研究報告

Application of Remote Sensing Techniques on Iron Oxide Detection from ASTER and Landsat Images of Tanintharyi Coastal Area, Myanmar

Myint Soe*, Toe Aung Kyaw** and Isao Takashima***

Abstract

The goal of this paper was to determine the effectiveness of remote sensing in the identification of iron oxide in the Tanintharyi coastal area, Southern Myanmar. The study used TNTmips version 6.9 software and the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) and Landsat Thematic Mapper data. Spectral properties are used to separate units in image data based on spectral reflectance in this paper. The iron oxide detection image was processed by ratioing VNIR B2/B1 in ASTER image and VNIR B3/B1 and SWIR B5/B4 in Landsat image. Principal component analysis (PCA) is an image processing technique that has been commonly applied to VNIR and SWIR sub region of ASTER data and Landsat images to locate iron oxide minerals. This technique indicates whether the materials are represented bright or dark pixels in the principal components according with the magnitude and sign of the eigenvectors loadings.

Keywords : iron oxide, spectral reflectance, band ratio, ASTER, Landsat, PCA

1. Introduction

Recently, Department of Geological Survey and Mineral Exploration (DGSE), under Ministry of Mines, Myanmar has carried out iron mineral exploration and prospecting for building iron industry at Tanintharyi region. This iron detection project from satellite images intends to provide the DGSE iron exploration works and future mineral exploration of Myanmar. The study used TNTmips version 6.9 software and the Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) and Landsat TM image data. This project is introduction of the application of remote sensing technique in DGSE for the mineral exploration concerned. Based on the data obtained from DGSE field parties of Tanintharyi area, attempt was made for spectral analysis and image processing.

Iron is a heavy, chemically active element. Native iron is rare in terrestrial rocks but fairly common in meteorites. Iron occurs in a wide range of ores in combination with others elements. The chief ores of iron are hematite (Fe_2O_3), goethite (FeO (OH)) and magnetite (Fe_3O_4). Ferriferous minerals found in ironstones include goethite, hematite, pyrite, siderite, limonite and chamosite.

Iron ore exploration was worked from early 20th century in Myanmar. A large iron ore, as observed by the author, exists in Kalagyun Island, about 10 km west of Myeik (Mergui). The ore mostly appears to be limonite and lateritic in nature(1). Considerable quantities of iron ore occur at Mavin Meaing Island (N12° 22', E98°30'), 16 km southwest of Myeik.

The study area is located in southern part of Myanmar, the west side of Tanintharyi coastal and lies between N 10° 00' to N 13° 53' and E 97° 15' to E 99° 51' (Fig. 1). The area covers approximately about 102675 km^2.

2. General geology

The Tanintharyi region is the southern part of the eastmost geotectonic belt of Myanmar, which is referred to either as the Shan-Tanintharyi Massif or simply as Karen-Tanintharyi Unit. Figure 2 shows the simplified geologic map of this area. Mergui Group of Carboniferous age formed as the basement and consists of thick sequence of folded argillite, greywacke and slate, with lesser amount of limestone, quartzite, agglomerate and congromerate. The Mergui Group is later intruded by tin bearing granitic rocks of late Mesozoic age.

Later, Tertiary rocks overly the Mergui Group and comprise of basal conglomerate, sandstone, claystone, mudstone and coal. Compared with other better-known areas, it is believed that the Tertiary sediments range from Oligocene to Miocene. Younger volcanic rocks such as rhyolite and basalt are scattered throughout the islands.

The name Mergui Series was given by T. Oldhem in 1856 to the unfossilliferous strata consisting of crushed shale, agglomerate, limestone and quartzite, and occures widely in the Tanintharyi region. The Mergui Series is pre-Carboniferous in age and underlies the Moulmein limestone.

The predominant rock type of the Mergui Series in Tavoy

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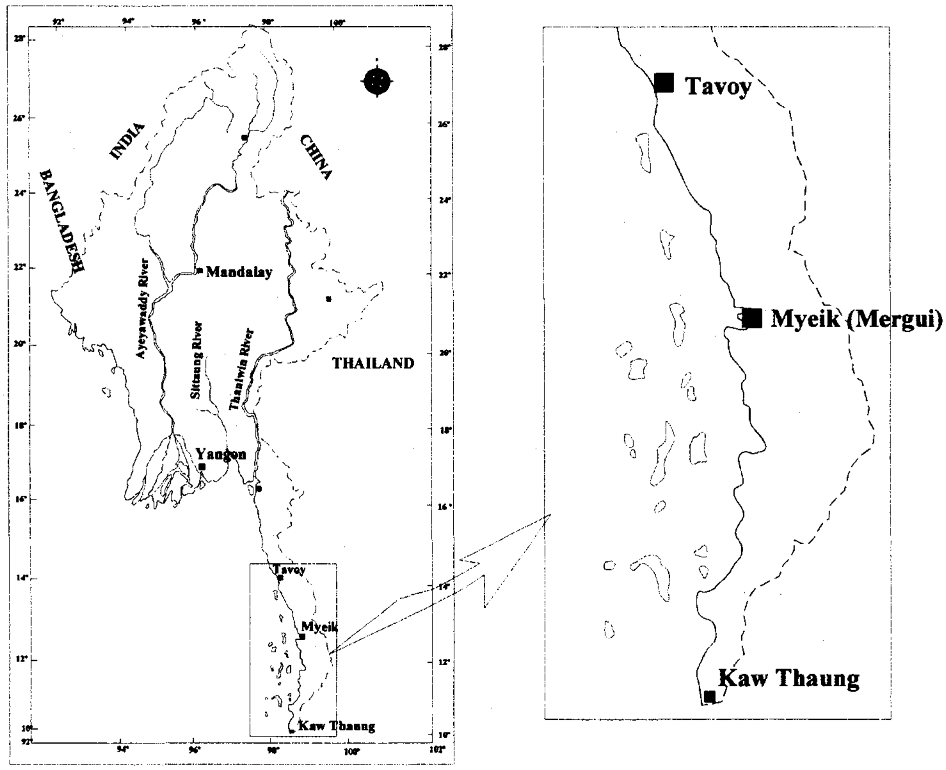


Fig.1. Location of study area.

district is argillite, fine grained rock of blue gray to black color at fresh, with obscure bedding and only incipient cleavage. The Carboniferous argillite is carrying small crystals of andalusite and silliminite with finely divided graphite. Similar Carboniferous shale with graphite are also found in some places in the Myeik area.

The next important rock type is dark grey or almost black "greywacke" which weathered to ashy brown color. This rock lacks bedding and composed of sub angular fragments of fine-grained rock in matrix identical with the argillites.

3. Methodology

Spectral properties are used to detect iron oxide minerals in image data. This is done interactively on computers using multispectral data. Using ASTER images are ASTL1B_030118040308, ASTL1B_031102040158, ASTL1B_031204040251, ASTL1B_031109040810, ASTL1B_ 031109040801, ASTL1B_04022040210 and Landsat TM image scenes are Nos. 130-51, 130-52 and 130-53. The United Stated Geological Survey (USGS) spectral library data are also used. The TNTmips version 6.9 software is used for image processing.

3.1. Iron detection by band ratio

Relative absorption band depth images of Al-OH, Mg-OH and CO_3 are useful for preliminary check. Among the partially successful classifications, the mineral composite image (consists of three ratio images of Landsat: Bands 5/7 ratio for clay mineral, Bands 5/4 ration for ferrous minerals, and Bands 3/1 ratio for iron oxides) (Fig. 3).

ASTER Visible Near Infra Red (VNIR), Short Wave Infra Red (SWIR) and Thermal Infra Red (TIR) scenes were generally used for identification of limonite, alteration clay minerals and alunite, and silica contents, respectively. The limonite image was processed by ratioing VNIR B2/B1, and then density sliced into three classes(2). Similar ratio method can be used in Landsat Thematic Mapper image B3/B1 (Fig. 4).

Ratios are prepared by dividing the grey level of a pixel in one band by that in another band. Ratios are important in helping to recognize ferruginous and limonitic cappings (gossans). A ratio of ASTER band 1 over band 2 will enhance the small contribution of iron oxide minerals at Boke Pyin area (75km south of Myeik) (Fig. 5 (a)). Similarly a ratio of ASTER band 1 over band 2 will discriminate zones of iron oxide at Myeik area (Fig. 5 (b)).

3.2 Iron detection by Principal Components Analysis (PCA) Method

Principal Components Analysis (PCA) can be used for image analysis as a data reduction technique that the information content from a number of bands is compressed into a few principal components. In other words, PCA can be used to reduce the dimensionality of the data while minimizing loss of information. In addition, PCA images may be more easily interpreted than the conventional color infrared composite.

The Principal Components transform is a standard method for deriving a new set of images with reduced spectral redundancy. PCA is probably the oldest and best known of the techniques used for multivariate analysis. The overall goal of PCA is to reduce the dimensionality

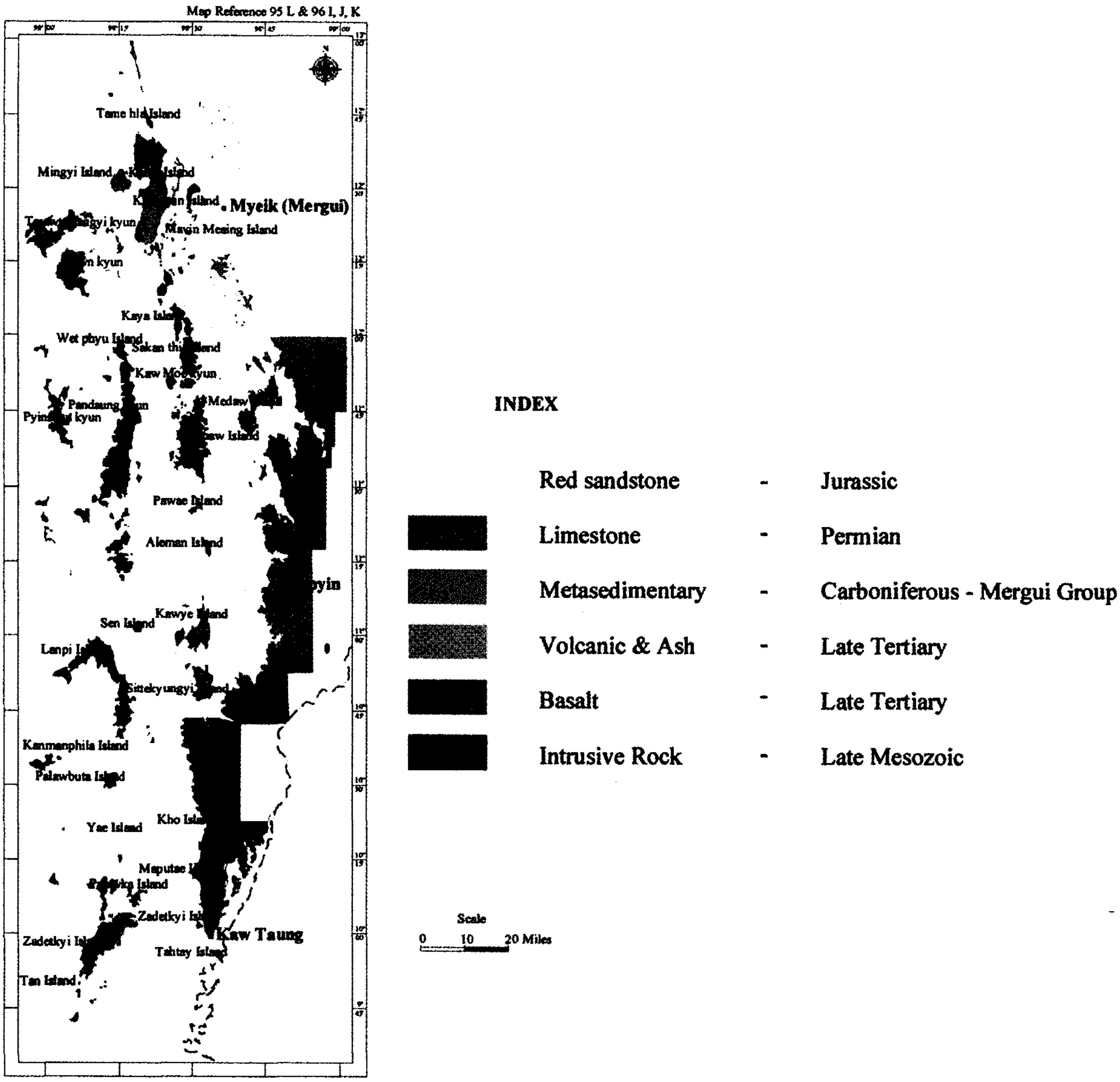


Fig. 2. Geological map of Tanintharyi area.

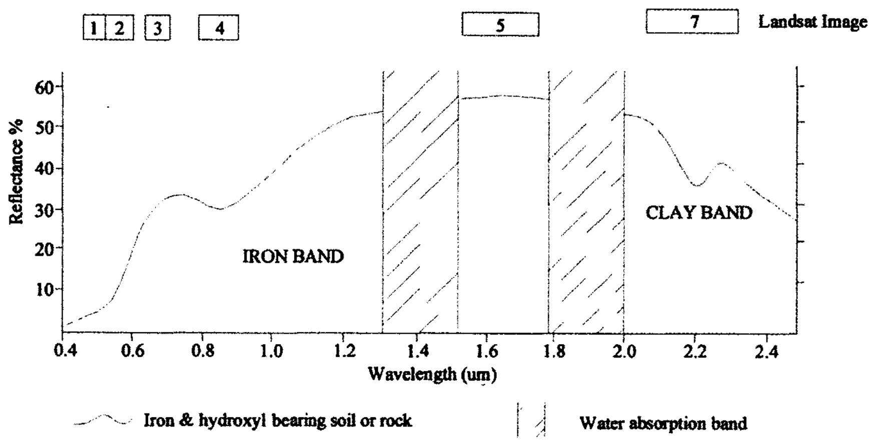


Fig. 3. A reflectance profile of the visible and IR parts of the emission spectrum, showing the changing reflectance profile of soil associated with special materials.

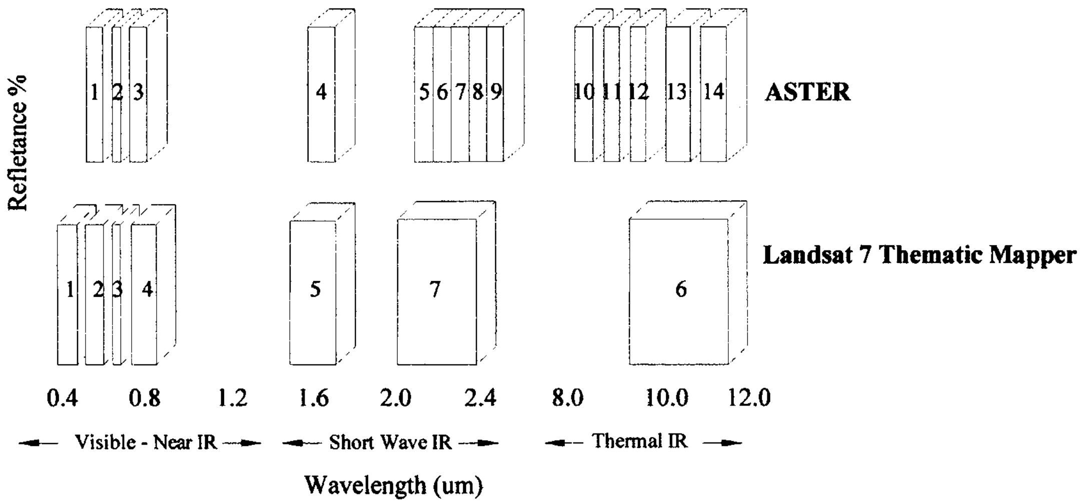
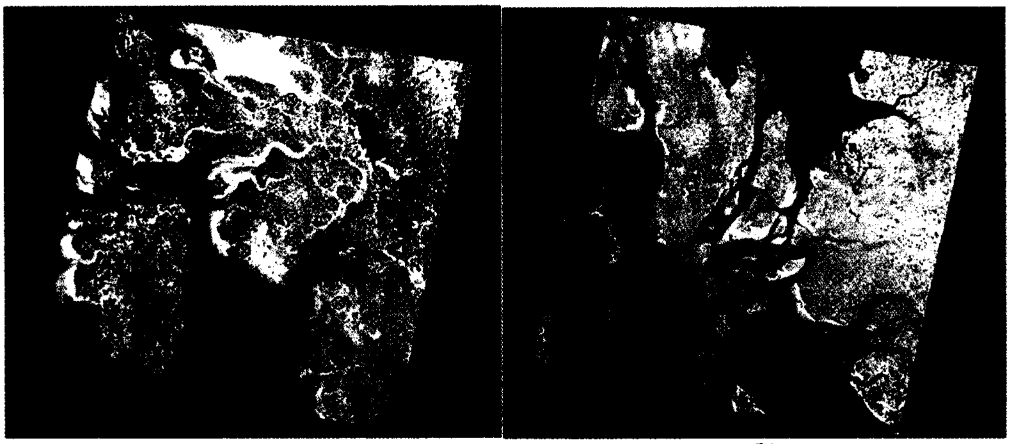


Fig. 4. Comparison of spectral bands between ASTER and Landsat7 Thematic Mapper.



(a) (b)

Fig. 5 Iron oxide detection from ASTER image (red) and iron outcrop field data (green).
(a) Boke Pyin area (left), (b) Myeike area (right).

Table 1 Landsat image 130-52 Principal Component Analysis Statistics, Tanintharyi area.

--- Eigenvalues and Associated Percentages ---

Axis	Eigenvalues	Percentages	Cumulative
1	2263.3467	72.1211	72.1211
2	800.5062	25.5080	97.6291
3	62.6717	1.9970	99.6261
4	8.7916	0.2801	99.9063
5	1.7261	0.0550	99.9613
6	1.2149	0.0387	100.0000

of data set, while simultaneously retaining the information present in the data.

The approach for the computation of the principal components (PCs) comprises the calculation of;

1. Covariance (unstandardised PCA) or correlation (standardised PCA) matrix
2. Eigenvalues, vectors
3. PCs

The eigenvector matrix used to calculate PCA for each subset was examined and identified PC contained for the target (mineral) information. The criterion for the identification is the same proposed by Loughlin(3). The PC that contains the target spectral information shows the highest eigenvector loading from the ASTER band, coincide with the target's most diagonostic features. The iron oxide has high reflectance values in Landsat TM image

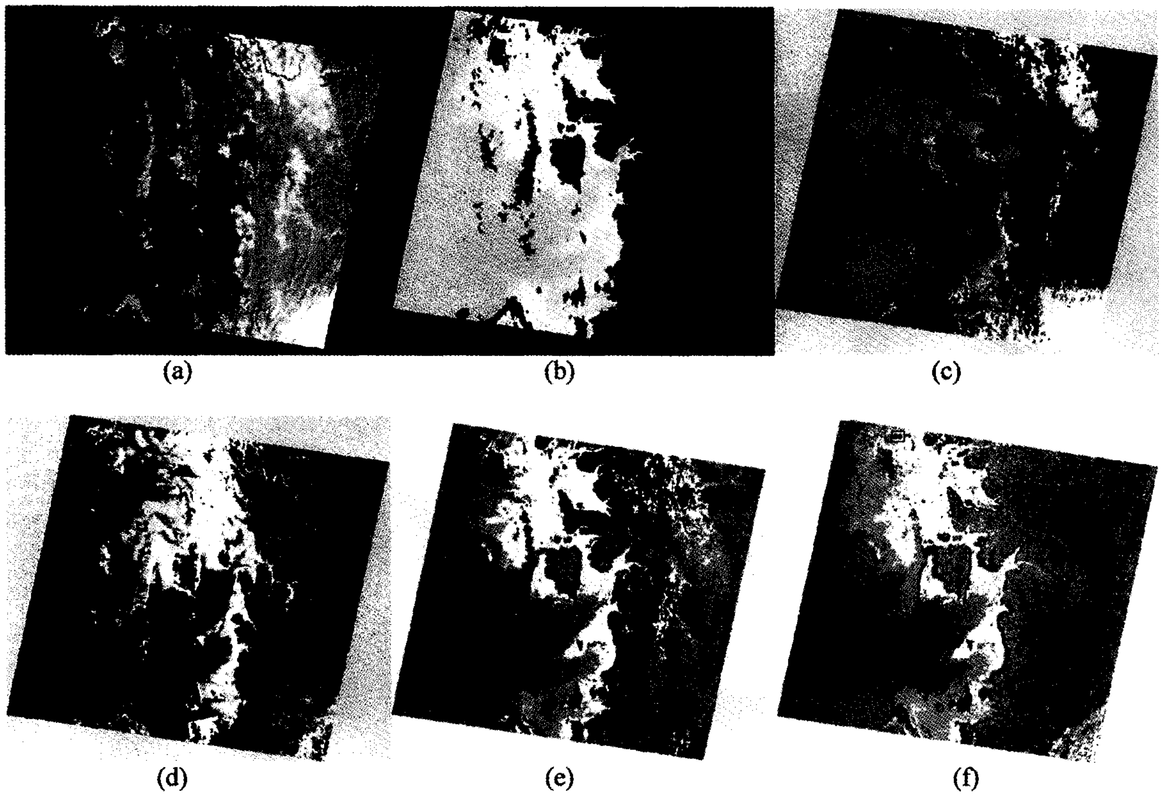


Fig. 6. Principal component analysis images (PC1 to PC6) of Tanintharyi coastal area, Landsat 130-52.

Table 2 The factor scores (eigenvectors) and factor loadings (degree of correlation) of each component from the matrix, Landsat image band 1, 2, 3, 4, 5, 7 of 130-52 Landsat data.

--- Eigenvectors ---

Axis	band1	band2	band3	band4	bnad5	band7
1	0.5504	0.2204	0.1958	0.6161	0.4595	0.1392
2	0.7451	0.2175	0.1249	-0.4787	-0.3779	-0.1000
3	-0.0780	0.0719	0.2703	*-0.6040*	*0.6420*	0.3722
4	*-0.3288*	0.4163	*0.7860*	0.1189	-0.2937	-0.0212
5	-0.1371	0.6513	-0.2935	-0.0992	0.2951	-0.6116
6	-0.0940	0.5491	-0.4113	0.0489	-0.2461	0.6765

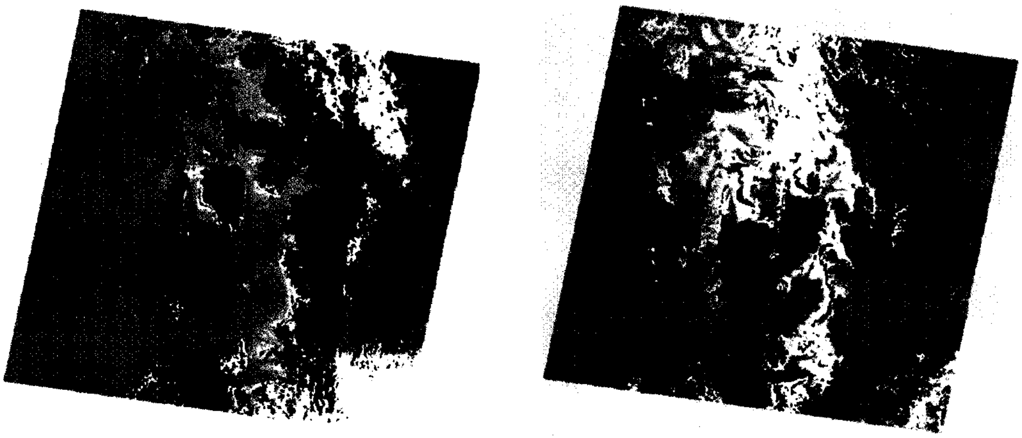
band 1 and 3, and ferrous mineral has high reflectance values in band 4 and 5 in Tanintharyi area.

PCA is an image processing technique that has been commonly applied to VNIR and SWIR sub region of ASTER and Landsat TM data to locate iron oxide mineral. The availability of spectral information in the VNIR and SWIR portions of the electromagnetic spectrum has been greatly increased. This allows detailed spectral characterization of surface targets, particularly of those belonging to the group minerals with diagnostic spectral features in this wavelength range.

3. 3 Data analysis

The principal component transformation is a multivariate statistical technique that selects uncorrelated linear combinations (eigenvector loadings) of variables. Each successively extracted linear combination, or principal component (PC), has a smaller variance. The principal component analysis is widely used for alteration mapping in metallogenic provinces. Through the analysis of the eigenvector values, it allows identification of the principal components that contain spectra information about specific minerals, as well as the contribution of each of the original bands to the components. This technique indicates whether the materials are represented bright or dark pixels in the principal components according with the magnitude and sign of the eigenvectors loadings. The technique can be applied on ETM+ and ASTER data(4).

PCA analysis is applied for Landsat TM data (Table 1). Figure 6 shows principal component analysis images (PC1 to PC6). The first PC shows the albedo. PC4 enhances the iron oxide bearing areas (Fig. 7) as this PC has higher loadings of band 1 and 3 (for ASTER band 1 and 2). PC3 enhances the ferrous mineral bearing areas as this PC has higher loadings of band 4 and 5 (Fig. 7). Iron oxide can enhance between 400 nm – 600 nm.



(a) (b)

Fig. 7. Iron oxide detection on PC4 and ferrous oxide detection on PC3 of Landsat TM image 130-52.

Fig. 8. Iron oxide detection on landsat TM image (Red) and iron outcrop field data of Tanintharyi area (Mosaic Landsat TM image 130-51, 130-52 and 130-53).

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Principal component analysis is done using six Landsat image 130-52 band as input Bands (Table 2). The first principal component does not contain spectral features relevant in this analysis, as it is a combination of all Bands. This component contains 72.12% of the variance of six bands. This PC1 gives information mainly on albedo and topography. Analysis of PC4 shows that the most important contributions come from Band 1 (-0.3288) and Band 3 (0.7860). Based on spectral characteristics of iron oxide, it follows that iron oxide will be mapped by bright pixels. Iron oxide image is obtained by using eigenvector loadings of PC4. The similar analysis of PC3 shows that the most important contributions come from Band 4 (-0.6040) and Band 5 (0.6420). Ferrous mineral image is obtained by using eigenvector loadings of PC3.

Principal component analysis is used to enhance or distinguish lithological differences. Spectral differences between rock types may be more apparent in principal component images than in single bands. Similar analysis is done on Landsat TM image 130-51 and 130-53 of Tanintharyi coastal area. Then mosaic image is processing and overlaies, and shows the PCA iron oxide results (Fig. 8).

4. Results

The nature of multispectral data is ivestigated in this study. ASTER and Landsat TM image data are required for iron oxide exploration in general and in Tanintaryi area, Myanmar in particular. Iron oxide spectral on ASTER and Landsat image should be confirmed by detailed field mapping.

ASTER and Landsat TM image can be widely used to generate exploration targets in Myanmar using the wavelengths characterized by iron absorption. ASTER data has more capability than Landsat data for enhancing iron oxide areas because of suitable band combination.

5. Discussion and conclusions

Although DGSE geologist has well experiences in satellite image interpretation in manually[5], application of remote sensing software has not approach systematically yet. This study deals first implementation of remote sensing techniques in mineral exploration in DGSE. So far the results obtained from image processing needs to differentiates whether true anomaly or false anomaly. Most of the lateritic iron occurrences surveyed by DGSE field parties located along the coast or along the beach of Myeik archipelago. Iron detection from ASTER and Landsat TM image encourages very much to find new iron ore areas. But some showed in land widespreadly. These could be reflection of some oxidized rocks of Mergui Group and granitic rocks. Some basaltic rocks in Medaw Island show some anomaly. Most of the detection along the coastal slips has coincided as lateritic iron outcrops and probed by field surveys.

In conclusion, remote sensing techniques or image processing method has successfully applied in this area.

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ミャンマー南部タニンサリュイ沿岸地域における ASTER 及び Landsat 衛星画像を使用したリモートセンシングによる鉄酸化物の検出

ミン スー*・トェ アウン キャウ**・高島 勲***

要　　旨

衛星画像の解析により、ミャンマー南部の鉄酸化物分布地域を検出した。利用した画像は ASTER と Landsat、解析ソフトは TNTMipsV.6.9 である。衛星画像の異なった波長の反射強度解析で鉄酸化物の分布域を求めた。利用した画像は、ASTER の可視近赤外波長の B2/B1 比と Landsat の同波長 B3/B1 比、短波長赤外の B5/B4 比である。これらの波長データを主成分分析により処理し、鉄酸化物が存在する地点からの反射強度が強くなるようにした。この結果、地表露頭に鉄酸化物が存在する地点を自動的に抽出できた。

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