The Characteristics and Interpretability of Land Surface Change and Implications for Project Design

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Abstract

The need for comprehensive, accurate information on land-cover change has never been greater. While remotely sensed imagery affords the opportunity to provide information on land-cover change over large geographic expanses at a relatively low cost, the characteristics of land-surface change bring into question the suitability of many commonly used methodologies. Algorithm-based methodologies to detect change generally cannot provide the same level of accuracy as the analyses done by human interpreters. Results from the Land Cover Trends project, a cooperative venture that includes the U.S. Geological Survey, Environmental Protection Agency, and National Aeronautics and Space Administration, have shown that land-cover conversion is a relatively rare event, occurs locally in small patches, varies geographically and temporally, and is spectrally ambiguous. Based on these characteristics of change and the type of information required, manual interpretation was selected as the primary means of detecting change in the Land Cover Trends project. Mixtures of algorithm-based detection and manual interpretation may often prove to be the most feasible and appropriate design for change-detection applications. Serious examination of the expected characteristics and measurability of change must be considered during the design and implementation phase of any change analysis project.

Introduction

Land-cover and land-cover-change data are critical to understanding and modeling our environment. For example, global environmental issues, such as increasing levels of greenhouse gases and the potential resultant global warming, have been well documented both in the general media and in scientific circles. There have been studies linking increases in greenhouse gases with continental- to regional-scale changes in land cover (Bounoua *et al.*, 2002), perhaps most notably with tropical deforestation in Amazonia (Fearnside, 1996; Fearnside and Guimaraes, 1996), but very little is known about the cumulative effects of localized land-cover change on climate and other global processes. Local activities, such as timber production, urban development, agricultural practices, and electricity generation, can all emit traces of carbon dioxide and other greenhouse gases that accumulate in the atmosphere and contribute to global climate modification. Together, these power plants, households, fields, and vehicles represent billions of point or small-area sources of emissions and aerosols (Wilbanks and Kates, 1999). Accurate land-cover and land-cover-change data at the local scale are crucial in inventorying these sources.

Climate modeling is only one type of research requiring land-cover data. Land cover and land-cover change can also have profound impacts on water quality and sedimentation (Lowrance *et al.*, 1985), the composition of plant and animal communities (Ojima *et al.*, 1994), fire regimes (Nepstad *et al.*, 2001), and many other processes. The challenge facing policy makers and scientists is the general lack of comprehensive data on the types and rates of land-use and land-cover changes (Loveland *et al.*, 2002).

With the launch of the first Landsat imaging satellite in 1972, large-area coverage data were available that provided a new source of information for those performing environmental studies. Widely accessible, remotely sensed imagery provided scientists with fixed, permanent snapshots of the Earth's surface, making it extremely useful for performing land-cover and land-cover-change studies. This characteristic, coupled with the increasing availability and power of computing resources, sparked great enthusiasm and optimism that finally a cheap, reliable data source was available from which land-cover data could be derived. Numerous analysis techniques have since been developed to derive land-cover and land-cover-change information. Techniques range from those relying heavily on manual interpretation to completely automated approaches. The potential value of the latter becomes obvious towards reaching a goal of an efficient, repeatable, and affordable means for monitoring the landscape. Although there is no doubt that automated systems would be of immense value, the question arises, have the semiautomated to automated procedures developed in the last 30 years provided a successful mechanized means for classifying and monitoring the landscape?

Initial attempts at semiautomated classification of land cover involved the use of spot densitometers to try to extract meaningful information from photographic prints. Such an approach may seem overly simplistic and out of date today. While digital land-cover and land-cover-change techniques have certainly advanced since these early attempts, is it possible that we are still guilty of overexploitation of the data? Are we expecting to extract more from the data than the data (and algorithms) are capable of supplying?

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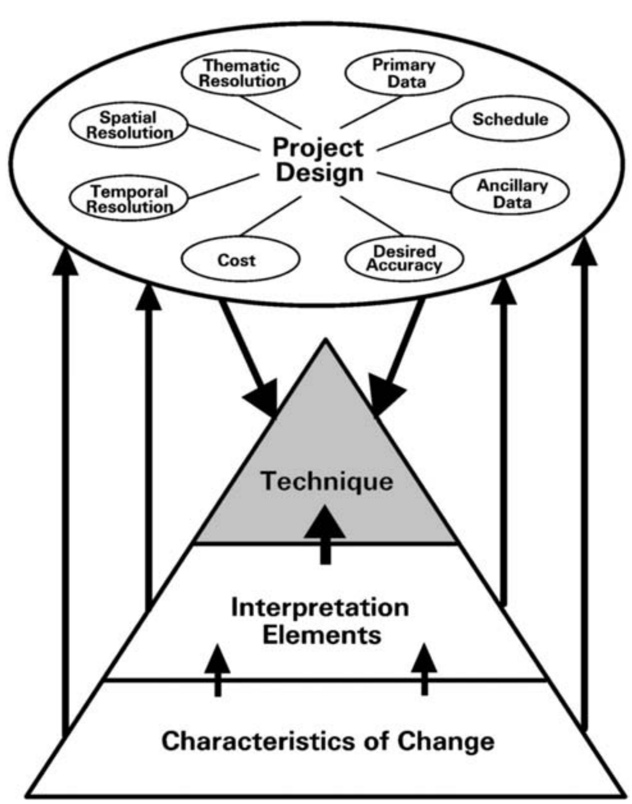


Figure 1. Techniques for detecting change are based on image elements that make interpretation possible. These elements, in turn, are based on the characteristics of change itself. Project design is based on the characteristics of change and the interpretability of that change. Technique, however, should not be a driving factor of project design. Instead, project design and the characteristics of change should drive the choice of technique.

As application of the data has exploded, there has often been the tendency to let the available software dictate the choice of methodology, using the provided algorithms to gather as much information as possible, without questioning results or suitability of the methodology (Ryerson, 1989). Methodologies and popular (and readily available) algorithms have often become the "tail wagging the dog," i.e., they have dictated the path and focus of land-cover and land-cover-change studies.

Figure 1 portrays the key elements to consider in the initial phases of designing a change analysis project. The characteristics of change, along with the interpretability of change as defined by the elements of interpretation, should be the driving forces in forming the design of any land-cover-change study. While this may seem elementary, we continue to see it overlooked in many studies. The interplay of project design, the characteristics of change, and the interpretability of change are what should drive the selection of technique. The most successful projects are those that first create a clear project concept and then select a methodology to best accommodate specific project goals.

What follows is a brief summary of commonly used change-detection techniques and the elements of interpretation that make detection of change possible from remotely sensed imagery. The majority of this paper is then dedicated to discussing the characteristics of change using examples from the U.S. Land Cover Trends Project (Loveland *et al.*, 2002) to illustrate these characteristics. We conclude by considering how all these factors can influence project design.

Change Detection Techniques

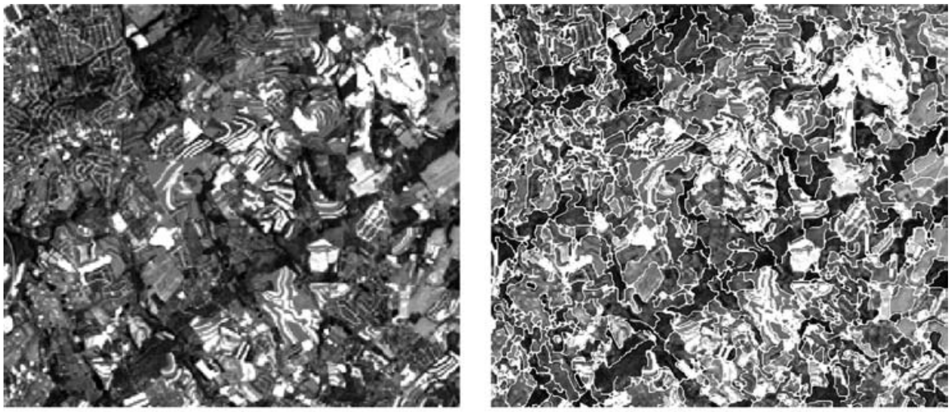
Methodologies for detecting change are based on the analysis of changes in the elements of interpretation outlined below. The choice of measurement variable is heavily dependent upon project goals, because the performance of a technique may vary widely depending upon the type of change that is being identified or upon the geographic context. A brief discussion of the commonly used algorithm-based approaches follows, along with a discussion of the manual interpretation of change.

Algorithm-Based Approaches

Spectral information recorded by the remote sensing instrument and products derived from the spectral data are the most commonly used measurement variables for detecting change. Algorithm-based approaches are especially likely to focus on the use of spectral data and spectral variability. Some of the most commonly used methodologies are simple image differencing (Weismiller *et al.*, 1977; Jensen and Toll, 1983; Vogelmann, 1988), image ratioing (Howarth and Wickware, 1981), and principal components analysis (Byrne *et al.*, 1980; Johnston and Haas, 1985; Ribed and Lopez, 1995). These techniques are all primarily used to generate a binary change mask.

Post-classification comparison of multiple thematic land-cover classifications has the advantage of creating a complete descriptive change matrix and has been widely used (Kumar *et al.*, 1993; Wilcock and Cooper, 1993; Massart *et al.*, 1995; Dimyati *et al.*, 1996). Change vector analysis (CVA) also has the advantage of providing a high level of information regarding the magnitude and nature of a surface change and has been widely used to monitor vegetation and vegetation condition (Lambin and Strahler, 1994; Dwyer *et al.*, 1997; Sohl, 1999). Other commonly used methodologies include the analysis of trends in various vegetation indices and other spectrally based band ratios and indices (Pickup *et al.*, 1993; Lambin and Ehrlich, 1997; Wang *et al.*, 2001; Kawabata *et al.*, 2001), spectral mixture modeling to analyze changes in sub-pixel land-cover modifications (Cochrane and Souza, 1998; Foschi and Smith, 1997; Roberts *et al.*, 1993), and fuzzy classification systems which replace hard classifications with probability estimates, allowing for multiple and partial class membership (Foody and Boyd, 1999). For a more detailed discussion on these and other algorithm-based approaches, examine the references cited above or the numerous papers outlining commonly used change analysis techniques (e.g., Singh, 1989; Mouat *et al.*, 1993; Yuan and Elvidge, 1998; Sohl, 1999).

Algorithm-based approaches have historically used the pixel as the basic element of measurement, with the measurement itself based on spectral properties (the interpretation elements of color/tone and brightness). Digital techniques for incorporating the other basic elements of image interpretation (pattern, site, association, etc.) have typically been limited in scope and application. Object-based classification has the ability to include additional interpretation elements beyond spectral information alone, and such approaches have become increasingly used in recent years with advances in desktop computing power. Object-based approaches first attempt to segment imagery into discrete image objects, i.e., contiguous groups of pixels with similar properties (Figure 2). Spectral information is only one component on which the segmentation is based, because characteristics such as shape, texture, and neighborhood relationships are also incorporated into the segmentation algorithm.



Landsat ETM+ - Bands 4,3,2 **Object-based Segmentation**

Figure 2. Automated image segmentation, the delineation of image objects by grouping contiguous pixels having similar properties, is an important component of human perception and the interpretation of remotely sensed imagery. Software tools that interactively or automatically segment imagery are becoming increasingly common.

Manual Interpretation of Change

Smiatek (1995) said that, while the "true" classifier does not yet exist in the remote sensing world, visual classification of imagery could be very accurate, implying that manual interpretation provides the highest level of accuracy obtainable. Heller and Johnson (1979), Gilmer *et al.* (1980) and Smiatek (1995) used manually interpreted sample data as a source of "correction" for wall-to-wall land-cover information derived from semiautomated algorithms, again implying the high level of accuracy afforded by manual interpretation versus purely algorithm-based approaches. The manual interpretation of imagery and aerial photography is often used to validate results from semiautomated change procedures (Cohen *et al.*, 1998; Hayes and Sader, 2001). There simply is an underlying assumption that reference data of higher quality can be developed from the manual interpretation of aerial photographs (Dobson and Bright, 1994). Mas and Ramirez (1996) found that the visual classification of Landsat Thematic Mapper (TM) imagery resulted in accuracies 10 percent higher than any of the various digital (semiautomated) methodologies that were tested.

The human interpreter has many advantages over an algorithm-based approach when one examines the elements of imagery (as outlined below) that make land cover and land-cover change interpretable. The spectral properties (tone/color and brightness) of an image provide the principal form of information when interpreting imagery, and algorithm-based approaches can identify differences in tone with more consistency and accuracy than a human interpreter. However, the complexity involved in the integration of the other image elements restricts their use in most algorithm-based approaches. The human interpreter can incorporate information from all elements in a deductive image interpretation process unmatched by any computer algorithm. The human interpreter can also incorporate ancillary information at a conscious or subconscious level, and, unlike automated methods which also may use ancillary data sets, can "change the rules" regarding the use of such data as situations or contexts change. Subjective information, such as conversations with persons familiar with the area, observations made during field work, or experiences with other regions similar to the study area, may also be used in the decision-making process. Even intuition, a truly human reaction to a situation, may be used. Under certain circumstances, the mental processes of deduction and association may allow the analyst to identify features not actually visible on the imagery, such as buried pipelines or a camouflaged military airfield (Avery, 1977; Philipson, 1980). Inclusion of these factors in the interpretation process results in an incredibly high level of deductive processing.

The human eye and mind represent an extremely sophisticated remote sensing system, one that is not completely understood, and one that is nearly impossible to mimic with a computer-based algorithm (Estes *et al.*, 1983). However, although the manual interpretation of imagery remains the primary technique for providing "truth" information for accuracy assessment procedures, it is used much less frequently as the primary technique for deriving land-cover-change information. The inherent advantages of manual interpretation cannot be ignored, but neither can the disadvantages. Particularly when land-cover and land-cover-change analyses of large areas are being done, algorithm-based methodologies are now much more cost effective and less time-consuming than methodologies relying on intensive manual interpretation. Although this paper focuses largely on thematic land-cover conversion, we note that digital techniques are generally superior for detecting subtle, within-class changes (changes in condition), such as forest thinning or changes in vegetation condition.

Interpretation Elements

The various techniques for detecting change are simply tools that are used to detect and analyze changes in the basic elements of interpretation. The elements of interpretation are those characteristics of land cover and land use that are represented on remotely sensed imagery and allow for the detection and analysis of land-surface change (see Figure 1). Several sources have described the various characteristics of imagery that allow the interpretation of land use and land cover (e.g., Avery, 1977; Estes *et al.*, 1983). These characteristics are also the key variables that are used in the interpretation of change:

- Color/Tone—The relative responses among all spectral bands.
- Brightness—The intensity of the spectral response.
- Size—The area of a discrete surface feature.
- Shape—The geometric form of a surface feature.
- Shadow/Height—Shadow effects related to feature height and viewing angle.

- Texture—The roughness or smoothness of an image feature, created by tonal repetitions within that feature.
- Pattern—Arrangement and repetition of surface features.
- Site—Geographic location or setting of a surface feature.
- Association—Spatial relationship of different surface features.

The order of the elements listed above provides a rough hierarchy of the complexity of interpretation involved in their use. The higher-level elements often require the integration of information from the lower-level elements. Of the aforementioned characteristics, color/tone generally conveys more information to the interpreter than any other element (Estes *et al.*, 1983). Most algorithm-based approaches for change detection rely on the detection and/or interpretation of changes in color/tone (spectral response). However, critical information, especially information on the nature of land-surface change, can be obtained by the proper use of the other basic elements of image interpretation (see Estes *et al.* (1983) for an excellent discussion of the elements of image interpretation and the exploitation of each).

TABLE 1. BECAUSE ENVIRONMENTAL ISSUES ARE COMMONLY ASSOCIATED WITH LAND CHANGING FROM ONE GENERAL TYPE TO ANOTHER, THE U.S. LAND COVER TRENDS PROJECT MAPPING LEGEND CONSISTS OF 11 GENERAL LAND-COVER AND LAND-USE TYPES BASED ON THE U.S. GEOLOGICAL SURVEY SYSTEM (ANDERSON *ET AL.*, 1976). FOR A MORE COMPLETE LEGEND DESCRIPTION, SEE LOVELAND *ET AL.* (2002)

Thematic Classes
Water Bodies
Developed (Urban and Built Up)
Mechanically Disturbed
Non-mechanically Disturbed
Natural Barren
Mines and Quarries
Forests and Woodlands
Grassland/Shrubs
Agriculture
Wetlands
Snow and Ice

Characteristics of Change (With Examples from the U.S. Land Cover Trends Project)

The effective use of remote sensing as a tool for generating land-cover information is highly dependent on the measurable quality of this information (Congalton and Green, 1999). All too often, applications research in remote sensing has been driven neither by the practical information needs of a user nor by a basic investigation of the information content of an image (Ryerson, 1989). To better select a technique to analyze land-cover change from remotely sensed imagery, it is necessary to understand the characteristics of change itself.

The Land Cover Trends project, a U.S. Geological Survey (USGS), Environmental Protection Agency (EPA), and National Aeronautics and Space Administration (NASA) effort, is investigating methodologies to estimate the temporal and spatial characteristics of contemporary land-cover change in the United States (Loveland *et al.*, 2002). The national scope of this project offers many examples of the characteristics of change across diverse landscapes and provides an opportunity to illustrate how these characteristics have influenced the overall project design. Estimates of change are being compiled on an ecoregion basis (Omernik, 1987) using a geospatial sampling approach and Landsat imagery. Random sets of square sample sites, either 20 km or 10 km on a side, are selected for each ecoregion. Land-cover data are interpreted for five imagery dates from 1973 to 2000 using Landsat Multispectral Scanner (MSS), Landsat Thematic Mapper (TM), and Landsat Enhanced Thematic Mapper (ETM+) data. Land-cover-change statistics are derived from interpreted land-cover data (60-meter minimum mapping unit) for each date. A complete description of project methodology and results for several ecoregions is provided in Loveland *et al.* (2002).

The Land Cover Trends project provides estimates of land-cover conversion based on a thematic classification system (see Table 1) roughly analogous to the Level 1 classification outlined by Anderson *et al.* (1976). Estimates are not currently provided for within-class changes in condition (e.g., changes in forest greenness levels) or for any continuous landscape variable. Methodologies, data sources, and other key components of project design often are quite different between studies focusing on thematic changes and studies addressing changes in continuous variables. The characteristics of change described in this paper refer primarily to thematic land-cover change (full land-cover conversion), although many may hold true for within-class changes in condition. While the Land Cover Trends project is not yet complete, it has provided information on the characteristics of thematic land-cover and land-use conversion for a large part of the eastern United States. With the number and variety of ecoregions that have already been studied, an understanding of the following general characteristics of contemporary land-cover change has been reinforced. With each individual characteristic of land-surface change, we note potential effects on general project design and provide specific examples regarding effects on the Land Cover Trends project.

Change Is a (Relatively) Rare Event

Full land-cover conversion usually covers little ground relative to the total study area. The Land Cover Trends project examines change for 6- to 8-year intervals. The percentage of land that thematically changes during each interval is generally quite small (see table in upper-left of Plate 1), with a median change per interval of only 3.1 percent. Rates of change have so far been recorded at as little as 0.4 percent (for the 1973–1980 time period in the Blue Ridge Mountains ecoregion) and as high as 10.7 percent (for the 1992–2000 time period in the Southeastern Plains ecoregion). So, land-cover change nearly always covers a relatively small percentage of the overall study area.

The relative rarity of full land-cover and land-use conversion has important implications in the choice of methodologies. Consider that, for a single-date land-cover classification based on remotely sensed imagery, an overall accuracy of 85 percent is often considered to be a "successful" classification. Potential accuracy of a change product computed from two land-cover products is the product of the accuracies of the two individual products, or roughly 72 percent (for two products with an 85 percent accuracy level). For the Land Cover Trends Project, even in a very dynamic ecoregion such as the Southeastern Plains where overall change can surpass 10 percent per time interval, direct comparison of independently produced land-cover classifications with such accuracy levels will result in errors of commission exceeding the actual amount of change itself. Because of the relative rarity of change, high accuracies must be maintained to obtain confident estimates of real change, regardless of the choice of methodology.

In order to achieve the highest accuracies possible, the Land Cover Trends project opted for a manual interpretation process to identify and record land-surface changes. For a description of the interpretation process, see Loveland *et al.* (2002). Every change reported for a sample block is assured of being manually identified, delineated, and analyzed, virtually eliminating the large errors of commission that can result from algorithm-based approaches. Similarly, true thematic land-cover changes that exhibit only minor spectral change can be accurately identified with the manual interpretation

Table 2. Average Patch Size (Hectares) for Various Common Land-Cover Transitions, by Ecoregion

Ecoregion	Forest to Developed	Forest to Disturbed	Forest to Mining	Forest to Agriculture	Agriculture to Developed	Agriculture to Disturbed	Agriculture to Mining	Agriculture to Forest
Piedmont	3.5	16.6	5.5	2.9	4.8	4.3	6.6	2.8
North Central Appalachians	0.9	8.4	6.9	2.3	1.6	3.0	5.9	3.0
Middle Atlantic Coastal Plain	4.9	14.6	13.6	9.0	6.7	6.9	2.7	7.4
Northern Piedmont	2.7	10.4	3.5	1.7	5.1	6.1	5.1	2.4
Southeastern Plains	2.2	13.2	6.9	2.7	1.5	3.3	8.0	3.9
Blue Ridge Mountains	3.5	11.2	4.9	3.8	4.8	5.3	0.6	5.4
Overall Averages	3.0	12.4	6.9	3.7	4.1	4.8	4.8	4.1

process, reducing the chances for errors of omission that might occur with the use of algorithms based on spectral response.

Change Occurs Locally and in Small Patches

Land-use and land-cover change is generally a local event, with relatively small patches of contiguous land affected by complete land-cover conversion at any one time. Patch size can be a function of time, because longer intervals between image dates allow more opportunity for change to occur, along with the associated coalescence of individual changed patches into larger patches. Typically, however, individual, distinct land-cover conversions occur locally and over relatively small areas. Table 2 shows the average patch size for various land-cover transition types for six ecoregions from the Land Cover Trends project. Although certain land-cover transitions exhibit larger average patch sizes (such as forest to clear-cut and forest to mining), patch sizes of most land-cover transitions average around 4 hectares for the ecoregions in this study. With a minimum mapping unit of 60-meter pixels, that corresponds to an average patch size of approximately 11 pixels.

Relatively coarse-scale imagery, such as the Advanced Very High Resolution Radiometer (AVHRR) (1-km pixels) and the Moderate Resolution Imaging Spectroradiometer (MODIS) (250-m pixels), may have limited value for many land-cover change investigations focusing on thematic conversion. Although these sensors can be quite useful for analyzing changes in continuous land-surface variables (such as regional changes in "greenness"), the scale of thematic land-cover change is often much finer than the detectors can resolve. Detecting thematic change can be a challenge even with the higher resolution satellite sensors, such as TM (30-m pixels) and MSS (80-m pixels). As a result, the Land Cover Trends project relies heavily on historical high-resolution aerial photographs to aid in the interpretation of Landsat data.

Change Is Geographically Variable

The spatial distribution of change can have important implications for project design. There has been a tendency for many land-cover and land-cover-change studies to use political delineations as the defining boundaries for study areas or to stratify study areas (Turner, 1990; Vogelmann *et al.*, 1998; Sohl, 1999). However, the distribution and characteristics of land cover and land-cover change are not necessarily strongly correlated with political units. More meaningful stratification can often be obtained by defining strata that relate to environmental and anthropogenic characteristics that affect land cover and land use. This is especially true if a sampling approach is being used, as with the Land Cover Trends project. Precision of change estimates in a sampling framework is directly related to the spatial variability of change within the study unit. The Land Cover Trends project selected ecoregions as a spatial stratifier because they were derived from a synoptic assessment of climate, landform, geology, soils, vegetation, hydrology, and land-use characteristics (Omernik, 1995), the integration of which should be reflected by patterns in land cover and land-cover change. Empirical evidence indicates strong relationships between ecoregions and land-cover patterns (Loveland *et al.*, 2002), suggesting that use of ecoregions as a sampling framework should reduce variability among the sampling strata. This should result in more precise estimates of change than would be obtained using sampling strata such as states or other political units.

As Plate 1 shows, the frequency of change varies substantially among ecoregions. Similarly, the sectoral pattern of change can vary substantially among ecoregions, with some ecoregions showing cycles of timber harvest and forest regeneration as the primary transition type (Southeastern Plains and Middle Atlantic Coastal Plain), while others show urbanization (Pine Barrens or Northern Piedmont) or expansion of mining lands (Central Appalachians) as the primary transition type. Rates and types of change exhibit obvious spatial variability, even among adjacent ecoregions (note the Piedmont ecoregion as compared to the adjacent Blue Ridge Mountains ecoregion). Land-cover and land-use change has a geographic context, a context which changes from region to region and which strongly affects the form(s) of change that occur.

Geographic variability also has implications on the transport of a methodology from one study area to another. The difficulty in many algorithm-based, semiautomated approaches lies in the consistent use of multi-date imagery when the context is continuously changing. Even the detection of the same type of land-surface change may be enhanced or hindered based on the geographic context in which that change is found. Consider the detection of urban development in a largely forested environment versus an arid one. Simple Normalized Difference Vegetation Index (NDVI) differencing (Yuan and Elvidge, 1998; Sohl, 1999) may work very well to detect change where forest land is cut for a residential development, but would be quite useless to detect a new residential development created in a dry sandy location. Geographic context matters, and can strongly affect the utility and effectiveness of a given change-detection methodology. While the creation of a "generic" land-cover change-detection algorithm that works in a variety of settings would be highly desirable, it often simply isn't feasible.

Change Cycles Are Temporally Variable

As well as varying spatially, different forms of land-cover/land-use conversion occur at different temporal scales. The inset chart in Plate 1 shows how overall change for nine eastern ecoregions varies considerably over four time intervals, with a general increase in the rate of change over time for most ecoregions. Choice of temporal resolution is a key component of project design and can strongly affect results.

A key difficulty with the detection of land-surface change is the proper detection and reporting of cyclic change. Unidirectional land-cover transitions, such as the conversion of an agricultural field or patch of forest to a developed (urban) use, are less problematic, because the transition can occur at any

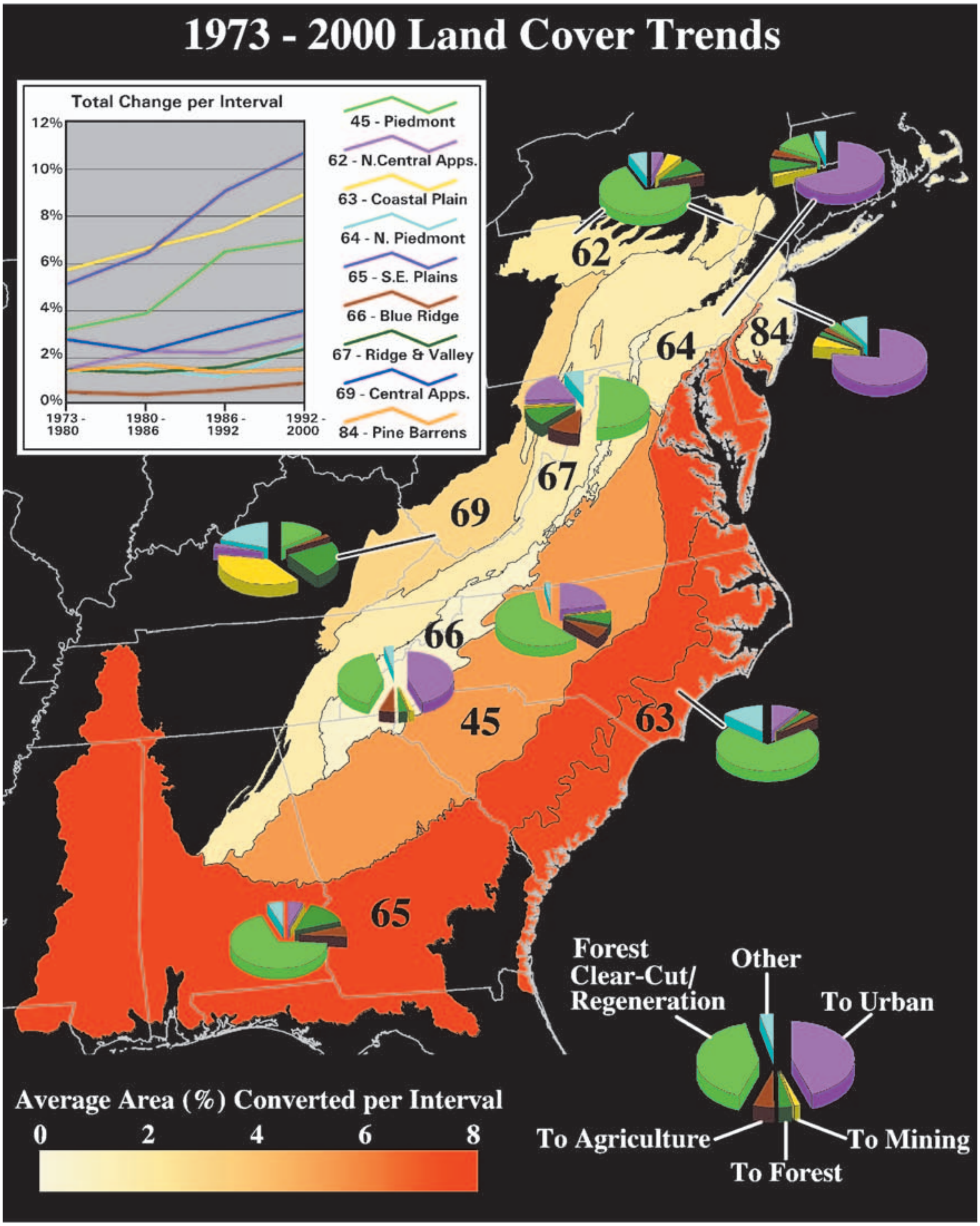
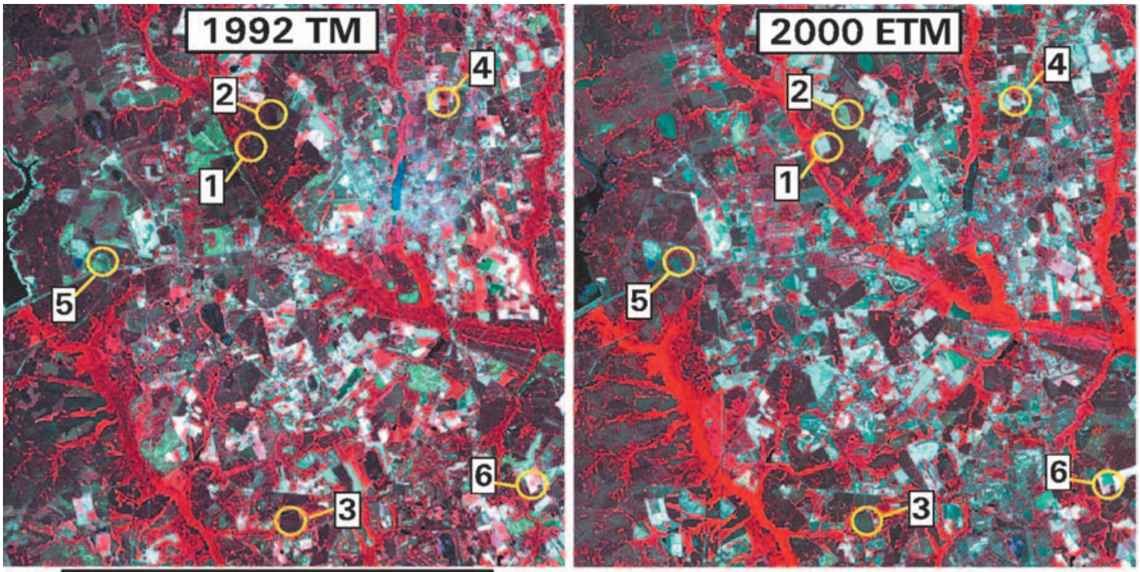
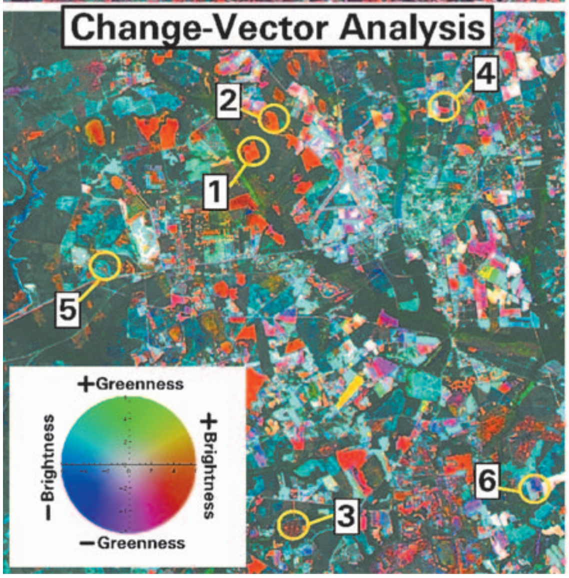


Plate 1. Characteristics of change for selected ecoregions in the eastern United States. Ecoregion shading, along with information in the inset graph, illustrates how overall change varies spatially and temporally. The exploded pie charts show how change varies sectorally among ecoregions.

point between target dates. However, cyclic changes, such as the timber-harvest/forest-regeneration cycle, may be undertabulated if target date extremes are too wide. For example, the managed slash pine and loblolly pine plantations in much of the Southeastern Plains ecoregion have optimum cutting and regeneration cycles as short as 21 years (Bailey, 1986). The potential to underestimate change certainly exists if target date extremes are longer than 20 years, but it also exists for intervals much shorter than 20 years because the rapid revegetation of cleared forest lands in the southeast often makes identification of cleared patches difficult just a few years following clearing (Figure 3). Conversely, the optimum cutting and regeneration cycle for forests of the Oregon Coast Range is 140 years (CRA, 2003), so longer change-detection intervals for harvest cycles may be selected for that region. While the selection of wide temporal intervals may result in an underestimation of cyclic change and may mask distinct trends, the selection of short temporal intervals could potentially result





	1992 Cover	2000 Cover	Change Magnitude (digital #)	Change Direction (degrees)
1	Conifer	Clear Cut	185	123
2	Conifer	Clear Cut	124	120
3	Conifer	Clear Cut	41	124
4	Green Field	Fallow Field	131	117
5	Clear Cut	Conifer Regrowth	108	306
6	Fallow Field	Green Field	100	300

NOTE: For a description of the change-vector analysis procedure used here and the derivation of magnitude and direction values, see Dwyer et al., 1997.

Plate 2. Change-vector analysis for 1992 and 2000 Landsat data for a 20-km sample block in the Southeastern Plains ecoregion. Changes are depicted both by magnitude and by direction in the brightness/greenness plane (see color wheel at lower left). Changes shown by the six points all represent modifications in land cover, not in land use (forest or agriculture). In complex landscapes such as this, similar land-cover transformations (conifer to clear-cut) can have vastly different spectral changes (see magnitude value, points 1, 2, and 3). Different types of land-cover transformations (forest or agricultural transformations above) can have very similar spectral changes in both direction and magnitude (see points 2 and 4, also points 5 and 6).

in an unnecessary and inefficient repetition of mapping effort. Consideration of the temporal characteristics of change is important when selecting temporal windows because the optimum window varies by transition type and region.

Change Is Spectrally Ambiguous

Landsat and Landsat-scale images have a very coarse spatial resolution compared to aerial photographs, the most widely used form of remotely sensed data before the introduction and widespread use of satellite imagery. As a result, of the elements commonly used to interpret imagery (color/tone, brightness, size, shape, shadow, texture, pattern, site, and association), only color and brightness are commonly used for most land-cover and land-cover-change mapping applications (Ryerson, 1989). For single-date land-cover mapping, the inherent assumption is that a direct correlation exists between a land-cover type and a unique spectral signature. It follows that, for change analyses, differences in spectral properties between dates imply a change in land cover and land use.

Although changes in spectral response between two dates of calibrated imagery generally do indicate some form of surface change, the transformation often is not a defined thematic conversion. Our desire to classify phenomena does not necessarily mean those phenomena can be sorted cleanly into categories. There are both conceptual and spectral reasons why this may be problematic. First, we are discretely partitioning a variable (land cover or land use) that is often better defined in terms of a continuum. Second, commonly used classification

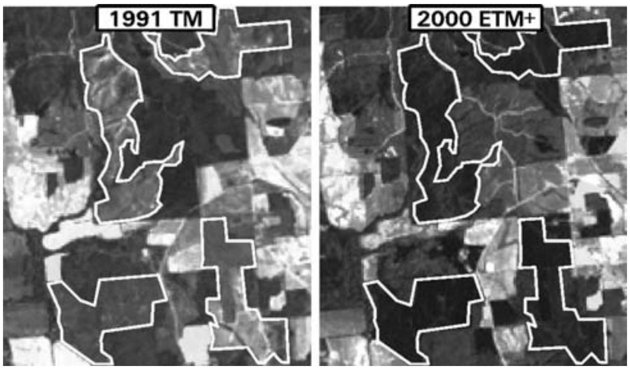


Figure 3. The four highlighted areas represent selected forest stands that were clear-cut prior to the 1991 TM date in a portion of the Southeastern Plains ecoregion. Note that, by the 2000 ETM+ date, cleared lands have revegetated and are virtually indistinguishable from other forest lands. Rapid revegetation of cleared forest lands in the Southeastern Plains and other ecoregions of the southeastern United States can result in an under-representation of the clear-cut/regeneration cycle if temporal endpoints of a change study are too wide. The Land Cover Trends project has chosen a temporal interval of 6 to 8 years to ensure adequate capture of such cyclic change.

systems are often hybrids of land-use and land-cover types. As a result, status as a recorded "change" may differ between classes, with only full land-*use* conversions designated as "change" for some classes, and subtler alterations in *cover* (or condition) being considered as "change" for others.

Consider the classification system used for the Land Cover Trends project (Table 1). All land *covers* associated with agriculture are classified under one thematic label that serves as a surrogate for land *use*, "agriculture." For example, fallow (bare) fields and planted fields both still meet the thematic criteria for "agriculture" or "cropland," yet as different cover types, their spectral responses are vastly different. For land *uses* associated with forests, two forms of potential land *cover*, "forest" (class 6) and "mechanically disturbed" (class 3, primarily clear-cut forest), are defined in the classification system. As the change vector analysis in Plate 2 shows, transformations from forest to clear-cut, a thematic change in the classification system, can be spectrally very similar to changes from a planted green field to a fallow field, a land-cover transformation not considered a thematic change in the classification system (because agriculture is classified by land use, rather than cover). A similar spectral relationship exists for the reverse case, clear-cuts regenerating to forest or fallow fields changing to planted fields. It is also often the case that true, thematically defined surface change has a very small or undetectable spectral change, as with the transition of barren agricultural fields to a low-density developed (urban) land use. The use of spectral information alone often cannot adequately distinguish between "change" and "no change" in many thematic classification systems. Even should a particular methodology correctly identify a changed patch of land, it is highly questionable whether the methodology could consistently and accurately provide information on the type of land-cover conversion that had occurred, given the similarity between different land-cover transformations on Plate 2.

Additional difficulties with using spectral data without supporting information are connected to image-related factors causing "false-positive" indications of change. Atmospheric effects are a source of difficulty for many change-analyses applications, because varying atmospheric conditions between dates will result in varying spectral signatures from even a completely unchanged land surface area. Similarly, factors such as changes in sun angles, Earth-Sun distances, and detector miscalibration can all result in spectral differences between image pairs. A prerequisite preprocessing step for many change-analysis techniques is thus to calibrate the images to a common radiometric reference using a variety of methods (Schott *et al.*, 1988; Caselles and Garcia, 1989; Hall *et al.*, 1991; Elvidge *et al.*, 1995). Such calibration techniques can compensate for several factors (at the cost of additional labor, cost, and time), but perhaps an even greater source of potential error lies with seasonal and climatological effects on spectral response. Most land-cover change applications strive to obtain "anniversary-date" imagery to minimize changes in spectral response due to seasonality issues. Unavailability of data because of cloud cover or other issues often makes this goal logistically unrealistic. Even if it were possible to consistently obtain perfect anniversary-date imagery, seasonal variation in weather patterns can still have a significant impact on spectral variation from year to year. The Land Cover Trends project avoids problems of image calibration by relying almost exclusively on manual interpretation. Although the project uses data from multiple sensors (MSS, TM, and ETM+), manual interpretation easily allows for the use of completely different sensors for temporal endpoints, something that would be extremely difficult to do with many algorithm-based approaches.

Implications for Project Design

Philipson (1986) stated that the widespread availability of microcomputers did not decrease the need for a human interpreter. The same can be said for change analysis studies conducted in the present day. When image interpreters require high levels of classification accuracy, such as for testing the accuracy of classification results, they rely on manual methods of interpretation. This is a particularly pertinent consideration for detecting thematic land-cover and land-use change, because results from the Land Cover Trends project have demonstrated that the characteristics of thematic change can make the use of algorithm-based approaches problematic. While manual interpretation may provide the greatest level of thematic classification accuracy, we recognize that it is also the most costly and time-consuming method. Algorithm-based approaches are generally more cost-effective and fast, but accuracy suffers, as can the ability to analyze types of change. For non-thematic classification variables, algorithm-based approaches may excel in detecting changes in land-cover condition.

Although each method may prove useful in different situations, the potential definitely exists to integrate both algorithm-based approaches and manual interpretation. For example, algorithm-based approaches excel at identifying areas of spectral change. Not all spectral change represents actual thematic change, but an algorithm-based approach can efficiently provide a "first-cut" change product that identifies areas of *potential* change. Manual interpretation can then be used to fine-tune the initial product. Gluch (2002) used such an approach to map urban growth near Salt Lake City. Sohl (1999) advocated the use of a hybrid approach, using a combination of simple image differencing and manual delineation of masks to map change in the United Arab Emirates. Woodcock *et al.* (2001) stated that a manual post-classification editing step is necessary for virtually all maps made with remotely sensed data, and they used such an approach for monitoring forest change in Oregon. Hybrid methodologies using both algorithm-based approaches and manual interpretation have the potential to improve the accuracy of many projects that previously relied solely on automated methods.

Based on the characteristics of land-surface change as revealed by the Trends project, we strongly recommend the use of manual interpretation to "clean up" change products created from algorithm-based approaches.

Regardless of project goals, the "best" approach for analyzing remotely sensed data should be determined within the context of the project goals, the available resources, and the available or acquirable data (Philipson, 1980). The Land Cover Trends project demonstrated that the context and characteristics of change vary by ecoregion. Consequently, there is no single methodology that can be automated and universally applied to all geographic regions or to all types of change analyses. Change is a moving target; the process of project design should begin with a proper appreciation of the characteristics of land-surface change within the context of the study, an understanding of the image elements that make land-surface change interpretable, and a familiarity with the tools through which land-surface change information can be extracted from imagery. For large-area studies, such as the Land Cover Trends project, geographic stratification prior to change analysis may significantly improve interpretation efficiencies and accuracies. Additionally, because various types of change occur with different temporal frequencies in different regions, selection of time intervals for change detection can affect perceived local dynamics. Those performing land-cover and land-use change studies should look beyond the software and algorithms currently residing on their computers and base project design (and choice of methodology) on project goals, geographic context, and the characteristics and interpretability of the targeted change variables.

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