Investigating the Utility of SPOT Multispectral Imagery for Forage Estimation on a Rangeland Site in Southeastern Idaho

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ABSTRACT

Field- or ground-based estimates of forage availability can be time consuming and fraught with errors due to the inherent heterogeneity found in semiarid rangelands. Satellite remote sensing offers the potential to improve forage estimation by incorporating rangeland variability into the modeling process by developing estimates based upon each and every pixel. The problem with this approach however, is that pixels are typically too large to offer meaningful results and the heterogeneity within each pixel can make forage estimation with remote sensing techniques just as difficult as using ground-based measures or estimates. While the size of MODIS pixels (1000m x 1000m) is admittedly too coarse for forage availability modeling, SPOT5 pixels (10m x 10m) may be sufficiently resolved to provide accurate forage estimations. To test this, a study was designed and is described in this paper. The results of this study suggest that reliable forage estimation with remotely sensed imagery will require spatial resolutions better than offered by the SPOT 5 sensor as the coefficient of determination (R2) did not exceed 0.18 with any band combination tested.

KEYWORDS: semiarid rangelands, NDVI, SAVI, NDSAVI

INTRODUCTION

Ground-based forage estimation can be a tedious effort especially in semi-arid rangelands due to large, expansive area and the uncertainty of prediction that arises when working in these heterogeneous landscapes. Nonetheless, biomass and especially forage estimates are some of the “main parameters used in range management” (Tueller 2001). While, remote sensing techniques have proven useful for estimating general biomass values over large areas (Tueller 2001; Wylie et al. 2002), the utility of remote sensing for estimating *only* the available forage as a component of total biomass has proven much more difficult. However, with state-of-the-art satellite imagery, the potential exists to accurately model forage. This study was designed to determine how well SPOT multispectral imagery (10 x 10 m pixels) could estimate available forage at the ISU O’Neal Ecological Reserve located near McCammon, Idaho using both simple regression and supervised classification techniques.

METHODS

Data Collection

A ground-based survey conducted during July 2006 resulted in 145 stratified random sample plots, each measuring 10 x 10 m. At each plot center point, vegetation considered adequate forage for cattle, sheep, and wild ungulates was determined using a $0.44m^2$ hoop that was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. Forage within the hoop was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag (all grass species, except cheatgrass (*Bromus tectorum*) were considered forage). The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley et al., 1995). The location and forage information of each sample plot was collected using a Trimble GeoXT GPS receiver with Windows Mobile PocketPC capable of sub-meter horizontal positional accuracy (+/- 0.9m @ 95% CI (Serr et al., 2007). These data points were saved in ESRI shapefile format.

Also, SPOT imagery was acquired on July 11, 2006. This imagery had 10 X 10 m pixels with reflectance measured in four visible wavebands (near infrared, red, green, and short-wave infrared). The imagery was geo-rectified and atmospherically corrected. Various vegetation indices were calculated using the SPOT imagery including normalized difference vegetation index (NDVI), normalized difference senescent vegetation index (NDSVI) (Qi and Wallace 2002), soil-adjusted vegetation index (SAVI) and a ratio-type index derived from the short-wave infrared band (SWIR) divided by the green band (Wylie et al. 2002). Calculation of these indices was accomplished using IDRISI Andes software (Clark Labs, Clark University, Worcester, MA).

Regression Analyses

Simple linear regressions were performed to evaluate the relationship between vegetation indices and the field-based forage measurements.

Supervised Classification

Supervised classification of the SPOT imagery was performed using a shapefile describing the forage measurements taken in the field. The mean of the four forage measurements taken at each point was used to represent forage availability at each point. A histogram was tabulated for all of the available data points and 10 classes were determined. Each p-quantile (probability) was used to re-bin the data (0.1 to 1.0). The final binning is shown in Table 1. This binning was done with understanding that if each individual forage estimate were treated as a specific class, the supervised classification results would be poor. For example, the classification algorithm would find difficulty in discriminating classes with very similar forage estimates. Each p-quantile from the cumulative distribution frequency of the forage data gave a reasonable number of data points for each class. This shapefile was randomly subsampled without replacement and 65 % (*n*= 94) of the points were reserved as training sites while the remaining 35 % (*n*=51) of points were used as validation sites. These points were rasterized using ArcMap (ArcGIS 9.1, ESRI) for use in IDRISI Andes. All classification procedures were performed in IDRISI Andes.

Table 1. Binning strategy for determining classes for supervised classification. Each p-quantile from the cumulative distribution frequency of the forage data gave a reasonable number of data points for each class.

Approx. p-quantile	Forage range (kg/ha)	Class
0.1	1-15	1
0.2	16-21	2
0.3	22-27	3
0.4	28-38	4
0.5	39-50	5
0.6	51-65	6
0.7	66-80	7
0.8	81-100	8
0.9	101-150	9
1.0	151-300	10

Maximum Likelihood Classification

Maximum likelihood is “a statistical description of the manner in which expected landcover classes should appear in the imagery, and then a procedure is used to evaluate the likelihood that each pixel belongs to one of these classes” (Eastman 2006). First, spectral signatures were created (extracted) from the training sites (field forage measurements) using the MAKESIG module. All SPOT spectral bands and the vegetation indices (NDVI, SWIR/Green, NDSVI, and SAVI) were chosen as the bands to extract spectral data from. The SIGSOMP module was then used to evaluate where, if any, differences occur between the training site input bands. As high correlations existed between many of the raster layers, there was difficulty encountered separating the spectral signatures. Therefore, principal components analysis (PCA) was performed to better capture the unique data within the input bands. The actual classification was done using the MAXLIKE module. Probabilities of each class were set to equal and the signature file created above using PCA was used. Lastly, an accuracy assessment of the classification was performed using the ERRMAT module which produces an error matrix of the input classification model. This matrix reports user and producer accuracies and errors. A kappa index of agreement (KIA) is also reported.

Classification Tree Analysis

Classification tree analysis (CTA), also called decision tree analysis, has leaves and branches where leaves represent classifications and branches represent "conjunctions of features that lead to those classifications" (Eastman 2006). Basically speaking, the software splits each pixel into probabilities of belonging to a certain class until a statistical threshold is reached and a decision is made to what class the pixel belongs. CTA has been reported to achieve consistently better accuracy than Maximum Likelihood (Frield and Brodley, 1997). Classification tree analysis (CTA) was carried out using the same basic tenets in maximum likelihood above by using the principal component images (from PCA). Error assessment techniques were used to evaluate classification performance as described above.

RESULTS AND DISCUSSION

Regression analysis

The regressions proved to be very limited in uncovering any valuable information regarding forage estimation. Figure 1 shows the correlations between each vegetation index and field forage measurements. It has been recently reported that a simple ratio vegetation index of the short-wave infrared spectral band (SWIR) divided by the green spectral band is a good estimator of forage (Mirik et al. 2005). In comparison with the regression results, this vegetation index did report the highest R^2 value (0.1796). A full comparison of the R^2 values can be seen in Table 2.

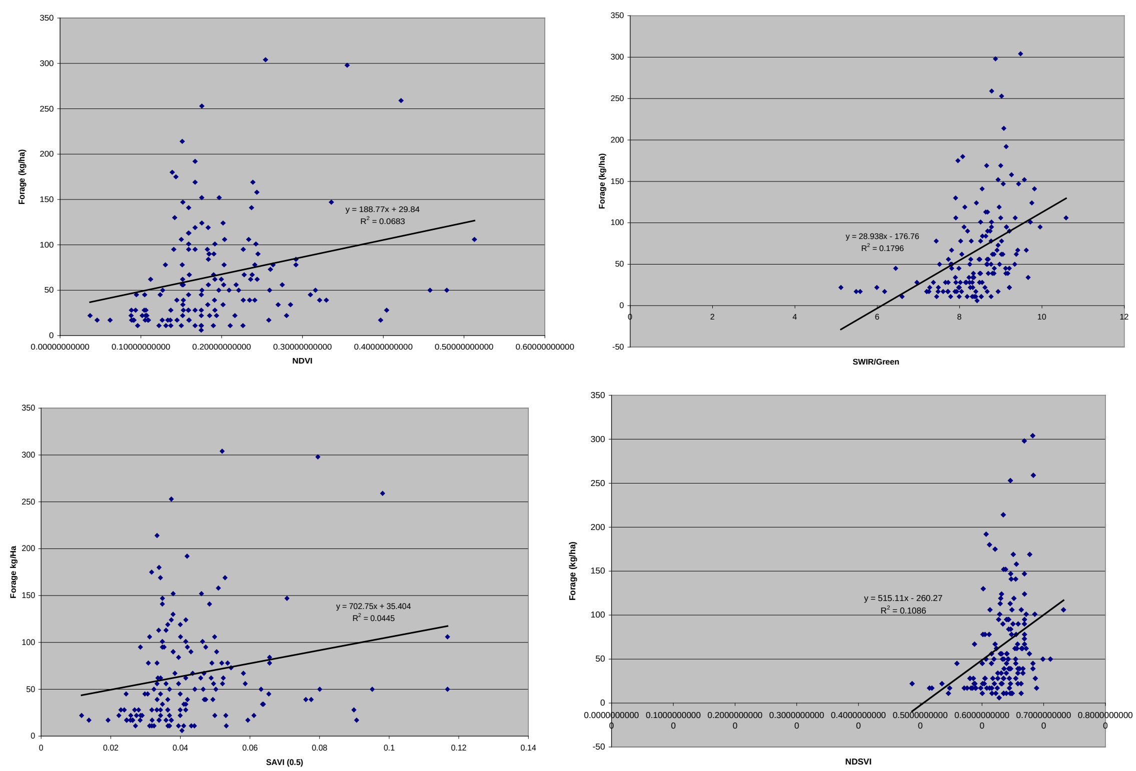

Figure 1. Linear regressions of different vegetation indices and forage estimates. Starting with the top left graph and continuing clockwise: NDVI, SWIR/Green, NDSVI, SAVI.

Table 2. Reported R^2 value of each vegetation indices correlated with forage estimates.

	NDVI	SWIR/Green	SAVI	NDSVI
Reported R^2	0.0683	0.1796	0.0445	0.1086

Maximum Likelihood Classification

Maximum likelihood classification performed poorly. The kappa index of agreement (KIA) was reported as 0.0385. Congalton (1991) suggests that a KIA of 0.60 or higher is needed to express statistical significance in relation to a classified geographic model. It was concluded that maximum likelihood also proved to be a poor estimator of available forage given the methods presented in this study.

Classification Tree Analysis

More hope was given to classification tree analysis (CTA) as it has been reported to frequently give better results that maximum likelihood classification. The CTA model is shown in Figure 2.

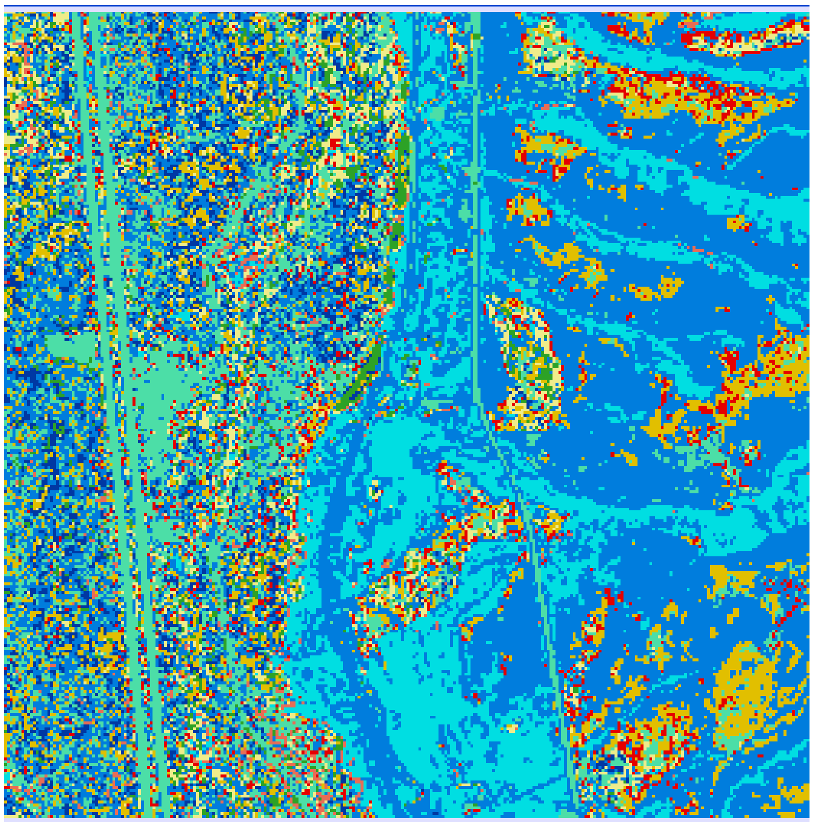

Figure 2. Forage estimation using classification tree analysis for the O'Neal Ecological Reserve and surrounding area.

CTA also proved limited in modeling forage availability (Table 3).

Table 3. Error matrix describing results of classification tree analysis (CTA)

Error Matrix Analysis of VS_CAT_GOOD1 (columns : truth) against CTA_CAT_1 (rows : mapped)

	1	2	3	4	5	
1	7	5	0	1	0	0.5000
2	5	4	2	1	3	0.7647
3	1	0	2	2	0	0.7143
4	0	1	1	0	0	1.0000
5	0	2	0	1	0	1.0000
6	0	0	0	2	0	1.0000
7	1	1	1	0	2	1.0000
8	1	0	0	0	0	1.0000
9	0	0	0	0	0	
Total	15	13	6	7	5	
ErrorO	0.5333	0.6923	0.6667	1.0000	1.0000	

	7	8	9	Total	ErrorC
1	0	1	0	14	0.5000
2	1	0	1	17	0.7647
3	1	0	1	7	0.7143
4	0	0	0	2	1.0000
5	0	0	0	3	1.0000
6	0	0	0	2	1.0000
7	0	0	0	5	1.0000
8	0	0	0	1	1.0000
9	0	0	0	0	
Total	2	1	2	51	
ErrorO	1.0000	1.0000	1.0000		0.7451

ErrorO = Errors of Omission (expressed as proportions)
ErrorC = Errors of Commission (expressed as proportions)

90% Confidence Interval = +/- 0.1004 (0.6447 - 0.8455)
95% Confidence Interval = +/- 0.1196 (0.6255 - 0.8647)
99% Confidence Interval = +/- 0.1574 (0.5877 - 0.9025)

KAPPA INDEX OF AGREEMENT (KIA)

Using CTA_CAT_1 as the reference image ...

Category	KIA
1	0.2917
2	-0.0263
3	0.1905
4	-0.1591
5	-0.1087
6	0.0000
7	-0.0408
8	-0.0200
9	0.0000

VS_CAT_GOOD1

Category	KIA
1	0.2649
2	-0.0385
3	0.2273
4	-0.0408
5	-0.0625
7	-0.1087
8	-0.0200
9	0.0000

Overall Kappa = 0.0718

Based upon KIA, CTA proved to be marginally better for modeling forage availability as opposed to maximum likelihood classification (0.0718 vs. 0.0385, respectively), however, Congalton (1991) notes that this level of KIA can be purely achievable through chance agreement alone. Figure 4 summarizes a regression of the validation sites as compared to the CTA. In the case of perfect 100% agreement (KIA = 1.0), the points plotted in Figure 4 would fall along a 1:1 line. The reported r value was -0.002185, highlighting the weakness of this model for forage estimation in this study.

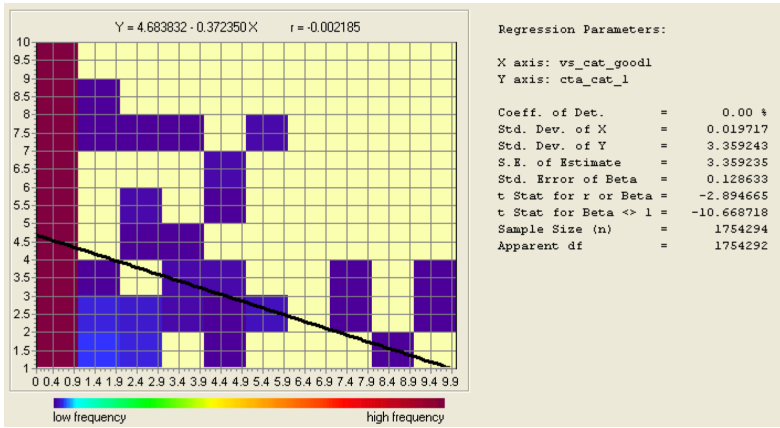

Figure 3. Regression of validation sites used for the forage estimation classification tree analysis.

CONCLUSIONS

Modeling forage availability using SPOT satellite imagery proved exceedingly difficult. Although disappointing, this result is not entirely surprising given the understanding that forage reflectance on a pixel-by-pixel basis is only a small component of the total reflectance signature for that pixel. The authors note that these field data were collected in July which is a time period when many if not all of the grasses are senescing. This alone could help explain why the NDSVI proved to report a marginally better R^2 value than other indices save for the biomass index (SWIR/GREEN).

Land managers rely on estimates of forage to help make decisions regarding stocking rates, wildlife conservation, and desertification issues. While the authors believe it would be worthwhile to continue to evaluate the utility of the methods presented in this paper (perhaps using imagery collected during different time periods such as before cattle grazing begins or before the senescence of grasses), these techniques are not currently reliable for management purposes.

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