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Estimation of leafy spurge cover from hyperspectral imagery using mixture tuned matched filtering

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Abstract

Leafy spurge, *Euphorbia esula* L. is an adventive, perennial weed that infests approximately 1.2 million ha of land in North America. It often forms dense stands that displace native vegetation and useful forage plants on rangelands and in riparian habitats. Leafy spurge is a good candidate for detection via remote sensing because the distinctive yellow-green color of its bracts is spectrally unique when compared to co-occurring green vegetation. During 1999, Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery was acquired in northeastern Wyoming and ground cover data were collected. Mixture tuned matched filtering (MTMF), a specialized type of spectral mixture analysis, was used to estimate leafy spurge canopy cover and map leafy spurge distribution. Overall performance of MTMF for estimating percent cover of leafy spurge for all sites was good ($r^2 = 0.69$) with better performance in prairie areas ($r^2 = 0.79$) and poorer performance occurring on wooded sites ($r^2 = 0.57$). However, results demonstrated that in open canopies with leafy spurge in the understory, the spectral signature is sufficiently distinct to be detectable. The techniques presented here could be used for constructing leafy spurge distribution and abundance maps with satellite hyperspectral data for larger regional areas.

1. Introduction

Invasions of exotic organisms have been proposed as one of the largest components of global environmental change, second only to habitat destruction (Vitousek, D'Antonio, Loope, & Westbrooks, 1996). Leafy spurge, *Euphorbia esula* L., is only one of hundreds of successful exotic plant species that have invaded North America. It is an adventive, perennial weed that infests approximately 1.2 million ha of land in North America (Lajeuness, Sheley, Duncan, & Lym, 1999). Its distribution includes the northern Great Plains of the United States and the prairie provinces of Canada (DeLoach, 1997). It often forms dense stands that displace native vegetation and useful forage plants on rangelands and in riparian habitats. Infestations of leafy spurge destroy the quality of grazing lands for cattle and horses (Bangsund & Leistritz, 1991; Beck, 1993; Hein & Miller, 1992), degrade the forage base and structure of wildlife habitat (Trammell & Butler, 1995), decrease plant diversity (Belcher & Wilson, 1989), and reduce land value (Leistritz, Bangsund, & Leitch, 1992).

One of the fundamental research needs in leafy spurge management, and in invasive plant management as a whole, is cost-effective, large-scale, and long-term documentation and monitoring of plant populations (Johnson, 1999). Leafy spurge populations usually cover large regions, and monitoring the entire area is needed to effectively reach conclusions about changes in distribution and amount. Ground survey work in large areas is prohibitively expensive and time-consuming (Everitt et al., 1995). Often, data generated from ground survey work are quickly outdated as weed populations change due to abiotic factors and control measures (Akiyama, Yamagata, Saibayama, Hayashi, & Fujita, 1989; Pitt & Miller, 1988; Thomas D. Whitson, personal communication). Survey questionnaires may be biased, and weed problems may even be exaggerated by land managers and land owners (Auld, 1971). Therefore, a method of monitoring is needed that can quickly and

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efficiently collect data over a large area on a routine basis. The lack of quantitative data hinders further research on the dynamics of exotic plant invasions, the assessment of different management implementations, and results in imprecision when making decisions about management and policy.

Using remotely sensed data to map leafy spurge would provide a valuable tool for documenting leafy spurge distribution and infestation levels. Differentiation of individual green plant species can be problematic because all green plants have similar spectral characteristics. Leafy spurge is a good candidate for detection via remote sensing because the distinctive yellow-green color of its bracts are likely to be spectrally unique compared to the co-occurring vegetation. Because spectral detail is necessary for differentiating similar materials, high spectral resolution data is the most appropriate for mapping individual plant species with a high level of accuracy and precision (Clark, King, Ager, & Swayze, 1995). Imaging spectrometers, or hyperspectral sensors, provide data in which each pixel in the image has a detailed set of reflectance values that allow interpretation of the pixel's spectrum. By using spectral mixture analysis to model each pixel spectrum as a linear combination of a finite number of spectrally distinct signatures or "endmembers," subpixel estimates of endmember abundance can be obtained (Adams, Smith, & Johnson, 1985; Smith, Ustin, Adams, & Gillespie, 1990). The main goal of this research was to map leafy spurge from hyperspectral imagery using spectral mixture analysis to obtain subpixel estimates of leafy spurge cover. This was compared to ground estimates of leafy spurge cover to assess the ability of hyperspectral remote sensing data to estimate leafy spurge cover.

2. Background

2.1. Spectral characteristics of green vegetation

The reflectance spectra of most green leaves are remarkably alike due to similarities in chemical composition and leaf structure (Gates, Keegan, Schleter, & Weidner, 1965; Knipling, 1970). Plant pigments, such as chlorophylls and carotenoids, have major effects upon the reflectance properties of green leaves in the visible wavelengths; whereas reflectance properties in the near-infrared (NIR) wavelengths are due primarily to differences in leaf structure (Gates et al., 1965; Slaton, Hunt, & Smith, 2001). Absorption by chlorophylls *a* and *b* dominate the visible wavelengths for most green plants with features occurring at 430 and 670 nm for chlorophyll *a* and at 460 and 650 nm for chlorophyll *b* (measured in dimethyl sulfoxide; Chappelle, Kim, & McMurtrey, 1992). However, these properties are not entirely responsible for the reflectance of vegetation canopies in remotely sensed imagery because a vegetation canopy is composed of a mosaic of leaves, flowers, stems, and shadow against a soil background (Hurcom, Harrison, & Taberner, 1996). The spectral values derived from remote sensing of vegetation are primarily due to reflectance at the canopy level; however, the chemical composition of plants can influence these values (Asner, 1998; Asner, Wessman, Bateson, & Privette, 2000; Jacquemond, Baret, Andrieu, Danson, & Jaggard, 1995; Martin & Aber, 1997).

2.2. Differentiation of plant species

Many different types of remote sensing data and image processing techniques have been used in the past to differentiate and map vegetation. Medium-resolution, multispectral satellite imagery, such as Landsat Thematic Mapper (TM) data, has adequate resolution spectrally and spatially for differentiating broad vegetation types, and in some cases, individual plant species with reflectance characteristics that are unique spectrally or temporally (Akiyama et al., 1989; Peters, Reed, Eve, & McDaniel, 1992; Taylor, 1990). However, the coarse spatial resolution limits detection to larger patches or infestations, and the coarse spectral resolution can result in unacceptable levels of uncertainty and error, or difficulties differentiating similar species. Higher spectral and radiometric resolutions are needed to resolve small differences in reflectance that would enable differentiation of plant species. Several weed species with distinctive spectral characteristics have been detected from high spatial resolution airborne imagery (Carson, Lass, & Callihan, 1995; Everitt, Alaniz, Escobar, & Davis, 1992; Everitt & DeLoach, 1990; Everitt, Escobar, Alaniz, Villarreal, & Davis, 1992; Everitt et al., 1994). This includes leafy spurge, which, due to the distinctive yellow-green color of its bracts, is detectable using aerial photography and digital video imagery (Everitt et al., 1995). It is especially visible in color infrared (CIR) aerial photography acquired during the peak flowering period.

2.3. Hyperspectral sensors

Imaging spectroscopy, or hyperspectral remote sensing, uses sensors such as the Airborne Visible Infrared Imaging Spectrometer (AVIRIS) to measure light that has been reflected from the Earth's surface in numerous continuous channels using band widths with a very narrow range of wavelengths (Green, Eastwood, & Williams, 1998). AVIRIS is operated by the Jet Propulsion Laboratory (JPL) and collects data in the spectral range of 400 to 2500 nm sampled by 224 spectral channels with a nominal 10 nm sampling (Green et al., 1998). It also has very high radiometric resolution (12 bits), resulting in an increased ability to distinguish fine differences in reflectance values among pixels.

AVIRIS was developed originally to resolve absorption features characteristic of mineral spectra, and to resolve characteristics of vegetation spectra (Goetz, Vane, Solomon, & Rock, 1985; Ustin et al., 1991). Data from AVIRIS have also been used in attempts to distinguish individual plant species based on their unique spectral properties particularly in the red, NIR, and MIR wavelengths (Green et al., 1998;

McGwire, Minor, & Fenstermaker, 2000; Okin, Roberts, Murray, & Okin, 2000; Roberts et al., 1998). Imaging spectroscopy data have also been used to successfully differentiate and map forest tree species (Kokaly, Clark, & Livo, 1998; Martin, Newman, Aber, & Congalton, 1998) and to map crop species in the San Luis Valley of Colorado with an overall accuracy of 96% (Clark et al., 1995).

2.4. Spectral mixture analysis

The spectral reflectance of a given pixel is characteristic of the mixture of component materials on the ground, each component has its unique spectral signature. Spectral mixture analysis assumes the pixel spectrum as a linear combination of a finite number of spectrally distinct endmembers (Adams et al., 1985; Smith et al., 1990). Spectral mixture analysis utilizes the high dimensionality of the AVIRIS imagery to produce a suite of abundance or fraction images for each endmember. Each fraction image shows a subpixel estimate of endmember relative abundance as well as the spatial distribution of the endmember (Adams et al., 1995). When the endmembers include vegetation, the endmember fraction is proportional to the areal abundance of projected canopy cover (Roberts, Smith, & Adams, 1993; Ustin, Smith, & Adams, 1993). Different varieties of spectral mixture analysis have been used to discriminate spectrally distinct types of vegetation with various levels of success (McGwire et al., 2000; Roberts et al., 1998).

Mixture tuned matched filtering (MTMF), a special type of spectral mixture analysis, is based on well-known signal processing methodologies (Harsanyi & Chang, 1994). It performs a "partial" unmixing by only finding the abundance of a single, user-defined endmember, by maximizing the response of the endmember of interest and minimizing the response of the composite unknown background, thus "matching" the known signature. The background material's data histogram is centered around 0.0, and the target (endmember) data distribution occurs in the upper tail of the histogram (Harsanyi & Chang, 1994). This technique produces images similar to standard spectral mixture analysis, with results presented as gray-scale images, which provide a means of estimating relative degree of match to the reference spectrum (where 1.0 is a perfect match). A major advantage for this study is that MTMF does not require signatures for the other endmembers that occur in the image (Boardman, Kruse, & Green, 1995).

3. Methods

3.1. Research area

The study area for this research is in Crook County in northeastern Wyoming, USA (latitude from 44.4° to 44.6° North and longitude from 104.6° to 104.9° West), on the northwestern edge of the Black Hills, a small mountain range that extends from northeastern Wyoming southeast into western South Dakota, USA. It consists of Devils Tower National Monument (DTNM) and approximately 65 km^2 of private land. Devils Tower is an eroded column that is the 264-m remnant of a vertically jointed volcanic intrusion (Karner & Halvorson, 1987). The private lands are used extensively for livestock grazing (cattle and sheep) with some areas of dryland farming and hay production.

The vegetation of the study area is a mosaic of ponderosa pine (*Pinus ponderosa*) communities, grasslands, sagebrush–grasslands, and pine–juniper (*Juniperus scopulorum*) woodlands occurring on a large gently undulating plateau of sedimentary rocks (Marriott, 1985). Riparian areas are characterized by willow (*Salix* spp.) and plains cottonwood (*Populus deltoides*) communities, with bur oak (*Quercus macrocarpa*) and green ash (*Fraxinus pennsylvania*) commonly occurring in draws. Elevations in the study area range from 1219 m along the Belle Fourche River to 1584 m at Missouri Buttes along the northern border of the study area. The average annual precipitation is 442 mm.

Leafy spurge is very well established throughout most of the study area. Period of flowering generally begins in late May, with the bracts showing, and ends in mid July (Lajeuness et al., 1999).

3.2. Acquisition and atmospheric correction of AVIRIS imagery

Airborne Visible Infrared Imaging Spectrometer (AVIRIS) imagery was acquired over the study area in northeastern Wyoming on July 6, 1999. The imagery was acquired from the NASA ER-2 aircraft flown at an altitude of 20 km with each pixel representing a ground area of approximately 20 × 20 m (Green et al., 1998). Two AVIRIS scenes (each approximately 11 × 9 km) covered much of the study area.

Each AVIRIS scene was first radiometrically corrected at the Jet Propulsion Laboratory. It was then atmospherically corrected to apparent surface reflectance using Version 3.1 of the ATmosphere REMoval Program, or ATREM (Gao, Heidebrecht, & Goetz, 1993; Gao, Heidebrecht, & Goetz, 1999; Goetz, Boardman, Kindel, & Heidebrecht, 1997). Because of the limited range of field spectroradiometer data (350–1050 nm), artifacts in the atmospheric correction at ultraviolet wavelengths, and AVIRIS band spectral overlap, a spectral subset of the AVIRIS data was taken. AVIRIS bands 6 through 32 and 35 through 68 (418–1000 nm) were used in the final analysis. A visual comparison of AVIRIS reflectance spectra with ground reflectance spectra (Fig. 1) showed a very good correspondence; therefore, we did not perform an additional empirical line atmospheric correction.

3.3. Field spectroscopy

Field spectroradiometer data were collected in late June 1999 between 10:00 AM and 2:00 PM MST on a clear,

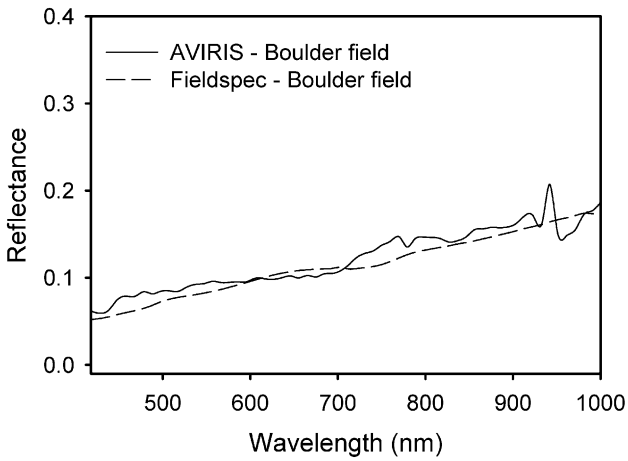

Fig. 1. Correspondence of corrected Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data with averaged field spectroradiometer data for a calibration site, the boulder field at the base of Devils Tower.

sunny day similar to the weather and sky conditions 2 weeks later on the day of the AVIRIS overflight. The spectra were acquired using an Analytical Spectral Devices (ASD, Boulder, CO) FieldSpec UV/VNIR Spectroradiometer. It was not possible to collect field spectroradiometer data on the day of the AVIRIS overflight due to instrument unavailability. The ASD FieldSpec UV/VNIR acquires continuous spectra from 350 to 1050 nm. Dark current and white reference (Spectralon panel) corrections were made approximately every 2–3 min. Each spectrum acquired in the field consisted of 25 individual measurements taken consecutively and averaged by the FieldSpec. Measurements were acquired using the bare tip of the fiber optic cable, which had a 25° field-of-view (FOV). All measurements were made with the optic tip about 1.3 m above the target material resulting in a FOV diameter of about 0.50 m. The tip of the fiber optic cable was held at arm's length with that side of the body perpendicular to the sun's azimuth.

The final spectrum for leafy spurge, other plant species, and calibration sites was calculated through postprocessing, which consisted of examining sets of 10 of the averaged field spectra, removing any extreme outliers, and averaging the remaining spectra. All field spectra were resampled to match the wavelengths and bandpass of the AVIRIS data, based on the 1999 wavelength calibration file supplied by JPL.

Two spatially and spectrally homogenous ground calibration sites were used in this study, including a large gravel natural gas pumping station compound and the boulder field surrounding the base of Devils Tower (Fig. 1). Only one calibration site was present in each of the two AVIRIS scenes. Each ground calibration site was characterized using the ASD FieldSpec Spectroradiometer along a series of transects with measurements being taken approximately every 5 m using the same methods described above.

3.4. Ground cover data collection for leafy spurge

During 1999, the same year that the AVIRIS data were acquired, extensive ground data collection was performed on field vegetation plots. Data were collected during the 2 weeks prior to and the 2 weeks following the AVIRIS flight. The ground plots were part of a concurrent study that documented leafy spurge percent cover in detail (Parker Williams, 2001). Sixty-six circular vegetation plots with a radius of 23 m were located within areas of leafy spurge infestation. Each plot's location was recorded using a selective availability encoded Rockwell Precision Federal Global Positioning System (GPS) unit (Rockwell International, Cedar Rapids, IA) and digital orthophotoquads. These locations were transferred onto the AVIRIS imagery from a digital orthophoto quad with an estimated positional error of 1 pixel. This technique and associated error is similar to what other researchers have reported (Hall, Foster, Verbyla, Klein, & Benson, 1998; Marsh, Walsh, & Sobrevila, 1994). It has been shown that positional error results in conservative bias of image assessments (Verbyla & Hammond, 1995); therefore, the unavoidable positional error introduced into this assessment would result in lower, or conservative, correspondence between AVIRIS and ground estimates of leafy spurge cover.

Each plot was also classified on the ground into three different topographical position types: riparian, draw, or upland, and into two different vegetation types: woodland or prairie. Leafy spurge cover was estimated using broad cover classes (0–5%, 5–25%, 25–50%, 50–75%, 75–95%, and 95–100%) for five, randomly located 1×2 m subplots. The midpoint value of the cover class was recorded as the leafy spurge cover for that subplot. Subplot values were then averaged to obtain an estimate of leafy spurge cover for the plot.

3.5. Image processing and analysis

In order to successfully employ MTMF, a series of image processing steps (Fig. 2) were completed to select the leafy spurge endmembers using field reflectance spectra and the AVIRIS imagery. Unlike many green plants, leafy spurge occurs in dense stands approaching 100% canopy cover in the study area, making selection of pure leafy spurge endmembers from the image data possible. First, the AVIRIS reflectance image was used as input into the minimum noise fraction (MNF) transformation (Green, Berman, Switzer, & Craig, 1988; Lee, Woodyatt, & Berman, 1990). By examining the eigenvalues and the spatial information contained in the output MNF transform images, the first 12 MNF transforms were carried forward in the analysis. Eigenvalues decreased and noise increased substantially after MNF transform 12 (Fig. 3). Second, the 12 MNF transforms were used as input into a Pixel Purity Index (PPI) analysis (Boardman et al., 1995) to identify potential endmembers in the AVIRIS imagery. A relatively high number

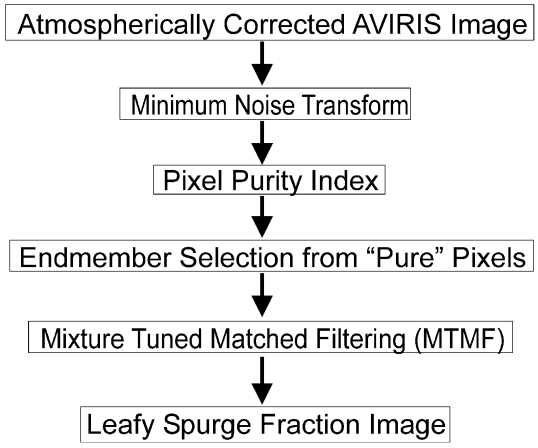

Fig. 2. Flowchart of the image processing steps used for mapping leafy spurge from the AVIRIS imagery using mixture tuned matched filtering (MTMF). This figure was modified from one by RSI (1999).

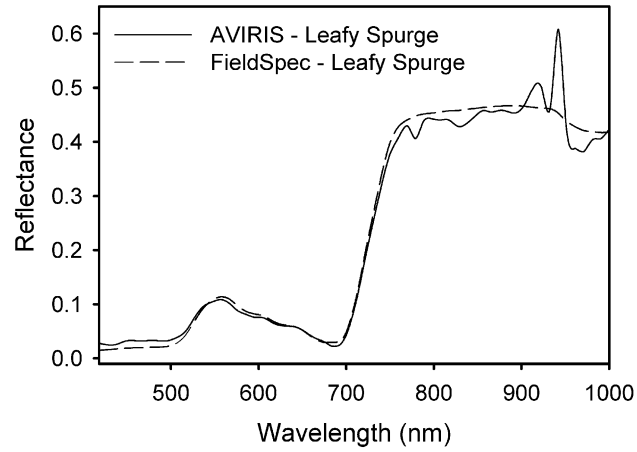

Fig. 4. Comparison of the average spectral signature of leafy spurge pixels from AVIRIS data selected as the endmember to leafy spurge spectra obtained by a field spectroradiometer.

of iterations (3000) and a high PPI threshold value (5) were used to eliminate large numbers of pixels and to emphasize the unique pixels. The output of "pure" pixels from the PPI procedure was examined using multidimensional visualization software (RSI, 1999). Pixels were interactively clustered and grouped based on their spatial relationship to each other and upon examination of their spectral signatures. All groups of pixels that did not contain a vegetation component as identified by their spectral signatures were removed from the multidimensional plot space, allowing finer discrimination of different vegetation pixels. The spectral signatures of each remaining pixel group were systematically compared to the resampled field spectra. The average spectral signature of a tightly clustered group of pixels matched the field spectra for leafy spurge (Fig. 4), and there were no confounding groups with similar spectral signatures.

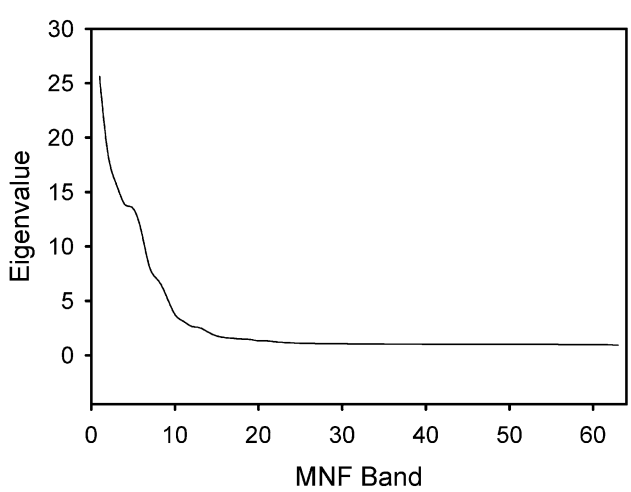

Fig. 3. Eigenvalues for the Minimum Noise Fraction (MNF) transform analysis. The MNF transforms are similar to a principal component analysis. The first 12 eigenimages were carried forward in the analysis and contained most of the useful image information.

The leafy spurge endmember from the AVIRIS image was used as the single endmember of interest in the mixture tuned matched filtering (MTMF) analysis. Ground knowledge of two training areas was used for initial development of the MTMF procedures. The field spectrum of leafy spurge from one of the training areas is compared to the pixel spectrum for this site (Fig. 4).

In order to assess the variation between remotely sensed and ground-measured cover of leafy spurge, data were stratified by both topographic position (riparian, draw, or upland) and vegetation type (woodland or prairie). The draw and riparian strata were combined due to a small sample size of riparian sites in the AVIRIS imagery. The relationships between MTMF estimates of subpixel leafy spurge abundance and ground estimates of leafy spurge cover were examined using simple linear regression analysis (Zar, 1999) for all sites and for sites in each strata.

4. Results and discussion

4.1. Field spectroscopy

The reflectance spectrum of leafy spurge clearly differed from other types of common green vegetation (Fig. 5). It was easily differentiated based primarily on values in the 500–700 nm wavelength region. Leafy spurge was consistently brighter than other vegetation between 500 and 650 nm. It also differed from other vegetation in the shape and magnitude of the characteristic chlorophyll absorption features between 550 and 685 nm (Fig. 5).

Furthermore, leafy spurge was distinguishable from yellow sweet clover (*Melilotus officinalis*), another prevalent yellow-flowering plant species in the study area (Fig. 6). Leafy spurge spectra have a much less reflectance in the chlorophyll-absorption region (550–685 nm) and much higher reflectance in the NIR (Fig. 6). The distinct spectral

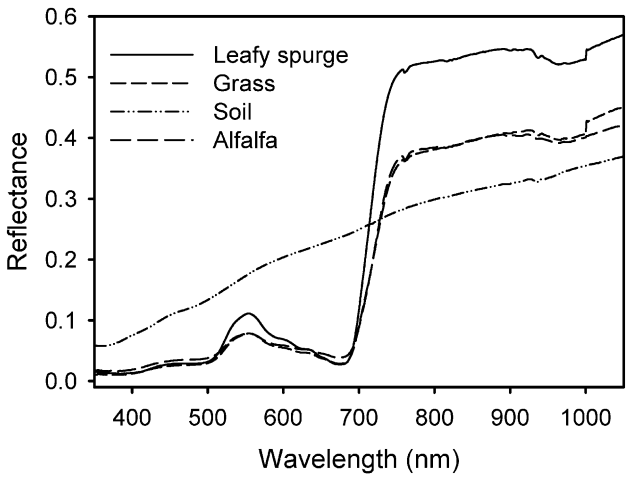

Fig. 5. Comparison of averaged field spectra for vegetation and soils. Grass and alfalfa have different canopy types.

reflectance of leafy spurge flowering bracts is uniquely yellow-green, which spectral features distinguish it from both typical green vegetation and yellow-flowering vegetation. However, there is no single wavelength that will distinguish leafy spurge from other vegetation.

4.2. Mixture tuned matched filtering fraction images

A false color composite of one AVIRIS scene is presented in Fig. 7a, showing the area surrounding Devils Tower National Monument. The dark areas of the image are generally coniferous forests, surrounding Devils Tower with more patches to the west (lower part of the image, Fig. 7a). The Bell Fourche River is visible along the eastern side of Devils Tower; the bright orange color of the fields along the river are indications of leafy spurge Fig. 7a. However, reliance on color alone causes some confusion with some soil types.

The output from the mixture tuned matched filtering (MTMF) analysis was a fraction image with values for each pixel representing the relative subpixel abundance of leafy spurge, and an infeasibility image with values ranging from 1 to 12 (Fig. 7b). Pixels with a high fraction value and a low infeasibility value (<6) had a high percent cover of leafy spurge, while those with high infeasibility values were not classified as leafy spurge. Infeasibility is an estimate on the degree that the various spectral components explain the pixel spectrum, similar to the constraint in standard spectral mixture analysis that the sum of endmember fractions must equal unity (Boardman, 1998). All ground sites used for the MTMF comparison were located in leafy spurge infestations, and all of these sites were classified as "leafy spurge present" in the analysis.

Overall performance of the MTMF for estimating percent cover of leafy spurge for all sites was good (Fig. 8). A significant linear relationship exists between the MTMF fraction and the ground cover estimate that was not significantly different from the one-to-one line ($P=0.82$). The standard error of the y-estimate was 0.0979, or about 10% cover. Whereas the data are from two community types and three topographic positions, the one-to-one relationship shows that, on average, the MTMF fraction is a measure of leafy spurge cover. Because other methods of remote sensing were not compared in this study, it is not known if the MTMF method with hyperspectral imagery is the best for mapping leafy spurge distribution and amount.

4.3. Effect of topographic position and vegetation type

Leafy spurge cover in sites located in draws was estimated slightly better than those located in upland areas (Fig. 9). The standard error of the y-estimate was 0.0877 and 0.0923 for draws and upland areas, respectively. The regression equations for the two topographic positions were significantly different from each other ($P=0.989$), with the slope for the draw regression line being less than 1 and the slope for the upland regression being greater than 1 (Fig. 9). There were only three plots in the AVIRIS imagery that were from the riparian sites, so these data were not included in the analysis for topographic position.

Total spurge cover was generally higher at draw sites than in upland sites (Fig. 9). The better estimation of cover at draw sites may be due in part to variability in leafy spurge phenology. Upland sites generally have less available moisture in late June and early July than do more mesic draw sites, so the flowering period ends earlier for the upland sites. Moreover, draw sites are generally more protected and warmer, so leafy spurge generally starts flowering earlier compared to upland sites. The draw sites will therefore have a long, uniform period of flowering whereas the upland sites will be dependent on local weather conditions. The variability of flowering period for upland sites may be a limiting

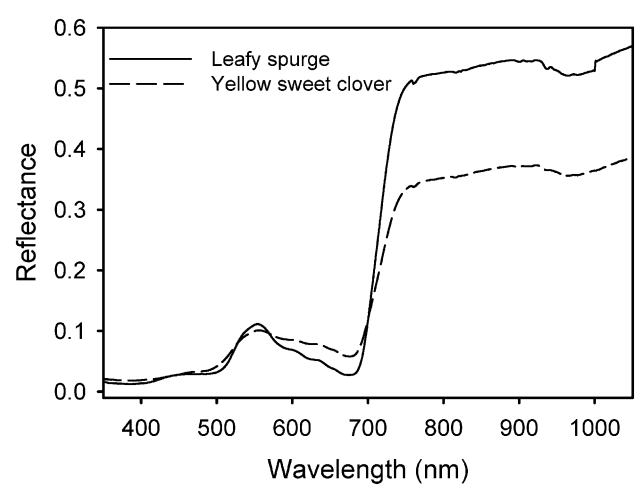

Fig. 6. Comparison of averaged field spectra for leafy spurge and yellow sweet clover. Yellow sweet clover is another common weed that flowers at the time of year as leafy spurge.

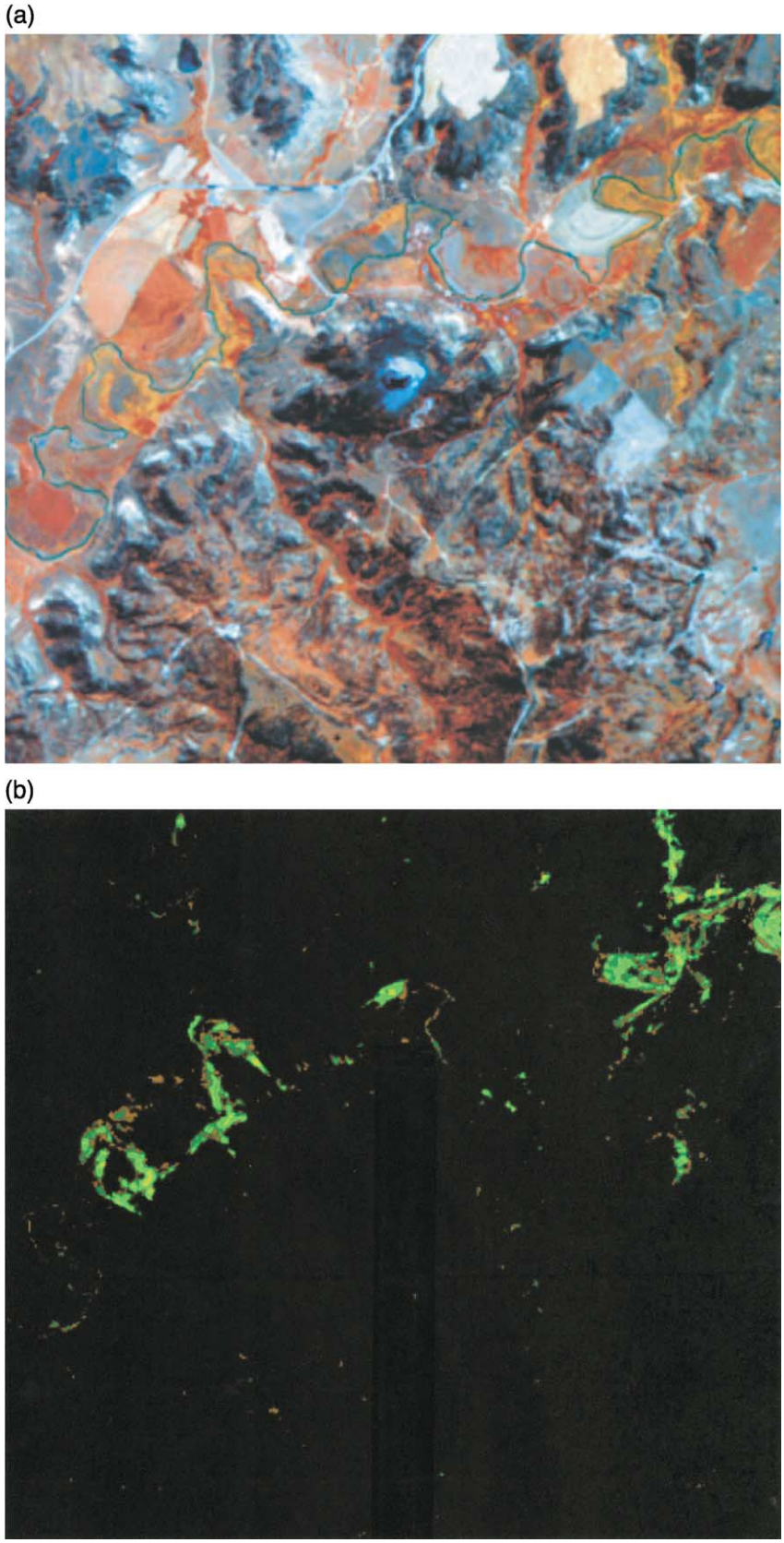

Fig. 7. (a) False color composite of the AVIRIS scene over Devils Tower National Monument. (b) MTMF fraction image for leafy spurge. The tops of the images point to the southeast. The bands used in the false color composite are: blue-band 23 (587 nm), green-band 33 (654 nm), and red-band 53 (845 nm). The color levels for the MTMF fraction are: black—0 to 0.10, dark green—0.10 to 0.30, light green—0.30 to 0.50, and yellow—greater than 0.50.

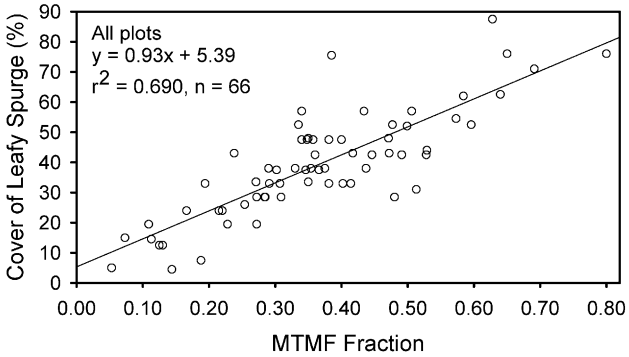

Fig. 8. Regression of MTMF fraction values against percent canopy cover of leafy spurge for all ground data.

factor for detection of leafy spurge due to year-to-year variability in precipitation.

The MTMF analysis performed very well on sites located in areas of prairie, which included sites in the three topographic positions (Fig. 10A). The standard error of the *y*-estimate was 0.0781. There was no significant difference between the prairie and woodland regression equations ($P = 0.546$). For the woodland areas, the MTMF analysis performed poorly in estimating leafy spurge cover (Fig. 10B), the regression for the woodland type had the largest standard error of the *y*-estimate (=0.125) of any topographic or landcover stratification.

The low significance of the regression equation for the woodland sites (Fig. 10B) may be explained in relation to tree canopy obscuring detection from an aerial perspective and variations in tree canopy cover, shade, and view angle between sites. Materials are often obscured by forest canopies, especially when viewed at off-nadir angles (Hall et al., 1998). Possibly, positional error in woodland areas may have a larger effect on image to ground correspondence than in nonwooded prairie. Finally, multiple scattering can lead to nonlinear mixing (Borel & Gerstl, 1994; Ray & Murray, 1996; Roberts et al., 1993), resulting in less precise estimates of leafy spurge cover from linear spectral mixture analysis. However, the fact that leafy spurge was detected as present in all of the woodland sites at all is an encouraging demonstration of the MTMF technique.

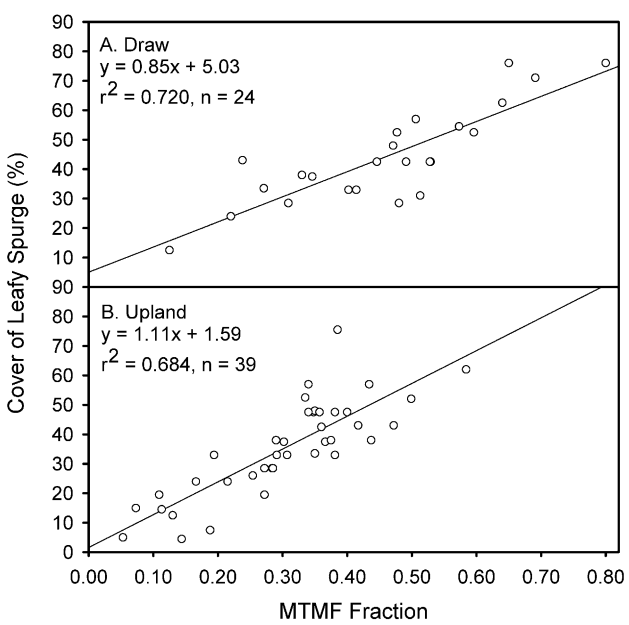

Fig. 9. Regression of MTMF fraction values against percent canopy cover of leafy spurge for two different topographic positions: (A) plots occurring in draws, and (B) plots occurring on upland sites. Data from all vegetation communities were used for the analyses.

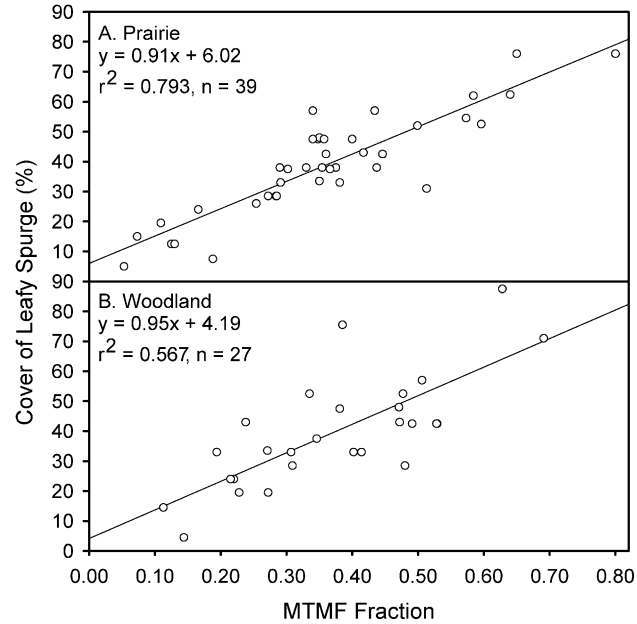

Fig. 10. Regression of MTMF fraction values against percent canopy cover of leafy spurge for two different vegetation communities: (A) prairies and (B) woodlands. Data from all topographic positions, including three riparian plots, were used for the analyses.

4.4. Mixture analysis and vegetation cover

Three other studies have been published that examine the relationship between field and remotely sensed data estimates of vegetation percent cover. Smith et al. (1990) and Elmore, Mustard, Manning, and Lobell (2000) estimated vegetation abundance in deserts from Landsat TM imagery using spectral mixture analysis; whereas McGwire et al. (2000) estimated percent green vegetative cover for areas of sparse vegetation in arid environments from Probe-1 hyperspectral data using spectral mixture analysis. Smith et al. found that remotely sensed data consistently underestimated the cover of vegetation consisting of open canopies such as desert shrubs when compared to ground estimates of percent canopy cover. This contrasts with our findings; however, leafy spurge plants are characterized by a fairly uniform dense canopy unlike the form of many desert shrubs. Elmore et al. show that spectral mixture analysis was superior to vegetation indices (Normalized Difference Vegetation Index) for estimation of green cover. Based on the

spectra of leafy spurge (Figs. 4–6), indices for leafy spurge based on combinations of green and red wavelengths will be very sensitive to the spectral resolution of the sensor.

For comparisons of spectral mixture analysis on airborne hyperspectral data to ground estimates of percent green canopy cover, McGwire et al. (2000) reported a regression slope of 1.074, with a Y intercept of 3.1%, and an $R^2 = 0.737$. Using hyperspectral data, they were able to achieve good estimates of vegetation canopy cover. They also suggest that the Y intercept represents a detection threshold of 3.1% green vegetation cover. Based on the sensitivity of MTMF, a leafy spurge detection threshold for all sites of 5.39% seems quite likely (Fig. 8). When examining green vegetation cover, the results of McGwire et al. are very comparable to the results of this study; however, they did not find predictable relationships between individual desert shrub species endmembers and their ground percent cover. This finding emphasizes the advantage of leafy spurge's unique bract color and growth habit in aiding discrimination using MTMF.

5. Conclusions

Mixture tuned matched filtering (MTMF) has been reported as a superior method for detection of materials in hyperspectral imagery (Boardman, 1998). It has been shown to outperform spectral mixture modeling and matched filtering, especially in cases of subtle, subpixel occurrences (Boardman, 1998). It also has the added advantage in cases of mapping individual materials of not requiring identification of all potential endmembers. MTMF performed very well for mapping leafy spurge and estimating leafy spurge canopy cover. Its sensitivity for detecting and estimating leafy spurge were very encouraging.

Leafy spurge has several characteristics that make it an ideal species for detection from remotely sensed data, so caution must be fostered when considering mapping other invasive species using hyperspectral data. Leafy spurge grows in large dominant stands, is a robust plant with a dense canopy, and has distinctive flowering bracts for a several weeks during the growing season. All of these factors make it easier to map than most other invasive species. Its habit of forming large uniform stands with a dense canopy probably also ameliorate problems of positional error and nonlinear spectral mixing, allowing good prediction. There was also a certain amount of uncertainty in the ground data collection, because it involved estimates using broad cover classes. However, keeping these things in perspective, mapping leafy spurge using hyperspectral remote sensing data is feasible and reasonably accurate for estimating percent cover within broad cover classes. Obviously, mapping leafy spurge under tree canopies is problematic. Although this is one limitation of the method, results demonstrated that in open canopies that have leafy spurge growing in the understory, it dominates the spectral signature sufficiently to be detectable. The techniques presented here could possibly be used for constructing leafy spurge distribution and abundance maps with satellite hyperspectral data for larger regional areas.

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