MINERAL PROSPECTIVE MAPPING OF CHITRADURGA SCHIST BELT USING EO-1 HYPERION DATA

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Abstract
NASA'S EO-1 Hyperion sensors launched in November 2000. It provides good opportunity to evaluate the spaceborne hyperspectral capabilities. Hyperion sensors cover 0.4 to 2.5µm range with 242 spectral bands at approximately 10nm spectral resolution and 30m spatial resolution from 705km orbit. The enhanced information contains sensors which provides, hyperspectral analysis methods, namely Minimum Noise Fraction- transformation (MNF) for data quality assessment and noise reduction as well as Spectral Angle Mapper (SAM) for classification of Mineral potential zones. The Classification results show the detailed information that can be extracted from the source of information. The analysis reveals that Hyperion scene is strongly affected by system induced radiometric interferences. As a result considerable amount of bands are to be discarded to allow satisfying results.

Key words: Hyperion, SAM, Mineral Potential

Introduction
Hyperspectral sensors have hundreds of channels, aircraft and satellite platforms which provide unique spectral datasets which are helpful in analyzing the surface mineralogy mapping (Goetz et al., 1985; Kruse et al., 2003, Debba et al., 2005, Vaughan et al., 2003). Compared to multispectral sensors hyperspectral images provide higher spectral resolution (Clark et al., 1990, Magendra and Sanjeevi 2014, Van der Meer 2012**)**. The Hyperion image has 30m spatial resolution, 242 channels and 7.7 km swath. In some of the minerals, the hyperspectral (Hyperion) sensor with 0.4-2.5µm spectral range (EO-1 User guide) rocks show good absorption and reflectance due to variation in physico-chemical properties. It helps in their exploration mapping (Clark et al., 1990; Hunt et al., 1971). The spectral reflectance can detect and identify the Earth surface and atmospheric constituents to measure the reflected spectra's component concentration. We can find the distribution of the component and validate by improving models. The processing of hyperspectral image is a challenging task. It consists hundreds of channels.

The selection of required channels with its good apparent reflection requires good skills. FLAASH uses the most advanced techniques for handling particular stressing atmospheric conditions such as the presence of clouds, cirrus and opaque cloud classification map adjustable spectral polishing for artifact suppression (ITT-Vis, 2010). The Hyperion image consist huge number of channels which are to be reduced dimensionally. The techniques like Minimum Noise Fraction (MNF) transform is used to reduce the number of spectral dimensions which are to be analyzed. The pure pixels are the most spectrally extreme pixels (Broadman et al., 1995), which spectrally correspond to the mixing end members. These end members form the base for the n- Dimensional visualization and each selected end members is spectrally matched with USGS spectral library.

Mineral mapping using hyperspectral remote sensing

The iron bearing minerals, hydroxyl bearing minerals sulphates and carbonates spectral features are covered in the near visible near infrared image (VNIR) and shortwave infrared (SWIR). Key spectral features in these regions allow identification of various materials using laboratory and field spectroscopy, including minerals, vegetation, man-made materials, snow and ice and water (Clark et al.,2003, Salisbury et al., 1991, Kruse 2012). Primary restrahlen of features are observed in silicates carbonates, and other minerals in the spectral range of 8-14µm (LWIR) wavelength range (Farmer, 1974; Salisbury et al., 1991).The mineral compositional differences and variability are correlated with small differences in absorption band position and shape in VNIR-SWIR (Gaffey, 1986; Salisbury et al., 1991; Duke, 1994; Cloutis et al.,2006, Kruse, 2012).

Study area and image data

The lithology of the part of Chitradurga schist belt 13036’25’’N, 760 35’49’’E (Fig 1) belongs to both Bababudan and Chitradurga groups. The Bababudan group of rocks represented by metabasalt-quartzite formations and NNW trending synclinal Kibbanahalli BIF formation extending from east of Kandikere up to Banasandra, wrapping around the CN Halli gneiss and joining the main CN Halli belt near Dodguni (Radhakrishna, 1967; Srinivasan and Sreenivas, 1975; Seshadri et al., 1981; Ramakrishnan and Vaidynadhan, 2008). Chitradurga Group of rocks covers most of the CN Halli schist belt, represented by quartz-sericite-chlorite schist, quartzite, carbonates, Mn formations and BIF. The Chitradurga group unconformally overlies Bababudan group (Devaraju and Anantha Murthy, 1976, 1977). EO-1 Hyperion data covering Chikkanayakanahalli area, acquired 14 April 2011. The image covers the spectral range of 0.4 to 2.5µm at 10nm bandwidth with 220 unique wavelength bands. The Level 1 radiometric (L1R) product is used in the research has 242bands. However, only 155 of them are calibrated from visible-to-infrared (VNIR) and short wave-infrared (SWIR) regions (Table 1). The scene characteristics of the Hyperion image of part Chitradurga Schist belt area. The Hyperion sensor has a nominal ground spatial resolution of 30m and 16bit radiometric resolution (EO-1 User Guide, 2003)

Materials and methods

The methodology includes preprocessing of Hyperion image, Dimensionality reduction and Image classification (Spectral Angel Mapper). An overview of the methodology adopted for the present study is presented as a flowchart in Fig 2. Preprocessing of Hyperion image is essential. The data is available in raw form and most the data sets are not geometrically calibrated. Error can occur in the datasets due to spectrometer material of the 242 a subset of 155 bands, spectrally subsetted from the hyperion data set.

Another common error to pushbroom sensors is vertical striping, which can be removed by identifying the bad bands and applying average values of neighboring pixels (Goodenough et al., 2003, Research System Inc.2003, Darmawan 2006, Hosseinjani et al., 2013). The Hyperion Image of the Study area is affected by the atmospheric error due to its time of acquisition. Thus atmospheric corrections of Hyperion images require reduction of atmospheric influence on the reflectance and filter out the target reflectance cleanly from mixed signal. Using FLAASH wavelength ranging through visible infrared and shortwave infrared can be corrected for atmospheric errors. The different parameters which are applied for running the FLAASH model on Hyperion image (listed out in Table 2). After the atmospheric correction the reflectance value of several bands of Hyperion data is found to be too low. The resulting value is set to be zero by the model. Therefore 155 bands are left

for further processing. To remove the smile seen in individual bands of Hyperion image and it is transformed into Minimum Noise Fraction (MNF) (Green et al.1998). The most useful information is obtained in the first few MNF bands and subsequent bands which have higher noises. MNF bands below one eigenvalue are not carrying useful information and contain noise. MNF with band value more than one is selected for removing the noise. Hence only 15 MNF –bands are maintained and retransformed to reflection data. The resulting reflectance dataset contains 155
bands. The combination of MNF Pixel Purity Index (PPI) and N-dimensionality visualizer the spectral endmembers are extracted (Envi user guide 2003, Boardman 1993; Boardman et al., 1995). The Pixel purity index is applied to 15 MNF-bands with the image of 10000 iteration factors and 2.5 thresholds, which allows in determining the pixels with high digital numbers called skewers (Broadman and Kruse, 1995). The pixel values are selected from the region of interest (ROI) of the area which are geologically familiar and compute for n-dimensional visualization (Hosseinjani et al., 2013). The spectra collected could be attributed to mineral zones; these spectra are matched with the USGS spectral library with a score of spectral analyst tool (ENVI user guide 2003, El-Nahry and Altenabas 2006). Based on the values of spectral analyst tool the Spectral Angle Mapper classification is made. The algorithm can be used for the identification of unknown spectra based on a measure similarity with one or more known spectra. SAM decides, spectral similarity by calculating spectral angle between two spectral vectors which have the same origin.

Result and discussion

In geological mapping, based on the spectral signatures, allows direct identification of iron minerals such as Hematite, goethite and jarosite in Visible-Near infrared (VNIR) and clay, carbonates, mica, sulfates and other minerals in Shortwave infrared(SWIR) and silicates and carbonates in long wave infrared (LWIR). The unique ability of hyperspectral remote sensing is to generate a spatial distribution of specific minerals. Mineral assemblages and mineral variability on the surface of the Earth makes it as an Ultimate tool for enhanced mapping. By spectral subsetting of Hyperion data we get 155 bands and vertical column is corrected. The FLAASH Model gives the atmospheric corrected image in which DN values are
corrected to reflectance value thus the spectral signature appear perfectly. The Minimum Noise
Fraction transform computes the normalized linear combinations of the original bars which maximize the ratio of the signal w.r.t. noise. The PPI proceeds by generating a large number of random N-dimensional vectors which are called skewers. Every data point is projected on each skewer along the direction with which it is pointed out. The data points which correspond to extreme values in the direction of skewer are identified and placed in a list. The pixel purity index image is determined by the MNF image for Hyperion dataset. The number 10000 iterations are chosen as 250 iterations per block, given a threshold of 3 and it is chosen for further selection of the region of interest (ROIs). Endmembers are selected for Spectral Angle Mapping. In the study area various endmembers are chosen with respect to their relevance. In the N-Dimensional visualizer the demarcated endmembers are separated in the region of interests and are saved. The endmember which are collected from ROI are matched with Standard USGS library in Spatial Analyst tool and with background of the study area and the spatial analyst score
are used for Spectral Angle Mapping (SAM) (Fig:2).

Conclusion

The results at the Chitradurga schist belt establish the data from the Hyperion data can be used to produce useful geologic (mineralogical) information. Hyperion data provides the ability to remotely map basic surface mineralogy. Minerals abundance mapping include calcite (7.40%), Iron Oxides (2.83%), Chromite (8.82%) and Chlorite (5.80%). These case histories demonstrate the analysis methodologies and level of information available from the Hyperion data. They also demonstrate the viability of Hyperion as a means of extending Hyperspectral mineral mapping.

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Receiving Station SGS Look Angle 3.32