High Spatial Resolution Hyperspectral Mapping for Forest Ecosystem at Tree Species Level

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Abstract

Integrated management of forest ecosystems requires an accurate and all-sided mastery of the forest information, of which forest ecosystem cover especially at tree species level is the most basic and important component. The study investigated and demonstrated the mapping potential of the forest ecosystem at tree species level from high spatial resolution hyperspectral images. The mapping performances of eight conventional classification methods including Maximum Likelihood (ML), Mahalanobis Distance (MaD), Minimum Distance (MD), Parallelepiped (P), Binary Encoding (BE), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID) and Support Vector Machine (SVM), were verified based on two noise treatments (noise fraction and noise removal) and three leaf growth periods (tender leaf period, young leaf period and adult leaf period). It could be confirmed that noise removal obviously contributed to improving the classification agreement and young leaf period was most suitable for mapping forest ecosystem at tree species level from high spatial resolution hyperspectral images. ML, P, BE and SID were not considered appropriate according to good results with overall accuracy and kappa coefficient exceeding 85% and 0.80 respectively. Though MD also produced a very high classification agreement, it could not cover up its poor potential to identify tree species by spectral features. Even if SVML, SVMP, SVMR and SVMS performed the stabllest and could generate good results across three periods, the best result was obtained by SAM. Except that the difference was significant between MD and SVMS at the 5% significance level in tender leaf period, the comparative tests did not provide more proof to show the significant difference between the methods considered appropriate.

Keywords

high spatial resolution hyperspectral image, mapping, forest ecosystem

Introduction

Forest ecosystems, which are defined as terrestrial ecosystems with the tree canopy covers more than 10% of the ground area (Matthews et al. 2000), supply a wide range of commodities sought by an expanding human population, such as structural materials, fuels and medicines, along with a wide range of critical ecosystem services including nutrient cycling, climate regulation, maintaining water balance and carbon sequestration (Klenner et al. 2009). Managing forests simultaneously for wood, biodiversity, carbon sequestration, energy, water quality, flood control, habitat and recreation is the 21st century challenge (Burger 2009). Integrated management requires an accurate and all-sided mastery of the forest information, of which forest ecosystem cover is the most basic and important component. Remote sensing and digital image analysis techniques, especially high spatial resolution hyperspectral images which have 48 or more bands with a spectral resolution of 20 nm or smaller and a spatial resolution of 5 m or less (Aspinall et al. 2002a), facilitate the acquisition and extraction of forest ecosystem information.

From high spatial resolution hyperspectral images, Cho et al. (2009) mapped three forest structural parameters including mean diameter-at-breast height (DBH), mean tree height and tree density of a closed canopy beech forest with accuracy 72.4%, 67.4% and 53.6%, respectively. Dehaan et al. (2007) quantified the distribution of blackberry in open canopies with an overall accuracy 92%. Aspinall (2002b) got an excellent agreement of mapping depicting large woody debris and three Populus spp. within a single genus in a riparian area in Yellowstone National Park, Wyoming, USA. However, there have been little studies on mapping the forest ecosystems at tree species level from high spatial resolution hyperspectral images. Furthermore, tree species composition is a primary attribute of forest ecosystems (Barbier...
et al. 2009), and single species or species groups of forest ground vegetation can be used as indicators for site conditions (Khanina et al. 2007).

This study was designed to: (i) investigate the mapping potential of the forest ecosystems at tree species level from high spatial resolution hyperspectral images; (ii) verify the mapping performance of eight conventional classification methods including Maximum Likelihood (ML), Mahalanobis Distance (MD), Minimum Distance (MD), Parallelepiped (P), Binary Encoding (BE), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID) and Support Vector Machine (SVM); (iii) understand the effects of noise treatments and leaf growth periods on the classification performance.

Data and Methodology

Site descriptions

The focus of this study is an incity forest park located within the east of Hachioji city in Japan (Fig. 1), a field science education research center affiliated with Tokyo University of Agriculture and Technology. The landscape covers approximate 65 ha with an elevation range of 140–180 m above sea level. The annual mean temperature is 15°C, and monthly mean temperature is highest in July and lowest in February, 33.1°C and 3.1°C respectively. The area receives an annual mean precipitation of 1,750 mm and an annual mean snowfall of less than 10 cm.

The landscape is partially deforested and subsequent regeneration has created complex mosaic of different vegetation communities. Quercus (Quercus serrata, Quercus acutissima, Quercus glauca) is dominant, with Pinus (Pinus densiflora and Pinus thunbergii), Cinnamomum camphora, Cryptomeria japonica, Phyllostachys bambusoides, Castanea mollissima, Prunus spp., Diospyros kaki, Prunus mume and grassland also occurring in various mixtures. Additionally, the other types of landuse include orchard, road, water surface and buildings.

Image data acquisition and pre-processing

High spatial resolution hyperspectral images of the study area for three different periods, which represented tender leaf period, young leaf period and adult leaf period respectively, and coincident field data area were used in the study. The images were acquired on 10 April, 22 May, 27 June in 2003 by an Airborne Imaging Spectrometer for Applications (AISA) Eagle system (Pasco Co. Ltd., Tokyo, Japan). AISA Eagle sensor was mounted

Fig. 1  Colorful image of the study area by bands 40 (660.85 nm), 25 (561.38 nm), and 8 (451.87 nm) as R, G, B channels.
on an aircraft flying along SW-NE path at an altitude of 1,198 m during cloud-free periods in the daytime. The images on 10 April and 27 June were collected with 1.5×1.5 m spatial resolution but for on 22 May with 2.0×2.0 m spatial resolution. All images included 72 bands located in the 406.92–898.55 nm spectral range with 6.3 nm nominal spectral resolution.

Images were georectified and atmospherically calibrated using the modified flat field method. Spectrum of a sample field were obtained using a spectrophotometer during the flight of AISA Eagle on that day, which were used for atmospheric calibration. These images were then processed to surface reflectance and imported into the Environment for Visualizing Images (ENVI 4.5, ITT Visual Information Solutions) software for the subsequent analysis.

Ground data collection

Based on the thematic vegetation map from the field investigation conducted in 2003, the study determined twelve ground cover classes including Cinnamomum camphora, Pinus, Cryptomeria japonica, Shadow & gap, Water surface, Grassland, Castanea mollissima, Bareland, Quercus, Diospyros kaki, Phyllostachys bambusoides, Prunus mume. A common rectangular area with 468×400 pixels for three different periods was selected for training and validation. In order to obtain pure distribution areas of mono tree species, supplementary surveys were implemented in 2009 referring to the minimum noise fraction (MNF) transform images. The colorfully composed image of the top three principal component bands resulted from MNF transform accumulated contributed 46.25% information toward the image, which clearly indicated pure distribution areas of tree species by different colors. Cluster sampling for training was adopted to contain all spectral features of one ground cover as possible, along with the validation area determination. The ground data was also imported into the ENVI software for determining image-derived class endmembers and validation pixels. Considering adequate and relative coincident amounts of validation pixels for each class, nine classes including Cinnamomum camphora, Pinus, Cryptomeria japonica, Shadow & gap, Water surface, Grassland, Castanea mollissima, Bareland and Quercus were used as validation analysis.

Image processing

Image of 22 May was resampled to 1.5×1.5 m spatial resolution coincident with the other two periods. In order to depress the negative impacts of the spectral feature average on the identification potential of ground cover, training pixels of each class were further subdivided into subclasses by the natural cluster of spectral features. All subclasses were used as endmember classes for classification and then merged before validation analysis. The most commonly used MNF transform was employed to segregate and remove noise. MNF transforms is usually adopted to determine the inherent dimensionality of image data, to segregate noise in the data, and to reduce the computational requirements for subsequent processing (Boardman and Kruse 1994). It is a linear transformation that consists of the following two separate principal component analysis rotations: the first rotation decorrelates and rescales the noise in the data by the noise covariance matrix; the second rotation implements a standard principal component analysis based on previous result (Green et al. 1988). The effects of noise treatments were investigated by three treatments such as no treatment, noise fraction and noise removal.

In this study, eight well-developed supervised classification methods, including Maximum Likelihood (ML), Mahalanobis Distance (MD), Minimum Distance (MD), Parallelepiped (P), Binary Encoding (BE), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID) and Support Vector Machine (SVM), were used to classify the forest vegetation at tree species level from high spatial resolution hyperspectral images. ML assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class (Evans 1998). In Mahalanobis Distance method, unknown pixels are assigned on basis of the distance referred to the mean vectors and covariance matrix (Maesschalck et al. 2000). MD calculates the Euclidean distance from each unknown pixel to the mean vectors for each class (Wacker and Landgrebe 1972). Parallelepiped classifies images using an n-dimensional parallelepiped with boundaries defined based upon the standard deviation from the mean of each selected class (Sivakumar et al. 2004). BE classifies all unknown pixels into the classes with the greatest number of match bands by encoding the data and reference spectrum into zero and one based on whether a band falls below or above the spectral mean (Mazer et al. 1988). SAM determines the spectral similarity between two spectra by calculating the angle between the two spectra, treating them as vectors in a space with dimensionality equal to the number of bands (Kruse et al. 1993). SID compares the similarity between two pixels by measuring the probabilistic discrepancy between two corresponding spectral signatures (Chang 2000). The basic idea of SVM is to find a hyperplane which separates the n-dimensional data perfectly (Vapnik 1995) and four popular kernel functions (Linear, Polynomial, Radial Basis Function and Sigmoid) were used here, which were abbreviated to SVML, SVMR, SVM and SVMS respectively. However, ML and MaD were only applied to noise removal images due to the limitation of training pixel numbers. With noise treatments and classification methods mentioned previously, images of three continuous periods were analyzed to understand the impacts of leaf growth periods on the classification performance.
Assessment and comparison for classification performance

As a simple cross-tabulation of the mapped class label against that observed in the ground or reference data for a sample of cases at specified locations, the confusion matrix is at the core of accuracy assessment (Canters 1997, Foody 2002). Based on the confusion matrix, overall accuracy (OA) and kappa coefficient (KC) were adopted to weigh the classification performance. Overall accuracy is the percentage of cases correctly allocated, which exceeding 85% is considered good (Thomlinson et al. 1999). Kappa coefficient is a statistical measure of classification agreement for qualitative (categorical) items, which exceeding 0.80 represents almost perfect agreement of the mapped data and validation data (Landis and Koch 1977). Furthermore, one of the most widely promoted means for classification accuracy comparison is through the comparison of kappa coefficients (Foody 2009). With this approach, the statistical significance of the difference between two independent kappa coefficients is calculated by a $z$-value with

$$z = \frac{k_1 - k_2}{\sqrt{\sigma^2_{k_1} + \sigma^2_{k_2}}}$$

where $k_1$ and $k_2$ represent respectively the kappa coefficients for two classifications and $\sigma^2_{k_1}$ and $\sigma^2_{k_2}$ their associated variance (Congalton and Green 1998).

Results and Discussion

The effects of noise treatments on classification agreement

With the generality of noise in high spatial resolution hyperspectral images, it is very necessary to make certain how noise treatments affect the classification agreement. For that reason, different noise-treated images including no treatment images, noise fraction images and noise removal images were classified with eight methods for every period. All classification agreement (kappa coefficient) was shown in Fig. 2.

From Fig. 2, under the circumstances of no noise treatment, only SAM and SID produced results with kappa coefficient exceeding 0.70 in the young leaf period. On the whole, there were
not satisfactory results with kappa coefficient exceeding 0.80 at all for eight methods across three leaf growth periods from the original high spatial resolution hyperspectral images without noise treatment.

In the tender leaf period, noise fraction and especially noise removal remarkably improved the classification agreement for MD, BE, SAM, SID, SVML, SVMP, SVMR and SVMS, and conversely noise fraction cut down it for Parallelepiped. In the young leaf period, noise removal greatly promoted the classification agreement for MD, BE, SAM, SVML, SVMP, SVMR and SVMS, but lowered it for P and SID. At the same time period, noise fraction improved the classification agreement slightly for SVML, SVMP, SVMR and considerably for MD and BE, but conversely lowered it for P, SAM and SVMS. Similar to the tender leaf period, noise removal was consistent with improving the classification agreement cross different methods and leaf growth periods, except for P and SID in the young leaf period.

Therefore, it could be confirmed that noise removal is a very important process to obtain the high quality mapping from high spatial resolution hyperspectral images. Meanwhile, it also demonstrated the excellent potential of MNF transform to separate and remove the noise of high spatial resolution hyperspectral images.

The effects of leaf growth periods on the classification overall accuracy

Vegetation has its own unique spectral signature, which can be used for identification of vegetation type. For the same vegetation type, the reflectance spectrum also depends on other factors such as the leaf growth periods. Thus, an essential component of mapping forest ecosystem is the identification of key leaf growth periods to determine when one vegetation species can best differentiate from others. In the study, the images of the study area for three continuous periods, which represented tender leaf period, young leaf period and adult leaf period respectively, were analyzed to understand the effects of leaf growth periods on the classification overall accuracy for every method. Fig. 3 gave the comparison of overall accuracy in three periods for eight methods and accuracy value was the best result of that period for each method.

For MD, BE, SVM and SVML, overall accuracy declined gradually from tender leaf period, young leaf period to adult leaf period, but conversely for SVMS. Relative to tender leaf period, it seemed that images of adult leaf period were more suitable to identify the forest vegetation for P, MAd and SAM. From the young leaf period, SID and SVMR received higher overall accuracy relative to tender leaf period and especially adult leaf period, which was just opposite to ML. Fig. 4 displayed the comparison of performance stability for classification methods.

ML, MAd and P manifested the worst stability with standard deviation great than 5 cross three periods. The stability for MD, BE, SAM and SID was moderate and SVML, SVMP, SVMR and SVMS performed stabelst. In general, SVML, SVMP, SVMR and SVMS were tolerant toward subtle variation in spectral features induced by leaf growth periods. Although the performance of MD and SAM fluctuated obviously with the different leaf growth periods, they submitted the most satisfactory results with overall accuracy greater than 90% in tender leaf period and young leaf period, respectively.

The comparative tests of classification difference

Classification accuracy statements are often compared in
remote sensing research and the central focus of such comparative analyses has been the magnitude of the difference between the accuracy values (Foody 2009). The methods with excellent performance were filtrated by a combination of overall accuracy and kappa coefficient exceeding 85% and 0.80 respectively. As a result, MD, SVML, SVMP, SVMR and SVMS can be used to map the forest ecosystem of tender leaf period; MaD, MD, SAM, SVML, SVMP, SVMR and SVMS can be used to map the forest ecosystem of young leaf period; SAM, SVML, SVMP, SVMR and SVMS can be used to map the forest ecosystem of adult leaf period. Moreover, the statistical significance of the difference between two excellent classification was calculated by a widely promoted z-value (Table 1).

In the tender leaf period, MD was obviously more excellent than the others. The difference was significant between MD and SVMS at the 5% significance level. The difference was significant between MD and SVML, SVMR at the 15% level. The difference was significant between MD and SVMP at the 20% level. The difference was significant between SVMP and SVMS at the 20% level. In the young leaf period, SAM was more outstanding than MaD and SVMS only at the 20% level. In the adult leaf period, there was no significance between methods beyond the 20% level, which proved that the forest in the adult leaf period promoted the mixture of spectra and complicated the classification so that it was difficult to show apparent difference between classification methods. Meanwhile, the fact that more methods received excellent results in young leaf period proved it was more suitable for forest ecosystem mapping at tree species level from high spatial resolution hyperspectral images.

### Table 1 The z-values between excellent classification methods

<table>
<thead>
<tr>
<th>Method</th>
<th>MD</th>
<th>SAM</th>
<th>SVML</th>
<th>SVMP</th>
<th>SVMR</th>
<th>SVMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tender leaf period</td>
<td>MD</td>
<td>1.5875</td>
<td>1.3007</td>
<td>1.4938</td>
<td>2.6761</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVML</td>
<td>–0.2416</td>
<td>–0.0530</td>
<td>1.1956</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMP</td>
<td>0.1846</td>
<td>1.3996</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMR</td>
<td></td>
<td></td>
<td></td>
<td>1.2243</td>
<td></td>
</tr>
<tr>
<td>Young leaf period</td>
<td>MaD</td>
<td>–0.3895</td>
<td>–1.4038</td>
<td>–0.3397</td>
<td>–0.4423</td>
<td>–0.0895</td>
</tr>
<tr>
<td></td>
<td>MD</td>
<td>–0.3532</td>
<td>0.0408</td>
<td>0.0043</td>
<td>–0.0769</td>
<td>0.3582</td>
</tr>
<tr>
<td></td>
<td>SAM</td>
<td>0.4479</td>
<td>0.3132</td>
<td>0.2140</td>
<td>1.3540</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVML</td>
<td>–0.0326</td>
<td>–0.1181</td>
<td>0.3441</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMP</td>
<td>–0.0754</td>
<td>0.3043</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMR</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.4073</td>
</tr>
<tr>
<td>Adult leaf period</td>
<td>SAM</td>
<td>–1.1288</td>
<td>–0.7730</td>
<td>–0.8856</td>
<td>–1.1286</td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVML</td>
<td>0.3528</td>
<td>0.2277</td>
<td>0.0512</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMP</td>
<td>–0.1209</td>
<td>–0.3176</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>SVMR</td>
<td></td>
<td></td>
<td></td>
<td>–0.1872</td>
<td></td>
</tr>
</tbody>
</table>
Cryptomeria japonica into Grassland on the same positions of A and B which were labelled in (b) of Fig. 5. Meanwhile, there was an obvious confusion between Pinus and Cryptomeria japonica in (a) on the same position of C. (c) misclassified Pinus into Prunus mume on the same position of C and misclassified Pinus into Cinnamomum camphora on the same position of D. (c) also did not identify Pinus on the same position of E. In the tender leaf period, the spectrum from stem and background were the most important interferences on account of sparse canopy. However, overmuch overlap of leaves from different tree species complicated the distinction of different tree species in the adult leaf period. Thus, it could be made certain that young leaf period was more suitable for mapping the forest ecosystem at tree species level, which resulted in previous results. Simultaneously, the results also proved the outstanding potential of SAM for mapping the forest ecosystem at tree species level.

Conclusions

The study has demonstrated the excellent mapping potential of the forest ecosystem at tree species level from high spatial resolution hyperspectral images. As the most commonly used processing technique, MNF transform could effectively separate and remove the noise of high spatial resolution hyperspectral images. Although whether noise fraction was able to improve the classification agreement was unregular, it could be confirmed that noise removal obviously contributed to improving the classification agreement for absolute majority methods cross different leaf growth periods. There were always some methods to produce good results for three periods, whereas majority excellent results were generated in young leaf period. It might be interpreted that stem and background interfered greatly with distinction of tree species on account of sparse canopy in the tender leaf period, and overmuch overlap of sparse leaves between different tree species complicated the distinction of them in the adult leaf period. The mapping performance of eight conventional classification methods including Maximum Likelihood (ML), Mahalanobis Distance (MaD), Minimum Distance (MD), Parallelepiped (P), Binary Encoding (BE), Spectral Angle Mapper (SAM), Spectral Information Divergence (SID) and Support Vector Machine (SVM) were also verified in the study. ML, P, BE and SID were not considered appropriate to identify and map the forest ecosystem at tree species level from high spatial resolution hyperspectral images according to criteria with overall accuracy and kappa coefficient exceeding 85% and 0.80 respectively. MaD performed well just occasionally. Though MD also produced very high classification agreement, Fig. 2 and Fig. 4 indicated an obvious drop-off of mapping potential in the rear two periods, which devulged its poor potential to identify tree species by spectral features. Visible misclassification in Fig. 5 (a) conflicted with its high agreement which might be aroused by randomicity of artificial sampling in validation areas. Even if SVML, SVMP, SVMR and SVMS performed stablest and could generate good results across all three periods, the best result was obtained by SAM. Except that the difference was significant between MD and SVMS at 5% significance level in tender leaf period, the comparative tests did not provide more proof to show the significant difference between the excellent methods considered appropriate. This study provided forest managers with scientific basis of mapping selection for forest ecosystem from high spatial resolution hyperspectral images by the view of noise treatments and classification periods.
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