

Exploration on image classifications abilities in identification of flowering trees in urban park

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Abstract. Monitoring flowering cherry blossoms is crucial in Japan as the flowering dates have been slowly advancing due to climate change. However, monitoring cherry blossoms during flowering time quite challenging especially in urban area which is high diversity ecosystems. We hypothesize that fuzzy classification has an ability to identify pixels of flowering Somei Yoshino (SY) (or known as *Prunus × yedoensis*) which is better compared to traditional method of classification. Maximum likelihood (ML) and Support Vector Machine (SVM) classifications as traditional image classification were employed on IKONOS image in identification of flowering cherry trees in an urban park. Meanwhile, Mixture Tuned Matched Filtering (MTMF) and Linear Spectral Unmixing (LSU) were employed as fuzzy classifications. Fuzzy classification of MTMF with overall accuracy (58.33%) and kappa value (0.45) shows promising result in identifying flowering SY tree compared to ML, SVM, and LSU classifications suggested that MTMF is a good technique to be used to map flowering SY tree in heterogeneous urban area. However, the accuracy of fuzzy classification could decrease due to limited number of available bands. Thus, the use of hyperspectral data can be used to stimulate new research idea, and drive to the future research to improve the classification results.

Keywords: Flowering Cherry Tree; Fuzzy Classification, Traditional Classification, Maximum Likelihood, Support Vector Machine, Mixture Tuned Matched Filtering, Linear Spectral

1. Introduction

Plant phenology was strongly controlled by climate [1]. This can be proved by 243 studied on flowering timing of plant species in England where almost all of the studies were significantly related to temperatures [2]. Meanwhile, Aono and Yasui [3] found that spring phenological events of cherry blossom for 732 years in Kyoto has changed according to imbalance temperature. Thus, identification and monitoring of cherry trees is essential. Identification of flowering cherry tree by using ground measurements are time consuming, expensive and resulting to lack of data information. Remote sensing technology has potential to provide spatiotemporal data which can be utilized to overcome the weakness of conventional method to develop an effective monitoring solution for the flowering cherry tree. Typically high spatial resolution multispectral data is used in previous studies and mostly focused



on green leaves as leaves the most dominant organ on vegetation and in forest monitoring [4-5]. Flowering tree classification is not often explore due to its weak spectral signal [6]. In contrast, previous studies has proved that classification accuracies is at best as the satellite imagery was collected during peak flowering time because spectral variations of flower could increase classification accuracy [6].

Various approaches of traditional and fuzzy classification has been utilized in the past regarding on plant such as extracting vegetation information[7] , deriving species richness and species composition information [8], and monitoring urban greenness [9]. Traditional classification works by selecting that class label with the greatest likelihood of being correct and only assigned one class per pixel because the feature space decision boundaries for this method are well-defined [10]. This type of classification is suitable to be applied in homogenous area such as croplands and water bodies [11]. Meanwhile, fuzzy classification allow multiple labels at each pixel where it assigned a pixel into several class membership [10, 12] . This probability-based classification's feature space decision boundaries is said to be fuzzy [10]. Usually, fuzzy classification is applied on heterogeneous areas such as residential areas and mixed forests. It is because heterogeneous characteristics of an area provide similar spectral responses from different kind of land use which introduced mixed-pixel problems[13].

To address the issues of mixed-pixel, this study hypothesize that the feasibility scale of fuzzy classification with the matched filter gave more encourage results in identifying flowering cherry trees in high heterogeneity urban area. Therefore, this study was carried out by exploring the ability of traditional and fuzzy classification approach in identifying Somei Yoshino (SY) (or known as *Prunus* × *yedoensis*) cherry trees within an urban park with the utilization of Maximum Likelihood (ML) classifier, Support Vector Machine (SVM), Mixture Tuned Matched Filtering (MTMF), and Linear Spectral Unmixing (LSU). All accuracies of the classifications employed on high spatial resolution IKONOS image used were finally compared to explore the capability of image classification.

2. Materials and Methodology

2.1 Study site

This study was conducted at Yanagisawanoike Park, Hachioji City, Tokyo, Japan. (35.6154° N, 139.3767° E) with elevation of 128 m. This park one of the spot for cherry blossom viewing. The most dominant species in this park isa deciduous Somei Yoshino (*Prunus* × *yedoensis*). There are some other cherry blossoms in this park like Kanzakura (*Prunus sato-zakura* “*Sekiyama*”), Mamezakura (*Prunus incisa*), and Shidarezakura (*Prunus sapchiana*), as well as other deciduous trees, such as Japanese red pine (*Pinus densiflora*) and hornbeam (*Carpinus laxifolia*), and evergreen trees, including camphor (*Cinnamomum camphora*), Chinese evergreen oak (*Quercus mysinaefolia*), and Japanese black pine (*Pinus thunbergii*). The mean canopy size of flowering SY tree during full bloom was 5 meters and the mean height of the tree was 3 meters [6].

2.2 Materials

2.2.1 Remote Sensing Data. Multispectral IKONOS imagery with 4-m spatial resolution and 4-bands was used in this study. The image was acquired on April 1, 2006. This image was chosen as on that date the cherry trees was in full bloom based on the information given by Japan Meteorological Agency (JMA). Image obtained has been geometric and radiometric corrected.

2.2.2 In-situ data collection. There are two types of data were collected in this study; (1) spectral reflectance and (2) Ground coordinate of flowering trees. Spectral reflectance were collected to validate the spectral reflectance of flowering SY in the IKONOS image by utilizing a spectroradiometer (ASD Fieldspec Pro) in April 2014. The data were collected at a spectral range of 0.35–2.5 μm with a spectral interval of 3.3 nm. The spectral reflectance of ten flowers from five blooming SY individuals were measured in a laboratory under dark conditions using a

spectroradiometer mounted at a nadir position 20 cm above the target with a 25° field of view. Ten readings for each sample was recorded and calculated the average of spectral data. The sensor was calibrated using a white Spectralon panel prior to data collection. X, Y- coordinate of Somei Yoshino trees, soil, dry grass, and evergreen trees were collected on April 1, 2014 using a handheld GPS unit (Garmin GPSmap 60CSx). Both of the data have been collected by Hassan et al. [6]. The X,Y coordinate was used later to assess classification accuracy.

2.3 Methodology

Texture analysis was first employed to IKONOS imagery using grey level co-occurrence matrix (GLCM) before applying traditional classifications. Spatial and spectral information of IKONOS image were extracted and examined after employing GLCM using 3×3 kernel window (Figure 1 and 2). Results obtained from GLCM were then used as input for traditional classification. Before employing fuzzy classification, IKONOS image has undergoes the Minimum Noise Fraction (MNF) so that it can be used for fuzzy classification later.

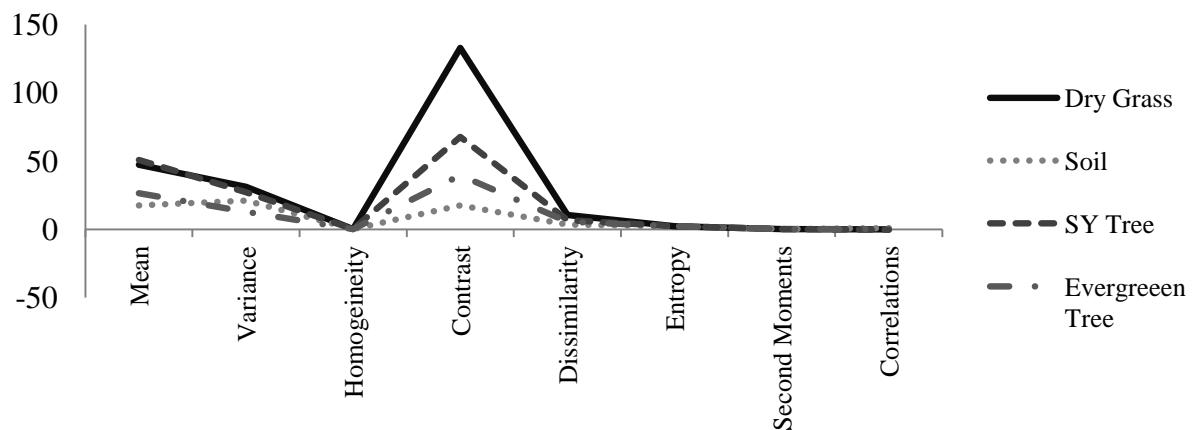


Figure 1. Mean values of textural features computed from training pixels for IKONOS image. The figure shows the textural analysis for dry grass, soil, SY tree, and evergreen tree.

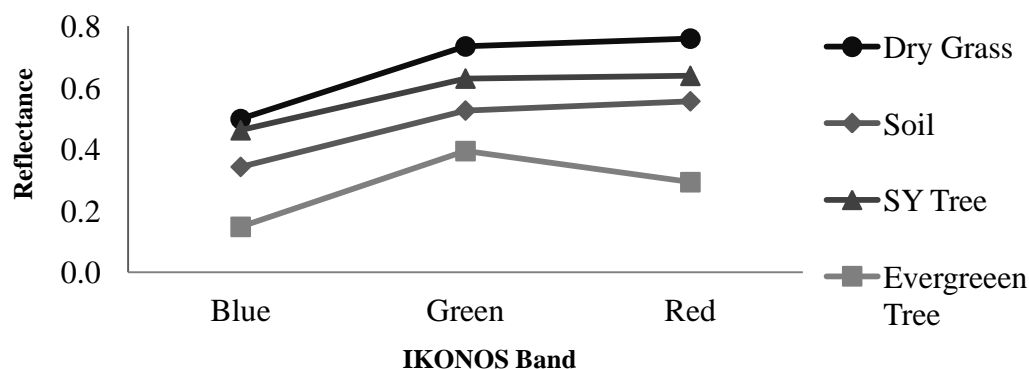


Figure 2. Mean spectral signature of the IKONOS image used to select training areas for dry grass, soil, SY tree, and evergreen tree.

There are four different classifications were used in this study; (1) Maximum Likelihood, (2) Support Vector Machine (SVM) from traditional classification and (3) Mixture Tuned Matched Filtering (MTMF) and Linear Spectral Unmixing (LSU) from fuzzy classification. The method used will be explained further in Table 1.

Table 1. Methods used in this study

ML	SVM	MTMF	LSU
<ol style="list-style-type: none"> 1. Samples of flowering SY tree, dry grass, soil, and evergreen tree classes were randomly selected by using the region of interest (ROI) tools based on Google Earth and knowledge of land cover types from the previous researcher. 2. MLC was conducted on the combination of texture (contrast) and spectral images with eight bands to improve the classification accuracy. 	<ol style="list-style-type: none"> 1. Training samples of flowering SY tree, dry grass, soil, and evergreen tree created before were used to perform image classification using SVM. 2. SVM were configured with default setting of polynomial kernel types to classify all classes using a combination of texture (contrast) and spectral images as well. 	<ol style="list-style-type: none"> 1. Endmembers of flowering SY tree, dry grass, soil, and evergreen tree were extracted by collecting training data of homogenous patches. They were used to generate the abundance maps. 2. Cumulative distribution function was used to determine the infeasibility score for 36 points of flowering SY tree that were lies across 40 pixels in the IKONOS imagery. Then, MF scores across these 40 pixels were categorized into five groups and the highest MF score is between $0.4 \leq MF \leq 0.8$. 	<ol style="list-style-type: none"> 1. ASCII file of endmembers (flowering SY tree, evergreen tree, dry grass, and soil) created before were used. 2. The spectra of each classes will automatically resampled to match the wavelengths of the MNF transformation of the reflection data being unmixed.

In summary, traditional classification of ML and SVM produced a thematic map where each classes were represented with different colours to discriminate the classes. Meanwhile, fuzzy classification of MTMF produced a grey scale map and the distribution of flowering SY tree were identified based on its composition which confirmed by the readings of infeasibility scale. On the other hand, LSU generate a grey scale thematic map as well, where the each pixels have the percentage of each classes.

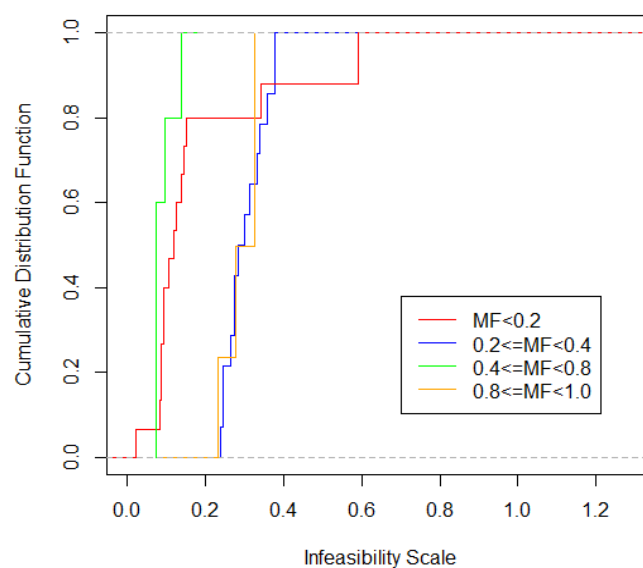


Figure 3. Best infeasibility scores for 36 points of flowering SY used to identify the feasibility of matched filter (MF) scores.

2.4 Accuracy Assessment

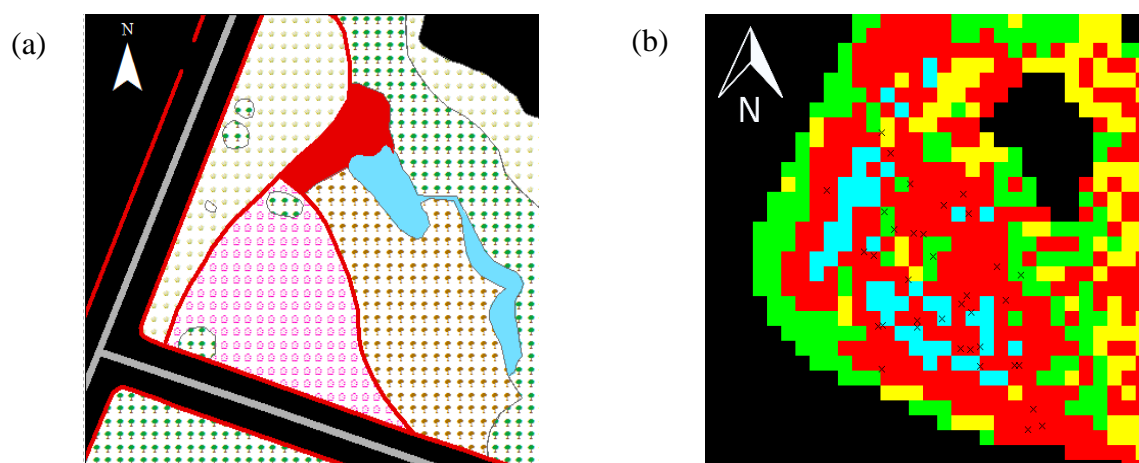
The accuracy of ML, SVM, MTMF and LSU were assessed using in-situ data collected. Producer's accuracy, user's accuracy, overall accuracy, and kappa coefficient were calculated for all classifications used. Producer's accuracy measures how accurate a certain area has been classified while user's accuracy measures the probability that a pixel classified into a given category actually represents that category on the ground. Subsequently, percentage of correctness were calculated using overall accuracy and measurement of the level of agreement between the observed and predicted classes were calculated using kappa coefficient [14–16]

3. Results and analysis

The IKONOS image used for this study have high differences in spectral pattern for contrast between each classes. Thus, the result of contrast image were used for classification. The classification result of ML were visually displayed in Figure 4 (b) and the map clearly shows that the spatial patterns of flowering SY tree were very compact resulting from ML classification because this ML identified evergreen and soil as SY tree even though texture analysis was applied. This making the map have flowering SY tree as a dominant feature. Meanwhile, SVM result (Figures 4 (b)) shows that the spatial patterns of flowering SY was less compact. In addition, it also could be visually observed that the distribution of flowering SY tree classified using SVM is not scattered in the map. It can be observed that SY tree, evergreen tree, dry grass, and soil classes were easily recognised by their well-grouped pixels

For MTMF, the pixels of masked building, asphalt road and lake had negative MF scores (Figure 4 (d)). These negative MF scores were considered as zero target abundance which means there is no target component [6, 17]. The map resulting from MTMF shows the composition of SY tree that comprises of 40% to 80% as the 36 points of flowering SY were distributed across 40 pixels MF scores lies on $0.8 \ 0.4 \leq MF \leq 0.8$. Pixels with MF scores < 0.4 indicates the soil, while MF scores > 0.8 indicates classes of dry grass, and evergreen tree. The result of infeasibility scores from the MTMF classification ranged between 0.04 to 18.53. These infeasibility score was used to produce color-coded maps for presenting SY tree distribution above specific abundance thresholds.

Figure 4 (e) shows the grayscale images SY tree fraction cover. LSU thematic maps have the pixels of masked building, asphalt road and lake as well where this value is classified as zero which refer that there is no target component. The unmix endmember for SY tree ranged from -4.853 to 3.818. The fraction value of one is represented by white color and zero is represented by black color. A number of 40 pixels where the 36 points of in-situ of SY tree lies were chosen to see fraction cover estimation for each pixel. The values ranges for those pixels are -1.673 to 2.311. The result of the LSU classification is a color-coded image as show in Figure 4 (e) showing the best SY tree match at each pixel.



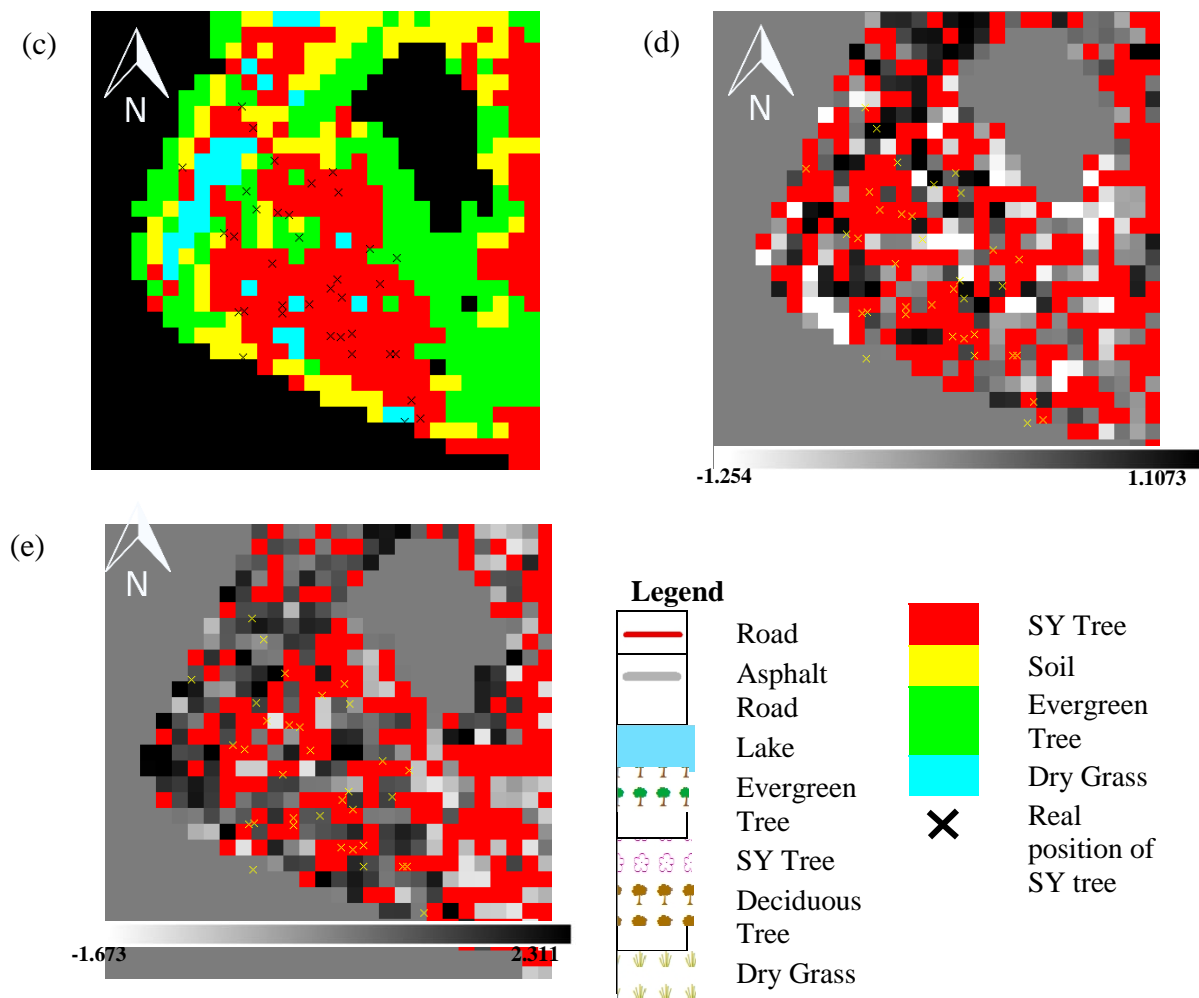


Figure 4. Classification results of land cover for Yanagisawanoike Park area by using different classification approaches: (a) Study area, (b) ML classification of the IKONOS image, (c) SVM classification of the IKONOS image, (d) MTMF classification of the IKONOS image, and (e) LSU classification of the IKONOS image.

Table 2. Image classification accuracies for MLC, SVM, MTMF and LSU approaches

Classification	Overall Accuracy (%)	Kappa Values	User's Accuracy of SY Tree (%)	Producer's Accuracy of SY Tree (%)
ML	50.00	0.3373	34.85	63.89
SVM	55.84	0.4153	40.68	70.59
MTMF	58.33	0.45	66.67	57.14
LSU	56.41	0.42	66.67	55.81

Based on Table 2, the overall accuracy and kappa coefficient was highly estimated by using MTMF followed by LSU, SVM, and ML. From the result, it is observed that user's accuracy of SY tree were better using fuzzy classification compared to traditional classification where the percentage were 66.67% (MTMF and LSU), 40.68% (SVM), and 34.85% (ML). On the other hand, producer's accuracy of SY tree were better using traditional classification than fuzzy classification where the readings were 70.59% (SVM), 63.89% (ML), 57.14% (MTMF), and 55.81% (LSU).

4. Discussion

Good readings from overall accuracy and kappa coefficient of MTMF compared to LSU classification was obtained in classifying flowering SY tree in an urban park. This is because high SY fractional cover estimated due to low spectral contributions in each pixel of IKONOS. In addition, the accuracy is high due to the number of endmember less than number of band. LSU's overall accuracy and kappa coefficient of SY estimation is lower than MTMF due to the limited number of endmembers for spectral unmixing. Misclassification occur because of the poor spectral differentiation of the pure pixels between the endmembers. User's accuracy of SY tree using MTMF and LSU is the same. However, the producer's accuracy of SY tree using MTMF shows satisfying result over LSU. LSU have slightly lower producer's accuracy because some of the SY tree were misclassified as soil.

SVM's overall accuracy and its kappa coefficient is better than ML. It is because SVM able to generate optimally separate hyperplanes, which can produce better accuracy results. Meanwhile, overall accuracy and kappa value generated from ML are relatively low due to the heterogeneous urban landscape of study area which cause mixed pixel problem. In comparison, the user's accuracy and producer's accuracy of SY tree is much better than ML when using SVM approach with the help of textural analysis. Confusion of flowering SY tree with evergreen tree and soil, lower the values of user's accuracy of ML as the flower have weak spectral response compare to evergreen tree and soil. According to [6], SY flower from the tree have no green leaves during peak blooming. Deciduous trees were often misclassified as soil because soil has higher reflectance compared to branches or trunks. Hence, additional training class of deciduous trees might be useful and could improve the accuracy of ML classification.

Overall, fuzzy classification outperformed traditional classification in term of overall accuracy, kappa value, and user's accuracy. However, the producer's accuracy for both MTMF and LSU were lower compared to traditional classifications, ML and SVM. As for fuzzy classification, it may be due to the limited number of IKONOS bands which making the flowering SY tree cannot be distinguish properly with soil and dry grass. If soil and dry grass pixels have the similar reflectance values with flowering SY tree, fuzzy classification are easily to classify these pixels as flowering SY tree. In addition, the possibility of overlapping between classes increased when the number of classes increased. Additional band is required to distinguish the flowering SY tree with other features [6].

In summary, the result of fuzzy classification of MTMF obtained was better than LSU for this study. MTMF is a partial unmixing method where the not all spectra are required for each endmembers as input to get accurate result. In contrast, LSU require more number of endmembers to have better result. In addition, through MTMF, flowering SY tree can be confirmed with infeasibility score but not for LSU. While, traditional classification of SVM achieved better result than ML when tested on the Yanagisawanoike park area. SVM capable to maximize margin between classes in the feature space but it sensitive to the outliers. ML usually produced a good classification result but it requires the assumption of normality of the training data. Lastly, fuzzy classification able to identify the pixels of flowering SY tree better compared to traditional classification as fuzzy work the best when applied at heterogeneous and mixed pixels area.

5. Conclusion

In conclusion, this study is done to help Forestry and Forest Products Research Institute (FFPRI) for the management of cherry tree preservation forest. In addition, it is also important for Japan Meteorological Agency (JMA) to control, planning, monitoring and managing urban cherry trees in the city with the use of mapping technology. The utilization of remote sensing approach could help with mapping the complexity of urban landscape. Based on the result obtained in this study, it is clearly that fuzzy method is advantageous compared to traditional method. However, the limitation number of spectral bands can affect the producer's accuracy of fuzzy classification to become lower. Therefore, identifying flowering tree can be explore by using AVIRIS hyperspectral data to improve the classification results for future research.

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