Challenges and Solutions for a Regional Land Use Change Analysis

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Abstract

A land use change analysis for Western Washington produced repeatable, yet accurate, results in a short-amount of time—primarily with automated methods. Combining ArcGIS® with eCognition Professional® and ERDAS Imagine®, we tested and showed that a relatively simple and repeatable object-oriented classification is a fast, accurate, and realistic method of land cover classification. Further processing of the land cover data using eCognition and a number of customized applications in ESRI® GIS software resulted in actual land use classes for a large study area. Interfacing with ArcGIS 9.x and ArcView 3.x, multiple applications were implemented to produce seamless land use maps for three time periods and the change in land use over those time periods. These data will be used for local decision making, as well as providing baseline land use data for tracking future change at a regional level.

Introduction

The USDA Forest Service's Forest Inventory Analysis (FIA) program routinely monitors and measures the nation's forest characteristics; the program is self-described as the "nation's forest census." As part of this monitoring, the program investigates and reports on the changing nature of land use patterns, especially how these land use patterns relate to change in forest cover and forest-related land uses.

The Pacific Northwest's FIA program recently produced a series of publications and findings related to land use change in western and eastern Oregon. Using aerial photographs at a selected number of Oregon's FIA points (the FIA has a permanent 3.4-mile grid system throughout the entire United States), a large number of people followed a fairly complicated procedure to interpret land use from the photo points; for western Oregon, approximately 24,000 photo points were analyzed for four different time periods: 1973, 1982, 1994 and 2000.

The results of this massive aerial photo interpretation project were impressive. Land use planners and policy makers are currently relying on this information to help shape policy and zoning changes in Oregon.

While the Oregon study was successful, it was costly and time-consuming. Additionally, the methods used in aerial photointerpreation are often interpreter-biased, meaning that different interpreters may decide on different land uses for the same photo point. In 2004, the FIA program contracted with the Rural Technology Initiative (RTI), a research and outreach center at the University of Washington's College of Forest Resources, to investigate the potential of using satellite images as a more cost-effective and repeatable process to determine and calculate land use and its associated change.

The project goals included:
Calculate and display land use change on non-federal lands in Western Washington, using time- and cost-efficient remote sensing and GIS technologies, keeping in mind the following:

- Develop methods that can be easily replicated for other areas of the Pacific Northwest;

- And, attempt to exceed the accuracy and efficiency of conducting a similar study based on aerial photointerpretation.

As any GIS-user can attest to, using satellite images for a land use classification can be difficult; however, the size of western Washington (approximately 16 million acres; Figure 1) is far too large to use aerial photographs for a seamless land use classification.

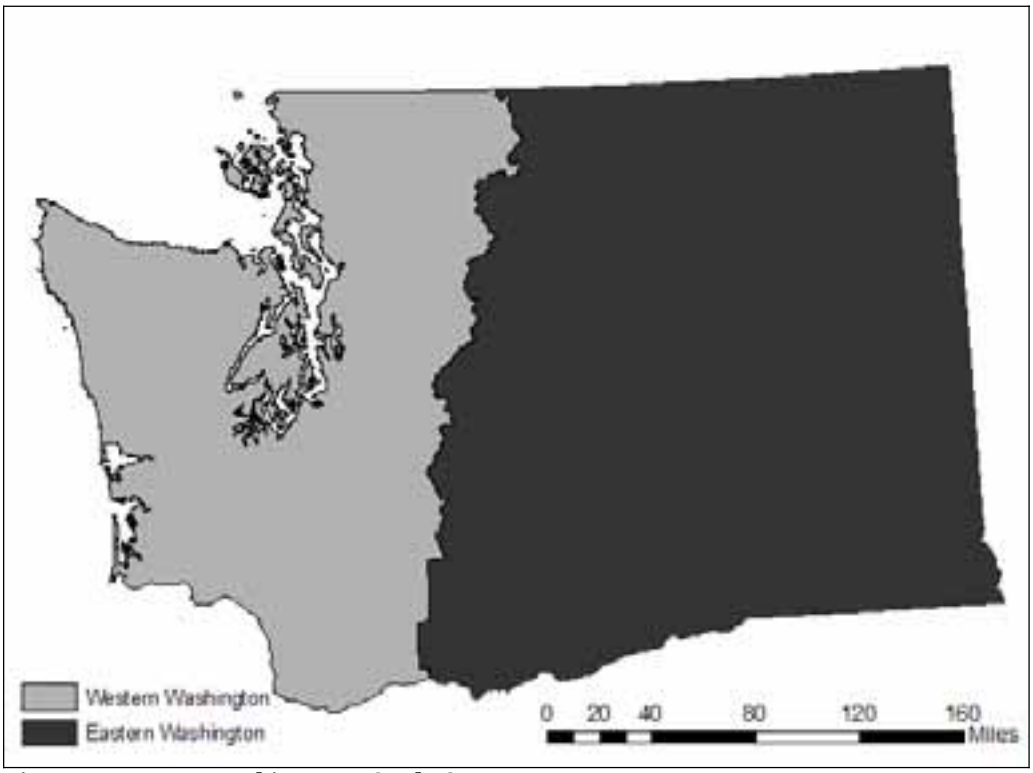

Figure 1: Western Washington—Study Area

Throughout this project, a series of challenges and obstacles were encountered, as with many GIS-based research projects, but especially when considering the above goals of easy replication and improved efficiency. This paper will explore some of those challenges and some of the creative solutions implemented to make this project successful.

Challenges and Solutions

Challenge #1: Statewide satellite images (i.e. AVHRR) that would cover the whole state do not have high enough resolution (small enough pixel size) to even begin to get at land use (not land cover).
Solution: Use Landsat images.

The attributes of the remote sensing platform are important considerations in regards to what it is that is desirable to detect on the ground (Duggin and Robinove 1990). Although land use could be better detected with high resolution images, such as Quickbird or IKONOS, the 30-meter by 30-meter pixel resolution of Landsat images, combined with the availability of consistent images since 1976 (Haack et al. 1987, Fung 1990), was appropriate for this project. Since this project's study area included close to 16 million acres, using higher-resolution data would have resulted in a prohibitively large amount of data to store, process, and analyze.

In order to find images already in public holding, and to be able to collaborate the finished product with other remote sensing-based projects in the USDA Forest Service, staff members at the PNW Corvallis office provided the Landsat images covering all of western Washington for 1988, 1996, and 2004 (scene locations shown in Figure 2).

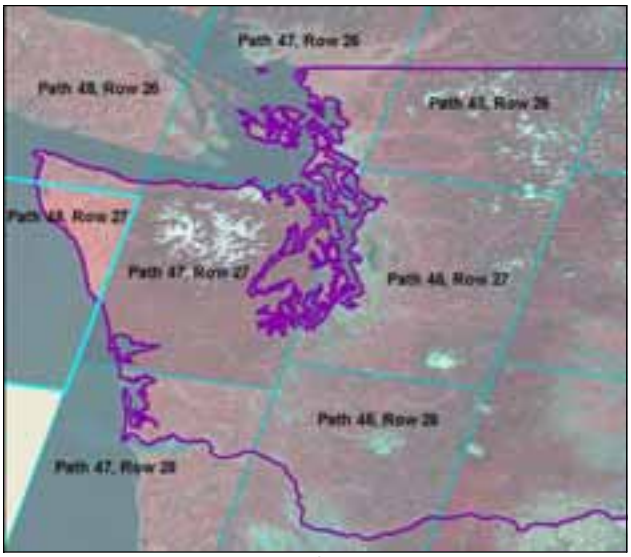

Figure 2. Paths and Rows of Landsat Scenes to Cover Western Washington

The moderate resolution of Landsat was ideal for this project given the large landscape involved and the three time-step periods. The time-steps were determined to take advantage of the most recent images available from the PNW office (2004) and the first thematic mapper (TM) images available in 1988; 1996 is the eight-year mid-point between the two dates. All of the 2004 images were precision geocorrected at the 1G level, most of the 1996 images were terrain corrected (processing level 10), and most of the 1988 images were geometrically corrected. The 24 images (8 for each year) were close in time during the summer to avoid seasonal and phonological differences in vegetation types and other seasonally land cover differences (Howarth and Boasoon 1983, Song and Woodcock 2003). The specific images acquired for this project are listed in Table 1, below.

Table 1. Image Information

Path	Row	Start (0 years)	Mid (8 years)	End (16 years)
46	26	8/31/1988	8/21/1996	8/11/2004
46	27	8/31/1988	8/21/1996	7/26/2004
46	28	8/31/1988	8/21/1996	7/26/2004, 8/11/2004
47	26	7/21/1988	8/12/1996	7/17/2004
47	27	7/21/1988	8/12/1996	7/17/2004
47	28	6/19/1988	7/11/1996	6/15/2004
48	26	9/30/1988	9/18/1995, 5/18/1997	7/24/2004
48	27	9/30/1988	9/18/1995	7/24/2004

While the atmosphere causes increases in the estimates of low reflectance and decreases the highly reflective surface estimates (Gilbert et al 1994), this project did not correct for atmospheric distortion. Pax-Lenney et al (2001) showed that correction for atmospheric interference did not statistically improve image classification, and Song et al (2001) found that as long as the training data was from the same image that was to be classified, and multiple images were classified separately,

atmospheric correction was unnecessary. Since this project aimed to provide easily repeatable and time-efficient results, this step was determined unnecessary; additionally, as discussed later, all training samples were taken from individual images. Finally, the change detection that was done in the land use change step was done with classified polygon layers, rather than comparing spectral values.

Challenge #2: Satellite images are more often used to classify land cover, rather than land use.
Solution: Use an object-oriented classification method, using multiple segmentation levels, rather than a traditional pixel-based classification method.

Land cover is the observed (bio)physical cover on the Earth's surface, while land use is the use is what the land is used for by humans (e.g. protected areas, timber land, etc.). While land cover allows us to see overall biophysical cover, land use allows us to see patterns of development, management practices, and more. Land use patterns are composed of a variety of land cover classes (i.e., forest, water, built-up, soil) with different spectral reflectance characteristics; these different land cover classes form, oftentimes, complex spatial patterns which can make identifying land use patterns using traditional pixel-to-pixel image classification more difficult (Barnsley and Barr 1996).

Pixel values are based on the averaged upwelling radiance from the ground detected by the sensor (Duggin and Robinove 1990). The reflectance of each pixel, 30-meters by 30-meters with Landsat images, can be translated into land cover classes, based on ground-based samples or other training data; the pixel classification can rarely be translated, however, into land use given the spatial distribution and size characteristics specific to each land use.

Object-based classification allows better land use classification options that pixel-based classification because the objects are immediately composed of pixels of similar spectral reflectance, allowing for spatial rules, such as shape and texture, to be applied during the classification process (Benz et al 2004). Object-based classification immediately reduces the salt-and-pepper effect of pixel classifications (Civco et al 2002) because similar pixels, dependent on user-set parameters, are classified as one object. Coupling object-based image classification with additional GIS-based spatial analysis, results in better determination of land use and other spatially-based characteristics (Blaschke et al 2004, Green et al 1994).

Challenge #3: Need to co-register 16 images in a relatively short amount of time.
Solution: ITP Find!

Land use and land cover changes are good indicators of overall landscape change (Blasckhe 2004a) because they affect economic and ecological characteristics (Blasckhe 2004b) and represent both human-developed and natural environments (Turner 1990). While land cover is the biophysical attributes, which can be detected fairly easily with remote sensing techniques, land use is the human use of the land (Gong and Howarth 1990). For example, forestry is a human land use that could be made up of a variety of different remotely detectable land covers, such as clearcut patches and deciduous or evergreen forest stands. A change in land cover does not always equate to a change in land use, and vice-versa (Green et al 1994).

Detecting patterns of change is done by identifying differences in the size or position of an object after observing it more than one time (Singh 1989). Before change can be detected, however, data from different time periods must be geometrically corrected (Mouat et al 1993). One method of

geometric correction, image-to-image registration, uses corresponding coordinate points to match two or more images so that he physical regions align, allows for accurate change detection (Dai and Khorram 1998). Image misregistration can lead to increased error in subsequent data processing (Berstein et al 1984).

Image registration is often very time-consuming, sometimes taking months to collect an adequate number of ground control points (GCPs). In order to produce accurately registered images in a relatively short amount of time, this project took advantage of a free application called ITPFIND that automatically finds image reference points for image rectification. It was written by Robert Kennedy from the USDA Forest Service, Pacific Northwest Research Station at Oregon State University. ITPFIND was written to run in IDL®, a software program for "data analysis, visualization, and cross-platform application development."

ITPFIND creates input and reference X and Y point text files for import to ERDAS IMAGINE® or other image rectification software; the application and documentation area available as a free download (http://www.fsl.orst.edu/%7Ekennedyr/) and Phil Hurvitz, at the University of Washington, wrote detailed instructions specifically for this project (http://gis.washington.edu/phurvitz/itpfind/).

For additional information about this process, which reduced the workload from an estimated four or five weeks to just under a week, see ESRI UC Paper 1523: *It's True! We Registered Sixteen Images in Under Two Hours!*

Challenge #4: Readying images for use in eCognition with repeatable and automated steps.
Solution: Developed a series of scripts for easy re-processing.

Clipping the images to the areas of interest significantly reduces processing time for each image. Areas off the coast of Washington and within large Forest Service and National Park lands were removed from the images by using the *Subset Image* command in *ERDAS Imagine*.

The first step was to create clipping shapefiles for use with an ArcView 3.x clipping script. The script uses a single clipping shapefile of Western Washington and then for each image creates a unique clipping shapefile. The process steps below have been generalized for reporting purposes but should be easy to follow for an experienced GIS analyst. The data sources shown in the table below (Table 2) were used to create the clipping shapefile.

Gifford Pinchot National Forest, Olympic National Forest, Mount Baker/Snoqualmie National Forest and National Park Service lands were merged into a *federal land* feature class. Other public entities like the Bureau of Land Management, the Fish and Wildlife Service and the Washington State Department of Natural Resources were not excluded from the analysis as their exclusion would not have significantly affected processing time.

A *western Washington* shapefile was generated by selecting only those counties west of the Cascade crest and merging them into a single shape. This shapefile, and the federal lands shapefile, were simplified using a 30-meter filter to speed processing time for the subsequent steps since retaining such accurate boundaries is of no use after being buffered. This simplified western Washington shapefile was buffered by 5000 meters to create an *external* shapefile, and the simplified Federal Land shapefile was buffered by 1000 meters to create an *internal* shapefile.

Table 2. Data Sources Used to Determine Analysis Area

Data Sources		
Name	Source	URL
wa_counties [Washington counties]	USGS GeoData 1:M DLG	http://edc.usgs.gov/geodata/
wa_wria [Washington Water Resource Inventory Areas]	WA Department of Ecology	http://www.ecy.wa.gov/services/gis/data/data.htm
Gpnf [Gifford Pinchot National Forest]	GPNF	http://www.fs.fed.us/gpnf/forest-research/gis/
Onf [Okanogan National Forest]	ONF	http://www.fs.fed.us/r6/data-library/gis/olympic/
Mbs [Mount Baker Snoqualmie National Forest]	MBS	http://www.fs.fed.us/r6/mbs/maps/gis.shtml
blm_ownership [Bureau of Land Management ownership]	BLM	http://www.blm.gov/nstc/jurisdictions/
fws_ownership [Fish and Wildlife ownership]	FWS	http://www.fws.gov/data/r1gis/boundary.html
nps_ownership [National Park Service Ownership]	NPS	http://www.nps.gov/gis/data_info/park_gisdata/wa.htm
wa_dnr [Washington Department of Natural Resources ownership]	WA DNR	http://www3.wadnr.gov/dnrapp6/dataweb/dmmatrix.html

Small islands and slivers (less than 10 square kilometers) were removed in both the *external* and *internal* shapefiles. The area included in the *internal* shapefile was erased from the *external* shapefile, and the result was clipped along the Cascade crest to create a *western Washington analysis area* shapefile.

The second step was to generate the individual image clipping shapefiles using a script in *ArcView*. The script gets the extent of each image and then extracts a new shapefile for that image from the master clipping shapefile (*western Washington analysis area*). These shapefiles were used in *ERDAS Imagine* to generate areas of interests (AOIs) to subset the images.

The third step was to clip the referenced images with the newly created clip shapefiles. This was done in *ERDAS Imagine*, using the defined AOIs and the *Subset Image* tool. A batch method was used to allow for the processing to occur at night when the computers were not in use. Using the batch method resulted in each image taking about 2 minutes to setup for batch processing and then 10 minutes to process.

Challenge #5: Classifying land use directly in eCognition turned out to be more difficult (and less predictable) than expected.
Solution: Took advantage of eCognition's multiresoltuion segmentation feature, but ran the land use analysis with alternative software.

One of the main goals of this project was to be able to identify low-density residential areas in forested regions, which are often classified only as forest cover using traditional image classification techniques. Multi-resolution classification allowed potential built-up objects to be identified at a fine scale and general land cover at a coarser scale; combining these two scales of information resulted in a detection of small potentially built-up areas in the middle of large tracts of forest or other vegetative cover. A relatively new software application, eCognition, was used to segment – the grouping of relatively homogenous pixels into objects – the images into the two different scales: built-up and general land cover. Although eCognition was intended to be used to determine land use from the two scales, the complexity and size of the data was too large for the program, and land use determination was run using ArcInfo Workstation and ArcGIS instead.

Figure 3 shows the same image segmented at the coarse scale (100) and the fine scale (5). The coarse scale allows for general land cover classification while the fine scale allows for distinguishing built-up features (roof tops, driveways, streets, etc.) from surrounding land covers.

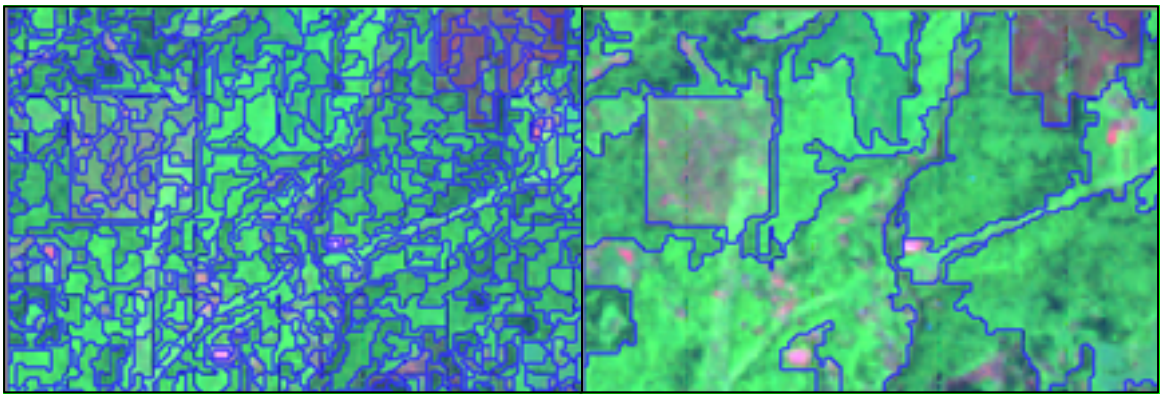

Figure 3. Fine Scale Segmentation Compared to Coarse Scale Segmentation

Challenge #6: The spatial analyses used to determine land use from the exported coarse land cover and fine built-up data was impossible to run using ArcGIS, personal geodatabases, ArcSDE, or shapefiles.
Solution: Converted all data to GRIDs and ran all spatial analyses in ArcInfo Workstation.

Originally, the exported IMG files were going to be run through a series of spatial overlay processes in ArcGIS. However, after two months of attempting to run the analysis using ArcGIS, geodatabases, shapefiles, and ArcSDE, it was determined that the only program that would not run out of memory due to the enormous file sizes of the classified data would be ArcInfo Workstation. Thus, the classified images were re-exported from eCognition and converted to GRIDs. This decision drastically improved the project's efficiency and ease of use for alternative analysis needs.

Challenge #7: The exported and classified files from eCognition needed to be mosaiced, but the object IDs were the same in all of the images.
Solution: Wrote a Visual Basics (VBA) routine to add constants to make unique IDs and used GRID to add the constant value to each IMG file.

In order determine land use across western Washington, the series of images from each year had to be mosaiced together into one image file (since land use crosses image borders). Unfortunately, the original IDs had to be changed to allow joining back to the attribute tables since the object IDs exported from eCognition were not unique to each image. The IMG attributes were exported to a Microsoft Access database and a new field was added to the attribute table, using a VBA routine. Continuing with the VBA routine, constant values (multiples of 100000: 100000, 200000, 300000, etc.) were added to each image's object IDs to create unique IDs. Afterward, all of the image object's attributes were appended into a master table for mosaicing and the same constant value was added using GRID to each IMG export file that matched the value added to the attribute table.

Challenge #8: Need to mosaic the best parts of each image.
Solution: Make masking polygons and clip each image as appropriate and then mosaic.

Using the original registered Landsat images, the images were moved up and down in the table of contents in an ArcMap document to create the least area of cloud, haze, and glare. During a mosaic process, however, a user will often want just a portion of an image rather than putting one entire image at the top (or bottom) of the hierarchy. Therefore, in order to achieve the best mosaiced image, some of the images had to be clipped before being added to the mosaic order.

If an image needed to be clipped to include just a portion of the area (for example, one image is completely cloud free except for a small area in one corner), a new polygon feature class with the same spatial properties of the respective image was created in ArcCatalog. This blank feature class was added to the ArcMap document and was edited, using the sketch tool, to cover the portion of the image that is best used in the mosaic process. Figure 4 shows the clipper (in purple) as to avoid the clouds on the left-hand side (within the white circle). The neighboring image contained much cloud cover, but was clear where this image was cloudy. Before clipping the image with this new feature class, it was necessary to perform a visual check to make sure that the image below (or above) would still result in a complete mosaic. Lastly, since the raster calculator cannot clip more than 3-bands, it was necessary to use ERDAS Imagine's data prep/subset image tool.

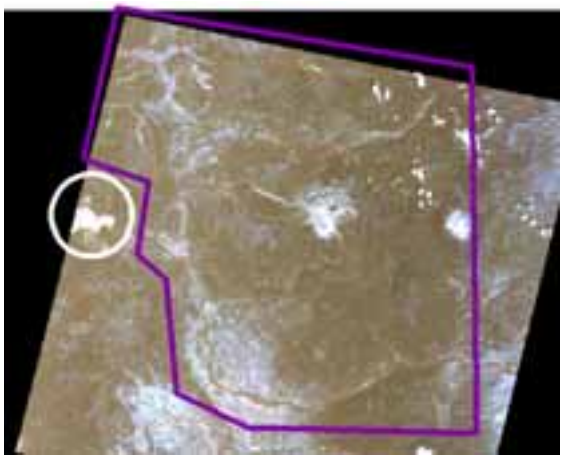

Figure 4. Clipper to Avoid Clouds

Challenge #9: Determine land use from the general, coarse-scale land cover and the fine-scale built-up layers with repeatable and self-documenting steps.
Solution: Build a series of AMLs to run the entire process in ArcInfo Workstation.

As discussed earlier, land cover is the biophysical characteristics of the landscape, while land use is made up multiple land cover types. Determining land use from satellite images require a series of overlay processes that neither eCognition, ArcGIS, or ArcSDE could handle. Additionally, it was necessary to devise a method that could be easily run again, with new input data, and altered to reflect different land use characteristics and definitions. A series of AMLs, written to run in ArcInfo Workstation, are described below.

CREATECPOLYS.aml: A "land cover" polygon GRID was created from the image objects exported from eCognition. Additionally, a GRID analysis was used identify water as determined by the Washington's Department of Natural Resources (WADNR) hydrography data. Any polygon that WADNR identifies as water was reclassified in the land cover data as water.

ELIMINATELC.aml: In order to reduce the amount of data in each GRID, small polygons were eliminated (land uses are usually large in size, unlike land cover, so it was assumed that data quality would be compromised). Using Arc and ArcPlot, any polygons less than 10-acres and not identified as water by the WADNR were eliminated. This resulted in "land use polygons" – which formed the spatial arrangement for the remaining attribute analysis.

ADDLUFIELDS.aml: The additional attribute fields needed to arrive at land use were added to the land cover attribute table using ARC.

CALCONTIGACRES.aml: Some of the land use definitions (described below) required a calculation of contiguous acres of similar land covers. Contiguous acres were calculated first by grouping similar land covers (dark and light spectrally reflective forest cover into a forest group) and then unioning land use cover and the new groups by joining on the land use cover number.

DEVSTATS.aml: In addition to contiguous acres, the land use definitions included development statistics: number of acres of each polygon that are developed, percentage developed, number of cells developed, number of development clusters, density of clusters per square mile, and more. Unioning land use cover with built-up cover (from the fine-scale built-up layer), by connecting to an Access database, exporting the attribute tables, and running a selection query using an AML, creates these development statistics.

LANDUSE.aml: Calculating land use involved running an AML to put each polygon is one of the groups listed in the first column in Table 3, based on the corresponding requirements listed in the subsequent columns. As shown, the GRIDs developed with the previous AMLs are necessary for the calculation of land use.

Table 3. Rules Used to Calculate Land Use

Calculating Land Use					
Land Use	LC Group	Percent Developed	Dev Density	Acres Contig	Other
Wildland Forest	Forest	< 2%	<= 4	> 640	
Rural Forest	Forest	< 20%	> 4 and <= 8	> 640	Not Wildland Forest
	Forest	0%		<= 640	Not Wildland Forest
	Forest	< 5%		> 640	Not Wildland Forest
Other Forest	Forest				Not Wildland Forest, Rural Forest
Intensive Ag	Ag	< 2%	<= 9	> 640	Not Intensive Ag
Mixed Ag	Ag	< 20%	<= 12	> 640	Not Intensive Ag
Other Ag	Ag				Not Intensive Ag, Mixed Ag
Rural Residential	Forest or Ag	> 20% and <= 50%		> 40	Not Wildland Forest, Rural Forest, Intensive Ag, Mixed Ag
Urban Residential	Built	<= 50%			
	Built	> 50%		<= 40	
	Not Built	> 50%			
Urban	Built	> 50%		> 40	
Water	Water				
Unknown	Unknown				

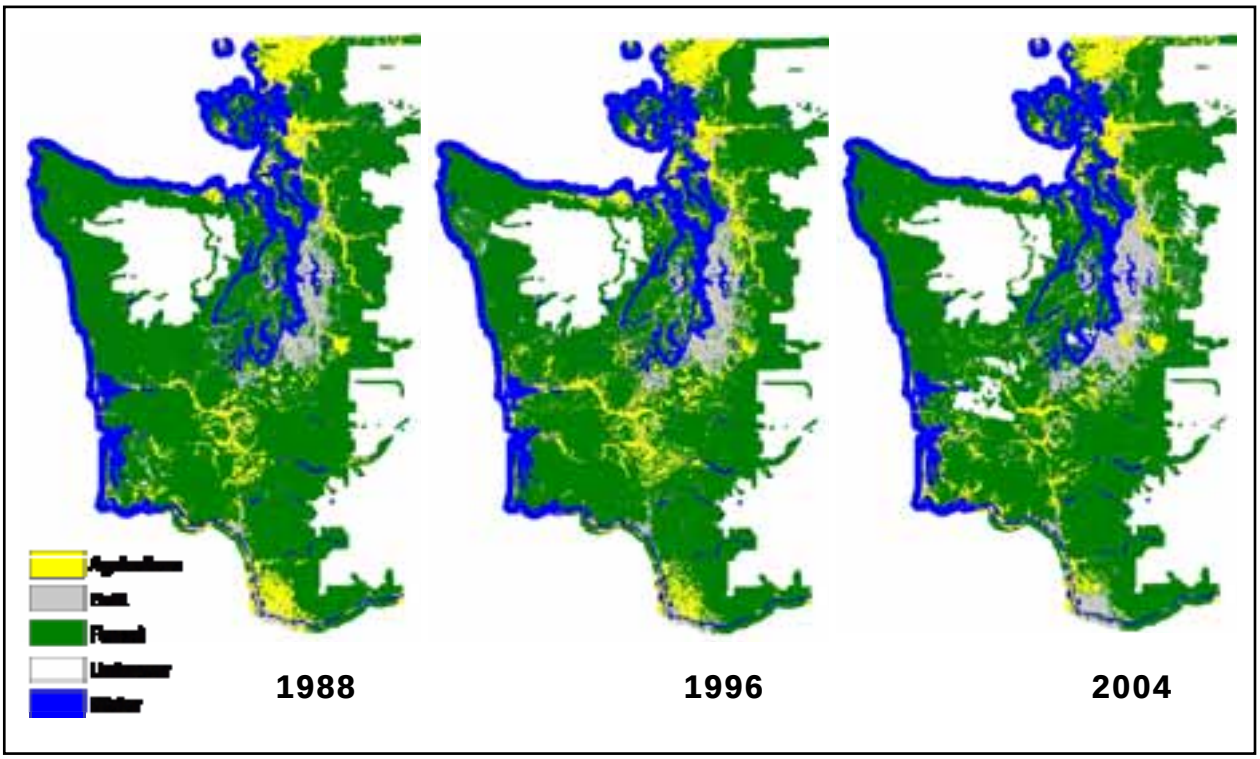

Figure 5. Land Use on Non-Federal Lands in Western Washington

CHANGE.aml: The final step in the project is the calculate change from one land use type to another. As can be expected with multiple land use classes, the number of possible changes (forest to urban, forest to agriculture, agriculture to forest, etc.) could be quite large. For simplicity, a one-way trajectory for change was assumed: a land use can only become more developed, not less developed. In the GRID polygons, each land use was coded with a number in ascending order: the most wild land use (wildland forest) has the lowest number and the most developed land use (urban) has the highest number. Using the *combine* function in GRID, the change matrix is calculated. Figure 6 shows the one-way trajectory and Figure 7 shows the areas in western Washington that changed from forest to anything non-forest and agriculture to built between 1988 and 2004.

Wildland Forest ⇨ Rural Forest ⇨ Other Forest ⇨ Intensive Ag ⇨ Mixed Ag ⇨ Other Ag ⇨ Rural Residential ⇨ Urban Residential ⇨ Urban ⇨ Water ⇨ Unknown

Figure 5. Land Use Change Trajectory

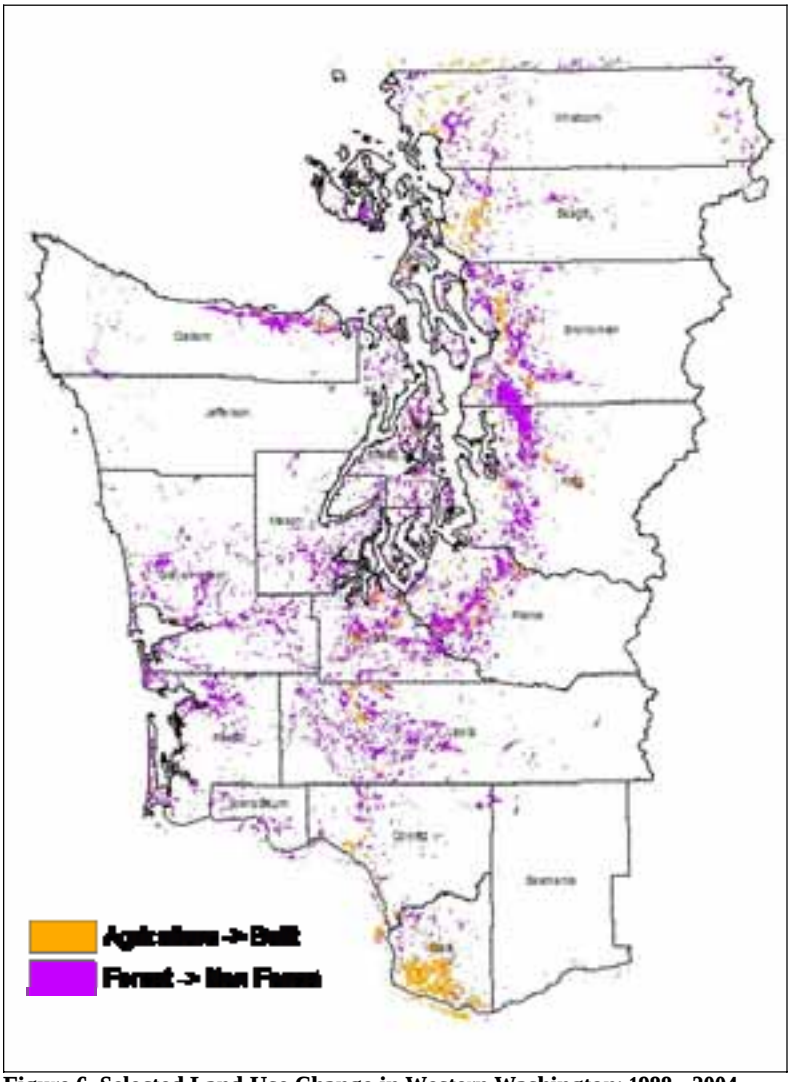

Figure 6. Selected Land Use Change in Western Washington: 1988 - 2004

Conclusion

A regional land use change analysis project can be a daunting task. This project required creative and often unexpected solutions to the many challenges a GIS analyst could encounter on similar projects. The use of automated scripts and AMLs drastically improved the efficiency of the project and allow for steps to be repeated quickly and accurately if the input data or the land use definitions changed. Although coarse, the resulting data from this project will serve as a starting point for assessing the land use change characteristics across and entire region.

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