

## Comparison of Tasseled Cap-based Landsat data structures for use in forest disturbance detection

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### Abstract

Landsat satellite data has become ubiquitous in regional-scale forest disturbance detection. The Tasseled Cap (TC) transformation for Landsat data has been used in several disturbance-mapping projects because of its ability to highlight relevant vegetation changes. We used an automated composite analysis procedure to test four multi-date variants of the TC transformation (called “data structures” here) in their ability to facilitate identification of stand-replacing disturbance. Data structures tested included one with all three TC indices (brightness, greenness, wetness), one with just brightness and greenness, one with just wetness, and one called the Disturbance Index (DI) which is a novel combination of the three TC indices. Data structures were tested in the St. Petersburg region of Russia and in two ecologically distinct regions of Washington State in the US. In almost all cases, the TC variants produced more accurate change classifications than multi-date stacks of the original Landsat reflectance data. In general, there was little overall difference between the TC-derived data structures. However, DI performed better than the others at the Russian study area, where slower succession rates likely produce the most durable disturbance signal. Also, at the highly productive western Washington site, where the disturbance signal is likely the most ephemeral, DI and wetness performed worse than the larger data structures when a longer monitoring interval was used (eight years between image acquisitions instead of four). This suggests that both local forest recovery rates and the re-sampling interval should be considered in choosing a Landsat transformation for use in stand-replacing disturbance detection.

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### 1. Introduction

The detection of forest disturbance is important in research and policy related to global carbon cycles. It is also useful for identifying spatial and temporal trends in forest management. At regional and greater scales, the only feasible means of monitoring forest change on a regular and continuous basis is with the aid of remote sensing. Landsat has been the workhorse sensor for regional analyses of forest cover and change (Cohen & Goward, 2004). Many change detection projects (e.g. Cohen et al., 2002; Franklin et al., 2001; Seto et al., 2002) have opted to work with

Landsat data that has been transformed using the Tasseled Cap transformation (Crist & Cicone, 1984; Kauth & Thomas, 1976). This transformation reduces the Landsat reflectance bands to three orthogonal indices called brightness, greenness and wetness. While there are clear operational savings involved with storing and processing only three spectral bands per image date instead of six, there has been little formal investigation of the impact of this transformation on the accuracy of change maps. The goal of this study was to quantify the degree to which it is possible to identify stand-replacing disturbance (disturbances removing almost all of the forest canopy) using different combinations of the Tasseled Cap indices in relation to the original Landsat bands and a newly developed Disturbance Index (DI).

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In this paper, spatially co-registered multi-date stacks of these competing transformations are called “data structures.” The framework for testing these data structures was multi-temporal composite analysis (Coppin & Bauer, 1996). In this procedure, a multi-date image is submitted to a classification algorithm that attempts to identify pixels exhibiting spectral characteristics consistent with a sudden loss of vegetation. This procedure has proven successful in several large-scale mapping projects (Cohen et al., 1998, 2002; Sader et al., 2003; Moeur et al., in press). Composite analysis was performed using each of the competing data structures in two coniferous forests in Washington, USA, and one mixed hardwood-conifer forest in the St. Petersburg region of Russia. The classifications produced using each of the data structures were compared using manually digitized maps of stand-replacing disturbance as a reference.

The choice of a data structure is a critical decision for several reasons. First, different data transformations respond to different compositional attributes (Cohen et al., 2001), and, in disturbance detection, transformations should be sought that maximize spectral distance and separability between “disturbed” and “undisturbed” forest conditions. Second, the duration of the spectral signal associated with disturbance varies among transformations, such that a project’s re-measurement schedule should be informed by the signal decay rate of the data structure used. Third, large-scale monitoring projects often cover a variety of forest types and conditions, so the transformation used must be robust across a range of conditions.

A final consideration in the choice of data structure is the potential for the reduction of redundant or unnecessary information. Aside from the higher storage and processing costs, higher-dimensional data structures (i.e. those composed of more bands per date) may in some cases result in lower classification accuracies (Hughes, 1968). If the

number of training samples is low in relation to the number of dimensions, the variance of class parameter estimates can be large, resulting in higher classification error (Fukunaga & Hayes, 1989). Thus, if the disturbance signal in competing transformations is equal in strength, duration, and robustness, the transformation composed of the fewest bands may be preferable.

The DI transformation that was tested here is expressed in a single band per date. The transformation itself, described later, is based upon the observation that recently cleared stands typically have a higher Tasseled Cap brightness value and lower Tasseled Cap greenness and wetness values than undisturbed forest areas. The DI plane of transformation (Fig. 1) divides Tasseled Cap space in a way that segregates pixels fitting this “disturbed” profile from all others. It is hoped that by testing DI and the other Tasseled Cap-related data structures in different disturbance detection scenarios, information will be gained regarding the sensitivity of each structure to sudden forest canopy removal. This information may contribute to the choice of appropriate transformations for Landsat data in future disturbance detection projects.

## 2. Methods

### 2.1. Study areas

Three study areas were used to compare the effectiveness with which different Landsat data structures facilitate forest disturbance composite analysis. Two of these areas were in physiographically distinct regions of Washington State. The East Cascades Washington (ECW) study area, centered at 47.3°N/120.9°W, included a 500,000 ha portion of the Path 45/Row 27 Landsat TM scene. The West Cascades

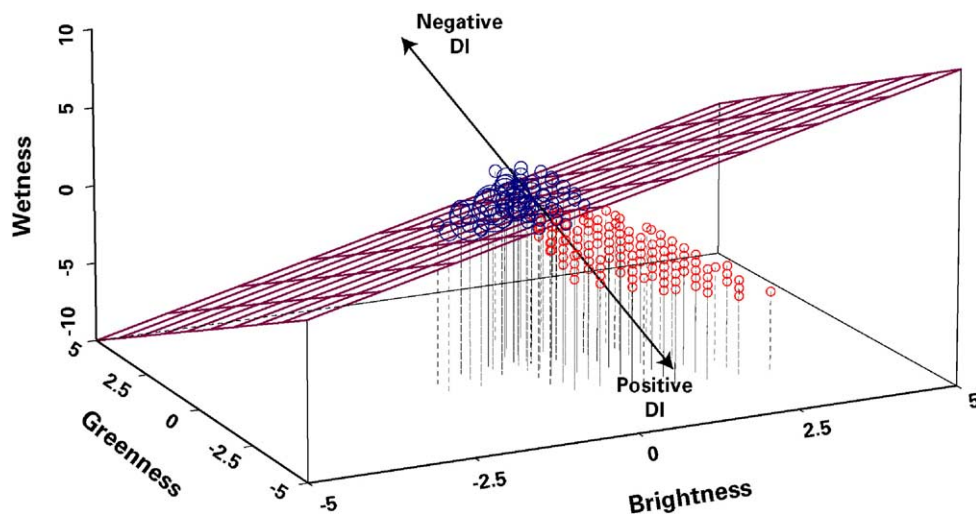


Fig. 1. Plane of transformation for the Disturbance Index in Tasseled Cap space. Values are taken from 1991 West Cascades Washington (WCW) study area. The units for each axis are standard deviations above or below the mean Tasseled Cap brightness, greenness, and wetness values of the scene’s forested pixels. Red circles represent pixels disturbed immediately prior to 1991; blue circles represent undisturbed pixels. The size of each circle is proportional to the number of pixels at that data point. Only data points representing at least .25% of the undisturbed and disturbed classes are plotted.

Washington (WCW) area, centered at 45.9°N/122.1°W, was a 381,000 ha subset of the Path 46/Row 28 scene. The ECW study area lies east of the crest of the Cascades, receives between 500 and 1800 mm of rain per year (PRISM., 2003) and is characterized by relatively open canopies of ponderosa pine (*Pinus ponderosa*) and Douglas-fir (*Pseudotsuga menziesii*). The WCW region lies west of the Cascade crest and receives greater rainfall, 2000–2550 mm of rain per year (PRISM., 2003), than the ECW site. The Douglas-fir and western hemlock (*Tsuga heterophylla*)-dominated forest of the WCW study area exhibits considerably denser canopy cover than ECW. Both areas supported large-scale forest harvesting during the two intervals studied (1988–1992, 1992–1996) and a 2700-ha stand-replacing fire occurred in the ECW area during the second interval studied.

The other study area, RUS, was a 420,000-ha section of the St. Petersburg region of Russia in Landsat scene Path 185, Row 19 (58.8°N/30.0°E). The natural vegetation of this region belongs to southern taiga type; major conifer species include Scots pine (*Pinus sylvestris*) and Norway spruce (*Picea abies*) both growing in pure and mixed stands. After disturbance, these species are often replaced by northern hardwoods including birch (*Betula pendula*) and aspen (*Populus tremula*). The climate is maritime with cool wet summers and long cold winters. Annual precipitation is 600–800 mm. The region is a part of the East-European Plain with elevations between 0 and 250 m a. s. l. The terrain is mostly flat and rests on ancient sea sediments covered by a layer of moraine deposits. Forests have been repeatedly harvested on 80–100 year rotation, and fire control is very effective throughout the region (Krankina et al., 2004).

## 2.2. Data structures tested

In each of three study areas, the first data structure tested was an 18-band composite stack of the 6 Landsat TM 30-m reflectance bands covering the three test dates (two intervals). Landsat data has been a common source of information for regional change detection projects because of its availability, resolution, and sensitivity to forest change. While the original 18-band composite images (hereafter called OB, for “original bands,”) incur high storage and computational costs, their inclusion in this study provides a baseline against which to judge the performance of lower-dimensional data transformations.

The Tasseled Cap transformation reduces the six TM reflectance bands of a single image date to three indices: brightness, greenness, and wetness ( $B$ ,  $G$ , and  $W$ ). Combining these indices for three dates, we tested a 9-band BGW composite of each study area. A six-band subset containing only  $B$  and  $G$  for the 3 years was also tested. This subset was investigated because of the ubiquitous use of just  $B$  and  $G$  in change detection projects, especially when Landsat MSS data is used. In addition, we tested  $W$  alone, because several studies have emphasized its value in

detecting variation in forest structural characteristics (Cohen & Spies, 1992; Collins & Woodcock, 1996; Skakun et al., 2003), which are clearly affected by stand-replacing disturbance.

## 2.3. The disturbance index (DI)

The final data structure tested as an input for composite analysis was the Disturbance Index. DI was designed for this study to highlight the un-vegetated spectral signatures associated with stand-replacing disturbance and separate them from all other forest signatures. Specifically, the DI is a linear combination of the three Tasseled Cap (Crist & Cicone, 1984; Kauth & Thomas, 1976) indices:  $B$ ,  $G$ , and  $W$ . The formulation of DI takes advantage of the assumption that recently cleared forestland exhibits high  $B$  and low  $G$  and  $W$  in relation to undisturbed forest (Fig. 1). This assumption was developed through pilot studies using imagery from different regions in the Pacific Northwest, and was further tested in the boreal forest of Canada and mixed forest of Virginia (J. Masek, personal communication).

For the DI transformation, linear combination of an image's  $B$ ,  $G$ , and  $W$  values is facilitated by first re-scaling (Eq. (1)) each band to its standard deviation above or below the scene's mean forest value,

$$B_r = (B - B_\mu) / B_\sigma$$

$$G_r = (G - G_\mu) / G_\sigma$$

$$W_r = (W - W_\mu) / W_\sigma, \quad (1)$$

where  $B_r$ ,  $G_r$ ,  $W_r$  = rescaled Brightness, Greenness, and Wetness,  $B_\mu$ ,  $G_\mu$ ,  $W_\mu$  = mean forest Brightness, Greenness, and Wetness,  $B_\sigma$ ,  $G_\sigma$ ,  $W_\sigma$  = standard deviation of forest Brightness, Greenness, or Wetness.

This re-scaling process normalizes pixel values across Tasseled Cap bands in a way that allows their subsequent algebraic combination (Eq. (2)). The reference population from which mean ( $\mu$ ) and standard deviation ( $\sigma$ ) values are drawn should be representative of the scene's forested pixels. The work reported here used a reference population composed of all pixels labeled as “forest” in pre-existing maps of land cover. This process is separate from the later selection of training data for supervised composite analysis. Once the three component indices are normalized, they can be combined linearly (Eq. (2)) as follows:

$$DI = B_r - (G_r + W_r). \quad (2)$$

Given the above assumptions that disturbed areas will have high positive  $B_r$  (brighter than average) and low negative  $G_r$  and  $W_r$  (less green and wet than average) values, recent cuts should display high DI values. Stands displaying low negative  $B_r$  and high positive  $G_r$  and  $W_r$  (e.g. young, fully regenerated stands) will exhibit low DI values,

and all others will tend toward zero, as shown in Fig. 1. This compression of undisturbed pixels toward a mean value simplifies the “unchanged” forest class, and may reduce the effort needed to correctly train that class in composite analysis. Since DI is a single band, the disturbance information present in three dates of imagery can be visualized in a standard RGB display (Fig. 2), which facilitates the training process in supervised composite analysis.

#### 2.4. Testing process

Supervised composite analysis (Coppin & Bauer, 1996) was used as a framework for comparing the above data structures. Composite analysis of multi-temporal Landsat imagery has proven to be an effective change detection technique in several regional-scale monitoring efforts (e.g. Cohen et al., 2002; Sader et al., 2003). In each study area, three dates of Landsat imagery (Table 1) were geo-rectified using an automated tie-point program described by Kennedy and Cohen (2003). In ECW and WCW, monitoring intervals of 4 years were used. In RUS, available imagery only allowed intervals of 7 years. No multi-date radiometric normalization was performed on these images. Since the change detection method used here, supervised classification, does not rely upon radiometric calibration of the input axes (Song et al., 2001), radiometric normalization was unnecessary. After spatially co-registering the three dates at each study area, the clearcuts and stand-replacing fires occurring over the two periods were manually digitized aided by simultaneous viewing of the Tasseled Cap imagery. Cohen and Fiorella (1998) found little difference between using Tasseled Cap data and other sources of reference data for identifying stand-replacing disturbance. The digitized

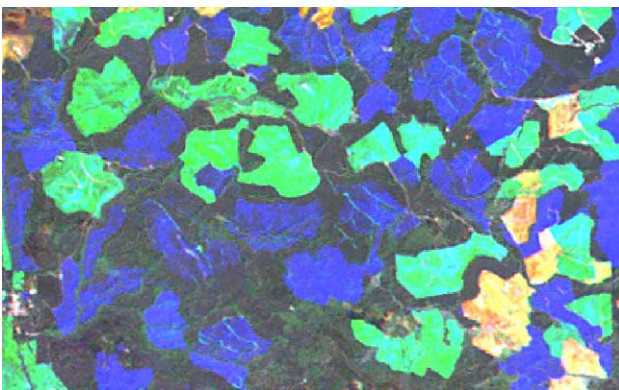


Fig. 2. Three dates of DI as viewed in a typical RGB monitor. The first date (1988) is plotted in the red color gun, the second (1992) in the green, and the third (1996) in the blue. Using the assumption that DI is high in disturbed areas, additive color logic can be used to interpret this multi-temporal image. Blue pixels have a high DI only in the third date, indicating disturbance between the second and third dates. Cyan-colored areas are high in the second and third dates but not the first, indicating a disturbance between the first and second dates. The yellowish colors, high in the red and green color guns and lower in the blue, indicate stands disturbed before the first date that are becoming re-vegetated by the third date.

Table 1  
Landsat TM and ETM+ imagery

Study Area	Path	Row	Acquisition date	Satellite
RUS	185	19	May 23, 1987	Landsat 5
RUS	185	19	July 13, 1994	Landsat 5
RUS	185	19	May 5, 2001	Landsat 7
ECW	45	27	July 23, 1988	Landsat 5
ECW	45	27	August 3, 1992	Landsat 5
ECW	45	27	July 13, 1996	Landsat 5
WCW	46	28	August 31, 1988	Landsat 5
WCW	46	28	September 9, 1991	Landsat 5
WCW	46	28	August 21, 1996	Landsat 5

disturbances were used to create “truth” layers against which to evaluate the accuracy of change maps produced using the data structures under study.

In each study area, six Landsat reflectance bands were combined to create a three-date “stack” (the 18 band OB structure). This stack was then used to create multi-temporal stacks of the transformations discussed earlier: *BGW* (9 bands), *BG* (6 bands), *W* (3 bands), and *DI* (3 bands). All of these data structures were masked to include only forest pixels, using the Interagency Vegetation Mapping Program land cover map (Weyerermann & Fassnacht, 2001) in ECW and WCW, and a locally produced land cover map for RUS. Each data structure (OB, *BGW*, *BG*, *W*, *DI*) was classified repeatedly using a maximum likelihood decision rule. Classifications were trained from a pool of the larger disturbances (>2 ha) that were digitized earlier. There were at least 400 disturbance polygons larger than 2 ha in both disturbance periods in each of the three study areas. Each data structure was classified 50 times with 5 randomly selected training polygons from each of the two periods, then 50 times with 10 training polygons per period, then with 15, up to 100 polygons per period. In other words, each data structure was classified fifty times at twenty levels of increasing amounts of training data. In addition to the two change classes sought in each classification, a fixed set of approximately 10 “no change” polygons was used in each classification to create a class for unchanged forest.

The resulting classifications were compared to the “truth” layer created from the digitized disturbances, resulting in a comprehensive error matrix for each classification. Table 2 displays an error matrix representative of the 50 trials at the level of training in the RUS study area that used 15 polygons per change period. From each such matrix, overall and kappa (see Congalton & Green, 1999) accuracies were derived. Kappa values of the classifications produced in the 50 trials at each level of training data were the basis for comparative analyses.

To test the duration of the disturbance signal in each transformation, the middle date was removed from each data structure, effectively doubling the length of the monitoring interval. The two pools of disturbance polygons in each study area were combined and were used to train a single change class. Accuracies of these longer-interval classifications were measured as before except that fewer levels of

Table 2  
Examples of error matrices used in comparison of data structures

DI		Reference				W		Reference			
		No change	Change period 1	Change period 2	Total			No change	Change period 1	Change period 2	Total
Map	No change	2,245,104	5235	7833	2,258,172	Map	No change	2,193,382	7298	10,303	2,210,983
	Change period 1	122,859	85,127	3864	211,850		Change period 1	111,608	80,300	3913	195,820
	Change period 2	58,249	4588	65,823	128,661		Change period 2	121,223	7352	63,304	191,879
	Total	2,426,213	94,950	77,520	2,598,683		Total	2,426,213	94,950	77,520	2,598,683
BG		Reference				BGW		Reference			
		No change	Change period 1	Change period 2	Total			No change	Change period 1	Change period 2	Total
Map	No change	2,235,637	9321	6628	2,251,585	Map	No change	2,163,777	5019	6128	2,174,924
	Change period 1	94,501	32,932	20,986	148,419		Change period 1	117,036	82,973	3633	203,642
	Change period 2	96,075	52,697	49,906	198,679		Change period 2	145,401	6,957	67,759	220,117
	Total	2,426,213	94,950	77,520	2,598,683		Total	2,426,213	94,950	77,520	2,598,683
OB		Reference									
		No change	Change period 1	Change period 2	Total						
Map	No change		1,892,549	4265	1,900,667						
	Change period 1		178,176	80,621	265,436						
	Change period 2		355,488	10,063	432,579						
	Total		2,426,213	94,950	2,598,683						

Matrices show the agreement, in number of pixels, between composite analysis results and manually digitized reference maps. These examples came from the RUS study area when 15 polygons were used to train the disturbance class for each period. Fifty classifications were produced with each data structure at each level of training data, and kappa statistics derived from the error matrices of these classifications were the basis of comparison among the different data structures.

training data were tested (5, 15, 25, . . .95 training polygons instead of 5, 10, 15, . . .100 polygons).

3. Results

Although overall accuracies (i.e. the percentage of pixels correctly classified) were-computed for the classifications at each site, kappa was considered a better measure of accuracy. Because the great majority of pixels are usually unchanged, overall accuracy is relatively insensitive to the quality of the change information. For example, if no effort was made at change detection in the WCW area and all of the pixels were mapped as “no change” for the 2 monitoring periods, the overall accuracy would still be 95%. The kappa value of this map, on the other hand, would be close to zero. Thus, all discussions of accuracy will refer to kappa accuracy.

Fig. 3 shows the mean kappa value of disturbance detection classifications produced at the RUS site with increasing numbers of training polygons. Although the relative performance of the different data structures varied among study sites (Fig. 4), the graph in Fig. 3 has two features representative of all sites. First, using more than 15 training polygons per change period resulted in little or

no improvement in accuracy. Second, the differences in accuracy between data structures, though small in some cases, were consistent across levels of parameterization.

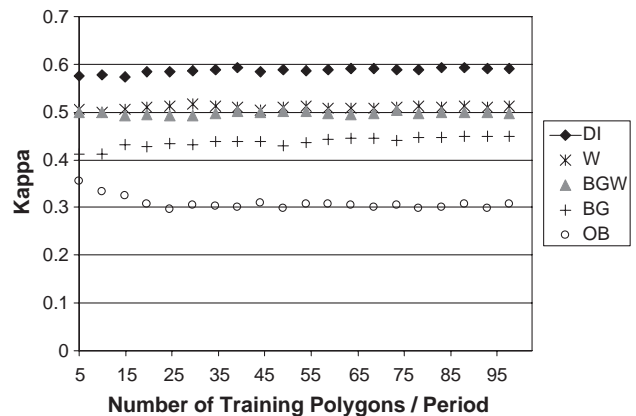


Fig. 3. Mean kappa values for change maps in RUS using two 7-year monitoring periods. At each level of parameterization (X-axis), a fixed number of randomly selected polygons per change period were used to train a supervised classification. Each data point represents the mean kappa of 50 change classifications using a given number of training polygons per change period. Change periods in this case were: disturbed 1987–1994 and disturbed 1994–2001. A constant set of 10 “no-change” polygons was also used in each classification.

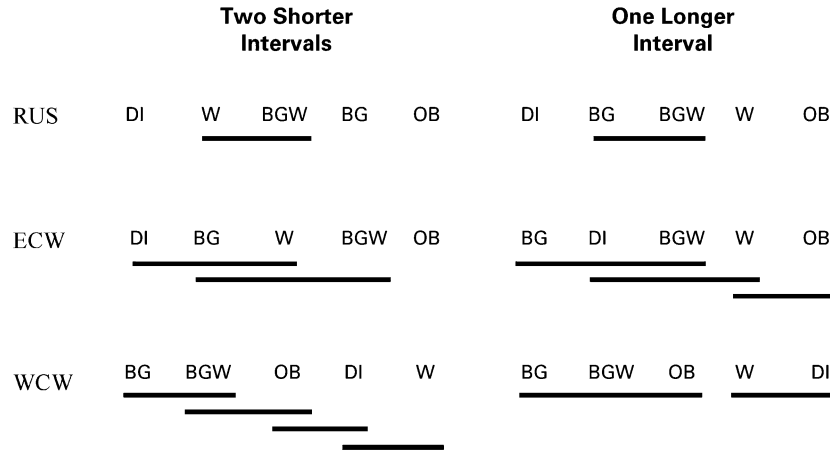


Fig. 4. Multiple comparisons among data structures. Structures are listed from left to right in descending order of mean classification kappa. Structures with statistically similar kappas (using  $p = .05$  Bonferoni simultaneous confidence intervals) are joined with underlines. Compared structures included: disturbance index (DI); Wetness (W); brightness and greenness (BG); brightness, greenness, and wetness (BGW); and the original Landsat bands (OB). The left column shows results using two shorter monitoring intervals (4 years each in ECW and WCW, and seven in RUS), and the right column shows results using a single, longer monitoring period (8 years in ECW and WCW, 14 years in RUS).

Therefore, a single representative level of parameterization was chosen for comparative analyses. Specifically, comparisons were made using 15 training polygons of stand-replacing disturbance per monitoring period (30, total, for the 2-period classifications) in addition to a constant set of ten polygons representing unchanged forest. Figs. 5 and 6 show the mean (of 50 trials) kappa accuracy of each of the tested data structures. Analysis of variance (ANOVA) at each site indicated that data structure had an effect on kappa at the  $p < .01$  level. Multiple comparisons of the performance of the different data structures were made using Bonferoni significant difference (BSD) method at the 95% confidence level; the results of this analysis are displayed in Fig. 4.

The performance of the various data structures varied among regions. The largest separation between data structures occurred in the Russian study site. DI performed significantly better than the Tasseled Cap structures, which in turn performed better than the original Landsat bands. This pattern was observed both in classifications using two 7-year monitoring periods and in those using a single 14-year monitoring period. In WCW, the structures composed of more than one band per year, including the original Landsat stack, outperformed the single-band structures of W and DI. The difference between multiple- and single-band structures increased using a longer monitoring period. There was little difference in performance in ECW; classification accuracies were statistically similar among

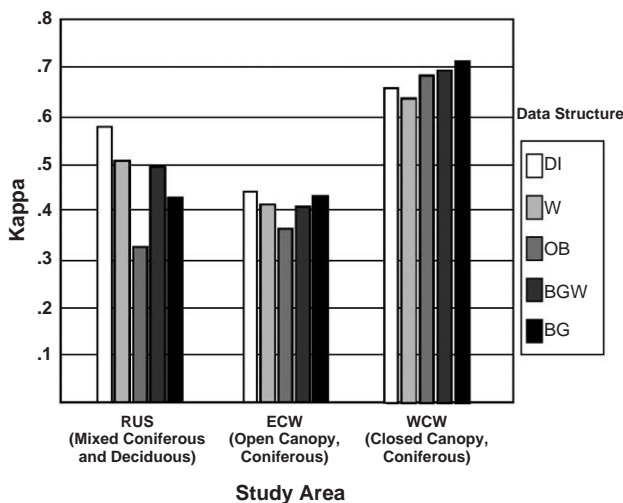


Fig. 5. Mean kappa values for composite analysis using different data structures to detect stand-replacing disturbance in two shorter monitoring periods. Kappas were determined using manually digitized polygons for each area as a reference. Change classes in each study area included: 1987–1994 and 1994–2001 in RUS; 1988–1992 and 1992–1996 in ECW; and 1988–1991 and 1991–1996 in WCW.

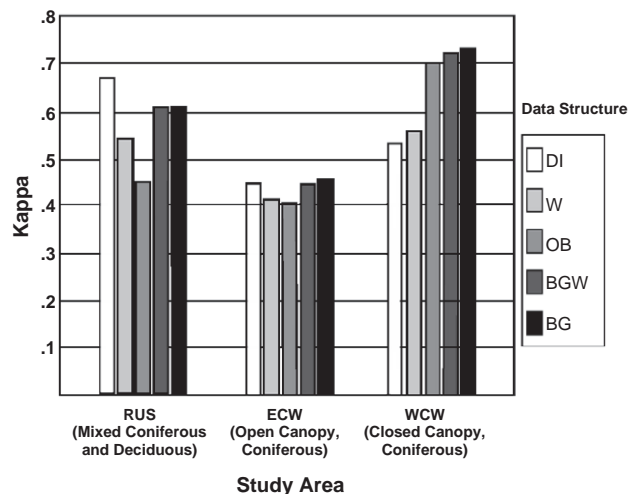


Fig. 6. Mean kappa values for composite analysis using different data structures to detect stand-replacing disturbance in one longer monitoring period. Kappas were determined using manually digitized polygons for each area as a reference. Change classes in each study area included: 1987–2001 in RUS, and 1988–1996 in ECW and WCW.

all data structures except the original bands, which lagged the others.

The most significant effect of using a longer monitoring period was seen in WCW, the wettest and most biologically productive of the sites. In this study area, the performance of the two single-band structures, DI and *W*, fell dramatically in relation to the performance of the other data structures (Fig. 6). The only change seen in ECW using the longer monitoring period was that the original bands gained in relation to *W*. DI remained significantly better than the other structures in RUS in the longer 14-year period, although the other single-band structure, *W*, declined in relation to *BGW* and *BG*.

## 4. Discussion

### 4.1. Choice of data structure for detection of forest disturbance

The accuracy of change detection through composite analysis was in many cases shown to depend on the transformation of Landsat data used to support the classification. In general, the Tasseled Cap-derived transformations (*BGW*, *BG*, *W*, DI) performed significantly better than the original Landsat TM band data. This suggests that the Tasseled Cap and Disturbance Index transformations successfully preserve and highlight information relevant to forest disturbance while simultaneously reducing the amount of information that must be processed and stored.

In general, the Tasseled Cap-derived structures produced equally accurate change classifications. Exceptions to this equality occurred in RUS when DI outperformed the others, and in WCW, where DI and *W* were outperformed by the structures containing more bands. These exceptions are likely related. WCW is the most mesic of the three study sites, and re-vegetation after disturbance is fastest there. Clearcuts or fires occurring in the beginning of a monitoring period may be covered with grass, shrubs or even small trees after only 4 years. In cases such as this, supplementary axes may be needed to characterize the more varied conditions observed following stand-replacing disturbance. Conversely, relatively slow re-vegetation at the RUS site may be related to the superior performance of DI there. Severe climate and poor soils contribute to lower succession rates at the RUS site. In addition, post-harvest re-stocking is less common in RUS than in Washington, and when recolonization does occur, it is usually led by relatively bright hardwoods. Slow recovery of conifers may minimize the spectral diversity of cuts occurring in different years during a particular monitoring period, thereby, simplifying the classes representing change in composite analysis. This simplification may allow the use of lower-dimension data structures.

The idea that more complex data structures are required to define the more complex (i.e. variable)

change classes is also supported by the results of disturbance detection using a longer monitoring period. Increasing the time between monitoring dates allows succession to create more variability among areas to be identified as disturbed. Accuracies produced by the single-band structures *W* and DI generally declined in relation to larger-dimension data structures when longer monitoring periods were used, particularly in WCW, where succession is fastest.

In RUS, DI actually performed better than the data structures containing more bands. This suggests that DI has an advantage in this area that goes beyond band depth. DI is designed to accentuate the separation between undisturbed forest and stands showing high brightness, low greenness, and low wetness, the presumed profile of recently disturbed forest. As long as rapid succession does not cause disturbed areas to deviate from this simplistic profile, the separation of disturbed and undisturbed forest that DI accomplishes may provide a fundamental advantage in identifying stand replacement. More work is needed to determine if shorter monitoring intervals could be used in areas of more rapid succession to produce the same advantage seen in RUS.

There are several factors to be considered in choosing a transformation of data to be used in the detection of stand-replacing disturbance. In general, simpler data structures are easier to store and process. Further, single-band transformations can be displayed multi-temporally in a single monitor to allow easy development of training data (e.g. Fig. 2). In terms of performance, although little difference was typically observed between any of the four TC-based transformations studied, DI performed the best in the simplest disturbance detection tasks, and the higher-dimension structures performed best in the most complex tasks. Consequently, succession rate and length of monitoring interval, both factors that influence the spectral variability of disturbed pixels, should be considered in the choice of a transformation for Landsat data in the detection of stand-replacing disturbance.

### 4.2. The Disturbance Index

The DI value of an area at a single date relates little of its disturbance history. DI simply quantifies how close in Tasseled Cap space a pixel is to the areas in the scene having the highest brightness and lowest greenness and wetness. Clouds and exposed rock can often have high DI values. When viewed in sequence, however, DI images provide a direct way to highlight pixels that move from an average forest condition to a disturbed condition. Fig. 7 shows the mean response of DI to stand-replacing disturbance in the three study areas. The DI of a stand typically goes from near zero or slightly negative before disturbance to between 2 and 5 after being disturbed.

The variability in DI values among the different study areas suggests that the contrast between disturbed and

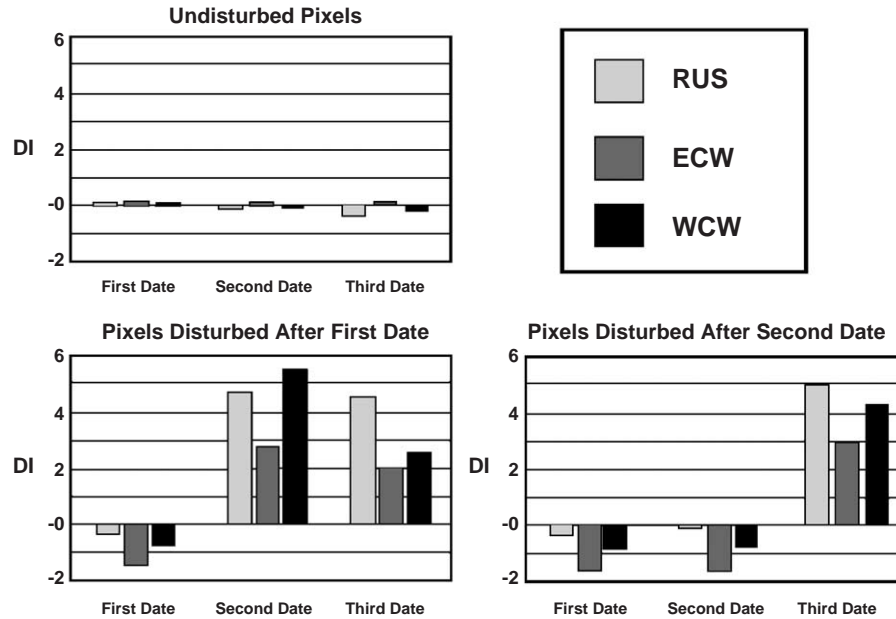


Fig. 7. Mean DI values before and after disturbance. Using the digitized “truth” layer developed for each study area, it was possible to track the mean DI values of three groups: unchanged pixels, pixels disturbed in the first interval, and pixels disturbed in the second interval. In all cases, a sharp increase in DI was observed at the time of disturbance although this increase varied by study area and by period.

undisturbed forest is different from ecosystem to ecosystem. Forests that are already bright, perhaps having a large hardwood or ground component in their signal, may show a smaller spectral change when cleared than darker conifer stands. For example, forests in ECW are relatively open, so the spectral distance between undisturbed and cleared forest, which is essentially what DI quantifies, is smaller than it is in the closed forests of WCW. Accordingly, the mean DI value for new cuts in ECW is 2.9, whereas new cuts average 4.8 in WCW (Fig. 7). DI values in RUS fall between these two sites, although RUS has a hardwood component not present in the others that further affects the contrast between disturbed and undisturbed forest.

In addition to varying geographically, the magnitude of DI can also fluctuate by interval within the same area (Fig. 7). For example, disturbed areas in the 1991 WCW image have a mean DI of 5.5 whereas disturbances in the same scene in 1996 average a 4.2 DI. This variability may result from atmospheric or phenological differences between the two images. Another potential source of variability is the dynamic nature of the reference or “norming” population used to rescale the Tasseled Cap indices that are input into the DI transformation. These rescaled indices are expressed in standard deviations above or below the mean forest value for each individual image. Since disturbance and re-growth may somewhat alter the mean forest condition from year to year, DI calibration may show a corresponding drift. The change detection method used here, supervised composite analysis, allowed date-specific parameterization of change classes, minimizing the need for cross-date normalization. However, a more automated thresholding procedure would require a more stable interpretation of DI. While it is clear

that careful radiometric normalization would contribute to DI stability, more research is needed to determine if alternate norming techniques, such as drawing the mean forest condition statistics solely from unchanged areas, would also add stability.

The construction of the DI transformation itself also merits more study. In the formulation given here, the rescaled Tasseled Cap indices are all given the same weight and are combined linearly. While this transformation has the advantage of simplicity and ease of interpretation, a more complex formulation may maximize the spectral separation between disturbed and undisturbed forest. If research reveals that the Tasseled Cap indices recover at different rates after disturbance, for example, it may be desirable in some cases to give a higher weight to the more stable components.

DI takes advantage of the fact that stand-replacing disturbance creates a strong and relatively predictable spectral signal. Although DI performed worse than larger data structures in the case (WCW, 8-year interval) where rapid succession and a longer monitoring interval allowed the disturbance signal to decay, it performed as well as any Tasseled Cap structure in all other cases and significantly better than others in RUS, where slow succession rates prolong the disturbance signal. DI has several properties that make it attractive for automated disturbance detection: it is easily calculated and interpreted; it reduces data storage and processing requirements; and it allows visualization of change between three dates in a single color monitor. The results of this study suggest that as long as monitoring interval length is attuned to the local succession rate, the use of DI to

detect stand-replacing disturbance involves no sacrifice in accuracy.

## 5. Summary

Five multi-temporal, Landsat-derived data structures (OB, BGW, BG, W and DI) were tested in change classification exercises in three ecologically distinct regions. The untransformed Landsat reflectance data performed as well as the Tasseled Cap-transformed data only in WCW, the study site with the most rapid re-vegetation rate. There was little difference in classification accuracy among the Tasseled Cap-based data structures. However, the DI structure, described here for the first time, created significantly more accurate disturbance maps in RUS, where forest recovery is slower than in the other areas. At the same time, DI produced less accurate maps (along with W, the other single-band transformation) in WCW when longer, 8-year monitoring intervals were used. These results suggest that as long as monitoring intervals are relatively short in relation to local forest recovery rates, simple transformations can be used in automated disturbance mapping to reduce Landsat data volume without sacrificing accuracy. In the most straightforward disturbance detection projects, the DI transformation may provide a significant advantage over the Tasseled Cap indices. It should be emphasized that the disturbances mapped in these exercises involved complete removal of vegetation; results from this study may not apply to the identification of more subtle forest changes. DI values for disturbed area were consistent neither across time nor space. While the supervised classification algorithm used here accommodated scene-specific interpretation of DI, more general use of the transformation will require methodology that standardizes the index. Research questions that may contribute to a more stable interpretation of DI include: the sensitivity of the index to varying “norming” populations; the behavior of DI after disturbance as stands develop, and the potential for using more complex formulations of the transformation.

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