Change Detection in Forest Ecosystems with Remote Sensing Digital Imagery

POL R. COPPIN*† and MARVIN E. BAUER**

** Dept. of Forestry & Natural Resources, Purdue Univ., West Lafayette, IN 47907, USA*
*** Dept. of Forest Resources, Univ. of Minnesota, St. Paul, MN 55108, USA*

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† Effective January 1996, P.R. Coppin will be at the Institute for Land and Water Management, K.U. Leuven, Vital Decosterstraat 102, 3000 Leuven, Belgium.

RUNNING TITLE
Digital Change Detection in Temperate Forests

CORRESPONDING AUTHOR:

Marvin E. Bauer
Department of Forest Resources
University of Minnesota
1530 N. Cleveland Avenue
St. Paul, MN 55108-6112

Phone: 612-624-3703
Fax: 612-625-5212
Email: mbauer@umn.edu

ABSTRACT

The world's forest ecosystems are in a state of permanent flux at a variety of spatial and temporal scales. Monitoring techniques based on multispectral satellite-acquired data have demonstrated potential as a means to detect, identify, and map changes in forest cover. This paper, which reviews the methods and the results of digital change detection primarily in temperate forest ecosystems, has two major components. First, the different perspectives from which the variability in the change event has been approached are summarized, and the appropriate choice of digital imagery acquisition dates and interval length for change detection are discussed. In the second part, preprocessing routines to establish a more direct linkage between digital remote sensing data and biophysical phenomena, and the actual change detection methods themselves are reviewed and critically assessed. A case study in temperate forests (north-central U.S.A.) then serves as an illustration of how the different change detection phases discussed in this paper can be integrated into an efficient and successful monitoring technique. Lastly, new developments in digital change detection such as the use of radar imagery and knowledge-based expert systems are highlighted.

KEY WORDS: Remote sensing, forest ecosystems, forest monitoring, digital change detection.

1. INTRODUCTION

The sustainability requirement of present-day forest ecosystem management necessitates resource data that are accurate and continuously updated. Until vertical aerial photos became available in the 1930's, forest managers were totally dependent upon resource information obtained on the ground. Aerial photography immediately proved to be a valuable asset, greatly facilitating the acquisition of much of the required knowledge. The launch of Landsat-1 in 1972 marked the beginning of satellite remote sensing for renewable resources applications. Because of their synoptic and repetitive data acquisition capabilities, satellite-based sensors hold the potential to detect, identify, and map canopy changes that are important to the forest ecosystem managers. Aldrich predicted in 1975 that "Even low-resolution data from the Landsat MSS scanner, if combined and enhanced, will disclose 80 to 90% of the exchanges of land use between forest and non-forest categories. In addition, such data will show 25 to 90% of the less distinct disturbances in the forest, depending on the category."

Digital change detection essentially comprises the quantification of temporal phenomena from multidate imagery that is most commonly acquired by satellite-based multispectral sensors. The scientific literature reveals, however, that digital change detection is a difficult task to perform. An interpreter analyzing large-scale aerial photography will almost always produce more accurate results with a higher degree of precision (Edwards, 1990). Nevertheless, visual change detection is difficult to replicate because different interpreters produce different results. Furthermore, visual detection incurs substantial data acquisition costs. Apart from offering consistent and repeatable procedures, digital methods can also more efficiently incorporate features from the infrared and microwave parts of the electromagnetic spectrum. This paper reviews the state-of-the-art of digital change detection in forest ecosystems, with emphasis on temperate forests. The paper extends that of Singh (1989) who provided the first comprehensive summary of methods and techniques of digital change detection.

Two fundamental assumptions that govern the use of digital sensors for change detection in forest ecosystems are:

1. Those phenomena that pertain to the realm of forest canopy dynamics and are of interest to the natural resource manager cause a change in electromagnetic radiation (EMR) values that can be remotely sensed. That change is large relative to EMR changes caused by differences in atmospheric conditions, illumination, and background conditions over the same time interval.

2. Any major variation over time in the remotely sensed EMR values for a particular forest ecosystem land parcel can be associated with an alteration in its reflective / emissive characteristics, which are a manifestation of biophysical properties of the surface.

2. CHANGE AND MULTIDATE IMAGERY

2.1. Change

Renewable natural resources such as forests are continuously changing, where change is defined as "an alteration in the surface components of the vegetation cover" (Milne, 1988) or as "a spectral/spatial movement of a vegetation entity over time" (Lund, 1983). The rate of change can be either dramatic and/or abrupt, as exemplified by large-scale tree logging; or subtle and/or gradual, such as growth of standing volume. Some forest cover modifications are human-induced, including deforestation for land-use conversion. Others have natural origins resulting from, for example, insect and disease epidemics.

Various classifications of change in forest ecosystems have been proposed. Aldrich (1975) approached the variability in forest cover from a thematic angle, enumerating nine general forest disturbance classes:

- no disturbance
- harvesting (areas subjected to timber removal operations)
- silvicultural treatments (e.g., thinning)
- land clearing (vegetation removal and site preparation)
- insect and disease damage (epidemic conditions)
- fire (prescribed burning and wildfire)
- flooding (man-caused and natural)
- regeneration (artificial or natural)
- other (not fitting any of the above categories).

A problem with this scheme is that the categories are not mutually exclusive. Colwell *et al.* (1980) suggested a more hierarchical framework (Table 1). Although this classification is mutually exclusive and totally exhaustive, it falls short by not providing a link between change event and causal agent. Finnish researchers (Hame, 1986) took a more mechanistic view and grouped the possible sources of temporal inconsistency in multidate imagery as shown in Table 2. Hobbs (1990) focused more on ecological aspects and differentiated between seasonal vegetation responses, interannual variability, and directional change. The latter may be caused by intrinsic vegetation processes (e.g., succession), land-use conversion, other human-induced changes (e.g., pollution stress), and alterations in global climate patterns (e.g., global warming).

Khorram *et al*. (1994) concentrated on the spatial environment in which the change occurs: "Some changes may affect entire areas uniformly and instantaneously, while others may take the form of slow advances or retreats of boundaries between classes, and still other changes may have very complex spatial textures." In the spatial context, they proposed four types of change whereby polygons either (1) become a different category, (2) expand, shrink, or alter shape, (3) shift position, or (4) fragment or coalesce.

The ability of any system to detect and monitor change in forest ecosystems depends not only on its capability to adequately deal with the initial static situation, but also on its capacity to account for variability at one scale, e.g., seasonal, while interpreting changes at another, e.g., directional (Hobbs, 1990). Moreover, detectability is a function of the "from" and "to" classes, the spatial extent, and the context of the change (Khorram *et al.*, 1994).

Not all detectable changes, however, are equally important to the resource manager. On the other hand, it is also probable that some changes of interest will not be captured very well, or at all, by any given system. Of particular interest to the forest ecosystem manager are the vegetation disturbances caused by short-term natural phenomena such as insect infestation and flooding, and changes resulting from human activities, e.g., resource exploitation and land clearing for development. While the former are likely to be temporary and in some cases self-correcting, evidence of the latter generally remains much longer.

Lund (1983) very appropriately stated that the forest manager's ability to successfully detect and identify change depends on four crucial factors:

1. The kind of information being sought and the prior knowledge of the anticipated alteration or movement (what do we want to know and how do the variables change over time?).
2. The stationary resource base against which change is sought (must reflect a permanence of information and be fully documented).
3. The selection of the method and the tools to detect and label, through repeated observations, the alteration or movement (involves timing and accuracy requirements).
4. The follow-up analysis to ensure that all other factors were indeed held constant.

The proper understanding of the nature of the change and the principles that enable its detection and categorization usually encompass more sophistication than the simple detection of the change event itself.

2.2. Imagery Acquisition

The appropriate selection of imagery acquisition dates is as crucial to the change detection method as is the choice of the sensor(s), change categories, and change detection algorithms. The problem has two dimensions: the calendar acquisition dates and the change interval length (temporal resolution).

Anniversary dates or anniversary windows (annual cycles or multiples thereof) are often used because they minimize discrepancies in reflectance caused by seasonal vegetation fluxes and sun angle differences. However, even at anniversary dates, or within anniversary windows, phenological disparities due to local precipitation and temperature variations present real problems. All else being equal, tree leaves reflect differently at the beginning and end of the growing season than in the middle. Their reflectance in the visible part of the EMR spectrum is higher in spring and autumn than in the middle of the growing season. Changes in the near infrared part of the spectrum are less distinct. The stage of change at a particular time in spring and autumn depends on the site, tree species and varying genotypes of the same species. Local seasonal effects are especially confusing during leaf-out and autumn coloration. Hame (1988) therefore concluded that for change detection, summer and winter are the best seasons because of their phenological stability. Selecting the summer, or the driest period of the year for the locale, will enhance spectral separability, yet minimize spectral similarity due to excessive surface wetness prevailing during other periods of the year (Burns & Joyce, 1981).

The optimal selection of the season for multitemporal forest cover change detection data acquisition remains a topic of contention in the pertinent literature. Moore & Bauer (1990) concluded that, for forest cover classification in North-Central Minnesota, imagery acquired in May was slightly superior to that acquired in September and significantly superior to summer scenes. Aldrich (1975), on the other hand, found that late spring and summer data considerably enhanced the discrimination of forest cover vegetation in Georgia. Jano & Pala (1984) stated that while the mapping of forest cutovers in pure or predominantly coniferous stands was optimal with early spring imagery, summer data did better for cutovers in deciduous stands.

Gregory *et al.* (1981) selected early fall imagery to detect openings in the forest canopy in Oklahoma because of the lower sun angle. Ekstrand (1989) cited the decreased influence in early fall of the larger part of the understory vegetation, ground surface, and lower tree foliage, on the spectral signature as the ultimate reason for deciding on September data acquisition for forest cover change detection in Sweden. Coppin & Bauer (1994) gave preference to mid-summer imagery at peak green for disturbance monitoring in northern Minnesota. Rather than searching for the optimal dates, Lambin and Strahler (1994b) approached change detection via the comparison of two (or more) time series of observations. They were looking at large-scale regional vegetation patterns in Africa, however, and the validity of the multitemporal concept (see 4.8) has not been specifically tested in forest ecosystem monitoring.

For most documented studies, the periodicity of the data acquisition seems to have been determined according to the availability of satellite data of acceptable quality. While visually analyzing Landsat-1 multispectral scanner (MSS) data for forest cover regeneration assessment, Aldrich (1975) concluded that a minimum time interval of three years was required to detect non-forest to forest changes. Colwell *et al.* (1980) judged a two-year separation between MSS scenes insufficient to reliably map revegetating areas in South Carolina. They advised a periodicity of at least five years. Gregory *et al.* (1981) reported that in southern Oklahoma three separate classes of clearcuts have been identified from processed Landsat MSS data: those created less than six years before image acquisition, those that date from six to 15 years before data capture, and those older than 15 years.

Park *et al.* (1983), again using Landsat MSS data, suggested a one-year interval to detect forest to non-forest (successional herbs, urban or agricultural development) changes, a three to five year interval to monitor non-forest to successional shrubs stage, and another five to ten years to detect the consecutive establishment of a forest cover. Coppin & Bauer (1995) tested two-, four-, and six-year intervals for canopy change detection and found that a two-year cycle was optimal to study aspen establishment and storm damage in the Great Lakes region with Landsat Thematic Mapper (TM) imagery. Their four- and six-year cycles performed best for human-induced and natural canopy disturbances such as thinning, cutting, and dieback.

3. DATA PREPROCESSING FOR CHANGE DETECTION

The primary challenge in deriving accurate forest cover change information is representative of the standard remote sensing problem: maximization of the signal-to-noise ratio. Inherent noise will affect the change detection capabilities of a system or even create unreal change phenomena. Causes of such unreal changes can be, for example, differences in atmospheric absorption and scattering due to variations in water vapor and aerosol concentrations of the atmosphere at disparate moments in time, temporal variations in the solar zenith and/or azimuth angles, and sensor calibration inconsistencies for separate images (Hame, 1988). Preprocessing of satellite images prior to actual change detection is essential and has as its unique goals the establishment of a more direct linkage between the data and biophysical phenomena, the removal of data acquisition errors and image noise, and the masking of contaminated and/or irrelevant scene fragments.

The requirements of multidate imagery when absolute comparisons between different dates are carried out is much more demanding than in the single-date case. Preprocessing commonly comprises a series of sequential operations, including calibration to radiance or at-satellite reflectance, atmospheric correction or normalization, image registration, geometric correction, and masking (e.g., for clouds, water, irrelevant features). Generally these procedures are followed by a data transformation to vegetation indices that are known to exhibit a strong positive relationship between upwelling radiance and vegetative cover. The principal advantages of vegetation indices over single-band radiometric responses are their ability to considerably reduce the data volume for processing and analysis, and their inherent capability to provide information not available in any single band. However, no single vegetation index can be expected to totally summarize the information in multidimensional spectral data space. Wallace & Campbell (1989) aptly indicated that adequate indices can be found for different purposes and that indices derived for one analysis may be inappropriate in another context.

Of the various aspects of preprocessing for change detection, there are two outstanding requirements: multidate image registration and radiometric calibration. It should be evident that accurate spatial registration of the multidate imagery is absolutely essential to digital change detection. In a study on the impact of misregistration on change detection simulations of MODIS data run with spatially degraded Landsat MSS images, Townshend *et al.* (1992) clearly demonstrated the need to achieve high values of registration accuracy if there is to be reliable monitoring of change. Their results showed that for spatial resolutions of 250 and 500 meters, errors of more than 50% of actual differences in the NDVI were caused by misregistration of one pixel. To achieve errors of only 10%, registration accuracies of 0.2 or less were required. However, change detection capabilities are intrinsically limited by the spatial resolution of the digital imagery. Further, residual misregistration at the below-pixel level commonly degrades the areal assessment of the change events somewhat, specifically at the change/no-change boundaries. This within-pixel shift is inherent to any digital change detection technique (Coppin & Bauer, 1994).

The second critical requirement for successful change detection is that a common radiometric response is required for quantitative analysis of multiple images acquired on different dates (Hall *et al.*, 1991). Duggin & Robinove (1990) strongly insist, we believe correctly, on the calibration of raw sensor data prior to any multitemporal analysis. Only through reliable radiometric calibration can a researcher be confident that observed spatial or temporal changes are real differences and not artifacts introduced by differences in the sensor calibration, atmosphere, and/or sun angle (Robinove, 1982). Hall *et al.* (1991) have developed a radiometric rectification technique that corrects or rectifies images from common scenes through use of sets of scene landscape elements whose reflectance is nearly constant over time. The technique provides a relative calibration and does not require sensor calibration or atmospheric turbidity data, although correction to absolute surface reflectance can accomplished if sensor calibration coefficients and an atmospheric correction algorithm (model) and atmospheric turbidity data are available. The technique resulted in data accurate to within 1% absolute reflectance in the visible and near infrared bands. Similar procedures have been used by Caselles & Garcia (1989), Conel (1990), and Coppin & Bauer (1994). Related calibration approaches which use atmospheric models for correction, but derive the atmospheric parameters from the satellite imagery include, Ahern *et al.* (1988), Chavez (1989), and Hill & Sturm (1991). All of these studies make it clear that only when all sources of variation but the surface cover can be adjusted for (absolute calibration) or normalized to a common standard (relative calibration) will it be possible to detect and identify changes in terrestrial vegetation from multidate imagery. With prior knowledge of the surface cover type, information from the change in reflective capacities of a surface between two dates can be related to increasing or decreasing amounts of vegetation cover (Milne, 1988).

The debate around the use of filtering as a preprocessing technique for change detection has not been settled. Riordan (1981) applied a modification of Nagao's and Matsuyama's edge-preserving image-smoothing algorithm to reduce minor variations in radiance values and to allow the comparison of relatively homogeneous groups of pixels. He judged the result ineffective. For tropical deforestation assessment, Singh (1989) tried both image smoothing and edge enhancements, but did not see any improvement in the final change detection accuracy with either method. Baraldi & Parmiggiani (1989), however, suggested the application of edge-preserving image-smoothing filters previous to image analysis in order to enhance the homogeneity of the spectral response of a thematic class and at the same time to eliminate noise effects.

Some researchers advocate the use of texture features for change detection. All consulted literature sources explicitly state, however, that texture information must only be used in conjunction with spectral data, and that both sources are complimentary to each other (e.g., He & Wang, 1990). Reed

(1988) cautioned the user community about the integration of texture measures in data analysis procedures. Classification accuracy is improved only under certain conditions. In his research, the addition of textural features, derived from a transformed vegetation index map of TM data, degraded the classification accuracy in distinguishing spectrally similar vegetation covers in all but one case. He conceded, however, that the choice of texture index (angular second moment and contrast) and window size (7x7 pixels) might have influenced the outcome significantly.

4. CHANGE DETECTION METHODS

All digital change detection is affected by spatial, spectral, temporal, and thematic constraints. The type of method implemented can profoundly affect the qualitative and quantitative estimates of the disturbance (Colwell & Weber, 1981). Even in the same environment, different approaches may yield different change maps. The selection of the appropriate method therefore takes on considerable significance. Most digital change detection methods are based on per-pixel classifiers and change information contained in the spectral-radiometric domain of the images. They combine both the procedures for change extraction (change detection algorithm) and those for change separation/labeling (change classification routine).

Change extraction and change separation / labeling are preliminaries to any change modeling. In other words, predicting with a statistical or ecological model using independent variables where, when, and/or why change occurs, requires prior detection, measurement, and categorization of land-cover change patterns. For example, Ludeke *et al.* (1990) have used logistic regression to model changes from forest to non-forest.

Statistical and/or spatial decision rules that are derived from a heuristic understanding of the change event often constitute the backbone of the separation/labeling exercise. These rules, however, are not change-detection-algorithm-specific; in other words, they can be applied irrespective of the algorithm that generated the change data. They comprise the complete range of pattern recognition procedures available to the image analyst, from edge enhancement and simple thresholding (visual or statistically-based), to supervised and unsupervised classification, to segmentation and spatial analysis rules. For example, Fung & LeDrew (1988) used thresholding in the form of a decision tree method, basing the spectral separability of their change classes on spectral plots for each indicator band. Hame (1988) substantiated the use of descriptive statistics to define and test change characteristics from the spectral modal values (highest frequency) of the change polygons, as derived from preparatory image segmentation and reference data. Other investigators have chosen linear discriminant analysis techniques to separate classes (Saraf and Cracknell, 1989).

A wide variety of digital change detection algorithms have been developed over the last two decades. They basically can be summarized in two broad categories to which different reviewers have attached definitions that vary in complexity and, to a certain extent, in coverage. Malila (1980) recognized the categories as change measurement (stratification) methods versus classification approaches. Pilon *et al.* (1987) amplified the description of the first category to "enhancement approaches involving mathematical combinations of multidate imagery which, when displayed as a composite image, show changes in unique colors". Singh (1989) changed the focus slightly by centering the definitions more on a temporal scale: simultaneous analysis of multitemporal data versus comparative analysis of independently produced classifications for different dates. Other scientists have employed multi-class schemes. In 1983, Nelson broadly characterized the change detection methods by detection algorithm and pattern recognition technique as used to delineate areas of significant alterations (Table 3). Milne (1988) grouped the algorithms under four broad headings based on the degree of complexity involved and the amount of computer processing required to derive the final product (Table 4).

Whatever combination of change detection algorithm and classification routine is applied, it is obvious that a wide assortment of alternatives exist and that all have varying degrees of flexibility and availability. As already stated, change classification routines are not specific to change detection. The overview that follows is therefore restricted to change detection algorithms only.

All change detection algorithms that have been found documented in the literature by early 1995 can be grouped into 11 distinctly different categories. The first seven are most frequently used for monitoring vegetative canopies, while the other algorithms are either less common or remain in an experimental stage. However, the order in which the algorithms are presented does not imply any ranking nor qualitative judgement. Moreover, because the algorithms are not necessarily independent of the data sources for which their implementation has been documented, examples typical for forest resources monitoring are given.

4.1. Monotemporal Change Delineation

In monotemporal change delineation, the pattern recognition routine itself functions as the change detection algorithm, encompassing all classification and enhancement methods developed for single-scene analysis. However, the technique relies heavily on strong assumptions about the initial state of the land cover. Generally these assumptions are based either on available historical records such as aerial photography and existing cartographic data, or on surrounding land parcels that are presumed to represent the state of the land cover before the disturbance.

Vogelmann & Rock (1988) successfully used sophisticated hybrid clustering routines on six-band TM data sets to map forest damage in Vermont. Lee (1988) utilized a particular type of Laplacian convolution filter on TM bands 3, 5 and 7 and on principal components 1 and 2, and was able to produce an edge detection feature that gave a clear one-pixel line surrounding the clear cut areas.

4.2. Delta Classification

Delta classification is also commonly referred to as "post-classification comparison". It involves independently produced spectral classification results from each end of the time interval of interest, followed by a pixel-by-pixel or segment-by-segment comparison to detect changes in cover type. By properly coding the classification results, a complete matrix of change is obtained, and change classes can be defined by the analyst.

The principal advantage of delta classification lies in the fact that the two dates of imagery are separately classified, thereby minimizing the problem of radiometric calibration between dates. By choosing the appropriate classification scheme, the method can also be made insensitive to a variety of types of transient changes in selected terrain features that are of no interest (Colwell *et al.*, 1980). However, the accuracy of the delta classification is totally dependent on the accuracy of the initial classifications. The final accuracy very closely resembles that resulting from the multiplication of the accuracies of each individual classification and may be considered intrinsically low. The difficulty thus lies in securing completely consistent, analogous and highly accurate target identifications for each iteration. Misclassification and misregistration errors that may be present in the original images are compounded and results obtained using delta classification are therefore frequently judged unsatisfactory (Howarth & Wickware, 1981). None of the delta classification applications described below indicated how the researchers handled the concept of multiplicative classification errors, nor did they incorporate a quantitative accuracy assessment against a standard reference data set.

Allum & Dreisinger (1986) individually mapped the land cover distribution near a mining complex in Ontario, Canada, into four categories: totally vegetated, partially vegetated, not vegetated, and water. A collapse of the delta classification change matrix computed for a ten-year interval from two MSS images produced three change classes: increase in vegetation, decrease in vegetation, and no change. They concluded that, for their purpose, delta classification provided a cost-effective method of monitoring major vegetation changes. Jakubauskas (1989) applied a very similar approach in a study of the impact of forest fire in the Huron National Forest in Michigan. An MSS scene from 1973, another from 1980, and a TM scene from 1982 were individually classified using an unsupervised classifier. Since all images were now reduced to categorical data, matrix operations within a geographical information system (GIS) environment easily allowed pixel-by-pixel analysis of land cover changes, and these changes were qualitatively related to the degree of burn severity developed from the Landsat data.

Xu & Young (1990) preceded their delta classification by a manual segmentation of the images according to ground features and characteristics of the scene. They then classified all segments separately for each date via a supervised maximum likelihood pattern recognition routine. They concluded that this approach, sometimes referred to as "prestratified delta classification", enabled them to avoid some obvious errors in classification (e.g., pixels classified as built-up areas on areas known to be moorlands in south-east Scotland).

A significant example of the use of the delta classification approach is the work of Hall *et al.* (1991b) in which Landsat images acquired in 1973 and 1983 were classified into five forest successional classes (clearings, regeneration, broadleaf, conifer and mixed). Application of a radiometric rectification technique (Hall *et al.*, 1991a) which corrected for between image differences in atmospheric effects and sensor calibration enabled classification of the 1973 image using 1983 ground data for classifier training. Following the two classifications a matrix of class changes over the 10-year interval was constructed and the transition rates between classes were calculated.

4.3. Multidimensional Temporal Feature Space Analysis

This change detection algorithm uses image overlay as a digital enhancement technique for on-screen change delineation. It comprises the one-step combination of a maximum of three individual bands (more steps are possible) which, when displayed as a composite image via the blue, green and red color guns of a cathode ray tube (CRT), portray changes in unique colors. The multidimensional temporal feature space analysis method seems to be most appropriate in natural environments where changes are relatively subtle. However, it provides the analyst with little information regarding the nature of the change (Pilon *et al.*, 1988). Its use is mostly restricted to the creation of binary change masks to eliminate no-change areas before further analysis with any of the other algorithms, or to the visual definition of training areas related to particular change phenomena.

Banner & Lynham (1981) obtained a better forest clear-cut identification and boundary delineation displaying MSS5 of time-1 via the blue CRT color gun and MSS5 of time-2 via the red color gun, than with multitemporal vegetation index differencing (see 4.5). Areas of change were highlighted in one of the two gun colors, while areas of no change appeared gray after adjustment of the color balance for the composite image. Hall *et al.* (1984) applied the same technique with MSS7 data, however, assigning the red color gun to the MSS7 of time-1 and the green one to the MSS7 of time-2. They were able to connect the variations in red hues to qualitative variations in aspen tree defoliation in Alberta, Canada. Areas without defoliation appeared yellow on the composite image. Rencz (1985), however, remarked that the fast vegetative regeneration in cutover areas precluded the use of any of the MSS reflective infrared bands for clear cut monitoring with this approach. Because of its relative insensitivity to this phenomenon, the use of red-band overlays was advised.

Werle *et al.* (1986) created composite multitemporal images to visually monitor clear cut and regeneration areas on Vancouver Island, Canada, assigning blue to TM3 for time-1, green to TM3 for time-2, and red to TM4 for time-2 on the CRT. In a multiseasonal assessment of regeneration cover in burned forest in Alberta, Canada, Kneppeck & Ahern (1989) applied another color combination: blue to TM4 for summer, green to TM4 for fall, and red to TM3 for summer. Alwashe & Bokhari (1993) merged TM bands 2, 4, and 5 of two different acquisition dates via an intensity-hue-saturation (IHS) transform to represent directly the bitemporal variations within one single image product. Vegetation differences showed up in distinctly different colors.

4.4. Composite Analysis

By using combined registered data sets, or corresponding subsets of bands, collected under similar conditions on nearly the same day of the year but from different years, classes where forest canopy change is occurring would be expected to have statistics significantly different from those where no change has occurred, and could be identified as such. The method can incorporate multistage decision logic and is sometimes referred to as "layered spectral / temporal change classification", "multidate clustering", or "spectral change pattern analysis". While this technique necessitates only a single classification, it is a very complex one, in part because of the added dimensionality of two dates of data. In numerous cases it requires many classes and many, often redundant features when no discriminant analysis has preceded the process. It furthermore demands prior knowledge of the logical inter-relationships of the classes and should only be used when the researcher is intimately familiar with the study area (Jensen, 1985). Burns & Joyce (1981) found the method to produce only change in forest cover *per se* without providing accurate information on the character of the change. Schowengerdt (1983) remarked that, since spectral and temporal features have equal status in the combined data set, they cannot be easily separated in the pattern recognition process. As a consequence, class labeling may be difficult. Researchers who have used this technique for forest change detection include, Colwell *et al.* (1980), Hall *et al.* (1984), and Sader (1988).

4.5. Image Differencing

Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments (Singh, 1989). It involves subtracting one date of imagery from a second date that has been precisely registered to the first. With "perfect" data, this would result in a data set in which positive and negative values represent areas of change and zero values represent no change.

Watanabe & Hatamura (1981) differenced MSS data to monitor felling and deforestation in Japan. They reported an accuracy of over 90%. Banner & Lynham (1981) used a multitemporal vegetation index difference based on calculated NDVI's for MSS data sets. They then density-sliced the difference vegetation index image. They found the method impractical for forest cutover delineation due to the sensitivity of the NDVI to grass growth and the development of other vegetation in the clear cuts, but useful for monitoring vegetative competition within the cutovers. Park *et al.* (1982) differenced MSS5 and MSS7 bands to monitor changes from forest to non-forest and non-forest to forest. Nelson (1983) delineated forest canopy changes due to Gypsy Moth defoliation in Pennsylvania more accurately with vegetation index differencing than with any other single band difference or band ratioing (see 4.6). Mukai *et al.* (1987) computed normalized difference channels for MSS5 and MSS6 to detect areas infested by Pine Bark Beetle in Japan. They were able to distinguish three classes of infestation with increasing band-5 and decreasing band-7 pixel values; light, moderate, and heavy.

Hame (1986) suggested histogram matching before differencing TM data so as to avoid situations where different image values cause identical differencing. In monitoring clear cuts over a one-year cycle, the TM3 difference channel, in combination with a feature describing estimated standing volume as derived from regressions of the spectral data on stand-based ground measurements, proved optimal. In a comparative analysis of the six reflective TM difference channels, Fung (1990) similarly found that the TM3 difference channel contained the highest information content for vegetative cover monitoring.

Jensen (1985) improved accuracy in urban change detection by additively incorporating a difference channel of a MSS5 derived second-order texture index as compared to simply thresholding the MSS5 difference channel. Coppin & Bauer (1994) suggested a standardization of the differencing algorithm (difference divided by the sum) to minimize the occurrence of identical change values depicting different change events.

4.6. Image Ratioing

Image ratioing is one of the simplest and quickest change detection methods. Data are ratioed on a pixel-by-pixel basis. A pixel that has not changed will yield a ratio value of one. Areas of change will have values either higher or lower than one.

To represent the range of the ratio function in a linear fashion and to encode the ratio values in a standard eight-bit code common to most PC-based image analysis software, a two-level (for values smaller than or greater than zero) normalizing function can be applied to all ratio values not equal to zero (Jensen, 1981). Because of the non-Gaussian bimodal distribution of ratioed multiple-date images, Riordan (1981) criticized the ratio change detection algorithm in combination with an empirical threshold definition as being statistically invalid. The areas delineated on either side of the distribution mode are not equal. Consequently the standard deviation cannot be used for threshold definition.

Howarth & Wickware (1981) combined MSS5 and MSS7 ratios in a single color composite. They found that, while the band-5 ratio emphasized changes in water level due to flooding, the band- 7 ratio assigned the brightest pixel values to areas where changes in vegetation cover were dominant. They were not able, however, to make a quantitative assessment of the changes.

4.7. Multitemporal Linear Data Transformation

Two linear data transformation techniques are frequently applied to multidate imagery that has been stacked in 2n-dimensional space (where n is the number of input bands per image): principal component analysis (PCA) and tasseled cap (Crist and Cicone, 1984). Multitemporal linear data transformations concentrate information pertaining to statistically minor modifications in the state of the forest canopy (minor as contrasted to the entirety of the image scene) in the lower components. Collins and Woodcock (1994) have recently developed a multitemporal generalization of the tasseled cap transformation. Application of the technique produced multitemporal analogs of the brightness, greenness, and wetness---the three primary dimensions of the tasseled cap transformation---and a component measuring change.

The exact nature of the principal components derived from multitemporal data sets is difficult to ascertain without a thorough examination of the eigen-structure of the data and a visual inspection of the combined images (eventually via multidimensional temporal feature space analysis, see 4.3). To avoid drawing faulty conclusions, the analysis should not be applied as a change detection method without a thorough understanding of the study area (Fung & LeDrew, 1987). The link between canopy change and tasseled cap transforms appears to be more solid, an observation supported by Collins and Woodcock (1994).

Richards (1984) applied PCA to two-date MSS imagery to monitor brushfire damage and vegetation regrowth over extensive areas in Australia. Provided the major portion of the variance in the multitemporal sequence was associated with correlated (constant, unchanged) land cover, areas of localized change were enhanced in some of the lower components, particularly principal components three and four. Ingebritsen & Lyon (1985) did exactly the same thing to detect and monitor vegetation changes around a large open-pit uranium mine in Washington and a wetland area in Nevada. Under the assumptions that the two original images both had an intrinsic dimensionality of two (first two principal components, rest primarily noise), that these dimensions were related to soil brightness and vegetation greenness, and that the change in land cover and/or vegetation condition exceeded some threshold value, four meaningful principal components resulted. They were stable brightness, stable greenness, change in brightness (somewhat analogous to an albedo difference signature), and change in greenness (somewhat similar to a near infrared / red ratio difference image). The latter component proved to be well-related to change in vegetative cover and insensitive to variations in slope and aspect.

According to Fung & LeDrew (1987), standardized PCA gave more accurate results because these PC's were found to be better aligned along the object of interest: change. Singh & Harrison (1985) concurred, citing a substantive improvement in signal-to-noise ratio and image enhancement by using standardized variables in the PCA. On the subject of subsetting the image to derive multitemporal PC's, the authors stated that, although even lower principal components can detect some land cover changes, the statistics extracted from data subsets are not recommended for change detection due to the great variability and uncertainty of the unextracted part of the data. They furthermore found the multitemporal PCA too scene-dependent and suffering from the serious drawback that no prior information was available regarding the nature of the components before actual processing.

Fung (1990) reported on a comparative analysis of a multidate standardized PCA and a multidate tasseled cap transformation of a multitemporal Landsat TM data set. The PCA rotation was based on the merged 12-band TM image. Three components were found associated with change: PC3 with changes in soil brightness, PC5 with changes in NIR reflectance and thus vegetative vigor, and PC6 with changes in the contrast between the middle infrared bands and the PAR (photosynthetically active radiation) bands, thus changes in wetness. The usefulness of these lower-order multidate PC's to highlight localized change was confirmed by Lee *et al.* (1989). They ran a principal factor analysis on the transformed image and found the lower-order PC's to contain significantly more unique variance. The tasseled cap transformation was carried out as follows: The spectral bands of the two dates were assigned the tasseled cap coefficients as derived by Crist & Cicone (1984) with positive coefficients for the first date and negative coefficients for the second. The derived vectors were not orthogonal and consequently were subjected to a Gram-Schmidt transformation. The process generated output vectors that were effectively orthogonal to each other. Three change tasseled cap images were produced detailing differences in greenness, brightness, and wetness. The greenness change image gave the highest classification accuracy among all resulting PCA and tasseled cap change-related images. Fung (1990) clearly advocated the use of the tasseled cap transformation. Under this algorithm, the inherent data structure could be clearly depicted and the derived variables were physically based and independent of scene content. Twelve TM input bands could moreover be reduced to two, maximum three, significant change bands. Collins & Woodcock (1994) similarly applied the Gramm-Schmidt orthogonalization process to map forest mortality, however, defining their own transformation coefficients.

While Hame (1988) concluded that the original TM bands accomplished more than the transformed features (bitemporal PC's or differences between paired PC's based on either the covariance matrix or the correlation matrix) to separate change classes in Finland, Coppin & Bauer (1994) found the second principal component of vegetation index band pairs to be an excellent indicator of change in the temperate forest cover in the north-central U.S.A. They reported, however, comparable results with the standardized differencing algorithm. Singh (1986) found simple image differencing more effective than multitemporal PCA for tropical deforestation monitoring.

4.8. Change Vector Analysis

The first automated change detection algorithm that took account of spatial scene characteristics was developed at the Environmental Research Institute of Michigan in the late seventies and is further identified as change vector analysis (CVA). It consolidates a tasseled cap transformation to greenness-brightness, an image segmentation to spatially contiguous pixel groups or "blobs", and a characterization of the movement of the individual segments in spectral space in terms of magnitude and direction (Malila, 1980).

Colwell *et al.* (1980) applied the algorithm in Kershaw County, South Carolina and found that, to be effective, it required precise image registration and normalization (changes in brightness needed to be scaled to be approximately equal to changes in greenness to avoid elliptical change thresholds) and a considerable amount of operator interaction. A forest mask had to be created, and parameters had to be set to control the formation of blobs and to threshold the change vectors for change, with respect to their magnitude (defining change from no change) as well as their direction (labeling the type of change). While the relative utility of the technique to assess the type of change was not clear, CVA performed well with respect to automated change indication.

Prior to computing change as a vector or distance in multispectral space, Yokota & Matsumoto (1988) applied a preliminary transformation to all raw digital numbers (new value = old value minus the average brightness over the six TM bands) to "accentuate" the disturbances. They then calculated a multiband Euclidean distance measure as the spectral differentiation norm. This measure was computed as the square root of the sum of the squares of the pixel value differences between the two dates over the six bands.

Lambin & Strahler (1994a) recently applied similar principles of segmentation and vector movement characterization to multitemporal vegetation indices, surface temperatures, and spatial texture data. Combined with principal component analysis of the change vectors, the technique proved to be effective in detecting and categorizing different land cover changes operating at different time scales in West Africa.

4.9. Image Regression

A mathematical model that best describes the fit between two multidate images of the same area can be developed through stepwise regression. The algorithm assumes that a pixel at time-2 is linearly related to the same pixel at time-1 in all bands of the EMR spectrum acquired by the sensor. This implies that the spectral properties of a large majority of the pixels have not changed significantly during the time interval (Vogelmann, 1988). The dimension of the residuals is an indicator of where change occurred. The regression technique accounts for differences in mean and variance between pixel values for different dates. Simultaneously, the adverse effects from divergences in atmospheric conditions and/or sun angles are reduced.

The critical part of the method is the definition of threshold values or limiting dimensions for the no-change pixel residuals. When Burns & Joyce (1981) applied the technique to each pair of spectral MSS bands for land cover change detection via a third-degree polynomial linear equation, they found the green band (MSS4) to perform better than the other band pairs, however, still with relatively low accuracy. Singh (1986), on the other hand, reported the highest change detection accuracy for tropical forest change detection with the regression method and the MSS5 band. A couple of years later (1989), he reviewed that statement and concluded that the regression method performed only marginally better than univariate image differencing techniques in detecting tropical forest cover changes.

4.10. Multitemporal Biomass Index

Rencz (1985) proposed a multitemporal biomass index for forest clear cut monitoring, using the ratio of an MSS7 and MSS5 difference at time-2 over an MSS7 and MSS5 sum at time-1. The results had a very limited usefulness; the error was concentrated in the omission of forest cutovers in which there remained a relatively large number of unfelled residual hardwoods.

4.11. Background Subtraction

In theory, no-change areas can be treated as having slowly varying background gray levels. These variations can be approximated by a background image, for example, a low-pass filtered variant of the original. A subtraction of such an approximation from the image potentially could be used to create a new data set that accentuates change phenomena. Singh (1986, 1989) used the technique in tropical deforestation monitoring with only modest results.

4.12. Comparison and Evaluation of Methods

The literature indicates that forest canopy changes can be detected by a variety of analysis methods. Although most methods provide generally positive results, few studies have compared and evaluated alternative approaches. Since Singh's 1989 paper, two recent studies have attempted to determine what change detection method is most appropriate. Using SPOT multispectral, multitemporal data, Muchoney and Haack (1994) compared four methods, merged PCA, image differencing, spectral-temporal (layered temporal) change classification, and post-classification change differencing, for identifying changes in hardwood defoliation by gypsy moth. Defoliation was most accurately detected by the image differencing and PCA approaches. Recently Collins and Woodcock (1996) have compared three linear change detection techniques, multitemporal Kauth-Thomas, PCA, and Gramm-Schmidt orthogonalization. Better / similar results were obtained with the multitemporal Kauth-Thomas and PCA methods than for the Gramm-Schmidt technique; however, the authors recommended the Kauth-Thomas approach because it identifies change in a more consistent and interpretable manner. These authors also examined to what extent the digital images should be preprocessed. Three levels of radiometric preprocessing, none, matched digital counts, and matched reflectances (full radiometric correction), were compared. Some form of radiometric correction was considered essential, but the intermediate level of radiometric calibration (matched digital counts) in which several invariant features were used to calibrate a regression equation to predict time-2 digital numbers from time-1 DN's was found to be as accurate and easier to apply than the full radiometric correction.

5. AN OPERATIONAL EXAMPLE

As an example of operational applicability of many of the concepts described above, we set out to design an optimized digital methodology for change detection in northern U.S. forest ecosystems. The pilot study was carried out within the framework of a NASA-sponsored project on the use of Landsat TM data for forest inventory (Bauer *et al*., 1994). It had as its principal goal the development of an objective technique that would provide a reliable first-level indication of forest canopy change for forest managers, with objectiveness allowing for automation and thus the application of the technique over large areas. While only a brief summary of the procedures and their outcome will be given here, details on both the digital image processing routines and the significance of the change detection results for forest ecosystem management can be found in two recently published papers (Coppin & Bauer, 1994, 1995).

Landsat TM imagery from three different years (1984, 1986, and 1990) were selected within a July-August anniversary window. The July-August window provided phenological stability (seasonal maturity), while the three selected years enabled an evaluation of the potential for mid-cycle inventory updating over two-, four-, and six-year periods. Preprocessing encompassed calibration to at-satellite reflectance, image registration and rectification to the UTM grid, atmospheric normalization and correction to at-ground reflectance, masking of the non-forest lands, and interpretability enhancement via vegetation index generation.

The intrinsic quality of the reference data (generated from 35mm CIR aerial photography) and the conditions imposed upon the change classification (classes mutually exclusive, totally exhaustive, hierarchical, and spatially and temporally consistent) made it necessary to group the canopy change events into four classes: net canopy loss, net canopy gain, storm damage, and no change. Digital change features were extracted from the bitemporal vegetation index pairs using both standardized differencing and selective multitemporal linear data transformation (PCA). Optimal features for classification were derived from statistical divergence measures. The five most prominent change features in descending order of occurrence were the standardized differences of brightness, second principal component of greenness, the second principal component of brightness, the second principal component of the green ratio, and standardized difference of greenness. Change maps were generated from a supervised classification procedure based on the maximum-likelihood decision rule.

Accuracy assessment was performed on an independent data set. At the pixel level, an overall thematic accuracy of 94% (Kappa coefficient of 0.82) was obtained for the six-year monitoring interval, 96% (Kappa of 0.83) for the four-year period, and 97% (Kappa of 0.76) for the two years. At the forest stand level and for the six-year interval, change (more than 90% of the pixels that make up the stand labeled as changed) was detected in 714 of the 759 stands that were reported in the reference data as having been affected by change events. Stand size was the limiting factor, because 43 of the 45 misclassified stands were smaller than one hectare. Although limited to spectrally-radiometrically defined change classes, results of this pilot study have demonstrated that the relationship between reflective TM data and forest canopy change is explicit enough, and the digital change detection methodology precise enough, to be of operational use in a forest cover change stratification phase prior to more detailed assessment. Parts of the research have been implemented in a statewide forest inventory system in Minnesota (Hahn *et al*., 1992).

6. NEW DEVELOPMENTS

The above review has concentrated on the development of data analysis algorithms and techniques for using satellite data, especially Landsat, for forest change detection. There are, however, a number of recent and expected advancements that will increase the accuracy and effectiveness of change detection with digital satellite data. Improvements in sensing systems, computer and image processing systems, ecosystem management models, and remote sensing algorithms and models can all be expected to improve the capability of satellite remote sensing for forest and ecosystem management (Hall, 1994).

In the latter half of the 1990's we will see the development and launch of an unprecedented number of satellite sensing systems. It now appears that by 2000 there will be 15-20 commercial and government satellites acquiring data at spatial resolutions of one to 30 meters. The Enhanced Thematic Mapper-plus (ETM+) being developed for launch on Landsat-7 in 1998 will have a 15-meter panchromatic band, a 60-meter thermal band, and a full-aperture calibration panel for improved absolute radiometric calibration. In addition, to these technical improvements, the 1992 Land Remote Sensing Act provides for distribution of the data at the cost of reproduction (expected to be \$400 to \$800 per scene). The ETM+ data will be supplemented by the availability from several U.S. commercial systems of panchromatic data at resolutions of one to five meters and multispectral data at resolutions of four to 15 meters. While these data will not provide the wide area coverage of Landsat or SPOT data, their high resolution is expected to generate widespread interest.

At the same time global data sets will be acquired by the Earth Observing System (EOS). In the context of change detection the Moderate Resolution Imaging Spectrometer (MODIS) with 36 spectral bands and spatial resolutions of 250 to 1,000 meters will be of particular interest. In addition to its daily global coverage, MODIS data may be used to atmospherically correct Landsat data (as well as MODIS data) for the effects of aerosols and atmospheric water vapor (Williams *et al*., 1994). The increased capability for radiometric calibration and atmospheric correction of Landsat and MODIS data should significantly increase the accuracy and effectiveness of change detection of forests and other ecosystems.

Digital change detection with multidate radar imagery has captured the attention of the research community only recently. While older studies were mostly restricted to airborne radar data sets (e.g., Cihlar *et al*., 1992; White, 1991), the availability since 1991-92 of multidate ERS-1 and JERS-1 synthetic aperture radar (SAR) imagery has made its use for change detection purposes much more feasible (Rignot & van Zyl, 1993; Villasenor *et al*., 1993). The potential for using multidate satellite-acquired SAR data for change detection will be further increased with the launch of the Canadian RARARSAT in late 1995.

Although geographic information systems (GIS) are not a new development, it is only in the past ten years that they have gained widespread acceptance as a practical tool for forest management. The incorporation of GIS technology in digital change detection methods enables the delivery of disturbance maps, derived from any descriptive change model, in a timely fashion at scales that are consistent with forest ecosystem management objectives. There has been growing interest in the integration of remote sensing and GIS; Dobson (1993) in describing a conceptual framework for integrating the two technologies cites 11 papers on the topic. Today, most image processing systems are integrated with, or at least compatible with, GIS systems, and classifications of remotely sensed data are commonly viewed as inputs to geographic information systems. At the same time increasing attention is being given to using GIS data layers as inputs to classification of remote sensing data. For example, Bolstad & Lillesand (1992), using an expert system linked to a GIS, used ancillary data layers of soils and topographic information to improve Landsat TM classifications of forest cover types. In spite of the inherent attractiveness of constructing temporal GIS's, Langran (199X) indicates that temporal GIS is largely still at the conceptual stage. Hall (1994) suggests that we will see further improvements in image analysis and display systems and integration of graphical user interfaces, data base management systems, and statistical analysis (including spatial statistics) and process modeling subroutines, along with GIS and image analysis functions. The components of such image analysis and display systems now exist, but they are not fully integrated.

Artificial intelligence or knowledge-based expert systems provide a way to integrate other features of vegetative cover categories besides spectral change information, thereby overcoming some of the limitations of the statistical classifiers. Such change category recognition methods make use of existing or prior knowledge of the scene content (e.g. original forest cover, location, size, relationship with other cover types, shape, etc.) to guide and assist the classification which follows spatial reasoning lines. As such, they parallel the interpretative procedures employed by a photointerpreter much more closely. The methods assume that there are similar and identifiable characteristics that each cover type possesses. Although artificial intelligence approaches to forest ecosystem change detection have remained in a preliminary conceptual stage of design (McRoberts *et al.*, 1991, and Mulder *et al.*, 1991), researchers developing forest and ecological models have incorporated inputs from remote sensing and GIS techniques to analyze spatial patterns and processes (Mladenoff & Host, 1994). Landscape and ecosystem simulation models and expert systems that utilize remote sensing and GIS inputs are being developed; examples include, LANDIS (Mladenoff *et al.*, 1994, and Land Use Change Analysis System [LUCAS] (Flamm and Turner, 1994). Land cover and change determined from remotely sensed imagery are integral components of such models.

In recent years the use of neural networks has gained considerable attention as an alternative to conventional approaches such as maximum likelihood classification (e.g., Benediktsson *et al.*, 1990; Bischof *et al.*, 1992). Most such studies cite increased classification accuracy as a primary reason for developing and applying this approach. One of the underlying advantages of neural networks is that prior knowledge or assumptions about the statistical distribution of the data are required. However, neural networks can also be computationally very complex and require a considerable number of training samples. Only one study (Gopal & Woodcock, 1995) was found in which an artificial neural network approach has been used for change detection and classification. The results showed that the technique produced higher classification accuracy than statistical classification of conifer mortality. While the authors concluded that it offers a viable alternative for change detection in remote sensing, it is not clear that the benefits of the higher accuracy outweigh the cost of the additional training data. The study also provided evidence that the same spectral signals and scene characteristics are being used by both the linear (e.g., Gamm-Schmidt orthogonalization) and neural network techniques, suggesting that it is the nonlinearities in the relationship between the spectral inputs and forest mortality patterns that accounts for the improved results using the neural network.

Lastly, we can look forward to the development of improved remote sensing image analysis algorithms and models (Hall, 1994). Recent initiatives in this area include land surface reflectance retrieval (Teillet, 1995) and atmospheric correction algorithms (Kaufman and Tanre, 1995), development of improved vegetation and soil indices (Huete *et al.*, 1994), and improved algorithms for estimation of land surface parameters (Hall *et al.*, 1995a). Ustin *et al.* (1993) describe an overall strategy for incorporating satellite-acquired imagery into ecological models, while Woodcock *et al.* (1994) and Hall *et al.* (1995b) describe methods for estimating forest biophysical structure from remotely sensed data. Woodcock *et a*l. combine the use of image segmentation to define stands with an invertible forest canopy reflectance model, while Hall *et al.* combine the use of mixture decomposition and geometric reflectance models. Signal processing techniques such as Fourier analysis have recently been used to examine frequency distributions of multitemporal AVHRR data (Andres *et al.*, 1994); the algorithm as applied to the Brazilian Amazon basin demonstrated clear capabilities in determining the seasonal and subseasonal variability of the forest cover. However, no references have been found yet on the applicability of the approach to the detection and measurement of "single event" changes.

7. CONCLUSIONS

The data-gathering capabilities of spaceborne remote sensors have generated great enthusiasm over the prospect of establishing remote sensing-based systems for the continuous monitoring of forests and other renewable natural resources. Although Aldrich's prediction in 1975 of the accuracy of satellite remote sensing for monitoring forest change was not quickly or easily achieved, today it is well established that remote sensing imagery, particularly digital data, can be used to monitor and map changes in forests and other land cover types. Recent results (e.g., Collins & Woodcock, 1994; Coppin and Bauer, 1995) have demonstrated that it is feasible to develop automated forest cover monitoring methodologies. When the inherent limitations of digital approaches are appropriately dealt with, preprocessing is adequately incorporated, and optimal change detection algorithms are selected, then Aldrich's prediction can be met.

Although all of the possible change detection methods have not been applied to the same data for evaluation, consideration of more than 75 change detection studies leads to the following conclusions:

1. Vegetation indices are more strongly related to changes in the scene than the responses of single bands.

2. Accurate registration of multidate imagery is a critical prerequisite of accurate change detection. However, residual misregistration at the below-pixel level somewhat degrades areal assessment of change events at the change/no-change boundaries.

3. Some form of image matching or radiometric calibration is recommended to eliminate exogenous differences, for example due to differing atmospheric conditions, between image acquisitions. The goal, aptly stated by Hall *et al.* (1991), should be that following image rectification all images should appear as if they were acquired with the same sensor, while observing through the atmospheric and illumination conditions of the reference image.

4. Image differencing and linear transformations appear to perform generally better than the other methods of change detection. Differences among the different change maps and their accuracies are undoubtedly related to the complexity and variability in the spatial patterns and spectral-radiometric responses of forest ecosystems, as well to the specific attributes of the methods used.

5. The capability of using remote sensing imagery for change detection will be enhanced by improvements in satellite data that will become available over the next several years, and by the integration of remote sensing and GIS techniques, along with the use of supporting methods such as expert systems and ecosystem simulation models .

Analysis of the literature provides ample evidence to support the conclusion that multidate satellite imagery can be effectively used to detect and monitor changes in forests, especially forest disturbance. At the same time we agree with the observation of Collins & Woodcock, (1996) that one of the challenges confronting the remote sensing research community is to develop an improved understanding of the change detection process on which to build an understanding of how to match applications and change detection methods.

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TABLE 1

Change detection classification system (Colwell et al., 1980)

<u>CHANGE</u>

- I. Forest Change
  - A. Loss of Vegetation
    - 1. complete
      - a. hardwood
      - b. conifer
      - c. hardwood/conifer mixture
    - 2. partial
  - B. Gain of Vegetation
    - 1. complete
      - a. hardwood
      - b. conifer
      - c. hardwood/conifer mixture
    - 2. partial
  - C. Undetermined change not associated with gain or loss of vegetation (e.g., phenology)

- II. Non-Forest Change
  - A. Loss of Vegetation
    - 1. complete
    - 2. partial
  - B. Gain of Vegetation
    - 1. complete
    - 2. partial
  - C. Undetermined change not associated with vegetation (e.g., bare to water)

<u>NO CHANGE</u>

Ignore in any further analysis -- not of interest

TABLE 2

Sources of inconsistency or change in multidate satellite imagery (Hame, 1986).

FIELD CHANGES
- I. Common
  - -seasonal
- II. Uncommon
  - Controlled
    - -cuttings
    - -treatments on regeneration areas
  - Uncontrolled
    - -damage
    - -deciduous shrubs growing

OTHER CHANGES
- I. Uniform areas possible
  - -sun angle differences
- II. Non uniform areas
  - -noise
  - -scattering
  - -striping
  - -rectification errors

TABLE 3

Digital change detection methods (Nelson, 1983).

Data Transformation Procedures	Analysis Techniques
Raw data	Standard deviation threshold
Difference	Supervised
Ratio	Spectral unsupervised
Vegetation index difference	Spectral/spatial unsupervised
Regression	Layered spectral/temporal
Principal components	
Change vector	
Post-classification	

TABLE 4

Classification of digital change detection techniques (Milne, 1988).

Complexity Groupings	Techniques
Linear Procedures	Difference images
	Ratioed images
Classification Routines	Post-classification change detection
	Spectral change pattern analysis
	Logical pattern change detection
	Layered spectral/temporal change detection
	Radiance vector shift
Transformed Data Sets	Albedo difference images
	Principal component analysis
	Vegetation indices
Others	Regression analysis
	Knowledge-based expert systems