The Use of Spectral Mixture Analysis to Study Human Incentives, Actions, and Environmental Outcomes

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The social science community has given increasing attention to the analysis of multitemporal satellite images in human dimensions of environmental change research. This article provides an overview of how image-processing techniques, such as radiometric calibration and spectral mixture analysis, can be applied. The application of these techniques is vital if the social science community wishes to develop a robust research program that allows the accurate comparison of distant but similar locations. Furthermore, by mapping the institutional landscape, the article demonstrates how social scientists can begin to understand landscape change by carefully relating human incentives to actions and actions to outcomes as measured by a set of multitemporal satellite images.

Keywords: global change, satellite images, institutional analysis, spectral mixture analysis, image restoration, institutional landscape

INTRODUCTION

Environmental policy makers, public officials involved in land management, and researchers studying the human dimensions of environmental change all hope to answer a particular question, each from their particular perspectives: In what ways is the landscape changing, and how are humans influencing those changes? Robust answers to this question are critical if we are to (a) understand the broad role humans play in the realm of global change as well as (b) guide officials at local and regional levels who are making real-life land use planning decisions and prioritizing the use of scarce public funds in land management.

The National Aeronautics and Space Administration's Landsat, or Land Monitoring Satellite system, has amassed an immense longitudinal archive of multispectral images for every location in the United States since its initiation in 1972. These images provide a wealth of information characterizing the country's forest resources as well as identifying where land cover is undergoing change. However, monitoring land cover using Landsat images has only just recently begun to significantly penetrate disciplines beyond the physical sciences. Most satellite-based case studies involve land-cover inventories, or classifications, at one point in

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time where the satellite data associated with each picture element, or pixel, of the image is assigned to one land-cover class. Programs such as the National Wetlands Inventory and state-level gap analysis provide examples of such inventory programs (IGAP, 1998; Scott et al., 1993). These studies typically employ classification schemes based on variations in satellite-derived digital numbers, or DN values, which, unlike reflectance values, are not physical units and thus have limited utility for comparison outside the specific image. Therefore, a given classification from one image cannot be easily applied to another image at a different location or time.

Recent technological advances now enable researchers, natural resource policy makers, and land managers to move beyond these traditional satellite image-based cross-sectional land inventories. Gigabyte storage volumes, Pentium-level or higher processors, cheaper random access memory, and more accessible geographic information system (GIS) and remote-sensing software allow even users of desktop PC platforms to conduct satellite-based image change analysis. Moreover, by first calibrating the image data so that picture element (pixel) values represent surface reflectance and then applying a relatively new remote-sensing analysis technique called spectral mixture analysis (SMA), the policy analyst or social scientist can move beyond a statistically relative and somewhat abstract land classification to one based on the physical measures of surface reflectance. Furthermore, SMA provides the ability to identify subpixel measures such as the percentage of land-cover components (e.g., soil, vegetation, water) that make up a pixel.

These advances are important for two reasons: First, SMA's subpixel analysis allows the researcher to use more effectively the older Landsat Multispectral Scanner data with coarse spatial resolution (59×79 square meters, roughly the size of a U.S. football field). Pixels of this size will rarely be exclusively one land-cover type and are more likely to be composed of mixtures of different types of land cover. Subpixel information is vital when working at this spatial resolution. Second, by radiometrically calibrating images to surface reflectance values and applying SMA, the analyst can develop land-cover classification schemes that are more apt to be replicated and directly applied to other Landsat images of comparable land-cover regions or ecosystems. Such broad-based classifications can be used to develop landscape change maps, which in turn can be linked with other geographic parameters known to drive human decision making and action. Efforts such as these are critical as we continue to address issues of scaling in global change research as well as make more practical policy and land management decisions.

This article provides an overview on how SMA might be applied to understanding land-cover change in a forested region and how this change can be related to human activities. The first part provides a discussion on the utility of the Landsat archive for this research agenda. Part 2 raises some open questions and discusses in more detail the problems related to standard image classification procedures as they are currently used. Part 3 presents a more technical discussion on traditional analytic techniques and then provides a description of how SMA works. Part 4 presents a brief example of one recent application of SMA in the context of public forest management in Indiana. It shows how we can begin to develop longitudinal studies of land-cover change based on surface reflectance values that can be replicated by other researchers using other Landsat images in comparable locations. It also presents two examples of how these analyses can be linked to human incentives and actions. The article concludes with a summary of the importance of this for the human dimensions of environmental change and global change research programs as well as for policy makers and land managers.

THE UTILITY OF LANDSAT MSS AND TM IMAGES FOR THE STUDY OF THE HUMAN DIMENSIONS OF ENVIRONMENTAL CHANGE

The Landsat system, designed in the 1960s and first launched in the early 1970s, was specifically developed for the observation of Earth's terrestrial surface (Campbell, 1996, p. 158). Tables 1 and 2 provide a summary of the Landsat system. Since 1972, six Landsat satellites or platforms have been launched. Landsat 5 continues to be operational, working well beyond its intended life span. Two primary sensor instruments exist on these platforms: the Multispectral Scanner (MSS) and Thematic Mapper (TM). MSS instruments were employed on Landsats 1 through 5. TM instruments were first included on Landsat 4, remain on Landsat 5, and an enhanced version will be launched on Landsat 7. There are several justifications for the use of MSS and TM imagery in studies concerning the human dimensions of environmental change, and many of these reasons are directly associated with scale issues discussed above.

First, both the MSS and TM data archives cover a broad spatial extent. Each individual scene acquired by both Landsat sensors covers a "footprint" on the Earth approximately 185 kilometers wide. Furthermore, since Landsat 1's launch in 1972, all of the Earth's terrestrial surface between 81º N and 81º S latitude has been subject to image acquisition (Campbell, 1996, p. 162).

Second, the Landsat data archive covers a relatively long temporal duration (more than 25 years). MSS technology began in 1972; TM technology began 10 years later in 1982. Although this cumulative period may be short in terms of the history of humanity, the time period covers a long enough temporal range to capture many of the human-induced changes that have occurred in forested landscapes. This is especially true in locations where land-cover change is rapidly occurring at present, such as in developing countries where tropical forests are being converted to agriculture or grazing land.

Third, the MSS and Landsat TM instruments provide a reasonably high degree of spectral resolution when compared to other remote-sensing platforms such as aerial photographs, France's SPOT, or India's IRS satellites. The MSS has four sensors, or bands, each sensitive to a different portion of the electromagnetic spectrum. As Table 2 shows, MSS Band 1 responds to light at visible green wavelengths (0.5-0.6 micrometers, or μm), Band 2 responds to light in the visible red portion of the spectrum (0.6-0.7 μm), and both Band 3 and Band 4 to different portions of near-infrared wavelengths (0.7-0.8 μm and 0.8-1.1 μm, respectively). Landsat TM data provide better spectral resolution, employing seven bands with sensors collecting additional data from the mid-infrared and thermal regions of the electromagnetic spectrum.

Although other technologies such as the National Oceanic and Atmospheric Administration's Advanced High-Resolution Radiometer or hyperspectral instruments such as the Airborne Visible/Infrared Imaging Spectrometer provide even better spectral resolution than Landsat data do (Campbell, 1996; Verbyla, 1995), the MSS instrument probably provides adequate data for addressing many of the questions being asked in the human dimensions of global change research program. Many of the activities humans undertake on the physical landscape are dramatic, involving vegetation-to-soil or soil-to-vegetation conversions. These types of changes provide a clear contrast in land-cover reflectance spectra (see Figure 1) that can be adequately captured using MSS band passes and most certainly with TM spectral resolution.

Fourth, the temporal sampling of the Landsat MSS and TM systems are relatively high. Location coverage repetition frequency was 18 days for Landsats 1, 2, and 3 and is 16 days

TABLE 1
Landsat Satellite Instrument Specifications

Instrument	Satellite Platform						
	Landsat 1: Launched 7/23/72; Out of Service 1/6/78	*Landsat 2: Launched 1/22/75; Out of Service 2/25/82*	*Landsat 3: Launched 3/5/78; Out of Service 3/31/83*	*Landsat 4: Launched 7/16/82 Operational (standby mode)*	*Landsat 5: Launched 3/1/84; Operational*	*Landsat 6: (failed to reach orbit) Out of Service*	*Landsat 7: (expected launch date, mid-1999)*
Multispectral Scanner (MSS)	X	X	X	X	X	—	
Thematic Mapper (TM)				X	X	—	X (Enhanced TM+)

SOURCE: Adapted from Campbell (1996).

TABLE 2
Summary of Instrument Sensors

Instrument	*Band*	*Spectral Sensitivity (micrometers)*	*Resolution (square meters)*
Multispectral Scanner (MSS)[a]	1	0.5-0.6 (green)	79×56
	2	0.6-0.7 (red)	79×56
	3	0.7-0.8 (near-infrared)	79×56
	4	0.8-1.1 (near-infrared)	79×56
Thematic Mapper (TM)	1	0.45-0.52 (blue)	28.5×28.5
	2	0.52-0.60 (green)	28.5×28.5
	3	0.63-0.69 (red)	28.5×28.5
	4	0.76-0.90 (near-infrared)	28.5×28.5
	5	1.55-1.75 (mid-infrared)	28.5×28.5
	6	10.4-12.5 (thermal)	28.5×28.5
	7	2.08-2.35 (mid-infrared)	28.5×28.5
Enhanced TM+	Same as TM, except:	Optical bands	28.5×28.5
		Thermal	60×60
		Panchromatic	15×15

a. In Landsat satellite platforms 1, 2 and 3, MSS bands 1, 2, 3 and 4 were referred to as bands 4, 5, 6, and 7 respectively.

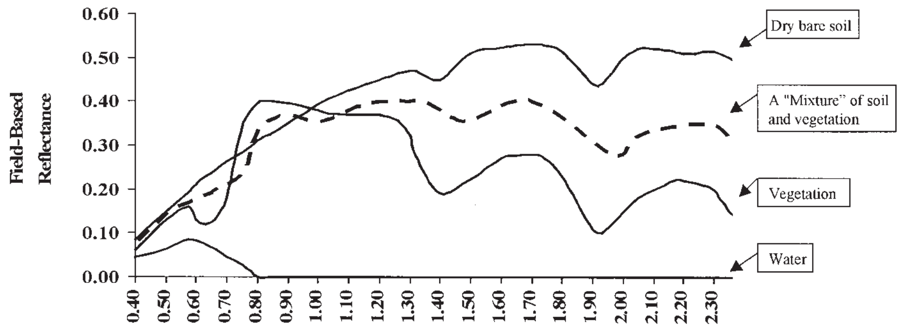


Figure 1: Typical Continuous Spectral Reflectance Curves for Vegetation, Soil, and Water and a Hypothetical Mixture Spectra
SOURCE: Adapted from Richards (1986).

for Landsats 4 and 5. This revisit frequency is probably adequate for addressing many of the most important human-induced processes related to landscape change. Although cloud cover may restrict acquisitions for any given location within these latitudes, there is likely a large temporal archive of good quality still available for sampling. In our south-central Indiana study region alone, we have identified approximately 150 Landsat MSS and TM images with low cloud cover taken during the 1972 to 1997 time period.

OPEN QUESTIONS RELATED TO THE UTILITY OF LANDSAT MSS IMAGES FOR HUMAN DIMENSIONS OF ENVIRONMENTAL CHANGE STUDIES

As the previous discussion indicates, there are ample reasons to consider the use of Landsat MSS and TM for studies relating human decision making and action to land-cover change. TM images are certainly appropriate given their high spatial and radiometric resolutions. However, as noted above, TM technology was first introduced in 1982, and about 16 years of inventory exists. But if we are concerned about the temporal grain of the phenomena of interest (such as forest cutting) and are concerned that a 16-year sampling period may not capture a specific human activity adequately, we may wish to expand the temporal duration of the image data set we use. By employing Landsat MSS images, we extend the temporal range by another 10 years back to 1972. For many change analyses, this added decade may be vital. However, there is one significant limitation in applying MSS data for these types of studies: the relatively poor spatial resolution provided.

Other satellite platforms described earlier, such as Landsat TM and SPOT, provide relatively fine spatial resolution with 28.5×28.5 meter and 10×10 meter spatial resolutions, respectively (Campbell, 1996). An MSS pixel is coarser, capturing roughly a 79×56 meter area on the ground. This coarse spatial resolution limits the amount of information related to human activities that MSS images can provide (Wilkie & Finn, 1996).

We therefore face a tradeoff. It is clear that for these types of questions, images with a higher spatial resolution are favorable, such as ones created by Landsat TM or SPOT, but MSS adds an important 10 years onto the time series. MSS images are also much less expensive than TM images. From this perspective, the use of Landsat MSS is certainly helpful, economically efficient, and could also be absolutely critical to adequately capture the temporal frequency of certain land-cover change phenomena.

TRADITIONAL ANALYSIS TECHNIQUES AND THE PROMISE OF SPECTRAL MIXTURE TECHNIQUES

The use of another technique, first developed by geologists and planetary scientists, called spectral mixture analysis, or SMA (Adams, Smith, & Gillespie, 1993; Adams, Smith, & Johnson, 1986; Smith, Ustin, Adams, & Gillespie, 1990a, 1990b), has the potential to make Landsat MSS-based (and TM-based) analyses more applicable to the study of fine spatial scale human-induced land-cover disturbance. SMA, also referred to as linear unmixing (ENVI, 1998), allows the analyst to move to a subpixel level of analysis and works with surface reflectance values, not image DNs (see below). The following section provides a brief summary of the more traditional image-analysis techniques and then describes SMA and how it might be used to improve the utility of Landsat MSS and TM image analysis for studies related to human dimensions.

Traditional Image-Analysis Techniques

Image-analysis techniques in this context refer to methods for displaying and interpreting band-to-band variations of multispectral satellite images. Generally, traditional image analysis involves a suite of tools including single-band analysis, color composite generation, band-to-band ratioing and vegetation indices, principal component analysis (PCA), and classification. These methods are widely used in analyzing Landsat images (Adams et al., 1993). For a more detailed description of each technique, see any standard remote-sensing textbook (e.g., Campbell, 1996). Only a brief synopsis will be included here.

Single-band analysis involves the review of individual bands of an image separately, using a gray-scale display. Color compositing techniques superimpose three bands together, displaying each band of information using the three colors: blue, green, and red. For instance, for MSS data, the visible green band is often displayed using blue, the visible red band is displayed as green, and the second infrared band is displayed as red. This simulates what would be generated if the image were taken using color infrared film (Lillesand & Kiefer, 1994). One limitation in using color composites is that only three channels of the information from a satellite image can be displayed at one time (Adams et al., 1993).

Band-to-band ratioing is another analysis technique that uses multispectral satellite images for the study of land cover. Vegetation indices are one group of methods that involve popular band-to-band ratios. Vegetation chlorophyll is known to absorb visible light, whereas a leaf's mesophyll tissue strongly reflects near-infrared light (Campbell, 1996). As the amount of vegetation increases within the boundaries of a pixel, surface reflectance in the visible red decreases, whereas reflection in the near-infrared increases (Hall, 1994). Vegetation indices, such as the normalized difference vegetation index (NDVI), take advantage of these properties. There are a number of indices that have been developed, but they all involve mathematical ratios or differences of the digital values of different spectral bands to produce a single value for each pixel.

NDVI and other such ratios are useful in that they can provide a measure of the vegetation content within each pixel. By employing the characteristic spectral response of vegetation, these indices allow the analyst to develop a measure of one component of each pixel. There are a variety of studies that have used ratios as part of their analyses (e.g., Cohen, 1991; Sader & Wynne, 1992; Tucker, VanPraet, Sharman, & Van Ittersum, 1985). One of the limitations of ratios is that they generally do not take advantage of all the available information contained in multispectral images, usually using only two bands (Adams et al., 1993).

Also, these indices may be influenced by many factors not associated with vegetation itself (e.g., soil background and sensor differences) (Campbell, 1996). These ratios are also sensitive to the particular atmospheric conditions on the day of acquisition because the atmosphere can cause light in the visible portions of the spectrum to be preferentially scattered. Many analyses may have employed vegetation ratios without removing these effects, which may lead to false conclusions (Robinove, 1982). Atmospheric correction is advised to remove the effects of atmospheric scattering (Teillet & Fedosejevs, 1995). Others emphasize the importance of radiometric calibration, together with atmospheric correction, to convert the image from raw DN values to surface reflectance before calculating these ratios to minimize sensor drift problems and other factors (e.g., Green, Schweik, & Hanson, 1998; Price, 1987). Unfortunately, the procedures required to remove much of the variance caused by nonvegetation effects are logistically difficult and not readily accessible to many researchers outside the remote sensing community. This topic will be discussed more fully later.

PCA is often used to remove interband correlation that typically exists within multispectral image data. PCA identifies linear combinations of the original band data of an image to produce component images representing the axes of maximum variation (Campbell, 1996). Often the purpose of PCA is to compress most of the information contained in a multiple-band image into a new image with fewer components. These product images are then used in place of the original band data (Lillesand & Kiefer, 1994). This procedure is sometimes helpful in preprocessing the data to remove instrument noise such as image striping (Idrissi, 1997). Some scholars are investigating the use of the higher components (e.g., Component 5 and higher in TM images) to identify patterns in human activity (B. L. Turner II, personal communication, February 22, 1998). One benefit of PCA is that it uses all the information provided in a multispectral image.

Classification methods are one of the most common analytic techniques applied to multispectral images (Adams et al., 1995). This becomes quite apparent when one traverses the remote-sensing literature of the 1970s, 1980s, and 1990s. Most texts related to remote sensing devote significant effort (sometimes the majority of the discussion of analysis) to image classification procedures (see, e.g., Campbell, 1996; Lillesand & Kiefer, 1994; Verbyla, 1995; Wilkie & Finn, 1996). Using a classification algorithm, these methods assign individual pixels of a multispectral image to discrete categories (Drury, 1990). The goal of this type of analysis is to greatly simplify continuous image data (7 bands of 8-bit data for TM) using quantitative techniques for identification of spectrally similar land-cover classes within the image (Lillesand & Kiefer, 1994).

Two types of classification procedures are popular and work in conjunction with one another. Unsupervised classification procedures group or cluster the multispectral values of the image into distinct classes (e.g., water, soil, and vegetation) based solely on the image statistics and produce a new raster (grid) map displaying the class designations within the image (Hall, 1994). Supervised classification involves the use of ground inventories to guide, or "train," the computer to assign appropriate clusters of data to certain land-cover classes (Hall, 1994). Various algorithm strategies (e.g., maximum likelihood) have been employed to classify pixels not assigned to training areas (Campbell, 1996). Many important human dimensions of environmental change studies use image classification as their dominant image-analysis method (to name a few: Brondizio, Moran, Mausel, & Wu, 1994; Lee & Marsh, 1995; Moran, Brondizio, & Mausel, 1994; Sader, 1995; Westman, Strong, & Wilcox, 1989). Others have combined analytic strategies by employing both classification and band-to-band ratios (e.g., Lee & Marsh, 1995; Wolter, Mladenoff, Host, & Crow, 1995).

One great advantage of classification methods is that they use all the information (bands) provided by multispectral images. However, there are two great limitations of classification procedures. First, only one land-cover category or class can be assigned to each pixel or cell of an image matrix. Yet, in many instances, the land represented by one 79×56 meter MSS pixel will be a mixture of multiple land-cover types. Second, most classifications employed are usually image dependent. Typically they are based on raw DNs and have not been converted to physical measures such as surface reflectance values (see the below discussion on image restoration). Nonsurface sources of variability, such as sensor, illumination, and atmospheric differences, remain within the image values and may influence the way the data are classified. Furthermore, because of scene dependence in classification, an expansion of geographic coverage within one individual scene may reveal a new land-cover type that may then alter classification groupings. For these reasons, classifications, based on satellite DNs without image restoration, may not be transportable to other geographic locations.

Spectral Mixture Analysis

Efforts have been made to address these limitations in classification techniques (e.g., Jackson, 1983). SMA is a promising technique developed from the efforts of Earth and planetary scientists (Adams & Adams, 1984; Adams et al., 1986; Bryan, Finger, & Chayes, 1969; Kornder & Carpenter, 1984; Smith et al., 1990a, 1990b; Ustin, Smith, & Adams, 1993).

Certain land-cover types (e.g., soil, water, and vegetation) have been shown to exhibit characteristic patterns of reflectance with wavelengths across the electromagnetic spectrum. Figure 1 shows typical reflectance spectra of general land cover derived from Landsat image data, sometimes referred to as stick spectra. Some landscapes may exhibit discrete and homogeneous land-cover types such as a lake. In instances such as these, pixel data may exhibit more “pure” forms of spectral responses (e.g., 100% water), and classification is an appropriate analytic technique.

In reality, however, land-cover surfaces are often composed of a variety of mixes of materials, and the distinction between them (especially from space) is not so clear. When a sensor observes a pixel composed of mixed types of surfaces, the reflectance spectra produced will not match any pure spectra like the examples shown in Figure 1. Rather, the pixel spectral response will exhibit a shape over the electromagnetic wavelength that is some mixture of spectra of those land-cover types present (Campbell, 1996). For example, a pixel composed of both soil and vegetation will have a spectral response that is some combination of the general soil and vegetation spectra (see the hypothetical mixture example shown in Figure 1). The objective of SMA is to identify primary spectral contributions within each pixel (Adams et al., 1993, p. 149). It provides a means for determining relative abundances of land-cover materials present in any given pixel based on the spectral characteristic of the material (ENVI, 1996).

SMA involves two main steps. The first step is to define a set of pure spectra for selected land-cover material, often referred to as endmembers. Endmembers can be identified using either (a) libraries of known spectra collected with a spectrometer in the field or in a laboratory, (b) libraries of known spectra from previous SMA studies, or (c) spectrally pure or “extreme” pixels identified within the images being analyzed. Most applications of SMA will use the third option because libraries of field-collected endmember spectra are rare, and field spectrometers are expensive and not readily available to researchers. The empirical portion of this article uses this third option.

SMA endmembers are selected by testing whether a given pixel’s spectra can be described as a mixture of pixel spectra previously analyzed or whether it is itself another endmember (Adams et al., 1993). A simple hypothetical illustration is provided in Figure 2.

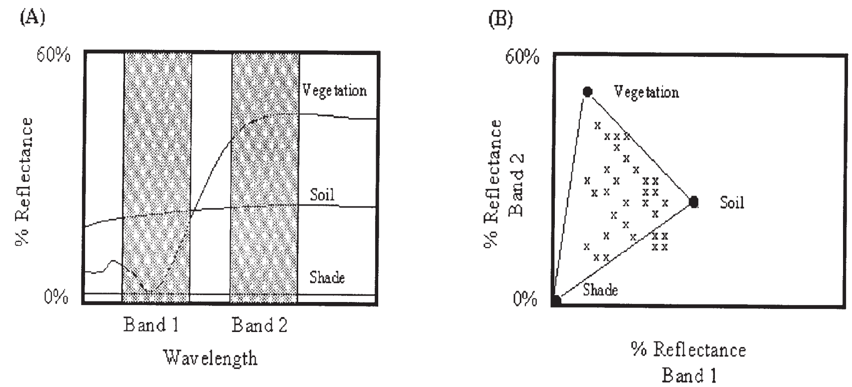


Figure 2: Graphic Representing Hypothetical Image Data for Spectral Mixture Analysis
SOURCE: Adapted from Adams, Smith, and Gillespie (1993, p. 152).

Figure 2A shows the spectra for vegetation, soil, and shade. The vertical gray bars represent the wavelength response for Bands 1 and 2. Figure 2B plots the reflectance values of various mixed pixels from an image for Band 1 and Band 2. Pixels composed of entirely one component—vegetation, soil, or shade—would plot at the corners of the triangle presented in Figure 2B. Pixel purity functions help to identify those pixels in an image that lie at the extremes of the pixel value distribution in *n*-dimensional space (ENVI, 1996). The number of endmembers chosen must be one less than the number of bands available in the multispectral image (ENVI, 1996). For MSS images with four bands, this means that up to three endmembers can be identified. For TM images, six endmembers can be identified if all seven TM bands are used; however, because Landsat TM's thermal band represents a fundamentally different wavelength, SMA analyses typically use only the six optical TM bands and therefore five endmembers (see, e.g., Adams et al., 1995). Once endmembers are identified, their reflectance values associated with image bands can be documented, presented in a form similar to Figure 2A, and stored in a spectral library for use in this and future studies.

The second step in SMA is to estimate, for each pixel, the abundance of each endmember contained within it by applying a linear mixing equation (Adams et al., 1993; ENVI, 1998). The general form of this equation, in matrix form, is as follows:

$$R^{[mxl]} = EM^{[mxn]} * X^{[nxl]} + e^{[mxl]}$$

where,

R = original image values calibrated to surface reflectance,
EM = endmember spectra matrix,
X = vector of unknown abundances or fractions,
m = number of image bands used,
n = number of endmembers used (must be $m - 1$ or less), and
e = root mean-squared (RMS) error in the fit of the model. It represents the sum of the squared residuals over all m bands.

This SMA equation is used to convert the existing image spectra values for each pixel into endmember fraction matrices. One fraction image is produced for each endmember along with the RMS error matrix. This procedure requires the fraction values produced in matrix X to be positive and sum to unity (Adams et al., 1993; ENVI, 1998). These fraction images can be created for each time point in a multitemporal set of satellite images all using the same endmember spectra.

To date, very few studies have applied SMA toward questions related to the human dimensions of environmental change. But it has great potential over the more traditional image-analysis techniques for several reasons. First, like classification and PCA, SMA uses all the information (bands) of a multispectral image.

Second, unlike many traditional classification methods, SMA is image independent. SMA endmembers can be identified from image data, field, or lab inventories or from endmember fraction libraries (Bateson & Curtiss, 1996). For this reason, time series or multiple geographic location SMA fraction coverages are more readily comparable than are products from classification products based on DNs.

Third, endmember fraction coverages represent physical properties of the landscape based on physical units: surface reflectance values. Classification maps often represent abstract human language artifacts—*forest* or *pasture*, for example—that may have different meanings to different people and are not directly tied to any measurable physical property. Two areas may be called a pasture but may be composed of very different vegetation types that exhibit very different spectral qualities. Analyses conducted using endmembers are based on specific spectral qualities of identifiable materials and not on human abstractions. They can therefore be more easily applied to other geographic areas.

Fourth, endmember fraction images are more appropriate for analysis of physical landscapes exhibiting a high degree of continuously varying land cover, such as most forested areas. This is especially important for studies of more continuous landscapes where changes in light reflectance are gradational, such as heavily forested areas. Although classification is quite useful in physical landscapes with discrete land forms, it is not as easily applied to land cover that is more continuous in nature and less easily distinguishable.

Fifth, and perhaps most important, SMA provides the spectral data in terms of multiple endmember fraction coverages and not as a single pixel classification, hence allowing a more detailed analysis of pixel contents (Adams et al., 1993). Because of this, some refer to the mixing approach as a subpixel analysis (ENVI, 1998). From this we can get a better idea of what mixtures of land-cover features comprise any individual pixel. The same amount of data is used in SMA and in classification techniques, but the employment of SMA endmembers and the production of endmember fraction images allow for a more detailed analysis of individual pixel contents. This is important even for satellite images with relatively good spatial resolution, such as Landsat TM, but becomes especially important when using coarse resolution instruments such as Landsat MSS.

The Importance of Image Restoration Procedures

Given these justifications for SMA and that SMA has been around for more than a decade (e.g., Adams & Adams, 1984), why has it not been more widely used? There are two answers to this question.

SMA requires the identification of pure reflectance spectra from the image itself or by using spectra libraries (Adams et al., 1993). The individual band DNs provided in the raw images received from U.S. repositories, such as EROS and Space Imaging/EOSAT, do not represent Earth surface reflectance values that can be immediately used. More than 15 years ago, Robinove (1982) recognized and nicely summarized the problem that still is prevalent today:

> Landsat digital images are commonly analyzed by using the digital numbers for each pixel recorded on computer-compatible magnetic tape. Although this procedure may be satisfactory when only a single, internally consistent image is used, the procedure may produce incorrect

> results if more than one image is used for analysis as in mosaics or temporal overlays. The digital numbers . . . vary depending on the calibration of the multispectral scanner in each satellite at a given time, the sun angle, the state of the atmosphere, the slope and aspect of the terrain, and surface cover. (p. 781)

To develop reflectance spectra of endmembers from the image itself, or use an endmember reference from a library, the image must have sensor, illumination, and atmospheric variation removed from the original image DNs. In other words, the DNs must be converted to surface reflectance. As Robinove suggests, this conversion, sometimes referred to as image restoration (Green et al., 1998; Jensen, 1996), is vital for any SMA temporal or spatio-temporal comparison.

SMA has not been used because it is logistically difficult to undertake full image restoration. When image comparisons are to be made, after preprocessing steps,[1] three main restoration processes should be undertaken: radiometric calibration, atmospheric correction (Chavez, 1989; Teillet & Fedosejevs, 1995), and radiometric rectification (Hall, Strebel, Nickeson, & Goetz, 1991). Radiometric calibration involves converting image DNs to radiance values and radiance to at-satellite reflectance[2] values (Hill, 1991; Markham & Barker, 1986; Robinove, 1982). Atmospheric correction removes the effects of the atmosphere (e.g., light scattering) thereby converting at-satellite reflectance values to surface reflectance (Ballew, 1975; Chavez, 1989; Teillet & Fedosejevs, 1995). Radiometric rectification normalizes a set of time-series image data to one given image. This ensures that time-series images are directly comparable to one another.

Although the information on how to conduct radiometric calibration is available, the literature is scattered and not readily available to the environmental change research community (Green et al., 1998). The procedures required differ by satellite platform and by sensor type. A literature review of major remote-sensing journals revealed that over the past 10 years only a small proportion of researchers actually converted DNs to surface reflectance values (Green et al., 1998). Classification of one time point or multiple time points (by applying the radiometric rectification procedures of Hall et al., 1991) can be conducted as long as the researcher has no interest in applying the same classification to another geographic area (Green et al., 1998). Because of this ability to normalize images taken at different times, but of the same location, the technical difficulties in converting DNs to surface reflectance values may appear to many to be not worth the effort. This decision to leave Landsat images in DN data space means that SMA cannot be considered a viable analysis option on these products. Over the past 2 years, we have worked to produce partially automated spreadsheets and accompanying documentation that allow the user to convert any Landsat TM or MSS image from DN representation to surface reflectance values (for more information on the availability of these procedures, contact either one of the authors).

The second answer to why SMA is not more widely used is more simple: SMA computer programs are largely unavailable. SMA itself is a fairly complicated process (see Adams et al., 1993) and is largely prohibitive unless software is written to allow such an analysis to be undertaken. At the point of this writing, surprisingly, SMA functionality is still not available as part of the general analysis tools in many of the most prominent image-processing packages. We have been able to identify two software packages that have this functionality. The first is research software called Impact, developed by Milton Smith, Steve Cothern, and Bill Gustafson at the Department of Geology's remote-sensing laboratory at the University of Washington. The second is ENVI®, a commercial remote-sensing software package with linear unmixing capability. With image processing and SMA now outlined, let us provide an example of how SMA can be applied to the study of human management of a public forest in south-central Indiana.

SPECTRAL MIXTURE ANALYSIS IN A PUBLIC FOREST OF SOUTH-CENTRAL INDIANA

As an example of the use of SMA for understanding the human dimensions of environmental change, we will focus the rest of our discussion on landscape change in one portion of the Hoosier National Forest, the Pleasant Run unit, which is located in south-central Indiana. The brief analysis that follows seeks to show how SMA can help identify differences in two forested landscapes subject to different management histories. For a more complete analysis of this area and other public forests in Indiana, see Schweik (1998).

Understanding the role humans play regarding landscape change in a particular region requires an investigation of what actions humans have taken over time and how these actions relate to the physical properties of land-cover reflectance. This involves examining the relationship between light reflectance and the physical land cover and how human activities alter that land cover. However, merely linking human actions to physical outcomes is not enough. If we are to truly understand human-environment relationships then we must understand how the incentive structures humans face in their day-to-day activities alter their decision-making processes and the actions they ultimately take (Ostrom, 1990, in press). If social scientists wish to link human decision making to information captured by satellites, *we must relate incentives to human actions, actions to outcomes, and outcomes to surface reflectance* (Schweik, 1998).

To undertake such a change analysis using satellite images and SMA requires a series of steps. First, we must carefully select the images we use in order to minimize weather and seasonal effects. Second, it is important to undertake a theoretical consideration of how light reflectance is related to the land cover we wish to study—in this case, a forested landscape. This is useful toward the development of appropriate endmembers for fraction image generation. Third, theoretical considerations must also be given to the incentive structures humans face that relate to the choice of actions they undertake in the region. This allows us to develop expectations on how humans have altered the physical landscape. Fourth, image processing is undertaken to convert the raw image DNs to surface reflectance values. Fifth, we must identify appropriate endmember locations and develop SMA fraction images. Finally, sixth, we can analyze SMA results and create other output products such as fraction-based classifications to assist in change analysis. We will briefly describe these steps below.

Image Selection

A crucial decision the analyst must make when undertaking change analysis using multispectral satellite images is image selection. Over the 25-year Landsat life span, there are a large number of images that might be selected for analysis for any particular location in the United States or elsewhere. Careful image sampling is particularly important for it allows the analyst to minimize unwanted sources of variability. We followed several steps in choosing the images to analyze.

First, we considered the temporal frequency of the human activities of interest. For this study, we are interested in public forest management. Forest-cutting, development, and preservation activities are most likely to be identified spectrally. Development and preservation activities will begin at a particular time point and then will most likely remain throughout the Landsat time series. Forest cutting in this region, however, will result in an initial pattern of disturbance followed by regrowth and possible cutting again after 30 or more years. Given that the Landsat system has been operational for more than 25 years, maximizing the temporal extent of the image time series can more appropriately sample the forest-cutting activity.

To capture the phenomenon of forest cutting throughout time, Landsat images are selected early in the archives duration (1972) and late (1997) with at least one image in between.

Second, we considered the ramifications of seasonal effects on spectral response. For the study of forest resources, a late summer scene when tree canopies are full is appropriate. Gaps where cutting exposes litter and soil are more apparent when a tree canopy is in full leaf cover than in fall or winter scenes. There is also a contrast between herbaceous growth and forests in late summer when dry conditions promote herbaceous senescence. For these reasons, we selected images acquired in September. The reader may also raise the concern of diurnal variability in satellite images. Fortunately, Landsat's sun synchronous orbit ensures that all images are taken at nearly the same time each day.

Third, we considered the year-to-year climatic variability in the images. In the study done by Schweik (1998), it became apparent that our selected 1985 image was dramatically different from two other time points. One hypothesis is that the difference is attributed to a higher-than-normal rainfall during that year. It is important, then, to select images that have had similar rainfall and temperature patterns during the months or even the year prior to image acquisition.

Finally, cost drives image selection. For this study, we used a georegistered time series of Landsat MSS images made available at no cost through the North American Landscape Characterization (NALC) program: 9/30/72, 9/1/85, and 9/28/92 (Lunetta, Lyon, Guindon, & Elvidge, 1998; NALC, 1997). Fortunately, the images made available through this program satisfied the first two selection criteria, but as noted above, the 1985 image exhibited significant spectral differences that are attributed to the higher rainfall that year.

Theoretical Considerations Related to the Spectral Properties of the Landscape

The analyst must next consider the spectrally important characteristics of the landscape under investigation. The human actions we wished to study were silviculture and development activities in a public forest. This meant considering the spectral characteristics of this broadleaf forest region.

The major factors that affect reflectance from a Midwestern oak-hickory forest canopy are leaf area and leaf optical properties that are a product of leaf morphology (Green, 1996). It is well understood that leaf chlorophyll absorbs sunlight predominantly at red (.65 μm) and blue (.45 μm) wavelengths for use in photosynthesis. Less green light (.55 μm) is absorbed by photosynthetic plants, thereby making them look green to the human eye. However, the reflectance spectra of vegetation spectra also reveals a significant peak at near-infrared wavelengths (.7 μm through 1.1 μm), an effect that the human eye cannot distinguish. This increase in reflectance is a response not to absorption by chlorophyll molecules but rather by scattering of light as it is reflected within the deeper internal structure of a leaf's spongy mesophyll (Campbell, 1996; Knipling, 1970).

In studies of similar oak-hickory forests in Missouri (Green, 1988, 1996; Green & Arvidson, 1986; Green, Arvidson, Sultan, & Guinness, 1985), distinctly high, near-infrared leaf-reflectance values were found to be associated with vegetation from xeric environments: areas with soils that exhibit low water-retention capacities. Alternatively, these studies report forest vegetation in wetter, mesic environments to exhibit lower leaf-reflectance values in near-infrared. Green (1996) attributes this phenomenon to different morphological qualities of the leaf internal structure as plants adapt to various environmental conditions: Xeromorphic leafs differ from mesomorphic ones by exhibiting a thicker outer cuticle layer (Kramer

& Kozolowski, 1960; Spurr & Barnes, 1992), a higher ratio of internal to external surface (Kramer & Kozolowski, 1960), and a thicker leaf with more palisade layers (Green, 1988). It is thought that these differences cause additional scattering of infrared light in xeromorphic leaves.

How do these phenomena relate to human actions on deciduous forests? Xeromorphic leaf structures are often produced as a result of topographic conditions and water availability factors. They also appear to have a relationship with age of forest vegetation (Schweik, 1998). Water is gathered by the root system of trees (Spurr & Barnes, 1992), and younger trees will exhibit less extensive root networks, which result in less access to soil moisture. Moreover, the canopy of younger trees, in an open stand that has recently been cut, will be exposed to more direct sunlight, thus promoting the development of more xeric leaf structures, than will similar species growing in more shaded conditions (Spurr & Barnes, 1992).

Schweik (1998) analyzed well-documented cutting areas in a state forest in Indiana and found that in general, environmental conditions and age-class appear to have a relationship with the amount of reflected near-infrared light. Xeric topographic environments and young vegetated stands reflect higher amounts of near-infrared light than do older forest vegetation or vegetation residing in more mesic environments. The choice of MSS imagery to maximize this study's temporal duration limits us to the selection of three endmembers (four bands minus one). For this study, we chose endmembers as follows: one endmember represents xeric (brighter near-infrared) vegetation, and one represents nonliving matter (exposed soil and developed regions). Because of the three-endmember limitation when using MSS images, the third endmember represents darker near-infrared vegetation and also shadowed vegetation (shade) (Adams et al., 1995). This endmember may also pick up pine stands as well because pine tends also to exhibit dark vegetation spectra. If we were using solely Landsat TM data, we would be able to employ five endmembers: xeric vegetation, mesic vegetation, soil, shade, and pine. See Adams et al. (1995) for one SMA example using TM imagery.

Theoretical Considerations About Human Behavior in the Region

Similar theoretical considerations must be addressed concerning human behavior and action in the region. Given that the forests studied are under public forest management, we focused our investigation on the national forest property manager. Taking a "new-institutionalist" approach to the study of these managers (e.g., see Eggertsson, 1990) and following Ostrom's (1990, in press) work, we assume that property managers face a suite of alternative actions that they and their employees might consider undertaking. They choose between alternative activities based on the incentive structures—the costs and benefits—that are established to encourage or discourage different types of activities. Broadly speaking, the suite of activity choices in Indiana public forests can be categorized as three types: commodity- (e.g., silviculture practices), recreation- (e.g., trail management), and preservation-related activities (Koontz, 1997).

The costs and benefits associated with any particular activity are influenced by attributes of the physical world, attributes of the human communities interested in the forest and the institutional landscape governing the area. The physical attributes of the region sometimes make the costs of undertaking an action so high that certain activities will not be considered, such as building a road on an extremely steep slope. Other activities may have extremely high costs because of the reaction or anticipated reaction of users of the public forest. Anticipated protests from environmental groups and landowners adjacent to the property may also increase the expected costs of particular activities such as clear-cutting of forest stands.

We define the institutional landscape as the set of rules that are established to determine the spatial distribution of where activities can and cannot be conducted along with the monitoring and sanctioning mechanisms used to enforce these rules (Schweik, 1997). A property manager's selection of certain activities to undertake is also encouraged or discouraged by the configuration of this institutional landscape. In the case of the Hoosier National Forest, legislation, revenue rules and allocations, standard operating procedures, and planning documents place significant constraints on where particular activities can be undertaken (Koontz, 1997; Schweik, 1998), and many of these restrictions involve a geographic component.

A full institutional history of the Hoosier Pleasant Run unit is beyond the scope of this article (see Schweik, 1998). But as an example, we will focus on two different regions of Pleasant Run that have had different institutional histories over roughly the past 20 years. These two units have different types of activities that are permitted, required, or prohibited within their boundaries as specified in the Hoosier forest management plans. The two areas of interest for this article are Area 5.1, designated wilderness in 1982, and Area 7.1, designated an intensive recreation area; their boundaries are identified in Figures 5 and 6.

From knowledge of the institutional histories and assumptions that the behavior of the property managers will largely comply with the incentive structures created by these institutional configurations, one can develop a set of expected and testable hypotheses related to forest land-cover change.

Hypothesis 1: The area designated as wilderness (Area 5.1) will exhibit little evidence of human disturbance and signs of natural vegetation regrowth. As the Deam Wilderness area ages, image pixels are expected to exhibit declining percentages of the xeric endmember and increasing percentages of the mesic endmember over time.

Hypothesis 2: The area designated as intensive recreation (Area 7.1) will exhibit higher levels of development activities and permanent soil exposure than will the wilderness area. Consistently higher percentages of the soil endmember will be found in this management area over time.

Image Processing

Image-processing steps involved a series of procedures to minimize nonsources of radiometric variability, such as that produced by the satellite and atmosphere, and to ensure geometric comparability. We first verified that the images had little or no variability produced by differences in sensor sensitivity (striping) and sensor power surges (speckle). Georeferencing has been performed on all NALC program scenes. This is a crucial step in change analysis and ensures comparability across the time series of images. The danger is that misregistration between images may be mistaken for land-cover change and could cause significant errors in change analysis results. The NALC program data sets have specifications of georeferencing error below one pixel (NALC, 1997). We performed additional georeferencing verification by overlaying a very accurate road network GIS coverage over each image to visually confirm the georeferencing of each image in the area of study. We then converted the image DNs to at-satellite reflectance and minimized atmospheric effects using the spreadsheet-based procedure that we developed (Green et al., 1998). We then normalized the 9/30/72 and the 9/1/85 image to the base 9/28/92 image using the radiometric rectification procedure developed by Hall et al. (1991). This processing converted the DNs of each NALC image to surface reflectance. These postprocessed images can now be readily compared.

Endmember Identification and SMA Fraction Image Development

The next step is to identify candidate xeric vegetation, mesic vegetation, and soil endmember pixels within the image region that exhibit extreme spectral qualities for their land-cover type (recall Figure 2B). The 9/28/92 MSS image was searched for locations that appear to be pure representations of these land-cover types. Xeric forests were identified in MSS images by their high near-infrared reflectances. In Indiana, they tend to be found on hill summit areas and on southwest-facing slopes. These areas have higher near-infrared reflectances and appear brighter in image composites. Mesic forest vegetation regions, on the other hand, tend to reside in valley bottoms (where water availability is high) and exhibit relatively darker near-infrared reflectance.

Searching for extreme pure endmember locations is an iterative process. First, we removed water areas from consideration by identifying those pixels that exhibited low values across all MSS bands. These locations were removed from consideration so that SMA did not have to model them. Next, we used three-dimensional scatter plots of band data to identify extremely bright soil and xeric vegetation locations. Three extremely bright soil locations, four extremely bright xeric vegetation locations, and three dark mesic vegetation locations were identified using this technique. Using differential global positioning systems technology with about five meters' accuracy, we verified these locations in the field to make sure they were indeed good examples of these endmember types. The spectra for all other pixels within the Hoosier forest region, theoretically, should be explained by linear combinations of these three endmember spectra.

Several SMA models were run combining various soil, xeric, and mesic/shade candidates. SMA output for each MSS time point is four new images: three representing the fractional percentage of each endmember for each pixel and the fourth representing the RMS error or goodness of fit of each model. Areas not modeled well are identified by high values in the RMS error image. The final model has to fit two selection criteria: (a) The spectral variability present is largely accounted for, and (b) the model produces endmember percentages that fall between 0% and 100% (ENVI, 1998; Ustin et al., 1993, p. 345). Time-series analysis requires a third criteria: The models must satisfy the first two criteria for all image dates. This modeling process is complicated by limitations in MSS degrees of freedom and because the mesic/shade endmember does not model both categories particularly well. The model that satisfied these conditions the best used endmembers of a cleared agricultural field, a xeric vegetation location residing on a summit and partially on a southwest-facing slope, and a mesic vegetation location that resides in a valley and is somewhat shaded. Figure 3 displays the stick spectra graphs for the final soil, xeric vegetation, and mesic vegetation endmembers chosen. The resultant fraction and RMS images produced from this SMA model for one region of the 9/28/92 time point are shown in Figure 4. Similar products were produced for the other dates.

The landscape in Figure 4 highlights an example that will help the reader interpret SMA-derived images. Circled in the image is a known area where a forest property manager office exists. Note that this area is very bright in the soil fraction image, meaning that these pixels have a high percentage of exposed soil. This area is also dark in the xeric endmember fraction image and, therefore, exhibits a low percentage of this endmember. Finally, it is moderately dark in the mesic/shade endmember, so some mesic vegetation and shadow also exist within this area. This provides an example of how SMA provides the analyst with the capability to conduct subpixel analysis—a capability not possible using traditional image classification

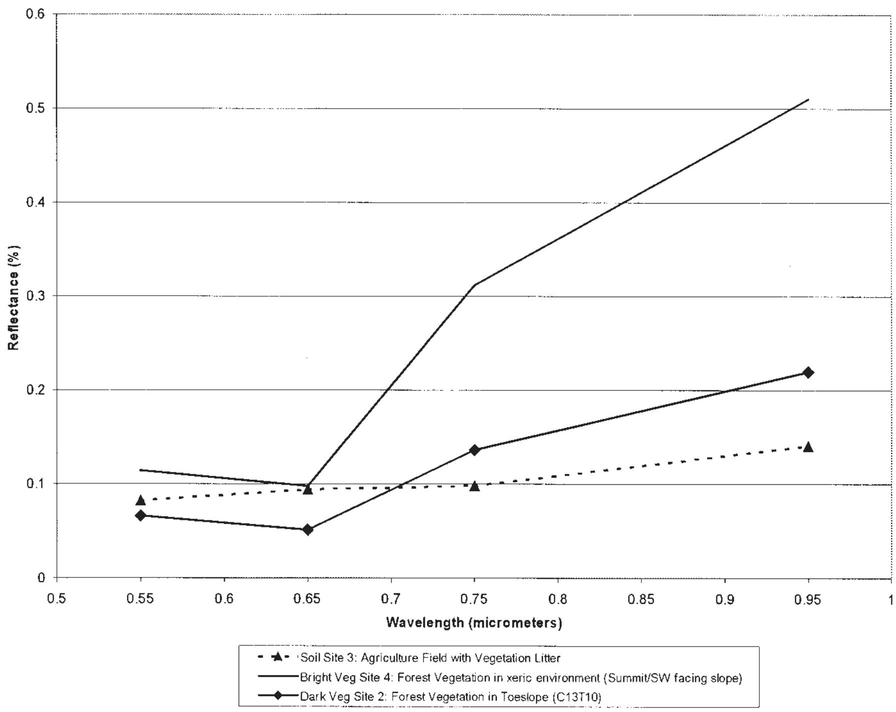


Figure 3: Stick Spectra of Chosen Endmembers: Soil, Bright (xeric) Vegetation, and Dark (mesic) Vegetation and Shade (Landsat Multispectral Scanner Path 21, Row 33, 9/28/92)

analysis techniques. By employing SMA, we have effectively moved our analysis from one depicting changes in reflectance to one depicting changes in surface composition—a measurement system much more accessible to the social science community. We now also have a mechanism to evaluate how well this system is defined for each pixel (the RMS image).

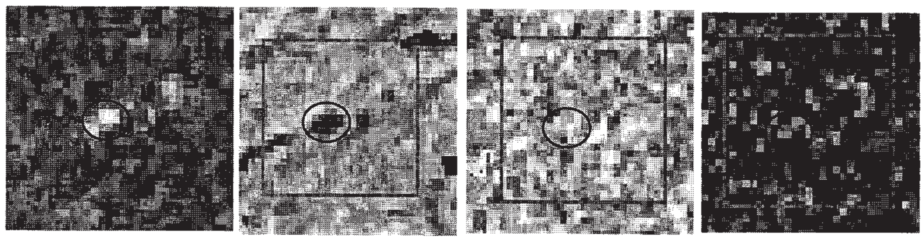
Change Map Creation and Analysis

With the SMA fraction images developed, several types of analysis techniques can be applied. Schweik (1998), for example, analyzed specific locations where known forest management activities have occurred and found that these SMA fraction images are sensitive to various types of cutting and development activities. However, the hypotheses stated above require an analysis at a broader spatial scale: the landscape.

Hypothesis 1 predicts that the Deam Wilderness will exhibit, overall, a general decline in the percentage of the xeric endmember with time. Because the institutional landscape for this area prohibits timber-cutting activities and the incentive structure strongly encourages property managers to adhere to this mandate, it is expected that vegetation in this area designated as wilderness will exhibit signs of aging across the time series. As trees get older, it is expected that the cell structure of their leaves will become less xeromorphic as their root systems become more extensive, accessing more moisture, and as a greater proportion of their leaves become protected from direct exposure to sunlight.

Interpretation Example: Forest Property Manager's Building and Parking Lot:

(1) High % Soil (bright),
(2) Low % Xeric\Young veg (dark),
(3) Moderate % in Mesic\Mature Veg and Shade (Shades of grey),
(4) Low RMS error (mostly dark)



(1) % Soil | (2) % Xeric/Young Vegetation | (3) % Mesic, Mature Vegetation and Shade | (4) RMS Error

Figure 4: Spectral Mixture Analysis for a Portion of the Landsat Multispectral Scanner 9/28/92 Image

NOTE: Bright white = high percentage; dark = low percentage; RMS = root mean squared.

A color composite image can be used qualitatively to test this hypothesis by assigning each of the three xeric fraction images of each time-point image to blue, green, and red. In the resulting image, different colors are associated with different temporal trajectories. The difficulty with this method is that the continuous nature of the fraction image data (and satellite image data in general) makes interpretation of the subtle color changes difficult. This is exactly why humans find classification maps so useful: They aggregate continuous data into a few discrete categories, greatly simplifying analysis.

Recall the earlier argument about traditional classification approaches being image dependent and not readily transferable to analyses of other images. Using SMA fraction images, the analyst can now develop classifications that no longer are based on statistical measures of a single image but are instead developed from endmember fractions, grounded in physical measures of reflectance, and acquired at specific locations on the Earth's surface. For example, the analyst can now define what he or she considers a xeric forest based on these percentages of certain materials. In our study, we define a xeric forest as one possessing 40% or higher of the xeric endmember and less than 40% of either the soil or mesic/shade endmembers.

With these definitions established, the analyst can easily convert the continuous data of the three endmember fractions for any image into a classification map based on endmember values using software modeling functionality.[3] Moreover, the same classification definitions can be used for each image time point, something that cannot easily be accomplished using traditional image classification procedures. Side-by-side image classification maps based on SMA fractions for the Wilderness area are shown in Figure 5,[4] and Figure 6 presents similar maps for the intensive recreation area. To demonstrate the utility of these products, let us now briefly address the hypotheses stated earlier and interpret these classification maps.

Hypothesis 1 predicted that given that Area 5.1 is treated as wilderness, the vegetation here will exhibit signs of continued forest aging. In terms of SMA fraction images, it is expected that the vegetation in the wilderness area will, in general, be more xeric in 1972 and

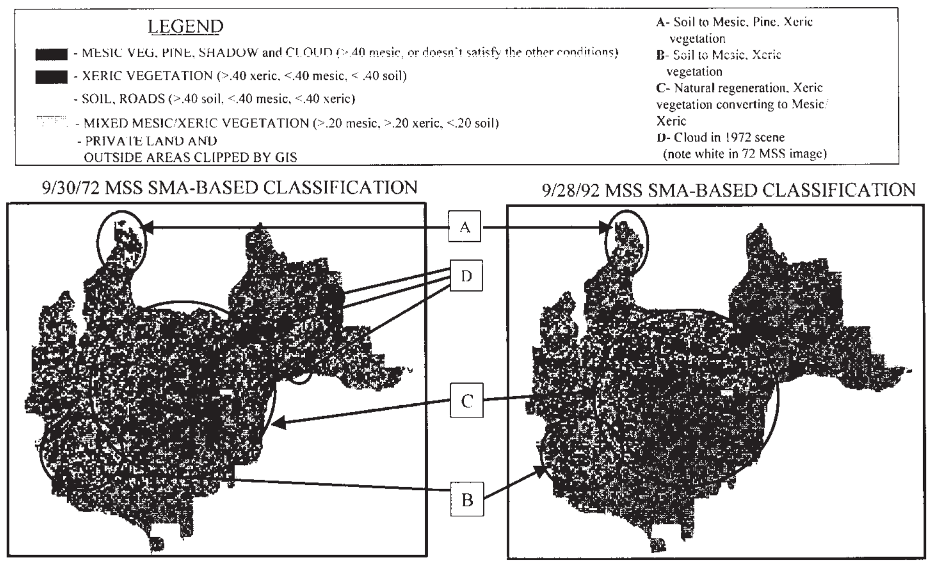


Figure 5: Change in the Hoosier National Forest Pleasant Run Unit Area 5.1 (Deam Wilderness)
NOTE: For a color version, visit the Web site at `http://www.indiana.edu/~cipec/publications/publications.html`. MSS = multispectral scanner; SMA = spectral mixture analysis.

move more toward mesic conditions in 1992 after 20 years of root growth and increasing moisture availability. Reviewing the side-by-side classification images in Figure 5, several pieces of evidence tend to confirm this hypothesis.

First, the northern peninsula of the Deam Wilderness, circled and labeled *A* in both maps of Figure 5, reveals a significant amount of exposed soil (light areas or gold in color) in the 1972 map, whereas in the 1992 map, it is replaced by a combination of the mesic vegetation/pine/shade class. A review of a September 1997 TM image reveals a significant pine stand on this peninsula. Because pine is not indigenous to this area, this suggests that a major planting initiative occurred in this area between 1972 and 1992, probably to protect soil erosion into the adjacent Lake Monroe.

Second, the conversion of soil to vegetation is apparent in the area identified by *B* in Figure 5, which exhibits a pattern we would expect in an area left alone to regenerate. Scattered soil-dominated pixels (gold) in 1972 have been replaced by more prevalent xeric spectra (red), mesic/pine/shade spectra (dark green), or a combination of xeric/mesic vegetation (bright green). Thus, as the Deam ages after its designation in 1982, forest vegetation appears to be returning.

Third, the large circles labeled *C* on the Figure 5 maps reveal a significant area that exhibits what appears to be following patterns of natural regrowth. Many of the stands that exhibited xeric (red) characteristics in 1972 remain xeric in 1992. We used a digital elevation model for the region to identify locations that are naturally more xeric in nature (e.g., summits and southwest-facing slopes). These areas would be expected to remain xeric over time because of the natural effects of their physical environment. But many other xeric-dominated

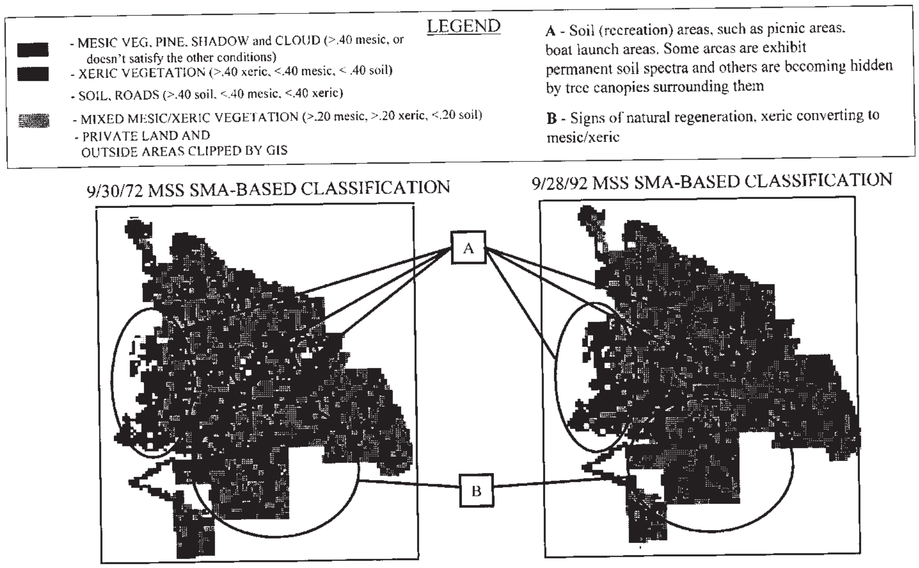


Figure 6: Change in the Hoosier National Forest Pleasant Run Unit Area Designated 7.1 (intensive recreation area)

NOTE: For a color version, visit the Web site at `http://www.indiana.edu/~cipec/publications/publications.html`. MSS = multispectral scanner; SMA = spectral mixture analysis.

areas in 1972 have been replaced in 1992 with higher percentages of mesic vegetation (bright green or dark green areas in the color versions of the maps). These areas take on the expected high-to-low xeric to lower xeric change trajectory that Schweik (1998) identifies as a spectral pattern of natural regrowth in these forests. This evidence also strongly supports Hypothesis 1.

Hypothesis 2 predicts that the high recreation area will exhibit patterns of development (permanent soil exposure and nonvegetative land cover) in areas where the property managers build or maintain recreation infrastructures. Reviewing areas identified by *A* in Figure 6 reveals a higher level of soil exposure in this area in 1972 than that found in the Deam Wilderness area. Note, however, that in 1992 much of this soil has been replaced with mesic or mesic/xeric land cover. The history of the area helps to explain this trajectory. The lake adjacent to this area was created in the mid-1960s. The soil exposure in 1972 is a result of significant recreation infrastructure development that occurred shortly thereafter. However, as time has passed, property managers have worked to allow the remaining forest surrounding these recreation areas to continue to age because larger trees are more visually appealing to visitors. Therefore, the change trajectory of the area identified by *A* depicts a management strategy of development coupled with visual enhancement (natural regeneration) efforts. As trees have aged, their canopies have grown and covered many of the developed areas (e.g., roads) that were more visible in the early development in 1972. Areas identified in Figure 6 by *B* in these maps exhibit a similar natural regeneration spectral trajectory as managers work to keep visual enhancement areas pleasing to visitors.

DISCUSSION AND CONCLUSION: THE PROMISE OF SMA FOR STUDYING THE HUMAN DIMENSIONS OF ENVIRONMENTAL CHANGE

The tremendous advances in desktop computing, even over the past 5 years, has produced great interest within the social science community on the use of multitemporal, multispectral satellite images for the study of human-environment relationships. The technology and know-how that used to only reside in the hands and minds of scholars with graduate degrees in remote sensing can now be more commonly applied by scholars in various disciplines such as geography, anthropology, public administration, and political science: all fields with an interest in understanding the human role in global change.

Let us summarize our main thesis. Multitemporal, multispectral satellite images, such as Landsat, are very useful in the study of the human dimensions of environmental change studies because the archive covers a tremendous spatial extent of the Earth's surface and more than a quarter century in duration with very frequent temporal sampling. Their radiometric and spatial resolution continues to improve as new satellites are launched. However, to link the information provided in these images to human incentives, actions, and outcomes such that comparisons can be made between studies, we must carefully process the images to remove nonsurface sources of variability that cannot be attributed to variations in land cover and land-cover change. To remove this variability, images should be processed from DNs to physical units: surface reflectance values, through radiometric calibration and atmospheric correction procedures. In doing so, analyses can be duplicated and replicated by researchers studying other locations, and accurate comparisons can be made across space and time. Furthermore, by reporting endmember characteristics and locations and applying SMA to generate endmember fraction images, the researcher can define classifications grounded on a physical measure of the Earth's surface: reflectance and based on how much of what material is present. By using the xeric/mesic distinction, we have classified our forests based on quantitative, ecologically significant properties tied to measurable forest properties such as leaf morphology. Unlike traditional classification, these categories can be readily applied and replicated by others working in distant but comparable environmental regions.

To understand the role humans have played in changing land cover, one must give careful attention to both natural as well as human parameters. The analyst must use effective sampling strategies and GIS products (e.g., digital elevation models or other topographic products) to account for natural influences such as rainfall, elevation, and slope aspect. To understand the human dimensions of change and the motivation behind them, the analyst should identify (a) the suite of alternative actions undertaken by humans in a particular context, (b) how these actions physically disturb the landscape and affect light reflectance, and importantly, (c) what incentive structures (e.g., rules, social norms, and legislation) have driven human decision-making and activity choice (Schweik, 1998). By linking incentives to actions and actions to outcomes measured with physically based yardsticks such as surface reflectance values, more straightforward human-environment relationships can be understood.

Image processing and SMA have the potential to produce other benefits as well. If physical relationships can be identified between vegetation reflectance and SMA percentages with other important global change parameters, such as those associated with forest health under climate change, researchers may be able to use spectral measurements as proxies for these vitally important but costly-to-measure parameters and develop image-based inventory estimates appropriate for particular forested landscapes.

We conclude with guidelines on how to link the study of human incentives and actions with SMA-based landscape measurements. The researcher/analyst should

1. investigate and document the incentive structures that drive human actions in the context of the study location;

2. inventory the suite of potential activity choices that humans in this area undertake;

3. consider the temporal frequency of land-cover disturbances that these activities will produce and select sufficient images to critically sample the phenomenon of interest;

4. control for season and weather effects through careful selection of satellite images;

5. identify a subset of locations where these actions have occurred and investigate the physical response produced in the image time series;

6. control for topographic effects through the use of GIS products such as a digital elevation models; and

7. convert the multispectral images from DNs to surface reflectance values such that nonsurface sources of variation can be removed and not attributed to human actions. In doing so, findings can be compared with other studies of similar forest types.

A much more detailed description and example of this process is shown in Schweik (1998). For more information, contact the authors or visit our World Wide Web site at `http://www.indiana.edu/~cipec`.

NOTES

1. Image preprocessing involves the removal of pixel-to-pixel variability not associated with atmospheric or surface phenomena. It involves the conversion of digital images from CD or tape to the appropriate image-processing software format, removing any artifactual noise from the image, such as line dropouts and line striping, and image georeferencing.

2. At-satellite reflectance describes the ratio of light received by the sensor from the entire Earth-atmosphere system over the solar irradiance at Earth-sun distances. These values still contain the effects of the atmosphere, such as scattering and absorption.

3. In our case, we use model maker, which is part of Imagine® software, to produce this classification.

4. These classifications cannot easily be interpreted in black and white. Therefore, the color classifications for this article are available at `http://www.indiana.edu/~cipec/publications/publications.html`.

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