PREDICTING URBAN GROWTH PATTERNS IN THE COASTAL SOUTHEASTERN UNITED STATES USING NEURAL NETWORKS

Kang S. Lu, Ph.D.
Department of Geography and Environmental Planning, Towson University, Towson, MD, 21252
Email: klu@towson.edu

Jeffery S. Allen, Ph.D.
South Carolina Water Resources Center, Clemson University, Clemson, SC 29634
Email: jeff@strom.clemson.edu

Guoxiang Liu, Ph.D.
Strom Thurmond Institute, Clemson University, Clemson, SC 29634
Email: lgreg@strom.clemson.edu

ABSTRACT

A focus of the Land Use-Coastal Ecosystem Study (LU-CES) was to evaluate the growth projections from the parcel level to the county level. Population and land development growth projected for the Southeast during the next two decades will put enormous pressure on economic, social and environmental resources. The ability to predict how many people will be immigrating to the region as well as the spatial patterns and directions of growth is crucial to planning and management efforts of municipalities, counties, states and regions.

This paper developed a multi-layer back propagation neural network to simulate future land use changes and potential ecological impacts. The neural net has not only an interconnected, hierarchal structure appropriate for addressing complex phenomena with spatial dependency problems, but also a predictive power that many conventional models fail to reach. Seven growth scenarios were developed for the simulation. Ecological impacts were assessed in terms of loss of vegetation cover, habitat areas, and species richness. The neural net substantially outperformed a logistic model developed using the same set of variables. Predicted changes in land use and ecosystems can be used as an early diagnosis for land use planning and resource management.

Key Words: Neural network, land use modeling, ecological impact, gap analysis, geographic information system

I. INTRODUCTION

Land use change is the leading cause of many ecological problems (Turner et al., 1994). While the process of a land development directly impacts and often destroys ecosystem components as well as species, the permanent human use of natural habitats indirectly affects biotic communities and individual species in various ways (Pearson et al., 1998; Miller et al., 2004). Introducing an exotic species may increase biodiversity at a location temporarily, but the spread of invasive species threatens the survival of native species (Walker, 1992). Unfortunately, changes in land use and ecosystem characteristics are not perceived as detrimental unless their negative impacts have cumulatively reached certain critical values that are often too severe to ignore, too late to avoid, or too costly to mitigate.

Public policy makers are often reluctant to make any significant move due to the associated economic cost of environmentally friendly land use practices; private land developers seldom are willing to add additional investment for saving a plant or animal species. Without quantified descriptions and specific locations of potential impacts, neither planners nor environmentalists can make convincing statements in promoting ecologically sustainable planning and development. Predictive modeling is not only a necessary step toward anticipating potential ecological effects of land use changes (Pearson e al., 1998), but also an important mechanism to generate quantitative, spatial, temporal, and visualized information crucial for advanced planning, impact assessment and public education (Allen and Lu, 2003). This paper proposes a neural network model for simulating and predicting future land use change and potential ecological impacts of that change in Beaufort County, South Carolina.

II. BACKGOUND

Land use modeling

It is extremely difficult to predict land use change due to the complexity of physical and human systems. Over the past half century, numerous models have been developed (Weigener, 1994; Southworth, 1995) but only a few have had significant influences on decision making in urban and land use planning (Lee, 1994; Allen and Lu, 2003). Among recently developed models, two modeling approaches have gained more popularity in the United States: the cellular automaton framework (Li and Yeh 2000) and the logistic framework.

SLEUTH is a tightly coupled, modified cellular automaton model of urban and other land class change. Its main component is the Clarke Urban Growth Model (UGM) (Clarke et al. 1996) which drives a second component, the Deltatron land cover model (Clarke, 1997). Built upon the Monte Carlo Random Modeling theory, SEUTH is able to simulate dichotomous land use change following self-modified growth rules determined by urban seeds, transportation, slope, and excluded land. Designed mainly for long-term, large-scale urban growth predictions, the current version of the model does not provide flexibility for the user to integrate factors such as population, land price, waterlines or sewer line or other variables that are of importance to local level land use decision making. A black box type of modeling process also discourages local planners' involvement in modeling process and dissemination of information about predicted urban growth.

Logistic regression modeling, binomial or multinomial, has been popular for several reasons (see Landis, 1994; Landis and Zhang, 1997; Allen et al. 2002; Wu, 1998; Lu, 2001; Allen and Lu, 2003). According to Allen and Lu (2003), the logistic framework is supported by the random utility theory (Landis and Zhang, 1997) and mathematically consistent with the entropy theory (Wilson, 1976); it is capable of handling discrete land use variables and the mix of both discrete and continuous independent variables; it is nonlinear in form to better represent the nature of the complex urban reality; it is flexible enough to be tailored to individual land use systems; and it is available from most statistical packages. However, due to both the complexity of urban land use systems and limitations of the model, it does not always provide satisfactory predictions, as several studies have shown (see Landis & Zhang, 1997; Lu, 2001; Allen and Lu, 2003). Like other mathematical models, the model assumes that all predictor variables be independent from one another. This assumption appears to contradict the hierarchical urban reality in which most factors are interrelated and interdependent. What are needed are alternative models that are conceptually sound and empirically reliable.

Neural network computing and generic algorithms have been proposed as possible alternative approaches to handle issues of complex systems (Sui, 1997). Although the first neural network models appeared in the early 1940s (McCulloch and Pitts, 1943), they were mainly applied in signal processing (Widrow and Stearns, 1985), control (Nguyen and Widrow, 1989; Miller et al. 1990), pattern recognition (Le Gun et al., 1990), medicine (Anderson, 1986; Anderson et al. 1986; Hecht-Nilsen, 1990), speech production and recognition (Sejinowski and Rosenberg, 1986; Lippmann, 1989), and business (Collins et al 1988). They were introduced to the geo-sciences and resource management only a decade ago (Openshaw, 1993; Wang, 1994; Gimblett et al., 1994; Fischer and Gopa, 1994; Gong, 1990; Thill and Mozolin, 2000**).** According to Openshaw and Openshaw (1997), the use of neural networks for modeling has four major potential benefits: better performance, greater representational flexibility and freedom from current model design constrains, the opportunity to handle explicitly noisy data, and the incorporation of spatial dependency in the net representation which is currently ignored. Unfortunately, only a few studies have explicitly applied the neural network approach to land use modeling (Wu and Webster, 1998; Webster and Wu, 1999; Yeh and Li, 2002;

Lu and Allen, 2004; Lin et al., 2005). The potential as well as the limitations of neural networks remains to be fully exploited.

Predictive ecological modeling

Predictive modeling or extrapolation in one form or another has always been a part of ecological study, but it became a "sine qua non" in the latter half of the 20th century (Miller et al., 2004). Most studies focus on spatially explicit extrapolations (Running et al., 1989) in which models or relationships are derived from one location or one scale and used to predict ecological patterns and processes at another location or scale. Running and colleagues (1989) coupled satellite data with ecosystem simulation to predict regional forest evapotranspiration and photosynthesis. Guisan and Zimmerman (2000) developed several models for predicting habitat distribution while Scott et al. (2002) discussed issues of accuracy and scale for predicting species occurrences. Mitchell and colleagues (2001) compared three models for predicting the presence of forest bird species in South Carolina in an effort to provide mangers with a method to assess the effects of forest management over large areas.

Extrapolating in both time and space is one of the four serious challenges facing ecological modeling (Bürgi et al., 2004). Although a number of studies have addressed temporal changes in biodiversity, habitat, and species richness from a historic perspective (Black et al., 1998, Hansen et al., 1998), few have quantitatively and spatially predicted changes in ecosystems, factors, processes or components far into the future. A lack of understanding of the relationship between the present and the future and the linkage between land use and ecosystems makes it impossible to build science-based planning and management tools for sustainable decision making. There remains a need for multidisciplinary studies and model integration.

Integrative modeling approach

The literature reveals an increased effort in the integration of land use modeling and ecosystem modeling to understand the linkage between human activities and natural systems (Pearson et al., 1998; Allen and Lu 2003; Goetz et al., 2004). Modelers in the land use tradition have started to explicitly incorporate a component of impact assessment in their predictive projects (Goetz et al., 2004). Researchers from the biological sciences, on the other hand, have extended their studies beyond the effects of landscape changes. For instance, Goetz and colleagues (2004) assessed the loss of forest and wetland, agricultural land and other land as a result of future urban growth in the Washington, DC-Baltimore Region from 1986-2030. Allen and Lu (2003) estimated the loss of forest land, cultivated farmland, wetlands, tidal creeks, shellfish beds and other historic landmarks and archeological sites based on the predicted urban growth in the Charleston region from 1994-2030. Pearson (1998) and colleagues utilized the multinomial logistic regression based LUCAS (Land-use Change Analysis System) model to simulate ecological effects of land cover change on species abundance and habitat distribution over 100 years.

The present study applied a similar integrative, simulative approach but developed a more robust neural network model to predict future land use change under different growth scenarios. The authors integrated the South Carolina Gap analysis data with predictive modeling to assess potential ecological effects of land use change in terms of loss of vegetation cover, habitat areas, and species richness in Beaufort County South Carolina. Three key questions intended to be investigated are: (1) whether the neural net is a better performing model than the logistic regression model; (2) what the future urban areas would look like in the next 30 years if different growth strategies are adopted; and (3) how vertebrate species are potentially affected as urban areas grow.

III. METHODS

Study area description

Beaufort County is considered a coastal tourism region in South Carolina and the South Atlantic Bight. Located along the coast between Charleston (South Carolina) and Savannah (Georgia), the county is well known for its historical downtown Beaufort, golfer's paradise of Hilton Head Island, Hunting Island State Park, and its adjacency to the ACE Basin Nature Reserve. Mild winter climate, coastal amenities, and sea island cultural heritage have not only attracted many immigrants and retirees to move to this county but have also led to a large scale of land development over the last decade. From 1990 to 2000, its population has increased by 39.93% from 86,425 to 120,935. The growth rate has tripled the national average (13%) and leads all counties in South Carolina. Meanwhile, the urbanized area expanded by 23.17% from 70.76 to 87.15

square miles. Targeted as one of the top seven retiree communities in the U.S., the county is anticipated to continue grow at a rapid pace in the near future. While local elected officials often seem more interested in building capacity and potential increases in tax revenue, the public is concerned about the possible aggravating negative impacts on coastal ecosystems. There has been a tremendous demand for future predictions of urban growth and its impacts on the environment.

Operational neural network design

A three-layer neural net (Figure 1) was designed to simulate and predict land use change in Beaufort County. For modeling a dichotomous change from a natural, semi-natural undeveloped state or rural use (0) to a developed state or urban use (1), one unit in the output layer is sufficient (Fischer and Gopal 1994). The input layer contains multiple units, which represent the major physical and human factors affecting locations and sequences of land developments. The 14 variables listed in Figure 1 are either statistically significant in the logistic regression model or represent unique categories of driving factors. For simplicity, the hidden layer also consists of the same number of units (14) as the input layer.

The authors implemented the design by developing a stand-alone neural network program using Visual Basic 6.0 for Windows. This program provides users the flexibility to select certain variables and to set network parameters as tailored to individual modeling needs. It also allows users to load two sets of data for training and testing respectively. In addition, the net model was integrated with a land use module written in

Avenue for ArcView (ESRI) to facilitate data preparation, sample extraction, spatial analysis, and spatial prediction. The land use module consists of several statistical models utilizing the production utilities provided by the SPSS statistical package.

Different sets of spatial data were prepared for the two baseline years, 1990 and 2000, respectively. Data for urban use were from the 1990 land cover generated from the South Carolina Gap Analysis and the 2000 parcel use provided by the Planning Department of Beaufort County. While the 1990 dataset was used as the net input to approximate the target, 2000 urban use for training, the 2000 dataset was used for future predictions and simulations. Spatial data from which variable grids were derived include TIGERS/Line files and Census Data (US Census Bureau, 1990 and 2000), water and sewer lines from South Carolina Department of Commerce, Digital Elevation Model (DEM) from South Carolina Department of Natural Resources, and protected lands from the Gap Analysis.

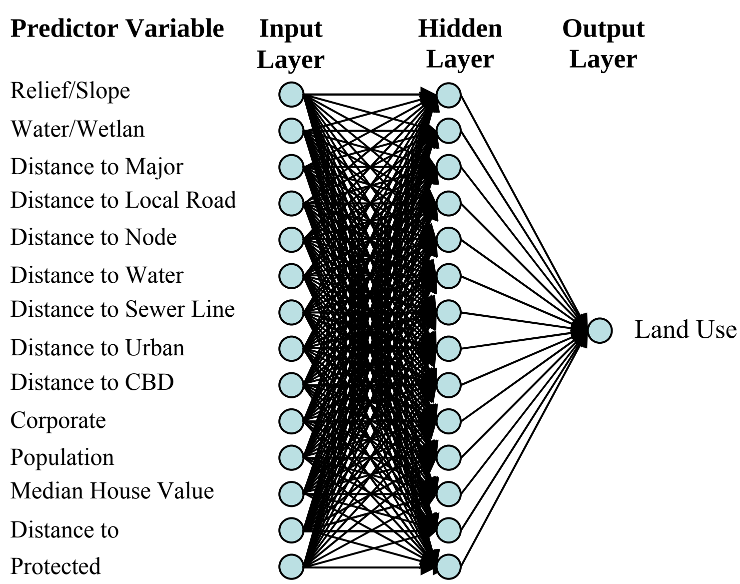

Figure 1. Operational neural network for predicting urban development in Beaufort County, South Carolina, USA.

We applied both conventional methods and some of the techniques developed by Lu and Allen (2004) for network training. Two sample datasets were generated using a random sampling method for net training and testing respectively. We also used the full population (data for the whole county) for spatial validation. We started training with all default parameters (maximum epochs = 3000, mean square error threshold = 0.05, Slope = 1, and minimum error reduction = 0.000001) except for the learning rate, which was 0.025. A smaller leaning rate or error correction increases not only the possibility of model convergence but also the likelihood of obtaining a better approximation and higher prediction accuracy. The method for training is the standard backpropagation algorithm in which biases and weights are updated for each input-output pair (Fausett 1994). We also ran the logistic regression model, the results of which were referred to as a benchmark for assessing the performance of the network model. The ultimate goal was to create a net that would be sufficiently trained with the ability to approximate the complex land use system but not over-fitted which could result in less power for future predictions.

Scenario-based simulation

The trained neural network was used to predict land transition probabilities for the county using a new input dataset for 2000. Since the net was trained from a sample covering only a ten-year span, it is unreasonable to apply the same default cut-off value

(0.5) for land use classifications for any year beyond 2010. It is assumed that future land developments will follow a spatial sequence determined by the predicted land transition probabilities. In other words, the land cell with the highest transition probability will turn into an urban cell first. For each growth scenario, we let urban grow until the cumulative urban area reached the demanded urban size calculated for a specific year and repeated the process for every year from 2000 through 2030.

We used the method developed by Allen and Lu (2003) to determine the demand of urban size, which can be calculated according to the following formula:

$$A_1 = R_g A_0 (P_1-P_0)/ P_0 +A_0, \tag{3.1}$$

where R_g is growth ratio; A_0 is the start-year urban size; A_1 is the end-year urban size; P_0 is the start-year population; and P_1 is the end-year population.

Growth ratio R_g is the ratio of the urban area growth rate, R_A, to the population growth rate, R_p. It is expressed as:

$$R_g = R_A / R_p, \tag{3.2}$$

or

$$R_g = \{(A_1-A_0)/A_0\} / \{(P_1-P_0)/P_0\}$$

or

$$R_g = \{P_0 /A_0\} \{(A_1-A_0) / (P_1-P_0)\}. \tag{3.3}$$

According to equation (3.3), the growth ratio is a product of initial population density (P_0 /A_0) and per capita land consumption ($(A_1-A_0) / (P_1-P_0)$) for the increased population. The concept, therefore, implicates the density of urban development and is often referred to as growth scatter index. For a given increased population, different growth ratios mean different densities and different demanded urban sizes as well.

The Census Bureau has made mid-term population projections through 2025 at a 5-year interval. We interpolated the total population for each of the between-years and extrapolated the projections through 2030. With this information known, the demand of urban area depends only on the growth ratio. For Beaufort Country, the ratio is 0.58:1 between 1900 and 2000, but ratios for the other seven coastal counties range from 1:1 to 6:1 over different periods of time (1973-1994 and 1985-1997). Local planners and resource managers wanted to see what the future would look like under all of these scenarios. Therefore, we calculated the demanded urban areas for all scenarios and simulated future growth from 2000 to 2030.

Ecological impact assessment

Ecological impacts associated with predicted urban developments were assessed in terms of change in vegetation cover, loss of vertebrate habitat, and reduction of species richness. The source data were generated from the South Carolina Gap-Analysis. The vegetation cover for 1990 was derived from the satellite imagery with a spatial resolution of 30 x 30 m. It has 27 vegetation types. To be consistent with the output of our urban predictions, two urban cover types in this dataset were combined to create a single type called urban. The land cover was in the ArcInfo (ESRI) grid format and accommodated GIS-based spatial analysis. At the time of the study, land cover for 2000 was not available. The 1990 land cover was used as the baseline data for change analysis. The overlap between this land cover and newly developed land for a specific year under a given scenario was the loss of vegetation cover.

The Gap database also contains rich information about the predicted distributions of 455 vertebrate species found in South Carolina. These species are classified into four groups: amphibian, bird, mammal and reptile. Areas identified in the distribution maps are their habitats. For habitat impact analysis, we selected only four species: two common species and two endangered species to examine the differentiated impacts of future urban growth. The former include green treefrog (*Hyla cinerea*) and red fox (*Vulpes vulpes*). The latter are red cockaded woodpecker (*Picoides borealis*) and wood stork (*Mycteria americana*). Red cockaded woodpeckers were classified as a federally endangered species in 1970. This species roosts only in the cavities of very old pine trees. Wood storks were listed as endangered in 1984 by the U.S. Fish and Wildlife Service. The storks nest 60 feet off the ground in cypress trees in wetland areas of Georgia, South Carolina and Florida. The habitat of each species covers multiple types of land cover. Its intersection with the predicted new urban areas was the net habitat loss for the species of concern.

Biodiversity was measured in terms of species richness or the number of species that exist at the same geographic location. The SC Gap database contains five spatial datasets for species richness, one for each individual species group and one for all species. Note that species richness varies substantially not only with different cover types but also with different locations within the same cover. We used only the average richness values for each of the three urban cover types to assess the potential impact. More specifically, each of the three average values derived from the cover types urban development, urban residential, and urban combined respectively were assigned to all urban areas in the 1990 land cover as well as predicted urban areas for an end year to create two separate urban species richness grids. When overlaying these two grids on the 1990 richness grid, we created a modified richness grid for 1990 and a richness grid for the prediction year. Differencing these two grids resulted in a species richness change grid, representing the potential impact of predicted land use change on species richness. By summarizing the richness change grid using the 1990 land cover, we can examine the impact on biodiversity by vegetation cover types.

IV. RESULTS

Classification success rates

The random sample dataset extracted for modeling calibration has 5528 records or land cells, 16.81% of which are developed. Results of omnibus tests indicate that the logistic regression model was significant for predicting land use change in the Beaufort County (χ^2 = 1731.152, df = 14, $p<0.01$), with a Cox & Snell R^2 of 0.27 and Nagelkerke R^2 of 45 respectively. The neural net constructed with the same variables was trained for only 476 epochs before the targeted mean squared error (0.05) was reached.

The neural net outperformed the logistic regression model in terms of classification accuracy (Table 1). The net improved the overall prediction accuracy by nearly 7 percentage points over the logistic model. Although models are very effective in predicting the nonurban use, with a classification accuracy of above 97% and the discrepancy is only 2.09, the neural network has demonstrated a greater capability to predict urban use and improved the prediction accuracy by 32.40 percentage points.

Table 1. Prediction success rates of the neural network and the logistic regression model for urban development in Beaufort County, South Carolina.

		Neural Net			Logistic Regression		
		Pred. Urban	Pred. Rural	Correct	Pred. Urban	Pred. Rural	Correct
		1	0	%	1	0	%
Obs. Urban	1	751	178	80.84	450	479	48.44
Obs. Rural	0	1	4598	99.98	97	4502	97.89
Overall	%			96.76			89.58

Both the neural net and logistic model tend to underestimate the developed land by misclassify more urbanized cells into undeveloped cells than otherwise. This may be partially due to the fact that the study area is still dominantly undeveloped. However, the neural network outperformed the logistic model in terms of total land cells misclassified. Error of omission and error of commission for the developed land from the neural network are 0.13% and 19.16% respectively, as compared to 17.73% and 51.56% from the logistic regression model. The relatively large areas under the three curves (Figure 2) generated from the neural network imply smaller risks involved if classification strategies change.

The neural net was also validated spatially using the full population or full dataset for the whole county. This was accomplished in a GIS environment because the dataset is too large to be effectively handled in a tabular format. Results of the spatial validation are similar to those obtained from the training data set. The classification success rates are 81.93% for urban development and 97.43% for the rural use. The overall prediction accuracy is also very high (99.00%). Error maps in Figure 3 indicate that the neural net model was able to predict more isolated developed land cells than the logistic model.

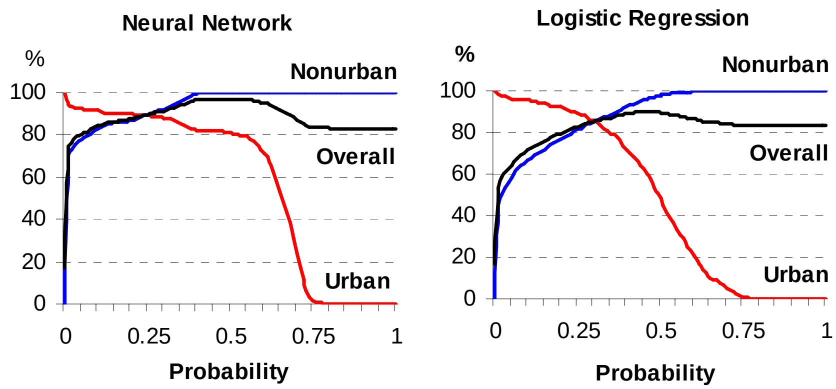

Figure 2. Prediction accuracy as a function of the cut-off value used for classifications. Areas under the accuracy curves generated by the neural network (left) are much larger than those generated by the logistic regression model (right).

Predicted urban growth

Predicted urban areas vary in size under different growth scenarios even with the same projected population growth (Table 2). At the current rate (0.58:1 ratio), the entire county will be built out by the end of this century. The remaining 180 square miles of unprotected developable land, constrained only by water and wetlands, will be converted for urban use. If the urban expansion increases to a 4:1 growth ratio, land development will reach its building capacity of 250 square miles by 2028. It takes only 20 years before this happens if the county grows as fast as Charleston County did during 1973-1994 with a growth ratio of 6:1. It appears that the bigger the growth ratio or the smaller the building density, the shorter time it will take to build out the entire county. Demanded urban sizes that exceed the 250 square mile capacity (shaded sells in Table 2) have to be accommodated at the cost of wetlands or by “spilling over” to adjacent counties.

For each growth scenario, a time series of predicted future urban extents was mapped on a yearly basis (Figure 4) for analyzing the spatial progression of urban development under a given scenario. Similarly, a scenario series of maps for a given year were created for comparing the urban extents and potential impacts (Figure 5). The map for the 0.58:1 growth ratio represents the future urbanized area if current trends continue, and the map for the 4:1 growth ratio depicts the build-out scenario with an urbanized area of 250 square miles.

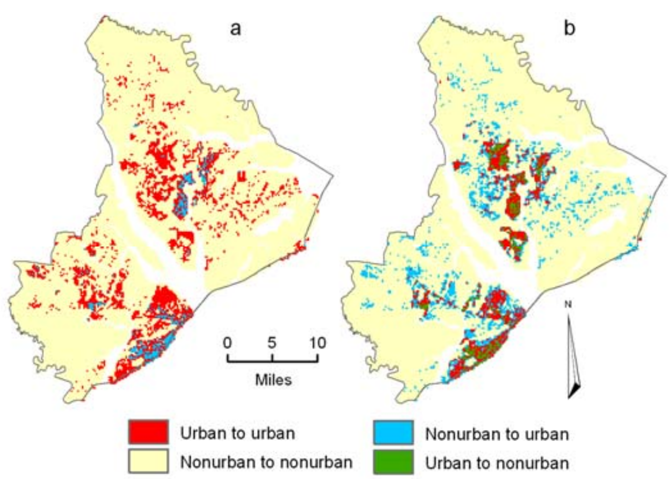

Figure 3. Spatial distribution of the classification error for the neural network and the logistic regression model used for predicting urban development in Beaufort County.

Potential ecological impacts

The most severe direct impact of urban expansion on terrestrial ecosystems would be the destruction and alteration of vegetation cover. Although the affected areas vary with scenarios, years, and vegetation covers, the top three affected land covers are maritime forest, cultivated land, and marsh wetland (Table 3), each of which will lose more than 47000 acres to urban developments even under the most conservative prediction. The loss could amount to more than a hundred thousands acres if the growth ratio is 2:1 or greater. Nearly half of the existing cultivated land, maritime forest, and scrubland will be altered by 2030 if urban expansion accelerates at a 3:1 ratio (Table 4). Figure 6 shows the distribution of three selected land cover changes under this growth scenario.

Table 2. Projected population growth and urban area growth (1990-2030) under different scenarios for Beaufort County, South Carolina.

Year	Population (counts)	Urban Area (in square miles)					
		Ratio 0.58:1	Ratio 1:1	Ratio 2:1	Ratio 3:1	Ratio 4:1	Ratio 5:1
2000	120937	87.15	87.15	87.15	87.15	87.15	87.15
2001	121609	87.43	87.63	88.12	88.60	89.09	89.57
2002	122281	87.71	88.12	89.09	90.06	91.02	91.99
2003	122953	87.99	88.60	90.06	91.51	92.96	94.41
2004	123625	88.27	89.09	91.02	92.96	94.90	96.84
2005	124297	88.55	89.57	91.99	94.41	96.84	99.26
2006	124969	88.84	90.06	92.96	95.87	98.77	101.68
2007	125641	89.12	90.54	93.93	97.32	100.71	104.10
2008	126313	89.40	91.02	94.90	98.77	102.65	106.52
2009	126985	89.68	91.51	95.87	100.22	104.58	108.94
2010	135800	93.36	97.86	108.57	119.28	129.99	140.70
2011	138120	94.33	99.53	111.91	124.30	136.68	149.06
2012	140440	95.30	101.20	115.26	129.31	143.37	157.42
2013	142760	96.27	102.88	118.60	134.33	150.05	165.78
2014	145080	97.24	104.55	121.95	139.34	156.74	174.14
2015	147400	98.21	106.22	125.29	144.36	163.43	182.50
2016	149720	99.18	107.89	128.63	149.38	170.12	190.86
2017	152040	100.15	109.56	131.98	154.39	176.80	199.22
2018	154360	101.12	111.24	135.32	159.41	183.49	207.58
2019	156680	102.09	112.91	138.66	164.42	190.18	215.94
2020	159000	103.06	114.58	142.01	169.44	196.87	224.30
2021	161300	104.02	116.24	145.32	174.41	203.50	232.58
2022	163600	104.98	117.89	148.64	179.38	210.13	240.87
2023	165900	105.94	119.55	151.95	184.35	216.76	249.16
2024	168200	106.90	121.21	155.27	189.33	223.39	257.44
2025	170500	107.87	122.87	158.58	194.30	230.01	265.73
2026	172888	108.86	124.59	162.02	199.46	236.90	274.34
2027	175276	109.86	126.31	165.47	204.62	243.78	282.94
2028	177664	110.86	128.03	168.91	209.79	250.67	291.54
2029	180052	111.86	129.75	172.35	214.95	257.55	300.15
2030	182441	112.86	131.47	175.79	220.11	264.43	308.76

Notes: (1) Population for 2005-2025 was estimated by the Bureau of Census; (2) population for 2025-2030 was projected by extrapolating the predicted trajectory; and (3) the total area of developable land is 250 square miles.

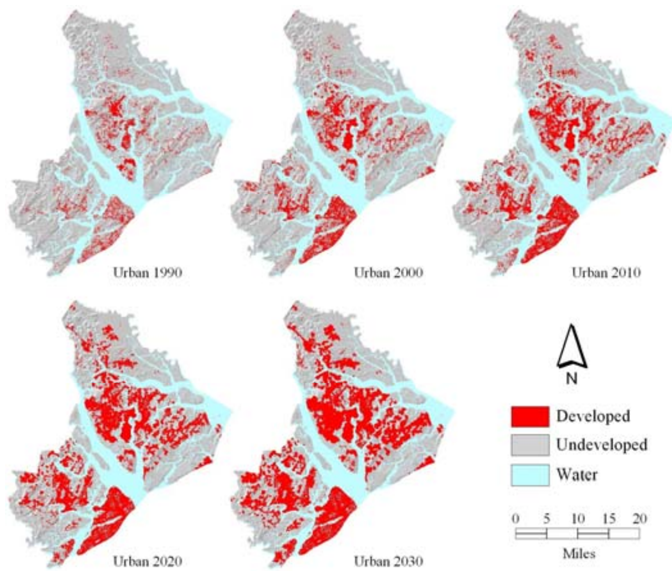

Figure 4. Time-series of urban development (2000-2030) predicted for Beaufort County based on the 3:1 growth ratio.

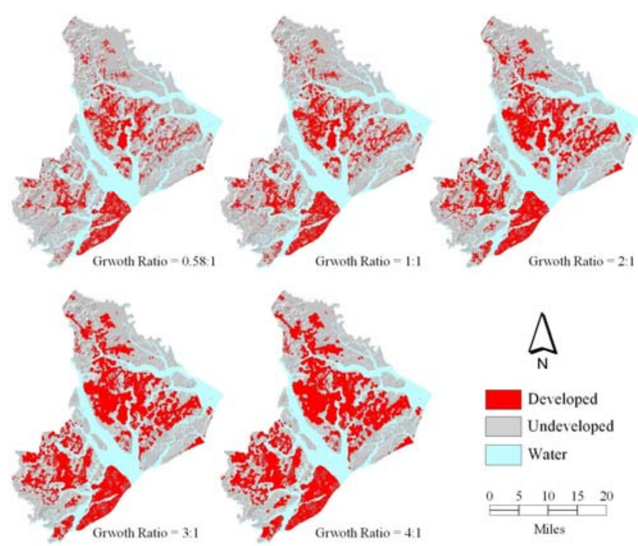

Figure 5. Predicted urban development through 2030 for Beaufort County under five possible growth scenarios.

The overall impact of the projected urban growth on biodiversity is not necessarily negative as measured by species richness. According to the SC Gap data, the average number of vertebrate species found in two urban covers (urban development and urban residential) is greater than that for all land cover in four of the five categories (Table 5). The category bird is the only exception. This is probably due to the fact that urban residential areas are among the richest land covers in biodiversity as the data have revealed. Of the two urban covers, urban development has fewer species visiting or residing even though it has more mammals than other land covers on average.

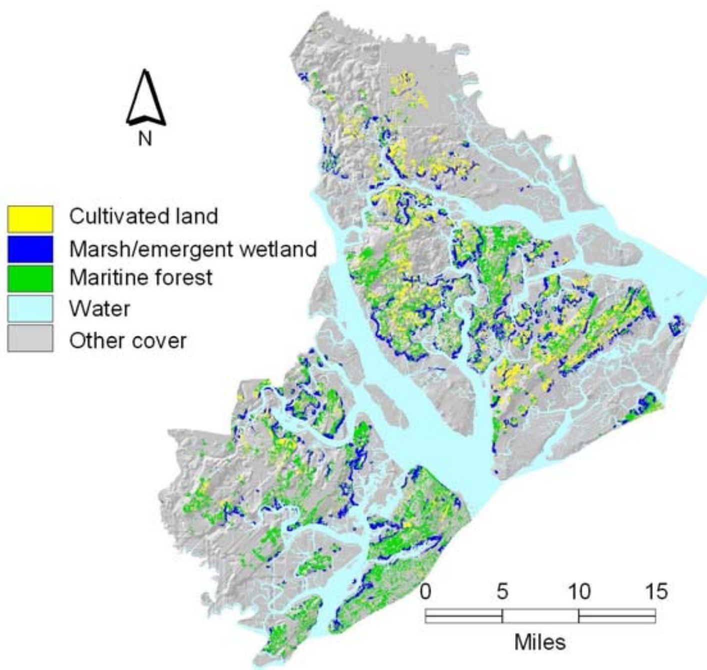

Figure 6. Distribution of cultivated land, marsh wetland, and maritime forest that suffer the most severe alteration as a result of predicted urban growth.

However, whether the impact is detrimental or not depends on the type of land cover affected. Figure 7 shows the categorical distribution of the average richness values for all vertebrate species in 1990 and 2030. The two urban cover types were combined first and then assigned the average richness value of 92 (Table 5). The 2030 urban area was assessed based on the 0.58:1 ratio that follows the current trajectory. Because we used 92 instead of 128 for residential cover or 121 for urban cover for calculation, the graph in Figure 7 represents the worst scenario of the three cases for richness impact assessment even though the urban prediction for 2030 is the most conservative one. In this case, about 4 vertebrate species will be lost for each land unit of 90 meters by 90 meters by 2030 and two-thirds of 24 land cover types concerned will see fewer species than they did in 1990. The most severe losses (more than 10 species) occur in grassland, maritime forest, freshwater, and sandy bare soil, the last of which may be due to data error. There are four types of land cover that will have minimal gain in species richness.

Table 3. Estimated land cover changes in acres for selected growth scenarios (1990-2030).

Land Cover Name	Area Developed or Altered (in Acres)				
	Ratio 0.58:1	Ratio 1:1	Ratio 2:1	Ratio 3:1	Ratio 4:1
Fresh water	6957	7864	9656	10804	11469
Marine water	14398	18670	33353	55285	75185
Marsh/emergent wetland	47750	66009	121830	194291	249703
Pocosin	287	380	614	850	972
Swamp	3618	4757	7501	10268	11938
Bottomland/floodplain forest	21572	29294	47448	66603	79397
Wet soil	1555	2066	3632	6020	7968
Wet scrub/shrub thicket	14678	19166	28942	38294	44635
Dry scrub/shrub thicket	16144	20267	28600	34849	38054
Sandy bare soil	4564	5486	7077	8175	8665
Open canopy/recently cleared forest	5420	7833	13557	19317	23060
Closed canopy evergreen forest/woodland	24337	32005	51831	73121	87488
Needle-leaved evergreen mixed forest/woodland	7588	10395	18058	25902	30379
Pine woodland	2813	3654	5658	7444	8636
Mesic deciduous forest/woodland	1345	1844	3258	4635	5515
Dry mixed forest/woodland	38	53	113	151	198
Mesic mixed forest/woodland	7	9	27	29	33
Grassland/pasture	28776	34104	43269	50179	53735
Cultivated land	63071	81617	118779	146425	160178
Wet evergreen	14594	18701	29425	39693	46051
Maritime forest	159989	194213	268720	329792	362704
Beach	967	1172	1539	1697	1819

Table 4. Estimated land cover changes in percentage for selected growth scenarios (1990-2030).

Land Cover Name	Area Destructed or Altered (%)				
	Ratio 0.58:1	Ratio 1:1	Ratio 2:1	Ratio 3:1	Ratio 4:1
Fresh water	24.11	27.25	33.47	37.44	39.75
Marine water	1.30	1.68	3.01	4.98	6.77
Marsh/emergent wetland	3.53	4.88	9.02	14.38	18.48
Pocosin	5.46	7.24	11.69	16.17	18.50
Swamp	9.62	12.65	19.95	27.30	31.74
Bottomland/floodplain forest	9.82	13.33	21.59	30.31	36.13
Wet soil	2.73	3.63	6.39	10.59	14.02
Wet scrub/shrub thicket	10.47	13.67	20.65	27.32	31.84
Dry scrub/shrub thicket	22.69	28.49	40.20	48.99	53.49
Sandy bare soil	27.04	32.50	41.92	48.43	51.33
Open canopy/recently cleared forest	7.95	11.49	19.88	28.33	33.82
Closed canopy evergreen forest/woodland	11.38	14.96	24.23	34.18	40.89
Needle-leaved evergreen mixed forest/woodland	9.88	13.53	23.51	33.72	39.55
Pine woodland	14.43	18.74	29.01	38.17	44.29
Mesic deciduous forest/woodland	9.44	12.93	22.85	32.50	38.68
Dry mixed forest/woodland	2.79	3.94	8.37	11.17	14.61
Mesic mixed forest/woodland	6.00	8.00	24.00	26.00	30.00
Grassland/pasture	28.83	34.17	43.36	50.28	53.84
Cultivated land	21.37	27.65	40.24	49.61	54.27
Wet evergreen	13.14	16.84	26.50	35.74	41.47
Maritime forest	22.83	27.71	38.34	47.05	51.75
Beach	10.51	12.73	16.71	18.43	19.76

Table 5. Average number of species by land covers type (1990).

Land Cover	Amphibian	Bird	Mammal	Reptile	All Species
Urban development	11	57	19	21	92
Urban residential	14	65	22	25	128
All urban cover	13	63	21	24	121
All land cover	12	67	15	22	116

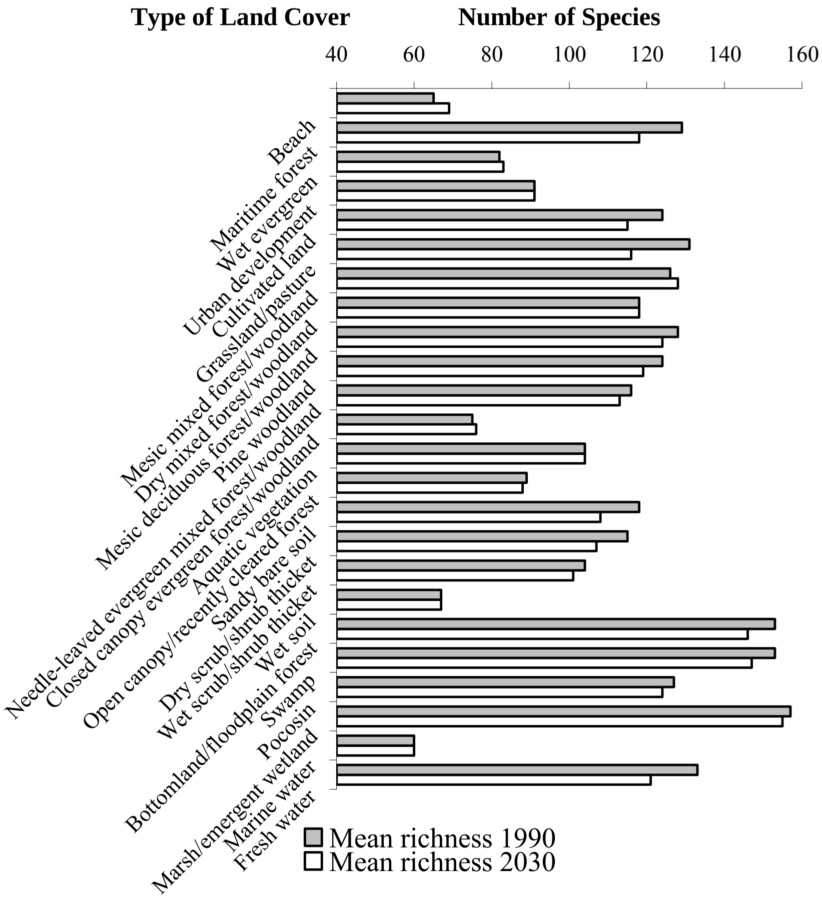

Figure 7. Predicted changes in biodiversity as measured by mean species richness for all vertebrates between 1990 and 2030. Notes: (1) urban areas were assigned the richness value of 92; (2) richness values were summarized by zones defined by the 1990 land cover.

We also generated similar graphs using average richness values of 128 and 121 for predicted new urban cover. The histograms of species richness exhibit a similar pattern for the non-urban cover types but more areas defined by these land cover types will gain rather than lose species because the two numbers are greater than the average richness values for all species. Unfortunately, the aforementioned three types of land cover are among the richest in number of species. Therefore, the overall impact of future land development is negative in terms of the species richness index or the sum of the richness values for all land cells in the county. Maps in Figure 8 depict the distribution of the gain and loss in species richness for each individual vertebrate group.

Predicted loss of habit also varies across the four selected species: green treefrog, red fox, red cockaded woodpecker and wood stork (Table 12). As a common amphibian species, green tree frogs have the largest habitat among the four species studied. They have been seen in 14 of 25 types of land cover in this region. Consequently, they potentially will suffer the worst loss in terms of the total area to be affected. Red foxes move in a wide range, but their habitat will shrink by nearly 40% in the next 30 years according to the most conservative prediction.

Table 12. Estimated habitat losses for selected species (1990-2030)

	Area (in acres)		Habitat Loss	
Common Name	1990	2030	Acres	%
Green Tree frog	301323.57	243374.81	57948.76	19.23
Red Fox	68338.83	41023.59	27315.24	39.97
Red Cockaded Woodpecker (Endangered)	20882.65	17984.84	2897.81	13.88
Wood Stork (Endangered)	135728.03	128129.46	7598.57	5.60

Note: Urban development through 2030 was predicted based on the current growth ratio.

Although loss of habitats of the two endangered species is relatively small, its ecological effect can be more detrimental. This is particularly the case for red cockaded woodpeckers whose habitat areas are small in size, fragmented, and dispersed in distribution (Figure 9). Beaufort County has only one relatively large, contiguous habitat area located around Bluffton in the southwestern part of the county, but the area has become the hottest spot for urban development over the last decade. By 2030, half of that area will be developed. This endangered species could disappear from the southern part of the county if that critical area is not protected in the future.

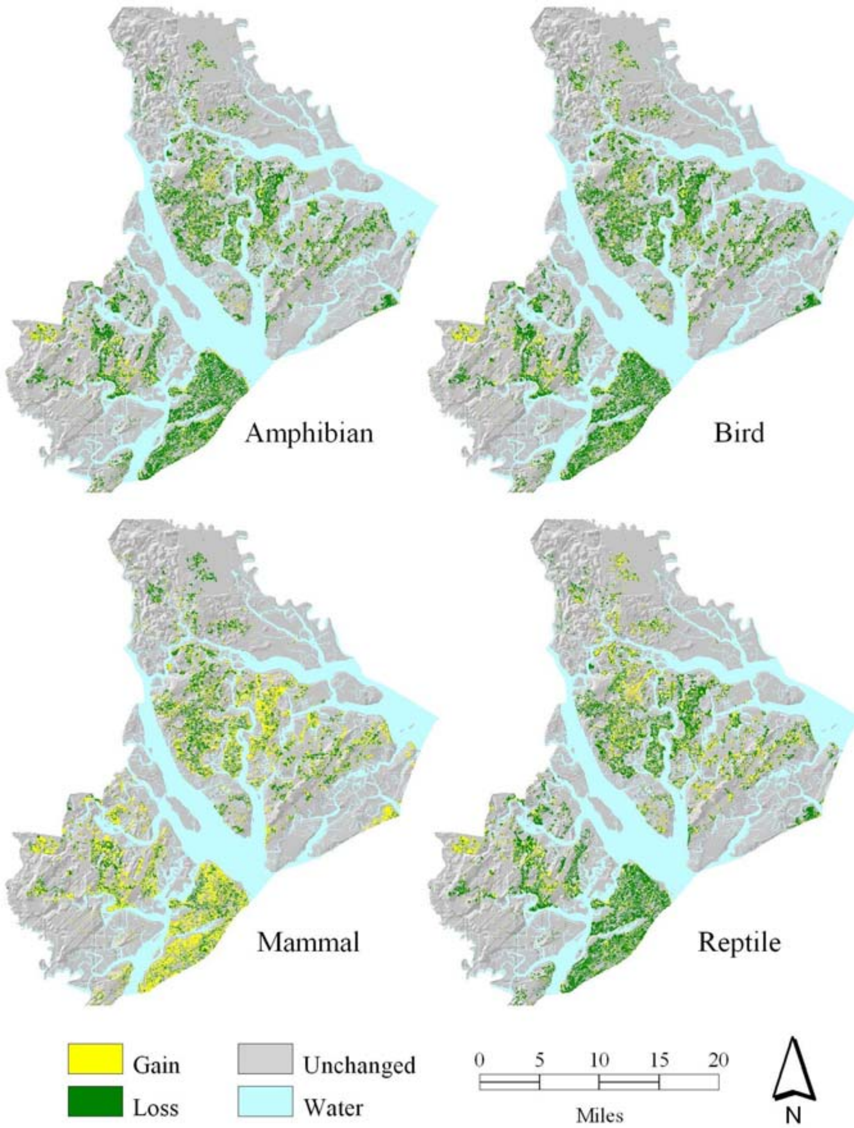

Figure 8. Gain and loss in species richness for four vertebrate groups: Amphibian, Bird, Mammal and Reptile as a result of urban development from 1990 through 2030.

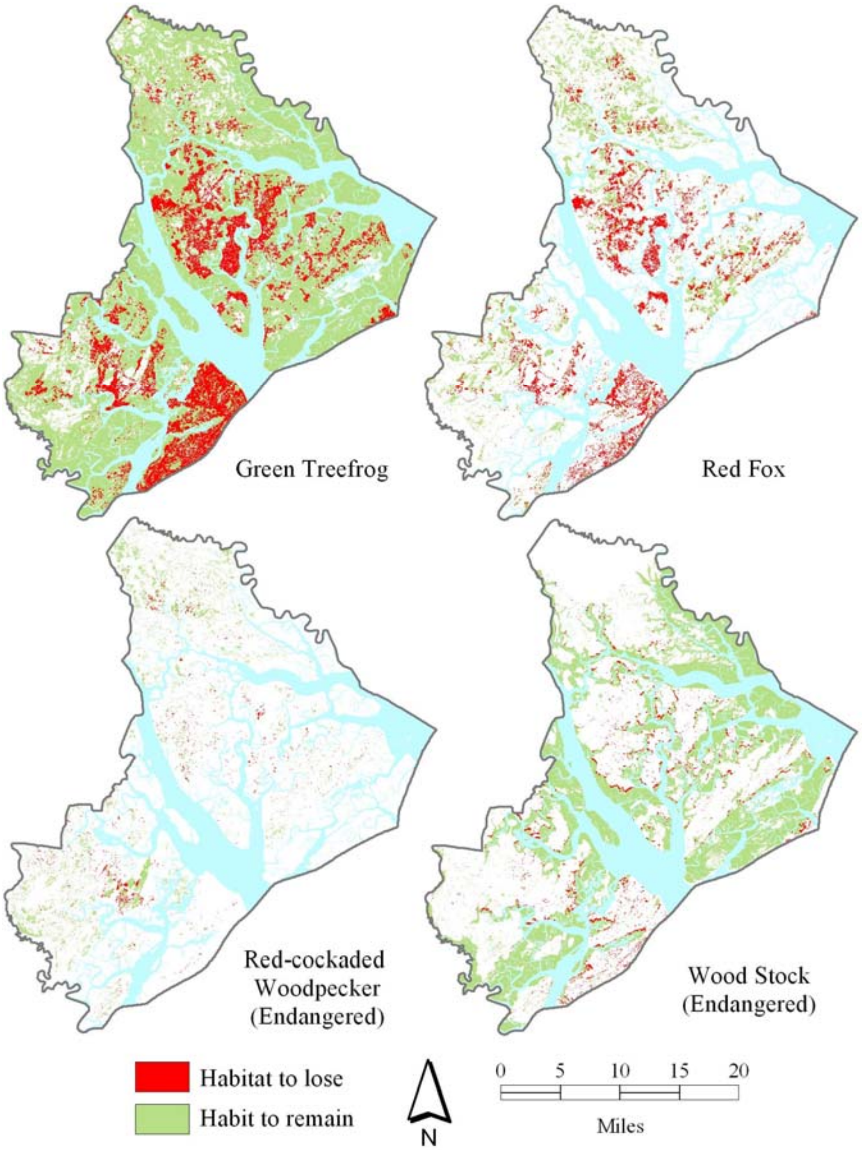

Figure 9. Impacts of predicted urban growth on the habitat areas for four selected species.

V. CONCLUSIONS

Land use continually changes in response to population growth and desires for economic expansion. Urban development becomes inevitable in order to accommodate the growth at the cost of ecosystem integrity. Predictive modeling and simulation using GIS technology and advanced statistical analyses provides us with different pictures of possible land use changes and allows us to assess their potential ecological impacts under different scenarios. In this study, we developed a neural network model for land use change and applied it to simulate future urban growth in Beaufort County. While the performance of the neural network is very encouraging, the predicted urban growth may be a cause for concern, especially if that growth comes at the expense of natural systems. According to the various modeling scenarios, it will not take long before the entire county becomes built-out. The potential impacts may vary. Common species always suffer the most regardless of our measurement methods. We may not have a chance to fully appreciate their value before they become rare or endangered in the future. Although biological implications of the predicted changes in vegetation cover and species richness remain unclear at the global or regional scale, anticipated losses of some critical habitat areas are certainly pushing the selected endangered species toward extinction in this region or along the coast. Development has multiple effects, which force us to make choices. As with any modeling effort, the future urban area may not turn out exactly as predicted even with improved models, but the message has no error: if we do not act wisely today, we will lose what we have tomorrow.

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