INTEGRATING SATELLITE IMAGES AND SPECIES-BASED VEGETATION MAPS TO MANAGE NATIVE GRASSLANDS

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ABSTRACT

Satellite image mapping of grasslands is problematic when species diversity occurs at a sub-pixel scale. We propose a method, called *melody classification*, to map ground cover units that group several spectral classes (colours). Melodies are defined as the normalized expected frequencies of each class within the ground cover unit. Starting from an unsupervised classification, an image is created showing the probability of finding each spectral class in the vicinity of each pixel. Each pixel is classified by comparing the melody in its neighbourhood with that of each ground cover unit. Accuracies are greatly enhanced over those of supervised classification. Melody classification can be applied to detect and monitor occurrence of particular species or groups of species in rangeland management.

KEYWORDS

Native prairie, satellite images, biodiversity, remote sensing

INTRODUCTION

Satellite remote sensing has been used effectively to subdivide landscape into units characterized by a uniform spectral response or a uniform texture. It is successful in differentiating water, fields, forest, urban areas, and by default unsubdivided grasslands. Statistics derived from satellite images can be used as surrogates for quantitative values such as Leaf Area Index and Intercepted Photosynthetically Active Radiation (Weiser et al., 1986). Remote sensing has been less applied to differentiate more subtle differences within grasslands due to different species composition. The grasslands manager might wish to map occurrence, introduction or spread of particularly desirable or undesirable species over large areas, and adapting image classification to this task would aid in this process. The present study defines and demonstrates a method, called *melody classification*, that produces enhanced accuracy using automated classification of grasslands into units each of which is defined by its diversity and spectral variability.

METHODS

Melody classification was developed using a Thematic Mapper (TM) image acquired July 29, 1993, of a portion of southern Saskatchewan between 106°-108°W, 49°-49°30'N, including most of Grasslands National Park. The area is in northern midgrass (*Stipa-Bouteloua*) prairie (Coupland, 1961). It has a local relief of 300m with some badlands topography. Three quarters of the land surface is covered with mixed grasses, which quadrat mapping has subdivided into units according to the presence of indicator or characteristic species that occur in varying percentages throughout the unit (Michalsky and Ellis, 1994; see Table I). These units are taken to be the vegetal response to differences in underlying ecological factors such as moisture and exposure, and mapping of these species groupings is used as a surrogate for ecological variables. The TM sensor includes six bands in visible, near-infrared and mid infrared wavelengths, with resolutions of 30x30m (Jensen, 1996). An additional thermal infrared band was not used in this study. From these bands, several transformations were obtained to enhance the separability of the different ground units of interest. Those chosen for the classificaiton include the Normalized Difference Vegetation Index (NDVI) (Perry and Lautenschlager, 1984), the second component of the tasseled cap transform, also called "greeness" (Crist and Cicone, 1986), and variance and entropy, both measures of texture (Haralick, 1979).

Standard supervised classification methods yielded user's accuracies of less than 20% (Table I). Supervised classification compares each candidate pixel to an overall mean and variance for the entire unit. It was hypothesized

1) that the units consist of a mosaic of individual pixels that differ from one another in their spectral response but do not have within themselves a uniform species composition. Few individual pixels approach the mean response for all pixels of the unit; and
2) that these individual pixels are not spatially distributed in a regular fashion that would allow unit discrimination by texture.

Melody classification proceeds in several steps. First, a convenient number of spectral signatures is extracted from the image through unsupervised clustering: these are the "colours" of individual pixels that group together in various combinations to form the ground units. The distribution of these colours within the image is then determined (i.e. the image is classified). Then, the probability of finding each of these colours within each defined ground unit is calculated using mapped quadrat sites, and the result normalized by the area occupied by the unit within the image, yielding an Association Index AI:

$$AI_{i,u} = 100(f_{i,u}/a_i)$$

where $f_{i,u}$ is the number of pixels of class (colour) i found in unit u, and a_i is the area of class i in the image. The value is then stretched to cover the range of 255 possible values in 8-bit data. The set of these probabilities, one number per class, is termed the *melody* of the unit (Fig. 1). The image classified in the first step is then treated to determine the probability of finding each colour in the immediate vicinity (an 11x11 pixel window) of each individual pixel: this gives an image showing the melody "sung" around each pixel. The result of this treatment is compared on a pixel-by-pixel basis with the melody for each unit. Each pixel is assigned to the ground unit with which its melody corresponds most closely.

RESULTS AND DISCUSSION

Melody classification for the Grasslands National Park area image improves accuracies to between 25% and over 50% for most of the grasslands units, and to 90% for the "disturbed" ground (Table I). The exceptions are units DP and AC, with accuracies below 1% for both methods. This is due to unit geometry rather than to a method problem. Patches of DP and AC are very small in aerial extent, and the neighbourhood of each pixel overlaps onto other units. This problem could be resolved with improved spatial resolution using a different sensor. The accuracies obtained are not in the high range achieved using spectrally uniform units (typically over 75%, e.g. Lauver and Whistler, 1993), but they are a significant advance over accuracies for diverse units. Work is being started to determine the increase in accuracy possible through increasing spectral and spatial resolution, and through the addition of other wavelength bands.

If each unit were composed of areas where uniform species cover several pixels, a spectral unit corresponding to each species could be created. However, the species diversity occurs at a sub-pixel scale, and melody classification is the best approach so far proposed to classifying this terrain.

Melody classification can be compared to pixel unmixing (Adams et al., 1993), which classifies a pixel according to its position along a continuum between end members, each of which exhibits a distinct spectrum. Pixel unmixing requires either laboratory-measured spectra of the objects of interest, and an image precisely corrected for atmospheric and electronic distortions; or that a sizeable area on the image be occupied by each of the objects of interest. In natural grasslands areas, neither of these conditions prevails: the first because spectra change with weather and plant maturation and atmospheric correction is notoriously difficult, and the second for reasons already explained. Melody classification offers a way to use satellite images to map areas marked by species diversity at a sub-pixel scale. It could be used to track dominance or presence of introduced desirable or undesirable species, or to note secular changes of species composition resulting from natural or human-induced changes in ecological variables. Research is under way to quantify its effectiveness in systems other than native grasslands.

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Table 1
Grassland map units, Grasslands National Park

MAP UNITS

Unit	Accuracy: supervised/ melody methods	Description
D	7.8% 90.9%	Formerly cultivated. invaded by *Elymus, Agropyron cristatum Artemisia frigida* (Russian Wild Rye, Crested Wheatgrass, Pasture Sage) DISTURBED
E	7.1% 19.7%	Eroded, partly invaded by *Rosa, Juniperus, Phlox,* forbs ERODED
T	1.5% 21.1%	*Acer negundo, Populus* (Manitoba Maple, Poplar) TREED
S	13.1% 20.8%	*Rosa, Potentilla, Amelanchier, Prunus, Salix, Shepherdia* (Rose family, Saskatoon, Wild Plum, Willow, Buffaloberry) SHRUB
JS	21.8% 25.0%	*Juniperus, Stipa* (Creeping Juniper, Green Needlegrass) SLOPED (>5%) GRASSLANDS
ASA	31.1% 25.8%	*Artemisia frigida, Stipa, Bouteloua gracilis, Agropyron smithii* (Pasture Sage, Green Needlegrass, Blue Grama Grass, Western Wheatgrass) SLOPED (>5%) GRASSLANDS
SA	4.4% 52.4%	*Sarcobatus, Atriplex* (Greasewood-Rillscale) VALLEY GRASSLANDS
AAO	6.8% 27.3%	*Artemisia frigida, Agropyron smithii, Opuntia* (Pasture Sage, Western Wheatgrass, Prickly-Pear Cactus) VALLEY GRASSLANDS
DP	0.8% 0.0%	*Distichlis, Puccinellia* (Alkali Grass-Nuttall's Salt-Meadow Grass) VALLEY GRASSLANDS
SB	17.0% 48.6%	*Stipa, Bouteloua gracilis, Agropyron smithii, Artemisia frigida* (Green Needlegrass, Western Wheatgrass, Pasture Sage) UPLAND GRASSLANDS
AC	0.2% 0.0%	*Agropyron smithii, Carex* (Western Wheatgrass, Sedge) UPLAND GRASSLANDS
HR	12.1% 33.3%	*Hordeum, Rumex* (Baltic Rush, Foxtail) UPLAND GRASSLANDS

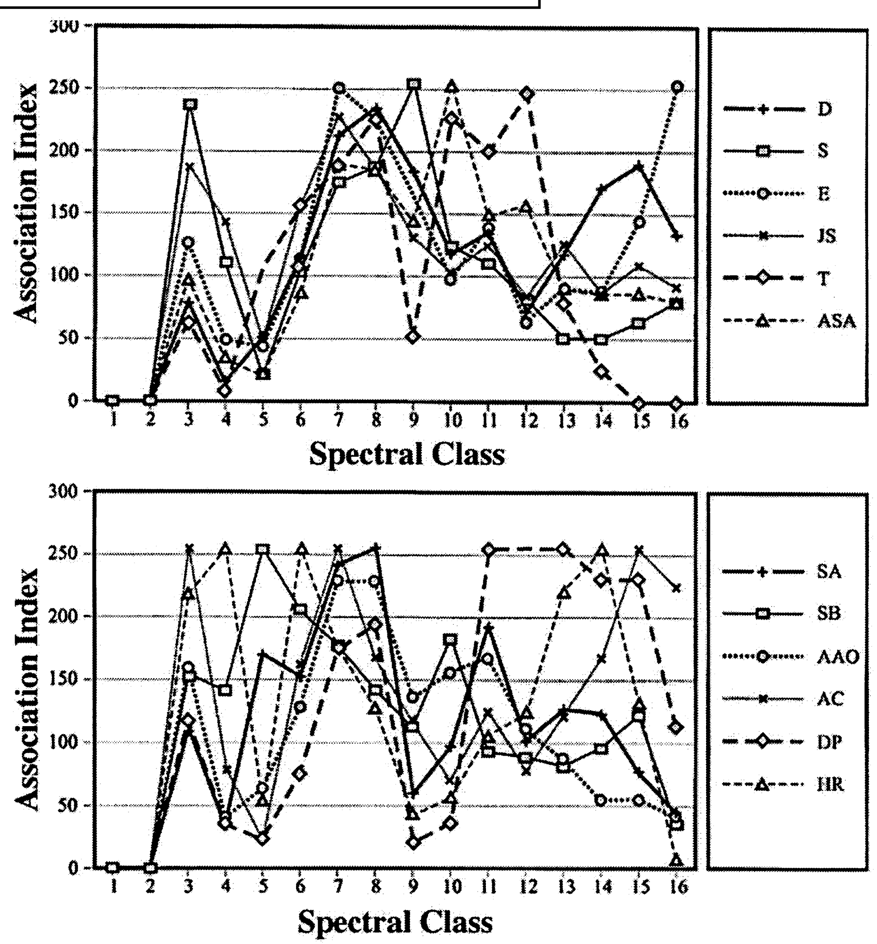

Figure 1
Melodies for 12 grassland units