Pacific Northwest Forest Change Detection Using Unsupervised Classification

Abstract

Timber is one of the Pacific Northwest's most abundant natural resources and harvest of this invaluable asset needs to be sustainably managed. In this study I used six, time sequential, Landsat satellite images with Tassel Cap Transformations to identify the change in timber harvest in a region of northwestern Washington State for five study periods. I then cross-referenced these spatial-temporal changes with land ownership data to quantify harvest rates for various groups including private, DNR, National Forest, and wilderness. In general, there was a total decrease of around 94% in harvest rates over the course of the study. Private land use saw the largest initial harvest rates with DNR, National Forest, and wilderness areas below that, in descending order. While this study was overall quite successful, ground truth data for training and testing purposes could have both improved and quantified the accuracy of the classification.

Methods

I used imagery obtained from the Landsat TM dataset for the years 1988, 1992, 1995, 2000, 2005, and 2011. Each image was taken during the summer months and consisted of a 2378 km2 area encompassing western Whatcom County from Bellingham Bay to Mt. Baker. The scene measured 1510 rows by 2520 columns with a resampled spatial resolution of 25 meters by 25 meters.

This analysis involved the manipulation of various scenes of the study area as described by Wallin (2015). For each time period ('88-'92, '92-'95, etc.), Wallin created a new file which contained the transformed Tasseled Cap brightness and greenness index values as outlined in

Cohen et. al. (1998). The new image file contained the two indices for each of the five time periods for a total of ten bands.

Following procedures outlined by Wallin (2015), I then performed an isodata unsupervised classification on the change file to determine clear-cut areas by year. I put the resulting spectral classes into information classes using the original change file and color-ir images (Figure 1A). These information classes represented each time period between imagery ('no change,' '88-'92, '92-'95, '95-'00, '00-'05, '05-'11). I then removed non-forest vegetation using an elevation mask (100 – 1700 m) and a land cover classification map (Quinn 2015; Figure 1B). I removed clear-cuts smaller than 2 ha using the sieve technique and filled small gaps using a clumping technique (Figure 1C) in accordance with Cohen et. al. (2002). I then compared final information classes with existing land ownership. All analyses were conducted in ENVI Classic.

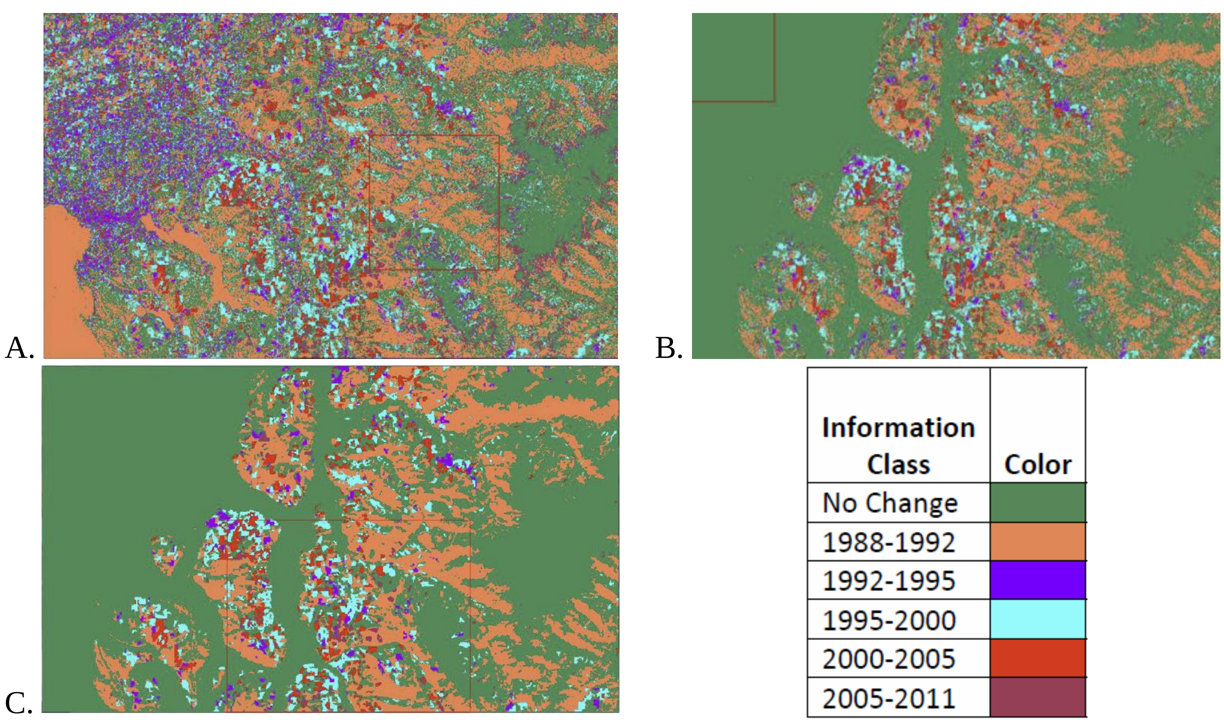

Figure 1. Product of the initial unsupervised classification (A.), the application of elevation and land cover masks (B.), and the final sieving and clumping techniques (C.).

Results

My initial analysis of forest disturbances resulted in a total harvest of 14,225 ha from 1988 to 2011 (Table 1). Approximately 43% of this total harvest occurred between 1988 and 1992 with the remaining harvest taking place from 1992 to 2011. Overall, there was a general decrease in harvest rates from 1531.8 ha year^{-1} in ’88-’92 to 590.5 ha year^{-1} in ’92-’95. Harvest rates stayed relatively constant from ’92-’05, and then saw a decrease of about 87% to 78 ha per year in ’05-’11. A representation of this trend can be seen in Figure 2. Over the course of the 23 year study period, a total of 11.6% of forested land within the study area was harvested.

Table 1. Total harvest and harvest rate in hectares and percent of total forested area.

Time Period	Years	Total Harvest (ha)	Harvest Rate (ha/year)	Total Harvest (% forest)	Harvest Rate (% forest/year)
‘88-'92	4	6,127.1	1,531.8	5.0%	1.3%
‘92-'95	3	1,771.6	590.5	1.4%	0.5%
‘95-'00	5	3,334.3	666.9	2.7%	0.5%
‘00-'05	5	2,524.8	505.0	2.1%	0.4%
‘05-'11	6	467.9	78.0	0.4%	0.1%
Total	23	14,225.6	-	11.6%	-

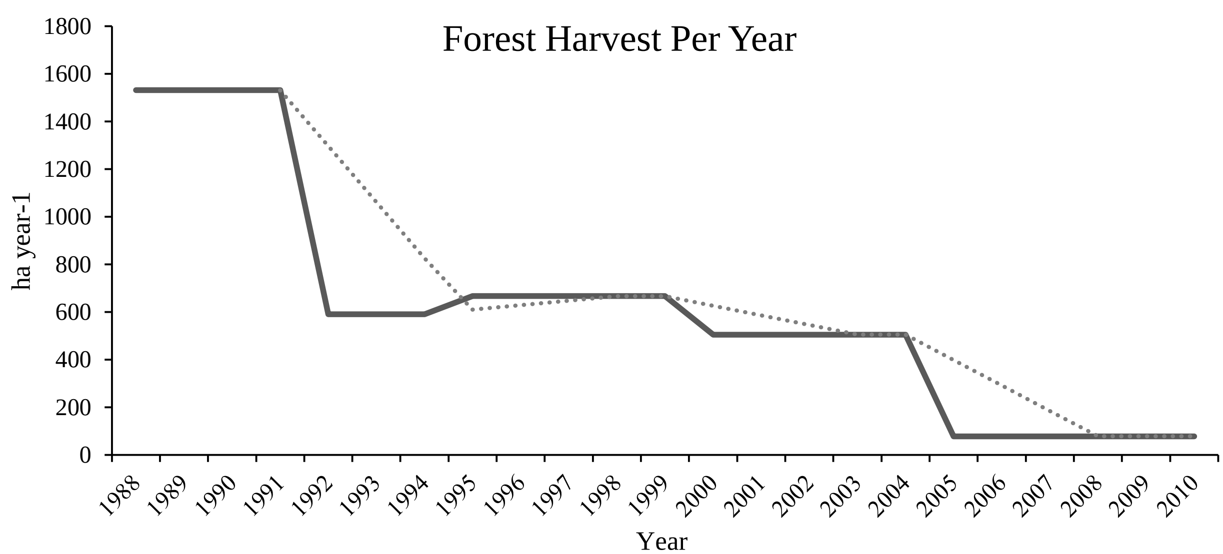

Figure 2. Forest harvest per year as averaged by analyses periods. Trend line shows a 5 year moving average of values.

By comparing spatial harvest events to existing land ownership areas, I was able to classify forest harvest within different ownership categories: National Forest (NF, Mt. Baker National Forest), Department of Natural Resources (DNR), Wilderness, and Private land. This reclassification indicated that from ’88-’92, harvest rates in private lands were almost 1.9 times that of DNR lands and more than 6 times that of NF lands (Table 2).

Table 2. Total harvest rates as area per year and percent total forested area of the study region per year for each of the land ownership categories: Wilderness, National Forest, Private, and Department of Natural Resources

		Wilderness		National Forest		Private		DNR	
Period	Years	ha/year	%/year	ha/year	%/year	ha/year	%/year	ha/year	%/year
‘88-‘92	4	30.9	0.47%	131.8	0.44%	928.3	1.84%	440.8	1.25%
‘92-‘95	3	0.0	0.00%	57.4	0.19%	372.3	0.74%	160.9	0.46%
‘95-‘00	5	0.0	0.00%	8.5	0.03%	384.4	0.76%	274.0	0.78%
‘00-‘05	5	2.2	0.03%	10.4	0.03%	299.6	0.59%	192.8	0.55%
‘05-‘11	6	0.0	0.00%	0.0	0.00%	61.6	0.12%	16.4	0.05%

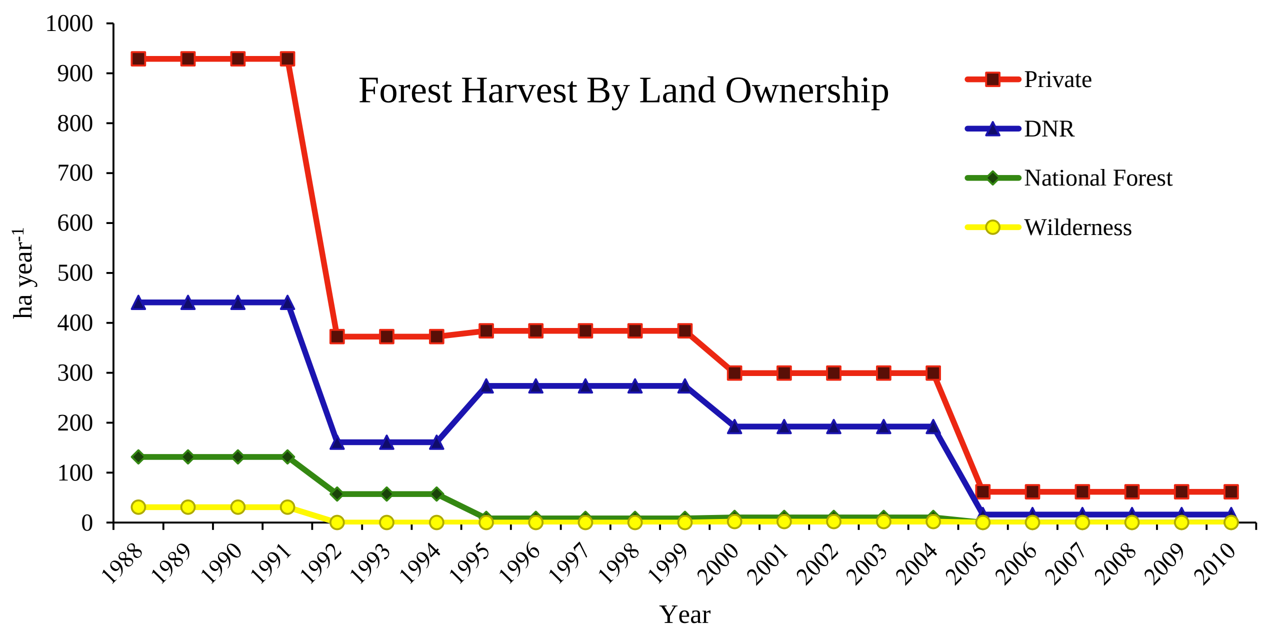

Figure 3. Forest harvest per year as averaged by analysis period for each land ownership category: Private, Department of Natural Resources, National Forest, and Wilderness. Values are not stacked.

Wilderness and NF lands had relatively low harvest rates compared to DNR and private land throughout each study period. Each land ownership category saw the greatest harvest rates during the ’88-’92 period, dropping by more than half in each category from ’92-’95. There was a small increase from ’95-’00 which dropped to less than 10% of highest levels by the ’05-’11 period. This trend can be observed in Figure 3.

Discussion

In this region, the majority of harvest comes from intensively managed private lands owned by timber harvesting companies (Wallin 2015). Forest harvest rates can often be directly correlated with timber prices and demand, which is dictated by the construction industry. During the latter half of the study period, construction rates were declining, which may have been a factor in the decline in harvest rates. Timber harvest on DNR lands is a major supplier to public funds however, like private harvest, it is effected by timber sale prices. This may explain the increase in harvest rates on DNR land from ’95-’00. Public demand may have warranted a slight increase in the harvest rates to fund existing projects. During this time period, private land harvest rates remained relatively constant.

In this study one would expect harvest rates to be significantly higher on private and DNR land as both are often intensively logged. Harvest rates can be expected to be lower in National Forests where logging regulations are strict and lowest in wilderness areas where logging is forbidden. The calculations generated from the combination of the timber harvest classification and land management image supported this hypothesis. From 1988-2011 the average rate of forested land harvested per year was highest on private land (0.81%) and lowest in wilderness areas (0.10%). The results for the latter ownership type may be inflated. When running an unsupervised classification it is hard to distinguish between timber harvest and natural disturbance. Both would display similar brightness values. This analysis detected a small number of forest cover change within wilderness classified areas. Currently, wilderness areas cannot be harvested for any natural resources including timber. It is possible that these areas were affected by fire or wind damages, however further analysis would need to be done to assess the validity of these claims (Wallin 2015).

A potential problem with this study arose when assigning spectral classes to information classes. My resulting ISODATA classification image contained 50 unique spectral classes, each needing to be assigned to one of six information classes. Although Landsat TM imagery was used to aid in accurately assigning spectral classes to information classes, the process was still rather subjective. Spectral classes are assigned based on the user's interpretation of imagery and users are forced to make tough decisions about this assignment. For example, alpine areas around Mt. Baker have a similar signature to areas logged between 2000-2005. This specific example was resolved using masks, but others may have not been resolved and would have a negative impact on our final results. The accuracy of this assessment is based on how the user decided to make these decisions. This aspect of the study could have been improved with the collection and utilization of ground truth points as training and testing data.

A second issue that likely affected the outcome of this study occurred when I masked out the non-forested areas. This mask was developed using an image classified by me in an earlier lab. While this image had an acceptable overall classification accuracy of 64.9%, this also means that 35.1% of the image was misclassified. Based on this knowledge, areas that were masked as being forest have the possibility of being incorrect. In a future application of this analysis it would be beneficial to base the non-forested area mask off of an image with a higher overall classification accuracy. Additionally, certain biases in the method, such as the elevation window for harvesting, the sieving parameter to eliminate noise, and the smoothing window for clumping, likely reduce the accuracy of the final classification as well.

Generally, this study seemed successful at quantifying timber harvest from 1988-2011. In comparison to original imagery in false and true color, my final classification does an acceptable job from a visual standpoint. Additionally, the quantitative results obtained seem reasonable based on the literature and observed trends were expected considering management practices. However, without a way of validating this study, for instance with ground truth data, the results can only be taken at face value and success is difficult to determine.

Works Cited

Cohen, W. B., M. Florella, J. Gray, E. Helmer, & K. Anderson. 1998. An Efficient and Accurate Method for Mapping Forest Clearcuts in the Pacific Northwest Using Landsat Imagery. *Photogrammetric Engineering & Remote Sensing, 64*(4), 293-300.

Cohen, W. B., T.A. Spies, R.J. Alig, D.R. Oetter, T.K. Maiersperger, & M. Fiorella. 2002. Characterizing 23 Years (1972-95) of Stand Replacement Disturbance in Western Oregon Forests with Landsat Imagery. *Ecosystems*(5), 122-137. doi:10.1007/s10021-001-0060-X

Quinn, D. 2015. *Unsupervised Classification of Whatcom County Using the ISODATA Clustering Algorithm.*

Wallin, D. 2015. *Lab V: Change Detection Using Unsupervised Classification with ENVI*. Retrieved from http://faculty.wwu.edu/wallin/envr442/ENVI/442_change_lab_ENVI.htm