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Hyperspectral data processing for repeat detection of small infestations of leafy spurge

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Abstract

Leafy spurge (*Euphorbia esula* L.) is an invasive plant species in the north central and western U.S. and southern Canada. Idaho has established populations in the north and southeastern regions which are spreading into new sites. This study demonstrates the ability of high resolution hyperspectral imagery to provide high quality data and consistent methods to locate small and low percent canopy cover occurrences of leafy spurge. Locating leafy spurge in its early stages of invasion is critical for land managers in order to prioritize treatment, conservation, and restoration activities. Hyperspectral data were collected in 2002 and 2003 for the study area in southeastern Idaho. The imagery was classified with the Mixture Tuned Matched Filtering (MTMF) algorithm. Although classifications from single date images provided discrimination of leafy spurge at approximately 10% cover in one 3.5 m pixel, for repeatability and consistency purposes, the threshold for leafy spurge discrimination is approximately 40% cover. We hypothesize that georegistration errors, small differences in leafy spurge reflectance, training endmember selection, and image processing and field validation biases between years influence multi-date detection limits. Although hyperspectral imagery is costly, in some situations, the advantages of having reliable and repeatable mapping abilities for discrimination of economically damaging invasive species such as leafy spurge outweigh the image and processing costs.

Keywords: Leafy spurge; Hyperspectral imagery; Mixture Tuned Matched Filtering; Accuracy assessment

1. Introduction

1.1. Background

Invasive plant species are an economic and biologic detriment to rangeland and riparian ecosystems across the western United States and Canada. In the State of Idaho, $10 million per year is spent in control measures alone (Northwest Natural Resource Group, 2003). This estimate does not include economic impacts of invasive plants to regional industries such as agriculture and livestock, which cost over $137 billion per year in the U.S. (Pimentel et al., 2000). Leafy spurge (*Euphorbia esula* L.) is a Eurasian exotic species first introduced to the U.S. in about 1827 (Whitson, 1999). Leafy spurge is listed as a noxious weed in the State of Idaho and in all western and north central states and southern Canada. Large infestations in Montana, Nebraska, North and South Dakota, and Wyoming have resulted in an annual economic impact on grazing and wildlands of approximately $129 million (BLM, 1998; Leitch et al., 1994). Further, leafy spurge contains a milky latex that can produce blisters and dermatitis in humans, cattle, and horses (Lajeunesse et al., 1999). This unpalatable aspect of leafy spurge has been demonstrated to reduce the forage utilization for cattle and wintering wildlife (Hein & Miller, 1992).

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Leafy spurge can spread up to approximately 10 m per year through root and seed propagation in environments with limited competition (Lajeunesse et al., 1999; Whitson, 1999). As small infestations grow larger, biodiversity is reduced and subsequently range site productivity and wildlife habitat are compromised (Belcher & Wilson, 1989). Land managers need tools to help them identify small infestations of leafy spurge because of its potential to spread rapidly into larger infestations. Identification of small infestations is complicated by the large land areas that land managers in Idaho and other western states are responsible for.

The main goal of this study was to identify small infestations (percent canopy cover) of leafy spurge using high spatial resolution hyperspectral remote sensing and to demonstrate the repeatability of these methods over 2 years. The study also explored explanations for differences between the data sets from both years. Successful discrimination of leafy spurge in this context assists managers in prioritization of treatment sites to reduce or prevent the impacts from leafy spurge invasion. Our research site was located along the flanks of the South Fork of the Snake River in the Swan Valley in southeastern Idaho, U.S., where leafy spurge is in preliminary stages of invasion (Fig. 1). This study is part of a NASA-funded initiative to bring science research and technology applications into an operational context for land managers such as county weed managers, Bureau of Land Management (BLM), and USDA US Forest Service (USFS).

1.2. Previous work

The use of remote sensing for the detection of noxious weeds and other vegetation has become a common tool to map large landscapes efficiently (Everitt et al., 1995b; Everitt & Yang, 2004; Lamb & Brown, 2001; Lewis et al., 2000). The use of multispectral imagery has been demonstrated to effectively map the distribution of ecosystem types and vegetative systems (Everitt et al., 2002; Lamb & Brown, 2001); however, the low spectral resolution of multispectral imagery is a major limitation. Imagery with higher spectral resolutions (e.g., hyperspectral) can provide

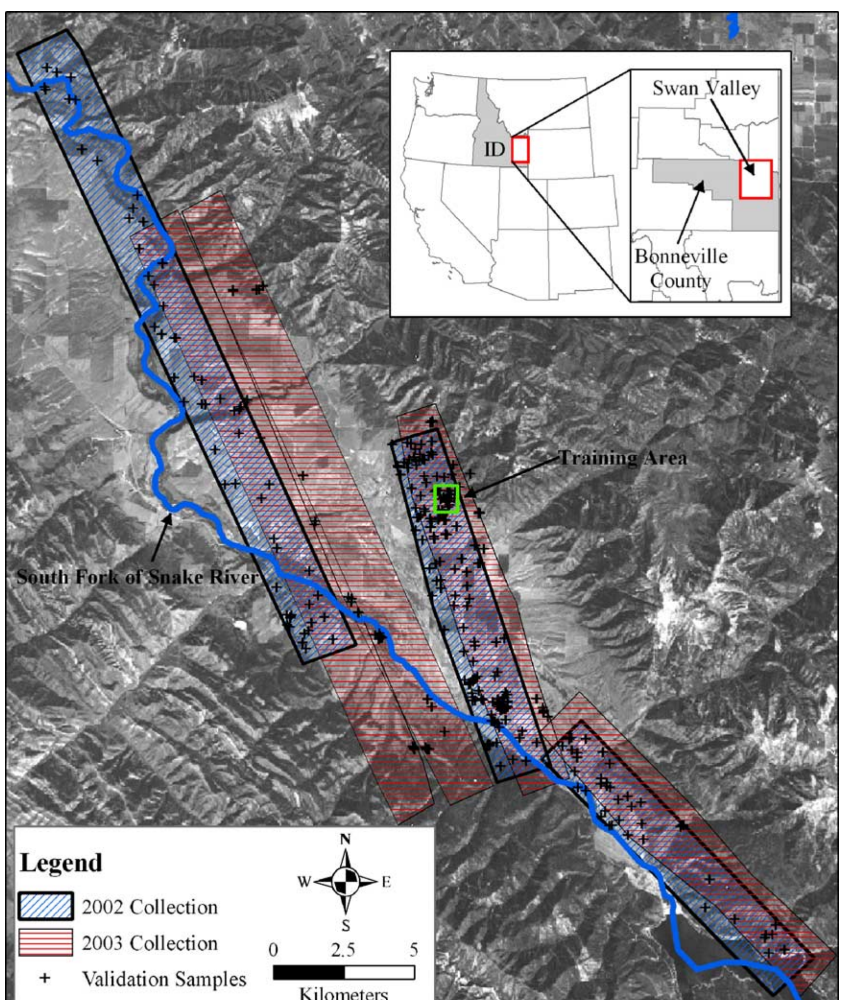

Fig. 1. Location of Swan Valley, Idaho, with locations of hyperspectral flightlines and validation samples.

increased species discrimination and biochemical differentiation (Aspinall et al., 2002; Lass & Prather, 2004; Lass et al., 2002; Lewis, 2003; Root et al., 2004; Underwood et al., 2003; Ustin et al., 2004; Vane & Goetz, 1993).

Leafy spurge is a good candidate for remote sensing detection because of its distinctive yellow green bracts when in bloom (Everitt et al., 1995a). This distinct bloom, coupled with the increased availability of remotely sensed imagery, has resulted in several recent remote sensing studies of leafy spurge (Anderson et al., 1999; Everitt et al., 1995a; O'Neill & Ustin, 2000; Williams & Hunt, 2002, 2004).

Everitt et al. (1995a) used color infrared photography and color video imagery to detect leafy spurge in North Dakota and Montana. This study found that the yellow green bracts are distinct in multispectral images and color photography. Imagery used in this analysis had very high spatial resolution (between 0.1 m and 0.5 m per pixel). Although no formal accuracy assessment was presented, the authors cite high performance accuracy of leafy spurge classifications with >25% canopy cover within a pixel. The methods provide a manual interpretation approach to large scale mapping of leafy spurge in imagery. Semi-automated processing of hyperspectral and other digital imagery provide an alternative to manual interpretation. Furthermore, the use of hyperspectral versus multispectral imagery has the potential to map percent cover as low as 10%.

Recently, a USDA-ARS sponsored research and demonstration program, The Ecological Area-wide Management (TEAM) Leafy Spurge, has concluded several years of research related to remote sensing of leafy spurge (TEAM Leafy Spurge, 2004). Anderson et al. (1999) used aerial photography for a change detection study in Theodore Roosevelt National Park between the years of 1993 and 1998. Results from the aerial photography classifications and geographic information systems (GIS) analysis indicated that over the 5-year period, leafy spurge infestations doubled, even under an aggressive weed management program.

O'Neill and Ustin (2000) presented hyperspectral (AVIRIS, 20 m pixels) detection of leafy spurge in Theodore Roosevelt National Park. This study illustrated methods in hyperspectral discrimination of leafy spurge, and found that the weed was best detected using a Minimum Noise Fraction (MNF) transform as input to the Spectral Angle Mapper (SAM) algorithm. Due to geometric errors, a statistical accuracy assessment was not presented; however, the authors cite good results based on a qualitative accuracy assessment.

Williams and Hunt (2002, 2004) applied the Mixture Tuned Matched Filtering (MTMF) classification algorithm (Boardman, 1998) to AVIRIS hyperspectral imagery to discriminate leafy spurge. They found hyperspectral imagery capable of discriminating leafy spurge with a Matched Filter score of 0.1, which roughly corresponded to 10% canopy cover of leafy spurge (Williams & Hunt, 2002). Williams and Hunt (2004) determined overall single classification accuracies between 75% and 97% for locating leafy spurge in a region dominated by large and high density infestations. This study demonstrated that hyperspectral data analysis is an effective tool for the automated mapping of leafy spurge.

Dudek et al. (2004) used AVIRIS hyperspectral imagery from 1999 and 2001 for change detection in Theodore Roosevelt National Park. Accuracies varied from 35% to 70%, though these results were influenced by georegistration issues. A qualitative analysis was performed and results indicated that percent cover was accurately represented by map classifications. Furthermore, this study identified a 40% decrease in leafy spurge cover between 1999 and 2001. Kokaly et al. (2004) used Compact Airborne Spectrographic Imager (CASI) data to investigate a decrease in overall leafy spurge cover between 2000 and 2001 in Theodore Roosevelt National Park. Overall accuracies were 74% using the USGS Tetracorder system (spectral feature comparison algorithm).

The study presented here builds upon the above cited work, focusing on the detection of small infestations (low percent canopy cover) of leafy spurge with hyperspectral imagery and on the repeatability of such methods for use in a long-term management strategy for Swan Valley and other similar sagebrush steppe ecosystems.

2. Methods

2.1. Study site

The Swan Valley (latitude 43° 20′ to 43° 40′ North and longitude 111° 5′ to 111° 35′ West) is located in Bonneville County, Idaho, approximately 60 km west of Jackson Hole, Wyoming. Palisades Reservoir is at the southeastern end of the valley and a hydroelectric dam controls the flow of the Snake River. The South Fork of the Snake River runs through the length of the valley (approximately 30 km), providing irrigation for farming and feeding riparian zones with abundant flora and fauna. The mountains bounding the Swan Valley are semi-arid, typified by native sagebrush-steppe vegetation. Agriculture and livestock grazing are the two main economies in the area.

The region provides an ideal environment for the spread of leafy spurge seed through water, anthropogenic, and animal transportation vectors. Leafy spurge was first found in the Swan Valley in the mid-1980s, and new infestations have been found annually since then. Many infestations of leafy spurge in Idaho are smaller than in surrounding western and Midwestern states (e.g., less than one-half hectare versus thousands of continuous hectares). In the Swan Valley, there are a few large (>1 ha) infestations; however, approximately 50% of infestations are smaller than 75 m^2. Leafy spurge infestations in the study area have an average cover of approximately 40% (oblique field cover estimation). Small infestations in the Swan Valley are in the early stages of invasion and have the potential for spreading through the region, as demonstrated by the few large infestations.

Aggressive control measures by landowners and county weed personnel coupled with competitive native vegetation have somewhat restricted the spread. Delineating leafy spurge infestations in the Swan Valley requires higher spatial resolution imagery than previous studies using AVIRIS (approximately 20 m pixels) because of the low spectral component that the small, low cover infestations contribute.

2.2. Image acquisition

HyMap hyperspectral data were collected by the HyVista over the study area on June 30th, 2002, at 18:47 UTC and again on June 29th, 2003, at 17:01 UTC. Solar noon on these dates was approximately 19:27 UTC. The HyMap data consist of 126 bands between 0.45 μm and 2.5 μm with a pixel size of 3.5 m×3.5 m. Bandwidths ranged from 15 μm in the visible and near infrared to 20 μm in the shortwave infrared. In 2002, three 1.8 km wide hyperspectral flightlines (totaling approximately 40 km in length) were collected. In 2003, similar areas were collected, as well as an additional data flightline approximately 1.8 km wide and 20 km long. The flightlines were modified slightly in 2003 to expand the area of the study (Fig. 1).

The geographic locations of the flightlines were designed to include a training area with one of the highest known percent canopy cover (hereafter referred to as percent cover) of leafy spurge in the Swan Valley, as well as to include a suite of known infestations of varying sizes and cover of leafy spurge. The training area is approximately 4300 m^2 with leafy spurge cover approaching 100% (Fig. 2). In order to evaluate the accuracy of the georegistration and spectral quality of the imagery, two control targets (approximately 50 m^2 each) were painted, one with ultra-flat black paint, and the other with ultra-flat white paint, and placed proximal to the training area. A Trimble GeoXT Global Positioning System (GPS) unit was used to determine the geographic location of the targets. The GPS data were differentially corrected. Similarly, an Analytical Spectral Device (ASD) hand-held FieldSpec Pro field spectroradiometer was used to determine the controls' spectral signatures. In addition, field spectral data for leafy spurge and other proximal vegetation were collected concurrent with image acquisition.

2.3. Image processing

The 2002 and 2003 imagery were preprocessed by HyVista, utilizing the HyCorr algorithm for atmospheric correction and conversion of radiance to reflectance data. This study used the reflectance data for analysis. Previous studies (Williams & Hunt, 2002) used the visible and near-infrared portions of the electromagnetic spectrum for classifications. However, after iterative processing, we found no distinct advantage of spectrally subsetting our data. Imagery from both years was processed as non-georeferenced mosaics to maximize the utility of the single large training area. All image processing was performed using the Environment for Visualizing Images (ENVI) version 4.0 software (Research Systems, Boulder, CO). MNF transforms were applied to the full spectral range of the reflectance data with the exception of band 1 (450 nm) and band 63 (1406 nm) in 2002, and band 63 (1406 nm), band 64 (1420 nm), and band 126 (2493 nm) in 2003, due to noise and water absorption. The advantage of using the MNF transform (versus raw reflectance data) is that the MNF decorrelates the data and reduces spectral redundancy,

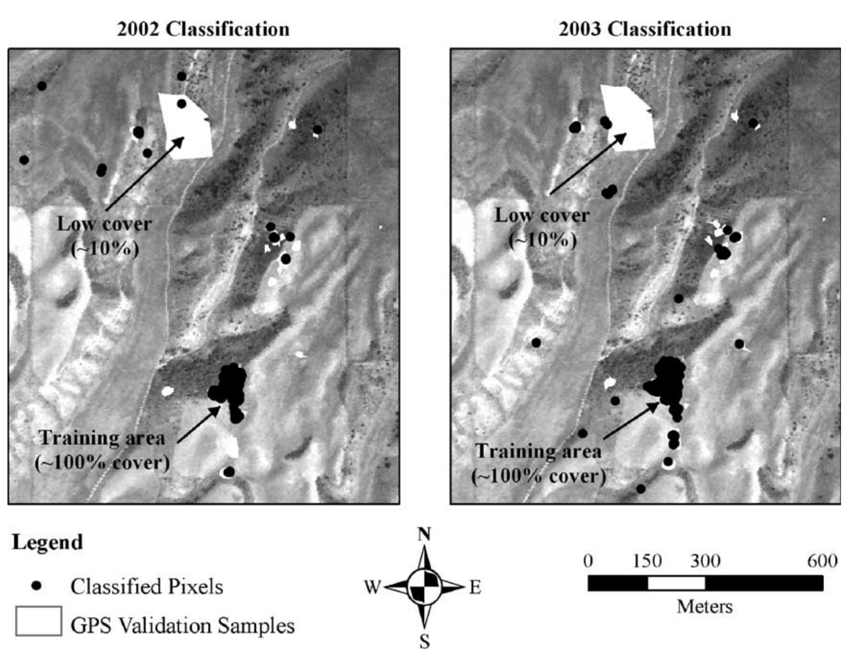

Fig. 2. Subset of the 2002 and 2003 classifications showing the location of the training area and differences in the classifications in a low cover (~10%) area.

thereby reducing the number of bands necessary to use for classification. MNF efficiently reorganizes decorrelated data (Green et al., 1988), and has been demonstrated to perform well in vegetative discrimination (Underwood et al., 2003). The entire image mosaic was used to estimate noise statistics. This large region was used based on experimentation with estimating noise statistics using dark band data and small, homogeneous subsets of the image. The experimentations are the subject of an associated study (Mundt et al., submitted for publication), which found that the use of a large image subset provides more accurate classification results when discriminating similar vegetation. Leafy spurge endmembers for each year were image derived from the same training area using known geographic locations and spectral profiles.

For each year's data set, the MNF transformed reflectance data were classified using the MTMF algorithm. In the 2002 data set, 74 MNF bands were used, and in the 2003 data set, 70 MNF bands were used, based on a 90% threshold of the cumulative MNF variance. The MTMF algorithm produces two values for each pixel in an image: (1) a value of infeasibility; and (2) a Matched Filter value (MF). Pixels predicted to contain leafy spurge were interactively selected from a scatter plot of MF values versus infeasibility values using the criteria of a maximum infeasibility threshold of 20 and a range of MF values between 0.1 and 1. Pixels with high MF values and low infeasibility values were considered to likely contain leafy spurge. Because this study area contains many small infestations of leafy spurge that are important to locate on an operational level, pixels with low MF values and low infeasibility values were also considered. In these cases, the infeasibility threshold was adjusted to accommodate the lower MF values. Further description of this methodology can be found in Mundt et al. (submitted for publication).

2.4. Validation

Raw data delivery and initial processing of the 2002 imagery were not completed in time for a preliminary validation during summer 2002. Therefore, the majority of the field validation took place during the summer of 2003 (for both the 2002 and 2003 data sets) with supplemental validation during summer 2004. Because leafy spurge has not been observed to spread more than 1 to 2 pixels (~3 to 7 m) over a 1 year period in Swan Valley, it is assumed for this study that the use of 2003 and 2004 field validation data is appropriate for imagery collected in 2002 and 2003. A total of 364 differentially corrected GPS polygons (referred to as validation samples) were collected and included 323 polygons collected in 2003 and 41 polygons collected in 2004 (these samples do not include the area used for classification training). Of the 364 polygons, 270 are located within the geographical bounds of the 2002 imagery and 214 are located within the geographical bounds of the 2003 imagery (Fig. 1). Polygon data were considered more desirable than point data in our surveys because in high spatial resolution images, the size and shape of positive reference polygons can be visually compared to the size and shape of an infestation classified in the imagery. Survey crews were given GPS coordinates to validate, half of which were predicted positive (leafy spurge presence) and half of which were predicted negative (leafy spurge absence) by image classifiers. To avoid potential survey bias, survey crews were not informed which validation samples were predicted positive and negative. The survey crews located each area in the field and in positive areas used GPS units to map the outside perimeter of the leafy spurge infestation and record the oblique field cover estimates. At points without leafy spurge, the field crews surveyed a minimum 50 m diameter area and recorded the corresponding vegetation. Positive prediction areas in this survey included approximately 80% of the predicted positive locations (excluding locations which were inaccessible), while negative locations were selected using a random location selection stratified by removing inaccessible and illogical locations (e.g., the tops of steep mountains, middle of lakes, and tops of buildings).

2.5. Accuracy assessment

Accuracy assessment in high spatial resolution hyperspectral imagery is a developing science, and recent publications have emphasized the importance of decisions pertaining to expressing the accuracy of thematic classifications (Congalton & Green, 1999; Foody, 2002; Lopez et al., 2004; Stehman & Czaplewski, 1998; Story & Congalton, 1986). While it is important that accuracies represent the sensitivity limits of the classifier, it is also necessary to provide land managers with a useful product that meets their needs for reliability and confidence. Our approach to accuracy assessment was intended to address two major criteria: (1) quantify the repeatability of high resolution hyperspectral images for discriminating spatially small infestations of invasive plants; and (2) reflect the needs of land managers to reliably locate infestations. When this project was initiated, local weed managers identified an assessment criterion of 70% for user's accuracy (percentage of pixels classified on the map which actually represent that category on the ground).

One of the major considerations in assessing the accuracy of remote sensing data from high spatial resolution imagery is understanding georegistration errors. We collected 44 differentially corrected ground control points (including the control targets) using GPS receivers in one of the flightlines in order to estimate the georegistration error of the HyMap data. Horizontal positional errors from these control points did not have a dominant directional shift, but expressed a minimum error of 5 m, a maximum error of 26 m, and a mean error of 13.6 m. Thus, a positive classification may occur at distances up to 26 m (>5 pixels) from the predicted location in the imagery. To test influences of geometric errors on classified products, producer's accuracy (percentage of reference pixels correctly classified) was optimized respective to buffering validation samples. The producer's accuracy increased in both years at small buffer distances and formed a sill near 14 m (Fig. 3). This sill had a similar value to the mean georegistration error in the image, and is thus interpreted as representing an optimal buffer distance to accommodate georegistration errors. For the purpose of this assessment, both positive and negative GPS validation samples were buffered by 15 m (just over 4 pixels) to accommodate this error. A buffering approach was also used by Williams and Hunt (2004), who collected ground validation plots that were larger (50 m by 50 m) than the spatial resolution of their AVIRIS image pixel size (20 m by 20 m).

There are several methods to express the accuracy of a remote sensing classification. An error matrix (array of numbers that express the number of sample units assigned to a particular category relative to the actual category as indicated by the reference data) (Congalton, 2004) of validation samples (polygons) as well as error matrices of related classification validation samples were constructed following methods presented by Congalton and Green (1999) (Table 1), and Foody (2004), respectively. The Kappa statistic is used to: (1) test whether the remotely sensed classifications are better than randomly assigning labels to areas; and (2) test the comparison of two matrices to investigate whether they are statistically, significantly different (Congalton, 2004).

Three separate accuracy assessments were performed: (1) using *all* GPS-acquired validation samples from 2002 and 2003 *that were located within the spatial extent of the respective imagery* (method 1); (2) using only those GPS-acquired validation samples > *30 m^2 in size and having > 40% cover of leafy spurge* (method 2); and (3) using only those validation samples *that fell within the extent of both the 2002 and the 2003 imagery* (method 3). These methods were chosen in order to compare the individual classifications between each year's data set and to determine if larger and relatively high cover infestations in Swan Valley had higher producer's and user's accuracies than smaller, low cover infestations. Because the image data sets were acquired over slightly different geographic areas between years, method 3 was considered in order to use the same validation data set for both years. Following these accuracy assessments, error matrices are presented for the assessment of the significance of the difference between the 2002 and 2003 classifications after Foody (2004).

Table 1
Accuracy assessment strategy with 15 m buffers of polygon data

	Positive	Negative
True	Any classified pixel occurs inside or within 15 m of the perimeter of a GPS reference positive sample.	No classified pixels occur inside or within 15 m of the perimeter of a GPS reference negative sample.
False	No classified pixels occur inside or within 15 m of the perimeter of a GPS reference positive sample.	Any classified pixel occurs inside or within 15 m of the perimeter of a GPS reference negative sample.

3. Results

Results of the accuracy assessments for leafy spurge presence demonstrated overall accuracies between 84% and

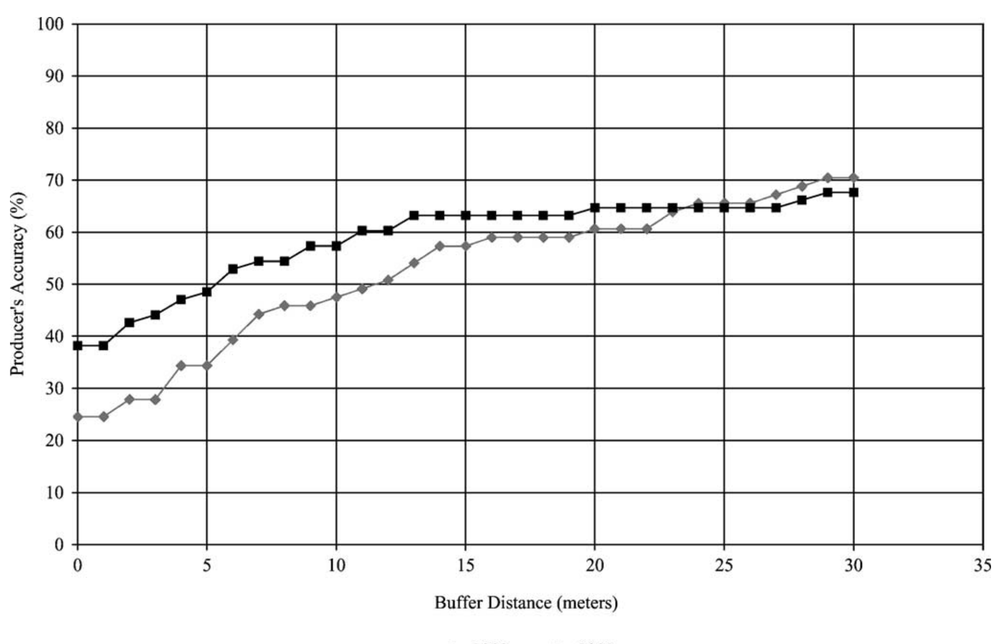

Fig. 3. Plot of buffer distance versus producer's accuracy for validation samples. Buffer distance equal to 15 m is used for accuracy assessments.

Table 2
Error matrix (in number of validation samples) and accuracies (in percent) for 2002 imagery using *all validation samples located within the spatial extent of the 2002 imagery* (method 1)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	34	8	42	81%
	Absent	27	201	228	88%
Column totals		61	209	270	
Producer's accuracy		56%	96%		
Overall accuracy		87%			

Table 4
Error matrix (in number of validation samples) and accuracies (in percent) for 2002 imagery using *validation samples > 30 m^2 in size and > 40% cover infestations of leafy spurge* (method 2)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	19	8	27	70%
	Absent	9	201	210	96%
Column totals		28	209	237	
Producer's accuracy		68%	96%		
Overall accuracy		93%			

94% (Tables 2–7). Producer's accuracies ranged between 50% and 68% in 2002 and 62% and 80% in 2003, while user's accuracies ranged between 70% and 81% in 2002 and 77% and 88% in 2003 (Tables 2–7). These accuracies are similar to accuracies derived by Dudek et al. (2004) and Kokaly et al. (2004). In method 1, using all available validation samples, the producer's accuracy was 56% in 2002 and 63% in 2003. Both of these accuracies are notably lower than the user's accuracy of 81% and 88% for 2002 and 2003, respectively. In method 2, using only larger and higher percent cover validation samples, the producer's accuracies were 68% and 80% in 2002 and 2003, respectively, while the user's accuracies were 70% and 77% in 2002 and 2003, respectively. In method 3, using only validation samples that were geographically located within both the 2002 and 2003 flightlines, the producer's accuracies were 50% and 62% in 2002 and 2003, respectively, and the user's accuracies were 74% and 88%, respectively.

Kappa values range from 0.52 to 0.75 for the 2002 and 2003 classifications (Table 8). Kappa significance was tested with a two-tailed Z-test with infinite degrees of freedom at 95% confidence interval (critical regions of ± 1.96). The null hypothesis, that a given Kappa was equal to zero, was rejected for all classifications (Table 8).

The test statistic (t-test) is used to compare the 2002 and 2003 Kappa values using a null hypothesis that the difference in the Kappa values between 2002 and 2003 (in each method) is equal to zero. The differentiability of these Kappa values was tested with a two-tailed t-test with infinite degrees of freedom at 95% confidence interval (critical regions of ± 1.96). Results indicate that the null hypothesis fails to be rejected for all comparisons between years (Table 8).

Because of uncertainty as to the statistical rigor of Kappa using related validation samples, this study also tested the differentiability of the classifications using methods presented by Foody (2004). This includes comparison matrices of the 2002 and 2003 classifications for all validation samples (Table 9), for all positive validation samples (Table 10), and for all negative validation samples (Table 11). Using the t-test and a 95% confidence interval, no significant difference was found between the classifications. In addition to these results, we also subjected the same error matrices to chi-squared and chi-squared continuity corrected significance testing, and in each case, we failed to reject the null hypothesis (there was not a significant difference between the 2 years at 95% confidence).

4. Discussion

To test the ability of hyperspectral imagery to detect leafy spurge infestations in 2002 and 2003, the MTMF algorithm was used for classification. Accuracy assessments were performed on each year's classified data set and compared. Project results illustrate that user's accuracies are all above 70%, meeting the threshold specified by the weed managers. Additionally, the study demonstrated that the image processing methods were repeatable between years. Comparison testing indicates that the Kappa values between years in each method failed to reject the null hypothesis that their differences equal zero, and Kappa results indicate that

Table 3
Error matrix (in number of validation samples) and accuracies (in percent) for 2003 imagery using *all validation samples located within the spatial extent of the 2003 imagery* (method 1)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	43	6	49	88%
	Absent	25	140	165	85%
Column totals		68	146	214	
Producer's accuracy		63%	96%		
Overall accuracy		86%			

Table 5
Error matrix (in number of validation samples) and accuracies (in percent) for 2003 imagery using *validation samples > 30 m^2 in size and > 40% cover infestations of leafy spurge* (method 2)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	20	6	26	77%
	Absent	5	140	145	97%
Column totals		25	146	171	
Producer's accuracy		80%	96%		
Overall accuracy		94%			

Table 6
Error matrix (in number of validation samples) and accuracies (in percent) for 2002 imagery using validation samples that *fell within the spatial extent of both the 2002 and the 2003 imagery* (method 3)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	17	6	23	74%
	Absent	17	126	147	86%
Column totals		34	132	170	
Producer's accuracy		50%	95%		
Overall accuracy		84%			

Table 8
Kappa (K) and significance testing at 95% confidence interval using all validation samples (method 1), using validation samples >30m^2 in size and >40% cover infestations of leafy spurge (method 2), and using only those validation samples that fell within the extents of both the 2002 and the 2003 data (method 3)

Classification	K	Z_{stat}	H_o: K=0	t_{stat}	H_o: ($K_{2002}-K_{2003}$)=0
2002 (method 1)	0.58	9.23	Reject	0.642	Fail to reject
2003 (method 1)	0.63	10.84	Reject		
2002 (method 2)	0.65	8.29	Reject	0.899	Fail to reject
2003 (method 2)	0.75	10.27	Reject		
2002 (method 3)	0.52	5.85	Reject	1.293	Fail to reject
2003 (method 3)	0.67	8.71	Reject		

t-test (t_{stat}) results correspond to the respective 2002 and 2003 pairs.

the classifications of leafy spurge in 2002 and 2003 have good agreement. Slight differences in the classifications between years were detected both in the error matrices and when visually interpreting the imagery. Regardless of these differences, leafy spurge detection was not significantly affected which indicates that the methods are applicable for baseline and change detection surveys in the Swan Valley and similar ecosystems. The discussion below explores and compares the accuracy assessments, provides potential explanations for the small differences in the classifications between 2002 and 2003, and explores spectral thresholds for leafy spurge. The discussion which explores differences in the classifications does not impact the significance of our study; however, it provides important considerations for all image processing studies.

4.1. Classification accuracy assessments

In all of the accuracy assessments, user's accuracies are higher than producer's accuracies, and overall accuracies are consistently high (above 84%). The difference between user's and producer's accuracies narrows in method 2. The results of method 3 indicate that the classifications over the same geographic area utilizing the same processing techniques are similar between years. However, the user's and producer's accuracies are lower than those derived in method 1. Though the weed manager's user's accuracy threshold was met, the lower producer's accuracies in methods 1 and 3 are of concern. MTMF is designed to reduce the number of false positives and thus increase producer's accuracies. In this study, MTMF did work as designed; however, a large number of false positives are attributed to multiple small infestations of leafy spurge. For example, producer's accuracies increased in method 2 (relatively large, high cover infestations) from method 1, and it is inferred that many of the false positives were low cover infestations. The higher producer's accuracies in methods 1 and 2 for the 2003 classification (versus 2002 classification) indicate that the 2003 classification likely identified more small infestations. The user's accuracies likely decreased in method 2 because the sample size of the true positives decreased while the true negatives stayed constant between methods 1 and 2. This hypothesis was tested by randomly sampling the number of positives in method 1 from 61 to 28 for 2002 and 68 to 25 for 2003 (to match the number of positive samples used in method 2) and recalculating the error matrices. In these cases, the user's accuracies decreased similarly for method 1 as in method 2. It is also notable that the Kappa values are higher in method 2 than in methods 1 and 3. This may be explained by the use of more uniform data (leafy spurge infestations >40% cover and >30 m^2) in method 2. The sample size may also have biased the Kappa values. Fifty validation samples per class have been empirically derived as the minimum number necessary for balance between what is practical and what is statistically necessary for accuracy assessments (Congalton & Green, 1999). This criterion was not met in method 2 because large infestations of leafy spurge are not abundant in Swan Valley. It was also not met in method 3

Table 7
Error matrix (in number of validation samples) and accuracies (in percent) for 2003 imagery using validation samples that *fell within the spatial extent of both the 2002 and the 2003 imagery* (method 3)

		Reference			
		Present	Absent	Row totals	User's accuracy
Classified	Present	21	3	24	88%
	Absent	13	129	142	91%
Column totals		34	132	166	
Producer's accuracy		62%	98%		
Overall accuracy		90%			

Table 9
Related agreement matrix for the 2002 and 2003 classifications using all of the validation samples that fell within the extent of both the 2002 and the 2003 imagery

		2002 Classification		
		Correct	Incorrect	Row totals
2003 classification	Correct	137	13	150
	Incorrect	6	10	16
Column totals		143	23	
Number of positives		34	t_{stat}=1.61,	
Number of negatives		132	no significant difference	

The number of positive and negative samples used is indicated.

Table 10
Related agreement matrix for the 2002 and 2003 classifications using only the positive validation samples that fell within the extent of both the 2002 and the 2003 imagery

		2002 Classification		
		Correct	Incorrect	Row totals
2003 classification	Correct	14	7	21
	Incorrect	3	10	13
Column totals		17	17	
Number of positives		34	t_{stat}=1.26,	
Number of negatives		0	no significant difference	

The number of positive samples used is indicated.

because of the reduced geographic area that was used in the accuracy assessment.

The number of negative validation samples used in the accuracy assessments is two to three times larger than the number of positive validation samples. In this study, this resulted in a positive bias in the overall accuracy, but a more conservative estimate of user's accuracy. The effects of using the same number of negative validation samples (chosen through random sampling) as positive validation samples were tested. User's accuracies increased by 9% to 35%, with the exception of the 2003 classification in method 3, which did not change. The overall accuracies generally decreased by 6% to 15%, and, by definition, producer's accuracies remained constant. Consequently, the decision was made to utilize all negative validation samples in the accuracy assessments, thereby generating conservative estimates of user's accuracies (rather than conservative estimates of overall accuracies) and capitalizing on the knowledge provided by including all available field data.

4.2. Comparison of 2002 and 2003 data sets

As noted previously, comparisons between the 2002 and 2003 classifications (Tables 9–11) indicate that there is no statistical difference between the classifications. In the majority of instances where leafy spurge was detected, it was detected in both years. However, visual comparison of a subset of the classifications of 2002 and 2003 (Fig. 2) indicates that there are cases in which leafy spurge was classified in 2002 but not in 2003, and vice versa. Overall, the results illustrate that slightly higher accuracies were obtained from the 2003 imagery than the 2002 imagery. There are several potential explanations for these differences, including georegistration and geometric issues, differences in leafy spurge reflectance (due to variations in leafy spurge phenology, solar zenith angles, and atmospheric conditions), endmember selection, and processing and field validation biases. Differences in accuracy are not likely due to changes in data collection or pre-processing because the signal-to-noise ratio of the HyMap instrument between data collection years was consistent (500:1; Cocks et al., 1998) and the same atmospheric correction was applied to both data sets. Further, care was taken to ensure that the data from both years were processed and classified using the same methods and criteria. The discussions below on georegistration and geometric errors, changes in leafy spurge reflectance, training endmember selection, and image processing and field validation biases are not confined to repeatability studies and are also significant for single-date image processing.

4.2.1. Georegistration and geometric errors

While high spatial resolution images are more likely to locate smaller infestations of a given target than coarse spatial resolution images, they are also associated with a higher degree of variability and geometric errors that are difficult to constrain or correct. Geometric errors are commonly large scale, such as a shift or rotation of the image (Aspinall et al., 2002); however, we also found a second level of geometric confusion in high spatial resolution airborne data, such as a one to three pixel local shift in non-uniform directions. This complicates accuracy assessment in that it is difficult to discern correct classifier performance affected by geometric imprecision as opposed to stochastic classification errors. Pixel shifts (georegistration errors) between the 2 years may have resulted in small differences in the expression of the leafy spurge distribution within a pixel. For example, one pixel with 100% cover in the 2003 imagery may be expressed as four pixels with 25% cover in the 2002 imagery, making it more difficult to detect.

4.2.2. Leafy spurge reflectance

Errors in the ASD instrument field calibration and changes in the spectral targets placed in the field between 2002 and 2003 resulted in the inability to compare ASD spectra between years. Subsequently, leafy spurge reflectance derived from the training area (the mean value of four non-adjacent pixels in the image) was evaluated between years, and slight differences were determined (Fig. 4). The 2003 reflectance is slightly higher in the near-infrared (NIR) and slightly lower in the short-wave infrared (SWIR) than the 2002 reflectance of leafy spurge. The mean difference in the reflectance values is approximately 4%.

The difference in reflectance values may be due to different solar zenith angles or that leafy spurge was at a more mature bloom in 2003 than in 2002. The latter

Table 11
Related agreement matrix for the 2002 and 2003 classifications using only the negative validation samples that fell within the extent of both the 2002 and the 2003 imagery

		2002 Classification		
		Correct	Incorrect	Row totals
2003 classification	Correct	123	6	129
	Incorrect	3	0	3
Column totals		126	6	
Number of positives		0	t_{stat}=1.00,	
Number of negatives		132	no significant difference	

The number of negative samples used is indicated.

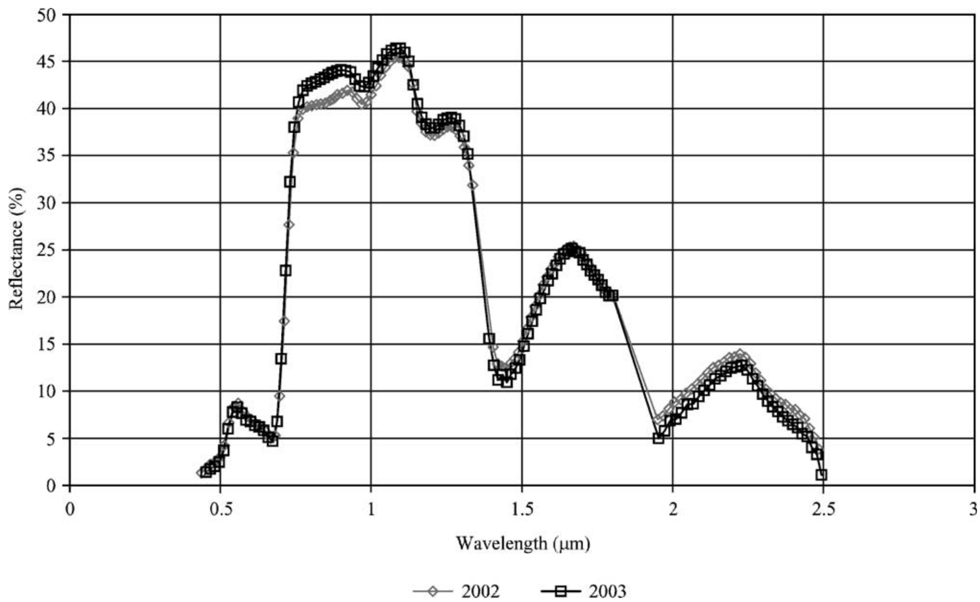

Fig. 4. Mean spectral reflectance of leafy spurge for four non-adjacent pixels consisting of approximately 100% leafy spurge cover from the 2002 and 2003 HyMap data.

hypothesis is supported by differences in the climate between years. The 2002–2003 winter produced a lower snowpack in the Swan Valley than the 2001–2002 winter, resulting in leafy spurge blooming earlier in 2003. Leafy spurge typically blooms in the region from mid-June to mid-July and it is likely that during the timing of the 2003 image acquisition, the leafy spurge was at a more mature bloom than in 2002. The higher peak bloom may have resulted in an internal cell structure that caused higher intercellular reflectance in the NIR. Likewise, higher water content during peak bloom may have caused the increased absorption in the SWIR in 2003. This increased absorption in the SWIR did not strongly affect the classification, which also supports our decision not to spectrally subset the data before processing.

Leafy spurge in the Swan Valley has not been observed to grow at rates faster than ~3 m to 7 m (1 to 2 pixels) in size per year; however, there is the chance that significant enough, growth between 2002 and 2003 allowed for better discrimination in 2003. It is also important to note that there was some unconstrained degree of chemical control of leafy spurge between data acquisition dates, which may have influenced accuracies. In the Swan Valley, land ownership and management is split between typically large, private ranches, Bonneville County, BLM, and USFS. While interagency cooperation can be difficult, local land ownership management practices are nearly impossible to coordinate and document. This results in difficulty in assessing classifier performance, such as false positives that may not actually be false, or false negatives that may actually be true. Ideally, a large-scale field validation could be performed concurrent with image collection; however, this is not always feasible in remote or access-restricted areas.

In addition to the climate and possible changes in growth, the change in leafy spurge reflectance may also have been caused by changes in solar zenith angles and atmospheric conditions between dates. Though both data sets were acquired at the end of June, the 2002 imagery was acquired 40 min before solar noon while the 2003 imagery was acquired 2.5 h before solar noon. The timing of the 2002 image acquisition would normally result in a viewing angle closer to nadir for flat terrain, the whisk broom design of the HyMap sensor coupled with variable topography in Swan Valley are additional factors that would cause inconsistent differences in reflectance magnitudes. Furthermore, during the early part of the 2002 summer, there were a larger number of fires in the Intermountain West than in 2003. Visibility was at least 40 km during the days of data acquisition in both 2002 and 2003; however, there may have been slightly more particulates in the atmosphere due to smoke in 2002. The effects of these particulates and the influence of the atmospheric corrections on smoke particulates across the visible, NIR, and SWIR are likely nonlinear but largely unknown.

4.2.3. Training endmember selection

The selection of training endmembers is a critical component in supervised remote sensing classifications. In our study, we quantified differences exceeding three standard deviations between leafy spurge endmember spectra selected using various techniques, including image extraction and separate calculations for field derived spectra using a hand-held field spectrometer. The endmember differences were likely associated with changes in solar zenith angle, differing stages of phenology, and/or variability in atmospheric corrections. We found that using the most extreme endmembers for classification resulted in a lower accuracy as opposed to using a mean reflectance endmember for training spectra (Mundt et al., submitted for publication). Other work by Bielski (2003) illustrates the importance of spatial and spectral considerations in endmember derivation. Additionally, different classification algorithms and different software packages will deviate slightly from each other.

Because the training site was used for classification of all hyperspectral lines, there is the possibility that the leafy spurge phenology and/or the image quality of the flightlines not containing the training site could have contributed error to the classifications. This is not likely because field observations indicated that the phenology of leafy spurge was consistent within years across the study area. Yet, there is the possibility that the mean endmembers used in the 2002 or 2003 classifications did not fully characterize all of the leafy spurge in the respective geographical extents, resulting in differences in the classification results.

4.2.4. Image processing bias

Producer bias in image classification is nearly impossible to avoid. Typically, processing of remote sensing imagery is iterative, in which a user will make repeated classifications, visually comparing them to expected distributions, adjusting their strategy, and re-classifying the data until an optimal product has been derived. While this iterative process likely produces a higher quality product, it also introduces many opportunities for user bias and lowers the possibility of accurately repeating the classification. This is especially true in MTMF given the non-linearity of the relationship between MF and infeasibility, perpetuated by convex geometrical relationships introduced by mixing of similar spectra (Boardman, 1993). Further bias can be introduced in accuracy assessments as a user begins to question the quality of the source data, geometric precision, and anthropogenic and natural artifacts that may affect classifications. While the methods used in this study are highly consistent between years, it is still important to consider that image processing differences may have influenced the classifications between years.

4.2.5. Field validation bias

Field validation is a significant component of any remote sensing study. In this study, the validation was a stratified random selection of both predicted positive and negative areas, though every effort was made to make the selection of validation samples random. As noted previously, a minimum of 50 GPS-acquired validation samples for each class is suggested. This study collected a total of 364 validation samples and satisfied the criterion of at least 50 samples per class for the method 1 accuracy assessments. However, in methods 2 and 3, this criterion was not satisfied.

The most difficult component of the field validation process was consistent estimation of percent cover of leafy spurge. Estimates of cover have been demonstrated to be highly variable between observers as well as from the same observer over time (McMahan et al., 2003). As previously stated, field estimations of vegetation were made from oblique views. This may provide an overestimation of vegetation cover in comparison to nadir assessments. Equally of importance to note is the use of 2003 and 2004 validation data with 2002 and 2003 imagery. If leafy spurge was at a more mature bloom in 2003 and change in growth did occur, then the validation data may have reflected these differences causing overestimation of populations in 2002.

4.3. Spectral thresholds for detecting leafy spurge

A common desire for land managers when assessing the efficiency of remote sensing classifications is to determine the percent cover of weeds and/or pixel size necessary for detection. In the iterative processing of these data sets, it became apparent that the detectable limits of a target are better described in terms of spectral components than they are in terms of percent cover or pixel resolution. Further, leafy spurge in a different state of maturity than the training pixels (e.g., more mature bloom) may have higher or lower detectable limits. The spectral component threshold for leafy spurge was determined by detailed analyses of the MF and infeasibility scatterplots. Similar to Williams and Hunt (2002), we found that an MF value of 0.1 was the approximate lower threshold for discerning leafy spurge.

Although it is simpler to consider the minimum units of a discrimination for a classifier in terms of spectral components (at the conceptual level), there is also a need to assess the percent cover above which a sensor is able to repeatedly differentiate a target in the field. To assess this, the producer's accuracy of the classification was optimized respective to canopy cover, and the results demonstrate that above 40% cover of leafy spurge, the sensor had consistent accuracy between years (Fig. 5). From this, it is inferred that 40% cover of leafy spurge in a 3.5 m pixel is the minimum required spectral component for *repeatable* detection. This is likely a conservative interpretation of the data due to the reasons discussed in the previous sections (e.g., georegistration, leafy spurge reflectance, endmember selection, processing, and field biases). It is noted that this cover estimation was derived from oblique field estimates, and validation samples may or may not have been entirely contained within one pixel in the image. Further, 40% cover should not be correlated to the lower threshold of detectability (MF value of 0.1). Leafy spurge with lower percent cover within a pixel was also correctly identified (e.g., 10% cover) (Fig. 2), though detection of the lower spectral component values have not demonstrated repeatability.

Pixels with infeasibility values >20 were not considered to contain leafy spurge, and similar to previous research, the selection of significant pixels at MF values lower than 0.1 was not achievable. The relationship between MF and infeasibility is non-linear, locally variable, and has not been discussed extensively in the literature. We found that

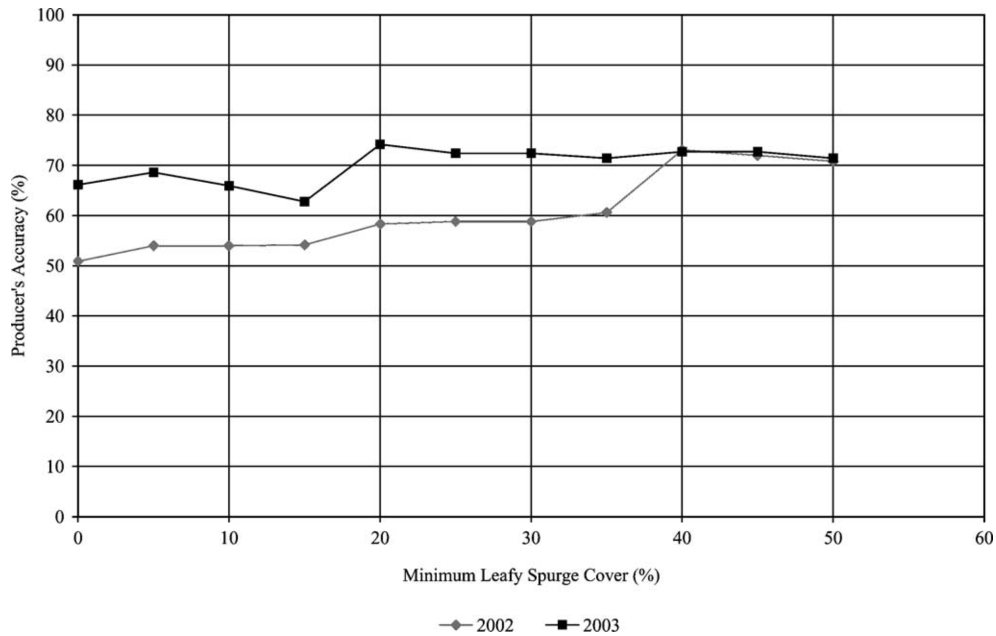

Fig. 5. Plot of minimum percent leafy spurge cover versus producer's accuracy for determining repeatability of percent cover discrimination.

significant pixel selection should be performed cautiously, especially in heterogeneous environments with high potential for spectral mixing (such as in this study, where targets are spatially small). We also found that true positive infestations with lower values of MF were often associated with lower values of infeasibility, while higher values of MF may have higher values of infeasibility. In this study, the selection of block threshold values such as presented in Williams and Hunt (2002) resulted in lower accuracies. This is likely due to the smaller spatial scale of leafy spurge infestations in the Swan Valley in comparison to those in Midwest states.

5. Conclusions

This project demonstrates the ability of high resolution hyperspectral imagery to develop repeatable inventories of small and low percent cover infestations of leafy spurge in riparian and mixed sagebrush-steppe environments. A MF threshold of 0.1 and an infeasibility value less than 20 were determined to be the most appropriate values for delineating leafy spurge in the Swan Valley. These findings can now be applied to image processing for change detection in the future in the Swan Valley and for baseline surveys in ecosystems similar to the Swan Valley. Because leafy spurge was not observed to change dramatically over 1 year in our study area, a second inventory would not need to be performed for several years. The study results indicate that for *repeatable* surveys, leafy spurge cover of at least 40% per 3.5 m pixel is necessary. While the MTMF algorithm was able to detect lower percent cover of leafy spurge in the 2002 and 2003 imagery, it was unable to do so in exact locations in both 2002 and 2003. This is likely a result of georegistration and geometric differences, changes in leafy spurge reflectance, training endmember selection differences, and image processing and field validation biases between years. Changes in leafy spurge reflectance between years are likely explained by slight differences in leafy spurge bloom and time of day of image acquisition. Regardless of these uncertainties, the hyperspectral data and image processing provided results that met the user's accuracy threshold of 70%. High spectral resolution is necessary to differentiate low percent cover infestations of leafy spurge, while high spatial resolution images assist in locating spatially small infestations. While hyperspectral imagery may be significantly more expensive than other imagery sources, it also demonstrates a more useful product than may be derived using other sensors. Therefore, the use of hyperspectral imagery may be the most cost-effective long-term management tool available.

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