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Doubly segmented proxy images for multi-scale landscape ecology and ecosystem health

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Abstract: Multi-band remotely sensed image data contain information on landscape pattern and temporal changes that are greatly underutilized in this technological era when monitoring of disturbance and ecological dynamics is increasingly important to address questions regarding sustainability of ecosystem health and climate change. Among the reasons for this loss of analytical opportunity are the inadequacy of methods for systematic extraction of pattern elements, incongruity between information paradigms for remote sensing and geographic information systems (GIS), and the sheer volume of remotely sensed image data when acquired regularly over time. Long-term cooperative landscape ecological investigations concerning habitat and change detection in conjunction with remote sensing and GIS have yielded a pattern-based approach to progressively segmenting images (PSI) that culminates in a doubly segmented image representation by sets of approximating signal vectors that serve as parsimonious proxies for pixel vectors.

The coarser level of segmentation is entirely congruent with raster map structures for GIS, and yet mimics the appearance of an image display by colorization using information on typical spectral properties of segments contained in attribute tables. The components of the coarser representation as spatial segments constitute explicit elements of pattern at several levels. The explicit nature of these pattern elements enables spatial pattern matching for change detection that resolves difficulties with phenological variability and continuity of sensor configurations over time. Conversion to segmented representation can be applied to multi-temporal change indices so as to elicit longer-term patterns of change from temporal sequences of images. The finer level of segmentation for spectral detail enables restoration of image bands in the manner of a low-pass filter for analysis according to the usual paradigms of remote sensing. Mapping of the residuals for the finer detail of image approximation provides further information on exceptional features of landscape ecological pattern.

Abbreviations: GIS – Geographic Information System, PHASE – Palette Homogeneity Among Segmentation Elements, PSI – Progressively Segmenting Images.

Introduction

Plant assemblages form and change in response to environmentally induced conditions with subsequent modifications by the presence of the plants themselves. Disturbances of the plant communities at various scales introduce further trajectories of development and redevelopment as mosaics of patches, ecotones, corridors, and gradients of landscape pattern (Forman and Godron 1986, Forman 1995, McGarigal and Marks 1995, Turner et al. 2001, Wilson and Gallant 2000). Although the level of understanding has become sophisticated regarding factors and processes underlying development of vegetative communities across landscapes, the inherent complexity continues to present challenges for monitoring changes in landscapes as they pertain to ecosystem health.

There is general agreement that the best prospects for analyzing and monitoring broad-scale change in plant canopies lie in remote sensing from satellites in conjunction with geographic information systems (Groombridge 1992, Miller 1994). The basis for this consensus is well illustrated in Figure 1, which is based on September 1991 image data acquired by the Landsat MSS sensor in four spectral bands and having approximately 60-meter spatial resolution.

This figure spans three major physiographic settings in Pennsylvania, with the central focus being on the strongly folded Ridge and Valley physiographic province characterized by forested ridges and agricultural valleys. The upper left (northwestern) corner is occupied by fragmented forest landscapes of the Appalachian Plateau de-

Figure 1. Broad-scale view of central Pennsylvania from Landsat MSS data acquired in September 1991 encompassing (central) Ridge and Valley Province, (upper left) Appalachian Plateau, and (lower right) Piedmont Plateau.

rived from thick sandstone that resists erosion and weathers to infertile soils. The extreme lower right (southeastern) corner shows the more subdued topography and fertile soils of the lower lying and predominantly agricultural Piedmont Plateau. A large reservoir, named Raystown Lake, is located near the center. The slanting line in the lower portion of is an anomalous artifact of the imaging systems.

There are several technological challenges, however, that have kept change detection more in the realm of research than of routine monitoring (Coppin and Bauer 1996, Lunetta and Elvidge 1998, Rogan et al. 2003). Temporal comparatives are the central concerns in this context. With regard to studying landscape dynamics by means of remote sensing, there are changes in appearance due to atmospheric conditions and phenology that are not informative relative to alteration of ecosystem status. Clouds and their shadows along with fog and snow constitute major atmospheric sources of interference for monitoring disruption of ecosystem processes. Saturated soil, standing water, and sediment from recent heavy precipitation can substantially alter the spectral reflectance of many environmental surfaces. Phenology pertains to annual cycles of senescence and growth in vegetation. Deciduous forests shed their leaves in the fall, giving rise to very different appearance between dormant season and growing season. With taller vegetation and/or topographic relief, there are also substantial localized changes in appearance during the day and between months at a given time of day that are due to shadows and sun angle. Likewise, temporal comparisons cannot be conducted effectively without making whatever spatial adjustments may be needed so that the images and/or maps will overlay each other accurately (Dai and Khorram 1998, Gong et al. 1992).

Changes in vegetative cover have different implications for ecosystem health depending on the context in which they occur (Myers et al. 1999, Patil and Myers 1999). Furthermore, some important changes in land cover entail much more pronounced contrast in spectral appearance than others. Fields having agricultural crops change gradually from being bare after tillage to closed green herbaceous plant cover, and then to senescence upon maturity and thence to harvest. To this intrinsic dynamic of agricultural areas is added change due to crop rotation, whereby a given field is planted to different crops in different years. Thus, agricultural areas tend to exhibit strong spectral changes even when the overall vegetation regime is not changing. Forests are constrained by climate in some ecological settings, but moist and mesic environments typically have herbaceous and shrubby areas being disturbance-induced transitional stages in succession to tree cover. Deforestation, reforestation, and fragmentation by land conversion to agriculture and urban have major implications for ecosystem health at landscape and regional scales. Even apart from human influence, however, forest landscapes have a natural disturbance regime due to wind, wildfire, and biotic causes such as insect infestations that create patchy openings of varying sizes in the general matrix of forest cover (Baker 1989). The most insightful environmental monitoring is aimed at tracking changes to determine whether there are changes in the change regime that would indicate progressive disruption of ecosystem processes with consequent loss of habitat integrity/connectivity and/or effects of possible global climate change (Patil et al. 2001).

Adding to the difficulties associated with inherent complexity of landscape change are differences in the data domains for analytical approaches. Spatially specific landscape ecological analysis is usually conducted largely within the framework of geographic information systems (GIS) that operate primarily on maps having definite legends and associated attribute tables. In contrast, remotely sensed multiband image data consist of quantitative multivariate sensor responses. GIS may provide limited image display facilities as backdrops for vector (line, polygon, and point) maps, but seldom offer much in the way of multivariate analytical support. The components of landscape pattern in image data thus tend to remain implicit rather than explicit. Even in conventional remote sensing analysis systems, there are logistical difficulties in handling the large volumes of data that come from repeatedly acquiring multiband images over time for purposes of environmental monitoring. These difficulties are compounded by possible copyright restrictions on access to image data. Finally, the sensor systems themselves evolve over time with improved technology introducing another source of temporal incomparability.

Consequently, there has been need for analytical approaches that promote synergism between multispectral remote sensing and GIS by bridging the differences in data frameworks, improving data management, facilitating explicit extraction of landscape pattern elements, and promoting temporal comparability over different scales. Several generations of research in this regard have given rise to an approach of doubly segmenting images that uses proxy signal vectors to map components of pattern for analysis of temporal consistency in a manner that is directly compatible with GIS informational frameworks. A duality of map and image information has resulted that is exemplified in Figure 1, which is a map that conveys image information.

PSI/PHASE pattern-based segmentation

Explanation of our approach begins with consideration of pattern. Pattern extraction, matching, recognition, presentation and analysis are hallmarks of artificial intelligence, but the term *pattern* itself remains indefinite. Pattern analysis often has a strong statistical tone with or without formal distributional models, but may be concerned more with adaptive heuristics for which the outcomes are essentially data dependent. Therefore, it is necessary to specify how pattern is construed for a particular context and the methods by which pattern analysis is to be conducted. Patterns of interest here occur in two related domains—the (physical) environmental domain over a particular spatial extent (scene), and the signal domain of environmental variables. Patterns are to be extracted in the signal domain as representations of patterns in the environmental domain.

Conceptualization

A principal pattern construct in the signal domain for present purposes is an ordered set of signal values for different environmental variables (bands or channels) as a *signal profile* or *signal vector*, with the two terms being equivalent. The signal profile charts signal value according to band number and can be visualized as in Figure 2. The band values are the components of a signal vector that can be (conceptually) envisioned as a point in a multidimensional space with one axis for each band. This multidimensional space is variously referred to as *signal space*, *feature space*, or *measurement space*. We generally use the term signal space. The length or norm of the signal vector is one indicator of overall signal strength or intensity. The vector difference between two signal vectors is a multidimensional expression of their dissimilarity; length of the difference vector is a scalar measure of dissimilarity.

A signal profile or vector is associated with each pixel of the image, and the density of occurrence for such vectors in signal space typically varies in the manner of constellations. A high density constellation is an opportunity for simplification and parsimony with only modest sacrifice of information. The vectors comprising a dense constellation can all be replaced by a single 'central' profile that adequately represents the profiles which it replaces. The central profile is both a *prototype* (in the sense that it is representative for its constellation) and a *proxy* (in that it replaces actual signal vectors for members of the constellation). A proxy profile may or may not have the same

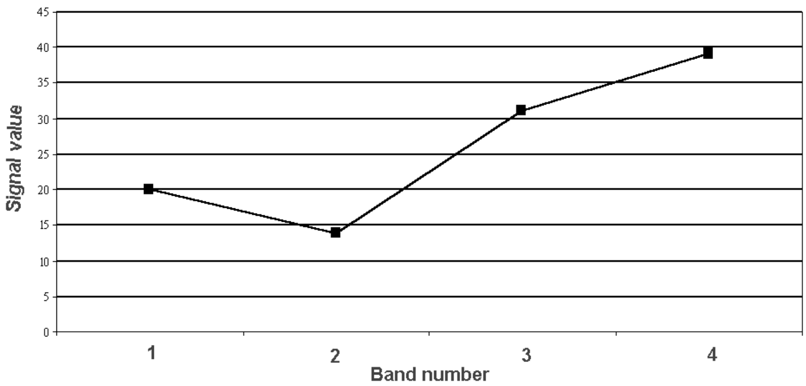

Figure 2. Illustrative signal profile.

ordered set of signal values as some actual pixel of the constellation. Such a *proxy signal profile* is an important pattern construct in the double segmentation scheme. One measure of the information cost of the proxy substitution is the *sum of squared lengths of the difference vectors between the actual pixel vectors and the proxy vector taken over all pixels in the constellation.* Such a substitution collapses the constellation to a point and gives all of those pixels the same appearance in an image of the scene extent.

At this juncture, some notation regarding different kinds of pattern elements is in order. A *P1* pattern element is an actual signal profile at a particular position in both signal coordinate space and pixel row/column image extent. A *P2* pattern element is a proxy profile occupying a particular vector position in signal space and defined with respect to a set of actual signal vectors but not having reference to any particular pixel position(s) in row/column image extent. A *P3* pattern element is a proxy profile substituted in a particular pixel position in row/column image extent. A *P4* pattern element is a *connected component* of *P3* elements in an image extent as a proxy profile pixel patch consisting of adjacent (by contact) proxy profile pixels and allowing a singleton pixel as a degenerate patch. A *P5* pattern element, also called an *image segment,* is the union of all *P4* elements having the same proxy profile. A *P6* pattern element is a *P5* pattern element and all of the adjacent (by pixel contact) *P4* elements for other proxy profiles along with other adjacent pixels (if any) that have not been subject to proxy substitution. The conversion of an image consisting of *P1* pattern elements into an image consisting of *P5* pattern elements is a *proxy (pattern) process.*

PSI is a proxy process of Progressively Segmenting Images that results in a primary an image extent for which the extracted patterns can provide an approximate image representation as a map of pixel positions for numbered proxy profiles with a supplemental table of signal values for the respective proxy profiles. To achieve *double segmentation,* a reverse process then ensues of aggregative clustering whereby the finer primary segments are grouped into coarser secondary segments with each secondary segment having a second-order proxy profile (proxy for proxy). The coarser level segments are important for pattern matching purposes across a temporal sequence of images as well as for pseudo-color display. Because of the role that secondary segments have in pseudo-color display, they are called *PHASE* segments as an acronym for Palette Homogeneity Among Segmentation Elements.

The inspiration for this research on proxy processes came from early work of Kelly and White (1993) on approximating compression of images by clustering in conjunction with their Spectrum software system for interactive mapping from image data. The potential efficacy of proxy processes will depend upon the degree of redundancy of signals received from various positions on the landscape, which is a function of landscape structure. Therefore, highly patterned (patchy) landscapes are more amenable to such representation than ones having spatial variation in the nature of smooth gradients. If a landscape as the environmental domain has a mosaic character of recurring kinds of patches (*sensu* landscape ecology), then environmental signal data collected in patches of a given kind should be considerably more alike than those collected in different kinds of patches. This should hold true regardless of how many signal variables (bands or channels) are measured, as long as the signal variables are directly or indirectly related to the nature of the patch. If the different kinds of patches have substantially distinctive expressions, then a well-chosen typical value for each kind of patch should represent any particular instance of that kind of patch reasonably well. If most instances of a kind of patch are suitably well represented by the typical, then substituting typical for individual values should retain the general character of structural pattern in the landscape. This is the intuitive basis or 'landscape logic' behind a proxy process, where a set of typical values for signal variables comprises a proxy profile. Kinds of patches are purposely left indefinite in this intuitive statement. To the degree that there are fewer proxy patterns than kinds of landscape patches, there are two levels of distortion. One is the distortion discussed earlier that comes from homogenizing a patch. The second results from failure to distinguish between different kinds of patches. The second level of distortion is not incurred by a 'smart' strategy in which there are more proxy profiles than there are kinds of patches, because the 'extra' proxies will simply provide a finer subdivision of those patches kinds having greater internal heterogeneity.

Although the general logic of image representation by proxy process is intuitively straightforward, strategies for arriving at them are not so apparent. A first question is how many *P2* proxy patterns to use. Without prior knowledge of the number of different kinds of patches in the landscape encompassed by the scene extent, there is no theoretical answer to this question. There is, however, a first practical answer in the context of image analysis and GIS. The number of segments that can be encoded in one byte of computer memory is 256. Many of the viewers in GIS software packages as well as those for remote sensing are also geared to 256 colors. This is also a computationally manageable number of states for pattern matching between different dates of imagery without incurring unwieldy combinatorial proliferation. One of the 256 states available in a byte is needed to indicate missing data, and it may be desirable to have a few states reserved for special uses such as highlighting. Therefore, we have chosen to use 250 *P2* proxy profiles as a basis for first approximation. Notwithstanding the advantages associated with 250 proxy profiles, this would allow no flexibility with regard to potential fidelity of representation for complex landscapes. Flexibility can be obtained by providing for a much larger number of proxy profiles, and then conducting a secondary aggregation operation to the level of 250.

The next question is how to obtain the *P2* proxy profiles that serve as surrogates for the multitude of actual *P1* pixel profiles. Theoretically based image segmentation usually focuses on some selected mathematical criterion of variation in the image, and then seeks to optimize the representation with respect to that criterion (Li and Gray 2000). From environmental and GIS perspectives, however, multiple criteria of a practical nature need to be considered. Approaches that are responsive to multiple criteria is often more a matter of strategizing than of optimizing.

P2 proxy profiles can be thought of bins of pixels and consideration must be given to reasons for preferring balance or imbalance in distribution of pixels among the bins. A simple and intuitively appealing strategy is to distribute the pixels equally among the bins. When applied on a band-by-band basis for image rendering, this strategy is often called 'histogram equalization'. Despite this, there are often good reasons for having some imbalance among the proxy profiles. To facilitate visual recognition of landscape pattern in image displays, it is important to give some emphasis to the unusual so that distinctive 'landmark' features are not unduly subdued even though they may constitute minor components of the landscape extent in the areal sense. Roads, riparian zones, right-of-way corridors, small water bodies, and localized clearings are often defining components of landscape spatial pattern both visually and ecologically. Proxy profiles representing relatively rare but distinctive landscape features will correspond to bins with comparatively small pixel frequencies.

Making the above concession to uncommon but prominent components of landscape pattern may entail having some more expansive portions of the image extent be visually identical due to having the same *P2* elements of pattern. The nature of common landscape components will depend upon the landscape itself. In forested landscapes, the forests are the common components. In arid landscapes, exposed mineral materials tend to be the common components. In watery landscapes, water surfaces constitute the common components. Although this is not always the case, the common components are frequently also relatively homogenous in nature. The subtle variations in forest canopy are typically less prominent than the differences that distinguish other non-forest elements from each other. Likewise, water surfaces typically have a relatively homogeneous appearance in relation to terrestrial components of the landscape. It is important to remember that pixels represented by the same proxy profile become indistinguishable from each other. Therefore, landscape pattern is expressed in the interspersion and juxtaposition of different profiles. Having large, contiguous areas of an image occupied by the same proxy profile will give the effect of viewing from a distance whereby broad-scale landscape structure is perceived. Then, however, there is little to be gained by attempting to 'zoom in' on a sector of the landscape in search of finer detail. It thus becomes important to avoid having a large proportion of the pixels represented by any particular one of the proxy profiles. This will guard against large areas that are devoid of detail, and will ensure some capability for exploring the landscape at multiple scales. A central issue of strategy, therefore, is deciding the degree to which disparate pixel frequencies for proxy profiles will be permitted.

A strategic question that arises from the foregoing considerations is how to gauge the degree of distinctiveness of a landscape component. Distinctiveness involves unusualness in two senses. One sense is rareness of occurrence in space. The other sense is degree of being dissimilar to other signal profiles. The latter aspect is the essence of contrast in a visual sense. While there is visual interplay between these two senses of unusualness, it is nevertheless possible to separate the decisions relative to strategy in these regards.

Consider first the degrees of dissimilarity among pairs of pixels without regard to frequency of occurrence, which depends on a collective expression of band-by-band differences in intensity values. Although a variety of dissimilarity measures have been proposed in the clustering literature (Everitt et al. 2001, Gordon 1999), we have employed *squared Euclidean distance* between signal vectors. Sometimes it is desirable to place special emphasis on particular bands. This can be accomplished by differentially weighting the squared band differences. The expression for contrast between signal profiles thus becomes

$$D_{ab}^2 = D^2(a,b) = \sum_{i=1}^{p} w_i (X_{ia} - X_{ib})^2 .$$

Here a and b indicate the signal profiles being compared, i is the band number, X is an intensity value for a signal band, p is the number of bands, and w_i is a weight for band i with w_i=1 as default. It would, of course, be possible to take the square root to obtain D, but this would substantially increase the computational effort with no apparent advantage.

In comparing an actual pixel profile a with its proxy profile b, $D^2{}_{ab}$ becomes a measure of the pixel-level signal distortion that results when the proxy replaces the actual profile. An optimization approach to segmentation might seek a set of k proxy profiles that minimizes the sum of such distortions over all pixels in the image, where k is specified by the user. In fact, the various k-means algorithms (Hartigan 1975, Hartigan and Wong 1979, Hastie et al. 2001) and, to some extent, the ISODATA algorithm (Ball and Hall 1965, 1967) all seek to do exactly this. However, these algorithms usually converge to "local" instead of global minima and, in consequence, are very sensitive to the initialization choices. Also, for massive data sets such as imagery with tens to hundreds of millions of pixels, the computational burden becomes prohibitive even for contemporary computers. A route to practicality lies in pursuing a strategy of successively improving approximations, as opposed to attempting optimization. Such a strategy is a *heuristic*. Heuristics are frequently employed in the context of artificial intelligence. Heuristics are typically chosen for robustness, speed, and general quality of performance. Robustness lies in absence of pathological cases where the strategy works poorly or not at all. General quality of performance lies in producing approximations that are useful. It may be necessary to evaluate performance of heuristics empirically. The heuristic developed by us for proxy representation of images (as *P5* pattern segments) proceeds through a series of stages. Each stage entails at least one pass through all of the pixels in the image file. A pass through all of the pixels is called a *scan*.

Initialization stage

The goal of the initialization stage is to obtain a set of 250 proxy profiles (*P2* pattern elements) that are well-dispersed throughout the populated portions of signal space. This stage begins by taking the first 250 non-duplicate pixel profiles in the image data file as provisional proxies. The closest (Euclidean distance) pair among the provisional profiles is then determined. Let the profiles of the closest pair be denoted by P_a and P_b. The profiles for the remaining pixels in the file are then examined one-by-one as possible candidates P_c to replace one of P_a or P_b. If replacing P_a or P_b by P_c would increase the distance of the closest pair, then the replacement is made, pairwise proximities are recomputed, and the new closest pair P_a and P_b is updated. In a replacement, the choice between P_a and P_b is made according to the smaller of the distances from P_c. The 250 proxy profiles thus obtained after a single scan of the image data file are also actual pixel profiles and will be referred to as *seeds*.

After the seeds are determined, the image file is scanned a second time and each pixel is assigned to the closest seed (ties are broken arbitrarily). These assignments partition the image into 250 subsets called *segments*. The segments are in one-to-one correspondence with the seeds and each segment is nonempty (since the seeds themselves are actual pixel profiles). This second scan of the image file also determines the longest and the shortest pixel profile within each segment—information that is needed for the next stage of the algorithm.

We note that the image analysis literature often requires that segments be spatially *connected* sets of pixels, in either the 4-neighbor or 8-neighbor sense (see Jain et al. 1999, p. 297, for example). In our use of the term, a segment does not have to be spatially connected.

Splitting stage

In the PSI approach, the approximation of an image by proxy signal profiles for segments is improved by progressively splitting selected segments into two sub-segments that may, in turn, be further split. Thus, segments proliferate as the splitting stage proceeds. The method of splitting is a polar process. Let the shortest (lowest intensity) signal vector in a segment be P_L and the longest (highest intensity) one be P_H. When a segment is split, those pixels having a profile closer (Euclidean distance) to P_L will comprise one sub-segment, and those closer to P_H will comprise the other sub-segment. Ties can be broken arbitrarily. A P_H vector for the first sub-segment and a P_L vector for the second sub-segment are each determined in the process of segregation. A proxy profile for each sub-segment is computed as the average of its P_L and P_H vectors.

In order to answer the question of which segments should be split, a *splitability index* is calculated for each of the current segments. The splitability index is given by

$$Sp = N_{\text{segment}} \times D^2 (P_L, P_H),$$

where N_{segment} is the size (number of pixels) of the segment and P_L and P_H are its polar vectors. Segments with larger index values are better candidates for splitting. Thus, the index prefers to split segments that are either exceptionally large in size or that exhibit large within-segment contrast. A segment can be split if its index value exceeds a threshold which is set equal to 1/16 of the current mean segment size.

Actual splitting occurs in a sequence of scans of the image data file. Prior to each scan, the threshold is calculated according to the current number of segments and each of the current segments is marked for splitting if its index value exceeds the threshold (however, due to memory allocation for internal data structures, a limit of 300 splits per scan is currently imposed). A segment can be split at most once during a splitting scan. The number of splitting scans is set by the user. The default setting of 9 scans typically results in 2000–2500 final *primary PSI segments*.

Aggregation stage

There is nothing in the splitting heuristic to prevent formation of small segments by asymmetric polar partition. Consequently, the splitting stage can result in several thousand segments of which many have relatively few pixels. A multiplicity of small segments is advantageous for accuracy of image approximation, but becomes intractable for pattern matching in change detection and is not accommodated by GIS viewers operating in pseudocolor (thematic) mode. Therefore, the final stage aggregates the primary PSI segments into 250 *secondary PHASE segments*. Since it is segments rather than pixels that are being aggregated, a scan through the pixel data is not required to do the aggregation. However, a final scan is required to map the pixels into their appropriate PHASE segments.

The clustering of PSI primary segments is done according to a novel hierarchical agglomerative scheme in which the basic elements are PSI segments and not pixels. To emphasize this, we use the term "grouping" to describe the procedure and the phrase "groups of segments" to refer to the clusters of segments that are formed along the way. The distance between basic elements (PSI segments) is the squared Euclidean distance between their proxy profiles (recall that each of the latter is the average of the segment's polar vectors P_L and P_H). This is extended to a distance between two groups of segments by *single linkage*, i.e.,

$$d(A,B) = \min_{s \in A, t \in B} d(s,t),$$

where A and B are the groups being compared, s ranges over the segments in A, and t ranges over the segments in B. The *size* of each segment is the number of pixels that it contains; the size of a group of segments is the sum of the sizes of its member segments (not the number of segments that it contains). The strategy is to eliminate segments (and subsequently groups) whose size is below a certain threshold. The threshold is set equal to

$$\frac{N_{\text{total}}}{4000} = \frac{1}{16}\frac{N_{\text{total}}}{250} = \frac{1}{16} \times \text{ Average size of final PHASE segments},$$

where N_{total} is the total number of pixels in the image. The general idea is that it becomes problematic even to locate segments smaller than $1/4000^{\text{th}}$ of a scene in an image display. Segments whose size is below threshold are marked for grouping. Marked segments are divided into two classes: the first class contains segments that were formed in the initialization stage and did not undergo splitting in the splitting stage; the second class contains the remaining marked segments. Segments in the first class are processed before those in the second class. Within each class, processing is in order of increasing length of proxy vectors (i.e., "darker" segments are processed earlier). When a marked segment is processed, it is grouped with the closest segment or group of segments using the single linkage distance described above. The grouping is done without regard to the size of this closest segment/group. If the size of the resulting group is still below threshold, it is grouped with its closest segment/group. Grouping continues up a hierarchy in this way until the threshold size is reached, at which point processing proceeds to the next marked segment that has not already been incorporated into a group. Processing is subject to two constraints. First, the number of segments in a group may not exceed 255 so that the within-group segments can be enumerated with a single byte of storage. Second, all processing halts as soon as the target of 250 groups (PHASE segments) is achieved even if this leaves some segments/groups with below-threshold sizes. If the target of 250 groups has not been reached after processing all marked segments, then the splitting tree from the splitting stage is collapsed inward toward the main branches until the target is achieved.

Each of the final 250 groups is assigned a proxy profile equal to the arithmetic average of the proxy profiles of its member PSI segments. These 250 proxy profiles of PHASE segments are then ordered according to vector length (brightness or intensity) so that the shortest (darkest) is numbered 1 and the longest (brightest) is numbered 250.

Dual mapping and tabulation of segments

Each primary PSI segment has a two-part number. The first part is the secondary PHASE cluster/segment to which it belongs, and this part is recorded as a byte binary value for the corresponding pixel positions**.**

Illustrative snippets of Landsat MSS image data

Two snippets of Landsat MSS data located near the middle of in central Pennsylvania are used for illustrative purposes. These are matched subimages of 1000 rows and 700 columns of pixels. They were obtained from the U. S. Geological Survey (USGS) under the North American Landscape Characterization (NALC) program (Lunetta et al. 1998). This program has assembled matched sets of three MSS images taken approximately 10 years apart for studying change in North American landscapes (Sohl and Dwyer 1998). One of these was imaged on September 6, 1972 and the other on September 7, 1991. Figure 3 shows the output of the segmentation process for 1972 and Figure 4 shows the output for 1991. Note particularly that the Raystown Lake reservoir was under construction at the time of the 1972 image. The four bands of the Landsat MSS sensor used are 0.5 to 0.6 micrometers (green), 0.6 to 0.7 micrometers (red), 0.7 to 0.8 micrometers (infrared 1), and 0.8 to 1.1 micrometers (infrared 2)**.**

Contrast, combination and color

Remote sensing image analysis conventionally keeps all bands available for direct selection in viewing, and any modifications that cannot be done dynamically in computer memory are accomplished by generating additional image bands. The PSI/PHASE approach is very different since the only mapping is of segments by identification numbers, while relying on attribute tables to convey characteristics of the segments. The basic tables produced by segmentation contain typical values by band for each segment, but these are not structured in a way that is directly accessible to GIS viewers.

Conventional viewers operate in two major modes. One way can be considered as *image mode* and the other as *thematic map mode*, although different viewers use different terminology for these two modes. In image mode, the values in a pixel file are interpreted directly as intensities. These intensities are translated in a proportional manner into illumination of a viewing screen, with low values giving low illumination and high values giving high illumination. What is considered low and high with respect to values is determined according to the conventions adopted in programming. In thematic map mode, the numbers in a pixel file are interpreted as identifiers for map categories and an auxiliary file is used to look up the manner in which the category should be depicted on the viewing screen. In a remote sensing context, thematic map mode is sometimes referred to *pseudo-color* mode. The term *pseudo-color* is not to be confused with *false color* that simply means a scene does not appear as it would to the naked eye.

A proxy representation as produced directly by segmentation is limited with respect to viewing capabilities. The secondary PHASE segments can be viewed directly in image mode or in thematic map mode. In either case, the nature of the rendition is the same. Each of the segments is assigned a graytone brightness level, increasing in regular brightness steps according to PHASE segment number. In effect, the PHASE segment or cluster number is treated directly as an intensity value. This is the manner of depiction in Figure 3 and Figure 4.

Contrast control by signal stretching and saturation

Depending on the particular combination of computer hardware and software, a viewer might offer 16, 64, 256,

Figure 3. PHASE output of segmentation process for September 1972 sample of Landsat MSS image in central Pennsylvania.

Figure 4. PHASE output of segmentation process for September 1991 sample of Landsat MSS image in central Pennsylvania.

or more levels of illumination for the viewing screen. The issues of stretching and saturation arise for portraying the respective bands of PSI/PHASE representations through their central values. These issues are addressed through a software module that prepares an auxiliary table specifying the relative (stretched) brightness for each band in each segment. To retain independence of viewers at this stage, the relative values range from zero to one.

Combining bands into synthetic signals as environmental indicators

A common investigative method for remote sensing is to formulate various combinations of bands as environmental indicators or 'indices'. The same can be done even more readily at the PHASE segment level in terms of entries for attribute tables. For example, the so-called NDVI (Normalized Difference Vegetation Index) is given by the formula

$$\text{NDVI} = (\text{Infrared} - \text{Red}) / (\text{Infrared} + \text{Red}).$$

This ratio tends to be high (bright) for vegetated areas and dark for areas lacking vegetation, with broadleaf foliage expressing somewhat more strongly than needle-leafed foliage. The reason for this is strong absorption of red light by chlorophyll in plants for photosynthesis, and strong reflection of near infrared by healthy green plants. Broadleaf trees have greater infrared reflectivity than needle-leaf trees.

Another example is a combination of total brightness, infrared subtotal brightness, and NDVI in a formulation that is intended to lend some emphasis to forest comprised of needle-leaf trees. This 'conifer' index is a novel conception in the current work. It is computed as

$$\text{Total brightness} + 0.5 \times \text{NDVI} \times (1\text{–IR})^2,$$

with truncation to a maximum value of 1.0.

Quantitative color

Generation of these brightness tables sets the stage for enabling manifold views of the segmented landscape information at the PHASE level of organization, but a particular rendering must be chosen via a module that does the mixing of colors in a virtual palette for painting a picture on a computer display in thematic mode. With the PSI/PHASE approach, there are many possibilities for developing renderings that are not conventional. For example, shifting the infrared band to green light instead of red light will usually induce green tones for vegetation with various effects on other kinds of environmental features. The cost of color printing prevents illustration here, but reference can be made to Myers (2003) at the www.environment.psu.edu/publictions/2003_6/2003_6_web.pdf URL.

Restoration and residuals

A relevant question is how well proxy (*P3*) profiles represent pixels, and whether some parts of an image are better represented than others. This is one of the relatively few questions that must be addressed while the original dataset is still available. The second part of this question calls for a map as an answer. Another question that has not been addressed is how to access the finer detail that resides in the PSI primary segments as opposed to the PHASE secondary segments.

Distortion, distance, and relative residuals

Substituting a proxy profile for the original signal profile of a pixel must lead to some distortion in subsequent representations of that pixel. Since the aggregate effect over the entire scene is to reduce the variability of signals, the dominant distortion will be homogenizing or 'smearing' by reduction of detail. For any given pair of pixel positions, however, the differences between their (*P3*) proxy profiles as compared to the differences between their original (*P1*) pixel profiles could be either increased or decreased.

A software module is provided that creates a map file of distortions as Euclidean distance between the actual signal vector for the pixel and the proxy signal vector that replaces it. These distortion distances are mapped in classes, with the classes being adjustable by the user. A color table is also provided so that a map of class numbers can be portrayed in the manner of an image. Figure 5 is a residual image for the September 1991 Landsat MSS sample image of central Pennsylvania with darker tones indicating larger discrepancies.

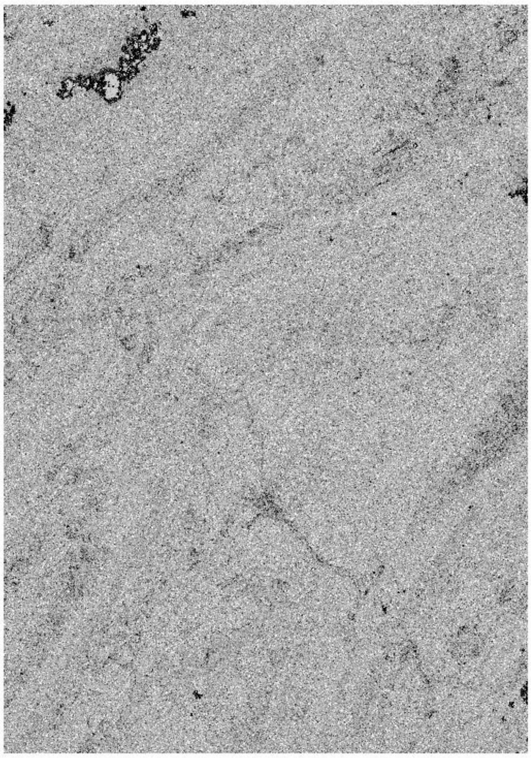

Figure 5. Residual image for September 1991 Landsat MSS image of central Pennsylvania with darker tones indicating larger discrepancies.

The spatial pattern in the residual image is of particular interest. An 'ideal' pattern would be one of uniform gray appearance, indicating that the errors of approximation were equal over the image area. The next most favorable pattern would be a random appearance indicating that the errors of approximation constitute 'white' noise relative to environmental features and locations. Typically, however, there is some nonrandom spatial patterning of the residuals. Then it becomes necessary to refer to the image itself to determine what kinds of environmental features have the least fidelity in their representation. In the case of Figure 5, the fringe areas of clouds are prominent with regard to residuals. Since clouds are typically nuisance features in the image anyhow, this is not a matter of concern. The stronger discrepancies are due to the spectral and spatial complexity of cloud fringes.

Restricted restoration

The indirect approach of tabular look-ups used with the byte-size PHASE segmentation does not extend readily to the thousands of primary PSI segments. The most expedient way of accessing this finer level of detail has proven to be selective (re)generation of approximations to the original band values for viewing and analysis in the conventional manner of remote sensing image processing technology (Gibson and Power 2000, Richards and Jia 1999).

A software module provides for generating approximate reproductions of selected bands for specified ranges of row and column numbers. This is accomplished by placing the proxy pattern for the corresponding PSI primary segment in each pixel. The result is a 'smoothed' or 'filtered' version of the multiband data having somewhat less variability than the original, due to removal of the intra-segment variability. This will usually have some beneficial effect of making the data less 'noisy'. It is possible, however, that it will also remove some of the information that could help to make subtle distinctions between different kinds of environmental features

There are several options for stretching of the image data as it is being restored. The data can be stretched on the high end, stretched on both ends, or not stretched at all. None of these stretches, however, involve any saturation. The differences in these modes of stretching will be dependent on the nature of the particular data. There will be a pronounced difference in the output for bands that have a very narrow range of values, but little difference for bands having a large range.

If conventional remote sensing software is not available, it is still possible to access the finer level of detail locally in a multi-scale manner. This is accomplished by restoring a multiband dataset for the local area of interest, and then doing a PHASE segmentation on the restored data with a reduced number of cycles.

Categorical classification

One of the important roles for imaging is as a medium for mapping. Such mapping is usually done in *thematic* mode whereby focus is on designating different portions of landscapes as belonging to one or another of a mutually exclusive set of categories or classes with respect to environmental features. The PSI/PHASE approach has twice been used for mapping generalized land cover for the entire state of Pennsylvania. Land cover mapping is integral to the detection and analysis of landscape change.

It must be acknowledged at the outset that the ideal of 100 percent correct classification is virtually never achieved. The classification enterprise thus becomes one of balancing errors of omission and of commission. Omission error is when an occurrence goes unrecognized. Commission error is when an occurrence of one kind is wrongly designated as being of another kind. Accuracy can also be reported differently from either map user versus map producer perspectives. The user perspective assesses accuracy as the areal proportion of class occurrences shown on a map that are in fact correct. The producer perspective assesses accuracy as the areal proportion of occurrences for a class on the landscape that are shown correctly on the map. A map could be 100% accurate for a particular class in the producer sense by correctly mapping all occurrences of that class, but still be inaccurate in the user sense by incorrectly mapping other types as belonging to that class (Congalton and Green 1999).

Computers excel at distinguishing among spectral expressions when comparing pixels, but human vision still holds an advantage for detecting differences in spatial patterns involving collections of pixels. The latter advantage does not extend, however, to objective description of the differences in spatial pattern that are perceived. Therefore, it is desirable to form a partnership between human analyst and computer in which each can contribute in its area of strength. Since most methods of computer-based pattern recognition also rely on some initial human designations to serve as 'training sets', it is appropriate to focus first on the human interpretive aspect.

Interpretive identification

There has been a sort of continuing tension between two modes of working with image information. The mode that is usually called photo-interpretation has a longer tradition of mapping and relies primarily on the capabilities of trained human vision to recognize environmental features on the basis of image clues such as size, shape, tone, texture, shadow, pattern, and location/association. The other mode relies less on human visual interpretation and more on ground reference information (or so-called ground truth) as a point of departure for quantitatively comparative computer vision in which pixel information is matched to the statistical properties of known samples.

Human photo-interpretation originally used paper prints and film transparencies whereby the analyst would delineate features of interest on clear overlay material with a fine-line marker. A more technologically sophisticated version uses a computer display of a scanned image document or a multiband image file instead of the hardcopy document, and a mouse-controlled cursor instead of a marker. This kind of interactive feature-delineation requires fairly sophisticated display software like that found in commercial remote sensing and GIS packages. Pseudo-color maps of PHASE secondary segments are advantageous in this regard. There is less computational overhead of data to be processed as the interactive work takes place, which makes the procedure more rapid. Some software systems that lack full image handling capability can handle the simpler pseudo-color form. Even if full image handling capability is available, the pseudo-color form can have prepackaged color so that skill in rendering images is not required of the mapping analyst.

Pseudo-color maps of PHASE secondary segments enable another mode of interactive mapping that is not available with actual multiband image data files. This also requires sophisticated map-display software such as ESRI's ArcView© GIS. This scenario entails overlaying things in a viewer. A PHASE segment map rendered in pseudo-color to mimic an image is brought into the viewer as a base layer. A second copy of the PHASE image-map is then placed on top of the first, and made entirely transparent so the user sees the base layer. A cursor query facility is used to determine what PHASE segment number resides at a location of interest. The legend for the temporarily 'transparent' PHASE map in the top layer is then modified to give this segment a distinctive color that appears superimposed on the pseudo-color layer below. The user can thus examine the spatial pattern for that segment and its relation to other segments. This combination of information is often sufficient to assign the segment to one of the legend categories for which mapping is underway. The top layer can be turned on and off so that the developing thematic map can be seen in relation to the mimicked image in the underlying PHASE base layer. Identification of clouds is an important step in change detection, and lends itself to this interactive/interpretive approach.

Algorithmic assignment of pixels

The conventional 'supervised' scenario for computer-assisted mapping from multiband data has a skilled image analyst acquire so-called 'ground truth' information from maps, documents, and/or field work. Instances of each mapping category are then located in an image display; these comprise a 'training set' from which statistical characterizations of the signal patterns for the various categories are identified. These characterizations serve as 'signatures' for quantitative pattern matching to assign category designations to the other pixels in the image. The rules for assigning pixels to categories can range from very simple to very sophisticated (James 1985, Tso and Mather 2001).

At the most simple pole is a set of thresholds or cutoffs specifying the lowest and highest values to be allowed for the class in each band. This simple method is often given the imposing name of parallelepiped, which is basically just a virtual 'box' in the multi-dimensional signal space where bands serve as axes. Methods for choosing the thresholds on the bands from training data can range from heavily statistical to empirically judgmental and can involve statistical measures and theoretical distributions or visual perusal of histograms.

A step up in sophistication is to compute the Euclidean distance of each candidate pixel from the central value(s) for the training set(s) of the categories, and assign the category for which this distance is a minimum. Setting a specific threshold distance for each class gives rise to virtual 'bubbles' instead of boxes. Several variations on the distance idea are equivalent to rotating and rescaling the spectral axes relative to the original bands so that the ratio of between-category to within-category variation is increased before computing distances in the transformed 'space'. The so-called 'maximum likelihood' version typically supposes that the variation within each category conforms to an idealized multivariate 'normal' distribution. Even this maximum likelihood strategy can be expressed in terms of generalized distances involving spectral transformations.

Even empiricism is not necessarily simple. Neural network approaches drawn from the field of artificial intelligence are computationally sophisticated but essentially empirical. While it is not the purpose here to undertake an exhaustive coverage of classification algorithms, it is important to note that the more sophisticated ways tend to place greater reliance on larger and presumably more representative selections of training sets. Also, the analyst often has only limited capability to override the automated assignments.

These conventional classification approaches become available at the PSI primary segment level by generating 'smoothed' approximations to the original bands. In so doing, one should not lose sight of the fact that 'smoothing' works to reduce the within-category variation among pixels since all pixels in any given primary segment will be identical. Likewise, the entire pixel population of a primary segment will necessarily be assigned to the same class. The focus here, however, is on a strategy that is geared to the level of PHASE secondary segments and places a premium on having the analyst retain final control of category assignments while having the computer make recommendations to guide these assignments.

Comparative classification of scene segments

PHASE secondary segments constitute clusters of PSI primary segments. The nature of the segmentation process allows some clusters to have many primary segments while others have only a few or even just one primary segment. Furthermore, the primary segments themselves typically have widely varying numbers of pixels. PSI/PHASE tables show the pixel count and the number of PSI primary segments for each PHASE secondary segment. In preparing to undertake categorical classification at the PHASE level, it is advisable to make note of these

Table 1. Schematic layout for information flow between the user and the PHASE classification system. The table on the left displays training information and determinations made by the user. The table on the left shows suggestions returned by the system in light of the current training information.

User Input

PHASE Segment	Category (label)			
	A	B	C	D
1	✓			
2				
3			✗	✗
4	✗			
5		✗		
6				
7			✓	
8				✓
⋮	⋮	⋮	⋮	⋮
250		✓		

Legend (user)
✓ DEFINITE
✗ REJECT

Legend (system)
++ PROBABLE
+ POSSIBLE

System Response

PHASE Segment	Category (label)			
	A	B	C	D
1				
2	+			
3		++		
4				
5			+	
6		++		
7				
8				
⋮	⋮	⋮	⋮	⋮
250				

size differences and exercise caution in classifying larger segments since these will encompass substantial sections of the image area.

An initial step in categorizing segments is to summarize within-segment complexity of the PHASE segments. One of the PSI software modules computes tables of statistics pertaining to variability between and within PHASE secondary segments. The statistics that are most relevant for classification are the minimum and the maximum of the standard deviations of signal (band) components for each segment as well as the segment centroids. Centroids are used instead of segment proxy vectors because standard deviations measure variability about mean values. Calculation of these statistics does require access to the original multiband image data but, once these tables are computed, the PSI/PHASE formulation becomes largely self-contained and normal usage no longer depends on possession of the original multiband dataset.

The PHASE classification scenario is supervised inasmuch as the analyst initiates the process by using a viewer that has an image query capability to determine the ID numbers of PHASE segments occupying locations for which the correct thematic category is known from ancillary information such as maps or other 'ground truth'. These PHASE segments become prototypes or 'training data' for classifying other PHASE segments into appropriate categories.

The PHASE classification system is highly interactive. The user supplies the system with training information regarding the current classification status of the (PHASE) segments. This is indicated schematically in where a checkmark (4) means that the segment is definitely a member of the indicated class. The ultimate goal is to have exactly one checkmark in each row of the table. Final classification decisions are the prerogative of the user—the computer can make suggestions but is not permitted to enter checkmarks into the table. A novel feature of the system is that the user can guide the computer away from inappropriate suggestions by entering a reject mark (8) to indicate that a given segment is not of a particular type.

With the training information as input, the classification module attempts to fill in blank cells in the table with either PROBABLE or POSSIBLE designations; the algorithm for doing this is explained below. A PROBABLE designation is strongly suggestive of class membership, to the degree that PROBABLE memberships are used by the program in searching for additional suggestive designations. A POSSIBLE designation is tentative to the degree that POSSIBLE memberships are not used by the program in searching for additional suggestive designations. The algorithm is constrained so that at most one of the DEFINITE, PROBABLE or POSSIBLE designations can appear in a given row. A row can be missing all three of these designations (row 4 in is an example) if the current training data are insufficiently informative regarding the corresponding segment. After viewing and mapping the suggested memberships, the user can edit the DEFINITE and REJECT declarations and make another run with alteration of parameters if appropriate.

Figure 6 shows the result of applying the process to classify water surfaces in the September 1991 Landsat MSS sample image. Some omission error is evident in the illustrative case of since narrow rivers have not been included in the water surfaces category. This is a compromise made in order to avoid commission error that would give cloud shadows the appearance of water surfaces.

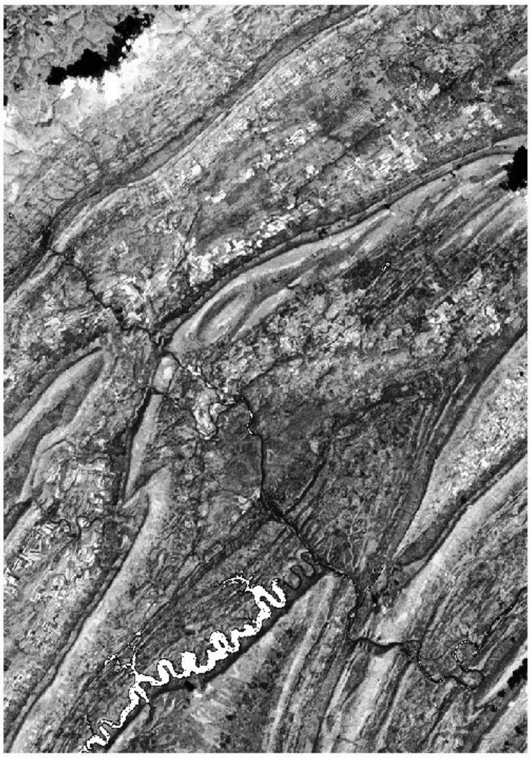

Figure 6. Thematic highlighting of water surfaces as white on a background of segment gray steps for September 1991 Landsat MSS sample image of central Pennsylvania.

Details of the PHASE suggestive classification algorithm

In addition to training information, the user provides the system with two (nonnegative) numerical parameters, α and β. Smaller values for these parameters reduce the program's willingness to assign PROBABLE and POSSIBLE designations, respectively. When the program returns, it provides information on alteration of parameters that might increase the number of suggested memberships.

Decisions regarding PROBABLE and POSSIBLE designations are made on the basis of (unsquared) Euclidean distance between segment centroids relative to within-segment standard deviations. For a given segment s and a given band i, let σ_{si} be the standard deviation of the band-i values for data points (pixels) in segment s. Also, with p as the number of bands, let

$$\sigma_s^{\min} = \min_{1 \le i \le p} \sigma_{x,i} \text{ and } \sigma_s^{\max} = \max_{1 \le i \le p} \sigma_{x,i}$$

Finally, let $d(s,t)$ be the unsquared Euclidean distance between the centroids of segments s and t.

For a given class c, the program examines all pairs of segments (s,t) where s is currently unassigned for c and where t is designated as either DEFINITE or PROBABLE for c. This means that row s in the table does not currently contain any of the DEFINITE or PROBABLE or POSSIBLE designations, cell (s,c) is empty, and cell (t,c) has either a DEFINITE or PROBABLE designation. Among such pairs, the one with the smallest between-centroid distance $d(s,t)$ is selected. This determines a triple (c,s,t). There is one such triple for each class c and they are examined in order of increasing $d(s,t)$ values. If

$$d(s,t) > \alpha(\sigma_s^{\min} + \sigma_t^{\min}),$$

the program proceeds to the next triple. Otherwise, cell (s,c) in the table receives a PROBABLE designation and the set of triples is recomputed. This continues until no more PROBABLE designations can be made. The program then makes POSSIBLE designations in the same manner except that parameter β replaces parameter α in the above decision rule.

The algorithm has a multiple-linkage variation in which the decision rule for PROBABLE designations uses maximum standard deviations instead of minimum and the candidate segment s must be within threshold distance of at least two current class members.

Mixed mapping methods

Many multiband mapping methods draw definite distinctions between 'supervised' and 'unsupervised' approaches (Gonzalez and Woods 1992, Pratt 1991). The basics of the supervised scenario have been set forth in the foregoing discussion whereby 'training sets' selected on the basis of 'ground truth' serve to determine 'signatures' against which pixel patterns are matched by computational comparison. The unsupervised scenario delays the appeal to ground truth until the later stages of the mapping process. In fact, it is not even necessary to have particular categories in mind at the beginning. Instead, a computational similarity (or dissimilarity) analysis is performed as a so-called 'clustering' operation that segregates the pixels into several groups with the members of any given group having substantial similarity of signal patterns. A sample of each cluster group is then investigated via ancillary information to determine its composition, and appropriate labels are thereby attached. Thus, the supervised approach starts with a predetermined legend and some specific knowledge of samples, whereas the unsupervised approach acquires specific information as needed and develops the legend in the course of the investigation.

The PSI/PHASE approach incorporates aspects of both the unsupervised and the supervised paradigms. The pattern-based segmentation with dual levels of detail has the nature of both divisive and agglomerative clustering concepts in statistics. However, the numbers of segments are far more numerous at both levels of detail than is typical of clustering for unsupervised analysis. The coarser level of segmentation with PHASE clusters is akin to what is sometimes called 'hyperclustering' in the context of image analysis, but finer level aggregations of PSI primary segments are much more numerous than hyperclustering would entail. Furthermore, hyperclustering groups pixels whereas PHASEs are clusters of segments. The multiplicity of segments invites application of supervised ideas at these levels, with the proviso that distributional assumptions would need to be modified in order to become formally statistical.

Detecting differences in serial scenes

The foregoing facilities of the PSI/PHASE approach support the primary purpose of detecting differences in successive scenes. Classification capability is needed for designating clouds in order to suppress their appearance of change. More sophisticated classification strategies can help to reduce the influence of agricultural land on apparent change. One such strategy is to conduct a narrowly conceived classification of agricultural land in a recent image, and then conduct a broadly conceived classification of forests and related naturalistic cover in an earlier image. It is important not to mask changes in areas that may have been disturbed from a naturalistic condition during the interval between the images. Therefore, the recent agricultural mapping becomes a preliminary mask for refinement by dropping any of the agricultural area that may have been of a naturalistic character at the time of the earlier image. Change indications are then suppressed in the remainder of the agricultural area by using it as a mask.

Multiple mappings

A seemingly straightforward solution to detecting differences would be consecutive compilation of categorical maps for conducting computerized comparison. This approach avoids potential phenological problems with shifting spectral signatures, since the classification of a category is conducted with a separate set of spectral signatures or segments in each scene. It also accommodates interim improvements in sensor systems and differing spectral signal segregation in band breakpoints. Consistent categories and mapping methods are essential, however, in order to avoid confounding comparative computations of change.

Consistency of categorical coding in consecutive compilations is problematic in practice because people and particulars of purpose and procedures progress over time. A different perspective produces differences in definitions of categories or even different types of categories that serve to confuse comparisons over time. Although there have been efforts to standardize land cover categories (Anderson et al. 1976), these have not led to the level of consensus needed for long-term monitoring. A further complication with comparative analysis of change in cover mappings is that classification errors from the individual maps combine as apparent change that compounds error in the result (Lunetta and Elvidge 1998). Therefore, the seemingly straightforward comparison of companion mappings has somewhat limited utility suited to situations where the mappings are done identically and mapping errors are minimal.

Compositing companion images

The general alternatives to comparing cover maps are to compare or composite spectral characteristics of companion images acquired at different times (Mas 1999, Rogan, Franklin and Roberts 2003, Singh 1989). The compositing approach is fundamentally different from the comparison approach. A temporal composite intermixes information on stability of land cover with information on changes, whereas temporal comparison segregates information on change from information on stability of cover types.

A temporal composite of two or more dates is obtained by 'stacking' image datasets from different times together so that each pixel has all of the bands from the different dates as elements of a single (extended) signal vector having higher dimensionality as if the images were all acquired by a single sensor. For pixel locations where the cover has not changed between dates, the bands should combine as an extended signature. However, each categorical change combination should express in a particular manner that differs from each of the static categories. Since it becomes very problematic to obtain training sets for all possible combinations of cover changes for purposes of supervised analysis, an unsupervised approach becomes more practical. The multiplicity of combined bands also complicates both data management and analysis. This provides incentive for data reduction without sacrificing major elements of pattern information.

PSI/PHASE pattern-based segmentation can serve a purpose similar to principal components in analysis of temporal composites. The stacked bands are subjected to segmentation in the usual manner of a multiband image. Changes will tend to be isolated in certain of the PHASE secondary segmentation patterns, but not necessarily as especially light ones or especially dark ones. Therefore, the initial graytone image formulation will tend not to be very revealing relative to changes, and it becomes necessary to work with various color renderings in order to make the changes evident. Figure 7 shows a PSI/PHASE conversion of the composited 1972 and 1991 Landsat MSS subscenes of central Pennsylvania. Careful perusal will show tonal distinctions that are drawn from both of the individual scenes, but these distinctions have subtle graytones instead of highlights. An exception to the subtlety is the appearance of cloud effects from both scenes in the upper left corner. Color is required in order to bring out the other change aspects that have been captured.

Direct difference detection

Although colorized multi-date composites can provide additional landscape details, they have the disadvantage of not definitely distinguishing change from stability. This ambiguity makes it necessary to investigate each color signature empirically to determine whether it is indicative of change. Lack of definite records on changes in the localities under investigation can make determination of change signatures difficult. Direct spectrally comparative indicators of change are thus of interest for use either with multi-date composites or separately (Howarth and Wickware 1981).

If images having the same set of spectral bands are available on successive dates, then an obvious possibility is to look at differences between the respective pairs of bands (Bruzzone and Prieto 2000). Particular kinds of differences will be most evident in certain bands, so that it may not be sufficient to examine the difference between just one band pairing. Therefore, it becomes desirable to incorporate differences for multiple band pairs into a single indicator of change. Euclidean distance between pixel patterns on different dates is a natural extension of differencing from one band to several bands. This follows from the fact that difference and Euclidean distance are numerically identical when there is only one band. In remote sensing jargon, the Euclidean distance between pixel patterns on two dates has usually been called 'length of change vector' as the basic indicator in *change vector analysis* (Chen et al. 2003, Johnson and Kasischke 1998, Lambin and Strahler 1994a, 1994b, Michalek et al. 1993).

Considering their very localized nature and the possibility of mixed-pixel effects, there is generally not much interest at the landscape level in single-pixel changes.

Figure 7. Grayscale rendering of PSI/PHASE conversion for multi-temporal composite of Landsat MSS subscenes from 1972 and 1991 in central Pennsylvania.

With regard to changes of a patchy nature, subtle variations among pixels in a patch constitute noise in what should be interpreted as a patch of change. Therefore, homogenizing of patches can serve to give a more crisp appearance to change indicator images. This is exactly the smoothing effect that is introduced by PSI/PHASE segmentation. Thus, the PSI/PHASE version of change vector length is to calculate the Euclidean distance between the proxy profiles at the PHASE secondary level of segmentation for different dates of imagery. Atmospheric anomalies such as clouds and their shadows are sources of false change (Hall et al. 1991, Song et al. 2001). Therefore, provision is made for designating lists of PHASE segments that are not to be considered as being change. The classification methods considered previously can be used to determine which PHASE segments should be ignored in this fashion.

Figure 8 is an image of PHASE change vectors for the Pennsylvania Landsat MSS sample scenes with darker tones indicating stronger change. It can be seen from that a major feature of change is the large sinuous Raystown Lake reservoir in the lower portion of the area. Construction for this impoundment was underway at the time of the

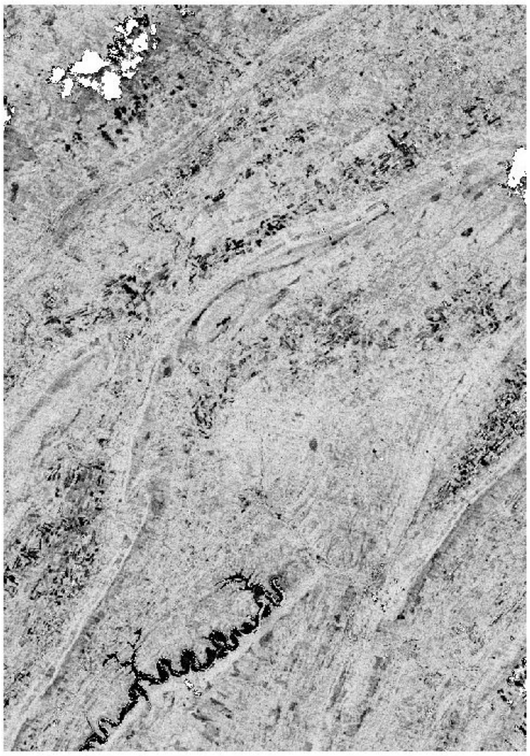

Figure 8. PHASE change-vector length as an indicator of landscape change from 1972 to 1991 as determined from Landsat MSS data for central Pennsylvania, with darker tones indicating change. The more dense clouds and cloud shadows have been excluded from change, and thus both appear as white.

1972 image, and the area was under water in 1991. The concentrations of agricultural fields in the valleys also appear as areas of change in signal pattern.

Spatial pattern matching

The conventional change vector and the foregoing PHASE equivalent are both constrained to usage when the same signals have been obtained on all occasions of data acquisition. Neither multiple mappings nor temporal composites are constrained in this manner, which appears to give them a broader scope of application. The PSI/PHASE segmentation process, however, entails a duality of spectral and spatial information that can be exploited to lift the constraint in an innovative manner. The essence of the innovation lies in analysis of shifts in (*P5*) segment structure over time. The key to the method is inter-date matching for segment counterparts. This counterpart approach focuses on consistency and inconsistency of spatial organization for image segments between dates, thus avoiding the presumption that sensing has been conducted in like manner.

One of the segment maps for a pair of dates is chosen as the base of comparison. For purposes of explication, let this be from date A. The other (linkage) segment map is then from date B. The matching is to be done at the level of PHASE secondary segments. Each (*P5*) PHASE segment in A occupies a particular set of pixel positions. These same positions in B are scanned to determine which of the B segments occurs most frequently there. This modal segment (in B) becomes a B-counterpart for the particular segment of A, as indicated in Figure 9. Every pixel in B thus has two signal profiles associated with it. One of these is the proxy profile for the date B segment to which it belongs. The other profile comes from looking in date A to see what segment occupies that position, and then taking its counterpart proxy profile in B. Euclidean distance between the two profiles is then computed as a

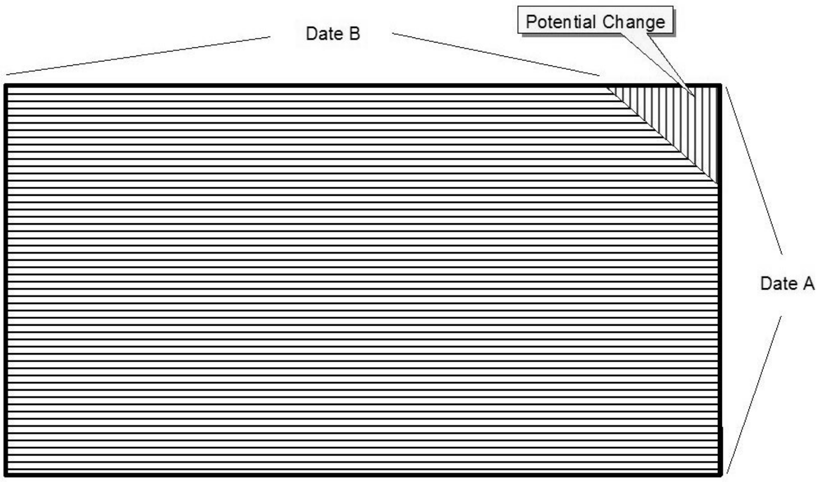

Figure 9. Diagram of spatial matching for date A and date B segments. Date B segment is dominant overlay for date A segment, thus constituting a counterpart.

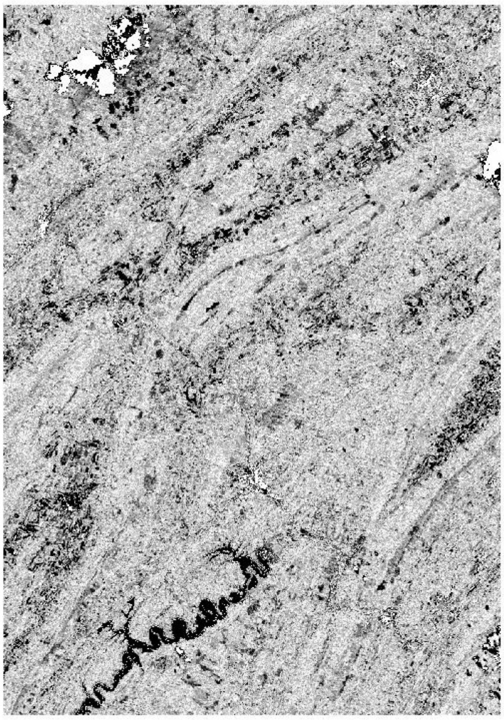

Figure 10. PHASE change-vector length determined by the indirect counterpart strategy as an indicator of landscape change from 1972 to 1991 as determined from Landsat MSS data for central Pennsylvania, with darker tones indicating change.

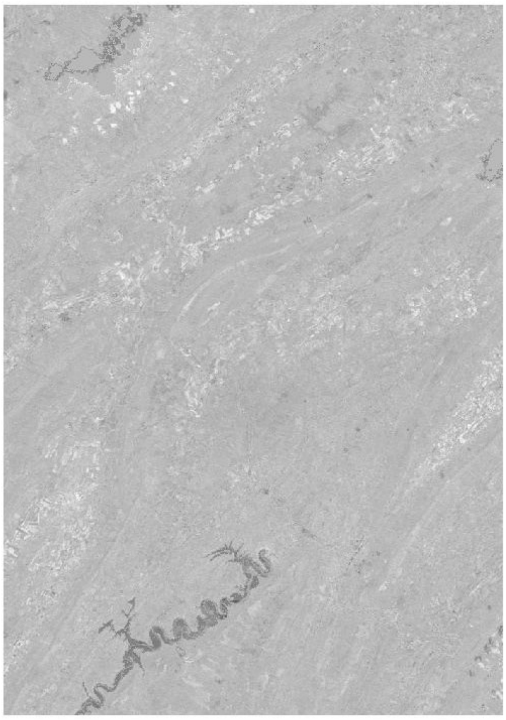

Figure 11. Image of scaled band 3 component of change as computed from Landsat MSS of central Pennsylvania from 1972 to 1991. Notice that the change for flooding of a reservoir is seen differently from changes in vegetative cover of land surface.

change vector length. Note that both of these profiles are from date B signal information. Since it is the spatial organization of segmentation that drives the matching, signal information from date A plays only an indirect role. If the spatial organization of segments is the same for both dates, then the two signal profiles will be the same. If the spatial organization of segments is consistent but not identical, then the two signal profiles will differ relatively little. Consistency may mean that some areas of coarser and finer subdivision have been exchanged between dates. If a pixel was associated with different regions having contrasting signal characteristics, however, then the two patterns will also differ considerably. In effect, a pixel is judged as being consistent or not by the company that it keeps in its segments on the two dates.

Figure 10 shows change vector mapping from this indirect counterpart strategy for comparison with Figure 8 that was produced by the direct strategy. For this purpose, the earlier image was designated as the base and the later one as the linkage. With this methodology, it is possible to do either forward comparisons in time or backward comparisons in time. A backward comparison would involve the later image as base and the earlier as linkage. Forward and backward comparisons will not necessarily yield exactly the same results.

Distinguishing kinds of change by combining indicators

Length of change vector is readily interpreted as an image, but does not discriminate between differences in spectral direction of change. Information on directions of change is embodied in a multi-layer dataset of scaled band differences. One possible scaling in this regard is that of direction cosines for the change vector, which simply amounts to dividing each band component by the length of the change vector (Chen et al. 2003). From an image display perspective, however, a more convenient scaling is one that centers and stretches the differences for each band to fit a byte range of 0 to 255 as shown in Figure 11 for the band 3 difference component. The real question is how to handle these or other multiple layers of information in combination so that distinctions in types of changes can be made and seen as images. The PSI/PHASE seg-

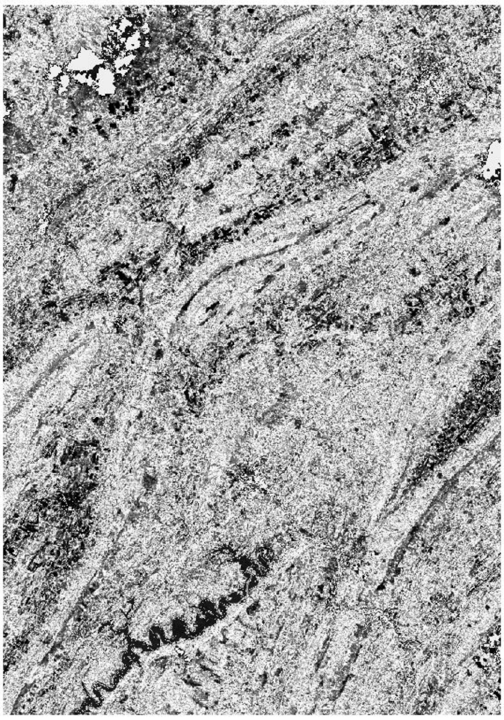

Figure 12. Graytone display of PHASE segmentation for dataset of multiple change indicators including band differences and change vector length from 1972 and 1991 Landsat MSS scenes in central Pennsylvania.

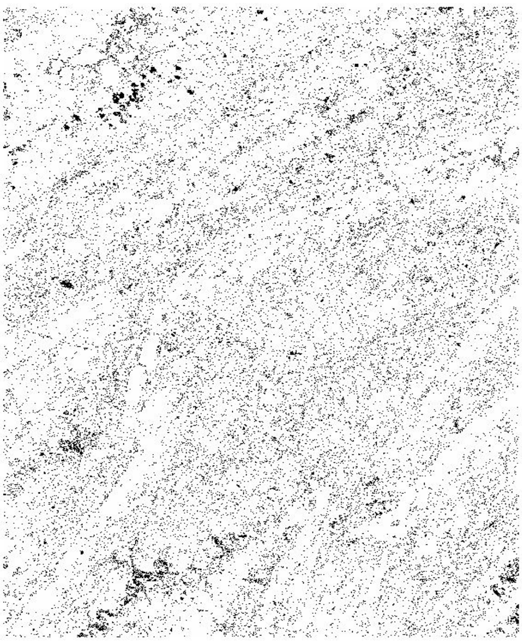

Figure 13. Image of residual map for PSI/PHASE segmentation of multiple change indicators shown in Figure 12, with darker areas indicating larger residuals.

mentation approach also provides an answer to this question. PSI/PHASE segmentation can be conducted on multi-layered change indicator data in like manner as for original multiband data. For band difference data this will combine information on direction of changes into a single image-map. A graytone map of segmented band differences for the Landsat MSS snippets is shown in Figure 12. However, a graytone display is not nearly as revealing as color in these circumstances. An interesting choice of colors is to treat length of change vector as red, the total of infrared band changes as green, and the total of visible band changes as blue (Myers 2003).

In working with a segmentation of multiple change indicators it is also prudent to obtain the residual map as described earlier in order to determine whether there are locations of strong change that have been dampened in the approximation. Figure 13 shows the residuals corresponding to Figure 12. In this case the larger (darker) residuals are associated primarily with clouds and with the Raystown Lake reservoir, both of which are strongly expressed in the segmentation itself.

Tracking three or more times

With conventional approaches to change detection there is considerable difficulty in tracking across three or more dates for purposes of determining persistence of changes in extended landscape monitoring. Another advantage of the PSI/PHASE approach is that the concept of segmenting multiple indicators extends quite naturally to analysis of change for three or more dates. The simplest version of this is working with a stack of change vector images for successive date pairs or successive change vectors from a base date. Color renditions of PHASE secondary segments will show different patterns of temporal persistence in different colors. Myers (2003) demonstrates this for the area of a large forest fire in northeastern China in terms of comparisons with a base date (see www.environment.psu.edu/publications/2003_6/2003_6_web.pdf).

In summary, the PSI/PHASE dual segmentation of images provides multiple benefits of data reduction, compatibility with GIS systems, data smoothing, analytical pattern matching, landscape pattern extraction and greater freedom in distribution of spatial information. It is especially versatile with respect to applications in monitoring landscape change.

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References

Anderson, J., E. Hardy, J. Roach and R. Witmer. 1976. *A Land Use and Land Cover Classification System for Use with Remote Sensor Data.* U. S. Geological Survey Professional Paper 964. Reston, VA: U. S. Geological Survey. 28 p.

Ball, D. J., and G. H. Hall. 1965. ISODATA, a novel technique for data analysis and pattern classification. Technical Report, Stanford Research Institute, Menlo Park, California.

Ball, D. J., and G. H. Hall. 1967. A clustering technique for summarizing multivariate data. *Behavior Science* 12: 153–155.

Baker, W. 1989. A review of models of landscape change. *Landscape Ecology* 2: 111–133.

Bruzzone, L. and D. Prieto. 2000. Automatic analysis of the difference image for unsupervised change detection. *IEEE Transactions on Geoscience and Remote Sensing* 38: 1171–1182.

Chen, J., P. Gong, C. He, R. Pu and P. Shi. 2003. Land-use/land-cover change detection using improved change vector analysis. *Photogrammetric Engineering and Remote Sensing* 69: 369–379.

Coppin, P. and M. Bauer. 1996. Digital change detection in forest ecosystems with remote sensing imagery. *Remote Sensing Reviews* 13: 207–234.

Congalton, R. and K. Green. 1999. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices.* Lewis Publishers/CRC Press, Boca Raton, FL.

Dai, X. and S. Khorram. 1998. The effects of image misregistration on accuracy of remotely sensed change detection. *IEEE Transactions on Geoscience and Remote Sensing* 36: 1566–1577.

Everitt, B. S., S. Landau and M. Leese. 2001. *Cluster Analysis*, Fourth edition. Arnold, London.

Forman, R. T. T. 1995. *Land Mosaics: The Ecology of Landscapes and Regions.* Cambridge Univ. Press, Cambridge, U.K.

Forman, R. T. T. and M. Godron. 1986. *Landscape Ecology*. John Wiley & Sons, New York.

Gibson, P. and C. Power. 2000. *Introductory Remote Sensing: Digital Image Processing and Applications.* Taylor and Francis, New York.

Gong, P., E. LeDrew and J. Miller. 1992. Registration noise reduction in difference images of change detection. *International Journal of Remote Sensing* 13: 773–779.

Gonzalez, R. C. and R. C. Woods. 1992. *Digital Image Processing*. Addison-Wesley Publishing Co., Reading, MA.

Gordon, A. D. 1999. *Classification*, 2nd edition. Chapman & Hall, Boca Raton, FL.

Groombridge, B. 1992. *Global Biodiversity: Status of the Earth's Living Resources*. Chapman & Hall, New York.

Hall, F., D. Strebel, J. Nickeson and S. Goetz. 1991. Radiometric rectification: Toward a common radiometric response among multidate, multisensor images. *Remote Sensing of Environment* 35:11–27.

Hartigan, J. A. 1975. *Clustering Algorithms*. John Wiley & Sons, New York.

Hartigan, J. A. and M. A. Wong. 1979. A *k*-means clustering algorithm [Algorithm AS-136]. *Applied Statistics* 28: 100–108.

Hastie, T., R. Tibshirani, and J. Friedman. 2001. *The Elements of Statistical Learning*. Springer, New York.

Howarth, P. and G. Wickware. 1981. Procedures for Change Detection using Landsat Digital data. *International Journal of Remote Sensing* 2: 277–291.

Jain, A. K., M. N. Murty and P. J. Flynn. 1999. Data clustering: A review. *ACM Computing Surveys*, 31: 264–323.

James, M. 1985. *Classification Algorithms*. John Wiley & Sons, London, UK.

Johnson, R. and E. Kasischke. 1998. Change vector analysis: A technique for the multispectral monitoring of land cover and condition. *International Journal of Remote Sensing* 19: 411–426.

Kelly, P. and J. White. 1993. Preprocessing Remotely-Sensed Data for Efficient Analysis and Classification. Applications of Artificial Intelligence 1993: Knowledge-Based Systems in Aerospace and Industry, Proceedings SPIE 1993. pp. 24–30.

Lambin, E. and A. Strahler. 1994a. Indicators of land-cover change for change vector analysis in multitemporal space at coarse spatial scales. *International Journal of Remote Sensing* 15: 2099–2119.

Lambin, E. F. and A. H. Strahler. 1994b. Change-vector analysis in multi-temporal space: a tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. *Remote Sensing of Environment* 48: 231–244.

Li, J. and R. Gray. 2000. *Image Segmentation and Compression Using Hidden Markov Models*. Kluwer Academic Publishers, Norwell, MA.

Lunetta, R. and C. Elvidge (eds.). 1998. *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications.* Ann Arbor Press, Ann Arbor, MI.

Lunetta, R., J. Lyon, B. Guindon and C. Elvidge. 1998. North American landscape characterization dataset development and data fusion issues. *Photogrammetric Engineering and Remote Sensing* 64: 821–829.

Mas, J. 1999. Monitoring land-cover changes: A comparison of change detection techniques. *International Journal of Remote Sensing* 20: 139–152.

McGarigal, K. and B. J. Marks. 1995. *FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure.* General Technical Report PNW 351, U. S. Forest Service, Pacific Northwest Research Station. 122 pp.

Michalek, J., T. Wagner, J. Luczkovich and R. Stoffle. 1993. Multispectral change vector analysis for monitoring coastal marine environments. *Photogrammetric Engineering and Remote Sensing* 59: 381–384.

Miller, R., ed. 1994. *Mapping the Diversity of Nature*. Chapman & Hall, New York.

Myers, W. 2003. Doubly segmented images for pattern-based approach to change detection. Final report on NASA Research Project NAG5-1054. Research Report PSIE 2003-6, Penn State Institutes of Environment, The Pennsylvania State University, Univ. Park, PA 16802 USA. 90 pp. + CD-ROM.

Myers, W., G. P. Patil and C. Taillie. 1999. Conceptualizing pattern analysis of spectral change relative to ecosystem status. *Ecosystem Health* 5: 285–293.

Patil, G. P., R. Brooks, W. Myers, D. Rapport and C. Taillie. 2001. Ecosystem health and its measurement at landscape scale: Toward the next generation of quantitative assessments. *Ecosystem Health* 7: 307–316.

Patil, G. P. and W. Myers. 1999. Environmental and ecological health assessment of landscapes and watersheds with remote sensing data. *Ecosystem Health* 5:221–224.

Pratt, W. 1991. *Digital Image Processing*. John Wiley & Sons, New York.

Richards, J. A. and X. Jia. 1999. *Remote Sensing Digital Image Analysis,* 3rd edition. Springer-Verlag, Berlin.

Rogan, J., J. Franklin and D. Roberts. 2003. A comparison of methods for monitoring multitemporal vegetation change using thematic mapper imagery. *Remote Sensing of Environment* 80: 143–156.

Rogan, J., J. Miller, D. Stow, J. Franklin, L. Levien and C. Fischer. 2003. Land-cover change monitoring with classification trees using landsat tm and ancillary data. *Photogrammetric Engineering and Remote Sensing* 69: 793–804.

Singh, A. 1989. Digital change detection techniques using remotely sensed data. *International Journal of Remote Sensing* 10: 989–1003.

Sohl, T. and J. Dwyer. 1998. North American landscape characterization project: the production of a continental scale three-decade landsat data set. *Geocarto International* 13: 43–51.

Song, C., C. Woodcock, K. Seto, M. Lenney and S. Macomber. 2001. Classification and change detection using landsat tm data: when and how to correct atmospheric effects. *Remote Sensing of Environment* 75: 230–244.

Tso, B. and P. Mather. 2001. *Classification Methods for Remotely Sensed Data.* Taylor and Francis, New York.

Turner, M., R. Gardner and R. O'Neill. 2001. *Landscape Ecology in Theory and Practice: Pattern and Process.* Springer-Verlag, Inc., New York.

Wilson, J. and J. Gallant (eds.) 2000. *Terrain Analysis: Principles and Applications.* John Wiley and Sons, Inc., New York.