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Detecting Cutleaf Teasel (*Dipsacus laciniatus*) along a Missouri Highway with Hyperspectral Imagery

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Cutleaf teasel is an invasive, biennial plant that poses a significant threat to native species along roadsides in Missouri. Flowering plants, together with understory rosettes, often grow in dense patches. Detection of cutleaf teasel patches and accurate assessment of the infested area can enable targeted management along highways. Few studies have been conducted to identify specific species among a complex of vegetation composition along roadsides. In this study, hyperspectral images (63 bands in visible to near-infrared spectral region) with high spatial resolution (1 m) were analyzed to detect cutleaf teasel in two areas along a 6.44-km (4-mi) section of Interstate I-70 in mid Missouri. The identified classes included cutleaf teasel, bare soil, tree/shrub, grass/other broadleaf plants, and water. Classification of cutleaf teasel reached a user's accuracy of 82 to 84% and a producer's accuracy of 89% in the two sites. The conditional κ value was around 0.9 in both sites. The image-classified cutleaf teasel map provides a practical mechanism for identifying locations and extents of cutleaf teasel infestation so that specific cutleaf teasel management techniques can be implemented.

Nomenclature: Cutleaf teasel, *Dipsacus laciniatus* L.

Key words: Roadside, hyperspectral remote sensing, weed detection.

Invasive weeds are highly competitive and spread quickly in most habitats (Czarapata 2005). For many invasive plants, distributions are not homogenous in natural areas. Instead, those species often aggregate into patches depending on seed dispersal, soil adaptation, microclimate, and topography (Shaw 2005a). Management of invasive weeds is a major challenge for land managers primarily because of limited resources and diverse patterns of weed distribution.

Cutleaf teasel (*Dipsacus laciniatus* L.) is an invasive, noxious weed in Missouri. It was first introduced in the 1840s from France for the textile industry in New York to align wool fibers (Terres and Ratcliffe 1979). The spread of cutleaf teasel has been facilitated by the construction of the interstate highway systems (Solecki 1993).

As a biennial plant, cutleaf teasel grows as a rosette in the first year and flowers during the summer of the next year. A single flowering plant may produce more than 33,000 seeds yr^{-1} (Bentivegna 2006), which could be dispersed up to 1.5 m (4.9 ft) around the parent plants (Werner 1975). Seed dispersal can also be facilitated by mowing or floating on water (Solecki 1993). As flowering plants die, open areas are filled by existing rosettes, as well as by new seedlings emergent in infested areas. Seedling emergence is relegated primarily to spring and fall (Bentivegna 2006). Rosette plants produce a dense canopy that ultimately excludes desirable species.

Dense patches of cutleaf teasel aggressively colonize low maintenance areas, such as roadside rights-of-way, which often serve as seed-dispersal corridors (Hoffman and Kearns 1997; Solecki 1993). Tall, flowering plants along highways can reduce traffic visibility and increase hazards to motorists (R. Swanigan, personal communication). Cutleaf teasel reduces the diversity of native, desirable species and prominent grasses, such as tall fescue [*Lolium arundinaceum* (Schreb.) S.J. Darbyshire]. Taproots of cutleaf teasel reduce the infiltration of water and increase water erosion compared with the presence of grasses (Lacey et al. 1989). Therefore, control of cutleaf teasel is needed to reduce the negative effects along roadsides.

Typical management of cutleaf teasel involves mowing and herbicide application. Mowing rosettes decreases the competitiveness of plants, but the time of mowing is

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Interpretative Summary

Cutleaf teasel is an exotic weed that infests roadside environments in Missouri. As a growing biennial, the plant develops as a rosette during the first year and bolts during the second. Dense patches contain flowering plants with understory rosettes. The objective of this work was to develop approaches for detecting cutleaf teasel patches with accurate assessment in a complex of species along a roadside. Thus, management of cutleaf teasel could be located at specific sites. Two hyperspectral images (63 bands with 1-m spatial resolution) were analyzed to detect cutleaf teasel along the Interstate Highway I-70 in mid Missouri. Classification of cutleaf teasel reached a user's accuracy of 82 to 84% and a producer's accuracy of 89% at the two sites. The image-classified teasel map provides a practical mechanism for identifying the locations and extents of cutleaf teasel infestation so that specific management techniques can be implemented.

critical. Plants mowed before flowering initiate new growth and produce viable seeds (Glass 1991). Mowing plants during flowering enhances the dispersal of seeds (Cheesman 1998) because viable seeds are produced within 12 d of flowering initiation (Bentivegna 2008). Herbicides commonly used for cutleaf teasel control include growth regulators and acetolactate synthase inhibitors. These compounds are applied postemergence. To reduce the expense and environmental effects of these herbicides, site-specific herbicide application is often desirable, with only the infested areas treated (Shaw 2005a, 2005b). However, detection of cutleaf teasel patches via field surveys is time consuming and dangerous along highways. For example, an estimated 40,000 vehicles d^{-1} use Interstate 70 in Missouri (R. Swanigan, personal communication).

Remote-sensing technology provides an effective method for large-area detection of plants growing in distinct patches. Currently, aerial digital photographs in true color or color infrared have been used widely to detect plants with unique spectral signatures (Wang et al. 2008). These photos are often called *multispectral images* because only three or four spectral bands (visible to near infrared) are used to record data. Although these multispectral images could reach meter-scale resolution, their application in identifying specific weed species in heterogeneous landscapes is limited primarily because of large variation in plant species, phenology, and biophysical conditions (Lawrence et al. 2006).

Hyperspectral remote sensing can record data in the visible to infrared region at much higher spectral resolutions. Instead of three to four broad bands from typical aerial images, hyperspectral images generate hundreds of bands at narrow bandwidths in the same spectral region. These narrow-band images can discriminate subtle, spectral differences between weeds and native species and thus improve the capability of separating target plants from other species (Lass et al. 2002). In past studies, hyperspectral imaging has been used to detect non-native species, such as Hottentot fig [*Carpobrotus edulis* (L.) N.E. Br.] (Underwood et al. 2003), spotted knapweed (*Centaurea stoebe* L.) (Lass et al. 2002; Lawrence et al. 2006), lead tree [*Leucaena leucocephala* (Lam.) de Wit] (Tsai and Chen 2004), and sericea lespedeza [*Lespedeza cuneata* (Dumont) G. Don) (Wang et al. 2008). Ustin et al. (2002) found that, among various classifiers, supervised methods were superior to unsupervised classifiers, and images with contiguous bands provided better results than did those with selected bands or band ratios (e.g., vegetation indices).

Most of these published studies were conducted in relatively monotypic landscapes, such as croplands and pastures. Only limited studies have been conducted regarding weed detection in highly heterogeneous environments, such as riparian habitat (DiPietro et al. 2002; Hamada et al. 2007) and native communities (Underwood et al. 2003). In a preliminary study, Wang et al. (2010) compared several hyperspectral classifiers in detecting cutleaf teasel in a highly diverse highway environment. The results showed that, when non-teasel land covers were masked out of the roadsides, the spectral angle mapper (SAM) classifier (Kruse et al. 1993) provided the best classification results. However, with limited ground truthing data because of the complexity of species composition along highways, its accuracy was 15% lower than the maximum-likelihood classifier (MLC) in a regular classification process (Bentivegna 2008). The present research aimed at reducing the dependency of training data and improving the validity of cutleaf teasel mapping using hyperspectral imagery along the Interstate Highway 70 (I-70) in mid-Missouri.

Materials and Methods

Study Area and Vegetation Composition. Two areas along a 6.44-km (4-mi) section of Interstate Highway 70 in Cooper County, MO, were explored in this study. A driving survey revealed several spots infested with cutleaf teasel. One was around Exit 89 (hereafter, Exit 89 site), and the other was close to the Lamine River (hereafter, Lamine site). Soil type at Exit 89 was loam with 5.4% soil organic matter (35% sand, 42.5% silt, and 22.5% clay), and at the Lamine site, soil was clay loam with 5.4% of organic matter (40% sand, 32.5% silt, and 27.5% clay). Tall fescue was the dominant plant species along I-70. Other species included sericea lespedeza, johnsongrass [*Sorghum halepense* (L.) Pers.], and common milkweed (*Asclepias syriaca* L.). Some shrub and tree species, such as oak (*Quercus* spp.), hickory (*Carya* spp.), and pine (*Pinus* spp.), were also observed.

A reference site with pure stands of cutleaf teasel was established in the 2,250 m^2 (24,219 ft^2) Bradford Research and Extension Center (BREC), University of Missouri. It was located 64 km east and 4 km south of the Lamine site.

This site comprised stands of pure rosette and flowering plants. Spectra of these stands were extracted from a hyperspectral image and served as reference spectra in this study. Soil at this site was a Mexico silt loam (fine, smectitic, mesic Vertic Epiaqualfs) (NRCS 2008).

Data Collection. At 10:00 A.M. to 2:00 P.M. on July 25, 2006, three hyperspectral images were acquired by the Center for Advance Land Management Information Technologies (CALMIT) at the University of Nebraska-Lincoln and Aviation Institute of the University of Nebraska-Omaha, supported by the Nebraska Airborne Remote Sensing Program. The platform of the sensor was a Piper Saratoga aircraft (NI86CA, Piper Aircraft Inc, 2926 Piper Drive, Vero Beach, FL 32960), with a flight height of 1,538-m aboveground level. The hyperspectral image was acquired with the AISA (Airborne Imaging Spectroradiometer for Application) sensor, a pushbroom imaging spectrometer built by Spectral imaging Ltd. Company (P.O. Box 110, Teknologiantie 18A, Oulu, 90571, Finland). Each image contained 63 bands at 9.8-nm bandwidth in a spectral region of 401 to 981 nm (visible to near-infrared wavelength), with a pixel size of 1 m (3.3 ft).

Weather conditions were conducive for data collection during the flight time. Average weather conditions were clear with 32 C (89.6 F) air temperature, 39% relative humidity, 4 m s^{-1} (13 ft s^{-1}) wind speed, and 815 W m^{-2} spectral radiations. The AISA images delivered by CALMIT were corrected radiometrically, atmospherically, and geometrically with the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes algorithm in the ENVI software (ENVI 1999; Exelis Visual Information Solutions, 4990 Pearl East Circle, Boulder, CO 80301). Each pixel was assigned a digital number to represent surface reflectance.

Image Classification. The highway environment was represented by patches of diverse land covers: bare soil, water, tall fescue–dominated grasses, cutleaf teasel, and other plant species, such as broadleaf forbs, shrubs, and trees. Grasses were more evident along the Exit 89 site, whereas more tree/shrub patches were observed along the Lamine site. For patches with similar vegetation types, spectral responses at different locations could vary based on heterogeneous biophysical conditions, such as plant height and density, soil fertility, and water availability. Therefore, it was difficult to identify representative training data sets from the AISA images at the two study sites. A stepwise, unsupervised/supervised hybrid classification algorithm was applied in this study to detect cutleaf teasel patches in a multi-step process.

Unsupervised classification groups image pixels statistically into a predefined number of clusters in an *N*-dimensional feature space and then extracts land-cover classes with the analyst's posteriori knowledge (Jenson 2004). It does not require training signatures for land covers and, therefore, minimizes the uncertainties of training-data selection in a heterogeneous environment (Schowengerdt 2007). In this study, we applied a commonly accepted, unsupervised classifier, the ISODATA (Iterative Self-Organizing Data Analysis Techniques) module in ERDAS Imagine V9.0. ERDAS Imagine 9, 2005; ERDAS, Inc. 5051 Peachtree Corners Circle, Norcross, GA 30092-2500). With iterative optimization, pixels of the AISA image were grouped into 300 clusters with the criteria of minimal spectral distances from cluster means and standard deviations. A convergence threshold of 0.95 was selected, which indicated that the process stopped when 95% of pixels remained unchanged between two adjacent iterations. Based on the analyzer's familiarity with the study sites, these clusters were visually compared with the AISA image and assigned to representative land cover types.

In this study, we assigned 20 classes to represent complex land covers and subtle variations in each cover type. For example, because of the extremely heterogeneous herbaceous cover along the highway, we assigned 10 classes of grasses/broadleaf forbs. Detailed information on the 20 classes is described in the results and discussion. To improve the validity in identifying cutleaf teasel, its signatures in both study sites were compared with pure stands of rosette and flowering plants in the reference site.

Spectral signatures of these ISODATA-extracted 20 classes were then recorded as a priori training data to perform a supervised classification process. Here, we adopted the MLC algorithm to classify the original AISA images. The 20-class MLC calculated *N*-space (n = 63 total bands in this study) variance and covariance to build a joint-probability density function for each class. Each pixel was assigned to the class with the highest probability. Although mathematically complex and computationally slower, the MLC was more accurate and provided higher spatial contiguity than did the ISODATA algorithm that was based on in-band statistics only. Because cutleaf teasel was the target species in this study, the 20 classes were regrouped into cutleaf teasel, water, bare soil, tree/shrub, and grass/broadleaf. Finally, a 5-by-5 majority filtering process was conducted to reduce noise in the classified patches (Lass et al. 2002; Okamoto et al. 2007).

Accuracy Assessment. To assess the unsupervised/supervised class maps in the two study sites, we adopted an error matrix approach for accuracy assessment (Congalton and Green 1999). With a stratified random-sampling rule (Congalton and Green 1999), 50 points for each class were extracted from a class map. For cutleaf teasel, ground truth at those points was confirmed with field surveys. Other classes, such as bare surface, water, grass/broadleaf, and trees, were easily identified via visual interpretation of 50-cm (19.7-in) resolution aerial photos taken by local vendors along I-70 in July 2007.

By comparing the image-classified and reference class types for the 250 points, an error matrix was constructed to specify the numbers that were correctly identified and those that were mis-identified as other classes. The overall accuracy, producer's accuracy, and user's accuracy of the classification were then calculated (Congalton and Green 1999; Jensen 2005). The overall accuracy was the ratio between the number of correct points (the points at which the classes were correctly identified) and all points used in the assessment (250 in this study). This ratio explained the general agreement between image-derived classes and ground-reference data. The producer's and user's accuracies could be better applied in examining the accuracy of a specific class, e.g., cutleaf teasel in this study. Producer's accuracy was the ratio between the number of correctly identified points of a specific class and all reference points of this class (ground truth). Therefore, it was a measure of omission error, indicating the underestimation that a patch was not identified in the classification. User's accuracy, on the other hand, was the ratio between the number of correct points of a specific class and all points that are assigned to that class (50 in this study). User's accuracy was a measure of commission error or assigning a patch to a class to which it did not belong (overestimation). Producer's and user's accuracies of cutleaf teasel explained the possibilities of its underestimation and overestimation in image-based teasel mapping at each study site.

Another commonly applied technique of accuracy assessment is κ analysis. The κ coefficient of agreement (κ value) is a multivariate statistic used to measure the agreement between the image-classified and ground-reference data (Jensen 2005). The range of κ values is from 0 to 1. A higher κ value indicates greater accuracy for the overall classification. Similarly, the conditional κ value was calculated as a measure of classification accuracy of a specific class. These variables provided a way to quantitatively evaluate the creditability of remote-sensing techniques for cutleaf teasel mapping.

Cross validation was also performed in both study sites to test the repeatability of the unsupervised/supervised approach in this study. Classification of one site was conducted using the training signatures of the other site. Then, its accuracies were compared with the ones using the original spectral signatures. In this way, we were able to assess the robustness of the approach and its feasibility if adopted in different areas or time frames.

Results and Discussion

Cutleaf teasel along I-70 was flowering at the time of acquiring the AISA image. The patches were composed of tall, flowering plants (up to 2.2-m with white flowers) and understory rosettes. Although flowering plants were not significantly shading understory plants (Werner 1977), rosettes intercepted up to 95% of the light (Bentivegna 2006). The spectral characteristics of flowering and rosette plants could be different based on photosynthetic rates and light interception. Consequently, the spectra of cutleaf teasel patches along I-70 varied with mixed composition of flowering and rosette plants.

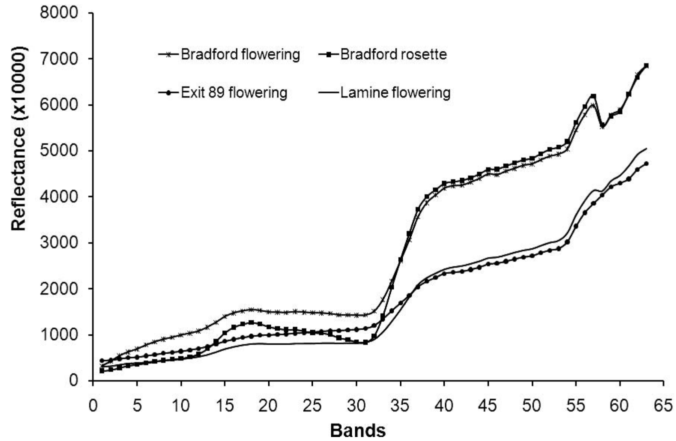

Figure 1. Sampled spectra of pure rosettes and flowering plants at Bradford Research and Extension Center (BREC) and mixed flowering/rosette plants of cutleaf teasel at the Exit 89 and Lamine, MO, sites.

At each study site, one sample patch of cutleaf teasel was selected, and its reflection spectrum was extracted from the AISA image. These spectra were a mixed response of flowering and rosette plants. Reference spectra of pure rosette and flowering plants were extracted at the reference site (BREC). In Figure 1, differences of the spectral signatures were evident between pure stands at BREC and mixed stands along I-70. Mature plants at BREC were in full flower, whereas flowering of highway plants was almost complete. Cutleaf teasel at BREC was established on a more-productive soil, which resulted in more fertile plants with less overall stress. As a result, cutleaf teasel at BREC exhibited a stronger spectral response than did plants at the Exit 89 and Lamine sites.

Spectral differences in Figure 1 could also be explained with plant physiology. Rosette plants absorbed more red light (the trough at bands 30–35) than did flowering plants at BREC, indicating that rosette plants were more photosynthetically active. Flowering plants at the highway sites had a similar spectral reflectance. However, the red absorption trough (bands 30–35) from chlorophyll in teasel leaves was more observable at the Lamine site than it was at the Exit 89 site. The green reflection peak from leaf chlorophyll was not clear at the Exit 89 site and its near-infrared reflection from internal leaf structures was lower than that at the Lamine site. These characteristics indicated that the sampled cutleaf teasel patch at the Lamine site contained a greater level of coverage with rosette plants.

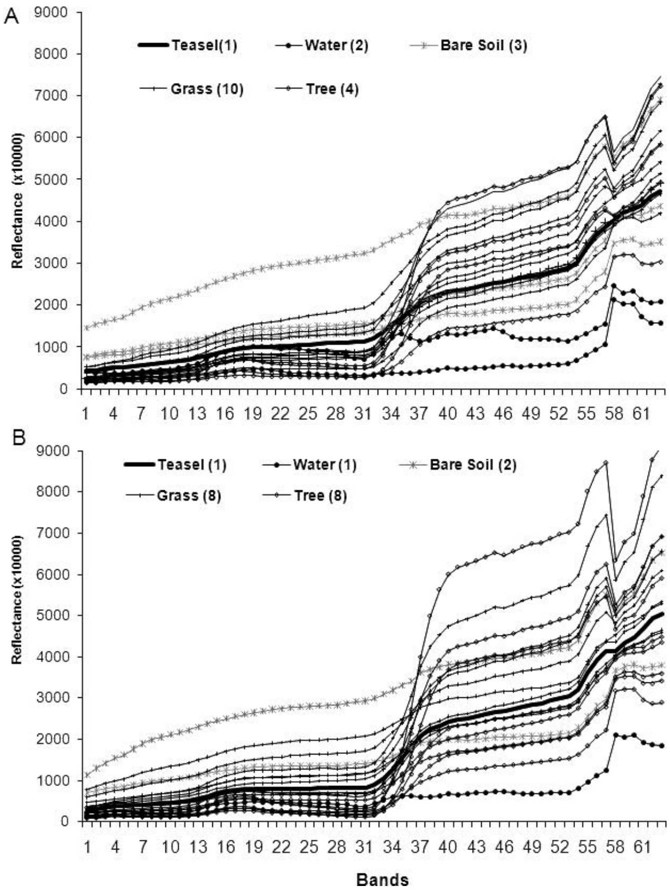

Figure 2. Spectra of the 20 training signatures (in five land cover categories) at the (A) Exit 89 site and the (B) Lamine, MO, site. The numbers in parentheses represent the number of classes in each land cover type.

Spectra of the 20 training signatures (in five land cover types) were extracted after regrouping the 300 clusters from unsupervised classification of the AISA images (Figure 2). Because of a heterogeneous landscape along the highway environment, multiple classes were often observed in a single land cover type. At the Exit 89 site, there were ten grass/broadleaves, four tree/shrubs, three bare soils, two waters, and one cutleaf teasel class among the training data sets. At the Lamine site, there were eight tree/shrubs, eight grass/broadleaves, two bare soils, one water, and one cutleaf teasel class among the training data sets. As shown in Figure 2, bare soil surfaces were characterized by a high response in visible bands (bands 1 to 31) and low slopes between visible and near-infrared bands (bands 31 to 40). Water surfaces had distinctively low reflectance in near-infrared bands. The vegetative classes, e.g., cutleaf teasel, grass/broadleaves, and tree/shrubs, had similar spectra, featuring a peak in green reflection, a trough in red absorption, and high near-infrared reflection in the spectra.

With the training signatures in Figure 2, the class map was developed using a supervised MLC method. Figure 3 describes the detailed information on cutleaf teasel at the Exit 89 site. To demonstrate, a ground picture of a cutleaf teasel patch (taken in July 2006) is shown in Figure 3A, which was also observed and marked in the enlarged AISA image (Figure 3B). The AISA image of the whole site is shown in Figure 3C (in color compositions of 472.35, 544.67, and 638.19 nm as blue, green, and red, respectively). In the class map at this site (Figure 3D), most cutleaf teasel patches were detected along the roadsides of I-70.

As an invasive plant, cutleaf teasel covered only limited area along the roadsides, whereas the Exit 89 site had threefold more pixels of cutleaf teasel than did the Lamine site. The Missouri Department of Transportation (MoDOT) frequently mows the center median and the first 4.5 m along the edge of the east- and west-bound lanes. Therefore, cutleaf teasel likely could not survive in those areas. Most cutleaf teasel patches were observed along the roadside, where slopes were often steeper than 18° and where rocks were present. In those areas, human disturbance was limited, and mowing was not possible. For management of teasel in those areas, establishment of competitive, desirable plants or repeated applications of selective herbicides are necessary.

The unsupervised/supervised classification approach in this study reached similar accuracies at the two study sites. When all five land-cover categories were considered, the overall accuracy was 92% at the Exit 89 site (Tables 1 and 2) and 90% at the Lamine site (Tables 3 and 4). The κ value was approximately 0.9 at both study sites (Table 2 and 4). With the exception of the grass/broadleaf class at the Lamine site, the non-teasel classes had omission errors of $< 10\%$. In other words, more than 90% of these classes were identified correctly. Grass/broadleaf at both sites was most likely to be overestimated. For example, at the Exit 89 site (Table 1), 55 points were classified as grass/broadleaf, whereas only 47 of those points belonged to that class in the ground-truth data. At the Lamine site, 53 points were classified as grass/broadleaf, whereas only 42 of those points belonged to that class in the ground-truth data (Table 3).

Cutleaf teasel was classified with a producer's accuracy (omission error) of approximately 90% at both sites. The user's accuracy (commission error) ranged from 82% at the Exit 89 site to 84% at the Lamine site. The errors were primarily from the confusion between cutleaf teasel and grass/broadleaf class. At the Exit 89 site, five cutleaf teasel points were misclassified as grass/broadleaf (underestimation of cutleaf teasel) and two grass/broadleaf points were misclassified as teasel (overestimation of cutleaf teasel). At the Lamine site, there were eight points in underestimation and five points in overestimation, all confused with grass/broadleaf points. The misclassification between cutleaf teasel and grass/broadleaf may result from mixed pixels along I-70 where cutleaf teasel often grows in narrow, long patches. At a 1m pixel size for the AISA images, some cutleaf teasel pixels

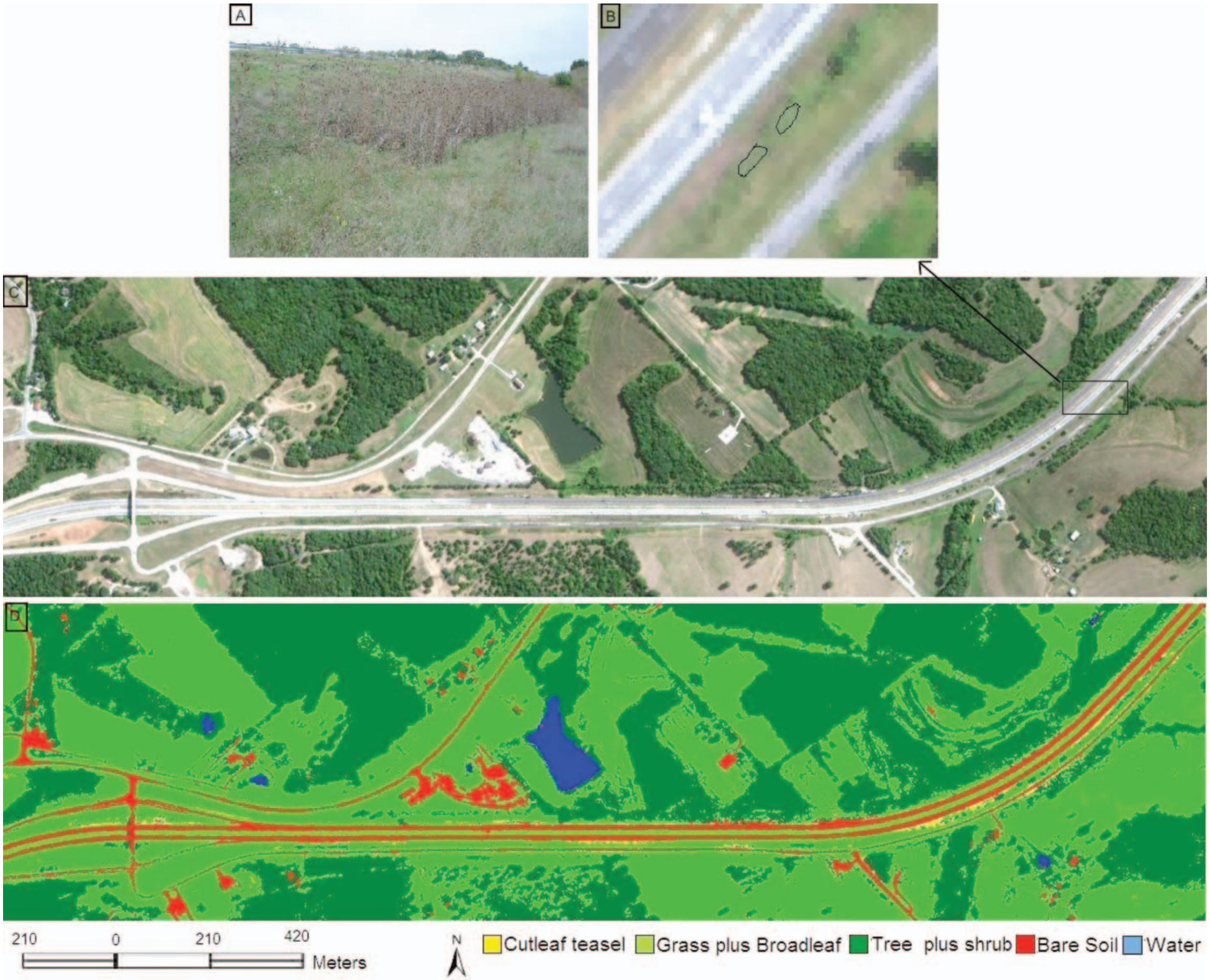

Figure 3. Cutleaf teasel patches (A) along Highway I-70 in July 2006, (B) a 1-m pixel of a cutleaf teasel patch at Exit 89, (C) an AISA (Airborne Imaging Spectroradiometer for Application) image (wavelengths of 472.35, 544.67, and 638.19 nm) of the study area, and (D) a classification map of cutleaf teasel using maximum-likelihood classification.

Table 1. Error matrix of the maximum-likelihood classification of AISA (Airborne Imaging Spectroradiometer for Application)–derived class map at the Exit 89 site, Cooper County, MO.[a]

	Ground reference					
Image-based class map	Cutleaf teasel	Water	Bare soil	Tree + shrub	Grass + broadleaf	Row total
Cutleaf teasel	**41**		4		5	50
Water		**50**				50
Bare soil	2		**46**		2	50
Tree/shrub	1			**47**	1	50
Grass/broadleaf plants	2		1		**47**	50
Column total	46	50	51	47	55	**250**

[a] Bolded numbers (diagonal) indicate the correctly classified pixels within each category.

Table 2. Producer's accuracy, user's accuracy, and κ coefficient matrix of the maximum-likelihood classification of AISA (Airborne Imaging Spectroradiometer for Application)–derived class map at the Exit 89 site, Cooper County, MO.

Class	Producer's accuracy	User's accuracy	κ Coefficient
Cutleaf teasel	89.1	82	0.80
Water	100	100	0.8
Bare soil	90.2	92	0.93
Tree/shrub	100	94	0.97
Grass/broadleaf plants	83.9	94	0.88
Overall accuracy	92.4		
κ Coefficient	0.91		

Table 4. Producer's accuracy, user's accuracy, and κ coefficient matrix of the maximum-likelihood classification of AISA (Airborne Imaging Spectroradiometer for Application)–derived class map at the Lamine site, Cooper County, MO.

Class	Producer's accuracy	User's accuracy	κ Coefficient
Cutleaf teasel	89.4	84	0.78
Water	100	90	1
Bare soil	95.9	94	0.9
Tree/shrub	87.5	98	0.93
Grass/broadleaf plants	79.3	84	0.92
Overall accuracy	90		
κ Coefficient	0.88		

were inevitably mixed with the dominant species, i.e., grass/broadleaf class in this study.

Classification errors of cutleaf teasel may also stem from the temporal variation between AISA image acquisition and the ground-reference data collected for accuracy assessment. Although cutleaf teasel reference points were identified during field surveys at the time of the AISA flight, other reference data were collected in an aerial photo acquired in spring 2007, almost 1 yr after the AISA image was acquired. Land cover may have changed during that period. Some cutleaf teasel patches may have been mowed or treated with herbicides by MoDOT. It was also possible that some cutleaf teasel plants died and were replaced by other species or remained bare soil. Some cutleaf teasel patches were located in rocky areas, and that may have affected cutleaf teasel detection. In fact, four pixels at the Exit 89 site were classified as bare soil, although cutleaf teasel patches were observed in the same area during field surveys.

Cross validation, i.e., applying the signature of one site to classify the image of the other site, did not perform as well as classifications with their own signatures (Table 5). The overall accuracy dropped to 68.4% at the Exit 89 site when applying the training signature acquired at the Lamine site, whereas it was 72.4% at the Lamine site when applying the signature at the Exit 89 site. For cutleaf teasel, there was apparent omission (low producer's accuracies) at both sites, indicating that cutleaf teasel cannot be well recognized when its signature was not statistically representative in the image, especially in areas at heterogeneous land surfaces. That is reasonable because cutleaf teasel covers only a few populations in both images and, therefore, was more sensitive to statistical properties in comparison with other land covers. The Lamine site had less cutleaf teasel population, which resulted in lower producer's accuracy than the Exit 89 site achieved. With cross signature, other land covers in each image also raised high confusion errors. Grasses were mostly overestimated at both sites (42.34 and 48.65% of user's accuracy, respectively), primarily because of their large spectral variations on the ground (there were 10 grass classes at the Exit 89 and eight at the Lamine sites.). For example, a large piece of pond at the Exit 89 site was classified as grass because of its impure water surface. Highways to the west of the Lamine site were also misclassified as grasses.

Results of our cross-validation analysis agree with DiPietro et al. (2002), who found poor accuracies in detecting giant reed (*Arundo donax* L.) when applying

Table 3. Error matrix of the maximum-likelihood classification of AISA (Airborne Imaging Spectroradiometer for Application)–derived class map at the Lamine site, Cooper County, MO.[a]

	Ground reference					
Image-based class map	Cutleaf teasel	Water	Bare soil	Tree + shrub	Grass + broadleaf	Row total
Cutleaf teasel	**42**				8	50
Water		**45**		5		50
Bare soil			**47**	1	2	50
Tree/shrub				**49**	1	50
Grass/broadleaf plants	5		2	1	**42**	50
Column total	47	45	49	56	53	**250**

[a] Bolded numbers (diagonal) indicate the correctly classified pixels within each category.

Table 5. Cross validation of the maximum-likelihood classification at the Exit 89 and Lamine sites, Cooper County, MO.

	Exit 89 (with Lamine signature)		Lamine (with Exit 89 signature)	
Class	Producer's	User's	Producer's	User's
Cutleaf teasel	44.44	72.73	23.91	84.62
Grass/broadleaf plants	81.03	42.34	70.59	48.65
Tree/shrub	97.87	95.83	70	100
Bare	88	91.67	100	67.74
Water	20	100	91.11	97.62
Overall accuracy	68.4		72.4	

signatures from one image to a second image acquired in a different flight line (even in the same overflight), possibly because of different sun angles, climate, and plant conditions. Similarly, the low accuracy of the cross validation in this study could come from different sizes, phenology, and species composition of the cutleaf teasel patches in the two sites. Dense patches of flowering plants were observed at the Exit 89 site, whereas a higher percentage of rosette plants grew at the Lamine site. The Lamine site was also characterized with sparse patches of flowering plants that grew in mixed composition with cutleaf teasel rosette, grass/broadleaf, and bare soil. These differences in cutleaf teasel patches resulted in different spectral signatures (as shown in Figure 2).

Nevertheless, the multi-step, unsupervised/supervised classification in this study reduced the necessity of accurate, intensive ground-training data. Although these data are often a prerequisite in most classification methods, they are difficult to collect in heterogeneous environments along highways. The results in such an environment, in this study, were comparable to studies conducted on relatively stable habitats. For example, using hyperspectral images, Lawrence et al. (2006) identified spotted knapweed and leafy spurge (*Euphorbia esula* L.) with 76 and 79% of user's accuracy, respectively, at different sites in Montana. Also, Ustin et al. (2002) was able to detect *Arundo donax* with accuracies of 90 to 98% in California. An approximately 89% producer's accuracy and 82 to 84% user's accuracy was achieved in this study, indicating that hyperspectral remote sensing could provide an effective approach to mapping cutleaf teasel in a unique, heterogeneous highway environment. The stepwise, unsupervised/supervised classification method was time consuming but was an easy-to-use approach and could be adopted by field users in local agencies with personnel who are not remote-sensing experts. Because cutleaf teasel patches are narrowly distributed along highways, their detection via regular aerial photos or ground observations is not practically feasible. Therefore, hyperspectral mapping of cutleaf teasel patches could provide important information for site-specific weed management along rights of way.

It should be noted, however, despite advances in sensor technologies and great mapping potentials, hyperspectral remote sensing has not been widely accepted as multispectral imagery because of the large image sizes and complicated data processes. Various efforts have been made to simplify the hyperspectral image process to enhance its potential applications. As one example, optimal-band selection has been tested in past years to remove redundant spectral bands and reduce image sizes (Bajcsy and Groves 2004; Becker et al. 2005). Also, together with increased interest in hyperspectral image applications, advanced image processing and classification methods are being explored to improve spectral signatures and classification accuracies (Bagan et al. 2008; Mutanga and Skidmore 2004; Wang et al. 2010). However, because of the complexity of roadside environments, it is difficult to determine the superior approaches that are reliable and repeatable in spatial and temporal dimensions (DiPietro et al. 2002). The low accuracies in cross validation in this research indicate that a more-robust method of cutleaf teasel mapping is needed. In the near future, we will continue our research toward optimal, practical detection of a target species in a complex highway environment.

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