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Mineral Mapping at Lonar Crater Using Remote Sensing

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Abstract: **Remote is the advanced technology used for various applications in mineral mapping, mineral identification, lithological discrimination and structural mapping etc. Lonar crater is a well-known impact crater in basaltic crust of rocks. With Hyperion satellite imagery, it is possible to analyze the Lonar crater remotely and comment on the mineralogy associated with it. The various geological, geochemical, mineralogical characterization studies has been done on crater-cum-lake till today but the remote sensing is not used prominently indicating some fruitful results. So the present study focuses on the use of hyperspectral images for mineral mapping and identification near and at the Lonar crater. The preprocessing techniques like bad band removal, destriping, radiometric correction and atmospheric corrections were applied. Then noise removal and dimensionality reduction was performed using modified PCA known as minimum noise fraction. Then the classification techniques Spectral Feature Fitting and Spectral Correlation Mapper were applied on the significant endmembers obtained after Pixel Purity Index and n-D Visualizer. The spectral signatures obtained were compared with USGS standard spectral library. The Alunite mineral was successfully mapped and identified with 88%, 89% and 90% at the different wavelengths at the Lonar Crater.**

Index Terms: **Hyperspectral, Lonar Crater, Mineral Identification, Remote Sensing, Spectral Signature.**

I. INTRODUCTION

Remote sensing is the advanced technology which deals with the acquisition of information about things, objects and/or phenomenon without in direct contact with them (Lillesand, 1999 (4th edition)). It is not possible to reach physically at every remote place for mineral exploration. But the exploration or investigation of minerals is possible with the help of remote sensing even if geologic or ground truth information is limited. Hence it would be a powerful tool for cost effective identification and analysis of minerals which greatly helps in improving the economy of the country. The geologists and others have to prospect the remote areas in search of mineral deposits. For pin pointing the potential deposits methods like geological surface mapping, sampling, geochemical analysis and measurements were used. The process of extracting the ore from rock and soil using a variety of tools and machinery has to be carried out. The geologist makes use of his intimate knowledge of Earth's surface to make educated guesses about the probable locations of mineral deposits. As geologist's goal is not only finding the natural resources but ultimately extracting them. The geologist spends bulk of his time for doing fieldwork in support of his hypotheses. Geologist determines a location which holds vast mineral deposits. Then geologist visits that site and physically examines it alongside cartographers and surveyors. The geologist performs testing, scour rock formations while supervising drill operations. Then analyzes drill samples for identifying the presence of resources beneath the ground and quantifying it. Based on his findings, then he advises the company about whether to proceed with extraction, and how to do so in the most efficient, cost-effective manner (King) (Stephen G. Peters)

With the advent of technology it is possible to analyze the earth surface and find out the components available on the earth surface. Various minerals available at earth surface can be identified and their potential applications can be explained with the help of remote sensing technology. Also remote sensing technology can be used for various applications such as monitoring the flood conditions, monitoring the growth of the agriculture plants, monitor the forest fires, monitor the deforestation as well as various application areas which can focused further by using remote sensing.

The multispectral and hyperspectral remote sensing have been used for mineral alteration mapping (Tangestani, 2002), mineral identification, lithological discrimination (Yarakkula, 2017)

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(Govil, 2019) (Gila Notesco, 2014) delivering the prominent results. But the multispectral remote sensing has certain limitations due to very few bands (tens of bands) of multispectral image. These limitations are overcome by the hyperspectral images as they are having hundreds of bands and some other features like high resolution. So the hyperspectral remote sensing can finely identify the minerals as compared to the multispectral remote sensing, also it is possible to construct the spectrum for each and every pixel from the hyperspectral image.

Lonar crater is a very old impact meteorite situated in the Buldhana district, Maharashtra. Lonar crater is situated within Deccan Plateau. The Lonar crater is the only impact structure which is easily accessible so it became of much interest for geologists (Maloof, Geology of Lonar Crater, India., 2010). The significant aqueous alteration to basalts occurred during the period between the formation of basalts and the impact event, filling many basaltic vesicles with zeolite, chalcedony, quartz and opal. The lake water is very alkaline and saline in nature. The water of the lake contains salt and soda which is found when evaporation reduces the water level.

Alunite can be used to recover the aluminium and potassium. Alunitization is the process in which alunite is formed due to the action of sulfuric acid on the feldspar which is potassium rich. The hydrothermal solutions produced makes alunite as rock forming mineral. This study focused on use of hyperspectral data for the mapping of Alunite mineral surrounding the Lonar crater. MNF (Minimum noise fraction) technique was applied to remove the noisy bands, PPI (Pixel Purity Index) and n-D Visualizer techniques were useful in forming the clusters of pure pixels enabling the effective mapping of Alunite. The classification algorithm SFF (Spectral Feature Fitting) and SCM (Spectral Correlation Mapper) were used for mapping and identifying the Alunite around the Lonar crater and at the crater rim.

II. LITERATURE SURVEY

Lonar crater is one of the four basaltic impact craters on the earth. The Lonar Lake is located at Latitude 19º 58’50’’ N and the longitude 76º 30’50’’E in the Buldhana district. The rim of the crater is about 20 meters above the surface of the surrounding land. The numbers of small hills with oval shapes are present around the basin of this crater. Its circumference is about 8 km and the base circumference is of 4.8km. The Lonar situated in district Buldhana of Maharashtra state. There is presence of shatter cones, also it shows shocked breccia with non-volcanic ejecta blanket. The basalt layers undergone deformations at inside, outside and in rim indicating the proof of impact origin of this crater. The crater has an oval shape. The basalt flows of 10-25 m are exposed in the crater wall these flow tops are unevenly altered preserving the reverse basalt stratigraphy.

Hyperspectral remote sensing is useful at various applications in the field of geology, mineral exploration, agriculture, forestry and environmental studies, etc. Hyperspectral remote sensing is an advanced space technology can be useful for the identification of minerals on the earth surface (Gore R. , 2016).

The study tried to understand the characteristics of the soil samples for their physical, mineralogical, electrical, magnetic and chemical properties which are extracted from the Lonar crater region. The crater soil samples also analyzed for various energy fields. The minerals identified in the samples were pigeonite and magnesium iron silicate mineral, it caused electrical conductivity and magnetization. The water of lake is having high salinity due to chloride and Sodium contents. The abundance of ferrous, sodium, aluminium and titanium indicating the presence of the minerals pigeonite, alunite, anorthite and albite; also zeolite- sodalite and cancrinite are the results of hydrothermal processes at the impact crater (Nevin Koshy, 2018) (Spray, Impact cratering on Earth, 2018) (Maloof A. C. S. S.-H.-B., 2007). They found breccia with clasts at the crater or near the rim (Koeberl C. &., 2004). The abundant glass fragments from mm to 10 cm were also found on the loose surface. At few locations they found glass fragments within the breccia known as suevite occurred in basaltic rocks.

Two types of spherules were found at Lonar crater. First type is spherules with vesicular surface texture having size in mm; second type is spherules with smooth surface and high magnetic susceptibility with size semi-millimeter. Relatively low zinc, Na2O and P2O5 in the small spherules were compared with basalt abundances indicated the exchange of volatiles between the surroundings and spherules. Chromium and Nickel were found in the small spherules concluding that the spherules may be formed by mingling chondritic impact material and basalt melts (Misra, 2009) (Farooq, 2011). Hyperspectral imaging is a powerful tool for the study of inaccessible and hilly regions. This study was focused for possible Pb-Zn-Ag-mineralization and provided an application around Mount Isa and George Fisher/Hilton mine, Queensland, Australia (Sandra Jakob, 2016). The Tricorder classification technique was used. A modified least-squares fitting algorithm was applied to evaluate the matching score. Results were also validated with FieldSpec FR (0.300-2.500 µm) spectroradiometer using SIMIS. There was major problem in the mineral identification, presence of non-photosynthetic vegetation in the APG terrains (Filho, 2000).

The hyperspectral remote sensing have the capability to identify and classify the weathered, altered and clay minerals as the profitable mineral zones which are generally associated with hydrothermal alteration zones. In this research work AVIRIS-NG was used for identification hydrothermally altered mineral zone in Bhilwara district of Jahajpur, Rajasthan. The spectral angle Mapper (SAM) and SFF techniques were used for the mapping of the minerals Clay group (montmorillonite, kaosmec, talc) and goethite leading to zones of profitable mineral deposits

(Mahesh Kumar Tripathi, 2019).

Ultramafic rock samples were collected for mapping dunite. The spectral measurements were taken for combining the average of spectral signatures. ASTER SWIR band data was used in adopting a combination with gamma transform. It contain the rationed image exhibiting the effective mapping of dunite (rsoy, 2019). Another study used the Hyperion Level 1 images which were geometrically and radiometrically corrected. The spatial distribution of Carboniferous and Cretaceous kaolin grade sand was identified. SAM classification was used for identifying the kaolinite distribution. (Mahmoud E. Awad, 2018).

The mineral abundance at Tamilnadu for mineral nontronite was identified. It contains iron in ample amount. It is available at Nilgiri hills of Tamil Nadu. The authors used hyperspectral images for mineral mapping. The preprocessing steps were performed viz. bad band removal, removal of stripes using destriping, radiometric calibration and atmospheric correction. Then MNF technique was applied to reduce noise bands and PPI for extracting pure pixels. The selected end members were compared with standard spectral libraries. In the Nontronite mineral gave the probability of 0.85 with SAM classification technique (Yarakkula, 2017).

The hyperspectral remote images have been used in lithological discrimination, mineral mapping and detecting vegetation cover in various geologic regions. There is difficulty in mineral mapping with low resolution images. The higher spatial resolution images can be used for more accurate or precise mapping of minerals. These dataset commonly suffers from atmospheric effects generating hurdles in further analysis. Hence atmospheric correction becomes necessary for accurate analysis. It is possible to eliminate the noise and direct mapping of the absorption features with high resolution data. The difficulties in mineral mapping are due to topographic disturbances and vegetation which affects the spatial distribution. The data was preprocessed for bad band removal, radiometric correction and cross-track illumination. The Spectra were analyzed with SFF algorithm which mapped Nontranite, Sphalerite, opal minerals by using ENVI 4.5. Thar Desert is abundant with calcrete-calcium carbonate (Ramakrishnan, 2014). FLAASH algorithm was applied on the hyperspectral data for atmospheric correction. Also the dataset was preprocessed for noise reduction and aerosol retrieval. MNF was used on VNIR and SWIR bands for spectral analysis (Ramakrishnan, 2014) (Govil, 2019).

Although number of geological, chemical, magnetic and electrical analysis done at Lonar crater but still unexplored for work through remote sensing. Also the hyperspectral imagery will give prominent results in mineral mapping and identification. So the proposed work focused on mineral mapping and identification at and near Lonar crater through remote sensing. The location of study area on the map of India is as shown in figure 1.

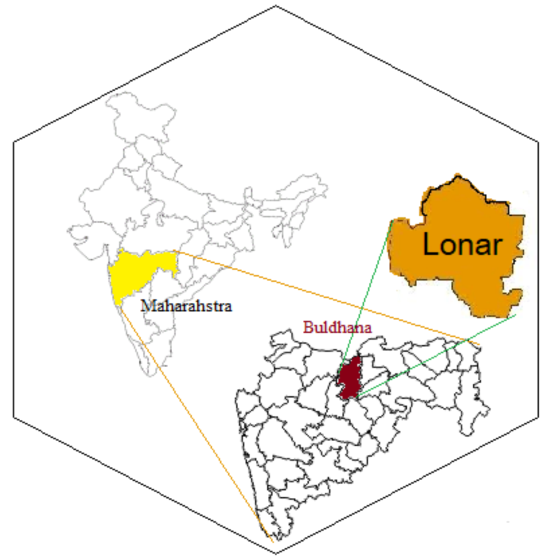


Fig. 1. Location of Study

The proposed method identified the presence of Alunite at Lonar crater. The abundance of Aluminium at Lonar crater was mapped (Nevin Koshy, 2018)with other minerals which indicating the impact of meteor at Lonar region. Alunite is a mineral with hydroxylated aluminium potassium sulfate.

III. Proposed Approach

The multispectral data is not sufficient due to very few bands for mineral identification. So the proposed approach focused on working hyperspectral data for the identification of minerals. The dataset required for this study was available from USGS (United States Geological Survey) EarthExplorer site and Glovis site of USGS. This product was created by the USGS. The dataset consists of hyperspectral images of Lonar Region located at Buldhana district of Maharashtra state. It contains data files of EO-1 Hyperion data in Hierarchical Data Format (HDF) or Geographic Tagged Image-File Format (GeoTIFF). The dimensions of input image are 256 x 3128 x 242. The acquisition year of this data is 2017. The image was acquired for datum WGS-84.

The methodology for mineral identification is given in the figure 2. Here the input data is the hyperspectral images of Hyperion sensor and need to be preprocessed before actual spectral analysis. It consists of 242 bands. During acquisition the Hyperion sensor captures some bands without information. These bad bands should be removed for further processing. Next step to perform is destriping where the number of strips need to be removed. Then Log Residue and IAR reflectance techniques should be applied to enhance the images more. The atmospheric correction need to be performed for reducing the effects due to water vapors and other atmospheric conditions.

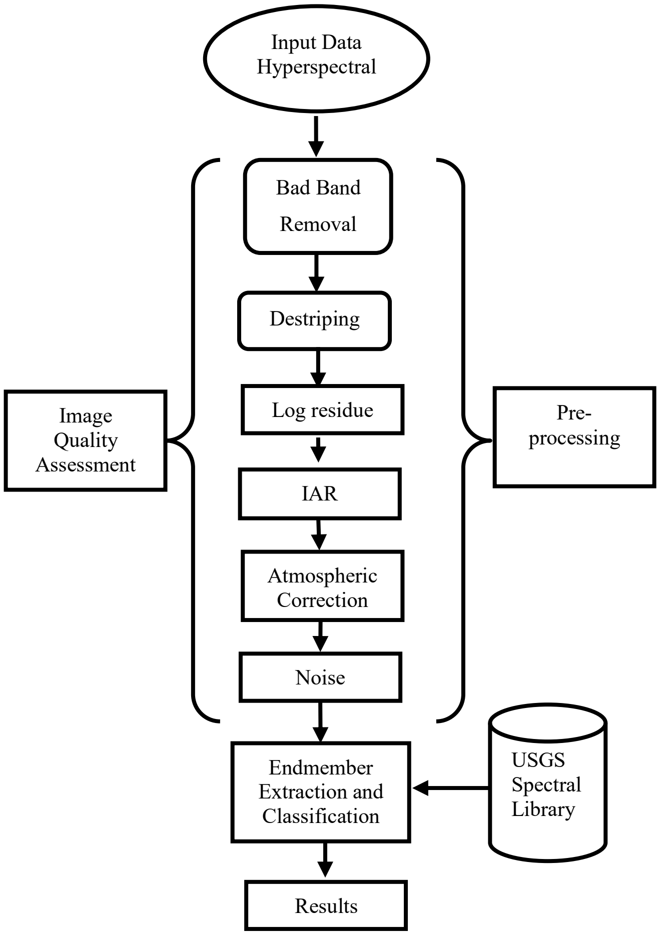
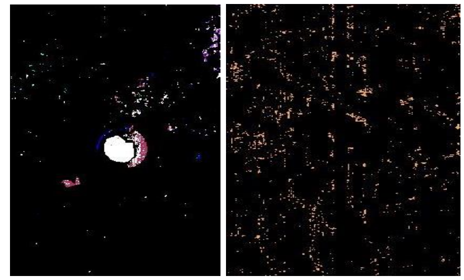


Fig. 2. Methodology

There are number of bands with noise. These noisy bands need to be handled with endmember selection technique. MNF technique applied and endmembers with minimum noise should be selected. Then PPI technique should be applied for extracting only the pure pixels from selected endmembers to achieve the spatial dimension reduction. The unique spectral classes should be determined then by applying the n-D Visualizer with rotating in the n-dimensional vector space. The classification techniques SFF, SCM and SAM can be applied and the spectral matching should be finally performed against USGS Spectral Library.

IV. Results and Discussion

The hyperspectral image was processed for bad band removal and destriping. The necessary preprocessing techniques like radiometric correction, atmospheric correction, noise removal and dimensionality reduction were performed. The best endmembers were extracted from the hyperspectral data. From these endmembers, the pure pixels were identified and grouped in order to identify the minerals. The different classes were obtained by combining the pure pixels. Figure 3 (a) specify the n-D classes with different colors which is output of classification and figure 3(b) is output of Alunite Mapping at Lonar crater and nearby.



a) b)

Fig. 3. Classification Output : a) Classes mapped with Colors b) Alunite Mapping

From the endmembers the spectrum were built which was compared with the standard spectral library, USGS and the minerals were identified at the Lonar crater. The SFF algorithm was applied on the MNF bands with mapping to the n-D classes. The output is shown in figure 4 below, mapping the Alunite distribution with its different classes. The colors for different Alunite spectra are: for Alunite GDS84 color is purple, for Alunite GDS83 orange, for Alunite GDS82-pink and for Alunite AL706-yellow. In Post classification, rule classifier was used and the threshold was set to the max values for mapping the different classes of Alunite.

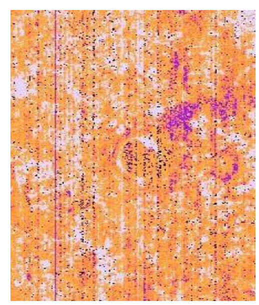


Fig. 4. Discrimination between Different Classes of Alunite

The figure 5 contains spectral matching results.

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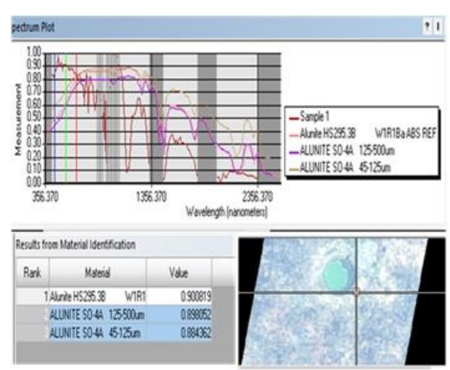


Fig.5. Alunite Mapping at Crater Rim

Also the Spectral Correlation Mapper (SCM) algorithm was used on the same hyperspectral data. The SCM algorithm is the modification over Spectral Angle Mapper algorithm. In this algorithm the data is standardized by using average of the two spectra. The output of SCM was the three matching spectra of Alunite of different wavelengths as shown in figure 5. It represents the sample spectrum (maroon color) with the matching spectra of Alunite. It also displays the accuracy score for match with USGS Spectral Library.

The accuracy score of Alunite as given in table I.

Table I. Accuracy score for Alunite Mapping

Name of Alunite (wavelength)	Accuracy
ALUNITE HS295.3B W1R1Ba ABS REF	90.0819 %
ALUNITE SO-4A 125-500um	89.8052 %
ALUNITE SO-4A 45-125um	88.4362 %

The mineral type of Alunite HS295 is Sulfate.

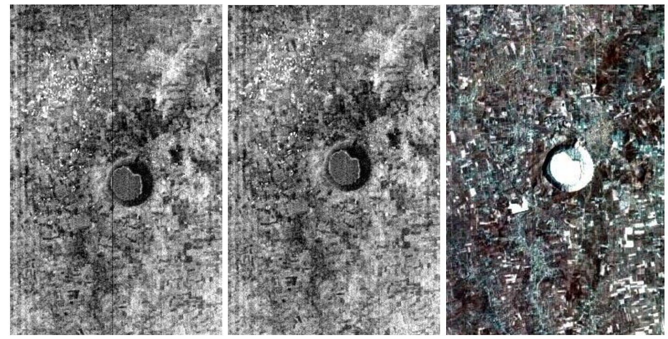
V. Experimental Section

The hyperspectral image consists of 242 bands. The true color image used as input image is as displayed in figure 6.

Fig. 6 Input Image

From these 242 bands 1 to 7 were not properly illuminated. Also bands 58 to 76 and bands 225 to 242 are bad bands. Also the bands 122 to 132, 165 to 182 and 221 to 224 contain water vapors. All these bad bands need to be removed. These bad bands does not contain information so must be removed. The figure 7(a) is an image after bad band removal for a band 8. For hyperspectral images, the stripes appear on the image during acquisition. These stripes may be problematic for further analysis as it is a noise appeared in the image.

Many bands suffer from the problem of striping. So the operation of destriping should be performed on the hyperspectral images. Pixels at stripes can be replaced with either the average values or the mean values of neighbouring columns. Here the stripe pixel values were replaced with average of neighbouring column's values. Stripe in figure 7(a) was removed for band 8 and result is as shown in Figure 7(b).



(a) (b) (c)

Fig. 7. Preprocessing Steps : a) Bad Band removal b) Destriping c) Log Residue

The number of preprocessing techniques were performed along with bad band removal and destriping like radiometric and geometric corrections. The result of Log Residue is shown in figure 7(c). Then IAR Reflectance was performed. The atmospheric correction is very important step in preprocessing Hyperion data. The FLAASH algorithm was applied to handle atmospheric effect. Then noise to be handled with techniques like PCA, MNF or ICA. It also helped in reducing the dimensions of the input data.

The next step performed was MNF. The MNF generated principle components with reduced noise. The eigenvalues were calculated for each MNF band. From number of eigenvalues only top eigenvalues having value greater then 1 were seleccted. Here 10 eigenvalue bands were selected. PPI applied on the MNF endmembers finding only the pure pixels. The n-D visualizer was applied to form the clusters of the pure pixels found at PPI technique. The SFF algorithm was then used for mapping Alunite at different wavelengths. From the endmembers the spectra for sample were generated and the SCM algorithm was applied for spectral analysis. The standard spectral library of USGS was used as a reference and Alunite spectra at different 3 wavelengths were used in spectral analysis.

Conclusion

This study focuses on the study of Lonar crater using remote sensing technology. The hyperspectral images were used for mineral mapping near Lonar crater remotely. The hyperspectral image consists of 242 bands, each band containing different information which would be helpful for the image analysis. Different preprocessing steps were performed on the Hyperion image like bad band removal, destriping, log residue, IAR Reflectance, atmospheric correction and noise reduction etc. The focus was on the analysis of hyperspectral images for mapping of the Alunite mineral at and near Lonar crater. The results of proposed method indicated the existence of Alunite mineral with accuracy of 90.0819% for Alunite HS295.3B W1R1Ba ABS REF, 89.8052% for ALUNITE SO-4A 125-500um and 88.4362% for ALUNITE SO-4A 45-125um. In future these results could be validated through field analysis using ASD FieldSpec spectroradiometer.

Lot of geochemical analysis has done till today on Lonar crater but no detailed study has been done ever through remote sensing. The previous findings can be validated through remote sensing providing the benchmark for further studies through remote sensing specially for remote places. Also the different minerals found through geological or chemical analysis at Lonar crater were Coesite, glass, Chromium and Nickel, ferrous, sodium can be mapped through hyperspectral remote sensing in future. Also this model will be useful for mineral identification at any location.

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