Detection of Bamboo by Sentinel-2: Evaluation of Algorithm, Seasonality and Spectral Band

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Abstract: *Abandoned bamboo forests rapidly encroach on artificial forests and agricultural areas, so it is important to study their distribution and dynamics. Remote sensing is an effective technique for mapping land cover over large areas. In order to accurately estimate the distribution of bamboo forests using the Multispectral Instrument (MSI) onboard the Sentinel-2 satellite, four classification algorithms (random forest, support vector machine, multilayer perceptron, and gradient boosting decision tree) were evaluated, with a particular focus on the seasonality of classification accuracy and the importance of spectral band. A land cover map of Kochi City was generated for each month using MSI data and reference maps. The performance of the algorithms in the bamboo forests was assessed based on the seasonal profiles of precision, recall, and F-measure. Permutation Feature Importance was used to measure the importance of spectral bands. The random forest classifier demonstrated slightly superior classification accuracy to the others, although the difference was smaller compared to the gradient boosting decision tree. The classification accuracy was high in May and remained relatively high from May through August. The reason was that high solar elevation and land surface phenology resulted in large differences in spectral reflectance between land cover classes. All algorithms considered bands 11 and 12 in the shortwave infrared region to be significant. In addition, bands 6 and 7 in the red-edge spectral region were of nearly equal importance in the support vector machine, multilayer perceptron, and gradient boosting decision tree algorithms. It has not been shown in previous studies using Landsat or SPOT, which do not have the red edge band. This study also presented seasonal profiles of misclassification of bamboo forests with other land cover types, such as evergreen broadleaf forests and deciduous broadleaf forests. It should be noted that the classification accuracy in this study would be slightly overestimated because we used data from the entire target region for training and evaluation, unlike other land cover classifications that use training data from selected regions. Nevertheless, our findings could improve the accuracy of mapping bamboo forests using optical remote sensors.*

Keywords: classification algorithm, land cover, Permutation Feature Importance, seasonal trend in detection accuracy

Introduction

Bamboo forests have been expanding in Japan, mainly because they have been abandoned due to decreased demand for bamboo poles and bamboo shoots. According to statistics from the Forestry Agency of Japan (2012, 2022), the area of bamboo forests was approximately 1610 km^2 in 2012 and 1750 km^2 in 2022. Bamboo forests often encroach on agricultural land and artificial timber forests, therefore, satellite remote sensing is expected to detect the distribution of bamboo forests over a large area. The satellite image classification is one of the most popular methods to monitor the land cover. Land cover classification is still an active area of remote sensing research, reflecting recent advances in machine learning. Since land cover classification using optical sensors is based on spectral reflectance, it is important to evaluate how classification accuracy is affected by seasonal and spectral characteristics of the target vegetation.

The objective of this research is to evaluate the four classification algorithms to detect the bamboo forest distribution, from the viewpoints of seasonality and spectral band. We used the Multispectral Instrument (MSI) on board the Sentinel-2 satellites, because its spatial and temporal resolutions were appropriate for our target area, Kochi City, Japan.

Literature Review

Koizumi et al. (2003) investigated the seasonality of the decision tree classification accuracy using Landsat-5 Thematic Mapper (TM). They found that the data observed in May was the most useful for extracting the bamboo stands. Murakami (2006) showed that the shortwave infrared bands of the Landsat-5 TM and the High-Resolution Visible and Infrared (HRVIR) sensor on board SPOT-4 were significant for classifying forest types including bamboo. Narisawa and Yonezawa (2023) detected the bamboo expansion after the Great East Japan Earthquake in the Miyagi Prefecture, Japan, using high-resolution satellite data from Preiades-1 and WorldView-3. They generated land cover maps using support vector machine (SVM) classifier with the accuracy greater than 80% for both scenes. The comparison of the two land cover maps showed the regrowth after the bamboo area was cleared. Inoue et al. (2024) used PlanetScope time series data to verify the optimal observation season for detecting the bamboo area in Fukuoka, Japan. The overall accuracy was highest in June and lowest in April. They also found that the red band and the vegetation index derived from red, green, and near infrared (NIR) bands were more important for accurate bamboo detection. Chen et al. (2024) investigated the mapping of aboveground biomass (AGB) of Moso bamboo using Sentinel-2 MSI and concluded that Random Forest (RF) algorithm excelled in estimating Moso bamboo forest AGB, particularly in May, and texture variables and vegetation physicochemical parameters are also important influencing factors to estimate the bamboo forest AGB. Li et al. (2019) proposed a Yearly Change Bamboo Index using data from two consecutive years and produced a Moso bamboo map by decision tree classification using this index to distinguish between on and off years of bamboo. Tamang et al. (2022) conducted the systematic review of research papers on remote sensing mapping of bamboo. They reported that a relatively large number of research has been carried out using Landsat, and RF algorithm has been popular in recent decades.

Methodology

a. Site and Data:

Our target area was a large part of Kochi City, Japan, as shown in Figure 1. The data in the yellow frame was used for analysis, the area was approximately 286 km^2.

We used 12 scene of Sentinel-2 MSI level 1C product for each month as shown in Table 1. We selected the MSI data observed in 2018, the same year as the ground truth map, but two scenes were observed in 2019 and one scene in 2020 due to cloud cover. Only the data for July 13, 2018 (shown in Figure 1) contains partial clouds, so the pixels inside the blue frame were removed from the analysis for all 12 scenes. We used nine bands from 2 to 8, 11 and 12, taking into account the 10m and 20m spatial resolutions. All data were converted to 10m resolution. The data were downloaded from the Copernicus Open Access Hub (https://scihub.copernicus.eu/).

Table 1: Observation Dates of Sentinel-2.

January 4, 2019	May 24, 2018	September 16, 2019
February 23, 2018	June 13, 2018	October 21, 2018
March 30, 2018	July 13, 2018	November 15, 2018
April 19, 2018	August 16, 2020	December 25, 2018

For the ground truth data of bamboo, we used bamboo map generated by Kochi Prefectural Forest Technology Research Center, as shown in Figure 2(a). The distribution of bamboo forests was registered in vector data by visual interpretation of aerial photographs with a spatial resolution of 25 cm. The polygon data was converted to the raster data with the same projection as Sentinel-2 data. For the ground truth of other land cover types, we used the High-Resolution Land-Use and Land-Cover Map of Japan (ver.21.11) provided by Japan Aerospace Exploration Agency (JAXA 2024), as shown in Figure 2(b). This map was generated using on a convolutional neural network (CNN) in a two-dimensional space spanned by a time axis and a feature axis, by combining satellite data such as Advanced Land Observing Satellite (ALOS) and Sentinel-2, existing maps such as vegetation maps and OpenStreetMap, ground truth information, and so on (Hirayama et al. 2022). The map projection was converted from the Latitude-Longitude projection to the Universal Transverse Mercator (UTM) projection to match the MSI image. Although this map also contains the bamboo class, we removed the bamboo pixels and then overlaid the above aerial photo-based bamboo map on this land cover map.

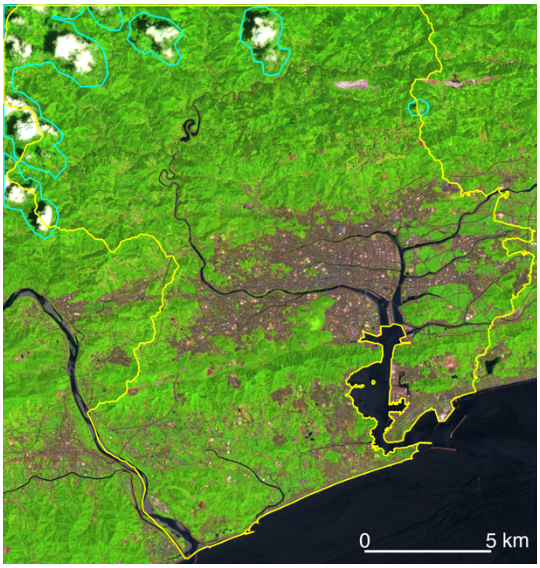

Figure 1: Research Site (Sentinel-2 MSI Image on July 13, 2018).

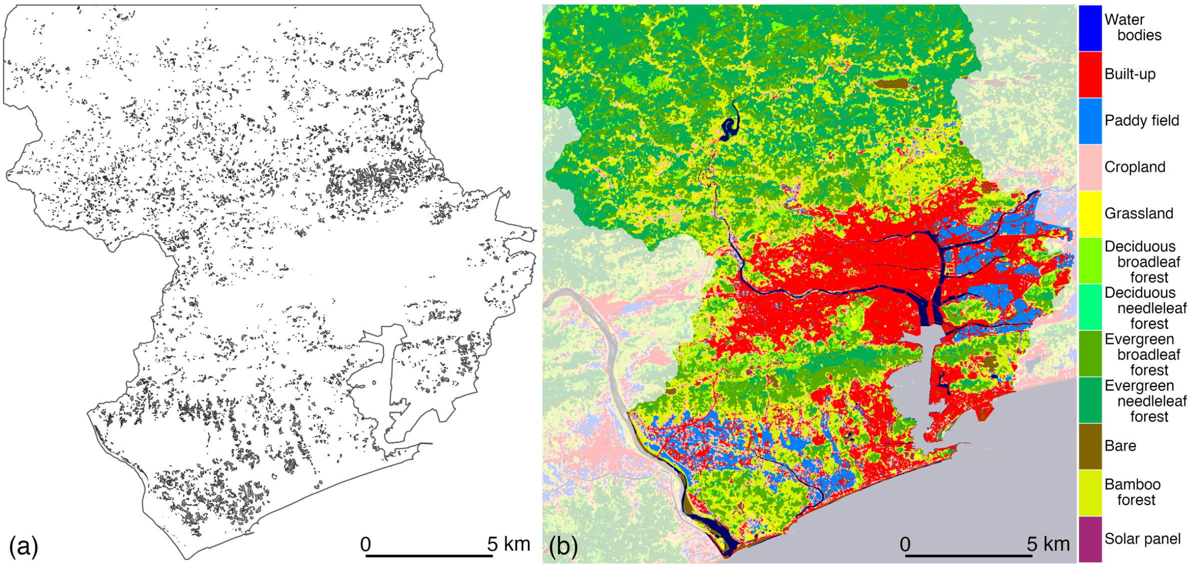

Figure 2: Reference Map of (a) Bamboo, and (b) Other Land Cover.

b. Data Extraction:

The purpose of the study is to evaluate the seasonality of the data and the importance of spectral bands for bamboo detection by land cover classification. Therefore, we extracted the training and test data from entire study area, although the land cover classification usually takes the training data from a portion of the study area. Prior to extraction, pixels along the boundary of the reference map polygon were removed with a single pixel width to avoid the mixing of land cover. The 9-band Sentinel-2 data were then extracted for all existing land cover pixels in the reference map. We had a large difference in the number of sample data by land cover, so the sample number was adjusted to that of bamboo by random selection if the sample number of other land cover was larger. As a result, the number of samples was 79645 pixels for bamboo forests, built-up, paddy field, evergreen broadleaf forest, and evergreen needleleaf forest, 32223 pixels for water bodies, 32704 pixels for croplands, 20815 pixels for grassland, 26970 pixels for deciduous broadleaf forest, 19890 pixels for bare land, and 3265 pixels for solar panels. From this data, we randomly selected 80% of each land cover for training, and the rest for testing. This data extraction was applied to 12 scenes. In order to select the same pixel positions in all scenes, a single seed value was used to generate the random numbers.

c. Classification Algorithms:

Four classification algorithms were used: Random Forest, Support Vector Machine, Multilayer Perceptron, and Gradient Boosting Decision Tree. Random Forest is an ensemble learning method that builds a strong model by combining multiple decision trees that are weak learners. The Support Vector Machine divides the two categories by a hyperplane determined to maximize the distance from the hyperplane to the nearest training data. We used the Radial Basis Function as the kernel function. Multilayer Perceptron (MLP) is a type of feed-forward neural network that consists of layers of processing units. Each unit calculates the weighted sum of the input data, feeds it into the activation function, and outputs the result. We used two hidden layers with the 128 and 64 units respectively. Gradient Boosting Decision Tree (GBDT) is an ensemble technique that combines multiple decision trees to build a more powerful model, similar to Random Forest. But it builds the decision trees so that the trees in turn correct the errors of the previous trees. We performed eXtreme Gradient Boosting (XGBoost) (Chen and Guestrin, 2016) with 100 decision trees of depth 3. These algorithms were implemented using scikit-learn (https://scikit-learn.org/). Except for the specific settings mentioned above, the other parameters used were defaults.

d. Accuracy evaluation:

We used Precision, Recall, and F-measure to evaluate the accuracy of bamboo forest detection. These are represented by the following equations:

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

$$F = 2 \times \frac{P \times R}{P + R} \tag{3}$$

where, P is the Precision, R is the Recall, F is the F-measure, TP is the number of pixels where the bamboo forest was correctly classified as bamboo forest (true positive), FP is the number of non-bamboo pixels incorrectly classified as bamboo (false positive), and FN is the number of bamboo pixels incorrectly classified to the non-bamboo classes (false negative), respectively. Precision and Recall are known as User's accuracy and Producer's accuracy, respectively. The F-measure indicates the harmonic mean of Precision and Recall, i.e. the overall accuracy. These scores were calculated for the bamboo class using the confusion matrix.

Permutation Feature Importance was used to evaluate the importance of the spectral bands. In general, classification accuracy decreases when certain features are randomly mixed between pixels. The more important the feature, the greater the loss of accuracy. Permutation Feature Importance measures importance based on the degree of accuracy loss when features are permutated one at a time (Breiman 2001). In this study, the F-measure for bamboo class was computed repeatedly while randomly mixing the training data for each band. The greater the drop in F-measure, the more important the band.

Results and Discussion

a. Seasonal Change of Bamboo Detection Accuracy:

Seasonal profiles of Precision, Recall, and F-measure are shown in Figure 3. For all algorithms, both Precision and Recall were high and stable from May to August. As a result, together with the F-measure, the three indices showed similar seasonal changes. One reason for the high classification accuracy during this period is the high sun elevation and low shadow effect. In winter, when the solar elevation is low, shadows cast by topography and tree canopy have a large effect, and the brightness of images can vary from place to place, even in bamboo forests. On the other hand, in summer, when the solar elevation is high, the influence of shadows is small, making it easier for the classifier to distinguish differences in reflectance by land cover. The highest F-measure was in May with 0.95 for all classification algorithms. It is consistent with the results of Koizumi et al. (2003), Tanigaki et al. (2012), and Inoue et al. (2024).

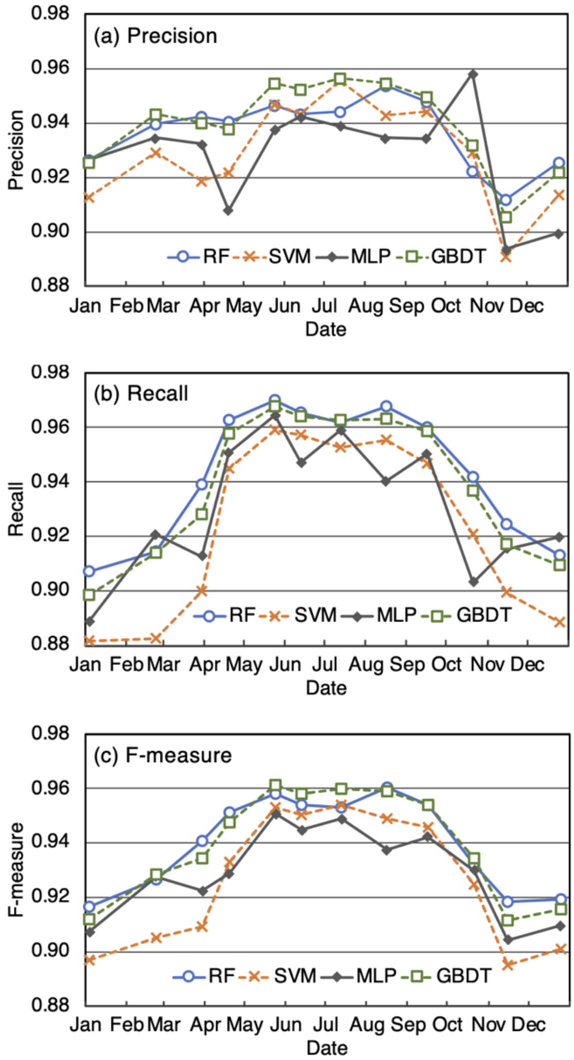

Figure 3: Seasonal Change of Bamboo Detection Accuracy.

The accuracy of all algorithms was generally above 90% throughout the year, and the differences between the classification algorithms were small. Detailed comparisons showed that the Precision of the GBDT was slightly more accurate in most periods. On the other hand, Random Forest performed slightly better in terms of Recall. As a result, either RF or GBDT was the most accurate for the harmonic mean, F-value, throughout the year. We reasoned that both are ensemble learning algorithms based on decision trees and could use the information in each band while suppressing overfitting. The SVM was less accurate throughout the year. We could speculate that this is due to the large overlap in the distribution of pixel data by land cover class in the multidimensional feature space, since SVM is an algorithm that divides a multidimensional feature space by hyperplanes. The multilayer perceptron was also not very accurate throughout the year. In addition, the accuracy varied greatly from scene to scene. For example, Precision had the highest accuracy in October across all algorithms and all seasons but was almost the lowest in November. We consider that MLP produces unstable classification results depending on the input data. Overall, RF and GBDT had slightly higher accuracy. However, the difference in the F-measure of the bamboo was at most 0.03 among the four algorithms, so we can conclude that the difference between the algorithms was small.

b. The importance of the spectral band:

Permutation Feature Importance for the Sentinel-2 MSI bands is shown in Figure 4. Boxplots were derived from the scores of 12 scenes during the study period. For all four classification algorithms, bands 11 and 12 (both in the shortwave infrared region) were of high importance for bamboo detection. It is consistent with the results of Murakami (2006) and Hashimoto et al. (2023). Although not shown here, these two bands were more important for all land cover classes than for bamboo alone, i.e. these bands contribute more to the classification of other land cover types. The importance of the other bands depended on the classification algorithm. RF and GBDT showed similar trends, with bands 2, 3, 6, and 7 equally important. We understand that both are ensemble learning based on a decision tree algorithm, so even if the information in one band is not available, the use of another band with a high degree of similarity will reduce the loss of accuracy to some extent. On the other hand, for the SVM and MLP, bands 6 and 7 (both in the red-edge region) were also important, in addition to bands 11 and 12. We assume that the relationships between bands are important in these algorithms because they use multiple bands simultaneously by kernel function or inner product. For all classification algorithms, bands 5 (red-edge) and 8 (NIR) were less important. In both bands, visual confirmation revealed small differences in contrast between vegetation types.

In addition to the importance of the shortwave infrared region reported in previous studies, the relatively longer spectral band in the red-edge wave region plays an important role in bamboo detection in SVM, MLP, and GBDT algorithms. Previous studies did not show this because their data did not have a red-edge band.

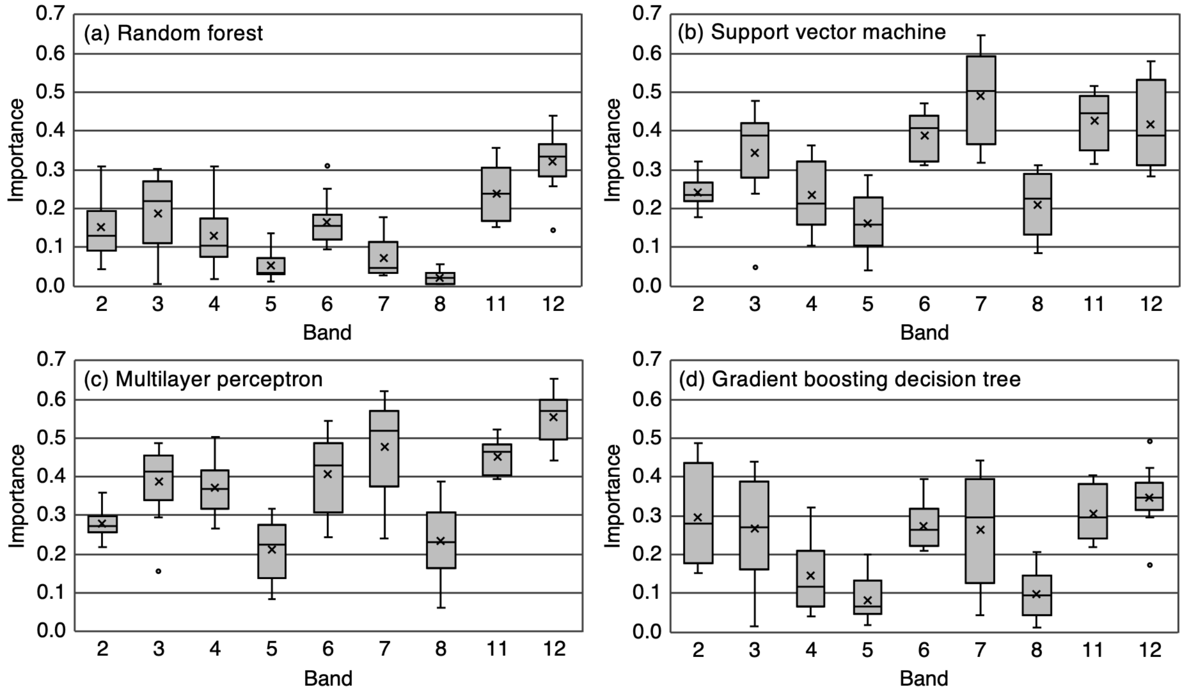

Figure 4: Permutation Feature Importance for the Sentinel-2 MSI Bands.

c. Misclassification of Bamboo Forest:

The seasonal profiles of the false negatives and false positives for the bamboo forest are shown in Figure 5 for each algorithm. In general, errors were larger in winter, reflecting the classification accuracy. Misclassification of bamboo and evergreen broadleaf forest (EBF) became more common in winter. This is probably because both bamboo forests and EBFs have green leaves in winter and similar spectral reflectance. Deciduous broadleaf forest (DBF) was gradually misclassified with bamboo forest from June to November, but the misclassification decreased sharply in December. It might reflect the seasonal change from leaf spreading to defoliation. Except for the false negative error in GBDT, relatively large errors were seen in the early spring at the end of March. This is because the bright green of the new leaves of deciduous trees is similar to the spectral reflectance of a bamboo forest at this time of year. Evergreen needleleaf forests (ENFs) were more likely to be misclassified with bamboo in winter, similar to EBF, and their evergreen nature made them more likely to be confused with bamboo forest.

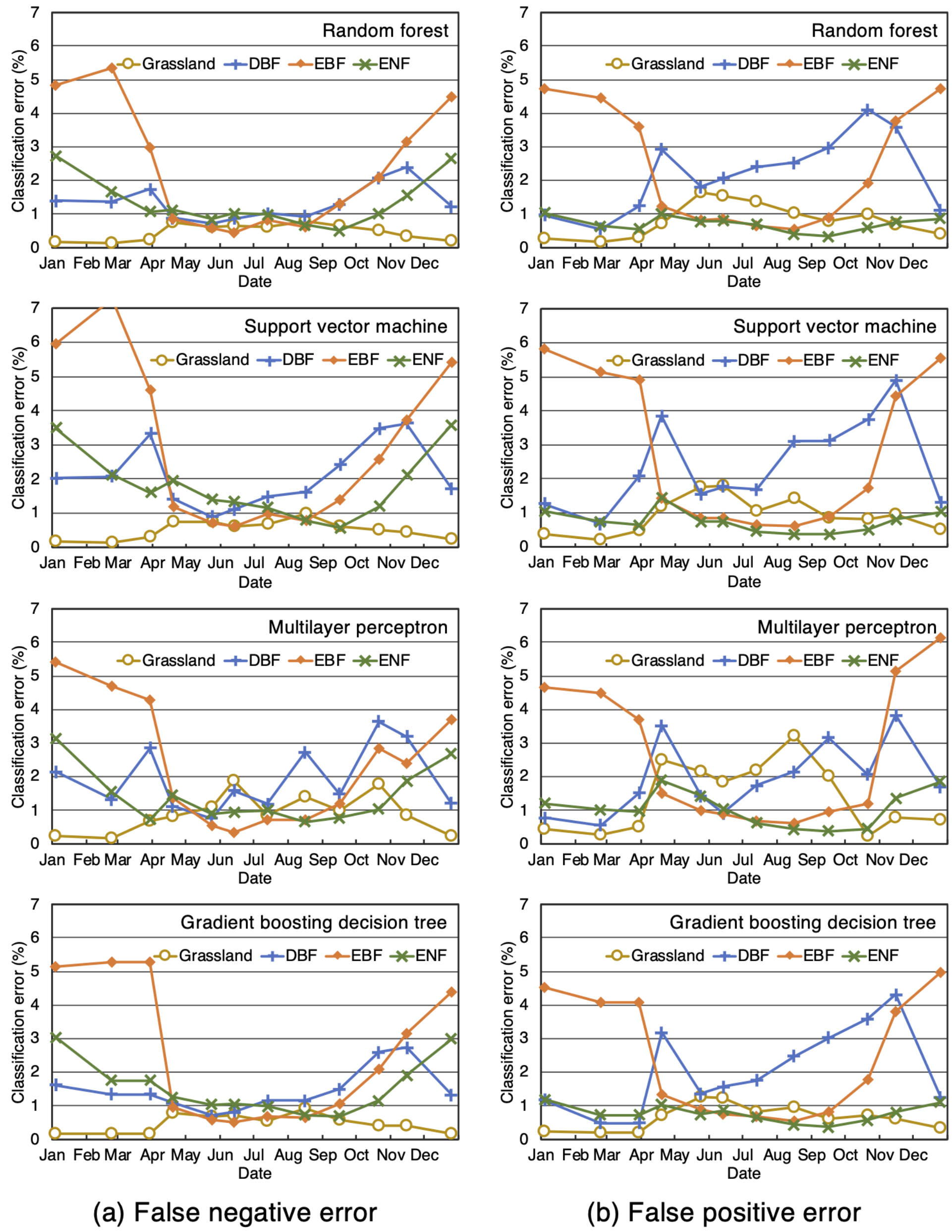

Figure 5: Seasonal Profiles of Misclassification for Bamboo Forest.

d. Discussions:

Unlike studies that use training data from selected regions, this study used data from the entire target region for training and evaluation. Therefore, we expect the accuracy to be slightly overestimated. For example, the highest Precision and Recall in the RF algorithm reached about 0.95 and 0.97, respectively (Figure 3). However, this was achieved by using 80% of the total data for training, which is different from the usual land cover classification. In addition, the land cover classification map generated using satellite data, not the ground-based reference data, was used for training and testing data other than bamboo forest. This could indirectly increase the accuracy of bamboo forest extraction.

Figure 6 compares the classification results in the southwestern part of the target area with the reference map. One reason for the high similarity might be that both were originally created by remote sensing. On the other hand, a sufficient number of training and test data increases the confidence in the results with respect to the timing of the data observations and important wavelength bands. Furthermore, by focusing only on bamboo forests rather than all land cover, our results could provide useful information for estimating the distribution of bamboo forests over a wide area using optical sensors.

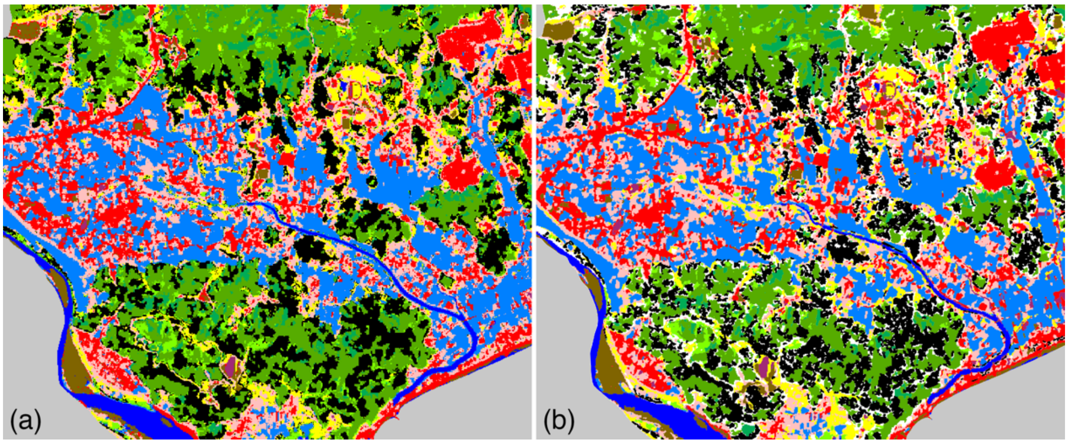

Figure 6: Comparison of (a) random forest classification in May and (b) reference data. The black area indicates the bamboo forest. Other colors are as shown in Figure 2.

Conclusion and Recommendation

We evaluated the influence of the time of observation and the importance of the spectral band for the detection of bamboo forest for the four classification algorithms using the Sentinel-2 MSI. There was no significant difference in the classification algorithms, but Random Forests was only slightly better. Regarding the observation period, all algorithms were highly accurate from May to August, with May being slightly better. The importance of the spectral wave region was high in the shortwave infrared bands 11 and 12 for all algorithms, and in addition, for the support vector machine, multilayer perceptron, and gradient boosting decision tree, the importance of bands 6 and 7 (both in the red edge region) was as high as in the shortwave infrared region. Our results showed that misclassification of bamboo forest occurred more frequently with evergreen broadleaf forest and deciduous broadleaf forest, but the rate of misclassification varied with the seasons, with evergreen broadleaf forest being misclassified more frequently in winter and deciduous broadleaf forest being misclassified more frequently in autumn.

The next advance in this study is the use of multi-seasonal data. The interaction of spectral reflectance observed in different seasons could improve the accuracy of classification, especially between bamboo forest and evergreen forest. Topography should be taken into account when using multi-period data in Japan, where steep mountainous terrain is common. Low solar elevations produce large differences in reflectance between sunny and shady mountain slopes. For example, a topographic correction may be necessary to obtain a reasonable and stable forest reflectance throughout the year (Matsuoka et al. 2020). Another perspective is the complementary use of other geographic data, such as high-resolution optical image or point clouds. High-resolution image provides texture information, and point clouds acquired by airborne laser scanner provide information on the height distribution and shape of the forest canopy. Integrating different types of information, such as texture and canopy shape, would highlight differences between forest types.

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References

Breiman, L. (2001). Random Forests. *Machine Learning*, Vol. 45, pp. 5-32. https://doi.org/10.1023/A:1010933404324

Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. *International Conference on Knowledge Discovery and Data Mining*, *13-17 August 2016*. pp. 785-794. https://doi.org/10.1145/2939672.2939785

Chen, L., He, A., Xu, Z., Li, B., Zhang, H., Li, G., Guo, X., & Li, Z. (2024). Mapping Aboveground Biomass of Moso Bamboo (*Phyllostachys Pubescens*) Forests Under Pantana Phyllostachysae Chao-induced Stress Using Sentinel-2 Imagery. Ecological Indicators, Vol. 158, Id. 111564. https://doi.org/10.1016/j.ecolind.2024.111564

Forestry Agency of Japan. (2012). Forest Resource Status Summary. Retrieved April 28, 2024, from https://www.rinya.maff.go.jp/j/keikaku/genkyou/h24/index.html

Forestry Agency of Japan. (2022). Forest Resource Status Summary. Retrieved April 28, 2024, from https://www.rinya.maff.go.jp/j/keikaku/genkyou/r4/index.html

Hashimoto, N., Kitazawa, H., Chikata, N., & Yamasaki, S. (2023). Attempt of Expansion Detection of Bamboo Forest in Kochi City by Classification Tree Using Existing Bamboo Location Data and Sentinel-2 Satellite Imagery. *Transactions of The Japanese Society of Irrigation, Drainage and Rural Engineering*, Vol. 91, No. 1, pp. II_1-II_7 https://doi.org/10.11408/jsidre.91.II_1

Hiramaya. S., Tadono, T., Ohki, M., Mizukami, Y., Nasahara, K.N., Imamura, K., Hirade, N., Ohgushi, F., Dotsu, M., & Yamanouchi, T. (2022). Generation of High-Resolution Land Use and Land Cover Maps in JAPAN Version 21.11. *Journal of The Remote Sensing Society of Japan*, Vol. 42, No. 3, pp. 199-216. https://doi.org/10.11440/rssj.42.199

Inoue, S., Ota, T., & Mizoue, N. (2024). Searching for the Optimal Acquisition Month for Bamboo Area Detection Using Satellite Constellation Images. *Japanese Journal of Forest Planning*, Vol. 57, No. 2, pp. 45-51. https://doi.org/10.20659/jjfp.57.2_45

JAXA. (n.d.). High-Resolution Land-Use and Land-Cover Map of Japan [2018 ~ 2020] (Released in November 2021 / Version 21.11). Retrieved September 11, 2024, from https://www.eorc.jaxa.jp/ALOS/en/dataset/lulc/lulc_v2111_e.htm

Koizumi, K., Tanimoto, C., & Piao, C. (2003). Extraction of Bamboo Stands by Observing Landsat-5 TM. *Journal of the Japan society of photogrammetry and remote sensing*, Vol. 42, No. 6, pp. 42-51. https://doi.org/10.4287/jsprs.42.6_42

Li, L., Li, N., Lu, D., & Chen, Y. (2019). Mapping Moso Bamboo Forest and its On-year and Off-year Distribution in a Subtropical Region Using Time-series Sentinel-2 and Landsat 8 Data. *Remote Sensing of Environment*, Vol. 231, Id. 111265. https://doi.org/10.1016/j.rse.2019.111265

Matsuoka, M., Moriya, H., & Yoshioka, H. (2020). Correction of Canopy Shadow Effects on Reflectance in an Evergreen Conifer Forest Using a 3D Point Cloud. *Remote Sensing*, Vol. 12, No. 14, Id. 2178. https://doi.org/10.3390/rs12142178

Murakami, T (2006). How is Short-wave Infrared (SWIR) Useful to Discrimination and Classification of Forest Types in Warm Temperate Region? *Journal of Forest Planning*, Vol. 12, No. 2, pp. 81-85. https://doi.org/10.20659/jfp.12.2_81

Narisawa, T., & Yonezawa, C. (2023). Monitoring of Bamboo Expansion Using High-resolution Satellite Imagery After the Great East Japan Earthquake. *Journal of the Japanese Agricultural Systems Society*, Vol. 38, No. 4, pp. 59-66. https://doi.org/10.14962/jass.38.4_59

Tamang, M., Nandy, S., Srinet. R., Das, A.K., & Padalia, H. (2022). Bamboo Mapping Using Earth Observation Data: A Systematic Review. J*ournal of the Indian Society of Remote Sensing*, Vol. 50, pp. 2055-2072. https://doi.org/10.1007/s12524-022-01600-0

Tanigaki, Y., Harada, I., Sekiyama, A., & Hara, K. (2012). Characteristics and Seasonal Variations in Reflectance of Evergreen Forest Including Madake and Mousouchiku Bamboo Determined by Using ALOS/AVNIR-2. *Journal of the Japan society of photogrammetry and remote sensing*, Vol. 50, No. 6, pp. 361-366. https://doi.org/10.4287/jsprs.50.361