IDENTIFYING CROP CULTIVATED AREAS USING MULTI-SATELLITE IMAGERY AND THE MACHINE LEARNING CLASSIFIERS

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ABSTRACT

Several new satellites have been launched in recent years, such as Worldview series, Pléiades and Kompsat-3. The efficiencies of these satellite imagery for classifying crop types need to be verified. However, with the improvement of spectral and spatial resolution of the satellite imagery, for their complex and the huge amount of information, traditional statistical methods have been unable to provide effective classification accuracy. Several scholars have adopted the machine learning algorithm, including back propagation neural network (BPNN), support vector machine (SVM) and random forests (RF), to classify the complicated imagery.

Therefore, this research applies the BPNN, SVM and RF classifiers using Worldview-2, Pléiades and Kompsat-3 images to interpret planted fields of garlic, vegetable, green manure and other crops in Sihhu Township of Yunlin County, Taiwan. The classified results indicated that Worldview-2 using the SVM classifier has the best result with 94.4% overall accuracy (Kappa 0.91), followed by Pléiades using the RF classifier with 85. 7% overall accuracy (Kappa 0.789) and Kompsat-3 using SVM with 83.6% overall accuracy (Kappa 0.76). Through the cross examination, the classification accuracies of Worldview-2 imagery is better than Pléiades and Kompsat-3 imagery and the SVM is better than the RF and the BPNN.

1. INTRODUCTION

Several new satellites have been launched in recent years, such as Worldview series, Pléiades and Kompsat-3. The quality of satellite images has improved, and the resolution and information load contained in these images have also increased. The complexity of the classification, however, has also increased because of its rich spectral and spatial information. Consequently, the conventional statistical method is inapplicable to accurately categorizing and interpreting complex and highly informative data (Lloyd et al., 2004). Several studies have used machine learning algorithms to remote sensing applications (Schapire et al., 2005), thus enabling categorizing and interpreting images through data classification. Artificial neural networks (ANNs) are a typical machine learning algorithm (Hophield, 1982) that involve a processing system imitating a biological neural network to generate a neural network-like calculation system. Back propagation neural network (BPNN), with a strong nonlinear mapping and generalization ability as well as fault tolerance, is the most widely used neural network. BPNN has been widely used in the remote sensing applications ((Kaur et al, 2013; Mahmon et al, 2014; Ahmed et al, 2015)). Another machine learning algorithm, the support vector machine (SVM) method, one of the machine learning algorithms, was developed according to the statistical learning theory. Studies have indicated that the classification accuracy of the SVM is higher than that of ANNs, decision trees (DTs), and maximum likelihood (ML) classifier. Therefore, the SVM has gradually become a popular algorithm in the machine learning domain and is widely used in research related to remote sensing (Castaings et al., 2010; Gustavo et al., 2004).

Breiman (2001) used the classification and regression tree (CART) method to develop the random forest (RF) method. RF inherits the advantages of CARTs for low calculation load and high explanatory power and improves the low accuracy in CARTs. Moreover, RF can be used to determine the relative importance of input variables; hence, this method is currently considered the most effective algorithm (Iverson et al., 2008). Relevant studies have involved classifying land cover types (Ghimire et al., 2011; Rodriguez-Galiano et al., 2012), differentiating spectral reflectance among tree species (Lawrence et al., 2006; Clark and Roberts, 2012), detecting landslide boundaries (Stumpf and Kerle, 2011), analyzing urban land use (Guo et al., 2011), and mapping bamboo distributions (Ghosh and Joshi, 2014). The aforementioned studies indicate that RF features higher accuracy and faster training site calculations than the other types of machine learning algorithms do.

For the aforementioned reasons, three classifiers are used in this study, including the BPNN, SVM and RF classifiers, to interpret various crop planted fields through WorldView-2, Pléiades and Kompsat-3 satellite images. The classification efficiencies for interpreting various crop planted fields are evaluated respectively using these three different classifiers and satellite images.

2. MATERIALS AND METHODS

2.1. Study Area

Yunlin County, features the major crop production in Taiwan. Hence, one township, Sihu, in this county was selected as the research site of this study (Figure 1). Sihu Township is located in the southeast region of Yunlin County. The total area of the township is 7711.89 Ha. Planted areas account for 5274.47 Ha (68.39%) of the township, ranking second highest in the county. A research site was established in Sihu and covered a range of two orthophotograph maps (1:5000). The map serial numbers are “94203048” and “94203038,” and the combined area of the maps is approximately 1240 Ha. Due to the dates of image acquired are different, it is difficult to compare the classification efficiencies for the three images. To conquer this problem, the areas planted same crops in 2013, 2014 and 2015 years are used in the analysis.

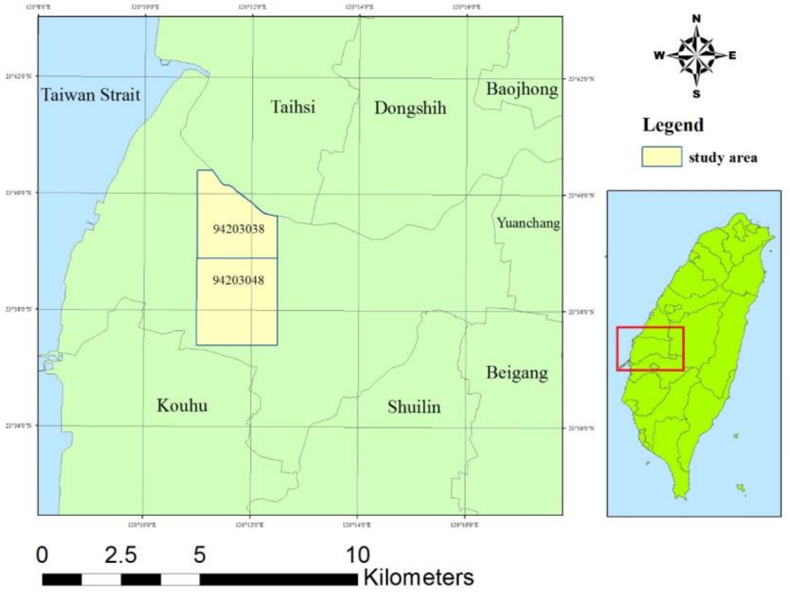

Figure 1. The study area locates inside the Sihu township of Yun-Ling county in Taiwan.

2.2. Collection of Ground Reference Data

After the field survey, garlic, vegetable, green manure, and nursery gardens are the major crop types in this area. Since at the time of images were acquired, most vegetables were harvested and the land were bared. The vegetation type and the bare land were recoded as the same class, bare lands. To correspond with the image acquired time, extensive fieldwork was executed on the following dates over the entire study area, including January 7th and 24th, 2013; January 7th, and 28th, February 11th and 21th, 2014; January 23th, and February 4th, 2015. The positions of crop types were recorded using the cadastral maps of the study area, and matching polygons were defined on the maps. The areas planted same crops for the three study years is shown in Figure 2.

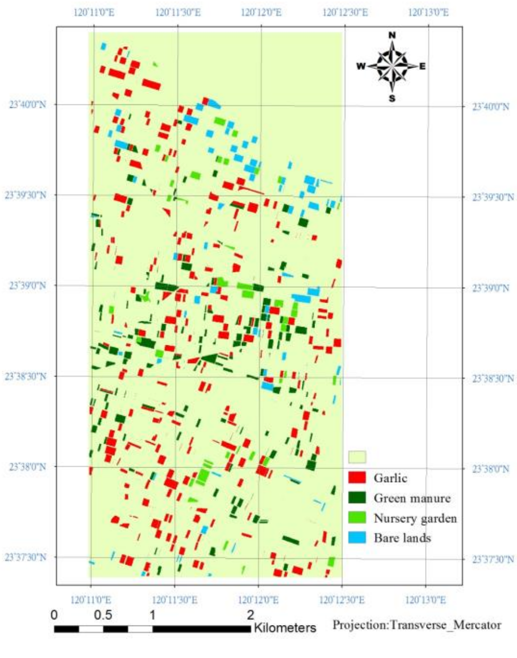

Figure 2. The ground truth of the study area.

2.3. Imagery Acquisition

The WorldView 2 imagery was acquired on December 22, 2012. A total of 11 bit data in nine spectral bands was acquired covering Coastal (400–450 nm), Blue (450–510 nm), Green (510–580 nm), Yellow (585–625 nm), Red (630–690), Red Edge (705–745 nm), NIR1 (770–895 nm), NIR2 (860–1040 nm), and Pan (450–800 nm) bands. Another image, the Pléiades imagery, was acquired on January 12, 2014. The very high spatial resolution Pleiades imagery is the product of Airbus Defense and Space. Five spectral bands was acquired covering Blue (430–550 nm), Green (500–620 nm), Red (590–710), NIR (740–940 nm), and Pan (470–830 nm) bands. The last image, the Kompsat-3 image, was acquired on December 19, 2014 is an optical high-resolution Korean observation mission of Korea Aerospace Research Institute. Five spectral bands was acquired covering Blue (450-520 nm), Green (520-600 nm), Red (630-690), NIR (740-900 nm), and Pan (450-900 nm) bands. Figure 3 is an example of the satellite images.

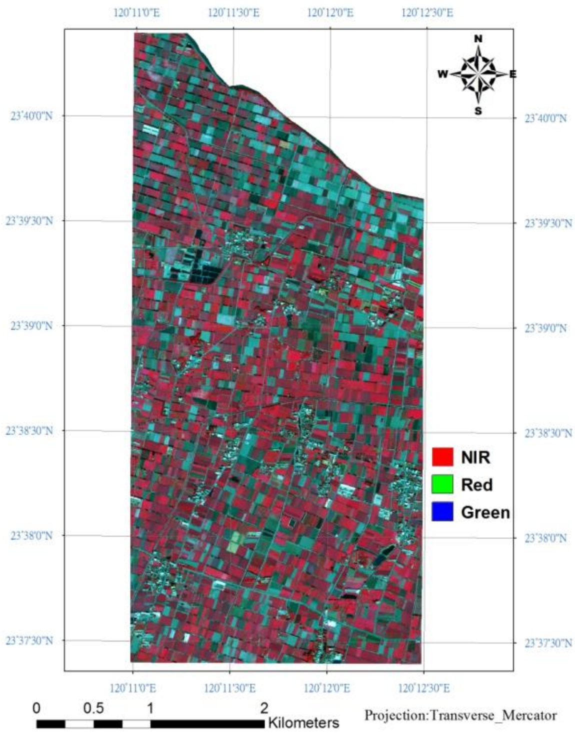

Figure 3. The WorldView 2 imagery of the study area dated December 22, 2012.

2.4. Classification Procedures

A supervised classification method was applied using BPNN, SVM and RF classifiers to interpret the WorldView-2, Pléiades and Kompsat-3 images of the garlic, green manure, nursery gardens, and bare lands at the research site. The identical training sites were used for three classifiers to compare the classification performances of the three classifiers. Totally, 76 training sites were used in the analysis, including garlic 20 sites, green manure 19 sites, nursery gardens 19 sites, and bare lands 18 sites. The separability analysis was then executed to reduce the confusions between classes. The threshold was set to 1700. The classified images were then overlaid with the crop cadastral maps through the geographical information system (GIS) object-based post classification (GOBPC) method (Shiu et al., 2012). Next, an accuracy assessment was conducted to examine the classification outcomes obtained through the three classifiers. The classification package used in this study was developed through open sources of MATLAB.

2.4.1. Back Propagation Neural Network (BPNN) Classifier

The BPNN classifier was used to interpret the image of the crop planted areas, and the outcomes were compared with those of the SVM and RF classifier. The basic idea of BPNN is that “the network training process is composed of the signal of the Forward Propagation and error Back Propagation two Processes like Forward Propagation, the training sample input from the input layer through hidden layer to output layer to predict the output of training samples. Determine whether the predicted output to meet the accuracy requirements, if the error of the predicted output and actual output does not meet the precision requirement and does not reach the maximum training time, then it will enter the error back-propagation phase, which is that error is transferred layer by layer in some form through the hidden layer to the input layer, and error is apportioned to each layer neural network, thus the error signal of each neuron as the basis of the right to amend the value of each neuron. Weight adjustment process is the network training process of learning, this process continuously loop until the network output error reduced to the required accuracy or to a pre-set maximum number of times” (Abdalla et al, 2010).

2.4.2. Support Vector Machine (SVM) Classifier

SVM is mainly used to identify the optimal separating hyperplane for differentiating two categories in a set of data, thus maximizing the margin between the two nearest samples of distinctive classes. The samples located on the maximized margin are called support vectors, and the bisecting plane of the margin is known as the optimal separating hyperplane.

2.4.3. Random Forest (RF) Classifier

The RF theory is explained in the aforementioned literature. Generally, RF is a group of large number of decision tree classifiers. Each decision tree develops depending on random sampling with replacement of the original training data. For each decision tree, a random subset of input predictors is used for splitting at each node. Finally the predicted class of an observation is determined by majority vote from all of the decision tree developed within the random forest (Ghosh and Joshi, 2014).

2.4.4. Establishing the Random Forest Classification Model

Establishing a RF classification model involves two parameters that must be configured by the user. These parameters are the number of DTs in a DT forest and the number of randomly selected bands used to generate each DT. The Out of Bag (OOB) estimate of error rates was used to adjust the number of DTs and bands. The lowest estimated error value was applied to construct a RF model for identifying garlic land cover, which was then used to classify the image of the target crop field. Examining combinations involving various band numbers within $\leq$ 5000 DTs confirmed that a band number of 2 or 3 yielded the lowest OOB estimate of error rates. Consequently, the band numbers of this study were set to 3. 5000 were also selected as the DT numbers to configure the RF classification model of this study.

2.4.5. Accuracy Assessment

After the aforementioned methods were applied to classify the remote sensing image of the target crop field, the classification outcomes were overlaid with the crop cadastral map to conduct the subsequent GIS analysis. Particularly, the method proposed by Shiu et al. (2012) was applied to overlay the classification outcomes with the crop cadastral map through the GOBPC method. Generally, GOBPC involves using a parcel as the object unit. The GIS zonal statistics are used to calculate the area of each land cover type in each parcel. Subsequently, each parcel is categorized according to the land cover type with the largest area in each parcel. An accuracy assessment was reported through an error matrix. Overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and kappa values were used to compare the efficiencies of each image for the BPNN, SVM, and RF classifiers.

3. RESULTS AND DISCUSSION

Table 1. The classification results of producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa for the WorldView-2 Image using BPNN, SVM and RF classifiers.

3.1 Classification Results of the WorldView-2 Image

Table 1 indicates the SVM classifier has the highest accuracy with OA of 94.4% and the Kappa value of 0.91, followed by BPNN (OA of 93.2%) and RF (OA of 90.7%). In general, garlic and green manure crops have higher PA and UA. Since some bare land pixels are mis-classified as nursery garden pixels, for example of SVM, the UA (67.9%) of nursery garden and PA (75.9%) of bare lands are the lower values. The reason of the highest omission error for the bare lands is the reflectance values of the bare lands and nursery garden are similar. Figure 4 is the classified map for the WorldView-2 imagery using the SVM classifier.

Table 1. The classification results of producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa for the WorldView-2 Image using RF, SVM and BPNN classifiers.

		Garlic	Green manure	Nursery garden	Bare lands
RF	Producer's Acc.	94.4%	94.7%	93.1%	70.7%
	User's Acc.	99.4%	97.2%	54.3%	94.8%
	Overall Accuracy	90.7%	Kappa		0.86
SVM	Producer's Acc.	100.0%	94.5%	93.1%	75.9%
	User's Acc.	99.1%	97.4%	67.9%	98.2%
	Overall Accuracy	94.4%	Kappa		0.91
BPNN	Producer's Acc.	98.1%	96.0%	95.3%	70.9%
	User's Acc.	99.4%	95.7%	63.1%	100.0%
	Overall Accuracy	93.2%	Kappa		0.90

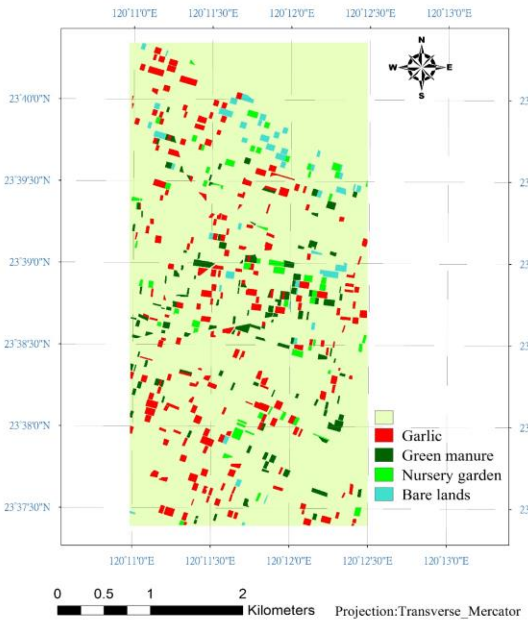

Figure 4 is the classified map for the WorldView-2 imagery using the SVM classifier.

3.2 Classification Results of the Pléiades Image

Table 2 indicates the RF classifier has the highest accuracy with OA of 85.7% and the Kappa value of 0.79, followed by BPNN (OA of 85.4%) and SVM (OA of 84.2%). The accuracy differences between three classifiers are mild. Similar to the results of WorldView-2 imagery, garlic and green manure crops have higher PA and UA. Since some bare land pixels are mis-classified as nursery garden pixels, for example of RF, the UA (47.7%) of nursery garden and PA (65.3%) of bare lands are the lower values. The reason of the highest omission error for the bare lands is the reflectance values of the bare lands and nursery garden are similar.

Table 2. The classification results of producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa for the Pléiades Image using RF, SVM and BPNN classifiers

		Garlic	Green manure	Nursery garden	Bare lands
RF	Producer's Acc.	85.2%	94.1%	100.0%	65.3%
	User's Acc.	100.0%	87.0%	47.7%	98.3%
	Overall Accuracy	85.7%	Kappa		0.79
SVM	Producer's Acc.	83.0%	94.9%	95.4%	64.6%
	User's Acc.	100.0%	81.8%	46.6%	98.8%
	Overall Accuracy	84.2%	Kappa		0.77
BPNN	Producer's Acc.	94.4%	76.9%	92.7%	62.7%
	User's Acc.	91.5%	96.9%	49.5%	98.2%
	Overall Accuracy	85.4%	Kappa		0.77

3.3 Classification Results of the Kompsat-3 Image

Table 3 indicates the SVM classifier has the highest accuracy with OA of 83.6% and the Kappa value of 0.76, followed by RF (OA of 82.9%) and BPNN (OA of 81.1%). Similar to the results of former analysis, garlic and green manure crops have higher PA and UA. Some bare land pixels are also mis-classified as nursery garden pixels. For example of SVM, the UA (46.9%) of nursery garden and PA (84.2%) of bare lands are the lower values. However, the PA for the green manure is only 59.3% for the BPNN classifier. This is different from other two images. In general, the overall performance of the Kompsat-3 image is not as good as the other two. The possible causes need to be further analyzed.

Table 3. The classification results of producer's accuracy (PA), user's accuracy (UA), overall accuracy (OA), and Kappa for the Kompsat-3 Image using RF, SVM and BPNN classifiers

		Garlic	Green manure	Nursery garden	Bare lands
RF	Producer's Acc.	80.6%	79.7%	100.0%	84.6%
	User's Acc.	95.5%	85.1%	48.1%	91.2%
	Overall Accuracy	82.9%	Kappa		0.75
SVM	Producer's Acc.	80.6%	82.7%	100.0%	84.2%
	User's Acc.	96.6%	89.2%	46.9%	89.5%%
	Overall Accuracy	83.6%	Kappa		0.76
BPNN	Producer's Acc.	88.7%	59.3%	93.8%	80.1%
	User's Acc.	82.3%	88.3%	55.5%	96.6%
	Overall Accuracy	81.1%	Kappa		0.70

4. CONCLUSIONS

The quality of new satellite images has improved, and the resolution and information load contained in these images have also increased. The complexity of the classification, however, has also increased because of its rich spectral and spatial information. The conventional statistical method has been complained inapplicable to accurately categorizing and interpreting complex and highly informative data. The machine learning algorithms, such as BPNN, SVM and RF, have been adopted to classify various land use/land covers and acquire promised results. In order to compare the effectiveness of various classifiers and satellite images for interpreting different crop types, this study utilizes the machine learning algorithms and the WorldView-2, Pléiades and Kompsat-3 satellite images to classify garlic, green manure, nursey garden, and bare lands. The study area is located at the Sihu township of Yunlin county and covered a range of two orthophotograph maps (1:5000). According to the errors of the classification results, the effectiveness of the BPNN, SVM and RF classifiers in categorizing the crop planted area was assessed.

The classification results indicates, for the WorldView-2 images, the SVM classifier has the highest accuracy with OA of 94.4% and the Kappa value of 0.91, followed by BPNN (OA of 93.2%) and RF (OA of 90.7%). For the Pléiades image, the RF classifier has the highest accuracy with OA of 85.7% and the Kappa value of 0.79, followed by BPNN (OA of 85.4%) and SVM (OA of 84.2%). For the Kompsat-3 image, the SVM classifier has the highest accuracy with OA of 83.6% and the Kappa value of 0.76, followed by RF (OA of 82.9%) and BPNN (OA of 81.1%). In summary, the classification accuracies of Worldview-2 imagery (OA of 94.4%) is better than Pléiades (OA of 85.7%) and Kompsat-3 (OA of 83.6%) imagery and the SVM is better than the RF and the BPNN.

In general, garlic and green manure crops have higher PA and UA for each classifier and image combination. Since some bare land pixels are mis-classified as nursery garden pixels, for example of SVM, the UA (67.9%) of nursery garden and PA (75.9%) of bare lands are the lower values. The reason of the highest omission error for the bare lands is the reflectance values of the bare lands and nursery garden are similar. However, for the Kompsat-3 image, the PA for the green manure is only 59.3% for the BPNN classifier. This situation differs from the others. The overall performance of the Kompsat-3 image is not as good as the other two. The possible causes need to be further analyzed.

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