

# A DECISION TREE CLASSIFIER FOR THE MONITORING OF WETLAND VEGETATION USING ASTER DATA IN THE POYANG LAKE REGION, CHINA

Ryo Michishita <sup>a,\*</sup>, Bing Xu <sup>a</sup>, and Peng Gong <sup>b</sup>

<sup>a</sup> Department of Geography, University of Utah 260 S. Central Campus Dr. Rm. 270, Salt Lake City, Utah, 84112-9155, United States - (ryo.michishita, bing.xu)@geog.utah.edu

<sup>b</sup> Department of Environmental Science, Policy, and Management, University of California at Berkeley 137 Mulford Hall, Berkeley, California, 94720-3114, United States - gong@nature.berkeley.edu

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## ABSTRACT:

This paper examines the applicability of binary decision tree (DT) classifier and ASTER data for the monitoring of wetland vegetation at plant family level (eight dominant plant families in the study area, bare soil, marshland, residential area, and waterbody) in the Banghu Lake, a seasonal lake in the Poyang Lake region. Two sets of ASTER Level-1B Registered Radiance at the Sensor products, ASTER On-Demand L2 Surface Kinetic Temperature products, and ASTER Digital Elevation Model products on April 17, 2006 and July 3, 2005 were used in this study. In addition to the reflectance of VNIR and SWIR bands, environmental variables which can be derived from ASTER products such as vegetation indices, water indices, topographic information, land surface temperature, and principal components were selected as the inputs of DT classifier. Field data collected in December, 2007 is grouped into training and testing samples for DT classification. DT performed poorly compared to those of maximum likelihood classification and support vector machines with the reflectance of VNIR and SWIR bands in single date. The classification accuracy was slightly improved by adding environmental indices and variables derived from ASTER products. In particular, topographic information, such as elevation, slope, and aspect, increased the classification accuracy the most. The classification accuracy is dramatically refined with the combination of multi-temporal ASTER inputs. However, mainly due to the problems with the training pixels for each class, overall and individual class accuracies remain low.

## 1. INTRODUCTION

Wetlands are one of the most important components of the whole ecosystem, accounting for 6.4% of the world's land area (9million km<sup>2</sup>). All wetlands share three common characteristics: the ability to hold water; the presence of moist to wet soil; and the presence of water vegetation (Batzer and Sharitz, 2000). In particular, the presence of water vegetation plays a very critical role in wetlands ecosystems. Recently, wetland vegetation has been threatened by human activities which will, in turn, threaten the whole wetland ecosystem (Mitsch and Gosselink, 2000). These human activities include wetland draining or filling, hydrological alterations, chronic degradation due to nonpoint source pollution, and the introduction of exotic species (Cronk and Fennessy, 2001). There are also increasing concerns about the impact of global change including climate change on plant populations (Ji, 2008). Wetland loss around the world has been extensive in terms of area and vegetation type.

In the past, information about wetland vegetation was obtained through field survey and aerial photo interpretation. In the last two decades, the development of remote sensing has replaced these methods for mapping wetland vegetation. The utilization of multi-temporal remote sensing data has improved the mapping accuracy of wetland vegetation (Lunetta, and Balogh, 1999). In addition, other environmental indices and variables derived from remote sensing data have been used for improving mapping accuracy of wetland vegetation (De Colstoun et al., 2003). However, the research of wetland vegetation mapping with the combination of multi-temporal remote sensing data and

these environmental variables has not been fully pursued yet (Zeng, et al., 2007).

Maximum likelihood classification (MLC), decision tree (DT), and artificial neural network have been widely used as the classifiers of wetland vegetation using remote sensing data (Miller and Franklin, 2002; Rogan et al., 2002; Goel et al., 2003). In particular, DT classifier has been the preferred method because it enabled people to classify vegetation and land cover from multiple sources of data from different measurement scales, without considering distributional assumptions. However, the results from the studies with these classifiers were totally different because they applied each method in different conditions. The comparison study of these classification methods using multi-temporal remote sensing data and other environmental variables, such as land surface temperature and topographic information, has seldom been conducted.

This study investigates the applicability of binary DT classifier and the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data for the monitoring of wetland vegetation. More specific objectives of this study are: (1) to examine whether DT classifier can perform better than other classifiers for the wetland vegetation classification at plant family level; (2) to evaluate how environmental indices and variables derived from ASTER data can improve classification accuracy with DT classifier; and (3) to study how multi-temporal ASTER data can improve classification accuracy with DT classifier.

## 2. STUDY AREA

We selected the Banghu Lake, a seasonal lake in the Poyang Lake region, as our study area (Figure 1.). Poyang Lake (115°47' - 116°45' E, 28°22' - 29°45' N) is located in the northern part of Jiangxi Province and to the southern bank of the lower reach of the Yangtze River. Water from five main rivers - Ganjiang, Huhe, Xinjiang, Raohe, and Xinshui - flows through Poyang Lake and discharges in the Yangtze River through a narrow passage at Hokou (Hui et al., 2007). Poyang Lake exhibits a large fluctuation in seasonal water level because water flows from these five rivers are different from one another (Chen and Lin, 2004). In the flood season, Banghu Lake is joined to Poyang Lake, and it is separated in dry season.

Poyang Lake wetlands serve as the largest wintering spot for wild migratory birds in Asia – recently reported as the intermediate host of avian influenza, and as a livable habitat for a snail species – the intermediate host of schistosome (Chen and Lin, 2004; Feare, 2007). Recently, the dramatic changes in landscape patterns in Poyang Lake wetlands due to economic growth and urbanization in the last few decades have brought the shrink of the wetlands, deterioration of water quality, and loss of biodiversity. For the control of avian influenza and

schistosomiasis, the dynamic modeling of wetland vegetation using remote sensing and other spatial datasets in Poyang Lake wetlands requires immediate action.

## 3. DATA COLLECTION AND PRE-PROCESSING

### 3.1 Field Data

Field data was collected in December, 2007. The areas covered with at least 45m\*45m squares of homogeneous land cover were recorded as sample plots. At each sample plot, name, height, coverage percent, and condition for first four dominant plants were recorded. Remarks on ground coverage were recorded as well. Handheld Global Positioning System (GPS) devices were used to acquire the geographic location of sample plots. 78 sample plots collected in the field were grouped into eight plant families (Table 1.), bare soil (BRS), and marshland (MSL). Sample plots were converted into 45m\*45m rectangular polygons and saved as a shape file in ArcGIS 9.2.

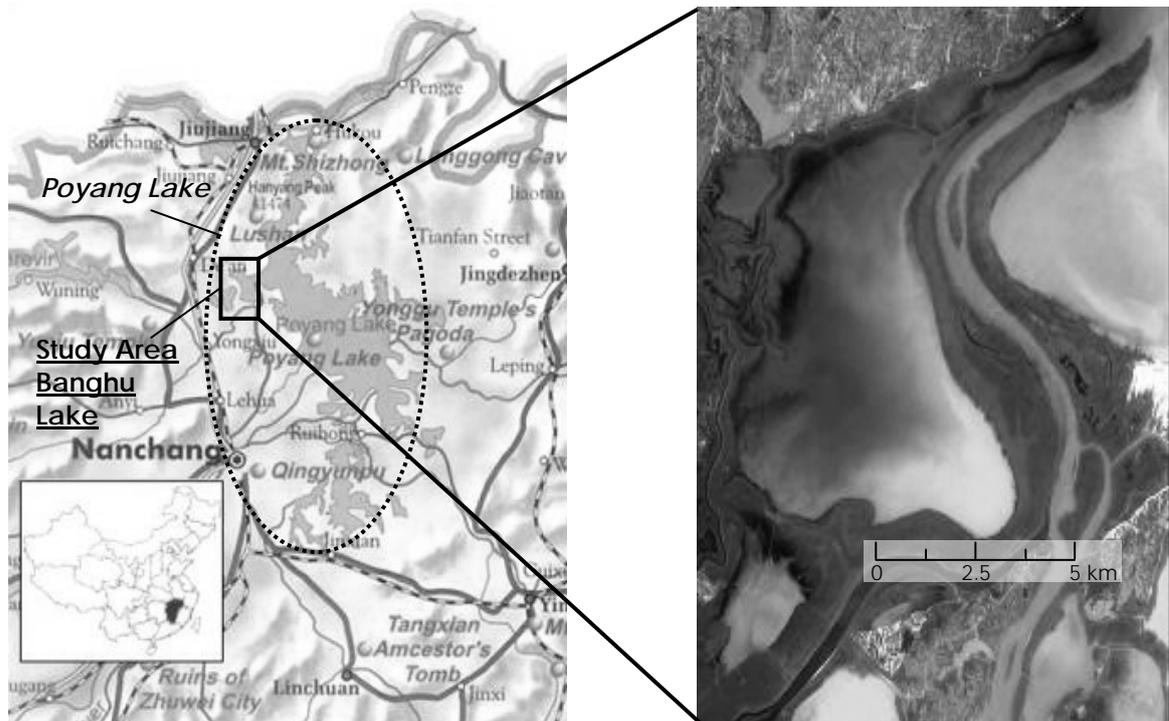


Figure 1. Study area – Banghu Lake in Poyang Lake region, Jiangxi Province, China

Family	Main Species
Compositae (CMP)	<i>Artemisia lavandulaefolia</i> DC, <i>Artemisia selengensis</i> Turcz,
Cyperaceae (CPR)	<i>Carex capillacea</i> , <i>Carex scabrifolia</i> , <i>Carex unisexualis</i> C.B. Clarke, <i>Eleocharis valliculosa</i> Ohwi
Graminae (GRM)	<i>Cynodon dactylon</i> (Linn.) Pers, <i>Paspalum paspaloides</i> (Michx.) Scribn, <i>Phalaris arundinacea</i> Linn <i>Phragmites australis</i> (Cav.) Trin. ex Steud, <i>Poa pratensis</i> Linn <i>Triarrhena lutarioriparia</i> L. Liou var. <i>lutarioriparia</i>
Polygonaceae (PLG)	<i>Polygonum hydropiper</i> Linn, <i>Polygonum thunbergii</i> Sieb. et Zucc, <i>Rumex maritimus</i> Linn
Porellaceae (PRL)	<i>Porella pinnata</i> linn
Potamogetonaceae (PTM)	<i>Potamogeton distinctus</i>
Roseceae (RSC)	<i>Potentilla limprichtii</i> J. Krause
Other Plants (OTP)	<i>Kalimeris Indica</i> (Asteraceae), <i>Coronopus Didymus</i> (Linnaeus) J. E. Smith (Brassicaceae) <i>Gossypium herbaceum</i> L (Gossypium), <i>Sapium sebiferum</i> (Linn.) Roxb (Euphorbiaceae) <i>T. pratense</i> (Fabaceae), <i>Camellia sinensis</i> O. Ktze (Theaceae)

Table 1. Dominant species in study area and their plant families

### 3.2 ASTER Data

Two ASTER data acquired on April 17, 2006 and July 3, 2005 were used in this study. Of a number of ASTER standard and on-demand data products, ASTER Level-1B Registered Radiance at the Sensor product (AST\_L1B), ASTER On-Demand L2 Surface Kinetic Temperature product (AST\_08), and ASTER Digital Elevation Model product (AST14DEM) are selected in this study.

After removing the effects of cross-talk in SWIR bands, AST\_L1B data were orthorectified using AST14DEM data and one geoid point (Iwasaki and Tonooka, 2005). Radiance at the sensor in all visible and near infrared (VNIR) and shortwave infrared (SWIR) bands of AST\_L1B data were then converted into spectral reflectance at the sensor (Tsuchida, 2008). No atmospheric corrections was performed because no information about atmospheric condition such as water vapor was available. Topographic effects were not removed because our study area was relatively flat and those effects can be ignored. We did not conduct any geometric correction among product data and strongly depended on the ground control point (GCP) sets assorted with each ASTER product. All data was resampled to 15 meters.

In addition to digital elevation model (DEM) and land surface temperature (LST), other environmental indices and variables which can be derived from ASTER data were also selected as the input of decision tree classifier. The normalized difference vegetation index (NDVI), the soil-adjusted vegetation index (SAVI) (Huete, 1988), the normalized difference water index (NDWI) (McFeeters, 1996) and the modified normalized difference water index (MNDWI) (Xu, 2005) for each data was calculated from the reflectance of VNIR and SWIR bands. Principal component analysis (PCA) was also performed with the reflectance of VNIR and SWIR bands for each data. The first principal components, explaining more than 95% of the variance, were selected. Slope and aspect were calculated using DEM. All input data in two periods (reflectance of VNIR and SWIR bands, two VIs, two WIs, elevation, slope, aspect, LST, and PC1-2) was stacked into one ENVI image file.

## 4. METHOD

The following analyses were carried out to investigate the applicability of DT classifier and ASTER data for the mapping

of wetland vegetation. Field sample plots were randomly separated into two groups – training samples and testing samples – roughly with the proportion of 60:40 (Table 2.). Each sample accounted for nine pixels of 15m resolution ASTER inputs because it was recorded only at the center of a 45m\*45m square of homogeneous land cover during the field data collection. Training samples of residential area (RDT) and waterbody (WTR) were also collected through the visual interpretation of both ASTER false color images. Training and testing sample pixels are the same throughout the whole analysis. Mean + one standard deviation method was utilized on pruning trees. All classification procedures were performed in ENVI 4.3 except DTs were built with the rpart package in R 2.6.1. The performance of the classifiers was evaluated only for plant family classes (first eight classes in Table 2.) based on overall accuracy, Kappa coefficient, and producer’s / user’s accuracy of each class. Confusion matrices for the classification results were omitted due to the space limitation.

Class	Field Sample	Training Sample	Testing Sample
Compositae (CMP)	45	27	18
Cyperaceae (CPR)	288	171	117
Graminae (GRM)	189	117	72
Polygonaceae (PLG)	27	18	9
Porellaceae (PRL)	27	18	9
Potamogetonaceae (PTM)	36	18	18
Roseceae (RSC)	27	18	9
Other Plants (OTP)	45	27	18
Bare soil (BRS)	9	9	0
Marshland (MSL)	9	9	0
Residential (RDT)	0	0	0
Waterbody (WTR)	0	0	0

Table 2. Number of sample pixels used for classification

### 4.1 Comparisons of Classification Techniques with Single Date ASTER Reflectance

To test the performance of DT classifier, the reflectance of ASTER VNIR and SWIR bands in 2006 was classified utilizing DT classifier. We also performed an MLC and a support vector

machine (SVM) (Huang et al., 2002) classification with the same ASTER inputs for comparison.

**4.2 DT Classifications with Different Combinations of Single Date ASTER Inputs**

To examine how environmental indices and variables derived from ASTER data can contribute to the improvement of classification accuracy with DT classifier, we performed a set of DT classifications with six different ASTER input combinations: (1) reflectance of VNIR and SWIR bands in 2006 (Ref) + vegetation indices (NDVI, SAVI: VI); (2) Ref + water indices (NDWI, MNDWI: WI); (3) Ref + elevation, slope, and aspect (TPG); (4) Ref + LST; (5) Ref + PC1-2 (PC); and (6) Ref + VI + WI + TPG + LST + PC (ALL).

**4.3 DT Classifications with Different Combinations of Multi-temporal ASTER Inputs**

To evaluate how multi-temporal ASTER inputs can improve DT classification accuracy, another set of DT classifications was executed with four different ASTER input combinations: (1)

reflectance of VNIR and SWIR bands both in 2005 and in 2006 (Ref06 + Ref05); (2) Ref06 + Ref05 + all environmental variables in 2006 (ALL06); (3) Ref06 + Ref05 + all environmental variables in 2005 (ALL05); and (4) Ref06 + Ref05 + ALL06 + ALL05.

**5. RESULTS**

**5.1 Performance of DT, MLC, and SVM Classifiers Using Single Date ASTER Reflectance**

The classification results with MLC, DT, and SVM classifiers are shown in Table 3. Classification accuracy indicates that classification with MLC performed the best (overall accuracy = 51.36%, Kappa = 0.30); with SVM, the second (overall accuracy = 46.46%, Kappa = 0.25); and the least accurate was DT (overall accuracy = 41.94%, Kappa = 0.26).

The classification with DT generated the highest producer's and user's accuracy for Compositae (CMP) and other plants (OTP)

Class Name	DT		MLC		SVM	
	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
CMP	66.67%	33.33%	29.41%	35.71%	0.00%	0.00%
CPR	46.30%	60.98%	47.62%	48.19%	62.96%	54.84%
GRM	51.39%	41.67%	40.91%	50.00%	47.22%	45.33%
PLG	22.22%	7.41%	0.00%	0.00%	0.00%	0.00%
PRL	44.44%	80.00%	50.00%	100.00%	77.78%	87.50%
PTM	38.89%	24.14%	0.00%	0.00%	50.00%	16.67%
RSC	0.00%	0.00%	33.33%	100.00%	0.00%	0.00%
OTP	27.78%	71.43%	26.67%	15.38%	0.00%	0.00%
Overall	41.94%		51.36%		46.46%	
Kappa	0.26		0.3		0.25	

Table 3. Accuracy Comparisons with Three Classifiers

Class Name	Ref+VI		Ref+WI		Ref+TPG	
	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
CMP	66.67%	33.33%	66.67%	33.33%	94.44%	39.53%
CPR	40.52%	68.12%	42.59%	67.65%	44.44%	70.59%
GRM	54.17%	38.24%	51.39%	39.36%	56.94%	47.13%
PLG	22.22%	7.41%	0.00%	0.00%	22.22%	7.14%
PRL	44.44%	80.00%	44.44%	80.00%	44.44%	80.00%
PTM	38.89%	24.14%	38.89%	24.14%	38.89%	24.14%
RSC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
OTP	27.78%	33.33%	72.22%	33.33%	16.67%	50.00%
Overall	40.42%		42.70%		45.19%	
Kappa	0.25		0.28		0.31	
Class Name	Ref+LST		Ref+PC		Ref+ALL	
	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
CMP	0.00%	0.00%	66.67%	35.29%	0.00%	0.00%
CPR	50.93%	58.61%	41.67%	58.44%	68.10%	63.20%
GRM	56.94%	39.81%	51.39%	39.78%	44.12%	65.22%
PLG	22.22%	7.69%	0.00%	0.00%	0.00%	0.00%
PRL	0.00%	0.00%	44.44%	80.00%	22.20%	50.00%
PTM	38.89%	31.62%	38.89%	23.33%	38.89%	33.33%
RSC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
OTP	16.67%	75.00%	77.78%	42.42%	50.00%	21.95%
Overall	40.00%		42.65%		47.92%	
Kappa	0.19		0.27		0.28	

Table 4. Accuracy Comparisons of Classifications with Single Date ASTER Reflectance and Environmental Indices / Variables

families. Only DT could classify Polygonaceae (PLG) family, although its producer's and user's accuracy remained low. MLC had the highest user's accuracy for CMP, Gramineae (GRM), Porellaceae (PRL), and Roseceae (RSC) families. MLC was the only classifier for RSC family, although its producer's accuracy was low. SVM obtained the highest producer's accuracy for Cyperaceae (CPR), PRL, and Potamogetonaceae (PTM) families. However, SVM could not classify CMP, PLG, RSC, and OTP families at all.

**5.2 DT Classification Using Single Date ASTER Reflectance and ASTER-derived Environmental Indices / Variables**

Table 4. shows the DT classification results using different combinations of single date ASTER inputs. The accuracy assessment results indicated that Ref + ALL could improve the overall accuracy DT classification the best, with an increase of 5.98% (41.94% to 47.92%), while Ref + TPG could make the best improvement in Kappa coefficient, with an increase of 0.05 (0.26 to 0.31). The addition of WI and PC could not contribute any notable improvement to the classification accuracy. Ref +

VI and Ref + LST negatively affected the accuracy.

For the individual plant families, Ref + TPG showed the greatest amount of improvement in both the producer's and

user's accuracy for CMP, and in the user's accuracy of CPR. The addition of VI did not have any significant effects on the classification accuracy. Ref + WI and Ref + PC made great improvements of the producer's accuracy for OTP. The addition of LST slightly increased the user's accuracy for PLG and OTP. Ref + ALL improved the producer's accuracy for CPR and the user's accuracy for GRM and PTM the most. The producer's and user's accuracy for PLG and RSC could not be improved significantly by adding any environmental indices and variables derived from ASTER products.

**5.3 DT Classification Using Multi-temporal ASTER Reflectance and ASTER-derived Environmental Indices / Variables**

Table 5. indicates the DT classification results using different combinations of multi-temporal ASTER inputs. Although every combination significantly improved the overall accuracy and kappa coefficient, the combination of Ref06 + Ref05 + ALL05 made most significant improvements, with the increases of 15.47% (41.94% to 57.41%) in the overall accuracy and 0.15 (0.26 to 0.41) in Kappa coefficient. Ref06 + Ref05 + ALL06 showed the least improvements both in the overall accuracy and in Kappa coefficient.

Class Name	Ref06+Ref05		Ref06+Ref05+ALL06		Ref06+Ref05+ALL05		Ref06+Ref05+ALL06+ALL05	
	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.	Prod. Acc.	User Acc.
CMP	33.33%	40.00%	33.33%	35.29%	100.00%	52.94%	61.11%	40.74%
CPR	78.70%	69.67%	68.10%	65.29%	75.93%	66.13%	69.83%	75.00%
GRM	51.39%	54.41%	43.06%	46.97%	44.44%	65.31%	56.94%	59.42%
PLG	22.22%	9.09%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
PRL	88.89%	100.00%	55.56%	50.00%	22.22%	100.00%	22.22%	100.00%
PTM	38.89%	31.82%	38.89%	30.43%	83.33%	51.72%	38.89%	23.33%
RSC	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
OTP	23.53%	80.00%	72.22%	37.14%	33.33%	22.22%	52.94%	26.47%
Overall	55.39%		50.72%		57.41%		52.80%	
Kappa	0.39		0.33		0.43		0.38	

Table 5. Accuracy Comparisons of Classifications with Multi-temporal ASTER Reflectance and Environmental Indices / Variables

For the individual plant families, the combination of Ref06 + Ref05 + ALL05 made the greatest improvements in both producer's and user's accuracy for CMP and PTM. Ref06 + Ref05 improved both the producer's and user's accuracy for PRL, the producer's accuracy for CPR, and the user's accuracy for PLG and OTP. Ref06 + Ref05 + ALL06 only showed significant improvement in the producer's accuracy for OTP. Ref06 + Ref05 + ALL06 + ALL05 resulted in the most improvement in both producer's and user's accuracy for GRM and the user's accuracy for CPR. RSC could not be classified by any combinations of multi-temporal ASTER reflectance and the environmental indices / variables derived from ASTER products.

**6. DISCUSSION**

All results from the comparisons of the classification methods for the reflectance of ASTER VNIR and SWIR bands have relatively poor classification accuracy, although DT can

classify CMP and OTP families more accurately than MLC and SVM. It is quite possible that the classes at plant family level defined in this study contain substantial training errors and/or spectral overlaps with other classes. Especially in this study, the definition of OTP family can largely affect the classification results because it consists of different plant families combined without considering their spectral characteristics. The poor accuracy also indicates that in this case, the imbalance in the field sample numbers among classes negatively affects the classification result. Particularly for DT classifier, this imbalance can produce better results for classes with larger numbers of training samples at the expense of classes with smaller numbers, as was discussed by de Colstoun et al. (2003). In order to archive more acceptable classification accuracy, we must reconsider the class definitions and make efforts to arrange the number of training pixels per class equivalently. Also, future field trips should be deliberately planned to collect roughly equal numbers of sample plots per class and as much variety of sample plots as possible, taking plant structures and soil conditions into account.

The classification with the combination of single date ASTER reflectance and the environmental indices and variables derived from ASTER products reveals that topographic information (TPG), such as elevation, slope, and aspect, can improve the classification accuracy the most. This result is consistent with the research by Zeng et al. (2007), although we do not assess which topographic information is primarily responsible for this improvement. The combination of ASTER reflectance (Ref) and TPG also makes a great improvement for the classification of CMP family. Temperature information (LST) does not contribute to the improvement of classification accuracy. It is well known that general temperature retrieval algorithms are largely affected by waterbody and shadows. Particularly in wetlands, the existence of water can lead to the less accuracy in temperature retrieval. It also can be inferred that AST\_08 product might not have enough spatial resolution and/or that its inter-scope registration might not be accurate enough for that purpose. To refine the accuracy of wetland plant classification with DT, other environmental indices and variables need to be tested. Particularly, information about soil condition would improve the classification accuracy. Also, texture information could contribute to the improvement, as Wright and Gallant (2007) examined.

The classification with the combination of multi-temporal ASTER reflectance and the environmental indices and variables derived from ASTER products shows that the combination of ASTER reflectance in 2006 (Ref06), that in 2005 (Ref05), and all environmental indices and variables in 2005 (ALL05) make the most improvement in classification accuracy. It should be noted that even in a place where the water level fluctuates seasonally like our study area, the combination of multi-temporal ASTER inputs significantly improves the classification accuracy. The addition of ALL05 improves the classification accuracy more than that of ALL06. It is possible that ALL06 contains more noise than ALL05. Atmospheric correction and topographic correction could reduce the noise in these inputs and consequently improve the classification accuracy. In addition, mis-classification can be reduced through the precise geometric correction between ASTER inputs in 2006 and those in 2005, because GCP sets assorted with ASTER products might include enough errors to affect the classification results. The inter-scope registration accuracy also might need to be examined. Finally, the improvement in classification accuracy of wetland vegetation at plant family level can be archived through other techniques, such as bagging and random forest, as well.

## 7. CONCLUSIONS

This study has revealed the applicability of ASTER data for the classification of wetland vegetation at plant family level using DT. Our results indicated that the performance of DT classifier is poorer than those of MLC and SVM classifiers when using the reflectance of VNIR and SWIR bands. By adding environmental indices and variables derived from ASTER products, the classification accuracy was slightly improved. The classification accuracy is dramatically refined with the combination of multi date ASTER inputs. However, overall and individual class accuracies remain low mainly due to the problems with the training pixels for each class.

ASTER is a unique sensor which provides us a variety of products that can be used for environmental analysis, particularly as the inputs for DT classifier, without the heavy burden of collecting different kinds of datasets from multiple data gateways. DT classifier can accommodate data with different scales and does not need any distributional assumptions. DT classifier is generally fast and insensitive to noise in inputs. Although there is still room for improvement, we believe that our approach is applicable to other remote sensing application fields as well.

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