Characterizing rangeland using multispectral remotely sensed data and multi-scale ecological units
by Catherine Cae Lee Maynard

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Land Resources and Environmental Sciences
Montana State University

Abstract:
In this study ecological range unit (ERU) delineations combined with multispectral satellite data were examined to address the need for consistent, spatially accurate, and temporally current methods to inventory rangeland and estimate relative biomass productivity in the context of ecologically sensitive site parameters. ERUs, Landsat 7 ETM+ combined band values, and vegetation index data from 13 scenes acquired from June 2000 to August 2002 were used as predictive variables in linear regression estimates of total biomass using field data collected from 263 locations within 24 ecological range sites on 5 Montana ranches. GIS spatial data analysis techniques were applied to certified soils data themes and published landscape level ecological units to produce the ERU categories used to stratify the field data collection and image analysis, and as a method to test the use of an independent data set for addressing the known influence of soil and site variability on the spectral response of vegetation. ERU categories, in combination with the near and mid-infrared bands (Band 4, 0.75 - 0.90 µm; Band 7 2.09-2.35 µm), were significant independent variables, and in linear regression predictions collectively explained 66% of the variability in total biomass (p-value< 0.001), as compared to 52% explained by the combined bands alone, suggesting that ERU categories might be accounting for a component of soil variability. This report also introduces an efficient, remote sensing directed method for preliminary identification of locations within ERUs where indicators of soil and site stability or biotic integrity might be outside the established means. A comparison between sites with spectrally anomalous brightness, greenness, and wetness Tasseled Cap indices and selected measurements of spectrally sensitive rangeland ecological health indicators were used to develop a classification method for locating and screening rangeland categories. Pixels where site productivity and exposed soil percentages were within average field ranges (non-anomalous) were identified with an overall accuracy level of 98% (K hat= 0.96). The results of this study support the use of moderate resolution spectral imagery combined with ecological site delineations to enhance efficient rangeland inventory, the effectiveness of rangeland monitoring, and ecologically sustainable management.

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Rick Lawrence | Rick Lawrence | 11/20/2003
Signature | Date

Approved for the Department of Land Resources and Environmental Sciences

Jon Wraith | Jon Wraith | 11-20-03
Signature | Date

Approved for the College of Graduate Studies

Bruce McLeod | Bruce R. McLeod | 11-20-03
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To my parents,

Walker Keith Lee (1929-1969)

Ruth Sloan Lee (1930-2000)

Who taught me a love of learning,

the need for organization and hard work,

and the beauty of this life.

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ABSTRACT

In this study ecological range unit (ERU) delineations combined with multispectral satellite data were examined to address the need for consistent, spatially accurate, and temporally current methods to inventory rangeland and estimate relative biomass productivity in the context of ecologically sensitive site parameters. ERUs, Landsat 7 ETM+ combined band values, and vegetation index data from 13 scenes acquired from June 2000 to August 2002 were used as predictive variables in linear regression estimates of total biomass using field data collected from 263 locations within 24 ecological range sites on 5 Montana ranches. GIS spatial data analysis techniques were applied to certified soils data themes and published landscape level ecological units to produce the ERU categories used to stratify the field data collection and image analysis, and as a method to test the use of an independent data set for addressing the known influence of soil and site variability on the spectral response of vegetation. ERU categories, in combination with the near and mid-infrared bands (Band 4, 0.75 – 0.90 μm; Band 7 2.09-2.35 μm), were significant independent variables, and in linear regression predictions collectively explained 66% of the variability in total biomass (p-value< 0.001), as compared to 52% explained by the combined bands alone, suggesting that ERU categories might be accounting for a component of soil variability. This report also introduces an efficient, remote sensing directed method for preliminary identification of locations within ERUs where indicators of soil and site stability or biotic integrity might be outside the established means. A comparison between sites with spectrally anomalous brightness, greenness, and wetness Tasseled Cap indices and selected measurements of spectrally sensitive rangeland ecological health indicators were used to develop a classification method for locating and screening rangeland categories. Pixels where site productivity and exposed soil percentages were within average field ranges (non-anomalous) were identified with an overall accuracy level of 98% ($K_{hat} = 0.96$). The results of this study support the use of moderate resolution spectral imagery combined with ecological site delineations to enhance efficient rangeland inventory, the effectiveness of rangeland monitoring, and ecologically sustainable management.

CHAPTER ONE

INTRODUCTION

Rangeland Inventory, Ecological Unit Mapping, and Remote Sensing

Rangelands include the diverse vegetation of native grass and shrublands, savannahs, forests, and deserts that occupy almost half of the Earth's surface, with grasslands alone occurring on over one-quarter of the planet's land area (Williams et al., 1968). These environments supply resources that have been used since the earliest human record for the grazing of domesticated livestock, providing habitat for wildlife and plant species, and supplying fundamental hydrologic and terrestrial ecosystem components (Campbell and Lasley, 1969; Langer, 1952; Pearse, 1971). In the United States, rangeland constitutes the largest of all land use categories, with an estimated 63% (398 million ha) of the nation's land area classified as grazing land (Holechek et.al, 1989; Laurenroth, 1979; CAST, 2002; NRCS, 1992). In Montana, over 55% of the state is rangeland which represents some of the greatest diversity in biophysical environments and plant community expressions found in the mountain foothills, plains, and prairie grassland ecosystems of the western United States (Shiflet, 1994). Montana's rangelands provide water, wildlife habitat, and recreational opportunities, in addition to the nearly 1.8 billion dollars annually that livestock production contributes to the State's economy (Montana Agricultural Statistics Bureau, 2002).

Throughout the U.S., private rangeland managers rely on a variety of federal programs to ensure the economic viability of their operations. From grazing allotments permitted on public rangeland to cost-sharing incentives for range improvements on private land, these programs provide resources and technical support to an industry with a traditionally low profit margin where annual profits or losses are often determined by slight seasonal or annual fluctuations in rangeland productivity.

Over the past century, issues regarding the status and condition of rangelands (Blaikie, 1987; Hess, 1992; Feller, 1992; Worster, 1992) have resulted in numerous legislative actions that prescribe the programs and policies of resource management and technical support agencies (Taylor Grazing Act, 1934; Multiple Use and Sustained Yield Act, 1960; Rural Development Act, 1972; Resources Planning Act, 1974; Federal Land Policy and Management Act, 1976; Soil and Water Resource Conservation Act, 1977). These laws and provisions detail the responsibilities federal agencies have to provide rangeland inventory, monitoring, and management support on public and private lands, and to periodically report to Congress with assessments of rangeland productivity, health, and ecological stability.

The most recent such reporting for private rangeland was included in the 1992 National Resource Inventory (NRI) produced by the Natural Resources Conservation Service (NRCS, 1992), which is scheduled to be repeated in 2003. This report rated 24.3% of the private rangelands inventoried in 'poor' or 'declining' condition with 59.6% of the rangeland in this category also exhibiting a downward trend. In the past decade, the concerns of the public and the scientific community regarding the ecological well being of public rangelands prompted the U.S. Departments of Interior and Agriculture to conduct a comprehensive study of the environmental impacts of livestock grazing and make recommendations for revised management alternatives. Known as "Rangeland Reform '94," this study identified 13-20% of upland and 20-22% of riparian habitats on Federal lands as not meeting the criteria for 'proper functioning condition', with an additional 30% and 46% of BLM upland and riparian habitats respectively classified as 'functioning at risk' (USDI, 1994).

Despite the long-recognized economic and environmental importance of rangeland resources, obstacles have inhibited improvements to rangeland management. These include the limitations current methods have for providing, with acceptable spatial accuracy, consistent and reliable inventories of rangeland productivity and condition, and for the identification of ecologically unique locations where management changes may enhance productivity and promote long-term ecological sustainability. This need for more efficient, affordable, robust, and defensible rangeland survey, evaluation, and prediction tools and techniques that can answer local, regional, and national management questions has been consistently identified by rangeland scientists (Tueller, 1989; Walker, 1995; West and Smith, 1997).

One of the more recent and comprehensive evaluations of modern rangeland issues succinctly stated:

> "...There is a need for inexpensive inventory, classification and monitoring methods with links for current ecological theory. These links must be robust so that as ecological theories change, the data can still be interpreted using new theories. This will involve a multiple attribute approach to the design of the inventory." (NRC, 1994).

Similarly, the Council for Agricultural Science and Technology's recently released issue paper further emphasizes that there is still,

> "...an urgent need for new tools and technology that synthesize existing knowledge to aid land managers in assessing and monitoring the status of grazing lands. New knowledge is needed to identify lands at risk of degradation, to forecast and to communicate early warning of potential problems..." (CAST, 2002).

These assessments come from a broad range of professional rangeland ecologists and managers who are intimately familiar with the strengths and limitations of currently available methods.

The techniques developed by range scientists over the past 50-60 years to inventory vegetation productivity classes by measuring kinds and amounts of vegetation include methods such as ocular estimates of cover percentages using the line-intercept or line-transect; or clipping, identification, separation, and weighing of vegetation by species on sample plots (Walker, 1995). These are all time consuming, labor intensive, and costly techniques given the remote and expansive nature of Western rangelands (Canfield, 1941; Eberhardt, 1978; Asrar et al., 1986; Ritchie et al., 1992).

Historic methods for addressing range condition can be traced to the early range condition guides developed by the Soil Conservation Service (SCS) as a management tool for ranchers and range managers (Dyksterhuis, 1949). First appearing in 1945, these guides relied on estimates of available forage to classify range condition (Bell, 1944; Humphrey, 1949). The well-established relationship between the nature and condition of soil and site properties and vegetation growth, productivity, and vigor provided the original basis for measures of productivity and plant community composition as surrogates in evaluations of overall rangeland status (Sampson, 1917; Anderson, 1955; Shiflet, 1973; Breckenridge, 1995; Herrick et al., 2001). The currently used method for rating existing vegetation productivity and plant community attributes known as "similarity indices," though now conducted and reported by ecological range unit, continues to rely on the comparisons between existing and potential vegetation productivity and plant community composition that have traditionally been considered adequate for rangeland status evaluations (Leonard et al., 1992; NRCS, 2000).

As scientific understanding of the complexity of biotic and abiotic ecological system processes has advanced, the concept of ecological range units has been promoted to provide a more comprehensive, site specific, ecological foundation for rangeland studies and the application of management practices (Jacoby, 1974; Society for Range Management, 1995; NRCS, 1997). Ecological units of various scales are identified by the integration of physical and biological components of the environment, which include climate, geomorphology, geology, soils, hydrology, and vegetation (Cleland, 1992). The term 'ecological site' is widely applied to components of terrestrial ecosystems. In the vernacular of range scientists 'ecological site' is accepted as synonymous with 'range site,' and has been defined as … "a kind of land with specific physical characteristics which differs from other kinds of land in its ability to produce distinctive kinds and amounts of vegetation, and in its response to management" (Creque et al., 1999; SRM, 1999; USDI, 2000).

Ecological site classification concepts have also been incorporated into the revised criteria for rangeland health evaluations that have recently been developed by interdisciplinary teams of private ranchers, academic experts, and land management scientists, and adopted as a monitoring protocol (USDI, 2000). Continuing the effort to better integrate ecosystem process theory, this method standardizes rangeland health evaluations using 17 indicators of soil/site stability, hydrologic function, and biotic integrity to incorporate extensive soil, vegetation, and site observations. This comprehensive method requires high levels of technical expertise and intensive field measurements to administer and consequently has not been exposed to widespread use, validation, or assimilation into common field operations. Changeable budgets and priorities, limited personnel and access to technology, as well as the extensive and often remote land areas involved, continue to constrain private landowners and land management technical support agencies from designing and implementing standardized inventory and monitoring techniques. The development of inventory methods that minimize the extent of locations requiring extensive field sampling, while providing reliable data that can easily be incorporated into annual and seasonal range management decisions, has also been inhibited by these constraints.

Among the emerging methods with the potential to provide this much needed information, the opportunities for applying satellite and airborne remote sensing technology to rangeland inventories have been studied in rangeland ecosystems around the world (Pearson and Miller, 1972; Asrar, 1986; Asrar, 1985; Graetz 1987; Tueller, 1989; Anderson, 1993; Pickup et al 1993; Bork et al., 1999; Drake et al., 1999; Everitt et al., 2001; Tueller, 2001; Washington-Allen et al., 1999; RangeView, 2003). Sensors aboard satellites currently orbiting the Earth such as the Advanced Very High Resolution

Radiometer (AVHRR), Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and the Moderate-Resolution Imaging Spectroradiometer (MODIS) provide individual spectral band and vegetation index data that have been demonstrated to be significantly correlated to field estimates of vegetation biomass in a variety of environments (Tucker, 1979; Lillesand and Kiefer, 1994; Elvidge and Lyon, 1985; Anderson et al., 1993; van Leeuwen, 1999; Thoma et al., 2002). For over 30 years, data from the moderate resolution, multi-spectral Landsat TM sensors have been examined as a source for rangeland inventory information (Maxwell, 1976; Tucker, 1979; Deering, 1980; Graetz and Gentle, 1982; Graetz et al., 1983; Pech et al., 1986; McGraw and Tueller, 1983; Richardson and Everitt, 1992; Tueller, 2001). The focus of many of these experimental remote sensing of rangeland studies has been to estimate productivity and to classify vegetation types (Asrar, 1989; Anderson et al., 1993; Clark et al., 2001; Tueller, 2001), again relying on the assumption that information regarding vegetation attributes would in turn answer ecological status questions important to land managers.

Remote sensing studies have consistently demonstrated that unique site and soil variations affect correlations between field-measured biomass and biomass predicted by satellite vegetation index data (Cippra et al., 1980; Elvidge and Lyon, 1985; Cihlar, 1991; Borel and Gershal, 1994). The highly variable percentages of exposed soil, composition of grass and shrub communities, variations in canopy height, distribution and cover, and ratios of green and senescent vegetation that are common to rangeland environments have been shown to complicate the use of red and near infrared ratio-based vegetation indices such as the Normalized Differenced Vegetation Index (NDVI), which is primarily associated with photosynthetically active green vegetation (Huete, 1988; Huete et al., 1985; Tueller, 1987; Elvidge, 1990; Qi et al,. 1994). To address the reflectance influences of soil backgrounds, modifications to the ratio-based NDVI vegetation index have been developed (Huete, 1988; Rondeaux et al., 1996; Baret et al., 1989; Qi et al., 1994) and the orthogonal transformation known as the 'tasseled cap', with its physically based indices of brightness, greenness, and wetness has been introduced (Kauth and Thomas, 1976; Crist and Cicone, 1984; Huang et al., 2002). These methods have taken the approach of accounting for soil background influences with adjustments to indices or weighted transformations of band values, yet with a reliance on the spectral data to address both soil and vegetation variability.

Although soil properties and site characterization data have long been recognized as critical components of other ecological studies, there has been limited research in the combined uses of multi-spectral imagery and spatial delineations of ecological sites to evaluate rangeland productivity, and even less experimentation with uses for identifying ecological status from a combination of these data sets (Washington-Allen et al., 1999; Hunt et al., 2003). A discussion of the historic and current research relevant to remote sensing of rangeland and the conceptual framework underlying ecological unit mapping is provided by the literature review in Chapter Two.

The issues of scale, resolution, cost of acquisition, pre-processing, and distribution logistics that have previously limited the use of satellite and other spatial data by private and public rangeland managers are rapidly being resolved. Emerging models for Internet distribution of national, state, and local mapping products and moderate resolution imagery, such as the current America View and National Map programs of the U.S. Geologic Survey, and cooperatives like the Upper Mid-West Aerospace Consortium (UMAC) have the potential to ensure that satellite imagery and high quality spatial data will be more easily accessible to the general public in the coming years (USGS, 2001). As the volume and availability of geospatial and multi-spectral data increases, however, consistent tools for interpreting multi-spectral image information in the context of ecological site characteristics are still lacking. To date, satellite imagery and ecological unit-based interpretive products are not in common-place use for the inventory, analysis, or monitoring of public and private rangelands. With the increasing availability of digital ecological unit mapping from the landscape to site-specific scales, fundamental standardized spatial themes are now in place for predicting relative productivity and classifying rangeland ecological status using both multi-spectral imagery, and reliable independent data sets to address soil and site variability.

This study was in part a response to the need expressed by rangeland managers and the Natural Resources Conservation Service (NRCS) to evaluate the applicability of Landsat 7 ETM+ data for estimating relative rangeland productivity and ecological health. Prior to the initiation of this study, UMAC negotiated for the acquisition of Landsat 7 ETM+ imagery that would be made available over high-speed Internet connections, at no cost, to participating farmers and ranchers in the five-state UMAC area (see Appendix D). UMAC cooperators had been previously provided with NDVI data from the 1- km resolution AVHRR sensors (EROS, 1992), and had expressed a need for image products with greater spatial resolution. The successful launch in April 1999 of the

National Aeronautics and Space Administration (NASA) satellite carrying the Landsat 7 ETM+ sensor, and the established cooperative between UMAC and NASA provided this opportunity. During the three-year period of this cooperative effort in Montana, five private ranchers volunteered to participate and were provided with satellite dishes with high-speed internet download capacities, basic image viewing computer software, Landsat 7 ETM+ imagery, and academic institution support to foster collaborative learning investigations of the land management information these data might provide. The imagery acquired was also made available to this research project for an examination of rangeland productivity and ecological status estimates that could be derived from Landsat 7 ETM+ multi-spectral data.

A primary objective of this research was to evaluate estimates of relative rangeland productivity from spectral response and to examine the relationship between these estimates and ecological units. For this portion of the study, Landsat 7 ETM+ band combinations, vegetation indices, and landscape and ecological range unit categories were tested as independent predictors in linear regression estimates of field-measured biomass. The details of this investigation are reported in Chapter Three.

A second, equally important objective was to investigate which (if any) indicators of rangeland ecological health might be correlated with measurements or indices from Landsat ETM+ spectral bands and to evaluate the relationship between spectral response, indicators of rangeland health, and ecological range units. This was accomplished by developing a classification of spectral indices to identify sites outside the range of average conditions for established ecological health parameters. This portion of the research project is presented in Chapter Four.

The methods described in this study have the potential to improve the efficiency of rangeland inventories without compromising the reliability of intensive field inventory. They are also flexible to the incorporation of data from other currently available sensors that were not included in this study or new satellite sensors as they are developed, and to future advancements in ecological hierarchy theory and ecological unit mapping.

CHAPTER TWO

LITERATURE REVIEW

Ecological Unit Mapping, An Historic Perspective

From a foundation of several centuries of descriptive botanical and plant geography studies, the environmental variables controlling the extent, distribution, and successional progression of plant communities across the Earth's continents, biomes, regions, landscapes, and local sites have been defined, described, and mapped using an impressive array of techniques (Merriam, 1898; Dice, 1943; Fenneman, 1946; Shelford, 1963; Holdridge, 1971; Kuchler, 1965; Bailey, 1976; Lugo et al., 1999). The recognition by Humbolt (1827) of the role of climate, geology, and other abiotic influences in controlling the regional distribution of vegetation type was confirmed by the observations of Schouw (1823), Warming (1909), and Schimper (1898), and developed into a classification by de Candolle (1847). This information was adopted and modified by the German climatologists, Koppen and Geiger (1936), into a climatic zone mapping system that has persisted to the present, and been the foundation of numerous life zone, biome, and eco-region mapping and characterization efforts.

The assumptions established in these basic works led to the emphasis on climate placed by Clements (1916, 1936) in his studies of plant succession and to the integration of abiotic and biotic environmental components into the concept of biosphere introduced by Vernadsky (1926) (Smith, 2000) and that of ecosystems expressed by Tansley (1935). Reflecting the adoption of these concepts, studies to describe and predict plant community dynamics, species composition, and successional progression are replete with discussions of abiotic influences (Whittaker, 1953, 1967; Bray and Curtis, 1957), and vegetation mapping efforts have come to incorporate, in some fashion, the environmental parameters that control site potential (Bailey, 1983). The need to reduce the spatio-temporal diversity of controlling biophysical variables into appropriately scaled, quantifiable units to facilitate vegetation studies is well elucidated in the historic works of Sukachev (1954) and Bray (1958), whose theory of order and complexity in natural systems influenced the concept of integrative levels initially presented by Feibleman (1954) and elaborated by Rowe (1961).

Quantitative ecological research over the past century has confirmed the importance of accounting for landscape level and site-specific environmental constraints in studies of vegetation dynamics, and landscape ecologists have incorporated these parameters into maps of biogeoclimatic zones (Demarchi et al., 1996), eco-zones, and eco-regions (Wiken, 1986; Omernick, 1987), domains, divisions, and provinces (McNab and Avers, 1994). In general, current ecological mapping systems combine the climatic properties of moisture and temperature regimes with the physical variables of geomorphology, geology, soils, and hydrology to delineate unique geographic occurrences of ecologically functional environments and their vegetative expressions (Rowe, 1981; Bailey, 1987, 1996). A useful synthesis of current and historic studies of relationships that have been explored between ecological processes and landscape patterns has been provided by Turner (1989).

The emphasis placed on environmental or biotic control models (Driscoll et al., 1984; Smith, 1986; Aber, 1991) has influenced how researchers have chosen to develop and refine ecological unit delineations and how the information has been used in the analysis of ecological phenomena (Connell and Sousa, 1983; Schoener, 1983; May, 1984; Allen and Diaz, 1989; Southwood, 1987; Legendre and Fortin, 1989; Borcard et al., 1992). Ecological unit mapping has been applied to analysis techniques for improving the accuracy of land cover classification maps (Homer et al., 2001); modeling sensitivity and resiliency to disturbances such as soil erosion (Nesser et al., 2001); portraying background differences in water quality (Omernick, 1995); and in studies of both animal and plant community structure and distribution (Cooper et al., 1999).

To quantify landscape and vegetation patterns, hierarchy theory is among the concepts that have been applied to provide a contextual foundation for organizing investigations (West and Shute, 1978; Allen and Starr, 1982; Conradsen, 1986; O'Neill et al., 1986; Bicheron and Leroy, 1999). Hierarchy theory incorporates the concepts of equilibrium and steady states to characterize the distribution of ecosystems and to identify ecological processes and interrelationships at the scales that they operate. Although levels within the ecological hierarchy are non-inclusive complex systems, often in a non-equilibrium state (Connell and Sousa, 1983; Wiens, 1984; DeAngelis and Waterhouse, 1987), the use of a hierarchical approach to environmental analysis reduces variability at several steps, becoming more site specific with each iteration (Palacios-Orueta et al., 1999).

Hierarchical ecological unit mapping results in landtype associations, landtypes, and soil map units that are nested within landscape level ecological units. At more refined scales within these delineations, predictable and repeatable patterns of spatial units emerge, based on a refinement of feature occurrence (Nesser et al., 1996). Site-specific ecological units are distinguished by increasing the resolution of source data and varying the emphasis of abiotic and biotic delineation criteria. Spatial units with increasingly specific expressions of site, soil, and vegetation properties, at progressively larger scales, are thus identified. As a result, hierarchical ecological unit mapping provides a method to link landscape-level ecosystem composition, structure, and function to site-specific attributes, from which increasingly accurate spatial representations of specific resource interpretations can be derived. The conclusion reached by Holecheck (1989), that rangeland vegetation type and productivity are determined by physical site characteristics at all scales, reinforces the role ecological units have come to play in traditional rangeland inventories (Dyksterhuis, 1949; Mabbut, 1978; Passey, 1982; Shiflet, 1994; NRC, 1994).

Current ecosystem characterization and analysis methods often incorporate the use of Geographic Information System (GIS) spatial data analysis tools to vary the scale, resolution, and level of detail at which climatic, geomorphic, hydrologic, vegetation, and soil features are integrated to address the desired interpretation(s). As a result, a new generation of ecological mapping has emerged (Johnston, 1987; Henebry, 1993; Hargrove and Luxmoore, 1997). Combining multi-spectral satellite data with spatial analysis modeling techniques has opened a door on new methods for analyzing the structure and variability of environmental components (Ludwig and Reynolds, 1988; Woodcock and Harward, 1992; Legendre, 1993; Legendre and Legendre, 1998; Hargrove and Hoffman, 1999; Dale, 1999; Liebhold and Gurevitch, 2002; Dale et al., 2002; Perry et al., 2002; Franklin and Stephenson, 2003). For example, a map predicting the spatial variability of potential rangeland vegetation for ecological sites in east central Montana was developed by integrating ecological niche theory with terrain modeling and climate gradient analysis (Jensen et al., 2001)

The value and importance of using ecological units in ecosystem studies at landscape and site-level scales has been well demonstrated. Their utility for developing, interpreting, and applying natural resource management information within a robust ecological context, however, has been slow to emerge. Inventory, assessment, and monitoring have been described by Graetz (1987) as the essential components of rangeland management. If properly applied, ecological unit data, remote sensing, and spatial analysis techniques can add the structure of an ecological hierarchy and the efficiency of computerized analysis to these resource management components. For the large and diverse ecosystems used as rangeland, which occupy over half of the Earth's land area, the reliable and efficient accomplishment of these tasks has been expressed as a critical need (NRC, 1997; CAST, 2002).

Remote Sensing and Rangeland Inventory

As remote sensing platforms and sensors have developed over the past four decades, corresponding efforts have been made to use spectro-radiometric data to inventory rangeland vegetation (Graetz et al., 1976; Maxwell, 1976, McGraw and Tueller, 1983, Tueller 2001). Developed for estimating leaf area index in a tropical rain forest, the first published vegetation index, the simple ratio (SR), was a ratio of the near-infrared (NIR, 0.800 μm), and red (0.675 μm) portions of the electromagnetic spectrum (Jordan, 1969). In arid and semiarid rangelands, where vegetation canopy height, distribution, and cover are highly variable, measurements of vegetation spectra can be dominated by the soil background, interfering with estimates of vegetation biomass and cover from this index (Knipling, 1970; Tueller, 1982). Accounting for the reflectance of soils and non-photosynthetic or senescent vegetation has posed a major challenge to reliable spectral measurements of rangeland vegetation attributes. To better estimate vegetation cover in grassland environments, by adjusting simultaneously for unrepresentative values in absorption and reflectance, the NIR/red index was modified into a ratio of the difference between NIR and red brightness values and their sums, the Normalized Differenced Vegetation Index (NDVI) (Rouse et al., 1973). Since its introduction, the NDVI has become a standard formula for spectral estimates of vegetation cover and biomass and has been widely applied to data from numerous sensors (Goward, 1985; Justice and Hiernaux, 1986; Walsh, 1987; Pilon et al., 1988; Weigand et al., 1991; Eidenshink, 1992; Benedetti et al., 1993; Kremer et al., 1993; Wade et al., 1994; Merrill et al., 1993)

Studies to examine the variable percentages of exposed soil, standing dead vegetation, and litter have employed various band combinations, indices, and modifications to the NDVI (Colwell, 1974; Wiegand et al., 1974;Tueller, 1987; Crippen, 1990; Galvao et al., 2000; Gitelson et al., 2002). To quantify the contribution of soil spectra to grass canopy reflectance in native short-grass prairies of Colorado, Tucker (1977) examined band relationships in the visible and NIR regions and found the greatest contrast between soil and green vegetation in the 0.70 to 0.80 μm range. The results of companion studies also revealed a linear plane in red/NIR spectral space corresponding with variations in the spectra of bare soil (Tucker, 1979). Richardson and Wiegand (1977) demonstrated a linear relationship between the perpendicular distance from the NIR/red soil line and vegetation density and proposed the perpendicular vegetation index. While useful for practical application, the concept of a universal soil line (Baret et al., 1993), with a single slope in red/NIR space does not accommodate for known differences between soil spectra, which can result in different red/NIR slopes within a single image (Ray, 1995; Gitelson et al., 2002). As green biomass decreases, the variable influence of standing dead biomass and soil backgrounds tend to dominate regression estimates of biomass from the NDVI (Tucker and Vanparet, 1985).

To minimize the influence of soil brightness on the NDVI, Huete (1988) designed the soil-adjusted vegetation index (SAVI) to provide equal vegetation index results for light and dark soil backgrounds in situations with reduced biomass. The SAVI applies an adjustment factor (L), ranging from 0 for high vegetation densities to 1 for very low densities, with .5 being the commonly used adjustment. A range of other specialized modifications to factor soil reflectance in the ratio vegetation indices have been published (Baret et al., 1989; Baret and Guyot, 1991; Qi et al., 1994). In a comparison between soil-adjusted NIR/red ratio indices and non-ratio band combinations for estimates of vegetation cover, Lawrence and Ripple (1998) reported regression results from non-ratio band combinations were necessarily superior to any from the NIR/red ratio based indices. Nevertheless, the NDVI and its functional equivalents (Perry and Lautenschlager, 1984) continue to be widely applied in remote sensing studies of vegetation attributes (Curran, 1980; Reeves, 2001; Shanahan et al., 2001; Tueller, 2001; Thoma et al., 2002).

Parallel efforts to associate spectral response with other physical scene features while addressing soil reflectance variability led Kauth and Thomas (1976) to apply a sequential orthogonalization technique to transform the four original Multispectral Scanner (MSS) spectral bands. This method applied an interpretive step to associate spectra with physical scene attributes and resulted in the 'tasseled cap' indices of soil brightness (SBI), greenness (GVI), yellow stuff index (YVI), and non-such index (NSI). The SBI successfully captured 98% of the variability in bare soil spectral response, and a soil line lying parallel to the brightness axis was identified. The data structure observed using the tasseled cap indices for agricultural crops (Kauth and Thomas, 1976) and for a very heterogeneous urban/agricultural/forested area in Louisiana was similar to that for rangeland data from Australia (Graetz and Gentle, 1982).

Following the changes in bandwidths from the MSS to Thematic Mapper (TM) sensors, tasseled cap transformation coefficients for the six Landsat 4 reflective bands were developed by Crist and Cicone (1984) using simulated TM data, which were then applied to actual TM digital numbers (DNs) and adjusted to improve the transformation matrix. This method weights the sum of the six reflective bands to calculate the brightness index (BI), which unlike the MSS SBI does not represent the direction of soil variability. The TM greenness index (GVI) is calculated by contrasting the sum of the visible and NIR bands, and is responsive to absorption of the visible and reflectance of the NIR wavelengths by green vegetation. Unlike the MSS tasseled cap indices, no YVI or NSI indices result from the TM transformations. Instead, by contrasting the sum of the visible and NIR bands with that of the longer IR bands, the wetness index (WI) is calculated, which when viewed with brightness, defines the plane of soils. Tasseled cap transformation coefficients for reflectance data from Landsat 5 TM have also been provided by Crist (1985). As atmospheric effects are not accounted for in these ground-based coefficients, however, atmospheric corrections must be applied prior to use. The development by Huang et al. (2002) of tasseled cap transformation coefficients for Landsat 7 ETM+ data, based on at-satellite reflectance, significantly expands the potential applications for using tasseled cap indices in large area studies involving multiple scenes and diverse ground conditions, as the conversion from DNs to reflectance normalizes for illumination geometry.

The Spectral Response of Soils and Senescent Vegetation

While methods to address the influence of soil reflectance on spectral estimates of vegetation were being explored, other researchers examined spectro-radiometric data to evaluate the physical and chemical properties of soils and to delineate soil map units. Strong correlations between various wavelengths and soil color, organic matter content, sand, silt, clay, and iron contents have been reported from laboratory and field studies (Bowers et al., 1965; Condit, 1970; Montgomery and Baumgardner, 1974; Cipra et al., 1980; Stoner et al., 1980; Stoner and Baumgardner, 1981). Landsat TM data has been found useful in locating soil series boundaries for a detailed soil survey (Kristof, 1971; Matthews et al., 1973; Lewis et al., 1975; Westin, 1976; Weismiller et al., 1977; Roundabush et al., 1985). Biomass development within grouped soil series was also highly correlated with vegetation index data (Lozano-Garcia et al., 1991). Studies using spectral data to differentiate between soil units and their properties have examined differing portions of the visible, near and mid-IR spectrum and different spectral band combinations than those used in vegetation indices (Swain and Davis, 1978; DeGloria et al., 1986; Escadafal et al., 1989; Roberts, 1991; van Deventer et al., 1997; Narayanana et al., 1998), and have shown correlations with soil moisture, organic matter, texture, and other physical and chemical properties that contribute to vegetation pattern distribution and biomass production (Waller et al., 1981; Harley and Smith, 1983; MacDonald et al., 1993; Levine et al., 1994).

In a comparison between ground-based spectro-radiometric and Landsat measurements from 16 soils, Cipra et al. (1980) found Landsat data could be used to distinguish five spectrally distinct groups based on soil color. When analyzed on the basis of parent material, native vegetation, and drainage characteristics, four groups were identified. The spectra of 62 soil types with highly variable surface conditions were studied by Satterwhite and Henley (1987), who found the reflectance of all soil types sampled increased directly with wavelength over the visible-NIR spectrum, and decreased as soil moisture content increased. Ratio-based vegetation indices have been shown to increase with dark or low reflecting soil backgrounds (Huete et al., 1985;

Elvidge and Lyon, 1985). Conversely, in some instances the tasseled cap GVI was observed to decrease with low reflecting soils (Huete et al., 1985; Huete and Jackson, 1987). On arid Australian rangelands Graetz et al. (1982) found the MSS red band alone most useful for discriminating between dry vegetation and high reflecting soils, and Pickup et al. (1993) observed that the Landsat MSS green and red bands provided better separation of vegetation and soil reflectance than the red and NIR.

The detection of dry or standing dead biomass also poses problems in the use of vegetation indices for rangeland biomass estimates (Tucker et al., 1983). The influence of senescent or non-photosynthesizing vegetation can produce similar results to highly reflective soil backgrounds (Gausman et al., 1975). While Hoffer and Johansen (1969) found senescent vegetation to have increased reflectance in the visible, near, and mid-IR regions, Asrar et al. (1986) observed grass canopy reflectance to decrease in the NIR (.69-1.30 μm) region and increase in all other bands, including the mid-IR (1.55-2.35 μm), as plants matured and their leaves became senescent. In studies of grazed and ungrazed rangelands, Stella et al. (1993) found the red reflectance values had a stronger relationship to biomass on un-grazed sites with a substantial component of dry biomass. Huete and Jackson (1987) observed the presence of standing yellow with green vegetation reduced the greenness signal of the PVI, GVI, and NDVI by 20-33%, indicating an influence by dry biomass on perpendicular, orthogonal, and ratio-based values.

Given the nature of multi-spectral satellite data and vegetation/substrate relationships, the responses are tightly interwoven and remain difficult to separate using the bandwidths of the Landsat sensor. Limitations posed by the spatial and spectral resolution of TM data have also been noted in many investigations. This has led remote sensing studies to test high frequency microwave radiometers to measure surface soil moisture content (Wang et al., 1984; Starks and Jackson, 2002), and laser altimeter measurements (Lidar) to examine surface roughness and vegetation canopy characteristics (Menenti and Ritchie, 1994).

The need to account for the effects of soil and site background effects when evaluating the spectral response of vegetation remains an issue and source of on-going study (Todd and Hoffer, 1998). Although vegetation indices have been consistently used to estimate the fraction of solar radiation intercepted by vegetation (VF), other methods have also been tested. Spectral mixture analysis of hyperspectral data, using reference reflectance end-members to model soils, shade, green, and non-photosynthetic vegetation has been used to effectively estimate vegetation cover (Roberts et al., 1993; Ustin et al., 1996). Neural networks have been applied to measure canopy gap fraction from NIR and red reflectance with superior results over vegetation indices (Baret et al., 1995). The fittingness of the soil line was recently shown to be sensitive to bandwidths and the position of band means, and an increase in the contrast between green vegetation and other scene components was achieved by positioning the red band in the 660-680 nm interval and the NIR band around 750 nm (Galvao et al., 1999, 2000, 2002). By using only the visible spectrum (550 – 700 nm), Gitelson et al. (2002) observed clear distinctions between the vegetation line and soil lines for pixels with varying vegetation fraction classes.

In the same year (1979) P. Greig-Smith's presidential address to the British Ecological Society focused on the importance of site-specific soil variation as an environmental control in determining the spatial heterogeneity, patchiness, and patterns in vegetation, C.J. Tucker presented the red and NIR soil line for use in multi-spectral vegetation studies. Given the divergent evolution of each of these disciplines, it is interesting to note that just over 20 years ago when plant ecologists were again emphasizing the significance of soils in vegetation studies, remote sensing scientists were beginning their struggle to account for the influence of soils in spectral response measurements of vegetation.

Remote Sensing of Rangeland Condition

Although the issues of site and soil background variability and senescent vegetation reflectance have influenced the ability of Landsat data to provide consistently reliable estimates of rangeland biomass, other studies have successfully used TM spectral features to identify rangeland vegetation types (Driscoll and Coleman, 1974; Carneggie et al., 1983; Tucker and Vanparet, 1985; Asrar et al., 1986; Sellers et al., 1988; Turner et al., 1992; Knick et al., 1997). In Argentina, Paruelo and Golluscio (1994) were able to successfully identify grass and shrub cover classes for dominant species functional groups from Landsat MSS data for use in a range assessment.

Remote sensing has also been applied to evaluate the impacts of grazing use and to identify rangeland condition or degradation (Mouat et al., 1981; McDaniel and Haas, 1982; Graetz et al., 1983; Graetz, 1987; Pilon, 1988; Uresk, 1990; Pickup et al., 1994;

Washington-Allen, 1999). In results from comparative studies, Graetz (1987) concluded that the weekly composited NDVI from the AVHRR sensor was adequate for pasture-level rangeland biomass estimates, but recommended Landsat TM data for evaluating soil erosion and landscape degradation. While the scale and resolution of the TM sensor has limitations for identifying the site-specific soil, vegetation, and hydrologic function attributes currently recommended as indicators of rangeland ecological health (USDI, 2000), other indicators that are measurable with moderate resolution multi-spectral data have been examined in rangeland health studies (Major et al., 1988)

The combination of aerial color-infrared photography with satellite multi-spectral imagery has proven useful for detecting various types of brush and invader species known to diminish the available grass forage production of rangelands and indicative of declining ecological stability (Tueller, 1989; Everitt et al., 1992; Everitt et al., 1995). Acquiring aerial photography corresponding with identifiable phenological stages is critical to the success of these investigations as some species are more readily identified during flowering or when the spectral signature of associated species might be diminished (Everitt and Villarreal, 1987; Myhre 1987; Everitt et al., 1992; Driscoll et al., 1997; Anderson et al., 1999; Everitt et al., 2001). For example, leafy spurge exhibited a distinguishing spectral response of higher visible reflectance in early summer (Everitt et al., 1995a), while redberry juniper was more easily distinguished from associated species in February (Everitt et al., 2001). Cover classes of Chinese tamarisk, also known as saltcedar, an introduced species that has invaded riparian areas throughout the western U.S., have been successfully identified and mapped using conventional color videography combined with field GPS data and GIS analysis techniques (Everitt et al., 1996).

In southeast Botswana, a maximum likelihood classifier was applied to MSS imagery from a 15-year period (1972-1987), and classes were used to assess changes in range condition from human and livestock populations during drought and non-drought periods (Ringrose et al, 1990). Pickup et al. (1994) was able to detect differing types of rangeland degradation by evaluating variations in average vegetation cover with distance from water as a function of seasonal and annual use and precipitation events. The patterns of change in vegetation cover estimated by MSS data were also successfully used to model cattle distributions and use intensity within specific landscape types (Pickup and Bastin, 1997), suggesting the potential for incorporating these models into decision support systems to improve the layout of pastures and water developments. In the United States, the Rangeland Analysis Geo-spatial Information Science (RANGES, 2000) program has used Landsat TM imagery in methods developed to assess rangeland condition for a pilot area in southern Arizona by providing estimates of the fractional cover, height, and weight of forage plants and shrubs.

The kinds and amounts of vegetative cover influence soil organic matter content, water holding capacity, permeability, and nutrient availability, all factors related to water infiltration, soil erosion, and evapotranspiration (Jenny, 1958; Brady, 2000). Consequently, remote sensing studies of rangeland condition have primarily focused on the ability of multi-spectral sensors to estimate cover, biomass, and species composition, with the understanding that changes in productivity and/or species composition are important indicators of rangeland degradation (Graetz et al., 1983; Turner and Dale, 1991; Paruelo and Golluscio, 1994; Palacios-Orueta et al., 1999). Methods to assess rangeland ecological health have also analyzed spectral properties that might be associated with reductions in soil quality and accelerated erosion because range condition or degradation is not always directly correlated with reduced levels of plant cover or growth (Ludwig, 1986; Washington-Allen, 1999). Soil organic matter content is closely related to soil quality, as it helps to regulate nutrient availability, and therefore is a useful indicator of soil erosion and rangeland degradation (Hassink et al., 1993; Brady, 2000). Differences in the relative amounts of exposed mineral soil have been distinguished (Smith et al., 1990; Todd and Hoffman, 1999) and used as an indicator of rangeland condition and degradation (Schlesinger et al., 1990). TM data, however, has demonstrated limited sensitivity to organic matter content (Coleman and Montgomery, 1987; van Deventer et al., 1997). A recently applied technique that shows promise for detecting degraded sites and monitoring change over time was the use of a moving standard deviation (MSDI) filter from the Landsat TM red band. Using this method, Tanser and Palmer (1999) were able to distinguish fence-line contrasts of rangeland with differing amounts of exposed soil and vegetation conditions for heterogeneous sites in South Africa.

Conclusions

Methods to characterize rangeland productivity and condition using remotely sensed data, although still primarily experimental, show significant potential for becoming standardized and incorporated into remote sensing guided inventory, assessment, and monitoring of rangeland productivity and ecological health. The information provided by satellite imagery, independent environmental data sets, and the spatial data analysis tools available with GIS and image processing computer software can help to provide consistent and accurate characterizations of rangeland environments. If combined with models that incorporate hierarchical levels of ecological process drivers, the need to identify ecological status and monitor change over time within an ecologically refined matrix of spectral groupings might also be met.

CHAPTER THREE

USING ECOLOGICAL UNITS IN MULTISPECTRAL ESTIMATES OF RANGELAND PRODUCTIVITY

Introduction

The need for affordable and robust rangeland survey, evaluation, and prediction tools is a subject of continuing concern for rangeland scientists (Graetz, 1987; Tueller, 1989; Walker, 1995; West and Smith, 1997; CAST, 2002; Hunt et al. 2003). Rangelands supply critical hydrologic and terrestrial ecosystem components for nearly one-half of the Earth's environments, and the resources they provide are vital to many local and national economies, giving these concerns global implications (Campbell and Lasley, 1969; Pearse, 1971; Holechek et al., 1989; Laurenroth, 1979).

The large, highly diverse, and remote physical expanses where rangelands often occur have posed a long-standing obstacle to the development of efficient, consistent, and spatially accurate methods to inventory rangeland productivity and ecological status (Asrar et al., 1986; Hunt et al., 2003). The inventory methods currently employed by rangeland managers are costly, labor-intensive, and time consuming; and are primarily limited to project level implementation (NRCS, 2000; Ritchie et al., 1992). In general these methods assume the established relationship between soil and site conditions, and vegetation productivity and species composition, as a basis for measures of overall rangeland productivity and ecological condition (Canfield, 1941; Eberhardt, 1978; Breckenridge et al., 1995). Consequently, they require extensive field sampling to collect biomass samples or ocular estimates of productivity, to classify site vegetation, and to evaluate site and soil stability.

As the basic principles of ecological process theory have been adopted by rangeland managers, inventory methods have come to rely on previously mapped and characterized ecological range units (ERUs) as a reference for comparisons between existing and potential site and vegetation attributes (West et al., 1994; NRC, 1994). Ecological unit mapping is an established method used to delineate unique geographic expressions of the environmental variables that control ecosystem processes and ecological differences at successively more refined scales. These mapping concepts have been incorporated into a variety of currently published landscape-level ecological map products (Bailey, 1983; Nesser et al., 1996; Omernick, 1987) that have been widely used in applications addressing global, regional, and local differences in vegetation types and productivity (Loveland et al., 1991; Homer and Gallant, 2001); analyzing the response of differing biophysical environments to natural and management related disturbance (Nesser et al., 2001); and providing a framework for biological assessments (Omernick, 1995; Cooper et al., 1999).

ERUs are the accepted ecological map unit scale for evaluating rangeland productivity and ecological status and are used to address the influence of environmental parameters such as climate, parent material, topography, and soils on site specific ecological potential (Shiflet, 1973; Laurenroth, 1979; NRCS, 1997; USDI, 2000). ERUs also form the controlling environment for measures of states and transitions intended to model the response of differing rangeland environments to natural disturbance and management practices (Westoby, 1989; Bestelmeyer et al., 2003; Stringham et al., 2003). At both landscape- and site-specific scales, ecological map units provide a useful template for efficient ecological inventories and ensuring that data analysis and interpretations are consistent with site potential differences (Nesser et al., 2001).

The potential of satellite and airborne remote sensing technology to support and improve rangeland inventories has been studied in a wide variety of rangeland ecosystems (Pearson and Miller, 1972; Graetz, 1987; Pickup et al., 1993; Bork, 1997; Washington-Allen et al., 1999; Bork et al, 1999; Everitt et al., 2001; RangeView, 2003; Tueller, 2001; Hunt et al., 2003). One of the primary goals of these experimental applications has been to provide reliable estimates of rangeland biomass, the driving information need behind many rangeland inventories. Spectro-radiometric data from various platforms, such as the Advanced Very High Resolution Radiometer (AVHRR), the Moderate-Resolution Imaging Spectroradiometer (MODIS), the Landsat Thematic Mapper (TM), and Landsat 7 Enhanced Thematic Mapper (ETM+) have been applied to estimates of rangeland biomass with varying levels of reliability (Tucker et al., 1983; Everitt et al., 1989; Tueller, 1987; Graetz, 1987 Anderson et al., 1993; Pickup, 1994; Bork et al., 1999). A recent study of rangeland in Montana found the weekly composited Normalized Differenced Vegetation Index (NDVI) from 1- km AVHRR imagery was able to account for 63% of the variability in green and senescent rangeland biomass for a variety of foothills and plains grassland sites (Thoma et al., 2002). Net primary productivity (NPP) algorithms derived from the MODIS sensor have further demonstrated the potential of satellite data to provide reliable regional estimates of rangeland productivity with improved spatial resolution over AVHRR indices (Reeves et al., 2001). Although the daily temporal frequency and weekly scene compositing of data from these sensors are advantageous, the 250 m to 1- km spatial resolution limits the site-specific ecological or management interpretations they can support.

Moderate resolution, multi-spectral Landsat satellite imagery has also been examined extensively as a source for providing rangeland inventory data (Maxwell, 1976; Graetz et al., 1983; McGraw and Tueller, 1983; Richardson et al., 1983; Pech et al., 1986; Anderson et al., 1993; Smith et al., 1990; Hunt et al., 2003). Applications using TM data, however, frequently encounter limitations posed by the 16-day overpass schedule and difficulties in adjusting for the differences between scenes in solar and atmospheric conditions (RangeView, 2003). Estimates of biomass using multi-spectral sensors such as the Landsat 7 ETM+ are also sensitive to variable percentages and types of exposed soil and to the differing amounts of green and senescent vegetation that are common to rangeland environments (Borel and Gerstl, 1994; Cippra et al., 1980; Elvidge and Chen, 1995; Huete et al., 1985; Mattikalli, 1996; Price, 1993). The influence of soil background variability on spectral response has been addressed by various modifications to ratio-based vegetation indices (Huete, 1988; Rondeaux et al., 1996; Qi et al., 1994) and band transformations (Kauth and Thomas, 1976; Crist and Cicone, 1984; Huang et al., 2002). The soil adjusted vegetation index (SAVI) (Huete, 1988) has been shown to provide equal vegetation index results for light and dark soil backgrounds in situations with reduced biomass (Major et al., 1990). The orthogonal, tasseled cap transformation (Crist and Cicone, 1984) has also been successfully used to distinguish between vegetation biomass and soil backgrounds (Graetz and Gentle, 1982; Todd and Hoffer, 1998). The use of independent data sets to account for site potential differences and soil background variability in estimates of rangeland biomass from multi-spectral imagery, however, has not been well explored in remote sensing studies at site-specific or landscape scales (West and Smith, 1997; Washington-Allen et al., 1999; Reeves et al., 2000).

The known relationship between ecological units and the variability in site, soil, and vegetation attributes suggests that ecological units might also be expected to explain a significant component of the variability in rangeland productivity as predicted by spectral response, thereby providing a tool for improving the efficiency of rangeland inventories by increasing the accuracy of remote sensing based estimates of rangeland vegetation. This study explored the use of landscape level ecological units and ERUs derived from spatially explicit site and soils data to account for the spectral variability of site properties and to address the influence of varying soil backgrounds on multi-spectral estimates of rangeland biomass. Using these previously mapped delineations in the sampling design and analysis allowed for environmental properties of known importance to inherent rangeland productivity and species composition differences (i.e., slope, aspect, drainage properties, parent material, climate) to be represented by one spatial theme, thus gaining efficiency over processing multiple spatial data sets to capture much of the same, yet less integrated, information.

To determine whether ecological unit differences influence biomass estimates, as measured by spectral response, Subsections and ERUs were tested with Landsat 7 ETM+ band combinations and vegetation indices as predictors in linear regression estimates of total biomass collected from a variety of heterogeneous rangeland environments. Previously published studies have established that regression on individual bands can explain more variability in vegetation response than regressions against band-ratioed indices, which are unable to represent the influence of the red and near-infrared (NIR) wavelengths independently (Lawrence and Ripple, 1998; Ripple, 1994). In spite of this inherent limitation, NIR/red ratio-based vegetation indices continue to be more widely applied than predictions using individual band combinations. To determine the bands, band combinations, or indices independently capable of explaining the greatest amount of rangeland biomass variability, regression results from individual bands and band combinations were compared with those from the Simple Ratio (SR), Normalized Differenced Vegetation Index (NDVI), the Soil Adjusted Vegetation Index (SAVI), and the tasseled cap greenness (GVI), wetness (WI), and brightness (BI). The models that best explained the variability in rangeland biomass were then used to evaluate the relationship between spectral biomass estimates and ERUs.

Methods

Field data for this study were collected from twenty-four ecological range units (ERUs) on five Montana ranches (Appendix A, Figures 1-6, Table 1). Each ranch was located within a different Landsat 7 ETM+ scene. Mean annual precipitation across the sites ranged from 250 – 480 mm and the topography varied from steep foothills to rolling plains with elevations between 460 and 1280 m. The dominant potential grassland vegetation ranged from wheatgrass-fescue-needlegrass to grama-needlegrass-wheatgrass.

Field samples were collected from random locations within each ERU. Sites that were inconsistent with their ERU classification or not of relatively homogenous site and vegetation attributes for at least a 900 m^2 area surrounding the plot were rejected. For each field sample biomass within a 0.75-m^2 area was clipped to ground level and ocular estimates of the percentage of exposed soil, plant community type, and soil surface characteristics were made. Biomass samples were dried and weighed. Field data for the 263 plots used in the analysis were collected over the period from 6 June 2000 to 14 August 2002. All field data were collected within 22 days of the corresponding Landsat ETM+ image date.

Thirteen Landsat 7 ETM+ scenes dating from June 8, 2000 to August 1, 2002 of the Level 1G NASA data product were used in the analysis. Geographic Information System (GIS) themes of ranch boundaries were used as a general perimeter for sub-setting the scenes. ERUs for the area within each ranch were generated from the Soil Survey Geographic Database (SSURGO) and the National Soil Information System (NASIS) data sets (NRCS, 2000). For the five ranches, 82 individual soil map units were aggregated to the 24 ERUs sampled. Published GIS themes for landscape level Section and Subsection ecological units (ECOMAP, 1993; Nesser et al., 1996) were spatially joined with ERUs and field data points. The digital numbers (DNs) for bands 1-5 and 7 were extracted for each sample point and used as individual band values and to calculate indices used in the regression equations.

The pixel to sample point method was used to allow for a precise identification of the sample point locations within the ecological unit polygons. One-meter resolution digital orthophotography (DOQQs) and 1:24,000 scale SSURGO soils themes were used as a cross-reference to identify point locations falling on pixel margins or polygon boundaries that required adjustment to the appropriate pixel; this affected less than 10 data points.

The SR and the NDVI were calculated from the red and NIR band values using the standard formulae of:

SR = Band 4/Band 3
NDVI = (Band 4 – Band 3)/(Band 4 + Band3)

Prior to calculating the SAVI and performing the Tasseled Cap transformation, the DN values for each of the 13 scenes were converted to exoatmospheric reflectance (Landsat 7 IAS Handbook, 2000). The following formula was used to calculate the SAVI:

SAVI = 1.5 ((Band 4 –Band 3)/(Band 4 + Band3 + 0.5))

Transformation coefficients developed for the Landsat 7 ETM+ sensor (Huang et al., 2002) were applied to calculate the tasseled cap BI, GVI, and WI values (Appendix C, Table 7).

A preliminary examination of the correlation between individual spectral bands and total biomass was conducted to compare linear relationships and evaluate the relationship between bands. A transformation of the response variable, total dry biomass, to the quarter root of field values was performed to meet the linear regression assumptions of homogeneity of variance and normality of residual distribution, following which a series of linear regression models were developed.

The first stage of the analysis included comparisons between four simple linear regression models each using transformed total biomass (TTB) as the dependent variable and the vegetation indices SR, NDVI, SAVI, and GVI as independent predictors. Next, a stepwise selection procedure using TTB regressed on the six individual TM bands (1-5 and 7) was conducted, and models using the tasseled cap BI, GVI, and WI estimates of TTB were developed. To account for the potential influence of between scene differences and differences between the image and field data collection dates, variables for each were introduced and tested for their importance. Comparisons between extra sums-of-squares F-test results were used to evaluate significant predictors and were used in conjunction with the analysis of variance (ANOVA) F-test comparisons between fitted models and the coefficients of determination (R^2) to evaluate the variability in biomass explained by the different models.

Following a preliminary analysis of 2000 data, a method to account for between scene and atmospheric differences (COST model) was tested using correction techniques for standardizing Landsat 7 ETM+ spectral data from scenes of varying dates and locations (Chavez, 1996). Results from other researchers studying rangeland biomass estimates from ETM+ data indicated that applying this technique to correct for radiometric and atmospheric differences between scenes might improve regression results (RangeView, 2003). This method both converts the DNs to reflectance and corrects for haze within the scene by using an image analyst selection of minimum band values in addition to the solar constants necessary for conversion to exoatmospheric reflectance (Appendix B). After applying this correction to each band, pixel values were extracted and models using corrected indices and band combinations as predictors of TTB were developed and compared with the results from models using uncorrected indices and combined band values.

Based on these comparisons, the models using transformed total biomass and uncorrected DN values for the NIR (0.75 – 0.90 μm) and mid-IR (2.09-2.35 μm) bands and the tasseled cap GVI and WI were selected for further testing in the second analysis phase with the introduction of Subsections and ERUs as categorical variables. Subsection and ERU categories were each introduced as predictor variables and evaluated within the models regressing TTB on ERUs and the NIR and mid-IR bands. The same procedure was again applied using Subsections, ERUs, and the GVI and WI.

Results

The application of the COST model for combined radiometric and atmospheric corrections (Chavez, 1996) did not result in significantly improved regression results over those obtained from the original DNs for the models using TTB and ratioed indices or the combined NIR and mid-IR bands, and did not eliminate or reduce the significance of the variable representing scene differences. As this correction technique requires the analyst to interpret and select target DNs within the scene that appear representative of surrogate "black bodies" represented in each spectral band, it was found to be somewhat subjective and not readily applied in a manner that could ensure consistency and repeatability of results. Based on these application issues and the results of model comparisons, additional development of models using these data sets was not pursued.

As single predictors in simple linear regression estimates of TTB the SR, NDVI, SAVI, and GVI were all significant independent variables (p-values all < 0.001), as were each of the six visible, NIR and mid-IR bands (p-values all < 0.01). The linear relationship between the red band (0.63-0.69 μm) and total biomass was reasonably strong (r= -0.58), and was also highly correlated to all other bands except Band 4, the NIR (0.75-0.90 μm); and most strongly (r=0.91) with the Band 7, the mid-IR (2.09 to 2.35 μm) region. The results of stepwise selection eliminated the red wavelength range from being included in the best fitting model and selected a combination of the NIR and mid-IR bands as the strongest predictors. When compared with models using the SR, NDVI, SAVI, or GVI, the near and mid-IR band model was able to explain more of the variability (52%) in TTB (Table 4).

Table 4. Simple linear regression models and coefficients of determination for estimates of transformed total biomass. *

Model	DN R^2	Reflectance R^2	COST Corrected R^2
SR	0.4577		
NDVI	0.4483	0.4117	0.4360
SAVI		0.4448	
GVI		0.4664	
GVI+WI		0.5109	
GVI+WI+SCENE		0.5342	
Band 4+Band 7	0.5269	0.5094	0.4756
Band 4+Band7+SCENE	0.5461		

* All variables and models significant at the p-value = 0.001 level.

The tasseled cap GVI +WI also explained a greater percentage of the variability in TTB (R^2=0.51, p-value <0.001) than any of the band ratioed indices, however brightness was not a significant predictor variable (p-value=0.9) for TTB when introduced with the WI and GVI. The difference in days between scene date and clip date did not exhibit a significant influence on the NIR and mid-IR band combination model (p-value = 0.6) nor was the GVI+WI model sensitive to this variable. The variability in TTB explained by the spectral response of these band combinations and indices was, however, influenced by scene differences.

Comparisons between the regression models combining spectral response with ecological unit and those using only the spectral response of the NIR and mid-IR band combinations, or the GVI and WI, in each case found the categories of site-specific ERUs and landscape level Subsections to be significant as main effects (p-value <0.001) and to result in better predictive models than those using spectral data alone (Table 5).

Table 5. Comparison of models using vegetation indices, ETM+ band combinations, and ecological range units (ERUs). *

Model	Multiple R^2	p-values
Band 4 + Band 7 + ERU + (Band 7 * ERU)	0.6631	B7*ERU interaction p-value = 0.03
WI + GVI + ERU + (GVI * ERU)	0.6500	GVI*ERU p-value = 0.05
NDVI + ERU + (NDVI * ERU)	0.6300	NDVI*ERU interaction p-value = 0.003
GVI+WI+ Subsection	0.5685	
Band 4 +Band 7 + Subsection	0.5783	

*All variables and models significant at the p-value <0.001 level unless otherwise specified.

The greatest percentage of variability in TTB (66%) was explained by using ERU categories combined with the NIR Band 4 (0.75 to 0.90 μm), and mid-IR Band 7 (2.09 to 2.35 μm), with an interaction term to address the relationship between Band 7 and ERU (R^2 = 0.6631). Comparable results were obtained by combining ERUs with the WI and GVI with an interaction between greenness and ERU (R^2 = 0.65) (Figure 9). Regression estimates were also improved by introducing the Subsection ecological units, increasing from 52% to 57% the variability in biomass explained by the NIR and mid-IR model. Estimates of TTB using the ERU and NIR and mid-IR model within individual scenes also confirmed the statistical significance of ERUs as a predictor. As indicated by the statistical significance of ERUs as independent predictors and the interaction between these categories and the mid-IR and GVI, the slopes of biomass estimates from these variables vary in combination with changes in ecological unit, influencing the variability in biomass explained by the regression estimates.

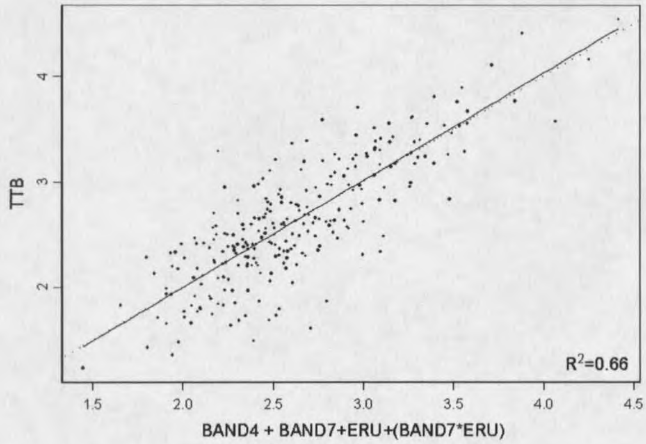


Figure 7. Scatter plot of total biomass on NIR, mid-IR, and ERU with regression line. Regression equations provided in Table 5.

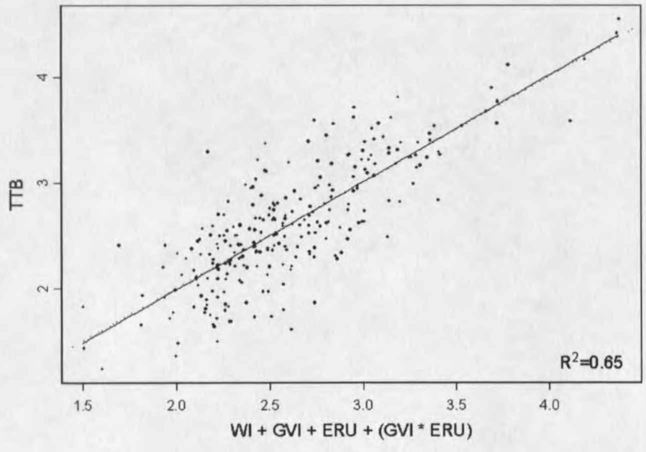


Figure 8. Scatter plot of total biomass on GVI, WI and ERU with regression line. Regression equations provided in Table 5.

Discussion

These results support the conclusion that stratification of spectral data by ERUs can improve linear regression predictions of relative rangeland productivity. Through the inclusion of ERUs, the variability of the population under study is refined, thereby reducing multi-spectral variability. The improved multi-spectral biomass estimates achieved by accounting for site and soil variability in this manner suggests the need to treat the spectral data within these delineations as distinct expressions of the vegetation/soils population, particularly in studies where an ecological framework for both image analysis and the application of interpretations is desired. As ERU categories are distinguished in part by soil differences, it is reasonable to assume that a portion of the additional variability in biomass explained by combining spectral response with ERUs is due to soil background reflectance. Since ERUs are also defined by their ability to support differing vegetation types, however, further study would be required to distinguish the spectral response differences due solely to the soil background reflectance differences between ERUs. The significance of ERUs when examined within individual scenes implies that the variability explained by ERUS addresses additional and different influences on spectral response than those associated with radiometric and atmospheric differences. A preliminary examination of regression estimates of biomass using spectral response and individual soil map units, the delineations from which ERUs are derived, demonstrated these categories were also significant as independent predictors and capable of further improving biomass estimates from spectral response. This suggests that in studies of more limited geographic scope, the use of individual soil map units to address soil background influences on spectral response would be beneficial. The scale and placement of the Subsection ecological units in relationship to scenes and study locations presented a difficulty in distinguishing between the variability in biomass explained by this level of ecological unit mapping and the uncorrected scenes. The estimates of biomass from the NIR and mid-IR and the GVI and WI models were however, improved by including Subsections categories.

The superior performance of the NIR and mid-IR bandwise model over the red and NIR ratio-based indices in estimating total rangeland biomass reinforces previous observations of the mathematical limitations of the NIR/red ratioed indices (Lawrence and Ripple, 1998). Likewise, the results indicating the GVI and WI to be more effective for predicting rangeland biomass than the NDVI or the other red and NIR ratioed indices adds support to questioning the reliance on traditional red and NIR ratio-based indices for estimating biomass under the conditions common to most rangelands. These results, indicating that a non-ratioed, two band combination can capture the greatest variability in rangeland biomass, are supported by observations of Australian rangelands (Graetz and Gentle, 1982). As previously observed (Lawrence and Ripple, 1998), the SAVI was also less sensitive to biomass variability than either the SR or the NDVI, which might suggest the standard adjustment factor used (0.5) was not appropriate for the diverse cover conditions of the sampled sites. In any event, the use of independent soils data in regression analyses might be a superior approach to accounting for soil variability over the use of soil-adjusted indices.

The combined influence of late season images and the predominance of field biomass measurements collected at times past the period of peak growth and photosynthetic activity are evidenced in the reduced predictive ability of the red and NIR ratioed indices and in the strength of the NIR and mid-IR regions in the bandwise regression results. Due to the conditions of extreme drought during the study, the vegetation present had low moisture content in all three field data collection periods, and vegetation production was well below average. These factors might have contributed to the failure of the red band to take on the predictive significance it commonly exhibits in vegetation studies. Conversely, the sensitivity of the mid-IR (2.08-2.35 μm) wavelength range to soil mineral content (Jensen, 1996) and to increasing amounts of senescent vegetation (Asrar et al., 1986), coupled with the unusually low soil moisture during the field-sampling period and high percentages of exposed soil or senescent vegetation on some sites, might have added to the enhanced influence of this spectral region. As much of the world's rangeland occurs in arid and semi-arid environments, often subject to periodic drought, with highly variable amounts of exposed mineral soil, these results further support the use of non-ratio spectral estimates of vegetation biomass in settings where the need to account for differing soil backgrounds is important.

The analysis methods and variables used in this study were able to account for up to two-thirds of the variability in green and senescent rangeland biomass across a wide variety of sites. Additional sources of variability might be attributed to radiometric, atmospheric, geo-referencing, or environmental influences. In this study, the GVI and WI are derived from radiometrically corrected data. As converting DNs to reflectance normalizes for illumination geometry, the model using these parameters accounted for a portion of the radiometric variability in spectral response that was not addressed by the uncorrected band combinations. While the variability in biomass explained by the NIR and mid-IR model was slightly higher, due to accounting for a portion of the radiometric variability, the tasseled cap GVI and WI model might indeed be superior. The correspondence of these indices with physical site features also provides interpretive advantages in estimating other parameters, such as soil moisture content, that are important to rangeland productivity.

The combined atmospheric and radiometric correction method applied (Chavez, 1996) did not produce improved results. While there is no lack of other atmospheric correction techniques and algorithms currently available for ETM+ data (Slater et al., 1985; Chavez, 1989; Moran et al., 1992), the difficulties encountered in acquiring appropriate atmospheric and ground data often discourage Landsat data users from applying atmospheric corrections (Huang et al., 2002). Within the objectives and constraints of this study the acquisition of source data required for other atmospheric corrections was not feasible.

A concerted effort was made to minimize geo-referencing error through close examination of data points following each image processing step. Given the grade of GPS equipment employed, NASA Level 1G image correction standards, the lack of additional image orthorectification to correct for terrain differences, and the mapping standard of the SSURGO, a limited number of data points might have been represented with incorrect pixel or ecological unit values, resulting in geo-referencing error and unaccounted for variability. Environmental factors such as precipitation events occurring in the time period between the image and field collection dates could have increased vegetation greenness or growth and reduced correlation with spectral response. Similarly, unreported grazing use, reducing field biomass, might have affected some data points, resulting in spectral values not fully corresponding with field conditions at the time of data collection. Accounting for these potential sources of variability in future studies would be expected to improve predictions of relative productivity.

Overall, these results indicate the use of non-spectral ecological unit data addresses important components of spectral variability and can provide a reliable and repeatable framework to support efficient, ecologically sensitive, remotely sensed inventories of rangeland productivity.

CHAPTER FOUR

A REMOTE SENSING DIRECTED METHOD FOR EVALUATING AND MONITORING RANGELAND

Introduction

The global importance of ecologically sustainable rangeland is well recognized (Graetz et al., 1986; Holocheck, 1988; Pickup et al., 1994; Walker, 1995; Eldridge and Freudenberger, 2000; Young and Clements, 2001; CAST, 2002). Rangeland ecological health, the accepted measure of ecological sustainability for rangelands, has been defined as, "the degree to which the integrity of the soil and ecological processes of rangeland ecosystems are maintained" (NRC, 1994). The ecological health and sustainability of rangeland used for livestock grazing requires effective management, which is dependent upon accurate and timely inventory data to support assessment and monitoring (Graetz, 1987; West and Smith, 1997). Systematic and spatially accurate techniques for consistently evaluating rangeland ecological health over large geographic areas have been slow to emerge and are not yet available, due to many practical and institutional obstacles (NRC., 1997; West and Smith, 1997; Tanser and Palmer, 1999; Washington-Allen et al., 1999; Hunt et al., 2003).

Current rangeland inventories are limited to project specific areas and employ the standardized similarity index (SI) method to make comparisons between field mapped productivity and vegetation community composition with that established for ecologically similar reference range sites (Jacoby, 1974; NRCS, 1997). This method requires on-site clipping or ocular estimates of field plot biomass to measure productivity and assigns a percentage class and similarity index to the current plant community and site properties to identify locations where use and/or management changes are needed.

A second, recently introduced, yet unrelated, technique for interpreting indicators of rangeland health is also now in limited use (USDI, 2000). This system indexes the condition of ecological rangeland sites based on ratings for 17 indicators of soil and site stability, biotic integrity, and hydrologic function that are intended to represent the basic parameters of ecosystem process drivers (Appendix C, Table 10). This is a time and labor-intensive method, costing an estimated \$500.00 – \$800.00 per site for field data collection (Hunt et al., 2003; Harrison, pers comm., 2003). Although detailed, site-specific data are provided by this method, it has not been demonstrated practically or economically feasible to employ as an overall inventory system. The successful application of either the similarity index or the ecological health indicator method requires the use of existing ecological range unit (ERU) maps and site data attributes to stratify sampling and interpret plot level data (NRCS, 1997).

Worldwide, spectral data from the Landsat Multi-spectral Scanner (MSS), Thematic Mapper (TM), and Enhanced Thematic Mapper Plus (ETM+) sensors have been available and tested as a potential information source for rangeland inventories for over 30 years. Varying levels of success in providing estimates of rangeland cover, biomass, and species composition have been achieved by using individual spectral bands, band combinations, and vegetation indices (Graetz et al., 1983; Anderson et al., 1993; Paruelo and Golluscio, 1994; Palacios-Orueta et al., 1999; RangeView, 2003; Thoma et al., 2002). Multi-spectral imagery, aerial photography, and videography have also been used to identify the presence of selected invasive plant species often associated with declining ecological stability (Tueller, 1989; Everitt et al., 1992; Everitt et al., 1996; Driscoll et al., 1997; BLM, 2000; Everitt et al., 2001). Ratio based multi-spectral vegetation indices commonly used for remote sensing estimates of biomass and cover are also sensitive to the spectral response of exposed soil - an important ecological health indicator (Guyot and Gu, 1994; Todd et al., 1998; Bork, 1999; Washington-Allen, 1999; BLM, 2000). Decreases in cover and productivity and changes in species composition are important indicators of biotic integrity and justify the use of these variables in both ground-based and remote sensing studies of rangeland condition. Impaired or degraded range condition, however, is not always directly correlated with reduced vegetative cover or productivity (Ludwig, 1986, Bork, 1997), which limits the reliability of vegetation attributes as primary indicators of ecological health status (Tanser and Palmer, 1999). This limitation reinforces the importance of accounting for soil background variability in remote sensing directed rangeland health studies.

The level of detailed species and community type identification required for similarity index interpretations is not considered to be within the current or anticipated future capability of moderate resolution multi-spectral satellite systems (Hunt et al., 2003). Further, many of the detailed site attributes required by the rangeland ecological health indicators are not detectable with the spatial and spectral resolution of ETM+ data. For example, TM data is not directly sensitive to organic matter content (Coleman and Montegomery, 1987; van Deventer et al., 1997). The content of soil organic matter helps to regulate nutrient availability and is closely related to soil quality, litter movement, and soil surface resistance to erosion - all important rangeland ecological health indicators (Karlen and Stott, 1994; Dormaar and Willms, 1998; Brady, 2000; USDI, 2000). Spectral response, however, is highly correlated with differences in the relative amounts of exposed soil (Smith et al., 1990a; Todd and Hoffman, 1999), and increases in the extent and distribution of soil heterogeneity have been used to indicate declining ecological stability in rangelands (Schlesinger et al., 1990; Turner and Gardner, 1991).

Spatial data analyses using standardized geographic information system (GIS) themes such as soil maps, digital elevation models, and hydrography are now recognized as valuable rangeland inventory tools. Models using slope, distance to water, and the distribution of potential vegetation types have been used to calculate carrying capacity and evaluate livestock use patterns (Holecheck, 1988; Hunt et al., 2003). In limited experimental situations, remote sensing data have also been combined with relevant GIS themes to detect changes in rangeland condition, but standardized methodologies have not been introduced and made available to rangeland managers (Creque et al., 1999; Washington-Allen, 1999; RangeView, 2003; Tueller, 2001; Ranges, 2000). This is due in part to the difficulties researchers have faced in acquiring consistently formatted, appropriately scaled, electronic, environmental data that could be readily incorporated into their image analysis models. The recent availability of the standardized Soil Survey Geographic Database (SSURGO) and the National Soil Information System (NASIS) digital soil map and attribute databases produced and distributed by the U.S. Department of Agriculture's Natural Resource Conservation Service (USDA, NRCS) reduces that obstacle (NRCS, 2000). These products provide a much-needed set of geo-spatially certified, nationally standardized, ecological site data necessary for rangeland inventory (NRCS, 1997). Ecological range units (ERUs), representing unique geographic expressions of environments with differing soil properties and potential vegetation types, can be generated from the SSURGO polygon and attribute data, and an ecologically sensitive, spatial template for image analysis generated. As these map units are the accepted ecological delineations for field-based rangeland inventories, they also provide a valid framework for testing remotely sensed directed ecological health evaluations.

Multi-spectral estimates of vegetation biomass and cover often rely on the Normalized Differenced Vegetation Index (NDVI) or its soil-adjusted derivatives (Rouse, 1973; Walsh, 1987; Huete, 1988; Pilon, 1988; Qi et al., 1994). The 'tasseled cap', orthogonally transformed, MSS and TM indices have also been successfully used to estimate cover and biomass and to identify rangeland sites exhibiting signs of degradation (Graetz and Gentle, 1982; Stella et al., 1993). The tasseled cap brightness component (BI) has been demonstrated sensitive to differing soil backgrounds (Todd and Hoffer, 1998), and positively correlated with changes in amounts of exposed soil due to decreased green vegetation (RangeView, 2003). The use of a moving standard deviation index (MSDI) and the red wavelength (0.63-0.69μm) to successfully detect differences between rangeland in acceptable or degraded condition (Tanser and Palmer, 1999) suggested a benefit to further exploring the analytical concept of a standard deviation threshold to identify distinctions between ecological health categories. Results reported in the previous chapter indicated linear regression estimates of rangeland biomass using the tasseled cap greenness (GVI) and wetness (WI) were superior to those using the NDVI or the soil adjusted vegetation index (SAVI). They also demonstrate that addressing soil variability using spectrally independent ecological range unit categories, combined with Landsat 7 ETM+ data, can further improve relative productivity predictions.

The primary objective of this study was to develop and test a satellite-based (Landsat 7 ETM+), remote sensing directed method for spectrally identifying sites within the range of average field conditions for each ERU. If demonstrated reliable and easily deployed, such a method might substantially reduce the time and effort required to conduct rangeland inventories by remotely identifying locations within the acceptable parameters for the selected ecological health indicators. Conversely, it could also provide an identification of spectrally anomalous sites, possibly indicative of anomalous ecological health status and requiring intensive field inventory. Such a system would, at the very least, help to establish a baseline characterization of current site attributes and spectral classes that might be used in the future development of spectrally sensitive assessment and monitoring of ecological health indicators.

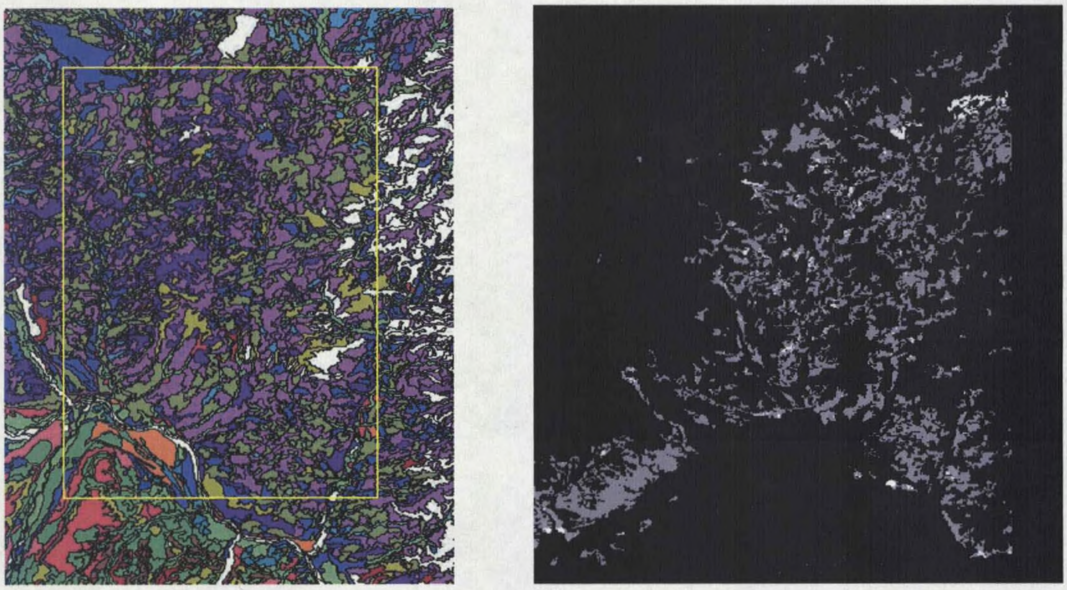
To accomplish this objective a landscape and site level screening process was designed to test whether the spectral means of the tasseled cap BI, GVI, and WI components for pixels within individual ecological range units could be used as a reference threshold for selected field indicators of biotic integrity (relative productivity) and soil/site stability (exposed soil surface). The established relationship between productivity and ecological health and the influence of soil background on spectral productivity estimates justified testing these indices in a spectral screening procedure.

The sensitivity of the tasseled cap indices to the physical site parameters of soil reflectance and amounts of green vegetation biomass, along with the design of the tasseled cap transformation, which results in brightness as the primary axis and greenness as the secondary axis, suggested these indices might be well suited as spectral indicators of the selected rangeland health parameters (Kauth and Thomas, 1976; Crist and Cicone, 1984; Huang et al., 2002). The inverse relationship between the amount of exposed soil and vegetation biomass on a given site, yet the inherently different ecological health information each variable provides, implied that this relationship might be exploited by using relative productivity and exposed soil as indicator variables (Washington-Allen, 1999; BLM, 2000). The previously demonstrated ability of the ERU categories to refine spectral distinctions of soil variability and improve spectral productivity estimates reinforced the value of examining the relationship between spectral response and rangeland ecological health status within an ecological unit template.

Methods

Twenty-four ERUs distributed across five Montana ranches formed the primary sampling and analysis units of this study (Appendix A, Figures 1-6, Table 1). Field data collected from 263 randomly located .75 m^2 plots included measurements of total dry biomass and percentages of exposed soil.

For each of the five ranches, subsets of Landsat 7 ETM+ scenes were created using GIS coverages of the ranch boundaries. To reduce the potential bias that could result from analyzing only sites within homogenous management types, the study areas fully incorporated each ranch with the perimeter buffered by 3-5 km in all directions. ERU polygons within each study area were generated from the published SSURGO data by aggregating individual soil map units to the 24 unique ERUs represented. These geographically unique polygons were used in all subsequent image processing and analysis steps (Table 9). Each of the 13 ETM+ scenes analyzed, dating from June 2000 to August 2002, was converted to exoatmospheric reflectance and transformed to the tasseled cap components using the Landsat 7 ETM+ coefficients (Huang et al., 2002) (Appendix B, Table 6; Appendix C, Table 7).



a) b)

Figure 9. a) Ecological range unit (ERU) polygons for Subsection 331Ga study area.
b) The multiple non-contiguous polygons of one ERU in the example study area.

To develop this experimental screening process, a normal distribution of BI, GVI, and WI pixels within each ERU was assumed, and the use of a selected standard deviation level (SSDL) for identifying the distribution and location of spectrally non-anomalous and anomalous pixels was tested by using sensitivity thresholds that could be adjusted based on the spectral sensitivity to field conditions indicated by the results. Field data and scenes from June 2000 to August 2000 were initially examined using sensitivity thresholds of one and two standard deviations from the spectral mean in both positive and negative directions for each of the BI, GVI, and WI components. After examining these results, to continue testing the methodology, an SSDL of 1.5 standard deviations from the mean was selected and used in the image classification model developed to assign pixels to anomalous or non-anomalous spectral categories.

Pixels within each ERU were classified into one of 27 categories representing all possible anomalous and non-anomalous combinations of the BI, GVI, and WI (see Appendix C, Table 8). This procedure resulted in a series of images, one for each ERU of each study area, for each image date, with non-anomalous pixels classified into one of the twenty-seven categories and anomalous pixels into the twenty-six remaining classes. Given the nature of the ecological range site map units, each of the subsequent fifty-nine images contained multiple, non-contiguous, complex polygons of the classified image data (Figure 9b, Appendix C, Table 9).

To assess spectral class accuracy with ecological health parameters, field data points for the 263 samples collected from June 2000 to August 2002 were analyzed in a classification matrix according to tasseled cap categories. Field measurements of total biomass and percentages of exposed soil were compared with spectral class assignments for anomalous and non-anomalous sample points. A classification accuracy assessment was performed to determine whether non-anomalous points were non-anomalous for field biomass and exposed soil values. The class accuracy for field data applied values within one standard deviation of the mean for productivity and exposed soil. Surface soil characteristics, presence of invasive species, and published attribute values for plant community productivity characteristics were used as ancillary field attributes. Published estimates of plant community productivity in the NASIS database included ranges for the categories of "favorable," "average," and "unfavorable" years, which are meant to correspond primarily with annual precipitation for the growing season. Since extreme drought conditions persisted in all study locations during the field sampling periods (2000-2002), the published ranges for "unfavorable" were used.

Results

Results indicated the two standard deviation threshold to be an overly inclusive representation of average field productivity and exposed soil conditions and overly exclusive for anomalies - capturing primarily rock outcrop and water bodies. The use of one standard deviation as a sensitivity threshold resulted in an improved overall identification of mean sites. It also resulted, however, in numerous data points within the mean of field conditions being misclassified as anomalous. Of the 263 sample points collected over the three-year period, 191 or 72% occurred within non-anomalous pixels for each of their respective ERUs and image dates. The remaining 72 field data points (28%) were located in anomalous pixels within 14 of the 26 other possible BI, GVI, and WI combinations and 15 of the ERUs. Sample data points did not occur in 12 of the 27 possible classes (Appendix C, Table 8).

For pixels classified as non-anomalous, three data points exhibited site attributes that were outside the range of average values for either productivity or exposed soil for their respective ERU and were determined to be misclassified. In one instance, vegetation on the site was dominated by Russian thistle (*Salsola kali*) and productivity was within the ERU average, however, a higher than average percentage of exposed soil was present (85%) and surface soil compaction was observed. The two other non-anomalous points determined to be misclassified exhibited exposed soil percentages within the average range, yet lower than average biomass productivity at the time of sampling. Both were located in areas that had undergone grazing use between the image and field collection dates.

Based on the criteria, one data point classified as anomalous was found to be within average values for both productivity and exposed soil. An examination of the individual BI, GVI, and WI component values for this pixel indicated the GVI was slightly under the 1.5 standard deviation threshold for the associated ERU, yet site productivity was within the mean. The classification accuracy assessment performed on the anomalous and non-anomalous categories resulted in an overall accuracy of 98.4%, for both anomalous and non-anomalous classes (Table 9).

Table 10. Error matrix for tasseled cap classification of non-anomalous and anomalous spectral categories.

Classified Data	Reference Data		
	Anomalous	Non-Anomalous	Row Total
Anomalous	71	1	72
Non-anomalous	3	188	191
Column Total	74	189	263

Producer's Accuracy	User's Accuracy
Anomalous = 71/74 = 95.9 %	Anomalous = 71/72 = 98.6 %
Non-anomalous = 188/189 = 99%	Non-anomalous = 188/191 = 98.4%

Overall Accuracy = (71+188)/263 = 98.4%
$K_{hat} = 0.96$

Field data for exposed soil percentages within all ERUs for pixels in the non-anomalous category ranged from 0 to 50% with an overall mean of 15%. Based on the published ranges for plant communities from the ERUs examined in this study, this overall range and those for individual ERUs were within the values for sites in similarity index classes representing fair to good ecological health conditions (NRCS, 1997).

A detailed examination of individual classes and field attributes indicated that field data points (n = 8) within image anomaly classes representing low brightness combined with greenness and wetness above or within the SSDL were distributed between seven ERU categories and exhibited higher than average relative productivity and lower than average exposed soil percentages (<0.05%) within their respective ecological range units. Included in these were sites where native rangeland had been converted to cultivated alfalfa and crested wheatgrass and locations with inclusions of shrub communities within ecological range sites otherwise dominated by grass communities (Figure 11). Productivity on sites within the anomaly class representing low brightness, high greenness, and high wetness ranged from 2000 to 3000 kg/ha, and substantial amounts of litter were observed.

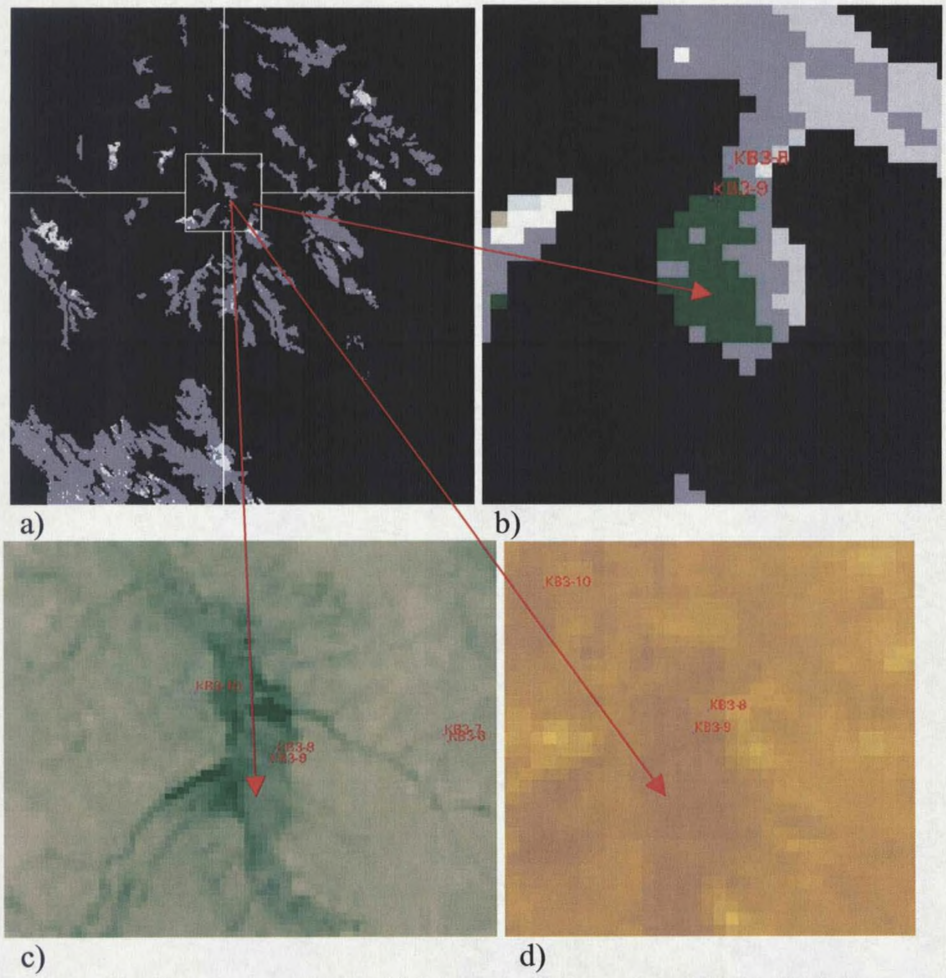
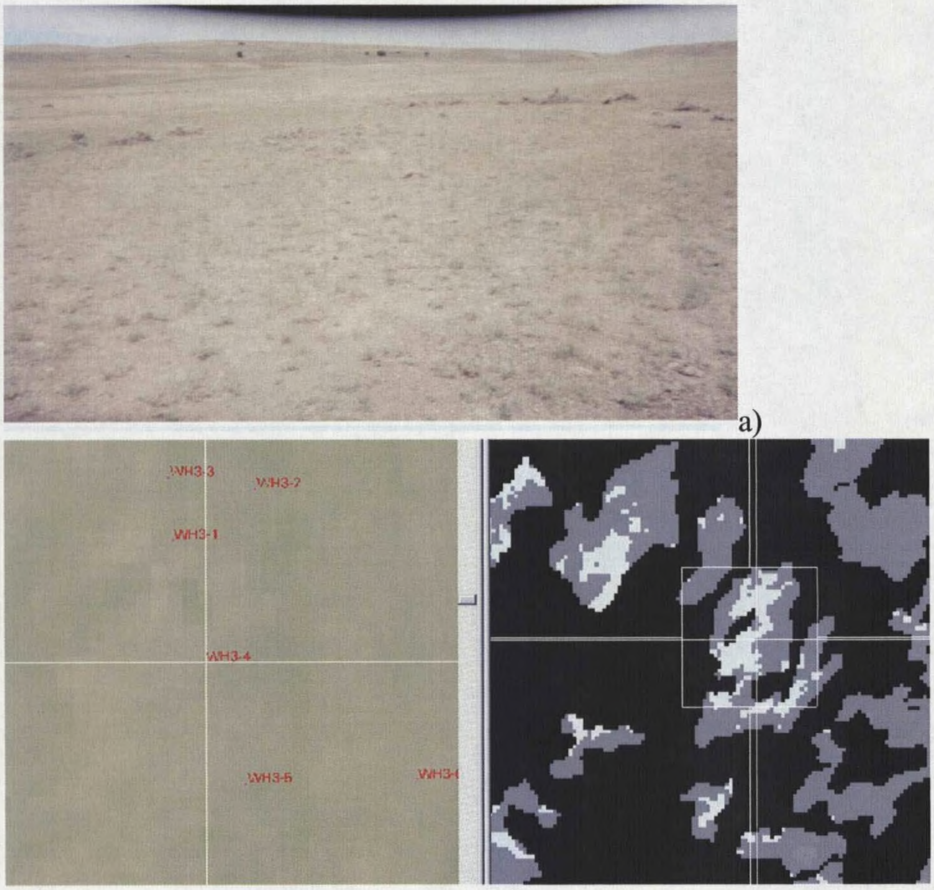


Figure 10. a) An example ERU image in Subsection 331Gc. b) Close-up of sample area within classified ERU with brightness < SSDL and greenness and wetness >SSDL. c) The greenness component of the classified ERU image in the example location. d) The brightness component of the classified ERU image in the example location.

Figure 11. Field conditions within example anomaly class with brightness <SSDL and greenness and wetness >SSDL.

Anomaly classes characterized by brightness values within the SSDL combined with greenness and wetness below or within the SSDL (n = 14) had consistently less than average productivity for the eight ERU categories represented and exposed soil ranging from 35% to 80%. Spectral classes also characterized by brightness values within the SSDL but contrasted with greenness and wetness within or greater than the SSDL (n = 23) were distributed among 10 ERUs. These sample points had above average productivity, and exposed soil percentages within the average for their ERU. Data points within this group of classes included riparian or shrub community inclusions and sites with limited or no grazing use.

A final group of anomalous spectral classes with distinct field characteristics was observed (n = 26). These classes were distinguished by having brightness values greater than the SSDL combined with greenness and wetness values below or within the SSDL. Field data points within these classes were found in 10 of the 24 ERUs. These points were characterized by low productivity (overall average 375 kg/ha) and higher than average percentages of exposed soil (>60% overall) for their respective ERU categories. Within the class representing high brightness and greenness within the SSDL and wetness less than the SSDL (n = 19), nearly half of the sites (47%) were within a single ERU from one of the five study areas. Sites within this group of spectrally anomalous classes included prairie dog towns, locations with active soil erosion, and locations within pastures with concentrated grazing use (Figure 12).



a)

b) c)

Figure 12. a) An example site within the anomaly class of brightness >SSDL and greenness within SSDL and wetness <SSDL. b) The greenness component for the example anomaly area. b) A close-up of the ERU anomaly image for the example area with brightness > SSDL.

Discussion

This remotely sensed screening of rangeland conditions successfully identified, with a high level of accuracy, sites within the range of average values for ecological health indicators representing relative productivity and site/soil stability. The reliability of this method over highly diverse rangeland environments suggests it has the potential to improve the efficiency of rangeland inventories. By spectrally identifying sites within acceptable ranges for key indicators of biotic integrity and soil and site stability field inventory efforts can be prioritized by status and location, the value of the field data collected can be enhanced, and areas of management concern might be identified more quickly and consistently.

This method accounts for site potential and spectral response differences by making comparisons between spectra and field conditions within locations expected to have similar soil backgrounds and vegetation types (ERUs). This enables linking spectral response to distinctions between these units in sensitivity and resiliency and with differing responses to natural and management related use and disturbance (Blum, 1996; Bestelmeyer et al., 2003). With this information, the land manager can be better equipped to evaluate current management or the management changes necessary to improve ecological health in the context of site potential.

The sensitivity of this spectral analysis method to site distinctions in soil background and relative productivity allows the remote sensing scientist the flexibility to refine the spectral sensitivity thresholds of each component and gives the range manager the opportunity to adjust field class parameters to further distinguish site differences. It also provides a consistent baseline of spectral and site data that can be used for monitoring change over time. Highly productive or under-utilized sites can be easily identified and assessed in relationship to adjacent use and management patterns. Images from different dates can be compared using the same spectral criteria and field parameters to detect the changes over a growing season and between years that are needed for a monitoring strategy.

By accurately screening sites of average productivity and soil/site stability within ERUs, this method identifies sites outside the range of average conditions for the selected indicators, where more extensive field evaluation might be required. The remote identification of locations needing comprehensive site evaluations could greatly increase the efficiency of the land managers' field time. The differences observed in the selected indicators of rangeland health status for spectrally anomalous and non-anomalous classes of the BI, GVI, and WI within ecological range sites imply that with further experimentation of the spectral sensitivity thresholds for these components, this spectral screening procedure could also accurately identify unique rangeland ecological health status categories. For example, of the field data points located in anomalous pixels distinguished by brightness values greater than the SSDL, nearly all met the field criteria of "poor condition" - suggesting this method has the potential to screen for sites at risk of degradation. Inventory results from this method, which distinguish between non-anomalous and anomalous sites based on repeatable spectral measurements, might also be considered more robust and defensible than those using the similarity index or the ecological health indicators, both of which partially rely on subjective ratings of field parameters and can result in different interpretations between observers.

Over the past decade, precision agriculture techniques have evolved to adopt the use of remote sensing data, geographic positioning system (GPS) guided field equipment, and digital soil and site mapping to evaluate productivity and site stability and improve the efficiency, accuracy, and ecological sensitivity of farming practices. Rangeland managers, whose resource information questions must be answered for physically large, highly diverse, and often remote locations, have previously lacked the image and spatial data analysis tools needed to provide the information for addressing these questions. This rangeland condition spectral screening method demonstrates the ability to provide accurate site and spectral distinctions and baseline information that might be used to answer rangeland condition questions and support the advancement of precision ranching methods.

CHAPTER FIVE

CONCLUSIONS

The ecological and spectral complexity of rangeland environments present numerous challenges to measuring relative rangeland productivity and condition from moderate resolution multispectral satellite data. The importance of analyzing spectral variability within ecologically sensitive parameters to improve these characterizations has been demonstrated by the results of this investigation. The use of non-spectral representations of repeatable and spatially explicit environmental parameters known to influence biophysical site potential has been shown to identify categories that are also spectrally distinct, thus reinforcing the importance of using ecological units in remote sensing applications intended to address the productivity, condition or ecological health of rangelands. These methods can be used to help identify locations where field conditions are not within average values for indicators of biotic integrity or soil and site stability for mapped ecological range units. This implies that significant time and cost efficiencies can be gained by implementing this remote sensing guided method, based on ecological range units, to design field data collection, analysis, and interpretation strategies. By implementing this screening method and the preliminary identification of site and spectral properties it provides, the need for comprehensive field sampling might be reduced and rangeland inventories conducted within condensed time frames. With further experimentation of adjustments to the selected standard deviation level (SSDL) and field parameter thresholds, the attributes of other ecological health indicators might also be associated with non-anomalous and anomalous spectral classes. If successful, this might lead to the development of an even more robust management tool that would allow rangeland managers to identify and prioritize sites requiring specific management strategies to enhance, improve, or maintain productivity and ecological stability.

In the course of this study, limitations in current image processing software were encountered and a need identified for technological improvements in the capabilities of image processing software to analyze image raster data within complex polygons having multiple attributes. The spatial resolution of the imagery was also observed to limit the geographic precision at which ecological unit delineations could be represented, although the spectral resolution provided meaningful detail. This suggests a need for research, development, and deployment of satellite sensors with higher spatial resolution combined with the spectral band properties of the ETM+ sensor.

The results of this investigation and countless others have provided a strong foundation for the direction of future investigations using remotely sensed data to characterize rangelands. While rangeland managers struggle with the complexities of interpreting and manipulating ecological and management interactions, it is the responsibility of remote sensing scientists to respond with their best efforts to analyze these complexities and determine the relevant information and interpretations that spectro-radiometric data might contain. There might never be a more pressing time in human history for the issues of ecologically sustainable land management to be addressed. The excesses of generations and the consequences of naïve choices have impacted the basic composition, structure, and function of many of the Earth's ecosystems. To scientists in pursuit of meaningful problems to analyze, those pertaining to the ability of our own planet's physical and biological resources to sustain its human population must be viewed as both pressing and necessary.

LITERATURE CITED

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Aber, J.D., and J. Meillo. 1991. Terrestrial Ecosystems. Saunders, Philadelphia, Penn.

Allen, T.F.H., and T.B. Starr. 1982. Hierarchy, Perspectives for Ecological Complexity. University of Chicago Press, Chicago, Illinois.

Allen, B.H., and D.V. Diaz. 1989. Federal and state site classification: two approaches with common goals. pp. 250-252 in: D.E. Ferguson, P. Morgan, and F.D. Johnson, compilers. Proceedings; Land Classifications Based on Vegetation: Applications for Resource Management. November 17-19, 1987, Moscow, ID. USDA Forest Service General Technical Report INT-257 Intermountain Forest and Range Expt. Sta., Ogden, Utah.

Anderson, K.L., and C.L. Fly. 1955. Vegetation-soil relationships in Flint Hills bluestem pastures. Journal of Range Management, 8:163-169.

Anderson, G.L., J.D. Hanson, and R.H. Haas. 1993. Derived vegetation indices for estimating above-ground biomass on semiarid rangelands. Remote Sensing of Environment, 45:165-175.

Anderson, G.L., C.W. Prosser, S. Haggar, and B. Foster. 1999. Change detection of leafy spurge infestations using aerial photography and geographic information systems. Proceedings of the 17th Biennial Workshop Color Aerial Photography and Videography in Resource Assessment (P. Tueller, editor), 05-07 May, Reno, Nevada, (American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland), pp. 223-230.

Asrar, G., E.T. Kanemasu, R.D. Jackson, and P.J. Pinter. 1985. Estimation of total above-ground phytomass production using remotely sensed data. Remote Sensing of Environment, 17:211-220.

Asrar, G., R.L. Weiser, D.E. Johnson, E.T. Kanemasu, and J.M. Killeen. 1986. Distinguishing among tallgrass prairie cover types from measurements of multi-spectral reflectance. Remote Sensing of Environment, 19:159-169.

Asrar, G., R.B. Mynemi,.Y. Li, and E.T. Kanemasu. 1989. Measuring and modeling spectral characteristics of a tall-grass prairie. Remote Sensing of Environment, 27:143-155.

Bailey, R.G. 1976. Ecoregions of the United States. Map (scale 1:7,5000,000). Ogden, Utah: U. S. Dept. of Agriculture, Forest Service. Intermountain Region.

Bailey, R.G. 1983. Delineation of ecosystem regions. Environmental Management, 7:365-373.

Bailey, R.G. 1987. Suggested hierarchy of criteria for multi-scale ecosystem mapping. Landscape and Urban Planning. 14:313-319.

Bailey, R.G. 1996. Ecosystem Geography. Springer-Verlag Inc., New York, N.Y.

Baret, F., G. Guyot, and D. Major. 1989. TSAVI: A vegetation index which minimizes soil brightness effects on LAI and APAR estimation. 12th Canadian Symposium on Remote Sensing and IGARSS'90, Vancouver Canada, 10-14 July 1989.

Baret, F., and G. Guyot. 1991. Potentials and limits of vegetation indices for LAI and APAR assessment. Remote Sensing of Environment, 35:161-173.

Baret, F., S. Jacquemoud, and J.F. Hanocoq. 1993. The soil line concept in remote sensing. Remote Sensing Reviews, 7:65-82.

Baret, F., J.G. Clevers, and M.D. Steven. 1995. The robustness of canopy gap fraction estimates from red and near-infrared reflectances: A comparison of approaches. Remote Sensing of Environment, 54:141-151.

Bell, H.M. 1944. Range Handbook, U.S.D.A. Soil Conservation Service, Western Gulf Region, Fort Worth, Texas. Mimeo, pp 352-356.

Benedetti, R., and P. Rossini. 1993. On the Use of NDVI profiles as a Tool for Agricultural Statistics: The Case Study of Wheat Yield Estimate and Forecast in Emilia Romagna. Remote Sensing of Environment, 45:311-326.

Bestelmeyer, B.T., J.R. Brown, K.M. Havstatd, R. Alexander, G. Chavez, and J.E. Herrick. 2003. Development and use of state-and-transition models for rangeland. Journal of Range Management, 56:114-126.

Blaikie, P., and H. Brookfield. 1987. Land Degradation and Society. Routledge, London.

Blum, W.E.H. 1994. Soil Resilience-General Approaches and Definition. Transact. 15th World Congr. Soil Sci. 2a, 233-237, Acapulco, Mexico.

Borchard, D., P. Legendre, and P. Drapeau. 1992. Partialling out the spatial component of ecological variables. Ecology, 73:1045-1055.

Bork, E.W. 1997. Rangeland condition assessment using high spatial and spectral resolution remote sensing. Ph.D. Dissertation, Dept. of Rangeland Res., Utah State University, Logan, Utah.

Bork, E.W., and S. J. Werner. 1999. Viewpoint: Implications of spatial variability for estimating forage use. Journal of Range Management, 52:151-156.

Bork, E. W., N.E. West, K.P. Price, and J.W. Walker. 1999. Rangeland cover component quantification using broad TM and narrow-band (1.4 nm) spectrometry. Journal of Range Management, 52:249-257.

Borel, C.C., and C. Gershal. 1994. Nonlinear spectral mixing models for vegetative and soil surfaces. Remote Sensing of Environment, 47:403-416.

Bowers, S.A., and R.J. Hanks. 1965. Reflection of radiant energy from soils. Soil Science, 100:130-138.

Brady, N.C., and R.R. Weil. 2000. Elements of the Nature and Property of Soils. Prentice Hall, Upper Saddle River, New Jersey.

Bray, J.R., and J.T. Curtis. 1957. An ordination of the upland forest communities of southern Wisconsin. Ecological Monographs, 27:325-349.

Bray, R. J. 1958. Notes Toward an Ecologic Theory. Ecology, 39:770-776.

Breckenridge, R.P., W.G. Kepner, and D.A. Mouat. 1995. A process for selecting indicators of rangeland health. Environmental Monitoring and Assessment, 36:45-60.

Campbell, J.R., and D. Lasley. 1969. The science of animals that serve mankind. McGraw-Hill, Inc. New York, N.Y.

Canfield, R. 1941. Application of the line interception method in sampling range vegetation. Journal of Forestry, 39:388-394.

Carneggie, D.M., B.J. Schrumpf, and D.M. Mouat, 1983. Rangeland applications. Manual of Remote Sensing (R.N. Colwell, ed.), American Society of Photogrammetry, Falls Church, Virginia, 2:2325-2384.

CAST. 2002. Issue Paper: Environmental Impacts of Livestock on U.S. Grazing Lands. Council for Agricultural Science and Technology, Krueger, W.C., M.A. Sanderson, M.A., (eds.) Number 22.

Chavez, P.S., Jr. 1989. Radiometric calibration of Landsat Thematic Mapper multi-spectral images. Photogrammetric Engineering and Remote Sensing, 55:1285-1294.

Chavez, P.S., Jr. 1996. Image-based atmospheric corrections - Revisited and improved. Photogrammetric Engineering and Remote Sensing, 62:1025-1036.

Cihlar, J., and R. Protz. 1973. Surface characteristics of mapping units related to aerial imagery of soils. Can. J. Soil Sci., 53:249-257.

Cihlar, J., L. St.-Saurent, and J.A.Dyer. 1991. Relation between the normalized difference vegetation index and ecological variables. Remote Sensing of Environment, 35:279-298.

Cipra J.E., D.P. Franzmeier, M.E. Bauer, and R.K. Boyd. 1980. Comparison of multi-spectral measurements from some non-vegetated soils using Landsat digital data and a spectroradiometer. Soil Sci. Soc. Am. J., 44:80-84.

Clark, P.E., M.S. Seyfried, and B. Harris. 2001. Intermountain plant community classification using Landsat TM and SPOT HRV data. Journal of Range Management, 54:152-160.

Cleland, D.T., T.R. Crow, P.E. Avers, and J.R. Probst. 1992. Principles of land stratification for delineating ecosystems. Pages 40-50 in: Taking an ecological approach to management. U.S. Forest Service Watershed and Air Management Publication WO-WSA-3.

Clements, F.E. 1916. Development and structure of the biome. Ecological Society Abstract.

Clements, F.E. 1936. Nature and structure of the climax. Journal of Ecology, 24:252-284.

Coleman, T.L., and O.L. Montgomery. 1987. Soil moisture, organic matter, and iron content effect on the spectral characteristics of selected vertisols and alfisols in Alabama. Photogrammetric Engineering and Remote Sensing, 53:1659-1663.

Collins, S.L. 1989. Experimental analysis of patch dynamics and community heterogeneity in tallgrass prairie. Vegetatio, 85:57-66.

Colwell, J.E. 1974. Vegetation canopy reflectance. Remote Sensing of Environment, 3:175-183.

Condit, H.R. 1970. The spectral reflectance of American soils. Photogrammetric Engineering and Remote Sensing, 36:955-966.

Connell, J.H., and W.P. Sousa. 1983. On the evidence needed to judge ecological stability or persistence. American Naturalist, 121:789-824.

Conradsen, K., and J. Gunnulf. 1986. A geological example of improving classification of remotely sensed data using additional variables and a hierarchical structure. In: ERIM, Environmental Research Institute of Michigan, Proceedings of the 19th International Symposium on Rem. Sens. Environ., pp.403-416, Rio de Janeiro, Brazil.

Cooper, S.V., and B.L. Heidel. 1999. Biodiversity and representativeness of Research Natural Areas on National Wildlife Refuges in Montana: designated areas within Benton Lake, Lake Mason, Medicine Lake, Red Rock Lakes and C. M. Russell National

Wildlife Refuges. Unpublished report to the U.S. Fish and Wildlife Service. Montana Natural Heritage Program, Helena.

Coronado-Quintana, J.A., and M.P. McClaran. 2001. Range condition, tenure, management, and bio-physical relationships in Sonora, Mexico. Journal of Range Management, 54:31-38.

Creque, J.A., S.D. Bassett, and N.E. West. 1999. Viewpoint: delineating ecological sites. Journal of Range Management, 52:546-549.

Crippen, R.E. 1990. Calculating the Vegetation Index Faster. Remote Sensing of Environment, 34:71-73.

Crist, E.P., and R.C. Cicone. 1984. Application of the Tasseled Cap concept to simulated Thematic Mapper data. Photogrammetric Engineering and Remote Sensing, 50:343-352

Crist, E.P. 1985. A TM tasseled cap equivalent transformation for reflectance factor data. Remote Sensing of Environment, 17:301-306.

Curran, P. 1980. Multi-spectral remote sensing of vegetation amount. Prog. Phys. Geogr., 4: 315-340.

Dale, M.R.T. 1999. Spatial pattern analysis in plant ecology. Cambridge University Press, Cambridge, MA.

Dale, M.R.T., P. Dixon, M. Fortin, P. Legendre, D.E. Myers, and M. Rosenberg. 2002. Conceptual and mathematical relationships among methods of spatial analysis. Ecography, 25:558-557.

Daubenmire, R. 1968. Plant communities: a text book on plant synecology. Harper and Row, New York, N.Y.

DeAngelis, D.L., and J.C. Waterhouse. 1987. Equilibrium and non-equilibrium concepts in ecological models. Ecological Monographs, 57:1-21.

de Candolle, A. L. P. P. 1858. On the Causes Which Limit Vegetable Species Toward the North, in Europe and Similar Regions. Annual Report of the Board of Regents of the Smithsonian Institution for the Year 1858 (1859):237-245.

Deering, D.W., and R.H. Haas. 1980. Using Landsat digital data for estimating green biomass. NASA Technical Memorandum #80727, Greenbelt, MD.

DeGloria, S.D., S.L. Wall, A.S. Benson, and M.L. Whiting. 1986. Monitoring conservation tillage practices using Landsat multi-spectral data. J. Soil and Water Conserv., 41:187-189.

Demarchi, D.A. 1996. An introduction to the ecoregions of British Columbia. Wildlife Branch, Ministry of Environment, Lands and Parks, Victoria, British Columbia, Canada.

Dice, L.R. 1943. The biotic provinces of North America. Ann Arbor, University of Michigan Press.

Dormaar, J.F., and W.D. Willms. 1998. Effect of forty-four years of grazing on fescue grassland soils. Journal of Range Management, 51:122-26.

Drake, N. A., S. Mackin, and J.J. Settle. 1999. Mapping vegetation, soils and geology in semiarid shrublands using spectral matching and mixture modeling of SWIR AVIRIS imagery. Remote Sensing of Environment, 68:12-25.

Driscoll, R.S., and M.D. Coleman. 1974. Color for shrubs. Photogrammetric Engineering and Remote Sensing, 40:451-460.

Driscoll, R. S., D.L. Jerkel, D.L. Radloff, D.E. Synder, and J.J. Hagihara. 1984. An ecological land classification framework for the United States. Misc. Publ. 1439, Washington, D.C., U.S. Department of Agriculture. 56 pp.

Driscoll, R.S., J.H. Everitt, R. Haas, and P.T. Tueller. 1997. Ranges and range management, Manual of Photographic Interpretation (W.R. Philipson, editor), American Society for Photogrammetry and Remote Sensing, Bethesda, Maryland, pp. 441-474.

Dyksterhuis, E.J. 1949. Condition and management of rangeland based on quantitative ecology. Journal of Range Management, 2:104-115.

Eberhardt, L.L. 1978. Appraising variability in population studies. Journal of Wildlife Management, 42:207-238.

ECOMAP, USDA. 1993. National hierarchical framework of ecological units. Unpublished administrative paper. U.S. Department of Agriculture, Forest Service, Washington, D.C

Eidenshink, J.C. 1992. The 1990 Conterminous U.S. AVHRR Data Set. Photogrammetric Engineering and Remote Sensing, 58:809-813.

Eldridge, D., and D. Freudenberger. 2000. (eds.) Proceedings of the VI International Rangeland Congress: People and Rangelands, Building the Future. 17-23 July, Townsville, Queensland, Australia, VI International Rangeland Congress, Aikenvale, Queensland, Australia, 2:778-780.

Elvidge, C.D., and R.J.P. Lyon. 1985. Influence of rock-soil spectral variation on the assessment of green biomass. Remote Sensing of Environment, 17:37-53.

Elvidge, C.D. 1990. Visible and infrared reflectance characteristics of dry plant materials. International Journal of Remote Sensing, 12:1775-1795.

Elvidge, C.D., and Z. Chen. 1995. Comparison of broad-band and narrow-band red and near-infrared vegetation indices. Remote Sensing of Environment, 54:38-48.

EROS Data Center 1992. Readme 1st, The 1996 Conterminous U.S. AVHRR Biweekly Composites. CD-ROM. National Mapping Division U.S. Geological Survey EROS Data Center, Sioux Falls, South Dakota.

Escadafal, R., M.D. Girad, and D. Courault. 1989. Munsell soil color and soil reflectance in the visible bands of Landsat MSS and TM data. Remote Sensing of Environment, 27: 37-46.

Everitt, J.H., and P.R. Nixon. 1985. Video Imagery: A New Remote Sensing Tool for Range Management. Journal of Range Management, 38:421-424.

Everitt, J.H., D.E. Escobar, M.A. Alaniz, and M.R. Davis. 1987. Using airborne middle-infrared (1.45-2.0um) video imagery for distinguishing plant species and soil conditions. Remote Sensing of Environment, 22:423-428.

Everitt, J.H., and R. Villarreal. 1987. Detecting huisache (Acacia farnesiana) and Mexican palo-verde (Parkinsonia aculeate) by aerial photography. Weed Science, 35:427-432.

Everitt, J.H., A.J. Richardson, D.E. Escobar, and R. Villarreal. 1989. Mapping Native Plant Communities with Color-Infrared Video Imagery. Proc. Twelfth Biennial Workshop on Color Aerial Photography and Videography in the Plant Sciences and Related Fields. American Society of Photogrammetry and Remote Sensing, pp. 30-38.

Everitt, J.H., M.A. Alaniz, D.E. Escobar, and M.R. Davis. 1992. Using remote sensing to distinguish common (*Isocoma cornophifia*) and Drummon goldenweed (*Isocoma drummondii*). Weed Science, 40:621-628.

Everitt, J.H., G.L. Anderson, D.E. Escobar, M.R. Davis, N.R. Spencer, and R.J. Andrascik. 1995. Using remote sensing for detecting and mapping leafy spurge (*Euphorbia esula*). Weed Technology, 7:981-987.

Everitt, J.H., D.E. Escobar, M.A. Alaniz, M.R. Davis, and J.V. Richerson. 1996. Using spatial information technologies to map Chinese tamarisk. Weed Science, 44:194-201.

Everitt, J.H., C. Yang, B.J. Racher, C.M. Britton, and M.R. Davis. 2001. Remote sensing of redberry juniper in the Texas rolling plains. Journal of Range Management, 54:254-259.

Feibleman, J.K. 1954. Theory of Integrative Levels. The British Journal for the Philosophy of Science, 5:59-66.

Feller, J.M. 1992. Grazing management on the public lands: opening the process to public participation. Land and Water Law Review, 26:571.

Fenneman, N.M. 1946. Physical divisions of the United States. Map (scale 1:7,000,000). U.S. Geological Survey, Reston, VA.

Frank, A.B., and J.K. Aase. 1994. Residue effects on radiometric reflectance measurements of northern Great Plains rangelands. Remote Sensing of Environment, 49:195-199.

Franklin, J., and J. Stephenson. 2003. Integrating GIS and remote sensing to produce regional vegetation databases: attributes related to environmental modeling. http://www.ncgia.ucsb.edu/conf/SANTA_FE_CDROM/sf_papers/franklin_janet/my_paper

Galvao, L.S., I. Vitorello, and R. Almeida Filho. 1999. Effects of band positioning and bandwidth on NDVI measurements of tropical savannas. Remote Sensing of Environment, 67:181-193.

Galvao, L.S., I. Vitorello, and M.A.Pizarro. 2000. An adequate band positioning to enhance NDVI contrasts among green vegetation, senescent biomass, and tropical soils. International Journal of Remote Sensing, 21:1953-1960.

Galvao, L.S., R.C. Moreira, and I. Vitorello. 2002. Improving the fittingness of soil lines and the dynamic range of vegetation indices by AVIRIS band positioning selection. Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) 2000. Workshop Proceedings.

Gausman, H.W., A.H.Gebermann, C.L. Wiegand, R.W. Leamer, R.R. Rodriguez, and J.R. Noriega. 1975. Reflectance differences between crop residues and bare soils. Soil Sci. Soc. Am. Proc., 39:752-755.

Gitelson, A.A., R. Stark, U. Grits, D. Rundquist, Y. Kaufman, and D. Derry. 2002. Vegetation and soil lines in visible spectral space: a concept and technique for remote estimation of vegetation fraction. International Journal of Remote Sensing, 23:2537-2562.

Gorham, E. 1954. Early view of relation between plant distribution and environmental factors. Ecology, 35:97-98.

Goward, S.N., C.J. Tucker, and D.G. Dye. 1985. North American Vegetation Patterns Observed with the NOAA-7 Advance Very High Resolution Radiometer. Vegetatio, 64:3-14.

Graetz, R.D., D.M. Carneggie, R. Hacker, C. Lendon, and D.G. Wilcox. 1976. A qualitative evaluation of Landsat imagery of Australian rangeland. Australian Rangeland Journal, 1:53-59.

Graetz, R. D., and M.R. Gentle.1982. The relationships between reflectance in the Landsat wavebands and the composition of an Australian semi-arid shrub rangeland. Photogrammetric Engineering and Remote Sensing, 48:1721-1730.

Graetz, R.D., M.R. Gentle, R.P. Pech, J.R. O'Callagahan, and G. Drewien. 1983. The application of Landsat image data to rangeland assessment and monitoring: an example from South Australia. Australian. Rangeland. Journal., 5:63-73.

Graetz, R.D., R.P. Pech, M.R. Gentle, and J.F. O'Callaghan. 1986. The application of Landsat image data to rangeland assessment and monitoring: the development and demonstration of a land image-based information system (LIBRIS). J. Arid Environ., 10:53-80.

Graetz, R.D. 1987. Satellite remote sensing of Australian rangelands. Remote Sensing of Environment, 23:313-331.

Greig-Smith, P. 1979. Pattern in vegetation. Journal of Ecology, 67:755-779.

Guyot, G., and X. Gu. 1994. Effect of Radiometric Corrections on NDVI-Determined from SPOT-HRV and Landsat-TM Data. Remote Sensing of Environment, 49:169-180.

Hammond, E. H. 1964. Classes of land-surface form in the forty-eight States. U.S.A. Annals Association American Geographers, 54 Map supplement No. 4. Scale 1:5 million.

Hargrove, W.W., and R.J. Luxmoore. 1997. A Spatial Clustering Technique for the Identification of Customizable Ecoregions. www.esri.com/library/userconf/proc97/PROC97/TO250/PAP226/P226.htm

Hargrove, W.W., and F.M. Hoffman. 1999. Using Multivariate Clustering to Characterize Ecoregion Borders. Computing in Science & Engineering, July/August 1999, pp.18-24.

Harley, J.L., and S.E. Smith. 1983. Mychorrhizal symbiosis. Academic Press, London.

Hassink, J., L.A., Bouwman, K.B. Zwart, and L. Brussard. 1993. Relationships between habitable pore space, soil biota, and mineralization rates in grassland soils. Soil Biology and Biochemistry, 25:47-55.

Henebry, G. 1993. Detecting change in Grasslands Using Measures of Spatial Dependence with Landsat TM Data. Remote Sensing of Environment, 46:223-234.

Herrick, J.E., W.G. Witford, A.G. de Soyza, J.W. VanZee, K.M. Havstad, C.A. Seybold, and M. Walton. 2001. Field soil aggregate stability kit for soil quality and rangeland health evaluations. Catena, 44:27-35.

Hess, K. 1992. Visions Upon the Land: Man and Nature on the Western Range. Island Press, Washington, D.C.

Hoffer, R.M., and C.J. Johannsen. 1969. Ecological potentials in spectral signature analysis. In: Remote Sensing in Ecology, P.L. Johnson (ed.) pp 1-29. University of Georgia Press, Athens.

Holdridge, L.R., W.C. Grenke, W.H. Hatheway, T. Liang, and J.A.Tosi. 1971. Forest Environments in Tropical Life Zones, A Pilot Study. Pergamon Press, New York.

Holecheck, J.L., 1988. An approach for setting the stocking rate. Rangelands, 10:10-14.

Holecheck, J.L., R.D. Piper, and C.H. Herbel. 1989. Range Management: Principles and Practices. Prentice Hall, Englewood Cliffs, New Jersey.

Homer, C., C. Huang, L.Yang, and B. Wylie. 2001. Development of a Circa 2000 Landcover Database for the United States. U.S.G.S. Draft White Paper, available at http://landcover.usgs.gov.

Homer, C.G., and A. Gallant. 2001. Partitioning the Conterminous United States into Mapping Zones for Landsat TM Land Cover Mapping, U.S.G.S. Draft White Paper, available at http://landcover.usgs.gov.

Huang, C., B. Wylie, C. Homer, and G. Zylstra. 2002. Derivation of a tasseled cap transformation based on Landsat 7 at-satellite reflectance. International Journal of Remote Sensing, 23:1741-1748.

Huete, A.R., R.D. Jackson, and D.F. Post. 1985. Spectral response of a plant canopy with different soil backgrounds. Remote Sensing of Environment, 17:37-53.

Huete, A.R. 1986. Separation of soil-plant mixtures by factor analysis. Remote Sensing of Environment, 19:237-251.

Huete, A.R., and R.D. Jackson. 1987. Suitability of Spectral indices for evaluating vegetation characteristics on arid rangeland. Remote Sensing of Environment, 23:213-232.

Huete, A.R. 1988. A soil-adjusted vegetation index (SAVI). Remote Sensing of Environment, 29:295-309.

Humbolt, A., and J.A. Bonpland. 1805. Essai sur la Geographi des Plantes Paris, Levrault, Schoell et Compagnie. 155 pp.

Humphrey, R.R. 1949. Field comments on the range condition method of forage survey. Journal of Range Mangement, 2:1-10.

Hunt, E.R. Jr., J.H. Everitt, J.C. Ritchie, S.M. Moran, D.T. Booth, G.L. Anderson, P.E. Clark, and M.S. Seyfried. 2003. Applications and Research Using Remote Sensing for Rangeland Management. Photogrammetric Engineering and Remote Sensing, 69:675-693.

Jacoby, P.W. (Chairman). 1974. A glossary of terms used in range management. Range Term Glossary Committee, Society for Range Management, Denver, Colorado.

Jenny, H. 1958. Role of the plant factor in the pedogenic functions. Ecology 39:5-16.

Jensen, J.R. 1996. Introductory Digital Image Processing: A Remote Sensing Perspective. Prentice Hall, Inc., Englewood Cliffs, New Jersey.

Jensen, M.E., J.P. Dibenedetto, J.A. Barber, C. Montague, and P. Bourgeron. 2001. Spatial modeling of rangeland potential vegetation environments. Journal of Range Management, 54:528-536.

Johnston, K.M. 1987. Natural resource modeling in the geographic information system environment. Photogrammetric Engineering and Remote Sensing, 53:1411-1415.

Jordan, C.F. 1969. Derivation of leaf-area index from quality of light on the forest floor. Ecology, 50:663-666.

Justice, C.O., and P.H.Y. Hiernaux. 1986. Monitoring the Grasslands of the Sahel using NOAA AVHRR data: Niger 1983. International Journal of Remote Sensing, 7:1475-1497.

Karlen, D.L., and D.E. Stott. 1994. A framework for evaluating physical and chemical indicators of soil quality. In: J.W. Doran, D.C. Coleman, D.F. Bezdicek, and B.A. Steward (eds). Defining soil quality for a sustainable environment. SSSA Special Publication Number 35. pp 53-72. Soil Science Society of America.

Kauth, R.J., and G.S. Thomas. 1976. The Tasseled Cap-a graphic description of the spectral-temporal development of agricultural crops as seen by Landsat. In Proceedings of the Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette, IN. pp. 41-51.

Knick, S.T., J.T. Rotenberry, and T.J. Zarriello. 1997. Supervised Classification of Landsat Thematic Mapper Imagery in a Semi-Arid Rangeland by Nonparametric Discriminant Analysis. Photogrammetric Engineering and Remote Sensing, 63:79-86.

Knipling, E.B. 1970. Physical and physiological basis for the reflectance of visible and near infrared radiation from vegetation. Remote Sensing of Environment, 1:155-159.

Koppen, W., and R. Geiger. 1936. Handbuch der Klimatologie, Berlin, Gebr., Borntraeger

Kremer, R., and S. Running. 1993. Community type differentiation using NOAA/AVHRR data within a sagebrush-steppe ecosystem. Remote Sensing of Environment, 46:311-318.

Kristof, S.J., and A.L. Zachary. 1971. Mapping soil types from multi-spectral scanner data. Photogrammetric Engineering and Remote Sensing, 40:1427-1434.

Kuchler, A.W. 1965. Potential natural vegetation of the conterminous United States. American Geographical Society. Special Publication No. 36. A. Hoen and Co. Baltimore, MD.

Langer, W.L. (ed.). 1952. An encyclopedia of world history. Houghton Mifflin Co., New York.

Laurenroth, W.K. 1979. Grassland primary production: North American grasslands in perspective, in Perspectives in Grassland Ecology (N. French, ed.), Springer-Verlag, New York, pp. 3-24.

Lawrence, R.L., and W.J. Ripple. 1998. Comparisons among vegetation indices and bandwise regression in a highly disturbed, heterogeneous landscape: Mount St. Helens, Washington. Remote Sensing of Environment, 64:91-102.

Legendre, P., and M.J. Fortin. 1989. Spatial pattern and ecological analysis. Vegetatio, 80:107-138.

Legendre, P. 1993. Spatial autocorrelations: trouble or a new paradigm? Ecology, 74:1659-1673.

Legendre, P., and L. Legendre. 1998. Numerical ecology. 2nd English edition. Elsevier, Amsterdam.

Leonard, S.G., G.J. Staidl, K.A. Gebhardt, and D.E. Prichard. 1992. Viewpoint: range site/ecological site information requirements for classification of riverine riparian ecosystems. Journal of Range Management, 45:431-435.

Levine, E., R. Knox, and W. Lawrence. 1994. Relationships between soil properties and vegetation at the Northern Experimental Forest, Howland, Maine. Remote Sensing of Environment, 47:231-241.

Lewis, D.T., P.M. Seevers, and J.V. Drew. 1975. Use of satellite imagery to delineate soil associations in the Sand Hills region of Nebraska. Soil Sci.Soc.Am.Proc., 39:330-335.

Liebhold, A.M., and J. Gurevitch. 2002. Integrating the statistical analysis of spatial data in ecology. Ecography, 25:553-557.

Lillesand, T.M., and R.W. Kiefer. 1994. Remote Sensing and Image Interpretation 3rd ed. John Wiley and Sons, Inc., New York.

Loveland, T.R., J.W. Merchant, D.O. Ohlen, and J.F. Brown. 1991. Development of a land-cover characteristics database for the conterminous U.S. Photogrammetric Engineering and Remote Sensing, 57:1453-1463

Lozano-Garcia, D., R. Fernandez, and C. Johannsen. 1991. Assessment of regional biomass-soil relationships using vegetation indexes. IEEE Transactions on Geosciences and Remote Sensing, 29:331-338.

Ludwig, J. 1986. Primary production variability in desert ecosystems. In: Whitford, W.G. (Ed.), Pattern and Process in Desert Ecosystems, pp. 5-17. Albuquerque, University of New Mexico Press

Ludwig, J.A., and J.F.Reynolds. 1988. Statistical ecology. John Wiley and Sons, Inc.

Lugo, A.E., S.L. Brown, R. Dodson, T.S. Smith, and H.H. Shugart. 1999. The Holdridge life zones of the conterminous United States in relation to ecosystem mapping. Journal of Biogeography, 26:1025-1038.

Mabbut, J.A. 1978. Desertification in Australia. Water Research Foundation of Australia, Report No. 4, Canberra, Australia, 127 pp.

MacDonald, J.D., L.R. Costello, and T. Berger. 1993. An evaluation of soil aeration status around healthy and declining oaks in an urban environment in California. Journal of Arboriculture, 19:209-219.

Major, D.J., F. Baret, and G. Guyot. 1990. A ratio vegetation index adjusted for soil brightness. International Journal of Remote Sensing, 11:727-740.

Major, D.J., S. Smoliak, G. Asrar, and E.T. Kanemasu. 1988. Analysis of spectral data for comparing rangeland and cultural practices in southern Alberta. Can. J. Plant Sci., 68: 1027-1023.

Matthews, H.R., R.L. Cunningham, and G.W. Petersen. 1973. Application of multi-spectral remote sensing to soil survey research in southeastern Pennsylvania. Soil Sci. Soc. Am. Proc., 37:88-93.

Mattikalli, N.M., E.T. Engman, L. R. Ahuja, and T.J. Jackson. 1996. Estimating soil properties from microwave remote sensing of soil moisture. In: E.T. Engman, G. Guyot and C.M. Marino (Editors), Remote Sensing for Agriculture, Forestry, and Natural Resources. SPIE, pp 89-101.

May, R. M., and G. Oster. 1976. Bifurcations and dynamic complexity in simple ecological models. American Naturalist, 110:573-599.

May, R.M. 1984. An overview: real and apparent patterns in community structure. Pages 3-16 in D.R. Strong. D. Simberloff, L.G. Abele, and A. B. Thistle, (eds.). Ecological communities: conceptual issues and the evidence. Princeton University Press. Princeton, New Jersey.

Maxwell, E.L. 1976. A remote rangeland analysis system. Journal of Range Management, 29:66-73.

McDaniel, K.C., and R.H. Haas. 1982. Assessing mesquite grass vegetation condition from Landsat. Photogrammetric Engineering and Remote Sensing, 48:441-450.

McGraw, J.F., and P.T. Tueller. 1983. Landsat computer-aided analysis techniques for range vegetation management. Journal Range Management, 36:627-631.

McNab, W.H., and P.E. Avers, comps. 1994. Ecological subregions of the United States: section descriptions. Admin. Publ. WO-WSA-5. Washington, DC. U.S. Department of Agriculture, Forest Service.

Merriam, C.H. 1898. Life zones and crop zones of the United States. U.S. Bureau Biol. Survey, 10:1-79. Washington, D.C.

Merrill, E.H., M.K. Bramble-Brodahl, R.W. Marrs, and M.S. Boyce. 1993. Estimation of green herbaceous phytomass from Landsat MSS data in Yellowstone National Park. Journal Range Management, 46:151-157.

Menenti, M., and J.C. Ritchie. 1994. Estimation of effective aerodynamic roughness of Walnut Gulch watershed with laser altimeter measurements. Water Resources Research, 30:1329-1337.

Montana Agricultural Statistics Bureau. 2002. Montana Department of Agriculture http://www. montana.ag.stats

Montana Experiment Station. 1973. Bulletin 671, Vegetation Rangeland Types in Montana. Montana State University, Bozeman MT.

Montgomery, O.L., and M. F. Baumgardner. 1974. The effects of the physical and chemical properties of soil on the spectral reflectance of soils. Technical Report 11-Lab. for Applications of Remote Sensing, Purdue Univ., West Lafayette, Ind.

Moran, M.S., R.D. Jackson, P.N. Slater, and P.M.Teillet. 1992. Evaluation of simplified procedures for retrieval of land surface reflectance factors from satellite sensor output. Remote Sensing of Environment, 41:169-184.

Mouat, D.A., J.B. Bale, K.E. Foster, and B.D. Treadwell. 1981. The use of remote sensing for an integrated inventory of a semi-arid area. Journal of Arid Environments, 4:169-179.

Narayanan, R.M., and B.D. Guenther. 1998. Effects of Emergent Grass on Mid-Infrared Laser Reflectance of Soil. Photogrammetric Engineering and Remote Sensing, 64:407-413.

National Research Council, Committee on Rangeland Classification, Board on Agriculture, (NRC). 1994. Rangeland health: new methods to classify, inventory, and monitor rangelands. National Academy Press, 2101 Constitution Avenue, Washington, D.C. 1994.

Natural Resource Conservation Service. 1992. National Resource Inventory, USDA, Washington, D.C.

Natural Resource Conservation Service. 1997. Range and pasture management handbook. USDA, NRCS, Grazing Lands Technology Institute, Ft. Worth, Tex. U.S. Gov. Printing Office.

Natural Resource Conservation Service. 2000. Soil Survey Geographic Database (SSURGO), and the National Soil Information System (NASIS). Soil Data Viewer, ver.1 USDA, Washington, D.C.

Nesser, J. A., G. Ford, C.L. Maynard, and D.S. Page-Dumrose. 1996. Ecological Units of the Northern Region: Subsections. United States Department of Agriculture Intermountain Research Station, General Technical Report INT-GTR-369.

Nesser, J.A., C.L. Maynard, and D.F. Lund. 2001. An ecological characterization of the Greater Yellowstone Area. U.S. Department of Agriculture, Forest Service, RMRS-GTR-78-CD.

Omernik, J.M. 1987. Ecoregions of the conterminous United States. Annals of the Association of American Geographers, 77:118-125.

Omernick, J.M. 1995. Ecoregions: A Spatial Framework for Environmental Management, Biological Assessment and Criteria: Tools for Water Resource Planning and Decision Making. W.S. Davis and T.P. Simon, (eds.). Lewis Publishing, Boca Raton, Fla. pp. 49-62.

O'Neill, R.V., D.L. DeAngelis, J.B. Waide, and T.F.H. Allen. 1986. A Hierarchical Concept of Ecosystems, Princeton Univ. Press, Princeton, NJ, 253 pp.

Palacios-Orueta, A., J.E. Pinzon, S.L.Ustin, and D.A.Roberts. 1999. Remote Sensing of Soils in the Santa Monica Mountains: II Hierarchical Foreground and Background Analysis. Remote Sensing of Environment, 68:138-151.

Paruelo, J.M., and R.A.Gollusccio. 1994. Range assessment using remote sensing in Northwest Patagonia (Argentina). Journal of Range Management, 47:498-502.

Passey, H., V.K. Hugie, E.W. Williams, and D.E. Ball. 1982. Relationships between soil, plant community and climate on rangelands of the Intermountain West. Technical Bulletin Number 1669, Washington, D.C. United States Department of Agriculture, Soil Conservation Service. 123 pp.

Pearse, C.K. 1971. Grazing in the middle-east: past, present and future. Journal of Range Management, 24:13-16.

Pearson, R.L., and L. D. Miller. 1972. Remote mapping of standing crop biomass for estimation of the productivity of the shortgrass prairie. Eighth International Symposium on Remote Sensing of Environment, Univeristy of Michigan, Ann Arbor, Mich., 1357-1381.

Pech, R., A.W. Davis, R.R. Lamacraft, and R.D. Graetz. 1986. Calibration of Landsat data for sparsely vegetated semi-arid rangelands. International Journal of Remote Sensing, 7: 1729-1750.

Perry, C.R., and L.F. Lautenschlager. 1984. Functional equivalence of spectral vegetation indices. Remote Sensing of Environment, 14:169-175.

Perry, J.N., A.M. Liebholt, M.S. Rosenberg, J. Dungan, M. Mirti, A. Jakomulska, and S. Citron-Pousy. 2002. Illustrations and guidelines for selecting statistical methods for quantifying spatial patterns in ecological data. Ecography, 25:578-600.

Pickup, G., and W.H. Chewings, 1988. Forecasing patterns of erosion in arid lands from Landsat MSS data. International Journal of Remote Sensing, 63:515-521.

Pickup, G., V.H. Chewings, and D.J. Nelson. 1993. Estimating changes in vegetation cover over time in arid rangelands using Landsat MSS data. Remote Sensing of Environment, 43:243-264.

Pickup, G., G.N. Bastin, and V.H. Chewings. 1994. Remote sensing based condition assessment for non-equilibrium rangelands under large-scale grazing. J. Appl. Ecology, 4:494-517.

Pickup, G., and G.N. Bastin. 1997. Spatial distribution of cattle in arid environments. J. Appl. Ecology, 34:657-667.

Pilon, P.G., P.J. Howarth, and R.A. Bullock. 1988. An enhanced classification approach to change detection in semi-arid environments. Photogrammetric Engineering and Remote Sensing, 12:1709-1716.

Price, J.C., 1993. Estimating leaf area index from satellite data. IEEE Transactions on Geoscience and Remote Sensing, 31:727-734.

Qi, J., A. Chehbouni, A.R. Huete, and Y.H. Kerr. 1994. A modified soil adjusted vegetation index. Remote Sensing of Environment, 48:119-126.

Ramensky, L.G. 1924. Die Grundgesetzmassigkeiten im Aufbau der Vegetationsdecke. (Russian). Vestn. opyt. Dela, sred-chernoz. Obl., Voronezh (Abstr. in Bot. Centrbl. N.F. 7:453-455, 1926).

RANGES. 2000. Rangeland analysis geo-spatial information science. http://www.ranges.edu

RangeView. University of Arizona. 2003. Geospatial Tools for Natural Resource Management. Evaluating the relationship between spectral indices and grazing. http://www.rangeview.arizona.edu/reports/grazing.html

Ray, T.W. 1995. Remote Sensing of Land Degradation in Arid/Semi-arid Regions. Ph.D. Thesis, California Institute of Technology

Reeves, M.C., J.C. Winslow, and S.W. Running. 2001. Mapping weekly rangeland vegetation productivity. Journal of Range Management, 54 (suppl):A90-A105.

Richardson, A.J., and C.L. Wiegand. 1977. Distinguishing vegetation from soil background information. Photogrammetric Engineering and Remote Sensing, 43:1541-1552.

Richardson, A.J., J.H. Everitt, and H.W. Gausman. 1983. Radiometric estimation of biomass and nitrogen content of Alicia grass. Remote Sensing of Environment, 13:179-184.

Richardson, A.J., and J.H. Everitt. 1992. Using Spectral Vegetation Indices to Estimate Rangeland Productivity. Geocarto International, 1:63-69.

Ringrose, S., W. Mataheson, F.Tempest, and T. Boyle. 1990. The development and causes of range degradation features in southeast Botswana using multi-temporal Landsat MSS imagery. Photogrammetric Engineering and Remote Sensing, 56:1253-1262.

Ripple, W.J. 1994. Determining coniferous forest cover and forest fragmentation with NOAA-9 Advanced Very High Resolution Radiometer data. Photogrammetric Engineering and Remote Sensing, 60:533-540.

Ritchie, J.C., J.H. Everitt, D.E. Escobar, T.J. Jackson, and M.R. Davis. 1992. Airborne Measurements of Rangeland Canopy Cover and Distribution. Journal of Range Management, 45:189-193.

Roberts, D. S. 1991. Separating spectral mixtures of vegetation and soils, Ph.D. thesis, University of Washington, June.

Roberts, D.S., M.O. Smith, and J.B. Adams. 1993. Green vegetation, non-photosynthetic vegetation, and soils in AVRIS data. Remote Sensing of Environment, 44:255-269.

Rondeaux, G., M. Steven, and F. Baret. 1996. Optimization of soil-adjusted vegetation indices. Remote Sensing of Environment, 55:95-107.

Roundabush, R.D., R.C. Herriman, R.L. Barmore, and G.W. Schellentrager. 1985. Use of Landsat multi-spectral scanning data for soil surveys on Arizona rangeland. J. Soil and Water Conserv., 40:242-245.

Rouse, J.W., R.H. Hass, J.A. Schell, and D.W. Deering. 1973. Monitoring vegetation systems in the great plains with ERTS. Third ERTS Symposium, NASA SP-351, I:309-317.

Rowe, J.S. 1961. The Level-of-Integration Concept and Ecology. Ecology, 42:420-427.

Rowe, J.S. 1980. The common denominator in land classification in Canada: an ecological approach to mapping. Forestry Chronicle, 56:19-20.

Rowe, J.S., and J.W. Sheard. 1981. Ecological land classification: a survey approach. Environmental Management, 5:451-464.

Sampson, A.W. 1917. Succession as a factor in range management. Jour. of Forestry, 15:593-596.

Satterwhite, M.B., and J.P. Henley. 1987. Spectral characteristics of selected soils and vegetation in northern Nevada and their discrimination using band ratio techniques. Remote Sensing of Environment, 23:155-175.

Schimper, Andreas F.W. 1898. Pflanzen-geographie auf Physiologischer Grundlage. Jena: Gustav Fischer. 876 pp. (English transl: Plant-geography Upon a Physiological Basis. Oxford, U.K. Claredon Press, 1903.

Schlessinger, W.H., J.F. Reynolds, C.L. Cunningham, L.F. Huennekr, W.M. Jaerel, R.A. Virginia, and W.G. Whitford. 1990. Biological feedbacks in global desertification. Science, 247:1043-1048.

Schoener, T.W. 1983. Field experiments on interspecific competition. American Naturalist, 122:240-285.

Schouw, J.F. 1823. Grunzuge einer allgemeinen pflanzengeographie. Glydendal, Berlin.

Sellers, P.J., F.G. Hall, G. Asrar, D.E. Strebel, and R.E. Murphy, R. 1988. The First ISLSPC Field Experiment (FIFE), Bull. Am. Meterol. Soc., 69:22-27.

Shelford, V. E. 1963. The Ecology of North America. University of Illinois Press, Urbana. 610 pp.

Shiflet, T.N. 1973. Range sites and soils in the United States. In: Arid Shrublands-Proceedings of the Third Workshop, United States/Australian Rangelands Panel pp 26-23. Society for Range Management, Denver, Colorado.

Shiflet, T.N. 1994. Rangeland Cover Types of the United States. Society for Range Management, Denver, CO.

Slater, P.N., S.F. Biggar, R.G. Holm, R.D. Jackson, Y. Mao, M.S. Moran, J.M. Palmer, and B. Yuan. 1986. Absolute radiometric calibration of the Thematic Mapper, Proceedings of the Society of Photo-Optical Instrumentation Engineers, 660:2-8.

Smith, R.L., 1986. Elements of Ecology. Harper & Row, Publishers, Inc. New York, N.Y.

Smith, M.O., S.L. Ustin, J.B. Adams, and A.R. Gillespie. 1990(a). Vegetation in deserts: I. A regional measure of abundance from multi-spectral images, Remote Sensing of Environment, 31:1-26.

Smith, M. O., S.L. Ustin, J.B. Adams, and A.R. Gillespie. 1990(b). Vegetation in deserts: II. Environmental influences on regional abundance. Remote Sensing of Environment, 31:27-52.

Smith, C.A. 2000. Historical reference to key ecological theories and their origin. Early classics in biogeography, distribution, and diversity studies. http://www.wku.edu/~smithch/biogeog/.

Society for Range Management. 1995. New concepts for assessment of rangeland condition. J. Range Manage., 48:271-282.

Society for Range Management. 1999. A glossary of terms used in range management. Society for Range Management. Denver, CO.

Soil Survey Staff. Keys to Soil Taxonomy, 5th edition. 1992. SMSS technical monograph No. 19. Blacksburg, Virginia: Pocahontas Press, Inc.

Soil Taxonomy: A basic system of Soil Classification for Making and Interpreting Soil Surveys. 1975. U.S. Department of Agriculture, Handbook 436, U.S. Government Printing Office.

Southwood, T.R.E. 1987. The concept and nature of the community. Pages 3-7 in J. H. R. Gee and P. S. Giller, (eds.). Organization of communities past and present. Blackwell Scientific, Oxford, England.

Starks, P.J., and T.J. Jackson. 2002. Estimating soil water content in tallgrass prairie using remote sensing. Journal of Range Management, 55:474-481.

Stella, T.W., R.M. Hoffer, and D.G. Milchunas. 1993. Comparison of Four Vegetative Indicies for Estimating Aboveground Biomass on Grazed and Ungrazed Rangeland. ASPRS-ASCM Annual Convention. New Orleans; Feb. 16-19, 1993.

Stoner, E.R., M.E. Baumgardner, L.L. Biehl, and B.F. Robinson. 1980. Atlas of Soil Reflectance Properties. Department of Agronomy and the Laboratory for Applications of Remote Sensing, Purdue Univ. Research Bull. 962.

Stoner, E.R., and M.R. Baumgardner. 1981, Characteristic variations in reflectance of surface soils. Soil Sci. Soc. Am. J., 45:1161-1165.

Stringham, T.K., W.C. Krueger, and P.L. Shaver. 2003. State and transition modeling: An ecological process approach. Journal of Range Management, 56:106-113.

Sukachev, V.N. 1958. On the Principles of Genetic Classification in Biocenology. Ecology, 39:364-367.

Swain, P.H., and S.M. Davis. 1978. Remote Sensing: The Quantitative Approach, McGraw-Hill, New York.

Tanser, F.C., and A.R. Palmer. 1999. The application of a remotely-sensed diversity index to monitor degradation patterns in a semi-arid heterogenous, South African landscape. Journal of Arid Environments, 43:447-484.

Tansley, A.G. 1935. The use and abuse of vegetational concepts and terms. Ecology, 16:284-307.

Task Force on Unity in Concepts and Terminology. 1995. New concepts for assessment of rangeland condition. Journal of Range Management, 48:271-282.

Thoma, D. P., D.W. Bailey, D.S. Long, G.A. Nielsen, M.P. Henry, M.C. Breneman, and C. Montagne. 2002. Short-term monitoring of rangeland forage conditions with AVHRR imagery. Journal of Range Management, 55:383-389.

Todd, S.W., and R.M. Hoffer. 1998. Responses of Spectral Indices to Variations in Vegetation Cover and Soil Background. Photogrammetric Engineering and Remote Sensing, 64:915-921.

Todd, S.W., and M.T. Hoffman. 1999. A fence-line contrast reveals effects of heavy grazing on plant diversity and community composition in Namaqualand, South Africa. Plant Ecology, 140:1-11.

Tucker, C.J., and L.D. Miller. 1977. Contribution of the soil spectra to grass canopy spectral reflectance. Photogrammetric Engineering and Remote Sensing, 43:721-726.

Tucker, C.J., 1979. Red and photographic infrared linear combinations for monitoring vegetation. Remote Sensing of Environment, 8:127-150.

Tucker, C.J., C.L. Vanparet, and A. Gaston. 1983. Satellite Remote Sensing of Total Dry Matter Production in the Senegalese Sahel. Remote Sensing of Environment, 13:461-474.

Tucker, C.J., and C.L. Vanparet. 1985. Satellite Remote Sensing of Total Herbaceous Biomass in the Senegalese Sahel: 1980-1984. Remote Sensing of Environment, 17:233-249.

Tucker, CJ., and P.J. Sellers. 1986. Satellite remote sensing for primary production. International Journal of Remote Sensing, 7:1395-1416.

Tueller, P.T. 1987. Remote sensing applications in arid environments. Remote Sensing of Environment, 23:143-154.

Tueller, P.T. 1989. Remote sensing technology for rangeland management applications. Journal of Range Management, 42:442-453.

Tueller, P. T. 2001. Remote sensing of range production and utilization. Journal of Range Management, 54:77-89.

Turner, M.G., and V.H. Dale. 1991. Modeling landscape disturbance. Pp 323-351 in Turner, M.G. and R. Gardner (eds.). 1991. Quantitative Methods in Landscape Ecology. Vol. 82. Springer-Verlag, New York.

Turner, C.L., T.R. Seastedt, M.I. Dyer, T.G.F. Kittel, and D.S. Schimel. 1992. Effects of management and topography on the radiometric response of tallgrass prairie. J. Geophys. Res., 18:855-866.

Turner, M.G. 1989. Landscape Ecology: The effect of pattern on process. Annu. Rev. Ecol. Syst., 20:171-97.

Turner, M.G., and R.H. Gardner (eds.). 1991. Quantitative Methods in Landscape Ecology: The Analysis and Interpretation of Landscape Heterogeneity. Springer-Verlag, New York, N.Y.

Uresk, D.W. 1990. Using multivariate techniques to quantitatively estimate ecological stages in a mixed short-grass prairie. Journal of Range Management, 43:282-285.

U.S. Department of Agriculture. 1981. Land resource regions and major land resource areas of the United States. Agriculture Handbook 296. U.S. Government Printing Office, Washington D.C.

U.S. Department of Interior. 1994. Draft Environmental Impact Statement, Rangeland Reform '94. Bureau of Land Management, Washington D.C.

U.S. Department of Interior. 2000. Interpreting Indicators of Rangeland Health, Ver.3. Technical Reference, 1734-1736., Bureau of Land Management, Washington D.C.

U.S. Geological Survey, 1987. Digital elevation models: USGS data user's guides. USGS, Reston, Virginia.

Ustin, S.L., J.B. Adams, C.D. Elvidge, M. Rejmanek, B.N. Rock, M.O. Smith, R.W. Thomas, and R.A. Woodward. 1986. Thematic mapper studies of semi-arid shrub communities. BioScience, 36:446-452.

Ustin, S.L., Q.J. Hart, L. Duan, and G. Scheer. 1996. Vegetation mapping on hardwood rangelands in California. International Journal of Remote Sensing, 17:3015-3036.

Van Deventer, A.P, A.D. Ward, P.H. Gowda, and J.G. Lyon. 1997. Using Thematic Mapper Data to Identify Contrasting Soil Plains and Tillage Practices. Photogrammetric Engineering and Remote Sensing, 63:87-93.

Van Leeuwen, W.J.D., and A.R. Huete. 1996. Effects of standing litter on the biophysical interpretation of plant canopies with spectral indices. Remote Sensing of Environment, 55:123-138.

Waller, S. S., M.A. Brown, and J.K. Lewis. 1981. Factors involved in estimating green biomass by canopy spectro-reflectance measurements. Journal of Range Management, 34:105-108.

Wang, J., T. Jackson, E. Engman, W. Gould, J. Fuchs, W. Glazer, P. O'Neill, T. Schmuggel, and J. McMurtrey. 1984. Microwave radiometer experiment of soil moisture sensing at Barc test site during summer 1981. Goddard Space Flight Center, Greenbelt, Maryland.

Warming, E. 1909. Oecology of Plants: An introduction to the study of plant communities. The Claredon Press, Oxford.

Washington-Allen, R.A., N.E. West, R.D. Ramsey, and C.T. Hunsaker. 1999. Characterization of the ecological integrity of commercially grazed rangelands using remote sensing-based ecological indicators. Proceedings of the VI International Rangeland Congress: People and Rangelands, Building the Future (D. Eldridge and D. Freudenberger, editors), 17-23 July, Townsville, Queensland, Australia (VI International Rangeland Congress, Aikenvale, Queensland, Australia), 2:778-780.

Webster, R., and M.A. Oliver. 1990. Statistical Methods for Soil and Land Resources Survey. Oxford University Press, Oxford.

Weismiller, R.A., I.D. Persinger, and O.L. Montgomery. 1977. Soil inventory from digital analysis of satellite scanner and topographic data. Soil Sci. Soc. Am. J., 41:1166-1170.

Weismiller, R.A., and S.A. Kaminsky. 1978. Applications of remote sensing technology to soil survey research. J. Soil and Water Conserv., 33:287-289.

West, N.E., and D.A. Shute. 1978. Alternatives for Ecosystem Classification and Their Implications for Rangeland Inventory. Proceedings of 1st International Rangeland

Congress, Denver Colorado, Aug. 14-18, 1978. Edited by Donald N. Hyder, pp. 174-176.

West, N.E., K. McDaniel, E.L. Smith, P.T. Tueller, and S. Leonard. 1994. Monitoring and interpreting ecological integrity on arid and semi-arid lands of the western United States. Report from the Western Regional Research Coordinating Committee on Rangeland Research, New Mexico Range Improvement Task Force, Rep. No. 37.

West, N.E., and E. L. Smith. 1997. Improving the monitoring of rangelands. Rangelands, 19:9-14.

Westin, F.C., and C.J. Frazeek. 1976. Landsat data, its use in a soil survey program. Soil Sci. Soc. Am. J., 40:81-89.

Westoby, M., B. Walker, and I. Noy-Meir. 1989. Opportunistic management for rangelands not at equilibrium. Journal of Range Management, 42:266-274.

Whittaker, R.H. 1953. A consideration of the climax theory: The climax as population and pattern. Ecol. Monogr., 23:1-44.

Whittaker, R.H. 1967. Gradient analysis of vegetation. Biol. Rev. 42:207-264.

Wicken, E. 1986. Terrestrial ecozones of Canada. Environment Canada. Ecological Land Classification Series No. 19. Ottawa, Ontario.

Wickland, D.E. 1991. Mission to planet earth: The ecological perspective, Ecology, 72:1923-1933.

Wiegand, C.L., A.J. Richardson, D.E. Escobar, and A.H. Gerbermann. 1991. Vegetation indices in crop assessments. Remote Sensing of Environment, 35:105-121

Wiens, J.A. 1984. On understanding a non-equilibrium world: Myth and reality in community patterns and processes, pp. 439-457 In: D.R. Strong, D. Simberloff, L.G. Abele, and A.B. Thistle (eds). Ecological Communities: Conceptual Issues and Evidence, Princeton Univ. Press, Princeton, N.J.

Williams, R.E., B.E. Allred, R.M. DeNio, and H.E. Paulsen. 1968. Conservation, development, and use of the world's rangelands. Journal of Range Management, 21:355-360.

Williams, B.K. 1993. Some observations on the use of discriminant analysis in ecology. Ecology, 64:1283-1291.

Woodcock, C.E., and J. Harward. 1992. Nested-hierarchical scene models and image segmentation. International Journal of Remote Sensing, 13:3167-3187.

Worster, D. 1992. Under western skies: nature and history in the American west. Oxford University Press. New York, N.Y.

APPENDICES

APPENDIX A

STUDY SITES AND ECOLOGICAL UNIT ATTRIBUTES

APPENDIX A.

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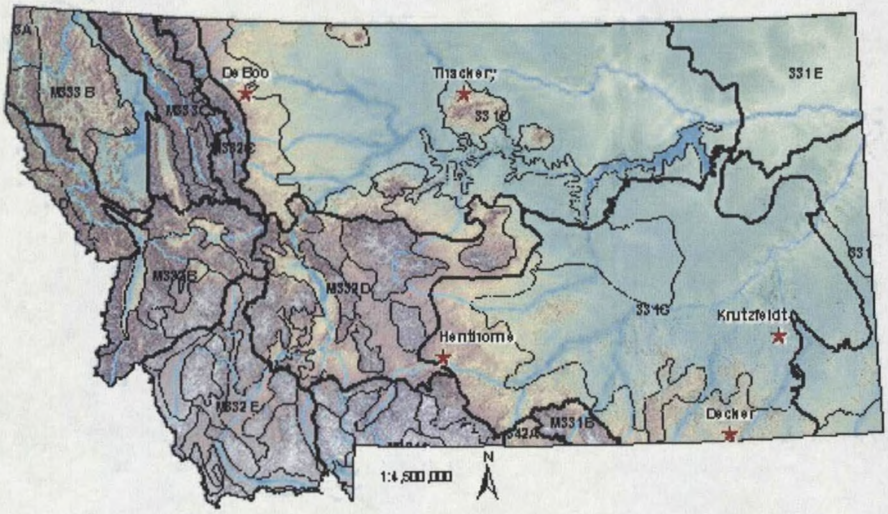

Figure 1. Location of study sites in Montana. The five study areas are indicated by a red star. The bold lines display Section boundaries, lighter lines are Subsection boundaries.

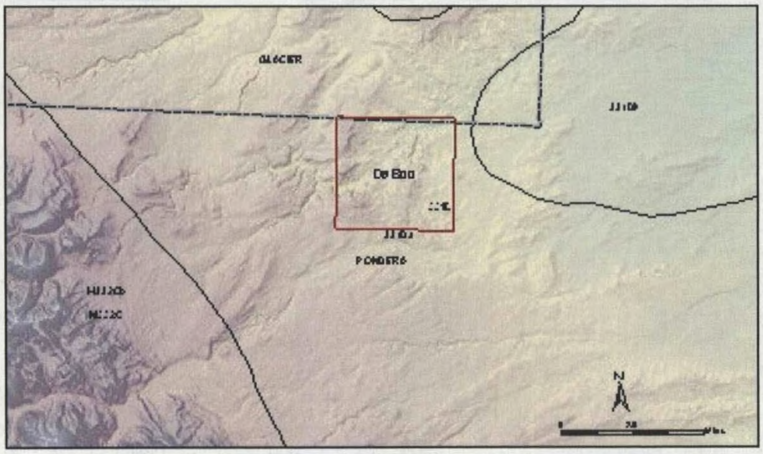

Figure 2. DeBoo Ranch: Section 331D: Northwestern Glaciated Plains.
Subsection 331Da: The Rocky Mountain Front Foothills.
This study area is approximately 15 km northwest of Dupuyer, Montana, (48° 28', -112° 40'). The landscape of the ranch has been strongly influenced by glaciation, with soils formed in till, outwash and alluvium underlain by calcareous shales. Soil temperature regimes are frigid, with typic ustic moisture regimes. Haploborolls, Argiborolls and Calciborolls represent the primary soil great groups. Dominant surface soil textures of the four ecological range units sampled ranged from clayey to silty.

APPENDIX A, CONTINUED

Figure 3. Thackery Ranch: Section 331D: Northwestern Glaciated Plains.
Subsection 331Db: Montana Isolated Mountain Ranges.
This study area is approximately 20 km south of Havre, Montana, (48° 21', -109° 31'). The landscape includes steep foothills, terraces, fans and narrow valleys formed in Tertiary volcanics and mixed sedimentary formations strongly influenced by continental glaciation. Frigid soil temperature regimes, and typic ustic moisture regimes are the norm, with dominant great groups including Argiborolls, Haploborolls and Ustorthents. Silty textured soils are common on the four ecological range units sampled.

APPENDIX A, CONTINUED

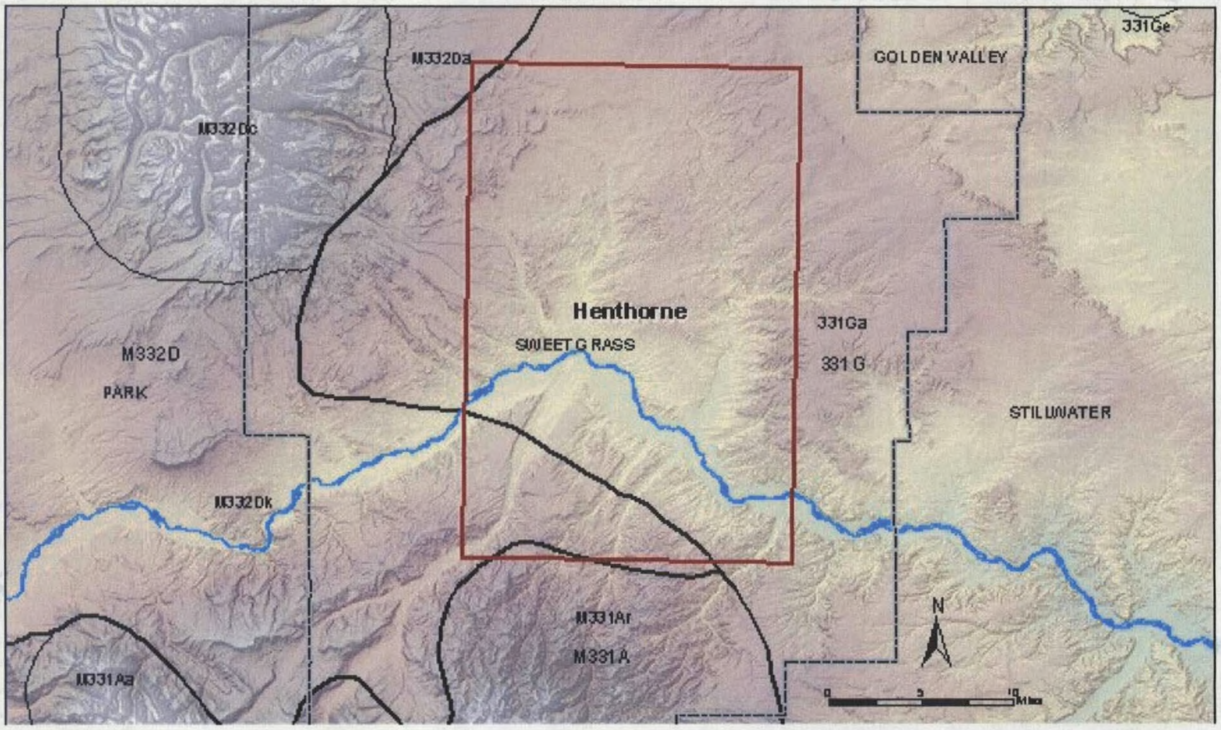

Figure 4. Henthorne Ranch: Section 331G: Powder River Basin; Section 332D Belt Mtns.
Subsection 331Ga: Montana High Plains and Foothills.
Subsection 332Dk: Central Montana Broad Valleys
This study area is situated approximately 30 km. north of Big Timber, Montana, (45° 53', -109° 52"). The landscape is predominantly low relief shallow plains formed in sandstone and shale. Soils on the six ecological range units sampled included Argiustolls, Ustorthents and Calciustepts with frigid temperature regimes and predominately clayey and silty textures.

APPENDIX A, CONTINUED

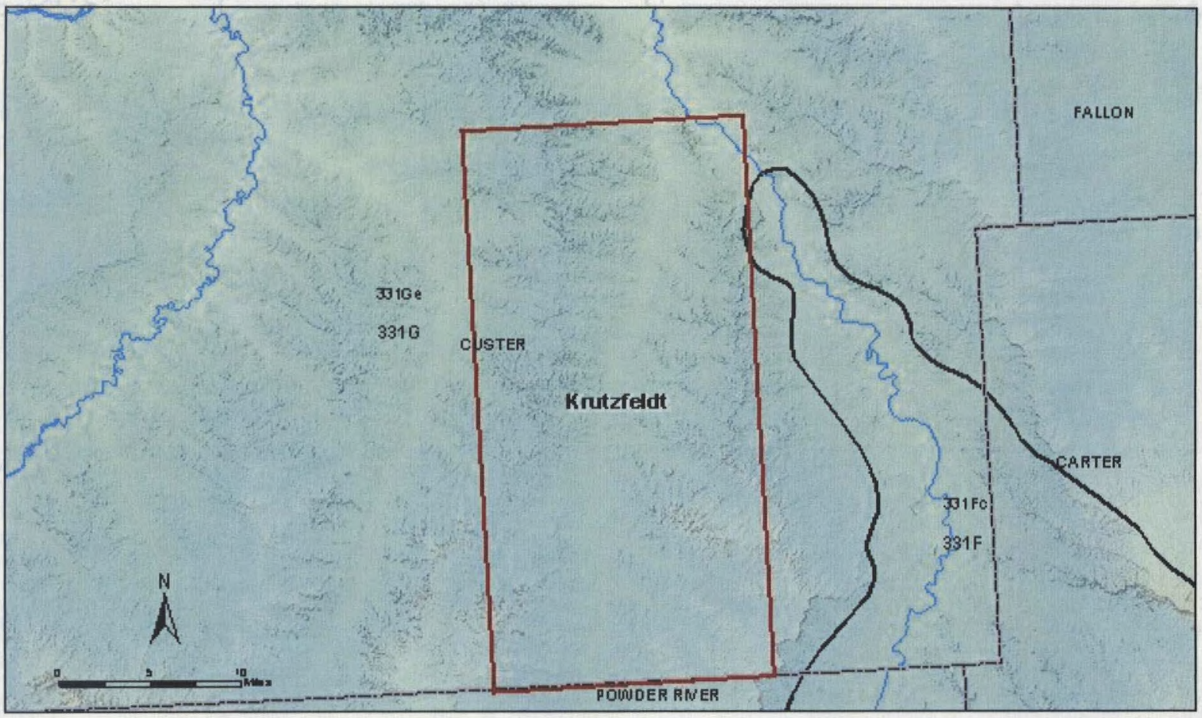

Figure 5. Krutzfeldt Ranch: Section 331G: Powder River Basin.
Subsection 331Ge: Montana Sedimentary Plains.
This study area included sites throughout the Mizpah drainage southwest of Miles City, Montana, (45° 46', -105° 18'). Landforms in the area are primarily rolling hills and plains formed in alluvium and residuum, underlain by shale and sandstone parent material. Expressions of scoria hills also occur in the area. Ustochrepts, Eutroboralfs and Ustorthents with frigid temperature regimes are common soil great groups of the six ecological range units sampled. Dominant surface soil textures vary from silty to clayey with microsite inclusions of shallow sand in depositional areas and outcrops.

APPENDIX A, CONTINUED

Figure 6. Bales and Decker Ranches: Section 331G: Powder River Basin.
Subsection 331Gc: Powder River Basin/Breaks/Scoria Hills.
The landscape of this study area is strongly influenced by the badlands and scoria hills that have formed from the sandstone, siltstone and shale common to this Subsection located in the Otter Creek drainage south of Ashland, Montana, (45° 4', -106° 6'). Soils in the Haplargid, Torrifluvent, Argiboroll, Ustorthent, and Camborthid great groups, with primarily frigid temperature regimes, and aridic and ustic, moisture regimes were all were represented on expressions of the eight ecological range units sampled.

APPENDIX A, CONTINUED

Table 1. Ecological range sites by ranches.

Ranch Samples(N)	Ecological Classification Name
DeBoo:	
Section 331D: Northwestern Glaciated Plains	
Subsection 331Da: The Rocky Mountain Front Foothills	
R052XN162MT (12)	Clayey, 10 - 14 ppt* zone, glaciated plains, north
R052XN161MT (3)	Silty, 10 - 14 ppt zone, glaciated plains, north
R046XN252MT (11)	Silty, 15 - 19 ppt zone, northern Rocky Mountain foothills
R052XN178MT (10)	Shallow, 10 - 14 ppt zone, glaciated plains, north
ERUs = 4 Ranch Samples = 36	
Decker/Bales:	
Section 331G: Powder River Basin	
Subsection 331Ge: Powder River Basin/Breaks/Scoria Hills	
R058AE002MT (26)	Clayey, 10 - 14 ppt zone, sedimentary plains, east
R058AE013MT (6)	Clay pan, 10 - 14 ppt zone, sedimentary plains, east
R058AE199MT (36)	Shallow Clay, 10 - 14 ppt zone, sedimentary plains, east
R058AE001MT (15)	Silty, 10 - 14 ppt zone, sedimentary plains, east
R058AE394MT (6)	Silty, 15 - 19 ppt zone, sedimentary plains, east
R058AE019MT (2)	Shallow, 10 - 14 ppt zone, sedimentary plains, east
R058AE392MT (2)	Shallow, 15 - 19 ppt zone, sedimentary plains, east
R058AE397MT (4)	Very shallow, 15 - 19 ppt zone, sedimentary plains, east
R058AE003MT (1)	Sandy, 10 - 14 ppt zone
ERUs = 8-9 Ranch Samples = 92	
Krutzfeldt:	
Section 331G: Powder River Basin	
Subsection 331Ge: Montana Sedimentary Plains	
R058AE002MT (4)	Clayey, 10 - 14 ppt zone, sedimentary plains, east
R058AE013MT (8)	Clay pan, 10 - 14 ppt zone, sedimentary plains, east
R058AE001MT (29)	Silty, 10 - 14 ppt zone, sedimentary plains, east
R058AE004MT (3)	Thin Silty, 10 – 14 ppt zone, sedimentary plains, east
R058AE019MT (5)	Shallow, 10 - 14 ppt zone, sedimentary plains, east
R058AE003MT (3)	Sandy, 10-14 ppt.zone, sedimentary plains, east
ERUs = 6 Ranch Samples = 52	

* Precipitation (ppt.) in inches.

APPENDIX A, CONTINUED

Table 1 cont.

Ranch Samples(N)	Ecological Classification Name
Thackery:	
Section 331D: Northwestern Glaciated Plains	
Subsection 331Db: Montana Isolated Mountain Ranges	
R046XC508MT (9)	Silty, 15 - 19 ppt zone, northern Rocky Mountain foothills, central
R046XC516MT (11)	Thin silty, 15 - 19 ppt zone, northern Rocky Mountain foothills, central
R046XC599MT (19)	Silty, steep, 15 - 19 ppt zone, northern Rocky Mountain foothills, central
R046XC506MT (12)	Shallow, 15 - 19 ppt zone, northern Rocky Mountain foothills, central
ERUs = 4 Ranch Sample = 51	
Henthorne:	
Section 331G: Powder River Basin	
Subsection 331Ga: Montana High Plains and Foothills	
R058AC040MT (3)	Silty, 10 - 14 ppt zone, sedimentary plains, central
R046XS104MT (3)	Silty, 15 - 19 ppt zone, northern Rocky Mountain foothills, south
R058AC041MT (17)	Clayey, 10 - 14 ppt zone, sedimentary plains, central
R046XS105MT (2)	Clayey, 15 - 19 ppt zone, northern Rocky Mountain foothills, south
R058AC057MT (5)	Shallow, 10 - 14 ppt zone, sedimentary plains, central
R058AC058MT (2)	Very shallow, 10 - 14 ppt zone, sedimentary plains, central
ERUs = 6 Ranch Sample = 32	

TOTAL ERU categories = 24
TOTAL SAMPLE = 263

APPENDIX A, CONTINUED

Table 2. Landsat 7 ETM+ scene, scene date and field biomass clipping dates.

Ranch/Path/Row	Scene Date	Clip Date
DeBoo		
4126	8/01/01	7/16/01
4026	7/13/00	7/18/00
Decker		
3529	6/08/00	6/14/00
3529	8/11/00	8/24/00
3529	7/29/01	8/21/01
Krutzfeldt		
3528	6/08/00	6/16/00
3528	8/27/00	8/25/00
3529	8/14/01	8/16/01, 8/17/01
3528	8/01/02	
Thackery		
3826	7/22/00	8/2/00, 8/3/00
3826	8/03/01	7/25/01,7/26/01
Henthorne		
3828	7/31/00	7/28/00
3828	8/03/01	8/7/01,8/08/01

APPENDIX B

RADIOMETRIC AND ATMOSPHERIC CORRECTIONS

APPENDIX B

Radiometric Corrections

Each of the 13 Landsat 7 ETM+ scenes used in the study was converted to radiance using the standard published formula:

Radiance = gain * DN + offset

Radiance = ((LMAX-LMIN)/(QCALMAX-QCALMIN))*(QCAL-QCALMIN)+LMIN

where: QCALMIN = 1
QCALMAX = 255
QCAL = Digital Number

Constants for LMIN1, LMAX1 are given in the IAS Landsat handbook which can be accessed over the worldwideweb at:
http://ltpwww.gsfc.nasa.gov/IAS/handbook/handbook_htmls/chapter11/chapter11.html

Gains and offsets used were appropriately adjusted for the two scenes acquired before July 2000 and all others collected after July 2000. Due to the geographic location and acquisition dates, all scenes used in this study had high gains in Bands 1,2,3,5 and 7 and low gains in Band 4 as published in the scene metadata. As gains and offsets can change with the condition of the sensor, Landsat data users should check for appropriate values each time an image is acquired. Conversion of full scene radiance values to reflectance was conducted using scene and scene date specific parameters of earth sun distance, solar elevation, and the band specific mean solar exoatmospheric irradiances (Table 3). The constants used in the calculations and conversions for the scenes used in this study are listed in Table 7. A unique image-processing model was developed for each scene to perform the radiance to reflectance conversions. The intent of developing unique processing models for each scene, rather than using an automated process that calculated and populated input values from a spreadsheet, was to allow for easy modification when analyzing future images, and to provide an image processing tool that could be easily understood and used by ranchers, students, or other researchers.

APPENDIX B, CONTINUED

The following radiance to reflectance formula was used:

$$\rho_p = \frac{pi * L_\lambda * d^2}{ESUN_\lambda * \cos \theta_s}$$

Where:
ρ_p = Unitless planetary reflectance
L_λ = Spectral irradiance at the sensor's aperture
d = Earth-Sun distance in astronomical units.
$ESUN_\lambda$ = Mean solar exoatmospheric irradiances (Table 3)
θ_s = Solar zenith angle in degrees

Table 3. ETM+ solar spectral irradiances.

Band	watts/(meter squared*um)
Band 1	1969.00
Band 2	1840.00
Band 3	1551.00
Band 4	1044.00
Band 5	225.7
Band 7	82.07

APPENDIX B, CONTINUED

Table 6. Image parameters for conversion to reflectance.

Scene Path/Row/Date	Julian Day	Earth/Sun Distance	Solar Elevation
352860800	160	1.012760	61.661907
352872901	210	1.015184	56.760261
352881100	224	1.013250	53.971153
352960800	160	1.012760	62.491699
352972600	208	1.015372	53.422077
352980102	213	1.014900	56.920670
352981401	226	1.012950	53.950756
352982700	240	1.008720	50.560527
382680301	215	1.014600	53.856029
382873100	213	1.014900	56.545795
382880301	215	1.014600	55.683777
402671300	195	1.016516	58.066860
402680101	213	1.014900	54.312000
412670701	188	1.016616	58.649551

APPENDIX B, CONTINUED

Chavez atmospheric correction model

To account for both scene and atmospheric differences the improved Chavez method for radiometric and atmospheric correction was applied (Chavez, 1996). This method both converts the DNs to reflectance and corrects for haze within the scene. The following section presents the manner in which it was applied in this study.

COST model input parameters

Solar zenith angle q

Date of image acquisition, Julian Day

The radiance to reflectance equation is:

$L_{1,min} = LMIN_1 + QCAL * (LMAX_1 - LMIN_1) / QCALMAX$

where QCAL is the minimum DN, QCALMAX = 255.

The radiance of a dark object for each band (assumed reflectance of 1%) was computed as:

$L_{1,1\%} = 0.01 * ESUN_1 * \cos^2 q / (p * d^2)$

where $ESUN_1$ = mean solar exoatmospheric spectral irradance (Table 6)

The haze correction was computed as:

$L_{1,haze} = L_{1,min} - L_{1,1\%}$

The final radiance to reflectance, with haze correction was computed as:

$r = p * d^2 * (Lsat^1 - Lhaze) / ESUN^1 * \cos^2 q$

ESUN1 was corrected to radiance in watts/m^2 for ETM+ data.

APPENDIX B, CONTINUED

Two methods were explored for establishing the minimum DNs (brightness values) for each reflective band that is needed for the LHAZE calculation. The first method selected the minimum DN from histograms for each band. Although this technique allows automating the selection of minimum DNs for incorporation into the LHAZE calculation, minimum DNs selected using this method were found to be unsuitable due to the 'halo' effect of low DNs on the perimeter of each scene. The use of a preliminary processing step to buffer and clip these pixels from the scene before running an automated selection of minimum DNs, was not experimented with in this study. Minimum DNs were derived from a visual display the location of dark object DNs with the corresponding band histogram. This technique requires the analyst to interpret and select target DNs that appear representative of surrogate "black bodies" represented in each reflective band. For each band the radiance of a dark object was extracted and used to compute the L_{min} for each band.

APPENDIX C

TASSELED CAP PARAMETERS AND ANALYSIS

APPENDIX C

Table 7. Tasseled cap transformation parameters (Huang et al. 2002).

Index	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	0.2630
Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388
Fourth	0.0805	-0.0498	0.1950	-0.1327	0.5752	-0.7775
Fifth	-0.7252	-0.0202	0.6683	0.0631	-0.1494	-0.0274
Sixth	0.4000	-0.8172	0.3832	0.0602	-0.1095	0.0985

Table 8. Codes and values of anomaly model classes and sample representation.

L (low), H (high), M (mean) refer to SSDL, see Chapter 4, pg. 55.
B (brightness), G (greenness), W (wetness) are tasseled cap components.

Code	Brightness/ Greeness /Wetness			n
0	BL	GL	WL	0
1	BL	GL	WM	0
2	BL	GL	WH	0
10	BL	GM	WL	0
11	BL	GM	WM	2
12	BL	GM	WH	1
20	BL	GH	WL	0
21	BL	GH	WM	2
22	BL	GH	WH	4
100	BM	GL	WL	5
101	BM	GL	WM	1
102	BM	GL	WH	0
110	BM	GM	WL	8
111	BM	GM	WM	191
112	BM	GM	WH	2
120	BM	GH	WL	0
121	BM	GH	WM	13
122	BM	GH	WH	8
200	BH	GL	WL	3
201	BH	GL	WM	2
202	BH	GL	WH	0
210	BH	GM	WL	17
211	BH	GM	WM	4
212	BH	GM	WH	0
220	BH	GH	WL	0
221	BH	GH	WM	0
222	BH	GH	WH	0

APPENDIX C, CONTINUED

Table 9. Landsat 7 ETM+ scene, scene date and ERU anomaly images.

Ranch/Path/Row	Scene Date	Clip Date	ERU Anomaly images*
DeBoo			
4126	8/01/01	7/16/01	161,162,178,252
4026	7/13/00	7/18/00	161,162,178,252
Krutzfeldt			
3528	6/08/00	6/14/00	004,001, 002,013,019
3528	8/11/00	8/24/00	001,003,004
3528	7/29/01	8/21/01	001,002,003,004,013,019
Decker			
3529	6/08/00	6/16/00	199,392,394,397
3529	8/27/00	8/25/00	001,002,003,019,199
3529	8/14/01	8/16/01, 8/17/01	001,002,003,013,199,392,394
3529	8/01/02	8/xx/02	001,002,013,199
Thackery			
3826	7/22/00	8/2/00, 8/3/00	506,599,516
3826	8/03/01	7/25/01,7/26/01	506,508,516,599
Henthorne			
3828	7/31/00	7/28/00	040,041,057,058,104,105
3828	8/03/01	8/7/01,8/08/01	040,041,057,058

* See Table 1. For detailed ERU codes and descriptions.

APPENDIX C, CONTINUED

Table 11. Indicators of rangeland health and attribute category association. (USDI, 2000)

Categories	S/S	HF	BI
Indicators			
1. Rills	x	x	
2. Water Flow Patterns	x	x	
3. Pedestals or Terracettes	x	x	
4. Bare Ground	x	x	
5. Gullies	x	x	
6. Wind-scoured blowouts and or Depositional Areas	x		
7. Litter Movement		x	
8. Soil Surface Resistance to Erosion	x	x	x
9. Soil Surface Loss or Degradation	x	x	x
10. Plant Community Composition and Distribution Relation to Infiltration and Runoff		x	
11. Compaction Layer	x	x	x
12. Functional/Structural Groups			x
13. Plant Mortality/Decadence			x
14. Litter Amount		x	x
15. Annual Production			x
16. Invasive Plants			x
17. Reproductive Capability of Perennial Plants			x

S/S = Soil/Site Stability
HF= Hydrologic Function
BI = Biotic Integrity

APPENDIX D

RESEARCH SUPPORT AND COOPERATORS

APPENDIX D

The need to address public access to remotely sensed data has been responded to by the National Oceanographic and Atmospheric Administration (NOAA) in a wide variety of ways. Public Access Resource Centers (PARCs), sponsored by the National Aeronautic and Space Administration (NASA), have promoted the formation of several localized technical support groups such as the Upper Midwest Aerospace Consortium (UMAC). This research was sponsored by UMAC and a cooperative agreement between Montana State University and the Natural Resources Conservation Service of the U.S. Department of Agriculture. The Montana State Library, Natural Resources Information System (NRIS) provided access to existing GIS data themes, computer hardware, software and technical support.

Private landowners Keith Bales, Chuck DeBoo, Gordon Decker, Butch Krutzfeldt and Wes Henthorne all generously allowed access to their ranches, advice and field assistance, as did Derek Bailey, manager of the Northern Montana Agricultural Research Center's Thackery Ranch.