Developing yearly maps of land cover and land use
to monitor freshwater habitat for salmonids in the western U.S.

Progress report
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Introduction

The National Marine Fisheries Service (NMFS) of the National Oceanic and Atmospheric Administration (NOAA) must report on the status of listed salmonids every five years in 26 ecologically significant units (ESUs) along the West Coast of the U.S. Because changes in type or quality of terrestrial habitat are thought to affect conditions in streams through changes in runoff, sedimentation, and thermal cover, it may be important to consider land cover and land use changes within ESUs when reporting on fish populations.

Most maps of land cover are derived from some source of remotely sensed imagery, including image data acquired both from aircraft and satellites. When considering appropriate remote sensing data for tracking change, the natural resource manager or scientist must consider a range of issues, including spatial grain, repeat time for imagery, cost of acquisition, cost of processing, ability to separate desired from undesired change, and cost and implementation of building the training and reference data for map creation (Kennedy et al. 2009). Careful consideration of these often-competing goals points to the type of remote sensing data on which to build the maps.

For regional to national-scale mapping of land cover, most mapping projects rely on satellite images taken by the Landsat Thematic Mapper (TM) instrument. The Landsat Thematic Mapper is the workhorse of regional and national-scale natural resource mapping (Cohen and Goward 2004) because it combines a relatively fine spatial resolution (30 by 30m pixels) with large coverage (each picture covers approximately 180 by 180km), and because it maps in multiple wavelengths of light that are useful for distinguishing fundamental types of vegetation, soils, and developed surfaces. Maps of land cover derived from Landsat TM imagery have been created at the national scale by the Landfire project, the USGS's National Land Cover Dataset (NLCD), NOAA's Coastal Change Analysis Program (C-CAP), and state-level GAP analysis programs.

More importantly for the analysis of land cover change, the Landsat TM data have the longest continuous record of land imaging in existence. The TM instruments have amassed archives of the Earth's land surface dating back to 1984, and were preceded by related sensors (MultiSpectral Scanners, or MSS) that can extend some analyses as far back as 1972. Increasingly, national-scale mapping programs have tapped the Landsat archive to produce maps of land cover change in addition to maps of one-point-in-time land cover maps. Although these maps of land cover change are consistent and are rich in information on land cover, they leave important gaps for monitoring terrestrial habitat change in relation to salmonids.

First, they are infrequent. The NLCD products exist nationally for 1992, 2001, and 2006, and the NOAA C-CAP products for three or four periods from the 1990s through 2006, depending on the area of the country. While TM image data exist for every year from the mid 1980s forward, creation of the NLCD and C-CAP maps requires significant expert intervention (and manual editing) to achieve the desired rich detail, making them costly to update. The resultant coarse temporal resolution of the maps means that relationships with fish population data could not take advantage of the yearly resolution of fish data.

Second, characterizing change is secondary to mapping state condition. For the NLCD products, significant effort was exerted to develop a high-quality 2001-era land cover map. Areas that had changed by 2006 were flagged and remapped; other areas were left with the 2001 map label (Xian et al. 2009). According to metadata accompanying the maps, the C-CAP strategy was similar but the method to flag change areas was not documented. In both cases, it is difficult to infer from the changes in land cover alone what agent caused the change and whether the change was durable or transitional. For example, a mapped transition from forest to barren could be either the beginning of an urbanization process or simply a transitory state in a cycle of forest management. From the perspective of chemical inputs to streams, hydrologic regime, and thermal cover, distinguishing urbanization from forest management would be critical, but this could not be achieved with the existing maps.

Thus, there is a need to complement existing efforts with maps that improve the temporal frequency of information and that better characterize the agent of change. Researchers at the Laboratory for Applications of Remote Sensing in Ecology (LARSE; a cooperation between Oregon State University and the USDA Forest Service's Pacific Northwest Research Station) have developed approaches that move toward meeting those goals. Mapping is achieved with LandTrendr (Kennedy et al. 2010), a set of automated algorithms to characterize the "life history" of each point on a landscape, and maps are evaluated with TimeSync, a visualization tool that allows expert interpretation of changes at randomly-selected validation points (Cohen et al. 2010). The underlying difference between these and prior methods is that the new methods take advantage of the dense time-series of TM imagery to characterize not only a change, but the conditions leading up and following that change. This approach allows better separation of change from false alarms, resulting in more stable maps over time, and provides core data to better separate cyclical from directional changes.

In the summer of 2010, NMFS established a cooperative agreement with LARSE to determine the best means of leveraging these tools for characterizing terrestrial habitat changes in support of salmonid monitoring. The project had three specific goals:

1. Characterize change events for every year in the period of record.
2. Characterize state condition (landcover) for every year in the period of record.
3. For both #1 and #2, develop approaches to corroborate these new high-frequency maps.

In Goal 1, change is directly observed and state conditions before and after change must be inferred. For Goal 2, the opposite is the case.

Study Area and General Method

Study area

The Puget Sound of Washington state was chosen as the first study area. It is important for several salmonid species, and has also experienced significant urbanization and forest management in the period of the Landsat TM record (1985 to present). The Puget Sound also offered a practical benefit for this methods study: Under other studies, LARSE had already conducted the time-consuming initial processing ("image pre-processing") for most of the images needed to map conditions in the Puget Sound (Figure 1). Thus, more effort could be focused on new methods for mapping specific to the needs of this project. Details on this image pre-processing are provided in Kennedy et al. (2010) and at the LandTrendr website (landtrendr.forestry.oregonstate.edu).

Figure 1. The Puget Sound study area (shaded) with Landsat path/row polygons (black polygons) overlaid. All maps created for this project involved images from five Landsat scenes. Within each scene's boundaries, stacks of images (with between 26 and 44 images per scene) from nearly every year between 1985 and 2009 (See Table 1) were acquired and processed through LandTrendr processing algorithms to create maps of landscape dynamics.

LandTrendr

The underlying role of LandTrendr (Landsat based detection of trends in disturbance and recovery) is simplification: For a time series of data points, algorithms are used to derive simple descriptors that capture interesting features while smoothing uninformative features (Figure 2). For this project, uninformative changes (essentially random noise) include variation in atmospheric condition, changes in sun angle illumination caused by day of year of image acquisition, phenological changes caused by day of year effects, etc. The descriptors that smooth these effects are straightline segments. Each segment has two endpoints called vertices that fully describe the time series; thus, we refer to the simplification process as "temporal segmentation." Segmentation-derived vertices are calculated for every 30 by 30m pixel on a landscape.

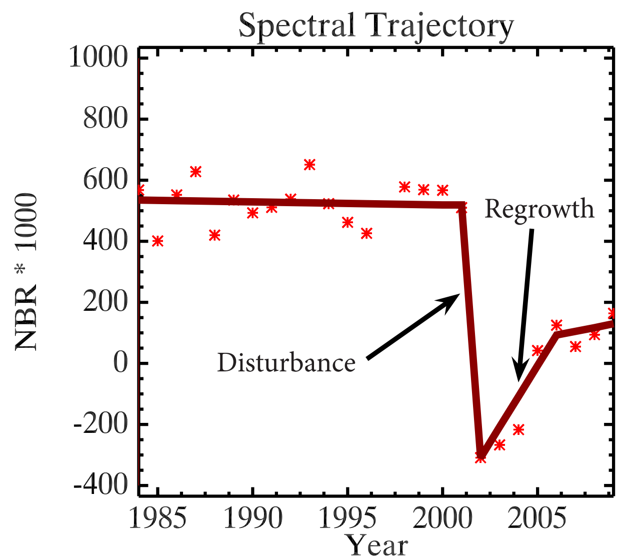


Figure 2. Simplification of time-series data using LandTrendr. Asterisk points represent measurements of reflected energy (here, for a derived index known as the "normalized burn ratio", or NBR) measured by Landsat sensors for a single 30 by 30m pixel over more than two decades. Year-to-year variation is caused both by uninteresting or random processes (atmospheric noise, date of image acquisition, etc.) and interesting processes (a large disturbance occurring between 2001 and 2002). The LandTrendr algorithms identifies straightline segments (solid line) that smooth the random noise while retaining information about interesting processes (both the disturbance and the subsequent recovery).

The segmentation-derived vertex datasets form the core of the all resultant LandTrendr map products (Figure 3). Two general types of map are possible: maps of change and maps of condition. Maps of change are derived by focusing on segments associated with processes of interest. For example, maps of disturbance can be produced by querying vertices for individual segments showing loss of vegetative cover (Kennedy et al. In review). Once disturbance segments are identified, the timing, magnitude of change, and pre- and post-disturbance segments can be queried to more fully characterize the disturbance. Alternatively, the vertex images can be used to stabilize the original Landsat image stacks to reduce sources of noise, creating Landsat-like stabilized images on which any standard image processing routines can be applied. The chief advantage in using stabilized images is that statistical models derived from one year of imagery can be applied more confidently to other years of imagery with reduced risk of false alarms.

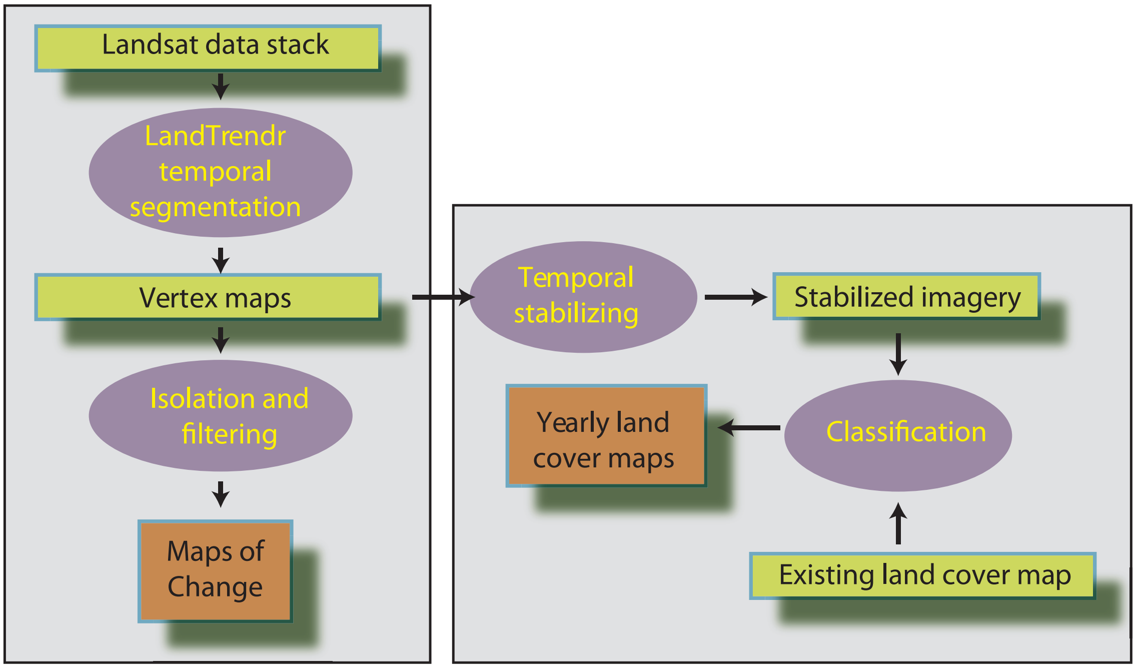


Figure 3. Overview of the two major mapping approaches using LandTrendr data. Vertex maps are an efficient means of capturing the segmentation results (e.g. Figure 3). By isolating segments of interest, maps of change can be produced. Alternatively, vertices can be used to stabilize input images to reduce effects of random year to year noise. These stabilized images can then be used to convert any existing land cover map into yearly land cover maps.

For this project, additional steps were needed to determine whether these map-products could be useful to meet the needs of the NMFS. First, change maps would need to be enriched by determining not only the timing, duration, and severity of change, but also the likely process or agent that caused the change. Of interest for salmonids in the Puget Sound are two primary agents or causes of change: urbanization and cyclical forest management. Because agents of change operate on areas larger than the individual pixels where the underlying LandTrendr algorithms run, this would require developing new techniques to define and characterize patches of influence. Moreover, the agents of change are highly variable and likely ill-behaved from a statistical perspective, requiring investigation of non-parametric mathematical approaches for labeling the changes. Second, the mapping would need to move outside of forested areas, wherein most mapping by LARSE had occurred beforehand. In particular, there was a need to understand changes occurring in populated areas, again for understanding the process of urbanization from both agricultural and forested starting conditions. Third, methods to corroborate or validate yearly maps had to be expanded. To date, methods had only focused on conditions at individual points, not the patches over which change attribution would be developed, and had focused on characterization of disturbance and recovery, not on verifying the land cover type at particular years.

Below, methods and results are presented for mapping of change (Objective 1) and mapping of yearly land cover (Objective 2). Validation approaches were developed and applied to each objective, and thus are described along with each method.

Objective 1: Change mapping

When satellite images are evaluated for change over time, the currency by which those changes are measured is reflected light. That currency has little value in salmonid monitoring, which requires that changes be characterized in terms of the processes causing the change. Objective 1 asks how well satellite-based changes can be converted into meaningful descriptors of change. We refer to this process as "change attribution labeling."

Overview of change attribution

The change attribution labeling process encapsulates four underlying strategies (Figure 4). The first is that change attribution labels only apply to patches, not to individual pixels. Thus, the rules to group pixels of disturbance into cohesive patches are important. Here, a strict rule of congruence was used: adjacent pixels showing a simultaneous onset of disturbance were grouped, assuming that simultaneity reflects similarity of process. Groups of pixels smaller than ~1 hectare (11 pixels) were filtered out to reduce impacts of noise and to make patches large enough to be interpretable in the attribution phase. [*Note that processes that evolve slowly or spread across a landscape, such as insect effects, may not be adequately grouped with this strict simultaneity rule. While such disturbance processes are rare in the Puget Sound ESU, they are common in drier forests of ESUs on the inland side of the Cascades in Washington and Oregon. In anticipation of this issue, a companion rule is being developed that allows floating windows of overlap when assigning patches; this rule will be tested on the next ESUs in the projec*t].

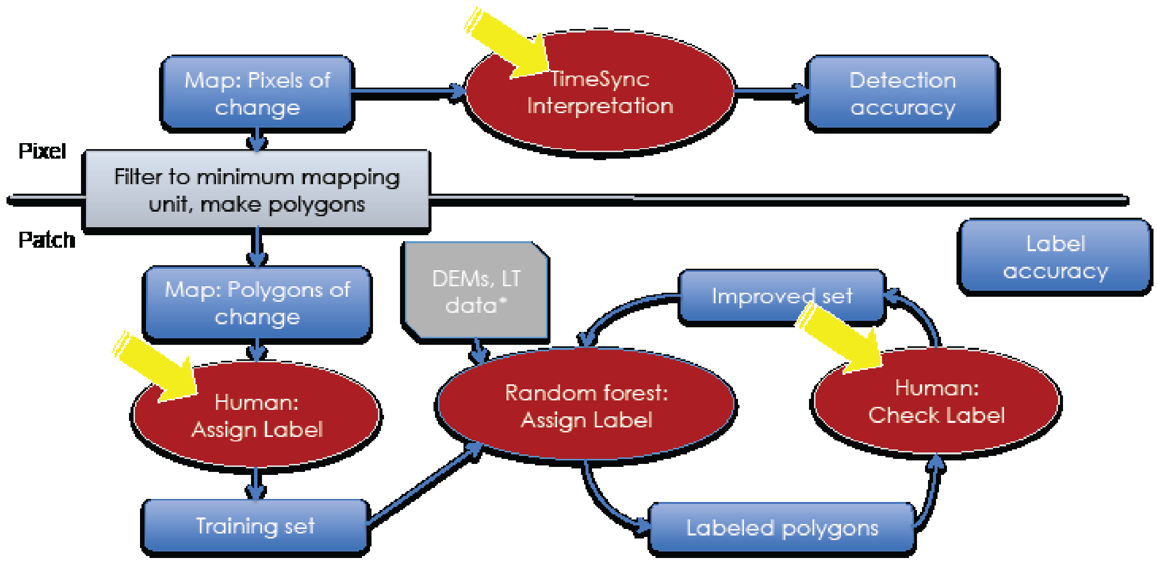


Figure 4. Overview of change attribution labeling process. Maps of disturbance at the pixel level were derived from yearly stacks of Landsat imagery using LandTrendr change detection algorithms. To move from pixel to patch (polygon), adjacent pixels experiencing abrupt disturbance were grouped when year of observed disturbance was common. For a subset of disturbance patches, a human interpreter examined both high-resolution photos and spectral temporal trajectories to assign a label of change. The multivariate classifier approach known as "random forest" (Breiman 2001) was used to link that truth dataset to spectral data and contextual data extracted for each disturbance patch. The resultant model was then applied to the full dataset to predict change labels, and then a subset of those patches re-interpreted, and, as necessary, a new model developed, etc.

The second strategy is to rely on the strengths of the human intelligence for labeling. Agents of change of interest are defined in terms that generally cannot be described with *a priori* rulesets needed by automated algorithms. Rather, human interpreters must evaluate a suite of factors when labeling the process that likely caused a given change on the landscape, including not only the character of the change itself, but what happened before and after, its spatial and temporal context on the landscape and in a human cultural milieu. Thus, the change attribution relies heavily on interpreters to develop a training dataset with labels assigned to selected patches of disturbance.

The third strategy is to use a statistical modeling technique that makes few assumptions about the form of the linkage between change attribution labels and the predictor variables used to model them. We used the approach known as "random forest" modeling (Breiman 2001), which: handles training and predictor datasets of any mathematical character, estimates error internal to the model, and predicts type in a voting-score format that separates clean predictions from those that are poorly resolved.

The final strategy is to use an iterative approach to interpretation and modeling to make better use of limited human interpretation resources. Because satellite data cover large areas and many years, attribution labels will be needed for tens of thousands of disturbance events. Because simple random sampling of the dataset would miss minority processes, some form of stratification would be ideal, but until labels are assigned to disturbance patches, there is no way to know how the multivariate predictor space relates to possible change labels. Thus, the model itself is used to aid in this process: the training dataset begins with purposive sampling driven by human knowledge of the change processes of interest, which are then used to develop a preliminary change attribution model. This model captures the bulk structure of the dataset, and thus can be used as a stratifier for a second round of training data. This process could repeat until models stabilize, at which point a final randomized sample would be used to assess model performance.

Details of change attribution

Development of disturbance patch maps

LandTrendr was run on images for the five scenes that intersect the Puget Sound ESU. *[NOTE: the word "scene" refers to the path/row address that is recorded every 16 days by the Thematic Mapper sensor; data recorded on a specific date is referred to as an "image"]* Most scenes had images for nearly every year between 1984 to 2009 (Table 1). Segmentation was applied to the Normalized Burn Ratio (Key and Benson 2005), or NBR, as the base for disturbance detection. Disturbances were identified as segments whose NBR decreased over time, creating a pixel-level map for each of the five scenes. These scene-level maps were mosaicked, and disturbances were then grouped according to the strict simultaneity rule and filtered to a 1 hectare minimum mapping unit (See Figure 5 for an example map). A total of 92,384 disturbance patches were identified.

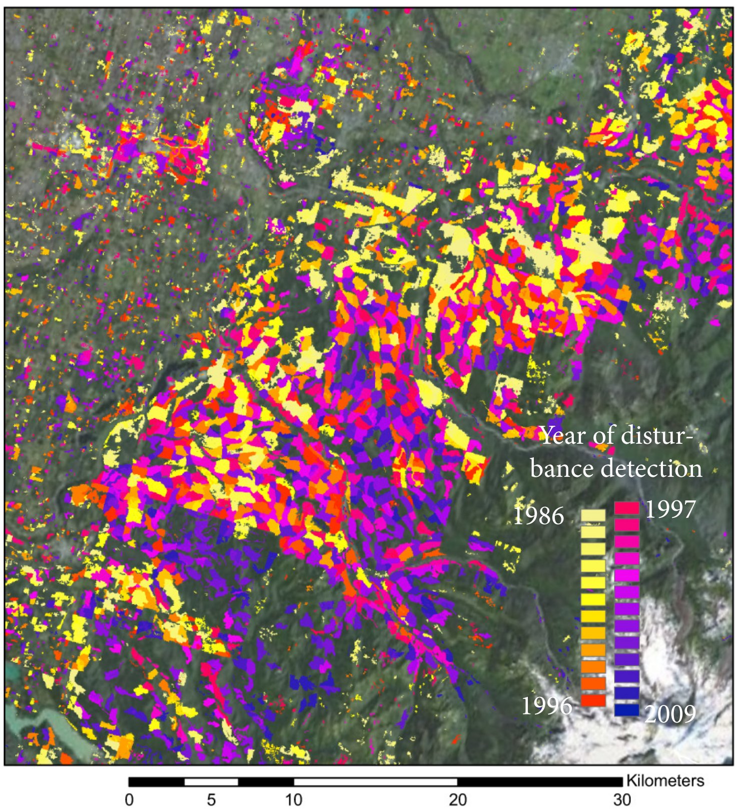


Figure 5. Example LandTrendr disturbance map for a small portion of the Puget Sound near Mt. Rainier. In this map, disturbances overlaid on a background image are mapped by the year in which the satellite first recorded them. Other properties of each disturbance polygon not shown in this figure include the disturbance magnitude (expressed in terms of estimated percent vegetation cover), disturbance duration (in years), pre- and post-disturbance condition (as represented by reflected light).

Table 1: Landsat image information for Puget Sound

Scene path/row	*Number of images (1984-2009)*	*Missing years?*
46/26	44	1997
46/27	38	1995
46/28	29	
47/26	26	1992, 1995
47/27	38	1995

For each disturbance patch, a suite of predictor variables was extracted (Table 2). Variables were chosen to describe each patch in terms of its topographic character, disturbance information, pre- and post-disturbance condition, recovery speed, and patch shape. Perimeter area ratio and shape index, which measures the complexity of patch shape compared to a standard square of the same size, were used to describe the patch shape.

Table 2. Predictor variables extracted for disturbance patches and used in attribution modeling.

Class	***Variable or Source***	***Units***
Topographic:	USGS digital elevation model	
	Elevation	meters
	Aspect	degrees
	Slope	degrees
Disturbance	Landsat via LandTrendr	
	Duration	years
	Magnitude	estimate % vegetative cover loss
	Delta spectral	mean change in tasseled-cap brightness, greenness and wetness
	Variability in spectral delta	stdv of change in tasseled-cap brightness, greenness and wetness
Pre-disturbance condition	Landsat via LandTrendr	
	Spectral mean	tasseled-cap brightness, greenness, and wetness
	Spectral variability	stdv of spectral mean
Post-disturbance condition	Landsat via LandTrendr	
	Spectral mean	tasseled-cap brightness, greenness, and wetness
	Spectral variability	stdv of spectral mean
Recovery trajectory	Landsat via LandTrendr	
	Delta spectral	mean change in tasseled-cap brightness, greenness and wetness
	Variability in spectral delta	stdv of change in tasseled-cap brightness, greenness and wetness
Patch shape index	ArcTools based on LandTrendr patches	
	Patch shape index	Unitless score

Patch interpretation

An objective of this project was to develop protocols for interpreting change processes at the patch level. The foundation of the approach was the general interpretation protocol used to assess change at the point level, described previously (Cohen et al. 2010). Thus, interpretation of Landsat time series image chips in conjunction with spectral trajectories were critical to the interpretation. Additionally, disturbance polygons were displayed in Google Earth to take advantage of the fine-resolution aerial photos available in that platform. These historical photos proved invaluable for assessing many land use changes (Figure 6).

There were several new challenges. There was limited ability to separate row crop from pasture-type agriculture because of infrequent airphotos. Thus, all transitions involving agriculture were labeled simply as transitions to or from agriculture, without any more detailed agriculture sub-class. Another occasional challenge arose with polygon boundaries defined by LandTrendr: In some cases, the boundaries of the polygons did not match well with the land cover patterns on the landscape, often being smaller or slightly shifted from obvious patches on the landscape. In these situations, the interpreter made an assessment of what appeared to be occurring in the majority area of the patch, and recorded the possible confusion in a database field for comments. In other cases, the patch was aligned well with that on the landscape, but no obvious change had occurred (likely a false positive from the algorithm). Thus, several "no change" classes were defined: agriculture to agriculture, urban to urban, and no change. The advantage of defining these classes is that the model building exercise can then explicitly predict when the LandTrendr disturbance map has produced a false alarm.

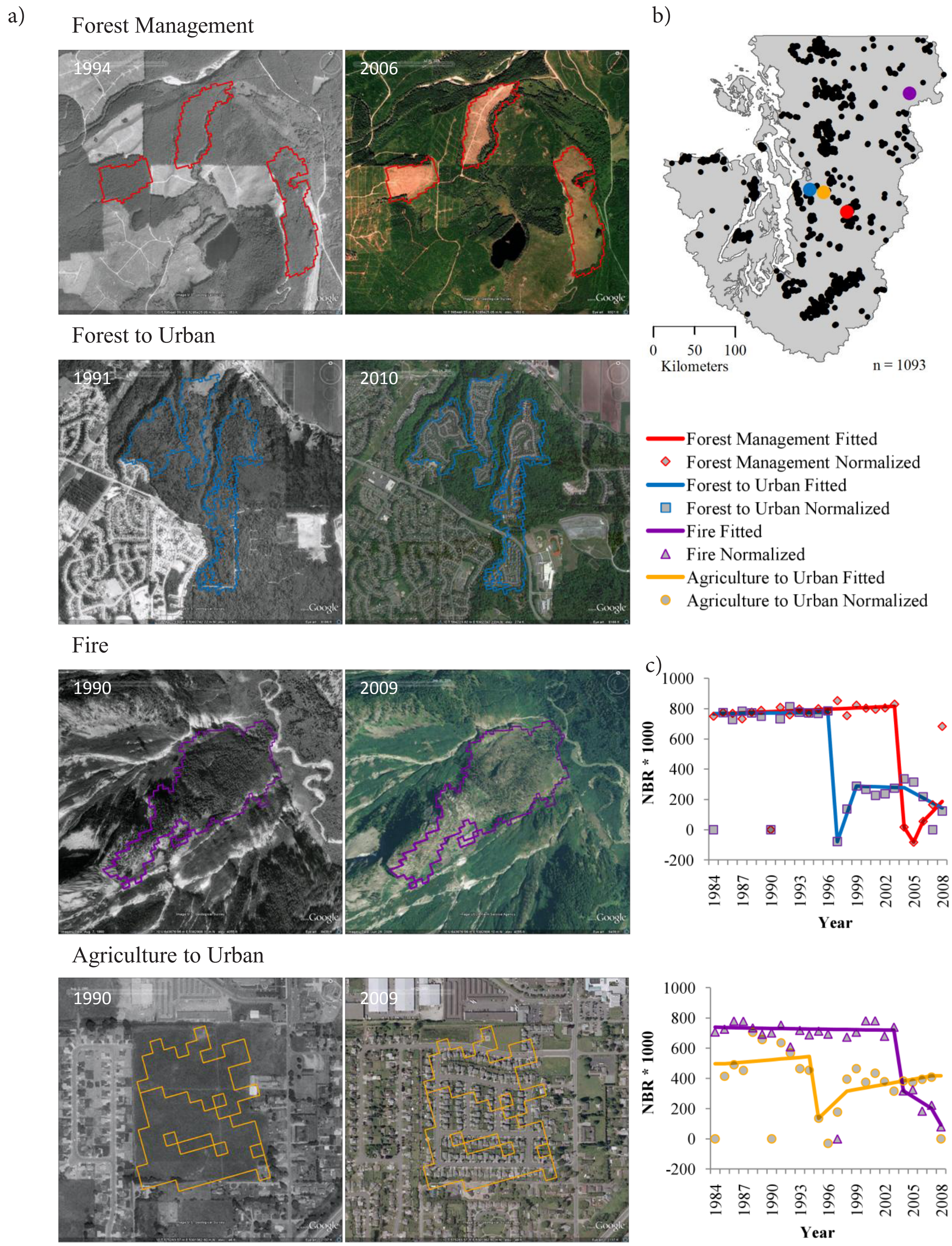


Figure 6. Examples of expert interpretation of change agent. We examined high-resolution images (a) at more than 1000 disturbance polygons defined using change detection algorithms (b), aided by temporal information on spectral evolution (c), to label change agent into one of nine change agent categories (See Table 3).

Change attribution labels were assigned by a trained interpreter to more than 1016 change patches. Selection of this initial set was purposive: Interpreters used knowledge of the processes occurring in the ESU to quickly identify zones where different types of change process would be occurring: agricultural transition to developed urban types, forest transition to urban type, and cyclic forest management. For each polygon, the interpreter used two main sources information to make assessments to assign change attribution labels: Historical airphotos available within the GoogleEarth platform, and time-series Landsat imagery and trajectory information available in the TimeSync platform (Cohen et al. 2010). Occasionally, other reference data could be brought to bear when interpretation was ambiguous, including fire perimeter data from the Monitoring Trends in Burn Severity (MTBS) project (mtbs.gov) and the USDA Forest Service's Forest Health Monitoring program's insect and disease polygons derived from airphotos. These data were used in random forest modeling to produce a first estimate of the change label. Those labels were then used to derive a second sample of 182 new patches for interpretation that accentuated change classes that were underrepresented or that appeared to be ambiguous in the change attribution space. For future work, this iterative process of modeling and interpretation of problematic classes could continue until models stabilized, but for the purposes of testing methods, only one cycle was used here.

The time involved in change attribution can be substantial, with the sample of 182 patches requiring approximately four person-days to complete. Many changes are easily and quickly labeled, but the challenges listed in the prior paragraph can require significant time and reference to varied datasets to resolve. The acquisition of additional training data from other studies in small areas, such as those developed in small areas based on air photos, may be a reasonable approach to increase sample size. In the future, citizen-science based approaches to interpretation through a web interface may also be a means of improving attribution models. With the iterative mapping/interpretation/re-modeling approach developed here, new inputs of attribution labels from any source could be incorporated directly into the work flow.

The final sample of 1198 disturbance patches captures a range of processes (Table 3). Change labels were defined at their most detailed level (column 1 in Table 3), but then grouped to simplified labels for the actual modeling process. These can further be grouped according to conceptual change types classified by whether they are cyclic or directional, and natural or anthropogenic. Change types were dominated by forest management, but this does not reflect a random sample. Rather, forest management patches often occur together in large groups, making it possible to select and label many forest management patches in one efficient step.

Table 3. Summary of patches with manual labeling of change class.

Change Class			# Patches
Detailed	***Simplified***	***Type***	
Ag to Ag	Ag to Ag	Cyclic - Anthropogenic	101
Ag to Urban Open & Low Intensity	Increasing Urban	Directional - Anthropogenic	21
Ag to Urban Medium & High Intensity			41
Forest to Urban Medium & High Intensity			84
Forest to Urban Open & Low Intensity			52
Open to Urban Medium & High Intensity			40
Clearcuts and Thins	Forest Management	Cyclic - Anthropogenic	692
Fire	Natural	Cyclic - Natural	41
Insect			12
Landslides & Windthrow			26
Stream flooding & channel migration	Stream		16
TransitionWithin Urban Medium & High	Within-urban transition	Cyclic - Anthropogenic	11
Transition Within Urban Open & Low			13
No change	No Change	No Change	48
		Total	1198

Random forest modeling

Random forest (Breiman 2001) is a non-parametric approach to predicting membership in groups based on a suite of predictor variables. It is based on classification and regression trees (CART), which create successive binary splits in predictor variable datasets to best separate groups of training data. They are attractive in not presuming normality in data and in allowing mixing of divergent groups. Rather than developing a single prediction with a single tree, however, random forest uses Monte Carlo type approaches to draw from the suite of predictor and training set variables to create many random instances of trees (hence, a "random forest" of trees), where each training point is voted on multiple times (Figure 7). The randomization approach makes it relatively robust to small sample sizes and co-variation among predictor variables. It also provides an internal estimate of the overall error of the model, known as the "out of bag error," (OOB Error). The voting scores for each item in the training dataset provide a sense for the confusion of the model for that item: items that are labeled correctly for every combination of trees are likely well-behaved and correct, while items receiving a variety of different votes are likely ambiguous and perhaps more likely to be incorrectly labeled.

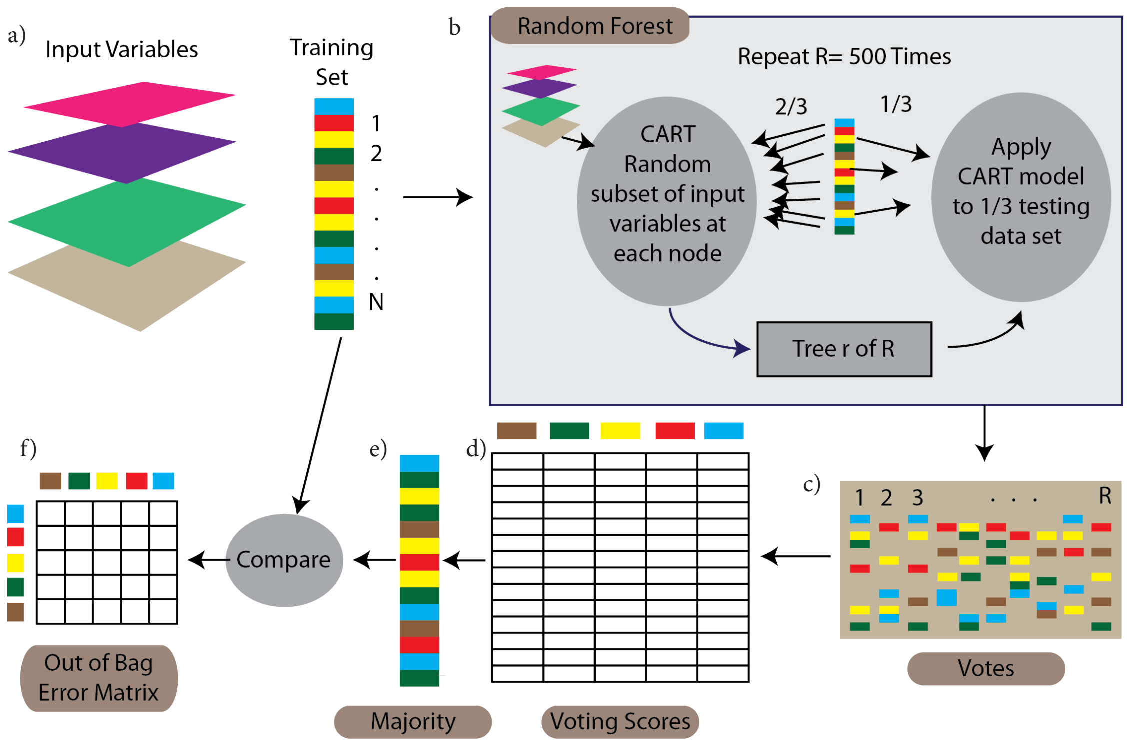


Figure 7. Overview of random forest modeling. a) Input variables (see Table 2) are extracted for polygons in a training dataset where expert interpretation of change agent has occurred. b) Classification and regression tree (CART) modeling is run using a random subset of 2/3 of training data, with a random sub-selection of input variables at each node in the tree. The rules in the tree are applied to predict agent for the remaining 1/3 of training data. This is repeated 500 times, resulting in (c) many votes of agent for each class (expectation: 500 / 3 votes for each training sample). Votes are tallied by class to create voting scores for each class in each training set sample (d). The majority class is considered the most likely, resulting in a final call for each sample in the training dataset (e). These predictions are compared against the original calls from the expert interpretation to create an "out of bag" error matrix.

The random forest model was built using the initial training dataset, applied back to the entire set of patches, and then used to draw a stratified sample for the remaining 182 patches. Using only 1198 out of 92,384 patches (a 1.3% sample), the OOB error was very favorable. The overall estimate accuracy of 84%, but this is dominated by high accuracy in the dominant forest management class. More important than the overall error is the evaluation of confusion among classes, indicated by number counts in the off-diagonal cells. In many cases, the error in the model reflects the fact that some change classes have conceptual overlap or may be ambiguous for the interpreter. For example, the class "within urban transition" was never predicted accurately, but most incorrect calls were for "increasing urban," which is in fact another type of transition within the urban class.

Table 4. Out-of-bag error estimates for change attribution. Numbers in each cell correspond to the count of patches in that category. Diagonal cells (shaded) are correct calls; off-diagonal cells are errors.

		Predicted							
		Ag to Ag	Increasing urban	Forest management	Natural	Stream	Within urban transition	No change	*Producer's accuracy*
Reference	Ag to Ag	86	13	0	0	0	2	0	*0.85*
	Increasing urban	35	181	14	0	0	1	7	*0.76*
	Forest management	1	10	671	6	0	0	4	*0.97*
	Natural	0	1	39	29	0	0	10	*0.37*
	Stream	0	1	2	0	13	0	0	*0.81*
	Within urban transition	5	18	1	0	0	0	0	*0.00*
	No change	1	11	3	2	1	0	30	*0.63*
	User's Accuracy	*0.67*	*0.77*	*0.92*	*0.78*	*0.93*	*0*	*0.59*	**0.84**

When developing random forest models, it is useful to understand the relative contributions of the input variables. Although the final prediction from random forest is based on votes from many hundreds of trees, each with different input variables, the random forest approach can produce estimates of the overall importance of each input variable across all trees by measuring the average decrease in variability when that variable is included in a model (as quantified by the decrease in the "Gini" coefficient). For the attribution model developed for the Puget Sound ESU, the top predictor variables encompass include topographic, patch size and shape, and spectral variables, indicating that no single source of information is sufficient to adequately assign change attribution labels (Table 5).

Table 5. Contribution of input variables to the final random forest attribution model. Only the top ten variables are shown.

Variable	*MeanDecrease Gini**	*Description*
dem	43.7	Mean elevation within patch
demRange	37.9	Maximum minus minimum elevation within patch
paratio	37.3	Patch perimeter divided by area
dw	32.9	Magnitude of disturbance in units of tasseled-cap wetness
slopeRange	29.9	Maximum minus minimum topographic slope
rg	27.1	Magnitude of post-disturbance recovery, in units of tasseled cap greenness
area	25.6	Patch area
slope	25.4	Mean slope within patch
rw	22.3	Magnitude of post-disturbance recovery, in units of tasseled cap wetness
dg	21.6	Magnitude of disturbance in units of tasseled-cap greenness
rb	19.3	Magnitude of post-disturbance recovery, in units of tasseled cap brigntness

* The mean decrease in the gini coefficient provides an estimate of the degree to which the variable reduce variability among patches in a group

Random forest validation

To evaluate whether the OOB error was a reasonable estimate of actual error, a blind validation was performed. A completely randomized sample of 140 disturbance patches was drawn from the entire ESU and interpreted without knowledge of the algorithm's label. As a random sample, the classes of change were distributed as they appear on the landscape, with rare classes being sparsely represented (Table 6). The distribution of error in the matrix was similar to that estimated by the OOB estimate, which indicates that the OOB error estimate may be a reasonable proxy when true validation is not possible.

The voting scores from random forest allow for a nuanced understanding of the errors in the model. While the maximum vote is typically used to assign a label to a patch, the second-highest vote can provide insight into the confusion of that label. If the second-highest voting score is accurate when the highest voting score is not, it suggests that the model is close enough to accuracy that a larger training dataset could improve accuracy. By giving credit to the algorithm when either the first or second label, match counts improved substantially (Table 7), suggesting that further iterations of the prediction/interpretation/remodeling cycle could improve accuracies.

Table 6. Attribution error determined by comparing modeled outputs to blind validation by an expert interpreter. Match is only credited if maximum voting score from model matches with expert interpretation.

		Modeled change agent based on top voting score						
		Ag to Ag	Increasing urban	Forest management	Natural	Stream	Within urban transition	No change
Change agent determined by expert interpretation	Ag to Ag	**11**	0	0	0	0	0	0
	Increasing urban	5	**24**	11	0	0	0	1
	Forest management	3	19	**37**	0	1	0	3
	Natural	0	0	1	**0**	0	0	0
	Stream	1	1	0	0	**0**	0	0
	Within urban transition	0	3	0	0	0	**0**	0
	No change	2	2	2	0	0	0	**11**
	Forest to Pasture*	1	0	0	0	0	0	0
	Forest to Barren*	0	0	1	0	0	0	0

* Category absent in original training dataset, and therefore not modeled

Table 7. As in Table 6 but match is credited if either of top two votes match interpreter.

		Modeled change agent based on either of top two voting scores						
		Ag to Ag	Increasing urban	Forest management	Natural	Stream	Within urban transition	No change
Change agent determined by expert interpretation	Ag to Ag	**11**	0	0	0	0	0	0
	Increasing urban	3	**33**	4	0	0	0	1
	Forest management	3	9	**48**	0	1	0	2
	Natural	0	0	1	**0**	0	0	0
	Stream	1	1	0	0	**0**	0	0
	Within urban transition	0	3	0	0	0	**0**	0
	No change	2	2	2	0	0	0	**11**
	Forest to Pasture*	1	0	0	0	0	0	0
	Forest to Barren*	0	0	1	0	0	0	0

* Category absent in original training dataset, and therefore not modeled

Random forest maps

To be useful for salmonid monitoring, change attribution labels must be mapped to the watersheds and reaches where fish population data are recorded. Thus, the change attribution model developed and validated in the prior section was applied to the entire disturbance patch population for the Puget Sound ESU, with the highest voting score used to assign labels [*Note: Second-highest voting scores could also be reported, depending on the desired use for the data and on the ability of the user to bring fuzzy labels into their analysis*].

The geographic distribution of change labels appears to corroborate that the method assigns labels appropriately. Over the entire ESU, the dominant pattern on the landscape is of forest management and urbanization (Figure 8). At the local scale where individual patches are evident, most transitions appear to be well-mapped (Figures 9, 10). However, there are cases where the two dominant classes (forest management and urbanization) appear to be over-predicted relative to minority classes (Figure 11). Even though random forest is better than other approaches at handling classes with small sample sizes, it appears that dominant classes in the training dataset may still have greater influence in the model building step. This is not unexpected: Map prediction must always balance errors toward and away from particular classes, and from the perspective of overall map error, a bias toward predicting the dominant classes is best. A benefit of the random forest approach, however, is that the class with the second-highest voting score can also be mapped (Figure 12), allowing greater understanding of the underlying model behavior. When the second-place class is correct, it suggests that greater training data could aid in mapping.

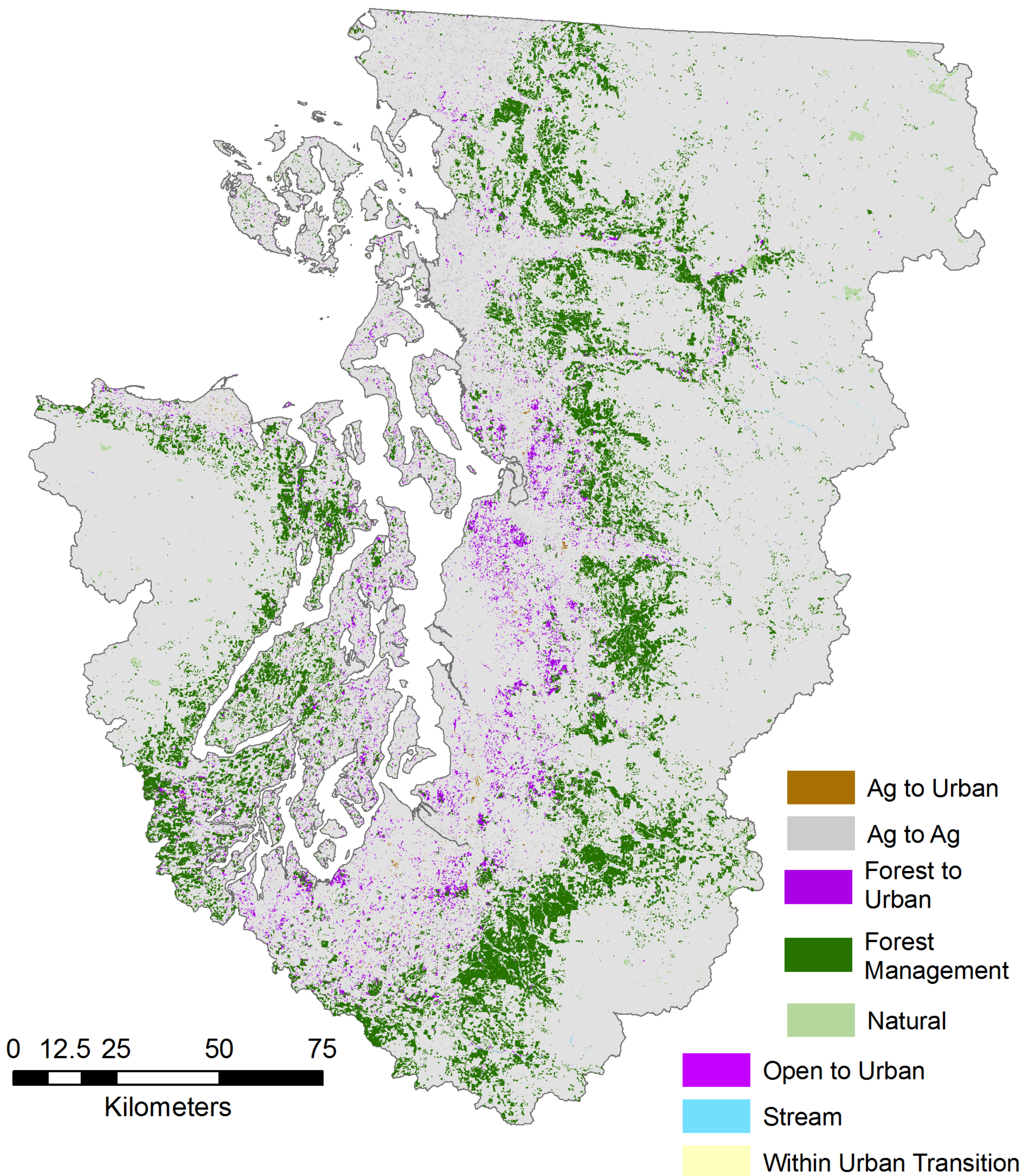


Figure 8. Change attribution mapped to the Puget Sound ESU. As expected, urbanization dominates the lowlands and forest management (harvest of forest followed by eventual return to forest) dominates the highlands.

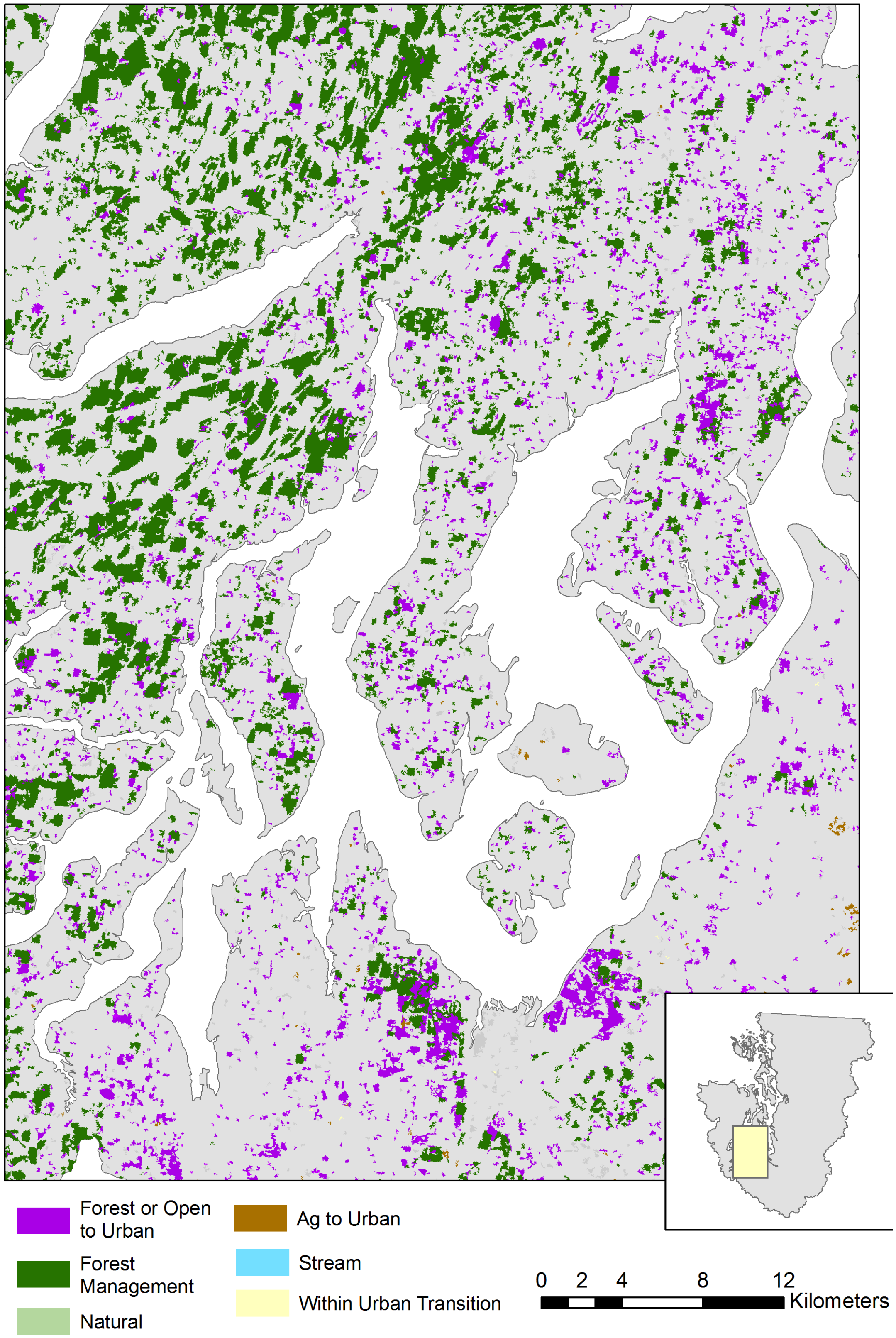


Figure 9. A close-up of attribution calls in the south sound area (including Olympia).

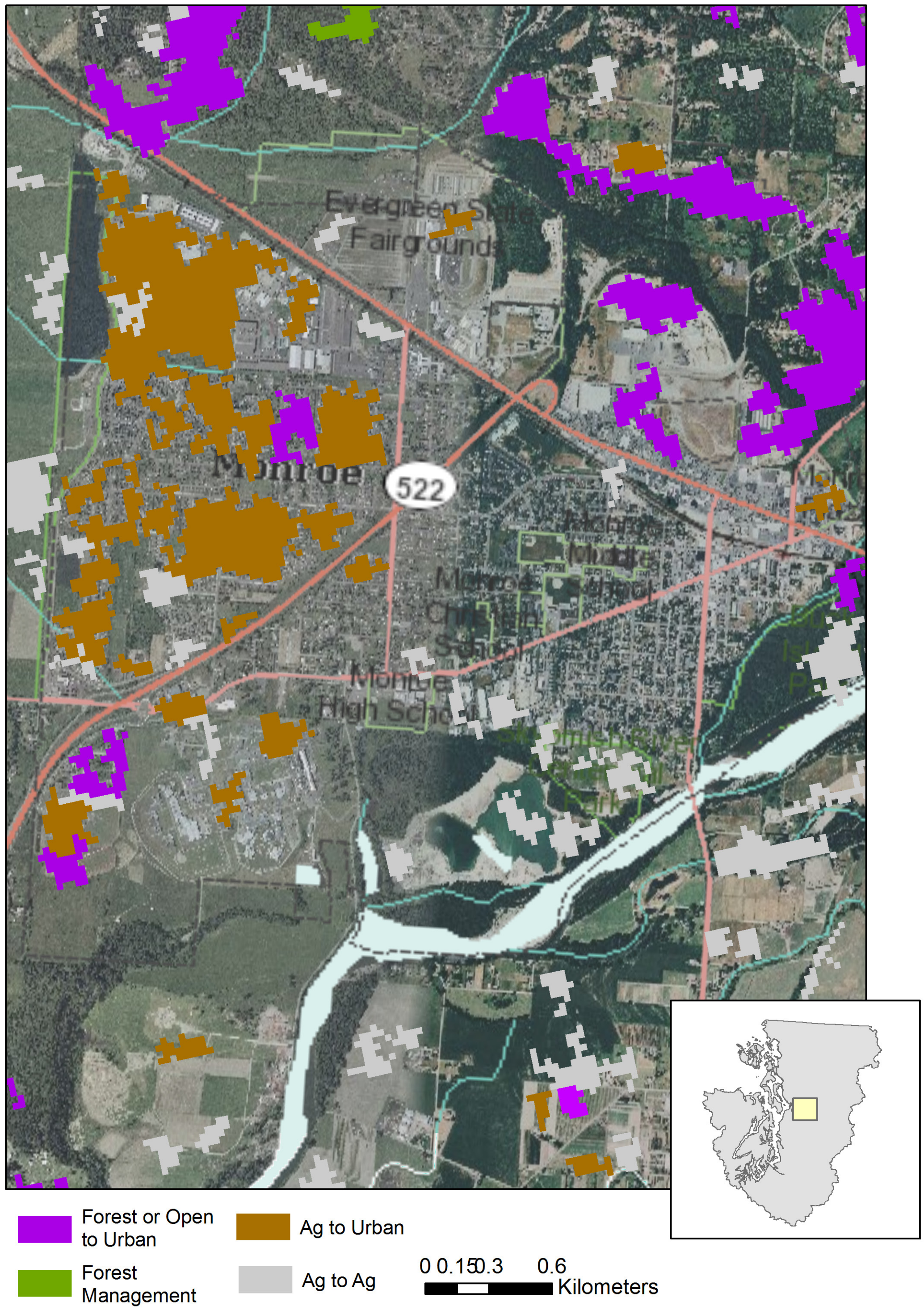


Figure 10. A close-up of attribution calls near Monroe, WA. Here, the change attribution labeling correctly identifies urbanization in both agricultural and forest settings.

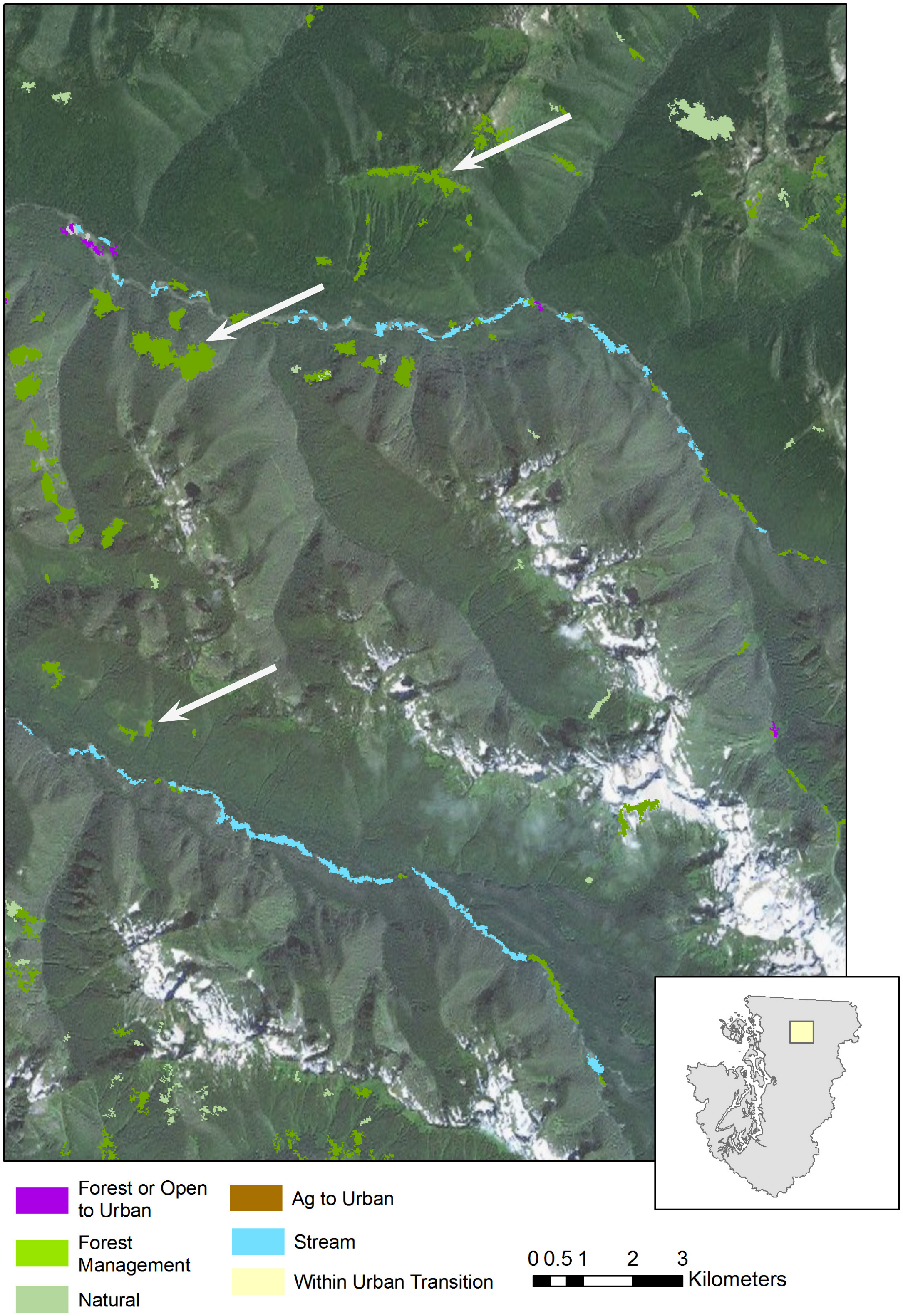


Figure 11. A close-up of attribution calls just north of Glacier Peak. Note that many stream disturbances are correctly labeled, as well as one natural event (top right), but that forest management appears to be over-predicted in areas that appear to be natural disturbances (three examples noted with arrows).

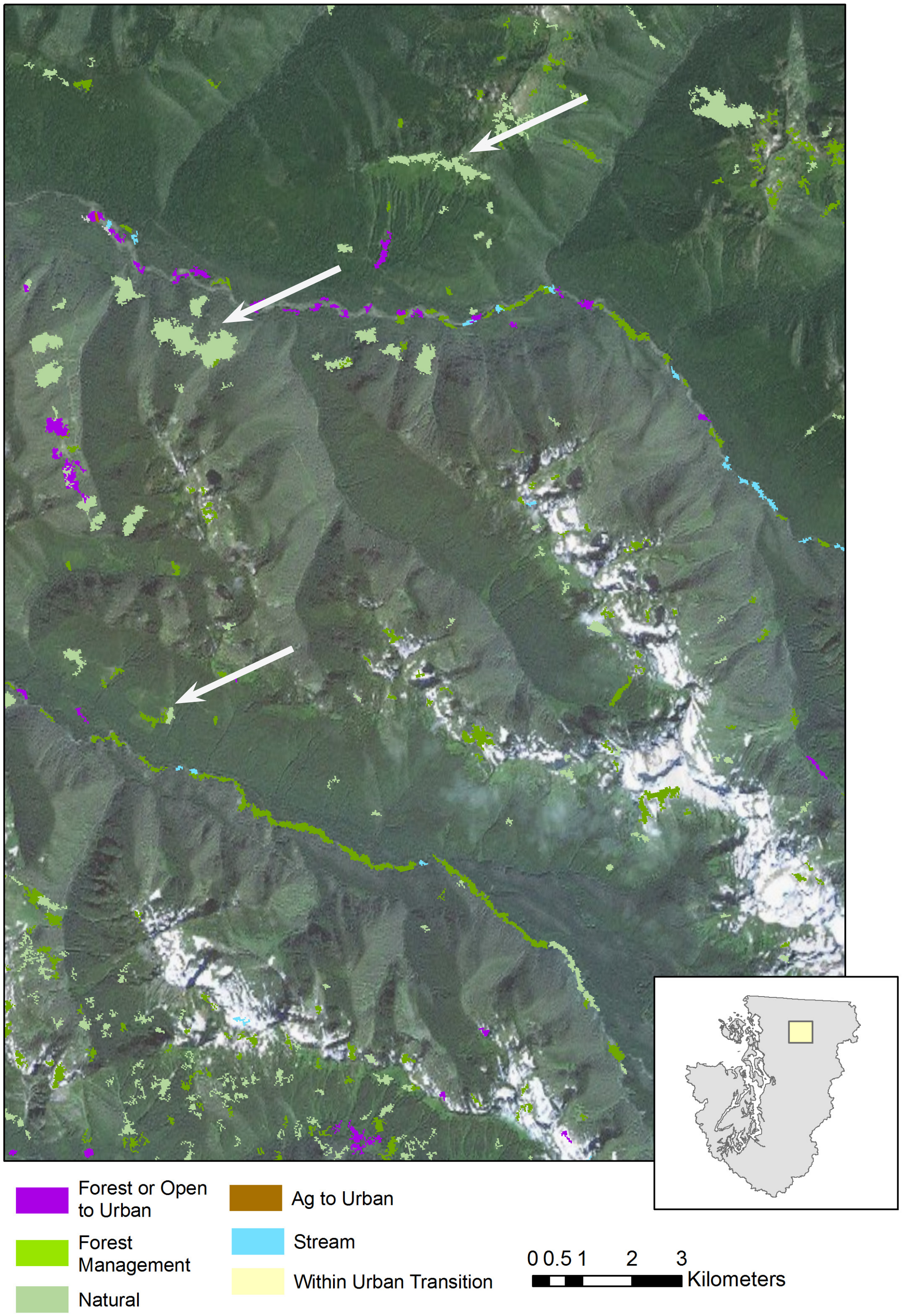


Figure 12. As for Figure 11, but for the class with the second-highest voting score. Note that many areas noted as erroneously mislabeled "forest management" would be correctly labeled as "natural." This suggests that the rare "natural" class could be improved with greater training data.

In addition to providing geographically-referenced information on change processes, the attribution labels can be linked back to the disturbance patches (as in Figure 5) to distribute them over time for the entire watershed (Figure 13). At the ESU-wide scale, the dominant change process in terms of area was forest management, followed by urbanization at one order of magnitude less in area. As noted above, it is likely that both of these dominant classes were overpredicted relative to the minority classes. Together, forest management and increasing urban represent nearly 78% of the training data; further effort in intepretation should be directed at improving representation of the minority classes.

Of note is the high proportion of the landscape in the “Ag to Ag” class. This indicates that the attribution process was successful in eliminating many false changes in the agricultural setting (Ag to Ag class). Agricultural fields experience wide swings in cover from year to year depending on crop type and date of image acquisition. The initial algorithm based on satellite data alone identifies these as durable changes, but the attribution process corrects them based on the conditions that precede and follow.

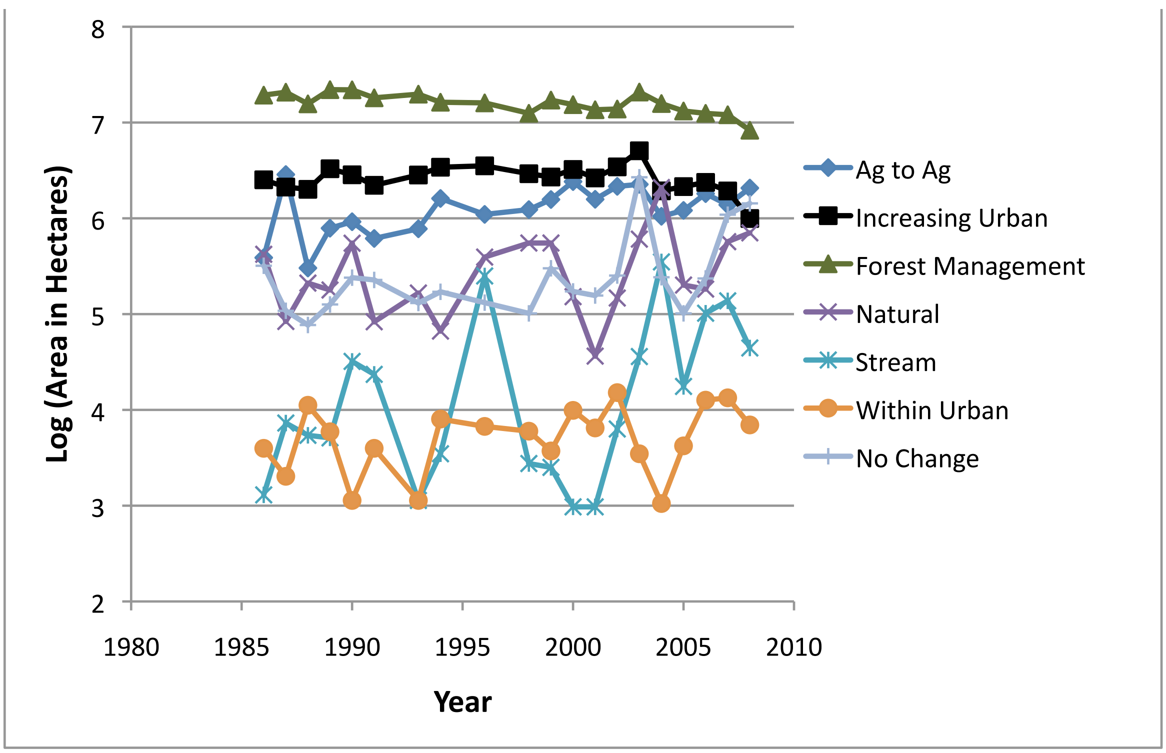


Figure 13. Yearly rates of change by agent in the Puget Sound ESU. Disturbance attribution applied to the entire ESU was linked to the year of disturbance and summarized across the entire watershed by area in each change class. The dominant change process is forest management, followed by urbanization. Ag to ag transitions are not actual changes in land use; rather, they indicate the change attribution model correcting the pixel-wise change map. [Note the log scale.]

Attribution: Conclusions

We conclude that the attribution process developed and described here can provide a useful means of characterizing change at the ESU-wide scale. With slightly more than 1% of the sample labeled, we produced map label maps of disturbance process over the entire ESU for 25 years. The maps were accurate for most classes, and where errors were suggested, it appears that an increase in sample size would improve the predictions. Interpretation of change label attribution appears feasible using a combination of prior methods (Cohen et al. 2010) and new approaches to handle labeling for entire polygons, but is relatively time-consuming compared to prior methods because of the ambiguities of defining change processes. Thus, the emphasis on efficient sampling for training data is high, and the iterative approach of modeling, predicting, and interpreting appears to be effective at mapping with small sample sizes. The random forest modeling approach works well for attribution, and the use of voting scores provides insight into model behavior. Moreover, the OOB error estimates track the error calculated in blind validation trial, suggesting that the OOB error estimates can be used as reasonable proxies for model error when resources for blind validation are limited.

Objective 2: Yearly land cover mapping

The methods in Objective 1 use the full time-series to describe the disturbance event itself, but do not describe the impact of those changes on the land cover conditions over time. The land cover status of a watershed at key points in the salmonid life cycle may ultimately be more relevant to monitoring than knowledge of timing and type of disturbance alone. In addition to overall land cover conditions within a watershed, two other factors may be particularly relevant: the land cover type in which disturbance occurs and the speed and direction of recovery after disturbance. Objective 2 asks whether LandTrendr-stabilized images can produce useful yearly maps of land cover condition.

Overview of yearly land cover mapping

<u>Background</u>

The development of land cover maps from satellite imagery has long been a focus in remote sensing science. At its most fundamental level, the process involves linking the spectral data (the measurements of reflected light energy quantified in the imagery) to training data acquired from another source (Richards 1993). The linkage is captured in a mathematical model, of which there are many types. Once captured for one point in time, that model can theoretically be applied to spectral data from times to create successive land cover maps. In practice, the success of this approach is limited by two key challenges.

The first challenge relates to the source imagery itself. The conditions captured in any given satellite image reflect not only the land cover of the surface, but also a range of ephemeral processes including phenological state, sun illumination angle, and atmospheric conditions above the surface. Because these ephemeral conditions vary from image to image even when the surface land cover has not changed, the color of the satellite image can similarly change when no durable change on the surface has occurred. If a classification model developed on one image is applied to a second image, these ephemeral changes introduce error in the classification. To avoid this problem, separate classification models can developed separately for each image, but in this case each classification's error is compounded with the other. Thus, large-area mapping programs often spend significant resources to develop a map from a single date, then use a two-date change detection approach to identify areas that have changed in the second date, and finally relabel *only the changed areas*, keeping the non-changed areas constant. While practical, this approach becomes highly dependent on the accuracy of the change mapping. The ideal approach would be land cover maps that incorporate information on both state and change.

The second challenge relates to the definition of the land cover classes. Although in theory any training data can be used, map robustness will be highest when the distinctions among training classes are closely related to distinctions in the spectral data. For single-date maps, hand-editing and inclusion of other spatial variables in the modeling process can resolve ambiguities among classes that are similar in terms of image color (spectral character). This can also improve mapping to distinguish between different *land uses* within the same *land cover* type. For example, herbaceous land cover may be either an agricultural land use, a natural prairie, or an urban open space, and the distinction among these types may best be resolved by proximity rules, inclusion of ancillary data, and manual re-labeling.

But when maps for multiple years are to be constructed, it is often not feasible to map non-spectral changes . Extending the example of herbaceous cover, a transition from natural prairie to urban open space may result in no tangible change in condition, and only could be captured with detailed knowledge of the site or with ancillary spatial data from which clues about land use could be inferred (such as repeat occasion airphotos showing development of small trails or out buildings). In practice, such case-specific data could not be consistently applied over large area mapping, and thus should not be relied upon for frequent land cover mapping. Similarly, hand-editing of maps, as is done by both the NLCD and C-CAP programs, is cost-prohibitive for annual maps. Thus, any yearly mapping effort must first establish land cover classes that are clearly related to image data.

<u>Strategy for this project</u>

LandTrendr segmentation provides a means of addressing the first major challenge. Because segmentation largely removes year-to-year variation in sun angle, phenology, and atmospheric effects, the vertex images derived from the temporal segmentation of a single index can be used to constrain image data in all other bands. The result is a stack of temporally stabilized images that smooth unwanted noise while retaining information on actual change. A key goal in this project was to determine how to best utilize these images in the context of land cover mapping.

The general strategy (outlined in Figure 3 above) was to use a classification algorithm to link an existing land cover map with stabilized imagery. Because of their wide geographic reach, two maps were considered as the basis for the existing land cover: the NLCD and C-CAP products. The two maps were developed with similar approaches and have similar map legends, with greater detail on wetland and near-shore classes in the C-CAP maps. However, the C-CAP maps do not extend inland far enough to capture the ESUs on the east side of the Cascade range, and thus could not be used when the project moves to those zones. Therefore, the NLCD maps (which are wall-to-wall for the entire country) were chosen as the basis. Note, however, that the methods are generalizable to other maps as needed.

Regardless of the map used as the training dataset, the second challenge to yearly mapping would remain: Land cover classes that are spectrally similar could not be separated based on the yearly spectral data alone. In both the NLCD and C-CAP maps, class labels include information that is not likely spectrally separable from single observation of imagery within the year (see Table 1 in the Appendix). Thus, a significant first step is derivation of land cover classes that would be both relevant for salmonid monitoring and distinguishable from spectral data.

Details of yearly land cover mapping

<u>Development of yearly stabilized images</u>

For each of the five image stacks intersecting the Puget Sound, LandTrendr segmentation based on the NBR index was used to temporally stabilize images of tasseled-cap brightness, greenness, and wetness (TC BGW) for the period 1985 to 2009. Because legacy data stacks were used to reduce the need to repeat costly pre-processing steps in this project, one or more scenes were missing data from 1992, 1995, and 1997 (Table 1 in prior section). Future work will fill in those years to fully utilize all years.

<u>Translating NLCD classes</u>

Not all NLCD classes are spectrally separable. The distinction between crop and pasture, for example, depends largely on intra-annual changes that are not reliably captured with a single image per year. [*Note: While it is possible to develop dual-date image stacks for the LandTrendr algorithms, the cost associated with such development would have curtailed other investigations in this initial project, and thus was not used.*] Additionally, the actual cover type of agricultural land use is highly variable; the designation of agricultural type is largely a land use designation (i.e. one that requires knowledge of the intent of the management for a given cover type). Similarly, the distinction between "developed open space" and many other land cover classes is essentially impossible without higher resolution imagery, and the open space designation is one of land use, not land cover. After significant investigation into modeling all NLCD classes in their original form, a system of simplified land cover classes was established to more closely align the NLCD classes with classes that were more robustly distinguished spectrally (Table 8). Note that some original NLCD classes were not modeled explicitly, as they were either defined largely by non-spectral characteristics (e.g. Developed – Open Space) or were spectrally similar to other classes (Mixed Forest; Shrub/Scrub).

Table 8. Crosswalk between original NLCD classes and simplified LT classes.

Original NLCD class	*New LT class*
Open Water	Open Water
Perennial Ice Snow	Snow-Ice-Barren
Developed - Open Space	Not used
Developed - Low Intensity	Not used
Developed - Medium Intensity	Developed - Medium-High Intensity
Developed - High Intensity	Developed - Medium-High Intensity
Barren Land	Barren Land
Deciduous Forest	Deciduous Forest
Evergreen Forest	Evergreen Forest
Mixed Forest	Not used
Shrub Scrub	Not used
Grassland Herbaceous	Herbaceous
Pasture Hay	Herbaceous
Cultivated Crop	Not used
Woody Wetland	Not used
Emergent Herbaceous Wetlands	Herbaceous

Sampling from 2001 NLCD map

A total of 7,000 pixel samples were drawn from the LT-converted NLCD map to develop a training dataset. Samples were distributed evenly across all LT classes to ensure that rare classes were well represented, with 1000 samples per class. To avoid spectral noise at the margins of patches in the original NLCD map, especially those classes that were not based on spectral data (e.g. road, river), all patches in the NLCD 2001 map were filtered to minimum of 25pixels before being considered for sampling. Thus, any patches of size less than 25 pixels were excluded from sampling population.

Random forest modeling

Based on the promising results obtained from the random forest approach, it was also used to build models between yearly-stabilized spectral imagery, topographic variables (elevation and slope) and LT classes. Out-of-box error for the classification was encouraging for all classes, with producer's accuracies (the reliability of the derived map in reproducing the training data) near 90% for most classes (Table 9). Barren land was least-well characterized, but error was primarily confusion with the Perennial Snow/Ice category. This is not unexpected, as the two classes border each other at high elevations, and some snow/ice mapped by NLCD in 2001 may not be truly perennial. Herbaceous cover was mapped somewhat less well than the other remaining classes, being confused with the developed, barren, and deciduous classes. This, too, is not unexpected. Sparse herbaceous cover can resembles unvegetated conditions (both barren and developed) late in summer when imagery was generally available, while dense, lush herbaceous cover can

Table 9. Out of box error for classification of LT classes based on 2001 LT-stabilized i

	Modeled								
		Open Water	Perennial Snow/Ice	Developed	Barren Land	Deciduous Forest	Evergreeen Forest	Herbaceous	Producer's accuracy
Reference	Open Water	**908**	3	31	10	14	22	12	*91%*
	Perennial Snow/Ice	4	**862**	0	124	0	6	4	*86%*
	Developed	5	0	**913**	3	16	4	59	*91%*
	Barren Land	24	139	23	**700**	8	35	71	*70%*
	Deciduous Forest	4	0	6	1	**894**	40	55	*89%*
	Evergreeen Forest	12	0	12	16	44	**886**	30	*89%*
	Herbaceous	7	0	53	62	73	36	**769**	*77%*

approach the vigorous green canopy of deciduous-leaved canopies.

<u>Development of yearly land cover maps</u>

The random forest model was applied to yearly LT-stabilized imagery for every available year. Although each pixel was assigned the class receiving the majority of votes, all voting scores were retained to allow more nuanced evaluation of the modeling process. Thus, this process resulted in 21 land cover files for the entire Puget Sound ESU, each file with a full suite of information on the land cover voting in a single year.

<u>Comparison with NLCD full legend</u>

For later interpretation of changes in the LT classes over time, it is important to understand how the modeled LT classes for the year 2001 relate to the more detailed NLCD classes (Table 10).

The following observations are of particular note:

- The LT herbaceous class overlaps with the greatest number of original NLCD classes, but is most closely associated with both of the agricultural land use types (pasture/hay and cultivated crop).
- The LT developed class is associated most strongly with the three dominant NLCD developed classes.
- The LT deciduous forest class is more strongly related to mixed forest than is the LT evergreen forest class.

- The NLCD developed open space class includes herbaceous and both types of forest class, as expected with an NLCD class definition that is defined primarily by land use.

Overall, the comparisons suggest that the LT classes capture the NLCD classes well, within the constraints of the more generalized definitions for the LT classes.

Table 10. Comparison of simplified LandTrendr (LT) classes in 2001 with original 2001 NLCD classes. Shown is the proportion of each NLCD class in the corresponding LT class, with shaded cells indicating more than 15% of the NLCD class in the LT class.

		LandTrendr map class						
		Open Water	Perennial Snow/Ice	Developed	Barren Land	Deciduous Forest	Evergreeen Forest	Herbaceous
NLCD class	Open Water	0.75	0.01	0.07	0.05	0.03	0.07	0.03
	Perennial Ice Snow	0.00	0.81	0.00	0.17	0.00	0.02	0.00
	Developed - Open Space	0.00	0.00	0.12	0.00	0.27	0.29	0.32
	Developed - Low Intensity	0.00	0.00	0.48	0.01	0.13	0.11	0.27
	Developed - Medium Intensity	0.00	0.00	0.82	0.01	0.03	0.02	0.12
	Developed - High Intensity	0.00	0.00	0.93	0.00	0.01	0.01	0.05
	Barren Land	0.02	0.12	0.04	0.66	0.01	0.06	0.09
	Deciduous Forest	0.00	0.00	0.02	0.00	0.79	0.10	0.09
	Evergreen Forest	0.00	0.00	0.01	0.02	0.07	0.87	0.03
	Mixed Forest	0.00	0.00	0.02	0.00	0.61	0.30	0.07
	Shrub Scrub	0.00	0.01	0.01	0.09	0.18	0.43	0.26
	Grassland Herbaceous	0.00	0.01	0.05	0.16	0.07	0.10	0.60
	Pasture Hay	0.00	0.00	0.06	0.00	0.10	0.01	0.82
	Cultivated Crop	0.00	0.00	0.05	0.00	0.11	0.00	0.83
	Woody Wetland	0.01	0.00	0.05	0.01	0.55	0.15	0.24
	Emergent Herbaceous Wetlands	0.03	0.00	0.10	0.05	0.17	0.05	0.59

<u>Post-processing of land cover maps</u>

Although the land cover maps developed from LT-stabilized imagery are very consistent over time, pixels near the statistical boundary between two classes can still modulate between classes over time, even though the overall signal is one of no-change. To reduce errors caused by this effect, a further post-processing step was undertaken. First, a modal base map was developed to represent the dominant conditions across the nearly 25 year record (Figure 14). Evergreen forest represents more than half of the Puget Sound ESU, with deciduous forest and herbaceous cover making up another significant portion of the ESU.

Yearly land cover maps were then adjusted using the modal base map: unchanged pixels were assigned the modal land cover, while disturbed pixels were assigned the modeled yearly landcover The result was a set of yearly land cover maps that are very stable where no disturbance has occurred, but that change yearly during and after disturbance. These maps are further referred to as "**LT land cover maps**."

Summarizing land cover at the basin-wide scale, several patterns emerge (Figure 15). Evergreen forest diminishes consistently from 1986 through nearly the end of the period, while developed (urban) cover increases relatively consistently. The herbaceous and deciduous appear to be transitional classes, with herbaceous cover rising quickly near the beginning of the period and slowly diminishing, while the deciduous classes increases steadily after an initial decline at the beginning of the period.

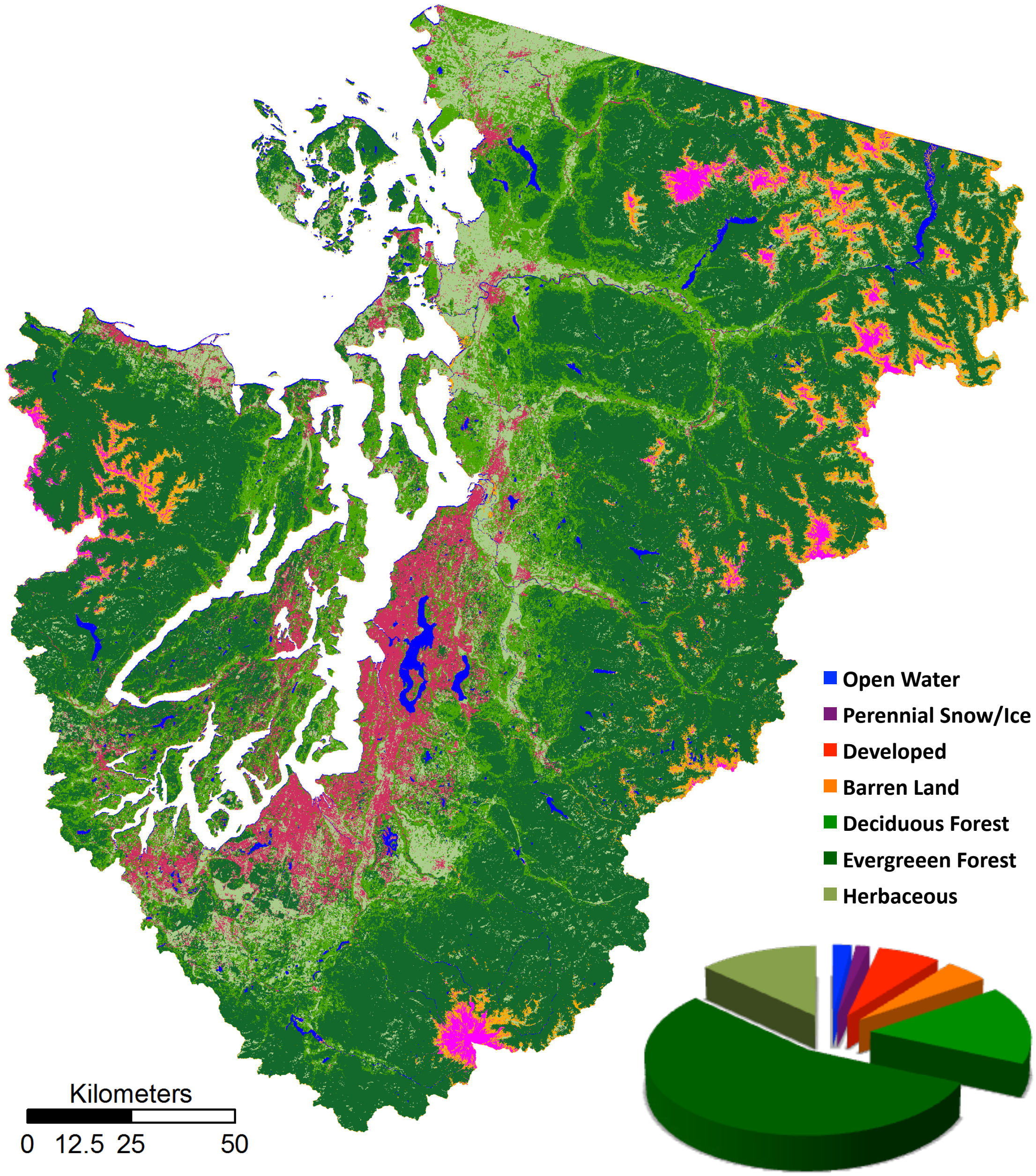


Figure 14. Land cover classes for the Puget Sound, 1986 to 2009, summarized from the modal base map. The modal base map represents for each pixel the land cover type occurring most frequently in the time period.

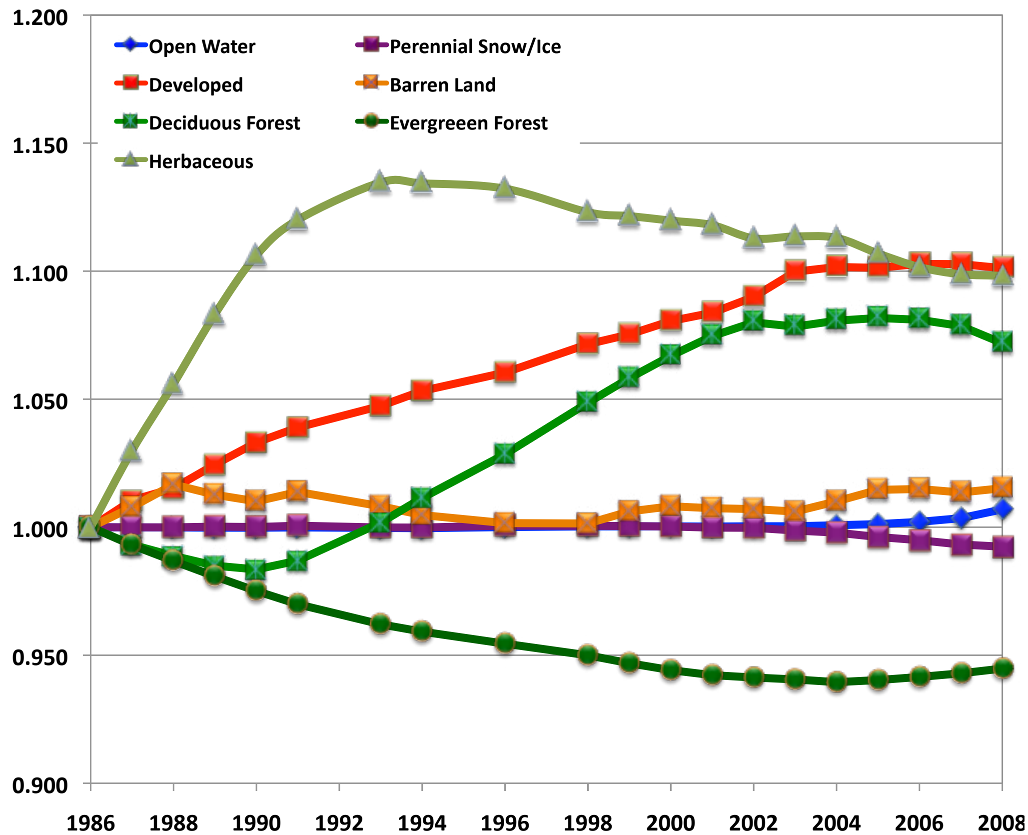


Figure 15. Temporal evolution of landcover classes in the Puget Sound, 1986-2009, scaled to the starting area of each class in 1986.

Interpretation of land cover for validation

To assess how well the land cover model performed, an independent evaluation of land cover class was undertaken. Interpetation of land cover occurred at 297 plots distributed across the ESU in a stratified random sampling design based on three strata of elevation (<150m, 150-300m, and 300+ m). As with the attribution labeling interpretation, the basis of this process was the standard TimeSync interpretation protocol. Unlike the attribution step, no patch-based assessment was needed here, making the protocol more consistent with a standard TimeSync interpretation. However, in addition to making the standard TimeSync interpretation calls, individual points were evaluated for land cover using all available high resolution historical airphotos in the GoogleEarth platform (Figure 16). Because each plot had as many as 10 photos available, more than 1500 individual land cover calls were made (Table 11). In addition to noting land cover type, the protocol included notation whether the plot was on or near an edge, and also whether the land cover decision was unambiguous, or whether a second land cover or land use type could have been present on the plot in the year of the photo.

Nearly 60% of plots were near edges between types, and approximately 30% of all land cover calls were somewhat ambiguous. The confusion matrix between first and second calls for land cover (with a different second call only happening when the first was ambiguous) shows that the agricultural, herbaceous, and deciduous forest classes were very difficult to confirm with single date (often black and white) photos. Note that interpreter calls were attempted at the maximum level of detail for the NLCD class map; this allowed for greater flexibility when comparing with LT-classes later.

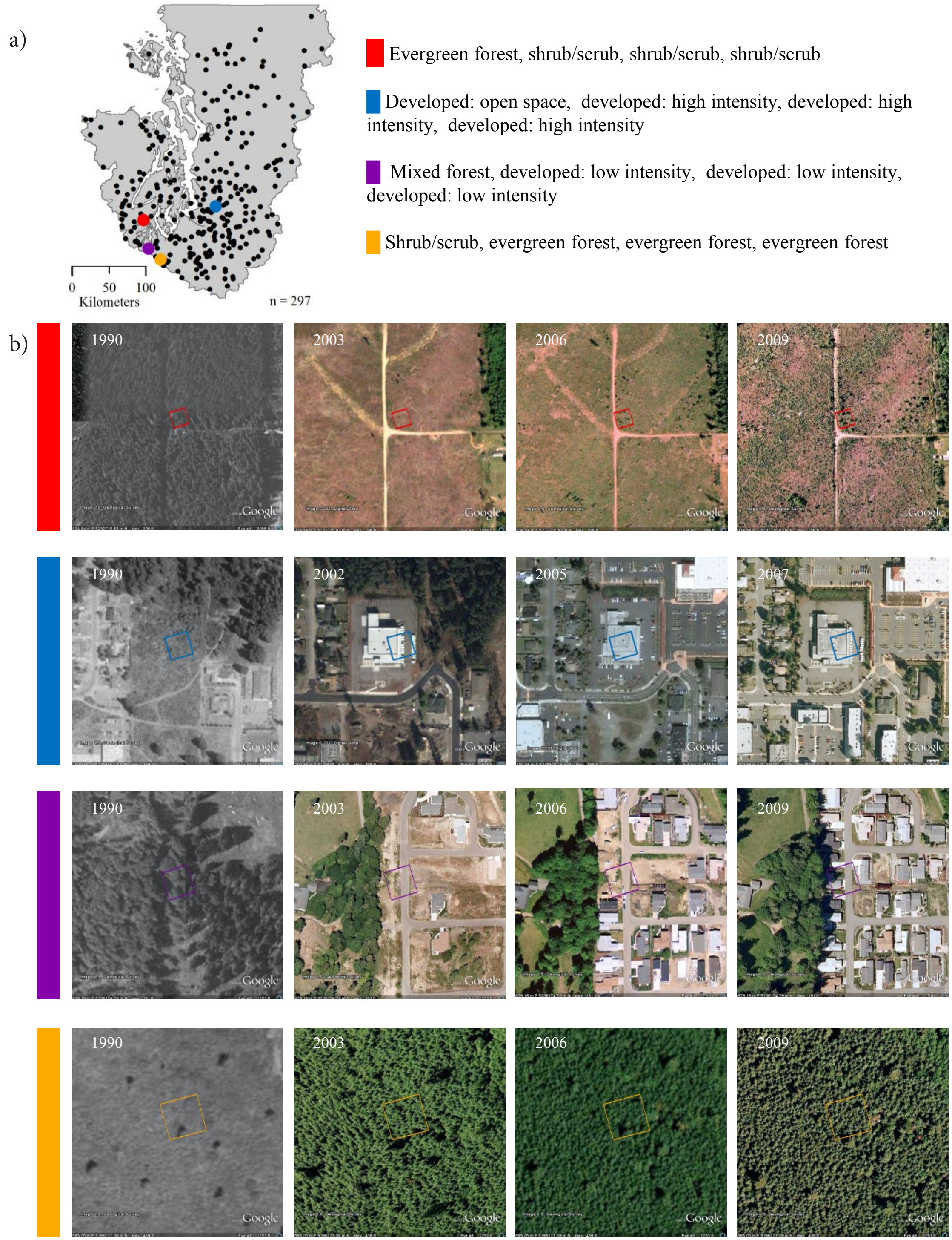


Figure 16. Examples of the land cover validation process. At 297 points (a), we evaluated historical airphoto imagery (b) available in GoogleEarth. Historical depth of imagery varied (see Table LC-4), but no plot had fewer than three photos (median of five per plot). For each plot, a primary and secondary interpretation of land cover class was recorded; secondary land cover calls differed from primary only when land cover was ambiguous.

Table 11. Summary of land cover interpretetation calls.	
Number of photos available per plot	
Minimum	3
Median	5
Maximum	10
Dates of photos	
1989-1994	224
1998-2004	364
2005-2010	1028
Nearness of plot to edges	
No edges within two pixels	680
Edge two pixels distant	272
Edge one pixel distant	561
Plot on an edge	102
Proportion not within 2 pixels of an edge	0.42
Ambiguous land cover	
Unambiguous land cover	69.80%
Ambiguous land cover	30.20%

Table 12. Confidence of interpreter landcover/land-use interpretations based on GoogleEarth airphotos. Sample points that are unambiguously in a single class have matching primary and secondary interpretations; sample points that are ambiguous are given different primary and secondary interpretations (off-diagonal of the matrix).

	Secondary interpretation																
		Barren Land	Cultivated Crop	Grassland Herbaceous	Pasture Hay	Shrub Scrub	Deciduous Forest	Evergreen Forest	Mixed Forest	Developed - High Intensity	Developed - Medium Intensity	Developed - Low Intensity	Developed - Open Space	Open Water	Perennial Ice Snow	Total interpreted	**Proportion unambiguous**
Primary interpretation	Barren Land	**24**	0	0	0	1	0	0	0	0	0	0	2	0	0	27	0.89
	Cultivated Crop	0	**0**	0	5	6	0	0	0	0	0	0	0	0	0	11	**0.00**
	Grassland Herbaceous	0	0	**0**	0	12	0	0	3	0	0	0	0	0	0	15	**0.00**
	Pasture Hay	0	0	15	**19**	10	0	0	12	0	0	0	0	0	0	56	**0.34**
	Shrub Scrub	13	0	5	0	**143**	8	9	14	0	0	0	0	0	0	192	0.74
	Deciduous Forest	0	0	0	0	0	**15**	5	53	0	0	0	0	0	0	73	**0.21**
	Evergreen Forest	0	0	0	0	2	0	**333**	113	0	0	4	6	0	0	458	0.73
	Mixed Forest	0	0	0	9	15	26	41	**276**	0	0	0	0	0	0	367	0.75
	Developed - High Intensity	1	0	0	0	0	0	0	0	**73**	2	0	1	0	0	77	0.95
	Developed - Medium Intensity	0	0	0	0	0	0	0	0	24	**82**	7	0	0	0	113	0.73
	Developed - Low Intensity	0	0	0	0	0	4	0	2	0	7	**62**	16	0	0	91	0.68
	Developed - Open Space	0	0	0	8	1	0	0	0	0	0	22	**64**	0	0	95	0.67
	Open Water	0	0	0	0	0	0	4	0	0	0	0	0	**35**	0	39	0.90
	Perennial Ice Snow	0	0	0	0	0	0	0	0	0	0	0	0	0	**1**	1	1.00

Validation of land cover map

Validation of the LT-land cover maps was based on linking interpretation calls both geographically and temporally to the appropriate location on the appropriate land cover map. These were then summarized across all plot instances and maps for a single confusion matrix (Table 13). Note that this matrix considers the land cover mapping to be a single model with equal error across all maps, and does not account for temporal autocorrelation among successive observations of land cover. It is also technically limited to the period of maps that overlap with the available airphoto observations (1989 to 2010).

The land cover validation results are encouraging. Most apparent confusion among classes is likely related to the aggregation of NLCD classes to LT-classes, and to the difficulty developing interpretation calls with airphotos. The NLCD class that was most widely distributed across mapped classes was Shrub/Scrub, which is primarily a transitional type made up of a variety of land cover conditions.

Table 13. Validation of LT-class land cover.

		Mapped land cover						
		Barren Land	Deciduous Forest	Developed	Evergreen Forest	Herbaceous	open water	Snow Ice
Interpreter call	Barren Land	10	0	9	0	2	0	1
	Cultivated Crop	0	5	0	0	4	0	0
	Deciduous Forest	0	41	0	10	7	0	0
	Developed - High Intensity	0	0	54	0	0	0	0
	Developed - Low Intensity	0	17	29	13	10	0	0
	Developed - Medium Intensity	0	0	63	14	4	0	0
	Developed - Open Space	0	6	18	0	48	0	0
	Evergreen Forest	1	32	9	291	16	0	0
	Grassland Herbaceous	0	9	0	0	2	0	0
	Mixed Forest	0	145	1	118	16	0	0
	Open Water	0	0	2	7	0	20	0
	Pasture Hay	0	7	1	4	31	0	0
	Perennial Ice Snow	0	0	0	0	0	0	1
	Shrub Scrub	7	21	24	33	57	0	0

Examples of yearly maps

The maps show the utility of describing the landscape on an annual basis over a long period of time (Figures 17 and 18). For the case of urbanization, frequent views allow capture of the spread of developed areas (Figure 17), including the building of roads before development. Also note that lower density development is captured as developed pixels within a matrix of new herbaceous cover (lawns). Frequent views also provide a means of capturing the cycles of forest management, with evergreen forest turning first to either barren or herbaceous, then to deciduous and finally to evergreen forest (Figure 18). But frequent views alone are not sufficient: the long period of record (mid 1980s to late 2000s) provides enough time to observe the entire cycle.

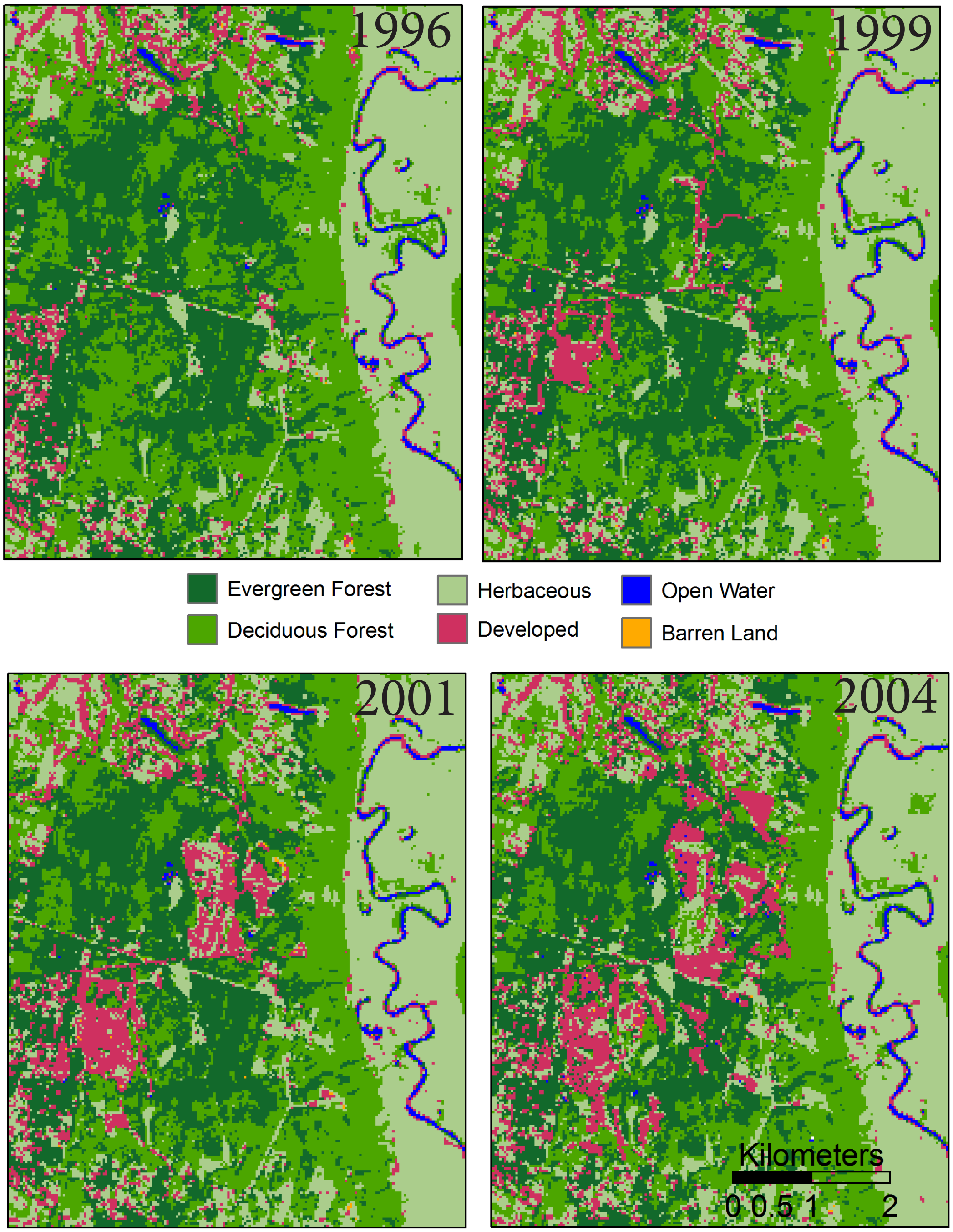


Figure 17. Selected yearly land cover maps for the Union Hill - Novelty Hill area east of Redmond, WA, for the years 1996, 1999, 2001, and 2004. Urbanization (noted with arrows) leads to both developed pixels and, in the case of lower-density suburban areas, developed pixels in a matrix of herbaceous pixels (lawns). The Snoqualmie River is shown on the right, meandering through an area with predominantly agricultural lands (herbaceous cover).

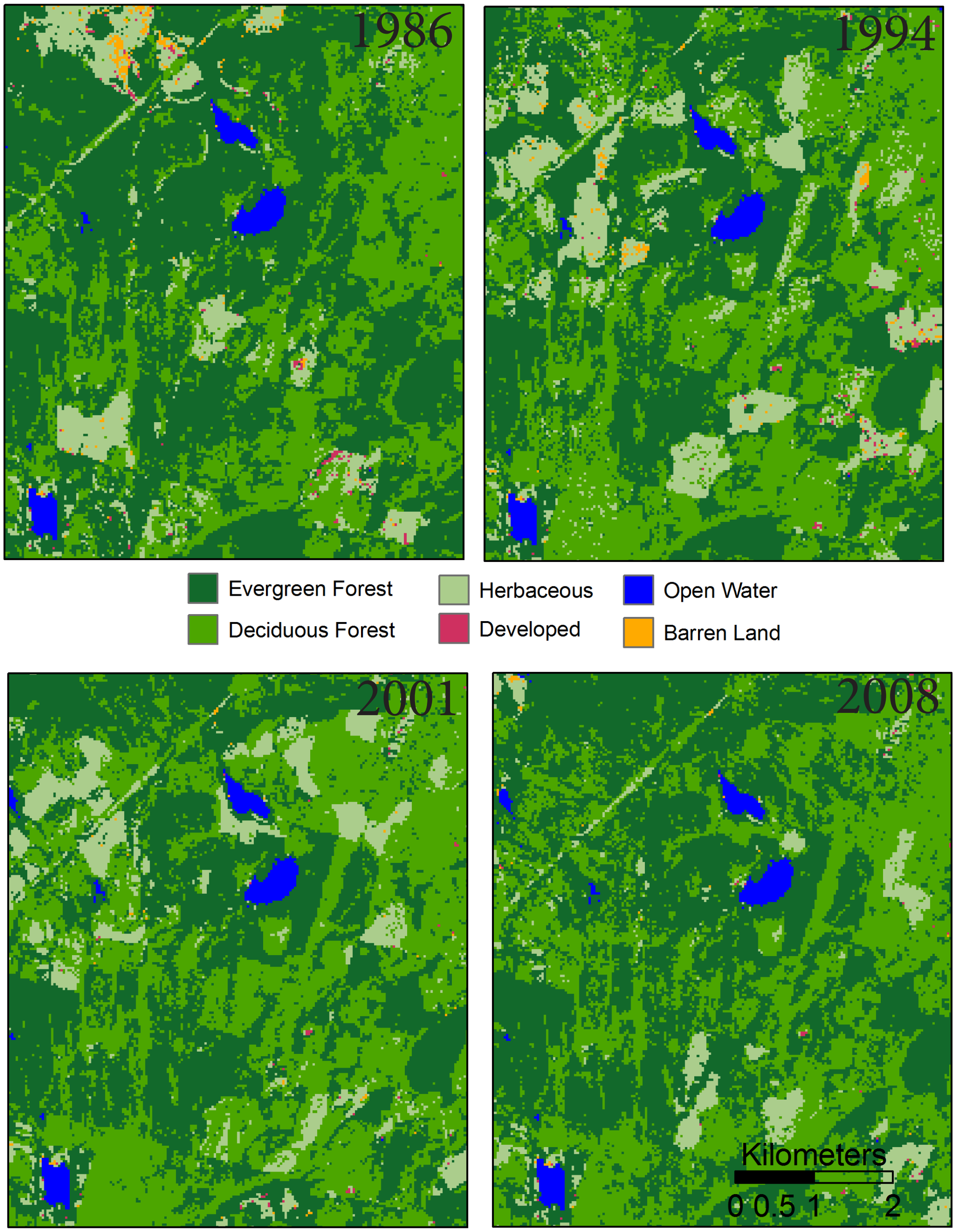


Figure 18. Yearly land cover maps for an area northeast of Duvall for the years 1986, 1994, 2001, and 2008. In contrast to the area shown in Figure 17, the dominant process of change here is forest management, with evergreen forest cycling briefly through barren, herbaceous, and eventually coniferous conditions. Note that the full process of change is best captured with frequent views over long periods. Also note that recent harvest occasionally has spectral properties matching those of the developed class, but that these transition back to vegetated classes.

Land cover progression

A potentially critical issue in the relationship between terrestrial land cover and the conditions in the streams is recovery after disturbance. The land cover maps provide a means of making this assessment: For all disturbance patches, the pre-disturbance land cover can be noted, followed by the progression of land cover types at one, two, three, etc. years after disturbances. Summarizing across all disturbances, several key features emerge (Figure 19). First, land cover progressions make sense ecologically, supporting the notion that the LT-class mapping is an appropriate means of capturing post-disturbance recovery. For example, evergreen forest transitions quickly to barren land, then herbaceous cover, and slowly accumulates both deciduous and eventually coniferous cover over time. Deciduous forest follows a similar trajectory, but with less barren land immediately after disturbance (likely reflecting a difference in forest management and ecological condition between the two forest types). Second, both herbaceous and deciduous forest were converted to the developed class at rates higher than was evergreen forest.

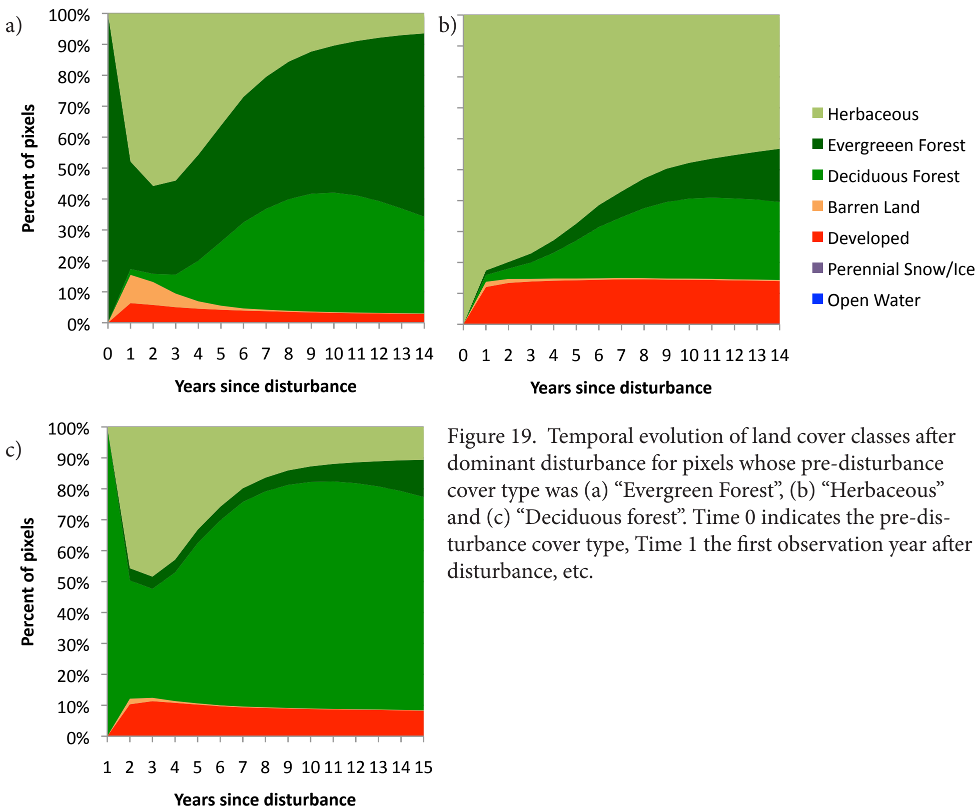
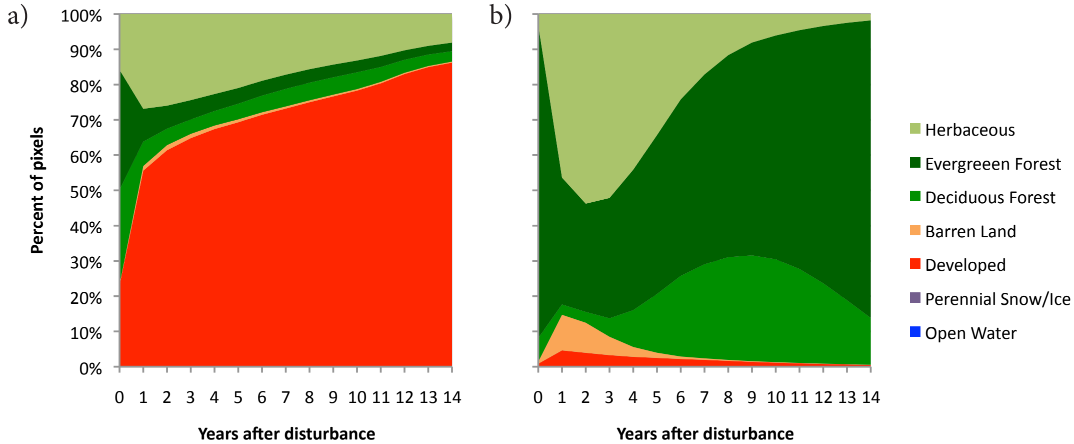


Figure 19. Temporal evolution of land cover classes after dominant disturbance for pixels whose pre-disturbance cover type was (a) "Evergreen Forest", (b) "Herbaceous" and (c) "Deciduous forest". Time 0 indicates the pre-disturbance cover type, Time 1 the first observation year after disturbance, etc.

Land cover transitions can also be evaluated relative to the condition they occupied at the end of the record (Figure 20). For example, all land cover types contributed to areas that were eventually developed (Figure 20a), with approximately 60% beginning in either deciduous or evergreen forest (time 0 in Figure 20a). Evergreen and deciduous forest, in contrast, mostly began as evergreen forest.



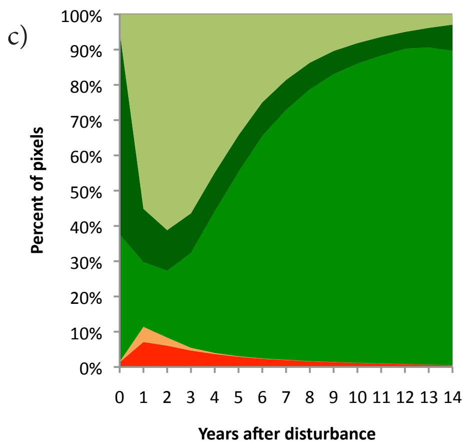


Figure 20. Temporal evolution of land cover classes after dominant disturbance for pixels that ended the observation period (2006, 2007, or 2008) in the (a) “Developed”, (b) “Evergreen forest” and (c) “Deciduous forest” classes. Time 0 indicates the pre-disturbance cover type, Time 1 the first observation year after disturbance, etc.

Summarizing by watershed

Although useful to understand land cover transitions at the basin-wide scale, the relevance to fish populations is much more localized. One useful level of aggregation is the watershed, as this captures the land cover conditions that affect the primary stream or river in which salmonid measurements would occur (Figure 21). In some watersheds, absolute change in different classes may be small, but relative change high. These data provide a means of testing whether state or change may have greater impact on conditions in the stream.

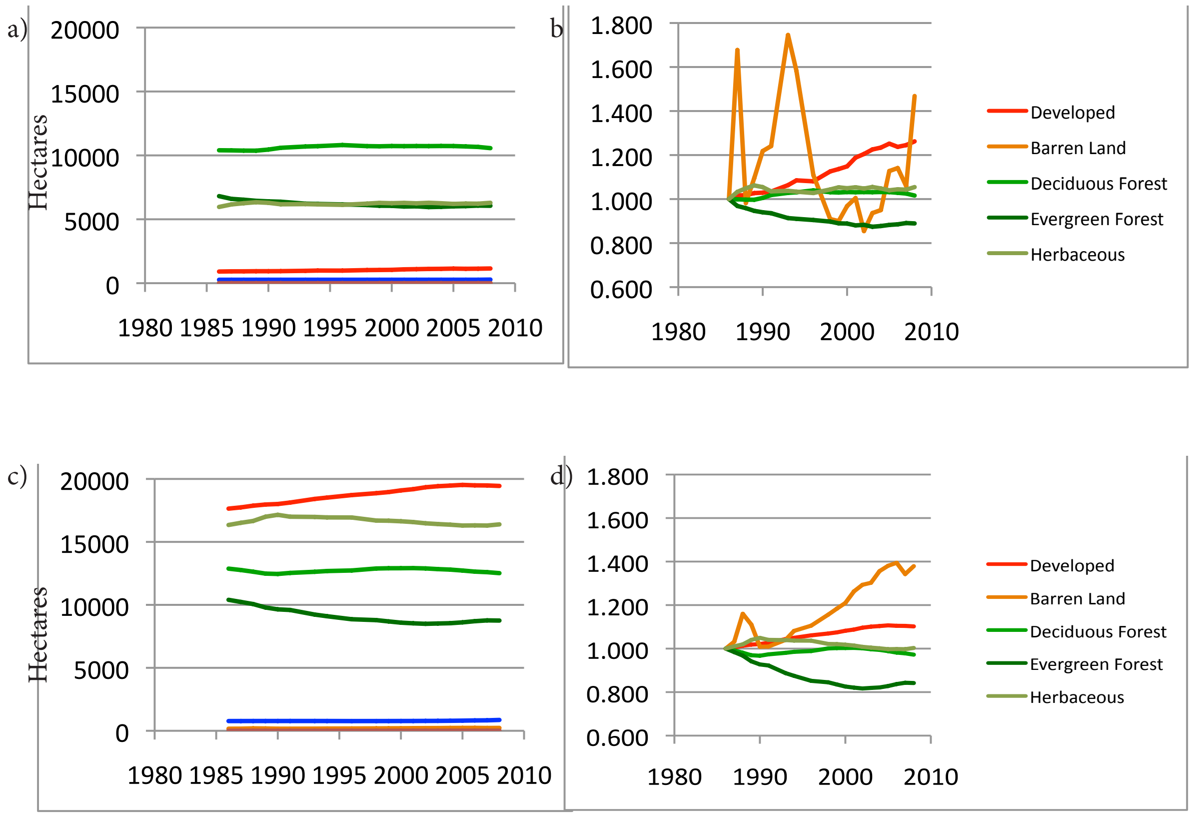


Figure 21. Progression of yearly land cover within two fifth-field watersheds in the Puget Sound ESU. Actual area (in hectares) for the Lower Snoqualmie (a) and Lower Green (c) watersheds. (b) and (d) are as for (a) and (b), but for relative area (vs. 1986 starting point). The Lower Green watershed had greater aboslute levels of developed land, but accrued it at a slower pace than did the Lower Snoqualmie, while the latter had a lesser relative loss of evergreen forest. Note that the barren class, though very small in absolute numbers, was extremely variable in proportions, as it primarily represents a transitional class in these watersheds.

Focusing only on the developed class, it is possible to summarize development rates within any given date range, and observe general spatial patterns of land use by watershed within the entire ESU. (Figure 22). Area in different developed classes can be compared between any arbitrary years, illustrating differential patterns of development spread through the basin over different intervals (Figure 22 b, c, d).

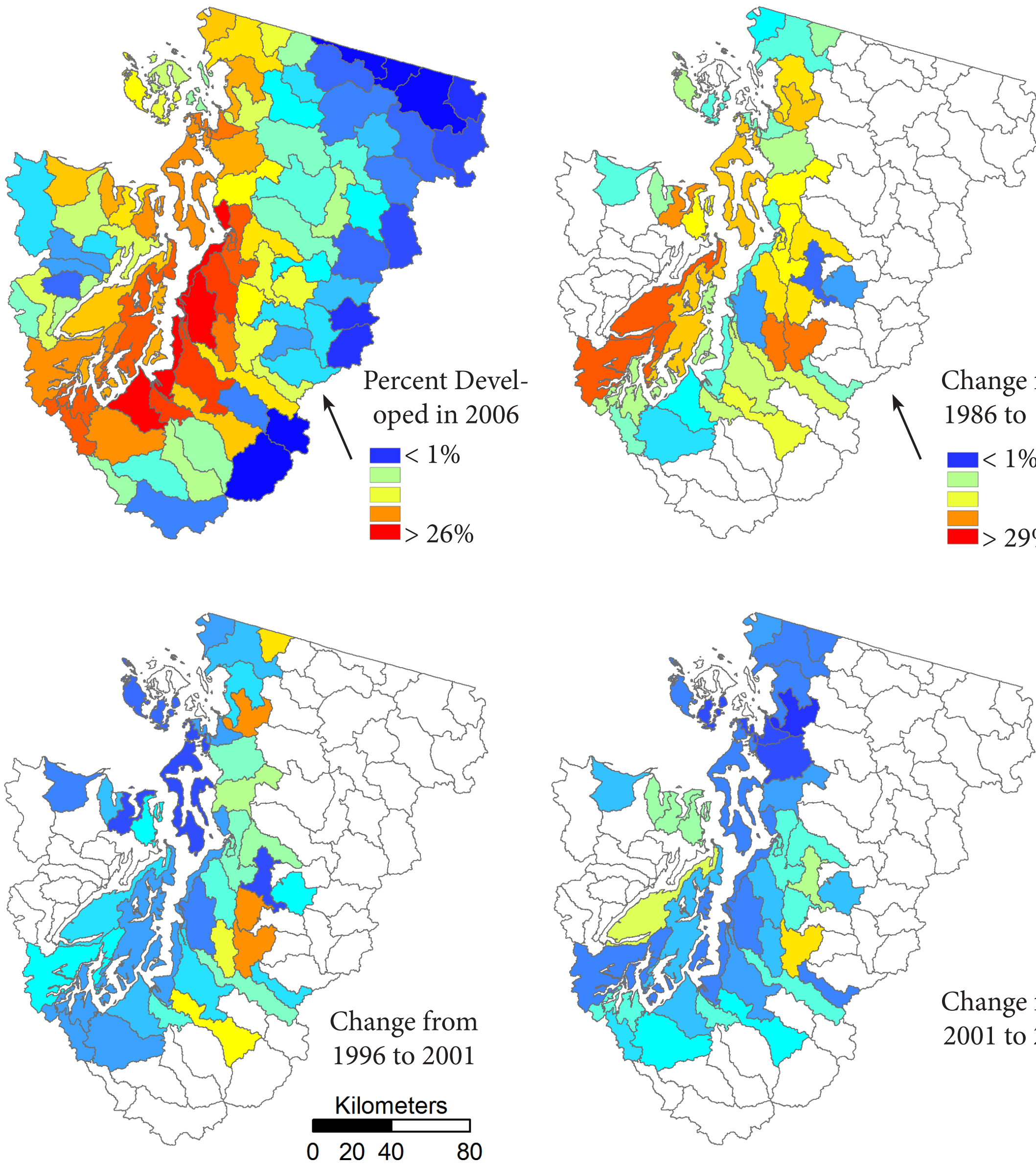


Figure 22. Land cover in the developed class summarized by fifth-field watershed. (a) Percent of watershed area mapped as developed in 2006. Remaining figures focus only on watersheds with 2% or greater developed cover in 2006. (b) Change in developed are from 1986 to 1996, relative to the 1986 area. (c) and (d) are as in (b), but for the 1996 to 2001 and the 2001 to 2006 intervals. Color gradations are scaled the same in (b), (c), and (d). Different basins experience different relative change over time as development patterns shift. Note that these rates are not scaled to change / year.

Comparison with other maps

As noted before, other national-scale map products exist for the Puget Sound ESU. The LT-based maps complement the national-scale maps by providing dense temporal coverage to link the more infrequent mapping conducted by national agencies. For years where NOAA or the USGS have spent significant effort developing and hand-editing maps, those maps can provide rich land use detail that is difficult to reproduce with the satellite imagery alone. However, the detail of these maps necessarily means that they can be produced rarely, and thus the dense temporal-approach described here can more fully describe the progression of land cover types when those types are described in terms of basic land cover classes rather than detailed land use classes (Figure 23). Where the maps overlap in time, they should be in approximate agreement. A comparison with the NOAA C-CAP product for the year 2001 shows that for the developed class, the LT-based maps do indeed provide a similar spatial depiction of the ESU (Figure 24).

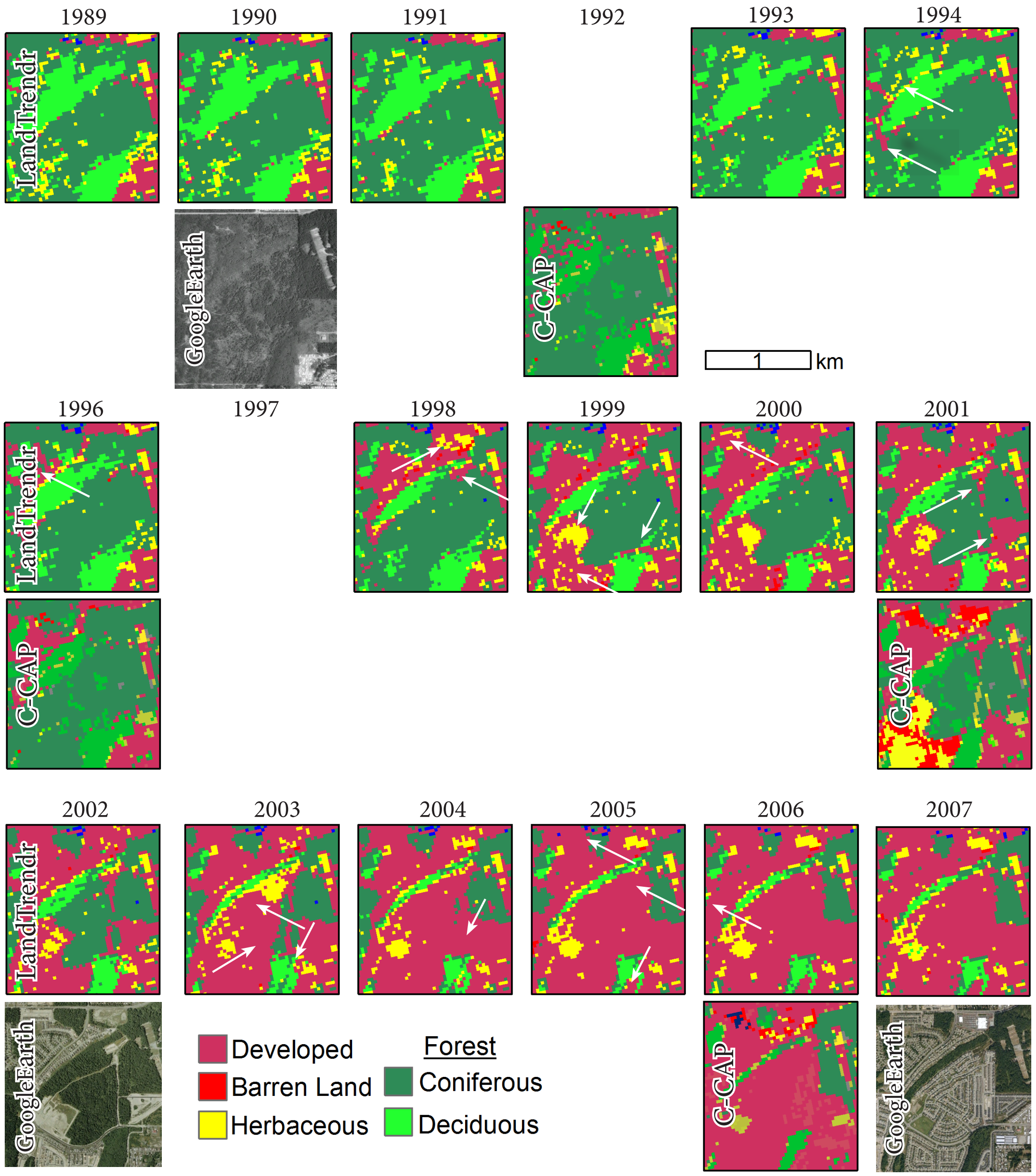


Figure 23. Comparison of urbanization viewed with annual vs. periodic land cover sources. LandTrendr-based maps (top rows in of three groups of image sequences) are near-yearly; white arrows indicate example areas of development from year to year. Landcover maps from C-CAP and airphotos acquired through GoogleEarth contain more information at any given point in time (C-CAP color schemes have been simplified for easier comparison with LandTrendr maps), but do not capture the year-to-year changes that the LandTrendr maps capture. Area of detail: North of Graham, WA.

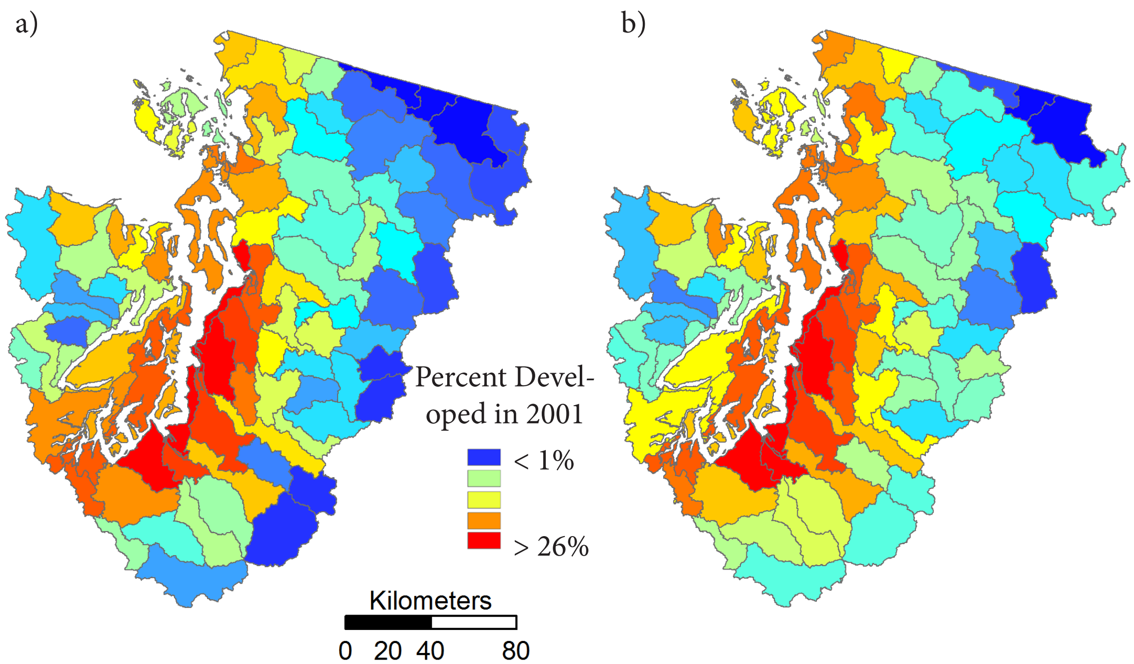


Figure 24. Comparing spatial patterns of area in high and medium developed classes for LT (a) and C-CAP (b) maps for the single year 2001. Although LT-based maps do not contain as many land-use distinctions as the C-CAP or similar NLCD products, these maps illustrate that they capture essentially the same spatial pattern when simple land cover definitions are used. However, they do so at on a yearly basis, complementing the rich thematic detail of the C-CAP maps with rich information on progressions over time.

Summary: Yearly land cover mapping

Yearly land cover mapping appears to be both feasible and useful for describing terrestrial land cover dynamics that may affect salmonid species. Our approach to yearly land cover mapping relies on temporally-stabilized imagery that emerges from the LandTrendr processing algorithms. Because the stabilization process retains important change information while also smoothing unwanted year-to-year noise, classification rules (here,using random forest) developed from a single training year based on an external map (here, the NLCD 2001 product) can be applied backwards and forwards to the entire time series. An important limitation of the approach is that the land cover classes must be spectrally separable. The resultant maps integrate both the state and the change conditions in a manner that appears to have appropriate thematic accuracy. By capturing both state and change, the yearly maps provide robust snapshots of each year as well as the progressions of change over time. In this way, they provide a useful complement to maps with greater thematic accuracy that can only be produced intermittently.

Integration of attribution and land cover

Although the change label attribution and the annual land cover mapping processes derive their information from the same temporal segmentation datasets, they are fundamentally different in their approach to summarizing change: change attribution focuses on change at the patch level without attempting to explicitly define the starting or ending conditions, while the land cover mapping focuses on conditions at the pixel level without attempting to define the cause of the change. Combining the two approaches provides greater insight into the processes occurring in the basin (Figure 25). For example, patches labeled as forest management largely begin and end in forested classes (Figure 25a) , but also contain transitional barren, developed, and herbaceous classes. As noted in Figure 18, the presence of pixels with the “developed” spectral signature is not surprising in recent clearcuts, as these have very low vegetative cover and can appear similar to developed lands spectrally. Focusing on the process of urbanization (Figure 25b) shows that pixels in the “developed” class are only a portion of the story: patches that are disturbed for urbanization eventually contain vegetative cover in the form of lawns and trees, and these managed areas near developed areas are captured by combining the patch-level attribution call with the pixel-level land cover calls. Because land use in these vegetated pixels is presumably different than the land use in similar classes in natural settings, the combination of these two labeling techniques may provide a better means of modeling impacts of land use, including irrigation, chemical use, etc.

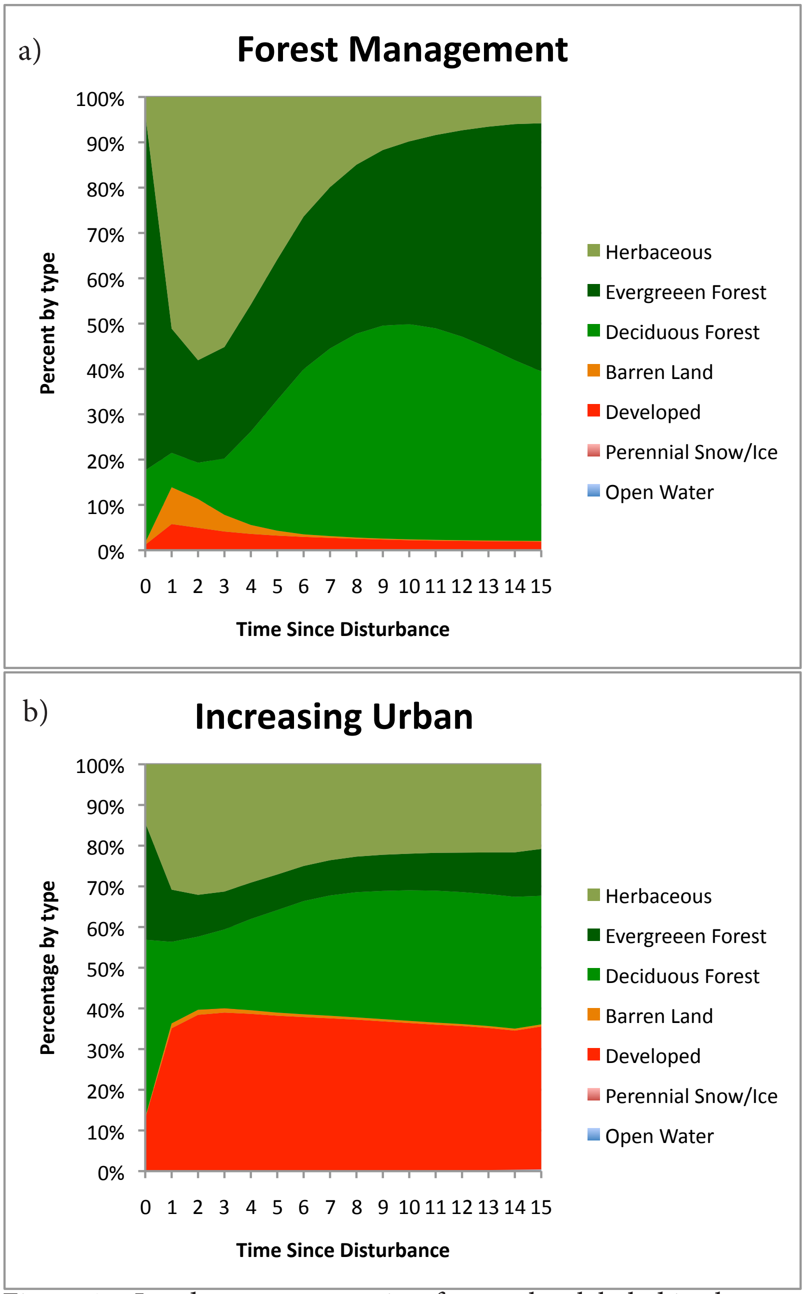


Figure 25. Land cover progression for patches labeled in the attribution phase as (a) forest management and (b) increasing urban. Forest management largely begins as coniferous forest and ends as either coniferous or deciduous forest, with barren and developed classes reflecting brief periods of complete loss of vegetation cover. Patches modeled as increasing urban do sometimes get labeled as urban, but also include some proportion of vegetated classes. As noted in Figure 17, these are likely related to suburban, low-density development with associated lawns and trees.

Overall summary

We developed two related approaches to characterize land cover change over large watershed areas. Based on algorithms that tap the Landsat Thematic Mapper archive, these approaches produce annual maps of generalized land cover type and of the causes of change. Applied to the Puget Sound ESU, the map products distinguish cyclical disturbances of forest management from directional disturbances caused by urbanization, and characterize the land cover transitions that occur both during and after the disturbances. In conjunction with development of these new methods, we developed new approaches to assess and validate map products. Based on these assessments, both yearly land cover mapping and change attribution mapping were achieved with reasonable accuracy using very small training datasets, and expected to increase if training datasets were to similarly increase. Taken together, these maps provide a rich temporal description of the landscape condition, complementing the sparser temporal maps produced under national or regional-scale mapping programs.

Appendix

Table A1. Definitions of land cover and land use in the NLCD maps.

Table A1: National Land Cover Database (NLCD) class definitions*	
11	Open Water - All areas of open water, generally with less than 25% cover of vegetation or soil.
12	Perennial Ice/Snow - All areas characterized by a perennial cover of ice and/or snow, generally greater than 25% of total cover.
21	Developed, Open Space - Includes areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20 percent of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes
22	Developed, Low Intensity - Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20-49 percent of total cover. These areas most commonly include single-family housing units.
23	Developed, Medium Intensity - Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50-79 percent of the total cover. These areas most commonly include single-family housing units.
24	Developed, High Intensity - Includes highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80 to100 percent of the total cover.
31	Barren Land (Rock/Sand/Clay) - Barren areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover.
41	Deciduous Forest - Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75 percent of the tree species shed foliage simultaneously in response to seasonal change.
42	Evergreen Forest - Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75 percent of the tree species maintain their leaves all year. Canopy is never without green foliage.
43	Mixed Forest - Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75 percent of total tree cover.
52	Shrub/Scrub - Areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions.
71	Grassland/Herbaceous - Areas dominated by grammanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing.
81	Pasture/Hay - Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20 percent of total vegetation.
82	Cultivated Crops - Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20 percent of total vegetation. This class also includes all land being actively tilled.
90	Woody Wetlands - Areas where forest or shrubland vegetation accounts for greater than 20 percent of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
95	Emergent Herbaceous Wetlands - Areas where perennial herbaceous vegetation accounts for greater than 80 percent of vegetative cover and the soil or substrate is periodically saturated with or covered with water.
* Taken from http://www.mrlc.gov/nlcd_definitions.php	

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