Land Cover Change and Ecosystem Services on the North Carolina Piedmont 1985 to 2005

by

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Abstract

Analyses of ecosystem processes are advanced through remote sensing and geostatistical modeling methods capable of capturing landscape pattern over broad spatial and temporal scales. Many ecological studies rely on land cover data classified from satellite imagery. In this, changes in land cover are often presumed to correlate with changes in ecosystem processes or services provided by ecosystems (e.g., watershed protection). Documenting changes in land cover requires that images be classified over time, often using historical images to document landscape change. But this is difficult to do for historical images because we cannot ground-truth old images, lacking actual land cover data from the past. I developed a land cover classification scheme using a classification and regression tree (CART) model generated from 2001 National Land Cover Dataset (NLCD) and Summer, Fall, and Winter triplets of Landsat 5 Thematic Mapper (TM) imagery. The model is robust to inter-annual variability in surface reflectance, and thus can be extended in time to classify land cover from images from any time, past or future. The model was used to predict land cover from 1985 to 2005, for a study region in the Piedmont of North Carolina. Temporal and spatial analyses focused on ecosystem services of carbon sequestration and biodiversity support as affected by forest fragmentation. This study offers a landscape-level identification of the relationships between spatial and temporal development patterns and the provision of ecosystem services. The project also represents the creation of a multi-annual land cover classification dataset of which few exist, thus providing a framework for further studies of landscape pattern and ecological processes.

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Acknowledgements

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Introduction

The effects of landscape pattern on ecological processes have long been recognized by scientists and reserve managers as crucial to understanding how such processes function on moderate and large scales (Turner, 1989; Hobbs, 1997). Identifying pattern in terms of process, and vice-versa, on a landscape, requires analyses at the correct spatial and temporal scale. Focusing on landscape-level ecological processes, monitoring becomes an essential task where field studies are not feasible and where change may take many years to become evident (Baker 1989).

This project focuses first on the task of quantifying the type of land cover change in the study area, and second on linking to and translating such change into calculations of ecosystem services either rendered or lost over time on the landscape. The most common definition of ecosystem services is that of Costanza et al. (1998): “the benefits human populations derive, directly or indirectly, from ecosystem functions”. Costanza, et al. list seventeen classes of ecosystem services, including air filtering (gas regulation), micro-climate regulation, noise reduction (disturbance regulation), rainwater drainage (water regulation), sewage treatment (waste treatment) and recreational / cultural values (Costanza, 1998; Bolund & Hunhammar, 1999). Recently, the provision of ecosystem services has emerged as a major focus of conservation and landscape assessments (Daily et al. 1997, NRC 2004, MEA 2005, Chan et al. 2006).

Certain elements of the landscape manifest the means of quantifying the total value of any given service, such as street trees, lawns / parks, urban forests, cultivated land, wetlands, lakes / sea, and streams for an urban environment (Bolund & Hunhammar, 1999). In many studies, such land cover elements are the land cover classes determined by the United States Geological Survey’s (USGS) 2001 National Land Cover Dataset (2001 NLCD). Seeking landscape elements connected with actual environmental services as the focus of the study, land cover change is used as the lens for scrutinizing such elements with respect to ecosystem services. That is, changes in land cover or land use are assumed to be associated with changes in the potential provision of ecosystem services. Environmental effects of land cover change that are considered and quantified as valuable services either lost from or provided by the environment include: the loss of environmentally fragile lands, reduced regional open space, greater air pollution, higher energy consumption, decreased aesthetic appeal of the landscape, loss of farmland, reduced biodiversity, increased runoff of storm water, increased risk of flooding, excessive removal of native vegetation, loss of carbon sequestration potential, monotonous and regionally inappropriate residential visual environment, absence of mountain views, urban heat islands, and ecosystem fragmentation (Johnson, 2001). Of those negative environmental effects caused by land cover and land use change, several are selected as being most appropriate to the study data and as those of interest to the project's clients.

This project is part of a larger, on-going study of the causes and consequences of landscape change in the Piedmont of North Carolina. The ecosystem services of interest are biodiversity support potential (especially forest wildlife), watershed protection, and carbon sequestration potential. The dominant land cover change on the study area is one of simultaneous afforestation and abandonment of farmland, along with an outward growth of urban and especially exurban areas (Noss, 1999). In addition to quantifying land cover change, this study provides a preliminary assessment of changes in biodiversity support and carbon sequestration potential as ecosystem services rendered from forest patches. This study will consider biodiversity support as a function of existing habitat and will therefore analyze the dynamics of forest fragmentation, or the breaking up of a habitat into smaller parcels over time (Forman, 1997; Fahrig, 2003). As studies of fragmentation have been criticized for their erroneous focus on the patch scale rather than on the landscape scale, this project offers a landscape-scale approach to understanding fragmentation (Fahrig, 2003).

Carbon sequestration potential of forest patches is estimated in terms of carbon represented by forest type and stand age. The flow of carbon throughout forest ecosystems to long term storage in wood and soil organic matter varies across forests of different ages, types, management regimes, and climates (Luyssaert, et al. 2007). However, forest carbon sequestration represents an important role in the global carbon cycle and an important factor in global climate change (Luyssaert, et al. 2007). This study seeks to take advantage of the long term land cover classification to look specifically at the amount of carbon sequestered over time and analyze sequestration trends by scaling up existing carbon estimations to the scale of the study area. In this study area, the dynamic of interest is the balance of small-scale afforestation (and hence carbon sinks) from the abandonment of agriculture, relative to the loss of forest (hence carbon sources) resulting from development.

The primary challenge of the study is to develop a time series of land cover maps, taking advantage of the rich historical archive of Landsat Thematic Mapper (TM) images available for the study area. Land cover is classified by capitalizing on correlations between land cover classes and the spectral signatures of satellite imagery. To extend the land cover classification to older images is difficult, because we typically lack ground data on actual land cover in the past (e.g, before a parcel was developed). Thus, the only alternative is to develop a classification based on current imagery and land cover, and then extend this classification to other time periods. This requires a model that is robust enough to overcome image noise and phenological differences over time, that is, applying the spectral signatures developed from one image to other images—the so-called signature extension problem (Botkin, 1989).

Objectives

My primary task in this project has been to develop a classification model capable of back-casting to previous years and also forecasting into the future, and to demonstrate the use of these classified data in applications concerned with the provision of ecosystem services. Specifically, I had three objectives:

(1) To develop a model to classify land cover from satellite imagery, with the aim of reproducing the 2001 National Land Cover Dataset data product;

(2) To extend this classification to images from 1985, 1990, 1995, and 2005.

(3) To demonstrate the use of this land cover time series to explore hypotheses about the provision of ecosystem services, focusing on biodiversity support potential as influenced by forest habitat fragmentation and carbon sequestration potential.

In this context, the primary concern in this project is the land cover classification model, with analyses of ecosystem services being more of a proof-of-concept. The classification model is important because, once robust methods have been codified, our approach can be extended to other regions over the rich archive of Thematic Mapper imagery. Likewise, the land cover time series represents a data infrastructure that can support a variety of further studies of the ecological consequences of landscape change.

Study Area

The study area for the project is 1.66 million hectares on the Piedmont Plateau of North Carolina at the intersection of Path 16 / Row 35 as defined by the Landsat World Reference System (WRS-2). The scene area was then clipped to county boundaries, including all or part of 13 counties (Figure 1). The NC Piedmont is characterized by extensive pine forests established in farm fields abandoned early in the twentieth century, which are succeeding naturally to hardwood dominance as well as being converted to suburbs around metropolitan centers. Piedmont soils are spatially complex, but the region’s topography is characterized by gentle relief, with broad river valleys draining extensive uplands. Phenologically, the area’s agricultural fields and pastures begin “greening up” in late March, with the deciduous forests following throughout the month of April. Responding variously to drought, storms, day-length, temperature (and ultimately harvest for crops), onset of winter senescence ranges from early September to early December. Over the past few decades, this area has been experiencing dramatic rates of development (North Carolina State Demographics). In particular, the Triangle region—framed by the cities of Raleigh, Durham, and Chapel Hill—has undergone explosive growth since the 1970s, a period captured almost in its entirety in the Landsat mission. The two dynamics of localized afforestation and equally localized development make the Triangle an ideal test case for exploring spatial patterns of landscape change and the ecological implications of this change.

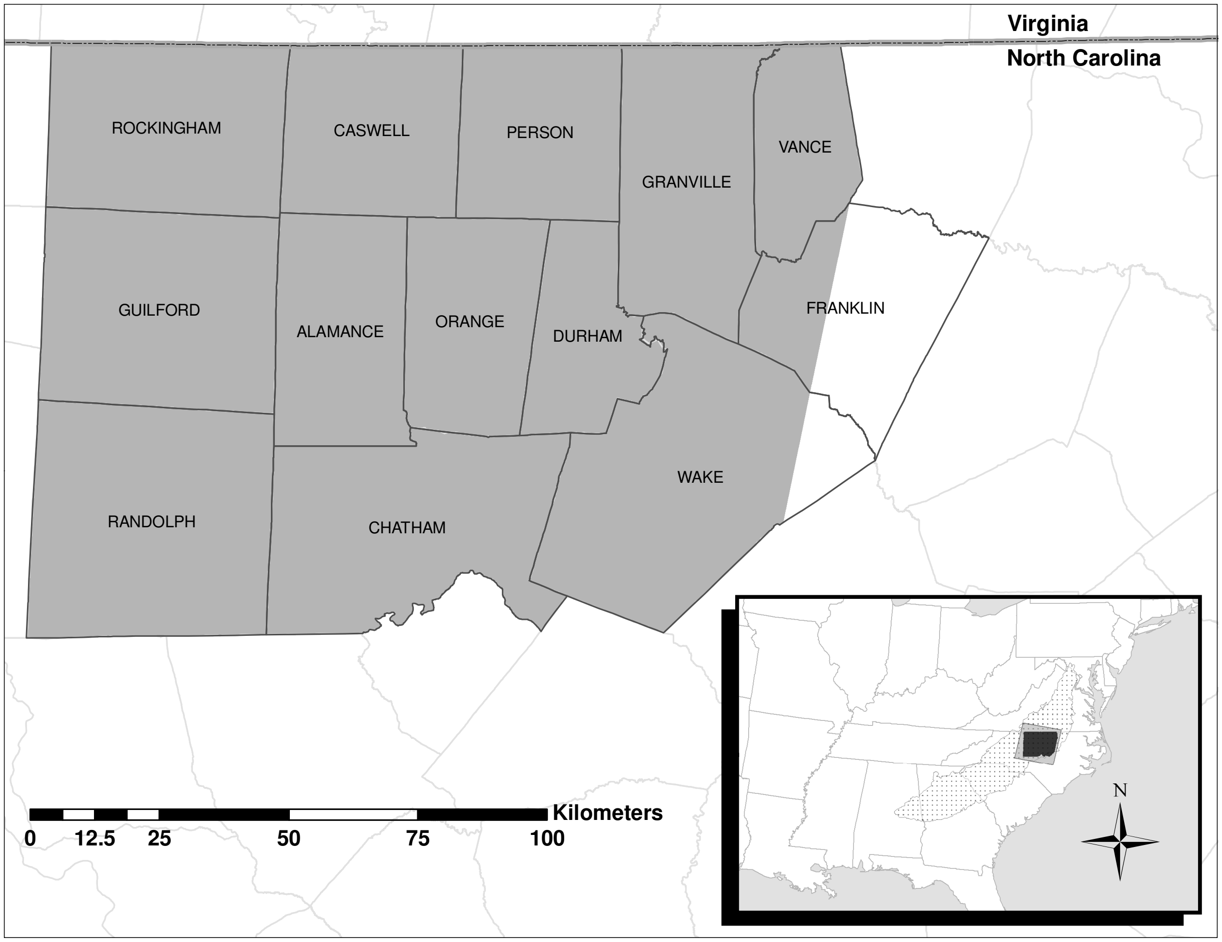
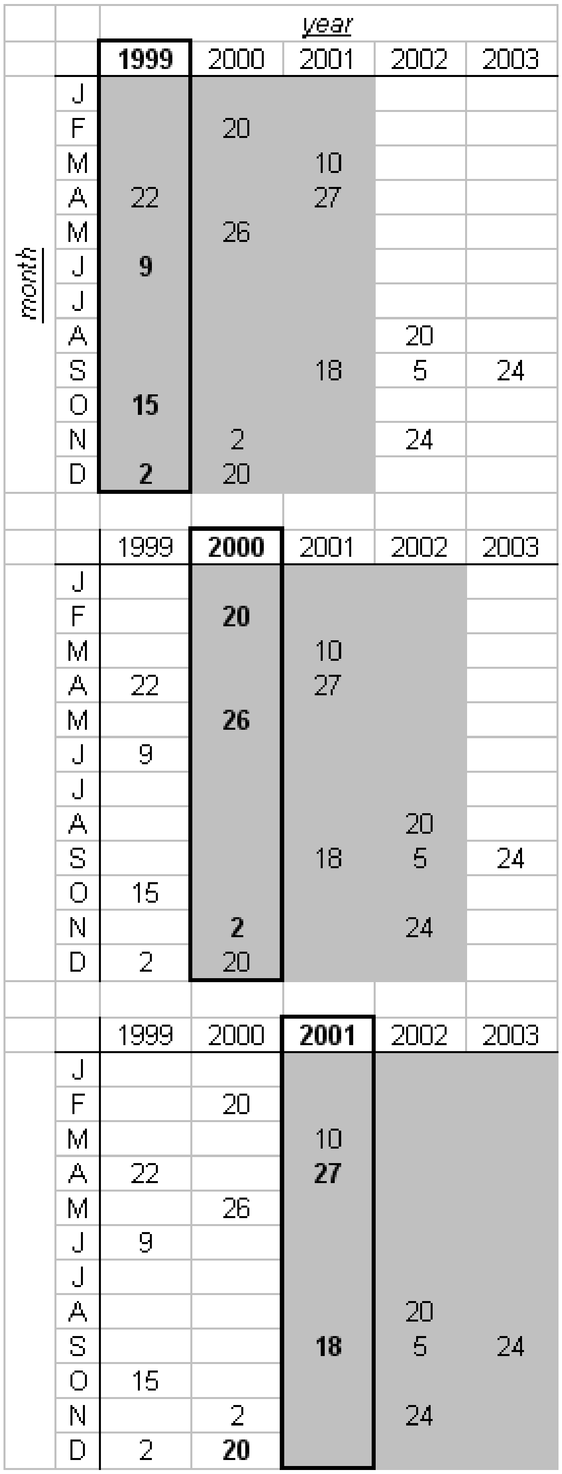


Figure 1. The study area, encompassing parts of 13 counties in North Carolina intersecting Path 16 / Row 35 of the Landsat World Reference System.

Table 1a. Project imagery: Training images (Bold font indicates extrapolation year and base extrapolation imagery; shaded area indicates imagery used to calculate subsequent vegetation index.

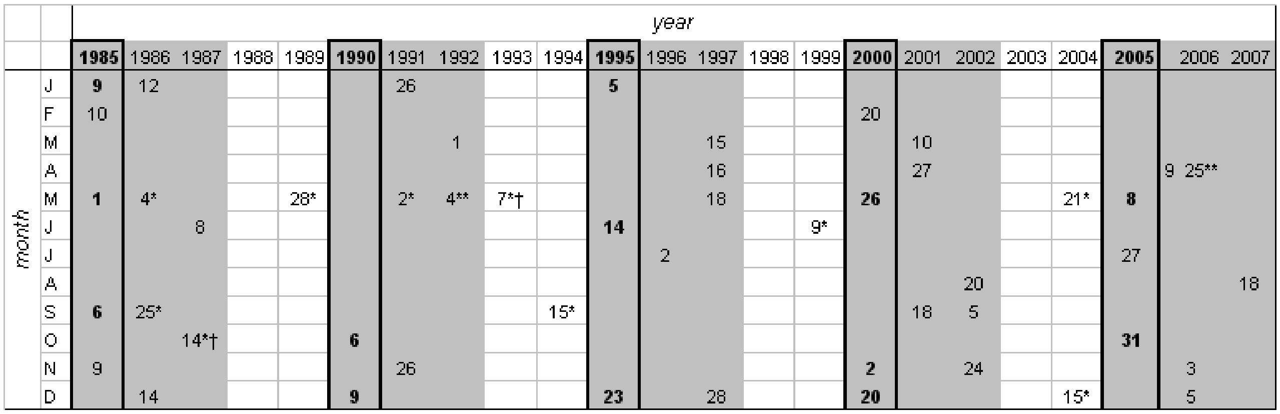


		year				
		1999	2000	2001	2002	2003
month	J					
	F		20			
	M			10		
	A	22		27		
	M		26			
	J	**9**				
	J					
	A				20	
	S			18	5	24
	O	**15**				
	N		2		24	
	D	**2**	20			

		1999	**2000**	2001	2002	2003
	J					
	F		**20**			
	M			10		
	A	22		27		
	M		**26**			
	J	9				
	J					
	A				20	
	S			18	5	24
	O	15				
	N		**2**		24	
	D	2	20			

		1999	2000	**2001**	2002	2003
	J					
	F		20			
	M			10		
	A	22		**27**		
	M		26			
	J	9				
	J					
	A				20	
	S			**18**	5	24
	O	15				
	N		2		24	
	D	2	**20**			

Table 1b. Project imagery: Extrapolation images Project imagery: Training images (Bold font indicates extrapolation year and base extrapolation imagery; shaded area indicates imagery used to calculate subsequent vegetation index; one star indicates imagery used to cloud-fill base imagery; two stars indicates imagery used to fill base imagery if initial filling was insufficient)(† 1987.10.14 used as primary filler for Fall 1990 image; † 1993.05.07 used as primary filler for Summer 1995 image)



		year																					
		1985	1986	1987	1988	1989	**1990**	1991	1992	1993	1994	**1995**	1996	1997	1998	1999	**2000**	2001	2002	2003	2004	**2005**	2006	2007
month	J	**9**	12					26				**5**												
	F	10															20							
	M								1					15				10						
	A													16				27					9 25**	
	M	**1**	4*			28*		2*	4**	7*†				18			**26**				21*	**8**		
	J			8								**14**				9*								
	J												2									27		
	A																		20					18
	S	**6**	25*								15*							18	5					
	O			14*†			**6**															**31**		
	N	9						26									**2**		24				3	
	D		14				**9**					**23**		28			**20**				15*		5	

Methods

Image Acquisition

Nine TM images were used to train the land cover classification model in Summer / Winter / Fall triplets: 06/09/99, 10/15/99, and 12/02/99; 05/26/00, 11/02/00, and 02/20/00; and 4/27/01, 09/18/01, and 12/20/00. Forty-three (for a total of fifty project images) additional TM images were used to calculate the subsequent vegetation indices, cloud-filling, and for extrapolation of the model (Table 1). All images were geometrically corrected to a mosaic of one meter resolution digital aerial photographs with a first-order polynomial transformation and nearest-neighbor resampling, radiometrically corrected to at-surface radiances applying the methods of Chander and Markham (2003), adjusted for sensor degradation using the methods of Teillet, et al. (2004), and finally atmospherically-corrected using the DOS3 Dark Object Subtraction approach (Song et al. 2003). Clouds and snow are also removed as appropriate.

Photo-interpreted (using 1999 aerial photography) training data developed by the USGS for the 2001 NLCD for the study area were made available to the project (Homer, et al., 2004). Data were provided in the form of several raster layers, with land cover data points spread across approximately 5 km^2 patches. The data points are composed of ten land cover classes excluding impervious surfaces. The impervious surfaces raster was provided on a continuous 0-100% scale, which was originally trained with per-pixel estimates of impervious surfaces using one-meter resolution orthophoto quadrangles calibrated input to a classification tree model (Homer, et al., 2004). Due to a small sample size of land cover points (excluding impervious surfaces data), USGS training data were set aside to be used for model validation. Training data were instead derived from the 2001 NLCD classification itself. This process is discussed below.

Data used for the 1999 and 2005 validations were interpreted from 1-foot resolution natural color (RGB) orthophotos acquired over Wake County in March 1999 and February 2005. Approximately 1000 (~100 / land cover class) points were randomly selected from model extrapolations for 1999 and 2005 after applying a 3x3-pixel focal variety filter. Identification of land cover category at these points was according to the 2001 NLCD class descriptions (Homer et al., 2004).

Model Development

Options for modeling landscape change include statistical models, geospatial models, and hybrid models. The current project methods are a combination of remote sensing analysis, statistical Classification and Regression Tree (CART) modeling, and GIS analysis. Remote sensing enables the use of unique spectral signatures of different terrestrial elements recorded by sensors mounted on airplanes or satellites for land cover classification and interpolation to digital maps. Classification accuracy is improved using CART statistical modeling. Finally, GIS provides a convenient platform for a variety of spatial data and associated analyses.

The classification model was developed in several steps, including the development of the training data, data preparation for input to a CART model, comparing alternative (competing) models to select the most robust and predictive version, and validation of this model (Figure 2).

Methods presented are solely those selected for the development of the land cover classification. A short discussion of additional methods attempted and ultimately rejected is included in the discussion.

Data Preparation

The initial tasks of the study were to develop a set of land cover observations to train the classification, and to select suitable imagery. Triplets of Summer, Fall, and Winter imagery were selected to represent intra-annual phenological variation from Spring green-up, to Fall senescence, to Winter die-off. Including multi-seasonal variation within the training data should thus create more robust spectral signatures for each class, which should provide more stable classifications over time. The three pairs of study images were chosen from the years 1999 to 2001 to match with the 2001 NLCD training data and classification. Tasseled-cap (TC) transformed versions of the images (Kauth & Thomas 1976) were used instead of the raw Landsat TM bands as data exploration suggested a more stable relationship between TC greenness (band two) and phenological changes than either the raw TM greenness band or the normalized difference vegetation index (NDVI).

The project training sample was formed by converting the 2001 NLCD classification to data points. To buffer against spatial misregistration between training data and land cover, training data were filtered using a moving five-by-five window to select points within homogeneous land cover zones. A goal of one thousand data points for each class was arbitrarily established as representing a sufficiently large number of observations for each class. A number of 2001 NLCD land cover classes were also removed from the projects training sample for three reasons. First, “barren land” (class 31) and “mixed forest” (class 43) could not be predicted well, and thus were removed. Second, “shrubland” (class 52) and “grassland” (class 71) were determined not to exist in the study area, and thus adding confusion to more realistic land cover classes of the study area. The two classes were therefore appropriately removed. Finally, the developed open space (class 21) was deemed meaningless in the current project. It was used in the 2001 NLCD as a non-urban class within the masked urban areas, and thus ought to be classified as an existing, non-urban land cover class. Therefore, the training sample included nine land cover classes: Water (11), low density urban (22), medium density urban (23), high density urban (24), deciduous forest (41), evergreen forest (42), pasture / hay (81), cultivated row crops (82), and woody wetlands (90). Training data were next filtered by a mask of all occurrences of clouds and snow both in the nine images 1999 to 2001 as well as for those used to calculate the subsequent vegetation index, discussed below. Additionally, since the inter-annual training methods to be discussed next assume no land cover change from 1999 to 2001, input images were screened for land cover changes by subtracting the first Principal Component (PC1) of the 1999 winter image from that of the 2001 winter image and removing pixels whose PC1 difference exceeded 3 standard deviations from the mean PC1 difference; this effectively censored training points that had changed over that time perio. Creation and filtering of the training data was completed using ESRI ArcGis 9.2 (ESRI, Redlands, CA).

Subsequent vegetation index (SVI). In preliminary classifications, phonological differences across image dates confounded efforts to distinguish among land cover types with contrasting phenological variability. To remedy this, we developed an index referred to as a "subsequent vegetation". SVI is a calculation of a maximum "greenness" value for a pixel among a group of images over a period of time. "Greenness" can be understood either as the raw TM band three, TC transformed band two, the normalized difference vegetation index (NDVI), or the enhanced vegetation index (EVI). The maximum value was recorded over a period of time to gain separability of those land cover classes that either change very little in greenness over time, such as urban classes, or those land cover classes that exhibit different levels of greenness depending on a specific time of the year, such as agricultural land cover. Specifically, the hope was that pixels typically very similar radiometrically in terms of their brightness values, such as agricultural fields and urban areas, can be separated as an agricultural field will be more likely to green-up over a period of time than an urban area. This project selected a three-year window as it best suited available imagery. SVI is calculated in Arc using a focal maximum tool.

Fitting the model: CART model creation and evaluation

We used classification and regression tree (CART) models to classify land cover types. CART presents a statistical technique suited for exploring and modeling large amounts of complex data, such as ecological data (Brieman, et al. 1984; De'Ath, et al. 2000). Trees explain the variation of a single response variable, which can be either categorical (classification) or numerical (regression) by one or more explanatory variables, which can also be either categorical or numerical (Brieman, et al. 1984; De'Ath, et al. 2000). The tree is constructed by splitting the data into two mutually exclusive groups at each node, a process which continues recursively in increasingly homogeneous partitions of the data.

In this case, we used CART to classify multinomial land cover classes (11 classes) in terms of breaks in the spectral data. Spectral extension was achieved by including the training data for all selected bands for all three years 1999-2001 simultaneously, which effectively incorporates inter-annual variability in the model-fitting process, forcing the CART to avoid using spectral variables with excessive inter-annual variation. The selected model used TC bands one to three, corresponding to brightness, greenness, and wetness, as well as an SVI of maximum NDVI values, which is also treated as a band. An SVI using NDVI was favored over an SVI using TC greenness because the NDVI variable was determined to better capture greenness. Thus, the model is fit by linking each land cover observation (~9000 per year, or ~27,000 total) to three seasons of spectral data, as well as to the SVI band, for a total of ten predictor variables and nine corresponding response variables, or land cover classes. This project uses the CART library *rpart* (Therneau & Atkinson, 2007) in the R Statistical Software package (R Core Developemnt Team, 2007).

Initial model validation using the 2001 NLCD as truth was an important initial baseline for evaluating each CART model. However, the logic of the CART, or which predictor variables split each class, was also considered. Extrapolating the model classification to additional years and considering the results of aerial truth validation were further factors used to evaluate the model.

Validation

Three model validations were performed by comparison of model predictions to: (1) NLCD 2001 estimates (model verification), (2) photo-interpreted land cover points used to train the NLCD 2001 land cover model, and (3) land cover points interpreted from aerial orthophotos acquired over Wake County in 1999 and in 2005. To minimize the effect of spatial misregistration on the 1999 and 2005 validations, a three by three cell focal variety filter was applied to the predicted classification, removing all pixels for which the count of land cover classes inside the moving window was greater than one.

Model extrapolation 1985 to 2005

Applying the CART outputs, the spectral thresholds corresponding to each land cover class, the classification is mapped in Arc. Spring, Fall, and Winter image triplets are selected for each model extrapolation year, and cloud-filled as appropriate with temporally similar imagery. SVI is also calculated for each extrapolation year using all available imagery. The years 1985, 1990, 2000, and 2005 are mapped. It was determined that sufficient imagery was not available for the year 1995, and the year is therefore not included in the study.

Ecosystem services

Biodiversity support / Fragmentation

The metrics calculated to quantify biodiversity support services rendered in the study area are based around the level of forest fragmentation over time. This application relied on ArcGIS to first create a mask of forest fragments over time, and Fragstats (McGarigal et al. 2002) to calculate a variety of landscape metrics, to make inferences to habitat loss or gain across the study area. Specifically, Durham County was targeted as a demonstation, as summarizing habitat pattern over the entire study area would average the results from highly developed areas along with relatively stable rural areas. As this illustration was intended as a proof-of-concept, the analysis can be revisited later in a more spatially nuanced manner.

To index habitat connectivity, I computed correlation length for forest cover types by year, and related this to total area of developed (urban) land cover at each time. Correlation length is a composite index based on patch size and shape; it summarize the effective traversability of habitat in the study area (Keitt et al. 1997). The distribution of patch sizes by year for Durham County was also tallied, as this distribution (especially the largest patches) has implications for population processes in habitat mosaics (Gardner et al. 1987, With and King 1997).

Carbon sequestration potential

A second application of the data is that of determining the amount of carbon within the study area and the change of carbon over time. The quantity of carbon *in situ* within the forest land cover types of the study area is estimated using data from the USDA Forest Service Forest Carbon Dynamics and Estimation for Sustainable Management project (Smith et al 2006). FORCARB has assembled forest ecosystem carbon yield tables which represent stand-level merchantable volume and carbon pools as a function of stand age (Smith et al. 2006).

FORCARB tables were developed for fifty-one forest types within ten regions of the United States, and this study selects three different forest types of the Southeast (Smith et al. 2006). By appending these tables with forest area data, the amount of carbon represented in the landscape is estimated. Due to the large study area, selecting a single forest type and age is impossible. Therefore, three forest compositions with associated stand ages, loblolly / short leaf pine, oak / pine, and oak / gum / cypress, are calculated in this report.

Forest area was calculated from each model extrapolation in ArcGIS.

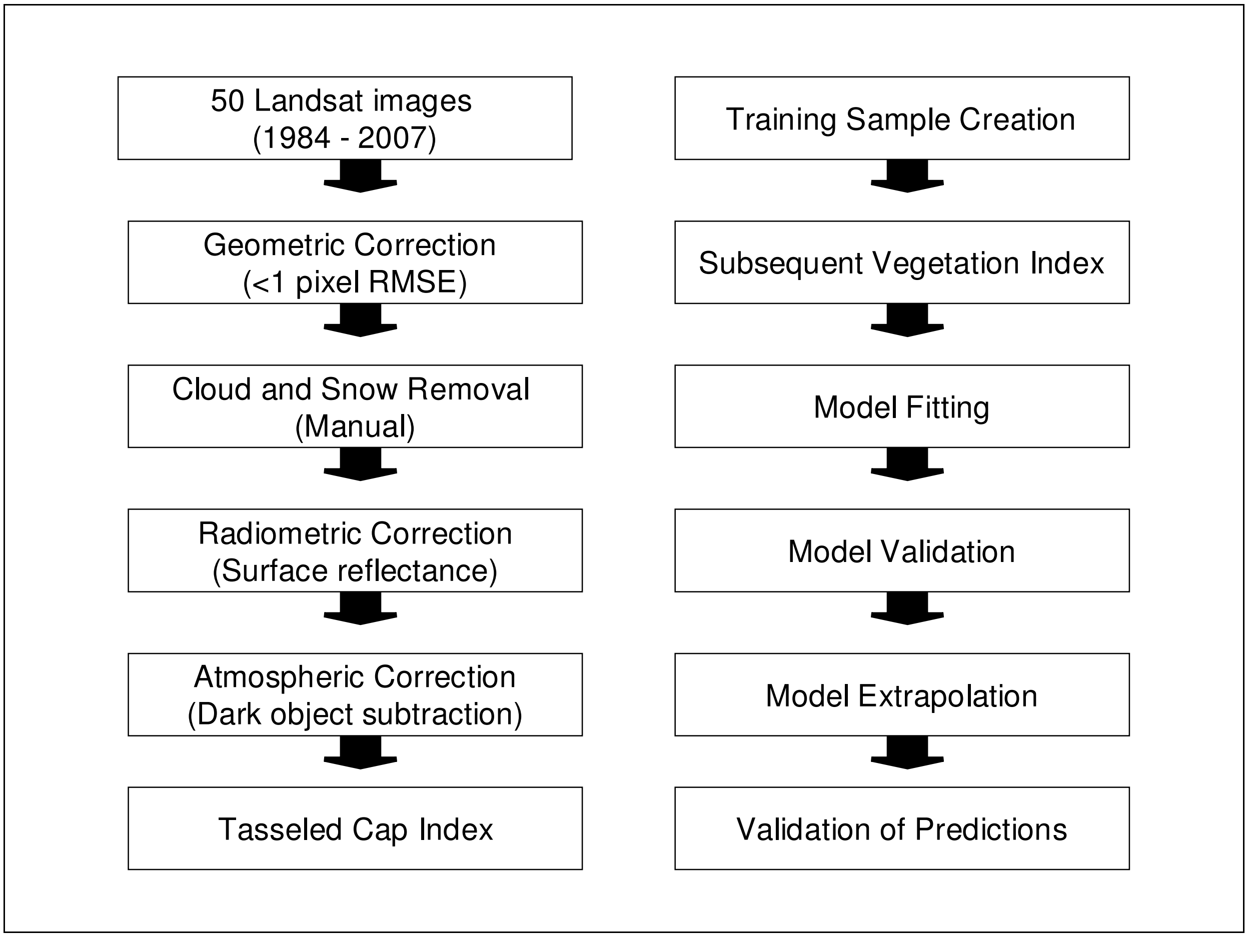


Figure 2. Project flow chart

Results

Land Cover Classification

The land cover classification model used a training sample of approximately one thousand observations for each of the nine input classes. As outlined in the methods, five of the fourteen originally available land cover classes are excluded from the training sample. Selection of land cover classes is discussed further below. The first two splits of the CART model selected Summer TC band one, brightness, to divide water (low brightness values) from everything else on the landscape. The second split used the subsequent greenness index to divide urban areas (low subsequent greenness values) from all else. Finally, Fall TC band one, brightness, was used to split the non-water and non-urban part of the landscape between more forested (low brightness values) and more herbaceous terrain (high brightness values). See the output CART in Figure 3.

Validation

Three different model validations are calculated: the study classification versus the 2001 NLCD, the study classification versus the 2001 NLCD training data, and an independent validation of the study classification specifically of Wake County using aerial photography for 1999 and 2005. Overall classification accuracy and kappa are calculated for each validation first of the overall nine land cover classes and then a generalized result to four classes.

Model validation

The model was validated using the 2001 NLCD as truth. For nine classes, overall accuracy was 0.71 and kappa was 0.67. For four classes, overall accuracy rises to 0.91 and kappa to 0.88. Thus, the model performs significantly better at predicting generalized land cover classes. Complete model validation by class for both nine and hour classes is included in Table 2.

Model extrapolation validation, 1999 and 2005 Wake County

Predicted classifications for the years 1999 and 2005 were validated by using aerial photography as “air-truth”, with ~100 filtered sample points per land cover class. In 1999, for nine classes, overall accuracy was 0.50 and kappa was 0.44. For four classes, overall accuracy was 0.82 and kappa was 0.75. In 2005, for nine classes, overall accuracy was 0.80 and kappa was 0.76. For four classes, overall accuracy was 0.92 and kappa was 0.88. Complete validation results for both nine and four classes for 1999 and 2005 are included in Tables 3 and 4.

Model extrapolation validation, 2000, using 2001 NLCD training data

Using the original 2001 NLCD training data made available to this project and set aside for validation, the 2000 prediction is tested. For nine classes, overall accuracy was 0.62 and kappa was 0.54. For four classes, overall accuracy was 0.87 and kappa was 0.79. Complete results included in Table 5.

Land cover change 1985 to 2005

From the literature, it was hypothesized that the dominant characteristics of land cover change would be that of urbanization surrounding population centers, with a loss of farmland due to development and natural afforestation (Noss, 1999). Land cover by percent of the landscape for four generalized classes, water, urban, forest, and herbaceous, are presented in Figure 4. Forest dips from 61% in 1985 to 57 and 58% in 1990 and 2000, but rises to 63% in 2005. Herbaceous areas of the landscape show a continuous drop from 26, to 22, to 20, to 18% of the landscape in perhaps the most dramatic land cover change. Urban areas, perhaps the most unstable of the classes due to the difficulty in accurately classifying the low intensity (suburban) land cover class, show a change from 12% in 1985, up to 20% in 2000, and down to 16% in 2005.

Mapped results for nine and four classes are included in Figures 5 to 9.

Ecosystem Services

Fragmentation. Results of the fragmentation for the forest classes in Durham County from 1985 to 2005 indicate both a reduction of the correlation length metric over time (Figure 5) as well as a linkage between urban coverage expansion and a loss of connectivity (Figure 6). The distribution of forest patch sizes remains relatively constant over time, with a slight increase in the number of small patches in later years (Figure 7). In fact, the landscape is dominated by a very few, extremely large patches even with high levels of urbanization; these patches merely become more perforated by localized development.

Carbon sequestration. To truly establish meaningful calculations of carbon storage represented by a landscape, it is necessary to tally specific forest types and stand ages. Such data was unavailable for a study area of the current extent. However, to look at the overall trend of change in carbon sequestration potential, 100-yr old oak-pine forest types (Appendix Table A) are selected. Results of such a forest type by total forested study area land cover show an increase of carbon sequestration of 9,348,406 metric tons from 1985 to 2005.

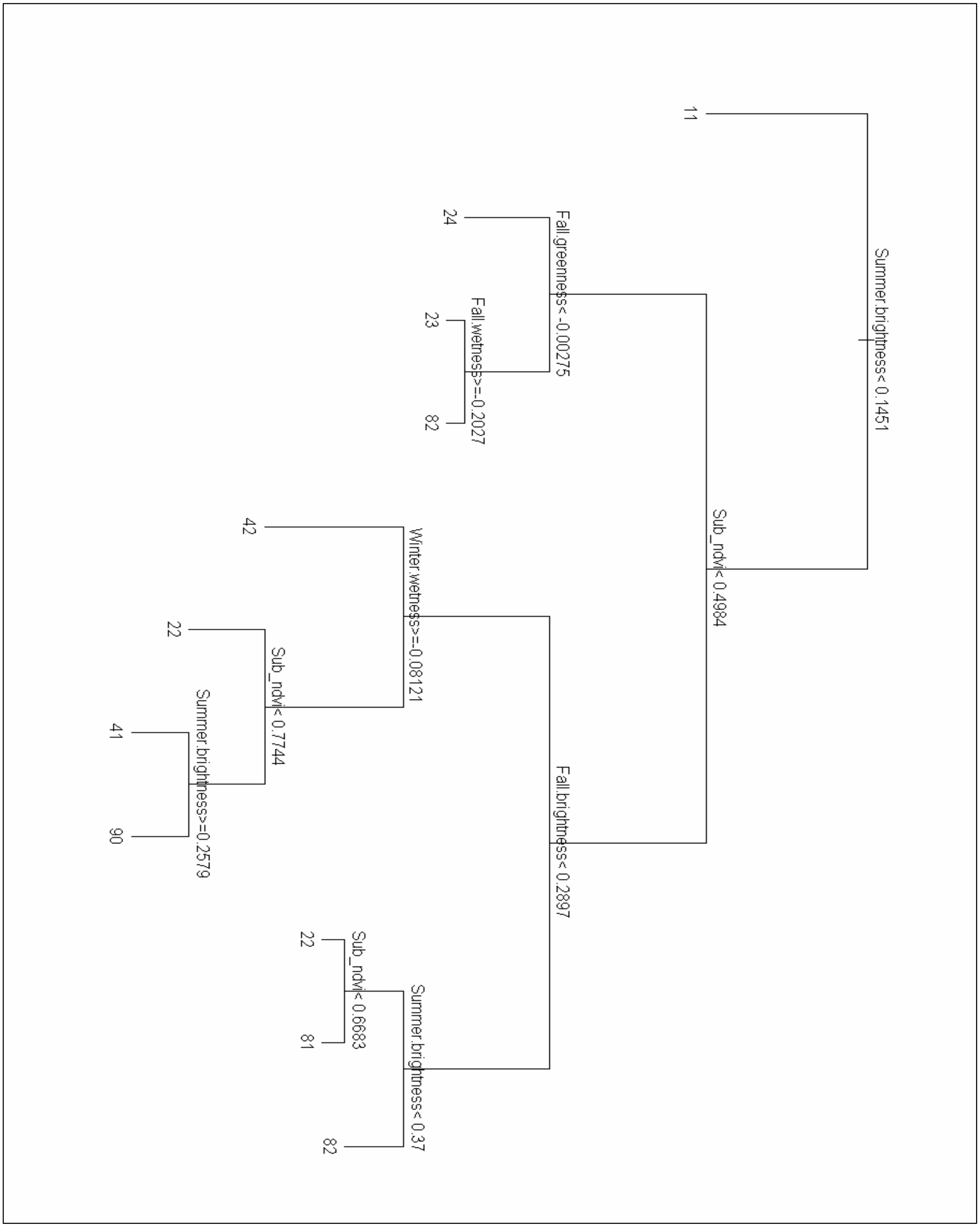
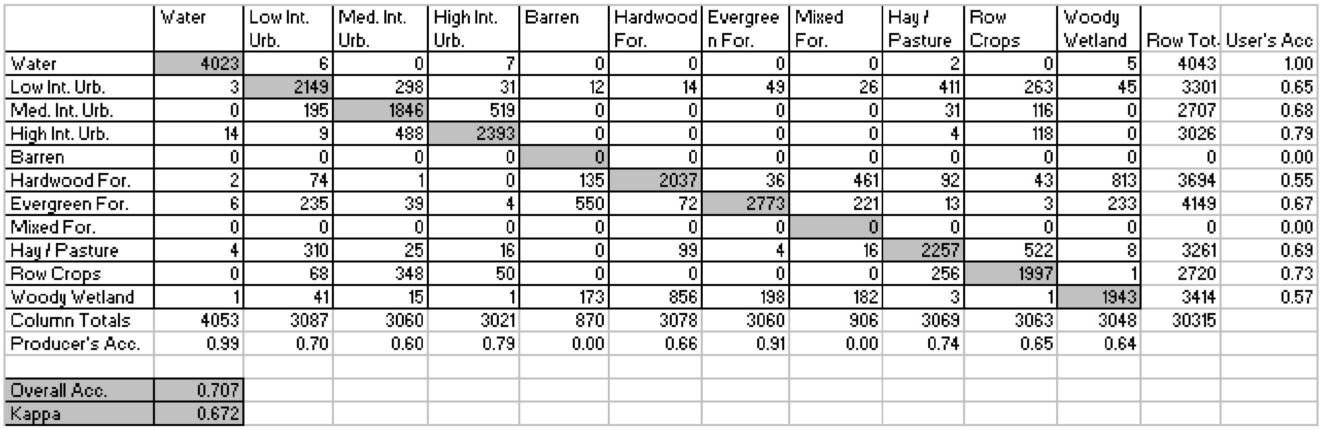


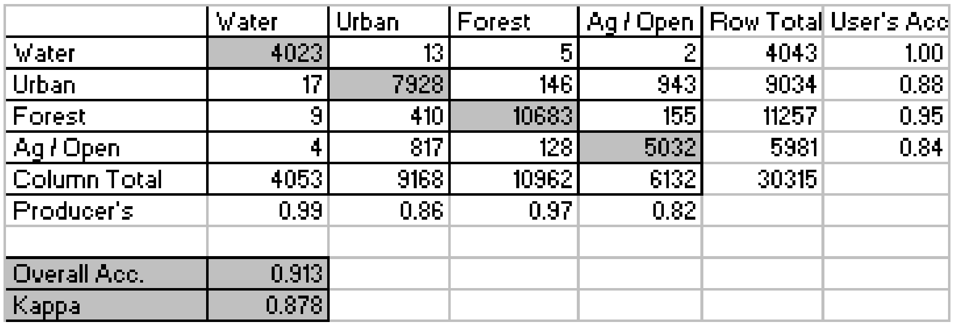
Figure 3. CART output

Table 2a. Model validation for nine classes, 2001 NLCD truth (including non-predicted Barren (31) and Mixed Forest (43) classes)

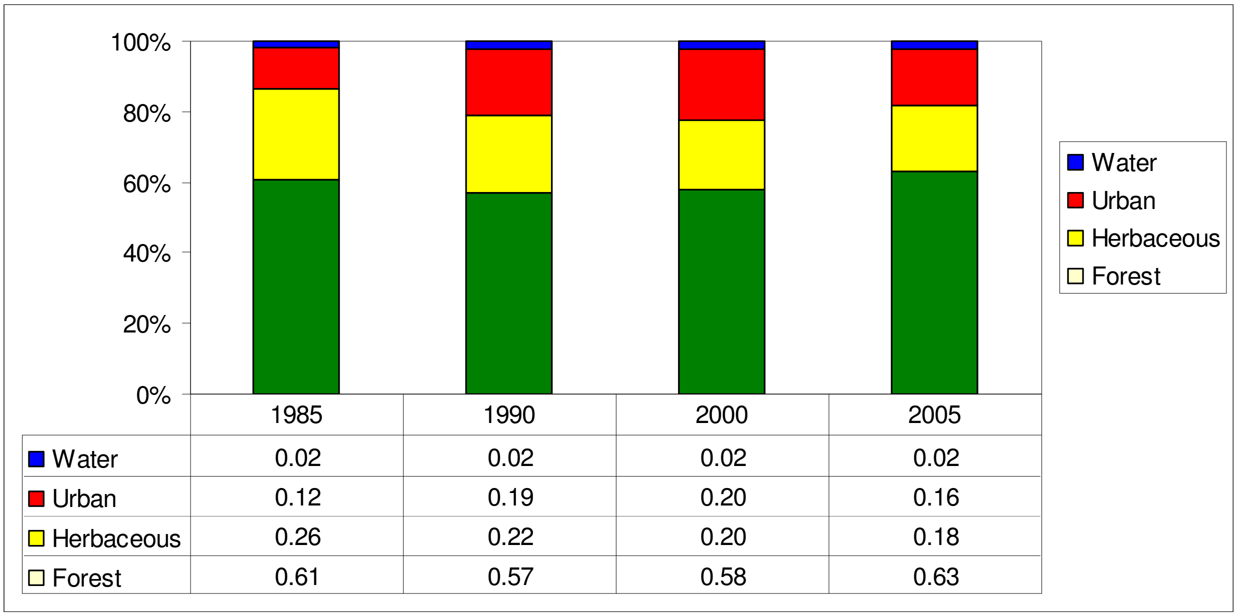


	Water	Low Int. Urb.	Med. Int. Urb.	High Int. Urb.	Barren	Hardwood For.	Evergreen For.	Mixed For.	Hay / Pasture	Row Crops	Woody Wetland	Row Tot.	User's Acc
Water	4023	6	0	7	0	0	0	0	2	0	5	4043	1.00
Low Int. Urb.	3	2149	298	31	12	14	49	26	411	263	45	3301	0.65
Med. Int. Urb.	0	195	1846	519	0	0	0	0	31	116	0	2707	0.68
High Int. Urb.	14	9	488	2393	0	0	0	0	4	118	0	3026	0.79
Barren	0	0	0	0	0	0	0	0	0	0	0	0	0.00
Hardwood For.	2	74	1	0	135	2037	36	461	92	43	813	3694	0.55
Evergreen For.	6	235	39	4	550	72	2773	221	13	3	233	4149	0.67
Mixed For.	0	0	0	0	0	0	0	0	0	0	0	0	0.00
Hay / Pasture	4	310	25	16	0	99	4	16	2257	522	8	3261	0.69
Row Crops	0	68	348	50	0	0	0	0	256	1997	1	2720	0.73
Woody Wetland	1	41	15	1	173	856	198	182	3	1	1943	3414	0.57
Column Totals	4053	3087	3060	3021	870	3078	3060	906	3069	3063	3048	30315	
Producer's Acc.	0.99	0.70	0.60	0.79	0.00	0.66	0.91	0.00	0.74	0.65	0.64		
Overall Acc.	0.707												
Kappa	0.672												

Table 2b. Model validation for four classes, 2001 NLCD truth



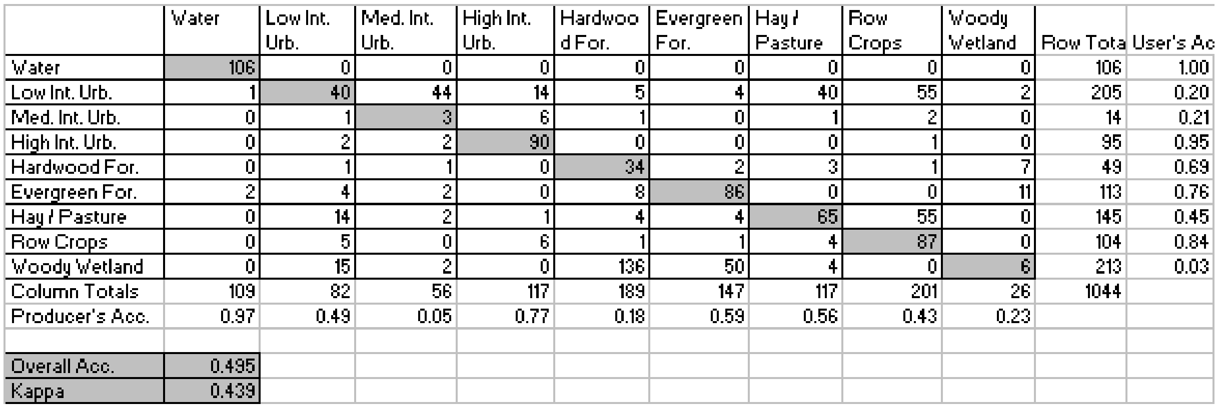
	Water	Urban	Forest	Ag / Open	Row Total	User's Acc
Water	4023	13	5	2	4043	1.00
Urban	17	7928	146	943	9034	0.88
Forest	9	410	10683	155	11257	0.95
Ag / Open	4	817	128	5032	5981	0.84
Column Total	4053	9168	10962	6132	30315	
Producer's	0.99	0.86	0.97	0.82		
Overall Acc.	0.913					
Kappa	0.878					



	1985	1990	2000	2005
🟦 Water	0.02	0.02	0.02	0.02
🟥 Urban	0.12	0.19	0.20	0.16
🟨 Herbaceous	0.26	0.22	0.20	0.18
☐ Forest	0.61	0.57	0.58	0.63

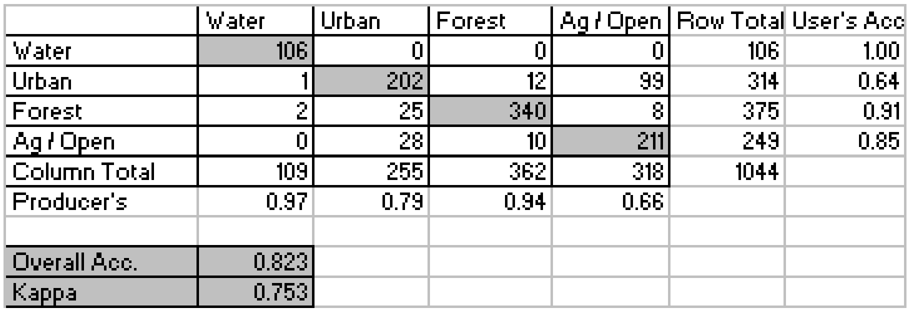
Figure 4. Percent of landscape by generalized land cover class 1985 to 2005

Table 3a. Validation of 2000 prediction for Wake County (using 1999 aerial photography), ~100 points / predicted land cover class, nine classes



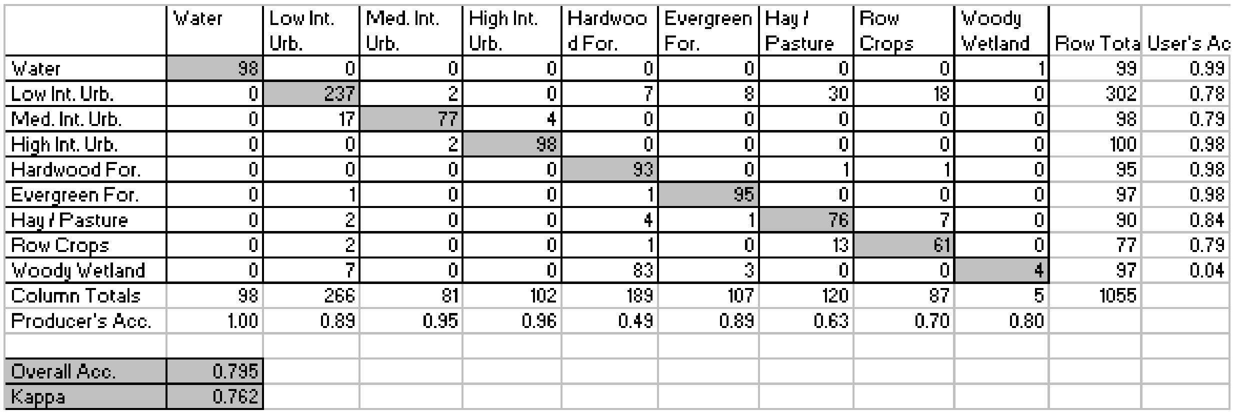
	Water	Low Int. Urb.	Med. Int. Urb.	High Int. Urb.	Hardwood For.	Evergreen For.	Hay / Pasture	Row Crops	Woody Wetland	Row Tota	User's Ac
Water	106	0	0	0	0	0	0	0	0	106	1.00
Low Int. Urb.	1	40	44	14	5	4	40	55	2	205	0.20
Med. Int. Urb.	0	1	3	6	1	0	1	2	0	14	0.21
High Int. Urb.	0	2	2	90	0	0	0	1	0	95	0.95
Hardwood For.	0	1	1	0	34	2	3	1	7	49	0.69
Evergreen For.	2	4	2	0	8	86	0	0	11	113	0.76
Hay / Pasture	0	14	2	1	4	4	65	55	0	145	0.45
Row Crops	0	5	0	6	1	1	4	87	0	104	0.84
Woody Wetland	0	15	2	0	136	50	4	0	6	213	0.03
Column Totals	109	82	56	117	189	147	117	201	26	1044	
Producer's Acc.	0.97	0.49	0.05	0.77	0.18	0.59	0.56	0.43	0.23		
Overall Acc.	0.495										
Kappa	0.439										

Table 3b. Validation of 2000 prediction for Wake County (using 1999 aerial photography), ~100 points / predicted land cover class, four classes



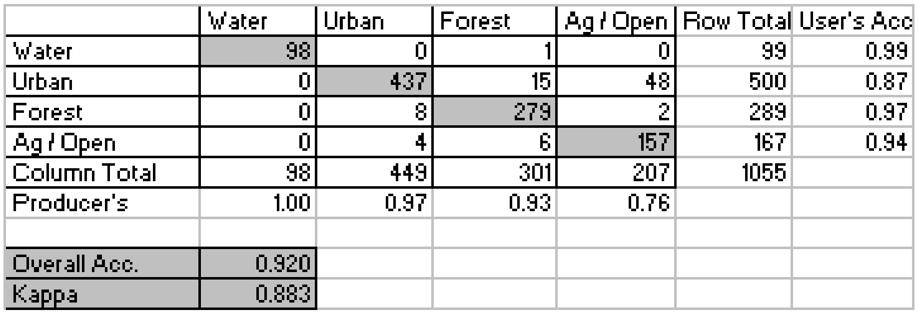
	Water	Urban	Forest	Ag / Open	Row Total	User's Acc
Water	106	0	0	0	106	1.00
Urban	1	202	12	99	314	0.64
Forest	2	25	340	8	375	0.91
Ag / Open	0	28	10	211	249	0.85
Column Total	109	255	362	318	1044	
Producer's	0.97	0.79	0.94	0.66		
Overall Acc.	0.823					
Kappa	0.753					

Table 4a. Validation of 2005 prediction for Wake County, ~100 points / predicted land cover class, nine classes



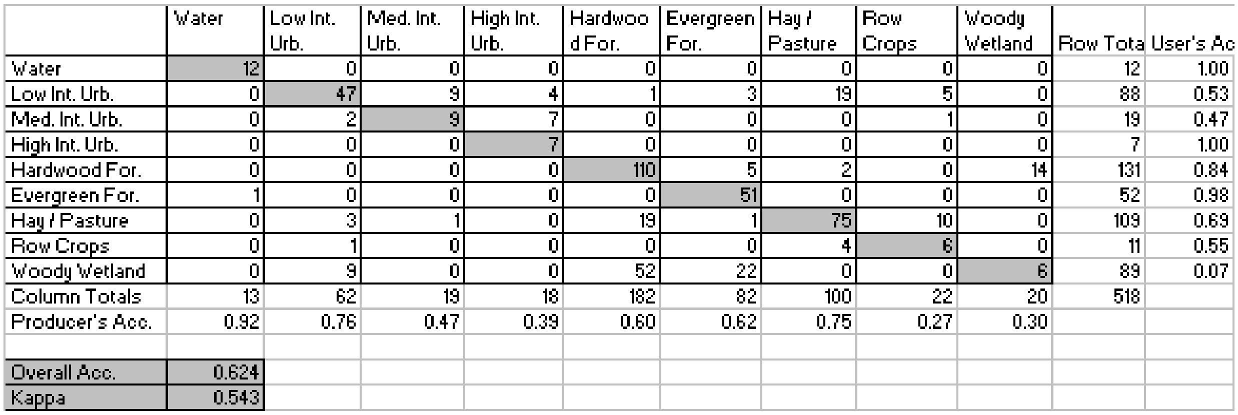
	Water	Low Int. Urb.	Med. Int. Urb.	High Int. Urb.	Hardwood For.	Evergreen For.	Hay / Pasture	Row Crops	Woody Wetland	Row Tota	User's Ac
Water	98	0	0	0	0	0	0	0	1	99	0.99
Low Int. Urb.	0	237	2	0	7	8	30	18	0	302	0.78
Med. Int. Urb.	0	17	77	4	0	0	0	0	0	98	0.79
High Int. Urb.	0	0	2	98	0	0	0	0	0	100	0.98
Hardwood For.	0	0	0	0	93	0	1	1	0	95	0.98
Evergreen For.	0	1	0	0	1	95	0	0	0	97	0.98
Hay / Pasture	0	2	0	0	4	1	76	7	0	90	0.84
Row Crops	0	2	0	0	1	0	13	61	0	77	0.79
Woody Wetland	0	7	0	0	83	3	0	0	4	97	0.04
Column Totals	98	266	81	102	189	107	120	87	5	1055	
Producer's Acc.	1.00	0.89	0.95	0.96	0.49	0.89	0.63	0.70	0.80		
Overall Acc.	0.795										
Kappa	0.762										

Table 4b. Validation of 2005 prediction for Wake County, ~100 points / predicted land cover class, four classes



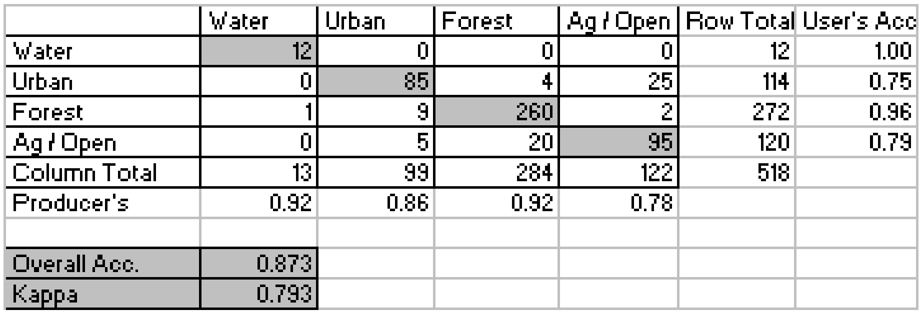
	Water	Urban	Forest	Ag / Open	Row Total	User's Acc
Water	98	0	1	0	99	0.99
Urban	0	437	15	48	500	0.87
Forest	0	8	279	2	289	0.97
Ag / Open	0	4	6	157	167	0.94
Column Total	98	449	301	207	1055	
Producer's	1.00	0.97	0.93	0.76		
Overall Acc.	0.920					
Kappa	0.883					

Table 5a. Validation of 2000 prediction, 2001 NLCD training data truth, nine classes



	Water	Low Int. Urb.	Med. Int. Urb.	High Int. Urb.	Hardwood For.	Evergreen For.	Hay / Pasture	Row Crops	Woody Wetland	Row Tota	User's Ac
Water	12	0	0	0	0	0	0	0	0	12	1.00
Low Int. Urb.	0	47	9	4	1	3	19	5	0	88	0.53
Med. Int. Urb.	0	2	9	7	0	0	0	1	0	19	0.47
High Int. Urb.	0	0	0	7	0	0	0	0	0	7	1.00
Hardwood For.	0	0	0	0	110	5	2	0	14	131	0.84
Evergreen For.	1	0	0	0	0	51	0	0	0	52	0.98
Hay / Pasture	0	3	1	0	19	1	75	10	0	109	0.69
Row Crops	0	1	0	0	0	0	4	6	0	11	0.55
Woody Wetland	0	9	0	0	52	22	0	0	6	89	0.07
Column Totals	13	62	19	18	182	82	100	22	20	518	
Producer's Acc.	0.92	0.76	0.47	0.39	0.60	0.62	0.75	0.27	0.30		
Overall Acc.	0.624										
Kappa	0.543										

Table 5b. Validation of 2000 prediction, 2001 NLCD training data truth, four classes



	Water	Urban	Forest	Ag / Open	Row Total	User's Acc
Water	12	0	0	0	12	1.00
Urban	0	85	4	25	114	0.75
Forest	1	9	260	2	272	0.96
Ag / Open	0	5	20	95	120	0.79
Column Total	13	99	284	122	518	
Producer's	0.92	0.86	0.92	0.78		
Overall Acc.	0.873					
Kappa	0.793					

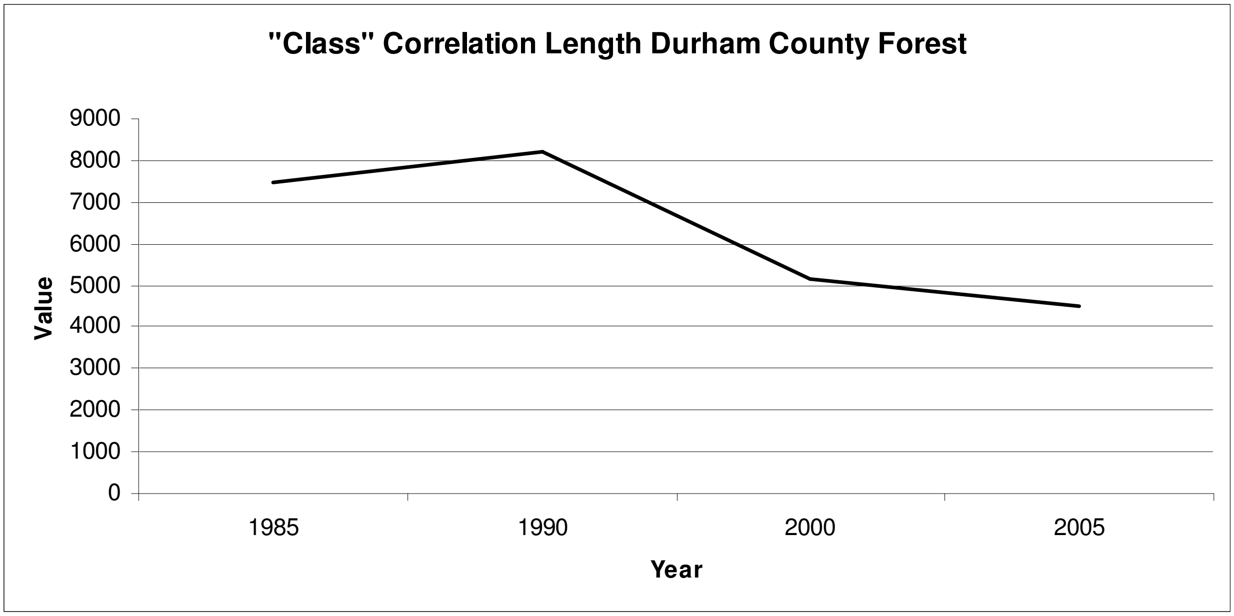


Figure 5. Forest class correlation length by year

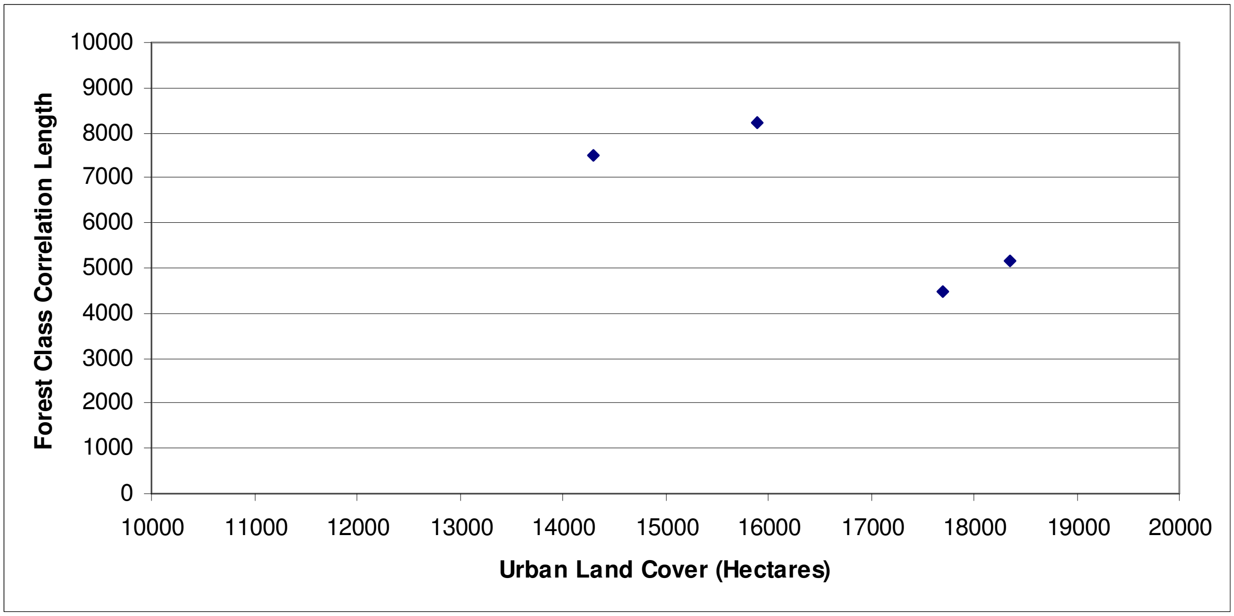
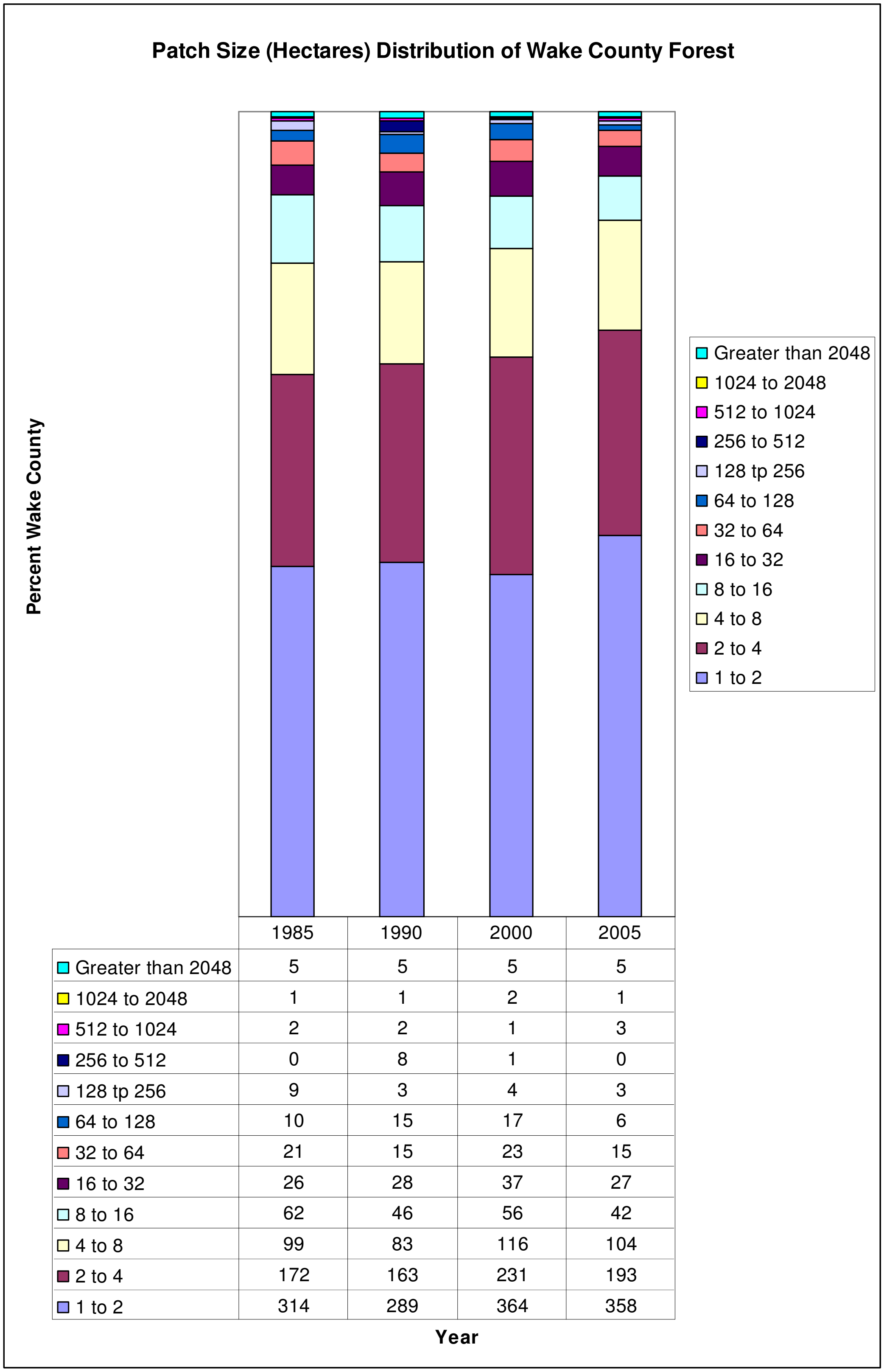


Figure 6. Forest class correlation length vs. urban coverage (points 1985, 1990, 2000, 2005 forest cover.



	1985	1990	2000	2005
■ Greater than 2048	5	5	5	5
■ 1024 to 2048	1	1	2	1
■ 512 to 1024	2	2	1	3
■ 256 to 512	0	8	1	0
■ 128 tp 256	9	3	4	3
■ 64 to 128	10	15	17	6
■ 32 to 64	21	15	23	15
■ 16 to 32	26	28	37	27
■ 8 to 16	62	46	56	42
■ 4 to 8	99	83	116	104
■ 2 to 4	172	163	231	193
■ 1 to 2	314	289	364	358

Figure 7. Distribution of forest patches within Wake County

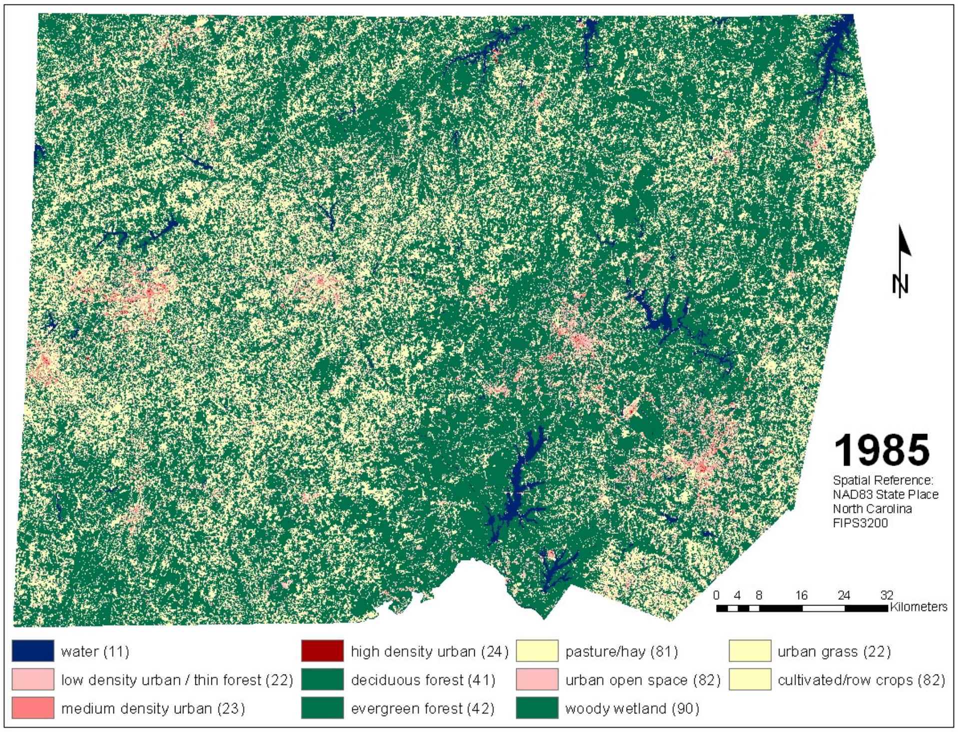


Figure 8: Generalized prediction for 1985

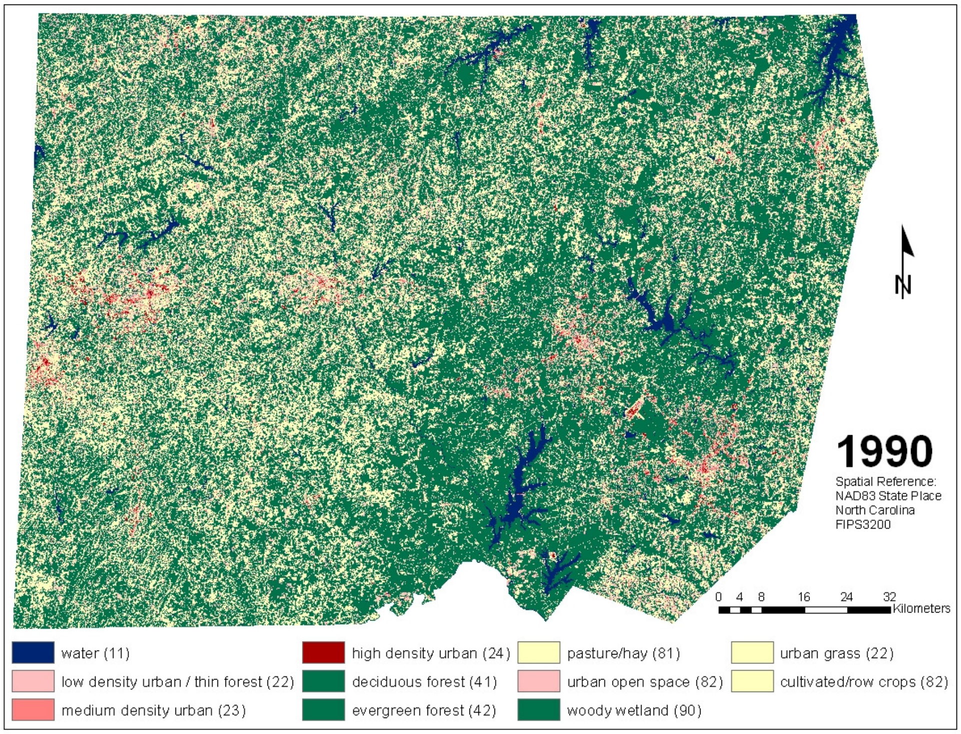


Figure 9: Generalized prediction for 1990

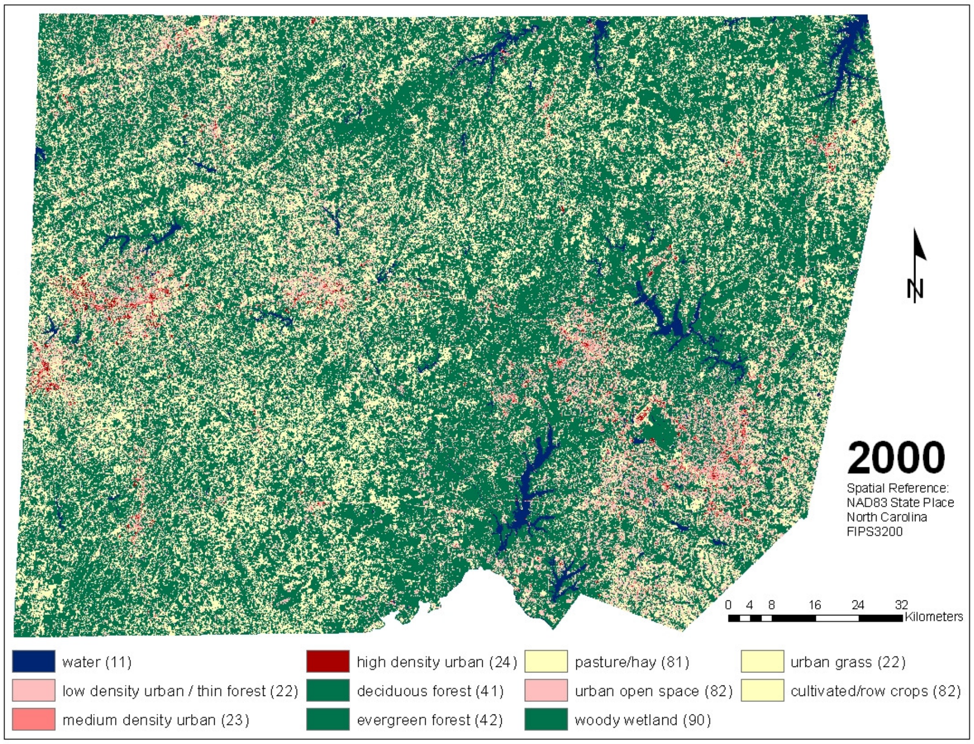


Figure 10: Generalized prediction for 2000

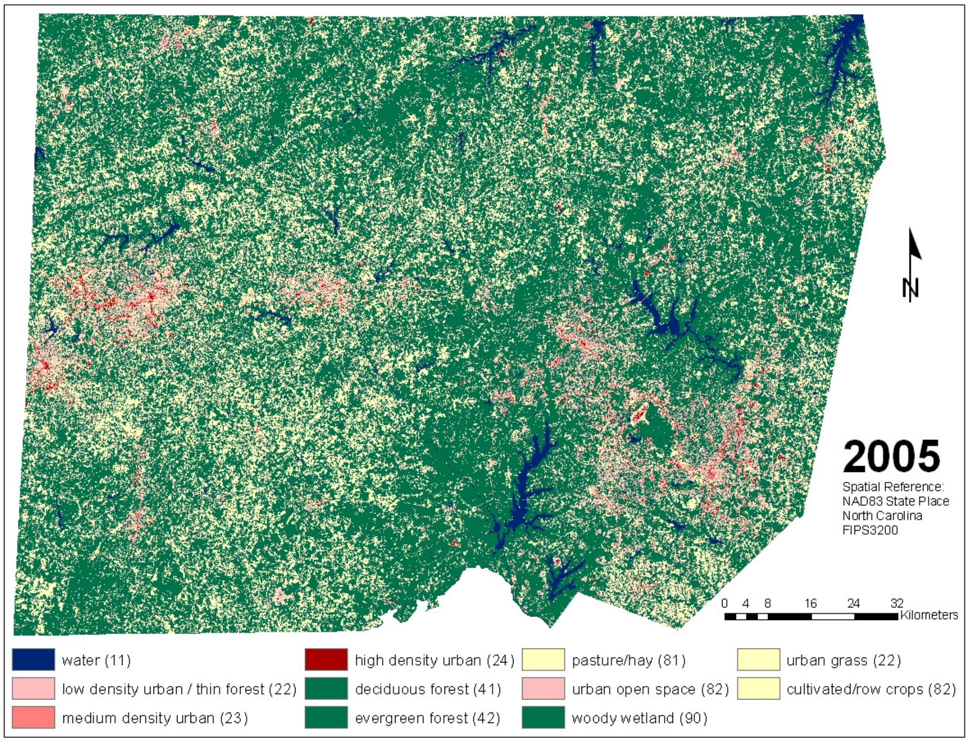


Figure 11: Generalized prediction for 2005

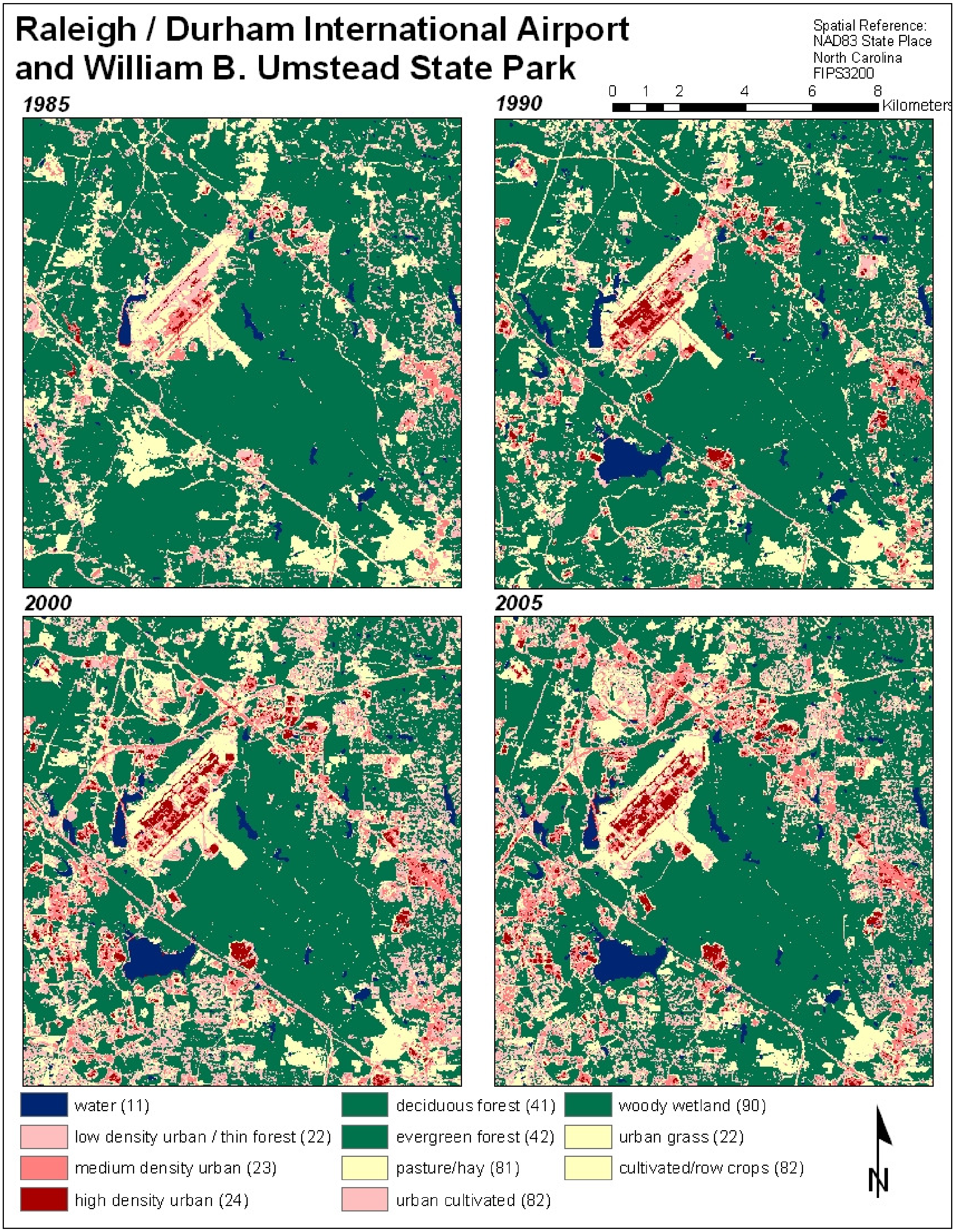


Figure 12: Zoom view of Raleigh Durham International Airport and Umstead State Park 1985 to 2005

Discussion

Significance and drawbacks of project methods and data

The land cover change dataset this project represents is one of a very few that exist (Johnson, 2001; Alberti, et al., 2003). The project has achieved its goal of classifying land cover at a high level of accuracy over a large area over time without the use of historical ancillary data. The creation of this multi-annual dataset is significant in itself as a case for land cover change to be studied. The project is more significant, however, for its methods, which could be applied to other areas of the United States to predict at a high level of accuracy land cover over the life-span of the Landsat Satellite program. More generally, the study represents important advancements for overcoming Botkin's (1989) “signature extension problem” and developing land cover spectral signatures robust to inter-annual variation. Specifically, these advances include the multi-annual and multi-seasonal training data set, and the use of the subsequent vegetation index. In terms of ecosystem services, this study offers two general applications of the dataset that demonstrate how calculations of ecosystem services can move beyond snapshots in time to make inferences of services rendered or removed from the ecosystem over time. As higher resolution satellite imagery becomes more readily available, the project methods could be applied to achieve more spatially accurate results.

Drawbacks to the project method certainly include the large amount of data necessary and cost of such data to drive the model. In addition to the substantial time and money needed to acquire the number of images that this project used, the necessary time and experience necessary to correctly process the images can be a barrier. On the other hand, TM imagery is scheduled to become free in the December 2008 (USGS, April 21, 2008, *public comm.*., see http://landsat.usgs.gov/images/squares/USGS_Landsat_Imagery_Release.pdf). After this, interest in similar applications likely will increase dramatically, and ease of project replication will be especially welcome.

The results of this study also represent an important tool for regional planners. Rafe Sagarin with the Nicholas Institute and the Durham Healthy Environment Working Group, and Kim Douglass, with the North Carolina Department of the Environment and Natural Resources' Natural Heritage Program have both stated strong interest in the prospect of attaining land cover change data over time for the NC Piedmont.

Specific Project Methods

Developing a training sample. Before selected a training sample developed from the 2001 NLCD classification itself, there were numerous attempts using the original training data points: adjusting the proportions of land cover represented by the sample to match that of the 2001 NLCD, filtering the sample to account for potential errors of image mis-registration, adding and removing classes, and boosting the number urban observations in the training sample. Choosing to create the training sample from the 2001 NLCD allowed for a sample of desired land cover classes large enough to develop spectral signatures capable of absorbing the intra-class variation across the landscape. One thousand points was selected as a large enough sample, but further experimentation of larger or smaller samples would be worthwhile.

Use of CART. Decision tree classification was the classification method chosen for the 2001 NLCD, which by their estimation was superior to spectral clustering, neural networks and other methods for the following reasons: 1) it is a non-parametric and thus classifies independent of class signature, 2) it functions as well for continuous as for nominal data, 3) it yields interpretable classification rules, 4) it is fast to train, 5) it is adept at handling efficiently large amounts of data (Homer, 2004). In this project, a great many different combinations of predictor variables were experimented with, and using CART allowed for an efficient way to study the effects of different combinations of inputs on the model.

It can be said confidently that the CART "tree" selected as best is assembled logically, in terms of which spectral variables are predicting which landscape elements (See Figure 2). The four-way split in the tree between water, intensive urban, forest, and herbaceous supports the four class generalization that this project favors. One reservation is the reliance CART has on the brightness TC band, as it uses the band to make four splits at the top of the model, middle of the model, and the end leaves. The initial splitting of the water from the landscape is inconsequential, as water is highly spectrally distinct and thus nearly any band could have worked. However, it was hoped that the important split between forest and herbaceous classes would have used a TC greenness band instead of brightness. Similarly, the splitting of evergreen forest from the remainder of the forest classes utilized high values of the Winter TC wetness band. This is perhaps the split that makes the least sense and that is worrisome in extrapolations of particularly moist or dry years. Depending on further extrapolation of the model to a variety of years, additional manipulation of the model input bands may be necessary to construct tree that offers a more stable set of spectral signatures.

Selection of land cover classes. 2001 NLCD classes are adapted from the Anderson Level II and III classification system for land use and land cover (USGS LCI). Many of the Anderson classes, especially the Level III classes, are best derived using aerial photography. It is not appropriate to attempt to derive some of these classes using Landsat TM data due to issues of spatial resolution and interpretability of data (USGS LCI). Over the course of this study, the conclusion was reached that it was both reasonable and necessary to select, adapt, and even remove 2001 NLCD land cover classes.

The process of selection and adaptation of 2001 land cover classes was decided upon in part due to the project goal of separating spectrally similar land use and land cover classes. 2001 NLCD masked out all urban area using a variety of ancillary data, and performed separate classifications on the masked and non-masked areas, which allowed for spectrally bright urban areas to not be confused with similarly bright agricultural areas. Thus, this project selected first nine classes that could be differentiated, and then generalized to four land cover classes. In this way, only the most robust class signatures were selected. Secondly, the 2001 NLCD land cover classifications are designed to describe the terrain of the entire United States. Several classes, including "shrubland" and "grassland" do not exist on the NC Piedmont, and were thus removed as their presence only added confusion to other, more realistic classes. Finally, there is the 2001 NLCD "developed open space" class 21, which is particularly troubling, but also important to this study, which deserves special discussion.

An early and on-going concern of the project was how best to negotiate the developed open space class 21, which was removed for the reason that it by definition does not in fact represent any particular land cover class but, rather, a juxtaposition of cover types. 2001 NLCD describes the class simply as less than twenty percent impervious surfaces, making the remaining eighty percent of any classified pixel a different, undefined land cover class. The dominant force of urbanization on the NC Piedmont, however, is one of suburban growth surrounding urban centers, which can often spectrally appear in thirty by thirty meter pixels as having approximately twenty percent impervious surface cover. The class is therefore problematic as it both necessary to describe suburban areas, but also not feasible to use the 2001 NLCD "developed open space" class to train the model as, spectrally, it is fundamentally fragmented.

The "developed open space" class was used in the 2001 NLCD essentially to absorb error within the urban masked area, as a class of everything that was not low, medium, or high intensity urban development. From intense confusion caused by the class in early classification attempts, it became necessary to completely remove the class. The hope in removing the class was to improve the model by forcing the CART to split up the area formerly classified as "developed open space" to land cover classes actually representative of the area. The same result of transferring class meanings was hoped for the removal of similarly non-existent "shrubland" and "grassland" classes.

Subsequent vegetation index (SVI). It was hypothesized following early modeling efforts that the significant confusion seen between urban classes and agricultural / herbaceous classes could be attributed to similar pixel brightness values between, for example, fallow fields and urban areas with reduced levels of impervious surface. Therefore, a subsequent vegetation index, or greenness value, for each data point was imagined as a way to achieve greater separability between classes. Functioning as imagined, using the SVI as a predictor variable in the CART resulted in higher overall accuracy as well as better separability between the low intensity urban development class and other classes. Thus, using SVI allows the model to more effectively confuse less and capture more intensely developed areas, including suburban areas. Significantly, before the use of the SVI, previous models had been unable to predict more than a single urban class.

A three-year window was selected as an appropriate temporal scale for the index, due in part to available imagery. Further experimentation with shorter or longer temporal windows should be performed. One drawback to the use of the SVI is a loss of temporal resolution as year to year change has been reduced to a single maximum value. Using multiple images in the calculation of the index can also result in a loss of spatial resolution, as fine detail, due to errors of mis-registration, may be incurred.

"Air-truthing" Validation. Using high-resolution aerial photography of a given year, with a land cover classification of the same year, a process of "air-truthing" is performed by comparing the prediction versus the truth. This project used winter imagery as it should best allow one to see a bare landscape without the confusion caused by greenery, as well as show clear distinctions between deciduous and evergreen land cover. A certain level of human error can be expected in validation of predicted classification. The first cause of human error is also related to the use of winter imagery for validation. Although it is easier to distinguish between

evergreen and deciduous forest, as well as see impervious surfaces that may be obscured otherwise, wetlands become more difficult to separate from deciduous forest and the pasture / hay class can be nearly indiscernible from certain types of cultivated crop fields. The second source of error is more related to the performer of the validation. During validation, one must keep in mind the spatial resolution of the classification, and make a judgment on mixed pixels at a 30 by 30 m square area. For example if a point lies in a field next to a road with several farm structures, the area ought to be judged as being low density urban development having 20 to 50% impervious surface. However, the point is still in a field surrounded by other fields, which could compel one to classify the pixel as hay / pasture. The potential of this error is reduced through a focal variety process performed on the sample points to select points that have a higher probability of being pure by being surrounded by pixels similar by land cover class. Other difficulties in classification are a result of land cover that does not easily fall into the desired land cover classes. For example, construction of any sort, as well as recently harvested timber or crops fall outside the nine classes selected for this study. It would be useful to have a “barren land” or “transitional land” class. However, the study was unable to develop a model that could predict such a class.

Ecosystem Services

Forest management requires reliable information on the status and condition of forests – interpreted from a broad context – and of change in forest conditions over time (Noss, 1999). As a proof-of-concept of how multi-annual land cover data can be translated to quantifications of ecosystem services, basic assessments of forest fragmentation and carbon storage were formulated.

Two metrics of fragmentation statistic were chosen for this study as important gauges of biodiversity support in forests. Correlation length was first selected, a metric of the average distance an organism can move from a random starting point within the patch before encountering the patch boundary. This metric, when scaled up to the class level, in the case forest, is considered to be a measurement of landscape connectivity representing the average traversability of the landscape for an organism that is confined to remain within a single patch (Keitt et al. 1997). For Durham County, correlation length decreased significantly from 1985 to 2005, indicating a reduction in forest connectivity. This pattern of fragmentation can also be understood in relation to urban growth as Figure 6 illustrates. The second metric of fragmentation selected was that of patch distribution by size. This measurement showed significant variation across the four study years. However, a trend of an increasing number of very small one to two hectare patches is evident. The fragmentation results are interesting in that forest cover in the study area hovers near 60% over this time period, which is close to the critical proportion of habitat cover emphasized in theoretical studies of habitat pattern based in percolation theory (Gardner et al. 1987, With et al. 1997). The contrast between rather high connectivity in this study area, relative to the random landscapes popularized in theory, warrants further exploration.

In terms of carbon sequestration potential, I have provided the baseline parameters needed to scale up existing specifications of carbon storage by forest type and age to the forest land cover predictions of this study. While it is impractical to select a single, or even average, forest type and forest stand age of a study area as large the current one, total carbon storage for a variety of forest types for multiple stand ages could be calculated with these coefficients, given more highly resolved information on stand ages and compositional types (Appendix A). This scaling up of field data demonstrates the potential of this dataset to monitor ecosystem services across a very large landscape using baseline calculations.

Conclusions

Project goals were threefold: (1) to develop a land cover classification model using no ancillary data to accurately reproduce the 2001 National Land Cover Dataset data product; (2) to extend the classification to images from 1985, 1990, 1995, and 2005; and (3) to demonstrate the use of this land cover time series to explore hypotheses about the provision of ecosystem services, focusing on biodiversity support potential as influenced by forest habitat fragmentation and carbon sequestration potential. Multiple model and prediction validations attest to the success of the initial two goals, and the basic analyses of ecosystem services representing a proof-of-concept of the potential of the dataset. With the soon-to-be freely available Landsat TM imagery, the methods of this study represent a potent tool for the classification of historical land cover and provide a timely answer to the conservation community’s call for robust assessments of ecosystem services broad both in spatial and temporal scales.

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Appendix A Total metric tons of carbon in all forest classes in study area per year, by forest type and stand age. Based on carbon storage figures from FORCARB project, USDA

Forest type	Stand age (years)	Volume (m3/ha)	Live tree (t/ha)	Standing dead (t/ha)	Understory (t/ha)	Down dead wood (t/ha)	Forest floor (t/ha)	Soil (t/ha)	Total nonsoil (t/ha)	1985	1990	2000	2005
Loblolly-shortleaf pine	0	0	0	0	4.2	9.9	12.2	72.9	26.3	9.99E+07	9.39E+07	9.52E+07	1.04E+08
Loblolly-shortleaf pine	5	0	11.1	0.7	4	8.4	6.5	72.9	30.6	1.04E+08	9.80E+07	9.93E+07	1.09E+08
Loblolly-shortleaf pine	10	19.1	22.6	1.3	3.6	7.5	6.4	72.9	41.4	1.15E+08	1.08E+08	1.10E+08	1.20E+08
Loblolly-shortleaf pine	15	36.7	31.3	1.6	3.4	6.8	7.5	72.9	50.7	1.24E+08	1.17E+08	1.19E+08	1.30E+08
Loblolly-shortleaf pine	20	60.4	40.8	1.9	3.2	6.6	8.7	72.9	61.2	1.35E+08	1.27E+08	1.29E+08	1.41E+08
Loblolly-shortleaf pine	25	85.5	50.3	2.1	3.1	6.5	9.8	72.9	71.9	1.46E+08	1.37E+08	1.39E+08	1.52E+08
Loblolly-shortleaf pine	30	108.7	58.2	2.3	3.1	6.6	10.7	72.9	80.8	1.55E+08	1.46E+08	1.47E+08	1.61E+08
Loblolly-shortleaf pine	35	131.2	65.6	2.4	3	6.7	11.5	72.9	89.3	1.63E+08	1.54E+08	1.56E+08	1.70E+08
Loblolly-shortleaf pine	40	152.3	72.5	2.5	3	6.9	12.2	72.9	97.1	1.71E+08	1.61E+08	1.63E+08	1.78E+08
Loblolly-shortleaf pine	45	172.3	78.9	2.7	2.9	7.2	12.7	72.9	104.4	1.78E+08	1.68E+08	1.70E+08	1.86E+08
Loblolly-shortleaf pine	50	191.4	85	2.7	2.9	7.5	13.2	72.9	111.3	1.85E+08	1.74E+08	1.77E+08	1.93E+08
Loblolly-shortleaf pine	55	208.4	90.3	2.8	2.9	7.8	13.7	72.9	117.4	1.92E+08	1.80E+08	1.83E+08	2.00E+08
Loblolly-shortleaf pine	60	223.9	95.1	2.9	2.8	8.1	14.1	72.9	122.9	1.97E+08	1.85E+08	1.88E+08	2.05E+08
Loblolly-shortleaf pine	65	238.4	99.6	2.9	2.8	8.3	14.4	72.9	128.1	2.02E+08	1.90E+08	1.93E+08	2.11E+08
Loblolly-shortleaf pine	70	252.9	104	3	2.8	8.6	14.7	72.9	133.2	2.07E+08	1.95E+08	1.98E+08	2.16E+08
Loblolly-shortleaf pine	75	264.6	107.6	3	2.8	8.9	15	72.9	137.3	2.12E+08	1.99E+08	2.02E+08	2.20E+08
Loblolly-shortleaf pine	80	277.1	111.4	3.1	2.8	9.1	15.2	72.9	141.6	2.16E+08	2.03E+08	2.06E+08	2.25E+08
Loblolly-shortleaf pine	85	289.5	115.1	3.1	2.8	9.4	15.5	72.9	145.9	2.20E+08	2.07E+08	2.10E+08	2.29E+08
Loblolly-shortleaf pine	90	299.6	118.2	3.2	2.7	9.6	15.7	72.9	149.4	2.24E+08	2.11E+08	2.13E+08	2.33E+08
Oak-pine	0	0	0	0	4.2	11.3	10.3	61.4	25.8	8.78E+07	8.26E+07	8.37E+07	9.14E+07
Oak-pine	5	0	7.4	0.6	4.1	9	5.8	61.4	26.9	8.89E+07	8.36E+07	8.47E+07	9.26E+07
Oak-pine	10	13.6	19.6	1.2	3.6	7.7	5.9	61.4	38	1.00E+08	9.41E+07	9.54E+07	1.04E+08
Oak-pine	15	27.8	29.3	1.6	3.5	6.7	6.8	61.4	47.9	1.10E+08	1.04E+08	1.05E+08	1.15E+08
Oak-pine	20	43.9	39	1.9	3.4	6.2	7.7	61.4	58.2	1.20E+08	1.13E+08	1.15E+08	1.25E+08
Oak-pine	25	59.3	46.8	2.1	3.3	5.8	8.6	61.4	66.5	1.29E+08	1.21E+08	1.23E+08	1.34E+08
Oak-pine	30	77.2	55.4	2.3	3.2	5.6	9.2	61.4	75.8	1.38E+08	1.30E+08	1.32E+08	1.44E+08
Oak-pine	35	96.8	64.4	2.5	3.2	5.7	9.8	61.4	85.5	1.48E+08	1.39E+08	1.41E+08	1.54E+08
Oak-pine	40	117.2	73.4	2.7	3.1	5.9	10.2	61.4	95.3	1.58E+08	1.48E+08	1.50E+08	1.64E+08
Oak-pine	45	136.4	81.6	2.8	3.1	6.1	10.6	61.4	104.2	1.67E+08	1.57E+08	1.59E+08	1.74E+08
Oak-pine	50	154.1	88.9	2.9	3.1	6.3	11	61.4	112.2	1.75E+08	1.64E+08	1.67E+08	1.82E+08
Oak-pine	55	171.4	96	3	3	6.6	11.3	61.4	119.9	1.83E+08	1.72E+08	1.74E+08	1.90E+08
Oak-pine	60	189.6	103.2	3.1	3	6.9	11.5	61.4	127.8	1.90E+08	1.79E+08	1.82E+08	1.98E+08
Oak-pine	65	204.5	109.1	3.2	3	7.2	11.8	61.4	134.3	1.97E+08	1.85E+08	1.88E+08	2.05E+08
Oak-pine	70	218.8	114.6	3.3	3	7.5	12	61.4	140.3	2.03E+08	1.91E+08	1.94E+08	2.11E+08
Oak-pine	75	234.5	120.6	3.4	2.9	7.8	12.1	61.4	146.9	2.10E+08	1.97E+08	2.00E+08	2.18E+08
Oak-pine	80	247.6	125.5	3.5	2.9	8.1	12.3	61.4	152.3	2.15E+08	2.02E+08	2.05E+08	2.24E+08
Oak-pine	85	259.4	129.9	3.5	2.9	8.3	12.5	61.4	157.2	2.20E+08	2.07E+08	2.10E+08	2.29E+08
Oak-pine	90	272.3	134.7	3.6	2.9	8.6	12.6	61.4	162.4	2.25E+08	2.12E+08	2.15E+08	2.35E+08
Oak-gum-cypress	0	0	0	0	1.8	10.2	6	158	18.1	1.77E+08	1.67E+08	1.69E+08	1.85E+08
Oak-gum-cypress	5	0	6.7	0.7	1.9	6.2	2.4	158	17.9	1.77E+08	1.67E+08	1.69E+08	1.84E+08
Oak-gum-cypress	10	9.8	18.8	1.9	1.8	4.5	2.4	158	29.3	1.89E+08	1.77E+08	1.80E+08	1.96E+08
Oak-gum-cypress	15	19.9	28.3	2.4	1.7	3.7	3	158	39.1	1.98E+08	1.87E+08	1.89E+08	2.07E+08
Oak-gum-cypress	20	32.7	38	2.8	1.7	3.5	3.8	158	49.7	2.09E+08	1.97E+08	1.99E+08	2.18E+08
Oak-gum-cypress	25	45.4	46.8	3.1	1.6	3.6	4.4	158	59.5	2.19E+08	2.06E+08	2.09E+08	2.28E+08
Oak-gum-cypress	30	58.1	54	3.4	1.6	3.8	5	158	67.8	2.27E+08	2.14E+08	2.17E+08	2.37E+08
Oak-gum-cypress	35	73.4	62.3	3.6	1.6	4.2	5.5	158	77.2	2.37E+08	2.23E+08	2.26E+08	2.47E+08
Oak-gum-cypress	40	92.2	71.9	3.9	1.6	4.7	6	158	88.1	2.48E+08	2.33E+08	2.36E+08	2.58E+08
Oak-gum-cypress	45	110.7	80.9	4.2	1.6	5.2	6.4	158	98.3	2.58E+08	2.43E+08	2.46E+08	2.69E+08
Oak-gum-cypress	50	128.1	89	4.4	1.5	5.7	6.8	158	107.5	2.67E+08	2.51E+08	2.55E+08	2.78E+08
Oak-gum-cypress	55	146.3	97.3	4.6	1.5	6.2	7.2	158	116.7	2.77E+08	2.60E+08	2.64E+08	2.88E+08
Oak-gum-cypress	60	166.1	105.9	4.7	1.5	6.7	7.5	158	126.5	2.86E+08	2.69E+08	2.73E+08	2.98E+08
Oak-gum-cypress	65	186.4	114.5	4.9	1.5	7.3	7.8	158	136.1	2.96E+08	2.79E+08	2.82E+08	3.08E+08
Oak-gum-cypress	70	205.7	122.5	5.1	1.5	7.8	8.1	158	145	3.05E+08	2.87E+08	2.91E+08	3.18E+08
Oak-gum-cypress	75	222.5	129.3	5.2	1.5	8.2	8.4	158	152.6	3.13E+08	2.94E+08	2.98E+08	3.26E+08
Oak-gum-cypress	80	237.9	135.4	5.3	1.5	8.6	8.6	158	159.4	3.20E+08	3.01E+08	3.05E+08	3.33E+08
Oak-gum-cypress	85	257.3	142.9	5.5	1.5	9.1	8.9	158	167.8	3.28E+08	3.09E+08	3.13E+08	3.42E+08
Oak-gum-cypress	90	278.9	151.2	5.6	1.5	9.6	9.1	158	177	3.37E+08	3.17E+08	3.21E+08	3.51E+08