is to identify the concentration of primary mineral (Fe) in the ore sample, and the results are related to spectral parameters with an appropriate pixel position. Five types of ore samples were collected from fifteen locations in the mining region covered within the Hyperion image (Fig. 1). Best samples (gray hematite, blue hematite, laminated ore, lateritic ore, and banded hematite quartzite) are selected for geochemical analysis after careful inspection of all field samples. Samples are physically crushed into 1–2 cm pieces, eliminating deleterious material, including weathered surfaces and veins. The chipped samples are washed carefully in distilled water to remove the surface dust and are dried. All the samples are crushed to 200 mesh in an agate pulverizer mixed meticulously for homogenization and representativeness of the sample. Small samples such as minerals and meteorites are usually crushed in steel or diamond mortars and ground manually in an agate mortar [23]. These ore samples are subjected to wet chemical analysis. The results of the investigation revealed that four types of samples (gray hematite, blue hematite, laminated ore, and lateritic ore) showed an enormous amount of iron (Fe) of (61.2–68.5) wt% with a considerably low level of SiO_2 (0.6–4.4) wt% and Al_2O_3 (0.3–6.6) wt%, respectively, whereas a sample (BHQ) showed a low amount of iron (31.9 wt%), a moderate amount of alumina oxide 1.3 wt%, and a high amount of silicon oxide (51.7 wt%). Furthermore, the ore samples contain other oxides such as P_2O_5 , TiO_2 , Cr_2O_3 , Co_2O_3 , CuO , MnO , ZnO , V_2O_5 , As_2O_3 , SO_3 , BaO , and MoO_3 which exist in considerably insignificant amounts. The ore sample, which has low iron (31.9 wt% Fe), is considered as a low grade and having other impurities (about 68.1 wt%). Mineralogical and geochemical studies of subgrade iron ore at the Bailadila mining region have been done by G.V. Rao [24].

4.7.2 X-ray fluorescence analysis

The primary and trace elements of iron ore samples can be better investigated by the XRF technique [25]. The primary element (Fe) is investigated for five types of samples collected in the field on wavelength-dispersive X-ray fluorescence (WD-XRF) instrument using powder pellet pressing technique. Machine calibration is subjected to the element that has to be analyzed. The primary constituents (Fe_2O_3 , SiO_2 , P_2O_5 , Al_2O_3 , Co_2O_3 , Cr_2O_3 , TiO_2 , and loss of ignition (LOI)) of fifteen samples of five different hematite iron ore samples are analyzed using the XRF technique. The Fe content in ore samples ranges from 32.1 wt% to 68.4

Fig. 7 Field photographs and reflectance spectra of **a** gray hematite, **b** blue hematite, **c** laminated ore, **d** lateritic ore, and **e** banded hematite quartzite (BHQ)

Fig. 8 Absorption features of hematite ore sample **a** before and **b** after continuum removal

Table 4 The matching score between image and field spectra

Field spectrum	Score	SAM	SFF	BE
Gray hematite	1.213	0.204	0.326	0.990
Blue hematite	1.310	0.321	0.345	0.985
Laminated ore	1.333	0.336	0.367	0.975
Lateritic ore	1.364	0.382	0.418	0.954
Banded hematite quartzite	1.387	0.413	0.432	0.924

wt%. Primary element (Fe) found during XRF analysis is shown in Table 3.

4.8 Correlating geochemical and spectral parameters

Geochemical analysis of five types of hematite ore samples covered within the Hyperion image is performed to relate with their appropriate pixel locations. A standard operating procedure is followed to analyze the relationship between spectral and corresponding geochemical parameters of the ore samples [26]. Analysis of spectral curves extracted from the image discloses that the intensity of absorption increases with increasing iron content in the near-infrared region. The strength of absorption also varies with clay content present in the sample [27]. Therefore, absorption features in the near-infrared region can be used to describe the iron oxide mineral content present in the field ore samples based on the significant spectral constraints like the position of absorption features, depth, and width [22]. During analysis, it is observed that the depth of absorption increases in the near-infrared region with increasing iron concentration. The sample having an iron content of more than 60% is more sensitive to absorption. Hence, even for a small raise in iron content, there is a significant

rise in depth of absorption. During the formation of iron oxides, higher energy is required for the phenomena of electronic transition [28]. It is observed that the correlation is relatively strong; the association between spectral parameters derived from the image and iron concentration is well recognized by this work. Empirical models were established based on precise correlations, such as those observed between iron content in the hematite ore samples and the depth of NIR absorption feature of the matching hematite ore sample which has the finest correlation ($R^2 = 0.843$) as shown in Fig. 11a. This directs that for a rise in the mass of iron from 14 to 60%, the depth of NIR absorption increases steadily and the strength of absorption is not sensitive to the increasing iron mass. However, for an increase from 60 to 70%, the strength of absorption is very subtle, i.e., even for a small increase in iron content; there is a substantial rise in the depth of absorption. The phenomenon of electronic transition during the formation of iron oxide perhaps requires higher energy even for a small increase in the iron content beyond 60% [28]. The width of the near-infrared absorption feature of the matching hematite ore sample has a negative correlation ($R^2 = 0.812$) as shown in Fig. 11b. It is evident that when the depth of absorption increases, the absorption feature inclines to become narrower and the width becomes smaller. While an increase in depth of the absorption feature is the reason, an increase in the width of the absorption feature is the effect. Thus, an exponential relationship similar to the depth of NIR absorption is seen in the case of the width of NIR absorption. These relationships suggest that we can attain a quantitative and qualitative description of the relationship between iron content in the hematite ores and the different spectral parameters. This description draws a correlation from the studies of Dawson and Curran [29]. The geochemistry and respective spectral parameters of various hematite ore samples are shown in Table 3.

Fig. 9 Comparison of image and field spectra of **a** gray hematite, **b** blue hematite, **c** laminated ore, **d** lateritic ore, and **e** banded hematite quartzite (BHQ)

4.9 Spectral angle mapper (SAM)

SAM computes the spectral similarity between the image spectrum and the reference spectrum taken either from the laboratory or reflectance spectrum collected from the field at natural atmospheric conditions [30]. SAM assumes

Fig. 10 The RMS error and histogram of **a** gray hematite, **b** blue hematite, **c** laminated ore, **d** lateritic ore, and **e** banded hematite quartzite

Fig. 11 **a** Empirical models relating Fe% in the hematite iron ores and depth of near-infrared absorption feature and **b** model relating Fe% in the iron ore samples and width of NIR absorption feature

that the data have been converted to apparent reflectance. While computing the SAM, each spectrum is considered as a vector in n -dimensional space [31, 32]. SAM measures the angular difference between image spectra and reference spectra for each pixel in radians represented in mathematical equation (Eq. (2)) [33]. The smaller the divergence, the higher the similarity, and the enormous difference means low similarity between the test (image spectrum) and the reference spectrum.

$$\cos \varphi = \frac{\sum_{i=1}^n t_i r_i}{\sqrt{\sum_{i=1}^n t_i^2} \sqrt{\sum_{i=1}^n r_i^2}} \quad (2)$$

where φ is the spectral angle, t refers to the test spectrum, r denotes the reference spectrum, and n denotes the higher number of bands. SAM classification is an automated, robust technique since it reduces the impact of shadiness issues to emphasize the image spectral features [34]. For every reference spectrum selected for the investigation of a Hyperion image, the spectral angle φ is calculated, which is meant for each spectrum of the image. This value (in radians) is allotted to the matching pixel in the SAM output image. The image spectra were endmember (Fig. 6) spectra extracted from Hyperion data. In this study, different types of hematite ore minerals conform to the geological background of the study area selected from the field spectral library such as different types of hematite ores associated with iron. The reference spectra for SAM were obtained after spectral matching between image spectra and field spectra [35]. Resampling of field spectra was done to ensure the resolution of endmember spectra consistent with field spectra. The SAM algorithm is utilized to generate a detailed mineral map. The numbers of reference spectrum or endmember are equal to the number

of outputs. The detailed classified map showed that the most excellent match at every image spectra (pixel) for every endmember appears for the actual angular distance between each image and the reference spectrum. The SAM classification map for Hyperion imagery shows good results for discrimination of types of hematite ores in the study area, because the thickness of iron ores is relatively vast and extends for several kilometers long. The probability of misclassification is very minimal because of no other mixed pixels, area exposure, and high spectral dimensions of the data. The classified iron ores map of the study area is shown in Fig. 12. The output of the geochemical analysis is correlated with the hematite ore minerals of corresponding locations assessed by spectral angle mapper. The finest match ($R^2 = 0.814$) is observed between iron content in the hematite ore samples and iron content estimated by spectral angle mapper (Fig. 13).

4.9.1 Accuracy assessment

The accuracy of the detailed map is assessed through the confusion matrix method. There are two methods to evaluate the accuracy of the results, i.e., through confusion matrix and the Kappa coefficient. In this study, the overall accuracy of the classified image is about 88.19% and the Kappa coefficient is 0.81 (Table 5).

5 Conclusions

This research work illustrates the practicability of using Hyperion imagery for mapping various types of hematite ores in hilly and inaccessible locations. The finest processed image spectra assisted in identifying the prominent absorption features (750–1100 nm) related to iron

Fig. 12 The classified map of hematite ore classes

Fig. 13 Correlation between Fe% in hematite ore samples and fraction of pixel values estimated by SAM

oxide minerals. Matching between image and field spectra through spectral feature fitting technique showed the best correlation. Prominent spectral absorption features of iron ore at a particular wavelength, location, and geochemical analysis of iron ore samples showed a good association. The depth and width of the absorption features of spectra are increasing with the increasing amount of iron content. The depth of absorption is increasing significantly, even a minute increase in the concentration of iron content in the sample. SFF is a robust method to compare the similarity

Table 5 Overall accuracy of classified map

SAM classification			
Category	Producer accuracy (%)	User accuracy (%)	Overall accuracy (%)
Gray hematite	92.20	91.14	88.19
Blue hematite	91.11	88.24	
Laminated ore	88.34	86.21	
Lateritic ore	86.21	87.31	
Banded hematite quartzite	84.54	86.62	

between field and image spectra of Hyperion data. Further, the classified map of Hyperion data resulted from the spectral angle mapper algorithm. RMSE values show the exceptional matching between image and field spectra which leads to an increase in the classification accuracy. The confusion matrix and the value of the Kappa coefficient show the accuracy of the classified output.

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Compliance with ethical standards

Conflict of interest The author declared that there is no conflict of interest.

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