CHARACTERIZATION OF FOREST FRAGMENTATION AND URBAN SPRAWL USING TIME SEQUENTIAL LANDSAT IMAGERY

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ABSTRACT

As part of the NASA funded Northeast Regional Earth Science Applications Center (RESAC) at the University of Connecticut, research is being conducted to identify and quantify forest fragmentation and urban sprawl in the 140 square mile Salmon River watershed in Connecticut. This research consists of two parts. First is the development of accurate and consistent general land cover maps and the identification of land cover change derived from Landsat Thematic Mapper and Enhanced Thematic Mapper satellite imagery. ISODATA unsupervised classification was used to generate a base classification image from 1985 Thematic Mapper imagery. A cross-correlation analysis procedure was employed to identify areas of land cover change which were used to generate subsequent classifications for the years 1990, 1995, and 1999. The second part of the research focuses on a method to generate images depicting the pattern of forest fragmentation and urban development from the derived classifications. Forest fragmentation measurements were derived that identify the condition of forest pixels for each of the four dates classified. These metrics describe a forest pixel as being interior, perforated, edge, transitional, patch, or undetermined. The extent of urban development is identifiable based on the change of designation for the forest pixels from interior forest to urban, forest edge, forest perforated, forest transitional, and forest patch. The techniques developed for this watershed will be extended to three other partner watersheds in the Northeast: the 265 square mile Stony Brook Millstone watershed in New Jersey, the 377 square mile SuAsCo watershed in Massachusetts, and the 200 square mile Presumpscot watershed in Maine.

INTRODUCTION

Concern about the economic, environmental and cultural toll of forest fragmentation and urban sprawl is growing in the United States and worldwide. Increased forest fragmentation due to urban development poses a threat to biodiversity, increases the amount of habitat edge effectively reducing interior habitat, and alters the region's biota to varying degrees (Saunders *et al.*, 1991; Vogelmann, 1995; Riitters *et al.*, 2000). However, the extent and rate of these land cover changes are not fully understood, particularly by local officials whose decisions about land use will determine the look and feel of the country's landscape for decades to come (Arnold, 1999). A primary objective of the NAUTILUS (Northeast Applications of Usable Technology In Land planning for Urban Sprawl) RESAC is to develop decision support system models for use by local land-use decision makers. It is the goal of NAUTILUS to not just generate simple landscape characterization statistics, but to develop specific metrics that describe forest fragmentation. These metrics will be used to develop maps that identify the location and type of fragmentation that is occurring and what land use condition is causing the fragmentation. Ultimately these tools can be applied by local officials to aid in community planning (Arnold *et al*., 2000). It is not our intent to provide species specific forest fragmentation analysis, but to provide an overview of the type of forest conversion that has already occurred. This information can help local decision makers better understand the affect of land use decisions.

Research is being conducted in the Salmon River watershed located in central Connecticut in the lower Connecticut River valley. The watershed is 140 square miles in size with land cover being dominated by forest (over

70 percent of the watershed). Non-woody vegetated lands (agricultural fields, golf courses, clear-cut forest areas, etc…) and urban lands each make up approximately 10 percent of the landscape. The main transportation route through the region is state highway 2, a four lane limited access highway that passes through the watershed from the northwest to the southeast and provides access to Hartford, 20 miles northwest of the watershed, from southeastern Connecticut. Of the 7 towns that intersect the watershed, 5 of these are considered some of the fastest growing towns in Connecticut. Additionally, the Salmon River watershed is a key component of the lower Connecticut River watershed, designated as one of the Last Great Places on Earth by The Nature Conservancy.

CONCEPT STUDY

An initial concept study was conducted on the Salmon River watershed using two dates of Landsat TM imagery spanning a period of ten years (1985 to 1995) (Lammey, 2000). One of the objectives of this study was to generate land cover information and landscape characterization statistics in a practical and time-efficient manner using ArcView, a commercial off-the-shelf GIS software package developed by the Environmental Science Resources Institute. ArcView is a relatively inexpensive GIS software package that is obtainable by most local decision makers, and its extensions provide many functional enhancements. The stand-alone ArcView deals with vector (discrete) data, such as lines, polygons, or points. However, for the more advanced analysis being conducted for this study, the Image Analysis®, Spatial Analyst®, and Patch Analyst* extensions were needed. The Image Analyst extension was necessary for image viewing, manipulation, and all automated classification of the TM images. The Spatial Analyst extension was required for the reclassification and map algebra operations. Lastly, the Patch Analyst extension was necessary for the generation of the spatial/patch statistics.

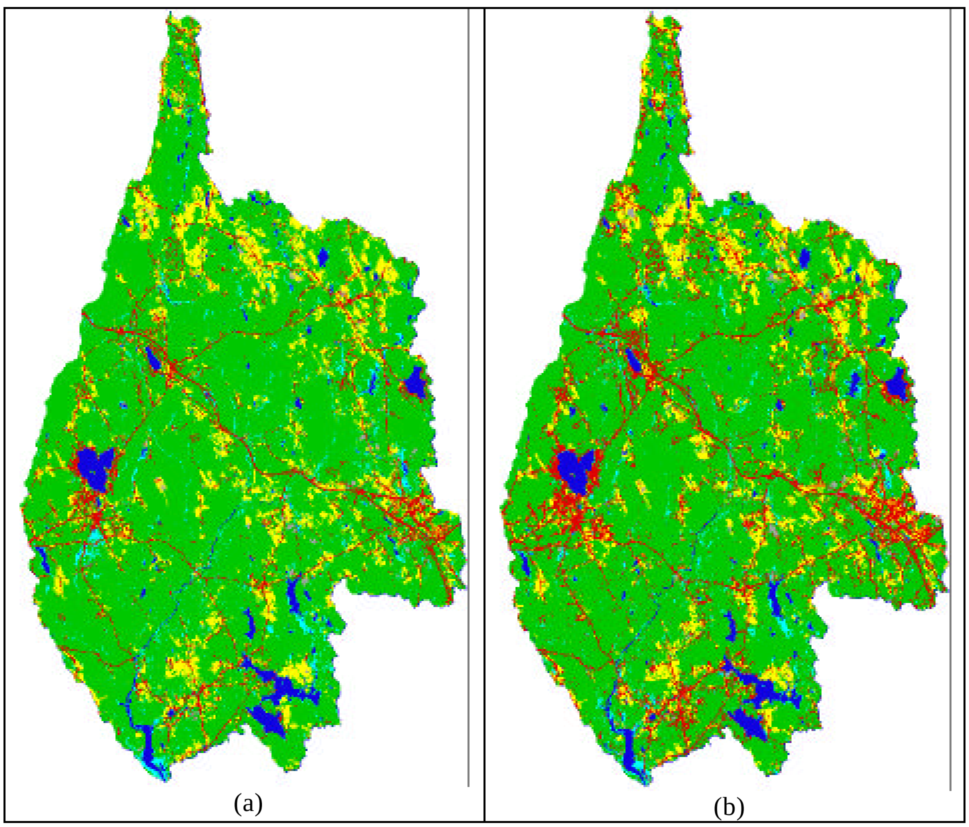


Figure 1. Land cover images for 1985 (a) and 1995 (b) Landsat Thematic Mapper images for the Salmon River watershed. Urban is red, non-woody vegetated is yellow, forest is green, water is blue, wetlands are cyan and barren is gray.

* Centre for Northern Forest Ecosystem Research (OMNR), Lakehead University, Thunder Bay, Ontario, Canada: http://flash.lakeheadu.ca/~rrempel/patch/

The classification process involved the categorization of the spectral information from two dates (April 24, 1895 and May 8, 1995) of springtime TM images using the ArcView Image Analyst extension. Image Analyst uses an ISODATA (Iterative Self-Organizing Data Analysis Technique) process to generate a specified number of clusters with similar spectral characteristics, that were then labeled as belonging to one of six general land cover categories (water, forest, wetland, urban, non-woody vegetated, and barren). Using Spatial Analyst, the classifications were reclassified into the six general land cover categories. To further improve the classifications, summertime TM imagery dated August 9, 1985 and August 28, 1995 were also classified and combined with the springtime classifications. Further improvements to the classifications occurred through the on-screen editing of gross errors. The final classification results for the 1985 and 1995 TM images can be seen in Figure 1.

Statistics to describe the characterization of the three land cover types of interest (urban, forest, and non-woody vegetated), were generated using the Patch Analyst extension of ArcView. Patch Analyst provides statistics based on groups of pixels having the same class value. Thus, a contiguous group of forest pixels will be a single patch, regardless of its shape. Statistics generated include number of patches, mean patch size, patch size standard deviation, total edge, mean perimeter to area ratio, and area weighted mean patch fractal dimension.

The results from this initial study can be viewed in Table 1. The number of patches of forest and non-woody vegetated increased due primarily to urban development. Increased number of patches resulted in decreased mean patch size for the forest and non-woody vegetated categories. The total edge and mean perimeter-to-area ratio increased (more edge habitat and more *unnatural* uniformity), and patch size standard deviation and area weighted mean patch fractal dimension decreased (less random or *natural* landscape characteristics). The most dramatic changes are indicated for forest, with the number of patches more than doubling and mean patch size and mean patch size standard deviation decreasing to less than half of what they were ten years previously.

Table 1. Patch Statistics for Forest, Non-woody Vegetated, and Urban areas from 1985 and 1995 land cover.

Year	Land Cover Category	Number of Patches (n)	Mean Patch Size (ha)	Patch Size Standard Deviation (ha)	Total Edge (km)	Mean Perimeter-Area Ratio	Area Weighted Mean Patch Fractal Dimension
1985	**Forest**	4016	7.28	129.19	1580	5123.75	1.24
	Non-woody Vegetated	4463	0.90	3.65	3504	4299.17	1.12
	Urban	4276	0.60	7.35	1701	1062.55	1.19
1995	**Forest**	8387	3.27	42.17	2657	10116.61	1.20
	Non-woody Vegetated	6074	0.65	2.82	4333	5360.05	1.11
	Urban	8012	0.58	25.38	1803	1142.95	1.26

This initial concept study provided valuable information on changes to the forest landscape. However, we wanted to go beyond providing just statistics, but to produce maps that identified the location of changes to the forest landscape. The remainder of this paper describes the techniques used to derive images of land cover and land cover change and images showing patterns of forest fragmentation within the Salmon River watershed over time.

INITIAL LAND COVER CLASSIFICATION

The first step needed to derive forest fragmentation and urban sprawl metrics was the production of a land cover image. A two-step ISODATA clustering technique was used for generation of the initial land cover image and was derived from a combined image of two seasons of Landsat TM image data dated April 26, 1985 and August 9, 1985, utilizing the six reflective and thermal bands. Using multi-seasonal imagery has been found to provide greater

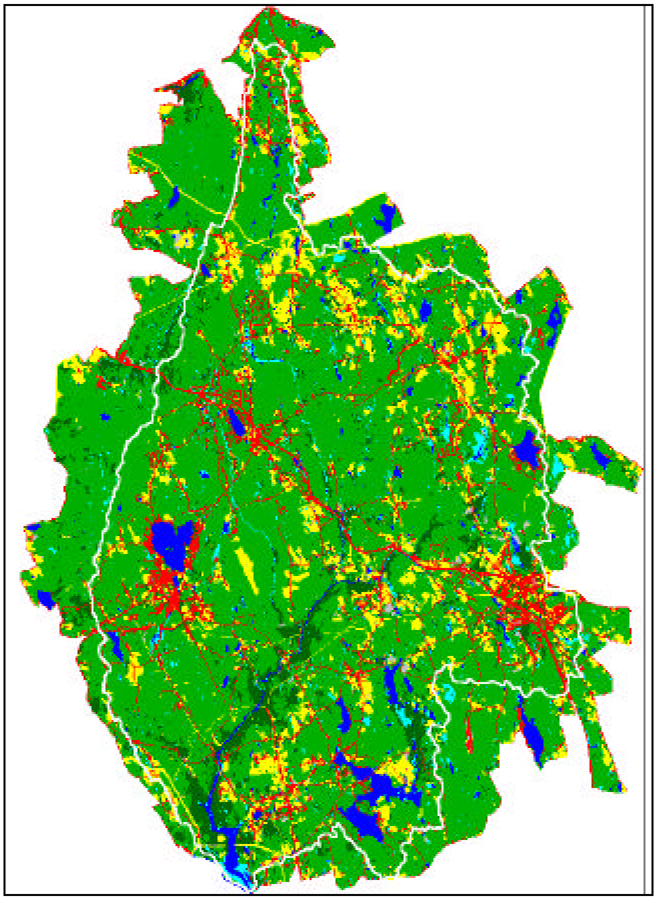


Figure 2. Classification of combined April 24, 1985 and August 9, 1985 Landsat Thematic Mapper images for the Salmon River watershed (outlined in white). Urban is red, non-woody vegetated is yellow, forest is green, water is blue, wetlands are cyan and barren is gray.

spectral depth due to the phenological differences between vegetation (Civco and Hurd, 1991; Fuller *et al*., 1994; Dobson *et al*., 1995, Civco *et al*., 1998). This has proven particularly beneficial when trying to separate urban lands from agricultural lands which tend to be fallow during mid-spring, but vegetated during mid-summer. ISODATA clustering was first applied to the full multi-seasonal 14-band image area to produce 75 spectrally separable classes. These classes were identified and labeled into one of eight informational land cover categories: urban land, non-woody vegetated land, deciduous forest, coniferous forest, water, wetland, barren land, and other. The "other" category contained clusters of pixels that were not readily identifiable as belonging to a single informational class. A second ISODATA clustering procedure was performed on these pixels with 50 output classes specified. These classes were identified and labeled into one of the seven land cover categories and added to the first classification to create a single 7 category land cover image.

Extensive on-screen digitizing was performed to eliminate apparent gross errors and to add isolated linear roads and utility right-of-ways to the classification. These linear features are important because they are fragmenting features of the forest landscape, yet the 30 meter pixel resolution of the Landsat Thematic Mapper image is not always capable of depicting these features using traditional classification techniques. Rasterized vector roads could have been embedded into the classification, but several instances of mis-registration between the TM image and the roads layer warranted the on-screen digitization of these features. To assist in the digitization process, the road layer, digital raster graphic USGS topographic maps, and recently acquired IKONOS imagery were consulted. An additional consideration for not embedding the roads layer is that the 1994 date of the roads coverage is not temporally compatible with the 1985 date of the TM imagery. The resulting classification can be seen in Figure 2. The boundary of the Salmon River watershed is shown in white. The area outside the watershed was included to provide fragmentation analysis on the complete forested areas intersecting the watershed. Linear fragmenting features (roads and utility right-of-ways) were used to create this outside boundary. The map has an overall classification accuracy of 90.0 percent.

CHANGE DETECTION

Several techniques for depicting changes in land cover were considered. These included independent classification and post classification change detection of four individual dates of Landsat imagery, the classification of a single multidate image composed of selected bands from each of the four dates of imagery, an RGB-NDVI color composite approach, and cross-correlation analysis (Hurd *et al.*, 1992; Sader and Winne, 1992; Hoffhine, 2000; Koeln and Bissonnette, 2000). Each of these techniques has advantages and disadvantages. Post classification change detection reduces the need for images with similar radiometric qualities and also provides information about which land covers changed from one date to the next. However, the accuracy of the change detection is dependent on the accuracy of each classification and any inconsistencies cause error in the form of false change or missed change. Classification of a multidate image produces consistent results between dates, but becomes increasingly difficult as more dates of imagery are added because of the need for additional categories to adequately describe land cover changes between dates. RGB-NDVI color composites are useful for identifying areas of change, but do not provide information about to and from land cover classes that have changed. The method is also restricted to analyzing three dates of imagery at one time.

Cross-correlation Analysis (CCA) was chosen as the method for determining land cover because it overcomes many of the limitations of conventional change detection methods. Cross-correlation Analysis is a change detection method developed by Earthsat, Inc. and measures the differences between an existing land cover image and a recent single date multispectral image (Koeln and Bissonnette, 2000). The benefit of this technique is that it eliminates the problems associated with radiometric and phenological differences that are so readily experienced when performing change detection.

Cross-correlation works by using the class boundaries from the base land cover image to derive an "expected" class average spectral response. This information is used to derive a Z-statistic for each pixel falling within a given land cover type. The Z-statistic describes how close a pixel's response is to the "expected" spectral response of its corresponding class value in the land cover image. Pixels that have undergone change between the date of the land cover image and the multispectral image will produce high Z-statistic values while pixels that have not changed will produce low Z-statistic values. The equation used is shown below:

$$Z_{jk} = \sum_{i=1}^{n} \left(\frac{r_{ijk} - m_{ic_{jk}}}{s_{ic_{jk}}} \right)^2$$

where
Z_{jk} is the Z score for a pixel of a given class.
i is the band number in the multispectral image
n is the number of bands
c_{jk} is the thematic class being analyzed
r_{ijk} is the reflectance in band i for pixels in a given class
μ_{ic} is the mean reflectance value in band i of all pixels in a given class
σ_{ic} is the standard deviation of the reflectance value in band i of all pixels in a given class

The methodology presented here varied somewhat compared to that presented in Koeln and Bissonnette (2000). The land cover image used was produced from the April 26, 1985 and August 9, 1985 Landsat TM images discussed previously. The 1985 land cover image was used to extract non-woody vegetated and barren lands, deciduous forest, and coniferous forest from a 7 band August 30, 1990 TM image to produce three multispectral images representing each of the land cover types extracted. Urban, water and wetland areas were not included in the CCA because it was assumed these classes would not significantly change, but, in the case of urban, increase with time. In addition, any noticeable changes would be edited during the on-screen digitizing process. The CCA procedure was applied to each of the 3 extracted images and the resulting bands summed together to produce a single thematic layer. The results of the CCA were visually examined with the corresponding 1990 TM image to determine the threshold that identified unchanged pixels from changed pixels. Thresholds varied between images. Those pixels considered to have changed were used to extract pixels from the multispectral image for each of the three land cover types. The deciduous forest and coniferous forest images were combined to produce a single image identifying changed forest pixels. ISODATA clustering was applied to the changed pixel images and the resulting clusters identified and labeled into one of the 7 land cover categories as was appropriate. The resulting land cover images were combined with the original 1985 land cover to produce an updated 1990 classification. On-screen digitizing was again employed to eliminate any apparent errors. Using the resulting 1990 land cover image, the CCA procedure was applied to an August 28, 1995 TM image and using the resulting 1995 land cover, this was applied to an August 31, 1999 Enhanced Thematic Mapper image. The final result is four land cover images representing that can be used to identify the land cover change over the four date sampling period. An example of the change pixels for the deciduous and coniferous land cover categories between 1985 and 1990 is shown in Figure 3.

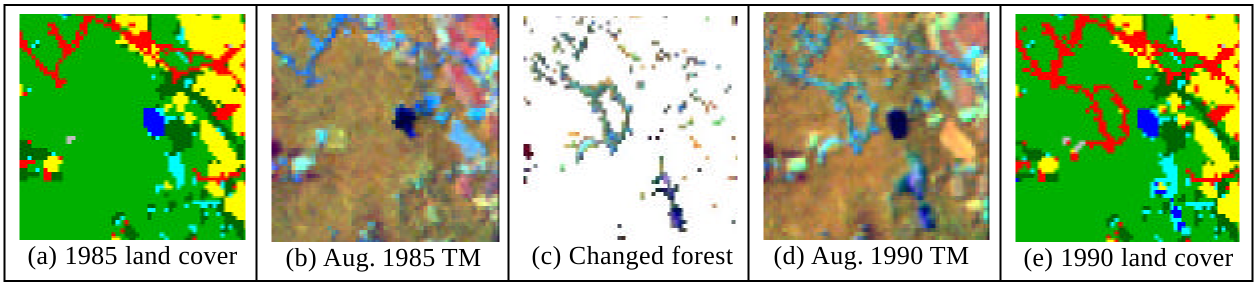


Figure 3. Example of the result of cross-correlation analysis on forest pixels between Aug 9, 1985 and Aug 30, 1990. Image (c) represents those pixels having a high likelihood of changing from forest.

IDENTIFYING PATTERNS OF LANDSCAPE FRAGMENTATION

Patch Analyst was applied to each of the four land cover images to produce statistics for each class. The land cover images were first reclassified into five groups. Forest contained the deciduous, coniferous, and wetland classes. Urban, non-woody vegetated barren and water remained as separate classes. Patch Analyst was applied to the forest class specifying a 4 direction clumping method. This was to prevent the loss of forest fragmentation caused by single pixel width roads. The remaining four classes were analyzed using an 8 direction clumping method. Statistics generated identified the number of patches, mean patch size, and the maximum patch size for each land cover category for each date.

Measurements identifying patterns of forest fragmentation were generated using methodology outlined in Riitters *et al*. (2000) for use in their research to identify patterns of forest fragmentation at a global scale. The procedure generates two values of information to characterize the forest pixel located at the center of a sliding window of fixed size. The first is Pf, which is the ratio of the number of forest pixels over the total number of pixels within the window that are not water. The second is Pff, which is the ratio of the number of pixel pairs in cardinal directions that are both forest over the number of pixel pairs in cardinal directions that are either both forested or one is forested. Because they are proportions, both Pf and Pff range from 0 to 1. Figure 4 illustrates the method for calculating the Pf and Pff values of a forest pixel within a 5x5 window. Given these values, six fragmentation categories can be derived based on the following assumptions (Riitters *et al*., 2000):

- Interior forest - all of the pixels surrounding the center pixel are forest. Pf = 1.0
- Perforated forest - most of the pixels in the surrounding area are forested, but the center pixel appears to be part of the inside edge of a forest patch, such as would occur if a small clearing was made within a patch of forest. Pf > 0.6 and Pf - Pff > 0.
- Edge forest - most of the pixels in the surrounding area are forested, but the center pixel appears to be part of the outside edge of forest, such as would occur along the boundary of a large urban area, or agricultural field. Pf > 0.6 and Pf - Pff < 0.
- Patch forest - pixel is part of a forest patch on a non-forest background, such as a small wooded lot within an urban region. Pf < 0.4.

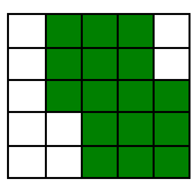


Figure 4. Illustration of the computation of Pf and Pff for a landscape represented by a 5x5 grid of pixels. Green represents forest pixels, white represents non-forest pixels. Of the 25 pixels represented, 16 are forest pixels (none are water). Pf therefore equals 16/25 = 0.64. Considering pairs of pixels in cardinal directions, the total number of adjacent pixel pairs is 40. Of these, 32 pixel pairs contain at least 1 forest pixel, and of those 23 pairs contain 2 forest pixels. Pff therefore equals 23/32 = 0.72. (adapted from Riitters *et al.,* 2000).

- Transitional forest - about half of the cells in the surrounding area are forested and the center forest pixel may appear to be part of a patch, edge, or perforation depending on the local forest pattern. $0.4 < Pf < 0.6$.
- Undetermined forest - most of the pixels in the surrounding area are forested, but this center forest pixel could not be classified as a type of fragmentation in the surrounding area. $Pf > 0.6$ and $Pf = Pff$.

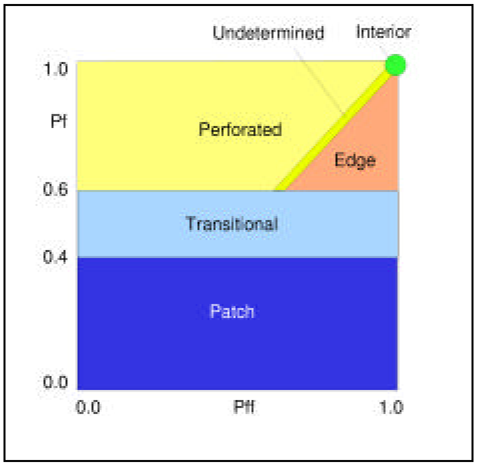


Figure 5. The model used to identify forest fragmentation categories from local measurements of Pf and Pff. (adapted from Riitters *et al.*, 2000).

To implement the process, the first step was to determine the size of the sliding calculation window. Research conducted by Riitters *et al.* (1997 and 2000) examined windows of various sizes and focused analysis on the smallest scaled window that was practical. The size of the window is ultimately related to the resolution of the data and the size of the smallest feature of interest. In our case, we were working with 30 meter resolution TM data and the smallest feature of interest was a single pixel, so the small forest patches found within urban regions would be identified. We examined window sizes from 3x3 pixels to 9x9 pixels. We found as the window size increased the number of perforated pixels also increased. The increase in window size also resulted in loss of interior forest. Based on these findings, a 5x5 window was utilized to maintain a fair representation of the proportion (Pf) of pixels in the window and to also maintain interior forest at an appropriate level. Figure 5 identifies how the Pf and Pff values are used to assign pixels to the six fragmentation categories defined.

Using a 5x5 pixel window to perform the Pf and Pff calculations produced an output image having a two pixel wide (60 meters) border along the fringe of interior forest designated primarily as perforated and edge. To maintain significant interior forest, we chose to buffer the resulting interior forest by 30 meters. Any forested pixel not identified as interior forest falling within this buffer zone was reclassified to interior forest. This process created a one pixel wide (30 meter) boundary around the interior forest. Comparing the resulting buffered fragmentation image with the original determined that approximately 75 to 78 percent of the pixels changed to interior were perforated pixels and 25 to 27 percent of the interior buffered pixels were edge. Less then 1 percent of the other fragmentation designations were changed by this procedure. Figure 6. displays the result of the application of the fragmentation model to the 1985 land cover image.

RESULTS AND DISCUSSION

Cross-correlation analysis applied to the Salmon River watershed land cover classifications performed well overall, but worked best when identifying changes from the forested categories to other categories. The non-woody vegetated areas, which include agricultural lands, were found to be too heterogeneous regarding the spectral characteristics of the class to provide reliable change analysis. This was due to the existence of agricultural areas in either fallow or vegetative conditions that resulted in large spectral differences between agricultural areas. The identification of the spectral mean for the non-woody vegetated class was therefore affected making it difficult to identify change from agriculture to urban, a class that typically has spectral characteristics similar to barren or fallow field conditions. Splitting the non-woody vegetated category into separate classes of vegetated and non-vegetated, or putting the non-vegetated areas into the barren category would have been preferable, but was not feasible because of the changing condition of individual agricultural areas from year to year.

Sample results of the land cover, TM, and fragmentation images are displayed in Figure 7. Looking in the upper left quadrant of each image, it is easy to see the advancement of a residential development into an interior forest patch over the four date sampling period. The result of this type of development is readily apparent in the fragmentation images, showing the potential value of generating such an image. The amount of interior forest decreased and the edge and perforated forest increased. The single forest patch was also divided into several smaller

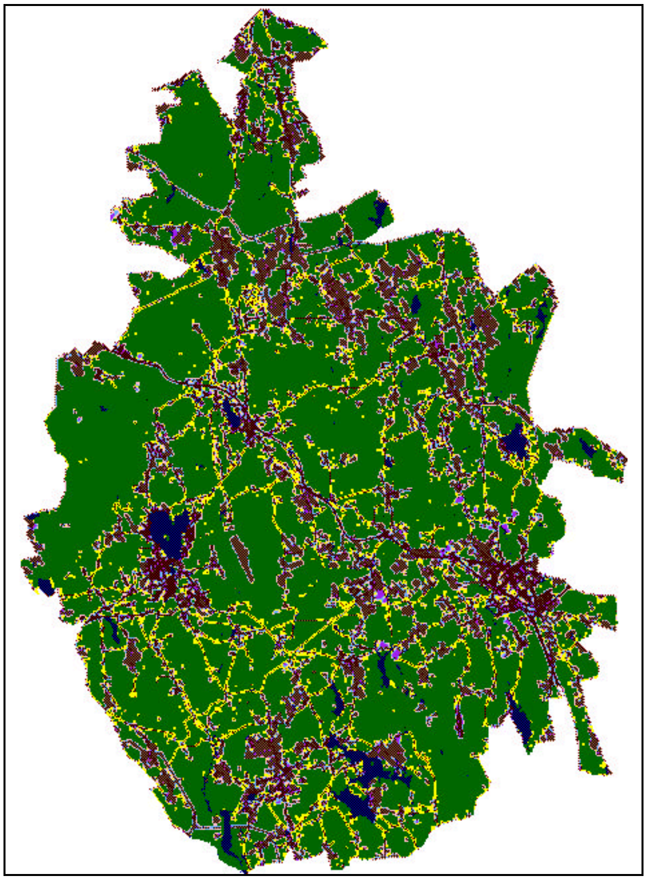


Figure 6. Result of the application of the fragmentation model to the 1985 land cover image. Green is interior forest, yellow is perforated forest, light orange is edge forest, light blue is transitional forest, purple is patch forest, and light green is undetermined forest.

patches. Initial examination of the fragmentation images also revealed the probable mis-identification of edge forest as perforated forest along road corridors a single pixel in width. Referring back to the definition of perforated and edge forest, the majority of the pixels within the calculation window were forest, but the non-forest pixels appear to be clumping based on the definition of Pf - Pff > 0. Essentially the model identifies the non-forest pixels as being an isolated opening in a forest canopy. To alleviate this problem, the threshold between perforated and edge produced by the difference of Pf and Pff was adjusted to a negative number. However, this adjustment began to affect the true perforated forest pixels surrounding isolated openings in the interior forest. The final threshold was set at Pf - Pff > -0.004 for perforated forest and Pf - Pff < -0.004 for edge forest. It is our belief that forest pixels located along corridors should be considered edge, not perforated. This is a part of the model that will need to be investigated further.

Examining Figures 8 through 10 reveals additional trends concerning fragmentation in the Salmon River watershed. Figure 8 shows the general trend of decreasing forest and increasing urban and non-woody vegetated land (the slight increase in the area of non-woody vegetated is primarily the result of forest clear cutting). This results in a decrease of interior forest and an increase in the edge, perforated and transitional forest categories. Figure 9 shows the change in the number of patches and the mean patch size for each of the land cover categories, excluding water. This graph illustrates the affect of human activity on the forest landscape. There are some interesting trends. The number of urban and non-woody vegetated patches increases substantially. This is due mostly to small clearings and construction of isolated houses (typically identified by fewer than 4 pixels on the land cover map) within the interior forest area, generally several pixels away from the urban road corridors. The slight decrease in the mean patch size for urban and non-woody vegetated support this conclusion. The large decrease in the mean patch size for forest indicates that urban development is de-centralized, particularly because the number of forest

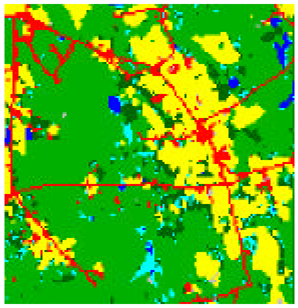
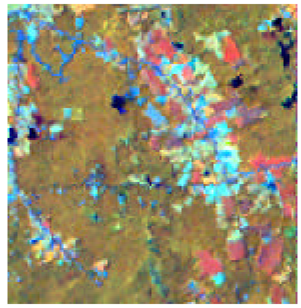
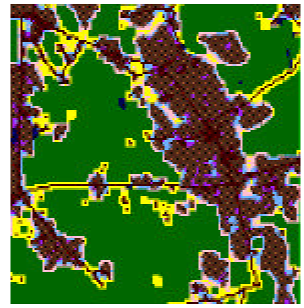
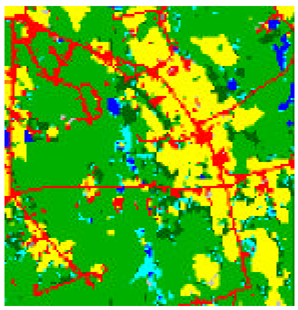
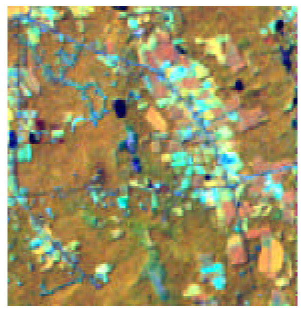
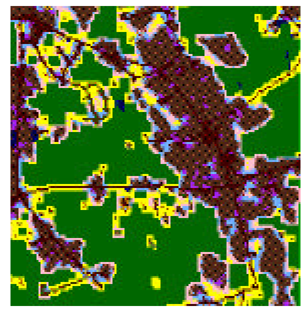
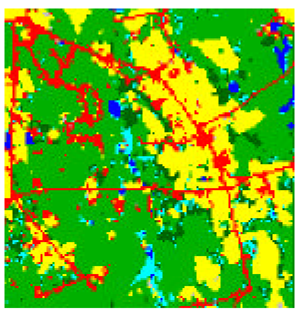
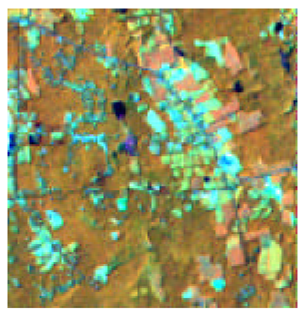
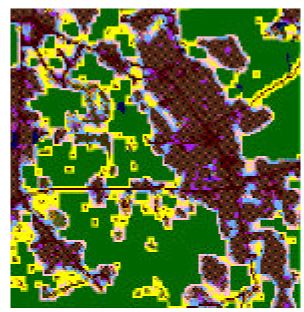
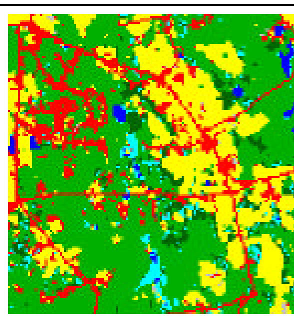
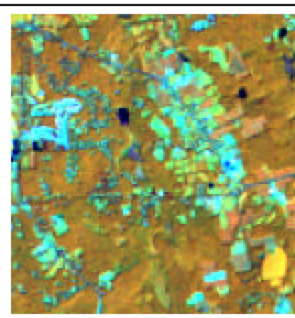
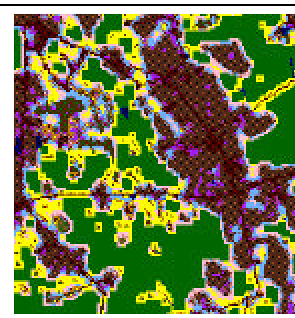
Year	Land Cover Image	Landsat Thematic Mapper Image	Fragmentation Image
1985			
1990			
1995			
1999			
	LEGEND URBAN NON-WOODY VEGETATED DECIDUOUS FOREST CONIFEROUS FOREST WATER WETLAND BARREN	**TM band combination** **Red = Band 4 (NIR)** **Green = Band 5 (NIR)** **Blue = Band 3 (red)**	**LEGEND** INTERIOR FOREST PERFORATED FOREST EDGE FOREST TRANSITIONAL FOREST PATCH FOREST UNDETERMINED FOREST

Figure 7. Comparison of land cover, multispectral Thematic Mapper and fragmentation images for a sample portion of the Salmon River watershed over the four date sample period.

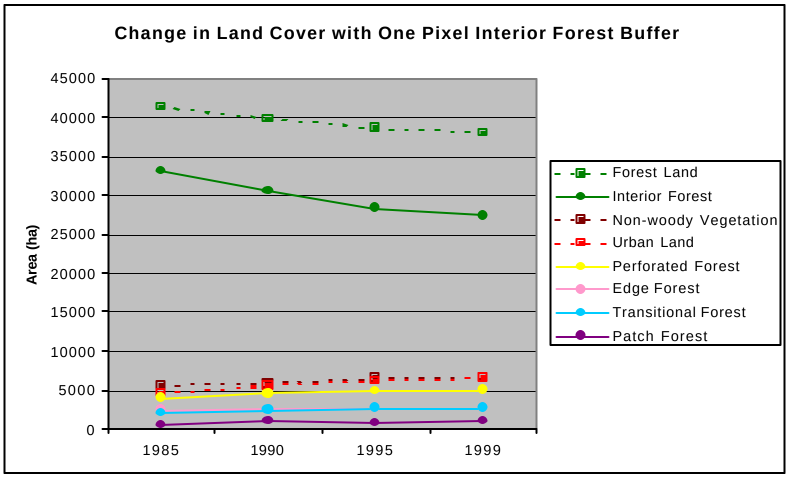


Figure 8. Graph identifying change in land cover and fragmentation categories for the four sample dates.

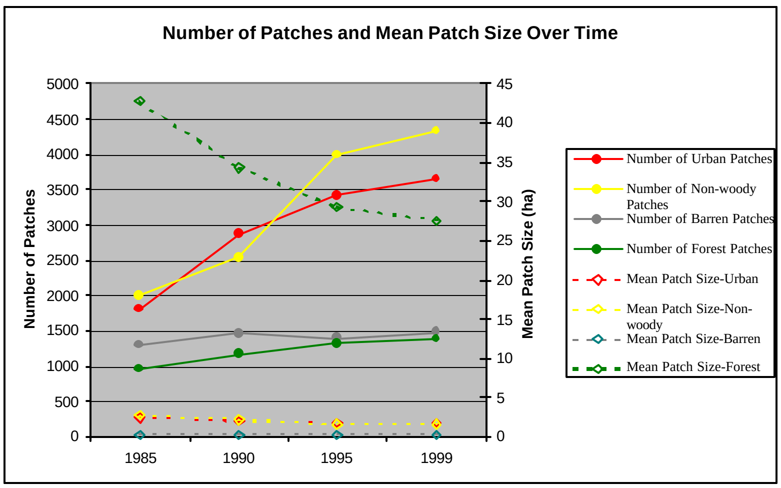


Figure 9. Graph identifying the change in number of patches and mean patch size for the land cover categories for the four sample dates.

patches only shows a modest increase. Figure 10 further supports this. In this figure, the magnitude of the increase in size of the largest urban patch compared to the decrease in the mean patch size of the forest patches in Figure 9 show that urban development is branching off of a single large urban patch (the primary road network) and is encroaching on numerous forest patches causing the mean patch size of forest to decrease. This is indicative to what could be an urban sprawl growth pattern. A more centralized growth pattern would still show an increase in urban patch size, but the mean patch size of forest would decrease less as would the number of forest patches.

CONCLUSIONS

The information produced in this research has provided valuable insight as to the condition of fragmentation in the Salmon River watershed. It clearly shows the advance of urban development and other human activity at the expense of interior forest. Additionally, this research has produced a usable procedure for creating landscape fragmentation information that can be applied to the other three study watersheds. In combination, the time series land cover information provides information on the type of change that is occurring in the landscape at a detailed scale. Generation of fragmentation statistics further describes the changes that are occurring and more importantly the generation of a fragmentation image to show the pattern of fragmentation will be beneficial to local land use decision makers to begin to better understand the ramifications of their land planning decisions.

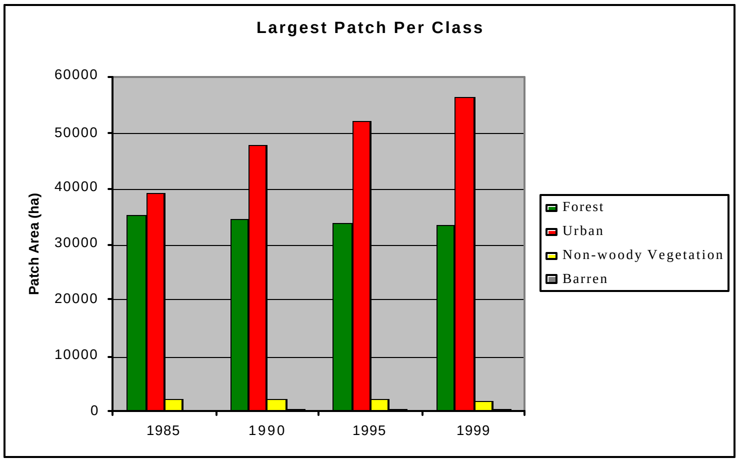


Figure 10. Graph showing the change in area for the largest patch of each land cover category for the four date sample period.

FUTURE RESEARCH

While the current procedures produce useful information, there are several avenues of research that will be applied to further develop the techniques presented here. One such avenue is the derivation of better land cover information. NAUTILUS is currently pursuing innovative techniques to improve classification accuracy and extract more detailed informational classes. Two techniques that are being explored are Artificial Neural Networks and Knowledge Based Expert Systems. These techniques will incorporate information aside from multispectral imagery. Additional information will include a measure of texture proposed by Haralick (1986) and based on brightness value spatial-dependency gray-level co-ocurrence to produce texture measures. Additional information will also include image segmentation features outlined by Tilton (2000) that will be used to divide the image into spectrally similar regions or objects that can be included in the knowledge based classifier and neural networks.

The benefits of improved classification images for identifying patterns of forest fragmentation are two-fold. First, having improved information would provide a more accurate picture of fragmentation and where it is occurring. Second, more detailed informational classes would allow for better analysis as to the cause of fragmentation. Some examples could include identifying the difference between types of urban development (commercial, residential, roads, etc…), neighborhood versus isolated home construction, expansion or abandonment of agricultural areas, and the appearance and subsequent disappearance of clear-cut areas.

Regarding further fragmentation analysis, a logical next step beyond determining forest fragmentation patterns for individual dates is the combination of dates to identify trends within the landscape. In addition is the creation of a model to label the type of fragmentation that is occurring.

ACKNOWLEDGEMENTS

This material is based upon work supported by the National Aeronautics and Space Administration under Grant NAG13-99001/NRA-98-OES-08 RESAC-NAUTILUS, *"Better Land Use Planning for the Urbanizing Northeast: Creating a Network of Value-Added Geospatial Information, Tools, and Education for Land Use Decision Maker*s". The authors would like to extend their appreciation to the assistance and advice to their colleagues in Project NEMO (http://nemo.uconn.edu). [SAES Scientific Contribution Number 2013]

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