TREE SPECIES CLASSIFICATION USING HYPERSPECTRAL IMAGE COMBINED WITH DIGITAL CANOPY HEIGHT MODEL

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ABSTRACT: We presents that tree species classification using hyperspectral image combined with digital canopy height model (DCHM) measured by airborne LiDAR. Although spectral information tended to be affected by the influence of the seasonal variation by phenology, etc., on the other hand, the information on canopy height thought that it was more robust to such factors, and it considered verifying the effect of addition of DCHM to spectral information. Moreover, we compared two classification approaches which are object-based and pixel-based image analysis. In the results, normal hyperspectral image with pixel-based classification indicated highest overall accuracy and kappa coefficient. However, DCHM combined image using pixel-based approach was the best average classification accuracy of tree species class. This study indicated us the significance of the pixel-based image analysis. In addition, DCHM related models were included by three of the 5th place of classification accuracy higher ranks. In conclusion, it proved that it is effective combined DCHM with hyperspectral data.

1. INTRODUCTION

Owing to an extremely fine spectral resolution with many bands, hyperspectral sensors can measure variation of the detailed pattern of spectrum reflection, enabling improved vegetative discrimination as compared with established multispectral methods (Plourde *et al.*, 2007; Jones *et al.*, 2010). An interest to Light Detection and Ranging (LiDAR) sensor technology to acquire the height information of ground feature has been also very high (Popescu and Wynn, 2004; van Aardt *et al.*, 2006). This study considered that tree species classification using hyperspectral image combined with digital canopy height model (DCHM) measured by airborne LiDAR. In the two-dimensional spectral information of ground surface like a satellite imagery or an aerial photo, even if it is a similar landcover, a geographical and seasonal change may occur, and the uncertainty of a classification output may be concerned. On the other hand, the information on canopy height thought that it was more robust to such factors. Moreover, an object-based image analysis (OBIA) may have feasibility to extract height information as the inherent feature of each tree species or landcover. In this study, we applied OBIA to the tree species classification of DCHM combined data and attempted to compare it with pixel-based approach or multispectral image.

2. MATERIALS AND METHODS

2.1 Study area

Tama Forest Science Garden which is one of the branch offices of Forestry and Forest Products Research Institute (FFPRI), Japan was research site of our study. That science garden is located at Hachioji city, Tokyo. The garden is the facilities for forest science research. Its location is in the easternmost end of Mount Takao, around 200 meters above sea level and its area is 57 ha. The most typical top canopy tree species are evergreen broad-leaved species such as blue Japanese oak (*Quercus glauca*) and Japanese chinquapin (*Castanopsis sieboldii*), deciduous broad-leaved species such as Japanese zelkova (*Zelkova serrata*) and konara oak (*Quercus serrata*), and coniferous species such as Japanese cedar (*Cryptomeria japonica*) and cypress (*Chamaecyparis obtusa*). Japanese cedar, cypress, Japanese bigleaf Magnolia (*Magnolia obovata*), Japanese zelkova, konara oak, Sawtooth Oak (*Quercus acutissima*), Japanese walnut (*Juglans mandshurica*), and loblolly pine (*Pinus taeda*) were chosen for the target tree species of this study.

2.2 Remote sensing data

In this research, the data of the Nippon Electric Co., Ltd. airborne hyperspectral sensor system (HSS) was employed. The specifications of this sensor are shown in Table 1. Observation was carried out in June, 2008. Acquisition of LiDAR data was performed by RAMS-e of Ener Quest Systems (Canada). LiDAR Measurement was carried out for the whole Tama Forest Science Garden in October, 2005, and digital surface model (DSM) and digital elevation model (DEM) of 1-m resolution are acquired from the data of footprint diameter 0.47m. Table 2 represents detailed information about LiDAR data.

2.3 Image Analysis

In this paper, analysis were carried out following with the workflow shown in Fig. 1, in order to examine the efficiency of DCHM combined image or OBIA in tree species classification. In 1st step, DCHM was created using DSM and DEM and, HSS image and DCHM data were combined. Moreover, a multispectral image was also prepared from HSS data. Based on the NDVI value computed from the multispectral image, non-vegetation was masked with specific NDVI value. In 2nd step, pixel-based and object-based image analyses were performed to each dataset. Finally the classification accuracies of each image were assessed in 3rd step.

Digital Canopy Height Model

DCHM is determined by taking the difference of digital surface model (DSM) and digital elevation model (DEM). In this analysis, the histogram of DCHM data indicated negative values which do not exist theoretically. It is considered to be the cause that the expression of fine-scale topographical feature was insufficient due to incomplete DEM generated by few last pulses, or mechanical filtering of the point with which it has not reached to ground surface (Setojima *et al.*, 2002). In this research, however, since it was thought that the reproducibility and validity of canopy cover surface are more important than the precision of geographical feature, any correction for DCHM was not employed. DCHM data was combined with HSS data. The DCHM combined image with the color composite of DCHM layer is shown in Fig. 2.

Principal component image

High redundancy exists in HSS data from the character of the sensor which arranges a narrow observation wavelength interval continuously (Addink *et al.*, 2007; Hamlyn and Robin, 2010). This would be also applied to the HSS data and the DCHM combined data of this research. Therefore, in this study, principal component analysis was applied to these two datasets, and in order to express data at less feature dimensions, the information between adjacent bands with high correlation was summarized. Principal component analysis was conducted to all the bands of the HSS data and the DCHM combined data, and determined to the 8th principal component (a principal component image attaches "-PC" to an end). Pixel-based and object-based image analyses were performed to these two types of principal component images like other images, and an accuracy assessment was carried out.

2.3.1 Pixel-based image analysis

Acquisition of training area and test area

The training area for a classification and the test area for accuracy assessment were selected from an image. Based on the spectral characteristics of the classification class in a HSS data, vegetation data and image interpretation, the polygon was delineated in the tree crown or similar canopy domain, and it divided to training area and test area. Furthermore, about tree species other than a classification class, the pixels which were in a 1.5-m buffer from the single tree point data were assigned as a class "others."

Feature selection

In the classification using hyperspectral data, the increase of computation time due to huge number of features (band) or the Hughes effect which improvement in classification accuracy stop at several dimensions and its accuracy decrease gradually may work as an obstacle (Kato and Iizaka, 2007). Therefore, it is important to choose the suitable number of features and to reduce a number of dimensions. About reduction of this number of dimension, the method of using principal component analysis (Yasuda, 2007), the method of optimal feature selection after linear transformation of the band (Jimenez, 1998; Addink et al., 2007; Kato and Iizaka, 2007) have been reported. In this research, two techniques of the direct selection from the original feature (band) and selection from a principal component image were applied. In selection of features, the Bhattacharyya distance which based on the difference of mean and covariance was employed and the combination of the feature which showed the maximum distance was determined. The optimal combination of feature was determine from all the combination for 1-10 dimensions, every five dimensions for 15-60 dimensions with the HSS image and the DCHM combined image. For other image, optimal feature combination was determined from all the combination of available dimensions.

Classification

The classification by a maximum likelihood method was performed using the combination of the determined features. The size of "unclassified class" was set to 5% of the whole image.

2.3.2 Object-based image analysis

Segmentation

In this analysis, the parameter of segmentation was established so that the object which matched single tree crown size might be generated. We prepared an unique scale parameter for image segmentation since scale parameter would be inherent to the data applied. Moreover, since the quality of data and layer composition of each dataset differed, other required parameters were also determined independently, comparing the output of segmentation with an image.

Training area setup and feature selection

Training area for object was set to the same area where used as a pixel-based method. However, since the minimum units used for analysis differed, both could not be made to match completely. Since the gap had occurred in the position of the object between images, after preparing training area automatically at the 75% overlap, it corrected manually. Features were selected from an average pixel value (Mean), standard deviation (Standard Deviation: Std) and a band ratio (Ratio) of object. These all are the features about the spectral information of an object. "Feature Space Optimization" function of Definiens Developer7.0 was applied for selection of features. This is a function to search the combination of features which shows the largest distant between classes in a feature space. In addition, gray level co-occurrence matrix (GLCM) of the amount of textural features expected to be effective in a classification was not applied by this study. That reason is because predominance to other features could not be identified.

Classification

Supervised classification method (Standard Nearest Neighbor) was performed using selected features.

2.4 Accuracy Assessment

Evaluation of classification accuracy for each image carried out with an overall accuracy and a Kappa coefficient derived from the error matrix created based on test area.

3. RESULTS

The classification accuracy of both pixel-based and object-based image analysis is indicated in Table 3. The best accuracy was achieved by pixel-based HSS (Kappa=0.625). Subsequently, pixel-based DCHM combined (Kappa=0.623) and pixel-based DCHM combined-PC (Kappa=0.620) followed. The best three were derived from pixel-based approach. In this analysis, pixel-based approaches were better than object-based one in accuracy. Regarding accuracy for each classification class (tree species), there were common tendency which for Japanese zelkova, loblolly pine, and understory indicated more accurate results, while konara oak and Japanese cedar relatively less than them. When the best user's accuracy each class was checked, although Japanese zelkova, Japanese cedar and loblolly pine were derived from object-based principal component image, others were derived it from top two of pixel-based classification.

4. DISCUSSION

The superiority of the pixel-based image analysis was shown in the result of this paper. Although there were also many reports (Mallinis *et al.*, 2008) which represented the efficiency of OBIA in accuracy, the significance of the OBIA was not able to be identified in this analysis. Insufficiency of spatial resolution could be considered as this reason. In order to generate the object of a single tree level appropriately, the spatial resolution (1.0 m) of NEC HSS and LiDAR data may be rather low. The unsuitably large pixel not only cannot express the detailed property of a subject to an observation object (single tree crown), but a large pixel generates the object which not reflected actual condition (Fisher, 1997; Addink et al., 2007). This is considered as a main factor which reduced the accuracy of OBIA.

When principal component analysis is applied to an original image, negative effect to the accuracy of PBIA, and positive one to OBIA. Regarding object-based image analysis, two principal component image gained appropriate results as long as classification accuracy and classification map were checked. Therefore, it is necessary for OBIAs using HSS data to reduce a number of dimension by such as principal component analysis. There is no other choice to reduce a number of dimensions because of selection of features and classification processing was indivisible in the OBIA technique of this research. This is considered to lead a decline of classification accuracy together with the characteristics of the HSS data mentioned above.

However, for some tree species such as Japanese zelkova, Japanese cedar and loblolly pine, its accuracy of OBIA of the principal component image was more than pixel-based one, therefore, there might be the potential of OBIA.

Especially, Japanese cedar which showed low accuracies in pixel-based classification presented high User's accuracies in OBIA. It is because there was little miss classification which occurred frequently from Japanese cedar to cypress and loblolly pine in the pixel-based classification. The features mainly selected in OBIA were related with standard deviation, seven of eighteen standard deviation related features were selected in DCHM-PC image. Since this feature evaluates the variation of the reflectance in an object, a similar feature does not exist on a pixel-based approach. This might be reason to indicate the improvement of the classification accuracy of a Japanese cedar. The mechanism of the result which the accuracy of OBIA showed an advantage over PBIA could depend on the same reason. Although tree species cannot be associated only for single pixel height information, if in the case of object unit, it will be expected that the possibility of discernment increases. This would be supported by representing the improvement of accuracy for Japanese zelkova and Japanese walnut whose accuracy was extremely low in PBIA. Konara oak indicated mere low level of 20% order in user's accuracy of all the classification. This is because of substantial miss classification to Japanese bigleaf Magnolia which shows similar spectral characteristics.

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Table 1 Specification of airborne hyperspectral sensor.

Data Acquisition Date and Time	2008/6/13 9:37 – 9:51 (JST)
Sensor	NEC Hyperspectram Sensor System
Altitude	1500 m
Spatial Resolution	1.0 m
Wavelength	400 – 1000 nm
Number of Bands	60
Band Wide	10 nm
Bit Rate	16 bit

Table 2 Specification of airborne LiDAR data.

Data Acquisition Date	2005/10/14
Sensor	RAMS-e
Altitude	1829m
Footprint diameter	0.47m
Scan wide	645m
Footprint Interval	2.18m (along track) 2.17m (cross track)
Field of View	20 degrees
Scan Rate	26Hz

Table 3 Overall accuracy and Kappa coefficient for all classification result.

Order	Image Dataset	Overall Accuracy (%)	Kappa Coefficient
1	(P) HSS	67.6	0.625
2	(P) DCHM combined	67.2	0.623
3	(P) DCHM combined-PC	67.1	0.620
4	(O) DCHM combined-PC	63.9	0.582
5	(P) HSS-PC	62.8	0.567
6	(O) HSS-PC	59.0	0.527
7	(P) Multispectral	52.1	0.455
8	(O) DCHM combined	50.9	0.447
9	(O) HSS	39.9	0.330
10	(O) Multispectral	38.0	0.314
11	(O) DCHM only	22.9	0.152
12	(P) DCHM only	20.3	0.127

(P): Pixel-based image analysis, (O): Object-based image analysis

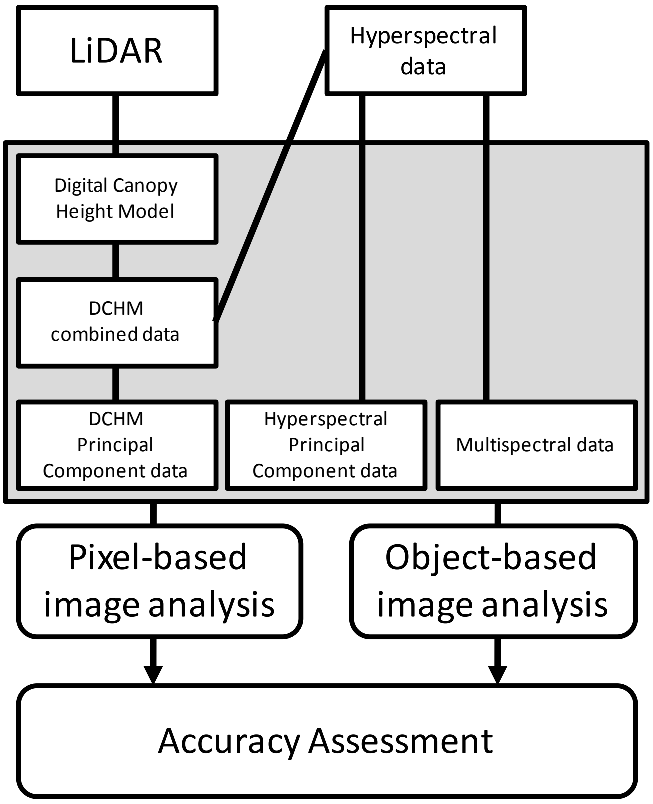

Fig.1 Workflow from original hyperspectral data and LiDAR data to accuracy assessment.

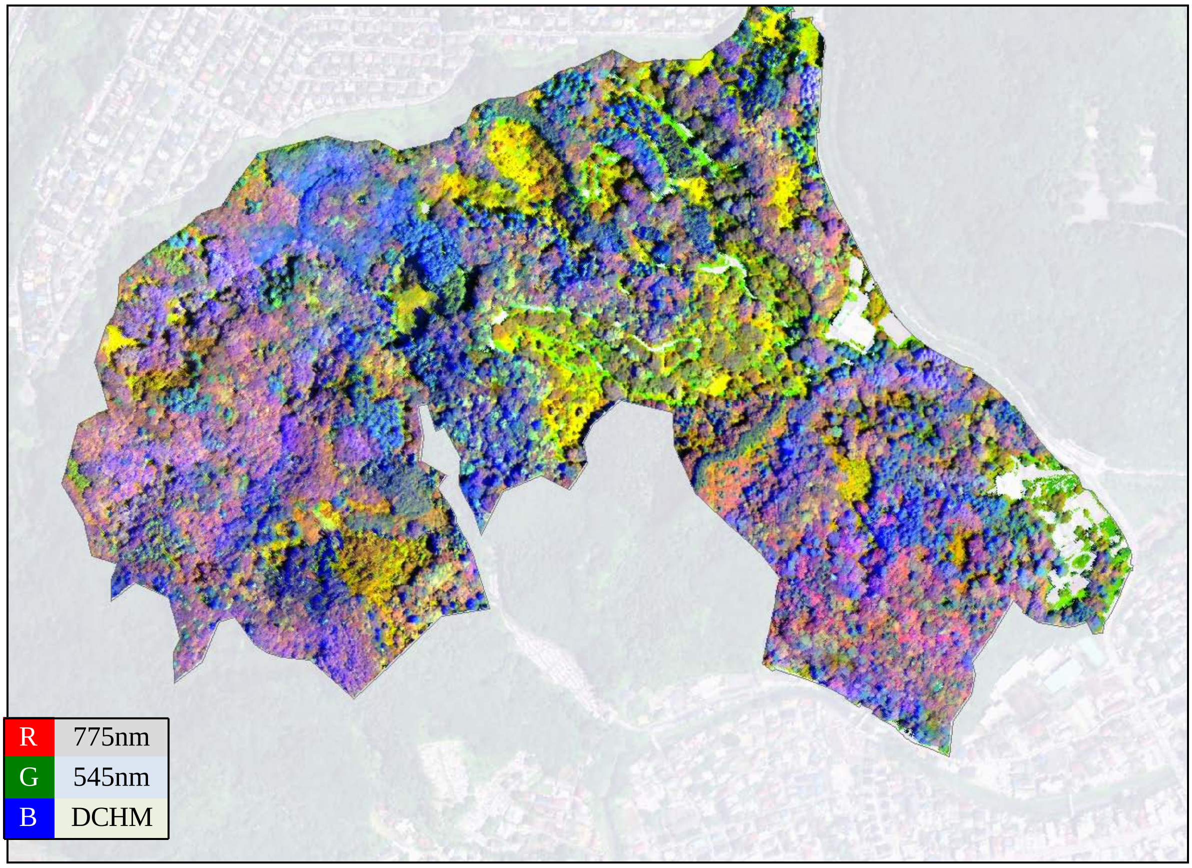

Fig.2 DHCM composition image. Even if it is the same top canopy layer, a broadleaved tree is expressed in magenta color and coniferous tree is blue due to the difference in the reflective intensity in a near-infrared region. Small trees or glass land with lower DCHM are represented yellowish composite color.