A Comparison Between Multi-Spectral and Hyperspectral Platforms for Early Detection of Leafy Spurge in Southeastern Idaho

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ABSTRACT

Knowledge of the distribution of invasive plants and early detection of these species is critical for both short and long-term management of ecological systems. This study compared the quality of products derived from various multi-spectral (Landsat 7, SPOT, and Quickbird) and hyperspectral (HyMap) imaging platforms for early detection of the invasive plant leafy spurge. For each platform, the study compared: 1) detection accuracy, 2) ease of processing, and 3) cost effectiveness. We found that both SPOT multispectral and HyMap hyperspectral data were able to yield reliable detection accuracies (≥70%) with reasonable processing demands. SPOT imagery yielded results which were most cost-effective; however, HyMap data allowed researchers to reliably detect smaller infestations.

Keywords: invasive weeds, *Euphorbia esula*, remote sensing, GIS

INTRODUCTION

Rangelands are a diverse land type covering large amounts of the earth's surface. They support wildlife and vegetation and are used to graze domesticated livestock for the production of meat, wool, and other goods. Recent concerns have centered over the condition of rangelands and their appropriate use. Overgrazing, drought, and weeds have all been cited as causes of rangeland degradation (Du Toit and Cumming 1999). Regardless of cause, few will argue that the condition of rangelands worldwide has declined in the past 50 years, and invasive weeds such as leafy spurge are a common symptom of degraded rangeland condition.

Much previous work has considered the issue of rangeland condition. In 1994, the National Research Council defined rangeland health as "the degree to which the integrity of the soil and the ecological processes of rangeland ecosystems are sustained". In 2002, Pyke *et al.* stated that rangeland health could be determined "by evaluating an ecological site's potential to conserve soil resources and by a series of indicators for ecosystem processes and site stability." In both of these definitions, soil resources play a prominent role in the definition of rangeland health. Additionally, effective hydrologic function is considered an important indicator of healthy rangelands (Pellant *et al.* 2003, Pyke *et al.* 2002); however, it is frequently treated independent of soil stability. In reality, vegetation, the soil upon which it grows, and the water cycling through the system are all intimately linked to rangeland health.

When rangelands are impacted so that one of the elements (soil, vegetative cover, water cycling) is disturbed, the other elements are affected as well. For instance, if 50% of vegetation cover is removed, soil exposure increases. This decreases the potential for water infiltration and increases the potential for erosion (Holecheck *et al.* 2001). As a result, soil water and aquifer recharge is reduced (Thurow and Hester 1997, Kemble and Carroll 2005). Furthermore, the exposed ground is vulnerable to invasive plants, which are frequently highly competitive annuals with little value in rangelands ecosystems.

Invasive plants can be used as an indicator of disturbance and declining rangeland condition (O'Brien et al. 2003). Knowledge of the distribution of invasive plants is important to land stewards who are responsible for developing strategies to remedy the declining condition. In the state of Idaho, invasive plants impact the ecosystem and cost approximately $10 million per year for control treatments alone (Northwest Natural Resource Group, 2003). Because much of Idaho (~70 %) is comprised of large tracts of public land, weeds can invade and quickly spread without detection. For these reasons, the use of remotely sensed imagery to detect and monitor invasive species for proactive management of rangelands is ideal (Lass et al 2005).

This paper compares and contrasts two remote sensing-based invasive plant detection studies focusing on leafy spurge (*Euphorbia esula* L.). The first study used multispectral imagery for leafy spurge detection in the Oxford Resource Area, Idaho and the second study used hyperspectral imagery for leafy spurge detection in the Swan Valley, Idaho. Both study sites are located in southeastern Idaho (Fig. 1) and funded by NASA grants. We used the following evaluation metrics, which were determined through discussions with land managers intending to integrate remote sensing into operational land management practices, to compare the products of both studies:

1) Detection accuracy: The imagery must yield classification user accuracy >70% to be considered reliable for implementation by land managers.
2) Ease of processing: The ability to process the imagery in a timely and repeatable fashion.
3) Cost-effectiveness: Cost of the imagery per square km and considerations for the cost of processing.

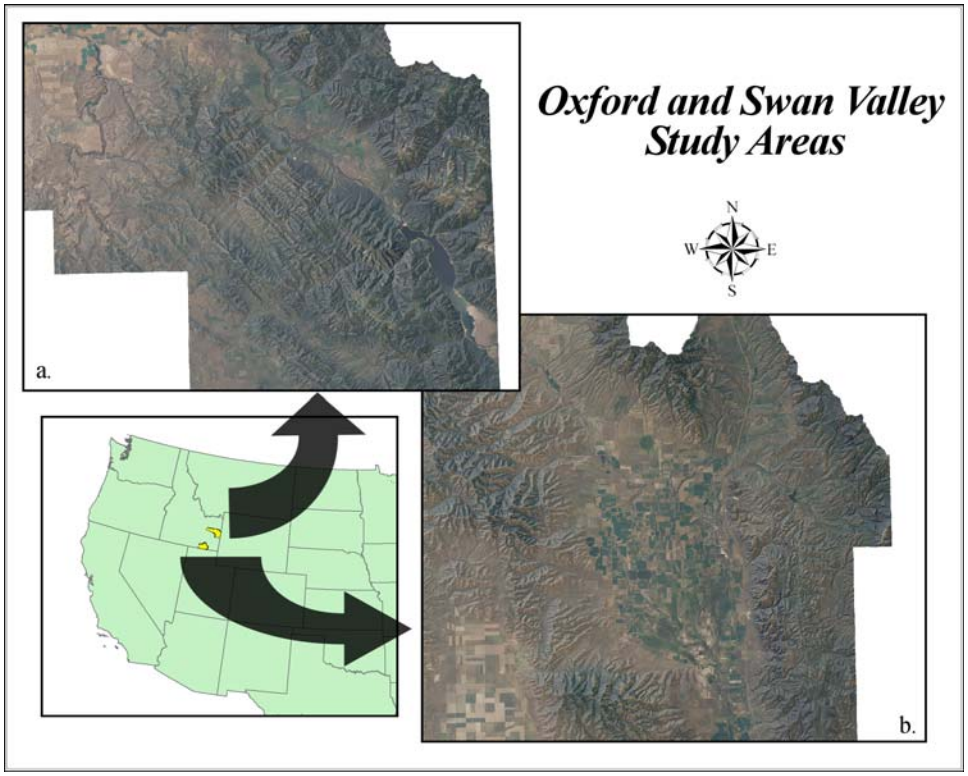

Figure 1. Location of Swan Valley (a) and Oxford Study Areas (b).

METHODS

We evaluated and compared multispectral and hyperspectral imagery for early detection of invasive plants using two discrete projects as case studies. The goal of the first project was to model small and patchy leafy spurge infestations in the Oxford resource area (USDA Forest Service) in southeastern Idaho using multispectral imagery (*i.e.*, Landsat 7, SPOT 5, and Quickbird). The goal of the second project was to model similar leafy spurge infestations using hyperspectral imagery (*i.e.*, HyVista's HyMap, Cocks et al., 1998) in remote areas of Swan Valley in southeastern Idaho to enable land managers to be proactive in weed treatments. In both studies, imagery and field samples were acquired during the summers of 2002 and 2003. Multispectral imagery were processed using Idrisi (Eastman 2003), whereas the hyperspectral imagery were processed using Environment for Visualizing Images (ENVI) version 4.0 software (Research Systems, Boulder, CO).

CASE STUDY 1: MULTISPECTRAL IMAGERY FOR THE OXFORD RESOURCE AREA

Study area

A model predicting the presence of leafy spurge was developed for the Oxford Resource Area in southeastern Idaho (Fig. 1), approximately 90 km southeast of Pocatello, Idaho (42° 5' 33" North, 112° 9' 44" West). These lands are managed by the USDA Forest Service as part of the Caribou-Targhee National Forest. This mountainous area has a mean elevation of 1800 m with peaks rising to 2294 m and is typified by Big Sagebrush (*Artemisia tridentata*), Balsamroot (*Balsamorhiza sagittata* (Pursh) Nutt.), Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco), Mountain mahogany (*Cercocarpus spp.*), choke cherry (*Prunus virginiana* L.), and service berry (*Amelanchier alnifolia* (Nutt.). In this area, numerous leafy spurge infestations were relatively small (<100 m^2) but with 76-95% canopy cover.

Imagery Collected

Three Landsat 7 scenes were collected on 26-June-2002, 12-July-2002, and 28-July-2002, one SPOT scene (10 m) was collected on 12-July-2002, and two Quickbird scenes were collected on 8-August-2002 and 23-June-2003. All images used in this study were acquired during leafy spurge bloom in June 2002 and 2003 (save for the 2002 Quickbird imagery) with pre-processed georectification. Six of the seven Landsat 7 (28.5 meters per pixel (mpp)) bands were used in this study (band 6 was not used). Similarly, SPOT 5 (10 mpp) and Quickbird (2.4 mpp) imagery were acquired for the area, and subsequent processing utilized all multispectral bands. Prior to classification, we tested the image georectification and corrected as necessary using first order polynomial transformation. In all cases, imagery was co-registered with field global positioning system (GPS)-derived control points (18 locations with an accuracy of +/- 0.96 m (95% CI)) and verified using geographic information systems (GIS) datasets (*i.e.* 1:24,000 scale roads). From this, we calculated a root mean square (RMS) error of < 4 pixels in all cases (RMS = 94.80 m for Landsat imagery (approximately 3 pixels), RMS = 2.62 m for SPOT imagery (sub-pixel), and RMS = 4.78 m (approximately 2 pixels) for Quickbird imagery). These errors have the potential to affect classification accuracy, especially when modeling a patchy target. If the target training site is not properly co-registered, then extracted spectral signatures will represent non-target responses and thereby yield poor classification accuracy.

Field Sampling Methods

Initial field data (n = 47) were collected early in the summer of 2003 using a map of known leafy spurge infestations provided by the USFS. Thirty-nine sites were considered leafy spurge training sites with mean percent cover between 51-75% (note: while some sites had greater percent cover of leafy spurge, there were not enough sites to located to support a classification). In addition to these initial sites, an additional 151 training sites were collected in June 2003. Forty-one of these sites were considered leafy spurge training sites while the remainder (n= 110) were considered non-target training sites. The approach of this study was to: 1) iteratively collect field locations of leafy spurge target and non-target sites, 2) perform classification and validation, and 3) add new validation sites ($n \geq 100$ annually) into the training site dataset to increase sample size and better account for the variability within the spectral signature of leafy spurge. This was repeated over the 2003 and 2004 field seasons resulting in a dataset containing 320 sites (103 leafy spurge sites and 217 non-target training sites). At each site, a point location was recorded and attributed with percent cover (using the following cover classes: 0%, 1-5%, 6-15%, 16-25%, 26-35%, 36-50%, 51-75%, 76-95%, and >95%) of leafy spurge, bare ground, shrub, litter, and grass. Points were used because of the small size of many infestation sites. Validated leafy spurge infestations in the study area had an average percent cover class of 36-50% and median cover class of 51-75%. Each training site's cover assessment described land cover for a $100m^2$ area. The location of each training site was acquired using a Trimble GeoXT GPS receiver with WAAS reception turned on. All training sites were occupied for approximately 2 minutes, or until a minimum of 120 positions were acquired by the receiver. All points were post-process differentially corrected using the Idaho State University GIS Training and Research Center Community Base Station located approximately 90 km from the study area. Horizontal positional accuracy of points collected following this protocol was determined to be +/-0.96 m (95% CI). This accuracy statement was determined using repeated control point measurements (Serr et al 2005).

Image Processing Methods

All field training site data were entered into Idrisi (Eastman 2003) where spectral signatures were extracted for leafy spurge and non-target sites. The data used for signature extraction and classification included a stack of normalized difference vegetation index (NDVI), soil adjusted vegetation index (SAVI), and several principal component loaded images (PCA). The PCA images used captured approximately 95% of the total variation within the original imagery bands (*i.e.*, bands 1-4 for Quickbird and SPOT imagery and bands 1-5 and 7 for Landsat imagery).

The extracted signatures were then purified using a threshold of 0.5 (McKay and Campbell 1982). Purification is a process whereby statistical outliers are identified and removed from the training site dataset. Because the multispectral platforms used in this study had different pixel sizes, the number of training sites used for classification also varied. Classification was performed using purified spectral signatures with Landsat imagery (n=69), SPOT imagery (n=85), and Quickbird imagery (n=111). Following purification, all images were classified using maximum likelihood supervised classifications, although minimum-distance to means, and various soft-classifiers were tested but failed to achieve better accuracy (Settle and Drake 1993, Sohn and McCoy 1997). Classification improvements were determined by examining overall, producer's and user accuracy estimates and by examining resulting Kappa statistics. Maximum likelihood has been used effectively by other researchers to classify leafy spurge (Casady et al 2005).

Validation Methods
Once the first modeling iteration was completed (using 47 leafy spurge training sites), researchers field validated the model using 151 independent validation sites (both leafy spurge and non-leafy spurge). The training and validation sites were then combined (n = 198) and used to produce a refined leafy spurge model during the fall/winter of 2003. The second iteration model was then field validated using 122 randomly located sites (within predicted leafy spurge and non-leafy spurge areas) in the summer of 2004. A final model was developed using all 320 sites for classification and validation. While this technique is sometimes considered invalid as it could introduce a bias of artificially inflated accuracies, this is true only when sample size is small. In our case, where the training site sample size was large, we detected no qualitative difference between model accuracies derived in this fashion versus the more traditional (but more time consuming) boot-strap technique (Efron 1979). Spectral signatures for the training sites were then purified and used to produce the final model which was validated using a standard error matrix and Kappa statistic (Titus et al 1984).

Classification Results
Using Landsat imagery, the results of accuracy assessments for leafy spurge presence indicate 82% overall accuracy, 93% producer's accuracy, and 52% user accuracy. In comparison, SPOT imagery produced 95%, 100%, and 74% accuracies (overall, producer's, and user accuracy, respectively) while Quickbird imagery produced 68%, 100%, and 25% accuracies (overall, producer's, and user accuracy, respectively) (Fig. 2). Kappa values were 0.54, 0.84, and 0.27 for Landsat, SPOT, and Quickbird imagery respectively.

CASE STUDY 2: HYPERSPECTRAL IMAGERY USE FOR THE SWAN VALLEY AREA
Study area
This study, beginning in Spring 2002, collected ground-based data and remote sensing imagery in Swan Valley, Bonneville County, Idaho (43° 20' to 43° 40' North, 111° 5' to 111° 35' West). 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 sagebrush-steppe vegetation. The region provides an ideal environment for the spread of leafy spurge seed through water, anthropogenic and animal transportation vectors. In the Swan Valley, there are a few large (>1 ha) leafy spurge 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% (derived from oblique field cover estimation methods).

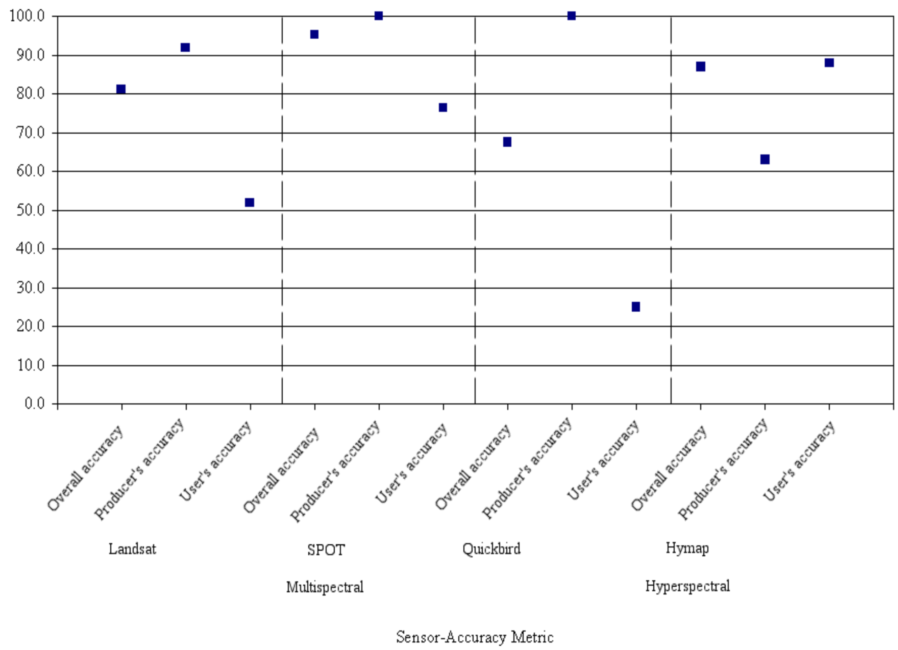

Figure 2. Accuracy of leafy spurge classification using various sensors (2003).

Imagery Collected

HyMap hyperspectral data were collected by the HyVista Corporation over the study area on June 30th, 2002, and again on June 29th, 2003 (Fig. 1), while leafy spurge was in full bloom. The HyMap data consists of 126 bands between 0.45µm and 2.5 µm with a pixel size of 3.5 m x 3.5 m (Cocks et al., 1998). 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.

Field Sampling Methods

The majority of the field sampling took place during the summer of 2003 (for both the 2002 and 2003 imagery datasets) with supplemental sampling during summer 2004. Because leafy spurge has not been observed to spread more than ~3 to 7m (1 to 2 pixels) over a 1 year period in Swan Valley, it is assumed for this study that the use of 2003 and 2004 field data is appropriate for imagery collected in 2002 and 2003 (Glenn et al., 2005). A total of 364 differentially corrected polygons (henceforth referred to as validation samples) were collected which included 323 polygons collected in 2003 and 41 polygons collected in 2004. Of the 364 polygons, 270 were located within the geographical bounds of the 2002 imagery and 214 were located within the geographical bounds of the 2003 imagery. The polygon data included leafy spurge presence/absence and ocular estimates of percent cover when leafy spurge was present. Bare ground, shrubs, and grass were also estimated. Polygon data were considered more desirable than point data in these surveys because in high spatial resolution images the size and shape of reference polygons can be visually compared to the size and shape of an infestation classified in the imagery.

Image Processing Methods

The 2002 and 2003 imagery were preprocessed by HyVista, Inc., utilizing the HyCorr algorithm for atmospheric correction and conversion of radiance to reflectance data. The vendor also geocorrected the images, however a residual georegistration error was estimated as < 15 m using ground control points (Glenn et al., 2005). Minimum Noise Fraction (MNF; Green *et al.*, 1988) transforms were applied to the full spectral range of the reflectance data using a large subset of the entire mosaic to estimate image noise statistics. Leafy spurge endmembers for each year were image derived from the same training area using known geographic locations and comparing to known spectral profiles of leafy spurge (Glenn et al., 2005). For each year's dataset, the MNF transformed reflectance data were classified using the Mixture Tuned Matched Filter (MTMF; Boardman, 1998) algorithm. MTMF has demonstrated a high degree of success in similar studies (Parker-Williams and Hunt, 2002; Dudek et al., 2004). 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 1.0. Pixels with high MF values and low infeasibility values were considered to likely contain leafy spurge. 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 discussion on this methodology is presented in Glenn et al. (2005) and Mundt *et al*. (2005).

Validation Methods

Field validation crews were sent to sites predicted to be either leafy spurge present or leafy spurge absent (selected using a stratified random method) to validate the model. This validation occurred in 2003 and in 2004, but unlike the Oxford study, this was not an iterative process. For the purpose of correcting for georegistration error, both positive and negative GPS validation samples were buffered by 15 m (just over 4 pixels). An error matrix of validation samples (polygons) was constructed following methods presented by Congalton and Green (1999). Kappa statistic was also used to test whether the remotely sensed classifications were better than randomly assigning classifications.

Classification Results

Results of the accuracy assessments for leafy spurge presence demonstrated overall accuracies of 86% and 87% for 2002 and 2003, respectively (Figure 2). For all validation sites, producer's accuracies were 56% in 2002 and 63% in 2003 while user accuracies were 81% in 2002 and 88% in 2003, and Kappa values were 0.58 in 2002 and 0.63 in 2003. When considering only validation sites with at least 40% cover leafy spurge, however, Producer's accuracies rose to over 70% in both 2002 and 2003 (Glenn *et al.*, 2005).

Accuracy Assessment

While it is important to 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. When this project was initiated, local weed managers identified user accuracy (percentage of pixels classified on the map which actually represent that category on the ground) assessment criteria of 70%.

Accuracy assessment in high resolution imagery is a developing science, and recent publications have emphasized the importance of decisions pertaining to expressing the accuracy of thematic classifications (Story and Congalton, 1986; Stehman and Czaplewski, 1998; Congalton and Green, 1999; Foody, 2002; Lopez et al., 2004). In both studies presented here, the approach to accuracy assessment addressed two criteria: 1) quantify the reliability of leafy spurge discrimination; and 2) determine the advantages/disadvantages of improved spatial and spectral resolution for land cover modeling.

RESULTS AND DISCUSSION

CASE STUDY COMPARISON

The resulting accuracies of the two case studies presented above were compared using the metrics of detection accuracy, ease of processing, and cost effectiveness. Different software and classification techniques were employed in this study in order to optimize each case study to yield the best results and take advantage of the software and techniques specifically designed for the imagery. A study comparing multispectral and hyperspectral image classification using one standard classification algorithm such as spectral angle mapper is feasible, however this technique was not considered optimal for either case study.

DETECTION ACCURACY

Only one multispectral platform (SPOT) satisfied the minimum user accuracy requirement specified above (70%). The HyMap hyperspectral sensor also satisfied the minimum user accuracy requirement. Overall accuracy was very similar when comparing SPOT and HyMap. Landsat and Quickbird imagery failed to yield satisfactory user accuracies. The low user accuracy of Landsat is likely due to the patchy nature of leafy spurge relative to the size of each pixel (approximately 900 m^2). The high spatial resolution of Quickbird (2.4 meters) likely reduces spectral confusion, and thus the poor accuracy is hypothesized to be due to co-registration errors between the GPS-acquired field training sites and image georectification. As noted above, the georectification RMS was 5 meters for Quickbird imagery, equating to roughly 2 pixels. While a buffering technique could have been applied to absorb this error, we would have subsequently included a large proportion of non-target features due to the small patch sizes of the target features, thus further complicating the accurate classification of the target. With patchy targets compounded by training site positional error, this level of positional error can help explain the unacceptable user accuracy. In addition, it should be pointed out that the acquisition date of Quickbird imagery was not as well timed, phenologically, as either SPOT or Landsat imagery. Therefore this imagery had a slight disadvantage. However, the disadvantage is considered minimal because all infestations were fairly small and patchy and not readily apparent even when in full bloom stage. Lastly, while the spatial resolution of SPOT 5 and Quickbird imagery varies greatly (10 m and 2.4 m respectively), the spectral resolution is very similar, especially in the green, red, and near infrared bands.

The accuracies from the hyperspectral case study were similar to accuracies derived by Dudek *et al.* (2004), Kokaly *et al.* (2004), and Parker-Williams and Hunt (2002). Using hyperspectral data we were detected 40% cover plots of leafy spurge in both 2002 and 2003. While some areas of 10% leafy spurge cover were detected in either 2002 or 2003, these low percent cover predictions were not repeatable (see a full description in Glenn et al., 2005).

It should be noted that two differences existed in how accuracy was assessed in these case studies. First, the sample size used in the hyperspectral study consisted of 270 and 215 validation samples for 2002 and 2003, respectively (Table 1 reflects the 2003 accuracy, see Glenn et al (2005) for all reported accuracies). In the Oxford study area, the validation sample size was 85 (Table 1). The second difference in accuracy assessment was that the hyperspectral study was validated using polygon ground-truth sites (to absorb georegistration error) whereas the Oxford multispectral study used point ground-truth sites. Another factor that may affect accuracy assessment is the number of samples used in the accuracy assessment.. For example, the larger number of absent polygons with the hyperspectral data may increase the overall accuracy while the small number of leafy spurge presence sites in the Oxford study may positively bias the user accuracy. Because co-registration error was not a concern with SPOT imagery, we doubt that its classification would have been improved by using polygon ground-truth sites. Therefore, the only tangible difference is in the number and distribution of validation sites used.

Table 1. Comparison between leafy spurge classification accuracies derived using SPOT (2002) and HyMap (2003) imagery.

		Ground-truth sites							
		Leafy spurge		Non-leafy spurge		Total		User Accuracy	
		SPOT	HyMap	SPOT	HyMap	SPOT	HyMap	SPOT	HyMap
Model Prediction	Leafy spurge	13	43	4	6	17	49	76%	88%
	Non-leafy spurge	0	25	68	140	68	165	100%	85%
	Total	13	69	72	146	85	214		
	Producer's Accuracy	100%	63%	94%	96%	Overall Accuracy		95%	86%

<u>EASE OF PROCESSING</u>

Processing SPOT imagery was minimal. In general, SPOT imagery was processed very easily, especially when using imagery already corrected for systematic and atmospheric errors. Apart from the basic processing already described above, the SPOT imagery was projected from Universal Transverse Mercator to Idaho Transverse Mercator (using cubic convolution resampling) and georectified to an RMS of 2.62 using a 1st order polynomial (affine) transformation. Classification was then performed using maximum likelihood within Idrisi.

While the processing of the hyperspectral imagery had a steep learning curve, similar processing steps were performed between the multispectral and hyperspectral datasets. Hyperspectral datasets are large, commonly over 1GB, and as such require significant computational resources. Hyperspectral processing is a relatively new application, and much of the methodology that is well defined for multispectral processing is not as clear for hyperspectral applications. As such, much time was spent evaluating methods and procedures while processing hyperspectral data, however once the methods were learned, the image processing was smooth and easily iterated.

<u>COST EFFECTIVENESS</u>

To quantify cost-effectiveness, we developed an effectiveness rating which was the quotient of percent user accuracy (when user accuracy satisfied the minimum requirement threshold (i.e., $\geq$70%)) and cost/km^2. It should be noted that a single square kilometer of imagery cannot be purchased as most all data providers require a minimum acquisition area. When minimum requirements were not met, the effectiveness rating was set to 100. The results of the cost-effectiveness evaluation are given in Table 2.

Table 2. Cost-effectiveness (A / B = C) comparison between satellite platforms for detection of leafy spurge in southeastern Idaho.

Platform		(A) Cost / km^2	(B) User Accuracy obtained	(C) Cost-effectiveness
SPOT	$	0.94	74%	0.01
HyMap	$	150.00	88%	1.70
Quickbird	$	30.00	25%	n/a
Landsat	$	0.01	52%	n/a

CONCLUSIONS

While overall accuracy, producer's accuracy and user accuracy are each important to understand how well a classification performed (Congalton 1991), User accuracy was the focus of this paper as it is a good measure of a predictive model's reliability and subsequent success with a land manager. This study demonstrated that both SPOT multispectral and HyMap hyperspectral imagery can be used to reliably predict the location of a patchy invasive weed such as leafy spurge. One advantage of HyMap hyperspectral imagery is that its pixel size is only 3.5 x 3.5 m. Importantly, we note that HyMap pixels are approximately 85% smaller (12.25m^2 versus 100.00m^2) than SPOT pixels offering a distinct advantage in early detection over numerous other sensors. However, SPOT's cost-effectiveness clearly has an advantage over hyperspectral imagery. In summary, for land management applications, cost- and field-effectiveness, along with time must be considered for each individual project.

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