Lithological Discrimination of Anorthosite using ASTER data in Oddanchatram Area, Dindigul district, Tamil Nadu, India

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***Abstract*— *The present study applies with hyperspectral remote sensing techniques to map the lithology of the Oddanchatram anorthosite. The hyperspectral data were subjected to Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Minimum Noise Fraction (MNF), Pixel Purity Index (PPI) and n-Dimensional Visualization for better lithology mapping. The proposed study area has various typical rock types. The PCA, ICA and MNF have been proposed best band combination for effectiveness of lithological mapping such as PCA (R: G: B=2:1:3), MNF (R: G: B=4:3:2) and ICA (R: G: B=3:1:2). The derived lithological map has compared with published geological map from Geological Survey of India and validated with field investigation. Therefore, ASTER data based lithological mapping are fast, cost-effective and more accurate.*

Keywords*— *ASTER, remote sensing techniques, Oddanchatram, anorthosite.

I. INTRODUCTION

Lithological mapping is an essential technique in various mineral prospecting studies, geological studies, hydrogeology etc. (Leverington and Moon 2012: Adiri et al. 2016).Lithological mapping and Mineral exploration are the hot domain in the geological investigations at present scenario. Advances in remote sensing and geographic information is a leading technique in the field of mineral exploration and lithological mapping exclusively hyper spectral remote sensing play a vital role for lithological mapping. Mineral exploration and lithological mapping through conventional geological techniques are tedious, expensive and time-consuming (Ramakrishnan and Bharti, 2015). Mapping through hyper spectral remote sensing is a very sophisticated and exciting way to provide accurate results. The present investigation carries the various techniques of hyper spectral remote sensing for lithological mapping with interpretation of lithology, structure and mineralization of the Oddanchadram area. The theme has been assessed the feasibility of using advanced data for detecting mineral assemblages and litho-structural analysis. Hyper spectral remote sensing is most popular and trend technology in mineral and lithological mapping, which is analysis of the reflectance data recorded by a hyper spectral sensor from a region or part of the earth surface (Kiran Kumari et al. 2014). Hyper spectral imaging spectrometers collect these radiance value sampled around ten nanometer intervals and with hundreds of spectral bands that used to construct the reflectance spectra similar to the laboratory spectra (Kiran Kumari et al. 2014). Hyper spectral sensors provide a unique combination of both spatially and spectrally contiguous images that allow precise identification of minerals (Goetz et al. 1985).Over the last few decades, mineral mapping and lithological discrimination have been worked using airborne hyper spectral sensors like ASTER data (Zhang et al. 2007). Previous studies have demonstrated that the identification of specific minerals and rocks through ASTER, such as alunite, kaolinite, calcite, dolomite, chlorite, quartz, talc, mangnetite, quartz, granitoid, granite, mangnesite, muscovite, anorthosite, serpentinites, metagabbors, metabasalts and limestone (Gomez et al. 2005: Qiu et al. 2006: Tommaso and Rubinstein. 2007: Amer et al. 2010: Aboelkhair et al. 2010: Wahi et al. 2013: Beiranvand Pour and Hashim 2014). They have concluded and suggested that the band ratio, Principle Component Analysis (PCA), Minimum Noise Fraction (MNF), Independent Component Analysis (ICA), Pixel Purity Index (PPI), n-D visualization and Spectral Angel Mapper (SAM) tools for lithological map study. In the present study, the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) hyper spectral remote sensing data have been used. Beiranvand Pour and Hashim (2012) stated that the ASTER remote sensor has sufficient spectral resolution in the shortwave length infrared radiation bands for mapping

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hydrothermal alteration zones of mineralization. As well as the PCA, ICA, MNF, SAM and PPI tools have been applied to achieve the investigation.

II. STUDY AREA

The present study area is chosen from Oddanchatram in Dindigul District, Tamil Nadu, India, which lies between10º20' to10º40 north latitude and 77º 40' to 77º 55' east longitude (Fig.1). The area of interest covered an area of 508 km^2. Oddanchatram is 35 km west of Dindigul, and 35 km east of Palani. Oddanchatram has normal weather conditions of 26 ºC and the humidity is 72%.The study area is located in base of Western Ghats in South India (Palani Hill). The study area is mainly an undulating, rugged terrain surrounded by a number of hillocks. In general, the drainage pattern of the study area is dendritic in the plains and sub-parallel in the hillocks. The drainage is mainly controlled by the geological structures. The altitude of the study area ranges from 220 to 1280 m.

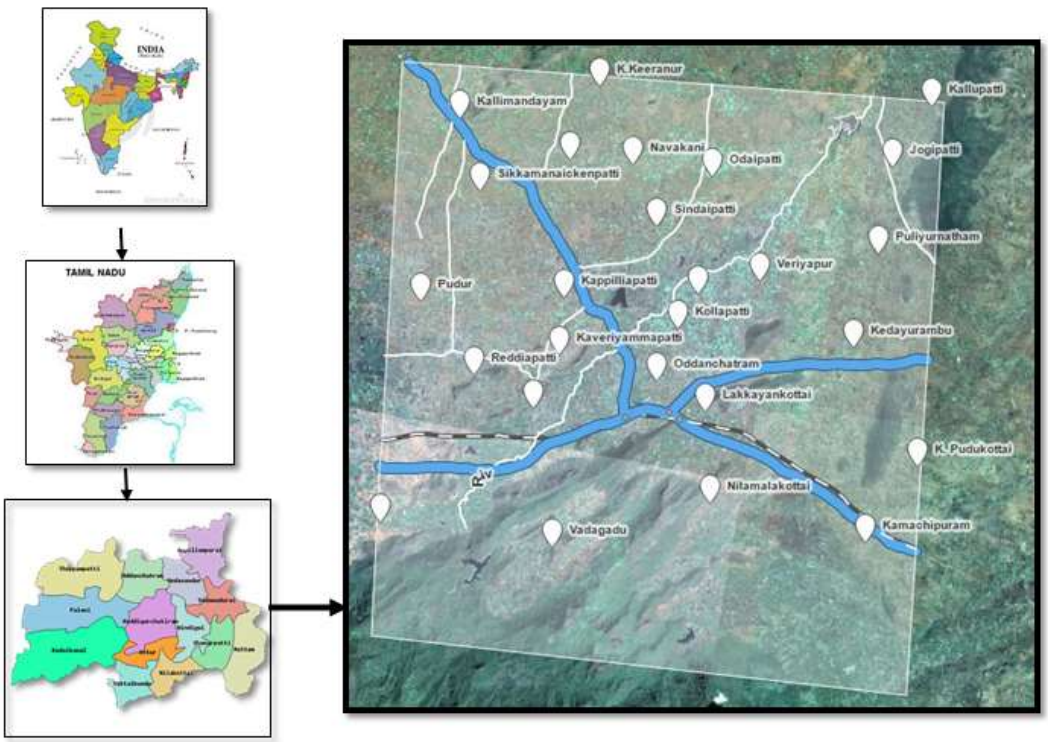

Fig.1: Key map of the study area

Geological Settings of the study area.

The present study mainly focusing the anorthosite of Oddanchatram area, near the town of Palani, Tamil Nadu, India. The surrounding country rock consists of basic granulites, charnockites, Garnet-Sillimanite gneiss, granitic gneiss, hornblende biotitic gneiss and meta-sedimentary rocks (Eiebe, R.A.1989). The anorthosite is clearly intrusive into the country rock and contains many large inclusions of previously deformed basic granulite and quartzite within 100 m of its contact.The anorthosite suite of rocks around about Oddanchatram, Tamil Nadu, India comprises anorthosites, gabbroic anorthosites, gabbros and norites. They display a dominant anorthosite facies concentrated in the central portions of the masses and relatively subordinate gabbroic anorthosite and gabbroic rocks segregated towards the marginal portions. Structural studies in the area have shown that the anorthosites constitute a phacolithic pluton emplaced in a NNE plunging anticlinal fold of metasediments, basic granulites and charnockites. A domical form is suggested for the mass by the outward dipping foliation all around (Narasimha Rao 1975). The anorhtositic rocks of Oddanchatram, is typical of Proterozoic anorthosites in that it is largely massive and coarse grained, particularly the central portions of the mass, show many igneous parameters like cumulate textures, normal zoning of plagioclase, occurrence of magmatic twin laws of plagioclase, flowage structures and euhedralism of some constituent minerals. This reveals that the suite of rocks is magmatic and also did not undergo much of post-emplacement deformation and metamorphism. It is probable that the parent gabbroic anorthosite magna was emplaced as a late stage orogenic pluton. The pegmatitic facies of the anorthositic rocks composed of very coarse crystals of amphibole and plagioclase noticeable in some of the outcrops is suggestive of the role played by the volatiles during the evolution of the rocks. Clinoamphibole is a more characteristic mafic constituent of the anorthosites than the pyroxenes. Megascopically the amphibole is of medium grain size and greenish black in colour. In some outcrops of the anorthositic rocks, a pegmatitic facies is found which contains coarse amphibole crystals measuring 4 cm to 6 cm in length (Narasimha Rao 1975). The geology map of the study area is given in Fig. 2.

III. MATERIALS AND METHODS

The following remote sensing data were used for the present study.

1. Advanced Spaceborne Thermal Emission and Reflection Radiometer data (ASTER)
2. ASTER- GDEM (30 m resolution)
3. Geological Survey of India Resource Map of Dindigul (Published).
4. ArcGIS 10.2
5. ENVI 5.1

Preprocessing (Atmospheric Correction)

The ASTER LB1 spectral bands VNIR and SWIR have been used in the present study. The VNIR and SWIR spectral bands were layered stacked and converted to BIL format. The spectral bands were orthorectified by projecting the raw data to the Universe Traverse Mercator (UTM) 44 N zone. The orthorectified images were applied to cross track illumination correction for eliminate the effects of energy overspill from band 4 into bands 5 and 9. Thecross-track illumination is very essential for SWIR bands for accurate results (Kumar et al. 2015). After, this process the bands were subjected to FLAASH atmospheric correction using ENVI 5.1 software.

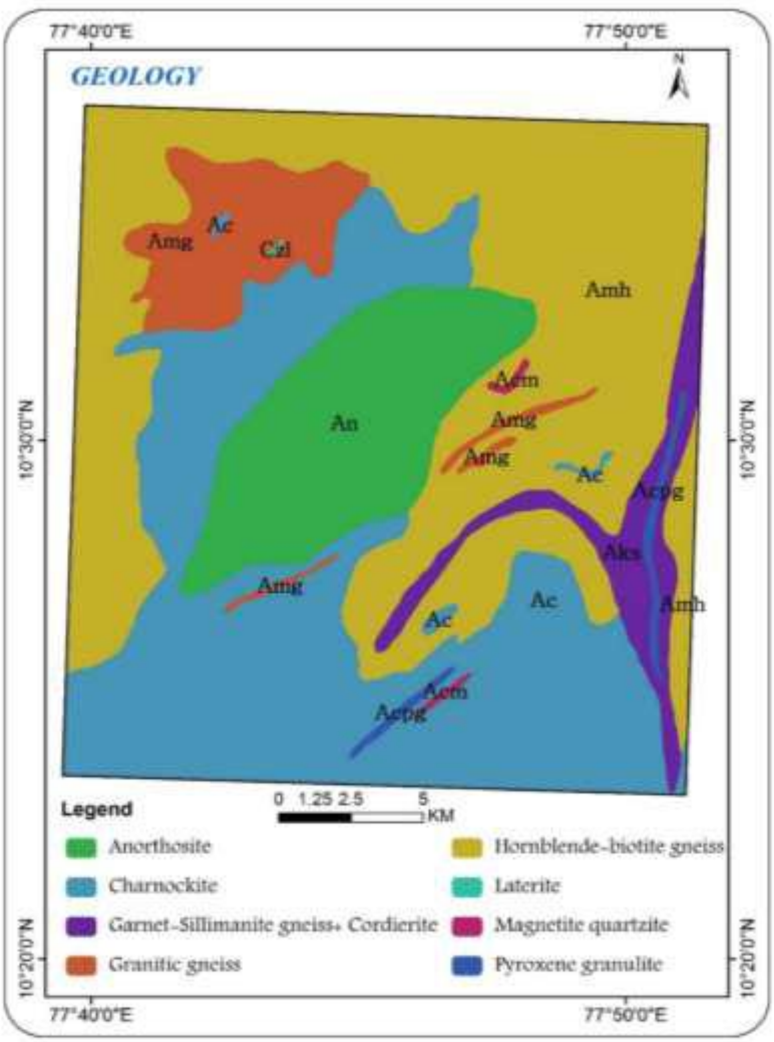

Fig.2: Geology map of the study area

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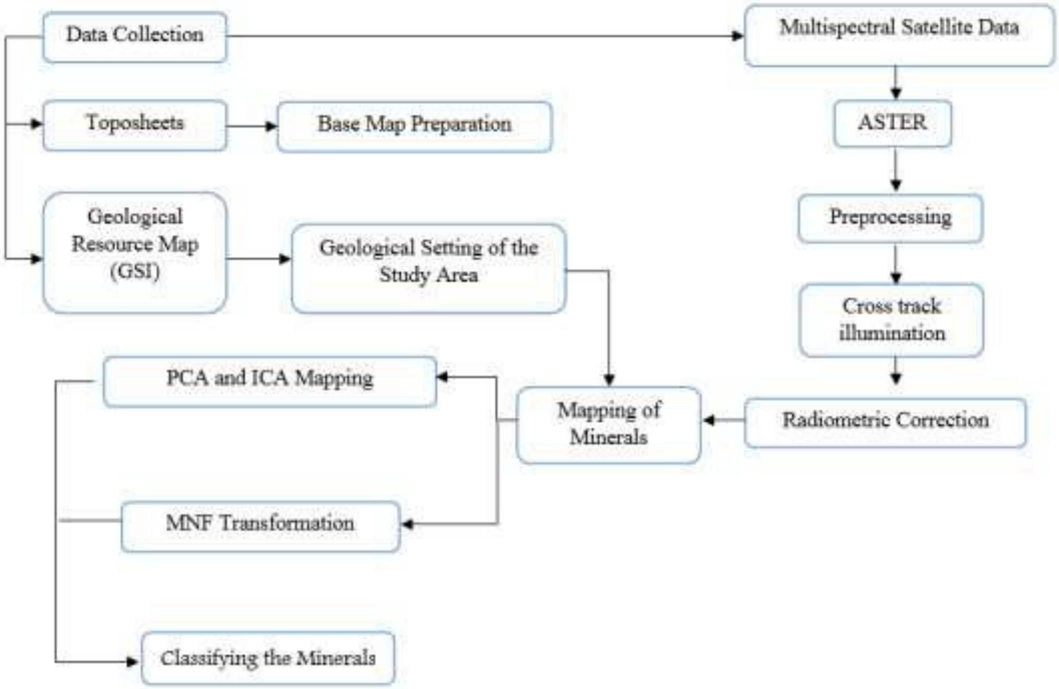

Fig.3: Flow chart methodology of the present study

IV. RESULTS AND DISCUSSION

The three subsystems of ASTER sensor, such as VNIR, SWIR and TIR has different roles to play in spectroscopy for geological applications. The ASTER data has offered a great opportunity of using these datasets for mapping of various lithological units of minerals, hydrothermal alteration and various enhancement techniques such as Principal Component Analysis (PCA), Minimum Noise Fraction (MNF), Independent Component Analysis (ICA), spectral mapping algorithms such as Spectral Angle Mapper (SAM) has been well employed in the study (Kumar et al. 2015).

ASTER image enhancement and analysis

Principal Component Analysis (PCA)

PCA is a statistical method to recognize data into several common factors using a linear transformation that projects data onto a new orthogonal axes coordinates. PCA is also used for separating information and noise in remote sensing data processing. The PCA transforms used to produce uncorrelated output bands, to segregate noise components and to reduce the spectral dimensionality of the data in such a way that first PC band contains a high variance value, the second PC band contains second high variance and the last PC band contains the minimum variance, high correlation and noise and hence PCA transforms helps to enhance and separate spectral signatures from the background.The first benefit of the PCA is that it may allow the summary or capture of the essential nature of the data set using a significantly reduced subset. The second benefit is that the procedure will lead to ameable physical interpretation, that is that it well extracts some hidden meaning from the data. In particular, the structures obtained from PCA in general are not independent because of possible higher order correlations.

Minimum Noise Fraction (MNF)

The MNF transformation is used to determine the inherent dimensionality of image data, segregate noise in the data, and reduce the computational requirements for subsequent processing. The MNF is the enhanced version of the PCA, which consist of two cascaded PCA rotations. MNF is a two steps process. First transformations compute the covariance matrix to decorrelate and rescale the noise to the data and its breaks the band to band correlation. Second transformation computes the eigen values, where bands having eigen values much greater than one contain coherent image and having eigen values near one contains noise (Fig.4.7). Using coherent portion, noise is removed from data. These coherent images will be taken only for further data analysis, this way MNF reduces the spectral dimension to the data. Similar to PCA output bands the first MNF band contains of high variance, the second MNF band contains the second high variance, but the last MNF band is highly correlated and noisy. The MNF transform has been extensively used in multispectral and hyperspectral data for feature extraction, noise whitening a spectral data reduction.

Independent Component Analysis

The PCA and MNF transform are based on second order statistics whereas ICA transforms use higher order statistics for the signal separation and feature extraction. ICA exploits higher-order statistics, which makes it more powerful in extracting irregular features within the data (Qian Du et al.2006). The ICA could reveal more spectral information as compared to PCA and MNF and, which could further enhance the image for better lithological discrimination. Similar to PCA and MNF output bands the first IC band contains minimum variance, high correlation and noise.

Derivation of Band Combination

Remote sensing analysis involved using the testing different band combinations and correlating these experimental data with a GSI resource map to choose the optimum band combinations for PCA, MNF and ICA transformation.

The result of PCA bands applied in RGB enabled the discrimination of different lithology of study area. According to the analysis in this study area, the best band combinations are derived from PCA (R: G: B=2:1:3) (Fig.4). In this band combinations provide different tonal variations in different lithology. According to this RGB, the Anorthosite rock shows magenta to maroon and slate blue to blue color. This tonal variation occurs due to disturbance of surface features. As well as the green to yellowish green color indicates the charnockite rock in the hilly region. Granitic gneissic rocks show dominantly yellowish green tone. Predominantly violet color indicates the hornblende biotite gneiss.

The result of MNF bands applied in RGB enabled the discrimination of different lithology of study area. According to the analysis in this study area, the best band combinations are derived from MNF (R: G: B=4:3:2) (Fig.5). However, the MNF band combinations provide a result of anorthosite rock in yellow to golden yellow color. Charnockite rocks show light green to dark green color. Granitic gneiss behaves yellow green to aquamarine color. As well as the hornblende biotite gneiss behaves like yellow green to golden yellow color.

The ICA best band combinations have been analyzed (R: G: B=3:1:2) (Fig.6), which help us to discriminate the better lithology of the study area. The anorthosite rocks provide violet to magenta and golden yellow color. Charnockite rock offers the parrot green color. Aquamarine to cyan color indicates granitic gneiss. Hornblende biotite gneiss shows different tonal variations like aquamarine and yellow color.

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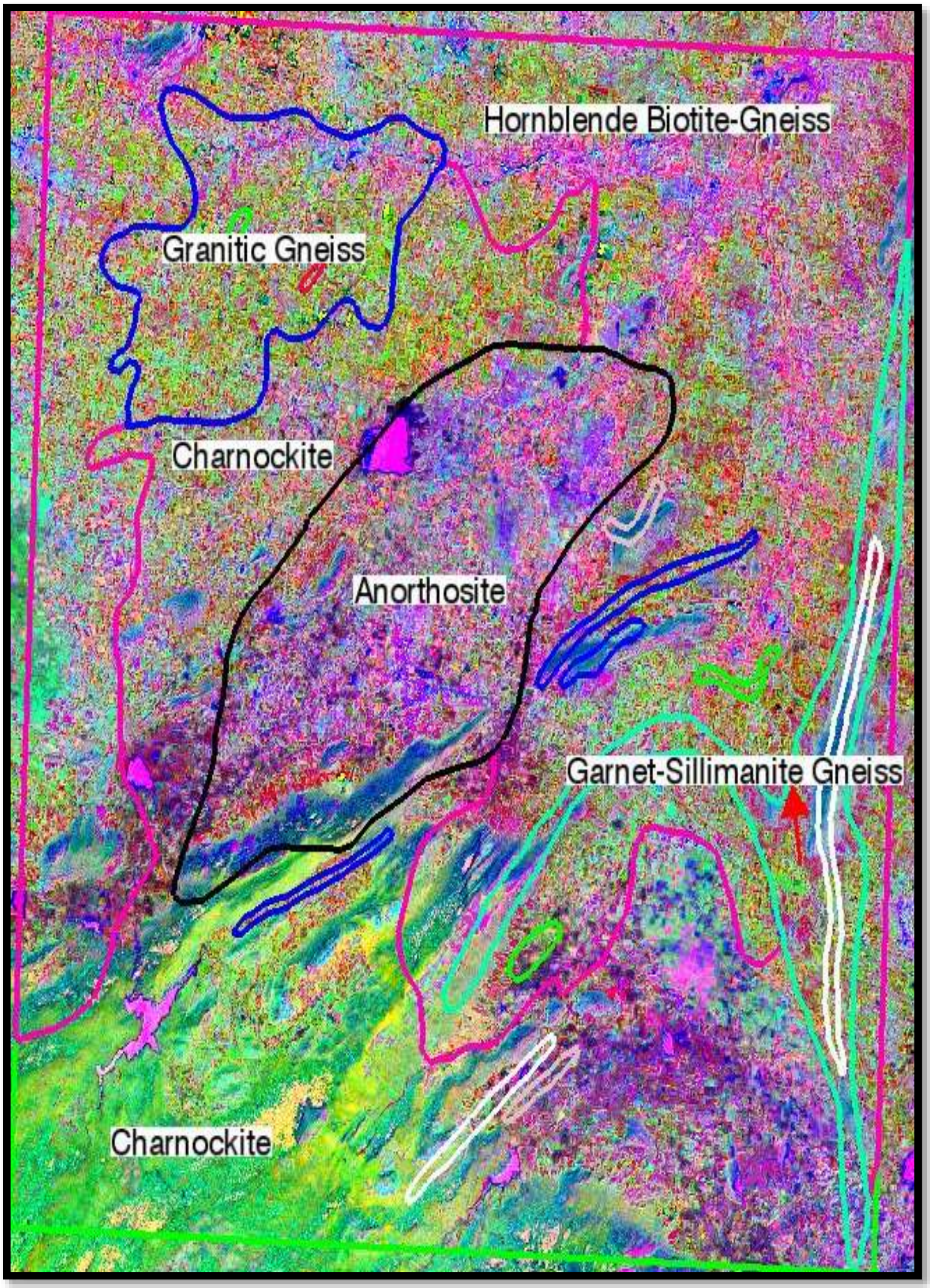

Fig.4: Result of (RGB=213) Principal Component Analysis map

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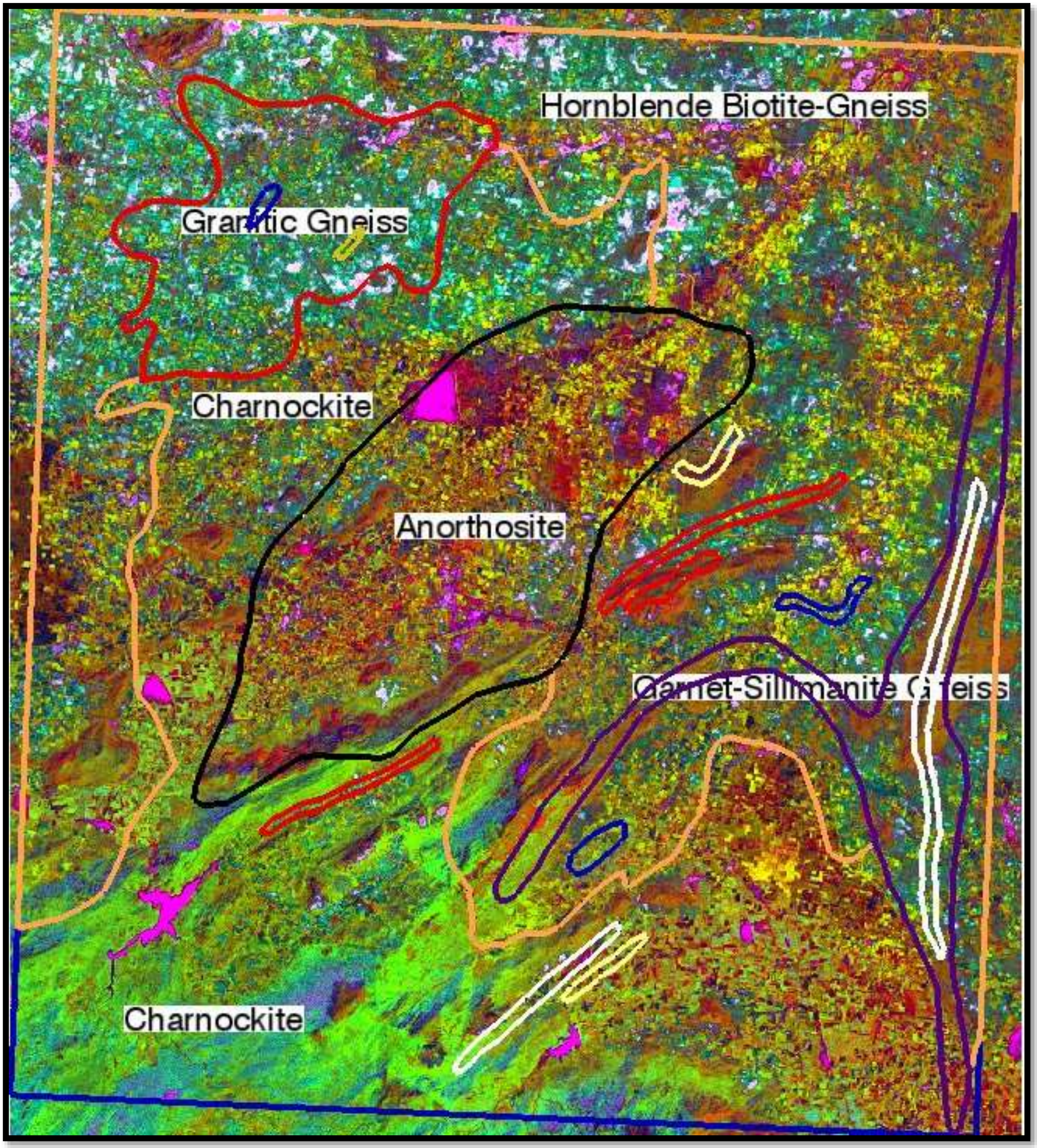

Fig.5: Result of (RGB=432) Minimum Noise Fraction

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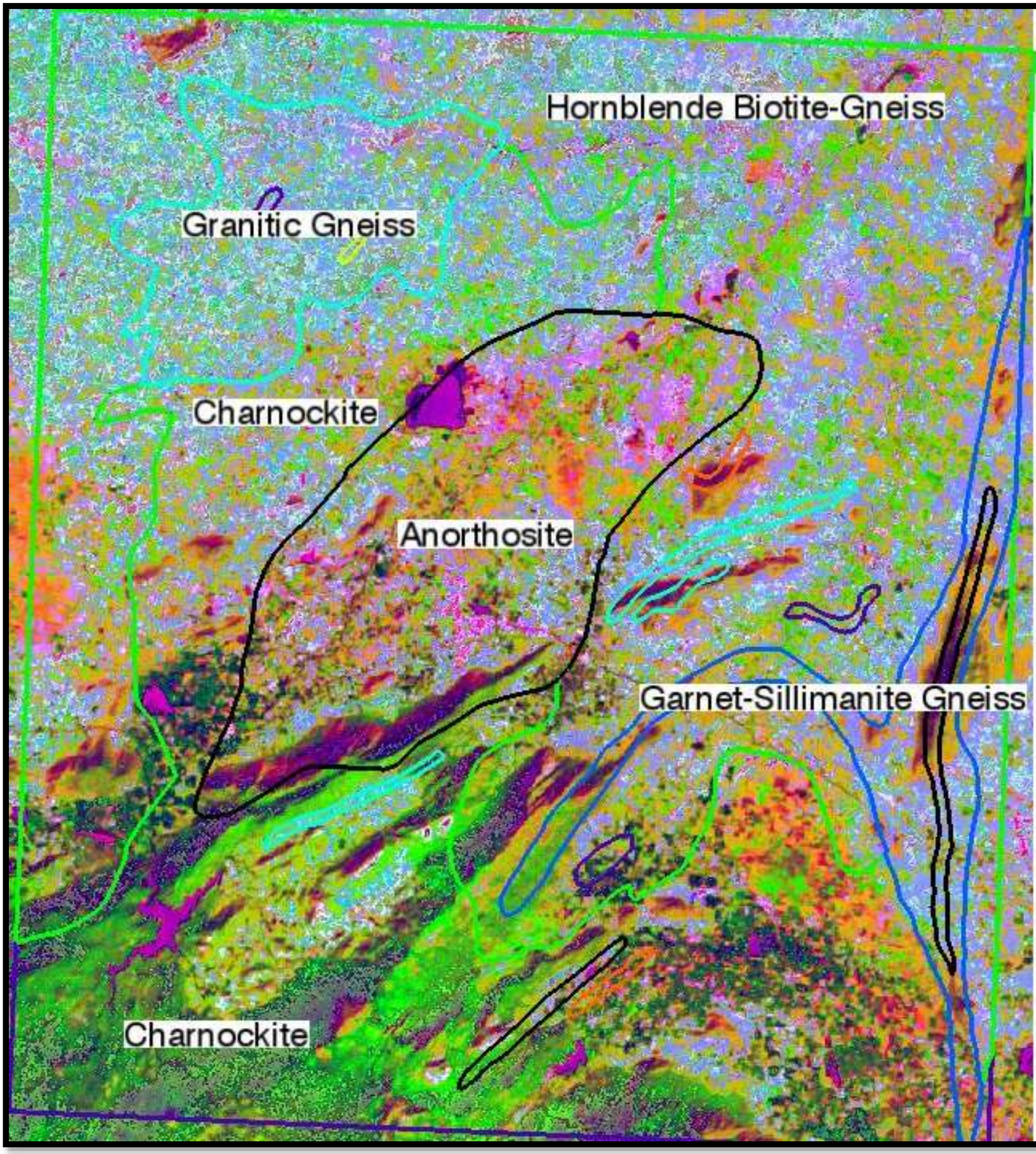

Fig.6: Result of (RGB=312) Independent Component Analysis map

V. CONCLUSION

The ASTER data based evaluation shows good correlation with field data for the lithological mapping.The ASTER subsystems such as VNIR +SWIR relative reflectance spectral analyses are highly helpful to detect and map the different litho units.The present study provides such new kind PCA, MNF and ICA band combinations for discriminating against the Anorthosites, Charnockite, Gneissic rocks.The band combinations proved itself and most effective in differentiating the various lithological units in kind of tonal variations.The image enhancement techniques such as PCA, MNF and ICA are recommended for the lithological discrimination studies.

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