INVASIVE SPECIES MAPPING USING LOW COST HYPERSPECTRAL IMAGERY

Steven Jay[1] – Research Assistant
Dr. Rick Lawrence[1] – Associate Professor
Dr. Kevin Repasky[2] – Associate Professor
Charlie Keith[2] – Research Assistant
[1]Department of Land Resources and Environmental Science
Montana State University – Bozeman
[2]Department of Electrical & Computer Engineering
Montana State University – Bozeman
128 AJM Hall
Montana State University
Bozeman, MT 59717
steve.c.jay@gmail.com
rickl@montana.edu
repasky@ece.montana.edu
charlie.keith@gmail.com

ABSTRACT

Invasive species monitoring regimes historically have been time consuming, expensive, and inefficient. Remote sensing is a logical approach to monitor invasive species; however, issues of cost, time, and accuracy often hamper current methods. We evaluated the ability of an affordable hyperspectral sensor to detect and classify leafy spurge (*Euphorbia esula*) patches in a rangeland setting. Collection of weekly ground-based images occurred throughout the 2008 summer in order to identify phenological stages at which leafy spurge can be accurately detected and mapped. Weekly images also provided a rare opportunity to evaluate time-series classifications with an imaging spectrometer, which traditionally would be cost prohibitive. We utilized the random forest algorithm for image classification. Classification accuracy initially matched previous leafy spurge detection studies using instruments that are more expensive; multiple date classifications might improve classification accuracy. Our future objectives include incorporation of this technique into both unmanned aerial vehicles (UAVs) and low flying aircraft to create a cost effective monitoring regime of invasive species.

INTRODUCTION

Leafy spurge (*Euphorbia esula*) is a perennial invasive species native to Eurasia (Leistritz et al. 2004; Belcher et al. 1989). Leafy spurge is classified as a poisonous plant, is toxic to most livestock, with the exception of sheep (Leistritz et al. 2004), and can cause dermatitis in humans (Hein et al. 1992; Messersmith et al. 1985). An estimated $26.4 million in grazing losses occur because leafy spurge is unpalatable to most livestock (Leistritz et al. 2004). Leafy spurge best establishes on bare mineral soil (Belcher et al. 1989) and is especially troublesome in non-tilled areas such as rangeland, wildland, and fallow cropland (Leistritz et al. 2004).

Management of leafy spurge is imperative to mitigate grazing and crop losses, but herbicide treatment is often ineffective (Leistritz et al. 2004). Sheep grazing and preventing human caused disturbance that clears the ground to mineral soil are somewhat effective at leafy spurge control (Hein et al. 1992; Belcher et al. 1989). It is often difficult to monitor whether management efforts are working, because leafy spurge grows in very large, dense stands, which can cover large regions that are difficult or expensive to monitor with ground-based methods (Parker Williams et al. 2002; Everitt et al. 1995). Global positioning system (GPS) along with geographic information systems (GIS) have allowed for slightly better mapping and monitoring results, but these techniques require a high initial financial investment (Maxwell et al. 2005) as well as adequate technological skills to be able to work in both the GPS and GIS systems.

Remote sensing is becoming more widely studied as a method of mapping and monitoring invasive species. Remote sensing has been successful detecting invasive species in previous studies (e.g., Lawrence et al. 2006a; Casady et al. 2005), but there are certain limitations associated with the technology. Remote sensing might be the best technique to map and detect invasive species, because images can cover large tracts of land quickly, detect small patches that otherwise might have been missed by ground surveys, and because topography, vegetation, and other ground objects do not obscure lines of sight from air- and space-borne sensors. The major limitations to remote sensing are the high cost to produce images, some sensors (especially satellites) have relatively low spatial and spectral resolution, temporal limitations, accuracy problems, and requirement of a high amount of technical knowledge to analyze and interpret the data.

Remote Sensing for Invasive Species

Two approaches have been suggested for detecting and monitoring invasive species with remote sensing; high spectral resolution with low spatial resolution and high spatial resolution with low spectral resolution (Underwood et al. 2003). High spectral techniques usually incorporate the use of hyperspectral sensors . Hyperspectral sensors are capable of collecting immense amounts of detailed spectral data, but cost, processing power, and user expertise has limited hyperspectral use (Thenkabail, et al. 2004). Invasive species detection and monitoring attempts have met varying degrees of success, but incorporation into widespread monitoring applications is still limited.

Random forest classification has been developed to classify both multispectral and hyperspectral imagery. Random forest classification is an ensemble of classification trees with an improved method of bootstrapping (Brieman 2001). Random forest classification can handle high dimensional data with minimal computational complexity. Random forest is a good approach because it does not overfit data and the use of random parameters keeps the bias low (Brieman 2001). The algorithm also provides an error estimate called the out-of-bag (OOB) error. This error estimate is calculated by classifying the training data not included in the bootstrap and calculating an error matrix on the unused training data (Brieman 2001).

Hyperspectral image analysis to detect leafy spurge has had mixed results. AVIRIS data classified with mixture tuned matched filtering (MTMF) in Devils Tower National Monument in July 1999 achieved an 86.99% accuracy when mapping leafy spurge as the primary cover type (Parker Williams et al. 2004). User's and producer's accuracy were 90% and 84%, respectively. These values were achieved using a threshold value of 0.10 for abundance. The best results of estimating leafy spurge cover were achieved in draws, while uplands tended to be classified more poorly (Parker Williams et al. 2002). MTMF has also been used to detect small infestations of leafy spurge in Swan Valley, Idaho with overall accuracies ranging between 87% and 93% depending on the percent cover of leafy spurge (Glenn et al. 2005). Higher accuracies were achieved, as expected, with higher percent coverage of leafy spurge. Application of the random forest algorithm to map leafy spurge and spotted knapweed in Madison County, Montana achieved 84% overall accuracy for spotted knapweed and 86% overall accuracy for leafy spurge (Lawrence et al. 2006b).

Random forest has had only limited use detecting invasive species, however, it has successfully classified vegetation species in both mixed and homogenous plant communities. Random forest's ability to classify species in mixed and homogenous plant communities makes it particularly interesting, because leafy spurge grows in both mixed plant communities as well as large homogenous stands. Random forest was able to classify mixed forest species with an overall accuracy of 82.8% (Gislason et al. 2006). This study found that random forest outperformed classification tree analysis (CTA) by approximately 4%. Random forest, however, did not result in the highest accuracy when compared to boosting classification algorithms, but random forest did have the advantage of being much faster and easier to perform than boosting (Gislason et al. 2006). Homogenous stands of agriculture crops have been classified with the random forest algorithm in England (Pal 2005). Overall accuracy was 88.37% when using only 100 trees to perform the classification, while an overall accuracy of 88.02% was achieved using 1200 trees. These results demonstrate that random forest is robust against overfitting data.

Use of Multi-temporal Imagery for Classification

Most of the studies above evaluated the ability to map plant species on a single date. This limits the studies' ability to detect plants that might be in different growth states. Yellow hawkweed, for example, was only detected during its flowering stage, which might have affected the accuracy of the study (Carson et al. 1995). Phenological differences could be avoided by collecting images at multiple dates during the growing season. Multi-date remote sensing, however, has been limited because of either cost or satellite temporal resolution. The few studies that have looked at multi-date remote sensing have had mixed results.

Yellow hawkweed and oxeye daisy were classified using three separate dates from early June to mid July. Results found there was significant variability in the percent cover from date to date for yellow hawkweed. The classification showed 8% cover for June 10, 12% cover on June 21, and 6% cover on July 17 for dense patches of yellow hawkweed. Values were more consistent for oxeye daisy, with 2% cover on June 10, 3% on June 21, and 4% on July 17. Researchers, however, did not attempt to use these multiple dates for a single classification (Lass et al.

1997). Authors attributed the change in accuracy during different growth times to poor classifications when yellow hawkweed was past its blooming stage.

High spatial resolution, multi-temporal IKONOS imagery of the Missouri Coteau was classified to map prairie pothole communities (Lawrence et al. 2006a). The authors used classification tree analysis (CTA). with multitemporal imagery. The classification was performed hierarchically, with three levels of discrimination with level 1 being the broadest classification and level 3 being several vegetation classes. Results of the study found that multi-temporal was important for distinguishing similar vegetation types with phenological variability.

Multi-temporal imagery was used to map and classify land cover types in the Greater Yellowstone Ecosystem (GYE) (Lawrence et al. 2001). This study used separate Landsat images from late June and mid August, although they did not compare using single date classifications to multi-date classifications. A hierarchical classification was performed, with level 1 being a broad classification and level 3 being a species and community level classification. Classification tree analysis was performed to classify land cover types and overall accuracies ranged from 96% for the level 1 classification, 79% for the level 2 classification, and 65% for the level 3 classification (Lawrence et al. 2001).

Leafy spurge was detected using a composite of images acquired on different dates to assess if using multiple dates improves classification accuracies (Casady et al. 2005). Classification using multiple dates showed improved classifications compared to single date classifications in June. There was no improvement to classifications when compared to late June and July imagery. This suggests that using a maximum-likelihood classifier only slightly improves using multiple dates for classification (Casady et al. 2005).

METHODS

Image Acquisition

Ground-based images were collected throughout the 2008 Summer beginning on May 20th and ending August 29th. Images were collected in a range setting in southwestern Montana near the town of Norris (fig. 1). The study area is not actively grazed by livestock and herbicides are not used in the area as a control. Biological control agents have been introduced to the area but it is not documented if biological controls have infested the study area. Eleven images were acquired for analysis (Table 1). Images were collected between 9-11am MST on cloud free days to reduce shading effects.

Images were collected with the Resonon Pika II hyperspectral sensor. The Pika II is a compact spectrometer that can be used in a variety of applications. The PIKA II has a spectral range of 400-900 nm, with a band width of 2.1 nm. The cross track field of view is 12^{o} and the bit depth and frame rate is 12 bit at 60 frames per second. The spectroradiometer was placed on a tripod and scanned a hillside across a small ravine (fig. 2). Several images were collected during each field visit and only the best images were selected for analysis.

Table 1. Dates hyperspectral images were collected

Image collection dates
May 20, 2008
June 3, 2008
June 13, 2008
June 19, 2008
June 25, 2008
July 3, 2008
July 9, 2008
July 23, 2008
August 1, 2008
August 15, 2008
August 29, 2008

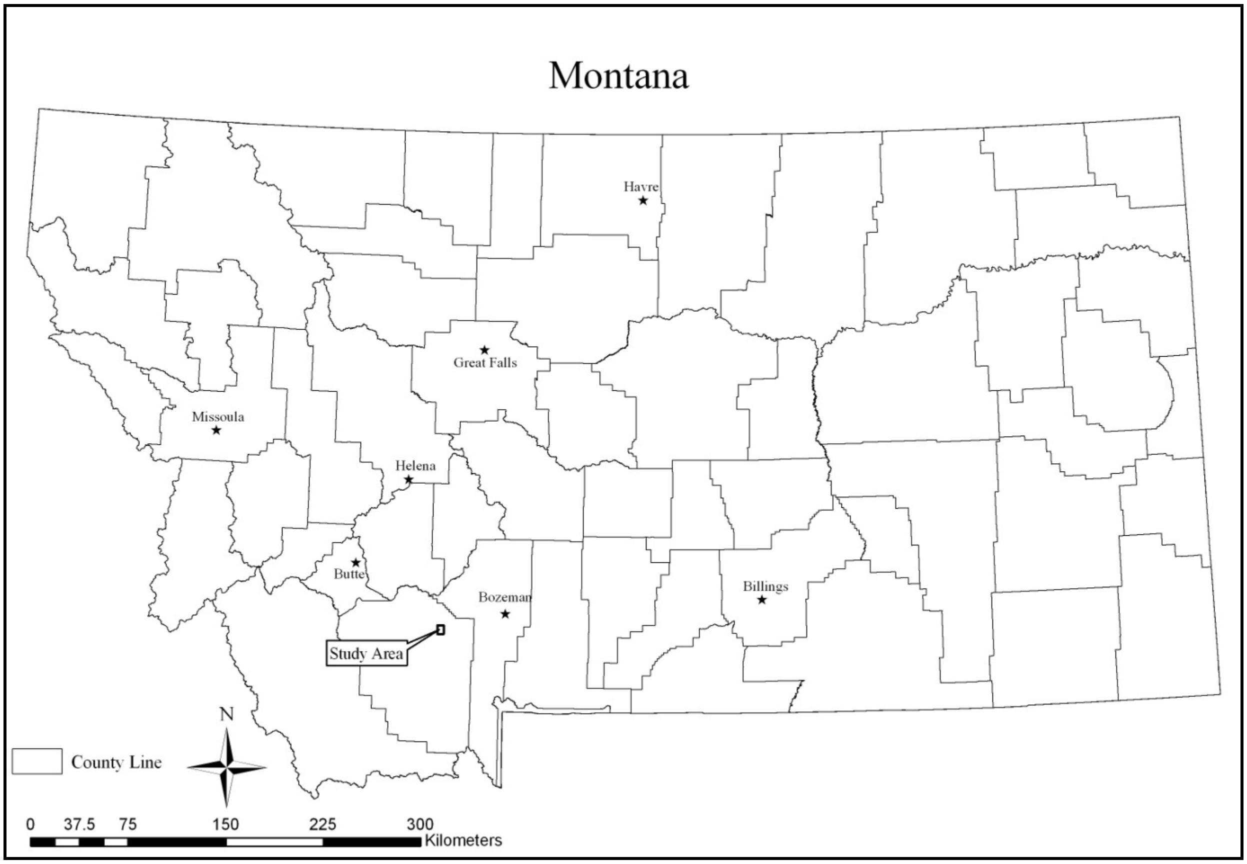


Figure 1. Location map of study area.

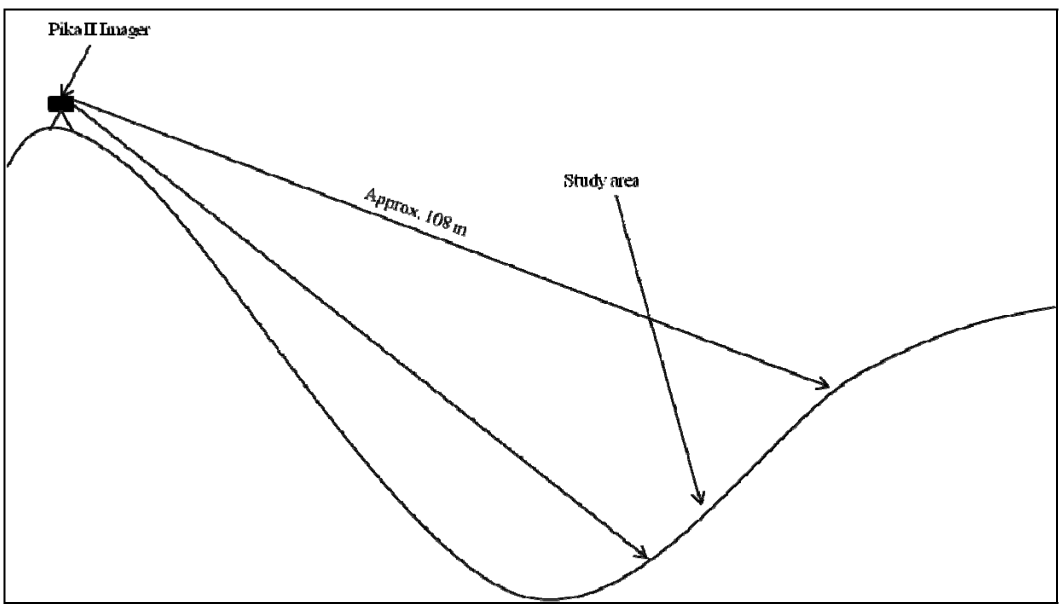


Figure 2. Basic schematic of ground-based study.

Thirty-five training sites were randomly placed across an approximately 100-m wide study area, were measured using sub-meter differentially corrected GPS and marked with a ground flag. Density measurements of leafy spurge at each training site using a one-meter diameter, circular sampling frame were conducted in late July. Leafy spurge densities ranged from 0 plants/m^2 to 174 plants/m^2. Three 2-m x 2-m blue ground tarps were laid out in the middle of the study area to assist with referencing images as well as help calculate pixel resolution. Image resolution was approximately 5 cm.

Image Analysis

Images were clipped to the extent of the study area. Training sites were determined by visually finding ground flags that were placed to mark the centers of training sites. Pixel resolution was determined by measuring the number of pixels between ground reference flags in the image and the distance between GPS points. These resolutions were checked by looking at the number of pixels in the 2-m x 2-m ground reference tarps. After the pixel resolution was calculated, pixels within a 0.5-m radius from the reference flag were extracted and averaged as training data. Pixels were averaged in order to reduce noise and keep the data set manageable. Training sites were then classified as either spurge present or no spurge present.

Analysis of training data was performed using the random forest algorithm (Brieman, 2001) and an error matrix and out-of-bag accuracy was produced for each image. The model was applied to the entire image to produce a classified image. This is done by processing each individual pixel in the image through the random forest model. Each pixel was then classified as either spurge present or no spurge present. Pixels were then paired with their original coordinates to produce a map displaying the areas where spurge was either present or absent.

Multiple date classification analysis was performed by referencing each image to the August 1st image using a single polynomial transformation and nearest neighbor resampling. Masks clipping out the ground reference tarps, training flags, and a juniper tree were used in order to simplify the data. A training set utilizing all of the data from each date was analyzed using random forest and variable importance plots were created. The variable importance plots determine which variables were most important in the development of the model. These variables were then analyzed to determine if a single date's information determined classification or if a range of dates were more important in the classification.

RESULTS AND DISCUSSION

Results from the single date classification show much promise to this technique being an accurate way to detect and monitor leafy spurge in a rangeland setting. Estimated accuracies for images analyzed from May 20th through August 1st range from 72% to 95%. Accuracies indicate that the best time to detect leafy spurge was in early July, when leafy spurge flowering was at its peak; accuracies then decline as the plants began to senesce (Fig. 3). Early classifications show that there was a lot of confusion between classes because most of the vegetation was young and an indiscernible green. As the growing season progressed, leafy spurge was more easily detected with its peak of detection during flowering (Fig. 4).

Class accuracies showed that the spurge class accuracies were highest in July when the spurge was predominately flowering (Table 2). Similar results have been obtained in other hyperspectral leafy spurge studies (see, e.g., Parker Williams et al. 2004; Glenn et al. 2005). The accuracies presented might not reflect actual accuracies because the OOB error estimate assumes random training data, however, in this case tarp and juniper training data was not placed randomly. Further work will mask the juniper and tarps from analysis to remove this issue. These preliminary results were very promising that the inexpensive Pika II spectroradiometer is comparable to more expensive sensors. Multiple date analysis has not yet been performed.

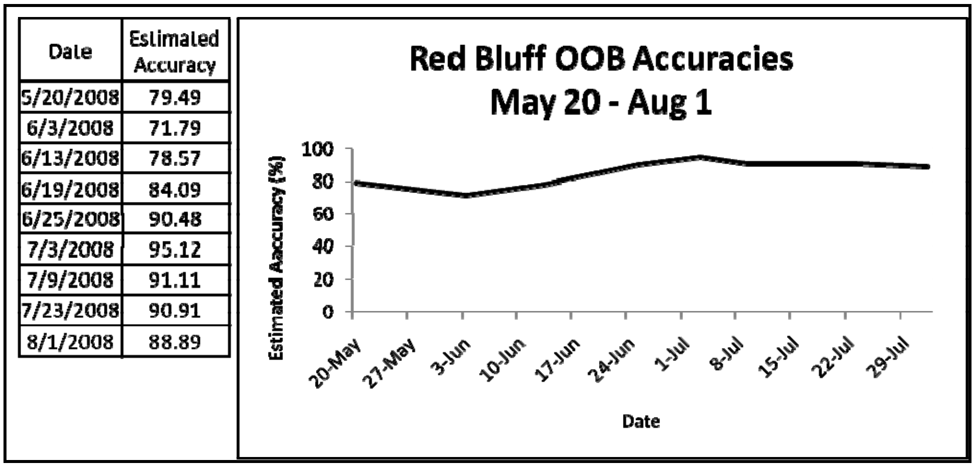


Figure 3. Estimated accuracies for single date classifications.

Table 2: Error matrix for each individual data classification (note: there was no tarp class for June 3 image).

May 20

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	0	0	5	0	0%
Juniper	0	4	0	0	100%
No Spurge	2	0	25	0	92.60%
Tarp	0	0	1	2	66.66%
Producers Accuracy	0%	100%	80.65%	100.00%	**79.50%**

June 3

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	0	0	6	N/A	0%
Juniper	0	3	1	N/A	75%
No Spurge	3	1	25	N/A	86.20%
Tarp	N/A	N/A	N/A	N/A	N/A
Producers Accuracy	0%	75%	78.12%	N/A	**71.79%**

June 13

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	1	0	5	0	17%
Juniper	0	3	1	0	75%
No Spurge	1	1	27	0	93.10%
Tarp	0	0	1	2	66.66%
Producers Accuracy	0%	100%	80.65%	100.00%	**79.50%**

June 19

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	2	1	3	0	33%
Juniper	0	4	0	0	100%
No Spurge	3	0	28	0	90.32%
Tarp	0	0	0	3	100.00%
Producers Accuracy	40%	80%	90.32%	100.00%	**84.09%**

June 25

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	3	0	2	0	60%
Juniper	0	4	0	0	100%
No Spurge	1	0	29	0	96.66%
Tarp	0	0	1	2	66.66%
Producers Accuracy	75%	100%	90.63%	100.00%	**90.48%**

July 3

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	4	0	1	0	80%
Juniper	0	3	0	0	100%
No Spurge	0	0	30	0	100.00%
Tarp	0	0	1	2	66.66%
Producers Accuracy	100%	100%	93.75%	100.00%	**95.12%**

July 9

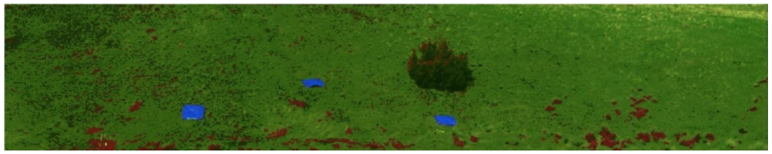
Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	4	1	1	0	67%
Juniper	0	4	0	0	100%
No Spurge	1	0	31	0	96.88%
Tarp	0	0	1	2	66.66%
Producers Accuracy	80%	80%	93.94%	100.00%	**91.11%**

July 23

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	4	0	2	0	67%
Juniper	0	4	0	0	100%
No Spurge	1	1	29	0	93.55%
Tarp	0	0	0	3	100.00%
Producers Accuracy	80%	80%	93.55%	100.00%	**90.91%**

August 1

Class	Spurge	Juniper	No Spurge	Tarp	Users Accuracy
Spurge	3	1	2	0	50%
Juniper	0	4	0	0	100%
No Spurge	2	0	30	0	93.75%
Tarp	0	0	0	3	100.00%
Producers Accuracy	60%	80%	93.75%	100.00%	**88.89%**

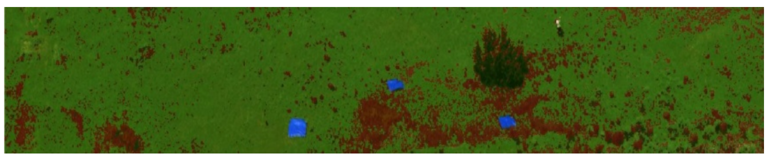


May 20

June 3

June 13

June 19



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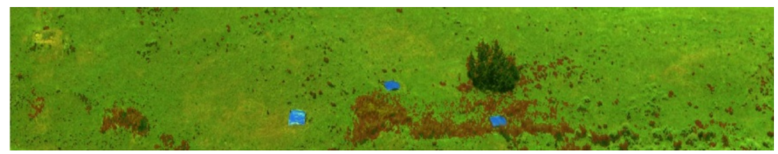
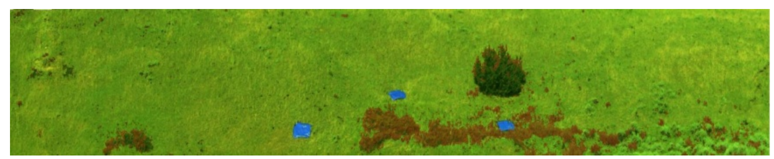
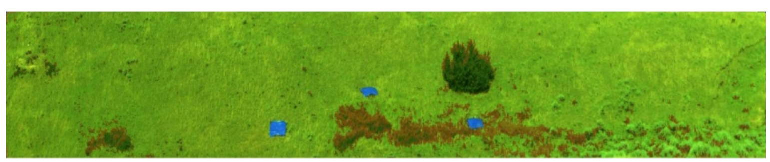


July 3

July 9



July 23



August 1

Figure 4. Classified images for each date. Red represents predicted leafy spurge; blue squares are 2 m x 2 m ground reference tarps. Images are approximately 100 m wide.

It should be noted that these results are preliminary and that accuracies might change as analysis continues. We have noted, in addition to the issues with the tarps and the juniper, that the random sampling of the study area did not include all potential vegetation types. Accuracies for single dates of imagery, however, are comparable to previous studies using high-end instruments such as Probe 1 and AVIRIS. We believe, therefore, that the ability to process multiple dates of imagery in a single classification might result in higher accuracies than have been historically achieved, as multiple flights within a single season have generally not been practical with high-end instruments because of cost and/or instrument availability.

CONCLUSION

The initial results of this study were very promising as the single date detections were comparable to other hyperspectral detection studies. Further analysis and reduction of some errors in the current analysis could lead to results that are even more promising. The development of inexpensive hyperspectral sensors could be a major breakthrough in hyperspectral remote science and lead to widespread application of hyperspectral data. The potential for multi-date hyperspectral analysis and multiple platforms (i.e., UAV and lightweight aircraft) is greatly increased with the development of an accurate, compact, and affordable hyperspectral sensor.

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