Estimating Dry Grass Residues Using Landscape Integration Analysis
by

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Introduction

The acreage of grassland and grassland-savannah is extensive in California, making direct measurement and assessment logistically impossible. Grasslands cover the entire Central Valley up to about 1200 m elevation in the Coast Range and Sierra Nevada Range. Kuchler's (1964) map shows 5.35 M ha grassland with an additional 3.87 M ha in Oak savannah. The goal of this study was to examine the use of high spectral resolution sensors to distinguish between dry grass and soil in remotely sensed images. Spectral features that distinguish soils and dry plant material in
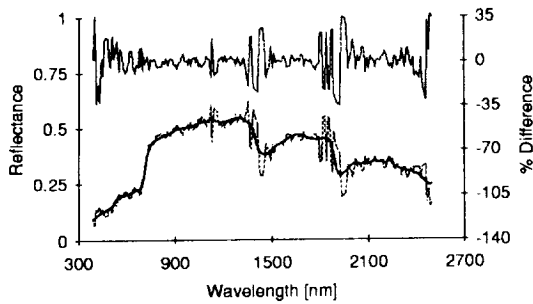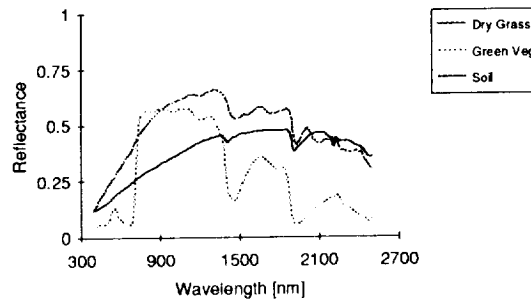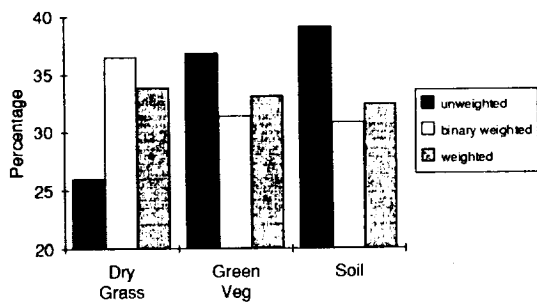
Figure 1a

Figure 1b
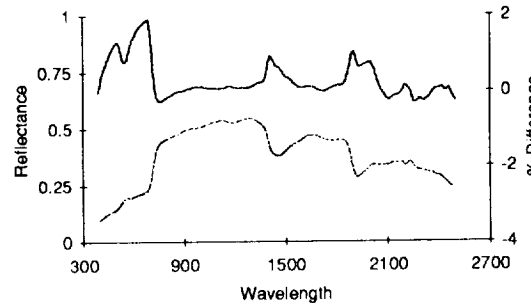

Figure 1c

Figure 1d

Figure 1: SMA performed on a weighted synthetic spectrum. Figure 1a shows the composite spectrum to be unmixed (with a noise term inversely proportional to the atmospheric transmission, above). Figure 1b shows the 3 endmember spectra used for unmixing. Figure 1c shows the results of SMA. Figure 1d shows the predicted spectrum from the unmixing and a ratio comparison (above) between the original and the signature predicted from the SMA.

the shortwave infrared (SWIR) region (Fig. 1b) are thought to be primarily caused by cellulose and lignin, biochemicals which are absent from soils or occur as breakdown products in humid substances that lack the narrow-band features. We have used spectral mixing analysis (SMA) combined with Geographic Information Systems (GIS) analysis to characterize plant communities and dry grass biomass. The GIS was used to overlay elevation maps, and vegetation maps with

the SMA results. The advantage of non-image data is that it provides an independent source of information for the community classification.

Test Site

The study area used for this research is located in the Central Coast Range just east of Lake Berryessa, CA. The area of approximately 80 km^2 includes the University of California's Stebbins Cold Canyon Preserve (SCCP). The complexity of the terrain results in a mosaic of grazed and ungrazed grasslands, oak woodlands, chaparral, riparian woodlands, agricultural cultivation, and other vegetation types. AVIRIS imagery was acquired on August 20, 1991 and August 20, 1992.

Spectral Mixture Analysis

We have assumed that the grasslands represent a reasonable approximation of linear spectral mixing up to a point of saturation at high biomass amounts. Results from an unconstrained SMA model using images calibrated to surface reflectance produced better fraction estimates than constrained reflectance models or unconstrained radiance models (Fig. 1c). Atmospheric bands were included in the SMA by using a weighting factor related to the transmission and scattering of a typical mid-latitude atmosphere MODTRAN prediction (Air Force Geophysical Laboratory), Figure 2.
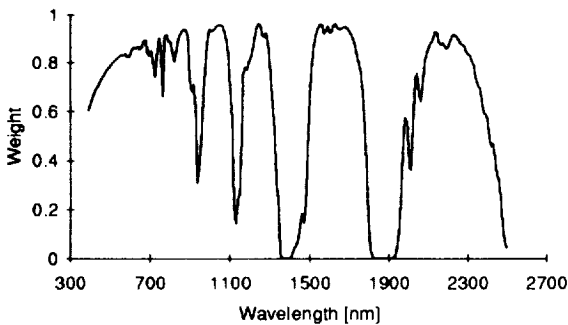

Figure 2: Weighting factor used for the SMA as a function of wavelength

The spectral library endmembers were measured in a Varian Cary 5E spectrometer of soil, dry grass, and other plant samples (leaves, bark) collected within the Berryessa study area. The GPS locations of these materials were included in our GIS data base. Specifically we used a *Heteromeles arbutifolia* (Toyon) leaf as the green foliar endmember, a Sehorn Clay Series soil, and a mixture of dry annual grass leaves for the dry grass endmember. Bark from *Quercus agrifolia* was used as a "woody" endmember.

We used the ARP and lignin/cellulose analysis program by Gao and Goetz (1990) to compare against the dry grass endmember fraction. We assumed that the cellulose/lignin estimate was a reasonable approximation of the biochemistry of dry leaf residues in this study. This analysis produced images having a more speckled appearance and larger variability between adjacent pixels then did the SMA results.

Landscape Integration

Topography data were used to predict "potential vegetation" types based on the landscape of the area and the physiographic dependence of the vegetation. These types of potential vegetation maps were combined with the SMA results to classify "actual vegetation" distribution. Digital Elevation Maps were produced for two USGS 7.5 min transparent overlays (Mt. Vaca and Monticello Dam). Because we were not able to perform all parts of this study in one package, we performed various parts of the work in Map and Image Processing System (MIPS), GRASS, and Arc/Info using both PC's and UNIX workstations. Elevation, aspect, slope, and accumulated runnoff (R.watershed module in GRASS) were used to define potential vegetation types using a

Maximum Likelihood Separator (MLS). The SCCP vegetation map (based on ground surveys) was used for training sites of six vegetation types.

The topographically developed classification scheme does well at separating the grassland from the oak woodlands, due to their aspect dependance, and also identifies riparian zones using the accumulation and elevation layers. Rock outcroppings are over-estimated and chaparral, the most abundant community in the region, is under-represented. This resulted because the initial chaparral classification was relegated to the areas unoccupied by the more topographically distinct grasslands and oak woodlands.

The SMA fractions were also used as data layers in the GIS for classification of the SCCP. The SMA-based MLS classification does a better job separating the dry grasslands from the other communities. This is not surprising since one of the endmembers selected for the SMA was of dry grass. Even so, the accuracy of the prediction is striking. The SMA method was less successful discriminating oak woodlands and riparian woodlands which have similar endmember fractions. This effect might be improved if a multiple endmember approach like that of Roberts et al., (1992) were adopted. The rock outcroppings were over-predicted and the chaparral regions were under-predicted. The lower specificity of chaparral may be due to a varying spectral signature.

Finally, the DEM layers and the SMA fraction layers were combined to determine a final "actual vegetation" map. The resulting map is a remarkably good representation of the vegetation type distributions based on comparisons against the SCCP vegetation map and against aerial photographs. In fact, the combined map is better at defining the vegetation type distributions than the more simplified ground-based vegetation map. The grassland predictions suffered slightly, due to topographic variables driving some predictions toward other vegetation types even when the dry grass fraction identifies grasslands. However, the chaparral distribution improves in this map compared to the previous maps. Also, the rock outcrops show closer agreement with the field-based map. The riparian and oak woodlands are also well separated and accurately located when compared with the field-based map.
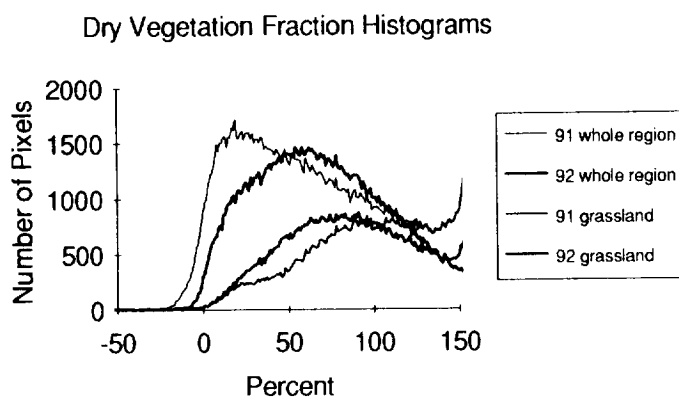
Dry Vegetation Fraction Histograms

Figure 3: Dry grass fractions for the larger Berryessa region (upper curves) and for the grasslands area only (lower curves).

The landscape parameter maps developed for the SCCP subset were then created for the larger area covered by the two AVIRIS overflights and the same classifications were performed for the entire region. A significant portion of the total image was classified as grassland (Table 1). However, we still require a map of the spatial variation in dry biomass to monitor dry grass residues. To determine biomass distribution in the dry grasslands, non-grasslands and areas where grazing is unlikely were masked.

The histogram of dry vegetation fractions for the whole area and for the areas classified as grassland are shown in Fig. 3. Both the 1991

and 1992 AVIRIS overflights show close agreement. As seen from the figure, most pixels having low dry vegetation fractions were classified as other vegetation types. To quantify the ranges of dry grass biomass, endmember fractions were divided into five frequency classes. These biomass classifications are consistent with spatial patterns in grassland biomass variation predicted. Predicted area coverage for all vegetation types is shown in Table 1.

Table 1. *Distribution of areal coverage by vegetation class for the Berryessa Region.*

Vegetation Class	Area Coverage (ha)
Oak Woodland	1262
Chaparral	2076
Riparian	990
Rock Outcrops	228
Grassland/no biomass	7
Grassland/low biomass	422
Grassland/medium biomass	1282
Grassland/high biomass	1516
Grassland/very high biomass	939
TOTAL	**8722**

Conclusion Summary

1. Spectral unmixing provides a good estimation of the spatial distribution of dry grass.
2. Spatial variation in endmember fractions represent varying proportions of these endmembers supporting conclusions of other authors (e.g., Gamon et al., 1993).
3. Masking non-grassland areas improves the ability to evaluate spatial variations in dry grass abundance.
4. Spectral measures alone are insufficient to separating and mapping all vegetation types in these communities.
5. Combined SMA and DEM data in a GIS produced vegetation maps as good or better then those based on field surveys.

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