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Application of Short Wave Infrared Hyperspectral Airborne Image Library for Quality Improvement of Land Cover Classification

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Recent research studies on land cover classification using hyperspectral imagery have focused on diversifying classification classes of land cover as well as improving the accuracy of classification by using the spectral information of each pixel. Conventional hyperspectral images contain wavelengths up to the visible near-infrared (VNIR) wavelength range or low-spatial-resolution images. This has made it difficult to obtain the various types of information of each pixel during land cover classification, and each class could not be assigned individual characteristics owing to the low level of distinction in the information of each pixel. To address this issue, in this study, we acquired images by airborne hyperspectral imaging, with the aim of improving the accuracy of land cover classification by using hyperspectral imagery with a high spatial resolution and spectral resolution resulting from having a wavelength range of 380–2400 nm, which includes the short wave infrared (SWIR) wavelength range. In addition, a spectral library was set up as a means to perform land cover classification using hyperspectral images, and a correlation analysis was carried out to assess the objectivity and accuracy of the spectral library. Moreover, the spectral library was used as a training sample during land cover classification, thereby enhancing accuracy. To assess the accuracy of the spectral library that was set up, the correlation between the spectral library in question with the image spectral library of hyperspectral images was analyzed, and the results showed a high correlation between 0.81 and 0.99. In the process of constructing the spectral library, the spectral library was corrected to the extent that the information in the hyperspectral image would not be lost, and it was constructed in a manner that would increase the accuracy of land cover classification. As a result of applying the finally constructed spectral library to the hyperspectral image land cover classification, a high classification accuracy of 92.9% was obtained.

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1. Introduction

High-resolution remote sensing data is used as an optimal tool in mapping and monitoring for object detection. A type of data produced from this process is a multispectral image with a relatively high spatial resolution, which enables accurate object detection, land cover classification, and real-time monitoring. Also, in addition to increasing the spatial resolution, the spectral resolution has been increased to produce hyperspectral images as a means to obtain information on the parts of RGB images that are difficult to read with the naked eye, and this has led to increased diversity of potential objects that can be detected.

A hyperspectral image has a substantially higher spectral resolution than a conventional multispectral image, and it is composed of a series of hundreds of bands with narrow band widths, which greatly increase the amount of information contained in one pixel in the image.[(1)] Such hyperspectral images have the advantage of obtaining a complete spectral reflectance curve for the surface compared with multispectral images composed of a smaller number of wide and discontinuous bands.[(2–4)]

For this reason, hyperspectral images are used in various fields and considered the most suitable images for object detection or land cover classification. Hyperspectral image sensors that are currently in use are mainly those installed in aircraft such as airborne visible/infrared imaging spectrometer (AVIRIS), compact airborne spectrographic imager (CASI), airborne imaging spectrometer for applications (AISA), hyperspectral digital imagery collection experiment (HYDICE), and HyMAP, whereas satellite sensors include Hyperion of the EO-1 satellite and compact high resolution imaging spectrometer (CHRIS) of the Project for On-Board Autonomy (PROBA) satellite.[(5)]

One of the ways to perform land cover classification using hyperspectral images is to set up a spectral library and designate the spectral data as training samples to carry out the classification.[(6,7)] Recent research on spectral libraries has involved setting up an indoor environment to create a spectral library[(8)] or on analyzing data acquired from the field. In one of the studies in which data were obtained from the field, a spectral library was established by using satellite hyperspectral imagery,[(9)] but in these images, there were many objects in a single pixel owing to low spatial resolution, which made it difficult to ensure distinction across different classes of spectral libraries.

Park *et al.*[(1)] built a spectral library using aerial hyperspectral imagery, but the hyperspectral images included those in the visible near-infrared (VNIR) G range and displayed limitations in obtaining information on forest pests, geology, and soil and in determining the water content and geological characteristics and materials of objects, which is a characteristic of the SWIR wavelength range. Zomer *et al.*[(10)] conducted a spectral library with high spatial and spectral resolution using airborne hyperspectral images including short wave infrared (SWIR) wavelengths.

However, because they used images obtained from the United States,[(10)] it may not be appropriate to use their spectral library in Korea, which differs from the U.S. in terms of geographic and biological characteristics. In addition, there is no measure of objectivity or accuracy for the spectral library, rendering it difficult to be used in practice. This is because when such spectral library is applied to land cover classification, it is not possible to perform the classification properly, which leads to low accuracy.

In this study, image data with high spectral resolution and spatial resolution data were acquired by using aerial hyperspectral images that include VNIR and SWIR wavelengths, and Korea was chosen as the target area of the study in order to build a spectral library with information on vegetation and soil among other factors that could be used in Korea. Figure 1 shows the overall research process. An imaging spectral library was established in hyperspectral imagery as follows, and a field spectral library was acquired from the field for a correlation analysis. This could be a measure that can be utilized by judging the objectivity and accuracy of the spectral library that has been built. Therefore, if there is an increase in the accuracy of the spectral library used as the training sample for land cover classification, the land cover classification itself will also exhibit high accuracy. This study could largely be divided into the establishment of a field spectral library, establishment of an imaging spectral library, correlation analysis of spectral libraries, and land cover classification.

As a method of building a field spectral library for analyzing data from hyperspectral images, spectral data were acquired in time for the day of aerial hyperspectral imaging, and data were acquired for five days from the date of imaging in order to maintain data consistency. The spectral data were corrected through white reference (WR) before the field spectral data were acquired, and data were obtained while considering the angle of the sun's rays. [11]

The imaging spectral library, which consists of reference data for assessing the accuracy of the field spectral library, was set up on the basis of the field survey data and Global Positioning System (GPS) location data at the time the field spectral library was acquired. Basic corrections of the images were made on the basis of geometric and atmospheric corrections as a preprocessing for the hyperspectral images.[11,12] The reflectance of 20 pixels for each class was then obtained from the corrected hyperspectral images based on the field survey data, after which the average of the spectral data for each band was calculated to set up the image spectral library.[13]

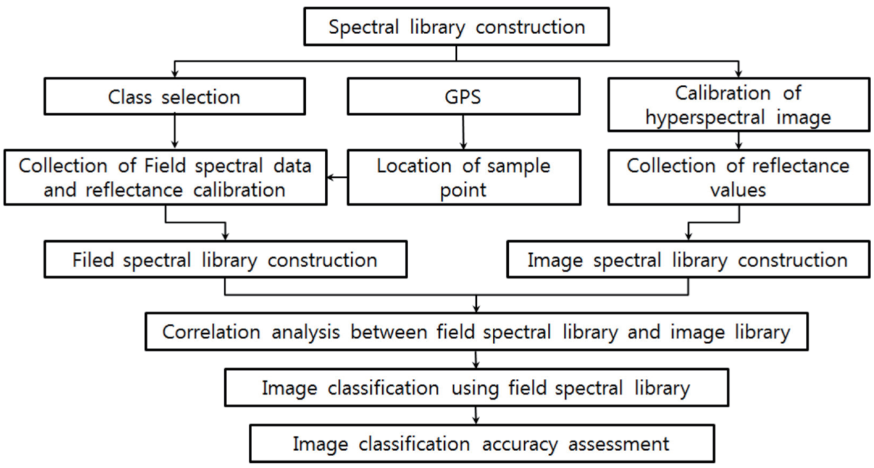


Fig. 1. Main flow chart of this study.

The correlation between the spectral library constructed using the field spectrometer and the spectral library constructed using airborne hyperspectral images was evaluated. The classes were selected on the basis of the field spectral library, and the coefficient of determination was used as a measure of accuracy. Lastly, the spectral library was used as a training sample, and land cover classification was performed for the entire image by selecting the reference data based on the attribute data from the field survey.

2. Materials and Methods

2.1 Description of study site

In this study, Haeryong-ri, Daesan-myeon, Gochang-gun, Jeollabuk-do Province, which is an area with diverse land cover, was chosen as the target area for the research carried out with the aim of improving the accuracy of land cover classification by setting up a spectral library of hyperspectral images. Figure 2 shows the target site, where it is easy to determine the classifications of vegetation and the characteristics of the soil and target objects such as moisture distribution using the SWIR wavelength range.

The imaging was performed on October 27, 2015. Hyperspectral image data were acquired, and spectral data for each class and the class with spectral data that do not change in the time series were identified.

2.2 Data acquisition

To set up a spectral library and use it for land cover classification using hyperspectral images, it is important to accurately match the hyperspectral image sensors and the spectral library. Also, the most important part of the process of improving the accuracy of land cover classification is that the corrections be performed before data acquisition to ensure that the data are consistent and objective.

Fig. 2. (Color online) Study site (Haeryong-ri, Daesan-myeon, Gochang-gun, Jeollabuk-do).

Accordingly, in this study, FINEX, an aerial hyperspectral sensor manufactured by AISA, was used to acquire spectral data that included the VNIR and SWIR wavelength ranges. The sensor in question had a spatial resolution of 2 m and included the VNIR (380–1000 nm) and SWIR (1000–2500 nm) wavelength ranges. It also had 448 bands and a spectral resolution of 3.4–5.7 nm. As for the field spectrometer, Field Spec 4 manufactured by Analytical Spectral Devices Inc. (ASD) was used to acquire field spectral data to build the spectral library. The sensor in question had a wavelength range of 350–2500 nm, which included VNIR and SWIR, and the total number of bands was 2151 with a spectral resolution of 1 nm.

Hyperspectral images were acquired during the fall season in Korea when humidity levels were low and the sky was clear without any clouds. This is because noise generated during data acquisition by the aerial hyperspectral sensor appears in the presence of moisture, and dry weather with low humidity made it easier to acquire the necessary data. Then, the field data were acquired, which was the most influential part in improving the accuracy of land cover classification. First, big data were built before the field data acquisition by obtaining 500 pieces of spectral data for each class over the course of five days from the start date of image data acquisition to ensure accurate matching with the aerial hyperspectral images.

Since there were no previously constructed objective and professional data, spectral data representing the characteristics of the target objects were considered as big data and were used after the unnecessary data were eliminated. It should be noted that field spectral data need to be acquired when the sky is as clear and cloudless as possible, and the angle of the field spectrometer sensor must be adjusted in consideration of the angle at which the sunlight is reflected.

Afterwards, the data needs to be corrected to ensure consistency because the amount of light varies over time and the weather differs depending on the time of data acquisition. The wavelength range in which the reflectance is 100% when WR is measured using a field spectrometer after performing corrections of the spectral reflectance using WR with a reflectance of almost 100%, as shown in Fig. 3, is the portion in which the corrections have been completed.

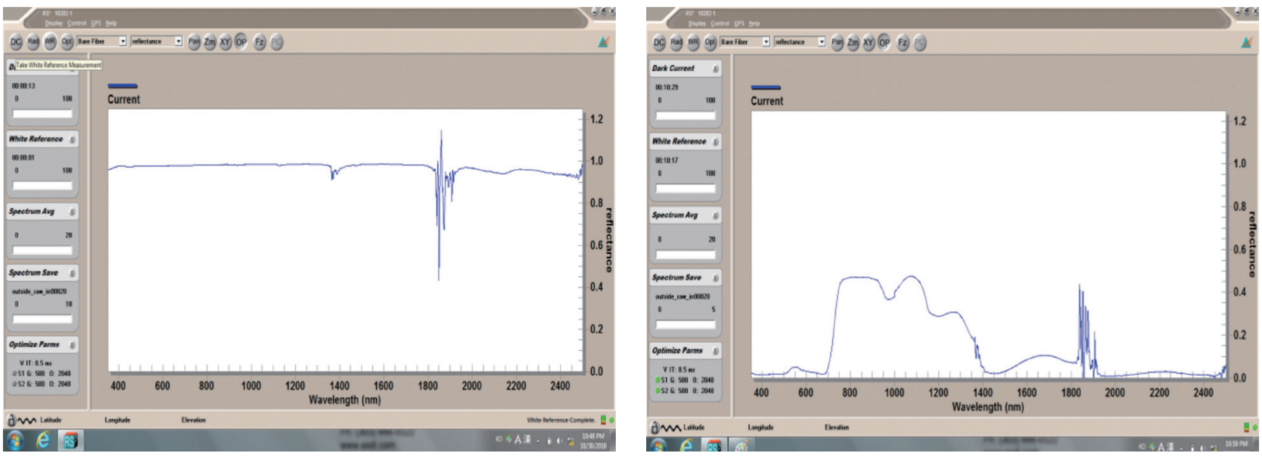
Fig. 3. (Color online) Calibration of white reference.

However, in the case of a wavelength range where the reflectance obtained is not 100% and there are areas that are reminiscent of sparks or areas with large differences. Those areas may have been caused by improper corrections or noise in the data value caused by another factor. Figure 4(a) shows the process of obtaining WR data after performing corrections using WR through the RS3TM spectral acquisition software, whereas Fig. 4(b) shows the values obtained from measuring the spectral data of objects after making the corrections. After acquiring the field data, the spatial coordinates of field data were obtained using GPS in order to determine the relationship between hyperspectral images and field data at the same location.

2.3 Construction of field spectral library

The field spectral library, which consists of data used as training samples for land cover classification using hyperspectral image, has the greatest impact on classification accuracy. Thus, to build a reliable field spectral library, there needs to be a process of eliminating or correcting the noise generated as a result of the atmosphere or water vapor in the data acquired by the field spectrometer in order to improve accuracy. In addition, to perform land cover classification by applying the spectral library that has been set up to hyperspectral images, the process of matching with the images is also necessary. With respect to this study, it was determined that a more accurate field spectral library could be built through the process of eliminating noise and the process of matching hyperspectral images and bands by using the spectral data that have been corrected during field data acquisition to improve the accuracy of land cover classification.

First, land cover classification performed with hyperspectral images using field spectral data acquired as part of the process of matching hyperspectral images and bands cannot be perfect in default settings in the case of applying the spectral angle mapping (SAM) technique in which the inner product is obtained with the reflectance of the two spectra assumed as the column vector.[1] Also, to apply the field spectral library acquired by using the field spectrometer to the



(a) (b)

Fig. 4. (Color online) Data acquisition using RS3TM SW: (a) WR reflectance and (b) data acquisition after calibration.

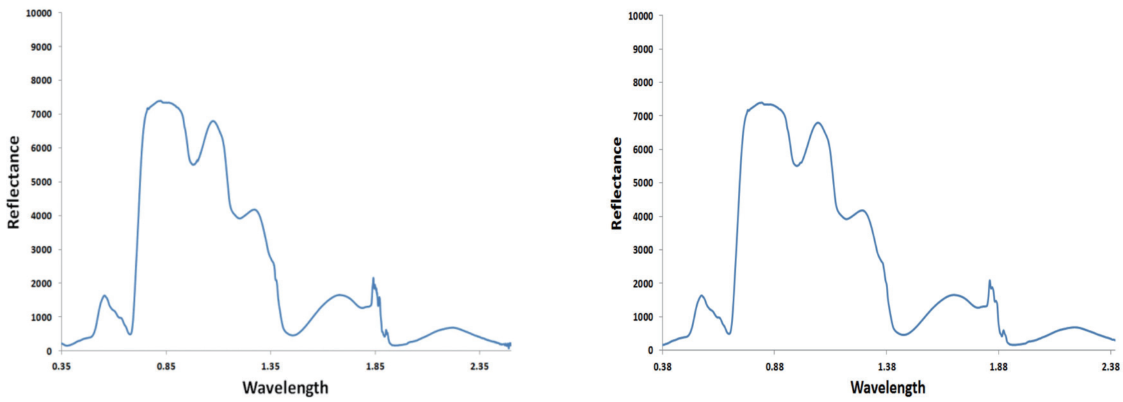
hyperspectral image land cover classification and to improve its accuracy, the bandwidths and the wavelength ranges of the hyperspectral images and the field spectral data must coincide. Column vector conversion was performed to classify the acquired spectral data, and interpolation was performed after determining the relationship between the data from the field spectrometer sensor and the aerial hyperspectral sensor.

This process showed that AISA FINEX, an aerial hyperspectral sensor, had a bandwidth of 3.4–5.7 nm, and Field Spec 4, a field spectrometer, had a bandwidth of 1 nm, indicating that the spectral resolutions of the two sensors did not match. Accordingly, interpolation was performed to match the bandwidths. In the case of interpolation, if the spectral reflectance at wavelength x_k of the spectral library obtained from the field spectrometer is y_k, and X_m, the wavelength of the hyperspectral library, exists between wavelength x_k and wavelength x_{k+1}, then y_m, the reflectance of the spectral library that contrasts with wavelength X_m, can be obtained using the following equation:

$$Y_m = \frac{y_k - y_{k+1}}{x_k - x_{k+1}} X_m + \frac{x_k \cdot y_{k+1} - x_{k+1} \cdot y_k}{x_k - x_{k+1}}, \tag{1}$$

where x_k and X_m denote the wavelength before and after interpolation and y_k and Y_m denote reflectance before and after interpolation, respectively.

The above interpolation was performed for all the bands of the field spectral library with a bandwidth of 1 nm in the wavelength range from 350 to 2500 nm using the macro function of Microsoft® Excel. The interpolation process was performed so that there would be 448 bands in the 380–970 nm (3.4 nm) range corresponding to VNIR and 970–2500 nm (5.7 nm) corresponding to SWIR based on the hyperspectral images. In conclusion, the field spectral library was built to have a wavelength range of 380–2500 nm and 448 bands in total. Figure 5(a) shows the cabbage spectral library before interpolation was obtained from the field spectrometer, whereas Fig. 5(b) shows the cabbage spectral library that was built after interpolation for matching the spectral resolution with the airborne sensor.



(a) (b)

Fig. 5. (Color online) Application of cabbage spectral library: (a) before and (b) after.

Even if the band matching process for the field spectral library is completed, the noise generated in the image during land cover classification using the spectral library is the main cause behind the reduced classification accuracy. Such noise is affected by the weather and humidity level at the time the field spectral data are acquired when the wavelength range is expanded to include SWIR, which is sensitive to humidity.

The areas where reflectance is not close to 100% or where peaks appear when data correction is performed using WR prior to the acquisition of spectral data are considered as noise. The noise generated when acquiring spectral information causes a problem of lowering the classification accuracy or correlation when assessing the correlation with the image spectral library or land cover classification in the form of a column vector. To solve this problem, noise was eliminated on the basis of the data correction performed before the field data acquisition.

To integrate the data sets from the five days into a single set of data, the criteria for noise elimination obtained on the day with the most noise among the five days was applied to the other days as well. Generally, major water absorption bands (1340–1480 nm and 1770–1970 nm) were excluded from the statistical analysis.[14]

Also, in the case of the noise generated in the wavelength ranges of 1340–1430 nm, 1810–1966 nm, and 2400–2500 nm based on the WR reflection curve shown in Fig. 6, it was considered that the humidity level was high at the time of data acquisition and thus noise was generated, as the wavelengths were absorbed by the main water absorption bands. To improve the accuracy of the spectral library, the said wavelength ranges were considered as noise wavelength ranges and were removed.

The SAM classification technique applied to land cover classification is used to determine the similarity of spectrum distribution by using the angle between the bands, and this was taken into consideration. The spectral data on the land class prior to noise removal are shown in Fig. 7(a), whereas the wavelength range after noise removal is shown in a linear form in Fig. 7(b). The 2400–2500 nm range, in particular, was removed from the entire wavelength range.

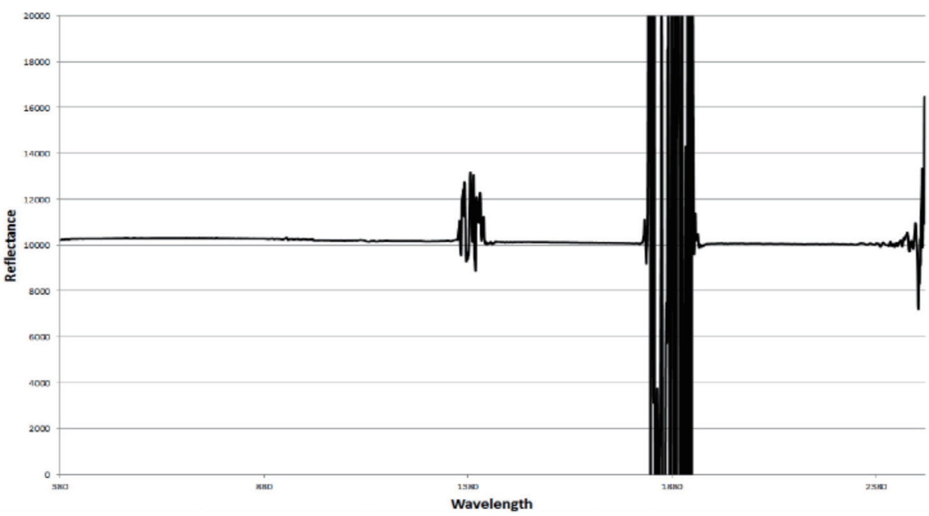
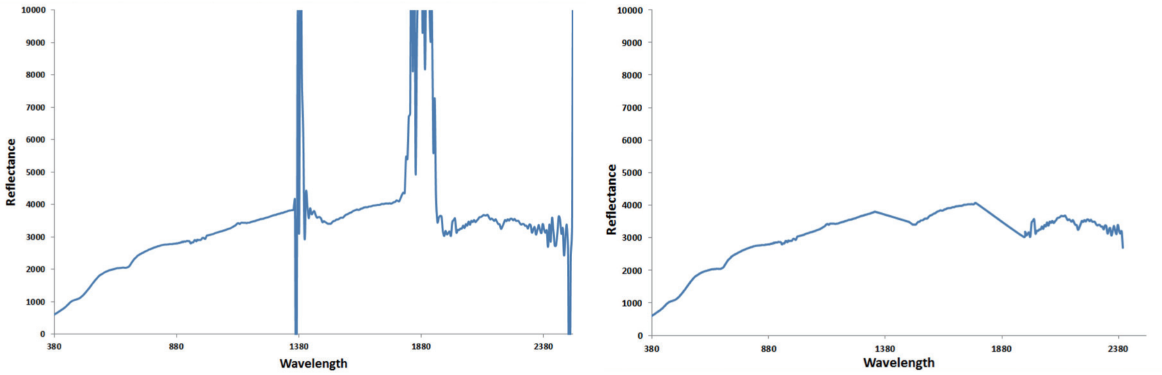


Fig. 6. White reference measurement after calibration.



(a) (b)

Fig. 7. (Color online) Noise removal: (a) before and (b) after.

2.4 Construction of image spectral library

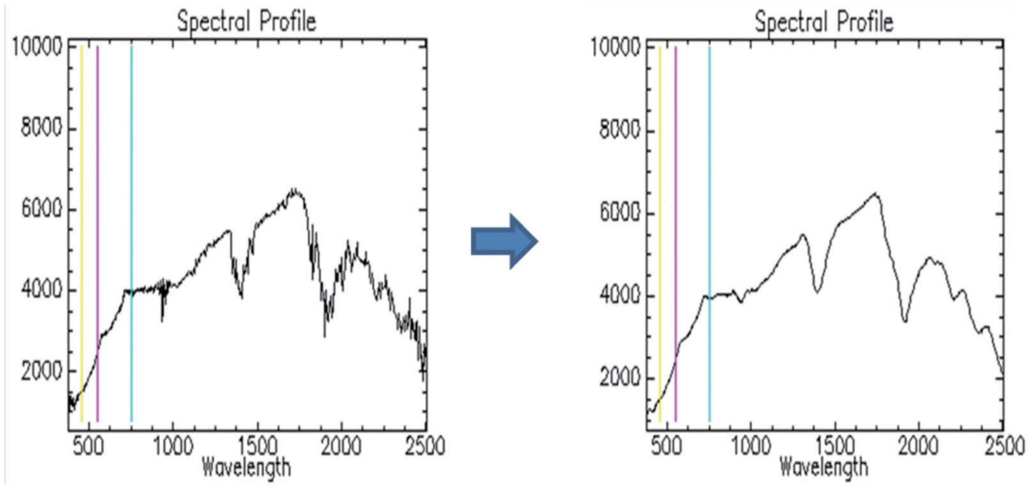
An image spectral library is used as a spectral library set up with aerial hyperspectral images in the pixel unit as reference data for determining the objectivity or accuracy of field spectral data. As for the image spectral library set up in this study, image wavelength curves from 20 locations for each class were extracted on the basis of the location and attribute data acquired from a field survey, and their average was calculated to be used as the basic data for the image spectrometric library. Afterwards, preprocessing, spectral smoothing, and matching between the field spectral library and bands were performed.

First, to perform land cover classification using hyperspectral images by applying the spectral library acquired from the field in image preprocessing, it is necessary to correct the image while considering the atmospheric state on the day of image acquisition as well as the location information. Geometric and atmospheric corrections, in particular, are essential types of correction.

Thus, geometric correction was performed on the hyperspectral images using CaliGeo PRO software based on the GPS/Inertial Navigation System (INS) data, and atmospheric correction was carried out using the Rese ATCOR software. In the case of hyperspectral images, there are a large number of bands, and if atmospheric correction is not performed properly, object detection or land cover classification cannot be performed accurately.

Therefore, the atmospheric correction of hyperspectral images is both important and highly sensitive. In addition, hyperspectral images in which atmospheric correction is not properly performed in the wavelength range where moisture absorption occurs, such as SWIR wavelength range, cannot be used for land cover classification.

Second, even if the image has undergone geometric and atmospheric corrections, there may be noise that looks like sparks on the preprocessed image, depending on the humidity level or the weather at the time of aerial photography. Whether or not correction is necessary depends on the extent to which there are sparks on the image. As for the images used in this study, there were sparks in many areas, and thus efforts were made to remove the sparks as much as possible by using the spectral smoothing tool of ENVI software. Figure 8(a) shows the wavelength curve



(a) (b)

Fig. 8. (Color online) Spectral smoothing tool application: (a) before and (b) after.

before the application of the spectral smoothing tool, while Fig. 8(b) shows the corrected wavelength curve after the smoothing process.

Third, to use the image spectral library as reference data for a correlation analysis after the image correction, the wavelength range removed when setting up the field spectral library due to noise generation must also be removed from the image. This process is necessary for improving the accuracy when using the field spectral library as a training sample for land cover classification. Therefore, the wavelength region that was removed due to noise generation when setting up the field spectral library was also removed from the hyperspectral images using the resize data tool of ENVI software.

As a result, the number of bands decreased from 448 to 383, and the final image correction was performed. Finally, after correcting the hyperspectral images, the image spectral library was set up on the basis of the average data of 20 pixels for each class. As for the method in which the library was set up, the attribution data were obtained through a field survey, the pixels by class were selected on the basis of the location information acquired via GPS, and the average was calculated after extracting the spectral data for each pixel using ENVI's region of interest (ROI) tool. Figure 9 shows the 20 pixels for each class presented using the ROI Tool, and Fig. 10 shows the curves plotted for all the classes of the image spectral library.

2.5 Correlation assessment

To assess the objectivity and accuracy of the field spectral library built in this study, the correlation between the spectral curve plotted for each class on the hyperspectral image and the spectral curve plotted for the field spectral library was assessed. Correlation assessment is typically performed to determine the relationship between two variables by determining the Pearson correlation coefficient (R). The coefficient of determination (R^2) is also a measure of the extent to which the estimated linear model fits the given data. This indicates the ratio of the

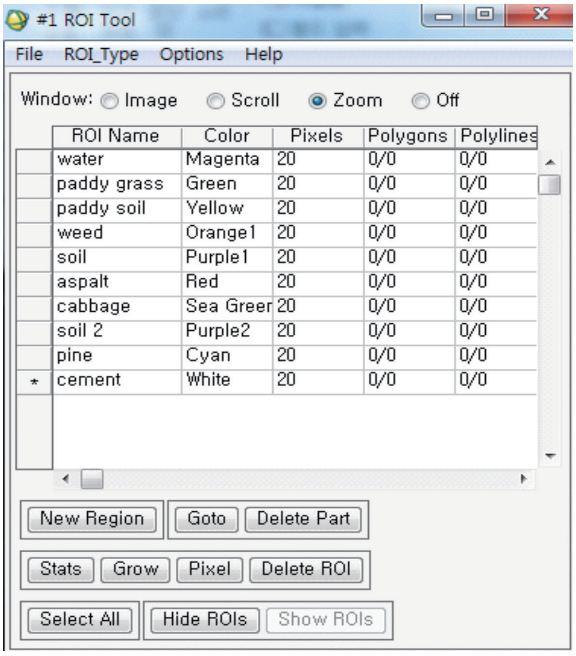


Fig. 9. (Color online) ROI selection by class.

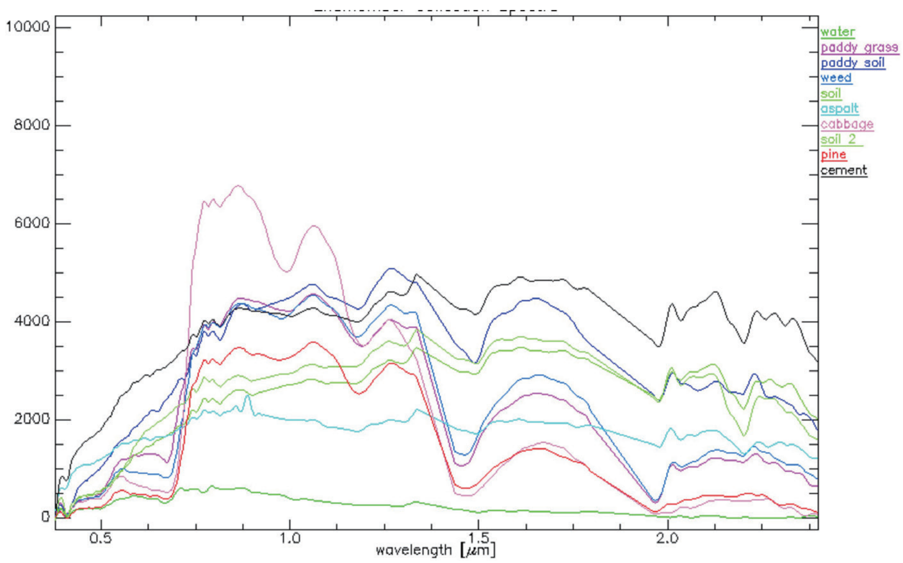


Fig. 10. (Color online) Image spectral library.

changes in the response variable that can be explained by the model. The result of this correlation assessment can be used as a measure for judging whether the actual ground spectral library is suitable for land cover classification using hyperspectral images.

A correlation assessment can present a measure based on which the suitability of the field spectral library for use in land cover classification using hyperspectral imagery can be determined. Therefore, in this study, the variable was designated as reflectance, and a correction analysis was performed for each class of the field spectral library and the image spectral library that have been set up. Generally speaking, if R is between 0.7 and 1.0, it is considered that there is a strong quantitative linear relationship.

The results of the correlation assessment in this study showed that the R^2 for water was 0.81, but it was between 0.93 and 0.99 for all other classes, indicating a high correlation. In other words, using the field spectral library in the hyperspectral image land cover classification will improve its accuracy. Table 1, presenting the results of assessing the correlation between the field spectral library and the image spectral library, shows the R and R^2 for each class. Figure 11, on the other hand, was plotted to compare the two spectral libraries by class.

Table 1
Pearson correlation coefficient (R) and coefficient of determination (R^2).

Item	Soil	Paddy soil	Weed	Cabbage	Soil 2
R	0.9866	0.9971	0.9926	0.9927	0.9652
R^2	0.97	0.99	0.98	0.98	0.93
Item	Water	Pine	Paddy grass	Asphalt	Cement
R	0.9016	0.9847	0.9855	0.9811	0.9988
R^2	0.81	0.96	0.97	0.96	0.99

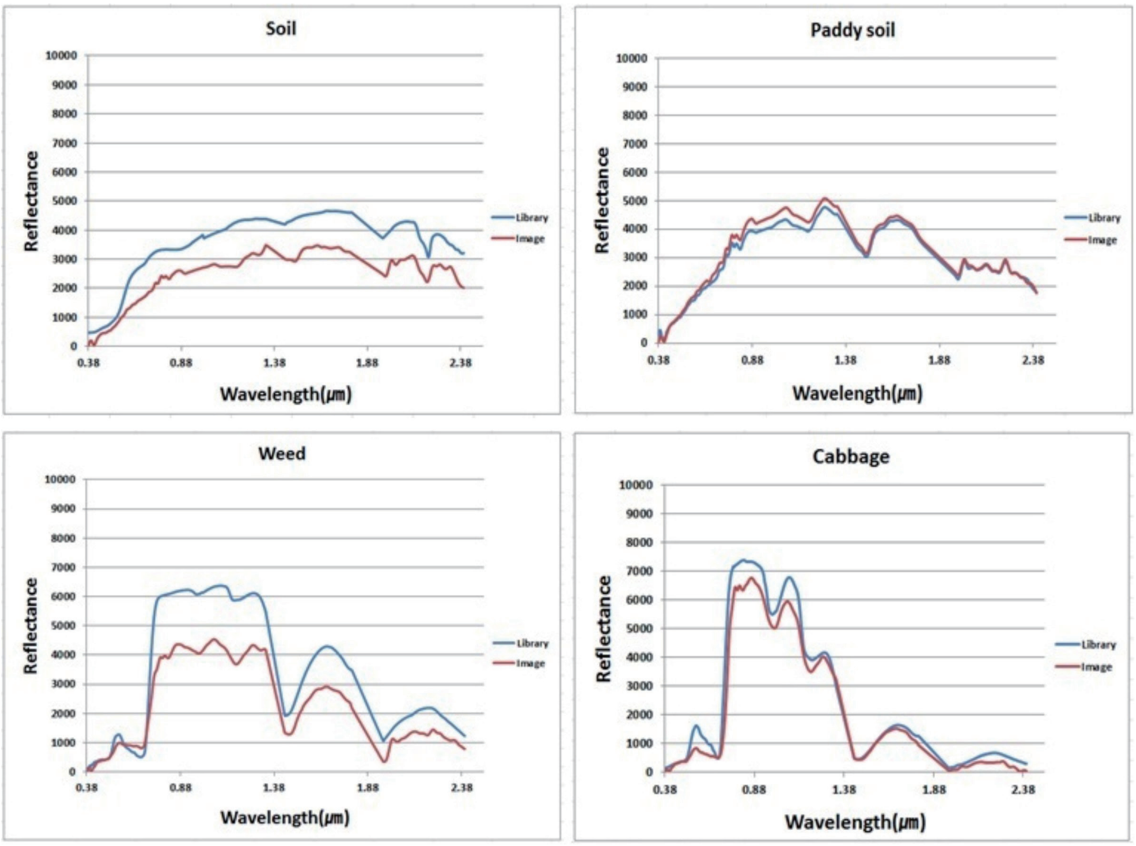


Fig. 11. (Color online) Comparison of image spectral library and field spectral library.

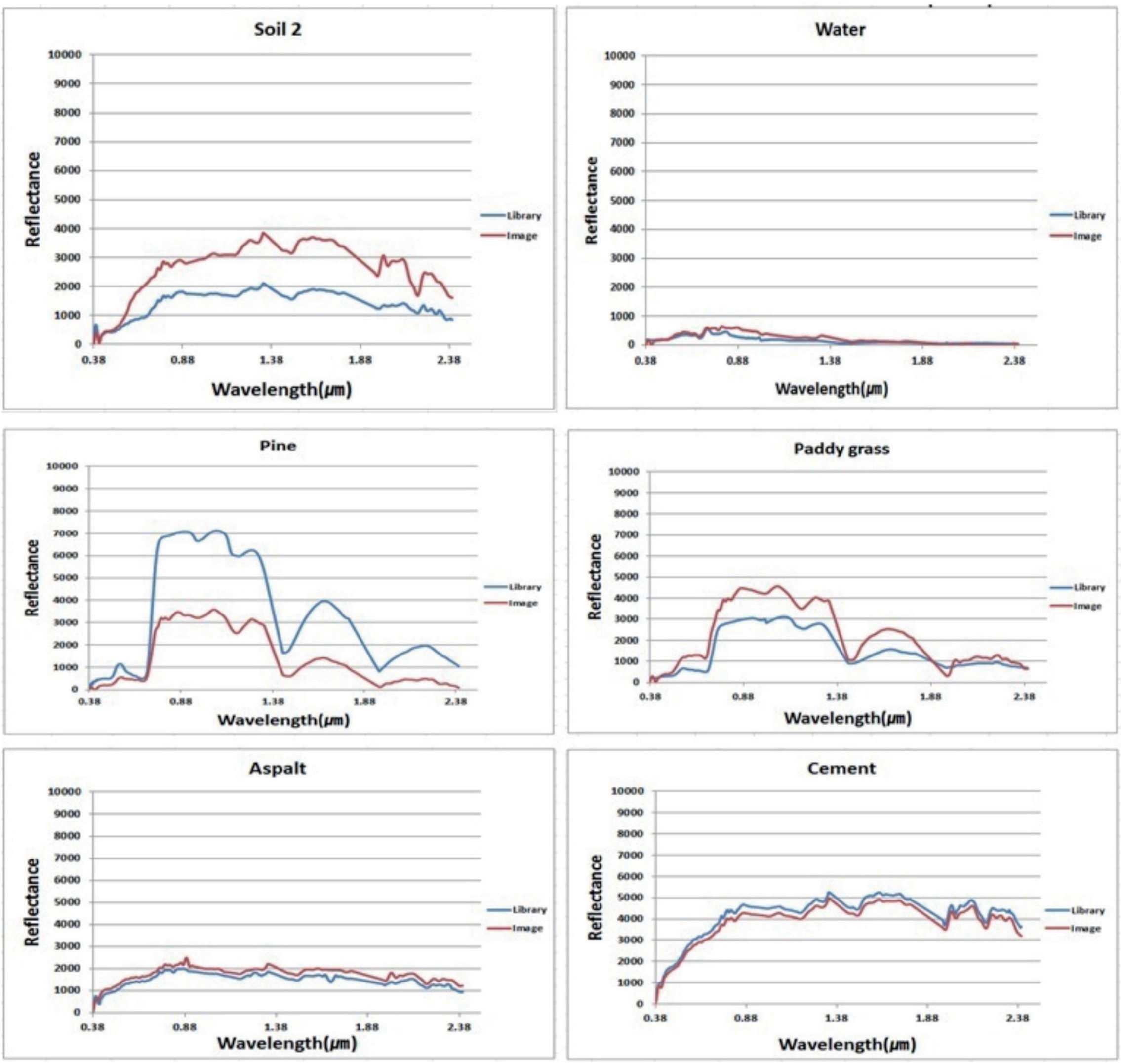


Fig. 11. (Color online) (Continued).

3. Results and Analysis

The purpose of this study was to build a spectral library of hyperspectral images that included SWIR wavelengths and to perform land cover classification, thereby improving classification accuracy and further subdividing the classes. To this end, a total of ten classes for land cover classification were selected, and hyperspectral image land cover classification was performed using the spectral library that was set up. The field spectral library was selected as the training sample, and the reference data were selected on the basis of a field survey and GPS location data so as to assess the accuracy of the land cover classification.

3.1 Test of land cover classification by SAM method

The SAM technique, which is a type of supervised classification, was chosen as the method of land cover classification using a spectral library. SAM involves expressing the spectral characteristics of each band obtained through a training sample for each pixel as vectors and determining whether they fall within the angle formed between the vectors.

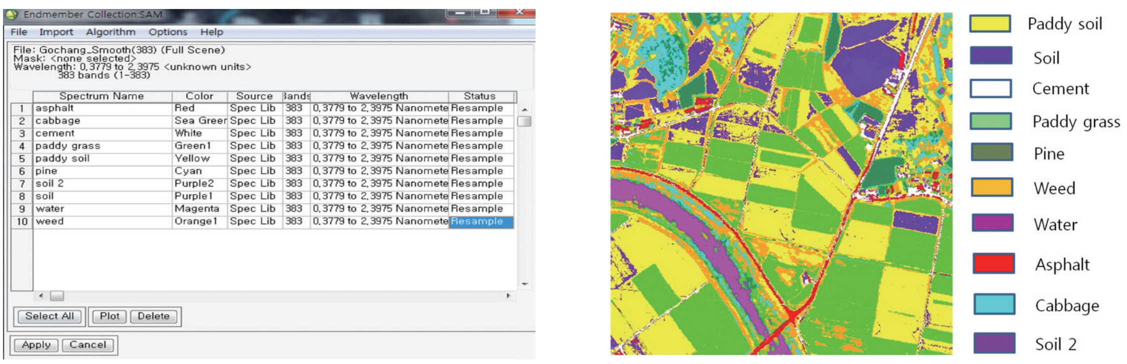
Classification is thus performed by examining how similar the patterns of the spectral reflectance curve of the training sample are to the pixels of the image.(15,16) SAM is a classification method that determines the similarity of spectrum distribution by calculating the inscribed angle of reflectance between the bands, and it is expressed as follows, with i,j signifying the coordinates and k representing the band.

$$SAM_{i,j} = \cos^{-1} \frac{\sum_{k=1}^{n} \left(x_{i,j,k} \times \gamma_{i,j,k} \right)}{\sqrt{\sum_{k=1}^{n} x^{2}_{i,j,k}} \times \sqrt{\sum_{k=1}^{n} \gamma^{2}_{i,j,k}}} \tag{2}$$

The spectral library that was applied showed 383 bands in total, just like the hyperspectral image after the band matching process was completed, and the wavelength range was 377.9–2397.5 nm, which was the same as that of the hyperspectral image. A total of ten classes were selected to build the said spectral library, and classification was performed for the whole image using the training sample. Figure 12(a) shows the results of applying the spectral library in question. Figure 12(b), on the other hand, shows the results of land cover classification performed using the spectral library.

3.2 Accuracy assessment of land cover classification using hyperspectral images

Error matrix, which involves assessing the reference data and result data, can be applied as a tool for assessing the accuracy of land cover classification using hyperspectral images. In



(a) (b)

Fig. 12. (Color online) (a) Endmember collection of SAM. (b) Result of land cover classification with SAM.

general, the columns represent the reference data, whereas the rows represent the classification results. The accuracy expressed by the error matrix is divided into four types: overall accuracy, producer's accuracy, user's accuracy, and Kappa coefficient.

Table 2 shows the accuracy of the land cover classification performed using the SAM method. User's accuracy was found to be outstanding, being above 83% in all classes, and it was actually over 90% except for cement, pine, and soil 2. Considering that the accuracy was 100% for water, it can be inferred that the spectral library for water was well constructed and could be used for other images. In the case of producer's accuracy, it was somewhat low for weed at 78.6%, but it was over 99% for paddy grass, paddy soil, water, and cabbage. This is considered to be sufficiently high to allow the spectral library in question to be applied to other images.

Table 3 shows the overall accuracy and Kappa coefficient obtained by applying the SAM method. The overall accuracy was found to be 92.97% and the Kappa coefficient was 0.92. Note that the United States Geological Survey (USGS)(17) suggests that land cover classification has been performed properly if the classification accuracy is found to be at least 89%.

Table 2
User's and producer's accuracies for each class.

Classes	User's accuracy		Producer's accuracy	
	Pixels	Percent (%)	Pixels	Percent (%)
1 - asphalt	74/75	98.67	74/85	87.06
2 - cabbage	69/71	97.18	69/69	100.00
3 - cement	49/58	84.48	49/58	84.48
4 - paddy grass	135/145	93.10	135/136	99.26
5 - paddy soil	125/132	94.70	125/126	99.21
6 - pine	60/72	83.33	60/66	90.91
7 - water	53/53	100.00	53/53	100.00
8 - weed	81/86	94.19	81/103	78.64
9 - soil	57/59	96.61	57/60	95.00
10 - soil2	51/60	85.00	51/55	92.73

Table 3
Overall accuracy resulting from the use of SAM.

Overall accuracy = (754/811) 92.9716%, Kappa coefficient = 0.9208											
Classes	Reference class										
	1	2	3	4	5	6	7	8	9	10	Total
1 - asphalt	74	0	1	0	0	0	0	0	0	0	75
2 - cabbage	0	69	0	0	0	2	0	0	0	0	71
3 - cement	9	0	49	0	0	0	0	0	0	0	58
4 - paddy grass	0	0	0	135	0	1	0	9	0	0	145
5 - paddy soil	1	0	3	0	125	0	0	1	0	2	132
6 - pine	0	0	0	0	0	60	0	12	0	0	72
7 - water	0	0	0	0	0	0	53	0	0	0	53
8 - weed	0	0	0	1	1	3	0	81	0	0	86
9 - soil	0	0	0	0	0	0	0	0	57	2	59
10 - soil 2	1	0	5	0	0	0	0	0	3	51	60
Total	85	71	56	140	131	72	60	111	66	14	806

Therefore, since the overall accuracy was found to be about 4% higher than 89%, the land cover classification performed in this study had high accuracy. Finally, the user's accuracy and producer's accuracy, the results of which are presented in Table 2, are found to be generally high, with similar levels of accuracy for each class. This shows that the final results of the land cover classification are highly reliable.

4. Conclusions

In this study, spectral libraries with the same wavelength range were built using hyperspectral images with a wavelength range of 380–2400 nm that includes the SWIR wavelength range, and they were then applied to land cover classification.

The methods of correcting data using WR when matching hyperspectral images with bands, removing noise generated during data acquisition, performing geometric and atmospheric corrections, and carrying out spectral smoothing and noise removal for the purpose of setting up spectral libraries were proposed.

Then, a correlation analysis was carried out to assess the accuracy of the spectral libraries, and the results showed that the coefficient of determination was only slightly low for the water class and that it was high, i.e., between 0.93 and 99, for all the other classes.

This showed that it is suitable to select the spectral library as a training sample for land cover classification. Finally, the results of performing land cover classification using the spectral library had an overall accuracy of 92.9%, which was higher than the accuracy level required for identifying the category of land covers by remote sensing (89%), and the Kappa coefficient was also found to be high at 0.92. Furthermore, the producer's accuracy and user's accuracy were found to be similar for each class, indicating high reliability.

Finally, the spectral library developed in this study showed high correlation with hyperspectral images with a wavelength range of 380–2400 nm, including SWIR. In the future, therefore, it is expected that this library will be used with spectral images having high spectral and spatial resolutions to more accurately classify not only the moisture information of objects, but also geological characteristics and materials.

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References

1 J. Park, J. Seo, J. Go, and G. Cho: J. Cadastre Land InformatiX **46** (2016) 240 (in Korean). https://doi.org/10.22640/LXSIRI.2016.46.2.239
2 A. Goetz, G. Vane, J. Solomon, and B. N. Rock: Science **228** (1985) 1147. https://doi.org/10.1126/science.228.4704.1147
3 A. Goetz: Remote Sens. Environ. **113** (2009) S5. https://doi.org/10.1016/j.rse.2007.12.014
4 M. A. Karaska, R. L. Huguenin, J. L. Beacham, M. H. Wang, J. R. Jensen, and R. S. Kaufmann: Photogramm. Eng. Remote Sens. **70** (2004) 125. https://doi.org/10.14358/pers.70.1.125

5 J. Seo, G. Cho, and J. Song: J. KAGIS **21** (2018) 205 (in Korean). https://doi.org/10.11108/kagis.2018.21.3.205
6 U. Heiden, K. Segl, S. Roessner, and H. Kaufmann: Remote Sens. Environ. **111** (2007) 537. https://doi.org/10.1016/j.rse.2007.04.008
7 N. Keshava: IEEE Trans. Geosci. Remote Sens. **42** (2004) 1552. https://doi.org/10.1109/TGRS.2004.830549
8 S. Kang, K. Lee, E. Jeon, I. Shin, S. Yu, and O. Kwon: J. Korean Soc. Hazard Mitig. **18** (2018) 375 (in Korean). https://doi.org/10.9798/KOSHAM.2018.18.4.375
9 N. R. Rao, P. K. Garg, and S. K. Ghosh: Precis. Agric. **8** (2007) 173. https://doi.org/10.1007/s11119-007-9037-x
10 R. J. Zomer, A. Trabucco, and S. L. Ustin: J. Environ. Manage. **90** (2009) 2170. https://doi.org/10.1016/j.jenvman.2007.06.028
11 A. Plaza, J. A. Benediktsson, J. W. Boardman, J. Brazile, L. Bruzzone, G. Camps-Valls, J. Chanussot, M. Fauvel, P. Gamba, A. Gualtieri, M. Marconcini, J. C. Tilton, and G. Trianni: Remote Sens. Environ. **113** (2009) S110. https://doi.org/10.1016/j.rse.2007.07.028
12 M. E. Schaepman, S. L. Ustin, A. J. Plaza, T. Painter, J. Verrelst, and S. Liang: Remote Sens. Environ. **113** (2009) S123. https://doi.org/10.1016/j.rse.2009.03.001
13 J. Shin and K. Lee: Korean J. Remote Sens. **28** (2012) 1225 (in Korean). https://doi.org/10.7780/kjrs.2012.28.4.3
14 M. Herold, D. A. Roberts, M. E. Gardner, and P. E. Dennison: Remote Sens. Environ. **91** (2004) 304. https://doi.org/10.1016/j.rse.2004.02.013
15 J. R. Jensen: Introductory digital image processing: a remote sensing perspective (Prentice Hall, New Jersey, 2005) pp. 431–465.
16 J. R. Jensen: Remote sensing of the environment: An earth resource perspective (Prentice Hall, New Jersey, 2000) p. 544.
17 R. N. Clark, G. A. Swayze, K. E. Livo, R. F. Kokaly, S. J. Sutley, J. B. Dalton, R. R. McDougal, and C. A. Gent: J. Geophys. Res. **108** (2003). https://doi.org/10.1029/2002JE001847

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