Modeling Vegetation Amount Using Bandwise Regression and Ecological Site Descriptions as an Alternative to Vegetation Indices

Catherine Lee Maynard
U.S. Department of Agriculture–National Resource Conservation Service, Montana, 1515 East 6th Avenue, Helena, Montana 59620

Rick L. Lawrence[1]
Montana State University, Land Resources and Environmental Sciences Department, P.O. Box 173490, Bozeman, Montana 59717

Gerald A. Nielsen
Montana State University, Land Resources and Environmental Sciences Department, P.O. Box 173120, Bozeman, Montana 59717

Gordon Decker
National Resource Conservation Service (retired), 6700 Springhill Road, Belgrade, Montana 59714

Abstract: Ecological site descriptions (ESDs) based on soil maps, Landsat 7 ETM+ band values, and vegetation index data from 12 scenes were used as predictive variables in linear regression estimates of total biomass using field data from five Montana ranches. Bandwise regression explained the most variability (53%) when ESDs were not included, followed by tasseled cap components (51%), the soil adjusted vegetation index (44%), and the normalized difference vegetation index (41%). ESDs improved the amount of variability explained to 66% for bandwise regression and 65% using tasseled cap components.

INTRODUCTION

One of the most important applications of remotely sensed data is the estimation of vegetation amount, whether in the form of percent cover, biomass, leaf area index, fraction of intercepted photosynthetically active radiation, or other measures. By far the most common means of making such estimations is through ordinary least squares

[1]Corresponding author; email: rickl@montana.edu

GIScience & Remote Sensing, 2006, **43**, No. 4, p. 1–14.

regression analysis. This method has the advantage of clearly modeling the relationship between the response variable and the spectral predictors, although the approach has been shown to have some shortcomings (Cohen et al., 2003). The dominant approach for such regression analyses has been to use the measured vegetation amount as the response variable and a vegetation index (in most cases the normalized difference vegetation index, NDVI) as the explanatory variable. This practice remains common, although it has been shown that it results in inferior biomass estimates when compared to those using non-indexed spectral data (Lawrence and Ripple, 1998).

Regression estimates of vegetation amount using vegetation indices encounter three major issues: First, the regressions are limited to the bands included in the index, usually red and near infrared, without consideration of whether other bands might improve the estimates; Second, indices restrict the ability to model the effects of different vegetation/energy interactions in different portions of the spectrum. Third, soil heterogeneity can affect spectral responses. The second issue can be seen best by a decomposition of a standard regression using vegetation indices into the component spectral bands. A common regression takes the form of:

$$\text{Vegetation amount} = \beta_0 + (\beta_1 * \text{NDVI}), \tag{1}$$

where β_0 and β_1 are the intercept and slope, respectively, of the regression line (Lawrence and Ripple, 1998). An alternative expression of this regression when NDVI is decomposed is:

$$\text{Vegetation amount} = \beta_0 + (\beta_1 * ((\text{Near IR - Red})/(\text{Near IR + Red}))). \tag{2}$$

It is evident from Equation 2 that a single coefficient, β_1, is applied to a combination of the near infrared and the red portions of the spectrum. The red portion of the spectrum, however, responds primarily to chlorophyll and leaf pigments, while the near infrared portion responds primarily to spongy leaf mesophyll. An effect of this difference in response is the tendency of red to saturate at a lower level than near infrared, resulting in a lower "spectral asymptote" for red (Ripple, 1985). Consequently, regression models have more explanatory power when each of these bands can be modeled with its own coefficient (Ripple, 1994; Lawrence and Ripple, 1998; Robinson et al., 2004).

The third known limitation of vegetation indices is the effect of soil variability on the relationship between vegetation amount and spectral response. This effect has been well documented by studies examining what effect variable percentages of exposed soil, standing dead vegetation, litter, and green biomass have on 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). A range of specialized modifications to factor soil reflectance in the ratio vegetation indices has been published (Huete, 1988; Baret et al., 1989; Baret and Guyot, 1991; Qi et al., 1994). The NDVI and its functional equivalents continue to be widely applied in remote sensing studies of vegetation attributes, notwithstanding these limitations (Curran, 1980; Perry and Lautenschlager, 1984; Bannari et al., 1995; Reeves et al., 2001; Tueller, 2001; Thoma et al., 2002). The tasseled cap transformation, which incorporates other bands, has also received widespread use, but again does not address soil variability, assuming an average soil response (Kauth and Thomas, 1976; Crist and Cicone, 1984; Huang et al., 2002). Bandwise regression, which allows separate coefficients for each band, allows the inclusion of other bands, and permits band transformations, has been shown to be superior to ratio indices in estimating biomass (Lawrence and Ripple, 1998), but it also fails to account expressly for soil variability.

We investigated an alternative to correcting indices for soil variability by using widely available ecological site descriptions (ESDs) (West et al., 1994; NRC, 1994) to account for landscape and site level differences in the spectral response of soils across differing backgrounds. This approach eliminates the need to assume a universal correction for varying soil lines and at the same time complements the advantages of using bandwise regression, as soils within ecological sites could simply be added as an additional regression variable.

Ecological site 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. Ecological sites address the influence of environmental parameters such as climate, parent material, topography, and soils on site-specific ecological potential for differing vegetation types (Shiflet, 1973; Laurenroth, 1979; NRCS, 1997). Ecological site descriptions provide a useful template for efficient ecological inventories and ensuring that data analysis and interpretations are consistent with site potential differences (Zonnefeld, 1989; Nesser et al., 2001). These mapping concepts have been incorporated into a variety of currently published landscape-level ecological site description products that have been widely used in applications addressing global, regional, and local differences in vegetation types and productivity; analyzing the response of differing biophysical environments to natural and management related disturbance; and providing a framework for biological assessments (Bailey, 1983; Merriam, 1988; Zonnefeld, 1986; Omernick, 1987, 1995; Loveland et al., 1991; Nesser et al., 1996, 2001; Cooper and Heidel, 1999; Homer and Gallant, 2001). ESDs attributed by subsection and derived from 1:24,000-scale SSURGO soils data are at a commonly used ecological site scale for evaluating rangeland vegetation types, productivity classes, and ecological health parameters and are consistent with accepted ecological mapping practices and current rangeland inventory methods in the United States and elsewhere (Shiflet, 1973; Wilson et al., 1984; Zonnefeld, 1989; Pickup et al., 1993; NRC, 1994; Willoughby, 1998).

Our first objective was to demonstrate that using bandwise regression would result in better regression models than using indices. We used the most common indices for this purpose, NDVI, Soil-Adjusted Vegetation Index (SAVI), and tasseled cap components, although we could have demonstrated this principle with any other of the many available indices. Our second objective was to determine whether including ecological sites and soils data in regressions might provide superior modeling of biomass (and, by logical extension, other measures of vegetation amount) compared to both traditional approaches using vegetation indices and bandwise regression without this information.

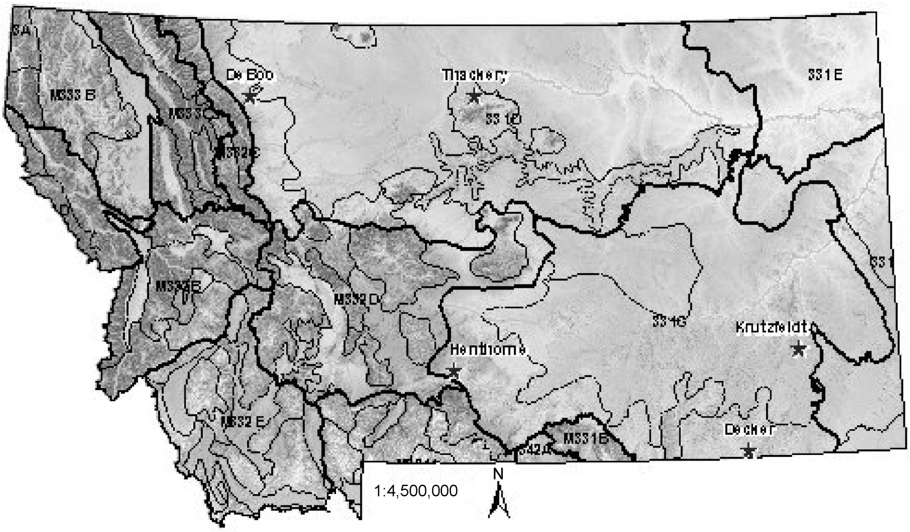

Fig. 1. Location of study sites in Montana. The five ranches are indicated by stars. The bold lines display section boundaries; lighter lines are subsection boundaries.

METHODS

Study Sites

Field data for this study were collected from 24 ecological site descriptions (ESDs) on five Montana ranches (Fig. 1). Each ranch was located within a different Landsat 7 ETM+ scene. Mean annual precipitation across the sites ranged from 250 to 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.

Data

Field samples were collected from approximately 11 random locations within each ESD. All green and senesced vegetation biomass within a single 0.75 m^2 area was clipped to ground level for each field sample. We recognized that these samples could not be expected to each represent the biomass of a Landsat 900 m^2 pixel; however, because the sample sites were randomly selected and therefore unbiased, we could expect the samples on average to represent the biomass within the pixels (Ramsey and Shafer, 2002). The identification of the plot location within the ecological sites sampled was based on a stratified random design based on ESD and the digital soil survey maps from which GPS coordinates were randomly generated for sample points within each ESD (Warren et al., 1990). Random points where site characteristics were inconsistent with the dominant vegetation and soil properties of the described ESD were rejected, and an alternative random plot was located. Clipped samples were dried and weighed. Field data for the 263 plots used in the analysis

Table 1. Landsat 7 ETM+ Scene (path/row), Scene Dates, Field Biomass Clipping Dates, and Days between Image and Clipping Dates for Data Used in the Study

Scene	Scene date	Field biomass clipping date	Days between image and clipping dates
35/28	06/08/2000	06/16/2000	8
35/28	08/27/2000	08/25/2000	2
35/29	06/08/2000	06/14/2000	6
35/29	08/11/2000	08/24/2000	13
35/29	08/14/2001	08/16–17/2001	2–3
38/26	07/22/2000	08/02–03/2000	11–12
38/26	08/03/2001	07/25–26/2001	8–9
38/28	07/31/2000	07/28/2000	3
38/28	08/03/2001	08/07–08/2001	4–5
38/29	07/29/2001	08/21/2001	23
40/26	07/13/2000	07/18/2000	5
41/26	08/01/2001	07/16/2001	16

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 (Table 1). We tested the significance of a variable to account for the difference between field and image collection dates to see if the large lags in some of the cases significantly affected our results, and in all cases the variable was not significant (p-value > 0.05).

Twelve 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 (Landsat 7 Handbook, 2002). Geographic registration of each image was within 0.5 root mean squared error. GIS themes of ranch boundaries were used as a general perimeter for sub-setting the scenes. ESDs for the area within each ranch were generated from published digital data of landscape level section and subsection ecological sites and the Soil Survey Geographic Database (SSURGO) (ECOMAP, 1993; Nesser et al., 1996; NRCS, 2000). The National Soil Information System (NASIS) database for each survey area was used as the reference source for mapped site characteristics. For the five ranches, 82 individual soil map units within five unique subsections were aggregated to the 24 ESDs sampled.

Pixel values for bands 1–5 and 7 were extracted for each plot corresponding to the closest pixel center coordinate to the plot GPS location and used to calculate predictor variables used in the regression equations. 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 soil unit boundaries that required adjustment to the appropriate pixel; this affected less than 10 data points.

Digital numbers were converted to exoatmospheric reflectance (Landsat 7 Handbook, 2002) for calculating all spectral indices. The NDVI was calculated from the red and NIR band values using the standard formula of:

$$\text{NDVI} = (\text{Band 4} - \text{Band 3})/(\text{Band 4} + \text{Band 3}). \quad (3)$$

The following formula was used to calculate the SAVI:

$$\text{SAVI} = 1.5\ ((\text{Band 4} - \text{Band 3})/(\text{Band 4} + \text{Band 3} + 0.5)) \quad (4)$$

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.

Measured total dry biomass was transformed to the fourth root of field values to meet the linear regression assumptions of homogeneity of variance and normality of residual distribution. This variable, the fourth root of total dry biomass (transformed total biomass or TTB), was used as the response variable for a series of linear regression models.

Analysis

The first stage of the analysis compared four linear regression models for estimating TTB, each using different predictor variables: (1) NDVI, (2) SAVI, (3) tasseled cap components, and (4) non-transformed reflective bands. Variable selection for the multiple regression models was accomplished using extra sums-of-squares F-tests (Lawrence and Ripple, 1998), and coefficients of determination (R^2) were used to evaluate the variability in biomass explained by the different models. Two models, one using band 4 (0.75–0.90 μm) and band 7 (2.09–2.35 μm) and the second using tasseled cap GVI and WI, were selected based on the regression results for further testing in the second analysis involving the introduction of ESDs into the regressions. ESDs were entered as a categorical variable, with each ESD assigned a value of 1 if the observation was located in that ESD or 0 if it was located in a different ESD (Ramsey and Shafer, 2002). The effect of this inclusion is to change the regression intercept for each ESD and, if there is a significant interaction term between a spectral band and the ESDs, to also change the slope of the regression line for each ESD.

A simple atmospheric correction method was evaluated for controlling scene-to-scene variability (Chavez, 1996) based on results from other studies of rangeland biomass using ETM+ data (RangeView, 2003). Effectiveness was evaluated by comparing regressions with and without the correction and by including a scene indicator variable in the regressions. Improvement in regression results or decreases in the significance of the indicator variable would indicate that the correction reduced scene-to-scene variability. The corrected data was not used in the analysis because neither test yielded improved results.

RESULTS

Final regression models excluding ESDs were all statistically significant (p-values all < 0.001; Table 2, Fig. 2). The model using NDVI alone explained less than half of the variability in TTB (41%). Adjusting for soil variability using SAVI did improve regression results, increasing variability explained by 3 percentage points. The use of

Table 2. Linear Regression Model Explanatory Variables[a]

Model	R^2
NDVI	0.41
SAVI	0.44
GVI+WI	0.51
Band 4+Band 7	0.53

[a]In each case, TTB was the response variable. Coefficients of determination are presented for regressions not including ESDs. All variables and models were significant at the $p = 0.001$ level.

non-transformed bands in a bandwise regression, which resulted in using bands 4 and 7, substantially improved results, increasing variability explained by 12 percentage points over NDVI and 9 over SAVI, directly addressing our first objective in demonstrating superior results with bandwise regression. Tasseled cap components, however, performed almost as well as non-transformed bands, explaining only 2% less variability. GVI and WI were included in the final regression using tasseled cap components.

Adding a variable representing ESDs to the regression using bands 4 and 7 and the regression using GVI and WI in each case found the categories of ESDs to be significant (p-values < 0.001) and to result in better predictive models than those not using ESDs (Table 3, Fig. 3). Interaction terms between ESDs and band 7 in the first case and between ESDs and GVI in the second case were significant (p-values ≤ 0.05), and were included in the final models. Inclusion of ESDs in the regressions improved variability explained in the tasseled cap-based regression by 14 percentage points and improved variability explained in the bandwise regression by 13 points.

DISCUSSION

The superior performance of the bandwise model over the ratio-based indices (NDVI and SAVI) in estimating biomass confirmed previous analyses regarding the limitations of indices (Lawrence and Ripple, 1998), although in the previous study the bandwise model included the same bands as the ratio-based indices, while here different bands were selected. The result indicating the GVI and WI to be almost as effective as the non-transformed bands is understood by examining the nature of the tasseled cap transformation. The tasseled cap components contain nearly the entire information content of the original bands, but projected onto different axes, which enables similar modeling flexibility to bandwise regression. The regressions were able to model the various spectral responses separately almost as effectively as they were with the non-transformed bands as a result. These results also add support to questioning the reliance on traditional red and near infrared ratio-based indices for estimating biomass under the conditions common to most rangelands and are supported by other observations of semi-arid rangelands (Graetz and Gentle, 1982).

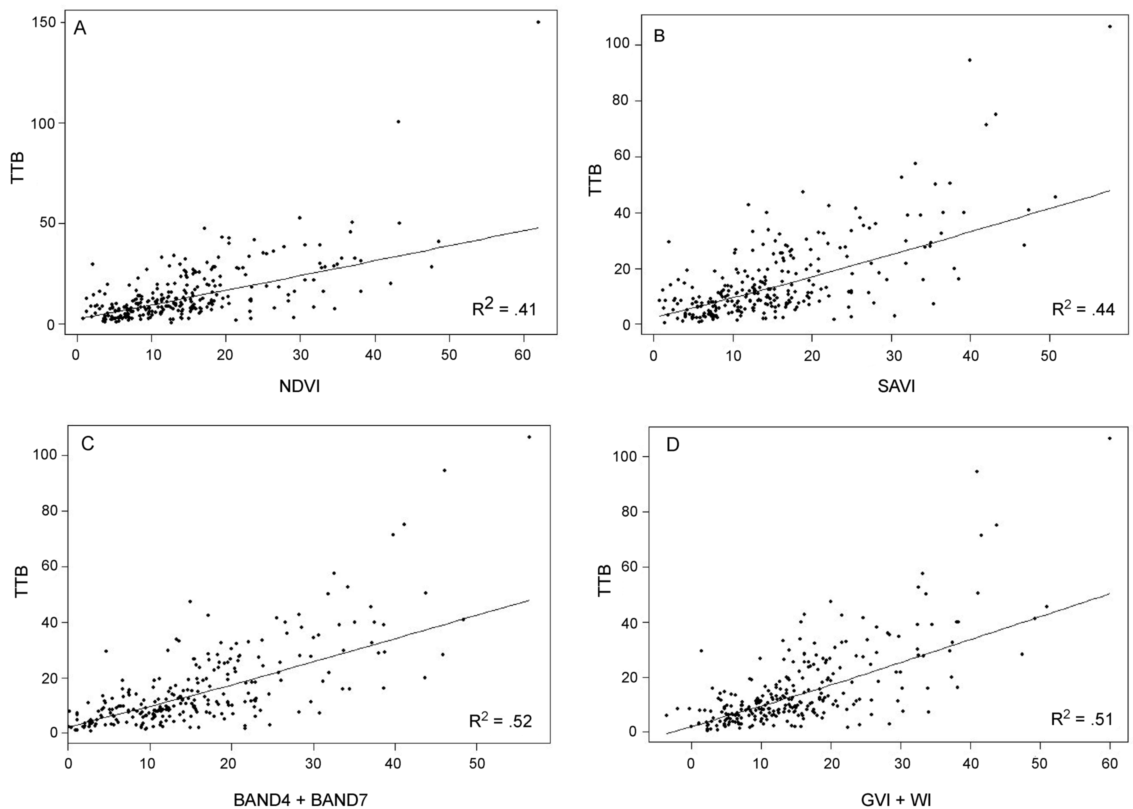

Fig. 2. Scatter plots of transformed total biomass on (A) NDVI, (B) SAVI, (C) band 4 (near infrared) and band 7 (middle infrared), and (D) tasseled cap wetness (WI) and greenness (GVI).

Table 3. Linear Regression Models for Bandwise Regression and Tasseled Cap Components Incorporating ESDs[a]

Model	Adjusted R^2	p-values > 0.001
Band 4 + Band 7 + ESD + (Band 7 * ESD)	0.66	B7 * ESD = 0.03
WI + GVI + ESD + (GVI * ESD)	0.65	GVI * ESD = 0.05

[a]TTB was the response variable in each case. All variables and models were significant at the $p < 0.001$ level unless otherwise specified.

SAVI, further, did not show substantial improvement over the NDVI, which might suggest the standard adjustment factor used (0.5) was not appropriate for the diverse cover conditions of the sampled sites and that modifying the adjustment factor for different soils might have different results (Lawrence and Ripple, 1998).

The significance of near infrared and middle infrared as compared with the more common combination of red and near infrared for biomass estimation might have been due to the influence of one or more of: (1) late season images and the predominance of field biomass measurements collected at times past the period of peak growth and photosynthetic activity; and (2) the low moisture content in the vegetation and below average productivity in all three of the field data collection periods due to the extreme drought conditions during the study time frame. Any of 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 middle infrared (2.08–2.35 μm) wavelength to soil mineral content and to increasing amounts of senescent vegetation, 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 (Asrar et al., 1986; Jensen, 1996).

Our results support stratification of spectral data by ESDs or other soils data to improve linear regression predictions of relative rangeland productivity across heterogeneous sites. It is reasonable to assume that a portion of the additional variability in biomass explained by incorporating ESDs was due to soil background reflectance, because ESD categories are distinguished in part by soil differences, and such differences have been shown to influence biomass estimates from spectral data (Huete, 1988). Inclusion of ESDs, individually and as part of interaction terms, apparently allowed the implicit “soil line” underlying each regression to vary depending on the characteristics of sites within each ESD. Statistically, including a categorical variable such as ESDs in a regression model changes the intercept and, as an interaction term, the slope of the regression line for each ESD (Ramsey and Shafer, 2002). 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/soil composition, particularly in studies where an ecological framework for both image analysis and the application of interpretations is desired. Further study would be required to distinguish the spectral

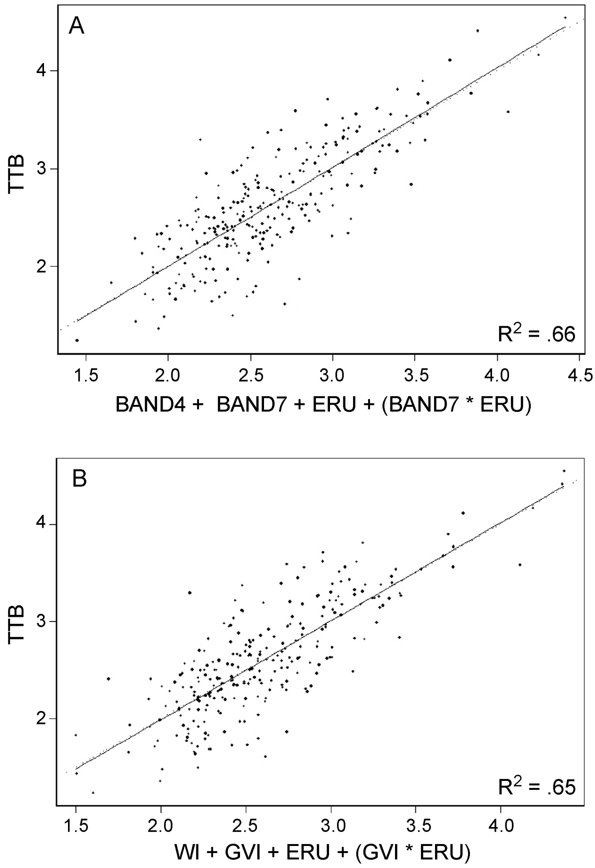

Fig. 3. Scatter plots of transformed total biomass on (A) band 4 (near infrared), band 7 (middle infrared), and ESD with regression line and (B) tasseled cap wetness (WI), greenness (GVI), and ESD with regression line. Regression equations are provided in Table 3.

response differences due solely to the soil background reflectance differences among ESDs.

Significant differences among ESDs existed within individual ETM+ scenes, as the regression results had significant p-values for each ESD. This finding demonstrated that the variability explained by ESDs extended beyond the possible scene-to-scene variability associated with radiometric and atmospheric differences among the scenes, because ESDs within the same scene were significantly different from each other (p-values < 0.05). Studies of more limited geographic scope or using higher resolution imagery might use individual soil map units that make up ESDs to address additional variability in soil background influences on spectral responses.

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. We expected that there might be substantial unexplained variability as a result of our sampling method that used a random 0.75 m^2 plot to represent each 900 m^2 covered by Landsat pixels. Additional sources of variability might be attributed to radiometric, atmospheric, geo-referencing, or environmental influences.

A concerted effort was made to minimize geo-referencing error through close examination of data points following each image-processing step. Residual error might have persisted, however, because of image rectification error, the lack of image correction for terrain differences, or the locational and informational quality of the SSURGO soils data. Environmental factors such as precipitation events occurring in the time period between the image and field collection dates, although few were recorded, could have increased vegetation greenness or growth and reduced correlation with spectral response; however, our statistical test for this effect demonstrated it to be not significant. 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 likely improve predictions of relative biomass productivity.

Based on our research and findings, we make the following recommendations.

1. Vegetation indices should be used for their presumed original purpose—that is, as comparative indices of relative vegetation amounts. Indices remain particularly valuable where reference data is not available to model vegetation amount. The practice of developing regression models (and possibly other models) of vegetation amount using solely vegetation indices as explanatory variables, however, should be limited to instances where the regression is being used to demonstrate the strength of the vegetation index. Otherwise, individual spectral bands should be used.

2. In cases of heterogeneous soils, consideration should be given to including appropriately scaled landscape-level ecological sites combined with soil maps as an additional explanatory variable to account for differences in soil lines.

3. Vegetation indices might be useful as interaction terms used in conjunction with individual spectral bands for regression analyses. Adherence to these recommendations will result in superior regression modeling of vegetation biomass using remotely sensed imagery.

REFERENCES

Asrar, G., Weiser, R. L., Johnson, D. E., Kanemasu, E. T., and J. M. Killeen, 1986 “Distinguishing among Tallgrass Prairie Cover Types from Measurements af Multi-Spectral Reflectance,” *Remote Sensing of Environment*, 19:159–169.

Bailey, R. G., 1983, “Delineation of Ecosystem Regions,” *Environmental Management*, 7:365–373.

Bannari, A. D., Morin, D., Bonn, F., and A. R. Huete, 1995, “A Review of Vegetation Indices,” *Remote Sensing Reviews*, 13:95–120.

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., Guyot, G., and D. Major, 1989, “TSAVI: A Vegetation Index which Minimizes Soil Brightness Effects on LAI and APAR Estimation,” in *12th Canadian Symposium on Remote Sensing and IGARSS’90*, Vancouver Canada, 10–14 July 1989.

Chavez, P. S., Jr., 1996, "Image-Based Atmospheric Corrections—Revisited and Improved," *Photogrammetric Engineering and Remote Sensing*, 62:1025–1036.

Cohen, W. B., Maiersperger, T. K., Gower, S. T., and D. P. Turner, 2003, "An Improved Strategy for Regression of Biophysical Variables and Landsat ETM+ Data," *Remote Sensing of Environment*, 84:561–571.

Colwell, J. E., 1974, "Vegetation Canopy Reflectance," *Remote Sensing of Environment*, 3:175–183.

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, Helena, MT: Montana Natural Heritage Program.

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.

Curran, P., 1980, "Multi-spectral Remote Sensing of Vegetation Amount," *Progress in Physical Geography*, 4:315–340.

ECOMAP, USDA, 1993, *National Hierarchical Framework of Ecological Units*, Washington, DC: U.S. Department of Agriculture, Forest Service, Unpubl. administrative paper.

Galvao, L. S., Vitorello, I., 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.

Gitelson, A. A., Stark, R., Grits, U., Rundquist, D., Kaufman, Y., 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.

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.

Homer, C. G. and A. Gallant, 2001, *Partitioning the Conterminous United States into Mapping Zones for Landsat TM Land Cover Mapping*, USGS Draft White Paper [http://landcover.usgs.gov].

Huang, C., Wylie, B., Homer, C., 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., 1988, "A Soil-Adjusted Vegetation Index (SAVI)," *Remote Sensing of Environment*, 29:295–309.

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

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*, West Lafayette, IN: Purdue University, 41–51.

Landsat 7 Handbook, 2002, [www.gsfc.nasa.gov/IAS/handbook/handbook_toc.html].

Laurenroth, W. K., 1979, “Grassland Primary Production: North American Grasslands in Perspective,” in *Perspectives in Grassland Ecology,* N. French (Ed.), New York, NY: Springer-Verlag, 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.

Loveland, T. R., Merchant, J. W., Ohlen, D. O., 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.

Merriam, G., 1988, “Landscape Ecology: The Ecology of Heterogeneous Systems,” in *Landscape Ecology and Management*, M. Moss (Ed.), Montreal, Canada: Polyscience Publ. Inc., p. 35–43.

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

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

NRC (National Research Council), Committee on Rangeland Classification, Board on Agriculture, 1994, *Rangeland Health: New Methods to Classify, Inventory, and Monitor Rangelands*, Washington, DC: National Academy Press.

NRCS (Natural Resource Conservation Service), 1997, *Range and Pasture Management Handbook*, Ft. Worth, TX: U.S. Government Printing Office.

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

Omernik, J. M., 1987, “Ecoregions of the Conterminous United States,” *Annals of the Association of American Geographers*, 77:118–125.

Omernik, J. M., 1995, *Ecoregions: A Spatial Framework for Environmental Management, Biological Assessment and Criteria: Tools for Water Resource Planning and Decision Making*, Boca Raton, FL: Lewis Publishing.

Perry, C. R. and L. F. Lautenschlager, 1984, “Functional Equivalence of Spectral Vegetation Indices,” *Remote Sensing of Environment*, 14:169–175.

Pickup, G., Chewings, V. H., and D. J. Nelson, 1993, “Estimating Changes in Vegetation Cover Over Time in Arid Rangeland Using Landsat MSS Data,” *Remote Sensing of Environment*, 43:243–263.

Qi, J., Chehbouni, A., Huete, A. R., and Y. H. Kerr, 1994, “A Modified Soil Adjusted Vegetation Index,” *Remote Sensing of Environment*, 48:119–126.

Ramsey, F. L. and D. W. Schafer, 2002, *The Statistical Sleuth: A Course in Methods of Data Analysis*, Belmont, MA: Duxbury Press.

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].

Reeves, M. C., Winslow, J. C., and S. W. Running, 2001, “Mapping Weekly Rangeland Vegetation Productivity,” *Journal of Range Management*, 54 (suppl.):A90–A105.

Ripple, W. J., 1985, "Asymptotic Reflectance Characteristics of Green Vegetation," *Photogrammetric Engineering and Remote Sensing*, 51:1915–1921.

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.

Robinson, A. P., Pocewitz, A. L., and P. E. Gessler, 2004, "A Cautionary Note on Scaling Variables That Appear Only in Products in Ordinary Least Squares," *Forest Biometry, Modeling and Information Sciences*, 1:83–90.

Shiflet, T. N., 1973, "Range Sites and Soils in the United States," in *Arid Shrublands—Proceedings of the Third Workshop*, Denver, CO: United States/Australian Rangelands Panel Society for Range Management, 26–23.

Thoma, D. P., Bailey, D. W., Long, D. S., Nielsen, G. A., Henry, M. P., Breneman, M. C., and C. Montagne, 2002, "Short-Term Monitoring of Rangeland Forage Conditions with AVHRR Imagery," *Journal of Range Management*, 55:383–389.

Tueller, P. T., 1987, "Remote Sensing Applications in Arid Environments," *Remote Sensing of Environment*, 23:143–154.

Tueller, P. T., 2001, "Remote Sensing of Range Production and Utilization," *Journal of Range Management*, 54:77–89.

Warren, S. D., Johnson, M. O., Goran, W. D., and V. E. Diersing, 1990, "An Automated Objective Procedure for Selecting Representative Field Sample Sites," *Photogrammetric Engineering and Remote Sensing*, 56:333–335.

West, N. E., McDaniel, K., Smith, E. L., Tueller, P. T., and S. Leonard, 1994, *Monitoring and Interpreting Ecological Integrity on Arid and Semi-Arid Lands of the Western United States*, Las Cruces, NM: Report from the Western Regional Research Coordinating Committee on Rangeland Research, New Mexico Range Improvement Task Force, Report No. 37.

Wiegand, C. L., Richardson, A. J., Escobar, D. E., and A. H. Gerbermann, 1974, "Vegetation Indices in Crop Assessments," *Remote Sensing of Environment*, 35:105–121.

Wilson, D. J., Tongway, D. J., Graetz, R. D., and M. D. Young, 1984, "Range Inventory and Monitoring," in *Management of Australia's Rangelands,* Harrington, G. N., Wilson, A. D., and M. D. Young (Eds.), Melbourne, Australia: CSRIO, 113–127.

Willoughby, M. G., 1998, *Rangeland Reference Areas: Seven Mile Creek Rangeland Condition and Trend from 1964–1997,* Edmonton, Canada: Alberta Environmental Protection, Land and Forest Service.

Zonneveld, I. S., 1986, "A Systematic Approach to the Evaluation of Rangeland Inventory Data," in *Rangelands, a Resource under Siege,* Proceedings of 2nd International Rangeland Congress, Canberra, Australia: Australian Academy of Science, 515–516.

Zonneveld, I. S., 1989, "The Land Unit—A Fundamental Concept in Landscape Ecology, and Its Applications," *Landscape Ecology*, 3:67–86.