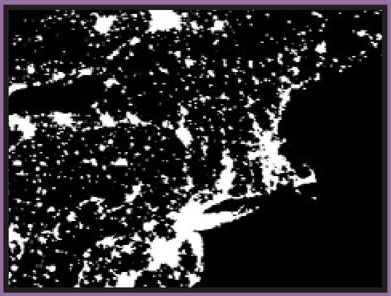
GISF Research Paper 003



Dynamic Models of Land Use Change in Northeastern USA

Developing Tools, Techniques, and Talents for Effective Conservation Action

Mary L. Tyrrell, Myrna H.P. Hall
and R. Neil Sampson

Global Institute of Sustainable Forestry

Program on Private Forests

Yale University
School of Forestry & Environmental Studies
Global Institute of Sustainable Forestry

Dynamic Models of Land Use Change In Northeastern USA

Developing Tools, Techniques, and Talents for Effective Conservation Action

Mary L. Tyrrell
Program on Private Forests
Yale School of Forestry and Environmental Studies

Myrna H.P. Hall
College of Environmental Science and Forestry
State University of New York

R. Neil Sampson
Yale School of Forestry and Environmental Studies
and the Sampson Group

August 2004
GISF Research Paper 003
Program on Private Forests

Yale University
School of Forestry and Environmental Studies
Global Institute of Sustainable Forestry
360 Prospect Street, New Haven, Connecticut 06511 USA

This project was supported by a grant from the USDA Forest Service, Cooperative Forestry

Acknowledgements

This project was made possible through the contributions, ideas, and support of many people. We are grateful to Larry Payne, Ted Beauvais, and Rick Cooksey of the USDA Forest Service, Cooperative Forestry, who understood the potential and provided funding for the project. The Yale School of Forestry and Environmental Studies (FES), Global Institute of Sustainable Forestry, and the State University of New York College of Environmental Science and Forestry (SUNY ESF) provided additional resources to support the project.

We would like to acknowledge the work of graduate students Steve Dettman and David Hobson at Yale FES and Susan Nixson and Sarah Deacon at SUNY ESF who worked on data collection, analysis, and formatting. Tagan Blake, now at Georgetown University, spent a summer collecting, formatting and organizing the Connecticut and Massachusetts data into one Thames data set, a significant contribution to the project. Michelle Decker, undergraduate at SUNY ESF, also contributed to the New York data collection.

We are grateful to Dan Civco and James Hurd at the University of Connecticut Center for Land use Education And Research (CLEAR) for their contribution of a newly created set of temporal land cover maps, which was an enormous benefit to the project. We would also like to acknowledge the work of Stephen Ambagis, at Clark University graduate student, now at Winrock International, who created the 2001 land cover map for the Catskill/Delaware area. New York City Department of Environmental Protection's (NYC DEP) GIS unit provided other very important data, in particular the 2000 tax parcel information. Our sincere thanks to Terry Spies and Barbara Dibeler of the NYC DEP. The many folks in state, town and county offices, who answered questions and provided data, are too numerous to mention, however we sincerely appreciate their help. The U.S. Census data used in the analysis was obtained from GEOLYTICS, E. Brunswick, NJ.

Tim Gregoire (Yale FES), René Germain (SUNY ESF), Steve Broderick (University of Connecticut), and Jack Mc Shane (Catskill Landowners Association) reviewed the first draft of this report and provided very thoughtful comments. The final report is much improved thanks to their input. René Germain also provided the 1984 parcelization data for the portions of Greene, Schoharie, Sullivan, and Ulster Counties that lie within the NYC Catskill/Delaware watersheds, which enabled us to analyze land parcelization as a driver of forest fragmentation.

And finally we would like to give special thanks to the following people for their ideas and support, particularly for connecting us to the local organizations and people in Connecticut, Massachusetts and New York, and for helping organize the community workshops: Steve Broderick, Senior Extension Educator/Forester for Connecticut; Bill Toomey, Quinebaug Highlands Project Director at The Nature Conservancy; and René Germain, at SUNY ESF, Coordinator of the New York City Watershed Model Forest Program.

Table of Contents

Summary

America's productive private forests are at risk, under threat of being converted to malls, housing developments, and personal green space. Conservationists and officials in many localities are asking what they can do to help conserve their forests and maintain local forest-based economies. This study is designed to test the ability of a dynamic simulation modeling tool—GEOMOD—to illustrate local and regional land use changes, both in the recent past and in the near future. It stems from the idea that if people know how rapidly their forest resource is being lost, where it is being lost, and what forces seem to be driving the losses, they will be better equipped to take effective conservation action.

With this project, we have successfully demonstrated the utility of using GEOMOD as a land use planning tool in areas under pressure from unplanned development and sprawl. Working with two sites, the Thames River Watershed in Connecticut and Massachusetts and the Catskill/Delaware water supply watersheds and surrounding region in New York, we have demonstrated a scientifically rigorous method of projecting likely future scenarios of development based on analysis of past rate and patterns of land use change.

In the Catskill/Delaware region we found that private forests are being converted to non-forest uses at a rate of a little over 1% per year, in a fragmented pattern. Without strong conservation intervention, that rate is likely to proceed for the next decade, resulting in the loss of another 162,000 acres of private forestland, and a much more fragmented forest resource, by the year 2011. Through statistical analysis, we found that in this mountainous region, the fragmentation that has occurred since 1992 follows a pattern of sprawling up the valleys and is most influenced by the proximity of urban areas, roads, and topography, particularly elevation and slope. Using a simple measure of "area of intact forest" vs. "perimeter of forest patches," the area:perimeter ratio was 187:1 in 1992; 150:1 in 2001 and is projected to be 105:1 in 2011. Forest patches are getting smaller, with more edge environment, which impacts everything from wildlife habitat, deer and tick populations, water quality, the potential for timber harvesting, recreation, aesthetics, and local economies.

Within the New York City Watersheds, forestland parcel size is decreasing and our analysis indicates that forest land that has been parcelized is 1.5 times more likely to be converted to other uses than land that has not been divided. The average parcel size in the region has gone from 18 acres in 1985 to 14 acres in 2000, clearly indicating increased parcelization of forestland since 1985. As evidence that parcelization (smaller ownerships) does lead to further forest fragmentation, our data from a sample of 122,000 acres, show that lands that had been parcelized between 1984 and 2000 experienced a higher rate of forest loss (8%) than those that had not been parcelized (5.5%).

In the Thames Watershed region, of the 740,000 acres of forest not permanently protected from development, 7.4% has been lost since 1985. This may seem like a fairly low rate over 17 years, but it is the pattern that is most troubling. If the same trend continues, we project that the Thames Watershed and surrounding towns will lose an additional 64,000 acres of forest, scattered across the landscape, in the next 17 years. The forests are more fragmented as shown by the area:perimeter ratio which was 421:1 in 1985, dropping to 381:1 in 2002. However, our projections out to 2022 indicate that the future trend may result in an infilling of developed areas hence elimination of smaller forest fragments and a mathematically higher area:perimeter ratio, although the remaining patches would not be larger than they were in 2002.

It is quite likely that our results in both regions actually overstate the amount of intact forest remaining. The land cover classification process, which uses 30-meter resolution satellite imagery, is much better at picking up

concentrated development than low density rural development. For example, a housing subdivision with large lots and trees would show up as partial forest in the satellite imagery. However, this is no longer the same forested habitat for wildlife as a large tract of unfragmented forest, nor is it a forest that can be managed for timber or other forest products.

Nonetheless, our results demonstrate that the rate and location of recent conversions of forest to non-forest cover, detected by modern interpretation of satellite imagery, can be used not only to study the past but to visualize possible future conditions. GEOMOD is able to take those past changes, compare them with a wide range of geophysical and socio-economic data, and derive a statistically robust correlation between past patterns of land use and land cover change and the most likely future continuation of those patterns.

The result is a visually powerful dynamic display of local land use change, coupled with a new understanding of the factors associated with that change. Using these tools, local leaders can bring new insight and energy to forest conservation and land use management programs. The local stakeholders in both areas have expressed tremendous interest in the results, which they believe would be particularly useful in local- and county- or regional-level planning efforts.

Introduction

There are some 10 million private forest ownerships in the United States, and that number has been estimated to be growing at the rate of around 150,000 a year.[1] At the same time, the area in privately-owned forest land has stayed roughly the same for decades. The obvious result is that America's forests are being divided into smaller and smaller ownerships. Nationwide, over 25 million acres of rural land were developed between 1982 and 1997, and over 10 million of those acres were forest before they were developed.[2] The clear implication is that forests are increasingly under threat from urban sprawl and other dispersed development.

These trends raise concerns in two general categories. The first is forest fragmentation—the breaking up of large contiguous forest areas into smaller, disconnected parcels separated by non-forest lands, roads, or other land use. The impacts of this fragmentation are often described in ecological terms. A landscape sprinkled with little patches of disconnected forest does not function in the same way as that landscape functioned when it was a single large forest. The impact on wildlife habitat can be severe, as many species cannot thrive or even survive in fragmented landscapes. Other impacts may be felt, for example, on water quality, as non-forest land uses often are associated with higher rates of water runoff, soil erosion, and nutrient and sediment loading to waterways with subsequent impacts on drinking water quality and aquatic habitat.

The second category of change is parcelization, the dividing up of private land into smaller ownerships. The impacts here are more often economic. Small ownerships, particularly those of less than 50 acres, are seldom managed to produce sustainable yields of forest products. Increasingly, they become private "green space" for their owners. The trees remain, but opportunities for sustainable production are largely lost. That might not sound like much of a problem in a large country where there are ample supplies of forest products to meet consumer demand. But over half of the timber used to produce wood and paper products in the United States comes from the smaller private ownerships held by families, institutions, and companies. And those are the forest tracts that are being converted to smaller and smaller parcels. The long-term impact, if not the immediate effect, is an important national concern.

It can be an important local concern as well. As more of the local forest resource is withdrawn from timber production, local mills and forestry businesses suffer. At some point, they begin to go out of business or move elsewhere. Mill closings have been common in recent years, and in many areas, the lack of available timber is one of the reasons. When a local mill closes, the remaining forest owners have less access to markets, and the feasibility of keeping their forests in sustainable production may become questionable. Increasingly, they will look to sell the land, and often it will be most profitable to break it up into small pieces and sell it to potential developers or homeowners. In this way, the processes of parcelization and fragmentation take on a cascading effect, where each forest sale strengthens and hastens the rate of local forest conversion.

As people buy small forest tracts and build homes, the scattered patterns of rural housing become a local economic issue. Rural homes impose significant costs on local services. Their owners need roads, schools, transportation infrastructure, waste disposal, law enforcement and other local services, and the fact that they are dispersed thinly across the region makes the cost of providing each service higher than where people live in more compact arrangements. Seldom do the property taxes paid by scattered rural houses cover the increased burden placed on local services.[3]

Despite these and other concerns in many communities over forest changes, there often seems to be little that can be done to address the situation. By the time the problem is recognized, it's a *fait accompli.* Once the forest is fragmented, it can possibly be restored by intentional management actions, but that process may take decades, and will be highly unlikely where the non-forest land uses are long-lasting. A landscape with a thousand small landowners can be re-assembled, theoretically, back into a few ownerships, but only with great difficulty. So the general situation is that once these forests become fragmented or parcelized, it is nearly impossible to restore their integrity.

It is hard to evaluate how rapidly these processes are taking place. Change often comes in the form of one small, seemingly insignificant event at a time, and the full effect of the cumulative change may not be evident for years. By the time the impacts are known, it is too late to do anything to alter them. Before the parcelization or fragmentation occurs, however, there are effective preventative measures for a community to consider. Depending on the local situation, it may be possible to use local planning and zoning to guide development into more desirable patterns. Improving local incentives for sustainable forest management sometimes takes the form of special tax programs for producing forest lands, or other ways to make sustainable forestry an attractive reason to hold land in production. Sometimes land with high conservation values can be placed under a conservation easement that limits development while providing compensation for lost land sale values.

This leads to the idea that communities could, if they knew where forest parcelization and fragmentation were most likely to occur in the future, design locally adapted conservation measures that would slow these changes or reduce their undesirable impacts. The question becomes: How does one see such phenomena in advance of their actual occurrence?

This project is an attempt to harness modern scientific tools to that task. We begin by studying the trends in land change over the recent past, using satellite imagery to identify where forests have been altered through fragmentation or parcelization. Once those areas have been identified, we seek to understand what underlying factors or drivers might have been the most important contributors to the change. If that can be understood, perhaps we can assume that similar conditions or driving factors may continue to be important in future land use changes. With such knowledge conservation program efforts can be prioritized to those forests most at risk, with some hope that success will be improved.

Since fragmentation and parcelization are very difficult to quantify, especially over a large land area, we have used change in forest cover as a surrogate measure of the extent to which the forest has become fragmented and parcelized. This is a reasonable approach in the northeastern United States, where the situation with change in forest cover is not so much large extensive clearing of forestland, but a patch–by-patch clearing for development. Forest fragmentation—conversion of a large, continuous forest into a scattering of small patches—can be readily seen in satellite imagery. It may not, however, be visible from the local roads and thus remains hidden from public view and consciousness. Parcelization is even less obvious, as property lines don't show on the land, and unless the new owners build roads and houses, the change may be difficult to discern.

This project demonstrates that past trends in parcelization and fragmentation, at least in the predominantly hardwood forests of New York and southern New England where the methods were tested, are possible to document. This is due, in large part, to the increasing skills in image processing and interpretation that we were able to attract to the effort. Those people are recognized elsewhere in the report, and their contributions were essential to the success of the analysis. Without an accurate means of comparing the current condition to past conditions, the chance of understanding the most likely future is greatly reduced.

Our research has shown what many land use and forestry specialists have felt to be the case. Further development and land use change is almost certain in these areas, at least into the foreseeable future. That change will not, however, affect all lands equally. Some areas are far more likely to experience it than others. Where a community can focus its conservation efforts on those areas identified as most at-risk, the chances of retaining a productive and sustainable forest while accommodating local growth trends are significantly enhanced.

GEOMOD, A Dynamic Land Use Change Modeling Tool

With this project, we have successfully demonstrated the utility of a spatial land use change model, GEOMOD, as a land use planning tool in areas under severe pressure from unplanned development and sprawl. Working with two sites, the Thames River Watershed in Connecticut and Massachusetts and the Catskill/Delaware water supply watersheds in New York (figure 1), we have demonstrated a scientifically rigorous method of projecting likely future scenarios of development based on analysis of past rate and patterns of land use change.

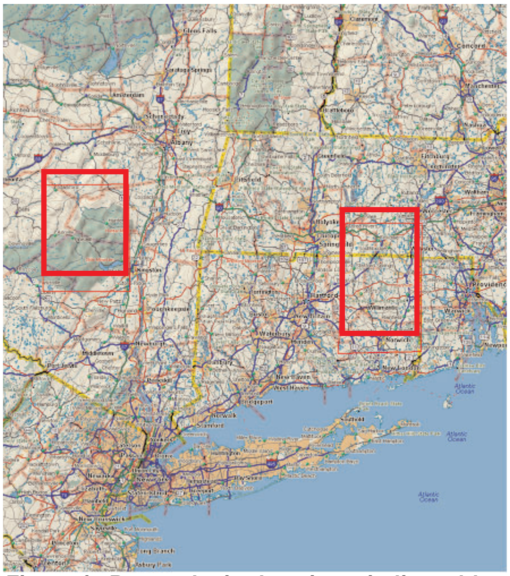


Figure 1. Research site locations, indicated by red boxes. Catskill/Delaware is on the left; Thames on the right. Source: DeLorme Topo USA.

GEOMOD, developed by researchers at the State University of New York College of Environmental Science and Forestry (SUNY ESF), predicts the rate and spatial pattern of land conversion based on past land use change.[4] Although there are many tools now being used by the conservation and land use planning communities, dynamic simulation, with its ability to visually portray the importance of cumulative effects, change over time, and driving forces, is an enormous enhancement to static GIS mapping or build-out analysis. GEOMOD is extraordinarily effective in helping people understand the dynamics of land use change, see where forests are most at risk of fragmentation and conversion to development, visualize future conditions, and plan strategic approaches to the mitigation of harmful trends. Knowing how, where, and why those changes are likely to occur can be a powerful tool for conservation organizations, community leaders, and citizens.

The Spatio-Temporal Modeling Approach

Spatial modeling, as we define it,[5] is the application of a numerical model that uses spatially distributed data to simulate landscape dynamics. In the case of land use change modeling it implies that the spatial distribution of various factors, such as topography, plays an important role in determining where humans exploit the landscape. There sometimes exists confusion about the terms land *use* and land *cover*, and they are often mistakenly used interchangeably. In this study we analyze the conversion of forest *cover* to non- or partial-forest *cover* for which the new *use* is presumed to be some type of human activity, such as residential housing. Thus we are in some ways working with both land *use* and land *cover*, the combination of which we refer to as LULC.

Spatial models of future LULC require two types of parameters—those that project how rapidly land is converted to other uses and those that indicate where the change will take place, i.e. rate and location. GEOMOD, a spatially explicit land use change model, identifies through a rigorous calibration/validation process those spatially distributed biophysical, and/or socio-economic variables that explain past and current development patterns, and projects them into the future assuming business as usual. It can be used to analyze any kind of LULC conversion, for example, forest to pasture or pasture to suburban residential development, if such changes can be detected through remote sensing.

The factors that often influence where people settle can include biophysical determinants such as topographic position (elevation and steepness of slope), distance from rivers, soil type, and/or socio-economic factors such as infrastructure, already-established settlements, distance to roads and markets, and density of population engaged in agriculture and forestry. Demographic factors, such as such as an aging population, which are available via population census may also explain why certain land is attractive to developers, or simply available for sale, .

The model allows for regional stratification in order to capture, for example, the effect of different government policies in different political units on the pattern and rate of landscape development. The basis for analysis is a time series of land cover maps derived from satellite imagery or aerial photographs. At least two time periods are necessary, with sufficient time between the two for change in forest cover to have occurred.

A model is a simplification of a complex system. An architect's model of a building to be constructed is an example. A computerized ecosystem model tries to capture and represent how the system works. We like to think of it as a formalization of our assumptions about that system. Building a model that can be relied upon requires a circular process of *calibration* and *validation* until the model gets as close to reality as is possible given the information we have at the current time. A good model thus begins by using historical, or what we call empirical data—measured and recorded—to calibrate the model. Some of these data must be held in reserve to validate the model's projections, in other words to see if the model is predicting correctly.

An example would be a model that predicts the growth of trees based on the type of soil they are planted in, and the amount of sunlight and precipitation they receive. To *calibrate* the model the researcher first needs data that show how much trees actually have grown in different soil, sun and moisture conditions. Then he/she writes the model to grow trees across the landscape based on the conditions found at each location. Finally, to determine how well the model is doing, the modeler checks his/her predictions against the growth information for other trees distributed across the landscape that were not used in the calibration process, and determines statistically how well the model has matched the real growth (volume or biomass) of this validation set of trees. The model's mathematical equations that express the relation between tree growth response and environmental conditions continues to be adjusted until the predictions match as closely as possible the real world.

An analysis of landscape change with GEOMOD is performed in the same way, testing the importance of different variables like "distance from roads" or "slope" of the terrain to determine where development has occurred at one point in time. Then, taking this information, the model projects where development is likely to occur in the future and then checks against a map of the "real" landscape at that point in time. The closer we are able to match the second time period, the more confidence we have that those are the important factors that will affect the future distribution of development in a region.

How well one factor, or a combination of factors, allows GEOMOD to predict the future time is measured by the kappa-for-location ($K_{location}$) statistic. The kappa statistic tells us how much better than chance alone the model is in predicting areas that will be converted from forest to non-forest (with "0" being no better than chance alone and "1" being a perfect predictor), i.e. the higher the kappa statistic the higher the factor's ability to identify correctly those forested areas that will be converted to non-forest in the future based on their attractiveness for development. Percent cells correctly simulated can be deceiving especially when little change has occurred in the landscape. The kappa adjusts for this. One could also test whether a predicted quantity of change is accurate using the kappa-for-quantity measure.[6]

Objective

Our objective in this study was to test whether the land use change model GEOMOD, heretofore applied principally in tropical forested landscapes of the less developed world,[7] could reveal important insights into how quickly, where, and in what pattern the working forested landscape of the highly developed northeastern United States is being lost to other forms of land use. In its application in the developing tropics the model's inputs have been limited to maps of primarily bio-physical properties, but seldom included spatially distributed socio-economic or demographic information. In the United States we wanted to test whether the addition of such information in the form of, for example, US census data, county tax parcel maps, and real estate and labor statistics, might enhance the model's predictive power. The model has previously been applied to one other area of the northeast, the Ipswich Watershed in Massachusetts, but there it primarily examined the influence of topography.[8]

Study Sites

After considering several possible sites in the northeast, the final selection was narrowed to two places, based on criteria developed by the project team in the early planning stages (see box on this page): a portion of the Catskill/Delaware region in New York, including most of the New York City municipal water supply watersheds; and the Thames River Watershed and surrounding towns in Connecticut, later expanded to also include the Massachusetts towns in the watershed.

These largely forested places are under tremendous pressure from local development and the sprawling metropolitan areas of New York City, Boston, Hartford and Providence (figure 2). As the largest unfiltered surface water supply in the country, the New York City Watershed is extremely vulnerable to potential changes in land use. Protecting the remaining forested landscape is a high priority for both the local communities and the urban population of New York City. The Thames River Watershed, in northeastern Connecticut and south-central Massachusetts, known as the "Last Green Valley" between New York and Boston, is home to the Quinebaug-Shetucket National Heritage Corridor, honoring both its present rural character and its past industrial history. Development pressures are typical of those being experienced throughout the northeast, and there are active forest conservation efforts in both places.

Criteria for Choosing Research Sites

- Local or regional interest and willingness to partner in the project on the part of conservation organizations, local governments, and citizens' groups.
- A reasonably-scaled study area that makes political sense to the local partners; is large enough to allow landscape inferences (such as watershed impacts); and fits within the technical constraints of GEOMOD for data analysis.
- Adequate existing data sets on physical, social and economic conditions so that the analysis can be readily constructed without the need for gathering a significant amount of new data.
- Land cover maps derived from remote sensing imagery enabling construction of past land cover history extending back 10-20 years.
- Contains large tracts of intact, privately-owned forest as well as areas that are already developed.
- Considered to be at risk of losing forest to development and of further forest fragmentation.
- Located within a region of conservation focus in order to maximize the project's contribution to the larger forest conservation agenda.
- At least one member of the research team familiar with the area to aid in background, contacts, and reality-checking.

Figure 2. Night lights over northeastern North America. The Catskill/Delaware (left) and Thames (right) watersheds are in the areas circled in red. Image from NASA Lights of the Earth web site.

The Catskill Mountains of New York[9]

Our New York study site lies in the Catskill Mountains about 100 miles northwest of New York City. Encompassing more than six counties and over 6,000 square miles of mountains, forests, rivers, and farmland, the Catskills are often referred to as America's First Wilderness because scholars trace the beginnings of the environmental conservation movement to this beautiful area. With almost three dozen mountain peaks over 3,500 feet in elevation and six major river systems that annually attract the world's most devoted fly fishermen, the Catskills are an ecological resource of significant importance. The region's rugged terrain has contributed over the years to a sense of the area as remote wilderness, in spite of its nearness to the country's largest population center.

The two most prominent features of the Catskill region today are the nearly 300,000 acres of public Forest Preserve land located largely within the Catskill Park, and the 1,584 square miles of catchment known as the Catskill/Delaware Watersheds that provide 90 percent of the New York City water supply. This unfiltered water supply has been made possible largely because in 1885 the New York State Legislature established the Catskill Forest Preserve to be set aside as Forever Wild. In 1904 the Catskill Park was created to establish an imaginary boundary, called the "blue line," around the Forest Preserve, and surrounding private land. Together the Preserve and the Park have grown over the years to approximately 700,000 acres, of which about 60% is private land.

But this is also a working landscape, and the coexistence of the two—wilderness and human society—side by side is considered a grand and visionary landscape experiment in the Catskills. Farms and forests of the region have provided livelihood to families for centuries. Catskill tanneries supplied most of the saddles used in the Civil War. Hides were shipped from South America for processing into leather. High-tannin bark was stripped from hemlock trees and used to tan hides. The furniture making industry followed, using the trees left behind. Cleared land was often sold for 50 cents an acre to mountain farmers. Furniture makers, lumberjacks, charcoal producers, hoopmakers (hoops were used to hold barrels together), and wood acid manufacturers all exploited the Catskill forest. Today, the cleared valleys and hillsides have returned to forest and forestry remains important on private lands, primarily as a source of lumber. But little by little that landscape is being carved into ever smaller parcels of land, and the effects of New York City weekend sprawl and development may have significant impact on the long term viability of forestry in this region.

The Thames River Watershed of Massachusetts and Connecticut[10]

The New England study area covers most of the Thames River Watershed and adjacent towns, almost 1900 square miles of rural and forested land in northeastern Connecticut and south-central Massachusetts. An estimated thirteen percent of this land is permanently protected from development, either in the form of public land or conservation easements. Known as the "Last Green Valley," it is one of the last largely rural areas remaining in the highly-developed section of the east coast between Boston and Washington, D.C. It is home to the Quinebaug Highlands, a 269 square mile region of mostly privately owned forestland in Connecticut and Massachusetts, identified as one of Connecticut's Last Great Places by The Nature Conservancy; the 4,000 acre Norcross Wildlife Sanctuary in Massachusetts; the Yale Myers Forest, a 7,000 acre research and teaching forest; several state forests; and the Pawcatuck Borderlands, a 200 square mile area of largely contiguous forest along the Connecticut-Rhode Island border. The Quinebaug-Shetucket Rivers Valley was declared a National Heritage Corridor in 1994, to help with efforts to protect the unique history and rural character of this New England valley.

The region is rich with wildlife and healthy hardwood and coniferous forests. The larger landowners manage their forests for timber and other forest values, and there are numerous small saw mills operating throughout the area. Now this rural region is under pressure from the intense development of surrounding urban and suburban areas. Bordered by Worcester, Massachusetts to the north, New London, Connecticut to the south, Providence, Rhode Island to the east, and Hartford, Connecticut to the west, the area has undergone significant land use changes over the past fifty years as housing and industrial development has encroached upon formerly rural and forested land. Because so much of the forestland is privately owned, there is no guarantee that unique natural areas like the Quinebaug Highlands will remain intact or immune to development pressures, and therefore a number of conservation organizations have mobilized an effort to protect this region from development.

Community Input

Local input was considered vital to ensure both that assumptions could be tested against local knowledge and that the results would be meaningful and useful to the communities who are working to conserve their forested landscapes and rural character. Two community workshops were held, one in New York on March 19, 2002, the other in Connecticut on May 21, 2002. Attendees included representatives of various local and regional conservation organizations and government agencies; local citizens; and forest landowners. (See appendix A for workshop summaries and lists of attendees). Follow-up workshops were held in each location to present the results and discuss ways to get this information into the local planning processes. Input and feedback from the participants was incorporated into the project plan, wherever feasible.

Working Hypotheses

A working hypothesis about what is driving land use change in each area was developed during the first community sessions, based on local knowledge and intuition. In some cases, these conclusions were supported by the findings in the project; in others, the findings seem to point elsewhere. In either case, developing and testing a working hypothesis helps focus the study on important factors and provides a useful way to bring out new or surprising findings in the study.

New York Catskill/Delaware Watersheds

Hypothesis: Parcelization is more of a current factor than fragmentation and will be hard to detect or predict.

Findings: Parcelization and fragmentation are both occuring; parcelization tends to lead to fragmentation—land that is parcelized is 1.5 times more likely to be subsequently fragmented than land that has not been divided into smaller ownerships; parcelization cannot be detected via satellite imagery unless accompanied by fragmentation.

Hypothesis: The pattern of forest fragmentation and conversion is determined primarily by distance from New York City, distance from major roads, distance from ski resorts/new resorts (growth nodes); New York City water supply watershed regulations; taxes; age of landowner; and population of permanent residents vs. housing units (second home development).

Findings: The pattern of forest fragmentation is driven primarily by distance from urbanized areas (meaning those areas characterized by residential, commercial, or industrial building), elevation, slope, distance from local and secondary roads and population density. Second home development is an important factor in regional land use change dynamics. Ski resorts and landowner age were slightly less important in predicting where development has occured in the past. However, it should be noted that the scale of the window of analysis means that more importance will be given in the model to urbanized areas (since there are more of them) than rural development, such as ski resorts. Regulations and taxes were not tested due to unavailability of adequate time-series spatial data for these factors.

Thames River Watershed

Hypothesis: Threats to forests are from parcelization, fragmentation, habitat destruction, and conversion.

Findings: Fragmentation of forestland has occurred since 1985, although new development is projected to happen mostly on smaller, isolated fragments of forestland near already developed land. This is partly due to the fact that much of the forestland in this region is under some type of protection from development. It was not possible to examine parcelization effects since we did not have sufficient data about land ownership changes.

Hypothesis: The rate of forest fragmentation and conversion are being driven mainly by population growth; zoning regulations; changes in timber markets; casino development; economic growth in nearby major cities; land prices; distance from major cities; upgrade and expansion of roads; and the collapse of the dairy industry. We assumed that the pattern would be a function of distance to roads, to major urban areas, casino development, and perhaps a variety of socio-economic factors that make places more attractive or more likely to be undergoing change.

Findings: The pattern of forest loss in this region is best predicted by distance from 1985 agricultural lands, soil type, and distance from urban areas. Population, casino development, and roads were somewhat less important drivers of land use change, as were most socio-economic factors anaylzed. However, socio-economic factors, prior settlement patterns, and soil types are inter-related and thus probably co-dependent with the top three drivers. We did not have a way to incoroprate the collapse of the dairy industry into the analysis; and data was not available at a useful scale and format for analyzing zoning regulations or changes in timber markets.

Data Creation and Collection

Two data sets are required in this method of modeling land use change over time: land cover, which is the dependent variable; and the so-called potential driving factors, or independent variables. The assumption is that land use change (using land cover as a surrogate for land use) is a function of one or more biophysical and socio-economic factors, such as land prices, population growth, and proximity to natural amenities.

Dependent Variable—Land Cover[11]

Land cover maps for each region were the primary source of information for both the rate and location of change in forest cover in the two regions over time. For the New York study we relied on the USGS 1992 National Land Cover Data (NLCD) with 21 categories (figure 3) as our time 1 baseline (model calibration). Classifying satellite imagery into land cover/land use classes is as much an art as a science, as totally different land uses can sometimes have the same reflectance values. Thus a critical step in classifying satellite imagery is to perform an accuracy assessment, by either ground-truthing or comparing with aerial photographs. For the region of our analysis (figure 4), we compared the 1992 land cover values to 1994 aerial photos and found 90% accuracy.[12] For a second time period we classified a May 2001 satellite scene to use for model validation (also visible in figure 4). Our post-classification assessment yielded 99% accuracy at the pixel level when compared to year 2001 digital orthorectified quarter quadrangle (DOQQ) aerial photographs.

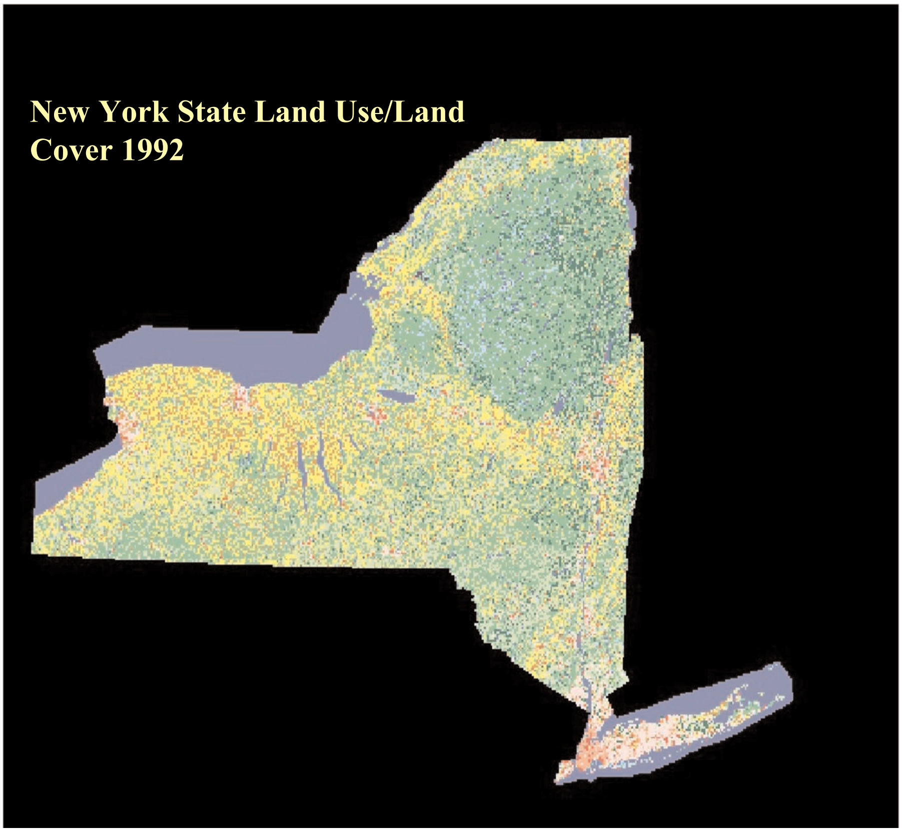


Figure 3. Baseline Map for Catskill-Delaware Study. Source: USGS National Land Cover Data Set.

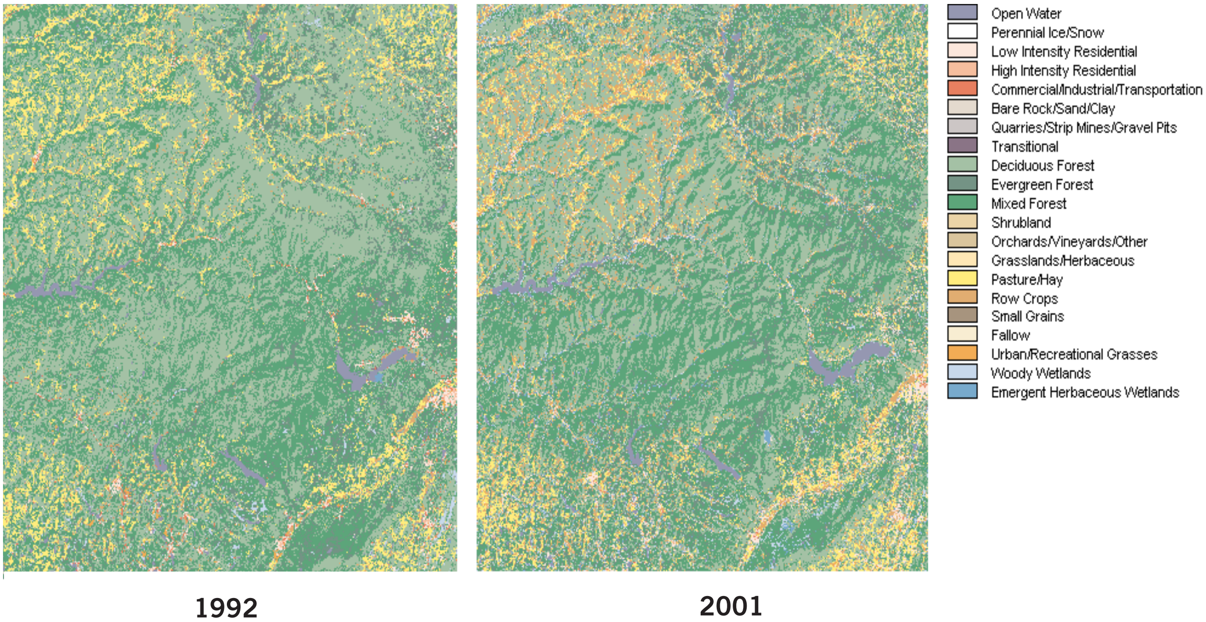


Figure 4. Window of analysis showing NLCD 1992 data juxtaposed with classified 2001 land cover for the Catskill-Delaware Region of analysis.

In the case of the Thames study, the Center for Land use Education And Research (CLEAR) at the University of Connecticut provided us with a four-year (1985, 1990, 1995, and 2002) land cover time series derived from satellite imagery[13] (figure 5). Eleven categories are delineated. "Agriculture" includes both cropland and pasture. As in other studies we have undertaken, agricultural lands are easily confused in the classification process with grasslands such as parks, and/ or with other grass and shrub-covered lands such as large lawns, fields, or meadows associated with residential or municipal property.[14]

We used 1990 as time 1 (model calibration), and 2002 for time 2 (model validation). The 1985 map allowed us to look at the relation of lands newly developed in 1990 with respect to lands already developed in 1985. It should be noted that, as we did not have more than two time series land cover maps for New York, it was not possible to use this "change from a previous time period" in the New York analysis. Our results, therefore, cannot be fully compared across both regions.

We stratified each region by political units. The New York region included parts of five counties centered on the New York City water supply catchments (figure 6). The Thames site included 59 individual towns in Connecticut and Massachusetts lying within the Thames watershed or immediately adjacent (figure 7). Public and private lands that are currently under conservation protection in the Thames, as well as public lands in New York acquired by both New York City and State to protect city drinking water quality, were excluded from analysis, as these lands are assumed to be unavailable for future development or other land use change (figures 8 and 9). Eighteen percent of the New York study area and thirteen percent of the Thames area is in this category.

Finally, all maps were reduced to two main categories. Those classified with the value "1" represent all forested land. A value of '2' indicates land that is in other uses such as agriculture, residential, industrial, commercial properties, etc. In the Thames the "Forest" class includes deciduous and coniferous forests and forested wetlands, while "Non-forest" represents the developed, turf and grass, agriculture, barren and utility classifications (Figure 10).

1985

2002

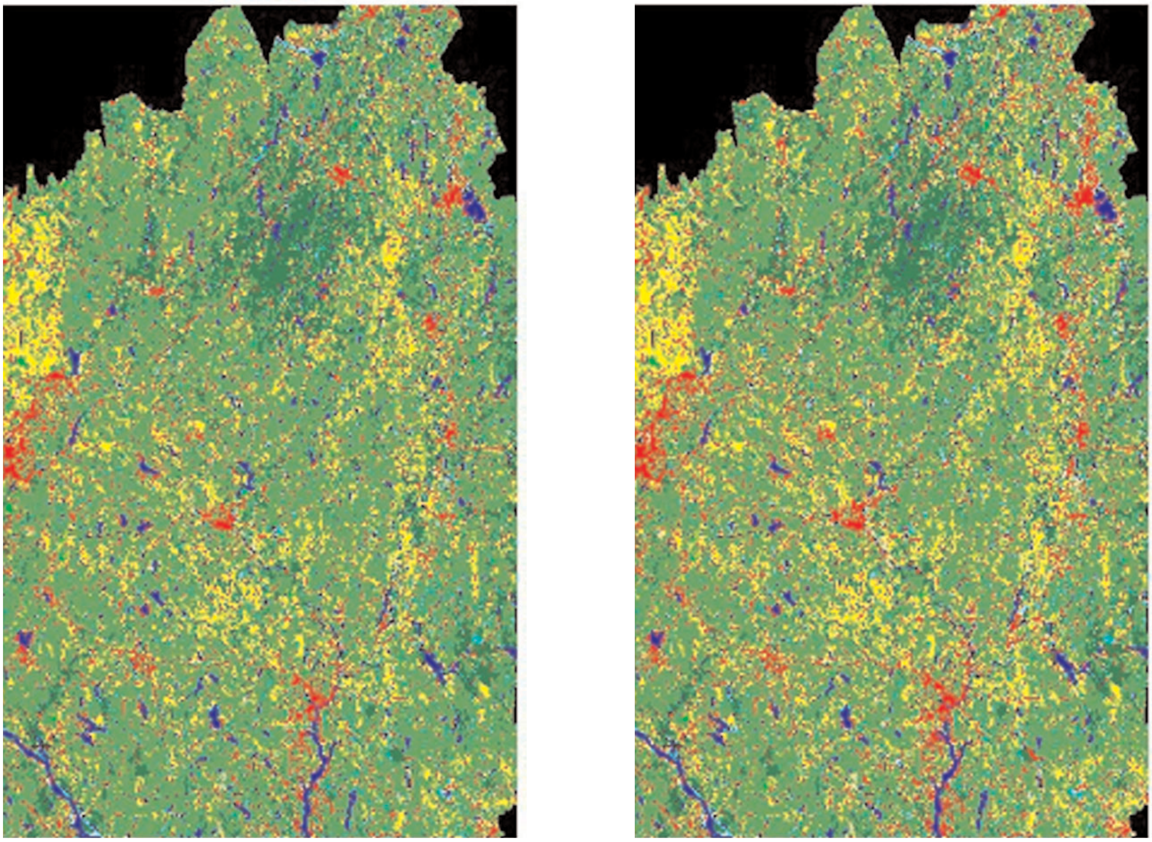
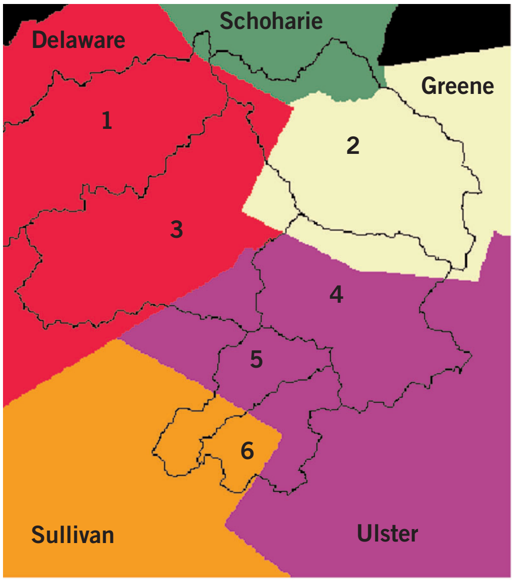


Figure 5. Land cover history for the Thames Watershed and surrounding towns, 1985 to 2002. Source: Center for Land use Education And Research (CLEAR) at the University of Connecticut.



Watersheds

1 - Cannonsville
2 - Pepacton
3 - Schoharie
4 - Ashokan
5 - Neversink
6 - Rondout

Figure 6. Study area boundary. Areas of New York City water supply watersheds and portions of counties included in study area.

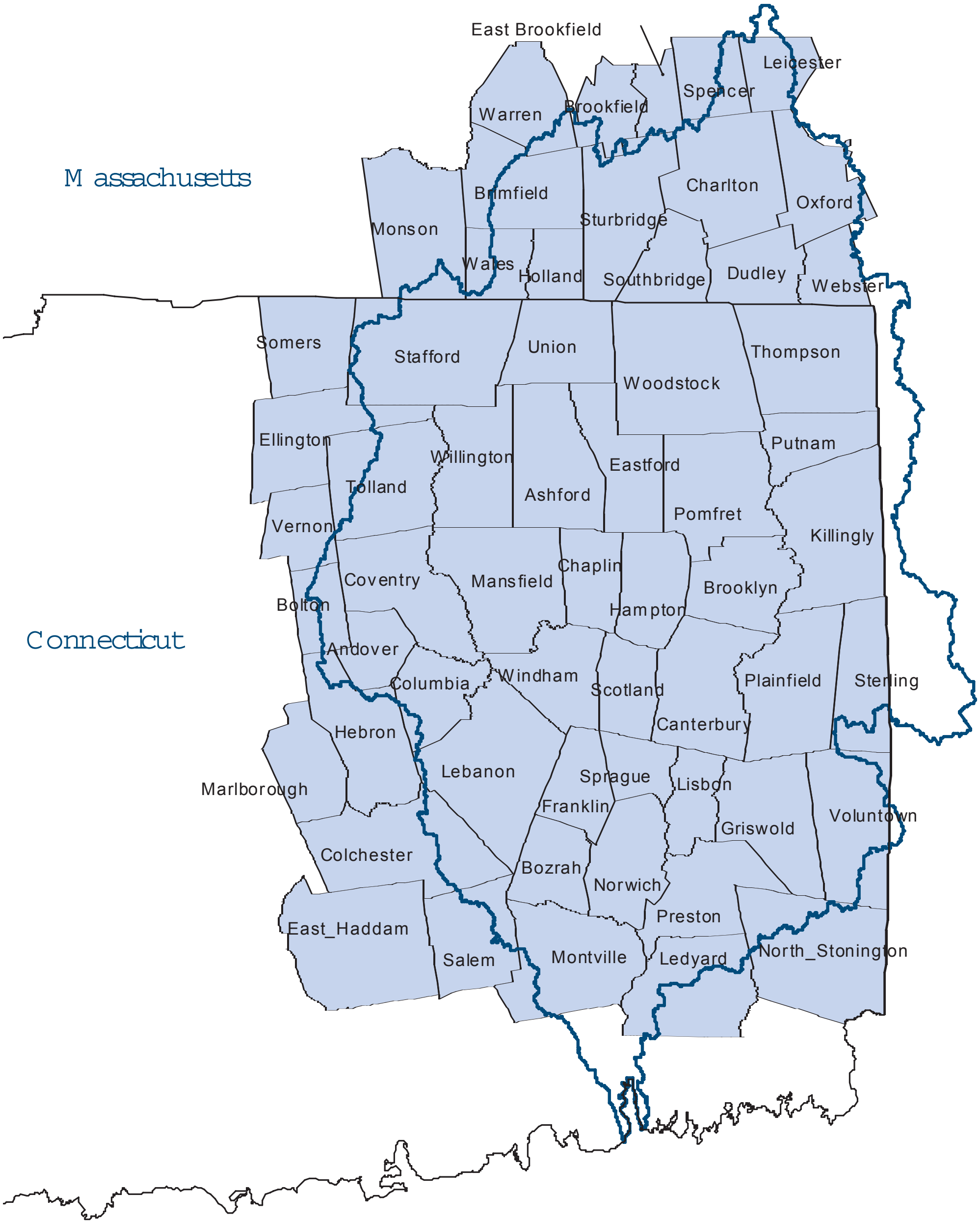


Figure 7. Towns of Massachusetts and Connecticut included in Thames Watershed study. The outline of the Thames Watershed is in dark blue

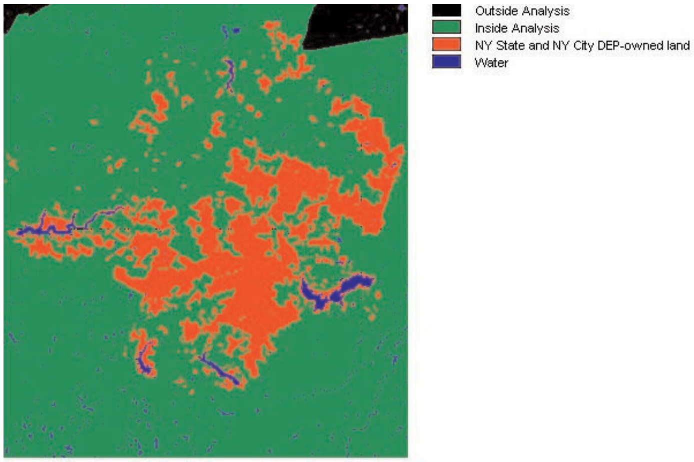


Figure 8. Public land excluded from New York study.

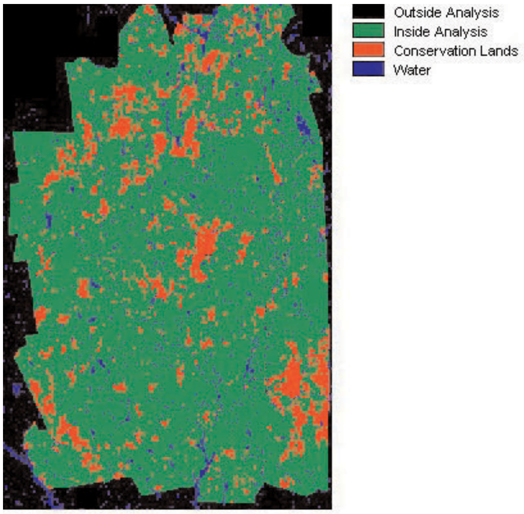


Figure 9. Thames Watershed public and private conservation areas excluded from analysis.

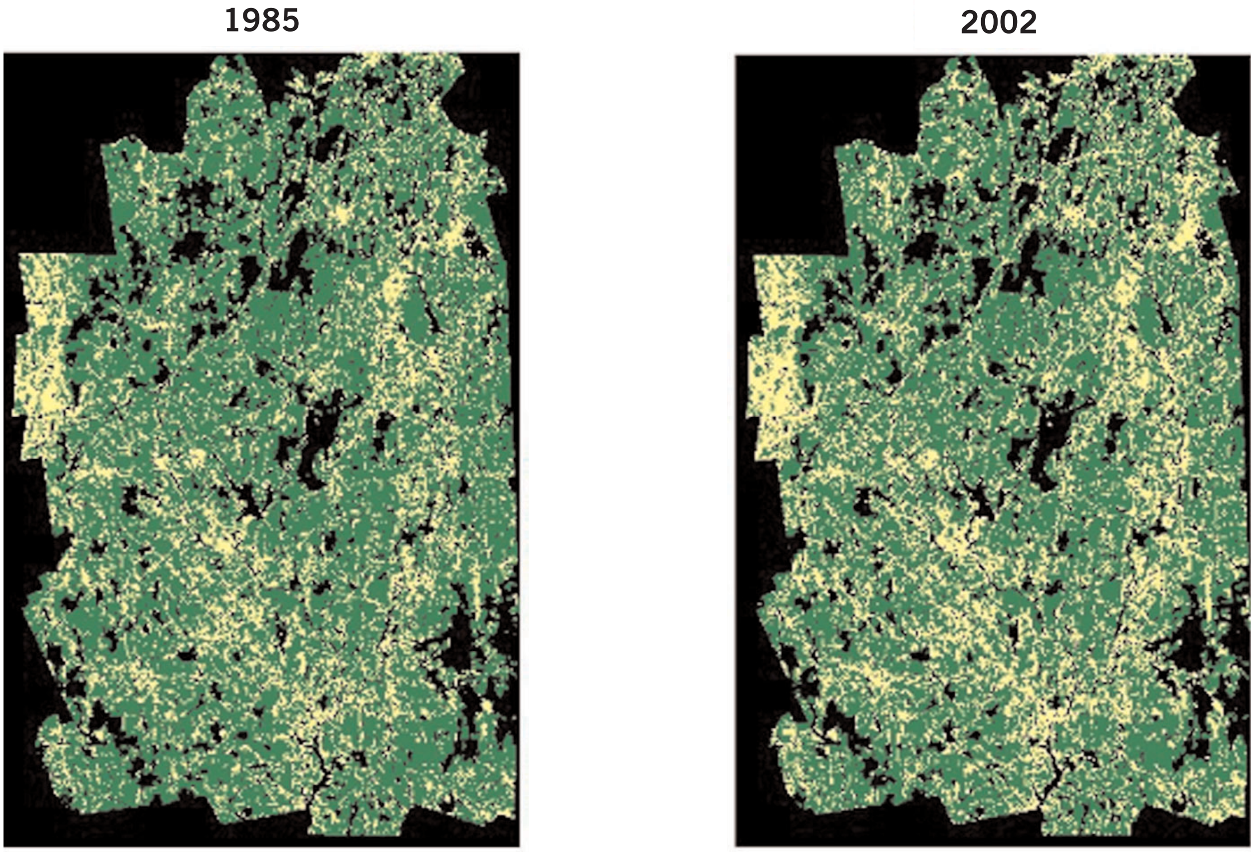


Figure 10. Thames Watershed 1985–2002 land cover reclassed to represent cells that are candidates for change and those that are not. Black areas indicate lands excluded from analysis—conservation lands and water.

In the Catskill-Delaware Region (figure 11) "Forest" includes deciduous, evergreen and mixed forest, and woody wetlands while "Non-forest" includes low and high intensity residential, commercial, industrial, transportation, hay, pasture, row crops, urban, recreational grasses, quarries, strip mines, and gravel pits. There is much debate about whether lands classified as "agricultural" in 1992 are in fact clear cuts reforesting or pasture lands reverting to forest, and whether the NLCD map overstates or understates the amount of land actually "deforested" as of 1992. The New York City Department of Environmental Protection map for the same time period shows (within the NYC water supply watershed only – figure 12) a much larger area in agriculture in 1992, particularly in the Cannonsville Watershed in Delaware County. Our accuracy assessment of this area of discrepancy on the 1992 NLCD map used in our analysis yielded 90% accuracy (using 1994 aerial photos as the reference criteria).

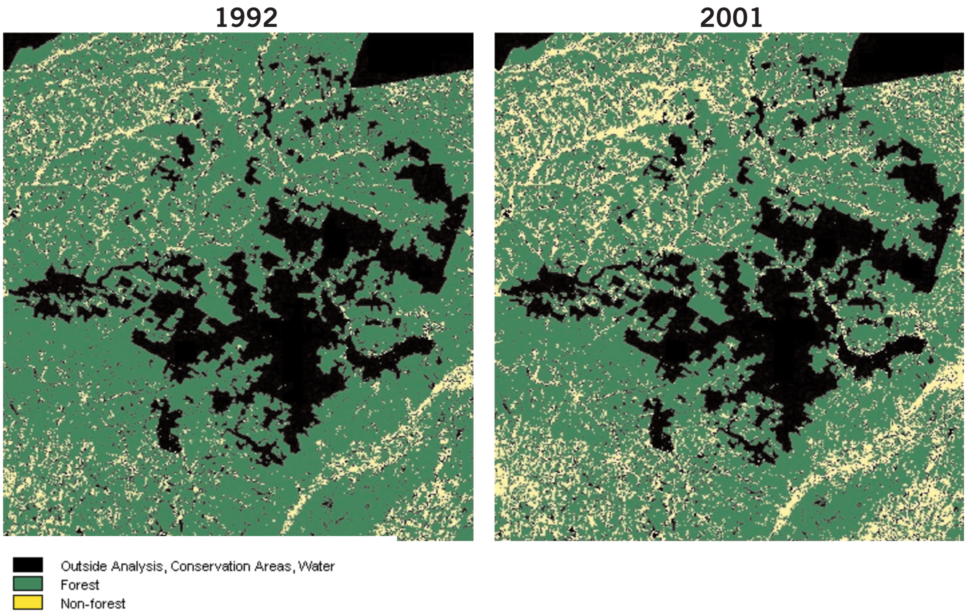


Figure 11. Catskill-Delaware reclassified 1992 and 2001 land cover. Black areas represent areas of water, wetlands, reforestation and NYC DEP and NY State lands masked out, i.e. not candidates for change from forest to non-forest.

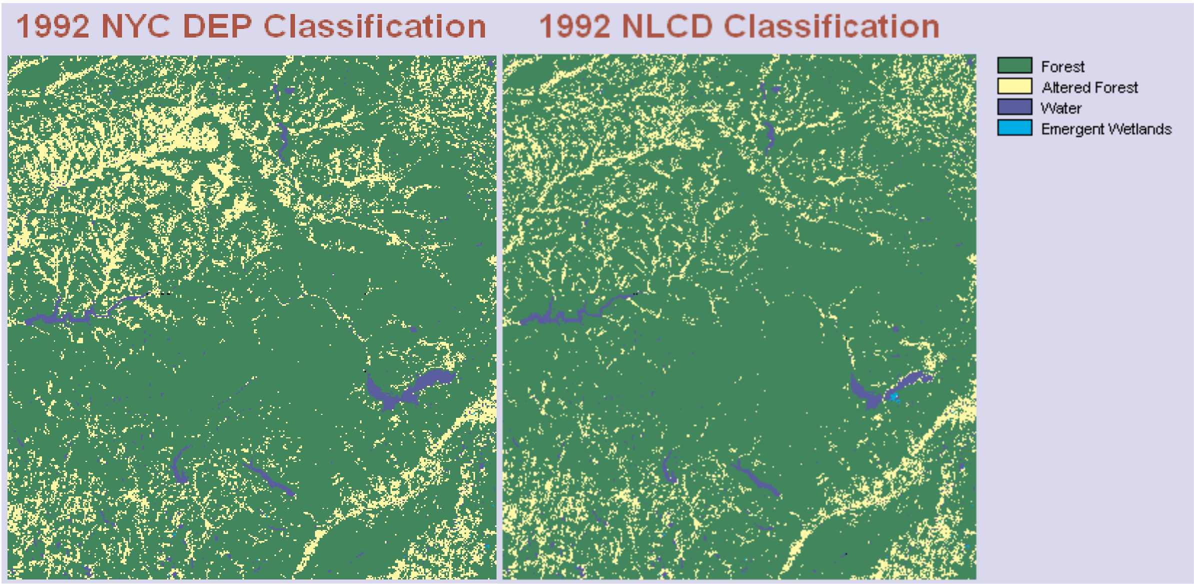


Figure 12. For comparison, the NYC DEP classification of Forest/Non-Forest in the watersheds is shown next to the NLCD '92 land cover map.

Independent Variables—Factors Affecting Location of New Developed Areas

An initial list of many possible drivers of land use change in the northeastern United States was derived from a combination of literature search, team experience/knowledge, and community input. The resulting list was then used to determine availability and usability of various data sets for incorporation into the modeling process (table 1).

		Included in Analysis	
		NY	CT/MA
Available for all three states in geospatial format at scale useful for analysis			
	Demographics: Population	x	x
	Distance from metropolitan growth nodes	x	x
	Housing density and type	x	x
	Hydrography	x	x
	Protected open space	x	x
	Railroads, utility lines		x
	Roads	x	x
	Second homes and non-resident owners	x	x
	Topography (elevation, slope, aspect)	x	x
Available, not in geospatial format; easily converted			
	Building permits		x
	Employment in the service economy		x
	Housing prices; housing sales		x
	Labor force by sector		x
	Unemployment rate		x
Available, not in geospatial format; not easily converted			
	Development nodes (casinos, ski resorts)	x	x
	Zoning regulations		
Available but at too course a scale for useful analysis			
	Economic cycles		
	Federal spending programs: Education, Transportation, Sewer & Water; Infrastructure		
	State spending programs: Education, Transportation, Sewer & Water; Infrastructure		
	Tax policies		
	Timber prices		
Not readily available for all three states, or not in useable format			
	Education demographics		
	Local economy - relative importance of farming, forestry, ranching, mining		
	Malls, big box stores		
	Property taxes - rates and structure		
	Ratio of land sale prices to timber stumpage prices		
	Real estate conveyance taxes		
	Rural Industry		
	Soils		x
	Timber markets		
	Transportation		
Did not investigate due to project resource constraints			
	Commuting distance from employment base		
	County business patterns		
	Emergence of "edge cities"		
	Employment in surrounding areas		
	Farm income		
	High amenity value natural features		
	Income		
	Land pricing		
	Land tenure patterns		
	Level at which land use planning takes place (municipal, county, region, state)		
	Level of regional cooperation and coordination		
	New jobs created by sector		
	Office and industrial parks		
	Population in surrounding areas		
	Schools data by school district		
	State of the planning process: how long in existence; age of plan; volunteer or paid staff		
	Tax rates in surrounding areas		
	Vitality of older cities and suburbs		

Table 1: Potential factors influencing where forest fragmentation and loss from sprawl occurs

The project encompassed three states, and many data were not available in all three. Socio-economic data have to cover the same time period as the land cover data to provide meaningful analysis of drivers. So that the broadest possible set of factors could be tested in at least one of the sites, data that were available only in Connecticut and Massachusetts were used in the Thames analysis, even though they were not available for the Catskill/Delaware analysis. Although this approach gives us more robust information about the availability and utility of socio-economic data and its relationship to forest fragmentation and parcelization dynamics, the disadvantage is that it limits our ability to draw conclusions about commonalities across the two sites.

Thus, with the exception of the US Census data that we purchased for 1990 and 2000, these data sets are not equivalent across both regions. In the Thames study we had state labor department employment information by town, including the number of employees in each labor sector, such as construction, which we thought might be an indicator of growth. For the Thames we also had information on housing, such as the number of home starts, building permits and sales, and median sales price. And finally we had a soil map for the Thames that we did not have for the New York study.

On the other hand, in the New York region we had tax parcel data for 2000 made available by the New York City Department of Environmental Protection. This allowed us to analyze who owns how much forestland in the region and whether or not these owners are local residents. Finally, in New York, the elevation data were higher resolution, although of the same scale (1:24,000) as the Connecticut/Massachusetts data. In both instances the hydrography (water features) data were not of the same scale as the hypsometric (elevation) data.

Data Collection

Collecting, organizing, formatting and managing geospatial data is time consuming; thus we limited our efforts to those data that were either readily available in geospatial format, or easily converted. The exception was the location of “growth nodes”, such as ski resorts and casinos. There is no geospatial data base of major developments (which would also include malls, and commercial and industrial parks), however, as input was strong at both community workshops that these growth nodes were important drivers of secondary development, we used a manual process to locate and georeference ski resorts and casinos in the study areas.

Data and sources included in the analysis are shown in appendix C. All three states have web sites where certain GIS (Geographic Information System) data layers (georeferenced, spatially explicit maps containing features such as rivers, roads, etc.) of mostly biophysical data and political boundaries can be downloaded. The United States Census Bureau is the original source of all population and housing data. The raw census data, available at the US Census Bureau web page, are very difficult to use, especially because the georeferencing is not automatic, but must be interpreted and managed by a technically proficient user. To avoid this resource-intensive work on data preparation, we chose to purchase data in an easy-to-use GIS format from Geolytics, a commercial company, which produces CDs of census data to the census block level in ArcView shape files and tables.

If data were not accessible on the state GIS web site, then a more intensive search was conducted by contacting various government offices. The socio-economic data obtained this way were then converted from either spreadsheets or hard copies to GIS files.

Combining data from two states, Connecticut and Massachusetts, was a major undertaking. Even the state boundaries in each state's GIS system do not exactly line up. Other GIS data, such as roads, based on census TIGER files, and hydrological features matched up very well. Socio-economic data layers (other than census) were created from individual files and documents and georeferenced to town boundaries, which was a relatively easy task once the town boundary maps were corrected for the state line problem.

The soils data were the most problematic. Although both Connecticut and Massachusetts have GIS files of county soil maps, they use different nomenclature for what are obviously the same soil types (most apparent at the state border). To derive one soil map for the entire Thames study area, the soil series in each state were classified into general categories (e.g. "Agawam fine sandy loam" was reclassified to "fine sandy loam"), and obvious discrepancies at the state border were corrected.

<u>Forest Products Industry Data</u>

Loss of forestland inevitably leads to loss of the local forest products industry, hence feeding a vicious economic cycle where landowners have no ability to sell forest products to support the cost of owning the land. Consequently, we wanted to include in the analysis some indicator of the size of the forest products industry over time in each of the study sites. An extensive effort was made to find some applicable data for the Thames study area, to no avail.

Town- and county-level data on the value of the Connecticut and Massachusetts wood and forest products industries were not readily available. Federal and state government offices and databases did not have the desired information. For instance, the County Business Patterns database had economic data at the county resolution, but it was limited to employment and payroll information, with no data available on the actual value of the industries. Conversely, the Bureau of Economic Analysis had data on the value of wood and forest product industries, but only at the state level, and they were unable to provide the county- and metro-level data from which their state reports were presumably assembled. Queries with the New England Agricultural Statistics Service and the Massachusetts and Connecticut Departments of Economic and Community Development yielded no information.

Industry and trade groups such as the American Forest and Paper Association, the Massachusetts Forestry Association, the New England Forestry Foundation, the Massachusetts Maple Producers Association, and academic institutions such as the University of Connecticut had state-level data, but nothing at finer resolutions.

The best source of data was the 1997 Economic Census, which had data at the county- and metro-level for the shipment values of manufactured goods, in addition to the sales values for wholesale and retail trade. Industries covered included lumber, paper, and wood products. Unfortunately, industry data were often listed as, "withheld to avoid disclosure," and therefore unavailable. Additionally, the Economic Census is only held every five years, and 1997 is the first year in which specific wood products information is available; prior to 1997, the lumber, paper, and wood products data are grouped nonspecifically under "wholesale," and "manufacturing," with no way to separate them into industry-specific information. The 2002 Economic Census is currently underway, but until those data are compiled, 1997 is the only year for which the desired data are available.

After a similar search of government and industry sources for the Catskill/Delaware region, it was determined that the forest industry data available for the region were generally not of a spatial or temporal resolution that would allow comparisons between the recent history of the timber industry in this region and land use/land cover changes.

Results—Catskill-Delaware Region

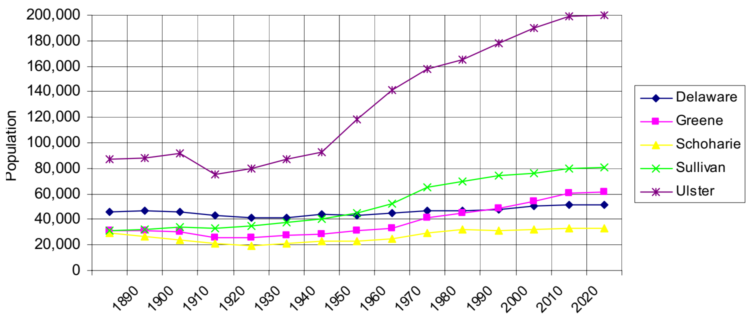
Empirical Rate of Forestland Loss and Apparent Causes

With the exception of Ulster County with prime Hudson Valley real estate, population growth in the counties included in our study area has been fairly flat going back as far as 1890 (figure 13). What these data do not reveal, however, is the flux in weekend and seasonal inhabitants, which promotes development of the facilities and services they require. Within the boundaries of the New York City Watersheds there are 68,400 parcels of private land covering over 900 thousand acres. As evidence of the ownership dynamics in this area, only 36,400 of these parcels covering 444,870 acres are owned locally, while people whose home address is outside the region own 32,000 parcels covering 482,250 million acres. This means that 52% of the private land is owned by non year-round residents, while 48% is locally owned. Thus resident population, as measured by the 10-year census, cannot be used in this region to predict a future rate of forest fragmentation. This is also evidenced by the widely varying discrepencies between the 1990 and 2000 population statistics and the Catskill forest cover in the five counties (figure 13).

Towns Included in Tax Parcel Ownership Analysis

Andes	Deposit	Hunter	Masonville	Shandaken
Ashland	Fallsburg	Hurley	Meredith	Sidney
Bovina	Franklin	Jefferson	Middletown	Stamford
Broome	Gilboa	Jewett	Neversink	Tompkins
Colchester	Halcott	Kortright	Olive	Walton
Conesville	Hamden	Lexington	Prattsville	Wawarsing
Delhi	Hardenburg	Liberty	Rochester	Windham
Denning	Harpersfield	Marbletown	Roxbury	Woodstock

Within the entire study area of 1.8 million acres, 376,000 acres are owned by the city and the state to protect NYC drinking water. Assuming that this land will be protected in perpetuity, we excluded it from our analysis, hence our results are focused on changes in the 1.4 million acres of private forestland in the region. Our findings indicate that private forests are disappearing at a rate of 16,187 acres (1.3 %) each year, for a total of 145,685 acres in the nine years between 1992 and 2001, in a pattern that is clearly evident of increased fragmentation of the forest resource. If that same trend continues, the region will lose another 162,000 acres of private forests by 2011. To arrive at this number, we derived the rate of forest conversion from the classified satellite imagery (1992–2001) and extrapolated that same rate into the future. This rate of forest loss may or



County	Population Change 1990-2000	Forest Cover Change 1992-2001
Delaware	1.76%	-7%
Greene	7.72%	-3%
Schoharie	- 0.87%	-3%
Sullivan	6.77%	-6%
Ulster	7.53%	-5%

Figure 13. Population statistics for counties in the area of analysis (left) and population vs. forest cover change (right).

	Forest 1992	Non-forest 1992	Forest 2001	Non-forest 2001	% Forested in 1992	% Forested in 2001	Acres of 1992 Forest Lost	Acres 1992 Non-forest Reforesting	Net Acres 'Forest' Lost
Delaware	366425	64820	322781	108464	83%	75%	49844	6200	43645
Greene	174780	18871	161274	32376	88%	84%	17048	3543	13506
Schoharie	83071	11188	76825	17434	86%	82%	8000	1754	6247
Sullivan	262040	38350	236681	63709	86%	79%	30846	5487	25359
Ulster	360527	48002	326569	81960	87%	80%	39946	5988	33958
Total	1246843	181230	1124129	303944	87%	79%	145685	22972	122714

Table 2: Catskill/Delaware forest history (acres). All numbers include only privately-owned lands.

may not remain the same in future years, and will likely have some relationship with economic activity, however, we were not able to find an economic database for the last 10 years at a scale that would allow us to look for correlations between economic activity and land use change.

In 1992 privately-owned lands were 86% forested. By 2001, they were 79% forested. Delaware, Ulster and Sullivan, are losing forest faster than Greene and Schoharie (table 2). At the same time that private forests were being converted to other uses, some land was apparently "reforesting," i.e. land that was not classified as forest in 1992 was by 2001 showing up as forest on the satellite imagery. Some of this land may be working forest, i.e., regrowth after silvicultural treatment; some may be former agricultural land acquired by the NYC DEP. This merits further investigation. Considering the "reforesting" areas, the net change was 122,714 fewer acres in private land classified as "forest." In spite of the regrowth, the overall loss of 12% of the private forestland over the nine-year period far exceeds the amount that is "reforesting," which is 1.5% of the private forestland in 2001.

Including the publicly-owned forest, the entire region analyzed went from 87% to 81% forested over this nine-year period (table 3), and we project this to drop to 76% by 2011. This projection includes "reforestation." If "reforesting" land is not developed in the meantime, it will take more than the time period of our projections to grow back into a full closed-canopy forest. Therefore these projections are likely to be on the high side, with actual forest cover somewhat lower.

	% Forest Including Public Land	
	1992	2001
Delaware	83%	76%
Greene	90%	87%
Schoharie	85%	81%
Sullivan	85%	78%
Ulster	90%	85%
Total	87%	81%

Table 3: Percent forested, including all lands, by county 1992 and 2001

Within the New York City Watersheds, parcel size is decreasing and our analysis indicates that forest land that has been parcelized is 1.5 times more likely to be converted to other uses than land that has not been divided. The average parcel size has gone from 18 acres in 1985 to 14 acres in 2000,[15] clearly indicating increased parcelization of forestland since 1985. As evidence that parcelization (smaller ownerships) does lead to further forest fragmentation, our data from a sample of 122,000 acres, show that lands that had been parcelized between 1984 and 2000 experienced a higher rate of forest loss (8%) than those that had not been parcelized (5.5%).

Of the six New York City watersheds located in the region of analysis, all but the Cannonsville are entirely represented. Of the total 1.8 million acres analyzed, 877,354 acres lie within the NYC water supply catchments. Clearly those with the most publicly-owned land experienced the least loss of forest cover from 1992 to 2001 (table 4). The portion of the Cannonsville Reservoir catchment that lies within the study region, which is 97%

private land, has lost 10 percent forest cover during the 9 year period. The Ashokan Watershed, with only 37% private ownership has lost only 2 percent, while the Neversink, with 45% private land has lost 1 percent of its forest. The reader is reminded that "forest cover" includes some reforesting land. The actual loss of 1992 forest is 19 percent in the Cannonsville and 2 percent in the least impacted basin, the Neversink. Overall the NYC catchments have gone from 88.7 percent "forest cover" to 84.2 percent in a nine year period, which includes a loss of 8 percent of the 1992 forest but a net change of only 4.5% due to reforestation of agriculture and forestry lands since 1992. The true loss, therefore, is somewhere between 4 and 8 percent or 0.4 and 0.9 percent per year. The watersheds were analyzed as potential determinants of the pattern of landscape development, but ranked low among candidate drivers based on the kappa statistic of validation (table 5).

NYC Watershed Basins	Cannonsville	Schoharie	Pepacton	Ashokan	Neversink	Rondout	Total Basins	Outside NYC Watersheds	Total Area Analyzed
Proportion Public land/Basin	2%	22%	20%	58%	53%	46%	29%	7%	17%
Percent Private Land	97%	77%	78%	37%	45%	50%	69%	92%	79%
Percent Water	0%	1%	2%	5%	3%	4%	2%	1%	2%
Percent Forested in 1992	75%	88%	89%	97%	97%	96%	89%	84%	87%
Percent Forested in 2001	65%	85%	84%	95%	96%	92%	84%	78%	81%
% Change	10%	3%	5%	2%	1%	4%	4%	6%	5%
% Loss of 1992 Forest	19%	7%	8%	3%	2%	5%	8%	11%	10%

Table 4: Change in forestland in the NYC Watersheds basins 1992 - 2001 (percentages are rounded).

Pattern of Forestland Fragmentation, the Empirically-Important Factors and Their Ability to Predict the Future Location of Development

In the Catskill-Delaware study we tested the ability of 18 factors to accurately predict where development (defined as change from forest to non-forest) occurred between 1992 and 2001. The results of our analysis show that development in the Catskill-Delaware region is driven primarily by the increasing number of non-local land owners desiring a piece of rural forested America, and the establishment of the facilities and services to support that weekend/vacation time population. In the five counties that surround the heart of this region the most important biophysical factors influencing what land is selected for development are elevation and slope, which is not surprising in a mountainous region. The socio-economic factors are distance to “urban” areas, population density, and the economic “infrastructure” of local and secondary roads (table 5).

We compared the simulated 2001 results using the “vulnerability” map for each factor, to the actual 2001 land use map. The goodness of fit between the simulated map and the actual map is indicated by the kappa statistic, which measures how much better than chance alone the model is in predicting areas that will be converted from forest to non-forest (with “0” being no better than chance alone and “1” being a perfect predictor). In this case, with our best driver set we achieved overall a 90.9% agreement between the simulated and the real map, with a very high kappa of 0.7319. It is interesting to note that while population density returned the same kappa as distance to secondary roads, including it with the top five drivers reduced the kappa, and hence the predictive power of the first five combined. Each additional driver tested in the model reduced the “goodness of fit” even more.

Zooming in to get a better view in figure 14, we illustrate the “goodness of fit” between the simulated 2001 and the actual 2001 map. Working with 30 x 30 meter square cells, the four classes represent 1) cells left in forest by the model that were in fact still forested in 2001 (correct), 2) cells simulated as converted from forest that were in actuality still forested in 2001 (incorrect), 3) cells left in forest by the model that were actually non-forest in 2001 (incorrect), and 4) cells simulated as non-forest that either remained as non-forest or were in fact

Individual Drivers - Unconstrained

Driver	Rank	Kappa	%Correct
Population Density	1	0.5370	84.31
Elevation	2	0.5255	83.92
Population over age 65	3	0.5239	83.86
Distance from Urban	4	0.5176	83.65
Distance from State Owned Lands	5	0.5176	83.65
Distance from Local Roads	6	0.5035	83.17
Distance from Agricultural Lands	7	0.5021	83.12
Slope	8	0.4983	83.00
Distance from Secondary Roads	9	0.4979	82.98
Distance from Ski Resorts	10	0.4970	82.95
Owner Occupied Housing	11	0.4939	82.85
Distance from Primary Roads	12	0.4901	82.72
Distance from Water	13	0.4885	82.66
Distance from Route 28	14	0.4854	82.56
Distance from NYC	15	0.4848	82.54
Aspect	16	0.4813	82.42
Distance from Hydrological Features	17	0.4812	82.42
Basins	18	0.4787	82.33
Top 5 Drivers		0.5633	85.27

Individual Drivers - Constrained Neighborhood

Driver	Rank	Kappa	%Correct
Distance from Urban Areas	1	0.7285	90.80
Elevation	2	0.7271	90.75
Slope	3	0.7263	90.72
Distance from Local Roads	4	0.7260	90.71
Distance from Secondary Roads	5	0.7255	90.69
Population Density	6	0.7253	90.69
Distance from State Owned Lands	7	0.7250	90.68
Distance from Primary Roads	8	0.7248	90.67
Distance from Hydrological Features	9	0.7241	90.65
Aspect	10	0.7241	90.65
Distance from Water	11	0.7241	90.65
Basins	12	0.7236	90.63
Distance from Route 28	13	0.7235	90.63
Population over age 65	14	0.7235	90.63
Distance from NYC	15	0.7232	90.61
Distance from Ski Resorts	16	.07229	90.61
Owner Occupied Housing	17	0.7227	90.60
Distance from Agricultural Lands	18	0.7224	90.59
Top 5 Drivers		0.7319	90.91

Table 5: Comparison of ability of individual drivers to re-create the 2001 landscape under an unconstrained simulation (left) and one restricted only to those cells falling within 30 meters of previously developed cells (right).

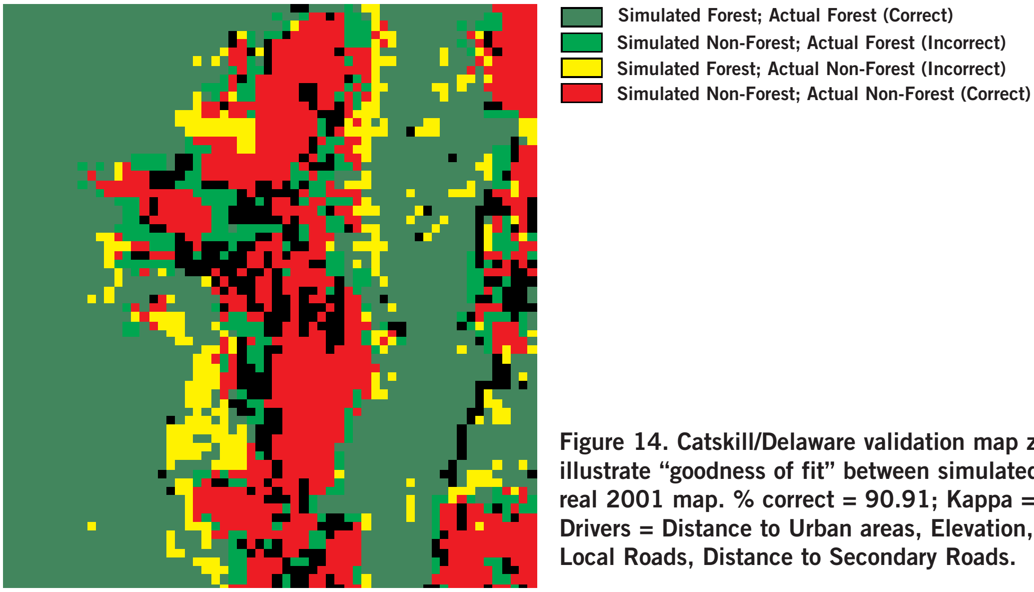


Figure 14. Catskill/Delaware validation map zoomed in to illustrate "goodness of fit" between simulated 2001 map and real 2001 map. % correct = 90.91; Kappa = 0.7319; Drivers = Distance to Urban areas, Elevation, Slope, Distance to Local Roads, Distance to Secondary Roads.

converted to non-forest use (correct). This is perhaps the most intuitive way to visualize how well the model can predict the actual pattern of development over the nine year period.

The model can be allowed to select all of the highest weighted cells across the region, or be constrained to a neighborhood. Under the unconstrained simulation the kappa was considerably less than that achieved when the model was constrained to select within a distance of 30 meters of already developed land. This suggests a strong clustering of development as opposed to dispersal of settlement.

Furthermore, the top six factors are not the most significant in all counties (table 6), highlighting the differences in the underlying topography, and we assume, the different socio-economic forces at play, as well as the land that is available for sale. For instance, the drivers of high development preference are distance from water in Delaware and Greene Counties, but distance from publicly-owned lands is more important in Schoharie and Sullivan Counties. Also, in the three counties with the greatest topographic variation—Schoharie, Sullivan and Greene, aspect is one of the top five factors. This illustrates a preference for both flat land, which lessens development costs, and aspect, an indicator of sunlight in a region of dark valleys. Elevation is one of the most predictive factors in 3 of the 5 counties.

Nonetheless, the kappa statistics are quite close for all factors, indicating the interdependence of topography, roads, population, and urban development. Using these factors in combination in the GEOMOD process has given us great predictive power to project the pattern of future land development. We believe such information can be very useful to communities, planners and developers.

Future Projections

Simulation of the future landscape was performed at the county level using the best set of drivers for each county (table 6). The time period selected for the projections was based on how far back we were able to analyze the rate of change, so that in the Catskills where we had land use data for only 1992 and 2001, we project forward only 10 years. For each county, we assumed the same rate and pattern of change that we have seen for the 1992-2001 period. Sites for future development were selected from the areas of highest weighting in the forest-fragmentation potentiality map (figure 15a).

Weights were derived based on the amount of development that has already occurred within each county on land with similar characteristics relative to the five factors from among distance from urban areas, elevation, slope, distance from local roads, secondary roads, primary roads, rivers, and population, that together yielded the best "goodness of fit" between the simulated and the real 2001 map for each county. For the final risk map used for future projections (figure 15a) "distance to urban areas," important in all five counties, was updated to reflect distance from all areas in "urban" uses by year 2001. This map, when summarized in three categories from high to low potential for development, allows communities to identify quickly those areas most at risk within their county. The areas of highest vulnerability exhibit a linear pattern that appears to follow roads, which follow streams up the narrow valleys, as has been the case in the past.

Although we received a lower kappa when analyzing the region as a whole, i.e. without stratification by county, figure 15b illustrates which areas regionally are most at risk based on previous development on land with similar characteristics relative to the five top factors for the region.

	TOTAL	DELAWARE	GREENE	SCHOHARIE	SULLIVAN	ULSTER
Distance from Urban Areas	90.80	90.70	90.97	91.64	90.55	90.80
Elevation	90.75	90.68	90.79	91.67	90.50	90.78
Slope	90.72	90.70	90.77	91.53	90.48	90.72
Distance from Local Roads	90.71	90.64	90.78	91.53	90.49	90.73
Distance from Secondary Roads	90.69	90.58	90.85	91.64	90.48	90.68
Population Density	90.69	90.61	90.80	91.48	90.42	90.73
Distance from State Owned Lands	90.68	90.49	90.72	91.64	90.58	90.71
Distance from Primary Roads	90.67	90.50	90.72	91.38	90.56	90.75
Distance from Hydrological Features	90.65	90.62	90.77	91.56	90.37	90.62
Aspect	90.65	90.43	90.80	91.59	90.50	90.69
Distance from Water	90.65	90.50	90.83	91.48	90.43	90.68
Basins	90.63	90.55	90.75	91.37	90.39	90.67
Distance from Route 28	90.63	90.43	90.70	91.54	90.59	90.62
Population over age 65	90.65	90.53	90.76	91.45	90.45	90.69
Distance from NYC	90.61	90.61	90.64	91.43	90.35	90.62
Distance from Ski Resorts	90.61	90.49	90.65	91.45	90.46	90.62
Owner Occupied Housing	90.60	90.43	90.70	91.46	90.43	90.66
Distance from Agricultural Lands	90.59	90.40	90.70	91.46	90.40	90.68
1ST						
2ND						
3RD						
4TH						
5TH						

Table 6: Although the first five drivers on the left provided the highest predictive power for the region as a whole, this table illustrates how different factors are important in different counties. For ease of interpretation the simple % correct is used here.

Using GEOMOD, we simulated the rate and pattern of forest fragmentation out into the future from 2001 to 2011 (figure 16). The results show Delaware and Ulster County respectively losing 55,000 and 44,000 acres of their 2001 forest cover by 2011 (figure 17). This is a reduction of 17% and 14% of each county's remaining privately-owned forest (table 7). For the entire region of analysis, using the 1992-2001 rates, we estimate that another 162,000 acres of privately owned forestland will be lost to development, leaving the area 76% forested (including public and reforesting lands) by 2011, down from 81% in 2001 (table 8). Not only does this imply loss of the working forested landscape but these results could have significant impact on New York City water quality as well. Of all the NYC water supply watersheds in the analysis, we project the greatest loss of forest cover in the Cannonsville Watershed—approximately 30,000 acres, amounting to 18% of its private forests by year 2011, followed by the Pepacton, which will lose 11% (figure 18).

Not only is there loss of forest, the remaining forest is more fragmented. Using a simple measure over the entire study area of "area of intact forest" vs. "perimeter of forest patches," the area:perimeter ratio was 187:1 in 1992; 150:1 in 2001 and is projected to be 105:1 in 2011. Forest patches are getting smaller, with more edge environment, which has implications for wildlife, invasive species, and water quality.

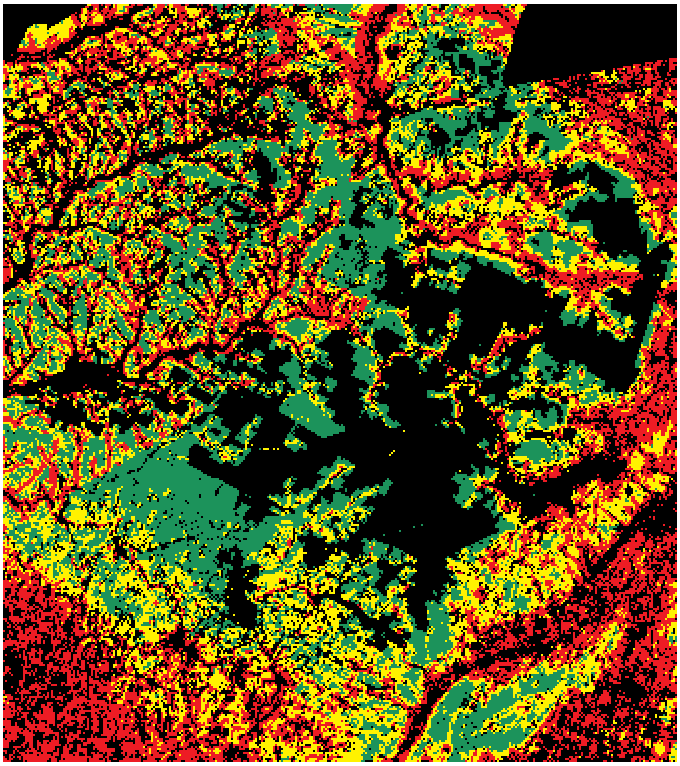


Figure 15a. Forest Fragmentation 'Potentiality' or 'Risk' Map calculated for each of the five Catskill-Delaware Counties included in the analysis. This map illustrates those areas within each county most and least likely to be developed based on which land has been the most desirable for development in the past.

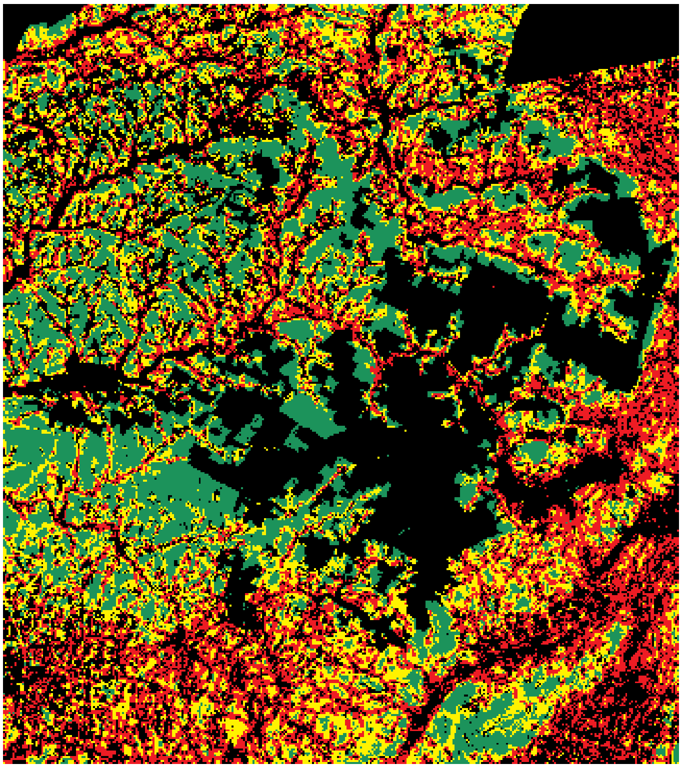


Figure 15b. Forest Fragmentation 'Potentiality' or 'Risk' Map for the Catskill-Delaware Region. In this map forested areas are categorized from high to low risk of development based on past regional patterns. Areas in red are those under greatest pressure for future development compared to other areas across the entire region.

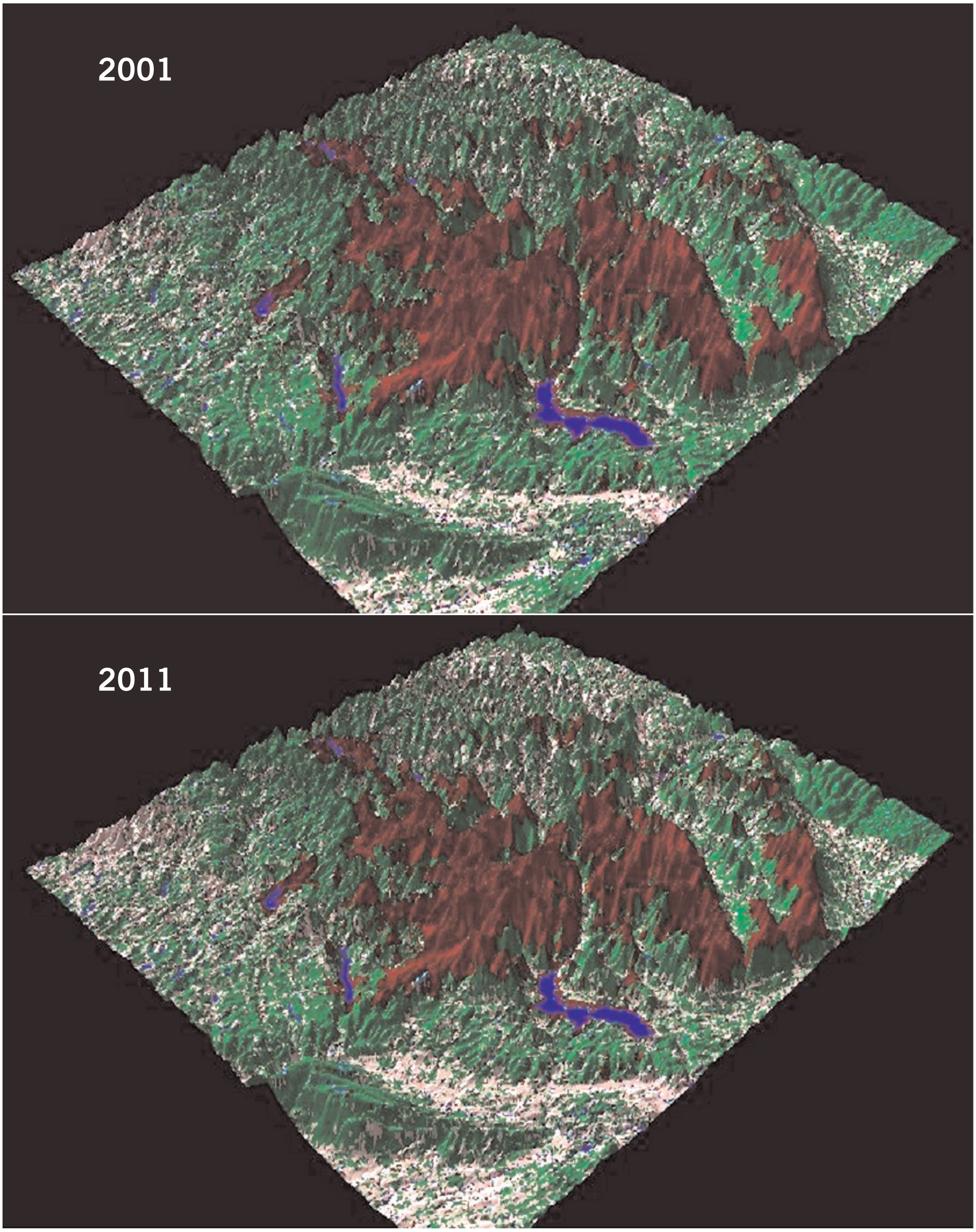


Figure 16. Catskill-Delaware forest fragmentation projections from 2001 (existing) to 2011. Green is forest, white non-forest, brown state- and city-owned lands, and blue water.

Acres Forest (Private Lands)

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Delaware	316581	311043	305504	299966	294428	288889	283351	277813	272275	266736	261198
Greene	157731	155837	153943	152048	150154	148260	146365	144471	142577	140683	138788
Schoharie	75071	74182	73293	72404	71515	70626	69737	68849	67960	67071	66182
Sullivan	231194	227767	224339	220912	217485	214057	210630	207203	203775	200348	196920
Ulster	320581	316143	311704	307266	302828	298389	293951	289512	285074	280636	276197
Total Acres	1101158	1084971	1068784	1052596	1036409	1020222	1004035	987848	971660	955473	939286
Net (adjusted for reforestation)	1078187	1059448	1040708	1021968	1003229	984489	965750	947010	928270	909531	890791
% Private Lands Forested											
Delaware	73%	72%	71%	70%	68%	67%	66%	64%	63%	62%	61%
Greene	81%	80%	79%	79%	78%	77%	76%	75%	74%	73%	72%
Schoharie	80%	79%	78%	77%	76%	75%	74%	73%	72%	71%	70%
Sullivan	77%	76%	75%	74%	72%	71%	70%	69%	68%	67%	66%
Ulster	78%	77%	76%	75%	74%	73%	72%	71%	70%	69%	68%
Total Acres	77%	76%	75%	74%	73%	71%	70%	69%	68%	67%	66%

Table 7: Catskill/Delaware forest fragmentation projections 2001-2011 by county. All numbers include only privately owned lands.

Acres Forest (All Lands, Public and Private)

% County Area in Forest	Total Acres in County	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Delaware	492860	83%	82%	81%	80%	80%	79%	78%	77%	77%	76%	75%	75%	74%	73%	72%	72%	71%	70%	69%	69%
Greene	288915	90%	90%	90%	89%	89%	89%	88%	88%	88%	87%	87%	87%	86%	86%	85%	85%	85%	84%	84%	84%
Schoharie	106681	85%	84%	84%	84%	83%	83%	82%	82%	82%	81%	81%	80%	80%	80%	79%	79%	78%	78%	78%	77%
Sullivan	326570	85%	84%	83%	82%	82%	81%	80%	80%	79%	78%	78%	77%	76%	76%	75%	74%	74%	73%	72%	72%
Ulster	590023	90%	89%	89%	88%	87%	87%	86%	86%	85%	85%	84%	84%	83%	83%	82%	82%	81%	81%	80%	79%
Total	1805050	87%	86%	85%	85%	84%	84%	83%	83%	82%	81%	81%	80%	80%	79%	79%	78%	77%	77%	76%	76%

Table 8: Total forest area historic and predicted by county (includes public and private land, and reforesting land).

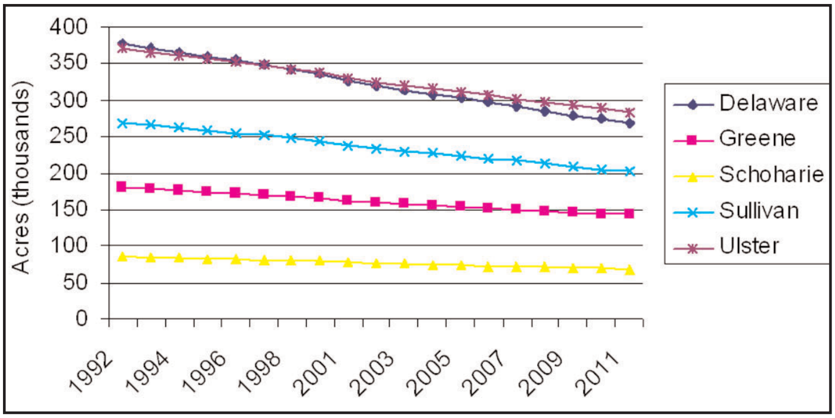


Figure 17(a). Forestlands per county 1992 - 2011. Empirical and linearly projected forest cover in the portion of the five counties included in the Catskill-Delaware study. Excludes public lands owned by the NY State DEC and NYC DEP and reforesting lands at 1992-2001 rate.

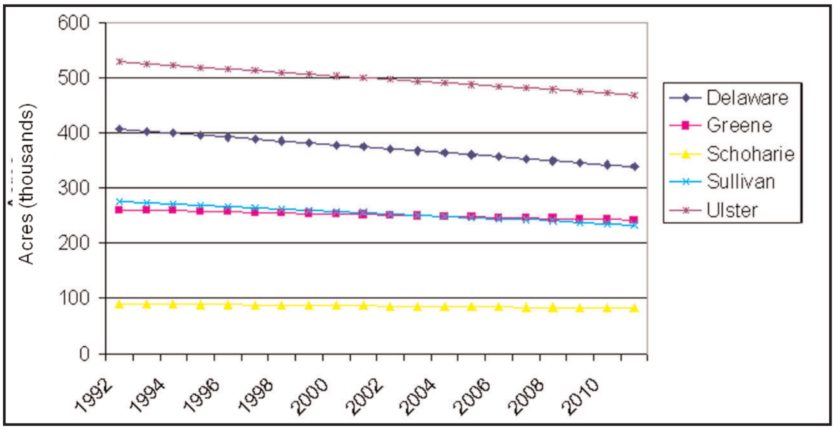


Figure 17(b). Forestlands per county 1992 - 2011. Empirical and linearly projected forest cover in the portion of the five counties included in the Catskill-Delaware study. Includes public lands owned by the NY State DEC and NYC DEP and lands reforesting at 1992-2001 rate.

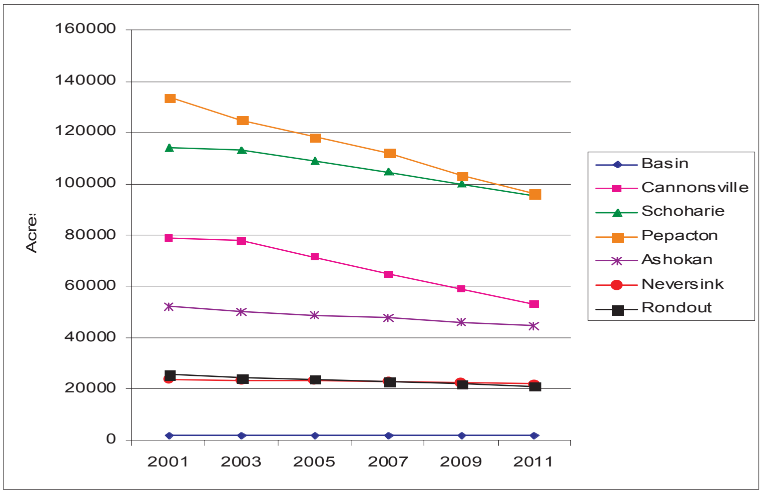


Figure 18. Catskill-Delaware forest area projections per NYC Water Supply Watershed 2001 - 2011.

Results—Thames Watershed

Empirical Rate of Forestland Loss and Apparent Causes

The Thames Watershed is part of the New England landscape, which has gone through tremendous changes in the past two centuries. From a completely forested wilderness in the 17th century, it was substantially cleared for farming by the mid-1800s. Then, as farms on these rocky soils were abandoned, much of the land grew back to a central hardwood forest. Dairy farming remained for much longer, but by the late 20th century, even that was mostly gone, with former pastures converted to housing developments with names like "Orchard Lane." Thus, the forests changed from being patches in a landscape of agriculture and industry in the mid-1800s to being the predominant landscape feature in the late 20th century.

Now, it seems as if the trends are reversing, with more and more forestland being cleared for development (table 9). In 1985 the land in our study area was 79% forested—by 2002 it had declined to 74%. Private lands not protected from development dropped from being 74% forested in 1985 to 69% forested in 2002. This loss of forest is not evenly distributed, but exhibits a pattern of distinct fragmentation. Some towns remain virtually unchanged in forest cover, while others have lost 10–12 % of their forest. Considering only the land that is available for development, that is, excluding forestland permanently protected by government ownership or conservation easement, then the situation is even more dramatic. Fifteen towns have lost more than 10% of their unprotected forestland in the past seventeen years.[16]

New housing development is clearly a factor in the changing landscape. Many towns in the study area are expanding residential development at a scale of 2 to 3 new houses per square mile each year (see appendix D).

Total Acres in Area of Analysis	2002	1,195,138
Acres Included in Analysis (land not permanently protected from development)	2002	993,183
Acres in Water	2002	45,943
Acres in Conservation Lands	2002	156,001
% Area in Water	2002	4%
% Area in Conservation Land	2002	13%
Total Acres of Forest	1985	940,702
	2002	887,973
% Forested	1985	79%
	2002	74%
Forest Cover (Excluding Conservation Lands)		
Actual (acres)	1985	738,747
Actual (acres)	2002	683,970
Projected (acres)	2008	665,747
	2013	650,561
	2018	635,375
	2023	620,189
% Loss 1985 - 2002		7%
% of 2002 Unprotected forest at risk	by 2013	5%
	by 2023	9%

Table 9: Thames Watershed 2002 land cover and projected changes through 2023.

Median housing prices, after declining in the mid-1990s, are on the rise again. Employment in the area, on the other hand, has remained relatively flat since 1990, indicating that new residents are likely commuting to urban areas for employment. Overall population has also remained fairly flat, so the expansion in housing means smaller households, in line with national trends. The population dynamics of the area are not easy to interpret, however, as many towns are losing population and many others gaining. For the most part, the smaller towns (under 15,000) are growing, while the larger towns (over 15,000) are losing people (figure 19). The town of Eastford, for example, with a population of 1,350 in 1990, gained 280 residents in the following ten years, a 21% increase. Three hundred or so new people in a small town can be a big drain on local resources.

We plotted the decline in forest cover since 1985 and fit two trend curves to the data set (figure 20). The best projection of loss of forestland over the next 20 years is probably somewhere between the conservative third order polynomial trend line that predicts a leveling off at around 680,000 acres, a loss of only 6,000 acres, and the more aggressive linear trend that predicts a loss of 60,000 plus acres. Nevertheless, for our projections we used the higher quantity of forest loss predicted by the linear trend since polynomial curves, given their inherent nature, are often reliable for only a small portion of a data set, and less reliable over a longer period of time.

Our analysis revealed that the highest loss of forest cover occurred in three Massachusetts towns, Webster, Oxford and Spencer, and the Connecticut towns of Vernon and Norwich (table 10). Interestingly, six of the ten towns with the highest rates of forest loss are also among the top ten towns with the least forest cover. This apparent relationship between total area developed and the on-going rate of forest loss coincides with our findings that the lands most vulnerable to deforestation are those neighboring already developed lands (see below). In contrast, five of ten towns experiencing the least forest loss since 1985 are among the ten towns with the highest percent forest cover.

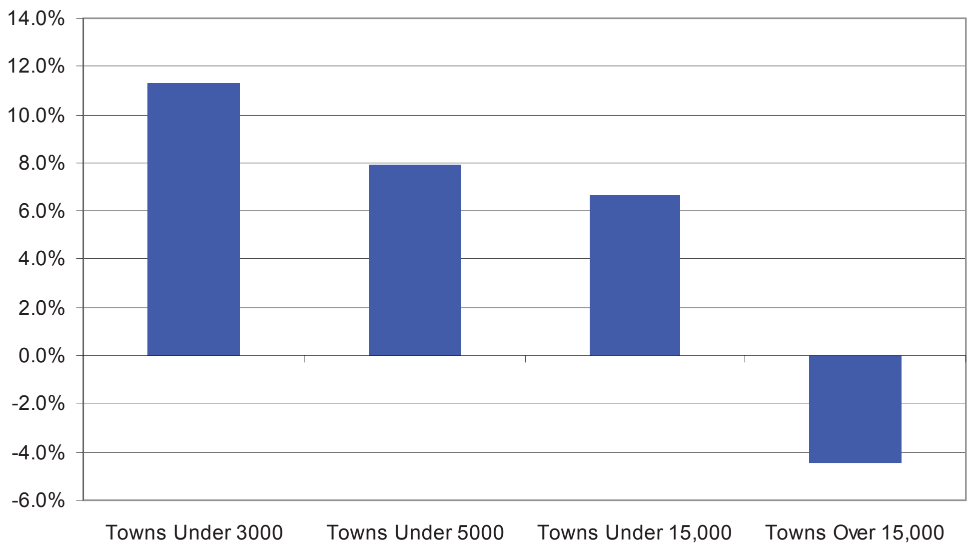


Figure 19. Population changes 1990–2000 for 59 towns in Thames Watershed study area.

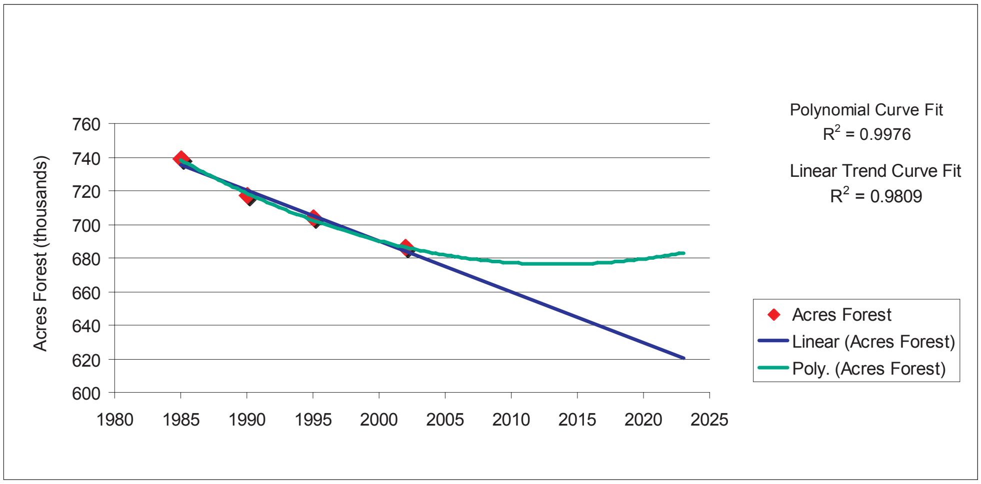


Figure 20. Analysis of 1985–2002 Thames Watershed forest cover and projection of trends to 2023.

Towns with top rate of forest loss 1985-2002	State	% loss of unprotected forest 1985 - 2002	Towns with least rate of forest loss 1985-2002	State	% loss of unprotected forest 1985 - 2002
Webster	MA	17	Union	CT	2
Oxford	MA	15	Holland	MA	3
Spencer	MA	13	Ashford	CT	3
Vernon	CT	13	Eastford	CT	4
Norwich	CT	13	Woodstock	CT	4
Plainfield	CT	12	Hampton	CT	4
Putnam	CT	12	Wales	MA	5
Leicester	MA	12	Scotland	CT	5
Windham	CT	12	Pomfret	CT	5
Charlton	MA	12	East Haddam	CT	5

10 least forested towns in 2002		% Forest Cover 2002	10 most forested towns in 2002		% Forest Cover 2002
Vernon	CT	47	Union	CT	91
Somers	CT	51	Wales	MA	91
Ellington	CT	52	Voluntown	CT	89
Norwich	CT	53	Holland	MA	86
Windham	CT	60	Chaplin	CT	85
Webster	MA	64	Eastford	CT	84
Putnam	CT	65	Stafford	CT	84
Lebanon	CT	65	Sturbridge	MA	84
Plainfield	CT	65	Brookfield	MA	84
Bolton	CT	66	Ashford	CT	83

Table 10: Thames Watershed towns with highest and lowest rate of forest loss (as a % of unprotected forestland) and highest and lowest forest cover (as a % total land area).

Pattern of Forestland Loss, the Empirically-Important Factors and Their Ability to Predict the Future Location of Development

In the Thames Watershed study we analyzed 34 different factors (table 11). We compared the simulated 2002 results using the "vulnerability" map for each factor, to the actual 2002 land use map. The "goodness of fit" between the simulated map and the actual map is indicated by the kappa statistic, which measures how much better than chance alone the model is in predicting areas that will be converted from forest to non-forest (with "0" being no better than chance alone and "1" being a perfect predictor).

The highest kappa, hence the best prediction of the pattern of land use change, was obtained using the combination of three factors: distance to 1985 agricultural land; soils; and distance to 1985 developed land, with the region stratified by town (table 12). This last factor can be construed to match distance from "urban" areas in the New York study. We found that using all of the top eleven factors actually slightly reduced the model's ability to match the 2002 landscape. More information does not, therefore, necessarily aid in landscape unit (cell by cell) selection precision. The top three factors were used for future land use change projections post-2002, but were updated to reflect distance from 1990 agricultural and developed areas.

Nonetheless, the kappa statistics are quite close for all factors, indicating the interdependence of topography, roads, population, and urban development. Using these factors in combination in the GEOMOD process has given us great predictive power to project the pattern of future land development.

Validation Statistics for Connecticut Spatial Drivers; Time 1 = 1990, Time 2 = 2002

Rank	Factor	Kappa for location
1	Distance from 1985 Agricultural Lands	0.8928
2	Soil type	0.8881
3	Distance from 1985 Urban Areas	0.8859
3	Population Over Age 65 (1990)	0.8859
4	Density of Housing Units (1990)	0.8858
5	Population Density (1990 Census)	0.8855
5	Distance to Secondary Roads	0.8855
6	Owner Occupied Housing Units (1990)	0.8850
7	Population Under Age 18 (1990)	0.8849
7	Distance to Railroads	0.8849
8	Elevation	0.8846
9	Distance to Major Rivers	0.8843
10	Distance to Local Roads	0.8840
11	Distance to Primary Roads	0.8839
12	Number of Home Sales (1990)	0.8830
13	Unemployment Rate (1990)	0.8828
13	Distance to Local Roads	0.8828
14	Town polygons	0.8826
14	Single Family Housing Permits (1990)	0.8826
14	Labor Force - Construction	0.8826
14	# House Building Permits	0.8826
15	Labor Force - Service Industry	0.8823
16	Labor Force 1990	0.8821
17	Mean Value Owner Occupied Housing Units (1990)	0.8817
18	Median Home Sales Price (1990)	0.8816
19	Distance to Primary Roads	0.8815
20	Distance to Power Lines	0.8810
20	Distance to Pipe Line	0.8810
20	Slope	0.8810
21	Aspect	0.8807
22	Distance to Rivers/Lakes	0.8802
23	Distance to Casinos	0.8801

Table 11: Validation results for 34 spatially distributed factors tested in the Thames Watershed study.

Rank	Combination	Strata	% Correct	Klocation
1	Distance from '85 Agriculture, Soil Type, Distance from ‘85 Developed	By Town	94.94	0.8987
2	Distance from '85 Agriculture, Soil Type, Distance from ‘85 Developed	Entire Region	94.91	0.8983
3	Distance from '85 Agriculture, Soil Type, Distance from ‘85 Developed, Population over age 65, Density of Housing Units	By Town	94.83	0.8966
4	Distance from '85 Agriculture, Soil Type, Distance from ‘85 Developed, Population over age 65,	Entire Region	94.79	0.8958
5	Distance from '85 Agriculture, Soil Type	Entire Region	94.75	0.8949
6	11 top factors	Entire Region	94.46	0.8891

Table 12: Combined predictive power of 2002 land use using 1985 and 1990 information.

Future Projections

The forest fragmentation potentiality or "development risk" map for the Thames watershed, based on the three most highly predictive factors, is reclassed for visualization purposes to show those areas most likely to be developed in the next 10 to 30 years (Figure 21(a)). This map shows which areas in each town are most vulnerable to development, based on distance to 1990 agricultural land, soils, and distance to 1990 developed land. Weights were developed based on the amount of development that has already occurred within each county on land with similar characteristics relative to these three factors. The factors used are those that together yielded the best "goodness of fit" between the simulated and the real 2001 map for each town.

Figure 21(b), shown for comparison's sake, illustrates which towns or areas of the watershed are more at risk than others when the region is analyzed without stratification by towns. The weights are derived from the amount of land across the entire area already developed in 2001 with similar characteristics relative to the top three drivers. We projected the future scenario for changes in land cover in the Thames Watershed (figure 22), selecting for non-forest use those cells most vulnerable for change within each town. (figure 21a), since we had received a higher kappa using stratification by town.

The most dramatic changes will occur in the Massachusetts towns of Webster, Oxford and Spencer, which by year 2012 could lose an additional 10.5 %, 9.1 %, and 8.5 % respectively of their 2002 forest not currently protected from development, and twice that by 2022. These are followed by the Connecticut towns of Vernon, Norwich and Plainfield, already some of the least forested towns in the study area (tables 10 and Appendix D).

In the Thames Watershed, forest fragmentation has increased from 1985 to 2002. Using a simple measure over the entire study area of 'area of intact forest' vs. 'perimeter of forest patches,' the area:perimeter ratio was 421:1 in 1985, dropping to 381:1 in 2002. Forest patches are getting smaller, with more edge environment, which has implications for wildlife, invasive species, and water quality. However, our projections out to 2022 indicate that the future trend may result in a loss of the smaller forest fragments which results in a higher area:perimeter ratio. This ratio change could deceptively be interpreted to mean elimination of forest fragmentation, and consolidation of forest patches. Rather, inspection of the maps shows an infilling of developed areas by elimination of smaller forest fragments. This mathematically changes the area:perimeter ratio of the remaining forest, but does not mean there will be a consolidation of forest patches.

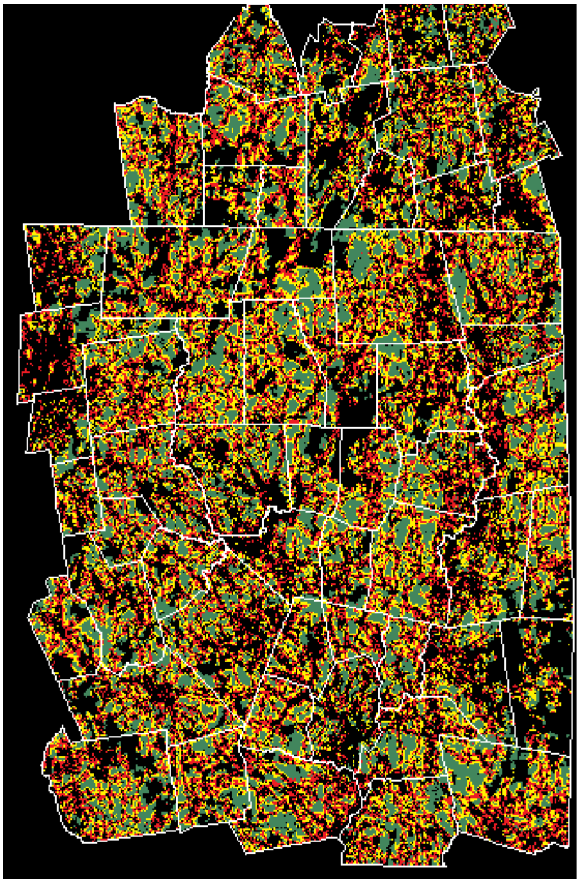
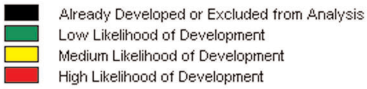


Figure 21a. Forest Fragmentation "Potentiality" or "Risk" Map calculated for each of the 59 towns in the Thames region of analysis. This map illustrates those areas within each town most and least likely to be developed based on which land within each town has been the most desirable for development in the past.



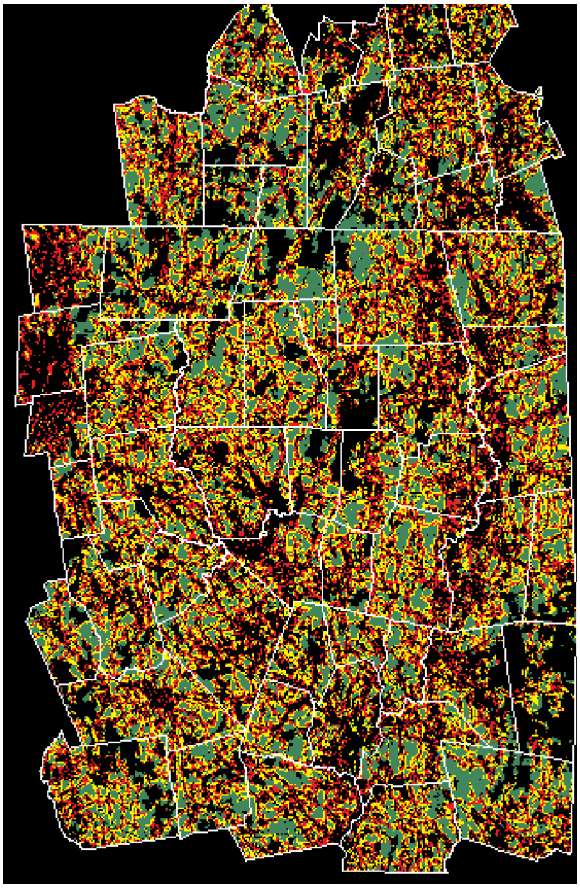


Figure 21b. Forest Fragmentation "Potentiality" or "Risk" Map for the Thames region. In this map forested areas are categorized from high to low risk of development based on past regional patterns. Areas in red are those under greatest pressure for future development compared to other areas across the entire region.

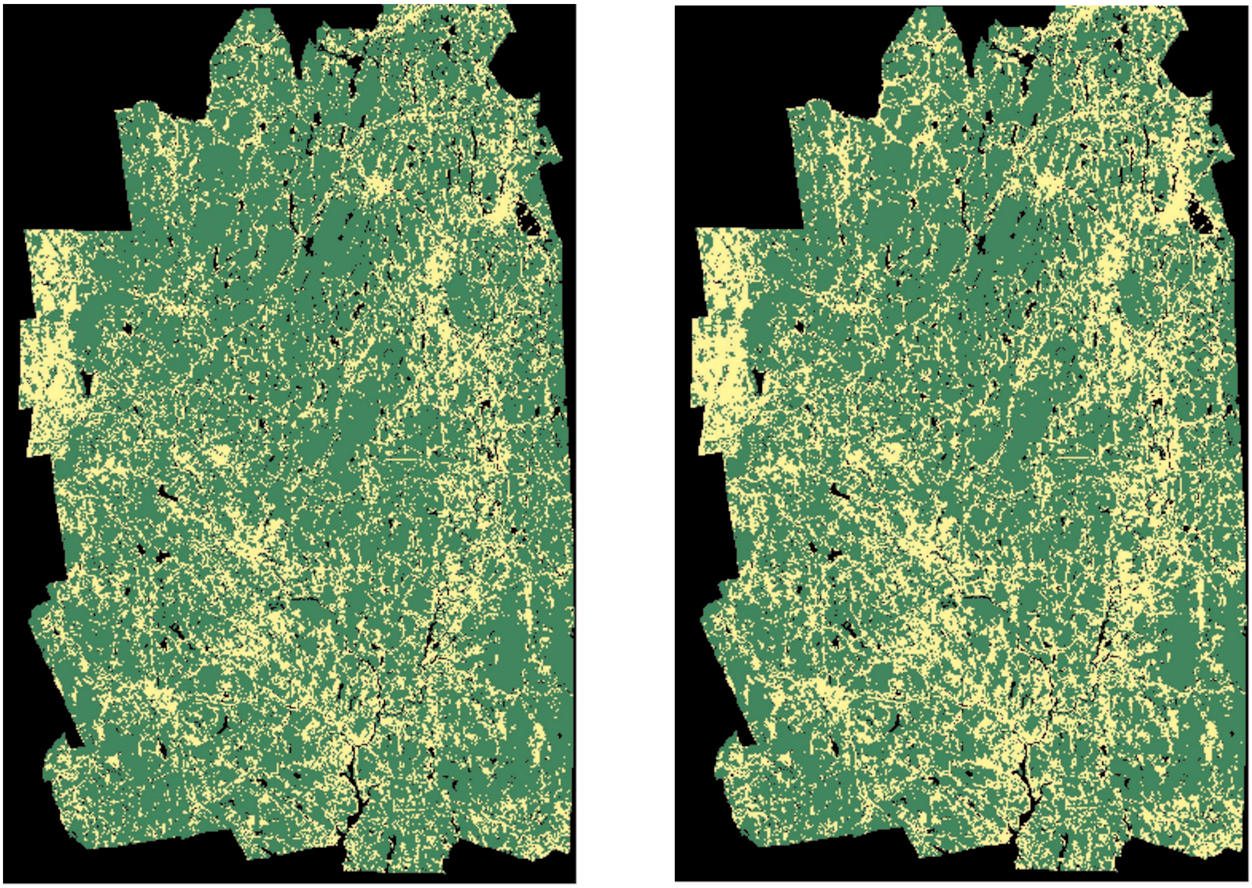


Figure 22. Thames Watershed forest fragmentation projections 2002 (existing) to 2022. Green represents forest (including conservation lands); yellow nonforest; and black water.

Conclusions

- The Catskill/Delaware region of New York and the Thames Watershed region of Connecticut and Massachusetts are losing forestland, and this trend will likely continue.

- Forests in the Catskill/Delaware region are increasingly fragmented, and this trend will likely continue. In the Thames Watershed, forest fragmentation has increased from 1985 to 2002, however, our projections out to 2022 indicate that the trend might be a loss of the smaller forest fragments which results in a higher area:perimeter ratio. This ratio change could deceptively be interpreted to mean elimination of forest fragmentation, and consolidation of forest patches. Rather, inspection of the maps shows an infilling of developed areas by elimination of smaller forest patches. This mathematically changes the area:perimeter ratio of the remaining forest, but does not mean there will be a consolidation of forest patches. The pattern of development in the Thames is less dispersed than that observed in the Catskills perhaps due to the fact that there is less private land available for development, or because of the type of development taking place.

- Ownerships are getting smaller (parcelization) in the Catskill/Delaware region and land that has been divided since 1984 is 1.5 times more likely to be fragmented than land that has not been parcelized during the past twenty years.

- As indicated by the discussions at the community workshops (Appendix A), local people know that their forests are becoming more fragmented and the rural character of their towns is changing, and they are asking for tools to help educate communities about the problems with growth and development in largely rural, forested areas.

- GEOMOD is a very useful tool for projecting future change in these areas and for helping communities visualize the impacts of seemingly innocuous, dispersed development in rural, forested areas.

- We are now able to identify where the highest risk seems to be of future forest fragmentation and loss within each area and within each county or town—a real benefit to conservation efforts.

- Already developed areas are nodes for expanded development. Towns with the least forest cover are losing the forest they have faster than towns that are mostly forested. Driving factors and indicators of development in the northeast are highly interdependent, thus no single one stands out as more highly predictive than others.

- Socio-economic data, although useful in understanding the demographic trends in an area, did not provide better predictive power than just bio-physical (topography) and socio-political (development and roads) factors alone. This is good news for broad application of GEOMOD in the northeast, because of all the factors we analyzed, the socio-economic data were the most time consuming to collect and format for the model.

- Based on the high kappa-for-location numbers that we achieved it appears that the predictive power of GEOMOD is much higher in the northeastern USA than in several of its applications in the tropics at the same scale, where it has been previously tested.[17] This is probably due to the advanced state of GIS data availability in the USA, but perhaps more importantly due to the higher resolution (level of information) of the publicly-available map inputs we employed, rather than the types of mapped data we tested. In the end biophysical factors and infrastructure remained the most powerful indicators of future settlement pattern, much as we and others, have found in the tropics.[18] Many of the other socio/demographic/economic factors we tested are probably co-dependent with these underlying factors. Even roads and towns are usually sited according to topographical factors, and historically navigable waterways. The imprint of the past is still very strong in both these regions. It follows that the population factors produced nearly equivalent kappas due to the fact that where there is development there are people, and where there is no "developed" landscape people are absent. This means that the model, having analyzed the percentage of cells in the map where, for example, the population density is high, will then look for those cells to "deforest," but in fact they are probably already in the non-forest class. Looking for flat land or western exposure is much easier, and there should be more variation in the selection and hence "goodness of fit" between factors. We would like to apply the model to one more northeastern location in order to make final recommendations about the best data sets for communities of the NE to use to project the business as usual landscape.

Recommendations

Ultimately, this research will be most widely applicable if the analytical tools and methods developed and tested in the study sites can be used by municipal, regional, county and conservation planners throughout the northeast. Our first job as researchers is to test the power of the tools. Having done that, our goal now is to put that power in the hands of the folks who are making the day-to-day decisions about land use planning. Once these local interest groups can analyze the land use change dynamics in their communities, they can project how these changes may affect the future of their landscape, their tax base and infrastructure demands, or critical areas of concern such as water quality, air quality, traffic, wildlife habitat, and recreation areas, and incorporate that knowledge into their policy and planning efforts.

Feedback from the community workshops indicates that this information would be extremely useful in the town, county and regional planning processes. We suggest, based on these discussions, that we create a CD in which the results of our research would be organized and presented in a way that would be easy for each town or county to "click" and see the local dynamics in their town and the surrounding area. This CD would be developed in collaboration with three or four "pilot" towns to fully utilize the information about forestland change and trends in socio-economic factors resulting from the analysis in a way that would be compelling and useful for the people and organizations whose every-day decisions affect land use change at the local scale.

To assure the predictive capability and overall usefulness of the model throughout the northeast, we recommend a third study site to increase our ability to test for commonalities of pattern and drivers of forestland change in the region. This will enhance our ability to indicate the broader implications about trends in land use change based on the trends detected in this study, and to guide communities in application of this model to their particular area. We found that in both the Catskill/Delaware and the Thames sites, the best predictors of the pattern of forest fragmentation were bio-physical and socio-political factors such as distance from previous development and roads. If this holds true in a third site, then it would be relatively simpler and less expensive to apply the model broadly in the northeast. Thus, in order to expand the potential for using GEOMOD as a land use planning tool, we recommend the following:

- Create a web-based workbook for using GEOMOD in the northeast including: types of data sets that are useful in predicting land use change and are widely available in standard formats; how to organize and format the data; how to run the model and interpret the results; and use of visualization tools for presentation of the model results.

- Adapt GEOMOD to run in ArcGIS. Currently GEOMOD is available in the IDRISI tool suite, however, ArcGIS is the most commonly used GIS tool by government and conservation organizations. Having an ArcGIS version of GEOMOD would make it much more likely that planning groups can use this tool.

- Create a web site for modeling and understanding land use change in the northeast featuring results of this research with emphasis on visualization tools and maps, annotated bibliographies of forest fragmentation literature, and resources for forest-focused land use planning tools for the northeast.

[1] Forest ownership numbers are extrapolated from the draft 2002 National Woodland Owner Survey (Butler and Leatherberry *forthcoming*).

[2] USDA Natural Resources Conservation Service 1997.

[3] Commonwealth Research Group 1995; Resource Systems Group 1999.

[4] Hall *et al* 1995a and 1995b.

[5] Hall *et al.* 2000.

[6] Pontius 2000.

[7] Hall *et al* 1995a and 1995b; Pontius *et al.* 2001; Hall and Dushku 2002.

[8] Pontius and Schneider 2001, Schneider and Pontius 2001.

[9] We wish to acknowledge the following agencies for much of the information found here: The Catskill.com website (www.catskillpark.com/catskills.html); The New York State Department of Environmental Conservation (www.dec.state.ny.us/website/dlf/publands/cats/); and The Catskill Center for Conservation and Development (www.catskillcenter.org).

[10] We wish to acknowledge the Connecticut Chapter of the Nature Conservancy (http://nature.org/wherewework/northamerica/states/connecticut/) and the Quinebaug-Shetucket Heritage Corridor, Inc. (http://www.thelastgreenvalley.org/) for much of the information found here.

[11] A description of the methods used for classification and post-classification assessment are found in Appendix B.

[12] For details on the accuracy assessment, refer to Appendix B.

[13] More information about the Connecticut Statewide Temporal Land Cover and Land Cover Change Project is available at www.clear.uconn.edu.

[14] Accuracy assessment for the Thames area is being done as part of the Connecticut state-wide land cover analysis project, and was not yet completed at the time of publication of this report.

[15] LaPierre and Germain 2003.

[16] See Appendix D for details on forest cover and forest loss by town.

[17] Hall and Dushku 2002; Dushku, Brown and Hall 2002.

[18] For a review see Chomitz and Gray 1996; Lambin 1997; and Kaimowitz and Angelsen 1998.

References Cited

Butler, B.J. and E.C. Leatherberry. Forthcoming. *USDA Forest Service 2002 National Woodland Owner Survey* (DRAFT). www.fs.fed.us/woodlandowners.

Chomitz, K. and D. Gray. 1996. Roads, land use, and deforestation: A spatial model applied to belize. *The World Bank Economic Review, Volume 16,* Number 3*:* 487-512.

Commonwealth Research Group. 1995. *Cost of Community Services in Southern New England.* Commissioned by Southern New England Forest Consortium, Inc.

Dushku, A., S. Brown and M.H.P. Hall. 2002. *Modeling the deforestation and carbon emissions baseline in the Rio Bravo Conservation and Management Area Climate Action Project 1993- 2035.* Web report. http://www.winrock.org/what/PDF/eco/Product%205%20GEOMOD%20to%20Rio%20Bravo%20CAP.pdf.

Eastman, J.R. 1999. *Idrisi32 Guide to GIS and Image Processing Volume 2*. ClarkLabs, Worcester, MA.

Hall, C.A S., C.J. Cleveland and R. Kaufmann, 1986. *Energy and resource quality: The Ecology of the Economic Process*. John Wiley and Sons, New York.

Hall, C.A.S., H. Tian, Y. Qi, G. Pontius, J. Cornell and J. Uhlig. 1995a. *Spatially Explicit Models of Land Use Change and Their Application to the Tropics*. DOE Research Summary, No. 31. (Ed. By CDIAC, Oak Ridge National Lab).

Hall, C.A.S., H. Tian, Y. Qi, G. Pontius, J. Cornell and J. Uhlig. 1995b. Modeling spatial and temporal patterns of tropical land use change. *Journal of Biogeography*, 22:753-757.

Hall, M.H.P. and A. Dushku. 2002. *Spatial Modeling of the Averted Deforestation Baseline for the Noel Kempff Mercado Climate Action Project, Bolivia*. Web report. http://www.winrock.org/general/Publications/EcoCoop.pdf.

Hall, M.H.P., C.A.S. Hall, and M.R. Taylor. 2000. Geographical modeling: The synthesis of GIS and simulation modeling, Chapter. 7, in C.A.S. Hall, (Ed.) *Quantifying Sustainable Development: the Future of Tropical Economies*. Academic Press, San Diego, CA. pp. 177-202.

Kaimowitz, David and Arild Angelsen. 1998. *Economic Models of Tropical Deforestation: A Review*. Bogor, Indonesia: Center for International Forestry Research.

Lambin, Eric F. 1997. Modeling and monitoring land-cover change processes in tropical regions. *Progress in Physical Geography* 21(3):375-393

LaPierre, S. and R.H. Germain. 2003. Parcelization of nonindustrial private forestlands in the New York City Watershed. Presented at *AWRA s International Congress on Watershed Management for Public Water Supplies*. New York City, NY July 1-2.

Pontius, Jr. R.G. and P. Pacheco. 2004. Calibration and validation of a model of forest disturbance in the Western Ghats, India 1920-1990. *GeoJournal*. In press.

Pontius, Jr. R.G., J. Cornell, and C. Hall. 2001. Modeling the spatial pattern of land-use change with GEO-MOD: application and validation for Costa Rica. *Agriculture, Ecosystems & Environment* 85(1-3):191-203.

Pontius, Jr. R.G. and L. Schneider. 2001. Land-use change model validation by a ROC method for the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment* 85(1-3):239-248.

Pontius, Jr. R.G. 2000. Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering & Remote Sensing* 66(8):1011-1016.

Resource Systems Group. 1999. *The Economic Impact of Open Space in New Hampshire*. Prepared for The Society for the Protection of New Hampshire Forests.

Schneider, L. and R.G. Pontius Jr. 2001. Modeling land-use change in the Ipswich watershed, Massachusetts, USA. *Agriculture, Ecosystems & Environment* 85(1-3):83-94.

USDA Natural Resources Service. 19*97 National Resources Inventory* (Revised December 2000). Washington, DC.

42

Appendix A: Community Workshops

Participants at Thames Watershed Community Workshops

Michael Altshul	Green Valley Institute
Dick Booth	Wyndham Land Trust
Fred Borman	CT DEP - Division of Forestry
Steve Broderick	UCONN Extension Forestry
Mark Buccowich	USDA Forest Service State and Private, Cooperative Forestry
Dan Civco	UCONN Laboratory for Earth Resources Information Systems
Ruth Cutler	Green Valley Institute
Dan Donahue	Norcross Wildlife Foundation
Phillip Elliott	Eastern Connecticut State University
Doug Emmerthal	CT Division of Forestry
Delia Fey	Town of Killingly
John Filchak	NE CT Council of Governments
Carl Fontneau	Towns of Columbia and Scotland
Kristin Foord	Massachusetts Executive Office of Environmental Affairs
Ken Goldsmith	Woodstock Conservation Commission
Reanna Goodreau	Town of Ellington Planning Department
Scott Gravatt	Eastern CT Conservation District
Myrna Hall	SUNY College of Environmental Science and Forestry
Brian Holdt	UCONN NRME
James Hurd	UCONN Laboratory for Earth Resources Information Systems
Steve Klemchuk	
Sara Laughlin	Town of Thompson
Tom Luther	Northeastern Area, State & Private Forestry
Carrie Magee	Yale School of Forestry and Environmental Studies
Andy McLeod	The Trust for Public Land
Karen Mollander	Durham Field Office, NA State &Private Forestry
Roger Monthey	USDA Forest Service
Susan Nixson	SUNY College of Environmental Science and Forestry
Jim Parda	CT Division of Forestry
Elizabeth Petruska	Yale School of Forestry & Environmental Studies
Neil Sampson	Yale School of Forestry & Environmental Studies/The Sampson Group
Art Talmage	Conwood Foresters/Connecticut Tree Farm
Eric Thomas	Department of Environmental Protection
Bill Toomey	The Nature Conservancy
Eric Trott	Coventry Town Planner
Mary Tyrrell	Yale School of Forestry & Environmental Studies
Edwin Vonderheide	Woodstock Conservation Commission
Susan Westa	Green Valley Institute
Paul Wilbur	Woodstock Conservation Commission
Emily Hoffhine Wilson	NEMO Project, Cooperative Extension, UCONN

Participants at Catskill/Delaware Watersheds Community Workshops

Anne Altshuler	Olive Natural Heritage Society
Aaron Bennett	The Catskill Center
Page Bertelsen	Yale School of Forestry & Environmental Studies
Tim Cox	Corporate Counsel Catskill Watershed Corporation
Michelle Decker	SUNY College of Environmental Science and Forestry
Steve Dettman	Yale School of Forestry & Environmental Studies
Brian Fisher	Watershed Agricultural Council
René Germain	SUNY College of Environmental Science and Forestry
Nat Gillespe	The Nature Conservancy
Myrna Hall	SUNY College of Environmental Science and Forestry
Henry Kernan	Forest Landowner
Maureen Krudner	U.S. Environmental Protection Agency
Jack McShane	Catskill Landowners Association
Jean Millar	Roxbury Planning Committee
Ken Neavey	Catskill Watershed Corporation
Christopher Olney	The Catskill Center for Conservation and Development
Jim Porter	New York City Department of Environmental Protection
John Potter	New York City Department of Environmental Protection
Neil Sampson	Yale School of Forestry & Environmental Studies/The Sampson Group
Matthew Schwab	New York City DEP
Michael Shaw	U.S. Environmental Protection Agency, NYC Watershed
Kate Schmidt	Cornell Cooperative Extension, Sullivan County
Mary Tyrrell	Yale School of Forestry & Environmental Studies
Rick Wyman	Edmund Niles Huyck Preserve and Biological Station

Forest Fragmentation/Land Use Change Modeling Project

Yale School of Forestry and Environmental Studies, Global Institute of Sustainable Forestry
and State University of New York College of Environmental Science and Forestry

Thames Site Workshop

Brooklyn, Connecticut
May 21, 2002

Agenda

Welcome and Introduction — Mary Tyrrell and Steve Broderick

TNC Quinnebaug Highlands Project — Bill Toomey

Project Overview — Neil Sampson

Comments and Feedback

GEOMOD Demonstration — Myrna Hall

Comments and Feedback

Hypothesis Formulation

Attendees

Myrna Hall, SUNY ESF
Neil Sampson, The Sampson Group and Yale FES
Mary Tyrrell, Yale FES
Carrie Magee, Yale FES
Susan Nixson, SUNY ESF

Steve Broderick, University of Connecticut Extension Forestry
Bill Toomey, The Nature Conservancy, Connecticut Chapter
Phillip Elliott, Eastern Connecticut State University
Dick Booth, Wyndham Land Trust
Art Talmadge, Conwood Foresters/ CT Tree Farm
Delia Putnam, Town of Killingly
Ruth Cutler, Green Valley Institute
Paul Wilbur, Woodstock Conservation Commission
Dan Donahue, Norcross Wildlife Foundation
Andy McLeod, Trust for Public Land
James Hurd, University of Connecticut

Summary of Comments and Feedback

Concerns, trends and perceived threats to the forests

- Most of the land is still forested and population fairly low
- Fragmentation, habitat destruction and conversion are the biggest threats
- No longer much forestry work of any significance
- Timber markets are narrowing down
- Parcelization is obvious
- Cheapest land in Connecticut and less than one hour from four major cities

- Local planning and zoning people do not necessarily distinguish between rural character and working land
- Need for public education
- Collapse of the dairy industry leading to development on ag lands
- Paper subdivisions legacy from the 1980s development boom
- Perceived drivers of forest loss and fragmentation
- Population growth
- Zoning (towns without zoning regulations; towns with “10-acre lot” type of zoning)
- Forests are not able to generate revenue due to narrowing of timber market
- Parcelization
- Casino development (pressure from the south)
- Threat of new casino development in the Q/S area
- Pinching of suburban areas leading to migration from suburbs to rural areas
- Land prices
- New houses; large homesteads
- Distance from major cities (Providence, Hartford, Worcester, New London)
- DOT investment in road improvement and expansion

Hypotheses

Parcelization is occurring and will eventually lead to forest fragmentation and loss.

Forestland change is driven by population growth, zoning regulations, narrowing of timber markets, casino development, land prices, distance from major cities, and DOT investment in road improvements and new roads.

Final Notes

The general sense was that this project has a lot to contribute to the forest conservation efforts in the area. Attendees expressed a lot of interest and willingness to work with the project team on many aspects of the research. Feedback was that this can be a tremendous educational tool; this type of time series projection is needed and will be very useful.

It was strongly suggested (requested) that the team include the Massachusetts portion of the Quinnebaug/Shetucket Heritage Corridor in the analysis. Many groups are working throughout the entire corridor and have worked hard to go beyond the political boundaries. The team agreed to consider the request, depending on whether or not UCONN can include that portion of Massachusetts in their land cover classification work being done for the project.

There was some amount of discussion of a sub-project to look at parcelization in the Corridor. This would be a very useful addition and some work has already been done to digitize tax maps in many towns. (Note: This would require additional funding.)

Forest Fragmentation/Land Use Change Modeling Project

Yale School of Forestry and Environmental Studies, Global Institute of Sustainable Forestry
and State University of New York College of Environmental Science and Forestry

Thames Site Results Workshop

Brooklyn, Connecticut
November 24, 2003

Agenda

Welcome and Introduction — Mary Tyrrell

Project Overview — Mary Tyrrell

Results: Land Use Changes in the Thames Watershed 1985 - 2002 — Myrna Hall

Next Steps: Phase II of Research Project — Mary Tyrrell

Questions, Comments, Feedback

Lunch Discussion: Putting land use change information and model results to good use

Attendees

Myrna Hall	SUNY College of Environmental Science and Forestry
Mary Tyrrell	Yale School of Forestry and Environmental Studies
Elizabeth Petruska	Yale School of Forestry & Environmental Studies
Michael Altshul	Green Valley Institute
Fred Borman	CT DEP - Division of Forestry
Steve Broderick	UCONN Extension Forestry
Mark Buccowich	USDA Forest Service State and Private, Cooperative Forestry
Dan Civco	UCONN Laboratory for Earth Resources Information Systems
Ruth Cutler	Green Valley Institute
Doug Emmerthal	CT Division of Forestry
Delia Fey	Town of Killingly
John Filchak	NE CT Council of Governments
Carl Fontneau	Towns of Columbia and Scotland
Kristin Foord	Massachusetts Executive Office of Environmental Affairs
Ken Goldsmith	Woodstock Conservation Commission
Reanna Goodreau	Town of Ellington Planning Department
Scott Gravatt	Eastern CT Conservation District
Brian Holdt	UCONN NRME
James Hurd	UCONN Laboratory for Earth Resources Information Systems
Steve Klemchuk	
Sara Laughlin	Town of Thompson
Tom Luther	Northeastern Area, State & Private Forestry
Karen Mollander	Durham Field Office, NA State &Private Forestry
Roger Monthey	USDA Forest Service
Jim Parda	CT Division of Forestry
Eric Thomas	Department of Environmental Protection
Bill Toomey	The Nature Conservancy
Eric Trott	Coventry Town Planner
Edwin Vonderheide	Woodstock Conservation Commission
Susan Westa	Green Valley Institute
Emily Hoffhine Wilson	NEMO Project, Cooperative Extension, UCONN

Summary of Comments and Feedback

Map Accuracy

- The agricultural class includes a lot of non-forested grasslands that could be associated with urban development; some residential development could be classified as "agricultural."
- The 1985/1990/1995/2002 land cover time series developed by CLEAR at UCONN is a unique resource and technically very reliable.

Factors Driving Loss of Forest: What else could be considered?

- Transportation networks: the three Massachusetts towns with little development are "protected" because they are located where there is no exit on the Massachusetts Turnpike for 30 miles.
- Commuting patterns and job vs. home location are hugely important for showing where and why development is occurring.
- Age of landowners and parcel size. Parcelization is important in this area. There was a lot of "paper" subdivision in the 1990s—land that was subdivided, but not developed. Development could happen very rapidly in these places.
- Absentee landownership is a factor.
- Does the amount of land permanently protected from development in a town have any effect on the amount of other land that is developed?
- The number of households seems to be more important than population.

Potential Uses of Research Results

- Towns would like to run the model with more refined, localized data; tweak the model and add additional layers (such as digital parcel maps).
- Useful for identifying lands at risk, which can be incorporated into planning efforts, particularly in conjunction with identifying lands critical for natural resource values.
- Good way to visualize the phenomenon of development generally following roads—as more roads get built, there is more development.

Final Notes

Overall, feedback on the usefulness of the research was very enthusiastic, and there was a great deal of interest in getting the information and tools to the people who would bring it back to their communities. Eleven folks volunteered to meet with the project team to discuss and work on how to get this out to towns and into a regional planning process. There was some discussion about the need to make it easy for non-technical folks to understand, which would be considered in the process.

Forest Fragmentation/Land Use Change Modeling Project

Yale School of Forestry and Environmental Studies, Global Institute of Sustainable Forestry
and State University of New York College of Environmental Science and Forestry

Catskill/Delaware Site Workshop

Liberty, New York
March 19, 2002

Agenda

Welcome and Introduction — Mary Tyrrell and Rene Germain

Project Overview — Neil Sampson

Comments and Feedback

GEOMOD Demonstration — Myrna Hall

Comments and Feedback

Hypothesis Formulation

Attendees

Rene Germain, SUNY ESF
Myrna Hall, SUNY ESF
Neil Sampson, The Sampson Group and Yale FES
Mary Tyrrell, Yale FES
Steve Dettman, Yale FES
Michelle Decker, SUNY ESF

Henry Kernan, Forest Landowner
Maureen Krudner, U.S. EPA
Michael Shaw, U.S. EPA
Jack McShane, Catskill Landowners Association
Chris Olney, The Catskill Center
Aaron Bennett, The Catskill Center
Ken Neavey, Catskill Watershed Corporation
Brian Fisher, Watershed Agricultural Council
Anne Altshuler, Olive Natural Heritage Society
Matthew Schwab, New York City DEP

Summary of Comments and Feedback

<u>Concerns, trends and perceived threats to the forests</u>

- Consideration of biodiversity and natural history in managing forests
- Need for consulting foresters to consider landscape scale
- High-graded forests
- Difficulty of reaching out to small landowners
- Lack of interest in timber (landowners); people own forestland for reasons other than growing and selling timber
- Affordability of the land over time
- A lot of land is not in the economic cycle

- Small, micro-land management is not financially feasible
- No market for lower quality materials
- Inability to manage the land, thus the forest is not a viable asset
- No system for NYC water consumers to pay for private landowners to maintain their forests
- NYC DEP has a priority land acquisition list
- A shift from commodity to non-commodity values
- Image of foresters
- Water quality problems—phosphorous and turbidity
- Degraded streams

Perceived drivers of forest loss and fragmentation

- Taxes
- Loss of pulpwood market
- Decline in number of timber processors; concentration towards bigger and bigger mills
- Large lot development
- Highest development along roads and water
- Second home development (Permanent vs. temporary residents)
- Parcelization
- Lack of education for homeowners, planning boards, zoning boards
- Lack of financial incentives for small landowners
- Lack of incentives for forest management
- Resort development (Bel Air) and consequent secondary development
- Regulation (NYC watershed)
- Distance to NYC and major thoroughfares (Thruway, Rt 17, Rt 28)
- Commuting distance
- Ski areas as growth nodes
- Topography
- Age of land owners
- Demand for new houses

Hypotheses

Parcelization is more of a current factor than fragmentation and will be hard to detect or predict.

Forestland change is driven by distance from NYC, distance from major roads, distance from growth nodes such as ski resorts and new resort development, watershed regulations, taxes, age of landowners, and the population of permanent residents vs. housing units (i.e. second home development).

Final Notes

The type of change that the area is experiencing may not be visible on satellite imagery, thus the feeling of some of the group was skepticism that this model will add much value to the work that is already being done in the area. The DEP is developing their own model to look at change in the watershed. The NYC watershed regulations are a complicating factor—they influence land use change, but will be difficult to account for in the model. The project team decided on a strategy to look at one township or county where parcelization data is available and determine if rural residential land use can be detected on satellite imagery.

Forest Fragmentation/Land Use Change Modeling Project

Yale School of Forestry and Environmental Studies, Global Institute of Sustainable Forestry
and State University of New York College of Environmental Science and Forestry

Catskill/Delaware Site Results Workshop

Liberty, New York
June 9, 2003

Agenda

Welcome and Introduction — Mary Tyrrell

Project Overview — Mary Tyrrell

Results: Land Use Changes in the Catskill/Delaware Watersheds 1992 - 2001 — Myrna Hall

Next Steps: Phase II of Research Project — Mary Tyrrell

Questions, Comments, Feedback

Lunch Discussion: Putting land use change information and model results to good use

Attendees

Page Bertelsen, Yale School of Forestry and Environmental Studies
Myrna Hall, SUNY College of Environmental Science and Forestry
Mary Tyrrell, Yale School of Forestry and Environmental Studies

Tim Cox, Corporate Counsel Catskill Watershed Corporation
Nat Gillepse, TNC Neversink Project
Henry Kernan, forest land owner
Jack McShane, forest land owner and Catskill Forest Association
Jean Millar, Roxbury Planning Board
Jim Porter, NYC DEP Watershed Hydrology Program
John Potter, NYC DEP Bureau of Water Supply
Kate Schmidt, Cornell Cooperative Extension, Natural Resource Educator
Mike Shaw, EPA NYC Watershed
Rick Wyman, Intl. Org. of Biological Field Stations

Summary of Comments and Feedback

Factors Driving Loss of Forest: What else could be considered?

A few of the comments were about what folks see as driving change in their towns:

- Second homes and the associated development (tax records show that 80% of the forest parcels within the study area are owned by non-residents)
- Proposed casinos
- Trend of increased publicity about the rural towns in the area, resulting in increased second home development and urban migration
- High land taxes

Potential Uses of Research Results

- To inform local (town) discussions about the balance of conservation and development
- To tie in with water quality/quantity models to predict water impacts of future development
- Input to local planning tools, especially zoning, to help with the process of planning for development in areas that are best used for development and conservation of high value foreslands
- Help towns make the connection between the forest and the town in terms of water, economics, etc. Towns in the area tend to consider forest as “abandoned” or “unproductive” agricultural lands, especially with regard to tax policies
- Help with the discussion about the value of working forests to the local economy

Final Notes

Overall, feedback on the usefulness of the research was very enthusiastic, with several people indicating that they could have definitely used our results in their recent town planning efforts. The feeling was that the unique ability to visualize potential land use change and identify areas at high risk of development, would be very useful at the local and county level. The towns of Andes, Roxbury, Delhi, and Bel Air, and Sullivan County were volunteered as places that would be interested in working with the project team to integrate this project into the local planning process. The EPA was very interested in linking this project to water quality models for the NYC Watersheds.

Appendix B: Satellite Imagery Classification

Accuracy Assessment of Year 2001 satellite image classification for the New York study

This classification followed as close as possible the protocol and standards reported for the 1992 NLDC for New York. The imagery used came from the Multi-resolution Land Characterization (MRLC) Consortium. All image preparation including georeferencing was completed by the MRLC prior to this classification.

The initial Landsat TM mosaics, all ancillary data sets, and the land cover product are all map-registered to an Albers Conical Equal Area projection. The following represents projection information for the final land cover product for the state of New York.

Projection: Albers Conical Equal Area
  Datum: NAD83
  Spheroid: GRS80
  Standard Parallels: 29.5 degrees North Latitude
    45.5 degrees North Latitude
  Central Meridian: 96 degrees West Longitude
  Origin of the Projection: 23 degrees North Latitude
  False Easting: 0 meters
  False Northing: 0 meters

Number of Lines (rows): 17455
Number of Samples (columns): 23005
Number of Bands: 1 Pixel size: 30 X 30 meters
Projection Coordinates (center of pixel, projection meters)
  Upper Left Corner: 1317210 meters(X),
    2663820 meters(Y)
  Lower Right Corner: 2007330 meters(X),
    2140200 meters(Y)

NOTE: Each state data set was extracted from the larger regional data set. State boundaries from the USGS 1:100,000 Digital Line Graph (DLG) series were used as the basis for extracting the state data. In many instances, the precision of the boundaries in the 1:100,000 DLG data does not match the spatial precision of the Landsat TM data. This is most apparent where state boundaries follow small rivers. To overcome the possibility of data being lost in the extraction process, a 300 meter (10 pixel) buffer was added to the state boundary used to extract the state data.

Caveats and Concerns:

As with the previous classification from the NLDC, we believe that the approach taken has yielded a very good general land cover classification product for a very large region. However, it is important to indicate that there might be some potential problems. Problem areas are listed below:

1) Unlike the previous classification of this region only one image from May of 2000 was used. The image acquired from April was predominantly snow covered and so relatively unusable. Therefore there was no leaf off image to use that is necessary for accurately defining roads and the like that will often become obscured when the forest cover leafs out.

2) Like the USGS there were some issues with accurate definition of the transitional barren class. Because there were very few known positive examples available for this class to use as training sites this class was omitted. As a result, those true areas of transition were lumped in with row-crops and pasture-hay classes.

3) Due to the confusion between clear-cuts, regrowth in clear-cuts, forested areas, and shrublands, no attempts were made to populate the shrubland classes. Any shrubland areas that exist in this area are classed in their like forest class, i.e., deciduous shrubland is classed as deciduous forest, etc.

4) Pasture-hay and Row-crop classes were also quite difficult to distinguish between due in part to the time of year. These two classes may be somewhat interchangeable in reality.

5) There were also some issues separating low intensity residential and transportation. In the 1992 classification transportation is lumped with industrial but in this classification some roads show up as low intensity residential.

6) Again due to the time of year and lack of a leaf off image the residential classes may be somewhat less representative than reality. Relatively pure training sites were used for this class and so those regions where homes are scattered about the landscape with lots of forest cover may have been missed in this classification.

Accuracy Assessment:

In accordance with the accuracy assessment completed for the 1992 New York NLDC, 15 land cover and land use classes were assessed, using 1:40,000-scale Digital Ortho quads as reference data. See methodology section of New York NLDC for specific details. The overall Kappa statistic for agreement was .74112 with a confidence interval of +/- 0.0777 at %99. The classes having the highest errors were the woody-wetland and urban-grass/recreational.

Misclassification errors seem to be from a number of possible sources. The DOQQ's used for the assessment came from 1999 and different months. Some changes appear to have occurred in that time. Also the geo-referencing for the TM imagery seems to have some problems in the northeast and northwest corners. There may also be some disagreement due to georeferencing errors between the TM image and the DOQQ's. See problems listed in Caveats and Concerns.

A complete accuracy assessment for this classification may be obtained by contacting Stephen Ambagis at (508) 353-6430 or sambagis@clarku.edu or sambagis@yahoo.com

23-Class National Land Cover Data Key

NOTE - All Classes May NOT Be Represented in a specific state data set.
The class number represents the digital value of the class in the data set.

<u>NLCD Land Cover Classification System Key - Rev. July 20, 1999</u>

Water	New Classification
11 Open Water	1
12 Perennial Ice/Snow	2
Developed	
21 Low Intensity Residential	3
22 High Intensity Residential	4
23 Commercial/Industrial/Transportation	5
Barren	
31 Bare Rock/Sand/Clay	6
32 Quarries/Strip Mines/Gravel Pits	7
33 Transitional	8
Forested Upland	
41 Deciduous Forest	9

42 Evergreen Forest	10
43 Mixed Forest	11
Shrubland	
51 Shrubland	12
Non-natural Woody	
61 Orchards/Vineyards/Other	13
Herbaceous Upland	
71 Grasslands/Herbaceous	14
Herbaceous Planted/Cultivated	
81 Pasture/Hay	15
82 Row Crops	16
83 Small Grains	17
84 Fallow	18
85 Urban/Recreational Grasses	19
Wetlands	
91 Woody Wetlands	20
92 Emergent Herbaceous Wetlands	21

For a complete description of the classes see the NLCD Land Cover Classification System Land Cover Class Definitions.

Accuracy Assessment of Year 1992 NLCD satellite image classification for the New York study

1992 Accuracy Assessment Results

Test Point From 92samp2	DOQQ tile	Test Point X coord	Test Point Y coord	LU ID# 1992 Landsat	Land Use Class 1992 Landsat	Actual LU 1994 DOQQ	Same as 92 Landsat
1	hamd_sw_t3	502302	4665633	9	deciduous forest	9	1
2	hamd_sw_t2	504915	4665731	9	deciduous forest	9	1
3	ande_sw_t2	514182	4664699	9	deciduous forest	9	1
4	ande_se_t3	516636	4663856	11	mixed forest	11	1
5	marg_se_t3	526663	4664392	11	mixed forest	11	1
6	hamd_sw_t0	501194	4668833	11	mixed forest	14, 15, or 16	
7	hamd_se_t1	508944	4668803	11	mixed forest	11	1
8	ande_sw_t3	511629	4666403	15	pasture/hay	15	1
9	ande_sw_t1	514805	4667228	9	deciduous forest	9	1
10	marg_sw_t0	520707	4668990	9	deciduous forest	9	1
11	marg_se_t1	529767	4667960	9	deciduous forest	9	1
12	hamd_sw_t0	501313	4670154	11	mixed forest	10	
13	hamd_nw_t2	504770	4671203	9	deciduous forest	15	
14	hamd_ne_t3	507565	4670732	11	mixed forest	11	1
15	ande_nw_t2	514816	4670950	9	deciduous forest	9	1
16	ande_ne_t2	518149	4670814	3	low intensity residential	3	1
17	marg_nw_t2	523958	4670684	9	deciduous forest	9	1
18	marg_nw_t2	525271	4670947	9	deciduous forest	9	1
19	marg_se_t0	527014	4670562	15	pasture/hay	15	1
20	marg_se_t1	529915	4670194	9	deciduous forest	9	1
21	hamd_nw_t1	504890	4674218	11	mixed forest	11	1
22	ande_nw_t3	512735	4672232	9	deciduous forest	9	1
23	ande_ne_t3	515568	4673400	9	deciduous forest	9	1
24	ande_ne_t2	519293	4672959	9	deciduous forest	15	
25	marg_nw_t2	523972	4673454	9	deciduous forest	9	1
26	marg_nw_t2	524147	4673098	9	deciduous forest	9	1
27	hamd_nw_t0	502079	4676763	9	deciduous forest	9	1
28	hamd_ne_t1	509278	4677298	9	deciduous forest	9	1
29	ande_nw_t1	514169	4675077	9	deciduous forest	11	

Test Point From 92samp2	DOQQ tile	Test Point X coord	Test Point Y coord	LU ID# 1992 Landsat	Land Use Class 1992 Landsat	Actual LU 1994 DOQQ	Same as 92 Landsat
30	ande_ne_t0	516155	4677275	11	mixed forest	11	1
31	hoba_sw_t3	520842	4677590	9	deciduous forest	9	1
32	marg_nw_t1	524532	4675030	11	mixed forest	11	1
33	marg_ne_t1	528443	4676241	15	pasture/hay	15	1
34	marg_ne_t1	530329	4677434	11	mixed forest	11	1
35	marg_nw_t0	523227	4675186	11	mixed forest	11	1
36	delh_sw_t2	504721	4680355	9	deciduous forest	9	1
37	delh_se_t3	507051	4680415	9	deciduous forest	4	
38	delh_se_t2	509484	4677986	15	pasture/hay	15	1
39	bloo_sw_t3	512757	4680052	11	mixed forest	11	1
40	bloo_se_t3	516276	4678795	9	deciduous forest	15	
41	hoba_se_t2	528866	4680673	9	deciduous forest	9	1
42	delh_sw_t0	501993	4682219	9	deciduous forest	9	1
43	delh_sw_t2	504556	4680908	9	deciduous forest	9	1
44	delh_se_t1	508939	4681809	9	deciduous forest	9	1
45	bloo_sw_t1	513940	4682777	11	mixed forest	11	1
46	hoba_sw_t1	523643	4681992	11	mixed forest	11	1
47	hoba_se_t0	527029	4682860	9	deciduous forest	9	1
48	hoba_se_t1	530327	4682072	9	deciduous forest	9	1
49	delh_se_t0	505383	4684060	9	deciduous forest	9	1
50	delh_ne_t2	509354	4686441	11	mixed forest	11	1
51	bloo_nw_t3	510385	4685124	11	mixed forest	11	1
52	bloo_ne_t3	516739	4686390	15	pasture/hay	15	1
53	bloo_ne_t2	519449	4685991	11	mixed forest	11	1
54	hoba_se_t1	528884	4683697	11	mixed forest	11	1
55	hoba_ne_t2	530646	4686439	11	mixed forest	11	1
56	delh_nw_t2	502996	4687942	9	deciduous forest	9	1
57	delh_ne_t0	505889	4689196	15	pasture/hay	15	1
58	delh_ne_t1	509345	4688786	11	mixed forest	11	1
59	delh_ne_t1	510292	4687998	15	pasture/hay	15	1
60	bloo_ne_t2	519467	4687055	15	pasture/hay	15	1
61	hoba_nw_t3	522640	4687564	11	mixed forest	12	
62	delh_nw_t0	502107	4689928	11	mixed forest	11	1
63	wdav_se_t3	506046	4691568	15	pasture/hay	15	1

Test Point From 92samp2	DOQQ tile	Test Point X coord	Test Point Y coord	LU ID# 1992 Landsat	Land Use Class 1992 Landsat	Actual LU 1994 DOQQ	Same as 92 Landsat
64	dave_sw_t2	515121	4691970	11	mixed forest	11	1
65	bloo_ne_t0	517243	4691020	11	mixed forest	11	1
66	bloo_ne_t1	518889	4691390	15	pasture/hay	15	1
67	hoba_nw_t1	523250	4690738	15	pasture/hay	15	1
68	hoba_ne_t0	526335	4689761	9	deciduous forest	9	1
69	hoba_ne_t0	527462	4690753	3	low intensity residential	3	1
70	hoba_ne_t1	529983	4691341	11	mixed forest	11	1
71	wdav_sw_t2	503384	4694126	9	deciduous forest	9	1
72	wdav_se_t3	506173	4693173	9	deciduous forest	9	1
73	wdav_se_t1	508406	4695291	9	deciduous forest	9	1
74	dave_se_t2	519095	4692754	11	mixed forest	11	1
75	harp_sw_t3	521874	4692864	15	pasture/hay	15	1
76	harp_sw_t2	525174	4694411	15	pasture/hay	15	1
77	wdav_sw_t0	502016	4695604	11	mixed forest	11	1
78	wdav_sw_t1	504933	4696532	11	mixed forest	11	1
79	dave_sw_t0	511578	4695389	15	pasture/hay	15	1
80	dave_sw_t1	514031	4695949	15	pasture/hay	15	1
81	dave_se_t0	517372	4696613	15	pasture/hay	15	1
82	harp_sw_t0	520731	4695437	9	deciduous forest	9	1
83	harp_sw_t0	522610	4695627	11	mixed forest	11	1
84	harp_se_t1	530601	4697696	11	mixed forest	11	1
85	wdav_nw_t3	500767	4699884	11	mixed forest	11	1
86	wdav_nw_t2	503767	4698589	9	deciduous forest	9	1
87	wdav_se_t1	508211	4698283	15	pasture/hay	15	1
88	dave_nw_t2	514940	4698638	11	mixed forest	15	
89	dave_se_t0	516730	4698319	9	deciduous forest	9	1
90	dave_ne_t2	518509	4699401	9	deciduous forest	9	1
91	harp_nw_t2	524720	4698590	15	pasture/hay	15	1
92	harp_ne_t3	528268	4700747	9	deciduous forest	15	
93	wdav_ne_t0	505602	4702669	9	deciduous forest	9	1
94	wdav_ne_t0	506478	4703792	11	mixed forest	11	1
95	dave_nw_t1	513705	4703885	9	deciduous forest	9	1
96	dave_ne_t0	516996	4703602	9	deciduous forest	9	1
97	harp_nw_t3	520834	4701457	15	pasture/hay	15	1
98	harp_nw_t2	524883	4701503	10	evergreen forest	10	1
99	harp_ne_t1	530119	4702121	15	pasture/hay	15	1
100	dave_ne_t1	519611	4704466	15	pasture/hay	15	1

Total Correct = 90/100

Also see: http://landcover.usgs.gov/accuracy/table3.asp

Connecticut Statewide Temporal Land Cover and Land Cover Change Project

(for the years 1985, 1990, 1995, 2002)

A General Overview

James Hurd, Center for Land use Education And Research, University of Connecticut

Introduction

This latest attempt at Connecticut statewide land cover mapping was undertaken by the *Center for Land use Education And Research* **(CLEAR)** in the College of Agriculture and Natural Resources at the University of Connecticut to help gain a better understanding of the extent of land cover changes occurring in the Connecticut landscape. The premise was to develop a temporal series of basic land cover information for four years (1985, 1990, 1995, 2002) that would allow us, among other potential uses, to apply landscape characterization models developed under the NAUTILUS program; a NASA Regional Earth Science Applications Center (RESAC). These models consist of forest fragmentation, state of forest fragmentation, urban (development) growth, and impervious surface estimation. Each of these models utilizes land cover information, and land cover that is consistent between each date is necessary to produce reliable results over time. To achieve this, a base land cover image (1985) was generated with subsequent land cover (1990, 1995, 2002) derived from it using cross-correlation analysis, a change detection method developed by Earthsat, Inc. 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.

Base Land Cover (1985)

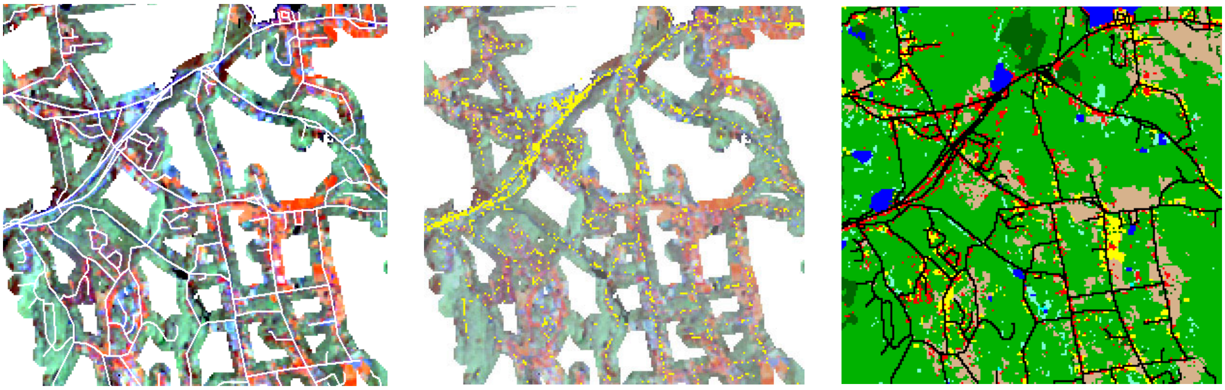
The primary source of image data came from an April 26, 1985 Landsat Thematic Mapper (TM) scene (path 13/row 31) covering most of the analysis area. The Landsat Thematic Mapper sensor collects data in seven regions of the electromagnetic spectrum (blue, green, red, near-infrared, 2 middle-infrared, and thermal) at 30-meter spatial resolution (60 –meters for the thermal band) and is well suited for land cover classification at a regional level. 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 state were extracted and substituted with a May 4, 1988 Landsat TM scene. Most of this area consisted of forested land cover and was not impacted by potential change in land cover between these two time periods. To derive land cover information, several classification techniques were used. These include sub-pixel classification, ISODATA unsupervised classification, supervised classification using the maximum likelihood classifier, and knowledge-based classification.

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. This layer was then buffered 5 pixels to either side of the road to account for areas of mis-alignment between the road layer and Landsat image data. All image pixels contained within the 5 pixel buffer area were extracted for analysis (Figure 1a). 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 actual rasterized road layer. The result of this procedure was the identification of additional developed pixels not identified using the sub-pixel classifier.

Figure 1b provides the results of the Sub-pixel Classifier and Knowledge-based classification applied to the road buffered image. The SPC and knowledge-based classification unfortunately 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. 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. The same techniques were used on the August 9, 1985 image covering the southeast portion of the analysis area.



a b c

Figure 1. 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.

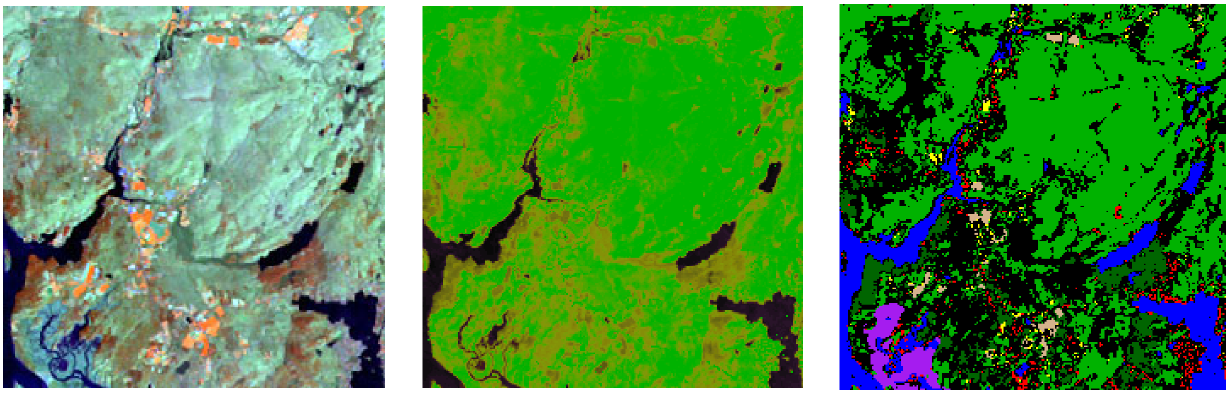
Complete Area Classification

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 (Table 1). ISODATA classification was performed generating 100 signature clusters. These clusters were then identified and labeled into the appropriate land cover category.

Table 1. Land cover classification scheme.

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

Maximum likelihood classification was applied to the entire statewide 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 2 provides an overview of this phase of the classification.



a b c

Figure 2. 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.

Pixels remaining as unclassified were again 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 classification layers were then merged to create a single classified image with all pixels being identified as belonging to a single category. 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, extensive 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 identify those pixels that were more problematic. Remaining errors would potentially be cleaned during the on-screen digitizing phase of the 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. 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.

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 pixels and non-changed pixels. Those pixels identified as changed were extracted from the August 30, 1990 image. ISODATA unsupervised 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. Figure 3 provides examples of preliminary land cover for the town of Tolland, Connecticut.

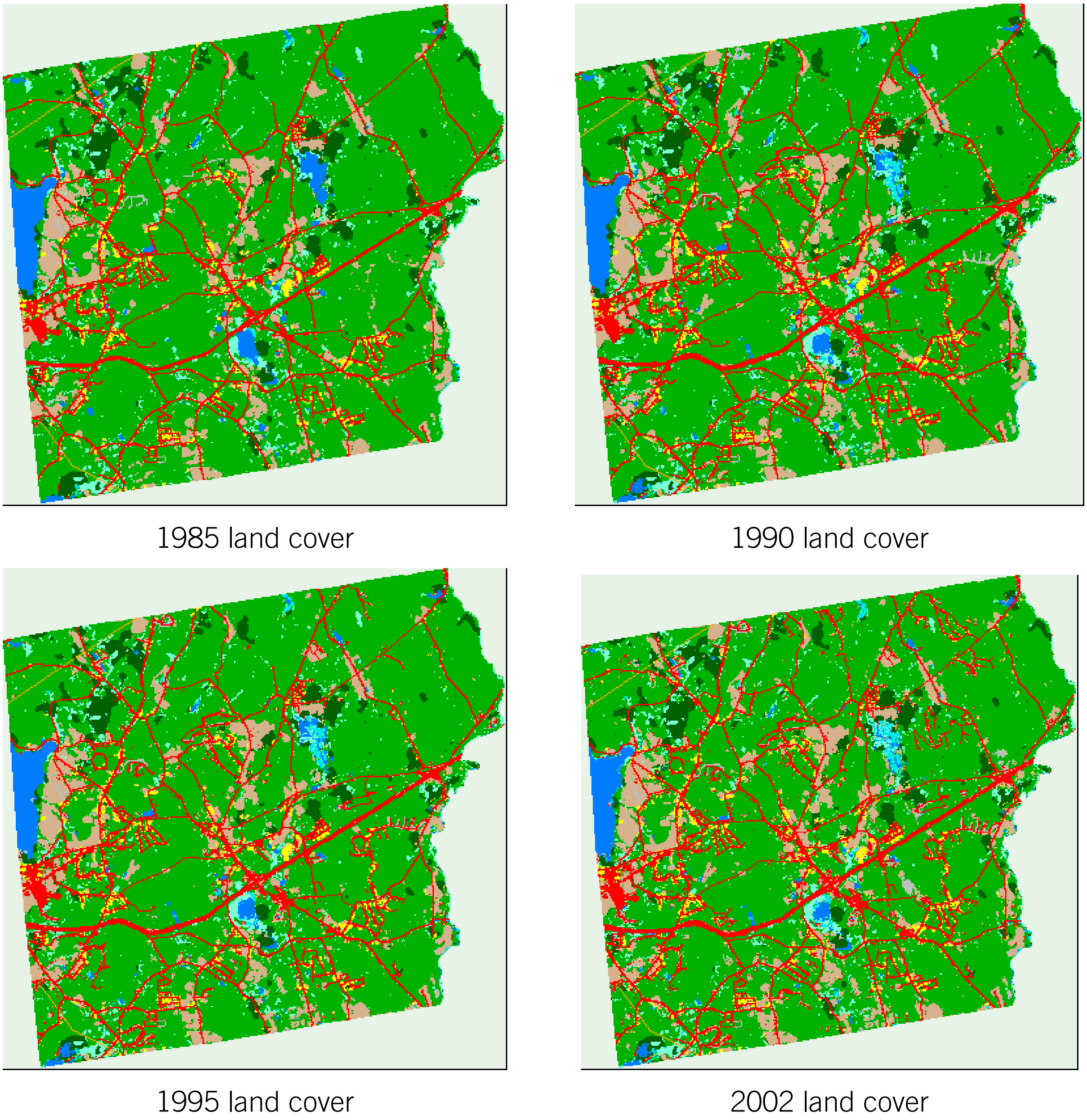


Figure 3. Preliminary results of land cover for the town of Tolland, Connecticut (developed is red, turf & grass is yellow, agriculture & other grasses is tan, deciduous forest is green, coniferous forest is dark green, water is blue, non-forested wetland is cyan, forested wetland is mint green, barren land is gray, and utility right-of-ways are orange).

Conclusion

The result of this work will provide CLEAR with a consistent set of land cover images on which to apply landscape characterization models. Together, the land cover information and results of the models will provide a suite of information that will be made available to community and state decision makers, and the general public, and provide a means for them to evaluate and quantify the results of past land use decisions, and to begin to grasp what type of future landscape current land use policies may produce.

Category Descriptions

Developed – includes high-density built-up areas which are typically associated with commercial, industrial and residential activities and transportation routes. These areas will contain a high percentage of land cover types such as concrete and asphalt surfaces, roofs, roads, and other impervious surfaces. Also includes some areas adjacent to highways and major roads. Most transportation routes identified by rasterizing statewide vector roads coverage.

Turf & Grass - a compound category of undifferentiated grasses associated mostly with developed areas. These areas will contain mostly cultivated lawns and cultivated lawns with a sparse tree over story such as is found in a typical residential neighborhood, turf farms, golf courses, and other maintained grassy areas. Also likely to include some agricultural fields due to similar spectral reflectance properties.

Agriculture & Other Grasses – includes mostly agricultural fields used for both crop production and pasture. Also includes grassy areas associated with development due to similar spectral reflectance properties and forest clear-cut areas.

Deciduous - includes typical southern New England mixed hardwood forests. Includes not only large expanses of forested land but inclusion of small patches of trees detectable by the Landsat sensor. Also likely to include scrub areas characterized by patches of small woody vegetation and undifferentiated grasses. Also some agricultural fields due to similar spectral characteristics.

Coniferous – includes typical southern New England mixed softwood forests. Includes not only large expanses of forested land but inclusion of small patches of trees detectable by the Landsat sensor.

Water - open water bodies and watercourses with relatively deep water and large enough to be resolved by the Landsat sensor.

Non-forested Wetland – includes areas depicted as being predominately wet throughout most of the year with a detectable vegetative cover. Also likely to include small river courses due to the similar spectral characteristics caused by the mix of water and vegetation land cover in a single Landsat pixel.

Forested Wetland - includes areas depicted as wetland, but with a more detectable vegetative cover. Also likely to include small river courses due to the similar spectral characteristics caused by the mix of water and vegetation land cover in a single Landsat pixel.

Tidal Wetland – includes emergent wetlands depicted as being predominately wet throughout most of the year with a detectable vegetative and located adjacent to the coastal region.

Barren - includes mostly non-agricultural areas relatively free from vegetation, such as sand, sand and gravel operations, bare exposed rock, mines, quarries, etc. Also likely to include some urban areas where the composition of construction materials spectrally resembles more natural materials, and bare soil agricultural fields.

Utility - includes identifiable utility right-of-ways. This category was manually digitized on-screen and was taken from the deciduous and coniferous categories only.

For information regarding this work, please contact:
James Hurd
Center for Land use Education And Research (CLEAR)
The University of Connecticut
jhurd@canr.uconn.edu
(860) 486-4610

Appendix C: Data Sources

MODEL INPUT DATA SOURCES

Data Type		Data Description	State	Scale
Biophysical Features	1	Digital Orthorectified Quarter Quadrangle Aerial Photography (1994 and 2001)	NY	1 meter and High resolution
	2	Elevation	CT/MA	30 meters
	3	Elevation	NY	USGS 1:24000
	4	Land Cover (1992)	NY	30 x 30 meter pixels
	5	Land Cover 2001Satellite Imagery	NY	30 x 30 meter pixels
	6	Land cover time series classifications for 1985, 1990, 1995, 2002	CT/MA	100 foot pixels
	7	Reservoir drainage basin boundaries	NY	USGS 1:24000
	8	Slope, aspect	CT/MA/NY	USGS 1:24000
	9	Soil types	MA	
	10	Soil types	CT	
	11	Water bodies	MA	USGS 1:24000
	12	Water courses by major watershed	MA	USGS 1:24000
	13	Water features; streams and water bodies	CT	USGS 1:24000
	14	Water features; streams and water bodies	NY	1:100,000
Political Features	15	Agricultural Districts	NY	county, 1:100,000
	16	Census Blocks	NY	county, 1:100,000
	17	County Boundaries	NY	county, 1:100,000
	18	Municipal Boundaries	NY	1:4,800
	19	Town Boundaries	CT	town
	20	Town Boundaries	MA	town
Socio-economic	21	Education	NY	census block
	22	Education, demographic data	CT	town
	23	Employment by sector	MA	town
	24	Employment in each major sector	CT	town
	25	Employment, commuting, poverty, income	CT	town
	26	Housing - median price	CT	town
	27	Housing - median price	MA	town
	28	Housing- number, year, value, tenure, size	CT	town
	29	Housing starts- total units, single family units	CT	town
	30	Housing starts- total units, single family units	MA	town
	31	Housing units (density); owner occupied units	CT/MA	census block
	32	Labor force; percent unemployed	CT	town
	33	Labor force; percent unemployed	MA	town
	34	Location of development nodes (casinos, ski resorts)	CT/NY	1:24,000
Socio-economic	35	Open Space/Protected Areas	CT	
	36	Open Space/Protected Areas	MA	
	37	Open Space/Protected Areas - Newly acquired lands	NY	1:4,800
	38	Open Space/Protected Areas - Pre-MOA NYC owned land	NY	1:4,800
	39	Open Space/Protected Areas - State owned lands	NY	1:4,800
	40	Population	CT/MA/NY	census block
	41	Property tax rates	MA	town
	42	Property tax rates	CT	town
	43	Railroads	NY	1:100,000
	44	Real estate conveyance tax revenues	CT	town
	45	Real estate conveyance tax revenues	MA	town
	46	Roads	NY	1:100,000
	47	Roads	CT	USGS 7.5 min
	48	Roads, utility transport lines, railroad lines	MA	USGS 7.5 min
	49	Tax Parcels (1985 parcel sample derived from above)	NY	town
	50	Tax parcels (2000)	NY	town
	51	Zoning	CT	
	52	Zoning areas for each MA town with universalized state zone definitions;	MA	town/zoning area

MODEL INPUT DATA SOURCES

	Source
1	NY GIS Clearing House
2	USGS National Elevation Dataset (NED).
3	Cornell University Geospatial Information Repository
4	United States Geological Society National Land Cover Data
5	United States Geological Society Multi-resolution Land Characteristics (MRLC)
6	University of Connecticut Center for Land use Education And Research (CLEAR)
7	New York City Department of Environmental Protection
8	Yale/SUNY ESF Research Project
9	MassGIS and MA Department of Food and Agriculture
10	University of Connecticut Map and Geographic Information Center (MAGIC)
11	MassGIS website
12	MassGIS website
13	University of Connecticut Map and Geographic Information Center (MAGIC)
14	US Census Bureau
15	US Census Bureau
16	US Census Bureau
17	US Census Bureau
18	New York State DEC
19	University of Connecticut Map and Geographic Information Center (MAGIC)
20	MassGIS website
21	US Census Bureau
22	Connecticut Department of Economic and Community Development
23	MA Division of Employment and Training
24	CT Labor Department: Office of Research
25	Connecticut Department of Economic and Community Development
26	CT Data Engine; Real Estate Transactions
27	Commonwealth of Massachusetts
28	Connecticut Department of Economic and Community Development
29	CT Department of Economic and Community Development
30	Commonwealth of Massachusetts
31	US Census Bureau
32	CT Labor Department: Office of Research
33	Mass Division of Employment and Training
34	Yale/SUNY ESF Research Project
35	NEMO Eightmile River Mapping Project; Green Valley Institute; UCONN MAGIC
36	National Park Service; Mass Department of Environmental Management; Norcross Wildlife Sanctuary
37	New York City Department of Environmental Protection
38	New York City Department of Environmental Protection
39	New York City Department of Environmental Protection
40	US Census Bureau
41	MA Department of Revenue
42	Connecticut Department of Economic and Community Development
43	US Census Bureau
44	CT Department of Revenue Services
45	Not available
46	US Census Bureau
47	University of Connecticut Map and Geographic Information Center (MAGIC)
48	ESRI Geography Network
49	New York City Department of Environmental Protection
50	New York City Department of Environmental Protection
51	Available by contacting each town; most not in geospatial in format
52	MassGIS website

MODEL INPUT DATA SOURCES

	Format and availability
1	Mr. Sid and GEOTIFF format, respectively
2	Digital Elevation Model in a grid format
3	The USGS 7.5-minute quadrangle DEM (10- by 10-m data spacing) is available in ASCII DEM format
4	Cornell University Geospatial Information Repository, in either Lat/Lon or UTM18 N, NAD83 GeoTiff format
5	Terrain and/or at-censor reflectance corrected raw satellite scenes, Path 14, Row 31
6	ERDAS Imagine file for CT/MA study area and for entire state of CT available from UCONN/CLEAR
7	Shape files, by arrangement only
8	Grid format, UTM Zone 18N, NAD83, all files were gridded to match
9	Soil polygon shape files on MassGIS except for Worcester County which is Pre-release data from Mass DFA
10	Soil polygon GIS shape files available at www.magic.lib.uconn.edu
11	for modified USGS standard map rectangles (10 areas); polygons available at http://www.state.ma.us/mgis/ftphd.htm
12	line file for each major watershed available at http://www.state.ma.us/mgis/ftpcl_.htm
13	GIS files available at www.magic.lib.uconn.edu
14	Cornell University Geospatial Information Repository, US Census Bureau 1998 Tiger Line Files
15	Cornell University Geospatial Information Repository, US Census Bureau 1998 Tiger Line Files
16	Census data for 1990 and 2000 in geospatial format from GeoLytics; http://www.geolytics.com/
17	Cornell University Geospatial Information Repository, US Census Bureau 1998 Tiger Line Files
18	
19	Town boundary GIS shape files available at www.magic.lib.uconn.edu
20	Town boundary GIS shape files available at http://www.state.ma.us/mgis/towns.htm
21	Census data for 1990 and 2000 in geospatial format from GeoLytics;
22	Tables available online at http://www.ct.gov/ecd/ under Research Data for most recent years; back data available hardcopy from DECD
23	http://www.detma.org/LMIHome.htm
24	
25	Tables available online at http://www.ct.gov/ecd/ under Research Data for most recent years; back data available hardcopy from DECD
26	Available at http://www.businessnewhaven.com:5002/businessnewhaven/realestateinfo.htm
27	
28	Tables available online at http://www.ct.gov/ecd/ under Research Data for most recent years; back data available hardcopy from DECD
29	Tables available online at http://www.ct.gov/ecd/ under Research Data for most recent years; back data available hardcopy from DECD
30	
31	Census data for 1990 and 2000 in geospatial format from GeoLytics; http://www.geolytics.com/
32	
33	http://www.detma.org/LMIHome.htm
34	GIS points created specifically for this project from street addresses
35	GIS shape files available from www.magic.lib.uconn.edu; updated open space layers for project area in CT provided by Green Valley Institute
36	GIS shape files from MassGIS and Norcross
37	Shape files, by arrangement only
38	Shape files, by arrangement only
39	Shape files, by arrangement only
40	Census data for 1990 and 2000 in geospatial format from GeoLytics;
41	http://www.dls.state.ma.us/allfiles.htm
42	Tables available online at http://www.ct.gov/ecd/ under Research Data for most recent years; back data available hardcopy from DECD
43	Cornell University Geospatial Information Repository, US Census Bureau 1998 Tiger Line Files
44	
45	
46	Cornell University Geospatial Information Repository, US Census Bureau 1998 Tiger Line Files
47	Census road categorization GIS files available at magic.lib.uconn.edu
48	Census 2000 tiger line files available at http://www.geographynetwork.com/data/tiger2000/index.html
49	Hand digitized from above by ESF graduate student Seth LaPierre
50	Tax parcel boundaries and ownership information made available by special arrangement
51	
52	GIS polygon files available at http://www.state.ma.us/mgis/ftpzn.htm

MODEL INPUT DATA SOURCES

	contact
1	http://www.nysgis.state.ny.us/
2	
3	http://cugir.mannlib.cornell.edu/index.jsp
4	
5	http://www.mrlc.gov/download_data.asp
6	Research Department, DECD; phone (860) 270-8021
7	Terry Spies, 71 Smith Ave., Kingston, NY 12401, 914-340-7527, tspies@catgis.dep.nyc.ny.us
8	
9	Research Department, DECD; phone (860) 270-8021
10	
11	Research Department, DECD; phone (860) 270-8021
12	Research Department, DECD; phone (860) 270-8021
13	
14	
15	
16	
17	
18	
19	
20	
21	
22	michael.trust@state.ma.us; daniel.marrier@state.ma.us
23	michael trust 617-626-1195
24	michael trust 617-626-1195
25	Business New Haven 1221 Chapel Street, New Haven, CT 06511; Tel: 203-781-3480
26	
27	
28	Patrick McGlamery; libmap1@uconnvm.uconn.edu; (860) 486-4589
29	Kolie Chang, Senior Research Analyst at DECD, 860-270-8167
30	
31	
32	
33	
34	
35	Michael Altshul at Green Valley Institute; maltshul@canr.uconn.edu; 860-486-4610
36	
37	Terry Spies, 71 Smith Ave., Kingston, NY 12401, 914-340-7527, tspies@catgis.dep.nyc.ny.us
38	Terry Spies, 71 Smith Ave., Kingston, NY 12401, 914-340-7527, tspies@catgis.dep.nyc.ny.us
39	Terry Spies, 71 Smith Ave., Kingston, NY 12401, 914-340-7527, tspies@catgis.dep.nyc.ny.us
40	http://www.geolytics.com/
41	860-566-3470
42	Department of Revenue Services
43	
44	Department of Revenue Services
45	
46	
47	None given
48	Barbara Hopson, GIS/Land Use Administrator 508-792-7712 ext.21
49	
50	Terry Spies, 71 Smith Ave., Kingston, NY 12401, 914-340-7527, tspies@catgis.dep.nyc.ny.us
51	
52	James Hurd at jhurd@canr.uconn.edu; 860-486-4610

Appendix D: Thames Watershed Town Data

THAMES STUDY AREA FOREST DATA

Town	Total Acres in town	Acres included in Analysis	Acres in Water	Acres in Conservation Lands	% Area in Water	% Area in Conservation Land	Total Acres of Forest		% Forested		Forest Cover (Excluding Conservation Lands) Actual (acres)	Actual (acres)	Projected (acres)				% Loss	% of 2002 Unprotected forest at risk	
							1985	2002	1985	2002	1985	2002	2008	2013	2018	2023	1985-2002	by 2013	by 2023
Connecticut																			
Andover	10057	8398	266	1394	3%	14%	8476	8125	84%	81%	6817	6463	6344	6244	6145	6045	5%	3%	6%
Ashford	25269	21598	907	2762	4%	11%	21416	20913	85%	83%	17744	17217	17047	16904	16762	16620	3%	2%	3%
Bolton	9432	8571	96	766	1%	8%	6533	6213	69%	66%	5672	5340	5230	5138	5046	4954	6%	3%	7%
Bozrah	12982	12205	272	506	2%	4%	10266	9727	79%	75%	9489	8923	8737	8582	8428	8273	6%	3%	7%
Brooklyn	18648	17598	595	454	3%	2%	13675	12754	73%	68%	12624	11682	11361	11094	10826	10559	7%	5%	9%
Canterbury	25758	23785	852	1124	3%	4%	20794	19773	81%	77%	18820	17770	17412	17114	16816	16518	6%	3%	7%
Chaplin	12570	8871	244	3451	2%	27%	11088	10701	88%	85%	7390	6972	6829	6709	6590	6471	6%	3%	7%
Colchester	31761	27572	774	3413	2%	11%	24582	22990	77%	72%	20393	18738	18190	17734	17278	16822	8%	5%	10%
Columbia	14040	12834	534	678	4%	5%	11060	10503	79%	75%	9854	9263	9071	8911	8751	8591	6%	3%	7%
Coventry	24488	22338	686	1462	3%	6%	18168	17185	74%	70%	16019	14968	14633	14354	14076	13797	7%	4%	7%
East Haddam	36230	27682	1403	7146	4%	20%	30499	29490	84%	81%	21950	20961	20612	20321	20031	19740	5%	3%	6%
Eastford	18776	12705	432	5646	2%	30%	16206	15853	86%	84%	10135	9776	9655	9554	9453	9352	4%	2%	4%
Ellington	22140	19743	540	1858	2%	8%	12611	11548	57%	52%	10214	9155	8789	8484	8178	7873	10%	7%	13%
Franklin	12590	11537	135	918	1%	7%	8893	8395	71%	67%	7839	7324	7153	7011	6869	6727	7%	4%	8%
Griswold	23651	17707	1062	4882	4%	21%	18339	16971	78%	72%	12394	10980	10504	10107	9711	9314	11%	7%	14%
Hampton	16276	12820	324	3131	2%	19%	13492	13084	83%	80%	10036	9607	9465	9346	9228	9110	4%	2%	5%
Hebron	23937	20122	584	3231	2%	13%	18484	17704	77%	74%	14669	13880	13607	13379	13151	12923	5%	3%	7%
Killingly	31968	28552	1862	1553	6%	5%	25076	23491	78%	73%	21660	19967	19418	18961	18504	18046	8%	5%	9%
Lebanon	35302	32298	1308	1695	4%	5%	24541	23094	70%	65%	21537	20021	19528	19117	18706	18296	7%	4%	8%
Ledyard	25543	21849	1532	2160	6%	8%	20851	19547	82%	77%	17157	15791	15329	14943	14558	14173	8%	5%	10%
Lisbon	10687	10075	485	127	5%	1%	8350	7750	78%	73%	7737	7109	6894	6715	6536	6357	8%	5%	10%
Mansfield	29177	24899	609	3660	2%	13%	21887	20576	75%	71%	17609	16203	15734	15343	14953	14562	8%	5%	10%
Marlborough	15032	12096	240	2696	2%	18%	12564	12104	84%	81%	9628	9165	9006	8874	8742	8611	5%	3%	6%
Montville	28316	25314	1708	1294	6%	5%	22194	20515	78%	72%	19192	17511	16923	16434	15944	15454	9%	6%	11%
North Stonington	35158	30445	893	3820	3%	11%	29421	27469	84%	78%	24707	22766	22073	21495	20918	20340	8%	5%	10%
Norwich	18776	16797	1121	857	6%	5%	11045	9963	59%	53%	9066	7923	7545	7231	6916	6602	13%	8%	16%
Plainfield	27561	24244	947	2370	3%	9%	19968	17992	72%	65%	16652	14573	13883	13307	12732	12157	12%	8%	16%
Pomfret	25972	22356	763	2856	3%	11%	19321	18608	74%	72%	15705	14969	14723	14519	14315	14110	5%	3%	5%
Preston	20317	18842	956	519	5%	3%	14889	13937	73%	69%	13414	12417	12092	11822	11551	11280	7%	4%	9%
Putnam	13040	11972	600	467	5%	4%	9467	8498	73%	65%	8399	7402	7065	6784	6504	6223	12%	8%	15%
Salem	19002	16477	454	2069	2%	11%	15804	14989	83%	79%	13280	12457	12181	11951	11722	11492	6%	4%	7%
Scotland	11997	9827	168	2002	1%	17%	9345	9020	78%	75%	7175	6838	6727	6635	6542	6449	5%	3%	5%
Somers	18318	17192	211	915	1%	5%	10438	9406	57%	51%	9311	8247	7894	7600	7306	7012	11%	7%	14%
Sprague	8839	8095	511	232	6%	3%	6834	6496	77%	73%	6090	5731	5609	5508	5406	5305	6%	4%	7%
Stafford	37567	27909	973	8677	3%	23%	32825	31699	87%	84%	23167	21986	21606	21290	20974	20658	5%	3%	6%
Sterling	17477	14733	240	2506	1%	14%	14659	13760	84%	79%	11916	10986	10669	10405	10141	9877	8%	5%	10%
Thompson	31137	27271	1533	2336	5%	8%	24995	23674	80%	76%	21129	19797	19346	18970	18594	18218	6%	4%	8%
Tolland	25739	23079	766	1893	3%	7%	20933	19579	81%	76%	18273	16918	16458	16075	15692	15309	7%	5%	9%
Union	19098	12177	836	6082	4%	32%	17609	17407	92%	91%	10689	10480	10412	10355	10299	10242	2%	1%	2%
Vernon	11601	10240	168	1192	1%	10%	6037	5459	52%	47%	4677	4057	3861	3697	3534	3370	13%	8%	16%
Voluntown	25457	9318	448	15693	2%	62%	23502	22711	92%	89%	7363	6597	6318	6086	5854	5622	10%	7%	14%
Willington	21466	19844	539	1098	3%	5%	17893	17132	83%	80%	16272	15464	15204	14987	14769	14552	5%	3%	6%
Windham	17771	15857	797	1114	4%	6%	11877	10743	67%	60%	9963	8767	8377	8052	7728	7403	12%	7%	15%
Woodstock	39485	36291	1623	1565	4%	4%	29243	28200	74%	71%	26049	24986	24630	24333	24036	23739	4%	2%	5%
Massachusetts																			
Brimfield	22586	18431	498	3654	2%	16%	19718	18555	87%	82%	15563	14296	13875	13523	13171	12820	8%	5%	10%
Brookfield	10613	5879	1153	3579	11%	34%	9340	8904	88%	84%	4605	4145	3998	3876	3754	3632	10%	6%	12%
Charlton	28176	23705	1820	2649	6%	9%	23121	21068	82%	75%	18650	16498	15808	15232	14657	14082	12%	7%	14%
Dudley	14037	11278	842	1915	6%	14%	10206	9470	73%	67%	7448	6688	6438	6231	6023	5815	10%	6%	12%
East Brookfield	6653	5259	983	412	15%	6%	5544	5192	83%	78%	4149	3781	3659	3558	3457	3355	9%	5%	11%
Holland	8375	6956	659	745	8%	9%	7392	7236	88%	86%	5972	5813	5761	5717	5673	5629	3%	2%	3%
Leicester	10460	8009	898	1553	9%	15%	8404	7723	80%	74%	5953	5243	5001	4800	4599	4398	12%	8%	15%
Monson	28673	24751	536	3405	2%	12%	24233	22887	85%	80%	20311	18854	18381	17987	17593	17199	7%	4%	8%
Oxford	17550	15443	1117	990	6%	6%	13091	11574	75%	66%	10984	9383	8871	8444	8017	7590	15%	9%	18%
Southbridge	13215	10025	586	2608	4%	20%	10496	9924	79%	75%	7306	6712	6520	6361	6201	6041	8%	5%	10%
Spencer	12218	7687	925	3605	8%	30%	10010	9317	82%	76%	5479	4744	4502	4300	4098	3897	13%	9%	17%
Sturbridge	24919	14157	1499	9278	6%	37%	21777	20940	87%	84%	11015	10139	9856	9620	9384	9148	8%	5%	9%
Wales	10234	5409	151	4660	1%	46%	9480	9279	93%	91%	4655	4444	4377	4321	4265	4209	5%	3%	5%
Warren	17685	14660	480	2544	3%	14%	15040	14196	85%	80%	12015	11111	10831	10598	10364	10131	8%	4%	8%
Webster	9334	7400	1798	134	19%	1%	6698	5956	72%	64%	4764	3972	3722	3514	3306	3097	17%	10%	21%
Total	1195138	993183	45943	156001	4%	13%	940702	887973	79%	74%	738747	683970	665747	650561	635375	620189	7%	5%	9%

THAMES STUDY AREA HOUSING DATA

	median home sale price			# home sales per square mile			residential building permits per square mile			
	1990	1995	2000	1990	1995	2000	1985	1990	1995	2000
Andover	$ 80,000	$115,500	$136,500	4.1	4.4	4.5	1.8	1.3	1.4	0.9
Ashford	$101,500	$ 68,750	$111,000	2.1	1.7	2.7	0.6	0.6	0.5	0.6
Bolton	$178,500	$110,000	$134,750	3.5	5.8	7.3	3.3	0.3	1.4	1.4
Bozrah	$107,000	$ 93,500	$114,450	1.2	1.7	1.9	0.7	0.5	0.6	0.5
Brimfield	$ 72,500	$ 60,000	$ 77,500	2.3	2.2	2.6		0.6	0.5	0.8
Brookfield	$ 89,900	$ 72,000	$ 98,900	2.5	3.3	6.0		0.0	0.2	0.5
Brooklyn	$100,000	$ 90,000	$112,000	5.0	3.9	5.3	1.4	1.0	0.8	0.9
Canterbury	$115,000	$ 94,000	$115,000	1.6	1.9	2.5		0.3	0.6	0.5
Chaplin	$124,900	$ 75,000	$ 99,750	1.2	2.5	2.6	0.6	0.6	0.0	0.7
Charlton	$105,000	$105,000	$153,500	3.8	4.5	6.7		0.0	1.1	1.9
Colchester	$138,825	$116,500	$135,950	5.1	7.3	6.8	3.5	0.0	2.3	1.9
Columbia	$144,000	$115,000	$137,750	3.0	3.7	6.1	5.9	0.7	1.2	1.1
Coventry	$122,700	$ 85,000	$120,000	5.5	6.3	8.0		1.8	1.3	2.1
Dudley	$100,000	$ 68,000	$125,000	6.2	6.1	10.9	2.0	1.6	2.0	3.6
East Brookfield	$108,000	$ 80,500	$115,500	4.8	4.2	3.8	0.8	0.3	0.1	0.3
East_Haddam	$106,000	$105,000	$137,510	2.8	3.1	5.2		1.1	0.8	1.3
Eastford	$ 75,500	$ 57,000	$ 90,000	0.7	1.2	1.4		0.5	0.3	0.2
Ellington	$140,000	$114,000	$149,900	5.1	5.6	8.9	9.0	1.2	1.4	3.7
Franklin	$147,750	$ 97,000	$129,000	1.4	1.6	1.9	0.8	0.3	0.2	0.5
Griswold	$105,000	$ 84,000	$111,250	4.7	5.1	6.2		1.5	1.4	1.1
Hampton	$ 99,500	$ 49,000	$111,500	1.0	1.6	1.8	0.3	0.4	0.6	0.7
Hebron	$152,000	$112,000	$148,900	3.3	5.4	5.1	3.2	0.5	1.4	1.1
Holland	$ 95,000	$ 77,500	$ 79,000	5.0	3.4	7.3		0.6	0.4	0.7
Killingly	$105,000	$ 80,000	$100,000	5.1	4.9	6.5	2.2	1.1	0.7	0.8
Lebanon	$110,000	$100,000	$110,000	2.4	2.2	2.6	1.3	0.7	0.4	0.8
Ledyard	$131,250	$112,250	$138,000	5.8	5.3	6.9	2.9	0.8	0.8	1.0
Leicester	$ 89,450	$ 89,950	$112,950	5.0	5.6	7.5	1.7	1.8	1.4	1.8
Lisbon	$125,000	$ 91,000	$119,750	2.8	4.6	4.3	2.1	0.8	1.3	1.1
Mansfield	$128,294	$108,000	$126,001	3.2	4.4	5.7	1.1	0.6	1.1	1.0
Marlborough	$157,000	$135,750	$165,000	2.9	4.5	6.3	2.0	0.3	0.9	1.5
Monson	$ 96,000	$ 92,250	$107,000	6.1	6.2	5.8	1.0	0.0	0.8	0.7
Montville	$120,000	$100,000	$119,500	4.6	5.2	8.2	1.8	0.7	1.3	1.8
North_Stoningto	$128,000	$122,000	$134,500	1.0	2.1	2.1		0.4	0.4	0.4
Norwich	$110,000	$ 75,000	$ 97,000	14.4	15.1	18.5	2.2	6.5	0.7	1.0
Oxford	$100,000	$ 88,750	$117,750	8.5	6.9	11.5	2.2		2.3	2.0
Plainfield	$100,000	$ 82,350	$ 97,000	4.6	4.8	7.8	1.6	1.2	1.1	2.0
Pomfret	$105,250	$103,870	$116,500	1.7	1.9	1.5	0.9	0.7	0.5	0.6
Preston	$105,000	$ 90,000	$125,000	1.7	2.5	2.9	1.0	0.4	0.7	0.6
Putnam	$100,000	$ 79,950	$ 91,750	7.4	7.1	7.8	1.7	0.5	0.8	0.6
Salem	$ 56,392	$143,000	$137,450	3.3	3.1	2.6	1.7	0.7	0.9	0.6
Scotland	$ 57,500	$ 38,500	$110,000	1.9	1.7	2.3	0.5	0.4	0.5	0.4
Somers	$178,000	$139,500	$140,000	4.3	4.2	6.9	1.6	0.7	0.6	2.0
Southbridge	$ 88,000	$ 76,900	$101,000	7.5	9.0	12.0	4.3	1.0	0.9	1.1
Spencer	$105,000	$ 83,000	$114,950	4.6	4.5	6.7		0.7	2.9	1.0
Sprague	$115,000	$ 71,000	$ 88,250	1.8	2.5	2.6	0.7	0.3	0.2	0.2
Stafford	$115,000	$ 85,000	$ 98,000	3.6	3.2	4.9	2.2	1.1	0.5	0.7
Sterling	$ 87,450	$ 63,700	$112,000	2.9	2.6	3.0	0.9	1.7	0.8	0.6
Sturbridge	$116,640	$105,000	$139,900	3.4	4.0	6.5	3.6	0.7	0.7	1.8
Thompson	$ 86,200	$ 75,000	$ 99,000	3.1	2.9	3.7	1.1	0.8	0.5	0.5
Tolland	$152,025	$122,200	$160,000	4.3	6.8	9.1	2.7	0.8	2.1	3.8
Union	$128,000	$ 35,000	$ 89,900	0.5	0.4	0.8	0.1	0.1	0.3	0.2
Vernon	$129,900	$106,250	$120,750	20.5	19.4	30.7	18.6	1.7	1.0	3.4
Voluntown	$106,500	$ 76,000	$114,950	1.1	1.4	1.5	0.5	0.5	0.5	0.4
Wales	$ 60,000	$ 65,302	$ 77,000	2.9	1.9	2.8			0.4	0.4
Warren	$ 75,000	$ 58,621	$ 88,750	3.2	3.1	3.4	1.3	1.8	0.5	0.0
Webster	$100,000	$ 84,500	$110,000	15.8	14.6	22.4	5.9	3.4	1.8	2.9
Willington	$136,000	$111,750	$124,250	2.2	2.4	3.1	1.8	0.6	0.4	0.5
Windham	$114,900	$ 77,000	$ 90,000	6.8	7.5	11.1	1.2	1.1	0.4	0.2
Woodstock	$ 89,900	$ 86,000	$108,000	3.2	2.7	3.3	1.2	0.8	0.4	0.8

THAMES STUDY AREA LABOR FORCE DATA

	Labor Force				Unemployment Rate (%)			
	1985	1990	1995	2000	1985	1990	1995	2000
Andover	1,410	1,577	1,511	1,650	3.6	4.4	4.9	1.6
Ashford	1,824	2,229	2,126	2,178	2.7	3.9	5.6	1.7
Bolton	2,458	2,857	2,650	2,747	3.5	3.2	4.5	1.5
Bozrah	1,350	1,419	1,451	1,464	4.5	6.6	5.2	2
Brimfield	1,115	1,462	1,615	1,541	4.2	5.7	6	3
Brookfield	1,249	1,508	1,416	1,412	4.3	6.6	4.7	2.7
Brooklyn	3,360	3,640	3,756	3,972	4.6	6.2	5.6	2
Canterbury	1,959	2,555	2,635	2,784	6.4	6.8	5.8	2.1
Chaplin	962	1,178	1,145	1,201	3.1	4.4	5.2	1.3
Charlton	3,314	5,208	5,310	5,462	4.8	5.8	5.8	2.7
Colchester	4,475	6,367	6,438	6,733	4.6	5.5	5.7	1.9
Columbia	2,095	2,705	2,581	2,691	4.2	3.6	4.6	1.4
Coventry	5,281	6,114	5,957	6,202	4.3	4.5	5.4	1.8
Dudley	4,645	5,201	5,068	4,898	3.1	6.2	4.8	2.9
East Brookfield	953	1,056	1,014	1,008	3.5	6.4	5.6	3.5
East Haddam	3,117	3,971	3,961	4,165	4	4.1	6.1	2.1
Eastford	583	760	821	898	3.8	4.2	5.1	1.7
Ellington	5,863	7,091	6,641	6,961	3.6	3.6	4.7	2.1
Franklin	1,077	1,080	1,101	1,102	5.2	4.6	4.5	1.5
Griswold	5,143	5,496	5,630	5,827	5.7	6.8	5.7	2.5
Hampton	781	1,011	1,033	1,133	4.5	4.1	4.5	2.1
Hebron	3,449	4,149	4,093	4,421	3.5	4	5	1.6
Holland	741	1,140	1,032	1,005	4	4.6	5.4	4.1
Killingly	8,167	8,889	8,891	8,644	8.5	9.6	7.9	4.2
Lebanon	2,646	3,552	3,389	3,364	3.5	4.9	6	2.1
Ledyard	7,070	7,884	7,960	8,092	3.4	3.8	3.9	1.6
Leicester	4,854	5,652	5,571	5,622	3.7	6	5.5	2.8
Lisbon	1,919	2,130	2,207	2,255	4	6.1	5.8	2.2
Mansfield	9,097	10,952	8,932	9,238	1.8	3.1	3.3	1.3
Marlborough	2,801	3,199	2,991	3,096	2.5	3.5	4.5	1.5
Monson	3,392	3,870	3,777	3,794	4.1	6	6.6	3
Montville	9,151	9,461	9,775	9,798	4.9	6.3	5.5	2.1
North Stonington	2,366	2,769	2,819	2,943	4.2	5.2	3.9	1.9
Norwich	20,401	19,356	18,975	18,876	6	7	6.2	2.9
Oxford	5,888	6,715	6,644	6,758	5	7	5.7	3
Plainfield	6,643	7,747	7,855	8,676	8.4	8.5	7.3	2.8
Pomfret	1,637	1,849	1,976	2,182	4.3	5.5	5.4	2
Preston	2,335	2,677	2,756	2,578	1.5	4.5	4.6	2
Putnam	4,522	4,658	4,557	4,822	7.7	9.3	7.4	3
Salem	1,508	1,936	2,066	2,055	4.3	6	6	1.8
Scotland	563	722	809	888	2.3	5.4	4.4	1.4
Somers	4,178	4,274	3,996	4,119	3.7	4	4.9	1.8
Southbridge	7,691	8,755	8,332	8,098	3.8	7.4	6.2	3.3
Spencer	5,314	6,093	6,069	6,197	3.4	6.2	5.4	2.6
Sprague	1,742	1,683	1,687	1,675	6.3	7.7	6.9	3.3
Stafford	5,276	6,100	5,761	5,896	5.9	5.4	6.4	2
Sterling	906	1,328	1,509	1,635	8.2	8.5	7.9	2.6
Sturbridge	2,945	4,242	4,151	4,218	5.6	5.4	4.3	2.3
Thompson	4,648	4,729	4,619	4,612	8.9	8.3	5.7	2.9
Tolland	5,929	6,778	6,657	7,201	3.4	3.2	4.4	1.3
Union	311	369	381	407	1	4.6	3.4	2.2
Vernon	16,404	18,440	16,604	16,592	4.4	4.8	5.5	1.8
Voluntown	892	1,265	1,308	1,380	8.9	8.7	8.4	3.2
Wales	523	852	894	833	8	6.9	5.3	3.8
Warren	1,556	2,281	2,462	2,368	3.4	6	5.1	3.3
Webster	7,068	8,401	8,037	8,110	4.9	7.8	6.1	3.4
Willington	2,815	3,823	3,524	3,484	3.2	3.8	4.6	1.5
Windham	11,139	11,322	10,341	10,115	6.6	5.8	7.6	3.1
Woodstock	2,962	3,400	3,630	4,001	4.4	5.2	4.3	1.9
Total	234,463	267,927	260,897	266,077				
Average					5%	6%	5%	2%

THAMES STUDY AREA POPULATION DATA

Town	Population 1990	Population 2000		Population change 1990 - 2000	% Population Change
Andover	2,612	3,066		455	17.4%
Ashford	3,816	4,073		258	6.8%
Bolton	4,685	5,031		346	7.4%
Bozrah	2,293	2,280		-13	-0.6%
Brimfield	3,027	3,343		316	10.4%
Brookfield	3,149	3,062		-87	-2.8%
Brooklyn	6,706	7,124		418	6.2%
Canterbury	4,518	4,724		206	4.6%
Chaplin	2,095	2,289		194	9.2%
Charlton	9,819	11,276		1457	14.8%
Colchester	11,145	14,537		3392	30.4%
Columbia	4,651	4,976		324	7.0%
Coventry	10,243	11,517		1273	12.4%
Dudley	9,878	9,969		91	0.9%
East Brookfield	2,166	2,096		-70	-3.2%
East Haddam	6,945	8,289		1344	19.4%
Eastford	1,352	1,630		278	20.6%
Ellington	11,347	12,848		1501	13.2%
Franklin	1,809	1,812		3	0.1%
Griswold	10,995	10,787		-208	-1.9%
Hampton	1,602	1,764		163	10.2%
Hebron	7,131	8,651		1520	21.3%
Holland	2,302	2,409		107	4.7%
Killingly	16,409	16,646		237	1.4%
Lebanon	6,132	6,923		791	12.9%
Ledyard	15,481	14,649		-833	-5.4%
Leicester	10,110	9,574		-536	-5.3%
Lisbon	3,905	4,096		191	4.9%
Mansfield	22,026	21,349		-677	-3.1%
Marlborough	5,553	5,733		180	3.2%
Monson	7,894	8,381		487	6.2%
Montville	17,567	18,544		977	5.6%
North Stonington	4,996	5,007		11	0.2%
Norwich	38,642	35,951		-2691	-7.0%
Oxford	13,015	13,378		363	2.8%
Plainfield	14,607	14,659		52	0.4%
Pomfret	3,132	3,782		649	20.7%
Preston	5,299	4,795		-504	-9.5%
Putnam	9,049	8,987		-61	-0.7%
Salem	3,380	3,817		437	12.9%
Scotland	1,263	1,574		311	24.6%
Somers	9,262	10,707		1445	15.6%
Southbridge	18,294	17,205		-1089	-6.0%
Spencer	9,815	9,272		-542	-5.5%
Sprague	3,161	2,985		-176	-5.6%
Stafford	11,229	11,312		83	0.7%
Sterling	2,394	3,079		685	28.6%
Sturbridge	8,074	7,842		-232	-2.9%
Thompson	9,213	9,076		-137	-1.5%
Tolland	11,161	13,148		1987	17.8%
Union	655	716		61	9.3%
Vernon	30,584	28,269		-2316	-7.6%
Voluntown	2,128	2,533		405	19.0%
Wales	1,564	1,733		169	10.8%
Warren	4,411	4,816		405	9.2%
Webster	19,025	16,253		-2772	-14.6%
Willington	6,075	6,004		-71	-1.2%
Windham	22,725	22,825		100	0.4%
Woodstock	6,085	7,171		1086	17.8%
Total	498,598	510,342		11744	2.4%