Change Detection using NALC MSS Triplicates to Set Forest Planning Context

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Abstract.—The USDA Forest Service has purchased the North American Landscape Characterization (NALC) Landsat Multispectral Scanner (MSS) triplicates (70's, 80's, and 90's) for every national forest in the United States. To encourage analysis and use of these data for forest planning, a change-detection training course was developed. The course covers basic methods and options for developing change detection maps including visual, post-classification comparison, image algebra, principal components analysis, and unsupervised techniques. The broad spatial and spectral resolutions of the MSS data preclude use of these data for detailed tree species and forest habitat mapping. However, the broad synoptic nature of these data sets, available over a 25-year time period, provides a useful context within which more detailed analyses and management planning can take place.

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Many tools and techniques are available to detect and monitor changes in land-cover and vegetation patterns. These techniques include professional knowledge of the area, sampling techniques, aerial photo interpretation, and digital image processing of satellite or airborne imagery. Digital image processing of remotely sensed data offers the benefits of quantifying change in a format compatible with digital GIS layers. The basic premise in using remote sensing data for change detection is that changes in land cover must result in changes in radiance values, and radiance due to land-cover change must be large with respect to radiance changes caused by other factors (Ingram and Robinson 1981). For example, the change in reflectance resulting from a clearcut must be greater than the differences in atmospheric conditions to successfully detect and interpret the change.

Several methods detect change using remotely sensed imagery. At least nine change-detection algorithms are commonly used (Jensen 1996), including the following:

- change detection using write function memory insertion;
- multi-date composite image change detection (single classification or principal components analysis);
- image algebra change detection (band subtraction or band ratioing);
- post-classification comparison change detection;
- multi-date change detection using a binary mask applied to date 2;
- multi-date change detection using ancillary data source as date 1;
- manual on-screen digitization of change;
- spectral change vector analysis; and
- knowledge-based vision systems for detecting change.

These techniques should be researched carefully prior to implementation, to determine which techniques best fit the needs of the researcher. For example, change output data can be continuous or categorical, and some techniques can use only one band or index at a time while others allow the simultaneous processing of multi–band data sets.

NALC Data Sets –Historically Valuable

The North American Landscape Characterization (NALC) Triplicates are available for the entire United States and parts of Mexico and Canada. The triplicates consist of three coregistered Landsat Multispectral Scanner (MSS) scenes and a composite of 60-m Digital Elevation Models for the area covered by the MSS scenes. The images were processed by the Earth Resources Observation Systems (EROS) Data Center and contain information from each of the past three decades (1973, 1986, and 1991 plus or minus 1 year). These images provide quantitative data on surface reflectance responses useful for evaluating management practices, disturbance, and successional changes over a large area. The images are also a valuable reference for future studies because they serve as an objective record of past patterns.

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The spatial resolution of acquired MSS data are course at 79 by 58 m. The MSS scenes in the NALC triplicates were resampled at EROS to 60- x 60-m pixels to simplify area and distance calculations and maintain compatibility with other digital data sets (i.e., Thematic Mapper, USGS 30 DEM's). The MSS acquires data in four broad spectral bands over the green, red, and two near infrared portions of the spectrum (0.5-0.6, 0.6-0.7, 0.7-0.8, and 0.8-1.1μm, respectively). The spatial and spectral resolutions of the MSS data are sufficient for evaluating landscape-level vegetation, or land-use changes.

Change Detection Training Course

Many different change-detection algorithms and techniques have been implemented. Muchoney *et al.* (1994) used principal components analysis, unsupervised, image differencing, and post-classification comparison change-detection techniques to monitor forest defoliation. Lyon *et al.* (1998) used image differencing with several vegetation indices to monitor vegetation change. Several change-detection procedures were compared for monitoring eelgrass populations in Great Bay, NH (Macleod *et al.* 1998). Methods incorporated into the change detection training course developed for the USDA Forest Service are:

- change detection using write function memory insertion (WFMI);
- multi-date composite image change detection (single classification or principal components analysis (PCA));
- image algebra change detection (band subtraction or band ratioing);
- post classification comparison (PCC) change detection;
- manual on-screen digitization of change; and
- multi-date composite unsupervised classification incorporating a visual color model change enhancement (UVCM).

Other change-detection techniques exist (Jensen 1996) but were not included in the course.

Unsupervised Classification Incorporating a Visual Color Model

A multi-date composite unsupervised classification incorporating a visual color model change enhancement technique was developed and incorporated into the classification portion of the multi-date composite change-detection portion of the training course. This technique combines the visual change coloring advantages of the WFMI technique, as well as the from-to change categories of classification. UVCM has the additional advantage of providing a means of evaluating the number of classes used prior to labeling classes by comparing the color contrast in the image with the color contrast in the WFMI technique.

METHODS

The change-detection training course developed for the USDA Forest Service integrates techniques most commonly used within the literature. Two dates, July 1974 (fig. 1a) and July 1992 (fig.1c), in the three-date NALC imagery time-series were used for analysis and methodology demonstration. The July 1985 (fig. 1b) image was not used because of significant cloud cover and shadow over the study area.

The study area for the project was the North Fork of the Payette River Watershed, north of McCall, ID (NW corner: 116°07'30", 45°15'; SE corner 115°52'30", 45°15'). This area burned extensively in the summer of 1994. The NALC Triplicates provide a means of evaluating the changes prior to the fire, and a means of comparing the ecological succession on the ground with historical conditions.

Change Detection Using Write Function Memory Insertion

This is a visual technique for exploring change in a two- or three-date composite image data set. First, a band useful for characterizing change is selected. Second, this band is assigned a unique color gun (red, green, and blue) for each date. The images are then displayed on a graphics device. The image will appear as grayscale in areas of no change, and will appear colored where change is present. The order the dates are displayed in the color guns will affect the color output according to additive color theory. The NIR band 4 was selected because it reflects highly in areas of photosynthetically active vegetation. The NIR also has different reflectance/absorption characteristics depending on the moisture level, leaf structure, and leaf age of the vegetation. These characteristics are helpful when evaluating broad vegetation changes as well as when distinguishing vegetated from non-vegetated areas. Because two dates were used in our analysis, NIR band 4 of the July 1992 MSS image was displayed in the red and green color guns and NIR band 4 of the July 1974 image was displayed in the blue color gun. This band combination produces a display where areas with higher brightness values in 1992 appear as shades of yellow, and areas with higher brightness values in 1974 as blue. According to additive color theory, equal intensities of red and green produce yellow where blue values are low, and blue where the values of red and green remain low, constant, and equal.

The output image may be interpreted, compared with, and used to check other techniques for change consistency or misclassification of change areas.

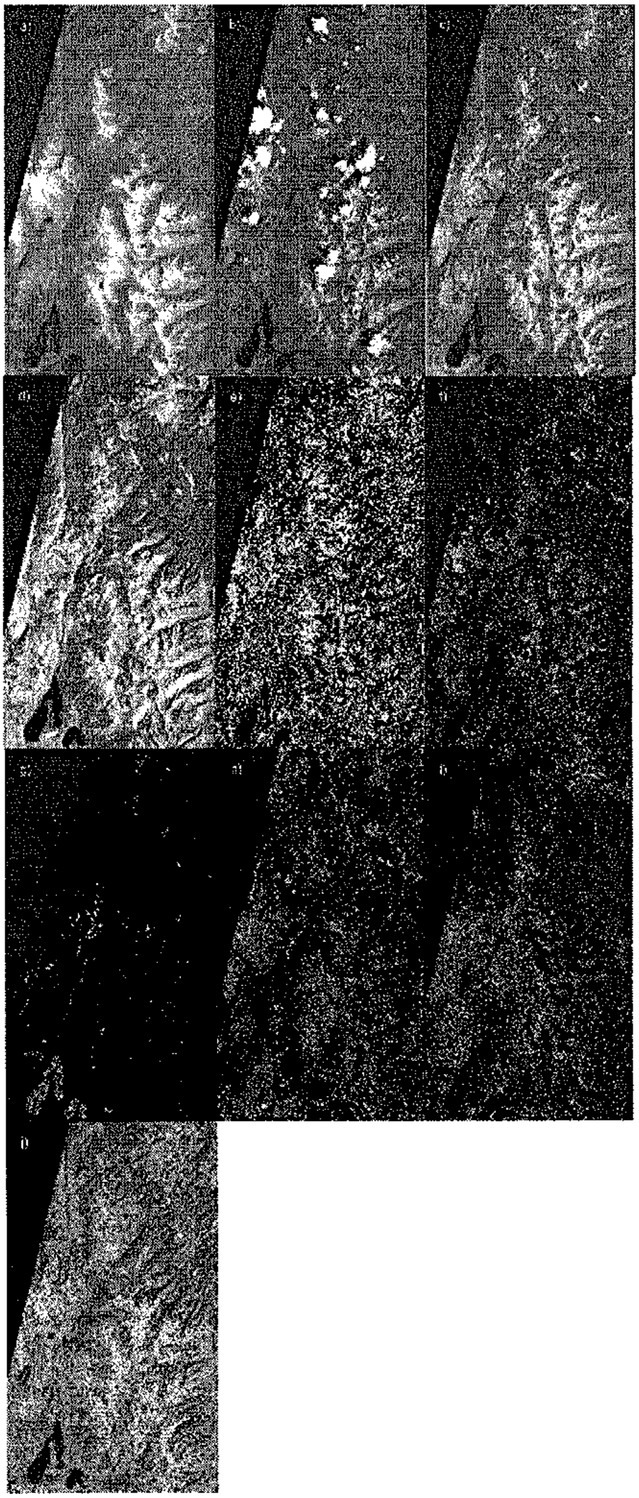

Figure 1.—*July 1974 MSS; b) July 1985 MSS; c) July 1992 MSS; d) Write Function Memory Insertion; e) Post Classification Comparison; f) Band 4 (NIR) Subtraction; g) Band 4 (NIR) Ratio; h) NDVI Subtraction; i) Principal Component analysis; j) Unsupervised Change Detection.*

Post-Classification Comparison

Post-classification comparison is the most commonly used quantitative method of change detection (Jensen 1996). This technique requires a separate classification for each date using the same or similar land-cover classification scheme (i.e., Anderson level II). Post-classification change detection is likely the most straight-forward change-detection process, but it also has the potential for being the least accurate (Macleod 1998). To limit the error in classification and provide consistency between classifications, a classification system based on the Anderson Land Use and Land Cover Classification (levels 1 and 2) System was developed (Anderson *et al.* 1976). The classes included were:

- herbaceous rangeland;
- shrub rangeland/deciduous forest;
- low density evergreen forest;
- medium density evergreen forest;
- high density evergreen forest;
- water;
- rock/mineral soil;
- shadow; and
- clouds.

Aerial photographs taken within a few years of the satellite imagery were used to help define homogeneous land-cover class areas suitable for training sites. Color 1:16,000 photographs taken in July 1976 were used for identifying and delineating training sites for the July 1974 MSS imagery. Color infrared 1:30,000 photographs taken in 1994 were used to define training site and ground truth data for the 1992 MSS imagery. These areas were located on the MSS data and compared with the photos to ensure the pattern was consistent with the photograph. Training sites were then delineated for use in classification.

Digital imagery training site samples for each information class (listed above) were compared (mean, range, standard deviation) and merged into individual spectral response functions. Merged training site histograms that did not approximate a unimodal distribution were discarded except in cases where land-cover types contained high variation. For example, the spectral responses of the rock/mineral soil class contained high variability likely due to differences in rock size, type, and topographic effects (i.e., slope, aspect, shading).

Supervised classification was performed using a parallel-epiped decision rule to presort the data into information classes. A maxim likelihood decision rule was then used to assign unclassified pixels and pixels in overlapping classes to a final class. After the classification was implemented, the modified Anderson information classes were assigned to the corresponding spectral clusters in the output image using the aerial photographs for cross-checking. Separate image clusters assigned to the same information class were then recoded into the same image class.

The resulting images were then combined using a matrix GIS operation. Matrix operations combine images on a pixel by pixel basis for comparison of changes. The matrix image contains from-to data important in evaluating change on both an individual pixel basis and in the broader image context. Significant changes of interest, such as conifer high density to shrub rangeland, conifer high density to conifer low density, and conifer medium density to herbaceous rangeland, were then assigned colors for visualization of these changes over the study area.

Image Algebra

Band subtraction and band ratioing are two common methods of image algebra change detection. In band subtraction, spatially registered images of time t_1 and t_2 are subtracted, pixel by pixel, to produce an image that represents the change between two dates (Singh 1989). The subtraction results in positive and negative values in areas of reflectance change and zero or near zero values in areas of no change (Jensen 1996). Band ratioing is the division of image brightness values in date 1 by the brightness values in date 2. The resulting image contains values near 1 in areas of no change and floating point values at change locations. In a ratio operation, values below 1 are compressed, so often two change images must be developed, each emphasizing a different tail in the image histogram.

To emphasize vegetation change, band 4 was used in both the subtraction and ratio techniques. In addition to band 4, a Normalized Difference Vegetation Index (NDVI = (Band 4 - Band 2) / (Band 4 + Band 2)) was used with the subtraction method. Divide-by-zero errors can occur with ratio operations in some software packages. To solve this problem, a pixel value of 1 was added to every pixel in both images before ratio calculation.

Image statistics were used to define change intensity levels. Pixels greater than one standard deviation from either side of the mean were assigned to a standard deviation level. For example, 1.0 to 2.0 standard deviations may serve as an interval. The standard deviation levels may then be assigned colors. A color ramp was used to assign a lighter shade of color to values closer to the mean and a darker shade to values farther from the mean. By applying the individual colors and brightness levels, quantifiable changes may be visualized for each tail of the image histogram.

Multi-date Composite

The multi-date composite change-detection methods demonstrated in the course included principal components analysis (PCA), unsupervised classification, and unsupervised classification incorporating a visual color model change enhancement. To perform these techniques, a multi-date image was first produced by adding all bands from date 1 to date 2 as additional layers. The resulting image contained the 1974 image bands in layers 1 through 4, and the bands from 1992 in layers 4 through 8.

Principal Components Analysis

PCA was performed on the two-date image using the Principal Components utility within *Erdas Imagine 8.3.1*. To interpret the components, a covariance matrix was calculated for each band within the multi-date data set. Standard deviations were also calculated for each band in the data set. The eigenvalues, eigenmatrix, covariance, and standard deviations were output to a spreadsheet to calculate the correlation between the original bands and the PCA components in the output image. The correlation matrix is used to determine if an individual component is related to a specific date band. The image can be interpreted visually by relating the bright pixels within the components to the statistics and photographs. The components were processed further through an Intensity, Hue, and Saturation (IHS) color slice. This separated the differing levels of brightness within the components and aided in exploration of definable changes.

Unsupervised Change Detection

The unsupervised change-detection procedure used an unsupervised classification on the multi-date composite image. If an appropriate number of classes are specified, the output image will capture change classes representing both change and no-change patterns. Because the input images would otherwise be similar, changes differentiate statistically (Weismiller *et al.* 1977). Three classifications with 20, 40, and 75 cluster classes were performed to evaluate the number of clusters needed to capture change in our study area. To ensure that most pixels were assigned to a spectral cluster, the convergence threshold was set to 98 percent and the number of iterations was set to run continuously until the threshold was achieved. Two additional columns, a 1974 class and a 1992 class, were added to the output image attribute file to provide a location for both 1974 and 1992 class names. Aerial photographs from both dates were used to identify land-cover types and assign information classes to the spectral clusters. The Anderson classification, as discussed above, was used as a guide, but additional information was added to account for variation in spectral clusters of similar land-cover classes. For example, conifer forest spectral clusters of equal stand density contained herb, brush, and mineral soil understories. The advantage of this technique is that only a single classification is required; unfortunately, it is often difficult to label the change classes (Jensen 1996). Experimentation with several classifications may be needed to determine the number of cluster classes needed to sufficiently capture change and class variation.

Unsupervised Classification Incorporating a Visual Color Model

A hybrid technique was used to capture the benefits of a categorical from-to structure and the visual change information immediately apparent from change detection using WFMI, and image algebra methods. The multi-date composite unsupervised classification incorporating a visual color model change enhancement technique is essentially the same as the unsupervised change-detection method except that a color model is used to initially color the output change classes by approximating the change coloring of the WFMI method. This was accomplished by using the "Approximate True Color" option in the Unsupervised Classification menu within *Erdas Imagine 8.3.1*. This option assigns an approximated color of a specific band combination to the spectral clusters in the classification. By applying the band combination used in the visual technique (Red = 1992 MSS band 4, Green = 1992 MSS band 4, and Blue = 1974 MSS band 4), change classes were colored in shades of gray, yellow, or blue. The output classified image was then compared to the WFMI technique. The number of spectral clusters used was evaluated by a visual comparison of the color contrast within the colored areas of the WFMI image. It was determined that 75 classes best captured the variation within the change areas.

RESULTS

Differences in the shape and distribution of the 1974 and 1992 image statistics suggested an overall difference between the two images. The July 1974 image contained maximum values much higher than the July 1992 image. Therefore, the mean and standard deviations of the 1974 data set were much different than the 1992 data. The maximum values within the 1974 image are found on the rocky mountain peaks throughout the area. There are two hypotheses to explain these high values. The first is that the peaks were covered with snow at the time of the 1974 imagery. The other is that highly reflective rock surfaces saturated the sensors onboard Landsat 1. If reflective surfaces were saturating the MSS sensor on Landsat 1, change in similar areas may be difficult to quantify. A review of weather data should help determine the cause.

Write Function Memory Insertion

The WFMI technique was very useful for initial identification of change areas and for comparison with changes identified by other techniques (fig. 1d). This method identified change verified by the photographs. It also helped in the identification of change that was not initially apparent in the photographs. Because the areas were highlighted, additional photo interpretation revealed forest thinning and tree mortality. A main advantage to the technique is that the contrast and purity of the colors in the band combination quantify a direction and magnitude of change. Potential limitations of this technique are that all analysis is visual; because the change image is just a band, combination change class information cannot be attached to the image, and change is quantified by reflectance differences in a single band. Changes in different wavelengths must be displayed independently. Although limitations to this technique exist, it is quick, simple to use, and can be implemented by most remote sensing and GIS software packages. It may be implemented as the first change technique applied in a change-detection study. Resource professionals can implement this technique with only basic knowledge of spectral biophysical properties of the land cover and additive color theory.

Post-Classification Comparison

Post classification comparison change detection was performed after a supervised classification of the two dates of imagery (fig. 1e). The information classes used in the classifications matched well when comparing the photographs to the output classified images. Most inconsistencies in the classified imagery were in regions of similar classes. Low- and high-spectral extremes of these classes are where misclassification is most likely to occur. These inconsistencies were greatly enhanced when the two images were combined in the matrix operation. Change between classes such as herbaceous rangeland and open forest, low-density forest and medium-density forest, or high-density forest and medium-density forest was less reliable due to insufficient data to resolve differences between the classes. However, distinct changes such as high-density forest to low-density forest, high-density forest to rangeland, or rangeland to water were very reliable when comparing the change to the photos. Post-classification comparison change detection requires the most time and the most expertise to achieve good classification accuracy. Macleod (1998) states, "the accuracy of the post-classification comparison change-detection technique may be poor because of combining the errors from both of the classifications." Classification errors are also not distributed equally throughout all classes. Change classes that attempt to quantify changes in similar from-to classes will have a much lower accuracy than classes that are more distinct. This classification technique is useful when broad, contextual change detection is desired, but may perform poorly when differentiating changes between similar classes.

Image Algebra

Image algebra change detection provides a rapid output change image. Band ratioing provided the simplest map of change (fig. 1g). This technique requires two separate ratios for each direction of change over the change time-series. The result is two separate images showing areas of increasing or decreasing digital number value changes. The output grayscale images distinctly highlighted major reflectance changes. The use of a standard deviation coloring scheme further enhanced interpretation of major changes. Minor reflectance differences are not as apparent as with band or index subtraction image algebra techniques.

Band Subtraction provided the best compromise between the detection of small reflectance differences and large reflectance differences (fig. 1f). Unlike band ratioing, subtraction images contain areas of both increasing and decreasing radiometric value change. This produces a gradational image that is initially difficult to interpret. After RGB color slices were applied to the standard deviation intervals, change was characterized by the gradations within the standard deviation classes and used to define change thresholds. A final output image may then display both direction and magnitude of radiometric change.

NDVI Subtraction did not perform as well as other methods. The output image showed a large amount of change area when compared with the other techniques (fig. 1h). The application of color slices to the standard deviation levels did little to improve the interpretation of the image. Major known changes appeared as low-level change. We suspect differences in sensor calibration for the different dates and the normalization for the NDVI calculation make it difficult to compare and compute change.

In all image algebra techniques, specific change classes cannot be attached to the image. For example, a cloud shadow to brush change could be represented by the same digital value difference as a dense forest to brush change. Attaching a specific context requires an additional classification of just the changed areas. This can be accomplished by using the thresholded image algebra output image as a mask to erase the unchanged area from the original imagery. The masked images could then be classified and combined in a matrix operation to define a from-to context.

Multi-date Composite

Principal Components Analysis

The differences in image statistics caused problems with the interpretation of the correlation between principal components and bands in the two-date image data set. Specific change was difficult to determine except in areas of significant change (fig. 1i). The outputs of the PCA change detection were difficult to interpret. Good ground truth data would greatly assist in interpretation of outputs.

Unsupervised Change Detection

Unsupervised change detection performed well once a sufficient number of classes were established. The simultaneous interpretation of spectral clusters using aerial photo interpretation for both dates may help limit some of the classification inconsistencies often found in the post-classification comparison technique. The classification accuracy may not be improved over PCC, but classification consistency between two separate classifications is not an issue when using the unsupervised technique. Unsupervised change detection on a multi-date composite image is classified by comparing the aerial photographs with several spectral cluster locations in the image. Post-classification comparison relies on an exclusive and finite number of training sites for classification. Several classifications were needed to determine a sufficient number of spectral clusters for this technique. The time required performing these separate classifications rivaled the time required for Post-classification comparison. The initial number of classes chosen for this technique should be set high to capture the variation in the imagery for each date. Seventy-five clusters were sufficient to detect change in our study area (fig. 1j). The number of classes required may increase with the number of spectral wavelengths represented in the data set and the extent and land-cover complexity of the study area.

Unsupervised Classification Incorporating a Visual Color Model

Multi-date composite unsupervised classification incorporating a visual color model change enhancement technique simplified the identification of change clusters. Evaluation time was greatly reduced over a normal unsupervised classification by comparing the immediate output from the classification algorithm with the WFMI technique (fig. 1d). Because evaluation of the number of classes is aided by the comparison of color contrast in the output image with the WFMI image, assigning information classes is not necessary in the initial class number evaluation. This contributes to substantial time savings over the traditional unsupervised change technique. The number of spectral clusters used in classification was considered acceptable when the color approximations in the classified image closely matched the colors in the visual change-detection technique. The coloring provided an initial change context of high to low and low to high radiance change. This context aided interpretation when assigning information classes to spectral classes in change areas and has the potential to reduce user error.

NALC Triplicates

The NALC triplicates were very successful in identifying human-caused and natural disturbance as well as climatic differences. Vegetation changes due to clearcuts, thinning, fire, insect mortality, and succession were all apparent in the output change images when compared with interpretation of the aerial photographs. Also apparent were water level and snow differences between dates. The specific nature of the change was not identifiable in the MSS imagery, but may be extracted through the use of additional GIS layers, professional knowledge of the area, and field interpretation. This was beyond the scope of our study, but could be a routine add-on for resource professionals working in an individual natural forests.

CONCLUSIONS

Many change-detection techniques exist, and the advantages and disadvantages of each should be considered before the selection of a specific method. Change detection using write function memory insertion was rapid and easy to use. It is useful as a first step because all other change techniques can be compared with this technique to see what kind of change is being detected (increasing or decreasing brightness value change) or where change may be misclassified. The main limitation is that the change detection is visual. Image algebra is also easy to implement but requires the definition of thresholds to identify real change. Many change images can be produced by image algebra using different bands, indices, and operators. The output images can be analyzed using image statistics, but categorical information classes cannot be attached to the image except when combined with a post-classification comparison or other ancillary data. Post-classification comparison is very useful when a from-to context is required. The individual images may be used in combination with GIS layers or future classified images to extract more change information. Drawbacks to this technique are the time involved in producing separate classifications, user error, and the potential to extract more information from the imagery than is spectrally available. Unsupervised classification may require extensive trial and error before an appropriate number of classes are selected. Unfortunately, information classes need to be attached to each trial to evaluate the change classification. Multi-date composite unsupervised classification incorporating a visual color model change enhancement technique provided the best compromise between an image classification and quick identification of change. The approximated color scheme used in the initial output image is very useful for determining a sufficient number of classes when compared to WFMI. The contextual coloring of change also allows for a faster, potentially more accurate classification of change.

The NALC triplicates can sufficiently define broad change. Interpretation of this change will require photo interpretation, ancillary data, and fieldwork data. The large temporal span of the NALC imagery may help the resource manager identify slow changes that are not easily perceived.

The initial choice of a change-detection algorithm should be based on the purpose of the change study and the limitations of the individual techniques. Successful change detection is also dependent on the data used and its limitations. Trying to extract more information from the imagery than the resolutions (spatial, spectral, and temporal) of the imagery may lead to poor accuracy as well as inappropriate change-detection results and interpretations.

LITERATURE CITED

Anderson J.R.; Hardy, E.E.; Roach, J.T.; Witmer, R.E. 1976. Land use land cover classification scheme for use with remote sensor data. Washington, DC: United States Government Printing Office.

Ingram, J.P.; Robinson, J.W. 1981. Change detection technique development for improved urbanized area delineation. Technical Mem. CSC/TM-81/6087. Silver Springs, MD: Computer Sciences Corporation.

Jensen, John R. 1996. Introductory digital image processing. 2nd ed. Upper Saddle River, NJ: Prentice Hall.

Lyon, J.G.; Yuan, D.; Elvidge, C.D. 1998. A change detection experiment using vegetation indices. Photogrametric Engineering and Remote Sensing. 64(2): 143.

Macleod, Robb; Russell, D.; Congalton, G. 1998. A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data. Photogrammetric Engineering and Remote Sensing. 64(3): 207-216.

Muchoney, Douglass; Barry, M.; Haack, N. Change detection for monitoring forest defoliation. Photogrammetric Engineering and Remote Sensing. 60(10): 2099-2119.

Singh, A. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing. 10(6): 989-1003.

Weismiller, R.A.; Kristof, S.J.; Scholz, D.K.; Anuta, P.E.; Momen, S.A. Change detection in coastal zone environments. Photogrametric Engineering and Remote Sensing. 43(12): 1533-1539.