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Attribution of disturbance change agent from Landsat time-series in support of habitat monitoring in the Puget Sound region, USA

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ABSTRACT

To understand causes and consequences of landscape change, it is often not enough to simply detect change. Rather, the agent causing the change must also be determined. Here, we describe and test a method of change agent attribution built on four tenets: agents operate on patches rather than pixels; temporal context can provide insight into the agent of change; human interpretation is critical because agent labels are inherently human-defined; and statistical modeling must be flexible and non-parametric. In the Puget Sound, USA, we used LandTrendr Landsat time-series-based algorithms to identify abrupt disturbances, and then applied spatial rules to aggregate these to patches. We then derived a suite of spectral, patch-shape, and landscape position variables for each patch. These were then linked to patch-level training labels determined by interpreters at 1198 training patches, and modeled statistically using the Random Forest machine-learning algorithm. Labeled agents of change included urbanization, forest management, and natural change (largely fire), as well as labels associated with spectral change that was non-informative (false change). The success of the method was evaluated using both out-of-bag (OOB) error and a small, fully-independent validation interpretation dataset. Overall OOB accuracy was above 80%, but most successful in the numerically well-represented forest management class. Validation with the independent data was generally lower than that estimated with the OOB approach, but comparable when either first or second voting scores were used for prediction. Spatial and temporal patterns within the study area followed expectations well, with most urbanization occurring in the lower elevation regions around Seattle–Tacoma, most forest management occurring in mid-slope managed forests, and most natural disturbance occurring in protected areas. Temporal patterns of change agent aggregated to the watershed level suggest substantial year-over-year variability that could be used to examine year-over-year variability in fish species populations.

1. Introduction

One of remote sensing's key roles is tracking change on landscapes. Changes affect the services a landscape can provide, making the monitoring of change critical in arenas such as habitat protection, water quality monitoring, economic delivery, and carbon sequestration (Vitousek, Mooney, Lubchenco, & Melillo, 1997). Changes on a landscape also reflect the forces causing change, which are often of fundamental scientific interest. Overarching change pressures, such as climatic warming or population growth, can influence the proximal change processes, such as severe storms or urbanization, that in turn cause the actual changes on landscapes. By detecting those landscape changes in a consistent manner over large areas over time, remote sensing may provide insight into the proximal processes causing it, and may even provide clues to the ultimate causes (Dubinin, Potapov, Lushchekina, & Radeloff, 2010; Fraser, Olthof, Carrière, Deschamps, & Pouliot, 2011; Myneni, Keeling, Tucker, Asrar, & Nemani, 1997). Thus, the better that landscape change can be characterized with remote sensing, the better that both the effects and causes of change can be understood.

Full characterization of change requires not just detection of a change, but also an understanding of the proximal cause of change: the "agent of change." In natural change processes, the agent refers to the natural phenomenon causing the change, such as a fire or landslide, while in anthropogenic change, the agent refers to the human activity causing the change, such as urban development or forest management. Different agents may imply quite different impacts and different ultimate pressures (Dale et al., 2001; Malmström & Raffa, 2000), even if

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the initial physiognomic manifestations of change in a remotely-sensed image are similar. For example, the clearing of a forest can be carried out for urban development or for silvicultural forest harvest, and while the initial forest clearing event appears identical in both cases, the longer-term carbon, habitat, and hydrological impacts are quite different.

Strategies to identify the agent of change are varied. In some cases, the agent, general location, and timing of the change are known before the study is undertaken, making it possible to infer the agent simply from the detection of change (Collado, Chuvieco, & Camarasa, 2002; DeRose, Long, & Ramsey, 2011; Griffiths et al., 2012; Healey, Yang, Cohen, & Pierce, 2006; Hostert, Roder, Hill, Udelhoven, & Tsiourlis, 2003; Olthof, King, & Lautenschlager, 2004; Sader, Bertrand, & Wilson, 2003; Schneider & Woodcock, 2008; Turner, Wear, & Flamm, 1996). In other cases, the change detection methodology and the geographic scope of its application limit the types of change agent that can be detected (Cohen, Fiorella, Gray, Helmer, & Anderson, 1998), or allow the inference of the change agent through post-hoc comparisons with other datasets and field observations (Vogelmann, Tolk, & Zhu, 2009) or through manual labeling of change (Healey et al., 2008; Schroeder, Wulder, Healey, & Moisen, 2011). When more agents and land cover types are involved, agents of change sometimes can be inferred from specific combinations of before and after land cover class (Alberti, Weeks, & Coe, 2004; Chan, Chan, & Yeh, 2001; Helmer et al., 2010).

As change mapping rapidly moves toward larger areas and to annual (or better) time-steps (Griffiths et al., 2012; Huang et al., 2010), existing methods will likely be insufficient. Increased temporal and spatial scope will increase the suite of expected change agents – including fires, floods, cyclic forest harvest, urbanization, and agricultural conversion – across several land cover classes — including forest, shrub, herbaceous, and urban types. Inference from land-cover transitions will not work well at an annual time-step, because the initial land cover transition is an intermediate state toward the final land cover class. Therefore, temporal context must be considered. Additionally, attribution at the pixel scale may not work well, because many anthropogenic change agents exert influence over a geographic patch within which a suite of pixel-scale cover transitions might occur (Barnsley & Barr, 1996). Ideally, the spatial arrangement or shape of the change (Stewart, Wulder, McDermid, & Nelson, 2009) or the shape and temporal context (Gómez et al., 2011) should be used to separate different types of change. Additionally, spatial context may be useful to distinguish types, but would require the human capacity to incorporate spatial and temporal context. Human interpreters cannot feasibly interpret all change events on large landscapes. Therefore, some form of automation is desirable.

Ideally, then, methods should be patch based, flexible enough to define diverse change agents within a single model paradigm, of consistent analytical structure, able to incorporate temporal information, and able to leverage human contextual skills to help define the overarching agent of change when complex land cover transitions occur.

In this paper, we develop a methodology that encapsulates these needs, and we test it in a study area where distinguishing among agents of change may become critical for habitat management: the Puget Sound in Washington state, USA. In the Puget Sound, threatened and endangered anadromous salmon species (*Oncorhynchus* spp.) utilize rivers that drain lands experiencing agricultural, urban, and forest management uses that may affect their survival (Burnett et al., 2009; Robinson, Newell, & Marzluff, 2005; Steel et al., 2012). Although salmon runs vary substantially from year to year, most populations have experienced long-term, substantial declines in recent decades (Gustafson et al., 2007; McClure, Holmes, Sanderson, & Jordan, 2003). Understanding both immediate and lagged effects of land cover and land use changes on long-term population trends will first require change agent attribution in a consistent manner across large basins at an annual time-step. Thus, the work reported here represents a test of that first step.

2. Methods

2.1. Study area

The Puget Sound study area (Fig. 1) was defined by the watershed boundaries of streams containing salmon populations belonging to a single evolutionarily significant unit (ESU) (Waples, 1995). It includes portions of five Landsat Thematic Mapper path–row addresses (using the World Reference System-II). At low elevations in coastal areas and valleys, agricultural and urban land uses dominate. At the higher elevations in the Cascade and Olympic Mountains that fringe the basin, conifer forests dominate (Franklin & Dyrness, 1988).

Terrestrial land cover changes prevalent in the Puget Sound could affect stream conditions. Clearcutting and partial harvest, common in this timber-producing region (Smith, Miles, Perry, & Pugh, 2009), could lead to a pulse of sediment delivery to salmon-bearing streams, and temporarily remove temperature-regulating shade from the streams. Agricultural land uses may deliver chronic loads of chemicals to nearby streams through runoff, and also diminish streamside vegetation that would otherwise shade and cool the stream. When either forest or agricultural land uses are converted to urban land use, streamside shade and runoff characteristics change as well (Booth, Hartley, & Jackson, 2002). Urban areas have expanded in recent decades as the region's economy diversified and population grew (Collins, Montgomery, & Sheikh, 2003). Against this backdrop of anthropogenic change, natural change processes also occur in the Puget Sound: wildfire, insect-related forest mortality, landslides, avalanches, windthrow, stream flooding and channel migration. Each of these natural change agents removes vegetation in some portion of the landscape, and thus could affect hydrological flows to streams as well as diminish shade to the streams.

2.2. Overview of methodology

Building from the rationale described in Section 1, four tenets of the change attribution methodology were initially identified.

1. Identify patches where a common change process occurs, and conduct analysis at that patch level
2. Place the change in its temporal context.
3. Leverage human interpretation to drive the analysis.
4. Model using flexible, non-parametric multivariate classification algorithms.

The overall workflow was based on those four tenets (Fig. 2). The first phase of the approach is pixel-level change detection, based on the temporal-segmentation change-detection approach of LandTrendr (Landsat-based detection of trends in disturbance and recovery; Kennedy, Yang, & Cohen, 2010). The LandTrendr algorithms temporally stabilize a time-series of Landsat Thematic Mapper images, and also identify the timing, magnitude, and duration of disturbances at the pixel scale (Kennedy et al., 2010). These disturbances at the pixel scale are grouped into patches based on rules of adjacency in space and time (Kennedy et al., 2012).

Patches are the foundation for the second phase of the approach. The strategy is to build a statistical model to predict the change agent using a suite of predictor variables defined at the patch scale. Predictor variables include landscape position, shape, slope, *etc.*, as well as the spectral properties of the temporally-stabilized images. These spectral variables provide patch-level information on the pre-disturbance condition, the magnitude of the change, and any post-disturbance directional change. Separately, training data are collected by interpreters examining individual patches of change. Initially, the interpreters select from the entire population of change patches those for which the agent of change can be interpreted with high confidence. These become the initial reference dataset on which a Random Forest (Breiman, 2001) model is built, linking these labels for the change agent with the predictor variables.

Fig. 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.

A predictive model is built from the training dataset, applied to the entire population of patches, and additional patches for interpretation are identified to fill out rare or confused classes, resulting in a larger combined dataset, on which a final model is built and applied to the entire population. Finally, a random sample of patches is drawn and interpreted to use an unbiased estimate of overall labeling success.

2.3. Change detection at the pixel scale

2.3.1. LandTrendr

For the five Landsat path/row scenes that intersect the Puget Sound study area, we applied LandTrendr preprocessing, segmentation, and disturbance mapping approaches described previously (Kennedy et al., 2010, 2012). We selected and downloaded from the USGS GLOVIS archive (glovis.usgs.gov) 175 Level L1T Landsat Thematic Mapper and Enhanced Thematic Mapper + (hereafter, collectively referred to as "TM") images from the years 1984 to 2009 within the mid-summer season of the study area (approximately July 1 to August 31) (Table 1).

As in Kennedy et al. (2010, 2012), we used simple atmospheric correction (COST; Chavez (1996)), relative normalization (MADCAL; Canty, Nielsen, and Schmidt (2004)), and cloud/shadow masking to construct a clean time-series of mid-growing-season imagery, and calculated the normalized burn ratio (NBR; Key and Benson (2004)) for each image.

LandTrendr temporal segmentation algorithms were then applied to the NBR time series, to identify breaks ("vertices") that separate time periods of consistent loss, gain, or stability in a single spectral index (Kennedy et al., 2010). In the second phase of segmentation, the progression of spectral data between vertices is approximated with straightline fitting, resulting in segments that define periods of consistent temporal progression.

Temporal segments that decreased in NBR from onset to end of segment were considered a disturbance, and only those segments with short duration signals (3 or fewer years) were used for further analysis. Only segments with 10% or greater relative vegetative cover loss were retained (Kennedy et al., 2010). For each disturbance event in each pixel, the following attributes were recorded: year of disturbance, vegetation cover estimated at the beginning of the disturbance event, duration of the process, and relative magnitude of change. Occasionally, single pixels would have more than one disturbance event, and both events were noted. Repeated over all pixels in the area, the result of this step was a disturbance map with attributes of disturbance for each pixel.

2.3.2. Fitting to other indices

Temporal segmentation based on the NBR index is useful to identify segment timing and initiation of disturbances, but no single spectral index adequately describes the multispectral character of conditions before or after change, nor the multispectral trajectory of post-disturbance recovery. To gain this useful information, we applied the second phase of segmentation (fitting) to force other spectral indices to comply with the vertex timing identified previously using the NBR index (Fig. 3). In our case, we chose to use the so-called "tasseled-cap" spectral indices (Kauth & Thomas, 1976) adjusted for reflectance factor data (Crist, 1985). The resultant fitted tasseled-cap data captured the multispectral evolution of each pixel without the year-to-year noise caused by sun angle, phenology, and atmospheric effects. For each pixel where a disturbance segment was noted in the prior step, tasseled-cap

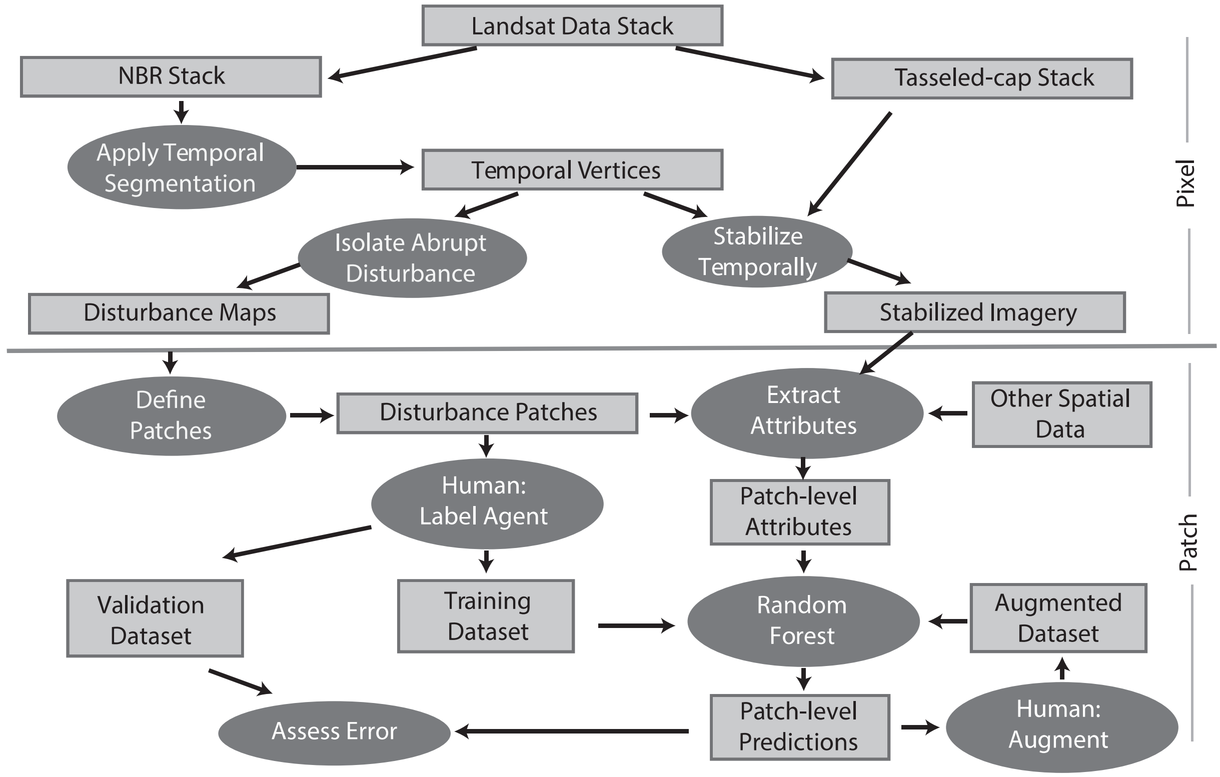

Fig. 2. Schematic of the change attribution labeling process. The top portion of the schematic occurs at the Landsat pixel grain, where LandTrendr algorithms identify disturbances and stabilize time-series tasseled-cap imagery. Based on temporal coherence and spatial adjacency, disturbance pixels are grouped into patches from which a variety of spectral and other spatial attributes are summarized, and for which trained interpreters label the agent causing the disturbance. These are combined within the Random Forest algorithm to predict change agent for all other patches in the map, and these predictions can then be compared against a validation dataset to assess true error.

Brightness (TCB), Greenness (TCG), and Wetness (TCW) values from these fitted trajectories were noted for the vertex at the onset and end of disturbance, as well as for the change between these two points. Additionally, the fitted tasseled-cap values for the vertex at the end of the post-disturbance segment were also recorded, as well as the difference between those and the immediate-post-disturbance vertex. Taken together, these tasseled-cap values represent an efficient means of characterizing the spectral properties of each pixel immediately before and after disturbance, and the spectral conditions of recovery.

2.4. Patch definition

To delineate patches, adjacent pixels experiencing disturbance in the same year were assumed to have experienced the same event, and were grouped together using an 8-neighbor adjacency rule. Patches with 11 or fewer pixels (*e.g.*, groupings smaller than approximately 1 ha) were removed from the dataset to avoid small, often-unverifiable disturbance events. Thus, we make no claim about disturbance events smaller than this size. Missing pixels surrounded on five sides by disturbance were filled in with values from those surrounding pixels; gaps up to 11 pixels maximum were filled in this manner using an iterative filling process.

The resultant disturbance map formed the basis for all further analysis. The map itself remained a raster layer at the 30 m grain size of the source Landsat pixels, but each pixel was associated with a patch of other pixels, allowing later summarization of patch-level characteristics. Each pixel retained information about the timing, relative magnitude, and duration of the greatest, abrupt disturbance occurring between 1985 and 2008.

Table 1
Landsat image information.

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

2.5. Assessment of disturbance detection

At 351 individual plots distributed randomly across all lands in the study area, we assessed the accuracy of the pixel-resolution disturbance maps using TimeSync (Cohen, Zhiqiang, & Kennedy, 2010). TimeSync interpretations agree strongly with independent reference data when and where those data are available, but have the advantage of being consistent across all years, ownerships, and applicable in a randomized design. We labeled each temporal segment as stable, growth, or disturbance, and for disturbance segments, we also assigned a relative magnitude of change (high, medium, or low).

To assess the accuracy of the maps, the 3 by 3 pixel human-interpreted footprint was intersected with the map of greatest abrupt disturbance, and a match was counted if the map and the interpreter agreed on the presence of a disturbance within 1 year of each other. To maintain consistency across the interpretation database and the map, comparison was made only with the largest disturbance noted by the interpreter that met the duration rule (abrupt disturbance three years or fewer in duration).

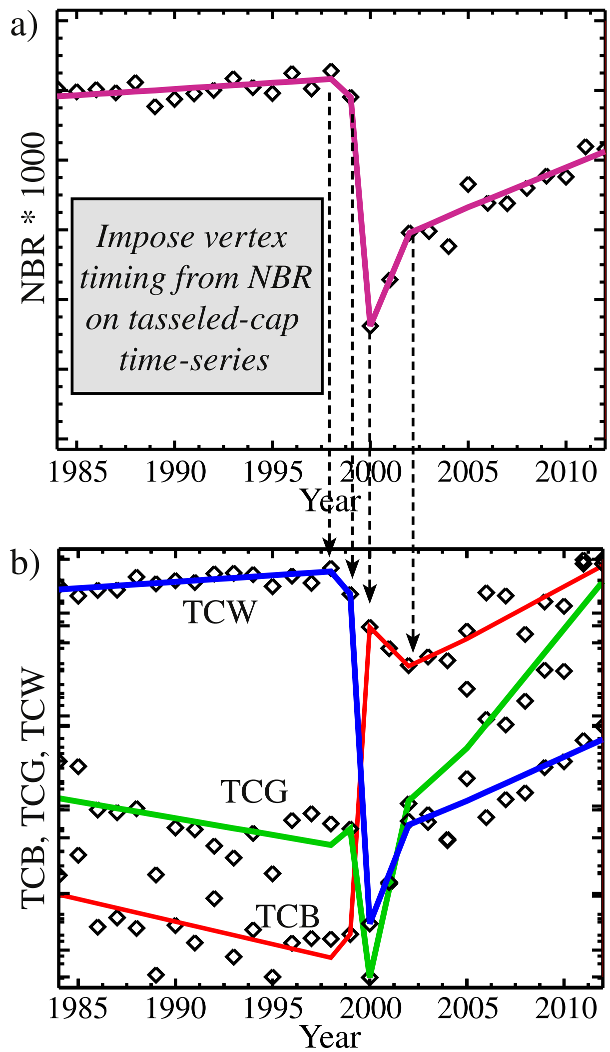

Fig. 3. Temporal segmentation and stabilization for the time series of a single pixel. a) Segmentation: algorithms identify vertices that separate distinct periods in the time-series of a spectral index that is particularly sensitive to disturbance (here, the normalized burn ratio, or NBR). Fitting algorithms then fit straight-line segments to the observed vertices to maximize a goodness-of-fit score. b) Stabilization: the vertices from the segmentation phase are transferred from the NBR segmentation onto the time series of other target indices, here the tasseled-cap brightness (TCB), greenness (TCG), and wetness (TCW) indices, and the same fitting algorithms applied to construct segments in the target indices. The fitted target indices capture greater spectral depth than the single segmentation index, but have year-to-year noise removed.

2.6. Extraction of predictor variables by patch

Disturbance patches were converted from raster to vector representation, creating an associated database record for each patch. For each patch, a suite of predictor variables was then attached to each patch's record by intersecting the patch with predictor variable spatial layers (examples in Fig. 4), and calculating summary statistics (mean, variance, *etc.* as appropriate) for the predictor variables (Table 2). These predictor variables were chosen to represent landscape position, patch shape, and the suite of LandTrendr-derived spectral properties that describe the pre-disturbance, disturbance, and post-disturbance characteristics of each patch.

Thus, the result of this step was a database for all disturbance patches, with each record containing a suite of predictor variable attributes for a patch. This attribute database could then be manipulated for all further attribution steps.

2.7. Interpreter-based attribution of change

For a subset of the disturbance patches in the disturbance map, trained interpreters used all available information to attribute the cause of change, following a set of standard protocols.

2.7.1. Sample selection

Samples were chosen in two phases. The initial set of patches was chosen purposively: we identified areas of the landscape where known change agents were active, and conducted change attribution interpretation on those areas. We focused on urbanizing fringes of the Seattle–Tacoma metropolitan area, and on areas in forestland where forest management effects (predominantly clearcuts) were easily and quickly defined. This initial selection process resulted in 1016 interpreted patches. A second, smaller set was chosen from maps predicted by the model (see Section 2.9) to augment rare and confused classes. Finally, a map validation set was chosen using a completely randomized draw across the entire patch population.

2.7.2. Datasets used to guide interpretation

Interpretation and labeling of past change processes is challenging for the same reason that validation of yearly disturbance maps is challenging: no external reference datasets exist with the spatial extent, temporal frequency, and thematic detail needed to create a truly independent and consistent record (Cohen et al., 2010). Therefore, to allow interpreters to determine the most likely agent of change for any given change patch, we used a mix of the Landsat imagery itself and historical airphoto data where available. We initially used the TimeSync interface (Cohen et al., 2010), which combines spectral image chips and trajectories drawn from the Landsat time-series. Separately, we displayed vectorized polygons of the sample patches in the GoogleEarth™ platform to make use of recent as well as historical photos; the historical photos were often invaluable to determine the type of change, as they allowed assessment of conditions before and after many changes in the database (Fig. 5).

For portions of the Puget Sound where fire is an active disturbance process, we also referenced the fire database from the Monitoring Trends in Burn Severity (MTBS.gov) project. Where forest insect mortality is prevalent, we used “sketch maps” obtained from the USDA Forest Service's Forest Health Monitoring program (Ciesla, 2006), where airborne observers record geospatial data on tree health every year (http://www.fs.usda.gov/main/r6/forest-grasslandhealth/). For these latter two projects, we separately loaded the relevant spatial data into the ArcMap™ interface along with our patch information.

2.7.3. Interpretation protocols

To better understand potential impacts on salmonid habitat, the core agents sought by the NMFS were: urbanization of non-urban types, intensification of urban uses, forest management, riparian-related change, and other natural change. Recognizing that these types would need to be separated spectrally, and that each change agent class could contain several unique from–to spectral classes, we developed an interpretation scheme that hierarchically split change agent processes into more granular types based on land cover before and after the change (Table 3).

Interpreters used all available datasets (Section 2.7.2) to guide interpretation of change. When ambiguity in interpretation arose, three principles were used to help resolve the call: shape, landscape context, and history. Patch shape is often a critical first assessment separating natural from anthropogenic changes, with anthropogenic changes having more regular edges. Landscape context refers to the types of change and land use that are nearby the target change; as extreme examples, consider that high-density urbanization rarely occurs in forest areas far from other urban areas, and wildfires rarely occur in cities. More subtle, low-severity fires in forests may look spectrally similar to moderate severity insect mortality, but often the condition of the landscape

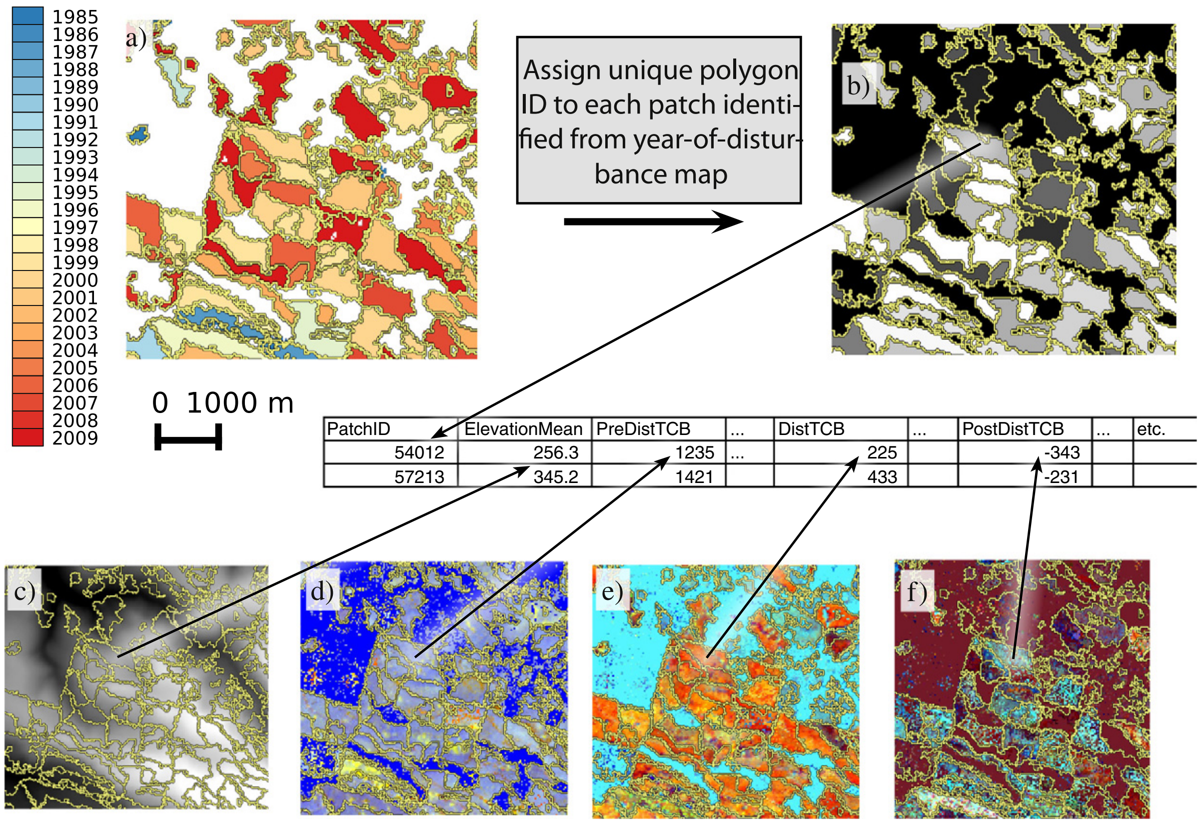

Fig. 4. Summarizing spatial predictor data at the patch scale. (a) Within the "year of disturbance" map, all adjacent pixels disturbed in the same year are grouped into patches whose boundaries are converted into a polygon coverage with unique polygon IDs for each patch. (b) The attribute table for each patch is then populated by summarizing other spatial predictor data for each patch, including typical landscape position predictors such as elevation (c) as well as LandTrendr-specific spectral data that capture conditions immediately before (d), during (e) and after (f) the disturbance.

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	Estimated % vegetative cover loss
	Delta spectral	Change in scaled tasseled-cap brightness, greenness and wetness units
	Stdv in delta spectral	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	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

around the target polygon can provide clues about which agent was more likely causing the change. History considers the appropriateness of the call relative to the spectral trajectory of change observed in the Landsat record. Because the Landsat record considers the entire time-series, it can often provide insight into the condition of the land before and/or after high-resolution photos are available, and can sometimes distinguish among types with high year-to-year variability.

For anthropogenic changes, an additional criterion was used to separate among types: intent. Often, forests are cleared and a single residential unit is built. Although the clearing itself is consistent with a forest management approach – and may even involve replanting of trees in a silvicultural management regime – the intent of the change was development, and from the perspective of long-term chemical and mechanical impact on neighboring streams, the functional use of that property is low-density residential.

In addition to the core list of change agents, we added an agent associated with false change: agriculture to agriculture change. The premise of the underlying change detection algorithm is that durable spectral change reflects durable land cover change. But in agricultural systems, drastic spectral changes occur often based on cropping system rotation, and the essentially random timing of image acquisition date can make some changes appear durable enough to trigger the time-series algorithm. These false change detections may, however, be distinguished from real land cover change when trained interpreters view the whole time series.

For each interpretation call, the analyst also recorded a measure of confidence (high, medium, or low). High confidence was scored when the land cover and land use could unambiguously be determined before and after the change (ideally by pre- and post-event airphotos), when the change was consistent with the land use context around it, and

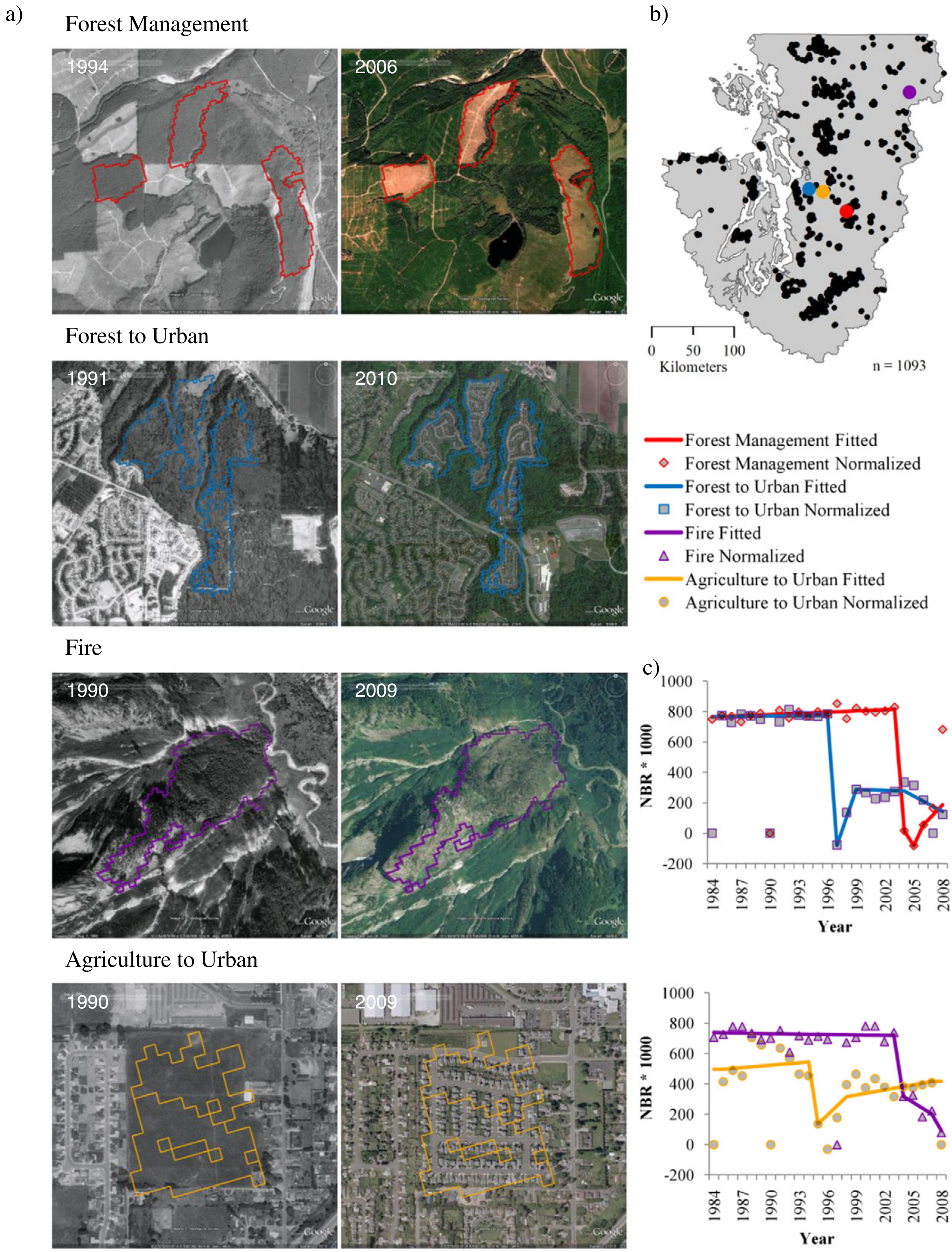

Fig. 5. Examples of expert interpretation of change agent. We examined high-resolution images (a) at more than 1000 disturbance polygons defined using change detection algorithms (b), aided by temporal information on spectral evolution (c), to label the change agent into one of nine change agent categories (see Table 3).

when the satellite data (both image chips and spectral trajectory) were consistent with the interpretation. If these components of change were not all present, the confidence score was diminished incrementally.

2.8. Modeling disturbance agent

Modeling of disturbance agent linked interpretation of patches (Section 2.7) with predictor variables extracted for those patches

(Section 2.6). For modeling, disturbance agents were aggregated into the seven-class "simplified" scheme noted in Table 3.

We used the Random Forest approach (Breiman, 2001) as implemented in the statistics package R to conduct modeling. Based on classification and regression trees, the Random Forest non-parametric design is attractive when the classes to be modeled are not normally distributed and/or disjunct in the predictor variable space. Using randomized subsets of both predictor variables and training sets at each node in the tree, the Random Forest approach generates many slightly different trees. For all of our runs, we set the number of trees to 500.

This Monte Carlo-type approach has disadvantages and advantages. Because the model prediction blends hundreds of trees, interpreting the importance of the predictor variables is more difficult than with a single tree. However, it is possible to estimate overall importance of any predictor variable across trees. Two benefits override this minor disadvantage. First, the randomization allows the use of shifting training and testing subsets of the data to provide robust internal estimates of error, known as "out-of-bag," or OOB, error. We set the training/testing proportions to 2:1 for all of our models. A second benefit to the randomization approach is that it produces a voting score for each prediction that reflects the number of different trees that chose a particular label for that patch. This provides a measure of uncertainty for each prediction and a means of determining where the training data space is poorly defined. If a given patch appears as the same change agent in most of the randomized trees, it suggests not only that the prediction is solid, but also that the patch lies in an area of training data space with little ambiguity. If a patch receives many different change agent labels across the randomized trees, it suggests that the definitions of the change agents overlap in that region of training data space. Fuzzy classification approaches can then be used to interpret a given outcome, such as examining both the first and second highest vote-getting classes.

2.9. Augmenting

We constructed a Random Forest model from our first set of 1016 interpreted patches and applied it to the entire dataset to make an initial prediction for all patches based on the highest vote-getter. From this initial prediction, we then identified an additional 182 patches in classes that were numerically underrepresented in the original sample. The strategy behind this selection rests on the assumption that the model will identify patches of the rare classes more efficiently than could be found through a manual search, even if some of those initial predictions are later determined to be incorrect. We then used the augmented training set to develop a new basic model and applied the new predictions to the entire dataset.

2.10. Post-modeling validation

Although OOB error is thought to be a reasonable assessment of error, our training dataset was not randomized, and may not represent the data space of the actual landscape well. Thus, we chose to validate our predictions using a completely independent dataset of 140 patches selected completely at random. These were interpreted in the same manner as the training data, and linked with the mapped predictions to create both standard error matrices (using the highest vote-getting class) and fuzzy error matrices (using either the first or second-highest vote-getting class).

3. Results

3.1. Change detection maps

Based on point-level comparison with human interpreters, the disturbance maps captured abrupt disturbance in the study area reasonably well, although non-detection of subtle disturbance events was relatively high (Table 4).

When aggregated to patches using the temporal-coherence and eight-neighbor rule (Fig. 6), 93,274 patches of disturbance were identified across the study area.

3.2. Interpretations

Interpretation was conducted at the granular level, and then simplified for subsequent modeling (Table 5). Of the 1198 patches identified for training, most were interpreted as forest management change processes, followed in number by urban and false change within agricultural settings. Within-urban transitions and stream-related disturbance were rare, even after attempts to augment the dataset.

3.3. Attribution maps

Change agent maps were constructed by assigning to each patch the top vote-getting agent from the Random Forest model. Visually, the spatial distribution of the modeled change agents follows expectations, with urbanization (both from forest and agricultural starting points) dominating the already-urbanized areas on the Puget Sound plain, and forest management dominating the hills and mountains fringing the basin (Fig. 7). False change from agricultural variability falls within the agricultural areas, and the few examples of natural change (predominantly fire) occur in protected forested regions.

Table 3
Attribution agent class definitions.

Agent class	Description	Simplified	Type
Agriculture to agriculture	Agricultural land use before and after apparent date; a false positive	Ag. to Ag.	Cyclic–Anthropogenic
Ag. to urban open & low intensity	Agriculture of any type converted to urban open space or rural housing		
Ag. to urban medium & high intensity	Agriculture of any type converted to higher density housing or to commercial/industrial use		
Forest to urban medium & high intensity	Forest of any type converted to urban open space or rural housing	Increasing urban	Directional–Anthropogenic
Forest to urban open & low intensity	Forest of any type converted to suburban housing or to commercial/industrial use		
Open to urban medium & high intensity	Open space converted to suburban or commercial/industrial use		
Clearcuts and thins	Any silvicultural treatment in forest	Forest management	Cyclic–Anthropogenic
Fire	Natural or prescribed burning of forest or shrubland		
Insect	Forest mortality likely caused by defoliators or bark beetles	Natural	
Landslides & windthrow	All naturally-caused earth movement; tree toppling caused by intense wind events		Cyclic–Natural
Stream flooding & channel migration	All riparian-related change in vegetation and channel	Stream	
Transition within urban medium & high	Intensification of urban use within an existing urban setting	Within-urban transition	Cyclic–Anthropogenic
Transition within urban open & low	Intensification of urban use within an existing urban setting		
No change	No apparent change in the land function; a false positive	no change	no change

Table 4
Agreement between point-based interpretation of disturbance using TimeSync and LandTrendr disturbance maps. Any pixel within a 3 × 3 pixel window with agreement is considered a match.

		TimeSync magnitude High	TimeSync magnitude Medium	TimeSync magnitude Low	LT commission non-disturbed
Matched segment	Fire	1	2	1	28
	Harvest	22	12	21	
	Other	2	0	2	
	Insect	0	1	0	
LT omission	Non-Disturbed	6	12	45	

3.4. Random Forest model reports

Out of bag error (OOB error) estimates from the Random Forest modeling suggested high overall accuracy across classes (overall accuracy 0.84), with some notable confusion (Table 6). Natural change processes (fire, landslides, insects, and windthrow) were often misplaced in the forest management class, and within-urban transitions were generally poorly modeled. Forest management was the class with the highest accuracy (0.97 producer's accuracy and 0.92 user's accuracy). In general, errors were relatively balanced between users' and producers' accuracies, suggesting that the model was parameterized appropriately for the information content of this dataset.

Although the absolute role of each predictor variable dataset cannot be uniquely identified in the Random Forest paradigm, the relative importance of predictor variables can be quantified by the penalty in predictive power when that variable is not present in a given tree's prediction. Variables with high importance impart a greater penalty with their absence, and this effect is quantified by the decrease in the "gini" coefficient (Breiman, 2001). For the attribution models used here, the ten most important variables included elevation metrics, patch metrics, and spectral metrics of change and recovery (Table 7).

3.5. Validation

With a small sample size, rare classes were unusual in the validation dataset (only 6 total observations across natural, stream, and within-urban transition classes). Thus, overall accuracies and accuracies of these very small classes should be treated with some caution.

Error rates using a standard accuracy assessment (considering only the top vote-getting label, Table 8) were generally lower than those suggested by the OOB error (Table 6). Focusing on the numerically more critical datasets, both forest management and increasing urbanization show inter-class confusion, and had user's and producer's

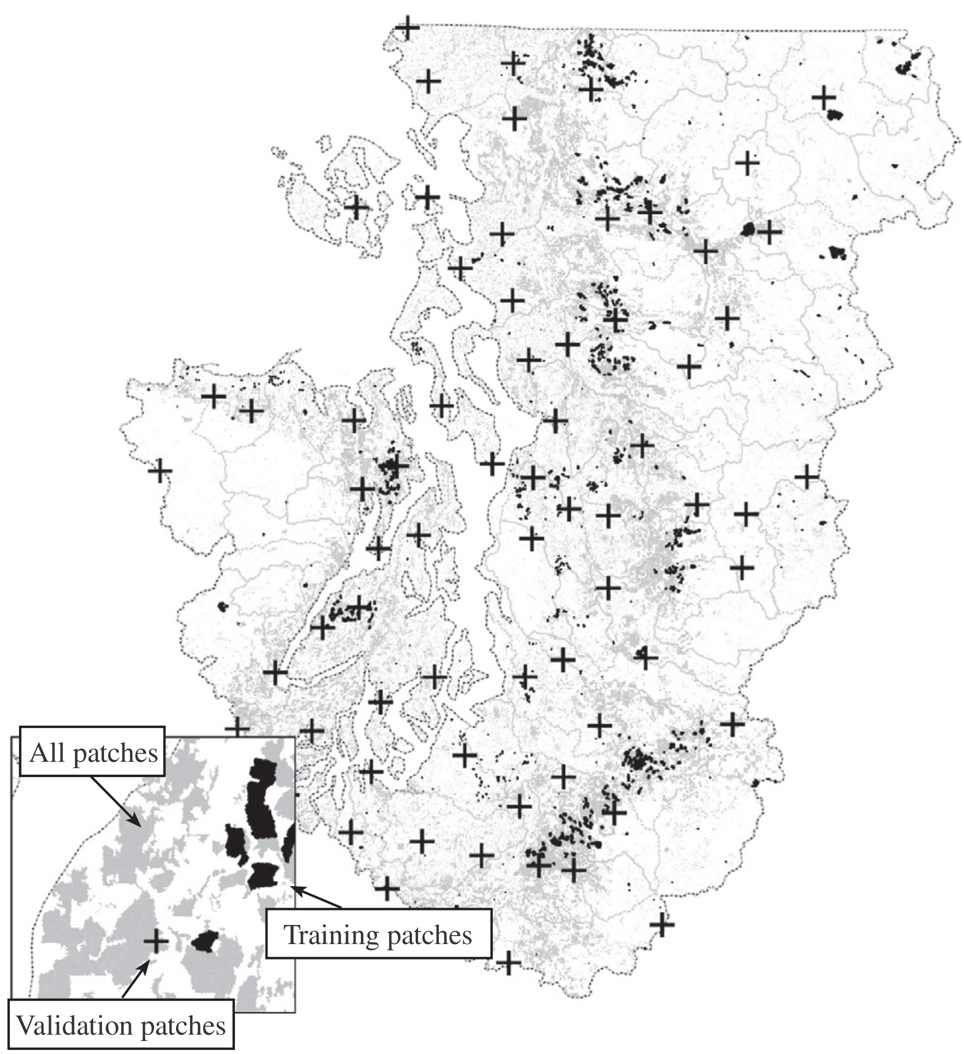

Fig. 6. Training (n = 1198) and testing (n = 140) patches shown against the full dataset of disturbances patches (n = 93,274). Training patches were chosen purposively to represent known change processes, while testing patches were chosen randomly.

Table 5
Summary of patches with manual labeling of change class.

Change class detailed	# Patches
Ag. to Ag.	101
Ag. to urban open & low intensity	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	692
Fire	41
Insect	12
Landslides & windthrow	26
Stream flooding & channel migration	16
Transition within urban medium & high	11
Transition within urban open & low	13
No change	48
Total	1198

accuracies ranging from 0.49 to 0.73. False change in agriculture had quite unbalanced accuracies, with producer's error high and user's accuracy low.

When fuzzy classification logic was used, however, error rates became much more aligned with the estimates from the OOB error tables, and were generally more balanced between user's and producer's accuracies (Table 9).

3.6. Summarizing by watershed and year

Salmon are often monitored at sites that integrate cumulative impacts of large watersheds, and thus any eventual comparisons between salmon populations and terrestrial disturbance require that disturbance agents be aggregated to a larger watershed. When aggregated to 5th-field watershed (Fig. 8), spatial distributions of change agent types follow expectations, with urbanization playing a greater role in the lowlands closer to the large metropolitan areas and forest management a greater role in foothill and mountainous forested areas outside of urban areas. Upper watersheds (fringing the boundary of the overall study area) contain significant proportions of protected land, a fact reflected in the lower rates of disturbance and the increasing dominance of natural processes (mostly fire). Because salmon populations vary considerably from year to year, the temporal resolution of the Landsat-based dataset is potentially useful. Change rates within watershed vary from year to year (Fig. 8 insets), and year-to-year variability persists even when disturbance agents are aggregated to the entire Puget Sound study area (Fig. 9). While these spatial and temporal patterns are not unexpected, they may provide the yearly variability necessary to test the impact of disturbance agents on yearly variability in fish populations.

4. Discussion

As satellite-based algorithms detect increasingly diverse change processes, the need to distinguish among the agents causing the change becomes critical. Not only do different change types have different impacts on natural and anthropogenic systems, they also provide insight

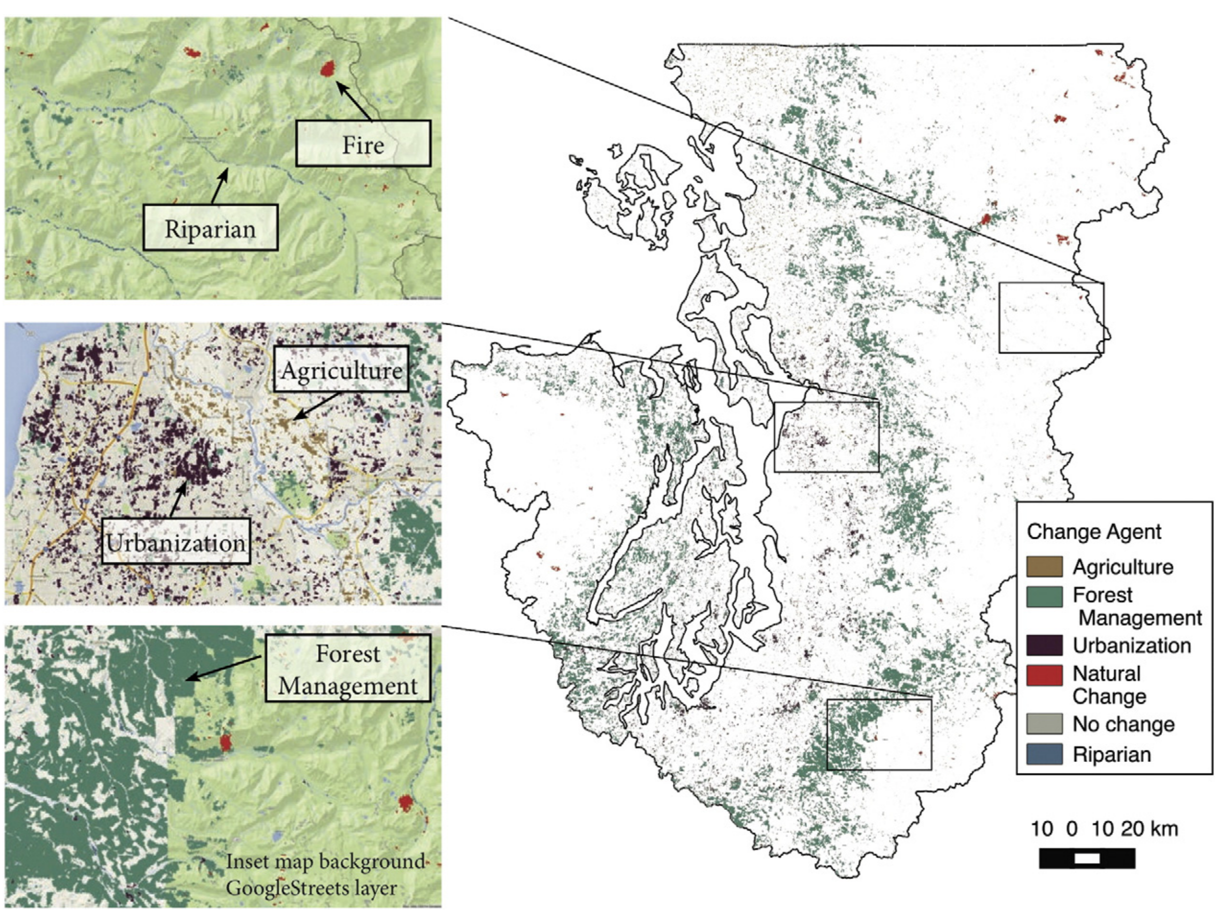

Fig. 7. Maps of disturbance attributed to change agent for the Puget Sound study area. Shown are the top vote-getting agent from Random Forest predictions on all 92,274 patches. Insets highlight examples of different agent types, illustrating the diversity of agents across the study area.

Table 6
Out-of-bag accuracy 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.

Reference \ Predicted	Ag. to Ag.	Increasing urban	Forest management	Natural	Stream	Within urban transition	No change	*Producer's accuracy*
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

Table 8
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.

Change agent determined by expert interpretation	Ag. to Ag.	Increasing urban	Forest management	Natural	Stream	Within urban transition	No change	*Total*	*Producer's accuracy*
Ag. to Ag.	11	0	0	0	0	0	0	11	1.00
Increasing urban	5	24	11	0	0	0	1	41	0.59
Forest management	3	19	37	0	1	0	3	63	0.59
Natural	0	0	1	0	0	0	0	1	0.00
Stream	1	1	0	0	0	0	0	2	0.00
Within urban	0	3	0	0	0	0	0	3	0.00
No change	2	2	2	0	0	0	11	17	0.65
Total	22	49	51	0	1	0	15		
User's accuracy	0.50	0.49	0.73	–	0.00	–	0.73		
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.

into the overall processes controlling landscape condition. Reaching this goal requires overcoming two central challenges. The first is related to scale mismatch: change detection in digital images occurs at the level of individual pixels, but change processes in the real world operate on areas larger or smaller than pixels, depending on the process. The second is related to separability: change agents are defined by natural and anthropogenic factors that have no connection with the spectral space on which the change is initially detected. Different change agents may have nearly identical spectral signatures of change at the pixel and even the patch level, and must be distinguished by factors completely outside the realm of remote sensing. Thus, the process of ascribing change necessarily moves away from a strictly remote sensing exercise toward one of statistical modeling and incorporation of other spatial inputs. Here, we have described one such approach applied to a time-series based change detection technique.

4.1. Conceptual considerations

An appropriate underlying pixel-based change detection approach is essential. A Landsat-based approach has the spatial resolution to capture many human-caused change agents, and the temporal reach to place changes in context. The LandTrendr method for time-series segmentation allows description of the disturbance in terms of its starting condition, the spectral character of the disturbance process, and the post-disturbance recovery processes, all of which are useful to distinguish among different change processes (Table 7).

Table 7
Contribution of input variables to the final Random Forest attribution model. Only the top variables are shown.

Variable	Mean decrease 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 brightness

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

These pixel level data are only the foundation onto which many other sources of information must be placed. Statistics describing the shape of a patch are fundamental in distinguishing between anthropogenic processes and natural processes. Statistics of landscape position and slope can be critical as well. Other variables that could provide landscape context are those related to factors not necessarily captured by physiographic information alone. For anthropogenic processes, land ownership might suggest policy or economic constraints that narrow the range of possible changes. For natural processes, summary ecological variables, such as ecoregion type, might be useful to narrow the biological agents or processes likely to occur at a site. Finally, proximity variables, such as "distance to stream," are also important both for processes that only occur in certain areas of the landscape. This is relevant both for natural processes (distance to stream helping predict where flood-related damage could occur) and anthropogenic processes (distance to road helping predict where development might occur).

Extra care should be taken when choosing variables for longer term, repeat-observation monitoring programs. Consistency over time demands that the same set of predictor variables result in the same label over time, requiring that all variables be defined to avoid a time-dependent bias. Proximity variables should only be chosen if the functional relationship is unlikely to change over time, or if the proximity variable itself can be updated in a timely fashion to match the pace of the change attribution. For example, if "distance to road" was important for predicting development, then the core spatial data on road occurrence would need to be updated at the same frequency as the mapping exercise. Similarly, landscape descriptors such as land ownership or ecozone type should either be updated as anthropogenic or climate change factors alter them.

Because the change attribution process can only describe the processes that are detected, it cannot provide insight into false negative error rates. This can lead to a slightly different change detection strategy than might be normally sought when solely conducting pixel-level change detection. Rather than attempting to balance false positive and negatives, an approach that minimizes false negatives – even at the expense of rising commission error – would be favored if subsequent patch-based change attribution can clean up false positives. Indeed,

Table 9
Fuzzy classification error table, where a match is credited if either of the top two votes match those of the interpreter.

Change agent determined by expert interpretation	Ag. to Ag.	Increasing urban	Forest management	Natural	Stream	Within urban	No change	*Total*	*Producer's accuracy*
Ag. to Ag.	11	0	0	0	0	0	0	11	1.00
Increasing urban	3	33	4	0	0	0	1	41	0.80
Forest management	3	9	48	0	1	0	2	63	0.76
Natural	0	0	1	0	0	0	0	1	0.00
Stream	1	1	0	0	0	0	0	2	0.00
Within urban	0	3	0	0	0	0	0	3	0.00
No change	2	2	2	0	0	0	11	17	0.65
Total	20	48	55	0	1	0	14		
User's accuracy	0.55	0.69	0.87	–	0.00	–	0.79		
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.

some false-positive error sources may better be detected using patch-based information such as shape or context.

Rules for delineation of patches are critical, and should be designed with respect to the change processes of interest. Here, the simple temporal congruence rule used to define patches is appropriate for most of the abrupt change processes affecting salmonid habitat in the Puget Sound, but may not be appropriate for other processes that either evolve slowly across a landscape, or are spatially discontinuous. We anticipate that requiring different rules will be necessary to define patches in salmonid habitat in drier ecosystems east of the Cascade Mountains in the Pacific Northwest.

Another important decision rests with the statistical approach used to model the attribution agents. At its core, the statistical modeling is a classification exercise, and as such could be carried out with any of the classification algorithms familiar to a remote sensing audience. Yet two specific characteristics of the change attribution situation deserve special consideration. First, the data space in which classification occurs is unlikely to be well-behaved, with mixtures of categorical and continuous variables of widely diverse ranges and sensitivities. Classification methods that assume normal distributions are likely inappropriate. Second, change agent definitions are defined by humans with little regard to the data space or the predictor variables available, which will often lead to fuzzy descriptors of change and poorly defined boundaries in the data space. Methods that ascribe too much certainty to the classification are unlikely to perform as well as those that allow fuzzy classification.

The ambiguity of change agent definition is also one of the factors affecting human interpretation of the change agent. Conceptually clean definitions often break down in the idiosyncratic reality of landscapes, particularly when multiple agents appear to be co-occurring, or when judging the intent of human actors. These issues are exacerbated when ancillary data on which to make those judgments are sparse, such as for historical changes that pre-date the available archive of high resolution airphoto data.

4.2. Assessing error

The LandTrendr algorithm appeared to capture the range of disturbance processes occurring across land cover types in the Puget Sound (Table 4). When comparing with human-based interpretation of time-

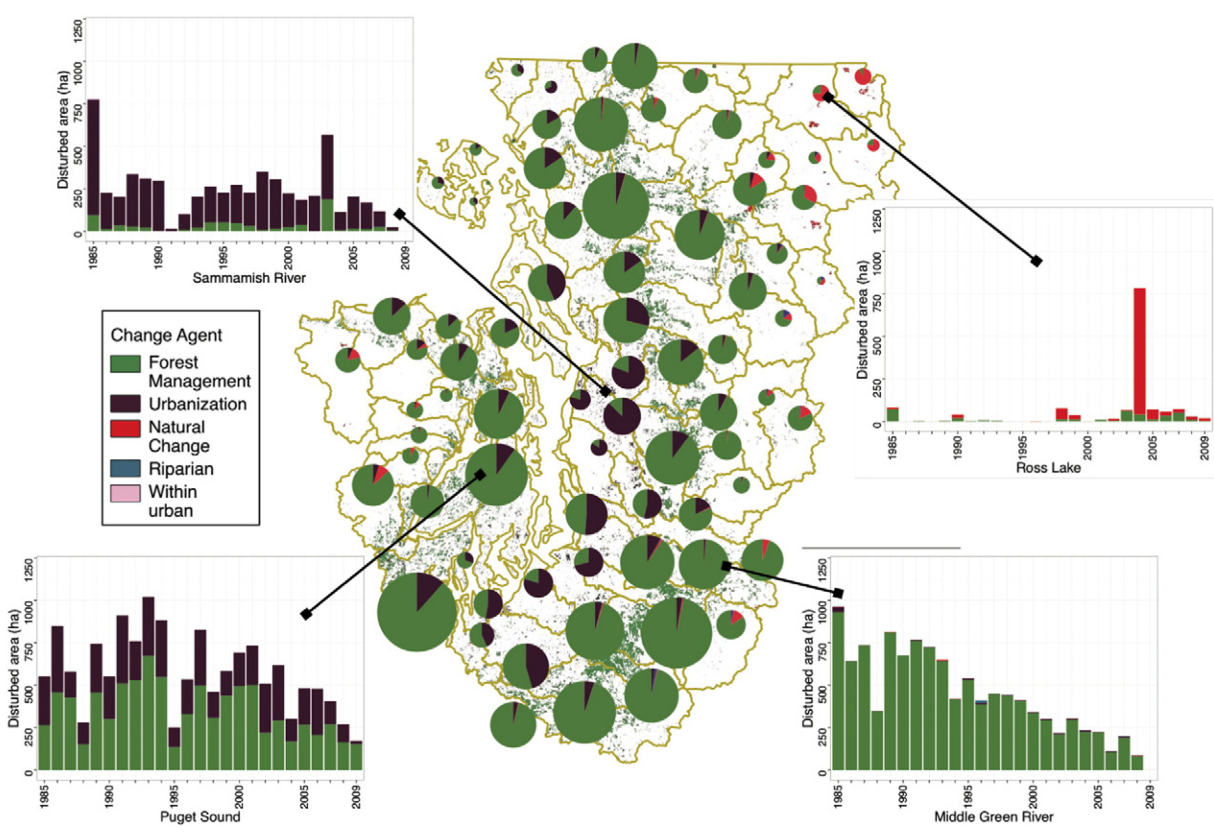

Fig. 8. Change agents aggregated by fifth-field watershed (delineated in gold) over time. Pie-chart size scaled to the cumulative proportion of each watershed affected by the disturbance. Color codes on bar charts and pie charts follow the same legend. False change categories “Agriculture” and “No Change” are not included in tallies. Note the predominance of urbanization in the central Puget Sound watersheds, of forest management in middle watersheds, and the relative lack of overall disturbance in upper watersheds (largely in protected status).

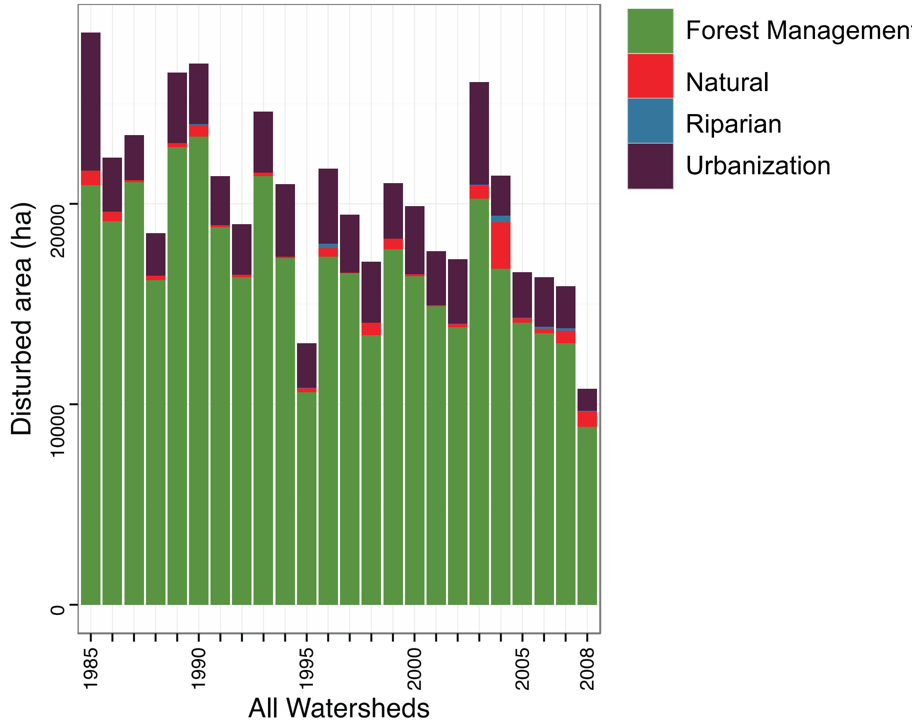

Fig. 9. Change agents aggregated over the entire Puget Sound over time. False change categories "Agriculture" and "No Change" are not included in tallies, and "Within Urban" transition are too rare to be visible. Most disturbances are associated with forest management. Disturbance rates by type vary considerably from year to year, potentially providing useful year-over-year contrast in tests of impact on salmon.

series information using the TimeSync tool (Cohen et al., 2010), success at detecting high and medium magnitude was reasonable, although very subtle processes were detected only at a rate of approximately 35%. This is consistent with our finding in solely forested systems (Kennedy et al., 2012), and as the detection algorithm improves, we anticipate greater success detecting the subtle change processes occurring very near the noise-value threshold.

Models of change agent corroborate the notion that attribution is best achieved when non-spectral characteristics of the change are taken into account (Table 5). The most important factor is a strong measure of landscape position (elevation). The next two most important predictors are the range of elevation within a patch and a measure of patch shape — both of which can only be defined when the change process is modeled as a patch. The spectral change of the disturbance only arrives as the fourth-most-important variable. Thereafter, a suite of predictor variables have a similar predictive power. Notably, several measures of post-disturbance recovery appear here, illustrating the importance of the temporal context in attribution of change in the Puget Sound. It is important to note the variables predicting change are highly particular to the system being studied. Most development occurs on the Puget Sound plain, where most forest management occurs on slopes in the surrounding mountains.

Despite these challenges, the Random Forest model of change processes in the Puget Sound is reasonably accurate. Out-of-bag (OOB) accuracy rates (Table 4) suggest that both producers and users of the mapped products would experience accuracies greater than 75% for many important change agents. A key exception is the "natural" category of change, which suffers from being a broad conceptual definition, from occurring primarily on the same portions of the landscape as the dominant forest management class, and from having relatively few observations. Some confusion in other classes may also be definitional. For example, when mis-predicted, the "no-change" observations are most often placed in the "increasing urban" class, but for some users this distinction in definition may not be relevant.

Complementing the estimates of OOB error from the model itself are measurements of error from a completely separate testing dataset. Using standard accuracy assessment approaches, accuracies were lower than those suggested by the OOB error approach, and generally less balanced between user's and producer's accuracies. Because error rates derived from a small validation dataset may be strongly affected by the stochastic nature of the classification method, these results should be interpreted with some caution. The fuzzy classification approach likely provides more insight into whether the model is generally representing the data space appropriately, even if the highest vote-getter is confused. Using this approach, accuracies of the dominant classes were much more aligned with the estimates from the OOB error tables, and were generally more balanced between user's and producer's accuracies. The model appears to be approximately correct in structuring the data space, but is unable to correctly place observations lying at the margins of classes.

The fuzzy classification information may be useful for iteratively improving the model. Predictions from the initial model run could be used to identify patches whose highest and second-highest voting scores are close to each other, and from this focused dataset a new group of training samples would be acquired. By focusing on the confused patches, limited resources for interpretation would be devoted to clarifying the margins of class boundaries rather than repeating observations in well-understood portions of the data space. The independent dataset could be retained to independently test each iteration of this training/prediction/augmentation cycle.

It is particularly notable that reasonable maps can be generated using a well-chosen training dataset of just over 1%, even when modeling diverse disturbance agents along a range of land cover types. When combined with the iterative model just described, it seems plausible that change attribution models could be leveraged quickly into new areas and incrementally improved as more users contribute corrective information.

4.3. Utility

The spatial distribution of change agents follows general expectations both at the local, event-scale (insets in Fig. 7) and at the watershed scale across the Puget Sound study area (Fig. 8). By corroborating patterns that make sense to managers and researchers, these maps increase confidence that change agent quantification can be achieved. Because it quantifies these processes at both local and regional scales, it will be useful for testing different hypotheses of the potential impacts on salmon (or lack thereof) of disturbance in relation to stream proximity and disturbance type. The temporal information can also be used to test lagged disturbance effects when evaluated at the watershed scale.

These results also suggest that the utility of the change attribution methods can be extended to other landscapes and change processes. Indeed, the core strategies applied at the Puget Sound scale here have already begun operational use at the more local scale of individual national parks in the region (Antonova, Copass, & Clary, 2013, 2014). It is also promising that the LandTrendr-based method had some success in non-forest systems, further bolstering the notion that time-series based approaches to understanding change can be applied generally (Fraser et al., 2011).

5. Conclusion

A key motivation behind this effort was to assess whether a change attribution strategy could provide to scientists and resources managers information on change processes at both local and watershed scales. The change attribution strategy described here appears to meet the need. The approach recognizes that change agents operate at scales beyond the pixel level, that spectral information alone can be ambiguous among agents, and that statistical approaches must leverage human interpretations and temporal information to predict agents of change. Notably, the approach appears to work across land cover types and a diversity of land change agents. Although reasonably accurate already, further work can be done to improve the overall efficacy of the approach and to extend the approach to other landscapes.

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