

REMOTE SENSING TO MONITOR MONOTYPIC WEED PATCHES IN SEMI-ARID
GRASSLANDS

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

MASTER OF SCIENCE

Plant Biology

2012

ABSTRACT

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Remote sensing technology has great potential for mapping weed distributions. Fine-scale weed distribution maps can provide means to evaluate the success of weed control methods, to guide selection of future control methods, and to examine factors that influence the creation and persistence of monotypic weed patches. Here I examined the effectiveness of different classification approaches in detecting dense monotypic patches of the late-phenology weeds *Taeniatherum caput-medusae* (medusahead) and *Aegilops triuncialis* (barbed goatgrass), among cool-season forage grasses (*Bromus* spp. and *Avena* spp.) across multiple years in semi-arid rangelands in northern California (USA). I found that color infrared photographs acquired at two key phenological periods produced more accurate classifications than those based on one image alone, and that inclusion of training sites did not improve the overall accuracy of a classification. I also examined the association of remnant litter with transitions in species dominance in medusahead, goatgrass or forage patches. Persistence of goatgrass-dominated patches was correlated with the amount of remnant litter present, but surprisingly that of medusahead was not, suggesting a potential need for different strategies in control of these two noxious species. Overall, this study shows that remote sensing can be used to create weed distribution maps of phenologically distinct species, and help us further understand community response to invasion and evaluate the effectiveness of management treatments.

ACKNOWLEDGEMENTS

I would like to thank my advisor, Dr. Carolyn Malmstrom, for her advice and support throughout the entire thesis process. I am also thankful to my committee members, Dr. Jennifer Lau, Dr. Ashton Shortridge and Dr. Jiaguo Qi, whose assistance helped focus and direct this project. This thesis would not have been written without the other members of my lab, including Colin Phillippo, Jarrod Morrice, Abbie Schrottenboer and Lisa Stelzner, who frequently edited and gave me feedback. And to Bob Goodwin, who was always able to give me the technical support that I needed.

I would like to give a special thank you to all the people in California who helped make this work possible, especially the ranchers who allowed me to hike their properties collecting data. And especially to Scott Butterfield, who helped focus this work and helped me appreciate the perspective of the land managers throughout the project.

Finally, I need to thank my family: My parents Steve and Gail Planck for endless support and encouragement throughout this entire process, revising drafts, and supplying baked goods when needed, and my sister, Kim Patel, who was always encouraging and willing to help when necessary.

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CHAPTER 1:
LITERATURE REVIEW

USE OF REMOTE SENSING TO MONITOR INVASIVE SPECIES IN SEMI-ARID
GRASSLANDS

1. Semi-Arid Grasslands: An Overview

Grasslands and other rangelands currently comprise of 45% of the Earth's terrestrial surface, not including Antarctica (Galvin et al. 2008). Globally, much of the area that was initially grassland has been converted by humans over time to agricultural lands. The grasslands that remain generally represent the more arid and less productive areas, which often are managed as rangelands, defined as lands predominantly used for grazing livestock (Galvin et al. 2008). In the United States, nearly 25% of the land area is devoted to rangelands, with nearly one-third classified as semi-arid rangelands. Located primarily in the west (Figure 1), semi-arid grasslands experience low precipitation but can support more species than arid environments (EPA 2010).

Semi-arid grasslands provide important economic and ecosystem services, including provisioning of forage for livestock (in the US, primarily beef cattle and sheep) and wildlife habitat. In addition, semi-arid rangelands provide amenities for people, including recreational opportunities and scenic vistas. Semi-arid rangelands promote biodiversity by providing forage for wild fauna and refuges for birds (Galvin et al. 2008, USDA 2008).

2. Management of Semi-Arid Rangelands

Good rangeland management practices often aim to increase rangeland productivity and prevent its degradation. The best management practices for a given location depend on soil type and local environmental conditions (DiTomaso 2000, Harrison et al. 2003) and may include prescribed burns or managed grazing. Prescribed burning is a valuable tool to help control unwanted species and reduce levels of senesced biomass. However, prescribed burns are more dangerous to implement than grazing and can be costly.

As a result, much attention in rangeland management is focused on developing optimal grazing strategies including livestock rotations that allow the land to rest and recover from intensive grazing (Cingolani et al. 2005, Gibson 2008). Grazing can increase the productivity of grasslands by increasing light availability through biomass removal and by increasing nitrogen availability through animal defecation (McNaughton et al. 1997), which creates small nutrient-rich patches that may alter competitive relationships among plants (Bakker et al. 2003, Veen et al. 2008). Finding the appropriate timing and duration of grazing for a given rangeland is a necessary part of developing management strategies that promote plant diversity. At the 1-meter patch scale, grazing can increase species richness (Bakker et al. 2003, DiTomaso et al. 2008), whereas at landscape scales grazing may decrease species richness (Dorrough et al. 2007). In general, overgrazing usually favors a low diversity plant community, dominated by grazing-tolerant species, while near-absence of grazing may create another type of low diversity system, one in which only the best competitors survive. As a result, moderate levels of grazing are frequently found to be best for rangeland management (McNaughton 1985, Dorrough et al. 2007, Veen et al. 2008), in keeping with the Intermediate Disturbance Hypothesis, which predicts that diversity is greatest at moderate disturbance frequency (Connell 1978). Increasing rangeland plant diversity improves wildlife habitat while simultaneously providing forage for livestock (McNaughton and Georgiadis 1986, du Toit 2011). Increasing plant diversity in rangelands can also help reduce variability in rangeland productivity under a range of weather conditions (Ives and Carpenter 2007, Suttle et al. 2007).

3. Effects of Litter in Semi-Arid Rangelands

Current management practices in grasslands, including grazing, mowing, and prescribed burns, influence plant diversity in part by manipulating litter patterns, which in turn influence species establishment and persistence. For example, fire, mowing and grazing remove large amounts of biomass and thereby create a high-light environment for new seedlings to germinate. These management practices can be used to mimic historic disturbances, such as naturally occurring burns or grazing by wildlife (Hobbs and Huenneke 1992, Sheley and Petroff 1999).

Plant litter influences nutrient cycling in ecosystems (Xiong and Nilsson 1999, Nagler et al. 2003). Litter can also influence future community composition by altering patterns of light penetration and soil evaporation (Jong and Klinkhamer 1985, Facelli and Pickett 1991, Rebollo et al. 2001, Drenovsky and Batten 2007, Amatangelo et al. 2008), with effects determined by community and litter type. In most rangelands, the more palatable species typically are also those that decompose faster because they are more nutrient-rich (Moretto et al. 2001, Koukoura et al. 2003). As a result, Koukoura et al. (2003) found that the dominant species in a Greek grassland were the species with the slowest litter decomposition rates, releasing the nutrients slowly over time.

Decomposition rates are also influenced by environmental factors, including temperature, solar radiation, and precipitation (Arriaga and Maya 2007). Species may gain competitive advantages by influencing the rate at which litter decomposes and releases nutrients into the environment, if the timing of release is disadvantageous for competing species (Drenovsky and Batten 2007).

4. Invasive Species in Semi-Arid Rangelands

Invasive species can alter the dynamics of semi-arid rangelands and their ability to provide ecosystem services. Invasive species have been introduced to rangelands both purposefully and unintentionally (Mack et al. 2000). In some cases, invasive species have been introduced to improve forage quality and are considered desirable by managers who aim for a high livestock yield. In California, for example, invasive grasses that provide good forage include *Bromus hordeaceus* and *Avena* spp. (Stromberg et al. 2007). But these species may not be desired by managers who wish to restore rangelands to a historical grassland species composition (Jackson et al. 1995). Species introduced unintentionally to US grasslands have decreased both the economic and social value of the rangelands. These species include *Aegilops triuncialis* (goatgrass), *Taeniatherum caput-medusae* (L.) Nevski (medusahead), *Bromus tectorum* L. (cheatgrass), *Euphorbia esula* L. (leafy spurge), *Centaurea solstitialis* L. (yellow star thistle), and *Centaurea* spp. L. (knapweed) (Sheley and Petroff 1999).

Environmental factors influence whether a rangeland will be invaded by an introduced species. In systems where water is limiting, as is common in remnant grasslands that are located at drier or less economically valuable sites, water availability and water efficiency of native and invasive species affect which species dominate the landscape (Funk 2007). Elevation (Thomsen and D'Antonio 2007), species land management (Sheley and Petroff 1999), and tolerance to grazing (Kimball and Schiffman 2003) will also impact which species will become dominant on the landscape.

The relationship between plant community diversity and community resistance to invasion is much more complex. One hypothesis that has received much attention over the years

is that increased species richness reduces invasibility (Elton 1958), but notable studies have found that this is not always the case (Harrison et al. 2001, Foster et al. 2002, Mattingly et al. 2007). For example, Foster et al. (2002) showed that light penetration, standing crop, and disturbance had a greater impact on a community's invasibility than did its species diversity. Others have found that increased species evenness had no influence on invasibility (Mattingly et al. 2007). Harrison et al. (2001) found that habitat patchiness on serpentine soils may impact invasibility more than species diversity. Patchiness may increase invasibility by increasing edge area that allows invasive species to establish (Harrison et al. 2001). Moreover, when specific patch types are adjacent to each other, they could create microenvironments that promote establishment of the invasive plant species (Harrison et al. 2001). Plant litter can also promote invasive species establishment if it creates a microenvironment that preferentially supports germination of the invasive plant species (Evans and Young 1970).

4.1 Patch Dynamics of Invasive Species in Rangelands

Invasive species in rangelands cause substantial problems when they form dense monotypic patches. The development of these patches is likely to be the product of several interacting factors including soil properties, grazing patterns and water availability (Bakker et al. 2003). Thus, advancing understanding of the effects of environmental factors on patch dynamics will help increase the effectiveness of management practices in rangeland ecosystems. Many managers experiment with changes in grazing regimes, as grazing is a form of disturbance that can influence patch formation (Kimball and Schiffman 2003, Cingolani et al. 2005, DiTomaso et al. 2008). It has been repeatedly shown that moderate disturbance increases species richness (Connell 1978, Hobbs and Huenneke 1992). Grazing allows the colonization of species that

would not be able to compete in ungrazed areas (Gibson 2008), reducing the presence of some monotypic patches. However, if a species is noxious and is avoided by grazers, grazing can increase weed patch density (Wan et al., Noy-Meir et al. 1989).

To understand long-term species interactions and quantify the efficacy of management practices, it can be valuable to monitor changes in monotypic patches over time. Changes in patch metrics, including patch size, number, and shape (often measured as an edge to area ratio), are frequently used to assess patch dynamics (O'Neill 1988). These metrics describe changes over time. To further consider what factors might drive vegetation change in patches, state-and-transition models are often used (Bestelmeyer et al. 2003, Bestelmeyer et al. 2009). State-and-transition models describe different vegetation states, such as patch types, the factors that influence transitions between those states, and the probability that particular transitions occur.

5. Remote Sensing and Invasive Species

Initially, the capability of remote sensing to detect invasive species was limited by spatial resolution and timing of satellite imagery (Lass et al. 2005, Weis and Sokefeld 2010). An increase in the availability of hyperspectral and high spatial resolution images taken at frequent intervals has improved capacity to map weed distributions, but limits to broader application of this approach remain. Enhancements in spectral resolution of imagery can improve weed detection capacity in some cases, but it remains difficult to distinguish weed species when their spectral signatures are similar to those of their native counterparts or when the two groups are well mixed, even with fine spatial resolution imagery (Lass et al. 2005). The most successful classifications have occurred when the invasive species differ in form or phenology from the native species (Ustin et al. 2002), and this is the approach I will focus on here.

5.1 Sensors and Images

Due to the cost of both high spatial resolution and hyperspectral imagery, gaining resolution in one category often means a diminished resolution in others. Newer sensors and satellites, such as IKONOS, are able to offer both fine resolution in both radiometric and spatial properties, but this imagery is expensive (Ustin et al. 2002, Ustin and Gamon 2010). The classification method best suited for a study will determine the degree of resolution necessary within each of these two categories, which will in turn aid in determining which sensor should be used.

There are many sensors and images available to determine the spectral signatures of species. Sensors providing aerial photography or satellite imagery give the spectral radiance of a large scene, whereas field spectroradiometers give the spectral radiance of a small focused area. The ability to link information between these two categories is difficult, and care in calibration must be taken. Even within a sensor category, there can be inconsistencies based on brand or method (Castro-Esau et al. 2006, Fisher and Mustard 2007).

A field spectrophotometer is useful for assessing small patches or quantifying spectral properties of species in a laboratory setting. To evaluate landscape scale interactions, either satellite or airborne imagery should be used. With satellite imagery, the typical user has limited control of the timing of image acquisition, and image quality can be poor due to atmospheric conditions. Images collected from aircraft generally offer higher resolution and greater control of the timing of image acquisition (Caylor 2000).

5.2 Multi-Temporal Analysis

Multi-temporal analysis provides insight into seasonal differences in productivity relationships among vegetation types (Oindo and Skidmore 2002, He et al. 2009). Detection of changes in vegetation seasonality on a landscape over time that can indicate the developing presence of species with different phenological properties (Reed et al. 1994, Crimmins and Crimmins 2008) or changes in land cover types (Lucas et al. 2007). Phenological characteristics used to differentiate weeds from their native counterparts include peak growing time, blooming time and flower characteristics (Bradley and Mustard 2005, Peterson 2005, Singh and Glenn 2009, He et al. 2011). On a broader scale, multi-temporal analysis can show relationships between species richness and productivity across an entire landscape over time (Fairbanks and McGwire 2004, Liu et al. 2008).

5.3 Spatial Resolution Analysis

Fine spatial resolution allows for detailed mapping of individual species or functional groups (Gergel et al. 2007, Thompson and Gergel 2008). Use of fine spatial resolution imagery can therefore enhance the estimate of species richness on a landscape (Gougeon and Leckie 2006, Rocchini et al. 2007). Spatial resolution options include high (submeter) resolution aerial photography, moderate resolution (30 m) Landsat imagery and (250 m) resolution MODIS scenes. Plant species that grow in small clusters across landscapes will not be easily detected in low or moderate resolution imagery (Jelinski and Wu 1996). Imagery with low or moderate spatial resolution also does not allow us to readily detect changes in patch size and edge movement, when patches are smaller than the imagery grain size (Turner 1989).

5.4 Spectral Resolution Analysis

Spectral resolution ranges from the broad spectral bands of multispectral imagery (often 0.6 – 1.1 μ m) to the fine bands of hyperspectral imagery, in which bands may be as narrow as 0.3 nm (Jensen 2005). Increasing the spectral resolution may increase the capability of detecting differences among species (Rocchini 2007, Rocchini et al. 2007). Technological advances in imagery have increased availability of hyperspectral data (Huang and Asner 2009), and improved our ability to detect weedy species with remote sensing (Ustin et al. 2002, Ustin and Gamon 2010, He et al. 2011). Hyperspectral imagery has shown improvements for detecting weed species when weeds have a distinct chemical composition, biogeochemical processes, or color in comparison to the native plants (Asner et al. 2008, He et al. 2011). Hyperspectral imagery is expensive and limited in availability, however; hyperspectral data can also be challenging to analyze, making the imagery less suitable for stakeholder evaluation.

5.5 Successes in Detecting Invasive Species

Detecting individual tree species in the tropics requires both high spatial resolution and hyperspectral data. In Hawaii, Asner et al. (2008) were able to use hyperspectral data to identify each species of tree in the local tropical rainforest. The hyperspectral imagery enabled the investigators to clearly separate nitrogen-fixing trees from the non-nitrogen fixing trees by detecting leaf nitrogen and phosphorous. However, they could not distinguish between invasive and non-invasive tree species without identifying the characteristics of each tree species (Asner et al. 2008). Clark et al. (2005) have also shown success in finding spectral differences between tree species but not between functional groups.

Studies distinguishing between plant species and functional groups in grassland systems have also been successful. Cheatgrass is a grassland invasive found in the western United States of America. Cheatgrass is phenologically distinct from the neighboring species. Two groups have successfully identified cheatgrass in Idaho using Landsat satellite imagery. Peterson et al. (2005) were able to use environmental variables including elevation and a heat index to create models showing that the difference in NDVI values between the early and late growing season was the best predictor of cheatgrass patch location. More recently, Singh and Glenn (2009) detected cheatgrass with a 76.8% accuracy using only the difference in NDVI values from multiple images from the Landsat combined with training sites from ground data. Malmstrom et al. (2004) were able to distinguish between late-season weeds and forage grasses in a single year using only the difference in NDVI values. However, the robustness of this approach for use on imagery obtained over multiple years has yet to be determined.

Other invasive species that have been successfully mapped with the assistance of phenological differences include down brome, leafy spurge, yellow star thistle and pepperweed (He et al. 2011). However, invasive species that are not phenologically distinct from their native counterparts have also been successfully detected through multi-band high spatial resolution, e.g., *Tamarix* spp. (tamarisk) or with high hyperspectral resolution, e.g., *Carpobrotus edulis* (iceplant) (He et al. 2011).

6. Case Study

6.1 Invasive Species in California Rangelands

California rangelands are predominantly semi-arid with a Mediterranean climate that features hot dry summers and cool rainy winters. Much rangeland is located in the central valley of the state. Some of these grasslands are in the foothills of the coastal range or in the foothills of the Sierra Nevada mountain range, in locations where the terrain is too hilly or the soil too poor for agriculture.

There are three groups of grasses that are found in these rangelands: native, introduced forage grasses, and weedy grasses. Common native grasses include *Nassella pulchra* (purple needle grass). Many of the native grasses are perennial bunchgrasses and do not compete well with introduced grasses under intense grazing (Stromberg et al. 2007). As a result, although these grasses can still be found in California rangelands, they are relatively uncommon. Common introduced forage grasses include *Bromus* spp. (Bromes) and *Avena* spp. (Oats). These grasses were introduced in the 1800's to the rangelands as forage for cattle and quickly dominated the landscape (Stromberg et al. 2007). While invasive, these introduced forage grasses are desired by ranchers for their high forage quality and, therefore, are not always a target for eradication. In contrast, two noxious weedy grass species introduced to these grasslands are targeted by rangeland managers for control or elimination. These weedy grass species are *Taeniatherum caput-medusae* (medusahead) and *Aegilops triuncialis* (goatgrass). These grasses were introduced in the late 19th century from Eurasia (Torell et al. 1961, Peters et al. 1996) and have since become dominant species in many rangelands.

Medusahead has been controlled most easily by the use of herbicide (DiTomaso et al. 2008) and fire conducted during seed set (DiTomaso et al. 2006). Sheep grazing has shown to be successful in controlling medusahead, but only under high grazing pressure during a narrow window of time in the spring (DiTomaso et al. 2008). Medusahead is less palatable than the forage grasses due to its higher silica content (Bovey et al. 1961), which makes grazing to control medusahead less successful when more palatable species are present.

Although goatgrass was introduced to the United States at the same time as medusahead, goatgrass has spread more slowly. It has only become a noxious weed in the past few decades (Peters et al. 1996), and its control has been less studied. Unlike medusahead, which can be controlled with herbicide in agricultural settings, goatgrass frequently invades winter wheat crops. Due to their similarity in growth patterns and genetics between goatgrass and winter wheat, herbicide is only effective when the wheat plants are herbicide resistant (Donald and Ogg 1991). Goatgrass has been controlled with fire, but requires at least two consecutive years of burning for control to be effective (DiTomaso et al. 2001).

Medusahead and goatgrass are similar in that both species have a phenology that is shifted later in the growing season than that of the introduced forage grasses. This shared plant characteristic suggests potential for using multi-temporal analysis to locate patches of medusahead and goatgrass. Mapping the patches of medusahead and goatgrass will allow land managers to both assess the effects of past management in controlling these weedy species and plan future management strategies.

7. Conclusions

Previous work has shown that it is possible to detect medusahead and goatgrass in northern California with high resolution aerial photography (Malmstrom et al. 2004). This study aims to compare the effectiveness of multi-temporal analysis for mapping weed distributions with that of a single-date analysis from imagery taken at key phenological times in the growing season. Weed patch distribution maps can be used not only to evaluate the success of weed control practices but also to examine the basic patch dynamics of invasive species as they change through time in location and size.

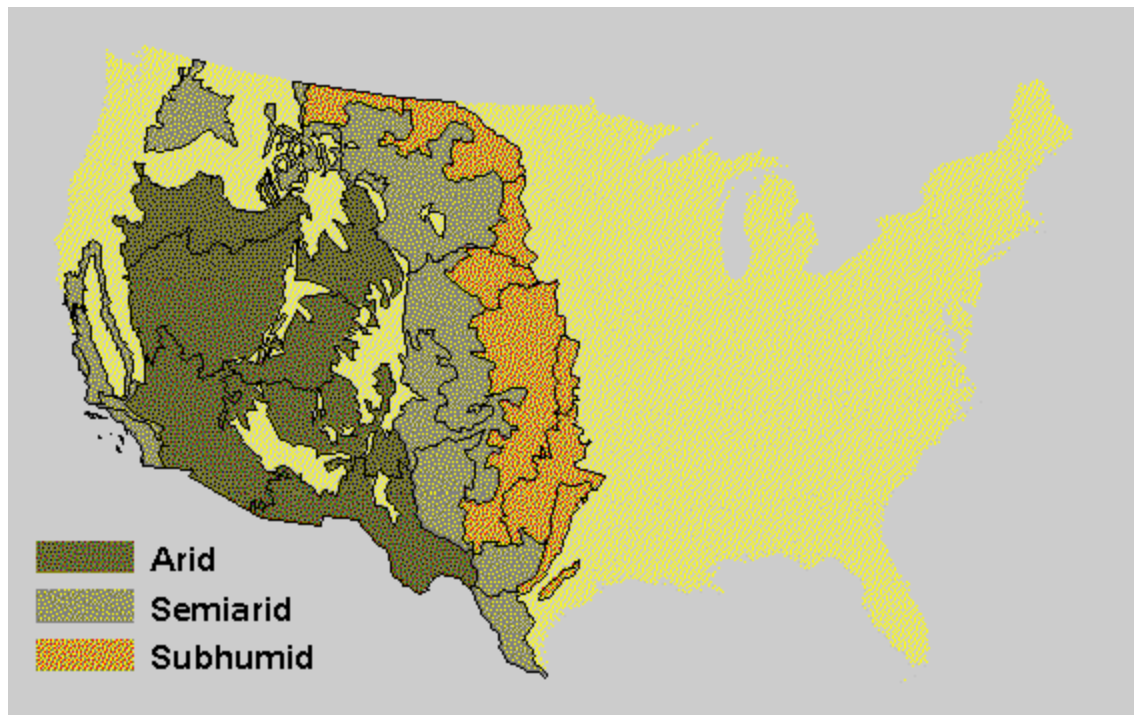


Figure 1. Distribution of arid and semi-arid grasslands in the United States (EPA 2010). For interpretation of the reference to color in this and all other figures, the reader is referred to the electronic version of this thesis.

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CHAPTER 2

INTERANNUAL ROBUSTNESS OF APPROACHES FOR MAPPING PATCHES OF PHENOLOGICALLY-DISTINCT INVASIVE WEED SPECIES IN CALIFORNIA GRASSLANDS WITH MULTI-TEMPORAL AERIAL PHOTOGRAPHY

Laura Planck

Abstract

Detection of invasive weed patches through remote sensing can help guide land management at the landscape scale. As part of a large rangeland restoration project in semi-arid grasslands in California, Malmstrom et al. (2004) previously demonstrated that unsupervised classification of fine-scale NDVI time series derived from digitized color infrared aerial photography acquired in spring and early summer (May) could be used to map the distribution of late-season invasive weedy grass species within a single year. To quantify how robustly this approach would work in multi-year studies of patch dynamics that require repeated measures of weed distribution over time, I tested the 2004 method with new data acquired in two later years (2008, 2009). I then compared the 2004 method with eleven other approaches that represent the application of three classification approaches (unsupervised, supervised, and Jenks optimization) to four different remote sensing data inputs. These inputs include (1) March and May NDVI evaluated together (“stacked”), as in 2004; (2) a NDVI difference image (March minus May); (3) March NDVI alone; and (4) May NDVI alone. The 2004 approach (unsupervised classification of the stacked March and May NDVI) was among the most effective approaches for both 2008 and 2009, with overall accuracies of 78.8-83.3% and kappa values of 0.54-0.65. The most robust approach was a modification of the original 2004 approach in which a NDVI difference image (March minus May) was used instead as the classification input, producing overall accuracies of 80.8-88% (Kappa: 0.60-0.66). Results from single-month images were less effective and less robust across years, with May imagery the least effective. These findings demonstrate that multi-temporal NDVI images can provide valuable maps of weed distributions for patch dynamics studies and evaluation of weed management strategies.

1. Introduction

Invasive weeds substantially reduce biodiversity values and forage productivity in North American grasslands. As weed abundance increases, the conservation value of grasslands and their utility as grazing land decreases, and in some cases the threat of conversion to other land uses concomitantly rises. Consequently, much effort and money is spent annually to manage weeds in grassland ecosystems (Bovey 1987, DiTomaso 2000). Unfortunately, studies of these management efforts often are conducted at the scale of a 1-m plot, without incorporating landscape variables and without means to quantitatively assess their utility across multiple years. Invasive weed management in grassland ecosystems could be applied more strategically and in a more cost-effective manner if affordable remote sensing approaches were developed to permit users to regularly map weed distributions.

Remote sensing and other geospatial techniques are developing quickly, driven by technological advances and business applications, but methods for mapping weed populations have remained limited by cost, complexity, and lack of broad applicability (Lass et al. 2005, Weis and Sokefeld 2010). Here I quantify the effectiveness of a novel approach developed in 2004 (Malmstrom et al. 2004) that uses multi-temporal, high-spatial resolution aerial photography to map invasive weed patch distributions in California grasslands during key phenological time periods when these weed species are visually distinct on the landscape. When successful across multiple years, this approach would have broad applicability for ranchers, conservation practitioners, land managers, and anyone else managing invasive weeds in grassland ecosystems.

Key invasive species that are priority targets for control in semi-arid grasslands include exotic annual grasses that form dense monotypic patches. These patches provide poor forage value, suppress more highly valued vegetation, and can come to dominate large swaths of the landscape. In California's semi-arid grasslands, two noxious weedy grasses have become particularly problematic: *Taeniatherum caput-medusae* (L.) Nevski (medusahead) and *Aegilops triuncialis* L. (barbed goatgrass). These annual grasses were introduced to California in the late 19th century from Eurasia (Torell et al. 1961, Peters et al. 1996) and are now established throughout the Western United States. Although differing in some traits, medusahead and goatgrass share several distinct characteristics. Both species produce unpalatable forage that is avoided by livestock, particularly as the plants mature, and generate a thick, mulching layer of litter that typically persists well into the next growing season (Bovey et al. 1961). In California's Mediterranean climate zones, these two species germinate with fall rains in October and November and then grow throughout the rainy winter season into the spring months. Cool-season forage grasses, including *Avena* and *Bromus* spp. (wild oat and brome), grow during this rainy season as well and are valued as livestock forage. However, the weedy grasses differ notably from the forage grasses in their end-of-season phenology. Whereas the forage grasses typically reach peak greenness in March–early April and then senesce in late April–May as the spring rains cease (Butterfield and Malmstrom 2009), the weedy species exhibit an extended late-season growing period that extends into the beginning of the summer drought period in May and June (Stromberg et al. 2007). As a result of the weeds' extended phenology, monotypic patches of medusahead and goatgrass can be clearly visualized in the field during late May and June as emerald green patches that contrast with the gold of senesced forage grasses (Figure 2).

With a group of cooperating ranchers and conservation practitioners, Malmstrom et al. began to investigate the usefulness of various weed mapping approaches and their utility for quantifying landscape-level impacts of land management actions (including grazing, prescribed fire, and herbicide application) across California grasslands in 2004 (Malmstrom et al. 2004, Butterfield and Malmstrom 2006, Butterfield and Malmstrom 2009, Malmstrom et al. 2009). This group found that in March and May there were notable spectral differences between patches of late-season weeds and those of annual forage grass species (Figure 2) and that the most successful classification methods relied on the use of multiple high-resolution aerial photographs acquired at these specific phenological periods (Malmstrom et al. 2004). Whereas there is typically a notable lag between the times of order and acquisition when requisitioning high-resolution satellite imagery from a commercial source, on-demand aerial photography provided the flexibility to acquire, process, analyze and use data on-the-ground within short and well-defined phenological time windows.

To evaluate the effectiveness of this approach for multi-year analysis of weed patch dynamics, I here compare the interannual robustness of the 2004 classification approach with that of several other mapping approaches based on NDVI-analogues derived from aerial photography. Because Malmstrom et al. (2004) found differences in phenology between weed and forage patches to be generally evident in both spring (March) and at the end of the growing season (May), I compared the use of different combinations of NDVI imagery (March and May NDVI; March-May NDVI, March NDVI alone, May NDVI alone) and three different methods for defining the NDVI characteristics associated with specific patch types (Jenks optimization method or goodness of variance fit, unsupervised classification, supervised classification). These methodological comparisons indicate that the initial 2004 approach as well as a modified version

can effectively detect weed patches across years in which environmental conditions differ. These methods thus offer basis for cost-effective monitoring of weed patch dynamics.

2. Methods

2.1 Study System

This study was conducted on privately-owned, semi-arid rangelands on the west side of the Sacramento Valley, CA (USA) near 39 degrees latitude. This region experiences a Mediterranean climate with a cool and rainy growing season that typically begins in September and extends through August. The summer dry periods (typically late May through September) are hot with average high temperatures of 33°C (National Climatic Data Center, Asheville, North Carolina). Peak precipitation typically occurs between December and February, with an average annual precipitation of 58.4 cm. During the years of our study, total precipitation was slightly below average; in 2008, precipitation was 55.8 cm and in 2009 it was 50.4 cm, as compared to 59.3 cm in the initial 2004 study (National Climatic Data Center, Asheville, North Carolina).

The previous analysis used a single map that described a continuum of vegetation classes dominated at one extreme by the weedy invasive grasses (medusahead and goatgrass, considered as a single functional class), and at the other by forage grasses, with intermediate mixes of the two functional classes in between (Malmstrom et al. 2004). In this study I sought to compare different classification and remote sensing inputs to determine which, if any, approach would most effectively work for studies in which weed patches needed to be mapped annually over a period of several years. For simplicity, I focused this analysis on a 2.5 km² portion of the watershed in which grazing had been restricted.

2.2 Image Processing

2.2.1 Acquisition

Aerial photographs were acquired by Pacific Aerial Surveys (Oakland, CA) using Kodak Aerochrome III Infrared Film 1443 with a minus-blue filter at a scale of 1:34,200. The film was then scanned with no color adjustments to create a digital image with approximately a 0.39-0.44 meter resolution. Spring photographs were taken on March 10th of 2008 and 2009, when the annual cool-season forage grasses are greener (shown as red in the color infrared image in Figure 3a) than the weedy grasses. End-of-growing season photos were acquired when weedy grasses were still green but forage grasses had senesced (Figure 3b) as judged from the ground. This date varied across years due to weather-driven variation in phenology. In 2008, the May image was acquired on May 5th; in 2009, images were acquired on both May 18th and 26th.

2.2.2 Orthorectification

Aerial photographs were orthorectified in the Leica Photogrammetry Suite in ERDAS Imagine 9.3 (Hexagon Group, Sweden). Ground control points were collected in the field using a Trimble GeoXH (Trimble, Sunnyvale, CA). A 2-m digital elevation model was developed by digitizing contours from a United States Geological Survey 7.5-minute quadrangle maps (USGS, Reston, VA) by Michigan State University's Remote Sensing and Geographic Information System Services and used to correct for changes in terrain. To reduce image-to-image variability, all of the photographs were orthorectified to a 2010 baseline aerial photograph.

2.2.3 Spectral Properties

To minimize shadowing effects and difference in illumination, I normalized the red and near infrared bands in a process analogous to calculating a Normalized Difference Vegetation Index (Tucker 1979) (NDVI, Equation 1).

$$\text{NDVI} = \frac{\text{Near Infrared Reflectance} - \text{Red Reflectance}}{\text{Near Infrared Reflectance} + \text{Red Reflectance}} \quad (\text{Eq.1})$$

Because the aerial photography-based NDVI values depend on the spectral properties of the aerial photography itself, the values are not identical to those of satellite imagery, but provide similar utility (Denison et al. 1996). CIR film is designed so that the red and infrared saturation intensities appear relatively similar to each other in order to produce an aesthetically pleasing image; as a result, NDVI values captured on film are typically lower than those captured by satellite-borne sensors, in which the infrared saturation intensity is permitted to be greater (Teillet et al. 1997).

2.2.4 Resampling

For standardization, digitized imagery was resampled to 1.0 meters from an original pixel size of 0.43–0.45 meters. This increase in pixel size to 1m increased the overall accuracy of the classification, because it brought the image grain and the field evaluations to a similar scale, and one that was appropriate for the degree of geositional error in measurements (Jelinski and Wu 1996). Increasing pixel size of imagery further (> 1m) reduced the accuracy of the classification (Appendix) because the image values began to include information from vegetation beyond that measured in the ground surveys.

2.3 Field Survey of Vegetation Composition

As part of a larger rangeland study, I surveyed with other colleagues the vegetation composition in 1-m radius circles at multiple points across my study site and in adjoining rangeland. To validate the classification methods examined in this study, I compared the classifications to field data from 88 points measured in May 2008, 104 in May 2009 and 78 in March 2010 when assessment was based on remnant senesced vegetation from the 2009 season.

At each visit to each point, the percent cover of key vegetation groups—including weedy invasive and forage grasses—was categorized by Daubenmire classes: 1) <5%, 2) 5.1 - 25%, 3) 25.1 - 50%, 4) 50.1 - 75%, 5) 75.1 - 95% and 6) 95.1 - 100% (Daubenmire and Cragg 1968). A point was considered to be dominated by either weedy grasses or forage species if the Daubenmire value for that vegetation category was greater or equal to 4 (> 50.1%) and if no other vegetation type had a Daubenmire value greater than or equal to 4. All other points were considered to have mixed composition. The definition of species-domination used here included some points in which the dominant vegetation type had lower cover values than used in the previous work for which vegetation with Daubenmire values greater than or equal to 5 were selected (Malmstrom et al. 2004); the change was necessary to increase the number of weed and forage dominated plots used for classification.

Points were located in the field using the Trimble Geo XH GPS unit. To navigate and return to points from previous years, real-time differential corrections were made using a Trimble Beacon Receiver communicating with a U.S. Coast Guard beacon. In 2009 and 2010, in addition to the Trimble Beacon, an antenna on a 2 m range pole was used to obtain a clear signal without interference from the user. To improve the precision of the collected ground truth data,

GPS field collected points collected in the field were adjusted by post-processing for atmospheric conditions that would affect accuracy (Trimble Pathfinder Office, Trimble, Sunnyvale, CA). The navigational accuracy of point locations in the field and post-processed points was approximately 30 cm (Trimble 2009), which was confirmed by benchmark tests.

2.4 Comparison of Classification Approaches

To find a classification approach that could be used across multiple years, I evaluated the robustness of eleven classification approaches based on NDVI-analogues. I considered the use of four different combinations of March and May NDVI imagery, which represent periods when the phenological differences between forage and weeds were most evident: 1. March and May NDVI (two images layered on top of each other); 2. March NDVI minus May NDVI (a single difference image; hereafter referred to as Δ NDVI); 3. March NDVI alone; and 4. May NDVI alone). The Δ NDVI approach was included because it has been shown to be a good metric for observing changes on a landscape (Mas 1999, Malmstrom et al. 2004) and because preliminary tests with this approach found strong correlation with ground data. Pixels with low or negative Δ NDVI (i.e., higher May than March NDVI values) are generally dominated by vegetation that stays green longer and senesces later, including the phenologically-shifted weedy invasive species considered here. Pixels with higher Δ NDVI are generally dominated by vegetation that senesces earlier in the season, including annual forage grasses.

With these four types of NDVI inputs, I used three different methods for delineating the characteristics of specific patch types: 1. Jenks optimization method or goodness of variance fit, 2. unsupervised classification, and 3. supervised classification (Table 1). The Jenks optimization method could not accept stacked imagery as an input, so this approach was applied only to the

nonstacked input types. All three methods for delineating weed patches relied solely on NDVI imagery and ground truth data; none utilized additional data (e.g., slope, aspect, or soil). Each method was applied to the 25 km² watershed which includes variability in management, but for simplicity, the accuracy was tested against the 2.5 km² ungrazed property.

2.4.1 Jenks Optimization Method

The Jenks optimization method of image classification was used to delineate natural breaks in a histogram of NDVI values in ArcGIS 9.3 (ESRI, Redlands, CA) in each imagery set, by determining the location of class breaks at which the means of each class differed most from each other and which produced the smallest deviation from the mean within each class (Jenks 1967). The natural breaks method can be applied only to a single layer of imagery because it optimizes the goodness of fit of a single value for the image. When applied to the Δ NDVI images, this approach defines patch divisions based on minimizing the standard deviation of each patch type, which correspond to known phenological phenomena. I used a five-class Jenks optimization, in which classes 1 and 5 captured the most extreme high and low Δ NDVI values, such as trees (Gamon et al. 1995), water bodies, and other non-target material. The intermediate classes 2-4 described surfaces with high, moderate, and low Δ NDVI values. Class 4, representing lower Δ NDVI values, was predicted to include late-season weed patches.

In adapting this approach for analyses based solely on May NDVI values, the two classes with the highest May NDVI values were considered non-grass classes because these values were outside of the range of most vegetation, and the third highest class was determined to be weeds. In the March classification, the class with the lowest March NDVI values had extreme low

values, representing areas with little to no vegetation. The class with the next lowest range of March NDVI values was identified as corresponding to weeds based on occurrence of weed points found within that class.

2.4.2 Unsupervised Classification

Unsupervised classification of the NDVI imagery was carried out using an Isodata classification in ENVI 4.7 (Exelis Visual Information Services Inc., Boulder, CO, United States). For this classification, I utilized a mask to remove non-grass pixels that represented trees, buildings and water to reduce their influence in the classification process. I did not use a mask with the natural jenks optimization method because this method created only five classes, which were broader and more inclusive. Likewise, I did not use a mask with the supervised classification because I could identify training sites free of non-grass elements and thus the mask/no-mask differences were minimized. The optimal settings for the unsupervised isodata classification were determined from iterative tests in which class number was adjusted; class number was set at 8 as found to be most useful in previous analysis (Malmstrom et al., 2004). Classification ran for 40 iterations with a pixel change threshold of 2.0% to create 8 classes for each year and set of imagery. Unlike the jenks optimization method, this approach can be used on multiple layers of imagery and focuses on decreasing the standard deviation of each class.

After classification, I evaluated imagery to determine which of the 8 classes were likely to represent weed patches. The percent of forage- and weed-dominated ground truth points were then calculated for each class. I calculated the average NDVI values for each class and visually compared the classified image with the original Δ NDVI image. Low Δ NDVI classes (ones with May-dominant phenology) that overlapped the visible May-dominant patches on the Δ NDVI

imagery were considered to be weed-dominated. The visual comparison was necessary because of the low numbers of reference points in some classes with small areas.

2.4.3 Supervised Classification

The parallelepiped supervised classifications were conducted in ENVI 4.7. The parallelepiped classification used 126 forage and 94 weed training sites in 2008 and 133 forage and 163 weed training sites in 2009, from the entire 25 km² watershed for reference to classify unknown pixels in the image. Using reference points from the entire watershed was necessary to obtain an adequate number of reference points for the classification, at least 30 per class, but preferably more (Tso and Mather 2009). To select training sites, I stratified ground truth data points from pure patches by property across the watershed and randomly selected half of these points from each property. To test the accuracy of the supervised classification, results were compared with the identity of the points in the target area not used in the classification (2008: 15 forage, 17 weed, and 12 mixed points; 2009: 19 forage, 19 weed and 15 mixed points; 2010: 46 forage and 33 weed points). An iterative approach was used to determine the optimal maximum standard deviation from the mean of the training site values to classify each input set. The most accurate classifications were produced when I used a standard deviation of 1.0 for forage grasses and 2.0 for the weed classes.

2.5 Classification Accuracy Metrics

For each classification approach, I used Starspan (CSTARS, Davis, California) to extract NDVI values and the class assignments for each ground truth data point (Rueda et al. 2005). To evaluate classification success, I calculated: 1) overall accuracy (Equation 2) to determine the

percent agreement between the ground truth data points and the classified image, 2) user's and producer's accuracies (Eq. 3, 4) to determine which vegetation types were classified most accurately, and 3) kappa values and kappa variances (Eq. 5-11) to determine the statistical significance of the classifications (Congalton 1991). User's accuracy describes the percentage of points classified correctly by map class (Eq. 3). The producer's accuracy (Eq. 4) describes the percentage of ground truth data points that are classified correctly as weeds or non-weeds (Congalton 1991).

$$\text{Overall Accuracy} = \frac{1}{n} \sum_{i=1}^k n_{ii} \quad (\text{Eq. 2})$$

$$\text{User's Accuracy} = \frac{n_{ii}}{n_{+j}} \quad (\text{Eq. 3})$$

$$\text{Producer's Accuracy} = \frac{n_{jj}}{n_{+j}} \quad (\text{Eq. 4})$$

To determine the statistical significance of the classifications, kappa values were calculated (Eq. 5),

$$K = \frac{p_0 - p_c}{1 - p_c} \quad (\text{Eq. 5})$$

where p_0 represents overall agreement and p_c represent chance agreement (Eq. 6),

$$p_c = \sum_{i=1}^k p_{i+} p_{+j} \quad (\text{Eq. 6})$$

and n is the total number of points tested. Kappa variances (Eq. 7) were calculated each year to determine the significance of the kappa values,

$$K_{Var} = \frac{1}{n} \left\{ \frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4} \right\} \quad (\text{Eq. 7})$$

where

$$\theta_1 = \frac{1}{n} \sum_{i=1}^k n_{ii} \quad (\text{Eq. 8})$$

$$\theta_2 = \frac{1}{n^2} \sum_{i=1}^k n_{i+} n_{+i} \quad (\text{Eq. 9})$$

$$\theta_3 = \frac{1}{n^2} \sum_{i=1}^k n_{ii} (n_{i+} + n_{+i}) \quad (\text{Eq. 10})$$

and

$$\theta_4 = \frac{1}{n^3} \sum_{i=1}^k \sum_{j=1}^k n_{ij} (n_{j+} + n_{+i})^2 \quad (\text{Eq. 11})$$

Kappa values adjust the overall accuracy of the classification by considering the probability that high accuracy results solely by chance (Congalton 1991). Kappa values below 0.40 indicate poor agreement between the classification and the ground truth data, values between 0.40 and 0.60 indicate fair agreement, values between 0.60 and 0.80 indicate good agreement, and values above 0.80 are considered excellent (Landis and Koch 1977, Congalton and Green 2009). The Z-test was used to determine if the classification was better than random at $\alpha=0.05$ (Congalton and Green 2009).

3. Results

3.1.1 May and March Stacked Imagery

March and May multilayer stacked image inputs produced overall accuracy values that ranged from 56.1 to 83.3% (Table 2). Unsupervised classification, the approach used by Malmstrom et al., (2004), generally gave the highest overall accuracy values with these inputs, ranging from 78.8 to 83.3% (Table 2) and the highest kappa values, ranging from 0.54 to 0.65 (Table 3), as compared to the supervised classification. Supervised classifications of the stacked images had lower overall accuracy values, ranging from 56.1% to 73.3% (Table 4).

Unsupervised classifications of the March and May multilayer images had greater user's accuracy values, ranging from 77.8% to 83.3% (Table 4) than the user's accuracy of the March and May stacked supervised classification.

3.1.2 March- May Difference

Unsupervised classifications of the Δ NDVI images, a different set of inputs than those used in 2004, had the highest overall accuracy values, ranging from 80.8 to 83.0% (Table 2), and kappa values, ranging from 0.60 to 0.66 (Table 3). Unsupervised classifications of the Δ NDVI images had user's accuracy similar to the unsupervised March and May multilayer stacked approach. The supervised classifications of the Δ NDVI images had higher user's accuracy values than the natural jenks and unsupervised classifications (Table 4). The user's accuracy values for the natural Jenks approach were also high, ranging from 80 to 90.5% (Table 4), indicating that weed patches identified from the classification schemes were correctly identified.

3.1.3 May Imagery

The overall accuracies from classifications based on May imagery alone were much lower than those from multi-month inputs, ranging from 40.9 to 71.8% (Table 2) and kappa values were less than 0.41 (Table 3). User's accuracy varied from 23.5 to 62.9% (Table 3), indicating that many patches classified as weeds were misidentified. Producer's accuracy ranged from 15.8 to 98.1% (Table 4), indicating occasional under-prediction of weeds.

3.1.4 March Imagery

Classifications based on the March imagery alone were somewhat better than those based on May imagery, but less successful than those based on two months' worth of images. Overall accuracy values ranged from 60.4 to 79.5% (Table 2) and kappa values from 0.21 to 0.57 (Table 3). User's accuracy values ranged from 40.9% to 100% (Table 4). The natural Jenks classification approaches overall showed greater user's accuracy than did the unsupervised and supervised classifications, ranging from 64.7 to 100%. Producer's accuracy values ranged from 18.2 to 78.8%, indicating that overall weed cover was under predicted (Table 5).

3.1.5 Training Sites

The training sites I chose to use for the supervised classification did not improve the classification as the unsupervised approach did a consistently better job of identifying weeds than did the supervised classification (Table 5).

4. Discussion

Remote sensing is an important tool for grassland weed management but it is still underused, despite soaring interest in geospatial technology. Constraints have included data cost, training requirements, and the lack of availability of high spatial, temporal and spectral resolution data. Spectral and morphological similarities among grass species add further challenges (Lass et al. 2005). One approach that circumvents some of the technological and economic barriers is to use aerial photography, which is less expensive than commercially available hyperspectral and high spatial resolution satellite imagery. Aerial photography offers spatial resolution that is sufficiently fine to detect patches as small as 1 m^2 , and it can be acquired within small time windows at specific phenological states when spectral and morphological differences between annual grass species are greatest.

This study shows that it is possible to obtain similar high accuracies with the same classification method across multiple years. The accuracy of the classifications across years was increased when images from more than one key phenological time period were used. I also found that using training sites, in a supervised classification, did not improve the classification accuracy; in fact, the natural variability among the training sites actually decreased classification accuracy in some cases. It is therefore possible that a different method for selecting training sites, or a reduced number of more carefully selected training sites could yield better classification results.

Overall, the results of this study support previous findings that indicated that unsupervised classification of stacked March and May imagery resulted in useful weed maps

(Malmstrom et al., 2004) and further suggest that this method may be effective across multiple years. Moreover, the findings suggest that accuracy may be further improved in some cases by combining two months of imagery into a single Δ NDVI images. The greater accuracy of the classification of the Δ NDVI values over the stacked NDVI values can likely be attributed to the fact that using Δ NDVI inputs forces the classification process to focus on phenological differences, directing the classification to be based on known differences between the two groups of grasses. Although there is more information contained within stacked NDVI layers, the compressed Δ NDVI inputs highlight phenological differences, which led to better results.

Because it would be more cost-effective to use a single aerial photograph per year, I also examined whether an accurate classification could be created from imagery captured on a single date. When imagery from a single month was used, March classification accuracies were greater than those from May, for at least two reasons. First, in this grassland system, the time period in March where the forage is greener than the weeds is longer than the time period in May when the forage has senesced and the weeds are still green. This results in a longer period of time when forage grasses have higher NDVI values than weed grasses, and a bigger window in which to acquire imagery. Second, phenologically-related patterns of greenness are more uniformly evident across all grassland portions of a watershed landscape in spring (March) than at the end-of-season (May), when patterns of senescence can be influenced more strongly by local variability in slope, aspect, and soil depth. Based on the variation of senescence across the landscape in May, I thought that timing of the May imagery would affect the overall accuracy. However, variability between the two 2009 May images was generally low, with the highest overall accuracy differences ranging between 1.2 and 15.1% (Table 2) and neither image yielded consistently better results than the other.

I found that accuracy was reduced with supervised classification, which used training sites, in comparison with the unsupervised classification in which training sites were not used. The large number and type of training sites used could account for the decrease in accuracy. An increase in the number of training sites is often correlated with an increase in classification accuracy (Foody and Mathur 2004, Tso and Mather 2009). However, accuracy might have improved if training site choices were narrowed to those with greatest purity in vegetation dominance.

My study benefited from the use of high resolution spatial imagery. With classifications based on images with moderate spatial resolution, like those produced by instruments on the Landsat or MODIS platforms, one cannot easily detect patch edges (O'Neill 1988, Jelinski and Wu 1996). The most consistently accurate classification approaches shown here were more accurate than those previously carried out by other teams using Landsat data for medusahead and cheatgrass classification with the inclusion of environmental variables (Peterson 2005) for medusahead (Cherr 2009) or cheatgrass (Singh and Glenn 2009). With high spatial resolution imagery, it is possible to define the edges of patches and thereby observe how weed patch size and shape, the diversity of patches, and how patches change or persist over time (O'Neill 1988, Herold et al. 2002).

4.1 Management Implications

Land managers in California's rangeland regions have expressed interest in the availability of weed patch distribution maps to evaluate the efficacy of weed management strategies and to help plan future management strategies for the future (Butterfield and Malmstrom 2006). Creating accurate weed distribution maps can aid land managers who want to

focus weed control efforts on the parts of their property with the greatest weed cover or where weeds stand the best chance of being controlled. In addition, weed distribution maps can help organize management strategies, such as optimizing the timing and location of grazing (DiTomaso 2000, DiTomaso et al. 2008), planning controlled burns (DiTomaso et al. 2006) or minimizing the amount of herbicide used (Monaco et al. 2005). To make such applications practical, the map production process needs to have a quick turnaround time and low cost. Because the approach described here is based on phenological differences in vegetation groups, it can be effective without reliance on more limited and costly hyperspectral imagery (He et al. 2011).

5. Acknowledgements

Thanks to Krista Jones, Chantal Stoner, Toshi Yoshida, Chuck Hughes, Todd Robinson, Chris Barber, Emily Flynn, Jarrod Morrice, Amy Motzny, Valerie Eviner, and Kevin Rice for field assistance. Thanks also to Robert Goodwin for geospatial technical assistance, to Chris Barber for initial classification work, to Jiaguo Qi, S. L. Ustin, and Michigan Surveyor's Supply for loaning equipment, and to David Ruiz at Pacific Aerial Surveys. I appreciate the many contributions of Jeanne Wirka, Judy Boshoven, and Vance Russell to the CalFed project success. This research was supported through grants from the United States Department of Agriculture CSREES NRI Program on the Biology of Weedy and Invasive Species (agreement number 2006-55320-17247) and CalFed (Project 01-N3), with assistance from AgBioResearch at Michigan State University. I would like to offer special thanks to the ranchers for their cooperation and use of their property.

Table 1. Approaches to classification compared in this study for each year of ground truth data points. X's represent combinations of approaches and imagery used.

Approach	Imagery Used			
	March and May	ΔNDVI	March NDVI	May NDVI
Unsupervised	X	X	X	X
Natural Jenks	---	X	X	X
Supervised	X	X	X	X

Table 2. Overall classification agreement (%) between ground truth data and the image classification for the eleven classification approaches for each year. May A images were taken on May 5th 2008 and May 18th 2009, and the May B image was taken on May 26th 2009. The year 2009a represents ground data collected in May of 2009, and 2009b represents ground data collected in March of 2010 (based on 2009 remnant vegetation). Unsupervised classification of stacked March and May imagery is the benchline approach previously tested (Malmstrom et al. 2004).

Classification Method	Year	Base Imagery Used				
		March and May	Δ NDVI	March	May A	May B
Unsupervised	2008	78.8*	81.8**	77.3*	61.4	----
	2009a	81.4**	83.0**	64.2	62.3	71.7*
	2009b	83.3**	80.8**	75.6*	65.4	59.0
Natural Jenks	2008	----	68.2	68.2	71.8*	----
	2009a	----	78.9*	73.6*	61.5	64.4
	2009b	----	85.9**	79.5*	55.1	58.4
Supervised	2008	73.3*	81.8**	72.7*	40.9	----
	2009a	58.5	73.5*	60.4	52.8	67.9
	2009b	56.1	75.6*	71.8*	50.0	51.2

* Good classifications (>70%)

** Excellent classification (>80%)

Table 3. Kappa values for each classification approach. May A images were taken on May 5th 2008 and May 18th 2009, and the May B image was taken on May 26th 2009. The year 2009a represents ground data collected in May of 2009, and 2009b represents ground data collected in March of 2010 (based on 2009 remnant vegetation).

Classification Method	Year	Base Imagery Used				
		March and May	Δ NDVI	March	May A	May B
Unsupervised	2008	0.54*	0.60**	0.50*	0.23	----
	2009a	0.58*	0.63**	0.29	0.25	0.41*
	2009b	0.65**	0.66**	0.52*	0.29	0.19
Natural Jenks	2008	----	0.23	0.21	0.41*	----
	2009a	----	0.50*	0.41*	0.17	0.20
	2009b	----	0.56*	0.57*	0.08	0.13
Supervised	2008	0.42*	0.59*	0.41*	0.41*	----
	2009a	0.21	0.42*	0.22	-0.12	0.20
	2009b	0.18	0.50*	0.44*	-0.06	-0.05

* Fair significance

** Good Significance

Table 4. Comparison of the user's accuracy (%) of the eleven approaches, showing the percentage of vegetation points within the weeds or forage and mixed patches that were actually weeds or non-weeds, respectively. May A images were taken on May 5th 2008 and May 18th 2009, and the May B image was taken on May 26th 2009. The year 2009a represents ground data collected in May of 2009, and 2009b represents ground data collected in March of 2010 (based on 2009 remnant vegetation).

Classification Method	Year	Base Imagery Used									
		Weeds					Forage or Mixed				
		March and May	Δ NDVI	March	May A	May B	March and May	Δ NDVI	March	May A	May B
Unsupervised	2008	77.8*	84.6**	76.9*	50.0	----	79.3*	80.7**	77.4*	72.7*	----
	2009a	83.3**	77.8*	50.0	48.0	57.1	81.9**	85.7**	80.0**	75.0*	88.0**
	2009b	83.3**	76.5*	66.7	58.8	55.6	83.3**	84.1**	84.6**	70.5*	63.6
Natural Jenks	2008	----	80.0**	100**	62.9	----	----	66.7	65.8	78.0*	----
	2009a	----	80.0**	64.7	46.2	50.0	----	78.5*	77.8*	70.8*	70.88
	2009b	----	90.5**	79.3*	47.1	51.9	----	75.4*	79.6*	61.4	62.0
Supervised	2008	66.7	90.9**	66.7	23.5	----	76.7*	78.7*	75.8*	51.9	----
	2009a	45.2	63.2	46.4	25.0	62.5	77.3	79.4*	76.0*	61.0	68.9
	2009b	49.1	70.6*	63.4	37.5	38.1	73.9*	80.0**	81.1**	55.6	56.1

* Good classifications (>70%)

** Excellent classification (>80%)

Table 5. A comparison of the producer's accuracy showing the percentage of weed or forage and mixed vegetation points that fell into the weed and non-weed classes from the three classification approaches. May A images were taken on May 5th 2008 and May 18th 2009, and the May B image was taken on May 26th 2009. The year 2009a represents ground data collected in May of 2009, and 2009b represents ground data collected in March of 2010 (based on 2009 remnant vegetation).

Classification Method	Year	Base Imagery Used									
		Weeds					Forage or Mixed				
		March and May	Δ NDVI	March	May A	May B	March and May	Δ NDVI	March	May A	May B
Unsupervised	2008	63.6	64.7	58.2	64.7	----	88.5**	92.6**	88.9*	59.3	----
	2009a	64.9	73.7*	73.7*	63.2	84.2**	90.8**	88.2**	47.1	61.2	64.7
	2009b	75.8*	78.8	84.8**	60.6	67.6	88.9**	82.2**	68.9	68.9	51.2
Natural Jenks	2008	----	24.2	18.2	98.1**	----	----	96.2**	100**	75.0*	----
	2009a	----	54.1	57.9	77.6*	43.2	----	92.5**	82.4**	68.7	76.1*
	2009b	----	57.6	69.7	48.5	42.4	----	95.6**	87.7**	60.0	70.5*
Supervised	2008	58.8	58.8	58.8	23.5	----	82.1**	96.3**	81.4**	51.2	----
	2009a	73.7*	63.2	68.4	15.8	26.3	50.0	79.4*	55.9	73.5*	91.2**
	2009b	81.8**	72.7*	78.8*	27.3	24.2	37.8	77.8*	66.7	66.7	71.1*

* Good classifications (>70%)

** Excellent classification (>80%)



Figure 2. Patches of weed and forage species as seen from the ground in May. Senesced vegetation is a mix of cool-season annual forage species, while green grass patches represent medusahead and goatgrass.

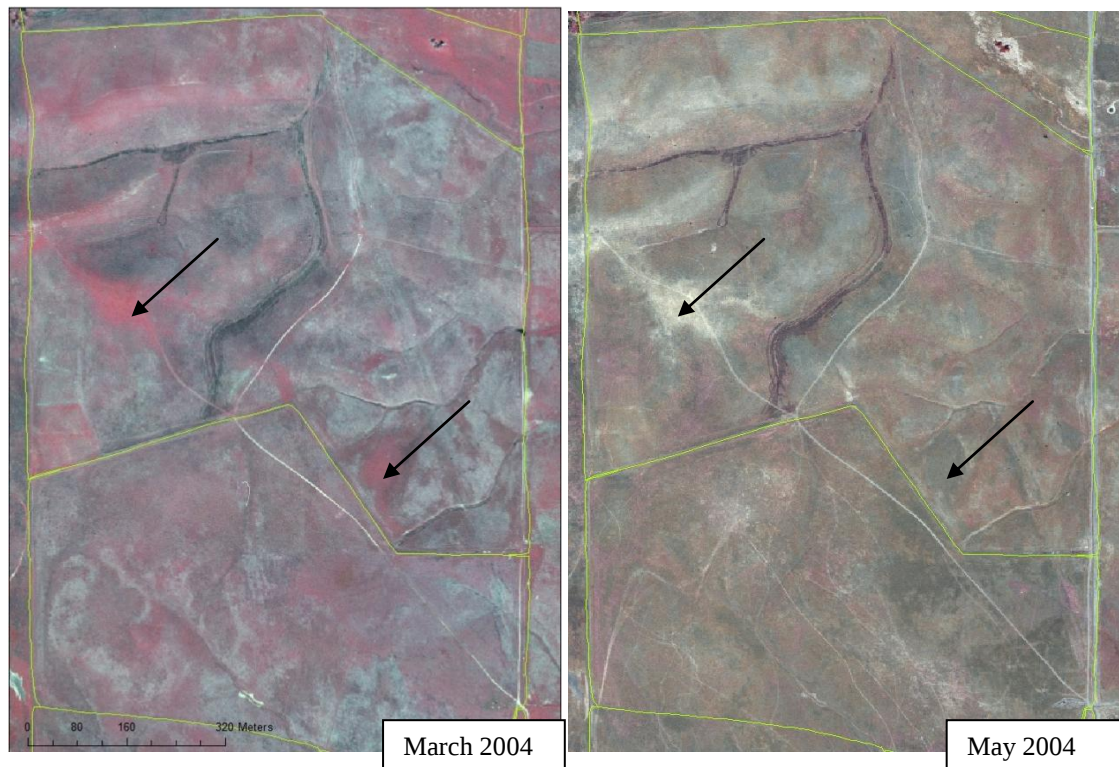


Figure 3. Color infrared aerial photography that shows the contrasts in seasonality of vegetation greenness (here evidenced in red) in forage-dominated and weed-dominated patches. Image on left was taken on March 10, 2004; image on right on May 25, 2004. (Credit: C. Malmstrom).

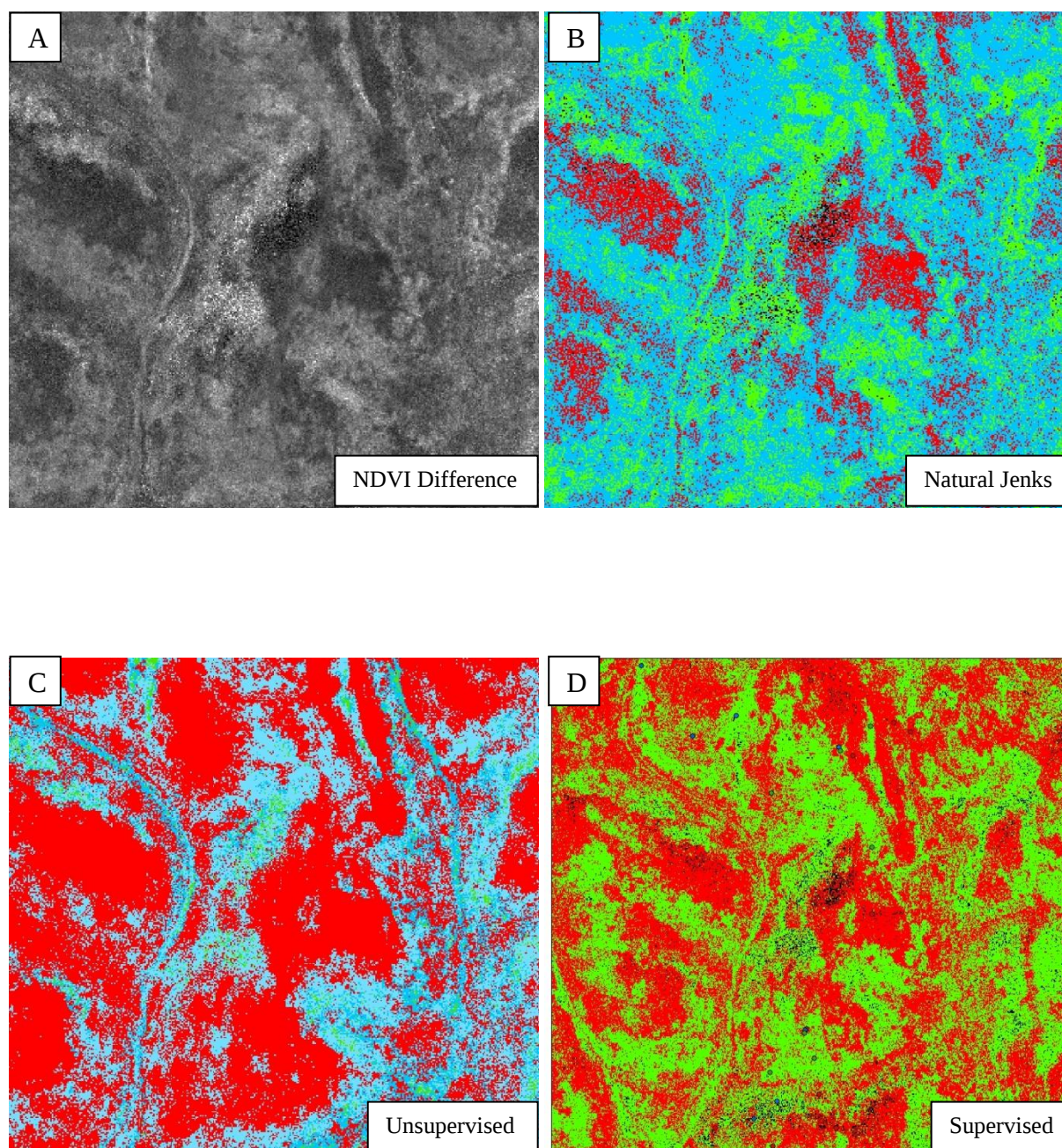


Figure 4. Comparison of a weed patch found on the ungrazed property in 2009 using (A) Δ NDVI imagery with the delineations from the (B) natural jenks, (C), unsupervised and (D) supervised approaches. On the Δ NDVI image, darker areas are more consistent with weed patches. In the classification images, weed classes are represented in red, forage and mixed classes are represented by blue and green, and unclassified areas are represented in black.

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CHAPTER 3

ENVIRONMENTAL FACTORS ASSOCIATED WITH WEED AND FORAGE PATCH TRANSITIONS IN SEMI-ARID CALIFORNIA GRASSLANDS

Laura Planck

Abstract

The development and persistence of monotypic weed patches in semi-arid rangelands reduces plant species diversity and rangeland quality over time. To evaluate the degree to which remnant litter and other environmental factors are associated with the formation and short-term persistence of monotypic patches of weed and forage grasses, I monitored 120 vegetation patches on five California rangeland properties for two years. In the first year, I identified 60 target weed patches in the field that were dominated by one of two noxious weedy grass species: goatgrass (*Aegilops triuncialis*) or medusahead (*Taeniatherum caput-medusae*), represented by 31 and 30 patches respectively. I likewise identified a comparable set of 59 patches dominated by cool-season forage grasses (a mix dominated by *Avena* and *Bromus* spp.). I considered a grass type to be “dominant” when (a) it covered 75% -100% of the patch area and (b) the cover of all other vegetation types was 0-50%. All other patch types were considered to be “mixed.” Patches were distributed across a 25 km² working landscape and represented a broad suite of slopes, aspects, and grazing regimes. I found that over two years only 10% of the forage patches and 23% of the goatgrass patches transitioned to other patch types, while 43% of the medusahead patches changed dominance. The best predictors of transitions in forage and goatgrass patches were greater representation of non-dominant species in the original community composition, phenologically-shifted greenness patterns, and lower levels of dominant-species litter in spring. However, none of these factors predicted transitions in medusahead patches, nor did the other environmental measures considered (slope, aspect, curvature, and soil quality). Although goatgrass and medusahead possess some similar characteristics, including a shared late-season phenology and deposition of thick litter, I conclude that the factors driving the two species’ patch dynamics differ in some notable ways and therefore merit separate, careful consideration.

Management strategies developed for one of these species may prove to be less effective for the other.

1. Introduction

Invasive plant species can become problematic in rangelands when they form dense monotypic patches that suppress more desirable species or prevent livestock grazing. It is thought that such patches develop when a threshold of some competitive advantage is crossed, and the invasive plant species is suddenly able to gain dominance over the other resident species (Clausnitzer et al. 1999, Callaway and Aschehoug 2000, Vilà and Weiner 2004, Blumenthal 2005). Once dense monotypic patches of weeds form, they may spread rapidly across a landscape (Frappier et al. 2003, Dilleuth et al. 2009), and decrease both plant species diversity (Foster et al. 2002, Jorge et al. 2004) and land value (DiTomaso 2000). Understanding which factors facilitate the development of monotypic weed patches and allow them to persist over time is essential for developing means to control invasive species and restore rangeland value (George et al. 1992, Suding et al. 2004, Malmstrom et al. 2009).

State-and-transition models are important tools that have been used to explore patch dynamics in rangelands (Jackson and Bartolome 2002). State-and-transition models consider the nature of thresholds in plant community composition and the factors that cause shifts from one state to another and drive patch emergence (Suding and Hobbs 2009). Experimental and observational studies used to parameterize such models often derive data from small plots (i.e., $\leq 1 \text{ m}^2$ in size), which may not well capture the influence of variables operating at broader spatial scales that may also contribute to patch transitions (Suding and Goldberg 1999). Nonetheless,

results from these small scale plots and other demographic studies have advanced understanding of the ways in which grazing, litter and weather affect the abundance and density of grassland species over time (Heady 1958).

To identify factors that promote development and persistence of monotypic weed patches in semi-arid grasslands and to quantify transitions among patch types, I monitored 120 naturally occurring patches of two noxious invasive weed species for two years on five private rangeland properties in a California watershed. I recorded transitions in species dominance during that period, and evaluated the extent to which transitions could be predicted by abiotic and biotic variables.

The patch dynamics of the noxious weedy grass species, *Taeniatherum caput-medusae* (medusahead) (L.) Nevski and *Aegilops triuncialis* L. (barbed goatgrass), are particularly intriguing because these species share a phenology that is offset from that of the more highly valued, resident cool-season forage grasses (*Bromus* spp. and *Avena* spp.) in these grassland communities. In the Mediterranean climate region of California, both weedy and forage species typically germinate with the first fall rains in October-November and then grow throughout the cool, rainy winter and spring. However, the forage grasses reach peak greenness in March and early April and then senescence in May, while the weedy species remain green for several weeks longer into the dry summer season. These differences in phenology permit the use of remote sensing to map and monitor the distribution and relative greenness of weed patches across broad areas (see Chapter 2). As a result, patches can be tracked over time, both from above and in the field, and the nature of any transitions in patch type examined.

In this study, I particularly examine the association of long-lasting litter with persistence or transition of patch types. Both medusahead and goatgrass have been shown to have litter that decomposes slowly (Evans and Young 1970, Drenovsky and Batten 2007), and ranch managers associate thick layers of remnant weed litter with reduced forage growth. Litter, or residual dry matter (RDM), has been previously identified as a factor with strong potential to facilitate the development of monotypic patches (Foster and Gross 1998, Xiong and Nilsson 1999). This study was motivated in part by the need to understand differences among species in litter persistence from one growing season into the next and to evaluate the extent to which litter persistence is a useful predictor of patch persistence or transition. I anticipated that persistence of recalcitrant litter from the noxious weeds would contribute to conversion of forage patches to weed-dominated ones, through suppression of growth of forage grasses.

2. Methods

2.1 Site

This work was conducted on five privately-owned rangelands on the west side of the Sacramento Valley in California, USA, (Hastings et al. 2005), near 39 degrees latitude. This region experiences a Mediterranean climate, which includes cool and rainy growing seasons beginning in October-November and ending in April-May. The summers are hot and dry, with average high temperatures near 33°C (National Climatic Data Center, Asheville, North Carolina). Annual precipitation for this region is 58.4 cm, with much of the precipitation occurring between December and February (National Climatic Data Center, Asheville, North Carolina).

2.2 Patch Identification and Field Measurements of Vegetation

Field measurements of vegetation patch properties were acquired at three time points: Yr 1 growing season end (May 2008), Yr 2 spring (March 2009), and Yr 2 growing season end (May 2009).

At the end of the Yr 1 growing season (May 2008), I identified 120 pre-existing vegetation patches that were dominated by one of three vegetation types: forage grasses, medusahead, or goatgrass. Throughout the study, I evaluated the dominant vegetation and percent cover of different plant species within a 1-m radius of a fixed, known point in each patch. I classified vegetation cover using the following Daubenmire categories for consistency: 0-5% cover (category 1), 5.1-25% (category 2), 25.1-50% (category 3), 50.1-75% (category 4), 75.1-95% (category 5) and 95.1-100% (category 6) (Daubenmire and Cragg 1968). I considered a patch to be dominated by a particular vegetation type when its cover exceeded 75% (Daubenmire category 5 or 6) and the cover of any other vegetation type was less than 50% (Daubenmire categories 1, 2 or 3 only).

The patches I monitored were initially at least 4 m^2 in size but were generally much larger, and distributed across a 25 km^2 area that included multiple different management regimes, three slope categories (flat, moderate, steep), and 4 types of general aspect (north, south, east and west). The geographic coordinates of each patch were acquired in the field with a Trimble GeoXH GPS unit (Trimble, Sunnyvale, CA). Coordinates were post-processed with Pathfinder Office (Trimble, Sunnydale, CA) for a final precision of approximately 30 cm (Trimble Navigation Limited 2009).

In spring of Yr 2 (March 9-14 2009), I revisited these same 120 points using the Trimble GeoXH GPS unit with real-time differential correction activated (US Coast Guard beacon signal) for navigation. At each point, I assessed the percent cover of plant species and measured the height of goatgrass, medusahead, and forage litter remaining, either standing erect or lying on the ground, from the previous growing season. I quantified percent cover and height of new green grass as a single class, because the species of juvenile plants could not be reliably identified at that stage. To calculate average heights for litter and green vegetation, five height measurements were taken for each material, including in the patch center and 0.5 m in each ordinal direction from the center. If there was no vegetation at the exact location, the nearest stem within the patch was measured.

At the end of the Yr 2 growing season (May of 2009), I evaluated vegetation properties at the points a third time. Post-processing analysis of all geographic coordinates indicated that the locations of the repeated measurements at each field location were no further than 1 m from each other, within the area of our initial survey, and generally were much more closely associated.

2.3 Seasonal Changes in Patch Greenness

To evaluate seasonal changes in patch greenness across the study period, I extracted NDVI values representing patch locations from previously processed color infrared aerial photography acquired on March 10 2008, May 13 2008, November 21 2008, March 10, 2009, and May 18 2009 (Pacific Aerial Surveys, Oakland, CA). Photographs were digitized and processed to produce NDVI-type values, as described in Chapter 2.

NDVI values at the exact location of each vegetation point surveyed on the ground were extracted from the imagery using StarSpan (Rueda et al. 2005). NDVI values were extracted from the original aerial photographs digitized between a 0.43-m and 0.45-m resolution.

2.4 Analysis

First, I evaluated the characteristics of each patch type, including seasonal patterns of greenness as derived from aerial imagery. Next, I developed a transition matrix that described the nature and direction of transitions evident from 2008 to 2009 (Table 6). Third, I compared the characteristics of patches that persisted with those that changed in dominance during this period. Finally, I used non-metric multidimensional scaling (NMDS) ordination in R (vegan and MASS packages (Oksanen 2011), to determine which of the measured variables were most associated with shifts in the dominant vegetation.

To quantify the characteristics for the NMDS ordination, I processed data collected in the field and with imagery. Litter and green vegetation height data collected in March of Yr 2 were average for each patch resulting in a single mean value. All Daubenmire values for litter and vegetation were translated into the average percent cover of the Daubenmire class (1: 2.5%, 2: 15%, 3: 37.5%, 4: 62.5%, 5: 85%, and 6: 97.5%. Slope, aspect and plan curvature for each patch was calculated from a 2-m DEM developed for the study site (see chapter 2). The land capability classification for each patch was extracted from the Yolo County Soil Survey (Andrews 1968).

A plot transition matrix was created by finding the percentage of forage, goatgrass and medusahead patches in Yr 1 that persisted or transitioned to another vegetation type in Yr 2. The mean and standard error of the NDVI values, subdominant species and litter cover were

calculated to determine the differences in these characteristics of patches that persisted and transitioned for all Yr 1 patch types.

For the ordination, NMDS was chosen because it can evaluate non-normal data, ranked data, and non-linear relationships. NMDS places data points in n dimensions and indicates which variables are driving points in any given direction. Key NMDS parameters include the number of dimensions (n), method of calculating distances between points, and the number of iterations to find the best solution. The number of dimensions was chosen based on the model with the smallest amount of stress, a measure of how well the points fit into the space, where high stress values indicate that dissimilar points are being inappropriately clumped in the ordination (McCune et al. 2002). A Bray-Curtis distance metric, a city-block semi-metric measure, was used because it is a better measure of similarity for ranked data than other common distance metrics, such as the Daubenmire values that were used in this study (McCune et al. 2002). One hundred iterations of the NMDS were run for each dimension to assure that the best point configurations were found. A summary of all variables considered in the NMDS model can be seen in Table 7.

To allow for species differences, separate NMDS ordinations were performed for patches dominated by forage, medusahead, and goatgrass. Three dimensions were selected for each species ordination for consistency and because at three dimensions the stress levels for all three species leveled off (Figure 5). There was little change in the final ordination when dimensions increased past 3. The final stresses were 9.77, 7.02 and 6.38 for forage, medusahead and goatgrass respectively (Figure 5), which are considered acceptable values (McCune et al. 2002). Variable vectors were then fit to the ordination using the `envfit` function of the `vegan` package in

R (Oksanen 2011), and R^2 and p-values were calculated for each vector (Table 7), showing how well each vector explains the distribution of points in the NMDS ordination.

3. Results

3.1. General Characteristics of Patch Types

Analysis of seasonal patterns of greenness, derived from NDVI values extracted from patch locations, demonstrates that the phenological differences between the forage and weed species are evident in both Yr 1 and Yr 2 (Figure 6). In both years, the mean NDVI for forage patches is greater than that for weed patches in spring (March) and lower than that of weed patches at the end of the growing season (May). Throughout, goatgrass NDVI values are less than or equal to those of medusahead patches, with the greatest divergence evident in Yr 2 spring (March 2009), when the NDVI values of 2008 medusahead patches are notably elevated. These elevated values are not explained by inclusion of values from 2008 medusahead patches that have transitioned to forage or mixed patches in 2009, as no significant difference in values was found between persistent and transitioned patches (see Figure 14).

In all patch types, Yr 1 litter evident in spring of Yr 2 was largely derived from the Yr 1 dominant species, as expected. In forage and medusahead patches, goatgrass litter was the second most abundant litter type; in goatgrass patches, forage litter was the second most abundant. Medusahead litter was least abundant, except in medusahead patches (Figure 7). The average height of the dominant litter was more than two-fold greater in forage and goatgrass patches than in medusahead patches (Figure 8). Height of juvenile grass at that time period was greatest in forage patches and shortest in medusahead patches.

3.2 Transitions Observed

Forage patches were the most stable type evaluated, with 90% (53/59) of Yr 1 patches remaining forage-dominated in Yr 2 (Table 6). Goatgrass was slightly less persistent with 77% (24/31) of Yr 1 goatgrass patches remaining goatgrass-dominated during this period. In contrast, medusahead patches were more ephemeral with only 57% (17/30) persisting from Yr 1 to Yr 2 (Table 6).

Forage patches were about equally likely to transition to goatgrass (2%, 1/59), medusahead (5%, 3/59), or mixed weeds/forage (3%, 2/59). However, goatgrass transitioned only to forage (13%, 4/31) or to mixed weeds/forage (10%, 3/31), not to medusahead (0%). Likewise, medusahead transitioned either to forage (26%, 8/31) or mixed weeds/forage (17%, 5/30), but never to goatgrass (0%).

3.3 Best Predictors of Transitions

For forage and goatgrass patches (Figures 9 and 10), the NMDS analysis clustered the patches that transitioned to other vegetation types, indicating that these patches shared some characteristics. In contrast, the medusahead patches that transitioned (Fig. 11) were distributed diffusely throughout the NMDS space and did not share particular characteristics.

For the forage and goatgrass patches, the main driving variables that separated patches that transitioned from those that did not were remnant litter, NDVI values, and subdominant vegetation. Forage litter cover and height were variables that most strongly influenced the distribution of points in the forage ordination ($r^2 = 0.72$, $p < 0.001$ and $r^2 = 0.80$, $p < 0.001$ respectively, Table 7). Forage patches that transitioned were found where both forage litter

height and cover were the lowest (Figure 9 and 12 c-d). Likewise, goatgrass litter cover and height strongly influenced the distribution of points in the goatgrass ordination ($r^2 = 0.85$, $p < 0.001$ and $r^2 = 0.71$, $p < 0.001$ respectively, Table 7), and the points with less remnant goatgrass litter were more likely to transition (Figures 10 and 13 c-d). In contrast, medusahead patches that transitioned were not notably different in litter cover or litter height from medusahead patches that persisted (Figures 11 and 14).

May NDVI values from 2008 and 2009 had moderate effects on the distribution of points in the forage ordination ($r^2 = 0.48$, $p < 0.001$ and $r^2 = 0.37$, $p < 0.001$, respectively, Table 7). Forage points that transitioned had higher May NDVI values in both 2008 and 2009 than did forage patches that did not transition (Figures 9 and 12 a-b). The goatgrass ordination was also strongly affected by the 2008 and 2009 March NDVI values ($r^2=0.59$, $p < 0.001$ and $r^2=0.47$, $p < 0.001$, respectively, Table 7). Goatgrass patches that transitioned to forage had higher March NDVI values than goatgrass patches that stayed the same (Figures 10 and 13a-b). In contrast, for medusahead patches, there was no discernible association of NDVI values during either month with patch transitions (Figures 11 and 14).

Cover of subdominant vegetation added further predictive power to transitions. For example, in the forage ordination, medusahead cover in 2008 was a strong variable in explaining the distribution of points ($r^2=0.40$, $p=0.001$, Table 7), with forage patches that transitioned exhibiting more medusahead cover than forage patches that persisted (Figures 9 and 15a). Likewise, the cover of forage grasses in 2008 had a strong influence on the distribution of points

in goatgrass ordination ($r^2 = 0.39$, $p = 0.003$, Table 7), where goatgrass patches that transitioned had a greater percentage of forage cover than goatgrass patches that remained the same (Figures 10 and 15b). However, in medusahead patches, percentage of non-medusahead vegetation did not help explain transitions (Figure 15c).

4. Discussion

Identifying factors associated with transitions and persistence of monotypic weed patches on a landscape provides valuable insight into grassland dynamics. This information can help refine state-and-transition models and guide the development and application of improved weed control strategies. In this study, I used NMDS ordination to identify factors that were positively associated with transitions among weed and forage patch types in an actively managed rangeland.

I predicted that increased weed litter cover would be associated with an increased likelihood that weed patches would persist over time, because the weed litter cover could alter soil moisture and light availability in ways that might benefit resource acquisition by the weeds during the late-season. I found such an association in goatgrass-dominated patches, in which those with greater goatgrass litter (cover, height) were less likely to transition (Figure 10). But this pattern was not evident in medusahead, although this species also produces litter that is slow to decompose (Bovey et al. 1961). This finding suggests that the similarities in life history strategy shared by medusahead and goatgrass, which also include their late-season phenology and invasive natures, mask some interesting differences among them and further suggest that optimum methods for controlling the two species may also differ.

Because the weed species have become increasingly problematic in the last several years, I expected a high proportion of forage-dominated patches to have transitioned to weed patches during this study. However, the total number of forage-dominated patches that transitioned to weed-domination was lower than expected, with only 10% converting. In contrast, over half of the medusahead patches transitioned back to forage (Table 6). One potential explanation for the low number of forage patches that transitioned to weeds is that the system has reached some sort of equilibrium, and/or that there are environmental barriers preventing the spread of weeds into the remaining forage patches.

The phenology of patch greenness in Yr 1 was one of the better predictors of persistence and transitions in forage and goatgrass patches. Forage plots that transitioned to weed-dominance exhibited higher NDVI values in the preceding May than forage patches that persisted. Likewise, goatgrass plots that transitioned to forage-dominance exhibited higher NDVI values in the preceding March than those that persisted. There are at least two reasons why patch phenology might be a good predictor of subsequent patch transition. One possibility is that the greenness measures are capturing the presence of early colonizers of the invading second vegetation type. I found a positive association between weed cover and forage plots that changed, which is consistent with the idea that these patches grow and change slowly over time (Frappier et al. 2003). The second possibility is that the local conditions are more consistent with an earlier or later phenology due to water retention or temperature, and thus allow a different species to be a better competitor in that part of the landscape (Hastings et al. 2005). In either case, these findings suggest that remote sensing monitoring of rangeland landscapes could flag patches with elevated late-season greenness for more intensive evaluation and monitoring in the field.

In addition, our findings reinforce the importance of developing species-specific understanding of litter dynamics. Management strategies, including grazing, fire and mowing are disturbances that remove biomass from the landscape, reducing the amount of litter the following year (Fahnestock and Knapp 1993, Dorrough et al. 2007, Kyser et al. 2008, Veen et al. 2008, Wallace et al. 2008). Altering litter quantities in grasslands does not affect all grass and forbs species equally (Sheley et al. 2009, Vaccaro et al. 2009), and the differences between these effects become larger the more years litter is allowed to accumulate in the system (Heady 1956). Unlike mowing and fire, grazing preferentially removes the biomass of the more palatable species, favoring the less palatable ones. Previous studies have shown that the timing of biomass removal is critical to the success of weed control (DiTomaso et al. 2001, MacDougall and Turkington 2007, DiTomaso et al. 2008), and grazing would need to be done at a time when the weeds are more desirable than the common forage grasses.

The effects of litter are strongest on species composition at the beginning of the growing season when seedlings are germinating (Suding and Goldberg 1999). Plant litter creates a microenvironment that may or may not be conducive to plants germinating at the beginning of the growing season (Heady 1958, Facelli and Pickett 1991, Suding and Goldberg 1999, Rebollo et al. 2001). A thick litter layer will decrease the amount of sunlight reaching the soil surface and affect the moisture levels by reducing the total precipitation that reaches the soil and slowing evaporation from the soil (Evans and Young 1970, Amatangelo et al. 2008). Invasive species can create more persistent litter and be more tolerant to litter than the native species. They can be more tolerant because their germination may only be delayed by persistent litter, whereas it is totally prevented for native species. (MacDougall and Turkington 2005).

In summary, among forage and goatgrass patches the probability of patch transition could be predicted in part by patterns of NDVI and remnant litter. However, predictors for transition in medusahead patches were not identified. This information may be used by land managers who wish to maintain forage or control goatgrass. The differences evident in patch transitions in goatgrass and medusahead suggest that these two weedy species may require different control methods, despite other similarities among the two invaders.

5. Acknowledgements

This research was funded by the United States Department of Agriculture CSREES NRI Program on the Biology of Weedy and Invasive Species (agreement number 2006-55320-17247). I would also like to thank the ranchers, who allowed us to use their private land to conduct this study and the technical assistance for the GPS unit and imagery analysis of Robert Goodwin and the Remote Sensing and Geographical Information System Services at Michigan State University. I also appreciate the technical help of J. Morrice and xx, V. Eviner, and K. J. Rice

Figures and Tables

Table 6. Transition matrix quantifying transitions among vegetation patches that were dominated by forage, medusahead and goatgrass in 2008. Diagonal, indicated in bold, highlights percentages of patches that persisted into 2009 as the same 2008 patch types. Patches that were no longer dominated by forage, goatgrass or medusahead when revisited in 2009 were labeled mixed.

2009 Dominance				
2008 Dominance	Forage	Goatgrass	Medusahead	Mixed
Forage (59 patches)	90% (53/59)	2% (1/59)	5% (3/59)	3% (2/59)
Goatgrass (31 patches)	13% (4/31)	77% (24/31)	0% (0/31)	10% (3/31)
Medusahead (30 patches)	26% (8/30)	0% (0/30)	57% (17/30)	17% (5/30)

Table 7. Variables used in the NMDS ordination and the associations of the variables with the ground data for each NMDS ordination. Percent cover values are mid-point values of percent cover range represented by each Daubenmire class.

Abbreviation	Description	NMDS Ordination Associations					
		Forage		Medusahead		Goatgrass	
		r^2	p	r^2	p	r^2	p
NDVI							
20080310	March 2008 NDVI	0.15	0.010	0.30	0.005	0.59	0.001
20080513	May 2008 NDVI	0.48	0.001	0.11	0.207	0.19	0.037
20081121	November 2009 NDVI	0.53	0.001	0.16	0.099	0.16	0.074
20090310	March 2009 NDVI	0.41	0.001	0.21	0.044	0.47	0.001
20090518	May 2009 NDVI	0.37	0.001	0.20	0.068	0.20	0.049
Forage Cover	Percent cover of remnant 2008 forage litter as measured in March 2009	0.72	0.001	0.48	0.001	0.27	0.011
Forage Height	Average height of remnant 2008 forage litter as measured in March 2009	0.80	0.001	0.48	0.001	0.68	0.001
ForageYr1	Percent cover of forage vegetation in May 2008	0.30	0.001	0.02	0.750	0.39	0.003

Table 7. (cont'd)

GG Cover	Percent cover of remnant 2008 goatgrass litter as measured in March 2009	0.24	0.002	0.62	0.001	0.85	0.001
GG Height	Average height of remnant 2008 goatgrass litter as measured in March 2009	0.27	0.002	0.60	0.001	0.71	0.001
GGYr1	Percent cover of goatgrass vegetation in May 2008	0.03	0.500	0.09	0.288	0.19	0.052
MH Cover	Percent cover of remnant 2008 medusahead litter as measured in 2009	0.31	0.001	0.68	0.001	0.62	0.001
MH Height	Average height of remnant 2008 medusahead litter as measured in 2009	0.30	0.001	0.67	0.001	0.49	0.001
MHYr1	Percent cover of medusahead vegetation in May 2008	0.40	0.001	0.03	0.678	0.24	0.025
Green Cover	Percent cover of new green grass in March 2009	0.00	0.983	0.06	0.449	0.03	0.650
Green Height	Average height of new green grass in March 2009	0.57	0.001	0.33	0.005	0.13	0.143
Aspect	Direction that slope faces (1-360°)	0.08	0.107	0.44	0.002	0.23	0.016
Slope	Angle of the hill slope (Degrees)	0.19	0.002	0.04	0.586	0.89	0.259
Curvature	Plan curvature: a measure of how convex or concave the patch is in relation to soil moisture and soil type	0.01	0.851	0.03	0.642	0.01	0.867

Table 7. (cont'd)

LCC	The degree to which land quality limits crop production (high values = increased limitations in land use)	0.12	0.029	0.06	0.429	0.19	0.055
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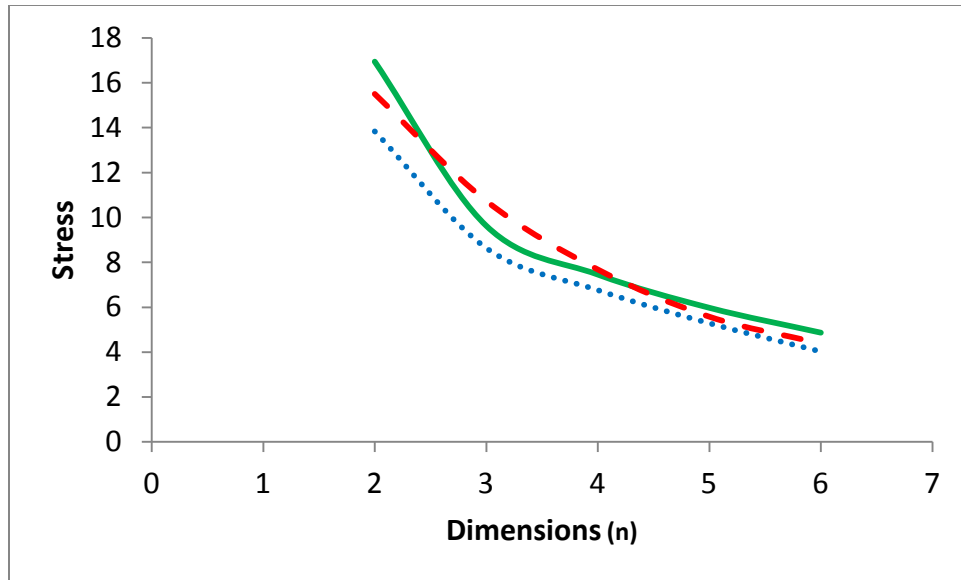


Figure 5. Relationships used to determine the optimal number of dimensions for the NMDS model for forage (—), medusahead (---) and goatgrass (····). The numbers of dimensions used in the final models were determined at the reflection point for each species (3 dimensions).

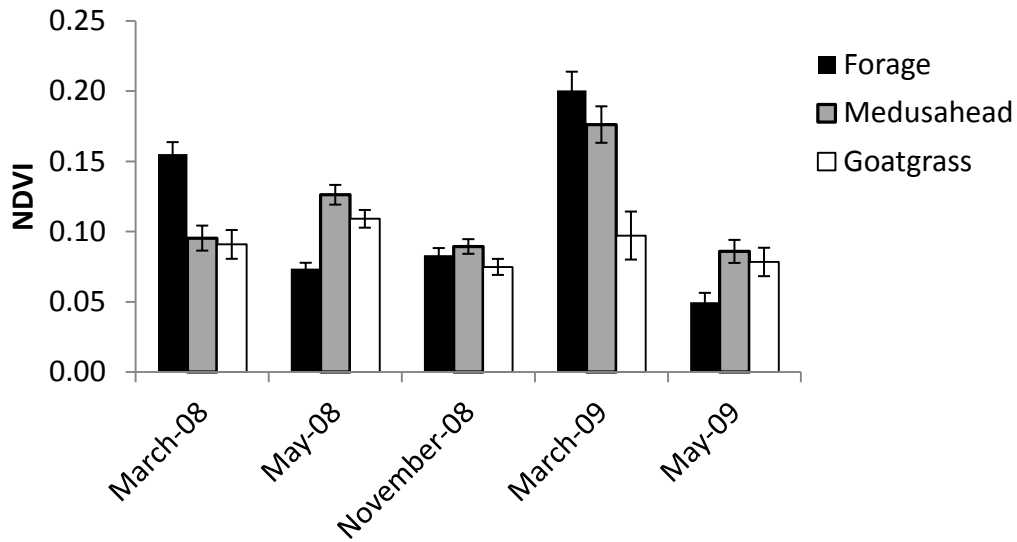


Figure 6. Seasonal changes in NDVI values extracted from color infrared photography for patches that were determined in 2008 to be dominated by forage, medusahead, or goatgrass Means ± 1 standard error.

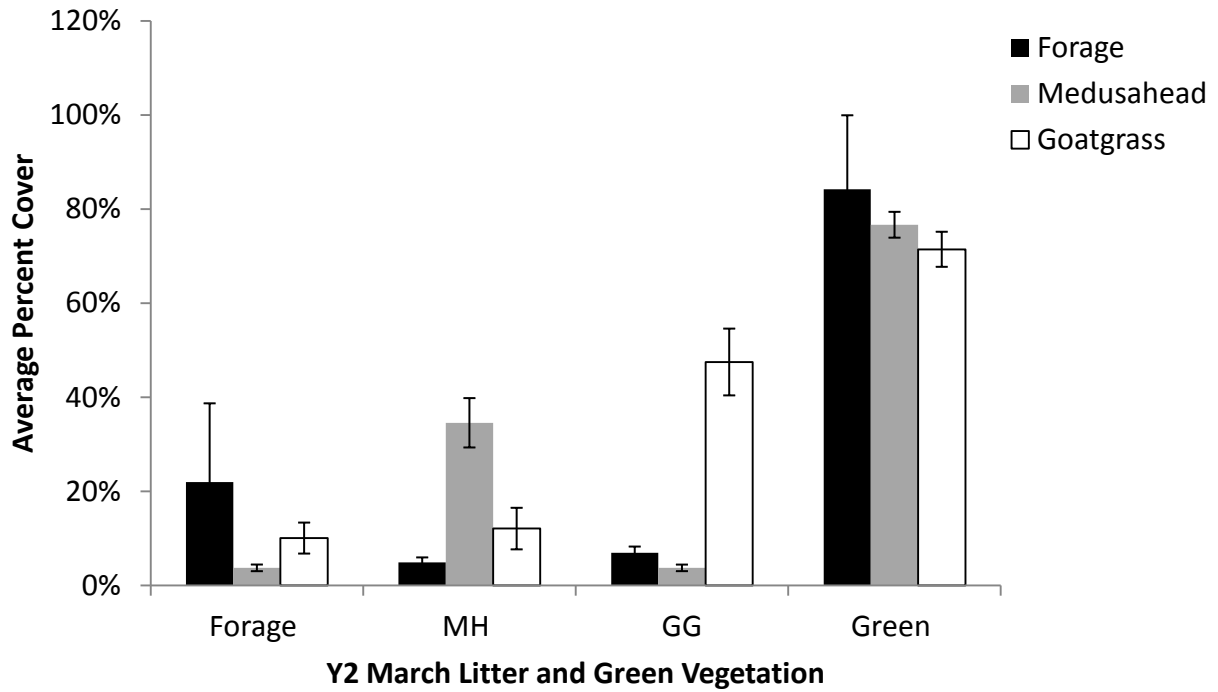


Figure 7. Mean percent cover of remnant 2008 litter and new 2009 green vegetation as measured in March 2009 for patches that were dominated in 2008 by forage, medusahead, or goatgrass. Represented by means $\pm$ 1 standard error.

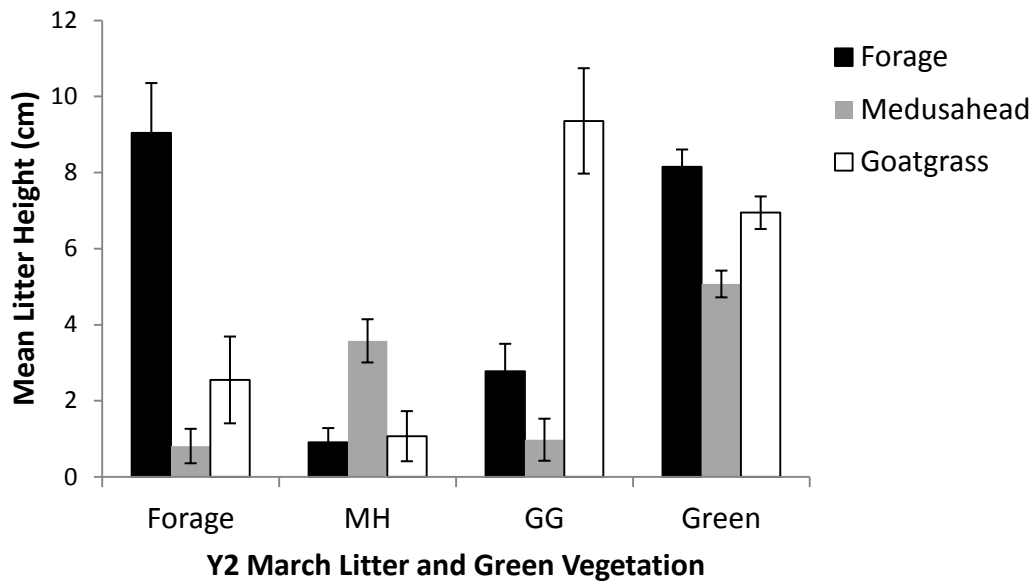


Figure 8. Mean height of the remnant 2008 litter of each species, and of new 2009 green grass, as measured in March 2009 in patches that were dominated in 2008 by forage, medusahead and goatgrass. Error bars represent one standard error.

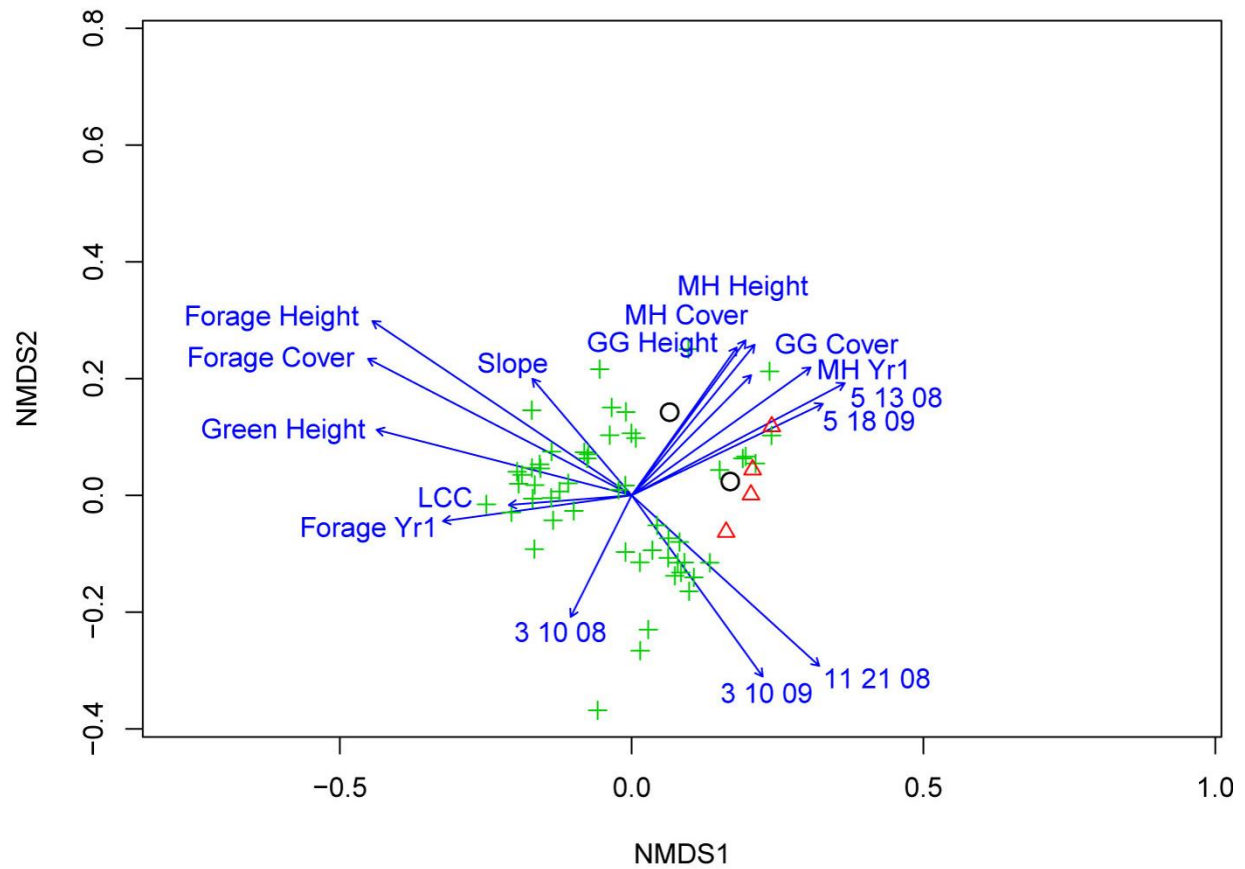


Figure 9. NMDS ordination of 2008 forage patches with vectors that indicate influence of each variable on patch clustering. Green (+) = 2008 forage patches that persisted into 2009, black (o) = 2008 forage patches that became mixed in 2009, and red (Δ) = 2008 forage patches that became weeds in 2009.

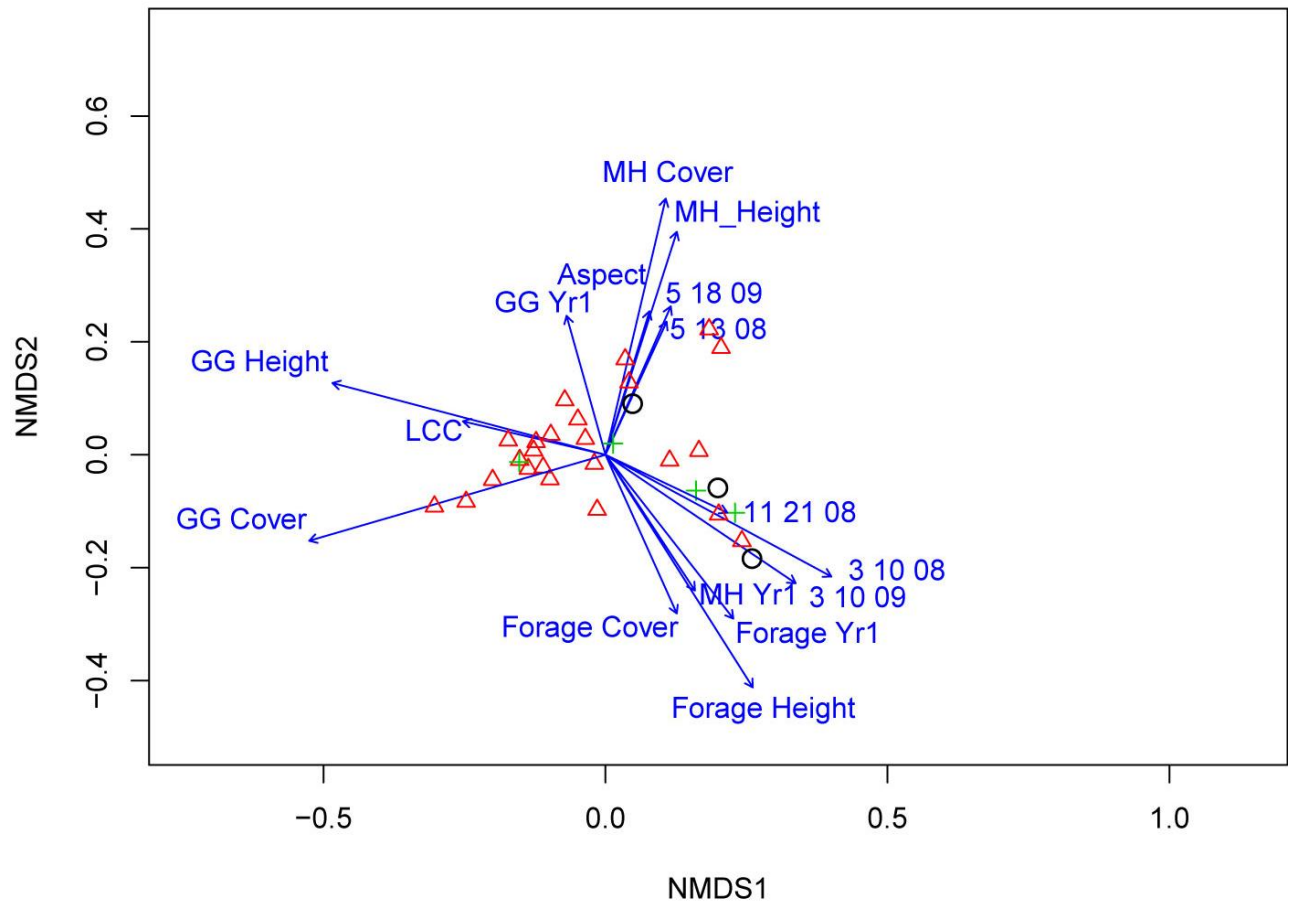


Figure 10. NMDS ordination of 2008 goatgrass patches with vectors that indicate the influence of variables on patches clustering. Red (Δ) = 2008 goatgrass patches that remained goatgrass-dominated into 2009, black ($\circ$) = 2008 goatgrass patches that became mixed in 2009, and green (+) = 2008 goatgrass patches that became forage-dominated in 2009.

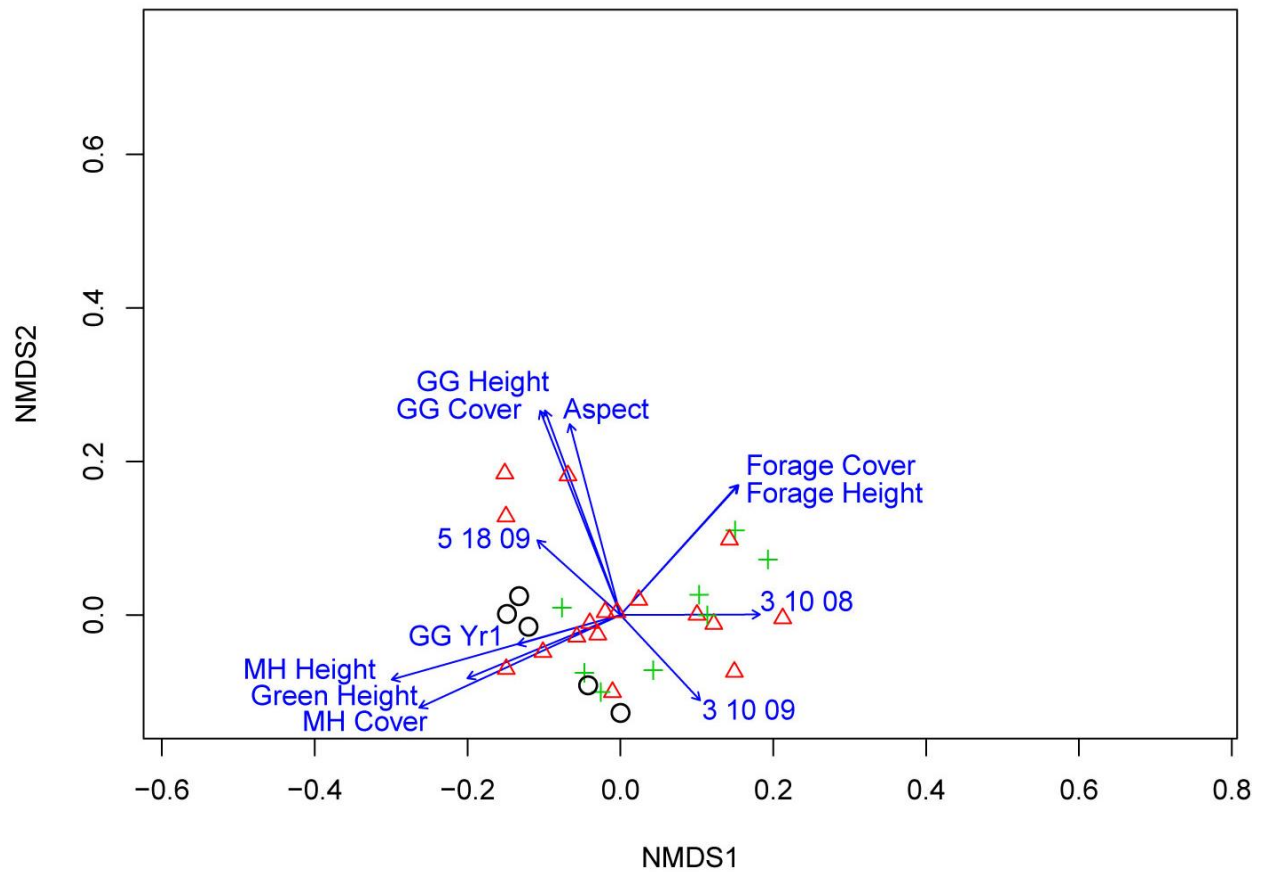


Figure 11. NMDS ordination of 2008 medusahead-dominated patches showing a lack of clustering in patches that switch from medusahead to forage, with vectors showing the influence of variables on the ordination. Red (Δ) = 2008 medusahead patches that remained medusahead into 2009, black ($\circ$) = 2008 medusahead patches that became mixed in 2009, green (+) = 2008 medusahead patches that became forage-dominated in 2009.

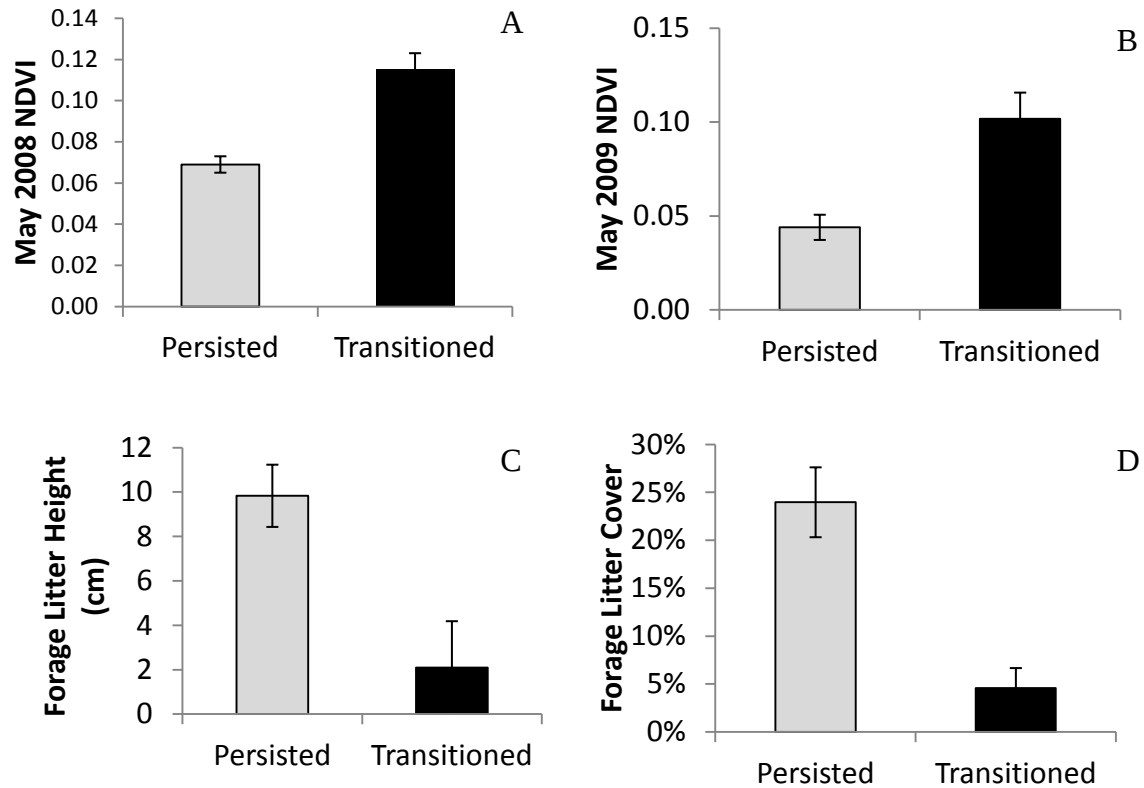


Figure 12. Characteristics of 2008 forage-dominated patches that persisted (grey) or transitioned to other vegetation types (black) in 2009. (A) Mean May 2008 NDVI values, (B) Mean May 2009 NDVI Values, (C) mean height of remnant 2008 forage litter as measured in March 2009, and (D) mean percent cover of remnant 2008 forage litter as measured in March 2009. Error bars represent $\pm$ one standard error.

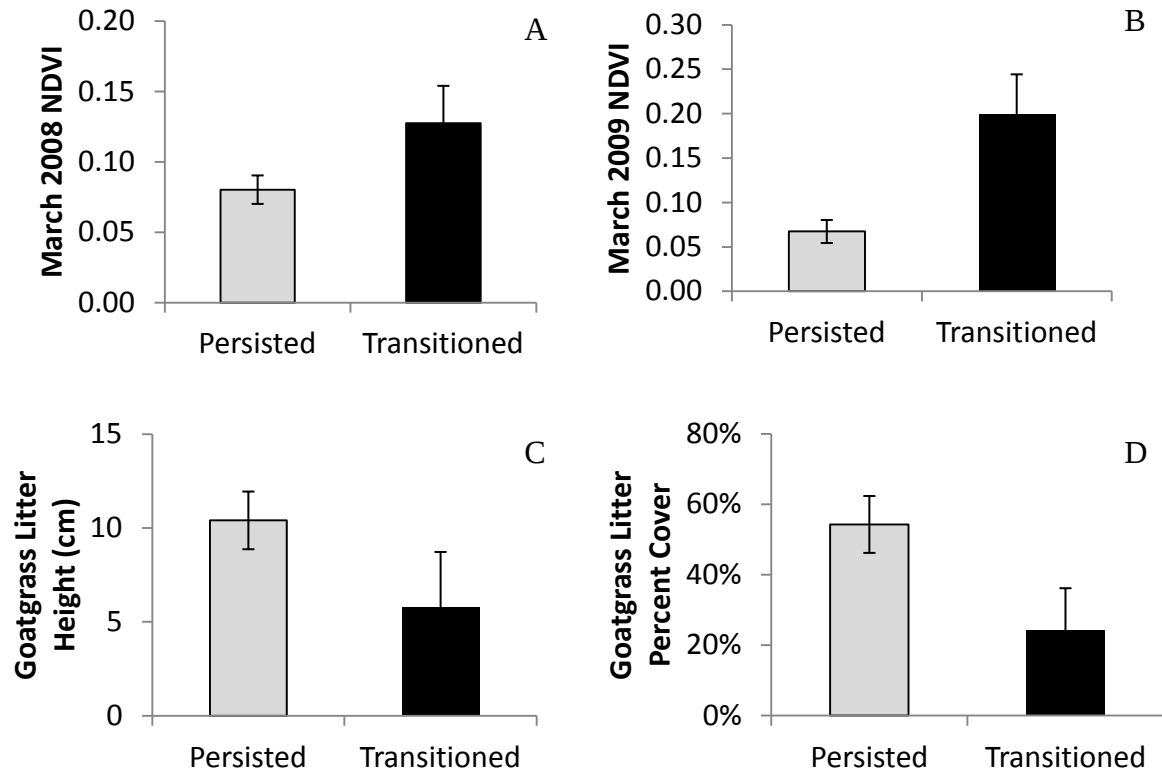


Figure 13. Characteristics of 2008 goatgrass-dominated patches that persisted (grey) or transitioned to other vegetation types (black) in 2009. (A) Mean May 2008 NDVI values, (B) Mean May 2009 NDVI Values, (C) mean height of remnant 2008 goatgrass litter as measured in March 2009, and (D) mean percent cover of remnant 2008 goatgrass litter as measured in March 2009. Error bars represent $\pm$ one standard error.

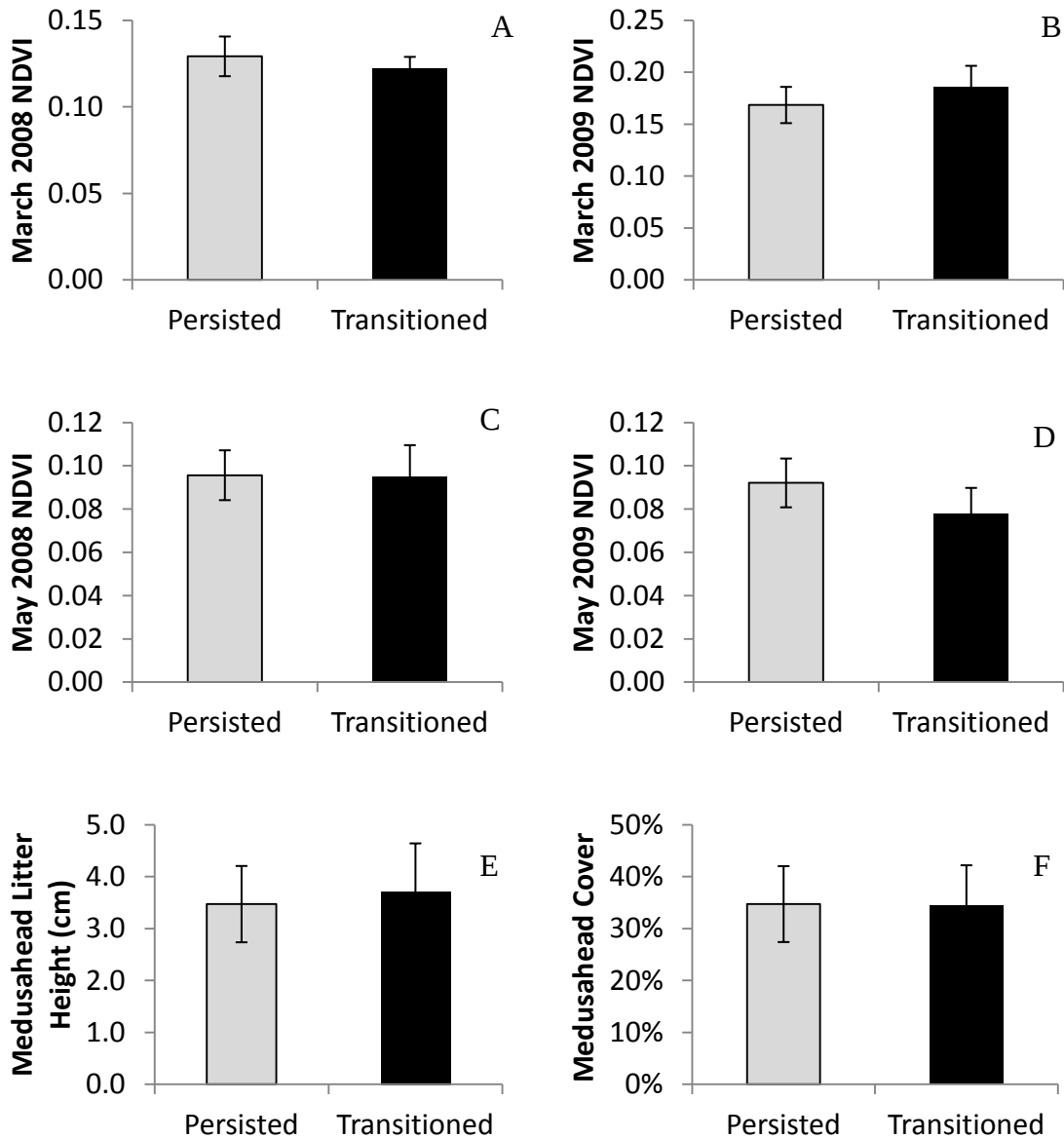


Figure 14. Characteristics of 2008 medusahead-dominated patches that persisted (grey) or transitioned to other vegetation types (black) in 2009. No significant differences were evident. (A) Mean March 2008 NDVI values, (B) mean March 2009 NDVI Values, (C) mean May 2008 NDVI values, (D) mean May 2009 NDVI values, (E) mean height of remnant 2008 medusahead litter as measured in March 2009mean, and (F) cover of remnant 2008 medusahead litter as measured in March 2009. Error bars represent $\pm$ one standard error.

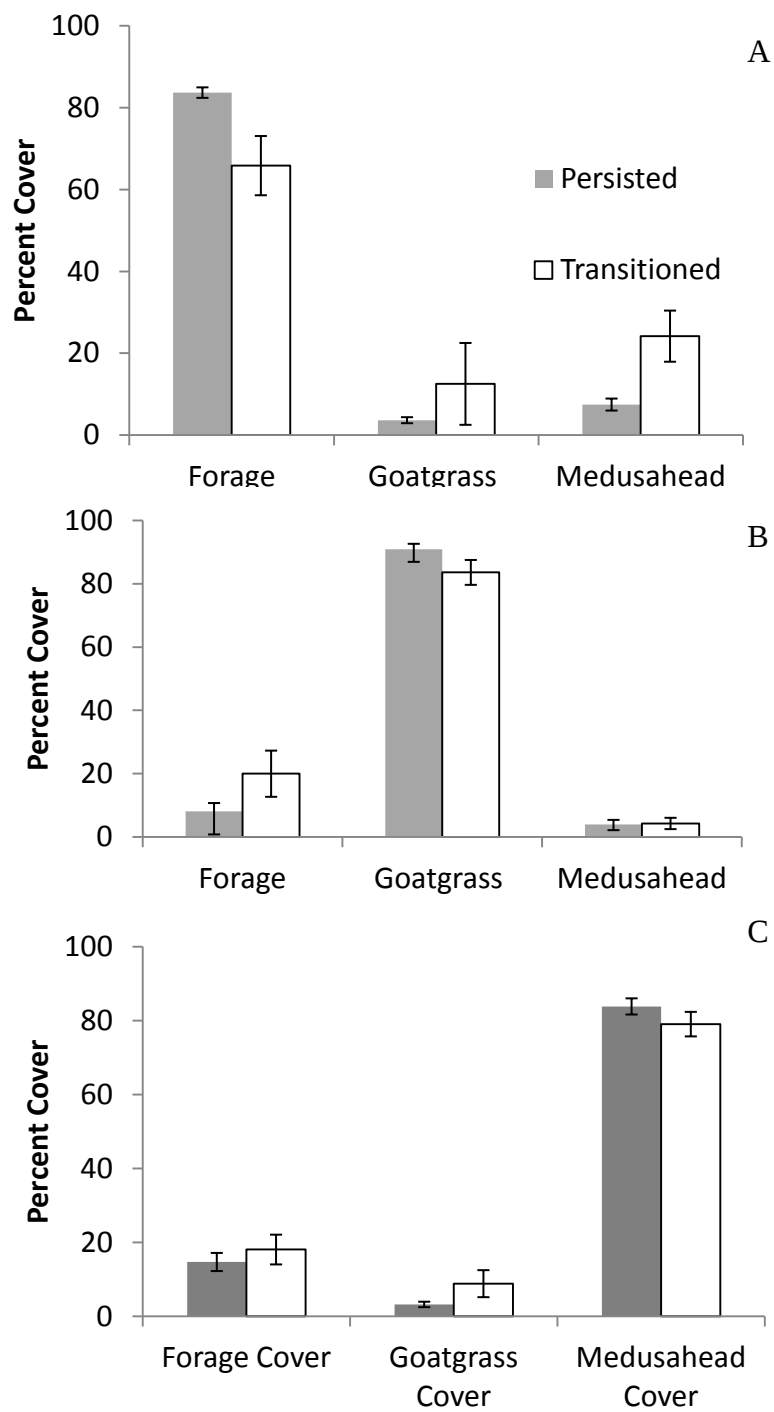


Figure 15. Comparison of community composition characteristics of 2008 patches that persisted or transitioned. (A) forage patches, (B) goatgrass patches, and (C) medusahead. Mean $\pm$ standard errors.

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APPENDIX

COMPARISON OF ORIGINAL IMAGERY AND RESAMPLED IMAGERY

Table 8. Overall percent agreement between ground truth data and the classification results from 2008 across all approaches and imagery.

Approach	<i>Resolution (m)</i>	Imagery			
		<i>March (%)</i>	<i>May (%)</i>	<i>March and May (%)</i>	<i>ΔNDVI (%)</i>
Natural Jenks	0.44	73.4	60	---	71.8
	1	68.2	71.8	---	68.2
Unsupervised	0.44	70.5	40.9	69.4	72.7
	1	77.3	61.4	78.8	81.8
Supervised	0.44	70.5	65.9	70.5	74.1
	1	75.0	68.2	70.5	84.1

Table 9. Overall classification results from 2009 across all approaches and imagery.

Approach	<i>Resolution (m)</i>	Imagery				
		<i>March (%)</i>	<i>May 18 (%)</i>	<i>May 26 (%)</i>	<i>March and May (%)</i>	<i>$\Delta NDVI$ (%)</i>
Natural Jenks	0.44	73.6	58.7	64.4	---	78.9
	1	73.6	61.5	64.4	---	78.9
Unsupervised	0.44	60.4	64.2	69.8	76.9	77.4
	1	64.2	62.3	71.7	81.4	83.0
Supervised	0.44	66.0	52.8	60.4	60.4	81.1
	1	56.6	64.2	62.5	67.9	69.8

Table 10. Overall classification results from 2009b across all approaches and imagery.

Approach	<i>Resolution (m)</i>	Imagery				
		<i>March (%)</i>	<i>May 18 (%)</i>	<i>May 26 (%)</i>	<i>March and May (%)</i>	<i>ΔNDVI (%)</i>
Natural Jenks	0.44	78.2	61.5	57.7	---	76.9
	1	79.5	55.1	58.4	---	85.9
Unsupervised	0.44	76.9	62.3	65.4	74.4	83.3
	1	75.6	65.4	59.0	83.3	80.8
Supervised	0.44	71.8	52.6	46.2	56.4	79.5
	1	71.8	53.4	51.3	64.1	85.9

Table 11. Comparison of the user's accuracy with 2008 data and imagery among the three classification approaches, indicating the percentage of the vegetation points within the weeds or non-weeds patches were actually weeds or non-weeds respectively. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Resolution (m)	Imagery							
		Weeds				Non-Weeds			
		March (%)	May (%)	March and May (%)	Δ NDVI (%)	March (%)	May (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	76.2	0	---	90.9	73.0	60.7	---	68.9
	1	100	62.9	---	80.0	65.8	78.0	---	66.7
Unsupervised	0.44	59.1	30.4	60.0	69.2	81.8	52.4	76.0	74.2
	1	76.9	50.0	77.8	84.6	77.4	72.7	79.3	80.7
Supervised	0.44	83.3	56.3	100	79.0	68.4	71.4	67.5	72.7
	1	80.0	58.8	70	100	73.5	74.1	70.6	79.4

Table 12. Comparison of the user's accuracy with 2009 data among the three classification approaches, indicating the percentage of the vegetation points within the weeds or non-weeds patches were actually weeds or non-weeds respectively. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Imagery										
	Resolution (m)	Weeds					Non-Weeds				
		March (%)	May 18 (%)	May 26 (%)	March and May (%)	Δ NDVI (%)	March (%)	May 18 (%)	May 26 (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	60.1	37.5	50.0	---	82.6	83.3	65.0	65.6	---	77.8
	1	64.7	46.2	50.0	---	80.0	77.8	70.8	70.8	---	78.5
Unsupervised	0.44	47.1	50.0	55.2	81.0	66.7	84.2	74.2	87.5	77.9	84.4
	1	50.0	48.0	57.1	83.3	77.8	80.0	75.0	88.0	81.9	85.7
Supervised	0.44	51.9	12.5	37.5	46.2	74.3	80.8	60.0	64.4	74.1	81.2
	1	40.9	50.0	40.0	60.0	82.4	67.7	64.7	67.4	69.8	78.1

Table 13. Comparison of 2009 data of the user's accuracy among the three classification approaches, indicating the percentage of the vegetation points within the weeds or non-weeds patches were actually weeds or non-weeds respectively. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Imagery										
	Resolution (m)	Weeds					Non-Weeds				
		March (%)	May 18 (%)	May 26 (%0	March and May (%)	Δ NDVI (%)	March (%)	May 18 (%)	May 26 (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	78.6	54.3	50.0	---	80.0	78.0	67.4	62.0	---	75.5
	1	79.3	47.1	51.9	---	90.5	79.6	61.4	62.0	---	75.4
Unsupervised	0.44	69.2	55.9	57.9	81.0	77.8	86.1	68.2	72.5	71.9	88.1
	1	66.7	58.8	55.6	83.3	76.5	84.6	70.5	63.6	83.3	84.1
Supervised	0.44	66.7	37.5	26.3	48.9	74.3	75.6	56.5	52.5	65.7	83.7
	1	65.7	44.4	30.8	63.2	82.4	76.7	54.8	55.4	64.4	88.6

Table 14. A comparison of the producer's accuracy with 2008 data indicating the percentage of weed and non-weed vegetation points fell into the weed and non-weed classes from the three classification approaches. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Imagery								
	Resolution (m)	Weeds				Non-Weeds			
		March (%)	May (%)	March and May (%)	Δ NDVI (%)	March (%)	May (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	48.5	0.0	---	30.3	90.2	98.1	---	98.1
	1	18.2	98.1	---	24.2	100	75.0	---	96.2
Unsupervised	0.44	76.5	41.2	63.6	52.9	66.7	40.7	73.1	85.2
	1	58.2	64.7	63.6	64.7	88.9	59.3	88.5	92.6
Supervised	0.44	29.4	52.9	23.5	45.5	96.3	74.1	100	92.3
	1	47.1	58.8	41.2	58.5	92.6	74.1	88.9	100

Table 15. A comparison of the producer's accuracy of 2009 data indicating the percentage of weed and non-weed vegetation points fell into the weed and non-weed classes from the three classification approaches. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Imagery										
	Resolution (m)	Weeds					Non-Weeds				
		March (%)	May 18 (%)	May 26 (%0	March and May (%)	Δ NDVI (%)	March (%)	May 18 (%)	May 26 (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	73.7	24.3	10.8	---	51.4	73.5	77.6	94.0	---	94.0
	1	57.9	77.6	43.2	---	54.1	82.4	68.7	76.1	---	92.5
Unsupervised	0.44	84.2	57.9	84.2	54.1	73.7	58.8	67.6	61.8	89.6	79.4
	1	73.7	63.2	84.2	64.9	73.7	47.1	61.2	64.7	90.8	88.2
Supervised	0.44	73.7	5.3	15.8	63.2	63.2	61.8	79.4	85.3	58.8	91.2
	1	47.4	5.3	21.2	31.6	63.2	61.8	97.1	83.8	88.2	73.5

Table 16. A comparison of the producer's accuracy for 2009b data indicating the percentage of weed and non-weed vegetation points fell into the weed and non-weed classes from the three classification approaches. A comparison between classification based on the original images, and images resample to a 1m resolution are also compared.

Approach	Imagery										
	Resolution (m)	Weeds					Non-Weeds				
		March (%)	May 18 (%)	May 26 (%0	March and May (%)	Δ NDVI (%)	March (%)	May 18 (%)	May 26 (%)	March and May (%)	Δ NDVI (%)
Natural Jenks	0.44	66.7	57.6	42.2	---	60.6	86.7	64.4	68.9	---	88.9
	1	69.7	48.5	42.4	---	57.6	87.7	60.0	70.5	---	95.6
Unsupervised	0.44	81.8	57.6	66.7	51.5	84.8	73.3	66.7	64.4	91.1	82.2
	1	84.8	60.6	67.6	75.8	78.8	68.9	68.9	51.2	88.9	82.2
Supervised	0.44	66.7	18.2	15.2	63.6	78.8	75.6	77.8	68.9	51.1	80.0
	1	69.7	10.8	12.1	36.4	84.9	73.3	88.9	80.0	84.4	86.7