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CHAPTER 6

Comparison of Methods for Detecting Conifer Forest Change with Thematic Mapper Imagery

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1.0 INTRODUCTION

Numerous methods have been applied to the problem of detecting forest cover changes with the aid of digital imagery. In their review of change detection methods, Coppin and Bauer (1996) recognize 11 distinct methods groups. Among these, some of the more commonly applied methods include image differencing, multitemporal linear data transformation, and composite analysis. In this chapter, these three methods are compared for detecting change in a conifer forest environment using Landsat Thematic Mapper imagery.

Image differencing involves simple image subtraction (Vogelmann, 1988; Price et al., 1992). For one image spectral band acquired at two separate dates over the same ground scene, image differencing explicitly captures the univariate magnitude of radiometric change. Similarly, the direction of change is captured as the sign (+ or –) of radiometric change. For multiple input spectral bands, difference images have a multivariate structure, with a calculated magnitude and direction for each temporal-pair of input bands. Malila (1980) describes a procedure whereby magnitude and direction are directly calculated in multivariate space. This procedure, known as change vector analysis (CVA), is an example of a multitemporal linear data transformation. Other examples are given by Fung and LeDrew (1987) and Collins and Woodcock (1994). In CVA, magnitude is computed as Euclidean distance and direction is computed as angle of change, with the former representing amount of land cover change, and the latter representing type. Composite analysis is little more than a classification procedure (e.g., unsupervised) applied to a layered, multitemporal image data set (Schowengerdt, 1983; Muchoney and Haack, 1994). Transformation of the original data into vegetation indices is common prior to composite analysis, but this is done for data reduction or to highlight certain vegetation cover features within the individual dates of imagery, not to highlight changes between the dates.

A perusal of the change detection literature supports Singh's (1989) claim that image differencing is likely the most widely used method, and in studies where image differencing has been compared with other methods, results generally indicate that image differencing exhibits superior performance (e.g., Singh, 1986; Muchoney and Haack, 1994; Coppin and Bauer, 1996). The ease with which images are subtracted from one another (or "differenced") and the inherent meaning such radiometric differences have in terms of cover change, both strongly contribute to the method's appeal and successful performance. Although CVA was introduced

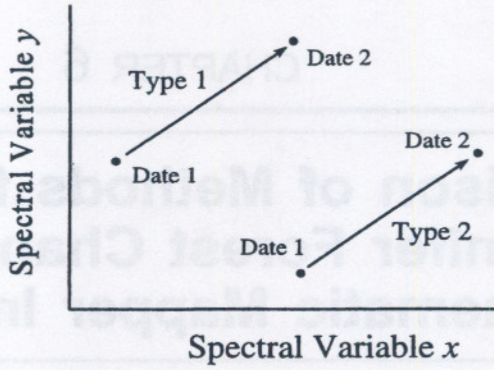

Figure 6.1. Two different types of land cover change with exactly the same amounts and directions of spectral change.

nearly two decades ago and has received little attention in the literature, it is likely to become the algorithm of choice for the land cover change product being developed for the MODIS sensor (Lambin and Strahler, 1994a). Because of this, CVA may be poised to become one of the most popular change detection algorithms over the next several years. Unlike image differencing and CVA, composite analysis might be considered undesirable because there is no distillation of original input bands into bands that explicitly characterize cover change.

One consideration in digital change detection that may be of major importance, but that has not received much attention, is the concept of a "reference image;" that is, a reference against which derived change information can be compared. This could be in the form of a land cover map at T_1 or T_2 in a two-date analysis, or a T_1 or T_2 spectral image that contains natural variations in reflectance of land cover categories. Composite analysis inherently involves reference imagery. In contrast, image differencing and CVA do not; that is, although they result in images that contain change information, all reference to original data are lost. This is a potential problem because two very different types of land cover change can have similar amounts and directions of spectral change, as illustrated in Figure 6.1. As such, there is likely under certain circumstances to be excessive confusion among cover change categories.

Recognizing the need for a reference image, Virag and Colwell (1987) used a land cover classification derived from the T_2 image as a reference for calculated change vectors. Collins and Woodcock (1996) extend the tasseled-cap transformation by defining a multitemporal tasseled-cap transformation (MKT) that has one stable, or reference output dimension, and one change output dimension for each input dimension. They then compared the MKT against Gramm-Schmidt orthogonalization in a study of forest mortality, and found that the MKT transformation gave superior results. Franklin et al. (1995) used discriminant function analysis to evaluate changes in forest cover due to insect defoliation. Discriminant function models based on a multidate, layered image data set (i.e., composite analysis) were 21 percent more accurate in predicting among three defoliation classes than were models based on image differencing. In the dense conifer forest condition of the region where this study was done, tasseled-cap wetness is very highly correlated with forest structure (Cohen and Spies, 1992; Cohen et al., 1995). For the first discriminant function of models based on composite analysis, 1988 wetness had a weighting of –1.50, with 1993 wetness having a relatively low weighting of –0.25. Tasseled-cap brightness and greenness were important contributors to this function only as temporal contrasts (–0.79 and 0.96 for 1988 and 1993 brightness, respectively; 0.46 and –0.44 for 1988 and 1993 greenness, respectively). This result suggests rather strongly that differences in multidate brightness and greenness were of great importance in distinguishing among defoliation classes, but only after natural variations in initial forest structure (prior to defoliation) were accounted for by a 1988 wetness reference image.

The purpose of this chapter is to initiate an exploration of the relative values of composite analysis, image differencing, and CVA for detecting changes in the dense forest environment of the Pacific Northwest region of the United States. This analysis involves a simple test of the three methods and includes some comparisons with and without a reference image, to determine its value in change detection. Descriptions of CVA in the literature do not appear adequate for fully understanding this potentially valuable change detection algorithm. Thus, prior to describing the test of methods, some theoretical considerations for change detection, with specific emphasis on CVA, are given. The description here is still inadequate, but we hope that it provides seed for additional insights by others.

2.0 THEORETICAL CONSIDERATIONS FOR CVA

Change vector analysis was developed for use with Landsat MSS data, in particular, for the two spectral dimensions of MSS data known as brightness and greenness (Kauth and Thomas, 1976). As described by Malila (1980), CVA is conceptually very simple (Figure 6.2). For a given image pixel, magnitude is calculated as the Euclidean distance between its location in brightness-greenness space on T_1 and its location on T_2:

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

where d=Euclidean distance, x_2 and y_2 are pixel brightness and greenness values for T_2, respectively, and x_1 and y_1 are pixel brightness and greenness values for T_1. The angle calculation requires establishment of a "baseline." Malila arbitrarily defined the baseline as parallel to the brightness axis (x), with its origin at the T_1 pixel vector and its terminus at the brightness value of T_2. The angle of spectral change is then measured relative to this baseline using standard trigonometric functions (e.g., sin, cos, or tan). In the resulting two-dimensional image, change is observed if the magnitude dimension exceeds a defined threshold.

The geometric concepts of CVA are applicable to any number of spectral bands, whether original scaled radiance, calibrated radiance, or transformed variables (e.g., reflectance, vegetation indices). Virag and Colwell (1987) present an analysis using three spectral dimensions, and they conceptually extend the procedure into n-dimensional space. For more than two spectral dimensions, they calculate magnitude of change as n-dimensional Euclidean distance:

$$d = \sqrt{\sum_{i=1}^{p} (DN_{2i} - DN_{1i})^2}$$

where i=spectral band number from 1.0 to p, DN_{2i}=pixel value at T_2 in band i, and DN_{1i}=pixel value at T_1 in band i. Rather than explicitly calculate the angular component of the change vector, however, Virag and Colwell approximate it using a multispectral positive and negative sector code accounting system. With this accounting system, 2^n sectors (directions) are possible: positive or negative spectral change in each of the n dimensions. This same sector coding

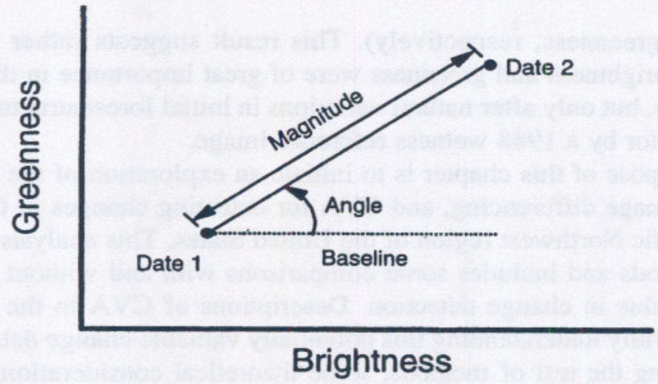

Figure 6.2. The concept of Change Vector Analysis in two spectral dimensions (adapted from Malila, 1980).

logic is used by Michalek et al. (1993) in their analysis of a coastal marine environment. Lambin and Strahler (1994b) use CVA with monthly composited AVHRR data. In their unique application of CVA, the 12 monthly NDVI observations of a given pixel for a given year constitute a 12-dimensional temporal vector for that pixel. Mathematically, the Lambin and Strahler (1994b) approach is exactly the same as that of Malila (1980) and Virag and Colwell (1987) for calculating change magnitude. Using two temporal NDVI vectors, one for T_1 and the other for T_2, magnitude of change between the dates is calculated as the Euclidean distance between the two 12-dimensional NDVI vectors. Lambin and Strahler (1994b) calculated neither the angle of change in any of the 12 dimensions, nor sector codes. Instead they chose to infer angularity from a principal components analysis on the 12 difference images derived from two-date NDVI data.

The approximations of directionality by Virag and Colwell (1987) and of Lambin and Strahler (1994b) are useful, but within the context of CVA there are other possibilities for more precisely describing the relative locations of two pixel vectors in n-dimensional space. One is to calculate more than a single angle. In the two-dimensional MSS tasseled-cap example of Malila (1980), magnitude and only one angle are required to precisely locate a T_2 pixel vector relative to a T_1 vector. This angle is measured in what Crist and Cicone (1984) refer to as the Plane of Vegetation (defined by the brightness and greenness axes). For the three primary dimensions of the Landsat TM tasseled-cap transformation, one also can measure an angle in the Plane of Soils (defined by the brightness and wetness axes), and in the Transition Zone (defined by the greenness and wetness axes). As each of these "views" of TM tasseled-cap data space contain different information about a ground scene, change vector angles measured within them should likewise contain different types of change information.

Another possibility is to explicitly define an angle of change relative to a new axis, or baseline k, as shown in Figure 6.3. This enables one to precisely define a T_2 pixel vector vis-a-vis a T_1 vector with two angles, ϕ and θ, and Euclidean distance magnitude d. The selection of x as the primary baseline is arbitrary, as use of y or z in combination with k would also precisely define the relative relationships of the two vectors. Furthermore, using ϕ and θ, d could be replaced by a distance measured along x, y, z, or k with no consequence.

Definition of a new baseline through original data space can be accomplished in more than one way. Figure 6.3 illustrates that one can define this baseline k within one of the existing planes, such as the Plane of Vegetation (x, y). An additional possibility is to define a baseline

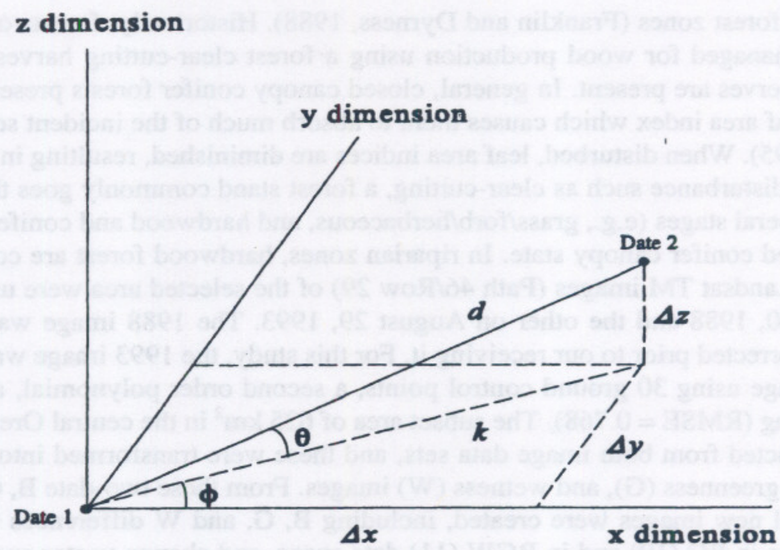

Figure 6.3. An example showing precise characterization of a change vector in three spectral dimensions. Required are establishment of a secondary baseline, *k*, in addition to the original baseline, *x*, and calculation of two angles, ϕ and θ, and distance *d*.

directly between a set of pixels that have changed, which (in Figure 6.3) is the same as defining the baseline along the distance *d*. A variant of this method is to use the Gramm-Schmidt orthogonalization procedure, as done by Collins and Woodcock (1994). In theory, a separate axis could be defined for each type of cover change of interest using this procedure. In such a case, one is less concerned about angles, as they are implicit in the baselines. Thus, the distances along these new baselines become the main source of change information.

3.0 PRELIMINARY TEST OF METHODS

To assist us in further understanding the relative values of composite analysis, image differencing, and CVA for detecting change in the dense conifer forest environment of the Pacific Northwest region of the United States, a simple test was conducted. This test had two specific objectives, the intent of which was to provide preliminary results that could be used to help design a more thorough and statistically rigorous study:

- Explore the relative values of composite analysis, image differencing, and CVA for detecting different degrees and types of forest disturbance and succession. These are compared in the context of both including and excluding a T_1 reference image.
- Determine the value of tasseled-cap wetness for forest cover change detection. Wetness has been valuable for forest cover mapping in the Pacific Northwest region (Cohen and Spies, 1992; Cohen et al., 1995), and recently, Collins and Woodcock (1996) found it to be the single most valuable indicator of forest change among several indicators tested in a different forest environment.

For this test, a 625 km^2 area in western Oregon near the H.J. Andrews Experimental Forest was selected. Many of the major conifer forest types of the central and northern Cascade Range are represented, including the western hemlock/Douglas-fir, Pacific silver fir, and mountain hemlock forest zones (Franklin and Dyrness, 1988). Historically, forests of this area have been largely managed for wood production using a forest clear-cutting harvest strategy, but some forest reserves are present. In general, closed canopy conifer forests present in the region have a high leaf area index which causes them to absorb much of the incident solar radiation (Cohen et al., 1995). When disturbed, leaf area indices are diminished, resulting in higher albedo. After a severe disturbance such as clear-cutting, a forest stand commonly goes through several intermediate seral stages (e.g., grass/forb/herbaceous, and hardwood and conifer brush) on its return to a closed conifer canopy state. In riparian zones, hardwood forest are common.

Two Landsat TM images (Path 46/Row 29) of the selected area were used: one acquired on August 30, 1988 and the other on August 29, 1993. The 1988 image was georeferenced and terrain corrected prior to our receiving it. For this study, the 1993 image was coregistered to the 1988 image using 30 ground control points, a second order polynomial, and nearest neighbor resampling (RMSE = 0.768). The subset area of 625 km^2 in the central Oregon Cascades Range was extracted from both image data sets, and these were transformed into tasseled-cap brightness (B), greenness (G), and wetness (W) images. From these two-date B, G, and W images (1-6) several new images were created, including B, G, and W differences (7-9), change vector magnitude in BG (10) and in BGW (11) data space, and change vector angles in BG, BW, and GW data space (12-14). To satisfy the two stated objectives, 10 combinations of the complete 14-image set were selected (Table 6.1). These were: (a) B and G differences and (b) B, G, and W differences; (c) BG change vector magnitude and angle; BGW magnitude with BG and BW angles (d), with BG and GW angles (e), with BW and GW angles (f), and with BG, BW, and GW angles (g); (h) d with 1988 reference B, G, and W images, (i) 1988 and 1993 B, G, and W images, and (j) 1988 and 1993 B and G images. The 1988 reference B, G, and W images were not combined with the B, G, and W difference images because mathematically, these comprise exactly the same data as the six original B, G, and W images (i), and would thus yield the exact same result as composite analysis.

The 10 selected band combinations were used to develop maps of forest cover change and then the results among the maps compared. For this comparison, two maps of forest cover developed from the two original TM images were used. The 1988 map was previously published (Cohen et al., 1995), and included three early-successional, mixed cover classes (open, semiclosed, and closed) and three closed-canopy conifer cover classes (young, mature, and old-growth). Subsequent to development of this map, a similar map was created from the 1993 data. The two maps were each formally assessed for errors and found to have accuracies in excess of 80 percent for the six forest cover classes. As an alternative to these two forest cover maps, the possibility of obtaining independent ground and airphoto reference data was considered, but given the preliminary nature of this study, the cost of obtaining forest change data for the specific time interval of interest was considered too costly.

To develop the forest cover change map for each band combination, a delta classification (Coppin and Bauer, 1996) developed from the 1988 and 1993 forest cover maps was used. This classification had 36 classes (the product of the number of classes in the two original maps), as shown in Table 6.2. Using the delta classification as a training set, each band combination to be tested was processed by a maximum likelihood supervised classification algorithm to develop a cover change map with 36 change classes. Then, the label of each cell of the delta classification was referenced to the label for each cell of the change map, resulting in a standard classification error matrix for each of the 10 change maps. We recognize that this had the effect of facilitating a positive accuracy bias, in that each map was nothing more than a simple reclassification of the training data. For this reason, these error matrices are referred to as "agreement" matrices. A potential source of "disagreement" in our test arises from the use of image data that

Table 6.1. Overall Percent Agreement for Different Numbers of Land Cover Change Classes and 10 Combinations (a-j) of Image Bands, Including Original (Reference) 1988 and 1993 Tasseled-Cap Brightness (B), Greenness (G), and Wetness (W) Images, and Those Derived from Change Vector Analysis (CVA) and Image Differencing. (Combinations below the dashed line include a reference image.)

Band Combination	3 Classes	7 Classes	36 Classes
Difference images			
(a) B,G	76.0	40.2	14.7
(b) B,G,W	76.4	48.7	19.1
Change vector analysis (CVA)			
(c) 2-dimensional (B,G) magnitude and angle BG	73.1	38.9	12.8
3-dimensional (B,G,W) magnitude and			
(d) angles BG and BW	71.6	45.8	15.2
(e) angles BG and GW	74.9	41.5	13.9
(f) angles BW and GW	72.9	45.6	14.2
(g) angles BG, BW, and GW	73.1	45.7	14.6
(h) d with 1988 reference B, G, and W	85.7	66.2	57.5
Composite Analysis			
(i) 1988 & 1993 B, G, and W	89.4	75.7	71.2
(j) 1988 & 1993 B and G	87.2	58.5	45.4

were not radiometrically normalized. But we do not consider this a great problem, as the ground scene was imaged through a clear atmosphere on both dates and the solar illumination angles were virtually identical between the two dates.

There was no formal characterization of errors in the delta classification, but it was assumed to be at least 60 percent accurate for the 36 classes, as each independent six-class map was at least 80 percent accurate and errors are expected to be multiplicative (Howarth and Wickware, 1981). Concerned that a delta classification with 36 classes was only minimally acceptable as a reference data source, the classification and agreement matrix process for each of the 10 band combinations was repeated with aggregated delta classification classes. The process was repeated once with a seven-class delta classification and once with a three-class delta classification (Table 6.2). Classes used for the seven-class strategy were: one no-change class (NC), three forest succession classes (i-iii), and three forest disturbance classes (iv-vi). For the three-class strategy, the classes were: no-change (NC), a single forest succession class (S), and a single forest disturbance class (D).

4.0 RESULTS AND DISCUSSION

The 10 band combinations used in this study can be compared using a summary of the agreement matrices for the 10 sets of change images created (Table 6.1). Not surprisingly, high levels of agreement were observed when only three classes of cover change were sought (no-change, succession, and disturbance), regardless of the band combination used (72–89 percent). However, those combinations excluding the 1988 reference brightness, greenness, and wetness image exhibited the poorest (72–76 percent), with all that included the 1988 reference image exhibiting the highest (86–89 percent), levels of agreement. All CVA combinations for which a reference image was excluded agreed slightly less with the delta classification than the combinations based solely on difference images (72–75 versus 76 percent). For all combina-

Table 6.2. The 1988 to 1993 Delta Classification Matrix. [Cell values are: original class number (1-36)—class label under grossest class aggregation (NC=no-change, S=succession, D=disturbance)—and class label for a more ecological significant class aggregation (NC, i-vi)].

1988 Vegetation Cover Class	1993 Vegetation Cover Class					
	Open	**Semi-Closed**	**Closed-Mix**	**Young Conifer**	**Mature Conifer**	**Old Conifer**
Open	1—NC—NC	2—S—i	3—S—i	4—S—ii	5—S—ii	6—S—ii
Semi-Closed	7—D—iv	8—NC—NC	9—S—i	10—S—ii	11—S—ii	12—S-ii
Closed-Mix	13—D—iv	14—D—iv	15—NC—NC	16—S—ii	17—S—ii	18—S—ii
Young Conifer	19—D—v	20—D—v	21—D—v	22—NC—NC	23—S—iii	24—S-iii
Mature Conifer	25—D—v	26—D—v	27—D—v	28—D—vi	29—NC—NC	30—S—iii
Old Conifer	31—D—v	32—D—v	33—D—v	34—D—vi	35—D—vi	36—NC—NC

tions, when three change classes were sought, the use of wetness in addition to brightness and greenness did not significantly increase agreement.

For seven change classes, overall agreements were below 50 percent for all combinations which excluded the use of a 1988 reference image. Of these seven combinations, those based only on brightness and greenness agreed least (39 and 40 percent). For the remaining five of these seven combinations in which wetness was included, image differencing agreed most (49 percent), with CVA combination agreeing between 42 and 46 percent. Use of the 1988 reference image to characterize seven forest change classes had a large impact on the level of agreement for CVA. The three-dimensional CVA based on the brightness-greenness and brightness-wetness angles resulted in 20 percent higher agreement when the 1988 reference image was used than when it was not (66 versus 46 percent). Using the six original bands (composite analysis), equivalent to using the difference images in combination with the 1988 reference image, resulted in a 27 percent higher agreement (49 versus 76 percent) relative to the three-dimensional image differencing combination. Unlike three change classes, when seven classes were sought, the composite analysis combination excluding wetness resulted in a significant decrease in agreement compared to the combination that included wetness (76 to 59 percent).

The greatest contrast among the 10 combinations occurred when evaluating the full suite of 36 change classes. For this number of cover change classes, both the relative and complementary values of a reference image, difference images over CVA images, and of wetness in addition to brightness and greenness is most apparent. All combinations that excluded the use of a reference image, exhibited less than 20 percent agreement. Use of the reference image increased agreement of CVA from 15 to 58 percent. For composite analysis, equivalent to image differencing with the use of a 1988 reference image, agreement increased from 19 to 71 percent. For the composite analysis combination excluding wetness, agreement was only 45 percent, compared to 71 percent when wetness was included. When no reference image was used, CVA had a slightly lower level of agreement than did image differencing.

Given that the use of a reference image in combination with CVA (h) resulted in a significantly greater level of agreement than did CVA without a reference image (d-g), it now becomes important to more closely compare the combination of CVA and a reference image (h) with composite analysis (i). As part of this further comparison it is important to better evaluate the value of wetness in composite analysis (i versus j) for change detection in a forest system. As such, these three band combinations are summarized in Table 6.3 by change class, for the seven-class example. In this comparison, CVA had higher agreement for all three succession classes than for the no-change and disturbance classes, with the highest agreement for Class ii (the progression from early-successional nonconifer forest to conifer forest). For this class, CVA had a slightly higher agreement (89 percent) than did composite analysis (86 percent). For composite analysis, the highest agreement, 89 percent, was for Class v (conifer forest changed to early-successional forest; i.e., forest clear-cut). This is in contrast to the relatively poor agreement of CVA for clear-cut mapping (68 percent). For all disturbance classes (iv-vi), composite analysis had about 20 percent greater agreement than did CVA, whereas for succession classes the differences in levels of agreement were significantly less pronounced and inconsistent. For the no-change class, composite analysis had about 10 percent higher agreement than CVA when a reference image was included, but for both, it was one of the more difficult classes.

The value of wetness was highly variable among cover change classes (Table 6.3). Although there was some value to the use of wetness for detecting changes associated with the nonconifer forests classes (i, ii, iv, and v), the primary importance of wetness was for detecting changes

Table 6.3. Percent Agreement for Each of Seven Vegetation Cover Change Classes for Three of the Band Combination Evaluated (h-j, Table 6.1). [Class i=succession within the nonconifer forest; Class ii=succession from nonconifer to conifer; Class iii=succession within the conifer forest; Class iv=disturbance within the nonconifer forest; Class v=disturbance from conifer to nonconifer forest; and Class vi=disturbance within the conifer forest (see Table 6.2)].

Class Label	CVA (3-Dimensional Magnitude, BG & BW Angles) with 1988 Reference Images (B,G,W)	Composite Analysis (B,G,W)	Composite Analysis (B,G)
Succession			
i	74.6	79.5	79.5
ii	88.9	86.1	82.1
iii	78.6	85.7	49.8
No-Change	60.5	69.9	54.5
Disturbance			
iv	42.3	63.1	52.5
v	68.4	89.3	80.6
vi	60.1	79.5	35.5

within the closed canopy conifer forest (Classes iii and vi). For composite analysis, there was a 36 percent difference in levels of agreement for succession within the conifer class (iii), depending on whether wetness was included or excluded. For disturbance within the conifer class (vi), the difference in agreement was 44 percent. This observation is consistent with Collins and Woodcock (1996), who found that in their study, wetness was the single most important indicator of conifer forest change.

5.0 CONCLUSIONS

Numerous methods exist for change detection using digital image data. In this study, three methods for detecting changes in a conifer forest environment with Landsat TM data were evaluated: image differencing, change vector analysis (CVA), and composite analysis. As commonly used, all three methods have several procedures in common. Needed are decisions concerning which original input bands to use (e.g., DN, radiance reflectance, vegetation indices), what type of classification algorithm to apply (e.g., supervised, neural-net), and a strategy for error assessment. Where they differ is in how the input bands are used prior to classification. Image differencing and CVA involve transformation of input bands into temporal change vectors, with the former being a band-by-band temporal subtraction, and the latter requiring derivation of spectral change magnitude and angle. Composite analysis uses the input bands directly in classification.

Although difference images and CVA magnitude and angle images represent direct characterizations of spectral change over time, they contain no reference to location within the original input data space. In contrast, because composite analysis uses input bands directly, they do contain this reference information. As such, natural variability in original and final (i.e., T_1 and T_2, respectively) land cover classes is directly incorporated into the change classification procedure. In this study, a T_1 reference image was combined with CVA magnitude and angle images, for comparison with CVA magnitude and angle images used alone in a classification of conifer forest change. Because image differencing used in combination with input T_1 images is mathematically equivalent to composite analysis, there was no reason to combine these images for further analysis.

The most important finding of this study was that use of a reference image was extremely important for accurate characterization of forest change. When no reference image was used, image differencing performed better than CVA, but only minimally so. Even in combination with a reference image, CVA did not compare well to composite analysis, with the disparity between them increasing as the number of cover change classes increased. The importance of using a reference image is illustrated in Figure 6.4. If only a brightness difference image is used in change detection, forest clear-cuts (Class v) are readily separable from all other change classes; however, all other classes are nearly impossible to separate accurately along a brightness difference axis alone. Including a 1988 reference brightness image with the brightness difference image enables accurate separation of the change class associated with early-successional forest progressing to conifer forest (Class ii), and to a somewhat lesser extent, the classes associated with succession within nonconifer forest (Class i). Other classes remain confused with brightness and brightness difference data alone, but become more separable with the addition of greenness and greenness difference, and wetness and wetness difference. Recall that the use of a reference image in conjunction with difference images provides precisely the same result as composite analysis when used in a change classification algorithm.

The tasseled-cap wetness feature has been important for separating different classes of conifer forest in the Pacific Northwest region of the United States, and has been shown to be important for conifer forest change detection in conifer forests elsewhere. In this study, wetness significantly improved the results of change detection analyses, especially for changes occurring within a closed conifer forest condition.

The existing literature on CVA falls short of discussing the complex nature of angle measurements in three or more spectral dimensions. As CVA magnitude is measured in terms of spectral Euclidean distance, its calculation is straightforward. Faced with calculating CVA angle, however, one has several choices. For just three spectral dimensions, *x*, *y*, and *z*, one can define an angle in *x-y*, *x-z*, and *y-z* space. Also, an angle can be calculated relative to one of the planes formed by these three axis pairs. For each additional spectral band, additional angle calculations are possible. In theory, only two angles in combination with magnitude are required to precisely locate a T_2 pixel vector vis-a-vis a T_1 vector in three dimensions; but as each angle provides a somewhat different view of the change data space, each angle likely contains different types of change information.

6.0 SUMMARY

Image differencing, change vector analysis (CVA), and composite analysis were compared for detecting changes in conifer forest cover using Landsat TM data. The concept of using a T_1 reference image in a two-date analysis was discussed, and results from use of a reference image were compared to results without the use of such an image. The importance of the tasseled-cap wetness feature in conifer forest change detection is evaluated. In a test of methods, composite analysis performed significantly better overall than either of the other two methods, with image differencing yielding slightly better results than CVA. Including a T_1 reference image with a two-date image difference data set is mathematically equivalent to composite analysis. Inclusion of a reference image with CVA, however, greatly improved the performance of CVA. Tasseled-cap wetness improved overall results when included with tasseled-cap brightness and greenness images, with the most marked improvement evident for

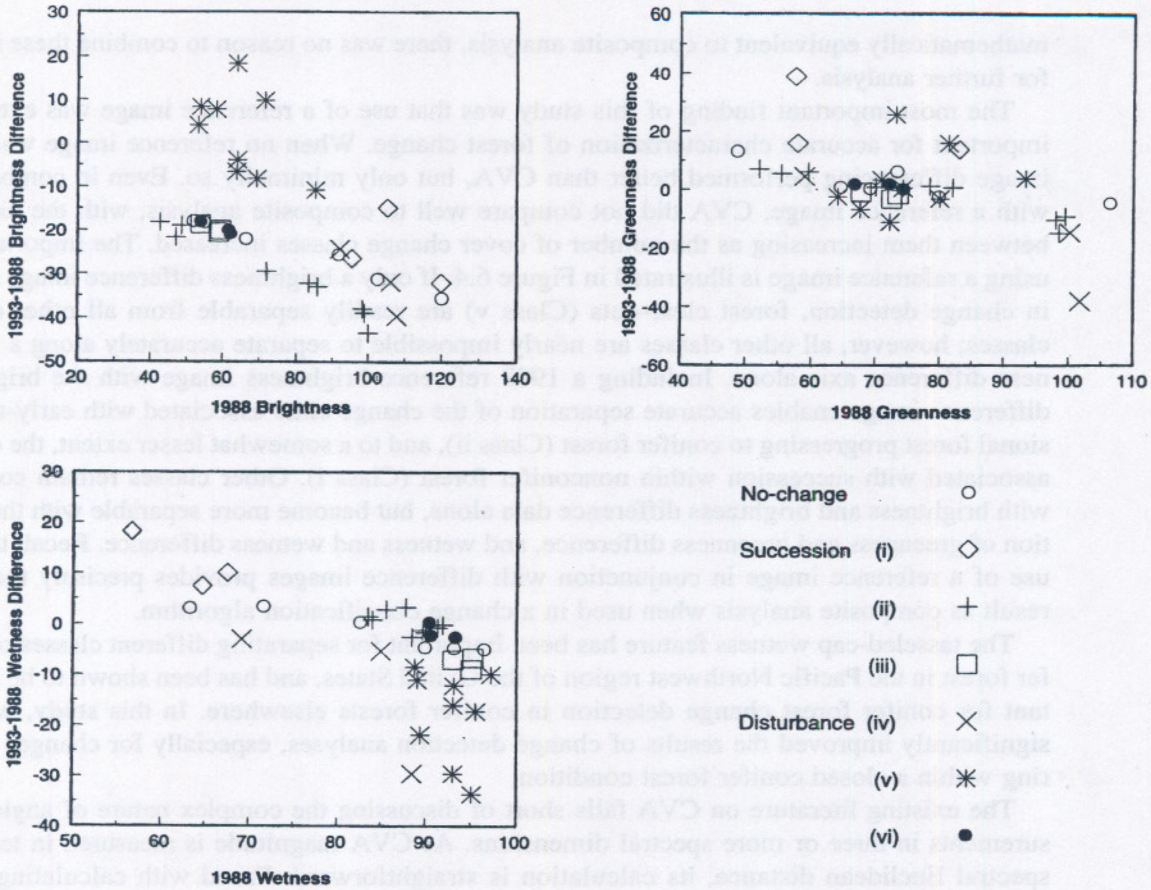

Figure 6.4. Mean temporal spectral differences for 36 forest cover change classes, as a function of original (1988 reference) mean spectral values for the Tasseled-Cap vegetation indices brightness (top, left), greenness (top, right), and wetness (bottom, left). The 36 cover change classes are grouped ecologically into seven classes: no-change, 3 succession classes, and 3 disturbance classes, as given in Table 6.2.

changes within the closed canopy conifer condition. CVA is an important change detection method that is inadequately described in the literature; in particular, the angular component of CVA appears not to be thoroughly appreciated. A discussion of CVA angle characterization with the intent of inspiring a closer evaluation of this potentially important change detection algorithm was presented.

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