Conceptualizing Pattern Analysis of Spectral Change Relative to Ecosystem Status

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Abstract

Change is recognized as being intrinsic to ecosystems, but is also the essence of instability and the outgrowth of situations that lack sustainability. Change is arguably the most fundamental symptom for onset of abnormality in ecosystem function, and change in change cannot be detected without sufficient monitoring to determine spatial and temporal aspects of characteristic change regimes across landscapes. It must also be recognized that change can be associated with either restoration or degradation.

A suite of recent developments in change detection using compressed multiband image data provides increased flexibility and practicality for systematic change detection on a regional basis. Combining such capability with conceptual extensions of spatial pattern analysis through echelons can provide a methodology for systematically monitoring spatial structure of spectral change across landscapes in order to profile characteristic broad scale regimes of change and to indicate trends in those regimes. Implementing these analytical scenarios with new generations of computers and remote sensors could lend a further dimension to tracking of ecosystem status over major regions.

Introduction

Sustainability and ecosystem health are watchwords of contemporary ecosystem management (Costanza 1991). These concerns permeate all levels and scales of ecological organization, with considerable current attention being devoted to watershed and landscape contexts (O'Neill et al. 1997). Notable in this regard are the ecological assessment atlas for the Mid-Atlantic Region of the United States (Jones et al. 1997) and the Index of Watershed Indicators (EPA 1997). These and similar efforts rely on spatially integrative indexes of ecosystem status. Many of these indexes are based on remotely sensed spectral data from satellite borne sensing systems, and several are formulated in terms of degree of change for particular spectral features such as the normalized difference vegetation index NDVI (Jones et al. 1997). Change is recognized as being intrinsic to ecosystems (Picket and White 1985), but is also the essence of instability and the outgrowth of situations that lack sustainability. Change is arguably the most fundamental symptom for onset of abnormality in ecosystem function, and change in change cannot be detected without sufficient monitoring to determine spatial and temporal aspects of characteristic change regimes across landscapes. It must also be recognized, however, that change can be associated with either restoration or degradation. Because of the diversity in change regimes for natural and humanized landscapes, monitoring must go beyond extent of change to pattern of change.

Change detection from remotely sensed data has extensive technical precedent, but also embodies continuing challenges with regard to both practical implementation and definitive results (Lunetta and Elvidge 1998). A suite of recent developments in our work on change detection using compressed multiband image data provides increased flexibility and practicality for systematic change detection on a regional basis. Combining such capability with conceptual extensions of our work on spatial pattern analysis for synoptic quantitative data can provide a methodology for systematically monitoring spatial structure of spectral change across landscapes in order to profile characteristic broad scale regimes of change and to indicate trends in those regimes. Implementing these analytical scenarios with new generations of remote sensors that are scheduled for deployment could lend a further dimension to tracking of ecosystem status over major regions.

Change Regimes for Landscape Settings

Figure 1 is a satellite-based image expression of change in visible and near-infrared wavelengths from September 6, 1972 to September 7, 1986 for a sector of the Ridge and Valley Physiographic Province in central Pennsylvania with darker areas indicating more pronounced change. Details of formulation for this image are considered later, but initial focus is on the spatial pattern of change that is depicted. The region is one of forests on steep and folded ridges trending from southwest to northeast with agricultural and urbanized development in the valleys between the ridges. The ridges appear in mostly lighter tones indicating relatively little change except for (usually) elongate patches representing clearcut forest harvest. The square near the top center of Figure 1 is illustrative in this regard. A clearcut creates a strongly contrasting change at the time of harvest, with subsequent progressive change of lesser degree as regrowth occurs. Partial mortality due to insect, disease, and other environmental influences results in (often patchy) thinning of the canopy that appears as more subtle change. Seasonal (phenological) changes in forest vegetation do not contribute substantially to Figure 1 since both of the parent images were taken at the same time of year prior to shedding of deciduous tree leaves.

The agricultural valleys appear as a mosaic of compact dark patches (of change) interspersed with lighter areas of lesser change, as illustrated by the small circle toward the upper right of Figure 1. The dark patches correspond to fields having a change of crop between the earlier and later dates. Since crop rotation occurs in any given year, the year-to-year pattern of change in such an area is much like a multi-year pattern of change unless the land is being converted to other uses. Strongly contrasting phenological changes occur in agricultural areas between early growing season when fields are tilled for planting, to middle of growing season with full crop canopy, to time of harvest . Agricultural areas having a mixture of row crops and forage crops are thus highly dynamic with regard to spectral change.

Spatially protracted changes not attributable to transient phenomena are of major interest with respect to ecosystem health. Figure 1 illustrates such a change due to development of a large reservoir in a meandering stream valley as marked by the small circle in the lower left (southwest) quadrant of the figure.

Aside from phenological effects, urbanized areas have substantial temporal stability. Progressive urbanization is, of course, a major component of patterned change with obvious implications for ecosystem health and environmental integrity of affected areas.

Atmospheric and weather phenomena induce temporal anomalies of change. Scattered clouds and their shadows create paired anomalies such as occur in the larger circle located in the southeast portion of Figure 1. More extensive clouds and fog can affect large areas, and so also for snow in winter seasons. Antecedent moisture and rainfall conditions may likewise induce ephemeral changes in reflectance of exposed soil. Floods and severe windthrow of trees are weather related change phenomena, but are not just anomalies with respect to ecosystem health. There may also be artifacts and variability in a change image due to systemic effects in the imaging processes.

A change signal can be conceived as an irregular surface having components of variability on different scales. There is variability on a microscale wherein the apparent change elements consist of one to a few image cells (pixels), with cells in Figure 1 being 60 meters on a side. Many of these microscale elements arise from lack of perfect registration between parent images or from edge pixels encompassing a mixture of cover types (mixed pixels). For routine environmental monitoring, it may be appropriate to treat such microscale features as being in the nature of noise which should be suppressed during pattern analysis.

Localized features consisting of more than a few image elements typically represent persistent or ephemeral environmental change rather than image anomalies. These may be isolated instances of change or components of a mosaic pattern of change. Localized change features may also have substructure consisting of superimposed peaks and pits.

Spatially protracted change features such as the reservoir in Figure 1 are also not necessarily simple surface elements. Such a feature can be a virtual mountain range of change with hotspots of change stacked upon vicinities of moderate change in the manner of complex hills. These are all potentially interesting and possibly diagnostic characteristics of spatial pattern in change.

Imaging Change from Spectral Data

Given two multiband spectral image data sets acquired with the same sensor, the most straightforward way of obtaining a spectral composite change image is by change vectors. The set of spectral values for each cell of each data set is treated as a vector, and the magnitude of the difference vector between the two data vectors for each cell is determined as a scalar measure of change. The change vector magnitudes are typically quantified as integers from 0 to 255 for storage in a byte and processing by image analysis software. This quantification carries only minimal constraints for rendering of images, since many image display facilities allow gray tones and color intensities to be reversed easily as has been done in Figure 1 to facilitate reproduction. Change vectors determined in this manner tend to be quite noisy because they incorporate the variability in both parent data sets. Calculating change vectors also requires that both of the parent data sets be ingested concurrently by the software, which can become cumbersome for large data sets with many bands having high spatial resolution.

Both the data handling burden and the noise influence can be reduced by calculating change vectors from compressed data sets instead of original data sets. Principal components have been popular for this purpose. Principal components are limited to linear compression, and the choice is somewhat arbitrary regarding the number of component axes to be retained. An alternative nonlinear method of compression through hyperclusters has been developed (Myers 1999), which compresses each data set to the equivalent of a single band containing cluster numbers in the cells along with a companion table of cluster attributes that includes the mean value for each band calculated over the cells in the cluster. The latter approach to image data compression carries the acronym PHASE for **P**ixel **H**yperclusters **A**s **S**egmentation **E**lements. This sort of compressed data set can be analyzed in similar fashion to an image and also handled as a **GIS** (geographic information system) layer. The spatial autocorrelation of environmental data tends to induce patches of cells belonging to the same cluster. A cluster-wise change vector can be computed from the spectral mean vectors of the cluster occurring in a cell on the two dates. The tendency for clusters to occur in patches also lends more spatial structure to the change image than would original data or principal components, with consequent reduction in noise and simplification of the change surface. The change image of Figure 1 was derived in this manner.

As just considered, a smoothing effect is inherent to compression when there is information loss, since it filters some variability from both data sets and thereby reduces the scope for variability in a change measure. There is no tendency inherent to general compression, however, that would mitigate concerns regarding phenological effects or enhance comparability of different sensing systems. PHASE compression is special in offering opportunity in both respects. Any given cluster in a PHASE compression occupies a particular set of cell positions in an image, which are not necessarily contiguous. Such a cluster thus constitutes a distributed spatial pattern. It is possible to tabulate the *spectral properties* of another spatially coincident image over the *cluster patterns* of a PHASE compression, thereby effectively producing a date 2 version of a date 1 image. It thus becomes possible to do the image comparison in a date 2 spectral context. If the *spatial organization* of the image has not changed, then difference between the actual and approximated date 2 renditions will be slight. This implies that a particular kind of forest might have leaves on a first date and be leafless on a second date without exhibiting change, provided that the two states of the forest cluster consistently relative to their surroundings. Likewise, different sensors might be used on the two dates provided that the sensors yield consistent organizations of space in the process of clustering.

Two strategies have been conceived for transferring properties of one image to compressed patterns (clusters) of another image. One strategy is by spatial averaging, and the other is by spatial matching. For spatial averaging, denote the pattern at row *i* and column *j* of scene *a* as Pa(i,j). Denote the (spectral) mean vector for Pa(i,j) over scene *a* as Pa(i,j)m(a). Denote the mean vector for Pa(i,j) over scene *b* as Pa(i,j)m(b). Denote the pattern occurring at row *i* and column *j* in scene *b* as Pb(i,j). Denote the mean vector for Pb(i,j) over scene *b* as Pb(i,j)m(b). Then the change criterion for row *i* and column *j* is the length of the difference vector between the vectors Pb(i,j)m(b) and Pa(i,j)m(b). Ramakomud (1998) has investigated this method of change determination, and found it to have advantages over change detection methods that involve direct spectral comparison. Interestingly, however, there were some differences in change features depending on which of the two images served as a reference. Forward reference corresponds to a forward look in time, while backward reference corresponds to a look back in time. Thus forward and backward reference both should be considered. With consistent scales, the most straightforward way of combining references is to give each pixel the value of whichever has the strongest indication of change in that position.

For the spatial matching approach, let Pa(i,j) and Pb(i,j) be cell (pixel) selectors of patterns in scenes *a* and *b* respectively. Let Pa(i,j)c(a) and Pb(i,j)c(b) denote centroid vectors of the respective patterns. Let Pb[Pa(i,j)] denote the spatially matched counterpart in scene *b* of the Pa(i,j) pattern in scene *a*. Let Pb[Pa(i,j)]c(b) denote the centroid vector over scene *b* for the Pb[Pa(i,j)] pattern. Then the change criterion is the difference vector of centroid vectors Pb(i,j)c(b) and Pb[Pa(i,j)]c(b). A simple method of spatial matching is to use the most frequently occurring (modal) pattern. Distinction between forward reference and backward reference must also be made. Whereas spatially averaged vectors can depart considerably from actual spectral values in sectors of extensive change, this is not so for spatial matching.

When scene data are acquired on more than two occasions, PHASE clustering can also be used to investigate temporal structure in changes. Change signals can be computed for different pairs of time periods, and then treated as bands in a multiband scene for extraction of hyperclusters. Temporal structure as revealed in the resulting clusters can help to determine both persistence of change and nature of change. For instance, recurring high-contrast changes in agriculture due to crop rotation have different temporal properties than forest clearcuts which show high initial contrast that fades gradually due to regrowth.

Because it is both temporally and spatially comparative, PHASE-based change determination offers considerably greater flexibility and stability for environmental monitoring than more traditional methods that are spectrally comparative only. It is this additional flexibility and stability coupled with objective methods of capturing spatial structure that lend promise to tracking of spectral change regimes in relation to ecosystem health which has heretofore been somewhat impractical.

Echelon Analysis of Spatial Structure in Change Signals

Spatial structure in surface variables is subjectively evident from visual examination of perspective graphics, but it has been elusive to capture objectively. Echelons have been conceived by Myers et al. (1997) to capture topological structure of a surface in a systematic and objective manner. Echelons partition a surface into stacked hillforms having specific geographic location, structural orders, and "family tree" relationships. Simple peaks are first-order echelons, foundations giving rise to only simple peaks are second-order echelons, a foundation for two or more second-order echelons has third order, and so on recursively. Echelons are determined entirely by saddles in the surface, which are topological critical points. Emergence of islands as floodwaters drain away makes a good metaphor. The simple peaks emerge first while being surrounded entirely by water (order one). The islands then merge to form compound islands as "bridges" (saddles) appear at the level of the water. It is these mergers that determine the echelon organization of the virtual terrain according to relative elevations of surroundings. Figure 2 is an illustrative profile schematic.

Surface features 1-5 in Figure 2 are simple peaks, and therefore first-order echelons. Features 6 and 7 are foundations that give rise to only simple peaks, and are thus of second order. In echelon terminology, a foundation is called a *founder* and the features to which it gives rise are called ascendants. Feature 8 is a foundation that gives rise to two echelons of order 2, so it has order three. Feature 9 is also of order 3 because a foundation must support two or more features of next order to make order increase. It is therefore not necessary that an order 2 echelon only have first-order ascendants. An order 2 echelon can have one ascendant that is also of order 2, but its other ascendant(s) must be of first order.

The relationships among founders and ascendants determine a genealogical tree for the echelons. A progressive increase of order for the surroundings of an echelon indicates surface complexity in the region. The amount by which an echelon rises above the founder is its *relief,* and the relief of a first order echelon is its *peaking.* The area covered by a first-order echelon is its *capping.* A first-order echelon with small capping that arises from a high order echelon is suggestive of "noise" in the signal that generates the surface. This is the case for feature 5 in Figure 2. More generally, first-order echelons that are small with respect to both peaking and capping are in the nature of "blips" in the surface that may not be of much interest.

Current computational facilities for determining echelons on a grid do the processing in stages, with every echelon being uniquely numbered. The first stage of processing finds the summits of first-order echelons. The second stage of processing completes the first-order echelons. The third stage of processing finds higher-order echelons in a top-down progression. The fourth stage of processing completes a table in which each echelon is a row and its properties are the columns. The fifth stage of processing determines the linkages for a tree according to founder and ascendant relations, but does not actually draw the tree.

Figure 3 is an order map for a 100x100 block of cells marked by the square near the upper center of Figure 1.The darkest shade indicates first-order echelons, and shades become progressively lighter for higher order echelons. This is a fifth-order surface (maximum echelon order is 5). In such a forested sector, regenerating cutover areas typically appear as larger complexes of graded shading. There are numerous cases of small dark patches in light surroundings that are characteristic of noise in the surface signal. The 10,000 cells in this block encompass 997 echelons, with 646 of these being first-order.

Current echelon computational facilities have a capacity limit of 65,280 echelons in a grid. Since there are approximately 1,000 echelons in a 100x100 image excerpt, it is apparent that processing the full change image having several thousand cells on a side would exceed the capacity of the system. Since many of the echelons are fine scale "noise", it follows that the noise would dominate a direct analysis of echelon spatial pattern. Such noise must therefore be filtered so that it does not obscure the coarser scale features of change. The software provides for three types of filtering. One type of filtering levels single-cell "blips" that extend upward as "spikes" or downward as "holes". A second smoothing facility does median filtering whereby the median of a nine-pixel block replaces the value of the central cell in the block. A third filtering facility imposes a minimum capping by shaving off smaller first-order echelons at their foundation level. The latter facility cannot be applied until all of the first-order echelons have been determined, so filtering by the other two methods may be necessary as a preliminary. Incomplete determination of higher-order echelons is permissible, except that tree relations will not be available unless the processing goes to completion.

Filtering single-cell blips from the demonstration block serves to reduce the number of first-order echelons to 366, with 597 echelons of all orders. This is a 40% overall reduction. Single-cell filtering does not, however, reduce the maximum echelon order which remains at five. Since this is just an example, further filtering is not pursued.

Pruning Profiles for Echelon Trees

The spatial pattern information of echelons is contained in the tree of founder and ascendant (or parent and child) relations and its couplings to the map and table of properties. However, examining a large tree graphically is both difficult and quite subjective. We have developed a pruning process by which to extract some major aspects of pattern information through observing change in structural variables as the tree is broken down.

Consider a pruning process on an echelon tree that recursively partitions the tree into an inner set of *limbs* and an outer set of *boughs*. The first pruning operation traces all terminal (order one) echelons down to the root while counting the echelons that comprise each path. The subset of terminals thus identified as having the maximum path is then retraced to determine which echelons are common to all such paths. The common echelon path moving upward from the root becomes the first (trunk) limb of the echelon tree. All other components of the tree are pruned away at the trunk forming a set of subtrees called boughs. This partitions the tree into a set of limb echelons and a set of bough echelons. Figure 4 illustrates the first stage of pruning on a simple tree.

In the second cycle of pruning, the process is conducted separately on each of the boughs. Each bough thus yields a limb and a set of boughs. This repartitions the tree into a larger set of limb echelons and a reduced set of bough echelons. Further cycles of pruning will eventually convert the boughs entirely to limbs, so that the bough fraction tends to zero. Some boughs will continue to yield residual boughs longer than others, depending upon depth of structure in the respective subtrees. It should be noted that a bough can consist of a single echelon.

Plotting limb fraction (percent) against cycle number in the pruning process yields a *divergence* profile of surface organization. Simple trees have the profile increase rapidly. Trees with more substructure have the profile increase more gradually. Trees with both simple and complex components have a profile with some abruptly rising and some more gradually rising components. Such a profile thus provides a generalized structural characterization of surface complexity, and differences in profiles indicate topological differences in surfaces.

A *scope* profile can be obtained by pruning in like manner, but plotting percent of cells (pixels) in limbs against cycle number. Since echelons vary in number of cells (even for the same order), such a profile captures the area scope for different degrees of complexity on the surface. If complexity is concentrated in certain sectors, this profile will have an initial steep rise.

A *bunching* profile can be obtained by pruning as before, but plotting number of boughs as a percent of order one echelons against cycle number. This profile is particularly sensitive to depth of structure and its consistency among the branches.

A *stacking* profile comes from the same pruning scenario, but plotting the percent of order one echelons in limbs against cycle number. This profile is indicative of propensity for echelon siblings to be of the same or different orders.

Table 1 contains the information for pruning profiles on the 100x100 example block without any filtering. Table 2 contains the information for pruning profiles when echelons are determined after filtering to remove single-cell variability with consequent 40% reduction in number of echelons. The filtering shortens the pruning process by one cycle. In this case, filtering has greatest shape impact on the bunching profile.

Echelon pruning profiles are appropriate for making comparisons among landscapes and tracking the evolution of surface complexity over time. A set of landscapes having similarity with respect to all four profiles will have substantial commonality of surface organization. Those among a set of landscapes that are unusual should have at least one of the profiles that is distinctive.

Summary

Ecosystem health and sustainability are ultimately matters of trajectories in regimes of change. Remote sensing systems have the capacity for yielding spectral information regarding change at landscape scales, but technical considerations have made routine change detection problematic. Spatial patterns of change are potentially diagnostic among landscapes, but systematic methods of characterizing spatial pattern have been lacking. Recent developments in spatially comparative change detection based on PHASE hyperclustering can alleviate some of the complications in producing change images. Echelon analysis provides a means of characterizing spatial pattern and determining comparative changes in spatial pattern over time. Pruning profiles from echelon trees capture important aspects of spatial organization for comparative purposes. Additional analytical tools for comparative analysis of trees could also contribute to the utility of echelons, and potential for adapting approaches of other disciplines has not yet been fully explored. A challenge for such adaptation lies in the large size of echelon trees having thousands of nodes. Working prototype software for PHASE and echelon analysis is programmed in generic C language, and is available on the World Wide Web through the http://www.erri.psu.edu/web/orser3.htm URL.

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