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An Assessment of Several Linear Change Detection Techniques for Mapping Forest Mortality Using Multitemporal Landsat TM Data

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Forest canopy changes can be detected by a variety of methods of analysis of multitemporal satellite images. Issues surrounding the use of remote sensing in operational forest monitoring include which change detection method is most appropriate, and to what extent scenes should be preprocessed for the minimization of irrelevant interdate differences. Results indicate better performance for principal component analysis and a multitemporal Kauth–Thomas transformation as compared to the Gramm–Schmidt orthogonalization process. There is little evidence to suggest that preprocessing beyond simple DN matching methods improves results. Relationships between change components and mortality are found to be specific to the particular image data being used and the particular forest type under study. Canopy change can be detected reliably, but precise estimates of mortality levels require calibration using field data in all new situations. Change in Kauth–Thomas wetness is the most reliable single indicator of forest change.

INTRODUCTION

It is well established that remotely sensed imagery can be used to monitor changes in land surface conditions. A large variety of methods of change detection have been proposed and applied, many of which are reviewed by Singh (1989). New methods continue to appear in the literature frequently (Collins and Woodcock, 1994; Lambin and Strahler, 1994; Gopal and Woodcock, 1995). All these methods perform reasonably well in certain situations and for certain applications. What is unclear is which methods are most appropriate for a particular application. One challenge that confronts the remote sensing community is to develop an improved understanding of the change detection process on which to build an understanding of how to match applications and change detection methods. The purpose of this article is to present a comparison of several change detection methods. This comparison is part of an effort to determine optimum methods for monitoring forest canopy changes due to drought-induced mortality.

Much research has been done on the spectral appearance of forest changes and on the methods which can be used to detect them. Nelson (1983) examined the utility of image differencing, image ratioing, and vegetation index differencing in detecting gypsy moth defoliation using Landsat MSS data. A difference of the MSS7 / MSS5 (near-infrared / red) ratio was found to be more useful in delineation of defoliated areas than any single band-pair difference or ratio. This indicates that vegetation indices generally have a stronger relationship to the phenomena of interest in the scene than do any single sectral band. Muchoney and Haack (1994) examined several approaches to detecting defoliation, including merged Principal Components Analysis (Byrne et al., 1980; Ingebritsen and Lyon, 1985; Fung and LeDrew, 1987), image differencing, spectral–temporal change classification, and postclassification differencing. Classifications of the principal components and of the difference images were found to yield generally higher classification accuracies than the other methods. Coppin and Bauer (1994) examined forest change detection by comparison of vegetation indices for different

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dates of imagery. The vegetation indices included the Kauth–Thomas (KT) indices of *brightness (B)*, *greenness (G)*, and *wetness (W)*, as well as NDVI, green ratios, and mid-infrared ratios. The indices were compared both by standardized differences and by examining the second principal component of two-date vegetation index data. The latter technique is referred to as as "selective principal component analysis" (Chavez and MacKinnon, 1994; Chavez and Kwarteng, 1989). It enhances contrast between the two bands used while not being adversely affected by differences due to exogenous variation. Differences in the KT *brightness* and *greenness* indices were found to be more strongly related to canopy changes than were differences in the other indices.

The studies discussed in the literature indicate a strong ability to monitor forest canopy changes using satellite data. A number of the image analysis approaches to change detection can be referred to as *linear techniques*, meaning that land cover change at each image location is associated with some linear transformation of a bitemporal spectral vector. Any linear change detection technique can be represented in matrix notation. For an n-element bitemporal spectral vector $\mathbf{x}$ and some $n \times m$ transformation matrix $\mathbf{T}$, define a vector $\mathbf{c}$ as

$$\mathbf{c} = \mathbf{T}'\mathbf{x}. \tag{1}$$

The matrix $\mathbf{T}$ is constructed in such a way that some or all of the m elements of $\mathbf{c}$ are associated with spectral changes between the two dates in question. A quantitative measure y of some type of land cover change is taken to be a function of these spectral changes:

$$y = f(\mathbf{c}). \tag{2}$$

So, given a transformation matrix and a function relating spectral change to landcover change, one may calculate a measure of some variable of interest for an entire multitemporal scene.

The best known linear change detection technique is multidate principal component analysis (PCA). In this case, the matrix $\mathbf{T}$ consists of the eigenvectors of the covariance matrix of the bitemporal image. The major components tend to account for variation in the image data that is not due to land cover change, and are termed *stable components*. Minor components tend to enhance spectral contrasts between the two dates, and are termed *change components*.

In a recent article, Collins and Woodcock (1994) present another linear technique which is essentially a multitemporal generalization of the well-known Kauth–Thomas transformation of multispectral data (Kauth and Thomas, 1976; Crist and Cicone, 1984a,b). The Gramm–Schmidt (GS) orthogonalization process is used to identify the column vectors of the transformation matrix. The method orthogonalizes spectral vectors are taken directly from a bitemporal image, in much the same way that the original Kauth–Thomas transformation was created for single-date imagery. When done carefully, the GS process can produce three stable components corresponding to multitemporal analogues of Kauth–Thomas B, G, and W dimensions, plus a change component associated with interdate differences.

An interesting linear transformation is proposed by Fung (1990), whereby components measuring changes in Kauth–Thomas, B, G, and W dimensions are defined by some manipulations of the published coefficients defining these dimensions. An extension of his methodology is presented here. The coefficients defining the KT dimensions for single-date Landsat TM data are shown in Table 1. If we call this matrix $\mathbf{K}$, consider the matrix $\mathbf{M}$ defined as follows:

$$\mathbf{M} = \frac{\sqrt{2}}{2}\begin{bmatrix} \mathbf{K} & -\mathbf{K} \\ \mathbf{K} & \mathbf{K} \end{bmatrix}. \tag{3}$$

$\mathbf{M}$ is a 12×12 matrix in which the first six column vectors are multitemporal analogues of the corresponding single-date KT components. The last six vectors represent *increases* in the corresponding KT dimensions. The factor $\sqrt{2}/2$ normalizes the vectors.

The matrix resulting from applying this process to the matrix in Table 1 is shown in Table 2, and could be called the "multitemporal Kauth-Thomas" (MKT) transformation matrix. Since only the first three KT dimensions have names, it is likely that only the first three change components will be associated with any kind of measurable scene changes. But the 12×12 matrix is useful because it is "complete" in that the total variation contained in the 12 transformed components is equal to that contained in the original data set.

The MKT matrix shown in Table 2 is in some ways exactly what both PCA and GS approaches to change detection try to accomplish. It defines components which partition the variation in the image into portions due to intrinsic variability and portions due to change. Furthermore, it is free of the purely statistical nature of PCA and the largely empirical nature of GS.

PCA, however, can automatically apply a first-order calibration to account for exogenous differences—such as differences in illumination, sensor calibration, and atmospheric conditions—to the extent that these differences have an overall linear effect on the remotely sensed signal (Chavez and MacKinnon, 1994; Collins and Woodcock, 1994). The MKT transformation has no such qualities. However, other techniques exist to account for such differences. A pair of images can be made to appear as if they have been collected under identical illumination and atmospheric conditions by radiometric matching techniques. Several variations on this theme have been presented (Hall et al., 1991; Schott et al., 1988). All methods use image values which one knows *a priori* should be identical for both dates, but

Table 1. Componenets of the Kauth–Thomas Transformation for TM Data (from Crist and Cicone, 1984b)

	B	*G*	*W*	*4*	*5*	*6*
TM1	0.3037	- 0.2848	0.1509	- 0.8242	- 0.3280	0.1084
TM2	0.2793	- 0.2435	0.1973	0.0849	0.0549	- 0.9022
TM3	0.4743	- 0.5436	0.3279	0.4392	0.1075	0.4120
TM4	0.5585	0.7243	0.3406	- 0.0580	0.1855	0.0573
TM5	0.5082	0.0840	- 0.7112	0.2012	- 0.4357	- 0.0251
TM7	0.1863	- 0.1800	- 0.4572	- 0.2768	0.8085	0.0238

which are not identical due to exogenous differences. These data are used to calibrate a regression equation by which the pixel values in the "subject" image are made to match those in the radiometric "master" image. Coppin and Bauer (1994) use radiometric matching as a part of a data optimization procedure which also includes transformation of sensor data to reflectance units, as well as haze removal.

This study examines the ability of the linear change detection techniques mentioned above to quantify forest changes due to conifer mortality. The utility of various change components for predicting forest mortality is assessed by regressing field-measured mortality levels on component scores. Thus the measure of change used as "ground truth" is a quantitative variable—loss in basal area in m^2/ha on a per-stand basis. This contrasts with the customary use of a binary change / no change categorization of the landscape, and allows additional precision in the assessment of relationships between spectral components and forest change.

Our goal is to determine optimum methods for operational monitoring of forest mortality for the U.S. Forest Service. The change detection methods mentioned above are examined regarding their ability to

Table 2a. Multitemporal Kauth–Thomas Transformation Matrix for TM Digital Counts Data

Stable Components						*Change Components*					
B	*G*	*W*	*4*	*5*	*6*	Δ*B*	Δ*G*	Δ*W*	Δ*4*	Δ*5*	Δ*6*
0.215	- 0.202	0.107	- 0.583	- 0.237	0.077	- 0.215	0.202	- 0.107	0.583	0.237	- 0.077
0.197	- 0.172	0.139	0.060	0.034	- 0.638	- 0.197	0.172	- 0.139	- 0.060	- 0.034	0.638
0.335	- 0.385	0.232	0.311	0.066	0.291	- 0.335	0.385	- 0.232	- 0.311	- 0.066	- 0.291
0.395	0.512	0.241	- 0.041	0.145	0.041	- 0.395	- 0.512	- 0.241	0.041	- 0.145	- 0.041
0.359	0.059	- 0.503	0.142	- 0.306	- 0.018	- 0.359	- 0.059	0.503	- 0.142	0.306	0.018
0.132	- 0.127	- 0.323	- 0.196	0.569	0.017	- 0.132	0.127	0.323	0.196	- 0.569	- 0.017
0.215	- 0.202	0.107	- 0.583	- 0.237	0.077	0.215	- 0.202	0.107	- 0.583	- 0.237	0.077
0.197	- 0.172	0.139	0.060	0.034	- 0.638	0.197	- 0.172	0.139	0.060	0.034	- 0.638
0.335	- 0.385	0.232	0.311	0.066	0.291	0.335	- 0.385	0.232	0.311	0.066	0.291
0.395	0.512	0.241	- 0.041	0.145	0.041	0.395	0.512	0.241	- 0.041	0.145	0.041
0.359	0.059	- 0.503	0.142	- 0.306	- 0.018	0.359	0.059	- 0.503	0.142	- 0.306	- 0.018
0.132	- 0.127	- 0.323	- 0.196	0.569	0.017	0.132	- 0.127	- 0.323	- 0.196	0.569	0.017

Table 2b. Multitemporal Kauth–Thomas Matrix for TM Reflectance Data

Stable Components						*Change Components*					
B	*G*	*W*	*4*	*5*	*6*	Δ*B*	Δ*G*	Δ*W*	Δ*4*	Δ*5*	Δ*6*
0.144	- 0.113	0.022	- 0.150	- 0.613	0.260	- 0.144	0.113	- 0.022	0.150	0.613	- 0.260
0.294	- 0.199	0.143	- 0.020	- 0.130	- 0.580	- 0.294	0.199	- 0.143	0.020	0.130	0.580
0.391	- 0.349	0.219	0.092	0.273	0.308	- 0.391	0.349	- 0.219	- 0.092	- 0.273	- 0.308
0.406	0.561	0.113	- 0.071	0.029	0.037	- 0.406	- 0.561	- 0.113	0.071	- 0.029	- 0.037
0.221	- 0.000	- 0.481	0.462	- 0.080	- 0.005	- 0.221	0.000	0.481	- 0.462	0.080	0.005
0.163	- 0.102	- 0.432	- 0.501	0.161	- 0.007	- 0.163	0.102	0.432	0.501	- 0.161	0.007
0.144	- 0.113	0.022	- 0.150	- 0.613	0.260	0.144	- 0.113	0.022	- 0.150	- 0.613	0.260
0.294	- 0.199	0.143	- 0.020	- 0.130	- 0.580	0.294	- 0.199	0.143	- 0.020	- 0.130	- 0.580
0.391	- 0.349	0.219	0.092	0.273	0.308	0.391	- 0.349	0.219	0.092	0.273	0.308
0.406	0.561	0.113	- 0.071	0.029	0.037	0.406	0.561	0.113	- 0.071	0.029	0.037
0.221	- 0.000	- 0.481	0.462	- 0.080	- 0.005	0.221	- 0.000	- 0.481	0.462	- 0.080	- 0.005
0.163	- 0.102	- 0.432	- 0.501	0.161	- 0.007	0.163	- 0.102	- 0.432	- 0.501	0.161	- 0.007

quantify forest mortality levels. The effects of preprocessing for the removal of exogenous differences are also examined, since the different methods are expected to be affected to a greater or lesser degree by such corrections. Another significant issue from an operational forest management perspective is generalization of the calculated component / mortality relationships, or how stable the relationship between multitemporal change components and mortality is across different forest types, times, and satellite images. This issue bears directly on the amount of field data required in future studies.

STUDY SITE

The Lake Tahoe Basin is located in the central Sierra Nevada Mountains on the California / Nevada border. The surface of the Lake is approximately 1900 m above sea level, and mountain peaks in the area reach well over 2700 m in elevation. The conifer forests of the Tahoe Basin are mostly composed of two forest types. At lower elevations and at low to flat slopes, one finds eastside pine (EP), whose dominant species are jeffrey pine (*Pinus jeffreyi*) and lodgepole pine (*Pinus contorta*). At the higher elevations and on steeper slopes, one finds mixed conifer (MC), including the species white fir (*Abies concolor*), red fir (*Abies magnifica*), sugar pine (*Pinus lambertiana*), western white pine (*Pinus monticola*), and incense cedar (*Libocedrus decurrens*).

The Tahoe Basin has been experiencing a drought for a number of years. The lack of available soil moisture weakens trees to the point where they are vulnerable to attack by insects. Insect infestation is the direct cause of tree mortality in most cases. Previous studies of mortality in the Tahoe Basin (e.g., Macomber and Woodcock, 1994) have focused attention on the MC zone, since most mortality was concentrated there. But recently considerable mortality has appeared in the EP zone as well, so that this study examines both forest types.

METHODS

Data

Assessment of associations between change components and mortality was done using field data for a number of test sites. Forest stands were delineated on 1:15,840 scale aerial photographs. Stands were chosen to be homogeneous with respect to species composition, tree size distribution, and density. They ranged in size from about 5 ha to 19 ha, with a mean size of about 9 ha. Field data were collected in two different seasons. During July 1991, 25 MC stands were visited. During July 1994, data were collected for 24 EP stands and 27 MC stands. One of the MC stands from the 1994 data had been logged extensively and was discarded from further analysis. In each sampled stand, a grid of sites was laid out, and at each site basal area was recorded using a variable-radius sampling technique (Dillworth and Bell, 1978). Estimates of basal area at each site within a stand were averaged to get an overall estimate of stand basal area in square meters per hectare. Furthermore, stand mortality was recorded by observing whether each sampled tree was alive, or had died within the previous 3 years. The data allow estimation of stand basal area for the 1988–1991 time period and the 1991–1994 time period, with differences ascribed to mortality.

Imagery consisted of three Landstat 5 TM scenes of the Lake Tahoe Basin from July 1988, July 1991, and July 1994. Images were each registered to a UTM projection. The study area was extracted from TM Bands 1, 2, 3, 4, 5, and 7 for all images.

This study would not have been possible if not for the existence of ancillary data from a previous forest mapping project (Woodcock et al., 1994). An important item was a digital map identifying individual forest stands for the Tahoe Basin. This map was created by a segmentation algorithm (Woodcock and Harward, 1992) which used several TM bands and a texture channel. This stand map made it possible to map mortality on a per-stand basis rather than a per-pixel basis, making the product of this analysis coincide more closely with forest management practices than would a pixel-based product. The use of multipixel stands as the basis for the analysis also minimizes the effects associated with unavoidable amounts of minor misregistration between images. Other useful ancillary data included a vegetation classification map, with categorical detail to the level of regional vegetation types. Thus it was possible to identify forest stands as being either of the EP or MC types. Most of the analysis which follows uses the 1991 / 1994 data set.

Image Preprocessing

In the analysis which follows, three different levels of preprocessing were examined. These are referred to by number in the remainder of this article.

1. No preprocessing. No radiometric matching or calibration was undertaken. This level of preprocessing was used to see how well different change detection methods account for exogenous differences on their own.
2. Matched digital counts (DNs). Spectral response for invariant features was matched between the two dates on a band-by-band basis. The 1994 image was chosen as the radiometric master image. Several invariant features in the scene were identified by visual inspection of the images, and included the surface of Lake

Tahoe as well as several rock outcrops. The spectral data for these features were used to calibrate a regression equation predicting 1994 DNs from 1991 DNs, and the resulting equations were applied to the 1991 data. This level of preprocessing was chosen because it is simple and relatively easy to do for any study.

3. Matched reflectances (full radiometric correction and matching). The 1994 image data were transformed to at-sensor radiances using the gain and offset information given in the image headers, then the 1991 data were matched to it by the methods described above. A haze-correction technique, described by Chavez (1988), was applied to the matched radiance data. The haze-removal algorithm involves initial selection of a haze value (histogram offset) for a single image band, followed by subsequent application of a relative scattering model to all bands. For each image band, the relative scattering model calculates an additive haze radiance, which is then subtracted from the image data. The method allows dark-object subtraction which is consistent from band to band with respect to a physically based atmospheric model. A final step of the full radiometric calibration was transformation of the haze-corrected matched radiances to reflectance units, using the equations and solar irradiance information given in Markham and Barker (1986). This level of preprocessing is probably the most complete radiometric correction that could be done on an ongoing basis without the use of an atmospheric model requiring observations of atmospheric conditions at the time of the satellite overpass.

Change Detection Methods

The three change detection methods examined in this study were the multitemporal Kauth–Thomas transformation (MKT), Gramm–Schmidt orthogonalization (GS), and multidate principal component analysis (PCA). The transformation matrix created in each case was applied to the spectral data for the field stands, yielding a number of component scores associated with each stand. A subset of the component scores was used to predict mortality levels in each case.

Multitemporal Kauth–Thomas Transformation

Table 2a gives the matrix defining the MKT transformation, and its construction is described in the introduction. The original KT coefficients used to create this matrix are taken from Crist and Cicone (1984b) and are meant to be applied to TM digital counts data, so that it is an appropriate transformation matrix for preprocessing levels 1 and 2. However, preprocessing level 3 produces reflectance data, so a reflectance factor MKT matrix was constructed using the transformation matrix published in Crist (1985) in Eq. (3) (Table 2b).

The ΔB, ΔG, and ΔW components are constructed in such a way that they measure increases in their associated KT dimensions. Component scores on these axes are linearly related to simple interdate differences of the KT dimensions, so that this methodology is closely associated with that of vegetation index differencing discussed in the introduction. Furthermore, these first three change components were assumed to be the only components associated with mortality.

Table 3. Gram–Schmidt-Derived Change Components[a]

Δ_1	Δ_2	Δ_3
0.468	−0.162	−0.071
0.199	−0.046	−0.041
0.255	−0.119	−0.102
0.414	0.296	0.383
−0.064	−0.541	−0.453
−0.012	−0.278	−0.362
−0.468	0.162	0.071
−0.199	0.046	0.041
−0.255	0.119	0.102
−0.414	−0.296	−0.383
0.064	0.541	0.453
0.012	0.278	0.362

[a] Δ_1 is the componenet for raw image data, Δ_2 is for matched DN data, and Δ_3 is for matched reflectance data. The stable components associated with Δ_1 and Δ_2 are the stable components from Table 2a, and the stable components associated with Δ_3 are those in Table 2b.

Gramm–Schmidt Orthogonalization

The method for producing a transformation matrix using the GS process (Collins and Woodcock, 1994) relies on identification of stable components based on selection of spectral vectors from the multidate image which are chosen as representative of these dimensions. This step is necessary prior to proper identification of any change components. Due to the empirical nature of such an approach, and the sensitivity of the results to the spectral vectors used to identify the stable components, a slightly different approach was used here. An initial set of stable components was taken as the first six components of the MKT transformation. A change component was created by using a spectral vector in the GS process which was chosen as representative of areas of high conifer mortality. The spectral data chosen for this purpose were taken from several high mortality stands in the study area, identified by field reconnaissance.

Three change components were thus identified, one for each level of preprocessing. The change components are shown in Table 3. Different levels of preprocessing make a difference in the derived components. At preprocessing levels 2 and 3, the change components look much like the ΔG component of the MKT matrices. But when no preprocessing is done, the signs of the component cells resemble those of ΔW, but the mid-infrared bands are weighted more weakly.

Principal Component Analysis

At each preprocessing level, principal component analysis was done using the 12-band merged data set. Input data for each analysis included all of the land and water area within the Lake Tahoe Basin, with the exception of Lake Tahoe itself. The transformation matrices are shown in Tables 4a–4c.

Most studies using PCA for change detection label the components as representative of quantities such as *change in brightness* or *change in greenness* based on examination of the column vectors of the transformation matrix. Labels are generally assigned based on similarities with vectors of the MKT transformation. In this case, patterns are not as clear as would be desireable, so that it is difficult to know *a priori* which of these vectors represent change and which account for other types of variation or are irrelevant. For this reason,

Table 4a. Principal Component Matrix for Raw Image Data

pc1	*pc2*	*pc3*	*pc4*	*pc5*	*pc6*	*pc7*	*pc8*	*pc9*	*pc10*	*pc11*	*pc12*
0.32	-0.55	0.01	-0.14	-0.11	-0.69	-0.19	-0.17	0.04	0.15	-0.05	-0.01
0.20	-0.32	0.07	-0.07	-0.13	0.20	0.15	0.15	-0.04	-0.22	0.83	-0.10
0.32	-0.44	0.02	-0.12	-0.17	0.40	0.39	0.27	-0.03	-0.05	-0.51	0.08
0.18	-0.02	0.69	-0.04	-0.15	0.36	-0.50	-0.27	-0.00	0.09	-0.05	0.01
0.47	0.47	-0.10	-0.56	-0.06	-0.08	-0.19	0.37	0.20	-0.06	0.00	0.00
0.31	0.16	-0.24	-0.29	0.08	0.15	0.26	-0.67	-0.42	0.11	0.05	-0.02
0.21	-0.13	-0.11	0.14	0.56	0.03	-0.35	0.07	-0.31	-0.58	-0.13	-0.12
0.14	-0.07	-0.04	0.08	0.35	0.07	-0.06	0.06	0.05	0.23	0.16	0.87
0.21	-0.09	-0.10	0.14	0.46	0.19	-0.04	0.14	0.18	0.63	0.06	-0.46
0.16	0.20	0.62	0.06	0.35	-0.32	0.55	0.01	0.05	-0.11	-0.01	-0.04
0.45	0.27	-0.05	0.65	-0.37	-0.12	-0.02	0.16	-0.34	0.11	0.02	0.02
0.28	0.05	-0.19	0.30	-0.04	0.10	0.06	-0.39	0.73	-0.30	-0.02	0.00

Table 4b. Principal Component Matrix for Matched DN Data

pc1	*pc2*	*pc3*	*pc4*	*pc5*	*pc6*	*pc7*	*pc8*	*pc9*	*pc10*	*pc11*	*pc12*
0.27	-0.53	0.08	0.07	-0.22	-0.51	-0.35	-0.37	-0.06	0.24	-0.04	-0.02
0.18	-0.33	0.11	0.01	-0.18	0.05	0.17	0.26	0.02	-0.24	0.79	-0.16
0.26	-0.43	0.07	0.04	-0.23	0.09	0.37	0.44	0.01	-0.16	-0.55	0.13
0.18	0.03	0.67	-0.04	-0.18	0.61	-0.17	-0.26	0.04	0.12	-0.04	0.01
0.46	0.43	-0.15	0.54	-0.28	-0.00	-0.25	0.16	-0.33	-0.11	-0.00	0.01
0.28	0.11	-0.22	0.31	-0.07	0.05	0.39	-0.30	0.68	0.21	0.05	-0.02
0.23	-0.20	-0.08	0.12	0.55	0.15	-0.40	-0.05	0.28	-0.54	-0.11	-0.12
0.16	-0.11	-0.03	0.08	0.34	0.08	-0.01	0.07	-0.08	0.22	0.22	0.85
0.23	-0.15	-0.09	0.08	0.46	0.19	0.09	0.20	-0.26	0.58	-0.00	-0.46
0.18	0.28	0.62	0.08	0.35	-0.52	0.30	0.04	0.00	-0.11	-0.01	-0.04
0.50	0.26	-0.11	-0.71	-0.07	-0.10	-0.20	0.23	0.22	0.11	0.01	0.02
0.31	-0.00	-0.21	-0.26	0.07	0.11	0.41	-0.55	-0.47	-0.29	-0.01	0.00

Table 4c. Principal Component Matrix for Matched Reflectance Data

pc1	*pc2*	*pc3*	*pc4*	*pc5*	*pc6*	*pc7*	*pc8*	*pc9*	*pc10*	*pc11*	*pc12*
0.13	-0.05	-0.32	-0.08	-0.01	-0.19	-0.01	0.06	0.78	0.48	-0.01	0.01
0.18	-0.02	-0.46	-0.10	0.07	-0.28	-0.02	0.06	-0.05	-0.41	0.69	0.11
0.24	-0.08	-0.53	-0.15	0.06	-0.35	-0.03	0.04	-0.43	0.09	-0.56	-0.09
0.25	0.62	-0.24	-0.03	0.46	0.52	0.03	-0.08	0.02	0.02	-0.02	-0.00
0.40	-0.06	0.41	-0.44	0.21	-0.09	0.40	0.51	0.02	-0.03	-0.01	-0.00
0.39	-0.24	0.21	-0.48	0.00	0.10	-0.43	-0.56	0.01	0.02	0.04	0.01
0.11	-0.06	-0.11	-0.01	-0.25	0.16	0.18	-0.08	0.35	-0.62	-0.41	0.40
0.16	-0.06	-0.14	-0.02	-0.38	0.24	0.25	-0.06	0.08	-0.16	0.05	-0.81
0.22	-0.11	-0.16	0.00	-0.45	0.33	0.37	-0.06	-0.28	0.42	0.20	0.41
0.26	0.67	0.21	0.02	-0.52	-0.35	-0.22	0.05	-0.01	0.00	-0.01	0.03
0.44	-0.07	0.19	0.59	0.24	-0.29	0.33	-0.41	0.03	0.00	0.01	-0.02
0.42	-0.26	-0.00	0.43	-0.03	0.27	-0.52	0.47	-0.00	-0.02	-0.01	-0.00

components significant for mortality prediction were chosen by a stepwise regression procedure (Kleinbaum et al., 1988). One consistency, however, among the three matrices is that, in each one, the fourth component seems to contrast the mid-infrared TM bands between the two dates.

RESULTS

Using the available data, the detection of changes due to mortality may be examined in a number of different ways. In the following sections, we look at: 1) differences in component / mortality relationships for different forest types, 2) differences in the results as a function of change detection methodology, 3) preprocessing level, and 4) differences arising when change components are applied to different sets of images.

Tables 5, 6, and 7 show the results of predicting mortality using GS-, PCA-, and MKT-derived components, respectively. In each table, regressions are divided by the preprocessing level of the data involved and the forest type(s) to which the equations apply. Each of the tables gives the parameter estimates for the regression and a p-value indicating a test for their significance. For the simple regressions (i.e., the ones for the GS components in Table 5), the p-value for the independent variable gives the probability of the true parameter value being nonzero and thus tests for the overall utility of the regression. In the multiple regressions of the other two tables, each p-value associated with an independent variable tests for the significance of that variable when the others have been taken into account. So in these cases, it can be thought of as a variable-added-last test.

Table 5. Results of Predicting Mortality from Gramm–Schmidt-Derived Change Components for Different Preprocessing Levels and Vegetation Types

Pre-processing[a]	*Vegetation Type(s)*	*Parameter*	*Value*	*p*	R^2
1	EP	Intercept	59.83	0.0040	0.2562
		Δ	−3.61	0.0116	
1	MC	Intercept	−65.07	0.0028	0.4061
		Δ	5.55	0.0005	
1	EP + MC	Intercept	−17.22	0.3116	0.0566
		Δ	2.01	0.0962	
2	EP	Intercept	5.65	< 0.0001	0.6929
		Δ	2.45	< 0.0001	
2	MC	Intercept	9.37	< 0.0001	0.5301
		Δ	3.22	< 0.0001	
2	EP + MC	Intercept	7.58	< 0.0001	0.5379
		Δ	2.87	< 0.0001	
3	EP	Intercept	4.97	< 0.0001	0.6995
		Δ	11.04	< 0.0001	
3	MC	Intercept	8.66	< 0.0001	0.6218
		Δ	13.97	< 0.0001	
3	EP + MC	Intercept	6.83	< 0.0001	0.6014
		Δ	12.81	< 0.0001	

[a] 1 = no preprocessing, 2 = matched DN values, 3 = full radiometric correction and calibration.

Table 6. Results of Predicting Mortality from PCA-Derived Change Components for Different Levels of Preprocessing and Forest Types

Pre-processing[a]	*Vegetation Type(s)*	*Parameter*	*Value*	*p*	R^2
1	EP	Intercept	−32.94	0.2053	0.7841
		PC4	1.81	< 0.0001	
		PC7	−2.57	0.0270	
		PC1	−0.08	0.0359	
1	MC	Intercept	−41.63	0.2389	0.7595
		PC4	2.70	< 0.0001	
		PC2	−1.32	0.0182	
		PC11	−5.90	0.1380	
		PC1	0.31	0.1443	
1	EP + MC	Intercept	7.20	0.7574	0.7281
		PC4	2.75	< 0.0001	
		PC2	−0.29	0.0231	
		PC11	−4.82	0.0891	
		PC10	−4.19	0.0182	
		PC6	1.96	0.0627	
2	EP	Intercept	47.40	< 0.0001	0.7263
		PC4	−2.32	< 0.0001	
		PC1	−0.16	0.0009	
2	MC	Intercept	−14.67	0.5020	0.7673
		PC6	2.94	0.0191	
		PC10	−7.32	0.0099	
		PC4	−3.07	0.0001	
		PC2	−0.90	0.0028	
2	EP + MC	Intercept	10.31	0.5615	0.7627
		PC6	2.19	0.0148	
		PC4	−2.95	< 0.0001	
		PC2	−0.81	< 0.0001	
		PC10	−4.85	0.0046	
		PC3	0.34	0.0094	
		PC9	−4.03	0.1296	
3	EP	Intercept	−3.71	0.2060	0.7762
		PC4	10.82	< 0.0001	
		PC6	6.40	0.0163	
		PC9	13.92	0.0990	
3	MC	Intercept	25.36	< 0.0001	0.7825
		PC4	15.56	< 0.0001	
		PC3	−7.65	< 0.0001	
		PC8	30.00	0.0213	
3	EP + MC	Intercept	3.94	0.5670	0.7656
		PC4	13.13	< 0.0001	
		PC3	−7.22	< 0.0001	
		PC5	7.09	0.0080	
		PC2	0.80	0.0337	
		PC8	15.21	0.0755	

[a] 1 = no preprocessing, 2 = matched DN values, 3 = full radiometric correction and calibration.

Different Forest Types

Examination of the different regression equations calculated for the EP and MC regional types reveals little consistency. When using the GS process to detect change, only a single change component is produced

Table 7. Results of Predicting Mortality from MKT-Derived Change Components for Different Preprocessing Levels and Forest Types

Pre-processing[a]	*Vegetation Type(s)*	*Parameter*	*Value*	*p*	R^2
1	EP	Intercept	25.67	0.0509	0.7191
		ΔB	0.96	0.1910	
		ΔG	−1.30	0.2204	
		ΔW	−1.12	0.2604	
1	MC	Intercept	−14.74	0.2042	0.7938
		ΔB	−1.02	0.1973	
		ΔG	0.35	0.7768	
		ΔW	−4.56	< 0.0001	
1	EP + MC	Intercept	−7.03	0.3550	0.7434
		ΔB	−0.70	0.1473	
		ΔG	−0.26	0.7587	
		ΔW	−3.93	< 0.0001	
2	EP	Intercept	5.04	0.0004	0.7320
		ΔB	1.37	0.1020	
		ΔG	−3.19	0.0147	
		ΔW	−0.57	0.6193	
2	MC	Intercept	7.17	0.0001	0.7700
		ΔB	−2.18	0.0086	
		ΔG	−0.34	0.8086	
		ΔW	−5.01	< 0.0001	
2	EP + MC	Intercept	5.84	< 0.0001	0.6914
		ΔB	−1.43	0.0133	
		ΔG	−1.11	0.2900	
		ΔW	−4.36	< 0.0001	
3	EP	Intercept	5.27	0.0002	0.7178
		ΔB	5.86	0.1646	
		ΔG	−10.71	0.0415	
		ΔW	−3.78	0.4667	
3	MC	Intercept	6.89	0.0001	0.7662
		ΔB	−10.36	0.0061	
		ΔG	1.20	0.8127	
		ΔW	−19.08	< 0.0001	
3	EP + MC	Intercept	5.77	< 0.0001	0.6938
		ΔB	−7.41	0.0056	
		ΔG	−0.33	0.9305	
		ΔW	−17.91	< 0.0001	

[a] 1 = no preprocessing, 2 = matched DN values, 3 = full radiometric correction and calibration.

(Table 5). In virtually every situation, both the intercept and the change component parameter estimate are considerably different for the two types. But there is a significant association in all cases.

For PCA (Table 6), sometimes there are components which are found to be significantly associated with mortality for both EP and MC stands. In all analyses done here, the fourth component is always significantly related to mortality. (Note that there is no reason generally to expect the *fourth* component of a PCA matrix to be useful—it is merely so in this study.) Tables 4a–4c show that this component always is heavily weighted in the mid-infrared TM bands, with loadings corresponding to the other TM bands tending to be small or insignificant. Thus this component would seem to be associated to some degree with changes in the KT wetness component, which also emphasizes the mid-infrared bands. The signs of these coefficients suggest that pc4 for preprocessing level 2 (matched DNs) is similar to *increases* in wetness while for the other two levels of preprocessing it is similar to *decreases*. This difference is reflected in the regression coefficients associated with this component (Table 6), which consistently show that increases in mid-infrared radiance are associated with increases in mortality, as would be expected. But in spite of this consistency in the PCA analyses, the stepwise component selection procedure never picks exactly the same set of components as being significant for both EP and MC stands.

Table 8. Results of Regressions Predicting Mortality from the ΔB, ΔG, and ΔW Components Individually, Using Matched DN Data

Vegetation Type(s)	*Parameter*	*Value*	*p*	R^2
EP	Intercept	8.25	< 0.0001	0.5288
	ΔB	2.67	0.0001	
EP	Intercept	3.87	0.0080	0.5757
	ΔG	−5.18	< 0.0001	
EP	Intercept	5.95	< 0.0001	0.6202
	ΔW	−3.26	< 0.0001	
MC	Intercept	13.93	< 0.0001	0.0214
	ΔB	0.94	0.4761	
MC	Intercept	7.77	0.0023	0.3889
	ΔG	−5.92	0.0007	
MC	Intercept	8.88	< 0.0001	0.6814
	ΔW	−4.28	< 0.0001	
EP + MC	Intercept	11.37	< 0.0001	0.1119
	ΔB	1.75	0.0176	
EP + MC	Intercept	5.82	< 0.0001	0.4235
	ΔG	−5.67	< 0.0001	
EP + MC	Intercept	7.39	< 0.0001	0.6356
	ΔW	−3.96	< 0.0001	

Table 7 shows the results for the MKT-derived change components. At all levels of preprocessing there are differences between which of the chosen components are significant when the others have been taken into account. However, Table 8 shows an assessment of the component / mortality relationships individually for the matched DN data. In nearly all cases, the ΔB, ΔG, and ΔW components are all significantly associated with mortality. The lone exception is that ΔB is not associated with change for MC stands. Additionally, the directions of these relationships are consistent with one another, even if their magnitudes are not. But the R^2's are only moderately high, indicating that there are multiple dimensions of change and that the multiple regression approach using all three components is a significant improvement. Also note that the individual component with the strongest and most consistent relationship with mortality is ΔW.

The above analysis indicates that mortality is nearly always marked by some increase in reflectance for the mid-infrared TM bands. However, the precise nature of this relationship differs between forest types. For this reason, the regression equations developed for the merged EP + MC dataset have little meaning, since the data points clearly come from two different populations.

Different Levels of Preprocessing

Comparisons of the different parts of Table 5 show how preprocessing affects the ability of GS to identify change. When no preprocessing is done, the change component is significantly related to mortality for both EP and MC stands, but the R^2 values indicate that the components are of marginal utility. Additionally, the regression equations for the different types are quite different at this level of preprocessing. The GS process relies on initial identification of the subspace of multispectral data containing unchanged pixel vectors. Change components are identified relative to this space. In this study, the six "stable" components of the MKT transformation are used for this purpose. But when the multitemporal data are not matched, there is no guarantee that unchanged locations have identical spectral values. Thus the intrinsic variation in the data is poorly defined, yielding a bad change component. A more empirical approach to identifying the stable components, discussed in Collins and Woodcock (1994), is useful in accounting for exogenous differences, but the approach was not used here due to the somewhat arbitrary nature of the input data selection process. Note that when the raw data are used, the change component has nearly negligible loadings associated with the mid-infrared TM bands (Table 3). The radiometric matching procedure in this case enhances mid-infrared differences for changed locations, giving the other change components higher loadings for these bands.

When any amount of radiometric matching is done, GS performs better. For preprocessing levels 2 and 3, change components are always strongly associated with mortality. The direction (if not the magnitude) of the relationship is consistent between vegetation types. It is apparent that GS does not account well for exogenous effects and requires their removal prior to application of the technique.

Tables 7 and 6 show the effects of preprocessing on MKT-derived and PCA-derived change components, respectively. It is often hypothesized that PCA automatically adjusts for exogenous effects and so should not be adversely affected when radiometric matching is not done. The similarity of the R^2 values across preprocessing levels indicates that this is the case, but a surprising result is that MKT performs virtually as well with radiometric matching as without it. It may be that in this case the radiometric differences that are corrected do not affect the chosen change components severely.

The R^2 values for MKT-derived and PCA-derived change components for preprocessing levels 2 and 3 are similar. It appears that virtually no predictive power is gained by the extra complexity of the techniques of full radiometric calibration.

Different Change Detection Methodologies

All of the change detection methods examined in this article are capable of providing good estimates of mortality in some situations, but there are important differences between the methods which should be considered when choosing one. The GS method of creating change components generally produces lower R^2 values than either PCA or MKT. Because of the way that a change component is created relative to a set of stable components, it is difficult to create more than a single component related to a given type of change. The fact that multiple components are significantly associated with mortality for the other change detection methods (Tables 6 and 7) indicates that change in spectral measurement space can be multidimensional, and so any method producing a single change component is less than ideal.

An additional weakness of the GS process is that it relies on selection of spectral vectors from the multidate image typical of the type of change being examined. In this study, the spectral "change" vector was taken from image locations that were identified by field reconnaissance as being locations of high conifer mortality. But there is some subjectivity involved in selecting such areas, and the resulting change components are sensitive to this input data.

The technique of principal component analysis produces good estimates of change. Most studies using PCA for change detection try to attach physical interpretations to the components based on their similarities to the change components of the MKT matrix. As mentioned above, such labels are not so readily attached to the components found in this study. This is why a stepwise regression procedure was used to select the change components from the PCA-derived transformation matrices. There is no way to know exactly which components will be associated with mortality without relying on this statistical procedure. Indeed, components which seem to be good candidates for representing change are often found not to be associated with it. For example, pc5 for the matched DN data (Table 4b) mainly contrasts TM Bands 1–4 between the two dates, and so seems likely to be associated with change. An examination of the stepwise regression results (Table 6) reveals that it is not. Thus, while multidate PCA can be effective, it represents the most empirical approach to mapping canopy change, with the weakest tie to a physical interpretation of the results.

With MKT-derived change components, there is good reason to believe *a priori* that ΔB, ΔG, and ΔW components will be strongly associated with land cover

Table 9. Correlations between Measured Mortality Levels for the 1988–1991 Time Period and Mortality Levels Calculated Using Components and Regression Equations Calculated for the 1991–1994 Time Period

CD Method	*Correlation*
MKT	0.5030
GS	0.6994
PCA	0.5371

change. In numerous studies, single-date TM data are found to be dispersed mainly in the three-dimensional *brightness / greenness / wetness* space, with the fourth, fifth, and sixth components containing little information relevant to vegetation studies. So measurements of inter-date differences in these quantities should be a good indicator of change. The results shown in Table 7 indicate that this is the case, and the fact that change information always seems to be contained in this well-defined set of change components is an advantage over PCA approaches. Essentially, MKT is able to identify change as well as PCA, but does so in a more understandable, consistent manner.

Different Images

All of the above discussion concerns images from 1991 and 1994, and field data relating to stand mortality during this period. An important issue in this study is the degree to which the results found for this set of images can be applied to other scenes. Questions to be answered include whether the components found to be related to mortality are applicable in other situations, and if so, whether the calculated component / mortality relationships still hold or whether they must be recalibrated. These questions are addressed using the 1988 and 1991 images and field data sets. While we are comparing two different multitemporal data sets covering the same area, conceptually it is similar to comparing two data sets of nearby areas. Radiometric matching was done for the 1988–1991 data set using the 1991 image as the radiometric master. This means that although the images are radiometrically matched, they are not matched to the same reference as the 1991–1994 data set. This was done because it is not possible to use a standard radiometric reference for all possible image sets, and thus it is more closely related to what would be done in practice.

The highest degree of generalizability of the results would be if the components and component / mortality relationships found for the 1991 / 1994 data set could be applied directly to the 1988 / 1991 data set. Table 9 shows the results of such an attempt. For each change detection method, the correlation between measured mortality levels and estimated mortality levels is given. Although there is significant correlation present in all cases, the strength of the relationships is less than that found in the initial dataset.

Table 10. Results of Predicting 1988–1991 Mortality Levels by Recalibration of Relationships with Components Derived for the 1991–1994 Time Period

CD Method	*Vegetation Type(s)*	*Parameter*	*Value*	*p*	R^2
MKT	MC	Intercept	6.71	< 0.0001	0.7271
		ΔB	1.94	0.0065	
		ΔG	−3.32	0.0136	
		ΔW	1.35	0.1821	
GS	MC	Intercept	5.87	0.0001	0.6081
		Δ	1.83	< 0.0001	
PCA	MC	Intercept	−62.23	0.0007	0.6874
		pc6	−0.17	0.8888	
		pc10	5.53	< 0.0201	
		pc4	−1.15	0.0467	
		pc2	−0.35	0.0516	

Table 10 shows the results of deriving new component / mortality relationships for the 1988 / 1991 data using the components that were found to be significant for the 1991 / 1994 data. The best results are obtained for the MKT-derived change components. But comparison with Table 7 (preprocessing level 2, MC stands) reveals that the exact component / mortality relationships are quite variable between different images. The same can be said for the GS components (see Table 5) and the PCA components (Table 6). Since the coefficients of determination are acceptable for all cases in Table 10, it seems that the change components that were derived for a different set of images have some ability to detect change in all cases, although their use in the precise estimates of mortality must be recalibrated for different scenes.

The situation corresponding to the least level of generalizability is illustrated by Table 11. Here we have calculated new GS and PCA components using the 1988 / 1991 image data directly. MKT is not included here because the change components are standard and need not be recreated. Tables 12 and 13 show the new GS change component and PCA matrix respectively. The GS change component looks quite similar to its counterpart for the 1991 / 1994 data set (Table 3). Both look somewhat like *decrease in greenness* components

Table 11. Results of Predicting 1988–1991 Mortality Levels by Calculating New Change Components and New Component/Mortality Relationships

CD Method	*Vegetation Type(s)*	*Parameter*	*Value*	*p*	R^2
GS	MC	Intercept	5.60	0.0001	0.6337
		Δ	1.85	< 0.0001	
PCA	MC	Intercept	−0.67	0.0077	0.6442
		pc4	1.35	< 0.0001	
		pc9	0.90	0.0007	

Table 12. Gramm–Schmidt-Derived Change Component for the 1988–1991 Data Set[a]

Δ
−0.054
−0.114
−0.195
0.066
−0.562
−0.355
0.054
0.114
0.195
−0.066
0.562
0.355

[a] The stable components associated with this component are those shown in Table 2a.

weighted somewhat more heavily in cells corresponding to the mid-infrared TM bands. The regression equation predicting mortality from this component (Table 12) is similar for the one corresponding to the old component (Table 11), and results in a slightly higher R^2 value. The PCA change components in this case are quite different from those found to be significant for the 1991 / 1994 time period. In this case, the R^2 for mortality prediction from these new change components is slightly lower than that for the previous set of components. This may be due to the fact that a greater number of components were used in Table 10.

CONCLUSIONS

A number of conclusions can be reached from the discussion above.

- Prediction of mortality levels for conifer stands can be done fairly well using any of the methods tested.
- Different levels of preprocessing for the removal of exogenous image effects do not always result in a major improvement in results. There is no evidence to suggest that a full detailed radiometric matching technique results in any improvement over a much simpler method. Since some amount of radiometric correction is desirable, the use of simple DN matching is recommended for change detection studies.
- Both the MKT and PCA methods of creating change components result in similar degrees of improvement over the GS method.
- While results are just as good for PCA as for MKT, the latter identifies change in a more consistent and interpretable fashion. As a result, we recommend the use of MKT-derived change components for the type of study discussed here.
- Change in KT wetness is a good general indicator of conifer mortality. All change detection methods discussed here produce change components which are heavily weighted in the mid-infrared TM bands. KT wetness captures the mid-infrared changes well, and is thus the most consistent single indicator of forest change.
- Beyond the general relationship between mid-infrared radiance and mortality, there is little consistency in component / mortality relationships between different forest types. While they all seem related to wetness changes consistently, there are often other spectral qualities to mortality which differ between vegetation types.
- Direct application of change components and their relationships to mortality to other scenes results in a decrease in predictive power. Recalculation of change components between scenes is unnecessary, but recalibration of their relationship to mortality significantly improves results.

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Table 13. Principal Components Matrix for Matched DN Data for the 1988–1991 Time Period

pc1	*pc2*	*pc3*	*pc4*	*pc5*	*pc6*	*pc7*	*pc8*	*pc9*	*pc10*	*pc11*	*pc12*
0.24	0.16	−0.11	−0.24	0.51	−0.08	−0.37	0.11	0.39	−0.51	−0.12	−0.12
0.16	0.08	−0.03	−0.15	0.31	−0.07	0.00	0.05	−0.09	0.17	0.23	0.87
0.25	0.12	−0.11	−0.23	0.44	−0.21	0.11	0.12	−0.33	0.56	−0.02	−0.42
0.15	−0.24	0.65	−0.15	0.30	0.47	0.38	−0.06	−0.00	−0.13	−0.01	−0.05
0.47	−0.31	−0.07	−0.49	−0.50	0.09	−0.08	0.30	0.25	0.16	0.01	0.02
0.31	−0.05	−0.21	−0.28	−0.14	−0.11	0.11	−0.62	−0.46	−0.38	−0.02	0.00
0.30	0.54	0.06	0.15	−0.13	0.58	−0.39	−0.19	−0.08	0.20	−0.05	−0.01
0.18	0.32	0.10	0.09	−0.12	−0.12	0.20	0.15	0.03	−0.21	0.82	−0.19
0.30	0.44	0.06	0.17	−0.17	−0.21	0.51	0.27	0.03	−0.15	−0.50	0.13
0.17	−0.01	0.66	0.08	−0.12	−0.56	−0.37	−0.22	0.04	0.12	−0.05	0.01
0.44	−0.44	−0.10	0.61	0.10	0.04	−0.18	0.28	−0.31	−0.15	0.01	0.00
0.29	−0.14	−0.22	0.32	0.12	−0.04	0.26	−0.49	0.59	0.27	0.06	−0.02

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