TEMPORAL CHARACTERIZATION OF CONNECTICUT'S LANDSCAPE: METHODS, RESULTS, AND APPLICATIONS

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ABSTRACT

Located between the two major metropolitan centers of New York and Boston, Connecticut is continuously faced with the difficult challenge of balancing natural resource protection with economic growth and development. Realizing the importance of spatial information in making informed land use decisions, researchers and educators at the University of Connecticut's Center for Land use Education and Research (CLEAR) are working to provide needed information, education, and assistance to local land use decision makers. Now a part of CLEAR, research conducted under NAUTILUS – NASA's Northeast Regional Earth Science Applications Center (RESAC) – is being used to identify and quantify impervious surfaces, urban growth, and forest fragmentation. The intent is to make this information available to local land use decision makers in Connecticut to assist them in planning activities.

Various techniques have been applied to generate statewide information from Landsat imagery. Estimates of percent impervious surfaces were derived directly from the image data by using sub-pixel classification. Urban growth and forest fragmentation models depend on land cover as their input information. Land cover was derived for four dates of imagery over a 17-year period using a variety of methods including sub-pixel classification, supervised and unsupervised classification, and cross-correlation analysis. The urban growth model identifies areas of urban development and categorizes growth into one of five types: in-fill, expansion, isolated, linear branching, or clustered branching. The forest fragmentation model classifies forest pixels as one of five types: interior, perforated, edge, transition, or patch. Additionally the state of forest fragmentation is calculated for selected areas. This paper describes the generation of each of these information layers and how they are being applied as tools for land use planning in Connecticut.

INTRODUCTION

For more than a decade, the University of Connecticut has initiated a series of projects that focus on land use and land cover as a research topic, and land use decision makers as an outreach audience. This work is driven by the fact that land use is the central issue underlying many of the most pressing concerns for most communities. Air and water quality, economic development, transportation, open space protection, community character, and farmland

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preservation are all closely connected to land use patterns and trends. As the landscape continues to urbanize, the role that land use plays in determining the quality of our water and air becomes increasingly more important to our health and well-being. However, land use is a local affair, with limited mechanisms for federal and even state programs to influence local land use decisions (General Accounting Office, 2001). Because land use is decided locally, in town and county commission meetings, the task of providing technical tools and education to local government officials is of critical importance (Arnold and Schueler, 2001; Arnold, 1999). Nowhere is this truer than in Connecticut, where each of the state's 169 municipalities individually determines land use through zoning, planning, economic development and other volunteer commissions, with little assistance from the state or federal agencies. Sprawl is also no stranger to Connecticut. Recent indicators show that over the past 30-years, the State's population increased only about 10% while the amount of developed land more than doubled. This trend is likely to worsen, as new estimates from the U.S. Census Bureau show that in the past decade, the state's national ranking for percentage population growth has jumped from 47th to 25th.

Understanding that there is a strong need for spatial information for the State of Connecticut that describes the character of the landscape, the *Center for Land use Education And Research* (CLEAR) at The University of Connecticut has taken on the task of deriving a series of statewide geo-spatial informational data products for four dates (1985, 1990, 1995, 2002) spanning a 17 year period. Based on models developed under NASA's Northeast Regional Earth Science Applications Center (RESAC) that focused on improving information and increasing understanding of urban and suburban growth, analysts at CLEAR are now applying them at the state level.

Three broad topical areas formed the core of the Northeast RESAC research program: extraction of point-in-time land use, land cover, and multitemporal (change) information from remote sensing data, development of improved methods to identify and quantify landscape elements of particular concern, and development of models and metrics to characterize better specific landscape trends. Each of these areas helps contribute to the understanding of landscape dynamics in the State. Land cover mapping and three measures of landscape characterization (forest fragmentation, urban growth, and impervious surface modeling) currently being applied at the statewide level are highlighted in this paper.

LAND COVER

Each of the three landscape characterization models utilizes land cover information. Land cover that is consistent between each date is necessary to produce reliable results over time. To achieve this, a base land cover image was generated with subsequent land cover derived from it using cross-correlation analysis, a change detection method developed by Earthsat, Inc. (Koeln and Bissonnette, 2000). The analysis area consists of the entire State of Connecticut including local watersheds that intersect the state boundary, and a portion of south central Massachusetts. Nine towns from south central Massachusetts and 26 towns in northeast Connecticut comprise the Quinebaug and Shetucket Rivers Valley National Heritage Corridor, a region, designated by the U.S. Congress as a unique national resource in 1994. This area maintains much of its historic rural character amidst one of the most urbanized regions in the country making it an important area to monitor and analyze in terms of landscape characterization over time.

Base Land Cover

The primary source of image data came from an April 26, 1985 Landsat Thematic Mapper (TM) scene (path 13/row 31) covering most of the analysis area. The extreme southeastern portion of the State of Connecticut was covered by an August 9, 1985 Landsat TM scene (path 12/row 31). Cloud and cloud shadow regions covering some of the northwest portion of the image were extracted and substituted with a May 4, 1988 Landsat TM scene. Most of this area consisted of forest cover and was not impacted by potential change in land cover between these two time periods. Figure 1 shows image data from 1985 covering the extent of the analysis area.

The purpose of the primary land cover images was to serve as source data to the landscape characterization models. Because these models only require basic land cover information, it was not necessary to develop a complex classification scheme that could result in decreased accuracy. Table 1 lists the 11 land cover categories that are identified in the land cover images.

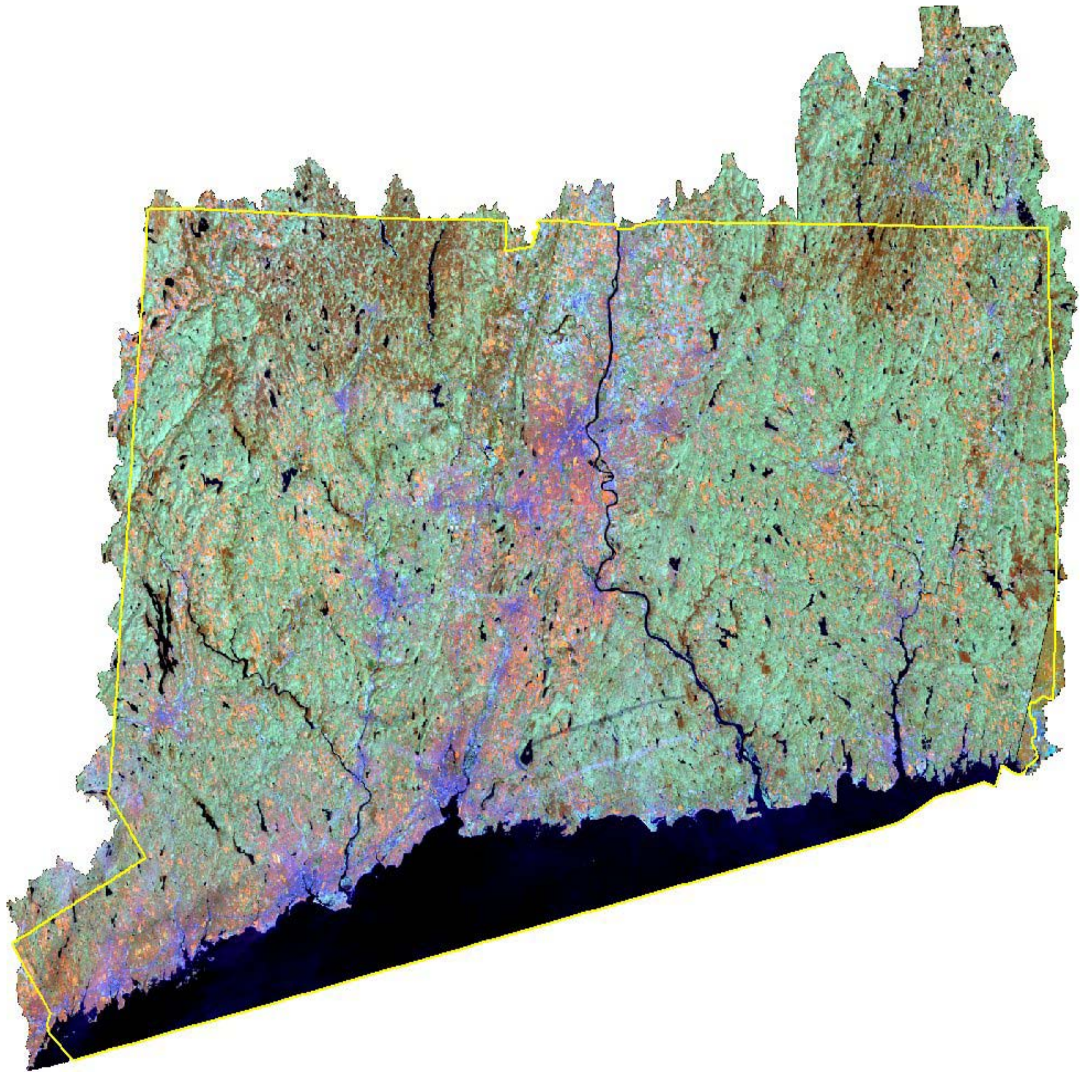


Figure 1. April 26, 1985 and August 9, 1985 Landsat TM images of the entire analysis area. Band combination displayed represents the near-infrared (band 4), middle-infrared (band 5) and red (band 3) portions of the electromagnetic spectrum.

Table 1. Land cover classification scheme.

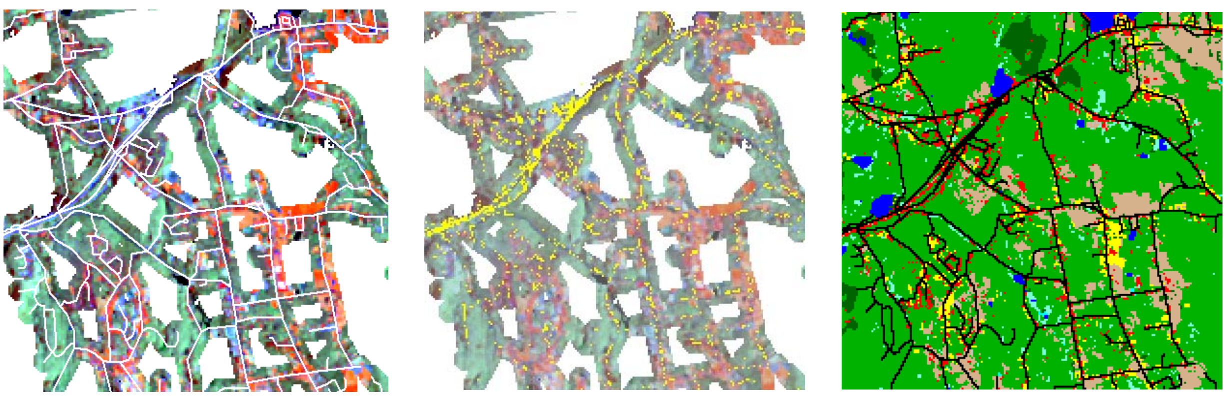
1. Developed	5. Coniferous Forest	9. Tidal Wetlands
2. Turf & Grass	6. Water	10. Barren Land
3. Agriculture	7. Non-forested Wetlands	11. Utility Right-of-Ways
4. Deciduous Forest	8. Forest Wetlands	

Road Network. Classification began with the April 26, 1985 image that was clipped to the analysis area. Classification of the road network was the first focus. Identification of major and local roads is critical to the successful application of the forest fragmentation and urban growth models and also proves useful for impervious surface estimation. In order to capture roads, vector road coverages were used to extract image data from the TM scene. All improved roads (paved) were selected from the vector road coverage and rasterized to the pixel size of the source imagery (100 feet). This layer was then buffered 5 pixels to account for areas of mis-alignment. All image pixels contained within the 5 pixel buffer area were extracted for analysis (Figure 2a). The intent was to create an image data layer on which the classifications of roads could be focused by minimizing non-road pixels. ERDAS

Imagine SubPixel Classifier™ (SPC) engineered by Applied Analysis Inc. (AAI) was used to classify road pixels. The SPC is a supervised classifier that enables the detection of materials of interest (MOIs) as whole or fractional pixel composition, with a minimum detectable threshold of 20 percent and in increments of 10 percent (i.e., 20-30%, 30-40%, … 90-100%). Because of tonal variations in the built landscape, MOIs representing different brightness classes of road and paved surfaces (i.e. dark, medium, and bright surfaces) were selected to be mapped Any pixel identified by the SPC, regardless of its percent composition, was considered a developed pixel.

Final results of the SPC did not fully extract the road network. To enhance further the results of the SPC, knowledge-based (KB) classification was employed. Those pixels not identified as developed through the SPC technique were extracted for further evaluation. Bands 4 and 5 showed the most contrast between developed pixels and other pixels. In the ERDAS Imagine Knowledge Engineer, a rule was created that used the value ranges (129 and 143 for band 4; 128 and 193 for band 5) to identify developed pixels that met the criteria for both bands. In addition, a pixel also had to be contained within the rasterized road layer. The result of this procedure was the identification of additional developed pixels not identified during the sub-pixel classification.

Figure 2b provides the results of the Sub-pixel Classifier and Knowledge-based classification applied to the road buffered image. The SPC and knowledge-based classification did not extract the full extent of the road network. To correct for this problem, the rasterized road layer was embedded with the final classification described in the next section and onscreen digitizing was conducted to remove areas of mis-alignment. While this may appear to be a step backward, enough pixels were identified as developed to prove invaluable in determining the true road alignment that is critical to the success of the forest fragmentation and urban growth models. Similar techniques were used on the August 9, 1985 image covering the southeast portion of the analysis area.



a b c

Figure 2. Example of the road network classification. (a) Extracted image pixels surrounding rasterized road network. (b) Classified road network pixels using the SBC and KB classifiers (yellow). (c) Embedded rasterized road network on final land cover.

Complete Area Classification. The remaining image pixels were then classified. To begin, those pixels identified as developed in the previous step were eliminated from the TM image. An area of approximately 180 square miles along the central coast of Connecticut was then subset from the overall analysis area for use in deriving classification signature statistics. This area was selected because it contained a significant amount of those categories identified in the classification scheme. ISODATA classification was performed generating 100 signature clusters. These clusters were then identified and labeled into the appropriate land cover category.

Maximum likelihood classification was applied to the entire analysis area using selected signatures derived through the ISODATA process. Classification was done one class at a time specifying a distance image as the output. The distance file produces an image whose pixel values represent the spectral distance from the class signature. The lower the value, the more similar a pixel is to a specific class signature. This procedure was repeated for each class. Visual examination of the distance image with the TM image resulted in the identification of thresholds that were used with the Knowledge Engineer to derive a land cover image. Additionally, tidal wetlands were identified based on a previous land cover project for the State of Connecticut based on spring and summer 1995 Landsat TM imagery. This 1995 land cover image was also used to identify further non-vegetated agricultural areas that were misclassified as developed due to the bright spectral reflectance. Figure 3 provides an overview of this phase of the classification.

Pixels remaining as unclassified were extracted from the TM image. ISODATA classification was performed on these remaining pixels. The clusters were identified and labeled into the appropriate category. The resulting classifications were then merged to create a single classified image with all pixels being identified as belonging to a single category. Next, several steps were taken to clean-up the classification. First, a digital elevation model was used to eliminate areas misclassified as wetlands due predominately to steep northwest facing slopes. Using the Knowledge Engineer, any pixel identified as non-forested or forested wetlands that fell on a slope of 12 degrees or more was reassigned to deciduous forest. Several majority filters were used to eliminate specific isolated pixels resulting in a more uniform classification. Lastly, detailed heads-up digitizing was used to remove any remaining apparent errors and to also include utility right-of-ways which can be considered significant fragmenting features to the forest landscape. Utility right-of-ways were digitized out of the deciduous and coniferous forest classes only. The overall intent in developing a land cover image using these various techniques was to continually eliminate those pixels that were easily classified and narrow down those pixels that were more problematic. Remaining errors would potentially be cleaned during the on-screen digitizing phase of the classification. Figure 4 provides the final results of the 1985 land cover for the entire analysis area.

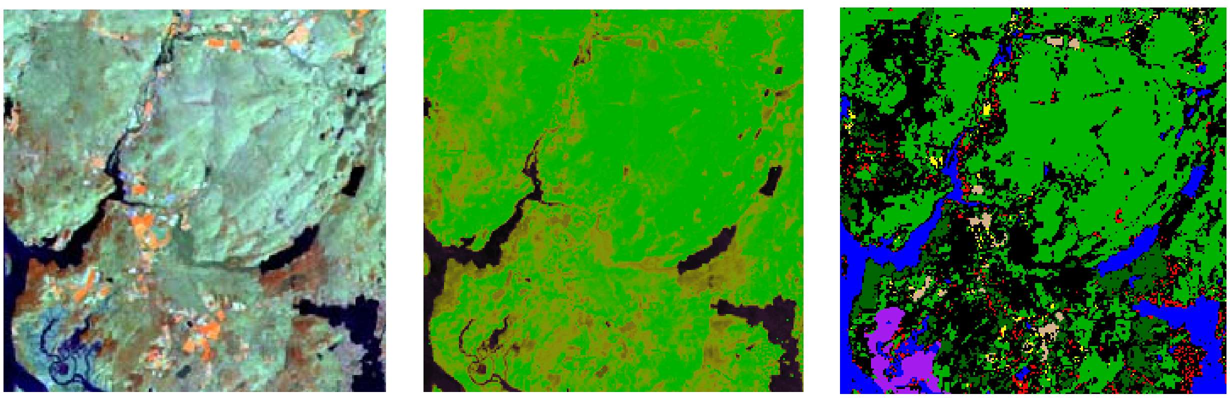


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Figure 3. Example of knowledge-based classification using distance images. (a) April 26, 1985 Landsat TM image. (b) Distance image for the deciduous forest class (green = more likely deciduous). (c) Resulting KB classification.

Subsequent Land Cover

Cross-correlation Analysis (CCA) was chosen as the method for determining subsequent land cover because it overcomes many of the limitations of conventional change detection methods and is able to produce a consistent set of land cover. Cross-correlation works by using the land cover categories identified in the base land cover image to derive an "expected" class average spectral response (Koeln and Bissonnette, 2000). 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 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. For more information on Cross-correlation Analysis, see the following references (Koeln and Bissonnette, 2000; Smith *et al*., 2002).

In the case of this work, CCA was applied to five groups of land cover categories. These groups include water; deciduous, coniferous and forested wetlands; turf & grass and agriculture; barren; and non-forested and tidal wetlands. Using the 1985 land cover, pixels belonging to each group were extracted from an August 30, 1990 TM image (*i.e.* for the deciduous, coniferous and forested wetlands group, pixels classified as these in 1985 were extracted from the August 30, 1990 TM image). The CCA procedure was applied to the extracted pixels and the results were visually examined with the recent image data to determine the threshold between probable change

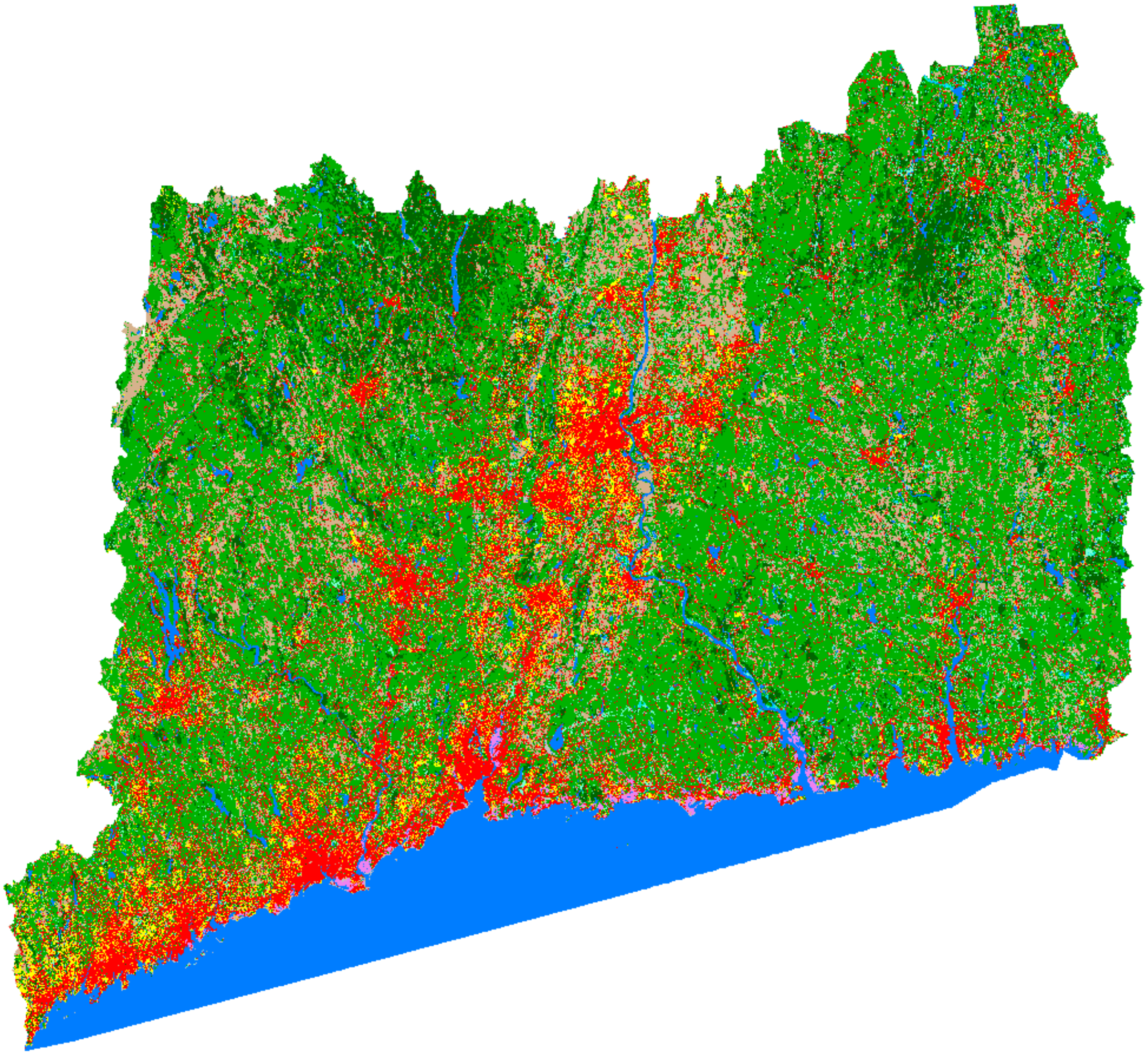


Figure 4. Land cover derived from April 26, 1985 and August 9, 1985 Landsat TM images representing 11 categories of land cover (developed, turf & grass, agriculture, deciduous forest, coniferous forest, water, non-forested wetland, forested wetland, tidal wetland, barren, utility right-of-ways).

pixels and non-changed pixels. Those pixels identified as changed were extracted from the August 30, 1990 image. ISODATA classification was performed to identify the category that each pixel now belonged. These steps were repeated for each class group. Figure 5 provides examples of CCA on the forest grouping between 1985 and 1990. Once completed, each group of classifications was combined into a single image and edited to remove apparent errors. These pixels were then fused with the previous land cover to produce an updated land cover image. This updated land cover was then used on an August 28, 1995 TM image and that updated land cover used on a September 8, 2002 TM image.

LANDSCAPE CHARACTERIZATION

CLEAR research has been directed at three dynamic elements of the landscape that are critically important to land use officials in Connecticut: forest fragmentation, urban growth and impervious surfaces. Each of these is briefly described in this paper and examples based on the new land cover information are provided. For more detailed information, these authors have reported on the development of these models in other publications. For forest fragmentation modeling, refer to Civco *et al.,* (2002) and Hurd *et al.,* (2002). For urban growth modeling, refer to Civco *et al.,* (2002) and Hoffhine Wilson *et al*., (2002). For impervious surface refer to Civco *et al.,* (2002) and Wilson *et al*., (2002). For impervious surface estimation, refer to Civco *et al.,* (2002);Civco and Hurd, (1997) and Flanagan and Civco, (2001).

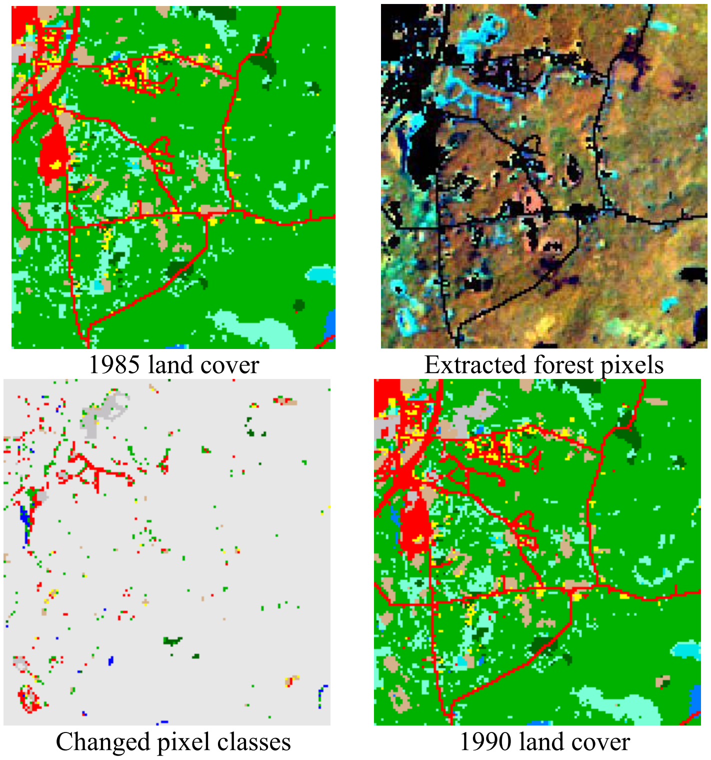


Figure 5. Cross-correlation analysis process.

Forest Fragmentation Model

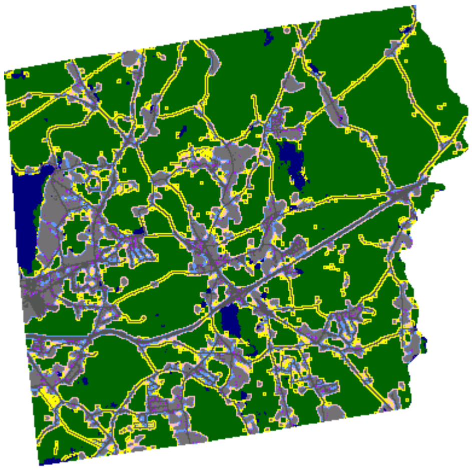
The primary goal of the forest fragmentation model was to develop an image that would allow a user to visualize easily the extent of forest fragmentation and track the change in fragmentation over time. The basis of this model comes from a forest fragmentation model developed by Riitters *et al.* (2000). Their model, which assess forest fragmentation at the global level, generates categories that describe the type of forest fragmentation condition that exists for a given forest pixel. These fragmentation types are interior forest, perforated forest, edge forest, transitional forest, and patch forest. These are briefly described below:

- Interior forest - all pixels in the surrounding area are forest.
- Perforated forest - most of the pixels in the surrounding area are forested, but some appear 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.
- Edge forest - most of the pixels in the surrounding area are forested, but some appear to be part of the outside edge of forest, such as would occur along the boundary of a large urban area, or agricultural field.
- Transitional forest - about half of the cells in the surrounding area are forested and these may appear to be part of a patch, edge, or perforation depending on the local forest pattern.
- Patch forest – very few forest pixels that are part of a forest patch on a non-forest background, such as a small wooded lot within an urbanized region.

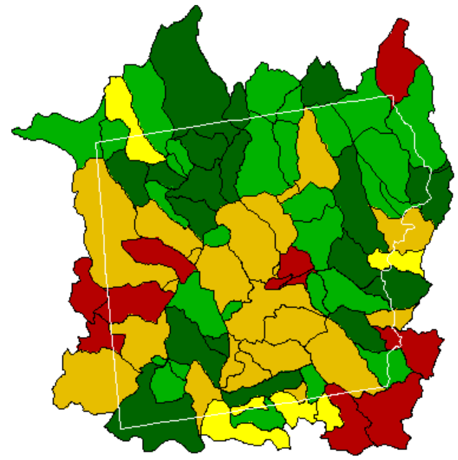
The model was modified to work with Landsat derived land cover (30-meter spatial resolution). In addition, an index that derives a more succinct view of the state of forest fragmentation for a region was developed. The premise was that while the forest fragmentation model produced valuable information, it was difficult to visualize easily the state of forest fragmentation for an area, track trends in forest fragmentation, and also identify areas where forest restoration might prove appropriate to reduce the impact of forest fragmentation. The state of forest fragmentation index complements the results of the forest fragmentation model. Figure 6 provides examples of both the forest fragmentation model and the state of forest fragmentation outputs. For the forest fragmentation images, gray and blue represent developed and water areas respectively. The other colors represent types of forest fragmentation with the green identifying interior forest. For the state of forest fragmentation, the colors range from green (low forest fragmentation) to dark red (severe forest fragmentation).

Urban Growth Model

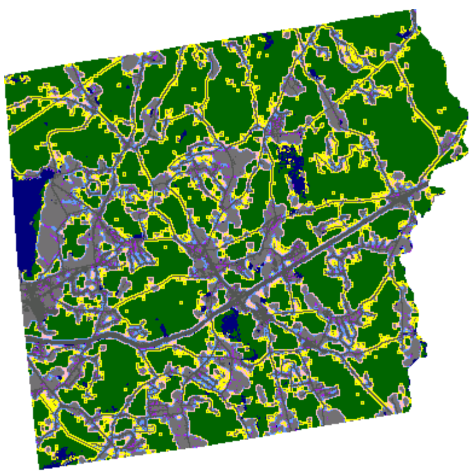
The urban growth model was developed to quantify and characterize types of urban growth. The model is a rule-based system that creates a change map that highlights new areas of development. Its development was based on the forest fragmentation model produced by Riitters *et al.* (2000). The result of the urban growth model is the identification of 5 types of urban growth. These are:



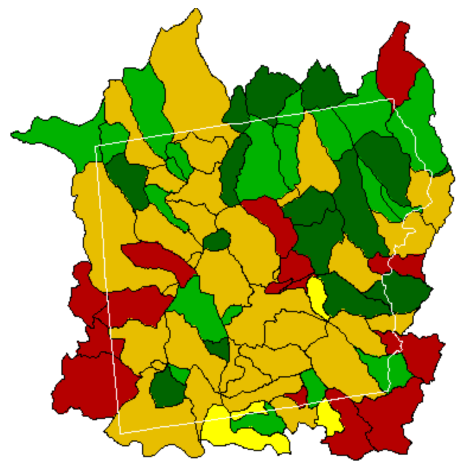
1985 forest fragmentation for Tolland, CT.



1985 state of forest fragmentation for local watersheds intersecting Tolland, CT.



2002 forest fragmentation for Tolland, CT.



2002 state of forest fragmentation for local watersheds intersecting Tolland, CT.

Figure 6. Forest fragmentation and state of forest fragmentation results.

- *Infill* growth - characterized by an undeveloped pixel surrounded by at least 40% developed pixels being converted to developed. Can be associated with the development of vacant land in already built-up areas.
- *Expansion* growth - characterized by an undeveloped pixel surrounded by some developed pixels (no more than 40%) being converted to developed. This conversion represents an expansion or "spreading out" of the existing urbanized patch.
- *Outlying* growth - characterized by a change from an interior undeveloped pixel to a developed pixel. This type of change indicates an area of development that is occurring some distance from existing urbanized areas. Outlying growth can be further divided into the following three growth types:
  - *Isolated* growth - characteristic of a new house or construction generally surrounded by undeveloped land cover and some distance from an existing urbanized area.
  - *Linear branching* - represents a new road or new linear development surrounded by undeveloped and some distance from existing urbanized areas.
  - *Clustered branching* - is characteristic of a new neighborhood or large built-up complex.

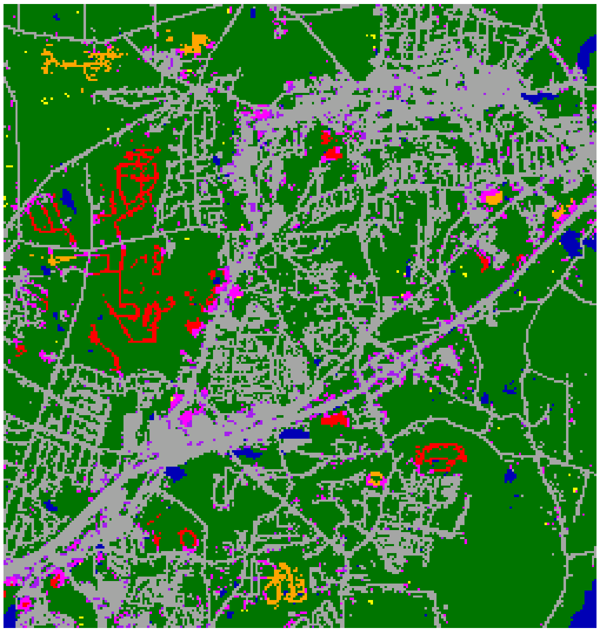


Figure 7. Example of the urban growth model output for the time interval of 1985 to 2002.

Figure 7 provides an example of applying the urban growth model to land cover information from 1985 and 2002. The gray and green colors represent existing developed and undeveloped areas respectively. Purple represents infill growth, magenta represents expansion growth, yellow represents isolated growth, red represents linear branching growth, and orange represents clustered branching growth.

Impervious Surfaces

Impervious surfaces are widely accepted as a reliable indicator of urbanization and its impacts on natural resources, particularly water resources (Arnold and Gibbons, 1996; Schueler, 1994) and are thus a valuable source of information to land use planners. CLEAR researchers have been long involved in investigating ways to measure impervious surfaces (IS) (Arnold *et al*., 1993; Stocker *et al*., 1999). Substantial effort has been directed towards direct subpixel percent IS modeling from Landsat TM data themselves (Civco and Hurd, 1997; Flanagan and Civco, 2001) with recent results of study sites indicating improvements in accuracy and geographic extensibility. At the time of this writing, impervious surface estimates for this analysis area are still under development, but a prototype method is being applied to Landsat data using the developed category from the land cover images to guide the analysis. In this method, pixels identified as developed in the land cover are extracted from the appropriate TM image (*i.e.* 1985 land cover and 1985 Landsat TM data). Subpixel classification is applied to the extracted pixels to derive an estimate of imperviousness. Pixels are classified as containing a percentage of impervious surfaces at 10 percent intervals. The benefit of deriving impervious surface information using this method is that the results will be consistent with the urban *footprint* on other data layers derived from the land cover information. In addition, using the land cover to focus analysis will minimize misclassification of impervious pixels that fall outside the developed category. Figure 8 shows the tentative results of impervious surface estimation using this approach. In this example, red indicates the highest percentage of impervious surfaces down to green that indicates the lowest percentage.

APPLICATIONS

The result of this work is a comprehensive spatial and temporal landscape characterization of the State of Connecticut that will be made available to all local decision makers and land use professionals within the state. CLEAR investigators have determined that moderate spatial resolution remote sensing based information is not widely used at the local level because local officials are most familiar and comfortable with site-level information and tools. Yet, in order to plan for both conservation and development, it is necessary to place site-level decisions within a wider perspective of the town, county, or watershed. Much of CLEAR's research and educational programs have focused on providing this perspective.

With an end user of local land use officials, dissemination of any geo-spatial information is critical. For the broadest impact, applications must be made accessible in several ways to accommodate

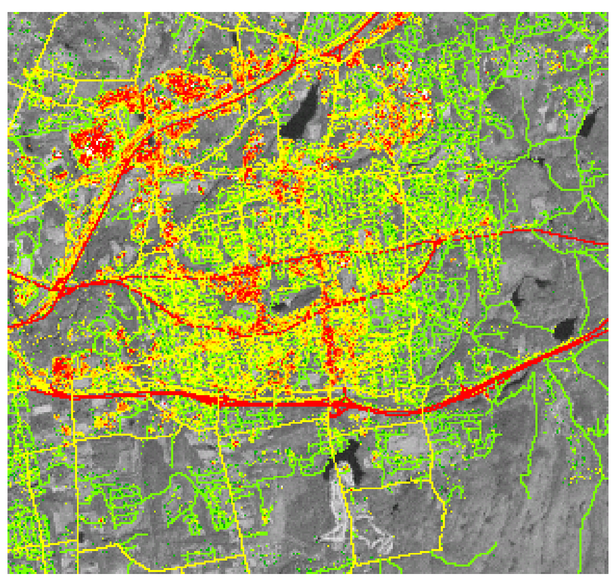


Figure 8. Impervious surfaces estimate from April 26, 2000 Landsat ETM image for the Manchester, CT area.

communities of differing levels of staffing, technological sophistication and planning expertise. At a minimum, these data will be made available via the Web through internet map servers, such as ESRI's ArcIMS and ER Mapper's Internet Web Server, which will be used as the user interface for interactively defining analysis areas, and viewing products. Data files will also be made available for download in a variety of formats.

Education is a core component of CLEAR. The landscape characterization information will be incorporated into the many educational programs conducted under CLEAR. One is the Non-point Education for Municipal Officials (NEMO) Project in both Connecticut and across the United States by way of the 26 National NEMO Network projects. The NEMO program provides workshops and information for making better land use decisions while utilizing valuable geospatial information, such as the landscape characterization products discussed here. Another program is the Green Valley Institute which is a formal collaboration between the Quinebaug and Shetucket Rivers Valley National Heritage Corridor and the University of Connecticut's College of Agriculture and Natural Resources aimed at assisting Heritage Corridor communities and citizens sustain their environment and quality of life while growing their economies. Landscape characterization information will also be incorporated into the UConn Extension Forestry program.

The benefit of these geo-spatial data products is that land use decision makers can review the past development patterns within their town and can also help these same officials to place their decisions within a broader spatial and temporal context. Questions that can be answered include: how much development has occurred within a town and when? Where has this development occurred? What is the primary type of development? How much impervious surface is within a watershed or other area? What is the impact of past development on the forest resources of the town? Figure 9 provides an example of how this data might be used to answer some of these questions for the town of Tolland, CT.

Tolland Case Study

Tolland is a rural town located in northeastern Connecticut. A major east-west interstate highway runs through the middle of town, and two state highways also serve the town on which the modest amount of commercial development is centered. Tolland is comprised mostly of forested land cover. Between the years 1985 and 2002, approximately 350 hectares of land was developed, with most of this conversion coming from forested land. New development has occurred throughout the town, but was most prevalent in the northern and eastern parts of town as identified in the urban growth map (Figure 9). Of the 350-hectare increase in development, nearly 50 percent, or 171 hectares was in the form of linear growth that can be considered an urban sprawl type growth. Regarding impervious surfaces, of the 57 local watersheds within the town of Tolland that contribute to the Willimantic River (forms the eastern boundary of the town), these watersheds contain a total of 3.69 percent impervious surfaces. The cumulative impact of impervious surfaces by the Town of Tolland on the water quality of the Willimantic River can therefore be considered minimal. For forest resources, of the 88 local watersheds intersecting or included in the town of Tolland, the level of forest fragmentation increased substantially for 26 of the watersheds from 1985 to 2002. Of the 29 local watersheds considered highly forested with low forest fragmentation (green watersheds in Figure 9) in 1985, 20 remained in that same state in 2002. Negative impacts to the forest landscape can be seen in the 1985 and 2002 state of forest fragmentation images with the decrease in green and dark green and increase in orange in reds over this time period (Figure 9). These are just a few examples of how these geo-spatial data layers can serve to answer questions regarding the characteristics of the landscape and help address the growing problem of how best to manage growth and protect natural resources.

CONCLUSIONS

Connecticut's landscape will continue to urbanize, and as it does, communities will continue to struggle with ways to accommodate economic growth while protecting natural resources and community character. Community officials need all the education, (accessible) data, and technical tools they can get to understand the changing landscape, and the relationship of these changes to land use decisions. The data products described here will be incorporated into a number of ongoing land use education projects in the state. Through these programs, land cover change and derived products will serve as powerful tools to help community leaders analyze the ultimate landscape results of past land use decisions, and to begin to grasp what type of future landscape current land use policies may produce.

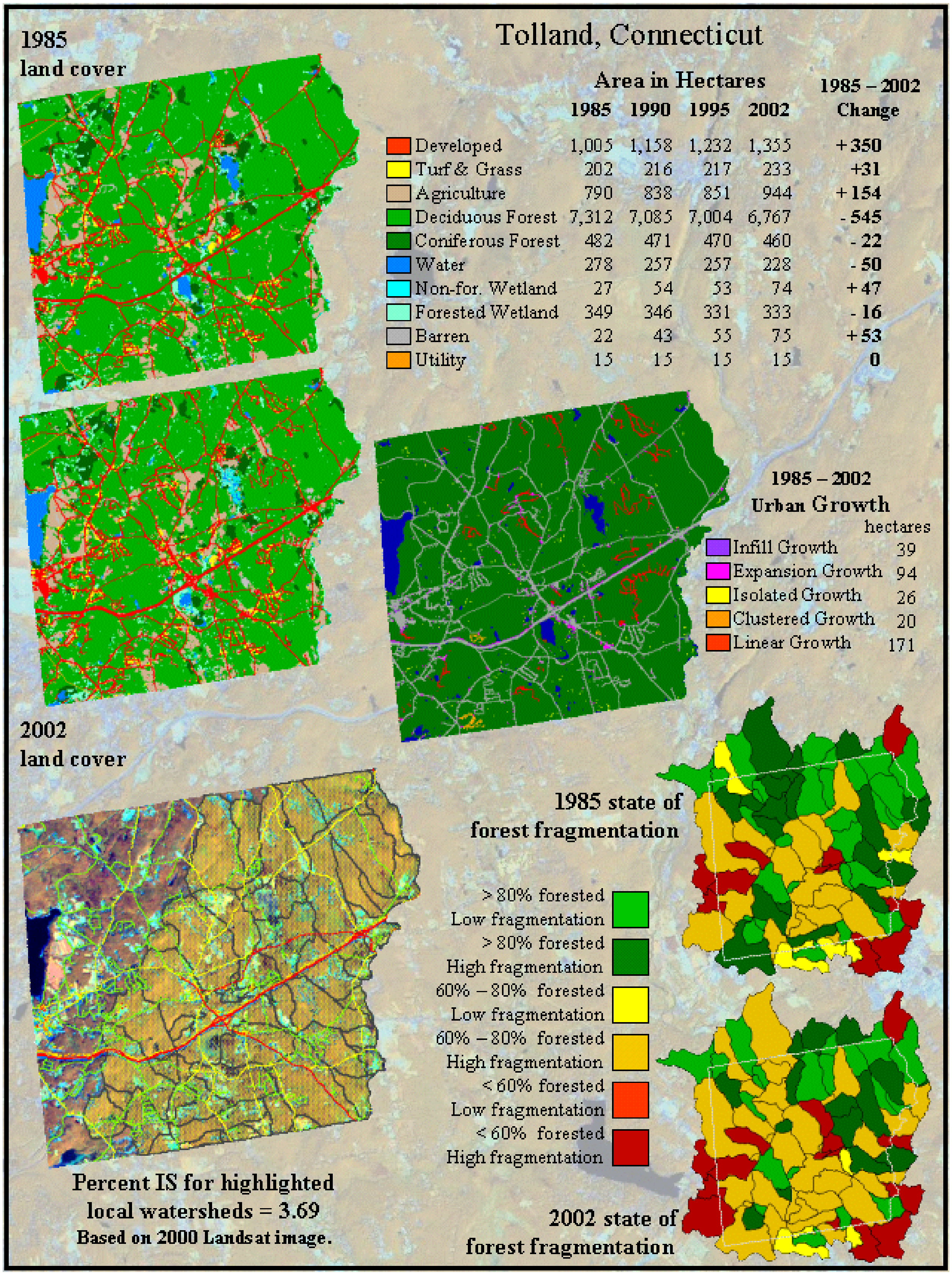


Figure 9. Example of land cover and landscape characterization model results for the town of Tolland, CT.

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