DETECTION OF LEAFY SPURGE (*EUPHORBIA ESULA*) USING AFFORDABLE HIGH SPATIAL, SPECTRAL, AND TEMPORAL RESOLUTION IMAGERY

by

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DEDICATION

For my parents, who provided me with the support and opportunity to achieve this goal.

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ABSTRACT

Leafy spurge is a designated noxious weed. Accurate mapping and monitoring of this species are needed to understand leafy spurge's extent and spread. Current methods are based on ground crews who survey patches. Development of an affordable technique to map and monitor leafy spurge would contribute to the control of this species. High spatial, temporal, and spectral resolution imagery was used to classify the amount of leafy spurge present with ground and aerial-based imagery.

A proof of concept study was performed in 2008 using ground-based images of an area infested with leafy spurge. This proof of concept project guided the development of the methods to be used for the 2009 aerial portion of the study. Thirty-five randomly selected reference points were selected in a range area in southwest Montana. These reference points were ground surveyed to record the density of leafy spurge in a 0.5-m radius area around the reference point. Images were captured approximately 108-m from the study area and classified using random forest classification. Multiple images were collected throughout the summer in order to determine at which time period leafy spurge is most easily detected. A classification using multiple image dates was also performed to determine if a time series of images improves classification. Single date accuracies were highest late in the summer with the highest single date classification achieving 83% accuracy. The multiple date classification significantly increased overall accuracy.

Several aerial images were acquired in southwest Montana over the 2009 summer. Fifty randomly selected 2-m x 2-m reference areas were surveyed for percent cover of leafy spurge as well as several other variables. Aerial images were collected at flight elevations between 300-m to 460-m. Classifications were performed using random forest classifier, and both single date and multiple date classifications were performed. Leafy spurge was most accurately detected early and late in the growing season, and significant classification accuracy increases were observed with the multiple date classification. Single date accuracies achieved 90% accuracy in early June, while multiple date classifications achieved over 96% accuracy.

CHAPTER 1

INTRODUCTION

Leafy spurge (*Euphorbia esula*) is a perennial noxious weed in 19 states (University of Georgia 2009) native to Eurasia (Belcher et al. 1989). Leafy spurge is classified as a poisonous plant, is toxic to most livestock, with the exception of sheep, 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 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 because of the high amount of man power needed to survey large plots of land (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.

Satellite and aerial imaging (hereinafter referred to as remote sensing) are becoming more widely studied as a method of mapping and monitoring invasive species. Remote sensing has been successfully used to detect invasive species in previous studies (e.g., Lawrence et al. 2006, Casady et al. 2005), but there are certain limitations associated with the technology. High resolution 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 might have been otherwise 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 very low spatial resolution, temporal limitations, accuracy problems, and requirement of a high amount of technical knowledge to analyze and interpret the data.

Hyperspectral images contain very narrow spectral bands, allowing for continuous measurements of the spectrum rather than discrete measurements. Much more data are held in a hyperspectral data cube than multispectral image. Differentiation between ground objects can be performed much more rigorously with the highly detailed spectral data in a hyperspectral image. Very subtle spectral differences in objects can be detected with a hyperspectral sensor allowing for potentially more accurate classifications. Even with hyperspectral instruments, however, mapping leafy spurge has been most successful when plant phenology best creates spectral distinctions among species (Parker Williams

et al. 2002). Phenology, however, can vary widely over relevant management scales due to landscape variability, making single-date based hyperspectral imaging problematic from a management perspective.

The development of inexpensive, compact, and versatile hyperspectral instruments provides the opportunity to collect hyperspectral data quickly, easily, and affordably, potentially over multiple dates. Images can be obtained in a variety of ways with a compact hyperspectral sensor. This study collected hyperspectral cubes with the PIKA II sensor from the ground as well as low altitude fixed wing aircraft. The same sensor could also be used with unamanned aerial vehicles (UAVs), balloons, and remote controlled aircraft, however, these platforms were not investigated.

Deep time series analysis of hyperspectral data is rare due to the typically high cost associated with contracting hyperspectral flights. In this case, deep time series analysis is the technique of using data from a time series of images to perform a single classification. This technique allows plant phenological change to be taken into consideration during classification. Using an affordable hyperspectral sensor, deep time series analysis and classification of two study areas infested with leafy spurge were performed. The flexibility of the sensor allowed for nearly weekly data collection throughout the growing season for two separate summers. Accuracies achieved generally were equal or better than previous studies using single date classifications performed with sensors that are more expensive.

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CHAPTER 2

REVIEW OF LITERATURE

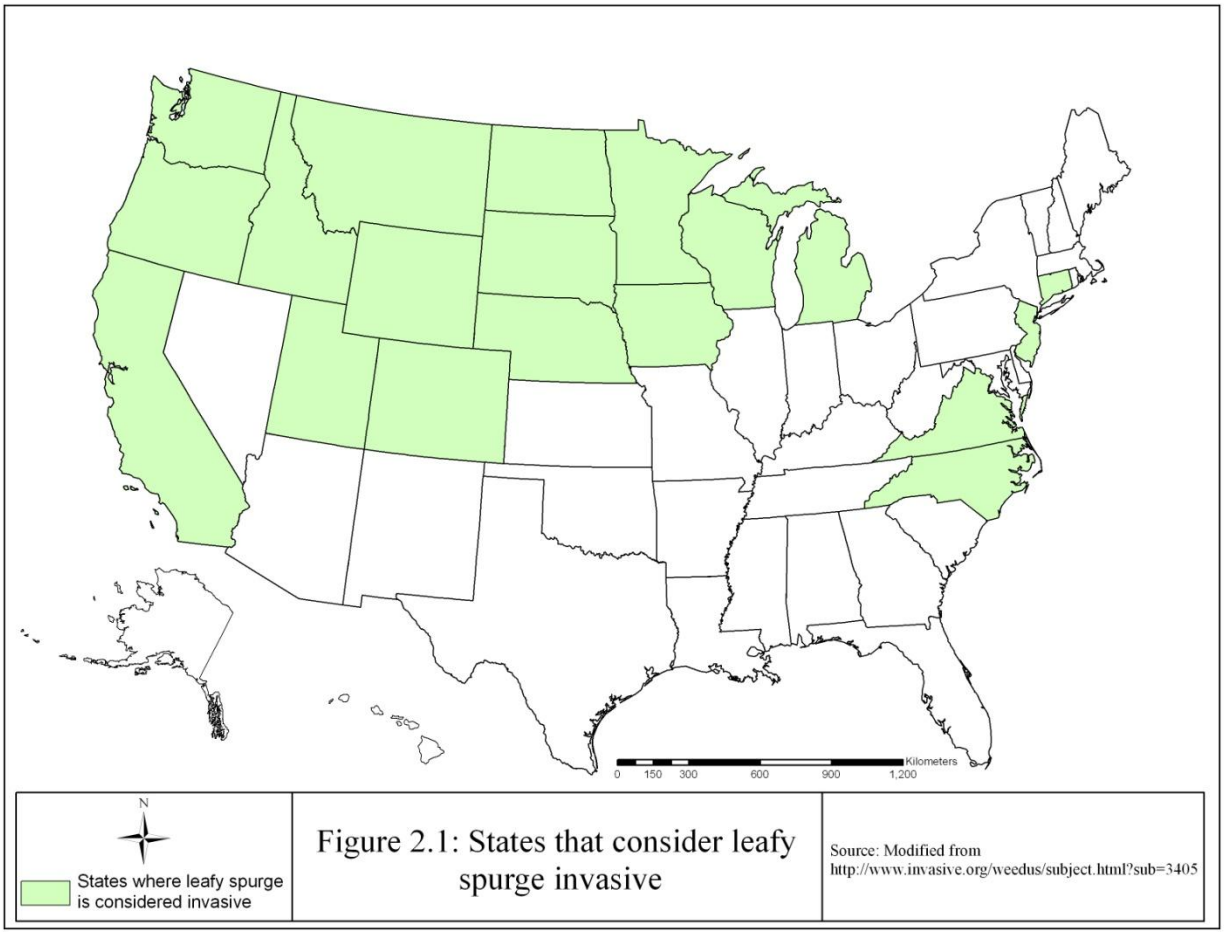
Leafy Spurge Biology

Spatial Extent of Leafy Spurge

Leafy spurge grows on a wide variety of terrain. It has been observed on floodplains, grasslands, ridges, and mountains (Hanson et al. 1933). It is native from Southwestern Europe (Portugal, Spain, and France) to Korea and from Northern Europe (Denmark and Finland) to Pakistan and China (USDA 2009) and was introduced to North America in the 19th Century (Leistritz et al. 2004). Leafy spurge is legally designated a noxious weed species in several states, especially in the northern plains and northwest (Figure 2.1). Leafy spurge is primarily found on untilled, noncropland habitats (Lym 1998), because tillage inhibits leafy spurge growth (Leistritz et al. 2004). These habitats include but are not limited to abandoned cropland, pastures, rangeland, woodland, roadsides, and waste areas (Dunn 1979, 1985; Selleck et al. 1962). Leafy spurge inhabits a wide range of environments from dry to subhumid and subtropic to subarctic, as well as a variety of topographic locations from glacial lakes to sand dunes and throughout temperate zones around the world (Lym 1998).

Leafy spurge is a very aggressive invader, often outcompeting native species when establishing in arid environments. Forage loss, caused by native species displacement, has been documented to decline by as much as 75% in some infested pastures (Lym et al. 1985; Reilly et al. 1979). Topographic changes, such as elevation

and aspect changes as well as water bodies, do not appear to affect leafy spurge spread and an estimated 657,000 ha have been infested in the four state northern Great Plains region of Montana, Wyoming, North Dakota, and South Dakota in 1993 (Leistritz et al. 2004). Infestation estimates are based on the amount of grazing lands that are infested with some leafy spurge, as reported by county weed inspectors (Bangsund et al. 1991).



Physiology

Leafy Spurge generally emerges early in the spring before most other plants (Messersmith et al. 1985). Emergence occurs in March in warmer climates such as Iowa

and Wisconsin and between April and May in colder climates such as North Dakota and Saskatchewan. Stem elongation and vegetative development becomes very rapid as the temperature increases through early June (Messersmith et al. 1985).

Research in Canada found leafy spurge inflorescence begins within one week of emergence (Best et al. 1980), produces pairs of opposite branches, and each branch can produce eight to sixteen branchlets (Selleck 1972). These branchlets all develop the characteristic greenish-yellow bracts from early to late May depending on climate and geography. The bracts are most prominent from late May through June and this is when leafy spurge is most discernable from other plants (Messersmith et al. 1985).

Flowering of leafy spurge typically appears with inflorescence and ends from late June through July (Selleck 1972). Seed development occurs from June through early August and is dependent on temperature and geography. Under certain circumstances, seed can be produced until the first frost (Messersmith et al. 1985). Leafy spurge begins senescence in early July through August during the hottest driest period of the summer. However, flowering may occur in the fall if growing conditions improve. Senesced plants often turn a reddish-brown to red or bluish-green to yellow color in August (Messersmith et al. 1985).

Leafy spurge is pollinated by insects and self-pollination is minimized by different timing between appearance of male and female flowers (Messersmith et al. 1985). Surveys in 1976 showed 196 insect species associated with leafy spurge and pollinators are believed to be soldier beetles (Bakke 1936), ground dwelling ants (Selleck 1972), and honeybees (Messersmith et al. 1985). Once the plant is fertilized, seed

production begins and a high amount of seed is produced when in competition with perennial grasses, indicating how highly competitive leafy spurge can be (Messersmith et al. 1985). Peak seed maturity occurs mid July through the fall (Best et al. 1980, Hanson et al. 1933).

Seed viability generally ranges from 60 to 80%, but depending on the source, viability varies widely (Messersmith et al. 1985). Seed dormancy lasts typically for five years (Selleck 1972), but some instances of dormancy have lasted up to eight years (Bowes et al. 1978). The most important variable in leafy spurge germination has been postulated as temperature (Messersmith et al. 1985). Experiments show that alternating the temperature between 20^{o} and 30^{o} C produced 84% germination, while constant temperatures resulted in 4-74% germination (Hanson et al. 1933). Seeds quickly take up water and increase seed weight up to 45%, resulting in quick germination of leafy spurge.

Leafy spurge is capable of vegetative reproduction with development of both root buds and crown buds, which produce stems. The roots grow deep and can produce buds at any point (Messersmith et al. 1985). These buds overwinter under the soil surface and produce stems in the same location annually (Messersmith et al. 1985). Root reserves supply carbohydrates for long-term survival and observations have shown a sharp decline in available carbohydrates in the spring, before emergence (Arny 1932). Root buds that do not produce stems are sloughed off during flowering and are replaced by new buds. Crown buds can live for several years, though the actual number is not known (Bowes et al. 1978).

Leafy spurge develops toxic latex that inhibits herbicide translocation, making herbicide control difficult (Messersmith et al. 1985). The toxic latex can poison cattle and cause dermatitis in humans, and as a result, cattle tend not to graze in areas heavily infested with leafy spurge (Hein et al. 1992).

Nitrogen, water, and climatic factors all strongly affect leafy spurge growth. Shoot height and weight decrease substantially when nitrogen levels are low (McIntyre 1967). Roots tend to be longer and more numerous under high levels of nitrogen, but this could also be attributed to number of other factors that accompany root growth (Messersmith et al. 1985). Internal competition for water has shown to have a large affect on root bud development (McIntyre 1979). Light conditions as well as soil temperature have both been shown to have an effect on leafy spurge growth. Shoots have been observed in low light levels in oak forests, however the number flowering shoots increases as light intensity increases (Selleck 1972). Leafy spurge also appears to prefer warmer soil temperatures, experiments show plants tend to look more vigorous and healthy when soil temperature was above 13.3^{o} C (Morrow 1979).

Leafy Spurge Control

Most leafy spurge management data is available from Lym's research in North Dakota. Herbicides were traditionally used to control leafy spurge in North Dakota with some success with long-term programs (Lym 1998). Most control however, has shifted to an integrated pest management (IPM) approach. An IPM system for leafy spurge includes mechanical removal, adding competitive grasses to the system, sheep grazing, and biocontrol agents (Lym 1998).

Herbicide treatment with picloram and 2,4-D is the most widely used treatment, and also the most effective herbicide at controlling leafy spurge. This treatment is expensive and takes several years for control to work (Lym 1987). Absorption rates of herbicide are low for leafy spurge with only about 30% uptake of herbicides and only 5% is translocated to leafy spurge roots (Lym et al. 1989). Poor absorption and translocation make herbicide management only effective on a small scale and therefore only small patches should be actively managed with herbicides. Larger infestations are more resilient to herbicide control and therefore an IPM scheme may be the only way to deplete an infestation's carbohydrate reserves (Lym 1998).

Biological control programs were initiated in the 1980s with some success (Lym 1998). The most successful biocontrol agent in North America has been flea beetles from the genus *Aphthona* (Anderson et al. 2003). These flea beetles emerge from the soil in the late summer and feed on leafy spurge leaves (Jonsen et al. 2001). Larvae live under the soil surface and feed on leafy spurge roots causing more damage than the adults who feed on leaves (Lym 1998). In eastern Montana, flea beetle has contributed to a 69% decline in leafy spurge abundance over 14 years (Lesica et al. 2009). Native species however, were slow to recover and overall alpha species diversity only increased 21%, not promising results in the context of vegetation recovery to a more desirable state (Lesica et al. 2009).

Effective control of leafy spurge has also been obtained with sheep grazing. Sheep appear not to have any adverse reactions to grazing leafy spurge (Landgraf et al. 1984). Sheep also do not selectively graze leafy spurge, and tend to prefer leafy spurge

late in the summer when grasses have senesced and leafy spurge is the only green vegetation available (Landgraf et al. 1984). A 98% reduction of leafy spurge was observed in a crested wheatgrass/leafy spurge pasture when continuously grazed by sheep from May to September for five seasons (Johnston et al. 1960). A combination of mowing and grazing reduced leafy spurge by 68% over 2 years and grazing alone reduced leafy spurge by 31% (Helgeson et al. 1939). Only after five years of grazing sheep and goats on leafy spurge in South Dakota did researchers see any decline in leafy spurge cover. When grazers were removed, leafy spurge reappeared at cover levels similar to pre-grazing (Cornett et al. 2006).

The most effective control of leafy spurge appears to be a combination of herbicide treatment, biological controls, and grazing. A combination of all three control methods, provides a cost-effective, long-term strategy that outperforms any single method (Lym 1998). Persistent, well thought-out strategies that deplete carbohydrate reserves in leafy spurge roots as well as early detection and treatment appear to be the best strategy at controlling leafy spurge (Lym 1998).

Remote Sensing

Remote Sensing for Invasive Species

Two approaches have been suggested for detecting and mapping invasive species with remote sensing; high spectral resolution with low spatial resolution and high spatial resolution with low spectral resolution (Underwood et al. 2003). With the development of more powerful computers high spatial and spectral data may be a viable option for invasive species detection and mapping. High spectral resolution techniques usually incorporate the use of hyperspectral spectrometers that record many continuous wavelengths. Hyperspectral spectrometers are capable of collecting immense amounts of detailed spectral data, but cost, processing power, and user expertise has limited hyperspectral use or application (Thenkabail, et al. 2004). Conversely, multispectral sensors use fewer bands, which require less processing power and user expertise and possibly higher spatial resolution. The tradeoff, however, is multispectral sensors cannot record as detailed spectral data as hyperspectral sensors (Thenkabail, et al. 2004). Invasive species detection and monitoring attempts with both types of sensors has met varying degrees of success (Table 2.1), but incorporation into widespread monitoring applications is still limited.

Table 2.1: Sample of reported overall accuracies for various invasive species detection studies. This list is by no means comprehensive.

Author	Species detected	Overall accuracy
Carson et al. 1995	*Hieracium pratense*	76-79%
Lass et al. 1996	*Centaurea solstitialis, Hypercium perforatum*	32-81%
Lawrence et al. 2006A	*Euphorbia esula, Centaurea maculosa*	84-86%
Hamada et al. 2007	*Tamarix* spp.	70-95%
Glenn et al. 2005	*Euphorbia esula*	84-94%
Parker Williams et al. 2002	*Euphorbia esula*	90%
Lass et al. 2002	*Centaurea maculosa*	95-97%
Underwood et al. 2003	*Carpobrotus edulis, Cartaderia jubata*	59-76%
Lass et al. 1997	*Hieracium pratense, Chrysanthemum leucanthemum*	57-75%
Casady et al 2005	*Euphorbia esula*	56-87%

Supervised and unsupervised classifications are two common classification techniques used to process spectral data. Supervised classification uses training data to match similar spectrum into different classes. Unsupervised classifications are necessary when there is no prior knowledge of the classes present on the ground. Areas with similar spectral response are clustered, then classified based on ground reference data. Supervised classification, on the other hand, occurs when classes are defined *a priori* based on field visits or aerial photographs. The known land cover classes are classified utilizing the *a priori* knowledge (Kotsiantis 2007). Detection and classification of invasive species, with supervised and unsupervised classifications, has had varying degrees of success (Carson et al. 1995, Lass et al. 1996).

Yellow hawkweed (*Hieracium pretense*), a noxious weed in Idaho, was detected using aerial imagery of infestations acquired with a large-format charge coupled device (CCD) with a spectral range of 400 nm to 1000 nm in four bands (blue-green, green, and two NIR bands) (Carson et al. 1995). Unsupervised and supervised classifications were performed on the imagery after a principal component analysis (PCA) was applied to the images. Results from the classification showed that both classifications were capable of detecting yellow hawkweed. Supervised classification achieved an overall accuracy of 79% and unsupervised classification achieved 76% overall accuracy. Unsupervised classification, however, predicted less hawkweed and more grass and shrub-forb vegetation than supervised classification in patches with moderate yellow hawkweed infestation. This misclassification resulted because study plots were small and there were only a few moderately infested plots. This study, while successful, was only able to detect hawkweed when it was flowering. This limits its use as a monitoring technique, because there is the possibility of misclassifying hawkweed plants that were not flowering. Unsupervised classifications have also detected yellow starthistle (*Centaurea solstitialis*) and common St. Johnswort (*Hypercium perforatum*) (Lass et al. 1996), but again these classifications were limited to working only when the plants are in bloom.

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 (Lawrence et al. 2006A). Random forest classification can handle high dimensional data with minimal computational complexity. The large number of trees produced requires a fair amount of computer memory

(Gislason et al. 2006). Random forest classification is a good approach because it does not overfit data and the use of random parameters keeps the bias low (Prasad et al. 2006). A drawback to random forest classification is that it is a "black box" approach. With several hundred trees voting on the correct classification, it is impossible to determine what the classification was based upon, thus the "black box" (Prasad et al. 2006). Variable importance, however, does provide some insight into the classification, so this approach is not as black box as neural networks.

Application of the random forest algorithm to map leafy spurge and spotted knapweed (*Centaurea maculosa*) in Madison County, Montana with 3-m to 5-m resolution hyperspectral imagery (128-band) achieved 84% overall accuracy for spotted knapweed and 86% overall accuracy for leafy spurge. Patch sizes ranged from six to 507-m^2 and ranged between 5-50% invasive species cover (Lawrence et al. 2006A). Random forest classification has had limited use detecting invasive species other than leafy spurge and spotted knapweed (e.g. Powell et al. in press); however, it has successfully classified vegetation species in both mixed and homogenous plant communities. The classification algorithm'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 classification was able to classify mixed forest species with 30-m Landsat MSS data achieving an overall accuracy of 82.8% (Gislason et al. 2006). This study found that random forest classification outperformed classification tree analysis (CTA) by approximately 4%. However, random forest classification did not result in the highest

accuracy when compared to boosting classification algorithms (Gislason et al. 2006). Homogenous stands of agriculture crops have been classified with 30-m Landsat ETM+ data with the random forest algorithm in England. 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 classification is robust against overfitting data (Pal 2005).

Mixture tuned matched filtering (MTMF) is a type of spectral mixing analysis. A partial unmixing of each pixel is performed by determining the abundance of a single user-defined endmember. An endmember is a spectrally pure feature usually measured in a controlled environment. The user-defined endmember is maximized in each pixel, and the unknown background response is minimized, thus matching the user-defined endmembers to spectral signatures in the image (Parker Williams et al. 2002). A grey-scale image was produced and provided an estimate of how well each pixel matches the endmember, with the value of 1.0 as a perfect match. This technique has the advantage that other spectral endmembers, which are not important, do not need to be determined (Parker Williams et al. 2002).

Mixture tuned matched filtering has been used to detect invasive species including leafy spurge and tamarisk (*Tamarix* spp.). Tamarisk is an exotic plant that has established widely in arid regions of the western United States (Hamada et al. 2007). Mixture tuned matched filtering was used to detect tamarisk in Southern California with mixed results. Mixture tuned matched filtering classification had significantly lower overall accuracy at determining percent cover when compared to other classification

techniques. The authors suggest that in order for MTMF to be used as a monitoring tool for tamarisk, further data processing or the use of ancillary data may be necessary (Hamada et al. 2002). Results were much better when MTMF was applied to detect leafy spurge. Researchers in eastern Idaho evaluating leafy spurge were able to achieve overall accuracies between 84% and 94%, and all users accuracies were above 70%, which meets the minimum threshold for use by weed managers (Glenn et al. 2005). Mixture tuned matched filtering also was able to detect leafy spurge in two different years with similar success, showing that this technique can be repeated in different years (Glenn et al. 2005). Leafy spurge in Devils Tower National Monument was detected using MTMF with a standard error around 10%. These researchers used ancillary data to help with the classification, unlike the tamarisk study, which might have helped them achieve high classification accuracy (Parker Williams et al. 2002). MTMF does not do as well when there is a mixture of plant species or when leafy spurge is not in dense patches, thus presenting some limitations to its use (Parker Williams et al. 2002).

Attempts to map and detect invasive species with other classification techniques have had more success (Lass et al. 2002). Spotted knapweed in Idaho and Montana was detected along a 2.5-km flight path using spectral angle mapping (SAM) with 3-5% classification error when classification angles were set at 10 to 13^{o} (Lass et al. 2002). SAM is a classification technique that uses the angle created by a known vector of spectral values and a vector of unknown spatial values. The narrower the angle the fewer pixels are used in the classification and the risk of not classifying objects increases (increase omission error). The wider the angle the more pixels are taken into account, but

the chance of overclassification increases (increase commission error) (Lass et al. 2002). In a separate classification study, invasive iceplant (*Carpobrotus edulis*) and jubata grass (*Cartaderia jubata*) were detected in Southern California by processing hyperspectral imagery with a minimum noise fraction (MNF) then applying band ratio indices. This method achieved overall accuracies of 76% and 59% respectively (Underwood et al. 2003). MNF is a data processing technique that utilizes two principal component analyses (PCA), one to remove uninformative data and the other to recombine the data into composite bands for faster processing (Underwood et al. 2003).

Use of Multi-Temporal Imagery for Classification

All of the studies above evaluated the ability to map plant species on a single date. This limits the ability to detect plants that might be in different growth states. Yellow hawkweed, for example, was only detected during its flowering stage and this might have affected the accuracy of the study (Carson et al. 1995). These phenological differences could be avoided by collecting images at multiple dates during the growing season. Using a range of dates to perform a classification may also detect changes in surrounding vegetation phenology and include that information in the classification. Multi-date remote sensing, however, has been limited because of either cost, especially with respect to airborne hyperspectral remote sensing, or satellite temporal resolution. The few studies that have looked at multi-date remote sensing have had mixed results.

Yellow hawkweed and oxeye daisy (*Leucanthemum vulgare*) were classified using three separate dates from early June to mid July (Lass et al. 1997). 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; this was verified using ground-truth images. Poor classification late in the growing season suggests that the best time to detect yellow hawkweed is either pre-bloom or during bloom (Lass et al. 1997).

High spatial resolution, multi-temporal IKONOS imagery of the Missouri Coteau was classified to map prairie pothole communities (Lawrence et al. 2006B). The authors used classification tree analysis (CTA), which is a statistical procedure used to create decision trees. Data are recursively divided into smaller divisions based on rules defined at each node (or branch) (Friedl et al. 1997). Classification tree analysis has advantages over other classification techniques, because it does not rely on any assumptions about the distribution of data, and it can handle many different sources of data as inputs into the decision trees (Lawrence et al. 2004). The algorithm, however, tends to focus on erroneous or outlier data, because it relies on obvious splits in the data, and this can result in misclassifications based on this erroneous outlier data. The algorithm also creates splits one at a time, and the order of the splits might not be optimal for the classification (Lawrence et al. 2004). CTA has also demonstrated its ability classifying data that has a multi-temporal component (Lawrence et al. 2000). The classification was performed

hierarchically, using three levels of discrimination with level 1 being the broadest classification and level 3 being several vegetation classes. Results of the study found that using multi-temporal information in their classification was successful, especially at broad classification scales. Accuracies ranged from 92% for the level 1 classification, 80% for the level 2 classification, and 72% for the level 3 classification (Lawrence et al. 2006B).

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, similar to the prairie pothole study, 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. CTA was used in similar fashion as the prairie pothole study, and overall accuracies ranged from 96% for the level 1 classification, 79% for the level 2 classification, and 65% for the level 3 classification. Authors attribute the low accuracies for the level 2 and 3 classifications to low spatial resolution and class overlaps between GIS layers and spectral layers. Attempts to resolve these issues with other classification techniques were not successful (Lawrence et al. 2001).

Leafy spurge was detected using a composite of IKONOS images acquired on different dates to assess if using multiple dates improved classification accuracies (Casady et al. 2005). Single date classifications were performed on images collected on

June 6, 2001, June 9, 2001, July 17, 2001, June 20, 2002, and September 2, 2002. These single date classifications were combined into a multi-temporal classification. The classification using the 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 suggested that when using a maximum-likelihood classifier there is only some improvement using multiple dates for classification. This improvement was not significant later in the growing season (Casady et al. 2005).

Spectral resolution also plays a role in classification accuracy. Classifications performed at 4-m, 2-m, 1-m, and 0.5-m resolutions showed changes in classification accuracy (Lass et al. 1996). As resolution increased, classification accuracy decreased from 81% to 78% when classifying four different classes in June. The increased error is attributed to gaps in the higher resolution data and high correlation between spectral bands and Yellow Hawkweed (Lass et al. 1996).

Classifications using multi-temporal data have had mixed results. Classification results tended to vary depending on the type of vegetation being mapped, the spatial scale of the classification, and the dates the images were acquired. Few, if any, studies have been performed using hyperspectral images to create multi-temporal classifications, and research needs to be expanded to use higher spectral resolution sensors over multiple dates.

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CHAPTER 3

GROUND BASED LEAFY SPURGE DETECTION

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). There are an estimated $26.4 million in grazing losses in Montana, South Dakota, North Dakota, and Wyoming, 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 has been 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 resolution techniques 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 have limited hyperspectral use and application (Thenkabail, et al. 2004). Typical research in remote sensing of invasive plant species is based in detection or determining only if a species is present or not. This only provides vague

information to land managers, as often there are different amounts of an invasive plant in different places. Determining the density or ground cover of an invasive plant will help land managers prioritize control of invasive plants on their land.

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 and producer's accuracies were 90% and 84%, respectively. 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. 2006A).

Random forest classification has been developed to classify both multispectral and hyperspectral imagery. This technique uses 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. It 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 sample and performing an accuracy assessment on this extra data (Brieman 2001).

Random forest classification has had only limited use for detecting invasive species (e.g. Powell et al. in press); however, it has successfully classified vegetation species in both mixed and homogenous plant communities. Random forest classification was able to classify mixed forest species with an overall accuracy of 82.8% (Gislason et al. 2006). This study found that random forest classification outperformed classification tree analysis (CTA) by approximately 4%. Random forest classification, however, did not result in the highest accuracy when compared to boosting classification algorithms, but random forest classification 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.

All 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 states of growth. Yellow hawkweed, for example, was detected only during its flowering stage, which might have affected the accuracy of the study (Carson et al. 1995). Analysis of a deep time series of images might provide an advantage to single date imagery, because it might be possible to account for phenological changes in plant species. Multi-date remote sensing, however, has been limited because of cost, especially with hyperspectral

imagery that is already very expensive, 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. 2006B). 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 image classification 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).

Utilizing an inexpensive scan-line hyperspectral sensor, weekly images of leafy spurge were acquired in southwestern Montana. This allowed for cost effective monitoring of leafy spurge phenological change throughout the growing season and testing if multiple date classification might increase overall classification accuracy. Three objectives were developed for this proof of concept study:

(i) Develop analysis methodology for aerial based detection;

(ii) Determine what time period provides the highest classification accuracy; and

(iii) Determine a detection threshold and/or develop meaningful classification ranks.

Materials and Methods

Study Site Description

The ground-based proof of concept study was conducted at the Red Bluff Research Ranch located approximately 48 km west of Bozeman, Montana and just outside the small town of Norris, Montana (Figure 3.1). Owned by Montana State University, the Red Bluff Research Ranch (RBRR) is a ranch that is used for researching livestock, particularly sheep. The study site is located in a western portion of the ranch that is remote and is not grazed. Insects were observed grazing on leafy spurge but not identified. Biological control beetles were never released on this portion of the ranch, so it is unclear if these were native or introduced biological control agents.

The study site was selected because it contained a range of leafy spurge

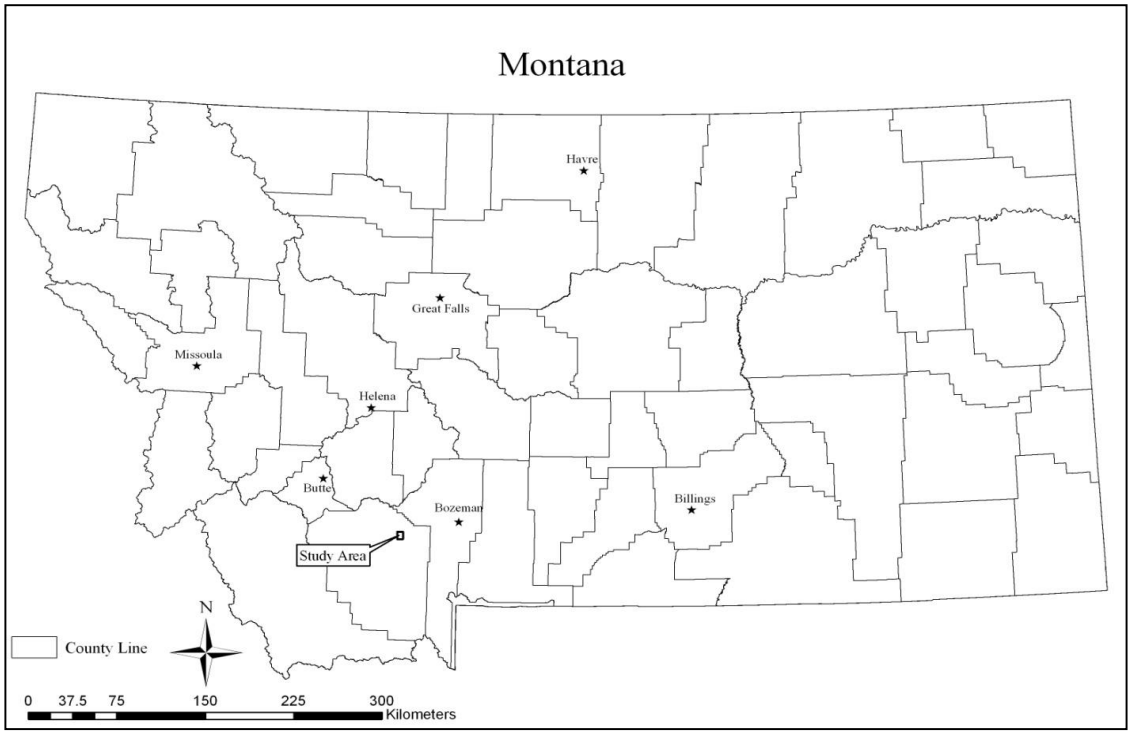


Figure 3.1: Location map of study site.

infestation with no recent anthropogenic disturbance, a large hill separated by a ravine to take images from (Figure 3.2), and relatively easy access by a road. The suitable infestation site contained a range of leafy spurge densities, ranging from areas with no spurge to areas with dense leafy spurge.

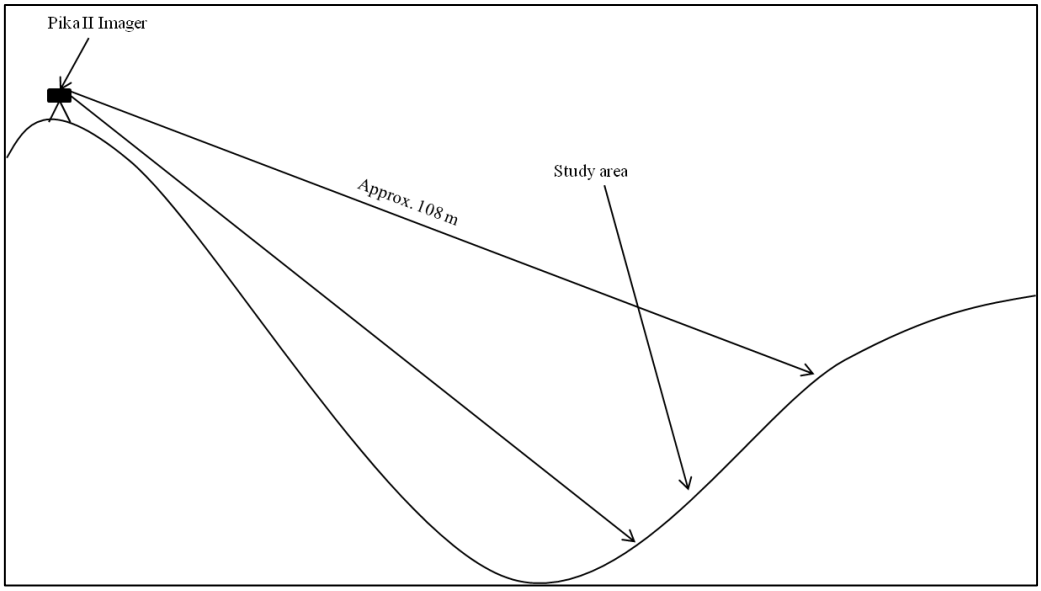


Figure 3.2: Basic schematic of the ground based study site.

The site had a hillside with an eastern aspect between 84^{o} E and 86^{o} E. The hillside slope ranged from 15^{o} on the southern portion, 21^{o} in the middle, and 16^{o} on the north. Elevation ranged from 1600-m above mean sea level (MSL) at the top of the slope to 1580-m above MSL at the bottom of the ravine. The spectrometer was set up approximately 108-m to the east of the middle of the study site at an elevation of 1608-m. The study site was 100-m wide and ranged between 27 m high on the southern boundary and 14 m high on the northern boundary.

Vegetation on the ranch was primarily range species including several grass species, juniper, and to a lesser extent small shrubs. Wildlife that was observed on the RBRR included mule and whitetail deer, antelope, gophers, coyotes, and rattlesnakes. It was possible that elk and game birds were also present within the study site, although they were never directly observed. Whitetail deer have been documented to graze on leafy spurge (Wald et al. 2005). Elk are also suspected browsers of leafy spurge (Wald et al. 2005); however, we observed no noticeable foraging of leafy spurge in our study site.

Data Collection

Eleven images were collected during the summer of 2008 (Table 3.1). Only the images taken from June 19 through August 29 were used in analysis. The first three images were not used because of a change in the experimental design following the June 13 image. The change in experimental design involved marking training sites with marker flags rather than using general training areas, increasing the number of training sites, and surveying the number of leafy spurge stems at each site. As a result, we

Table 3.1: Dates ground based images were acquired.

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

analyzed only eight of the eleven images.

Images were collected between 10 a.m. and 12 p.m. when the sun was most directly above the study site. Multiple images were taken on each date and visual analysis in the laboratory determined which image was most suitable for analysis. Images were selected for analysis if they were focused, contained no smeared pixels, contained the entire study site, and training sites were easily detected.

Thirty-five randomly selected training sites were used to train the random forest model (Figure 3.3). Training sites were delineated with an orange marker flag and leafy spurge stems were counted within a 0.5 m radius of the training flag. Stem counts were performed August 1, 2008 before the leafy spurge began senescence. Training sites were also mapped using a Trimple GeoXH unit with a Trimble Hurricane antenna to collect sub-meter accuracy differential GPS positions.

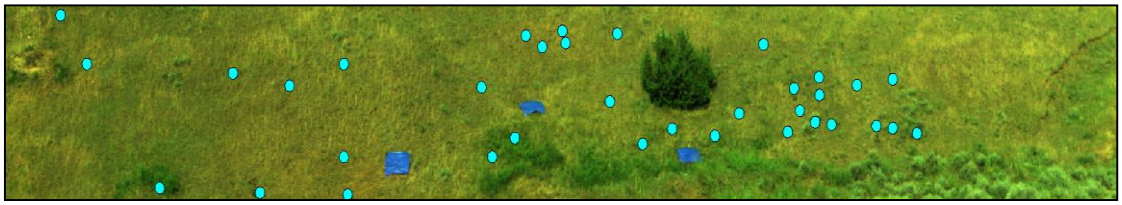


Figure 3.3: Cyan circles indicate the location of the 35 randomly placed training points. Each circle has 0.5 m radius and all leafy spurge stems within the training sites were counted.

After an image was selected and training sites detected, pixel resolution was calculated for each image. Pixel resolution was determined by counting the number of pixels between training sites and dividing the number of pixels by the ground distance between training points. These resolutions were further checked by calculating the

number of pixels contained in the 2-m x 2-m ground reference tarps laid out on the study area. Resolutions for the images were all approximately 0.05 m (Table 3.2).

Table 3.2: Pixel resolution for the ground based images.

Image Date	Resolution (m)
6/19/2008	0.055504
6/25/2008	0.056347
7/3/2008	0.05454
7/9/2008	0.050212
7/23/2008	0.055033
8/1/2008	0.054949
8/15/2008	0.051254
8/29/2008	0.053793

Data Analysis

Image Preprocessing: A first order polynomial transformation was used to georeference the images and root mean square error (RMSE) values ranged from 1 to 2.5. Georeferencing was checked visually to determine all training sites lined up correctly. A mask was applied to all images in order to remove features that were not found naturally in the study site (i.e. training marker flags and ground reference tarps). Areas also included in the mask were, a large juniper tree that was not sampled in any of the training data, areas outside the study area, and areas showing large spectral differences due to changes in the slope of the hill. Each image was then degraded to a 0.3 m resolution to approximate the resolution of an airborne image.

Training data were extracted from each training site after the images were degraded. Two hundred and ten (210) training values were used for the classification.

Each training pixel was matched with the number of leafy spurge stems counted within a 0.5-m radius of the training point. Leafy spurge stem counts ranged from zero stems to over 170 stems/0.5-m^2 at the most densely infested site. Single date classifications and multiple date classifications were performed utilizing the training data.

Single Date Analysis: The random forest classification (Breiman 2001) algorithm was used to classify the images and analysis was performed in S-Plus statistical software. The randomly selected 35 training sites were imported into the software with all 160 bands included. Several classifications were performed for each date. Two different classification intervals were used. The first classification scheme was the quantile classification, which determines class breaks by dividing each class based on the number of stems into the same number of observations within every class. The other classification technique used was the geometric interval classification, which uses a geometric series to create class breaks. A geometric series is a pattern of values in which a constant coefficient can be multiplied by each value in the series. The interval between classes is then calculated based on the geometric series and by calculating the minimum square sum of an element per class, ensuring a similar number of values in each class as well as consistent changes between class intervals. Both of these techniques were used to break the data down to four classes (dense spurge, moderate spurge, low spurge, and no spurge). After the initial classification, classes were combined into either three classes (dense spurge, low spurge, and no spurge), or two classes (spurge or no spurge). A change in the number of classes resulted in the removed class being moved to the next

higher class (e.g., low spurge classification was changed to moderate spurge classification).

Determination of a detection threshold was performed by repeating multiple iterations of a binary classification. Each classification increased the stem count threshold between leafy spurge present and leafy spurge absent. The threshold was increased until a density of 28 stems was achieved. After this point, classification accuracy increase was minimal as well as few training points contained densities higher than this.

Multiple Date Analysis: Multiple date analysis with hyperspectral data is rare due to the high costs of collecting hyperspectral imagery. This study was performed to see if multiple image dates significantly improved classification accuracy. Variable importance plots were used to determine which dates random forest classification relied on most in the classifications. All of the training data from throughout the study period was combined into one data set. A classification was performed by the random forest algorithm in S-plus statistical software. The same classification schemes as the single date classifications were tested and compared to the single date classification out-of-bag (OOB) error estimates.

Results

Single Date Classification Results

Geometric and Quantile Classifications: Classification accuracies for the single date classifications generally increased as the growing season progressed and as the number of classes decreased, although with the geometric classes the kappa statistic consistently decreased between three and two classes (Figure 3.4). When classifying four classes the quantile classification outperformed the geometric classification, however, when there were less than four classes being classified geometric classification outperformed quantile classification, but not significantly ($t = -0.579$, $df = 42.40$, $p = 0.56$) (Table 3.3).

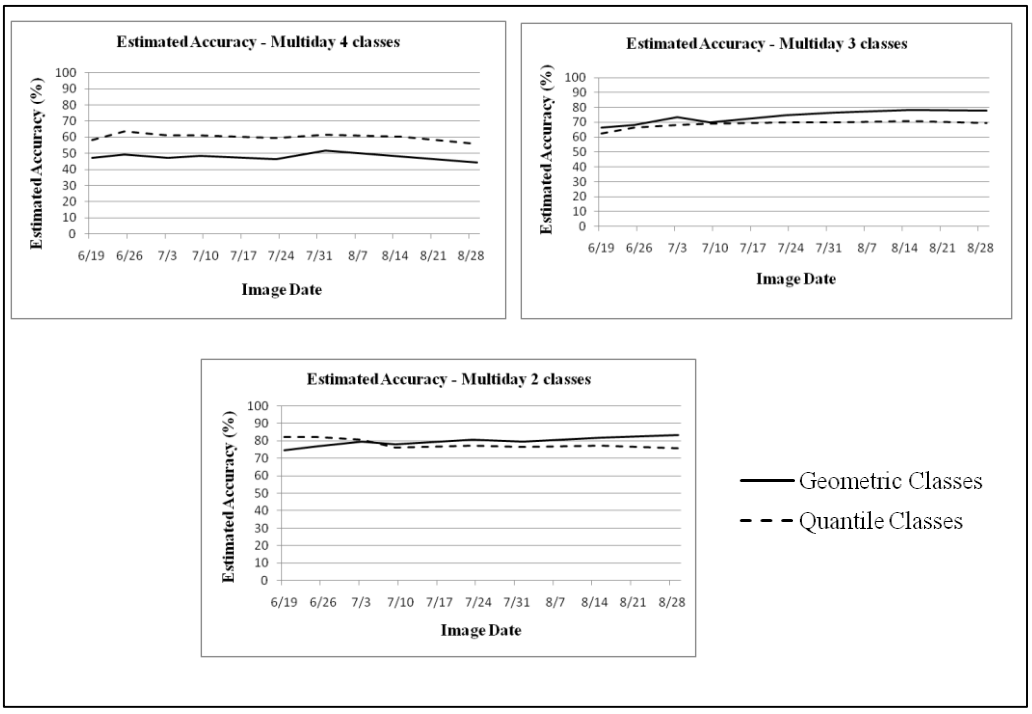


Figure 3.4: Estimated accuracies throughout the study period and for each classification type.

The single date classification with the highest accuracy was the geometric two-class classification on August 29, 2008, which achieved an estimated accuracy of 83.3% (kappa = 0.58). The best three-class classification was the August 15, 2008 geometric classification, which achieved an estimated accuracy of 78.35% (kappa = 0.63). The most accurate four-class classification was the August 15, 2008 quantile classification, which achieved an estimated 63.56% (kappa = 0.51) accuracy (Table 3.4).

Variable importance plots for the geometric and quantile classifications showed high amounts of importance was placed on the 500 to 650 nm portion of the spectrum, as well as, high importance in the NIR portion of the spectrum early in the growing season (Figure 3.5). Reflectance values also changed for areas with no leafy spurge and areas with leafy spurge as the growing season progressed (Figure 3.6). In both cover types, we see that the peak of reflectance occurred on July 9. As the growing season progressed, the NIR reflectance of the vegetation decreased as the plants senesced. The reflectance spectrum for August 29 shows a typical reflectance spectrum for dead or senesced plants.

Threshold Results: Results from the threshold study were analyzed to determine if a certain density of leafy spurge significantly increased classification accuracy. The July 3 image averaged the highest classification accuracy for the threshold study. However, the highest accuracy was the August 29 image. The accuracy for August 29 with the threshold set at 36 stems/0.5-m^2 was 96.4%. The threshold for the majority of the dates occurred between 8-11 stems/m^2, where the average accuracy significantly increased ($t = -10.24$, $df = 99.75$, $p < 0.01$) (Table 3.5)

Multiple Date Classification Results

The results from the multiple date study significantly improved classification accuracy ($t = -3.671$, $df = 26.91$, $p < 0.0011$), especially when attempting to detect different densities of leafy spurge. The four class geometric classification accuracy improved from 51.76% to 76.62% (kappa = 0.66) (Figure 3.7). Multiple date analysis also improved the other geometric classification levels from 73.64% to 81.59% (kappa = 0.68) and 83.33% to 84.58% (kappa = 0.62) for the three and two class classifications, respectively.

Table 3.3: Estimated out of bag (OOB) error and estimated OOB accuracy for quantile and geometric classifications.

Geometric Classes

Image #	Date	# Classes	OOB	Accuracy	Kappa
1	6/19	4	55.65	44.35	0.19
1	6/19	3	33.76	66.24	0.42
1	6/19	2	25.21	74.79	0.38
2	6/25	4	51.93	48.07	0.25
2	6/25	3	31.62	68.38	0.44
2	6/25	2	23.08	76.92	0.38
3	7/3	4	48.24	51.76	0.31
3	7/3	3	26.36	73.64	0.55
3	7/3	2	20.5	79.5	0.51
4	7/9	4	53.73	46.27	0.22
4	7/9	3	29.96	70.04	0.49
4	7/9	2	22.03	77.97	0.48
5	7/23	4	51.68	48.32	0.26
5	7/23	3	25.23	74.77	0.56
5	7/23	2	19.37	80.63	0.51
6	8/1	4	52.94	47.06	0.24
6	8/1	3	23.58	76.42	0.6
6	8/1	2	20.52	79.48	0.5
7	8/15	4	50.59	49.41	0.27
7	8/15	3	21.65	78.35	0.63
7	8/15	2	18.18	81.82	0.54
8	8/29	4	52.98	47.02	0.24
8	8/29	3	22.07	77.93	0.61
8	8/29	2	16.67	83.33	0.58

Quantile Classes

Image #	Date	# Classes	OOB	Accuracy	Kappa
1	6/19	4	44.1	55.9	0.41
1	6/19	3	37.33	62.67	0.38
1	6/19	2	21.53	82.06	0.56
2	6/25	4	39.55	60.45	0.47
2	6/25	3	33.8	66.2	0.44
2	6/25	2	17.94	82.06	0.56
3	7/3	4	38.57	61.43	0.47
3	7/3	3	31.61	68.39	0.44
3	7/3	2	19.46	80.54	0.64
4	7/9	4	40.48	59.52	0.48
4	7/9	3	30.97	69.03	0.49
4	7/9	2	24.05	75.95	0.61
5	7/23	4	38.87	61.13	0.48
5	7/23	3	29.97	70.03	0.51
5	7/23	2	22.6	77.4	0.54
6	8/1	4	38.87	61.13	0.48
6	8/1	3	30.21	69.79	0.5
6	8/1	2	23.32	76.68	0.53
7	8/15	4	36.44	63.56	0.51
7	8/15	3	29.02	70.98	0.52
7	8/15	2	22.8	77.2	0.54
8	8/29	4	41.85	58.15	0.44
8	8/29	3	30.53	69.47	0.5
8	8/29	2	24.19	75.81	0.51

Table 3.4: Estimated OOB accuracies (%) for all images and classifications ordered from highest accuracy to lowest. G= geometric classification; Q = quantile classification.

Image #	Date	# classes	oob	accuracy
G8	8/29	2	16.67	83.33
Q1	6/19	2	21.53	82.06
Q2	6/25	2	17.94	82.06
G7	8/15	2	18.18	81.82
G5	7/23	2	19.37	80.63
Q3	7/3	2	19.46	80.54
G3	7/3	2	20.5	79.5
G6	8/1	2	20.52	79.48
G7	8/15	3	21.65	78.35
G4	7/9	2	22.03	77.97
G8	8/29	3	22.07	77.93
Q5	7/23	2	22.6	77.4
Q7	8/15	2	22.8	77.2
G2	6/25	2	23.08	76.92
Q6	8/1	2	23.32	76.68
G6	8/1	3	23.58	76.42
Q4	7/9	2	24.05	75.95
Q8	8/29	2	24.19	75.81
G1	6/19	2	25.21	74.79
G5	7/23	3	25.23	74.77
G3	7/3	3	26.36	73.64
Q7	8/15	3	29.02	70.98
G4	7/9	3	29.96	70.04
Q5	7/23	3	29.97	70.03
Q6	8/1	3	30.21	69.79
Q8	8/29	3	30.53	69.47
Q4	7/9	3	30.97	69.03
Q3	7/3	3	31.61	68.39
G2	6/25	3	31.62	68.38
G1	6/19	3	33.76	66.24
Q2	6/25	3	33.8	66.2
Q7	8/15	4	36.44	63.56
Q1	6/19	3	37.33	62.67
Q3	7/3	4	38.57	61.43
Q5	7/23	4	38.87	61.13
Q6	8/1	4	38.87	61.13
Q2	6/25	4	39.55	60.45
Q4	7/9	4	40.48	59.52
Q8	8/29	4	41.85	58.15
Q1	6/19	4	44.1	55.9
G3	7/3	4	48.24	51.76
G7	8/15	4	50.59	49.41
G5	7/23	4	51.68	48.32
G2	6/25	4	51.93	48.07
G6	8/1	4	52.94	47.06
G8	8/29	4	52.98	47.02
G4	7/9	4	53.73	46.27
G1	6/19	4	55.65	44.35

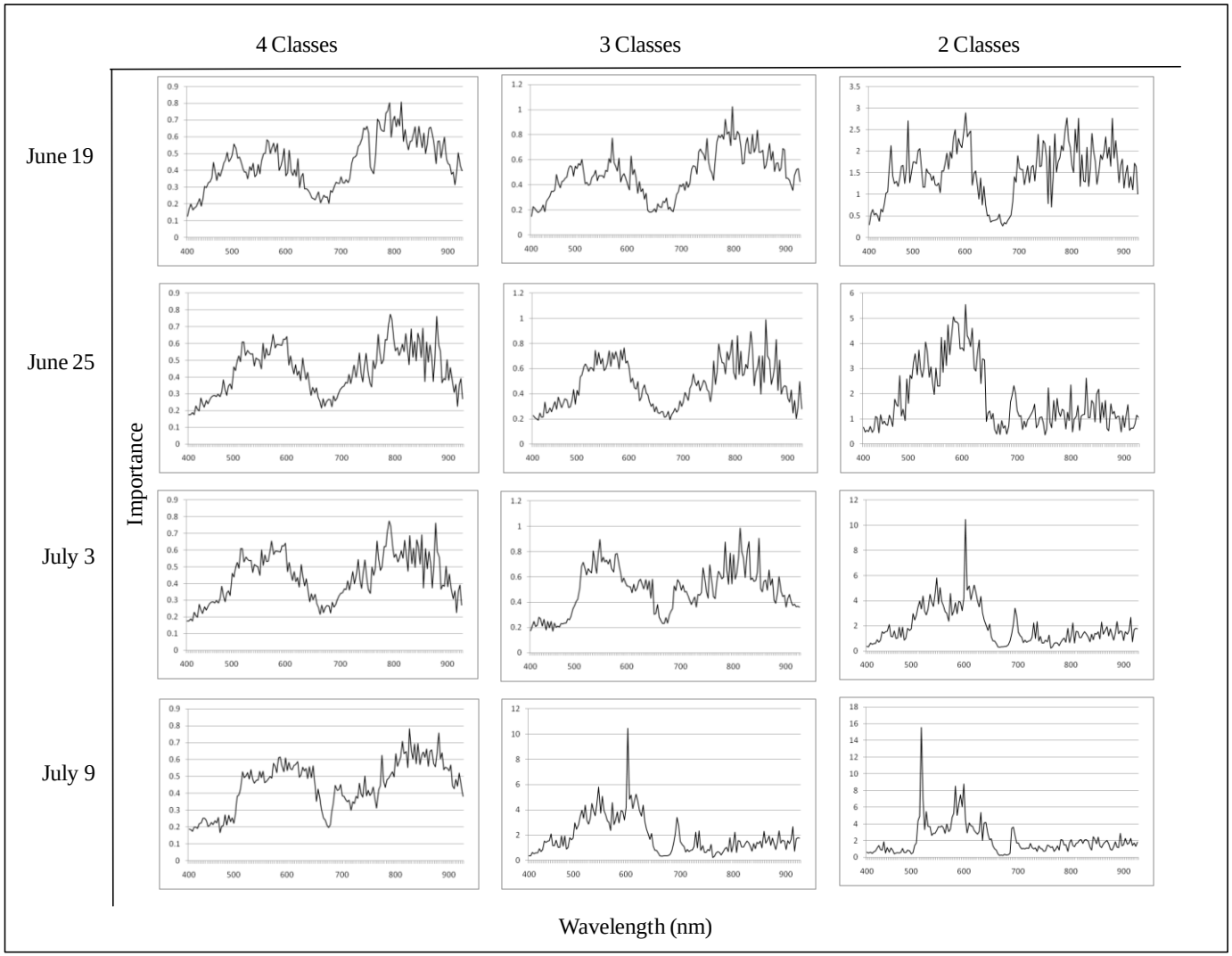
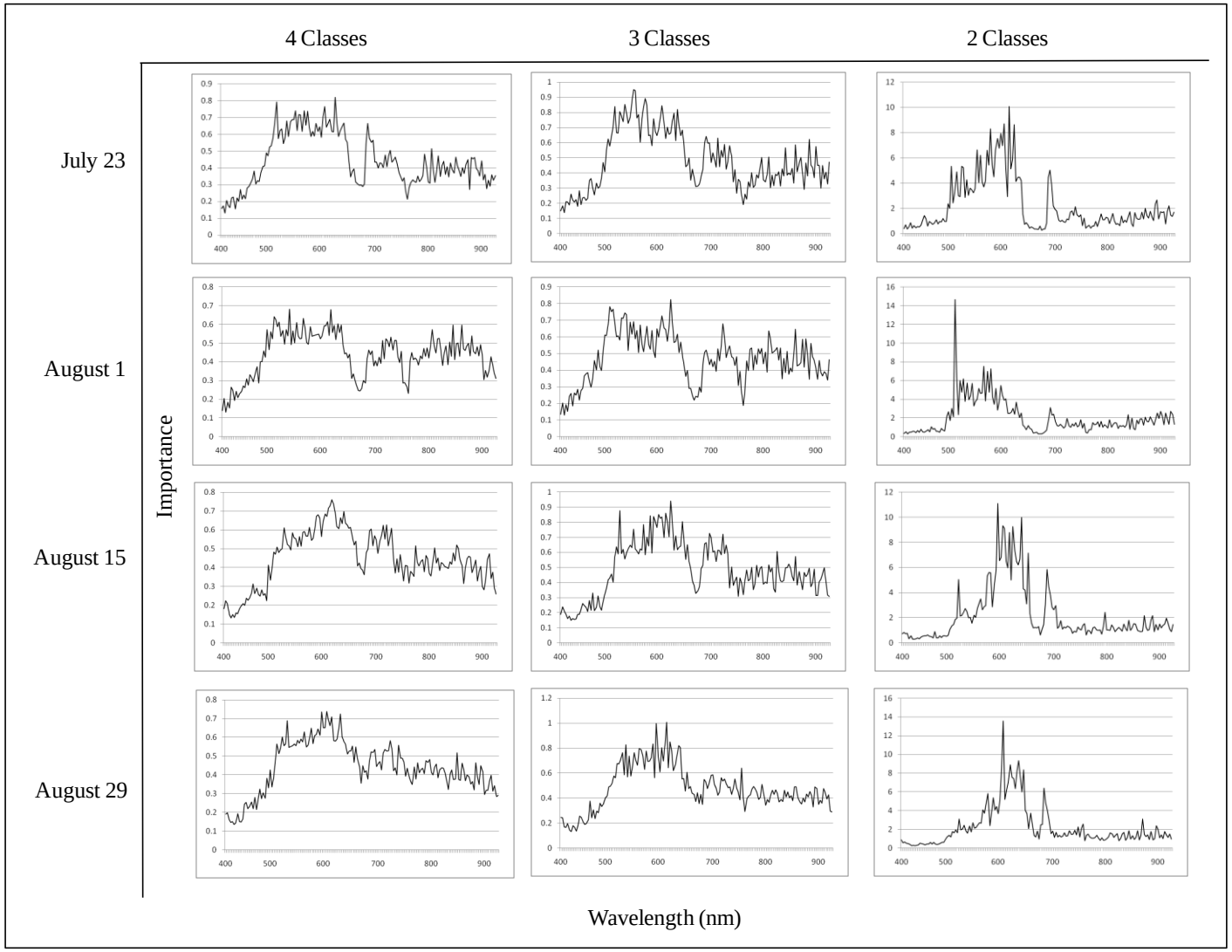


Figure 3.5: Variable importance plots for each classification scheme. Variable importance is on the Y-axis and wavelength in nm is on the X-axis.

Figure 3.5: Continued



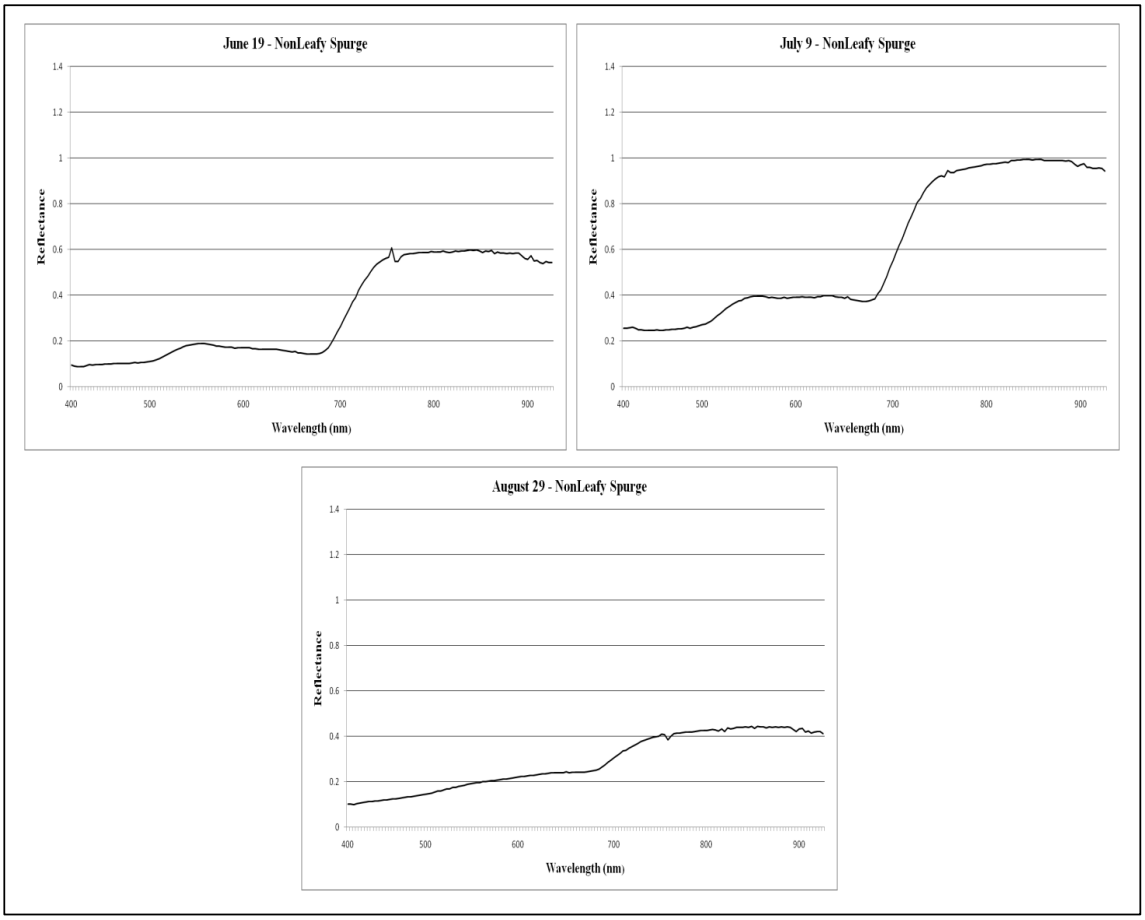


Figure 3.6: Sample spectrums of the four geometric classes from three different times during the growing season (June 19, July 9, and August 29).

Figure 3.6: Continued

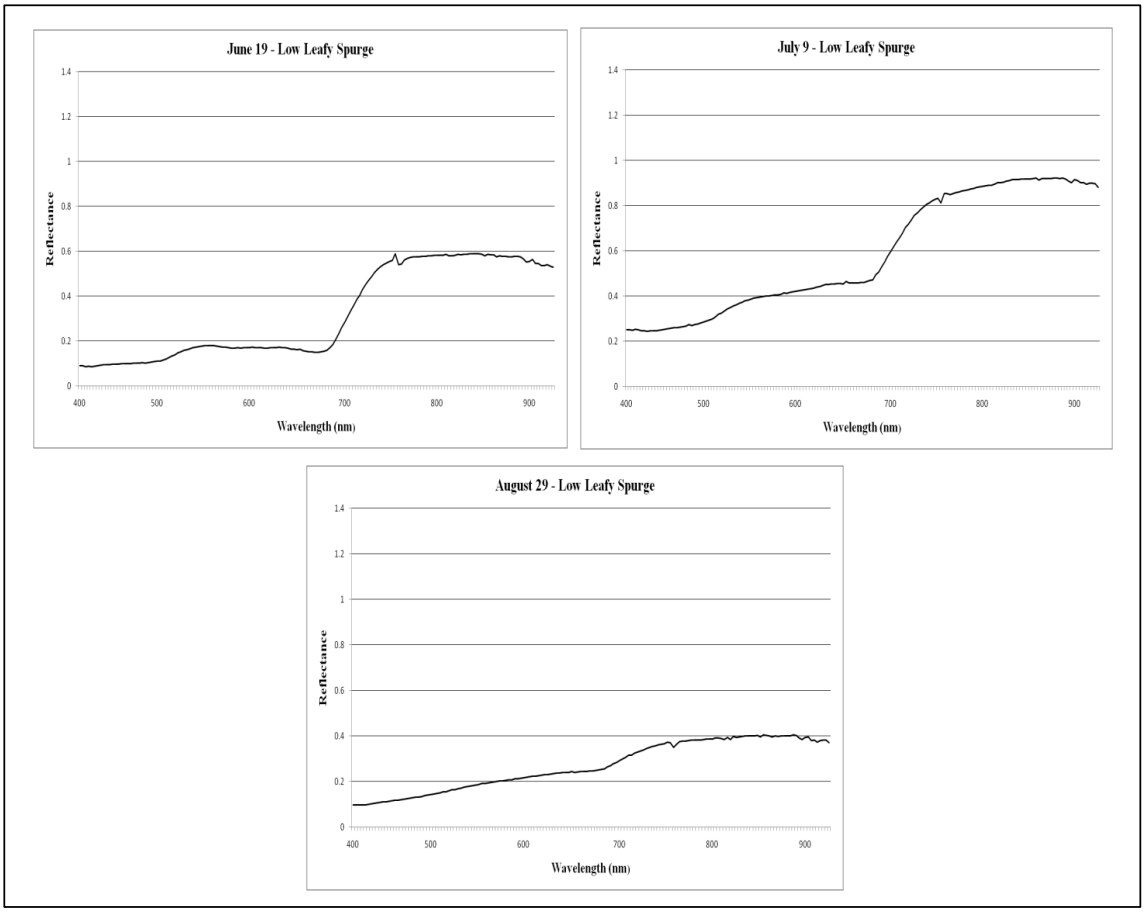


Figure 3.6: Continued

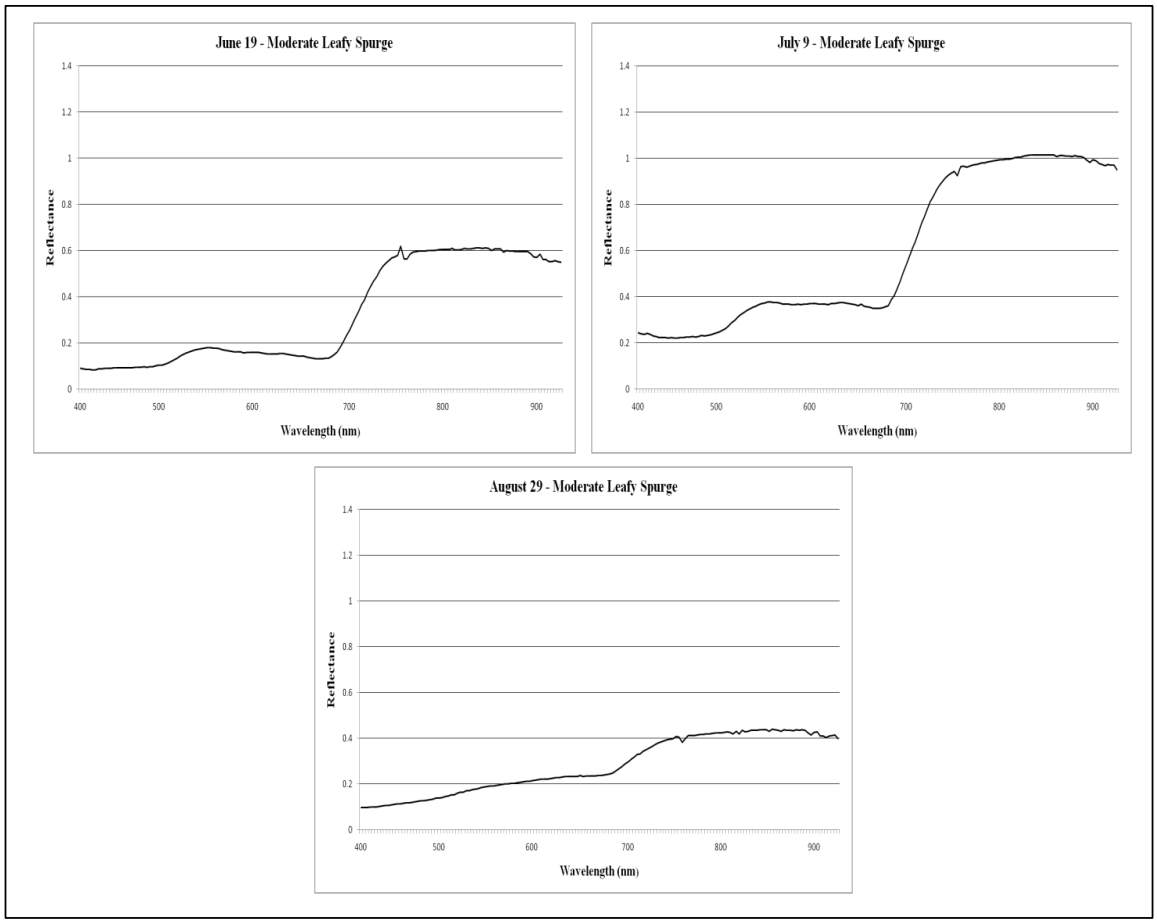


Figure 3.6: Continued

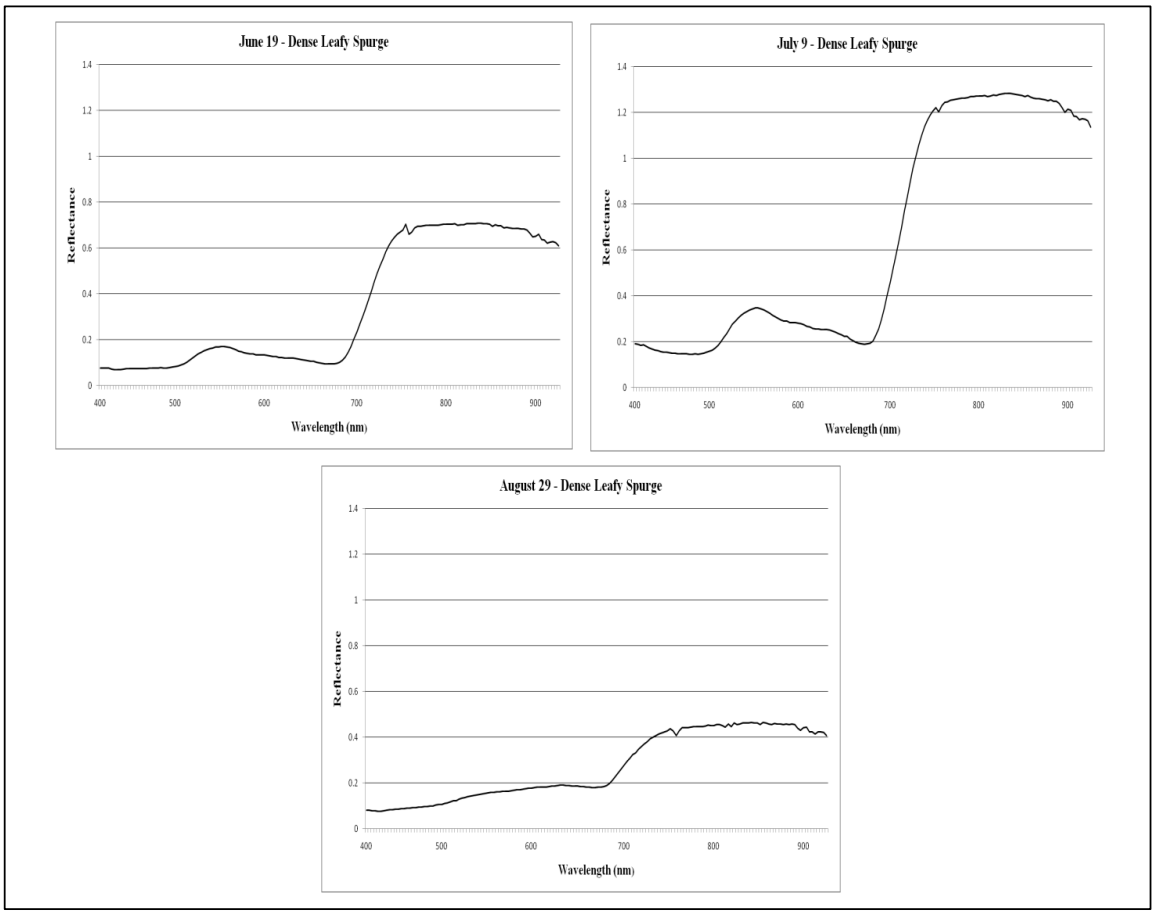


Table 3.5: Estimated OOB accuracies for the threshold study. Note the increase in accuracy as the threshold increases.

Count	stms/m2	6/19/2008	6/25/2008	7/3/2008	7/9/200	7/23/2008	8/1/2008	8/15/2009	8/29/2009
0	0	75.21%	77.00%	78.66%	77.09%	80.63%	79.04%	81.82%	85.14%
1	1	75.21%	74.79%	80.33%	76.65%	80.63%	79.04%	80.95%	84.23%
2	3	75.21%	79.49%	83.68%	75.33%	76.58%	79.04%	78.79%	82.43%
3	4	75.21%	79.49%	78.24%	79.30%	71.17%	75.11%	73.16%	73.87%
6	8	76.50%	79.49%	78.66%	78.85%	73.87%	75.98%	73.59%	74.77%
7	9	82.10%	84.62%	80.33%	82.82%	75.68%	80.79%	79.65%	81.08%
9	11	84.62%	85.90%	84.94%	87.67%	85.14%	86.03%	84.42%	83.33%
11	14	83.76%	85.90%	87.87%	89.43%	84.68%	87.34%	87.45%	85.59%
12	15	86.32%	92.74%	92.47%	89.87%	84.68%	86.46%	86.15%	86.04%
15	19	90.17%	94.02%	92.05%	89.87%	88.29%	91.27%	88.74%	89.64%
18	23	88.03%	92.31%	90.79%	91.19%	91.89%	93.45%	90.48%	91.44%
19	24	90.60%	93.59%	93.72%	94.71%	94.14%	93.89%	95.24%	95.05%
28	36	92.70%	93.59%	93.72%	94.10%	95.50%	95.63%	95.24%	96.40%

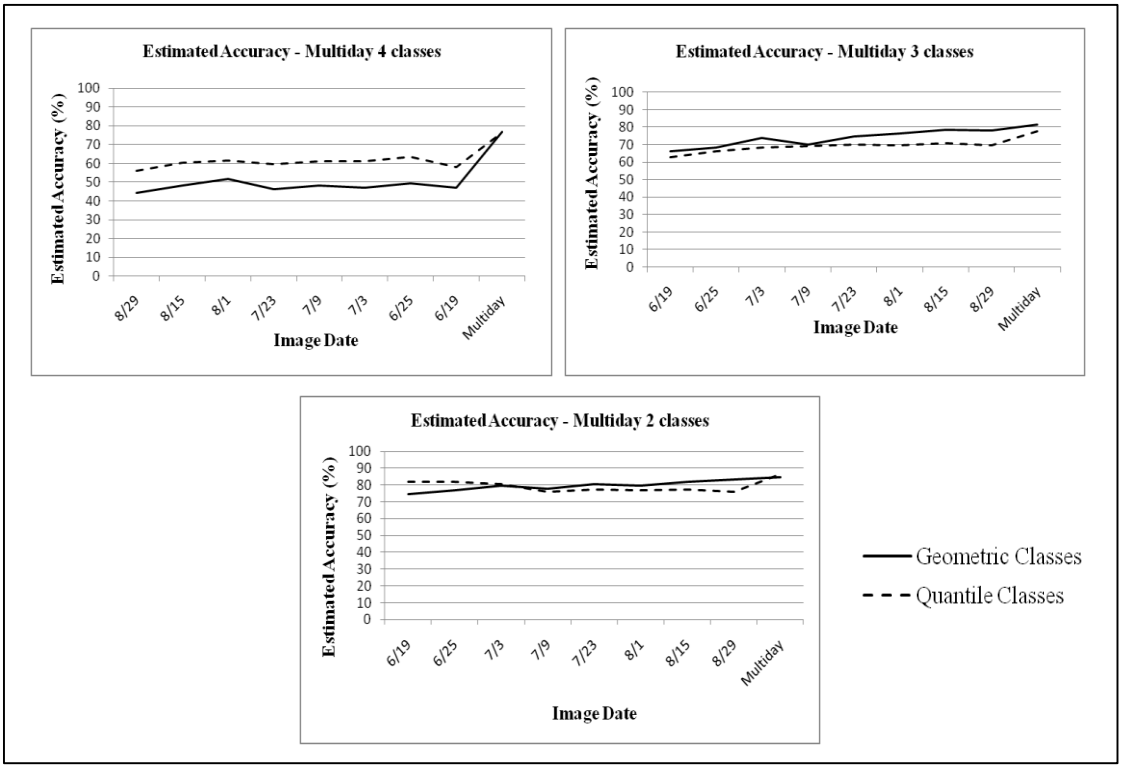


Figure 3.7: Plot of the estimated accuracy for all the dates including the multiple date analysis. Notice the large increase in accuracy for the multiday classification in the four-class classification.

Variable importance played a large role in determining if multiple date classification is a worthwhile technique. Looking at which dates played the most important role in the classification we can determine if random forest classification is classifying based on a single date, a combination of a few dates, or a combination of all the dates. Evaluation of the ground-based variable importance plot for the multiple date classifications suggests a combination of dates in early July played the most important role in classification, as well as high importance placed on the August 29 image (Figure 3.8).

Threshold Results: A study to determine a classification threshold for the multiple date classification was performed as well. This portion of the study was conducted the same way as the single date threshold study. The multiple date threshold

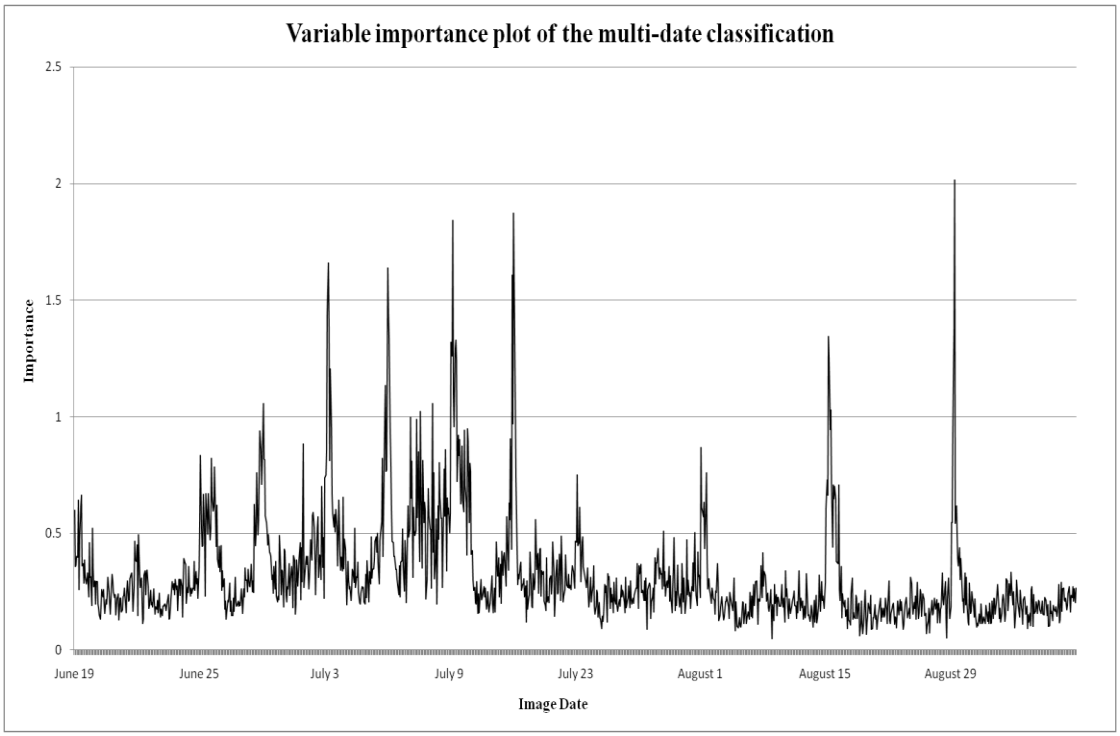


Figure 3.8: Variable importance plot of the multiple date classification.

results were similar to those of the single dates' results. Estimated accuracy generally increased as the threshold increased (Figure 3.9). The largest increase in accuracy occurred between eight and 11 stems/m^2 increasing from 80.6% to 87.56% (Table 3.6).

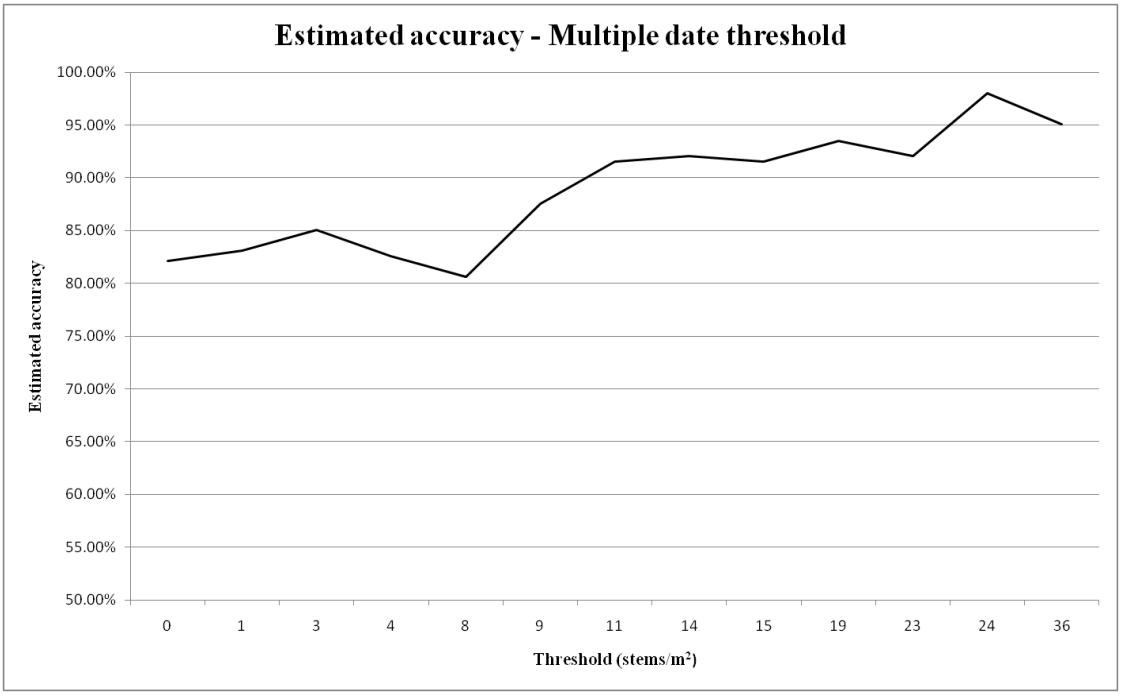


Figure 3.9: Estimated accuracy of the multiple date threshold study. The largest increase in accuracy occurs between eight and 11 stems/m^2.

Discussion

The classification accuracies achieved in this study are comparable to other hyperspectral leafy spurge studies. One unique difference in this study compared to other leafy spurge mapping projects is the incorporation of classifying different densities of leafy spurge. Classification of different densities is very useful to land managers so that they might be able to detect small and moderate sized patches and begin control on them

before the plant has a chance to spread. It can also assist with ecologist hoping to model spatial and temporal spread of a species.

The reflectance spectrum for leafy spurge is consistent with previous research on leafy spurge canopy reflectance. Everitt et al. (1995) found leafy spurge had higher reflectance values than most surrounding vegetation using a GSFC Mark-II three-band radiometer. Reflectance values in this study for dense leafy spurge training sites showed much higher reflectance values than low or moderate leafy spurge cover (Figure 3.10).

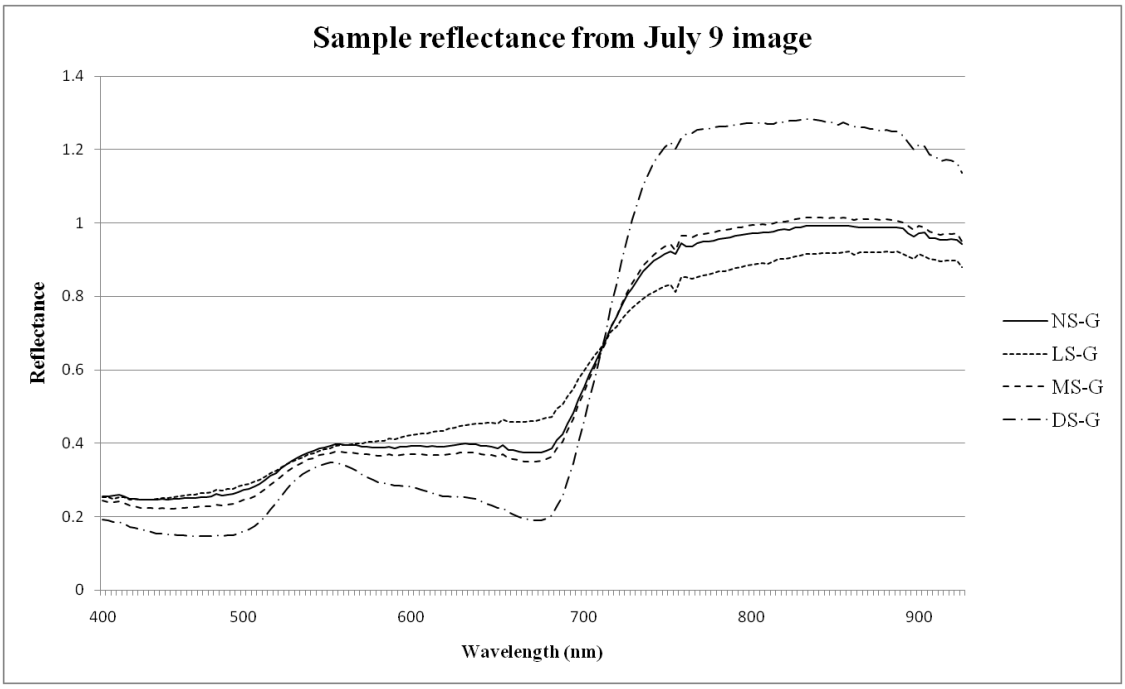


Figure 3.10: Sample spectrum of the four geometric classes on July 9, 2008. NS-G = No Spurge, LS-G = Low Spurge, MS-G = Moderate Spurge, DS-G = Dense Spurge. Note the differences between dense leafy spurge and the other classes.

These results successfully tested our first objective of this study. Testing the reliability and spectral accuracy of the Pika II allowed us to develop our basic classification methodology for the aerial portion of the study. Some issues were also

discovered with the methodology that allowed better methods to be developed for the next phase of the project. The first issue addressed was that stem density was not a good indicator of the amount of leafy spurge present. Some training sites had high densities with very small plants, which resulted in much less cover than some sites with fewer, but larger plants. As a result, percent leafy spurge cover would be measured for the aerial study, rather than leafy spurge density. The lack of significant difference between the two classification schemes, also suggests that a new classification scheme might be necessary when analyzing aerial imagery, especially if percent cover rather than leafy spurge density is the dependent variable. Finally, changes in leafy spurge amount and growth varied over the summer, but training data were based only on one survey. This resulted in changing the methods for the aerial study to collect training data concurrently with the images.

Despite these promising results, the consistent decrease in kappa values shows that a more robust classification scheme is needed. Kappa values are a measure of how much of the classification accuracy is due to random chance (Table 3.6). A kappa value of zero would be completely random chance, while a kappa value of one would indicate a perfect classification. In this case, the kappa value decreased as the number of classes decreased, indicating that some of the higher accuracies were a result of random chance that some pixels were classified correctly.

Table 3.6: Estimated out-of-bag (OOB) accuracies (%) for the multiple date threshold study. The threshold was determined to be between 8 and 11 stems/m^2.

Count	stms/m2	Multiday
0	0	82.09%
1	1	83.08%
2	3	85.07%
3	4	82.59%
6	8	80.60%
7	9	87.56%
9	11	91.54%
11	14	92.04%
12	15	91.54%
15	19	93.53%
18	23	92.04%
19	24	98.01%
28	36	95.04%

Determination of the best period to detect leafy spurge was also performed. The highest accuracies were achieved late in the growing season with the August 15 image having the highest average accuracy. This is contrary to previous work, which found that late May through June was the best time to differentiate leafy spurge from other vegetation in the region (Messersmith et al. 1985). One possibility why these results do not reflect this previous research is that leafy spurge remained green much later in the growing season than other vegetation. Analysis of the variable importance plots supports this possibility as more importance is placed on the 500-600 nm portion of the spectrum as the growing season progresses.

The multiple date results showed a marked improvement in classification accuracy. This result suggests that using multiple dates from throughout the growing season can lead to much higher classification accuracies. High importance was placed on

the early July images. There are a couple of possibilities as to why this occurred. An abnormally cold, wet spring and early summer might have caused leafy spurge to bract later in the summer than under a more normal year resulting in high contrast between the yellow-green bracts and surrounding vegetation that was not detected in earlier or later dates. Alternatively, surrounding vegetation's phenology might have changed during this period and this was detected in the classification.

The threshold results for both the single and multiple date classifications were similar. The consistent threshold for significantly increasing classification accuracy was between 8 and 11 stems/m^2. The increased accuracy at this point may be a result of leafy spurge cover reaching a detectable threshold at this density. Sites with lower leafy spurge densities obviously had lower amounts of cover therefore making it more challenging to detect leafy spurge accurately.

Conclusion

Mapping and monitoring invasive plant species is important in maintaining healthy and productive rangelands. Ground based surveys are typically expensive and difficult to perform, and might not provide the best results. Satellite and aerial imagery have been researched for the purpose of detecting and mapping invasive plants, but they are often limited by expense and resolution. Investigating affordable, high-resolution sensors might solve some of the current issues revolving around invasive plant mapping.

The Pika II sensor is affordable and relatively easy to set up and use. The ground based experiment with the Pika II sensor showed that it was able to obtain results similar

to sensors that are more expensive. The results obtained in this study also directed the development of a future methodology for aerial images taken with the Pika II sensor. Multiple image dates throughout the summer allowed for the determination of when leafy spurge was most accurately detected. Deep time series analysis also determined that a combination of image dates achieves significantly higher classification accuracies. Despite these positive results, further work is needed to investigate detection of leafy spurge based on canopy cover rather than density and if this sensor is accurate for larger study areas.

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CHAPTER 4

AERIAL DETECTION OF LEAFY SPURGE USING HIGH SPATIAL, SPECTRAL, AND TEMPORAL RESOLUTION IMAGERY

Introduction

The development of affordable hyperspectral sensors presents exciting new opportunities in vegetation monitoring and detection. Inexpensive, low-elevation flights provide the opportunity to collect affordable, high spatial and spectral resolution imagery and for the first time combine this with high temporal resolution. Inexpensive sensors can also be purchased by small businesses and universities and provide the opportunity to collect data at will. The Pika II hyperspectral sensor, developed and manufactured by Resonon Incorporated, is a compact pushbroom sensor that records the spectrum from 400-940 nm in up to 148 bands (http://www.resonon.com). The Pika II sensor has previously been used successfully to detect vegetation stress due to a controlled underground CO_2 gas release (Keith et al. 2009) as well as discriminate between microbial communities (Polerecky et al. 2009).

Despite the apparent advantages of affordable hyperspectral imaging there are problems associated with the images. The large data sets require powerful computers and classification tools (Thenkabail et al. 2004), and the sensors are liable to image warping due to aircraft roll, pitch, and yaw (Jensen et al. 2008). The image warping errors are often corrected with complex vector algorithms, which use GPS (global positioning system), elevation, and INS (inertial navigation system) data to relate sensor location in

relation to the ground location for each pixel (Jensen et al. 2008). These programs however, are expensive and need to be unique to each sensor.

Classification of hyperspectral data requires an algorithm with the ability to process and accurately classify large data sets. The random forest algorithm utilizes a combination of classification trees to vote on the most popular class for a data point (Breiman 2001). Each classification tree is developed with a bootstrap sample of the reference data and each node split is determined with a predictor variable selected from a random subset of predictors. Each tree is then used to predict the class of a pixel, and the class receiving the most votes is assigned to the pixel (Breiman 2001, Lawrence et al. 2006). Random forest classification has been used in cancer research and prevention (Izmirlian 2006), gene selection and classification (Diaz-Uriarte 2006), and land cover classification (Gislason 2005). An advantage random forest classification has over typical classification and regression trees is that pruning of the classification trees is not necessary (Lawrence et al. 2006A). Pruning is the technique of simplifying classification and regression trees by subjectively removing some of the nodes and branches created. Not needing to prune in random forest classification removes the need for subjective decisions being introduced into the classification as well as saving time (Lawrence et al. 2006A). The algorithm also develops an error estimate that is a reliable estimate of classification accuracy, enabling all collected reference data to be used for model development (Breiman 2001, Lawrence et al. 2006A). The out-of-bag (OOB) error estimate is calculated by using the "out-of-bag" portion of the data to test the model's accuracy. The OOB error estimate can be calculated because random forest classification

uses a random subset of the predictor variables to build the trees. During each bootstrap iteration, the predictor variables not selected during tree construction are then classified by the tree that was constructed with the bootstrap sample. These predictions are then combined to calculate an error rate (Brieman 2001). The random forest classification algorithm also provides a variable importance measure. This measurement is estimated by measuring the increase in OOB error when the data for a particular variable is changed while the rest of the variables remain unchanged (Brieman 2001).

Few time series analyses of hyperspectral data exist, and most look at vegetative phenological change (Hestir et al. 2008, Sakamoto et al. 2005, and Strachan 2001). Studies that use a combination of phenological stages to increase classification accuracy are rare. Change in classification accuracy due to plant development has been observed in yellow hawkweed and oxeye daisy (Lass et al. 1997) but it is unclear if similar changes will be observed in other species. Multispectral, multiple date images of the Missouri Coteau and Greater Yellowstone Ecosystem have been successfully classified utilizing data from several dates (Lawrence et al. 2006A, Lawrence et al. 2006B). An attempt to classify leafy spurge utilizing multiple date analysis was performed using a maximum-likelihood classifier. Slight improvement in classification was noted, however improvements were only significantly better than classifications performed in June and no improvement was observed for images acquired later in the growing season (Casady et al. 2005).

Leafy spurge (*Euphorbia esula*) is an aggressive invasive species that has invaded large areas of the Northern Plains of the United States. Leafy spurge is toxic to horses

and cattle, and as a result, large amounts of grazing land are no longer productive (Hein et al. 1992). Mapping and monitoring leafy spurge is imperative to its control. In the past, ground based mapping has been the primary method of mapping and monitoring invasive species, however, leafy spurge tends to grow in very large stands that can be difficult to accurately map on the ground (Parker Williams et al. 2002). Research in remote sensing has made progress in mapping invasive species; however, there are still several issues with accuracy, timing, and resolution.

Hyperspectral images are images acquired with narrow, continuous bands. This allows a more continuous spectrum to be collected than sensors that collect only collect few distinct bands. The continuous data of hyperspectral imagery allows for precise spectral measurements of the objects being analyzed. Hyperspectral imagery has been used to map invasive species including leafy spurge (Parker Williams et al. 2002, Glenn et al. 2005). AVIRIS images of Devils Tower National Monument achieved nearly 87% accuracy when leafy spurge was the primary cover species (Parker Williams et al. 2002). HyMap images over eastern Idaho were classified to detect small infestations of leafy spurge and obtained between 87% and 93% classification accuracy (Glenn et al. 2005). These two studies both utilized the mixture tuned match filtering (MTMF) classification technique. This technique uses a defined spectrum, or endmember, to find objects that closely match the user-defined spectrum.

Analysis of multiple date classification is rare and only a few studies have looked at its ability to classify vegetation accurately. Leafy spurge is most spectrally different from other vegetation in late May through June (Messersmith et al. 1985), and by

collecting images during this time, we can test if leafy spurge is more easily detected early in the growing season. Combining the data from multiple dates into one classification and analyzing variable importance might indicate if early images are more important in the classification than later images.

Several study objectives could be developed because of the flexibility of owning a hyperspectral spectrometer and access to affordable flights. Random forest classification was tested to determine if it was capable of detecting leafy spurge in high spectral, temporal, and spatial resolution imagery. Several classifications were performed over the 2009 summer field season, to test the sensor's ability to perform single-date classifications, determine which single dates provide the highest accuracies, and the efficacy of using multiple dates in a single classification.

Materials and Methods

Study Area

A 1.15-ha study area was selected on private property immediately adjacent to the Madison River, Montana, USA. The study site was located approximately 37 km west of Bozeman, MT at an elevation of 1336 m above mean sea level (Figure 4.1). This small tract of private land was not currently grazed or managed in any way. The study area contained a wide variety of leafy spurge infestation as well as several native and non-native plant species (Table 4.1). There is no current control of leafy spurge or any other

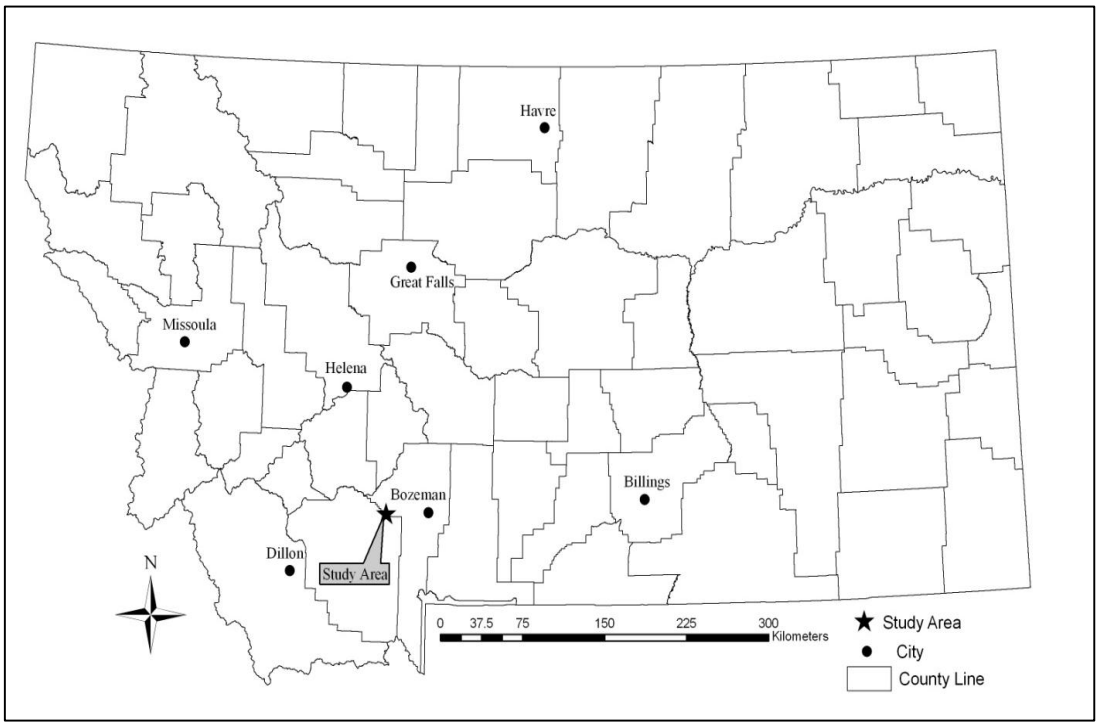


Figure 4.1: Study area location.

Table 4.1: Common species found in study area. Scientific names are USDA nomenclature.

Common Name	Scientific Name
downy brome	*Bromus tectorum* L.
desert alyssum	*Alyssum simplex* Rudolphi
houndstongue	*Hieracium cynoglossoides*
Kentucky bluegrass	*Poa pratensis*
silky lupine	*Lupinus sericeus*
mullein	*Verbascum thapsus*
prairie sage	*Artemisia frigida*
prickly pear cactus	*Opuntia fragilis*
smooth brome	*Bromus inermis*
western salsify	*Tragopogon dubius*
wild oat	*Avena fatua*

non-native species in the study area. Several species of wildlife were observed in the field, including whitetail deer, rabbits, bull snakes, and rattlesnakes. The study site was contained by the property boundary on the north, the Madison River on the west, an irrigation ditch on the east and the irrigation ditch head gate to the south. The study site was flat, removing the need for orthorectification. Additionally, there are no manmade structures within study area and it sees little human travel.

Image Acquisition and Data Collection

A single-engine aircraft operated by Kestral Aerial was used for image flyovers. The first images were collected approximately 300 m above ground level. Later, flights were changed to an elevation of approximately 460 m above ground level in order to obtain a wider field of view. The Pika II sensor was mounted above a viewing hole in the

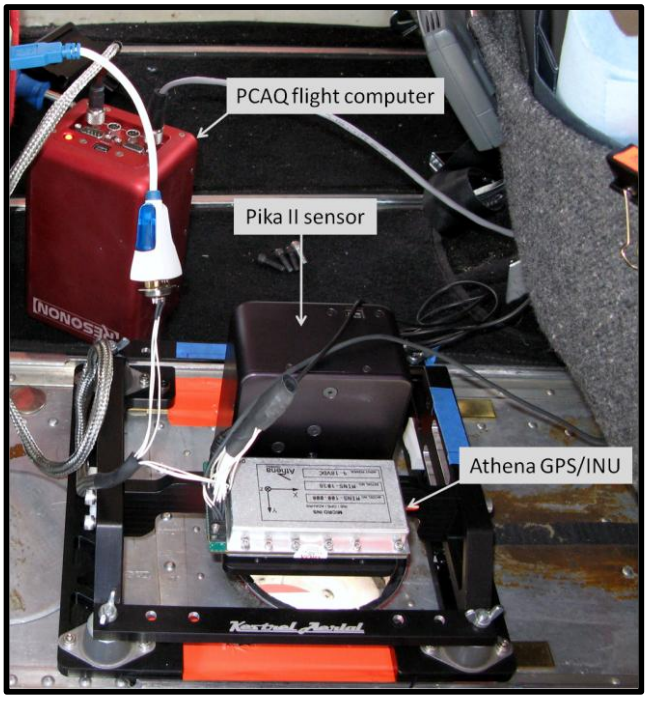


Figure 4.2: Sensor setup in aircraft.

bottom of the aircraft's fuselage and connected to a Resonon PCAQ flight computer and an Athena INS/GPS system (Figure 4.2). Reference sites were selected using ESRI ArcGIS random point generator and located with a sub-meter accuracy Trimble GeoXH GPS unit; 2-m x 2-m blue and silver tarps were used as georefencing targets.

Images were collected on average 10 days apart and spanned from May 29, 2009 through August 29, 2009 (Table 4.2). Variations in image dates were due to inclement weather, pilot availability, and image quality. Vegetation surveys were conducted concurrently with image collection and included percent leafy spurge cover, numbers of leafy spurge stems, percent cover other species, percent dead or senesced vegetation cover, and percent cover of bare ground. Vegetation surveys were conducted using four, 1-m^2 sampling frames around each reference point for a total of 50 reference points. Percent cover was estimated based on Daubenmire's cover classes (Table 4.3) (Daubenmire 1959). These broad classes reduce the chance of consistent human error and the incorporation of small classes to include low and high cover allows for sufficient precision (Daubenmire 1959). Early in the study, vegetation trampling became apparent around the reference points. Concern over the spectral integrity of the reference sites was raised. To avoid further damage to the reference point's vegetation, special care was taken to stand only in certain positions around the reference sites. This allowed for areas damaged by trampling to be avoided when collecting reference data (Figure 4.3).

Table 4.2: Image collection dates.

Image Acquisition Dates
May 29, 2009
June 4, 2009
June 19, 2009
June 29, 2009
July 7, 2009
July 16, 2009
July 23, 2009
July 30, 2009
August 6, 2009
August 29, 2009

Table 4.3: Daubenmire cover classification used for vegetation surveys.

Daubenmire Cover Class	
D1	0-1%
D2	1-5%
D3	5-25%
D4	25-50%
D5	50-75%
D6	75-95%
D7	95-100%

Data Analysis

Image Preprocessing

Raw images were severely warped and attempts to correct for image warping due to roll resulted in very high positional error (3.5-15.5 RMSE) as well as low classification results (66-79% OOB accuracies). Roll correction was based on an algorithm developed by Jensen et al. (2008). This technique requires a straight, visible line to be within the

image, and the algorithm corrects for roll by shifting pixels left or right to make the straight object appear straight (Figure 4.4). Modification of this technique was necessary for the study area because there were no visibly straight lines. Using the roll and GPS data from the Athena GPS/INS and assuming the plane flew in a straight line, trigonometry was used to estimate the distance necessary to shift the pixels. This simple roll correction was investigated because unlike pitch and yaw, roll correction only requires pixels to be shifted, thus removing the need to resample the data and potentially lose some spectral integrity (Miller 2001). The other correction method investigated was a custom vector-tracing algorithm developed for Resonon. This algorithm combines GPS and INS data to calculate a pixel's relation on the ground from the airplane. This technique requires resampling and potentially compromises spectral integrity, but low RMSE values (Table 4.4) and high classification results minimized these concerns.

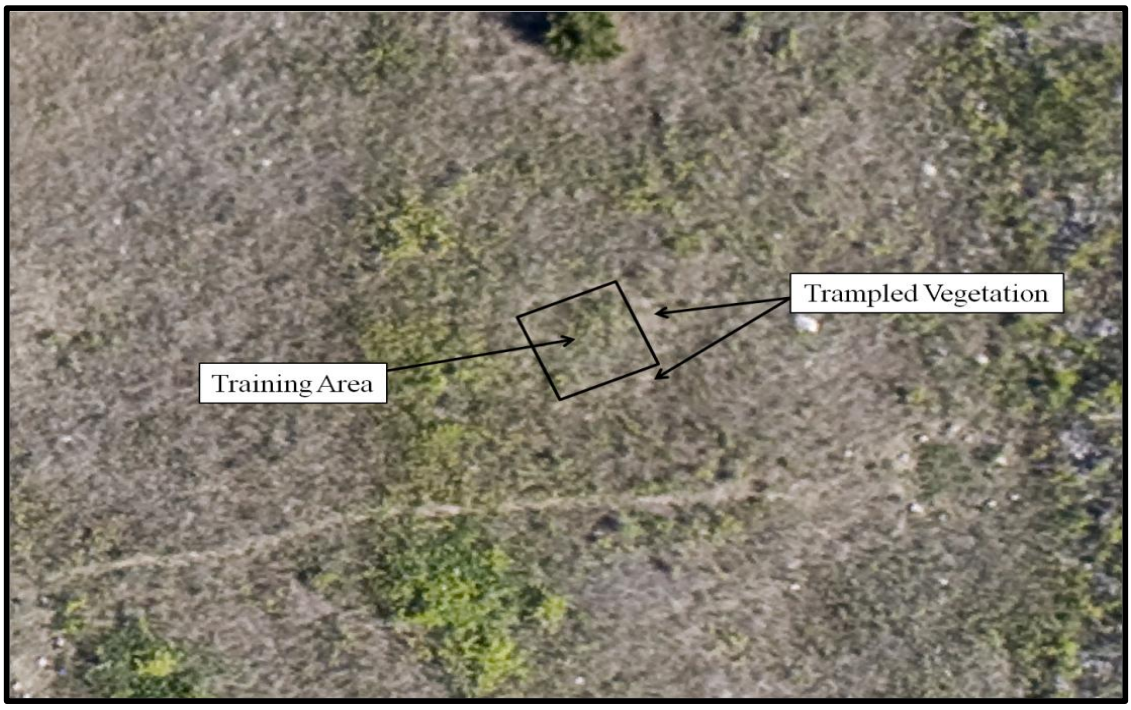


Figure 4.3: Example of trampled vegetation at a reference site.

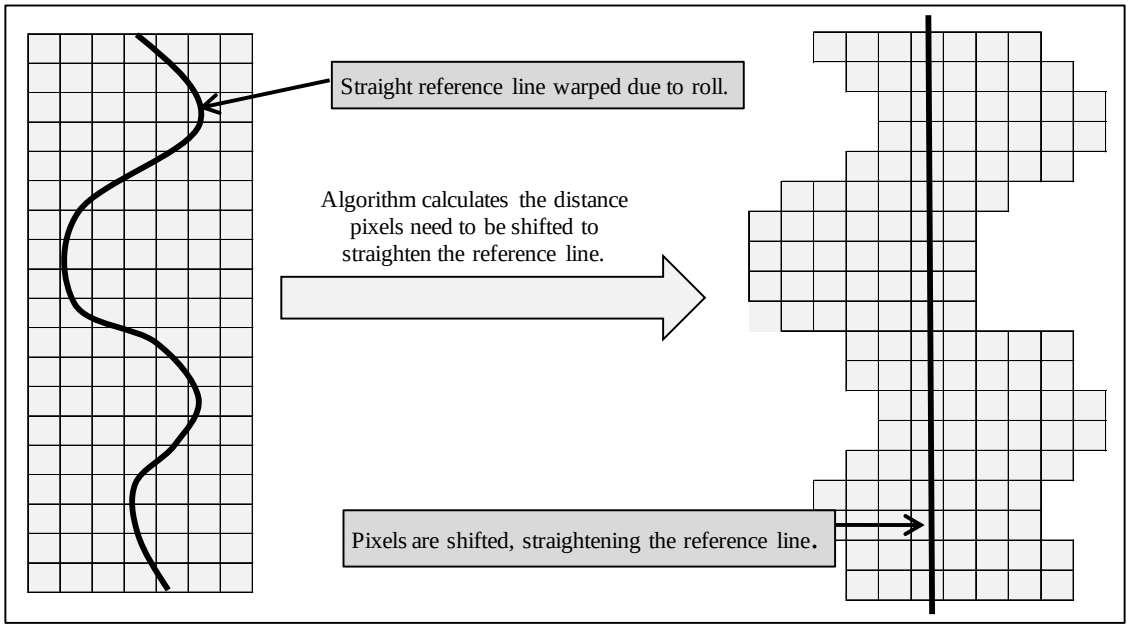


Figure 4.4: Simple example of how the roll correction algorithm works (Adapted from Jensen et al. 2008).

Table 4.4: Positional error values for the geometrically corrected Resonon Images.

RMSE Values		
Date	**RMS**	**Polynomial order**
5/29/2009	0.83	2nd order
6/4/2009	0.88	1st order
6/19/2009	1.24	2nd order
6/29/2009	1.94	1st order
7/7/2009	1.07	1st order
7/16/2009	1.08	1st order
7/23/2009	0.83	1st order
7/30/2009	1.14	1st order
8/6/2009	1.27	1st order
8/29/2009	1.40	2nd order

The images were further geometrically corrected, following the ray tracing correction, using GPS data points marking the ground-reference targets and applying a polynomial geometric correction. These ground targets were placed along two separate transects spaced 50 m apart and located 10 m perpendicular from the transect (Figure 4.5). Each image was masked to the study area following georeferencing. Reference data were surveyed using a sub-meter accuracy GPS unit and provided the basis for detecting the location of each reference site. 4-m^2 areas of interest (AOIs) were centered on each reference point and spectral information was collected for all 50 randomly placed reference points (Figure 4.5).

Single Date Analysis: The data from each date's 50 reference points were separately classified by date with the random forest algorithm (Brieman 2001). The reference data was not subset and contained all 80 bands collected (Table 4.5). Each classification used the 80 spectral bands as predictors and Daubenmire cover classes were treated as the response.

Very large classification trees combined with the high-resolution hyperspectral imagery prevented the entire study site from being classified using the models developed by the random forest classifier. Instead, the study area was subset into images that were 30-m x 30-m sections to be classified and mapped. Classification was performed in S-plus software and the resulting classified maps were developed in ArcGIS.

Multiple Date Analysis: The multiple date image analysis involved the step of stacking each date's image into a single image stack. The output image contained 768

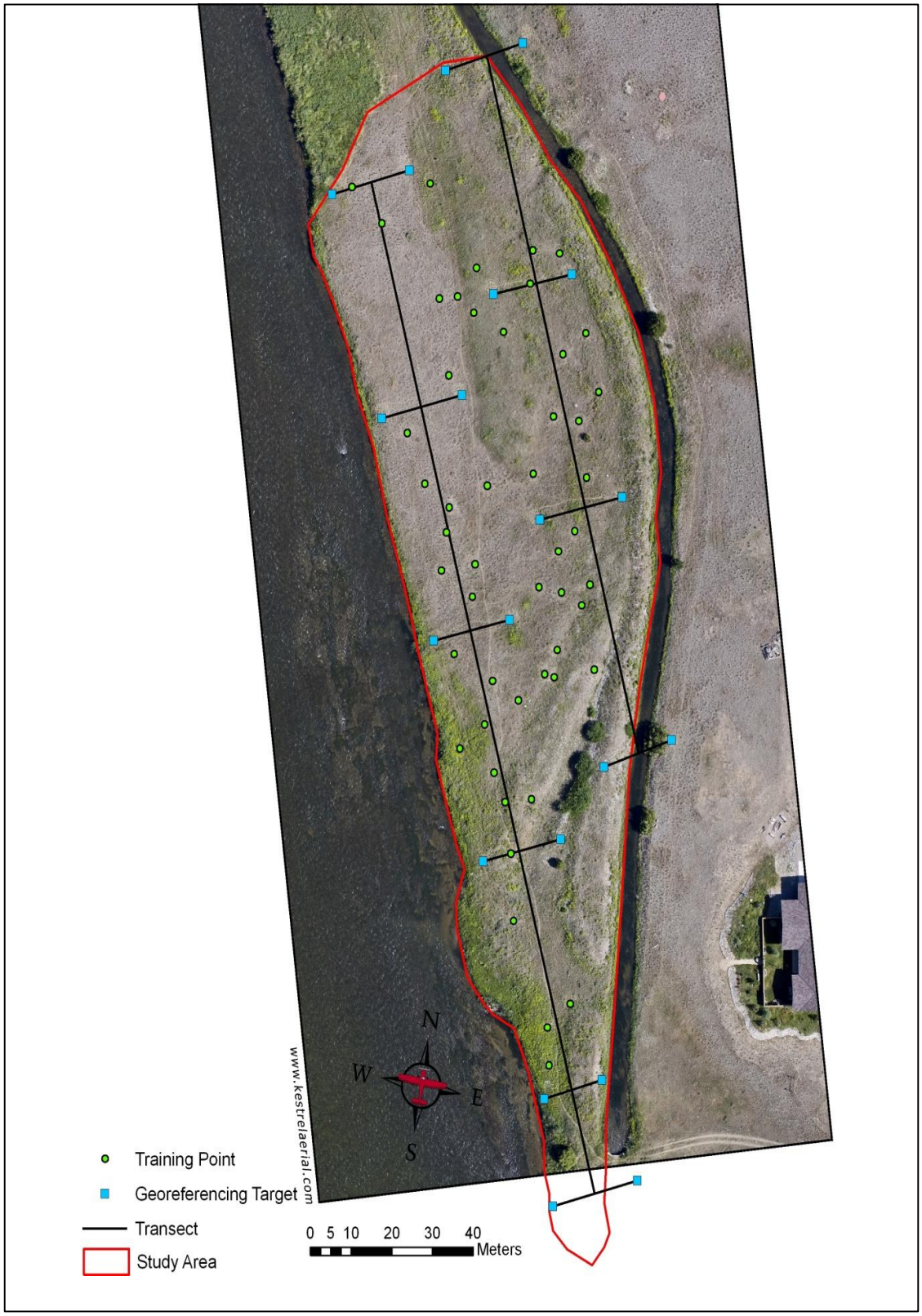


Figure 4.5: Study area design.

bands (nine images with 80 bands and one image with 48) that represented all combined dates' spectrum. Reference data were collected in the same manner as the single date classifications. This data set was then classified with random forest classification and the response variables were the average Daubenmire cover of leafy spurge from throughout the summer.

The resulting random forest model and image required high amounts of computer memory and only very small subsets could be mapped (approx. 10 m x 10 m). As a result, no maps for the multiple date classification were developed, as the very small subsets do not contain a variety of classes to analyze visually.

Table 4.5: Summary of each image's resolution and the number of bands analyzed.

Date	# Bands	Resolution (m)	Description
5/29/2009	80	0.2025	
6/4/2009	80	0.2013	After this date flight elevation increased resulting in lower resolutions.
6/19/2009	48	0.3676	Hardware malfunction resulted in only 48 bands.
6/29/2009	80	0.3559	
7/7/2009	80	0.3177	
7/16/2009	80	0.3088	
7/23/2009	80	0.3116	
7/30/2009	80	0.3117	
8/6/2009	80	0.3224	
8/29/2009	80	0.3267	

Results

Single Date Classification Results

Single date classification achieved between 73% and 90% estimated OOB accuracy with kappa values between 0.61 and 0.86 (Table 4.6). The highest OOB estimated accuracy achieved was 90.45% (kappa = 0.86) on June 3, 2009, while the lowest accuracy was obtained on June 19, 2009 with an accuracy of 73.04% (kappa =

0.61). The higher resolution images had higher classification accuracies; they were resampled to 0.31-m resolution and reclassified to determine whether the higher accuracies were the result of differences in resolution. Classification accuracy for May 29 decreased from 85.35% (originally 0.20-cm) to 80.18% and accuracy for the June 4 image decreased from 90.45% (originally 0.20-cm) to 84.75% (Figure 4.6) with the resampled data.

The variable importance plots showed high amounts of importance was placed in the 500 to 600 nm portion of the spectrum, and, depending on the date, in the 700-750 nm portion of the spectrum (Figure 4.7). As the growing season progressed, reflectance values decreased for each cover type. The 0-1% leafy spurge cover and the 1-5% leafy spurge cover classes showed similar spectrums, which reflected areas of low vegetation cover. As the cover of leafy spurge increased to greater than 5% cover, spectrums were

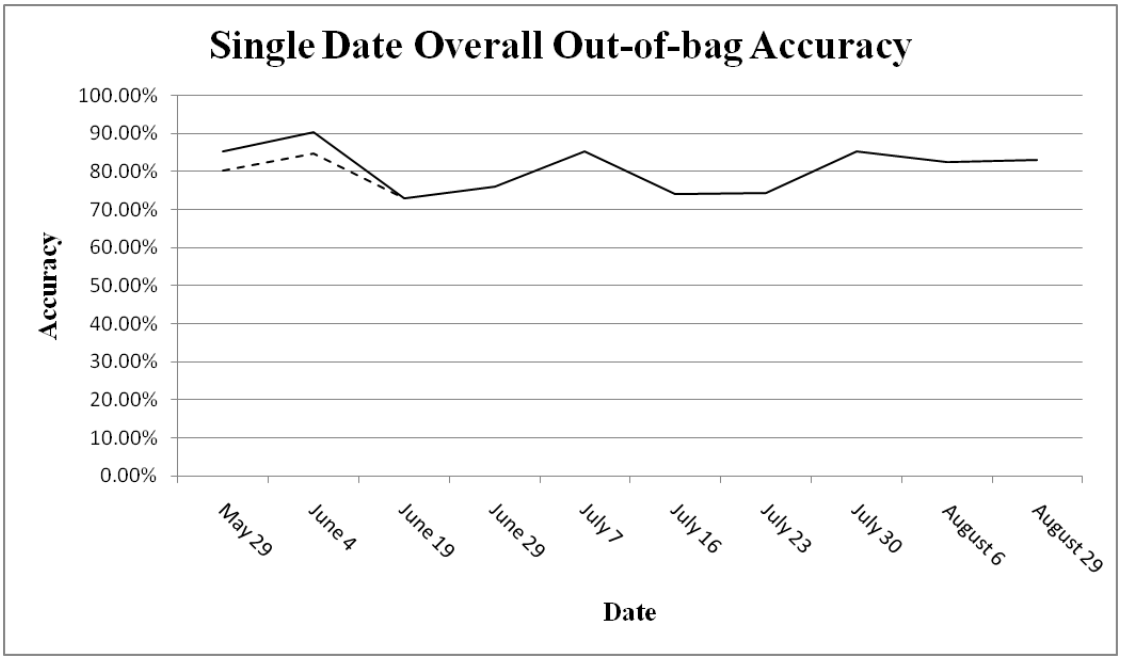


Figure 4.6: Estimated overall out-of-bag accuracies for the single date classifications. The dashed line represents the accuracy for the resampled images.

similar to general vegetation cover (Figure 4.8). The spectral graphs for each reference site are not "pure", meaning that they show signals from more than just the vegetation cover. This resulted in the odd shape of the curves, especially for areas with lower leafy spurge cover.

This change in the spectrum raised the question of whether the classification was simply classifying green vegetation cover and not leafy spurge. This was difficult to test, as there was no reference point that contained high vegetation cover with little or no leafy spurge. To determine if random forest classification was classifying green vegetation rather than leafy spurge, a linear regression between total vegetation cover and leafy spurge cover was performed. Results from the regression show a significant relationship between total cover and leafy spurge (p-value < 0.01). Total vegetation cover explained over half the variance in the regression ($R^2 = 0.6338$), but there was still a substantial amount of variance not explained by this relationship. While a large portion of the variance was detected by the random forest classification, the relationship between total vegetation cover and leafy spurge heavily influenced classification accuracy.

Classified maps of each date showed changes in leafy spurge phenology over the growing season (Figure 4.9). As the growing season progressed, the amount of dense leafy spurge increased through mid July, after mid July, the leafy spurge began senescence, and the amount of dense spurge decreased in August. Differences in image spatial resolution could also be observed in the classified maps.

Table 4.6: Confusion matrices for each single date classification.

May 29

	0-1%	1-5%	5-25%	25-50%	Users
0-1%	1235	110	57	0	**88%**
1-5%	185	1514	210	0	**79%**
5-25%	60	194	2251	7	**90%**
25-50%	0	3	45	73	**60%**
Producers	**83%**	**83%**	**88%**	**91%**	**85.35%**

Kappa **0.78**

June 4

	0-1%	1-5%	5-25%	25-50%	Users
0-1%	1375	43	18	0	**96%**
1-5%	117	1515	161	0	**84%**
5-25%	11	147	2363	9	**93%**
25-50%	0	12	55	175	**72%**
Producers	**91%**	**88%**	**91%**	**95%**	**90.45%**

Kappa **0.86**

June 19 48 bands

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	274	13	58	0	0	79%
1-5%	25	339	161	0	0	65%
5-25%	60	116	679	16	0	78%
25-50%	0	8	48	113	17	61%
50-75%	0	1	10	13	74	76%
Producers	**76%**	**71%**	**71%**	**80%**	**81%**	**73.04%**

Kappa **0.61**

June 29

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	370	46	16	0	0	86%
1-5%	44	534	172	7	0	71%
5-25%	10	173	846	55	5	78%
25-50%	0	16	100	264	0	69%
50-75%	0	0	8	1	46	84%
Producers	**87%**	**69%**	**74%**	**81%**	**90%**	**75.93%**

Kappa **0.66**

July 7

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	514	7	5	0	0	98%
1-5%	28	484	110	2	0	78%
5-25%	7	99	923	25	0	88%
25-50%	0	10	79	257	4	73%
50-75%	0	0	0	6	43	88%
Producers	**94%**	**81%**	**83%**	**89%**	**91%**	**85.32%**

Kappa **0.79**

July 16

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	370	96	41	0	0	73%
1-5%	72	635	99	53	0	74%
5-25%	10	109	875	44	4	84%
25-50%	0	58	129	149	2	44%
50-75%	0	2	2	1	44	90%
Producers	**82%**	**71%**	**76%**	**60%**	**88%**	**74.17%**

July 23

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	327	94	30	0	0	73%
1-5%	64	641	111	12	0	77%
5-25%	11	152	547	89	0	68%
25-50%	0	17	98	501	18	79%
50-75%	0	0	0	15	49	77%
Producers	**81%**	**71%**	**70%**	**81%**	**73%**	**74.39%**

July 30

	0-1%	1-5%	5-25%	25-50%	Users
0-1%	480	55	14	0	**87%**
1-5%	81	733	78	0	**82%**
5-25%	11	104	909	4	**88%**
25-50%	0	1	54	226	**80%**
Producers	**84%**	**82%**	**86%**	**98%**	**85.38%**

Kappa **0.79**

August 6

	0-1%	1-5%	5-25%	25-50%	50-75%	Users
0-1%	407	89	30	0	0	77%
1-5%	81	839	48	0	0	87%
5-25%	30	92	728	9	4	84%
25-50%	0	19	39	102	1	63%
50-75%	0	0	0	4	45	92%
Producers	**79%**	**81%**	**86%**	**89%**	**90%**	**82.63%**

August 29

	0-1%	1-5%	5-25%	25-50%	Users
0-1%	724	131	8	0	**84%**
1-5%	131	802	83	3	**79%**
5-25%	5	88	754	14	**88%**
25-50%	0	0	20	85	**81%**
Producers	**84%**	**79%**	**87%**	**83%**	**83.04%**

Kappa **0.75**

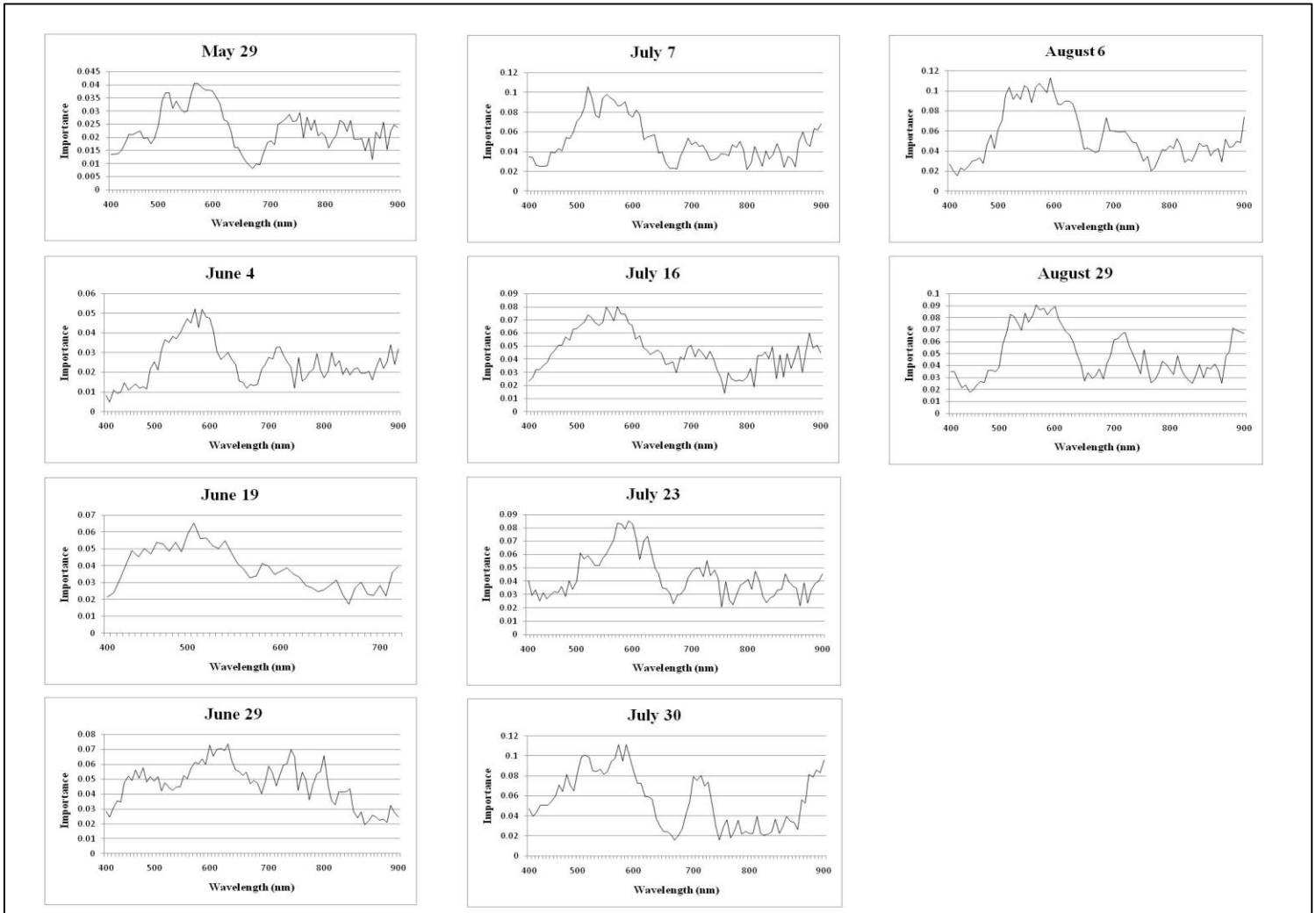


Figure 4.7: Variable importance plots for each single date classification.

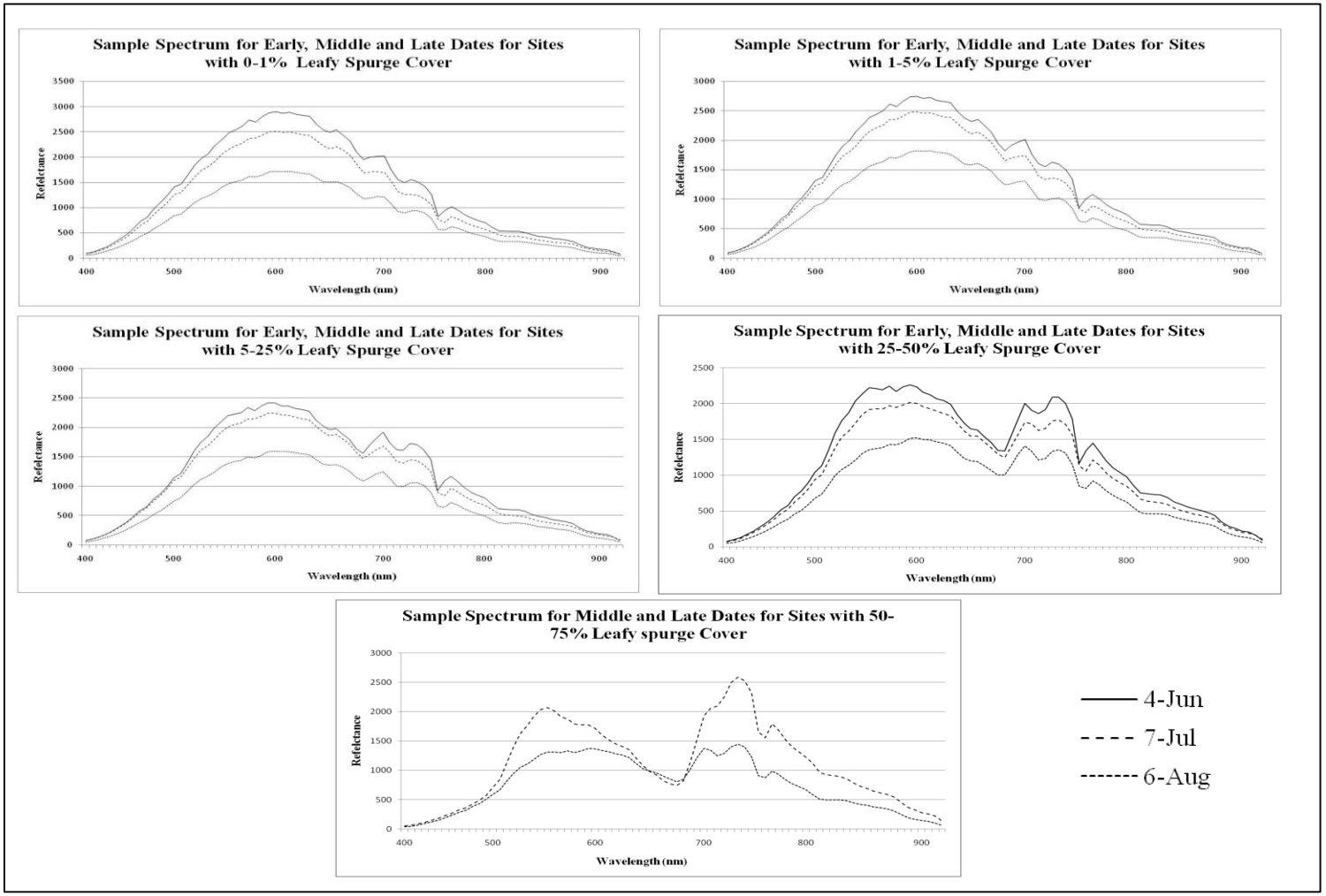


Figure 4.8: Sample spectrum from early, middle and late dates for each leafy spurge cover class. These spectrum plots are not pure signals from leafy spurge, this results in the strange spectral pattern observed. Noise from other senesced vegetation as well as background soil resulted in the atypical spectral plots.

Multiple Date Classification Results

Combining the spectrum from the all of the data collected over the summer into a single classification, resulted in significant accuracy improvements over single date classifications ($t = -8.1342$, $df = 9.00$, p-value < 0.01). The multiple date classification achieved 96.6% OOB accuracy with a kappa value of 0.95. User's accuracies (commission errors) range between 92% and 100% OOB accuracy (Table 4.7). High user's accuracies are important for noxious weed detection because high commission errors may result in overestimation of the amount of an invasive plant species being present.

Variable importance, defined by a gini index, indicates the most important dates in the multiple date classification are July 16 and July 23 (Figure 4.10). Within these dates, the bands between 500-650 nm hold the highest importance. Importance decreases substantially between dates often approaching zero, indicating that the change between dates hold little importance and rather the green to red portion of the spectrum of each image is the basis for classification. Despite the high importance placed on the mid-July images, the band that received the highest importance in the multiple date class was the 930 nm band on August 6. This high importance could be a result of water stress in leafy spurge, as reflectance values between 900 and 970 nm have shown correlation to water stress (Penuelas et al. 1998). Review of the spectrum from the multiple date classification supports the variable importance plots (Figure 4.11). Spectral differences between low spurge classes (0-5% cover) and high spurge classes (>5% cover) are most apparent in the July 16 and July 23 image.

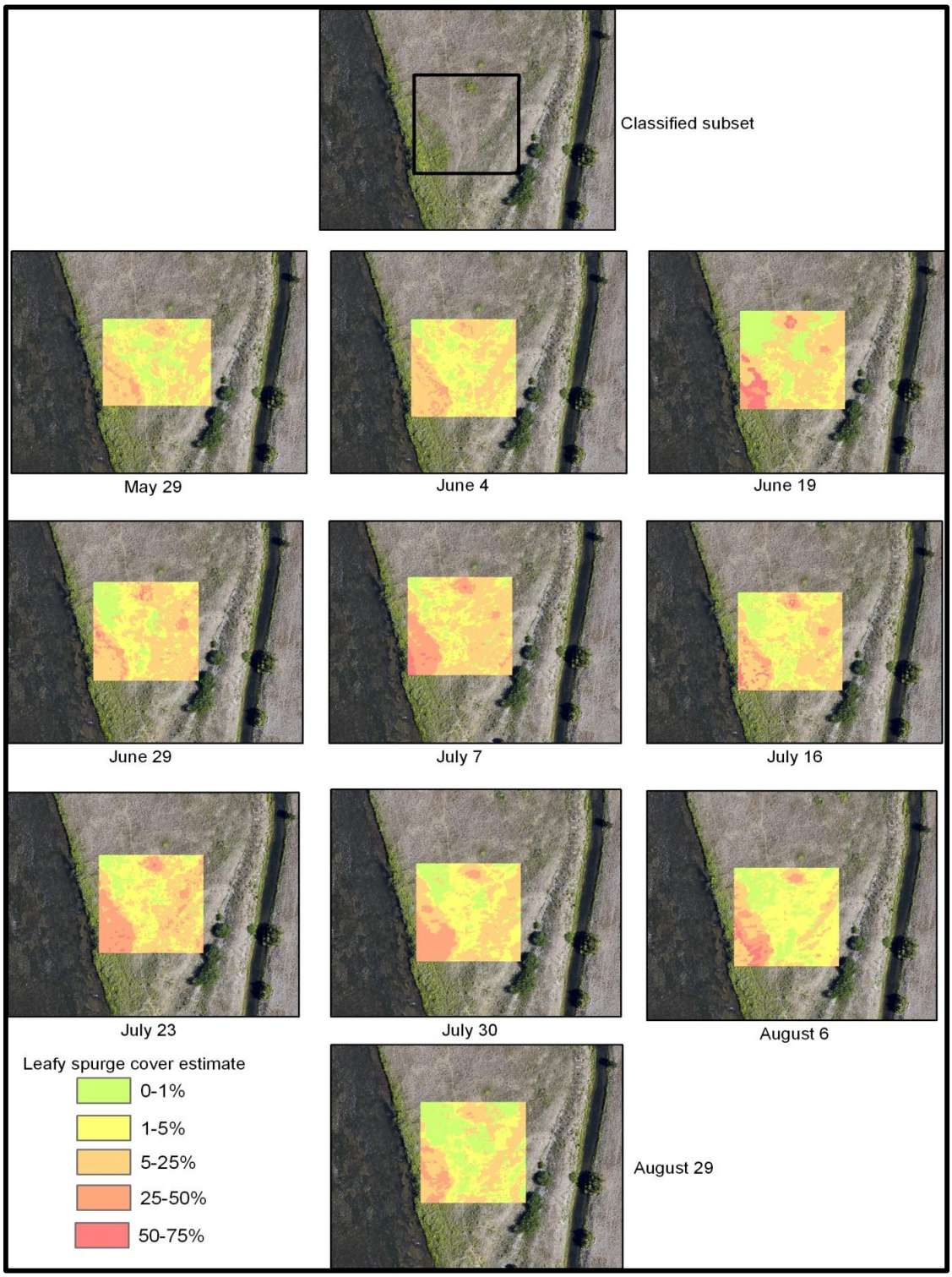


Figure 4.9: Classification of a subset of the data. The image on top shows the 30-m x 30-m area that was classified.

Table 4.7: Multiple date confusion matrix.

	0-1%	1-5%	5-25%	25-50%	Users	
0-1%	1231	100	0	0	**92%**	
1-5%	100	1918	1	0	**95%**	
5-25%	0	2	2297	0	**100%**	
25-50%	0	1	1	361	**99%**	**Kappa**
Producers	**92%**	**95%**	**100%**	**100%**	**96.59%**	**0.95**

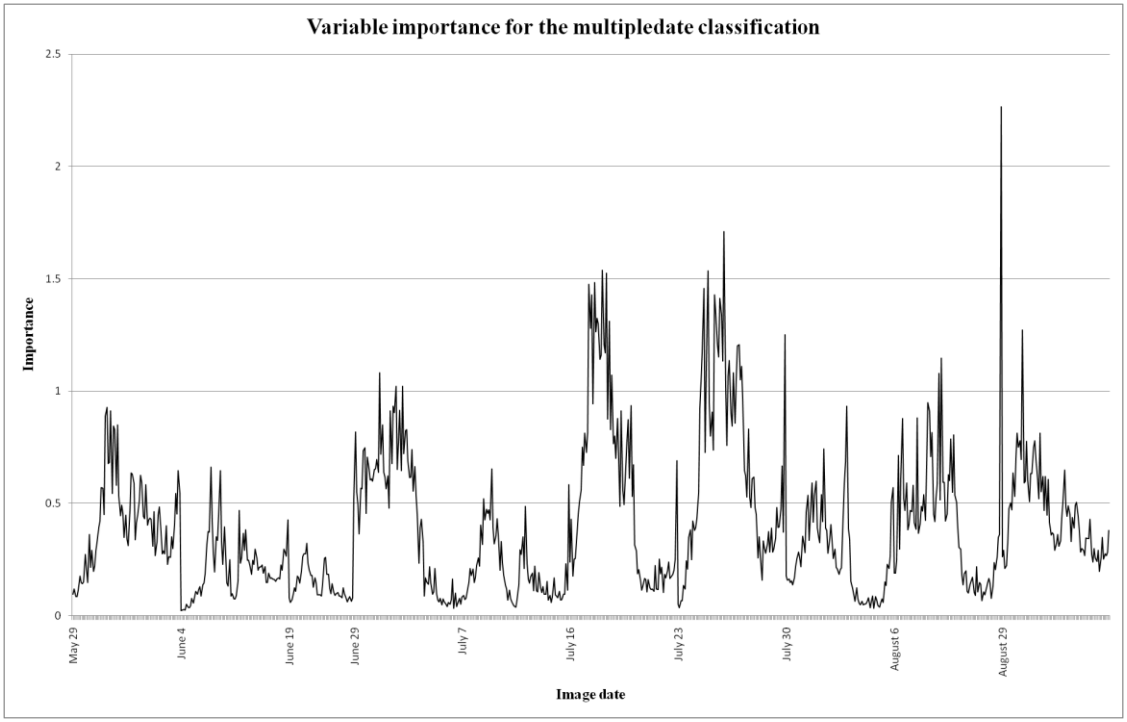


Figure 4.10: Variable importance plot for the multiple date classification.

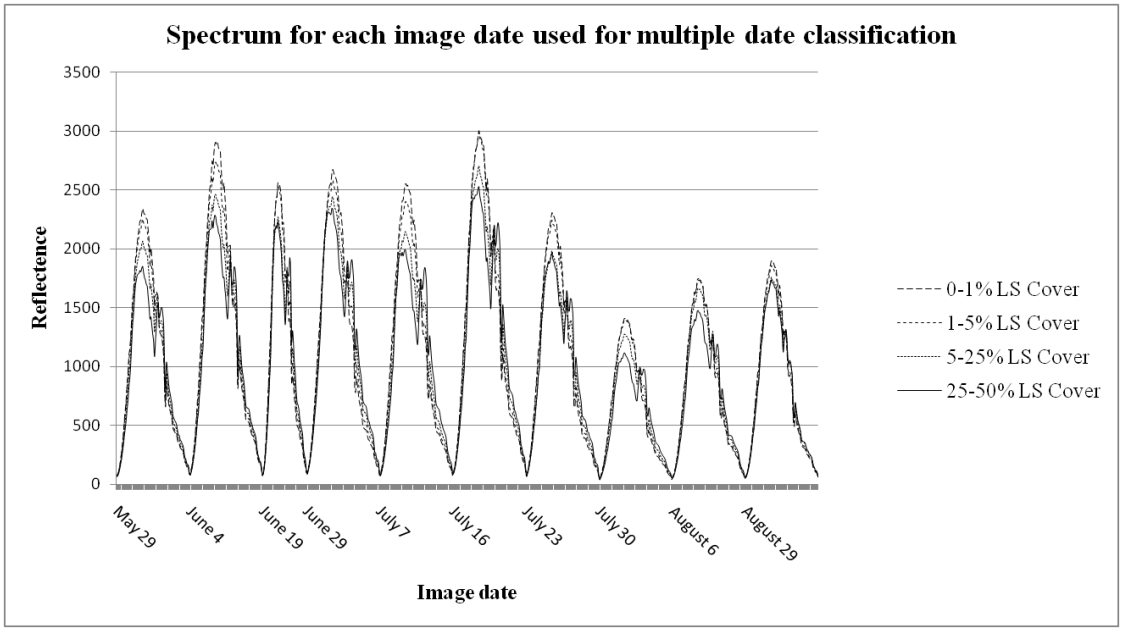


Figure 4.11: Combined spectrum used in the multiple date classification.

Discussion

Single Date

While not directly comparable, the single date classifications are similar to previous leafy spurge hyperspectral classifications. Lawrence et al. (2006A) achieved 86% overall classification accuracy utilizing the random forest classification algorithm in Madison County, Montana. Accuracies between 84% and 94% were achieved with the use of mixture tuned match filtering (MTMF) in eastern Idaho (Glenn et al. 2005). Spectral angle mapper achieved overall accuracies of 66% (Driscoll 2002), maximum likelihood classification achieved 50% overall accuracy, and conventional classification trees achieved 70% overall accuracy (Lawrence et al. 2006A). Classification OOB accuracies obtained with the Pika II sensor range between 74% and 90%, indicating that

the sensor is capable of detecting leafy spurge accurately when compared to more expensive or lower spatial resolution imaging techniques.

Despite these promising results, analysis of the variable importance plots as well as the spectrum for each class may suggest some un-accounted error in our model. Random forest classification's reliance on data from the 500 to 600 nm region of the spectrum indicates that the green to red portion of the spectrum is the primary basis for classification. This could possibly result in confusion between green vegetation and leafy spurge. While this was difficult to test directly, because there were no reference sites with little or no leafy spurge but high amounts of other vegetation cover, we can test if there is a strong correlation between total vegetation cover and leafy spurge cover. A high correlation between the two indicates that we are simply classifying green vegetation and not leafy spurge, while a weak correlation between other vegetation and leafy spurge indicates that the random forest classification is detecting something more than just green vegetation. The regression results between total vegetation cover and leafy spurge cover ($R^2 = 0.63$) indicated that only some of the variance of leafy spurge cover was explained by the total amount of vegetation cover. There was a large amount of variance however, that was not explained by total vegetation cover, and we can presume this variance was taken account in the random forest model but a large portion of the high accuracy may be explained by total vegetation.

The June 4 image obtained the highest OOB classification. Initially this agrees with previous research that found leafy spurge is most different from other vegetation in late May and early June (Mesersmith et al. 1985). However, it is unclear if this is the

sole reason why high accuracy was achieved on this date. After the first two images were collected, the flight path elevation was raised approximately 150 m in order to obtain a wider field of view for the sensor, at the cost of losing some spatial resolution. Spatial resolution decreased from 0.21-m to 0.31-m after June 4. These two images were resampled to 0.31 m resolution with the nearest neighbor technique and reclassified, in order to test resolution's role in classification. The reclassified images decreased in accuracy approximately 5% for both dates. The May 29 overall estimated OOB accuracy decreased from 85.35% to 80.18%, and the June 4 image decreased from 90.45% to 84.75%. This decrease indicates that resolution does play a role in classification accuracy, however, it may not be a significant relationship ($t = 1.5873$, $df = 1.98$ $p = 0.2548$).

Multiple Dates

Performing a single classification using multiple dates of imagery significantly increased overall classification when compared to all single date classifications. A classification accuracy of 96.6% is very high, especially for classifying different levels of leafy spurge cover. This high accuracy has many implications for land managers and for leafy spurge detection and mapping. Obtaining high accuracies presents an opportunity to not only map and detect leafy spurge but also be able to estimate how much leafy spurge is present.

Random forest classification's success in the multiple date imagery can be analyzed with the variable importance plots. High general importance is placed in the

green portion of the July 16 and July 23 images. This high importance could be due to the phenological change in other vegetation as the other species began senescence (Figure 4.12) while leafy spurge remained green. The high importance placed on the 930 nm band on August 6 image at first appears to be an outlier. There is a possible explanation, though, as to why this particular band held such high importance. Previous research has shown that there is high correlation between the 900-970 nm portion of the spectrum and water stress in plants. As plants are stressed for water, there is a decrease in reflectance in this portion of the spectrum (Penuelas et al 1998). Areas of dense leafy spurge show higher reflectance in the 930 nm portion of the spectrum in the August 6 image, indicating that random forest classification may be detecting the difference in water stress between the senesced vegetation and the still green leafy spurge. This subtle difference appears to carry a lot of weight in the multiple date classification.

One of the obvious limitations to the multiple date classification of hyperspectral imagery is the large data sets created, which can be difficult to classify. This prevents

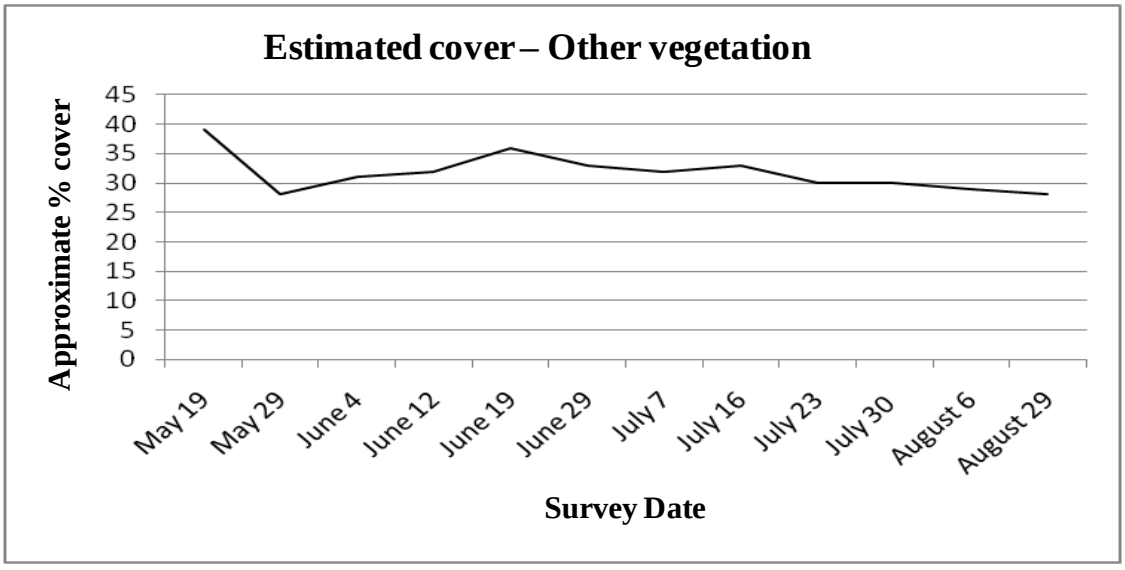


Figure 4.12: Change in other vegetation cover over the summer.

visual analysis of the classification that might help determine some of the errors in the model. Future developments in software, hardware, and processing methods will eventually solve the problems associated with analyzing massive file sizes (the multiple date image is over 11GB in size).

Reference data: Despite attempts to minimize reference set errors, as with most supervised classifications there were some problems associated with our reference data. The most obvious problem was not enough randomly selected reference points to survey all vegetation cover in the study area. Large bushes and trees were never sampled, and therefore they could not train the random forest model. This lack of a broad range of reference points might explain why a little over half the variance of the training data is explained by total vegetation cover. Vegetation trampling and survey resolution both affected the classifications. Vegetation damage and trampling from the repeated surveys lowered the overall cover of the reference sites and biased our data towards sampling only lower leafy spurge cover. Even reference sites in dense patches of leafy spurge tended to have lower cover values associated with them due to vegetation damage from surveying. This resulted in inherent underestimations of cover in the classification maps. Survey resolution also played a factor in the classification. Each reference point covered a range of vegetation cover and some reference points had both areas of very dense spurge and no spurge at all. Images were too low of resolution to account for this variation in the reference data and resulted in generalizations about the cover at each reference point.

Conclusion

High spectral and spatial resolution images have many benefits in the field of vegetation mapping and detection. Immense amounts of data are contained in the high spectral and spatial resolution images. This amount of data allows for accuracies equal to other leafy spurge detection studies that used more expensive hyperspectral spectrometers with lower spatial resolution images (Lawrence et al. 2006A, Glenn et al. 2005, Parker Williams et al. 2002). Problems with the data arise when trying to process it. Limitations in computational power as well as analysis techniques are still challenges to be overcome in the field of high resolution remote sensing.

The ability of small businesses and universities to purchase hyperspectral spectrometers at a reasonable price will open up many new doors in remote sensing. Being able to collect data when conditions permit, allows researchers to incorporate temporal aspects into their research as well as investigate new data collection and processing techniques that may not have been possible when contracting sensors or purchasing images. Investigations into uses for new platforms such as unmanned aerial vehicles (UAVs), remote controlled aircraft, and balloons will become possible as sensors become smaller and more flexible.

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CHAPTER 5

CONCLUSION

Frequent images of areas with leafy spurge infestations were collected utilizing an affordable, compact hyperspectral sensor. These data were used to test what period of the summer provided the best classification accuracy, as well as the efficacy of a single classification performed on multiple image dates. This sort of high temporal resolution analysis is rare for hyperspectral sensors, and this was a more rigorous deep time series analysis than any reviewed in the literature. Results showed significant improvements in classification accuracy when using spectral data from the entire summer. Classifications were typically based on differences in the green to red portion of the spectrum in mid to late July. Water stress in leafy spurge later in the growing season may have also played a role in the classification.

Affordable, compact hyperspectral sensors that can be used on a variety of platforms and perform as well as more expensive sensors will provide many new opportunities in the field of remote sensing. Remote sensing techniques that are inexpensive, collect high spectral and spatial resolution images, and can be deployed quickly on a variety of platforms, provide many advantages over other remote sensing techniques. Despite these apparent advantages, there are also shortcomings with these sensors. The high-resolution nature of these sensor's images is a result of low altitude flight paths, which limits the ability to cover very large areas quickly, and thus more flight time might be necessary to cover the same swath as a lower spatial resolution

satellite. The amount of data contained in a high-resolution hyperspectral data cube is immense, which can cause problems with data analysis. Some computers processors can process these very large data files, however a typical computer will often struggle performing rigorous analysis of the data.

Random forest classification has been shown to be successful classifying large datasets. This classification algorithm is robust to overfitting and provides a non-biased internal error estimate. This allows the entire data set to be analyzed and no data needs to be withheld for validation. Random forest classification was used successfully to classify both single date images as well as a multiple date image in this study. The high classification accuracy obtained in this study was remarkable compared to other leafy spurge remote sensing studies (Lawrence et al. 2006, Casady et al. 2005, and Glen et al. 2005). The classification accuracies achieved in this study were similar to other studies, with the exception that all of the other studies were simply performing detection, while this project successfully estimated the amount of leafy spurge cover within broad classes.

The proof of concept ground-based study performed during the summer of 2008 help direct the methodology for the 2009 aerial study, and showed that both the Pika II sensor and random forest classification were capable of detecting and classifying different amounts of leafy spurge, and that multiple date classification improved classification accuracy. Performing a proof of concept study helped detect and resolve any problems with the methodology before purchasing flight time. Spectral data collected with the Pika II sensor was also sound and was able to be classified accurately. The proof of concept study found that it was much easier to detect dense (>11 stems/m^2)

patches of leafy spurge; however, it also determined that density might not be the best metric to base classifications because percent cover can increase with the same density of plants over the growing season. Multiple date classification from the 2008 proof of concept study showed increases in overall classification accuracy especially when classifying multiple densities of leafy spurge.

Aerial images collected during the 2009 summer built on the 2008 ground based study. Using the results and problems experienced during the 2008 study, much more rigorous reference data were collected. Classifications achieved higher accuracies using percent cover leafy spurge rather than density as the classification metric, thus dealing with the problems experienced in the 2008 study. Single date classifications were most accurate either early or later in the growing season, typically when leafy spurge was bracting or surrounding vegetation began senescence. Classification accuracies of estimated leafy spurge cover were similar to previous studies examining only presence or absence; the ability to estimate different amounts of cover sets this study apart from previous leafy spurge remote sensing research. Estimating the percent cover of an invasive plant species using remote sensing is very valuable to land resource management. Detection of different cover amounts of an invasive species allows for greater control on the management of an invasive species. Estimating percent cover accurately also has many implications in ecology. Efficient, large-scale monitoring of plant spread, movement, and phenology will allow for better understanding of plant spatial and temporal dynamics thus improving management and control of invasive species. The significant increase in classification accuracy obtained by classifying

multiple dates of imagery also shows promise in remote sensing classifications. The high accuracies obtained with random forest classification of high spatial, spectral, and temporal resolution data should provide more confidence in remotely sensed classification data.

High spatial and spectral resolution remote sensing is an emerging science. Only recently have breakthroughs in these technologies allowed for the development of affordable and accurate hyperspectral imagers. Many of the limitations found in this study will no longer be issues as hyperspectral and computer technology advance.

The work presented in this study presents a foundation to build upon for the future use of high spectral, spatial, and temporal resolution remote sensing. More testing of the Pika II is needed to prove its robustness in a variety of situations, this includes; detection and mapping of multiple plant species, and determination of its effectiveness when performing other forms of analysis such as leaf area index, biomass, productivity, etc. Problems faced in this project included; determining the best leafy spurge measurement metrics (i.e. cover vs. density), intrusive sampling, lack of vegetation diversity in reference sites, and quality control of both reference and spectral data, and these issues will need more research in order to clarify some of the results obtained in this study. Some of these problems could be solved by developing a standard operational protocol for these sensors; this would also standardize these sensors for comparisons between different areas. Collection of reference data may also need more research and experimentation to ensure consistent data as well as less intrusive data collection techniques. The highly intrusive nature of the reference data collected in this study

resulted in problems with vegetation damage and trampling. Experimentation with flight paths, elevation, and wider-angle lenses will also help determine the most efficient and cost effective way to collect data over large swaths of land.

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