

**Development of transformation method  
of multispectral imagery into hyperspectral imagery  
for detailed identification of metal and geothermal  
resources-related minerals**

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**Development of transformation method of  
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I would like to dedicate this work to the memory of my father and to my loving family.

## **Declaration**

I hereby declare that except where specific reference is made to the work of others, the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements. This dissertation is 160 pages long, including front matter, text, figure, tables, references, and appendix.

Nguyen Tien Hoang

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## **Abstract**

Hyperspectral remote sensing is superior to multispectral remote sensing because of continuous reflectance spectra that enable detailed, precise mapping of the earth surface compositions. Because of this spectral feature, hyperspectral remote sensing has been applied to various fields, particularly land surveys including mineralogy, biology, and environmental monitoring. However, hyperspectral imagery has a shortcoming of swath width, which is much narrower than multispectral imagery. In addition, no hyperspectral imager has covered entirely the earth surface. These conditions point to a need for hyperspectral transformation of multispectral images to extrapolate the coverage area of hyperspectral imagery. Landsat series imagery is the most suitable data source of this transformation, because it represents the longest-operating earth observation that has accumulated high-quality images for all the land areas. Based on those background, this dissertation completes the results of a study that has developed a new method, Pseudo-Hyperspectral Image Transformation Algorithm (PHITA), to transform multispectral imagery into pseudo-hyperspectral imagery. This advanced method contributes to more detailed identification of minerals and mineral deposit exploration than traditional multispectral remote sensing. This dissertation is composed of the following six chapters.

Chapter 1 summarizes important backgrounds to understand the goals of the dissertation. Simulation of a hyperspectral image from a multispectral image is an innovative technique by compensating the disadvantages of each image type.

Although several preceding studies have succeeded in simulating a hyperspectral image from a multispectral image, they verified their methods only for the overlapped areas of both the images. In this study, PHITA was validated even for areas outside the original coverage of hyperspectral image.

Chapter 2 explains in detail the development of PHITA to transform a multispectral image into a pseudo-Hyperion image using correlations between band reflectance data in their overlapped area. Landsat 7 ETM+ and Hyperion images are selected as an example for the transformation. Effectiveness of the hyperspectral transformation was multiply evaluated by general image appearance, spectral reconstruction, statistical indices, and mineral mapping. The validation methods and data preprocessing are also presented in this chapter.

Chapter 3 demonstrates and discusses the results of the Hyperion image transformation from ETM+ image by PHITA. The resultant pseudo-image has a number of high-quality Hyperion bands of the same scene size as the ETM+ image. The pseudo-Hyperion image was proven very similar to the original band reflectances, because of large Pearson's correlation coefficients (generally  $> 0.94$ ), small RMS error (mostly  $< 0.016$ ), high structural similarity, and similar appearance of the color composite image. Using a reference mineral map built from an AVIRIS image and field surveys as ground truth, an advantage of the pseudo-image is clarified for the Cuprite hydrothermal alteration area in the western United States. The identification and mapping accuracies of metal deposit-related minerals were high even in areas outside the original Hyperion scene.

Chapter 4 extends the PHITA to transform Landsat 5 TM, Landsat 8 OLI, and EO-1 ALI sensor images into pseudo-Hyperion images. By choosing a part of the Fish Lake Valley geothermal prospect area in the western United States for a case study, the pseudo-Hyperion images produced from the TM, ETM+, OLI, and ALI images by PHITA were confirmed to be applicable to a mineral mapping of geothermal resource exploration. Using a reference map as the ground truth,

three main minerals (muscovite and chlorite mixture, opal, and calcite) were identified with high overall accuracies from the pseudo-images. The highest accuracy was obtained from the ALI image, followed by ETM+, TM, and OLI images in descending order. The TM, OLI, and ALI images can be alternatives to ETM+ imagery for the hyperspectral transformation that aids the production of pseudo-Hyperion images for areas without high-quality ETM+ images because of the scan line corrector failure, and for long-term global monitoring of land surfaces.

Chapter 5 examines the capability of PHITA for simulating an airborne hyperspectral image, AVIRIS, from OLI and ASTER images and a possibility of joint spectral and spatial downscaling. In this experiment, PHITA follows the principles of supervised machine learning workflow with a training area in the United States and a validation area in the northern Chile. These are typical hydrothermal deposit areas. The pseudo-AVIRIS image has 205 bands and a downscaled spatial resolution of 15 m, half of the multispectral spatial resolution. Pseudo-reflectance spectra were generally agreeable with the original spectra. The OLI-based pseudo-image was superior in the spatial downscaling but inferior in the spectral downscaling. Using 4-m SASI-based mineral map as ground truth of the distribution of selected minerals, the ASTER-based pseudo-image was confirmed to be sufficiently applicable to mineral identification and mapping for an area that contains the Sierra Gorda Copper-Molybdenum Mine, a large porphyry copper deposit in the northern part of the study area.

Finally, Chapter 6 summarized the essential results of each chapter as a grand conclusion of this study. Important future works are also discussed in this chapter to develop furthermore PHITA studies for global exploration of mineral and geothermal resources.

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# Chapter 1

## Introduction

### 1.1 Multi-and hyperspectral geologic remote sensing

Resource-related minerals on the Earth surface in sparsely vegetated areas can be detected and mapped from remotely sensed image by combining geological and structural mappings with the recognition of hydrothermally altered rocks. Generation of epithermal vein-type deposits has been mostly related to hydrothermal alteration of the adjacent country rocks (Sabins, 1999). For the detection, passive optical sensors have been used widely for geological applications, ranging from a few spectral bands to more than 100 contiguous bands that cover visible to shortwave infrared (SWIR) region of the electromagnetic spectrum. Development of multi- and hyper-spectral geologic remote sensing is classified into the Landsat era, Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) era, and hyperspectral era (van der Meer et al., 2012).

From the early stage of Landsat era, fundamental image processing methods such as band ratio and principal component analysis were applied to identify iron oxide and hydroxyl minerals, because they could be related to the presence of hydrothermal alteration (van der Meer et al., 2012). However, mineral mapping using Landsat image is limited in accuracy because only one SWIR band is



Table 1.1 Examples of ASTER mineral indices after Kalinowski and Oliver (2004).

| Mineral type                             | Band ratio      | Comments                        |
|------------------------------------------|-----------------|---------------------------------|
| <b>Iron</b>                              |                 |                                 |
| Ferric iron ( $\text{Fe}^{3+}$ )         | 2/1             |                                 |
| Ferrous iron ( $\text{Fe}^{2+}$ )        | 5/3 + 1/2       |                                 |
| Laterite                                 | 4/5             |                                 |
| Gossan                                   | 4/2             |                                 |
| Ferrous silicates                        | 5/4             | Fe oxide Cu-Au alteration       |
| Ferric oxides                            | 4/3             | Can be ambiguous                |
| <b>Carbonates / Mafic Minerals</b>       |                 |                                 |
| Carbonate / chlorite / epidote           | (7+9)/8         |                                 |
| Epidote / chlorite / amphibole           | (6+9)/(7+8)     | Endoskarn                       |
| Amphibole / MgOH                         | (6+9)/8         | Can be either MgOH or carbonate |
| Amphibole                                | 6/8             |                                 |
| Dolomite                                 | (6+8)/7         |                                 |
| Carbonate                                | 13/14           | Exoskarn                        |
| <b>Silicates</b>                         |                 |                                 |
| Sericite / muscovite / illite / smectite | (5+7)/6         | Phyllic alteration              |
| Alunite / kaolinite / pyrophyllite       | (4+6)/5         |                                 |
| Phengitic                                | 5/6             |                                 |
| Muscovite                                | 7/6             |                                 |
| Kaolinite                                | 7/5             | Approximate only                |
| Clay                                     | (5x7)/(6x6)     |                                 |
| <b>Silica</b>                            |                 |                                 |
| Siliceous rocks                          | (11x11)/(10x12) |                                 |
| $\text{SiO}_2$                           | 13/12, 12/13    |                                 |

available even in the latest Landsat 8 Operational Land Imager (OLI) image. With six bands in the SWIR region, ASTER improved the qualitative results of mineral presence by producing many mineral indices (Table 1.1) or using spectral unmixing approaches (Hosseini and Tangestani, 2011). For example, a case study in the Cuprite and Mountain Pass areas of USA demonstrated that main mineral groups composed of argillic, phyllic alteration, and propylitic minerals could be detected and distinguished from ASTER images. However, detailed separation of kaolinite versus alunite was low accuracy in this study (Mars and

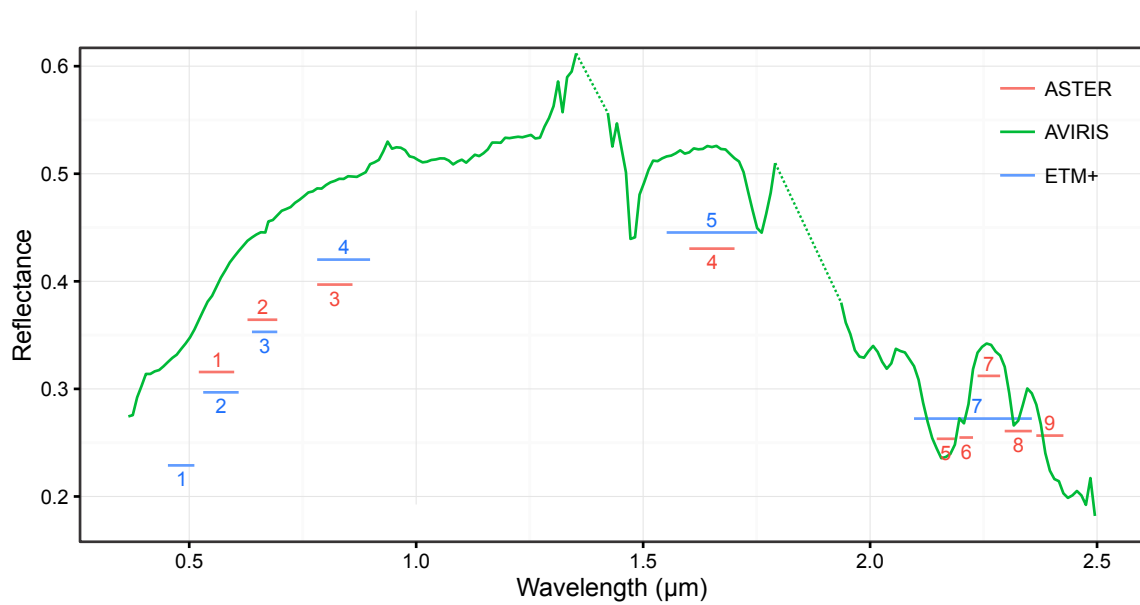


Fig. 1.1 Reflectance spectra of alunite-bearing rock retrieved from AVIRIS, ASTER, and Landsat 7 ETM+ images. Each spectrum is an average of the spectra from three adjoining pixels collected in Cuprite area of the western United States. Regions of strong atmospheric absorption (dotted lines) have been deleted. Numbers attached to lines mean corresponding ASTER (red) and Landsat 7 ETM+ (blue) bands.

Rowan, 2010). On the contrary, 36 mineral categories were successfully mapped and separated within the same area using the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) image, which is a representative hyperspectral data so far. These categories include Fe-bearing minerals, sulfates, carbonates, kaolinite, and alunite (Swayze et al., 2014). The differences of spectral absorption features between minerals can easily be distinguished by using hyperspectral images having hundreds of contiguous bands with high spectral resolution (Koike and Kouda, 2016). Comparison of reflectance spectra of alunite-bearing rock retrieved from AVIRIS, ASTER, and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) images is shown in Figure 1.1. Two main absorption features of alunite at 2.16  $\mu\text{m}$  and 2.32  $\mu\text{m}$  are clearly recognized from the AVIRIS image.

## 1.2 Motivation

As described in Section 1.1, hyperspectral remote sensing is superior to multispectral remote sensing because of continuous reflectance spectra that enable detailed, precise mapping of earth surface compositions. This enables detailed discrimination of various types of Earth surface materials (Thenkabail et al., 2011; Winter et al., 2007). Because of this spectral feature, hyperspectral remote sensing has been applied in various fields, particularly land surveys involving mineralogy, biology, and environmental monitoring (Marshall and Thenkabail, 2015; Thenkabail et al., 2011). Hyperspectral instruments have been increasingly developed including airborne sensors, such as AVIRIS and HyMAP, and spaceborne sensors, such as Earth Observing One (EO-1) Hyperion, Compact High Resolution Imaging Spectrometer (CHRIS), Hyperspectral Imager Suite (HISUI), Hyperspectral Precursor and Application Mission (PRISMA), and the Environmental Mapping and Analysis

Table 1.2 Examples of current and future hyperspectral missions.

| <b>Sensor</b>                  | <b>AVIRIS</b> | <b>HyMAP</b>  | <b>EO-1 Hyperion*</b> | <b>CHRIS</b> |
|--------------------------------|---------------|---------------|-----------------------|--------------|
| Country                        | USA           | Australia     | USA                   | UK           |
| Spatial resolution (m)         | 4–20          | 2–10          | 30                    | 18/36        |
| Spectral resolution (nm)       | ~10           | 10–20         | ~10                   | 1.3–12       |
| Wavelength range $\mu\text{m}$ | 0.4–2.5       | 0.44–2.5      | 0.4–2.5               | 0.41–1.05    |
| Number of bands                | 224           | 128           | 242                   | 19/63        |
| Swath at nadir (km)            | 1.9–11        | Variable      | 7.65                  | 14           |
| Launch year                    | 1987          | N/A           | 2000                  | 2001         |
| <b>Sensor</b>                  | <b>HISUI</b>  | <b>PRISMA</b> | <b>EnMAP</b>          |              |
| Country                        | Japan         | Italy         | Germany               |              |
| Spatial resolution (m)         | 30            | 30            | 30                    |              |
| Spectral resolution (nm)       | 10–12.5       | ~12           | 5–10                  |              |
| Wavelength range $\mu\text{m}$ | 0.4–2.5       | 0.4–2.5       | 0.4–2.5               |              |
| Number of bands                | 185           | 237           | 244                   |              |
| Swath at nadir (km)            | 30            | 30            | 30                    |              |
| Launch year                    | ~2018         | ~2018         | ~2019                 |              |

\*The EO-1 satellite has been decommissioned since 30 March 2017

Program (EnMAP) (Table 1.2). However, hyperspectral image has a shortcoming of swath width, which is much narrower than multispectral image. Furthermore, data resources of hyperspectral remote sensing are limited by both acquisition time and coverage area. No hyperspectral imager has covered the entire Earth surface. In contrast, multispectral remote sensing has covered all areas for a long time, albeit using a small number of bands (Sun et al., 2015). This points to a need for hyperspectral transformation of multispectral imageries to extrapolate the coverage area of hyperspectral image. Simulation of a hyperspectral image from a multispectral image is also an innovative technique with which to compensate the disadvantages of each image type. Landsat series image may be the most suitable source for this transformation, because it represents the longest-operating earth observation that has accumulated high-quality land images across the globe.

### 1.3 Literature review

Several studies have succeeded in simulating a Hyperion image from a EO-1 Advanced Land Imager (ALI) image (Chen et al., 2008; Liu et al., 2009) and CHRIS image from an ETM+ image (Berezowski et al., 2012). Their methods were a modified spectral response function derived from pixel-mixing principles (Berezowski et al., 2012; Chen et al., 2008) and a universal pattern decomposition method (UPDM), which is a spectral unmixing approach (Liu et al., 2009). Because both used only standard spectral profiles to identify soil, water, and vegetation, it is difficult to produce a detailed classification map with different types of surface materials from simulated hyperspectral images. Other relevant methods include the Color Resolution Improvement Software Package (CRISP), which transforms a multispectral image into a synthetic hyperspectral image (Winter et al., 2007), and the Spectral Resolution Enhancement Method (SREM), which incorporates a spectral angle weighted minimum distance matching method into CRISP (Sun et al.,

Table 1.3 Summary of previous methods for simulation of a hyperspectral image from a multispectral image.

| Method              | Pixel-mixing                                            | UPDM              | SREM                                    |
|---------------------|---------------------------------------------------------|-------------------|-----------------------------------------|
| Approach            | Modified spectral response function                     | Spectral unmixing | Linear transformation                   |
| Multispectral image | ALI                                                     | ALI               | ALI                                     |
| Simulated image     | Hyperion                                                | Hyperion          | Hyperion                                |
| Target area         | Overlap areas of hyperspectral and multispectral images |                   |                                         |
| Application         | Simple land cover classification                        |                   |                                         |
| References          | Chen et al. (2008)                                      | Liu et al. (2009) | Sun et al. (2015); Winter et al. (2007) |

2015). SREM was applied to simulate a cropped AVIRIS image from a simulated Landsat 5 Thematic Mapper (TM) image generated by spectral resampling of the original AVIRIS image, and a Hyperion image from an ALI image. However, neither CRISP nor SREM performed well for zones of heterogeneous material distribution within a scene. In addition, these previous studies verified their methods only for the overlap areas of hyperspectral and multispectral images and for simple land cover classifications (Table 1.3). Therefore, as far as we know, there has been no simulation of a Hyperion image from a Landsat image and for an area outside the original scene.

## 1.4 Objectives

The introduction above frames the advantage of hyperspectral imagery and the importance of hyperspectral transformation of multispectral imageries. This research therefore aims to achieve the following main objectives:

1. To develop a new method, Pseudo-Hyperspectral Image Transformation Algorithm (PHITA), for transforming a multispectral image into a pseudo-hyperspectral image,

2. To identify which factors affect the hyperspectral transformation accuracy,
3. To apply the pseudo-hyperspectral image to metal and geothermal resources-related mineral mapping.

This advanced resultant image must aid more detailed identification of minerals and mineral deposit exploration than traditional multispectral remote sensing. Therefore, the originality of this research is high and PHITA can enhance the potential of a large multispectral dataset over the long term by transformation into pseudo-hyperspectral images for global land surfaces.

## 1.5 Structure of dissertation

The content of the dissertation is summarized in Figure 1.2 and divided into the six chapters as follows.

**Chapter 1** provides important background information for understanding the goals of the dissertation. Simulation of a hyperspectral image from a multispectral image is an innovative technique with which to compensate the disadvantages of each image type. Several studies have succeeded in simulating a hyperspectral image from a multispectral image but these previous studies verified their methods only for the overlap areas of the both images. In this study, the proposed method is validated even for areas outside the original coverage of hyperspectral image.

**Chapter 2** explains in detail the development of PHITA to transform a ETM+ image into a pseudo-Hyperion image using correlations between band reflectance data in overlap spatial area of ETM+ and Hyperion images. Effectiveness of the hyperspectral transformation is multiply evaluated by general image appearance, spectral reconstruction, statistical indices, and mineral mapping. The validation methods and data preprocessing are also presented in this chapter.

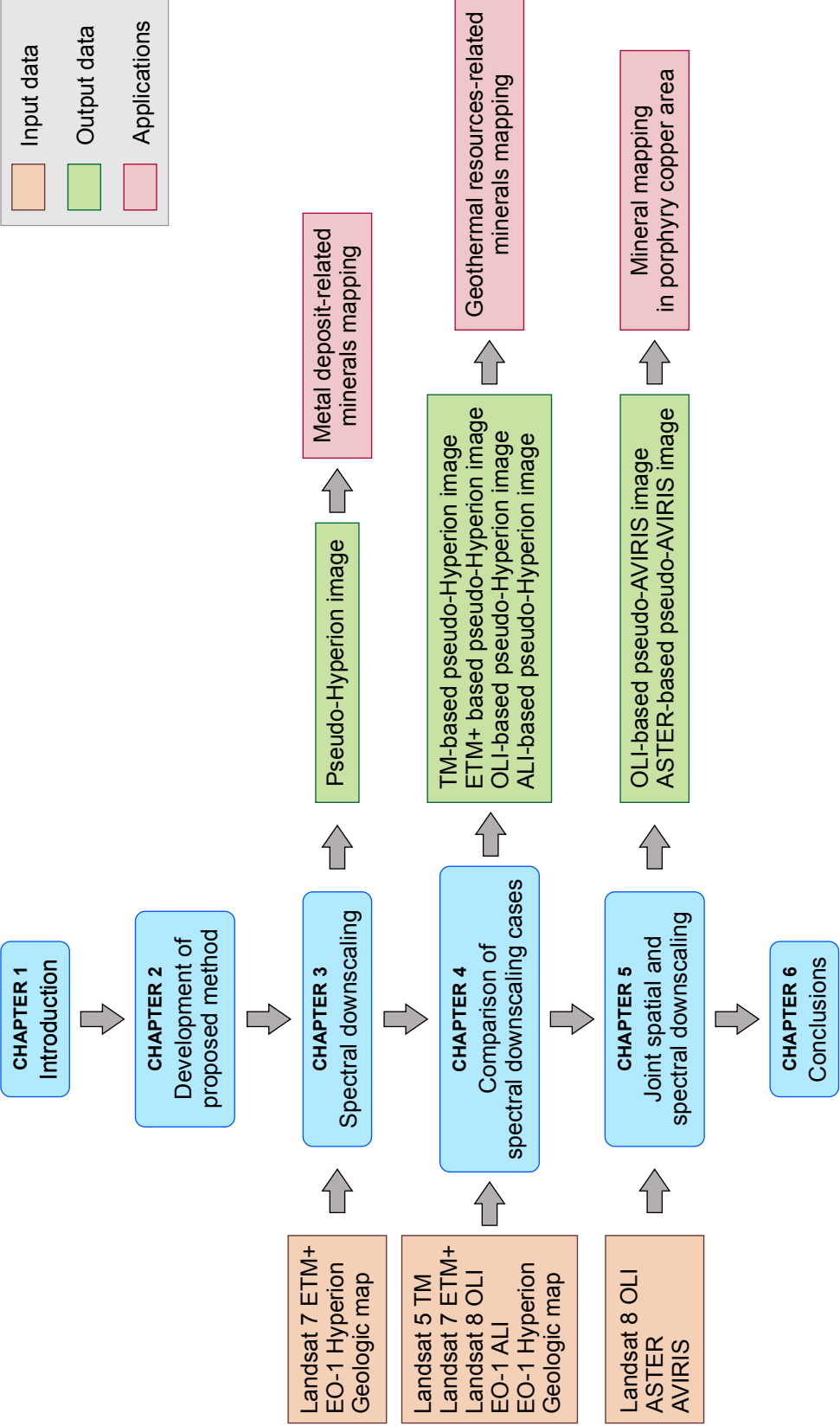


Fig. 1.2 The summary of dissertation structure.

**Chapter 3** demonstrates and discusses the results of the Hyperion image transformation from ETM+ image by PHITA. The resultant pseudo-image has a number of high-quality Hyperion bands of the same scene size as the ETM+ image. Using a reference mineral map built from an AVIRIS image and field surveys as ground truth, an advantage of the pseudo-image is clarified for the Cuprite hydrothermal alteration area in the western United States.

**Chapter 4** extends the PHITA to transform TM, OLI, and ALI sensor images into pseudo-Hyperion images. By choosing a part of the Fish Lake Valley geothermal prospect area in the western United States for study, the pseudo-Hyperion images produced from the TM, ETM+, OLI, and ALI images by PHITA are applied to geothermal resources-related mineral mapping. The best multispectral image of spectral downscaling is identified.

**Chapter 5** examines the capability of PHITA for simulating an airborne hyperspectral image, AVIRIS, from OLI and ASTER images and a possibility of joint spectral and spatial downscaling. In this experiment, PHITA follows the principles of supervised machine learning workflow with a training area in the United States and a validation area in the northern Chile. The pseudo-AVIRIS image has 205 bands and a downscaled spatial resolution of 15 m, half of the multispectral spatial resolution. Finally, **Chapter 6** gives general conclusions of the dissertation and discusses future significant works.



# Chapter 2

## Development of PHITA

### 2.1 Introduction

This research aims to develop a new method, PHITA, that can be used with any type of multispectral and hyperspectral images. In this chapter, ETM+ and EO-1 Hyperion are chosen as their typical images. Using the correlation of band reflectances between ETM+ and Hyperion data, an ETM+ image is transformed into a pseudo-Hyperion image whose the numbers of bands and scene size are equal to high-quality bands of Hyperion and a Landsat image, respectively. The advantage and applications of PHITA are shown in Chapter 3, 4 and 5.

EO-1 Hyperion is a representative hyperspectral sensor, and its images have been applied to agriculture, forestry, environmental monitoring, and geological mapping (Galvão et al., 2005; Giardino et al., 2007; Kruse et al., 2003; Rautiainen and Lukeš, 2015; Thenkabail et al., 2004). The sensor covers the 0.4–2.5  $\mu\text{m}$  wavelength range with 242 bands, at  $\sim 10\text{-nm}$  spectral resolution and 30-m spatial resolution (Miura et al., 2006). Despite having a greater number of bands with high spectral resolution, a Hyperion image scene is much narrower than a Landsat image for technical reasons (Table 2.1). In addition, the Landsat dataset has global coverage and the longest continuous space-based record of Earth's land, whereas

Table 2.1 Data specifications of Landsat 7 ETM+ and EO-1 Hyperion images.

| Parameters          | Landsat 7 ETM+          | EO1-Hyperion          |
|---------------------|-------------------------|-----------------------|
| Wavelength range    | 0.4–2.4 $\mu\text{m}^*$ | 0.4–2.5 $\mu\text{m}$ |
| Spectral resolution | 60–260 nm               | ~10 nm                |
| Spectral coverage   | Discrete                | Continuous            |
| Number of bands     | 7                       | 242**                 |
| Swath width         | 185 km                  | 7.5 km                |
| Spatial resolution  | 30 m, PAN: 15 m         | 30 m                  |
| Temporal resolution | 16 days                 | Variable              |

\*Excludes thermal bands, \*\*only 198 bands are calibrated

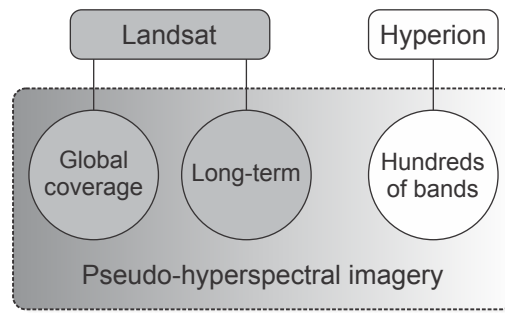


Fig. 2.1 Combination of advantages of Landsat and Hyperion images in a pseudo-hyperspectral image.

Hyperion provides a discrete dataset with the aforementioned limitation. If a Landsat image can be successfully transformed into a Hyperion image, the latter pseudo-hyperspectral image should be useful to various remote sensing fields by incorporating the advantages of each image type (Figure 2.1).

The EO-1 satellite follows approximately one minute after Landsat 7 along the same ground track (Pearlman et al., 2001) (Figure 2.2). Because of their similar orbits and same acquisition dates, the conditions of the atmosphere and solar illumination strength are almost the same between Hyperion and Landsat 7 images, except for a small difference in solar zenith angle (Zhao et al., 2010). Moreover, their same spatial resolutions (30 m) enable highly accurate coregistration of Hyperion-to-ETM+ images. These specifications mean the images obtained are

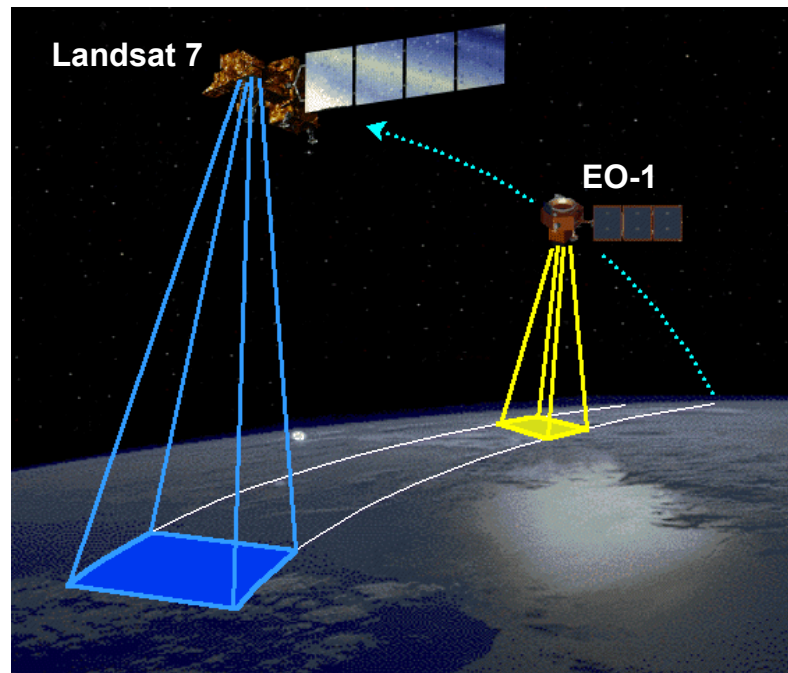


Fig. 2.2 EO-1 scans a small part of the same location on the ground 1 minute after Landsat 7 (Source: Wikimedia Commons<sup>†</sup>).

appropriate for syntheses of ETM+ bands from narrower Hyperion bands (Barry et al., 2002; Jarecke et al., 2001; Nikolakopoulos et al., 2008; Zhao et al., 2010), and additionally, they provided a reasonable trial for the inverse transformation of ETM+ to Hyperion images in this study.

## 2.2 PHITA

Because the bandwidth of ETM+ is much wider than that of Hyperion (Table 2.1), band reflectance of ETM+ is regarded as a weighted sum of reflectances from several Hyperion bands. This idea has been used to synthesize an ETM+ band reflectance from Hyperion reflectances at narrow multiple bands in preceding studies (Barry et al., 2002; Jarecke et al., 2001; Nikolakopoulos et al., 2008) by deriving the weights from the relationship of the spectral responses between Hyperion and ETM+ bands. Therefore, a linear relationship might hold between

<sup>†</sup><https://commons.wikimedia.org/wiki/File:EO-1formationflying.png>

an ETM+ band and each Hyperion band, whose wavelength ranges overlap fully or partially. Another linear relationship holds in reverse, which is found in the CRISP sharpening algorithm (Winter et al., 2007) that simulates a hyperspectral image ( $Y$ ) from a multispectral image ( $X$ ) using a simple linear transformation, e.g.:

$$GX = Y + r, \quad (2.1)$$

where  $G$  and  $r$  denote a filtering matrix and the Gaussian random error, respectively. The spectrum at each pixel occupies each column of the matrices  $X$  and  $Y$ . Under a condition that  $G$  is a global average optimization and is constant for all pixels in the overlap area between hyperspectral and multispectral images, it can be determined by a least squares calculation as (Sun et al., 2015):

$$G = YX^T(XX^T)^{-1}. \quad (2.2)$$

Then, a simulated hyperspectral spectrum can be expressed as

$$\begin{bmatrix} y'_{1(j)} \\ y'_{2(j)} \\ \vdots \\ y'_{A(j)} \end{bmatrix} = \begin{bmatrix} g_{1,1} & g_{1,2} & \cdots & g_{1,B} \\ g_{2,1} & g_{2,2} & \cdots & g_{2,B} \\ \vdots & \vdots & \ddots & \vdots \\ g_{A,1} & g_{A,2} & \cdots & g_{A,B} \end{bmatrix} \cdot \begin{bmatrix} x_{1(j)} \\ x_{2(j)} \\ \vdots \\ x_{B(j)} \end{bmatrix} \quad (2.3)$$

or

$$\vec{y'}_{A(j)} = G\vec{x}_{B(j)}, \quad (2.4)$$

where  $\vec{y'}_{A(j)}$  is the simulated hyperspectral spectrum with  $A$  bands and  $\vec{x}_{B(j)}$  is the given multispectral spectrum with  $B$  bands at pixel  $j$ . Finally, an element of  $\vec{y'}_{A(j)}$  such as  $y'_{1(j)}$  at band 1 can be derived by a form of multiple linear regression

between the hyperspectral band 1 and all the multispectral bands as

$$y'_{1(j)} = g_{1,1} \cdot x_{1(j)} + g_{1,2} \cdot x_{2(j)} + \cdots + g_{1,B} \cdot x_{B(j)}, \quad (2.5)$$

for which each row of  $G$  corresponds to a regression coefficient vector. Based on this concept, PHITA has been developed using a multiple linear regression model of the band reflectances, in which the Hyperion band is a dependent variable and the six ETM+ bands of visible-to-near infrared (VNIR) and SWIR are predictor variables:

$$\rho_{ij}^H(\lambda) = \beta_{0i} + \beta_{1i} \cdot \rho_{1j}^L(\lambda) + \beta_{2i} \cdot \rho_{2j}^L(\lambda) + \beta_{3i} \cdot \rho_{3j}^L(\lambda) + \beta_{4i} \cdot \rho_{4j}^L(\lambda) + \beta_{5i} \cdot \rho_{5j}^L(\lambda) + \beta_{6i} \cdot \rho_{6j}^L(\lambda) + \epsilon_{ij}, \quad (2.6)$$

where  $\rho_{ij}^H(\lambda)$  represents the reflectance of the Hyperion band  $i$  and location (pixel)  $j$ ;  $\beta_{0i}$  is the intercept for  $i$ ;  $\beta_{1i}$ ,  $\beta_{2i}$ ,  $\beta_{3i}$ ,  $\beta_{4i}$ ,  $\beta_{5i}$ , and  $\beta_{6i}$  are unknown regression coefficients between the ETM+ bands and  $i$ ;  $\rho_{1j}^L(\lambda)$ ,  $\rho_{2j}^L(\lambda)$ ,  $\rho_{3j}^L(\lambda)$ ,  $\rho_{4j}^L(\lambda)$ ,  $\rho_{5j}^L(\lambda)$ , and  $\rho_{6j}^L(\lambda)$  are reflectances at  $j$  of ETM+ bands 1, 2, 3, 4, 5, and 7 (except for thermal band 6), respectively; and  $\epsilon_{ij}$  is a random error (residual).

The regression coefficients are determined by the standard least squares method, but that method occasionally causes an overfitting problem. Use of predictor variables relevant to the dependent variable is crucial to obtain an accurate regression model. One of the essential improvements of PHITA over CRISP is the variable selection. In contrast to CRISP, which uses the same multispectral band set to simulate every hyperspectral band, PHITA selects the most suitable multispectral bands for each hyperspectral band. A well-chosen set of multispectral bands is known to improve transformation accuracy (Winter et al., 2007). Preliminary PHITA results clarified that the number of ALI or ETM+ bands for simulation varied depending on the Hyperion band (Hoang and Koike, 2015, 2016). To avoid overfitting and to evaluate model accuracy, Bayesian model averaging (BMA) is

applied and the best model is selected from a set of possible models. BMA is superior to traditional approaches such as stepwise regression, because it can deal with model uncertainty inherent in the variable selection problem (Genell et al., 2010). This uncertainty is quantified by averaging high-likelihood models in a model class and approximating a posterior probability of the average model, as follows (Raftery et al., 1997).

We let  $M = (M_1, M_2, M_3, \dots, M_K)$  be a set of all possible models, in which at least one is correct and  $\omega$  is a quantity of interest. The posterior probability of  $\omega$  conditioned by data  $D$  is defined as

$$P(\omega|D) = \sum_{k=1}^K P(\omega|D, M_k) P(M_k|D), \quad (2.7)$$

where  $P(\omega|D, M_k)$  is the posterior probability of  $\omega$  conditioned by model  $M_k$  and  $P(M_k|D)$  is the posterior probability of  $M_k$  as the correct model.  $P(M_k|D)$  is written using a Bayesian rule, as

$$P(M_k|D) = \frac{P(D|M_k) P(M_k)}{\sum_{h=1}^K P(D|M_h) P(M_h)}, \quad (2.8)$$

where  $P(D|M_k) = \int P(D|\phi_k, M_k) P(\phi_k|M_k) d\phi_k$  is the marginal likelihood function of model  $M_k$ ;  $P(M_k)$  is the prior probability of  $M_k$ ;  $\phi_k$  is the vector of parameters of  $M_k$ ;  $P(D|\phi_k, M_k)$  and  $P(\phi_k|M_k)$  are the likelihood and prior density of  $\phi_k$  under  $M_k$ , respectively.  $P(D|M_k)$  can be approximated using the Bayesian information criterion (BIC) as

$$2\log P(D|M_k) \approx 2\log P(D|\varphi_k) - \Theta_k \log n = -\text{BIC}_k, \quad (2.9)$$

where  $\Theta_k = \dim \phi_k$  is the number of independent parameters in  $M_k$ ,  $\varphi_k$  is the maximum likelihood estimator, and  $n$  is the number of observations. The best

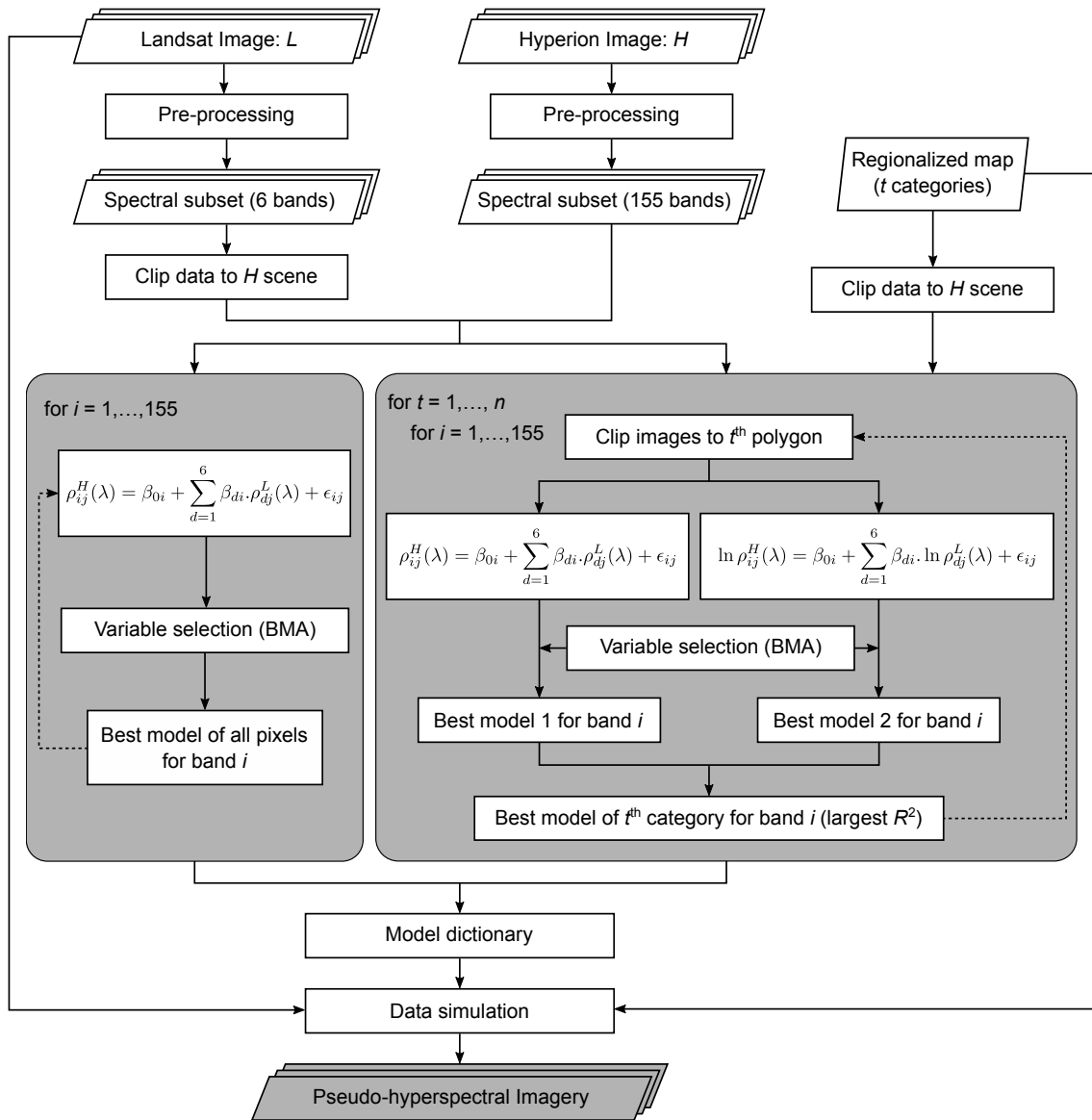


Fig. 2.3 Analytical flow of PHITA to transform Landsat 7 ETM+ image to pseudo-hyperspectral image, with the same number of high quality Hyperion bands. The regionalized map is a geological map of a distribution of rock types.

model minimizes the BIC value and maximizes the posterior probability. More details of BMA are given in Raftery et al. (1997); Raftery and Painter (2005) and Hoeting et al. (1999). The BMA package in the R programming language (Raftery et al., 2015) was used to select predictor variables.

PHITA consists of three main steps: 1) data preparation; 2) model dictionary building; and 3) data simulation (Figure 2.3). In the first step, a set of 155 stable

Hyperion bands were selected from the original 242 bands for the main processing, by excluding low-quality bands that were uncalibrated, duplicated or noisy from atmospheric effects. The stable bands so selected were 10–57 (447–926 nm), 81–97 (952–1115 nm), 101–119 (1154–1337 nm), 134–164 (1487–1791 nm), and 182–221 (1971–2365 nm), which were confirmed to be of high quality by Jupp et al. (2002). In the second step, the model dictionary is a set of best multiple linear regression models from Eq. 2.6 that were built from band reflectance data exclusively from the overlap area of ETM+ and Hyperion images. The least squares method that is used to estimate unknown regression coefficients is described in Appendix E. Based on our preliminary validation of PHITA, linear correlation between the pseudo- and original reflectance data was strong in areas covered uniformly by only a few types of surface materials (Hoang and Koike, 2015). Then, the model dictionary was built using two cases of PHITA: one without a geological map (PHITA Case 1) and the other with it (PHITA Case 2). For PHITA Case 1, the models were generated from all pixels in the overlap area. For PHITA Case 2, a geological map of rock-type distribution was used as a conditional variable with which to calculate the models for every band within each category (rock type in this case), assuming that each category is composed of relatively homogeneous surface materials. Because model accuracy is reduced by data that are much skewed from a normal distribution, the band reflectance data were transformed to logarithmic to reduce the bias in the distribution.

Finally, the pseudo-Hyperion image was simulated for a full ETM+ scene using the model dictionary. Some categories might appear only outside the overlap area of the ETM+ and Hyperion images. In such a case, the regression models from Case 1 were used to simulate the pseudo-Hyperion image covered by those categories in Case 2.



## 2.3 Data preprocessing

As part of the data preparation step, systematic and random noise in the Hyperion image data owing to a push-broom hyperspectral imager must first be reduced. Typical Hyperion image noises are smile effects and vertical streaks. The smile effect is an across-track wavelength shift from the central wavelength through change in dispersion angle with ground position. This effect is observable by transforming an image into minimum noise fraction (MNF) space and its magnitude appears as a brightness gradient in the first eigenvalue image. There are three smile correction methods (Goodenough et al., 2003): (1) moving linear fit and interpolation, (2) column mean adjusted in radiance space, and (3) column mean adjusted in MNF space. Here, the first method was used prior to de-striping because of its capability of retaining spectral fidelity. Stripes that are parallel to columns in an image were then removed by the local de-striping method (Datt et al., 2003; Farifteh et al., 2013), matching the mean and standard deviation of each column with those of all data of the corresponding band (Farifteh et al., 2013):

$$\hat{\rho}_{efi} = (\rho_{efi} - \mu_{fi}) \frac{\sigma_i}{\sigma_{fi}} + \mu_i, \quad (2.10)$$

where  $\rho_{efi}$  and  $\hat{\rho}_{efi}$  are the original and de-striped pixel values at row  $e$ , column  $f$  and band  $i$ ;  $\mu_{fi}$  and  $\sigma_{fi}$  are the mean and standard deviation of the data in column  $f$  at band  $i$ , and  $\mu_i$  and  $\sigma_i$  are those of all band- $i$  data. An example of de-striped image (Figure 2.4) proves usefulness of the method.

Next, atmospheric correction was applied to both ETM+ and Hyperion images using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module of ENVI software. FLAASH calculates the pixel surface reflectance,  $\rho(\lambda)$ , from the spectral radiance at a sensor pixel,  $L_\lambda$ , as follows

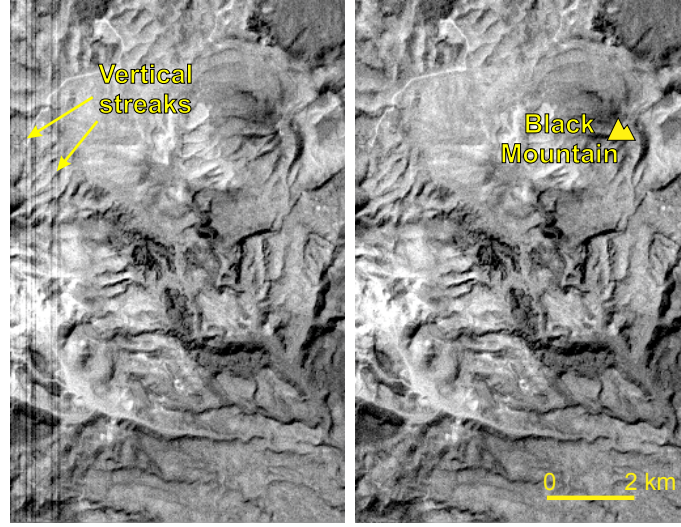


Fig. 2.4 Original Hyperion band 57 image (left) of Black Mountain area in the western United States and its de-striped image (right).

(Adler-Golden et al., 1999):

$$L_{\lambda} = \left( \frac{A\rho(\lambda)}{1 - \rho_e(\lambda)S} \right) + \left( \frac{B\rho_e(\lambda)}{1 - \rho_e(\lambda)S} \right) + L_{\lambda}^a, \quad (2.11)$$

where  $\rho_e(\lambda)$  is an average surface reflectance for the pixel and a surrounding region,  $S$  is the spherical albedo of the atmosphere,  $L_{\lambda}^a$  is the radiance back scattered by the atmosphere,  $A$  and  $B$  are coefficients depending on atmospheric and geometric conditions.  $A$ ,  $B$ ,  $S$ , and  $L_{\lambda}^a$  are determined from MODTRAN calculations by assuming a certain model atmosphere, aerosol type, and visible range.

A topographic correction followed to correct brightness distortion caused by change in solar illumination strength ( $IL$ ). The Shuttle Radar Topographic Mission digital elevation model dataset with 90-m spatial resolution was used to compute the incident angle  $\gamma_I$  between the normal direction to the ground surface and solar ray direction. The  $IL$  value (-1 to 1) is calculated from the slope angle ( $\theta_p$ ), solar zenith angle ( $\theta_z$ ), solar azimuth angle ( $\phi_a$ ), and aspect angle ( $\phi_o$ ) (Goslee, 2011):

$$IL = \cos\gamma_I = \cos\theta_p\cos\theta_z + \sin\theta_p\sin\theta_z\cos(\phi_a - \phi_o). \quad (2.12)$$

Using  $IL$ , horizontal reflectance ( $\rho_h$ ) was calculated by the non-Lambertian, C-correction method (Teillet et al., 1982):

$$\rho_h = \rho_T \left( \frac{\cos\theta_z + c_i}{IL + c_i} \right), \quad (2.13)$$

where  $\rho_T$  is reflectance on an inclined surface,  $c_i$  is a coefficient to relate  $\rho_T$  at band  $i$  to  $IL$  by linear regression;  $\rho_T = w_i + z_i IL$ , in which  $w_i$  and  $z_i$  are regression coefficients and  $c_i = w_i/z_i$ .

Finally, the Hyperion image was coregistered with the ETM+ image using a first-degree polynomial warp with nearest-neighbor resampling and at least 20 ground control points (GCPs) for each Hyperion scene. The root mean square error (RMSE) for the GCP coregistration was conditioned to be less than 0.6 pixels.

## 2.4 Validation methods

### 2.4.1 Comparison metrics

Effectiveness of the hyperspectral transformation was multiply evaluated by general image appearance, spectral reconstruction, statistical indices, and mineral mapping. The following seven statistical indices were used to clarify accuracy of each multispectral image in the hyperspectral transformation: Pearson's correlation coefficient (PCC), RMSE, peak signal-to-noise ratio (PSNR), "erreur relative globale adimensionnelle de synthèse" (or relative global dimensional synthesis error; ERGAS), universal image quality index (UIQI), structural similarity index (SSIM), and spectral angle mapper (SAM). These are common statistical indices that have been used to validate image reconstruction methods. It is necessary to calculate different indices because each index has a certain limitation in revealing all characteristics of simulated image quality.

PCC measures linear correlation between the pseudo- and original Hyperion images by

$$\text{PCC}_i = \frac{\sum_{j=1}^n (\rho_{ij}^H(\lambda) - \mu_i^H) (\rho_{ij}^{\hat{H}}(\lambda) - \mu_i^{\hat{H}})}{\sqrt{\sum_{j=1}^n (\rho_{ij}^H(\lambda) - \mu_i^H)^2} \sqrt{\sum_{j=1}^n (\rho_{ij}^{\hat{H}}(\lambda) - \mu_i^{\hat{H}})^2}}, \quad (2.14)$$

where  $\rho_{ij}^{\hat{H}}(\lambda)$  is a pseudo-reflectance and  $\rho_{ij}^H(\lambda)$  is an original reflectance at coregistered pixel  $j$  and band  $i$ ,  $\mu_i^H$  and  $\mu_i^{\hat{H}}$  are means of all pixel in  $i$ , and  $n$  is the total number of pixels in  $i$ . RMSE is that between the pseudo- and original reflectances as

$$\text{RMSE}_i = \frac{\sum_{j=1}^n \sqrt{(\rho_{ij}^{\hat{H}}(\lambda) - \rho_{ij}^H(\lambda))^2}}{n}. \quad (2.15)$$

PSNR (Huynh-Thu and Ghanbari, 2008) is a widely used indicator of the quality of image reconstruction, as

$$\text{PSNR} = \frac{\sum_{i=1}^h 10 \log_{10} \left( \frac{\text{MAX}_i^2}{\text{MSE}_i} \right)}{h} \quad (2.16)$$

$$\text{MSE}_i = \frac{1}{n} \sum_{j=1}^n (\rho_{ij}^{\hat{H}}(\lambda) - \rho_{ij}^H(\lambda))^2, \quad (2.17)$$

where  $\text{MSE}$  is mean squared error,  $\text{MAX}_i$  is maximum reflectance in the original band  $i$ , and  $h$  is the number of pseudo-Hyperion bands (= 176 in this study). The standard ERGAS index (Wald, 2000) quantifies spectral quality of the pseudo-Hyperion image by

$$\text{ERGAS} = 100 \frac{a}{b} \sqrt{\frac{1}{h} \sum_{i=1}^h \left( \frac{\text{RMSE}_i}{\mu_i^H} \right)^2}, \quad (2.18)$$

where  $a/b$  is the pixel-size ratio between the pseudo-Hyperion and multispectral images. UIQI (Wang and Bovik, 2002) measures the quality of pseudo-Hyperion image as

$$\text{UIQI}_i = \frac{\sigma_i^{H\hat{H}}}{\sigma_i^H \sigma_i^{\hat{H}}} \cdot \frac{2\mu_i^H \mu_i^{\hat{H}}}{(\mu_i^{H^2} + \mu_i^{\hat{H}^2})} \cdot \frac{2\sigma_i^H \sigma_i^{\hat{H}}}{(\sigma_i^{H^2} + \sigma_i^{\hat{H}^2})}, \quad (2.19)$$

where  $\sigma_i^H$ ,  $\sigma_i^{\hat{H}}$  and  $\sigma_i^{H\hat{H}}$  are standard deviations of all reflectances in band  $i$ . UIQI is a combination of three factors, i.e., loss of correction in the first term of Equation 2.19, luminance distortion (second term), and contrast distortion (third term). The SSIM index (Wang et al., 2004) is an effective measure of the quality of image reconstruction using structural similarity of two images from a human perspective criterion as

$$\text{SSIM}_i = \frac{(2\mu_i^H \mu_i^{\hat{H}} + C_1)(2\sigma_i^{H\hat{H}} + C_2)}{(\mu_i^{H^2} + \mu_i^{\hat{H}^2} + C_1)(\sigma_i^{H^2} + \sigma_i^{\hat{H}^2} + C_2)}, \quad (2.20)$$

where  $C_1$  and  $C_2$  are constants to stabilize the calculation when  $\mu_i^{H^2} + \mu_i^{\hat{H}^2}$  or  $\sigma_i^{H^2} + \sigma_i^{\hat{H}^2}$  is close to zero. SSIM is equivalent to UIQI when  $C_1 = C_2 = 0$ . MSSIM is the average SSIM of all bands and takes the value 1 for the same two images. Finally, SAM measures spectral distortion between the pseudo- and original Hyperion images as

$$\text{SAM} = \frac{1}{n} \sum_{j=1}^n \arccos \left( \frac{Z_j^H \cdot Z_j^{\hat{H}}}{\|Z_j^H\|_2 \cdot \|Z_j^{\hat{H}}\|_2} \right), \quad (2.21)$$

where  $Z_j^H$  and  $Z_j^{\hat{H}}$  are reflectance spectra at pixel  $j$ . Generally, larger PCC, PSNR, UIQI, and SSIM values and smaller RMSE, ERGAS, and SAM values ensure the accuracy of the hyperspectral transformation that adequately fits the original image.

### 2.4.2 Mineral mapping

Two mineral maps were produced from the original and pseudo-Hyperion images, using the Spectral Hourglass Wizard package within ENVI for hyperspectral

image data and following the step-by-step workflow of hyperspectral image-based mineral mapping in Kruse et al. (1997) (Figure 2.5). The resultant mineral map from the original Hyperion image and a reference mineral map were used as ground truth to evaluate classification accuracy of the pseudo-image. First, the mineral mapping began with the FLAASH correction for reflectance and followed the MNF transformation to segregate noise and select high-quality band data via two rotations, using principal component analysis. The first rotation was for decorrelating and rescaling the noise using principal components of the noise covariance matrix, and the corrected image was rotated again using the principal components derived thereby. Second, the Pixel Purity Index (PPI) was computed from the MNF output to collect the most spectrally pure pixels in the image. Third,  $n$ -dimensional visualization of large PPI value pixels was performed to locate and group the purest pixels into classes. Mineral endmembers were then

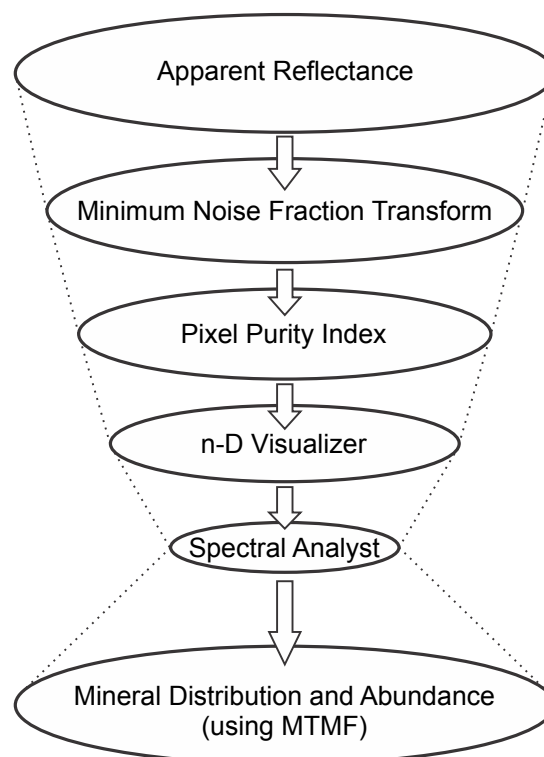


Fig. 2.5 Workflow of hyperspectral data analysis for mineral mapping (Kruse et al., 2003).

identified by comparing spectral profiles of the purest pixels with the United States Geological Survey (USGS) spectral library and considering their locations in a reference mineral map. Finally, distribution and abundance maps of selected minerals were clarified by Mixture Tuned Matched Filtering (MTMF) and MNF endmember spectra (see Appendix D).

## **Chapter 3**

# **Spectral downscaling with application to metal deposit-related minerals mapping**

### **3.1 Introduction**

Hyperspectral remote sensing is superior to traditional multispectral remote sensing in detailed spectral information but has limited spatial and temporal coverage. Those limitations require an innovative technique that can simulate hyperspectral imagery from multispectral imagery with global coverage, continuous acquisition, and a small number of bands. For this, a combination of Hyperion and Landsat 7 ETM+ images is a representative target. The new method, PHITA, is proposed in Chapter 2 to transform Landsat 7 ETM+ imagery into pseudo-Hyperion imagery using correlations between Landsat and Hyperion band reflectance data. Each correlation is defined as a multiple linear regression model selected through BMA, in which Hyperion and Landsat bands are dependent and predictor variables, respectively. The resultant pseudo-image has a number of high-quality Hyperion



bands of the same scene size as a Landsat image. In this chapter, the validation and application results of the pseudo-Hyperion image are presented.

## 3.2 Data and study area

We used one ETM+ and five EO-1 Hyperion cloud-free image scenes at the border of California and Nevada in the western United States. Their specifications are summarized in Table 3.1 and coverages shown in Figure 3.1. ETM+ and Hyperion scenes acquired on 23 July 2001 were chosen as Base scenes to build the model

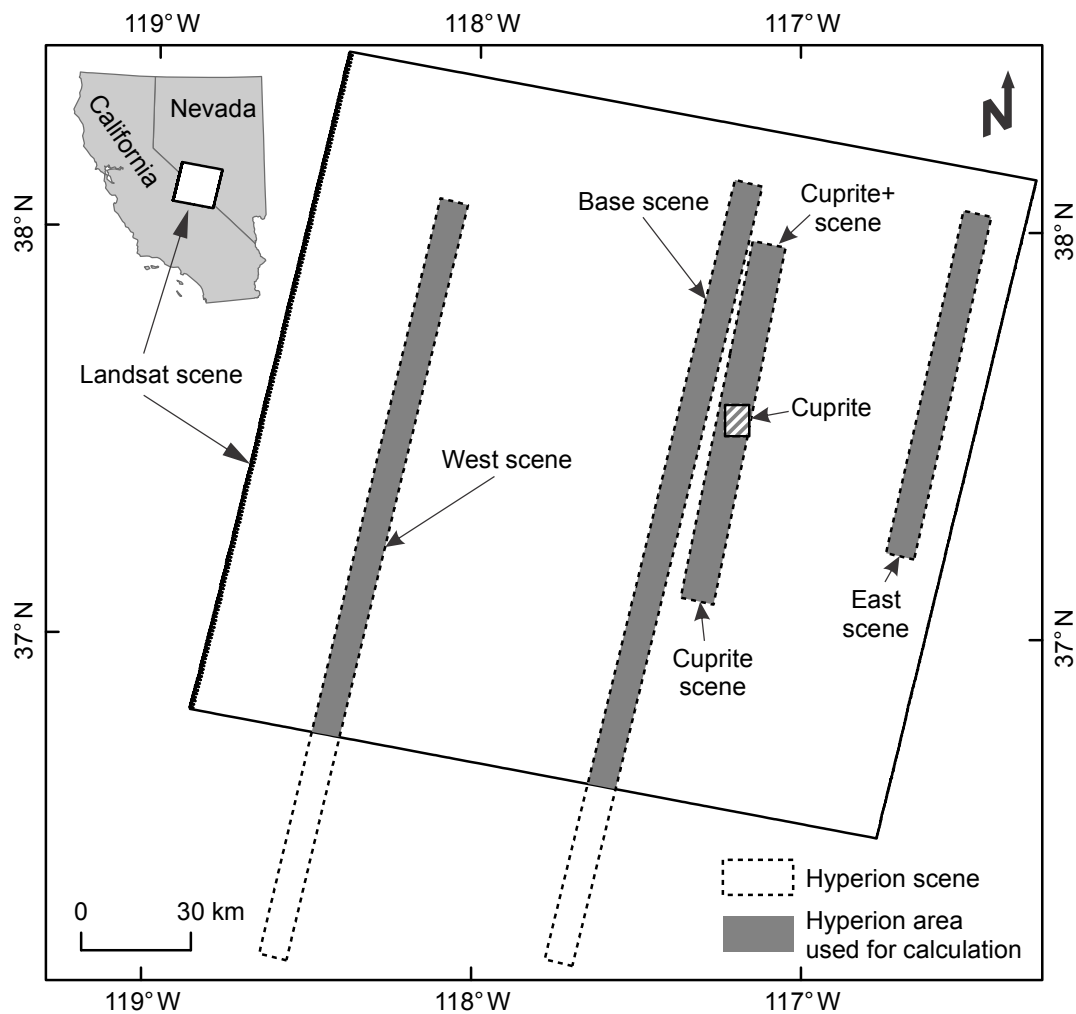


Fig. 3.1 Geographic locations of Landsat 7 ETM+ and Hyperion image scenes. Cuprite and Cuprite+ scenes largely overlap.

Table 3.1 Specifications of Landsat 7 ETM+ and Hyperion image scenes used.

| Sensor   | Scene name | Acquisition date | Start time (UTC) | Orbit Path/Row | Target Path/Row | Look angle (degrees) | Application          |
|----------|------------|------------------|------------------|----------------|-----------------|----------------------|----------------------|
| ETM+     | Base       | 2001/07/23       | 18:16:35         | 41/34          | 41/34           | N/A                  | PHITA                |
| Hyperion | Base       | 2001/07/23       | 18:17:37         | 41/34          | 41/34           | 1.497                | PHITA and validation |
| Hyperion | Cuprite    | 2011/09/19       | 17:59:06         | 39/34          | 41/34           | -22.284              | Validation           |
| Hyperion | Cuprite+   | 2011/09/04       | 18:20:03         | 42/34          | 41/34           | 13.325               | Validation           |
| Hyperion | East       | 2002/10/07       | 18:09:56         | 40/34          | 40/34           | -4.3313              | Validation           |
| Hyperion | West       | 2001/06/21       | 18:17:51         | 41/34          | 41/34           | -5.0111              | Validation           |

dictionary for simulating the pseudo-Hyperion image with the same swath width as the ETM+ scene. The purpose of the other Hyperion scenes was to verify the quality of the pseudo-image extension outside the Hyperion Base scene.

The ETM+ scene area, which is mostly desert with sparse vegetation because of an extremely arid climate, covers entirely the Hyperion East, Cuprite and Cuprite+ scenes. It overlaps about three-fourths of the Base and West scenes. The ETM+ scene and the Hyperion Cuprite and Cuprite+ scenes include the well-known Cuprite site formed by extensive development of late-Miocene advanced argillic zones of iron-bearing minerals, clays, micas, sulfates and carbonates (Swayze et al., 2014). The Cuprite area consists of two main centers (Figure 3.2), which were formed by hydrothermal alteration and enriched metals such as gold, silver, and copper. Because of the geological and surface conditions, Cuprite has been a suitable site to test the accuracy of mineral mapping through various remote sensing imagery produced by airborne and orbital visible, near-infrared, thermal-infrared, and hyperspectral sensors (Swayze et al., 2014).

A strong relationship was reported between acquisition time during a year and the signal-to-noise ratio (SNR) of a Hyperion image (Kruse et al., 2003). The SNR of Hyperion SWIR band data increases in summer and minimizes in winter. Therefore, we chose Hyperion image scenes in summer or early autumn. Their acquisition times were nearly identical, around 6:00 pm (UTC) or 11:00 am (local time), but the years and look angles vary (Table 3.1). The maximum difference in look angle is 35.6°.

A recent USGS mineral map of the alteration zones of the Cuprite area, prepared by Swayze et al. (2014) using 0.4–2.5  $\mu\text{m}$  AVIRIS reflectance spectral data and based on field surveys, was selected for the ground truth. A geologic map of 17 rock types used in the PHITA was acquired from the USGS Mineral Resources Online Spatial Data website (<http://mrddata.usgs.gov/geology/state/>) by compiling geologic

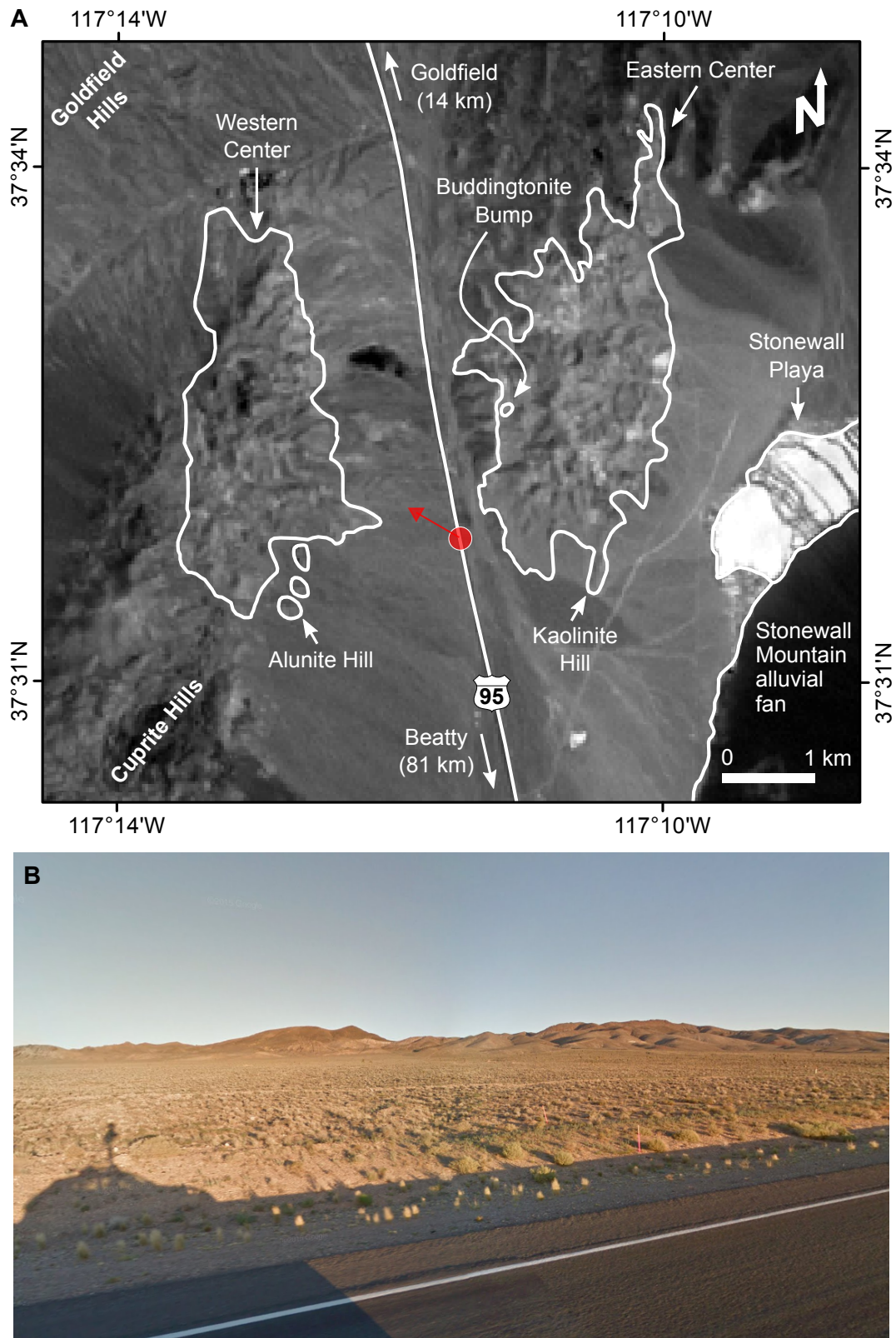


Fig. 3.2 (A) Selected zones showing distributions of key minerals (alunite and kaolinite) in Cuprite area, overlaid on ETM+ band 7 image. Zones were digitized from a map from Swayze et al. (2014). (B) The field photo of Cuprite area taking from the location of the red circle with an arrow that is shown on the above map (Source: Google Maps).

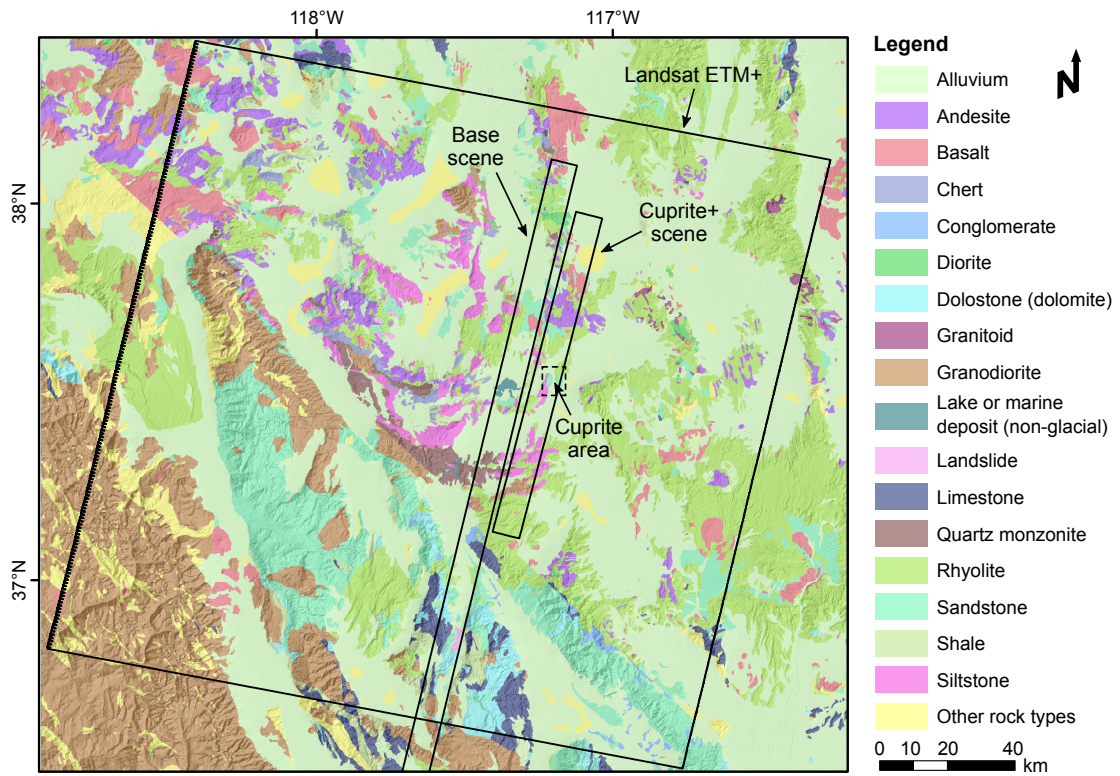


Fig. 3.3 Simplified geologic map of the study area showing distribution of 17 rock types. Rectangles are coverages of Landsat 7 ETM+ and Hyperion image scenes. Yellow zones indicate rock types not in the Hyperion Base scene.

maps of California (scale 1:750,000) and Nevada (scale 1:500,000) and also from a detailed geologic map of the Cuprite area by Swayze et al. (2014) (Figure 3.3).

## 3.3 Results

### 3.3.1 Model dictionary

Examples of multiple linear regression models between the Hyperion Base and ETM+ band reflectance data for PHITA Case 1 are summarized for several Hyperion VNIR and SWIR bands in Table 3.2. Several Hyperion bands (e.g., band 11) are related to all ETM+ bands as predictor variables, but other bands involve four or less ETM+ bands. ETM+ bands 1 and 4 appeared the most frequently (152 times among 155 total models), indicating that they are key bands, while band 7 was the

Table 3.2 Examples of multiple linear regression models between Hyperion Base and ETM+ band reflectance data. The values given in parentheses are central wavelengths of the Hyperion bands in nanometers.

| Hyperion band<br>(nm) | Values of intercept and regression coefficients (see Eq. 2.6) |              |              |              |              |              |              | $R^2$ | Posterior<br>probability |
|-----------------------|---------------------------------------------------------------|--------------|--------------|--------------|--------------|--------------|--------------|-------|--------------------------|
|                       | $\beta_{0i}$                                                  | $\beta_{1i}$ | $\beta_{2i}$ | $\beta_{3i}$ | $\beta_{4i}$ | $\beta_{5i}$ | $\beta_{6i}$ |       |                          |
| Band 10 (447)         | 379.0                                                         | 0.8204       | 0.2825       | 0            | 0            | -0.0989      | 0.0439       | 0.855 | 1.0                      |
| Band 11 (457)         | 356.4                                                         | 0.7919       | 0.3301       | -0.0307      | 0.0139       | -0.0977      | 0.0458       | 0.862 | 1.0                      |
| Band 12 (468)         | 354.2                                                         | 0.7809       | 0.3463       | -0.0408      | 0.0207       | -0.0829      | 0.0341       | 0.867 | 1.0                      |
| Band 159 (1740)       | 94.7                                                          | -0.3434      | 0.4150       | -0.2670      | 0.0642       | 0.8704       | 0.1406       | 0.921 | 1.0                      |
| Band 160 (1750)       | 91.9                                                          | -0.3665      | 0.4402       | -0.2804      | 0.0531       | 0.8567       | 0.1588       | 0.920 | 1.0                      |
| Band 161 (1760)       | 85.2                                                          | -0.3955      | 0.4603       | -0.3142      | 0.0557       | 0.8530       | 0.1741       | 0.918 | 1.0                      |
| Band 218 (2335)       | 56.9                                                          | -0.1260      | -0.1030      | -0.1205      | 0.3674       | -0.4654      | 1.2389       | 0.849 | 1.0                      |
| Band 219 (2345)       | 97.8                                                          | -0.0295      | -0.1968      | -0.1261      | 0.3770       | -0.4028      | 1.1677       | 0.850 | 1.0                      |
| Band 220 (2355)       | 121.3                                                         | 0            | -0.2023      | -0.0825      | 0.3233       | -0.3565      | 1.1076       | 0.822 | 1.0                      |

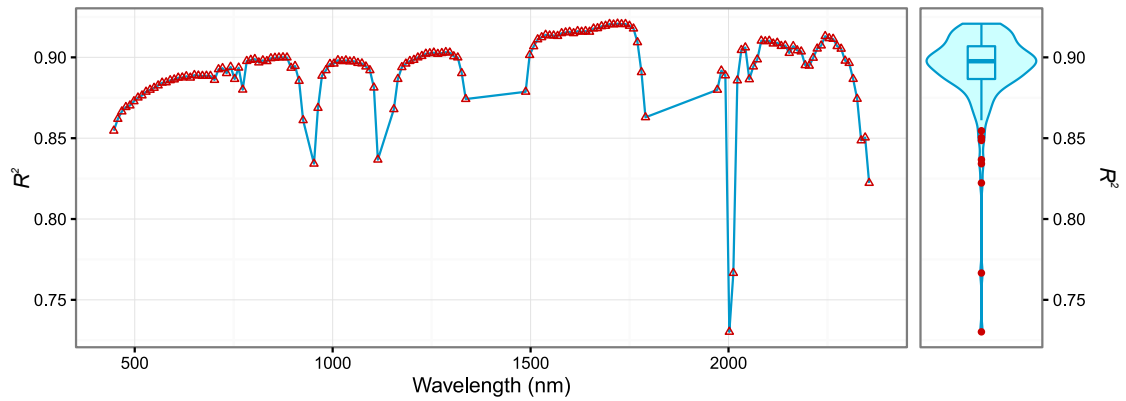


Fig. 3.4  $R^2$  values in 155 Hyperion bands (left) and their statistical distribution in violin plot (right) of all models for PHITA Case 1.

least frequent (145 times). However, these frequencies changed with area, owing to differences in surface material type and coverage of each type. This was shown in our previous PHITA application (Hoang and Koike, 2015), in which ETM+ band 5 had the highest frequency in a small area, with a few surface material types. As a rule, the regression coefficient of the ETM+ band covering the wavelength range of the Hyperion band in the corresponding model became the largest. Because the coefficient of determination  $R^2$  largely exceeded 89%, model accuracies were considered high and the relationship between each Hyperion band and selected ETM+ bands in each model was strong for the overlap area, supporting the hypothesis of PHITA.  $R^2$  was particularly large for bands in the 1497–1770 nm range ( $> 90.5\%$ ) and was relatively small for bands near the atmospheric absorption ranges and/or containing substantial noise. Maximum, median and minimum  $R^2$  were 92%, 90% and 73%, respectively (Figure 3.4). For PHITA Case 2 using a geological map, the models were built for each Hyperion band and each rock type. This increased the maximum  $R^2$  to 96%. An example of regression diagnostics is shown in Appendix E.



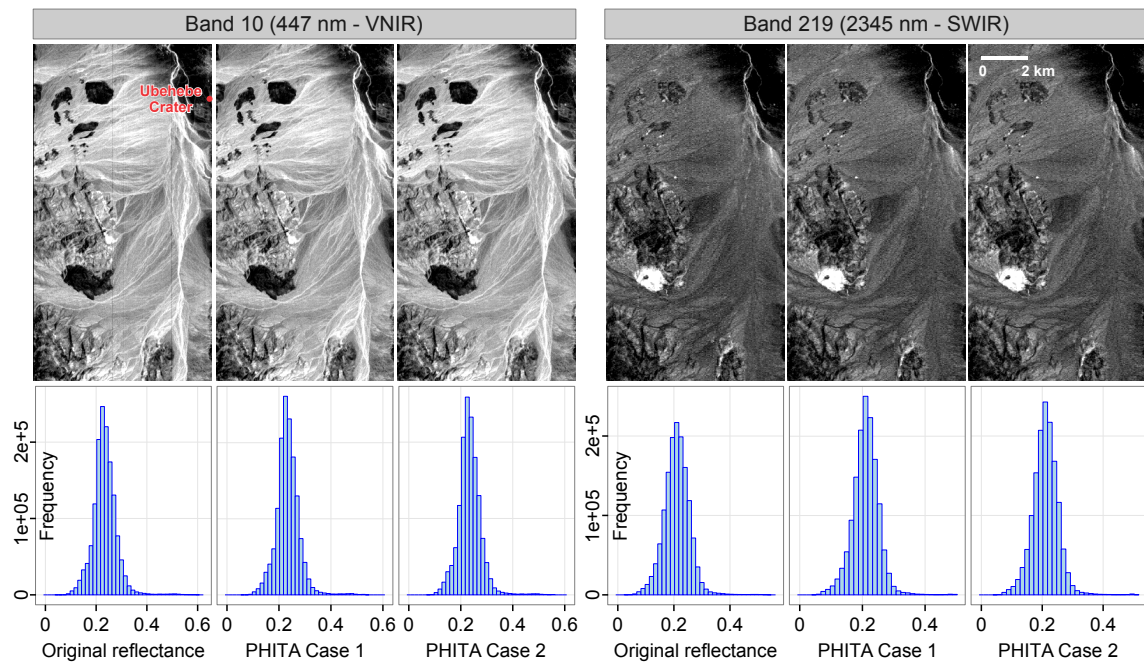


Fig. 3.5 Comparison of grayscale images near Ubehebe crater of a part of the original Hyperion Base scene and pseudo-Hyperion scenes transformed by PHITA from Landsat 7 ETM+ image, Cases 1 and 2. VNIR band 10 (447 nm) and SWIR band 219 (2345 nm) were selected for comparison. The histograms show reflectance distribution of all pixels in each band, with bin width 0.015 nm.

### 3.3.2 Validation of pseudo-Hyperion image by general appearance

Based on the model dictionary, the ETM+ image was transformed into a pseudo-Hyperion image with 155 bands in the 447–926, 952–1115, 1154–1337, 1487–1791, and 1971–2365 nm ranges. The number of simulated pseudo-bands was much greater than 106 in a preceding study (Liu et al., 2009). As an example, the PHITA was first verified by comparing the pseudo-Hyperion image with the original Base image for a VNIR and SWIR band, in the same area. A sub-scene near the Ubehebe crater was selected for this comparison, because of a mixture of various surface features. Clearly, topographic features, texture, and color tone of the pseudo-image of the two bands appeared very similar to the original image, as in PHITA Cases 1 and 2 (Figure 3.5). This similar appearance and little noise were confirmed



over all 155 bands. Another notable PHITA feature was that vertical opaque stripes in the original bands were completely removed in the pseudo-images by the transformation. Reflectance histograms of pseudo-images match well with those of the original image for the two bands, although they are shifted slightly toward larger values (Figure 3.5).

We also compared color images of natural and false-color composites using three visible bands (R: 681 nm, G: 529 nm, and B: 468 nm) and three SWIR bands (R: 2103 nm, G: 2204 nm, and B: 2345 nm), for the northern edge of Death Valley National Park (USA). This area is chiefly covered by Jurassic intrusion rocks in the Hyperion Base scene (Figure 3.6) and has been targeted for testing imaging spectrometers for mineral mapping since 1983 (Kruse et al., 2003, 1993; Kruse, 1988). The SWIR color composite is generally used to emphasize differences in mineral and rock types. The natural color composite of the pseudo-images of PHITA Cases 1 and 2 is nearly identical to the original image, except that its colors are slightly darker. Slight differences in reflectance between the original and pseudo-images are difficult to determine from the grayscale image (Figure 3.5), but such differences in each band image are emphasized by the color compositions.

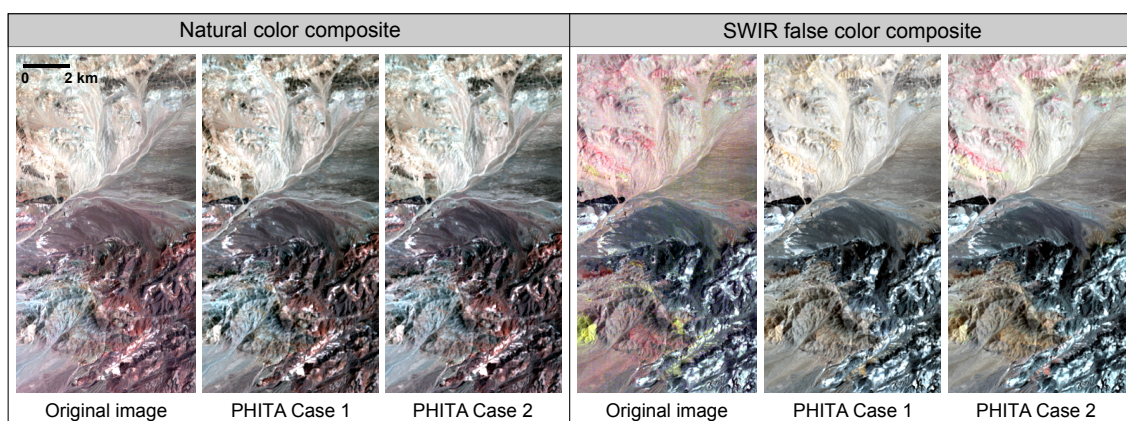


Fig. 3.6 Comparison of natural color composite images (R: 681 nm, G: 529 nm and B: 468 nm) and SWIR false-color composite images (R: 2103 nm, G: 2204 nm and B: 2345 nm) between a part of the original Hyperion Base scene and pseudo-Hyperion scenes, for PHITA Cases 1 and 2. Selected area is northern edge of Death Valley National Park in the United States.

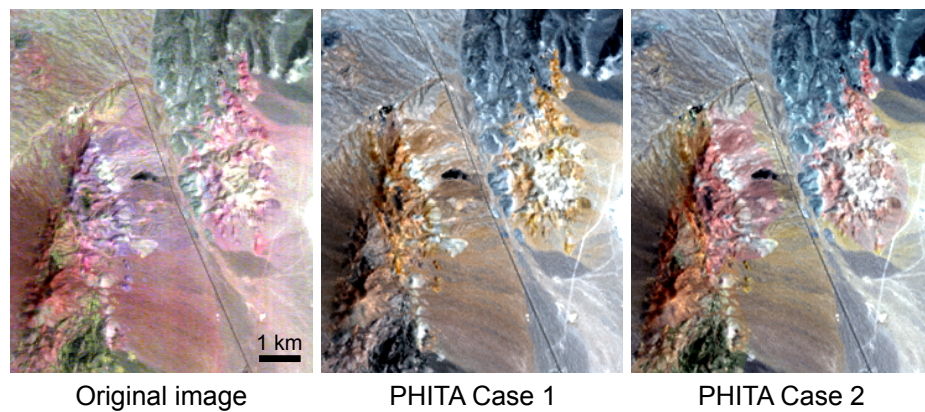


Fig. 3.7 Comparison of SWIR false-color composite (R: 2103 nm, G: 2204 nm and B: 2345 nm) of the original Hyperion image with pseudo-Hyperion images, for PHITA Cases 1 and 2 and Cuprite area. Because this area is outside the Hyperion Base scene, the Case 1 and 2 images are extensions of the scene simulated by model dictionary.

In contrast, the SWIR color composite images are different between the two cases. The Case 2 pseudo-image is more similar to the original image than the Case 1 image, in which red and chartreuse colors are nearly nonexistent. Those colors are retained in the Case 2 image but with lighter tones. This superiority was also confirmed for an area outside the Hyperion Base scene (Figure 3.7), for which the SWIR color composite for the Cuprite area in Case 2 has a tone resembling that of the original image, unlike the tone of the Case 1 image.

### 3.3.3 Statistical verification of pseudo-Hyperion image

The pseudo-Hyperion image was cropped to Base, Cuprite, Cuprite+, East, and West scenes. The PCC and RMSE of the cropped pseudo-Hyperion images versus the original five Hyperion images for reflectances in the 155 simulated bands revealed strong correlations for both PHITA cases. That is, there were large PCC and small RMSE values, particularly for the Base scene (Figure 3.8A). Most PCCs and RMSEs for that scene are  $> 0.94$  and very small ( $< 0.016$ ), respectively, except for outliers such as band 185 data, with the minimum PCC (0.86). The PCC and RMSE ranges of the Base scene are much narrower than the other Hyperion

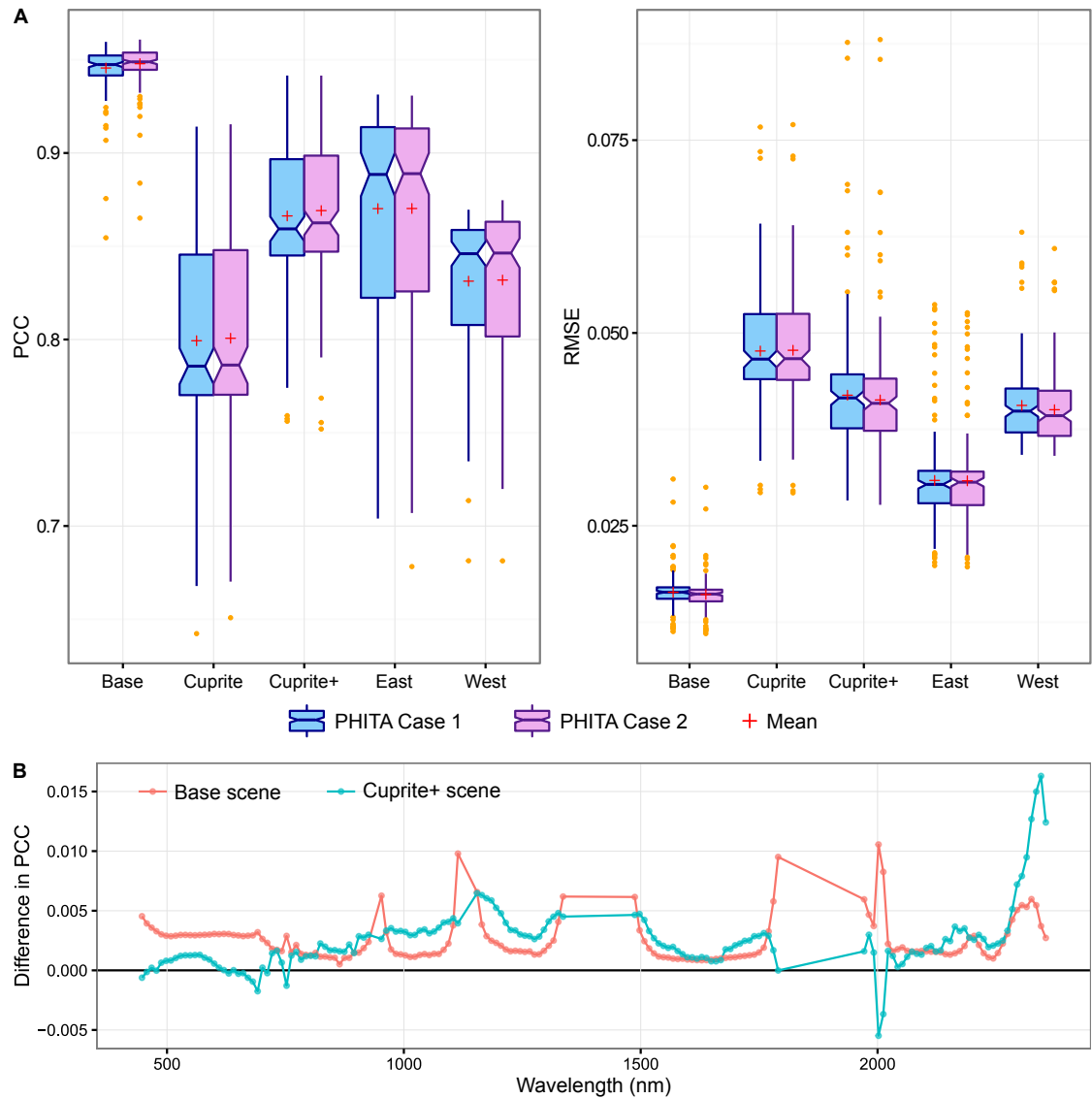


Fig. 3.8 (A) Scene-by-scene comparison of PCC and RMSE reflectances in 155 simulated bands between original Hyperion and cropped pseudo-Hyperion images, output from PHITA Cases 1 and 2. Each cropped pseudo-Hyperion image covers the same area of a corresponding original Hyperion image. (B) Subtraction of PCC between original and pseudo-Hyperion images by PHITA Case 1 from PCC between the original and pseudo-Hyperion images by Case 2 in all bands of the Base and Cuprite+ scenes.

scenes. This indicates that simulation accuracies of reflectances are uniform over the Base scene. Although correlations of the Cuprite+, East, and West scenes are weaker than those of the Base scene, their PCCs are largely greater than 0.85, 0.82, and 0.80, respectively. The reason for the poorest correlation of the Cuprite

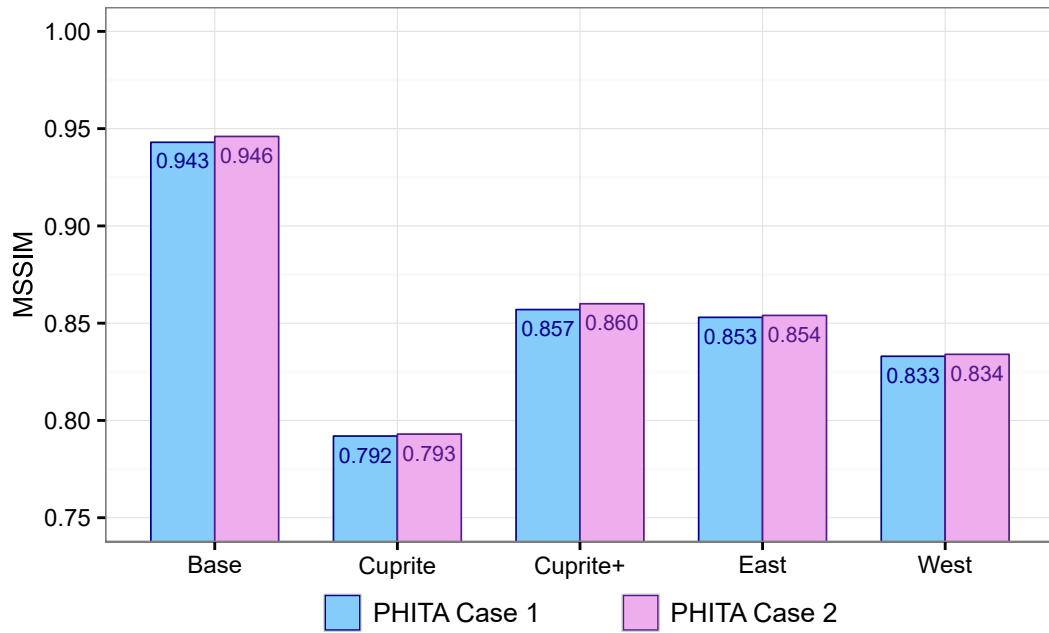


Fig. 3.9 Scene-by-scene comparison of MSSIM values between the original and pseudo-Hyperion images, output from PHITA Cases 1 and 2.

scene caused by the difference in look angle from the Base scene is described later in Section 5 and illustrated in Figure 3.17. The results reveal that for all Hyperion scenes, mean and median values of PCC and RMSE are slightly larger and smaller, respectively, for PHITA Case 2 than Case 1. The superiority of Case 2 was affirmed more clearly in the Base and Cuprite+ scenes by the difference of two PCC values, which was calculated by subtraction of PCC between the original and pseudo-Hyperion images in Case 1 from PCC between those images in Case 2 for each band (Figure 3.8B). A positive difference indicates the superiority of Case 2 to 1, and a negative one the reverse. All Base-scene bands and most Cuprite+ scene bands (except for a limited number of visible bands and two SWIR bands) had larger PCCs in Case 2 than in Case 1. Similarly, all MSSIM values of PHITA Case 2 were slightly higher than Case 1 (Figure 3.9), which means the structural features of the original Hyperion image were preserved better in Case 2. Another important point is the trend of agreement between MSSIM and the mean PCC in that these maximum values are commonly found by the Base scene. The maximum

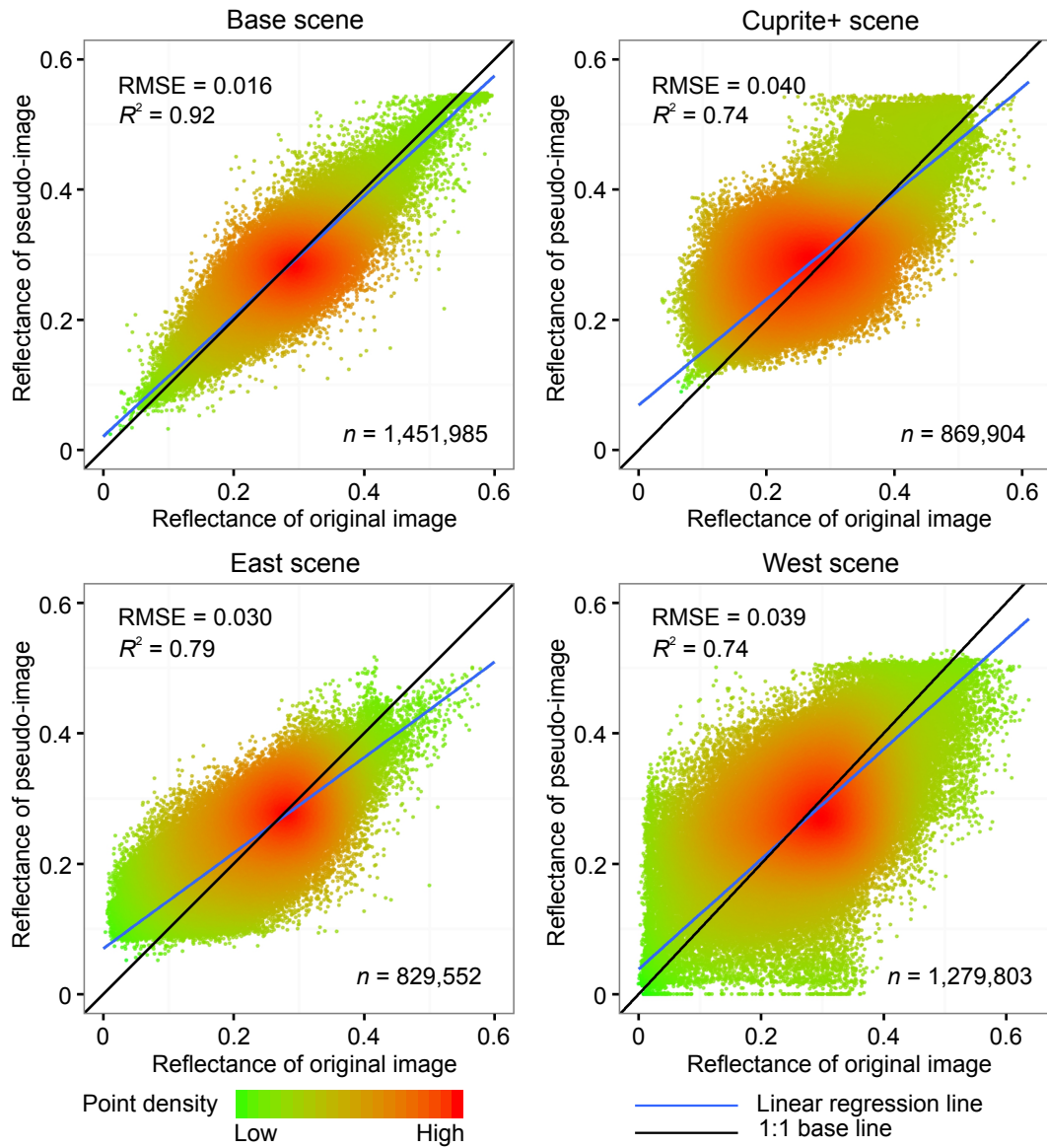


Fig. 3.10 Example of reflectance scatter plots between the original Hyperion image and pseudo-Hyperion image from PHITA Case 2 and band 159 (1759 nm). Regression lines and number of pixels  $n$  in the Base, East, West and Cuprite+ scenes are included.

MSSIM value is attributable to the production of the optimum model dictionary from the overlap area between the Hyperion Base and ETM+ images.

The accuracy of Case 2 was further tested by the similarity of reflectances between the original and pseudo-Hyperion images of band 159 (1759 nm) (Figure 3.10). Because its PCC is near the mean of PCCs of all bands, this band is regarded as typical. Sufficient accuracy of the method is demonstrated by the

strongest linearity ( $R^2 = 0.92$ ) of the Base scene and, although by a smaller value ( $R^2 > 0.74$ ), by the Cuprite+, East, and West scenes. This linearity was observed mostly in the other pseudo-bands. As the square root of variance, RMSE represents the average deviation of the pseudo-reflectance to the original reflectance. All RMSE values are regarded to be low: Base scene has the smallest RMSE (0.016), followed in ascending order by the RMSEs of the East (0.030), West (0.039), and Cuprite+ (0.040) scenes. This trend of accuracy is the same as  $R^2$ . Because of the statistical suitability of PHITA Case 2, the pseudo-Hyperion image it produced was selected for further validation by mineral mapping.

### 3.3.4 Spectral profile of endmembers

The most important criterion for verifying the PHITA is its capability for reconstructing reflectance spectra of surface materials. For assessing this, spectral profiles between the original and pseudo-Hyperion images inside and outside the Base scene were compared. For the Base scene, six main categories in the geological map (alluvium, basalt, granodiorite, limestone, rhyolite, and sandstone) and one pixel representing each category were selected for this comparison (Figure 3.11). Although the pseudo-reflectance spectra are slightly smoother, their trends mostly follow those of the original spectra common to all the categories. In addition to the statistical analyses, this result further verifies the suitability of the pseudo-Hyperion images.

In the outside area, kaolinite, vegetation, and water were selected as typical materials and their spectral profiles were extracted from the Cuprite+, East, and West scenes, respectively. Their distributions and locations were identified from the mineral map of Swayze et al. (2014) and Google Earth images. Comparison of spectral profiles between the original and pseudo-Hyperion images from PHITA Case 2 reveals general agreement of their trends (Figure 3.12); they were nearly



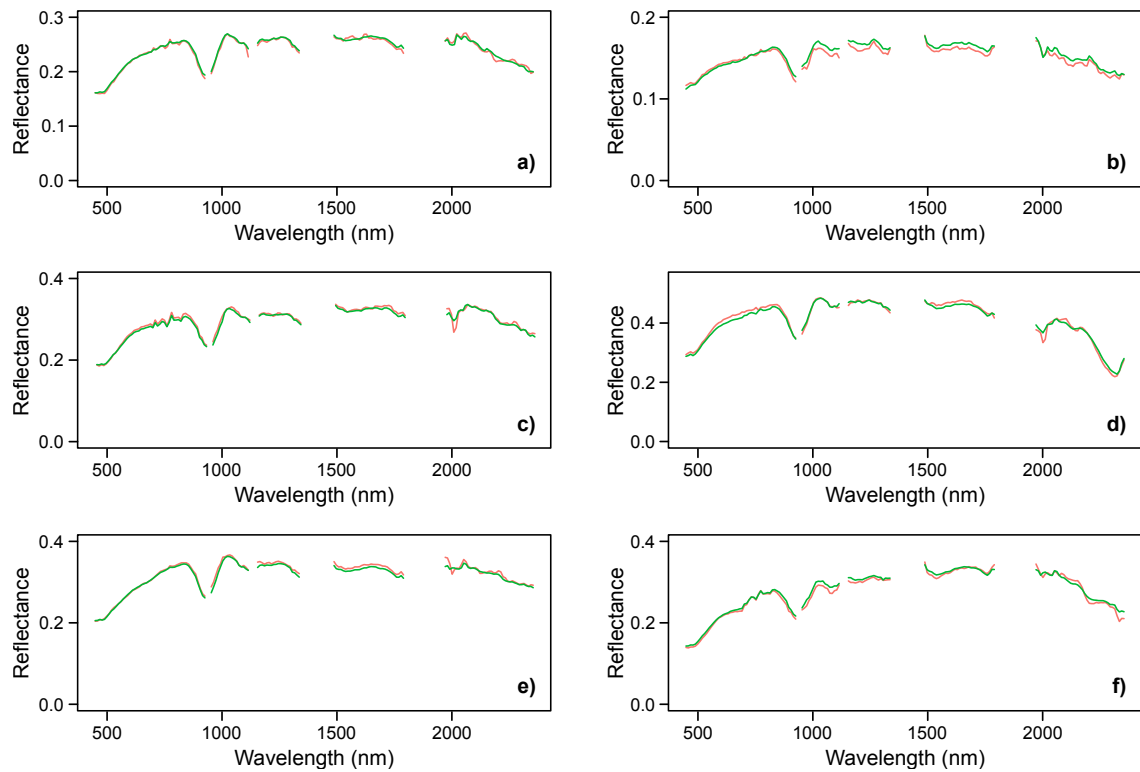


Fig. 3.11 Comparison of spectral profiles of soil between the original (red) and pseudo-Hyperion images (green) of six main categories in the geological map: (a) alluvium, (b) basalt, (c) granodiorite, (d) limestone, (e) rhyolite, and (f) sandstone for one pixel representing each category.

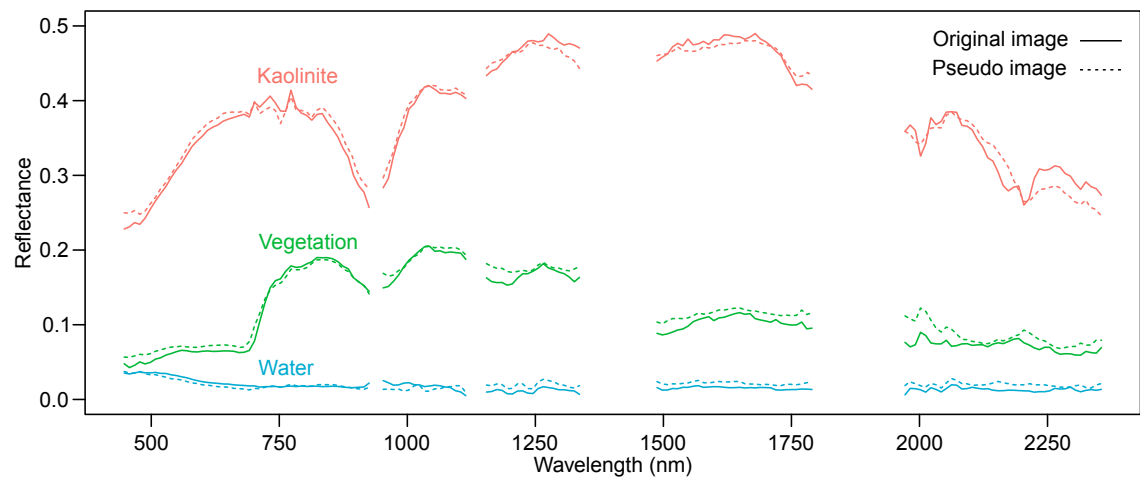


Fig. 3.12 Comparison of spectral profiles of kaolinite, vegetation and water between the original Hyperion and pseudo-Hyperion images from PHITA Case 2. Each profile was taken from the mean value of  $2 \times 2$  pixels in the Cuprite+, East and West scenes.

identical for the water with a flat profile. Although pseudo-reflectance was slightly greater than the original for the vegetation, specific features including a green reflectance peak (near  $0.55\ \mu\text{m}$ ), red absorption ( $\sim 0.66\text{--}0.67\ \mu\text{m}$ ), near infrared (NIR) peak ( $\sim 0.72\ \mu\text{m}$ ), and a strong reflectance increase from visible to NIR and water absorption (around  $1.44$  and  $1.93\ \mu\text{m}$ ) were reconstructed in the pseudo-spectral profile. For the pseudo-reflectance of kaolinite, values are almost identical to the original in the  $0.45\text{--}1.01\ \mu\text{m}$  range, but generally smaller than those at longer wavelengths. Although Al-OH combined absorption near  $2.2\ \mu\text{m}$  is weaker than for the original, their appearances are decisive for partially extracting kaolinite from the background and other endmembers. The capability of reconstructing reflectance spectra of minerals is discussed in greater detail in the next section.

### 3.3.5 Mineral mapping

Minerals in the Cuprite area were characterized by reflectance spectra in the SWIR region ( $2.0\text{--}2.4\ \mu\text{m}$ ) (Kruse et al., 2003; Swayze et al., 2014). Then, the mineral mapping was done using data of original and pseudo-Hyperion reflectances from the area. Moreover, mineral mapping using SWIR reflectance is impossible using ETM+ imagery with only one SWIR band. This limitation is useful for proving the superiority of the pseudo-Hyperion image.

The most remarkable feature of the plots of MNF eigenvalues (Figure 3.13) is that the eigenvalues of the pseudo-Hyperion image are larger than those of the original Hyperion image at 27 of the 36 MNF bands, showing that more information is contained in the pseudo-image. In both images, the eigenvalues converge to become small after the first several MNF bands. Only MNF bands whose eigenvalues were larger than the inflection point and images that were spatially coherent were used in the mineral mapping. In this study, 15 MNF bands



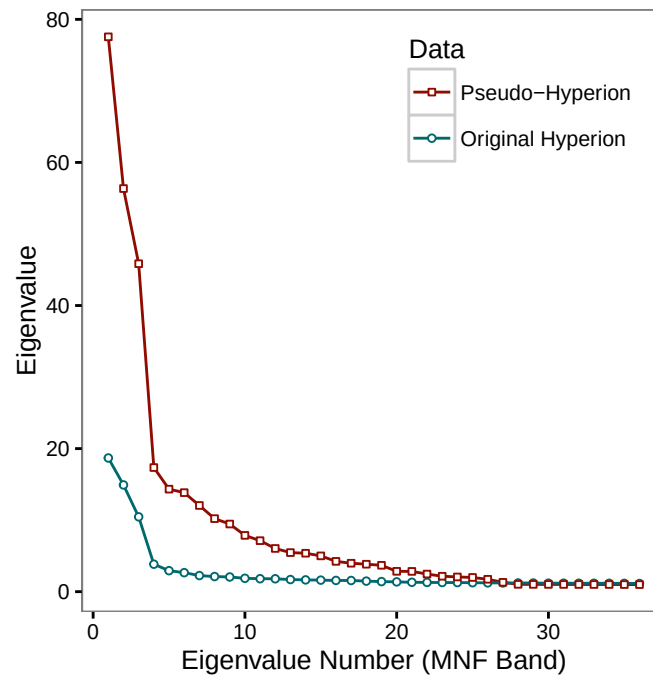


Fig. 3.13 MNF eigenvalues of original and pseudo-Hyperion images of the Cuprite area.

of the pseudo-Hyperion image could be used for MTMF in contrast with the 6 MNF bands of the original Hyperion image.

As the main endmembers in the Cuprite area, five minerals (kaolinite, alunite, muscovite, hydrated silica (chalcedony and/or opal), and calcite), were chosen based on the result of pure pixels and the field survey of Swayze et al. (2014). SWIR reflectance spectra of each endmember were collected from the pure pixels in an n-dimensional scatter plot and then averaged (Figure 3.14). General patterns of the pseudo-spectra correspond with the original Hyperion spectra common to all endmembers. However, absorption features of kaolinite, alunite, and muscovite were not fully reproduced in the pseudo-spectra in terms of absorption wavelengths. A shortcoming was that the 2.17- $\mu\text{m}$  absorption of alunite shifted to 2.2  $\mu\text{m}$ , where kaolinite absorption occurs. This may cause misclassification of these minerals in the mapping.

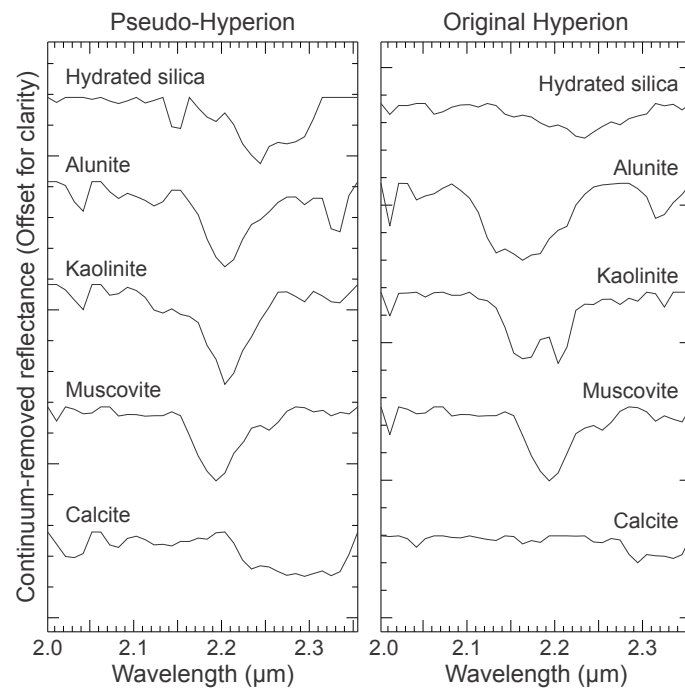


Fig. 3.14 Comparison of reflectance spectra of selected minerals between pseudo-Hyperion (left) and original Hyperion images (right).

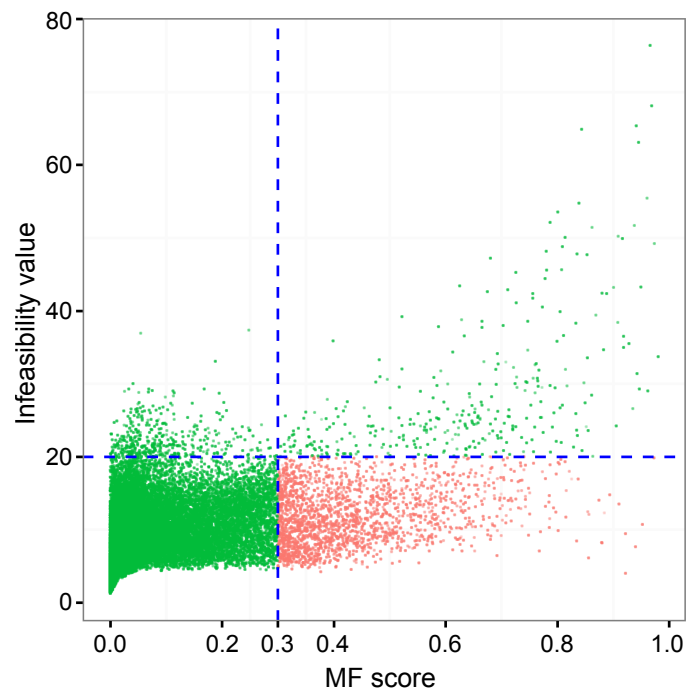


Fig. 3.15 Scatter plot of infeasibility values versus MF score, retrieved from a pseudo-Hyperion image for a selected mineral (alunite in this case). Blue lines are thresholds for selecting pixels (red dots), for which the probability of alunite presence is estimated to be high.

MTMF provides a set of two-rule images, showing the MF score and infeasibility value at each pixel by comparing the spectrum of each endmember. From this, the mineral map of the distribution and abundance of a selected mineral can be produced. Based on the scatter plot trend between the MF score and infeasibility value (Figure 3.15), a selected mineral was assigned to pixels with small infeasibility values and large MF scores, where 1.0 is a perfect match. In this study, infeasibility values below 20 were considered likely to contain the target endmembers. Subsequently, the optimal threshold of the MF score was selected on a case-by-case basis, which was well represented the USGS mineral map and field survey data. At a pixel in which multiple endmembers were mixed, the endmember with the largest MF score was selected as the representative mineral.

The mineral maps from the original and pseudo-Hyperion images correspond with each other, except for kaolinite and hydrated silica (Figure 3.16). By including unclassified pixels, overall agreement (OA) of the pseudo-mineral map with the original mineral map was 86.38%, with a Kappa coefficient (KC) of 0.61 (Table 3.3). The ranges of producer's accuracy (PA) and user's accuracy (UA) were 29.76–93.24% and 19.67–99.48%, respectively. In both PA and UA, kaolinite, hydrated silica, and calcite accounted for the minimum, low, and maximum values, respectively. Of all kaolinite pixels, 29.76% were classified correctly, whereas 19.25% were misclassified as alunite and 45.28% were unclassified. Mineral identification accuracy of the original Hyperion image was also lower than that based on the AVIRIS image for the same Cuprite area, as demonstrated by Kruse et al. (2003). Therefore, both the original and the pseudo-Hyperion images should be evaluated for their mineral mapping accuracy using the USGS mineral map by Swayze et al. (2014) as the ground truth.

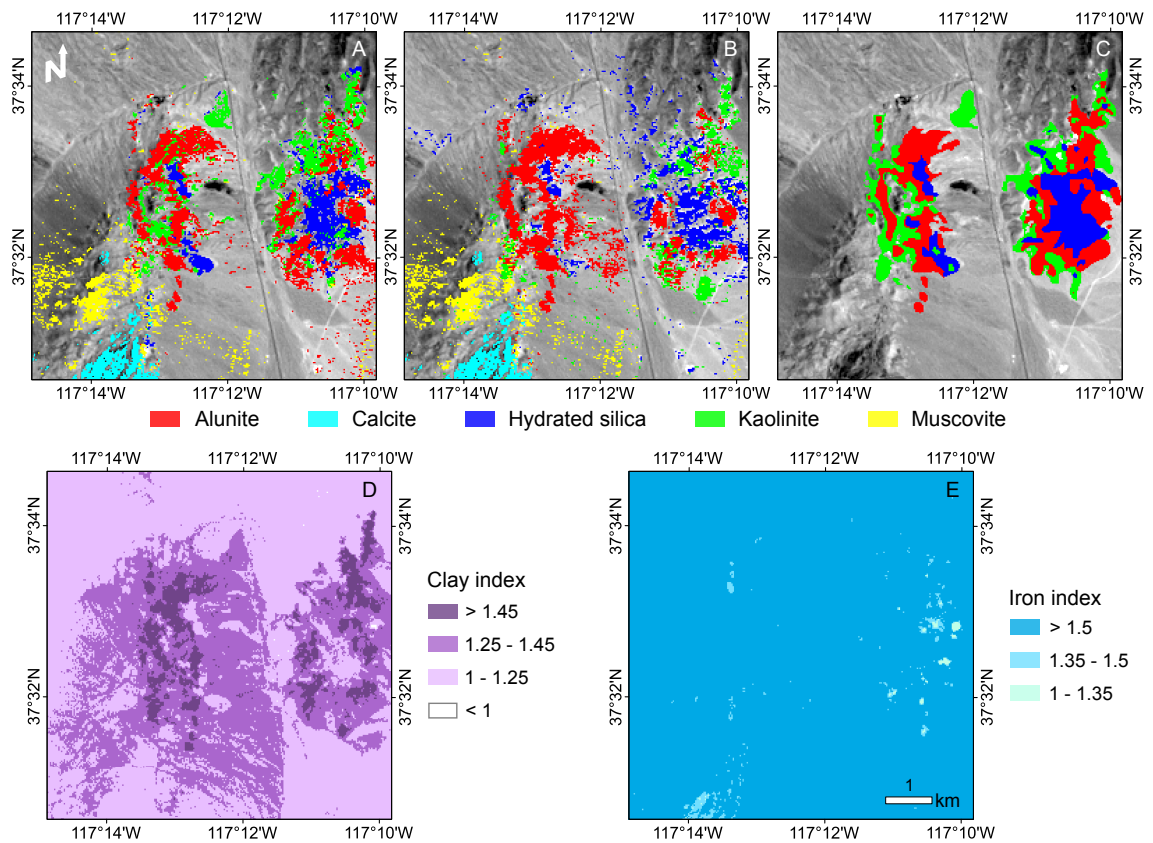


Fig. 3.16 MTMF mineral maps showing the most dominant endmember in each pixel, produced from the pseudo- (A) and original (B) Hyperion images, and their comparison with the mineral map (C) obtained from Swayze et al. (2014). Background is grayscale pseudo-Hyperion image of band 195 (2103 nm). In addition, level slices of the clay index (D) and iron index (E) from the original Landsat ETM+ image, which was transformed into the pseudo-Hyperion image, are included to demonstrate the high precision of pseudo-image-based mineral mapping.

Table 3.3 Confusion matrix showing mineral identification accuracy of pseudo-Hyperion MTMF results compared with original-Hyperion MTMF result. Overall accuracy is 86.38% and Kappa coefficient = 0.61.

| Pseudo-Hyperion<br>(pixels) | Original Hyperion (pixels) |         |         |           |           |                 | Total<br>(pixels) | User's<br>accuracy (%) |
|-----------------------------|----------------------------|---------|---------|-----------|-----------|-----------------|-------------------|------------------------|
|                             | Unclassified               | Alunite | Calcite | Kaolinite | Muscovite | Hydrated silica |                   |                        |
| Unclassified                | 46430                      | 1316    | 67      | 849       | 161       | 1023            | 49846             | 93.15                  |
| Alunite                     | 987                        | 3062    | 2       | 361       | 5         | 217             | 4634              | 66.08                  |
| Calcite                     | 5                          | 0       | 965     | 0         | 0         | 0               | 970               | 99.48                  |
| Kaolinite                   | 1628                       | 273     | 0       | 558       | 1         | 377             | 2837              | 19.67                  |
| Muscovite                   | 0                          | 0       | 1       | 34        | 1785      | 23              | 1843              | 96.85                  |
| Hydrated silica             | 1049                       | 17      | 0       | 73        | 9         | 970             | 2118              | 45.80                  |
| Total (pixels)              | 50099                      | 4668    | 1035    | 1875      | 1961      | 2610            | 62248             |                        |
| Producer's<br>accuracy (%)  | 92.68                      | 65.60   | 93.24   | 29.76     | 91.02     | 37.16           |                   |                        |

Table 3.4 Confusion matrix showing mineral identification accuracy of pseudo-Hyperion MTMF results compared with the mineral map used as ground truth. Overall accuracy = 88.38% and the Kappa coefficient = 0.61.

| Pseudo-Hyperion<br>(pixels) | The mineral map (pixels) |         |           |                 | Total<br>(pixels) | User's<br>accuracy (%) |
|-----------------------------|--------------------------|---------|-----------|-----------------|-------------------|------------------------|
|                             | Unclassified             | Alunite | Kaolinite | Hydrated silica |                   |                        |
| Unclassified                | 49219                    | 1263    | 1505      | 672             | 52659             | 93.47                  |
| Alunite                     | 1216                     | 2736    | 603       | 79              | 4634              | 59.04                  |
| Kaolinite                   | 504                      | 714     | 1419      | 200             | 2837              | 50.02                  |
| Hydrated silica             | 100                      | 216     | 159       | 1643            | 2118              | 77.57                  |
| Total (pixels)              | 51039                    | 4929    | 3686      | 2594            | 62248             |                        |
| Producer's accuracy (%)     | 96.43                    | 55.51   | 38.50     | 63.34           |                   |                        |

Table 3.5 Confusion matrix showing mineral identification accuracy of original-Hyperion MTMF results compared with the mineral map used as ground truth. Overall accuracy = 84.95% and the Kappa coefficient = 0.48.

| Original-Hyperion<br>(pixels) | The mineral map (pixels) |         |           |                 | Total<br>(pixels) | User's<br>accuracy (%) |
|-------------------------------|--------------------------|---------|-----------|-----------------|-------------------|------------------------|
|                               | Unclassified             | Alunite | Kaolinite | Hydrated silica |                   |                        |
| Unclassified                  | 48238                    | 1453    | 2116      | 1288            | 53095             | 90.85                  |
| Alunite                       | 1247                     | 2757    | 611       | 53              | 4668              | 59.06                  |
| Kaolinite                     | 582                      | 461     | 732       | 100             | 1875              | 39.04                  |
| Hydrated silica               | 972                      | 258     | 227       | 1153            | 2610              | 44.18                  |
| Total (pixels)                | 51039                    | 4929    | 3686      | 2594            | 62248             |                        |
| Producer's accuracy (%)       | 94.51                    | 55.93   | 19.86     | 44.45           |                   |                        |

Because the mineral map was prepared only for the two main hydrothermal alteration centers in the Cuprite area, muscovite and calcite were not included. Comparison of the classification results of the original and pseudo-Hyperion images with the mineral map reveals significantly better accuracies of the pseudo-image than of the original image (Tables 3.4 and 3.5), as indicated by the increased PA and UA of kaolinite by 18.64% and 10.98%, respectively and of hydrated silica by 18.89% and 33.39%, respectively. Both the PA and UA of alunite were slightly higher in the original image, while those of unclassified pixels were slightly lower. Overall, the pseudo-image increased the OA (88.38%) by 3.43% and the KC (0.61) by 0.13 in comparison with the original image. This demonstrates the adequate accuracy of the pseudo-Hyperion image outside the base scene for mineral identification and mapping.

In processing ETM+ images, the traditional method is to use band ratios to detect and identify hydrothermal alterations, e.g., band 5/7 as the clay index for alunite and clay minerals (Figure 3.16D) and band 3/1 as the iron index for iron minerals (Figure 3.16E). Large values of these band ratios signify a high possibility of the presence of clay or iron minerals. Other methods (e.g., principal component analysis and color composite ratio imagery) are available for mineral potential mapping; however, the identification of mineral name and type is impossible using Landsat imagery alone (Sabins, 1999; van der Meer et al., 2012). Thus, this represents further confirmation of the effectiveness of the PHITA.

### 3.4 Discussion

Similarities of the original and pseudo-Hyperion images were different for the Hyperion scenes. The pseudo-image of the Base scene was the most strongly correlated with the original image. This was demonstrated by large PCCs and MSSIMs, small RSMEs (near zero), strong linearity, and nearly indistinguishable

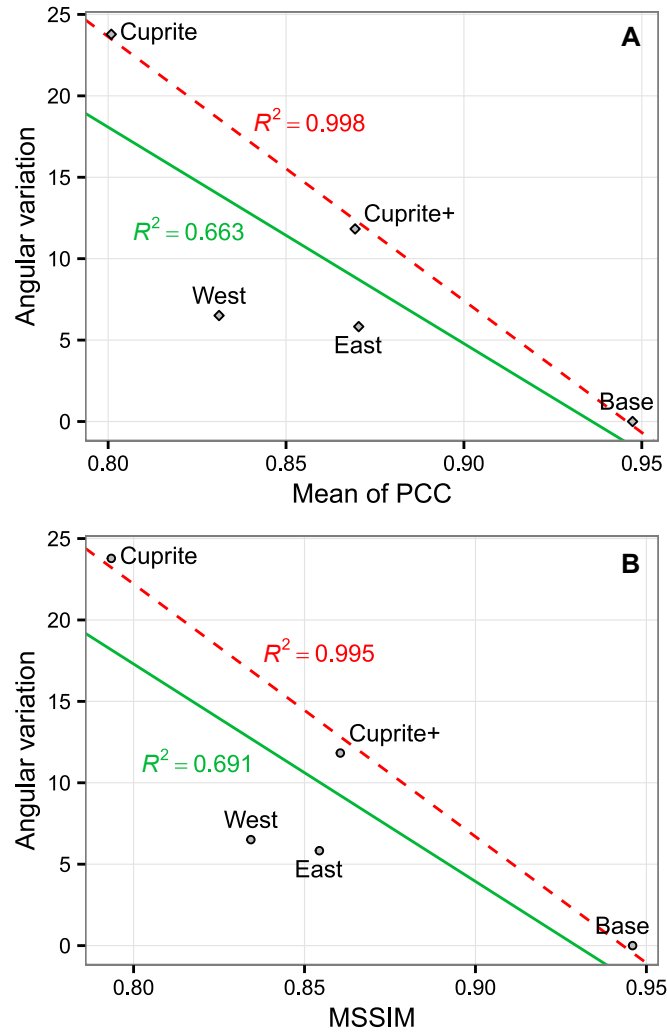


Fig. 3.17 Relationship between variation of look angle and statistical indices for all Hyperion scenes: (A) mean PCC and (B) MSSIM. Angular variation is defined by the absolute difference in look angle between the Base scene and another scene. The PCC and MSSIM signify the similarity between the original Hyperion image and pseudo-Hyperion image from PHITA Case 2. Green solid and red dashed lines represent the regression lines for all scenes and for a subset of the Base, Cuprite, and Cuprite+ scenes (covered by nearly identical surface materials), respectively.

grayscale images. This similarity was because the model dictionary was built from the Base scene. Although similarities of the other four scenes outside the Base scene were weaker than that scene, their correlations were unexpectedly high so that the PCC means exceeded 0.8 (Figure 3.17A). This also demonstrates the PHITA capability. The mean PCC was the poorest for the Cuprite scene, despite its location near the Base scene. Because the PCC means are not related



to distance from the Base scene, the most probable control on the correlation is the variation in look angle of the Hyperion scene from the Base scene, which was  $5.8^{\circ}$ – $23.8^{\circ}$  (Table 3.1). In fact, the mean PCC has a negative correlation ( $R^2 = 0.66$ ) with that variation (absolute difference in look angle between the Base scene and another Hyperion scene). Interestingly, the correlation was perfect for  $R^2 \approx 1$  with selection of Cuprite, Cuprite+, and Base scenes whose surface materials were almost the same (Figure 3.17A). Therefore, the correlation decreased with increasing variation of look angle. The MSSIM has the same trend as the mean PCC (Figure 3.17B). Both relationships of look angle variation with the mean PCC and MSSIM prove that the variation of look angle is a strong controlling factor on the correlation outside the Base scene. Another influence on the correlation may be a difference of surface materials within and outside the Base scene. This is because thick vegetation and water bodies cover a significant area of the East and West scenes, respectively, in contrast with the Base scene with its rock and soil cover (Figure 3.18). This difference generally alters the reflectance spectra of endmembers in the pseudo-image compared with those of the original image, and can decrease the negative correlation. This is revealed by the PCC means of the East and West scenes below the regression line (Figure 3.17).

In calculating the multiple linear regression models for all pixels in each Hyperion band, PHITA Case 1 weakened the reflectance spectra characteristics of endmembers. Greater simulation accuracy in Case 2 than in Case 1 is due to use of the geologic map as supplementary information. It should be noted that the transformation accuracy of the PHITA is affected by the difference in surface materials between the overlapped and nonoverlapped areas of the ETM+ and Base Hyperion images. For an ETM+ scene that includes several Hyperion scenes of different locations, a Hyperion scene that contains most of the principal surface materials in the ETM+ scene needs to be selected for accurate transformation. Because the principal coverages in the Base scene are soil and rock, the geologic

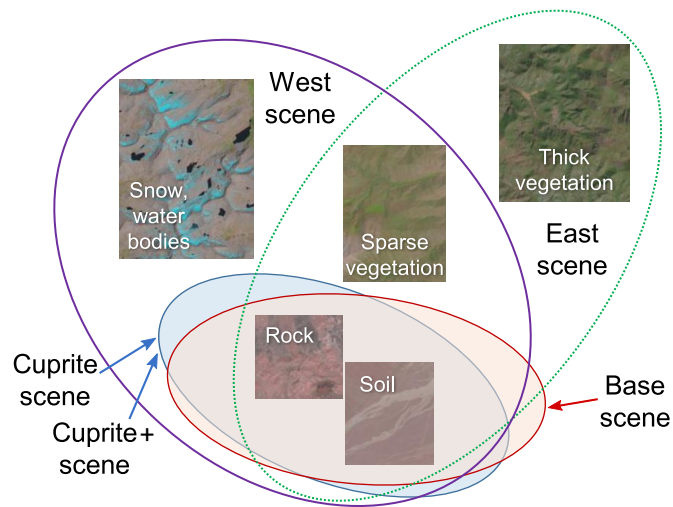


Fig. 3.18 Difference in principal land-cover materials in Hyperion scenes. Representative land-cover materials are shown by a part of a natural-color composite image. Each ellipse represents a set of principal land covers in a scene; e.g., the West scene is mainly covered by snow, water bodies, sparse vegetation, rock, and soil.

map is useful for building independent regression models of each surface material area and accurate mineral maps. However, land-use and land-cover maps should be more effective than the geologic map for a scene with heterogeneous surface materials. A normalized difference vegetation index (NDVI) map or one based on a new vegetation index superior to NDVI (Hede et al., 2015), calculated from an ETM+ image, could be used for vegetation mapping using the pseudo-Hyperion image. For example, different model dictionaries could be built for each NDVI interval in the range 0.0 to 1.0, e.g., 0.0–0.2, 0.2–0.5, 0.5–0.8, and 0.8–1.0.

The MNF analysis in the 2.00–2.36  $\mu\text{m}$  region revealed that the pseudo-Hyperion image is less noisy than the original image. One plausible explanation is that the pseudo-image was transformed from the low-noise ETM+ image; another is that the geologic map used in the PHITA increased the quantity of information in the pseudo-image. This helps the pseudo-Hyperion image produce a mineral map with better accuracy than the original Hyperion image, even though some endmember spectra were not simulated well. The latter phenomenon caused the

appearance of unclassified and misclassified pixels. The imperfectly reconstructed reflectance spectra may partially originate from noise in the original Hyperion bands, which is strong in the region with wavelengths longer than 2.25  $\mu\text{m}$ . The coregistration accuracy between the Hyperion and the ETM+ images was also an influence on spectra reconstruction. Because of this Hyperion-to-ETM+ image coregistration error, a pseudo-spectrum becomes a product of mixing two or more endmembers and/or pixels with different pure levels. This causes unsuccessful reconstruction of the absorption doublet of kaolinite at 2.16 and 2.20  $\mu\text{m}$ : only the 2.20- $\mu\text{m}$  absorption that appears in many other minerals such as hydrated silica and muscovite was reconstructed at present. The coregistration accuracy might be improved using high-resolution digital elevation model data for precise selection of GCPs or using an advanced coregistration algorithm with many GCPs. Other essential factors regarding mineral classification accuracy of the pseudo-image were the same as for the Hyperion image, as discussed in the literature (Kruse et al., 2003). Compared with AVIRIS, the pseudo-image has coarser resolution (30 m versus 15.7 m), experiences stronger atmospheric effects because of the difference in data acquisition height (705 km versus 20 km), and has different spectral resolution and observation bands. Consequently, improving pseudo-image quality requires that the Hyperion image must be stringently preprocessed to reduce noise and coregistered exactly with the ETM+ image to avoid spectral mixing. A spatial downscaling technique for the Hyperion and the ETM+ images is also necessary to improve mineral classification accuracy.

### 3.5 Conclusions

As a method of transforming a Landsat ETM+ image into a pseudo-Hyperion image, the PHITA was developed. A total of 155 pseudo-band reflectances were simulated with high accuracy by the multiple linear regression models, between

each Hyperion and ETM+ band reflectances. The pseudo-Hyperion image was successfully extended to the same size as the ETM+ scene. Pseudo-image quality was verified by the general appearances of mono-band and color composite images, statistical analysis, and application to mineral mapping. This showed that the images were strongly correlated, and had strong linearity and an appearance similar to the original Hyperion image. The correlation between the original and pseudo-Hyperion images was improved by using a geological map as a conditional variable to calculate the regression models for each rock-type area. Pseudo-reflectance spectra were generally similar to the original spectra. Using the USGS mineral map as ground truth, the pseudo-image was confirmed to be sufficiently applicable to mineral identification and mapping in the Cuprite area, because their accuracies were better than those of the original Hyperion image. Consequently, the PHITA was proven effective and has the potential to globally transform accumulated ETM+ images into pseudo-Hyperion images for any area without Hyperion coverage. Undoubtedly, the PHITA is not limited to these images; another representative multispectral sensor image, ASTER, is an attractive target for hyperspectral transformation.

A limitation of the present PHITA is that some endmember spectra were not well simulated in the pseudo-image. As a result, these endmembers were not extracted or were misclassified in the Cuprite mineral map. This situation can be improved by better preprocessing of the Hyperion image and more accurate coregistration of the Hyperion-to-ETM+ image. The present study is the first step toward simulating the pseudo-Hyperion image at global scale. The overall quality of the pseudo-image needed to be verified for accuracy based on the mineral mapping over the entire ETM+ scene. However, this could not be accomplished in this study because of the limitation of the ground truth area and the amount of reference data. In the case of an ETM+ scene overlaid by several Hyperion scenes at different locations, the accuracy of the extrapolated area of the pseudo-image

is probably guaranteed by selecting the optimum base scene that contains most of the principal surface materials contained within the entire Landsat scene. Our next step is to evaluate the PHITA capability for other geologically important areas and other multispectral images, and to check the consistency of regression models using images with different acquisition dates.

## **Chapter 4**

# **The best multispectral image of spectral downscaling for detecting minerals specific to geothermal area**

### **4.1 Introduction**

The results of Chapter 3 show that PHITA has the ability to transform accumulated ETM+ images into pseudo-Hyperion images for areas with no Hyperion coverage and produce global hyperspectral images. PHITA uses ETM+ images for the transformation because of similarities in orbit and acquisition time between the Landsat 7 and EO-1 satellites. However, 22% of image data have been lost in each ETM+ scene, because of failure of the scan line corrector (SLC) since 31 May 2003 (Wulder et al., 2011). Optical sensors that have a spectral band design similar to the ETM+, TM, OLI, and ALI sensors can compensate the degradation of ETM+ images.

Although several research works simulated Hyperion imagery using ALI imagery (Chen et al., 2008; Hoang and Koike, 2016; Liu et al., 2009) and AVIRIS imagery using TM imagery (Sun et al., 2015), there is still no accuracy comparison

of hyperspectral transformations from different multispectral images. Therefore, alternative capabilities of the other ETM+ images for the hyperspectral transformation must be clarified. This motivation is not limited to finding a candidate for filling the gap in ETM+ images, but is directed at new applications of pseudo-Hyperion images to monitoring spatiotemporal changes in earth phenomena and mineral and energy resource exploration. Because the TM, ETM+, OLI, and ALI images were acquired in different periods, long-term, pseudo-Hyperion images can be generated if the transformation accuracy of the multispectral images is equivalent.

Based on the above background, this part aimed to clarify the following unsolved problems by selecting mineral identification capabilities in a geothermal prospect area as a case study:

1. Can the TM, OLI, and ALI images substitute the ETM+ image for Hyperion transformation?
2. What are the mineral identification accuracies of the resultant pseudo-images?
3. Which is the best multispectral sensor for the Hyperion transformation?
4. Which factors affect transformation accuracy?

The resultant pseudo-images transformed from TM, ETM+, OLI, and ALI images, which have the same number of high-quality Hyperion bands, must contribute to detailed mineral mapping, thereby producing long-term hyperspectral images for global monitoring of land surfaces.

## 4.2 Data and study area

### 4.2.1 Overview of TM, ETM+, OLI, ALI, and Hyperion images

Landsat 5, 7, and 8 satellites have the same circular, sun-synchronous, and near-polar  $98.2^\circ$  inclined orbit at altitude 705 km. They also have the same repeat cycle of 16 days, similar equatorial crossing time from 9:30 to 10:16 am local time, same scene size ( $185 \text{ km} \times 180 \text{ km}$ ), and same definition of path and row of each scene in the Worldwide Reference System (Roy et al., 2014; Teillet et al., 2001). The EO-1 satellite is approximately one minute after Landsat 7 along the same ground track (Pearlman et al., 2001), but the swaths of its ALI and Hyperion images, 36 and 7.6 km respectively, are much narrower than that of Landsat images. Absolute radiometric calibration uncertainties of the TM, ETM+, and OLI sensors are 5%, 5%, and 3%, respectively (Helder et al., 2008; Markham and Helder, 2012). The OLI sensor was improved over the ETM+ sensor in terms of larger signal-to-noise ratio, higher radiometric resolution, and more precise image geometry (Irons et al., 2012). Spatial resolutions of the four sensor images and Hyperion image are the same, 30 m, except for thermal and panchromatic bands that are not used for PHITA.

Brief band specifications of Landsat and ALI images are as follows (Chander et al., 2009; Irons et al., 2012; Roy et al., 2014). TM and ETM+ sensors have six VNIR and SWIR bands. Compared to them, the OLI sensor has narrower corresponding spectral bands and two new VNIR bands at a shorter blue wavelength ( $0.43\text{--}0.45 \mu\text{m}$ ) and shorter SWIR as a cirrus band ( $1.36\text{--}1.39 \mu\text{m}$ ). There are nine VNIR and SWIR bands of the ALI sensor, in which a shorter-wavelength NIR band ( $0.775\text{--}0.805 \mu\text{m}$ ) and longer-wavelength NIR band ( $1.2\text{--}1.3 \mu\text{m}$ ) do not overlap those of the OLI sensor.



Table 4.1 Main specifications of Landsat and EO-1 sensors.

| Parameters                      | Landsat   |           | EO-1      |           |            |
|---------------------------------|-----------|-----------|-----------|-----------|------------|
|                                 | TM        | ETM+      | OLI       | ALI       | Hyperion   |
| Spectral range (μm)             | 0.5–12.5  | 0.5–12.5  | 0.4–12.5  | 0.4–2.4   | 0.4–2.6    |
| Spatial resolution (m)          | 30 (120*) | 30 (60*)  | 30 (100*) | 30        | 30         |
| Swath width (km)                | 185       | 185       | 185       | 36        | 7.6        |
| Spectral resolution**           | 60–270 nm | 60–260 nm | 20–180 nm | 20–270 nm | ~10 nm     |
| Spectral coverage               | Discrete  | Discrete  | Discrete  | Discrete  | Continuous |
| Total number of bands           | 7         | 8         | 9         | 10        | 242***     |
| Crossing time (a.m. +/- 15 min) | 9:45      | 10:00     | 10:00     | 10:01     | 10:01      |

\*Thermal bands, \*\*excludes thermal bands, \*\*\*44 not calibrated bands, plus 2 overlapping bands

Table 4.2 Scene specifications of imagery used in the study.

| Image    | Acquisition date | Start time (UTC) | Path/Row | Solar zenith angle (degrees) |
|----------|------------------|------------------|----------|------------------------------|
| Hyperion | 2001/06/21       | 18:17:51         | 41/34    | 24.96                        |
| TM       | 2001/06/13       | 18:07:40         | 41/34    | 26.12                        |
| ETM+     | 2001/06/21       | 18:16:46         | 41/34    | 24.72                        |
| OLI      | 2013/06/14       | 18:29:16         | 41/34    | 22.27                        |
| ALI      | 2001/06/21       | 18:17:53         | 41/34    | 24.83                        |

The Hyperion sensor is a push-broom hyperspectral imager composed of two VNIR and SWIR spectrometers. There are 242 contiguous spectral bands from 0.4 to 2.6  $\mu\text{m}$ ; these include 70 and 172 bands of 10-nm spectral bandwidth for the VNIR and SWIR spectrometers, respectively. Among the 242 bands, 44 are not calibrated and 2 are overlapped (Pearlman et al., 2001), and several bands are of low quality because of noise from atmospheric effects (Jupp et al., 2002; Thenkabail et al., 2004). Main specifications of all five sensors are summarized in Table 4.1.

### 4.2.2 Experimental data

Each cloud-free scene image of the TM, ETM+, OLI, and ALI sensors and one Hyperion scene image, which covered the border of California and Nevada in the western United States, were selected for PHITA. All scenes were at path 41 and row 34 and their acquisition dates were in mid-June, including the same date (21 June 2001) for the ETM+, ALI and Hyperion images, and eight days prior to that for the TM image (Table 4.2). The solar zenith angles of the first three images are almost identical ( $\sim 25^\circ$ ), and those of the TM and OLI images are similar. The acquisition of the OLI image was twelve years after the others. Coverage areas of the TM, ETM+ and OLI images are nearly identical, and their areas of overlap with the Hyperion image are also the same, except that the edges of the OLI image are rotated about  $3^\circ$  clockwise from the two other images (Figure 4.1). Therefore, the OLI pixel columns are not in parallel with those of Hyperion. The overlap area of the ALI image with the Hyperion image is narrower than the other three images. Overlap areas of all the multispectral images with the Hyperion image include seven main rock types, i.e., alluvium, andesite, basalt, chert, rhyolite, sandstone, and siltstone.

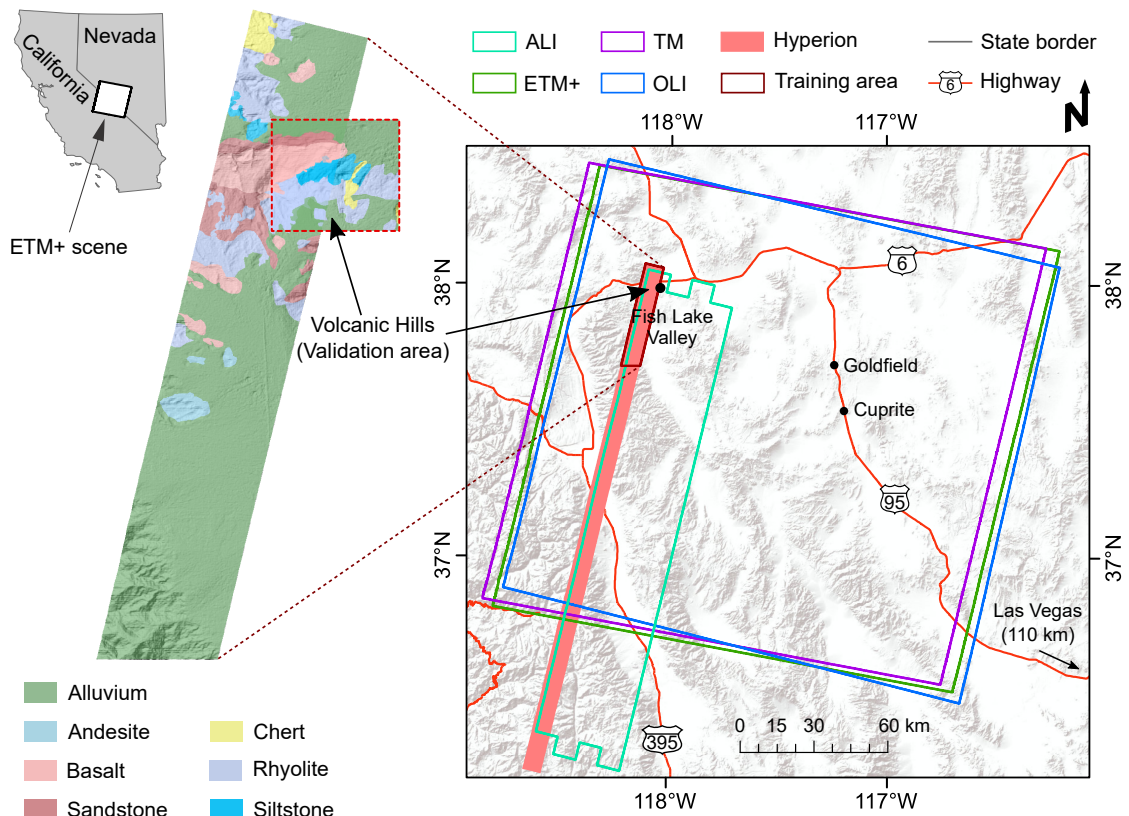


Fig. 4.1 Geographic locations of Landsat and EO-1 image coverages, with a simplified geologic map of selected case study area including seven main rock types, after USGS Mineral Resources On-Line Spatial Data.

### 4.2.3 Study area

The study area is mostly desert with sparse vegetation and an extremely arid climate (Figure 4.2), and contains well-known hydrothermally altered and mineralized fields with metal deposits such as Cuprite and Goldfield. These fields were selected to test the accuracy of mineral mapping through analyses of various multispectral and hyperspectral images (e.g., (Carrere, 1990; Swayze et al., 2014)). We chose the Volcanic Hills, in the north central Fish Lake Valley geothermal prospect area (Figure 4.1), for verification of PHITA mineral mapping accuracy. The Fish Lake Valley is an approximately northeast–southwest trending endorheic valley in southwestern Nevada. Deep oil exploration discovered geothermal potential in this field in 1970 from high temperatures in boreholes, with a maximum of

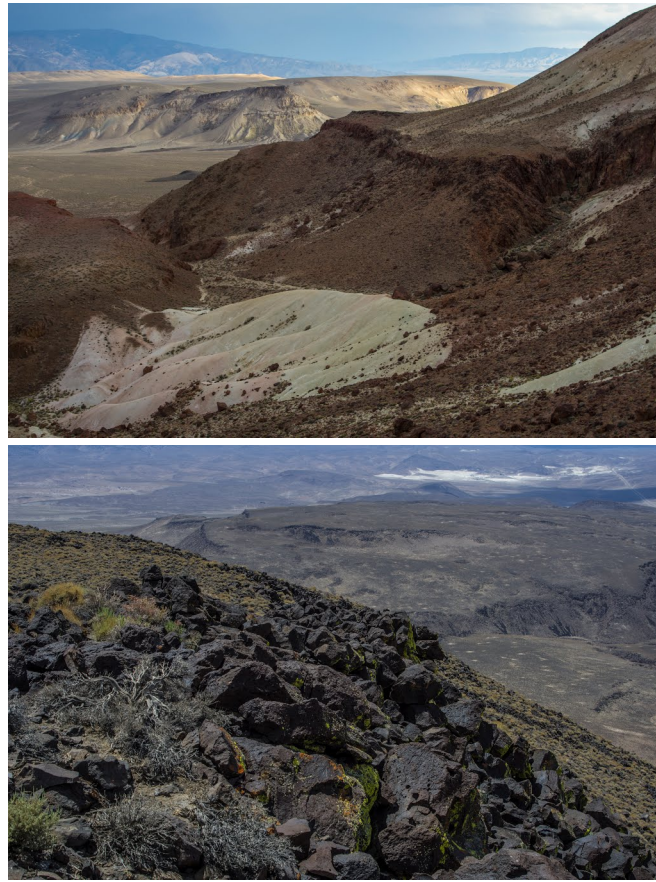


Fig. 4.2 The photos of the Volcanic Hills area (Source: Panoramio<sup>†</sup>).

204°C at depth 2484 m (Littlefield and Calvin, 2014). This field has recently been subjected to applications of airborne hyperspectral images (HyMap, AVIRIS, and ProSpecTIR) with high spatial resolutions (2–4 m) to identify and locate geothermal indicator minerals (e.g., (Kratt et al., 2009; Littlefield and Calvin, 2014; Martini et al., 2004)). The selected TM, ETM+, OLI and ALI images cover the Volcanic Hills, but the Hyperion image covers only half (Figure 4.1). Therefore, this field is suitable to compare the accuracy of pseudo-Hyperion images transformed from those multispectral images and evaluate the mineral mapping capability using the pseudo-images.

<sup>†</sup>[http://www.panoramio.com/photo/ID\(ReplaceID=103050724or103050634\)](http://www.panoramio.com/photo/ID(ReplaceID=103050724or103050634))

## 4.3 Methods

### 4.3.1 Hyperspectral transformation

PHITA was originally based on multiple linear regression models that can be applied to each of the Hyperion and Landsat ETM+ bands, in which the Hyperion band is a dependent variable and ETM+ bands are predictor variables. The details of PHITA are given in Hoang and Koike (2016). PHITA can be extended to any multispectral image (TM, OLI, and ALI as in the present study) with the following general notation of multiple linear regression models for hyperspectral transformation:

$$\rho_{ij}^H(\lambda) = \beta_{0i} + \sum_{d=1}^m \beta_{di} \cdot \rho_{dj}^X(\lambda) + \epsilon_{ij}, \quad (4.1)$$

where  $\rho_{ij}^H(\lambda)$  represents the reflectance of Hyperion band  $i$  and pixel  $j$ ;  $\beta_{0i}$  is the intercept for  $i$ ;  $\rho_{dj}^X(\lambda)$  is the reflectance of multispectral band  $d$  at  $j$ ;  $\beta_{di}$  is an unknown regression coefficient between  $d$  and  $i$ ;  $\epsilon_{ij}$  is a residual;  $m$  is the number of given multispectral bands, which is 6 for TM and ETM+, 7 for OLI, and 9 for ALI. The correspondence between the Hyperion and multispectral bands for each wavelength range is summarized in Figure 4.3. After excluding uncalibrated, duplicated, and strong atmospheric absorption bands, the selected 176 Hyperion bands were 8–57 (0.427–0.925  $\mu\text{m}$ ), 79–120 (0.933–1.346  $\mu\text{m}$ ), 128–166 (1.427–1.810

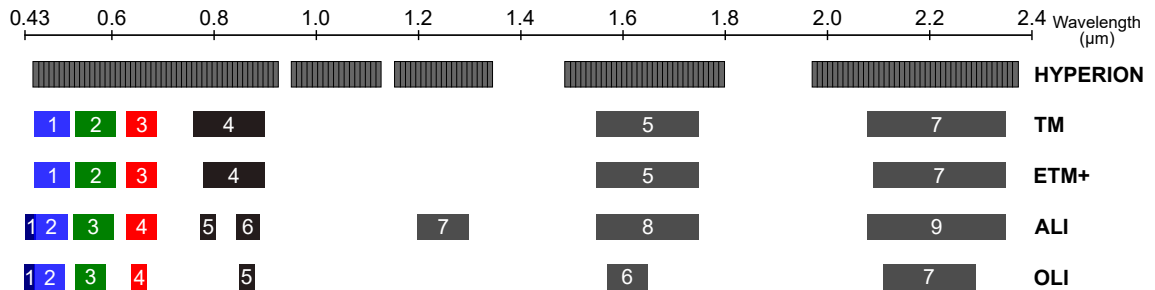


Fig. 4.3 Wavelength ranges of selected Hyperion and multispectral bands for hyperspectral transformation of TM, ETM+, OLI and ALI images into pseudo-Hyperion images.

$\mu\text{m}$ ), and 179–223 (1.942–2.385  $\mu\text{m}$ ). To evaluate model fitness and avoid overfitting, BMA was used to independently select the best combination of multispectral bands and each Hyperion band, which takes the minimum BIC and highest posterior probability (Raftery et al., 1997; Raftery and Painter, 2005).

The main steps of the PHITA are summarized in Figure 4.4. First, a training area was selected from all or part of overlap area between the Hyperion and multispectral images to generate the regression models of Equation 4.1. Because the acquisition year of OLI imagery was very distinct from the others, the upper part of the Hyperion image was chosen as the training area, which had stable surface conditions because the main coverage was by soil and rock, with almost no anthropogenic effects. Additionally, this area partially includes the Volcanic

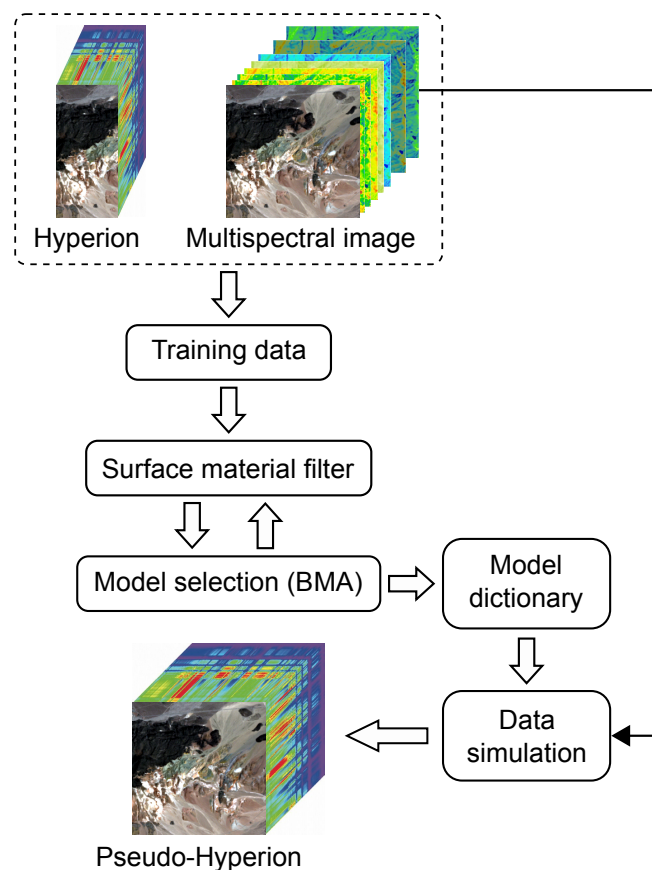


Fig. 4.4 Workflow of constructing pseudo-Hyperion image using PHITA.

Hills, our validation area for mineral mapping accuracy. The training area of the ALI image was narrower, 72% that of the other images (Figure 4.1).

The next step was the use of a geologic map of rock-type distribution as a surface material filter, because the regression models with BMA were constructed for each rock type shown in Figure 4.1. The training area had more rock types than the validation area. Finally, pseudo-Hyperion images of 176 bands were simulated using the model dictionary from each multispectral image for the training and validation areas (Volcanic Hills), which corresponded to two transformation cases inside and outside the overlap area, respectively. The programming with three main steps is summarized as follows.

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#### Algorithm of PHITA

---

**Input:** Hyperion image  $H$ , multispectral image  $M$ , filter (geological map), and boundaries of training and validation areas.

**Output:** Pseudo-Hyperion images  $\hat{H}_t$  and  $\hat{H}_v$  for training and validation areas, respectively.

**For**  $i = 1, 2, \dots$ , the maximum band number of  $H$  do

1. **Initialize**  $\vartheta$  polygons of rock type distributions;

2. **Initialize** empty sets  $\hat{H}_{t0}$  and  $\hat{H}_{v0}$  for training and validation areas,

respectively, set  $\hat{H}_t = \hat{H}_{t0}$  and  $\hat{H}_v = \hat{H}_{v0}$ ;

3. **For**  $\vartheta = 1, 2, \dots$ , max-iteration do

- Clip  $H$  and  $M$  to the polygon of  $\vartheta^{th}$  rock type,
- Initialize Equation 4.1,
- Variable selection by BMA,
- Calculate  $\hat{H}_t^\vartheta$  and  $\hat{H}_v^\vartheta$  using the best models,
- $\hat{H}_t = \text{mosaic}(\hat{H}_t \text{ and } \hat{H}_t^\vartheta)$ ,  $\hat{H}_v = \text{mosaic}(\hat{H}_v \text{ and } \hat{H}_v^\vartheta)$ ;

4. **Calculate** statistical indices (see Section ??);
  5. **Write**  $\hat{H}_t$  and  $\hat{H}_v$  of band  $i$  into TIFF files.
- 

### 4.3.2 Image preprocessing

All multispectral and Hyperion images were corrected for atmospheric and topographic effects using the FLAASH module of ENVI software and non-Lambertian C-correction method, respectively. A push-broom Hyperion image suffers from systematic and random noises known as the spectral smile and vertical streaks, which must be reduced in a pre-processing step. The smile effect was corrected using a moving linear fit and interpolation method following (Goodenough et al., 2003). Then, the stripes were removed by the local de-stripping method (Datt et al., 2003). Finally, a first-degree polynomial warp with the nearest-neighbor resampling method and at least 15 ground GCPs were used to co-register each multispectral image to the Hyperion image. The RMSE for the co-registration of GCPs was conditioned to be less than 0.5 pixels. More details of preprocessing methods are described in Section 2.3.

## 4.4 Results

### 4.4.1 Comparison of general appearance

Using the PHITA model dictionary, the TM, ETM+, OLI and ALI images were transformed into pseudo-Hyperion images for the training area and validation of the Volcanic Hills area. The first PHITA evaluation simply compared general appearances of the natural color composite original and pseudo-images, using three visible bands (R: 0.681  $\mu\text{m}$ , G: 0.529  $\mu\text{m}$ , and B: 0.468  $\mu\text{m}$ ) for the upper part



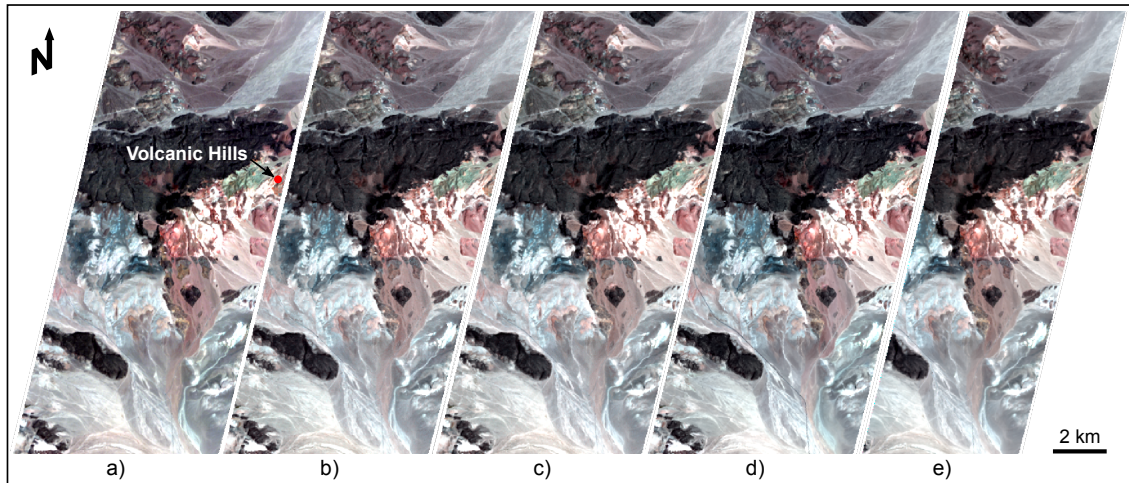


Fig. 4.5 Comparison of natural color composite images (R: 0.681  $\mu\text{m}$ , G: 0.529  $\mu\text{m}$ , and B: 0.468  $\mu\text{m}$ ) between a part of (a) the original Hyperion and pseudo-Hyperion images transformed from (b) TM, (c) ETM+, (d) OLI, and (e) ALI images. Selected area partially covers Volcanic Hills in the north-central Fish Lake Valley geothermal prospect area (Figure 4.1).

of the training area partially covering the Volcanic Hills. This sub-area is chiefly overlain by Tertiary rhyolite ash flow tufts (Littlefield and Calvin, 2014). Obviously, all the natural color composited pseudo-Hyperion images were identical to the original image (Figure 4.5), because the topographic features, textures, and color tones of pseudo-images are nearly the same as the original. This confirms the usefulness of the PHITA, in that it produces pseudo-images almost equivalent to the original image in general appearance.

Table 4.4 Comparison of means of statistical indices for matching of reflectances in all bands between original and pseudo-Hyperion images transformed from TM, ETM+, OLI and ALI images by PHITA for training area.

| Image | PCC   | RMSE  | PSNR  | UIQI  | ERGAS | SAM   | MSSIM |
|-------|-------|-------|-------|-------|-------|-------|-------|
| TM    | 0.956 | 0.019 | 29.46 | 0.955 | 7.74  | 0.037 | 0.955 |
| ETM+  | 0.959 | 0.018 | 29.58 | 0.957 | 7.55  | 0.036 | 0.957 |
| OLI   | 0.945 | 0.021 | 28.44 | 0.944 | 8.70  | 0.037 | 0.944 |
| ALI   | 0.964 | 0.017 | 30.76 | 0.963 | 6.57  | 0.034 | 0.963 |

### 4.4.2 Statistical comparison

For the training area, all the statistical indices (PCC, RMSE, PSNR, ERGAS, UIQI, and SSIM) indicated that the four pseudo-Hyperion images were strongly correlated with the original image for the relationship of reflectances in all 176 bands (Figure 4.6). Most PCCs, UIQIs and SSIMs of the TM, ETM+ and ALI based images, and > 50% of those of the OLI-based image exceeded 0.95. All the quality indices of the ALI-based image had a narrower range than the other images, which signifies that simulation accuracies of the latter image were uniform across all bands. However, the hyperspectral transformation did not perform well for some bands, as shown by outliers of all indices in common to all images. The ALI and OLI based images tended to have the maxima and minima of the PCCs, PSNRs, UIQIs, and SSIMs, respectively, whereas opposite tendencies were evident in the RMSEs and ERGASs. Accuracy of the ETM+ based image was slightly better than the TM-based image according to the quality indices. Therefore, based on the statistical indices, the transformation accuracy was highest for the ALI image, followed by the ETM+, TM and OLI images in descending order. This order is more clearly shown by the mean values of indices for all bands (Table 4.4), whose orders of accuracy were the same, except that the SAMs of the TM, ETM+ and OLI based images were not very different.

Accuracy of Hyperion image reconstruction can be addressed more in detail using SSIM values of the 176 bands (Figure 4.7), because SSIM is the most popular index for measuring similarity between two images. The most conspicuous feature of SSIMs common to the four pseudo-images is that the values tend to decrease in wavelength ranges affected by atmospheric conditions such as absorption of water vapor (0.933–0.943, 1.124–1.144, 1.346, 1.426–1.477, 1.800–1.810, and 1.942–1.962  $\mu\text{m}$ ),  $\text{O}_2$  (around 0.690 and 0.760  $\mu\text{m}$ ), and  $\text{CO}_2$  (1.952–2.012  $\mu\text{m}$ ). Generally, the SSIMs were slightly larger in the VNIR region than in the SWIR region. The

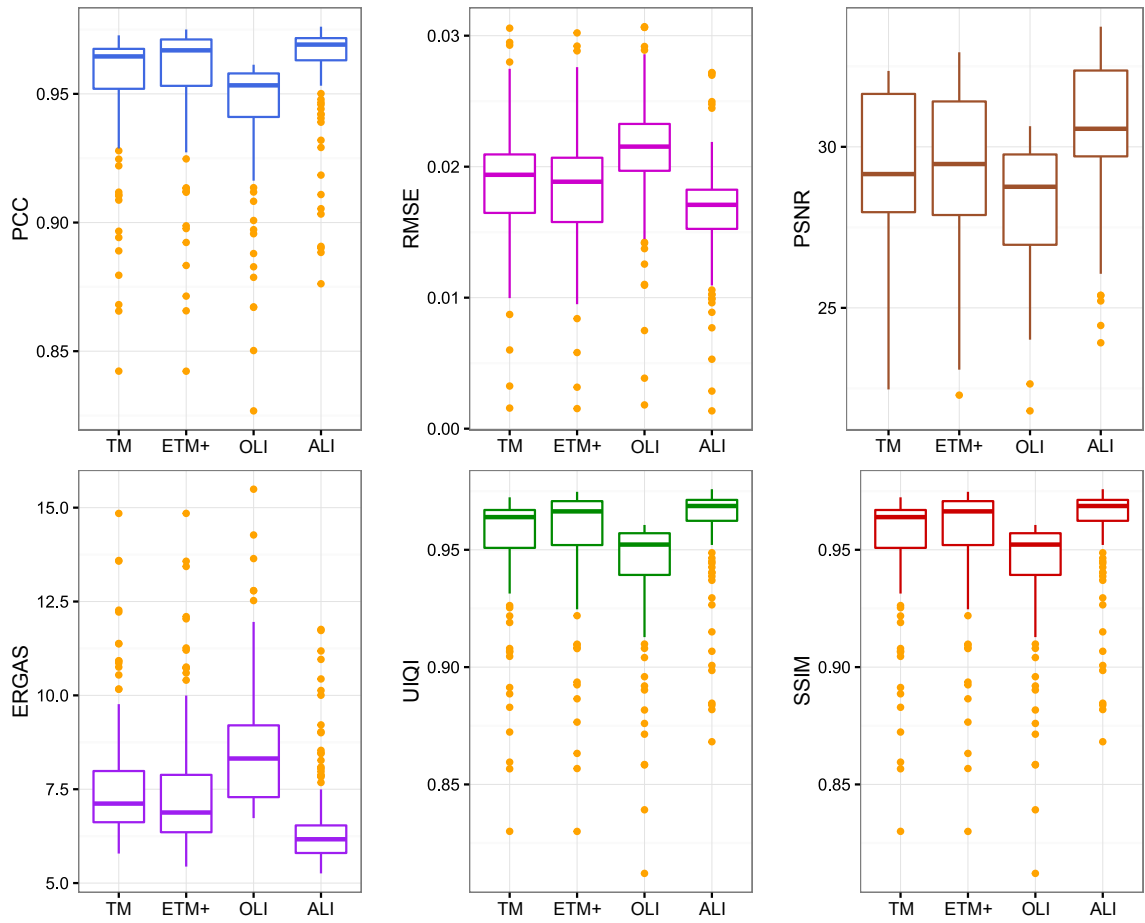


Fig. 4.6 Box plots of six statistical indices (PCC, RMSE, PSNR, ERGAS, UIQI, and SSIM) for matching of reflectances in 176 bands between original and pseudo-Hyperion images transformed from TM, ETM+, OLI, and ALI images by PHITA for training area.

ALI-based imagery had the largest SSIMs over nearly all bands, except for the 0.732–0.915  $\mu\text{m}$  region in which SSIMs of the ETM+ based image were minutely larger than those based on ALI. The best accuracy of the ALI-based image is appeared particularly in the region  $> 2.0 \mu\text{m}$ , in which the differences in SSIMs between the ALI-based and other three images were remarkable. On the contrary, SSIMs of the OLI-based image had minima across all bands. Superiority of the ETM+ based image over the TM-based image decreased in the SWIR region, in which their SSIMs were nearly identical.

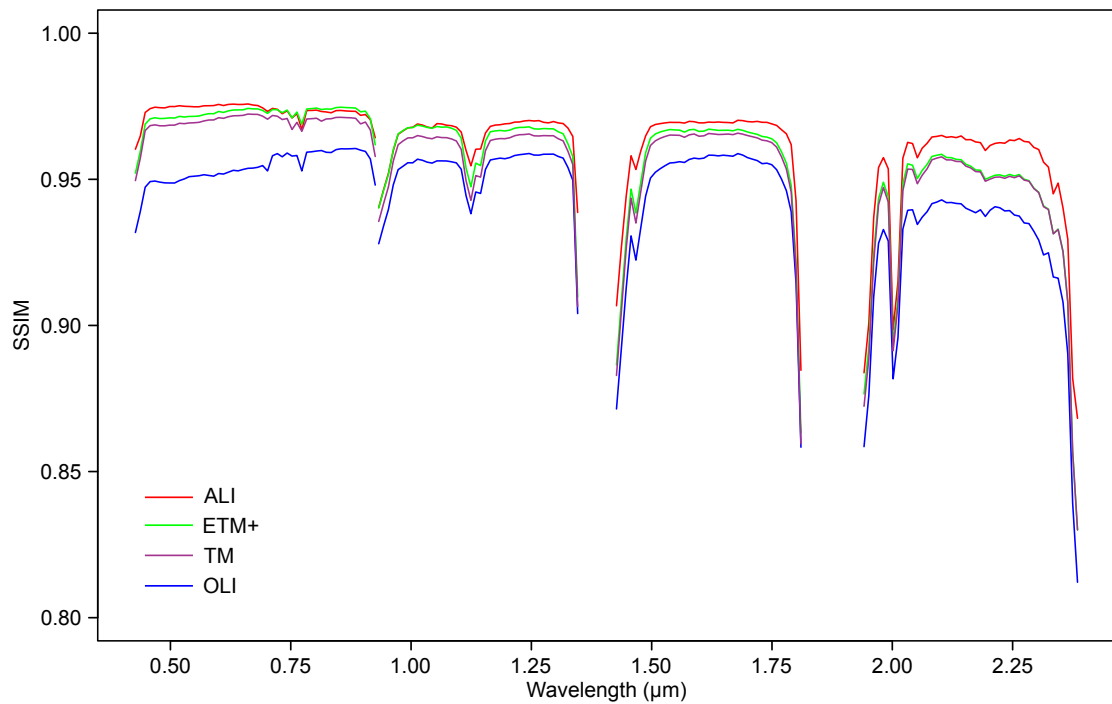


Fig. 4.7 Comparison of SSIM values for transformation accuracy of four multi-spectral images in each of 176 bands for training area, similar to Figure 4.6 and Table 4.4.

#### 4.4.3 Comparison of spectral reconstruction accuracy

Accuracy of reflectance spectral reconstruction was evaluated for typical surface materials in the study area, i.e., rock composed mainly of muscovite and chlorite mixtures, soil, and vegetation. Their distributions were delineated from the mineral map prepared by Littlefield and Calvin (2014) and high-resolution Google Earth images. Each spectral profile was the mean spectrum in a  $2 \times 2$  pixel window in the training area. This window size was determined as optimal to minimize the mixing of surface materials and pixel misalignment from image co-registration error. The spectral profiles of three materials were generally in agreement between the original and pseudo-Hyperion images, common to the four multispectral images, and this agreement was stronger in the VNIR region than in the SWIR region (Figure 4.8). Another common feature was that the pseudo-reflectance spectra were smoother than the original spectra.

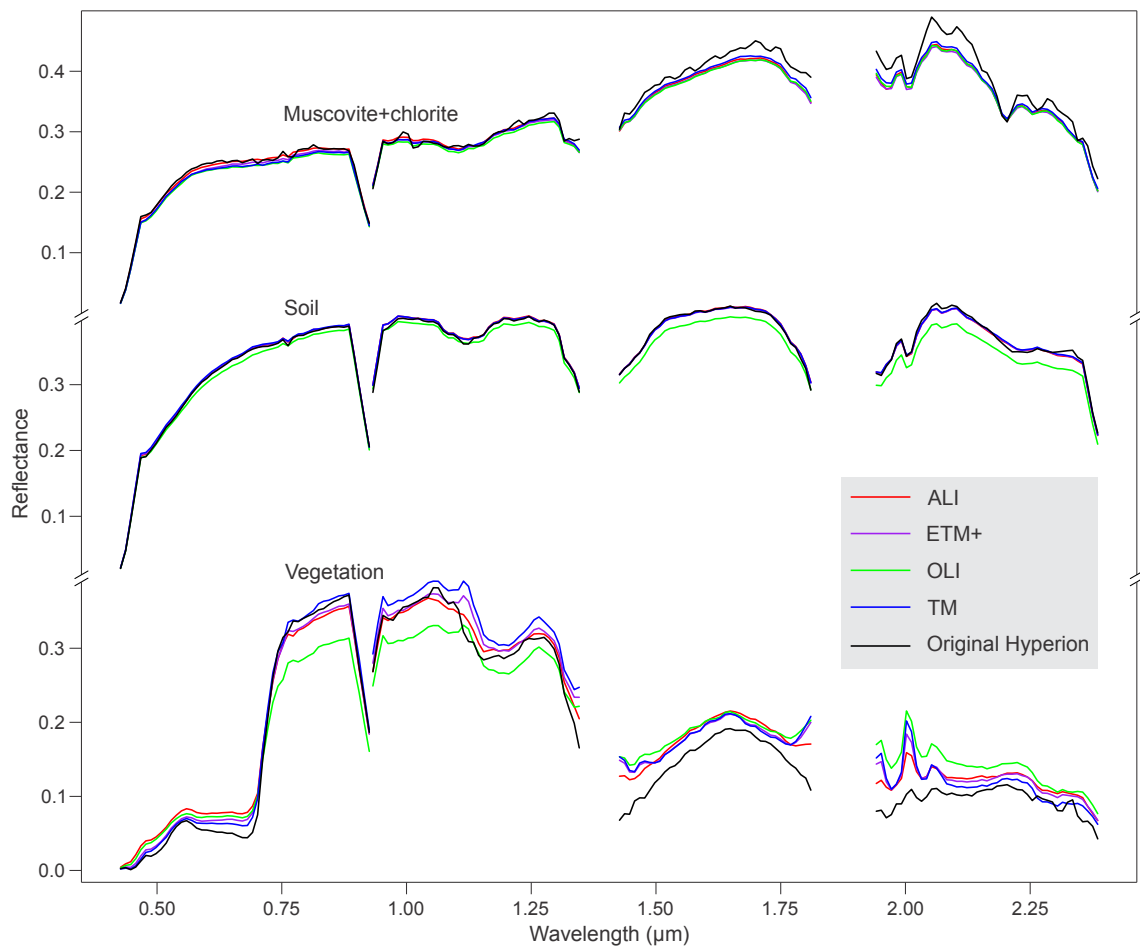


Fig. 4.8 Comparison of spectral profiles of muscovite and chlorite mixtures, soil, and vegetation between original and pseudo-Hyperion images transformed from four multispectral images. Each profile shows mean spectra in a  $2 \times 2$  pixel window in training area.

Among the three materials, the pseudo-(muscovite + chlorite) spectral profiles were similar to the original spectral profile for all pseudo-images in the VNIR and SWIR regions. The soil spectral profiles were almost perfectly reconstructed from the TM, ETM+ and ALI based images for all bands, whereas the profile from the OLI-based image was shifted to and overall lower reflectance. An interesting advantage of the PHITA is that vegetation spectra were adequately reconstructed from the TM, ETM+ and ALI-based images, despite sparse vegetation cover in the training area. In particular, a green reflectance peak around  $0.55 \mu\text{m}$ , red absorption at  $\sim 0.66\text{--}0.67 \mu\text{m}$ , red-edge centered at  $\sim 0.72 \mu\text{m}$ , and reflectance peak

in the far NIR at  $\sim 1.28 \mu\text{m}$  clearly appeared in the pseudo-spectral profiles. These findings demonstrate a powerful PHITA capability for reconstructing reflectance spectra, regardless of a wide or narrow distribution of the selected surface materials. Although the spectral reconstruction accuracy of the OLI-based image was the poorest, the major absorptions were correct in its pseudo-spectral profile.

#### 4.4.4 Comparison of mineral mapping accuracy

Reflectance spectra in a part of the SWIR region ( $2.0\text{--}2.4 \mu\text{m}$ ) were used to identify minerals from the original and pseudo-Hyperion images of the Volcanic Hills, in which muscovite and chlorite mixtures, opal or chalcedony, and calcite were the main endmembers based on the identification of purest pixels and detailed mineral maps of Kratt et al. (2009) and Littlefield and Calvin (2014). Figure 4.9 compares

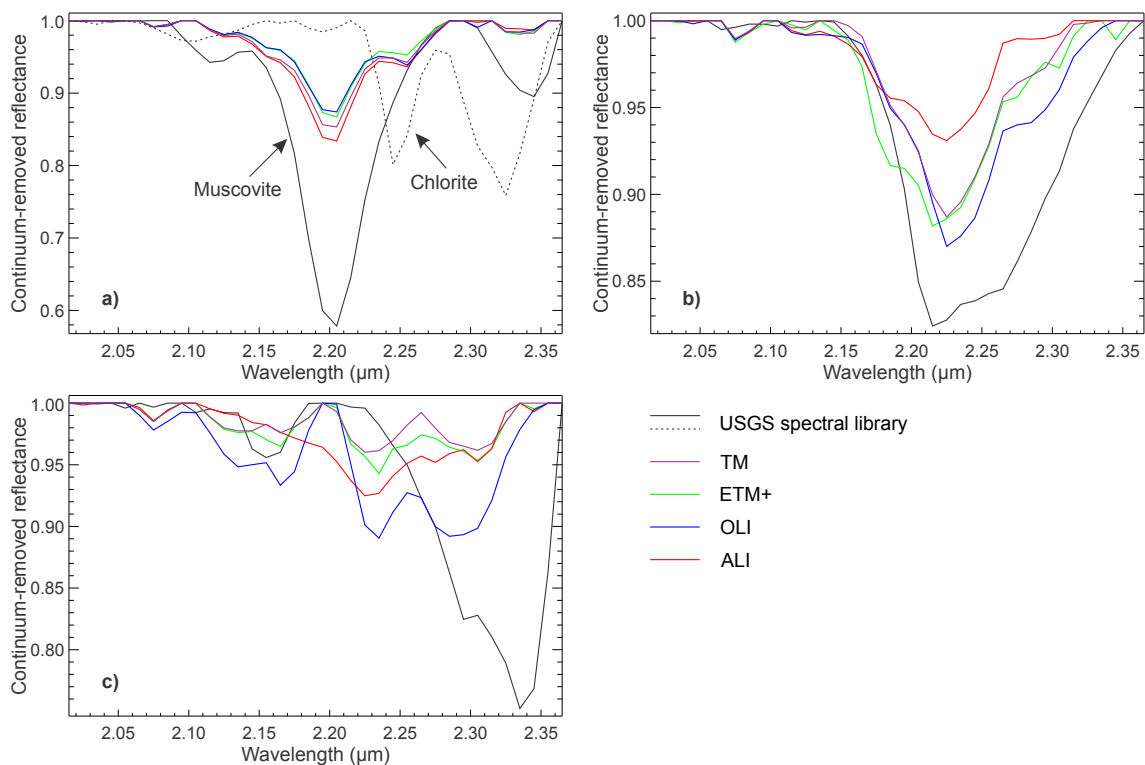


Fig. 4.9 Comparison of pseudo-reflectance spectra of (a) muscovite and chlorite mixtures, (b) opal or chalcedony, and (c) calcite from purest pixels of pseudo-Hyperion images transformed from four multispectral images, with reflectance spectra of these minerals derived from USGS spectral library.

reflectance spectra of these selected endmembers derived from the USGS spectral library with those of the pseudo-Hyperion images transformed from the four multispectral images. Those pseudo-spectra were average spectra of the purest pixels that were classified in an  $n$ -dimensional scatter plot. Muscovite and chlorite have remarkable reflectance absorption in the SWIR region at 2.2 and 2.35  $\mu\text{m}$  and 2.25 and 2.32  $\mu\text{m}$ , respectively. Common to the four pseudo-reflectance spectra of the muscovite and chlorite mixtures, there is deep absorption at 2.2  $\mu\text{m}$  and shallow absorption at 2.25  $\mu\text{m}$ , which correspond to the absorptions of muscovite and chlorite, respectively. A broad shallow absorption at  $\sim 2.34$   $\mu\text{m}$  is from combined absorptions of the two minerals. The pseudo-reflectance spectra of opal or chalcedony well match the wavelength of a broad Si–OH absorption feature at 2.2  $\mu\text{m}$ , although all four absorptions were shallower than the reference reflectance; in particular, the spectrum from the ALI-based image is the shallowest and the other three are nearly identical. Reproducibility of the reflectance absorption at 2.33  $\mu\text{m}$  of calcite caused by  $\text{CO}_3^{2-}$  is weak, because the absorption wavelengths are shifted to shorter values around 2.3–2.32  $\mu\text{m}$ . All four absorptions are shallower and broader than the reference spectra, and the pseudo-spectra vary with the multispectral images.

For the mineral mapping, the abundance and distribution of each selected endmember were estimated by an MF score threshold and infeasibility values, which were  $> 0.3$  and  $< 20$ , respectively. These thresholds were chosen to minimize misclassification of the main endmembers and were fixed for the four pseudo-Hyperion images. The resultant endmember distributions were compared with a reference map, which was based on analyses of HyMap, AVIRIS, and ProSpecTIR images with high spatial resolutions (2–4 m), and field surveys by Kratt et al. (2009) and Littlefield and Calvin (2014). This was done to verify the accuracy of mineral classification. The classification accuracies were summarized by a confusion matrix (Table 4.5) and quality indices of the mineral identification (Table 4.6) excluding

Table 4.5 Confusion matrix indicating mineral identification accuracy of MTMF results of pseudo-Hyperion images, from comparison with reference map prepared by Kratt et al. (2009) and Littlefield and Calvin (2014). Unclassified pixels were not included in accuracy counts.

| <b>Pseudo-Hyperion (pixels)</b><br><i>TM-based image</i> | <b>Reference map (pixels)</b> |         |       | <b>Total (pixels)</b> | <b>User's accuracy (%)</b> |
|----------------------------------------------------------|-------------------------------|---------|-------|-----------------------|----------------------------|
|                                                          | Muscovite+chlorite            | Calcite | Opal  |                       |                            |
| Muscovite+chlorite                                       | 1324                          | 10      | 1     | 1335                  | 99.18                      |
| Calcite                                                  | 49                            | 75      | 1     | 125                   | 60.00                      |
| Opal                                                     | 1                             | 0       | 77    | 78                    | 98.72                      |
| Total (pixels)                                           | 1374                          | 85      | 79    | 1538                  |                            |
| Producer's accuracy (%)                                  | 96.36                         | 88.24   | 97.47 |                       |                            |
| <i>ETM+-based image</i>                                  |                               |         |       |                       |                            |
| Muscovite+chlorite                                       | 1308                          | 18      | 1     | 1327                  | 98.57                      |
| Calcite                                                  | 15                            | 95      | 0     | 110                   | 86.36                      |
| Opal                                                     | 9                             | 0       | 82    | 91                    | 90.11                      |
| Total (pixels)                                           | 1332                          | 113     | 83    | 1528                  |                            |
| Producer's accuracy (%)                                  | 98.20                         | 84.07   | 98.80 |                       |                            |
| <i>OLI-based image</i>                                   |                               |         |       |                       |                            |
| Muscovite+chlorite                                       | 751                           | 13      | 0     | 764                   | 98.30                      |
| Calcite                                                  | 21                            | 55      | 1     | 77                    | 71.43                      |
| Opal                                                     | 0                             | 0       | 71    | 71                    | 100.00                     |
| Total (pixels)                                           | 772                           | 68      | 72    | 912                   |                            |
| Producer's accuracy (%)                                  | 97.28                         | 80.88   | 98.61 |                       |                            |
| <i>ALI-based image</i>                                   |                               |         |       |                       |                            |
| Muscovite+chlorite                                       | 1493                          | 11      | 2     | 1506                  | 99.14                      |
| Calcite                                                  | 0                             | 159     | 11    | 170                   | 93.53                      |
| Opal                                                     | 0                             | 0       | 104   | 104                   | 100.00                     |
| Total (pixels)                                           | 1493                          | 170     | 117   | 1780                  |                            |
| Producer's accuracy (%)                                  | 100.00                        | 93.53   | 88.89 |                       |                            |



Table 4.6 Overall accuracy and Kappa coefficient for agreement of endmember class between each pseudo-Hyperion image and reference map. These results exclude unclassified pixels.

| Indices              | TM    | ETM+  | OLI   | ALI   |
|----------------------|-------|-------|-------|-------|
| Overall accuracy (%) | 95.97 | 97.19 | 96.16 | 98.65 |
| Kappa coefficient    | 0.81  | 0.88  | 0.86  | 0.95  |

unclassified pixels, whereas accuracies including the unclassified pixels are shown in Tables 4.7 and 4.8. The resultant mineral maps generated from the pseudo-Hyperion images for the Volcanic Hills are compared in Figure 4.10.

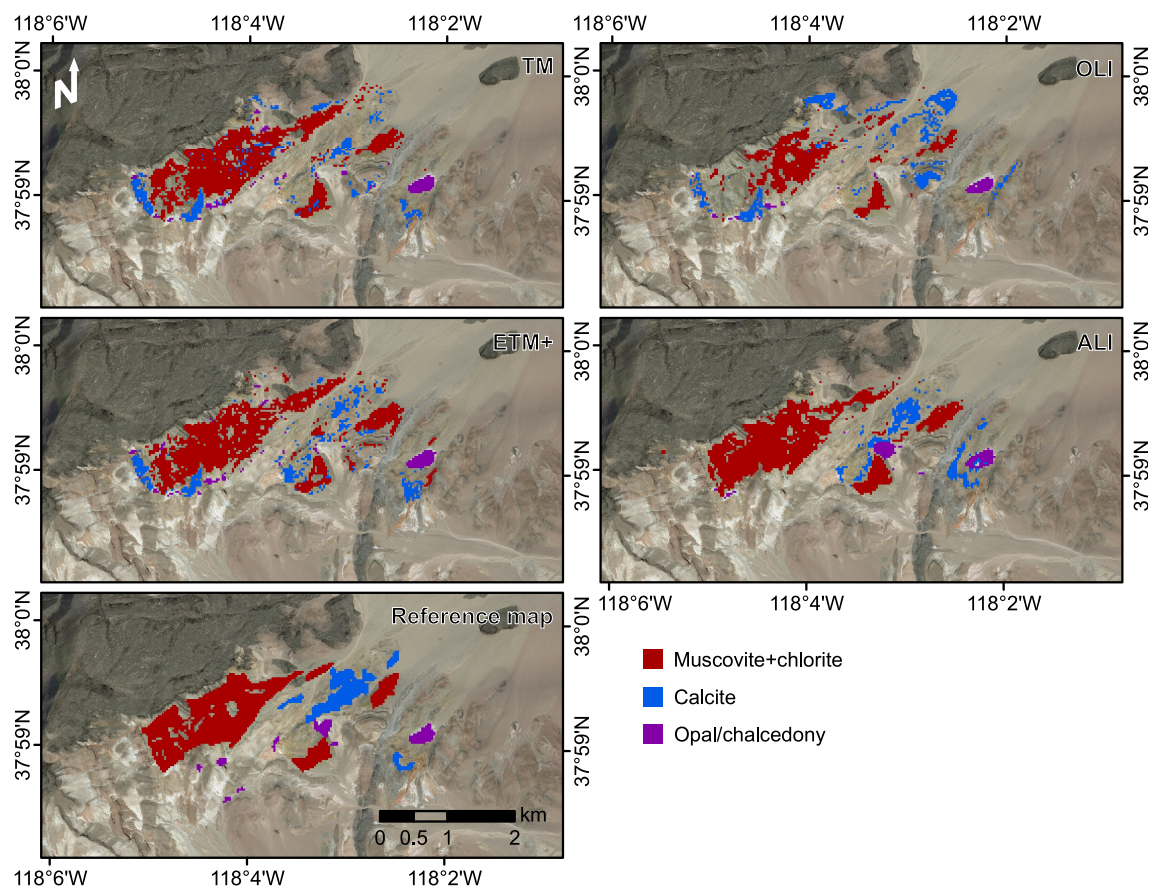


Fig. 4.10 MTMF mineral maps showing most dominant endmember at each pixel for the Volcanic Hills, produced from pseudo-Hyperion images transformed from four multispectral images and their comparison with reference map based on Kratt et al. (2009) and Littlefield and Calvin (2014). A Google Earth image was used for the background of each map.

Table 4.7 Confusion matrix indicating mineral identification accuracy of MTMF results of pseudo-Hyperion images, by comparison to reference map. Unclassified pixels were included in accuracy counts.

| <b>Pseudo-Hyperion (pixels)</b> |        | <b>Reference map (pixels)</b> |                    |         |      | Total<br>(pixels) | User's<br>accuracy (%) |
|---------------------------------|--------|-------------------------------|--------------------|---------|------|-------------------|------------------------|
| <i>TM-based image</i>           |        | Unclassified                  | Muscovite+chlorite | Calcite | Opal |                   |                        |
| Unclassified                    | 265    | 391                           | 380                | 109     | 1145 | 23.14             |                        |
| Muscovite+chlorite              | 0      | 1324                          | 10                 | 1       | 1335 | 99.18             |                        |
| Calcite                         | 0      | 49                            | 75                 | 1       | 125  | 60.00             |                        |
| Opal                            | 0      | 1                             | 0                  | 77      | 78   | 98.72             |                        |
| Total (pixels)                  | 265    | 1765                          | 465                | 188     | 2683 |                   |                        |
| Producer's accuracy (%)         | 100.00 | 75.01                         | 16.13              | 40.96   |      |                   |                        |
| <i>ETM+-based image</i>         |        | Unclassified                  | Muscovite+chlorite | Calcite | Opal |                   |                        |
| Unclassified                    | 265    | 433                           | 352                | 105     | 1155 | 22.94             |                        |
| Muscovite+chlorite              | 0      | 1308                          | 18                 | 1       | 1327 | 98.57             |                        |
| Calcite                         | 0      | 15                            | 95                 | 0       | 110  | 86.36             |                        |
| Opal                            | 0      | 9                             | 0                  | 82      | 91   | 90.11             |                        |
| Total (pixels)                  | 265    | 1374                          | 85                 | 79      | 1538 |                   |                        |
| Producer's accuracy (%)         | 100.00 | 74.11                         | 20.43              | 43.62   |      |                   |                        |
| <i>OLI-based image</i>          |        | Unclassified                  | Muscovite+chlorite | Calcite | Opal |                   |                        |
| Unclassified                    | 265    | 993                           | 397                | 116     | 1771 | 14.96             |                        |
| Muscovite+chlorite              | 0      | 751                           | 13                 | 0       | 764  | 98.30             |                        |
| Calcite                         | 0      | 21                            | 55                 | 1       | 77   | 71.43             |                        |
| Opal                            | 0      | 0                             | 0                  | 71      | 71   | 100.00            |                        |
| Total (pixels)                  | 265    | 1765                          | 465                | 188     | 2683 |                   |                        |
| Producer's accuracy (%)         | 100.00 | 42.55                         | 11.83              | 37.77   |      |                   |                        |
| <i>ALI-based image</i>          |        | Unclassified                  | Muscovite+chlorite | Calcite | Opal |                   |                        |
| Unclassified                    | 265    | 272                           | 295                | 71      | 903  | 29.35             |                        |
| Muscovite+chlorite              | 0      | 1493                          | 11                 | 2       | 1506 | 99.14             |                        |
| Calcite                         | 0      | 0                             | 159                | 11      | 170  | 93.53             |                        |
| Opal                            | 0      | 0                             | 0                  | 104     | 104  | 100.00            |                        |
| Total (pixels)                  | 265    | 1765                          | 465                | 188     | 2683 |                   |                        |
| Producer's accuracy (%)         | 100.00 | 84.59                         | 34.19              | 55.32   |      |                   |                        |

Table 4.8 Overall accuracy and Kappa coefficient for agreement of endmember class between each pseudo-Hyperion image and reference map. These results include unclassified pixels.

| Indices              | TM    | ETM+  | OLI   | ALI   |
|----------------------|-------|-------|-------|-------|
| Overall accuracy (%) | 64.89 | 65.23 | 42.56 | 75.33 |
| Kappa coefficient    | 0.43  | 0.44  | 0.22  | 0.58  |

The confusion matrix excluding the unclassified pixels demonstrates that every pseudo-Hyperion image had high accuracies of mineral identification, as demonstrated by PAs and UAs exceeding 96% and 98% for muscovite and chlorite mixtures, respectively, 80% and 60% for calcite, and 88% and 90% for opal. OA and KC maximized with the ALI-based image (98.65% and 0.95), followed by the ETM+, OLI, and TM based images in descending order (Table 4.6). Even the minimum KC from the TM-based image had a large value, 0.81. The main detection errors were opal misclassified as calcite by the ALI-based image (9.4% of total opal pixels) and calcite misclassified as muscovite and chlorite mixtures by the ETM+, OLI, and ALI based images (15.9%, 19.1%, and 6.5% of total calcite pixels, respectively).

By including the unclassified pixels, the OA and KC of all pseudo-Hyperion images decreased to the ranges 42.56%–75.33% and 0.22–0.58, respectively, much smaller than those without the unclassified pixels. However, these figures are consistent with the result of Kruse et al. (2003) that showed a decline of mineral identification accuracies of a Hyperion image from the inclusion of unclassified pixels, using the same method as in the present study. The successful identification of the three main minerals demonstrates a noteworthy advantage of the pseudo-images as compared with the four multispectral images, which could only show the potential existence of mineral groups such as iron or clay (Sabins, 1999; van der Meer et al., 2012).

The most unsatisfactory PHITA result is that many pixels of calcite in the reference map were not identified from the pseudo-Hyperion images. This was shown by low PAs in the confusion matrix, i.e., 16.1% for the TM-based image, 20.4% for the ETM+ based, 11.8% for the OLI-based, and 34.2% for the ALI-based, which originated from the low reconstruction accuracy of the reflectance spectrum of calcite as mentioned previously (Figure 4.9). Additionally, classification accuracies of opal were relatively low, common to the four pseudo-images. For both PA and UA of all pseudo-images, calcite, opal, and muscovite and chlorite mixtures generally accounted for the minimum, small, and maximum values, respectively, except that the UAs of opal in the case of OLI and ALI based images had maximum values. OA and KC of the OLI-based image were the poorest, which mainly originated from the fact that 56% of the muscovite and chlorite mixture pixels in the reference map could not be identified and were categorized as unclassified pixels. Both OA and KC of the ETM+ based image were higher than those of the TM-based image. Similar to the case excluding the unclassified pixels, the highest accuracy was achieved by the ALI-based image, as indicated by increases of OA and KC relative to the ETM+ based image, by 10.1% and 0.14, respectively.

Although the distribution area of muscovite shown in the reference map is very limited (Figure 4.11), in addition to the three main endmembers, we attempted to identify the muscovite distribution from the pseudo-Hyperion images. This approach is helpful to compare the level of detail of the resultant mineral maps. Only the pseudo-image from the ETM+ image succeeded in detecting this minor mineral, with a classification accuracy ~20%. Both the reflectance spectra of the muscovite and chlorite mixtures and the muscovite in this pseudo-image had strong and weak absorption at 2.2 and 2.35  $\mu\text{m}$ , respectively, and the bottom of weak muscovite absorption curve is precisely at 2.35  $\mu\text{m}$ , as with the reference muscovite spectrum in the USGS library. However, the absorption bottom of the muscovite and chlorite mixture shifted toward shorter wavelengths. One

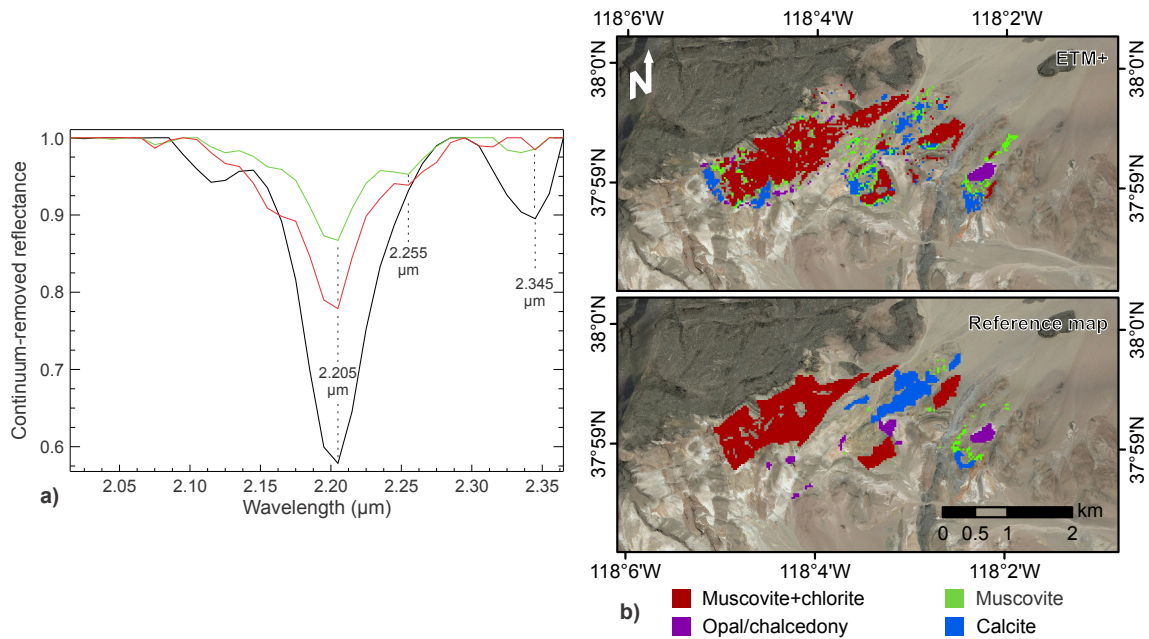


Fig. 4.11 (a) Comparison of reflectance spectra of muscovite and chlorite mixtures (green) and muscovite (red) in pseudo-Hyperion image transformed from ETM+ image with muscovite spectrum in the USGS library (black) and (b) comparison of MTMF mineral map of that pseudo-Hyperion image with reference map that includes muscovite distribution added to the map of Figure 4.10.

feature different from the reference is that both had minute absorption at 2.26 μm (Figure 4.11A), which decreased the classification accuracy of the two endmembers. This misclassification was mainly at the periphery of the muscovite and chlorite mixture distribution (Figure 4.11B). Although muscovite was added to the reference map in Figure 4.10, its distribution is limited. The muscovite pixels appear much more in the pseudo-image.

## 4.5 Discussion

The greatest accuracy of the ALI-based image can be attributed to: (1) greater overlap of wavelength ranges with the Hyperion image than the other three multispectral images and (2) earth observation concurrent with Hyperion because of sensors onboard the same satellite. The overlap of wavelength ranges between the Hyperion and multispectral bands are crucial to the hyperspectral transformation

accuracy of the PHITA, which assumes a linear relationship of the Hyperion and multispectral reflectances between their bands. The same orbit and acquisition time equalize atmospheric conditions and solar illumination strength between the Hyperion and ALI images. The acquisition time of the ETM+ image is closer to that of the Hyperion image than the TM image, which can account for the better transformation accuracy of the ETM+ image, even though the band specifications of the ETM+ and TM sensors are nearly the same.

There are three possible reasons for the lowest transformation accuracy of the OLI image. The first is the narrower wavelength ranges of the OLI sensor relative to the ETM+ and TM sensors between the corresponding bands. For instance, the spectral response functions of the blue, green, and red bands of the OLI sensor overlap with those of corresponding bands of the ETM+ sensor, by 82.76%, 71.08%, and 60.63%, respectively. The spectral response functions of one NIR and two SWIR bands of the OLI sensor are entirely included in those of corresponding bands of the ETM+ sensor. However, overlaps are only 23.14%, 42.22%, and 66.69%, respectively, because of the narrow ranges of the OLI bands (Roy et al., 2016). Accordingly, linear relationships of reflectances that may hold between the ETM+ and Hyperion bands are not partially applied to the OLI bands. The second reason is difficulty in correct co-registration of the OLI image to the Hyperion image. This is because, as described in Section 4.2.2, pixel columns of the OLI and Hyperion images are not parallel. Although the training area is an arid land covered mostly by soil and rock, reflectances may have changed between those two images because of a long interval in acquisition time (12 years). This change in surface condition is the third reason.

In general, mineral identification accuracies of all the pseudo-images declined when unclassified pixels were included in the accuracy counts. This reduced identification may be attributable to the difference in spatial resolution between the Hyperion image (30 m) and the reference map generated from airborne

hyperspectral images (2–4 m). The coarser resolution causes a problem with mixing of reflectance spectra of two or more materials in a pixel. Because of this effect, many pixels that did not have strong spectral correlation with the purest pixels of each endmember were not well classified in the resultant mineral maps. Therefore, a spatial downscaling technique integrated with the PHITA is indispensable to improve mineral identification accuracy. The lowest PA and UA of calcite for all the pseudo-images related to the unsuccessfully reconstructed spectra may have largely originated from the absence of calcite in the training area. An interesting result was that the distribution of a minor mineral, muscovite, could be identified and mapped by the pseudo-Hyperion image from the ETM+ image, but could not be identified from the ALI-based image. This was likely caused by a different size of training area, i.e., that of the ETM+ image was wider than that of the ALI image.

## 4.6 Conclusions

This study is the first examination of hyperspectral transformation accuracies from multispectral images for an arid area using TM, ETM+, OLI and ALI sensor images and a Hyperion sensor image for typical multispectral and hyperspectral images, respectively, and the PHITA. Inside and outside the overlap area of the two types of image, transformation accuracies of matching between the original and pseudo-Hyperion images were evaluated using multiple criteria, i.e., general appearance, spectral reconstruction, statistical indices, and endmember distributions. We demonstrated high accuracies of PHITA transformation of reflectances in a limited number of bands into the available 176 bands for the overlapped training area image, common to the four images. Among them, the highest and lowest accuracies were obtained from the ALI and OLI images, respectively, and accuracy of the ETM+ image was slightly better than that of the TM image. The overlap of

wavelength ranges between the Hyperion and multispectral bands, and similar surface conditions between the training and transformation area, were considered crucial to hyperspectral transformation accuracy.

In the case excluding unclassified pixels, classification accuracies of the three main minerals (muscovite and chlorite mixtures, opal, and calcite) were satisfactorily high from every pseudo-Hyperion image. Although those accuracies declined upon the inclusion of unclassified pixels, the results were similar to a preceding study that used a Hyperion image for mineral mapping under the same surface conditions as in our case study area (the Volcanic Hills, a part of the Fish Lake Valley geothermal prospect area). Thus, the pseudo-Hyperion images produced by the PHITA from the TM, ETM+, OLI and ALI images were confirmed as sufficiently applicable to mineral identification and mapping of arid or semiarid mineralized areas similar to the study area. TM, OLI, and ALI images can be alternatives to an ETM+ image for the hyperspectral transformation. This transformation may contribute to global monitoring of detailed changes in land use and land cover, vegetation dynamics, and other land environmental issues such as mining. Because of the Landsat 7 SLC failure, such alternatives are also necessary to fill gaps of ETM+ images after May 2003. In addition to the increase in spectral resolution that was the main theme in this study, increase in image spatial resolution is indispensable to precise identification and detailed mapping of target materials for resource exploration. The integration of increases in both spectral and spatial resolution should be an important next step.



# **Chapter 5**

## **Joint spatial and spectral downscaling in a porphyry copper area**

### **5.1 Introduction**

From Chapter 2 to 4, PHITA has been developed for transforming Landsat and EO-1 ALI images into a spaceborne hyperspectral image, EO-1 Hyperion image. PHITA was proven effective and has the potential to globally transform accumulated Landsat images into pseudo-Hyperion images for any area without Hyperion coverage. However, some mineral endmember spectra were not well simulated in the pseudo-image. The essential factor regarding mineral classification accuracy of the pseudo-image is a coarse spatial resolution of 30-m. A pseudo-spectrum becomes a product of mixing two or more endmembers. In addition, it is difficult to reconstruct similar SWIR spectra of some minerals, such as kaolinite and alunite, with high accuracy because only one SWIR band is available in Landsat imagery.

An airborne hyperspectral imager, AVIRIS, is more advantage than Hyperion sensor in term of spatial resolution and high SNR. AVIRIS is an optical sensor

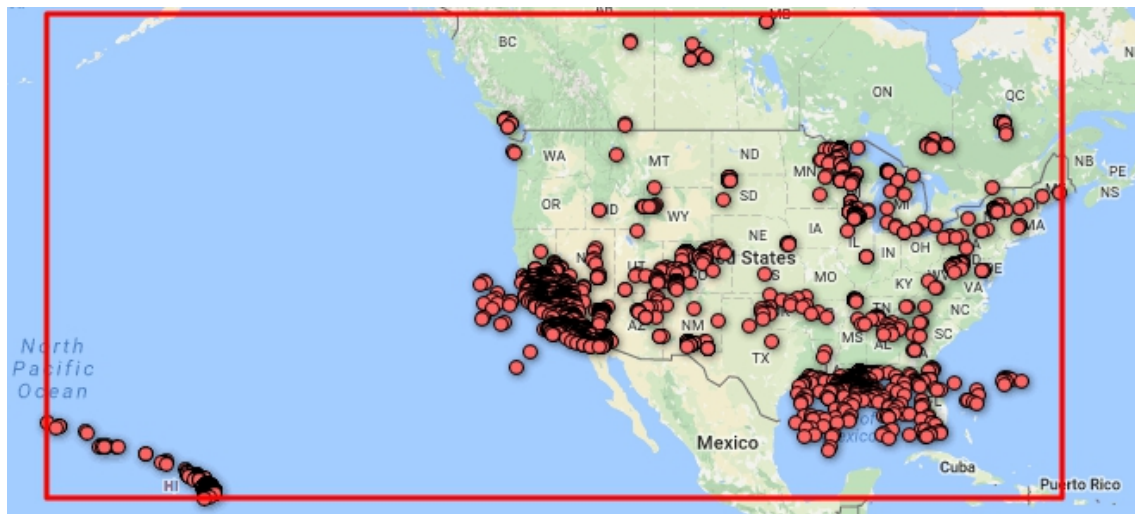


Fig. 5.1 The locations (red circles) of archived AVIRIS data scenes.

that delivers a calibrated image of upwelling spectral radiance at 224 contiguous spectral bands from 400 to 2500 nm, with a spatial resolution of 4 - 20 m. Acquiring new AVIRIS images can be costly and time consuming. An AVIRIS flight has to be requested months in advance and can cost upwards of \$70,000. Obtaining AVIRIS archived data from the years 2006 to 2017 is free of charge though the AVIRIS Data Products Portal ([https://aviris.jpl.nasa.gov/alt\\_locator/](https://aviris.jpl.nasa.gov/alt_locator/)). Earlier archived data from 1992 can be ordered by using an online form at [https://aviris.jpl.nasa.gov/cgi/ordering\\_aviris\\_data.php](https://aviris.jpl.nasa.gov/cgi/ordering_aviris_data.php). However, the spatial coverage of the archived data is very limited and only in the United States and Canada (Figure 5.1). Therefore, it is helpful to transform Landsat imagery into AVIRIS imagery. With six bands in the SWIR region, ASTER is also a promising multispectral imagery to improve the hyperspectral transformation accuracy by PHITA.

This chapter examines the capability of PHITA for simulating AVIRIS band reflectances from Landsat 8 OLI and ASTER images and a possibility of joint spectral and spatial downscaling. The pseudo-AVIRIS image has the same number of AVIRIS bands and a downscaled spatial resolution of 15 m, half of the original Landsat spatial resolution. Especially, PHITA uses correlations between

OLI/ASTER and AVIRIS band reflection data of an overlapped area in the United States, and then extrapolated to nonoverlapped area in Chile.

## 5.2 Methods

### 5.2.1 Pansharpening and data preprocessing

As a part of the data preparation step, the multispectral bands of OLI image were pansharpened to spatially downscale the PHITA input data. By merging the high resolution panchromatic (PAN) band with the low spatial resolution multispectral bands, the OLI image could be downscaled to a higher spatial resolution of 15 m that was the same as the PAN band. Nowadays, many image pansharpening algorithms have been proposed. However, there is no single pansharpening method demonstrated promising results to retain both spectral and spatial qualities, and the most suitable pansharpening technique varies with study areas (Snehmani et al., 2016). A popular algorithm, the enhanced Gram-Schmidt spectral sharpening method (GS), and a recently developed algorithm, Nearest Neighbor Diffusion Based Pan Sharpening method (NND), were chosen in this study. The resultant OLI images that are pansharpened by GS and NND are abbreviated as GS OLI and NND OLI, respectively.

GS uses the spectral response function of a given sensor to estimate a pansharpened image. The main steps of GS are summarized as follows (Aiazzi et al., 2006):

1. The original full resolution panchromatic (PAN) band is downsampled to the size of the multispectral bands. Let denote this resampled PAN band as  $P$ .
2. Estimate scalar constants,  $\alpha$ ,  $\beta$ ,  $\gamma$ , and  $\delta$  in a linear combination:

$$P = \alpha \cdot B + \beta \cdot G + \gamma \cdot R + \delta \cdot NIR + \varepsilon, \quad (5.1)$$

where  $B$ ,  $G$ ,  $R$ , and  $NIR$  are blue, green, red, and near infrared bands, respectively.

3. Simulate a pseudo-low resolution PAN band,  $\hat{P}$ , as

$$\hat{P} = \alpha \cdot B + \beta \cdot G + \gamma \cdot R + \delta \cdot NIR. \quad (5.2)$$

4. Import the simulated PAN band and seven multispectral ( $MS$ ) bands of the OLI image into the Gram-Schmidt transformation, deal with every band as a high dimensional vector, and make all bands to be orthogonal. The transformation starts with the simulated PAN band as the first vector by

$$\hat{P}' = \hat{P}, \quad (5.3)$$

then

$$MS'_1 = MS_1 - \frac{\langle \hat{P}', MS_1 \rangle}{\langle \hat{P}', \hat{P}' \rangle} \hat{P}', \quad (5.4)$$

$$MS'_2 = MS_2 - \frac{\langle \hat{P}', MS_2 \rangle}{\langle \hat{P}', \hat{P}' \rangle} \hat{P}' - \frac{\langle MS'_1, MS_2 \rangle}{\langle MS'_1, MS'_1 \rangle} MS'_1, \quad (5.5)$$

$\vdots$

$$MS'_7 = MS_7 - \frac{\langle \hat{P}', MS_7 \rangle}{\langle \hat{P}', \hat{P}' \rangle} \hat{P}' - \sum_{k=1}^6 \frac{\langle MS'_k, MS_7 \rangle}{\langle MS'_k, MS'_k \rangle} MS'_k, \quad (5.6)$$

5. Reverse the Gram-Schmidt transform using the same transform coefficients, but on the high resolution bands. The results of this inverse Gram-Schmidt transform generate the pan-sharpened multispectral bands.

NND assumes that each pixel spectrum in a pansharpened image is a weighted linear mixture of the spectra of its immediate neighboring superpixels which are groups of spatially connected similar pixels, have the scale between the pixel level and the object level and can be generated from oversegmentation. It treats each

spectrum as its smallest element of operation. Using NND, the pansharpened image PM is calculated as

$$\begin{aligned} \text{PM}(s, t) = & \frac{1}{k(s, t)} \sum_{\psi=1}^9 \exp \left[ -\frac{N_{\psi}(s, t)}{\chi^2} \right] \\ & \times \exp \left[ -\frac{\|(s, t) - (s_{u,v}, t_{u,v})\|_{s,t,\psi}}{\chi_s^2} \right] M(u, v; s, t, \psi), \end{aligned} \quad (5.7)$$

where  $(s, t)$  denotes the position of a pixel in the high resolution coordinate,  $M(u, v; s, t, \psi)$  is the spectrum vector of neighboring superpixels  $(u, v)$  corresponding to pixel  $(s, t)$ , and  $\psi$  is in accordance with diffusion regions.  $s_{u,v}$  and  $t_{u,v}$  are the center pixel locations of the nine neighboring superpixels  $(u, v)$ .  $k(s, t)$  is a normalization factor,  $\chi$  and  $\chi_s$  are the intensity (range) and spatial smoothness factors that control the sensitivity of the diffusion, respectively. The recommended value of  $\chi_s$  will mostly resemble a bicubic interpolation kernel, which roughly gives  $\chi_s = \text{pixel size ratio} \times 0.62$ .  $\chi$  is calculated from

$$\chi^2(s, t) = \min[N_{\psi}(s, t)], \psi = 1, 2, \dots, 9, \quad (5.8)$$

where  $N_{\psi}(s, t)$  provides a similarity metric between pixel  $(s, t)$  to its neighboring superpixels as

$$N_{\psi}(s, t) = \sum_{(p,q) \in \Omega_{\psi}(s,t)} |P_0(s, t) - P_0(p, q)|, \psi = 1, 2, \dots, 9, \quad (5.9)$$

where  $\Omega_{\psi}(s, t)$  defines the diffusion region for each of the nine neighboring superpixels from the original full resolution PAN band  $P_0$ . More details of NND are given in Sun et al. (2014).

The 30-m SWIR bands of ASTER image and all 16.4-m AVIRIS band images were resampled to 15-m spatial resolution. Subsequently, the ASTER and AVIRIS images were coregistered to the pansharpened OLI image. Next, atmospheric

and topographic corrections were applied to all OLI, ASTER, and AVIRIS images by FLAASH module of the ENVI software and the non-Lambertian C-correction method, respectively, as described in Section 2.3.

### 5.2.2 Hyperspectral transformation

Every reflectance spectra of surface materials usually follow certain rules or "behaviors" in which a reflectance value at a channel can be predicted from reflectance values of "key" channels. Here, the channel means a very narrow band. Based on this idea, PHITA has been developed by assuming that multiple linear regression models can be hold between each of AVIRIS band reflectances and OLI/ASTER band reflectances, in which each AVIRIS band is a response variable and OLI/ASTER bands are predictor variables. All the models were collected into a model dictionary from a training area. The model dictionary was then used to simulate pseudo-AVIRIS images for a transformation area. Therefore, PHITA follows the principles of supervised machine learning workflow (Figure 5.2).

In this experiment, we used mineral indices, which was calculated from OLI/ASTER bands, as additional predictor variables for giving rough geological information to image pixels instead of using a geological map. When a geological map is already prepared for the target area, this map can be used. The general form of the multiple linear regression is defined as

$$\rho_{ij}^{AV}(\lambda) = \beta_{0i} + \sum_{d=1}^m \beta_{di} \cdot \rho_{dj}^X(\lambda) + \sum_{l=1}^n \beta_{li} \cdot INDEX_{lj} + \epsilon_{ij}, \quad (5.10)$$

where  $\rho_{ij}^{AV}(\lambda)$  represents the reflectance of AVIRIS band  $i$  and pixel  $j$ ;  $\beta_{0i}$  is the intercept for  $i$ ;  $\rho_{dj}^X(\lambda)$  is the reflectance of multispectral band  $d$  at  $j$ ;  $\beta_{di}$  is an unknown regression coefficient between  $d$  and  $i$ ;  $\epsilon_{ij}$  is a residual;  $INDEX_{lj}$  is a mineral index  $l$  at  $j$ ;  $\beta_{li}$  is an unknown regression coefficient between  $l$  and  $i$ ;  $m$  is the number of given multispectral bands, which is 7 for OLI and 9 for ASTER; and  $n$  is the

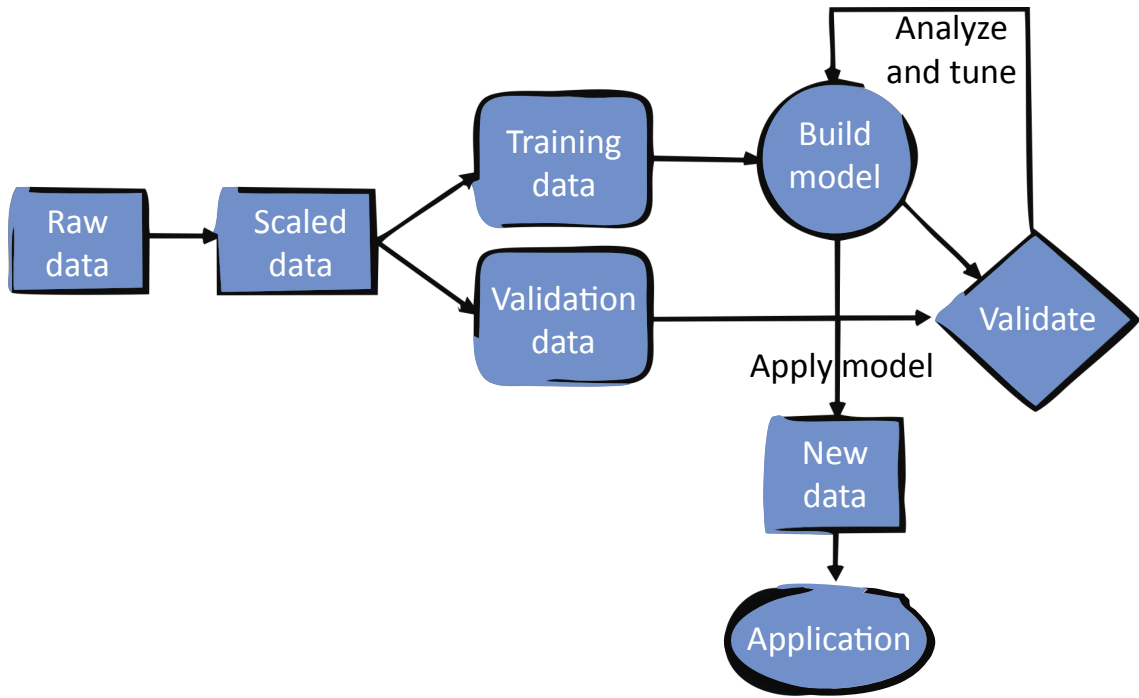


Fig. 5.2 Supervised machine learning workflow<sup>†</sup> in PHITA.

number of mineral indices. We used two OLI mineral indices including clay and iron indices, and four ASTER mineral indices including OH bearing altered minerals index (OHI), kaolinite index (KLI), alunite index (ALI), and calcite index (CLI). All the mineral indices were defined by Ninomiya (2003) to emphasize the absorption of band reflectance by division with reference band reflectance and/or multiplication of such two divisions as

$$\text{Iron index} = \text{Band4} / \text{Band2}, \quad (5.11)$$

$$\text{Clay index} = \text{Band6} / \text{Band7}, \quad (5.12)$$

$$\text{OHI} = (\text{Band7} / \text{Band6}) \cdot (\text{Band4} / \text{Band6}), \quad (5.13)$$

$$\text{KLI} = (\text{Band4} / \text{Band5}) \cdot (\text{Band8} / \text{Band6}), \quad (5.14)$$

$$\text{ALI} = (\text{Band7} / \text{Band5}) \cdot (\text{Band7} / \text{Band8}), \quad (5.15)$$

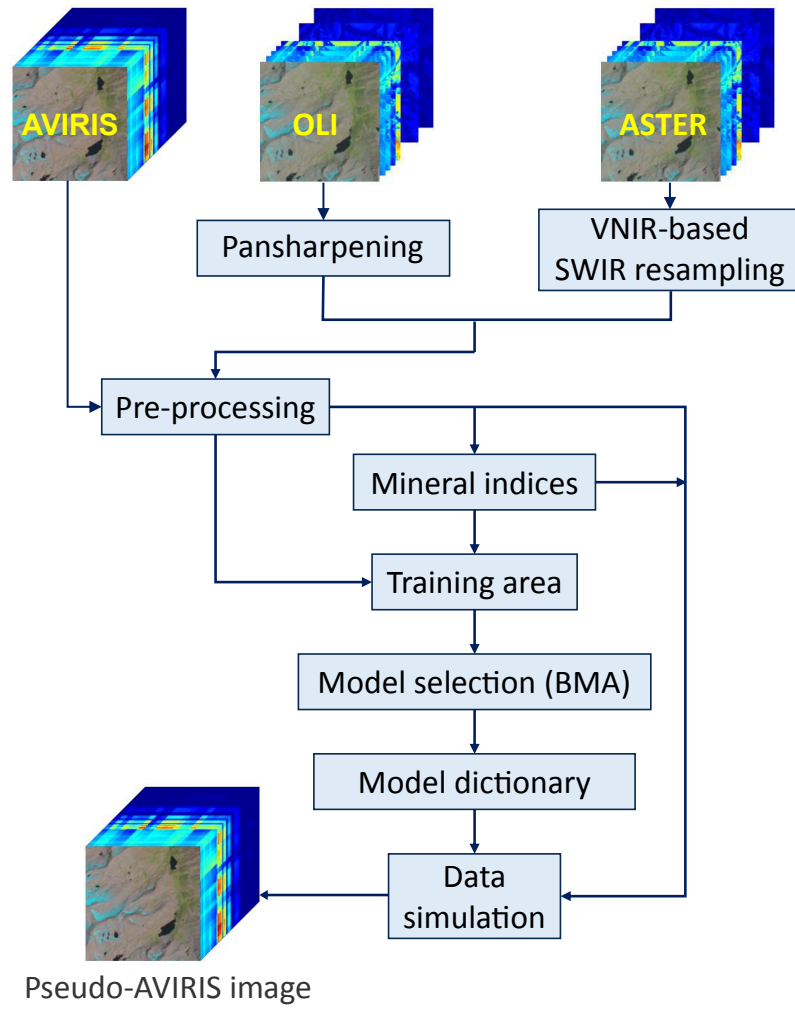


Fig. 5.3 Workflow of constructing pseudo-AVIRIS image by PHITA. OLI and ASTER images are transformed separately.

$$CLI = (\text{Band6} / \text{Band8}) \cdot (\text{Band9} / \text{Band8}). \quad (5.16)$$

To avoid overfitting and to evaluate model accuracy, BMA is applied and the best model is selected from a set of possible models by it. Consequently, PHITA consists of three main steps: 1) data preparation, 2) model dictionary building, and 3) data simulation (Figure 5.3).

Again, accuracy of the hyperspectral transformation was examined by general image appearance, the seven statistical indices (PCC, RMSE, PSNR, ERGAS, UIQI, SSIM, and SAM), spectral reconstruction, and mineral mapping using the Spectral

<sup>†</sup>Adapted from Velumani (2014)



Hourglass Wizard package in the ENVI software. More details of these techniques were described in Section 2.4. In this experiment, SAM was used to generate distribution and abundance maps of selected minerals instead of MTMF.

### 5.3 Data and study area

Two data sets were used separately for building the model dictionary and for mineral mapping in a transformation area. Three cloud-free scene images in total that were each one image of OLI, ASTER, and AVIRIS sensors were chosen to build the model dictionary. These scenes cover the Cuprite area in which their overlaps were scaled into a training area and a validation area (Figure 5.4A). Both the two areas include seven main rock types, i.e., alluvium, basalt, playa, rhyolite, sandstone, shale, and siltstone. More details of the Cuprite area were described in Section 3.2.

Athoother OLI and another ASTER scene images were selected for the transformation area which is located in the Atacama Desert in the northern Chile (Figure 5.4B). This desert area is ideally suited for testing remote sensing capability for mineral identification and mapping because of its sparse vegetation under an extremely arid climate. The Sierra Gorda Copper-Molybdenum Mine in the northern Region II of Chile (Figure 5.5), approximately 4.5 km from the town of Sierra Gorda at an elevation of approximately 1,700 m (Comi et al., 2015), is included in the transformation area. The Calama City, home of the Chuquicamata Mine known as the world largest open pit copper mine, is located about 60 km northeast of the study area (Figure 5.4B). The Sierra Gorda mine, which is hosted by andesite, rhyolites and sedimentary rocks, is a typical porphyry copper deposit formed in the Late Eocene to Early Oligocene Metallogenic Belt. It has low grade copper-molybdenum-gold mineralization, of which reserves is estimated as 1.5Bt at the average grade of 0.4% Cu, 0.02% Mo, and 0.065g/t Au (<http://www.mining-technology.com/projects/sierra->

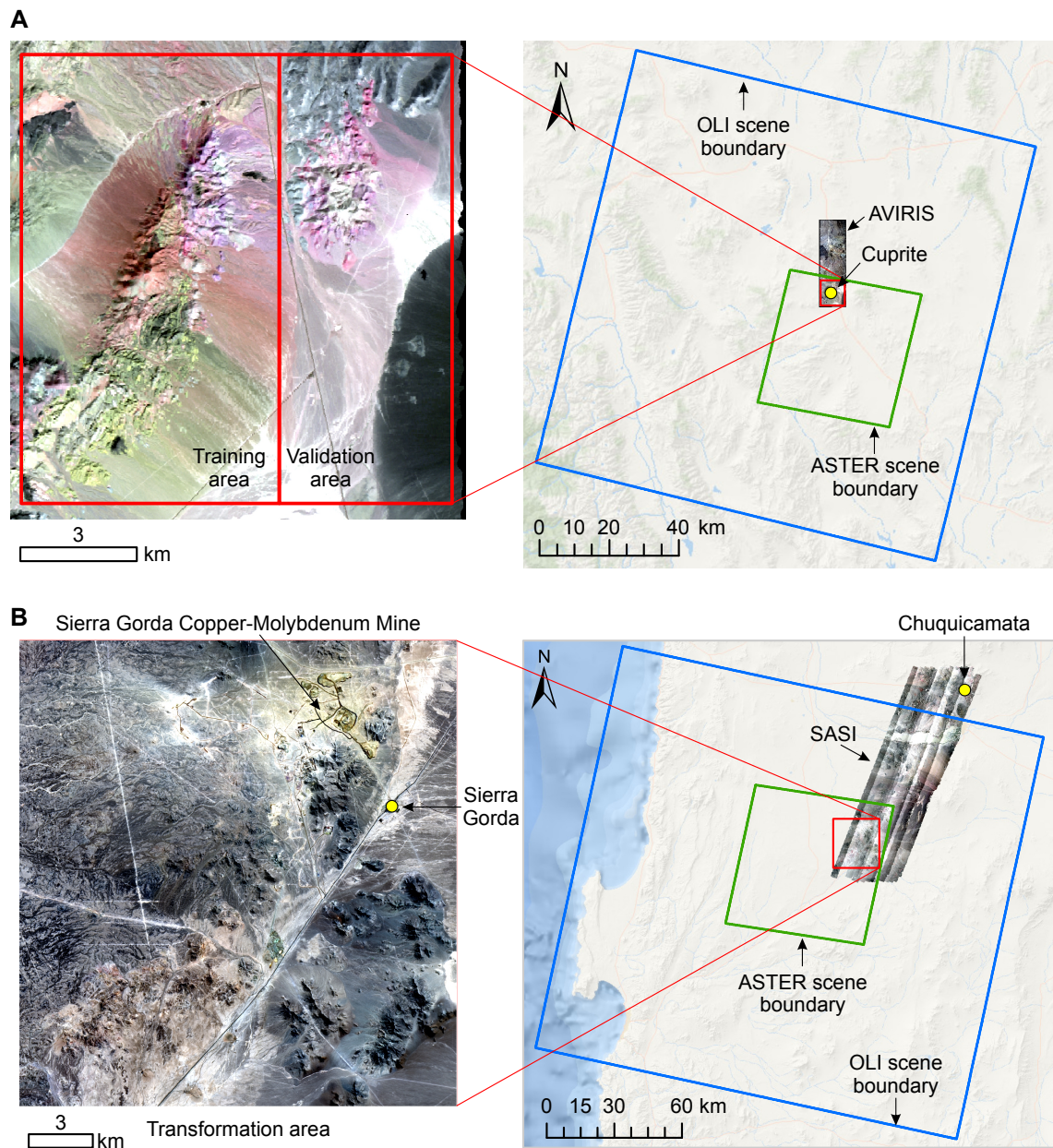


Fig. 5.4 (A) Geographic locations of Landsat 8 OLI, ASTER, and AVIRIS image scenes in the western United States with selected training and validation areas. (B) Geographic locations of Landsat 8 OLI, ASTER, and CASI+SASI image scenes in the northern Chile with selected transformation area.

gorda-copper-molybdenum-mine/). The transformation area is chosen in Chile to examine the possibility of hyperspectral transformation of PHITA for an area far away from the training area. If AVIRIS image can be successfully simulated in this case, AVIRIS data will be extrapolated outside the border of the United States.



Fig. 5.5 The photo of the Sierra Gorda Copper-Molybdenum Mine located in the richest copper basin in Chile – the Atacama Desert in the Antofagasta region (Source: KGHM International Ltd.<sup>†</sup>).

A Compact Airborne Spectrographic Imager (CASI) and Short-wave-infrared Airborne Spectrographic Imager (SASI) image was used to generate a reference map that was compared with mineral maps using resultant pseudo-AVIRIS images. The CASI+SASI sensors cover a wavelength range of 0.38-2.45  $\mu\text{m}$  with hundreds of bands and high spatial resolution of 4 m. The CASI+SASI image is highly useful for precise mappings of minerals in arid areas.

The general characteristics of OLI, ASTER, AVIRIS, and CASI+SASI image scenes are summarised in Table 5.1. Some anomalous saturation of values has been observed in ASTER Bands 5 through 9 since May 2007. This problem is attributed to an increase in ASTER SWIR detector temperature believed to be caused by increased thermal resistance in the SWIR cryocooler. The slow increase in SWIR detector temperature did not become a problem until early in 2007, and it did not really affect data quality until the detector temperature exceeded 83°K. Because of the SWIR failure, no high quality ASTER scenes have been retrieved after the

<sup>†</sup>[http://g4.forsal.pl/p/\\_wspolne/pliki/1813000/1813033-657-323.jpg](http://g4.forsal.pl/p/_wspolne/pliki/1813000/1813033-657-323.jpg)



Table 5.1 Specifications of OLI, ASTER, AVIRIS and CASI+SASI image scenes used.

| Sensor    | Acquisition date | Start time (UTC) | Path/ Row | Target area             |
|-----------|------------------|------------------|-----------|-------------------------|
| OLI       | 2013/04/27       | 18:29:02         | 41/34     | Training and validation |
| OLI       | 2013/04/19       | 14:38:37         | 1/76      | Transformation          |
| ASTER     | 2007/03/18       | 18:45:22         | 41/34     | Training and validation |
| ASTER     | 2006/12/04       | 14:53:51         | 1/76      | Transformation          |
| AVIRIS    | 2013/03/06       | 18:35:00         | 41/34     | Training and validation |
| CASI+SASI | 2013/01/12-16    | 13:05–16:40      | 1/76      | Transformation          |

above selected scene for the same area. Coverage areas of the OLI, ASTER, AVIRIS, and CASI+SASI images are shown in Figure 5.4, which highlights a much wider area of the OLI images than the other images.

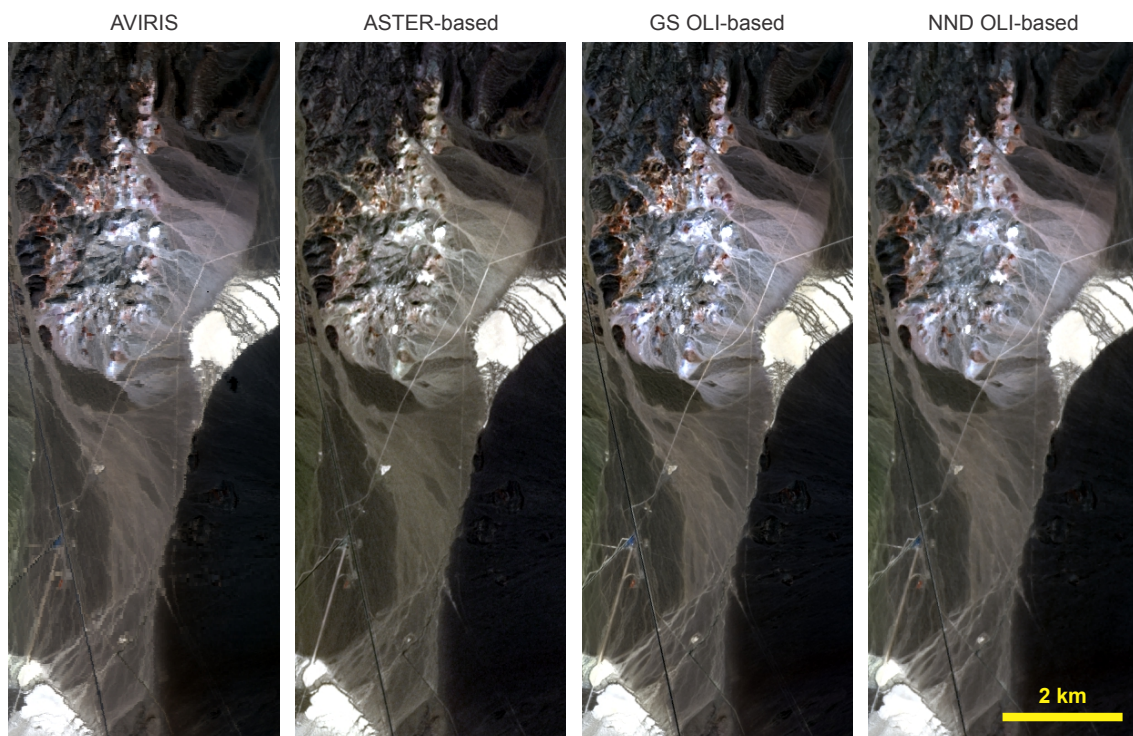


Fig. 5.6 Comparison of natural color composite images (R: 0.658  $\mu\text{m}$ , G: 0.560  $\mu\text{m}$ , and B: 0.482  $\mu\text{m}$ ) of the validation area in eastern center of Cuprite area between original AVIRIS and pseudo-hyperspectral images transformed from GS OLI (OLI image is pansharpened by the enhanced Gram-Schmidt spectral sharpening method), NND OLI (OLI image is pansharpened by the Nearest Neighbor Diffusion Based Pan Sharpening method), and ASTER images.

## 5.4 Results

### 5.4.1 Comparison of general appearance

Using the model dictionary of PHITA, the GS OLI, NND OLI, and ASTER images were transformed into pseudo-AVIRIS images with 205 bands for the training, validation, and transformation areas. The first evaluation of PHITA is simply to compare the general appearances of natural color composite between original and pseudo images using three VNIR band reflectances (R: 0.658  $\mu\text{m}$ , G: 0.560  $\mu\text{m}$ , and B: 0.482  $\mu\text{m}$ ) in the validation area. In general, both the natural color composited OLI-based pseudo-AVIRIS images are almost identical to the original image as proved by Figure 5.6, because the topographic features, textures, and color tones of pseudo-images are almost similar to the original image. There is slight change in the color of the ASTER-based image.

The second evaluation of PHITA is the general appearance comparison of false-color composite between the CASI+SASI image and the pseudo images using three SWIR band reflectances (R: 2.087  $\mu\text{m}$ , G: 2.187  $\mu\text{m}$ , and B: 2.326  $\mu\text{m}$ ) in the transformation area (Figure 5.7). The most noteworthy advantage of PHITA is that the different color contrasts among the scan lines of the CASI+SASI image could be thoroughly removed in all the pseudo-images. Surprisingly, the surface conditions can be seen more clearly in the pseudo-images than the original image.

However, a discrepancy between the ASTER-based pseudo-image and the original image can be mainly identified in the upper part of transformation area, such as the site of Sierra Gorda Copper-Molybdenum Mine, which is caused by the temporal change in surface materials and condition. In addition, zoom-in windows showed that the ASTER-based pseudo-image was coarser than both the OLI-based pseudo-images, and all the pseudo-images were not as sharp as the CASI+SASI image. Therefore, more precise spatial downscaling is necessary for



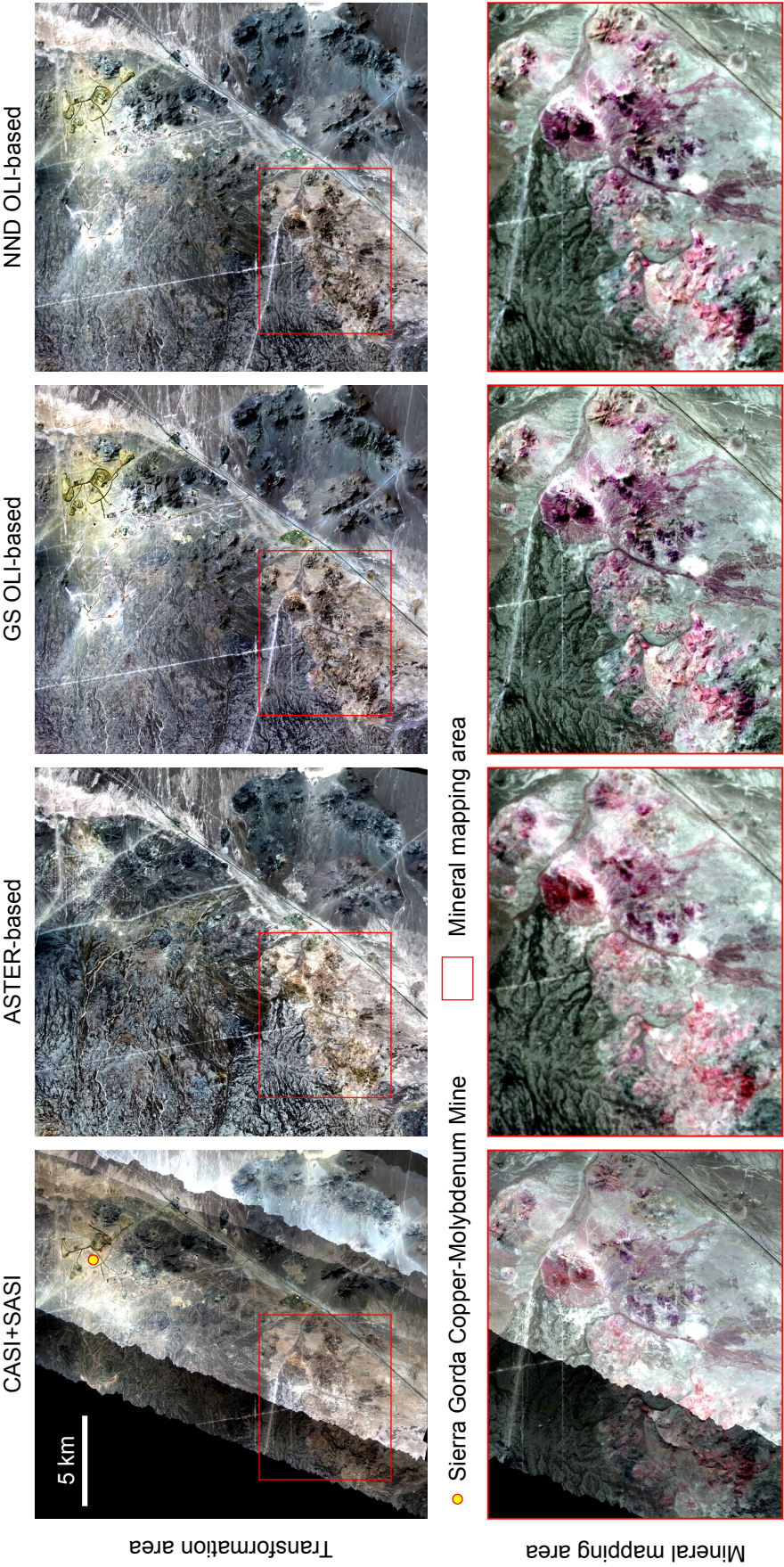


Fig. 5.7 Comparison of false-color composite images (R: 2.087  $\mu\text{m}$ , G: 2.187  $\mu\text{m}$ , and B: 2.326  $\mu\text{m}$ ) of the transformation area containing the Sierra Gorda Copper-Molybdenum Mine in Chile between CASI+SASI image and pseudo-AVIRIS images transformed from GS OLI, NND OLI, and ASTER images.

the next step.

### 5.4.2 Statistical validation

For the training area, all the statistical indices, PCC, RMSE, PSNR, ERGAS, UIQI, and SAM confirms that all the pseudo-AVIRIS images are significantly correlated with the original image for the relationship of reflectances at the 205 bands (Figure 5.8 and Table 5.2). Based on the statistical indices, the transformation accuracy of the NND OLI-based image is the highest, followed by the ASTER-based and GS OLI-based images in descending order. However, the differences

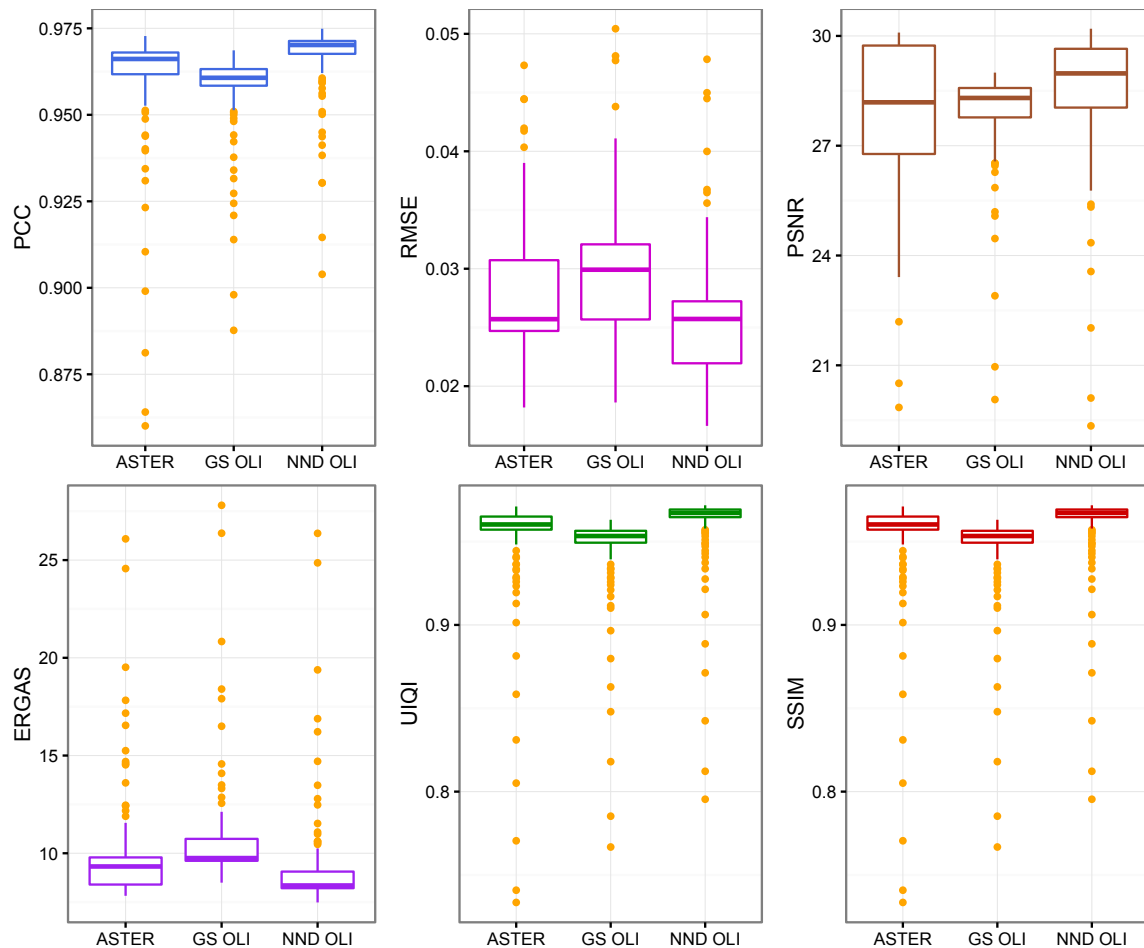


Fig. 5.8 Box plots of six statistical indices, PCC, RMSE, PSNR, ERGAS, UIQI, and SSIM for the matching of reflectances at 205 bands between original and pseudo-AVIRIS images transformed from the GS OLI, NND OLI, and ASTER images by PHITA for the validation area.

Table 5.2 Comparison of means of statistical indices for matching of reflectances in all bands between original and pseudo-Hyperion images transformed from GS OLI, NND OLI, and ASTER images by PHITA for validation area.

| Image   | PCC   | RMSE  | PSNR  | UIQI  | ERGAS | SAM   | MSSIM |
|---------|-------|-------|-------|-------|-------|-------|-------|
| ASTER   | 0.962 | 0.027 | 28.03 | 0.954 | 9.9   | 0.077 | 0.954 |
| GS OLI  | 0.959 | 0.029 | 28.04 | 0.948 | 10.6  | 0.085 | 0.948 |
| NND OLI | 0.968 | 0.025 | 28.63 | 0.962 | 9.2   | 0.087 | 0.962 |

between the pseudo-images are not big. Most PCCs, UIQIs, and SSIMs of all the pseudo-image exceed 0.95. These large values and small RMSE have proven the transformation accuracy of PHITA in term of statistical analysis.

### 5.4.3 Comparison of spectral reconstruction accuracy

Accuracy of reflectance spectral reconstruction was evaluated for four main minerals (alunite, kaolinite, muscovite, and Na-montmorillonite) in the validation area. Each spectral profile was the mean spectra in a  $2 \times 2$  pixels window. This window size was determined as the optimal to minimize the mixing of surface materials and the pixel misalignment originated from the image co-registration error. The spectral profiles were generally agreeable between the original and pseudo-AVIRIS images (Figure 5.9). This spectral agreement was the best in the case of muscovite. Although the pseudo-spectral profiles did not perfectly fit to the original profiles, main reflectance absorptions were successfully reconstructed in all the pseudo-spectral profiles, except for kaolinite around  $2.16 \mu\text{m}$ . In this region, the absorption depths of OLI-based profiles is deeper than that of the original profile. This doublet combination absorption of kaolinite is not clear in the ASTER-based profile.



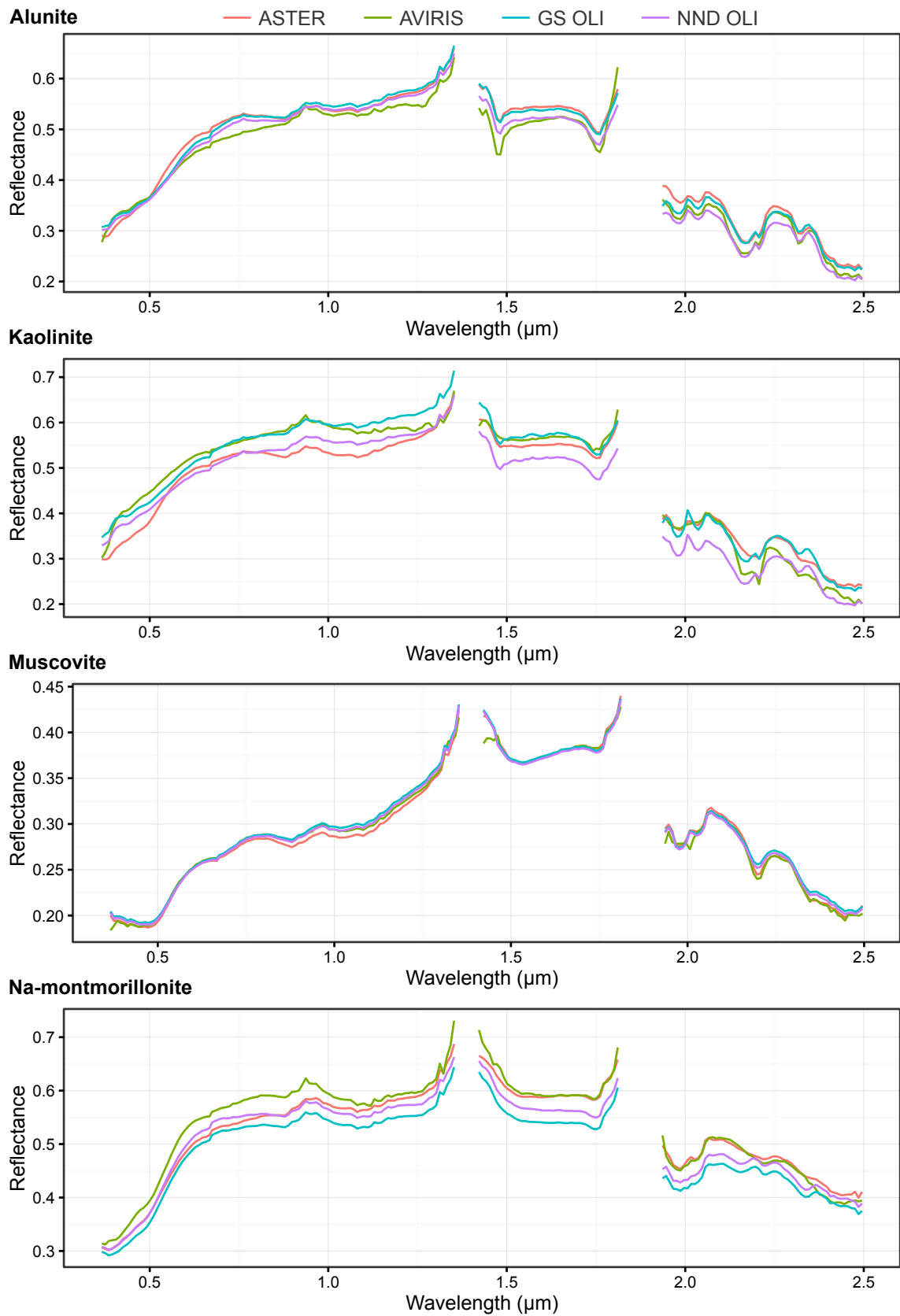


Fig. 5.9 Comparison of spectral profiles of main minerals in the validation area between the original and pseudo-AVIRIS images transformed from GS OLI, NND OLI, and ASTER images. Each profile is the mean spectra in a  $2 \times 2$  pixels window.

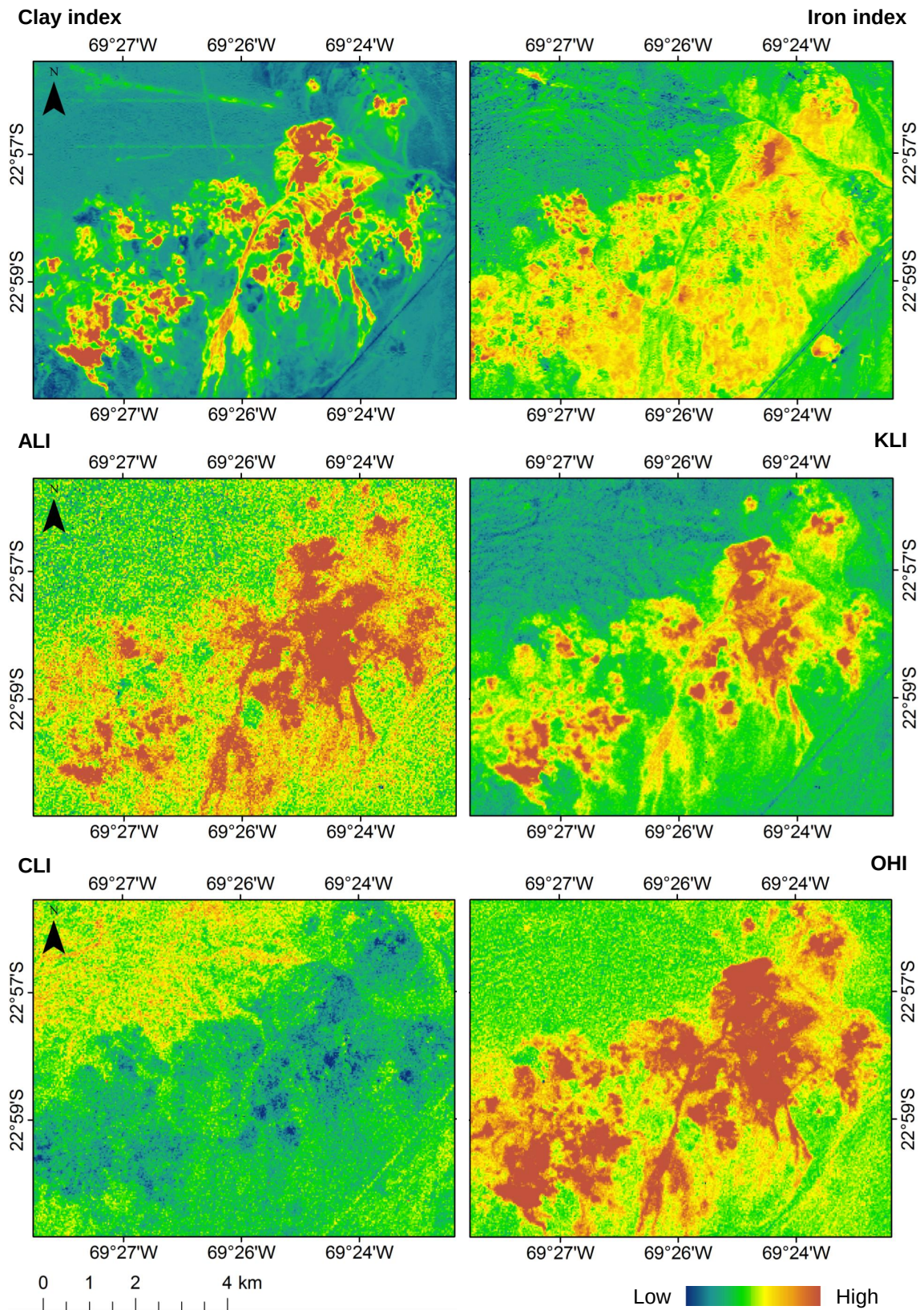


Fig. 5.10 Mineral indices calculated from the original OLI and ASTER images that were transformed into the pseudo-AVIRIS images. Indices from ASTER are OHI: OH bearing minerals, KLI: kaolinite, ALI: alunite, and CLI: calcite. This area is the mineral mapping area shown in Figure 5.7.

#### 5.4.4 Comparison of mineral mapping accuracy

Figure 5.10 shows mineral indices calculated from the original OLI and ASTER images that were transformed into the pseudo-AVIRIS images. The selected area is located about 11 km southwest of the Sierra Gorda Copper-Molybdenum Mine. Use of mineral indices is the most traditional image processing method to detect hydrothermal alterations. However, it is impossible to identify mineral endmembers only based on this method. Obviously, most locations with the high values of clay index, ALI, KLI, and OHI are overlapped with each other. Therefore, the selected area must be appropriate for proving the effectiveness and accuracy of the pseudo-images. The surface condition of this area is also relatively stable.

The SASI bands were selected for mineral detection and mapping because the mineral indices show clearly the presence of clay and OH bearing group minerals. Spectrally pure pixels were firstly extracted and classified into two mineral endmembers by the PPI. Their spectral profiles were shown in Figure 5.11. Alunite was identified by a broad absorption feature of reflectance near 2.16  $\mu\text{m}$ , together with a shallower feature at 2.32  $\mu\text{m}$ . The alunite spectra could almost perfectly be reconstructed from the ASTER-based pseudo-image. Contrary to it, the right shoulder of the broad absorption of reflectance was lower and the 2.32  $\mu\text{m}$  absorption was shallower in the case of the OLI-based pseudo-images.

Another endmember, disordered kaolinite was identified by comparison with the USGS spectral library. Because an absorption doublet at 2.16 and 2.2  $\mu\text{m}$  was not shown clearly, the identification of disordered kaolinite was uncertain. This may be caused by a mixing product of well-ordered kaolinite and dickite/alunite/halloysite. General patterns of the ASTER-based disordered kaolinite spectra corresponded with the SASI spectra. Although the NND OLI-based disordered kaolinite spectra was close to the SASI spectra, the main reflectance absorption doublet was not correctly reconstructed.

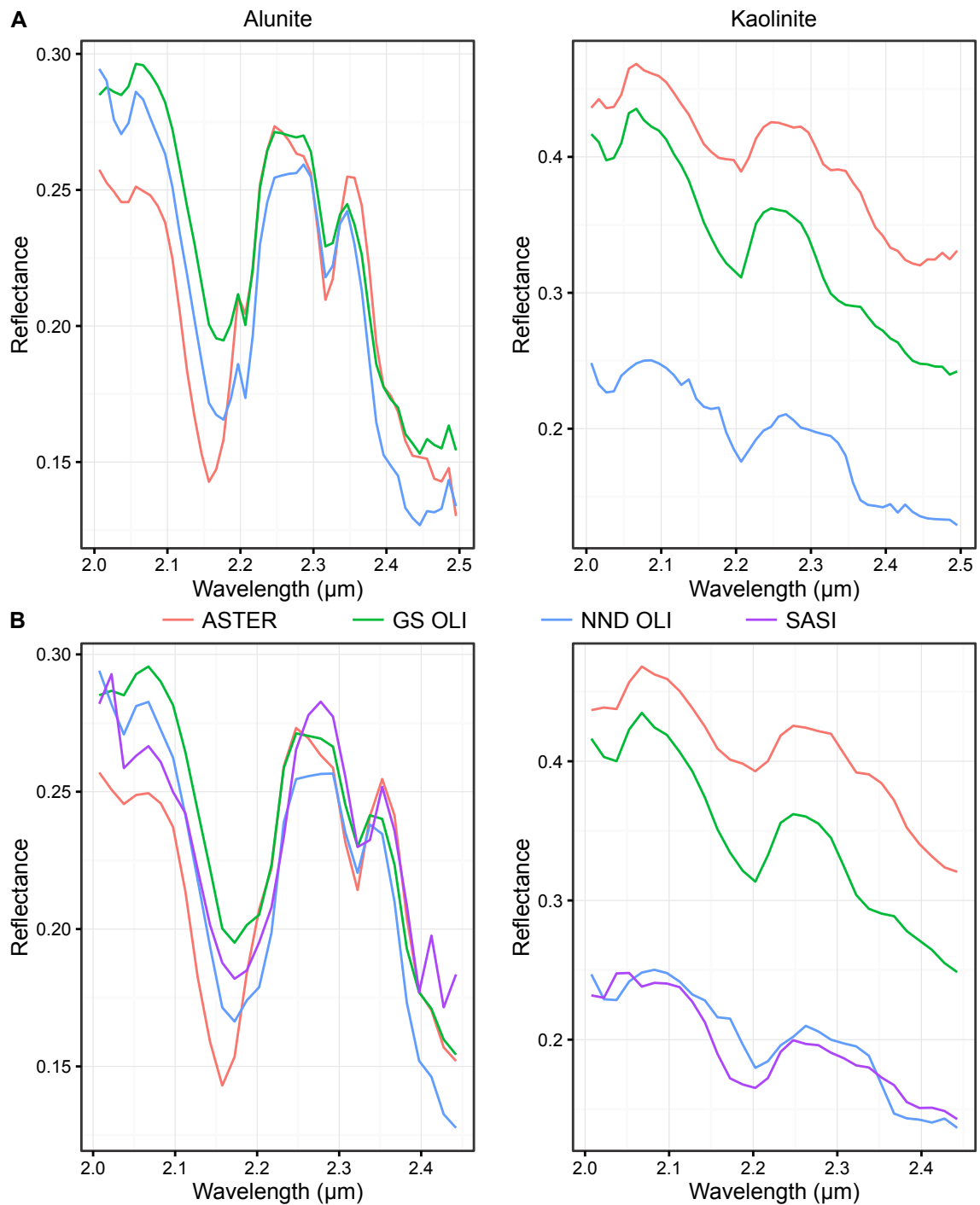


Fig. 5.11 (A) Comparison of SWIR pseudo-spectral reflectance of selected minerals between pseudo-AVIRIS images. (B) Comparison of resampled SWIR pseudo-spectral reflectance and original SASI spectral reflectance of selected minerals. Each spectra is the mean of a purest pixel group.



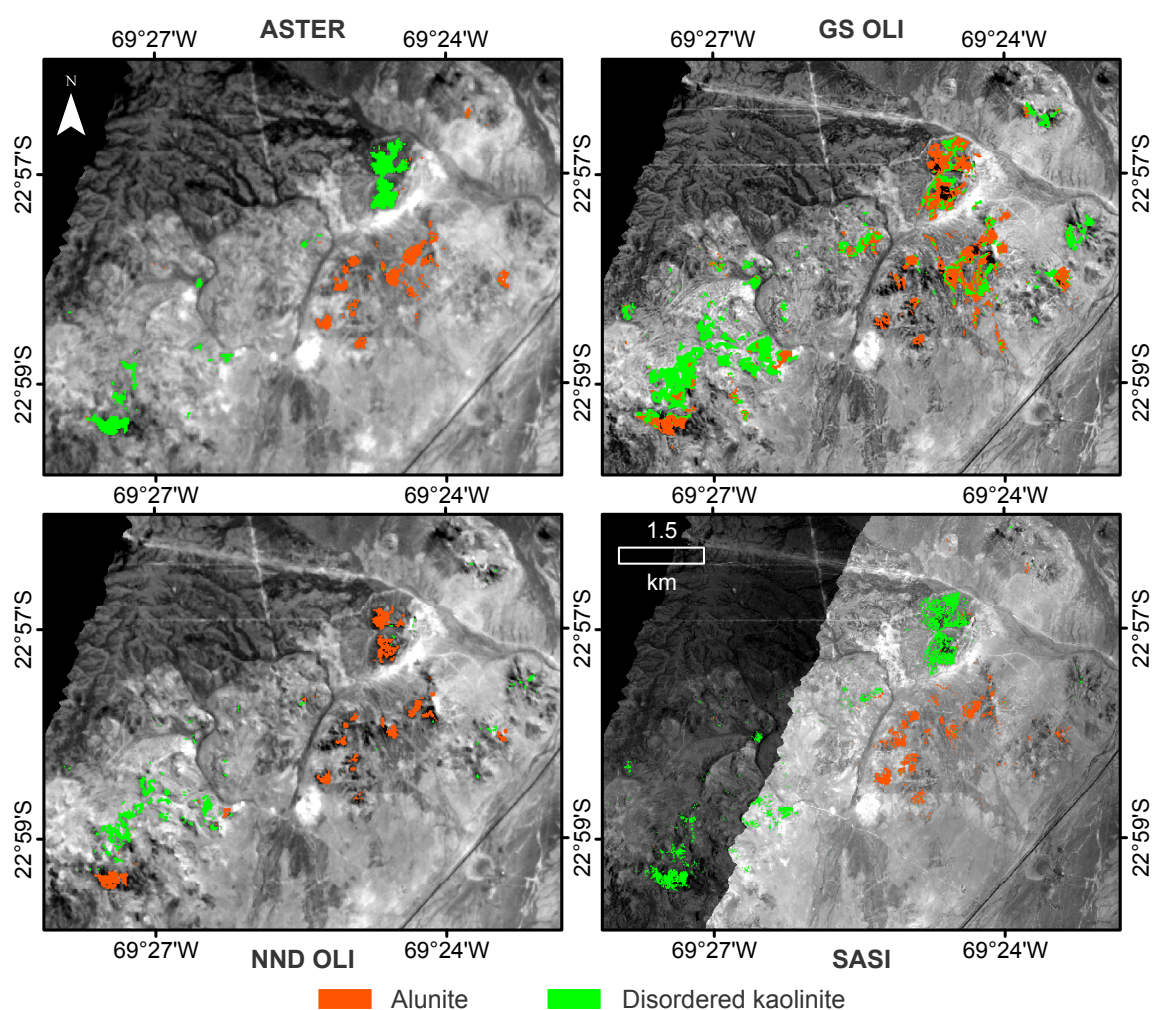


Fig. 5.12 SAM mineral maps showing the most dominant endmember in each pixel (alunite or disordered kaolinite), produced from the CASI+SASI image and pseudo-AVIRIS images, which shows better correspondence of the distributions by the ASTER-based pseudo-image. The mineral mapping area is near the Sierra Gorda Copper-Molybdenum Mine shown in Figure 5.7.

Consequently, in both cases of the selected minerals, the spectral reconstruction accuracy of the ASTER-based pseudo-image was better than that of the both OLI-based images. Distribution and abundance maps of alunite and disordered kaolinite were prepared by SAM as shown in Figure 5.12.

Because no mineral map was found for the study area, the SASI SAM result was used as a ground truthing of the mineral classification of the pseudo-images. The classification accuracies are summarized by a confusion matrix (Table 5.3) and quality indices of the mineral identification (Table 5.4) including the unclassified

Table 5.3 Confusion matrix showing mineral identification accuracy of pseudo-AVIRIS image SAM results compared with CASI+SASI SAM result used as ground truthing of mineral distribution

| <b>Pseudo-AVIRIS (pixels)</b> |  | <b>SASI image (pixels)</b> |                      |         | <b>Total (pixels)</b> | <b>User's accuracy (%)</b> |
|-------------------------------|--|----------------------------|----------------------|---------|-----------------------|----------------------------|
| <i>ASTER-based image</i>      |  | Unclassified               | Disordered kaolinite | Alunite |                       |                            |
| Unclassified                  |  | 289814                     | 1499                 | 720     | 292033                | 99.24                      |
| Disordered kaolinite          |  | 965                        | 2234                 | 16      | 3215                  | 69.49                      |
| Alunite                       |  | 1125                       | 10                   | 1297    | 2432                  | 53.33                      |
| Total (pixels)                |  | 291904                     | 3743                 | 2033    | 297680                |                            |
| Producer's accuracy (%)       |  | 99.28                      | 59.68                | 63.80   |                       |                            |
| <i>GS OLI-based image</i>     |  | Unclassified               | Disordered kaolinite | Alunite |                       |                            |
| Unclassified                  |  | 280181                     | 702                  | 926     | 281809                | 99.42                      |
| Disordered kaolinite          |  | 7456                       | 1155                 | 126     | 8737                  | 13.22                      |
| Alunite                       |  | 4267                       | 1886                 | 981     | 7134                  | 13.75                      |
| Total (pixels)                |  | 291904                     | 3743                 | 2033    | 297680                |                            |
| Producer's accuracy (%)       |  | 95.98                      | 30.86                | 48.25   |                       |                            |
| <i>NND OLI-based image</i>    |  | Unclassified               | Disordered kaolinite | Alunite |                       |                            |
| Unclassified                  |  | 289511                     | 2496                 | 1227    | 293234                | 98.73                      |
| Disordered kaolinite          |  | 1821                       | 143                  | 3       | 1967                  | 7.27                       |
| Alunite                       |  | 572                        | 1104                 | 803     | 2479                  | 32.39                      |
| Total (pixels)                |  | 291904                     | 3743                 | 2033    | 297680                |                            |
| Producer's accuracy (%)       |  | 99.18                      | 3.82                 | 39.50   |                       |                            |

Table 5.4 Overall accuracy and Kappa coefficient for agreement of endmember class between each pseudo-AVIRIS image and the CASI+SASI image. These results include unclassified pixels.

| Indices              | ASTER | GS OLI | NND OLI |
|----------------------|-------|--------|---------|
| Overall accuracy (%) | 98.54 | 94.84  | 97.57   |
| Kappa coefficient    | 0.61  | 0.27   | 0.28    |

pixels. These confusion matrices reveal that the ASTER-based pseudo-image gave higher overall accuracies than the both OLI-based images. Because the distribution area of minerals occupy a small ratio of the whole mapping area and more than 30% of alunite and disordered kaolinite were unclassified, the KC of ASTER-based pseudo-image was 0.61. The KC of GS OLI and NND OLI based pseudo-images decreased by 0.27 and 0.28, respectively. The low KC of OLI-based images is caused by poorly reconstructing of disordered kaolinite.

## 5.5 Discussion

The model dictionary built in the United States can be applied successfully in Chile. This result proves that the effectiveness of PHITA is not depend on the distance between the training and transformation areas, but it is controlled by the similarity of surface materials of the both areas. In fact, there is abundance of clay minerals in both the Cuprite area and the mineral mapping area near the Sierra Gorda Mine. However, the most unsatisfactory PHITA result is the reconstruction of kaolinite spectra. In both the validation and transformation areas, the kaolinite and disordered kaolinite spectra were not simulated successfully using the OLI image. Possible reason for this low transformation accuracy are that the OLI image only has one SWIR band and one index related to clay mineral.

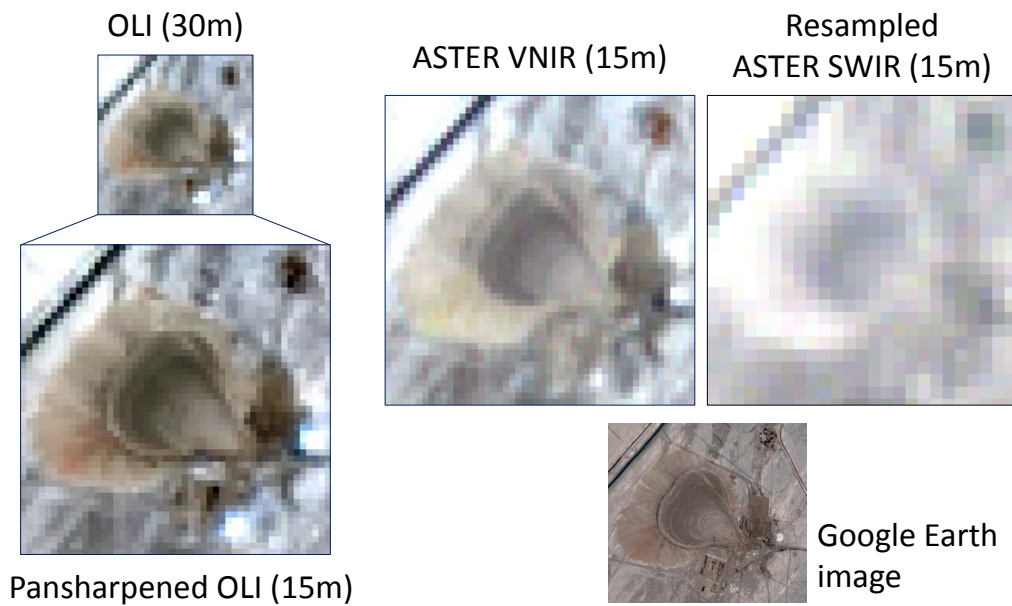


Fig. 5.13 Comparison of false-color composite images among a part of original OLI, pansharpened OLI, ASTER VNIR, and resampled ASTER SWIR images. Selected area is around a closed open-pit mine, located about 13 km south of the town of Sierra Gorda.

By using GS and NND methods, the spatial resolution of original OLI image could be downscaled better than that of the ASTER SWIR image (Figure 5.13). Because the statistical indices were calculated based on the correspondence at each pixel, the pan-sharpening method contributed to increase the statistical transformation accuracy of the OLI-based images. However, the ASTER-based pseudo-image revealed the better effectiveness in terms of the spectral reconstruction. The most plausible control factor on this improvement is that the ASTER image has much more SWIR bands and mineral indices than those of the OLI image. Both the transformation accuracies of OLI- and ASTER-based images can be enhanced by a more advanced spatial downscaling technique. In addition, an integration of OLI and ASTER multispectral bands should be considered for an area that has kept almost the same surface materials, land uses, and topography with time.



## 5.6 Conclusions

PHITA was successfully applied to simulate AVIRIS image from the Landsat 8 OLI and ASTER images. A total of 205 pseudo-band reflectances were simulated with high accuracy for each of OLI and ASTER images over two area that contains the Cuprite area in the western United State and the Sierra Gorda Copper-Molybdenum Mine in the northern Region II of Chile, respectively. The quality of pseudo-AVIRIS images were verified by the general appearances of color composite images, statistical analysis, spectral reconstruction, and application to mineral detection and mapping.

Pseudo-reflectance spectra were generally agreeable with the original spectra. The OLI-based pseudo-image was superior in the spatial downscaling using GS and NND methods, but inferior in the spectral downscaling. Using the SASI-based mineral map as a ground truthing of distribution of the selected minerals, the ASTER-based pseudo-image was confirmed to be sufficiently applicable to mineral identification and mapping in the study area because of its high OA and KC. Alunite and disordered kaolinite were selected for this mapping. However, the classification accuracies of OLI-based image were significantly low. Our next step is to improve PHITA by incorporating a more advanced spatial downscaling technique.

# Chapter 6

## Conclusions and future works

### 6.1 Conclusions

Hyperspectral remote sensing is superior to traditional multispectral remote sensing in detailed spectral information but has limited spatial and temporal coverage. Those limitations require an innovative technique that can simulate hyperspectral imagery from multispectral imagery with global coverage, continuous acquisition, and a small number of bands. Based on this background, this dissertation presents the results of a study to develop a new method, PHITA, to transform a multispectral image into a pseudo-hyperspectral image. This advanced image aids more detailed identification of minerals and mineral deposit exploration in arid and semi-arid areas than traditional multispectral remote sensing.

PHITA was originally based on multiple linear regression models that can be applied to each of the Hyperion and Landsat ETM+ bands, in which the Hyperion band is a dependent variable and ETM+ bands are predictor variables. This is the first study that has succeeded in producing a pseudo-Hyperion image with 155 high-quality bands of the same scene size as an ETM+ image. Through verification of transformation accuracy by statistical analyses and surface mineral mapping, the pseudo-Hyperion image was proven very similar to the original band

reflectances, because of large PCC (generally  $> 0.94$ ), small RMSE (mostly  $< 0.016$ ), high structural similarity, and similar appearance of the color composite image. Using a reference mineral map built from an AVIRIS image and field surveys as ground truth, an advantage of the pseudo-image is clarified for the Cuprite hydrothermal alteration area in the western United States. The identification and mapping accuracies of metal deposit-related minerals were high even in areas outside the original Hyperion scene. Featured absorptions were reconstructed in pseudo-reflectance spectra of the typical minerals in the area. The results can enhance the potential of a large Landsat-series dataset over the long term by transformation into pseudo-Hyperion images for global land surfaces.

This study also extends the PHITA to transform TM, OLI, and EO-1 ALI sensor images into pseudo-Hyperion images. By choosing a part of the Fish Lake Valley geothermal prospect area in the western United States for study, the pseudo-Hyperion images produced from the TM, ETM+, OLI, and ALI images by PHITA were confirmed to be applicable to mineral mapping. Using a reference map as the truth, three main minerals (muscovite and chlorite mixture, opal, and calcite) were identified with high overall accuracies from the pseudo-images. The highest accuracy was obtained from the ALI image, followed by ETM+, TM, and OLI images in descending order. The TM, OLI, and ALI images can be alternatives to ETM+ imagery for the hyperspectral transformation that aids the production of pseudo-Hyperion images for areas without high-quality ETM+ images because of SLC failure, and for long-term global monitoring of land surfaces.

PHITA was examined for simulating an airborne hyperspectral image, AVIRIS, from OLI and ASTER images and for a possibility of joint spectral and spatial downscaling. In this experiment, PHITA follows the principles of supervised machine learning workflow with a training area in the United States and a validation area in the northern Chile. The pseudo-AVIRIS image has 205 bands and a downscaled spatial resolution of 15 m, half of the multispectral spatial resolution.

Pseudo-reflectance spectra were generally agreeable with the original spectra. The OLI-based pseudo-image was superior in the spatial downscaling but inferior in the spectral downscaling. Using 4-m SASI-based mineral map as ground truth of distribution of selected minerals, the ASTER-based pseudo-image was confirmed to be sufficiently applicable to mineral identification and mapping for an area that contains the Sierra Gorda Copper-Molybdenum Mine in the northern Region II of Chile.

In conclusion, the following are two important points to keep in mind when using PHITA: (1) the input multispectral and hyperspectral images should be preprocessed and coregistered carefully, (2) the surface materials of the training area used to build the model dictionary should be similar to that of the transformation area. PHITA is very promising as it fills a gap of hyperspectral data by simulating the pseudo-hyperspectral images from available and continuous multispectral data. Although its performance was not perfect, the resultant pseudo-images generate more detailed identification of minerals than typical multispectral images. Therefore, PHITA can produce useful mineralogic information and update geologic maps of many areas in the Earth.

## 6.2 Future works

A shortcoming of the present PHITA is that some endmember spectra were not well simulated in the pseudo-image. As a result, these endmembers were not extracted or were misclassified in mineral maps. This situation can be improved by better preprocessing of the hyperspectral image and more accurate coregistration. A spatial downscaling technique integrated with the PHITA is also indispensable to improve mineral identification accuracy. The present study is the first step toward simulating the pseudo-hyperspectral image at global scale. The overall quality of the pseudo-image needed to be verified for accuracy over the entire multispectral

scene. However, this could not be accomplished in this study because of the limitation of the ground truth area and the amount of reference data. In addition, the present application target is mineral mapping in arid and semi-arid areas with the small effects of vegetation. PHITA should be applied to thick vegetation areas and other applications, such as vegetation mapping or environmental quality monitoring.

# References

- Adler-Golden, S. M., Matthew, M. W., Bernstein, L. S., Levine, R. Y., Berk, A., Richtsmeier, S. C., Acharya, P. K., Anderson, G. P., Felde, G., Gardner, J., et al. (1999). Atmospheric correction for short-wave spectral imagery based on modtran 4. In *Proc SPIE Int Soc Opt Eng*, volume 3753, pages 61–69. [CrossRef]
- Aiazzi, B., Baronti, S., Selva, M., and Alparone, L. (2006). Enhanced gram-schmidt spectral sharpening based on multivariate regression of ms and pan data. In *Geoscience and Remote Sensing Symposium, 2006. IGARSS 2006. IEEE International Conference on*, pages 3806–3809. IEEE. [CrossRef]
- Barry, P. S., Mendenhall, J., Jarecke, P., Folkman, M., Pearlman, J., and Markham, B. (2002). EO-1 Hyperion hyperspectral aggregation and comparison with EO-1 Advanced Land Imager and Landsat 7 ETM+. In *Geoscience and Remote Sensing Symposium, 2002. IGARSS '02. 2002 IEEE International*, volume 3, pages 1648–1651 vol.3. [CrossRef]
- Berezowski, T., Chormanski, J., and Chan, J.-W. (2012). Preliminary validation of a method for simulating hyperspectral bands from multispectral images. In *Geoscience and Remote Sensing Symposium (IGARSS), 2012 IEEE International*, pages 4283–4286. [CrossRef]
- Canty, M. J. (2014). *Image analysis, classification and change detection in remote sensing: with algorithms for ENVI/IDL and Python*. CRC Press. [Google Scholar]
- Carrere, V. (1990). Mapping alteration in the goldfield mining district, nevada, with the airborne visible/infrared imaging spectrometer (aviris). In *Thematic Conference on Remote Sensing for Exploration Geology - Methods, Integration, Solutions, 7th, Calgary, Canada*, pages 365–378. Environmental Research Institute of Michigan. [Google Scholar]
- Chander, G., Markham, B. L., and Helder, D. L. (2009). Summary of current radiometric calibration coefficients for landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113(5):893–903. [CrossRef]
- Chen, F., Niu, Z., Sun, G., Wang, C., and Teng, J. (2008). Using low-spectral-resolution images to acquire simulated hyperspectral images. *International Journal of Remote Sensing*, 29(10):2963–2980. [CrossRef]

- Comi, T., Garcia, C., Potulsha, A., Opazo, J., and S., G. (2015). Sierra gorda chile's new copper-molybdenum operation. *Mining Engineering*, 67(7):23–30. [CrossRef]
- Datt, B., McVicar, T., Niel, T. V., Jupp, D., and Pearlman, J. (2003). Preprocessing eo-1 hyperion hyperspectral data to support the application of agricultural indexes. *IEEE Transactions on Geoscience and Remote Sensing*, 41(6):1246–1259. [CrossRef]
- Farifteh, J., Nieuwenhuis, W., and García-Meléndez, E. (2013). Mapping spatial variations of iron oxide by-product minerals from EO-1 Hyperion. *International Journal of Remote Sensing*, 34(2):682–699. [CrossRef]
- Galvão, L. S., Formaggio, A. R., and Tisot, D. A. (2005). Discrimination of sugarcane varieties in Southeastern Brazil with EO-1 Hyperion data. *Remote Sensing of Environment*, 94(4):523–534. [CrossRef]
- Genell, A., Nemes, S., Steineck, G., and Dickman, P. W. (2010). Model selection in Medical Research: A simulation study comparing Bayesian Model Averaging and Stepwise Regression. *BMC Medical Research Methodology*, 10(1):1–10. [CrossRef]
- Giardino, C., Brando, V. E., Dekker, A. G., Strömbeck, N., and Candiani, G. (2007). Assessment of water quality in Lake Garda (Italy) using Hyperion. *Remote Sensing of Environment*, 109(2):183–195. [CrossRef]
- Goodenough, D., Dyk, A., Niemann, K., Pearlman, J., Chen, H., Han, T., Murdoch, M., and West, C. (2003). Processing hyperion and ali for forest classification. *IEEE Transactions on Geoscience and Remote Sensing*, 41(6):1321–1331. [CrossRef]
- Goslee, S. (2011). Analyzing Remote Sensing Data in R: The landsat Package. *Journal of Statistical Software*, 43(1):1–25. [CrossRef]
- Green, A. A., Berman, M., Switzer, P., and Craig, M. D. (1988). A transformation for ordering multispectral data in terms of image quality with implications for noise removal. *IEEE Transactions on geoscience and remote sensing*, 26(1):65–74. [CrossRef]
- Hede, A. N. H., Kashiwaya, K., Koike, K., and Sakurai, S. (2015). A new vegetation index for detecting vegetation anomalies due to mineral deposits with application to a tropical forest area. *Remote Sensing of Environment*, 171:83–97. [CrossRef]
- Helder, D. L., Markham, B. L., Thome, K. J., Barsi, J. A., Chander, G., and Malla, R. (2008). Updated radiometric calibration for the landsat-5 thematic mapper reflective bands. *IEEE Transactions on Geoscience and Remote Sensing*, 46(10):3309–3325. [CrossRef]
- Hoang, N. T. and Koike, K. (2015). Development of bayesian-based transformation method of landsat imagery into pseudo-hyperspectral imagery. In Bruzzone, L., editor, *Image and Signal Processing for Remote Sensing XXI*, volume 9643. SPIE. [CrossRef]

- Hoang, N. T. and Koike, K. (2016). Hyperspectral transformation from eo-1 ali imagery using pseudo-hyperspectral image synthesis algorithm. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, XLI-B7:661–665. [CrossRef]
- Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999). Bayesian model averaging: a tutorial (with comments by M. Clyde, David Draper and E. I. George, and a rejoinder by the authors. *Statistical Science*, 14(4):382–417. [CrossRef]
- Hosseinjani, M. and Tangestani, M. H. (2011). Mapping alteration minerals using sub-pixel unmixing of aster data in the sarduiyeh area, se kerman, iran. *International Journal of Digital Earth*, 4(6):487–504. [CrossRef]
- Huynh-Thu, Q. and Ghanbari, M. (2008). Scope of validity of PSNR in image/video quality assessment. *Electronics Letters*, 44(13):800–804. [CrossRef]
- Irons, J. R., Dwyer, J. L., and Barsi, J. A. (2012). The next landsat satellite: The landsat data continuity mission. *Remote Sensing of Environment*, 122:11–21. [CrossRef]
- Jarecke, P., Barry, P., Pearlman, J., and Markham, B. (2001). Aggregation of Hyperion hyperspectral spectral bands into Landsat-7 ETM+ spectral bands. In *Geoscience and Remote Sensing Symposium, 2001. IGARSS '01. IEEE 2001 International*, volume 6, pages 2822–2824. [CrossRef]
- Jupp, D., Datt, B., Lovell, J., Campbell, S., King, E., et al. (2002). Discussions around hyperion data: background notes for the hyperion data users workshop. In *CSIRO Earth Observation Centre*. Available online: [ftp://ftp.eoc.csiro.au/pub/djupp/Hyperion/Workshop/Minimal\\_Set/Documents/Hyp\\_Wsn.pdf](ftp://ftp.eoc.csiro.au/pub/djupp/Hyperion/Workshop/Minimal_Set/Documents/Hyp_Wsn.pdf) (accessed on 24 May 2017).
- Kalinowski, A. and Oliver, S. (2004). Aster mineral index processing manual. *Remote Sensing Applications, Geoscience Australia*, 37:36. [Google Scholar]
- Koike, K. and Kouda, R. (2016). Recent trends of remote sensing technologies applied to metallic mineral and geothermal resources exploration. *Journal of MMIJ*, 132(6):96–113. [CrossRef]
- Kratt, C., Coolbaugh, M., Peppin, B., and Sladek, C. (2009). Identification of a new blind geothermal system with hyperspectral remote sensing and shallow temperature measurements at columbus salt marsh, esmeralda county, nevada. *Geothermal Resources Council Transactions*, 33:481–485. [Google Scholar]
- Kruse, F., Boardman, J., and Huntington, J. (2003). Comparison of airborne hyperspectral data and eo-1 hyperion for mineral mapping. *IEEE Transactions on Geoscience and Remote Sensing*, 41(6):1388–1400. [CrossRef]



- Kruse, F., Lefkoff, A., and Dietz, J. (1993). Airbone imaging spectrometry expert system-based mineral mapping in northern Death Valley, California/Nevada, using the Airborne Visible/Infrared Imaging Spectrometer(AVIRIS). *Remote Sensing of Environment*, 44(2):309–336. [CrossRef]
- Kruse, F. A. (1988). Imaging Spectrometry use of airborne imaging spectrometer data to map minerals associated with hydrothermally altered rocks in the northern Grapevine Mountains, Nevada, and California. *Remote Sensing of Environment*, 24(1):31–51. [CrossRef]
- Kruse, F. A., Richardson, L. L., and Ambrosia, V. G. (1997). Techniques developed for geologic analysis of hyperspectral data applied to near-shore hyperspectral ocean data. In *Presented at the Fourth International Conference on Remote Sensing for Marine and Coastal Environments*, volume 17, page 19, Orlando, Florida, USA. Environmental Research Institute of Michigan. Available online: [http://www.hgimaging.com/PDF/Kruse\\_erim97\\_marine.pdf](http://www.hgimaging.com/PDF/Kruse_erim97_marine.pdf) (accessed on 24 May 2017).
- Littlefield, E. F. and Calvin, W. M. (2014). Geothermal exploration using imaging spectrometer data over fish lake valley, nevada. *Remote Sensing of Environment*, 140:509–518. [CrossRef]
- Liu, B., Zhang, L., Zhang, X., Zhang, B., and Tong, Q. (2009). Simulation of EO-1 hyperion data from ALI multispectral data based on the spectral reconstruction approach. *Sensors*, 9(4):3090–3108. [CrossRef]
- Markham, B. L. and Helder, D. L. (2012). Forty-year calibrated record of earth-reflected radiance from landsat: A review. *Remote Sensing of Environment*, 122:30–40. [CrossRef]
- Mars, J. C. and Rowan, L. C. (2010). Spectral assessment of new aster swir surface reflectance data products for spectroscopic mapping of rocks and minerals. *Remote Sensing of Environment*, 114(9):2011–2025. [CrossRef]
- Marshall, M. and Thenkabail, P. (2015). Advantage of hyperspectral EO-1 hyperion over multispectral IKONOS, GeoEye-1, WorldView-2, landsat ETM+, and MODIS vegetation indices in crop biomass estimation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 108:205–218. [CrossRef]
- Martini, B., Hausknecht, P., Pickles, W., and Cocks, P. (2004). The northern fish lake valley pull-apart basin: geothermal prospecting with hyperspectral imaging. *Geothermal Resources Council Transactions*, 28:663–667. [Google Scholar]
- Mitchell, J. and Glenn, N. F. (2009). Subpixel abundance estimates in mixture-tuned matched filtering classifications of leafy spurge (*euphorbia esula* l.). *International Journal of Remote Sensing*, 30(23):6099–6119. [CrossRef]

- Miura, T., Huete, A., and Yoshioka, H. (2006). An empirical investigation of cross-sensor relationships of NDVI and red/near-infrared reflectance using EO-1 Hyperion data. *Remote Sensing of Environment*, 100(2):223–236. [CrossRef]
- Montgomery, D. C., Peck, E. A., and Vining, G. G. (2015). *Introduction to linear regression analysis*. John Wiley & Sons. [Google Scholar]
- Nikolakopoulos, K. G., Tsombos, P. I., Skianis, G. A., and Vaiopoulos, D. A. (2008). EO-1 Hyperion and ALI bands simulation to Landat 7 ETM+ bands for mineral mapping in Milos Island. In *SPIE Remote Sensing*, pages 711010–711010. International Society for Optics and Photonics. [CrossRef]
- Ninomiya, Y. (2003). A stabilized vegetation index and several mineralogic indices defined for aster vnir and swir data. In *Geoscience and Remote Sensing Symposium, 2003. IGARSS'03. Proceedings. 2003 IEEE International*, volume 3, pages 1552–1554. IEEE. [CrossRef]
- Pearlman, J., Carman, S., Segal, C., Jarecke, P., Clancy, P., and Browne, W. (2001). Overview of the hyperion imaging spectrometer for the NASA EO-1 mission. In *IGARSS 2001. Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No.01CH37217)*. IEEE. [CrossRef]
- Raftery, A., Hoeting, J., Volinsky, C., Painter, I., and Yeung, K.-Y. (2015). BMA: Bayesian model averaging.
- Raftery, A. E., Madigan, D., and Hoeting, J. A. (1997). Bayesian model averaging for linear regression models. *Journal of the American Statistical Association*, 92(437):179. [CrossRef]
- Raftery, A. E. and Painter, I. S. (2005). Bma: an r package for bayesian model averaging. *R news*, 5(2):2–8. [Google Scholar]
- Rautiainen, M. and Lukeš, P. (2015). Spectral contribution of understory to forest reflectance in a boreal site: an analysis of EO-1 Hyperion data. *Remote Sensing of Environment*, 171:98–104. [CrossRef]
- Raykov, T. and Marcoulides, G. A. (2012). *Basic statistics: An introduction with R*. Rowman & Littlefield Publishers. [Google Scholar]
- Roy, D., Kovalskyy, V., Zhang, H., Vermote, E., Yan, L., Kumar, S., and Egorov, A. (2016). Characterization of landsat-7 to landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment*, 185:57–70. [CrossRef]
- Roy, D., Wulder, M., Loveland, T., C.E., W., Allen, R., Anderson, M., Helder, D., Irons, J., Johnson, D., Kennedy, R., Scambos, T., Schaaf, C., Schott, J., Sheng, Y., Vermote, E., Belward, A., Bindaschadler, R., Cohen, W., Gao, F., Hipple, J., Hostert, P., Huntington, J., Justice, C., Kilic, A., Kovalskyy, V., Lee, Z., Lymburner, L.,

- Masek, J., McCorkel, J., Shuai, Y., Trezza, R., Vogelmann, J., Wynne, R., and Zhu, Z. (2014). Landsat-8: Science and product vision for terrestrial global change research. *Remote Sensing of Environment*, 145:154–172. [CrossRef]
- Sabins, F. F. (1999). Remote sensing for mineral exploration. *Ore Geology Reviews*, 14(3-4):157–183. [CrossRef]
- Snehmani, Gore, A., Ganju, A., Kumar, S., and Srivastava, P. (2016). A comparative analysis of pansharpening techniques on quickbird and worldview-3 images. *Geocarto International*, pages 1–17. [CrossRef]
- Sun, W., Chen, B., and Messinger, D. W. (2014). Nearest-neighbor diffusion-based pan-sharpening algorithm for spectral images. *Optical Engineering*, 53(1):013107–013107. [CrossRef]
- Sun, X., Zhang, L., Yang, H., Wu, T., Cen, Y., and Guo, Y. (2015). Enhancement of spectral resolution for remotely sensed multispectral image. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(5):2198–2211. [CrossRef]
- Swayze, G. A., Clark, R. N., Goetz, A. F. H., Livo, K. E., Breit, G. N., Kruse, F. A., Sutley, S. J., Snee, L. W., Lowers, H. A., Post, J. L., Stoffregen, R. E., and Ashley, R. P. (2014). Mapping advanced argillic alteration at cuprite, nevada, using imaging spectroscopy. *Economic Geology*, 109(5):1179–1221. [CrossRef]
- Teillet, P., Barker, J., Markham, B., Irish, R., Fedosejevs, G., and Storey, J. (2001). Radiometric cross-calibration of the landsat-7 ETM+ and landsat-5 TM sensors based on tandem data sets. *Remote Sensing of Environment*, 78(1-2):39–54. [CrossRef]
- Teillet, P., Guindon, B., and Goodenough, D. (1982). On the slope-aspect correction of multispectral scanner data. *Canadian Journal of Remote Sensing*, 8(2):84–106. [CrossRef]
- Thenkabail, P. S., Enclona, E. A., Ashton, M. S., Legg, C., and Dieu, M. J. D. (2004). Hyperion, IKONOS, ALI, and ETM+ sensors in the study of african rainforests. *Remote Sensing of Environment*, 90(1):23–43. [CrossRef]
- Thenkabail, P. S., Lyon, J. G., and Huete, A. (2011). *Hyperspectral Remote Sensing of Vegetation*. CRC Press, Boca Raton, Florida, USA. [CrossRef]
- van der Meer, F. D., van der Werff, H. M., van Ruitenbeek, F. J., Hecker, C. A., Bakker, W. H., Noomen, M. F., van der Meijde, M., Carranza, E. J. M., de Smeth, J. B., and Woldai, T. (2012). Multi- and hyperspectral geologic remote sensing: A review. *International Journal of Applied Earth Observation and Geoinformation*, 14(1):112–128. [CrossRef]
- Wald, L. (2000). Quality of high resolution synthesised images: Is there a simple criterion? In *Third conference "Fusion of Earth data: merging point measurements,*

- raster maps and remotely sensed images*", pages 99–103, Sophia Antipolis, France. SEE/URISCA. [Google Scholar]
- Wang, Z. and Bovik, A. (2002). A universal image quality index. *IEEE Signal Processing Letters*, 9(3):81–84. [CrossRef]
- Wang, Z., Bovik, A., Sheikh, H., and Simoncelli, E. (2004). Image quality assessment: From error visibility to structural similarity. *IEEE Transactions on Image Processing*, 13(4):600–612. [CrossRef]
- Winter, M. E., Winter, E. M., Beaven, S. G., and Ratkowski, A. J. (2007). Hyperspectral image sharpening using multispectral data. In *2007 IEEE Aerospace Conference*, pages 1–9. IEEE. [CrossRef]
- Wulder, M. A., White, J. C., Masek, J. G., Dwyer, J., and Roy, D. P. (2011). Continuity of landsat observations: Short term considerations. *Remote Sensing of Environment*, 115(2):747–751. [CrossRef]
- Zhao, H., Jia, G., and Li, N. (2010). Transformation from hyperspectral radiance data to data of other sensors based on spectral superresolution. *IEEE Transactions on Geoscience and Remote Sensing*, 48(11):3903–3912. [CrossRef]

# Appendix A

## Abbreviations

|        |                                                                |
|--------|----------------------------------------------------------------|
| ALI    | Advanced Land Imager                                           |
| ALI    | Alunite index                                                  |
| ASTER  | Advanced Spaceborne Thermal Emission and Reflection Radiometer |
| AVIRIS | Airborne Visible / Infrared Imaging Spectrometer               |
| BIC    | Bayesian information criterion                                 |
| BMA    | Bayesian model averaging                                       |
| CASI   | Compact Airborne Spectrographic Imager                         |
| CHRIS  | Compact High Resolution Imaging Spectrometer                   |
| CLI    | Calcite index                                                  |
| CRISP  | Color Resolution Improvement Software Package                  |
| EnMAP  | The environmental mapping and analysis program                 |
| EO-1   | Earth Observing One                                            |
| ERGAS  | Erreur relative globale adimensionnelle de synthèse            |
| ETM+   | Enhanced Thematic Mapper Plus                                  |
| FLAASH | Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes |
| GCP    | Ground control point                                           |
| GS     | The enhanced Gram-Schmidt spectral sharpening method           |
| HISUI  | Hyperspectral Imager Suite                                     |

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|            |                                                         |
|------------|---------------------------------------------------------|
| HyMAP      | An airborne hyperspectral sensor                        |
| Hyperion   | Hyperspectral Imager                                    |
| KC         | Kappa coefficient                                       |
| KLI        | Kaolinite index                                         |
| Landsat    | Land Remote-Sensing Satellite                           |
| MNF        | Minimum noise fraction                                  |
| MSSIM      | The average SSIM                                        |
| MTMF       | Mixture-tuned matched filtering                         |
| NDVI       | Normalized difference vegetation index                  |
| NIR        | Near infrared                                           |
| NND        | Nearest Neighbor Diffusion Based Pan Sharpening method  |
| OA         | Overall agreement                                       |
| OHI        | OH bearing altered minerals index                       |
| OLI        | Operational Land Imager                                 |
| PA         | Producer's accuracy                                     |
| PAN        | Panchromatic                                            |
| PCC        | Pearson's correlation coefficient                       |
| PHITA      | Pseudo-Hyperspectral Image Transformation Algorithm     |
| PPI        | Pixel Purity Index                                      |
| PRISMA     | Hyperspectral Precursor and Application Mission         |
| ProSpecTIR | VNIR – SWIR Hyperspectral Instrument of SpecTIR company |
| PSNR       | Peak signal-to-noise ratio                              |
| RMSE       | Root mean square error                                  |
| SAM        | Spectral angle mapper                                   |
| SASI       | Short-wave-infrared Airborne Spectrographic Imager      |
| SLC        | Scan line corrector                                     |
| SREM       | Spectral Resolution Enhancement Method                  |

|      |                                        |
|------|----------------------------------------|
| SSIM | Structural similarity index            |
| SWIR | Shortwave infrared                     |
| TM   | Thematic Mapper                        |
| UA   | User's accuracy                        |
| UIQI | Universal image quality index          |
| UPDM | Universal Pattern Decomposition Method |
| USGS | United States Geological Survey        |
| VNIR | Visible-to-near infrared               |

# Appendix B

## Mathematical notations

|                                                     |                                                                                     |
|-----------------------------------------------------|-------------------------------------------------------------------------------------|
| $G$                                                 | filtering matrix                                                                    |
| $X$                                                 | multispectral image                                                                 |
| $Y$                                                 | hyperspectral image                                                                 |
| $r$                                                 | the Gaussian random error                                                           |
| $i$                                                 | hyperspectral band                                                                  |
| $j$                                                 | image pixel                                                                         |
| $\vec{y}_{A(j)}$                                    | simulated hyperspectral spectrum with $A$ bands at $j$                              |
| $\vec{x}_{B(j)}$                                    | given multispectral spectrum with $B$ bands at $j$                                  |
| $\rho_{ij}^H(\lambda)$                              | reflectance of the Hyperion band $i$ and pixel $j$                                  |
| $\rho_{1j}^L(\lambda), \dots, \rho_{5j}^L(\lambda)$ | reflectances at $j$ of ETM+ bands $1, \dots, 5$ , respectively                      |
| $\rho_{6j}^L(\lambda)$                              | reflectances at $j$ of ETM+ bands 7                                                 |
| $\beta_{0i}$                                        | intercept for $i$                                                                   |
| $\beta_{1i}, \dots, \beta_{6i}$                     | unknown regression coefficients between the ETM+ bands<br>and the Hyperion band $i$ |
| $\varepsilon_{ij}$                                  | random error (residual)                                                             |
| $M$                                                 | set of all possible models                                                          |
| $\omega$                                            | quantity of interest                                                                |
| $D$                                                 | data                                                                                |



---

|                                     |                                                                                                           |
|-------------------------------------|-----------------------------------------------------------------------------------------------------------|
| $M_k$                               | model $k$                                                                                                 |
| $\phi_k$                            | vector of parameters of $M_k$                                                                             |
| $\Theta_k$                          | number of independent parameters in $M_k$                                                                 |
| $\varphi_k$                         | maximum likelihood estimator                                                                              |
| $n$                                 | number of observations or the total number of pixels in band $i$                                          |
| $e$ and $f$                         | row and column of a pixel                                                                                 |
| $\rho_{efi}$ and $\hat{\rho}_{efi}$ | original and de-striped pixel values at $e, f$ and $i$                                                    |
| $\mu_{fi}$ and $\sigma_{fi}$        | mean and standard deviation of the data in $f$ at $i$                                                     |
| $\mu_i$ and $\sigma_i$              | mean and standard deviation of all band- $i$ data                                                         |
| $\rho(\lambda)$                     | pixel surface reflectance                                                                                 |
| $L_\lambda$                         | spectral radiance at a sensor pixel ( $\mu\text{W}/(\text{cm}^2 \cdot \text{sr} \cdot \text{nm})$ )       |
| $\rho_e(\lambda)$                   | average surface reflectance for a pixel and a surrounding region                                          |
| $S$                                 | spherical albedo of the atmosphere                                                                        |
| $L_\lambda^a$                       | radiance back scattered by the atmosphere ( $\mu\text{W}/(\text{cm}^2 \cdot \text{sr} \cdot \text{nm})$ ) |
| $A$ and $B$                         | coefficients in $L_\lambda$                                                                               |
| $IL$                                | solar illumination strength                                                                               |
| $\gamma_I$                          | incident angle (rad)                                                                                      |
| $\phi_a$                            | solar azimuth angle (rad)                                                                                 |
| $\phi_o$                            | aspect angle (rad)                                                                                        |
| $\rho_h$                            | horizontal reflectance                                                                                    |
| $\rho_T$                            | reflectance on an inclined surface                                                                        |
| $c_i$                               | coefficient to relate $\rho_T$ at band $i$ to $IL$                                                        |
| $w_i$ and $z_i$                     | regression coefficients                                                                                   |
| $\hat{H}$                           | pseudo-image                                                                                              |

---

|                                        |                                                                                     |
|----------------------------------------|-------------------------------------------------------------------------------------|
| $H$                                    | original image                                                                      |
| $\rho_{ij}^{\hat{H}}(\lambda)$         | pseudo-reflectance at pixel $j$ and band $i$                                        |
| $\rho_{ij}^H(\lambda)$                 | original reflectance at pixel $j$ and band $i$                                      |
| $\sigma_i$                             | standard deviations of all reflectances in $i$                                      |
| $\mu_i$                                | means of all pixel in $i$                                                           |
| $MSE$                                  | mean squared error                                                                  |
| $MAX_i$                                | maximum reflectance in an original band $i$                                         |
| $h$                                    | number of pseudo-hyperspectral bands                                                |
| $a/b$                                  | pixel-size ratio between the pseudo-hyperspectral and multispectral images          |
| $Z_j$                                  | reflectance spectra at pixel $j$                                                    |
| $\rho_{dj}^X(\lambda)$                 | reflectance of multispectral band $d$ at $j$                                        |
| $m$                                    | number of given multispectral bands                                                 |
| $\alpha, \beta, \gamma$ , and $\delta$ | scalar constants in a linear combination                                            |
| $B, G, R$                              | blue, green, and red bands, respectively                                            |
| $NIR$                                  | near infrared band                                                                  |
| $MS$                                   | multispectral band                                                                  |
| $(s, t)$                               | position of a pixel in the high resolution coordinate                               |
| $M(u, v; s, t, \psi)$                  | spectrum vector of neighboring superpixels $(u, v)$ corresponding to pixel $(s, t)$ |
| $\psi$                                 | a difusion region                                                                   |
| $s_{u,v}$ and $t_{u,v}$                | center pixel locations of neighboring superpixels $(u, v)$                          |
| $k(s, t)$                              | normalization factor                                                                |
| $\chi$                                 | intensity                                                                           |
| $\chi_s$                               | spatial smoothness factors                                                          |
| $PM$                                   | pansharpened image                                                                  |
| $P$                                    | resampled PAN band                                                                  |

|                           |                                                                         |
|---------------------------|-------------------------------------------------------------------------|
| $P_0$                     | original full resolution PAN                                            |
| $N_\psi(s, t)$            | similarity metric between pixel $(s, t)$ to its neighboring superpixels |
| $\rho_{ij}^{AV}(\lambda)$ | reflectance of AVIRIS band $i$ and pixel $j$                            |
| $INDEX_{lj}$              | mineral index $l$ at pixel $j$                                          |

# Appendix C

## Summary of used remote sensing data

Table C.1 Spectral range and spatial resolution (SR) of TM, ETM+, OLI, ALI, and ASTER bands.

| TM   |                     |                        | ETM+ |                    |                       |
|------|---------------------|------------------------|------|--------------------|-----------------------|
| Band | Spectral range (μm) | SR (m)                 | Band | Spectral range(μm) | SR (m)                |
| 1    | 0.452–0.518         | 30                     | 1    | 0.452–0.514        | 30                    |
| 2    | 0.528–0.609         | 30                     | 2    | 0.519–0.601        | 30                    |
| 3    | 0.626–0.693         | 30                     | 3    | 0.631–0.692        | 30                    |
| 4    | 0.776–0.904         | 30                     | 4    | 0.772–0.898        | 30                    |
| 5    | 1.567–1.784         | 30                     | 5    | 1.547–1.748        | 30                    |
| 6    | 10.45–12.42         | 120 (30 <sup>+</sup> ) | 6    | 10.31–12.36        | 60 (30 <sup>+</sup> ) |
| 7    | 2.097–2.349         | 30                     | 7    | 2.065–2.346        | 30                    |
|      |                     |                        | PAN  | 0.515–0.896        | 15                    |
| OLI  |                     |                        | ALI  |                    |                       |
| Band | Spectral range(μm)  | SR (m)                 | Band | Spectral range(μm) | SR (m)                |
| 1    | 0.435–0.451         | 30                     | 1    | 0.433–0.453        | 30                    |

|         |             |                        |     |             |    |
|---------|-------------|------------------------|-----|-------------|----|
| 2       | 0.452–0.512 | 30                     | 2   | 0.450–0.515 | 30 |
| 3       | 0.533–0.590 | 30                     | 3   | 0.525–0.605 | 30 |
| 4       | 0.636–0.673 | 30                     | 4   | 0.633–0.690 | 30 |
| 5       | 0.851–0.879 | 30                     | 5   | 0.775–0.805 | 30 |
| 6       | 1.566–1.651 | 30                     | 6   | 0.845–0.890 | 30 |
| 7       | 2.107–2.294 | 30                     | 7   | 1.200–1.300 | 30 |
| 8 (PAN) | 0.503–0.676 | 15                     | 8   | 1.550–1.750 | 30 |
| 9       | 1.363–1.384 | 30                     | 9   | 2.080–2.350 | 30 |
| 10      | 10.60–11.19 | 100 (30 <sup>†</sup> ) | PAN | 0.480–0.690 | 10 |
| 11      | 11.50–12.51 | 100 (30 <sup>†</sup> ) |     |             |    |

| ASTER |                    |        |
|-------|--------------------|--------|
| Band  | Spectral range(μm) | SR (m) |
| 1     | 0.520–0.600        | 15     |
| 2     | 0.630–0.690        | 15     |
| 3     | 0.760–0.860        | 15     |
| 3B    | 0.760–0.860        | 15     |
| 4     | 1.600–1.700        | 30     |
| 5     | 2.145–2.185        | 30     |
| 6     | 2.185–2.225        | 30     |
| 7     | 2.235–2.285        | 30     |
| 8     | 2.295–2.365        | 30     |
| 9     | 2.360–2.430        | 30     |
| 10    | 8.125–8.475        | 90     |
| 11    | 8.475–8.825        | 90     |
| 12    | 8.925–9.275        | 90     |
| 13    | 10.25–10.95        | 90     |
| 14    | 10.95–11.65        | 90     |

<sup>†</sup>Products are resampled to 30-meter pixels.

Table C.2 List of all image scenes (except for CASI+SASI image) used in this study.

| Sensor   | Scene identifier                                | Acquisition date | Chapter |
|----------|-------------------------------------------------|------------------|---------|
| ETM+     | LE70410342001204EDC00                           | 2001/07/23       | 3       |
| Hyperion | EO1H0410342001204111P1_PF1_01                   | 2001/07/23       | 3       |
| Hyperion | EO1H0410342011262110KF_SGS_01                   | 2011/09/19       | 3       |
| Hyperion | EO1H0410342011247110KF_SGS_01                   | 2011/09/04       | 3       |
| Hyperion | EO1H0400342002280110PZ_PF1_01                   | 2002/10/07       | 3       |
| Hyperion | EO1H0410342001172110P3_PF1_01                   | 2001/06/21       | 3, 4    |
| TM       | LT50410342001164XXX02                           | 2001/06/13       | 4       |
| ETM+     | LE70410342001172EDC00                           | 2001/06/21       | 4       |
| OLI      | LC80410342013165LGN00                           | 2013/06/14       | 4       |
| ALI      | EO1A0410342001172110P3_PF1_01                   | 2001/06/21       | 4       |
| OLI      | LC80410342013117LGN02                           | 2013/04/27       | 5       |
| OLI      | LC80010762013109LGN01                           | 2013/04/19       | 5       |
| ASTER    | AST_L1T_00303182007184521_20150518173520_117614 | 2007/03/18       | 5       |
| ASTER    | AST_L1T_00312042006145351_20150517074817_82003  | 2006/12/04       | 5       |
| AVIRIS   | f130306t01p00r06                                | 2013/03/06       | 5       |

# Appendix D

## Brief description of the MNF and MTMF

### D.1 MNF transformation

The MNF transformation was modified from Green et al. (1988) and implemented in ENVI to segregate noise in the image data. Because it was used to maximize the SNR rather than maximizing variance, it is to be preferred over principal component analysis. The MNF transformation are summarized as follows (Canty, 2014).

A noisy hyperspectral image  $Y$  is represented as a sum of signal  $S$  and noise  $N$  components:

$$Y = S + N. \quad (D.1)$$

If the both components have normal distribution with a mean of zero and respective covariance matrices  $\Sigma_S$  and  $\Sigma_N$ , the covariance matrix  $\Sigma$  for  $Y$  is also the sum of signal and noise contributions as

$$\Sigma = \Sigma_S + \Sigma_N. \quad (D.2)$$

In ENVI, the MNF transformation consists two separate principal components analysis. The first transformation diagonalizes  $\Sigma_N$ , after which  $\Sigma_N = I$ , the identity matrix. We let  $T$  is the transformation matrix and the resultant random vector  $R_0$  is defined as

$$\begin{aligned} R_0 &= T^\top Y, \\ T^\top \Sigma_N T &= D_N, \end{aligned} \quad (D.3)$$

where  $D_N$  is a diagonal matrix whose diagonal elements are the variances of the transformed noise component  $T^\top N$ . Subsequently, a new random vector  $R_1$  is given by

$$R_1 = D_N^{-1/2} R_0 = D_N^{-1/2} T^\top Y. \quad (D.4)$$

Here, the covariance matrix of  $R_1$  is

$$\Sigma_{R_1} = D_N^{-1/2} T^\top \Sigma T D_N^{-1/2}. \quad (D.5)$$

The second transformation is performed on  $R_1$  to calculate the random vector  $R_2$  representing the MNF components as:

$$R_2 = U^\top R_1, \quad (D.6)$$

where  $U^\top \Sigma_{R_1} U = D_{R_1}$ . Therefore, the overall transformation is determined as

$$R_2 = U^\top D_N^{-1/2} T^\top Y. \quad (D.7)$$

The SNR in the band  $i$  of  $Y$  can be expressed as

$$SNR_i = \frac{1}{\lambda_i} - 1, \quad (D.8)$$



if  $\mathbf{D} = \text{Diag}(\lambda_1, \dots, \lambda_N)$  and

$$\boldsymbol{\Sigma}_N \mathbf{V} = \boldsymbol{\Sigma} \mathbf{V} \mathbf{D}, \quad (\text{D.9})$$

where  $\mathbf{V}$  generates a linear transformation  $\mathbf{Y}' = \mathbf{V}^\top \mathbf{Y}$  of image bands for which  $\text{SNR}_i$  is maximum. Note that with Equation D.7 we can write  $\mathbf{R}_2 = \mathbf{V}^\top \mathbf{Y}$ , where  $\mathbf{V} = \mathbf{T} \mathbf{D}_N^{-1/2} \mathbf{U}$ , then

$$\begin{aligned} \boldsymbol{\Sigma}_N \mathbf{V} &= \boldsymbol{\Sigma}_N \mathbf{T} \mathbf{D}_N^{-1/2} \mathbf{U} \\ &= \mathbf{T} \mathbf{D}_N \mathbf{D}_N^{-1/2} \mathbf{U} && \text{from Equation D.7} \\ &= \mathbf{T} \mathbf{D}_N^{1/2} \mathbf{U} \\ &= \mathbf{T} \mathbf{D}_N^{1/2} (\boldsymbol{\Sigma}_{R_1} \mathbf{U} \mathbf{D}_{R_1}^{-1}) \\ &= \mathbf{T} \mathbf{D}_N^{1/2} \mathbf{D}_N^{-1/2} \mathbf{T}^\top \boldsymbol{\Sigma} \mathbf{T} \mathbf{D}_N^{-1/2} \mathbf{U} \mathbf{D}_{R_1}^{-1} && \text{from Equation D.5} \\ &= \boldsymbol{\Sigma} \mathbf{V} \mathbf{D}_{R_1}^{-1}. \end{aligned} \quad (\text{D.10})$$

Equation D.10 will be the same as Equation D.9 if  $\mathbf{D}$  is replaced by  $\mathbf{D}_{R_1}^{-1}$ , that leads to

$$\lambda_{R_1 i} = \frac{1}{\lambda_i} = \text{SNR}_i + 1, \quad (\text{D.11})$$

based on Equation D.8. Therefore, the eigenvalues calculated by ENVI's MNF transformation,  $\lambda_{R_1 i}$ , are equal to 1 correspond to "pure noise".

## D.2 MTMF

MTMF uses a MNF transformed input data to suppress background noise and estimates the sub-pixel abundance of a target material. The MTMF method performs two main steps: (1) matched filtering (MF) for abundance estimation and (2) mixture tuning to identify false positive pixels (Mitchell and Glenn, 2009). The output from MTMF includes two rule images corresponding to the MF score and the infeasibility value for each identification of the target material. The MF score

is calculated by an orthogonal subspace projection operator based on matching MNF transformed spectra of every pixels to that of the pure pixels, where 1.0 is a perfect match. The infeasibility value is measured in noise sigma unit that vary in DN scale with an MF score (Figure D.1) and indicate the feasibility of the MF result. The low infeasibility value and high MF score indicate should be chosen to correctly map pixels.

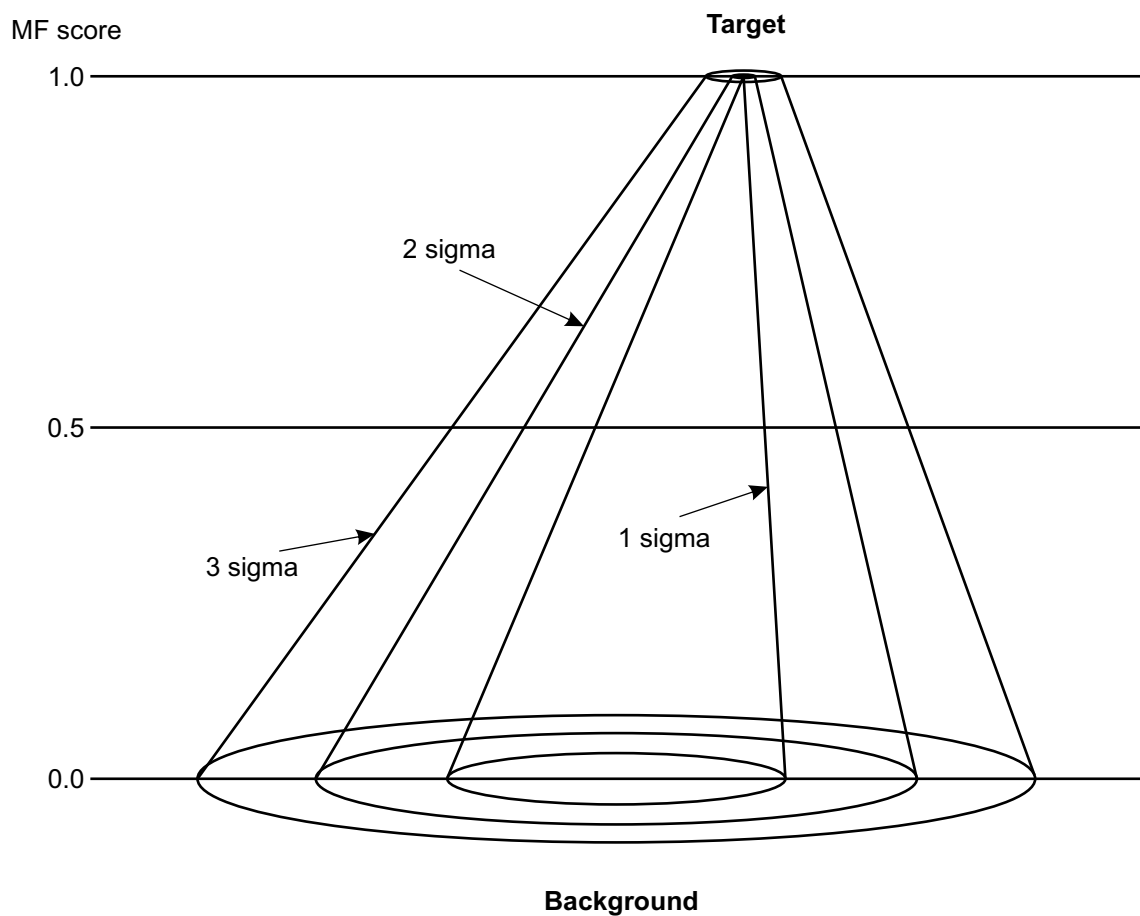


Fig. D.1 Relationship between infeasibility values in noise sigma units and MF scores (Source: <https://www.harrisgeospatial.com/docs/MTMF.html>).

# Appendix E

## Multiple linear regression

### E.1 Estimation of the model parameters

In PHITA, BMA is used for variable selection and each hyperspectral band is considered separately. Subsequently, the method of least squares is used to estimate the regression coefficients. A multiple linear regression model between a hyperspectral band  $y$  and a multispectral image  $X$  can be expressed in matrix notation (Montgomery et al., 2015) as

$$y = X\beta + \epsilon, \quad (\text{E.1})$$

where

$$y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, \quad X = \begin{bmatrix} 1 & x_{11} & x_{12} & \cdots & x_{1k} \\ 1 & x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix}$$

$$\boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{bmatrix}, \quad \boldsymbol{\epsilon} = \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_n \end{bmatrix},$$

$n$  is the number of pixels, for example,  $n \approx 1.5$  millions in Chapter 3, and  $k$  is the number of the most suitable multispectral bands.

To derive the least squares estimator  $\hat{\boldsymbol{\beta}}$  for the parameter vector  $\boldsymbol{\beta}$ , we minimise the sum of squares of the errors, that is

$$S(\boldsymbol{\beta}) = \sum_{i=1}^n \epsilon_i^2 = \boldsymbol{\epsilon}^\top \boldsymbol{\epsilon} = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^\top (\mathbf{y} - \mathbf{X}\boldsymbol{\beta}). \quad (\text{E.2})$$

Then  $\hat{\boldsymbol{\beta}}$  must satisfy

$$\left. \frac{\partial S}{\partial \boldsymbol{\beta}} \right|_{\hat{\boldsymbol{\beta}}} = -2\mathbf{X}^\top \mathbf{y} + 2\mathbf{X}^\top \mathbf{X} \hat{\boldsymbol{\beta}} = 0, \quad (\text{E.3})$$

which simplifies to  $\mathbf{X}^\top \mathbf{X} \hat{\boldsymbol{\beta}} = \mathbf{X}^\top \mathbf{y}$ . Therefore, the least squares estimator is given by

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{y}, \quad (\text{E.4})$$

or can be expressed in detail as

$$\begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \vdots \\ \hat{\beta}_k \end{bmatrix} = \begin{bmatrix} n & \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i2} & \cdots & \sum_{i=1}^n x_{ik} \\ \sum_{i=1}^n x_{i1} & \sum_{i=1}^n x_{i1}^2 & \sum_{i=1}^n x_{i1}x_{i2} & \cdots & \sum_{i=1}^n x_{i1}x_{ik} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \sum_{i=1}^n x_{ik} & \sum_{i=1}^n x_{ik}x_{i1} & \sum_{i=1}^n x_{ik}x_{i2} & \cdots & \sum_{i=1}^n x_{ik}^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^n y_i \\ \sum_{i=1}^n x_{i1}y_i \\ \vdots \\ \sum_{i=1}^n x_{ik}y_i \end{bmatrix}. \quad (\text{E.5})$$

Because  $n \gg k$ , the unknown parameter vector can be solved stably by the least squares method.

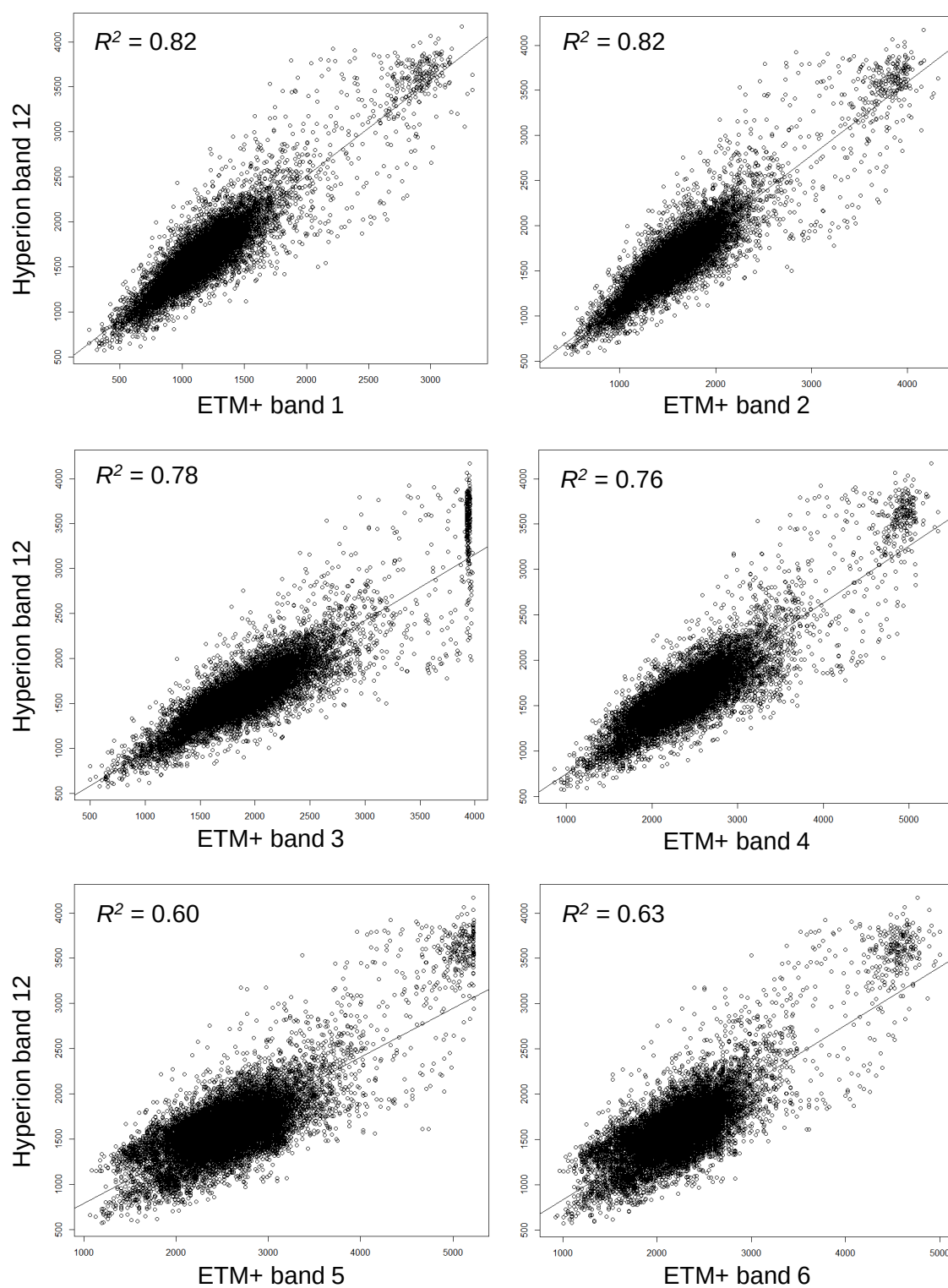


Fig. E.1 Example of reflectance scatter plots between the original Hyperion band 12 and ETM+ multispectral bands. Reflectance value is  $\% \times 10^4$ .

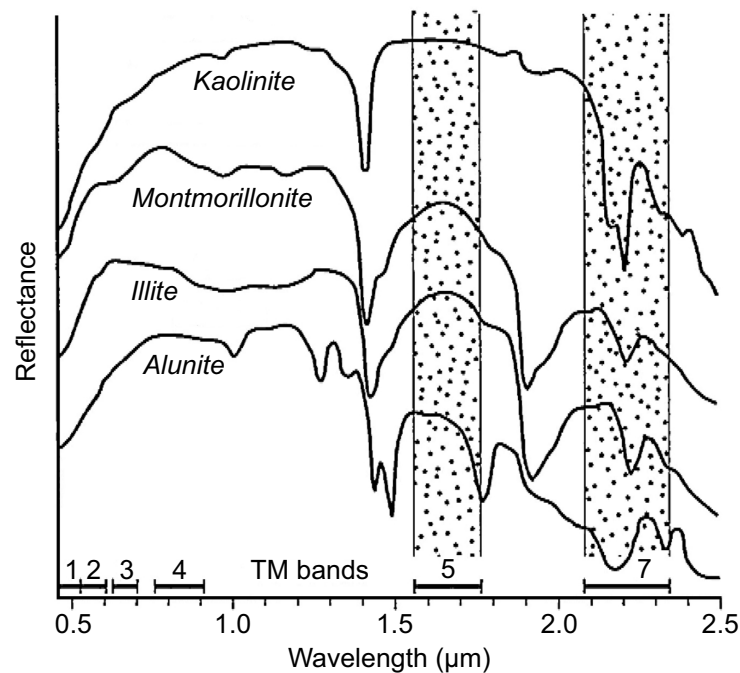


Fig. E.2 Reflectance spectra of alunite and clay minerals (Sabins, 1999).

## E.2 Regression diagnostics

This section shows an example of regression diagnostics between Hyperion band 12 and ETM+ bands. The Hyperion band 12 has strongest correlation with the ETM+ band 1 and 2. Although the correlations of the other ETM+ bands are decreased, their  $R^2$  are greater than 0.6 (Figure E.1). The correlation of Hyperion band 12 with nonoverlapped ETM+ bands must be related to similar spectral pattern of surface materials. Indeed, Figure E.2 shows that a mineral has a higher reflectance in SWIR wavelengths also has a higher reflectance in VNIR wavelengths.

The linear regression model of Hyperion band 12 was further tested by the main assumptions of ordinary least squares regression (Raykov and Marcoulides, 2012):

- *Linearity*: If the dependent variable is linearly related to the independent variables, there should be no systematic relationship between the residuals

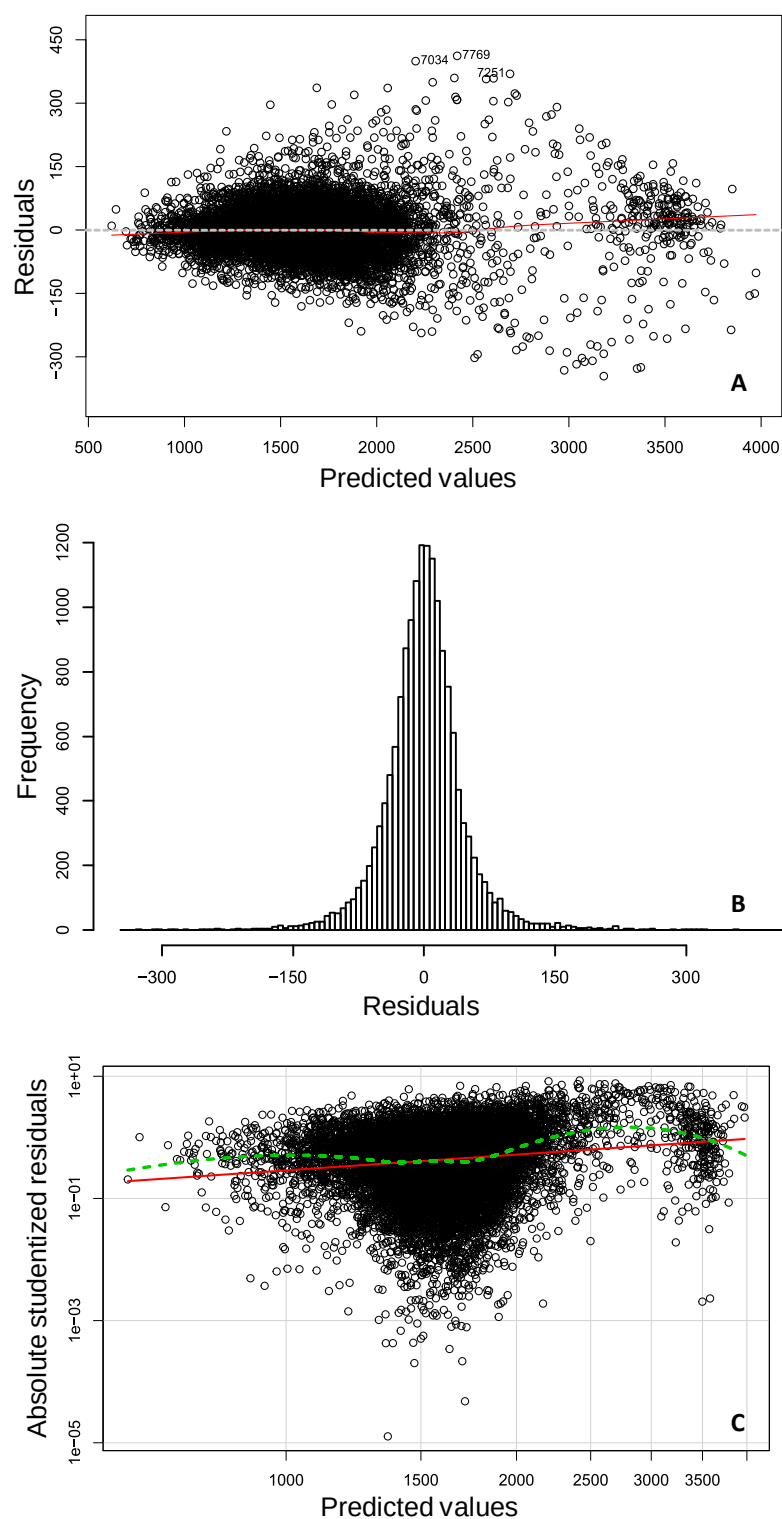


Fig. E.3 Diagnostic plots for the regression between Hyperion band 12 and ETM+ bands. Reflectance value of each pixel is  $\% \times 10^4$ .

and the predicted values. Figure E.3A shows that there is no evidence of such relationship.

- *Normality*: The residual values should be normally distributed with a mean of 0. Normally distributed residuals mean the model has generated acceptable random error (Figure E.3B).
- *Homoscedasticity*: This means that different values of the response variable have the same variance in their errors, regardless of the values of the predictor variables. If the model meet the constant variance assumption, the Spread-Level plot should shows the points that form a random horizontal band around a horizontal line of best fit (Figure E.3C).
- *Independence of errors*: This assumes that the errors of the response variables are uncorrelated with each other. The Durbin–Watson test obtained the D-W Statistic score of 1.93 and the nonsignificant p-value ( $p=0.814$ ) that suggests a lack of autocorrelation and, conversely, an independence of errors.