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Data fusion and classifier ensemble techniques for vegetation mapping in the coastal Everglades

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This study examined the applicability of data fusion and classifier ensemble techniques for vegetation mapping in the coastal Everglades. A framework was designed to combine these two techniques. In the framework, 20-m hyperspectral imagery collected from Airborne Visible/Infrared Imaging Spectrometer was first merged with 1-m Digital Orthophoto Quarter Quads using a proposed pixel/feature-level fusion strategy. The fused data set was then classified with an ensemble approach based on two contemporary machine learning algorithms: Random Forest and Support Vector Machine. The framework was applied to classify nine vegetation types in a portion of the coastal Everglades. An object-based vegetation map was produced with an overall accuracy of 90% and Kappa value of 0.86. Per-class classification accuracy varied from 61% for identifying buttonwood forest to 100% for identifying red mangrove scrub. The result shows that the framework is promising for automated vegetation mapping in the Everglades.

Keywords: data fusion; classifier ensemble; vegetation mapping; Everglades

1. Introduction

The Greater Everglades of South Florida are the largest subtropical wetland in the United States. It has been designated as a World Heritage Site, International Biosphere Reserve and Wetland of International Importance for its unique combination of hydrology and water-based ecology that supports many threatened and endangered species (Davis *et al.* 1994). However, human activities in the past century have severely modified the Everglades ecosystem, resulting in a variety of environmental issues in South Florida (McPherson and Halley 1996). In 2000, US Congress authorized the Comprehensive Everglades Restoration Plan (CERP 2012), a $10.5-billion mission expected to take 30 or more years to complete. The CERP contains many pilot projects, and many of which require accurate and informative vegetation maps, because the restoration will cause dramatic modification of plant communities (Doren *et al.* 1999). Monitoring changes of vegetation communities can measure the progress and effects of restoration on environmental health (Doren *et al.* 1999, Griffin *et al.* 2011).

Current vegetation information to support CERP is mainly from field studies and manual interpretation of large-scale aerial photographs using stereo plotters

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(Rutchey *et al.* 2008, Jones 2011). With the emergence of hyperspectral remote sensing techniques, it has been anticipated that the manual procedures can be superseded by automated digital image analysis. Hyperspectral sensors collect data in hundreds of relatively narrow spectral bands throughout the visible and infrared portions of the electromagnetic spectrum. They are more powerful than traditional multispectral sensors in vegetation mapping due to their rich radiometric content. The application of hyperspectral analysis has become an important area of research for wetland mapping in the past decade (Zhang and Xie 2012). However, most of the available hyperspectral sensors such as Earth Observing-1 (EO-1)/Hyperon and Airborne Visible/InfraRed Imaging Spectrometer (AVIRIS) collect data with a relatively coarse spatial resolution (i.e. 20–30 m; Rogan and Chen 2004). This may limit their applications in the Everglades, because many regions have a high spatial and spectral heterogeneity and some communities are present in the form of small patches or linear/narrow shapes (Welch *et al.* 1999). Such limitations may be overcome by data fusion techniques, which integrate data and information from multiple sources to achieve refined/improved information for decision-making. With the increasing availability of multi-sensor and multi-resolution images, data fusion has become a valuable tool in image interpretation (Pohl and Van Genderen 1998, Solberg 2006, Zhang 2010). Our literature review demonstrates that many studies combined hyperspectral imagery with Light Detection and Ranging (LiDAR) data (e.g. Hill and Thomas 2005, Geerling *et al.* 2007, Jones *et al.* 2010, Cho *et al.* 2012) or with synthetic aperture radar (e.g. Huang *et al.* 2010) to improve vegetation characterization. But few attempts have been made to integrate hyperspectral data with fine spatial resolution images for the same purpose.

Most researchers used endmember-based algorithms to classify hyperspectral imagery (Zhang and Xie 2012). These classifiers could not produce the expected results in complex wetlands due to the difficulties inherent in determining hyperspectral endmembers, a shortage of comprehensive spectral libraries for different wetland plants, and/or the violation of an assumption in the algorithms that only one spectral representative (i.e. the endmember) exists for each vegetation type. Traditional classifiers, such as maximum likelihood and minimum distance, also could not generate high accuracies, because they are not able to characterize the high degree of spatial and spectral heterogeneity of the Everglades even after the dimensionality of hyperspectral data was reduced (Zhang and Xie 2012).

Two contemporary machine learning algorithms, Random Forest (RF) and Support Vector Machines (SVMs), have shown promise in hyperspectral image classification (Crawford *et al.* 2003, Ham *et al.* 2005, Lawrence *et al.* 2006, Chan and Paelinckx 2008, Mountrakis *et al.* 2010, Naidoo *et al.* 2012). The RF is a decision tree based ensemble classifier proposed by Breiman (2001). The premise of an ensemble algorithm is that a combining classifier is often more accurate than any individual one within the ensemble. A key feature of RF is that it can handle high-dimensional data sets, which makes it attractive for processing hyperspectral data (Chan and Paelinckx 2008). Rodriguez Galiano *et al.* (2012) and Ghimire *et al.* (2012) find that RF is useful in classifying complex landscapes, indicating that it may be valuable in Everglades mapping. An alternative to RF is SVMs, which are well known in pattern recognition and were introduced to remote sensing in the past decade (Huang *et al.* 2002, Melgani and Bruzzone 2004). The SVMs are able to produce higher accuracy than traditional classifiers with a smaller number of training data sets. This is particularly appealing for hyperspectral data classification,

because the high dimensionality can often decrease classification accuracy if limited training data are available (Hughes 1968). The SVM research in remote sensing has increased in the past decade, as evidenced by a recent review in Mountrakis *et al.* (2010). Both RF and SVMs have been explored for hyperspectral data classification, but previous application in mapping heterogeneous wetlands has been limited (Zhang and Xie accepted). The RF and SVMs differ in classification performances among different classes (Waske *et al.* 2009, Zhang and Xie accepted), which suggests that a combination of the strengths of them may improve the result. But this has not been explored in previous studies to the best of our knowledge.

It is known that pixel-based methods may lead to 'salt-and-pepper' effect in mapping heterogeneous landscapes. It has been well documented that the issue can be overcome by object-based image analysis (OBIA) techniques that classify objects instead of pixels. In one recent review of OBIA techniques, Blaschke (2010) concludes that OBIA is effective for processing high spatial resolution data. Several studies have evaluated OBIA approaches for wetland mapping and find that they can generate higher accuracy compared with pixel-based methods (e.g. Harken and Sugumaran 2005, Kamal and Phinn 2011). The object-based mapping methods are desirable to generate informative (i.e. without salt-and-pepper effect) and accurate vegetation maps for the Everglades.

Data fusion and classifier ensemble are popular techniques in remote sensing, as evidenced by several review papers (Pohl and Van Genderen 1998, Solberg 2006, Zhang 2010, Du *et al.* 2012). However, studies to combine these two techniques for object-based vegetation mapping in complex wetlands are limited. Ensemble analysis based on RF and SVMs for processing fused hyperspectral data is even scarcer. In this study, we designed a framework to combine data fusion and classifier ensemble techniques for object-based vegetation mapping in the Everglades. In the framework, a pixel/feature-level fusion strategy was first developed to fuse 20-m hyperspectral imagery (224 bands) and 1-m aerial photographs (3 bands). The fused data were then classified using RF and SVM algorithms. The final vegetation map was generated through an ensemble analysis based on a decision fusion strategy. The objective of this study is to examine whether data fusion and classifier ensemble techniques can improve vegetation classification accuracy in the Everglades.

2. Study area and data

Terrapin Bay was selected as the study area (Figure 1). It is a flat and wet terrain area dominated by typical coastal wetland plant communities, such as mangroves. The bay is a portion of Florida Bay in the Everglades National Park. The park is bounded by the Gulf of Mexico to the west, the Tamiami Trail and mostly state lands to the north, and the Florida Keys to the south and south-east. The selected area is located in an important transitional zone where fresh water and salt water meet. This zone incubates a number of economically valuable crustaceans. The CERP will greatly modify the freshwater flow into Florida Bay to restore its original ecosystem. Change of vegetation community over this transitional zone is a critical indicator of restoration success. Detailed vegetation maps can guide the path of restoration.

Data used for this study include airborne hyperspectral imagery, digital aerial photographs and vegetation species reference data. Hyperspectral data were collected by AVIRIS on 23 March 1996 in a project entitled Assessment of Coral

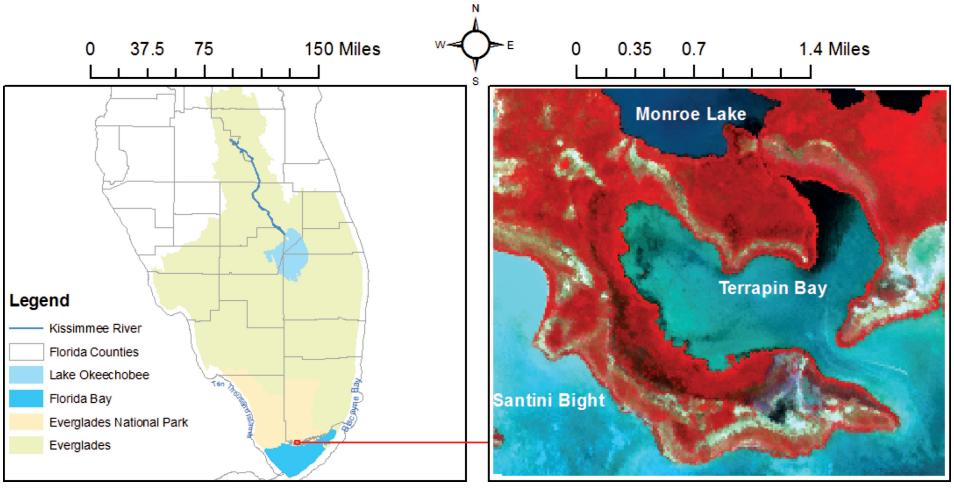

Figure 1. Map of South Florida, the Everglades, and study area displayed in a colour composite generated from the hyperspectral data.

Reef Habitat in National Marine Sanctuary, Florida. The AVIRIS collects calibrated hyperspectral data in 224 contiguous spectral channels with wavelengths from 0.4 μm to 2.5 μm. The acquired AVIRIS data have a spatial resolution of 20 m. Fine spatial resolution aerial photographs were collected on 27 December 1994 by the National Aerial Photography Program (NAPP). The US Geological Survey (USGS) orthorectified these aerial photos into data products known as Digital Orthophoto Quarter Quads (DOQQs). The accuracy and quality of DOQQs meet National Map Accuracy Standards. Colour infrared (CIR) DOQQs with a spatial resolution of 1 m were used for this study. The DOQQs also provide a base to georeference the hyperspectral data. Both hyperspectral data and aerial photographs were collected in dry season of the Everglades (from November to April) before CERP started and within a reasonable time span, which provides a good basis for evaluating vegetation mapping using data fusion techniques.

Reference data for this study came from a vegetation database produced through a project entitled Vegetation Map and Digital Database of South Florida's National Park Service Lands (Welch *et al.* 1999). The University of Georgia and the South Florida Natural Resources Center at Everglades National Park created this database from NAPP CIR aerial photographs collected in 1994–1995 using photo-interpretation techniques. Note that the reference data were manually interpreted from the same DOQQs used in this study. A hierarchical Everglades Vegetation Classification System was used in this database. Vegetation classes are organized under eight major headings: forest, scrub, savanna, prairies and marsh, shrub land, exotics, additional classes and special modifiers (Madden *et al.* 1999). Each major heading is further subdivided into classes corresponding to plant communities. The vegetation database was formatted to ArcGIS shape files with polygon features geographically aligned to the USGS DOQQs using the Universal Transverse Mercator projection. To accommodate the complex Everglades vegetation patterns, a three-tiered classification scheme was developed by assigning a polygon with a dominant species that accounts for more than 50% of the vegetation in this polygon. Secondary and

tertiary classes are added as required to account for mixed plant communities. The vegetation database was validated by extensive global positioning system (GPS)-assisted field observations including helicopter and automobile surveys. The database is reported to have an average accuracy of 90% and is currently serving as a baseline for monitoring vegetation changes in CERP.

The extracted reference data for the selected study area are shown in Figure 4(b). Nine dominant vegetation types were observed: lather leaf (exotic species), buttonwood forest, white mangrove forest, black mangrove forest, red mangrove forest, mixed mangrove forest, subtropical hardwood forest, succulent herbaceous prairie and red mangrove scrub. Based on the Florida Exotic Pest Plant Council (FLEPPC, 2012), lather leaf (*Colubrina asiatica*) is an exotic species to be eliminated in South Florida. We randomly selected 1482 image objects as the reference data for the study area by following a spatially stratified data sampling strategy, in which a fixed percentage of samples were selected for each class. The number of samples for each vegetation type was estimated based on the results of image segmentation and the reference vegetation database. The segmentation process to generate image objects is detailed in Section 3. The collected reference data were randomly split into two halves with one for calibration and the other for validation.

3. Methodology

3.1. Data preprocessing

Visual examination revealed that bands 1–3, 7, 107–116, 133, 152–170, 174, 177, 201, 205, 207–208, 214–224 need to be removed in the hyperspectral data due to water absorption and low signal-to-noise ratio in these bands. Completely dark or white layers, as well as visually noisy bands with many randomly distributed black or white pixels, were dropped. This resulted in 173 bands to be used for further processing. To effectively conduct data fusion, the hyperspectral data were georeferenced to the DOQQs. We masked out the non-vegetation covers, such as open water, since the main concern of this study was vegetation. Hyperspectral data contain a tremendous amount of redundant spectral information. The minimum noise fraction (MNF) method (Green *et al.* 1988) is commonly used to reduce the high dimensionality and inherent noise of hyperspectral data. We conducted the MNF transformation in ENVI 4.7 and selected the first 20 MNF eigenimages which are most useful and spatially coherent. Previous studies have shown that MNF transformed data can significantly improve the accuracy of vegetation mapping in the Everglades (Zhang and Xie 2012). We thus only considered the MNF images in further analysis.

3.2. A framework to combine data fusion and classifier ensemble techniques

Data fusion methods can be grouped into three categories: pixel-level fusion, feature-level fusion and decision-level fusion (Zhang 2010). Pixel-level fusion combines raw data from multiple sources into single resolution data to improve the performance of image processing tasks. Information may be lost during the data resampling procedure if the spatial resolution of input data sources is different (Solberg 2006). Feature-level fusion extracts features (e.g. edges, corners, lines and textures) from each individual data source and merges these features into one or more feature maps for further processing. Combination of these features consists of complex procedures. Decision-level fusion commonly conducts a preliminary classification

for each individual data source first and then combines the classification results into one outcome based on a decision fusion strategy.

For this study, we designed a framework to combine all three data fusion techniques for vegetation mapping (Figure 2). In the framework, the 20-m hyperspectral data set was merged with 1-m CIR DOQQs using a pixel/feature-level fusion strategy. The DOQQs were segmented first to extract object features (i.e. textures), and then the extracted features were combined with pixel-level values of hyperspectral data to generate a fused data set. The fusion procedure was conducted at the object level. Since the fused data set is from features of DOQQs and pixels of hyperspectral imagery, the fusion strategy is referred to as a pixel/feature-level fusion. Three advantages were expected from the strategy: (1) no information is lost because there is no data resampling in this procedure; (2) additional object-based texture information can be extracted from DOQQs, which is valuable in vegetation classification; and (3) small patches and linear/narrow shape vegetation covers can be delineated due to the fine spatial resolution of DOQQs. Two machine learning algorithms (RF and SVM) were used to pre-classify the fused data. The final outcome was derived through ensemble analysis of two classification results using a decision-level fusion strategy. Note that the decision-level fusion strategy was based on classification results of the fused data set, rather than making a decision from classification results of the individual data sources. Consequently, an object-based vegetation map was generated and evaluated based on commonly used accuracy assessment approaches.

3.3. *Image segmentation and data fusion*

We used the multi-resolution segmentation algorithm in eCognition Developer 8.64.1 (Trimble 2011) to generate image objects from the DOQQs. The segmentation algorithm starts with one-pixel image segments and merges neighbouring segments together until a heterogeneity threshold is reached (Benz *et al.* 2004). The heterogeneity threshold is determined by a user-defined scale parameter, as well as

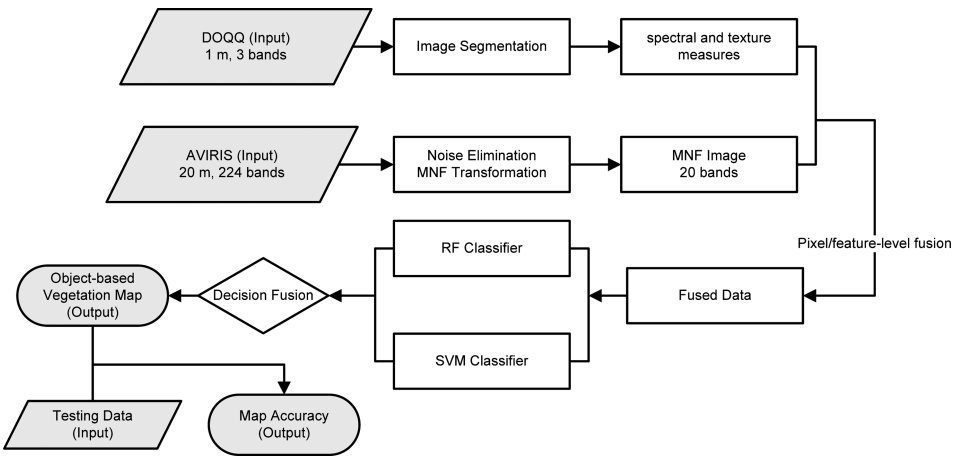

Figure 2. Designed framework to combine data fusion and classifier ensemble techniques for vegetation mapping in the Everglades.

colour/shape and smoothness/compactness weights. The image segmentation is scale-dependent, and the quality of segmentation and overall classification are largely dependent on the scale of the segmentation (Liu and Xia 2010). In order to find an optimal scale for image segmentation, an unsupervised image segmentation evaluation approach (Johnson and Xie 2011) was used. It begins with a series of segmentations using different scale parameters and then identifies the optimal image segmentation using an unsupervised evaluation method that takes into account the global intra-segment and inter-segment heterogeneity measures. A global score (GS) is calculated by $GS = V_{norm} + MI_{norm}$, where V_{norm} (normalized weighted variance) measures the global intra-segment goodness, and MI_{norm} (normalized Moran's I) measures the global inter-segment goodness. More details in computing V_{norm} and MI_{norm} can be found in Johnson and Xie (2011). The GSs were used to determine the optimal scale for segmentation. For our study area, a series of segmentations were carried out with 10 different scale parameters (10–100 at an interval of 10). Preliminary analyses revealed that scale parameter larger than 100 generated many under-segmented objects and those smaller than 10 produced many over-segmented objects. Therefore, the segmentations were not evaluated for scale parameter smaller than 10 or larger than 100. The curve of GS vs. scale parameter is shown in Figure 3. The best segmentation scale is the one with the lowest GS score, i.e. 60, and it was used to segment the DOQQ data. All three bands (near-infrared, red and green) of the DOQQs were set to equal weights. Colour/shape weights were set to 0.9/1.0 so that spectral information would be considered most heavily for segmentation. Smoothness/compactness weights were set to 0.5/0.5 so as to not favour either compact or non-compact segments.

Following segmentation, object-based features were extracted for vegetation discrimination. Object-based texture measures from fine spatial resolution imagery have been proved valuable for vegetation classification (e.g. Yu *et al.* 2006, Zhang and Xie 2012). Conventional kernel-based texture methods often utilize a fixed-size moving window over which to calculate texture measures for each pixel. It is challenging to determine the appropriate window size. The OBIA offers the

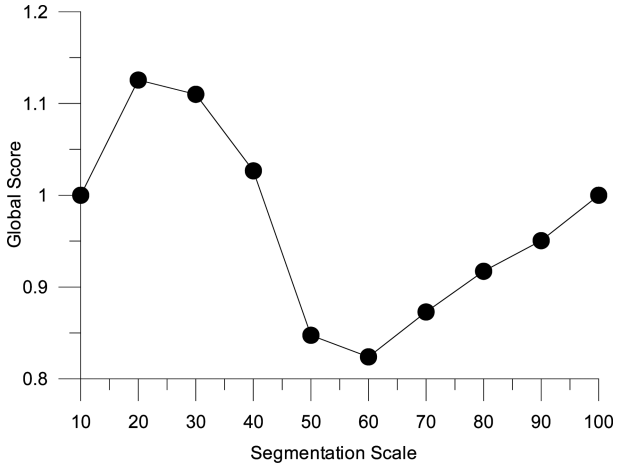

Figure 3. Calculated GSs in terms of segmentation scales.

capability for identifying relatively homogeneous regions of varying shapes and sizes in an image. Texture extraction from image objects is more reasonable (Warner 2011). Such object-based texture measures were thus used in this study. We extracted first-order and second-order metrics for each band of the DOQQ data in eCognition including mean, standard deviation, contrast, dissimilarity, homogeneity, entropy and angular second moment. The grey-level co-occurrence matrix algorithm was used to extract the second-order texture measures. The directionally invariant texture measures were produced by calculating the mean of the texture results in all four directions (0°, 45°, 90°, and 135°). Detailed algorithms can be found in Trimble (2011).

To combine the object-based features from DOQQs with pixel-level values from hyperspectral data, the image objects from the segmentation procedure were converted to vector polygons. A mean spectral profile from hyperspectral data was first calculated for an image object and then merged with its texture measures. The fused object-based feature data set from DOQQ and hyperspectral imagery was used for vegetation classification.

3.4. Classification algorithms: RF and SVM

The RF and SVM algorithms were employed to pre-classify the fused data set. The RF is a decision tree based ensemble classifier. To understand this algorithm, it is helpful to first know the decision tree approach. The decision tree splits training samples into smaller subdivisions at 'nodes' using decision rules. For each node, tests are performed on the training data to find the most useful variables and variable values for split. The RF consists of a combination of decision trees where each decision tree contributes a single vote for assigning the most frequent class to an input vector. The RF increases the diversity of decision trees to make them grow by changing the training set using the bagging aggregating (Breiman 2001). Bagging creates training data by randomly resampling the original data set with replacement. Data selected from the input sample for generating the next subset are not deleted. A key feature of RF is that the computational complexity is simplified by reducing the number of input features at each node, which makes it particularly appealing in hyperspectral data classification. Different algorithms can be used to generate the decision trees. The RF often adopts the Gini Index (Breiman 2001) to measure the best split selection. More descriptions of RF can be found in Breiman (2001) and in remote sensing context in Chan and Paelinckx (2008), Rodriguez-Galiano *et al.* (2012) and Ghimire *et al.* (2012). The RF classification was implemented using Weka 3.7, an open-source data mining program (Hall *et al.* 2009). Two parameters need to be defined: the number of decision trees to create (k) and the number of randomly selected variables (m) considered for splitting each node in a tree. The RF is not sensitive to m, and it is often blindly set to $\sqrt{\mathrm{M}}$(M is the total number of variables; Gislason *et al.* 2006).

The SVM is a nonparametric supervised learning classifier. The aim of SVMs is to find a hyperplane that can separate the input data set into a discrete predefined number of classes in a fashion consistent with the training samples (Vapnik 1995). Detailed descriptions of SVM algorithms were given by Huang *et al.* (2002) and Melgani and Bruzzone (2004) in the context of remote sensing. Kernel-based SVMs are commonly used for remote sensing image classification, among which the radial basis function (RBF) and the polynomial kernels are frequently employed. The RBF

needs to set the kernel width (γ), and polynomial kernel needs to set the degree (p). Both kernels need to define a penalty parameter (C) that controls the degree of acceptable misclassification. The setting of these parameters can be determined by a grid search strategy which tests possible combinations of C and γ in a user-defined range (Hsu *et al.* 2010). The original SVM algorithm was designed for binary classification. Several strategies including one-against-one and one-against-all have been developed to solve multiclass problems. These solutions divide a multiclass problem into a set of binary problems, making it feasible for multiclass classification. We selected one-against-one strategy, because one-against-all strategy needs estimating complex discrimination functions (Melgani and Bruzzone 2004) and thus, may lead to unexpected classification result. The SVM classifier was implemented using Library for Support Vector Machines (LIBSVM) developed by Chang and Lin (2011). Both kernels were tested to find the best model for the fused data set.

3.5. *Ensemble analysis*

The final classification was conducted through an ensemble analysis of the outputs from SVM and RF. An ensemble analysis approach is a multiple classification system with the aim to obtain better classification by combining the outputs of several classifiers. The classifiers in the system generally should produce accurate results but show some differences in classification accuracy (Du *et al.* 2012). A range of strategies have been developed to combine the outputs from multiple classifiers, such as the majority vote, Bayesian average method and fuzzy integral (Du *et al.* 2012). Among these strategies, the majority vote (each individual classifier votes for an unknown input pixel/object) is straightforward and commonly used (Kuncheva 2004). The final class label for an input pixel/object is determined by the majority votes of classifiers. A key problem of the majority vote is that all the classifiers have equal rights to vote without considering their performances on each individual class. A weighting strategy may mitigate this problem by weighting the decision from each classifier based on their accuracies obtained from the reference data (Moreno-Seco *et al.* 2006). Since there are only two classifiers in our study, we combined the majority vote and the weighting strategy to fuse two outputs. If votes from RF and SVM for an input image object are same, then this object will be assigned to the voted class. If votes are different, then this object will be assigned to the class with higher classification accuracy by one of the classifiers.

3.6. *Accuracy assessment*

Considerable research has been conducted for accuracy assessment in remote sensing (Foody 2002). Among various methods, the error matrix and Kappa statistic (Congalton and Mead 1983) are frequently adopted and serve as the standard approaches. For this study, we constructed the error matrix and calculated the Kappa statistics for accuracy assessment. The error matrix can be summarized as an overall accuracy and Kappa value. The overall accuracy is defined as the ratio of the number of validation samples that are classified correctly to the total number of validation samples irrespective of the class. The Kappa value describes the proportion of correctly classified validation samples after random agreement is removed. To evaluate the statistical significance of differences in accuracy between different classifications, the nonparametric McNemar test (Foody 2004) was

adopted. The difference in accuracy of a pair of classifications is viewed as being statistically significant at a confidence level of 95% if z-score is larger than 1.96.

4. Experiments and results

To test the performance of the designed framework for vegetation mapping in the Everglades, two experiments were designed to examine whether the fused data can improve the accuracy of vegetation classification. Experiment 1 used the features derived from DOQQs, and Experiment 2 used the fused data set. Both the RF and SVM algorithms were used to classify the two data sets. For the RF classifier, the number of randomly selected variables for splitting node (i.e. m) was set to 3 after several trials. A number of tests using different number of trees (50–300 at an interval of 50) revealed that $k = 150$ resulted in the highest accuracy. For the SVM algorithms, after a number of trials using polynomial and RBF kernels, the polynomial kernel with the degree parameter (p) set to 2 and penalty error parameter (C) set to 2.0 generated the best result. The overall accuracies and Kappa values from these two classifiers are presented in Table 1. To examine the statistical significance, the Kappa z-score statistical tests based on the error matrix were conducted. The z-score values are also displayed in Table 1. The classifications based on DOQQ data alone produced an overall accuracy of 68% and 65% with a Kappa value of 0.53 and 0.48 from the RF and SVM, respectively. The fused data increased the accuracy to 89% and 85% with Kappa values of 0.85 and 0.79 using RF and SVM, respectively. Statistical tests illustrated that these results are significantly better than a random classification (Table 1). McNemar tests demonstrated that the fused data significantly improved the classification results (z-score = 11.5 using RF; and z-score = 10.1 using SVM between DOQQ and fused data).

The classification accuracies are different for some types between two classifiers using the fused data, as shown in Table 2. The RF produced higher overall accuracy than the SVM model, but SVM model generated higher accuracies than RF for discriminating lather leaf, buttonwood forest, black mangrove forest and red mangrove scrub. It suggests that a combination of two classifiers may improve the classification for their complementary strength in classifying different classes. In fact, the difference in outputs from multiple classifiers is an assumption of classifier ensemble techniques. Table 3 shows the overall accuracy and Kappa value from the ensemble analysis based on the outputs of RF and SVM. The ensemble analysis indeed improved the accuracy to 90.3% with a Kappa value of 0.86. The

Table 1. Classification accuracies from the DOQQ and fused data using RF and SVM algorithms.

	RF			SVM		
	Overall accuracy	Kappa value	z-Score	Overall accuracy	Kappa value	z-Score
DOQQ	68%	0.53	22.8*	65%	0.48	20.2*
Fused data	89%	0.85	53.9*	85%	0.79	44.3*

Notes: RF, Random Forest; SVM, Support Vector Machine. For the RF classifier, $m = 3$ and $k = 150$. For the SVM model, the polynomial kernel was used with $p = 2.0$ and $C = 2.0$. *Significant with 95% confidence level.

Table 2. Classification accuracies for each vegetation type from RF and SVM algorithms.

Vegetation species	Accuracy (%)	
	RF	SVM
1. Lather leaf	62.5	87.5
2. Buttonwood forest	47.8	60.9
3. White mangrove forest	94.2	90.5
4. Black mangrove forest	60.0	80.0
5. Red mangrove forest	87.3	77.8
6. Mixed mangrove forest	70.4	70.4
7. Subtropical hardwood forest	83.3	83.3
8. Succulent herbaceous prairie	97.2	87.2
9. Red mangrove scrub	92.0	100.0

Notes: RF, Random Forest; SVM, Support Vector Machine.

Table 3. Error matrix for the generated classification map from the designed framework.

Species	1	2	3	4	5	6	7	8	9	Row total	PA (%)
1	7	1								8	87.5
2	2	14	6				1			23	60.9
3			278			7		8	2	295	94.2
4				4				1		5	80.0
5			5		55	2		1		63	87.3
6			16		1	69		12		98	70.4
7							5	1		6	83.3
8			4			2		212		218	97.3
9									25	25	100.0
Col. total	9	15	309	4	56	80	6	235	27	741	
UA (%)	77.8	93.3	90.0	100.0	98.2	86.3	83.3	90.2	92.6	Total accuracy: 90.3% Kappa value: 0.86	

Notes: UA, user's accuracy; PA, producer's accuracy. Classification result is displayed in row, and the reference data are displayed in column.

improvement is statistically significant at a 95% confidence level (z-score = 2.1 between RF and ensemble; and z-score = 4.3 between SVM and ensemble). The error matrix from the ensemble analysis is also shown in Table 3. The producer's accuracy (PA) changed from 60.9% to 100%, and the user's accuracy (UA) varied from 77.8% to 100% (Table 3). It is worthy to note that a higher accuracy (PA = 87.5% and UA = 77.8%) was obtained for lather leaf (class 1), an exotic species in South Florida.

According to Fleiss (1981), Kappa values larger than 0.75 suggest strong agreement, and Landis and Koch (1977) suggest that Kappa values larger than 0.81 indicate an almost perfect agreement. Our designed framework produced the Kappa value of 0.86, indicating that it is effective for vegetation mapping over the study area. An object-based vegetation map was thus produced using the fused data set and ensemble analysis of RF and SVM (Figure 4(a)). The object-based vegetation map is more informative and useful than a traditional pixel-based one that may be noisy due to the high degree of spatial and spectral heterogeneity of the Everglades.

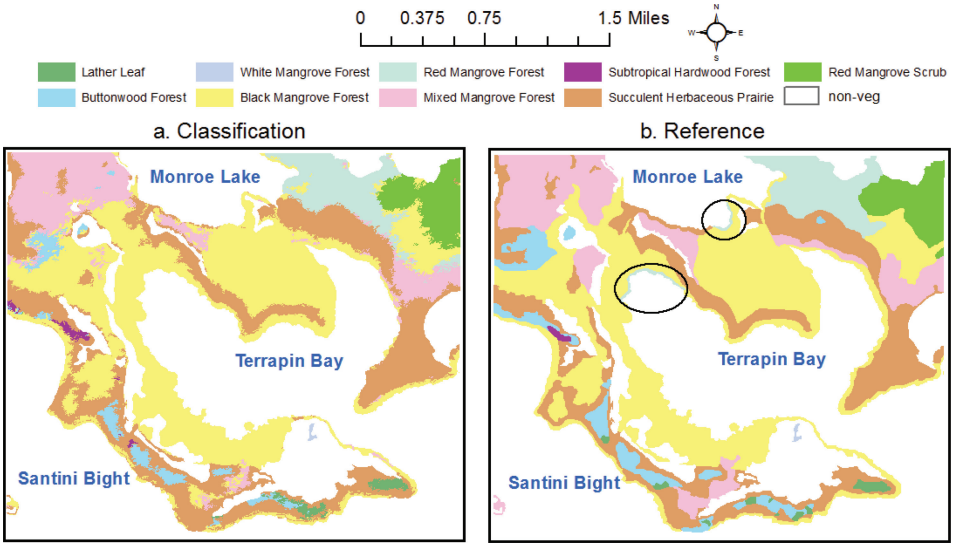

Figure 4. Generated vegetation map (a) and the reference map (b).

For comparison, the reference map from the Everglades Vegetation Database is shown in Figure 4(b). There is a general agreement on the spatial distribution of vegetation types between two maps. Mangrove dominated the landscape with black mangrove forests mainly distributed along the margins of the bay. Succulent herbaceous prairie were mainly presented in strips, and mixed mangrove forests were observed mainly over upland. Further examination reveals some differences between two maps. Firstly, the reference map looks more homogeneous for some regions. Secondly, two strips of red mangrove forests were presented in the reference map, as highlighted by the black circles in Figure 4(b). These two strips were found to be covered by black mangrove forests from our classification. Differences were also observed for some small patches, such as the one in the south-western corner of the study area. It is difficult to determine which map is better, given the fact that the reference map was generated by manual interpretation and compilation of aerial photos. Errors and uncertainties are also unavoidable in the interpretation procedure.

5. Summary and discussion

Mapping vegetation species in the Everglades is challenging due to its high spatial and spectral heterogeneity (Griffin *et al.* 2011). Current vegetation information to support CERP is mainly from large-scale aerial photo-interpretation techniques based on the stereo plotters (Rutchey *et al.* 2008). With the advent of hyperspectral techniques, it has been anticipated that the generation of vegetation maps with adequate accuracy can be automated (Jones 2011). However, exploration of hyperspectral data with coarse spatial resolution in the Everglades is not simple. Hirano *et al.* (2003) used the same hyperspectral imagery as our study to map a portion of the coastal Everglades and reported an overall accuracy of 66%. They argued that the moderate accuracy was mainly caused by the coarse spatial

resolution of the hyperspectral data (i.e. 20 m). To mitigate this problem, we proposed to combine coarse spatial resolution hyperspectral data with fine spatial resolution DOQQs in order to increase the classification accuracy. Hyperspectral imaging relies primarily on spectral features to map land covers, whereas fine spatial resolution imagery relies more on spatially invariant features to identify targets (Shaw and Burke 2003). A combination of two sources should have better performance in wetland mapping. Our study illustrates that the integration of fine spatial resolution DOQQs and hyperspectral data is effective for vegetation mapping for the Everglades. The fusion procedure is able to complement the shortages and take advantage of the benefits of each individual data source. The fused data have been proved more powerful for vegetation classification. The developed pixel/feature-level fusion strategy successfully combines the spatial features of DOQQ data and rich spectral contents of hyperspectral data. Small patches and vegetation covers with linear/narrow shapes could be discerned with the fused data. Application of data fusion techniques is a critical factor for the achieved accuracy (an overall accuracy of 90%) in this study.

Recent studies from Griffin *et al.* (2011) and Zhang and Xie (2012) find that machine learning classifiers are useful in vegetation mapping in the Greater Everglades. Griffin *et al.* (2011) examined the classification tree algorithms for mapping Kissimmee prairie ecosystem by combining Landsat imagery, soil data and digital elevation model (DEM). Zhang and Xie (2012) applied a neural network classifier for mapping the Caloosahatchee River watershed from fine spatial resolution hyperspectral imagery. In this study, we examined anther two machine learning algorithms, RF and SVM, for vegetation mapping in the coastal Everglades from a fused data set. For the study area, RF generated an overall accuracy of 89% and a SVM model produced an overall accuracy of 85%, suggesting good performances of both classifiers. However, the two classifiers showed diversity in per-class classification accuracy, which is primarily caused by the discrepancies in the concepts of two classifiers. The RF looks for optimal decision trees to group data, whereas SVMs look for the optimal hyperplane to categorize data. Note that classification diversity is the basic assumption of ensemble classifiers, which drives us to explore the potential of an ensemble analysis based on RF and SVMs for vegetation classification. Our experimental analysis demonstrated that the ensemble analysis from the outputs of RF and SVMs significantly improved the classification. An object-based vegetation map was produced with an overall accuracy to 90.3% and Kappa value of 0.86.

In summary, we designed a framework to combine data fusion and classifier ensemble techniques to automate vegetation mapping in the Everglades. Because the spaceborne hyperspectral sensors (e.g. EO-1/Hyperion) and fine spatial resolution multispectral sensors (e.g. QuickBird and IKONOS) have similar spatial and spectral characteristics as the data used in this study (i.e. AVIRIS and DOQQs), the designed framework has potential to map wetland vegetation types over larger areas. The in-orbit EO-1/Hyperion is providing 30-m hyperspectral data with 220 bands to the public at no cost. The NAPP collects fine spatial resolution aerial photos at the national level with an approximate time frequency of 5 years and also provides free high-quality DOQQ data to the public. Local government agencies frequently collect large-scale aerial photos for various purposes in the Everglades. The framework is assumed to be useful for building or updating vegetation databases in the complex wetlands at reduced expenses with these data sources. This is particularly attractive

for the ongoing CERP. For broad area mapping, computation cost may be a problem when applying RF and SVMs in pixel-based classification. However, for the object-based classification used in this study, image objects were minimum classification units, i.e. classification primitives, instead of individual pixels. The amount of classification primitives was greatly reduced through the segmentation process. Therefore, computation complexity was not a problem for implementation of the designed framework.

Note that the designed framework was only tested in the selected study area. To examine its robustness and extensibility, considerable additional work is needed in other wetland areas with different species compositions and spatial patterns. Combining more data sources (e.g. LiDAR, DEM and geo-environment data) in the framework may further improve the classification accuracy. Additionally, it is informative to compare the classification results using different data fusion strategies and decision fusion schemes. Inclusion of more advanced classifiers such as neural networks in the framework may be helpful as well. These will be major dedications in our future work. It is anticipated that this study can benefit global wetland mapping in general, and the Everglades in particular.

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