CHARACTERIZATION OF SUBURBAN SPRAWL AND FOREST FRAGMENTATION THROUGH REMOTE SENSING APPLICATIONS

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INTRODUCTION

Problem Statement

Natural Resource Management in the 21st Century: A Focus on Communities. The United States is suburbanizing. The environmental, economic, and societal impacts of development – *i.e.*, changes in land cover from agricultural and forested regimes to suburban and urban landscapes – are not well understood, or even adequately characterized. This is especially true of *sprawl* -- the attenuated, land-consumptive pattern of suburban development that has dominated the American landscape since the advent of the interstate highway system after World War II. Concern about the economic, environmental and cultural toll of sprawl is growing, particularly in our rapidly-developing coastal areas (Bank of America, 1995; Sierra Club, 1997) and throughout the Northeast (Maine State Planning Office, 1997; Vermont Agency of Natural Resources, 1998; EPA Region One; 1998).

Ultimately, the issue of sprawl must be addressed through land use decisions made at the county, township and municipal levels of government. Nonpoint source pollution, habitat fragmentation and other sprawl-related impacts are emblematic of the new era of diffuse and incremental environmental problems stemming from our land use practices. And, land use is overwhelmingly decided at the local level, by municipal and county commissions; many of these local officials are elected or appointed volunteers, with little or no training in land planning or environmental science.

Community leaders comprise a vast – and vastly under-served – group that is critical to our ability, as a nation, to manage global change. They are the end-user group upon which the work described in this paper is focused. A concerted effort is needed to provide our communities with information, easily-used tools, and educational programs that will enable them to factor in land cover changes – particularly those related to sprawl -- when planning and developing their communities.

The Role of Geospatial Technologies in Helping Local Land Use Decision Makers. Geospatial information and tools can be a critical asset for local and regional land use decision makers in planning and designing better communities. Geospatial technologies can provide the key information that allows local natural resource managers – both individual property owners and land use commissioners – to put their case-by-case land use decisions within the broader context of the community, county, or watershed. Geospatial technology can assist them to:

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- characterize their landscape
- prioritize their natural resources
- project land use patterns, helping them to visualize alternative futures
- educate their constituency
- share information and resources needed to truly reach consensus on a future course for their communities.

However, there are significant impediments to making geospatial technology truly useful at the *local* level. Unlike professional federal and state natural resource managers, local leaders have limited access to geospatial data and technology, and are constrained in their capacity to develop uses for this information relevant to their world. Land use decision makers need both improved land cover data, and improved, *meaningful* access to the data. Providing data and maps is simply not enough -- colorful, impressive maps created with remote sensing (RS) and geographic information system (GIS) data are becoming the modern equivalent of the *dreaded report that sits on a shelf*. To improve local land use decisions, the power of RS and related technologies must be made accessible through a *value-added* approach -- one that integrates basic and applied research with simple-to-use, widely available applications, and outreach education addressing their specific needs as end-users. RS, GIS and other geospatial tools must be simplified, explained and otherwise tailored through professional educators and applications experts with thorough experience in the world of the particular end-user targeted.

The University of Connecticut has been the home to a series of projects focused on making RS information truly useful at the local level, the most notable of which is the Nonpoint Education for Municipal Officials (NEMO) Project (Arnold *et al.*, 1996; Arnold *et al.*, 1993). Although the NEMO[5] Project has had considerable success with its techniques, (Stocker *et al.*, 1999), project participants felt that improvements to their RS database and educational delivery methods would be critical in addressing the issue of sprawl.

Approach

NAUTILUS is a new NASA Regional Earth Science Applications Center (RESAC), located at the University of Connecticut. The acronym **NAUTILUS** stands for *Northeast Applications of Useable Technology In Land planning for Urban Sprawl.* NAUTILUS and other NASA RESACs are charged with *developing new methods for bringing together the research, service and user communities to apply NASA's research results to practical, societal problems.* Within those general marching orders, the specific mission of NAUTILUS is *to make the power of remote sensing technology accessible and useable to local land use decision makers concerned with suburban/urban sprawl and its impacts on natural resources.* To accomplish this, NAUTILUS consists of a three-part Work Plan that involves remote sensing *research*, Web and CD-based *applications* and visualization tools; and on-the-ground *educational* outreach.

PROJECT OBJECTIVES

NAUTILUS's three year work plan focuses on these major elements: (1) basic and applied remote sensing research; (2) tailored applications for the research results through GIS and WWW tools; (3) local outreach and education making use of the National NEMO Network. NAUTILUS objectives can be summarized as follows:

Research

- improved basic land use and land cover information
  - *multitemporal, multiresolution remote sensing and collateral data*
  - *innovative processing*
    - *artificial neural networks*
    - *knowledge-based expert systems*
    - *data fusion*
    - *spectral and spatial-based classification*

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[5] Nonpoint Education for Municipal Officials: http://www.canr.uconn.edu/ces/nemo/

- improved impervious cover estimates
  - *using artificial neural networks*
- characterization of suburban sprawl
  - *temporal characterization*
  - *sprawl index*
- landscape characteristics and indices for forest fragmentation
  - *land use classification and change detection*
  - *landscape spatial statistics over time*

Applications

- develop interactive models for multi-scenario, multi-factor build-out analyses
- create accessible community visualizations tools via the Internet and personal computers
- investigate improved visualizations through three-dimensional data displays

Outreach

- incorporate NAUTILUS land cover information and applications into targeted watershed educational programs in four Northeast states
- pilot the use of information kiosks for broad-based community outreach

NAUTILUS's geographic focus will be on the Northeast region. Remote sensing, GIS and various decision support systems are often touted as tools to assist *natural resource managers*, meaning federal and state agency staff. Much of the truly critical natural resource management takes place through the local land use process, and thus is in the hands of local (regional and municipal) officials. Working with an *end*-user group, that is truly at the *end* of the process, requires large amounts of data, sophisticated applications, and an intensive outreach effort. Therefore, NAUTILUS is taking a *pilot project approach*, at least initially, working with partners and study watersheds in Connecticut, Massachusetts, Maine, and New Jersey. Such an approach has worked very well for NEMO, for which numerous success stories based on well-done pilot projects have served as effective educational examples for a much wider audience. At the time that this manuscript was written, the RESAC had been in existence for less than one year, but much progress had already been made on the research, applications, and outreach fronts. Yet much remains to be done. The remainder of this paper focuses on some of the preliminary results to date.

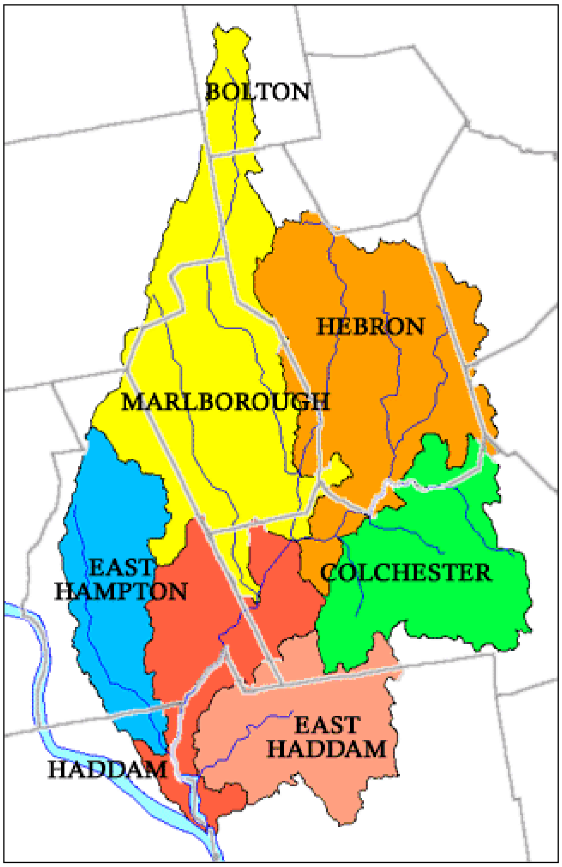

Figure 1. Salmon River Watershed study area

RESEARCH PROCEDURES AND PRELIMINARY RESULTS

Land Use and Land Cover Change

Remote sensing data from the Landsat family of satellites were chosen as the basis for determining land use change for the first pilot project study area – the Salmon River Watershed in Connecticut (Figure 1). Data include MSS, TM, and ETM+ from 1973 to 1999. At present, land cover classification has been concentrated on springtime, leaf-off imagery, although the value of multiseasonal data is well-known and they will be incorporated into future analysis. NAUTILUS will continue to add to this archive of Landsat data for this watershed as well as the others. To date, eight Landsat MSS and TM images of the Salmon River Watershed have been analyzed, using an unsupervised, post-classification labeling approach: 1973 MSS, 1976 MSS, 1981 MSS, 1983 MSS, 1985 TM, 1988 TM, 1993 TM, and 1995 TM. Following the creation of 200 clusters, land cover classifications were labeled into general categories of urban, agriculture, forest, water, wetland, and barren. Figure 2 shows a false-color composite for each image and the corresponding land cover for a small sample portion of the study area. Although difficult to detect in the MSS imagery, it can be noticed in the 1976 MSS image the beginnings of a residential development occurring in the upper central portion of the image. This development occurred at the loss of forest land cover. Over time, the development has increased in size and becomes more readily apparent in the TM images. Also noteworthy is the construction of a *cul-de-sac* in the 1995 TM image. The land cover changes were captured and identified in each of the classification images. Grouped together for ease of comparison, Table 1 presents the number of hectares for each land cover grouping for each of the eight dates for the entire Salmon River watershed. Although varying from year to year due to the phenological and atmospheric differences among the images classified, the classification totals identify a subtle trend towards an increase in urbanization and decrease in forest land cover over the 22 year period.

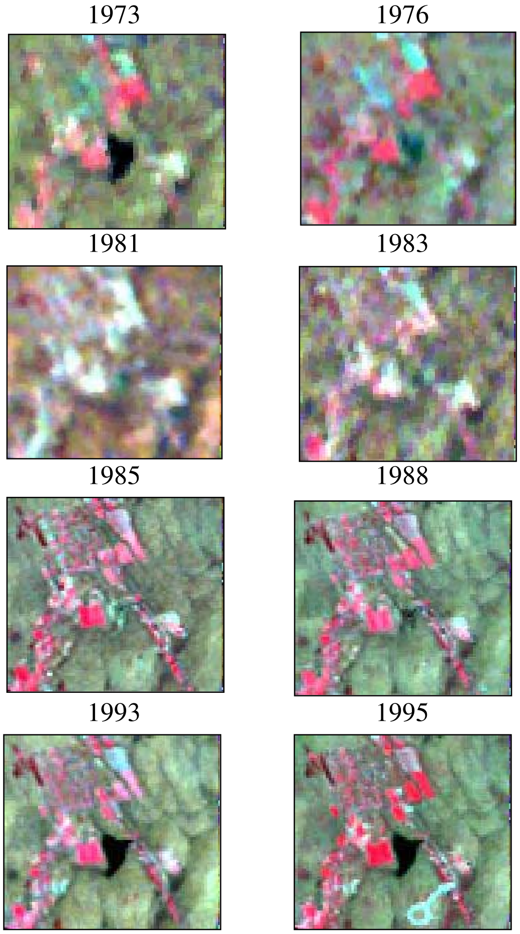
1973 1976
1981 1983
1985 1988
1993 1995

Figure 2a. Landsat MSS and TM data

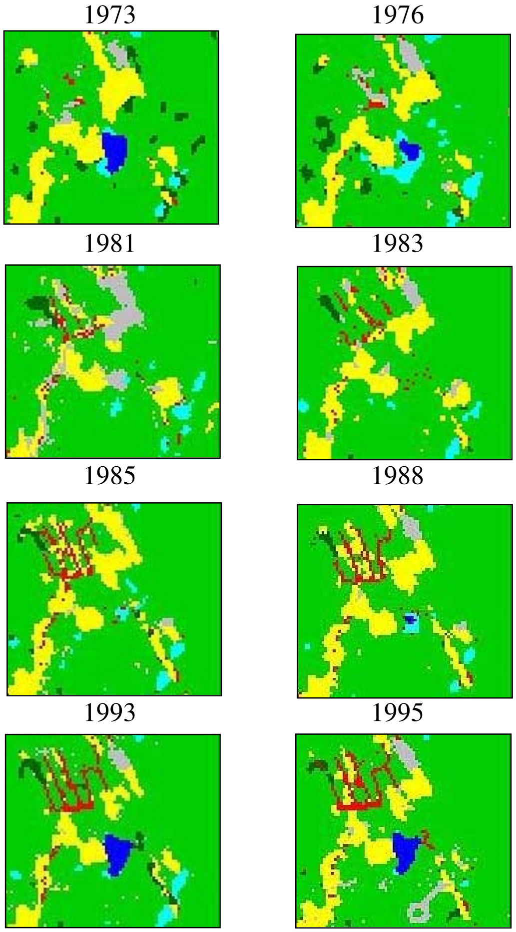
1973 1976
1981 1983
1985 1988
1993 1995

Figure 2b. Land use and land cover

	Urban	Agriculture/Barren	Forest/Wetland	Water
1973	985	5,375	31,213	1,197
1976	1,133	4,781	31,187	1,663
1981	1,561	4,502	31,467	1,232
1983	1,399	4,229	31,591	1,545
1985	1,343	5,103	30,756	1,563
1988	1,514	5,125	30,542	1,582
1993	1,451	3,891	31,778	1,643
1995	1,561	5,265	30,544	1,393

Table 1. Salmon River Watershed land cover areal extent: 1973-1995 (hectares)

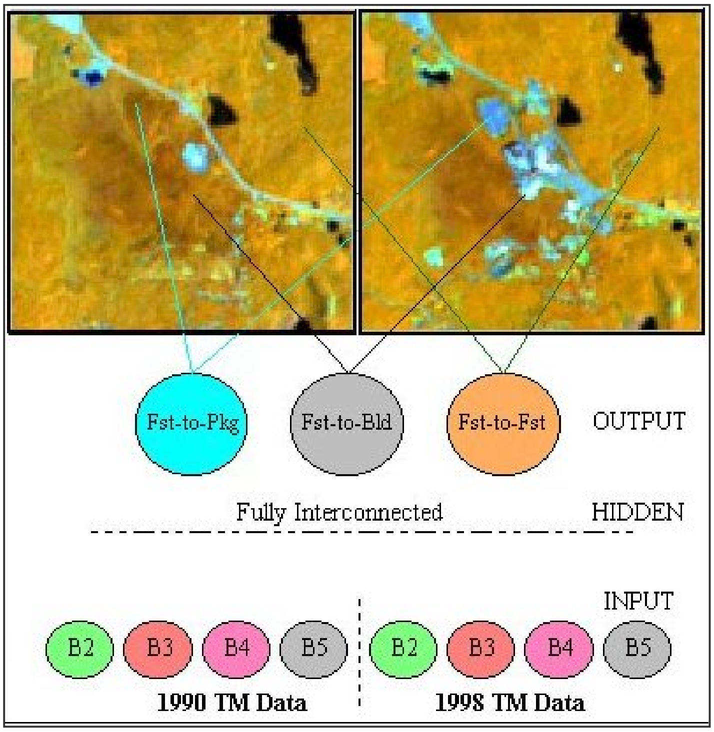

Figure 3. Neural network predicted forest-to-urban change

A proof-of-concept study has been performed in which forest to non-forest land use change has been detected with a high degree of success using a backpropagation neural network. Similar pioneering work has been reported by Dai and Khorram (1999). Four bands (2,3,4,5) of TM data from 1990 and 1998 were classified into three output classes of forest-to-parking lot, forest-to-building, and forest-to-forest (*i.e.*, no change). The network consisted of eight input elements, a single hidden layer, and three output elements, corresponding to the three classes. The proof-of-concept land cover change neural network produced classifications with an accuracy of 97.3 (*n*=20), 95.8 (*n*=24), and 100.0 (*n*=81) percent, respectively, with an overall classification accuracy of 97.4 percent. The structure of this network and the images used are shown in Figure 3. Research is continuing into the design of a series of neural networks, using a similar architecture and classification paradigm, able to detect and classify land use change from T_1 to T_2. The land cover change categories selected will emphasize non-urban to urban, at least at Anderson Level I classification. Other types of land use and land cover change will be detected and classified, as well (such as agriculture to forest, or forest to barren). The times of Landsat TM (and hopefully ASTER) data will span the 1972 to present record and include MSS, TM, and ETM+ imagery.

Urban Sprawl and Forest Fragmentation

It is well-known that urbanization and suburbanization in the Northeast has increased rapidly in the post-World War II era, and indicators are that this will be the case in the foreseeable future. Much of this urban growth, or *sprawl*, has been at the expense of agricultural and forest lands. A hypothesis of the NAUTILUS project is that through time, urban land area has increased, while forest and agricultural land area has decreased, and that the remaining forests and farmlands have become highly fragmented (*i.e.*, more *patches* and smaller average patch size). Research is being conducted in this project to determine the degree of fragmentation of the landscape over time, throughout the record of available digital remote sensing data. The techniques being developed use readily available and widely used geospatial software, notably ArcView® GIS and its extensions, including Image Analysis®, Spatial

Analyst®, and Patch Analyst[6], an extension incorporating many spatial statistical measures of FragStats (McGarigal and Marks 1993; McGarigal, 1998). The use of these software tools was based on the desire to make the methods developed as transportable to other users and other locations (*i.e.*, no highly specialized or customized software required).

To date, Landsat TM data from 1985 and 1995 have been classified using ArcView Image Analysis's clustering tool. Typically, as many as 100 spectral clusters were derived from the spring (*leaf off*) TM data and reduced to six general classes (urban, grassland, forest, water, water, and barren). Because of spectral similarities between bare soil agriculture in the spring and barren lands, information from the summer TM was used to resolved some of the confusion. Pixels with uncertain classification, as well as cloud and cloud shadow, were classified as *Other*. These *questionable* pixels were eliminated from both images and omitted from further analysis. Figure 4 shows the Landsat TM data (Bands 4, 5, and 3) for the entire watershed and the corresponding land cover classifications.

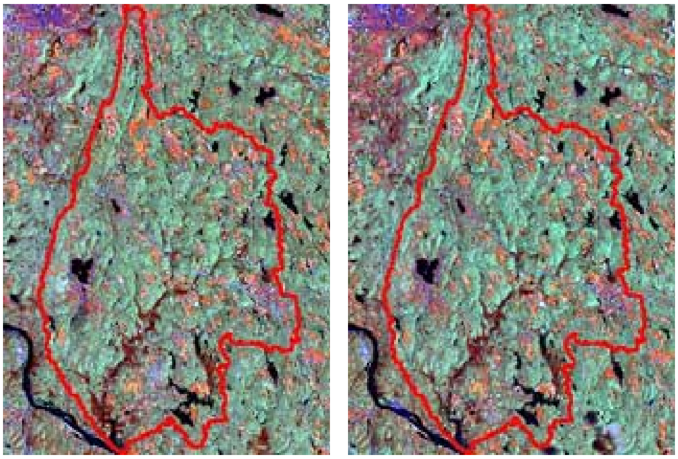

Figure 4a. 1985 and 1995 springtime Landsat TM.

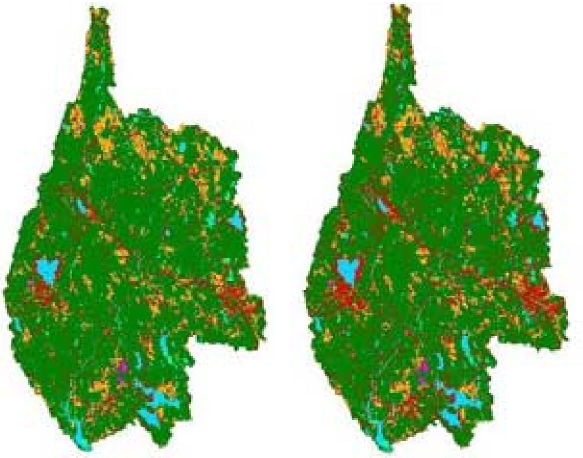

Figure 4b. 1985 and 1995 general land cover.

The land cover data, in an ArcView Spatial Analyst Grid format, were processed with the public domain Patch Analyst Extension, extracting data on class area, number of patches, average patch size, total edge, and others. Table 2 summarizes some of these statistics for three classes of interest --urban, agriculture, and forest – for 1985 and 1995.

	Total Class Area (ha)		**Number of Patches (n)**		**Mean Patch Size (ha)**		**Total Edge (km)**	
Class	**1985**	**1995**	**1985**	**1995**	**1985**	**1995**	**1985**	**1995**
Urban	3005	4802	485	1192	6.20	4.03	1623	2400
Forest	29756	28045	1312	1697	22.68	16.53	2622	3061
Agriculture	3689	3485	2373	2608	1.55	1.34	1289	1296

Table 2. Selected landscape statistics for urban, forest, and agricultural land: 1985 & 1995

From Table 2, it can be seen that urban land area has increased by nearly 60% over this decade, while both agricultural and forest land decreased by approximately 6% each, the latter not much different from the five percent statewide reduction noted for the period 1984-1988[7]. The number of patches of each land use increased, by 145%, 30%, and 10%, respectively for urban, forest, and agriculture. Mean patch size for forest and agricultural lands decreased by 27% and 14%, respectively. While total class edge changed little for agricultural land, it increased by

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

[7] *Where Have All The Trees Gone?* The Hartford (CT) Courant, Tuesday, February 22, 2000. p. B5.

48% for urban land and 17% for forest land. Collectively, these statistics demonstrate, at least for the decade studied and using the land use data derived, that the forested and agricultural landscape are becoming both smaller in area and more fragmented.

Improved Land Use Classification

Research is continuing not only with artificial intelligence (AI) approaches to land cover change detection, but also with development of improved methods for general land use classification. The main objective of this aspect of the research is to produce as thematically-rich and spatially-detailed land use information as possible from remote sensing and ancillary data. A goal is to approach, and even surpass, Anderson Level II categories, using principally, but not exclusively, satellite image data. Multisource, multispectral, multiresolution data, including Landsat TM and ETM+, SPOT Panchromatic, ADAR 5500, Ikonos, DOQQs, and others[8] are being used for different levels of detail. Ancillary data include Digital Line Graphs (DLGs) for hydrography and transportation, and Digital Elevation Models (DEMs) and their derived products (slope, aspect, illumination). The need for measurements other than just spectral reflectance is apparent, given the types and properties of the source data and the desired land cover classes. These include features from the spatial domain, such as image texture, object shape and size, proximity to other known cover types, derived both internally from the remote sensing image data and from other sources, such as the DLGs, and other spatial descriptors. Two distinct, yet parallel, approaches are being investigated: *Knowledge-based Expert Systems* (KBES) and *Artificial Neural Networks* (ANN). In order to assess the relative performance of each method, the data and information used and the classes obtained will be kept as consistent as possible.

Knowledge-based Expert Systems development is being performed using the *Knowledge Engineer* engine available in ERDAS Imagine® 8.4, and will build upon research conducted previously by the principal author (Civco, 1989). This rule-based approach to land cover and land use classification has the ability to incorporate a measure of certainty in the knowledge base and likewise *fuzziness* in the classification (for example, how much like *Urban*, or *Forest*, *etc*.). Figure 5 shows a small and simple KBES classification under development for the Salmon River Watershed study area.

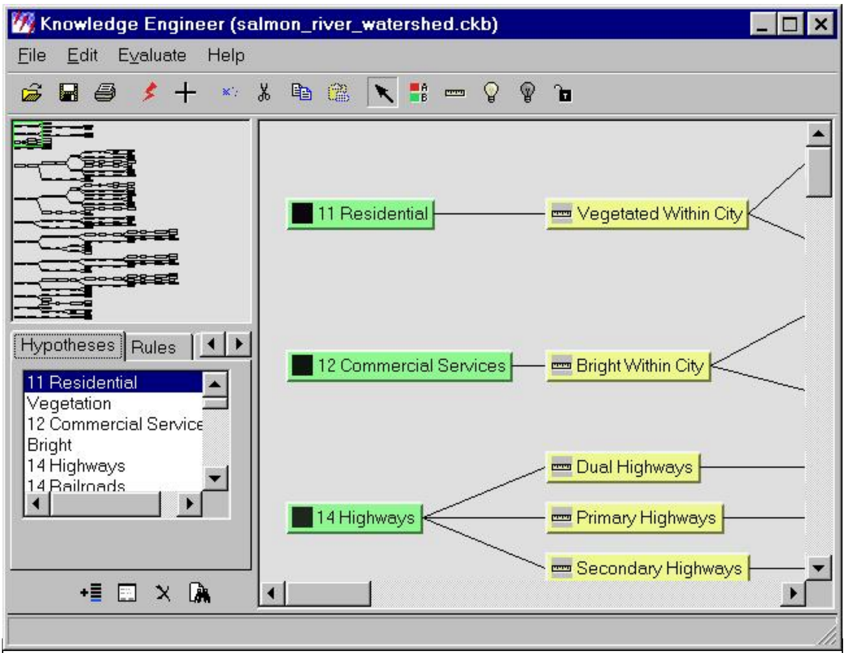

Figure 5. ERDAS Imagine Knowledge Engineer design window for Salmon River Watershed from Landsat 7 ETM+ data

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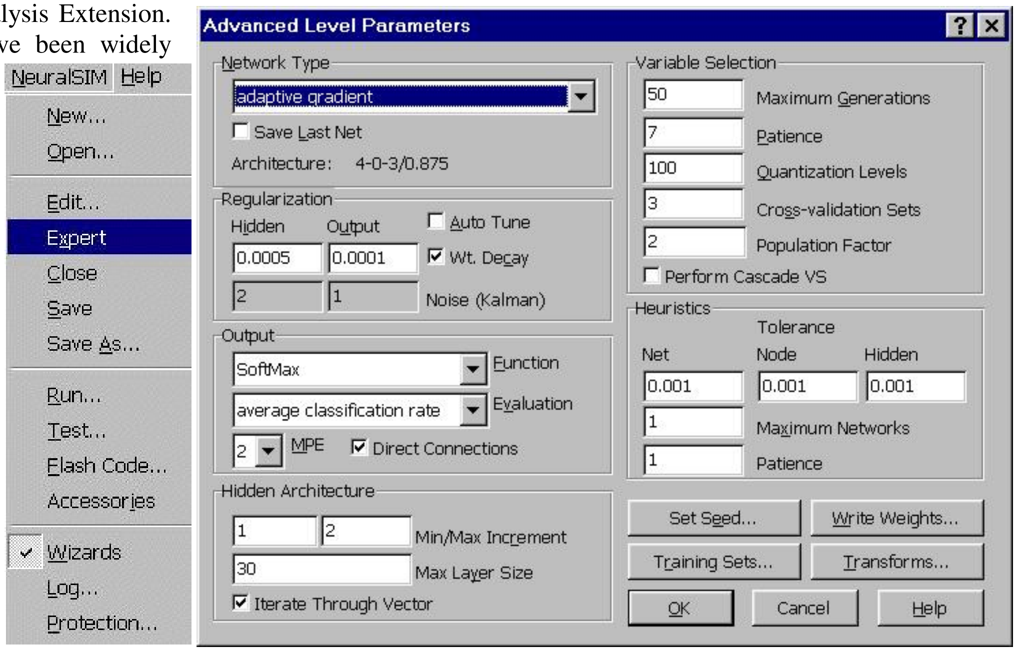
[8] This project has been approved for the acquisition of Hyperion and ALI data after the launch of EO-1, now scheduled tentatively for June 2000.

Artificial Neural Network classification is being performed with NeuralSIM®, from Aspen Technology. NeuralSIM is a general-purpose neural network development shell, the interface for which is provided through Microsoft Excel®, and provides a wide range of tools for creating, testing, refining, and deploying trained networks. The adaptive gradient, back-propagation paradigm in NeuralSIM is being used to classify the same land use types as are being defined with the KBES classifier. Trained networks will be deployed as stand-alone code (C++ or Visual Basic), as well as incorporated into commercial image processing products, likely ER Mapper, ERDAS Imagine, or ArcView Image Analysis Extension. Although ANNs have been widely used by these investigators previously (Civco, 1993; Wang and Civco, 1996; Zhou and Civco, 1997), a controlled, systematic comparison with the results of both a knowledge-based approach and the maximum likelihood using multisource data for the Salmon River Watershed has not previously been conducted. At the time of this writing, this research was in its beginning phase.



Network Type
adaptive gradient
☐ Save Last Net
Architecture: 4-0-3/0.875

Regularization
Hidden 0.0005
Output 0.0001
☐ Auto Tune
☑ Wt. Decay
2 1 Noise (Kalman)

Output
SoftMax Function
average classification rate Evaluation
2 MPE
☑ Direct Connections

Hidden Architecture
1 2 Min/Max Increment
30 Max Layer Size
☑ Iterate Through Vector

Variable Selection
50 Maximum Generations
7 Patience
100 Quantization Levels
3 Cross-validation Sets
2 Population Factor
☐ Perform Cascade VS

Heuristics

Tolerance Net	Node	Hidden
0.001	0.001	0.001

1 Maximum Networks
1 Patience

Figure 6. NeuralSIM menu selections and advanced parameter window.

Multitemporal Image Processing

The NAUTILUS RESAC is intent on providing tools to assist local planners in understanding and visualizing land use change and urban sprawl. One of those methods, in addition to the land use change maps and neural network-based urban change models, is through the use of animated multitemporal satellite remote sensing data. Toward this end, eight scenes of Landsat MSS and TM data from 1973 to 1995, acquired at near-anniversary dates (*i.e.*, April-May during the *leaf-off* season in the Northeast) have been radiometrically-adjusted to one another. While techniques such as linear regression using temporally invariant targets to normalize multidate imagery are being investigated (Heo and FitzHugh, 2000), non-linear histogram matching among the near infrared, red, and green bands of MSS and TM has found to be very effective. Because these multitemporal images are being animated in a movie loop, as smooth of a transition as possible from one date to the next is required. Because the time interval between successive Landsat images is not consistent, a temporal interpolation method was developed to *synthesize* inter-date images. This is simply a weighted linear combination of two bounding years' of Landsat data to create an intermediate one. For example, a near infrared-red-green image for 1984, for which there are no springtime Landsat MSS or TM images of acceptable quality for the study area, was generated from the 1983 MSS and 1985 TM as the simple average of the histogram-matched bands. To synthesize 1986 data, the following algorithm was used: ((2*1985 + 1988)/3), and likewise for 1987 data, the procedure was ((1985 + 2*1988)/3). Figure 7 shows the false-color composites for an urbanizing area for the time sequence 1985 to 1995 at two-year increments. The entire record of Landsat data from 1973 to 1995, consisting of both actual and *fictional* images, has been formatted as an animation suitable for display with most PC-based media players.

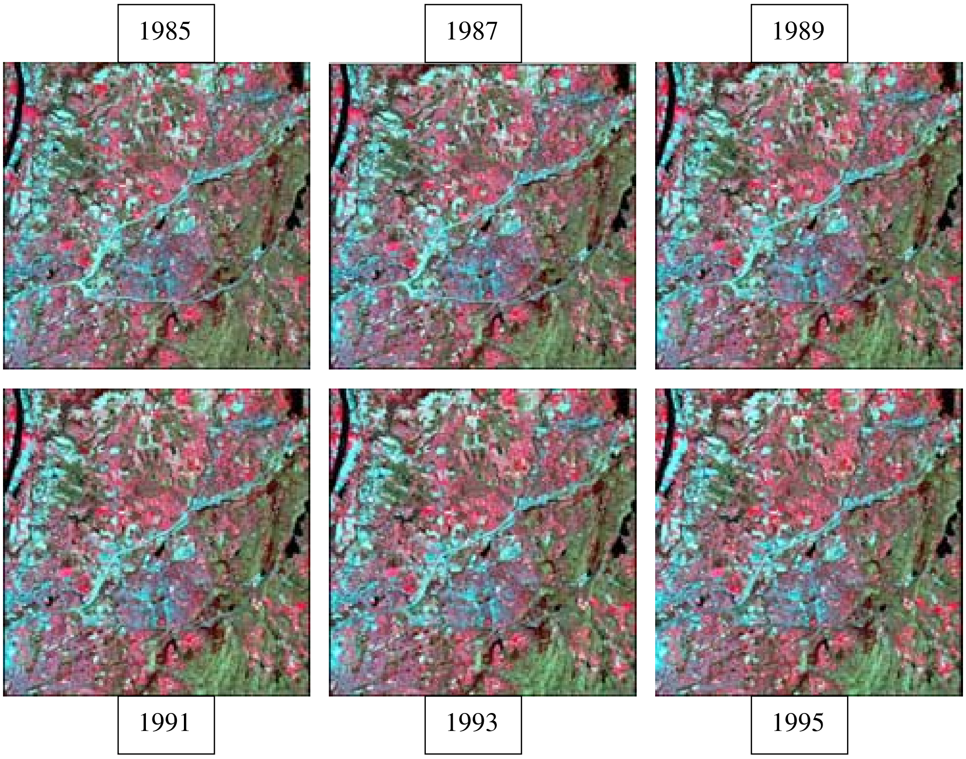


Figure 7. Landsat false-color composite multitemporal image sequence

Multiresolution Image Processing

A number of satellite and airborne remote sensing data types are being used for land cover mapping, urban sprawl and land use change analysis, and impervious surface modeling. These include Landsat MSS, Landsat TM and ETM+, SPOT Panchromatic, Digital Orthophoto Quarter Quads (DOQQ), and ADAR 5500, the latter of which were acquired by the NAUTILUS project under NASA's Scientific Data Purchase (SDP) program[9]. Ikonos panchromatic and multispectral data are to collected for a portion of the study area under the SDP, as well. Examples of these data for a small portion of the town of Marlborough, CT, within the Salmon River Watershed, are shown in Figure 8.

Impervious Surface Modeling

Impervious land cover is widely accepted as an indicator of urbanization and its impacts on both water quantity and water quality (Schueler, 1994; Arnold and Gibbons, 1996). The NEMO Project incorporates estimates of impervious cover derived from assigning impervious cover coefficients to generalized land use/land cover categories, and also conducts build-out analyses of imperviousness based on zoning regulations (Giannotti, 1999.) However, improved impervious cover data is needed if this information is to be used directly by local land use officials. These estimated values tend to be too generalized and do not depict the true spatial pattern of impervious surfaces in an area. This has led to the need for the development of a model which would allow analysts to generate an impervious surface map for a given study area at a finer level of biophysical discrimination, such as described by Ridd (1995).

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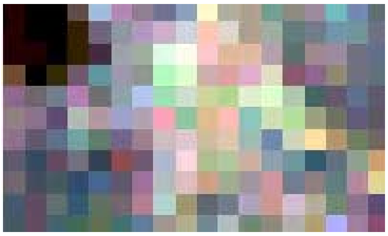
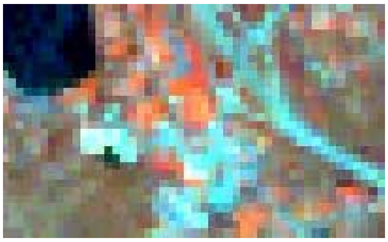
[9] Administered through NASA's Stennis Space Center Commercial Remote Sensing Program at http://www.crsp.ssc.nasa.gov/databuy/dbmain.htm

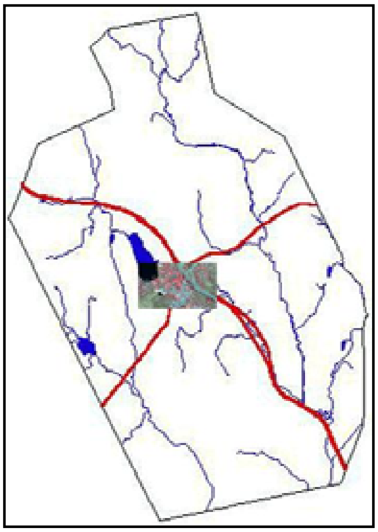


MSS (80 m)

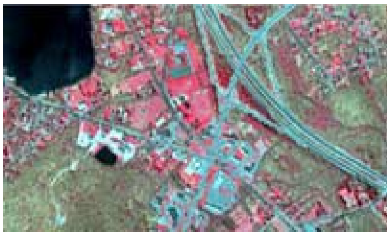


TM (30 m)

SPOT (10 m)



DOQQ (1 m)



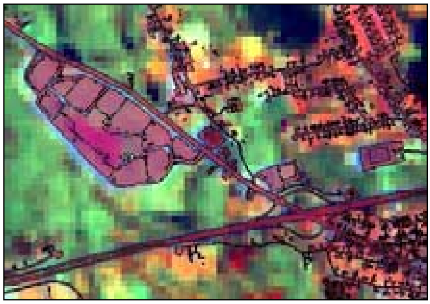
ADAR (1 m)

Figure 8. Marlborough, CT showing insert of five springtime remote sensing data types.

Research underway addresses the development of a method for the generation of percentage impervious surface data from Landsat Thematic Mapper (TM) imagery, at the sub-pixel level, using an artificial neural network as the modeling tool and high-resolution digital aerial and satellite imagery for sub-pixel calibration. Neural networks have proven to be effective analysis mechanisms that involve complex relationships between remote sensing measurements and biophysical parameters (Civco, 1993; Ridd *et al.*, 1992). The general procedures of the work presented here can be found in Civco and Hurd, 1997.

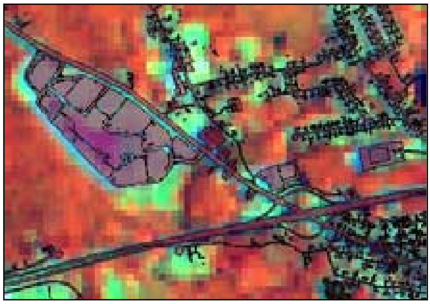
Neural network training data are comprised of ratios, based on the 7 reflective TM bands from two different seasons, as well as from high calibrated, digitized reference data acquired from 2-meter digital aerial photographs. Neural network software, AspenTech NeuralSIM®, is used to map input patterns into output percentages for the seven land class categories of vegetation, water, barren land, bright roof, medium roof, dark roof, and asphalt. A linear regression equation is then derived, per category, mapping initial neural network predictions, to the known impervious values in the 0 and 100 percent pixels. The neural network is then tested on unseen calibration datasets, containing identical input ratios as the training dataset. The per pixel, percent impervious land cover is a known variable for the calibration dataset, its value having been calculated using high accuracy vector planimetric data, which include items such as building and house footprints, roads, driveways, and parking lots. The linear regression equations derived from the training data are then applied, per category, to the predicted values per pixel for the calibration data thereby stretching the prediction values to a range of {0, 100}. Total impervious land cover, per pixel, is then derived by subtracting from 100% the sum of the predicted values for the classes of vegetation, water, and barren land. This value is then compared to the known impervious surface percentage value.

Figure 9 depicts (a) actual percent impervious coverage derived from vector planimetric data superimposed on a Landsat TM false-color composite, (b) the corresponding percent imperviousness rasterized to 30-meters, and (c) the neural network-derived impervious surface. The general degree of agreement between actual and predicted imperviousness can be seen in Figures 8a and 8b. It can be observed that the neural network is able to successfully predict the larger impervious surface features such as the shopping mall, and major roads. Further research will endeavor towards sensitizing the neural network to the less prominent impervious features, such as suburban housing and primary and secondary roads. For 1995 year Landsat data the correlation between actual and predicted was 0.83, and for 1998 it was 0.78. The neural network model is being developed and tested for its general extendibility. A final version will be made to the user-community either as a stand-alone program or as a *plug-in* for a commercial-off-the-shelf (COTS) GIS software package.



Spring TM

Figure 9a. Spring and Summer TM data with planimetric overlay



Summer TM

Figure 9. Actual and predicted perecent impervious cover.

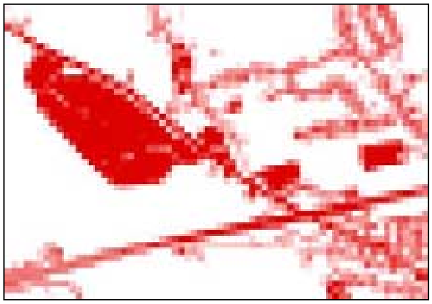


Figure 9b. Actual percent imperviousness

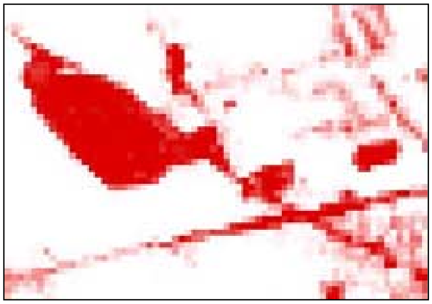
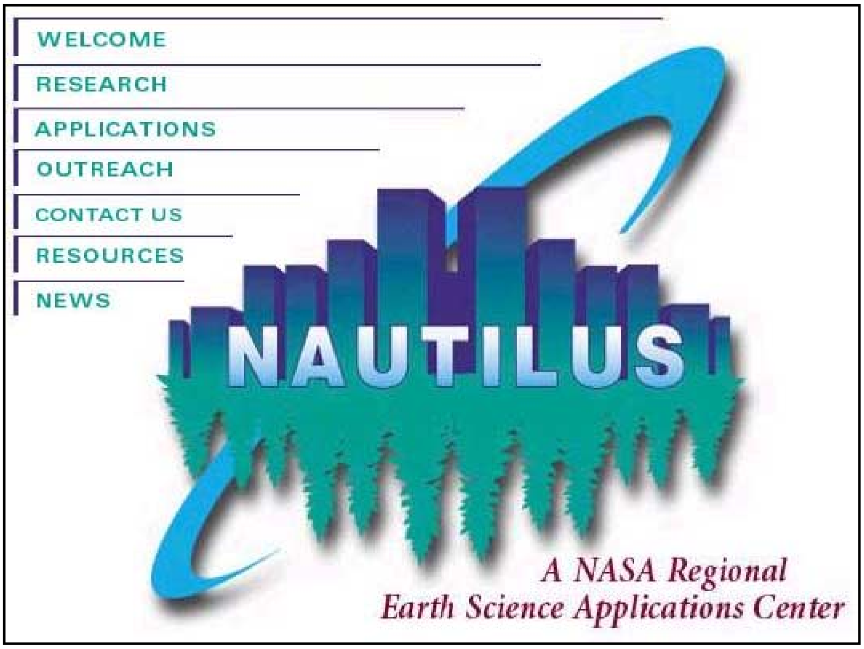


Figure 9c. Neural network predicted imperviousness

DISCUSSION AND DIRECTION

Future research will address topics such as urban growth modeling, urban land use suitability and optimal allocation, and development of sprawl and forest fragmentation *indices.* Research, however, is only one-third of the NAUTILUS work plan. Internet and CD applications making use of the research results will be developed. Interactive mapping, 3-dimensional landscape visualization, and land cover change animations are some of the applications that we hope to deliver via a multi-media approach that includes the Internet, CD-ROMs, and the placement of user-friendly GIS kiosks in the study area watersheds. The groundwork has already been laid to incorporate project research and applications into on-the-ground educational programs in the four target watersheds in Maine, Massachusetts, Connecticut and New Jersey. A Watershed Partners Group has been formed from representatives of multi-agency consortia in each of these areas, to assist in their participation in NAUTILUS and facilitate their eventual use of project products. As feedback from these educational efforts is received, we see the formation of an iterative process that continues to drive advances in the practical use of remote sensing technology. More information about this project can be found on the NAUTILUS website at http://resac.uconn.edu.



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