Discriminating Invasive Crested Wheatgrass (*Agropyron Cristatum*) in Northern Mixed Grass Prairie Using Remote Sensing Technology

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Abstract

Invasive crested wheatgrass in the Grasslands National Park cause biodiversity decrease and irreparable damage to prairie ecosystems. Controlling and managing invasive species require new methods to map and monitor their presence and spread. Traditional mapping techniques based on field observation and data collection are considered time-consuming, subjective, and always very limited in spatial extent and economically for relatively large areas. Remote sensing techniques provide a potential solution to this problem. However, previous work has been limited because of low spatial and spectral resolution of some data sources. The principal challenges in using remote sensors to detect invasive species lie in the spectral similarity across species and invasive species often mixing with the native species. This paper discusses how SPOT-5 imagery with 10-m resolution can be used to detect invasive crested wheatgrass in the mixed prairie. Several vegetation indices, including Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Simple Ratio (SR), and Triangulated Vegetation Index (TVI), were initially selected and their spectral separability in separating crested wheatgrass and natives was examined. A new vegetation index, ExpNDMI, was derived from NDMI by incorporating an adjustment factor (L) to enlarge the difference among classes; and, further, performing a exponential transformation upon the modified index to suppress the variations in all classes. An artificial Neural Netwok (ANN) classifier based on back propagation (BP) algorithm was employed to classify crested wheatgrass and native grasslands in this study. The results indicated that ExpNDMI could significantly increase the spectral separability between crested wheatgrass and native grasslands and improve the classification accuracy. The highest overall accuracy of 79% was obtained. Band/VI combination with ExpNDMI improved the classification accuracy by more than 4% than the combination without ExpNDMI. The result of this study suggests that single-date SPOT 5 image with 10 m resolution could be useful in discriminating crested wheatgrass from natives in the mixed grasslands, and thus may reduce the dependence on the multitemporal data.

Introduction

Approximately one quarter of North America's remaining mixed-grass prairie lies within the Canadian Provinces of Alberta and Saskatchewan. Plants fix carbon and contribute most to the floral diversity and net primary productivity of the region (Andrew et al., 2003). However, Invasive grasses, or non-native species, have threatened rare and endangered plant and animal species, and altered biodiversity and ecosystem function on the prairie (Bakker et al., 2003). Invasive species preempt native grass establishment and have been cited as the greatest obstacle to native grass restoration (Bakker et al., 2003). Invasive plant species result in economic and biologic detriment to rangeland and riparian ecosystems across the western United States and Canada. For instance, in the State of Idaho, the United States, $10 millions per year is spent in control measures alone. This estimate does not include economic impacts of invasive plants to regional industries such as agriculture and livestock, which cost over $137 billion per year in the U.S. (Lass et al., 2005).

Crested wheatgrass (*Agropyron cristatum*) is a long-lived, cool season, introduced grass with extensive root systems, and is adapted to a wide variety of soils and can cope with severe drought stress (Hanks et al., 2005). This species can withstand weed competition and tolerates insect depredation. These biological and ecological Characteristics of crested wheatgrass made it easily established in the cold, semiarid climate of the northern Great Plains (Asay et al., 1996). Large areas of abandoned croplands in the western U.S. were seeded with crested wheatgrass during the 1930's (Hanks et al., 2005). More than a million hectares were seeded with this species in both Montana and Canada prairie (Hanks et al., 2005). Some of these communities have remained virtual monocultures for more than 50 years without apparent successional trends (Asay et al., 1999). The widespread crested wheatgrass has invaded native grassland and raised concerns regarding its ecological impact. Crested wheatgrass invasion of mixed-grass prairie was associated with lower diversity within and among plant communities, and appears to simplify the composition of mixed-grass prairie landscapes.

Figure 1. Crested wheatgrass (*Agropyron cristatum*).

Monitoring the presence and spread of non-native species will be vital to help the Park managers control or remove the invasive species. Traditionally, vegetation mapping and assessment techniques have been based primarily on field observation and data collection. These traditional mapping and assessment techniques are considered time-consuming, subjective, and always very limited in spatial extent and economically for relatively large areas (Peterson et al., 2002). The use of the remotely sensed imagery has been demonstrated a cost-effective method to identify invasive species of grassland and their spread into the native grasslands. In contrast to field-based surveys, imagery can be acquired for all habitats, over a much larger spatial area, and in a short period of time (Underwood et al., 2003).

At the early stage, large-scale aerial photographs were used to detect invasive plants (Havens et al., 1997; Kotschy et al., 2000; Krumscheid et al., 1998; Lathrop et al., 2003; Rice et al., 2000; Warren et al., 2001). The major disadvantage for using aerial photography is only feasible to collect data over a relatively small spatial area because of the high cost of image acquisitions (Lass et al., 2005). In view of the shortcomings with aerial photography, more and more researchers have applied satellite-based imagery, mainly the hyperspectral and multispectral images, to detect invasive species from the native plants. The continuous nature of spectra inherent to hyperspectral imagery, such as AVIRIS and CASI, can be utilized to differentiate vegetation species because the large number of narrow wavebands is able to capitalize on both the biochemical and the structural properties of the target invader (Underwood et al., 2003). There have been a lot of studies using hyperspectral imagery to map invasive weed species such as leafy spurge (O'Neill et al., 2000), Brazilian pepper (Lass et al., 2004), spotted knapweed (Lass et al., 2002), and yellow starthistle (Lass and Thill, 2000), and reached satisfactory accuracies. Mundt et al. (2005) used hyperspectral imagery to discriminate hoary cress in southwestern Idaho, USA, and obtained a maximum producer's accuracy of 82%. A study indicated that spotted knapweed was detectable using hyperspectral data when cover densities were greater than 70% and populations were larger than 0.1 ha (Lass et al., 2002). Glenn et al. (2005) applied HyMap hyperspectral data with a resolution of 3.5 m to detect leafy spurge, and the study demonstrated the ability of high resolution hyperspectral imagery to locate small and low percent canopy cover of leafy spurge. These results showed that hyperspectral sensors, especially with high resolution, might improve the ability to distinguish between vegetation species. Numerous investigators have also worked on developing techniques for using multispectral data in invasive species mapping and detection (Zhang et al., 2002; Vrindts et al., 2002). Peterson (2005) noted that *B. tectorum* cover was detectable from a single date of Landsat Thematic Mapper (TM) imagery. Lass et al. (2005) studied the potential use of SPOT imagery to detect an agricultural weed, *Ambrosia artemisiifolia* L.. The spatial resolution of the latest generation of satellites (e.g., IKONOS and QUICKBIRD) can greatly advance detecting and mapping of invasive plant populations (Fuller, 2005). Although satellite imagery with higher spectral and spatial resolution can be available and mixing of reflectance signals can be avoided at a great extent, limited success has been achieved and invasive population could also not be detected if it is mixed with other vegetation or too small until the invasive species has reached dominance (Lass et al., 2005).

Vegetation in different phenologies exhibits different spectral signature. Most have utilized phenologically related measures (phenological differences between species) calculated from spectral vegetation indices to distinguish invasive species from native plants using multitemporal data and obtained satisfactory accuracy (Underwood et al, 2003; Egbert et al., 1997; Liu et al., 2002). Repeat images acquired weeks to months apart provide an excellent method of exploiting phenological methods of discriminating species. However, combining images of multiple dates presents special challenges. Mis-registration or differences in illumination may limit the usefulness of multitemporal data sets especially if the data have only a limited number of spectral bands. Also, it may not be possible to collect cloud-free data during an optimal period.

Vegetation index (VI) is very useful for detecting invasive plants when they senesces before native vegetation. The normalized difference vegetation index (NDVI) is the most recognized vegetation index and has been successfully used to predict potential distribution of Dyers woad (*Isatis tinctoria* L.) (Lass et al., 2005) and detect downy brome (*Bromus tectorum* L.) in rangeland (USGS, 2003). However, a fundamental problem with the VI approach for detecting species is its lack of generality. The debate over the optimal index of vegetation in arid lands is ongoing (Peterson, 2005). Due to similar cellular chemistry and architecture across species, vegetation reflectance is generally similar in the visible (VIS) and near-infrared (NIR) wavelengths (Cochrane, 2000), and absorption features for live vegetation are often overlapping (Schmidt et al., 2003). This situation makes it problematic to use vegetation indices to discriminate invasive species from native plants in a heterogeneous landscape (Lawrence et al., 2006). Therefore, accurate classification at species level is still difficult.

The principal challenges in using remote sensors to detect invasive species lie in the spectral similarity across species and invasive species often mixing with the native species. There does seem to be very little information on the spectral properties of crested wheatgrass in the scientific literature and little literature specifically on using single- data SPOT to map crested wheatgrass in mixed prairie. The objectives of this study are to assess the feasibility of discriminating crested wheatgrass in the mixed grass prairie using several potential vegetation indices derived from single date SPOT data and develop a modified version vegetation index of NDMI that is expected to improve the separability in separating the invasive crested wheatgrass from native grasses.

Methods

Description of the study area

The study area, Grasslands National Park of Canada (GNP), is located in southwestern Saskatchewan near the international border of Canada and United States. The park serves as an *in situ* gene pool to protect part of the biodiversity of the planet. The two separate blocks that comprise the park and cover approximately 906.5 sq. km. lie between the villages of Val Marie and Killdeer (Fig. 2). This study limited its focus on west block of GNP (GNP annual report, 1997).

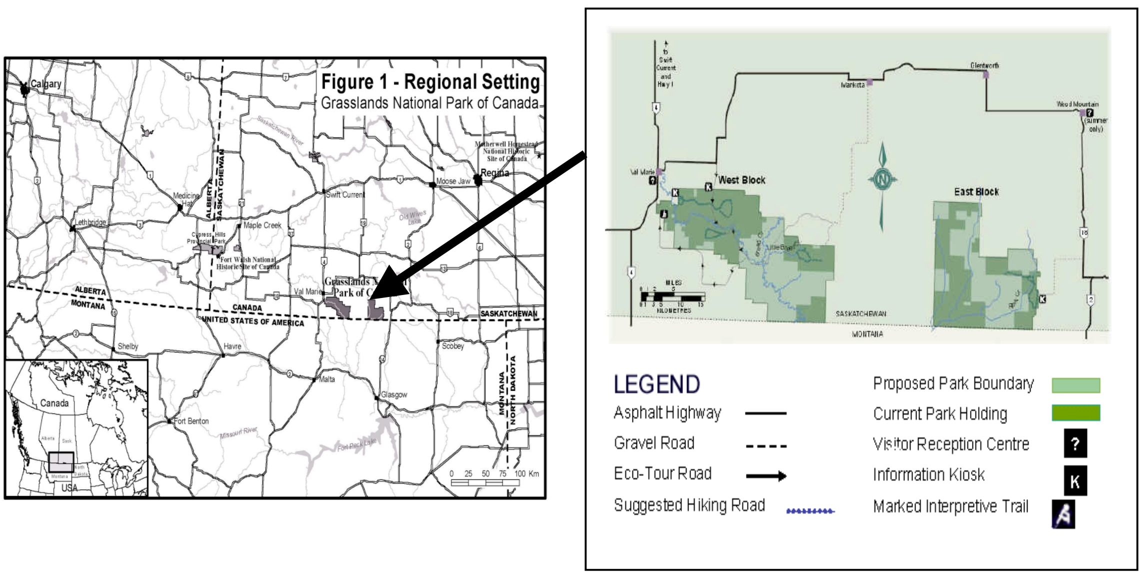

Figure 2. Location of Grassland National Park.

The park is characterized by semi-arid climate, gently rolling hills, coulees, badlands, and wide-open spaces, with wide areas of grasslands. “Mixed-grass prairie” best describes the particular type of grassland associated with the park. The dominant vegetation species include needle-and-thread grass, blue grama, June grass, sagebrush, greasewood, prickly pear, cactus, creeping juniper, western wheat grass, rose, buckbrush, shrubby cinquefoil, thorny buffalo berry, willow, dry land sedges, spikemoss and lichens. However, the Park has also experienced impact from invasive plants. At least 24 non-native plant species have been reported in the Park, Most of the non-native species are either weedy species associated with surrounding agriculture, or species that have been seeded within the boundaries of the Park for agricultural purposes (Peniuk, 1998). One of the major invasive species, crested wheat grass, is of concern because it is used as hay/pasture species and continues to dominate the areas where they were seeded. The potential impacts of crested wheatgrass on park resources and adjacent lands include displacement of native species, interference with the function of natural ecosystems, reduction of native plant populations, reduction of the quality of wildlife habitat and reduction of total plant cover (Peniuk, 1998).

Field data collection and remote sensing imagery

Field data collection was performed in later June and early July, 2005. Two hundred sixty one (261) point-based field samples were obtained and each field sample was located using a GPS (Garmine 76). The sample points were randomly selected from crested wheatgrass and native grassland, respectively. Cover percentage, dominant species, and topographic data were collected on each point. On each point, only one land cover type was included at the extent of 60 m from the point location. Field data were used as training sites and accuracy assessment of classification.

A SPOT 5 image (27 July, 2006) was used in this study, which covers the west block of GNP. The SPOT 5 image has 4 bands (Green, Red, NIR, and MIR) with a spatial resolution of 10 m. The SPOT satellite imagery was georectified to a Universal Transverse Mercator (UTM) projection in order to match the field data. Over 30 GPS ground control points and DEM were used to correct distortions in raw images with Satellite Orbital Modelling The RMS of the registration was controlled to be less than half pixel. The influence of the atmosphere degradation was removed and the digital number (DN) of the image was converted to reflectance by the radiometric correction.

Vegetation indices selection

Finding a vegetation index that discriminates the species of interest from other species has been the focus of many studies (Baret et al., 1989; Broge et al., 2001; Haboudane et al., 2002). Even in the literature, the bands and indices used vary from one study to another. However, it is not the purpose of the present study to evaluate the entire suite of vegetation indices reported in the literature; rather the focus will be on a few selected indices that have shown to be good candidates for the discriminating invasive species. Several broad-band vegetation indices, including Normalized Difference Vegetation Index (NDVI), Normalized Difference Moisture Index (NDMI), Soil Adjusted Vegetation Index (SAVI), Modified Soil Adjusted Vegetation Index (MSAVI), Simple Ratio (SR), and Triangulated Vegetation Index (TVI), were selected for this study based on their performance demonstrated in the previous studies (Davidson et al., 2003; Baret et al., 1989; Huete, 1988). These indices are based on either the combination of chlorophyll absorption band (Red band) and NIR band located in the high reflectance plateau of vegetation canopies (NDVI, SAVI, MSAVI, and SR), or NIR and MIR band located within a region of water absorption (NDMI), or chlorophyll reflection band (green band) and chlorophyll absorption red band (TVI). The calculation formulation of these proposed vegetation indices are listed in table 1 (L represents the soil reflectance factor; a constant of 0.5 was used for this study area).

Table 1. Vegetation Indices Used for Discriminating Crested Wheatgrass.

VI	Formula
NDVI	(NIR-Red)/(NIR+Red)
NDMI	(NIR-MIR)/(NIR+MIR)
SAVI	((1 + L)*(NIR – Red)) / (NIR + Red + L)
MSAVI	((NIR – Red) / (NIR + Red + L))*(1+L)
SR	Red / NIR
TVI	TVI = 0.5 * (120 * (NIR – Green)) – (200 * (Red – Green))

Modifying VI for discriminating crested wheatgrass

The classification of vegetation species using remote sensing data is mostly controlled by the spectral variation within species (intra-species) and the spectral variation between species (inter-species). However, the spectral separability between invasive and native species presents challenges for their accurate classification because the reflectance of vegetation from different species is usually very similar (Schmidt et al., 2003). The spectral separability is determined by the spectral mean differences between species and variation in the same species (Zhang et al., 2006). Numerous factors can lead to substantial spectral variance within species, including reflectance, absorption, and transmission properties of leaves and canopy, dead material, illumination, topography, and soil moisture (Zhang et al., 2006; He, et al., 2006). Some researchers have examined several methods, such as wavelet transformation and derivative analysis, for reducing spectral variation within species (Zhang et al., 2006). Although the derivative of reflectance spectra has been applied to reduce background signals and enhance subtle spectral features in detection of vegetation species, some results suggest that it may not be optimal for species identification in using hyperspectral data because it does not effectively decrease the spectral variation within species (Zhang et al., 2006). Zhang et al. (2006) found that wavelet transform can be capable of reducing variation within species at coarse scale of wavelet coefficients and can be a very useful tool for species identification. However, wavelet coefficients at fine scales may not be informative for the purpose of identification of vegetation species, and wavelet analysis can not enlarge inter-class variability among classes. Thus, a more global view of reflectance may be more useful for the identification of vegetation species than simply observing the reflectance at finely resolved spectral bands. Also, the specific wavelet features and scale may vary for different species and ecosystems (Zhang et al., 2006).

Examining of the spectral curves we found that the largest difference between crested wheatgrass and native species occurs in NIR and MIR bands. It means that NDMI, which is calculated from the two bands, may be a promising variable to separate the two vegetation types. NDMI has proven to be a better greenness measure and showed less saturation effects when the LAI /living biomass reaching higher level (Saltz et al., 1999). However, the difference of NDMI between the two vegetation types is limited and not large enough to distinctly separate crested wheatgrass and native grasses because of higher variances. For the purpose of reducing intra-class variations and enlarging inter-class difference, an adjustment factor (*L*) was incorporated to enlarge the difference among classes; further, an exponential transformation was performed upon the modified index to suppress the variations within class. The exponential NDMI is formulated as follows (equation 1):

$$ExpNDMI=Exp((MIR-NIR)/(MIR+NIR-L)) \quad (1)$$

The difference of ExpNDMI between classes increases with the increasing adjusting factor L, while the intra-variation also increases, in spite of their different increasing rates (Fig. 3). In order to get the optimal L value, we introduced a simple spectral separability index (SSI, equation 2, Bruce et al. (2002)) to assess the spectral separability. SSI takes into account both the inter-class and intra-class variability. A higher inter-class variability and smaller intra-class variability will result in a larger SSI value. The larger the SSI value, the better the spectral separability. In this study, we changed the value of *L* from 0 to 0.4 at an interval of 0.01 to investigate the relationship between the difference of classes and the variations in classes using the spectral data within training area, and found *L* = 0.2 to be the optimal adjustment value that obtained the largest SSI (Fig. 4).

$$SSI_{ij}=(Mean_i-Mean_j)^2 *(1/SD_i^2+1/SD_j^2) \quad (2)$$

SSI_{ij} -- spectral separability index between class i and class j

SD—Standard Deviation

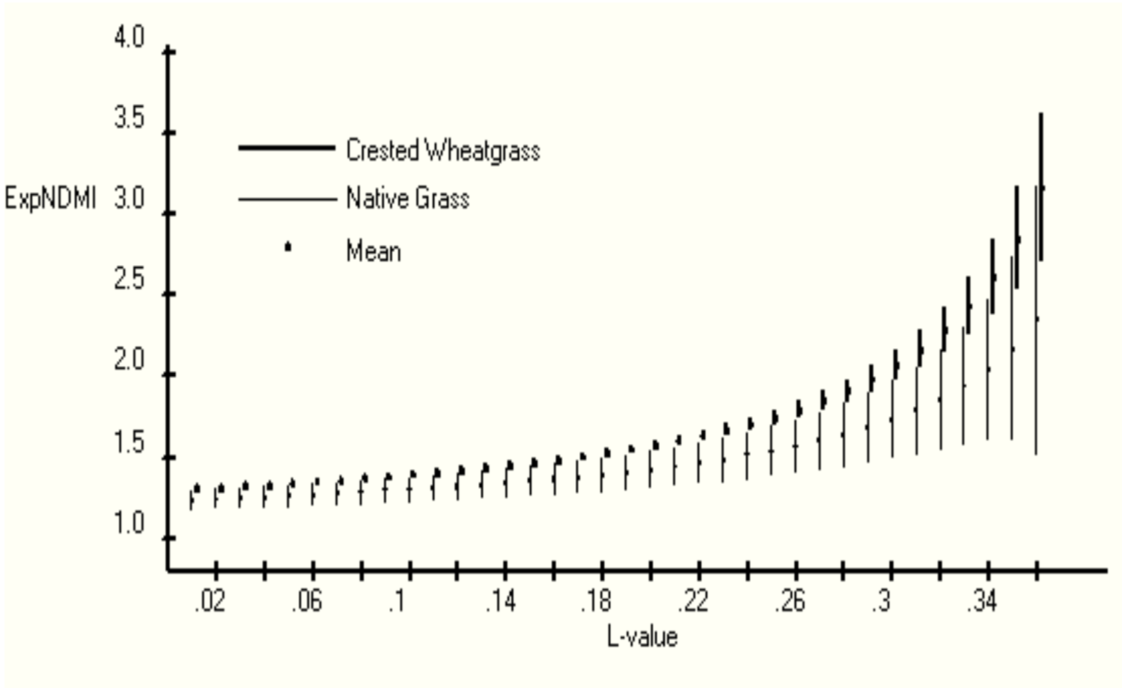

Figure 3. Average ExpNDMI + 1 SD (standard deviation) for crested wheatgrass and native grasslands *vs* the change of adjustment factor L.

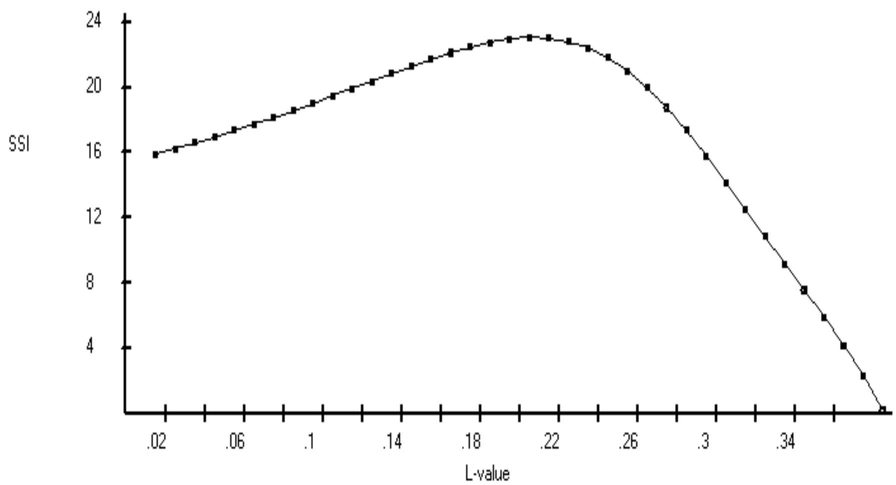

Figure 4. Spectral separability index (SSI) vs adjusting factor *L*. Higher SSI value indicates the better separability between native grasslands and crested wheatgrass.

Statistic feature analysis

Initial analyses of the reflectance spectra, including the calculations of the mean, standard deviation in all bands and VIs, were done on the two classes using the extracted reflectance based on the training sites. Because the classification accuracy mainly depends on the spectral difference among classes, we focused our analysis on the spectral separability of each band or VI on the two classes. The aforementioned SSI was applied to assess the ability of each band or VI in distinguishing the vegetation species. Bands or VIs with low separability were excluded as input in the classification.

Band selection, classification, and accuracy assessment

The point-based field data were used as training area by buffering 20 meters to represent the four pixels of SPOT 5 imagery. Given a number of bands of remotely sensed data and their transformations (e.g., vegetation index), it would require a complex algorithm to identify, from all the possible combinations, the best band combination for classification. In this study, the bands or vegetation indices were selected as inputs for classification based on their spectral separability. Bands or VIs with larger SSI value were selected.

An artificial Neural Netwok (ANN) classifier based on back propagation (BP) algorithm was employed to classify crested wheatgrass and native grasslands in our study. An ANN can realize any arbitrarily complicated, generically nonlinear functional relationship between its input and its outputs by superposition of the elementary node functions (Mutanga et al., 2004). The advantage of neural network methods is that no prior statistical information is needed about the input data, and makes no assumptions about the nature of the data distribution and is not, therefore, biased in their analysis (Kulkarni, 1998). The effectiveness of artificial neural networks to solve highly non-linear problems such as land-cover classification based on multispectral imagery has been demonstrated (Mutanga et al., 2004).

In order to investigate the ability of ExpNDMI in discriminating crested wheatgrass from native grasslands, classifications using band combinations with ExpNDMI and without ExpoNDMI were tested with BP-ANNs. Also, an unsupervised automated classification method was applied first to generate a grasslands "mask" for further classification of crested wheatgrass and native grassland, which might reduce the calculation time and the uncertainty of classification caused by other land covers.

One hundred sixty seven (167) plots were used in post-classification accuracy assessment. Three types of accuracies were calculated: overall accuracy, producer's accuracy, and user's accuracy. The three types of accuracy were compared for different band/VI combinations.

Results and discussions

Spectral separability between native grasslands and crested wheatgrass

Fig. 5 shows atmospherically corrected reflectance of native grasslands and crested wheatgrass by four SPOT bands and different VIs. Similar spectral pattern is found for the two vegetation types, e.g., higher reflectance in NIR band and lower reflectance in Red band. On average, crested wheatgrass has lower reflectance in all bands comparing to the native grasslands, despite the very small difference occurring in MIR band. This may be due to the lower photosynthetic rates and stomata1 conductance of crested whatgrass than the native grasses in the summer months (Nowak et al., 1986), while it coincides with the image acquisition date of this study. Crested wheatgrass is a cool season plant, and it tends to go semi-dormant during midsummer months. The spectral reflectance features of crested wheatgrass and native grasslands may reflect phenological and compositional differences in the vegetation. Comparing to native species, there are more abundant senesced vegetation in crested wheatgrass pastures (e.g., litters. He, et al., 2006) that probably contributes to the lower reflectance (Thomson et al., 1990). Also, crested wheatgrass has rougher surface than native range, which may lead to the lower reflectance.

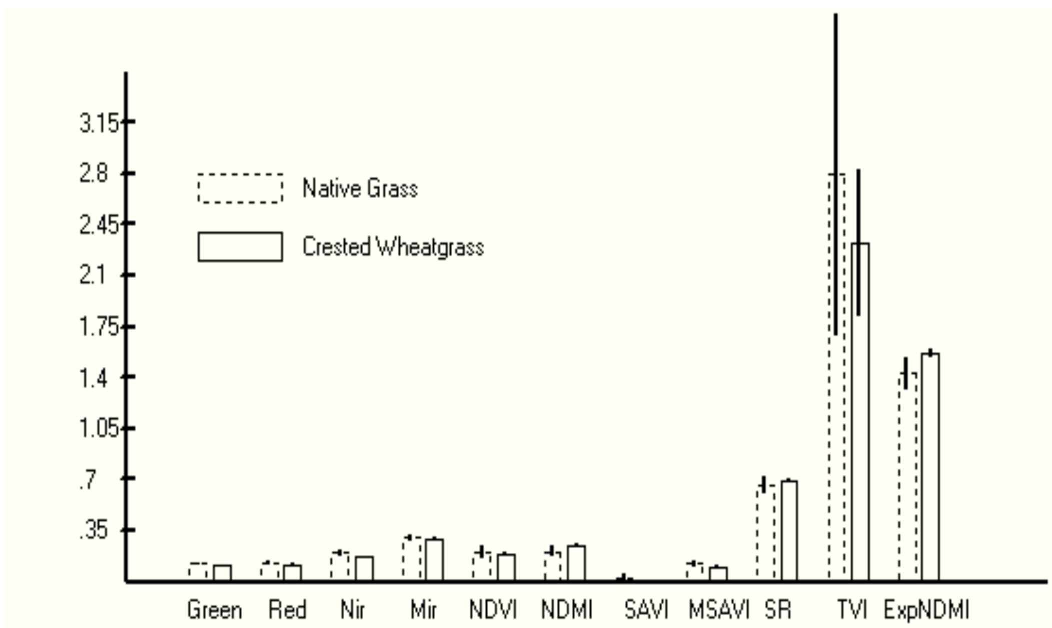

Figure 5. Reflectance mean and 1st SD (standard deviation, indicated in bold line) in SPOT bands and VIs for crested wheatgrass and native grasslands.

With regard to the differences between single bands for the two class of vegetation, the greatest reflectance difference was found in the NIR (Fig. 6) and it showed the maximum spectral separability in the four SPOT bands. Green band also show better separability in comparison to red and MIR bands. This may be caused by the green band to be more sensitive than the red band in detecting leaf chlorophyll variation. Differences between the two vegetation types in the NIR band may be due to their differences in plant photosynthetic rates; —NIR wavelengths are more reflected by healthy, photosynthetically active vegetation, while crested wheatgrass has lower photosynthetic rates in the midsummer (Nowak et al., 1986). NDMI, which is calculated from NIR and MIR, showed the highest separability between native grassland and crested wheatgrass among the initially selected VIs. This is due to the greatest spectral difference in the NIR and similar reflectance in MIR for the two vegetation types. The limited success of other indices is related to the fact that the reflectances in all bands are similar for the two vegetation types. The ExpNDMI, which is modified from NDMI, exhibits largest separability among the VI group and all single SPOT bands. Comparing to the NDMI, ExpNDMI greatly increased the spectral separability because it can significantly reduce the intra-species variation and enlarge the inter-species variation. It would be expected to increase the classification accuracy of invasive crested wheatgrass. Some VIs, such as TVI, revealed significant overlap in the spectral space, and therefore, reached very lower separability in the discriminating of crested wheatgrass from natives. Separablity has helped in selecting proper bands and VIs to be included in the classification of crested wheatgrass. Bands or VIs with lower separability were excluded from the classification inputs.

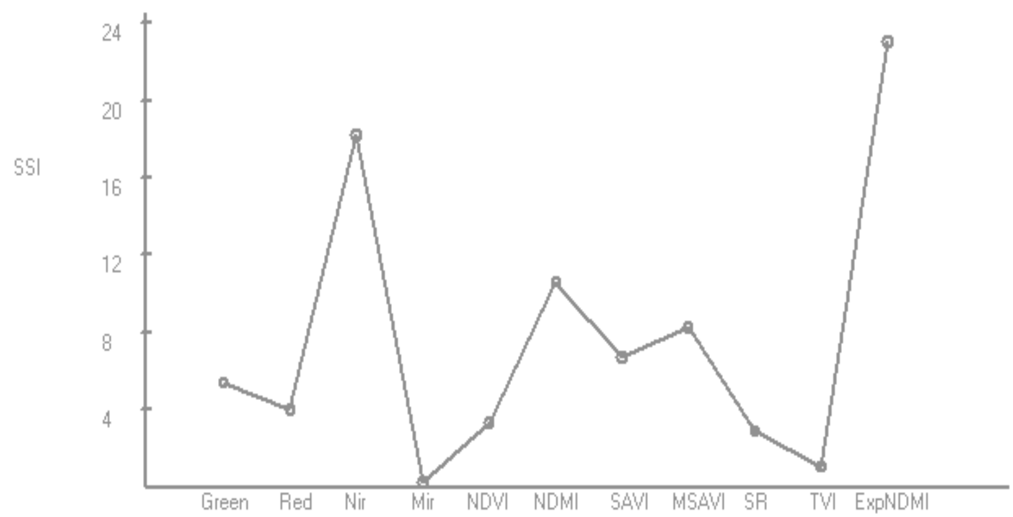

Figure 6. SSI for SPOT bands and VIs on separability of crested wheatgrass and native grasses.

Classification and accuracy assessment

Based on the spectral separability analysis, bands and vegetation indices were selected for which the native grasses and crested wheatgrass were spectrally different. The classification was performed using two combinations: one with the SSI greater than 4.0 (including Green, NIR NDMI, SAVI, MSAVI, and ExpNDMI) and another with the SSI greater than 8.0 (including NIR, NDMI, MSAVI, and ExpNDMI). An artificial Neural Netwok (ANN) classifier based on Back Propagation (BP) algorithm was applied to classify crested wheatgrass and native grasslands. One input Layer (2 nodes for per channel), two hidden Layer (8 nodes for per layer), and one output Layer (2 nodes) were designed for the neural network, and sigmoid function was used as activation function. For the purpose of investigating the performance of ExpNDMI in the discriminating crested wheatgrass, another two combinations were tested. One was with ExpNDMI (Green, NIR, SAVI, MSAVI, and ExpNDMI) and another was without ExpNDMI, while substituted by NDMI (Green, NIR, SAVI,MSAVI, and NDMI).

Table 2. Classification Accuracy for Different Combinations (ANNs Classifier).

Band/VI combinations		Producer's accuracy	User's accuracy	Overall Accuracy	Overall Kappa
Green, NIR, NDMI SAVI, MSAVI, ExpNDMI	Natives	81.1%	85.1%	79.4%	0.568%
	CW	76.6%	75.0%		
NIR, NDMI, MSAVI ExpNDMI	Natives	86.8%	80.7%	78.8%	0.537%
	CW	65.6%	71.0%		
Green, NIR, SAVI, MSAVI ExpNDMI	Natives	82.1%	81.3%	77.1%	0.510%
	CW	68.8%	69.8%		
Green, NIR, NDMI, SAVI MSAVI	Natives	82.1%	76.3%	72.9%	0.409%
	CW	57.8%	66.1%		

Note: CW=crested wheatgrass

An evaluation of classifications using increasing numbers of bands and VIs showed an improvement in overall classification accuracy and overall kappa (Table 2). Combination of Green, NIR, NDMI, SAVI, MSAVI, and ExpNDMI obtained the highest overall accuracy of 79%. Due to the lack of previous research results, we could not conduct the comparison with other studies related to the crested wheatgrass detection. However, we may believe this is a higher accuracy in the case of using single date imagery. The misclassification between natives and crested wheatgrass could be attributed to many factors. The major cause could be the spectral similarity between the two vegetation types. Although SPOT 5 image with higher spatial resolution was applied in this study, its lower spectral resolution could not discern the subtle difference between the two vegetation types, especially when they are mixed with each other.

The result of classification using combination with ExpNDMI layer showed that ExpNDMI could improve the classification accuracy by more than 4% than the combination without ExpNDMI. This result indicates that ExpNDMI is much better to reflect the spectral difference between crested wheatgrass and native grasslands than NDMI. ExpNDMI had the highest separability among all the bands and VIs because it can significantly suppress the intra-class variation and enlarge the inter-class variation.

A visual inspection of the crested wheatgrass classification map (Fig. 7) indicates that the crested wheatgrass was over-classified, especially in the low-left of the map. The area is almost exclusively native prairie. This may be due to the reflectance of plants in this area to be very similar to that of crested wheatgrass community. This result is consistent with the previous studies that indicated that there is a tendency for the invasive species to be over-classified, that is, more pixels are identified as invasive species than actually exist (Lass et al., 2002).

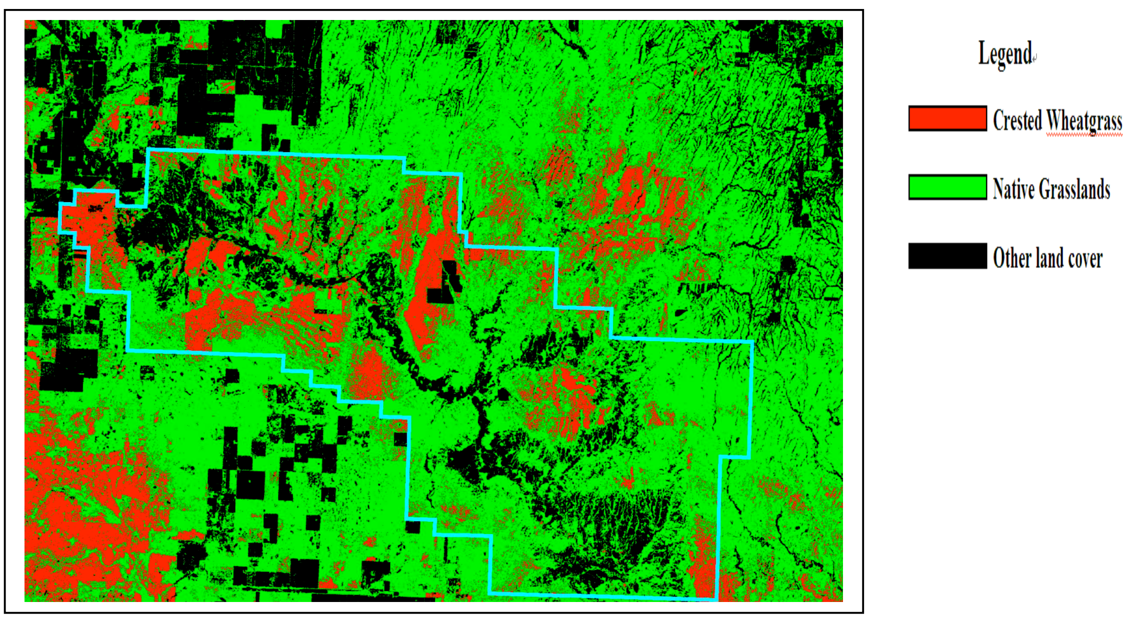

Figure 7. Crested wheatgrass classification map.

We acquired a digital vegetation map of the GNP region from Parks Canada. This map was created only for lands within the GNP boundary for which the Park held title in 1993. The inventory was initiated to fulfill requirements of the GNP resource management program, particularly the formulation and implementation of a management plan for the Park. The resulting vegetation map was based on the interpretation of 1:12,500 scale airphotos (collected 1982) and a subsequent intensive field survey (carried out in 1993).

By comparing the classifying map (Fig. 7) with the previous digital vegetation map, we can find the striking difference between the two maps and a great expansion of crested wheatgrass since then, in spite of the fact that the crested wheatgrass was over-classified in this study.

Conclusions

In this research we assess several selected vegetation indices applied in discriminating crested wheatgrass from natives in mixed grass prairie. The results showed that the single-date SPOT 5 image used in this study can classify crested wheatgrass with 79% of overall accuracy, and the proposed ExpNDMI can reduce intra-group variation and enlarge inter-group variation, further, improve the ability to discriminate invasive crested wheatgrass from natives at 4% of the overall accuracy. We speculate that the accuracy can be improved with a multi-temporal approach, especially an image from early spring. Results of this study demonstrated that previous vegetation indices have limitations in discriminating the two plant types and ExpNDMI obtained better separability than other selected VIs for the two grass types, and could increase classification accuracy of crested wheatgrass and native grasslands in the study area. Single date SPOT 5 imagery with proper acquisition season could be useful in discriminating crested wheatgrass from natives in the mixed grasslands, and thus may reduce the dependence on the multitemporal data, which may be difficult or impossible to obtain cloud-free data during an optimal period.

Since vegetation reflectance depends on a complex interaction of several internal and external factors that may vary greatly in time and space and from one species to another, no universal spectral pattern between two vegetation species can be expected to exist. Consequently, this pattern will be site-, time- and species-specific, and therefore not directly applicable for large-scale operational use. Although higher spatial and spectral resolution is desirable in order to avoid mixing of reflectance signals originating from different vegetation types, the spectral similarity at species level is still the greatest challenge in discriminating invasive species. Therefore, the methods and the new developed vegetation index, ExpNDMI, in this research were limited to our study area.

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