Identifying the Causes of Landscape Change in the North Coast and Cascades Network Parks: Final Report for Task Agreement J8W07110003 to PNW CESU Agreement H8W07110001

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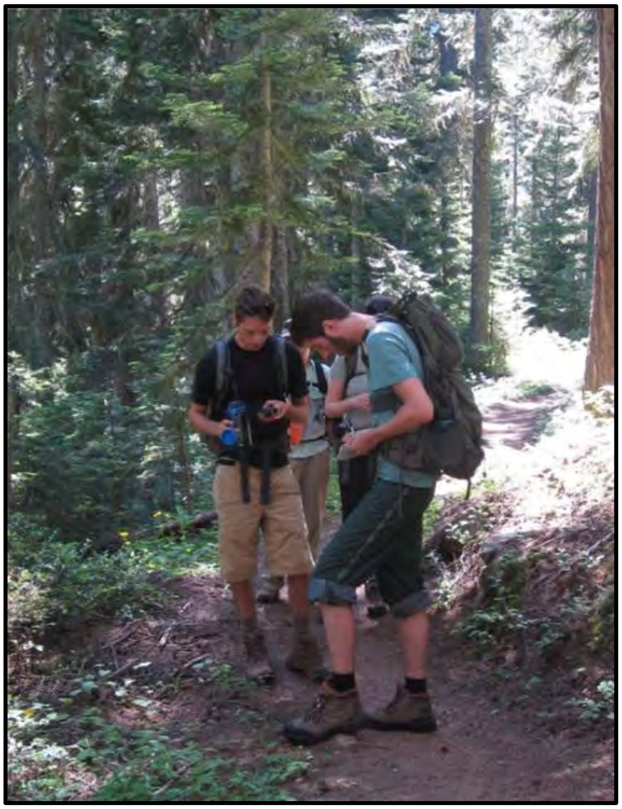

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Introduction

National Parks contain scenic and dynamic landscapes where natural disturbance processes dominate. Examples of disturbance agents are wildland fires, landslides, avalanches, floods, insect damage and windthrow. Monitoring the location, severity and types of disturbances occurring in the parks, including any variation in those factors associated with climate change, is a priority for park managers. Therefore landscape dynamics has been selected as one of seven core ―Vital Signs” tracked by the NPS North Coast and Cascades Network (NCCN) Inventory and Monitoring Program. In cooperation with academic partners from Oregon State University, NCCN has developed a landscape monitoring method using new remote sensing change detection method called LandTrendr (Thompson et al. in review). This method generates geographic information system (GIS) maps of landscape change from 1986 to the present for areas inside and outside NCCN park boundaries.

After the location and extent of disturbances were mapped, a change agent needed to be determined for each disturbance. Following a remote sensing workshop in 2002, a set of eight agents were selected as of interest to the NCCN (Table 1). NCCN developed a Random Forest statistical model to classify disturbances into one of the categories shown in Table 1 based on spectral characteristics of the disturbance and its location on landscape. A tenth agent called ―No Visible Change” was added to the model to represent areas that had undergone change that was not of interest to the network. These ―uninteresting” changes included annual variations in cloud cover, snow level, phenology, topographic shadow, and soil moisture.

Table 1. Original North Coast and Cascades Network landscape change monitoring goals.

Landscape Change Agent
Avalanche chute clearing
Landslide
Debris Flow
Fire
Insect/disease defoliation in forest
Riparian disturbance
Clearcut
Rural development
Windthrow

The collaborative project between NPS and Western Washington University (WWU) funded by this cooperative agreement was initiated in order to provide student interns the opportunity to conduct lab- and field-based accuracy assessment of these labeled landscape change maps. The objectives of the project were threefold:

1) provide students with an opportunity to gain educational experience with both computer-based remote sensing methods and field work,

2) provide NPS with validation of the statistical agent labeling model using aerial photo interpretation method and field work,

3) determine the viability of using students in any future aerial photo and/or field-based map assessments.

We wanted to achieve disturbance labeling accuracies in the 80th percentile that would be similar to those generated by the validation techniques provided by the Random Forest statistical package. The expectation was that validation using aerial photography and spectral characteristics of disturbances would be as accurate as, or more accurate, than validation using field visits. We also hoped that the students would be able to learn to identify disturbance agents correctly with no prior experience with aerial photo interpretation and only using the training provided by park staff.

Methods

Six students from Western Washington University (WWU) signed up for the internship. The first phase of the internship was to conduct the accuracy assessment of the disturbance labels generated by the Random Forest statistical model. Students worked in the WWU GIS lab to identify disturbance agents at three NCCN parks (Mt. Rainier (MORA), North Cascades (NOCA), and Olympic (OLYM) using aerial photography in Google Earth and disturbance spectral characteristics generated from Landsat satellite images. Training was provided prior to beginning of actual work to help students differentiate various disturbance agents.

Once the aerial photo interpretation was completed, the WWU students conducted field work at NOCA, hiking to areas where LandTrendr had detected change. Students used aerial photos and GPS to locate the disturbance areas, identified the disturbance type, and recorded site characteristics such as disturbance shape and location on landscape. An effort was made to include all types of disturbances in field visits; however some types were underrepresented due to their infrequent occurrence in the study area or access difficulties.Results of field work were compiled into one dataset and students performed two types of accuracy assessment:

1) Disturbance agents identified in the field were compared to the agents generated by looking at aerial photography in the lab.

2) Disturbance agents identified with aerial photography in the lab were compared to agents generated by the Random Forest statistical model.

Finally, students summarized their results and prepared reports found in Appendices A through G of this document. Student reports also contain detailed information on aerial photo interpretation and field methods.

Results

At North Cascades National Park, students labeled 2069 disturbances using aerial photography. This random sample of disturbances represents approximately 10% of disturbances found inside and 20% of disturbances found outside the park boundary. Student-generated labels were then compared to disturbance labels generated by the Random Forest statistical model. If one assumes that the agents chosen by students in the lab are ―correct," accuracy of the random forest-generated labels ranged from 52.3 to 74.2 percent with an average of 60.1 percent (Appendices A through F).

Following validation work in the lab, 320 disturbances were visited in the field at NOCA. The following general areas in the park were sampled: Bridge Creek drainage, areas along Devil's Dome loop trail, areas along Highway 20, Cascade River Road and Ross Lake, and Stehekin Valley and adjacent trails. The same disturbances were labeled again in the lab using aerial photography. Students compared field and aerial photography assessments to determine the degree of agreement between the two methods of agent identification. Agreements ranged between 68 and 83 percent, with an average of 73.28 percent (Appendices A through F).

Both types of assessments revealed a number of commonly confused categories including Fire and Insect, No Visible Change and Insect, Clearcut and Development, and various mass movement categories. It was determined that some labeling categories needed to either be combined or redefined to achieve greater separation between disturbance agents. For example, Debris Flows were often confused with Landslides or Riparian disturbances because they possessed elements of both those categories. The label of No Visible Change, which suggested lack of disturbance, was renamed to Annual Variability to more accurately represent the spectral variability of events that are found in this category. With the goal to achieve greater separation between Rural Development and Clearcut category, the Rural Development label was changed to just Development and redefined to represent disturbances where buildings and infrastructure occupy the majority of the area covered by the disturbance patch. Some categories, such as Windthrow and Insect/Disease, proved to be too specific. These categories were renamed to include multiple landscape disturbances that produce similar spectral and visual outcome. Table 2 shows a list of new labeling categories.

Table 2. Landscape disturbance types monitored by the NCCN.

Landscape Disturbance Types	
New Label	**Previous Label**
Avalanche	Avalanche chute clearing
Clearing	Clearcut
Development	Rural Development
Fire	Fire
Forest Collapse	Windthrow
Forest Decline	Insect/disease defoliation in forest
Mass Movement	Landslide
Mass Movement	Debris Flow
Riparian	Riparian disturbance

After labeling categories were combined or redefined, student results and Random Forest model were updated to match the new categories and accuracy matrices were rerun to see if new disturbance combinations would improve the results. Even though there were improvements in majority of cases and better consistency was achieved (a range between 59.44 and 67.33 percent with an average of 64.8 percent (Appendix G)), the improvement was not significant enough to achieve our goals of at least 80 percent accuracy. We felt this was the result of using old definitions of disturbance categories and that accuracies could improve if new definitions were used and better training was provided to the students. This hypothesis was tested by having an experienced park staff perform a photo-based accuracy assessment using new category definitions on the same disturbances that were evaluated in the field (Appendix H). Three hundred and twenty seven disturbances were evaluated. An accuracy of 81.04 percent was achieved when comparing aerial photo interpreted labels with Random Forest generated labels. A lower accuracy of 72.17 percent was achieved when aerial photo interpreted labels were compared with disturbance labels generated in the field.

To improve future training and validation results, a new study guide was developed that contained descriptions and definitions of each disturbance category and provided examples of disturbances as seen on an aerial photo, a series of Landsat images, and a spectral graph (Appendix I). Two students, A. Hayes and S. Clary, who participated in earlier work, were retained on volunteer basis to receive new training and blindly redo earlier validation using new definitions. Table 3 shows new validation results with an achieved overall accuracy of 84.1 percent.

Table 3. Confusion matrix displaying correlation between disturbance agent assignments determined using aerial photography with disturbance agent assignments generated by the computer model (RF Model).

	Aerial Photo Interpretation												
RF Model	Agricultural	Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
Agricultural	108			4	1			1		1		115	93.9
Annual Variability		148				7		4	1			160	92.5
Avalanche		1	89	3		1		12	7			113	78.8
Clearing		3	14	357	5	7		28	5	3	2	424	84.2
Development	14			50	43			1		3		111	38.7
Fire			2			100		2				104	96.2
Forest Collapse			2			1	1	1				5	20.0
Forest Decline		2	1	5		13		252				273	92.3
Mass Movement		1				1		1	26			29	89.7
Riparian				3	3	1		1	1	32		41	78.0
Unknown											0	0	N/A
Grand Total	122	155	108	422	52	131	1	303	40	39	2	1375	
Producer's Accuracy	88.5	95.5	82.4	84.6	82.7	76.3	100.0	83.2	65.0	82.1	0.0		

Overall Accuracy: **84.1**

At Mountain Rainier National Park, students labeled 1540 randomly selected disturbance patches using original definitions. These patches represent about 20 and 40 percent of disturbances inside and outside of park boundary, respectively. After the new disturbance category definitions were developed, these patches were relabeled in the lab using the aerial photography method by one of the students. Part of the newly labeled sample will be used by NCCN for development of a Random Forest statistical model specific to MORA. Remaining sample will be used for validation purposes.

At Olympic National Park, students were able to label 2029 disturbances, out of 4404 originally selected, using the photo interpretation method. These labels will be reevaluated using new definitions of disturbance categories and used for Random Forest model development and validation of OLYM results.

Conclusions

Working with WWU students on this project has allowed the NCCN to achieve all the goals identified during the project planning stages. NCCN was able to evaluate the agents of change originally proposed for monitoring (Table 1) with respect to the new disturbance mapping methodology. Using inputs from students, as well as information gathered in the field, some of the disturbance types were updated in order to better reflect evolving understanding of disturbance processes and updated current terminology. In some cases the new label represented inherent uncertainty about the proximate cause of disturbance, especially in cases where there are interactions among disturbance types.

This project also allowed NCCN to evaluate two different approaches to validating disturbance agent labels generated by a statistical model. Field validation proved to be problematic, because the project involved assessment of large areas inside and outside park boundaries and because disturbance events occurred in areas that were difficult to access. Validation using the combination of aerial photos and TimeSync proved a better method because; 1) it provided different perspectives, both visual and spectral of the disturbances, 2) it allowed viewing of the entire disturbance patch in all cases, 3) older disturbances could be viewed on their corresponding older aerial photos, and 4) there was no doubt about the location and boundaries of the disturbance patches, which was the case on the ground due to irregular patch shapes combined with typical GPS position error. The ―Unknown” disturbance label was used less frequently in the lab compared to the field. Based on this experience, office validation was determined to be a more effective method of accuracy assessment for the Random Forest labeling model.

The project provided excellent educational opportunities for students, who learned first-hand about modeling landscape dynamics in natural areas, applied GIS, GPS and remotely sensed data in scientific research, learned how to use GPS equipment for navigation and data collection, and wrote, in a majority of cases, their first scientific report.

Lab validation using aerial photos is a cost-effective approach to generate field-based accuracy assessment data of landscape change maps that are increasingly being used by federal agencies for monitoring purposes. With some adjustments to training, WWU students could be used again to perform accuracy assessments for this or similar projects. NPS involvement in this project supports the research and educational mission of WWU and the academic mission to provide leadership in natural resource studies.

References

Thompson, C. C., N. Antonova, R. K. Kennedy, Z. Yang, J. Braaten and W. Cohen. In Review. Protocol for Landsat-based Monitoring of Landscape Dynamics in North Coast and Cascades

Network Parks V2. Natural Resource Report NPS/2012/NRR—2012/XXX. National Park Service, Fort Collins, Colorado.

Appendix A

Student Report

Allyson Hayes

INTRODUCTION

There are over 84 million acres of national park lands in the United States. (NPS 2011). It is the responsibility of our National Park Service (NPS) to protect and preserve these lands. However, with the lack of information about the animals, plants and ecosystems that make up these parks, it is difficult to fulfill this responsibility. To address this problem, in 1999, the NPS announced the Natural Resource Challenge as an action plan for preserving natural resources (Stanton 1999). It centered on the idea that in order to better protect and preserve our national parks, we must first be fully informed about what exactly we are protecting and preserving. The biggest duty of this challenge involves expanding the inventory and monitoring effort, specifically in response to landscape changes. Inventories provide baseline information about natural resources in the parks, and monitoring of ecosystem health will reveal important trends which can be used to prepare for and manage for landscape responses to climate change (Antonova & Thompson 2011). It would require an unfeasible amount of human power, time and money to physically go into our parks to inventory and monitor every acre of the landscape. A more efficient tool is necessary to accurately document and regularly monitor our parks' landscape changes. Remote sensing allows for cost-efficient landscape monitoring with fine temporal and coarse spatial resolution, giving the NPS the best tool to capture landscape characteristics at regular intervals, showing patterns over time. This project involves the accuracy assessment of a computer-generated model, which was created using remote sensing techniques to locate areas of landscape disturbance and to determine the size, severity and agent of those disturbances. The disturbance processes monitored by this model include avalanche chute clearing, fire, defoliation due to insect and disease, landslides, riparian changes, wind throw, clearing due to logging, and rural development. This project focuses on one of the largest parks of the North Coast and Cascades Network of the NPS: North Cascades National Park (Figure 1). This park, as well as a 10-mile buffer area around it, is the starting point for this project, which, if successful, will eventually be implemented in all the network parks.

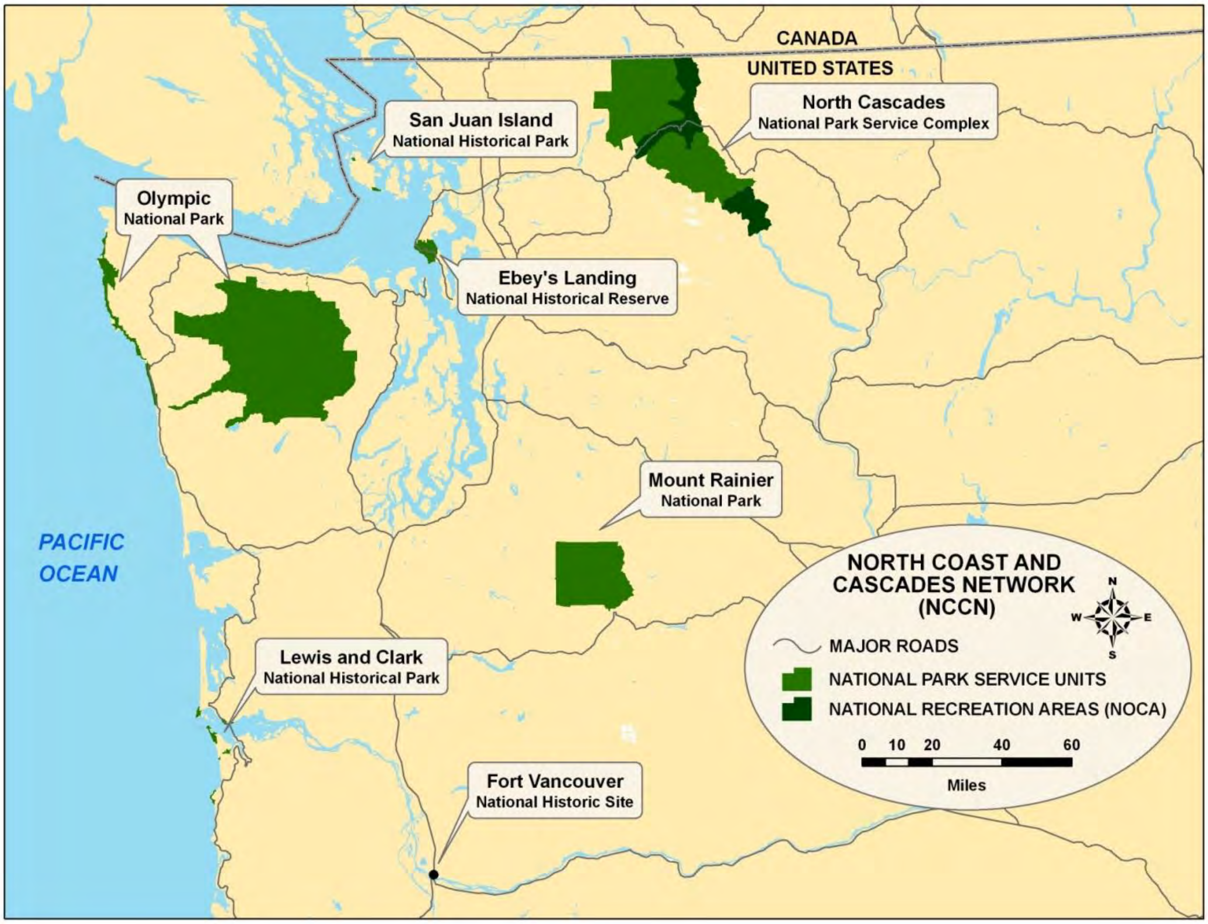


Figure 1 North Coast and Cascades Network of the NPS, located in Washington State. The network is comprised of seven parks- four that are largely historic; San Juan Island, Ebey's Landing, Fort Vancouver, and Lewis and Clark, as well as three large wilderness parks; Mount Rainier, North Cascades and Olympic. (Cartography by N. Antonova)

METHODS

Computer Model:

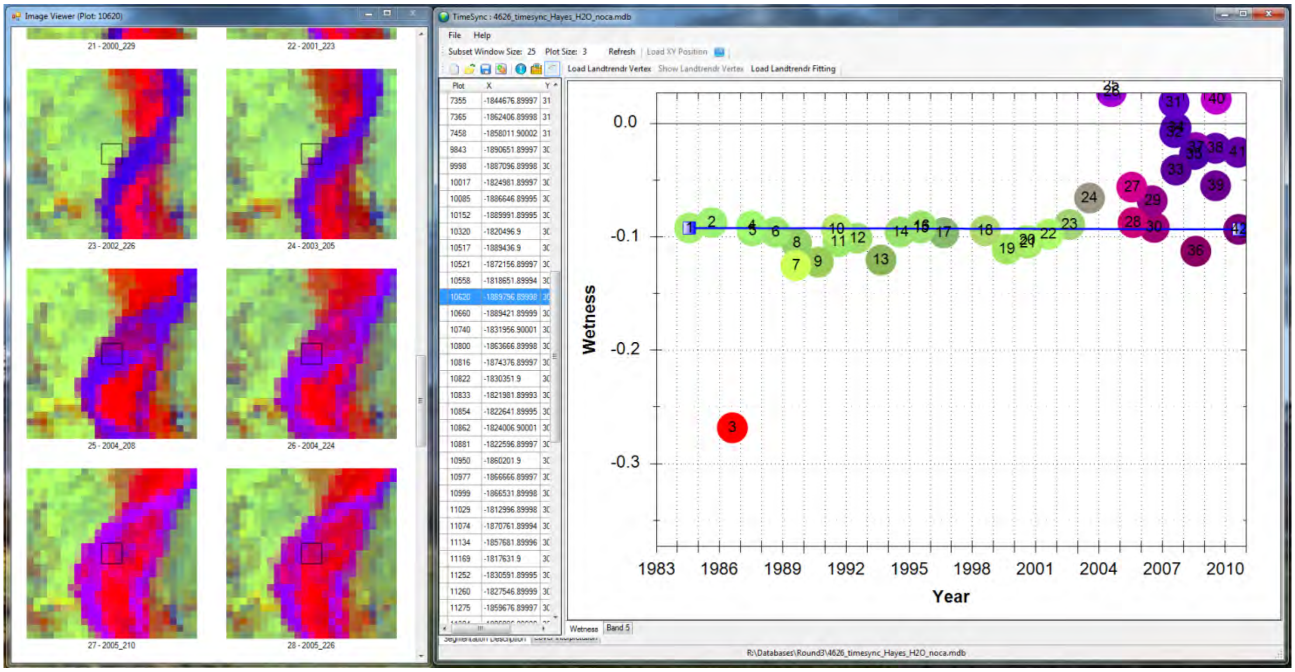
A model was developed by the North Coast and Cascades Network along with Oregon State University for monitoring landscape changes in large parks using Landsat satellites. This algorithm was dubbed LandTrendr, for Landsat-based Detection of Trends in Disturbance and Recovery. It maps patches of disturbance on a landscape by tracing pixel trajectories through a stack of yearly images. More specifically, the process involves preparing a stack of yearly satellite imagery, extracting spectral trajectories for each pixel, statistically identifying and fitting trajectory segments with consistent trends, extracting summary information from each of these segments, and mapping areas of disturbance. The mapped disturbances are then labeled with a disturbance agent using a statistical model based on spectral and topographic variables associated with each disturbance (Antonova & Thompson 2011). The validation process compares computer-generated labels with labels that were assigned in-field or in-lab using aerial photography.

In-Lab Disturbance Agent Assignment:

Western Washington University interns, Robert Bryson, Shelby Clary, Allyson Hayes, Monica Ponce-McDermott, Ian Oehler, and Nathan Schaller were given the task to assign disturbance agent labels (Table 1) to the LandTrendr-generated disturbance polygons. We used Google Earth aerial photography alongside transformed Landsat TM satellite imagery to attach an agent label to each disturbance polygon. The Landsat imagery was transformed using a tasseled-cap transformation. This transformation allows the user to view major spectral components of a landscape scene by reducing spectral bands down to three dimensions, wetness, greenness and brightness (Campbell 2007). TimeSync software was used to display the entire stack of transformed Landsat image chips centered on each disturbance polygon identified by the LandTrendr model. This software also displayed a trajectory of the wetness values in each image which highlighted trends over time, aiding in the assignment of disturbance agents (Figure 2). The first step in identifying a disturbance agent was to look at the aerial photo in Google Earth, zooming out to become familiar with the landscape context. Next, we zoomed in to the disturbance and used the time slider feature to view aerial photos from different years to determine if vegetation was removed (Figure 3). We would then look at the TimeSync trajectory to see if wetness declined or increased significantly around the year of the disturbance. We also looked at the Landsat tasseled cap imagery chips to see if spectral changes around the year of disturbance occurred. Lastly, if a fire was suspect, we used historical fire polygon data to confirm fire agents.

Table 1 List of all possible disturbance agents assigned in this study. * The agent label "no visible change" was assigned when disturbance polygons were located in high elevation areas, where no removal of vegetation occurred and the disturbance was likely due to phonological changes. † "Unknown" was assigned when an obvious disturbance occurred, but the agent was indiscernible. ‡ "Water" was assigned to polygons located directly on bodies of water where the disturbance was detected because of changes in water volume.

Disturbance Agents	
Agricultural	Landslide
Avalanche	No Visible Change*
Clearcut	Riparian
Debris Flow	Unknown†
Development	Water‡
Fire	Wind
Insect/Disease	



Plot	X	Y
7355	-1844676.89997	31
7365	-1862406.89998	31
7458	-1858011.90002	31
9843	-1890651.89997	30
9998	-1887096.89998	30
10017	-1824981.89997	30
10085	-1886646.89995	30
10152	-1889991.89995	30
10320	-1820496.9	30
10517	-1889436.9	30
10521	-1872156.89997	30
10558	-1818651.89994	30
10620	-1869796.89998	30
10660	-1889421.89999	30
10740	-1831956.90001	30
10800	-1863666.89998	30
10816	-1874376.89997	30
10822	-1830351.9	30
10833	-1821981.89993	30
10854	-1822641.89995	30
10862	-1824006.90001	30
10881	-1822596.89997	30
10950	-1860201.9	30
10977	-1866666.89997	30
10999	-1866531.89998	30
11029	-1812996.89998	30
11074	-1870761.89994	30
11134	-1857681.89996	30
11169	-1817631.9	30
11252	-1830591.89995	30
11260	-1827546.89999	30
11275	-1859676.89997	30

Figure 2 A screenshot of TimeSync software displaying a 2003 riparian channel changing disturbance. The trajectory (right) shows a prominent increase in wetness in 2003, indicative of a riparian channel change disturbance. On the left is an image viewer showing the transformed Landsat image chips centered on the disturbance, spanning from 1984 to 2010. The top two visible chips are from before the disturbance, and the last four are years following the disturbance. Note the changes in spectral values. When paired with Figure 3, the Google Earth aerial photography before and after the disturbance, the disturbance agent can easily be declared as riparian with high confidence.

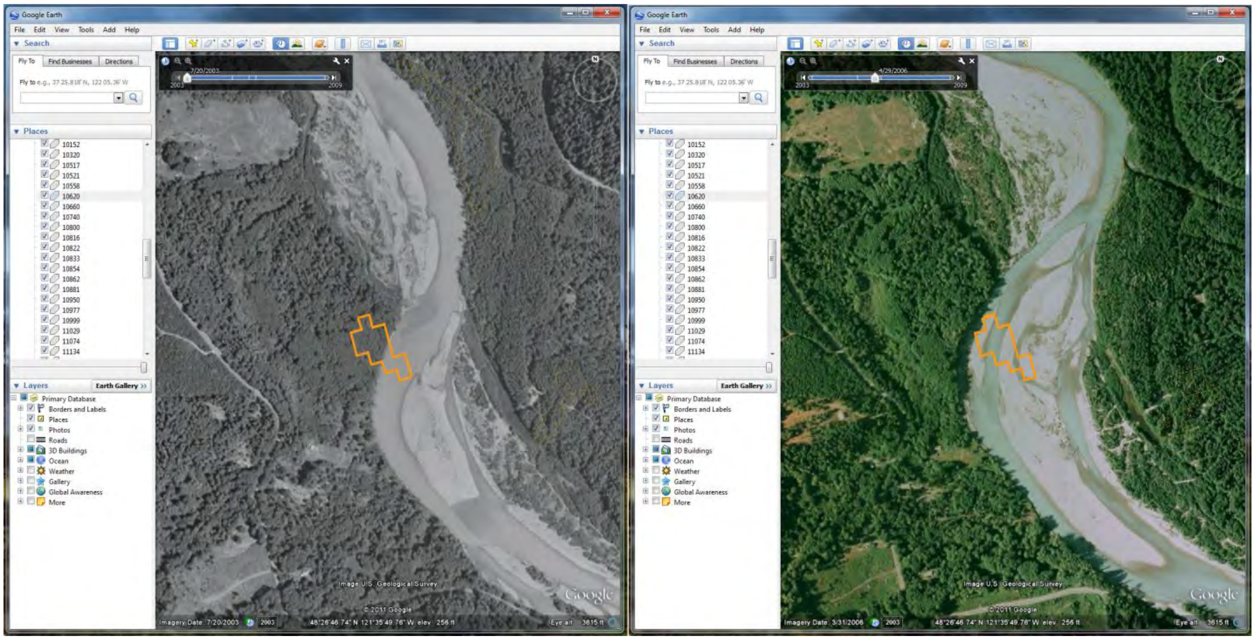


Figure 3 Google Earth aerial photographs before (left) and after (right) a riparian channel changing disturbance. Disturbance polygon is shown here in orange. Notice how the polygon is predominately in a forested cover type in the before image, and completely within the stream cover type in the after photo.

In-Field Disturbance Agent Assignment:

Interns went on two eight-day field research trips to the North Cascades National Park and surrounding lands. We were trained by NPS employees on how to accurately identify disturbance agents in the field, including specific signs of insect and disease damage (Figure 4). We had the locations of disturbance polygons loaded onto GPS units and used those to navigate to each polygon and assign a disturbance agent based on what we saw. In the case where a polygon was inaccessible by foot, (i.e. a polygon was located across a valley) we would navigate to the nearest location, usually perpendicular to the polygon, to assign disturbance agents. In addition to disturbance agents, interns recorded their level of certainty, UTM location, distance from polygon and other observations.

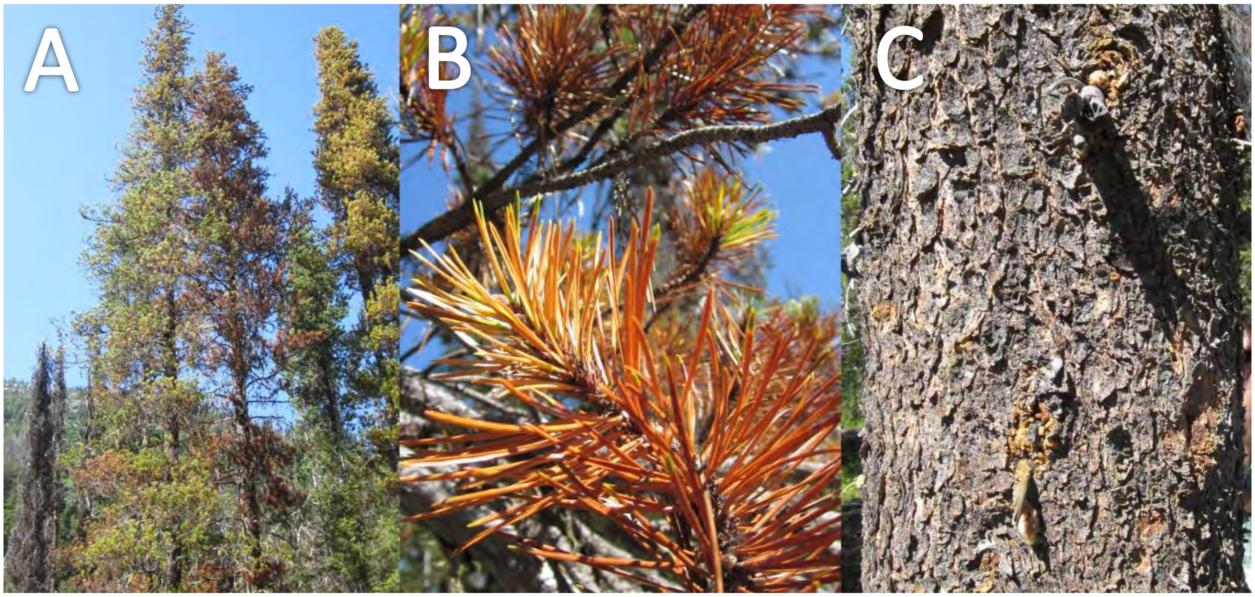


Figure 4 Signs of a tree infected by the Mountain Pine Beetle, one of the most common causes of tree mortality in the North Cascades National Park. (A) Stand of Lodgepole Pine infested by Mountain Pine Beetle. Old dead trees are gray, and newly killed trees show an indicative, bright orange color. (B) Close up of newly killed Lodgepole Pine needles. (C) Trunk of an infested Lodgepole Pine with "pitch tubes", an attempt by the tree to extract the unwanted intruders.

Accuracy Assessment

In this study, we performed two types of accuracy assessments. The first, in- field vs. in-lab was to determine the validity of identifying disturbance agents using aerial photography. The second, *Computer Model vs. In-Lab,* was to assess how well the computer model was at assigning disturbance agents.

After field work was complete, the 320 polygons identified in the field were recorded in a database and all interns were given these same disturbance polygons to be analyzed and labeled using aerial photography. We used the same in-lab, aerial photo disturbance agent assignment methods as previously mentioned. We then compared the disturbance agent assignments made in the field with our in-lab agent assignments to first determine the validity of identifying disturbance agents using our in-lab, aerial photography technique. Next, we compared all the agent assignments made in-lab for the North Cascade National Park disturbance polygons with those generated by the computer model determine how well the model and in-lab methods correlated in assigning disturbance agents.

RESULTS

In-Field vs. In-Lab Disturbance Agent Assignments:

The comparison between the disturbance agent calls made in-field and those made in-lab with aerial photography and TimeSync, showed an overall accuracy of 68.1% with a kappa statistic of 0.56 (Table 2). The disturbance agents with high correlation (greater than 50% user and producer accuracies) were avalanche, clearcut, fire, insect/disease and riparian. Those with low or zero correlation were agricultural, debris flow, development, landslide, no visible change, unknown, water and wind. There was much confusion with avalanche and debris flow agent assignments.

Computer Model vs. In-Lab Disturbance Agent Assignments:

The comparison between the disturbance agent calls made by the computer model and those made in-lab with aerial photography and TimeSync, showed an overall accuracy of 54.4% with a kappa statistic of 0.46 (Table 3). The disturbance agents with high correlation (greater than 50% user and producer accuracies) were agricultural, clearcut, debris flow and fire. Those with low or zero correlation were avalanche, development, insect/disease, landslide, no visible change, riparian, unknown, water and wind. No visible change and insect/disease were the two agents with the largest confusion. I assigned 114 disturbances to have no visible change, while the computer model agreed with only 43 of those as no visible change and assigned 47 to be insect/disease, and 24 to be other various disturbance types. The computer model assigned an insect/disease agent label to 103 polygons while I only agreed with 35 of those labels and assigned 47 of those as no visible change and 21 to be other various disturbance types.

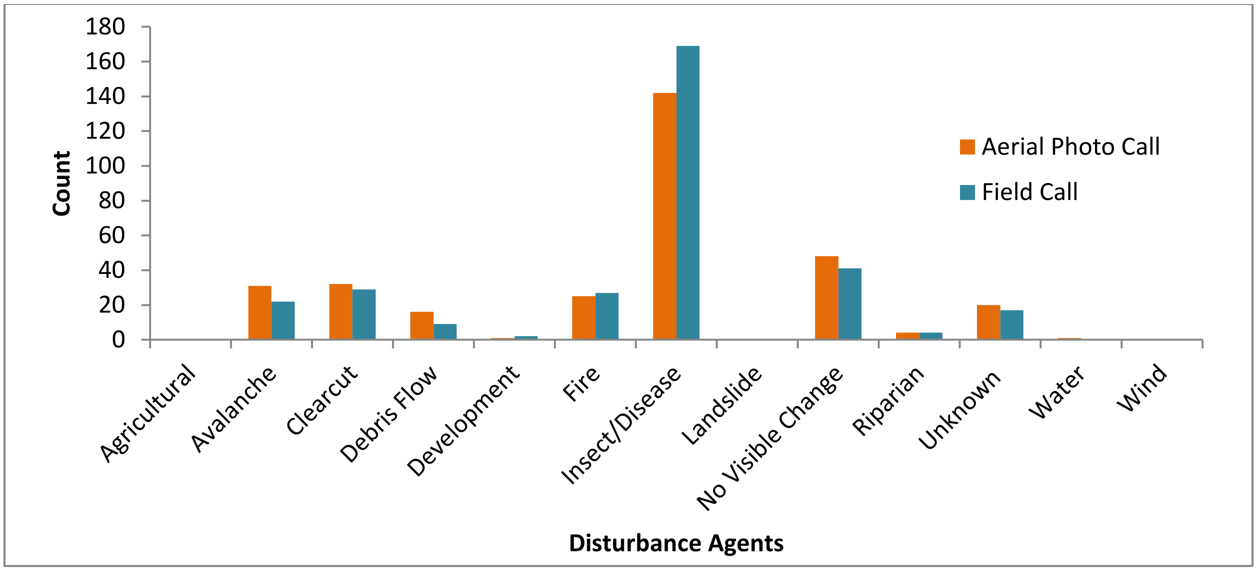


Figure 5 Shows differences in occurrence of each of the disturbance agents between ones determined in-lab using aerial photography and transformed Landsat chips and those determined using in-field techniques.

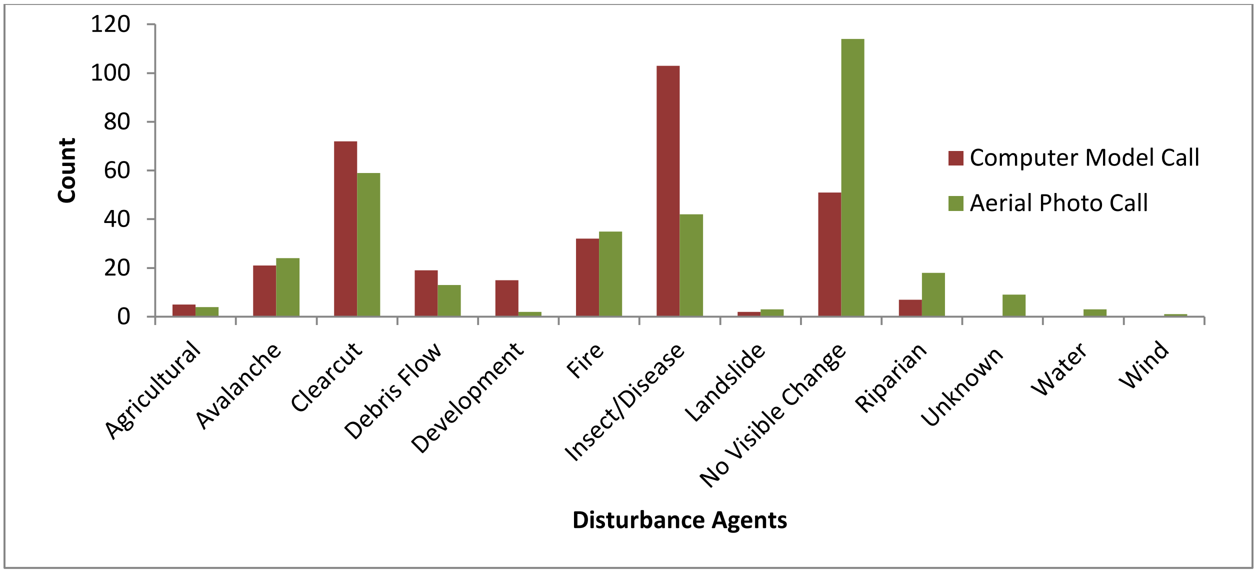


Figure 6 Shows differences in occurrence of each of the disturbance agents between the computer-generated agent calls and those determined using aerial photography and transformed Landsat chips.

Table 2 Confusion matrix displaying correlation between disturbance agent assignments determined in the field (Field Call) with disturbance agent assignments determined using aerial photography (Aerial Photo Call). Kappa statistic ($\hat{k}$) determines how much better the classification is than one resulting from chance. For this study, the classification was 56% better than a random assignment of disturbance types.

$$\hat{k} = \frac{observed\_accuracy - chance\_agreement}{1 - chance\_agreement}$$

		Field Call														
		Agricultural	Avalanche	Clearcut	Debris Flow	Development	Fire	Insect/Disease	Landslide	No Visible Change	Riparian	Unknown	Water	Wind	**Grand Total**	**User's Accuracy**
Aerial Photo Call	Agricultural														**0**	**N/A**
	Avalanche		16		4			7		1		3			**31**	**51.6%**
	Clearcut			28		2				2					**32**	**87.5%**
	Debris Flow		2		4			5		3	1	1			**16**	**25.0%**
	Development						1								**1**	**N/A**
	Fire						21	4							**25**	**84.0%**
	Insect/Disease		2		1		5	128				6			**142**	**90.1%**
	Landslide														**0**	**N/A**
	No Visible Change		2					24		17		5			**48**	**35.4%**
	Riparian			1				1			2				**4**	**50.0%**
	Unknown									17	1	2			**20**	**10.0%**
	Water									1					**1**	**0.0%**
	Wind														**0**	**N/A**
	Grand Total	**0**	**22**	**29**	**9**	**2**	**27**	**169**	**0**	**41**	**4**	**17**	**0**	**0**	**320**	
	Producer's Accuracy	**N/A**	**72.7%**	**96.6%**	**44.4%**	**0.0%**	**77.8%**	**75.7%**	**N/A**	**41.5%**	**50.0%**	**11.8%**	**N/A**	**N/A**		

Overall Accuracy	**68.1%**
Kappa Statistic	**0.556805**

Table 3 Confusion matrix displaying correlation between disturbance agent assignments determined using aerial photography (Aerial Photo Call) with disturbance agent assignments generated by the computer model (Computer Model Call). Kappa statistic ($\hat{k}$) determines how much better the classification is than one resulting from chance. For this study, the classification was 46% better than a random assignment of disturbance types.

$$\hat{k} = \frac{observed\_accuracy - chance\_agreement}{1 - chance\_agreement}$$

		Aerial Photo Call														
		Agricultural	Avalanche	Clearcut	Debris Flow	Development	Fire	Insect/Disease	Landslide	No Visible Change	Riparian	Unknown	Water	Wind	**Grand Total**	**User's Accuracy**
Computer Model Call	Agricultural	3		1							1				**5**	**60.0%**
	Avalanche		9		1			1		9				1	**21**	**42.9%**
	Clearcut		4	48	1	1	2	3		9	1	3			**72**	**66.7%**
	Debris Flow		2		10		1		3	1	2				**19**	**52.6%**
	Development	1		5		1					8				**15**	**6.7%**
	Fire						24	2		5		1			**32**	**75.0%**
	Insect/Disease		5	4	1		6	35		47		2	3		**103**	**34.0%**
	Landslide		1								1				**2**	**0.0%**
	No Visible Change		3				2			43		3			**51**	**84.3%**
	Riparian			1				1			5				**7**	**71.4%**
	Unknown														**0**	**N/A**
	Water														**0**	**N/A**
	Wind														**0**	**N/A**
	Grand Total	**4**	**24**	**59**	**13**	**2**	**35**	**42**	**3**	**114**	**18**	**9**	**3**	**1**	**327**	
	Producer's Accuracy	**75.0%**	**37.5%**	**81.4%**	**76.9%**	**50.0%**	**68.6%**	**83.3%**	**0.0%**	**37.7%**	**27.8%**	**0.0%**	**0.0%**	**0.0%**		

Overall Accuracy	**54.4%**
Kappa Statistic	**0.461553**

DISCUSSION

This study was motivated by the NPS Natural Resource Challenge, and the purpose of this project was to determine whether using this agent labeling statistical model could act as a more efficient tool than manual labeling in aiding the NPS in accurate inventories and monitoring of landscape dynamics in and around the parks. Although the model did show a moderate correlation with in-lab accuracy assessments (Table 3), due to substantial opportunity for error in this study, it is difficult to confirm or dismiss the prospective utility of this model.

Opportunity for error:

Generally when a confusion matrix is constructed, there is a predicted class that is tested against an actual class (ground truth). There is much error associated with both confusion matrices in this study because the determination of actual ground truth classes was not always unambiguous This large opportunity for error is problematic in testing how well the model is at identifying disturbance agents.

In Table 3, the computer model agent calls are the predicted class and the in-lab aerial photo agent calls are the actual class. At the start of this project, the interns were not professional aerial photo-interpreters, and could have easily labeled disturbances with incorrect agents. For example, it took me a few weeks to be able to identify insect disturbances using the in-lab technique, resulting in me unknowingly dismissing slight dips in wetness and labeling disturbance as “no visible change.” If more time was allowed, I would go back and blindly re-assign agent labels to all the polygons now that I am more familiar with the aerial photography and trajectory characteristics of each disturbance. I would then perform a second confusion matrix in the hope of obtaining a more valid accuracy assessment.

In Table 2, the in-lab aerial photo agent calls are the predicted class and the in-field agent calls are the actual class. In the field, many of the disturbances we saw were unreachable by foot, so we had to view them from a distance, usually across a valley. At times it was difficult to determine where exactly the disturbance polygon was located based on aerial photo maps. Much of the agent call discrepancies in Table 2 may be due to analyzing an incorrect location on the landscape. Error in the field may have also spawned from analyzing disturbances that occurred years prior to analyses. A lot can change in terms of regrowth over the years, and many of the polygons we were analyzing in the field were associated with disturbances that occurred over 10 years ago which may have led to assigning inaccurate agent labels. In addition, there was much confusion associated with debris flow and avalanche disturbances (Table 2). This may be due to the fact that both of these disturbances can overlap in space and in their spectral characteristics. Many debris flows occur within old avalanche chutes, and from a distance, look similar, especially if the disturbance occurred years ago and regrowth has begun.

In addition to methodological errors in the field, the small sample size (Table 2) corresponding to some disturbance categories on the confusion matrix added some unavoidable error to this study. Working in the field, we were not able to reach a sufficient number of polygons relating to each of the disturbance types due to random assignment of polygons, landscape composition, time limitations, etc. In the field, we saw very few instances of agricultural, debris flow, development, landslide, riparian and wind disturbances. Increasing the sample sizes of many of these disturbance categories is essential to be able to more accurately assess the performance of the model.

Overall, the computer model performed in moderate correlation with the in-lab agent assignments, with a kappa statistic of .46 (Table 3). This means the computer classification was 46% better than a random assignment of disturbance types. Despite the discrepancies between the in-lab agent labels assignments and the model label assignments, there is definitely some moderate correlation, suggesting the model is correctly identifying many of the disturbances. The next step may be to perform the in-lab methods again with a more experienced eye to determine if the correlation values improve and to increase the sample size of the aforementioned disturbance categories.

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Appendix B

Student Report

Ian Oehler

Introduction

The goal of the NPS Natural Resource Challenge is to better understand the health of our park‟s natural ecosystems. One way to accomplish this is to gain a more sufficient awareness of relationships that effect ecosystem health. Knowing climate change has the potential to alter how ecosystems function, and importantly in our case the relation of ecosystem health to natural disturbances, monitoring the parks changing landscape dynamics seems crucial. Natural Disturbances have a particularly heavy influence on an ecosystems health. Because of this, understanding and analyzing how changing disturbance variables like distribution, size, and frequency in the North Coast and Cascade Parks network seem to be of great importance. Of course assessing accuracies of modeling and analyzing tools that look at disturbances across landscapes is critical. As with any scientific work assessing the accuracy of methodology used to obtain new data might be just as important as getting the end results.

For this reason our goal was an attempt at assessing the accuracy of a statistical model that assigns agents to disturbances. Our team looked at data which identified disturbances across the landscape of North Cascades, Olympic, and Mount Rainier National Parks and spanned from 1985 until the present. These disturbances are assigned by LandTrendr, a program which identifies trends of disturbance and recovery by looking at spectral value changes. The data inputted into LandTrendr is taken from Landsat imagery which dates back approximately 25 years. Another part of the accuracy assessment work was looking at aerial photos in conjunction with spectral imaging which displayed patterns of changing values. These values are associated with „greenness‟ and „wetness‟ changes and represent vegetation patterns across the landscape. The disturbances we encountered and recorded were agriculture, avalanche, fire, insect/disease, landslides, riparian, wind, clear-cuts, and human development.

Methods

Our team‟s job was to translate and document data associated with disturbance events found by Landtrendr. By doing this we could later come back and look at accuracies. We put each event into one of the twelve disturbance categories mentioned above. Accomplishing this involved interpreting aerial photos and Timesync imaging to choose the correct disturbance associated with each event. Our main area of study was the North Cascades National Park but we also examined disturbances throughout Mount Rainier National Park and Olympic National Park. Because this is such a large area with many disturbance events the most efficient method was to be in lab looking at aerial photos along with each disturbance events imaging via Timesync.

Assessing the accuracy of the disturbances called in the lab required us to go in the field and observe disturbance events there. We spent a total of 16 days backpacking in the North Cascades observing and documenting disturbance events first hand. Our team‟s interpretation of the data, which was presented by Timesync, coupled with high resolution aerial photos, from Google Earth, was our methodology for interpreting and analyzing a disturbance. To monitor such a large timeframe and area of parks land, Landsat satellite imagery along with high resolution aerial photos were used. Landsat imagery has been collected yearly since 1985. Because of this when observing changes in the overall „wetness‟ of groundcover vegetation about 25 years of data is available. Varying degrees of changes in the „wetness‟ and the subsequent recovery of vegetation over time correspond with different disturbance agents. For each disturbance event identified by Timesync a spectral trajectory and image stack are created that is unique to each event. This is shown in Figure 2 and is an example of an image stack and trajectory that shows a fire event on a healthy forest. Most disturbance events shared characteristics with other disturbances of the same agent and eventually patterns become evident when using Timesync. When documenting each disturbance event we had three options for showing our confidence level. These being a 1-3 scale with 3 being the most confident and 1 being very unsure.

Results

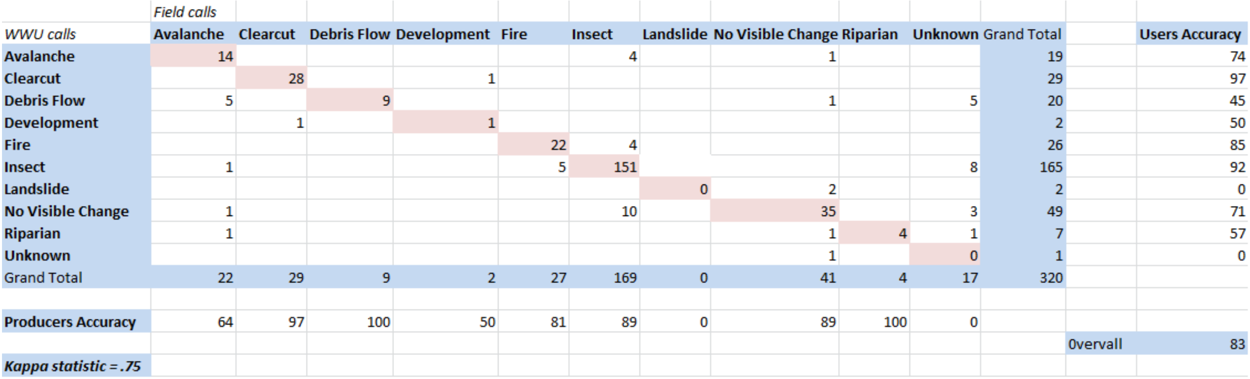
Many of my disturbances that I identified in the North Cascades area were located near Lake Chelan and were caused by fire damage on the landscape. Although fire damage was the most visible from an aerial perspective insect damage was the most common in the area. In populated regions outside of the North Cascades Park the most common disturbance was agriculture and development. Disturbances that I identified in the Mount Rainier National Park were mostly insect with riparian also being common. Disturbances outside of the Mount Rainier Park in the area were mostly clear cuts and located on the west side of Mount Rainer. In the Olympic National Park region virtually all of the disturbance events that I identified were clear cuts. Most of my disturbances that I identified generally followed a pattern that was based on vegetation cover, placement on the landscape in relation to position on hill slopes, and whether the location was inside or outside park boundaries. I frequently found that the most difficult disturbance to identify with a high degree of certainty to be the insect/disease agent. The trajectory for insect damage would often be very close to unchanging but very subtle declines in wetness were the most common.

Our field work consisted of two separate eight day excursions into the backcountry of the North Cascades National Park. We spent six days on each trip day hiking to disturbance events and documenting what we found. Overall the most common disturbance across the landscape that we observed was insect and disease damage. From my experience this disturbance happens to be the most difficult to call in the lab. We observed in the field though that insect damage is very noticeable on the landscape. We found that spruce budworm and mountain pine beetle damage to be the most prevalent insects affecting trees.

As indicated by the overall accuracy‟s shown in both tables, my aerial photo interpretation is in higher agreement with the field calls then with the automated disturbance model. Also important to notice in the two error matrix tables is the kappa statistic. Table 1, which shows the agreement between aerial photo calls (WWU calls) and field data (Field calls), reports of kappa of .75. This suggests that an observed call is 75% better than a call made by chance. Table 2, which shows the agreement between aerial photo calls (WWU calls) and automated disturbance model (computer calls), reports a kappa of .61. And in the same way this suggests that an observed call is 61% better than one made by chance.

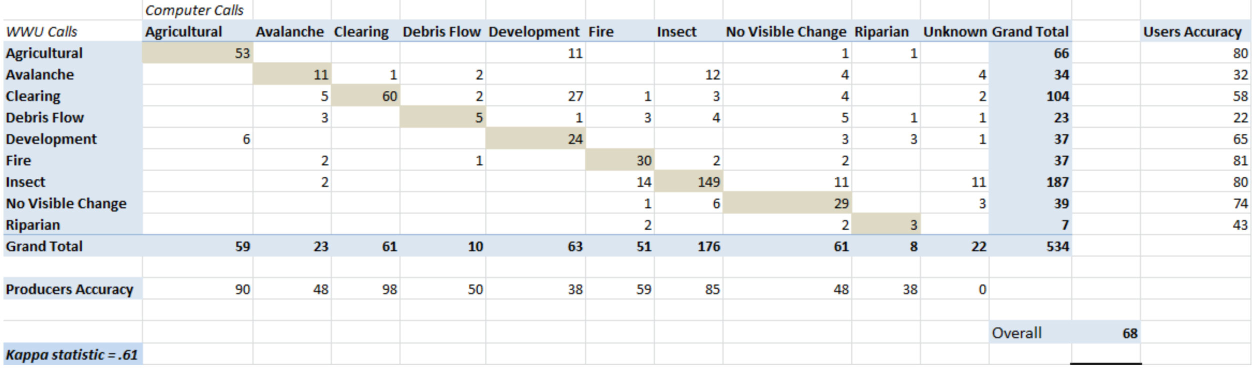
Discussion

I found that the process of identifying disturbances in the field was much different than doing it in the lab setting. In the field you are deprived of a couple of tools which we had access to in the lab. This along with the varied topographic landscape of the North Cascades makes identifying disturbances slightly more difficult. We also found that many disturbances were impossible to observe from even relatively close distances because of vegetation cover. Again this varies from the lab setting where aerial views of each disturbance were available. The long time frame of data that is available helped greatly when trying to identify the patterns that emerged due to disturbance events. It‟s interesting that agreement between insect identification for both of my error tables is so high, as I have mentioned identifying the insect/disease agent was difficult for me. The reason behind this is that many of my insect calls were of low certainty but despite this it appears that many of them were correct. When comparing both error matrixes it‟s obvious that Table 1 has higher agreement accuracies for all three of the accuracy categories. The most obvious explanation for this difference is making calls in the field provided a more certain and accurate analysis of a disturbance event. Being that the purpose of this work is to assess the accuracy of the model looking at both error matrixes seems to be the most helpful way to do this while at the same time presenting the related data.



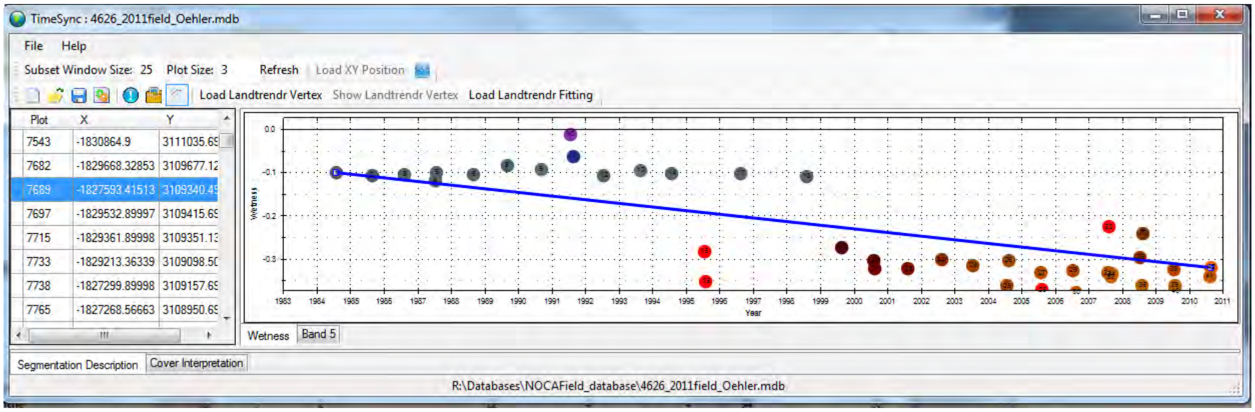
	Field calls												
WWU calls	**Avalanche**	**Clearcut**	**Debris Flow**	**Development**	**Fire**	**Insect**	**Landslide**	**No Visible Change**	**Riparian**	**Unknown**	Grand Total		**Users Accuracy**
Avalanche	14					4		1			19		74
Clearcut		28		1							29		97
Debris Flow	5		9					1		5	20		45
Development		1		1							2		50
Fire					22	4					26		85
Insect	1				5	151				8	165		92
Landslide							0	2			2		0
No Visible Change	1					10		35		3	49		71
Riparian	1							1	4	1	7		57
Unknown								1		0	1		0
Grand Total	22	29	9	2	27	169	0	41	4	17	320		
Producers Accuracy	64	97	100	50	81	89	0	89	100	0			
												0vervall	83
Kappa statistic = .75													

Table 1.



	Computer Calls												
WWU Calls	**Agricultural**	**Avalanche**	**Clearing**	**Debris Flow**	**Development**	**Fire**	**Insect**	**No Visible Change**	**Riparian**	**Unknown**	**Grand Total**		**Users Accuracy**
Agricultural	53				11			1	1		**66**		80
Avalanche		11	1	2			12	4		4	**34**		32
Clearing		5	60	2	27	1	3	4		2	**104**		58
Debris Flow		3		5	1	3	4	5	1	1	**23**		22
Development	6				24			3	3	1	**37**		65
Fire		2		1		30	2	2			**37**		81
Insect		2				14	149	11		11	**187**		80
No Visible Change						1	6	29		3	**39**		74
Riparian						2		2	3		**7**		43
Grand Total	**59**	**23**	**61**	**10**	**63**	**51**	**176**	**61**	**8**	**22**	**534**		
Producers Accuracy	90	48	98	50	38	59	85	48	38	0			
											Overall	**68**	
Kappa statistic = .61													

Table 2.



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Subset Window Size: 25 Plot Size: 3

Plot	X	Y
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7682	-1829668.32853	3109677.12
7689	-1827593.41513	3109340.49
7697	-1829532.89997	3109415.69
7715	-1829361.89998	3109351.13
7733	-1829213.36339	3109098.50
7738	-1827299.89998	3109157.69
7765	-1827268.56663	3108950.69

R:\Databases\NOCAField_database\4626_2011field_Oehler.mdb

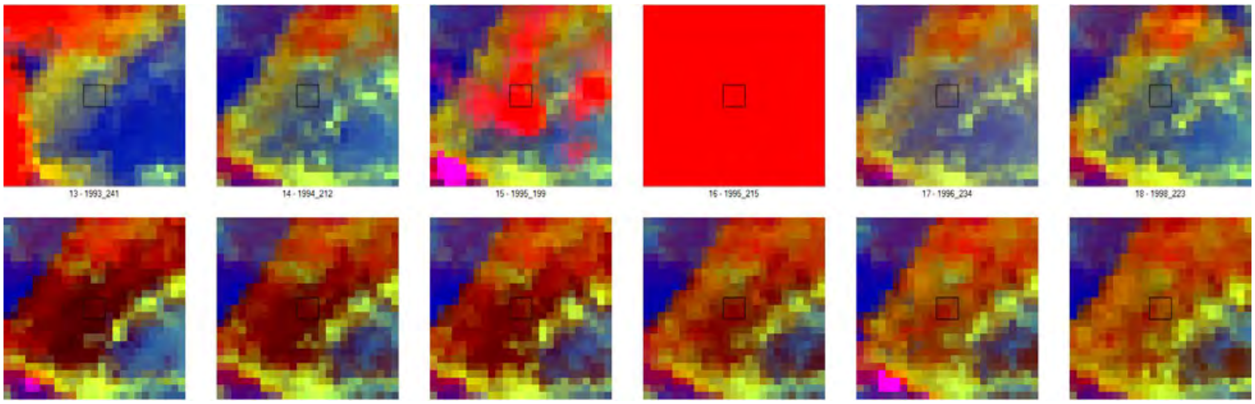


Figure 2.

Appendix C

Student Report

Monica Ponce

Introduction

The objective of this internship was to validate the use of LandTrendr to identify landscape disturbances within the North Coast and Cascade Network (NCCN) of parks. Once the disturbances are identified accurately the information will be used to facilitate the National Parks Service Inventory and Monitoring Program. With LandTrendr as a tool fewer resources would be needed for ground truthing and manual identification of disturbances.

The North Coast and Cascade Network of parks includes Olympic, North Cascades, Rainier, Lewis and Clark, Fort Vancouver, Ebey's Landing and San Juan Island National Historic Park. For this internship we were only focusing on North Cascades, Mount Rainier, and Olympic National Parks. Our data analysis mainly focuses on North Cascades National Park.

By monitoring landscape change within the NCCN parks we will be better prepared and more equipped to make management decisions. In order to monitor landscape changes we need to know what the most common landscape disturbance types are. Based on previous assessments the most common disturbance types in our interest parks are avalanche, fire, debris flow, riparian, landslide, insect/disease, wind, clear cut, agriculture and development. The goal is that with the use of LandTrendr various common disturbances will be easily and quickly identified.

Methods

In order to identify disturbance polygons in the national parks we were provided with identification training, specifically what criteria best represent the different disturbance types. Using Landsat satellite imagery with tassel cap transformation we were able to identify various dimensions of brightness, greenness, and wetness. These three dimensions were visualized with gradients of color allowing, for example, a closed canopy conifer forest to be distinguished from a broadleaf forest simply by color. With an understanding of what different vegetation types look like we were able to better detect when environments change from one type of habitat to another. Also by looking at the color patterns of a specific location over a period of time we were more confident in identifying not only when a disturbance took place but what type of disturbance it was. This process is known as LandTrendr and will be referred to as such.

After receiving the identification training we were each given a segment of the polygons to identify with disturbance agents using LandTrendr and confirming our identifications with aerial photography. These polygons were selected at random and each student was focused on specific areas in the three national parks. Our later ground truthing and data analysis focused on North Cascades National Park and thus that is where the rest of the methods described here refer to. My specific study sites for the North Cascades Park where in the northwestern park area and around the outside of the southern tip of the park. These identifications were used to compare against the computer model's identifications (See results).

The next step was for us to go into the field (ground truthing) to identify as many of the North Cascades polygons as was feasible. The polygons identified in the field focused on the outside central western border of the park and the southern third of the park. Also once in the field we were given specific training regarding detection of various insect infestations. The two most common insect infestations encountered were Spruce Budworm and Mountain Pine Beetle. This insect training allowed for more detailed disturbance identification.

Once in the lab we were each given the same polygons that we identified in the field for identification with the use of LandTrendr and aerial photography. The lab identifications were used to compare against the field identifications (See results).

In order to compare our ability to label disturbance agents with the ability of the model to label the disturbances error matrices were created. By creating error matrices we can further investigate areas of discrepancy. We also calculated our user, producer and total accuracies along with our Kappa Statistics. This information tells us how precise we were in labeling the agents along with how useful the labeling model will be for future use.

Results

Based on my error matrix for aerial photography versus field calls (See attached error matrix) the only types of disturbances that were not seen in both instances were development (only seen in the field) and landslide (only seen with aerial photos). My user accuracy was 50% or above for 4 of the 10 disturbance types (clear cut, fire, insect/disease and riparian) and below 50% for 6 of the 10 disturbance types (avalanche, debris flow, development, landslide, no visible change and unknown). My producer accuracy was 50% or above for 6 of the 10 disturbance types (avalanche, clear cut, fire, insect/disease, no visible change and riparian) and below 50% for 4 of the 10 disturbance types (debris flow, development, landslide, and unknown). My total accuracy was 70.63%. Discrepancies between aerial photography and field calls larger than 10 polygons only occurred in one situation. Using aerial photos I claimed 37 polygons were no visible change while in the field we said they were insect/disease. Other smaller common discrepancies included avalanches and unknowns in the field being called various other disturbances with the photos. My Kappa statistic was 0.59.

Based on my error matrix for the model versus aerial photography (See attached error matrix) the types of disturbances that were not seen in both instances were unknown, water and wind (all only seen in the aerial photos). My user accuracy was 50% or above for 4 of the 10 disturbance types (avalanche, fire, no visible change and riparian) and below 50% for 6 of the 10 disturbance types (clear cut, debris flow, insect, unknown, water and wind). My producer accuracy was 50% or above for 6 of the 10 disturbance types (avalanche, clear cut, debris flow, fire, insect and riparian) and below 50% for 4 of the 10 disturbance types (no visible change, unknown, water, and wind). My total accuracy was 57.33%.

Discrepancies between the model and aerial photography larger than 10 polygons only occurred in two situations. The model claimed 56 polygons were insect while using the photos I said they were no visible change. Also the model claimed 11 polygons were insect and I said they were fire from the aerial photos. Other smaller common discrepancies included avalanches, fire, no visible change and unknown polygons with aerial photos being called other disturbances with the model. My Kappa statistic was 0.44.

Discussion

Aerial Photography versus Field Calls

Not seeing development in the lab may have been due to the event being recent and the images not being up to date. Also only seeing the landslide with aerial photos may be because of the scale and age of the event. In the field we may not have been able to see the entire landslide and possibly labeled it as avalanche if the vegetation was growing back.

In regard to my user accuracy for 4 of the 10 disturbance types (clear cut, fire, insect/disease and riparian) when I look at a aerial photos I have a 50% or greater chance of the disturbance type being labeled correctly in the field and for 6 of the 10 disturbance types (avalanche, debris flow, development, landslide, no visible change and unknown) below a 50% chance of being labeled correct in the field. Meaning my user accuracy is not very good in the areas of avalanches, debris flows and no visible change. This is where I may need more training or practice to increase my accuracy. The areas where I have trouble in the field may be due to scale and my inability to see the big picture. In this segment of polygons landslides and development were not that common, had they been my user accuracy may have been better.

With respect to my producer accuracy for 6 of the 10 disturbance types (avalanche, clear cut, fire, insect/disease, no visible change and riparian) when I’m in the field I have a 50% or greater chance of the disturbance type being labeled correctly on the aerial photos and for 4 of the 10 disturbance types (debris flow, development, landslide, and unknown) below a 50% chance of being labeled correctly on the aerial photos. Meaning my producer accuracy is not very good in the areas of debris flows and unknown polygons. Debris flows may have been troublesome with the aerial photos because of my lack of confidence in identifying the difference between a debris flow and a riparian disturbance, where in the field it may be easier to tell the difference. Unknowns may be due to a lack of light or poor lighting over the polygons, making it difficult to id. As mentioned previously landslides and development were not common disturbances.

The 37 polygons of no visible change, labeled by photo, that were insect/disease in the field may have been due to scale and perception. In the field it was easier to see the affected trees and being amongst them may make it seem like every tree is infected. With this perception of insect infestation everywhere we may have been more likely to label disturbances that way.

Model versus Aerial Photography

Unknown polygons may have been seen with aerial photos because a person was labeling them and the model would automatically designate a disturbance type. With a computer model there would not be doubt in the identification process. Also the model may have had a stricter or more streamline evaluation process; basically it is either this or that.

With my user accuracy for 4 of the 10 disturbance types (avalanche, fire, no visible change and riparian) when I look at the model I have a 50% or greater chance of the disturbance type being labeled correctly in the aerial photos and for 6 of the 10 disturbance types (clear cut, debris flow, insect, unknown, water and wind) below a 50% chance of being labeled correct in the photos. Meaning my user accuracy is not very good in the areas of clear cut, debris flow and insect. Comparing the model to my aerial photos for North Cascades may be misleading due to the fact that my early identifications may not have been as accurate as my later identifications. There was a learning period that wasn't taken into consideration. Insect identification was for sure something that I got more confident in labeling over time. Within the polygons wind and water were not that common. The model may not have recognized the water as a different disturbance type.

With regard to my producer accuracy for 6 of the 10 disturbance types (avalanche, clear cut, debris flow, fire, insect and riparian) when I'm looking at the aerial photos I have a 50% or greater chance of the disturbance type being labeled correctly in the model and for 4 of the 10 disturbance types (no visible change, unknown, water, and wind) below a 50% chance of being labeled correctly in the model. Meaning my producer accuracy is not very good in the area of no visible change. Once again this is where my later training with the insects helped me to better tell the difference between a subtle insect disturbance and no visible change. Unknowns, wind and water were very few polygons to test accuracy.

Large discrepancies between the model and aerial photography were 56 polygons the model labeled as insect while using the photos I said they were no visible change. This may be due to my lack of understanding of the subtleties of insect infestations especially at the beginning of the internship. Also in reference to the 11 polygons the model labeled as insect and I labeled as fire from the aerial photos may be due to my ability to distinguish between large polygons that are partially burned or near fire and from insect polygons.

In line with using humans to identify disturbances, longer training periods may reduce large areas of error along with a more specific list of identification criteria. The time spent in the field allowed for a big picture understanding of what disturbances actually look like not just snap shots on the computer. However these steps to improve accuracy would require more resources.

	Field											
Aerial Photo	Avalanche	Clearcut	Debris Flow	Development	Fire	Insect/Disease	Landslide	No Visible Change	Riparian	Unknown	**Grand Total**	**Users**
Avalanche	15		5			5		5		3	33	45.5
Clearcut		28		1							29	96.6
DebrisFlow	3		2								5	40.0
Development				0							0	N/A
Fire					22	4					26	84.6
Insect/Disease					5	122				7	134	91.0
Landslide	2		1				0	2			5	0.0
No Visible Change	1		1	1		37		33		5	78	42.3
Riparian	1							1	4	2	8	50.0
Unknown		1				1				0	2	0.0
Grand Total	**22**	**29**	**9**	**2**	**27**	**169**	**0**	**41**	**4**	**17**	**320**	
Producers	68.2	96.6	22.2	0.0	81.5	72.2	N/A	80.5	100.0	0.0		

Overall	**70.63**
Kappa Statistic	**0.59**
Correlation	🟩
Large Error	🟥

	Aerial Photo											
Model	**Avalanche**	**Clearcut**	**DebrisFlow**	**Fire**	**Insect**	**NoVisibleChange**	**Riparian**	**Unknown**	**Water**	**Wind**	**Grand Total**	**Users**
Avalanche	17				2	6	1				26	65.4
Clearcut	5	1	1	8		7		1			23	4.3
DebrisFlow	3		1	1		3	1				9	11.1
Fire				23	1	4		2			30	76.7
Insect	7			11	66	56			1		141	46.8
NoVisibleChange	2			2		61		1			66	92.4
Riparian					1		3			1	5	60.0
Unknown								0			0	N/A
Water									0		0	N/A
Wind										0	0	N/A
Grand Total	**34**	**1**	**2**	**45**	**70**	**137**	**5**	**4**	**1**	**1**	**300**	
Producers	50.0	100.0	50.0	51.1	94.3	44.5	60.0	0.0	0.0	0.0		

Overall	**57.33**
Kappa Statistic	**0.44**
Correlation	🟩
Large Error	🟥

Appendix D

Student Report

Shelby Clary

Accuracy Assessment of Disturbance Monitoring in the North Coast and North Cascades Network

The goal of this project was to assist the National Parks Service Inventory and Monitoring Program with its monitoring of landscape dynamics in the North Coast and North Cascades Network (NCCN). The project sought to assess the accuracy of the LandTrendr software used to identify disturbances within the NCCN, including North Cascades, Mount Rainier and Olympic National Parks. Disturbed areas in these three parks were identified using LandTrendr software that also assigned them a specific agent of disturbance. Disturbance categories included land converted for agricultural use, avalanches, clear cuts, debris flows, land development, fire, insect infestation, landslides, riparian disturbances, wind throws, unknown disturbances and areas with no visible change, suggesting these areas were incorrectly identified. Once LandTrendr made designations, data was analyzed visually on computers and assigned a disturbance agent independent of the LandTrendr assignment. In addition to this second analysis, selected areas from this data were also surveyed onsite in North Cascades National Park and once again given disturbance designations independent of the LandTrendr findings. These field calls were then compared to both the LandTrendr findings for North Cascades National Park and the visual assignments done on the computer to generate error matrices giving a better idea of the accuracy of the monitoring program.

Identification of the disturbed areas in the NCCN began with feeding tasseled-cap transformed Landsat aerial images of all three parks over multiple years into the LandTrendr program, thus determining if a disturbance had occurred and labeling that disturbance with a specific agent. The tasseled-cap transformation took the Landsat aerial image and simplified it into three bands, representing how much brightness, wetness and greenness were in each pixel of the image, to produce a false color image used by LandTrendr and later Timesync. Once Landsat images from multiple years were analyzed by LandTrendr and disturbed area identified, only those found to have occurred in less then five years, ‗fast disturbances', were further visually analyzed. This visual analysis of the Landsat aerial images and tasseled-cap images and trajectories in Timesync resulted in a new set of calls being made about the agent of disturbance for each area, independent of any previous designation made by LandTrendr. These visual calls comprise the data set used for the first comparison against LandTrendr software in the creation of Table 1 on page 2.

Selected areas were further examined through survey in the field on east side of North Cascades National Park. Each plot was assessed individually on site, and in some cases from a distance, and assigned an agent of disturbance independent from both earlier LandTrendr and visual assessments already made. This data comprises the second set that was compared against calls made by LandTrendr used in Table 2 on page 3.

After all data was collected, analysis of the selected data sets began by summarization in an error matrix. The first set of data being compared was the visual calls made on computer for

Table 1. Computer calls compared to LandTrendr calls

	Agricultural	Avalanche	Clearing	Debris Flow	Development	Fire	Insect	Landslide	NoVisible Change	Riparian	Unknown	Grand Total	User's Accuracy
Agricultural	63				6							69	91.3
Avalanche		5	4	1								10	50.0
Clearing		1	89		6		3					99	89.9
DebrisFlow				1								1	100.0
Development	1		2		8		1					12	66.7
Fire			1	1		2				1		5	40.0
Insect		2	2	1			50					55	90.9
Landslide				1		1		0				2	0.0
NoVisible Change	1	3	6	4	1	2	23		30			70	42.9
Riparian	2		2	1	1					5		11	45.5
Unknown		1	5				1				0	7	0.0
Grand Total	**67**	**12**	**111**	**10**	**22**	**5**	**78**	**0**	**30**	**6**	**0**	**341**	
Producer's Accuracy	**94.0**	**41.7**	**80.2**	**10.0**	**36.4**	**40.0**	**64.1**	**0.0**	**100.0**	**83.3**	**0.0**		**74.2**

Table 2. Field calls compared to LandTrendr calls

	Avalanche	Clearcut	DebrisFlow	Development	Fire	Insect	Landslide	NoVisible Change	Riparian	Unknown	Grand Total	User's Accuracy
Avalanche	12		6			4		5		3	30	40.0
Clearcut		28		1							29	96.6
DebrisFlow	5		0								5	0.0
Development				1							1	100.0
Fire			1		22	14					37	59.5
Insect			1		5	133		3		7	149	89.3
Landslide	2		1				0				3	0.0
NoVisible Change	1					11		25		5	42	59.5
Riparian	1	1				1		1	4	2	10	40.0
Unknown	1					6		7		0	14	0.0
Grand Total	22	29	9	2	27	169	0	41	4	17	320	
Producer's Accuracy	54.5	96.6	0.0	50.0	81.5	78.7	0.0	61.0	100.0	0.0		70.3

North Cascades National Park only, Mount Rainier and Olympic being excluded, against the LandTrendr outputs for those same areas. The second data set included only the areas that had been surveyed in the field at North Cascades compared to the LandTrendr outputs for those same areas.

The overall error resulting from the matrix created to compare visual calls to the LandTrendr calls was 74.2%, meaning that these calls were 74.2% accurate when compared to LandTrendr. Especially low points in user and producer accuracy occurred for the landslide and unknown categories, where the agent was assigned accurately 0% for the time. The overall error resulting from the second matrix, that compared field calls to LandTrendr calls, was 70.3%. Low points in user and producer accuracy occurred in the debris flow, no visible change and unknown categories with 0% of agents accurately assigned.

Sources of error for this project relate to both LandTrendr and assessments made by individuals. In some instances, the classification scheme set up to group disturbance agent lacked an appropriate category in which to place a disturbance, for example an area where trees had been thinned but were not necessarily completed cleared. This resulted in classifications to being readjusted to fit disturbances types which otherwise would not fit into a certain category. There is also the issue of individuals not being able to determine the exact agent for an area on ether a computer or in the field. The agent could be placed into the ‗unknown' category, but this category was not recognized in LandTrendr and thus it resulted in larger than normal error for that category in the error matrix. There is also error that results from simply making the wrong visual call either on a computer or in the field that also generates errors in accuracy.

Overall, LandTrendr software produced results that tended to be more accurate then those made by humans visually. In some instances such as with landslides in the first error matrix, visual calls did not produce a single correct result when assigning a disturbance agent. Visual calls made on both the computer and in the field also consumed considerable amounts of time, as well as a lesser but still relevant amount of funds, for results typically less accurate then LandTrendr findings. Additionally, field surveys were limited in terms of accessibility to study sites, only those on or near trails or visible from them were assessable. While the time spent to verify the accuracy of this program was valuable, it would appear that further assessments of accuracy on the LandTrendr program would prove unnecessary.

Appendix E

Student Report

Nathan Schaller

I. Introduction

Landscapes change over time as a result of changes in land use and weather-driven natural disturbances. Throughout this landscape dynamics project our team of GIS interns and specialists identified agents of previously mapped landscape disturbances both by means of working in a computer lab and also going out in the field. The landscape disturbances were mapped using stacks of yearly Landsat images of North Cascades National Park and surrounding areas. This is most easily described as a satellite that flies over the entire park each year, and scans for changes in greenness, wetness and brightness. Our team was given a random sample of all the disturbances for the study area ranging from the year 1985 to 2010, represented by a polygon with a plot ID. Our task was to identify a disturbance agent for each of these disturbances using aerial photo interpretation techniques. Agents were picked from the following list: agricultural, avalanche, clear cut, debris flow, development, fire, insect/disease, landslide, riparian, wind, no visible change, or unknown. We chose the "unknown" or "no visible change" agents when no logical conclusion could be made about what we were examining on the aerial photos. For example, commonly we would label disturbance polygons that would appear at very high elevations as "no visible change". These events were insignificant in the sense that there was most likely no disturbance, but they do stay in our model and are an important part of our data sets. Our team had two week long field trips where we went out into the park, viewed some disturbances polygons first hand. The main goal of the field trips was to get a variety of different disturbance agents so once we got back to the lab we would run the assessment models to see how accurate we were while viewing these polygons from different perspectives. Earlier I mentioned that our team was testing the accuracies of disturbance polygons identified by remote sensing because of its useful ability to span very large areas, much of which were inaccessible by foot.

II. **Description of the Study Area**

During this accuracy assessment, our team had to identify disturbances both inside and outside of park boundaries. Our study area included a 10-mile buffer zone around the park where we sampled our out of park disturbances. The first backpacking excursion took us to the west side of the park to the Bridge Creek trailhead and down south through the Bridge Creek drainage. As we camped in a couple different locations like the Fireweed and North Fork camps down the drainage, the team split up into groups of 2 to 4 people to go out on day hikes to identify as many visible disturbance polygons as possible. The Bridge Creek drainage is on the east side of the Cascades, meaning we were hiking in the drier, warmer part of the park. At the end of our trip, we were given a boat ride along the whole length of Ross Lake and back so we could have even another perspective of seeing the disturbances.

For the second trip, our team was broken into two groups which each took on a different section of the park then both groups met back up at the research station in Newhalem, WA to gather the data. We identified disturbance agents for polygons along Flat Creek, Park Creek Pass, Goody Ridge, Stehekin Valley and Cascade River Road.

Photos from the field:

Top Left – Debris Flow in Stehekin Valley

Top Right – Shelby Clary in front of large fire disturbance

Bottom Left - Land slide on the way to Flat Creek

Bottom Right – Ally Hayes on a debris flow looking towards the Bridge Creek drainage

In the computer lab each intern was given disturbance polygons that were located both inside and outside of the North Cascades Nation Park boundaries. Since the data for the first accuracy assessment was strictly inside park boundaries, much of the computer work that had polygons both inside and outside played a part in the second accuracy assessment. Earlier I listed the twelve different agents that our team was trying to identify. These disturbances vary greatly between inside and outside the park boundaries. While studying areas that are inside the park boundaries we would find only natural agents such as avalanches, debris flows, fires, insect infestations, landslides, riparian changes, or wind throw events.

III. **Methodology and Approach**

User‟s and Producer‟s Accuracies

For each of our accuracy assessments we had to find the user‟s accuracy, which in short is the number of correctly identified polygons in a given disturbance over the number of polygons that claimed to be in that disturbance class. The user‟s accuracies can be seen in column "N" for assessment 1 and column "O" for assessment 2 on the next page. After we found the user‟s accuracy we had to find the producer‟s accuracy which can be calculated by taking the number of correctly identified disturbances of a given class over the number of polygons actually in that class. The producer‟s accuracies can be seen in row 15 for assessment 1 and row 16 for assessment 2 on the following page.

After both the user‟s and producer‟s accuracies were calculated, we were instructed to find the total accuracy for each error matrix. The total accuracy can be calculated by taking the number of correct disturbances over the total number of disturbances. This percentage shows a summary value which does not reveal if there was some error between classes or if some classes might have been really bad and some really good. This is why our model included the user‟s and producer‟s accuracies.

Sampling

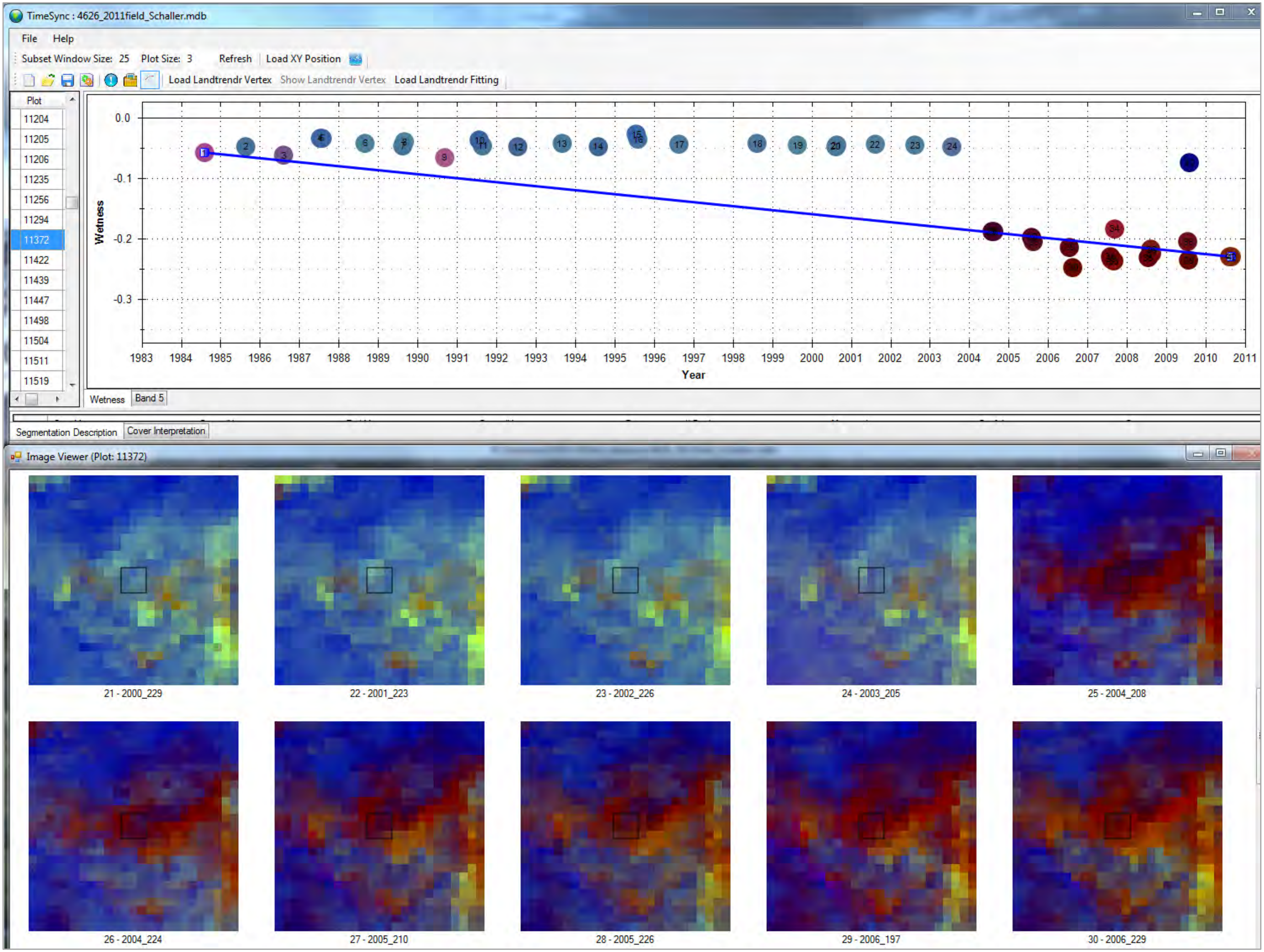
To stay unbiased and random, the several groups of polygons that were distributed throughout the interns were sampled from an extremely large number (14,123) of returned disturbance polygons using a method known as "stratified random sampling". Since the remote sensing provided us with just over 14 thousand results, another question one might ask about this project is how we selected which disturbance polygons to use for our testing. Once again our GIS specialist selected stratified random sampling as our sampling method. Stratification is the process of dividing members of the population into homogeneous subgroups before sampling. Within these subgroups stratified sampling has the minimum number of disturbances randomly placed into each category. This method often improves the results by reducing sampling error.

Google Earth and Timesync

While identifying disturbance polygons in the lab we used two main programs, Google Earth, and Timesync. On Google Earth I was able to view aerial photos, many which contained photos from the past, with the disturbance polygons layered on top. With Timesync, we were given image stacks containing colored pixels from the year 1985 to 2010 for each polygon along with a trajectory of that particular polygon‟s "wetness". On the next page I provided a screenshot of what the Timesync layout looks like with a disturbance‟s trajectory above and image stacks below. This particular disturbance was a very large fire, as you can see around the year 2004 when the wetness index instantly plummets. How the pixelated image stacks work is that there is a tasseled-cap transformation of the data we receive from remote sensing which leaves us with three major dimensions or "bands" known as brightness, greenness and wetness. These three bands are shown as different colors in the image which then correspond to different conditions on the ground. For example, dense vegetation would appear as some shade of blue green and a complete lack of vegetation would appear as red or orange. Our team would be given the plot ID for the disturbance and the year the event was suspected to have taken place. We would then try to identify a change between the images before the event year and the images after to help us decide what disturbance the polygon could have been.

Kappa Statistic

Our lead GIS specialist selected the Cohen‟s kappa coefficient as a statistical measure for our qualitative items, or as I have been labeling them, our disturbance agents. This statistical calculation provides us with a percent accuracy when two individuals (either field data vs. lab data or WWU data vs. computer generated data) attempt to assign an agent to the same thing (the disturbance polygons). This statistic takes into account the fact that the observers will sometimes agree or disagree simply by chance. A kappa of 1 indicates a perfect agreement, whereas a kappa of 0 indicates agreement equivalent to chance. For example, a kappa of .57 would suggest that an observed classification is 57% better than one resulting from chance. So in simpler terms, the closer that the kappa statistic is to 1, the more accurate we were when labeling the agent of disturbance polygons.


TimeSync : 4626_2011field_Schaller.mdb

Subset Window Size: 25 Plot Size: 3

Image Viewer (Plot: 11372)

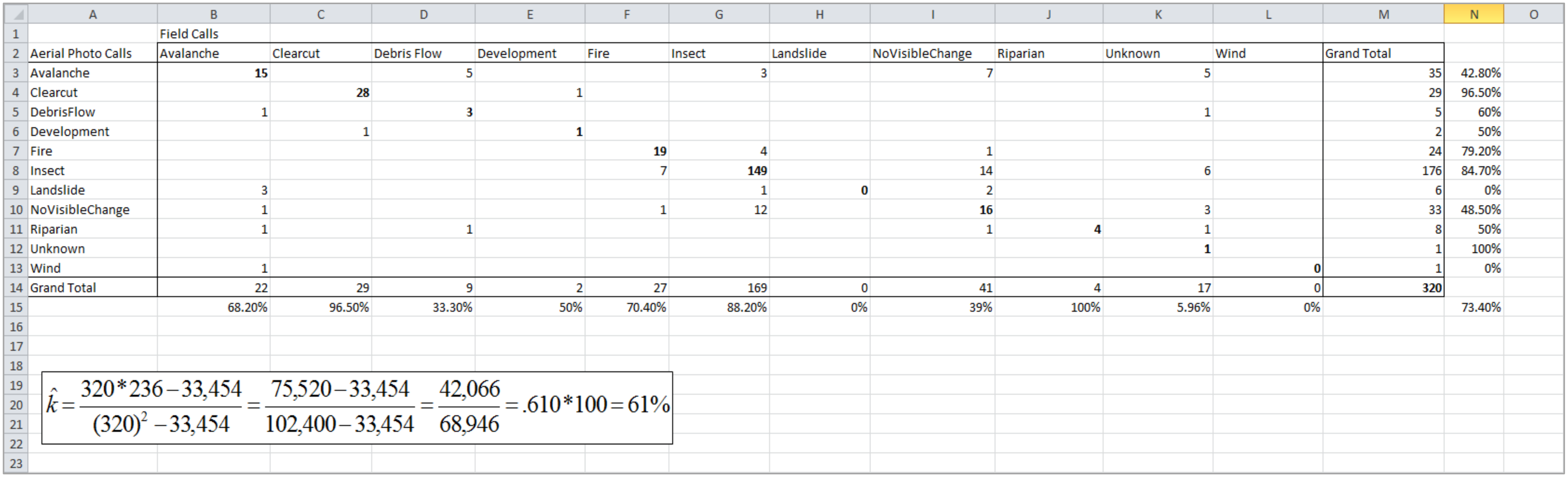
IV. **Results**

Most points on the Earth‟s surface have what one may call a “life history” that has been captured in images taken by Landsat satellites. Luckily, the North Cascades just happens to be one of those places. With a little help from a vast archive of Landsat satellite images called Landtrendr; statistical algorithms separated trends from noise and thereby identified periods of stability and of change for every pixel (shown on previous page). Our team‟s landscape dynamics model began its process by filtering the Landtrendr results to exclude disturbances that were too small or had too weak of a signal. Then once we had our desired collection of disturbance polygons, the other interns and I had to validate the model results by using aerial imagery. Most of the disturbances that we recorded from the first trip turned out to be insect infestation or disease polygons.

Once we moved to disturbance polygons located outside park boundaries the majority of them seemed to be human-related disturbances such as clear cuts and rural development. Since each intern was given a different group of polygons to identify for the second assessment, most of my polygons that were outside the park ended up being located near Everson, WA and Peaceful Valley on the west side of the mountains. While in the lab, many of the sampled polygons that I examined appeared west of the park within the study area buffer. I found what seemed to be hundreds of clear cuts in that area, and only a few natural disasters.

As explained before, the kappa statistic is what our landscape dynamics model is truly relying on. The kappa for assessment 1 was .610 meaning that an observed classification is 61% better than one resulting from chance. The kappa for assessment 2 was .419 again meaning that an observed classification is 41.9% better than one resulting from chance.

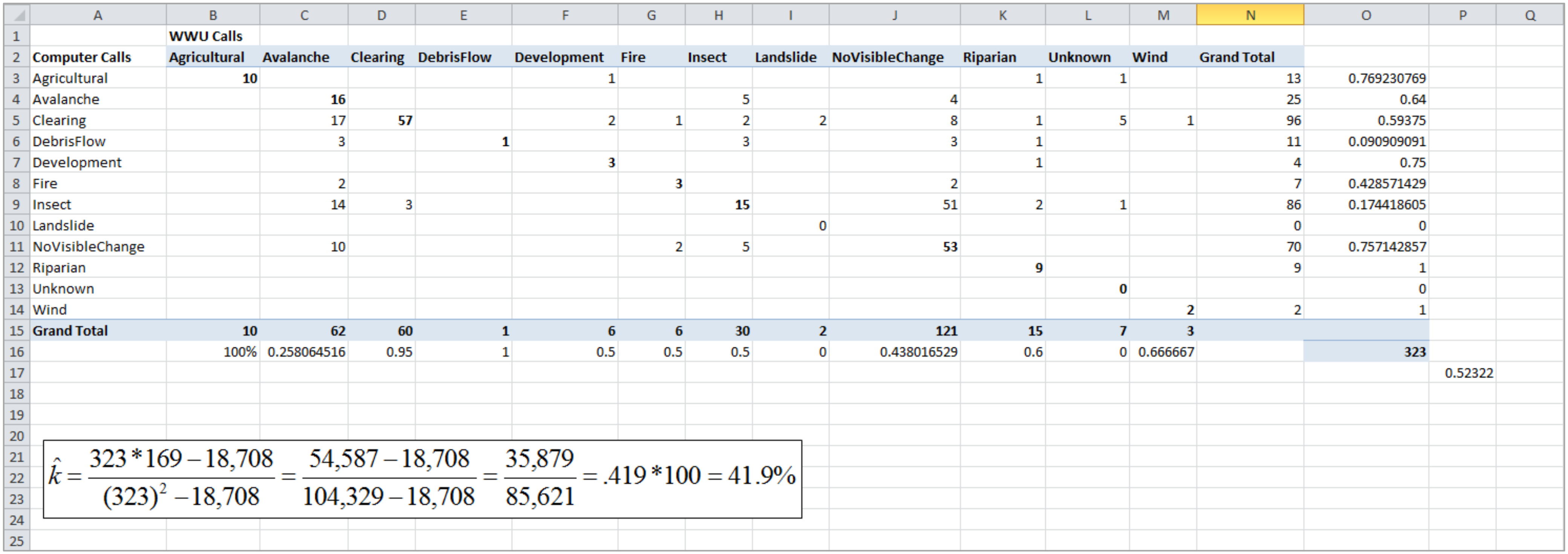
Assessment 1 – Total Accuracy = 73.4%   Kappa Statistic = 61%



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		Field Calls												
2	Aerial Photo Calls	Avalanche	Clearcut	Debris Flow	Development	Fire	Insect	Landslide	NoVisibleChange	Riparian	Unknown	Wind	Grand Total	
3	Avalanche	**15**		5			3		7		5		35	42.80%
4	Clearcut		**28**		1								29	96.50%
5	DebrisFlow	1		**3**							1		5	60%
6	Development		1		**1**								2	50%
7	Fire					**19**	4		1				24	79.20%
8	Insect					7	**149**		14		6		176	84.70%
9	Landslide	3					1	**0**	2				6	0%
10	NoVisibleChange	1				1	12		**16**		3		33	48.50%
11	Riparian	1		1					1	**4**	1		8	50%
12	Unknown										**1**		1	100%
13	Wind	1										**0**	1	0%
14	Grand Total	22	29	9	2	27	169	0	41	4	17	0	320	
15		68.20%	96.50%	33.30%	50%	70.40%	88.20%	0%	39%	100%	5.96%	0%		73.40%

$$\hat{k} = \frac{320*236-33{,}454}{(320)^2-33{,}454} = \frac{75{,}520-33{,}454}{102{,}400-33{,}454} = \frac{42{,}066}{68{,}946} = .610*100 = 61\%$$

Assessment 2 – Total Accuracy = 52.3%   Kappa Statistic = 41.9%



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1		**WWU Calls**														
2	**Computer Calls**	**Agricultural**	**Avalanche**	**Clearing**	**DebrisFlow**	**Development**	**Fire**	**Insect**	**Landslide**	**NoVisibleChange**	**Riparian**	**Unknown**	**Wind**	**Grand Total**		
3	Agricultural	**10**				1					1	1		13	0.769230769	
4	Avalanche		**16**					5		4				25	0.64	
5	Clearing		17	**57**		2	1	2	2	8	1	5	1	96	0.59375	
6	DebrisFlow		3		**1**			3		3	1			11	0.090909091	
7	Development					**3**					1			4	0.75	
8	Fire		2				**3**			2				7	0.428571429	
9	Insect		14	3				**15**		51	2	1		86	0.174418605	
10	Landslide								0					0	0	
11	NoVisibleChange		10				2	5		**53**				70	0.757142857	
12	Riparian										**9**			9	1	
13	Unknown											**0**			0	
14	Wind												**2**	2	1	
15	**Grand Total**	**10**	**62**	**60**	**1**	**6**	**6**	**30**	**2**	**121**	**15**	**7**	**3**			
16		100%	0.258064516	0.95	1	0.5	0.5	0.5	0	0.438016529	0.6	0	0.666667		**323**	
17																0.52322

$$\hat{k} = \frac{323*169-18{,}708}{(323)^2-18{,}708} = \frac{54{,}587-18{,}708}{104{,}329-18{,}708} = \frac{35{,}879}{85{,}621} = .419*100 = 41.9\%$$

V. **Discussion and Conclusions**

After seeing the results from the two accuracy assessments, it becomes clear that there is definitely something causing the accuracy to be low. But first off, Ill discuss which disturbance agents were most accurately indentified. For the first assessment there was a slight bias in terms of the frequency of the agents. For example, the first assessment contained 176 insect disturbances, 149 of which were identified accurately. The other agents had about 20 to 30 polygons, each with varying results when it comes to accurate identification. I believed the reason to be because of our location out in the drier portion of the Cascades where there were less disturbances caused by moisture and/or the ability for a hillside to retain its structure. So although the first assessment was slightly "insect biased", the second statistical test was set up to get a more random sampling of disturbance agents from the park. The total accuracy for the first assessment was slightly higher than the second‟s, but then again, the two tests had some key differences which played a large role in determining the total accuracies and kappa statistics.

The accuracies of the two assessments might be low due to a few errors from the disturbance polygon interpretations. These errors could be from either problems within the labwork/indentification process or errors in our selected method of remote sensing. While working on the computer trying to accurately classify the polygons, there was an issue from the "positional error". While looking at aerial photos, a better reflection of the image could have helped us tell what the agent was. Also, a big portion of the error came from the fact that people make mistakes, giving the results of the assessments some interpreter error. When thinking about how the satellites found the disturbance polygons, the accuracies were low thanks to the fact that remotely sensed data cannot capture specific disturbance types, no matter how obvious they are. Other sources of error could be things as little as there being atmospheric effects masking subtle differences in the agents that would have let us easily identify them.

When trying to improve the accuracy of my classifications out in the field, I resorted to using land use and land cover maps to incorporate other data. I did this to get a better feel for what has happened in that area over time, and overall to give myself more information about that specific disturbance polygon. While in the lab I was able to change the grain of the spectral data or of the pixels given to me in the Timesync program. All in all, interpreting the accuracies of these different agents can yield ideas for an improvement of future disturbance classification.

Appendix F

Student Report

Robert Bryson

		Field Calls											
		Avalanche	Clearing	Debris Flow	Development	Fire	Insect/Disease	Landslide	No Visible Change	Riparian	Unknown	Grand Total	User's Accuracy
Photo	Avalanche	15		5			4		6	1	3	34	44.1
	Clearcut		28		1							29	96.6
	Debris Flow	4		3								7	42.9
	Development				1							1	100.0
	Fire					22	10					32	68.8
	Insect/Disease	1				5	154		22		10	192	80.2
	Landslide	2						0				2	0.0
	NoVisibleChange						1		11		1	13	84.6
	Riparian		1	1					1	3	2	8	37.5
	Unknown								1		1	2	50.0
	Grand Total	22	29	9	2	27	169	0	41	4	17	320	
	Producer's Accuracy	68.2	96.6	33.3	50.0	81.5	91.1	N/A	26.8	75.0	5.9		

Overall Accuracy	74.37
Kappa Statistic	0.61

		Photo												
		Avalanche	Clearcut	DebrisFlow	Development	Fire	Insect	Landslide	NoVisibleChange	Riparian	Unknown	Water	Grand Total	Users
Computer	Avalanche	6	1						1				8	75.0
	Clearcut	2	63				10		17	8	1		101	62.4
	DebrisFlow	2		2				1	2				7	28.6
	Development		6		2		1		1		1		11	18.2
	Fire					4	1		1		1		7	57.1
	Insect	2	2			1	20		38			3	66	30.3
	Landslide							0					0	N/A
	NoVisibleChange	1					4		32				37	86.5
	Riparian				1				1	5			7	71.4
	Unknown										0		0	N/A
	Water											0	0	N/A
	Grand Total	13	72	2	3	5	36	1	93	13	3	3	244	
	Producers	46.2	87.5	100.0	66.7	80.0	55.6	0.0	34.4	38.5	0.0	0.0		

Overall Accuracy	54.92
Kappa Statistic	0.42

Appendix G

Accuracy Matrices/Updated Categories

		TimeSync (Hayes)												
		Agricultural	Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Agricultural**	**2**											2	100.0
	Annual Variability		**60**	3			5		1			4	73	82.2
	Avalanche		6	**13**			1	1	1	1		1	24	54.2
	Clearing		8	3	**43**		1		4	1		3	63	68.3
	Development	1			12	**2**					2		17	11.8
	Fire		3				**27**		3			1	34	79.4
	Forest Collapse			1				**0**					1	N/A
	Forest Decline		39	2	3		1		**29**	1	3		78	37.2
	Mass Movement		2	3						**10**	1		16	62.5
	Riparian	1			1				1	1	**15**		19	78.9
	Unknown											**0**	0	N/A
	Grand Total	4	118	25	59	2	35	1	39	14	21	9	**327**	
	Producer's Accuracy	50.0	50.8	52.0	72.9	100.0	77.1	0.0	74.4	71.4	71.4	0.0		

Overall Accuracy	61.47
Kappa Statistic	0.54

		TimeSync (Oehler)												
		Agricultural	Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Agricultural**	**70**	1			11					5		87	80.5
	Annual Variability		**21**		1		5					2	29	72.4
	Avalanche		6	**1**					2			2	11	9.1
	Clearing	1	2		**33**	17	1					2	56	58.9
	Development	10	3		**1**	**35**					2		51	68.6
	Fire			1			**26**		2	1			30	86.7
	Forest Collapse							**0**					0	N/A
	Forest Decline		15				11		**23**		1	1	51	45.1
	Mass Movement		1				2			**2**			5	40.0
	Riparian					4	1				**5**	1	11	45.5
	Unknown											**0**	0	N/A
	Grand Total	81	49	2	35	67	46	0	27	3	13	8	**331**	
	Producer's Accuracy	86.4	42.9	50.0	94.3	52.2	56.5	N/A	85.2	66.7	38.5	0.0		

Overall Accuracy	65.26
Kappa Statistic	0.59

		TimeSync (Ponce)											
		Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Annual Variability**	**86**	2			3		2		1	2	96	89.6
	Avalanche	8	**25**				1	3		2		39	64.1
	Clearing	4	2	**1**		5			1			13	7.7
	Development				**0**							0	N/A
	Fire	4				**24**		2			2	32	75.0
	Forest Collapse					1	**0**					1	N/A
	Forest Decline	34	4			11		**63**				112	56.3
	Mass Movement	1	1			1			**1**	1		5	20.0
	Riparian									**2**		2	100.0
	Unknown										**0**	0	N/A
	Grand Total	137	34	1	0	45	1	70	2	6	4	**300**	
	Producer's Accuracy	62.8	73.5	100.0	N/A	53.3	0.0	90.0	50.0	33.3	0.0		

Overall Accuracy	67.33
Kappa Statistic	0.56

		TimeSync (Clary)												
		Agricultural	Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Agricultural**	**61**			**1**	1							63	96.8
	Annual Variability		**39**		2		1			1		1	44	88.6
	Avalanche			**5**	3				2		1		11	45.5
	Clearing		5	4	**84**	2	1		2		1	6	105	80.0
	Development	8	1		8	**8**					1		26	30.8
	Fire		2				**2**			1			5	40.0
	Forest Collapse							**0**					0	N/A
	Forest Decline		17		1	1			**50**			1	70	71.4
	Mass Movement		3	1					1	**1**			6	16.7
	Riparian		3				1				**8**		12	66.7
	Unknown											**0**	0	N/A
	Grand Total	69	70	10	99	12	5	0	55	3	11	8	**342**	
	Producer's Accuracy	88.4	55.7	50.0	84.8	66.7	40.0	N/A	90.9	33.3	72.7	0.0		

Overall Accuracy	75.44
Kappa Statistic	0.68

		TimeSync (Schaller)												
		Agricultural	**Annual Variability**	**Avalanche**	**Clearing**	**Development**	**Fire**	**Forest Collapse**	**Forest Decline**	**Mass Movement**	**Riparian**	**Unknown**	**Grand Total**	**User's Accuracy**
RF Model	**Agricultural**	**8**										1	9	88.9
	Annual Variability		**73**	12			2		6		2		95	76.8
	Avalanche		5	**24**	1				7				37	64.9
	Clearing		5	16	**56**	1		1	1	2	7	4	93	60.2
	Development	2				**5**							7	71.4
	Fire			1			**4**		1				6	66.7
	Forest Collapse							**2**					2	N/A
	Forest Decline		33	8	3				**14**		4	2	64	21.9
	Mass Movement		1	1					1	**1**	1		5	20.0
	Riparian										**5**		5	100.0
	Unknown											**0**	0	N/A
	Grand Total	10	117	62	60	6	6	3	30	3	19	7	**323**	
	Producer's Accuracy	80.0	62.4	38.7	93.3	83.3	66.7	66.7	46.7	33.3	26.3	0.0		

Overall Accuracy	59.44
Kappa Statistic	0.49

		TimeSync (Bryson)												
		Agricultural	**Annual Variability**	**Avalanche**	**Clearing**	**Development**	**Fire**	**Forest Collapse**	**Forest Decline**	**Mass Movement**	**Riparian**	**Unknown**	**Grand Total**	**User's Accuracy**
RF Model	**Agricultural**	**0**			**1**								1	0.0
	Annual Variability		**45**	2					7				54	83.3
	Avalanche		2	**9**	2								13	15.4
	Clearing		23		**60**				12		8	1	104	1.9
	Development				7	**2**						1	10	20.0
	Fire						**4**		1			1	6	66.7
	Forest Collapse						1						1	N/A
	Forest Decline		19	1	2				**16**				38	42.1
	Mass Movement		2	1						**2**			5	40.0
	Riparian		2			1				1	**8**		12	66.7
	Unknown											**0**	0	N/A
	Grand Total		93	13	72	3	5	0	36	3	16	3	**244**	
	Producer's Accuracy		48.4	15.4	2.8	66.7	80.0	N/A	44.4	66.7	50.0	0.0		

Overall Accuracy	59.84
Kappa Statistic	0.47

Appendix H

Accuracy Matrices

Project Lead

		Field (all students/project lead)											
		Annual Variability	Avalanche	Clearing	Development	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Annual Variability**	**30**						10	1		3	44	68.2
	Avalanche	2	**10**			1		16	3	1	4	37	27.0
	Clearing	1	5	**29**	1			2	1		1	40	72.5
	Development				**0**							0	N/A
	Fire		3			**15**		2				20	75.0
	Forest Collapse						**0**	1				1	0.0
	Forest Decline	3	2			9		**144**			8	166	86.7
	Mass Movement	3	1					1	**5**			10	50.0
	Riparian	2	1			2				**3**	1	9	33.3
	Unknown										**0**	0	N/A
	Grand Total	41	22	29	1	27	0	176	10	4	17	**327**	
	Producer's Accuracy	73.2	45.5	100	0.0	55.6	N/A	81.8	50.0	75.0	0.0		

Overall Accuracy	72.17
Kappa Statistic	59.38

		TimeSync (Project Lead)										
		Annual Variability	Avalanche	Clearing	Fire	Forest Collapse	Forest Decline	Mass Movement	Riparian	Unknown	Grand Total	User's Accuracy
RF Model	**Annual Variability**	**42**	1				1				44	95.5
	Avalanche		**20**		1		15	1			37	54.1
	Clearing	1	7	**30**			1			1	40	75.0
	Fire		4		**15**		1				20	75.0
	Forest Collapse					**0**	1				1	0.0
	Forest Decline	5	3		4		**150**			4	166	90.4
	Mass Movement	1	4				2	**3**			10	30.0
	Riparian	1			2			1	**5**		9	55.6
	Unknown									**0**	0	N/A
	Grand Total	50	39	30	22	0	171	5	5	5	**327**	
	Producer's Accuracy	84.0	51.3	100	68.2	N/A	87.7	60.0	100	0.0		

Overall Accuracy	81.04
Kappa Statistic	0.72

Appendix I

Developed Training Materials for TimeSync Interpretation

This guide is designed to help identify and label landscape disturbance types in the lab and in the field as part of the validation of disturbance type labels generated by the RF model. This appendix provides written descriptions of the disturbances, describes their typical position on the landscape and suggests tips to help reduce confusion when identifying various disturbance types. Figures in this appendix show examples of disturbances as seen on true color aerial photography and Landsat imagery that has undergone the Tasseled Cap transformation. The figures also provide examples of typical pixel spectral trajectories as seen in TimeSync software application. The colors used in the descriptions below refer to the hues of the Tasseled Cap imagery, which is used to visualize disturbances on Landsat scenes. For further guidance on interpreting the Tasseled Cap hues, the user should consult the first version of the protocol (Kennedy et al. 2007).

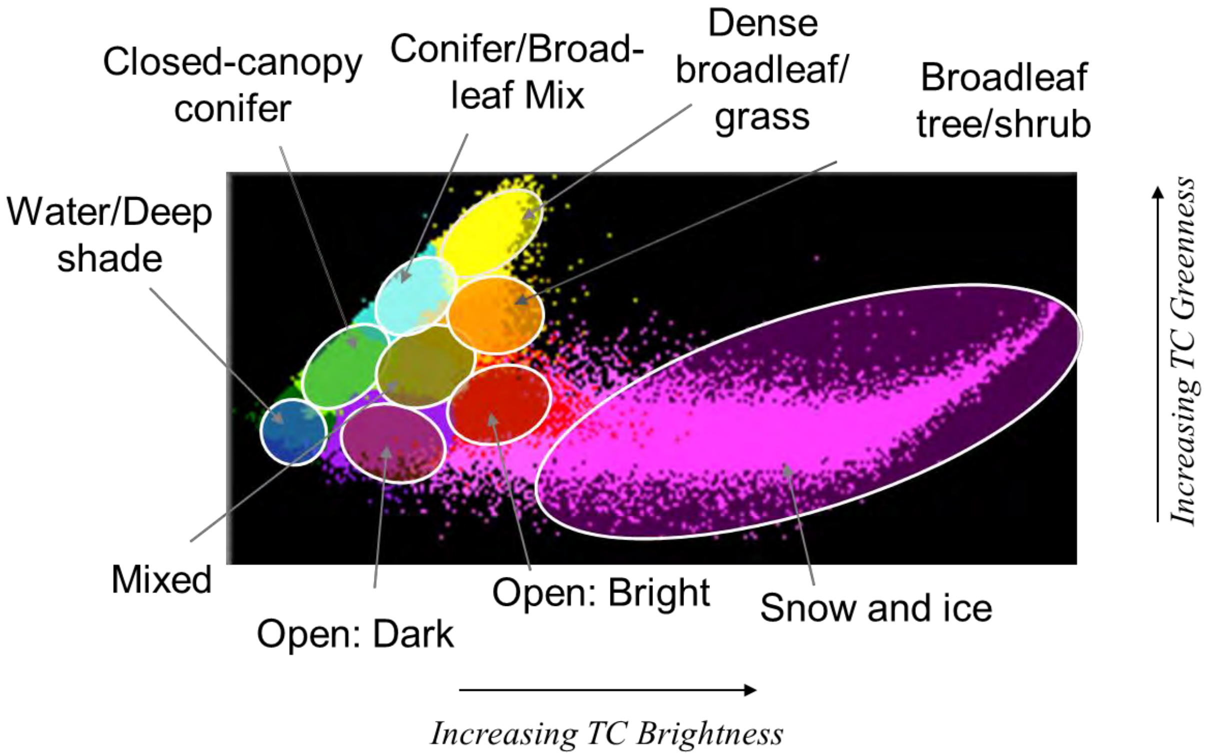


Figure I.1. Colors of typical land cover classes as seen on Landsat imagery that has undergone the tasseled cap (TC) transformation. Dark features such as shade, water or dark conifer canopy appear dark green or blue. Colors lighten as canopy structure decreases in complexity and canopy compositions shifts from evergreen to deciduous. Open:Dark are often shadowed areas with little vegetation. Open:bright is typically exposed rock or parking lots.

1. Agriculture

This class is found predominately outside the park boundaries and is extensive in the NOCA study area, especially the Chilliwack Valley of British Columbia. This disturbance type is also found in the OLYM and MORA study areas, but to a lesser extent. Agricultural areas are dynamic landscapes, with fields undergoing cyclical planting, growth, harvesting and plowing. The specific changes in phases captured by LandTrendr within a given annual analysis will depend on the imagery dates. Fields are typically red or brown if recently plowed or left fallow and bright green or yellow if planted.

Figure I.2 shows an example of a disturbance patch that would be placed in the ―Agriculture” class. Aerial photography shows the patch located within a matrix of agricultural land use. The 2005 Landsat Tasseled Cap image shows the patch being planted with some kind of broadleaf crop (light green color). The 2006 Landsat image shows loss of greenness and transition to brown tones. This coloration usually corresponds to ground cover that has some vegetation and some bare earth components, suggesting that the field was recently planted. The TimeSync trajectory is typical for this type of disturbance, showing cyclical nature of agricultural activities and switching between bare earth and planted cover types.

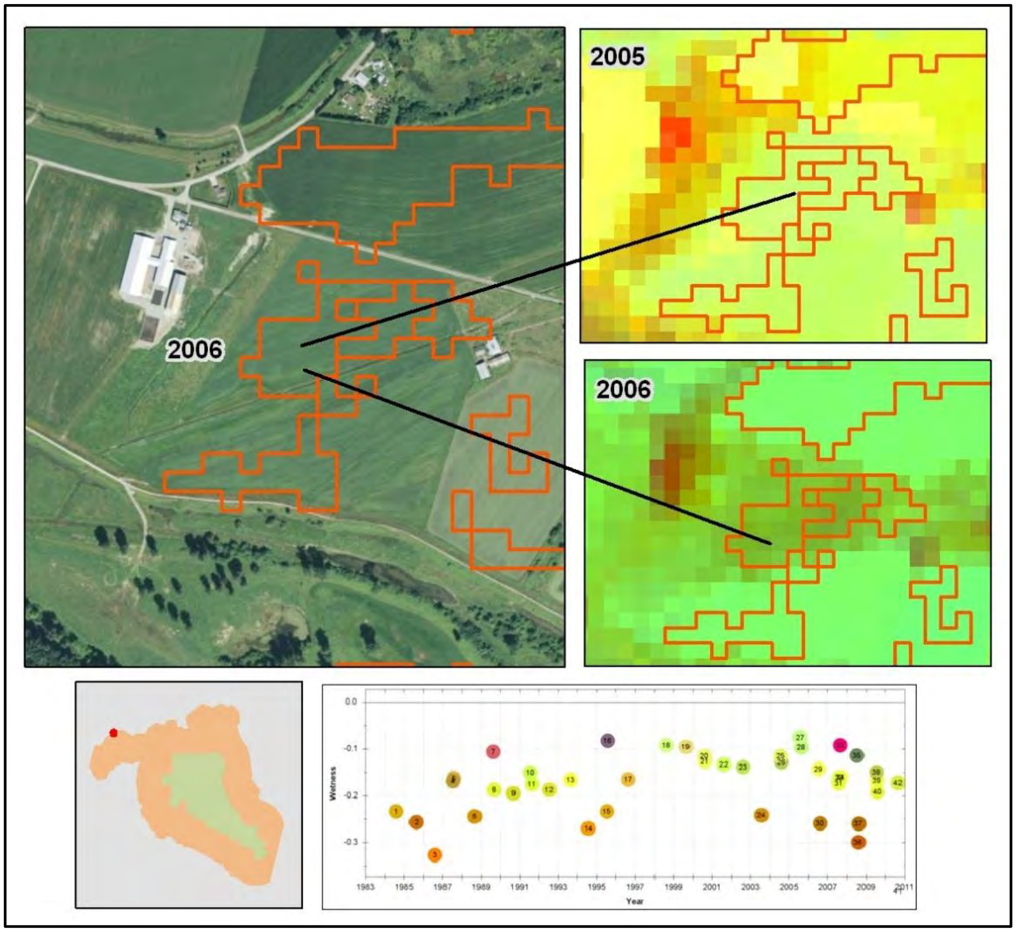


Figure I.2. Agriculture. The image on the left image shows LandTrendr disturbance polygons with associated dates overlaid on an aerial photograph. The images on the right show the same areas on the Tasseled Cap Landsat chips prior to and after the disturbance.

2. Annual Variability

This category was created to be able to model and remove polygons detected by LandTrendr that do not capture change of interest to the NCCN. Usually, these changes are associated with variability in snow cover, clouds, terrain shadows, or vegetation phenology that is not removed in the image processing steps and is of great enough magnitude to pass through filtering. Annual variability polygons are generally only found in high elevations areas with limited vegetation, such as above the tree line. The interpreter must exercise care in determining a polygon of this class truly shows no change. The TimeSync trajectories of these disturbances usually show high degree of variability throughout the time period being examined and are dominated by red, brown and orange hues. Figure I.3 shows an example of a polygon that would be placed in the –Annual Variability” class. Landsat Tasseled Cap images from 2000 and 2006 are not significantly different, except for slight variation in hues most likely related to differences in soil moisture during the image acquisition dates.

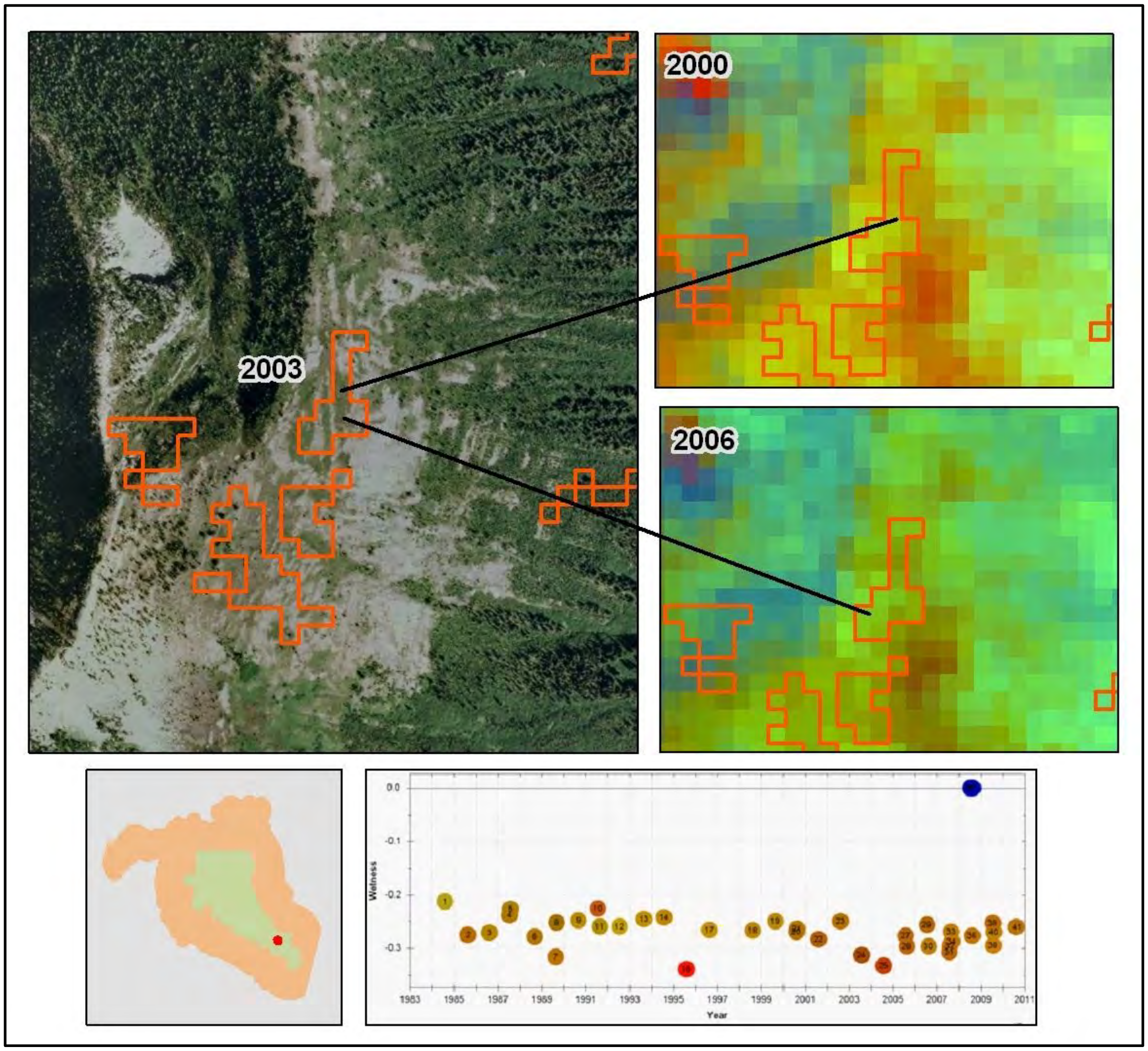


Figure I.3. Annual Variability. The picture of the steep and partially vegetated upper valley wall shows no visibly detectable change between 2000 and 2006 Landsat chips, even though change was detected for 2003. Note the impact of changes in soil moisture and phenology as the trajectory and imagery changes from orange to red to brown hues.

3. Avalanche

Avalanches originate in snow receiving zones on ridges or high on the valley wall. They are typically long, linear polygons, although some events can be broken up into multiple smaller polygons depicting areas of greatest removal of vegetation. If the avalanche occurred in an existing avalanche chute, the TimeSync trajectory usually starts in bright greens and yellows, which are representative of low statured, mostly broadleaf vegetation – small conifers, deciduous shrubs and herbs (Fig. I.4). If swaths of forest were removed, the TimeSync trajectory will start as greenish blue, representative of mature conifer forest. As avalanches typically remove some but not all of the vegetation, the trajectory after the disturbance is typically shown in hues of red, brown and tan. Higher magnitude avalanches occasionally traverse the valley floor and leave a large pile of downed trees in their wake, which can usually be seen in the aerial photography.

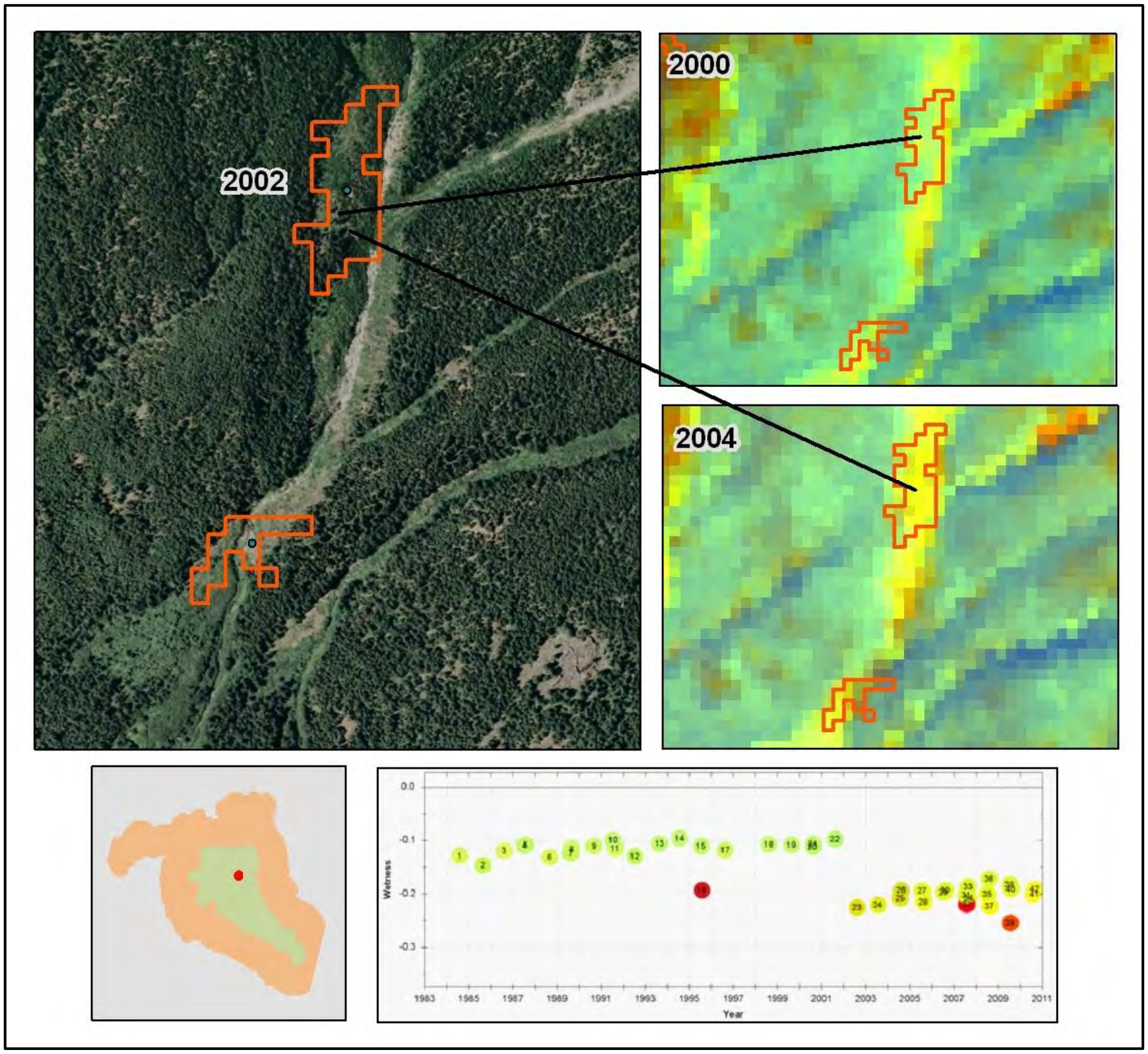


Figure I.4. Avalanche. The 2002 avalanche has removed patches of vegetation as it traveled down the existing avalanche chute.

4. Clearing

The clearing category covers disturbances that mostly occur in areas outside the park boundaries that are under active forest management or are adjacent to development in rural areas. Clearing disturbances include a range of forest management practices, from –clearcuts” in which nearly all the forest canopy is removed, to more patchy harvests such as select cuts, to thinning, to chemical treatment of broadleaf species. Typically, the clearing trajectory in TimeSync starts with greens and blues that indicate a mature conifer forest (Fig. I.5). The trajectory then shifts to bright reds, oranges or browns that indicate open ground and quickly transition to greens that darken as regrowth becomes more mature and transitions from broadleaf to conifer types. In the aerial photography the cleared ground looks very brown and occasionally looks burned or black. Following the clearing, the trajectory usually shows the recovering broadleaf vegetation in a bright green, which slowly transitions to darker greens and blues of the conifer forest.

In the aerial photography the heights of the regrowing vegetation can be difficult to discern, but the regrowth is typically uniform and the polygon is typically an angular shape. Frequently, smaller linear polygons are detected a year or two prior to and adjacent to clearing polygons - these are logging roads that are built prior to clearing to access the logging site. These types of clearing will typically have a similar spectral trajectory, but might contain more blue and dark green hues if the road is surrounded by undisturbed conifer forest.

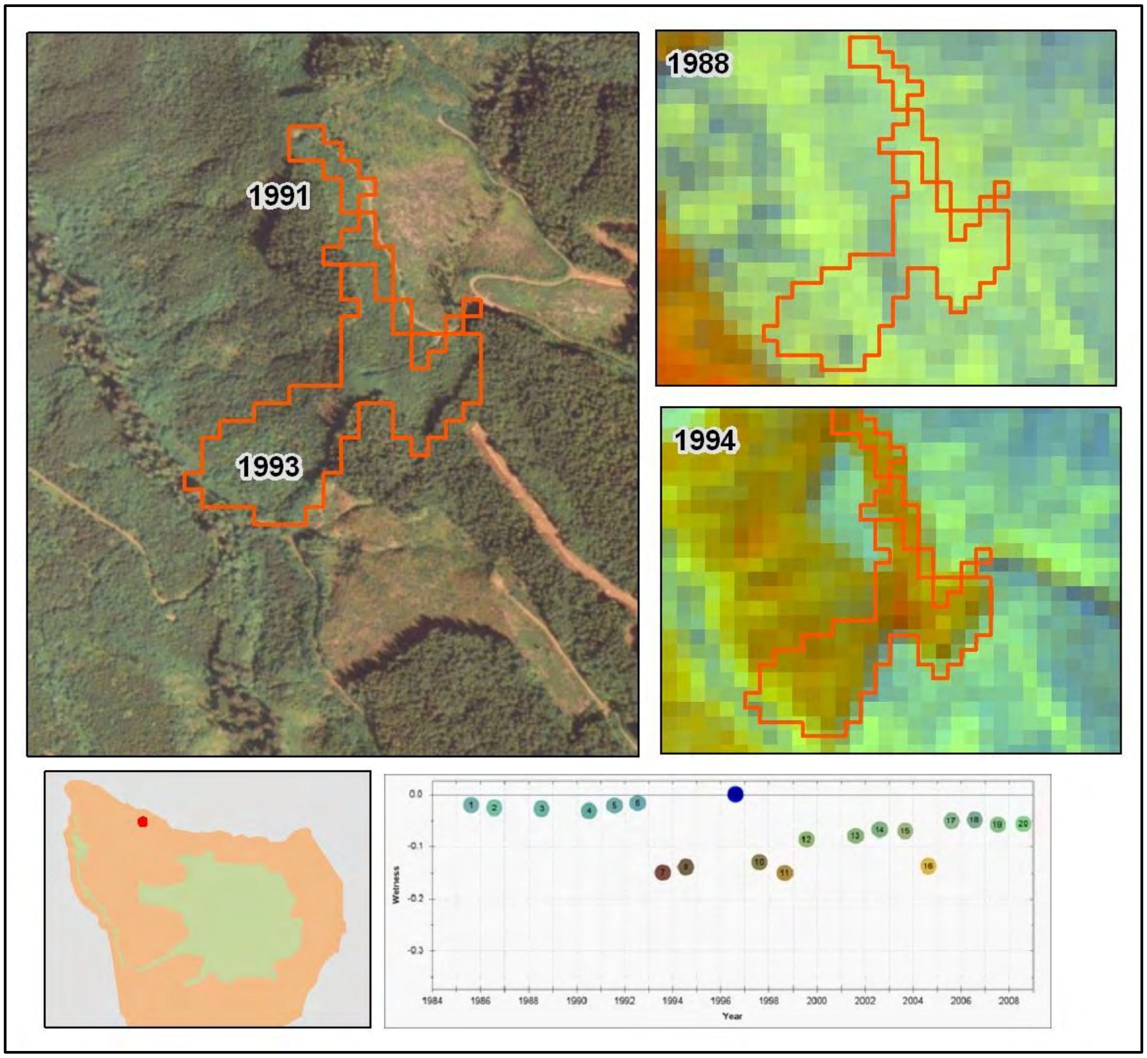


Figure I.5. Clearing. The aerial photo shows a 1993 clearcut that was preceded by a 1991 clearing for a road. Spectral values of the TimeSync trajectory and Landsat Tasseled Cap images from prior to and after the disturbance clearly show transition between blue and green hues representative of conifer forest to browns and oranges of bare ground. The spectral trajectory shows quick transition to vegetation following the disturbance. Disturbances associated with thinning or chemical treatment will usually show a small dip in the trajectory while the recovering vegetation is still mostly broadleaf. The recovery then continues and hues quickly change to darker green and blue representative of conifer forest. These trajectories will only be associated with clearings that happened prior to 1985 and do not show the original clearing (Fig. I.6, below).

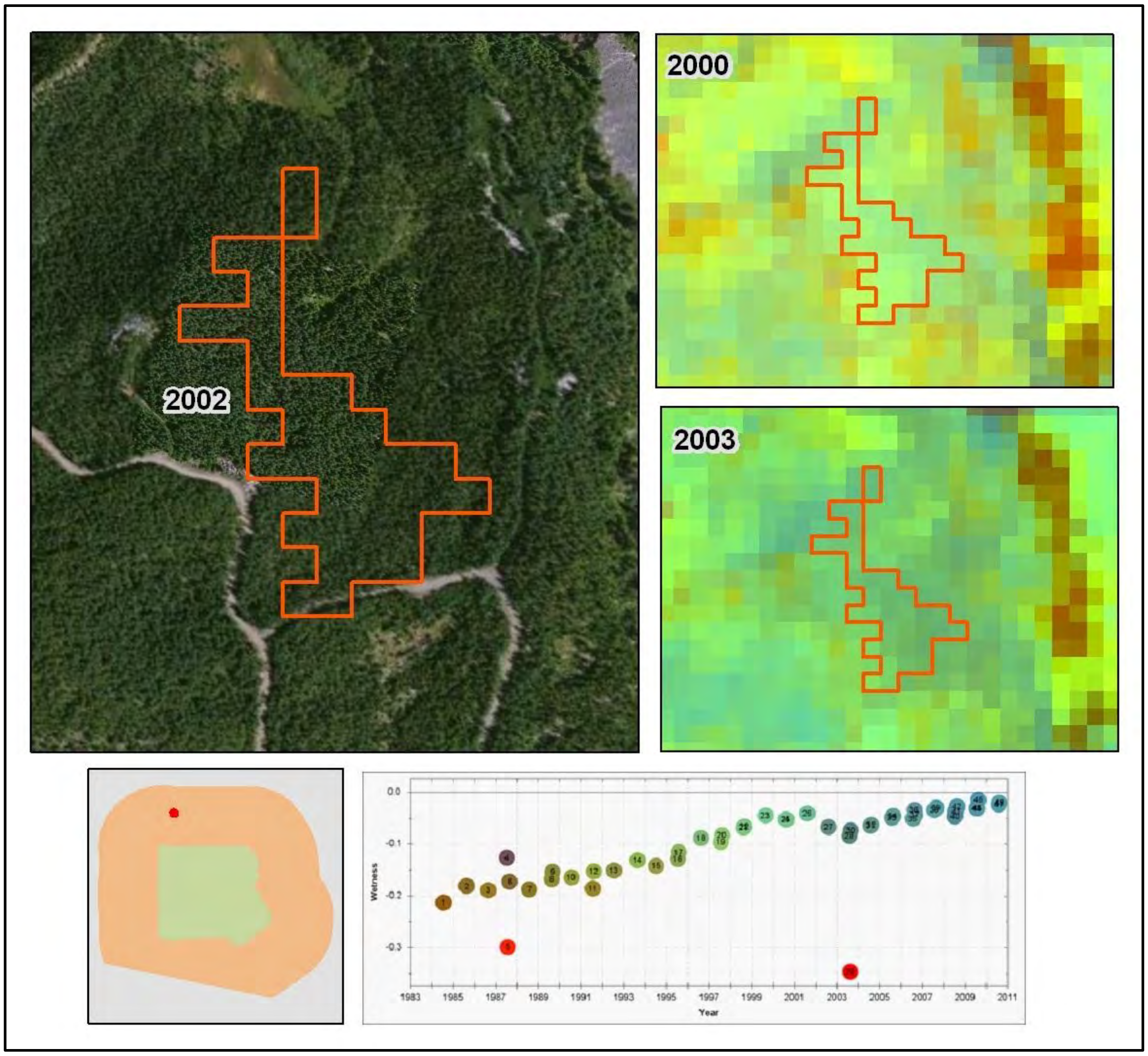


Figure I.6. Clearing - thinning. A disturbance polygon depicting either chemical or mechanical treatment of a pre-1985 clearcut. The first part of the TimeSync trajectory shows broadleaf vegetation growth. After the treatment, the trajectory dips temporarily and resumes upward climb with hues that are more representative of conifer vegetation.

The Clearing category also includes clearing that is associated with low density rural development. Interpreter should assess how much of the disturbance polygon is occupied by buildings after clearing has occurred. If buildings occupy the minority of the pixels within the polygon and the polygon clearly outlines the cleared area around the construction, the polygon should be labeled with –Clearing” category. If buildings are large enough and occupy the majority of the disturbance polygon, the area should be labeled –Development.”

In very rare cases, in the forest lands adjacent to OLYM, it can be difficult to distinguish windthrow from clearing and, depending on the resolution of the aerial photo, it might be difficult to determine if trees remain on the ground. Interpreter should look for clues such as logging roads, or distinctive fan pattern of skid areas due to high-line logging operations, before labeling the disturbance as —Clearing.”

Clearing is found extensively around OLYM, on the west side of the MORA study area and west and north of NOCA. Some clearing polygons can also be detected within NOCA along the Seattle City Light power line corridors and in the Stehekin Valley.

5. Development

Development areas show a complete removal of the vegetation and transformation to a built landscape, with driveways, houses, cars, and other evidence of urbanization. Development can range from a few house structures to entire parking lots. Development can sometimes be captured though several years, with the first years appearing as clearing, followed by road and then house construction. For the purposes of this protocol, development label should only be assigned to areas that have a significant portion of the area occupied by buildings and paved surfaces. An addition to building construction, the interpreter should look for trajectories that indicate that the patch remains open following the disturbance, rather than returning to the forested state characteristic of clearing and regrowth (Fig. I.7).

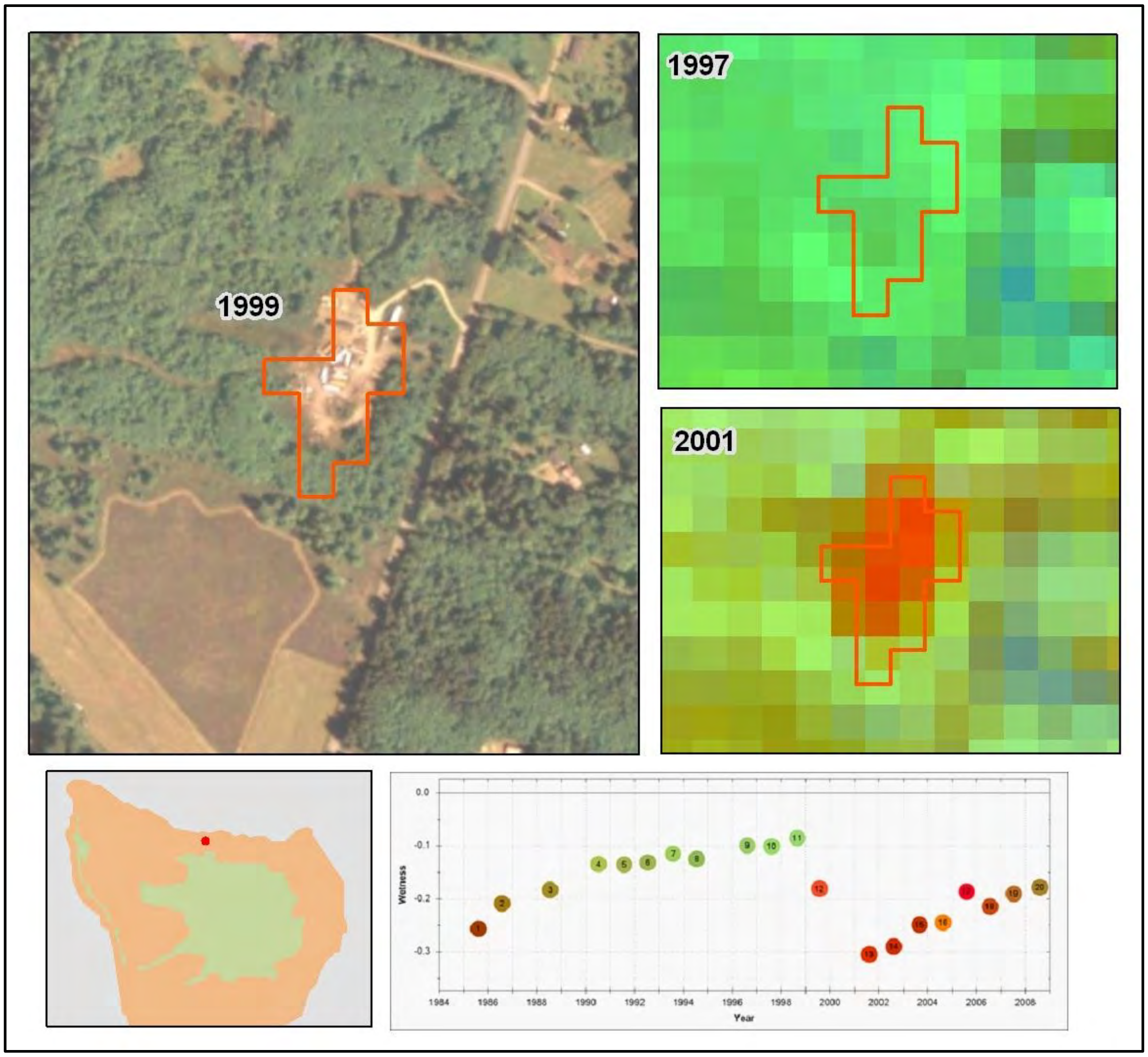


Figure I.7. Development. Landsat Tasseled Cap images show dramatic transition from vegetated to bare ground cover types between 1997 and 2001, captured by LandTrendr as a 1999 disturbance polygon. TimeSync trajectory transitions from green to bright red colors, indicating that the area remained clear of vegetation following the disturbance. The 1995-1998 portion of the trajectory indicates a regrowth pattern from a previous disturbance suggesting that the area was cleared prior to 1985 and then cleared again for development.

6. Fire

Any fire of significant acreage will likely be corroborated from external sources. During the validation, the interpreter should overlay disturbance polygons with most recent fire perimeters from park databases. However, some fires outside park boundaries, or of either lower intensity and/or smaller size, may not be recorded. Fires tend to leave standing trees with no foliage, which can be seen in the aerial photography as thin shadows. Fire polygons are often large. Some lower intensity fires leave behind a mix of dead and singed trees. Sometimes active burning and smoke can been seen in the aerial photography, since the photos are usually taken in August. The trajectory in the TimeSync is similar to clearing- changing from blue and green of conifers to a mix of brighter colors where the vegetation has been completely burned, to orange for shrubby new growth (Fig. I.8).

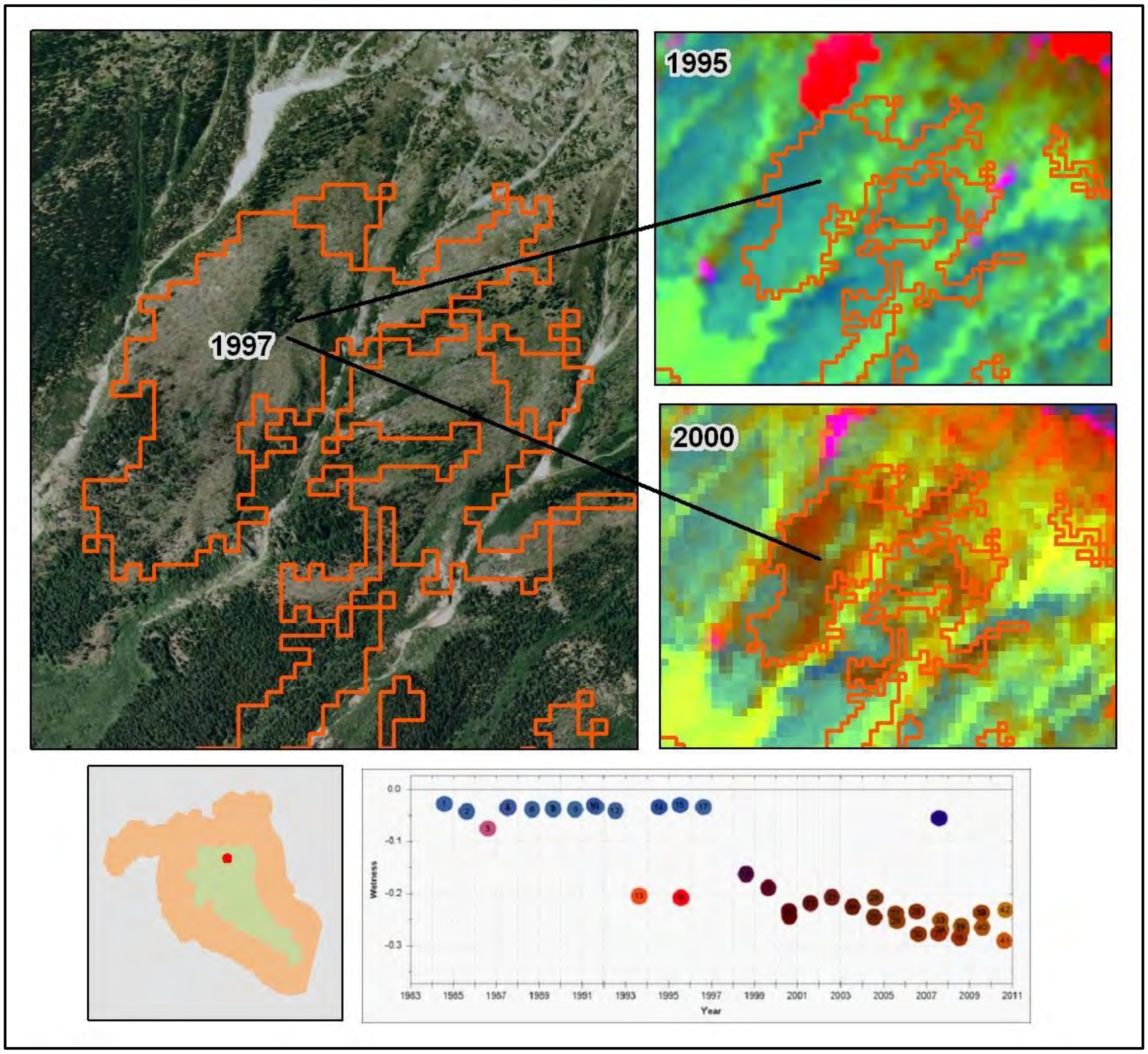


Figure I.8. Fire. Landsat Tasseled Cap images prior to and following a large 1997 fire show clear transition from mature conifer forest, represented by bluish green colors, to bare ground with minimal vegetation component, represented by browns and oranges.

7. Forest Collapse

The forest collapse category primarily includes forest areas where the trees have been both broken off and toppled to the ground in major wind events. This category is rare at NOCA and MORA. It is more common at OLYM, especially in the Quinault, Hoh, and Queets River valleys on the west side of the park and also in the northeast corner of the park. This category also includes areas where the forest collapse is due to root rot - the structural outcome is similar and the agent is typically hard to determine just from the imagery. Large Forest

Collapse disturbances can build on themselves, with subsequent events occurring in the vicinity of the original polygon. TimeSync trajectory of these events often shows some green vegetation remaining after the disturbance, either because some of the trees are still standing or the foliage of the downed trees is not completely dead (Fig. I.9). On the aerial photograph the interpreter should look for downed tree trunks. Windthrow events usually occur in areas on the landscape that are exposed to wind, either on top of ridges and knolls or along rivers.

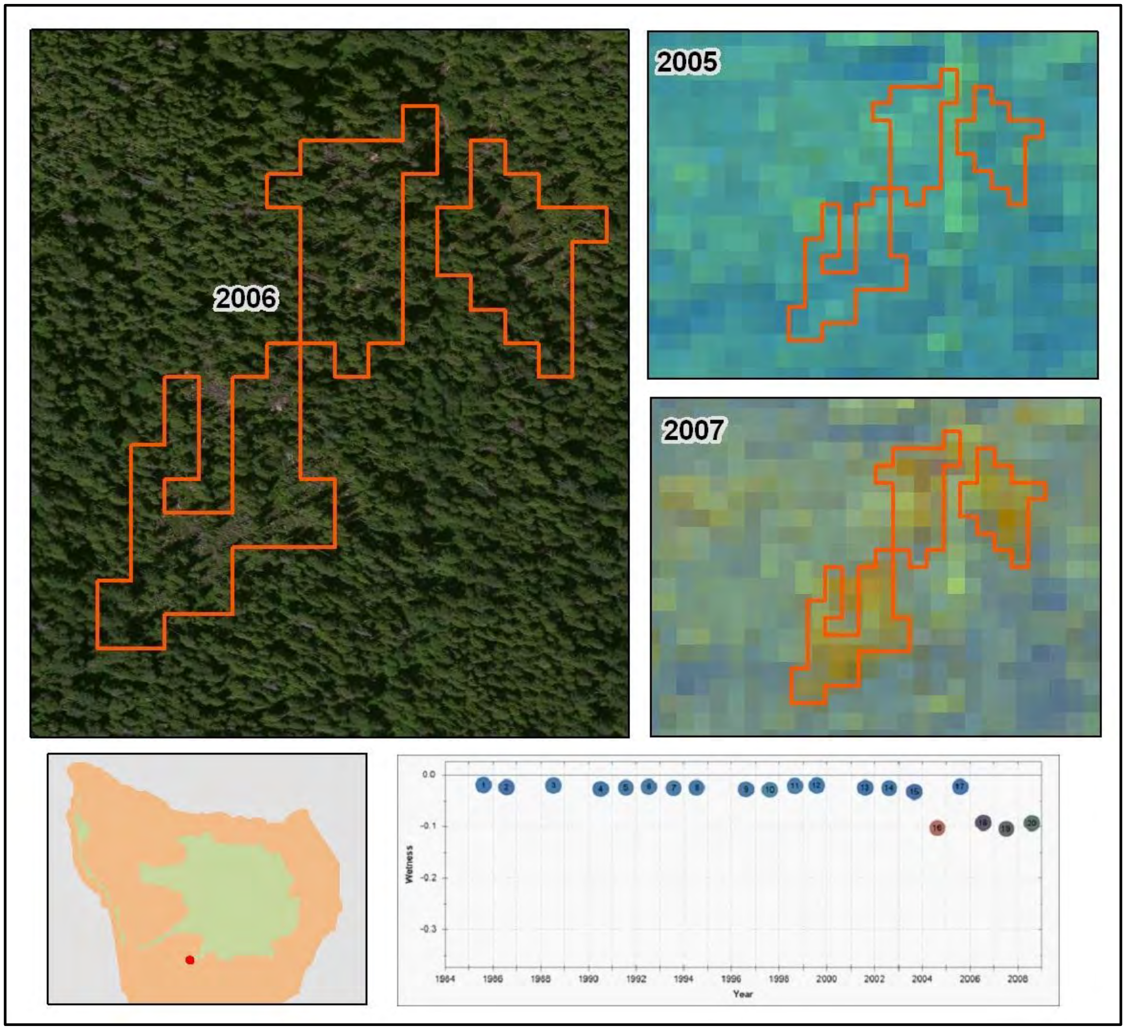


Figure I.9. Forest Collapse. A 2006 windthrow event at Olympic National Park. Tasseled Cap Landsat image from 2005 shows darker blue and green pixels of a mature conifer forest transitioning to brown and orange pixels of mixed bare earth and vegetation in 2007 following the 2006 event. TimeSync trajectory shows distinct reduction in wetness that is not as dramatic as would be expected from a total removal of vegetation.

8. Forest Decline

This category is usually assigned to disturbance areas where forest cover still remains, but has undergone slow changes in spectral values that represent a loss of greenness and wetness. Interpreting the color change in TimeSync is therefore more challenging. The interpreter will see a very slight dip in the trajectory with decrease in blueness and greenness. However, the decrease is not big enough to suggest change from conifer to broadleaf vegetation or bare earth (Fig. I.10).

The decreasing greenness of the forest can be difficult to discern in the aerial photography. In some stands the decline is due to LandTrendr detecting individual trees which have completely died. These dead trees appear in the aerial photos as bright red or yellow. In some stands the decline is due to the tip and top limbs of a significant proportion of the trees succumbing to some pathogen. This type of decline shows up as a subtle greying of the canopy in the aerial photos and can be hard to discern if the color balance of the photos is poor. In addition, disturbance polygons in this category can have both types of declining trees. In general, the interpreter should place in this category any disturbance polygon where forest canopy has not been removed or thinned in any way. Forest decline can in some cases be corroborated with polygons from the Forest Service's Forest Health Monitoring program (FHM). One should be cautioned, however, that the FHM polygons are not spatially accurate and should not be used as a definitive outline or location of the disturbance.

Although Forest Decline can be found at any elevation, it is most prevalent at higher elevations especially on the east sides of study areas of MORA, NOCA and OLYM, which are drier.

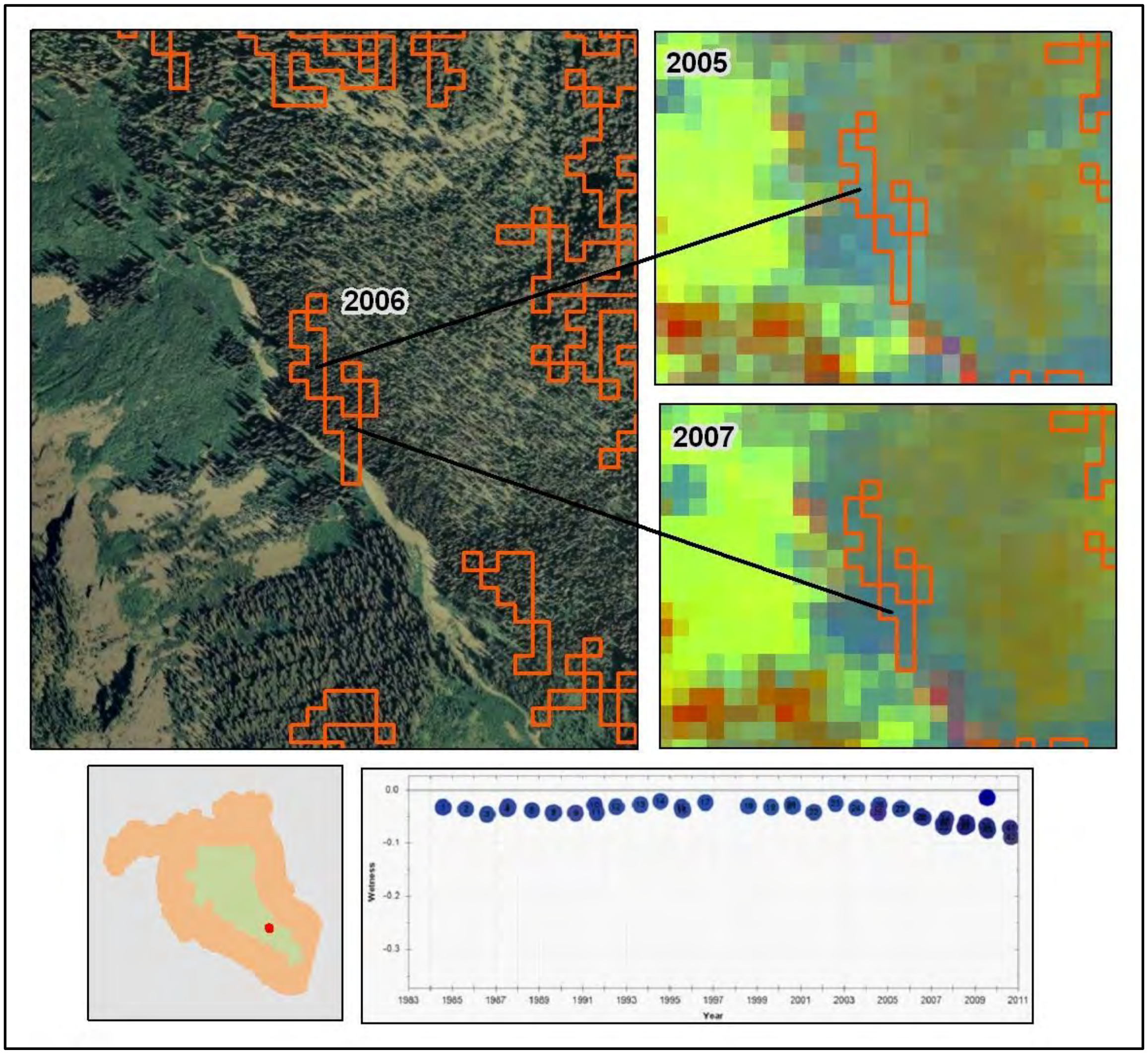


Figure I.10. Forest decline. Landsat Tasseled Cap images from prior to and after the 2006 disturbance show no significant change in pixel coloration suggesting no transition in cover type. The spectral trajectory, however, shows a slight dip in wetness, indicative of reduction in vegetation vigor.

9. Mass Movement

This category includes a variety of vegetation-removing disturbances that expose rock or bare ground. Larger events are typically called landslides, and are found on valley walls away from streams or creeks. Most landslides totally remove vegetation and are often persistent. Some rare events, however, are better described as

―soil creeps” or ―slumps” and are characterized by only partial removal of vegetation. Debris flows are mass movements associated with water discharge, such as streams. Mass movements are distinguished from the riparian category in that they occur on valley walls, perpendicular to the valley floor. Riparian category is associated with disturbances found on the valley floor, along low gradient rivers. Mass movements are distinguished from avalanches by the magnitude of the disturbance: mass movement leaves little to no vegetation; and by shape and context. The interpreter should look for persistent red and orange colors in the TimeSync trajectory following the disturbance (Fig. I.11).

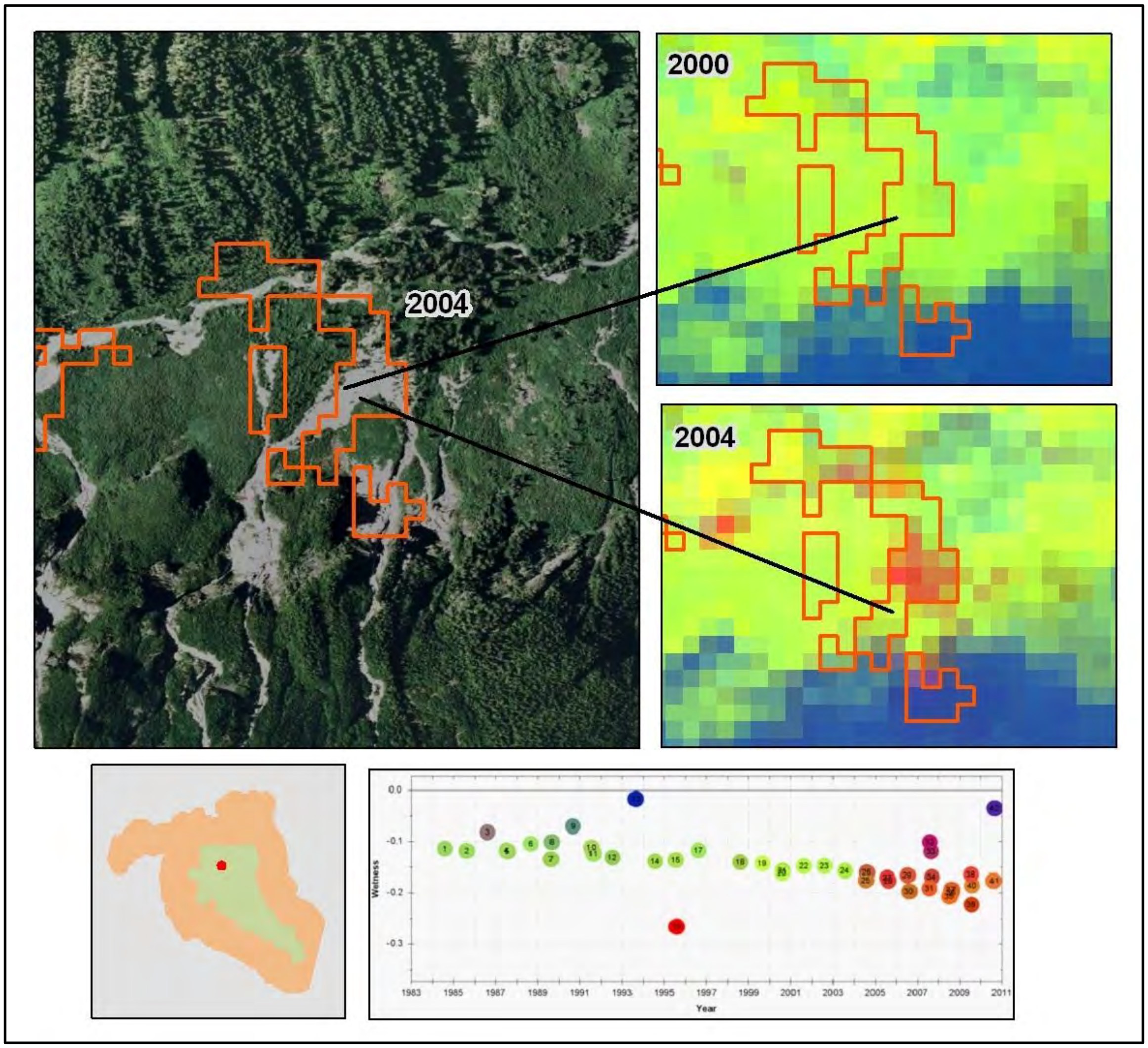


Figure I.11. Mass Movement. In 2004 debris flow at North Cascades National Park, bright green colors characteristic of broadleaf vegetation are replaced by bright reds and browns following total vegetation removal. Note that the wetness component of the trajectory has not dropped significantly, suggesting presence of moisture in the soil.

10. Riparian

Riparian polygons are restricted to the valley floor where the gradient is much lower and the valley floor is wider. Typical riparian polygons show areas where either conifer or broadleaf vegetation previously existed and have been converted to either active river channel, with water, or river bank, with gravel and sediment. The spectral trajectories of these disturbances show either sudden increase in wetness or brightness, depending on the resulting cover type. These disturbances are usually easily identified on aerial photos (Fig. I.12).

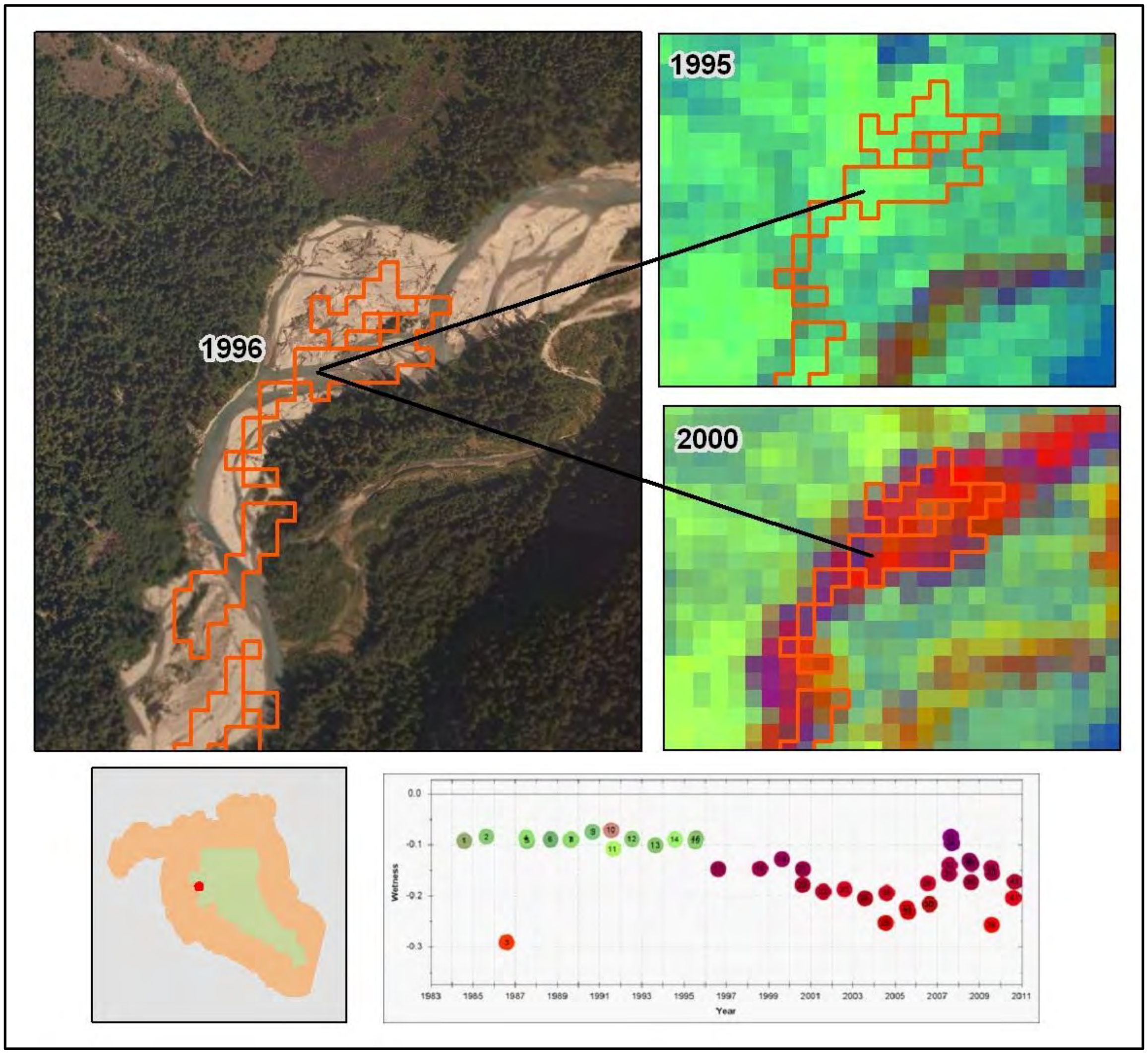


Figure I.12. Riparian. This 1996 disturbance can easily be categorized as “Riparian” by its location in the large river channel. Dramatic and persistent decrease in greenness is evident in both the tasseled cap Landsat imagery and the TimeSync trajectory. Note the presence of blue tones following the disturbance that are indicative of some water pixels present within the disturbance polygon.

The riparian category also includes forested and mixed-forested polygons in the riparian floodplain that have been inundated either temporarily or permanently. It is difficult to verify the change in these areas as often the forest canopy looks the same in the aerial photography. It is possible that these areas are undergoing some hydrologic change which has either increased soil moisture past the current species‘ tolerance, or which has brought alluvial material that has buried roots past species‘ tolerance. It is also possible that the decline is due to root rot, or some other pathogen and LandTrendr has detected the canopy death that precedes eventual collapse. The interpreter should place these disturbances in the riparian category even if there is no evidence of tree collapse, but there is a clear increase of wetness signal in the trajectory (Fig. I.13).

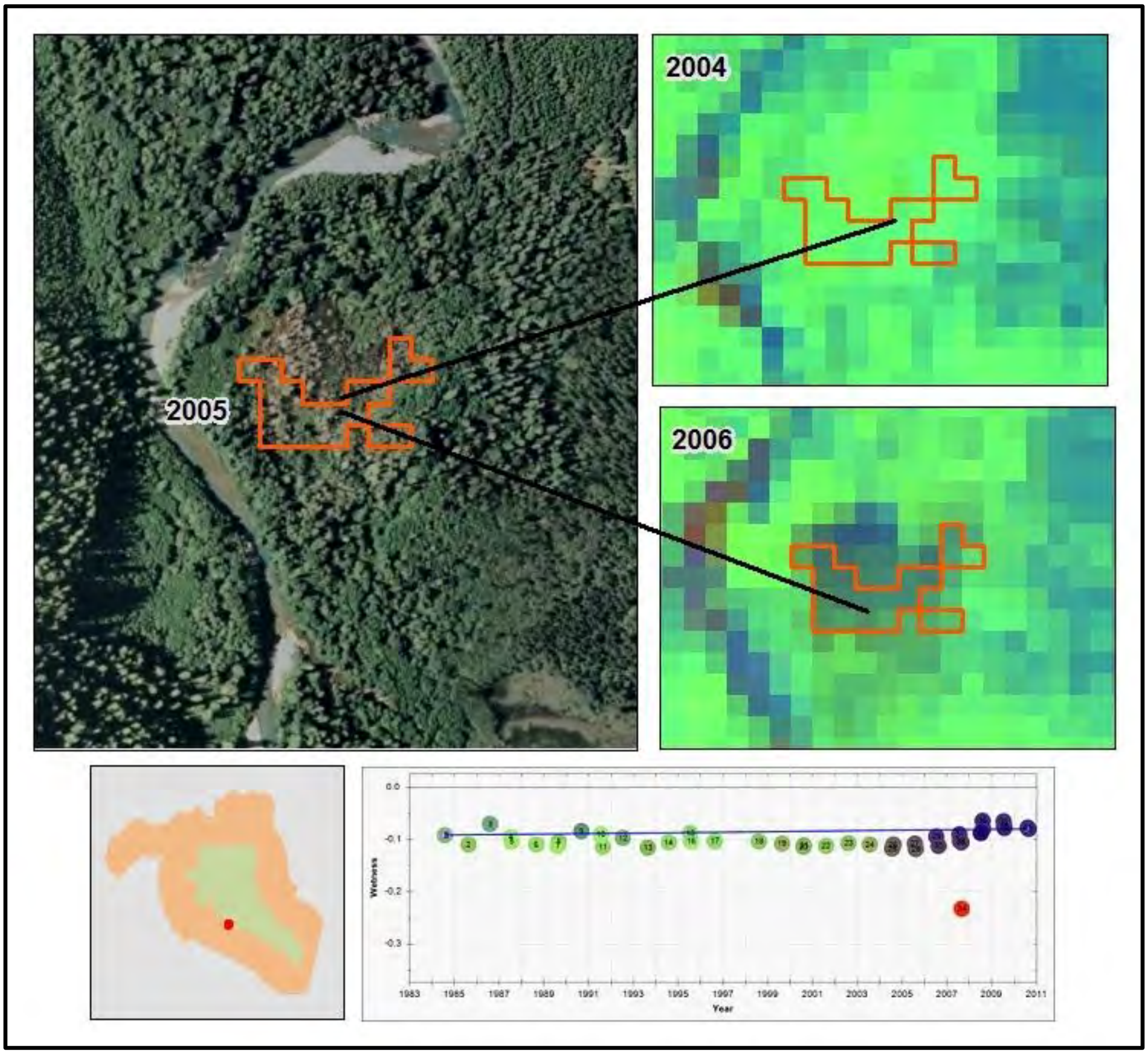


Figure I.13. Riparian - innundation. This disturbance polygon located close to a river shows spectral and visual signs of inundation. Both the Landsat imagery and TimeSync trajectory indicate an increase in wetness.

11. References

Kennedy, R.E, W.B. Cohen, A.A. Kirschbaum and E. Haunreiter. 2007. Protocol for Landsat-based monitoring of landscape dynamics and North Coast and Cascades Network Parks: U.S. Geological Survey Techniques and methods 2-G1.