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COGONGRASS INVENTORY AND MANAGEMENT

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16. Abstract

(Insert Abstract) A field study was conducted from 2005-2006 to test broad scale classification of cogongrass [*Imperata cylindrica* (L.) Beauv.] on Mississippi highway rights of ways with aerial imagery. Four mosaics of high resolution multispectral images of median and rights of way along Interstate 59 between Meridian and Laurel, Ms and rights of way along MS Hwy 528 between Bay Springs, MS and Interstate 59 were used for analysis and classification. The basis for this study was to test basic user classification methods on high resolution imagery for broad scale detection of cogongrass. The imagery was analyzed by supervised and unsupervised classification techniques based on a 5-class system in ERDAS imagine. The unsupervised classification technique began with 100 classes which were narrowed down to the five classes of interest, whereas the supervised classification technique trained the system for the five classes of interest. Near infrared (NIR), red, green, and blue spectral reflectance values for each known class area within the images, along with spatial patterns and expert knowledge, were analyzed and used to train and recode the classified image. Areas of the images suspected to be cogongrass, other roadside vegetation, road/bare soil, forest, and shadow/water were used to train the system for supervised classification and used to recode the unsupervised classification. A database of GPS points of known locations for each class within each image were used to test the accuracy of each classification. Overall accuracies for supervised classification of the images ranged from 85 to 95%, while unsupervised classification resulted in 75 to 90% accurate. Producers' accuracies for the cogongrass class ranged from 54 to 71% with unsupervised techniques; however, supervised classification techniques resulted in 54-100% accuracy to depict cogongrass. Both classification techniques produced 100% cogongrass class user's accuracies for all images. All other classes produced lower user's accuracies. The results from this study show good results for cogongrass detection with basic knowledge classification techniques.

17. Key Words (Insert Key Words to identify project during future literature searches Cogongrass, *Imperata cylindrica* (L.) Beauv.# IMPCY[1]. Near infrared; GPS, Global Positioning System; GIS, Geographic Information System; NDVI, Normalized Difference Vegetative Indices	18. Distribution Statement Unclassified

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[1] Letters followed by this symbol are a WSSA-approved computer code from Composite List of Weeds, Revised 1989. Available only on computer disk form WSSA, 810 East 10th Street, Lawrence, KS 66044-8897

INTRODUCTION

Cogongrass is a more widespread problematic weed each year. Though control measures of this invasive weed have been widely investigated, eradication has yet to be achieved. Therefore the spread of this grass into new areas is more of a concern. While some control can be found obtained with glyphosate and imazapyr, detection of current and new populations with remotely sensed data has found new interest (Johnson and Bruce 2005). Because the invasion of cogongrass in Mississippi and throughout the southeastern United States is so widespread, detection and classification methods for broad-scale control seems to be the new frontier. One of the needs in weed management as a whole is adequate, cost-effective, large-scale, and long term methods to map and monitor plant populations (Williams and Hunt 2004, Johnson 1999, and Anderson et al. 2003). Geographic Information Systems (GIS), Global Positioning Systems (GPS), and remote sensing are powerful tools to acquire and study geographic data quickly and accurately and may lead to easier ways to detect and control invasive weeds (Long and Srihann 2004). Remote sensing is defined as techniques to obtain information of a target through analysis of data acquired by a device with no physical contact with the target (Lillesand and Kiefer 2000). Remote sensing technologies have been widely studied for many agricultural practices such as detection of disease, herbicide drift, and weed infestations (Danielsen and Munk 2004; Buering 2004; Koger et al. 2003). Satellite and aerial imagery have been studied, with some success, for the detection of cogongrass; however, aerial platforms may provide greater spectral and spatial resolution for the scale of the area that can be covered (Johnson and Bruce 2005). Huang et al. (2001)

hypothesize that automatically detection of cogongrass through remotely sensed data can efficiently provide precise information to monitor the spread of the invasive.

Because many remote sensing devices operate in the blue, green, red, and near infrared regions of the electromagnetic spectrum, they can discriminate radiation, absorption, and reflectance of vegetation. When multispectral imagery is used for invasive weed detection, the weed needs to have distinguishing characteristics for successful classifications. These attributes can help pinpoint the spectral characteristics of a specific type of vegetation to map populations for subsequent treatments for control or other purposes for that species. Williams and Hunt (2004) stated that after flower emergence, the conspicuous yellow-green bracts of leafy spurge, which are spectrally distinct from other vegetation, can be used distinguish populations with hyperspectral remotely sensed data. Cogongrass also has a distinct yellowish tinge most of the season of active growth and has been found to be distinguishable with hyperspectral remote sensing (Huang et al. 2001). Hunt et al. (2006) state that hyperspectral imagery is currently difficult to process, requires expertise to process imagery, and almost always exceeds budgetary constraints. This brings about concern for an efficient, user-friendly, and cost-effective manner to remotely sense invasive weeds. The yellowish tinge and circular growth patterns of cogongrass may prove to be a distinction which allows for detection and classification of high spatial resolution multispectral imagery with basic techniques.

The basic concept behind remote sensing assigns variables into categories of useful information, commonly known as image classification (Williams and Hunt 2004).

Long and Srihann (2004) state that classification is a simple way to visualize major features of an image by identification of visual or data values for every pixel in the image. There are numerous methods to process and classify images, many of which can be complicated and require a great amount of time and remote sensing knowledge. If high spatial resolution multispectral imagery is used, the two basic remote sensing processes which are most effective for land cover and change detection are supervised and unsupervised. The ERDAS Imagine software performs classifications based on the spectral analysis of an image for identification of terrestrial features (Long and Srihann 2004). Spatial characteristics can also be observed to train and classify features within the image. These spatial features (size, shape, orientation) of objects are revealed by changes in average spectral properties that occur at boundaries (Ketting and Landgrebe 1976). Grey (2005) found supervised classification techniques of high spatial resolution multispectral imagery to be a difficult, but effective, technique for detection of certain morningglory species in soybeans with 75% accuracies. Gibson et al. (2004) also found it difficult to distinguish between velvetleaf and giant foxtail with multispectral imagery. These studies, however, dealt with weed detection in agricultural crops and had relatively low weed stand density. In most instances along highway rights of ways, cogongrass is found in scattered stands which are almost a monoculture of the invasive. Weeds, such as cogongrass, which have morphological characteristics that can be readily distinguished spectrally from other vegetation can be good targets for lower spectral resolution imagery (Hunt et al. 2006). For this reason, classification of high spatial resolution imagery may result in higher classification accuracies than found in a crop systems.

MATERIALS AND METHODS

Aerial images were taken in 2005 and 2006 of Interstate 59 median and rights of way between Meridian and Laurel, MS and Highway 528 rights of way between Bay Springs, MS and Interstate 59 in March and May with a GeoVantage camera system. This camera system provided a 4 band multispectral image with the blue band centered at 450 nm, the green band centered at 550 nm, the red band centered at 650 nm, and the near-infrared band centered at 850 nm. It had a spectral resolution of 80 nm in the visible spectrum and 20 nm for the NIR band**.** The spatial resolution was +/– 1 m with a visible resolution of 0.25 m. Four image mosaics were used to distinguish cogongrass from other roadside vegetation, bare soils/roads, forests, and shadows/water on highway rights of ways. A database of field collected GPS points, which represented each class, was accumulated for image interpretation and accuracy assessment. Erdas imagine and ArcMap software packages were used to perform image analysis and classifications. Unsupervised and supervised (maximum likelihood) classification techniques were used and evaluated for their effectiveness to detect cogongrass stands. The unsupervised classification technique began with 100 classes which were narrowed down to the five classes of interest, whereas the supervised classification technique trained the system for the five classes of interest. Due to the size of the areas of observation, and limited ground truth data, training sites were created based on expert knowledge of spectral (NIR, red, blue, and green reflectance values) and spatial (size, shape, color, and orientation) patterns of each class. These training sights were used to train the supervised classifier and recode the unsupervised classifier. A 7x7 neighborhood filter was used for each output to remove “salt-and-pepper” misclassifications. The classified images were applied to the ground truth data for accuracy assessments. The results of this analysis yielded Producer’s and User’s accuracies for each class, and an overall accuracy of the classifier. Producer’s accuracy, which is known as the error of omission, is the probability that the ground truth data has been classified correctly. User’s accuracy, also known as the error of commission, is the probability that the classes produced from the classifier actually match that class on the ground (ground truth data).

RESULTS AND DISCUSSION

For this study, supervised and unsupervised classification methods were implemented in 5-class systems for detection of cogongrass along highway medians and rights of ways. Supervised classifiers allow the user to define signatures of spectral and spatial information for each class which are used to classify, while unsupervised classifiers allow the user to define the number of classes but require no training and are largely carried by the software (Long and Srihann 2004). The supervised classifier provided greater overall accuracies, up to 95% as shown in Table 4.1. This was to be expected since the training procedure is used in supervised classification. Only Image 4 provided greater overall accuracy for the unsupervised method, however, it produced the second lowest overall accuracies of 85 and 87% for the supervised and unsupervised methods, respectively. Although easier and less time is required, unsupervised classification is analyzed by the software. It relies on spectral data alone which can cause more misclassification than a trained system. On average, the supervised classification method only provided 5% greater overall classification accuracy than the unsupervised method. This may be due to the recode process performed on the unsupervised images, which is based on user knowledge of the spatial and spectral features of the image. Because pixels of similar spectral characteristics are classified by the unsupervised system, some pixels classified alike are inseparable and result in misclassification regardless of recode. As represented in Table 4.1 either classification technique produced sufficient overall accuracies of 75 to 95%.

Although a 5-class system was used, the ultimate goal was to evaluate the system for cogongrass detection accuracies. The classifiers were effective to identify cogongrass from the images. Tables 4.2, 4.3, 4.4, and 4.5 reveal higher user’s than producer’s accuracies for the cogongrass class regardless of image or classification method. The average user’s accuracy, represented in Table 4.6, for the cogongrass class was 100% regardless of classification method. Only the shadow/water class with a supervised classifier produced an average user’s accuracy of 100%. All other classes produced average user’s accuracy between 80 and 96% and 75 and 90% with the supervised and unsupervised classifiers, respectively. This suggests a higher probability that cogongrass classified on the image will be cogongrass in the field. The roadside vegetation and forest classes in image 1 and roadside vegetation class in image 4 produced the lowest user’s accuracies between 60 and 79%. These lower accuracies may be due to some confusion among forest, roadside vegetation and cogongrass classes, and may have resulted in some under or over-classification of one or more of the classes. Each class provided acceptable user's accuracy for every image regardless of classification technique.

Producer's accuracy for cogongrass was lower with both classification methods. As represented in Table 4.3, the supervised classification method of image 2 provided a producer's accuracy of 100% for the cogongrass class, while all other images produced below 78%. All other classes provided higher producers accuracies than the cogongrass class. On average, the cogongrass class resulted in 72 and 62% producer's accuracies for the supervised and unsupervised classifiers, respectively. All other classes ranged between 77 and 100% with the supervised system, and from 79 to 98% with the unsupervised classifier. This suggests a lower probability that the cogongrass ground truth points were correctly identified by the system. In future research, more ground truth data are needed than were available in this study. Lack of knowledge and experience with the image analysis methods combined with costs of more accurate ground truth data collection equipment may have skewed the overall accuracy of classification of these images downward.

CONCLUSION

Results from this study show acceptable levels of classification accuracy from either a supervised and unsupervised classification method. Both the supervised and unsupervised classification techniques have the ability to distinguish between the cogongrass, roadside vegetation, road/bare, forest, and shadow/water classes when high spatial resolution multispectral aerial imagery are used. The cogongrass class received high user's accuracy in each image from either classification technique, however, on average all other classes provided greater producers accuracy. There were some misclassifications, which is to be expected with most remote sensing applications. Due to the lower classifications seen for the roadside vegetation, it is suspected that over-classification of the cogongrass class occurred. This over-classification of the cogongrass class is presumed to be the result of a confusion of it and the roadside vegetation class. However, as a beginning point of detection and estimation of the scope of an invasive weed problem, an over-classification is more desirable than an under-classification. The results from this study were acceptable for the ground truth data at hand. Future research may center its focus on a small area as a baseline classification with maximum ground reference, and then apply to the broad scale area.

LITERATURE CITED

Anderson, G.L., D.S. Delfosse, N.R. Spencer, C.W. Prosser, and R.D. Rhichard. 2003. Lessons in developing successful invasive weed control programs. J. Range Manage. 56:2-12.

Buehring, N.W. 2004. Alternative methods for herbicide spray drift detection in corn and cotton. Ph.D. Dissertation. Dept. of Plant and Soil Sciences, Mississippi State Univ., Mississippi State, MS.

Danielsen, S. and L. Munk. 2004. Evaluation of disease assessment methods in quinoa for their ability to predict yield loss caused by downy mildew. Crop Prot. 23:219-228.

Gibson, K.D., R. Dirks, C.R. Medlin, and L. Johnston. 2004. Detection of weed species in soybean using multispectral digital images. Weed Technol. 18:742-749.

Gray, C.J. 2005. Utility of remote sensing for soybean and weed species differentiation. Ph.D. dissertation. Mississippi State University. Mississippi State, MS. 52-53p.

Huang, Y., L.M. Bruce, J. Byrd, and B. Mask. 2001. Using wavelet transform of hyperspectral reflectance curves for automated monitoring of Imperata cylindrica (Cogongrass). Geoscience and Remote Sensing Symposium. IEEE. 5:2244-2246.

Hunt, R., R. Hamilton, and J. Everitt. 24 March 2006. Mapping weed infestations using remote sensing. United States Department of Agriculture Forest Service Remote Sensing Applications Center. 13 July 2007 http://www.fs.fed.us/eng/rsac/invasivespecies/documents/mapping.pdf.

Johnson, D.E. 1999. Surveying, mapping, and monitoring, noxious weeds on rangelands, p.19-35. *In*: R.L. Sheley and J.K. Petroff (ed.) Biology and Management of Noxious Rangeland Weeds. Oregon State Univ. Press, Corvallis, Ore.

Johnson, W. and L.M. Bruce. 2005. Spectral and spatial resolution effects on remotely sensed data used to detect invasive species. IEEE. ?Find out what volume?

Koger, C.H., D.R. Shaw, C.E. Watwon, and K.N. Reddy. 2003. Detecting late-season weed infestations in soybean (*Glycine max*). Weed Technol. 17:696-704.

Lillesand, T.M. and R.W. Kiefer. 2000. Remote sensing and image interpretation, 4th Ed. John Wiley and Sons, New York, New York. pp.724.

Long, W., III and S. Srihann. 2004. Land cover classification of SSC image: unsupervised and supervised classification using erdas imagine. IEEE.4: 2707-2712.

Williams, A.E.P, and E.R. Hunt, Jr. 2004. Accuracy assessment for detection of leafy spurge with hyperspectral imagery. J. Range Management. 57:106-112.

Table 4.1. Overall classification accuracies for classification technique generated from the May 2005 images.

	Supervised	Unsupervised
Image	------------------- %	-------------------
1	85	75
2	95	90
3	95	88
4	85	87
Averaged	90	85

Table 4.2. Classification accuracies for classification technique generated from the May 2005 image 1.

Class	Supervised		Unsupervised	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
	-- % --			
Cogongrass	100	54	100	54
Roadside Vegetation	67	80	61	73
Road/Bare	100	100	100	100
Forest	79	100	60	55
Shadow/Water	100	100	73	100

Table 4.3. Classification accuracies for classification technique generated from the May 2005 image 2.

	Supervised		Unsupervised	
Class	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
	-- % --			
Cogongrass	100	100	100	71
Roadside Vegetation	100	93	82	93
Road/Bare	82	100	75	100
Forest	92	100	100	92
Shadow/Water	100	86	100	86

Table 4.4. Classification accuracies for classification technique generated from the May 2005 image 3.

Class	Supervised User's Accuracy	Supervised Producer's Accuracy	Unsupervised User's Accuracy	Unsupervised Producer's Accuracy
	%			
Cogongrass	100	78	100	56
Roadside Vegetation	86	92	80	92
Road/Bare	100	100	92	100
Forest	92	100	90	82
Shadow/Water	100	100	85	100

Table 4.5. Classification accuracies for classification technique generated from the May 2005 image 4.

Class	Supervised User's Accuracy	Supervised Producer's Accuracy	Unsupervised User's Accuracy	Unsupervised Producer's Accuracy
	---------- % ----------			
Cogongrass	100	57	100	65
Roadside Vegetation	67	91	76	100
Road/Bare	100	100	92	92
Forest	82	100	100	86
Shadow/Water	100	93	88	100

Table 4.6. Averaged classification accuracies for classification techniques generated from the May 2005 images.

Class	Supervised		Unsupervised	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
	---------- % ----------			
Cogongrass	100	72	100	62
Roadside Vegetation	80	77	75	90
Road/Bare	96	100	90	98
Forest	86	100	88	79
Shadow/Water	100	87	87	89