Remote Sensing of Ecological Processes: A Strategy for Developing and Testing Ecological Models Using Spectral Mixture Analysis

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I. Introduction

Regional and global environmental issues require that ecologists address the applicability of ecological models across diverse scales. How well physical processes (e.g., photosynthesis, respiration, evapotranspiration), measured and understood on leaf-to-canopy scales, can be extrapolated to large regions is uncertain. In many cases, it is impossible to test models extended to larger scales because the relevant measurements are lacking at the appropriate resolutions. Remote sensing is one of the emerging technologies that has the potential to extend measurements over spatial scales ranging from the microscopic at shorter wavelengths to the global over a broad range of wavelengths. Remotely sensed images can be obtained from a variety of sensors, from portable CCD cameras to satellites. Further, remote sensing offers tools to formulate and test ecological hypotheses at larger scales. Figure 19.1 illustrates the spatial scales of most direct methods of environmental measurements and observations in comparison with scales of current satellites. The most useful contributions of remote sensing technology to ecology are likely to be based on frequently repeated multispectral measurements covering very large areas.

The new satellite systems provide not merely photographic representations of the surface of the Earth but also physical measurements of the absorptance, reflectance, and emittance properties of landscapes, obtained in a spatial matrix and repeated at frequent temporal intervals. Remote sensing measurements convert photons received by a sensor from pixels (smallest resolvable surface areas) arrayed in a spatial context into voltages that are digitized. Information about the surface is derived from the spectral characteristics and their spatial and temporal patterns. These data can be used to explore ecological properties and processes in ecological models only after the data are converted from the raw digital numbers at each wavelength interval to ecological properties, a process that usually requires three models: remote sensing models that calibrate and convert the raw data into more usable forms, connecting models that translate the data into ecological variables, and ecological models that use measured variables to predict states and processes.

A fundamental property of matter is that it absorbs and emits energy at specific wavelengths; the absorption spectrum is determined by the chemical composition and structure of the compounds present. Many plant compounds now are identified routinely using spectroscopic assays n the laboratory (e.g., Weyer, 1985; Marten *et al.*, 1989), suggesting that spectral characteristics could be used to measure biogeochemical properties at other scales. Vegetation spectra are most varied at the level of biochemical constituents and cell structure (Fig. 19.1). As spatial scales increase, spectral variation decreases nonlinearly, with a trajectory that is understood incompletely. The changing variance results largely from the averaging of some components, including vegetation, soils, and other extraneous effects, for example, atmospheric conditions, as spatial scales increase. There are fewer spectrally unique components at coarser scales because most materials are mixtures of the "pure" materials from finer scales. One of the key issues in relating remote sensing to ecological models is the identification of the factors that define the spectral variance across scales. Ultimately, the overlapping levels of measurement should make it possible to construct testable ecological models that cross all scales.

Approaching problems at new scales often requires conceptualizing the component issues with fresh perspectives. Current ecological models generally interpret multispectral images in terms of-preexisting paradigms [e.g., estimates of leaf area index (LAI), identification of species or community types] rather-than develop new measurement definitions that take full advantage of the qualities and scales of remote sensing images. The analytical tools used to interpret images also have limited the development of new organizational definitions because most of the tools are not designed to test hypotheses, an essential step in synthesizing new paradigms. None of the current remote sensing analysis procedures, including spectral mixture analysis (SMA), appears to function correctly under all environmental conditions. Finally, most approaches use only a few spectral bands and are unable to make use of the array of data available. SMA is, however, one of the few image-processing approaches that can use the spectroscopic information from a wide range of sensors. It is flexible for a variety of applications and provides a constant frame of reference from which to make quantitative interpretations of biophysical changes over space and time. These features can be used to develop a robust strategy for testing and validating ecological models at large scales.

A. Current and Future Earth Observing Satellites

Many airborne and spaceborne remote sensing systems are available for research, presenting a diverse array of optical, radar, and thermal sensors. The current satellites sensors are listed in Fig. 19.1. Although no single sensor was designed to provide measures of all the vegetation properties of ecological interest, all satellites have the potential to provide at least some ecological information. The traditional approach to vegetation measurements using satellite data involves contrasting signals from red and near-infrared channels, chosen because vegetation and soils display large differences in reflectance because of the strong chlorophyll absorption feature of green plants. Determining ratios of red to near-infrared reflectance is the most commonly applied procedure for detecting vegetation (Jackson, 1983; Sellers, 1985,1987; Tucker and Sellers, 1986); thus, most ecologically oriented remote sensing studies have relied on this type of information (Roughgarden *et al.*, 1991).

We are beginning a new era in remote sensing with instruments of far greater capability than current satellites. Procedures must be developed that can make full use of the information these instruments will produce. Over the next decade, the Earth Observing System (EOS) with its many new sensors will become available; aircraft prototypes are available now for research. Collectively, the EOS sensors will measure most regions of the solar spectrum that are transmitted through the atmosphere (Rasool, 1987; Covault, 1989; Wickland, 1991). If ecologists continue to beat date from these new sensors as surrogates for traditional ecological measurements (e.g., biomass, leaf area index, and species-based community descriptions) without reconsidering ecological paradigms, it is unlikely that remote sensing will alter present concepts or realize its potential contributions in ecology. The challenge of reformulating concepts and developing new paradigms may have contributed to the, thus far, limited application of remote sensing in ecology.

II. Relevant Ecological Measurements

At the simplest level, remotely sensed images visually describe spatial landscape patterns: the location, areal extent, and changes over time of communities and ecosystems. Applications to deeper ecological questions require firm linkages between environmental properties and electromagnetic fluxes at different wavelengths. The first step in developing the connections is to consider the variables required by ecological models and the data provided by present and future satellites.

All landscapes are complex. They are composed of heterogeneous mosaics of varying community composition and structure, perhaps impossible to characterize--fully at the landscape scale. As an example, consider a temperate forest ecosystem and the changes in age distribution, density, gap fraction, and species composition that occur as the forest matures. Figure 19.2 depicts a chronosequence, from early second growth forest to climax forest, and illustrates how some forest properties vary with time (Peet, 1981;-Peet and Christensen, 1987). The relatively stable LAI reveals few of the significant ecosystem changes. Most remote sensing models applied to ecological problems have focused on estimating LAI, although many other canopy properties could be estimated. Detailed information about the surface structure can be obtained by using multiple viewing angles, a range of wavelengths, and by combining optical and radar signals. Geometric models have been used to estimate stand structure and gap fractions from image texture (e.g., optical models, Li and Strahler, 1985, 1986, 1988; Smith *et al.*, 1990 a,b; microwave models, Sun and Simonett, 1988; McDonald *et al.*, 1990; Ulaby *et al.*, 1990) but these have received little ecological application thus far. Geometric remote sensing models assess both the large-scale geometry of the landscape (topography, texture, community distributions) and the fine-scale architecture of the canopy. Therefore, they should be applicable to a wide range of environmental problems.

The magnitude of net CO_2 flux, as indicated by the size and direction of arrows in Fig. 19.2, varies with structural properties and successional stage. Water, other atmospheric gases, and nutrients also vary in magnitude with the structural properties of the system. Because the rates of exchange of gases and nutrients, and the energy flow, change with the structure of the ecosystem, knowledge of the location and distribution of physiognomic types and their density, size, and biomass will provide key parameters for assessing biophysical processes and ecosystem dynamics. Multispectral measurements do not correspond to these entities directly, but it is increasingly practical to infer these and other canopy properties from the spectral measurements.

III. Current Approaches to Remote Sensing

Several approaches to developing physically interpretable remote sensing models have been proposed, each with some strong features and some limitations (e.g., see Asrar, 1989; Ulaby and Elachi, 1990; Wickland, 1991). Because a complete review of these models is beyond the scope of this chapter, we present a few examples using SMA as a model analysis tool to illustrate the types of ecological properties under investigation in remote sensing research and some of the implications for understanding ecological processes over a range of spatial scales.

The path from satellite data to ecological interpretation involves several steps. Here, we concentrate on the step that converts the remote sensing data into some parameter or parameters relevant to an ecological analysis. Developing ecological interpretations from relevant parameters may involve a range of additional steps. For example, if spatial patterns in chlorophyll or canopy water can be detected spectrally (Tucker, 1977, 1979, 1980; Jackson, 1986; Gao and Goetz, 1990), how can such information be incorporated into gas exchange or biometeorological process models? If other biochemicals can be detected, as suggested by reports of spatial patterns in canopy lignin and cellulose (Wessman *et al.*, 1988; Elvidge, 1990; Roberts *et al.*, 1990; Wessman, 1990), how can this information be incorporated into a better understanding of community relationships and function? Lignin may serve as a surrogate for the biophysical properties that control microbial decomposition rates (Meentemeyer, 1978; Melillo *et al.*, 1982). Lignin gradients in the upper canopy surface, as measured by spaceborne sensors, may, however, be related more closely to the architectural distribution of foliar and stem biomass than to soil nutrient conditions. Considerable ecological research remains to be done before such parameters can be used to interpret the biophysical state of the ecosystem.

A. Spectral Mixture Analysis of Images

Spectral mixture analysis has a complex history in remote sensing and analytical spectroscopy (Adams *et al., 1991*), but we restrict our discussion to efforts to interpret multispectral images as mixtures of surface materials (e.g., vegetation and soils) and processes (e.g., illumination, atmospheric effects, and instrument calibration) within a single analytical framework (e.g., Adams *et al.*, 1986, 1989, 1992; Gillespie *et al.*, 1990a; Roberts *et al.*, 1990; Sabol *et al.*, 1990; Smith *et al.*, 1990 a,b). This analysis assumes that the pixel spectra that make up an image are composed of mixtures of the spectra of several dominant scene components (Fig. 19.3). SMA transforms the pixel-to-pixel spectral variability of images into concentrations of reference "end members." The reference end members are the reflectance spectra of materials (e.g., plant organs, litter, soils, rocks collected from the site or from similar ecosystems) measured under specified conditions. The methods used to define the number and types of end members vary with the application, but include statistical procedures (e.g., factor analysis) to identify the intrinsic dimensionality of the data, or specification of materials of known interest. The selected end members must be distinct and have spectra that are not reproduced by mixtures of the other end members in the scene. The criteria for selecting the set of end members are (1) that the set accounts for the image spectral variability and (2) that the set produces end member concentrations within physically realistic limits (i.e., between 0 and 100%).

B. Ecological Measurements from Remote Sensing Data

It is useful to define two levels of components in an image, namely, dominant and subordinate spectral factors. Dominant spectral factors correspond to scene components that affect the overall shape of the spectrum, whereas subordinate factors typically correspond to subtle absorption features that usually are localized over a few bands. The dominant spectral variation in-images is caused by mixtures of a few surface materials distributed over the landscape in varying proportions. Typically, a given scene contains four to eight identifiable components. The number of identifiable components is relatively insensitive to the number of spectral bands. Even the 224-band Airborne Visible Infrared Imaging Spectrometer (AVIRIS), which acquires a continuous spectrum over the 400-to 2500-nm wavelength range, does not increase this number. Relatively few scene components have been identified over a broad range of scales (from meters to globe); these include a few types of foliage, wood, litter, a few contrasting types of soils, and shade or shadow. However, not all components are resolvable in a given image because of the particular mixtures and their spectral contrasts.

To illustrate how these properties may be used to interpret the ecology of a region, we applied SMA to a small segment of an AVIRIS image from Owens Valley, California, near the town of Independence. Mixtures of only four spectral materials—shade, foliage, and two soil types (tan and gray)—account for 98% of the image variation. The spectra for these materials are shown in Fig. 19.3. The dominant surface factors (Plate 3) were very similar using image data of Owens Valley acquired in three different seasons (spring, fall, and winter) and from two instruments [Landsat Thematic Mapper (TM) and AVIRIS]. The same end members emerged from each analysis. Seasonal differences appeared as varying proportions of shade, soil, and vegetation. Despite differences in spectral and spatial resolutions, seasons, time-of-day, atmospheric depth, and other factors, SMA predictions were consistent.

The suite of identifiable end members varies somewhat between studies and sites. In the Amazon Basin near Manaus, Brazil, Adams *et al.* (1990) identified shade and only one soil type, but were able to separate the vegetation end member into foliar (green) and wood-litter components. TM studies of temperate conifer forests and arid regions (e.g., the Grand Desertio) produce similar suites of scene components. The fact that a similar suite of end members is obtained from several different optical sensors over a wide range of ecosystems and seasons suggests that the end members should be considered spectral building blocks for constructing landscape models. Differences in landscape processes are likely to depend on how the units are assembled and how, or which, components interact.

Analytical flexibility is important for cases in which only some of the ecologically important surface components can be identified. Generally, fine-grained studies for small regions will define more end members than coarse-grained studies of larger regions. Thus, repeated analyses on spatial or spectral subunits of the image may increase the number of identified components, or additional components may be identified from the residual or unmodeled spectral variance, as described next. For the AVIRIS example, we find that the vegetation abundances are dependent on the spectral region included in the analysis (Plate 4). This wavelength-specific sensitivity results because photosynthetically active radiation is absorbed efficiently in the visible region, whereas little energy is absorbed in the near-infrared range These differences result in less sensitivity in the visible region than in either of the infrared regions. The fact that the spatial patterns do not coincide fully indicates that the information content from different wavelength regions is not identical. The different levels of end member recognition as the spectral range is varied produce patterns analogous to fractals.

C. Quantifying Scene Components

The fractional abundances of the end members and residual must sum to one for each pixel. End member concentrations can be displayed (Plate 5) and analyzed hierarchically using geostatistical or geometric approaches (Mousset-Jones, 1980; Woodcock and Strahler, 1987; Davis, 1989).

Soil types are determined by the parent geological material, surface deposition, and weathering patterns (Plate 5A, C). Here, the gray soils are less weathered than the older tan soils, although both are derived from Sierra Nevada granitic sources (Smith *et al.,* 1 990a). The vegetation fractions are proportional to the areal abundance of projected canopy cover (Plate 5D) and are independent of community composition. In Owens Valley, the vegetation end member is a composite spectrum that includes both photosynthetic and nonphotosynthetic canopy biomass. It identifies not a specific species but a canopy type typical of the semiarid vegetation of the region. Repeated observations provide a mechanism to evaluate changes in the abundance, distribution, or types of end members, as might occur if land use, climate, or other factors (e.g., herbivory or pathogens) change.

The shade end member (Plate 5B) accounts for illumination differences at all spatial scales in the images. It is less directly interpretable in ecological terms than soil and vegetation maps since shade is dependent on sun angle and topography and varies with time. However, the related properties of incident radiance and net radiation have ecological significance in the context of surface energy exchange (Smith *et al.*, 1990b). The effects of topographic shading may be removed using a terrain correction model; the residual surface roughness then includes patterns caused by canopy architecture (Smith *et al.*, 1990 a,b). These patterns may be used to infer community physiognomy (e.g., grasses, shrubs, and trees) and surface texture, which may be processed further to estimate canopy closure and gap structure at appropriate scales. Further development of canopy radiation transfer models should improve estimates of additional canopy architectural properties (see reviews Ross, 1981; Goel, 1988,1989; Ross and Myenni, 1990). These models will provide a strong theoretical basis for linkage to canopy gas exchange and energy balance.

There is potential for further development of texture information to improve interpretations of landscapes. Identification of community or ecosystem boundaries (e.g., to describe habitat fragmentation and loss and the distribution of corridors) provides information about the composition and physical integrity of the ecosystems in the landscape. Texture and gradient analysis may be used to examine relationships between physiognomic units and the proportions of photosynthetic and nonphotosynthetic biomass. It may be practical to develop canopy models based on remote sensing of functional characteristics derived from canopy geometries or physiogomic types (e.g., Horn, 1971; Tilman, 1988).

The interactions and association of end members can be evaluated for edaphic and climate-related patterns. In Owens Valley, communities are distributed edaphically. Spectral classification was possible because of the combined effects of soil and vegetation gradients (Ustin *et al.,* 1986). Temporal differences also provide an opportunity for separating community types since phonological patterns vary widely among communities in a landscape. Improved methods of visualizing complex data relationships are needed. The association of end members can be examined using false-color images (Plate 6 A,B). Areas predominantly of one end member are red, blue, or green; mixtures are intermediate. The spatial interactions among end members that are apparent in Plate 6 were not obvious in the raw image data or in the gray-scale end member images (Plates 4 and 5). For example, Plate 6 demonstrates that the vegetation patterns differ depending on the wavelength interval used. In the visible region, there is little spectral contrast among surface types, while there is maximum contrast in the near-infrared. These differences result in less sensitivity for detecting vegetation in the visible region than in either of the infrared regions. It may be possible to use wavelength-specific sensitivity to characterize vegetation properties under different conditions. More detailed examination of scene components, as illustrated in Plate 6B, provides a mechanism to probe ecosystem interactions among edaphic, topographic, and community structure factors.

D. Identifying Major Scene Components

Determining the identity and the characteristics or state of vegetation and soils is one of the most frequent uses of remotely sensed data. However, achieving this goal has been elusive; vegetation and soil characteristics have been hindcast more frequently than predicted. Using SMA, unknown components in images may be identified by comparing them with reference spectra using spectral matching or other statistical distance procedures (e.g., Clark *et al.*, 1990; Goetz *et al.*, 1990; Smith *et al.*, 1990 a,b). The basic similarity in physiology and biochemistry of plants restricts the range of spectral variability, compared with that in soils and geologic minerals. Pigments and water produce the most important absorption features in plant canopies. The spectral features of plants differ mainly in the magnitude of band depths, widths, and shapes, but not in wavelength position. Cumulative responses to a variety of stress agents produce a similar suite of spectral changes as chlorophyll and water are lost from the canopy. Thus, direct searching for specific features is less helpful than in geological applications.

The presence of unique absorption bands can be used to infer the chemical and physical state of the surface. Although spectral matching can be used directly on the image data (e.g., Goetz *et al.*, 1985; Wessman *et al.*, 1988; Wessman, 1990), many absorption bands of biological interest are weak, for example, lignin or cellulose, or the compounds may be in low concentration in the environment, for example, unusual soils. In these cases, it may not be possible to detect the characteristic absorption bands directly. Sometimes a spectrum of interest resembles a mixture of other materials. For example, the spectrum of dry grass resembles mixtures of shade, green foliage, and soil. In the Owens Valley example (Fig. 19.3 and Plate 5), the green vegetation end member itself is a spectral mixture of foliage and stems. It is impractical to have a reference set of spectra for all possible environmental materials and their mixtures. Thus, stratifying the images using SMA before applying more specific interpretative procedures may improve identifications of specific compounds.

E. Error Analysis

Validation is, perhaps, the most overlooked aspect of image analysis. Field data are usually insufficient to validate the results of image analyses directly because of differences in scales and the inability to sample the full range of spectral variability. Efforts have focused on integrated analyses requiring multidisciplinary simultaneous constraints (e.g., Smith *et al.*, 1990b) as a way to provide intrinsic validation. Instrument and atmospheric calibrations are integrated into the system of equations used in the SMA; potential solutions that require calibrations outside of instrument operation range and atmospheric conditions (available from external sources) provide a check on the model.

The residual spectral variation, remaining after SMA, can be displayed as an image in which both the spatial and spectral patterns can be used to evaluate sources of analysis error. The residual fraction is usually near the magnitude of instrument noise (<3% maximum brightness). Weather fronts, air pollution, moisture gradients, and pathogens have very different spatial and temporal patterns; these provide some basis of assigning casual factors for observed patterns. For example, mismodeling of atmospheric conditions produces different error patterns than does incorrect instrument calibration or improper end member selection.

F. Identifying Minor Scene Components

Areas in the scene that show poor fit with the mixture model provide a diagnostic tool for developing a physical explanation for departures. The four end members from the AVIRIS example (Plate 5) left only a mean 2% residual spectrum over all bands. However, the residuals at specific bands may be higher or a few pixels in the image may have high mean residuals. The residual spectrum may be used to identify minor scene components, such as specific biochemicals or minerals, present either in low concentration over the scene or having spatially restricted distributions. The spatial distribution of the residual variance at three wavelengths of the 171 used in the SMA illustrated in Plate 6C. Spatially distinct patches on the valley floor correspond to irrigated and mesic plant communities that are modeled poorly by the semiarid shrub end member. Examinations of partial correspondences between vegetation and other end members, as illustrated in Plate 6, provide a mechanism by which to examine ecological interpretations carefully. Because of the difficulty in validating remotely sensed images, or even visualizing the information in such a complex data set, careful cross-evaluation of many alternative descriptions of the data provides confidence for conclusions. These figures demonstrate how our understanding of the image data varies with our perspective and how an approach such as SMA can be used to test and validate ecological interpretations. The interactions of residuals from different wavelength regions may be examined visually through color, intensity, and spatial patterns (Plate 6C) or statistically (e.g., with clustering routines). The distinct color patterns show that many of the patches have unique spectral assemblages. These spatial patterns may provide clues for identifying new or additional end members.

The varying patterns provide clues for identifying surface conditions and biogeochemistry. Most departures from the SMA model represent irrigated patches on the valley floor and occur on the near-infrared plateau (986 nary), the trailing edge of the infrared plateau (1254 nary), the visible bands (574 nary), and in the vicinity of bands where liquid water has adsorptions (e.g., 1333 nary), all of which are shown in Plate 7. Although the vegetation end member provides the best overall fit for the entire Independence Creek watershed, the area shown in Plate 7 was chosen to illustrate spatial and intensity differences in residuals at different wavelengths. A typical residual spectrum of a pixel is shown in Fig. 19.3. The residual spectra of pixels selected from the image may be examined to identify the wavelength regions showing the most significant departures from the SMA model. Figure 19.4, selected from 12 different vegetation patches on the valley floor, shows high residuals occurring at the long wavelength edge of chlorophyll absorption band (650-750 nary), on the near-infrared plateau (750-950 nary), and near the water bands in the shortwave infrared region (1400-1500 nary). Compared with the vegetation end member, the residuals show that vegetation from these sites has higher reflectance (positive residual) in the chlorophyll region (671 nary), about equal reflectance in the 945-nm region, and lower reflectance (negative residual) in the 1648-nm region. These spectral patterns indicate that the selected vegetation end member was less green and drier than vegetation in these patches, consistent with their more mesic condition. Changes in the proportions of photosynthetic and nonphotosynthetic canopy can be followed over time or space, either through changes in the choice of end members or by changes in the residual spectrum.

Although the residuals shown in Plates 6C and 7 and Fig. 19.4 do not correspond to adsorptions of specific biochemicals, such identifications are feasible (Gillespie *et al.*, 1990a-, Roberts *et al.*, 1990). In most cases, the residuals show deviations from the modeled spectra by only a few bands in width (10-50 nm) and by a small percentage of maximum reflectance, consistent with many biogeochemical absorption features. Many of the 12 areas selected from the valley floor show similar positive and negative trends, but if areas with more diverse surface conditions were examined, the patterns could be distinctly different.

IV. Conclusions

Remote sensing has significant potential for providing the synoptic landscape-scale data needed to develop models at new levels of ecological organization. Realizing the full potential of this technology will require developing new paradigms in ecology and remote sensing analysis. We used SMA as an example of an organizational strategy to transform raw images into variables more directly related to ecological models. SMA can be applied to many types of remotely sensed data; it has been used to analyze Viking Lander data from Mars (Adams *et al.*, 1986), multiband thermal infrared data (Gillespie, 1990b), Thematic Mapper and other satellite data (Smith *et al.*, 1990 a,b), and AVIRIS data (Roberts *et al.*, 1990). The reference spectra provide a constant frame of reference from which to interpret spectral variability in images, allowing evaluation of spatial and temporal characteristics of the terrestrial landscape.

Both major and minor sources of spectral variance, including biogeochemical conditions, can be derived and analyzed using SMA. By characterizing the sources of image variance, SMA can function in series with other analyses to classify the land surface, characterize the structure of the landscape, and estimate some properties related to physiological or biogeochemical states. The SMA procedure is well adapted to provide the first step in such a hierarchical series by providing a mechanism for testing alternative hypotheses.

The technology of imaging spectrometry is new, and its potential remains relatively untested, largely as a result of the inability of most remote sensing procedures to use the full range of spectral information and the lack of ecological models capable of using the information from this new technology. Several steps are crucial to developing remote sensing models generally useful for ecological applications: (1) identification of the spectral components; (2) explicit tests of assumptions linking the spectral components to ecological characteristics; and (3) ecological models formulated to use the spatial, temporal; and spectral information from spaceborne sensors.

V. Summary

If ecologists wish to develop models that use remote sensing data to validate our emerging conceptual views of Earth ecosystems, it will be necessary to create a new ecological paradigm consistent with the spectral data from satellite systems. An overall strategy to incorporate remotely sensed images into ecological models requires an examination of conceptual frameworks within ecology and the image processing tools used to relate remote sensing data to ecological processes. We discussed applications of remotely sensed images and links to variables needed for ecological models. SMA is one approach to processing digital image data over a broad range of spatial scales and spectral wavelength regions. It provides a method for hypothesis testing and is particularly useful for evaluating imaging spectrometer or other multiband data. SMA produces measurements with a constant frame of reference, a necessary condition for interpreting the structural and biochemical conditions of ecosystems and landscapes.

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List of Figures

Figure 19.1 Relative spectral variation as a function of spatial scale and level of biological organization, from biochemicals to global biosphere. The spatial scales typical of direct measurements and satellite sensors are indicated. Current satellites are the Advanced Very High Resolution Radiometer (AVHRR), the Landsat series Multispectral Scanner (MSS), the Thematic Mapper (TM), the European Systeme Probatoire d'Observation de la Terre (SPOT), and the European Radar Satellite (ERS-1). The minimum pixel resolution is shown at the tip of the arrows and the field-of-view of the sensor is shown by the line length.

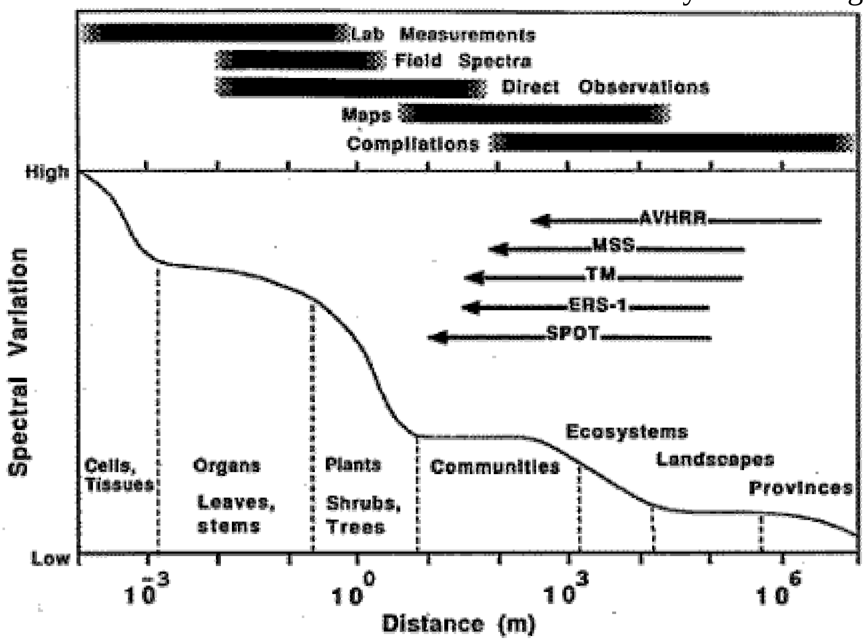

Figure 19.2 Typical chronosequence of secondary pine-hardwood forests succession in the eastern United States. The upper tree profile depicts community dynamics and canopy properties expressed as percentage of maximum values, illustrating changes in ecosystem structure, canopy gaps, LAI, and biomass. The typical range of maximum LAI is 6-8 (Nehmeth, 1971), of pine density is 1,000-30,000 tress/ha, of hardwood density is 5000-6000 trees/ha, of above ground pine biomass is 20-40 kg/m^2, and of above ground hardwood biomass is 18-30 kg/m^2 (Peet and Christensen, 1987). The lower tree profile illustrates differences in the canopy location of maximum signal derived from optical and radar sensors.

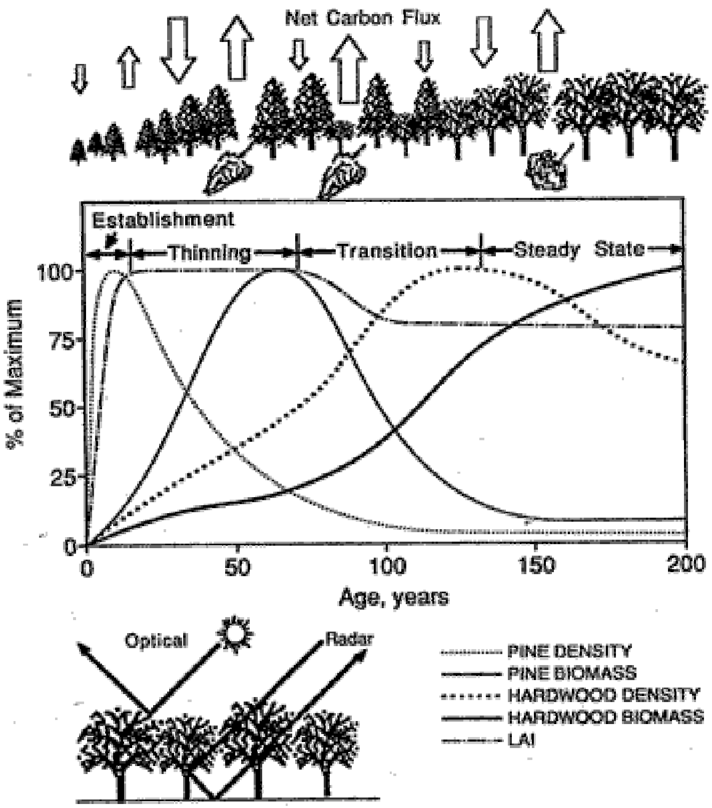

Figure 19.3 Three reflectance end members used to model spectral variation from an AVIRIS scene covering part of Owens Valley, California, a typical mixed pixel spectrum, and a residual spectrum. Mixtures of these end members—49% vegetation (foliage from semiarid shrub species), 19% shade, 30% granitic (gray) soil, and 0% weathered (tan) soil (not shown)—provide a best fit to the measured pixel. Image mixtures are calculated from the multispectral variation on a pixel-by-pixel basis, using a simple linear calibration (Smith *et al.*, 1990 a,b). The residual spectrum represents the remaining pixel variation unaccounted for by the model.

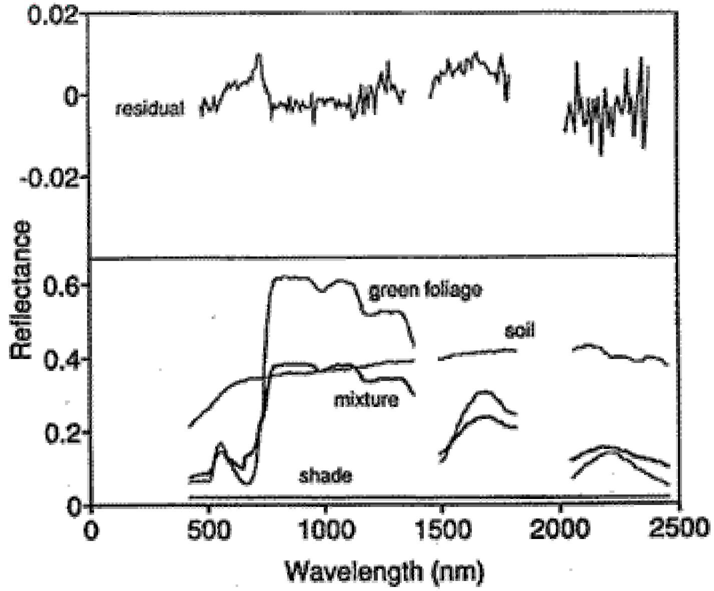

Figure 19.4 Contour plot of (A) positive (higher reflectance) and (B) negative (lower reflectance) residuals across the 400-to 2500-nm spectrum, extracted from 12 separate locations (means of 9 pixels) on the valley floor. The maximum deviation from the model was <±0.3 and the mean <±0.2. Biogeochemical properties represented by the residual spectra may be identified by comparison with spectra of known materials through spectral matching routines.

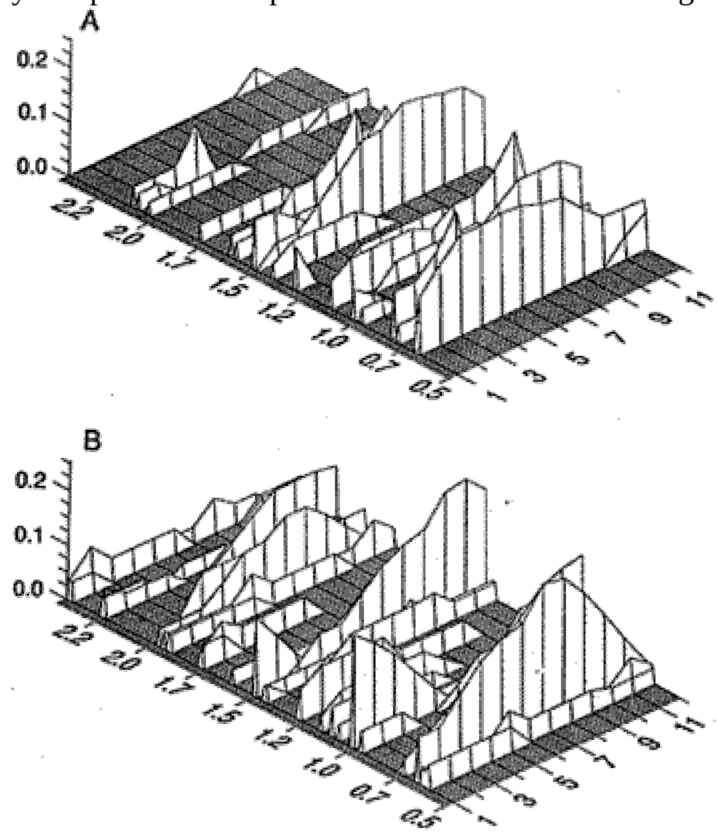

Plate 3 (A) AVIRIS vegetation end member front the Sierra Nevada bajada (left edge of image) and the floor of Owens Valley, California, including the city of independence (right edge of image), at junction of Independence Creek (upper center, extending from the left to right) and the toe of the alluvial fan, obtained July, 1989. (B) Thematic Mapper (TM) vegetation end member from May 1985, and (C) TM, December 1982. Note that A is a higher resolution image and covers only the central area within the black frame in B. The Sierra Nevada bajada is missing from the left side and the Owens River is missing from the right side of the images. Images are color-density sliced into low (0-20%, gray), intermediate (21-30%, yellow), and high (>30% green) vegetation cover classes. The vegetation end member image overlays the shade end member (shown as gray tones), which adds some information about topography to the display.

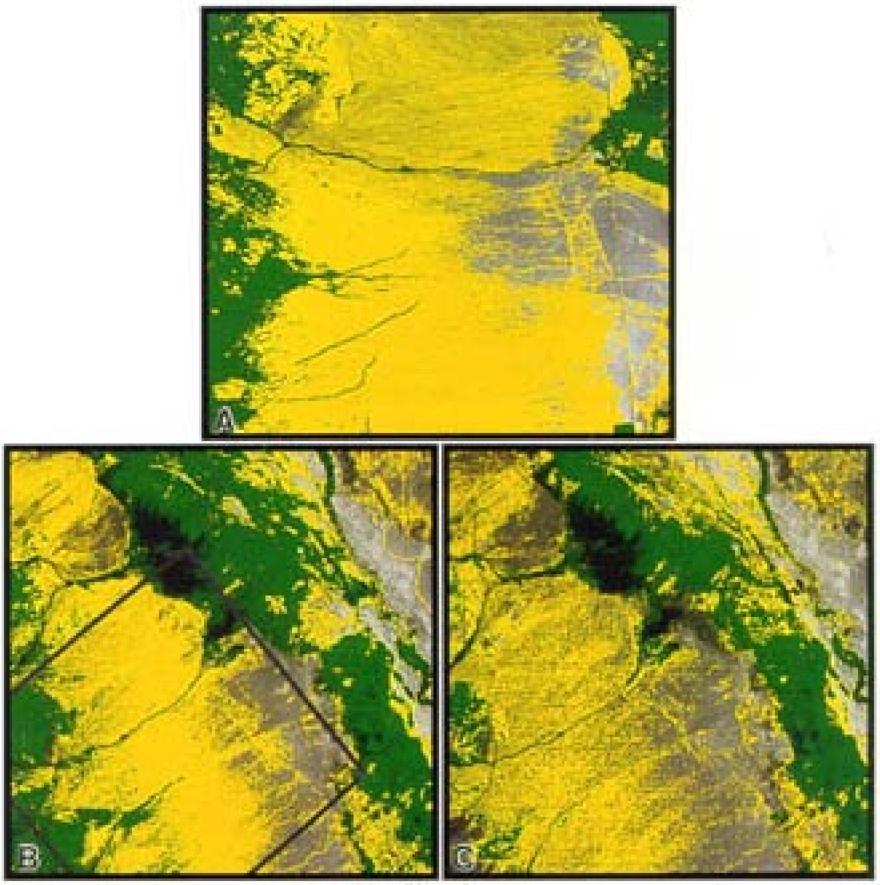

Plate 3

Plate 4 Vegetation end member concentrations calculated from three spectral regions. The visible wavelengths (473-643 nm, A) have limited spectral contrast, making mixtures of vegetation, soils, and shade difficult to separate. The regions in the near-infrared (783-877 nm, B) and the shortwave infrared (1286-2375 nm, C) have greater contrast between vegetation and background materials, and increased spectral resolution of vegetation. The relative abundance of each end member corresponds directly to the image brightness. Note that these images only include a small area around Independence, California, seen in the upper right in Plate 3A.

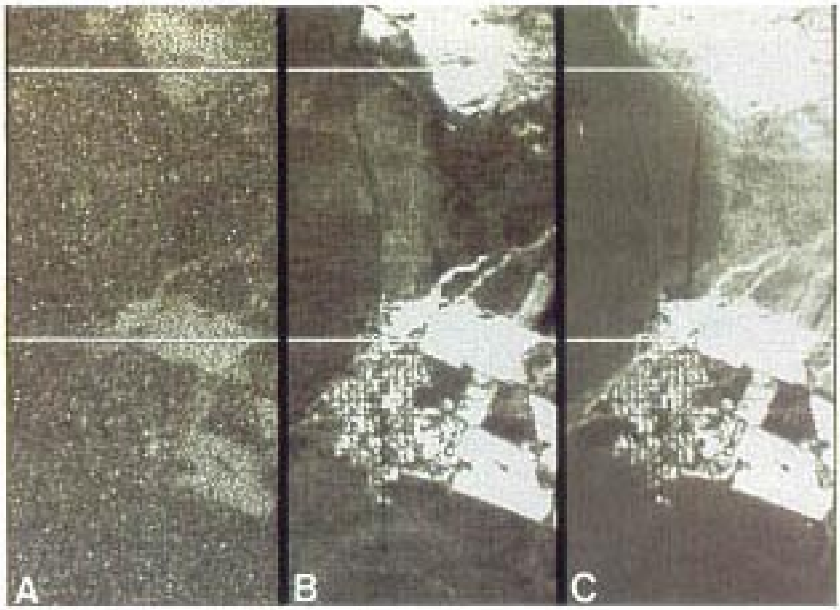

Plate 4

Plate 5 Fraction images of the four reflectance end members derived from 171 AVIRIS bands. Atmospheric water vapor bands and bands of low signal/noise were excluded from the analysis. Images from left to right show the gray soil (A), shade (B), tan soil (C), and vegetation (D) end members. The relative abundance of each end member corresponds directly to the image brightness; fractions sum to unity.

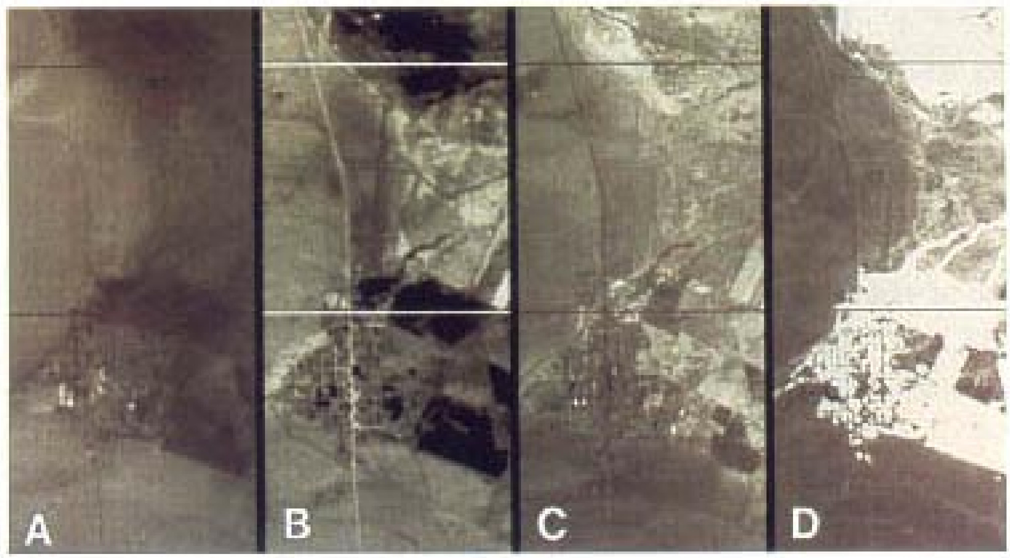

Plate 5

Plate 6 Composite false-color images formed from three end members or residuals. Images derived from analyses of satellite data may be recombined into new composite images displaying properties not visualized-directly in the original data. (A) Composite image showing interactions among the visible (blue), near-infrared (green), and shortwave infrared (red) vegetation fractions. The spatially distinct areas differentially contribute to the composite vegetation end member from the three spectral regions. (B) Composite image of the three end members: tan soil (red), vegetation (green), and gray soil (blue). The hue varies with the magnitude of the numerical value; colors depend on the relative proportions of the end members in each pixel. (C) Composite image of residuals at 525-nm (blue), 809-nm (green), and 1100-nm (red) regions. The high residuals are not random but show clear wavelength-specific spatial associations suggesting biogeochemical differences in surface conditions.

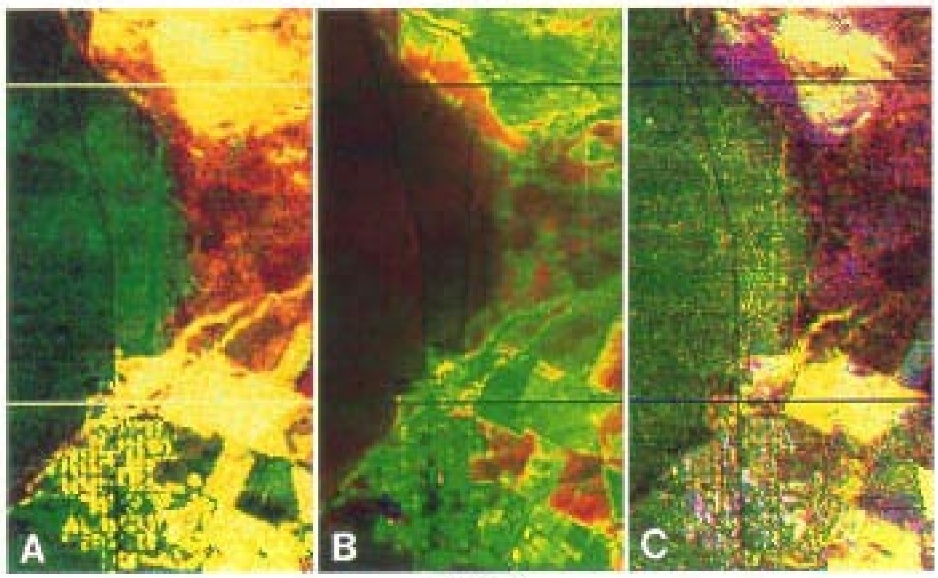

Plate 6

Plate 7 Residual images (difference between calibrated reflectance and estimated mixture spectrum) show areas where mixtures of the four end members do not fit the measured spectral variation at specific wavelengths (shown from left to right are 574, 986, 1254, and 1333 nary).

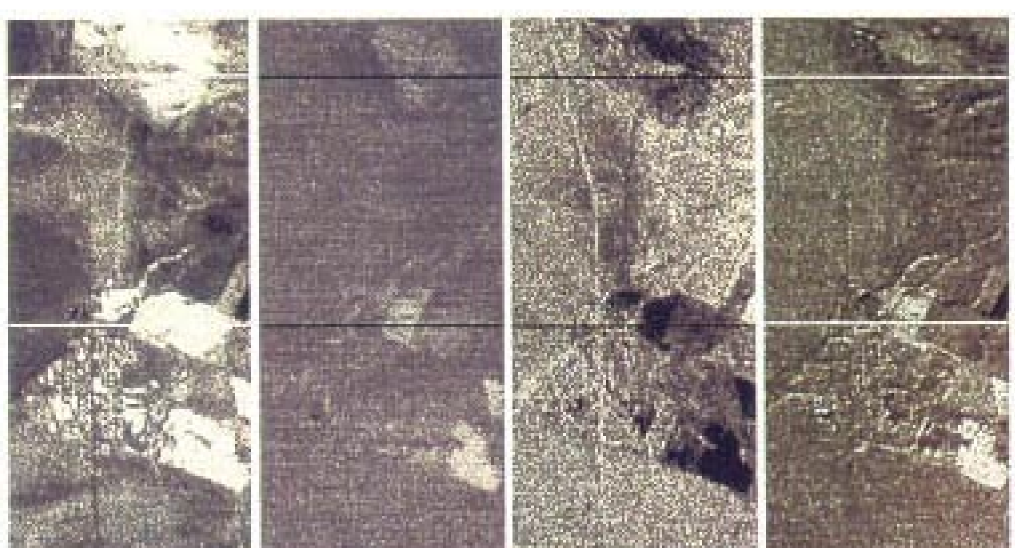

Plate 7