# CAMPARISON OF DECIDUOUS SPECIES CLASSIFICATION BETWEEN HYPERSPECTRAL AND MULTISPECTRAL IMAGE

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**ABSTRACT:** Hyperspectral (HS) data is consisted with continuous hundreds bands with narrow band width that is advantage to detail classification and quantitative remote sensing than multispectral (MS) data. In this study, we tried to compare capability between hyperspectral and multispectral image on deciduous species classification.
We used two image datasets those are CASI-1500 HS image and simulated TM image. CASI-1500 image has 96 bands in 380nm-1050nm and 1.25m of spatial resolution which was acquired on Oct. 26, 2010. Simulated TM image is generated from CASI-1500 image using spectral response function (SRF) of Landsat TM which has 4 bands within wavelength range of CASI-1500 image. Study area is consisted with 24 deciduous species that is planted and preserving homogeneous forest stands. To compare capability of two HS and MS image, supervised classification (SAM) was tried for 12 species among 24 species because leaves of the other species shown leaf-off condition when image acquisition. The training and test samples were collected for sunlit and shadow canopies respectively by forest map and eye interpretation. CASI-1500 image shows higher accuracy than simulated TM image from classification results. Additionally, some confused species were merged to a class then HS image shows capability to classify higher number of species than MS image.

## 1. INTRODUCTION

Hyperspectral (HS) image can acquire detail spectral signature of vegetation with hundreds of narrow and contiguous spectral bands while multispectral (MS) image has limitation to get detail spectral signature due to broad band width. With this advantage, HS image were used for many previous studies related with vegetation mapping that present difference of detailed spectral signature (Cho et al, 2010; Demir and Erturk, 2010).

As previous study operate to classify 4 classes in multi-temporal data using Maximum likelihood decision rule by CASI imaging data(Leckie et al, 2005). Also there was study that species discrimination depends on signature of each species, and distinguish between forest and non-forest using CASI and HyMap imaging data (Lucas et al, 2008), this study was operated band selection using Multiple Discriminant Analysis technique. In other study, advanced SAM used to classify forest using HiFIS and LiDAR, GPS-IMU, consequently, it acquire classification accuracy over 50% (Cho et al, 2010). and then the other study was that mapping seagrass, biomass in difference time using Landsat 5, CASI-2 and Quickbird-2, this work assesses seagrass mapping, cover and biomass accuracy by three type sensors, consequently, airborne hyperspectral data (CASI-2) better classified than multispectral data or high spatial resolution image (Phinn et al, 2008).

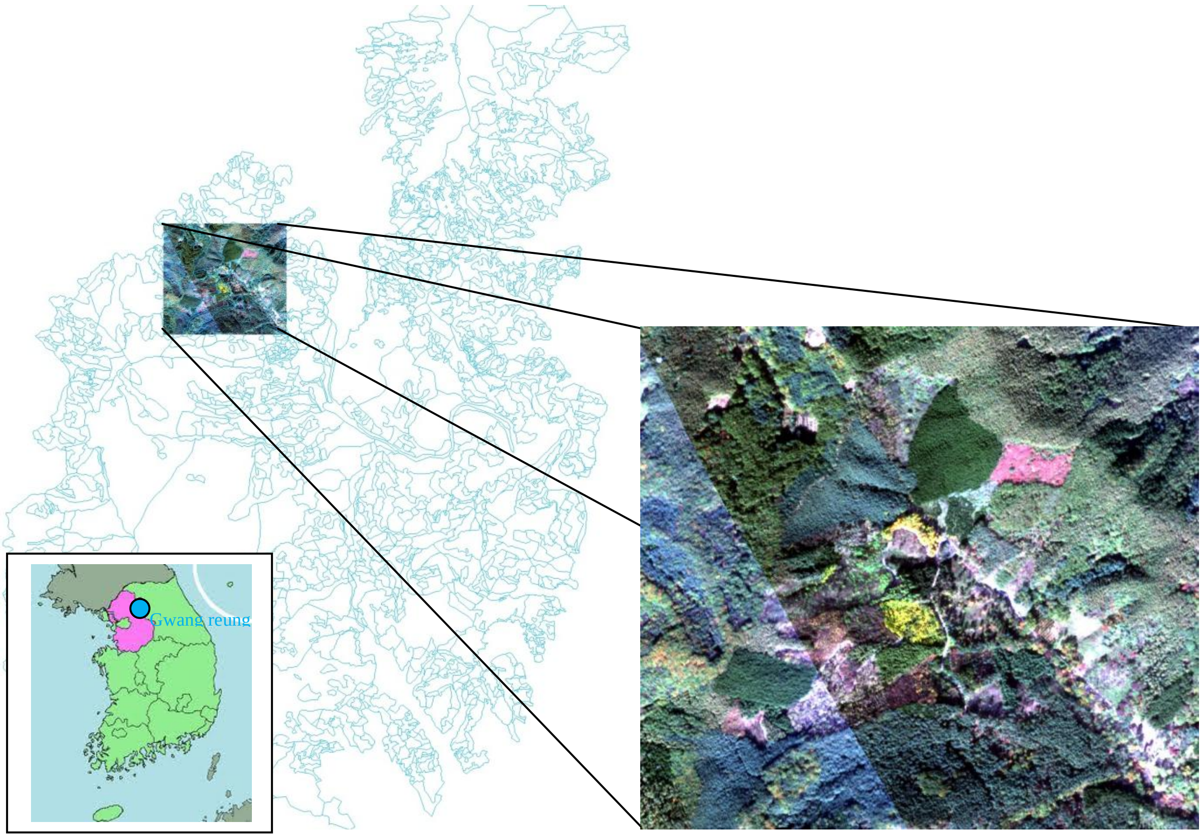
In this study, we are trying to investigate capability between Hyperspectral imaging data and Multispectral imaging data for species classification.

## 2. MATERIAL AND METHODS

### 2.1 Study Area

KNA (Korea National Arboretum) is located Gwangneung Experimental Forest of the Korea Forest Research Institute(127°7'30.72523"E, 37°48'0.42761"N to 127°11'59.17548"E, 37°41'59.31795"N) between Namyangju-si and Pocheon-si of Gyeonggi province in South Korea. The study area is dominated by an natural forest including 35 species of trees both deciduous forest and conifer forest. Among the rest KNA regions, we used a part of that was consisted of mixed forest including deciduous forest.

12 species were selected among 35 species which were planted deciduous forest, because of excepted for fallen leaves, conifer forest, and not homogeneus forest. We had used 12 species of trees that *Ailanthus altissima*, *Quercus rubra. phellodendron*, *Cornus controversa*, *Zelkova*, *Cercidiphyllum*, *Ginkgo biloba*, *Liriodendron tulipifera*, *Populus tomentiglandulosa T.B.Lee*, *Acer triflorum Kom*, *Eucommia ulmoides Oliver*, *Chamaecyparis pisifera*.




Fiqure 1. Study area of KNA loacated Gwangneung in South Korea

### 2.2 CASI-1500 and Simulated TM image

For comparison of classification capability between hyperspectral image and multispectral image, acquired by the Compact Airborne Spectrographic Imager (CASI) 1500 that have by 96 of spectral band in 380 to 1050nm of continuous coverage not only visible wavelength but also near infrared wavelength and 40 degrees total field of view by high spatial resolution of 1.25m, this image was taken by October 2010, and it is season start of fallen leaves or occur change of color leaves according to species type. To acquire comparable Multispectral image, TM image was simulated from the CASI-1500 image using SRF of TM. Simulated TM has 4 bands (band1-4) in wavelength range of CASI-1500.

Figure 2 showed spectral response function of each TM band. It could be found that each band present Gaussian distribution. Equation (1) shows how to calculate TM bands using SRFs, defined by

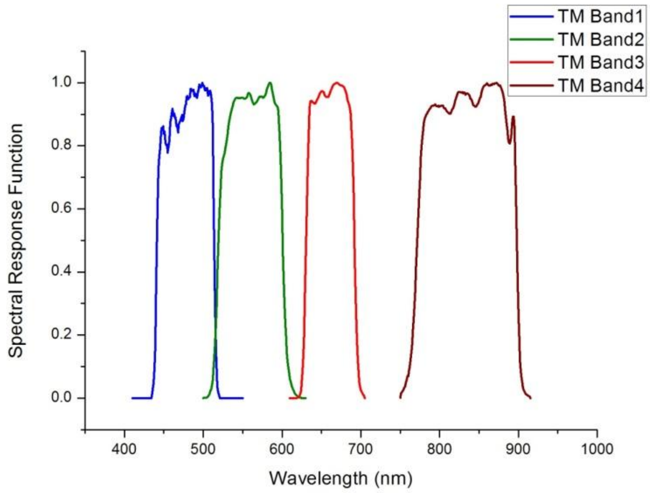



Figure2. spectral response function (SRFs) of Landsat TM corresponding to wavelength of CASI-1500 image (blue is band 1, green is band 2, red is band 3, brown is band 4).

$$TMband(N) = \frac{\sum_{i=1}^{n} SR_i \times HS_i}{\sum_{i=1}^{n} SR_i} \qquad (1)$$

Where, N is TM band number that was acquired by data value of CASI-1500, '$i$' and '$n$' is first and last band number of CASI-1500 bands corresponding to SRFs of each band related TM, '$SR$' is spectral response function corresponding to band i, finally, each TM bands is obtained by dividing from summarize SR that add up SRFs of TM corresponding to CASI-1500 band number.

Forest map was used as a reference data to collect training and test sites which were validated by field survey because forest map was generated in 2007.

### 2.3 Supervised Classification

For the study, we selected 10 of training site and 30 of test site according to homogeneous in each classes,
Spectral angle mapper(SAM) was used to classify tree species using HS and MS image respectively. SAM classify classes with comparison of spectral angle between reference and target spectral vector in N-dimensionality space (Cho et al, 2010). SAM assumed each species have unique spectral identity or spectral signature, difference of spectral signature of species was present variability such as topography, soil condition, climatic property (Cho et al, 2010). SAM was difined as (2) angle between two spectra ($S_i, S_j$),

$$SAM(S_i, S_j) = \theta(S_i, S_j) = \cos^{-1}\left( \frac{\sum_{l=1}^{L} S_{il}, S_{jl}}{\left[\sum_{l=1}^{L} S^2_{il}\right]^{1/2} \left[\sum_{l=1}^{L} S^2_{jl}\right]^{1/2}} \right) \qquad (2)$$

'$\theta$' is angle of between two spectra, $L$ is the number of bands. SAM classifier must defined maximum angle that specified maximum acceptable angle between the endmember spectrum vector and the pixel vector.

In this paper, we tried to yield classification accuracy result from to classify species using SAM with CASI-1500 and Simulated TM, respectively.

### 2.4 Accuracy assessment

For comaparison between two image data, we obtained confusion matrix about each classification image data, and verified significant of difference of classification accuracy. Established paper intoroduced method that verified whether can significant or not. This methods could verified confidence through Z-test using Kappa Coefficient of confusion matrix corresponding to image data, respectively(Congalton et al, 1983; Congalton, 1991; Foody, 2004) . Z-test calculated by independent kappa coefficient that obtained by each confusion matrix presented by Equation (3)

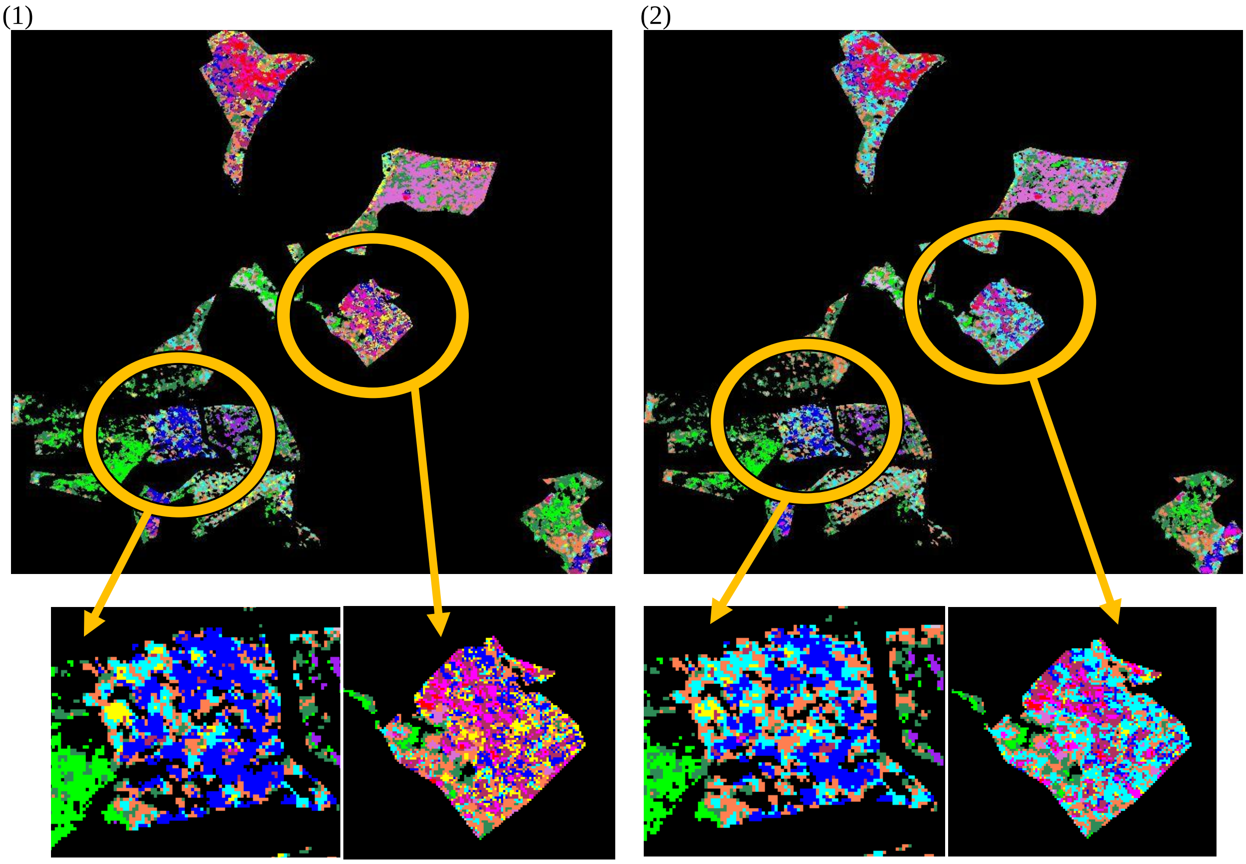
$$z = \frac{K_1 - K_2}{\sqrt{V_1^2 + V_2^2}} \quad (3)$$

where $K$ is kappa coefficient of each classification image, and $V$ is to estimate variance of accuracy in confusion matrix. When level of significance of 95%, null hypothesis ($H_0$) of no significant difference was rejected if $|Z| > 1.96$. Consequently, alternative hypothesis ($H_1$) that reliable difference of classification accuracy would be adopted (Foody, 2004).

## 3. RESULT

### 3.1. Classification results

Figure 3 shows classification result of CASI-1500 and simulated TM image respectively that *Quercus rubra* and *Zelkova* forest stands were well classified than simulate TM. However the other species shown similar classification results by eye interpretation.




Fiqure 3. (1) Result of classification using SAM classification technique in CASI-1500, in left circle, blue color was classified correctly Zelkova. And purple color was classified correctly Quercus rubra in right circle. (2) in Simulated TM

**3.2 Classification Accuracy**

Table 1 shows overall accuracy and Kappa coefficients for classification results of CASI-1500 and simulated TM that overall accuracy and Kappa coefficient of CASI-1500 shows about 10% higher accuracy than simulated TM. Table 2 shows producer's accuracy for each 12 species that 4 species shows over 10% higher accuracy than simulated TM. However the other species shows similar accuracy.

As if Table 1 showed, overall accuracy obtained by CASI-1500 imaging data was better distinguish deciduous species than it obtained by Simulated TM at same time in same area.

Table 1. Result of overall accuracy and kappa coefficient through SAM both CASI-1500 and Simulated TM

| | CASI-1500 | Simulated TM | Difference |
|---|---|---|---|
| Overall Accuracy | 75.2778 % | 66.6667% | 8.6111% |
| Kappa Coefficient | 0.7304 | 0.6366 | 0.0938 |

Table 2. Result of producer's accuracy of each classes and difference between CASI-1500 and simulated TM

| Class | Producer's Accuracy | | Difference |
|---|---|---|---|
| | CASI-1500 | Simulated TM | |
| *Ailanthus altissima* | 90.00% | 90.00% | 0.00% |
| *Quercus rubra* | 53.33% | 40.00% | 13.33% |
| *Phellodendron* | 66.67% | 66.67% | 0.00% |
| *Cornus contraversa* | 53.33% | 30.00% | 23.33% |
| *Zelkova* | 63.33% | 56.67% | 6.66% |
| *Cercidiphyllum* | 93.33% | 90.00% | 3.33% |
| *Ginko biloba* | 93.33% | 90.00% | 3.33% |
| *Liriodendron tulipifera* | 83.33% | 60.00% | 23.33% |
| *Populus tomentig landulosa T.B.Lee* | 90.00% | 93.33% | -3.33% |
| *Acer triflorum Kom* | 100.00% | 100.00% | 0.00% |
| *Eucommia ulmoides Oliver* | 56.67% | 50.00% | 6.67% |
| *Chamaecyparis pisifera* | 60.00% | 33.33% | 26.67% |

**3.3 significance of difference between classification results**

To inspect confidence of difference of accuracy, we used Z-test by two sided test. Congalton (1983) showed that Z-test acquired by Kappa coefficient to obtain two classification images was verified by Z-statistic value rejected null hypothesis ($H_0$). Table 3 shows Z-statistics between CASI-1500 and simulated TM which shows 12.0359 that is higher than 1.96. From this Z-test, CASI-1500 could show better classification result than simulated TM at 95% confidence level.

Table 3. Test of significant difference between confusion matrix

| Pairwise comparison | Result | |
|---|---|---|
| | Z statistic | At the confidence level of 95% |
| CASI-1500 vs Simulated TM | 12.0359 | Significant |

**4. CONCLUSIONS**

In this paper, we tried quantitative comparison of capability for tree species classification between HS and MS image. CASI-1500 image converted to TM image using spectral response function (SRF) then two image were classified by SAM respectively. The classification accuracy was about 10% higher for HS image than MS image and it was significantly better result by Z-test at 95% confidence level. Consequently, HS image has more capability for tree species classification than MS image that could contribute to generate detail forest map.

**5. ACKNOWLEDGEMENT**

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