ABSTRACT

McKERROW, ALEXA JACQUELINE. Mapping and Monitoring Plant Communities in the Coastal Plain of North Carolina: A Basis for Conservation Planning. (Under the direction of Drs. Thomas R. Wentworth and Jaime A. Collazo).

The most effective tool for conservation of biodiversity is high quality information on the extent and status of species and their habitats. To guide that conservation, the National Gap Analysis Program (GAP) has been working to develop thematically rich maps of land cover that can be used to assess the conservation status of native plant communities and as a basis for modeling the predicted distributions of species. In this research our goal was to develop a high quality land cover map using change detection, as the basis for monitoring plant communities and species habitats over time.

To that end we mapped the Ecological Systems of the Onslow Bight (North Carolina coastal plain) using Landsat TM satellite imagery and ancillary datasets (e.g., soils, wetlands). We tested the application of decision tree modeling for mapping 6 forested systems and integrated image objects and a decision tree model to map managed evergreen stands. A total of 42 land cover classes were mapped with an overall accuracy of 77% and a kappa statistic of 0.75.

Using the 2001 land cover map as a base, we mapped the amount of land cover change between 1992 and 2001 using Change Vector Analysis. Change categories were labeled using a combination of unsupervised classification, decision tree modeling, and decision rules based on adjacency to rivers. Change was mapped on 13% of the landscape. Accuracy of the change/no change map was estimated at 95% with a kappa statistic of 0.75. The probability that a point on the map was misclassified as change was 21% and the probability that a point known to represent change was mapped as no change was 17%.

Using the 1992 and 2001 land cover maps we modeled the predicted distributions of 141 vertebrate species for both dates. The species were selected because they had been identified by either the North Carolina Wildlife Resources Commission in their State Wildlife Action Plan (SWAP, 123 species) or by the Partners in Flight (PIF, 38 species)

Program as priority species in need of conservation action. We quantified change between the two dates and provide summaries by species and by agency list.

Finally, we quantified the overlap in the hotspots for the predicted distributions and the existing conservation network. Hotspots were identified as those areas predicted to have at least 28 SWAP priority species or 13 PIF priority species. Seventy percent of the existing conservation lands (status 1 and 2) in the Onslow Bight co-occurred with hotspot areas for both SWAP and PIF, while only forty percent of the lands that are not managed (status 4) met those criteria. In other words, the existing managed lands are capturing priority areas based on the two agency species lists, which will lead to more effective conservation of those taxa.

Mapping and Monitoring Plant Communities in the Coastal Plain of North Carolina: A Basis for Conservation Planning

By

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DEDICATION

This work is dedicated to my life partner Milo Pyne, and my family, Margaret, Andrew, Joan, Kelly, Mary, Nancy, Ann and Andy. Thank you each for being who you are and for being in my life.

BIOGRAPHY

I attended college at Colorado State University, where I took my first Plant Community Ecology Course and was hooked on studying ecology. While there I worked at the Natural Resource Ecology Laboratory, where I learned laboratory skills as a technician in the soils laboratory. More importantly, I was exposed to the long-term ecological research program and ecological research, including field work at the Konza Prairie, otter research at Rocky Mountain National Park and antelope research in Wyoming.

I was fortunate to land my first post-bachelors job with the Ecosystems Center at the Marine Biological Laboratory where I spent three summers at Toolik Lake, Alaska and winters in Woods Hole, Massachusetts. It was in Woods Hole that I attended a symposium on biotic impoverishment and heard seminars on the use of remote sensing in environmental monitoring and tropical ecology. My lab experiences and new interest in international conservation brought me to North Carolina State University for a Master of Science degree in Forestry with a soil science concentration. I was able to attend the Organization for Tropical Studies Managed Tropical Ecosystems Course. Drs. Charles Davey, Cheryl Palm, and Erick Fernandez guided me through that M.S. degree and allowed me to travel to Manaus, Brazil to be involved with a NCSU/EMBRAPA project at KM 54.

My next adventure was a move to Tennessee to be with my partner, Milo. Once there, I started doing contract work with the Tennessee Natural Heritage Program. Milo's position as State Botanist gave us many opportunities to explore that wonderfully diverse state. Soon I found a niche at the Tennessee Wildlife Resources Agency working on the Tennessee State Gap Analysis Project. An opportunity to come to North Carolina and continue working with GAP and to pursue a doctorate was too good to pass up. While at North Carolina State University I have participated in the North Carolina Gap Analysis Project and expanded the scope to include the Southeastern and Northeastern U.S.

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Over the course of my career I have had a series of incredible teachers. I thank each of them for what they taught me, especially A. William Aldredge (CSU), W. A. Jackson (NCSU), Cheryl Palm (NCSU), Martha Groom (formerly NCSU), George Hess (NCSU) and Thomas Wentworth (NCSU).

I owe a great deal of gratitude to the National Gap Analysis Program for funding and supporting this research. Mike Scott and Mike Jennings, whose dedication built the program, have changed the course of conservation in the United States. Without Kevin Gergely's mentoring I would not have made it through this degree. The camaraderie of the GAP personnel, Kevin, Jocelyn, Jill, Nicole, and Ann has been a bonus.

I would like to thank the friends and family who have enriched my life over the past decade. I thank: Nonna and Jeff for sharing wonderful meals, conversations, and your wisdom; Sarah and her family who have been there for me forever; Maggie whose encouragement has made the difference; and June for your constant friendship over the past fifteen years.

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PREFACE

Mapping and Monitoring Plant Communities in the Coastal Plain of North Carolina: A Basis for Conservation Planning

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Decades after the international community first realized its magnitude, the decline in global biodiversity continues. The number of imperiled species is increasing and the acreage of degraded natural systems continues to rise. During the past twenty years the National Gap Analysis Program (GAP) has been working to provide data and analyses to help guide proactive conservation and management. Based on the assumption that the most effective time to manage for a species is before it becomes imperiled, GAP has been working with partners to develop a framework for conservation of all vertebrate species and the natural systems upon which they depend.

My goal in this dissertation was to explore in depth the methods and analyses that can be employed to monitor natural systems and habitats through time. Specifically, I wanted to test the current approaches for land cover mapping and change detection and to use the results of that work in a conservation assessment that could be used by a variety of natural resource management agencies.

Chapter one represents a review of the current literature with respect to vegetation mapping in the United States. It details a variety of approaches that are being used and includes a discussion of the national classification systems (National Vegetation Classification System, Ecological Systems Classification) currently in use.

Chapter two details the mapping of vegetation of the Onslow Bight of NC. I used Landsat TM satellite imagery and a combination of ancillary datasets to map the Ecological Systems of the area. The change detection described in Chapter three allowed the creation of a two date time series (1992 and 2001) for the Ecological Systems of Onslow Bight.

In chapter four I integrated the results of the land cover mapping and the change detection with datasets from the Gap Analysis Program in a conservation assessment. In that assessment we focused on two natural resource agencies, the North Carolina Wildlife Resources Commission (WRC) and Partners in Flight (PIF), to test the approach to conservation assessment and monitoring. That assessment involved the mapping of predicted vertebrate distributions for 139 species. We used lists of priority species from the two groups, the WRC State Wildlife Action Plan (123 species) and the PIF's list of priority avian species (38 species with 18 unique to this list) for the Southeastern Coastal Plain Bird Conservation Region. In chapter four I also summarized the changes in the extent of the Ecological Systems of the Onslow Bight, as well as the predicted distributions for the 123 species for 1992 and 2001. Finally, we compared the areas predicted by the models to be rich in priority species against the existing conservation network and a series of newly acquired easements and determined the level of overlap. This comparison formed the basis for creating "scorecards" characterizing the gains and losses for both Ecological Systems and the predicted distributions of priority species both within and outside the conservation network. The scorecards are proposed as an approach to objectively quantifying the conservation status for natural resource agency priorities. The priority species richness maps are proposed as an objective basis for assessing offered acquisition projects and for proactively identifying conservation actions for an area.

Recent trends in remote sensing for vegetation mapping in the United States.

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Abstract

High quality land cover data is the key to an effective assessment of the status of vegetation of the United States. Recent innovations in mapping technology are making it possible to map vegetation over large areas with relatively high levels of thematic detail. During the past decade the vegetation mapping discipline has seen major advances in vegetation classification, satellite imagery, and mapping approaches. The development of the National Vegetation Classification System and Ecological Classification System provides a framework for map legends that are ecologically meaningful and consistent across the country. Access to satellite imagery and synergy between national mapping programs has greatly increased the efficiency of land cover mapping in the U.S. Finally, methods for large area mapping (e.g., image stratification, decision tree modeling, and pattern recognition) are providing a solid foundation for mapping the vegetation of the country. In this review we discuss the evolution of vegetation mapping methods during the past decade, describe some of the national programs involved in vegetation mapping, and provide an overview of the current status of vegetation classification systems in the U.S.

In a Nutshell

- The ability to map vegetation over large areas is the basis for effective land management and conservation.
- The feasibility of vegetation mapping over large areas is rapidly accelerating.
- The National Vegetation Classification System and Ecological Systems Classification are evolving to provide a much-needed framework for vegetation mapping in the U.S.

- New innovations (e.g., pattern recognition, hyperspectral and hyperspatial imagery) are currently limited to small extents, but should become practical for large area mapping soon.

Introduction

Vegetation mapping has undergone a considerable change in the last decade. In particular, integrating the perspective gained from space has made vegetation mapping of large areas possible. Changes in how government programs acquire and distribute remotely sensed data, and advances in computing power and mapping techniques, are removing some of the previously existing barriers to mapping large extents. The application of geographic information systems (GIS) science has also rapidly expanded, with agencies incorporating spatial data into their programs, and universities increasing opportunities for training. As a result, researchers and land managers are increasingly reliant on spatial data for inventory, management, and planning. Today, vegetation mapping is done from local to global scales, and those maps inform studies on global climate change (Freidl et al. 2003), deforestation (Skole and Tucker 1993), desertification (Hanan et al. 1991), habitat management (Scott et al. 1993, Scott and Jennings 1998, Lowry et al. 2005) and wildfire planning (Falkowski et al. 2005) (Figure 1.1). Recent innovations in data availability and mapping methodology have allowed the development of a global land cover map (Belward et al. 1999), a standard protocol for rapidly mapping general land cover of the U.S. (Homer et al. 2004), detailed large scale vegetation maps for some National Parks and Wildlife Refuges (Welch et al. 2002), vegetation maps for large regions (Lowry et al. 2005), and land cover change maps for the coastal regions (NOAA CCAP 2006). Table 1.1 provides a summary of programs currently involved in national mapping efforts in the U.S.

Just as important as the advances in mapping techniques, the standard vegetation classification systems that have been developed over the last decade are vastly improving the utility of the maps being developed. The National Vegetation Classification System (NVC; Grossman et al. 1998) was the first attempt at a nationally consistent system for all terrestrial vegetation. That classification and the Ecological Systems Classification (Comer et al. 2003) are the most broadly applied classification systems in vegetation mapping in the United States today.

The goal of this review is to summarize the recent developments in mapping techniques and vegetation classification specific to current mapping programs in the United States and to discuss some of the common tradeoffs (e.g., among extent, spatial resolution, and thematic resolution) to be considered when planning or evaluating a mapping project. In this review we are aiming for two general audiences, the ecologist considering a vegetation mapping project, and land managers who need to evaluate the land cover and vegetation maps they encounter in the course of their careers.

Target Map Classes

The first step in a successful mapping project is the identification of the target map classes. The intended use of the final map and the limitations of the data being used to create it will determine and constrain the number and definition of these classes.

A priori vs. derived map classes

There are two general methods for determining the vegetation classes: selecting from an a priori classification scheme or deriving the classes from a study area-specific dataset. In many maps, photo-interpretation is used for gathering data to train image classification or for directly mapping land cover. In those cases, the legend is determined by the ability to distinguish the target classes consistently in the photography. In this case, the photo-interpretation key represents the a priori classification scheme. Other examples of a priori classification systems are the detailed vegetation classification systems (Daubenmire and Daubenmire 1968, Schafale and Weakley 1990) for areas where plant community ecologists have focused their work. Classification systems vary depending on their geographic extent and the resource-specific objectives of the classification. It was not until 1998 that the U.S. had its first national-level classification of vegetation, the National Vegetation Classification System (NVCS; Grossman et al. 1998). Because of the importance of this a priori classification to national programs we discuss recent developments in detail below.

An alternative to a priori map classes is the use of detailed plot sampling and quantitative analysis of species composition to derive a classification scheme. The latter most often rely on cluster analysis and ordination techniques to determine the appropriate number and identity of vegetation classes in a study area. Each derived classification is a reflection of the dataset used in its development; as the datasets become richer with continued sampling, the spatial extent and thematic resolution of the derived classifications increase accordingly (Peet and Allard 1993, Reid et al. 1995, Newell et al. 1997, and Simon et al. 2005).

National vegetation classification systems

As the technology for mapping vegetation over large areas matured in the early 1990s, the lack of a standard classification system became increasingly problematic. The

NVCS was developed as a hierarchical classification scheme in an attempt to address the need for a classification scheme that was national in scope and thorough (Jennings 1997). It was developed as a hierarchical classification scheme similar in concept to that used in the United Nations Educational, Scientific, and Cultural Organization international classification of vegetation (UNESCO 1973). The NVCS hierarchy has 7 levels; in the upper five levels it includes physiognomic, structural, growth-form, phenological, and environmental information (Table 1.2). The lowest two levels incorporate species composition information. Dominant and/or indicator species of the uppermost or dominant layer (e.g., the canopy in a forest) determine the alliance classification, and additional subcanopy and/or ground layer species help define the associations. Currently, the Vegetation Subcommittee of the Federal Geographic Data Committee is drafting a revision of the NVCS standard (ESA Panel on Vegetation Classification 2004). If adopted, that revised standard may alter the structure of the hierarchy, while encouraging collaboration toward the evolution of the detailed content of the NVCS through a peer review process.

Since 1998 many programs have attempted to implement mapping of the NVCS at various levels of the hierarchy. The most successful of these has been the National Park Service (NPS) Mapping Program (http://biology.usgs.gov/npsveg/). NPS has been systematically mapping many of the national parks at the association level, the finest level of the NVCS. The Park Service has been able to achieve a high thematic resolution with extensive field work and manual interpretation of large scale aerial photography (TNC and ESRI 1994).

In the mid-1990s the USGS Biological Resources Division's Gap Analysis Program (GAP) selected the Alliance level of the NVCS as the basis for a state-by-state set of target map classes, but reliable (consistent and accurate) representation of these classes could not be achieved. This was due to an incompatibility between the spatial scale of the vegetation types on the ground and the scale of the available imagery and ancillary data. Scaling back to the Formation (the next highest level in the hierarchy) would have meant a loss of important ecological context. In the short-term this led to a shift in the target map legend for the individual state GAP projects (Pearlstine et al. 1998) and a broader call for an ecologically meaningful and "mappable" classification system. With support of groups like The Nature Conservancy and the National Gap Analysis Program, NatureServe ecologists were able to build on the extensive research and data of the NVCS to develop the first draft of this new classification, the Ecological Systems of the United States (Comer et al. 2003). Each system is intended to represent a group of associations tied together by landscape level ecological processes. It is important to note that this classification is not hierarchical and, while it is informed by the NVCS, it is a parallel system. The only direct link between the two classifications is at the finest level of the NVCS, the association (Figure 1.2). Because ecological processes (flooding, fire, wind) are central to the definition of the Ecological Systems, ancillary data are often necessary for mapping where spectral data alone would be insufficient.

Trends in satellite-based mapping

In their book "Vegetation Mapping", Kuchler and Zonneveld (1988) provided the first broad introduction to the field of satellite-based mapping. In 1994, Zhu and Evans published a forest map for the United States based on 1x1km Advanced Very High Resolution Radiometer (AVHRR) imagery, and, in 1997, Friedl and Brodley tested the use of decision tree modeling for satellite based mapping. By the mid-1990's, the National Land Cover Dataset (NLCD) and GAP state projects were making important advances in large area mapping. Below we present a summary of the traditional methods used in remote sensing and a discussion of recent innovations, including the use of multi-temporal imagery and the integration of ancillary spatial data and remote sensing.

Landsat imagery and vegetation mapping

Currently, Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM) sensors dominate the field with respect to large area vegetation mapping in the United States. The National Gap Analysis Program, NOAA Coastal Change Analysis Program (CCAP), and the Landfire Project all use Landsat imagery as the base for detailed vegetation mapping for large regions of the U.S. Landsat TM and ETM sensors acquire data for 6 and 7 spectral bands, respectively, at a spatial resolution of 30x30 m. Each of the Landsat sensors acquires data on a 16 day return cycle, although cloud cover and seasonal variability limit the number of those acquired images that might be suitable for mapping. The broad application and reliance on Landsat imagery for vegetation mapping in the U.S. is reflected in the following discussion. For a treatment of the use of Landsat in broader ecological applications see Cohen and Goward (2004).

Manual interpretation vs. automated computer mapping

The general trend in satellite-based land cover mapping is from manual methods toward an increased reliance on computer assisted and automated mapping methods. Early uses of satellite imagery as the base layer for mapping involved manual delineating and labeling of polygons. For example, the first generation vegetation map for the Washington State GAP project was developed through visual interpretation of Landsat TM imagery and field visits to guide the labeling of polygons (Grue 1997). Similarly, in their assessment of coastal sage scrub, Davis et al. (1994) used Landsat TM to delineate patterns, combined with field reconnaissance, interpretation of aerial photographs, and reference to historic maps in the labeling stage. The success and feasibility of manually delineating patterns in vegetation depend on the skill of the interpreter, the quality of the reference data, and the complexity of the vegetation being mapped.

The two traditional automated computer mapping approaches for image classification are unsupervised and supervised classification (Jensen 2004). In an unsupervised classification, each pixel in the image is assigned membership to an image cluster based on the statistical similarity of the pixel to a cluster. Similarity is determined by calculating the mean of all of the pixels currently assigned to a cluster for each band in the imagery. Clustering is an iterative process where pixels are sorted into a predetermined number of bins (clusters) based on the mean of the pixels currently assigned to each cluster. In each iteration, the membership of each pixel is re-evaluated based on the means of the clusters. Labeling of the imagery to generate a map is then done using training data to identify the most likely vegetation type for each cluster. In this case, the clusters represent groupings of the data that must then be interpreted and labeled relative to the map legend.

In contrast to an unsupervised method, which requires that data for labeling classes be gathered after the membership of pixels has been assigned, a supervised method utilizes a training dataset, derived in advance and used to train the classification. The goal in developing the training dataset is to select homogeneous training areas that represent the range of variability for each target map class. In the classification stage, each pixel in the study area is compared to the groups of pixels in each area of the training dataset and the pixels are assigned a map class if they are statistically similar to one of the training signatures. With a small study site or a generalized map legend, either a supervised or unsupervised approach is likely to be adequate for mapping vegetation. The accuracy of an unsupervised classification will depend on the target map legend, input imagery, and the analyst's ability to discriminate the land cover classes in the imagery. Supervised classification is most sensitive to the quality of the training data and the algorithm (e.g., maximum likelihood, minimum distance) used to label the land cover classes.

Multi-temporal imagery

As access to imagery and processing power increased, references to the use of multi-temporal imagery for mapping became more prevalent in the literature (Egbert et al., 1995; Wolter et al. 1995). A current example of the use of multi-temporal imagery for land cover mapping is the National Land Cover Dataset (NLCD 2001; Homer et al. 2004). That database includes the creation of three seasonal image mosaics (spring, leaf on, and leaf off) for each mapping zone in the U.S. (Yang et al. 2001). Such mosaics are also being used for the Gap Analysis Program, NOAA's Coastal Change Analysis Program (CCAP), and the Landfire Project, as well as in mapping for the NLCD 2001. For each of those efforts, the temporal variation is being used indirectly to assist in refining the land cover classifications and treat each date of imagery as an independent source of information.

Other approaches use information from the multi-temporal images directly, either by incorporating information about the change vectors (Lunetta et al. 2001) or by selecting which image(s) to use in classifying specific vegetation types. For example, Townsend (1997) used a hierarchical approach in which coarse vegetation types were mapped and then refined by developing unique combinations of multi-temporal image bands and band ratios for refinement of the detailed wetland classes. Wolter et al. (1995) used a similar hierarchical approach with specific band combinations from various image dates to map forest types in northwestern Wisconsin. Incorporating multi-temporal imagery increased the thematic resolution of maps from both Landsat (Mickelson et al. 1998, Wolter et al. 1995, Slaymaker et al. 1996) and Advanced Very High Resolution Radiometer imagery (Stoms et al. 1998, Zhu and Evans 1994).

Integrating ancillary data and remote sensing

Methods for integrating ancillary spatial data and remote sensing can be generally categorized as image stratification (either pre- or post-classification; Edwards et al. 1995, Gao et al. 2004); preponderance of evidence decision rules (Sader et al. 1995, Lunetta et al. 2001, Felicisimo et al. 2002); generalized linear modeling (Moisen and Edwards 1999); gradient nearest neighbor (Ohmann and Gregory 2002); or evidential reasoning approaches, including decision tree modeling (Duguay and Peddle 1996, Homer et al. 2004).

Image stratification by ecological region

In the Utah and Southwest GAP Projects (Edwards et al. 1995; Lowry et al. 2005), ecological regions were used to stratify the study area. In each case the assumption was that variability with respect to the target map classes would be lower within regions than among them. Similar logic was used in the development of the mapping zones for the NLCD 2001 (Homer and Gallant 2001). In that effort, the mapping zones were delineated based on five criteria - size, physiography, land cover patterns, spectral patterns, and the placement of the map zone edges that would later need to be mosaicked with adjoining zones. Large area mapping involved mapping across many satellite scenes. If each scene is mapped individually, adequate training data for each land cover class being mapped must be located within each of those scenes. If however, the imagery is mosaicked and then divided based on ecoregion, the mapper may be able to map the same classes with a lower number of training points overall. Another potential advantage is the reduction in edge matching, assuming the ecoregion boundaries do represent transition lines for the classes being mapped. The potential disadvantage is increased spectral variability within a region if the satellite scenes mosaicked to create a region have high variability in phenological or atmospheric conditions (Homer et al. 1997).

Preponderance of evidence decision rules

Several projects have found they could improve the accuracy of their vegetation mapping by incorporating preponderance of evidence decision rules, also known as weighting criteria. A decision rule can be based on expert knowledge or can be derived from the data. For example, if floodplain forests only occur within 100 meters of a river, a rule can be established that floodplains can only be mapped within that distance. Similarly, if 95% of the training sites for floodplain forest occur within 100 meters of the river, a probability of 95% can be applied to pixels within 100 m of the river and a 5% probability for pixels at greater distances. Incorporating variables such as elevation, terrain type, and proximity to rivers improved the vegetation map for a site in the Arctic National Wildlife Refuge (Joria and Jorgenson 1996). In that study, the application of GIS-based decision rules to an unsupervised classification produced a better vegetation map than either the unsupervised classification alone, or a supervised classification based on the same training data. Similarly, the Utah GAP Project adopted a two-phase mapping approach in order to improve its vegetation map (Edwards et al. 1995). Summary statistics for the clusters from the unsupervised classification were used to determine weighting criteria used in ancillary modeling within each ecological region of the state. Edwards et al. (1995) found that the majority of cover classes (31 of 36) were improved with the use of this ancillary modeling.

Generalized linear modeling

An early example of using generalized linear modeling to integrate satellite imagery and ancillary spatial data for mapping vegetation is the study of Glacier National Park (Brown

1994). Generalized linear modeling, like traditional linear regression, relies on least squares criteria to model the response variable from the predictor variables. In this study, four vegetation types (open canopy forest, closed canopy forest, meadow, and unvegetated) were modeled from insolation potential, snow accumulation potential, and soil moisture potential. Moisen and Edwards (1999) also used generalized linear modeling to integrate topography, spatial coordinates, and spectral data with traditional forest inventory data for northern Utah, and they were able to improve the precision of forest timber volume estimates over methods based on the plot data alone.

Gradient nearest neighbor

Ohmann and Gregory (2002) used gradient nearest neighbor to successfully map forest structure and physiognomy for Coastal Oregon. This method translates the results of traditional direct gradient analysis (Gauch 1982) into a spatial framework by assigning map labels based on nearest neighbor imputation. In Ohmann and Gregory (2002), Landsat TM spectral bands and derivatives were first integrated with ownership, topographic, geologic, and climatic data derivatives and then analyzed using canonical correspondence analysis to model forest types. The map was then created by assigning each pixel in the study site to the class of its nearest neighbor (minimum Euclidean distance) in gradient space. While Gradient Nearest Neighbor has been successfully applied to mapping structure and physiognomy, it had not been previously used to map vegetation type. Currently the approach is being tested with respect to mapping Ecological Systems in the Northwestern U.S.

Decision tree modeling

Decision tree modeling is a supervised classification method that has been broadly applied in the social and medical sciences for decades. It was not until the 1990s that the potential for use in land cover applications became apparent (Michaelson et al. 1994, Duguay and Peddle 1996). Decision trees rely on recursive partitioning of the training dataset to create a hierarchical tree in which a series of nodes represent a binary split of the dataset into branches. The method for splitting the data depends on whether the response variable is categorical (discriminant analysis or logistic regression) or continuous (multiple regression). In keeping with the tree theme, the terminal nodes where the map classes are assigned are called leaves (Figures 1.3a and b).

Friedl and Brodley (1997) examined the application of the decision tree process to land cover mapping at three scales (AVHRR at 1 x 1 ^{o}; AVHRR at 1x1 km; and Landsat TM at 30x30 m) and found that, in each case, decision trees performed better than either the linear discriminant functions or the more traditional supervised classification approach (e.g., maximum likelihood classification).

The adoption of the decision tree classification as a central component of the NLCD 2001 protocol (Homer et al. 2004) means that the approach is being applied throughout the U.S. for land cover mapping. The database includes three components - general land cover (NLCD 2001), canopy closure, and impervious surface estimations. Regression tree modeling is used to generate the estimates of canopy closure, and impervious surface (Yang et al. 2003, Homer et al. 2004) and decision tree modeling is used in the development of the 23-class land cover layer. The first large area mapping effort to incorporate decision tree modeling for mapping vegetation types in the U.S. was the Southwest GAP Project (Lowry et al. 2005, see Case Study).

Pattern recognition

An additional innovation in mapping is the use of pattern recognition, in which texture or context information for individual pixels is used in combination with the spectral information to create image objects (Figure 1.4). In their discussion, “What’s the matter with pixels? Some recent developments in interfacing remote sensing and GIS”, Blaschke and Strobl (2001) provide a thoughtful summary of the need to pay attention to pattern in land cover mapping. They proposed location and context as “new paradigms” in remote sensing. Some of their concepts can be related back to work by Ryherd and Woodcock (1996), who showed the importance of incorporating texture information into image segmentation. In that study, forests of various canopy densities and mixtures of tree canopy sizes were simulated to test the accuracy of forest pattern delineation with and without texture as an input. In southern Montana, Fisher et al. (2002) tested the application of two pattern recognition approaches to mapping. They were able to map 27 cover classes, using supervised classification based on image objects, with overall accuracies greater than 70%. In the same study they found they were able to map five sagebrush and greasewood species with over 90% accuracy using the same methods.

The use of pattern recognition in large area vegetation mapping is limited (Fisher et al. 2002, Chapter 2 and 3 this volume). Current applications tend to involve highly structured land cover or land use classes (e.g., roads, buildings) with an emphasis on high resolution imagery (e.g., IKONOS, digital orthophotography; Elmqvist and Khatir 2007). The application of pattern recognition in mapping based on lower resolution imagery for natural resource applications is expanding (Lucas et al. 2007, Fisher et al. 2002, Chapter 2 and 3 this volume).

Future Trends

We can expect that, over the next few years, decision tree modeling will continue to be the dominant method for large area vegetation mapping. At the same time, it is likely that the application of pattern recognition and higher resolution satellite imagery (hyperspectral and hyperspatial) will become increasingly common as barriers to their use (limited access, high cost, and limited processing capabilities) are removed. The continued evolution of the NVCS, including the adoption of a new hierarchy structure and continued inventory work, will make use of that classification for large area mapping practical.

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References

Belward, A. S., J. E. Estes, and K. D. Kline. 1999. The IGBP-DIS Global 1-Km land-cover data set DISCovery: A project overview. Photogramm Eng Rem S 65:1013-1020.

Blaschke, T. and J. Strobl. 2001. What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GIS—Zeitschrift für Geoinformationssysteme 6:12–17.

Brown, D. G. 1994. Predicting vegetation types at treeline using topography and biophysical disturbance variables. J Vege Sci 5:641-656.

Cohen, W. B. and S. N. Goward. 2004. Landsat's role in ecological applications in remote sensing. BioSci 54:535-545.

Comer, P., D. Faber-Langendoen, R. Evans, S. Gawler, C. Josse, G. Kittel, S. Menard, M. Pyne, M. Reid, K. Schulz, K. Snow, and J. Teague. 2003. Ecological Systems of the United States: A working classification of U.S. terrestrial systems NatureServe, Arlington, VA.

Daubenmire, R. and J. B. Daubenmire. 1968. Forest vegetation of eastern Washington and northern Idaho. Technical Bulletin 60. Washington Agricultural Experiment Station, College of Agriculture, Washington State University, Pullman, 104 pp.

Davis, F. W., P. A. Stine, and D. M. Stoms. 1994. Distribution and conservation status of coastal sage scrub in southwestern California. J Vege Sci 5:743-756.

Ecological Society of America Vegetation Panel. 2004. Vision statement and report on panel activities. http://www.esa.org/vegweb/#panel. Viewed 12/1/07.

Edwards, T.C., Jr., C. G. Homer, S. D. Bassett, A. Falconer, R. D. Ramsey, and D. W. Wight. 1995. Utah Gap Analysis: an environmental information system. Technical Report 95-1, Utah Cooperative Fish and Wildlife Research Unit, Utah State University, Logan, Utah. 1189pp + 2 CD-ROMs.

Egbert, S. L., K.P. Price, M. D. Nellis, and R. Lee. 1995. Developing a land cover modeling protocol for the high plains using multi-seasonal thematic mapper imagery. Proceedings of the Annual Convention and Exposition. American Congress on Surveying and Mapping / American Society for Photogramm Eng Rem S 3:836-845.

Elmqvist, B. and A. R. Khatir. 2007. Journal of Arid Environments. The possibilities of bush fallows with change roles of agriculture – An analysis combining remote sensing and interview data from Sudanese drylands. J. of Arid Envir 70:329-343.

Duguay, C. R. and D. R. Peddle. 1996. Comparison of Evidential Reasoning and Neural Network Approaches in a Multi-Source Classification of Alpine Tundra Vegetation. Can J of Rem S 22:422-403.

Falkowski, M. J., P. E. Gessler, P. Morgan, A.T. Hudak, M.S. Alistair. 2005. Characterizing and mapping forest fire fuels using ASTER imagery and gradient modeling. For Ecol and Manage 217:129-146.

Fisher, C., W. Gustafson, and R. Redmond. 2002. Mapping Sagebrush/Grasslands from Landsat TM-7 Imagery: A Comparison of Methods. Report to the US DOI - Bureau of Land Management. Billings, MT 1-21. http://sagemap.wr.usgs.gov/Docs/BLM_sagecompare.pdf. Viewed 12/1/07.

Friedl, M. A. and C. E. Brodley. 1997. Decision tree classification of land cover from remotely sensed data. Rem S Envir 61:399-409.

Gao, J., H, Chen, and Y. Zha. 2004. Knowledge-Based Approaches to Accurate Mapping of Mangroves from Satellite Data. Photogramm Eng Rem S 17:1241-1249.

Gauch, H. G., Jr. 1982. Multivariate Analysis and Community Structure. Cambridge University Press, Cambridge.

Grossman, D. H., D. Faber-Langendoen, A. S. Weakley, M. Anderson, P. Bourgeron, R. Crawford, K. Goodin, S. Landaal, K. Metzler, K. D. Patterson, M. Pyne, M. Reid, and L. Sneddon. 1998. International classification of ecological communities: Terrestrial vegetation of the United States. Volume I. The National Vegetation Classification System: Development, status, and applications. The Nature Conservancy, Arlington, Virginia. 126 p.

Grue, C.E., K. M. Cassidy, and K. M. Dvornich. 1997. Washington State Gap Analysis Project Final Report. Submitted to USGS. Biological Resources Division. National Gap Analysis Program. Five volume cd-rom set.

Hanan, N. P., Y. Prevost, A. Diouf, and O. Diallo. 1991. Assessment of desertification around deep wells in the sahel using satellite imagery. J Applied Ecol 28:173-186.

Homer, C. G. and A. Gallant. 2001. Partitioning the Conterminous United States into Mapping Zones for Landsat TM Land Cover Mapping, USGS Draft White Paper, 2001. 7 p.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. Development of a 2001 National Landcover Database for the United States. Photogramm Eng Rem S 70:829-840.

Homer, C. G., R. D. Ramsey, T. C. Edwards, Jr. and Alan Falconer. 1997. Landscape Cover-Type Modeling Using a Multi-Scene Thematic Mapper Mosaic. Photogramm Eng Rem S 63:59-67.

Jensen, J. R. 2004. Introductory Digital Image Processing. 3rd Edition, 2004. Prentice Hall. 526 p.

Jennings, M. D. 1997. Progressing toward a standardized classification of vegetation for the U.S. U.S.G.S. Biological Resources Division. National Gap Analysis Program Bulletin 6:16-19.

Joria, P. E. and J. E. Jorgenson. 1996. Comparison of three methods for mapping tundra with Landsat digital Data. Photogramm Eng Rem S 62:163-169.

Lowry, J. H. Jr., R. D. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W. Kepner, J. Kirby, L. Langs, J. Prior-Magee, G. Manis, L. O'Brien, K. Pohs, W. Rieth, T. Sajwaj, S. Schrader, K. A. Thomas, D. Schrupp, K. Schulz, B. Thompson, C. Wallace, C. Velasquez, E. Waller, and B. Wolk. 2005. The Southwest Regional Gap Analysis Project Final Report on Land Cover Mapping Methods. Report to the U.S.G.S Biological Resources Division. National Gap Analysis Program 1-50. http://ftp.nr.usu.edu/swgap/swregap_landcover_report.pdf. Viewed 10/15/07.

Lucas, R., A. Rowlands, A. Brown, S. Keyworth, and P. Bunting. 2007. Rule-based classification of multi-temporal satellite imagery for habitat and agricultural land cover mapping. J of Photogramm Rem S 62:165-185.

Lunetta, R., J. Ediriwickrema, J. Iames, D. Johnson, J. Lyon, A. McKerrow and A. Pilant. 2001. A Quantitative Assessment of a Combined Spectral and GIS Rule-Based Land-Cover Classification of the Neuse River Basin, North Carolina, USA. Photogramm Eng Rem S 69:299-310.

Mickelson, J. G., D. L. Civco, J. A. Silander, Jr. 1998. Delineating Forest Canopy Species in the Northeastern United States Using Multi-temporal TM Imagery. Photogramm Eng Rem S 64:891-904.

Moisen, G. G. and T. C. Edwards, Jr. 1999. Use of generalized linear models and digital data in a forest inventory of northern Utah. J of Agricul, Biol, and Environ Stat 4:372-390.

National Oceanographic and Atmospheric Administration. Coastal Services Center. 1995-present. The Coastal Change Analysis Program (CCAP). Charleston, SC: NOAA Coastal Services Center. http://www.csc.noaa.gov/crs/lca/ccap.html. Viewed 12/1/07.

Newell, C. L., R. K. Peet, and J. C. Harrod. 1997. Vegetation of Joyce Kilmer-Slickrock Wilderness, North Carolina. University of North Carolina – Chapel Hill, Curriculum in Ecology and Department of Biology. 282 pages.

Ohmann, J. L. and M. J. Gregory. 2002. Predictive mapping of forest composition and structure with direct gradient analysis and nearest neighbor imputation in coastal Oregon, U.S.A. Can J For Res 32:725-741.

Pearlstine, L, A. McKerrow, M. Pyne, S. Williams, and S. McNulty. 1998. Compositional groups and ecological complexes: a methodological approach to realistic GAP mapping. Gap Analysis Bulletin No. 7. National Gap Analysis Program, Moscow, Idaho, USA. http://www.gap.uidaho.edu/Bulletins/7/CGECAMABVM.htm. Viewed 12/1/07.

Peet, R.K. and D.J. Allard. 1993. Longleaf pine vegetation of the Southern Atlantic and Eastern Gulf Coast regions: A preliminary classification. Proc Tall Timbers Fire Ecol Conf 18:45-81.

Reid, M., P. Bourgeron, H. Humphries, and M. Jensen. 1995. Documentation of the modeling of potential vegetation at three spatial scales using biophysical settings in the Columbia River Basin Assessment Area. Report to the U.S. Forest Service. 195 pp.

Ryherd, S. and C.E. Woodcock, 1996. Combining spectral and texture data in the segmentation of remotely sensed images. Photogramm Eng Rem S 62:181-194.

Sader, S.A., D. Ahl, and L. Wen-Shu. 1995. Accuracy of Landsat-TM and GIS Rule-Based Methods for Forest Wetland Classification in Maine. Rem S Environ 53:133-144.

Scott, J.M., F. Davis, B. Csuti, R. Noss, B. Butterfield, C. Groves, H. Anderson, S. Caicco, F. D'Erchia, T.C. Edwards, Jr., J. Ulliman, and R.G. Wright. 1993. Gap Analysis: A geographic approach to the protection of biological diversity. Wildlife Monographs. 123: 1-41.

Scott, J. M. and M. D. Jennings 1998. Large-Area mapping of biodiversity. Annals of the Missouri Botanical Garden: 85:34-47.

Simon, S.S., T.K. Collins, G.L. Kauffman, W.H. McNab, and C.C. Ulrey. 2006. Ecological zones in the Southern Appalachians: first approximation. Research Paper SRS-41. U.S. Department of Agriculture, Forest Service, Southern Research Station. Asheville, North Carolina. 41 p.

Skole, D. and C. Tucker. 1993. Tropical deforestation and habitat fragmentation in the Amazon: Satellite data from 1978 to 1988. Science 260: 1905-09.

Slaymaker, D. M., K. M. L. Jones, C. R. Griffin, J. T. Finn. 1996. Mapping deciduous forests in New England using aerial videography and multi-temporal Landsat TM imagery. In Gap Analysis: A landscape approach to biodiversity planning. Editors J. M. Scott, T. H. Tear, and F. W. Davis. ASPRS. Bethesda, Maryland. 87-102.

Stoms, D. M., M. J. Bueno, F. W. Davis, K. M. Cassidy, K. L. Driese, and J. S. Kagan. 1998. Map-guided classification of regional land cover with multi-temporal AVHRR data. Photogramm Eng Rem S 64:831-838.

The Nature Conservancy and Environmental Systems Research Institute, Inc. 1994. Final Draft: Field Methods for Vegetation Mapping. Prepared for the U.S. Department of Interior, National Biological Survey and National Park Service. (http://biology.usgs.gov/npsveg/fieldmethods/indexdoc.html; Viewed 12/18/06.

Welch, R., M. Madden, and T. Jordan. 2002. Photogrammetric and GIS techniques for the development of vegetation databases of mountainous areas: Great Smoky Mountain National Park. Photogramm Eng Rem S 57:53-68.

Wolter, P. T., D. J. Miadenoff, G. E. Host, and T. R. Crow. 1995. Improved Forest Classification in the Northern Lakes States Using Multi-Temporal Landsat Imagery. Photogramm Eng Rem S 61:1129-1143.

Yang, L., C. Homer, K. Hegge, C. Huang, B. Wylie, and B. Reed. 2001. A Landsat 7 Scene Selection Strategy for a National Land Cover Database. Proceedings of the IEEE 2001 International Geoscience and Remote Sensing Symposium, Sydney, Australia. http://search.yahoo.com/search?fr=slv1-&p=A+Landsat+7+Scene+Selection+Strategy+for+a+National+Land+Cover+Database Viewed 12/1/07.

Zhu, Z. and D. L. Evans. 1994. U.S. forest types and predicted percent forest cover from AVHRR data. Photogramm Eng Rem S 60:525-531.

Table 1.1 National mapping programs in the United States.

Program	Target Map Units	Primary Use	Base Imagery	Mapping Extent	Approach
NOAA-CCAP National Oceanic and Atmospheric Administration Coastal Change Analysis Program http://www.csc.noaa.gov/crs/lca/ccap.html	Land Cover	Coastal planning and monitoring	Landsat	Coastal Zone	Decision trees and spectral differencing
GAP National Gap Analysis Program http://gapanalysis.nbii.gov	Ecological Systems	Conservation planning, plant communities, wildlife habitat modeling	Landsat	Regional	Decision trees, pattern recognition, manual delineation, expert opinion
Landfire Landscape Fire and Resource Management Planning Tools Project http://www.landfire.gov	Ecological Systems	Wildfire planning	Landsat	National	Decision trees
NLCD National Land Cover Database Project http://www.mrlc.gov	Land Cover	Inventory, planning, and monitoring	Landsat	National	Decision trees
NPS National Park Service Vegetation Mapping Program http://biology.usgs.gov/npsveg	National Vegetation Classification	Inventory, planning, monitoring.	Aerial photographs	Park specific	Photo interpretation
http://biology.usgs.gov/npsveg					

Table 1.2. United States National Vegetation Classification System's hierarchy. Hierarchy as adopted in the 1997 FGDC standards (Grossman et al. 1998).

Level	Primary Basis for Classification	Example
Class	Growth form and structure of vegetation	Woodland
Subclass	Growth form characteristics, e.g., leaf phenology	Deciduous Woodland
Group	Leaf types, corresponding to climate	Cold-deciduous Woodland
Subgroup	Relative to human impact (natural/semi-natural, or cultural)	Natural/Semi-natural
Formation	Additional physiognomic and environmental factors, including hydrology	Temporarily Flooded Cold-deciduous Woodland
Alliance	Dominant/ diagnostic species of uppermost or dominant stratum	*Populus deltoides* Temporarily Flooded Woodland Alliance
Association	Additional dominant/ diagnostic species from any strata	Populus deltoides – (*Salix amygdaloides*) / *Salix exigua* Woodland

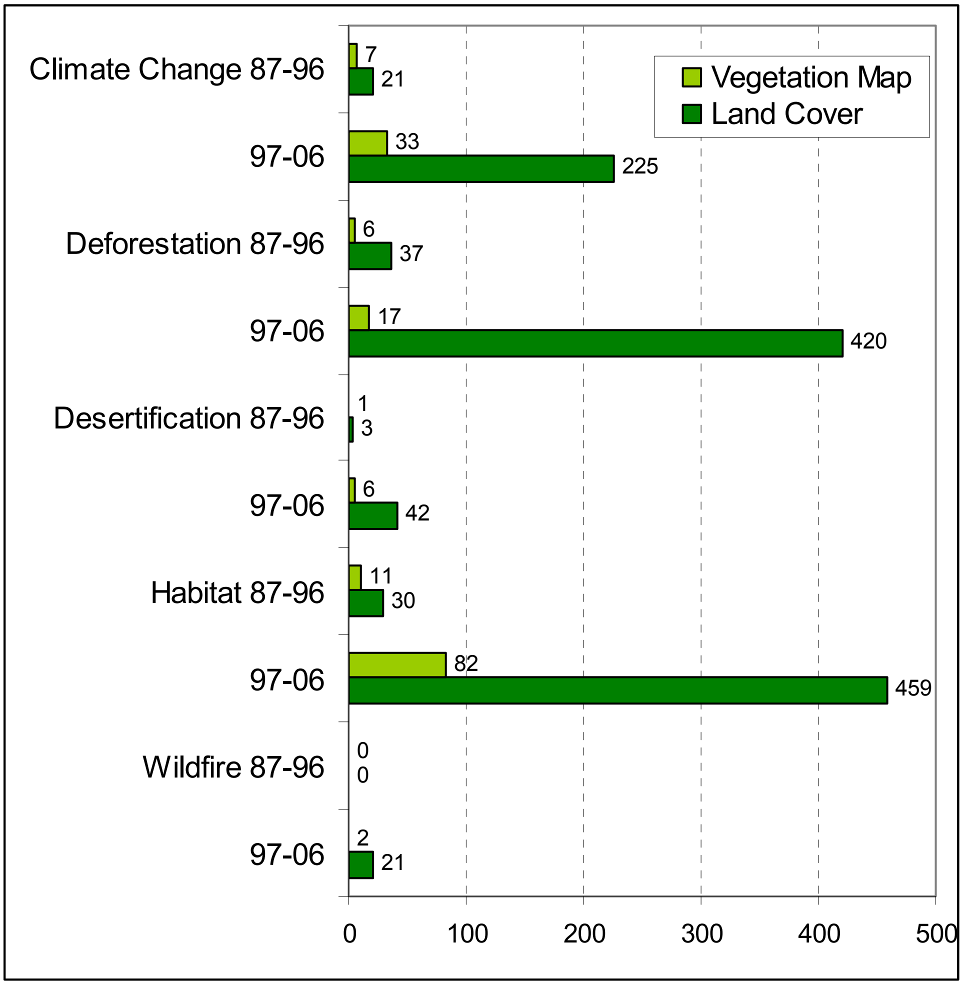

Figure 1.1. A summary of the literature.
An increase in citations related to land cover or vegetation map related to climate change, deforestation, desertification, habitat, and wildfire in the past decade. Comparisons between search results for 1987-1996 and 1997-2006 show an increase in each research topic. The Web of Science search engine was used to quantify the number of citations that met the criteria of incorporating either vegetation map or land cover with a secondary subject. For example, between 1987 and 1996 there are no citations that link Wildfire with vegetation map or land cover; by 2006 there were 2 citations for vegetation map and 21 for land cover.

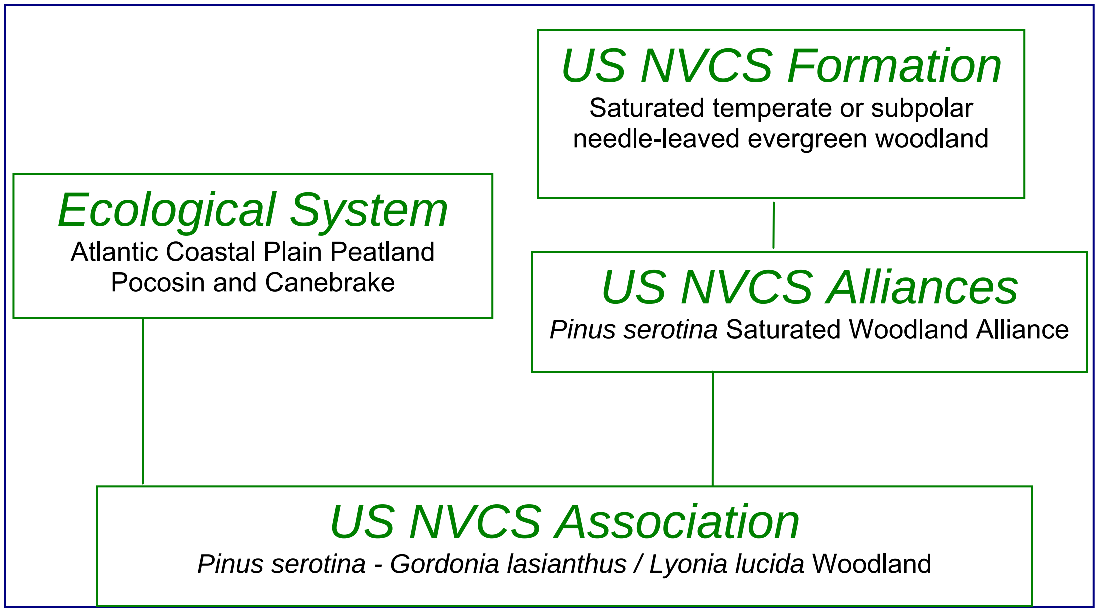

Figure 1.2. Relationship between the National Vegetation Classification System and the Ecological Systems Classification. Both the Ecological System Classification and the National Vegetation Classification System are informed by the finest level of the NVCS, the association level (Grossman et al. 1998 and Comer et al. 2003).

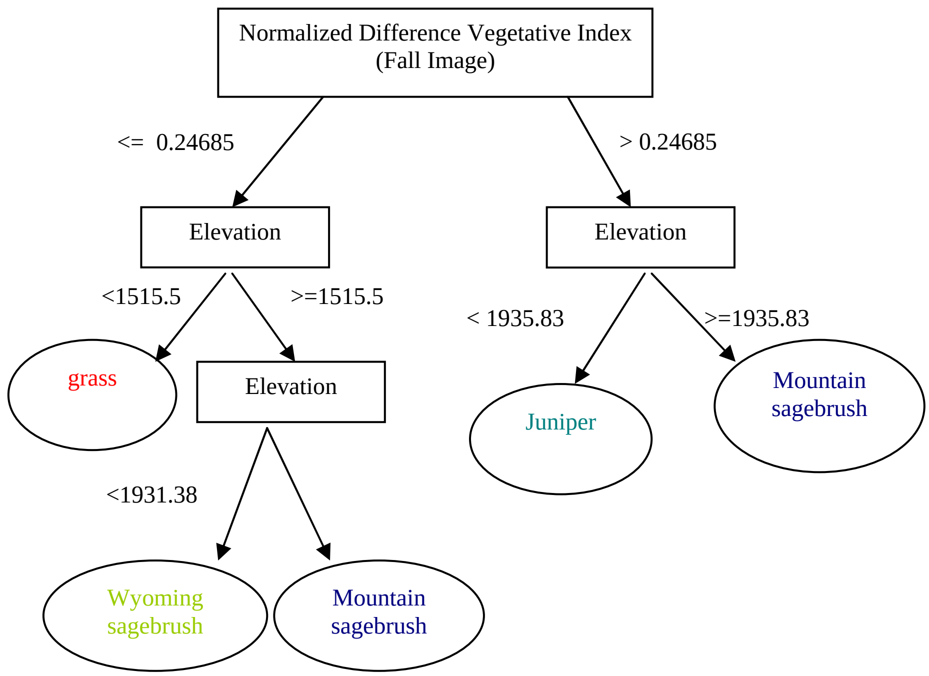

Figure 1.3a. Example of a decision tree from the Southwest Gap Analysis Project. This decision tree used Normalized Difference Vegetation Index (NDVI) and elevation thresholds to map a general grass cover type and three Ecological Systems including the Inter-Mountain Basins Big Sagebrush Shrubland and Colorado Plateau Pinyon-Juniper Woodland (Lowry et al. 2005). Sample data provided by J. Lowry.

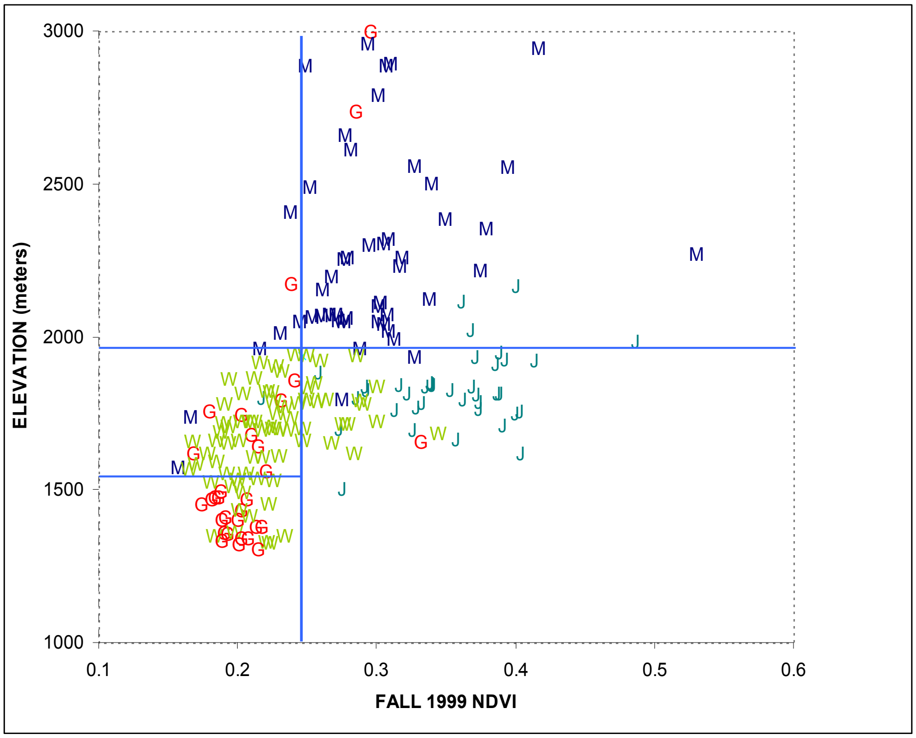

Figure 1.3b. Thresholds from the Southwest GAP decision tree are shown as axes in two-dimensional space. Following the right side of the decision tree (Figure 1.3a; Lowry et al. 2005), the first split of the data is made at the Normalized Difference Vegetation Index value of 0.24685. That decision isolates most of the mountain sagebrush (M) and Pinyon-Juniper woodland (J) training sites from the remaining data. A second split determines the classification of mountain sagebrush above 1935.5 meters and Pinyon-Juniper at lower elevations. Note the inclusions of Wyoming sagebrush (W) in the lower right quadrant would be errors in this model.

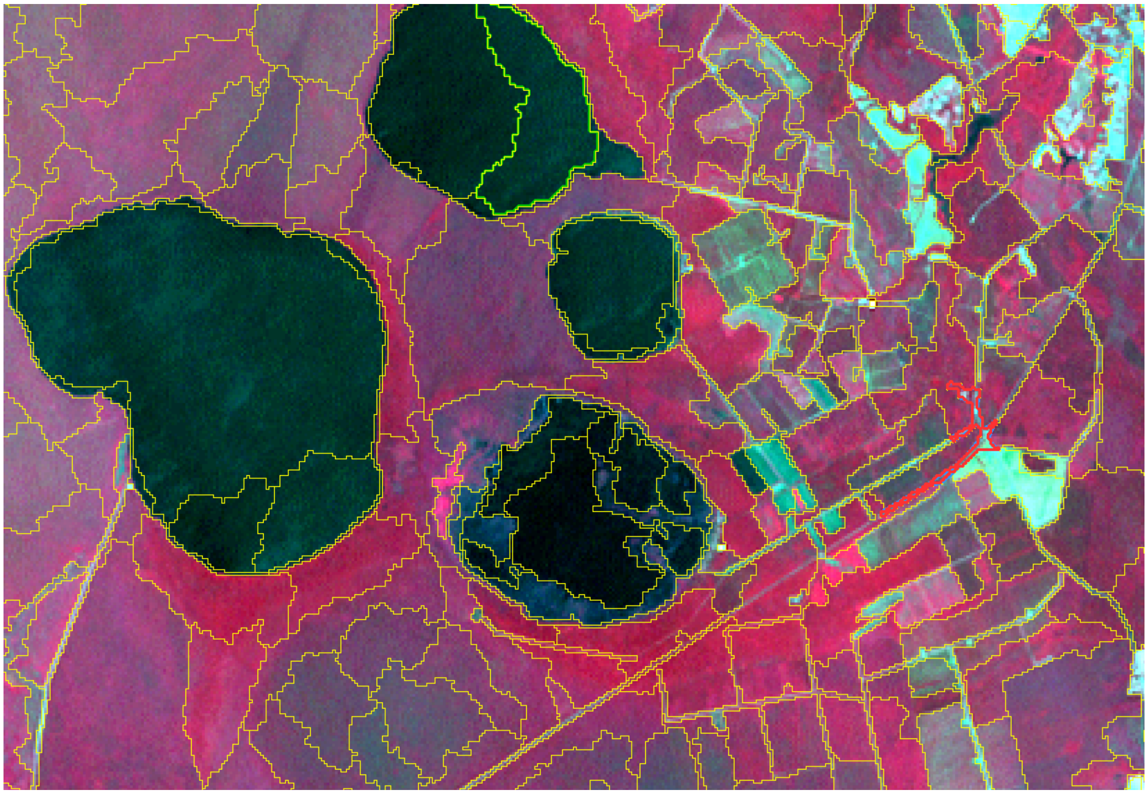

Figure 1.4. Image objects for a small area of the Croatan National Forest. Objects displayed over the Landsat TM image used to generate them. Image objects allow for hierarchical classification by incorporating data on both super-object and sub-object characteristics. In this case, shape index might be an important object level character, while variation of the pixels within an object, a sub-object characteristic, may be relevant as well.

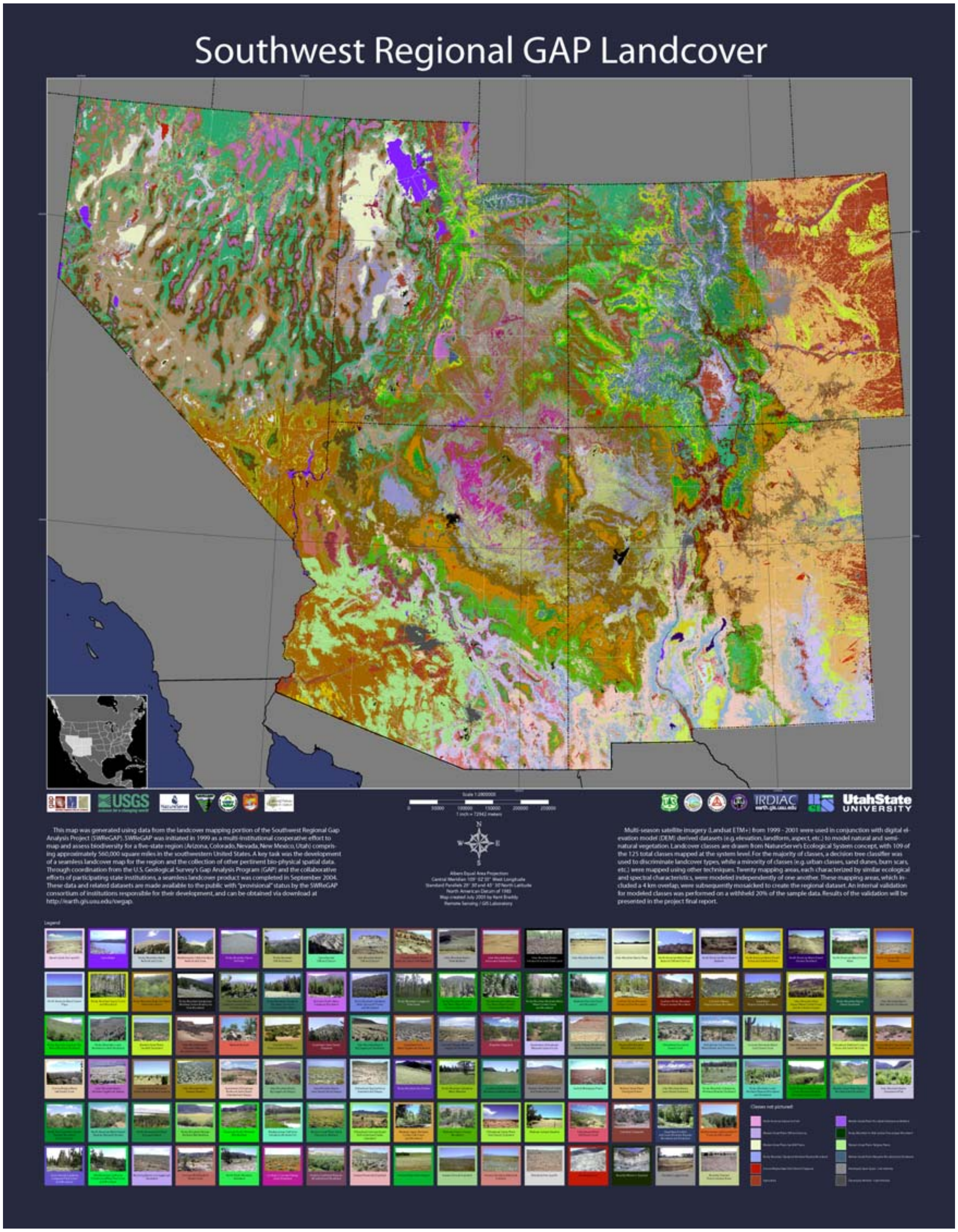

Figure 1.5. Southwest GAP Regional Land Cover Map. Map legend includes 125 land cover classes and 109 Ecological Systems (Lowry et al. 2005).

Case Study: Southwest GAP Project Regional Land Cover Map (Lowry et al. 2005).

In this case we highlight the series of choices made by the Southwest Gap Analysis Project for mapping vegetation over a 5 state area. The final map, shown below, includes 125 map classes, with 109 Ecological Systems represented (Figure 1.5).

Target Map Classes: For this project a total of 109 Ecological Systems were mapped. Prior to mapping, extensive field work was done to collect vegetation data that would inform the classification system, as well as act as training and assessment data. For a complete description of the 109 map classes based on the Ecological Systems Classification or to download the data, see the Southwest GAP land cover report (http://earth.gis.usu.edu/swgap/landcover.html).

Automated vs. Manual Delineation: The decision tree process used for this project is an automated supervised classification method. The training data provide the a priori class labels, and the decision tree model determines the best series of binary splits of the data to predict the labels based on those training data. In this case, over 93,000 training data points were gathered; 20% of those points within each target map class were randomly selected and set aside for the final accuracy assessment, and the remaining 80% were used to “train” the decision tree.

Satellite-based mapping: The base imagery for the project was Landsat Enhanced Thematic Mapper (ETM) imagery acquired within a three year time period (1999 to 2001).

Multi-temporal imagery: In order to take advantage of seasonality, three seasons (spring, summer, and fall) of images were used. A total of 237 Landsat scenes were required to cover the study area for the three seasons.

Integrating Ancillary Data with remote sensing: Landsat ETM satellite images and image derivatives, including the Normalized Difference Vegetation Index and tasseled cap brightness, greenness, and wetness indices, were used in the decision tree modeling.

Digital Elevation Models (DEM) and derivatives including slope, aspect and landform. In this study the researchers had compiled data including geology, State Soil Geographic Database (STATSGO), and 1x1km meterologic data, but decided not to include those data in the modeling because of differences in the scale of the satellite data and those data sources.

Image stratification: Twenty five distinct mapping zones were developed for the project. Each mapping zone was treated independently, and once completed, all zones were mosaicked to create the final regional product.

Decision tree modeling: For each mapping zone, decision tree modeling was used to map the natural vegetation of the zone. Non-modeled classes included land cover types such as agriculture, developed, and water. For the modeled classes, the training data were used as the response variables in a decision tree process, with the satellite imagery and ancillary data sources described above as the predictor variables.

Lowry, J. H. Jr., R. D. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W. Kepner, J. Kirby, L. Langs, J. Prior-Magee, G. Manis, L. O'Brien, K. Pohs, W. Rieth, T. Sajwaj, S. Schrader, K. A. Thomas, D. Schrupp, K. Schulz, B. Thompson, C. Wallace, C. Velasquez, E. Waller, and B. Wolk. 2005. The Southwest Regional Gap Analysis Project Final Report on land cover mapping methods. Report to the U.S.G.S Biological Resources Division. National Gap Analysis Program. 50 pp. (http://ftp.nr.usu.edu/swgap/swregap_landcover_report.pdf)

Manis, G. C. Homer, D. Ramsey, J. Lowry, T. Sajwaj, and S. Graves. 2000. The development of mapping zones to assist in land cover mapping over large geographic areas: A case study of the Southwest ReGAP Project. National Gap Analysis Bulletin. Bulletin No. 9. http://www.gap.uidaho.edu/Bulletins/9/bulletin9/bulletin9html/tdomzailcmolga.html#t6

Mapping Ecological Systems in the Coastal Plain of North Carolina.

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Abstract

Many of the plant communities of North America are in decline, due to a variety of stresses including land use change, climate change, and plant pests, diseases, and decline syndromes. Accurate maps of the current extent of those communities will enhance our ability to assess their true status and will provide a baseline for monitoring future changes. The U.S. National Gap Analysis Program has been working on regional projects to test methods for mapping and modeling plant communities to create a consistent and ecologically meaningful land cover map of the U.S. In this project, our goal was to test methods for mapping and modeling Ecological Systems in the Coastal Plain of the southeastern U.S. Specifically we were interested in testing the application of image stratification and decision tree modeling for mapping the Ecological Systems in the Onslow Bight region of North Carolina. We were also able to test the influence of county level (SSURGO) and state level (STATSGO) soil data in decision tree modeling. Decision tree modeling worked well for five of the six evergreen and nonriverine wetland systems, but the Atlantic Coastal Plain Upland Longleaf System was not well mapped by our method. The decision tree process performed best with the full complement of input variables, and by testing the decision tree with and without the two levels of soils data, we were able to observe an interaction between those two data layers in the modeling process. The model in which both soils datasets were included predicted both the occurrence of ecological systems that cover large extents and those that occur in relatively small patches. Overall accuracy using conditional probabilities was estimated at 77% and the Kappa statistic was 0.75. In general, by incorporating a variety of techniques specific to the target map classes, we were able to successfully map most of the Ecological Systems described by NatureServe for the Onslow Bight.

Keywords: Landsat TM, Ecological Systems, vegetation mapping, decision tree, pattern recognition, image objects.

Introduction

We explored the challenges of mapping and modeling the vegetation of the coastal plain region of the Southeastern U.S. The National Gap Analysis Program (GAP) has as its mission "keeping common species common." During the past decade, the program has conducted and funded research in support of that mission. The overriding goal is providing three key datasets that can be used to assess the conservation status of plant communities and terrestrial vertebrate species in the United States: land cover, vertebrate species distributions, and land management status. These layers have been used to identify "gaps" in species protection by identifying areas that support vertebrate species or plant communities that are currently under-represented in the conservation network. The accuracy and thematic resolution of the land cover maps influence the relevance of the analysis with respect to conservation and habitat modeling.

With that in mind, GAP has been focusing on the development of regionally consistent and ecologically meaningful maps. The Southwest Gap Analysis Project has recently completed a detailed land cover map for five southwestern states (Lowry et al. 2005). The work described here is part of the ongoing Southeastern GAP, in which a land cover map for nine states is being developed. While topographic relief and geology are drivers of vegetation pattern in much of the U.S., the vegetation of the Coastal Plain is often determined by underlying soils and hydrologic processes. Accurately mapping vegetation in the low relief, highly diverse landscape of the Coastal Plain is challenging because of the limited resolution in the elevation data available nationwide. We chose the Onslow Bight for this project because of our ongoing collaboration with The Nature Conservancy on a Landfire Pilot Project. This collaboration would provide a meaningful test of the applicability of the map legend, as well as the final map.

The Atlantic Coastal Plain supports a diverse mosaic of vegetation, including maritime forests and associated beach communities, upland longleaf pine woodlands, pocosins, and riverine and nonriverine wetland communities (Wells 1928, Schafale and Weakley 1990). Soils, hydrologic processes, and disturbance (specifically fire, tides, and salt spray) are primary factors in determining patterns in the vegetation of the Coastal Plain (Wells 1928, Wells and Shunk 1938, Boyce 1954, Kologiski 1977, Komarek 1968, Christensen 1988).

In addition to the complexity of the vegetation, the long history of human settlement and the rapid rate of land use change make mapping the natural communities in the region especially challenging. According to a World Wildlife Fund assessment (Ricketts et al. 1999) the Atlantic Coastal Plain of the Carolinas is an endangered ecological region in need of “immediate protection of remaining habitat and extensive restoration.” These authors estimated that only about 12% of the Mid-Atlantic Coastal Plain habitats can be considered intact. Wyant et al. (1991) suggested that anthropogenic disturbance (timber harvest and fire suppression) will continue to have the greatest influence on the extent and composition of the forests of the Coastal Plain of North Carolina.

Study Objectives

Our objective was to develop an effective methodology for mapping Ecological Systems of the Atlantic Coastal Plain. Two immediate uses of that map would be a conservation assessment of the Ecological Systems of the area and input into modeling predicted distributions of vertebrate species. The goals of the study included 1) testing the application of the Ecological Systems Classification in mapping in a ecologically diverse but topographically homogeneous area, 2) testing the use of decision tree modeling for mapping Ecological Systems, and 3) quantifying the impact of including soils data, both county-level (SSURGO) and state-level (STATSGO) in the modeling process.

The Ecological Systems Classification was recently developed (Comer et al. 2003) in response to a need for a nationally consistent vegetation classification system that could be used as the target map legend for large area mapping. Previous mapping efforts in the Southeast (Pearlstine et al. 1999) have shown that the coarse-scale resolution of available imagery and the limited availability of ancillary datasets for mapping have significantly limited our ability to map vegetation at fine levels of thematic detail. In this work we wanted to test our ability to develop a map based on the Ecological Systems Classification, using a hierarchical approach including image stratification with decision tree modeling as the final step in that approach.

Specifically we wanted to examine the consequences of incorporating county-level soils data, testing the hypothesis that these detailed data would improve the accuracy and/or thematic resolution of the vegetation map. We were specifically interested in the influence of the SSURGO data because it is not currently available nationwide, so we wanted to understand the potential impact of not including it in our mapping efforts.

Background

Status of the Dominant Plant Communities in the Atlantic Coastal Plain.

There are seven dominant plant communities in the Atlantic Coastal Plain, all of which are decreasing in area, some more drastically than others. A summary of the current status of each of those communities follows.

Longleaf Pine

The longleaf pine (*Pinus palustris*) ecosystem is one of the best known examples of an endangered ecosystem in the coastal plain (Jose et al. 2006, Noss et al. 1995, Ware et al. 1993, Noss 1988). The factors that led to its decline include timber harvest, agricultural clearing, grazing, free ranging hogs, and turpentine production (Frost 1995). More recently, fire suppression and the associated invasion of hardwoods has led to a decline in the remaining longleaf stands. Less than 2% of the original distribution of longleaf remains, with less than half of that being managed with prescribed fire (Frost 2006).

Pocosin

One of the distinctive plant communities of the Atlantic Coastal Plain is the peatland pocosin. This nonriverine wetland community often has an open canopy of Pond Pine (*Pinus serotina*) and a dense evergreen shrub understory (Kologiski 1977, Wells 1928). Historically, pocosins are thought to have occupied as much as 908,000 hectares in North Carolina (Wilson 1962, Richardson 1981). In 1989, 608,000 hectares of pocosin remained, half of which could be characterized as being in a natural state (Richardson and Gibbons 1993). Thus two thirds of the original extent for this plant community has been lost or severely degraded.

Nonriverine Wet Hardwood Forest

Another threatened plant community of the Coastal Plain Region is the nonriverine wet hardwood forest. Based on extensive field survey data, Schafale (1999) estimated a loss of 1730 hectares of this community between 1990 and 1999. That represents a loss of 52% of its known 1989 extent. To estimate the potential presettlement extent, Schafale (1999) identified the soil series known to support nonriverine wet hardwood forest in Currituck and Hyde counties. Schafale restricted that analysis to soils well documented with respect to supporting the nonriverine forests and, thus is likely underestimating the true presettlement representation. The total area of the suitable soils was 16,300 hectares (40,278 acres) and the total area of known sites supporting the forest in 1998 was 556 hectares (1373 acres) meaning that as little as 3.4 percent of the original extent remains.

Atlantic White-cedar Forest

Atlantic White-cedar forest is another critically endangered wetland type that occurs in the coastal plain of North Carolina (Noss et al. 1995). In his review, Frost (1987) was able to document records of this community throughout most of the Coastal Plain counties of North Carolina, and Ashe (1894) estimated that it covered 80,940 hectares. In a 1997 inventory, any stand over 1.6 hectares (4 acres) that had Atlantic White-cedar in the canopy was reported (Davis and Daniels 1997). The greatest remaining concentrations occurred in the counties adjacent to the Dare Peninsula.

Maritime Communities

Maritime forest and associated dune communities occur throughout the barrier islands of North Carolina. In these forests, the broad-leafed evergreen trees, live oak (*Quercus virginiana*) and upland laurel oak (also known as sand laurel oak or Darlington Oak (*Q. hemisphaerica*)), often co-occur with loblolly pine (*Pinus taeda*). These systems have been affected throughout their range by coastal development. Less than half of the remaining maritime forests in the southeast are within the conservation network (DeVivo et al. 2005). The dynamic nature of barrier islands means that even systems within the conservation network are threatened. Under normal conditions these island communities are constantly shifting over time, invading newly accreted sands and being reduced on the eroding sides of barrier islands (Bellis 1980, Bourdeau and Oosting 1959). These processes can occur slowly in response to the geomorphologic processes or can occur more rapidly with differential re-establishment of the plant communities following a storm event. As urban development continues, the ability of the natural systems to migrate with the changing landscape becomes more limited. Continuing sea level rise, possibly exacerbated by global climate change, will intensify the threats to coastal communities.

Bottomland Forests

Harris et al. (1984) estimated a loss of 78% of the original extent of bottomland forests in the Southeastern United States. Wetland classification has not traditionally made a distinction between floodplain forests and nonriverine wetland forests, which makes estimating the loss for the bottomland types difficult. When considering all palustrine forested wetlands, Hefner and Brown (1985) estimated that 92% of the 2.2 million hectares lost in the 20 years prior to the mid-1970s occurred in the Southeast. Between the mid-1970s and mid-1980s it is estimated that North Carolina lost more than 40,469 hectares (100,000 acres) of palustrine forested wetland (Dahl et al. 1991).

Carolina Bays

Carolina bays are a unique type of isolated wetland that occur in the outer Atlantic Coastal Plain from New Jersey to Florida (Sharitz 2003), with the greatest concentrations in the Carolinas. Because of their geomorphology the bays are recognizable from space as elliptical basins of wetlands within a matrix of upland. The substrate, either peat or clay-based, influences the plant communities they support (Schafale and Weakley 1990). Historically, many of these wetlands have been drained for conversion to agriculture or tree plantations. More recently, the interpretation of the Clean Water Act that removes these wetlands from protection makes Carolina bays especially vulnerable (Sharitz 2003). Estimates of the historic number of bays vary widely, making it difficult to estimate the proportion that has been lost (Richardson and Gibbons 1993, Prouty 1952).

Previous Mapping Efforts in the Coastal Plain.

A variety of land cover maps with varying degrees of thematic and spatial detail exist for the Coastal Plain of North Carolina. Most recently, the North Carolina GAP land cover map (McKerrow et al. 2006) provides the first comprehensive coverage with a map legend that emphasizes natural vegetation types. In that project, mapping of the vegetation types in the coastal plain was based on detailed county-level soil survey data, National Wetland Inventory Data (USFWS 2006), and Landsat TM imagery. In the

Onslow Bight portion of that land cover map, there are 39 cover types, 21 of which represent natural vegetation types. The vegetation classification system used (Pearlstine et al. 1999) was developed in collaboration with NatureServe and was a precursor to the Ecological Systems Classification (Comer et al. 2003) currently being used by GAP and other national mapping programs.

Frost and Costanza (2006) mapped the presettlement vegetation of the Onslow Bight Study area using county-level soils data and topography. The county level soils data (SSURGO) were cross-walked based on expert opinion into 21 vegetation types, the majority of those being variants on longleaf pine communities.

Lunetta et al. (2003) mapped the general land cover of the Neuse River Basin. The southeastern portion of that river basin study area intersects the Onslow Bight. In that classification, Satellite Pour l'Observation de la Terre (SPOT) and Landsat Enhanced Thematic Mappter (ETM) imagery were used in combination with ancillary datasets to map land cover. To classify crops (corn, tobacco, cotton, soybean, and hay/pasture) the authors used differences in the Normalized Difference Vegetation Index (NDVI) from two time periods. Vegetation types were limited to Anderson Level II type classes (e.g., forested wetlands, deciduous forest).

The Center for Geographic Information and Analysis in North Carolina contracted with EarthSat Corporation to produce a statewide land cover map in 1996. That classification included more detail in the vegetation types, with descriptions of most classes being based on physiognomy (e.g., broadleaf evergreen forest), and a few being based on general biogeography (e.g., mountain conifer) or the dominant species mix (e.g., oak/gum/cypress). The statewide map included 23 land cover classes (EarthSat 1997).

Zhu and Evans (1994) mapped the forest types of the coterminous U.S. using 1- by 1-km Advanced Very High Resolution Radiometer (AVHRR) imagery. Four forest types based on the Society of American Foresters (SAF) classification were mapped in the Atlantic Coastal Plain region (Oak - Gum - Cypress, Oak - Pine, Loblolly - Shortleaf - Pine, and Longleaf - Slash Pine).

Richardson (1981) developed a map of the pocosins and Carolina bays of North Carolina, and Schafale (1999) has developed a map of nonriverine wet hardwood forests. Aerial photo interpretation was used for mapping both of these high conservation priority vegetation types.

Methods

Study site

We included the thirteen counties that intersect the Onslow Bight Landscape as defined by The Nature Conservancy Onslow Bight Rapid Assessment Pilot Project (Figure 2.1). The area covers approximate 250,000 km^2 and intersects portions of the Atlantic Coastal Flatwoods Section and the Coastal Plains and Flatwoods Lower Section of the Forest Service's Ecological Regions Map (Keys and Carpenter 1995). With respect to ecological regions as described by Omernik (EPA 2004), the majority of the study area occurs within the Middle Atlantic Coastal Plain, with a small fraction overlapping the Southeastern Plains Region. Relief in the region is minimal, peaking at 50 meters with most of the area being under 15 meters above sea level. The northeastern corner of the study area was partially submerged in the post-glacial period and is referred to as the embayed region (Robinson 1979). To the south, marine terraces are considered to be a region of emergence, making swamps less common and creating conditions for defined river valleys. The vegetation represents a complex mosaic of wetland and upland plant communities, many of which are fire dependent.

Target Map Classes

We adopted the NatureServe Ecological Systems Classification (Comer et al. 2003) as our target map legend. The goal for the Southeast Regional GAP is a regionally consistent land cover map and this classification was designed as an ecologically meaningful classification that could be mapped using mid-scale remotely sensed data. There are 25 Ecological Systems in the Atlantic Coastal Plain Region of North Carolina (Table 2.1). Each Ecological System is attributed with a landscape pattern (matrix, linear, large or small patch) that describes the spatial extent and configuration of that system. For example, the Atlantic Coastal Plain Longleaf Pine Woodland is considered a matrix system, meaning it historically occurred throughout the landscape with other systems (linear, large patch and small patch) embedded within it. Complete descriptions for each of the Ecological Systems are available through the NatureServe Explorer Encyclopedia (www.natureserve.org/explorer).

For a few of the Ecological Systems, we added modifiers to describe variations in vegetation structure that occur within that type. For example, we identified three potential modifiers of the Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest (Taxodium, Oak, and Atlantic White-cedar dominated) representing common cover type variants in the dominant canopy species resulting from hydrologic regime and fire history. In addition to the vegetation types, some modified classes from the National Land Cover Dataset (NLCD; Homer et al. 2007) were added to make the land cover classification more meaningful for habitat modeling. A range map for each of the Ecological Systems to be mapped was created by NatureServe ecologists for the Southeast GAP. These ranges were based primarily on the linework in Omernik's ecoregional coverage (EPA 2004), but in some cases delineations were made based on the range of one of the dominant canopy species in examples of the Ecological System.

Satellite Imagery and Ancillary Data

<u>Landsat TM</u>

We used Landsat TM image mosaics created at the U.S.G.S. Earth Resources Observation Systems Data Center (EDC) as a part of the National Land Cover Dataset national mapping effort (Homer et al. 2001, Homer et al. 2002). In that effort, the U.S. was divided into a series of mapping zones and each zone was mapped independently. The zones were delineated based on five criteria - size, physiography, land cover patterns, spectral patterns, and natural breaks in land cover that would facilitate edge matching of the map zones (Homer and Gallant 2001). This delineation method overcomes some of the issues of heterogeneity often encountered when the study area is defined using political (e.g., state) boundaries. For Ecological Systems level mapping, even these zones can be relatively heterogeneous. For example, the mosaic for mapping zone 58 (Atlantic Coastal Plain of North and South Carolina) includes a variety of vegetation types from maritime forests to Sandhills longleaf pine woodlands. We dealt with that variability by further dividing the study area into subzones.

Preprocessing at EDC included identification of three target image dates using multi-temporal normalized difference vegetation index (NDVI; Yang et al. 2001) to guide the selection of the imagery for three seasons (leaf on, leaf off and spring). Once the range of target dates was identified, the analysts created seasonal mosaics. In cases where the images from the target dates were of poor quality, imagery from the same season in an alternate year was selected.

Portions of 14 Landsat TM images were used to create the image mosaics for Zone 58, with dates ranging from September 1999 to as late as June 2002 (Table 2.2). For each of the seasonal mosaics both the 6 reflectance bands and a three-band (brightness, wetness, and greenness) tasseled cap transformed images were used. This was the case in both the NLCD 2001 mapping effort for this zone, as well as for this study (Huang et al. 2002). For a complete discussion of the preprocessing steps taken at EDC see Homer et al. 2002.

Land Cover, Impervious Surface, and Canopy Closure

The Southeast Gap Analysis Project had previously collaborated with U.S.G.S. in the development of the NLCD 2001 database (Homer et al. 2007). A sixteen class land cover map was produced using hierarchical decision tree modeling at the Biodiversity and Spatial Information Center (BaSIC) at North Carolina State University (U.S.G.S. 2003b). The Impervious and Canopy closure estimates were modeled using sub-pixel classification and regression tree modeling at the Natural Resource and Spatial Analysis Laboratory (NARSAL) at the University of Georgia (USGS 2003a and c). Each of the three datasets was based on the same Landsat TM mosaics described above. In Zone 58, we included additional wetland categories consistent with the mapping of palustrine and estuarine types used by the Coastal Change Analysis Programs map legend (NOAA – CCAP 2006; Table 2.3).

We used the NLCD 2001 land cover both as an input layer for mapping some of the Ecological Systems, as well as for masking the anthropogenic types. Canopy closure was used as an input into modeling of managed evergreen cover as well as in the decision tree modeling for several of the Ecological Systems.

Soils

We derived two soils datasets from the Natural Resource Conservation Service to be used as inputs into the modeling process. The State Soil Geographic Database (STATSGO) is a national database developed at a 1:250,000 scale (NRCS 2007). For each map unit in the STATSGO data, the component soil series and the percentage representation for each of those series in the average soil unit is described in the database. These soils maps were developed by generalizing existing soils information. The Soil Survey Geographic Database (SSURGO) includes detailed county-level soil series maps developed at a scale of 1:24,000 (NRCS 2007). From the SSURGO data we calculated the average percentage organic matter for each soil series using the official soil descriptions. To account for the contribution of organic matter, we adjusted the percentage of each of the mineral fractions (sand, silt, and clay) by subtracting the percent organic matter from 100 percent to determine a correction factor. We derived the percentage sand, silt, and clays for each soil series by translating the soil texture (loam, sandy loam, clay) based on the soil texture triangle (Soil Survey Staff 1990). The adjustment to include organic matter in the soil texture calculation was then applied to the sand, silt, and clay percentages, making the combination of sand, silt, clay, and organic matter percentage total 100%. For each fraction a single data layer was generated (see below).

Correction Factor for Mineral Fractions = 100 - Average % Organic Matter
Layer 1: Adjusted % sand = % sand * Correction
Layer 2: Adjusted % silt = % silt * Correction
Layer 3: Adjusted % clay = % clay * Correction
Layer 4: Average % Organic Matter

To develop the STATSGO data layers, we used the same process for determining the percentage organic matter and the adjusted percentages for sand, silt, and clay for each soil series. The proportional representation of each soil series in a STATSGO unit was then used to weight the contribution of that series to the larger unit. The compositional representation for soil series in each STATSGO unit is reported in the STATSGO database. Our approach is similar to that taken to develop the CONUS-SOIL dataset (www.soilinfo.psu.edu) developed for the conterminous U.S., but we have included organic matter as a fourth soil fraction.

National Wetlands Inventory

We used the National Wetland Inventory in the development of the NLCD 2001 for mapping zone 58, which includes the Onslow Bight study area (U.S.G.S. 2003b). For that effort two data layers were derived from the National Wetland Inventory Data (U.S. F.W.S.): a wetland/upland layer and a layer that corresponded to general wetland classes including palustrine wetlands (forest, shrub, and emergent) and estuarine wetlands (forest, shrub, and emergent). These data layers were used as input layers for decision tree modeling of the wetland vs. upland forest, shrub, and emergent land cover classes for the NLCD 2001. We used an unsupervised classification based on the spring imagery to refine the boundary at the palustrine/estuarine interface. For the systems level mapping, these derived layers were used as input into the decision tree modeling.

Landform

We derived landforms using the National Elevation Dataset (NED) 30 meter elevation data. Preprocessing steps included identifying areas with anomalies (e.g., striping) in the elevation data, replacing those areas with other data if they were available and, if not, using directional filtering. The landform calculations were modeled using the approach outlined by Anderson et al. (1998).

Image Objects

We used the pattern recognition software eCognition to segment the spring image mosaic into objects. Object boundaries were determined through interactive calculations of homogeneity. In each step the homogeneity of an object after being merged with its neighbor was calculated; if the heterogeneity of the new object exceeds the predetermined threshold level, the objects were not merged. Two indices of homogeneity were used in image segmentation - color vs. shape and smoothness vs. compactness - and they could be weighted by the analyst. In this study we used a color parameter of 0.3 (scaled 0 to 1) and smoothness parameter of 0.5 (scaled 0 to 1). In other words, we weighted spectral homogeneity slightly higher than shape homogeneity and gave equal weighting to smoothness and compactness. The scale parameter determined the size of the objects that can be generated and therefore determined the threshold for the maximum heterogeneity allowed in an object (the higher the scale parameter, the more heterogeneous the objects). In this case we used a scale parameter of 30, which resulted in over 57,000 objects. For a technical discussion of homogeneity calculations for color and shape indices see Zhong et al. (2005). Those objects were used for delineating specific areas of interest, refining boundaries from other datasets so they matched the spectral data, and as input in decision tree modeling. Summary statistics for eight input variables were generated for each object for use in modeling (Table 2.4).

Reference Data

Training and assessment data were compiled from both field data and aerial photograph interpretation. Digital aerial photographs acquired as a part of the Southeast Gap Analysis Project were interpreted directly to Ecological Systems and their modifiers. The North Carolina GAP reference points were relabeled based on a cross-walk from that classification, an early version of a systems based classification (Pearlstine et al. 1999), to the current Ecological Systems classification. North Carolina Natural Heritage Plant Community data and plot data from the North Carolina Vegetation Survey (Peet et al. 1998) were incorporated by cross-walking the plant community labels to the Ecological Systems (Table 2.5). All points were then carefully screened against the 2001 imagery and 1998 digital orthophoto quarter quads (DOQQs) to check for land cover changes and to apply modifiers to the appropriate classes. Finally, areas with few or no training data reference points were photo interpreted. Once the reference data were compiled, they were stratified by ecological system or cover class and a random sample of at least 25% of the points was removed for use in the final assessment.

Ecological Systems and Managed Pine Mapping

Riverine Systems

We mapped the riverine Ecological Systems by intersecting the National Hydrologic Dataset (NHD) streams with image objects derived in eCognition. The object generation was done for the entire study area so the patterns derived from the imagery would be consistent for the entire length of a river or stream. Final editing was done manually to add objects missed by the NHD stream data and to remove objects that were dominated by successional or anthropogenic vegetation types (clearcuts, plantations). Pixels representing non-vegetated types (urban, agriculture, barren) were then removed, leaving only the vegetated pixels within the stream or river corridor.

Once the floodplain areas had been mapped, the hydrology data were used to classify the Ecological Systems based on flow accumulation and water type. Using the DEM and NHD data, the flow accumulation for each stream segment was calculated in ArcGIS. In order to “force” the modeled flow to follow the NHD stream network, the streams were “burned” into the DEM prior to calculating the flow accumulation. More specifically, the elevation for any grid cell that intersected a stream was lowered by 100 meters. A threshold based on the number of grid cells contributing to the flow at each point along the stream network was then used to create three categories of streams: small stream (< 100,000), river (100,000 – 1,000,000), and large river (> 1,000,000).

Finally, streams and rivers were characterized by water type, blackwater or brownwater. Streams originating in the coastal plain tend to be black water, while those originating in the Piedmont tend to be brownwater, with a higher sediment load (Schafale and Weakley 1990). A blackwater/brownwater classification of streams was done for the entire Coastal Plain, with all streams or rivers originating in the coastal plain being classed as blackwater, and those with origins in the Piedmont being classed as brownwater. In a few cases, sufficient flow contributed from coastal streams overcomes the fact that a river originated in the Piedmont. We used the literature and expert review to reclassify portions of these rivers as blackwater.

By intersecting river size with water type, five riverine systems were mapped:

- Atlantic Coastal Plain Large River Floodplain – Brownwater Modifier
- Atlantic Coastal Plain Large River Floodplain – Blackwater Modifier
- Atlantic Coastal Plain Blackwater Stream Floodplain Forest
- Atlantic Coastal Plain Brownwater Stream Floodplain Forest
- Atlantic Coastal Plain Small Brownwater River Floodplain Forest

Maritime Systems

The coast of North Carolina presents a unique set of mapping challenges. The barrier islands and coastline along the mainland represent relatively small acreages with a distinct suite of plant communities. Maritime forest, dunes and grasslands, tidal swamp forests, and marshes all co-occur in relatively small patches and are often intermixed with urban cover types. In order to map the Ecological Systems along the coast, an area of interest was created using the image objects previously described and Omernik's ecoregional boundaries (EPA 2004). A 3 km buffered version of the Carolina Barrier Islands and Coastal Marshes ecoregion was intersected with the image objects to create the subzone for mapping. By selecting objects as the new linework, boundary issues between the coarse scale ecoregional linework and the imagery were minimized. At the same time, the image objects tied the new line work and boundaries to the base imagery, which was important along the coast, where the shapes of the islands are changing over time.

By restricting the area being mapped, the number of map classes within the maritime area of interest was limited, making it possible to recode from the detailed version of the NLCD 2001 land cover classification. For example, upland evergreen forests were recoded as Atlantic Coastal Plain Southern Maritime Forest and estuarine forested wetlands were recoded as Atlantic Coastal Plain Tidal Wooded Swamp. The barren classes were mapped by manually delineating areas to be recoded based on location. For example, barren land and grassland herbaceous pixels along the outer coast were recoded to the Atlantic Coastal Plain Southern Dune and Maritime Grassland, while inland barren land was mapped as either bare sand, bare soil, or mines (see Inland Barren Classes).

There were five dominant Ecological Systems mapped in the maritime region:

- Atlantic Coastal Plain Central Salt and Brackish Marsh
- Atlantic Coastal Plain Embayed Region Tidal Salt Marsh
- Atlantic Coastal Plain Central Maritime Forest
- Atlantic Coastal Plain Southern Dune and Maritime Grassland
- Atlantic Coastal Plain Southern Tidal Wooded Swamp

Upland Deciduous Forests

Landforms were used to separate the Atlantic Coastal Plain Mesic Hardwood and Mixed Forest from Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest. If the NLCD 2001 land cover was deciduous or mixed forest and the landform was slope crest, flat summit, North/Northeast side slopes, or North/Northeast cove/ravine then it was mapped as the ACP Mesic Hardwood and Mixed Forest. All remaining deciduous forests were classified as ACP Dry and Dry-Mesic Oak Forest. Given the lack of topography in the coastal plain, the vast majority of the study area was modeled as dry or moist flats. Two distinct exceptions occurred along the bluffs of the Cape Fear and Neuse River, where small patches met the criteria for this decision rule.

Atlantic White-cedar

Although the Atlantic White-cedar Forest was not treated as a distinct Ecological System, it has been recognized by others as a distinct plant community (Schafale and Weakley 1990) and is considered to be critically endangered (Noss et al. 1995). We therefore decided to map it as a modifier of the Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest. In the current Ecological Systems Classification, Peatland Atlantic White-cedar Forest is proposed as a provisional Ecological System. We mapped this type using aerial photo interpretation with color infrared digital orthophoto quarter quads (DOQQs) as the base layer. While most of the Atlantic White-cedar Forest in North Carolina occurs north of the Onslow Bight, several small patches were mapped in the Green Swamp of Brunswick County.

Natural Lakeshores

There are five natural lakes in the Onslow Bight study area. Three of those lakes have occurrences of the Southeastern Coastal Plain Natural Lakeshore. To map those sites, the leaf off tasseled cap image mosaic was used to generate image objects in eCognition (scale 5, shape index 0.1, compactness 0.7) and the objects at the land/water interface with mixed pixel signature were labeled as lakeshore.

Carolina Bays

Carolina Bays were photo-interpreted using DOQQs as the base imagery. The dominant land cover from the NLCD 2001 within each bay was then used to distinguish the Atlantic Coastal Plain Clay-Based Carolina Bay Wetland from the Atlantic Coastal Plain Peatland Pocosin -Carolina Bay Wetland. Bays dominated by deciduous wetland forest or water were mapped as clay-based, while those dominated by evergreen wetland forest or shrubs were mapped as the peatland type. We chose not to use the underlying soils data to define clay-based vs. peatland, because altered hydrology or fire regime can result in a shift to a more evergreen dominated community (Schafale and Weakley 1990), although the rate and likelihood of that change is poorly understood.

Managed vs. Natural Evergreen

Prior to mapping natural systems, the managed pine stands throughout the mapping zone were classified using a decision tree model. Pixels mapped in NLCD 2001 as evergreen forests were subset from the leaf off tasseled cap image mosaic and forty clusters were generated using Imagine Isodata algorithm (Lieca 2003). A stratified random sample of 750 points was then generated based on those clusters for photo-interpretation. The stratification by clusters was done to ensure even coverage of interpreted points throughout the different images in the mosaic and throughout the range of conditions for evergreen forests. Each of the 750 points was located on 1998 DOQQs and interpreted as managed or natural. In cases where the cover class in the DOQQ was not evergreen or the point was near a boundary with a non-evergreen type, that point was discarded. In all, 679 points (320 managed, 359 natural) were labeled for use in decision tree modeling.

See5 software (RuleQuest Research Release 2.02; Quinlan 1993) was used in the decision tree modeling process. The datalayers used in modeling managed vs. natural evergreen for zone 58 are listed in Table 2.4. In addition to the imagery inputs, image objects generated in eCognition were included with 8 context variables. Object specific mean canopy closure, area, shape index, compactness, border length, as well as mean leaf off tasseled cap brightness (band 1), standard deviation of the leaf off tasseled cap brightness, and mean spring tasseled cap brightness were included as inputs.

The decision tree classifier was run with all 679 points, with boosting (10 trials). Boosting is an interactive classification process in which each of the previous run trials is used to identify which training data records are incorrectly classified. A weighting scheme is then used to prioritize decisions that will correctly classify those records in the current trial. For each trial 10% of the points were removed and used in the cross validation for the model. Once the decision trees had been generated, the See5 Classifier version 2.02 was used to translate the decision trees into maps of managed vs. natural evergreen forest.

Evergreen and Nonriverine Ecological Systems

After removing the previously mapped or modeled Ecological Systems and anthropogenic types, there were six forested systems to be mapped (Table 2.6). For these forest types, we had a total of 548 points in the Onslow Bight study area. Of those, 248 were set aside for model assessment and 300 were used as training data in a decision tree modeling process.

RuleQuest See5 software was used to test both the decision tree modeling approach and the effects of including a variety of input data layers for mapping these Ecological Systems. Input layers available for modeling are listed in Table 2.4. In each case the See5 Classifier was run with boosting of 10 trials, global pruning of 25%, and a minimum of 2 cases per terminal leaf. Cross-validation was not used because of the limited number of samples for each of the Ecological Systems being mapped and because the independent assessment was to be run.

In order to assess the influence of several of the key data layers we ran multiple classifications and varied the input layers included in the model. Of primary interest was the influence of the state level STATSGO soils data, as well as the county level SSURGO data. We ran five variations of the classification including 1) Full model, all input layers were included; 2) No STATSGO, the four texture bands from the state level soils data were also excluded (% sand, % silt, % clay, % organic matter), but all other input layers were the same; 3) No SSURGO, the county level soils data layers were excluded; 4) No STATSGO and No SSURGO, all layers derived from soils data were excluded; and finally 5) No datasets derived from vector data, including soils, National Wetland Inventory, and Image Objects were included in the models. Without vector inputs, the final model would be reliant on imagery and land cover derived from imagery alone. Each decision tree generated was then applied to create a map of the Ecological Systems to be assessed.

Inland Barren Classes

Mines and unconsolidated shore were recoded from the NCLD 2001 barren class using an area of interest. The remaining barren pixels were then classified as bare sand if the reflectance in the leaf on tasseled cap brightness band was greater than 80. Lower reflectance pixels were mapped as bare soil.

Successional Shrub and Herbaceous Classes

We used an unsupervised classification to identify transitional vegetation across zone 58. Clusters were generated from the spring and leaf on image mosaics using the Imagine Isodata algorithm and labeled as transitional based on photo interpretation for each of the clusters. Those pixels were then clumped to create two patch sizes (2 and 10 hectares). The greenness band from the spring image mosaic was then subtracted from the greenness band of the leafon image mosaic to create a greenness difference image. Small patches that showed a relatively large decrease in greenness (< - 14.5) and large patches with any loss (< 0) were classified as clearcut shrub or clearcut herbaceous. Shrub and herbaceous pixels not mapped as clearcuts were then labeled as other herbaceous or other shrubland.

Salt/Brackish vs. Fresh Water

The National Wetland Inventory palustrine/estuarine wetlands data were used as a guide for manually delineating the split between the salt/brackish water and freshwater.

In the NLCD 2001 land cover there were many emergent wetland pixels scattered throughout the study area. A large number of those represented wet areas within agricultural fields or other anthropogenic cover classes and not “true” wetlands. We allowed those pixels to be recoded based on the majority membership in the image object in which they occurred. For example, palustrine emergent within an object with a majority of member pixels classed as Large River Blackwater Forest was recoded to

Large River Blackwater Herbaceous. In another example, objects dominated by herbaceous clearcut pixels would be recoded as herbaceous clear cut.

Post Processing

Individual map classes from the processes described above were combined with the NLCD 2001 urban and agricultural classes to create final land cover map. We then used Smart Eliminate (Ver. 1.0) within the NLCD Mapping Tool to generate the final map with a minimum mapping unit of 4 pixels (0.5 hectares).

Accuracy Assessment

The models for the evergreen forest and woodland systems were assessed with 248 independent data points that had been set aside prior to modeling. Plant community data from the Natural Heritage Program has been gathered based on inventories for specific plant communities, so we assumed a stratified random sampling design in our assessment. In order to account for the variation in the acreage of the Ecological Systems and the number of assessment points, we used marginal frequencies to estimate map accuracy (Card 1982, Stehman 1997). Formulas for estimating the Kappa coefficient and for testing for differences in models were based on Stehman (1996).

To assess the managed vs. natural evergreen classification we first combined the two model outputs, with spatial coordinates (XY) and without spatial coordinates (NOXY), into a single image with four classes. They were: (1) agree managed, (2) agree natural, (3) XY classified it as managed when the NOXY model classed it as natural and (4), XY classified it as natural when NOXY mapped it as managed. The two categories of disagreement were then used to generate a stratified random sample of 100 points based on their extent in the map, and those points were used to assess the areas of disagreement in the models.

The accuracy for the final land cover map was assessed using a combination of independent assessment points for natural systems and a stratified random sampling for the anthropogenic classes. To account for potential shifts in the imagery, a buffer of 85 meters was used summarize the land cover for each reference point. We used the Hawth’s Analysis Tools extension for ArcMap to generate the buffers and summarize the land cover within those buffers. If the land cover type was the majority cover type in the buffer it was considered correct; if not, the majority cover class was reported as the off-diagonal cover class. We again used marginal frequencies to estimate the overall accuracies and per class statistics.

Results

Vegetation Map of the Onslow Bight

The final vegetation map for the Onslow Bight contained 39 land cover classes including 26 Ecological Systems and their modifiers (Figure 2.2). The most abundant cover classes in the study area were Row Crop (19%), Open Water – Brackish-Salt (13 %), and Managed Pine (10%; Table 2.5). ACP Peatland Pocosin (9%), ACP Northern Wet Longleaf Pine Savanna and Flatwoods (8%), and ACP Dry and Dry-Mesic Oak Forest (5%) were the most extensively mapped Ecological Systems.

Overall accuracy, the proportion of the map correctly classified, was estimated at 77 percent and the Kappa statistic based on marginal frequencies was 0.75 (Table 2.7). The four accuracy estimates derived from the marginal frequencies are similar to the producer's and user's accuracies, and the commission and omission errors from a standard error matrix, but they represent the data as proportions of both the row totals and column totals of the population of pixels mapped. By "conditioning" the accuracy estimates based on the relative acreage of each class, the estimates of overall accuracy, commission estimates, and Kappa are improved. Stehman (1997) provides a thorough discussion of the advantages of incorporating marginal proportions in accuracy measures. In this study we reported two measures of accuracy for each cover class. A third (commission error) and a fourth estimate (omission error) can be derived from the information provided.

π - Probability that a site is correctly mapped given the reference data;

λ - Probability that a site is correctly classified given the map class;

φ - Commission error $(1 - \lambda)$;

θ - Omission error $(1 - \pi)$.

As with most thematically complex maps, the accuracy of individual classes varies widely. Below we present the results by general category. Manually delineated cover types, Carolina Bays, Atlantic White-cedar, and Natural Shoreline and some rare cover classes (Bare soil, ACP Large River Floodplains – herbaceous modifiers) were not included in the assessment. The confusion matrix based on the initial assessment points are reported in Appendix 2.1.

Riverine Systems

Relative to the reference data, the ACP Large River Floodplain Systems had high accuracies, 96 percent for the brownwater and 90 percent for the blackwater type. Accuracy relative to the mapped class was slightly lower at 67 and 70 percent for brownwater and blackwater types, respectively. The ACP Small Blackwater River Floodplain was less well mapped with 49 percent relative to the reference data and 65% relative to the mapped class. Most of the error for this river system came from confusion with ACP Fall-line Sandhills Longleaf Pine Woodland and ACP Blackwater Stream Floodplain Forest. The commission error of the ACP Blackwater Stream Floodplain was high, 82 percent (100 – 18). For that class, confusion with ACP Tidal Wooded Swamp and ACP Small River Floodplain forest was the main source of error.

Maritime Systems

ACP Central Maritime Forest had an accuracy of 42 percent relative to the reference data, but 80 percent relative to the mapped class. Seven of the 22 reference points for maritime forest were mapped as ACP Central Salt and Brackish Tidal Marsh. When revisiting the assessment points against the imagery, we found several of the reference data points to be located on very small patches of maritime forest. The ACP Southern Dune and Maritime Grassland had a similar pattern: where it was mapped it was accurate (80 percent), but relative to the reference points the accuracy was low (20 percent).

The ACP Embayed Region Tidal Salt and Brackish Marsh was more accurately mapped (π = 87%) than the ACP Central Salt and Brackish Tidal Marsh (π = 55 %). Given the large homogeneous patches of marsh in the embayed region relative to the southern extent of the study area, this is not surprising. Much of the omission error in the central marsh system was due to confusion with open water and other herbaceous. A similar pattern was seen in the freshwater marsh systems; the embayed region system (π =100%) was more accurately mapped than the ACP Central Fresh-Oligohaline Tidal Marsh System (π =12%).

ACP Tidal Wooded Swamp was one of the problematic Ecological Systems in the final map (π = 4 %, λ = 50%). Confusion occurred between this class and several of the riverine classes, as well as the ACP Northern Wet Longleaf and ACP Peatland Pocosin Systems.

Upland Deciduous Forests

Ninety-nine percent of the upland deciduous pixels were labeled as the ACP Dry and Dry-Mesic Oak Forest System. Accuracy for that class relative to the reference points was estimated at 87 percent, and commission error was 38 percent, with most of the confusion being with the ACP Mesic Hardwood and Mixed Forest System. The mesic system had very low accuracy relative to the reference data (< 1%), but where it was mapped it did occur (λ = 100 percent).

Evergreen Forests and Nonriverine Ecological Systems

We discuss the results of the individual decision tree models below. The final map and this accuracy assessment are based on the map from Full Model Input. With the exception of the ACP Upland Longleaf Pine Woodland (π = 37%, λ = 100%), each of the model classes had high accuracies. ACP Peatland Pocosin was most accurately mapped with π = 89 percent and λ = 78. Where it was mapped, the ACP Upland Longleaf Pine Woodland tended to be present, so commission errors were low. The main source of omission error for this upland pine type was confusion with the wet longleaf pine, “other shrub”, and the “other herbaceous” map classes. The confusion between several of the longleaf types and the map class “other herbaceous” is worthy of consideration and we cover that in the discussion section.

The primary issue for the nonriverine systems is the commission error in the ACP Nonriverine Swamp and Wet Hardwood Forest – Taxodium (φ = 50%). In many cases, this nonriverine type was mapped where ACP Tidal Wooded Swamp, Pocosin, and Salt and Brackish Marsh actually occur.

Successional Shrub and Herbaceous Classes

We were reasonably successful at mapping the successional classes. Other herbaceous was the most abundant of these cover types, representing 8% of the total study area. Commission error in the other herbaceous class came from confusion with three of the longleaf pine systems, as well as ACP Peatland Pocosin and the ACP Central Fresh-Oligohaline Tidal Marsh.

Salt/Brackish vs. Fresh Water

When considering the reference data, tidal wooded swamp (4%) and bare sand (8%) had the lowest accuracies. ACP Embayed Region Tidal Salt and Brackish Marsh had 100% agreement between the reference data and the map. As described in the decision tree modeling section, the ACP Upland Longleaf Pine Woodland was underrepresented in the map with accuracy relative to the reference data of 37 percent; only 2 of 10 reference points for this type intersected the type. At the same time, the restricted nature of class meant that no reference points from other cover types were mapped as upland longleaf, hence a commission error of 0 percent.

The final map included 12,954 hectares of the ACP Upland Longleaf Pine Woodland. The accuracy of the class relative to the reference data was low (37 percent): 8 of the 10 reference points for this class were misclassified; 4 of those 8 were mapped as the ACP Northern Wet Longleaf Pine Savanna and Flatwoods.

Managed vs. Natural Evergreen Decision Tree Modeling

The boosted and cross-validated (10 fold) error rates were 24.8% (standard error 1.9) for the model with x,y coordinates (XY), and 22.8% (standard error 1.0) without spatial coordinates (NOXY). Spatially, there was 87% agreement between the areas mapped as managed and natural by the two decision tree models. When compared visually across the entire mapping zone, date band artifacts in the model that excluded the x,y coordinates were apparent. While the cross-validation numbers indicated a similar error rate between the two models, the inclusion of the coordinates in the model seemed to compensate for date band issues in the image mosaics. In addition to the visual inspection, the independent assessment using 100 points showed that for the areas of disagreement between the two models, the model with XY included did slightly better (Table 2.8). The XY model had lower error rates for both the managed and natural class when compared to the NOXY model.

Evergreen and Nonriverine Ecological Systems Decision Tree Modeling

The Kappa statistics for all the models tested were reasonable, ranging from 0.313 to 0.513. The model with the full complement of input variables performed the best as measured by the proportion correctly classified (65%) and the Kappa statistic (0.512). The worst model with respect to Kappa was the model that excluded the SSURGO data Table 2.6). When both soils datasets were excluded, the model performed better than when only one or the other was included as input, indicating some advantage of using both scales of information. Finally, when all vector inputs were excluded, including both soils layers, the proportion correctly classified (54%) and the Kappa statistic (0.36) were low but slightly better than those of the No SSURGO model.

The Full model predicted three times the acreage of the ACP Upland Longleaf when compared to the other models. For four of the five models, the ACP Wet Longleaf or Pocosin wetlands were most abundant in the final maps. The exception was the No STATSGO model that resulted in 36% of the evergreen forest systems being classified as the Sandhills Longleaf type. The nonriverine types are mapped at between 11 and 17% of the modeled extent, about 4% of the entire study area.

The rates of omission and commission by Ecological System and Model are shown in Figures 2.2 and 2.3. In general the Peatland Pocosin was most accurately mapped class using this method. That system had the lowest omission (16%) and commission rates (16%) for the full input model. The ACP Upland Longleaf was consistently poor, with omission rates ranging from 84 to 100% and commission rates between 67 and 100%. Removing STATSGO from the models increased the commission error for both upland longleaf types, Sandhills Longleaf and the ACP Upland Longleaf. The confusion matrices for each of the decision tree models are presented in Table 2.9.

When comparing the model outputs visually, the full Input model mimicked the patterns in the imagery most closely and had fewer isolated pixels (speckles) scattered throughout the map (Figure 2.4a-e). The No SSURGO and No STATSGO maps had some relatively large patches of Peatland Pocosin. This may reflect the influence of the rulesets on the National Wetlands Inventory Data. When the model was forced to use only spectral data and general land cover alone (No Vector Model), the large patches were speckled with pixels of a variety of the other Ecological Systems.

Discussion

The overall accuracy (77%) and Kappa statistic (0.75) for the map of Ecological Systems of the Onslow Bight indicated that a thematically rich and ecologically meaningful map can be produced in this complex landscape. Our approach was hierarchical and represented a unique combination of automated techniques (decision tree modeling, pattern recognition, geographic information system geo-processing) and manual methods (use of range maps for limiting the mapped distribution, photo-interpretation, and manually delineating cover types). The added thematic detail and accuracy came at the cost of expediency.

It is important to recognize that in the hierarchical approach the errors are additive: as soon as the map at one level of the hierarchy is established, all other options for those pixels are removed. In this case, the accuracy of the ACP Tidal Wooded Swamp may have been the result of earlier assignment of pixels to the riverine mask. Similarly, as soon as the managed vs. natural evergreen forest mask was complete, errors inherent in that layer cascaded through the remaining mapping steps. We attempted to minimize this through continuous quality assurance, but over such a large expanse, locally significant errors are always possible.

Target Map Units

In general we feel that the Ecological Systems Classification is working as a set of ecologically meaningful target map units. This reflects their being developed in response to a need for an ecologically based vegetation classification system that could be mapped using mid-scale remotely sensed data. Within the Southeast the state-based GAP projects had spent considerable energy attempting to map within the hierarchy of the National Vegetation Classification System (NVCS) and having to develop map classes that incorporated the NVCS concepts into broader, more context-based units. The Ecological Systems Classification was developed using a similar approach. The Association Level of the NVCS provides the rich species composition information that informs the Ecological Systems Classification. Biogeography and the underlying processes (fire, flooding) inform the context of the Ecological Systems, making it a useful classification for mapping. If adopted, proposed changes to the NVCS (FGDC 2006, ESA Panel on Vegetation Classification 2007) will incorporate some of the same types of information within the classification hierarchy that make the Ecological Systems Classification useful. In addition, that standard would allow for a robust method for proposing and adopting changes to the NVCS, including the hierarchy, through a peer review process.

While the Ecological Systems Classification described the majority of the vegetation types in the Coastal Plain thoroughly, there were some local variations we felt were important to recognize. As described in the introduction, the Atlantic White-cedar Forest is recognized by some ecologists as a distinct type, so we wanted to map that type specifically. Currently, NatureServe has described a Southern Atlantic White-cedar Peatland Forest as a provisional type, but the correct level of recognition of this cover type as a separate Ecological System remains unresolved (Pyne pers. comm.). The Ecological System Classification seems to be a good synthesis of the well studied systems of North Carolina's Coastal Plain. This project definitely benefits from years of work in developing the classification scheme for North Carolina. The ability of the Ecological System Classification to describe and represent vegetation in other regions and states will be determined by future applications and research.

Image Stratification

Previous mapping experience in the Gap Analysis Program, as well as preliminary trials for mapping the NLCD 2001 land cover in the southeast showed that stratifying the study area either by ecological boundaries or by land cover category (riverine/nonriverine; wetland/nonwetland) improved mapping results (Edwards et al. 1995; McKerrow and Earnhardt 2004). In this study it is impossible to tease apart the influence of stratifying the study area directly, but the assessment of the individual classes mapped and the natural vs. managed pine models give an indication of the utility of the approach. Even within the decision tree process, incorporating the vector datasets improved the models with respect to three of the six evergreen and nonriverine classes being mapped.

Decision tree modeling – Managed vs. Natural

Decision tree modeling was a useful approach for two of our critical mapping steps, discriminating managed vs. natural evergreen, and for modeling the evergreen and nonriverine wetlands.

In the managed vs. natural evergreen modeling we found that, by incorporating the x,y coordinates in the decision tree model, the accuracy of the final binary map was improved by removing date band artifacts. While both models performed equally well according to the cross-validation, the distribution and type of the errors warranted the selection of one model (XY) over the other (NOXY).

While we have not specifically tested differences in the spatial configuration of the mapped cover classes with and without image objects as a model input, when we examined preliminary models we saw that speckling within the patches of managed or natural stands was reduced. Because we expect most stands to be relatively homogeneous (either all managed or all natural), we decided to incorporate the image object data.

Decision tree modeling – Evergreen and Nonriverine Systems

Once the list of cover classes and the number of pixels to be mapped as evergreen and nonriverine systems were narrowed down, the approach worked well for mapping five of the six classes we tried. It is possible that results could be improved using a stepwise modeling approach, perhaps using evergreen types as a single model and nonriverine as its own model. We felt we had segmented the image to such an extent already that running two levels of models would be overly complicated. Also we thought the differences in the types (upland/wetland, evergreen/deciduous) should be distinguishable given the input data.

One potential improvement to our process would be to address the commission error of the Other Herbaceous class in the three longleaf pine Ecological Systems. In this effort we did not post-process the Other Herbaceous pixels in order to assign them to an Ecological System as a modifier. The commission error indicates that we should develop an approach to accurately assign herbaceous and shrub pixels to an Ecological System based on context or proximity.

Comparing the impact of including a variety of input datasets into the decision tree modeling, removing the SSURGO data had the highest negative impact on Kappa. Interestingly, removing all soils related information (SSURGO and STATSGO) resulted in a higher Kappa value than when either soil layer was used alone. This indicates an interaction between the large scale SSURGO data and the small scale STATSGO data in the modeling. When STATSGO was excluded, the Peatland Pocosin System was less accurately mapped, and, given the extent of that class, its influence on the Kappa statistic was high.

Even with the relatively unbalanced set of training data for these systems, the decision tree model did well. While the ideal would be to have a more even distribution of training data, that ideal is often not feasible when mapping land cover. In this study, we had an excellent source of high quality training data for the natural vegetation communities of the Onslow Bight; however, even then the number of points (9) for the high priority ACP Upland Longleaf System was limited, due to the few known occurrences in the study area.

Conclusion

Given the complexity of land cover and vegetation in the Onslow Bight, we chose to take a hierarchical approach to mapping. Pattern recognition allowed us to incorporate some contextual information in our classification steps and was successfully integrated with decision tree modeling for mapping the managed stands of the Coastal Plain. Decision tree modeling was successful for mapping five of the six Ecological Systems, once the areas to be mapped and the number of cover classes were reduced. As we discovered, decision tree modeling did not map all of the target map classes well and the choice of input data greatly influenced the accuracy and spatial patterning of the final map. For this area, the interaction between the county-level and state-level soils data is especially important, and we found it was best to remove both from the model rather than include one or the other, an important finding given the fact that the county-level soils data are not yet available nationally. The map developed using our approach will serve as a good baseline for assessing most of the Ecological Systems and for modeling the predictive distributions for vertebrate species of the Onslow Bight. Some types will require further work, specifically the Atlantic Coastal Plain Upland Longleaf.

Future work could include developing two models for mapping the Ecological Systems we modeled with a single decision tree, incorporating additional ancillary data as input into the models, and testing non-decision tree approaches to mapping the ACP Upland Longleaf.

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References

Anderson, M. G., M. D. Merrill, and F. B. Biasi. (1998) Connecticut River Watershed Analysis: Ecological communities and Neo-tropical migratory birds. Final Report Summary. Eastern Conservation Science of The Nature Conservancy. 36 p.

Ashe, W. W. (1894) The forest lands and forest products of eastern North Carolina. N.C. Geological Survey Bulletin. 128 pp.

Bellis, V. (1980) The vegetative cover on the barrier islands of North Carolina. Veroffentlichungen des Geobotantischen Institutes Rubel, Zurich 69: 121-144.

Bourdeau, P.F. and H. J. Oosting. (1959) The maritime live oak forest in North Carolina. Ecology 40(1) 148-152.

Boyce, S. G. (1954) The salt spray community. Ecological Monog. 24: 29-67.

Card. D. H. (1982) Using known map category marginal frequencies to improve estimates of thematic accuracy. Photogrammetric Engineering and Remote Sensing. 48(3)431-439.

Christensen N. L. (1988) Vegetation of the Southeastern Coastal Plain. p. 317–363. *In* M. G. Barbour and W. D. Billings (eds.) North American Terrestrial Vegetation. Cambridge University Press, New York, NY, USA.

Comer, P., D. Faber-Langendoen, R. Evans, S. Gawler, C. Josse, G. Kittel, S. Menard, M. Pyne, M. Reid, K. Schulz, K. Snow, and J. Teague. (2003) *Ecological Systems of the United States: A Working Classification of U.S. Terrestrial Systems.* NatureServe, Arlington, Virginia.

Davis, K. and S. M. Daniels. (1997) Inventory of the remnant Atlantic White-cedar stands in North Carolina. In Proceedings: Atlantic White-cedar: Ecology and Management Symposium. T. Shear and K. O. Summerville (editors). U.S. Forest Service Southern Research Station. General Technical Report SRS-27. pp. 82.

DeVivo, J. C., E. DiDonato, M. W. Byrne, and C. J. Wright. (2005) Appendix 7 - Conceptual models of southeast coast network ecosystems. *In* Vital signs monitoring in the Southeast Coast Inventory & Monitoring Network - Phase I (draft) Report. National Park Service, Southeast Coast Network, Atlanta, Georgia.

Earth Satellite Corporation. (1997) Comprehensive land cover mapping for the State of North Carolina: Final Report," March 1997.

Ecological Society of America Vegetation Panel. (2007) Report on Panel Activities. (http://www.esa.org/vegweb/panelActivities.php).

Edwards, T.C., Jr., C. G. Homer, S. D. Bassett, A. Falconer, R. D. Ramsey, and D. W. Wight. (1995) Utah Gap Analysis: an environmental information system. Technical Report 95-1, Utah Cooperative Fish and Wildlife Research Unit, Utah State University, Logan, Utah. 1189pp + 2 CD-ROMs.

Environmental Protection Agency. (2004) Level III and IV Ecoregions of EPA Region 4. U.S. Environmental Protection Agency, National Health and Environmental Effects Research Laboratory, Western Ecology Division, Corvallis, OR. Scale 1:2,000,000.

Federal Geographic Data Committee. (2006) National Vegetation Classification Standard, Version 2. Working Draft. Vegetation Subcommittee. November 30, 2006. FGDC-STD-005 (Version 2). http://www.fgdc.gov/standards/projects/FGDC-standards-projects/physiognomic-levels/Draft_FGDC_Std_November_edits3.pdf. 128 p.

Frost. C. C. and J. Costanza. (2006) A map of the presettlement vegetation of the Onslow Bight. Developed for The North Carolina Nature Conservancy Field Office.

Frost. C. C. (2006) History and future of the longleaf pine ecosystem. In: The Longleaf Pine Ecosystem: Ecology, Silviculture, and Restoration. S. Jose, E. J. Jokela, and D. L. Miller (editors) New York. Springer. Pp. 9 – 42.

Frost, C. C. (1995) Presettlement fire regimes in southeastern marshes, peatlands, and swamps. Proceedings of the 19th Tall Timbers Fire Ecology Conference. pp. 39 – 60.

Frost, C. C. (1987) Historical overview of Atlantic whitecedar (*Chamaecyparis thyoides*) in the Carolinas. Pages 257-264 *in* A. D. Laderman, editor. Atlantic whitecedar Wetlands. Westview Press, Boulder, Colo.

Harris, L.D., R. Sullivan, and R.L. Badger. (1984) Bottomland hardwoods: valuable, vanishing, vulnerable. University of Florida, Cooperative Extension Service, Gainesville. 17 pp.

Homer, C., J. Dewitz, J. Fry, M. Coan, N. Hossain, C. Larson, N. Herold, A. McKerrow, J. Nick VanDriel, and J. Wickham. (2007) Completion of the 2001 National Land Cover Database for the Coterminous United States. Photogrammetric Engineering and Remote Sensing. 73(4) 2007 pp. 337-341.

Homer, C. G., and A. Gallant. (2001) Partitioning the conterminous United States into mapping zones for Landsat TM land cover mapping, USGS Draft White Paper, 2001.

Homer, C. G., C. Huang, L. Yang, and B. Wylie. (2002) Development of a circa 2000 landcover database for the United States. Proceedings of the American Society for Photogrammetry and Remote Sensing Annual meeting April, 2002. Washington D.C.

Huang, C., Wylie, B., Yang, L., Homer, C., and Zylstra, G. (2002) Derivation of a tasseled cap transformation based on Landsat 7 at-satellite reflectance. International Journal of Remote Sensing. Vol. 23, No. 8, pp. 1741–1748.

Jose, S., E. J. Jokela, and D. L. Miller. (2006) The longleaf pine ecosystem: ecology, silviculture, and restoration. Springer, New York. 438 p.

Keys, J. E., Jr. and C. A. Carpenter. (1995) Ecological units of the Eastern United States: first approximation. Map compiled at 1:1,000,000. United States Department of Agriculture, Forest Service.

Kologiski, R. L. (1977) The phytosociology of the Green Swamp, North Carolina. Technical Bulletin. No. 250. December 1977. North Carolina Agricultural Experiment Station. 101 pp.

Komarek, E. V. (1968) Lightning and lightning fires as ecological forces. In: Tall Timbers Fire Ecology Conference Proceedings 8:169-197.

Lieca Geosystems GIS & Mapping. (2003) ERDAS Field Guide. 7th edition

Lowry, J. H, Jr., R. D. Ramsey, K. Boykin, D. Bradford, P. Comer, S. Falzarano, W. Kepner, J. Kirby, L. Langs, J. Prior-Magee, G. Manis, L. O'Brien, T. Sajwaj, K. A. Thomas, W. Rieth, S. Schrader, D. Schrupp, K. Schulz, B. Thompson, C. Velasquez, C. Wallace, E. Waller and B. Wolk. (2005) *Southwest Regional Gap Analysis Project: Final Report on Land Cover Mapping Methods*, RS/GIS Laboratory, Utah State University, Logan, Utah.

Lunetta, R.S., J. Ediriwickrema, J. Iiames, D. Johnson, J. G. Lyon, A. McKerrow, and A. Pilant. (2003) A quantitative assessment of a combined spectral and GIS rule-based land-cover classification in the Neuse River Basin of North Carolina. Photogrammetric Engineering and Remote Sensing. 69(3) March 2003. pp. 299-310.

Pearlstine, L., A. McKerrow, M. Pyne, S. Williams, and S. McNulty. (1999) Compositional groups and ecological complexes: a method for Alliance-based vegetation mapping. Gap Analysis Bulletin, E. Brackney and M. Jennings (eds.), U.S. Geological Survey, Biological Resources Division, Moscow, Idaho.

McKerrow, A. J., S. G. Williams, and J. A. Collazo. (2006) The North Carolina Gap Analysis Project: Final Report. North Carolina Cooperative Fish and Wildlife Research Unit. Submitted to: The National Gap Analysis Program. U.S. Geological Survey, Biological Resources Division. 2 dvd set.

McKerrow, A. J. and T. S. Earnhardt. (2004) Southeast Gap Analysis: a regional approach to land cover mapping. Proceedings American Society of Photogrammetry and Remote Sensing. May 23-28, 2004. Denver Colorado. 2004 (70) 8 p.

National Oceanographic and Atmospheric Administration. Coastal Services Center. 1995-present. (2006) The Coastal Change Analysis Program (CCAP). Charleston, SC: NOAA Coastal Services Center. (http://www.csc.noaa.gov/crs/lca/ccap.html) Accessed *12/1/2007*.

Natural Resources Conservation Service, United States Department of Agriculture (2007) State Soil Geographic (STATSGO) http://www.ncgc.nrcs.usda.gov/products/datasets/statsgo/index.html. Accessed *12/1/2007*.

Natural Resources Conservation Service, United States Department of Agriculture. (2007) Soil Survey Geographic (SSURGO). http://soildatamart.nrcs.usda.gov/SSURGOMetadata.aspx. Accessed *12/1/2007*.

Noss, R. F. (1988) The longleaf pine landscape of the Southeast: Almost gone and almost forgotten. Endangered Species Update 5(5):1-8.

Noss, R., LaRoe, E., & J. M. Scott. (1995) Endangered ecosystems of the US: A preliminary assessment of loss and degradation (Bio. Rept. 28). Washington, DC: US Department of Interior, National Biological Service.

Pearlstine, L., A. McKerrow, M. Pyne, S. Williams, and S. McNulty. (1999) compositional groups and ecological complexes: a method for alliance-based vegetation mapping. Gap Analysis Bulletin, E. Brackney and M. Jennings (eds.), U.S. Geological Survey, Biological Resources Division, Moscow, Idaho.

Peet, R. K., T. R. Wentworth, and P. S. White. (1998) A flexible, multipurpose method for recording vegetation composition and structure. Castanea 63:262-274

Prouty W. F. (1952) Carolina bays and their origin. Bulletin of the Geological Society of America. 63:167–224.

Quinlan, J. R. (1993) C4.5: programs for machine learning. Morgan Kaufmann series in machine learning. Morgan Kaufmann Publishers, San Mateo, Calif. 302 pp.

Richardson, C. J. (ed.). (1981) Pocosin wetlands: an integrated analysis of coastal plain freshwater bogs in North Carolina: Hutchinson Ross, Inc., Stroudsburg, PA, USA.

Richardson, C. J., and J. W. Gibbons. (1993) Pocosins, Carolina bays and mountain bogs. Pages 257-310 in W. H. Martin, S. G. Boyce, and A. C. Echternacht (editors), Biodiversity of the southeastern United States: Lowland terrestrial communities. New York: John Wiley.

Ricketts, T.H., E. Dinerstein, D. M. Olson, C. J. Loucks, W. Eichbaum, D. DellaSala, K. Kavanagh, P. Hedao, P. T. Hurley, K. M. Carney, R. Abell, and S. Walters. (1999) Terrestrial Ecoregions of North America: A Conservation Assessment. World Wildlife Fund. Island Press. Washington D.C. 485 pp.

Robinson, P.J. (1979) The physiography of North Carolina, Veroff. Geobot. Inst. ETH, Stiftung Rubel, Zurich, 68, 61-69.

Schafale, M. P. (1999) Nonriverine Wet Hardwood Forests in North Carolina: Status and Trends. Report to the North Carolina Natural Heritage Program, Raleigh, NC. 14 p.

Schafale, M.P., and A.S. Weakley. (1990) Classification of the natural communities of North Carolina, third approximation. N.C. Natural Heritage Program, Raleigh, N.C. 325 pp.

Sharitz, R, R. (2003) Carolina bay wetlands: unique habitats of the Southeastern United States. Wetlands. 23(2)55-562.

Soil Survey Staff, Natural Resources Conservation Service, United States Department of Agriculture. (1990) Keys to soil taxonomy. SMSS Technical Monograph No. 19. Fourth Edition. Virginia Polytechnic Institute and State Univesity. 423 pp.

Stehman, S. V. (1997) Selecting and interpreting measures of thematic classification accuracy. Remote Sensing of the Enviroment. 62:77-89.

Stehman, S. V. (1996) Estimating the kappa coefficient and its variance under stratified random sampling. Photogrammetric Engineering and Remote Sensing. 62(4)401-405.

U.S. Fish and Wildlife Service. (2006) National Wetland Inventory: A strategy for the 21st century. Plan.http://www.fws.gov/nwi/Pubs_Reports/NWI121StatFNL.pdf

U.S. Geological Survey. (2003a) National Land Cover Database Zone 58 impervious surface estimates. Sioux Falls, SD. http://www.mrlc.gov.

U.S. Geological Survey. (2003b) National Land Cover Database Zone 58 Land Cover. Sioux Falls, SD. http://www.mrlc.gov.

U.S. Geological. Survey (2003c) National Land Cover Database Zone 58 Tree Canopy estimates. Sioux Falls, SD. http://www.mrlc.gov.

Ware, S., C. C. Frost, and P. Doerr. (1993) Southern mixed hardwood forest: the former longleaf pine forest. Pages 447-493 *in* W. H. Martin, S. G. Boyce, and A. C. Echternacht, editors. Biodiversity of the Southeastern United States: Lowland Terrestrial Communities. Wiley, N.Y.

Wells B. W. (1928) Plant Communities of the coastal plain of North Carolina and their successional relations. Ecology. 9:230–242.

Wells, B. W. and I. V. Shunk. (1938) Salt spray: an important factor in coastal ecology. Torrey Bot. Club Bulletin. 65: 485-492.

Wilson, K. A. (1962) North Carolina wetlands, their distribution and management: North Carolina Wildlife Resources Commission, Raleigh, NC, USA. Federal Aid in Wildlife Restoration Project W-6-R.

Wyant, J. G., R. J. Alig, and W. A. Bechtold. (1991) Physiographic position, disturbance, and species composition in North Carolina coastal plain forests. Forest Ecology and Management. 41 (1991) 1-19.

Yang, L., C. Homer, K. Hegge, C. Huang, B. Wylie, and B. Reed. (2001) A Landsat 7 Scene Selection Strategy for a National Land Cover Database. IEEE. (2001) 1123 – 1125.

Yang, L., C. Huang, C. G. Homer, B. K. Wylie, and M. J. Coan. (2003) An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. Canadian Journal of Remote Sensing. Vol. 29 (2) 230-240.

Zhu, Z. and D. L. Evans. (1994) U.S. forest types and predicted percent forest cover from AVHRR Data. Photogrammetric Engineering and Remote Sensing. 60(5)525-531.

Zhong, C., Z. Zhongmin, Y. Dong Mei, and C. Renxi. (2005) Multi-Scale Segmentation of the High Resolution Remote Sensing Image. Geoscience and Remote Sensing Symposium, IGARSS Proceedings. IEEE: 3682-3684.

Table 2.1. Target vegetation map classes for the Onslow Bight, North Carolina. Note: Abbreviations, Atlantic Coastal Plain (ACP), Large (L.), and Small (Sm.) are used throughout the table.

Category/ Pattern	System Name (Map code)	Modifier	System Code
Palustrine Forested Wetlands			
Linear	ACP Large River Floodplain (4)	Brownwater Forested	CES203.066a
Linear	ACP Large River Floodplain (6)	Blackwater Forested	CES203.066c
Sm. patch	ACP Clay-Based Carolina Bay Wetland (11)		CES203.245
Linear	ACP Blackwater Stream Floodplain Forest (14)		CES203.247
Linear	ACP Small Blackwater River Floodplain Forest (16)		CES203.249
Linear	ACP Small Brownwater River Floodplain Forest (18)		CES203.250
Matrix	ACP Northern Wet Longleaf Pine Savanna and Flatwoods (32)		CES203.265
L. patch	ACP Peatland Pocosin (33)	Pocosin	CES203.267a
L. patch	ACP Peatland Pocosin (34)	Bay Shrubland	CES203.267b
L. patch	ACP Nonriverine Swamp and Wet Hardwood Forest (39)	Oak	CES203.304a
L. patch	ACP Nonriverine Swamp and Wet Hardwood Forest (40)	Taxodium/ Nyssa	CES203.304b
L. patch	ACP Nonriverine Swamp and Wet Hardwood Forest (41)	Atlantic White-cedar	CES203.304c
Palustrine Emergent Wetlands			
Large	Southeastern Coastal Plain Natural Lakeshore (2)		CES203.044
Linear	ACP Large River Floodplain (90)	Brownwater -Herbaceous	CES203.066b
Linear	ACP Large River Floodplain (91)	Blackwater - Herbaceous	CES203.066d
Sm. patch	ACP Embayed Region Tidal Freshwater Marsh (26)		CES203.259
Sm. patch	ACP Central Fresh-Oligohaline Tidal Marsh (42)		CES203.376
Estuarine Wetlands			
L. patch	ACP Southern Tidal Wooded Swamp (8)		CES203.240
L. patch	ACP Embayed Region Tidal Salt and Brackish Marsh (27)		CES203.260
Matrix	ACP Central Salt and Brackish Tidal Marsh (35)		CES203.270
Upland Forest			
Sm. patch	ACP Dry and Dry-Mesic Oak Forest (9)		CES203.241
L. patch	ACP Mesic Hardwood and Mixed Forest (10)		CES203.242
Matrix	ACP Fall-line Sandhills Longleaf Pine Woodland (21)		CES203.254
Sm. patch	ACP Central Maritime Forest (28)		CES203.261
Matrix	ACP Upland Longleaf Pine Woodland (37)		CES203.281
Beach Systems			
L. patch	ACP Southern Dune and Maritime Grassland (36)		CES203.273
Linear	ACP Central Sandy Beach (3)		CES203.064

Table 2.2. Path/Rows and Landsat TM image acquisition dates for the Onslow Bight study area.

	Season of Imagery		
Path/Row	Spring	Leaf off	Leaf on
14/35	**Mar. 1, 2000**	**Sept. 23, 1999**	**May 4, 2000**
14/36	**Mar. 23, 2000**	**Oct. 30, 2001**	**May 20, 2000**
15/35	**Mar. 8, 2000**	**Sept. 30, 1999**	**May 14, 2001**
15/36	**Feb. 21, 2000**	**Nov. 6, 2001**	**May 11, 2001**
16/36	**Mar. 5, 2002**	**Nov. 10, 2000**	**June 9, 2002**

Table 2.3. Wetland map classes included in Zone 58 in addition to the NLCD 2001 legend.

NLCD Level II Class	Zone 58 Class
Forested Wetland	**Palustrine Deciduous Forested Wetland**
	Palustrine Evergreen Forested Wetland
	Palustrine Scrub/Shrub Wetland
	Estuarine Forested Wetland
	Estuarine Scrub/Shrub Wetland
Emergent Wetland	**Palustrine Emergent Wetland**
	Estuarine Emergent Wetland

Table 2.4. Data layers available for use in decision tree modeling and for mapping.

Input layers	Variable type	Description
Landsat Leaf off[ab]	**Continuous**	**6 reflectance bands (1,2,3,4,5,7)**
Landsat Leaf on[ab]	**Continuous**	**6 reflectance bands (1,2,3,4,5,7)**
Landsat Spring[ab]	**Continuous**	**6 reflectance bands (1,2,3,4,5,7)**
Landsat Leaf off tasseled capped[ab]	**Continuous**	**Brightness, greenness, wetness**
Landsat Leaf on tasseled capped[ab]	**Continuous**	**Brightness, greenness, wetness**
Landsat Spring tasseled capped[ab]	**Continuous**	**Brightness, greenness, wetness**
Land Cover[ab]	**Categorical**	**Open water, open space developed, low intensity developed, moderate intensity developed, high intensity developed, barren land, unconsolidated shore, deciduous forest, evergreen forest, mixed forest, scrub/shrub, grassland/herbaceous, pasture/hay, cultivated crops, forested wetland, emergent wetland**
Landform	**Categorical**	**Steep slope n/ne, steep slope s/sw, slope crest, flat summit, cove/ravine, dry flat, moist flat, slope bottom, stream, lake/river**
National Wetlands Inventory[b]	**Categorical**	**Open water, unconsolidated shore, upland, palustrine forest, palustrine shrub, estuarine forest, estuarine shrub, palustrine emergent, estuarine emergent, palustrine aquatic bed, estuarine aquatic bed**
Wetland modifier[b]	**Categorical**	**Palustrine, estuarine, ditched/drained**
SSURGO[b]	**Continuous**	**% sand, silt, clay, organic matter**
STATSGO[ab]	**Continuous**	**% sand, silt, clay, organic matter**
Image Objects[ab]	**Continuous**	**Mean spring tasseled capped brightness, standard deviation spring tasseled capped brightness, mean leaf off tasseled cap brightness, mean canopy closure, area, shape, border length, compactness**

[a] indicates the layer was used as input in decision tree modeling for managed vs. natural pine.

[b] indicates the layer was used as input in decision tree modeling for Ecological Systems.

Table 2.5. Crosswalk between North Carolina Natural Heritage Program's Natural Community and NatureServe's Ecological Systems Classification. Alphabetical suffix to System Code represents GAP modifier.

NCNHP Community Name	System Code	Ecological System Name
Basic Mesic Forest (CP)	CES203.242	ACP Mesic Hardwood and Mixed Forest
Bay Forest	CES203.267	ACP Peatland Pocosin
Brackish Marsh	CES203.270	ACP Central Salt and Brackish Tidal Marsh
Coastal Plain Bottomland Forest	CES203.066c	ACP Large River Floodplain – Blackwater Forested
Coastal Plain Bottomland Forest	CES203.247	ACP Blackwater Stream Floodplain
Coastal Plain Bottomland Forest	CES203.249	ACP Small Blackwater River Floodplain
Coastal Plain Levee Forest	CES203.066c	ACP Large River Floodplain - Blackwater Forested
Coastal Plain Levee Forest	CES203.249	ACP Small Blackwater River Floodplain
Coastal Plain Small Stream Swamp	CES203.247	ACP Blackwater Stream Floodplain
Cypress--Gum Swamp (Blackwater)	CES203.066c	ACP Large River Floodplain – Blackwater Forested
Cypress--Gum Swamp (Blackwater)	CES203.249	ACP Small Blackwater River Floodplain
Dry Oak--Hickory Forest	CES203.241	ACP Dry and Dry-Mesic Oak Forest
Dry-Mesic Oak--Hickory Forest	CES203.241	ACP Dry and Dry-Mesic Oak Forest
Dune Grass	CES203.273	ACP Southern Dune and Maritime Grassland
Estuarine Fringe Loblolly Forest	CES203.240	ACP Southern Tidal Wooded Swamp
High Pocosin	CES203.267	ACP Peatland Pocosin
Low Pocosin	CES203.267	ACP Peatland Pocosin
Maritime Dry Grassland	CES203.273	ACP Southern Dune and Maritime Grassland
Maritime Evergreen Forest	CES203.261	ACP Central Maritime Forest
Maritime Shrub	CES203.261	ACP Central Maritime Forest
Maritime Shrub Swamp	CES203.240	ACP Southern Tidal Wooded Swamp
Maritime Swamp Forest	CES203.240	ACP Southern Tidal Wooded Swamp
Maritime Wet Grassland	CES203.273	ACP Southern Dune and Maritime Grassland
Mesic Mixed Hardwood	CES203.242	ACP Mesic Hardwood and Mixed Forest
Mesic Pine Flatwoods	CES203.281	ACP Upland Longleaf Pine Woodland

Table 2.5. continued.

NCNHP Community Name	System Code	Ecological System Name
Nonriverine Swamp Forest	CES203.304b	ACP Nonriverine Swamp and Wet Hardwood - Taxodium
Nonriverine Wet Hardwood Forest	CES203.304a	ACP Nonriverine Swamp and Wet Hardwood - Oak
Pine Savanna	CES203.265	ACP Northern Wet Longleaf Pine Savanna and Flatwoods
Pine/scrub Oak Sandhill	CES203.254	ACP Fall-line Sandhills Longleaf Pine Woodland
Pond Pine Woodland	CES203.267	ACP Peatland Pocosin and Canebrake
Salt Flat	SEGAP112	Open Water (Brackish/Salt)
Salt Marsh	CES203.270	ACP Central Salt and Brackish Tidal Marsh
Salt Shrub	CES203.270	ACP Central Salt and Brackish Tidal Marsh
Tidal Cypress--Gum Swamp	CES203.240	ACP Southern Tidal Wooded Swamp
Tidal Freshwater Marsh	CES203.376	ACP Central Fresh-Oligohaline Tidal Marsh
Tidal Red Cedar Forest	CES203.240	ACP Southern Tidal Wooded Swamp
Upper Beach	CES203.064	ACP Central Sandy Beach
Wet Pine Flatwoods	CES203.265	ACP Northern Wet Longleaf Pine Savanna and Flatwoods
Xeric Sandhill Scrub	CES203.254	ACP Fall-line Sandhills Longleaf Woodland

Table 2.6. Ecological Systems model results. Amount and accuracy statistics for the evergreen forest Ecological Systems modeling. Note: t represents the number of training data sites used in modeling and n represents the number of sites used for the assessment.

	Sample size	Model				
	Training (Assessment)	Full Model	No STATSGO	No SSURGO	No STATSGO or SSURGO	No Vector
		Hectares modeled (% of study area)				
Sandhills Longleaf	t = 67	132,443	254,296	159,306	122,609	100,671
	n = 54	(19)	(36)	(23)	(17)	(14)
ACP Wet Longleaf	t = 109	213,149	157,629	267,535	239,963	270,624
	n = 87	(30)	(22)	(38)	(34)	(38)
Pocosin	t = 95	230,961	177,678	174,224	258,474	242,515
	n = 86	(33)	(25)	(25)	(37)	(34)
ACP Upland Longleaf	t = 12	21,007	356	2,147	8,553	1,146
	n = 9	(3)	(< 1)	(< 1)	1	(<1)
Nonriverine - Oak	t = 7	48,074	69,725	67,051	59,008	44,138
	n =6	(7)	(10)	(9)	(8)	(6)
Nonriverine - Taxodium	t =10	61,110	47,060	36,481	18,136	47,650
	n = 6	(9)	(7)	(5)	(3)	(7)
Total	t = 300 n = 248	---------------------------706,774 ha (100%) ----------------------				
PCC		65	51	63	63	54
Kappa 95% C.I.		0.513 +- 0.014	0.411 +- 0.011	0.325 +- 0.12	0.444 +-0.012	0.366 +-0.012

Table 2.7. Per class acreage and accuracy statistics for the Onslow Bight land cover. Note: π - probability that a site is correctly mapped given the reference data; λ - probability that a site is correctly classified given the map class; θ - omission error (1 – π) and φ - commission error (1- λ) can be derived from the information provided.

Class Name	Ha	π	λ	n
ACP Large River Floodplain - Brownwater Forest (4)	25,468	96	67	7
ACP Large River Floodplain - Blackwater Forest (6)	32,783	90	70	35
ACP Clay-Based Carolina Bay Wetland (11)	164			
ACP Blackwater Stream Floodplain Forest (14)	34,743	82	18	4
ACP Small Blackwater River Floodplain Forest (16)	56,433	49	65	49
ACP Small Brownwater River Floodplain Forest (18)	12			
ACP Northern Wet Longleaf Pine Savanna and Flatwoods (32)	197,593	75	77	94
ACP Peatland Pocosin - Pocosin (33)	225,295	89	78	89
ACP Peatland Pocosin - Carolina Bay Shrubland (34)	5,464			
ACP Nonriverine Swamp and Wet Hardwood Forest - Oak (39)	37,072	78	67	6
ACP Nonriverine Swamp and Wet Hardwood Forest - Taxodium (40)	36,649	74	50	7
ACP Nonriverine Swamp and Wet Hardwood Forest - Cedar (41)	30			
Southeastern Coastal Plain Natural Lakeshore (2)	449			
ACP Large River Floodplain - Brownwater Herbaceous (90)	270			
ACP Large River Floodplain - Blackwater Herbaceous (91)	308			
ACP Embayed Region Tidal Freshwater Marsh (26)	2,471	100	50	1
ACP Central Fresh-Oligohaline Tidal Marsh (42)	4,759	12	88	24
ACP Southern Tidal Wooded Swamp (8)	8,167	4	50	59
ACP Embayed Region Tidal Salt and Brackish Marsh (27)	36,386	100	94	33
ACP Central Salt and Brackish Tidal Marsh (35)	24,117	55	86	47
ACP Dry and Dry-Mesic Oak Forest (9)	135,542	87	63	19
ACP Mesic Hardwood and Mixed Forest (10)	157	<1	100	13
ACP Fall-line Sandhills Longleaf Pine Woodland (21)	109,668	53	67	74
ACP Central Maritime Forest (28)	10,129	42	80	22
ACP Upland Longleaf Pine Woodland (37)	12,954	37	100	10
ACP Southern Dune and Maritime Grassland (36)	7,306	20	88	35
Open Water - Fresh (61)	18,426	100	47	8
Open Water - Brackish/Salt (62)	333,645	100	89	58
Barren - Bare Sand (67)	53	8	100	5
Barren - Bare Soil (68)	3			
Barren - Quarry/Mine (69)	233	28	100	5
Managed Pine (73)	243,391	98	93	44
Successional Scrub/shrub - Clear Cut (74)	3,897	60	100	6
Successional Scrub/shrub - Other (76)	65,404	79	67	15
Successional Herbaceous - Clear Cut (79)	4,862	100	75	6
Successional Herbaceous - Other (80)	200,954	76	56	37
Pasture/Hay (77)	15,423	55	83	7
Row Crop (78)	471,263	98	85	80
Urban - Developed Open Space (63)	100,640	68	81	21
Urban - Low Intensity Developed (64)	41,342	92	100	11
Urban - Medium Intensity Developed (65)	10,559	96	100	7
Urban - High Intensity Developed (66)	2,750	100	83	5
Total	2,517,231			947

Table 2.8. Accuracy assessment of the areas of disagreement in the XY and NOXY models for natural vs. managed evergreen.

		Reference		
Model		**Managed**	**Natural**	**Accuracy**
NOXY	**Managed**	**10**	**36**	**22%**
	Natural	**18**	**36**	**67%**
	Accuracy	**36%**	**50%**	**46%**
XY	**Managed**	**18**	**36**	**33%**
	Natural	**10**	**36**	**78%**
	Accuracy	**64%**	**50%**	**54%**

Table 2.9. Confusion matrices for raw assessment points in each model. Class 21 – ACP Fall-line Sandhills, 32-ACP Northern Wet Longleaf, 33 -ACP Peatland Pocosin, 39-ACP Nonriverine Swamp and Wet Hardwood - Oak and 40 - ACP Nonriverine Swamp and Wet Hardwood – *Taxodium*.

		Reference						
		21	32	33	37	39	40	Total
Full Input	21	38	27	4			1	70
	32	15	48	9	7			79
	33	1	11	72	1	1	1	87
	37			1	1	3		5
	39					2	2	4
	40		1				2	3
	Total	54	87	86	9	6	6	248
		Reference						
		21	32	33	37	39	40	Total
No STATSGO	21	38	52	20	7	2	4	123
	32	16	24	6	1			47
	33		9	58	1	1		69
	37				0			0
	39		1	2		2		5
	40		1			1	2	4
	Total	54	87	86	9	6	6	248
		Reference						
		21	32	33	37	39	40	Total
No SSURGO	21	35	25	6	3		2	71
	32	15	43	19	4			81
	33	3	15	61		1	2	82
	37		2		1			3
	39		1			3	1	5
	40	1	1		1	2	1	6
	Total	54	87	86	9	6	6	248
		Reference						
		21	32	33	37	39	40	Total
No SSURGO or STATSGO	21	33	27	6	5	1	3	75
	32	17	40	10	2			69
	33	1	16	70	1	1	1	90
	37	2	3		1			6
	39		1			2		3
	40	1				2	2	5
	Total	54	87	86	9	6	6	248
		Reference						
		21	32	33	37	39	40	Total
No Vector	21	27	20	5	5	2	5	64
	32	25	46	18	4			93
	33	1	19	63		1	1	85
	37		1					1
	39		1			1		2
	40	1				2		3
	Total	54	87	86	9	6	6	248

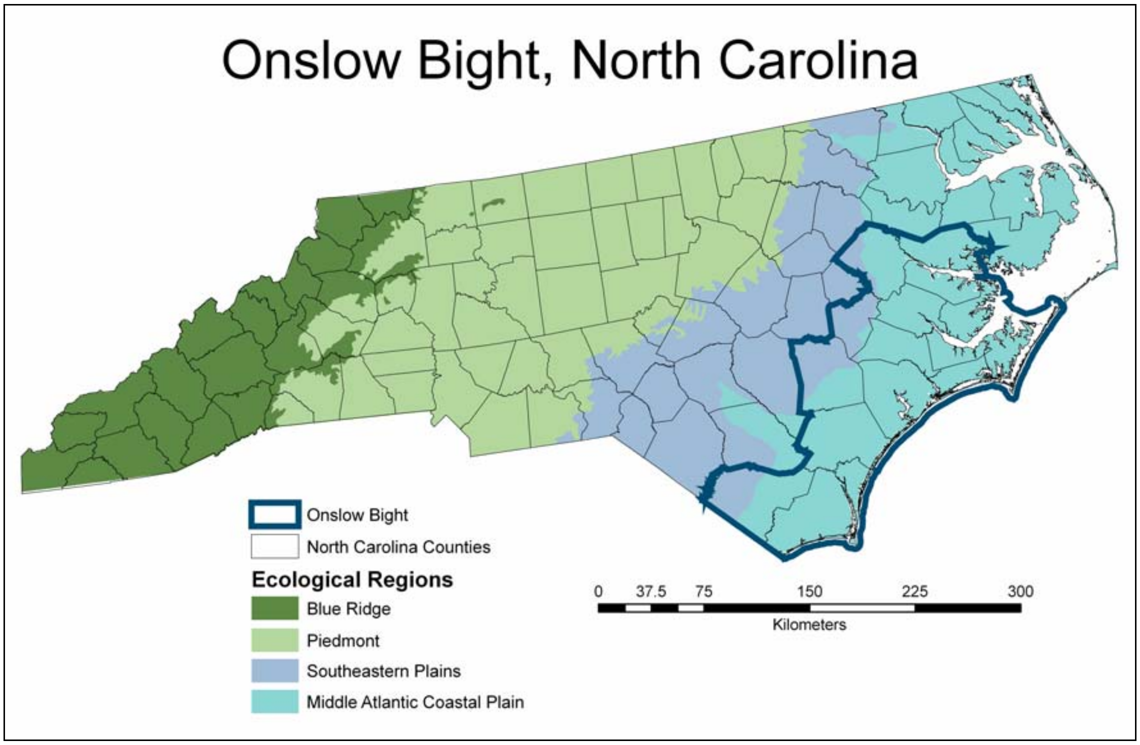

Figure 2.1. Location map for the Onslow Bight Study Area with county boundaries and Ecological Regions. Ecological regions delineated based on Omernick's ecoregional classification (EPA 2004).

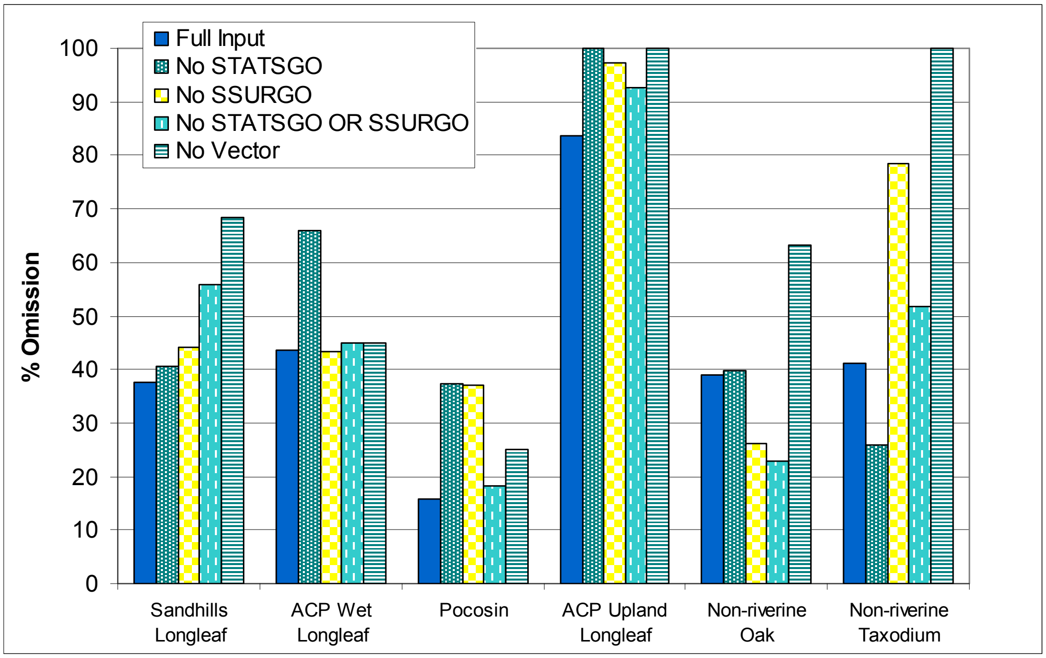

Figure 2.2. Omission error for each Ecological System by model.

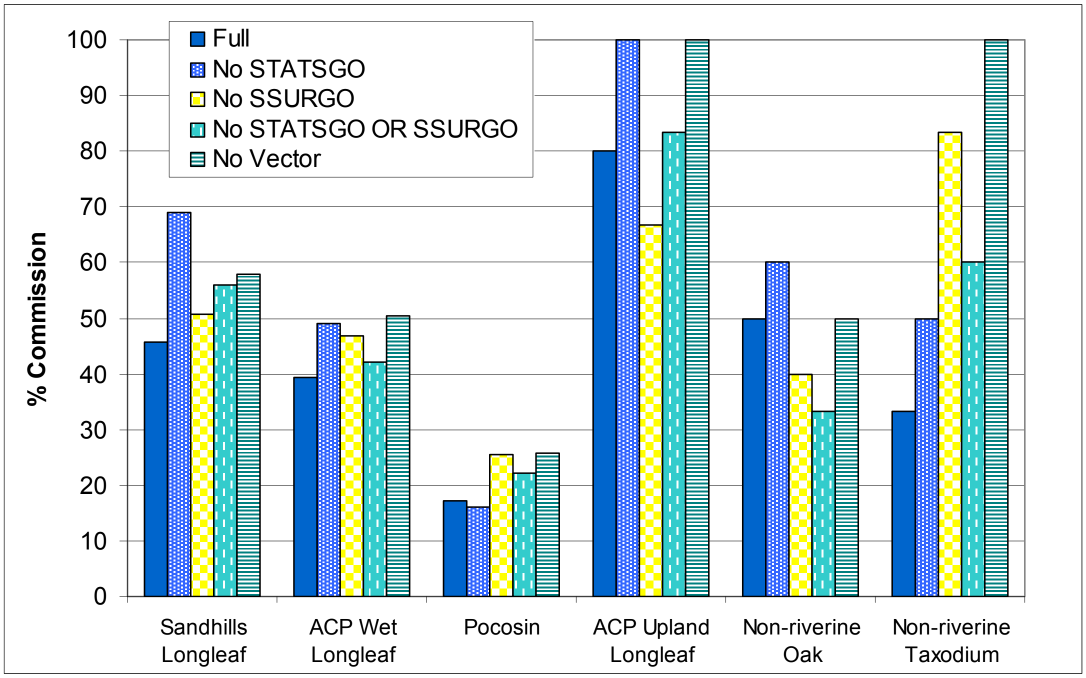

Figure 2.3. Commission error for each Ecological System by model.

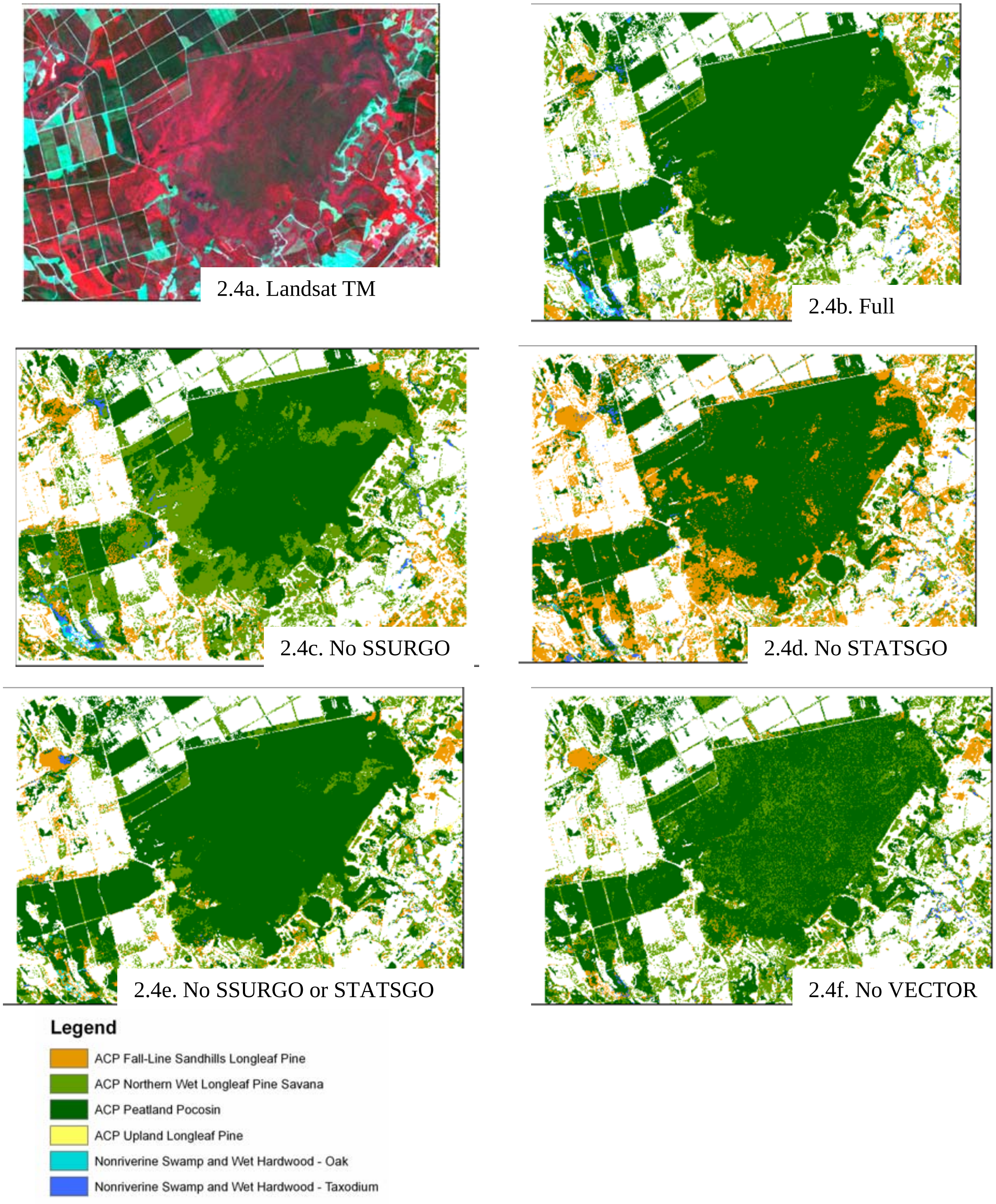

Figure 2.4a – e. Comparison of maps of the evergreen and nonriverine Ecological Systems. Differences resulting from various input layers used in decision tree modeling and one date, leaf on Landsat TM imagery (2.4a) for the Green Swamp area.

Image objects and change vector analysis for monitoring changes in the plant communities in the Onslow Bight, North Carolina.

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Abstract

Effective conservation planning requires information on both the content and context for the resources to be conserved. Land cover mapping and change detection are one set of tools that provide both the content (spatially explicit land cover) and the context (land cover changes). Our goal was to develop an approach to change detection that could be used with a thematically rich land cover map. We used the 2001 Ecological Systems map developed by the Southeast Gap Analysis Project as our baseline dataset. Our study area was the Onslow Bight in the Middle Atlantic Coastal Plain of North Carolina. The method combined Change Vector Analysis (CVA), image segmentation (image objects), and regression tree modeling to back cast to a 1992 era land cover map. The overall accuracy based on marginal frequencies was 95% with a Kappa of 0.78. There was a 21% probability that a point that did not change was misclassified as one that had changed, and a 17% probability that a change was missed. Thirteen percent of the study area was mapped as having changed. Most of the land cover changes were between anthropogenic land cover types, but the approach provided the context necessary to map the changes in the Ecological Systems of the Onslow Bight. Using this approach we were able to accurately map change in a complex landscape and to avoid a common mistake of over-mapping change in the agricultural classes. In future work we hope to find methods for automating portions of the process, specifically: (1) setting the initial change thresholds based on the magnitude of change between image dates; and (2) classifying the class-specific types of change.

Keywords: Change Detection, Change Vector Analysis, Image Objects, Ecological Systems, Gap Analysis Program.

Introduction

Land Cover Change in the Southeastern Coastal Plain.

The pattern and extent of land cover change have important implications for conservation in the Southeastern United States. Changes in water and habitat quality can affect species and plant communities directly, while habitat fragmentation, shifts in fire or flooding frequency and intensity, and altered hydrology can indirectly affect the system's and species' ability to respond to changing conditions. In the Status and Trends Program's assessment of land cover change for 6 ecoregions of the Southeastern U.S., Loveland and Acevedo (2006) estimated that 18% of the area in the Middle Atlantic Coastal Plain (*sensu* EPA 1999) had changed during the twenty seven year period between 1973 and 2000, representing an annual net change of 0.6%. The dominant types of change they documented for these ecoregions included changes among forest, mechanically disturbed land (clearcut shrublands or grasslands), and agriculture.

Historically, the Southeast has undergone tremendous changes in natural vegetation. Prior to settlement, longleaf pine woodlands were the dominant vegetation type in the uplands (Frost 1993). Extensive river corridors bisected the upland matrix and concentrations of non-riverine wetlands covered vast acreages. Today row crop agriculture and managed pine are the most extensive cover types. In a conservation assessment of the U.S. and Canada, the World Wildlife Fund identified the Middle Atlantic Coastal Forests Ecoregion as an outstanding region in need of "immediate protection of remaining habitat and extensive restoration" (Ricketts et al. 1999). In order to accomplish protection and restoration efficiently, current maps of the existing land cover and a standard approach for detecting changes are needed. We contributed to that process as a part of our work with the National Gap Analysis Program and their cooperators.

Ecological Systems of the Onslow Bight.

The National Gap Analysis Program has been mapping the vegetative communities of the U.S. for more than fifteen years, working with a variety of partners to identify efficient and effective mapping methods. One of the major barriers to successful mapping in the earlier projects was the lack of a vegetation classification system that could: (1) describe plant communities; (2) be used in conservation planning; and (3) be mapped using remotely sensed imagery and the available ancillary data. During the past 10 years a concentrated effort to develop a nationally consistent vegetation classification that could be mapped with current technology has been underway in the U.S. One result of that work is the Ecological Systems Classification developed by NatureServe (Comer et al. 2003). That classification has been adopted as the target map unit for the National Gap Analysis Program. As a part of the Southeast Gap Analysis Project, an Ecological Systems map was developed for nine southeastern states (AL, FL, GA, KY, MS, NC, SC, TN, and VA). Now that the Ecological Systems map has been completed, the challenge of identifying a method for monitoring changes through time can be addressed.

Approaches to Change Detection.

Common approaches to satellite image-based change detection have been characterized as pre-classification and post-classification techniques (Lunetta 1998). Pre-classification methods are those in which the spectral data are used to identify change areas prior to labeling land cover and include image differencing and composite image analysis methods. Post-classification change detection is a simple overlay process in which two land cover products are compared and change is mapped as areas of disagreement between the two dates.

Image differencing techniques identify change as some minimum difference (threshold) between the two dates of imagery. That difference can be based on the comparison of individual bands (band differencing) or on some index that has been derived from the imagery. Change detection experiments are often based on differences in vegetation indices such as the Normalized Difference Vegetation Index (NDVI; Lyon et al. 1998).

Composite analysis involves combining data from two or more dates of imagery before classifying land cover changes. Two methods based on image composition include Principal Component Analysis (PCA) and Change Vector Analysis (CVA). In PCA a linear transformation of the data is performed and the derived components represent the major axes of variability in the dataset. In change detection applications, the first PCA axes generally represent the variability across the study area, while the higher order axes tend to represent subtle variations. The goal is to use those higher order components to identify the change areas. For example, Mas (1999) used a Selective Principal Component Analysis (SPCA) in which the bands from two dates of imagery were combined (stacked) to create a single image and the principal components derived for that image. Band 1 of the SPCA image represented the majority of the variation in imagery and therefore explained variability common to the two dates of imagery, while band 2 captured variation between the two dates and was used to identify change areas.

In Change Vector Analysis the direction of change (gains or losses) and the magnitude of the difference between two images are used to classify change (Chen et al. 2003, Hayes and Sader 2001, Johnson and Kasiscke 1998). For the case of a two band image, the vector represents the line that connects a common point on the ground in two-dimensional space (Figure 3.1). The direction of that line can be used to identify the type of change that has occurred and the length of the line represents the magnitude of the change. For example, in Figure 3.1 the line represents a large difference in band 1 and a moderate difference in band 2. For the unchanged site, the shift in both axes is minor, indicating some variability (noise) between the images, but not a significant shift in reflectance.

Post classification change detection is most appropriate when the two land cover maps are developed with a common methodology. If that is not the case, differences in approach often overwhelm true differences in land cover (Lunetta 1998, Singh 1989).

Pixel-based and Patch-based Change Detection.

The majority of satellite based change detection experiments rely on pixel to pixel comparisons (Homer et al. 2007, Lunetta et al. 2002, Lunetta 1998, Lyon et al.

1998, Dobson et al. 1995). More recently, experiments implementing patch based change detection are becoming more common (Blaschke 2005, Al-Khudhairy et al. 2005, Laliberte et al. 2004, Bruzzone and Fernandez Prieto 2000a).

Bruzzone and Fernandez Prieto (2000b) used a patch-based approach to change detection to reduce the errors introduced by spectral variability in imagery, as well as the registration errors inherent in multi-date analyses. Blaschke (2005) argued that the context of a pixel, a characteristic ignored in pixel to pixel based comparisons, provides significant information to help in accurate mapping. He also asserted that using such information would, in some cases, go further in resolving issues of accurately mapping mixed pixels than an increase in the spatial resolution of the image data being used.

Study Objectives

We were interested in identifying a method for detecting change in a thematically rich land cover map. Specifically, we wanted to use the newly available 2001 GAP Ecological Systems map for the Onslow Bight as a base and perform back-casting to identify the pattern and types of land cover changes that had occurred between 1992 and 2001. Finally, in addition to characterizing the changes in the land cover, we planned to use the change map to describe the patterns of change in the predicted distributions for vertebrate species in the Onslow Bight.

In a broader sense, we wanted to identify an approach that could be used by the Gap Analysis Program for updating Ecological Systems maps. GAP has focused on developing high quality baseline land cover datasets and requires a method for updating those. The cost of land cover mapping is significant and, once complete, the most effective method for updating might be through change detection. A variety of approaches for identifying change exist (Lunetta 1998), but the application of those approaches across large areas and at the level of detail of the Ecological Systems maps has not been tested. Currently, NOAA's Coastal Change Analysis Program has the most experience with large area change detection (NOAA-CCAP 2007). That program successfully monitors change between 28 land cover classes. The land cover classification used by CCAP is based on vegetation structure, hydrology, and physiognomy. USGS has recently initiated an effort to detect change nationally, based on the 1992 and 2001 NLCD datasets (Homer et al. 2007). That effort will determine change between 6 general land cover classes in order to rapidly assess change for the coterminous U.S. Future plans include developing protocols for detecting change among the 21 land cover classes of the NLCD 2001. Again, that classification is based on vegetation structure, hydrology, and physiognomy, and does not include a species composition component. In this study we planned to perform that evaluation and, if successful, identify an effective approach to meeting the goal of efficient updating for GAP's land cover maps.

Study Area

Our study area, the Onslow Bight, covers more than 250,000 km^2 of land in the Coastal Plain of North Carolina. The area supports a diverse set of natural plant communities including maritime forests, coastal marshes, pocosins, and longleaf pine woodlands (Figure 3.2). The area was first settled in the early 1700s. Currently, coastal development, forest management, and farming are the dominant land uses in the region. Lands in public management represent 5% of the area, with Department of Defense, U.S. Fish and Wildlife Service, and the N. C. Wildlife Resources Commission managing the majority of those lands. The most extensive land cover in the study area is row crop agriculture, followed by open (salt and brackish) water. The Atlantic Coastal Plain Peatland Pocosin is the most extensive Ecological System in the present landscape (Figure 3.2).

Methods

There were three major steps in our change detection process.

1. Pre-processing the imagery, determining the change vectors, and identifying the potential change areas (Figure 3.3);
2. Labeling change for the Non-Urban land cover classes (Figure 3.4); and
3. Labeling change for the Urban areas (Figure 3.5).

Imagery

Two leaf-on Landsat image mosaics developed by U.S.G.S. Earth Resources Observation Systems Data Center (EDC) were used for detecting change between 1992 and 2001 (Figure 3.6). The 2001 mosaic has been used in both the development of the National Land Cover Dataset (NLCD 2001) and the Ecological Systems map for the Onslow Bight Study area (See Chapter 2 this volume). The 1992 mosaic was created as a part of a national effort to map changes in land cover between 1992 and 2001 for six general land cover classes (Homer et al. 2007). We wanted to test a method that relied on Landsat TM image mosaics available through the Multi-resolution Landscape Characterization Consortium (MRLC) to meet the broader objective of identifying an approach that could be implemented on a larger scale.

While the mosaics were developed with the goal of creating a homogeneous seasonal snapshot for each mapping zone, the spatial extent of those zones and local variation in weather conditions (cloud cover, haze, smoke) made that impossible. Therefore, each mosaic contains several different dates of imagery. For a complete discussion of the process for creating the mosaics, see Yang et al. (2001). When combining two mosaics for the purpose of change detection the combinations of image dates might be problematic, depending on the level of detail being sought and the change detection method being applied. Because we were trying to detect change in 42 land cover classes, we chose to treat each date / band combination, 9 in all, as distinct sub-zones for classifying change.

Change Vector Analysis

We used tasseled cap (TC) transformed images so the vectors between our two dates of imagery would represent gains or losses in brightness, greenness, and wetness. This transformation has been used in a variety of change detection studies for similar reasons (Sohl 1999, Johnson and Kasischke 1998, Dwyer et al. 1996). This transformation is essentially a principal components approach to data reduction, where the axes in the derived dataset have been forced to represent brightness, greenness, and wetness (Crist and Kauth 1986, Kauth and Thomas

1976). The name tasseled cap comes from the hat-like pattern that is often observed when the distribution of pixels is graphed along two of the new axes (Figure 3.7). The transformation is accomplished by providing a transformation matrix specific to the image source, where the coefficients have been derived using training sites representing the full range of brightness, wetness, and greenness (e.g., soil, vegetation, and water; Huang et al. 2002). In this study, we used the tasseled cap transformed image mosaics developed by the MRLC (Huang et al. 2002) to calculate the change vectors based on differences in brightness, greenness and wetness between 1992 and 2001 image mosaics.

Below are the formulas for calculating the magnitude and direction (cosine) of change (Chen et al. 2003).

Magnitude = Square root [(TC92 Brightness – TC01 Brightness)^2 + (TC92 Greenness – TC01 Greenness)^2 + (TC92 Wetness – TC01 Wetness)^2]

Cosine (brightness) = (TC92 Brightness – TC01 Brightness) / Magnitude
Cosine (greenness) = (TC92 Greenness – TC01 Greenness) / Magnitude
Cosine (wetness) = (TC92 Wetness – TC01 Wetness) / Magnitude

Image Objects

The change vector direction and magnitude images were combined to create a four-band image that we used to generate image objects using eCognition Elements 4.0 software (Definiens Imaging 2004). Objects were generated using a region-merging technique (agglomerative approach), where each pixel was assigned to a single object in the first iteration of the image segmentation. In subsequent iterations, the characteristics of each object were compared to those of its neighboring objects and if a threshold of similarity is met, the objects were merged (Benz et al. 2004). More specifically, a size threshold (scale) and homogeneity characteristics of the object (shape index and compactness) determined when two neighboring objects are merged.

Those objects were used as our analysis unit for detecting change in the non-urban areas. The derived image objects represented homogeneous patches with respect to the four bands of data used as input. For change areas, the type of change and the "from" and "to" categories within an object would be homogeneous as well, as long as the objects being generated were the same size or smaller than the scale of the land cover changes. We increased the scale of the objects stepwise, so the largest objects used in the analyses represented aggregations of the finest scale objects (scale level 1 = 10, level 2 = 15, level 3 = 20, shape index = 0.3 and compactness = 0.5).   Each of the scale 20 objects, the largest objects generated, was then attributed with the mean magnitude difference of the pixels within the object, the mean for each of the change vectors (brightness, greenness, wetness), and the majority land cover class from the Ecological Systems map.

Identifying and Labeling Change Areas in Non-Urban Land Cover

We used the 2001 Ecological Systems map for the Onslow Bight as the base image. In other words, the "to" category for any change was based on the 2001 map. The complexity of the map legend with 42 land cover classes made labeling the "from" categories for change especially challenging. In addition to the number of possible combinations, the combination of natural systems and anthropogenic types in a single map complicated the issue further. However, there were very few logical land cover changes that would be expected between Ecological Systems. One exception would be the shift from the Atlantic Coastal Plain (ACP) Southern Tidal Wooded Swamp "to" or "from" ACP Central Salt and Brackish Tidal Marsh. At the same time, many combinations between the anthropogenic types and shifts from Ecological Systems into anthropogenic types were likely. For that reason we chose to label change for each land cover class separately.

To remove the image objects with little spectral change between 1992 and 2001, we used a threshold based on the mean magnitude. We compared the objects from each land cover class to the two dates of imagery and interactively selected a difference threshold. A conservative threshold of 25 removed unchanged objects from further consideration. The objects with a magnitude greater than 25 represented “potential” change areas. In this study, the potential change areas represented a significant proportion of the landscape.

In order to characterize the “true” change and to label the 1992 land cover class for those areas, we ran unsupervised classifications for each of the 2001 land cover classes within each of the sub-zones. While this approach meant that many classifications were required, it was necessary in order to capture the level of detail sought. For each unsupervised classification, from 10 to 20 clusters were generated with the pixels from the four-band magnitude and cosine imagery. The fact that we used the cosine imagery in the clustering meant that the clusters inherently contained data on the direction of change between the two dates. For example, for pixels with the same magnitude of change, the direction of change, such as a loss of greenness or a gain in brightness, would be the discriminant variable in the clustering process. Assigning the mean magnitude and cosine to each pixel within an image object meant that each pixel within an image object fell within the same cluster in the unsupervised classification. Therefore we were classifying patches of change as opposed to pixels for the non-urban areas.

For each cluster, the 1992 imagery, 2001 imagery, and Digital Ortho-Photo Quarter Quads (DOQQs) from 1993 and 1998 were used to identify whether that cluster represented change. For the change clusters, the 1992 land cover classification was assigned if it could be photo-interpreted. For changes from a natural vegetation type in 1992 to an anthropogenic type in 2001, the clusters were flagged for mapping with either ancillary data or using the decision tree modeling process described below. Therefore, we had three ways to label the 1992 land cover class for change areas: labeling from photo-interpretation, decision tree modeling, and adjacency to riverine systems in the 2001 land cover map.

Two decision tree models (managed pine/other, forested systems) were used to map the non-riverine areas of change for the 1992 map. First, a binary model of managed pine cover versus all other cover classes was created by selecting 50,000 points from the no change areas of the map. Those points were used to train a See 5.0 decision tree model (Quinlan 1993). Imagery inputs into the model included the six reflectance bands of the 1992 Landsat spring imagery mosaic and the three TC derivatives from the same mosaic. Ancillary data included the National Wetlands Inventory class (e.g., palustrine emergent, palustrine forested) and modifier (ditched/drained, estuarine, or palustrine), soil texture (percent sand, silt, clay, and organic matter) layers from both state-level (STATSGO) and county-level (SSURGO) soils data. The cross-validation error based on 1,000 points was 16.7% for the managed pine/other model. It is important to remember that the cross-validation at this point is simply a measure of how well the decision tree process can mimic the existing map, and not a true measure of error. Areas not classified using this model were classified as riverine based on adjacency to the riverine classes in the 2001 map, or through the second decision tree model.

In order to map riverine and stream systems in the 2001 land cover map, ancillary data were used to provide the necessary context. Specifically, the National Hydrologic Dataset and National Elevation Dataset were used to categorize floodplains with respect to flow accumulation. We used an adjacency rule to map areas of change in the 1992 land cover that represented one of the riverine systems. Riverine systems from the 2001 land cover and the change patches were clumped. Patches of change that were contiguous with a riverine system were then labeled as that system; all others were modeled using the decision tree modeling process.

The change areas not mapped as managed pine or a riverine type were classified based on a second decision tree process. A new set of 50,000 points from the area was sampled from seven forested classes (see below). Those points were used to train the classification with the same input layers as described above for the managed pine modeling process. The cross-validation based on 1,000 points indicated an error rate of 30% for this final model. Again, this error rate simply relates to the ability of the model to match the land cover for the map based on areas that had not changed.

Ecological Systems modeled for the Onslow Bight using decision tree modeling were:

- Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest
- Atlantic Coastal Plain Fall-line Sandhills Longleaf Pine Woodland
- Atlantic Coastal Plain Northern Wet Longleaf Pine Savanna and Flatwoods
- Atlantic Coastal Plain Peatland Pocosin and Canebrake
- Atlantic Coastal Plain Upland Longleaf Pine Woodland
- Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest – Oak Dominated
- Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest – Nyssa Dominated

Identifying and Labeling Change in Urban Classes

To map changes in urban land cover, we used a combination of decision tree modeling and post-classification change detection. In the 2001 land cover map for the Onslow Bight we used the National Land Cover Dataset (2001) urban classification. That classification was developed by applying thresholds to a dataset of impervious surface estimates (Table 3.1; Yang et al. 2003). In order to back-cast to the 1992 urban classification we estimated the percentage impervious surface using the 1992 image mosaics, both the reflectance and TC transformed images. Specifically, we used the 2001 impervious surface estimates (0-100%) to train a Recursive Partitioning Tree in Jmp 6.0.2 (SAS Institute 2007). First, we removed areas of possible change in the urban classes by excluding any image objects that had been identified with a mean difference magnitude of greater than 25. The remaining areas were available to be sampled using a stratified random sampling (10,000 samples). To account for variability between the dates of imagery used to create the 1992 mosaic (Figure 3.6: 15 June 1989, 10 June 1993, 16 May 1993 and 23 May 1993), we developed regression tree models specific to three time periods (June 1989, June 1993, and May 1993). Those regression trees were then used to map the estimates of impervious surface.

The same thresholds used in the NLCD 2001 process were then applied to map the urban categories. If the 1992 urban class was different from the 2001 class, those pixels were identified as change in post-classification change detection. Areas with less than 20% impervious surface in the 1992 map had to be treated differently. It was possible for an area to represent a natural vegetation type in 1992 and an urban class in the 2001 map. In order identify the true “from” category for those areas we ran an unsupervised classification and labeled clusters that represented natural vegetation in 1992. Clusters representing anthropogenic types were labeled from the clusters, and the forested pixels that could not be photo-interpreted were mapped using the riverine adjacency rule and the decision tree process described above.

Accuracy Assessment

Because we were interested in both a general assessment and in learning as much as we could about the confusion in the mapped change areas, we used an uneven sampling design (Khorram et al. 1994). Specifically, we used a two stage design with the first stratum being the change/no change classification and the second being the 1992 land cover classification. We generated four hundred assessment points within the change areas based on the proportions of the 1992 land cover classification, with a minimum sample of 3 samples per class. Similarly, a stratified random sampling of the no change was done but with fewer points, in this case 150.

For each of the assessment points, we used the 1993 black and white DOQQs and 1998 color-infrared DOQQs as reference. With the difference in the acquisition dates between the DOQQs and the Landsat imagery used in the mapping, we checked the points against the imagery as well. We excluded points where an obvious change had occurred between the image and the photographs. For each point we identified whether a change in land cover had occurred and, if so, what type of change was represented. We assessed the accuracy of the binary change map using the marginal frequencies in the change map. Categorical changes were assessed on a per class basis.

Results

Amount and distribution of change

Total change in the land cover between 1992 and 2001 was estimated at 334,066 hectares, representing 13.3% of the Onslow Bight. In general, change was dispersed evenly throughout the study area (Figure 3.8). Two of the larger concentrations of land cover change were expansion of an existing mine and a cluster of timber stands in the southern inner coastal plain. Conversely, there were several areas with a lack of mapped change. For example, the Croatan National Forest, Angola Bay State Game Land, and Holly Shelter State Game Land had relatively little change.

As expected, the majority of changes occurred among anthropogenic land cover classes (Table 3.2). In absolute acreage, the largest change was a shift from Managed Pine in 1992 to Other Herbaceous in 2001 and the second largest change was a shift from Pasture/Hay in 1992 to Row Crop Agriculture in 2001 (Table 3.2). Managed Pine was the land cover class with the greatest net loss in acreage (62,931 ha) representing 2.5% of the study area. The Other Herbaceous class showed the greatest increase with an overall net gain of 73,000 ha or 2.9% of the Onslow Bight.

Relative to their 1992 mapped acreages, five of the Ecological Systems had no mapped changes (Table 3.3). Those included the Southeastern Coastal Plain Natural Lakeshore, Atlantic Coastal Plain Mesic Hardwood and Mixed Forest, Atlantic Coastal Plain Clay-Based Carolina Bay Wetland, Atlantic Coastal Plain Small Brownwater River Floodplain Forest, and Atlantic Coastal Plain Nonriverine Swamp and Wet Hardwood Forest – Atlantic White Cedar Modifier (Table 3.3).

Six of the twenty four Ecological Systems mapped had up to 1% change detected, and 10 systems had between one and ten percent change. Three Ecological Systems had greater than 10% change relative to the 1992 acreage. Those included the Atlantic Coastal Plain Southern Tidal Wooded Swamp (11.3%; 979 ha), the Atlantic Coastal Plain Dry and Dry-Mesic Oak Forest (11.9%; 13,710 ha), and the Atlantic Coastal Plain Northern Wet Longleaf Pine Savanna and Flatwoods (11.8%; 22,504 ha)

For twenty-three of the twenty-four Ecological Systems the primary loss in acreage was due to a conversion to one of the anthropogenic cover types. The Atlantic Coastal Plain Southern Tidal Wooded Swamp was the only Ecological System with a majority of the change being a shift to another Ecological System. Specifically, 609 ha of the 1992 ACP Tidal Wooded Swamp acreage was mapped as either Atlantic Coastal Plain Embayed Region Tidal Salt or Brackish Marsh (524 ha) or Atlantic Coastal Plain Tidal Freshwater Marsh (85 ha) in the 2001 land cover map.

The four most common transitions from an anthropogenic land cover type in 1992 to an Ecological System in the 2001 were:

1. From Managed Pine class to ACP Northern Wet Longleaf Pine (13,870 ha);
2. From Managed Pine to ACP Dry and Dry-Mesic Oak Forest (3,285 ha);
3. From Clearcut Herbaceous to the ACP Peatland Pocosin (11,385 ha); and
4. From Other Shrub to ACP Dry and Dry-Mesic Oak Forest (7,552 ha).

Accuracy Assessment

Of the 550 assessment points generated, 547 could be interpreted with respect to change based on the available DOQQs. When considering the binary change/no change assessment for the Onslow Bight, an overall accuracy based on the marginal proportions (Card 1982) was 95%, with a kappa statistic of 0.78 (Table 3.4). Because we had sampled the change areas more intensively, we used an estimator for Kappa specific to a stratified random sampling design (Stehman 1996). For areas mapped as “changed” the accuracy (lambda) was estimated to be 79%; conversely, the omission error for changed areas was 21%. For the areas mapped as “no change”, lambda was 97%, indicating 3% omission error. The probability that the map was correct given the “true” class or a reference site is 83% for the Change areas and 97% for the No Change areas. In other words, the probability of commission error was 17% in the Change areas and 3% in the No Change areas.

Values ranged from 0 to 100% for both the change and no change accuracies (Table 3.5). With proportional sampling, many of the map classes had a low number of assessment points. We have included all of the cover classes in Table 5 for reference, but limit our discussion to the classes with the higher sample sizes. The Atlantic Coastal Plain Peatland Pocosin, the most extensive Ecological System in the area, had 56% accuracy with respect to the classification of change, and 63% with respect to areas that had not changed. In this case, areas in the 2001 map that represented various stages of regeneration (Successional Herbaceous Clear-cut, Successional Shrubland Clear-cut), following the clearing of ACP Peatland Pocosin, had been mapped as ACP Northern Wet Longleaf Pine Savanna in the 1992 land cover map. The ACP Northern Wet Longleaf Pine Savanna had relatively low accuracies, with an estimate of 46% for the Change classification and 33% for the No Change. Most of the error in the No Change classification for the ACP Northern Wet Longleaf Pine Savanna represented areas that had been cleared prior to 1992 and were in some stage of regeneration in 2001. This specific error indicates that many of the areas mapped as the ACP Northern Wetland Longleaf Pine Savanna in the 2001 Ecological Systems map should be reevaluated with respect to mapped extent and condition.

Discussion and Conclusions

Applicability of the Method

Based on quantitative and qualitative assessment of the change map, our approach worked well for identifying areas of true change in the Onslow Bight. The estimate of 13% change over a nine year period represents a net annual change rate of 1.4% which is comparable to finding of the Land Cover Status and Trends results (Loveland and Acevedo 2006, Loveland et al. 2002). Auch (2006) estimated the annual rate of change at 1.1% for the period between 1992 and 2000 for the Middle Atlantic Coastal Plain, where the Onslow Bight is centered.

The types of changes reported by Auch (2006) for the Middle Atlantic Coastal Plain included an estimated 0.21% increase in forest and a net decrease for wetlands of 0.71%. For the Onslow Bight we estimated a 7.40% decrease in forest cover between 1993 and 2001 when Managed Pine was included as a forest type. When forests excluding Managed Pines were considered, a net increase in 1.42% occurred. The wetland estimate was also different for the study area, with a net increase of 3.91% represented primarily by an increase in the ACP Peatland Posocin Woodlands due to regeneration on previously harvested sites. Auch (2006) estimated an increase in mechanically disturbed land at 0.17%. When we combined the herbaceous classes, Clearcut Herbaceous and Other Herbaceous, we estimate an increase of 9.19%, while the combined shrub classes (Clearcut Shrubland and Successional Shrublands) lost 0.57%. The increase in acreage of the early successional herbaceous classes is in keeping with the observation from the Status and Trends report (Loveland and Acevedo 2006; Auch 2006) that the clearing and regenerating cycle in the Middle Atlantic Coastal Plain occurs unevenly through time. Auch (2006) concluded that much of the mechanically disturbed lands observed in 2000 will succeed back into wetland and forested systems. In the Onslow Bight the increase in the ACP Peatland Pocosin bears that out, although shifts between managed pine and the successional classes were the most common changes observed in the non-agricultural cover types of the study area.

We estimated an increase of 2.71% in urban land cover between 1992 and 2001. The areas of change in urban land cover are generally concentrated around the major coastal cities (Wilmington, Jacksonville, and New Bern) and inland in the vicinity of Kinston. In addition to these focal areas, a considerable amount of change was mapped adjacent to the existing road network. Road widening and development along the road corridors contributed to this change. For the entire Middle Atlantic Coastal Plain Auch (2006) estimated an increase of urban land cover between 0.55 and 0.66% for the 1992 – 2000 time period. While the Middle Atlantic Coastal Plain includes several larger coastal cities, large portions are less suitable to development, so the discrepancy between the estimated increase in urban land between our estimate and the Status and Trends report is not surprising.

Change Vector Analysis for the Non-Urban Areas

The use of the CVA based on tasseled cap transformed images seems most appropriate to link differences measured to the changes in the landscape. Using subzones based on the date-band image combinations allowed us to compensate for the differences in phenology across the study areas. This improved our ability to identify true change. In addition, the use of the per class unsupervised classification allowed us to label class-specific transitions and to avoid a common issue in the region of over-mapping agricultural fields as change areas due to short term phenological changes.

The conservative threshold to remove non-change areas prior to the unsupervised classification meant that we classified most of the area represented by any land cover class. We did not find an effective method for automating the selection of a less conservative "no change" threshold. Ideally an approach to categorizing the vectors and the expected set of transitions and magnitude could be used to automate the process. Dwyer et al. (1996) did some work with respect to using rose diagrams from CVA as a visualization tool that would allow analysts to interactively select change categories based on magnitude (length of petals) and direction. Further work on applying that tool to complex change detection problems would be useful in addressing these issues.

Image Objects

Using image objects seemed to reduce much of the noise associated with pixel based change detection and allowed us to effectively identify patches of land cover change. The attribution of the objects with the majority land cover class and the use of the objects in the class-specific unsupervised classification meant that in some cases errors were introduced for objects containing more than one land cover class. Adjusting the scale of the image objects or generating objects within each cover class, as opposed to simply attributing the objects with the majority land cover, may reduce some of this error. The gain in the change detection accuracy is unlikely to warrant the increased level of effort that modification would require.

Classification Issues

The complexity of the map legend and the inclusion of modifiers that relied on spatial and temporal context (e.g., Clearcut Herbaceous) were the most challenging aspect in this study. If we were to collapse the classification with respect to the anthropogenic types that rely on temporal information, the approach could still be applied to a complex map legend with respect to the natural systems, and would identify general shifts in the structure of the anthropogenic classes.

A specific case where one of the target map classes relies on context was the open space developed class of the NLCD 2001. For that class, knowing the spatial context of the type determined its membership. In the NLCD 2001 mapping process, a mask for the urban land cover classes was used to restrict the mapping of urban classes to urban centers and transportation corridors. Areas with low impervious surface within the mask could then be labeled as Open Space Developed. While this would not create much of an issue in mapping change forward from a specific date since the general trend is for urban expansion, in this study it made the labeling of those low imperviousness areas problematic. Areas that were natural vegetation in 1992 could be considered Open Space Developed based on proximity to an urban center, or could be mapped as natural forest type if the surrounding area had not yet been developed. In others words, in order to separate the open space developed areas in the 1992 map from natural forest types, we had to create an urban mask for the 1992 time period. While this is an issue for back-casting to map change, it is not likely to be an issue in detecting change when the base map represents the earlier time period. In other words, once an area has been converted to urban land cover that limits the types of changes that are likely to occur for an area.

With our approach, errors in the original classification have the potential to cascade through the change detection and the labeling of land cover classes in the changed areas. While some errors can be caught at the unsupervised classification stage, most will not. For example, in the issue of the ACP Northern Wet Longleaf Pine Savanna and Flatwoods, many of the patches of this type were misclassified in the 2001 land cover map when they actually represented regenerating shrublands. The low canopy closure and presence of pine trees at low densities led to errors in the original land cover map. Those errors were then propagated when back-casting to the 1992 land cover classification. We addressed the issue of errors by documenting the per-class accuracy both at the land cover mapping and the change detection stage (Chapters 2 and 3 of this volume). In order to fully investigate the errors with respect to the final 1992 land cover map, an independent assessment of the per-class accuracy of that map could be done; similarly, a stratified sampling of the transitions between 2001 and 1992 could be performed as well.

Summary

In general, the types of changes documented in this study for the Onslow Bight are not surprising. This area has been settled for hundreds of years and the shifting mosaic of anthropogenic types across the landscape reflects that. The fact that fifteen of the twenty four Ecological Systems mapped showed a net conversion to anthropogenic cover classes between 1992 and 2001 is disturbing. Those natural systems have already been reduced to a fraction of their historic distributions. In future efforts we plan to integrate this change information with Southeast Regional GAP's species habitat distribution modeling to investigate the potential impacts of these changes specific to changes in habitat availability.

Our approach, integrating image objects with change vector analysis, allowed us to successfully map change in a complex landscape. We were able to identify changes in the Ecological Systems and the land cover classes that serve as important habitat for wildlife. Using the tasseled cap imagery provided information specific to the class-specific changes, in which we were interested, while avoiding the common issue of over-estimating change in agricultural sites. This methodological advance worked well for the Onslow Bight, but should be applicable to a wide range of landscapes, where it is important to detect relatively subtle changes.

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References

Al-Khudhairy, D.H.A, I. Caravaggi, and S. Glada. 2005. Structural damage assessments from Ikonos data using change detection, Object-oriented segmentation, and classification techniques. Photogrammetric Engineering and Remote Sensing, 71(7)825-837.

Auch , R.F. 2006, Middle Atlantic Coastal Plain: Ecoregion Assessment. Loveland, T.R. and Acevedo, W., eds., *in* Status and Trends of Eastern United States Land Cover**,** U.S. Geological Survey Scientific Investigations Report.

Benz, U.C., P. Hofmann, G Willhauck, I. Ligenfelder, and M. Heyden. 2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. Journal of Photogrammetry and Remote Sensing, 58(3-4) 239-258.

Blasche, T. 2005. Towards a Framework for Change Detection Based on Image Objects. Remote Sensing and GIS for Environmental Studies. S. Erasmi, B. Cyffka, M. Kappas editors. Gottinger Geoggraphische Abhandlungen. 113, Gootingen, 2005.

Bruzzone, L. and D. Fernandez Prieto. 2000a. Automatic Analysis of the Difference Image for Unsupervised Change Detection. IEEE Transactions on Geoscience and Remote Sensing, 38(3)1171-1182.

Bruzzone, L. and D. Fernandez Prieto. 2000b. An adaptive parcel-based technique for unsupervised change detection. International Journal of Remote Sensing, 21(4) 817-822.

Chen, J., P. Gong, C. He, R. Pu, and P. Shi. 2003. Land-Use/Land-Cover Change Detection Using Improved Change Vector Analysis. Photogrammetric Engineering and Remote Sensing, 69(4)369-379.

Comer, P., D. Faber-Langendoen, R. Evans, S. Gawler, C. Josse, G. Kittel, S. Menard, M. Pyne, M. Reid, K. Schulz, K. Snow, and J. Teague. 2003. Ecological Systems of the United States: A Working Classification of U.S. Terrestrial Systems NatureServe, Arlington, VA.

Crist, E. P. and R.J. Kauth. 1986. The tasseled Cap De-Mystified. Photogrammetric Engineering and Remote Sensing 52(1) 81-86.

Definiens Imaging 2004. eCognition Elements Users Guide 4. Definiens Imaging GmbH, München, Germany. 26 pp.

Dobson, J.E., E. A. Bright, R. L. Ferguson, D. W. Field, L. L. Wood, K.D. Haddad, H. Iredale III., J.R. Jensen, V. V. Klemas, R. J. Orth, and J. P. Thomas. 1995. NOAA Coastal Change Analysis Program (C-CAP): Guidance for Regional Implementation. NOAA Technical Report NMFS 123.

Dwyer, J. L., K. L. Sayler, and G. J. Zylstra. 1996. Landsat Pathfinder Data Sets for Landscape Change Analysis. IEEE, International Geoscience and Remote Sensing Symposium Proceedings, 1996:547-550.

Environmental Protection Agency. 1999. Level III Ecoregions of the Coterminous United States. U.S. E.P.A. National Health and Environmental Effects Laboratory, Corvallis OR. (1:7,500,000 scale map).

Frost, C. C. 1993. Four centuries of changing landscape patterns in the Longleaf Pine ecosystem. pp. 17-43 In S. Hermann (ed.) Proc. Of the Tall Timbers Fire Ecology Conference, No. 18. The longleaf Pine Ecosystem; Ecology, Restoration and Management. Tallahassee, FL: Tall Timbers Research Station.

Johnson, R.D. and E.S. Kasiskchke. 1998. Change vector analysis: a technique for the multispectral monitoring of land cover and condition. International Journal of Remote Sensing, 19(3)411-426.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. Development of a 2001 National Landcover Database for the United States. *Photogrammetric Engineering and Remote Sensing*, 70(7)829-840.

Homer, C., J. Dewitz, J. Fry, M. Coan, N. Hossain, C. Larson, N. Herold, A. McKerrow, J. Nick VanDriel, and J. Wickham. 2007. Completion of the 2001 National Land Cover Database for the Coterminous United States. Photogrammetric Engineering and Remote Sensing. 73(4) 337-341.

Huang, C., B. Wylie, L. Yang, C. Homer, and G. Zylstra. 2002. Derivation of a tasseled cap transformation based on Landsat 7 at-satellite reflectance. International Journal of Remote Sensing, 23(8)1741 – 1748

Kauth, R. J. and G.S. Thomas. 1976. The tasseled Cap -- A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT. *Proceedings of the Symposium on Machine Processing of Remotely Sensed Data*, Purdue University of West Lafayette, Indiana, 1976, pp. 4B-41 to 4B-51.

Khorram, S., G. S. Biging, N. R. Chrisman, D. R. Colby, R. G. Congalton, J. E. Dobson, R. L. Ferguson, M. F. Goodchild, J. R. Jensen, and T. H. Mace. 1994. Accuracy Assessment of Land Cover Change Detection. CGC Report No. 101. Prepared for NOAA C-CAP 70 pages.

Laliberte, A. S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., and Gonzalez, A.L. (2004). Object oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. Remote Sensing of Environment, 93:198-210.

Loveland, T. R., and W. Acevedo. 2006. Land Cover Change in the Eastern United States. Last accessed November 5, 2007 (http://edc2.usgs.gov/LT/LCCEUS.php).

Loveland, T. R., T. L. Sohl, S. V. Stehman, A. L. Gallant, K. L. Sayler, and D. E. Napton. 2002. A Strategy for Estimating the Rates of Recent United States Land-Cover Changes. Photogrammetric Engineering and Remote Sensing, 68(10) 1091-1099.

Lunetta, R. S. 1998. Applications, Project Formulation, and Analytical Approach. In: Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. Editors Lunetta and Elvidge. Ann Arbor Press, Chelsea Michigan. Pp 1-19.

Lunetta, R. S., J. Ediriwickrema, D. M. Johnson, J. G. Lyon, and A. J. McKerrow. 2002. Impacts of vegetation dynamics on the identification of land-cover change in a biologically complex community in North Carolina, USA. Remote Sensing of the Environment, 82(2002) 258-270.

Lunetta, R. S., J. F. Knight, J. Ediriwickrema, J. G. Lyon, L D. Worthy. 2006. Land-Cover Change Detection Using Multi-temporal MODIS NDVI Data. Remote Sensing of Environment, 105:142-254.

Lyon, J. G., D. Yuan, R. S. Lunetta, C. D. Elvidge. 1998. 64(2) 143-150. A Change Detection Experiment Using Vegetation Indices. Photogrammetric Engineering and Remote Sensing, 64(2)143-150.

Mas, J.F. 1999. Monitoring land-cover changes: a comparison of change detection techniques. Int. Journal Remote Sensing, 20(1)139-152.

National Oceanographic and Atmospheric Administration. Coastal Services Center. 2007. 1995-present. The Coastal Change Analysis Program (CCAP). Charleston, SC: NOAA Coastal Services Center. Last accessed 7 November 2007 at http://www.csc.noaa.gov/crs/lca/ccap.html.

Quinlan, J. R. 1993. C4.5: programs for machine learning. Morgan Kaufmann series in machine learning. Morgan Kaufmann Publishers, San Mateo, Calif. 302 pp.

Ricketts, T. H., E. Dinerstein, D. M. Olson, C. J. Loucks, W. Eichbaum, D. DellaSala, K. Kavanagh, P. Hedao, P. T. Hurley, K. M. Carney, R. Abell, and S. Walters. 1999. Terrestrial Ecoregions of North America: A Conservation Assessment. Island Press, Washington, D.C. 485 p.

SAS Institute. 2007. Effective Data Mining Using Jmp Partition Platform. Statistical Discovery from SAS. http://www.jmp.com/software/whitepapers/partition_platform/index.shtml accessed Dec. 1. 2007.

Singh, A. 1989. Digital change detection techniques using remotely sensed data. International Journal of Remote Sensing, 10(6)989-1003.

Sohl, T. L. 1999. Change Analysis in the United Arab Emirates: An Investigation of Techniques. Photogrammetric Engineering and Remote Sensing, 65(4)475-484.

Stehman, S. V. 1996. Estimating the Kappa coefficient and its variance under stratified random sampling. Photogrammetric Engineering and Remote Sensing, 62(4) 401-402.

Yang, L., C. Homer, K. Hegge, C. Huang, B. Wylie, and B. Reed. 2001. A Landsat 7 Scene Selection Strategy for a National Land Cover Database. IEEE International Geoscience and Remote Sensing Symposium Proceedings, 2001:1123 – 1125.

Yang, L., C. Huang, C. G. Homer, B. K. Wylie, and M. J. Coan. 2003. An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. Canadian Journal of Remote Sensing, 29 (2) 230-240.

Table 3.1. Thresholds used to categorize urban land cover classes from impervious surface estimates. Categories and definitions used by the National Land Cover Dataset 2001 (Homer et al. 2004).

Urban Category	Impervious Surface --- % ---	Definition of Urban Class
High Intensity Urban	> 80	Includes highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80 to100 percent of the total cover.
Medium Intensity Urban	50 – 79.9	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50-79 percent of the total cover. These areas most commonly include single-family housing units.
Low Intensity Urban	20 – 49.9	Includes areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20-49 percent of total cover. These areas most commonly include single-family housing units.
Open Space Developed	< 20	Includes areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20 percent of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes.

Table 3.2. Major Categories of land cover change between 1992 and 2001 in the Onslow Bight.

	1992										
2001↓	**9**	**21**	**32**	**33**	**73**	**74**	**76**	**77**	**78**	**79**	**80**
	Land Cover Change in Hectares										
9 - ACP Dry and Dry-Mesic Oak Forest	--	36	128	84	3,285	2,141	7,553	58	1,571	2,724	2,099
21 - ACP Fall-line Sandhills Longleaf Pine Woodland	53	--	135	168	813	224	19	24	79	408	2,135
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	312	84	--	520	13,870	823	345	44	199	9,976	3,362
33 - ACP Peatland Pocosin	11	46	2,278	--	1,620	5,295	188	11	64	11,386	725
73 - Managed Pine	295	34	188	626	--	8,365	70	34	798	**21,922**	251
74 - Clear Cut Shrub	410	56	120	43	2,043	--	0	0	0	69	9
76 - Other Shrub	3,510	786	2,664	427	14,708	50	--	18	510	2,922	1,309
77 - Pasture/Hay	77	14	42	5	59	16	1	--	0	6	8
78 - Row Crop	1,768	1,121	3,321	446	15,693	21	643	**25,904**	--	182	918
79 - Clear Cut Herbaceous	385	417	313	216	866	1	23	3	4	--	0
80 - Other Herbaceous	7,882	6,127	10,698	8,077	**40,079**	53	1,468	1,590	3,986	367	--

Table 3.3. Percent land cover change between Ecological Systems between 1992 and 2001. Changes reported as a percent of the 1992 acreage. Anthropogenic and non-system cover types (e.g., open water, agriculture, urban) summarized in the "Other" category.

2001↓ 1992 →	**2**	**4**	**6**	**8**	**9**	**10**	**11**	**14**	**16**	**18**	**21**	**26**	**27**
2 - Southeastern Coastal Plain Natural Lakeshore	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4 - ACP Large River Floodplain – Brownwater	0.0	99.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0
6 - ACP Large River Floodplain – Blackwater	0.0	0.0	99.3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8 - ACP Southern Tidal Wooded Swamp	0.0	0.0	0.0	88.7	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0
9 - ACP Dry and Dry-Mesic Oak Forest	0.0	0.0	0.0	0.1	88.1	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	0.0
10 - ACP Mesic Hardwood and Mixed Forest	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11 - ACP Clay-based Carolina Bay	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0	0.0	0.0	0.0
14 - ACP Blackwater Stream Floodplain	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	99.5	0.0	0.0	< 0.1	0.0	0.0
16 - ACP Small Blackwater River Floodplain	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.1	0.0	< 0.1	0.0	0.0
18 - ACP Small Brownwater River Floodplain	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	0.0
21 - ACP Fall-line Sandhills Longleaf Pine Woodland	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.9	0.0	90.9	0.0	0.0
26 - ACP Embayed Region Tidal Freshwater Marsh	0.0	0.0	0.0	**2.1**	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	94.2	0.0
27 - ACP Embayed Region Tidal Salt and Brackish Marsh	0.0	0.0	0.0	**6.0**	< 0.1	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	99.9
28 - ACP Central Maritime Forest	0.0	0.0	0.0	0.5	< 0.1	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	0.0
33 - ACP Peatland Pocosin	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	< 0.1	0.0	< 0.1	0.0	0.0
34 - ACP Carolina Bay – Peatland Pocosin	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
35 - ACP Central Salt and Brackish Tidal Marsh	0.0	0.0	0.0	< 0.1	< 0.1	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0
36 - ACP Southern Dune and Maritime Grassland	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
37 - ACP Upland Longleaf Pine Woodland	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1
39 - ACP Nonriverine Swamp and Wet Hardwood – Oak Dominated	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	0.0	< 0.1	0.0	0.0
40 - ACP Nonriverine Swamp and Wet Hardwood – Nyssa Dominated	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	< 0.1	< 0.1	0.0	< 0.1	0.0	0.0
41- ACP Nonriverine Swamp and Wet Hardwood – Atlantic White Cedar	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42 – ACP Central Fresh-Oligohaline Tidal Marsh	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Other	0.0	< 0.01	< 0.01	**1.0**	**11.5**	0.0	0.0	< 0.01	< 0.01	0.0	**8.7**	**5.8**	< 0.1
Total (Ha)	449	25331	32787	8709	131507	157	134	32874	54725	12	115525	1903	35152
Net Change 1992 – 2001 (Ha)	0	+137	-5	-541	+4034	0	+30	+1868	+1708	0	-5857	+567	+1234

Table 3.3. continued.

2001↓ 1992 →	**28**	**32**	**33**	**34**	**35**	**36**	**37**	**39**	**40**	**41**	**42**	**Other**	**Total (Ha)**
2 - Southeastern Coastal Plain Natural Lakeshore	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	449
4 - ACP Large River Floodplain – Brownwater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	25468
6 - ACP Large River Floodplain – Blackwater	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	32783
8 - ACP Southern Tidal Wooded Swamp	< 0.1	< 0.1	< 0.1	0.0	0.0	0.2	< 0.1	< 0.1	0.0	0.0	1.1	< 0.1	8167
9 - ACP Dry and Dry-Mesic Oak Forest	< 0.1	0.1	< 0.1	0.0	0.0	0.0	< 0.1	< 0.1	< 0.1	0.0	0.0	< 0.1	135542
10 - ACP Mesic Hardwood and Mixed Forest	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	0.0	157
11 - ACP Clay-based Carolina Bay	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	164
14 - ACP Blackwater Stream Floodplain	0.0	< 0.1	< 0.1	0.0	0.0	0.0	0.0	< 0.1	< 0.1	0.0	0.0	< 0.1	34743
16 - ACP Small Blackwater River Floodplain	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	0.0	0.0	0.0	< 0.1	56433
18 - ACP Small Brownwater River Floodplain	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12
21 - ACP Fall-line Sandhills Longleaf Pine Woodland	< 0.1	< 0.1	< 0.1	0.0	0.0	0.0	< 0.1	< 0.1	< 0.1	0.0	0.0	< 0.1	109668
26 - ACP Embayed Region Tidal Freshwater Marsh	0.0	< 0.1	< 0.1	0.0	0.0	< 0.1	0.0	< 0.1	< 0.1	0.0	0.0	< 0.1	2471
27 - ACP Embayed Region Tidal Salt and Brackish Marsh	0.0	< 0.1	0.0	0.0	0.0	< 0.1	0.0	< 0.1	0.0	0.0	0.0	< 0.1	36386
28 - ACP Central Maritime Forest	97.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	10129
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	< 0.1	88.2	< 0.1	0.0	0.0	0.0	0.1	0.7	0.2	0.0	0.0	< 0.1	197593
33 - ACP Peatland Pocosin	< 0.1	**1.2**	94.6	0.0	0.0	0.0	0.0	< 0.1	< 0.1	0.0	0.0	< 0.1	225295
34 - ACP Carolina Bay – Peatland Pocosin	0.0	0.0	0.0	99.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	< 0.1	5464
35 - ACP Central Salt and Brackish Tidal Marsh	1.0	0.0	0.0	0.0	90.8	0.1	< 0.1	< 0.1	0.0	0.0	0.0	< 0.1	19699
36 - ACP Southern Dune and Maritime Grassland	< 0.1	0.0	0.0	0.0	0.9	90.7	0.0	0.0	0.0	0.0	0.0	< 0.1	7306
37 - ACP Upland Longleaf Pine Woodland	0.0	0.0	0.0	0.0	0.0	0.0	96.1	0.0	0.0	0.0	0.0	< 0.1	12954
39 - ACP Nonriverine Swamp and Wet Hardwood – Oak Dominated	0.0	< 0.1	0.2	0.0	0.0	0.0	< 0.1	91.6	< 0.1	0.0	0.0	< 0.1	37072
40 - ACP Nonriverine Swamp and Wet Hardwood – Nyssa Dominated	0.0	< 0.1	0.1	0.0	0.0	0.0	< 0.1	0.2	95.1	0.0	0.0	< 0.1	36649
41- ACP Nonriverine Swamp and Wet Hardwood – Atlantic White Cedar	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	100.0	0.0	0.0	30
42 – ACP Central Fresh-Oligohaline Tidal Marsh	< 0.1	0.0	0.0	0.0	0.0	< 0.01	< 0.1	0.0	0.0	0.0	98.7	0.0	4759
Other	**1.6**	**9.7**	**4.8**	0.3	**8.3**	**8.6**	**3.6**	**7.2**	**4.4**	0.0	0.1	94.3	1517841
Total (Ha)	10025	190217	215293	5383	20848	6804	12064	34332	33875	30	4725	1544372	2517231
Net Change 1992 – 2001 (Ha)	+104	+7376	+10003	+82	-1150	+502	+890	+2740	+27740	0	+34	-26531	

Table 3.4. Accuracy assessment for the binary change map of the Onslow Bight. Lambda (λ) provides an estimate of accuracy given the mapped class. Theta (Θ) is an estimate of the accuracy given the reference data, or “true” class.

Map ↓	Reference		
Assessment Points	**Change**	**No Change**	**Total**
Change	308	81	389
No Change	4	154	158
	312	235	547
Probabilities			**Mapped Proportions**
Change	0.10541	0.02772	0.13313
No Change	0.02194	0.84492	0.86668
True Marginal Proportions	0.12736	0.87265	1.0
Accuracy Statistics			
λ	79.2%	97.5%	
Omission	20.8%	2.5%	
Θ	82.8%	96.8%	
Commission	17.2%	3.2%	
Overall Accuracy	95.0%		
$Kappa_{stratified}$	0.78		

Table 3.5. Change/ no change accuracy by 1992 land cover class.

Map Class	Change		No change		Accuracy	
	Correct	Incorrect	Correct	Incorrect	Change	No Change
	---------- n ----------				---- % ----	
2 - ACP Large Natural Lakeshore			3			100
4 - ACP Large River Floodplain - Brownwater	4		2	1	100	67
6 - ACP Large River Floodplain - Blackwater	3		4		100	100
8 - ACP Southern Tidal Wooded Swamp	1		3	1	100	75
9 - ACP Dry and Dry-Mesic Oak Forest	10	2	5	3	83	63
10 - ACP Mesic Hardwood and Mixed Forest			3			100
11 - ACP Clay-Based Carolina Bay Forested			2			100
14 - ACP Blackwater Stream Floodplain Forest		3	3	2	0	60
16 - ACP Small Blackwater River Floodplain Forest	1		3	3	100	50
18 - ACP Small Brownwater River Floodplain Forest			1			100
21 - ACP Fall-line Sandhills Longleaf Pine Woodland - Open Understory	12	1	4	3	92	57
22 - ACP Fall-line Sandhills Longleaf Pine Woodland - Scrub/Shrub Understory	2				100	
23 - ACP Fall-Line Sandhills Longleaf Pine Woodland - Loblolly	4	1			80	
26 - ACP Embayed Region Tidal Freshwater Marsh	2		2		100	100
27 - ACP Embayed Region Tidal Salt and Brackish Marsh		1	4	3	0	57
28 - ACP Central Maritime Forest	3	3	3	2	50	60
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	6	7	5	10	46	33
33 - ACP Peatland Pocosin	10	9	5	2	53	71
34 - ACP Peatland Pocosin – Carolina Bay	2	1	3		67	100
35 - ACP Central Salt and Brackish Tidal Marsh		1	3	2	0	60
36 - ACP Southern Dune and Maritime Grassland	2		3	1	100	75
37 - ACP Longleaf Pine Woodland	1	1	3	1	50	75
39 - ACP Nonriverine Swamp and Wet Hardwood Forest - Oak Dominated	3		4		100	100
40 - ACP Nonriverine Swamp and Wet Hardwood Forest - Taxodium/Nyssa	4	2	2		67	100
41 - ACP Nonriverine Swamp and Wet Hardwood Forest - Atlantic White Cedar			2			100
42 - ACP Central Fresh-Oligohaline Tidal Marsh			2	1		67

Table 3.5 continued.

Map Class	Change No change		No Change		Accuracy	
	Correct	Incorrect	Correct	Incorrect	Change	No Change
	---------- n ----------				---- % ----	
61 - Open Water (Fresh)	3	1	1	1	75	50
62 - Open Water (Brackish/Salt)	1		7	1	100	88
63 - Developed Open Space	7		5		100	100
64 - Low Intensity Developed	3		4	4	100	50
65 - Medium Intensity Developed	1		6	2	100	75
66 - High Intensity Developed			3	1		75
67 - Bare Sand	1		3	1	100	75
68 - Bare Soil	2		1	1	100	50
69 - Quarry/Strip Mine/Gravel Pit			4	1		80
71 - Unconsolidated Shore (Beach/Dune)	2			1	100	0
73 – Managed Pine	48	25	5	6	66	45
74 - Successional Shrub/Scrub (Clear Cut)	10	7	2		59	100
76 - Successional Shrub/Scrub (Other)	7	6	2	4	54	33
77 - Pasture/Hay	22	2	2	1	92	67
78 - Row Crop	4	1	9	10	80	47
79 - Successional Herbaceous (Clear cut)	37	10	0	0	79	
80 - Other Herbaceous	11	1	4	5	92	44
90 - ACP Large River Floodplain Forest - Brownwater Herbaceous			2			100
91 - ACP Large River Floodplain Forest - Blackwater Herbaceous			1			100

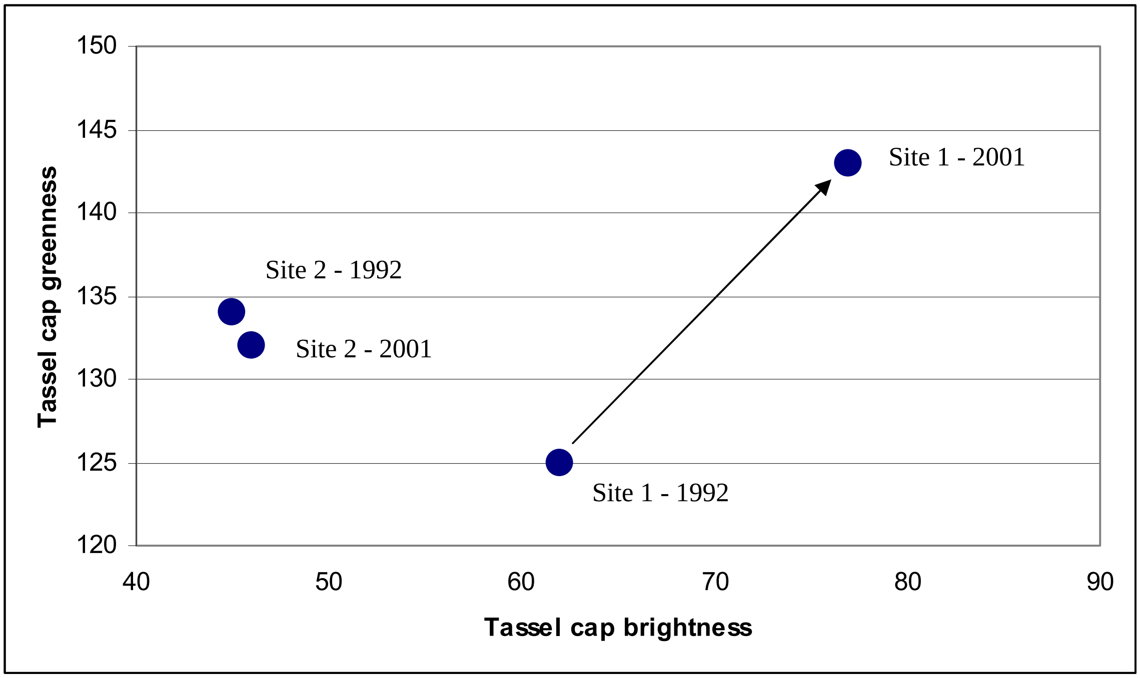

Figure 3.1. Examples of change vectors for two sites. Illustrates the change vector for site that had changed from managed pine to a pocosin site (Site 1). There was a gain in both brightness and greenness for Site 1 between 1992 and 2001. Site 2 illustrates an area where land cover had not changed and the differences in both brightness and greenness are small.

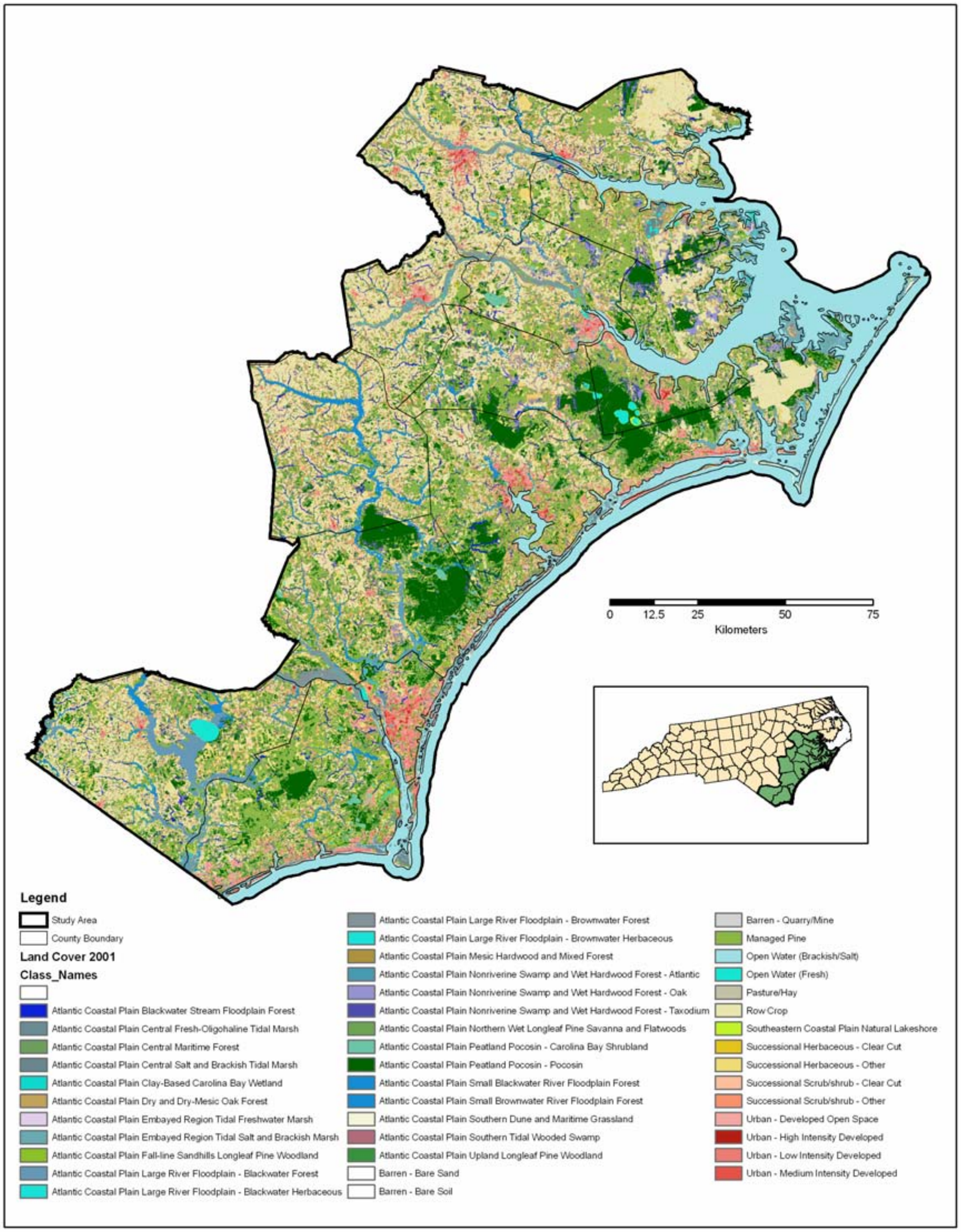

Figure 3.2. Southeast Gap Analysis Project's land cover map for the Onslow Bight, NC.

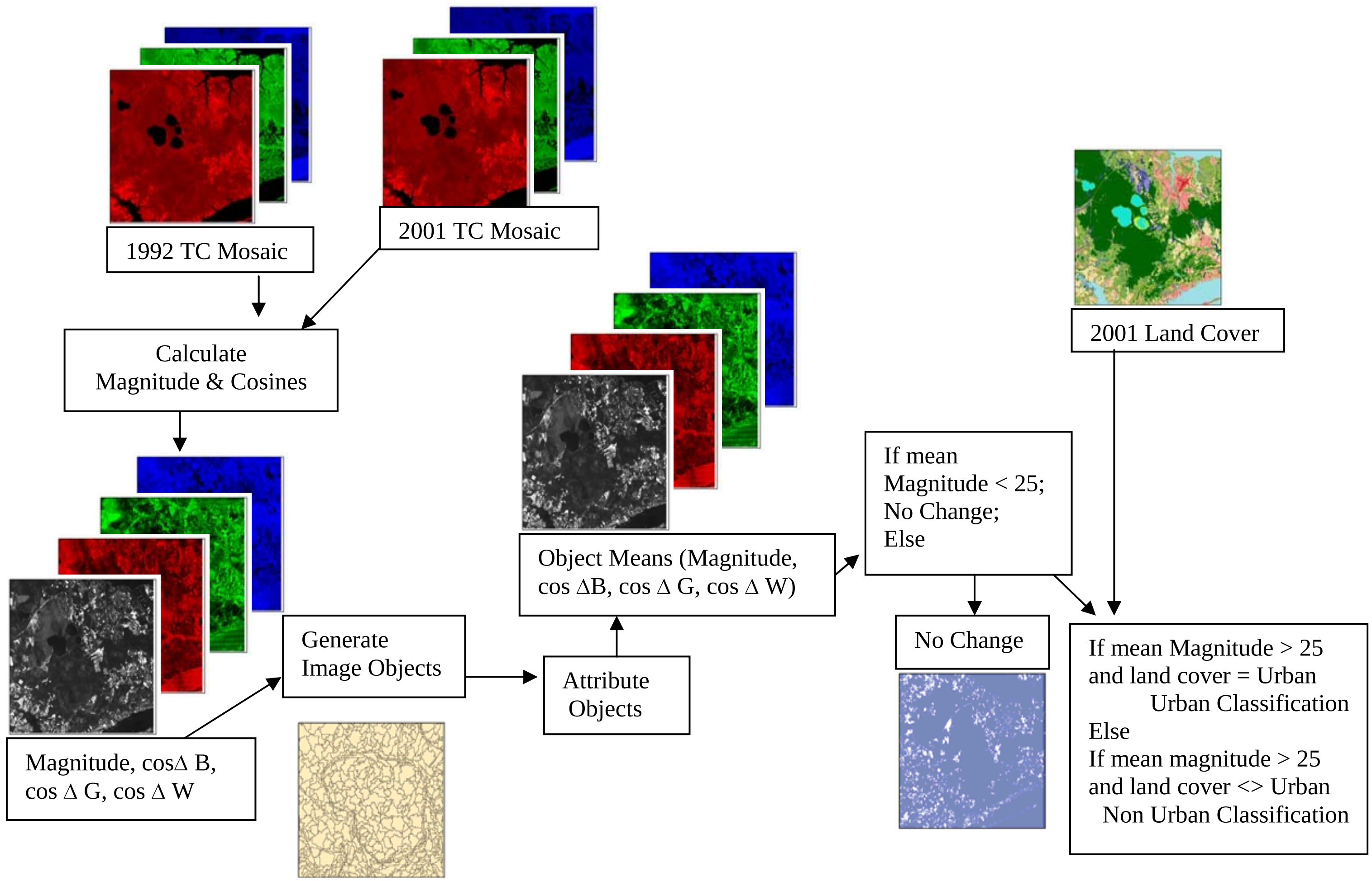

Figure 3.3. Flow Diagram of the preprocessing steps and identification of potential change areas.

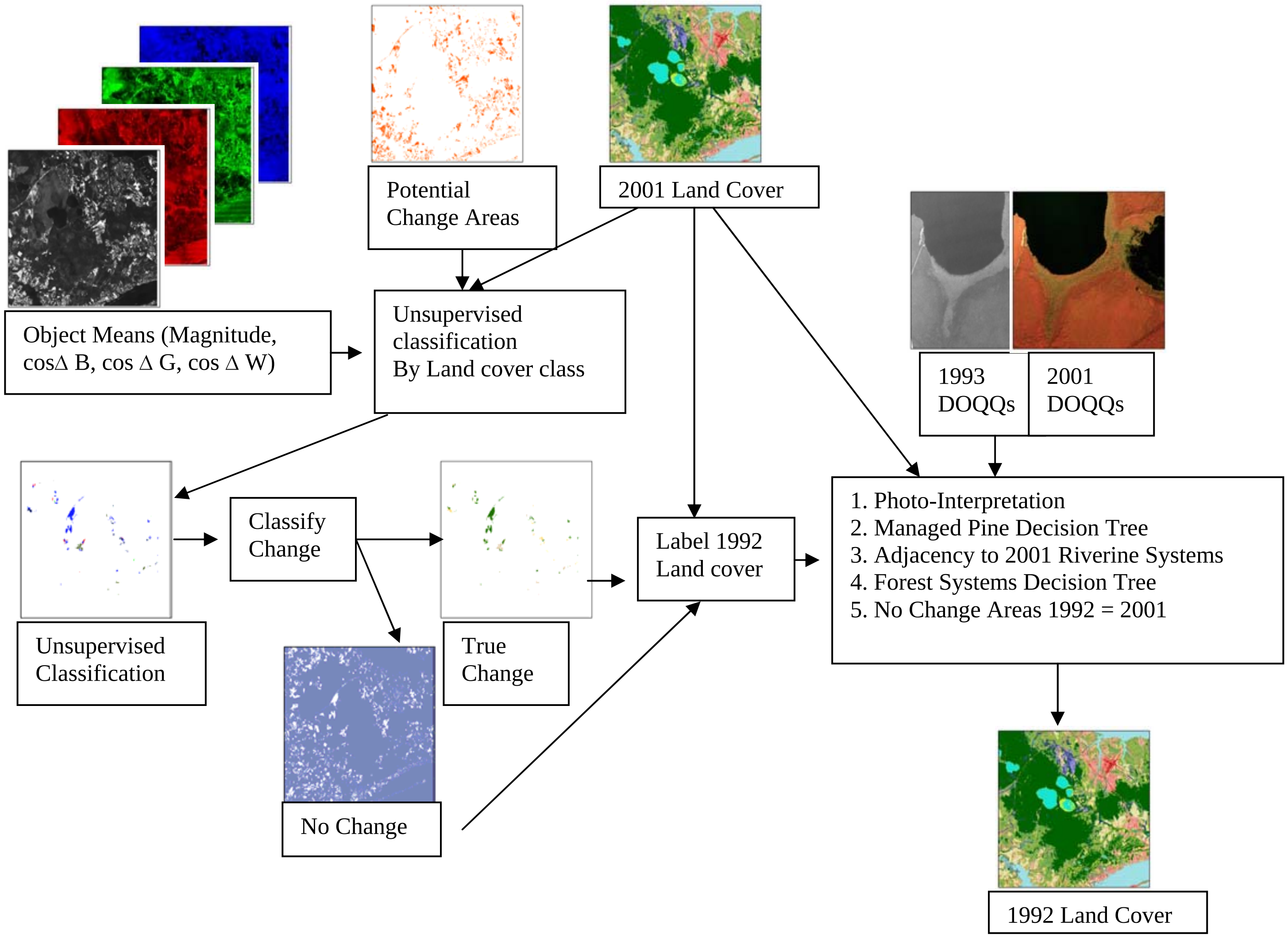

Figure 3.4. Flow Diagram for change detection and labeling the 1992 land cover for the non-urban areas.

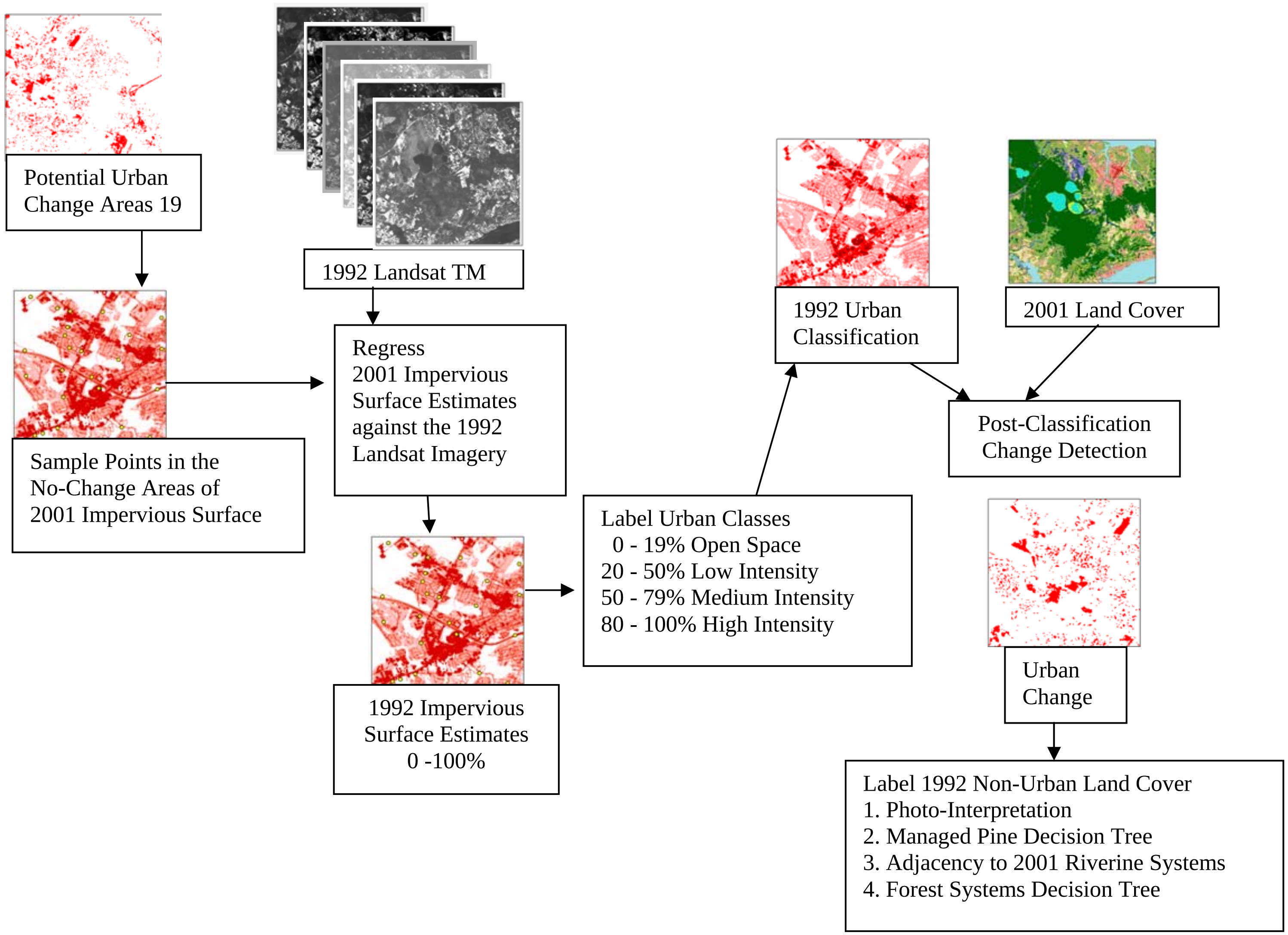

Figure 3.5. Flow Diagram for change detection and labeling the 1992 land cover for urban areas.

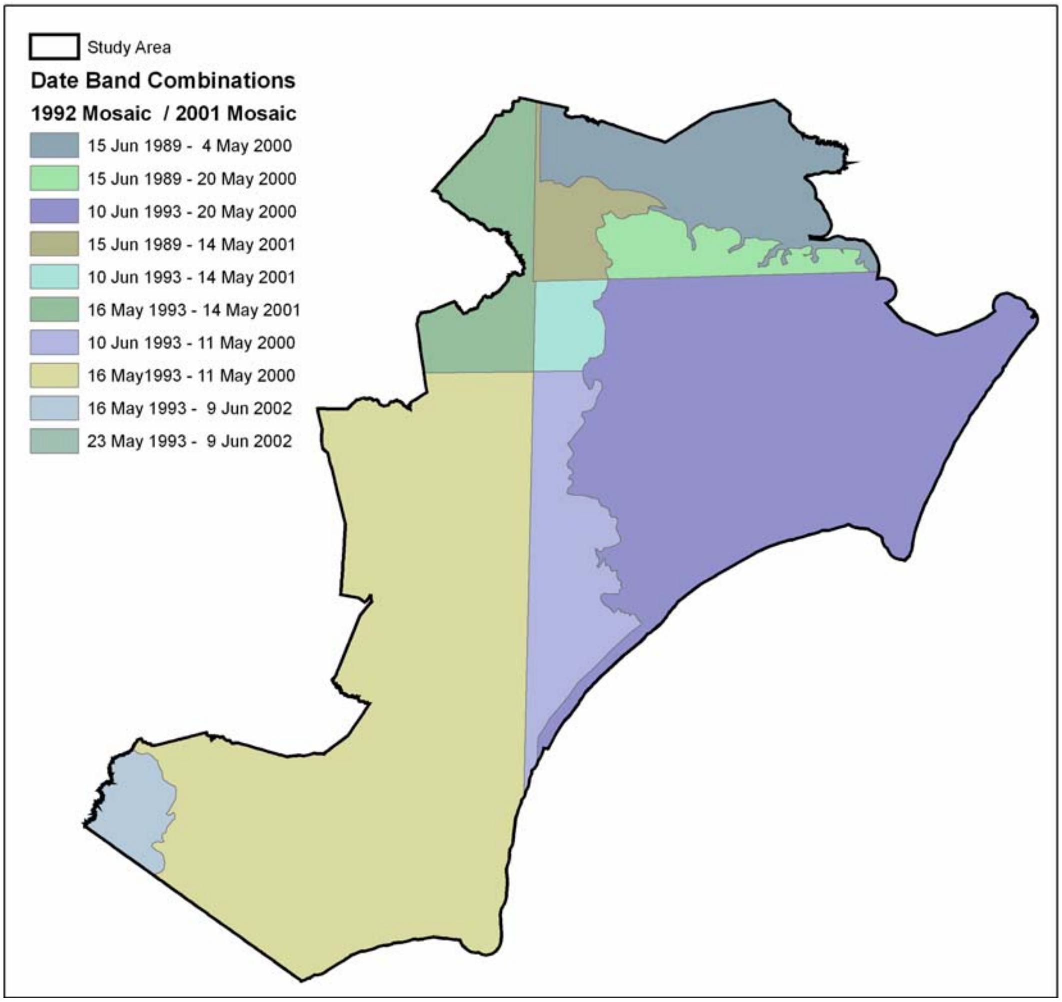

Figure 3.6. Date Band Combinations in the 1992 and 2001 Landsat Image Mosaics.

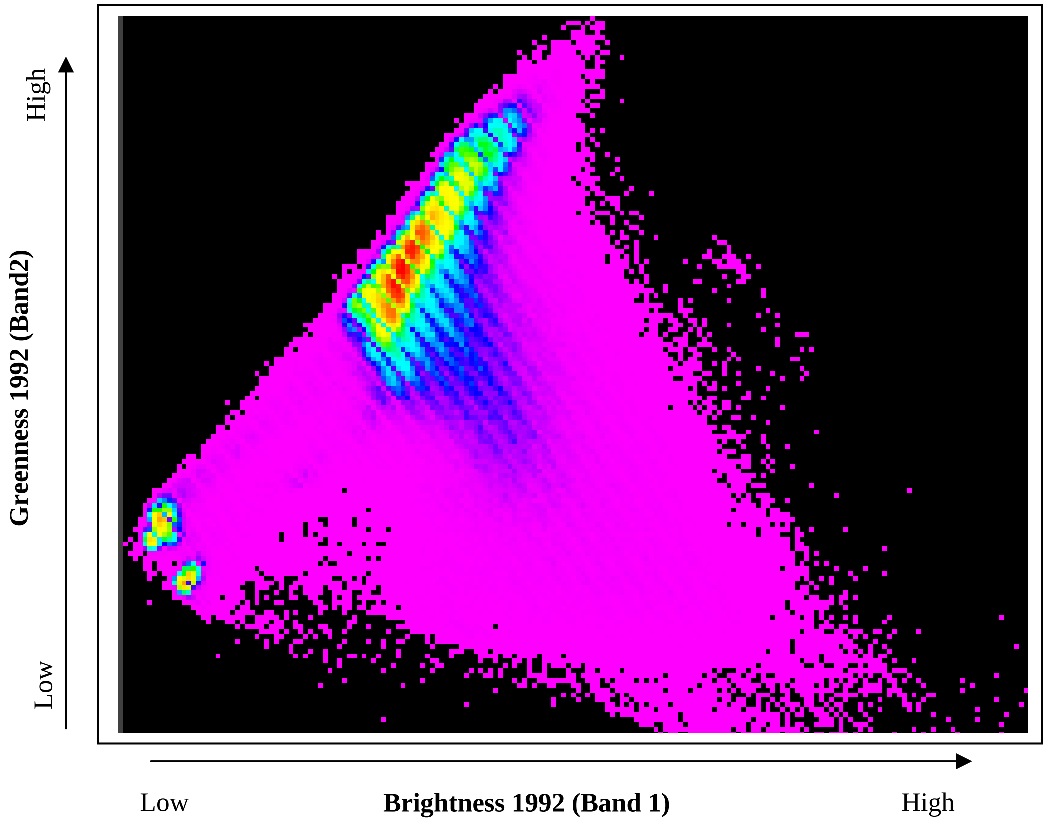

Figure 3.7. Feature space image demonstrating the characteristic "tasseled cap" pattern for a portion of Onslow Bight study area. Note: The color intensity indicates the number of pixels in the image that occur in that portion of the feature space, with purple being low frequencies and red being the highest.

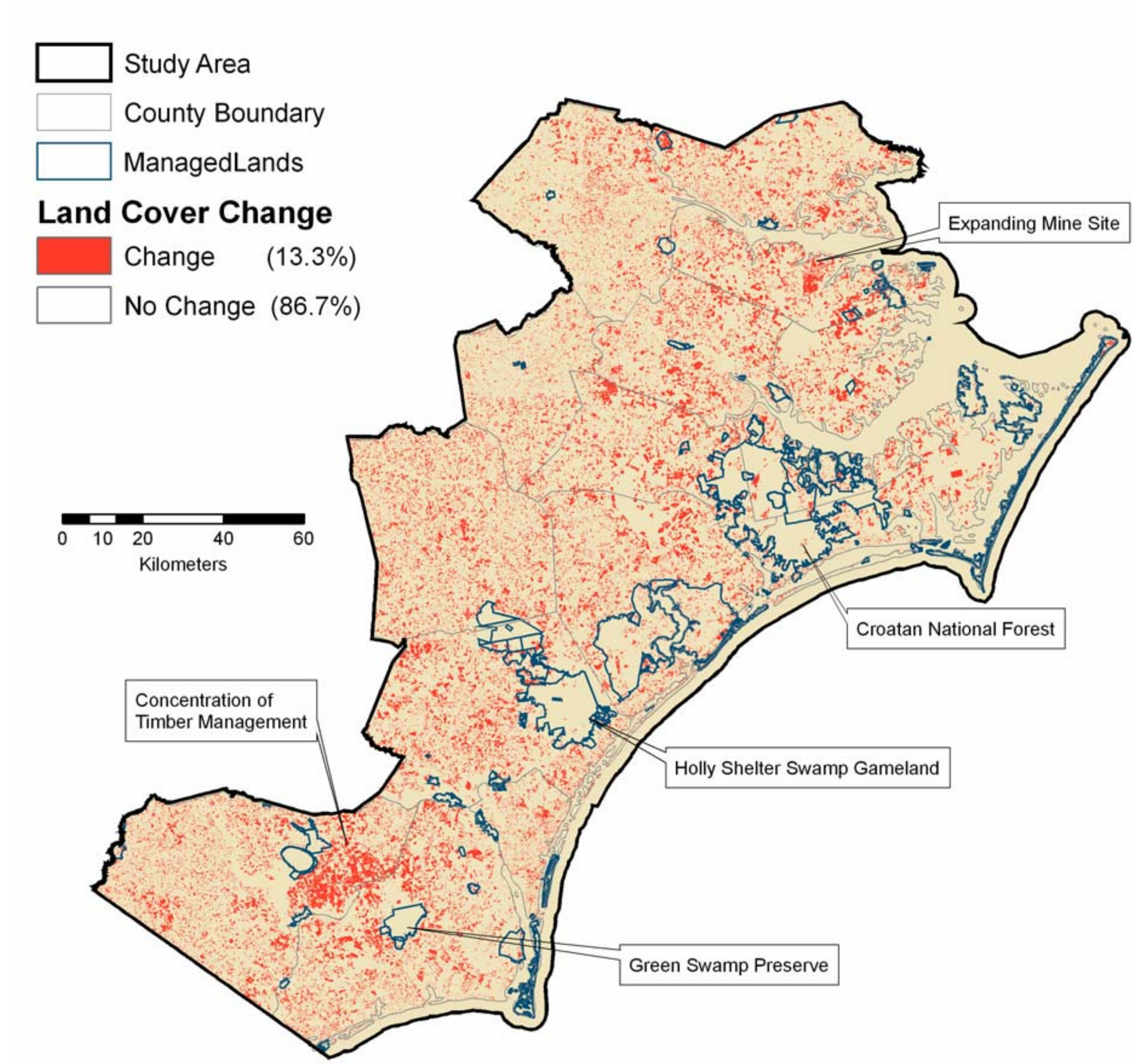

Figure 3.8. Land cover change areas in the Onslow Bight 1992 – 2001.

Tools for assessing and monitoring conservation status: A case study from the Onslow Bight, NC.

Alexa J. McKerrow, Thomas R. Wentworth, Jaime A. Collazo, Martha J. Groom, George R. Hess, and Heather M. Cheshire.

Abstract

The National Gap Analysis Program (GAP) has as its mission "keeping common species common". In support of that mission the program has conducted and funded research during the past decade with the goal of providing three key datasets used to assess conservation status: detailed land cover, predicted distributions of terrestrial vertebrate species based on application of habitat models, and land stewardship. We explored the use of these datasets in combination with a change detection analysis to assess the conservation status of Ecological Systems and vertebrate species of the Onslow Bight Landscape. We modeled predicted distributions for 141 priority vertebrate species identified in the North Carolina State Wildlife Action Plan (SWAP) and by Partners in Flight (PIF) as the basis for our conservation assessment. We were specifically interested in three general questions:

- Were there gains or losses in the extent of Ecological Systems and species predicted distributions between 1992 and 2001?
- When translated to a spatial framework, was there agreement on the ground between agency priorities?
- How well did the conservation network do with respect to capturing priority areas?

By integrating species models from the two dates, we were able to quantify the gains and losses of the priority species for the two programs. Using the 2001 version of the predicted distribution models, we mapped richness hotspots for the two agency lists. The hotspots for the two lists, areas with at least 28 of the SWAP priority species and areas with at least 13 of the PIF priority species, included nearly one-third (32%) of the landscape. Forty-seven percent of the area did not meet the hotspot criteria for either list and twenty-one percent met the criteria for one agency or the other. When we compared the hotspot maps to the existing conservation lands and new acquisitions, we found that both existing conservation lands and the newly acquired easements were biased toward the hotspots, with 70% of the existing conservation network on lands that met the hotspot criteria for both agencies, and 50% of the new acquisitions doing the

same. The approach outlined is responsive to individual agency priorities and allows for an objective assessment of the change in status of species habitat over time.

Keywords: Ecological Systems, Gap Analysis Program, State Wildlife Action Plans, Partners in Flight, Bird Conservation Region, Complementarity Analysis

Introduction

The Case for Spatially Explicit Conservation Tools

More than four decades ago the decline in biological diversity was officially recognized as an international crisis. In the early 1960s the World Conservation Union started the IUCN Red List to identify endangered species. Today that list includes 41,415 species, and 16,360 of them are considered threatened (IUCN 2007). The United States followed suit in 1966 with the Endangered Species Preservation Act (1966) and the subsequent Endangered Species Act (1973). In both cases, the need for maintaining diversity by conserving individual species was seen as central to the welfare of people.

The list of material benefits provided by species (e.g., food, fiber, and medicine) and the potential for future innovations and discoveries (option values) provided for by intact natural systems motivate the conservation of biodiversity (Callicott 2006, Edwards-Jones 2006; Scott et al. 1995). Finally, individuals and communities have ethical and aesthetic values directly tied to the conservation of biological diversity.

Even with the incentives to conserve biodiversity, the number of listed species is increasing and deleterious changes in the landscape are out-pacing our knowledge. Once listed, the cost to maintain a species can be high and long-lasting. As Scott et al. (2005) summarized, recovery is best described as a continuum; once endangered, a species may be “conservation – reliant”, requiring constant intervention. Unfortunately, for many species an accurate understanding of their status is impossible to assess. Wilcove and Master (2005) suggest that the data for 85% of the species (plants, animals, and fungi) in the United States are insufficient to determine their status accurately. Without a complete inventory, conservationists rely on surrogates for biodiversity (e.g., indicator species, keystone species, and species guilds) to identify conservation priorities.

Given the level of the threats, the rate of change, and the lack of a complete assessment, we need proactive approaches to conservation. Wilcove and Master (2005) suggest one alternative favored by many conservation biologists - the use of a “coarse-filter” approach to protection, with ecological communities acting as the screen.

For nearly twenty years, the National Gap Analysis Program has been advocating a coarse filter approach to planning. As early as 1993 Scott et al. saw the power of analyzing biodiversity data in a spatial context. In the preface to the 2000 issue of the special edition of Landscape Ecology devoted to the use of gap analysis, Burke (2000) suggested that the intersection of landscape ecology and conservation biology was the most promising front for effective species conservation.

Assuming the cost of conservation is lower for intact systems, the National Gap Analysis Program has been developing land cover and vertebrate species richness as two indicators of biodiversity (Scott et al. 1993, Scott and Jennings 1998). Since the program was initiated many changes have occurred in the technology and the methods have evolved, but the concept remains the same: proactively manage biological diversity to keep common species common.

Most recently, the GAP has actively engaged partners to integrate the gap data into their agency-specific analyses. Two of the most promising collaborations include State Wildlife Action Plans (SWAPs) and the Partners in Flight (PIF).

Ongoing Conservation Planning Efforts

State Wildlife Action Plans

Recently State and Tribal Wildlife Agencies in the U.S. developed their first comprehensive State Wildlife Action Plans (SWAPs). Those plans were required before those agencies would be eligible for funding through the Wildlife Conservation and Restoration Program. For many state agencies this was the first time they had access to funding specifically for the management of non-game and non-threatened and endangered species. In order to fulfill the guidelines set out by Congress, each plan had to address eight required elements (Table 4.1, USFWS 2007). Once an agency completed its plan, it had access to funding to implement the work outlined in the plan.

In a review of the action plans specific to urbanization, Defenders of Wildlife (2006) identified some key components that would make planning most effective. Some of those included protecting priority species and habitats, protecting connectivity and large habitat patches in the identification of priorities, sharing maps of priority habitats and priority conservation areas, and giving planners spatial data that identify sensitive resources. Each of these components depends on spatially explicit data tied to species habitats and land management.

Partners in Flight

Partners in Flight (PIF) is a consortium of government and non-government agencies and individuals working to conserve bird species. The partnership formed in 1990 in response to the declining populations of migratory land birds. In order to address the full range of issues related to these species, the consortium works both within the United States and internationally to develop conservation plans and to identify priority species in need.

The PIF planning process is a two stage process, assessing the status and trends for each avian species, and then setting priorities on the continental and regional scales (Panjabi et al. 2005). Each species is assessed based on size criteria related to population trends, species distribution, and threats (Table 4.2, Rich et al. 2004). Priorities are then set at the continental and regional (Bird Conservation Regions – BCR) scale based on a weighted scoring process to identify species of continental concern. A second category, continental stewardship species, identifies as species with a large percentage of their population within a single avifaunal biome for a part of the life cycle (breeding season, non-migratory portion of the non-breeding season). At the regional scale priorities are set based on scoring criteria that link regional and continental scores. Species of regional concern are those that have high regional scores, are vulnerable to threats within the region, and where the representation within a region is proportionally high relative to the global distribution.

Study Objectives

Early in its history, the Gap Analysis Program identified areas of high species richness outside the existing conservation network as priorities for conservation (Scott et al. 1993, Kiester et al. 1996). A “gap” represented an area in the landscape that was not being managed for biodiversity but did represented habitat for a high number of terrestrial vertebrates. Over time the GAP datasets have evolved to better address the needs of natural resource agencies, each of which have their own prioritization schemes or mandates.

Our objective in this study was to create a database that provides a spatial framework for monitoring and reporting with respect to the overall GAP goal of keeping common species common, while at the same time tailoring the analyses to our partners. We wanted to design an approach based on Gap Analysis Program datasets that could be applied to a variety of conservation questions. Specifically, we wanted to test the applicability of the GAP datasets and a change analysis in addressing questions specific to the priority species lists for the North Carolina Wildlife Resources Commission and Partners in Flight.

Study Area

The Onslow Bight study area includes parts of 13 counties in Coastal North Carolina and covers an area of 250,000 km^2. Eight of Omernik’s Level IV ecoregional boundaries intersect the study area (Figure 4.1; EPA 2004). Having been settled for hundreds of years, the area has undergone tremendous change. Much of the landscape today is dominated by agriculture and timber production (Auch 2006), with concentrations of urban growth centered in Wilmington, New Bern, and along the transportation corridors.

The Onslow Bight supports a diversity of plant communities, some of which have had their extents reduced dramatically by the history of settlement in the area. Historically the Carolina Flatwoods region supported a matrix of longleaf pine woodland (Frost 2006, Frost 1993). The Mid-Atlantic Floodplains and Low Terraces (EPA 2004) bisect the area and are characterized by bottomland hardwood forests and cypress gum swamps. Concentrations of pond pine woodlands and nonriverine swamps and wet hardwoods occur within what Omernik classifies as the Swamps and Peatlands ecoregion. The Carolinian Barrier Islands and Coastal Marshes support narrow strands of maritime forest and dune vegetation in the uplands and vast expanses of salt and brackish marshes occur on the landward side of the barrier islands and in protected portions of the embayed region to the north.

Methods

Land Cover Mapping

Land cover was mapped using 2001 satellite imagery for the Onslow Bight as a part of the Southeastern Gap Analysis Project. The resulting land cover map was developed using Landsat TM satellite imagery as the baseline dataset. In that map, the general land cover classes (for example, water, agriculture, and urban) were incorporated from the National Land Cover Dataset (NLCD 2001), while the vegetated classes were mapped using a combination of expert derived decision rules, image objects, and decision tree models (Chapter 2 this volume). The Ecological Systems Classification (Comer et al. 2003) was the basis for the map legend. A total of forty two land cover classes were included in the final map legend. Overall accuracy was 77% and the Kappa statistic based on a stratified sampling was 0.75. Per-class accuracies for the Ecological Systems varied considerably. For a complete description of the methods and results for the land cover map, refer to Chapter 2.

Change Detection

In order to quantify the changes in the extent of land cover and predicted distributions for species, we used two versions of the land cover map, one representing the 1992 time period and another for 2001. As mentioned above, a 2001 Ecological Systems map had been created already. The only 1992 land cover for the study area, the North Carolina GAP land cover, had been developed using different methods and map legend (McKerrow et al. 2006). To create a map for 1992 that was consistent with the 2001 map, we used a spectral change detection process to identify areas of potential change, we then labeled the 1992 map for areas that had changed and labeled unchanged areas with the 2001 land cover classes. The two land cover maps were used to characterize the changes in Ecological Systems and predicted species distributions in the assessment phase of this work.

To create the 1992 land cover map, a change vector analysis (CVA) was used to identify areas of potential change between 1992 and 2001. The change vectors were calculated from tasseled cap transformed images from 1992 and 2001. Areas with a high magnitude of change between the two dates were identified as potential change areas. Those areas were then classified with respect to the 1992 land cover class. For the non-urban areas identified as potentially changed, an unsupervised classification was used to identify “true change” areas. That classification was based on the difference image (magnitude) of change and the direction of change between 1992 and the 2001 Landsat imagery.

Areas of change in non-urban areas were then labeled with respect to the types of change that had occurred by one of three methods, aerial photo-interpretation, decision rules based on ancillary data, or decision tree modeling. Urban areas identified as potential change areas were mapped using impervious surface estimation, similar to the approach used in the 2001 NLCD land cover dataset (Homer et al. 2004, Homer et al. 2007, and Yang et al. 2003). We estimated a net change of 13% for the study area between 1992 and 2001. The accuracy of the change/no change map was estimated at 95% with a Kappa of 0.78 based on a stratified random sample. For a complete description of the change detection, see Chapter 3.

Species Modeling

The Southeast Gap Analysis Program has developed a database for 614 terrestrial vertebrate species that occur in the nine southeastern states (AL, FL, GA, KY, MS, NC, SC, TN, and VA). The database includes information on key parameters needed to model predicted distributions of habitat for each of those species. The database represents a compilation of literature and expert opinion. Reviews of the habitat parameters were conducted by project personnel at each of the three universities involved in the Southeast Gap Analysis Project (North Carolina State University, University of Georgia, and Auburn University). The models integrate species range maps, habitat affinity information (suitable land cover types), and ancillary data to map the predicted distributions (Table 4.3). Appendix 4.1 includes the list of the specific habitat modeling parameters used for the species in this study.

Based on the North Carolina GAP data, more than 300 terrestrial vertebrate species had a portion of their range within the study area (McKerrow et al. 2006). As a part of the later regional effort, the Southeast GAP modeled distributions for 47 amphibians, 153 birds, 53 mammals, and 63 reptiles that had with some portion of their distribution predicted to occur in the Onslow Bight.

In this study, we used Southeast GAP's vertebrate database to create two models for each species of interest, one based on the 1992 land cover and another based on the 2001 land cover. For model parameters derived directly from the land cover (e.g., patch size, edge, or urban avoidance) we created two versions of each data layer (1992 and 2001) for use in the habitat modeling. For ancillary data layers not derived from the land cover (e.g., species range maps, landforms), we assumed no change had occurred in the 9 year period. The only model parameters that did change were those derived from the 1992 and the 2001 land cover maps.

Land Stewardship Data

We used the Southeast Regional GAP Stewardship dataset for land ownership and management information. That dataset covers nine southeastern states and documents state and federal ownership and management. The Gap Analysis Program's Stewardship provided information about the management status (a critical attribute) in addition to information about who owns and manages the land (Crist 2000). There are four Status categories as defined by GAP (Table 4.4). A gap status is assigned for each parcel based on a series of decisions that characterize the permanence of protection, management intent, and the scope and extent of management activities (Figure 4.2). The assignment of the gap status was based on information gathered from published descriptions of agency mandates, management plans, or interview with key personnel responsible for management of a parcel.

We wanted to study the new land acquisitions with respect to their placement relative to priority areas identified by the analysis. The most comprehensive dataset that tracks acquisition dates consistently is the conservation easements database maintained by the North Carolina State Properties Office. That dataset represents the conservation easements that have been put in place by the state. Those easements can be acquired through agreements with the full range of land owners (e.g., private, non-governmental organization, local government), but the easement is held by the state of North Carolina. Therefore we restricted our analysis of the new acquisitions to only the properties with conservation easements acquired by the state since 1992.

Analysis

Gap Analysis

In a separate effort, a preliminary gap analysis of the Southeastern Regional land cover types was conducted by intersecting the regional Stewardship database with the nine state land cover map (Table 4.5). We used a threshold of 10% of the mapped distribution to identify gap cover types. From that analysis, eight of the Ecological Systems in the Onslow Bight were identified as gaps with less than 10% of their mapped distributions on GAP Status 1 and 2 lands throughout the region.

While those under-represented types became a primary focus for our land cover analysis, the historic loss of natural vegetation in the region makes it difficult to justify ignoring even those types that are considered well-represented in the conservation network. Therefore, we included Ecological Systems that are currently well-represented in our discussions.

We performed a gap analysis for the Onslow Bight for the Ecological Systems and terrestrial vertebrates identified as priorities in the NC SWAP and PIF plans. We intersected the mapped distribution of the element (Ecological System or vertebrate species) within the Onslow Bight with the stewardship data and calculated the proportion of each ecological system and vertebrate species' predicted distribution represented in Status 1, 2, 3 or 4 lands (water bodies greater than 40 ha were excluded). Gaps were then identified as any land cover or species within the study area with less than 10% of the distribution within Status 1 and 2 lands.

State Wildlife Action Plan

The North Carolina Wildlife Resources Commission went through an elaborate process of interviewing biologists and conducting public forums to identify the species of greatest conservation concern for the first State Wildlife Action Plan (NCWRC 2005). That plan identified 214 terrestrial vertebrates as priorities, including 29 subspecies. The Southeast GAP had modeled 205 of these species in North Carolina. The nine species in the SWAP that were not modeled by GAP included several winter residents as well as ones that rarely breed in the state (Table 4.6). Our analysis included 123 terrestrial vertebrate species that occur in the Onslow Bight (20 amphibians, 56 birds, 15 mammals, and 32 reptiles). The complete list of the priority species and the criteria used to select them in the SWAP are included in Appendix 4.2.

Partners in Flight

Thirty-eight avian species that occur in the Onslow Bight have been ranked by Partners in Flight as of regional or continental concern for the Southeastern Coastal Plain Bird Conservation Region (BCR 27; Table 4.7). Twenty of those taxa had also been identified as priorities in the SWAP; so 18 PIF continental or regional priority species are unique to this list.

Scorecard Process

We needed an efficient method for summarizing the gains and losses of areas of the Ecological Systems and vertebrate species. We decided to use a scorecard process, in which gains and losses are categorized into one of five categories - major losses, minor loss, no change, minor gain, major gains - that could be summed by taxa or for a list of Ecological Systems or priority species. Scorecards for both Ecological Systems and priority species were developed by summarizing the 1992 and 2001 mapped extents by management status. Based on the changes in predicted distributions between 1992 and 2001 each element was assigned one of the following five categories:

- - - a loss of greater than 20% in the predicted distribution occurred
- \- a loss of between 5 and 20%
- 0 no difference - 5 to + 5%
- \+ a gain of between 5 and 20%
- ++ a gain of over 20%

The thresholds established are subjective. A 5 % change in either direction was considered insignificant due to the variability inherent in classifying two dates of imagery. Changes between 5 and 20% were considered significant but minor relative to those where more than 20% of the 1992 areal extent was lost or gained. We wanted to highlight those species and Ecological Systems whose distributions were changing and felt that a loss of more than 20% represented a substantial threat to a species and a 20% gain indicated success that would warrant further exploration.

The gains and losses in acreage for each element were calculated by summarizing the area of the mapped (Ecological System) or predicted distribution (vertebrate species) within the Onslow Bight. We were interested to know if there the trends were similar for the conservation lands (Status 1 and 2) and for the landscape in general. For this analysis we summarized both the 1992 and the 2001 distributions against the Southeast Regional GAP Stewardship dataset. That dataset represents a current snapshot of the managed lands in the study area. By keeping the stewardship dataset constant, the changes in the land cover and the predicted distributions were limited to changes based on the land cover changes, and not confounded by changes in ownership or management between the two dates.

Richness Maps

Species richness maps for the SWAP and PIF were created to provide a spatial representation of the agency-specific priorities across the study area. The richest sites on the SWAP map represented areas where predicted habitat for sixty-four priority species occurred. The richest areas on the PIF map had a total of 26 species. We created hotspot maps for each agency list, by setting a threshold of one half of the total richness (34 for SWAP and 13 for PIF) to create two binary (hotspot / not hotspot) maps. Those maps were then summed to create a map with values of 0, 1, or 2 representing the number of hotspots in an area. While the advantage of these maps is a study area wide representation of the information regarding hot spots, we recognized the lack of information with respect to the species being served by any one site. Therefore we report the species specific changes in the scorecard process and propose a complementarity analysis for the Onslow Bight as a follow-up to this study.

Results and Discussion

Scorecard for the Ecological Systems in the Onslow Bight

The scorecard for the Ecological Systems indicates that for the eight Ecological Systems that are under-represented at the regional scale, three had estimated gains of more than 5% of their 1992 acreage: ACP Longleaf Pine Woodland, ACP Blackwater Stream Floodplain Forest and ACP Clay-Based Carolina Bay Forested Wetland (Table 4.8).

The gains in ACP Longleaf Pine Woodland represent regeneration on sites that were mapped as clearcut herbaceous in 1992. The increase in the ACP Blackwater Stream Floodplain can be attributed to regeneration from non-forest land cover types into forests along the riparian corridors. The increase for the ACP Clay-Based Carolina Bay Forested Wetland is more likely an artifact of a mapping error. While the increase represented a relatively large percentage, it actually accounts for change of 20 hectares within a single Carolina Bay in the Lyman area of Duplin County. In that case the bay had been correctly mapped as ACP Peatland Pocosin – Carolina Bay in the 1992 land cover map and as the clay based Ecological System in the 2001 land cover. Between the two dates it appears that a timber operation had opened up the canopy, causing an error in the 2001 map. The remaining five regional priority types had no changes in extent during the 9 year period (Table 4.9)

The summary for all Ecological Systems mapped for the Onslow Bight, including the gap systems discussed above, indicates that thirteen remained unchanged, nine had gains in acreage, and one, the ACP Southern Tidal Wooded Swamp showed a decline of 531 ha or 6% of the 1992 distribution (Table 4.10). Spatially, the loss of the tidal swamp is concentrated in patches along the Pamlico River shoreline near the Pamlico Sound.

Considering the changes in representation within the stewardship categories, three Ecological Systems had relatively large shifts in representation within a specific GAP Status. The ACP Fall-Line Sandhills Longleaf Pine Woodland lost 720 ha on Status 3 lands. The majority of the extant acreage of that Ecological System is mapped on Department of Defense lands and that is where the majority of that loss was mapped as well. The ACP Northern Wet Longleaf Pine Savanna and Flatwoods System lost 1,199 ha on Status 3 lands. In this case, the Croatan National Forest and Department of Defense lands have the greatest concentrations of this system, including the areas of change. Finally, the ACP Southern Dune and Maritime Grassland showed an increase of 514 ha along the outer banks in the Status 2 lands of the National Park Service. Accreting sands along barrier islands accounted for the observed increase on these lands.

Scorecard for Priority Species in the Onslow Bight

On Status 1 and 2 lands, seventeen of the 123 species modeled had increases in the extent of their predicted distributions between 1992 and 2001 (Figure 4.3). Ninety-six species showed no major changes (less than 5% change in either direction) and ten species had lost habitat according to our models. Three bird species had an estimated increase of greater than 20% of their predicted distribution. Considering status 3 and 4 lands, thirteen species showed gains, sixteen decreased, and predicted habitat for ninety-four species had no change. For all taxa, most species had no change (< 5% gain or loss) in the predicted distributions between 1992 and 2001. It is important to note that the Status 1 and 2 lands make up less than 5% of the Onslow Bight; therefore the changes in proportion of the Status 3 and 4 lands tend to represent much larger acreage changes than do the changes reported relative to the Status 1 and 2 lands.

Because the SWAP species list does not incorporate life history it is not surprising that there are both gains and losses within each of the taxa and across the full list. In order to identify species that are most impacted by the changes, the species-specific gains and losses are graphed in Figures 4.4 – 4.7. The trend for most individual species is no change in predicted habitat. Some notable exceptions are described here. The spotted salamander (*Ambystoma maculatum*) showed a large relative decrease in predicted distribution on Status 1 and 2 lands, which represented a decrease from 5 hectares to 3 hectares due to clearing of a single site. The modeled losses on Status 3 and 4 were also related to forest clearing. Gopher frog (*Rana capito)* is predicted to occur in small patches throughout the study area in longleaf pine woodlands, changes in the predicted distribution occur where those woodlands have been cleared.

There were three bird species that utilize open grassland habitats with notable patterns. The grasshopper sparrow (*Ammodramus savannarum)* had a large increase (205%) in predicted distribution, going from 22,813 ha to 24,363 ha on Status 3 and 4 lands. That predicted increase is related to a concentration of timber harvest, resulting in an increase in the extent of herbaceous land cover in the inner coastal plain, where the species occurs. Dickcissel (*Spiza americana*) had a decline (59 ha to 47 ha) in predicted distribution on Status 1 and 2 lands, where regeneration from open sites into forest occurred between 1992 and 2001. Mississippi Kite (*Ictinia mississippiensis*) also had a large decline in predicted distribution on status 3 and 4 lands where regenerating forests replaced successional grasslands and shrublands.

There were two reptile species [loggerhead turtle (*Caretta caretta*) and leatherback turtle (*Dermochelys coriacea*)] with relatively large losses on both Status 1 and 2 lands and Status 3 and 4 lands. Both of these species are restricted to the Outer Banks with relative small acreages modeled as predicted habitat. The restricted acreage of available habitat (beaches and maritime grasslands) means that changes in land cover for a relatively small area can have a large impact on the predicted distributions for these species. In this case, changes from open water habitats to marsh on the landward side of the Outer Banks led to the decline in the predicted distributions for these species.

Of the 123 species on the SWAP list, eighty-two are gap (< 10% on Status 1 & 2) species within the study area. Of the thirty-eight Partners in Flight species all but three, the seaside sparrow, wood thrush (*Hylocichla mustelina*), and yellow-billed Cuckoo (*Coccyzus americanus*) are gap species. In the region approximately 10% of the lands are in management, meaning that for most species will have a large proportion of their predicted distribution outside the conservation network. In other words, at a 10% threshold, most species in the southeast will be identified as gap species. One exception is the species that were restricted to areas where managed lands were concentrated, such as the seaside sparrow, with most of the habitat predicted within the USFWS Refuge and National Park Service lands of the Outer Banks.

Priority Species Hotspots

The spatial distributions of the hotspots for the 123 SWAP species and the 38 PIF species are similar within the Onslow Bight (Figure 4.10). Concentrations occur for both agency lists along the river corridors and the large remaining peatland areas of the Onslow Bight. In the inner coastal plain, the hotspots are linked to the remaining forest patches. Figure 4.11 presents the hotspot maps for the two agencies, based on a threshold of one-half of the maximum number of species predicted to occur at any one site. For SWAP, the maximum richness was 56 species and for PIF the maximum richness was 26 species, so thresholds were set at 28 and 13 respectively.

How Well Does the Existing Network Do?

Figure 4.12 shows the areas where managed lands and habitat rich areas co-occur. 27% of the landscape was identified as a hotspot for both the SWAP and PIF priorities (Figure 4.12). When we summarized relative to the new easements, 50% of the land met the criteria of high priority species richness for both agency lists. The existing managed lands exceed that proportion, with 70% of the Status 1 & 2 and 53% of the Status 3 lands meeting the hotspot criteria for both agencies. Only 29% of the lands not in management (Status 4) met the criteria for both lists and nearly half (49%) of the Status 4 area would not be a priority based on the agency lists.

Summary

Conservation Status in the Onslow Bight

The majority of the priority species within the Onslow Bight were identified as gap species at the 10% threshold. One of the Ecological Systems that were under-represented at the regional level (ACP Blackwater Stream Floodplain) gained acreage between 1992 and 2001, while the other gap systems remained stable. Two of the longleaf pine-dominated systems lost acreage. Given the fact that those types occupy small remnants of their historic distributions, those losses are important. Some of the vertebrate species had large changes in predicted distributions between 1992 and 2001. Many of those shifts in predicted habitat can be attributed to the relatively large changes in the anthropogenic cover types between the two dates. For species with long or complex life histories, a temporal component should be added to the model of predicted habitat.

The two agencies did have considerable overlap in the priority areas based on the hotspot analysis, and the existing conservation lands and newly acquired easements had a fair amount of overlap with those priorities.

Importance of Data Quality at Every Stage

At every stage of the analysis, the accuracy and detail in the datasets determine the utility of the database for monitoring conservation status. The land cover map had to be detailed and accurate, because errors cascaded through every step of the analysis (change, habitat modeling, and analyses). Similarly, errors in change detection will impact the predicted distribution models. The vertebrate species models are especially sensitive to the selection of the habitat affinity information; therefore, the cross-walk between habitat and land cover types is critical. Finally, the consistency and accuracy of the stewardship boundary information and attribution can change the ranking of a species or land cover type.

To specifically test the impact of error throughout the modeling process, we are planning a sensitivity analysis for the models, to test the impact of various error rates on the extent and distribution of the predicted distributions and the score cards generated from those distributions.

As with any complex database, refinement over time is likely to happen. The GAP has put into place a framework that should allow for that refinement. The adoption of the Ecological Systems classification and the mapping approach is based on years experience with other map legends and the mapping protocols. In addition, the development of regional datasets through centralized research labs increases the consistency of delineation of the land cover, making them more useful. The habitat modeling database is structured to accommodate changes, but to allow transparency. Standards for the mapping and attribution of the land stewardship data are in place.

Finally, the improvements in land cover mapping and change detection will continue to improve our assessment of natural plant communities and will provide better model inputs. Without a parallel effort to improve species modeling, including field studies to improve our understanding of the life histories of each of the priority species, our ability to successfully monitor and manage species is diminished.

Applicability of the Approach

Teder et al. (2006) argued that an effective monitoring program requires two elements, data on taxa and ecosystems. In their proposed approach, the distribution of the elements needs to be mapped and assessed. Finally, they suggest that repeating the process is necessary for a true monitoring effort. In this research, we have identified the priority species within the study area, mapped their distributions, and assessed the status of their available habitat over time. Using the GAP datasets (land cover, vertebrate models, and stewardship) in combination with change detection, we have designed a coarse filter approach to monitoring of both taxa and ecosystems. With GAP datasets coming online for entire regions, the approach is transferable. The spatial data provide an effective method for communicating with respect to assessment, and the approach is applicable to assessing the status of both Ecological Systems and vertebrate species. While our study area had been delineated based on political boundaries (counties) we were able to set the priority list based on science by linking with results from the Southeast Regional gap analysis (under-represented Ecological Systems) and state and national priority lists (SWAP, PIF).

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References

Auch , R.F. 2006. Middle Atlantic Coastal Plain: Ecoregion Assessment. Loveland, T.R. and Acevedo, W., eds., *in* Status and Trends of Eastern United States Land Cover, U.S. Geological Survey Scientific Investigations Report.

Burke, V. J. 2000. Landscape ecology and conservation. Landscape Ecology. 15(1-3).

Callicott, J. B. 2006. Conservation values and ethics. In Principals of Conservation Biology. Editors M.J. Groom, G.K. Meffe, and C. R. Carroll. Sinauer Associates, Inc. Sunderland, Massachusetts, U.S.A.

Comer, P., D. Faber-Langendoen, R. Evans, S. Gawler, C. Josse, G. Kittel, S. Menard, M. Pyne, M. Reid, K. Schulz, K. Snow, and J. Teague. 2003. Ecological Systems of the United States: A working classification of U.S. terrestrial systems NatureServe, Arlington, VA.

Crist, P. J. 2000. Mapping and categorizing land stewardship. Version 2.1.1. In: A handbook for conducting Gap Analysis. Accessed (14 October 2007) from http://www.gapanalysis.nbii.gov.

Defenders of Wildlife. 2006. Linking conservation and land use planning: using state wildlife action plans to protect wildlife from urbanization. Defenders of Wildlife. Washington D.C. 60 pp.

Edwards-Jones, G. 2006. Ecological economics and nature conservation. In: Principals of Conservation Biology. Editors M.J. Groom, G.K. Meffe, and C. R. Carroll. Sinauer Associates, Inc. Sunderland, Massachusetts, U.S.A.

Environmental Protection Agency. 2004. Level III and IV Ecoregions of EPA Region 4. U.S. Environmental Protection Agency, National Health and Environmental Effects Research Laboratory, Western Ecology Division, Corvallis, OR. Scale 1:2,000,000.

Frost. C. C. 2006. History and future of the longleaf pine ecosystem. In: The longleaf pine ecosystem: ecology, silviculture, and restoration. S. Jose, E. J. Jokela, and D. L. Miller (editors) New York. Springer. Pp. 9 – 42.

Frost, C. C. 1993. Four centuries of changing landscape patterns in the Longleaf Pine ecosystem. pp. 17-43 In S. Hermann (ed.) Proc. Of the Tall Timbers Fire Ecology Conference, No. 18. The longleaf Pine Ecosystem; Ecology, Restoration and Management. Tallahassee, FL: Tall Timbers Research Station.

Homer, C., C. Huang, L. Yang, B. Wylie, and M. Coan. 2004. Development of a 2001 National Landcover Database for the United States. *Photogrammetric Engineering and Remote Sensing*. 70(7)829-840.

Homer, C., J. Dewitz, J. Fry, M. Coan, N. Hossain, C. Larson, N. Herold, A. McKerrow, J. Nick VanDriel, and J. Wickham. 2007. Completion of the 2001 National Land Cover Database for the Coterminous United States. Photogrammetric Engineering and Remote Sensing. 73(4)337-341.

IUCN - International Union for the Conservation of Nature and Natural Resources. 2007. Red List of Threatened Species. Accessed (Oct.14. 2007) from http://www.iucn.org/themes/ssc/redlist2007/index_redlist2007.htm

Kiester, A. R., J. M. Scott, B. Csuti, R. F. Noss, B. Butterfield, K. Sahr, and D. White. 1996. Conservation Prioritization Using Gap Data. Conservation Biology. 10(5)1332 – 1342.

McKerrow, A.J., S.G. Williams, and J.A. Collazo. 2006. The North Carolina Gap Analysis Project: Final Report. North Carolina Cooperative Fish and Wildlife Research Unit, North Carolina State University, Raleigh, North Carolina. xiv + 110 pp. + appendices.

North Carolina Wildlife Resources Commission. 2005. *North Carolina Wildlife Action Plan*. Raleigh, NC. 577 pp.

Panjabi, A., E. Dunn, P. Blancher, W. Hunter, B. Altman, J. Bart, C. Beardmore, H. Berlanga, G. Butcher, S. Davis, D. Demarest, R. Dettmers, W. Easton, H. Gomez de Silva Garza, E. Iñigo-Elias, D. Pashley, C. Ralph, T. Rich, K. Rosenberg, C. Rustay, J. Ruth, J. Wendt, and T. Will. 2005. The Partners in Flight handbook on species assessment. Version 2005. Partners in Flight Technical Series No. 3. Last accessed Oct. 18, 2007. Rocky Mountain Bird Observatory website: http://www.rmbo.org/pubs/downloads/Handbook2005.pdf

Prendergast, J. R. R.M. Quinn, and J. H. Lawton. 1999. The Gaps between theory and practice in selecting nature reserves. Conservation Biology. 13(3)484-492.

Rich, T. D., C. J. Beardmore, H. Berlanga, P. J. Blancher, M. S. W. Bradstreet, G. S. Butcher, D. W. Demarest, E. H. Dunn, W. C. Hunter, E. E. Iñigo-Elias, J. A. Kennedy, A. M. Martell, A. O. Panjabi, D. N. Pashley, K. V. Rosenberg, C. M. Rustay, J. S. Wendt, and T. C. Will. 2004. Partners in Flight North American Landbird Conservation Plan. Cornell Lab of Ornithology. Ithaca, New York. http://www.partnersinflight.org/cont_plan/default.htm.

Scott. J. M., Dale D. Goble, J. A. Wiens, D. S. Wilcove, M. Bean, and T. Male. 2005. Recovery of imperiled species under the Endangered Species Act: the need for a new approach. 7(3)383-389.

Scott, J, M., E. D. Ables, T. C. Edwards, R. L. Eng, T. A. Gavin, L. D. Harris, J. B. Haufler, W. H. Healy, F. L. Knopf, O. Torgerson, and H. P. Weeks. 1995. Conservation of biodiversity: perspectives and the future of the wildlife profession. Wildlife Society Bulletin. 23(4)646-657.

Scott, J. M., F. Davis, B. Csuti, R. Noss, B. Butterfield, C. Groves, H. Anderson, S. Caicco, F. D'Erchia, T. C. Edwards, J. Ulliman, and R. G. Wright. 1993. Gap Analysis: a geographic approach to protection of biological diversity. Wildlife Monographs. Supplement to The Journal of Wildlife Management. 57(1)1993.

Scott, J. M. and M. D. Jennings. 1998. Large-area mapping of biodiversity. Annals of the Missouri Botanical Garden. 85(1)1998.

Teder, T, M. Moora, E. Roosaluste, K. Zobel, M. Partel, U. Koijalg, and M. Zobel. 2006. Monitoring of biological diversity: a common ground approach. Conservation Biology. 21(2)313-317.

USFWS. 2007. Administrative Guidelines for State Wildlife Grants. Last accessed (15 October 2007) federalasst.fws.gov/swg/2007%20SWG%20Guidelines.pdf.

Wilcove, D. S. and L. L. Master 2005. How many endangered species are there in the United States. Frontiers in Ecology. 8(3)414-420.

Yang, L., C. Huang, C. G. Homer, B. K. Wylie, and M. J. Coan. 2003. An approach for mapping large-area impervious surfaces: synergistic use of Landsat-7 ETM+ and high spatial resolution imagery. Canadian Journal of Remote Sensing. Vol. 29 (2) 230-240.

Table 4.1. Eight required elements for the State Wildlife Action Plans. Guidelines for developing the wildlife action plans are summarized by USFWS (2007).

1	***Information on the distribution and abundance of species of wildlife***, *including low and declining populations as the state fish and wildlife agency deems appropriate, that are indicative of the diversity and health of the state's wildlife; and,*
2	***Descriptions of extent and condition of habitats and community types*** *essential to conservation of species identified in (1); and,*
3	***Descriptions of problems*** *which may adversely affect species identified in (1) or their habitats,* ***and priority research and survey efforts*** *needed to identify factors which may assist in restoration and improved conservation of these species and habitats; and,*
4	***Descriptions of conservation actions*** *proposed to conserve the identified species and habitats and priorities for implementing such actions; and,*
5	***Proposed plans for monitoring*** *species identified in (1) and their habitats, for monitoring the effectiveness of the conservation actions proposed in (4), and for adapting these conservation actions to respond appropriately to new information or changing conditions; and,*
6	***Descriptions of procedures to review the plan*** *at intervals not to exceed ten years; and,*
7	*Plans for* ***coordinating the development, implementation, review, and revision of the plan with federal, state, and local agencies and Indian tribes*** *that manage significant land and water areas within the state or administer programs that significantly affect the conservation of identified species and habitats.*
8	***Broad public participation*** *is an essential element of developing and implementing these plans, the projects that are carried out while these plans are developed, and the species in greatest need of conservation.*

Table 4.2 The six Partners in Flight species assessment factors. Rich et al. (2004) describe the process for assessing and prioritizing species for Partners in Flight.

Population Size (PS) indicates vulnerability due to the total number of adult individuals in the global population. Evaluation of PS is based on the assumption that species with small populations are more vulnerable to extirpation or extinction than species with large populations. Scores were assigned using population estimates derived from Breeding Bird Survey abundance data (Rosenberg and Blancher in press) or from other sources (see Appendix B).
Breeding Distribution (BD) indicates vulnerability due to the geographic extent of a species' breeding range. The underlying assumption of BD is that species with narrowly distributed breeding populations are more vulnerable than those with widely distributed populations. BD was assessed at a truly global scale, whereby the entire range of the species was considered in the evaluation.
Non-breeding Distribution (ND) indicates vulnerability due to the geographic extent of a species' non-breeding range, with the assumption that species narrowly distributed in the non-breeding season are more vulnerable than those that are widely distributed. In practice, we did not consider range size during migratory periods, or phenomena such as migratory bottlenecks. Instead, evaluation of ND was based on the range of a species when populations are relatively sedentary (i.e., "winter"). As with BD, ND was assessed at a truly global scale.
Threats to Breeding (TB) indicates vulnerability due to the effects of current and probable future extrinsic conditions that threaten the ability of populations to survive and successfully reproduce in breeding areas within North America. Evaluation of TB included anthropogenic threats to breeding habitats, as well as other factors (e.g., competition with exotic species) that interfere with reproduction.
Threats to Non-breeding (TN) indicates vulnerability due to the effects of current and probable future extrinsic conditions that threaten the ability of North American breeding populations to survive over the non-breeding season. Evaluation of TN included anthropogenic threats to habitat, as well as other factors affecting survival during winter and migration periods.
Population Trend (PT) indicates vulnerability due to the direction and magnitude of changes in population size over the past 30 years. Species declining by 50% or more over this period are considered most vulnerable, whereas species with increasing trends are least vulnerable. The Breeding Bird Survey was the primary source of data, but Christmas Bird Count or specialized data sources were used where available and appropriate. Thus, PT was based on the best available breeding or non-breeding data indicating overall trend in those populations that breed in North America.

Table 4.3. Categories of the model parameters used in the Southeast GAP's habitat modeling.

Code	Attribute Name	Data source
HdMd	Hand modeling	Model within range variability
XFlW	Flowing water	National Hydrologic Dataset
FFlW	Buffer into flowing water	
IFlW	Buffer in from water	
XOpW	Open water	Southeast GAP Land Cover
FOpW	Buffer from open water	
IOpW	Buffer into open water	
XWtV	Wet vegetation	Southeast GAP Land Cover
FWtV	Buffer from wet vegetation	
IWtV	Buffer into wet vegetation	
Sali	Salt water	Southeast GAP Land Cover
StVe	Stream velocity	National Hydrologic Dataset, National Elevation Dataset
FaMn	Flow accumulation minimum	
FaMx	Flow accumulation maximum	
EdTy	Edge Type	Southeast GAP Land Cover
EdWd	Edge ecotone width	
XIFor	Interior forest	
IFBu	Buffer into forest	
XCPc	Contiguous patches	
SCPc	Contiguous patch size	
ICPc	Buffer into contiguous patches	
FCPc	Buffer from contiguous patches	
XNPc	Non-contiguous patch	
PNPc	Non-contiguous patch percolation	
SNPc	Non -contiguous patch size	
Avod	Avoid mask	National Land Cover Dataset
ElMn	Minimum elevation limit	National Elevation Dataset
ElMx	Maximum elevation limit	
LClf	Landform - Cliffs	National Elevation Dataset
LStS	Steep slopes	
LSlC	Slope crests	
LUpS	Upper slopes	
LFlS	Flat summits	
LSiS	Side slopes	
LCov	Coves	
LDrF	Dry flats	
LMoF	Moist flats	
LWtF	Wet flats	
LSlB	Slope bottoms	
AxBf	Auxiliary land cover units	Southeast GAP Land Cover

Table 4.4. Definitions for the GAP Status codes.

Status 1: An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a natural state within which disturbance events (of natural type, frequency, intensity, and legacy) are allowed to proceed without interference or are mimicked through management.
Status 2: An area having permanent protection from conversion of natural land cover and a mandated management plan in operation to maintain a primarily natural state, but which may receive uses or management practices that degrade the quality of existing natural communities, including suppression of natural disturbance.
Status 3: An area having permanent protection from conversion of natural land cover for the majority of the area, but subject to extractive uses of either a broad, low-intensity type (e.g., logging) or localized intense type (e.g., mining). It also confers protection to federally listed endangered and threatened species throughout the area.
Status 4: There are no known public or private institutional mandates or legally recognized easements or deed restrictions held by the managing entity to prevent conversion of natural habitat types to anthropogenic habitat types. The area generally allows conversion to unnatural land cover throughout.

Table 4.5. Representation of the Ecological Systems of the Onslow Bight in the Southeast. ACP = Atlantic Coastal Plain.

Ecological System	Representation on Status 1 & 2 Lands	Area
	-- % --	-- ha --
9 - ACP Dry and Dry-Mesic Oak Forest	1	1,249,080
10 - ACP Mesic Hardwood and Mixed Forest	1	385,467
28 - ACP Central Maritime Forest	13	15,693
21 - ACP Fall-line Sandhills Longleaf Pine Woodland*	2	747804
37 - ACP Longleaf Pine Woodland	1	1,845,248
36 - ACP Southern Dune and Maritime Grassland	56	13,407
14 - ACP Blackwater Stream Floodplain Forest	1	799,206
4 - ACP Large River Floodplain – Brownwater	4	926,923
6 - ACP Large River Floodplain – Blackwater	12	500,003
40 - ACP Nonriverine Swamp and Wet Hardwood Forest - Taxodium/Nyssa Modifier	14	323,547
39 - ACP Nonriverine Swamp and Wet Hardwood Forest - Oak Dominated Modifier	12	185,333
11 - ACP Clay-Based Carolina Bay Forested Wetland	7	9,793
33 - ACP Peatland Pocosin	19	616,511
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	3	141,621
8 - ACP Southern Tidal Wooded Swamp	24	26,073
42 - ACP Central Fresh-Oligohaline Tidal Marsh	24	68,619
26 - ACP Embayed Region Tidal Freshwater Marsh	21	6,038
2 - SCP Large Natural Lakeshore**		183
35 - ACP Central Salt and Brackish Tidal Marsh	27	337,210
27- ACP Embayed Region Tidal Salt and Brackish Marsh	36	60,786

* Includes three modifiers of the ACP Fall-line Sandhills Longleaf Pine Woodland Ecological System (Loblolly Pine, Open Understory, and Scrub Shrub Understory)

** Water bodies excluded from the terrestrial gap analysis.

Table 4.6. Vertebrate species included in the North Carolina State Wildlife Action Plan but not modeled by Southeast GAP.

Taxa	Scientific Name	Common Name	Reason Not Modeled
AMPHIBIAN	*Eurycea sp. 1*	Sandhills Salamander	Species not yet described
AVIAN	*Carduelis pinus*	Pine Siskin	Not in breeding range
AVIAN	*Calidris canutus*	Red Knot	Not in breeding range
AVIAN	*Calidris alba*	Sanderling	Not in breeding range
AVIAN	*Asio flammeus*	Short-eared Owl	Not in breeding range
AVIAN	*Coturnicops noveboracensis*	Yellow Rail	Not in breeding range
MAMMALIAN	*Trichechus manatus*	Manatee	Aquatic species
REPTILIAN	*Eretmochelys imbricata imbricata*	Hawksbill Sea Turtle	Rare breeder in the region
REPTILIAN	*Lepidochelys kempii*	Kemp's Ridley Sea Turtle	Rare breeder in the region

Table 4.7. Partners in Flight priority bird species of the Onslow Bight.
(CC – continental concern, RC - regional Concern, CS - continental stewardship species, RS - regional stewardship species)

Family	Scientific Name	Common Name	CC	RC	CS	RS
Emberizidae	*Ammodramus maritimus*	Seaside Sparrow* **	Y		Y	Y
Accipitridae	*Buteo lineatus*	Red-shouldered Hawk*			Y	
Accipitridae	*Buteo platypterus*	Broad-winged Hawk*		Y		
Apodidae	*Chaetura pelagica*	Chimney Swift		Y		Y
Cuculidae	*Coccyzus americanus*	Yellow-billed Cuckoo		Y		Y
Picidae	*Colaptes auratus*	Northern Flicker		Y		
Odontophoridae	*Colinus virginianus*	Northern Bobwhite		Y		
Tyrannidae	*Contopus virens*	Eastern Wood-Pewee		Y		
Parulidae	*Dendroica discolor*	Prairie Warbler	Y	Y	Y	Y
Parulidae	*Dendroica pinus*	Pine Warbler*			Y	Y
Picidae	*Dryocopus pileatus*	Pileated Woodpecker*				Y
Tyrannidae	*Empidonax virescens*	Acadian Flycatcher			Y	Y
Turdidae	*Hylocichla mustelina*	Wood Thrush	Y	Y		
Icteridae	*Icterus spurius*	Orchard Oriole				Y
Laniidae	*Lanius ludovicianus*	Loggerhead Shrike		Y		
Picidae	*Melanerpes carolinus*	Red-bellied Woodpecker			Y	
Picidae	*Melanerpes erythrocephalus*	Red-headed Woodpecker	Y			
Parulidae	*Oporornis formosus*	Kentucky Warbler	Y			
Parulidae	*Parula americana*	Northern Parula				Y
Cardinalidae	*Passerina ciris*	Painted Bunting	Y	Y		
Cardinalidae	*Passerina cyanea*	Indigo Bunting*			Y	Y
Picidae	*Picoides borealis*	Red-cockaded Woodpecker	Y	Y	Y	Y
Picidae	*Picoides pubescens*	Downy Woodpecker*				Y
Emberizidae	*Pipilo erythrophthalmus*	Eastern Towhee*		Y	Y	Y
Thraupidae	*Piranga rubra*	Summer Tanager*				Y
Paridae	*Poecile carolinensis*	Carolina Chickadee*				Y
Hirundinidae	*Progne subis*	Purple Martin*				Y
Parulidae	*Protonotaria citrea*	Prothonotary Warbler*	Y		Y	Y
Sittidae	*Sitta pusilla*	Brown-headed Nuthatch	Y	Y	Y	Y
Cardinalidae	*Spiza americana*	Dickcissel	Y			
Emberizidae	*Spizella pusilla*	Field Sparrow		Y		
Icteridae	*Sturnella magna*	Eastern Meadowlark		Y		
Troglodytidae	*Thryothorus ludovicianus*	Carolina Wren*			Y	
Mimidae	*Toxostoma rufum*	Brown Thrasher*		Y		Y
Tyrannidae	*Tyrannus tyrannus*	Eastern Kingbird		Y		Y
Vireonidae	*Vireo flavifrons*	Yellow-throated Vireo*			Y	Y
Vireonidae	*Vireo griseus*	White-eyed Vireo*			Y	Y
Parulidae	*Wilsonia citrina*	Hooded Warbler			Y	Y

*Species not included in the NC State Wildlife Action Plan.
** Species not a gap species in the Onslow Bight.

Table 4.8. Land cover scorecard. Changes in the extent and representation of Ecological Systems in the Onslow Bight. Ecological Systems in bold are considered gaps at the 10% threshold for the Southeast Region. The Southeast GAP Status map from 2001 was used to summarize both the 1992 and 2001 acreages by status (Status categories are defined in Table 4.4). Change is calculated relative to the 1992 total.

* Includes three modifiers of the ACP Fall-line Sandhills Longleaf Pine Woodland Ecological System (Loblolly Pine, Open Understory, and Scrub Shrub Understory).
** Small and large river floodplain systems were combined in the preliminary Southeastern GAP.
*** Carolina Bay Peatland Pocosin combined with ACP Peatland Pocosin in the preliminary Southeastern Gap Analysis.
**** Water bodies excluded from the terrestrial gap analysis.

Table 4.8 continued.

	1992 Area by GAP Status				2001 Area by GAP Status				Change	Score
Ecological System	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**		
	Area (ha)				Area (ha)				%	
9 - ACP Dry and Dry-Mesic Oak Forest	**44**	**217**	**6,509**	**124,629**	**44**	**178**	**6,319**	**128,957**	**-3.12%**	**0**
10 - ACP Mesic Hardwood and Mixed Forest	**0**	**0**	**5**	**152**	**0**	**0**	**5**	**152**	**-0.11%**	**0**
28 - ACP Central Maritime Forest	11	835	1,391	7,775	14	844	1,421	7,840	-1.08%	0
21 - ACP Fall-line Sandhills Longleaf Pine Woodland*	**320**	**1,616**	**11,491**	**102,049**	**318**	**1,476**	**10,767**	**97,078**	**5.05%**	**+**
37 - ACP Longleaf Pine Woodland	**25**	**31**	**600**	**11,403**	**34**	**27**	**609**	**12,280**	**-7.39%**	**-**
36 - ACP Southern Dune and Maritime Grassland	119	3,023	805	2,247	143	3,571	954	2,583	-17.05%	-
14 - ACP Blackwater Stream Floodplain Forest	**15**	**53**	**2,268**	**30,505**	**15**	**55**	**2,321**	**32,318**	**-5.69%**	**-**
4 - ACP Large River Floodplain – Brownwater	**0**	**1,811**	**0**	**23,485**	**0**	**1,811**	**0**	**23,644**	**-0.63%**	**0**
16 - ACP Small Brownwater River Floodplain Forest**	4	1,737	530	52,397	4	1,761	481	54,128	-3.12%	0
6 - ACP Large River Floodplain – Blackwater	0	3,139	1,208	28,363	0	3,132	1,284	28,290	0.01%	0
18 - ACP Small Blackwater River Floodplain Forest**	0	0	0	12	0	0	0	12	0.00%	0
40 - ACP Nonriverine Swamp and Wet Hardwood Forest - Taxodium/Nyssa Modifier	228	943	1,807	30,888	228	1,038	1,810	33,564	-8.19%	-
41 – ACP Nonriverine Swamp and Wet Hardwood Forest – Atlantic White Cedar Modifier	0	0	0	30	0	0	0	30	0.00%	0
39 - ACP Nonriverine Swamp and Wet Hardwood Forest - Oak Dominated Modifier	31	416	513	33,335	31	423	540	36,067	-8.06%	-
11 - ACP Clay-Based Carolina Bay Forested Wetland	**0**	**0**	**0**	**134**	**0**	**0**	**0**	**164**	**-22.71%**	**--**
33 - ACP Peatland Pocosin	17,408	31,215	33,918	132,722	17,508	31,404	34,753	141,613	-4.65%	0
34 -ACP Peatland Pocosin – Carolina Bay***	0	1,097	184	4,100	0	1,097	186	4,180	-1.52%	0
32 - ACP Northern Wet Longleaf Pine Savanna and Flatwoods	**1,038**	**3,225**	**18,033**	**167,845**	**954**	**3,279**	**16,897**	**176,424**	**-3.90%**	**0**
8 - ACP Southern Tidal Wooded Swamp	108	297	1,778	6,515	104	231	1,750	6,082	6.11%	+
42 - ACP Central Fresh-Oligohaline Tidal Marsh	0	65	270	4,382	0	67	301	4,383	-0.71%	0
26 - ACP Embayed Region Tidal Freshwater Marsh	34	66	78	1,638	35	56	81	2,293	-35.77%	--
2 - SCP Large Natural Lakeshore****	17	0	37	216	17	0	37	216	0.00%	0
35 - ACP Central Salt and Brackish Tidal Marsh	13	2,949	2,541	15,322	13	2,837	2,747	18,492	-15.67%	-
27- ACP Embayed Region Tidal Salt and Brackish Marsh	4,446	4,431	4,712	21,546	4,461	4,736	4,891	22,279	-3.51%	0

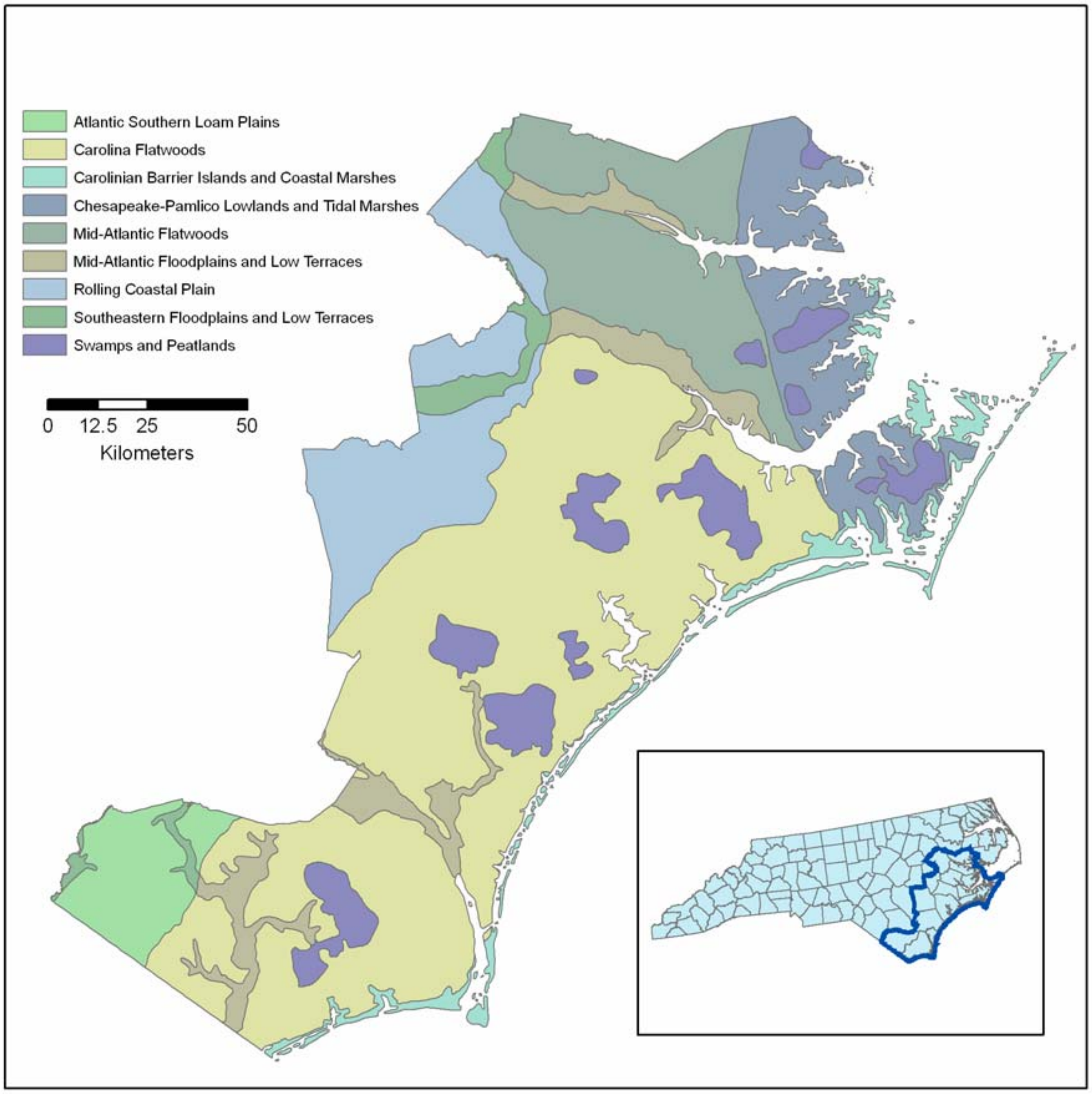


Figure 4.1. The Onslow Bight study area and Environmental Protection Agency Level IV ecoregions.

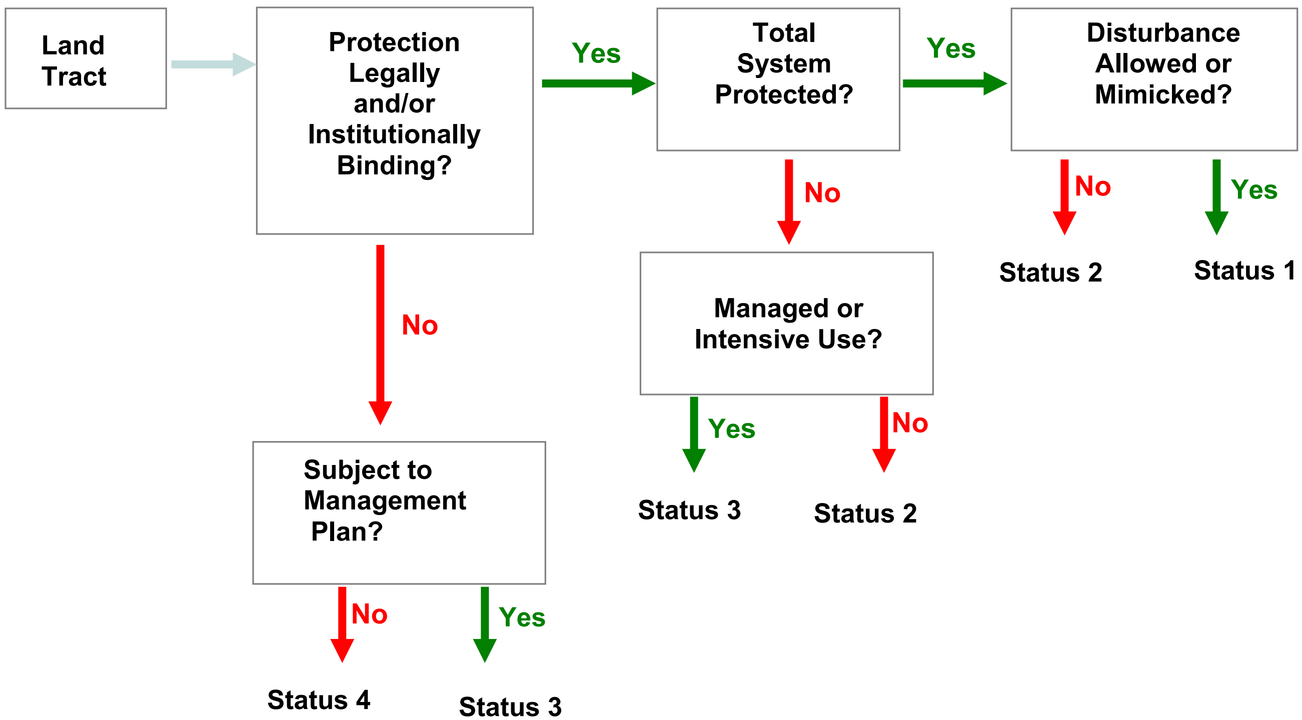
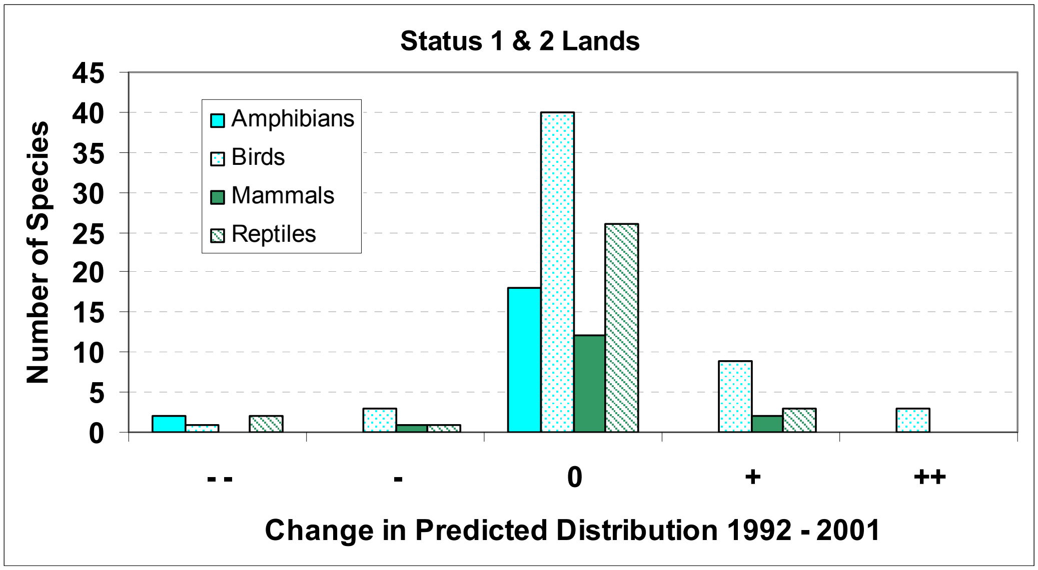


Figure 4.2. Dichotomous key used to determine the GAP Land Management Status.



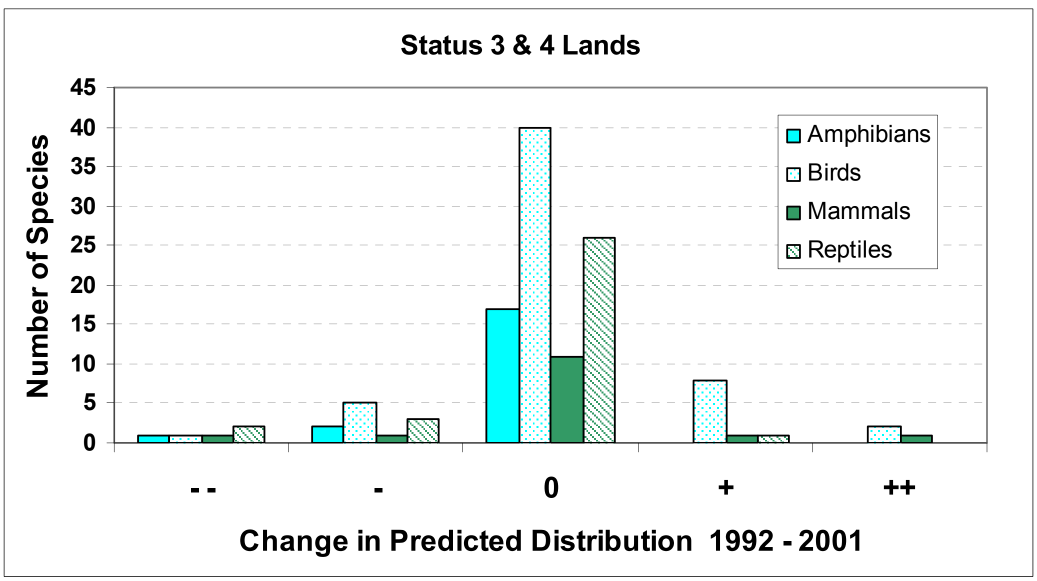
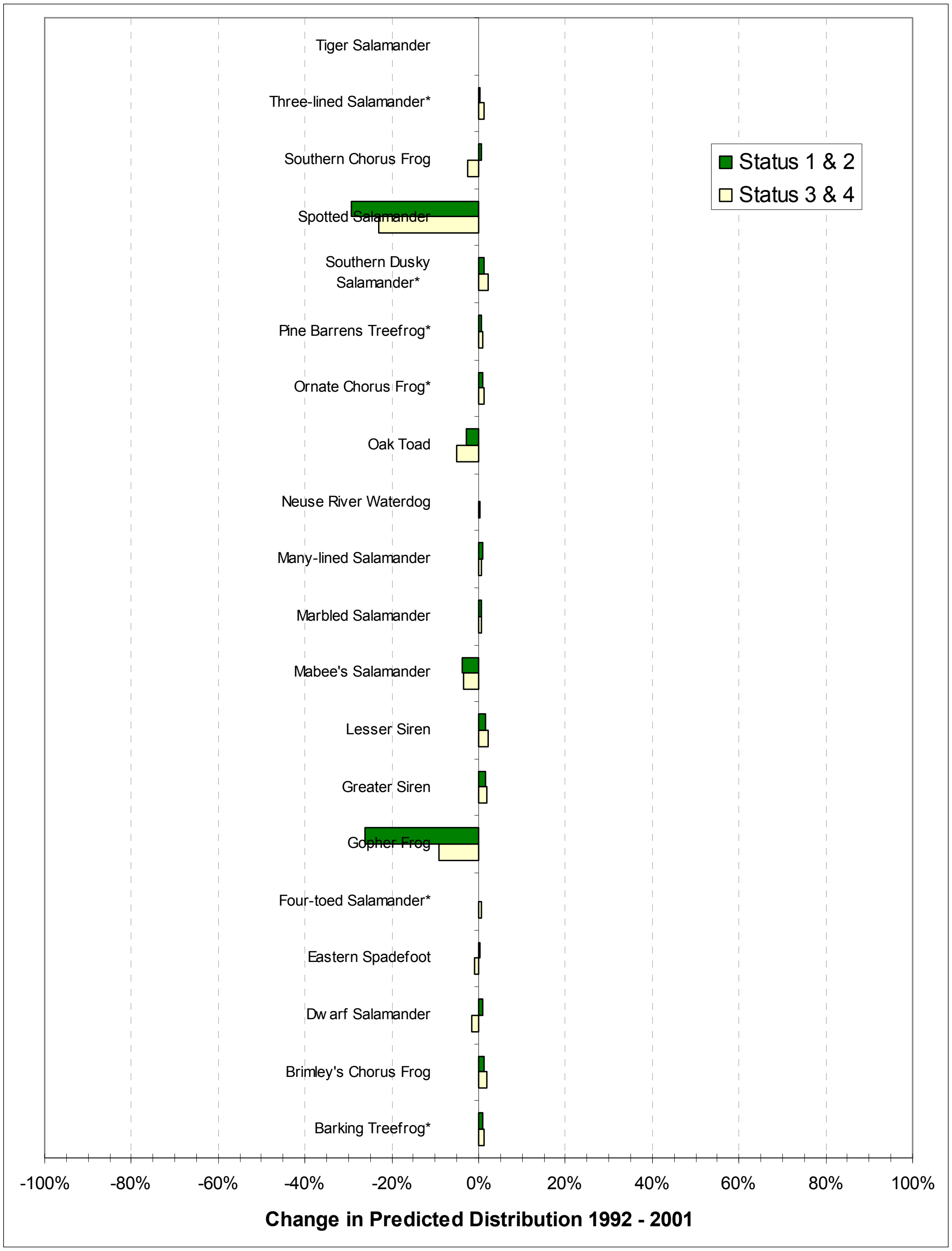
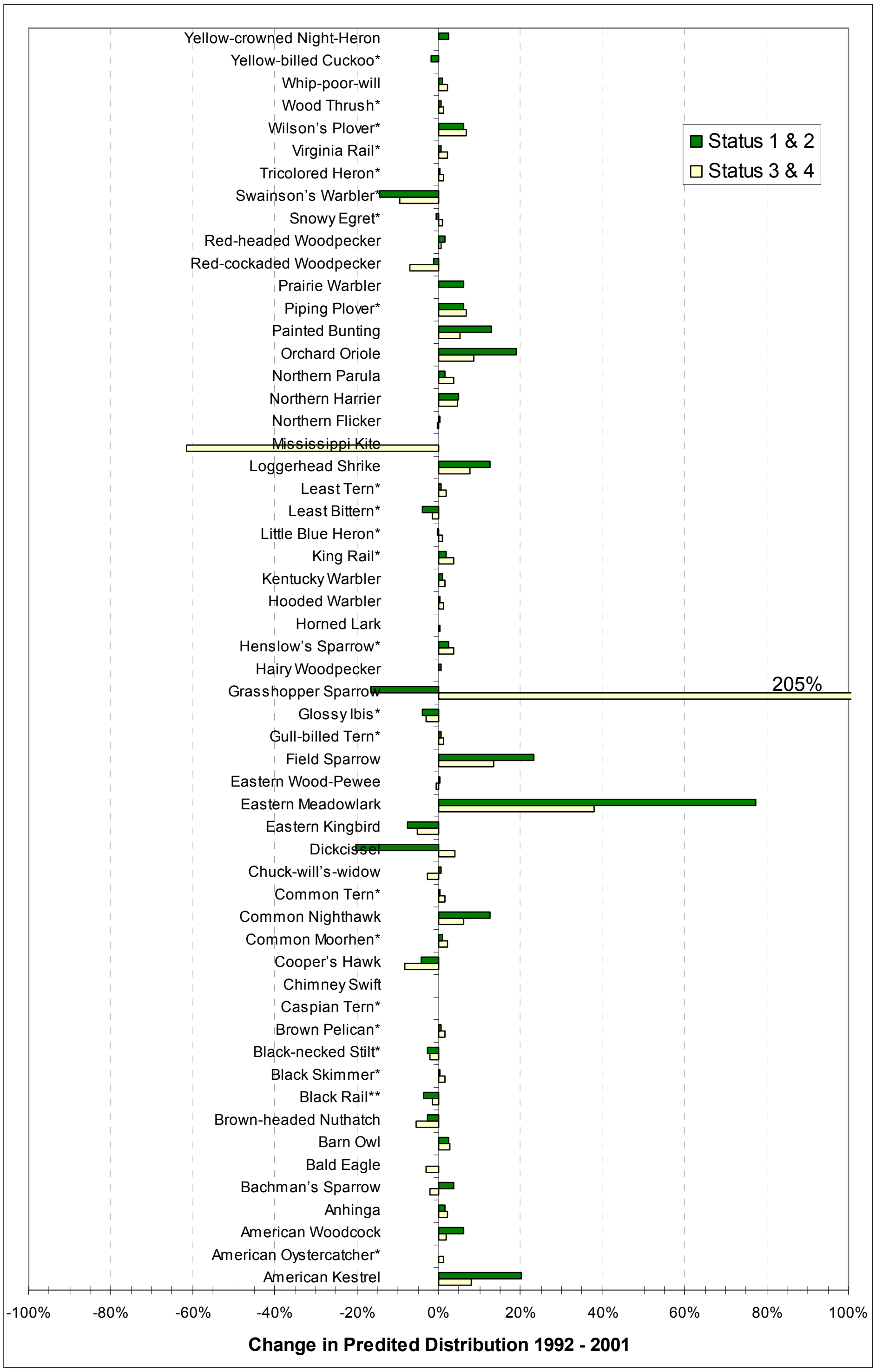


Figure 4.3 a and b. Scorecards for the State Wildlife Action Plan species on Status 1 and 2 lands (a) and on Status 3 and 4 lands (b). Graphs indicate the number of species with relative loss or gain in their predicted distribution between 1992 and 2001.



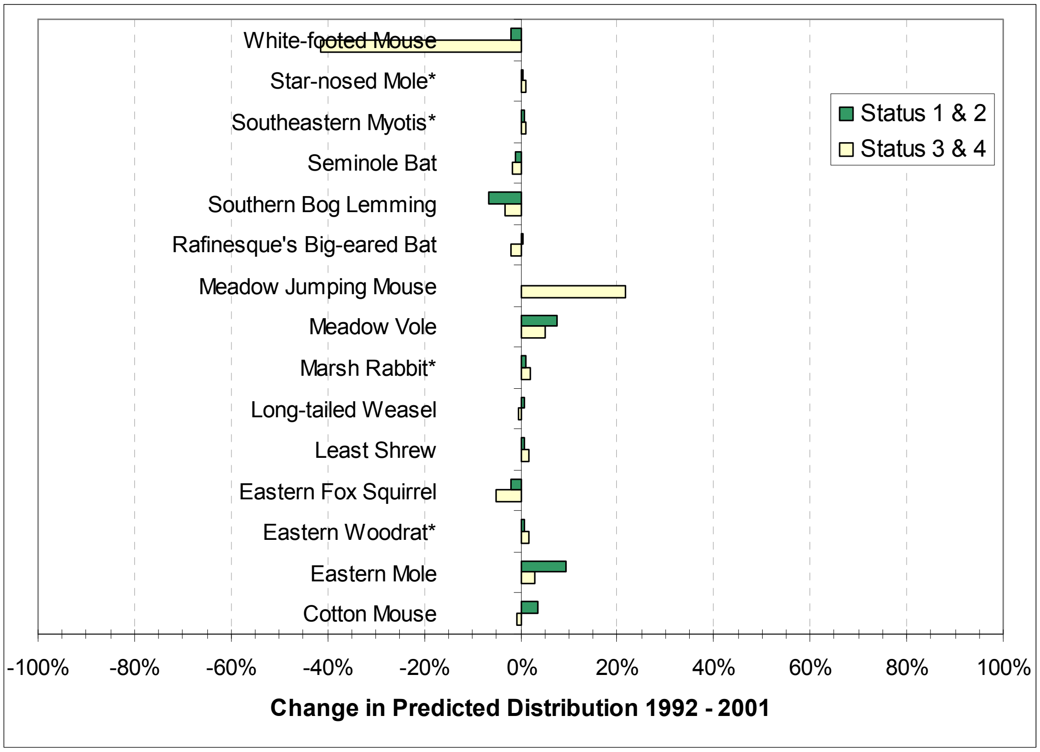
* indicates the species is NOT a gap species within the study area at a 10% threshold.

Figure 4.4. Changes in the predicted distributions for 20 amphibian species of concern in the North Carolina State Wildlife Plan.



* indicates the species is NOT a gap species within the study area at a 10% threshold.

Figure 4.5. Changes in the predicted distributions for 58 bird species of concern in the North Carolina Wildlife Action Plan.



* indicates the species is NOT a gap species within the study area at a 10% threshold.

Figure 4.6. Changes in the predicted distributions for 15 mammal species of concern in the North Carolina State Wildlife Plan.

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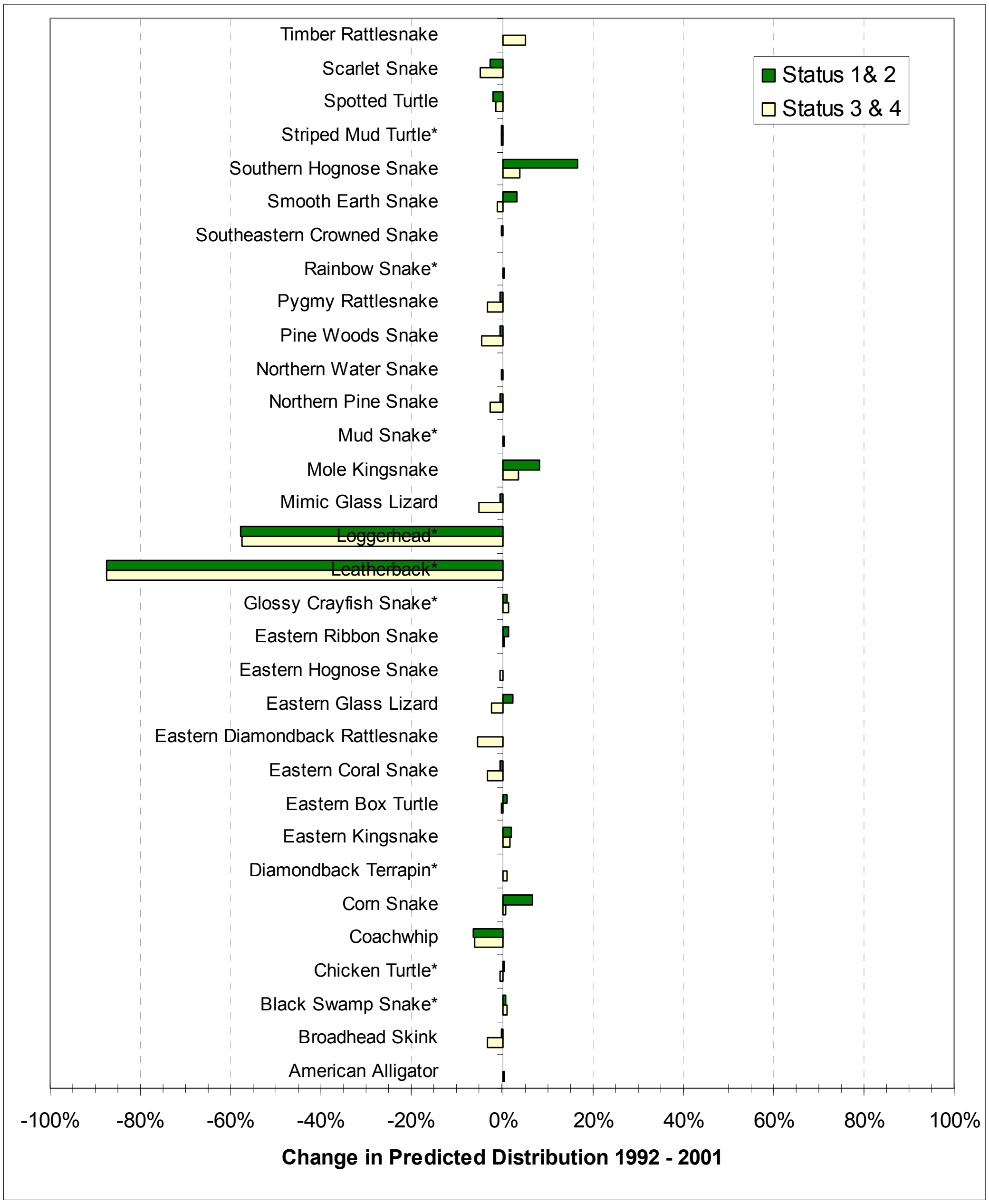


* indicates the species is NOT a gap species within the study area at a 10% threshold.

Figure 4.7. Changes in the predicted distributions for 32 reptilian species of concern in the North Carolina State Wildlife Plan.

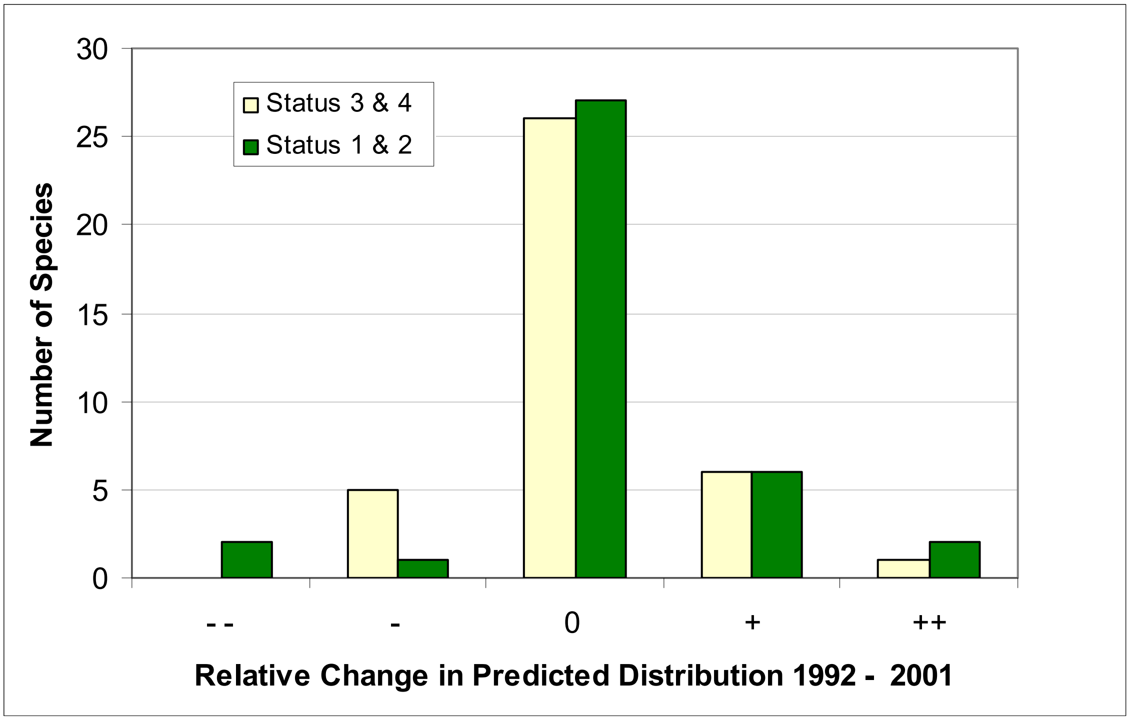
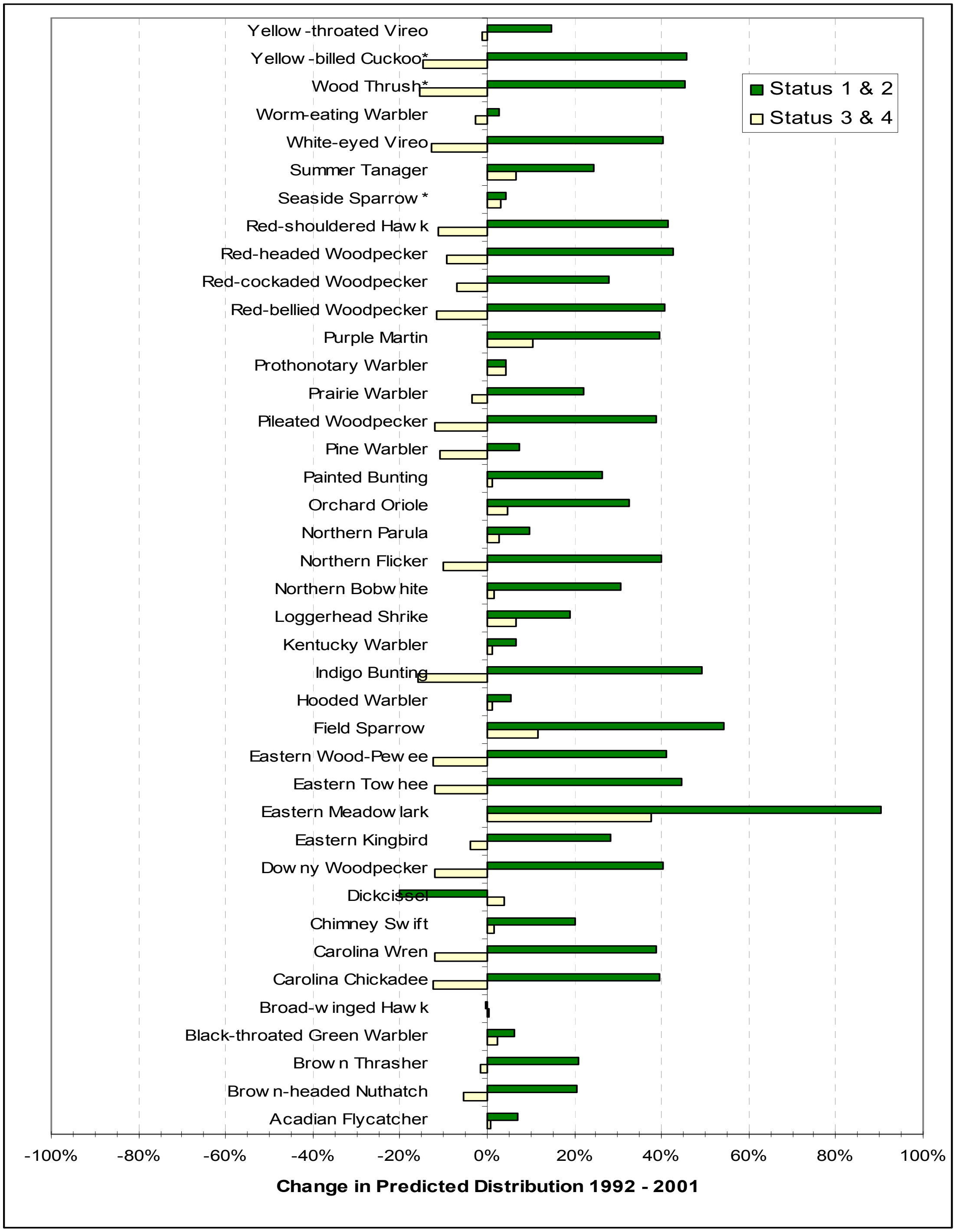
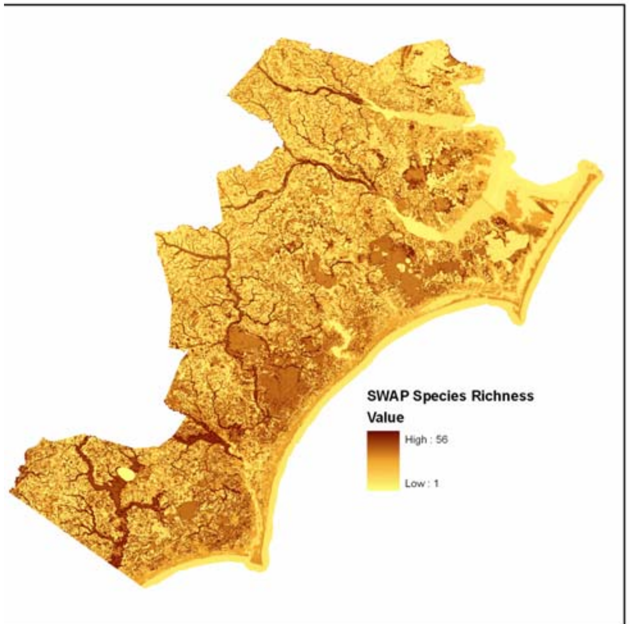


Figure 4.8. Score Card for Partners in Flight species of the Onslow Bight. Gains and loss of predicted habitat for thirty-eight priority bird species scored relative to 1992 extents.



* indicates a species is not a gap species in the Onslow Bight.

Figure 4.9. Changes in the predicted distributions for 38 Partners in Flight priority bird species.



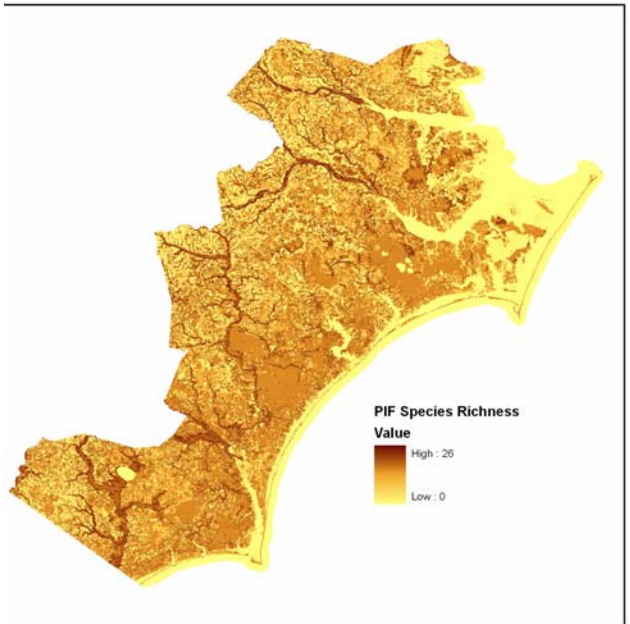


Figure 4.10. Species richness maps for the State Wildlife Action Plan and Partners in Flight priorities. A total of 125 species models were combined for the SWAP richness and 40 for the PIF richness maps.

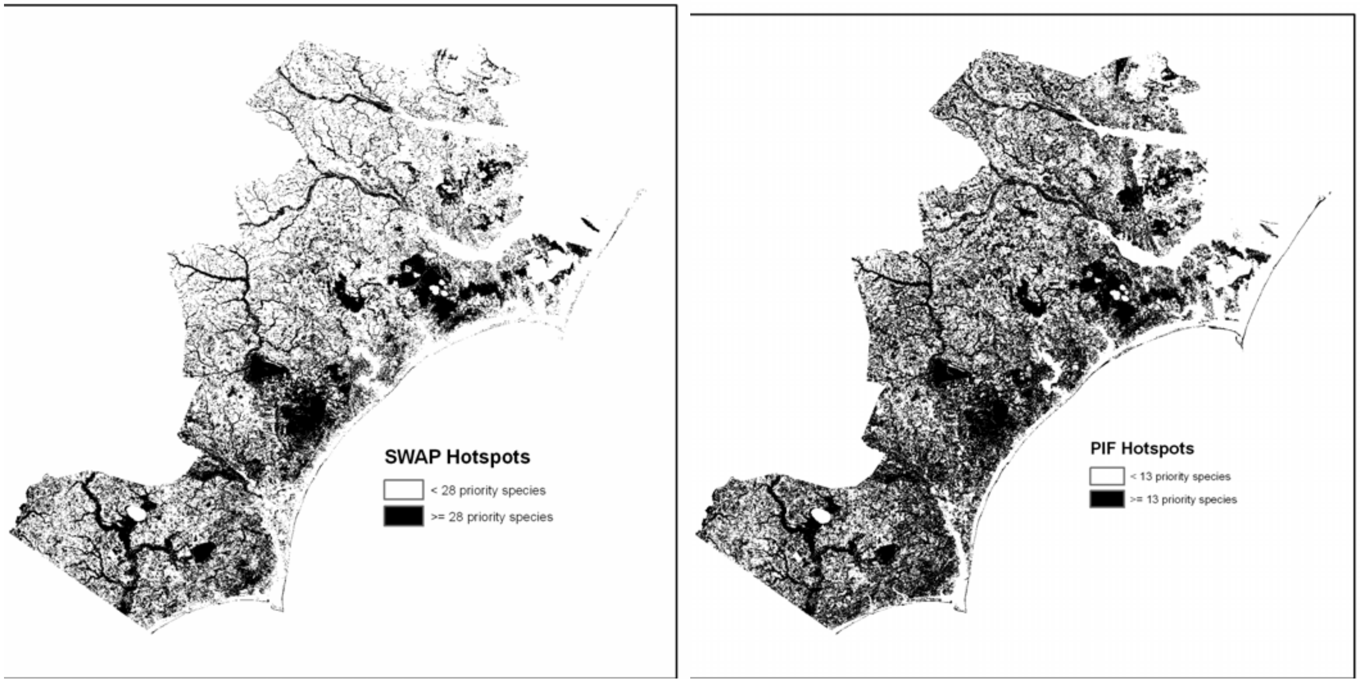


Figure 4.11. Priority species hotspots for the State Wildlife Action Plan and Partners in Flight. Thresholds of one half of the maximum species richness for any one site was used to define a hotspot (>28 species for SWAP and >13 for PIF)

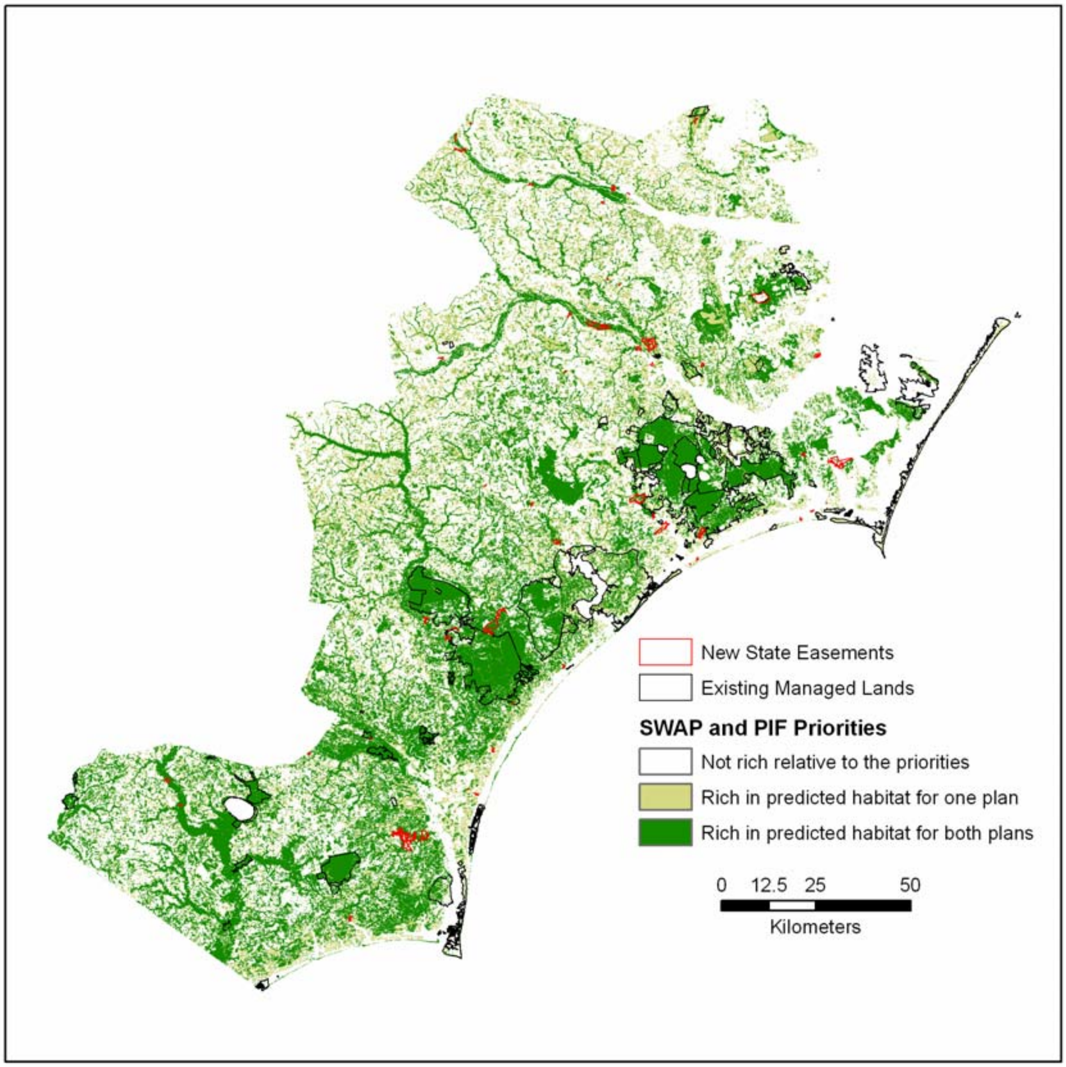


Figure 4.12. New state acquisitions relative to hot spots for SWAP and PIF priority species richness. Existing managed lands are outlined in black, state easement acquired after 1992 are outlined in red. Areas with zeros represent areas that had fewer than half of the priority species for either agency list predicted to occur. Areas with ones met the hotspot criteria for one agency, but not the other, and areas with twos represent hotspots for both agency lists.

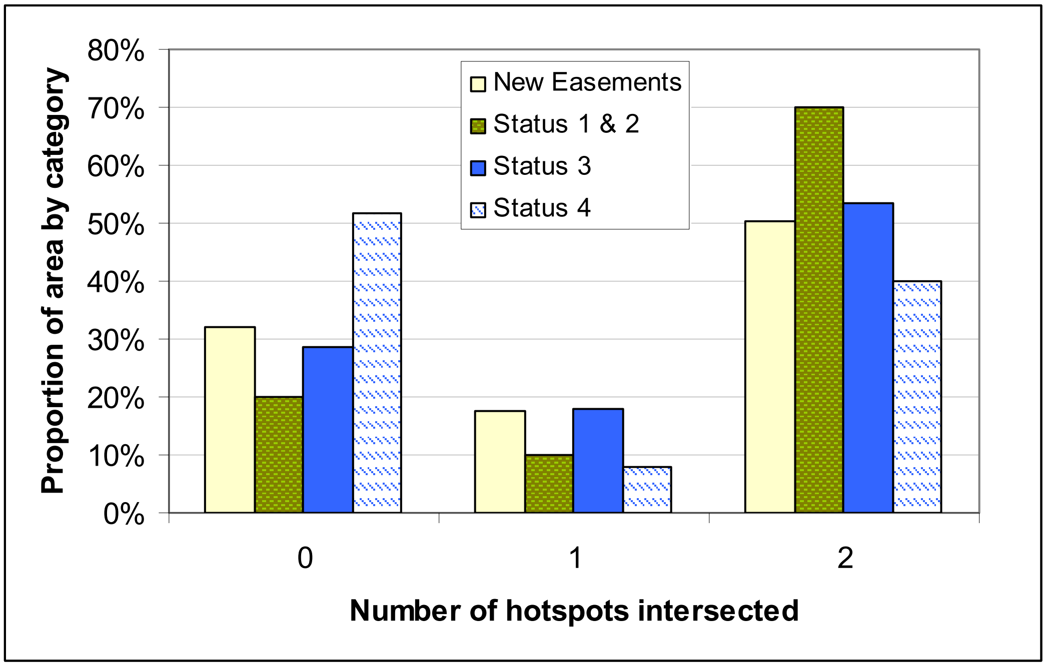


Figure 4.13 Distribution of managed land relative to predicted hotspots for the SWAP and PIF species lists. State easements acquired after 1992 compared with land management based on GAP Status. Proportions reported as a percent of the land area in that category (New easements) that intersect 0, 1, or 2 hotspots.

APPENDICES

Appendix 2.1. Accuracy Assessment Confusion Matrix for the Ecological Systems Map of the Onslow Bight. These point counts were used in combination with the mapped acreages to estimate accuracy using marginal frequencies.

	4	6	8	9	10	14	16	21	26	27	28	32	33	34	35	36	37	39	40	41	42	61	62	63	64	65	66	67	69	73	74	76	77	78	79	80	
4	6		2																1																		9
6	1	33	8		1		1	2					1																								47
8			7		1		1				1	1	2								1																14
9				15	4		1	1							1									1												1	24
10					1																																1
14			4		1	3	5													1	2			1													17
16		2	9				30												1		3													1			46
21			10	2		1	6	54				6									1											1					81
26			1						1																												2
27			1							33	1																										35
28			1								8				1																						10
32			5		1		2	5				75	3				4													2							97
33			8		2		2					4	73				1	1	1	1																	93
34								1					8	0																							9
35											7				42																						49
36											4					30																					34
37																	2																				2
39			1		1													4																			6
40			1										1		1			1	4																		8
41																				1																	1
42															1						7																8
61			1																	1	6	8	1														17
62											1				1	5							57														64
63				1				2																13													16
64																									10												10
65																										6											6
66																										1	5										6
67																												4									4
69																													4								4
73												1												2						42							45
74																															5						5
76								3									1															12		1		1	18
77																															1		5				6
78					1			1																3								2	2	77		5	91
79																												1	1						6		8
80				1			1	5				7	1				2				4			1	1									1		30	54
	7	35	59	19	13	4	49	74	1	33	22	94	89		47	35	10	6	7	4	24	8	58	21	11	7	5	5	5	44	6	15	7	80	6	37	947

Appendix 3.1 Land cover map units for the Onslow Bight area.

Code	Man Unit Name	Category
2	ACP Large Natural Lakeshore	wetland
4	ACP Large River Floodplain - Brownwater	wetland
6	ACP Large River Floodplain - Blackwater	wetland
8	ACP Southern Tidal Wooded Swamp	wetland
9	ACP Dry and Dry-Mesic Oak Forest	forest
10	ACP Mesic Hardwood and Mixed Forest	forest
11	ACP Clay-Based Carolina Bay Forested	forest
14	ACP Blackwater Stream Floodplain Forest	wetland
16	ACP Small Blackwater River Floodplain Forest	wetland
18	ACP Small Brownwater River Floodplain Forest	wetland
21	ACP Fall-line Sandhills Longleaf Pine Woodland - Open Understory	forest
26	ACP Embayed Region Tidal Freshwater Marsh	wetland
27	ACP Embayed Region Tidal Salt and Brackish Marsh	wetland
28	ACP Central Maritime Forest	forest
32	ACP Northern Wet Longleaf Pine Savanna and Flatwoods	forest
33	ACP Peatland Pocosin	wetland
34	ACP Peatland Pocosin – Carolina Bay	wetland
35	ACP Central Salt and Brackish Tidal Marsh	wetland
36	ACP Southern Dune and Maritime Grassland	barren
37	ACP Longleaf Pine Woodland	forest
39	ACP Nonriverine Swamp and Wet Hardwood Forest - Oak Dominated	wetland
40	ACP Nonriverine Swamp and Wet Hardwood Forest - Taxodium/Nyssa	wetland
41	ACP Nonriverine Swamp and Wet Hardwood Forest - Atlantic White Cedar	wetland
42	ACP Central Fresh-Oligohaline Tidal Marsh	wetland
61	Open Water (Fresh)	water
62	Open Water (Brackish/Salt)	water
63	Developed Open Space	urban
64	Low Intensity Developed	urban
65	Medium Intensity Developed	urban
66	High Intensity Developed	urban
67	Bare Sand	barren
68	Bare Soil	barren
69	Quarry/Strip Mine/Gravel Pit	mine
71	Unconsolidated Shore (Beach/Dune)	barren
73	Managed Pine	forest
74	Successional Shrub/Scrub (Clear Cut)	manage pine
76	Successional Shrub/Scrub (Other)	shrub
77	Pasture/Hay	agriculture
78	Row Crop	agriculture
79	Successional Herbaceous (Clear cut)	herbaceous
80	Other Herbaceous	herbaceous
90	ACP Large River Floodplain – Brownwater Herbaceous	wetland
91	ACP Large River Floodplain – Blackwater Herbaceous	wetland

Appendix 3.2. Complete change matrix for all 42 land cover classes 1992 – 2001.

To 2001	2	4	6	8	9	10	11	14	16	18
2	448.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	25122.4	0.0	0.0	0.7	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	32571.9	0.0	0.5	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	7728.8	4.9	0.0	0.0	0.7	0.0	0.0
9	0.0	0.0	0.0	6.8	115797.0	0.0	0.0	16.0	0.5	0.0
10	0.0	0.0	0.0	0.0	0.0	156.8	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	133.6	0.0	0.0	0.0
14	0.0	0.0	0.0	57.3	2.0	0.0	0.0	32704.8	2.2	0.0
16	0.0	0.0	0.0	0.0	1.9	0.0	0.0	0.5	54211.5	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	12.0
21	0.0	1.1	0.0	2.3	53.3	0.0	0.0	29.3	493.2	0.0
26	0.0	0.0	0.0	185.1	17.6	0.0	0.0	1.9	0.0	0.0
27	0.0	0.0	0.0	524.2	9.2	0.0	0.0	2.1	0.0	0.0
28	0.0	0.0	0.0	47.0	9.0	0.0	0.0	0.3	0.0	0.0
32	0.0	1.0	0.0	0.5	312.2	0.0	0.0	15.2	0.0	0.0
33	0.0	0.0	0.0	0.0	11.4	0.0	0.0	31.1	10.5	0.0
34	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.0	0.0
35	0.0	0.0	0.0	27.5	19.4	0.0	0.0	0.0	0.0	0.0
36	0.0	0.0	0.0	1.1	0.4	0.0	0.0	0.0	0.0	0.0
37	0.0	0.0	0.0	2.8	4.8	0.0	0.0	0.1	0.0	0.0
39	0.0	0.2	0.0	0.0	29.2	0.0	0.0	34.6	0.4	0.0
40	0.0	0.7	0.0	0.0	64.2	0.0	0.0	2.3	3.1	0.0
41	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42	0.0	0.0	0.0	35.8	0.8	0.0	0.0	0.0	0.0	0.0
61	0.0	59.5	61.1	2.1	132.8	0.0	0.0	0.5	0.0	0.0
62	0.0	0.0	0.0	20.3	0.5	0.0	0.0	0.0	0.0	0.0
63	0.0	0.0	0.0	0.0	318.8	0.0	0.0	0.0	0.0	0.0
64	0.0	0.0	0.0	0.0	122.7	0.0	0.0	0.0	0.0	0.0
65	0.0	0.0	0.0	0.0	37.5	0.0	0.0	0.0	0.0	0.0
66	0.0	0.0	0.0	0.0	6.4	0.0	0.0	0.0	0.0	0.0
67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
68	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
69	0.0	0.0	0.0	0.4	219.7	0.0	0.0	0.0	0.0	0.0
71	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
73	0.0	0.0	0.0	0.5	295.4	0.0	0.0	1.7	0.0	0.0
74	0.0	0.0	0.0	12.7	410.5	0.0	0.0	0.0	0.0	0.0
76	0.0	0.2	0.0	44.3	3510.2	0.0	0.0	3.6	1.0	0.0
77	0.0	0.0	0.0	0.0	77.4	0.0	0.0	0.0	0.0	0.0
78	0.0	0.0	0.0	0.1	1768.9	0.0	0.0	13.2	0.2	0.0
79	0.0	0.0	0.0	3.8	385.2	0.0	0.0	0.0	0.0	0.0
80	0.0	0.4	0.0	5.3	7882.2	0.0	0.0	16.7	2.7	0.0
90	0.0	145.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
91	0.0	0.0	154.4	0.0	0.5	0.0	0.0	0.0	0.0	0.0
1992	449	25,331	32,787	8,709	131,507	157	134	32,874	54,725	12
2001	449	50,661	65,575	17,417	263,014	314	267	65,749	109,450	24

Appendix 3.2 continued

To2001	21	26	27	28	32	33	34	35
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	9.2	0.0	0.0	0.0	0.1	0.1	0.0	0.0
6	0.8	0.0	0.0	0.0	0.0	0.1	0.0	0.0
8	55.8	0.0	0.0	5.5	156.7	12.7	0.0	0.0
9	35.6	0.0	0.6	2.1	127.7	83.7	0.2	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	30.3	0.0
14	5.9	0.0	0.0	0.0	784.7	15.8	0.0	0.0
16	8.3	0.0	0.0	0.0	6.0	2.5	0.0	0.0
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	104992.3	0.0	0.5	5.0	134.7	168.5	0.0	0.0
26	56.3	1793.2	0.2	0.0	135.5	20.0	0.0	0.0
27	49.5	0.0	35131.9	0.2	60.8	4.0	0.0	0.0
28	42.4	0.0	0.0	9723.1	20.5	1.4	0.0	0.0
32	84.2	0.0	0.3	2.3	167713.0	519.7	0.0	0.0
33	49.3	0.0	0.2	2.3	2278.9	203568.3	0.0	0.0
34	1.0	0.0	0.0	0.0	0.5	3.5	5338.0	0.0
35	33.6	0.0	0.0	104.7	25.9	4.2	0.0	18932.6
36	1.8	0.0	0.0	15.8	3.5	0.1	0.0	181.7
37	0.4	0.0	16.0	0.0	7.4	1.8	0.0	0.0
39	21.0	0.0	0.0	0.0	110.5	403.9	0.1	0.0
40	11.7	0.0	0.0	0.0	114.6	164.7	0.0	0.0
41	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42	11.6	0.0	0.0	1.2	6.1	1.4	0.0	0.0
61	70.1	110.3	0.0	0.6	58.1	31.7	0.0	0.0
62	12.0	0.0	0.0	5.4	9.3	4.3	0.0	10.0
63	636.5	0.0	0.0	0.0	623.3	215.6	0.0	0.0
64	493.6	0.0	0.0	0.0	295.4	165.2	0.0	0.0
65	96.7	0.0	0.0	0.0	74.8	42.1	0.0	0.0
66	19.4	0.0	0.0	0.0	23.9	4.8	0.0	0.0
67	0.0	0.0	0.0	10.6	0.0	0.0	0.0	0.0
68	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
69	169.0	0.0	0.0	1.9	100.0	12.2	0.0	1708.3
71	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
73	33.6	0.0	0.7	2.3	187.6	626.6	0.0	0.0
74	55.5	0.0	0.0	0.0	119.7	42.6	0.0	0.0
76	786.1	0.0	0.0	1.3	2663.6	427.1	0.2	0.0
77	13.5	0.0	0.0	2.3	41.8	4.8	0.0	0.0
78	1121.8	0.0	0.0	15.1	3321.5	445.9	0.0	0.0
79	417.2	0.0	0.0	116.6	313.3	216.4	0.0	15.8
80	6127.3	0.0	1.7	7.0	10698.2	8077.2	13.9	0.0
90	1.9	0.0	0.0	0.0	0.0	0.1	0.0	0.0
91	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total 1992	115,525	1,903	35,152	10,025	190,217	215,293	5,383	20,848
Total 2001	231,049	3,807	70,304	20,050	380,435	430,586	10,765	41,697

Appendix 3.2 continued

To2001	36	37	39	40	41	42	61	62	63
2	0.0	448.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	25122.4	0.0	0.0	0.7	0.0	0.0	0.0
6	0.0	0.0	0.0	32571.9	0.0	0.5	0.0	0.0	0.0
8	13.7	0.0	0.0	0.0	7728.8	4.9	0.0	0.0	0.7
9	0.3	0.0	0.0	0.0	6.8	115797.0	0.0	0.0	16.0
10	0.0	0.0	0.0	0.0	0.0	0.0	156.8	0.0	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	133.6	0.0
14	0.0	0.0	0.0	0.0	57.3	2.0	0.0	0.0	32704.8
16	0.0	0.0	0.0	0.0	0.0	1.9	0.0	0.0	0.5
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.1	0.0	1.1	0.0	2.3	53.3	0.0	0.0	29.3
26	3.2	0.0	0.0	0.0	185.1	17.6	0.0	0.0	1.9
27	20.2	0.0	0.0	0.0	524.2	9.2	0.0	0.0	2.1
28	0.0	0.0	0.0	0.0	47.0	9.0	0.0	0.0	0.3
32	0.0	0.0	1.0	0.0	0.5	312.2	0.0	0.0	15.2
33	0.0	0.0	0.0	0.0	0.0	11.4	0.0	0.0	31.1
34	0.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0	0.0
35	7.7	0.0	0.0	0.0	27.5	19.4	0.0	0.0	0.0
36	6173.0	0.0	0.0	0.0	1.1	0.4	0.0	0.0	0.0
37	0.5	0.0	0.0	0.0	2.8	4.8	0.0	0.0	0.1
39	0.0	0.0	0.2	0.0	0.0	29.2	0.0	0.0	34.6
40	0.0	0.0	0.7	0.0	0.0	64.2	0.0	0.0	2.3
41	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42	0.5	0.0	0.0	0.0	35.8	0.8	0.0	0.0	0.0
61	3.7	0.0	59.5	61.1	2.1	132.8	0.0	0.0	0.5
62	577.1	0.0	0.0	0.0	20.3	0.5	0.0	0.0	0.0
63	0.0	0.0	0.0	0.0	0.0	318.8	0.0	0.0	0.0
64	0.0	0.0	0.0	0.0	0.0	122.7	0.0	0.0	0.0
65	0.0	0.0	0.0	0.0	0.0	37.5	0.0	0.0	0.0
66	0.0	0.0	0.0	0.0	0.0	6.4	0.0	0.0	0.0
67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
68	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
69	0.0	0.0	0.0	0.0	0.4	219.7	0.0	0.0	0.0
71	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
73	0.3	0.0	0.0	0.0	0.5	295.4	0.0	0.0	1.7
74	0.0	0.0	0.0	0.0	12.7	410.5	0.0	0.0	0.0
76	0.5	0.0	0.2	0.0	44.3	3510.2	0.0	0.0	3.6
77	0.0	0.0	0.0	0.0	0.0	77.4	0.0	0.0	0.0
78	2.2	0.0	0.0	0.0	0.1	1768.9	0.0	0.0	13.2
79	0.1	0.0	0.0	0.0	3.8	385.2	0.0	0.0	0.0
80	0.9	0.0	0.4	0.0	5.3	7882.2	0.0	0.0	16.7
90	0.0	0.0	145.2	0.0	0.0	0.0	0.0	0.0	0.0
91	0.0	0.0	0.0	154.4	0.0	0.5	0.0	0.0	0.0
Total 1992	6,804	449	25,331	32,787	8,709	131,507	157	134	32,874
Total 2001	13,607	449	50,661	65,575	17,417	263,014	314	267	65,749

Appendix 3.2. continued

To2001	64	65	66	67	68	69	71	73	74	76
2	0.0	0.0	0.0	448.6	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	9.2	0.0	25122.4	0.0	0.0	0.7	0.0	0.0
6	0.0	0.0	0.8	0.0	0.0	32571.9	0.0	0.5	0.0	0.0
8	0.0	0.0	55.8	0.0	0.0	0.0	7728.8	4.9	0.0	0.0
9	0.5	0.0	35.6	0.0	0.0	0.0	6.8	115797.0	0.0	0.0
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	156.8	0.0
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	133.6
14	2.2	0.0	5.9	0.0	0.0	0.0	57.3	2.0	0.0	0.0
16	54211.5	0.0	8.3	0.0	0.0	0.0	0.0	1.9	0.0	0.0
18	0.0	12.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	493.2	0.0	104992.3	0.0	1.1	0.0	2.3	53.3	0.0	0.0
26	0.0	0.0	56.3	0.0	0.0	0.0	185.1	17.6	0.0	0.0
27	0.0	0.0	49.5	0.0	0.0	0.0	524.2	9.2	0.0	0.0
28	0.0	0.0	42.4	0.0	0.0	0.0	47.0	9.0	0.0	0.0
32	0.0	0.0	84.2	0.0	1.0	0.0	0.5	312.2	0.0	0.0
33	10.5	0.0	49.3	0.0	0.0	0.0	0.0	11.4	0.0	0.0
34	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.4	0.0	0.0
35	0.0	0.0	33.6	0.0	0.0	0.0	27.5	19.4	0.0	0.0
36	0.0	0.0	1.8	0.0	0.0	0.0	1.1	0.4	0.0	0.0
37	0.0	0.0	0.4	0.0	0.0	0.0	2.8	4.8	0.0	0.0
39	0.4	0.0	21.0	0.0	0.2	0.0	0.0	29.2	0.0	0.0
40	3.1	0.0	11.7	0.0	0.7	0.0	0.0	64.2	0.0	0.0
41	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
42	0.0	0.0	11.6	0.0	0.0	0.0	35.8	0.8	0.0	0.0
61	0.0	0.0	70.1	0.0	59.5	61.1	2.1	132.8	0.0	0.0
62	0.0	0.0	12.0	0.0	0.0	0.0	20.3	0.5	0.0	0.0
63	0.0	0.0	636.5	0.0	0.0	0.0	0.0	318.8	0.0	0.0
64	0.0	0.0	493.6	0.0	0.0	0.0	0.0	122.7	0.0	0.0
65	0.0	0.0	96.7	0.0	0.0	0.0	0.0	37.5	0.0	0.0
66	0.0	0.0	19.4	0.0	0.0	0.0	0.0	6.4	0.0	0.0
67	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
68	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
69	0.0	0.0	169.0	0.0	0.0	0.0	0.4	219.7	0.0	0.0
71	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
73	0.0	0.0	33.6	0.0	0.0	0.0	0.5	295.4	0.0	0.0
74	0.0	0.0	55.5	0.0	0.0	0.0	12.7	410.5	0.0	0.0
76	1.0	0.0	786.1	0.0	0.2	0.0	44.3	3510.2	0.0	0.0
77	0.0	0.0	13.5	0.0	0.0	0.0	0.0	77.4	0.0	0.0
78	0.2	0.0	1121.8	0.0	0.0	0.0	0.1	1768.9	0.0	0.0
79	0.0	0.0	417.2	0.0	0.0	0.0	3.8	385.2	0.0	0.0
80	2.7	0.0	6127.3	0.0	0.4	0.0	5.3	7882.2	0.0	0.0
90	0.0	0.0	1.9	0.0	145.2	0.0	0.0	0.0	0.0	0.0
91	0.0	0.0	0.0	0.0	0.0	154.4	0.0	0.5	0.0	0.0
Total 1992	54,725	12	115,525	449	25,331	32,787	8,709	131,507	157	134
Total 2001	109,450	24	231,049	449	50,661	65,575	17,417	263,014	314	267

Appendix 3.2. continued

To2001	77	78	79	80	90	91	Total 2001
2	0.0	0.0	0.0	0.0	0.0	0.0	449
4	0.2	0.9	333.6	0.5	0.0	0.0	25,468
6	1.3	4.5	1.4	1.0	0.0	0.0	32,783
8	2.8	2.3	6.9	49.5	0.0	0.0	8,167
9	58.1	1571.4	2723.7	2099.3	0.0	0.0	135,542
10	0.2	0.0	0.0	0.0	0.0	0.0	157
11	0.0	0.0	0.0	0.0	0.0	0.0	164
14	3.8	37.0	511.7	208.5	0.0	0.0	34,743
16	2.2	9.0	1426.4	14.2	0.0	0.0	56,433
18	0.0	0.0	0.0	0.0	0.0	0.0	12
21	24.1	79.5	408.4	2135.3	0.0	0.0	109,668
26	0.3	1.8	25.7	2.3	0.0	0.0	2,471
27	7.9	1.1	0.6	1.1	0.0	0.0	36,386
28	0.4	0.0	31.2	114.3	0.0	0.0	10,129
32	43.6	199.4	9976.1	3361.7	0.0	0.0	197,593
33	11.0	64.4	11386.0	725.1	0.0	0.0	225,295
34	0.0	0.0	98.5	12.2	0.0	0.0	5,464
35	0.5	41.3	1.7	5.1	0.0	0.0	19,699
36	0.0	0.0	0.0	6.1	0.0	0.0	7,306
37	0.4	11.8	572.0	436.6	0.0	0.0	12,954
39	43.2	204.3	2614.6	103.4	0.0	0.0	37,072
40	5.8	67.3	2482.7	95.9	0.0	0.0	36,649
41	0.0	0.0	0.0	0.0	0.0	0.0	30
42	0.0	1.0	0.2	0.3	0.0	0.0	4,759
61	0.7	442.2	39.4	35.6	0.0	0.0	18,426
62	0.2	1.8	0.2	0.8	0.0	0.0	333,645
63	0.0	0.0	0.0	0.0	0.0	0.0	100,640
64	0.0	0.0	0.0	0.0	0.0	0.0	41,342
65	0.0	0.0	0.0	0.0	0.0	0.0	10,559
66	0.0	0.0	0.0	0.0	0.0	0.0	2,750
67	0.0	0.0	0.0	5.6	0.0	0.0	53
68	0.0	0.0	0.0	0.0	0.0	0.0	3
69	10.8	409.8	0.0	202.3	0.0	0.0	4,652
71	0.0	0.0	0.0	0.0	0.0	0.0	0
73	35.7	797.9	21921.8	251.3	0.0	0.0	243,391
74	0.0	0.0	69.1	9.3	0.0	0.0	3,897
76	17.9	509.9	2921.8	1309.4	0.0	0.0	65,404
77	12967.0	2076.8	6.1	7.9	0.0	0.0	15,423
78	25904.1	420982.0	182.1	917.6	0.0	0.0	471,263
79	2.7	3.5	2337.8	0.0	0.0	0.0	4,862
80	1589.9	3985.6	367.2	115942.2	0.0	0.0	200,954
90	0.0	0.0	0.0	0.0	118.8	0.0	270
91	0.1	0.7	0.0	0.0	0.0	142.0	308
Total 1992	40,735	431,507	60,447	128,055	119	142	
Total 2001	81,469	863,014	120,894	256,109	238	284	

Appendix 4.1. Model parameters specific to the species distribution models in this study.

strSppSeas	HdMd	XFlW	FFlW	IFlW	XOpW	FOpW	IOpW	XWtV	FWtV	IWtV	Sali	StVe	FaMn	FaMx	EdTy	EdWd	XIFor	IFBu	XCPc	SCPc	ICPc	FCPc	XNPc	PNPc	SNPc	Avod	ElMn	ElMx	LClf	AxBf
BABATR	n	n	0	0	Y	120	60	Y	0	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BABCFR	n	Y	30	30	Y	30	30	Y	30	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	30
BADWSA	n	n	0	0	Y	30	0	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAEASP	n	Y	250	30	Y	250	30	n	250	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAFOSA	n	Y	30	0	Y	30	0	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAGOFR	n	n	0	0	Y	500	0	n	0	0	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAGRSI	n	Y	X	30	Y	0	30	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BALESI	n	Y	0	30	Y	0	30	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAMASA	n	n	0	0	Y	250	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAMBSA	n	n	0	0	n	0	0	Y	250	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAMLSA	n	Y	60	0	Y	60	0	n	0	0	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BANRWA	n	Y	30	X	n	0	0	n	0	0	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAOATO	n	n	0	0	Y	X	30	n	0	0	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAOCFR	n	n	0	0	Y	60	30	Y	0	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BAPBTR	n	Y	60	0	Y	60	0	Y	60	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BASDSA	n	Y	60	0	Y	60	0	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BASPSA	n	n	0	0	Y	250	0	Y	250	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BASRFR	n	n	0	0	Y	30	30	Y	30	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BATHSA	n	Y	60	0	Y	60	0	Y	60	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	1000	n	0
BATISA	n	n	0	0	Y	250	0	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	3350	n	0
BBAMBI	n	Y	500	30	Y	500	30	Y	500	120	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBAMKE	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	13	0	0	n	0	0	‘-	0	0	n	60
BBAMOY	n	Y	X	30	Y	X	30	Y	0	X	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBAMWO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	E	250	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBANHI	n	Y	250	1000	Y	250	1000	Y	250	1000	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBBACS	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	3	0	0	n	0	0	‘-	0	0	n	0
BBBAEA	n	Y	500	X	Y	500	X	n	0	0	W	V	0	0	NE	0	AFI	120	Y	10	0	1000	n	0	0	M	0	0	n	0

Appendix 4.1 continued.

BBBANO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	100	0	0	n	0	0	‘-	0	0	n	60
BBBHNU	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	762	n	0
BBBLRA	n	n	0	0	Y	250	0	Y	250	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBBLSK	n	n	0	0	Y	X	500	Y	0	X	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBBNST	n	n	0	0	Y	250	60	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBBRPE	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBBTNW	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	100	0	0	n	0	0	‘-	0	0	n	0
BBCATE	n	n	0	0	Y	X	250	Y	0	X	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBCHSW	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	M	0	0	n	0
BBCOHA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	120
BBCOMO	n	n	0	0	Y	120	60	Y	120	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBCONI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBCOTE	n	n	0	0	Y	X	1000	n	0	0	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBCWWI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	500	not	0	n	0	0	0	n	0	0	‘-	-47	518	n	0
BBDICK	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	10	0	0	n	0	0	‘-	0	0	n	0
BBEAKI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	E	250	not	0	n	0	0	0	n	0	0	‘-	-47	914	n	0
BBEAME	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	6	0	0	n	0	0	‘-	-47	1219	n	60
BBEAWP	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	1371	n	0
BBFISP	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	2	0	0	n	0	0	M	0	0	n	30
BBGBTE	Y	n	0	0	Y	500	500	Y	0	X	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBGLIB	n	Y	120	30	Y	120	30	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBGRSP	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	50	0	0	n	0	0	H	0	0	n	0
BBHAWO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	2	0	0	n	0	0	‘-	0	0	n	0
BBHESP	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	30	0	0	n	0	0	‘-	0	0	n	0
BBHOLA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBHOWA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	15	0	0	n	0	0	‘-	-47	1200	n	0
BBKEWA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	17	0	0	n	0	0	‘-	-47	1150	2346791011	0
BBKIRA	n	n	0	0	Y	250	0	Y	250	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBLBHE	n	Y	X	30	Y	X	30	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBLEBI	n	Y	500	30	Y	500	30	Y	500	120	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBLETE	n	Y	X	250	Y	X	250	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	250
BBLOSH	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	52	0	0	n	0	0	‘-	-47	600	n	0

Appendix 4.1 continued.

BBMIKI	n	Y	1000	0	Y	1000	0	Y	1000	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBNOBO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	8	0	0	n	0	0	M	-47	975	n	0
BBNOFL	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	500	n	0	0	0	n	0	0	‘-	-47	1219	n	0
BBNOHA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBOROR	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	60	n	0	0	0	n	0	0	‘-	-47	762	n	0
BBPABU	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	500	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBPIPL	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBPRAW	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	60	not	0	n	0	0	0	n	0	0	‘-	-47	1220	n	0
BBRCWO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	40	0	0	n	0	0	‘-	0	0	n	0
BBRHWO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	1000	not	0	n	0	0	0	n	0	0	‘-	-47	762	n	0
BBSNEG	n	Y	X	30	Y	X	30	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBSWWA	n	Y	250	0	Y	250	0	Y	250	X	W	V	0	0	NE	0	not	0	Y	350	0	0	n	0	0	‘-	-47	1200	78101112	0
BBTRHE	n	Y	X	30	Y	X	30	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBVIRA	Y	n	0	0	Y	250	0	Y	250	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBWEWA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	21	0	0	n	0	0	‘-	0	0	2346711	0
BBWIPL	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BBWOTH	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	1	0	0	n	0	0	‘-	-47	1325	n	0
BBWPWI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	250	n	0	0	0	n	0	0	‘-	240	1219	n	0
BBYBCU	n	n	0	0	Y	120	0	Y	120	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	1066	n	0
BBYCNH	n	Y	500	30	Y	500	30	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMCOMO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	-47	600	n	0
BMEAMO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMEAWO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMEFSQ	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	30
BMLESH	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMLOWE	n	Y	500	0	Y	500	0	Y	0	X	W	V	0	0	ESW	250	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMMARA	n	n	0	0	Y	120	0	Y	120	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	M	0	0	n	0
BMMEVO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMMJMO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMRBBA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMSBLE	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	79101112	0
BMSEBA	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	1000
BMSOMY	n	Y	500	0	Y	500	0	Y	0	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0

Appendix 4.1 continued.

BMSTMO	n	Y	30	0	Y	30	0	Y	30	X	FW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BMWHMO	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	120	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRAMAL	n	n	0	0	n	0	0	n	0	0	W	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	M	0	0	n	0
BRBRSK	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRBSSN	n	Y	30	120	Y	30	120	Y	0	X	W	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRCHTU	n	Y	200	0	Y	250	30	Y	250	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRCOAC	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	250
BRCOSN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	500
BRDITE	n	Y	150	X	Y	120	X	Y	0	X	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BREAKI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	250	n	0	0	0	n	0	0	‘-	0	0	n	0
BREBTU	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	250	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRECSN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BREDRA	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	Y	45	0	0	n	0	0	‘-	0	0	n	120
BREGLI	n	Y	30	0	Y	30	0	Y	60	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BREHSN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	500	n	0	0	0	n	0	0	‘-	0	0	n	0
BREISN	n	Y	120	60	Y	120	60	Y	60	60	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BREPSO	n	Y	60	X	Y	60	60	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRGRSN	n	Y	60	60	Y	60	60	Y	0	X	FW	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRGRTU	n	n	0	0	n	0	0	n	0	0	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRLEAT	n	n	0	0	n	0	0	n	0	0	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRLOGG	n	n	0	0	n	0	0	n	0	0	BW	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRMGLI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRMOKI	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRMUSN	n	Y	60	0	Y	60	0	Y	0	X	W	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRNOPS	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRNWSN	n	Y	30	120	Y	30	120	Y	30	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRPISN	Y	n	0	0	n	0	0	Y	250	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRPYRA	n	Y	2000	0	Y	2000	0	Y	2000	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRRASN	n	Y	60	120	Y	60	60	Y	60	X	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRSCWS	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	AFI	250	n	0	0	0	n	0	0	‘-	0	0	234567	0
BRSESN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	ESW	500	not	0	n	0	0	0	n	0	0	‘-	-47	610	n	0
BRSHSN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRSMTU	Y	Y	120	60	Y	120	60	Y	120	X	W	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRSPTU	n	Y	250	60	Y	250	60	Y	250	X	W	SV	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRSRSN	n	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	n	0
BRTIRA	Y	n	0	0	n	0	0	n	0	0	W	V	0	0	NE	0	not	0	n	0	0	0	n	0	0	‘-	0	0	1234567	200

Appendix 4.2. North Carolina State Wildlife Action Plan species used to develop the Onslow Bight scorecard. Criteria for inclusion in the SWAP include State and Federal Status and Rank, state level Partners in Flight priorities (PIF), negative population trends (NT), and lack of knowledge (KD; NCWRC 2005).

Taxon	Scientific Name	Common Name	Status	Rank	PIF	NT	KD
AMPHIBIAN	*Ambystoma mabeei*	Mabee's Salamander	SR	S3,G4		X	
AMPHIBIAN	*Ambystoma maculatum*	Spotted Salamander				X	
AMPHIBIAN	*Ambystoma opacum*	Marbled Salamander				X	
AMPHIBIAN	*Ambystoma tigrinum*	Tiger Salamander	T	S2,G5		X	
AMPHIBIAN	*Bufo quercicus*	Oak Toad	SR	S3,G5			
AMPHIBIAN	*Desmognathus auriculatus*	Southern Dusky Salamander					X
AMPHIBIAN	*Eurycea guttolineata*	Three-lined Salamander					
AMPHIBIAN	*Eurycea quadridigitata*	Dwarf Salamander	SC	S2,G5T2Q		X	
AMPHIBIAN	*Hemidactylium scutatum*	Four-toed Salamander	SC			X	X
AMPHIBIAN	*Hyla andersonii*	Pine Barrens Treefrog		S3,S4,G4		X	
AMPHIBIAN	*Hyla gratiosa*	Barking Treefrog				X	
AMPHIBIAN	*Necturus lewisi*	Neuse River Waterdog	SC	S3,G3		X	
AMPHIBIAN	*Pseudacris brimleyi*	Brimley's Chorus Frog		S3,S4,G5		X	X
AMPHIBIAN	*Pseudacris nigrita*	Southern Chorus Frog				X	
AMPHIBIAN	*Pseudacris ornata*	Ornate Chorus Frog	SR	S3,G5		X	
AMPHIBIAN	*Rana capito*	Gopher Frog	T	S2,G3		X	
AMPHIBIAN	*Scaphiopus holbrookii*	Eastern Spadefoot				X	
AMPHIBIAN	*Siren intermedia*	Lesser Siren				X	X
AMPHIBIAN	*Siren lacertina*	Greater Siren					X
AMPHIBIAN	*Stereochilus marginatus*	Many-lined Salamander					
AVIAN	*Accipiter cooperii*	Cooper’s Hawk	SC	S3,S4B,S4N,G5	X	X	X
AVIAN	*Aimophila aestivalis*	Bachman’s Sparrow	SC	S3B,S2N,G3	X	X	
AVIAN	*Ammodramus henslowii*	Henslow’s Sparrow	SR	S3B,S1N,G4	X	X	X
AVIAN	*Ammodramus savannarum*	Grasshopper Sparrow		S3B,S1N,G5	X	X	
AVIAN	*Anhinga anhinga*	Anhinga	SR	S2B,G5			
AVIAN	*Botaurus lentiginosus*	American Bittern	SR	S1B,S3N,G4	X	X	X
AVIAN	*Caprimulgus carolinensis*	Chuck-will’s-widow			X	X	
AVIAN	*Caprimulgus vociferus*	Whip-poor-will			X	X	
AVIAN	*Chaetura pelagica*	Chimney Swift*			X	X	
AVIAN	*Charadrius melodus*	Piping Plover	T (T)	S2B,S2N,G3	X	X	
AVIAN	*Charadrius wilsonia*	Wilson’s Plover	SR	S3B,SZN,G5	X	X	
AVIAN	*Chordeiles minor*	Common Nighthawk				X	
AVIAN	*Circus cyaneus*	Northern Harrier	SR	S1B,S4N,G5	X	X	
AVIAN	*Coccyzus americanus*	Yellow-billed Cuckoo*				X	
AVIAN	*Colaptes auratus*	Northern Flicker*			X	X	
AVIAN	*Colinus virginianus*	Northern Bobwhite*			X	X	
AVIAN	*Contopus virens*	Eastern Wood-Pewee*			X	X	

Appendix 4.2 continued.

AVIAN	*Dendroica discolor*	Prairie Warbler*			X	X	
AVIAN	*Egretta caerulea*	Little Blue Heron	SC	S3B,S3N,G5	X	X	
AVIAN	*Egretta thula*	Snowy Egret	SC	S3B,S3N,G5	X	X	
AVIAN	*Egretta tricolor*	Tricolored Heron	SC	S3B,S3N,G5	X	X	
AVIAN	*Eremophila alpestris*	Horned Lark			X	X	X
AVIAN	*Falco sparverius*	American Kestrel		S3B,S5N,G5	X		
AVIAN	*Gallinula chloropus*	Common Moorhen			X		X
AVIAN	*Haematopus palliatus*	American Oystercatcher		S3B,S4N,G5	X	X	
AVIAN	*Haliaeetus leucocephalus*	Bald Eagle	T (T)	S3B,S3N,G4	X	X	
AVIAN	*Himantopus mexicanus*	Black-necked Stilt	SR	S2B,G5		X	
AVIAN	*Hylocichla mustelina*	Wood Thrush*			X	X	
AVIAN	*Icterus spurius*	Orchard Oriole*			X	X	
AVIAN	*Ictinia mississippiensis*	Mississippi Kite	SR	S2B,G5	X		
AVIAN	*Ixobrychus exilis*	Least Bittern		SZN,G5	X	X	X
AVIAN	*Lanius ludovicianus*	Loggerhead Shrike*	SC	S3B,G4T4	X	X	
AVIAN	*Laterallus jamaicensis*	Black Rail	SR	S3B,S2N,G4	X	X	X
AVIAN	*Limnothlypis swainsonii*	Swainson's Warbler		S3B,SZN,G4	X	X	
AVIAN	*Melanerpes erythrocephalus*	Red-headed Woodpecker*			X	X	
AVIAN	*Nyctanassa violacea*	Yellow-crowned Night-Heron		S3B,SZN,G5	X		X
AVIAN	*Oporornis formosus*	Kentucky Warbler*			X	X	
AVIAN	*Passerina ciris*	Painted Bunting*	SR	S3V,SZN,G4	X	X	
AVIAN	*Pelecanus occidentalis*	Brown Pelican	SR	S3B,S4N,G4	X		
AVIAN	*Picoides borealis*	Red-cockaded Woodpecker*	E (E)	S2,G3	X	X	
AVIAN	*Picoides villosus*	Hairy Woodpecker					X
AVIAN	*Plegadis falcinellus*	Glossy Ibis	SC	S2B,SZN,G5	X	X	
AVIAN	*Rallus elegans*	King Rail		S3B,S2N,G4G5	X	X	X
AVIAN	*Rallus limicola*	Virginia Rail			X		X
AVIAN	*Rynchops niger*	Black Skimmer	SC	S3B,S3N,G5	X	X	
AVIAN	*Scolopax minor*	American Woodcock			X	X	
AVIAN	*Sitta pusilla*	Brown-headed Nuthatch*			X	X	
AVIAN	*Spiza americana*	Dickcissel*		S2B,SZN,G5	X	X	X
AVIAN	*Spizella pusilla*	Field Sparrow*			X	X	
AVIAN	*Sterna antillarum*	Least Tern	SC	S3B,SZN,G4	X	X	
AVIAN	*Sterna caspia*	Caspian Tern	SR	S1B,S2N,G5		X	
AVIAN	*Sterna hirundo*	Common Tern	SC	S3B,SZN,G5	X	X	
AVIAN	*Sterna nilotica*	Gull-billed Tern	T	S3B,SZN,G5	X	X	
AVIAN	*Sturnella magna*	Eastern Meadowlark*			X	X	
AVIAN	*Tyrannus tyrannus*	Eastern Kingbird*			X	X	
AVIAN	*Tyto alba*	Barn Owl		S3B,S3N,G5	X	X	
AVIAN	*Wilsonia citrina*	Hooded Warbler*			X		

Appendix 4.2 continued.

MAMMAL	*Condylura cristata*	Star-nosed Mole	SC	S2,G5,T2Q			X
MAMMAL	*Corynorhinus rafinesquii*	Rafinesque's Big-eared Bat	T	S3,G3,G4		X	
MAMMAL	*Cryptotis parva*	Least Shrew					X
MAMMAL	*Lasiurus seminolus*	Seminole Bat		S3B,SZN,G5			X
MAMMAL	*Microtus pennsylvanicus*	Meadow Vole					X
MAMMAL	*Mustela frenata*	Long-tailed Weasel		S3,S4,G5			X
MAMMAL	*Myotis austroriparius*	Southeastern Myotis		S2?,G3,G4		X	X
MAMMAL	*Neotoma floridana*	Eastern Woodrat	T (CP)	S1,G5T5 – CP		X	
MAMMAL	*Peromyscus gossypinus*	Cotton Mouse					X
MAMMAL	*Peromyscus leucopus*	White-footed Mouse	SC	S2,G5,T1 - CP		X	
MAMMAL	*Scalopus aquaticus*	Eastern Mole					X
MAMMAL	*Sciurus niger*	Eastern Fox Squirrel	SR	S3,G5		X	
MAMMAL	*Sylvilagus palustris*	Marsh Rabbit					X
MAMMAL	*Synaptomys cooperi*	Southern Bog Lemming	SR	S2,G5,TS - CP		X	
MAMMAL	*Zapus hudsonius*	Meadow Jumping Mouse		S3,G5			X
REPTILE	*Alligator mississippiensis*	American Alligator	T (T)	S3,G5		X	
REPTILE	*Caretta caretta*	Loggerhead	T (T)	S3B,S3N,G3		X	
REPTILE	*Cemophora coccinea*	Scarlet Snake				X	X
REPTILE	*Clemmys guttata*	Spotted Turtle		S3,G5			
REPTILE	*Crotalus adamanteus*	Eastern Diamondback Rattlesnake	E	S1,G4		X	
REPTILE	*Crotalus horridus*	Timber Rattlesnake	SC	S3,G4		X	
REPTILE	*Deirochelys reticularia*	Chicken Turtle	SR	S3,G5		X	X
REPTILE	*Dermochelys coriacea*	Leatherback	E (E)	SAB,SZN,G3		X	
REPTILE	*Elaphe guttata*	Corn Snake				X	
REPTILE	*Eumeces laticeps*	Broadhead Skink					X
REPTILE	*Farancia abacura*	Mud Snake					X
REPTILE	*Farancia erytrogramma*	Rainbow Snake					X
REPTILE	*Heterodon platirhinos*	Eastern Hognose Snake					X
REPTILE	*Heterodon simus*	Southern Hognose Snake	SC	S2,G2		X	X
REPTILE	*Kinosternon baurii*	Striped Mud Turtle		S3?,G5			X
REPTILE	*Lampropeltis calligaster rhombomaculata*	Mole Kingsnake					X
REPTILE	*Lampropeltis getula getula*	Eastern Kingsnake					X
REPTILE	*Malaclemys terrapin*	Diamondback Terrapin	SC	S3,G4,T4		X	
REPTILE	*Masticophis flagellum*	Coachwhip	SR	S3,G5		X	X
REPTILE	*Micrurus fulvius*	Eastern Coral Snake	E	S1,G5		X	X

Appendix 4.2 continued.

REPTILE	*Nerodia sipedon*	Northern Water Snake	SC	S3,G5,T3			
REPTILE	*Ophisaurus mimicus*	Mimic Glass Lizard	SC	S2,G3		X	X
REPTILE	*Ophisaurus ventralis*	Eastern Glass Lizard		S3,G5			X
REPTILE	*Pituophis melanoleucus melanoleucus*	Northern Pine Snake	SC	S3,G4T4		X	
REPTILE	*Regina rigida*	Glossy Crayfish Snake	SR	S2,S3			
REPTILE	*Rhadinaea flavilata*	Pine Woods Snake		S3,G4			X
REPTILE	*Seminatrix pygaea*	Black Swamp Snake	SR				X
REPTILE	*Sistrurus miliarius*	Pygmy Rattlesnake	SC	S3,G5		X	
REPTILE	*Tantilla coronata*	Southeastern Crowned Snake				X	X
REPTILE	*Terrapene carolina carolina*	Eastern Box Turtle					
REPTILE	*Thamnophis sauritus*	Eastern Ribbon Snake					X
REPTILE	*Virginia valeriae*	Smooth Earth Snake					X

Appendix 4.3. Species codes, scientific and common names.

Species codes are a combination of the residency status (B – breeding), taxa (A – amphibian) and a four character code based on the common name.

AMPHIBIAN	BABATR	Hyla gratiosa	Barking Treefrog
AMPHIBIAN	BABCFR	Pseudacris brimleyi	Brimley's Chorus Frog
AMPHIBIAN	BADWSA	Eurycea quadridigitata	Dwarf Salamander
AMPHIBIAN	BAEASP	Scaphiopus holbrookii	Eastern Spadefoot
AMPHIBIAN	BAFOSA	Hemidactylium scutatum	Four-toed Salamander
AMPHIBIAN	BAGOFR	Rana capito	Gopher Frog
AMPHIBIAN	BAGRSI	Siren lacertina	Greater Siren
AMPHIBIAN	BALESI	Siren intermedia	Lesser Siren
AMPHIBIAN	BAMASA	Ambystoma mabeei	Mabee's Salamander
AMPHIBIAN	BAMBSA	Ambystoma opacum	Marbled Salamander
AMPHIBIAN	BAMLSA	Stereochilus marginatus	Many-lined Salamander
AMPHIBIAN	BANRWA	Necturus lewisi	Neuse River Waterdog
AMPHIBIAN	BAOATO	Bufo quercicus	Oak Toad
AMPHIBIAN	BAOCFR	Pseudacris ornata	Ornate Chorus Frog
AMPHIBIAN	BAPBTR	Hyla andersonii	Pine Barrens Treefrog
AMPHIBIAN	BASDSA	Desmognathus auriculatus	Southern Dusky Salamander
AMPHIBIAN	BASPSA	Ambystoma maculatum	Spotted Salamander
AMPHIBIAN	BASRFR	Pseudacris nigrita	Southern Chorus Frog
AMPHIBIAN	BATHSA	Eurycea guttolineata	Three-lined Salamander
AMPHIBIAN	BATISA	Ambystoma tigrinum	Tiger Salamander
AVIAN	BBACFL	Empidonax virescens	Acadian Flycatcher
AVIAN	BBAMBI	Botaurus lentiginosus	American Bittern
AVIAN	BBAMKE	Falco sparverius	American Kestrel
AVIAN	BBAMOY	Haematopus palliatus	American Oystercatcher
AVIAN	BBAMWO	Scolopax minor	American Woodcock
AVIAN	BBANHI	Anhinga anhinga	Anhinga
AVIAN	BBBACS	Aimophila aestivalis	Bachman’s Sparrow
AVIAN	BBBAEA	Haliaeetus leucocephalus	Bald Eagle
AVIAN	BBBANO	Tyto alba	Barn Owl
AVIAN	BBBHNU	Sitta pusilla	Brown-headed Nuthatch
AVIAN	BBBLRA	Laterallus jamaicensis	Black Rail
AVIAN	BBBLSK	Rynchops niger	Black Skimmer
AVIAN	BBBNST	Himantopus mexicanus	Black-necked Stilt
AVIAN	BBBRPE	Pelecanus occidentalis	Brown Pelican
AVIAN	BBBRTH	Toxostoma rufum	Brown Thrasher
AVIAN	BBBTNW	Dendroica virens	Black-throated Green Warbler
AVIAN	BBBWHA	Buteo platypterus	Broad-winged Hawk
AVIAN	BBCACH	Poecile carolinensis	Carolina Chickadee
AVIAN	BBCARW	Thryothorus ludovicianus	Carolina Wren
AVIAN	BBCATE	Sterna caspia	Caspian Tern
AVIAN	BBCHSW	Chaetura pelagica	Chimney Swift
AVIAN	BBCOHA	Accipiter cooperii	Cooper’s Hawk
AVIAN	BBCOMO	Gallinula chloropus	Common Moorhen
AVIAN	BBCONI	Chordeiles minor	Common Nighthawk

Appendix 4.3 continued.

AVIAN	BBCOTE	Sterna hirundo	Common Tern
AVIAN	BBCWWI	Caprimulgus carolinensis	Chuck-will's-widow
AVIAN	BBDICK	Spiza americana	Dickcissel
AVIAN	BBDOWO	Picoides pubescens	Downy Woodpecker
AVIAN	BBEAKI	Tyrannus tyrannus	Eastern Kingbird
AVIAN	BBEAME	Sturnella magna	Eastern Meadowlark
AVIAN	BBEATO	Pipilo erythrophthalmus	Eastern Towhee
AVIAN	BBEAWP	Contopus virens	Eastern Wood-Pewee
AVIAN	BBFISP	Spizella pusilla	Field Sparrow
AVIAN	BBGBTE	Sterna nilotica	Gull-billed Tern
AVIAN	BBGLIB	Plegadis falcinellus	Glossy Ibis
AVIAN	BBGRSP	Ammodramus savannarum	Grasshopper Sparrow
AVIAN	BBHAWO	Picoides villosus	Hairy Woodpecker
AVIAN	BBHESP	Ammodramus henslowii	Henslow's Sparrow
AVIAN	BBHOLA	Eremophila alpestris	Horned Lark
AVIAN	BBHOWA	Wilsonia citrina	Hooded Warbler
AVIAN	BBINBU	Passerina cyanea	Indigo Bunting
AVIAN	BBKEWA	Oporornis formosus	Kentucky Warbler
AVIAN	BBKIRA	Rallus elegans	King Rail
AVIAN	BBLBHE	Egretta caerulea	Little Blue Heron
AVIAN	BBLEBI	Ixobrychus exilis	Least Bittern
AVIAN	BBLETE	Sterna antillarum	Least Tern
AVIAN	BBLOSH	Lanius ludovicianus	Loggerhead Shrike
AVIAN	BBMIKI	Ictinia mississippiensis	Mississippi Kite
AVIAN	BBNOBO	Colinus virginianus	Northern Bobwhite
AVIAN	BBNOFL	Colaptes auratus	Northern Flicker
AVIAN	BBNOHA	Circus cyaneus	Northern Harrier
AVIAN	BBNOPA	Parula americana	Northern Parula
AVIAN	BBOROR	Icterus spurius	Orchard Oriole
AVIAN	BBPABU	Passerina ciris	Painted Bunting
AVIAN	BBPIPL	Charadrius melodus	Piping Plover
AVIAN	BBPIWA	Dendroica pinus	Pine Warbler
AVIAN	BBPIWO	Dryocopus pileatus	Pileated Woodpecker
AVIAN	BBPRAW	Dendroica discolor	Prairie Warbler
AVIAN	BBPROW	Protonotaria citrea	Prothonotary Warbler
AVIAN	BBPUMA	Progne subis	Purple Martin
AVIAN	BBRBWO	Melanerpes carolinus	Red-bellied Woodpecker
AVIAN	BBRCWO	Picoides borealis	Red-cockaded Woodpecker
AVIAN	BBRHWO	Melanerpes erythrocephalus	Red-headed Woodpecker
AVIAN	BBRSHA	Buteo lineatus	Red-shouldered Hawk
AVIAN	BBSESP	Ammodramus maritimus	Seaside Sparrow
AVIAN	BBSNEG	Egretta thula	Snowy Egret
AVIAN	BBSUTA	Piranga rubra	Summer Tanager
AVIAN	BBSWWA	Limnothlypis swainsonii	Swainson's Warbler
AVIAN	BBTRHE	Egretta tricolor	Tricolored Heron
AVIAN	BBVIRA	Rallus limicola	Virginia Rail
AVIAN	BBWEVI	Vireo griseus	White-eyed Vireo

Appendix 4.3 continued.

AVIAN	BBWEWA	Helmitheros vermivorus	Worm-eating Warbler
AVIAN	BBWIPL	Charadrius wilsonia	Wilson's Plover
AVIAN	BBWOTH	Hylocichla mustelina	Wood Thrush
AVIAN	BBWPWI	Caprimulgus vociferus	Whip-poor-will
AVIAN	BBYBCU	Coccyzus americanus	Yellow-billed Cuckoo
AVIAN	BBYCNH	Nyctanassa violacea	Yellow-crowned Night-Heron
AVIAN	BBYTVI	Vireo flavifrons	Yellow-throated Vireo
MAMMALIAN	BMCOMO	Peromyscus gossypinus	Cotton Mouse
MAMMALIAN	BMEAMO	Scalopus aquaticus	Eastern Mole
MAMMALIAN	BMEAWO	Neotoma floridana	Eastern Woodrat
MAMMALIAN	BMEFSQ	Sciurus niger	Eastern Fox Squirrel
MAMMALIAN	BMLESH	Cryptotis parva	Least Shrew
MAMMALIAN	BMLOWE	Mustela frenata	Long-tailed Weasel
MAMMALIAN	BMMARA	Sylvilagus palustris	Marsh Rabbit
MAMMALIAN	BMMEVO	Microtus pennsylvanicus	Meadow Vole
MAMMALIAN	BMMJMO	Zapus hudsonius	Meadow Jumping Mouse
MAMMALIAN	BMRBBA	Corynorhinus rafinesquii	Rafinesque's Big-eared Bat
MAMMALIAN	BMSBLE	Synaptomys cooperi	Southern Bog Lemming
MAMMALIAN	BMSEBA	Lasiurus seminolus	Seminole Bat
MAMMALIAN	BMSOMY	Myotis austroriparius	Southeastern Myotis
MAMMALIAN	BMSTMO	Condylura cristata	Star-nosed Mole
MAMMALIAN	BMWHMO	Peromyscus leucopus	White-footed Mouse
REPTILIAN	BRAMAL	Alligator mississippiensis	American Alligator
REPTILIAN	BRBRSK	Eumeces laticeps	Broadhead Skink
REPTILIAN	BRBSSN	Seminatrix pygaea	Black Swamp Snake
REPTILIAN	BRCHTU	Deirochelys reticularia	Chicken Turtle
REPTILIAN	BRCOAC	Masticophis flagellum	Coachwhip
REPTILIAN	BRCOSN	Elaphe guttata	Corn Snake
REPTILIAN	BRDITE	Malaclemys terrapin	Diamondback Terrapin
REPTILIAN	BREAKI	Lampropeltis getula getula	Eastern Kingsnake
REPTILIAN	BREBTU	Terrapene carolina carolina	Eastern Box Turtle
REPTILIAN	BRECSN	Micrurus fulvius	Eastern Coral Snake
REPTILIAN	BREDRA	Crotalus adamanteus	Eastern Diamondback Rattlesnake
REPTILIAN	BREGLI	Ophisaurus ventralis	Eastern Glass Lizard
REPTILIAN	BREHSN	Heterodon platirhinos	Eastern Hognose Snake
REPTILIAN	BREISN	Thamnophis sauritus	Eastern Ribbon Snake
REPTILIAN	BREPSO	Apalone spinifera spinifera	Eastern Spiny Softshell
REPTILIAN	BRGRSN	Regina rigida	Glossy Crayfish Snake
REPTILIAN	BRGRTU	Chelonia mydas	Green Turtle

Appendix 4.3 continued.

REPTILIAN	BRLEAT	Dermochelys coriacea	Leatherback
REPTILIAN	BRLOGG	Caretta caretta	Loggerhead
REPTILIAN	BRMGLI	Ophisaurus mimicus	Mimic Glass Lizard
REPTILIAN	BRMOKI	Lampropeltis calligaster rhombomaculata	Mole Kingsnake
REPTILIAN	BRMUSN	Farancia abacura	Mud Snake
REPTILIAN	BRNOPS	Pituophis melanoleucus melanoleucus	Northern Pine Snake
REPTILIAN	BRNWSN	Nerodia sipedon	Northern Water Snake
REPTILIAN	BRPISN	Rhadinaea flavilata	Pine Woods Snake
REPTILIAN	BRPYRA	Sistrurus miliarius	Pygmy Rattlesnake
REPTILIAN	BRRASN	Farancia erytrogramma	Rainbow Snake
REPTILIAN	BRSCWS	Tantilla coronata	Southeastern Crowned Snake
REPTILIAN	BRSESN	Virginia valeriae	Smooth Earth Snake
REPTILIAN	BRSHSN	Heterodon simus	Southern Hognose Snake
REPTILIAN	BRSMTU	Kinosternon baurii	Striped Mud Turtle
REPTILIAN	BRSPTU	Clemmys guttata	Spotted Turtle
REPTILIAN	BRSRSN	Cemophora coccinea	Scarlet Snake
REPTILIAN	BRTIRA	Crotalus horridus	Timber Rattlesnake