Final Report on High Resolution Change Detection Project

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Executive Summary

The High Resolution Change Detection project was designed to explore the feasibility of using high-resolution aerial imagery (1 m resolution National Agriculture Inventory Program data) to detect changes in land-cover from 2006 to 2009 in selected WRIAs of the Puget Sound region. Early in the project we defined land cover change as the transition from forest landcover to a human dominated landcover, i.e., developed areas. High resolution imagery is preferable to medium resolution imagery (30m Landsat pixels) for mapping change because important areas such as riparian vegetation and marine shorelines cannot be accurately delineated at the resolution of 30-m pixels. However, high resolution imagery is difficult to work with in an automated manner due to the volume of information it contains (large file size per unit ground area), the effect of solar position on illumination (shadows) and high local variability of imagery within single land cover classes (e.g., forest of different age can look very different in aerial photography). With the help of relatively new software and computing power, we used a combination of supervised classification to isolate shadows and areas devoid of vegetation, image segmentation to create homogenous regions for statistical analysis, and high-efficiency methods for analyst review of sampled change locations.

The "high-efficiency methods for analyst review" were crucial to the success of this project as over 30,000 individual polygons were reviewed in the accuracy assessment portion of the study. Because change occurs at very low rates on an annual basis, finding change locations against an enormous backdrop of nonchanging data is an arduous task. For example, WRIA 7 (the Snohomish River Basin), which is 480,000 ha in size, is represented by 4.8 billion pixels and 514,293 polygons or cover polygons after analysis. The initial predictive model that we developed labeled only 5,121 polygons as having changed between 2006 and 2009. That is, the model successfully separated the initial 514,293 polygons into the 1% predicted as change and 99% as non-change. To improve accuracy we developed high-efficiency methods for analyst review that automates the individual review of all computer indentified change polygons (5,121 for Snohomish WRIA). That is, all polygons predicted as change are qued up and individually displayed for both time periods, which allows the analyst to determine if the change is real. Of the 5121 predicted change polygons, the review process verified that 3165 polygons had actually changed and 1956 did not change. Of the 3,165 change locations mapped between 2006 and 2009, 2,670 (84%) were smaller than 1 ha and thus undetectable by coarser imagery (Landsat). By reviewing all predicted change polygons, we effectively eliminated commission error such that every mapped polygon has been verified as change, i.e., 50% of the vegetation in the polygon (estimated visually) was changed into a developed land cover class. Errors of omission were assessed by randomly selecting a sample of polygons predicted as non-change and subjecting those to analyst review. In WRIA 7 we reviewed 3,834 polygons and found 29 (0.7% of polygons) that actually changed. By expanding the percentage of the

changed area that the model missed to the entire WRIA, we estimated that 4,848 acres of change took place beyond the 10,678 acres we mapped. Of the mapped change areas, 2.9 acres were within 60.9 m (200-ft) of the Washington Department of Ecology's (DOE) marine shoreline delineation and 73 acres were within 100 m of a WDFW documented fish-bearing streams.

The final product shows that 100% of the areas mapped as change exhibited real change over the time period examined here. Of the areas not mapped as change, we estimate that 1 out of every 246 acres mapped as no-change was actually change. These results were consistent over the four WRIAs that we analyzed in this project.

Grant background and introduction

In December 2009, the Salmon Recovery Funding Board (SRFB) awarded WDFW a grant in the amount of $115,000 to evaluate the feasibility of using high resolution aerial photography to track land use change in four WRIAs in the Puget Sound region. In particular, the SRFB was interested in changes to riparian and nearshore areas which are known to affect salmon habitat quality. As of 2009 the primary data source for tracking land-use/land-cover change was the NOAA Coastal Change and Analysis Program's change layer derived from National Land-Cover Data (NLCD) analysis of Landsat remote sensing data. Landsat data is recorded at a resolution of 30 m pixel. This resolution is too coarse for change detection with regard to riparian corridors or immediate upland vegetation at the marine shoreline In 2009, high resolution aerial imagery became available for two recent time-periods, 2006 and 2009 for the entire state of Washington. These data have a resolution of 1 m and are expected to be generated every 3 or 4 years. High resolution data of this sort is difficult to classify using automated techniques due to its size (WRIA sized files are many gigabytes of data) and the high level of variability introduced by illumination (e.g., sun angle, topography, atmospheric scattering) and complex cover types (e.g., single large tree represented by many pixels). Due to these complications WDFW proposed a simplification of output by just mapping major changes in vegetation such as forest-clearing and conversion of relatively mature shrub/grasslands to bare ground or developed areas. This type of change is a significant predictor for decline of salmon utilization in streams (Bilby and Mollot 2008) and these transitions are relatively easier to identify with high certainty than transitions between different vegetation classes or different levels of urbanization. Moreover, vegetation clearing is typically an instantaneous change which can be captured over short time periods.

Project Area

We completed 3 and nearly finished a fourth (WRIA 8) of the 19 WRIAs in Puget Sound as part of this project including the Lower Skagit (WRIA 3), the Snohomish (WRIA 7), the Kitsap peninsula (WRIA 15) and the Duwamish-Green (WRIA 8). Each of these areas posed different challenges for automating change detection. The Lower Skagit had a large percentage of agricultural lands, the Snohomish had a relatively high proportion of snow in one of the two time periods, Kitsap has by far the most shoreline of any WRIA and the Duwamish-Green which contains the greater Seattle metropolitan area has a significantly larger portion of urban lands than the other WRIAs .

Methods

This project was split into five major steps.

1. Image preparation

2. Spectral vegetation and shadow modeling
3. Image segmentation
4. Training and statistical modeling
5. Analyst review and accuracy assessment

Image Preparation

The raw imagery was acquired from the 2006 and 2009 National Agriculture Inventory Program (NAIP). NAIP is a federal program with optional state support for flying specific areas and utilizing different photographic capture parameters. The data is delivered in tiles suitable for streaming over broadband lines. These tiles were in 64 km^2 and 100 km^2 pieces. To create WRIA wide images, we pieced the individual tiles together using Erdas Imagine 10.0. The 2006 data was provided with a pixel size of 0.5 m. The 2009 data was provided at 1.0 m. We resampled the 2006 data up to one meter using the cubic convolution setting in Imagine. For example the Skagit began with 304 tiles from 2006 and 194 tiles from 2009. The mosaic of three-band image from 2009 resulted in about a 14 gb image. The 2009 image initially had four bands (red, green, blue, near-infra red [NIR]). The RGB bands were extracted to be paired with the 2006 imagery.

In order to assess spectral differences (potential change) between two image dates, the range of brightness values can be adjusted using a technique called a Histogram match so that pixels depicting similar conditions have more similar values. Histogram matching expands or compresses the range of values in one image to more closely match a second image's range. A review of the band-wise histograms revealed the 2006 imagery was more evenly distributed. For this reason the 2009 image was histogram matched to the 2006 histogram to utilize the greatest range of spectral information. A simple band-wise difference image was created by subtracting the 2006 RGB bands from the 2009 RGB bands. The 2009 NIR band was used only for vegetation modeling (see below) since the 2006 did not contain an NIR band.

Spectral vegetation and shadow modeling

The NIR band is regarded as highly sensitive to vegetation density and is key to calculating all major vegetation indices [e.g., Normalized Difference Vegetation Index (NDVI)] (Lillesand, Kiefer et al. 2004). We used the NIR and green bands to classify vegetation density classes using ERDAS' [feature space classification] tool. While NDVI uses the NIR and red bands, we found the NIR and green bands to have greater separation in plots of spectral density. We identified three spectral regions that appeared to separate areas observed as non-vegetation, grass/field and mature shrub/forest. Of these the non-vegetation class was the most important as it was used in both the segmentation procedure (described below) and the change modeling. For the segmentation procedure we used a simple non-veg/veg mask. For modeling we used polygon proportions in the three different vegetation levels, high medium and low, which approximated land cover with trees, grass or no-vegetation. We did this instead of using simple NDVI because it allowed us to classify images based on two dimensions instead of a single index derived from the two bands.

One of the oft-cited difficulties in automatically processing high-resolution imagery is the presence of shadows. Shadows were a source of confusion in many places where the sun angle was in opposing directions between the two image dates. Tree crowns appeared either dark or light depending on illumination angle and ground shadows often lay in opposite directions. For the purpose of automatically detecting change, different sun angles presents a serious obstacle as areas can be speckled with light and dark patches between image dates due solely to angle of the sun.

However, shadows were also a source of information. The presence of shadows is an indicator of height variation and thus a useful way to separate homogenous green forest stands from homogenous green agricultural fields. Due to the inter-annual cycle of crop production, agricultural lands are constantly changing over the course of days or weeks depending on growth, harvest and moisture. Agricultural lands provide a particularly difficult problem for spectral-based change detection.

Areas in shadow also present a challenge for the segmentation procedure (described below) because the information content in the shadow area is much lower than in illuminated areas. Very finely detailed segmentation will generally create segments out of shadowy areas or merge intermittent shadows into segments providing contaminated summary spectral values. Even with 1-m resolution imagery a shadow edge can be smoothed enough to enhance the appearance of a light to dark gradient from non-shadow to shadow as opposed to a sharp distinct boundary. This smoothing can make the spectral values at proximate pixels quite similar across shadow boundaries and result in a general blurring of segment boundaries.

To help minimize the shadow effect we created shadow masks from the blue and green bands using a similar procedure as in the NIR vegetation density mapping. We delineated an area in blue-green feature space using ERDAS Imagine that corresponded with the darkest areas of the image, the shadows. This approach created a sharp line in the previously mentioned gradient darkening. This line tended to over- or under-map shadows depending on location because the illumination across whole WRIAs was not uniform. The difference was generally expressed in the amount of shadow so that a heavily shadowed forest might appear to be a large mix of shadow and non-shadow where a brightly lit open oak might have a considerably smaller mapped shadow area due to an overall brighter region. Shadow masks were created for both the 2006 and 2009 imagery.

Image Segmentation

When analyzing 1m aerial imagery, individual pixels often represent only a portion of an individual landscape feature such as a tree or a house. A tree may be covered by hundreds of pixels that appear to the human eye as a feature but, to the computer are simply an area of similarly colored squares (pixels). This contrasts strongly with Landsat pixels which tend to average over multiple features such as trees or houses because of the resolution of the pixel is large relative to the mapped feature. If an ideal scale of analysis would detect a single suburban lot clearing, then the data resolution must be of a size such that an average single home lot of 1/4 acre (U.S. Census Bureau 2011) can be recognized and located. With Landsat, a single pixel is almost ¼ acre. With 1 m imagery that same area is represented by 900 pixels. While a single Landsat pixel may unambiguously represent a single ¼ acre change, to do so, that pixel must be precisely located over the exact area of change (i.e., edge match). Thus, while the size of a Landsat pixel is theoretically acceptable for the minimum area criteria, Landsat does not adjust for placement or lot shape. Therefore to reliably map change at small scales, smaller pixels must be aggregated into statistically homogenous regions, representative of different landscape features or land-cover areas through the process of image segmentation.

We used Definiens (Trimble) eCognition and eCognition server to perform the segmentation. The segmentation step was completed using 6 spectral bands and two thematic layers, shadows and no-vegetation. Areas were separated into 3 x 3 km tiles and segmented individually. Segment size in eCognition is controlled by a variance parameter referring to the spectral variance within a segment. Larger variance parameters lead to larger segments. Since variance controls areal extent, areas of highly homogenous land cover (e.g. large forest tracts) will generate larger segments than areas of high variability (e.g.. suburban residential housing). Segment creation can occur hierarchically either starting with very small segments and aggregating them or starting with large segments and recursively splitting them. We used the latter approach as it tends to locate big landscape features allowing refinement at smaller scales. In our initial large segmentation we used the three visible band layers from the 2009 NAIP imagery and the three difference layers calculated between the 2006 and 2009 NAIP imagery.

Due to the almost infinite way segmentation parameters can be set, resulting segments can differ markedly based on segmentation methods. Our goal with segmentation was to separate areas of significant vegetative change between the two time periods as individual segments.

We used two thematic layers to constrain the segmentation to some specific boundaries. The thematic layers were the 2009 shadow layer and the 2009 low vegetation layer as described in the previous section. The shapes of the shadow features tended to be very complex in areas with mature vegetation (meandering around tree crowns with different heights), while being relatively simple in urban areas (straight lines next to buildings) and mostly absent in agricultural areas (1 m resolution imagery smoothes over shadows between adjacent row crops). This produced shadow segments with markedly different shape characteristics, a feature we expected would inform the statistical change model. Also by separating the shadow regions, the remaining pixels tended to have more homogenous tones. We ran models using a combination of 2006 and 2009 shadows but found the additional 2006 shadows forced intersections in the segmentation. In many cases the additional intersection split up change areas making them harder to detect.

Training and Statistical Modeling

Change prediction was done by classifying a sample of image polygons as to the type of change or lack of change that was visible by observing image triplets (2006 image, 2009 image and their difference image). We then used polygon attributes to build a predictive model to separate changed from non-changed polygons. The training sample was stratified into two populations based on the values of the green band difference. The split value varied between study areas depending upon the histogram of change values. For example in WRIA 7 strata were split into polygons with dGreen values above 150 and below. Since landscape change is a relatively rare event the use of stratification ensured a representative sample was available for model building. We used the Random Forest recursive modeling algorithm (R package) to build the model (Breiman 1984). Random Forests is an extension of classification and regression trees (CART) that is relatively resistant to collinear variables and sampling artifacts. Random Forests builds a large number of CART models each with a subset of the predictive data and the model data. The prediction for each data point is the class with the majority of predictions from the multiple trees. System memory is an issue with building large trees. We used 1500-3000 trees (automated individual model runs) depending on the size of each data set.

The attributes in the prediction set came from several sources. The segmentation software (eCognition 8) allows for the calculation of many shape and spectral parameters for each polygon in addition to contextual variables based on landscape position or values from surrounding polygons. We retained ~25 variables from eCognition (Table 7). We also sampled the 2006 and 2009 shadow masks and the 2009 NIR vegetation density layer with each polygon. This provided us with a proportion shadow and proportion high/low/no veg for each polygon. In WRIA 7 we also used elevation to help account for snow differences between the images.

Analyst Review and Accuracy Assessment

The predictive model results in two populations of classified polygons, those predicted to have changed and those that have not changed. The relative proportions of these two populations are highly unequal with changed polygons generally making up less than 2%. Prediction error can be described as "errors of commission", when a polygon is incorrectly predicted to be change, and "errors of omission" when a changed polygon has been labeled no-change. Since the errors of commission are potentially much smaller and directly reflected in the final change product, we wanted to review all polygons predicted as change. Reviewing polygons within a GIS, especially with very large image files, is a very time consuming process. We developed a tool to sub-sample the imagery based on a polygon layer that facilitates rapid viewing of the clipped images in a separate program. Using this tool we viewed all predicted change polygons and verified which were actually change. This effectively eliminates model errors of commission. Omission error was estimated through sampling. We sampled approximately 1-3% of the remaining non-change polygons for changes that were not detected by the statistical model. By summing the acres mapped and expanding the omission rate over the remaining acreage we derived an overall estimate of changed acreage.

Results

The primary results for this project are the change polygons themselves. Change mapping has been completed for WRIAs 3, 7, 8 and 15 with post-analysis summaries pending for WRIA 8. The purpose of the change analysis was to provide the area and location of change as defined above and to estimate non-mapped change (omission error) through statistical sampling of the remaining area. The estimate of additional non-mapped change is a by-product of our rigorous accuracy assessment method. The mapped change locations provide information on the relative size of changes and their location. The applications for these results involve analyses geared towards assessing their proximity or intersection with other important locations such as riparian corridors, wetlands, urban growth areas and marine shorelines.

In the following section we summarize the primary results, number and area of change polygons and non-mapped change estimates. Following the summary we will show four brief examples of analyses showing some applications for the high-resolution change polygons.

In Table 1 the total change locations and area are provided for each WRIA. The change polygons tend to represent individual change events which lets us calculate representative statistics on the extent and frequency of change events. Raster change products like CCAP characterize each individual pixel as to whether or not it is change so deriving change event distributions is difficult. The mean change size in Table 1 is for all change polygons. In most case a few large forestry tracts significantly skew the mean so we also show the median value.

Table 1: Overall segmentation summaries with general WRIA characteristics

Total Change Summaries	WRIA 3	WRIA 7	WRIA 15
Total Change Locations (# of polygons)	1237	3164	1740
Total Change Area (acres)	5750	10032	5420
Average Area per polygon (acres)	4.65	3.17	3.12
Median Area per polygon (acres)	0.93	0.70	0.69

Change with evidence of permanent urbanization

The subset of those change locations with evidence that those changes were relatively permanent (presence of roads, housing, urban adjacency), are shown in Table 2. In the lower Skagit (WRIA 3) and Snohomish (WRIA 7) about half of the change locations had signs of development. In Kitsap (WRIA 15) 82% of the change locations were associated with urbanization. The average change areas were largely influenced by large forestry tracts but the medians in all three were less than 1 acre.

Table 2: Change locations showing with visible indications of permanent conversion

Change to Development Summaries	WRIA 3	WRIA 7	WRIA 15
Permanent Change Locations (# of polygons)	658	1534	1433
Permanent Change Area (acres)	1182	2307	1449
Annual Rate of Change (% of total WRIA area)	0.082%	0.057%	0.105%

Each predicted change location from the statistical model was individually reviewed. Change locations that had roads or buildings or were adjacent to urban areas were assumed to be permanent change as opposed to rotational forestry, natural disturbances or other resource uses. These changes included clearings for new housing-tracts and commercial development as well as numerous locations of single dwelling or partial lot clearings.

The non-mapped change estimates (Table 3) are derived from the omission portion of the accuracy assessment. The area of non-mapped change in the omission analysis was calculated by multiplying the estimates of proportion of land that changed not detected in our model by the area of the WRIA. Change detection is usually done in one of two ways, mapping change or estimating change through sampling. The CCAP change detection product is an example of mapped change where each pixel is assessed and error rates are reported as commission and omission errors. In other studies change is assessed through sampling, often performed with high resolution images as we use here. Change is reported as regional rates of change with error expressed as a confidence bound on the rates. Here we present a hybrid approach that maps as much change as possible, estimates what likely change remains and provide estimates of detection errors. Effectively we eliminate the commission error portion of the mapping methods and also provide regional rates as with the sampling methods.

Table 3: Estimates of non-mapped change derived from sampling. Unmapped change is estimated by sampling polygons predicted by the statistical model as non-change. The acreage reported here is in addition to the mapped change, thus the estimated total change is the sum of the mapped change and estimated omission error. The proportion of estimated total change non-mapped is the percentage of the total change estimate consisting of non-mapped areas.

Estimated Non-mapped Change	**WRIA 3**	**WRIA 7**	**WRIA 15**
Sample size of non-change polygons	3017	3834	4833
Omission errors in sample (polygons)	31	29	70
Total sampled non-change area (acres)	12419	10678	8864
Omission error polygon’s area (acres)	55	36	60
Omission error area / Total sampled area	0.44%	0.34%	0.68%
Non-mapped change estimate (acres)	1599	4848	2871
Total change estimate mapped plus non-mapped (acres)	7349	14880	8292
Proportion of estimated total change non-mapped	22%	33%	35%

Example 1: Shoreline and riparian change

Among the most important lands in Puget Sound are marine shorelines and riparian corridors. We used the DOE Shorezone and WDFW fish distribution layers to locate these important lands in relation to change events. We used a 200 ft (61 m) buffer for shorelines because the Shorezone Management Act specifically notes the 200 ft area upslope from the Ordinary High Water Mark as being the primary area of concern. We used a 100 m buffer for all streams. While stream buffers are wider what most Critical Area Ordinances call for, different buffers widths can be readily analyzed for specific applications. In Table 4, the number of change polygons intersecting one of the buffers is reported along with the "clipped" area that lies within the buffered boundary. The stream analysis used WDFW's fish distribution layer which is a map of stream reaches with observed fish occurrences. The changes along these streams were split into three categories: forestry, permanent and natural. The natural category was added to reflect riparian changes that we interpreted from the photographs to be the result of stream course changes. The cause of the events causing the stream course changes may reflect upstream disturbances but is only noted to differentiate those types of change from change resulting from clearing for development or from forest harvest.

Table 4: Marine shoreline and riparian analysis. We created buffers around linear water features: 61 m around marine shorelines (DOE shorezone data) and 100 m around WDFW documented fish bearing streams. The number of intersecting change areas is listed below along with the total area of the changes and the area within the buffers. The total length of shoreline and documented fish-bearing stream is included for reference.

	WRIA 3	WRIA 7	WRIA 15
MARINE SHORELINE ANALYSIS			
Total length of shoreline in WRIA (km)	275	125	838
Number of change polygons intersecting shoreline	10	11	43
Change in polygons intersecting shoreline area (within 61 m) 200 ft shore Polygons (acres)	34	12	35
Change within 200 ft shore (acres)	3.2	2.9	7
RIPARIAN ANALYSIS			
Total length of Fish Bearing Streams in WRIA (km)	467	2022	909
Development change polygons			
Number of development change polygons intersecting stream buffers	57	69	128
Stream, Buffer Polygons (acres total)	268	191	1333
Stream Buffer Polygons (acres clipped)	67.5	73	188
Non-permanent change polygons			
Number of non-permanent change polygons intersecting stream buffers	30	33	19
Buffer Polygons (acres total)	336	1379	567
Buffer Polygons (acres clipped)	53	163	114
Natural disturbance change polygons			
Number of natural change polygons intersecting stream buffers	22	166	5
100-m fishdist Buffer Polygons (acres total)	83.5	199	2.3

Example 2: Change across tax parcel designations

The change polygons provide locations where land-cover was altered. Among many possible questions is the issue of which land-use designation were associated with land-cover changes. We used the current Puget Sound wide parcel database obtained from the DOE in April 2011to link land-use designations to the areas of change. We summed over the change areas using tax roll classes from the changed parcels. In each WRIA the five most common tax roll classes were determined for all WRIAs and reported here. We hypothesize that change in two of the most common tax classes, Undeveloped Land and Single-Family homes, would usually be permanent. The percentage development in Undeveloped and Single-Family units is shown as a check on the designation of permanent vs. non-permanent change. Areas exceeding 100% may indicate more land was permanently changed than was labeled so in our analysis. Areas with less than 100% may indicate that we overestimated the amount of permanent change.

Table 5: Tax parcel designation analysis. We used tax parcel designations to determine land-use categories most often subject to change. We report the number of parcels affected and the total area of the changes within tax roll categories for each of the five most abundant categories by area in each WRIA.

Parcel Analysis	**WRIA 3**	**WRIA 7**	**WRIA 15**
Designated forest land 84.34 RCW (# of parcels)	336	477	221
Designated forest land (acres)	2659	4941	2388
Govt services (# of parcels)			48
Govt services (acres)			156
Public timberland/non-desig forest (# of parcels)	194	283	94
Public timberland/non-desig forest (acres)	1490	1149	885
Single Family Units(# of parcels)	622	2036	1175
Single Family Units (acres)	451	1119	659
Undeveloped land (# of parcels)	321	1263	967
Undeveloped land (acres)	368	1462	1086
Ag classified under current use 84.34 (# of parcels)	211		
Ag classified under current use (acre)	249		
Open Space land under 84.34 RCW parcels		247	
Open Space land under 84.34 RCW (acre)		587	
Percent Undev & Single Fam (of Developed change)	69%	112%	120%

Example 3: Change within Growth Management Areas

The Growth Management Act is the key piece of legislation in the State of Washington designed to foster long-range land-use planning and prevent urban sprawl. To assess the effectiveness of the GMA our next analysis looked at the proportion of changed area within and outside of the Growth Management Areas. The UGA permanent percentage is simply the proportion of change area classified as permanent within the combined city and Urban Growth Area boundaries. The intent of the UGAs is to reduce urban sprawl by providing regions for intensifying development. The percentage of permanent change within the UGAs is one measure of their impact on regional development trajectories. The results of the parcel tax roll analysis combined with the listed UGA permanent change in the Lower Skagit suggests the assignment of permanent change may have been too liberal outside of the UGA.

Table 6: Results for Growth Management Area change. We used the current city boundaries and Urban Growth Area (UGA) layers from April 2011 to identify which change locations occurred within the cities or UGAs. The number of change locations and their total area are reported. Additionally the percentage of permanent change in each WRIA within the city and UGA boundaries is reported. The percent growth within the city and UGA is also a GMAP measure.

Urban Growth Area Change (permanent)	**WRIA 3**	**WRIA 7**	**WRIA 15**
Change locations inside the GMA (# of polygons)	190	538	340
Change area inside the GMA (acres)	232	1138	737
Permanent change inside UGA (%)	20%	49%	51%

Example 4: Change in Ecological Systems

Our last example is concerned with assessing which vegetation types are being converted to development. We intersected the change polygons with the US Gap program's 2008 Ecological Systems map to assess which systems were subject to change.

Ecological systems are classification units developed by NatureServe. An ecological system is defined as "a group of (existing) plant community types that tend to co-occur within landscapes sharing similar ecological processes, substrates, and/or environmental gradients." The purpose of this classification system is to provide an intermediate scale for mapping efforts, ecological assessments, and for establishing conservation priorities." [1]

Table 7 lists ecological systems form the USGS Gap program by change area in WRIA 3. As expected the majority of the ecological systems affected are a mixture of douglas-fir and western hemlock systems. An interesting exception is 142 acres of North Pacific Lowland Riparian Forest and Shrubland. Much of the change to this system appears to be the result of channel migration as opposed to clearing for development.

[1] http://www1.dnr.wa.gov/nhp/refdesk/communities/ecol_systems.html

Table 7: Acreage of ecological systems undergoing change between 2006 and 2009 in WRIA 3. All of these figure present change with no attempt to determine if those changes are permanent

Ecological System	Acres
North Pacific Maritime Mesic-Wet Douglas-fir-Western Hemlock Forest	2948
North Pacific Dry-Mesic Silver Fir-Western Hemlock-Douglas-fir Forest	1544
North Pacific Maritime Dry-Mesic Douglas-fir-Western Hemlock Forest	564
North Pacific Mesic Western Hemlock-Silver Fir Forest	203
Harvested forest-shrub regeneration	171
North Pacific Lowland Riparian Forest and Shrubland	142
Harvested forest-tree regeneration	109
Harvested forest-grass regeneration	106
North Pacific Dry Douglas-fir-(Madrone) Forest	104
Developed, Low Intensity	98
Pasture/Hay	89
Cultivated Cropland	56
Temperate Pacific Freshwater Emergent Marsh	30
North Pacific Shrub Swamp	20
North Pacific Broadleaf Landslide Forest and Shrubland	10

Feasibility Analyses

Our original proposal discussed several possible feasibility studies as additions to this project. These included an analysis on roads and road crossings, permanent vs. non-permanent vegetation changes, and quantifying changes to at least 2 additional ecological systems. During the course of this work, we determined that the NAIP data was inappropriate for assessing road crossings due primarily to the fact that crossings are often obscured by trees adjacent to the road. The question of assessing permanent vs. non-permanent change was ultimately incorporated directly into the accuracy assessment analysis. Permanent change had visible signs of development (e.g., roads, buildings, etc) or was adjacent to populated areas as opposed to non permanent change represented by rotational forestry activities or where the intent of the change was indeterminable. The final feasibility question was concerning change within specific ecological systems. Since the current project does not seek to classify vegetation types, but only to map major vegetative loss, mapping change in existing ecological systems is readily straightforward and done by simply intersecting the change locations with the ecological systems maps. We provided an example of this for WRIA 3 above.

Projected Future Costs and Analyses

Change Detection proceeds in 5 major steps . The time estimates below refer to an average 400,000 acre WRIA but due to the human-task to machine-task partitioning are probably not greatly different for WRIAs ranging in size up +/- 50%

Image acquisition/preparation: 3-5 days. Computer processing capacity is the primary bottleneck here. Multiple areas can be processed simultaneously with little additional time.

Spectral based shadow and vegetation modeling: 1-2 days. This task is largely constrained by an analyst's hands on time for the classification.

Image segmentation: 4-7 days. Of this time about 2 days are required for the analyst's model set-up and review with the remaining time consumed by machine processing.

Training and statistical modeling: 3-5 days. This task is primarily analyst limited and consists of both statistical modeling and hand classifying training data. This assumes a classified training set of 5,000 locations.

Accuracy assessment: 5-7 days. This task primarily consists of an analyst reviewing polygons predicted to be change and conducting an accuracy assessment set of 5,000 polygons for omission errors.

Analysis and Report preparation:2- 5 days (this task can vary considerably depending on the number of analyses required)

The per WRIA workload will range from 18-31 days depending on size, image rectification and required post-change detection analyses. Currently 4 WRIAs have essentially been completed and 3 more will be completed as part of a separate project. This leaves 12 WRIAs remaining for the 2006-2009 change detection period. We expect to receive 2011 data in early 2012 which could provide an additional update for the 2009-2011 time period.

Digital Data Availability

These layers are available upon request from Ken Pierce, Landscape Spatial Analyst, WDFW 360 902-2564.

Change Polygons: The change polygons for all four WRIAs are available on DVD.

Accuracy Assessment data: The image triplets used for each training polygon and for the commission and omission analyses are available on DVD along with the beta version of the triplet-AAViewer.

WRIA Imagery: Mosaics can be obtained on a hard drive. Total space requirements depend on imagery requested. Individual date mosaics for each WRIA range from about 10-55 gb each.

References

Bilby, R. and L. Mollot (2008). "Effect of changing land use patterns on the distribution of coho salmon (*Oncorhynchus kisutch*) in the Puget Sound region." Canadian Journal of Fisheries and Aquatic Sciences 65(10): 2138-2148.

Breiman, L. (1984). Classification and regression trees. Belmont, Calif., Wadsworth International Group.

Lillesand, T. M., R. W. Kiefer, et al. (2004). Remote sensing and image interpretation, John Wiley & Sons Ltd.

U.S. Census Bureau, C. H. R., Series H150/09 (2011). American Housing Survey for the United States 2009. Washington, DC, U.S. Government Printing Office.