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ENHANCING RANGELAND SUSTAINABILITY WITH REMOTE SENSING AND COLLABORATIVE INFORMATION EXCHANGE

By

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ABSTRACT

ENHANCING RANGELAND SUSTAINABILITY WITH REMOTE SENSING AND COLLABORATIVE INFORMATION EXCHANGE

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Remote sensing is a powerful tool for range management, but is used by only a small fraction of private range managers. Factors limiting use of remote sensing may include i) its cost and complexity, and ii) a dearth of means by which to quantify senescent biomass. Senescent biomass is a significant forage resource for livestock during dry periods in grasslands. My research examines factors that influence the use of remote sensing by private range managers and are associated with the use of remote sensing for estimating rangeland biomass.

To understand what factors limit the use of remote sensing data by managers, I conducted surveys with managers participating in a rangeland stewardship program in California, in which they were provided with regular remote sensing-based analyses of their properties. My work showed that managers of larger, commercially active ranches found the experimental use of remote sensing to be a positive experience that convinced them that this technology could help improve management. This suggests that the broad use of remote sensing by managers of privately-held, commercial rangelands may be limited in part by the simple lack of opportunity to test these technologies. Programs that assist ranchers in obtaining appropriate products may thus be a cost-effective way to enhance conservation on private rangelands. My findings suggest that voluntary self-

analysis by ranchers of the landscape dynamics of their own properties is likely to lead to more engaged conservation efforts than top-down prescriptions.

Many grasslands experience a significant annual dry period, during which senescent biomass is the dominant canopy component. During these periods, remote sensing indices such as the normalized difference vegetation index (NDVI) underestimate total biomass (green and senescent), which can have significant consequences for end-of-the-season management decisions. Even though the general effect of senescence on the NDVI-biomass relationship is well understood, no study has characterized this effect in detail for annual grasses. To determine the period during which a single NDVI-biomass relationship is useful, I grew annual grasses, and measured canopy properties weekly from germination to the end of the season. NDVI underestimated biomass by increasingly large amounts as the canopy transitioned from dominance by green to senescent biomass. When the entire season was considered, the species-specific NDVI-biomass equations were remarkably similar, suggesting that a single equation may be robust to the structural and phenological differences that exist among annual grasses.

I used spectral measurements from these same grass stands to develop and evaluate a vegetation index describing the mean PAR absorbed by the surface (MAPAR) for senescent biomass estimates. Under some conditions, MAPAR was significantly correlated to total biomass throughout the season, including periods when senescent biomass was dominant. However, the utility of MAPAR declined as the soil moisture or organic matter content increased, and also when significant stem lodging occurred. These findings suggest that MAPAR, or a MAPAR-like index, may prove valuable as a tool for evaluating senescent biomass in dry regions, such as California rangelands.

For my wife, Frances Knapczyk
And for my family, Lynn, Sue, Steve, Stacy, and Shelly Butterfield

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INTRODUCTION

Background

Rangelands comprise approximately 315 million hectares, or some 40% of the land mass in the United States (World Resources Institute 1996). Of this, approximately one-half is privately-owned (USDA Natural Resources Conservation Service 2000) and thus susceptible to pressures from urbanization (e.g., Heady and Child 1994, Smith 2000, Haver 2001, Jensen 2001). Rangelands are composed of grasses, forbs, shrubs, and trees, and are predominantly used for livestock grazing in the western United States (Heady and Child 1994). Rangelands can include natural grasslands, savannas, shrublands, many deserts, tundra, alpine communities, coastal marshes, and wet meadows (Heady and Child 1994, Barbour et al. 1999).

Rangelands in the western United States provide a variety of ecosystem services, including forage for grazing animals, clean air, and open spaces, and habitat for native wildlife and plant species (Heady and Child 1994). Rangelands can also serve as high quality watersheds if levels of residual dry matter (RDM)--the amount of dry plant material on the ground at the beginning of the season--are maintained within recommended ranges (Bartolome et al. 2002) and if riparian areas are properly managed (e.g., fenced and either ungrazed or grazed only irregularly and by a small number of grazing animals). In addition, rangeland ecosystems provide important economic services, including supporting an approximately $80 billion beef and cattle industry as well as private recreational (e.g., hunting) pursuits (World Resources Institute 1996, Mitchell 2000)

Because of the collective importance of the services that rangeland ecosystems provide, the "health" of rangelands often directly influences the economic well-being of communities in the region, as is the case in the western United States (Heady and Child 1994, Mitchell 2000, O'Brien et al. 2003). Defining and monitoring rangeland health is a complex process, and one for which a variety of state and federal agencies (e.g., the Bureau of Land Management) as well as nonprofit organizations (e.g., the Central Coast Rangeland Coalition) have developed their own unique systems (e.g., Bureau of Land Management 1996, Ford et al. 2006). In these systems, rangeland health is often evaluated by assessing a number of the following indicators: (i) degree of soil stability and watershed function; (ii) integrity of nutrient cycles and energy flows, including plant productivity and the presence of desirable forage species; (iii) resistance and resilience to unexpected or catastrophic disturbances, which is evaluated by measuring multiple factors including age class distributions and plant vigor; (iv) maintenance of biological diversity and habitat quality; and (iv) socio-economic sustainability of the rangeland and ranching operation (The Nature Conservancy 2000, 2005, 2006, Ford et al. 2006). Here, I define socio-economic sustainability as the use of rangeland resources in such a way as to meet present living costs while preserving natural resources and income sources for future generations.

Enhancing rangeland "health" and achieving long-term sustainability are important goals for many ranchers and conservation biologists, and thus motivating factors for much work, including my own research. Because they are such broad goals, however, my work has focused on the more immediate specific steps of evaluating and expanding remote sensing use by land managers, with a particular focus on using remote sensing to evaluate properties, such a biomass production, that are integral to analyses of rangeland health, as described above. In the long-term, scientific advances in this area, in combination with economic analyses, will likely help managers meet goals in rangeland sustainability.

Broad questions about rangeland health and sustainability are important because at present many rangeland ecosystems and the communities they support are threatened by multiple factors, which include: (i) rising levels of invasive noxious weeds (e.g., Mack 1989, D'Antonio and Vitousek 1992, Vitousek et al. 1996, DiTomaso 2000); (ii) global warming, which threatens to make rangelands more vulnerable to invasion by exotic species (e.g., Alward et al. 1999); (iii) nitrogen deposition, which can favor the increased dominance of exotic species (McLendon and Redente 1991, Field et al. 1992, Fenn et al. 1998, Koide et al. 1998, Weis 1999, Aber and Melillo 2001); and (iv) urbanization (e.g., Heady and Child 1994, Wilcove et al. 1998, Smith 2000, Haver 2001, Jensen 2001). In combination, these threats are making it increasingly difficult for private range managers to maintain economically viable ranch operations (Leitch et al. 1994, World Resources Institute 1996, Mitchell 2000). As economic margins decline while rangeland property taxes and the value of land for urban development rise, more rangeland managers--even many of whom who are part of multi-generation ranching families--consider selling their properties (The Nature Conservancy 2005). When ranches are converted to urban and suburban uses, large areas of open space are then lost, along with the ecosystem and economic services that these rangelands provided (The Nature Conservancy 2000, 2005, 2006, Heady and Child 1994). Such sales therefore can have lasting detrimental consequences, not only for the native species that live there but also for human communities (World Resources Institute 1996, Roling and Wagemakers 1998, Mitchell 2000, The Nature Conservancy 2005).

In my research, I chose to work with private range managers, because they are important contributors to the management and overall conservation of rangeland ecosystems. Many of these managers are strongly committed to conservation in order to preserve viable ranching operations for future generations of their families (Jensen 2001, Butterfield and Malmstrom 2006, The Nature Conservancy 2006). In addition, private range managers possess a wealth of invaluable expert knowledge about ecological dynamics in their regions, often described as "local ecological knowledge"(Berkes et al. 2000, Olsson and Folke 2001).

Interest in local ecological knowledge, or knowledge held by a specific group of people (e.g., the western range management community in this case) about their local ecosystems and the interplay among organisms and their environment (Olsson and Folke 2001), has grown recently within the scientific community. Researchers have shown that such knowledge can contribute to the conservation of biodiversity (Gadgil et al. 1993), the protection of endangered species (Colding 1998), the preservation of threatened ecological processes (Alcorn 1989), and increases in the overall sustainability of resource use (Berkes et al. 2000).

To meet the growing needs and pressures of management in rangeland ecosystems, range managers have begun to evaluate new management practices designed to decrease levels of noxious weeds and in the process increase total biomass production. These practices include prescribed burning, short-duration, high-intensity grazing (SDHI), and seeding of native perennial bunchgrasses (e.g., Thomsen et al. 1990, Taylor and Ralphs 1992, Coppock and Birkenfeld 1999, Krueter et al. 2001, Malmstrom et al. 2004, DiTomaso and Johnson 2006). Noxious weeds, such as yellow starthistle (*Centaurea solstitialis* L.), medusahead (*Taeniatherum caput-medusae* (L.) Nevski), and leafy spurge (*Euphorbia esula* L.), are especially problematic in rangeland ecosystems in the western United States because of their negative impact on livestock operations (Lusk et al. 1961, Lym and Kerby 1987, Young 1992, Callihan et al. 1992, Callihan et al. 1995, Vitousek et al. 1996, DiTomaso 2000, DiTomaso and Johnson 2006). Noxious weeds can reduce livestock carrying capacity (Lym and Kerby 1987, Heady and Child 1994, Leitch et al. 1994), and quickly decrease biomass production (Mooney et al. 1986, Mack 1989, D'Antonio and Vitousek 1992) as well as the quality (e.g., nutritional value) of forage available for grazing animals (Lusk et al. 1961, Barry 1995). Some noxious weeds (e.g., yellow starthistle) can even be toxic to livestock (Panter 1990). Once noxious weeds have become established, the cost associated with the management of the ecosystem as a whole increases greatly (Roche and Roche 1991, Leitch et al. 1994, Randall 1996, DiTomaso 2000, Tu et al. 2001, DiTomaso and Johnson 2006).

To gain assistance in evaluating these new management practices, some managers have formed watershed collectives with each other and forged relationships with non-profit conservation organizations and university scientists who can provide scientific analyses (e.g., Haver 2001, Jensen 2001, Qi et al. 2002, Malmstrom et al. 2004, The Nature Conservancy 2000, 2005, 2006). These collaborations provide managers the unique opportunity to evaluate a variety of different practices in combination with one another, and to collaborate in assessing which practices will decrease noxious weeds and increase levels of desirable forage species most. In many cases, it is likely that managers could increase the effectiveness of their ranch operations if they were able to monitor rangeland vegetation in detail over their entire properties each year. This capability would be especially helpful for identifying noxious weed infestations when they are small and more easily controlled and/or eradicated (Everitt et al. 1995, Lass et al. 1996, Boswell 2000, Lass et al. 2002, Everitt et al. 2006, DiTomaso and Johnson 2006). However, managers often cannot monitor their entire properties each year using ground-based efforts alone because their ranches are large and ecologically complex (George and Fulgham 1989, Rowan and Conner 1995, Tueller 1989, Coppock and Birkenfeld 1999, Tueller 2001).

Remote sensing, however, can help managers conduct annual property-wide assessments of range condition (Tueller 1989, Hunt et al. 2003, Wallace et al. 2003, Lass et al. 2005, Washington-Allen et al. 2006). For example, managers can use remote sensing data to quantify the effect of their management practices on noxious weed spread and biomass production from scales of individual pastures to entire watersheds. This allows managers to quantify the impact of each practice within the context of non-management induced variations, such as those related to topographic and soil differences (Tueller 1982, Richardson and Everitt 1992, Pickup et al. 1994, Wessman et al. 1997, Wallace et al. 2003).

Range managers can also use remote sensing data to expand the temporal scale of their analyses. Many satellite sensors acquire data at least twice a month across western United States rangeland ecosystems. Some of these sensors, like the Landsat series, have been acquiring data for more than 20 years. For example, because of the time period over which it has been acquired, Landsat satellite data can provide managers the unique opportunity to analyze the effects of their current management practices within the context of historical land use and land cover changes across their properties (Paruelo and Golluscio 1994, Saltz et al. 1999, Wallace et al. 2003, Malmstrom et al. 2004, Shaw 2005, Reeves et al. 2006, Washington-Allen et al. 2006). This capability, for example, allows managers to determine which practices were most successful in the past at decreasing noxious weed levels, and thus to focus future management efforts on those which were most effective (Malmstrom et al. 2004, Washington-Allen 2006). Remote sensing data can also provide managers the unique ability to evaluate the impact of their current management practices across temporal scales from months to decades (e.g., Tucker et al. 1983, Pickup et al. 1994, Wessman et al 1997, Wallace et al. 2003). This capability enables managers to base management decisions on both short- and long-term biomass and weed trends (e.g., Hunt et al. 2003, Lass et al. 2005, Mustafa et al. 2005, Everitt et al. 2006, Mundt et al. 2006).

Despite their value, remote sensing data currently are used by only a small fraction of range managers (Tueller 1982, 1989, Daberkow and McBride 2000, 2003). The low use rates of innovative technologies, like remote sensing, often indicate either that the technology has not been successfully introduced to the end-user (i.e., the range manager in this case) or that the end-user does not see its utility (Fliegel 1993, Kreuter et al. 2001, Daberkow and McBride 2003).

Another potential limitation is the current lack of remote sensing approaches for quantifying total biomass during time periods when senescent biomass is present. Senescent biomass is an important forage resource in grass-dominated rangeland (grassland) ecosystems for a substantial portion of the year (e.g., George and Fulgham

1989, Richardson and Everitt 1992, Frank and Aase 1994, Qi et al. 2000). During dry periods, senescent biomass is the only forage resource available for grazing animals (George and Fulgham 1989, Richardson and Everitt 1992, Frank and Aase 1994, Qi et al. 2000). In these ecosystems, this can mean that senescent biomass is the only forage resource available for up to six months during the year (George and Fulgham 1989, Prince 1991, Saltz et al. 1999).

The amount of senescent plant material on the ground at the beginning of the season, known as residual dry matter (RDM), is also an important indicator of rangeland health (Bentley and Talbot 1951, Heady 1956, Bureau of Land Management 1996, Bartolome et al. 2002, Guenther and Christian 2005, Ford et al. 2006). In grazed grasslands, RDM is primarily composed of the foliage and stem biomass of grasses and forbs from the current season (Bartolome et al. 2002, George et al. 2006). However, in ungrazed grasslands, RDM can also include dry tree leaves, woody debris, and grass and forb litter from previous growing seasons (i.e., more than a year old). In western rangeland ecosystems, properly managed RDM can reduce soil erosion, and thus increase biomass production of desirable forage species and decrease levels of broadleaf noxious weeds, such as yellow starthistle (Bartolome et al. 1980, McDougald et al. 1982, Heady and Child 1994, George and Menke 1996, Molinar et al. 2001, Bartolome et al. 2002). RDM measurements are used not only by range managers, but also by federal agencies, such as the Bureau of Land Management, for compliance monitoring across federally owned and/or managed grassland ecosystems (Bureau of Land Management 1996). In addition, RDM assessments are used by range management specialists and conservation organizations, such as The Nature Conservancy, for both compliance and effectiveness monitoring across conservation easements (e.g., Guenther 1998, The Nature Conservancy 2000, 2005, 2006, Molinar et al. 2001, Guenther and Christian 2005).

Remote sensing data have been used for more than 30 years to quantify green biomass in grassland ecosystems (Rouse et al. 1974). However, during periods when senescent biomass is present, vegetation indices, such as the normalized difference vegetation index (NDVI), underestimate total biomass. NDVI is calculated using surface reflectance (R) values in the red (0.63–0.69 μm) and near infrared (NIR) (0.76–0.9 μm) spectral regions as:

$$NDVI = (R_{NIR} - R_{red}) / (R_{NIR} + R_{red}) \qquad \textbf{[Eq. 1]}$$

NDVI is highly correlated to green biomass because it is calculated using the red spectral region, which is sensitive to chlorophyll amount, and the NIR region, which is sensitive to both leaf internal and canopy structure (Rouse et al. 1974, Tucker 1979). Thus, as green biomass increases, NDVI increases. However, as vegetation senesces, chlorophyll degrades and leaf internal structure declines (Tucker 1979). This results in NDVI values more similar to that of the soil background (Huete et al. 1985), and causes NDVI to be a poor predictor of total biomass during these time periods (e.g., Tucker 1979, Tucker et al. 1983, Gamon et al. 1995).

To assess grassland condition during time periods when senescent biomass is present, researchers have thus developed a variety of approaches, including: 1) thermal remote sensing data coupled to NDVI measurements (French et al. 2000); 2) vegetation indices that use the shortwave infrared region (SWIR: 2000–2300 nm) (e.g., Qi et al. 2000); and 3) techniques such as spectral mixture analysis of the SWIR region (e.g., Gamon et al. 1993). The SWIR region has been used because it contains cellulose (2090 nm and 2270 nm) and lignin (2130 nm and 2270 nm) absorption features that are masked by water in green vegetation but become evident as vegetation senesces (Roberts et al. 1993). While each of these techniques has been used successfully in grassland ecosystems to produce estimates of fractional senescent vegetation cover, [or the areal proportion of the surface covered by senescent vegetation (White et al. 2000)], none can be directly used to quantify biomass, either total (green plus senescent) or senescent. For range management operations, fractional cover is not always in itself an adequate indicator of rangeland condition because it is not a direct surrogate of productivity as stand biomass is (Pickup et al. 1994).

To increase the utility of remote sensing data for biomass management in rangeland ecosystems it is therefore imperative that we more clearly define the limits of green vegetation indices (like NDVI) throughout the season as well as develop new remote sensing approaches that can be used when senescent biomass is present. The studies in this dissertation were motivated by the lack of detailed information about the effect of senescence on the NDVI-biomass relationship for grass species and grass mixes that dominate western grassland ecosystems. This detailed information is important because it enables analysis of the error associated with the use of NDVI for biomass estimates during time periods when senescent biomass is present.

The objectives of my dissertation were: 1) to identify limitations associated with the use of remote sensing data by private range managers and to evaluate the impact of the use of remote sensing data on manager decision-making, 2) to increase the accuracy of NDVI-green biomass estimates in grassland ecosystems, and 3) to develop a new remote sensing approach for the quantification of biomass that can be used in grassland ecosystems when senescent biomass is present.

Organization of the Dissertation

For my thesis research I examined three fundamental questions regarding the use of remote sensing data by private range managers in California. First, what factors influence the use of remote sensing data by the private range management community and how does the use of remote sensing impact decision-making? Second, during what part of the growing season can a single NDVI-biomass equation (i.e., biomass = *f*(NDVI)) be accurately used in annual grasslands with mixed species composition? And, third, are there alternative means for quantifying senescent biomass from satellite data that are accessible and affordable for private range managers?

In Chapter 2, *Experimental use of remote sensing by private range managers and its influence on management decisions* (Butterfield and Malmstrom 2006), I used case study analyses to examine how the characteristics of range managers and their properties influence the use of remote sensing data. I found that remote sensing data were most likely to be used and invested in by range managers who had recently implemented other new practices and who believed remote sensing products would help increase ranch profitability. In these cases, managers found that remote sensing data allowed them to extend their intensive management efforts to a greater proportion of their properties and to base their management decisions on multi-year forage and weed analyses.

In Chapter 3, *Phenological effects on remotely-sensed biomass estimates in annual grasslands*, I used annual grass stands planted in an agricultural field on the campus of Michigan State University in East Lansing, Michigan to examine in detail the impact of canopy senescence on NDVI-biomass estimates. I used these data to determine the phenological period during which a single NDVI-biomass equation could be used in annual grasslands with mixed species composition. I found that in all stand types, NDVI could be used to estimate green biomass throughout the season, regardless of the proportion of senescent biomass present. Furthermore, all stand types displayed similar phenological relationships between NDVI and biomass, reaching maximum NDVI and maximum biomass simultaneously. Last, when the entire season was considered, the species-specific NDVI-biomass equations were remarkably similar, suggesting that a single equation may be robust to the structural and phenological differences that exist among common grass species.

In Chapter 4, *Remote sensing-based estimates of senescent biomass: Common problems and a new approach in annual grasslands*, I propose a new vegetation index for senescent biomass estimates, MAPAR (the mean PAR absorbed by the surface), and examine its potential for landscape-scale RDM estimates in western grassland ecosystems. Across dry, light-colored sandy loam soils, MAPAR was correlated with senescent biomass across a wide-range of conditions. However, the utility of MAPAR declined where the soil was darker, either due to increased soil moisture or organic matter content, and also when significant stem lodging occurred. In most western grassland ecosystems, such as those found in California, soil is often low in organic material (e.g., 2–10 %). In addition, across grazed grasslands, stems often do not reach heights where stem lodging would be a significant issue. Therefore, these results suggest that MAPAR may be a valuable approach for estimating senescent biomass, or RDM, in grazed grassland ecosystems.

I conclude the theses with a summary of future research directions that were inspired by my dissertation research in Chapter 5.

CHAPTER 2

EXPERIMENTAL USE OF REMOTE SENSING BY PRIVATE RANGE MANAGERS AND ITS INFLUENCE ON MANAGEMENT DECISIONS

Abstract

Although remote sensing has many potential applications for range management, its use by range managers has thus far been limited. To investigate the factors that encourage use of remote sensing and to examine its influence on decision making by individuals who manage privately owned rangeland, we evaluated the decision-making processes of three ranch owners and one professional ranch manager who were introduced to remote sensing while collaborating with us in a rangeland stewardship program in California. Two of the participants had extensive ranching experience (11 to > 20 years) and managed large cattle ranches (1000 to > 2000 ha) and two had less experience and managed smaller sheep ranches (< 200 ha). During the five-year program, the participants implemented a series of new management practices, including prescribed burning, rotational grazing, and seeding of native grasses, with the aim of reducing noxious weeds and increasing productivity. We used remote sensing to quantify the effect of these practices and provided ranch-wide remote sensing analyses to each manager on a password-protected website. Using case study methodologies, we found that managers of larger, commercially active ranches found the experimental use of remote sensing to be a highly positive experience that convinced them that this technology could help address difficult management situations and increase ranch profitability. This suggests that the broad use of remote sensing by managers of privately-held, commercial rangelands may be limited in part by the simple lack of opportunity to test these technologies. Programs that assist ranchers in obtaining

appropriate remote sensing products may thus be a cost-effective way to enhance conservation on private rangelands. Our findings suggest that voluntary self-analysis by ranchers of the landscape dynamics of their own properties is likely to lead to more engaged conservation efforts than top-down prescriptions.

Introduction

Few range managers currently use remote sensing products to inform their management decisions (Daberkow and McBride 2000, Hunt et al. 2003, Washington-Allen 2006), even though remote sensing offers valuable means of assessing the influence of management practices on forage production (e.g., Pickup et al. 1994) and invasive noxious weed spread (e.g., Lass et al. 1996) across large range units. Several studies have examined factors influencing the use of innovative technologies in general (Fliegel 1993, Rogers 1995, Röling and Wagemakers 1998, Daberkow and McBride 2003) and of specific range management technologies, such as cattle vaccines (Harris et al. 1995) and prescribed burning (Kreuter et al. 2001). To our knowledge, however, no study has sought to identify factors that promote the use of remote sensing technologies by range managers or investigated how the use of remote sensing can influence manager decision-making. With other innovative technology, low use rates have often been found to indicate either that the technology has not been successfully introduced to the end user (in this case, the range manager) or that the end user does not see its utility (Fliegel 1993, Kreuter et al. 2001, Daberkow and McBride 2003). In the case of remote sensing, use may also be limited by its cost and complexity or by the lack of opportunity to try it.

California's rangelands are a good example of a system in which broad use of remote sensing technologies could benefit range managers by allowing them to assess management techniques for weed control and forage improvement over large areas. Since first settled by European immigrants, California's rangelands have been under pressure from human activities, which have resulted in the conversion of this system from one dominated by native vegetation including annual forbs and perennial bunchgrasses to one dominated by introduced annual grasses (Heady 1977, D'Antonio and Vitousek 1992). These introduced annual grasses, which have relatively high forage value, have supported an extensive ranching economy in the state for more than 150 years (George and Fulgham 1989). Today, however, a wave of introduced noxious species, including yellow starthistle (*Centaurea solstitialis* L.; all nomenclature follows Hickman (1993)), medusahead (*Taeniatherum caput-medusae* (L.) Nevski), and barbed goatgrass (*Aegilops triuncialis* L.), are spreading through the region, reducing rangeland productivity and threatening the economic sustainability of established ranches (Maddox and Mayfield 1985, Young 1992, Peters et al. 1996). Unlike the previously established exotic species, these new invaders provide poor forage during most of the season (Bovey et al. 1961, Lusk et al. 1961, Callihan et al. 1982, Callihan et al. 1995, Peters et al. 1996). To manage the noxious weeds, range managers are testing a variety of new management approaches, but it can be costly for them to assess the consequences of the new approaches with on-the-ground surveys alone, given the extent of their properties. Remote sensing offers an opportunity for managers to evaluate large areas more quickly and cost-effectively.

To identify factors that promote the use of remote sensing by range managers and to investigate the influence of remote sensing on range management decisions, we used an in-depth, case-study approach to examine the experimental use of remote sensing products by four individuals who manage private rangelands in the Western Sacramento Valley foothills in California, as part of a five-year rangeland stewardship program (1999-2004) (Malmstrom et al. 2004). Managers were involved in the program primarily because they wanted to increase the productivity of their land and decrease noxious weed levels (Table 2.1). To do this, they tested a series of new management practices (Table 2.2). None of these managers had specifically used remote sensing data to make management decisions on his or her property prior to involvement in our study.

Here, we examine 1) the ways in which managers' ranching approaches and previous ranching experiences influenced their interest in and use of our experimental remote sensing products, and 2) the ways in which the remote sensing products in turn influenced the managers' decision-making. We produced a broad suite of remote sensing products, which included a time series of spring forage estimates for the watershed, and a map of noxious weed distributions. This information was presented to the managers through an interactive website that allowed each to view his or her property as a whole or on a field-by-field basis. Data were presented in graphs and as maps, which could be selected to show estimated values for a given time period or patterns of change across years. We conducted surveys and interviews with all four managers before and after they worked with these remote-sensing materials and then used case study methodologies to analyze their responses.

Table 2.1. Motivation for involvement in the stewardship program. Responses were given in survey 1, before managers were provided access to the remote sensing products, on a Likert scale (1 = no motivation to 5 = high motivation).

	Cattle 1	Cattle 2	Sheep 1	Sheep 2
Increasing forage production	5	5	5	1
Decreasing noxious weeds	4	3	5	3
Establishing native bunchgrasses	5	1	2	1
Promoting landowner outreach	4	2	4	5
Increasing water quality	5	2	1	1

Table 2.2. Management practices tested during the stewardship program.

Cattle 1	
1 unit totaling 12.1 ha	Prescribed burning, seeding of native bunchgrasses, rotational grazing
2 units totaling 157.8 ha	Prescribed burning, rotational grazing
6 units totaling 157.8 ha	Rotational grazing
1 unit totaling 1011.7 ha	Fencing planned
Cattle 2	
1 unit totaling 16.2 ha	Rotational grazing (spring only)
6 units totaling 550.4 ha	Rotational grazing (fall only)
1 unit totaling 26.3 ha	Prescribed burning, seeding of native bunchgrasses
Sheep 1	
1 unit totaling 24.3 ha	Rotational grazing, prescribed burning, seeding of clover
3 units totaling 97.1 ha	Prescribed burning, seeding of native bunchgrasses, rotational grazing
2 units totaling 46.5 ha	Prescribed burning, rotational grazing
Sheep 2	
1 unit totaling 16.2 ha	Prescribed burning, seeding of native bunchgrasses, rotational grazing
1 unit totaling 16.2 ha	Rotational grazing

Methods

Growing season terminology

Most California rangelands experience a Mediterranean climate, distinguished by a moderate fall-winter-spring growing season and a prolonged summer drought. We thus consider time in terms of "biological" years that begin in fall at the end of the summer drought (i.e., September 200N) and continue into August of the following calendar year (200N + 1). We refer to September–November as fall, December–February as winter, March–May as spring, and June–August as summer. For most annual range grasses, the growing season begins in fall with the first rains, continues through the wet winter, and reaches its peak in spring. By late May, most annual range grasses are senesced, but the newer noxious weeds may remain green later into the summer.

Remote sensing products

To produce maps of green spring forage values, we used field-calibrated algorithms to estimate green forage biomass from NDVI (normalized difference vegetation index) values derived from Landsat satellite imagery acquired in late March or early April of each year from 1999 to 2004 (Malmstrom et al. 2004). We used Landsat imagery both because of its availability and cost effectiveness to private range managers as well as the appropriateness of its spatial scale (30 m) for rangeland forage analyses. Forage estimates were made only at the peak of the growing season when green biomass was dominant, because we found that remote sensing algorithms for quantifying senescent biomass previously developed for southwestern systems (Qi et al. 2000) failed to perform adequately in the California annual grasslands (Malmstrom et al. 2004). To map the distribution of two dominant noxious weeds–medusahead and goatgrass–we used a time series of fine spatial resolution (1 ft) aerial photography acquired at key phenological time points when these weeds showed reflectance patterns distinct from the more valuable forage grasses (Malmstrom et al. 2004). To provide managers interactive access to the remote sensing products, we built a password-protected website on which each manager had access to information about only his or her own property. The website offered managers whole-property and field-by-field access to spring forage maps from 1999–2004, forage change maps comparing differences across years, a quantitative 5-year forage analysis, a map of noxious weed distribution in 2004, and land use history and weather data.

Surveys and interviews of land managers

To gather baseline information about the managers' experiences, practices, and attitudes, we asked each manager to complete a survey in March 2004, prior to introducing him or her to the remote sensing materials. This survey contained 25 multiple-choice Likert scale questions (Miles and Huberman 1994, Strauss and Corbin 1998) and ten short-answer ones. Among the subjects we explored were the managers' 1) assessment of the current range conditions at their property and the need for new management approaches, and 2) previous experiences with using new management practices such as prescribed burning for weed control. We interviewed each manager individually to clarify his or her responses and to gather additional information about management approaches used on his or her property and its land use history.

We then showed all four managers how to use the project website to access the remote sensing products, and gave them five months (March–August 2004) in which to explore the products and test their utility for management decision-making. In August, we re-surveyed and interviewed the managers to determine to what extent they had used the remote sensing products, how the products had influenced their decision-making, and what improvements might increase their interest in using remote sensing in the future. Like the first survey, the second one contained 25 multiple-choice Likert scale and ten short-answer questions, about half of which were identical to those asked in the first survey. Both surveys adhered to Dillman's (1978) guidelines, except that we did not use follow-up mailings because our group was small enough to contact by phone.

Analysis of responses

Because our study group was by necessity small, we used case study methodologies to analyze manager responses (Yin 2003). Case studies provide the opportunity to intensively examine the experiences and responses of a smaller group of managers, who represent elements of a larger management community. While case studies provide substantial insight into manager motivation, care must be taken when extrapolating results from individual case studies to other situations. To construct the case studies, we first coded the survey and interview data to identify manager responses in two broad categories of interest (Miles and Huberman 1994, Strauss and Corbin 1998): 1) *Manager characteristics and experience* and 2) *Influence of remote sensing on management decisions*. *Manager characteristics and experience* included descriptive information about each manager and his or her management operations; *Influence of* *remote sensing on management decisions* included information about how each manager used remote sensing data to evaluate his or her success in meeting his or her own management objectives. During the coding process we sought illuminating quotations from each manager that provided insight into his or her own unique story.

We used the managers' responses from the second set of surveys and interviews to determine their response to the remote sensing products. We defined the use of remote sensing during the study as the extent to which managers accessed the website and our remote sensing products with the purpose of using the products to evaluate the impact of their management efforts and to decide which approaches to use in the future. We also quantified the managers' self-reported planned intent to use these same remote sensing products for management evaluations in the future and to invest in new remote sensing data and products for their properties.

Results

We present each case study individually, with two sections within each: 1) *Manager characteristics and experience,* which discusses the characteristics of each manager and his or her management operations and motivations for involvement in the stewardship program; and 2) *Influence of remote sensing on management decisions,* which discusses how each manager used the experimental remote-sensing products to evaluate his or her management strategies, and his or her suggestions about how the products could be improved to enhance their value for private range managers such as themselves or for long-term management planning. To protect their privacy, the managers and case studies are referred to by code names: Cattle 1, Cattle 2, Sheep 1, and Sheep 2.

Cattle 1

Manager characteristics and experience. At approximately 2000 ha, Cattle 1 was the largest ranch studied. Cattle 1 has been family-owned for over 20 years and has been used primarily for commercial cattle grazing during that time. The landowners' motivations for involvement in the stewardship program were diverse but centered on the desire to increase ranch productivity (Table 2.1). Both the current and former managers (son and father) agreed that it was important to increase the value of their land, especially given pressure from urbanization, governmental regulations, and global competition, so that their family business "makes it to the next generation." The father believed "grazing alone maintained feed for cattle" and that "burning and seeding native perennials was too expensive" to be a property-wide solution. However, his son believed that to "preserve the ranching way of life in California" it was necessary to implement management strategies that took advantage of new technologies and cooperative partnerships. His outlook was evident in the diversity of management practices implemented during the program (Table 2.2). Rotational grazing, the practice of alternating periods of grazing and rest among two or more fenced pastures throughout the season, was an especially distinctive change that occurred in the last 1–2 years of the program because the ranch had previously used set stocking rates. Cattle 1's manager believed that "decreasing stocking rates in the spring would allow more re-growth and, combined with burning in the summer, would have a positive effect on forage."

Influence of remote sensing on management decisions. Before working with the remote sensing products, Cattle 1's manager believed that there was a "place for remote sensing in ranching," but emphasized that it could never replace the skills of a rancher. He believed that remote sensing would allow him to quickly visualize forage and weed levels across his entire property, which would allow him to compare fields enrolled in the program with those being managed with a traditional grazing approach.

After evaluating the remote sensing products on the project website, Cattle 1's manager concluded that he could use the weed map and the time series of forage estimates to determine whether the programs' restoration efforts had made impacts on weed control and forage production that were large enough to justify their continued use. During the second interview, for example, he discussed how his analysis of the remote sensing maps had led him to conclude that "while burning increased forage levels the year following the burn, two years later medusa was back and forage levels were where they were before the burn." Therefore, "burning is only beneficial if used along with seeding of good competitors, such as native perennial grasses." He indicated that his evaluation had also led him to conclude that his rotational grazing efforts had increased forage and decreased weeds during the 2003–04 growing season. This conclusion was significant in a management context because "managing with cattle requires fewer additional inputs of time and money compared to burning and seeding."

Based on the value he gained from the remote sensing products we produced for the lower portion of his ranch, Cattle 1's manager requested that we also produce similar products for the ranch's upper portion. He found this upper 1000-ha portion to be more difficult to manage because of its ruggedness, size, and lack of fencing, and so had not yet tried restoration efforts in it (Table 2.2). The additional forage maps led Cattle 1's manager to conclude that forage increases in the closely managed lower portions of the property had been much greater than those in the upper portions. He believed that these differences were due to his inability to "control cattle and visually inspect" the upper portions of the property "throughout the season." He believed that remote sensing data would allow him to address both issues, and he planned to use the forage maps to coordinate fencing of the upper portion in 2004–05 and to monitor forage thereafter (Table 2.2). His first-hand experience of remote sensing's capacity to quantify management effects and help enhance management efforts in remote terrain led Cattle 1's manager to increase the amount of money that he would be willing to invest annually in these technologies from approximately $100 (survey 1) to $500 (survey 2), with the latter value exceeding the cost of an entire Landsat Thematic Mapper (TM) scene ($425).

The outreach efforts at Cattle 1 involved a two-way exchange of information between scientists and range managers. This exchange allowed us to produce remote sensing products customized for the experience level and management needs of Cattle 1's manager. Cattle 1's manager emphasized that the remote sensing did not change *what* management strategies he believed were possible, but rather the means by which he could assess their effectiveness: "This is what I meant when I said remote sensing was only a tool. It helps me see the effects of management, but it cannot do them for me." Voicing an important common theme among the case study group, he indicated that he believed that the increasing challenges of ranching were making cooperation between ranchers and scientists even more important. This program confirmed to him that such partnerships "improve the chances of rancher survival."

Cattle 2

Manager characteristics and experience. At approximately 1200 ha, Cattle 2 was the second largest ranch in our sample. Cattle 2 is family-owned, commercially grazed by cattle, and managed by a professional range manager with over 20 years of ranching experience. Cattle 2's manager participated in the program to increase ranch productivity (Table 2.1). He felt rotational grazing was the best way to accomplish this because it "did not require an additional investment of time and money."

Influence of remote sensing on management decisions. Prior to evaluating the project's remote sensing products, Cattle 2's manager was receptive to incorporating remote sensing data into his management regime because he believed that there was a "pressing need to increase the productivity and profitability" of his ranch and that these tools would allow him to "directly meet these needs." Cattle 2's manager felt remote sensing would be useful for analyzing forage and weed levels before and after grazing events. He believed that if monthly forage maps were available, he could make grazing adjustments during the season, which would allow him to maximize the time his cattle spent grazing while maintaining adequate forage for the following season. In addition, he thought that using the forage and weed maps together would allow him to determine whether there was "good feed in a field or just medusa."

After viewing the 2004 weed map, Cattle 2's manager was surprised to see high weed levels across select grazing fields. Even though he knew noxious weeds were a significant threat across his property, he believed that he had limited their impact with grazing alone. He concluded that weed increases were due not to the ineffectiveness of his grazing efforts, but rather to seasonal water limitations that restricted grazing to the spring when the weeds were maturing and thus unable to be grazed effectively by cattle. During the interview, he used the forage and weed maps together to show us that fields grazed only in the fall had both increased forage (Table 2.2) and decreased weed levels.

Even though Cattle 2's manager focused on grazing as a tool to manage his property, the size of the ranch prevented him from tracking these effects "across every field at the same time." After analyzing the time-series forage maps, he was encouraged by the capacity of remote sensing to allow him to track forage levels across different fields simultaneously without extensive field work and to easily compare values from growing seasons. Like Cattle 1's manager, Cattle 2's manager also believed that remote sensing data would allow him to more intensively manage the upper portions of his property, which would increase ranch productivity. Because of this potential, Cattle 2's manager increased the amount of money that he planned to invest annually in these technologies from approximately $0 (survey 1) to $500 (survey 2).

The collaborative nature of the landscape analysis effort motivated the managers of Cattle 1 and 2 to share their forage and weed species maps with one another, which allowed Cattle 2's manager to see the benefits of practices he did not implement during the program, such as the multi-year effect of burning and seeding with perennial grasses (Table 2.2). While the results did not substantially change his mind about which practices were most successful, they did convince him to try burning and seeding a 16-ha field heavily infested with medusahead and under seasonal grazing restrictions (Table 2.2), beginning in 2005.

Sheep 1

Manager characteristics and experience. Sheep 1 was the largest sheep ranch in our sample, but at approximately 170 ha it was significantly smaller than both cattle ranches. The ranch was purchased by the current landowner in 1998 and subsequently grazed by about 200 ewes. This manager initially had little commercial ranching experience but is highly educated and made considerable efforts to increase her knowledge of ranching during the program by enlisting the help of range managers and scientists. In addition, because ranching is not her primary occupation, she has employed a professional range manager to assist her. In this study, we interacted solely with the landowner-manager herself. Her motivations for involvement in the program were diverse, but she emphasized increasing ranch productivity and decreasing noxious weed levels (Table 2.1).

When purchased in 1998, Sheep 1 was dominated by medusahead and yellow starthistle. To restore it, half of the property was burned in the summer of 1999 and then seeded with native perennial bunchgrasses in the fall of 2000. Unfortunately, bunchgrass populations did not immediately take hold. During the 2000–01 growing season, the landowner was thus forced to confine her sheep to the unburned portion of her property, which led to overgrazing. More fields were burned in 2000–03, with varying degrees of success; the most success occurred in a 24-ha field where the landowner used intensive short-duration grazing followed by burning and seeding with clover (Table 2.2).

Influence of remote sensing on management decisions. Even before evaluating the remote sensing products, Sheep 1's manager felt that forage and weed maps would provide her with an essential overview of her ranch and a means to "determine which management practices worked and which fields needed to be attacked next." Because almost every hectare of Sheep 1 was involved in a restoration test, Sheep 1's manager had the unique opportunity to see the short- and long-term effects of a variety of management efforts in combination with rotational grazing practices (Table 2.2).

Before analyzing the remote sensing products, Sheep 1's manager did not believe prescribed burning was a long-term solution for her property because of its "cost, danger, and varied results." After the unsuccessful restoration efforts of 1999–2000, Sheep 1's landowner expected this portion of her property to have low forage levels and large areas of medusahead and goatgrass. The remote sensing products supported these beliefs, and contributed to her conclusion that prescribed burns alone were not effective enough to offset their high cost. In addition, the time-series forage and weed maps led Sheep 1's manager to decide that rotational grazing in combination with other practices, such as sowing good weed competitors, was the most effective strategy for increasing forage and decreasing weeds on her property. Because remote sensing data allowed Sheep 1's manager to base her management efforts on multi-year forage trends, she increased the amount of money that she planned to invest annually in these technologies from approximately $100 (survey 1) to $500 (survey 2).

Sheep 1's manager believed that the outreach efforts were an important part of the stewardship program. She felt these efforts were a model for how programs should be carried out in the future and that "the in-person visits were essential components of establishing trust and sharing knowledge." Like other participants, she emphasized the value of collaborative research, and she indicated that she believed that "California farm land was being swallowed up by developers and that projects like this should serve as models for how scientists and landowners can work together."

Sheep 2

Manager characteristics and experience. At approximately 30 ha, Sheep 2 was the smallest ranch in this study. The managers have owned the ranch for approximately 20 years but have never commercially managed the forage on their property. Sheep 2's managers were involved in the stewardship program to increase collaborative interactions with scientists and other participating landowners and to help conserve the grassland habitat on their property (Table 2.1). Sheep 2's managers did not manage the forage or weed levels on their property during the program, but they did allow project scientists and other property owners to conduct restoration tests on their property (Table 2.2).

Influence of remote sensing on management decisions. After accessing the website, Sheep 2's managers responded that while the website "looked great," they had "no need for weed maps or analyses of management practices." They emphasized that if their property were larger the remote sensing products would be helpful, but because it was so small they could "walk across the property if they needed to see what was going on." Although Sheep 2's managers did not believe that the website was useful on their property, they did see the benefit of time-series forage and weed maps, commenting that "seeing how the land has changed allows us to see whether we are part of the problem or part of the solution."

Discussion

Factors influencing the use of remote sensing by managers

In this experimental test of the value of remote sensing for private ranch managers, we produced and offered, at no cost to the managers, a suite of remote sensing products tailored to the managers' needs and worked individually with each manager to ensure that any questions or concerns s/he had about how to access the products on the project website could be addressed promptly. In doing so, we thereby removed or reduced several barriers that might otherwise prevent private managers from experimenting with remote sensing as a management tool, such as its cost and potential uncertainty on the managers' part about how to get appropriate products for their properties. We then examined, among our case study group, what other factors came into play in determining the degree to which each manager was willing to "use" the remote sensing products we provided to analyze them and draw conclusions from them about the success of their management strategies. In addition, we evaluated the influence of the experiment on the managers' self-reported willingness to purchase remote sensing products in the future.

In general, it has been found that several criteria need to be met for users to begin to use and invest in new technology. Rogers (1995) and Somers (1998) concluded, for example, that end users must first believe that there is a relative advantage (e.g., financial) to using the new technologies, and then have the opportunity to determine how best to incorporate these technologies into their current practices. In our study, the three managers whose properties are used for commercial livestock production (Cattle 1, Cattle 2, Sheep 1) spent the most time analyzing and evaluating the remote sensing data and were most interested in purchasing remote sensing products in the future. These three managers concluded that remote sensing provided tools that could help maximize their properties' productivity and that they would like to cooperatively purchase additional remote sensing products in the future. After experimenting with the remote sensing products, all three managers of commercially active properties increased the amount of money they indicated they would be willing to spend on remote sensing data. Individually, their planned annual investments of approximately \$500 would each be enough to purchase an entire single Landsat TM scene (a 170 x 183 km scene costs \$425). If pooled, their planned annual investments of approximately \$1500 would be large enough to purchase multiple TM scenes and additional GIS data for their properties, or additional aerial photographs for noxious weed mapping. While our expectations of use and investment did not initially assume that cost-sharing would be necessary, from this particular study, we would conclude that at least in the early stages of use collaborations between managers increase the likelihood of investment by decreasing the annual financial obligation to any one manager. Unlike the other managers, the managers of the smaller, commercially inactive property (Sheep 2), spent less time evaluating the remote sensing data and were uninterested in purchasing products in the future.

Consistent with Rogers' and Somers' findings, it was evident that the managers who used the remote sensing products most extensively during our study and who were interested in purchasing products in the future were those who believed that the remote sensing technologies could offer them management advantages. The managers of the three commercially active ranches believed that their current management efforts were not optimized and that there was thus a need for new management approaches on their properties. These managers had participated in the stewardship program in order to increase forage production and decrease invasive noxious weed levels across their properties (Table 2.1), and they were willing to test new management approaches to meet these goals (Table 2.2). In other situations, Hanselka et al. (1990) and Kreuter et al. (2001) likewise found that managers were more likely to use and invest in new range management technologies if range conditions across their properties were poor. In contrast, the managers of Sheep 2, while impressed by the remote sensing products, did not see a need to test new management approaches and thus were less interested in exploring the utility of remote sensing.

The managers most interested in using the remote sensing products not only felt that there was a need to try new management approaches but also believed that using remote sensing could effectively help them do it. Likewise, Kreuter et al. (2001) concluded that "Brush Busters" management approaches were broadly used and invested in across Texas rangelands because of their perceived effectiveness in decreasing brush and increasing productivity. During our study, the managers of Cattle 1, Cattle 2, and Sheep 1 each had at least one experience that convinced them that they could increase the productivity and profitability of their property by using these particular remote sensing products to inform their management decisions. For example, the managers of Cattle 1 and 2 concluded that forage and weed species maps provided them with the opportunity to monitor their rotational grazing efforts more intensively during the season, which allowed them to maximize the time cattle spent grazing while making sure adequate forage was left for the following season. In addition, they were convinced that remote sensing approaches would allow them to extend their rotational grazing efforts to the upper portions of their properties, where increases in forage had been much smaller than in their more intensively managed lower portions. Sheep 1's manager had recently implemented a series of strategies aimed at increasing forage production and decreasing weed levels (Tables 2.1 and 2.2). She was able to use the multi-year forage analyses to determine the effectiveness of these efforts and to develop a comprehensive adaptive management strategy for her property. In contrast, the managers of Sheep 2 did not see the need to explore whether remote sensing could help increase ranch productivity or profitability because their ranch was not commercially active.

Influence of remote sensing on decision-making

Range managers are skilled in reading and assessing landscapes and maps, and our case study group readily transferred these skills to interpreting remote sensing data and incorporating it in to their management analyses. Among our manager group, those managing commercially active properties believed that remote sensing data allowed them to base their decision-making process on multi-year forage trends across their entire properties, rather than on one-year forage changes across individual pastures. The ability to view multi-year forage trends allowed those managers who were actively managing their land to quantitatively assess the forage impact of new management practices they tested during the stewardship program, and to determine whether these practices were short-term fixes or long-term solutions to problems such as increasing noxious weed levels. For example, the multi-year analyses enabled the managers of both Cattle 1 and Sheep 1 to conclude that they would only invest in prescribed burning in the future if it was done in coordination with seeding of good competitive forage grasses like native bunchgrasses or clovers; otherwise, the positive impact of fire on noxious weeds is too temporary (1–2 years) for commercial range management operations to justify its expense and potential hazard.

The remote sensing products used in this study were developed with the input of our manager group. Mutual discussion of the remote sensing products during the program helped us tailor the website and forage maps to the needs and experiences of each manager, and also provided a forum in which to elicit information from managers about historical land use and past management strategies. Historical land use data is an invaluable resource for managers seeking to assess the long-term influence of management strategies and other factors such as invasive species and climate change. However, on many private ranches, including well managed ones, data on stocking rates and other land use information are often not kept in a detailed or consistent manner. Through involvement in this study, our manager group was able to determine for themselves the value of coordinating remote sensing analyses with on-the-ground management data, and as a result, expressed increased commitment to keeping more detailed management (e.g., grazing) records for decision-making in the future.

An important theme expressed throughout by the manager case study group was the importance of collaboration, among ranchers and between ranchers and scientists, in finding ways to optimize rangeland management in regions facing pressure from forces such as urbanization and invasive species. This sentiment contrasts with historical expressions of enmity between conservation biologists and Western ranchers (e.g., Jensen 2001) and indicates the overwhelming need for innovation to protect remaining rangelands as conservation and cultural resources (e.g., Weiss 1999). Our findings suggest that voluntary engagement in collaborative rangeland analyses not only can increase the success of stewardship programs like this one, but is also more likely to be effective in supporting long-term efforts to improve rangeland conditions than top-down prescriptions. Our work demonstrates that such collaborations can foster the development and application of innovative management technologies and thereby facilitate efforts to enhance rangeland sustainability.

Management Implications

Our findings suggest that one hurdle impeding the broad use of remote sensing by managers of privately-held, commercial rangelands may simply be the lack of opportunity to test it. When given this opportunity, all of the commercially active managers in our case study group responded very positively and found creative ways to effectively use it to evaluate their management efforts. These managers chose to use our remote sensing products during the study and indicated they intended to use them and buy more products in the future because the experimental tests convinced them that such remote sensing products would help optimize their management practices and increase ranch productivity and profitability.

Although the cost of some remote sensing products can be high, relatively low-cost data have been traditionally available to the public through well established programs such as the Landsat data acquisition program. When such imagery are available, use of remote sensing by private range managers can be economically feasible, particularly if consortia of managers with properties falling within the same satellite scenes can collaboratively cost-share and obtain technical support from local universities or agencies. We hope that these findings will encourage more private range managers and scientists to collaborate on efforts to incorporate remote sensing into commercial range management and rangeland restoration efforts. Continued support of regular image acquisition by reliable, appropriate-scale satellite systems with public data availability is essential to this aim.

CHAPTER 3

PHENOLOGICAL EFFECTS ON REMOTELY-SENSED BIOMASS ESTIMATES IN ANNUAL GRASSLANDS

Abstract

Remote sensing data can provide range managers the means to more efficiently quantify the effects of their management efforts on biomass production across large range units. Vegetation indices such as the normalized difference vegetation index (NDVI) have been used for more than 30 years in rangelands to quantify green biomass. In many grass-dominated rangeland (grassland) ecosystems, however, there is a significant dry period, during which time senescent biomass is the dominant forage resource for livestock. During these periods, indices like NDVI underestimate total biomass and are thus largely unhelpful as management tools. Both at the beginning and end of the growing season, forage can consist of a mix of senescent and green material. Use of NDVI to estimate total biomass during these periods must be carefully evaluated. Even though the general effect of senescence on the NDVI-biomass relationship is well understood, no study has specifically characterized this effect in detail for grass species that are representative components of grassland systems globally. To examine the impact of senescence on NDVI-biomass estimates and to determine the phenological period during which a single NDVI-biomass equation (i.e., biomass = f(NDVI)) is useful for estimating biomass in mixed species stands, I grew annual grass species in monoculture and in mixtures in a common garden on the campus of Michigan State University in East Lansing, Michigan, and measured a suite of stand canopy parameters weekly from germination to the end of the season. In all stands tested, there was an approximately 40-

day lag between maximum NDVI and maximum biomass. During this period, there was a simultaneous decrease in NDVI with increasing senescent vegetation cover. The result was that NDVI values at maximum biomass in week 9 were similar to those in week 1, even though biomass increased, on average, from 27.0 g/m^2 in week 1 to 372.0 g/m^2 in week 9. When the entire season was considered the species-specific NDVI-biomass equations were remarkably similar, suggesting that a single equation may be robust to many of the structural and phenological differences that exist among grass species and therefore can be used to estimate biomass in grassland ecosystems with mixed species composition.

Introduction

Currently there are many remote sensing tools available that range managers could use to help manage biomass on their properties (e.g., Tueller 1989, Hunt et al. 2003, Washington-Allen et al. 2006, Butterfield and Malmstrom 2006). Range managers are particularly interested in the potential for using remote sensing data to quantify month-to-month variability in herbaceous biomass, the stem and foliage biomass of grasses and forbs that is the primary forage resource for livestock (Malmstrom et al. 2004, Butterfield and Malmstrom 2006). Remotely-sensed images with fine spatial resolution (e.g., 30 m) can be used to assay grassland conditions at the pasture level (Wylie et al. 2002, Malmstrom et al. 2004, Mustafa et al. 2005, Washington-Allen et al. 2006). In the western United States, range managers are experimenting with using satellite-based green biomass estimates to evaluate the effectiveness of their management approaches, as a way to enhance ranch profitability (Qi et al. 2000, Qi et al. 2002, Malmstrom et al. 2004, Butterfield and Malmstrom 2006).

Now that green biomass estimates have proven valuable, managers are interested in using similar remote sensing products to evaluate management effects during periods when senescent biomass is present (Qi et al. 2000, Qi et al. 2002, Butterfield and Malmstrom 2006). Senescent biomass is an important forage resource for livestock in grass-dominated rangeland (grassland) ecosystems during dry periods (George and Fulgham 1989, Richardson and Everitt 1992, Frank and Aase 1994, Maselli et al. 1998, Qi et al. 2000, Hoare and Frost 2004). However, while there are many remote sensing approaches for the quantification of green biomass (Rouse et al. 1974, Kauth and Thomas 1976, Tucker 1979, Huete 1988, Major et al. 1990, Qi et al. 1994), none allows for the direct quantification of senescent biomass.

Efforts to use remote sensing data to quantify senescent biomass in grasslands have met with limited success. A major difficulty is associated with separating the spectral profile of senescent biomass from that of the soil background (Huete et al. 1985). There has been some success in quantifying the fractional cover of senescent vegetation, [or the areal proportion of the landscape occupied by senescent vegetation, not biomass (White et al. 2000)], by employing approaches that take advantage of the shortwave infrared region (SWIR: 2.0–2.3 μm), which is sensitive to changes in canopy water content (Gamon et al. 1993, Qi et al. 2000, Asner and Heidebrecht 2002). The SWIR region has been used because it contains cellulose (2090 nm and 2270 nm) and lignin (2130 nm and 2270 nm) absorption features that are masked by water in green vegetation but become evident as vegetation senesces (Roberts et al. 1993). For example, NDSVI, the normalized difference senescent vegetation index (Qi. et al. 2000), uses similar principles to those associated with the calculation of NDVI, the normalized difference vegetation index (Rouse et al. 1974), but substitutes reflectance in the NIR region with reflectance in the SWIR region. In southwestern rangeland ecosystems, this allowed Qi et al. (2000) to distinguish the fraction of the ground covered by senescent biomass from that of bare soil. To estimate end-of-the-season biomass values, others have used time integrals of NDVI (Tucker et al. 1983, Tucker et al. 1985, Prince 1991, Wylie et al. 1991). However, these approaches do not satisfy range management needs for biomass management because they either do not directly estimate biomass or can do so only for some times of the year. These capabilities would be particularly important for assessing grazing decisions during dry periods (George and Fulgham 1989, Pickup et al. 1994, Wessman et al. 1997, Saltz et al. 1999).

While research on the use of remote sensing for senescent biomass estimates continues, the accuracy of green biomass estimates may be increased by characterizing in detail the impact of senescence on the relationship between NDVI and biomass in grass species that are representative of grassland ecosystems globally. Vegetation indices, like NDVI, were designed to quantify green biomass only, not total biomass (Tucker 1979). Thus, most grassland researchers have limited their use of NDVI to parts of the season when green biomass is dominant (e.g., Gamon et al. 1995, Wylie et al. 2002, Malmstrom et al. 2004). However, in many grassland ecosystems, the transition from dominance by green to senescent biomass varies from year-to-year, and for significant portions of the season the canopy is a mix of both biomass types (George and Fulgham 1989, Richardson and Everitt 1992, Frank and Aase 1994, Maselli et al. 1998, Qi et al. 2000, Hoare and Frost 2004).

Although the general effect of senescence on NDVI-biomass estimates is well understood, especially in crop species (Tucker et al. 1980, Hatfield 1983), no study has specifically characterized this relationship for grass species or grass mixes. This detailed information for grass species and grass mixes that are representative of grassland ecosystems globally is important because it enables analysis of the error associated with the use of NDVI for biomass estimates during time periods when senescent biomass is present. Without detailed phenological information for representative grasses species and grass mixes, estimates of biomass cannot be accurately made during the transition period from dominance by green to senescent biomass. This is especially problematic in range management situations where within-season management decisions can have a large impact on biomass production. The aim of this study was to quantify weekly variability in the canopy properties of three annual grass species that are representative of annual grasslands globally throughout an entire vegetation cycle, from germination to the end of the season, to determine the time period that a single NDVI-biomass equation (i.e., biomass = f(NDVI)) could be used in grassland ecosystems with mixed species composition.

Methods

Experimental Design

To examine the effect of canopy senescence on remotely-sensed biomass estimates in different annual grasses, I established stands of three annual grass species:

Avena fatua L. (wild oats; all nomenclature follows Hickman (1993)), *Bromus hordeaceus* L. (soft chess), and *Lolium multiflorum* Lam. (annual ryegrass) in an agricultural field on the campus of Michigan State University in East Lansing, Michigan in 2003. I established the plots in Michigan in order to have continuous access to instrumentation. Use of a Michigan site for this experiment was considered acceptable because the aim was to examine general temporal variation in the properties of annual grass canopies in detail during a single growing season, not to develop a site-specific NDVI-biomass equation for any one grassland site.

I chose these species because all three are often common components of grassland ecosystems in the western United States (Hickman 1993, http://plants.usda.gov/), and are also representative of annual grasslands globally. Two of the species, *A. fatua* and *L. multiflorum*, are naturalized in Michigan as weeds (Voss 2001), so I was confident that they would complete their entire phenological cycle, from germination through senescence, during the study period. In addition, I was intrigued by the structural differences among these three species, including stem thickness, stem (stand) density, and stem height (Crampton 1974, Hickman 1993, http://plants.usda.gov/), and the potential impact these differences may have on NDVI-biomass estimates in mixed species stands throughout the season. For example, *A. fatua* has thicker stems and on average grows taller than *B. hordeaceus* and *L. multiflorum*; however, both *B. hordeaceus* and *L. multiflorum* generally have greater stem densities than stands of *A. fatua* (S. Butterfield, personal observation). I used an experimental approach in order to reduce the impact of two potential sources of variability in grassland ecosystems: 1) background plant litter from previous growing seasons, and 2) changing grazing management regimes. To ensure that no litter was present, the field was tilled prior to the experiment.

To capture among-species variation in seasonal trajectories, I planted single-species stands of high-density *A. fatua* (1,000 plants/m^2) and low-density *A. fatua* (500 plants/m^2), *B. hordeaceus* (6,000 plants/m^2), and *L. multiflorum* (2,000 plants/m^2), and one mixed species stand containing *A. fatua* (500 plants/m^2) and *B. hordeaceus* (4,000 plants/m^2). I used these densities to broadly emulate those conditions found in annual grasslands in the western United States (http://plants.usda.gov/). I chose the *A. fatua-B. hordeaceus* mixture because these species are often co-dominants in California annual grassland ecosystems (S. Butterfield, personal observation). There were 10 replicates of each stand type. I planted the stands in 1–m x 6–m plots in a randomized complete block design. There were 6 different 1–m^2 plots within each 1–m x 6–m plot. The soils in the field were Riddles-Hillsdale sandy loam 2–6%.

Measurements

NDVI. I measured surface reflectance in the experimental plots weekly for 15 weeks, from 11 June 2003 (approximately two weeks after seed germination) until 1 October 2003 (when most stands had senesced and begun to disintegrate). To do this, I used a UniSpec-DC field hyperspectral radiometer with a 20°-field-of-view fore optic (PP Systems Inc., Amesbury, MA). The UniSpec-DC detects spectral intensity in 256 bands, distributed between 0.3 and 1.1 μm, with a resolution of 3.7 nm. I made measurements with the radiometer in nadir orientation, centered 1.43-m above each 1-m^2 plot on a boom attached to a tripod. The ground resolution of these measurements was 0.25-m^2. To estimate the contribution of the soil background, I also measured surface reflectance in plots of bare soil weekly. To minimize sun angle and shadowing effects, I collected spectral data within one hour of solar noon, which was calculated using data found at http://www.wunderground.com/. I converted spectral intensity to reflectance using a Spectralon panel (Labsphere Inc., North Sutton, NH). To calculate NDVI, I used mean reflectance (R) values in the red (0.63–0.69 μm) and NIR (0.76–0.9 μm) regions as:

$$NDVI = (R_{NIR} - R_{red}) / (R_{NIR} + R_{red}) \qquad \textbf{[Eq. 1]}.$$

Biomass. To permit comparisons of NDVI and herbaceous biomass, I harvested the stem and foliage biomass from 1-m^2 plots within each 1–m x 6–m plot at six time points during the growing season. For each harvest, I clipped biomass at ground level from the 0.25-m^2 portion of the 1-m^2 quadrat viewed by the radiometer. I then dried the biomass at 65°C to constant mass, separated it into green and senescent portions, and weighed it. I harvested biomass within a few hours of the spectral measurements. I chose the harvest dates to ensure that two samplings occurred within each of three canopy stages: 1) *early growth*, germination to maximum greenness (defined as maximum NDVI); 2) *canopy maturation*, onset of senescence to maximum biomass (green plus senescent); and 3) *canopy decline*, maximum biomass to the end of the season.

LAI. To develop a set of nondestructive proxy data that could help me interpolate the biomass values, I took indirect measurements of canopy leaf area index (LAI) weekly using a sunfleck ceptometer (AccuPAR, Model No. PAR-80 Decagon Devices, Inc., Pullman, WA). The ceptometer uses broadband PAR (photosynthetically active radiation) sensors that cannot readily distinguish between green and senescent canopy components (Gholtz et al. 1991, Gamon et al. 1995, White et al. 1997). Thus, I defined

LAI as the total one-sided area per unit ground area of all aboveground canopy components, including green *and* senescent foliage and stems (Decagon Devices 2001).

AccuPAR-based LAI measurements require the determination of leaf angle distribution and leaf absorptivity constants as well as measurements of the radiation above and below the canopy. I calculated LAI as:

$$\mathrm{LAI} = [(1 - 1/2\mathrm{K})\, f_b - 1] \ln \tau \,/\, \mathrm{A}\, (1 - 0.47\, f_b) \qquad \textbf{[Eq. 2]},$$

where K is the canopy extinction coefficient, f_b is the fraction of incident PAR, τ is the fraction of transmitted PAR, and A is a function of leaf absorptivity in the PAR band (Decagon Devices 2001). The canopy extinction coefficient, K, is a function of solar zenith angle, leaf distribution parameters, and sun conditions (Jones 1992). While the leaf distribution parameter can vary substantially between crop species (e.g., 0.76 for maize to 3.03 for strawberry), these differences are minimal for similar annual grass and crop species (Jones 1992, Decagon Devices 2001). Because I did not have specific leaf distribution values for any of the species used in this study, I used the same value, 1.0, for all five stand types and took measurements within one hour of solar noon and as much as possible under the same sun conditions. I selected this leaf distribution parameter because it represented an average value for annual grass and crop species with similar growth habits and canopy structural characteristics in the Decagon manual (Decagon Devices 2001). I took five measurements within each 0.25-m^2 quadrat viewed by the radiometer and calculated the mean.

fAPAR. $f\mathrm{APAR}_{\mathrm{total\ canopy}}$ (hereafter referred to as *f*APAR), which is used interchangeably in the literature with *f*PAR, indicates the fraction of PAR absorbed by green *and* senescent canopy components together (Gholtz et al. 1991, Gamon et al. 1995, Asner and Wessman 1997, White et al. 1997, Serrano et al. 2000a, Serrano et al. 2000b). In grass stands, measurements of $f\mathrm{APAR}_{green}$, or the fraction of PAR absorbed by *green* foliage, have traditionally been used to estimate photosynthetic rates (e.g., Monteith 1977, Gamon et al. 1995). However, measurements of $f\mathrm{APAR}_{green}$ and $f\mathrm{APAR}_{total\ canopy}$ have also been used to estimate grass stand biomass (Le Roux et al. 1997, Asner et al. 1998, Bremer et al. 2001). Thus, to permit comparisons between *f*APAR and biomass, I separately measured *f*APAR each week using the AccuPAR ceptometer. The *f*APAR measurements require four readings per measurement: one each with the ceptometer facing upward both above and below the canopy and one each with the ceptometer facing the ground above and below the canopy. *f*APAR was then calculated as:

$$f\mathrm{APAR} = 1 - t - r + tr_s \qquad \textbf{[Eq. 3]},$$

where t is the fraction of incident radiation transmitted by the canopy, r is the fraction of incident radiation reflected to the sensor above the canopy, and r_s is the reflectance of the soil surface (Decagon Devices 2001). I took five sets of measurements within each 0.25-m^2 quadrat viewed by the radiometer and calculated the mean.

Vegetation characteristics. To compare remotely-sensed measures of changes in canopy phenology with on-the-ground measures, each week I also measured mean canopy height and estimated the fractional cover of green vegetation, senescent vegetation, and soil. I calculated mean canopy height using stems in six randomly located circular plots, with a diameter of 9.0 cm, within each 0.25-m^2 quadrat viewed by the radiometer. I estimated cover using Daubenmire classes (Daubenmire 1968): 1 = 0–5%; 2 = 5–25%; 3 = 25–50%; 4 = 50–75%; 5 = 75–95%, and 6 = 95–100%. In statistical analyses, I used midpoint percentiles to represent cover class values: 1 = 2.5%, 2 = 15%, 3 = 37.5%, 4 = 62.5%, 5 = 85%, and 6 = 97.5%.

Biomass equation analyses. To analyze the relationships between biomass and NDVI, *f*APAR, and LAI, I used General Linear Model procedures in SYSTAT 10.2 (SYSTAT Software Inc., Richmond, CA). To compare the biomass equations (i.e., biomass = *f*(X), where X = NDVI, *f*APAR, or LAI) among species types, I used Analysis of Covariance (ANCOVA), in which species (*Avena*, *Bromus*, *Avena-Bromus*, and *Lolium*) was the independent categorical effect variable, NDVI, *f*APAR, or LAI were covariates, and biomass was the response variable. The two *Avena* monoculture treatments were not significantly different for the NDVI ($p = 0.437$), *f*APAR ($p = 0.054$), or LAI ($p = 0.461$) biomass equations, so I combined them for the ANCOVA analyses. For the ANCOVA NDVI analyses, only green biomass was considered because NDVI is only used for estimates of green biomass. For the NDVI and *f*APAR analyses, biomass values were transformed with the natural log to meet ANCOVA assumptions. In all cases $p \quad 0.05$ was considered significant.

Results

Seasonal canopy dynamics

Three distinct phenological phases were evident in all of the annual grass species. *Early growth* extended from germination until the canopy reached maximum greenness in week 5 (Figure 3.1a). *Canopy maturation* began in week 6, when senescent vegetation cover became evident (Figure 3.1c) and NDVI began to fall (Figure 3.1a), and ended in week 9 when maximum biomass (Figure 3.1b), *f*APAR (Figure 3.1a), and height (Figure

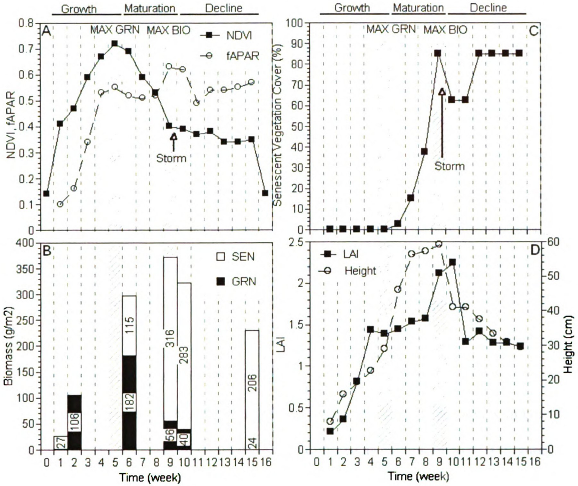


Figure 3.1. Seasonal changes in A) NDVI and *f*APAR; B) green (GRN) and senescent (SEN) biomass; C) senescent vegetation cover; and D) LAI and height. Values are mean weekly measurements averaged over all five stand types (N = 50) during *early growth*, *canopy maturation*, and *canopy decline*. Weeks 5 and 9 (shaded columns) were maximum greenness (MAX GRN) and maximum biomass (MAX BIO). All five stand types were combined because they displayed the same phenological trends except in weeks 9 and 10; a severe storm caused stem lodging in the *Avena* and *Avena-Bromus* plots in week 9, which impacted height and cover estimates in weeks 9 and 10 (see text for details).

3.1d) were reached. At this point, the canopy was almost entirely senescent (Figures 3.1b and 3.1c), and NDVI values were similar to those from week 1 (Figure 3.1a). During *canopy maturation*, there was an approximately 20% increase in biomass (Figure 3.1b). *Canopy decline* began in week 10 and continued until week 15, during which time the senesced grass canopies began to disintegrate. In week 9, after measurements were taken, a strong storm caused stem lodging in the *Avena* and *Avena-Bromus* stands, and resulted in a height decrease at week 10 (Figure 3.1d). The subsequent canopy openings allowed weed growth in these plots, leading to a short-term increase in green vegetation cover (decrease in senescent cover), until weeds were removed (Figure 3.1c).

Relationship between NDVI, fAPAR, and biomass

During *early growth*, NDVI and *f*APAR values increased in parallel with green biomass until the point of maximum greenness (defined as maximum NDVI) (Figures 3.1a, 3.1b, 3.2a, and 3.2b). Because of the difficulty of predicting the date of maximum greenness a priori, I did not harvest biomass exactly on the date but shortly thereafter. Trends in LAI, the non-destructive proxy of biomass ($R^2 = 0.71, p < 0.001$), suggest that biomass increased throughout *early growth* from germination through maximum greenness (Figures 3.1d and 3.2c). However, once the canopy started to senesce and lose greenness (week 6), NDVI values began to fall and diverged from biomass and LAI, which continued to increase until maximum biomass was reached four weeks later. Thus, during *canopy maturation* and *decline* NDVI was a poor predictor of canopy biomass. When the entire season was considered, however, NDVI was significantly correlated to green biomass ($R^2 = 0.78, p < 0.001$).

Figure 3.2. Seasonal relationships between biomass and A) NDVI, B) *f*APAR and C) LAI during *early growth*: germination (harvest 1: week 1) to maximum greenness; *canopy maturation*: onset of senescence (harvest 3: week 6) to maximum biomass (harvest 4: week 9); and *canopy decline*: maximum biomass to the end of the season (harvest 6: week 15). Harvest 2 occurred in week 2 during *early growth* and harvest 5 in week 10 during *canopy decline*. Values represent weekly means from *A. fatua-B. hordeaceus* (open squares), *A. fatua* (open circles), *B. hordeaceus* (closed triangles), and *L. multiflorum* (closed circles) stands. Numbers indicate biomass harvests, not weeks.

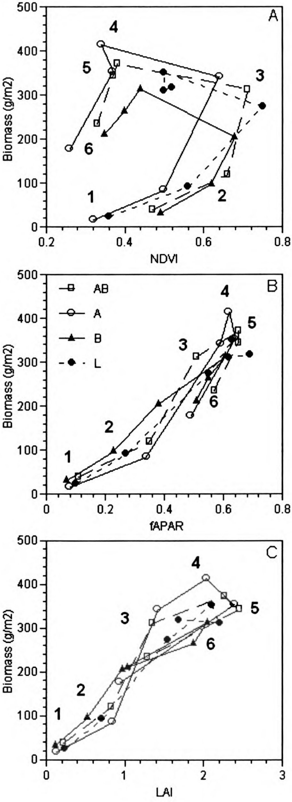


Figure 3.2.

Unlike NDVI, *f*APAR continued to climb with both biomass and LAI from week 5 to 9 (Figures 3.1 and 3.2). Thus, *f*APAR was significantly correlated to biomass throughout the season ($R^2 = 0.82, p < 0.001$). Note that mean *f*APAR values decreased slightly between weeks 6 and 8. I did not sample biomass each week during this period. However, trends in LAI suggest that biomass values leveled off (Figures 3.1a and 3.1d).

Generality of biomass equations

All of the stand types displayed similar phenological relationships among NDVI, *f*APAR, LAI, and biomass throughout the season (Figure 3.2). NDVI significantly underestimated biomass in all of the stand types after harvest 3 in week 6, or the point in the season when canopy dominance transitioned from green to senescent biomass. *f*APAR increased in all of the stands along with biomass and LAI during *canopy maturation* and reached its maximum value at harvest 4 in week 9 (Figures 3.2b and 3.2c). *f*APAR then decreased, along with biomass and LAI, from harvest 4–6 (week 9 to 15) as the senesced canopies began to disintegrate during *canopy decline*. Consequently, unlike NDVI, *f*APAR was significantly related to biomass in all of the stand types from harvest 1 through harvest 6.

The NDVI, *f*APAR, and LAI biomass equations differed significantly among the stand types tested (e.g., Species * NDVI, $p < 0.05$) (Table 3.1). All of the stand types reached maximum greenness and maximum biomass together (Figure 3.2). The *Avena–Bromus* mixed stands had biomass equations intermediate between the *Avena* and *Bromus* monocultures (Table 3.2; Figures 3.3, 3.4, and 3.5). In addition, when the entire season was considered, the only pronounced differences in the biomass equations

Table 3.1. ANCOVA results for differences in biomass equations among stand types. Species, the independent categorical effect variable, include: *A. fatua*, *B. hordeaceus*, *L. multiflorum*, and *A. fatua-B. hordeaceus*.

Biomass = *f*(X)	**Df**	**F**	***P***
X = NDVI			
NDVI	1	669.76	< 0.001
Species	3	8.04	< 0.001
Species * NDVI	3	6.23	< 0.001
Error	213		
X = *f*APAR			
*f*APAR	1	1225.12	< 0.001
Species	3	17.16	< 0.001
Species * *f*APAR	3	12.98	< 0.001
Error	216		
X = LAI			
LAI	1	1018.93	< 0.001
Species	3	1.38	0.15
Species * LAI	3	2.16	0.01
Error	226		

Table 3.2. Stand-specific biomass equations. NDVI equations are based on green biomass data only[1]. *f*APAR[2] and LAI[3] equations are based on green plus senescent biomass data[4]. Note that these biomass equations are given for comparative purposes only, not as definitive equations for all grassland situations. See Figure 3 for a graphical representation of these equations.

Biomass = *f*(X)	**Equation**	**R^2**	***P***
X = NDVI			
Avena	$y = 1.19e^{8.51x}$	0.91	< 0.001
Avena-Bromus	$y = 1.80e^{6.64x}$	0.86	< 0.001
Bromus	$y = 2.14e^{6.13x}$	0.87	< 0.001
Lolium	$y = 2.64e^{6.07x}$	0.93	< 0.001
X = *f*APAR			
Avena	$y = 12.45e^{5.35x}$	0.91	< 0.001
Avena-Bromus	$y = 32.54e^{3.53x}$	0.90	< 0.001
Bromus	$y = 50.65e^{2.86x}$	0.85	< 0.001
Lolium	$y = 27.78e^{3.78x}$	0.88	< 0.001
X = LAI			
Avena	$y = 200.21x + 24.46$	0.75	< 0.001
Avena-Bromus	$y = 196.15x + 47.86$	0.73	< 0.001
Bromus	$y = 189.98x + 60.62$	0.81	< 0.001
Lolium	$y = 179.07x + 50.94$	0.76	< 0.001

[1] NDVI values used to develop these equations ranged from approximately 0.20 to 0.80.
[2] *f*APAR values used to develop these equations ranged from approximately 0.05 to 0.80.
[3] LAI values used to develop these equations ranged from approximately 0.05 to 3.0.
[4] Biomass values used to develop these equations ranged from approximately 5 g/m^2 to 565 g/m^2.

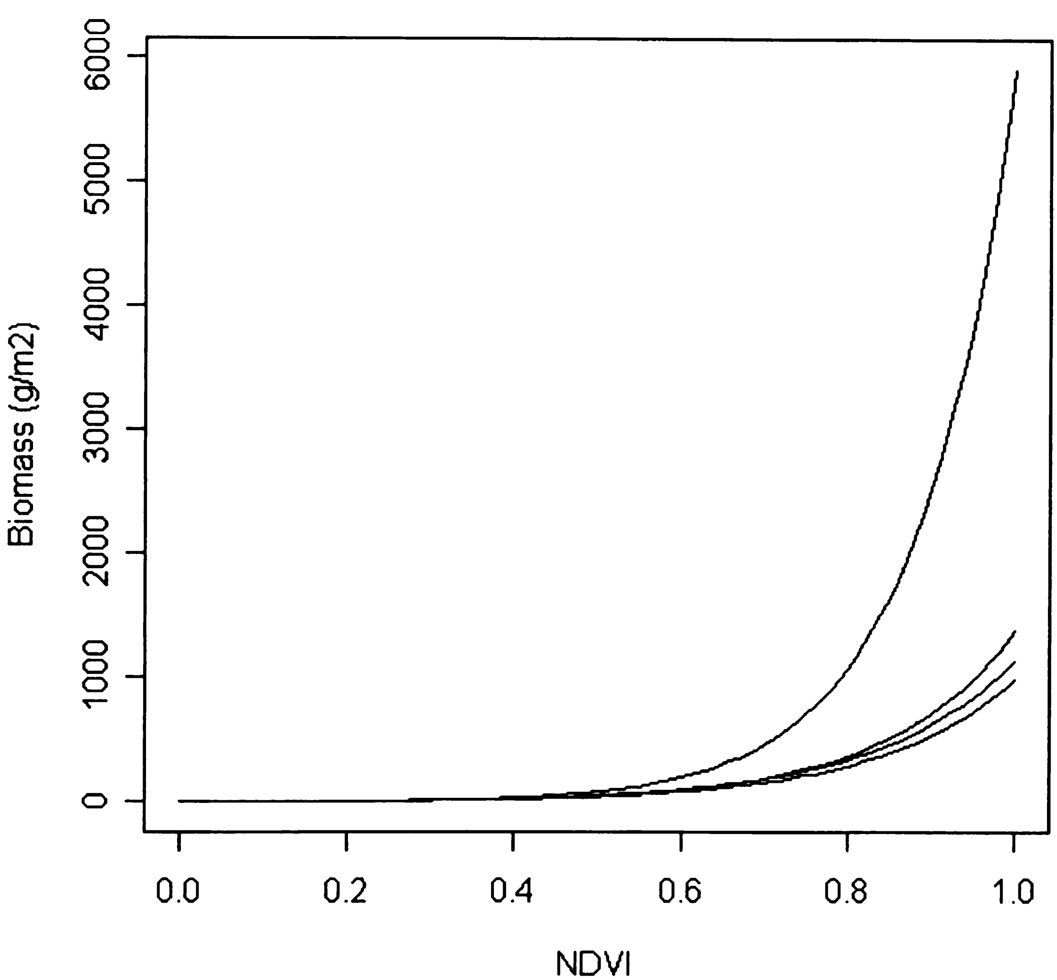


Figure 3.3. Stand-specific biomass relationships. NDVI-biomass relationships represent data for green biomass only. See Table 2 for equations, R^2 and p values, and footnotes detailing the range of values used to develop these equations. The top line is *A. fatua*, the 2nd line from the top is *A. fatua-B. hordeaceus* mixture, the 3rd line from the top is *B. hordeaceus*, and the bottom line is *L. multiflorum*.

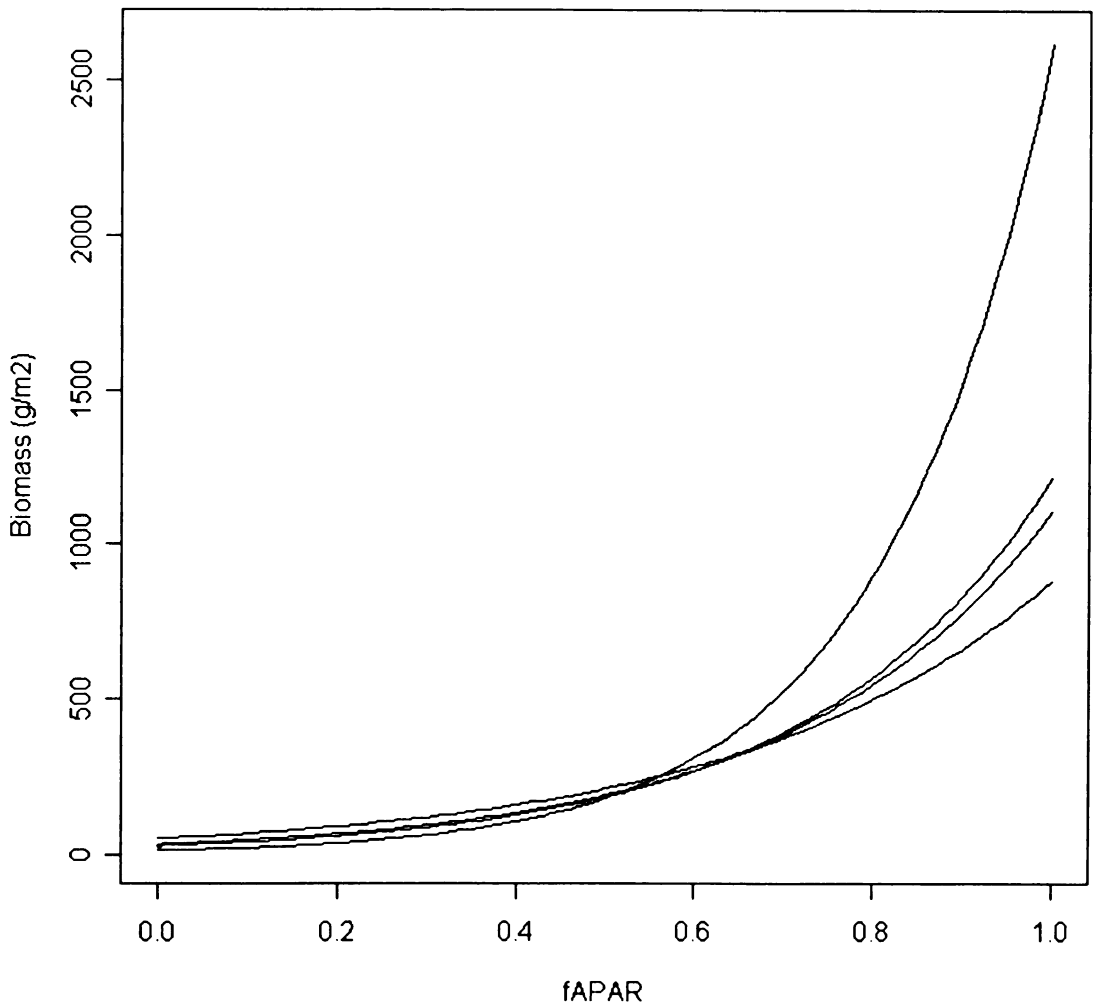


Figure 3.4. Stand-specific biomass relationships. *f*APAR-biomass relationships represent data for green plus senescent biomass. See Table 2 for equations, R^2 and p values, and footnotes detailing the range of values used to develop these equations. The top line is *A. fatua*, the 2nd line from the top is *L. multiflorum*, the 3rd line from the top is *A. fatua-B. hordeaceus* mixture, and the bottom line is *B. hordeaceus*.

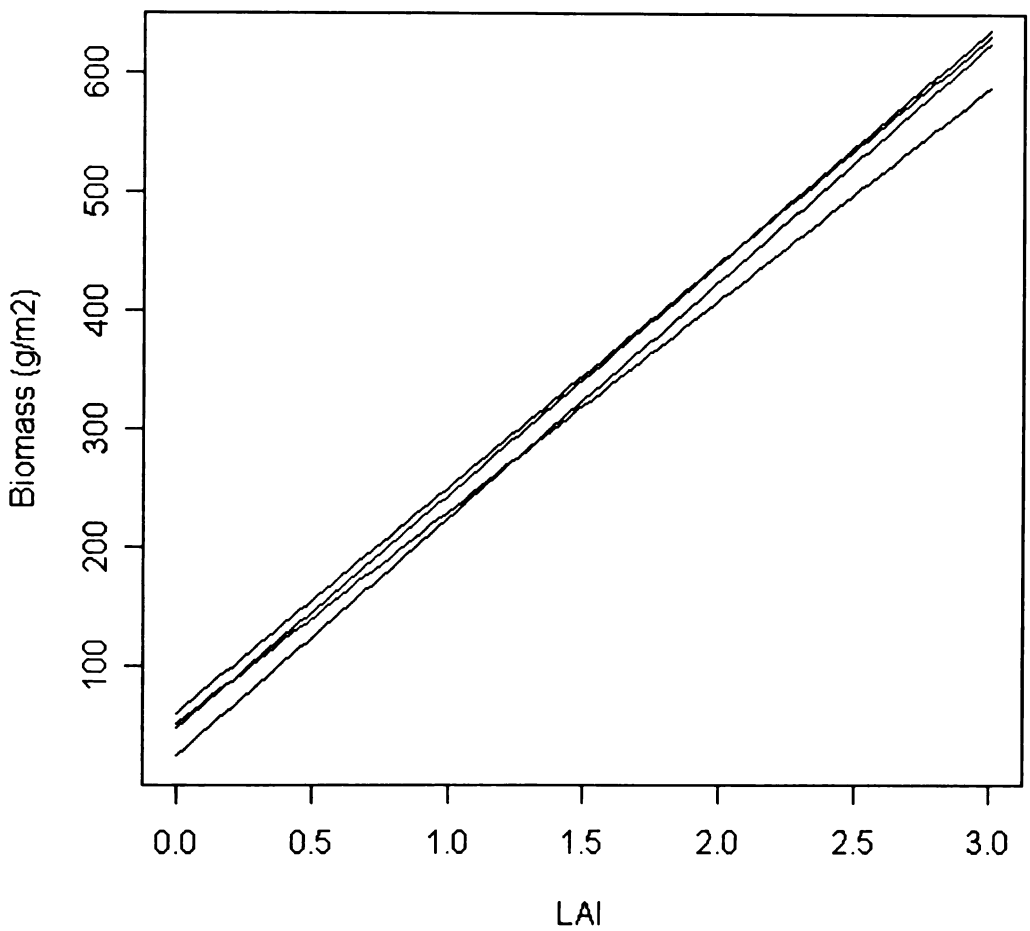


Figure 3.5. Stand-specific biomass relationships. LAI-biomass relationships represent data for green plus senescent biomass. See Table 2 for equations, R^2 and p values, and footnotes detailing the range of values used to develop these equations. The top line is *B. hordeaceus*, the 2nd line from top is *A. fatua-B. hordeaceus* mixture, the 3rd line from the top is *A. fatua*, and the bottom line is *L. multiflorum*.

occurred in the *Avena* stands at NDVI and *f*APAR values > 0.7 (Figures 3.3 and 3.4). Thus, because biomass increases exponentially with increases in NDVI and *f*APAR (Figures 3.3 and 3.4), small stand-specific changes in NDVI or *f*APAR above 0.7 could lead to large differences in biomass estimates (Table 3.2).

Discussion

Although NDVI has been used for several decades to estimate green biomass in grassland ecosystems (Tucker et al. 1983, Richardson and Everitt 1992, Gamon et al. 1995, Qi et al. 2000, Wylie et al. 2002, Mustafa et al. 2005), to my knowledge this is the first study to examine seasonal variability in NDVI-biomass relationships in annual grass stands. My findings establish that, like perennial grasslands (e.g., Williams 1970, Tothill 1977, Veenendael 1996, Parihar 1999, Bremer et al. 2001), annual grass communities experience a substantial lag between maximum greenness (maximum NDVI) and maximum biomass, here approximately 40 days (Figures 3.1, 3.2a and 3.2b). During this lag period, biomass increased on average by approximately 20% (Figure 3.2b) even though NDVI decreased (Figure 3.1). Collectively, these findings demonstrate that a significant amount of above-ground production occurs during *canopy maturation* in grassland ecosystems, which NDVI-like indices cannot measure. Consequently, estimates of annual biomass production based on NDVI at maximum greenness will fail to account for the additional biomass production that occurs as NDVI decreases. This is a point of importance not only for range managers but also for carbon modelers who seek to derive productivity estimates from vegetation indices, like those derived from the

MODIS NDVI (e.g., Huete et al. 1999) and/or *f*APAR products (e.g., Knyazikhin et al. 1999).

In all stand types tested, *f*APAR and biomass were significantly correlated throughout the season, regardless of canopy phenological and/or structural attributes (Figure 3.2). This was the first such finding for stands of annual grasses dominant in western semi-arid annual grassland like those found in the Central Valley of California (Malmstrom et al. 2004, Butterfield and Malmstrom 2006), although a strong season-long correlation between *f*APAR and biomass has also been found in other grassland ecosystems, including African savannah (Le Roux et al. 1997), Kansas tallgrass prairie (Bremer et al. 2001), and dry Texas grassland (Asner et al. 1998). As in these other grassland systems, *f*APAR in this study increased during *canopy maturation* because biomass and LAI increased (Figure 3.1) and so thus did the total amount of radiation absorbed by green *plus* senescent foliage and stems (Asrar et al. 1984, Asner et al. 1998, Serrano et al. 2000b, Jorgensen et al. 2003). Currently, *f*APAR cannot be measured directly from satellite data, so thus cannot be used to quantify stand biomass throughout the season across large grassland landscapes. However, these findings do highlight the potential importance of ground-based *f*APAR measurements for biomass estimates in grassland ecosystems, particularly when senescent biomass is dominant and vegetation indices such as NDVI cannot be used.

To my knowledge, this was the first study to explicitly test the commonly held assumption that remotely-sensed biomass equations can be applied in grasslands with similar species composition or phenological traits. I found that there were significant differences in all three equation types tested (e.g., biomass = *f*(NDVI)) (Table 3.1), most likely as a result of differences in stand structural attributes (e.g., stem height, LAI, and stem density, the number of stems per unit ground area). For example, the *Bromus* and *Lolium* plots had greater NDVI per unit biomass than *Avena* plots (Figure 3.2a), most likely because *Bromus* and *Lolium* stem densities and vegetation cover (data not shown) were greater. It is also possible that this finding was a result of differing leaf nitrogen contents, although I did not explicitly test this as part of this study. Hull and Mooney (1990) found greater leaf nitrogen content in both *B. hordeaceus* and *L. multiflorum* than in *A. fatua*. Leaf nitrogen content is positively correlated to total chlorophyll amount in annual grasses (Gaborcik 2003) and thus also to total PAR absorbance and NDVI (Tucker 1979, Gamon and Surfus 1999). *Avena* plots, on the other hand, most likely had greater *f*APAR per unit biomass values than both *Bromus* and *Lolium* plots (Figure 3.2b) because they had greater LAI, biomass, and height values (Asner et al. 1998).

Even though I found that all three equation types (e.g., biomass = *f*(NDVI)) were significantly different among the species tested (Table 3.1), when the entire season was considered there were remarkable similarities in these equations (Figures 3.3, 3.4, and 3.5). The most pronounced differences occurred in the *Avena* stands at NDVI and *f*APAR values > 0.7 (Table 3.2; Figures 3.3 and 3.4). NDVI values > 0.7, when they do occur, are most likely to be limited to periods of maximum greenness (Figures 3.1 and 3.2), when both green cover and green stand biomass are greatest (Myneni and Williams 1994, Gamon et al. 1995, Bremer et al. 2001, Wang et al. 2001, Fensholt et al. 2004). *f*APAR values > 0.7, on the other hand, are most likely to occur from maximum biomass to the point in the season when stand biomass starts to decline (e.g., from stem disintegration). *Avena* stands with NDVI and *f*APAR values > 0.7 are those which are dense and have tall, thick stems. In these stand types, a "general" biomass equation would likely underestimate stand biomass. However, tall, lush *Avena* stands are not common in grazed grassland ecosystems (Butterfield, personal observation). In addition, in a number of grassland studies, including those in annual grasslands and tallgrass prairies, satellite-based NDVI values did not reach 0.7, even when the canopy reached maximum greenness (Gamon et al. 1995, Wang et al. 2001, Wylie et al. 2001). Together, these results suggest that a single equation will be most effective if developed in stands with similar species composition. However, they also suggest that under most conditions biomass equations are robust to the structural and phenological differences that exist among common annual grasses and thus can be used to estimate stand biomass in grasslands with mixed species composition.

CHAPTER 4
REMOTE SENSING-BASED ESTIMATES OF SENESCENT BIOMASS: COMMON PROBLEMS AND A NEW APPROACH IN ANNUAL GRASSLANDS

Abstract

The value of remote sensing as a management tool in annual grasslands would be enhanced if remote sensing could be used to directly quantify senescent herbaceous biomass (dry forage). Globally, senescent biomass is the dominant forage resource for livestock in grassland ecosystems during dry periods. Current approaches for quantifying dry forage do not provide estimates of biomass, only of fractional senescent vegetation cover, which is the areal proportion of the landscape occupied by senescent vegetation. However, in range management operations, cover is not always an adequate indicator of range condition, and is a less useful metric of forage production than is stand biomass. In Chapter 3, I demonstrated that measurements of *f*APAR, the fraction of PAR (photosynthetically active radiation) absorbed by the canopy, could be used to quantify senescent biomass. However, *f*APAR is a ground-based measurement and cannot be derived directly from satellite data, which limits its utility for large scale management. To address this issue, I developed a new index, called MAPAR, which estimates the mean PAR absorbed by the surface and which was based on a *f*APAR index developed by Asner et al. (1998) in grass leaves using hyperspectral reflectance data. Unlike *f*APAR, MAPAR can be derived directly from reflectance data, and so can be retrieved both in the field as well as from satellite sensor data. In this study, I examined whether MAPAR could be used to estimate senescent biomass in annual grass stands. Because MAPAR is a measure of surface absorbance, I also used these grass stands to examine how changes in soil background conditions, such as cover, moisture, and organic matter

content, influenced the utility of MAPAR for biomass estimates. I found that across dry sandy loam soils MAPAR was significantly correlated to senescent biomass. However, the utility of MAPAR was reduced in stands where significant stem lodging occurred and under conditions where the soil background was darkened, either from increases in soil moisture or organic matter content. In California annual grassland plots with canopy leaf area index (LAI) values ranging from <0.2 to 6, MAPAR was significantly correlated to biomass. In these same plots, the ground-based MAPAR measurements were significantly correlated to satellite-based ones, despite the difference in spatial scale (1-m^2 vs. 900-m^2) between the two. Collectively, these results suggest that MAPAR could be used to estimate senescent biomass in annual grasslands under some conditions. However, the application of MAPAR is most likely limited to situations where either fractional soil cover is <15% or the soil is both dry and low in organic matter content.

Introduction

During dry periods in many grass-dominated rangeland ecosystems around the world (hereafter referred to as grasslands), senescent herbaceous biomass, which consists of the dry foliage and stems of grasses and forbs, is a dominant forage resource (e.g., Bentley and Talbot 1951, George and Fulgham 1989, Prince 1991, Frank and Aase 1994, Saltz et al. 1999, Qi et al. 2000). In addition, in these systems the amount of senescent biomass on the ground at the beginning of the season, referred to as residual dry matter (RDM) (Hedrick 1948, Bentley and Talbot 1951), is an important determinant of rangeland condition. RDM quantities represent the combined effects of the previous season's production and of use by grazing animals of all types (Bartolome et al. 2002).

Some RDM measurements also include dry matter contributions from tree foliage, woody debris, and grass and forb biomass more than one year old (e.g., Guenther 1998, Bartolome et al. 2002). RDM is an especially important range indicator because of its known impact on soil erosion, biomass production, and forage quality (Morrison et al. 1993, Frank and Aase 1994, Heady and Child 1994, George and Menke 1996, Bartolome et al. 2002).

A remote sensing-based approach for the quantification of senescent biomass would provide range managers the means to assess annual grassland conditions and grazing decisions throughout the season and to better optimize annual use of grassland resources. Currently, such a tool does not exist: it is difficult to discriminate senescent biomass from soil backgrounds because senescent biomass lacks the unique signature of green biomass present in the visible and near-infrared spectral regions (Huete and Jackson 1987, Streck et al. 2002). To assess grassland conditions during times when senescent biomass is dominant, a variety of approaches have been developed including: 1) thermal remote sensing data coupled to NDVI, the normalized difference vegetation index (French et al. 2000); 2) spectral vegetation indices that use the shortwave infrared (SWIR: 2000–2300 nm) region (McNairn and Protz 1993, van Deventer et al. 1997, Qi et al. 2000, Daughtry 2001, Nagler et al. 2003); and 3) spectral mixture analysis of the SWIR region (e.g., Gamon et al. 1993). The SWIR region has been used because it contains unique, relatively narrow cellulose (2090 nm and 2270 nm) and lignin (2130 nm and 2270 nm) absorption features that are masked by water in green biomass, but are exposed as biomass senesces. All of these approaches have been used with some success in grassland and cropping systems, but mainly to estimate fractional senescent vegetation cover, or the areal proportion of the landscape occupied by vegetation (White et al. 2000), not biomass. These approaches are further limited by reliance on datasets to which range managers typically do not have access.

In Chapter 3, I demonstrated that ground-based measurements of *f*APAR[1], or the total fraction of photosynthetically active radiation[2] absorbed by the canopy, could be used to quantify senescent biomass under some conditions in stands of annual grasses, supporting the findings of Le Roux et al. (1997) in African savannah, Asner et al. (1998) in dry Texas grasslands, and Bremer et al. (2001) in Kansas tallgrass prairie. *f*APAR is calculated as:

$$fAPAR = 1 - t - r + tr_s \quad \textbf{[Eq. 1]}$$

where t is canopy transmittance, r is canopy reflectance, and r_s is soil reflectance. *f*APAR was measured in the above studies using a AccuPAR ceptometer (Decagon Devices, Inc., Pullman, WA).

*f*APAR increases with biomass because the total amount of radiation absorbed by foliage and stems increases (Asner et al. 1998). Asner et al. (1998) concluded that senescent grass stands can absorb as much PAR as green grass stands, even though the fraction that is used for photosynthesis (i.e., $fAPAR_{green}$) decreases with increasing senescence. Other authors have concluded that as a grass or crop canopy transitions from dominance by green to senescent biomass, PAR absorption is primarily dependent upon LAI and the density of vegetation (e.g., Asrar et al. 1984, Serrano et al. 2000b, Jorgensen et al. 2003) rather than the total proportion of green biomass. However, *f*APAR cannot be derived directly from satellite data because sensors cannot measure canopy

[1] *f*APAR is used interchangeably in the literature with *f*PAR
[2] PAR: 400–700 nm

transmittance or distinguish the contribution of soil to the overall reflectance signal. This limits the applicability of *f*APAR for large-scale range management.

Researchers interested in landscape-scale "*f*APAR" measurements have traditionally used NDVI to estimate $f\text{APAR}_{green}$ (Field et al. 1995, Knyazikhin et al. 1999, Los et al. 2000), or the fraction of PAR absorbed solely by green foliage, because there is a strong linear relationship between NDVI and $f\text{APAR}_{green}$ (Asrar et al. 1984, Hatfield et al. 1984, Sellers 1985, Choudhury 1987). However, NDVI and *f*APAR values for whole canopies, including senescent fractions, are less correlated (Gamon et al. 1995, Asner and Wessman 1997). Thus, *f*APAR values for canopies with senescent elements must be derived by other means (Asner et al. 1998). One such strategy proposed by Asner et al. (1998) used hyperspectral instrumentation and an integrating sphere to measure *f*APAR:

$$f\text{APAR} = \frac{\sum_{n=1}^{k} (1.0 - r_n - t_n)}{k} \qquad \textbf{[Eq.2]}$$

where k = # bands from 400–700 nm; r_n = reflectance in band n; and t_n = transmittance in band n. However, this approach has limited field applicability because it uses an integrating sphere to derive both reflectance and transmittance, which is not practical with rangeland stands.

Motivated by the findings of Asner et al. (1998) and the strength of the season-long relationship that I found between *f*APAR and biomass in stands of annual grasses ($R^2 = 0.82, p < 0.001$) (Chapter 3), I analyzed hyperspectral reflectance data that was taken simultaneously with these *f*APAR measurements to explore whether radiometer-based PAR reflectance trends were similar to ceptometer-based *f*APAR trends. During the transition from dominance of green to senescent biomass that occurred from maximum NDVI in week 5 to maximum biomass in week 9 (Figure 4.1), I found that reflectance in the PAR region decreased, and that mean PAR surface absorbance, *MAPAR* (Eq. 3), increased with *f*APAR, canopy leaf area index (LAI), and biomass (Chapter 3). Because MAPAR development was motivated in part by the *f*APAR equation used in Asner et al. (1998) (Eq. 2), it is important to note the similarities and differences between these equations; while both equations use reflectance values from the entire PAR spectrum (400–700 nm), MAPAR (Eq. 3) does not include a transmittance value in its calculation.

To determine whether MAPAR could be used to estimate senescent biomass, I measured MAPAR and harvested biomass from stands of annual grass species planted in an agricultural field in East Lansing, Michigan (42° 44' 10'' N, 84° 28' 59'' W). Because MAPAR is an index of surface absorbance, I also used these stands to examine how changes in the soil background, such as cover, type, and condition, influenced the utility of MAPAR for biomass estimates.

To determine the limitations of using ground-based MAPAR measurements in annual grasslands, I investigated whether the index could be used to estimate green biomass in 1-m^2 plots located in Winters, California (38° 30' 45'' N, 121° 29' 33'' W) with LAI values ranging from near zero to six. I was particularly interested in testing MAPAR in annual grasslands where LAI values >5 because other studies have shown that indices, such as NDVI, can saturate under these conditions in both annual crop (Asrar et al. 1984, Hatfield et al. 1984) and grass species (Gamon et al. 1995).

Finally, based on these analyses, I examined whether MAPAR could be used to

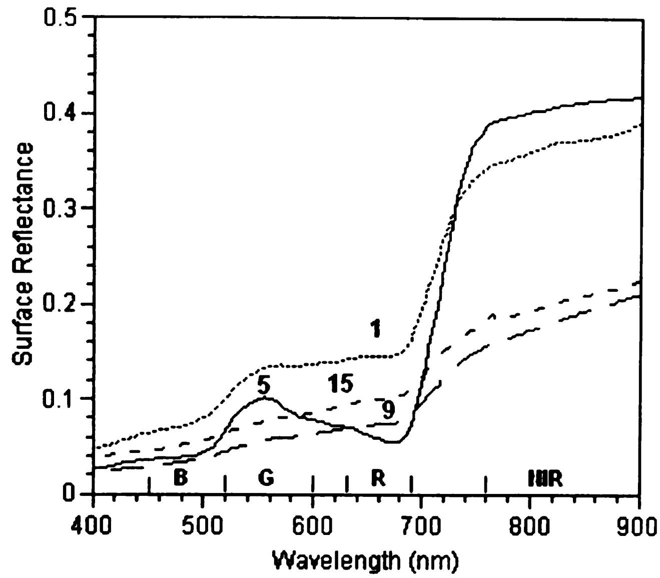


Figure 4.1. Seasonal changes in surface reflectance in stands of *Avena* (high and low density), *Bromus*, *Avena-Bromus*, and *Lolium* from week 1 ("germination") to 5 (maximum greenness: maximum NDVI) to 9 (maximum biomass, *f*APAR, and LAI) to 15 (canopy death). Values represent weekly means across all five stand types. Surface reflectance was derived from UniSpec measurements. The blue (B: 450– 520 nm), green (G: 520–600 nm), red (R: 630–690 nm), and near-infrared (NIR: 760–900 nm) wavelength regions for Landsat satellite sensors are identified for reference.

estimate landscape-scale RDM in grassland ecosystems in the western United States, where LAI would typically range from <0.5 to 3 (Gamon et al. 1995, Knyazikhin et al. 1999) depending upon the slope and aspect of the site (Bartolome et al. 2002) and the management methods in use (Harris et al. 2002).

Methods

Index conceptualization in Michigan grass stands

For this study, I focused on four of the five stand types described in Chapter 3: *Avena fatua* L. (all nomenclature follows Hickman (1993)) low density, *A. fatua* high density, *Bromus hordeaceus* L., and *A. fatua–B. hordeaceus* mixed stands. I excluded *Lolium multiflorum* Lam. because I wanted to focus on only species present in both monoculture and mixed stands. There were 10 replicates of each stand type. The soils in the Michigan grass stands (Chapter 3) were Riddles-Hillsdale sandy loam 2–6%. Prior to the experiment, the field was tilled, so there was no litter from the previous growing season present. This study considered the relationship between PAR absorption and herbaceous biomass, the foliage and stem biomass of the grass species tested.

MAPAR. I measured surface reflectance in the Michigan grass stands using a UniSpec-DC field hyperspectral radiometer with a 20°-field-of-view fore optic (PP Systems Inc., Amesbury, MA). The UniSpec-DC detects spectral intensity in 256 bands, distributed from 300 to 1100 nm, with a resolution of 3.7 nm. I made measurements with the radiometer in nadir orientation, centered 1.43-m above the target portion (0.25-m^2 ground resolution) of each plot. To minimize sun angle and shadowing effects, I collected spectral data within one hour of solar noon. I converted spectral intensity in to reflectance using a Spectralon panel (Labsphere Inc., North Sutton, NH).

To calculate MAPAR in the Michigan grass stands using the UniSpec data, I used reflectance values in the PAR region as:

$$\mathrm{MAPAR}_{full} = \frac{\sum_{n=1}^{k} (1.0 - r_n)}{k} \qquad \textbf{[Eq. 3]}$$

where k = # bands from 400–700 nm; and r_n = reflectance in band n.

In this case, MAPAR_{full} uses the entire PAR spectrum, from 400 to 700 nm. There are 92 bands present in these wavelength regions in the UniSpec data. All radiation hitting a surface must be reflected, absorbed or transmitted so that reflectance + absorbance + transmittance = 1 (Bowers and Hanks 1965). For the MAPAR calculation, I assumed that transmittance through the canopy was zero. Therefore, incoming radiation was either reflected back to the sensor or absorbed by the surface (vegetation + soil). This assumption was made partly by necessity, as the UniSpec-DC, like satellite sensors, cannot measure canopy transmittance in the field. For the whole canopy/soil system, this assumption is met because reflectance is the sum of the direct reflected light from the canopy plus the fraction of the transmitted light that is reflected from the soil *or* understory and then re-transmitted through the canopy (H. Jones, personal communication). This assumption is false for individual leaves or under conditions where canopy LAI is low or vegetation is patchy (Goudriaan 1977, Jones 1992, Asner et al. 1998, Asner et al. 2000). Thus, I assumed that a certain level of error would be possible when calculating MAPAR early in the season when LAI was low, but that this error would most likely decrease as the season progressed and fractional vegetation cover and LAI increased (Chapter 3). I examined this assumption directly as the Michigan grass stands progressed from germination in week 1 (low LAI and cover values) to maximum biomass in week 9 (high LAI and cover) (e.g., Table 4.1).

I calculated MAPAR using mean PAR absorbance values rather than total PAR absorbance values or the integral of PAR reflectance, as is the case for some measurements of broadband albedo (the fraction of incident radiation reflected by a surface) (e.g., Maurer et al. 2002). I chose to do this because I was interested in developing a reflectance-based index that possessed a similar "*f*APAR-like" ability to estimate senescent biomass (Chapter 3) and Asner et al. (1998) had used a similar equation to measure *f*APAR in grass leaves using hyperspectral radiometer data (Eq. 2). For this same reason, I initially calculated MAPAR in the Michigan grass stands using the entire PAR spectrum (400 – 700 nm) rather than wavelength regions corresponding to individual satellite sensors (e.g., Landsat: 450–520, 520–600, 630–690 nm). I address the impact of this decision and of scaling ground-based MAPAR measurements to satellite scales in *Tests of MAPAR in California annual grasslands*. While I focused on mean PAR absorbance in this study, the dynamic ranges of mean and total PAR are similar and total PAR absorbance was also a significant predictor of biomass season-long ($R^2 = 0.60$, $p < 0.001$). This suggests that these measures may be used interchangeably.

Biomass. I used 1) biomass data from six time points throughout the season, and 2) weekly LAI data (Chapter 3) to examine the seasonal ability of MAPAR to estimate biomass, both green and senescent. LAI was significantly related to biomass throughout the season in the Michigan grass stands used this study ($R^2 = 0.71$, $p < 0.001$).

Table 4.1. Phenological effects on MAPAR-based estimates in the Michigan *Bromus* stands. Fractional cover values represent weekly means. Fractional soil cover was calculated as the midpoint of Daubenmire classes (Daubenmire 1968). Fractional senescent cover is the percentage of total vegetation cover. Biomass was only harvested six times over the growing season. R^2 values represent relationships with MAPAR. Significant at: $p<0.001$ = ***, $p<0.01$ = **, and $p<0.05$ = *.

Week	Soil Fraction	Proportion of vegetation cover that was senescent	LAI (R^2)	*f*APAR (R^2)	Biomass (R^2)
1	62.5	0	0.00	0.00	0.75***
2	15	0	0.82***	0.95***	
3	15	0	0.71***	0.72***	0.94***
4	15	0	0.78***	0.79***	
5	2.5	0	0.70***	0.34	
6	2.5	2.5	0.86***	0.61*	0.11
7	15	15	0.71***	0.70***	
8	15	37.5	0.75***	0.34	
9	15	97.5	0.56*	0.48*	0.60**
10	15	85	0.72***	0.70***	0.76***
11	15	85	0.81***	0.78***	
12	37.5	97.5	0.58*	0.88***	
13	37.5	97.5	0.73***	0.77***	
14	37.5	100	0.46*	0.56*	
15	37.5	100	0.51*	0.56*	0.69***
Season			**0.73*** **	**0.62** **	**0.91*** **

Therefore, I used LAI as a non-destructive surrogate for biomass.

I used General Linear Model (GLM) procedures in SYSTAT 10.2 (SYSTAT Software Inc, Richmond, CA) to analyze the relationships between MAPAR and *f*APAR, LAI, and biomass. To compare the MAPAR-biomass equations (i.e., biomass = *f*(MAPAR)) developed for the green (harvests 1–3; weeks 1, 3, and 6) and senescent (harvests 4–6; weeks 9, 10, and 15) time periods, I used Analysis of Covariance (ANCOVA). In the ANCOVA analyses, time period (green vs. senescent) was the independent categorical effect variable, MAPAR was the covariate, and biomass was the response variable. For these analyses, biomass values were natural-log-transformed to meet ANCOVA assumptions. Relationships with p 0.05 were considered significant.

Solar zenith angle tests. I analyzed weekly relationships 1) between mean MAPAR values (*Avena*, *Bromus*, and *Avena-Bromus*) and solar zenith angle (SZA), a significant component of the BRDF; and 2) between MAPAR and LAI, *f*APAR, and biomass in the Michigan *Bromus* stands. Solar zenith angle is the angle measured at the earth' surface between the sun and the zenith (Liang et al. 2002). I focused on the *Bromus* stands because they provide a broad range of fractional vegetation and soil cover ratios for evaluating the effectiveness of MAPAR for estimates of biomass (Table 4.1). Across vegetated surfaces, NDVI and albedo have been shown to increase independently of changes in canopy structure at SZA values >40° (Qi et al. 1995, Danaher 2002). NDVI increases with SZA because of reduced illumination and increased shadowing of the soil background, and increased illumination of the vegetated surface (Danaher 2002). Using this logic, MAPAR, which is broadly inversely related to NDVI (and albedo), values could be expected to decrease at SZA values >40°. This effect is reduced across bare soil (Qi et al. 1995), although Idso et al. (1975) showed that albedo increased at SZA values >40° as well. I calculated SZA using software available at http://solardat.uoregon.edu/SolarPositionCalculator.html, together with sun rise and sun set data found at http://www.wunderground.com/.

Soil background effects. Soil background effects are known to have a large influence on remotely-sensed biomass estimates (e.g., Huete 1988). To estimate the contribution of the soil background to the MAPAR measurements in the Michigan grass stands, I measured surface reflectance in plots of bare soil (Riddles-Hillsdale sandy loam 2-6%) weekly, and compared MAPAR with weekly measurements of *f*APAR, LAI, and biomass in the *Bromus* and *Avena* stands. In these stands, I was able to examine the ability of MAPAR to discriminate vegetation from background soils in plots with fractional vegetation cover values ranging from 2.5% to 97.5%. I also made additional soil measurements in an adjoining agricultural field at the Michigan State University Plant Pathology farm located in East Lansing, Michigan with Houghton Muck organic (80%) soils. In addition, I made measurements outside using pots with Riddles-Hillsdale sandy-loam (dry/wet), sand (dry/wet), and Houghton Muck (dry/wet) soils, respectively. I used repeated measures (paired) t-test procedures in SYSTAT 10.2 to analyze the differences between MAPAR-based vegetation and soil values; mean weekly values were calculated and used for each analysis. In all cases p 0.05 was considered significant.

To address the reliability of MAPAR for biomass estimates in different soil background conditions than those used in this study, I compiled reflectance data from both soil and vegetation on different soil types from the literature (Table 4.2). I broadly

Table 4.2. The influence of soil type and condition on the ability of MAPAR to discriminate vegetation from soil.

Soil measurements taken as part of this study: MAPAR for green vegetation 0.93–0.97; senescent vegetation 0.91–0.95.					
	Series	**Texture**	**Condition**	**MAPAR value**	**Site**
Light soil		Sand	dry/wet	*0.82/0.88*	E. Lansing, MI
	Riddles-Hillsdale	Sandy loam	dry	*0.84*	E. Lansing, MI
	Sehorn	Clay	dry	*0.85*	Winters, CA
	Sehorn-Balcom	Silty clay	dry	*0.85*	Winters, CA
	Capay	Silty clay	dry	*0.87*	Winters, CA
Dark soil	Riddles-Hillsdale	**Sandy loam**	**wet**	***0.90***	**E. Lansing, MI**
	Tehama	Loam	dry	*0.90*	Winters, CA
	Houghton	Muck; organic	dry/wet	*0.90/0.96*	E. Lansing, MI
Other surface	Road/Gravel/Rock		dry	*0.86*	Winters, CA

Soil conditions (from the literature) where MAPAR may (Light) or may not (Dark) be applicable for biomass estimates					
	Series	**Texture**	**Condition**	**Site**	**Citation**
Light soil	Superstition	Sand	dry	Tucson, AZ	Huete and Jackson 1987
	Chelsea	Sand	dry	W. Lafayette, IN	Hoffer 1978
	Derby	Loamy sand	dry	Manhattan, KS	Bowers and Hanks 1965
	Whitehouse-B	Sandy clay loam	dry	Tucson, AZ	Huete and Jackson 1987
	Richfield	Clay loam	wet	W. Lafayette, IN	Price 1994
	Sehorn	Clay	dry	Lake Berryesea, CA	Ustin et al. 1996
	Pembroke	Clay	dry/wet	W. Lafayette, IN	Hoffer 1978
	Newtonia	Silt loam	dry/wet	Manhattan, KS	Bowers and Hanks 1965
	Princeton	Silt	dry/wet	W. Lafayette, IN	Hoffer 1978
	Aquic Xerofluent	Silt	dry	Gironia, Spain	Serrano et al. 2000
Dark soil	Derby	Sandy loam	wet	Manhattan, KS	Bowers and Hanks 1965
	Cloversprings	Loam	dry	Tucson, AZ	Huete and Jackson 1987
	Flom	Loam	dry	W. Lafayette, IN	Price 1994
	Carlisle	Muck; organic	dry	W. Lafayette, IN	Hoffer 1978

categorized soils as light-colored or dark-colored. For those soils used in this study, I defined "light-colored" soils as those that had MAPAR values significantly lower than both green and senescent vegetation, and "dark-colored" soils as those with MAPAR values greater than green and senescent vegetation. For example, I categorized the Riddles-Hillsdale sandy-loam soil (2-6% organic matter content) used in the Michigan grass stands as light-colored (Table 4.2) because the average MAPAR value (0.84) was significantly lower than values for both the green (0.93–0.97) and senescent (0.91–0.95) vegetation throughout the entire season. By necessity, I included MAPAR values only for the measurements that I took as part of this study. In all other cases, I broadly categorized soils as "light" or "dark" based on their published reflectance curves as well as their similarity to soils used in this study.

Tests of MAPAR in California annual grasslands

fAPAR, LAI, and biomass. To test the reliability of MAPAR for biomass estimates in grassland ecosystems, I collected data from 80 1.0-m^2 plots randomly distributed across annual grasslands located in Winters, California (Malmstrom et al. 2004, Butterfield and Malmstrom 2006) from 28–29 March 2003; the period of maximum greenness at this site. I determined the coordinates of each plot with a Trimble Pro XRS GPS unit (Trimble Navigation Limited, Sunnyvale, CA) using real-time differential correction. At each plot, I measured MAPAR, *f*APAR, and LAI and assessed Daubenmire fractional cover (Daubenmire 1968), and then clipped all of the aboveground biomass. To facilitate comparisons between ground-based MAPAR measurements and those from Landsat satellite data (see *Satellite-based MAPAR estimates*), I calculated MAPAR from field spectroradiometer data using the Landsat bandwidths as:

$$MAPAR_{tm\,(unweighted)} = \frac{\sum_{n_{blue}=1}^{k_{blue}} (1.0 - r_{n_{blue}}) + \sum_{n_{green}=1}^{k_{green}} (1.0 - r_{n_{green}}) + \sum_{n_{red}=1}^{k_{red}} (1.0 - r_{n_{red}})}{k_{blue} + k_{green} + k_{red}} \qquad \textbf{[Eq. 4]}$$

where k_{blue} = # of bands from 450–520; k_{green} = # of bands from 520–600;

k_{red} = # of bands from 630–690; $r_{n_{blue}}$ = reflectance in blue band n;

$r_{n_{green}}$ = reflectance in green band n; $r_{n_{red}}$ = reflectance in red band n;

with UniSpec data, $k_{blue} + k_{green} + k_{red} = 65$;

and with Landsat data, $k_{blue} + k_{green} + k_{red} = 3$

Note that when using Eq. 4 to calculate MAPAR there are regions within the PAR region that are not included (e.g., 400 to 450 and 600 to 630). The relationship between $MAPAR_{full}$ (Eq. 3) and $MAPAR_{tm\,(unweighted)}$ is represented in Figure 4.2 using the Michigan *Bromus* stands and the California annual grassland plots. $MAPAR_{full}$ was greater than $MAPAR_{tm\,(unweighted)}$ under all conditions tested, including when green biomass, senescent biomass, and the soil background were dominant. In the Michigan *Bromus* stands and California annual grassland plots, this effect was reduced as MAPAR (and biomass, LAI, and cover) increased.

I did not separate green and senescent biomass; therefore, biomass includes both components. I dried biomass at 65°C to constant mass and weighed it. The soils in these plots were either light-colored Sehorn clay or Sehorn-Balcom silty clay, or dark-colored, Tehama loam (Table 4.2). I used GLM procedures in SYSTAT 10.2 to compare

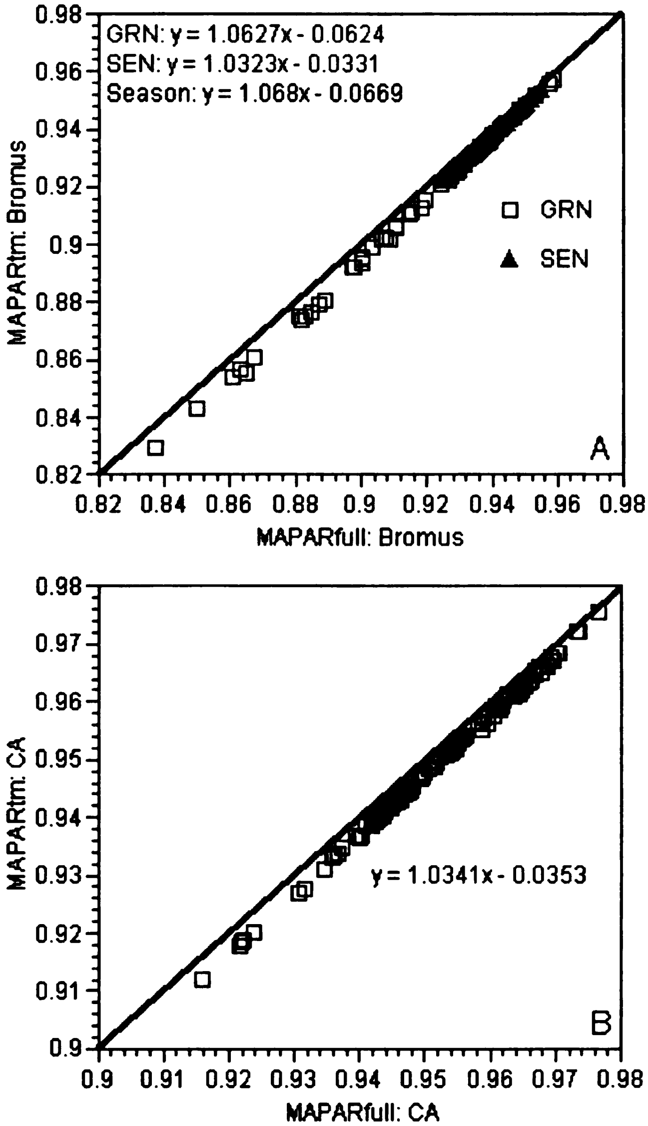


Figure 4.2. Relationship between $MAPAR_{full}$ (Eq. 3) and $MAPAR_{tm\ (unweighted)}$ (Eq. 4) in A) the Michigan *Bromus* stands (N = 150) and B) the California annual grassland plots (N = 169). Relationships in the *Bromus* stands are shown for the green (GRN: weeks 1-7) and senescent (SEN: weeks 8-15) periods as well as for the entire season (weeks 1-15).

MAPAR with *f*APAR, LAI, and biomass.

To estimate the contribution of soil background to MAPAR measurements in the California annual grassland plots, I measured surface reflectance in plots of bare soil from all three soil types. In all cases, the soils were dry (Table 4.2) and data were collected within the same +/- one hour of solar noon window as the vegetation measurements. To analyze the differences between vegetation and soil values I used one-sample t-test procedures in SYSTAT 10.2; p 0.05 was considered significant.

Satellite-based MAPAR estimates. To examine whether I could use satellite-based MAPAR measurements to predict on-the-ground conditions, I acquired a Landsat Enhanced Thematic Mapper (ETM+) L1G geo-referenced image from 28 March 2003 that coincided with the field measurements in the annual grassland in Winters, California. Level 1G ETM+ imagery are delivered as calibrated digital numbers, which I converted to top-of-the-atmosphere (TOA) reflectance using ERDAS Imagine 8.6 (Leica Geosystems, Atlanta, GA). I then converted the TOA reflectance values to surface reflectance with the 5S radiative transfer model (Vermote and Roger 1996). I calculated $MAPAR_{tm\ (unweighted)}$ values for each pixel using Eq. 4. When using actual Landsat data, the summation terms in Eq. 4 are not needed because there is only one reflectance value per pixel in the blue, green, and red bands, respectively. Because these bands are not equal in size (e.g., 70, 80, and 60 nm, respectively), if values are not weighted by bandwidth, the $MAPAR_{tm\ (unweighted)}$ value (Eq. 4) may diverge somewhat from the $MAPAR_{full}$ values (Eq. 3) derived from UniSpec measurements under some conditions. Differences may also exist because there are missing spectral regions in the $MAPAR_{tm\ (unweighted)}$ calculation (Eq. 4) when compared to $MAPAR_{full}$ (Eq. 3).

To analyze the effect of weighting vs. not weighting $MAPAR_{tm}$ by bandwidth, I used the UniSpec data from the Michigan *Bromus* stands and California annual grassland plots. I calculated MAPAR in the *Bromus* stands using the $MAPAR_{full}$ (Eq. 3) and $MAPAR_{tm\,(unweighted)}$ (Eq. 4) equations as well as a $MAPAR_{tm\,(weighted)}$ equation weighted for Landsat bandwidth. (Note: I did not weight $MAPAR_{full}$ for UniSpec bandwidth differences because the UniSpec bands are equal in size, 3.7 nm). The $MAPAR_{tm\,(weighted)}$ equation has the same denominator as the $MAPAR_{tm\,(unweighted)}$ equation (Eq. 4) (i.e., $k_{blue} + k_{green} + k_{red}$), but the numerator for $MAPAR_{tm\,(weighted)}$ is different and is calculated as:

$$\frac{\left[bw_{blue} * \left(\sum_{n_{blue}=1}^{k_{blue}} [1.0 - r_{n_{blue}}]\right)\right] + \left[bw_{green} * \left(\sum_{n_{green}=1}^{k_{green}} [1.0 - r_{n_{green}}]\right)\right] + \left[bw_{red} * \left(\sum_{n_{red}=1}^{k_{red}} [1.0 - r_{n_{red}}]\right)\right]}{bw_{blue} + bw_{green} + bw_{red}}$$

where k_{blue} = # of bands from 450–520; k_{green} = # of bands from 520–600; k_{red} = # of bands from 630–690; r_{nblue} = reflectance in blue band n; r_{ngreen} = reflectance in green band n; r_{nred} = reflectance in red band n; and bw = bandwidth.

I calculated $MAPAR_{tm}$ in the California annual grassland plots using the unweighted and weighted (Eqs. 4 and 5) equations. $MAPAR_{tm\,(weighted)}$ was greater than $MAPAR_{tm\,(unweighted)}$ under all conditions tested (Figure 4.3). This occurred because while both equations have the same denominator (e.g., $k_{blue} + k_{green} + k_{red} = 65$) (Eqs. 4 and 5), the numerator for the $MAPAR_{tm\,(weighted)}$ equation (Eq. 5) was always greater, often 3–4X greater, than the numerator for the $MAPAR_{tm\,(unweighted)}$ equation (Eq. 4). In the Michigan *Bromus* stands this led to large differences in MAPAR-based biomass estimates; in all cases, $MAPAR_{tm\,(weighted)}$-based biomass estimates (y = 6E-29 * EXP(71.97x)) were smaller than $MAPAR_{tm\,(unweighted)}$-based estimates (y = 3E-08 * EXP(24.23x)) for a given

Figure 4.3. Relationships between A) $MAPAR_{tm\ (unweighted)}$ (Eq. 4) and $MAPAR_{tm\ (weighted)}$ (Eq. 5), and B) $MAPAR_{full}$ (Eq. 3) and $MAPAR_{tm\ (weighted)}$ in the Michigan *Bromus* stands (N = 150); B) $MAPAR_{tm\ (unweighted)}$ and $MAPAR_{tm\ (weighted)}$ in the California annual grassland plots (N = 169).

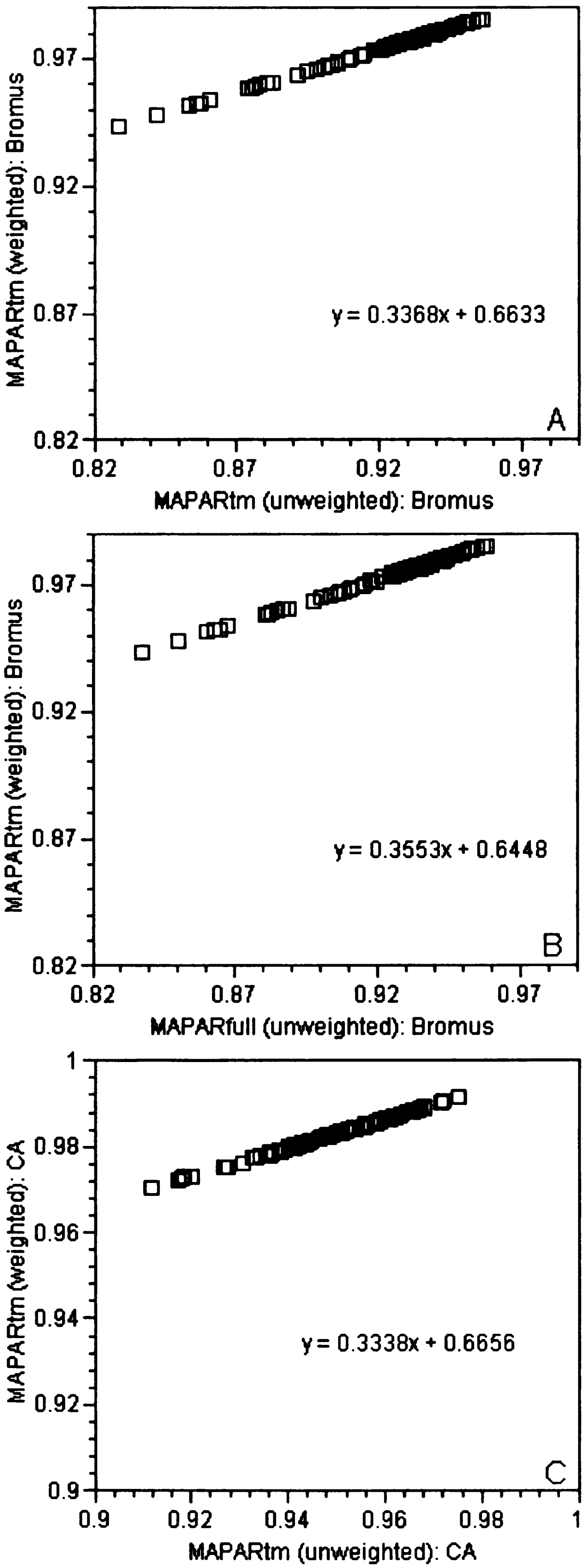

0.97
0.92
0.87
0.82
MAPARtm (weighted): Bromus
y = 0.3368x + 0.6633
A
0.82
0.87
0.92
0.97
MAPARtm (unweighted): Bromus
0.97
0.92
0.87
0.82
MAPARtm (weighted): Bromus
y = 0.3553x + 0.6448
B
0.82
0.87
0.92
0.97
MAPARfull (unweighted): Bromus
1
0.98
0.96
0.94
0.92
0.9
MAPARtm (weighted): CA
y = 0.3338x + 0.6656
C
0.9
0.92
0.94
0.96
0.98
1
MAPARtm (unweighted): CA

Figure 4.3.

MAPAR value. This occurred because as $MAPAR_{tm\ (weighted)}$ values got larger (vs. those which were unweighted) stand biomass values remained the same. For this study, I chose to calculate MAPAR with Landsat data using Eq. 4 because this allowed for the most direct comparison with ground-based MAPAR measurements used in this study, and also allowed for the greatest consistency between the California field plot comparisons and those from the Michigan grass stands. In addition, the $MAPAR_{tm\ (unweighted)}$ dynamic range (e.g., in the Bromus plots 0.825–0.955) was larger than the $MAPAR_{tm\ (weighted)}$ dynamic range (e.g., in the Bromus plots 0.945–0.985), which could allow for greater discrimination of MAPAR and/or biomass values within a heterogeneous grassland. However, end users should consider this weighting issue when deciding which MAPAR equation is most appropriate for their own situation.

I compared the Landsat-based $MAPAR_{tm\ (unweighted)}$ values to those from the 80 1-m^2 quadrats. I compared quadrat values to those from Landsat pixels in which they were nested. When more than one quadrat fell within a given 900-m^2 Landsat pixel, the quadrat values were averaged before comparison.

To examine whether satellite-based MAPAR measures could discriminate bare soil from both senescent and green vegetation, I randomly extracted Landsat-scale (900-m^2) bare soil values from cultivated fields in Winters, California using a 9 May 2001 ETM+ image for the senescent period and the 28 March 2003 image for the green period. I processed the May image using the same methodology described above. I extracted the soil values from fields with dry light-colored Capay silty clay and dark-colored Tehama loam soils (Table 4.2). I used these fields, instead of smaller bare soil patches, to decrease the likelihood of mixed pixel effects. The fields had been harvested 2–4 weeks before image acquisition, so the soil moisture conditions of bare ground were accurately represented. I determined harvest dates using additional Landsat data acquired as part of Malmstrom et al. (2004). One drawback of this approach is that cultivated land can be texturally different than bare ground in a grassland ecosystem. However, this is likely secondary to the sub-pixel mixing effects that would have occurred if I had used smaller patches. I used t-test procedures in SYSTAT 10.2 to analyze differences. In all cases *p 0.05* was considered significant.

Results

Tests of MAPAR in Michigan grass stands

fAPAR, LAI, and biomass. $MAPAR_{full}$, *f*APAR, LAI, biomass, and NDVI increased in all of the Michigan grass stands between week 1 and week 5. At week 5, all plots achieved maximum greenness (defined as maximum NDVI) (Figure 4.4). NDVI decreased thereafter due to increasing canopy senescence. In contrast, $MAPAR_{full}$, *f*APAR and LAI continued to increase until week 9, when maximum biomass occurred. Notably, $MAPAR_{full}$ followed the phenological trends in all three canopy variables through week 15, including the decreases from week 9 to 11. $MAPAR_{full}$, *f*APAR, and LAI values did not change markedly from week 11–14 (Figure 4.4), thus causing the $MAPAR_{full}$-biomass (Figure 4.5a), -*f*APAR (Figure 4.6a), and -LAI (Figure 4.6b) relationships to saturate around $MAPAR_{full}$ values of ~0.936. This phenomenon was reduced somewhat in the *Bromus* stands (Figure 4.5b).

Across weeks and stand types, mean $MAPAR_{full}$ was strongly and significantly correlated to mean *f*APAR, LAI, and biomass (Figures 4.5a and 4.6); this correlation was

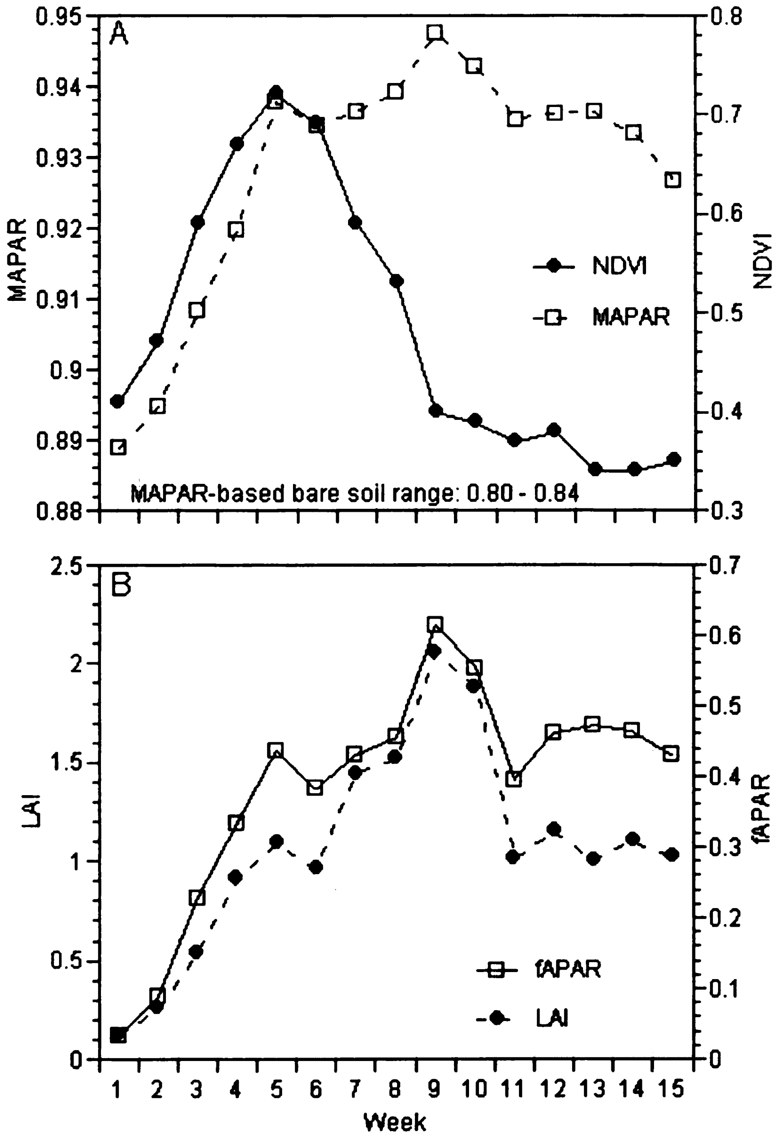


Figure 4.4. Seasonal changes in A) NDVI and $MAPAR_{full}$ (Eq. 3) and B) *f*APAR and LAI; week 5 is maximum greenness and 9 is maximum biomass. Between weeks 9 and 10, there was a strong storm that caused significant stem lodging and facilitated invasion by green weedy vegetation; LAI decreased as the plots were weeded. Values represent weekly means for the Michigan *Avena* (high and low density), *Bromus*, and *Avena-Bromus* stands (n = 40).

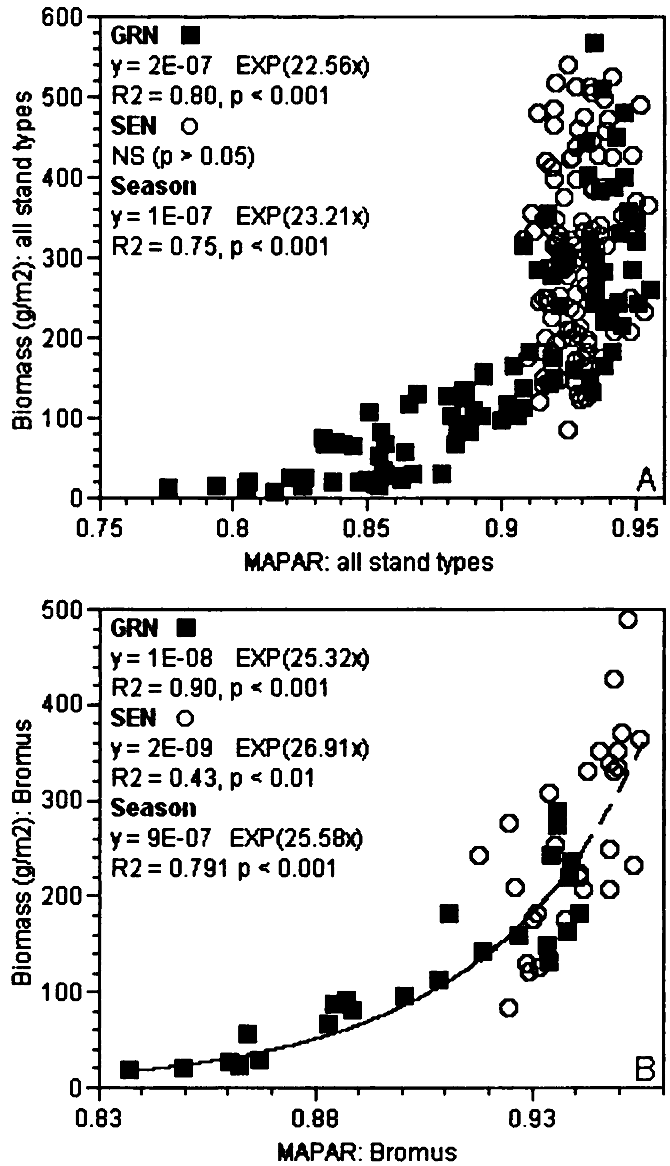


Figure 4.5. Seasonal patterns in the relationship between $MAPAR_{full}$ (Eq. 3) and biomass in A) all of the Michigan stand types combined (*Avena* high and low density, *Bromus*, and *Avena-Bromus*), and B) *Bromus* stands alone. Relationships are shown for the green (GRN: harvests 1–3; weeks 1, 3, and 6) and senescent (SEN: harvests 4–6; weeks 9, 10, and 15) periods as well as for the entire season. In B), the solid line is for the GRN time period and the dashed line is for the SEN time period.

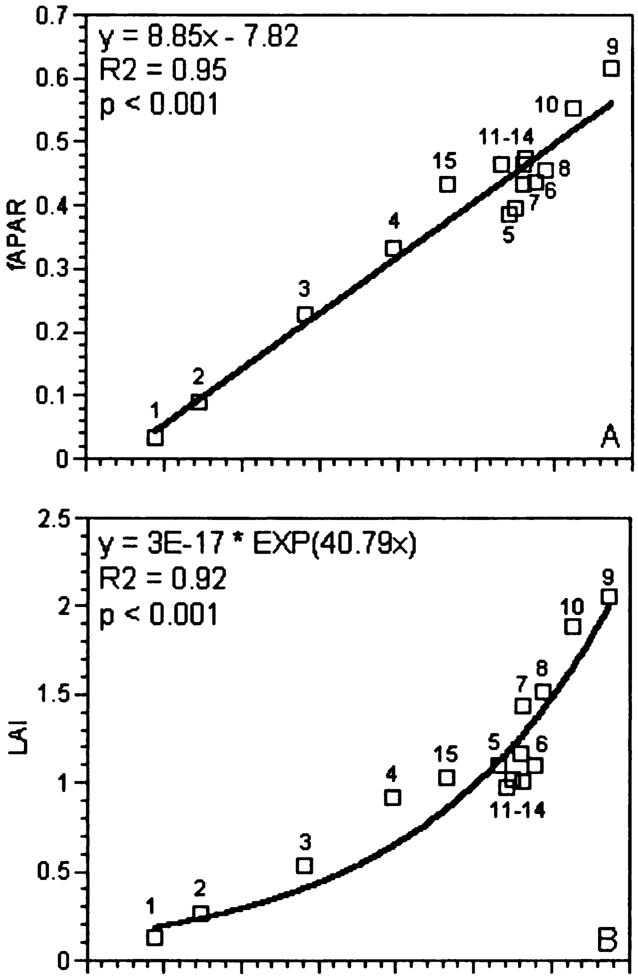


Figure 4.6. Seasonal relationship between $MAPAR_{full}$ (Eq. 3) and A) *f*APAR, and B) LAI. Numbers (1–15) represent weeks, not harvests. Values represent means in the Michigan *Avena*, *Bromus*, and *Avena-Bromus* stands (n = 40).

also significant in the *Bromus* stands alone (Table 4.1; Figure 4.5b). When data from all four stand types were combined, $MAPAR_{full}$ was significantly correlated to biomass during the green period (week 1–7) and for the entire season (week 1–15) (Figure 4.5a). However, during the senescent time period (week 8–15), $MAPAR_{full}$ and biomass were not significantly correlated (Figure 4.5a). In *Bromus* stands, $MAPAR_{full}$ and biomass were significantly correlated during both the green and senescent time periods (Figure 4.5b). In addition, in *Bromus* stands the green and senescent biomass equations (Figure 4.5) were not significantly different ($MAPAR_{full}$ * Time, $df = 1$, $F = 0.068$, $p = 0.795$).

Solar zenith angle tests. $MAPAR_{full}$ increased with solar zenith angle (SZA) from week 1 to 9 in the Michigan grass stands (Figure 4.7). During this time period, there was a significant positive relationship between $MAPAR_{full}$ and SZA ($R^2 = 0.60$, $p < 0.05$). However, this relationship lost its significance as $MAPAR_{full}$ decreased from week 10 to 15, while SZA continued to increase (Figure 4.7). Solar zenith angles were greater than 40° in weeks 14 and 15. During this period, the decrease in $MAPAR_{full}$ may have occurred independently of the decreases in stand biomass and LAI (Figure 4.4). $MAPAR_{full}$-based bare soil values ranged from 0.80–0.84, but were the same, 0.84, in week 1 and 15. In the *Bromus* stands, $MAPAR_{full}$ was significantly correlated to *f*APAR, LAI, and biomass within individual weeks, when SZA was constant (Table 4.1). $MAPAR_{full}$ was significantly correlated to all three variables throughout the season, except for weeks 1 (not significant for *f*APAR or LAI), 5 and 8 (*f*APAR), and 6 (biomass).

Soil background effects. The soil background was dominant in the *Bromus* stands in week 1 (Table 4.1) and in the *Avena* stands in weeks 1–3 and 11–15 (fractional soil

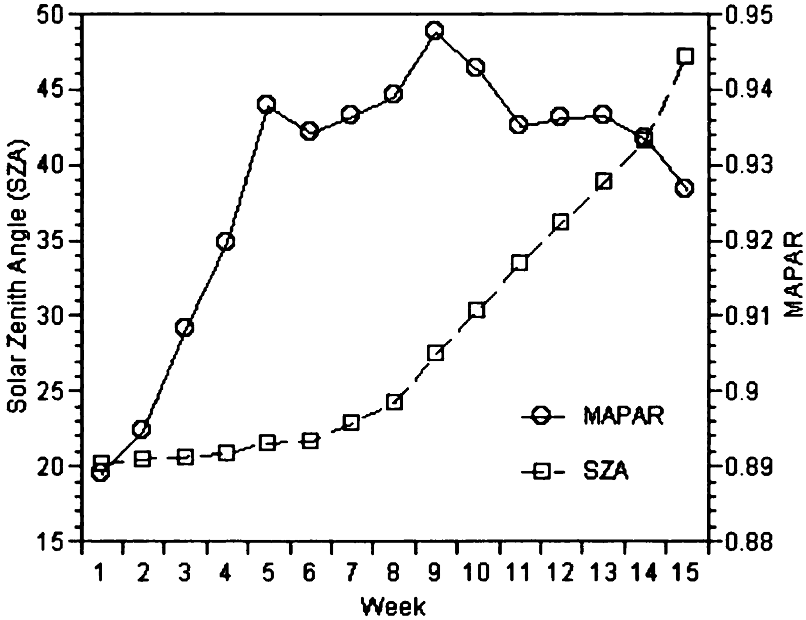


Figure 4.7. Seasonal relationship between $MAPAR_{full}$ (Eq. 3) and solar zenith angle (SZA, measured in degrees). $MAPAR_{full}$ values represent weekly means for the Michigan *Avena* (high and low density), *Bromus*, and *Avena-Bromus* stands (n = 40).

cover: 62.5–97.5%). In the *Bromus* stands, $MAPAR_{full}$ values in week 1 were correlated only with biomass, not with *f*APAR or LAI, which were difficult to measure when vegetation was short and cover was low. In the *Avena* stands, $MAPAR_{full}$ was significantly correlated to LAI in weeks 1–3, and 11, 12, and 14 ($R^2 = 0.49, 0.50, 0.50, 0.56, 0.62, 0.49$; $p < 0.05$). In these same stands, $MAPAR_{full}$ was significantly correlated to *f*APAR in weeks 1–3 and 15 ($R^2 = 0.72, 0.76, 0.55, 0.45$; $p < 0.05$) and biomass in weeks 1, 3, and15 ($R^2 = 0.66, 0.76, 0.47$; $p < 0.05$). Throughout the season in the Michigan grass stands, $MAPAR_{full}$ values from dry soil were significantly lower than those from vegetation (Table 4.3). Values from dry Houghton Muck soils were similar to, and in some cases larger than vegetation values (Table 4.2), although they were still significantly lower overall (Table 4.3). As soil moisture increased, soil values increased and became similar to, or greater than, vegetation values (Table 4.2).

Tests of MAPAR in California annual grasslands

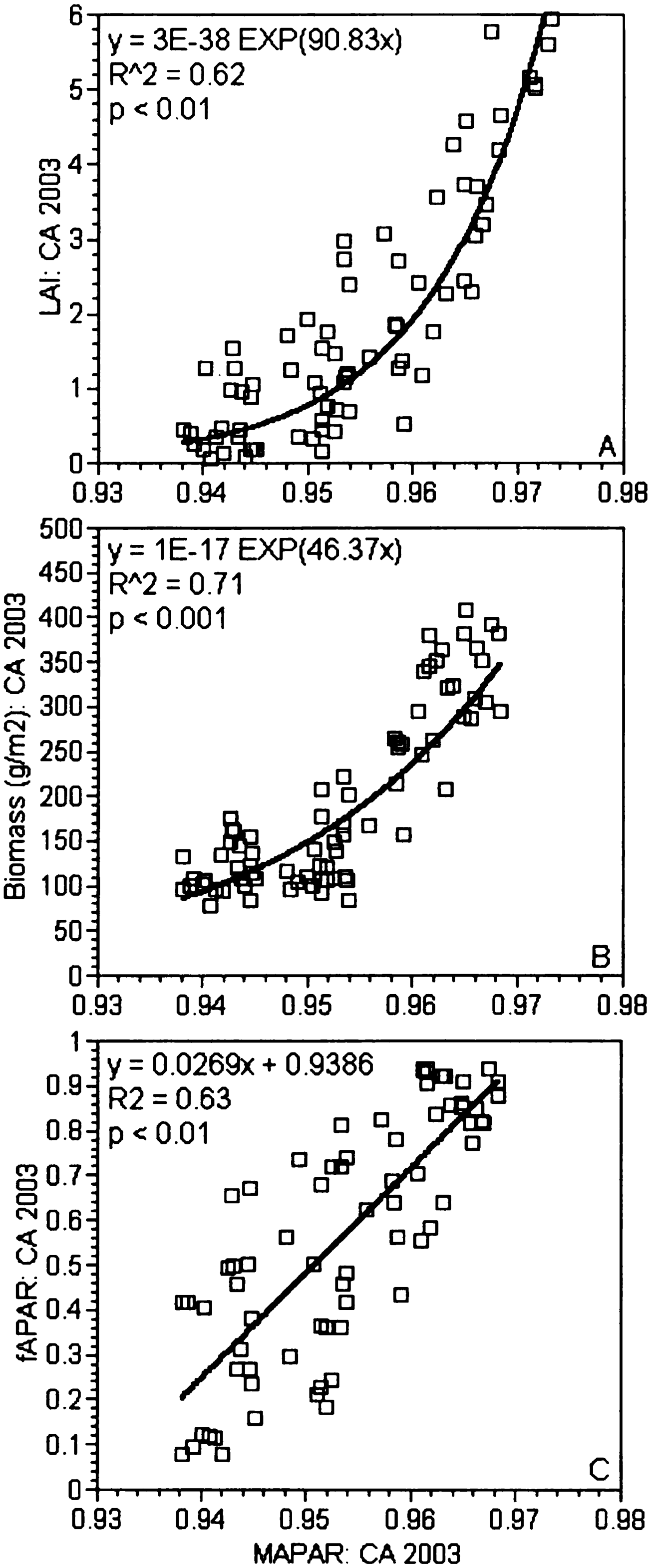
fAPAR, LAI, and biomass. In the California annual grassland plots, $MAPAR_{tm\ (unweighted)}$ measured with field instruments was significantly correlated to LAI, biomass, and *f*APAR during the period of maximum greenness (Figure 4.8). Notably, unlike with NDVI-like indices (Asrar et al. 1984, Hatfield et al. 1984), the MAPAR-based relationships did not appear to saturate at LAI values >5. Dry bare soil values for Sehorn clay, Sehorn-Balcom silty clay, and Tehama loam soils were significantly lower than vegetation values (Table 4.3).

Satellite-based MAPAR estimates. Overall, in the California annual grassland plots, the ground- and Landsat-based $MAPAR_{tm\ (unweighted)}$ values were significantly

Table 4.3. Results of the t-tests for differences between MAPAR-based vegetation and soil values. The Michigan grass stand comparisons were made using green and senescent biomass data (weeks 1–15). For the ground-based California annual grassland comparisons, only green biomass was considered. The Landsat satellite-based California annual grassland comparisons were made either in May, when senescent biomass was dominant, or March, when green biomass was dominant.

Soil Type	Soil–Vegetation Comparison	t	df	*P*
Experimental plots (Michigan)				
Riddles-Hillsdale sandy loam	Green and senescent	-17.00	14	<0.001
Houghton Muck organic	Green and senescent	-6.02	14	<0.001
Natural grasslands – ground (California)				
Sehorn clay/ Sehorn Balcom silty clay/ Tehama loam	Green	-13.23	10	<0.001
Natural grasslands – Landsat (California)				
Capay silty clay– May	Senescent	-22.35	19	<0.001
Tehama loam– May	Senescent	-16.88	19	<0.001
Capay silty clay– March	Green	-26.86	19	<0.001
Tehama loam– March	Green	-25.47	19	<0.001

Figure 4.8. Relationship between $MAPAR_{tm\,(unweighted)}$ (Eq. 4) and A) LAI, B) biomass, and C) *f*APAR in California annual grassland plots during the period of maximum greenness (28–29 March 2003). $MAPAR_{tm\,(unweighted)}$ was derived from UniSpec measurements. LAI and *f*APAR were derived from AccuPAR measurements.



y = 3E-38 EXP(90.83x)
R^2 = 0.62
p < 0.01
LAI: CA 2003
A
y = 1E-17 EXP(46.37x)
R^2 = 0.71
p < 0.001
Biomass (g/m2): CA 2003
B
y = 0.0269x + 0.9386
R2 = 0.63
p < 0.01
fAPAR: CA 2003
C
MAPAR: CA 2003

Figure 4.8.

correlated ($R^2 = 0.47, p < 0.001$). In most cases, Landsat-based $MAPAR_{tm\ (unweighted)}$ values were lower than ground-based estimates, with differences ranging from 0.0004 to 0.0189. Landsat-based $MAPAR_{tm\ (unweighted)}$ soil values for both light-colored Capay silty clay and dark-colored Tehama loam soils (Table 4.2) were significantly lower than senescent and green vegetation (Table 4.3).

Discussion

A remote sensing-based approach for the quantification of biomass that could be used by managers regardless of the dominance of green or senescent biomass would revolutionize biomass management in grassland ecosystems globally. Armed with this tool, managers could assess grassland conditions, including RDM levels, throughout the season and make real-time grazing decisions across large grassland units. One of the main reasons such a tool has yet to be developed is the difficulty and expense associated with quantifying senescent biomass (Huete et al. 1985, Huete and Jackson 1987, Streck et al. 2002).

I tested the utility of the MAPAR index as a tool to estimate senescent biomass because it behaved similarly to *f*APAR throughout the season (Figure 4.4) and could be directly derived from accessible satellite sensor data (i.e., Landsat). I found that, across the dry sandy loam soils in this study, MAPAR closely followed the seasonal trajectory of *f*APAR, LAI *and* biomass (Figure 4.4; Chapter 3), demonstrating that in dry light-colored soils (Table 4.2) MAPAR was sensitive to phenological changes that occur in annual grass species.

It is important to define MAPAR in relation to albedo because albedo is a common measurement used in the remote sensing literature (e.g., Qi et al. 1995, Liang et al. 2002) as well as a current end-product of the MODIS satellite sensor (Lucht et al. 1998). It is intriguing to imagine a future situation where MAPAR values could be extracted directly from MODIS data. MODIS, like the UniSpec data, acquires ground reflectance data across the entire PAR spectrum using bands with approximately the same bandwidth (10–15 nm in the case of MODIS). In general, MAPAR and albedo are inversely related; as albedo increases, MAPAR decreases. However, this relationship can vary depending on the surface type (and thus the magnitude of canopy transmittance) and bidirectional reflectance distribution function (BRDF), as well as the instrument being used to measure albedo. Ground-based albedo measurements, for example, are most commonly acquired using an albedometer. Unlike a radiometer which measures reflectance at a single view angle (e.g., nadir), an albedometer integrates the amount of radiation reflected by a surface over all view angles. Thus, across non-Lambertian surfaces, like the grass canopies measured in this study, reflectance and albedo can differ significantly depending on the BRDF (Liang et al. 2002).

MAPAR in Michigan grass stands

For range management decision-making, it would be ideal to use a single biomass index all season long. In this study, when all of the Michigan stand types were grouped, the season-long MAPAR-biomass relationship was significant (Figure 4.5a). However, the relationship appeared to saturate at MAPAR values near ~0.936. As a result, when only the senescent period was considered, MAPAR was not significantly correlated to biomass (Figure 4.5a). This may indicate that the dynamic range of MAPAR is insufficient for late-season biomass estimates, either because of the amount of biomass on the ground or because of the proportion of senescent biomass present.

However, it is also possible that the saturation phenomenon was an artifact of the stem lodging event that occurred in the *Avena* and *Avena-Bromus* stands during week 10. This conclusion is supported by the MAPAR-biomass relationship in the *Bromus* stands as well as in the stands of *Lolium multiflorum* (Chapter 3), which were not impacted by the stem lodging event. The radiation regime of a plant canopy is a function of photon scattering by leaves, stems, and soils (Jones 1992). The contribution of leaf, stem, and soil optical properties to canopy PAR absorption is modulated by LAI, leaf angle distribution, and foliage clumping (Asner et al. 1998), which determine the density and optical depth of the canopy (Ross 1981). As grass stems lodge at the end of the season, the density and optical depth of the canopy may be reduced (Ross 1981, Jones 1992, Asner et al. 1998), thus decreasing the amount of PAR absorbed by the canopy independently of biomass. In addition, stem lodging may cause openings in a grass canopy, which in some instances could also decrease PAR absorption (Ross 1981, Jones 1992, Asner et al. 1998) without parallel decreases in canopy LAI or biomass. In the Michigan *Bromus* stands, the saturation phenomenon was reduced (Figure 4.5b) and MAPAR was significantly correlated to biomass during the senescent time period (Figure 4.5b; Table 4.1). Likewise, MAPAR was significantly correlated to biomass during the senescent time period in the Michigan *Lolium* stands ($R^2 = 0.55, p < 0.001$). The saturation phenomenon does highlight a potential limitation of MAPAR in grassland ecosystems, where lodging is possible at the end of the season once vegetation has senesced and stem integrity has declined.

A single species-specific biomass equation could be applied throughout the season for *Bromus* (Figure 4.5b) and *Lolium* ($y = 2E\text{-}06e^{20.40x}$, $R^2 = 0.91, p < 0.001$) stands. Based on these results, I recommend using a single equation for the green and senescent time periods assuming there is not a significant amount of stem lodging. Future efforts should be directed at testing the impact of canopy structural attributes on the relationship between MAPAR and biomass throughout the season.

Like other reflectance-based indices, MAPAR measurements are influenced by the BRDF, as a function of sun-surface-sensor geometry, canopy architecture and optical properties, soil background properties, and illumination conditions (Deering 1989). While I tried to control for as many of these factors as possible in the Michigan stands, I did not make any specific BRDF corrections. One important component of the BRDF that was not controlled for was solar zenith angle (SZA). SZA increased in the plots from ~20° in week 1 to 47° in week 15 (Figure 4.7). Studies designed to address BRDF effects have shown that increases in SZA above 40° can cause reflectance-based indices, like NDVI, as well as albedo to increase across vegetated surfaces (Qi et al. 1995). NDVI increases because of reduced illumination and increased shadowing of the soil background, and increased illumination of the vegetated surface (Danaher 2002). Because MAPAR is broadly inversely related to reflectance-based indices like NDVI as well as to albedo, it is possible that during weeks 13–15, when SZA was greater than 40° (Figure 4.7), MAPAR values could have decreased independently of the decreases in stand biomass and LAI (Figure 4.4). However, the results from this study suggest that the SZA effect was most likely secondary to the relationship between MAPAR and biomass. For example, in the *Bromus* stands, MAPAR was significantly correlated to biomass, as well as *f*APAR and LAI, within individual weeks when SZA was constant and therefore not impacting the predictive capacity of MAPAR (Table 4.1).

Because MAPAR is an index of surface absorbance, it is important to understand how changes in the soil background influence the reliability of MAPAR. In general, dry soils are usually more reflective than vegetation in the visible regions and less so in the near infrared regions (Bowers and Hanks 1965). However, as moisture and organic matter content increase and the color of the soil darkens, the amount of radiation absorbed by soil increases and the differences in reflectance between soil and vegetation decrease (Bowers and Hanks 1965) (Table 4.2). As a consequence, MAPAR-based bare soil values increased, and the ability to discriminate vegetation decreased, when the light-colored sandy loam soils used in the Michigan grass stands were wet. In addition, MAPAR was not as effective for biomass estimates on dark-colored soils high in organic matter content, such as Houghton Muck (80%) (Table 4.2). The soil background effect would likely decrease as vegetation cover and LAI increase, and the canopy closes (Hoffer 1978). Before using MAPAR, a manager should assess soil conditions across his or her property. If *both* fractional soil cover on average is greater than 15% (canopy cover is <85%) and the soil is either wet or has high organic matter content (Table 4.2), I would not recommend using MAPAR for biomass estimates.

MAPAR in California annual grasslands

MAPAR derived from UniSpec measurements was significantly correlated to LAI, biomass, and *f*APAR (Figure 4.8) at maximum greenness in California grassland plots with LAI values from <0.2 to 6. These results, together with those from the Michigan stands, suggest that across these soil types and conditions the dynamic range of MAPAR may be sufficient to predict a large range of *f*APAR, LAI, and biomass values that are naturally present during the period of maximum greenness.

Although it was outside the scope of this study to test MAPAR at the landscape-scale throughout the entire season, I found that MAPAR measurements from 1-m^2 plots were significantly correlated to those from 900-m^2 Landsat pixels. Combined with the encouraging results from the Michigan grass stands and California annual grassland plots, these results support testing MAPAR at the landscape scale using Landsat or MODIS satellite data. Such tests would initially focus on identifying how sub-pixel level changes in soil cover, type, and condition as well as vegetation condition (e.g., stem lodging) impact the broad-scale applicability of MAPAR for biomass estimates.

MAPAR for RDM estimates

An important management application of the MAPAR index is landscape-scale RDM estimates. Currently methods used by range managers are ground-based (e.g., Clawson et al. 1982) and time intensive, and have varying accuracy (Bartolome et al. 2002). While remote sensing-based RDM approaches have been developed for crop systems (Daughtry 2001, Streck et al. 2002, Nagler et al. 2003), these approaches rely on instruments and datasets to which private range managers usually do not have access. A more accessible remote sensing-based RDM approach, which could be applied to Landsat or MODIS data, for example, would likely increase the number of managers who use remote sensing to monitor RDM levels. I did not specifically test the ability of MAPAR to make RDM estimates in grassland ecosystems. However, MAPAR successfully estimated biomass where conditions were like those a manager may encounter during the period when RDM estimates are made: 1) senescent vegetation cover is dominant, 2) the soil background and vegetation are dry, and 3) biomass values range from 900–2350 kg/ha (Figures 4.5 and 4.6; Table 4.1) (Bartolome et al. 2002). Because of the sensitivity of MAPAR to soil background conditions, it may be difficult to apply MAPAR in situations where RDM is low (e.g., on flat slopes and swales, <450 kg/ha), which is an important issue to monitor in the future.

MAPAR, as calculated in this study, had two main limitations: the utility of MAPAR for biomass estimates decreased as the soil darkened (Table 4.2) and when grasses lodged (Figure 4.5a). There may be alternative MAPAR-based approaches that decrease some of these soil background and vegetation condition limitations (Table 4.4). Two possible approaches to test in the future are: 1) use MAPAR to quantify biomass at maximum biomass and then estimate RDM using the field-based guidelines developed by Bartolome et al. (2002); and 2) use MAPAR for interannual RDM comparisons (i.e., RDM change detection). A change detection approach is promising because it would provide the user the means to minimize the influence of the soil background (type, condition) in the retrieval of biomass (and RDM) data (Mas 1999, Jensen 2000). In its simplest form, change detection involves subtracting values (e.g., biomass) of one satellite image from a second image that has been precisely registered to the first (Singh 1989). Because images would be acquired at the same time of the year, soil background

Table 4.4. MAPAR-based RDM approaches. The Direct Approach quantifies fall RDM directly using data acquired before the first fall rains. The Indirect Approach estimates fall RDM using data acquired in late spring at maximum biomass together with the Bartolome et al. (2002) RDM algorithm. The Change Detection approach does not quantify fall RDM directly, but instead can be used to identify pastures where RDM levels are trending outside of the recommended range.

	How does it work?	What does a manager need to assess in order to effectively use?	Where will it work most effectively?	Advantages	Disadvantages
Direct Approach	Quantify RDM in the fall before the first rains	Soil condition Vegetation cover Vegetation condition Topography	Soils dry and low in organic matter content Vegetation cover >85% No significant lodging "Flat" grassland areas	Direct RDM measurements; Can apply a single senescent biomass equation	Most likely limited to situations where soil cover <15% and stem lodging is not significant
Indirect Approach	Quantify biomass at maximum biomass, then estimate RDM using the algorithm in Bartolome et al. (2002)	Soil condition Vegetation cover Vegetation condition Topography Grazing/management regime	Soils dry and low in organic matter content Vegetation cover >85% No significant lodging "Flat" grassland areas No grazing/mowing/fire May–October	Additional biomass data at maximum biomass: can use to help maximize annual grazing duration; Stem lodging effect reduced	Most likely limited to situations where soil cover <15%; Not a direct RDM measurement; Assumes grazing, etc. absent after maximum biomass
Change Detection Approach	Calculate the absolute differences in fall RDM levels between years	Soil conditions Vegetation conditions Precipitation regimes	Soil conditions similar between years	Accounts for soil background and topography effects	Not a direct RDM measurement

conditions would likely be the same in both images. Thus, “change” would be due to changes in biomass (or RDM) rather than soil cover, type, or condition (Hallum 1993). Both of the RDM approaches detailed in Table 4.4 have certain advantages and disadvantages. However, the findings from this study are sufficiently encouraging to suggest that testing these approaches across grassland ecosystems would be worthwhile.

CHAPTER 5

CONCLUSIONS

Although my dissertation research has answered several questions about the use of remote sensing in rangeland ecology, it has also led to many more. Having identified factors that influence the use of remote sensing data by private range managers and examined ways in which remote sensing use impacts manager decision-making, I am now interested in investigating in more detail the economic impact of remote sensing approaches on a diverse group of ranching operations. It would be valuable, for example, to better understand whether there is a threshold sum that ranchers are willing to spend on remote sensing data, as a function of their ranching operations' size and diversity (as measured in terms of acreage, head of cattle, diversity of land uses, etc.), as well as to continue to adapt the development and delivery of remote sensing data to the unique needs of individual range managers.

Although quantifying the economic impact of remote sensing data on ranching operations may be challenging, such an assessment would be invaluable to managers interested in using remote sensing data. For example, an economic assessment could identify particular situations (e.g., a large ranch with many livestock and a widespread weed infestation) in which investment in remote sensing data was likely to be worthwhile. Alternatively, an economic analysis might conclude that remote sensing is generally a cost-effective management tool in which land managers should more broadly invest, but that its use is limited by availability and training. Without a full economic analysis of the impact of remote sensing on ranch profitability, it is likely that few range managers will want to make long-term commitments to investing in remote sensing data.

My dissertation research examined a few of many possible applications of remote sensing data for biomass and weed management in grassland ecosystems (e.g., Tueller 1989, Hunt et al. 2003). It is clear that remote sensing data can provide managers means to evaluate management decisions across a variety of spatial and temporal scales and to focus management practices on those which most efficiently increase rangeland health, primarily by decreasing noxious weeds and increasing levels of desirable forage species. It is less clear however, which remote sensing applications are most useful for private range managers and therefore likely to be invested in by the managers themselves. My study was the first to specifically address the use of remote sensing data by private range managers. Future efforts should be directed at evaluating similar questions of use and impact across a broad and diverse group of range managers and ranching operations. Such work would help answer questions concerning, for example, the importance of the size of the ranching operation on the use and investment in remote sensing data. In addition, as remote sensing data continue to be refined and new applications are developed which allow managers to evaluate measures of rangeland health at finer spatial and temporal scales (e.g., Lass et al. 2005, Mustafa et al. 2005, Everitt et al. 2006, Mundt et al. 2006), it is imperative that we evaluate how to best deliver these data to managers and train managers in how to apply them to their individual management situations.

The range managers in California with whom I worked were interested in investing in remote sensing data because they believed these data could help them optimize their ranching operations and increase the protection of their ranches' natural resources (Butterfield and Malmstrom 2006). However, this group of managers, unlike most range managers, enjoyed free access to remote sensing data and training in its use for five years. Without this support, it is likely that this manager group would have been less interested in investing in remote sensing data. There are a number of reasons why this may be the case, which should be investigated in the future, including: (i) the perceived costs to individual managers and uncertainties about how to obtain appropriate remote sensing products, and (ii) concerns that remote sensing data could be used by government agencies or conservation organizations to regulate private grazing and/or land management operations in an authoritarian manner (S. Butterfield, personal communication). Collaborations like the ones discussed in Butterfield and Malmstrom (2006) can help alleviate some of these difficulties by providing a forum in which scientists, managers, agency staff, and non-profit conservation organizations can develop cost-sharing collectives (e.g., for purchasing and processing remote sensing data) and products tailored to different, often unique management situations. These collaborations can also provide opportunities for exploring and addressing concerns managers may have about the use of remote sensing data as a regulatory tool across their properties.

Such collaborations appear to be powerful means through which to develop remote sensing products that are accurate, affordable, and easy to use in operational range management contexts. Because of the pressures currently associated with maintaining profitable range management operations in the western United States (Roche and Roche 1991, Leitch et al. 1994, World Resources Institute 1996, Mitchell 2000, O'Brien et al. 2003) and because private lands often contain high-quality ecosystems and species of conservation interest (e.g., The Nature Conservancy 2000, 2005, 2006), collaborations like those described in Butterfield and Malmstrom (2006) are likely to become more common in the future.

My dissertation research also examined the properties of a new vegetation index, MAPAR, which could be used under some conditions to quantify senescent biomass. Future efforts will be focused on testing the applicability of MAPAR (and of associated remote sensing-based approaches) at the landscape-scale and on identifying how sub-pixel level changes (in soil cover, type, and condition as well as vegetation condition) impact the use of MAPAR for senescent biomass estimates. An important application of MAPAR to the range management and conservation communities is its use as an indicator of residual dry matter (RDM). RDM is particularly interesting to conservation organizations and their partners (e.g., The Bureau of Land Management 1996, Guenther and Christian 2005, The Nature Conservancy 2006) because it can strongly influence biomass production and noxious weed spread. Although I did not specifically test the ability of MAPAR to make RDM estimates as part of my dissertation work, I did find that MAPAR successfully estimated biomass under conditions like those under which a range manager would normally estimate RDM (i.e., senescent vegetation cover is dominant, the soil background and vegetation are dry, and biomass values range from 900–2350 kg/ha). Because MAPAR is sensitive to changes in soil background conditions, the application of MAPAR for RDM estimates is likely limited to situations where fractional soil cover <15% or the soil is both dry and low in organic matter content. Future efforts should be directed at testing the limits of MAPAR across a wide range of grassland conditions using fine and moderate resolution satellite data, such as that from Landsat TM and MODIS.

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