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Remote Sensing of Environment 101 (2006) 115 – 126
Remote Sensing of Environment
www.elsevier.com/locate/rse

Application of two regression-based methods to estimate the effects of partial harvest on forest structure using Landsat data

Sean P. Healey [a,*], Zhiqiang Yang [b], Warren B. Cohen [a], D. John Pierce [c]

[a] US Forest Service, Pacific Northwest Research Station, 3200 SW Jefferson Way, Corvallis, OR 97331, United States
[b] Department of Forest Science, Oregon State University, 321 Richardson Hall, Corvallis, OR 97331, United States
[c] Washington Department of Fish and Wildlife, 600 Capitol Way N, Olympia, WA 98501-1091, United States

Received 1 September 2005; received in revised form 23 November 2005; accepted 10 December 2005

Abstract

Although partial harvests are common in many forest types globally, there has been little assessment of the potential to map the intensity of these harvests using Landsat data. We modeled basal area removal and percent cover change in a study area in central Washington (northwestern USA) using biennial Landsat imagery and reference data from historical aerial photos and a system of inventory plots. First, we assessed the correlation of Landsat spectral bands and associated indices with measured levels of forest removal. The variables most closely associated with forest removal were the shortwave infrared (SWIR) bands (5 and 7) and those strongly influenced by SWIR reflectance (particularly Tasseled Cap Wetness, and the Disturbance Index). The band and indices associated with near-infrared reflectance (band 4, Tasseled Cap Greenness, and the Normalized Difference Vegetation Index) were only weakly correlated with degree of forest removal. Two regression-based methods of estimating forest loss were tested. The first, termed "state model differencing" (SMD), involves creating a model representing the relationship between inventory data from any date and corresponding, cross-normalized spectral data. This "state model" is then applied to imagery from two dates, with the difference between the two estimates taken as estimated change. The second approach, which we called "direct change modeling" (DCM), involves modeling forest structure changes as a single term using re-measured inventory data and spectral differences from corresponding image pairs. In a leave-one-out cross-validation process, DCM-derived estimates of harvest intensity had lower root mean square errors than SMD for both relative basal area change and relative cover change. The higher measured accuracy of DCM in this project must be weighed against several operational advantages of SMD relating to less restrictive reference data requirements and more specific resultant estimates of change.
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Keywords: Change detection; Partial harvest; Landsat

1. Introduction

Forest harvests that remove only a part of the canopy are common throughout much of the world. In addition to allowing the extraction of saleable forest products, partial harvests may also address a range of other silvicultural goals. These goals may include: improving the ability of retained trees to grow vigorously, providing seed and ameliorating conditions for a new cohort of trees, and increasing the stand's value as wildlife habitat (Smith et al., 1997). Partial cutting has also traditionally been used in the management of tree density in young stands and has increasingly been considered as a means of reducing fire risk (Brown et al., 2004; Fight, 2004). The Pacific Northwest of the United States, like other regions (e.g., Sader et al., 2003), has seen an increase over the last several years in the frequency of partial harvest (McNeel & Dodd, 1996; Oregon Department of Forestry Annual Reports, 1989–2003).

Satellite-based monitoring is likely the most realistic means of mapping forest harvests across the many ownership boundaries in the Pacific Northwest. While public agencies routinely publish spatially referenced harvest practice information, private landowners often consider such data proprietary. Information about harvest practices on private land is available from tax records, but is provided in a spatially generalized

* Corresponding author. Current address: US Forest Service, Rocky Mountain Research Station, 507 25th St., Ogden, UT 84401, United States.
E-mail addresses: seanhealey@fs.fed.us (S.P. Healey), zhiqiang.yang@oregonstate.edu (Z. Yang), wcohen@fs.fed.us (W.B. Cohen), piecedjp@dfw.wa.gov (D.J. Pierce).

0034-4257/$ - see front matter © 2005 Elsevier Inc. All rights reserved.
doi:10.1016/j.rse.2005.12.006

format (e.g., Oregon Department of Forestry Annual Reports provide such information only at the county level). Because of its synoptic and historical nature, Landsat satellite data has been a useful source of forest disturbance information at the regional scale (Cohen & Goward, 2004). Landsat data has been used to create relatively accurate regional-scale maps of stand-clearing harvests in the Pacific Northwest (Cohen et al., 2002; Moeur et al., 2005), but no work has extended the use of Landsat data to the identification of partial harvests in the region. We investigated two regression-based approaches to estimating the intensity of partial harvests occurring in central Washington from 1996 to 2004. In doing so, we also explored the relative ability of various transformations of Landsat data to predict removal of cover and basal area in this region.

1.1. Background

The Washington Departments of Fish and Wildlife (WDFW) and Natural Resources (WDNR) were interested in reviewing the spatial patterns and effects of harvests occurring between 1996 and 2004 in and around sensitive habitat for the northern spotted owl (*Strix occidentalis caurina*). The most useful existing source of information for harvest locations was a spatially referenced database of harvest permits granted during the period in question. This database had some shortcomings with respect to estimating the effects of harvest on habitat, however. First, not all permitted activities were actually carried out, and of those that were, harvests rarely filled out the entirety of delimited permit boundaries. Also, the database did not address harvest intensity. Depending on the structural effects of a harvest, a stand may or may not retain characteristics that meet spotted owl habitat requirements (Washington Administrative Code 222-16-085). WDFW therefore required a spatially referenced map of harvest intensity that could be used to address harvest effects on owl habitat. Remote sensing was seen as a potential means to map harvests in WDFW's large and varied area of interest in a uniform and retrospective way. Landsat data has had a significant role in such studies, and several studies have suggested the potential of Landsat data to map partial canopy removals (Franklin, 2001).

Changes in percent cover and basal area were chosen as measures of harvest intensity because these structural variables were relevant to owl habitat definitions and because previous studies have shown them to be correlated with Landsat data (Franklin, 1986; Cohen & Spies, 1992; Cohen et al., 1995, 2001). Mapping efforts were focused on two areas in central Washington (Fig. 1) that contained a high concentration of recognized Spotted Owl Special Emphasis Areas (Federal Register, 1996; Washington Administrative Code 222-10-041). Ultimately, harvest maps were used to assess the degree to which management activities have impacted the extent and configuration of owl habitat in the region (Pierce et al., 2005).

1.2. Use of relationships between spectral and inventory variables to estimate harvest intensity

A relatively thorough dataset comprised of historical photos, management records, and field plots permitted estimation of

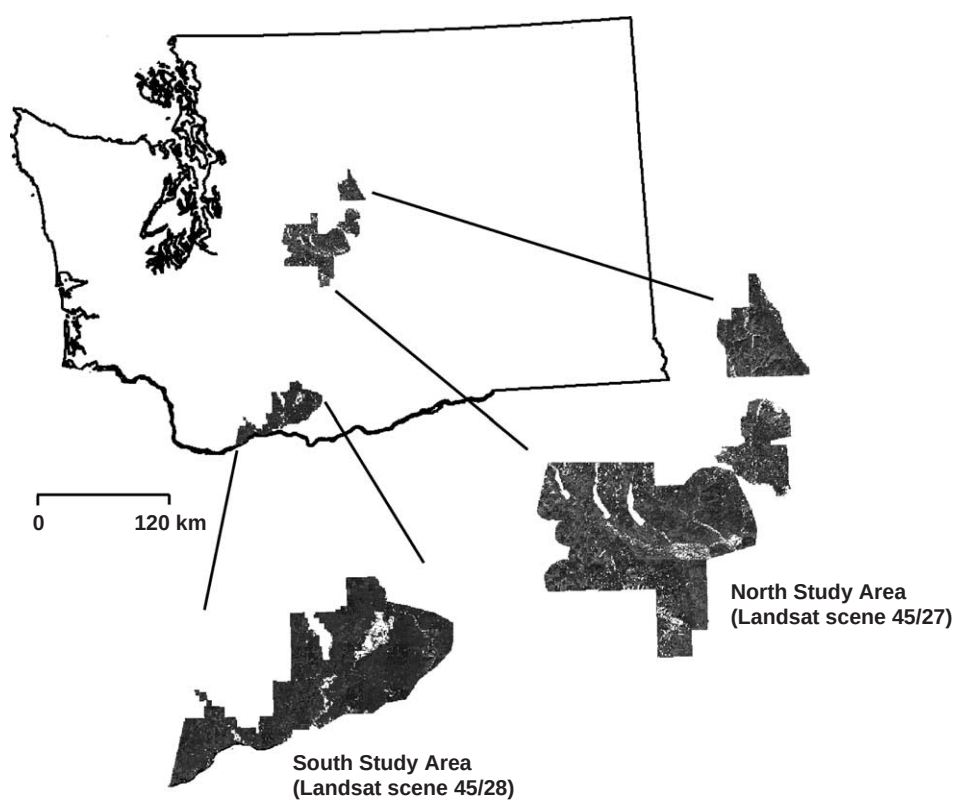

Fig. 1. Location of study areas in western Washington, USA. Tasseled Cap brightness of the study areas is displayed.

harvest intensity as the change in two forest attributes, basal area and canopy cover. Changes were modeled as continuous variables, which not only increased the precision of the spectral variable selection process, but also produced flexible change estimates that could later be binned into categories appropriate for a range of objectives. Two modeling approaches were explored. The first, hereafter called "state model differencing" or SMD, was based upon the construction of a date-invariant relationship between spectral variables and the forest inventory variables. Assuming acceptable relative radiometric normalization among image dates, this approach allowed estimation of the basal area or percent canopy cover for a particular area at different times. Estimates for successive dates could then be compared (differenced) in order to produce an estimate of change. The other approach, "direct change modeling" (DCM), involved regression of measured changes in basal area and cover against differences in spectral values for corresponding dates.

There were two primary lines of inquiry in this study: (1) comparison of Landsat bands and derived indices for use in support of partial harvest measurement; and (2) assessment, through a leave-one-out cross-validation procedure, of how well the DCM and SMD modeling approaches were able to predict the measured changes in our reference data. In regards to the first question, several studies have noted that the general spectral response to canopy reduction involves increased reflectance in the visible and shortwave-infrared (SWIR) portions of the electromagnetic spectrum and decreased reflectance in the near-infrared (NIR) range (Franklin, 2000; Häme, 1991; Olsson, 1994). This response is consistent with certain physical changes in the stand that may be expected upon partial canopy loss: higher soil and litter reflectance in relation to canopy reflectance, lower water absorption, and greater shadow fraction (Franklin et al., 2000). However, slash patterns (Nilson et al., 2001), understory and residual tree growth response (Franklin et al., 2000), and shifts in species composition (Olsson, 1994) may mitigate the expected spectral response after a stand is thinned. In characterizing the intensity of partial harvests, it is therefore important to choose spectral variables that are sensitive to the canopy removal of interest but that are relatively insensitive to these site-specific factors.

Prior studies have emphasized the importance of SWIR in differentiating partial canopy removal. Olsson (1994) found that bands 5 and 7 were the most effective Landsat bands for predicting basal area removal. Spectral composite indices featuring SWIR have also been used effectively to detect partial forest removals. Tasseled Cap wetness (TCW) (Crist & Cicone, 1984), which emphasizes SWIR reflectance, has been identified as a reliable indicator of both forest structure and forest structure change (Cohen et al., 1995; Collins & Woodcock, 1996; Franklin et al., 2000; Skakun et al., 2003). Jin and Sader (2005) found NDMI, which contrasts SWIR and NIR reflectance, to be at least as accurate as TCW in supporting the detection of disturbance intensity in Maine. In the present project, these and other Landsat-derived spectral variables were compared according to their relationship with four forest inventory variables: basal area, percent cover, relative basal area removal, and relative percent cover change. Only single-variable models were considered because of strong multicollinearity between most of the spectral indices with respect to the variables predicted.

Independent of the spectral variable selection process, cross-validation was used to assess the relative error rates of the SDM and DCM change detection approaches. The relative change in basal area and percent cover was predicted for each plot using both SMD and DCM with information from all other plots used as training data. So that cross-validation results would be directly comparable, plots that did not have the multi-temporal reference measurements needed for DCM were dropped from both approaches. Since cross-validation used only a portion of the dataset, this cross-validation procedure was used only to compare SMD and DCM, not to compare spectral variables. Together, it was hoped that the variable selection and cross-validation processes would lead to insight both into the basic effect of partial harvests in the region on surface reflectance and into the ability of two change detection approaches to quantify the effects of those harvests.

2. Methods

2.1. Study area

The boundaries of the study area were chosen to include several designated Spotted Owl Special Emphasis Areas (Fig. 1). Forests in this region are coniferous, dominated primarily by Douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*), with ponderosa pine being replaced by western hemlock (*Tsuga heterophylla*) in the western part of the southern study area and by grand fir (*Abies grandis*) in the upper elevations. Elevations range from 500 m above sea level near the Columbia River to approximately 2800 m near the crest of the Cascade Mountains. Topography influences the amount of rainfall in the area, with average precipitation ranging from 600 to 3000 mm/year across the two areas (Spatial Climate Analysis Service, 2005). The northern study area is centered at 47.3° N/120.9° W, and the southern area is centered at 45.9° N/121.5° W.

Forest cover in the area ranges from relatively open to completely closed, with canopy structure ranging from relatively uniform monoculture plantations to highly complex older forests. The area has a long history of timber management, and numerous permits for both even- and uneven-aged harvests were granted for each 2-year interval in the 1996–2004 study period (WDNR, 2004). Although the area is located in a region where stand-replacing fires are common, a Landsat-based map of stand-replacing disturbances (created following Cohen et al., 2002) showed no such fires in the area from 1996–2004. Aerial sketch mapping of insect activity (WDNR, 2003) showed a few areas of mortality in the study area between 1996 and 2003. However, the density of attacked trees was quite low (typically fewer than 10 trees/hectare) in our study area, and insect activity was therefore not explicitly considered in the modeling process.

2.2. Reference data

Three types of reference data were used to train and then cross-validate the spectral models for partial harvest: a harvest

permit database, field plots, and historical aerial photos. This permit database (WDNR, 2004) was used to identify likely sites of harvest activity between the years 1996 and 2004. Field crews were dispatched in the summer of 2004 to sites on accessible land in the study area where harvest permits had been granted in the previous eight years. Land was deemed accessible if it was under state, federal or municipal ownership or if it belonged to cooperating private companies. Recent Landsat images for target stands were visually inspected, and plots were sited in areas within the stand that displayed relatively uniform spectral characteristics. Seven plots were also sited in accessible stands where harvest permits had been granted but where no activity was visible from the imagery. Each one-hectare plot was composed of nine fixed-radius subplots (Fig. 2). The radius for the subplots in a given plot was fixed at 5, 10, or 12.5 m, depending on the density of the stand. Larger subplots were required to obtain adequate sample sizes in lightly stocked stands, whereas smaller subplots could be used to efficiently sample denser stands. Generally, subplot size was chosen so as to provide 10–15 trees per subplot (90–135 per 1-ha plot).

A number of inventory measurements were recorded at each subplot, including: the diameter at breast height (DBH), species, and canopy class of all trees with DBH greater than 10 cm. The diameter of all stumps at a height of 14 cm was also recorded. Further, the height and basal diameter (diameter measured at a height of 14 cm) was recorded for a representative tree for each canopy class (dominant, co-dominant, intermediate, suppressed) found in the subplot. The ratio of basal diameter to DBH for all such trees (Fig. 3) was later used to estimate the DBH and basal area of the trees removed from the stand. The percentage basal area removed from a plot was calculated as the basal area of the stumps divided by basal area of the combined stumps and live trees in the plot. No attempt was made to back-calculate the basal area of live trees at the time of harvest, which may have occurred up to 8 years prior to the stand survey.

Eighty-four plots were established in which live tree basal area information was recorded. For 38 of these plots, basal area change was not calculated because local harvest records indicated that multiple partial harvests had occurred in the last

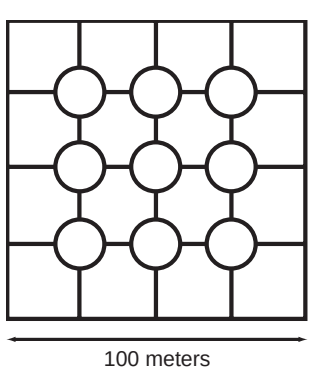

Fig. 2. Field plot layout, showing the location of circular subplots and scale of re-sampled 25-m Landsat pixels within each 1-ha plot. The radius of each subplot was fixed for each plot at 5, 10, or 12.5 m, depending on the density of the measured stand.

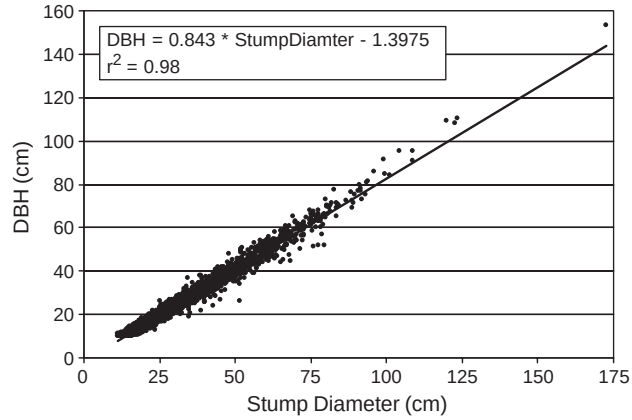

Fig. 3. The relationship between basal ("stump") diameter at 14 cm height and diameter at breast height (DBH) for all live trees in which basal diameter was measured (N=1983). This relationship was used to estimate the DBH and basal area of harvested trees using stump diameter measurements.

20 years and that not all of the stumps could be attributed to the time period of interest.

Percent canopy cover was estimated for most plots in both 1998 and 2002 using 1 : 15,000 nominal scale black and white aerial photographs (1998) and 1-m color orthophotos (2002). Photo coverage was available for 83 and 77 plots in 1998 and 2002, respectively. Estimates were made using a percent tree cover key that exhibited a variety of different clumping arrangements for each of 10 (10% cover) classes from 5% to 95% canopy cover. The value for a given plot for a given year was determined using the average estimate among three photointerpreters. Canopy cover change between 1998 and 2002 was calculated as the difference between cover estimates for the two dates.

To summarize, current basal area was measured at each plot, basal area removal was measured in plots where existing stumps could confidently be attributed to harvests in the study period, and percent cover was estimated for 2 dates where supporting photography was available.

2.3. Spectral data

Five late-summer Landsat TM and ETM+ images in two-year intervals were acquired for both the north and the south study areas (Table 1). Frequent image acquisition has been recommended to combat the potentially ambiguous effects of

Table 1
Landsat images used in this study

Landsat scene (WRS2)	Acquisition date	Landsat sensor
Path 45, Row 27	Jul. 13, 1996	TM
Path 45, Row 27	Aug. 4, 1998	TM
Path 45, Row 27	Aug. 9, 2000	TM
Path 45, Row 27	Jul. 22, 2002	ETM+
Path 45, Row 27	Sep. 21, 2004	TM
Path 45, Row 28	Jul. 13, 1996	TM
Path 45, Row 28	Aug. 4, 1998	TM
Path 45, Row 28	Aug. 9, 2000	TM
Path 45, Row 28	Sep. 24, 2002	ETM+
Path 45, Row 28	Aug. 20, 2004	TM

forest re-growth following partial harvest (Jin & Sader, 2005; Wilson & Sader, 2002). For each study area, the 1996 image was chosen as a geospatial reference, and all other images were co-registered to that image using an automated approach developed by Kennedy and Cohen (2003). All the images were resampled to 25 m resolution during this process, using the UTM projection and WGS84 datum. The 1998 path 45/row 27 scene was used as the reference for radiometric calibration. The COST atmospheric correction model of Chavez (1996) was applied to that image to convert digital counts to reflectance. Then, the other four images from row 27 were relatively normalized to it using the multivariate alteration detection (MAD) method of Canty et al. (2004), adapted by Schroeder et al. (unpublished). The 1998 row 28 image was then normalized to the row 27 reference image using the image overlap area and the remaining four images of row 28 were subsequently normalized to the row 28 1998 image.

In addition to the Landsat reflectance bands (1–5, 7), several other Landsat-derived indices were computed. After all images had been converted to reflectance and normalized to a Landsat 5 reference scene, Tasseled Cap brightness (TCB), greenness (TCG), and wetness (TCW) images were created using coefficients published by Crist (1985). Also derived for each image was the Disturbance Index (DI), which has been used to detect stand replacing disturbances (Healey et al., 2005; Masek, 2005). In this transformation, Tasseled Cap components are first re-scaled to standard deviations above or below a forest mean condition, and are then linearly combined in a way that approximates their spectral similarity to clearcuts (which are assumed to have high brightness, and low greenness and wetness). This combination (Eq. (1)),

$$\mathrm{DI} = \mathrm{TCB}_{\mathrm{re-scaled}} - (\mathrm{TCG}_{\mathrm{re-scaled}} + \mathrm{TCW}_{\mathrm{re-scaled}}), \tag{1}$$

typically produces high positive values in highly-disturbed areas and values near zero in most other forested areas. DI has not been tested in partial harvest situations.

The normalized difference vegetation index (NDVI), a measure of the ratio of NIR to red reflectance, was also calculated (Eq. (2)) for each image, using:

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{red})/(\mathrm{NIR} + \mathrm{red}) \tag{2}$$

Further, the normalized difference moisture index (NDMI), was also calculated (Eq. (3)). This index takes advantage of one of the SWIR channels (band 5; Jin and Sader, 2005) using the equation:

$$\mathrm{NDMI} = (\mathrm{NIR} - \mathrm{SWIR})/(\mathrm{NIR} + \mathrm{SWIR}) \tag{3}$$

For each plot center, a 16-pixel (1-ha) neighborhood (see Fig. 2) of pixel values was extracted from each of the spectral bands and indices. The average spectral value in this neighborhood was the spectral signature associated with each plot for a given date and band. In some cases, pixels were removed from this averaging operation because they contained unanticipated heterogeneity (new roads, clouds). Since plots were the modeling unit in this project, it was desirable to use plots that were as structurally and spectrally homogenous as possible. Inventory measurements from sub-plots overlapping removed pixels were removed from forest condition calculations.

2.4. Modeling the relationship between spectral and forest inventory variables

In this project, SMD and DCM were used to estimate partial harvest intensity in terms of relative reductions in forest canopy cover and basal area. Accordingly, there were four regression-based modeling efforts: creation of date-invariant models of cover and basal area for use in SMD, and models of basal area and cover change for use in DCM. Regression analysis has been a popular empirical method of modeling the relationship between spectral data and forest attributes (e.g., Butera, 1986, Turner et al., 1999). However, traditional (i.e., ordinary least squares, OLS) methods of regression are not sufficient when resulting biophysical surfaces derived from remote sensing are subsequently used to drive ecosystem process models or characterize habitat. With OLS regression, the variance of the predictions is commonly compressed relative to the variance of the observations (Cohen et al., 2003; Curran and Hay, 1986). The degree of compression is a function of the correlation between the spectral data and the biophysical variable of interest: low correlation, high compression, and vice versa. In this study, orthogonal RMA (reduced major axis) regression method was used. Cohen et al. (submitted for publication) recently demonstrated the value of RMA relative to OLS regression to predict tree cover and leaf area index across a number of sites in the western hemisphere.

Preliminary bivariate-plots showing the relationships between all possible 2-way combinations of spectral values corresponding to the inventory plots suggested strong multi-collinearity among the spectral measures under investigation. Further, forward step-wise regression suggested that a second spectral variable rarely made a significant contribution in explaining the variance in the forest inventory data. For simplicity's sake, therefore, only models using a single spectral term were further considered. In the variable-selection process, spectral bands were assessed in their relationship to the inventory data using their respective coefficients of determination (R^2). This process is outlined below for the four primary inventory variables (basal area, cover, basal area change, cover change).

The static (date-invariant) relationship between basal area and the spectral variables was determined using basal area measured in 2004 and corresponding spectral values from imagery that had been cross-normalized with images from all other dates. The static relationship between percent cover and spectral data was derived from the percent cover estimates obtained from 1998 1 : 15,000 nominal-scale black and white aerial photographs and 1998 spectral values. In both cases, some plots had to be discarded either because disturbances occurred between the date of the reference information and the date of the imagery or because within-plot heterogeneity prevented unambiguous interpretation of the mean spectral

value. This left 71 plots for basal area modeling and 76 plots for cover modeling.

Relationships between spectral changes and changes in the inventory variables were assessed using reference data from two dates in concert with contemporaneous spectral differences. Cover change was assessed at 54 plots by combining the 1998 photo data with a similar interpretation of 2002-era color orthophotos. Linear models using the absolute difference in cover between these two dates (Cover98 − Cover02) were consistently weaker than models using relative cover change ((Cover98 − Cover02) / Cover98). Accordingly, cover change throughout this paper is expressed in terms relative to the original percent cover.

Basal area change was likewise better captured in relative terms ((Basal $\text{Area}_{\text{pre-removal}}$ − Basal $\text{Area}_{\text{post-removal}}$) / Basal $\text{Area}_{\text{pre-removal}}$); thus, removals of basal area (as measured with stump data) were expressed as percentage decreases relative to the starting basal area. The spectral change associated with each harvest operation was calculated by taking the difference in spectral values from the dates immediately preceding and following harvest. Harvest dates were determined in consideration of the harvest permit database and through visual interpretation of the time series of Tasseled Cap images for each plot.

Only one plot in our dataset displayed relative basal area removal of 60–80 percent. A similar phenomenon was found in the dataset of Olsson (1994), and it is possible that removals of this magnitude are uncommon in our study area. It also appeared that although the relationship between spectral change and basal area change was relatively linear for all spectral variables up to 60% removal, different relationships occurred above 60% removal. Thus, it was decided to limit this model to values between 0% and 60% removal; only plots in that range (a total of 42) were used to create the basal area DCM model, and only that range of prediction was considered in the variable selection and cross-validation processes.

Logarithmic transformations were performed upon the basal area and cover variables in order to linearize them in relation to the spectral variables. Relative cover change and basal area removal were relatively linear with respect to the spectral variables without transformation. Comparison of the R^2 values of each of these linear relationships was the basis for evaluating the preliminary potential of each spectral band or index for supporting prediction of harvest intensity.

2.5. Comparison of DCM and SMD through cross-validation

The above variable-selection process did not address the larger question of how well SMD and DCM predict relative basal area and cover removal. This question was the focus of a leave-one-out cross validation analysis. For each plot, comparable DCM and SMD estimates of relative basal area and cover change were developed with data from all other plots. Estimates were then compared plot-wise with change information from remeasured reference data, and the root mean square error (RMSE) for each approach was calculated. So that SMD and DCM would be directly comparable, the absolute estimates resulting from SMD were transformed to relative terms to match the output of DCM, and only those plots with reference information supporting both SMD and DCM were used. Since basal area removals above 60% could not be predicted with our data using DCM, plots showing greater than 60% removal were left out of both the DCM and SMD basal area cross-validation exercises. All degrees of cover change were considered, however.

In the leave-one-out process, SMD and DCM were used to predict both the measured relative cover change between 1998 and 2002, and the relative basal area removal represented by the stumps measured in 2004 and attributed to harvest in one of four 2-year intervals (1996–1998, 1998–2000, 2000–2002, and 2002–2004). Forty-two plots were available to support this cross-validation procedure for basal area, and 54 plots were available for cover. Cross-validation was repeated using each of the spectral variables under study (bands 1–5, 7, TCB, TCG, TCW, DI, NDVI, and NDMI).

2.6. Using SMD to map owl habitat loss

The harvest mapping methods investigated here were intended to be integrated into a larger analysis carried out by WDFW and WDNR of how harvests have affected spotted owl habitat in the last several years (Pierce et al., 2005). WDFW and WDNR used SMD estimates of cover change to identify harvests resulting in the loss of owl habitat. A description of this process is included here to illustrate a practical application of the methods under investigation. While it is out of the scope of this paper to detail how WDFW and WDNR defined and identified owl habitat in the region, the use of SMD cover change estimates to update habitat maps followed relatively simple rules. If previously mapped owl habitat dropped either from above 70% canopy cover to below 70% cover, or from 50–70% to below 50% cover, it was assumed that the structural elements needed to support owl populations had been removed. SMD was used to identify harvests because it provided needed absolute estimates of both pre- and post-harvest cover. A “state” model for percent cover was developed with photo-based estimates of 1998 cover in conjunction with 1998 TCW values. This model was then applied to each Landsat scene, and estimated cover values from successive dates were compared to identify areas in which cover was estimated to drop below the 70% and 50% thresholds. A masking step was devised to minimize spurious identification of such pixels. Tasseled Cap-transformed image pairs from each 2-year interval were submitted to an independent supervised classification to differentiate “changed” from “unchanged” pixels. Only pixels identified as “changed” in this classification were permitted to be labeled as harvest by SMD.

Errors in the resultant maps of habitat loss were assessed using repeated cover measurements. Photos were used to determine whether plots had dropped below the habitat-critical 70% and 50% cover thresholds between census dates, and results were compared to SMD-based classifications of habitat loss. In most cases (64 plots), the assessed interval was 1998 to 2002 because photos were available for those 2 dates. For 10

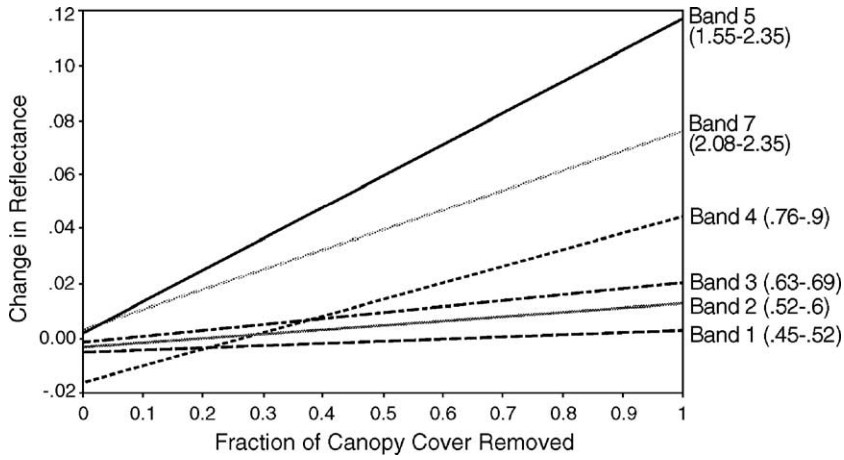

Fig. 4. Relationship between canopy cover removal and change in reflectance. Cover was assessed for 54 plots at two different dates using aerial photography, and changes were plotted against corresponding spectral differences in 6 Landsat bands.

plots disturbed between 1996 and 1998, it was possible to use earlier 1993 1-m color orthophotos to determine "pre-harvest" cover conditions; thus, the tested interval for these plots was 1996 to 2002. Plots thinned after the latest (2002) photo mission, as well as plots in which no harvest occurred, were estimated for the 1998–2002 interval.

3. Results

3.1. Spectral variable selection

The general relationship between spectral change and thinning intensity was plotted in terms of both percent cover (Fig. 4) and basal area (Fig. 5). Reference information was available from 54 plots for Fig. 4 and 46 plots for Fig. 5. For Fig. 5, 5 additional clearcut areas (100% removal) were identified using aerial photos, and the spectral signatures of these areas were used to augment available plot data. SWIR reflectance (bands 5 and 7) displayed relatively strong positive relationships with removal of both cover and basal area. Weaker increases in reflectance were seen in bands 1–3. NIR response to thinning intensity was slightly different when measured by cover loss as opposed to basal area loss. Although decreases in NIR reflectance were seen in both measures when little or no harvest occurred, more complete removals resulted in increasing reflectance when measured by cover change and very little change when measured by basal area. Since slightly different subsets of plots were available for each figure, these discrepancies may highlight previous findings (e.g., Franklin et al., 2000; Nilson et al., 2001) that NIR reflectance is sensitive to factors such as understory composition that are independent of the degree of forest removal.

The strength of the relationship (R^2) between spectral variables and relevant inventory variables was used in the variable selection process. Table 2 summarizes the strength of the relationships between the 12 Landsat-based variables and the inventory variables forming the basis for SMD (basal area and percent cover) and DCM (relative removal of basal area and cover). Coefficients were not strictly comparable among inventory variables because relative basal area removal was only predicted in a range of 0% to 60%. Nevertheless, coefficients were comparable within each forest inventory measure, and although R^2 is not an absolute measure of a

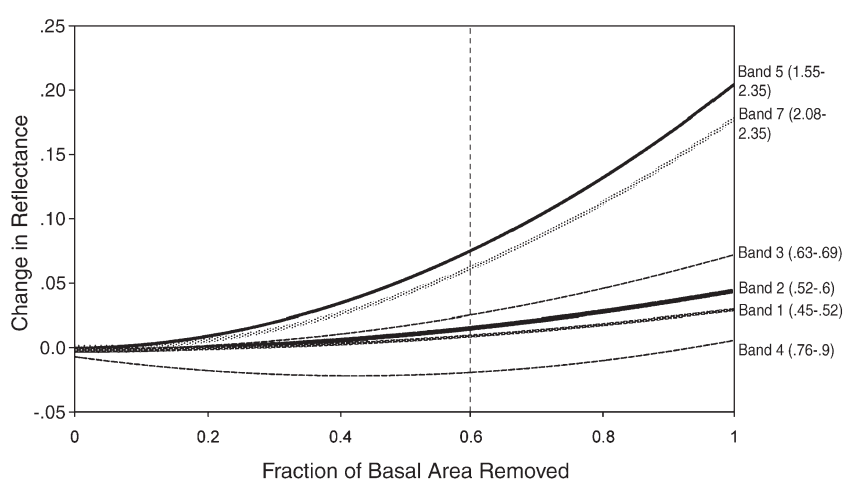

Fig. 5. Relationship between basal area removal and change in reflectance. Basal area removal was inferred from reference data for 62 plots ranging from 0% to 100% removal. Only plots undergoing basal area removal of 60% or less were ultimately considered in the (linear) regression-based DCM method described in this paper.

Table 2
Variable selection results

	Ln Basal Area, 2004 $N=71$	Ln Cover, 1998 $N=76$	Relative Cover Change, 1998–2002 $N=54$	Relative Basal Area Removal up to 60% removal, multiple 2-year periods $N=42$
Band 1	0.055	0.476	0.185	0.086
Band 2	0.315	0.662	0.447	0.313
Band 3	0.388	0.736	0.357	0.502
Band 4	0.071	0.064	0.209	0.057
Band 5	0.548	0.745	0.636	0.618
Band 7	0.566	0.759	0.647	0.601
TCB	0.367	0.264	0.551	0.317
TCG	0.000	0.226	0.044	0.288
TCW	0.579	0.762	0.635	0.630
DI	0.555	0.761	0.636	0.645
NDVI	0.221	0.632	0.204	0.475
NDMI	0.434	0.695	0.492	0.641

Values represent the coefficient of determination (R^2) for simple linear or log–linear relationships between reference data and contemporaneous spectral data. These relationships form the basis for the SMD (the Basal Area and Cover variables) and DCM (Relative Cover Change and Relative Basal Area Removal) change estimation approaches. The number of observations (N) for each relationship was dependent upon the availability of reference data.

model's value, certain general trends were apparent. First, spectral variables dominated by SWIR (band 5, band 7, DI, wetness, and, to a lesser extent, NDMI) showed the closest relationship to all forest and forest change variables. DI may be categorized as SWIR-dominated because further exploration showed that DI was highly correlated with wetness in this dataset. The relationship between wetness and the four change-related inventory variables is plotted in Fig. 6; also displayed are the RMA regression lines and coefficients. The other SWIR-influenced bands showed similar relationships with the field data. In general, the two untransformed SWIR bands (5 and 7) were as strongly correlated with the inventory variables as their derivative indices.

The weakest relationships with the forest change variables were shown by band 1, band 4, and TCG. The dataset also showed an apparently negative effect of NIR (band 4) in the indices into which it is integrated. For example, NDMI is a ratio of bands 4 and 5, and while it was more correlated to the forest and forest change variables than band 4, it was less correlated, in all variables except basal area change, than band 5 alone. The same presumed negative effect of band 4 was observed in NDVI, a combination of bands 3 and 4. Likewise, TCG, in which band 4 is strongly weighted, displayed only weak relationships with the forest structure variables. In general, variable selection highlighted the importance of SWIR, as the indices strongly influenced by SWIR — i.e., wetness, DI, band 7 and band 5 — had the most explanatory power for the forest change variables.

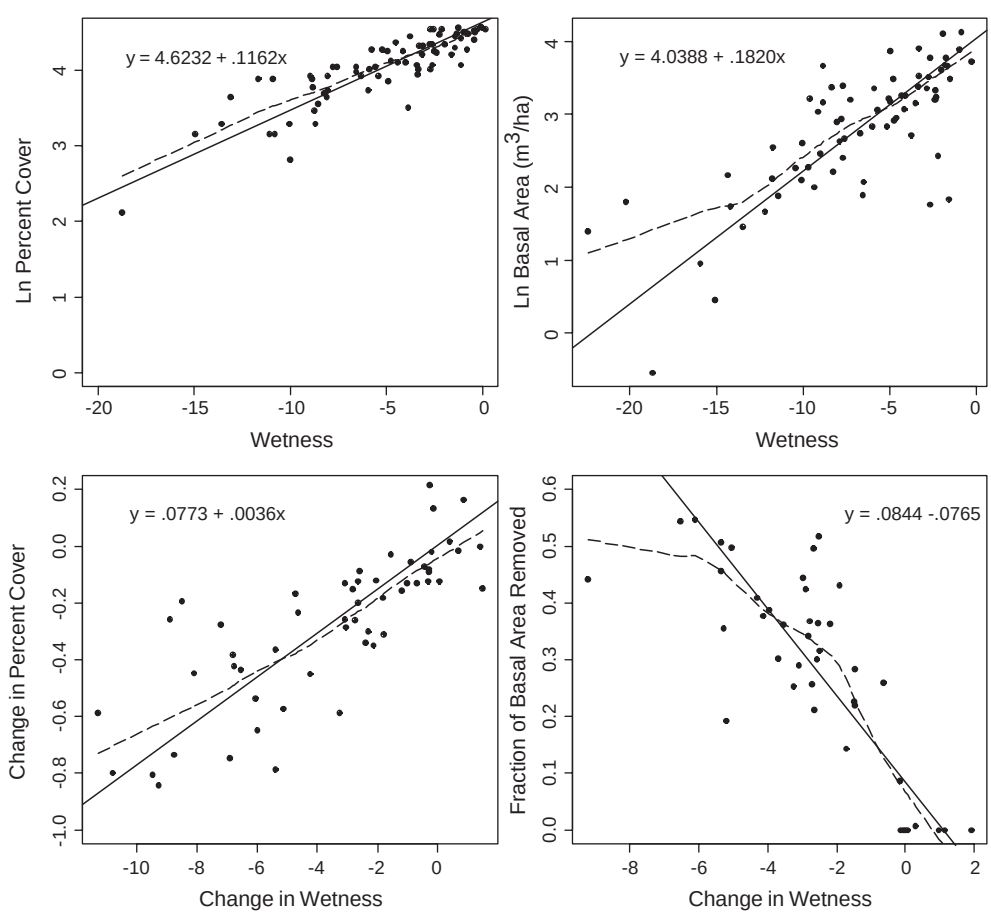

Fig. 6. Relationships between Tasseled Cap wetness and: percent canopy cover, basal area, change in percent canopy cover, and the fraction of basal area removed. RMA regression lines and equations are shown in each graph. Also displayed is a dashed loess smooth line (span = .67), illustrating the fit of the regression lines to the data.

Table 3
Root mean squared error (in percent relative change) resulting from the leave-one-out cross-validation procedure

	Relative Basal Area Removal (42 plots)		Relative Cover Change (54 plots)	
	DCM (%)	SMD (%)	DCM (%)	SMD (%)
Band 1	21.4	93.5	28.3	42.3
Band 2	16.9	77.1	21.7	33.4
Band 3	13.8	39.5	24.3	31.3
Band 4	22.0	27.3	27.7	40.9
Band 5	**12.1**	**18.3**	**17.0**	**25.7**
Band 7	**12.4**	**18.2**	**16.7**	**26.8**
DI	**11.5**	**16.6**	**17.1**	**27.3**
NDVI	14.2	39.6	27.8	33.9
NDMI	**11.3**	**14.7**	**20.6**	**30.0**
TCB	16.8	46.8	19.1	29.4
TCG	17.2	22.6	33.2	38.5
TCW	**11.9**	**15.8**	**17.1**	**26.4**

SWIR-influenced spectral variables (in bold: bands 5 and 7, TCW, DI, NDMI) produced more stable estimates of change than those not featuring SWIR (bands 1–4, TCB, TCG, NDVI). Basal area change was modeled only for 0 to 60% removal, whereas relative cover change was modeled up to 100% removal.

3.2. Comparison of DCM and SMD

While the variable-selection phase of the project considered simple relationships between spectral data and the forest inventory measures, the cross-validation phase integrated these relationships into estimates of forest removal based upon the SMD and DCM approaches. DCM produced lower root mean square error (RMSE) for prediction of both percent cover loss, which was modeled for up to 100% loss, and percent basal area reduction, which was modeled only up to 60% loss (Table 3). However, SMD-based estimates using the most effective spectral variables (TCW, DI, band 5, band 7, and NDMI) were within 5% of those resulting from DCM for basal area removal (17% RMSE compared to 12%) and within 10% for cover change (26% to 16%).

An extremely high error rate was noted for bands 1 and 2 in cross-validation for basal area SMD. SMD's reliance on two separate applications of a “state” model to estimate change likely contributed to this error rate; the errors inherent in each application may have compounded one another, particularly in cases where the original state model was weak. The relationship between bands 1 and 2 and the spectral variables was so weak, for example, that the regression coefficients used for some of the plots in the leave-one-out process were positive while others were negative, leading to large prediction errors. The fact that this phenomenon was not seen with other variables such as band 4 and TCG, which according to the variable selection results were also weakly correlated with basal area, was possibly a factor of sample size. As plots were dropped from the original dataset to enable direct comparison of cross-validation results, the impact of spectral outliers increased either by their retention or exclusion. Thus, because this cross-validation generally incorporated fewer samples and was designed only to compare the relative error rates between SMD and DCM, it was considered a less appropriate means of comparing spectral variables than the variable-selection process. Nevertheless, cross-validation results generally supported the trend noted in the variable selection process: SWIR-dominated indices produced the most accurate estimates of change.

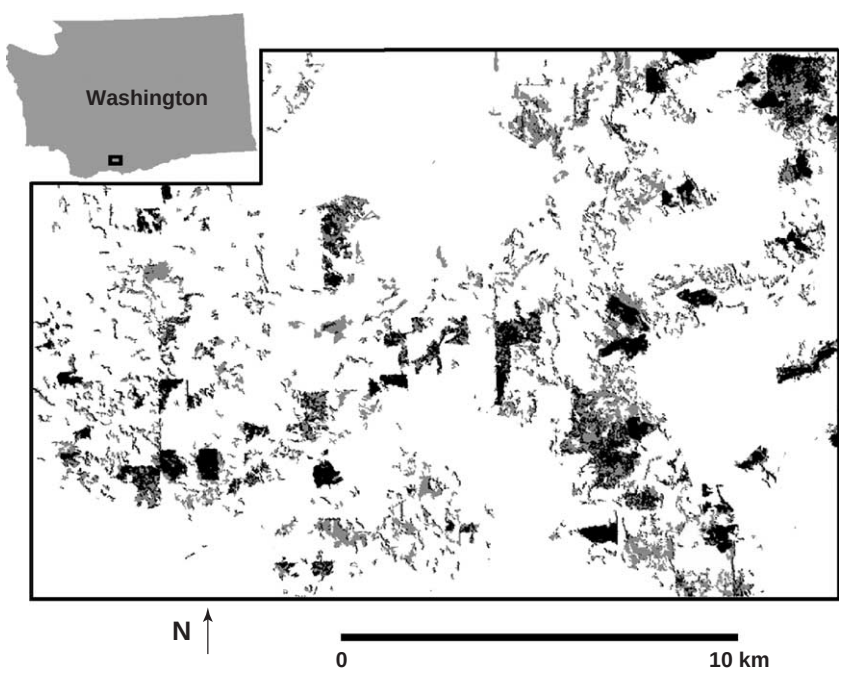

Fig. 7. Detail of a map of harvest impacts on owl habitat between 1998 and 2000 in the southern focus area. Areas in white were classified as “no change” in a preliminary multi-temporal supervised classification. Of areas identified as “changed,” classes for habitat loss (black) and no habitat loss (grey) were created by binning, at the pixel level, SMD results to match Washington forest practices criteria.

Table 4
Error matrix for classes of interest to WDFW and WDNR

Measured condition	SMD-based prediction		Total	Producer's accuracy
	No Habitat Loss	Habitat Loss		
No Habitat Loss	36	7	43	0.84
Habitat Loss	11	20	31	0.65
Total	47	27	74	
User's accuracy	0.77	0.74		
Overall accuracy				0.76

Habitat Loss was defined as overstory removal resulting in cover conditions below state forest practices criteria for spotted owl habitat. Observed values came from repeated photo measurements for 74 plots.

3.3. Use of SMD-based maps to support an assessment of owl habitat change

Modified SMD maps depicting harvests reducing cover from above 70% to below 70% and from 50–70% to below 50% were used by WDFW and WDNR to analyze changes in owl habitat. While discussion of this analysis is not within the scope of this paper, an example of one of the cover change maps used is shown in Fig. 7. For each 2-year interval, these maps depicted: areas identified as unchanged by an independent supervised classification (white), areas with cover trajectories consistent with habitat loss (cover above 70% to below 70% or 50–70% to below 50% — black), and areas where estimated cover changes did not meet criteria for habitat loss (grey). An error matrix was constructed (Table 4) for two classes: those re-measured plots that did and those that did not undergo changes in percent cover consistent with the loss of spotted owl habitat. Fifty-six out of 74 re-measured plots (76%) were mapped correctly with respect to these classes.

4. Discussion

4.1. Which spectral variables are most sensitive to forest structure changes associated with partial harvest?

The general spectral response to forest removal shown in Figs. 4 and 5 conforms to a pattern that has been relatively consistent across several studies (Franklin, 2001): harvest coincided with an increase in visible and SWIR reflectance and a decrease in NIR reflectance. Few studies have assembled datasets designed to support the modeling of forest harvest effects as a continuous variable. Thus, there is little information on how consistently and with what order of detail these general spectral trends can be used to estimate degrees of harvest intensity. In this context, our results provide information about which Landsat-based variables are most sensitive to the forest structure changes that accompany partial harvests in the Pacific Northwest.

The relative performances of the spectral bands considered in the variable selection phase of this study have two broad implications. First, SWIR, as represented by bands 5 and 7, TCW, DI, and potentially NDMI, is the most useful range of the Landsat spectrum for characterization of forest structure change. This corroborates results obtained both by studies classifying tree mortality/removal into general levels of intensity (Franklin et al., 2000; Jin and Sader, 2005; Skakun et al., 2003) and by those measuring forest change as continuous variables (Olsson, 1994; Collins and Woodcock, 1996). The relative value of the various data transformations in predicting harvest intensity varied slightly among inventory variables, and would likely vary further in different forest systems and with different harvest practices. Healey et al. (2005) demonstrated that the relative value of different Landsat transformations for supporting harvest-detection can vary by ecosystem; in fact, of the three ecosystems they studied, the region containing the current study area showed the least differentiation among alternative transformations in terms of supporting accurate harvest detection. However, it would seem that for harvest characterization in our study area, the benefits of processing data beyond the original Landsat SWIR bands are minimal. For projects involving large areas and multiple dates, elimination of this additional processing may offer a considerable reduction in processing time. The value of indices relative to SWIR bands alone should be tested in the future for consistency in other regions.

The second implication of our results is that the relationship between NIR and forest structure change is relatively inconsistent. TCG, in which NIR is heavily weighted, and band 4 were both weakly correlated with the forest structure variables in the variable-selection exercise. NDVI and NDMI, which incorporate NIR in ratios with red and SWIR, respectively, were less correlated to forest structure and forest change variables than their non-NIR components alone. Given the ubiquitous application of NDVI in forest change detection, the sometimes deleterious effect seen here of NIR was significant. These results underscore findings of other studies that suggest the general relationship between NIR and forest structure can be compromised by factors like understory conditions (Danson and Curran, 1993), slash patterns (Nilson et al., 2001), and species differences (Olsson, 1994). Thus, whereas SWIR bands showed relatively strong and consistent relationships with measures of forest removal, the relationship between our ground data and the NIR bands was more tenuous.

4.2. Approaches to modeling harvest intensity

The primary objective of this study was to test two change estimation approaches, DCM and SMD, in their ability to measure partial harvest with multi-temporal Landsat data. The leave-one-out cross-validation process was developed to assess and compare errors involved with predictions of harvest intensity produced through these two approaches. In our study area, DCM and SMD both produced estimates of relative forest change with reasonably low RMSE when using SWIR-based spectral bands and indices. The lower error rates achieved with DCM were expected because relative change was modeled as a single variable with a single error term instead of the difference of two independently modeled “state” estimates, each with their own error term.

However, there are a number of practical advantages to SMD that, depending on the resources and needs of a project, may

counterbalance the measured increase in error. First, SMD has simpler reference data needs than DCM since it is concerned only with identifying the static relationship between spectral data and forest condition. As long as cross-date radiometric normalization is reliable, one can pull reference data from any date, match it to contemporaneous spectral data, and use it to build a state model. That state model can then be applied to similar imagery from any dates of interest to estimate change. This flexibility, along with the elimination of the need to re-measure each plot, represents a significant operational advantage. Furthermore, unlike DCM, SMD does not require pre-selection of disturbed areas for selecting plot locations. Such areas may be rare, which may limit the number of available plot locations, and their identification may add considerable pre-processing time. Multi-date reference information is still needed for validation, but this requires a considerably lower volume of such data.

Another advantage of SMD is the specificity of its results. Theoretically, DCM can provide an estimate of absolute change (i.e., the gross difference in a forest structure variable). However, in our dataset, the relationship between spectral differences and absolute change was inconsistent because of the lack of a reference point. For example, a reduction in cover from 90% to 65% resulted in a much different spectral change than from 25% to 0%. This phenomenon was consistent with the findings of Cohen and Fiorella (1998), who demonstrated the inadequacy of using spectral differences alone for forest change characterization. So in our study, DCM could only accurately be modeled in terms of relative change (change as a percent of the starting value). Because SMD provides an estimate of forest condition for both before and after a harvest, harvest effects are estimated in absolute terms.

The pre- and post-harvest reference points implicit in SMD estimates of change were critical in the mapping of our study area to meet WDFW's needs. Habitat loss was defined not in terms of gross removal, but by the ability of the stand to meet cover-based criteria for habitat both before and after harvest. The need for specific cover estimates for both before and after harvest necessitated the use of SMD.

The mere application of either SMD or DCM to a series of normalized Landsat imagery does not necessarily constitute a map. These approaches, rather, provide raw estimates to be used in a map in light of the needs and tolerances of the user. WDFW was concerned primarily about identifying harvests that removed stands from pre-defined, cover-based definitions of owl habitat. Flexibility to conform to varying classes of interest is one of the strengths of modeling change as a continuous variable as opposed to committing to a single classification scheme. Although both the DCM and SMD processes may produce continuous estimates of change, the flexibility of SMD is augmented by the reference points implicit in its estimates.

Our results suggested that in the conifer-dominated forests of the Pacific Northwest, relatively strong relationships exist between SWIR-dominated spectral bands and measures of harvest intensity. Further, both DCM and SMD can be used with these bands to produce estimates of relative basal area and cover removal with less than 25% RMSE. Although DCM estimates of harvest intensity were more accurate than SMD estimates, SMD's more flexible reference data requirements and model output may be better suited to the resources and needs of some mapping projects.

Acknowledgements

The authors are grateful for the financial and logistical support of WDNR and WDFW, and particularly acknowledge the expertise of Brian Cosentino and Shelly Snyder of WDFW. This work was also supported by the Northwest Forest Plan Interagency Monitoring Program. Also deserving credit are hardworking field technicians: Erik Haunreiter, Albert Foster, Mathew Bibeau, Alicia Billings, and Sean Sheldon. Finally, the authors appreciate the cooperation of American Forest Resources of Ellensburg, WA.

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