4-17-2008

A Multitemporal Analysis of Georgia's Coastal Vegetation, 1990-2005

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by

CHARLES F. BREEDEN III

Under the Direction of Jeremy E. Diem

ABSTRACT

Land and vegetation changes are part of the continuous and dynamic cycle of earth system variation. This research examines vegetation changes in the 21-county eco-region along coastal Georgia. The Advanced Very High Resolution Radiometer (AVHRR) with Normalized Difference Vegetation Index (NDVI) data is used in tandem with a Principal Component Analysis (PCA) and climatic variables to determine where, and to what extent vegetation and land cover change is occurring. This research is designed around a 16 year time-series from 1990-2005. Findings were that mean NDVI values were either steady or slightly improved, and that PC1 (Healthiness) and PC2 (Time-Change) explained nearly 99 percent of the total mean variance. Healthiness declines are primarily the result of expanding urban districts and decreased soil moisture while increases are the results of restoration, and increased soil moisture. This research aims to use this analysis for the assessment of land changes as the conduit for future environmental research.

INDEX WORDS: Remote Sensing, AVHRR-NDVI, Principal Components Analysis, Vegetation Change, Coastal Landcover, Soil-Moisture

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of

Master of Arts

in the College of Arts and Sciences

Georgia State University

2008

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May 2008

ACKNOWLEDGEMENTS

I would first like to thank my thesis director Dr. Jeremy Diem. Without his time, tutelage, and knowledge of remote sensing, climate, data, and professional-scholarly writing, this project would not have been possible. I would also like to thank my committee members Drs. Jeremy Crampton and John Allensworth for their time and meaningful contributions to both my academic career and this writing. My director and committee members have made my scholastic experience invaluable, and I cannot thank them enough.

So far as this writing goes, I would like to acknowledge the Arizona Regional Image Archive-sponsored by the state Office of Arid Land Studies, The University of Arizona, and NASA, for providing the AVHRR-NDVI imagery. I would like to acknowledge NOAA for climate data from the Climate Diagnosis Center, and for Landsat ETM+ data from the Coastal Services Center. I would also like to acknowledge the NARSALab at the Odum School of Ecology-University of Georgia for the supplied Landsat ETM+ raster imagery.

I wish to thank Dr. Susan Walcott, Dr. Paul Knapp, and Dr. Timothy La Tour for introducing me to the Department of Geosciences at Georgia State. I would like to thank my sister, April, for her countless number of hours spent helping to facilitate *my* graduate education – reading, reviewing, and making my work possible. I wish to thank my parents Frank and Linda for all their patience, encouragement, wisdom, and support. And finally, I want to thank the lovely Monica for, well, being the best thing in the world!

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CHAPTER ONE

INTRODUCTION

1.1 Remote Sensing of Vegetated Areas

Approximately thirty percent of the world is covered with land, and seventy percent of that land is covered with vegetation. Vegetation is one of the most important components in unraveling the dynamic changes that constantly occur on the surface of the earth. Additionally, the response of the earth system to natural variations and anthropogenic forces on the land surface has become an increasingly important question in recent years due to the progress in space-based observations coupled with observation programs targeted at the numerical modeling of weather and climate (De Beurs et al. 2004). With the multitude of space-based platforms currently available, scientists are able to examine terrestrial transitions and long-term changes to assess the ramifications of particular human activities (Petorelli et al. 2005).

Remotely sensed data is that which comes from the earth observation programs that are not in direct contact with the earth itself. Fundamentally, space-based platforms like the Moderate Resolution Imaging Spectrometer (MODIS), Geostationary Operational Environmental Satellite (GOES), Mediate Resolution Image Spectrometer (MERIS), and the Advanced Very High Resolution Radiometer (AVHRR) are very capable of observing large changes in earth system dynamics (Rogan et al. 2002). However the biophysical parameters may be measured, they play an important role in engaging several overarching questions about the anthropogenic role in environmental transformation. The first of these questions is, how can multi-temporal AVHRR-NDVI data highlight coastal vegetation change? What particular modes of technology

are most appropriate in given areas? What is the relationship between vegetation changes and climate variability? And most importantly, why are these transformations (if any) occurring?

Very little vegetation research (beyond sedimentary geophysical) has been achieved in the remote sensing arena along the eastern United States. Much of the research in this region is the result of mapping projects done through the National Oceanic and Atmospheric Administration in conjunction with project Landsat (Wang et. al 2003). This is especially true in examining vegetation changes along coastal areas. Many observation projects delve into urban areas and those further inland because of several difficulties involved in the image analysis process that include cloud albedos/interference, Rayleigh scattering, multitude refraction (especially along rocky coastlines), and differential absorption (Danson 1998).

1.2 The Advanced Very High Resolution Radiometer (AVHRR)

The AVHRR sensor is a digital archive sensor developed by NOAA in conjunction with the Satellite Services Branch of the National Climatic Data Center to collect long time-series data on a global scale (NOAA AVHRR 2006). The Sun-synchronous, polar-orbiting satellites that carry the AVHRR have been used since 1978, and continue to provide unhindered global, terrestrial coverage. Substantial progress has been made in using AVHRR data for land-cover characterization and the mapping of daytime and nighttime clouds, snow, ice, and surface temperature (Jenson 2005). The AVHRR is particularly useful with regard to revisit times (twice daily) over other sensors like the Landsat Thematic Mapper (ETM+) with a sixteen-day temporal resolution. The frequency of revisits allows for expansive temporal coverage, which helps to increase the likelihood for cloud-free images and to alleviate problems associated with the lesser

bi-directional reflectance distribution function (BRDF), that can invalidate many remotely sensed images (Brown et al. 2006).

The AVHRR is designed to capture electromagnetic energy along five spectral bandwidths (Table 1). For land cover change and classification, bands one and two are the most important spectral resolutions the AVHRR provides (Deering et al. 1980). Vegetated land appears dark in band one due to the chlorophyll absorption of red light, whereas with band two, vegetation reflects near-infrared radiation, yielding bright tones that acutely distinguish the vegetation-water class deviance (Jenson 2005). In this regard, the AVHRR with its massive capacity swath width (2700 km) is very effective in monitoring large-area vegetation changes over time (Yang et al. 2005).

The AVHRR is an optimal image capturing sensor for vegetation analyses over long periods. Spectral reflection of healthy green vegetation adopts an atmospheric viewing window that best suits sensors like the AVHRR (Gong et al. 2003). Leaf pigments act differently per exposure to particular electromagnetic wavelengths. The primary chlorophyll absorption bands of healthy vegetation occur in the 0.43 – 0.45 µm and 0.65 – 0.66 µm range in the visible spectrum, so in the blue, green and especially red bands. The primary water absorption bands occur intermittently between 0.97 – 2.7µm, between near and mid infrared wavelengths (Jenson, 2005). The AVHRR, among its five bands and eight-bit radiometric resolution, is distinctly capable of capturing wavelengths with high vegetation reflectance values. This is why the AVHRR is best suited for collecting NDVI information.

Table 1, NOAA (AVHRR) System Spectral Resolutions

Band	NOAA, 6, 8, 10 Spectral Resolution (µm)	NOAA, 7, 9, 11,12-14 Spectral Resolution (µm)	NOAA 15-18 Spectral Resolution (µm)	Band Utility
1	0.580-0.68	0.580-0.68	0.580-0.68	Daytime cloud, snow, ice, NDVI
2	0.725-1.10	0.725-1.10	0.725-1.10	Land/water interface, NDVI, vegetation mapping
3	3.55-3.93	3.55-3.93	3*A*: 1.58-1.64 3*B*: 3.55-3.93	Snow/ice discrimination, day/night cloud surface temp mapping
4	10.50-11.50	10.30-11.30	10.30-11.30	Day/night cloud surface temp mapping
5	None	11.50-12.50	11.50-12.50	Cloud and surface temps, day/night cloud mapping, removal of atmospheric H20 path radiance
IFOV at nadir	1.1 x 1.1 km			
Swath Width	2700 km at nadir			

(Jenson 2005, www.noaa.gov/avhrr.html)

1.3 The Normalized Difference Vegetation Index – NDVI

The normalized difference vegetation index is derived from the red – near infrared reflectance ratio (Rouse et al. 1974). The formula is based on the relationship that chlorophyll accumulating within leaves of healthy green vegetation absorb red wavelengths, whereas the mesophyll leaf structures and water within the leaf scatter near infrared (Running 1990). NDVI values, which are unitless, range from –1 to +1, where positive values yield high amounts of vegetation, both deciduous and otherwise, where negative values correspond to sparse or non-existent vegetation (Myneni 1995).

The relationship between NDVI and vegetation productivity is well established, and the link between this index and the fraction of absorbed photosynthetic active radiation intercepted (fAPAR) has been well documented theoretically (Sellers 1992) and empirically (Asrar 1984, Pettorelli et al. 2005). Moreover, direct effects of climatic conditions on biomass and phonological and phonological patterns of vegetation as assessed by the use of NDVI have been reported for ecosystems, as have the feedback effects of vegetation for local climate (Wang et al. 2003, Zhang et al. 2005).

NDVI ratios are available, or can be processed from the many multispectral imaging systems that make use of the red and near infrared wavelengths. This makes the AVHRR a very popular and idealistic platform from which to create these composite images, for two reasons. The first reason is that of the five available bands, the AVHRR contains both needed bands to create the NDVI composite. Secondly, the AVHRR is a long-duration platform that has rapid return times. The AVHRR has produced an uninterrupted time-series (updating twice daily) since 1980, which is why the AVHRR – NDVI combination is one of the most applicable and popular ways to study time-series vegetation and climate.

NDVI values have come to represent a myriad of uses related to ground cover study, yet another reason for the index popularity. The NDVI was originally used to generate maps, particularly those of vegetation distributions and productivity in Africa (Tucker et al. 1985). The NDVI enables the differentiation of ecosystem functionality, along with the quantification of annual net primary productivity (ANPP) to distinguish ground cover characteristics along multiple scalar distributions (Running 1990).

1.4 Principal Components Analysis (PCA)

The principal component analysis is a technique for simplifying a dataset, by reducing multidimensional datasets to lower dimensions for analysis (Fukanaga 1990). PCA performs a linear transformation on a set of correlated random vectors to represent them in a new space such that they are uncorrelated (Ünsalan et al. 2004). PCA is an orthogonal linear transformation that transforms the data to a new coordinate system such that the greatest variance by any projection of the data comes to lie on the first coordinate (the first principal component), the second greatest variance on the second coordinate, and so on. PCA can be used for dimensionality reduction in a data set while retaining those characteristics of the data set that contribute most to its variance, by keeping lower-order principal components and ignoring higher-order ones (Joliffe 2002).

Researchers utilizing a principal components analysis coupled with AVHRR-NDVI data have had great success in developing earth-system vegetation studies (Ma et al. 2006). The fundamental benefit to using a PCA for composite, multi-temporal NDVI studies has been the ability for researchers to successfully couple digital number values (DN) on one rotation axis with time-series data on the other. This allows for the analysis of landcover change, over time, examining areas when and if change greatly occurred (Unsalan et al. 2004). Researchers have

chosen (as a process of data reduction) to assign AVHRR-NDVI, DN values along the primary axis (first principal component loading) and time along the second principal component axis. Researchers have found that eliminating redundancy and decorrelating the spectral information into lesser components exhibits values for overall biomass in the primary component and biomass variability in the second component (Eastman et al. 1993, Mora et al. 1996).

In most of these studies, encompassing many distinct geographic zones and topographic variation, researchers were able to link change rates (if any) to several discrete timeframes (Fung et al. 1987). Included in these studies, using a PCA, allowed for scientists to generate maps of when and where change was most readily occurring. Scientists in this way were able to assess seasonal, interannual, and decadal studies for vegetation fluctuations in given areas (Fung et al. 1987, Teillet et al. 1997). Scientists were also able to assess the coherence of a dataset (in specific timeframes) compared with ground truthings; but this is a less significant result considering the reluctance of many scientists to tie satellite volume estimates with field acreage measurements (Sellers et al. 1994).

A major finding of using a PCA is that tracking interannual vegetation growth (because of NDVI) can be a comparable measurement any where in the world. The PCA has been used in numerous studies (which each use one another) to explicate the relationship of seasonality with vegetation growth (van Leeuwen et al. 2006, Eastman 1992, Ecklundt et al. 1993). The importance of this research is that it can then be evaluated with seasonal classifications from multiple areas, and used as a precursor for a great deal of further statistical research. The AVHRR-NDVI is best suited for a PCA because of the regularity in the sensor algorithms, and it has demonstrated completely the benefits of examining scalar data by using a high loading component in time (Senay et al. 2000). Unsalan and Boyer's work using a PCA with AVHRR-

NDVI has been invaluable because of this trait as they have shown the capacity to prepare an uncorrelated dataset as a statistical preliminary in the examination of multiple-area seasonality (Unsalan et. al 2004). The work of Mora and Merchant also demonstrates the versatility of using AVHRR-NDVI data coupled with the PCA for specific regional, and interannual studies (Mora et al. 1996). Because of this, PCA serves as a necessity in regional areas and global studies alike.

Additional findings of the PCA include that the PC1 (NDVI) values are responsible for explaining the vast majority of mean pixel variance (Fung et al. 1994). The PC2 results (time/change) are typically responsible for the next highest loading percentage of variance, and additional components account for nominal percentages of variance – usually less than one percent (Roberts et al. 1994). Variance has also not significantly changed during time-series analyses, as demonstrated by Mora and Merchant. In this study, PC1 variance shifted by less than 7 percent annually, while PC2 variance shifted less than 15 percent annually (Mora et al. 1996).

1.5 NDVI and Climatic Variables

The use of statistical analysis with multiple variables is in direct response to the composition of NDVI data (Running 1990). The purpose is to connect the variables of causation with the NDVI composite values (Tait et al. 2003). The demonstration of these links, via temperature and precipitation, is a dynamic measure of vegetation conditions, those of the environment around it, and anthropogenic forcing to both (Petorelli et al. 2005).

Many authors have focused on the link with climate, and the variability thereof, on a global scale (Myeni et al. 1997). Many others (as the purpose of this research) have sought the

estimation of NDVI values and landscape-vegetation change on a regional scale (Goetz et al. 2006, Julien et al. 2006). The NDVI has been a successful index measure for the application of remotely sensed data to be researched, both temporally and spatially. The connections between vegetation productivity, incidence, habitat management, dilapidation, and those of anthropogenic activities can assure the careful monitoring of land cover changes. Ultimately, NDVI values and land cover change can be used to monitor and explain the stringent and dynamic situation between our earth system and the human environmental interaction, for better environmental and planning policy in the future.

The strength of using AVHRR-NDVI data with additional variables is consistent with the work of many researchers (Rouse et al. 1975, Running 1990, Deering et al. 1975). In fact, researchers have been highly successful in linking particular variables within the continuum of NDVI change (Pettorelli et al. 2005). Some of the variables associated include climatic ones like rainfall, ground and atmospheric temperature, flooding, ground level water constituents, and circulation patterns.

One major correlation analysis utilizing NDVI as the dependent variable has been with ground level temperature. Many scientists have used temperature as a component for assessing (successfully) whether satellite-derived data and temperature rates are consistent (Yang et al 2006, Piao et al. 2006). They have found that with increasing temperature rates, there is a declining sensitivity for plant growth, and (using time-series) a mutual loss of plant ability to adapt to persistently higher temperatures (Piao et al. 2006). Scientists have also discovered that the correlation coefficient between NDVI and temperature in temperate (mid latitude) regions may be significantly different than those in northerly latitudes (Los et al. 2001). This means that

the continuum of temperature change is more significantly occurring where most vegetation is present – the scanning ability for drier plant species in higher latitudes withstanding.

Another major contribution using AVHRR-NDVI correlation is the relationship between NDVI values and precipitation. Researchers have countlessly linked higher rates of precipitation with higher AVHRR-NDVI values (Piao et al. 2006, Los et al. 2001, Braswell et al. 1997). This includes interannual and seasonal studies between differentiating locales, and usually does not contain the caveat about latitude relegated to NDVI and temperature (Braswell et al. 1997, Zhou et al. 2001). The aforementioned studies also used soil moisture percentages for the parsimony of assessing fewer (and interdependent) variables. The major findings here are related to climate change and the rising levels of both temperature and precipitation. Areas may, and have, had specific quandaries because of the competing role of temperature and precipitation to their local vegetation growth (recognized by NDVI) (Adegoke et al. 2002).

1.6 NDVI and Statistical Analysis

Linear regression as a process of ascertaining the incidence of trends is also commonly used when examining time series composite data. However, the calculated significance of the estimated parameters becomes unreliable in this testing – resulting in an increased probability of falsely rejecting the null hypothesis of no trend (De Beurs et al. 2004).

Researchers have sought to link a larger climate change with AVHRR-NDVI values for some time. Regression using the Mann-Kendal statistic, along with a multiple linear diagnostic has been a popular method (De Beurs et al. 2005). To a great extent, the inclusion of multiple linear regression, as a product of codependent satellite measurement, is typically the lesser of the three major statistical research areas (van Leeuwan et al. 2006). Scientists have found it difficult

to link ground measurements with remotely sensed imagery (in context to finite volumes) when compared with correlation or regression analyses (van Leeuwan et al. 2006). This is to say that scientists would prefer to use in situ data other than derived data when approximating volumes. Regression can be a powerful asset when fully understanding that correlations exist with normalized satellite values, and not with taxonomic certainty (De Beurs et al. 2005).

Scientists have used correlation as a way of connecting multiple variables simultaneously to NDVI data. The primary reason for this is by way of regional study, where regions are tracked over long periods to decide if topographic and atmospheric variables significantly impact vegetation values (Tucker 1985). The findings of these studies have included the successful linking of particular variables – temperature, rainfall, and soil moisture – with AVHRR-NDVI changes (Singh et al. 2006, Senay et al. 2000). In fact, most scientists using this type of testing have concluded that soil moisture and precipitation are the key variables in determining NDVI changes when using multitemporal, AVHRR data (De Beurs et al. 2005, Tucker 2001). They were then able to discern or predict the capacity for ongoing NDVI values to match precipitation trends using a long image time series dataset, like the AVHRR (Running 1990, Piao 2006).

The drawbacks to using this type of data are also founded in that derived information is only as sound as a sensors capacity for processing. Per previously mentioned, scientists have been reluctant to use derived data for both correlation and regressions sake, knowing that said prediction does not necessarily correspond to ground volumes (van Leeuwan et al. 2006). This being said, scientists have had limited success in the prediction of vegetation volumes, and the major findings of this, are again, limited to evaluating ground volume estimates with satellite predictability (Von Storch et al. 1999). Multiple linear regression is used, but with an image series, is limited to a widened margin of error (Ünsalan et al. 2005).

1.7 Landcover Change on the Southeastern Coast

There have been several landcover change studies that employed multitemporal data in the southeastern United States. Most of the research has employed multi-sensor comparisons, and image differencing/ratioing because of the costs associated with obtaining time-series imagery (Roberts et al. 1994). Studies using the Landsat MSS, TM, and image differencing have been popular by several remote sensing scientists along the southeastern coast (Jenson 1986). Most of these studies employ moderate to finer resolution imagery, which is more suited to differencing/ratioing over shorter periods of time (Holben 1986). Scientists have found image differencing to be well suited in this region for uncovering vegetation changes as a precursor to volume estimates. One such study includes Savitsky 1986 where he examined how South Carolina phrenology was changing using Landsat MSS data (Savitsky 1986). It was determined that landcover identification could arise from the use of image ratioing for identification capabilities at finer resolutions (Savitsky 1986, Gallo et al. 1989).

There a limited number of studies that employ AVHRR-NDVI information along the southeastern coastal plain. Primarily, these have used multi-sensor approaches and have focused on the Florida coastline (Brown et al. 2006). There have been a very narrow group of studies which have used a single sensor, time-series, PCA approach to examine land cover change (Roberts et al. 1994). The Roberts et al. 1994 study found consistent findings with earlier works (Fung et al. 1987, Eastman 1992) concerning the usefulness of unstandardized PCA when examining coastal imagery. In this case, NDVI served sufficiently as a primary component coupled with Change as a secondary one in coastal Florida. No additional factor scores were associated with interannual imagery, so each season could be assessed independently throughout the time series (Roberts et al. 1994). It was found that using components in this way produces

satisfactory results for determining biomass healthiness and biomass change over a time. These methods are also consequently more robust than if image differencing and ratioing had been used alone. In the Roberts et al. 1994, and Mora et al. 1996 studies, it was concluded that coastal plain vegetation values were remaining steady. In Zhou et al. 1999, it was concluded that eastern plain values for NDVI were moderately rising (Zhou et al. 1999). In each of these studies (Roberts et al. 1994, Mora et al. 1996, Zhou et al. 1999) anthropogenic causes were primarily attributed to central change areas, with moderate influences from certain climatic conditions. Unfortunately, no such studies have been employed in coastal Georgia.

1.8 Research Question

The major research of this thesis is specified under the following question:

How has vegetation changed in coastal Georgia over the sixteen year period, 1990-2005?

Landscape and vegetation change can be an especially ambiguous term, so by change, this is determined by examining component images designed to distinguish time-series differences. Change in this circumstance means a differentiation in values throughout many years of imagery. This value change (using NDVI values) would mean that canopy or ground vegetation growth, had either increased in total volume or subsided. Therefore, along the 11 – county eco-study zone, higher positive values indicate more change in each area.

It is very difficult to compare interannual data in this way because of Georgia's four distinct seasons, and discriminating seasonal values. This is why a time-series study from 1990-2005 is an effective way of analyzing these changes from year to year. With this data duration, coastal areas can be studied through seasons, as interannual assessments are much more difficult to evaluate (Tucker et al. 1981).

This type of study is important because it allows for scientists to remotely (and over large scales) witness and calculate long-term terrestrial changes to the environment. It also allows for scientists to pose questions in analysis of such data that addresses continuing study interests like the particular areas where landscape change is most prevalent, and where possible ramifications of anthropogenic activity are most severe. Essentially, the value of this research is that on a regional level, remotely sensed data can be used for witnessing and evaluating changes in a sensitive ecological area that has never been studied in this way. This type of research is important because of the convenience and cost-effectiveness that allows for scientists to use remotely sensed data to convene on the environmental issues. This type of research is the conduit for analyzing and preparing new technologies and methodologies for assessment of the human-environmental interaction.

CHAPTER TWO

METHODOLOGY

2.1 Study Region

The Georgia coastline provides an excellent study area since there exists little previous research in the region utilizing an AVHRR-NDVI time series. Additionally, the landscape is both relatively flat and heterogeneous in context to vegetation (Clayton 1992). The Georgia mainland is bordered to the east by a system of functional barrier islands, marshes, and coastal waterways. The chain of barrier islands extends the entire breadth of the coast. It is inundated with vegetation resulting from salt and brackish marshes, marine estuaries, and interrelated ecosystems containing Spanish moss, old growth forests of the loblolly pine and hardwood oak, and the oak-gum-cypress forests in low-lying dune areas (Oertel 1975).

The scientific determination of what constitutes the coastline is a more difficult, and less refined, definition. The determinates of the Georgia geologic coastline have been a process of separating the state into specific geographic entities based on criteria like topography, altitude, drainage patterns/watersheds, soil taxonomy, interannual climatic variability, and biological diversity – including both animal and plant phenology (Clark et al. 1976). Scientists disagree on the extent of the area occupied by the coastal region, designated by the aforementioned criteria as the southern or lower coastal plane (Clayton 1992). In general, however, many geologists have chosen a section of the twenty-one county 'ecoregion' from Burke to Echols counties, that extends inland by 45 miles (72km), as the boundary of this lower coastal plane – and the chosen study area for this research (Huddlestrun, 1988). This section includes Effingham, Chatham, Bryan, Long, McIntosh, Wayne, Glynn, Brantley, Camden, Charlton, Ware, and

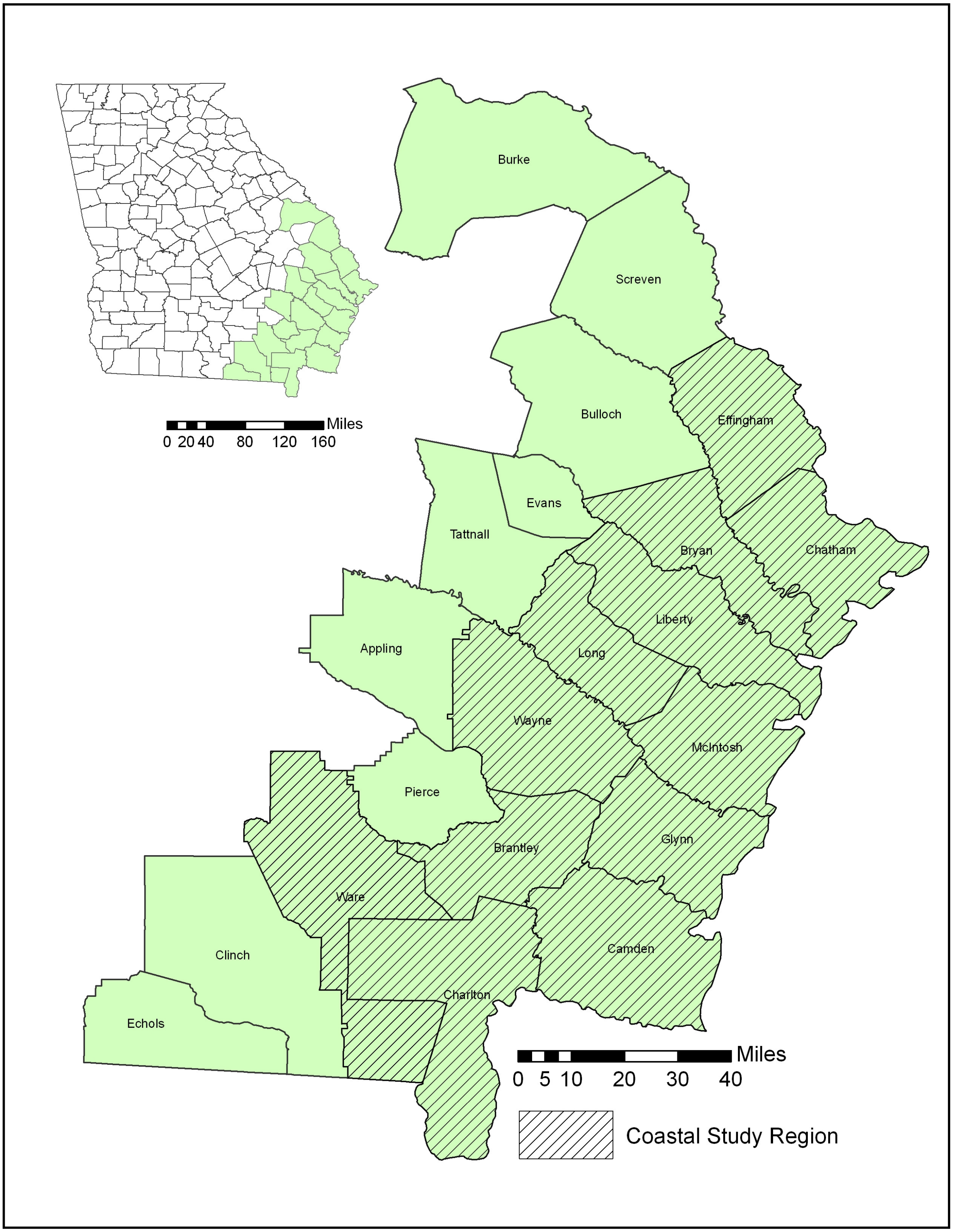

Figure 1, Georgia Ecoregion and Coastal Study Zone

Liberty Counties (Figure 1). Historical geologic work in this region has focused primarily on rock and soil sampling, formation mapping, topography, fluvial processes, and erosion (Harper 1914). Therefore, the study area includes a selection from the ecoregion, and the images (for purposes of collecting NDVI values) were clipped corresponding to the county borders at the 70 km range (detailed below).

2.2 Data Preparation

Data from the AVHRR Pathfinder 14 polar orbiting satellite is available twice daily. Each of the daily capture includes (initially) nine bands of information including AVHRR spectral bands 1-5, NDVI, solar radiance zenith, satellite zenith, and the relative azimuth. The NDVI is the only composite bandwidth because of the format's flexibility with the AVHRR swath width. Since the AVHRR is a global coverage satellite, the NDVI is a superior index for vegetation studies given its comparability with multiple land types (Cihlar et al. 1991). Each of the daily images is calculated within certain parameters for a specified reflectance (0 to 255, 8-bit radiometric resolution) and geo-registered to the Lambert Azimuthal equal area projection.

Images are registered on the 14-day composite for the selection of the best image in a two-week period. This is to select two images per month that are free from clouds. The superior 14-day composites are then registered using the Julian calendar, creating a tenth band of information that is a unique identifier for the image source and time.

Cloud free images are essential for the monitoring of vegetation cycles because land surfaces cannot be studied (multispectral) through weather cycles. Reflectance from cloud top canopies inhibits the quality of measuring underlying conditions; therefore, the two-week composite is best suited. It has been shown that cloud free, composite AVHRR data can produce

temporally and spatially adequate continuity for studying a vegetation time-series (Holben 1986). Each image providing significant cloud-free coverage and possible nadir (viewing angle directly beneath sensor) is included and can post between 15-30 images in each composite.

The satellite calculates images and solar viewing cycles (geometry) for eastern and western hemisphere coverage, then computes the satellite zenith angle and relative azimuthal angle, and then scientists radiometrically correct and enhance that data. (after the fact). The radiometric image correction is of particular importance because the AVHRR did not include preflight calibration for channels 1-5, does not exercise on-board calibration, and is significantly difficult to calibrate in-flight. The AVHRR launch, space flight duration, zero gravity environment, post-flight sensor degradation, and pre-launch calibration coefficients from NOAA have been problems for correcting radiometric errors (Rao 1987, Price 1987).

NDVI values are effectively captured and processed in a normalized coefficient measurement of –1 to 1, where values larger than zero mean a positive vegetation presence and values less than zero reveal there is none. This value can also be scaled for maximum iterations using the sensors radiometric resolution so that NDVI values can be used to discriminate water, snow, barren ground, and agriculture versus tree top canopies (volumes). More information on AVHRR-NDVI preparation and calibration can be obtained from Price 1987, Kelly et al. 1991, and the USGS Earth Resources Observation and Science (EROS) Lab.

2.3 Image Collection

The most effective way to study vegetation cycles was to examine time-series data. The 16-year (1990-2005) AVHRR data are used in this way to compare seasonal changes in NDVI values over this period. The first item was to organize and assess what data is available and

conversely, what data is unavailable. In the sixteen-year period, a maximum of 416 images (26 per year, 16 years) could be used for this study. Unfortunately, the data must also be atmospherically corrected for water vapor concentrations and only about half (208) of the dataset were. Water vapor in the atmosphere impairs the sensors ability to effectively analyze reflectance, so a corrective algorithm has to be used (USGS initially processed the usable portion of the dataset). However, the data is organized and available effectively enough (high enough temporal resolution) to be used over the study region. The original Pathfinder, NDVI coterminous US composites (NDVI processed) were collected from the USGS, provided with help from the Arizona Regional Image Archive – at the University of Arizona.

The most efficient way to analyze the data is through a layer stacking method. Since the data is already processed concerning cloud-free imagery, refined through the 14-day cycle, and processed into the NDVI (AVHRR bands 2, 1), the only item that remains is to compress the images into one larger image that can be analyzed and spatially processed to expose time series changes. After looking at a line graph, the available data shows peaks at Julian days 52, 136, 220, and 328, effectively exhibiting an even distribution in all four seasons.

In context to data selection, the Julian data peaks were chosen in each year for the best available seasonal data (Figure 2). Sixteen images from each season (per year, per cycle) were chosen to organize this data for a clear spatial and coherent temporal resolution for examining year-to-year data. There are a ready number of images for each season to contain all sixteen years worth of data. In fact, the highest loading data (NDVI) for the time series occurs in spring and summer. The regular collection of this data is effective enough to analyze seasonal and long-term changes using the multitemporal approach, and this is how the images were processed.

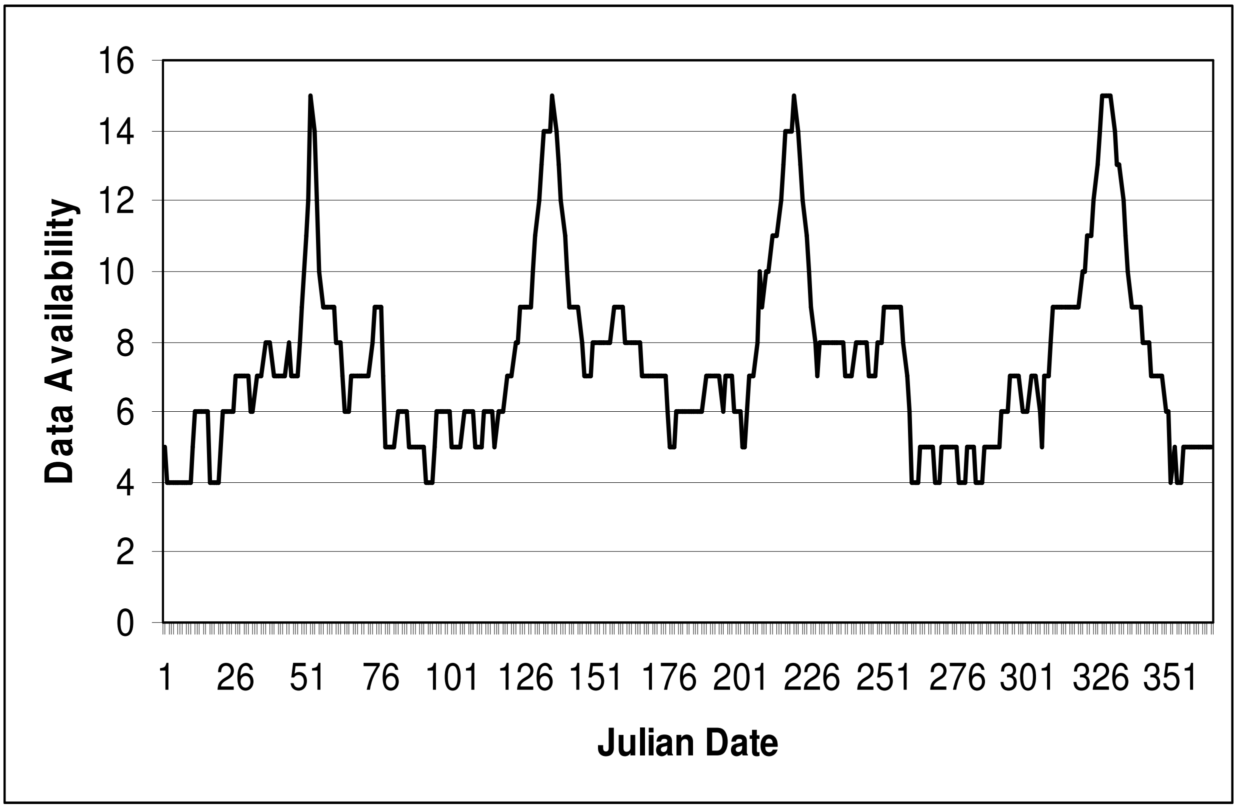

Figure 2, AVHRR-NDVI Data Availability

2.4 Image Analysis

The first analysis was completed by way of layer-stacking the images into one, larger, composite image. This means that all the images were combined into a single, spatial dataset where pixel analysis occurred. So, where a single image contains a single band of digital numbers (DN) to examine, that layer-stacked image contains all sixteen years of data, by season. The image can be viewed as a single entity, but it is further a composite of all the annual and interannual data. This allows for the pixel analysis over time. Though the image is a single entity, the underlying data is not. Items were added, scrutinized, and removed at will from this image given the guise of particular seasonal study. In this way, data can be chosen at will and represented in a single image (with corresponding values). The images can also highlight pixel and NDVI value changes (over time). By this, the image can represent seasonal changes (highlighted per pixel) from year to year. This accomplishes the task of witnessing where changes occur, most readily or otherwise, and when in fact they occurred.

The imagery was then overlain with borders (county) and the pixels were clipped around those borders with an area of interest (AOI) to assess only those which occurred in the coastal study zone. Resulting imagery appears in one scales focusing entirely on the coastal study area (1:1,000,000). These images are those which adhere to the layer AOI, and include both healthiness and change information.

The use of the layer-stacking method allows for a statistical preliminary to assess total pixel value changes. This was accomplished by the use of principal components analysis (PCA). PCA as a data reduction technique, highlighted changes as they occurred across two or more axes. In this case the axes were time (Change) on the y-axis, and, on the x-axis, NDVI seasonal value. The data were then processed in this way using this technique as a statistical preliminary.

The process uses an unstandardized PCA (Tucker et al. 1985) which means that each season and corresponding loadings are dependent on the layer-stacked images alone. Therefore, change values are dependent on the range of values input by season rather than on the graduated NDVI scale (Roberts et al. 1994). In this way, image values are unrotated and are reverent to seasonal values alone – as not to be mired from interannual values.

The PCA was performed as a seasonal study using the statistical methods of research in Roberts et al. 1994, Mora et al. 1996, and van Leeuwen et al. 2006. Each image is a 16-layer (band) organized by season. Each principal component was selected and processed in order to explicate new pixel values. The first principal component (PC1) was NDVI; the second component (PC2) was time. PC1 represents overall biomass for the 16-year study period, whereas PC2 represents biomass variability over the same. PC1 is known to exhibit spatial NDVI values because of corresponding DN values where low values are areas of the least biomass and high values are the areas of the most biomass. PC2 is known to exhibit biomass variability because of differentiating scores (compared with NDVI) where only high, positive values show change and all other values show no change. This process generated images where it can be determined what force was responsible for differentiating pixel values over the entire time series – NDVI, time, or unknown variables. Using seasonal means calculated from every pixel DN in each of the counties in the coastal region, (per county, per year, per season) it determined either the total number (and percentages) of pixels in each image that can be explained through NDVI greenness values, changes attributed to time (seasonal anomalies, annual declines), or pixels whose values could not possibly have been the results of changes on either of the two components. The post-PCA imagery was used to explain pixel values over the

time-series, and it is seasonally dependent. Therefore, since the PCA was done separately for each season, results will appear thusly.

Post-PCA imagery was processed for exposition at the aforementioned scale in two ways. First, the PCA images were processed and those images will appear by season. Secondly, the same group of images was processed from the PCA for pixel change detection. The resulting imagery for PC1 exhibits a value density from green to brown, where the highest loading (healthiest) values for each season are the richest green. These dark brown areas are the least healthy (per season) throughout the time-series. An image following the PC1 contains polygons generated outside two standard deviations (+2,-2) to show the most and least healthy areas for each season individually. The following PC2 images range from blue to red, where deep blue pixels mean no change and deep red pixels mean high positive change values. This method adheres to the Mora et al. 1996 method of highlighting areas where NDVI is significantly varying and helps to visualize areas of noteworthy change.

PC2 images were further processed to highlight areas of such noteworthy change as to exhibit them individually. This was accomplished by generating binary rasters from each seasonal PC2 image. The change image for each season was assigned pixel values of zero and one. High change areas (loadings greater than two standard deviations on one tail) were assigned one, and all remaining values zero. These images were then converted into unsmoothed polygons that adhere to the original raster layer and exhibit the threshold values alone. These polygons were converted to AOIs, similar to how the PC images were generated, and then used to slice the preliminary seasonal layer stacks. This allows for the capture of each polygon’s yearly NDVI-mean for correlation testing. These polygons appear red (displayed for high

change) with a gray outline for perspective. Imagery was processed by season, so each season will have an image with red polygons exhibiting the highest levels of change.

Using the PC2 (Change) images as the cursory from which to assess NDVI and climatic effects on the study zones difference, several polygon areas were determined for each season. The high values extending outside of two standard deviations revealed upwards of fifty separate polygons for each season. Some of these polygons were too small (single 1km pixels) for a representative change area, so chosen polygons were much larger. Thusly, the largest contiguous polygons for each season were chosen for density and spatially diverse purposes.

2.5 Correlation Testing

NDVI was evaluated using the Spearman Rank-Order (Spearman-Rho) correlation testing to establish if significant performance trends existed within the time series duration (per season). A similar assessment was performed with the high change areas. The next statistical measure using the same methods from Unsalan et al. 2004 was to correlate post-PCA values with physiographic variables in order to explain landcover vegetation changes. This compares NDVI values with extemporaneous variables like temperature, precipitation, and soil moisture. This is a type of correlation coefficient that is not image dependent. So changes were predicted using a correlation diagnostic, though unfortunately, those changes cannot be viewed. The collection of controlling variables was an effective technique to discuss climatic variation on seasonal growth. Utilizing the previous work that soil moisture highly correlates with NDVI values, (Adegoke et al. 2002, Lozano-Garcia et al. 1991) a non-parametric correlation test (Spearman Rank Order) was used to see if NDVI values corresponded with regional soil moisture trends. Similar tests were performed using the additional variables of temperature and precipitation. Soil moisture

was chosen over each of these variables for additional examination of aggregate NDVI totals because of interannual variation and the usually high correlations over temperature and precipitation in NDVI studies (Martin 1993). Values for soil moisture, temperature, and precipitation in the ecoregion were collected from the National Climatic Data Center, Climate Diagnosis Division, from the National Oceanic and Atmospheric Administration.

To assess coastal soil moisture correlation in the study region, the Spearman Rank-Order Correlation Coefficient was again chosen to determine if a relationship existed. This was chosen because the means for soil moisture and for NDVI were processed by season, and there are not a sufficient number of observations from which to assess with a parametric test. The performed test was a one-tailed assessment. This was chosen on par with the literature findings in strong correlations, even though the two testing groups' means (because of seasons) were collected from different populations. A one-tailed test provides a rigorous and thorough way of assessing a potential relationship.

Polygons generated from the PC2 images were correlated using the Spearman test as well. The mean NDVI from change areas was examined against temperature, precipitation, and soil moisture from NOAA Climate Division data in the SE Georgia region. This was used as the predicate for determining (in areas which change most greatly occurred) if climatic or anthropogenic forcings were primarily responsible for the landcover change.

2.6 Landcover/Landuse Assessment

After the images were processed and tested for correlation, individual changes and mean NDVI totals were assessed against coastal landcover and above ground biomass. Three maps were generated which exhibit landcover types and uses in the coastal region. Data for the

landcover map (Figure 3) was derived from the NOAA Coastal Services Center (CSC) from Landsat ETM+ imagery (2001). Data for the latter, forest types map (Figure 4), was from the Natural Resources Spatial Analysis Laboratory (NARSAL), at the Odom School of Ecology – University of Georgia. Forest Inventory information was taken from Landsat ETM+ imagery and processed by NARSAL for the Georgia Gap Analysis Program, 2003. Data for urban areas (Figure 5) was taken from census data processed in the National Atlas of Urban Areas, 2000. Part of this assessment was from the correlation diagnostic to determine whether or not changes were induced through climatic or anthropogenic activity. This information was compared to trends in both NDVI and in landcover change to discern where and why landcover was changing along the Georgia coastal plain.

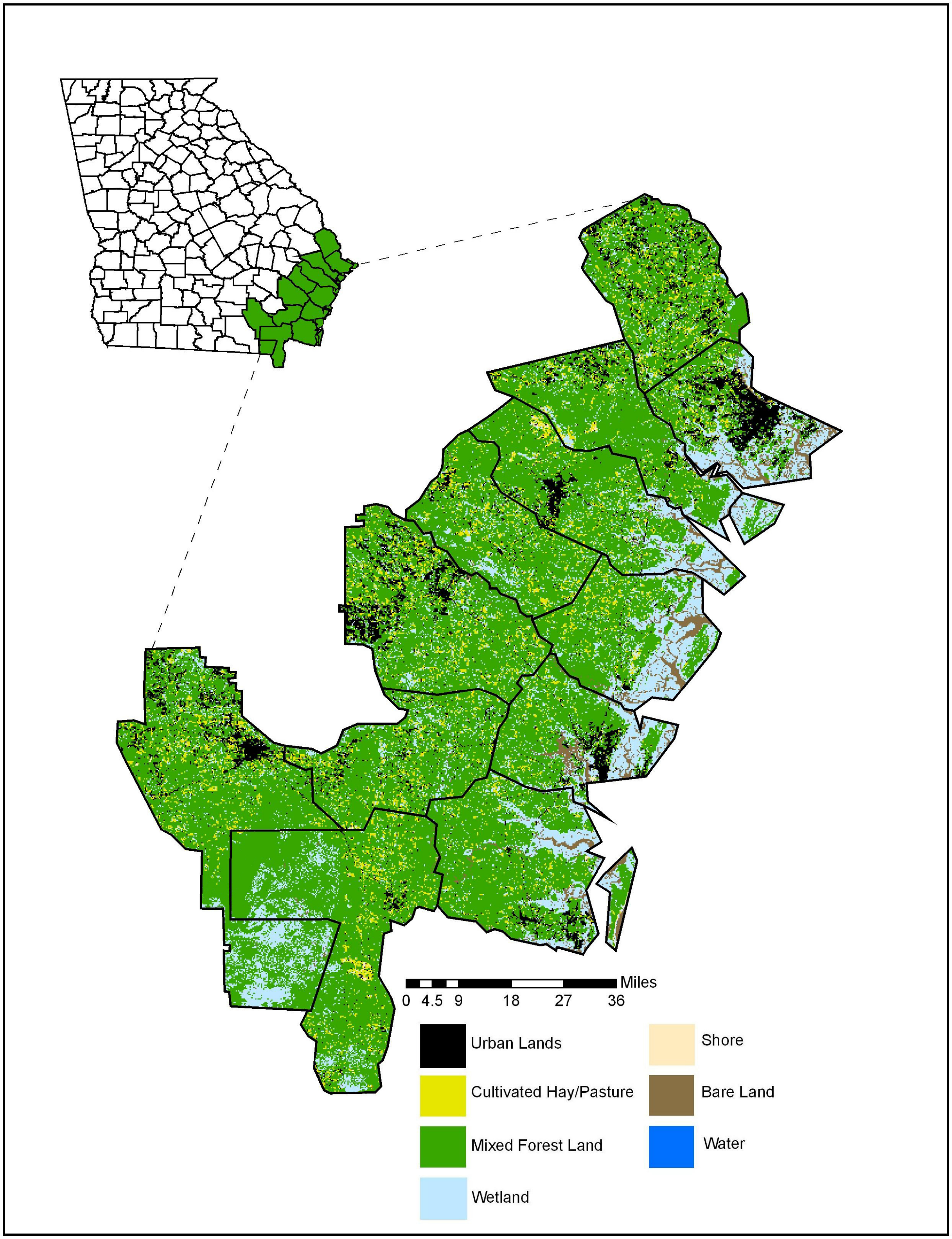

Figure 3, Georgia Coastal Landcover (NOAA CSC 2001)

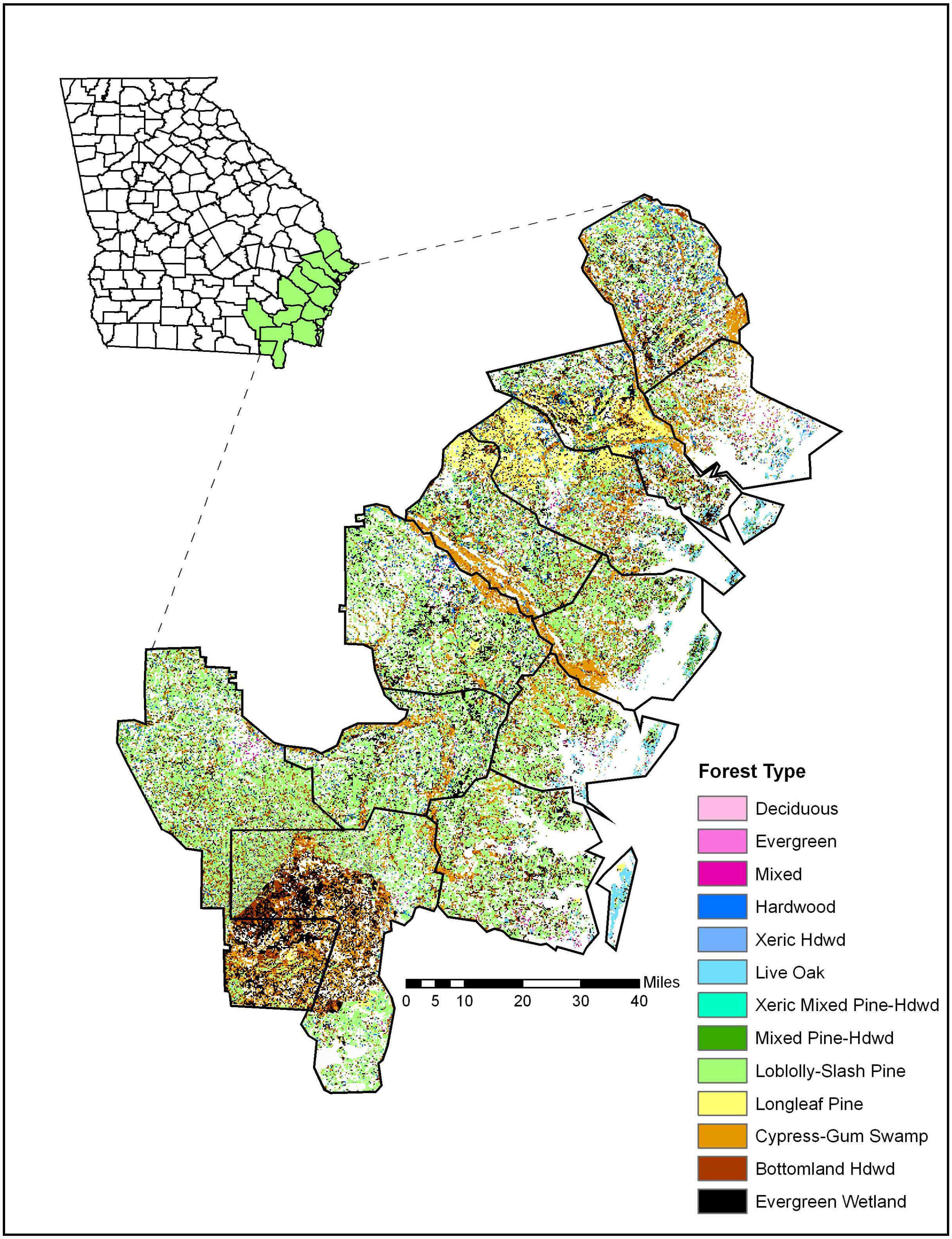

Figure 4, Georgia Coastal Forest Types (NARSAL 2006)

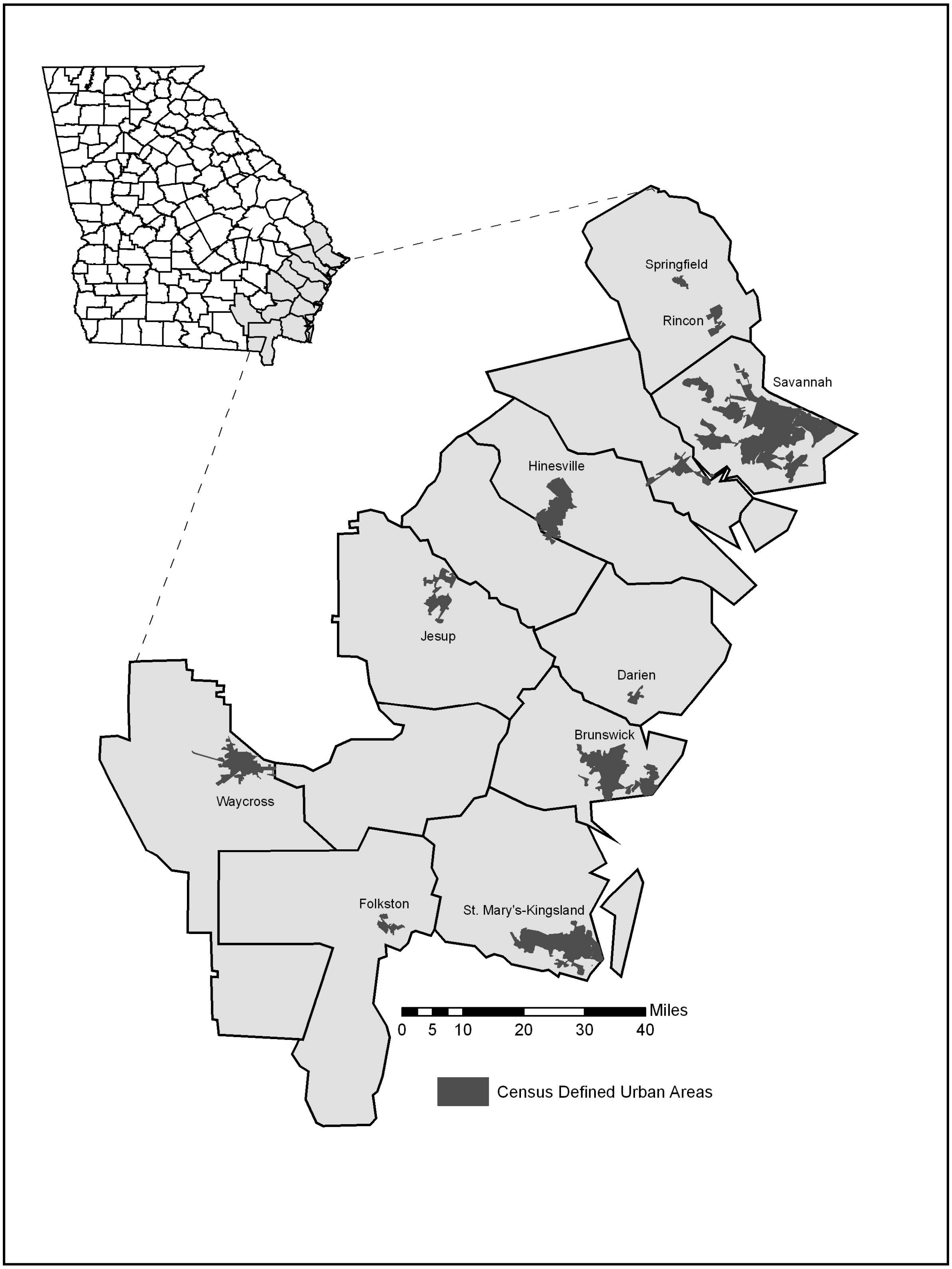

Figure 5, Georgia Coastal Urban Areas (US Census 2000)

CHAPTER THREE

RESULTS

3.1 Explained Component Variance

Once the PCA was performed, component scores and explained variance (Table 2) were similar to findings from previous research (Roberts et al. 1994, Mora et al. 1996). It was determined that the primary component was responsible for explaining more than 96 percent of the total mean variance. In each of these seasons, the explained variance was actually higher than this figure. Component two scores represented between one and three percent of the variance. Remaining components constituted a negligible percentage of scores (<1 percent).

3.2 Overall Greenness

3.2.1 Fall

Fall PC1 includes values that were high in several key areas. Some of the aggregately highest values for fall include the northern coast, the inland areas from Effingham County south, the interior west, and the upturned "V" in the very south study zone (Figures 6, 7). Typical NDVI values in these areas ranged from 0.32-0.35. These highly scoring values are comprised of a multitude of forest and land cover types. In these areas is a good deal of deciduous forest, some of which (upturned V) is protected. The consistently healthiest areas are those including mixed-pine hardwood forests and loblolly-slash pine forests.

Fall values for some of the least healthy areas include the "central corridor" stretching from Hinesville to the coastline, the bottom Okefenokee wetland, and major urban zones (Savanna, Waycross). Typical NDVI values fall in the 0.28-0.31 range for these areas. Land topography in the area is primarily urban including Savanna, Waycross, and Hineville-Fort

Stewart. Land near the Fort is also heavily inundated with longleaf pine stands. The central corridor also contains gum swamp that runs the breadth of the study zone, and these values are especially low. The southern swamp land, protected by a thick border-forest barrier to the north, also reflects lowly. This area is a mixture of gum swamp and heavily flooded land.

Fall values ranged by county were similar to regional findings. There was not a great deal of value difference between counties during the study period. Fall counties with some of the best vegetation healthiness include Charlton, Effingham, and Bryan, Counties. These counties experienced healthy vegetation in the 0.33-0.35 (mean) range consistently. Values with some of the lowest NDVI returns include Chatham, Liberty, Long, Wayne, and McIntosh Counties with healthiness in the 0.3-0.33 NDVI range.

Table 2, Explained Eigenvalue Variance by Season*

Component	Winter	Spring	Summer	Fall
1	98.065	97.515	97.222	96.052
2	1.012	2.25	2	3.12

* Components for NDVI (Overall Healthiness) (1) and Time-Change Image (2)

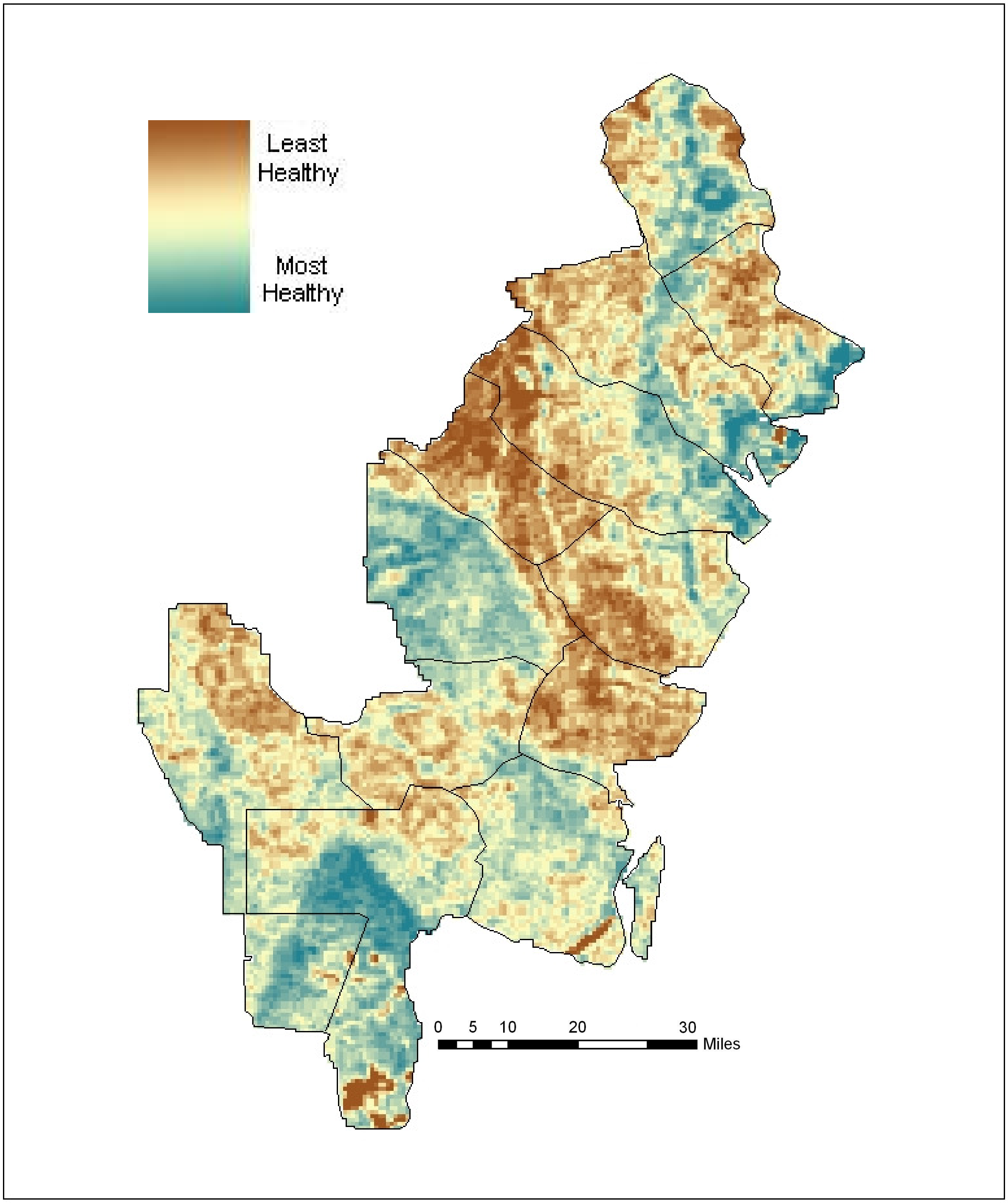

Figure 6, Fall PC1-NDVI (Healthiness)

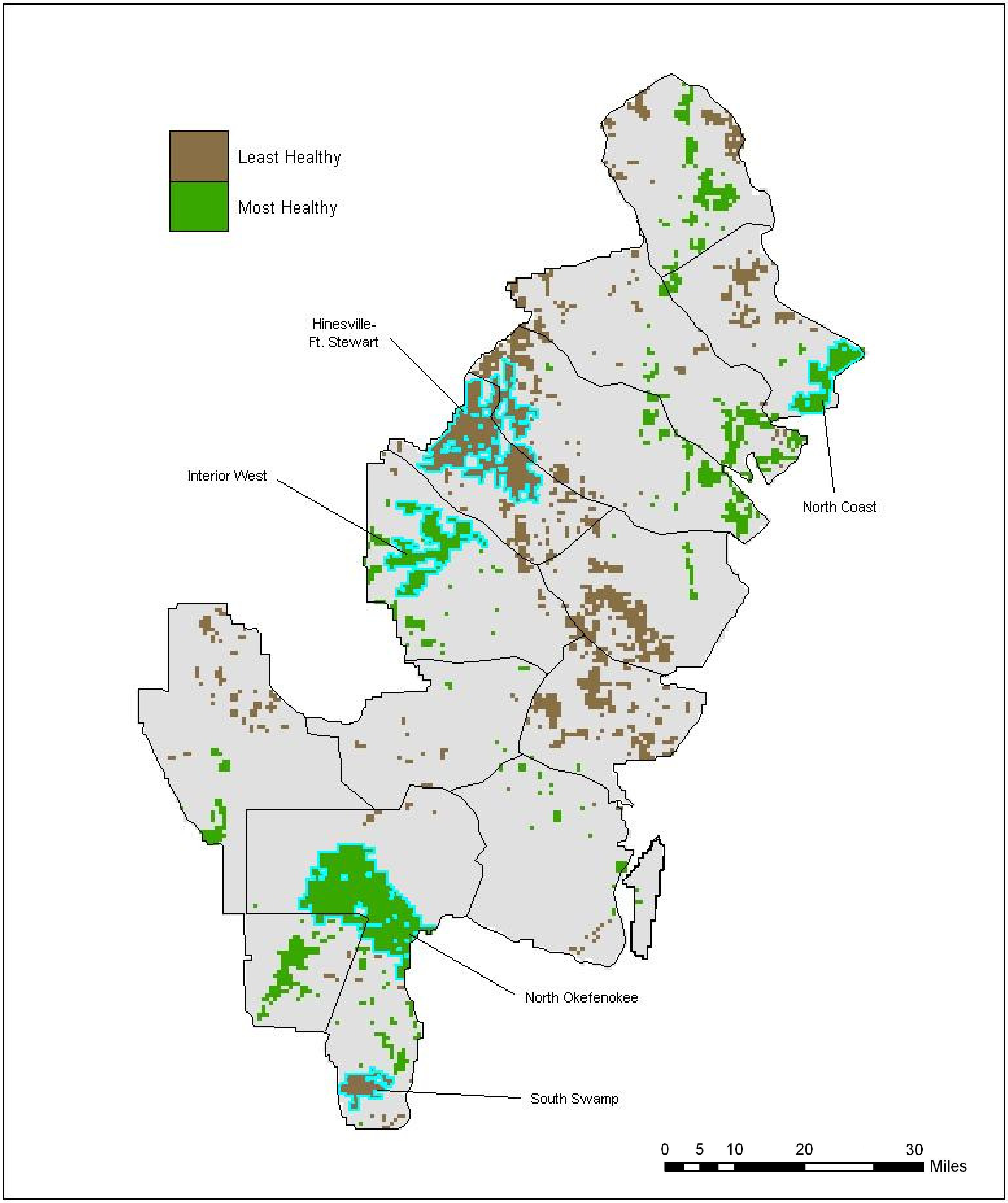

Figure 7, Fall High & Low Growth Polygons

3.2.2 Winter

Winter PC1 includes values that were high in several key areas. Some of the aggregately highest values for winter include, the upturned "V" and surrounding areas (Figures 8, 9). Typical NDVI values in these areas were in the 0.31-0.34 range. Landcover in these areas includes deciduous forest, some of which (upturned V) is protected. The consistently healthiest areas are those including mixed-pine hardwood forests and loblolly-slash pine forests.

Winter values for some of the least healthy areas include the southern swamp portion, the central corridor (Hinesville-Ft. Stewart), urban areas, and coastal wetland. Typical NDVI values in these areas lies within the 0.28-0.31 NDVI range. Landcover in these regions includes flooded wetland, urban density, gum swamp, and longleaf stands.

Winter values ranged by county are similar to regional findings. There was not a great deal of value difference between counties during the study period. Winter areas with the best vegetation healthiness include Ware, Brantley, and Glynn counties. Values in these areas exceed 0.35 NDVI range. Areas with some of the least healthy vegetation include Liberty, Long, Bryan, and Chatham Counties. Healthiness in the 0.3-0.34 NDVI (mean) range occurred in these areas. Correlation testing revealed strong positive correlations for NDVI growth by year.

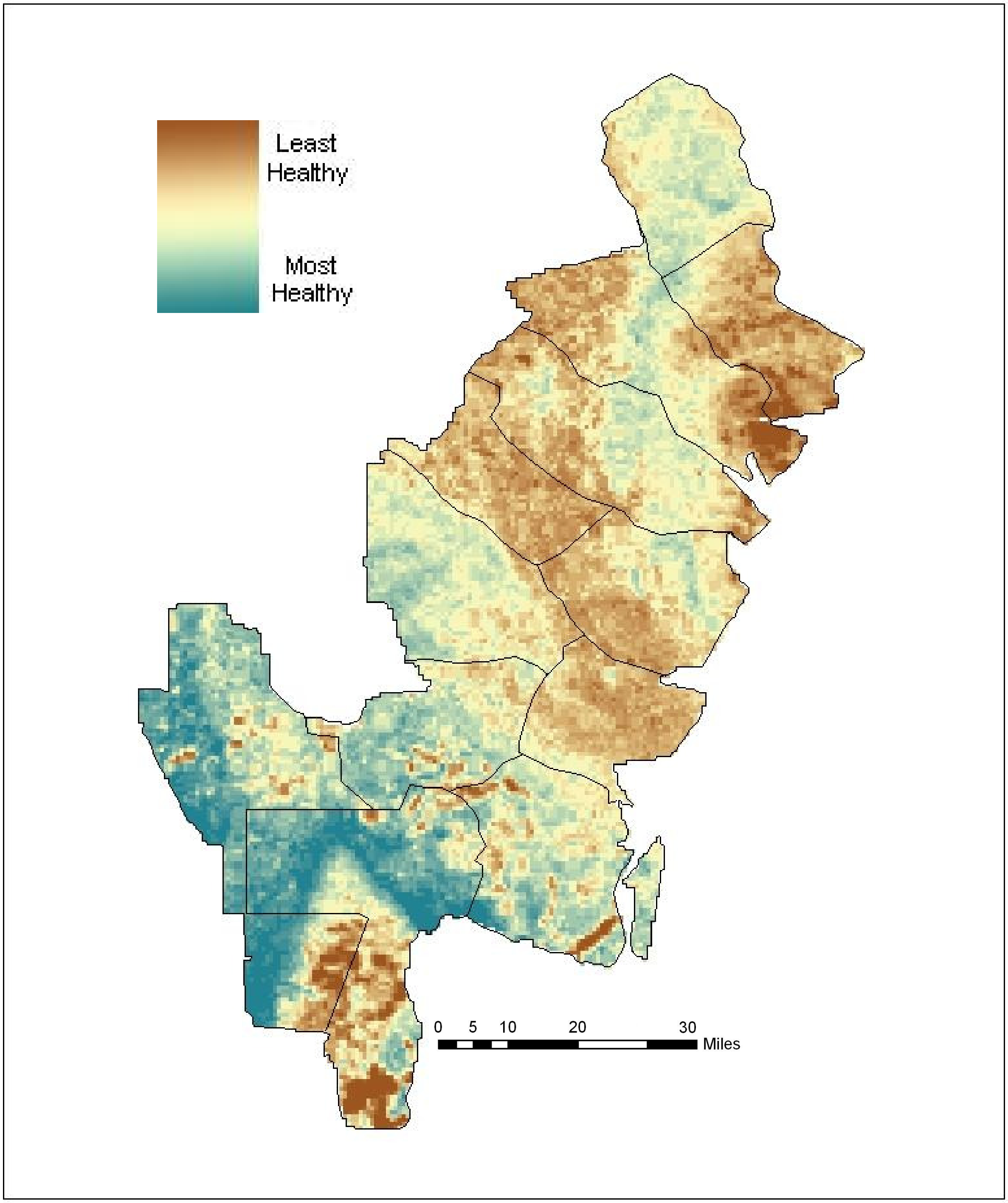

Figure 8, Winter PC1-NDVI (Healthiness)

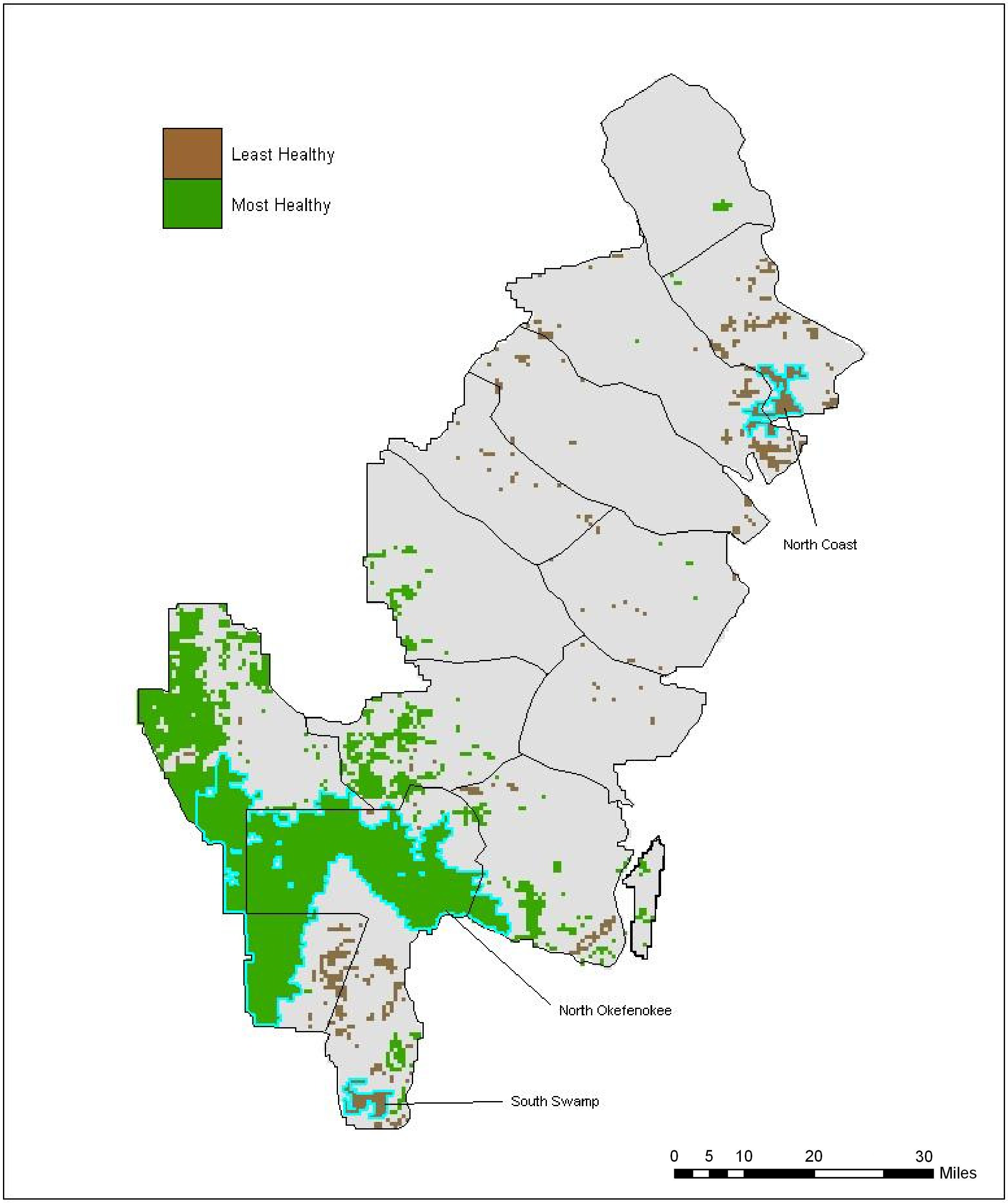

Figure 9, Winter High & Low Growth Polygons

3.2.3 Spring

Spring PC1 includes values that were high in several key areas.   Some of the aggregately highest values for spring include the interior west, the upturned "V", the interior west, and to some degree, the northeastern coast (Figures 10, 11). NDVI values were typical in the 0.54-0.59 range for these areas. Values in these areas remain steadily higher than the rest of the study zone. In these areas is a good deal of deciduous forest, some of which (upturned V) is protected. The consistently healthiest areas are those including mixed-pine hardwood forests and loblolly-slash pine forests.

Spring values for some of the least healthy areas include the top and central corridor, major urban areas, and heavily flooded lands within the south swamp. NDVI values in these areas were typically in the 0.49-0.53 range. Land topography in the area is primarily urban including Savanna, Waycross, and Hineville-Fort Stewart. Land near the Fort is also heavily inundated with longleaf pine stands. The central corridor also contains gum swamp that runs the breadth of the study zone, and these values are especially low. The southern swamp land, protected by a thick border-forest barrier to the north, also reflects lowly.

Spring values ranged by county were similar to regional findings. There was not a great deal of value difference between counties during the study period   spring areas with the best vegetation healthiness include Charlton, and Wayne Counties. Values in these areas exceed the 0.56 NDVI range. Areas with some of the least healthy vegetation include Bryan, Liberty, Chatham, and Long Counties. Healthiness in the 0.49-0.53 NDVI range occurred in these areas.

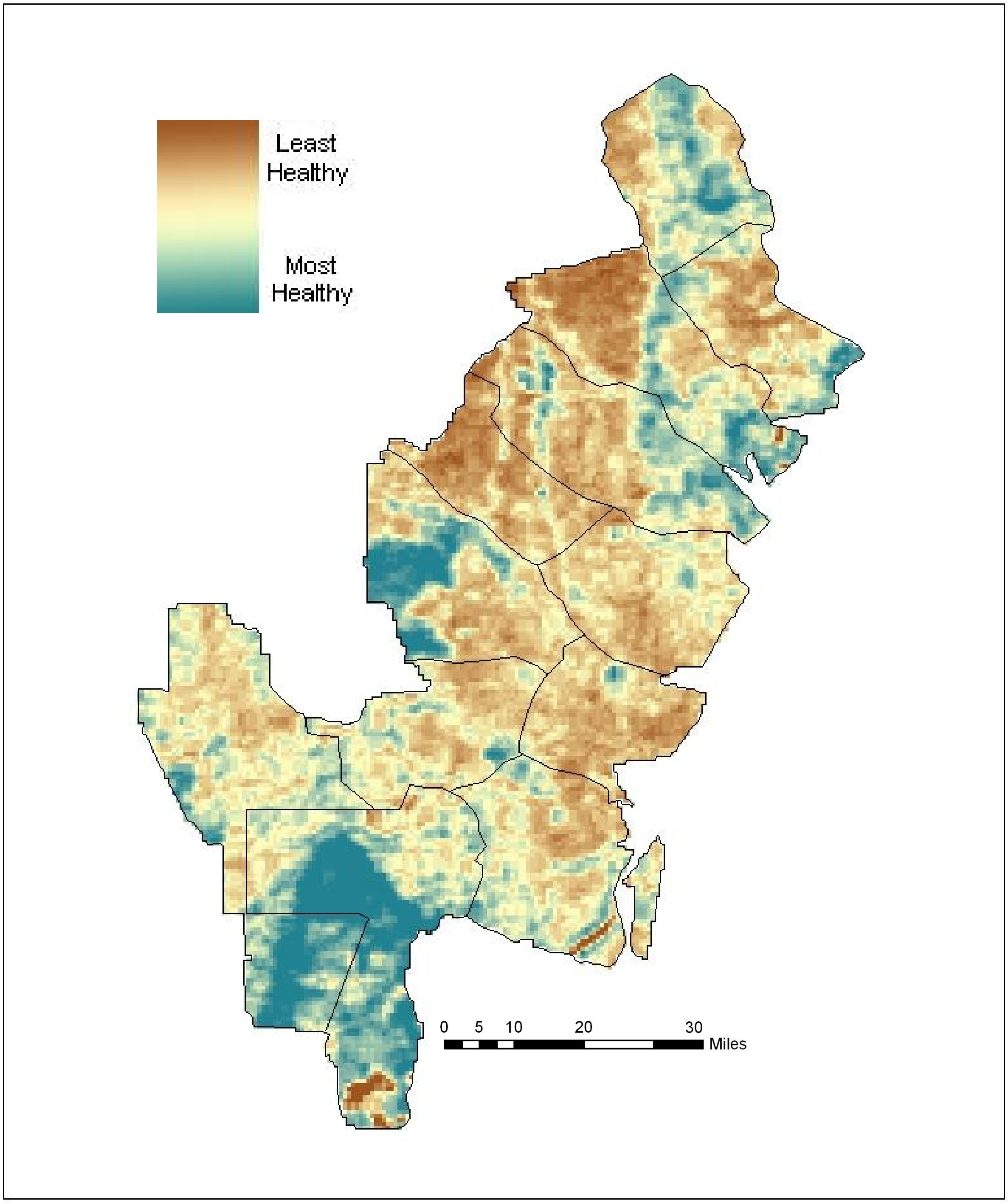

Figure 10, Spring PC1-NDVI (Healthiness)

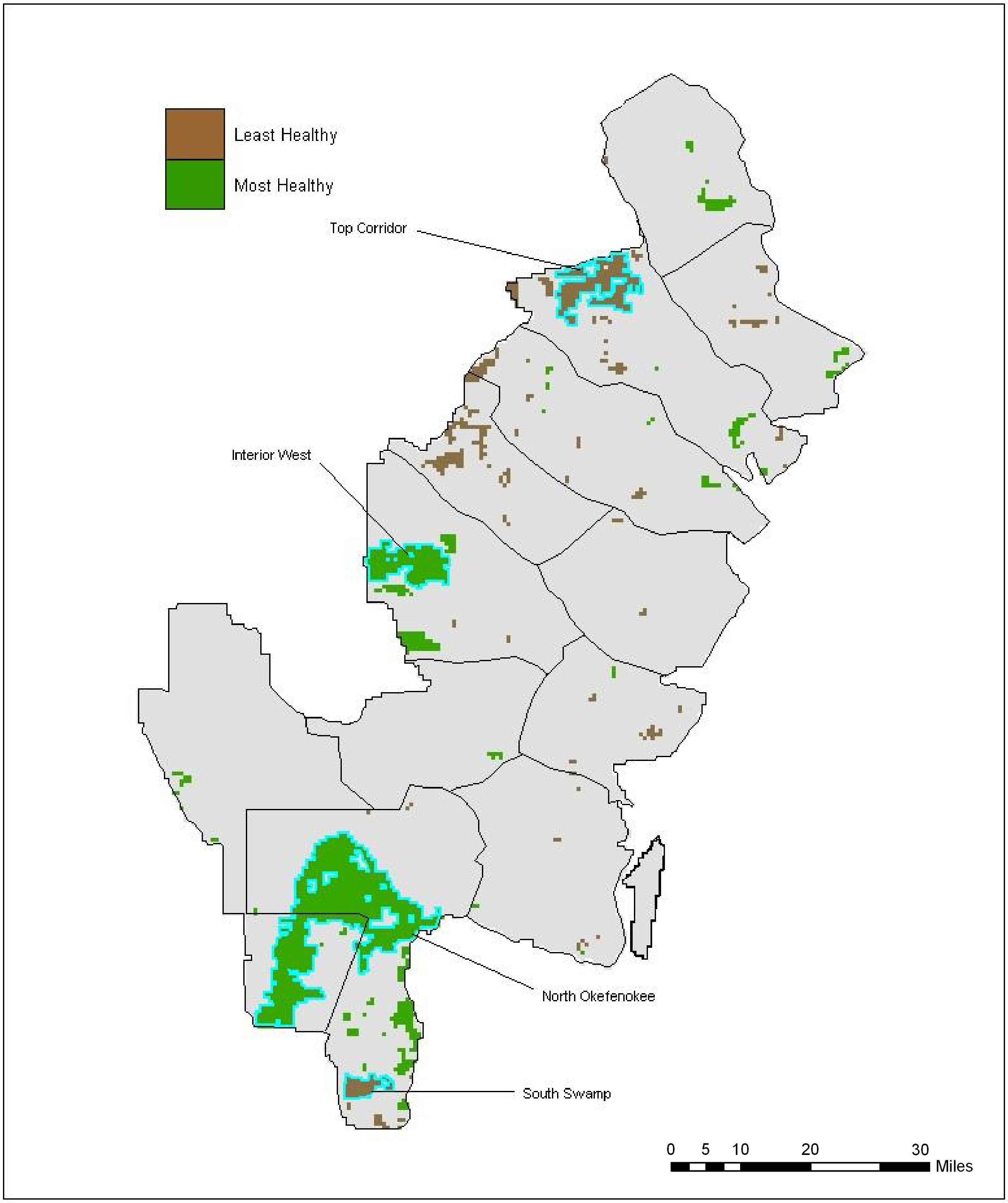

Figure 11, Spring High & Low Growth Polygons

3.2.4 Summer

Summer PC1 includes values that were high in several key areas. Some of the aggregately highest values for summer include, the south central interior and to some degree, the upturned “V” (Figures 12, 13). Typical NDVI values fell within the 0.46-0.48 range in this area. Landcover in these areas includes some deciduous (and protected) forest, along with mixed-pine, xeric, and mixed pine-hardwood species.

Summer values for some of the least healthy areas include the southern swamp, and the Hinesville-Fort Stewart central corridor. NDVI values were typically in the 0.41-0.45 range for these areas. Landcover in these areas is primarily urban. The surrounding area to Hinesville-Fort Stewart is inundated with longleaf-pine stands, while the areas of the southern swamp are highly flooded.

Summer values ranged by county are similar to regional findings. There was not a great deal of value difference between counties during the study period summer areas with the best vegetation healthiness include Glynn and Brantley Counties. Values in these areas exceed the 0.46 NDVI range. Areas with some of the least healthy vegetation include Liberty, Long, Ware, and Effingham counties. Healthiness in the 0.41-.044 NDVI range occurred in these areas.

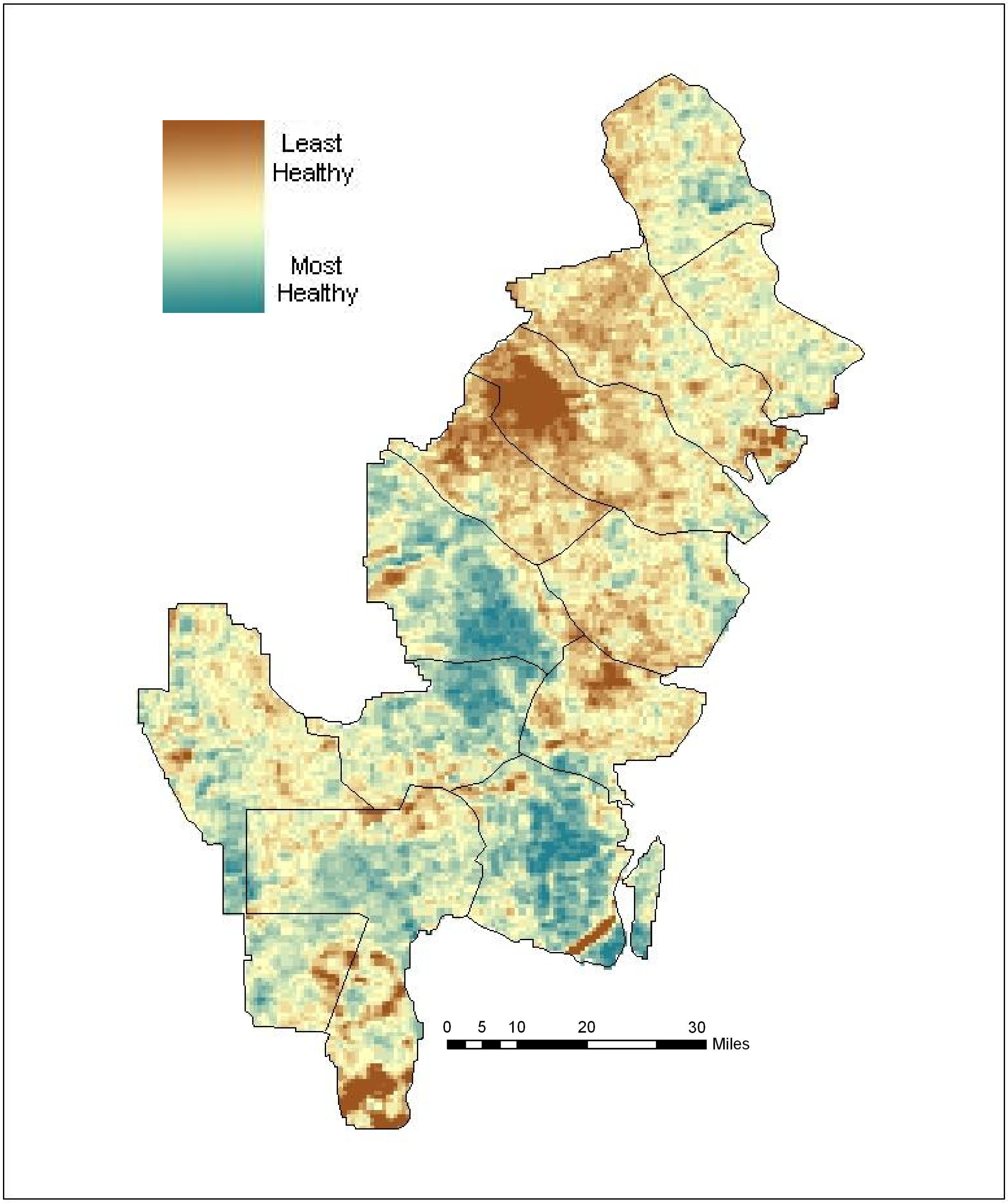

Figure 12, Summer PC1-NDVI (Healthiness)

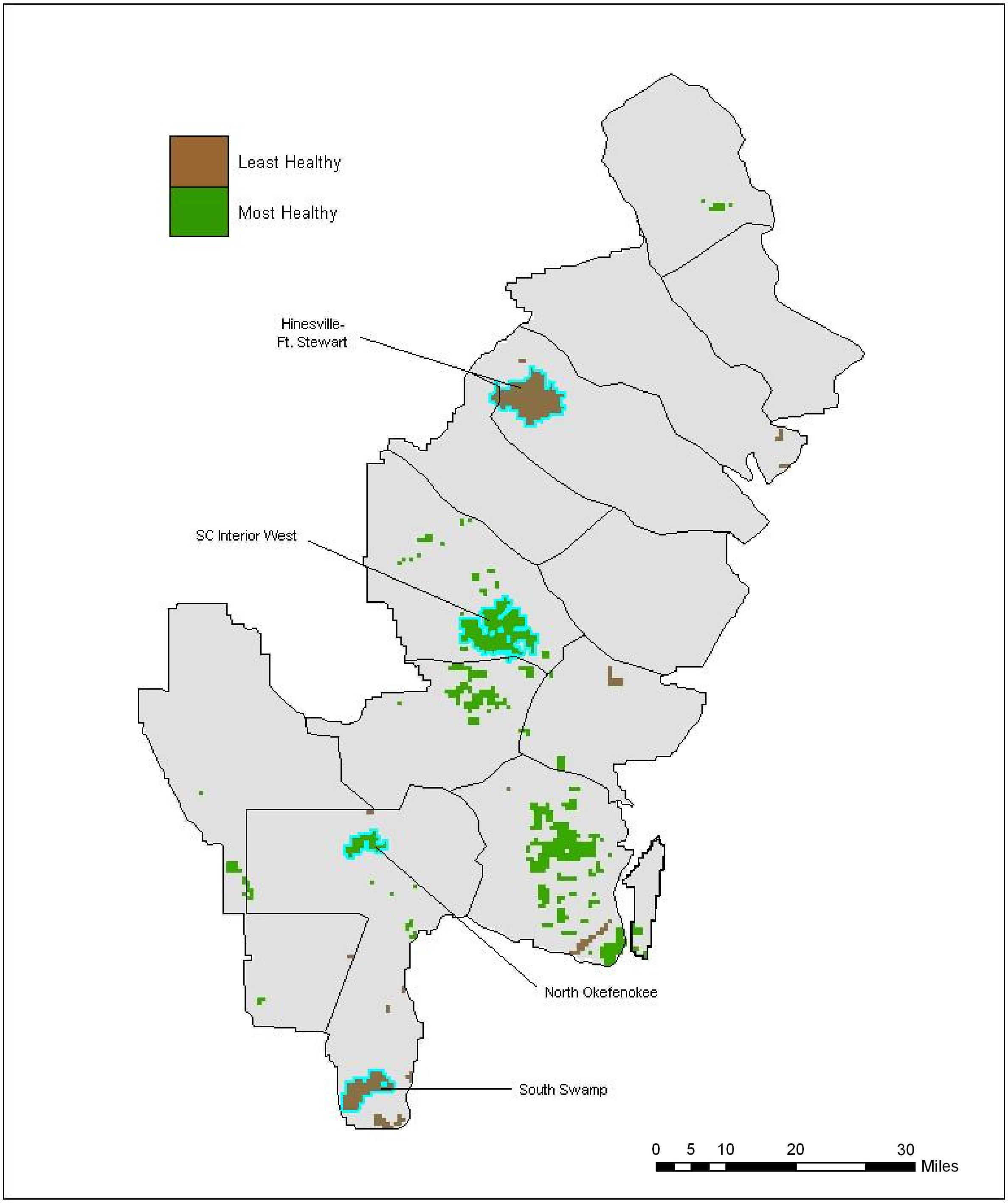

Figure 13, Summer High & Low Growth Polygons

3.3 Temporal Variability and NDVI Value Trends

3.3.1 Fall

Results for fall include seasonal data that was significantly lesser in the year to year assessment. In each of the images, and within each of the county selections, values were aggregately declining (Figures 16, 17). The most significant declines were found in the mid-coastal study region and included Brantley, McIntosh, Long, Camden, and Liberty counties. Conversely, Chatham, Bryan, and Ware counties experienced sporadic increases in vegetated areas, though not sufficiently enough to subvert a steady decline.

In the sixteen year study period, NDVI values in each of the eleven counties in the ecoregion declined. The fall season was the only one in which, in each of the pixel selection zones, every county experienced some level of greenness decline. Most notably were Brantley, Glenn, Camden, and Liberty counties whose terminal NDVI values decreased in the 0.05 to 0.03 range. Each of these counties has a coastline. However, Bryan and McIntosh counties also have coastlines, but did not share in lesser terminal NDVI values to the extent of the aforementioned (0.02-0.01).

Counties that experienced the greatest value declines also experienced the steadiest rate of decline, especially Charlton and Brantley counties. Bryan county, which experienced the least decline in total greenness (-0.01), is the county with the highest fall variability. Bryan County's NDVI value peaked in 1996 to 0.42 and declined rapidly thereafter. This average is even higher than those of Glynn County (the aggregate highest NDVI) over the study period. The occurrence is not uncommon, as the subsequent lesser changing counties exhibited larger annual variances than did counties with larger total declines. Chatham, McIntosh, and

Effingham counties similarly shared this trend, with elevated NDVI values in 1996 – the highest year for total fall NDVI values.

The intensity of fall change areas was diverse and occurred in a few key areas. These areas were more fully examined within the high change imagery and include generated polygons for (the): 1) North Okefenokee, 2) Hinesville-Fort Stewart, 3) Northeast Coast, and 4) Interior West (Figures 14, 15).

Values for the North Okefenokee area coincide with heightened NDVI variables along the vegetated buffer zone. Heightened value change areas for the Hinesville-Fort Stewart area coincide with reduced NDVI variables, which include portions of the central corridor, and are predominantly less healthy than the surrounding area. Changes to the northeastern coast connect to primarily positive healthiness trends. The same is true for the interior west. However, there are stages where values are not changing and include large swaths in the central corridor and extend northwest toward the Savannah area.

Yearly values can also add to the declining comprehensive incidence of high-change fall NDVI (Figure 18). Total values declined over sixteen years, however, this was generally the trend after the 1995-1996 peak period. From 1990 forward, values were gradually declining with the exception of 1995 and 1996. NDVI values resumed declining afterward, toward the lowest values extending onward to 2005.

The NDVI correlation (Table 3) for the season only confirms this with high negative, significant correlations. Polygon one (North Okefenokee) shows signs of a very weak negative correlation, but this correlation is not significant (Table 4). This suggests diminishing values are more resulting from climatic conditions (soil moisture) than to urban growth (protected area).

Values within polygon one are declining, but to a much lesser extent than the other three areas. Fall values are also offset due to the recurrence of the 1996 value anomaly.

The correlation evaluation revealed that NDVI values were significantly declining over the breadth of the study area. There was a strong negative correlation concerning NDVI values over time. Also, there is an anomaly for 1996, where NDVI values peaked and then commenced recession thereafter. This is discussed in more detail later with climate correlations.

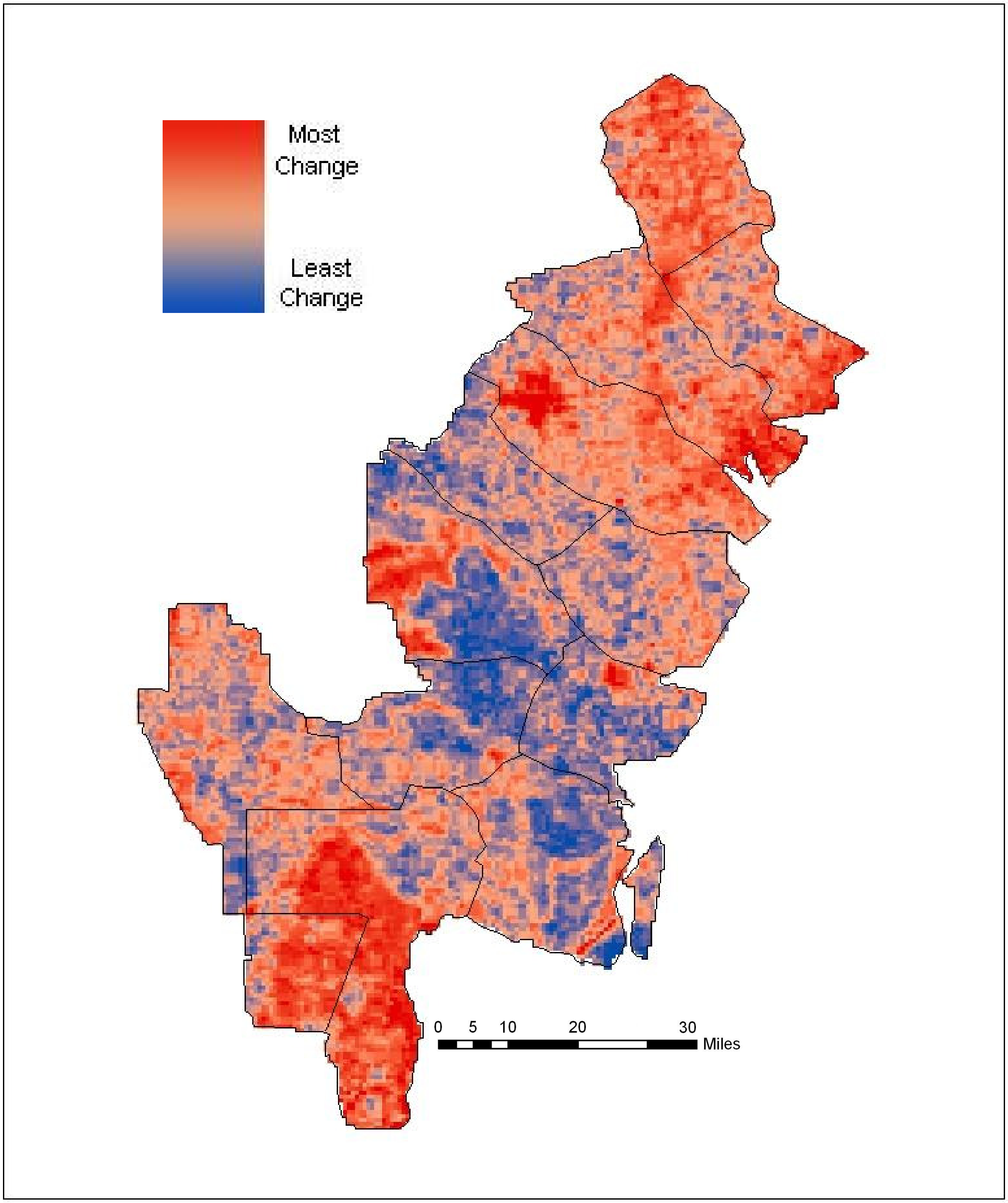

Figure 14, Fall PC2-Change Image (Time)

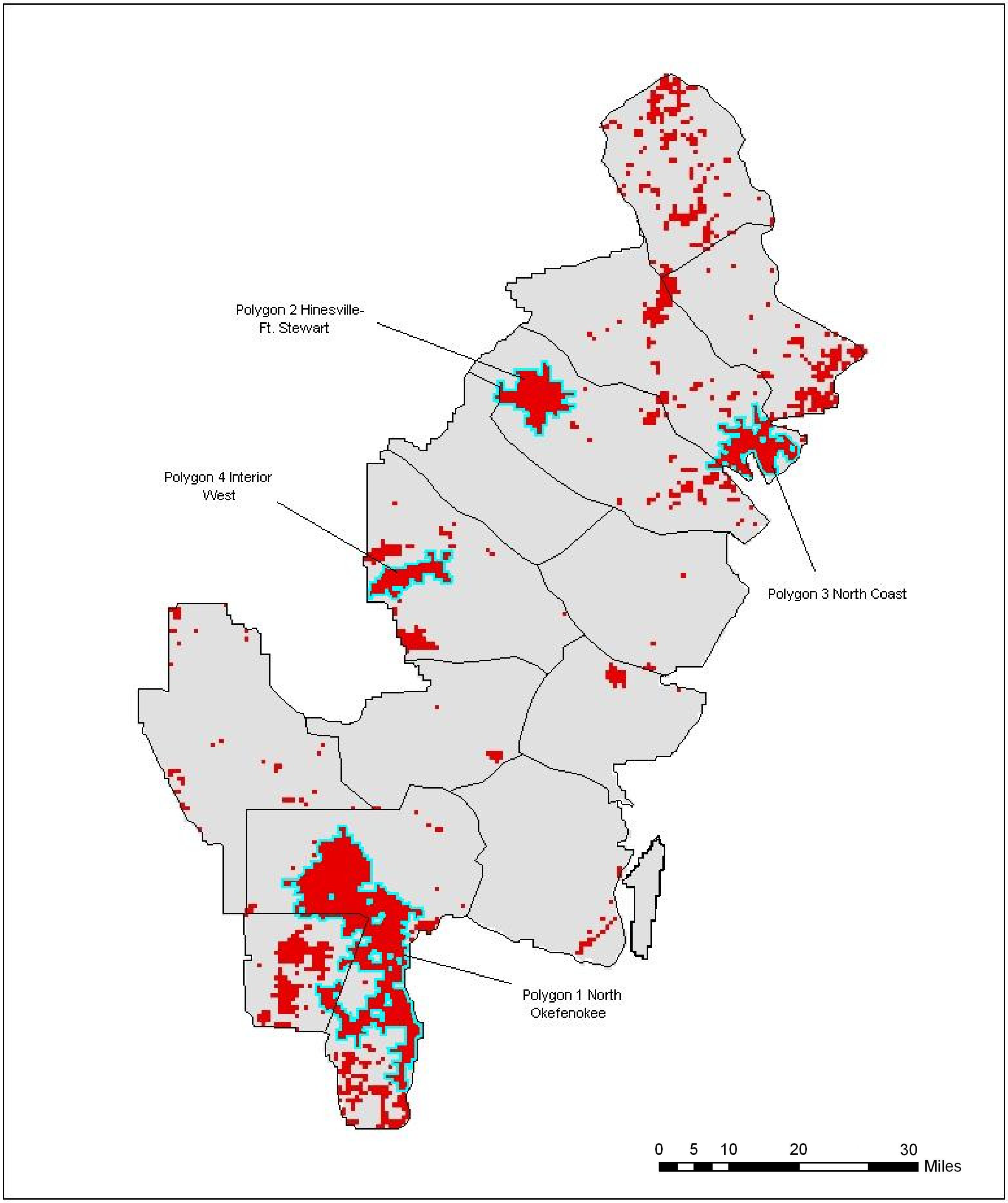

Figure 15, Fall Extreme-Variability Polygons

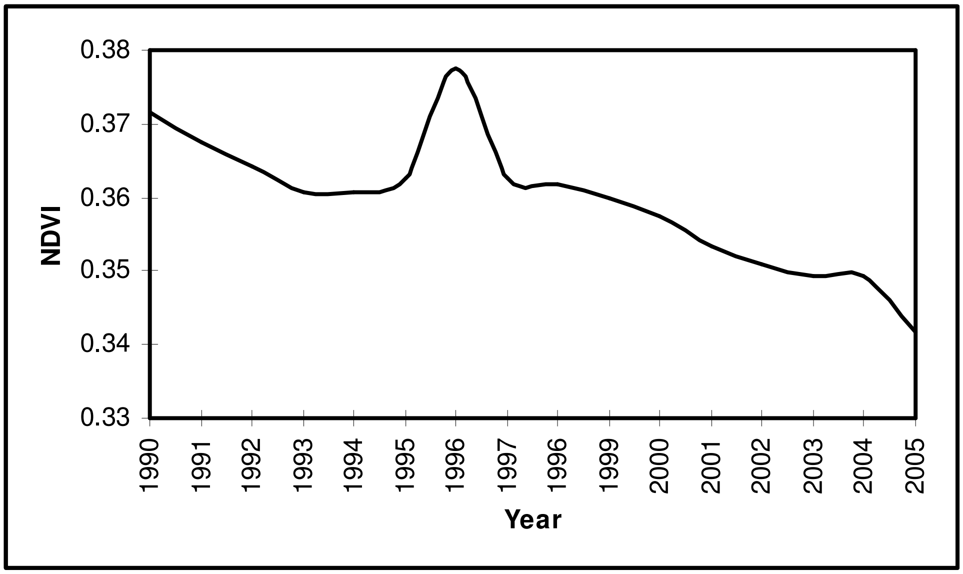

Figure 16, Fall NDVI Results

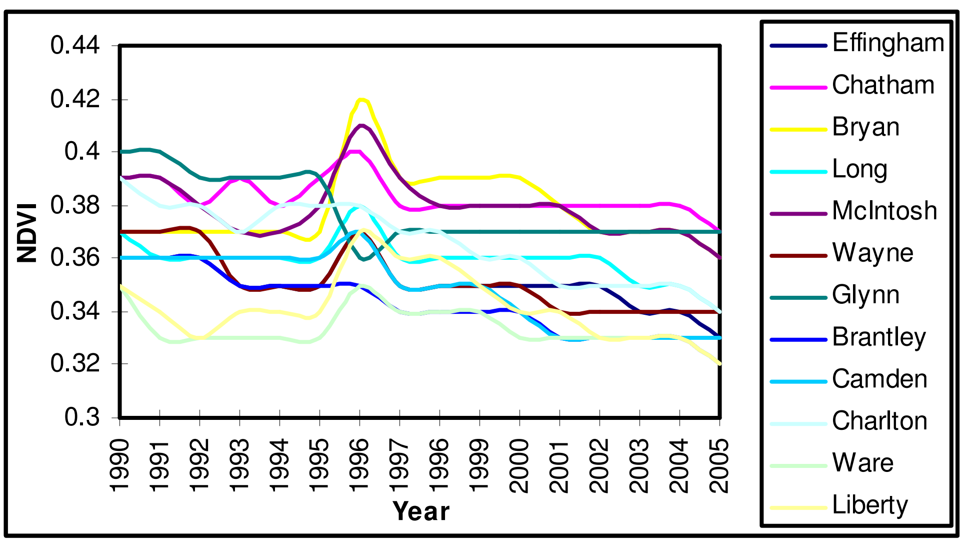

Figure 17, Fall NDVI Results by County

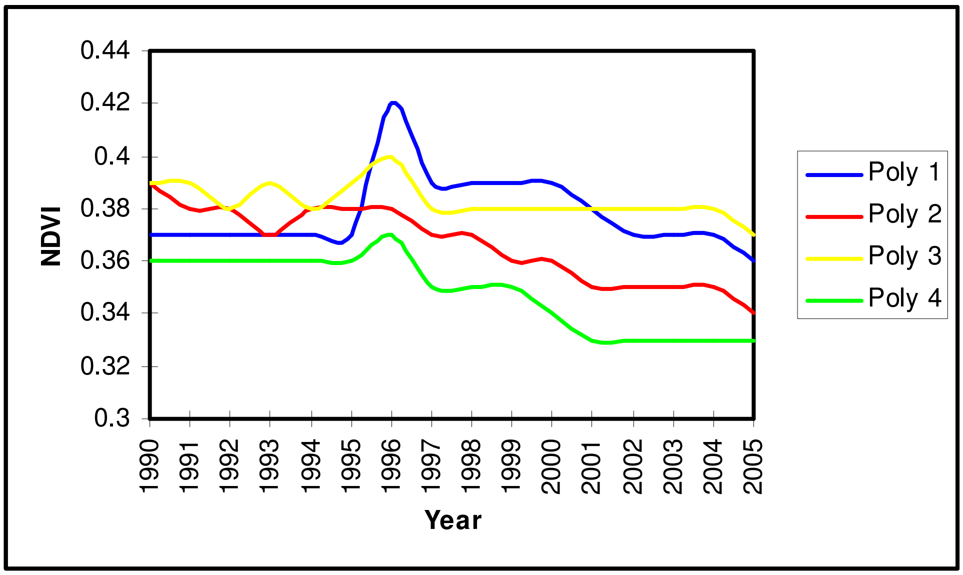

Figure 18, Mean Fall NDVI Values for High-Change Areas

3.3.2 Winter

Across the entire study region, and throughout the entire time analysis, each county experienced positive NDVI greenness measurements (Figure 22). Winter values increased at high rates extending from the end of fall into the beginning of spring. Areas that experienced the highest positive values (0.04 to 0.05) were Effingham, Chatham, Ware, Glenn, and Brantley counties. As each of these counties are considered to be coastal counties within the ecoregion, some of the highest increases came from counties bordering the ocean and inland counties alike. Some of the lower areas (0.02 to 0.03) were Bryan, Long, Wayne, and Camden counties. The incidence is similar to lower loading counties' distribution where some are inland and the others are ocean-bordering.

Yearly averages were also on the rise (Figure 21). This is important because of the overall deduction that NDVI increases were not solely attributed to a few counties. Some counties did see higher increases, yet the amassed evaluation of the entire region revealed a steady increase. Winter averages (DN) rose in plateaus: 0.32 through 1994, 0.33 through 1996, 0.34 through 2003, and 0.35 -0.36 through 2004-5.

The lowest greenness increases were from Wayne County and Long counties - primarily inland areas. Over the entire time study, Wayne experienced an overall increase of 0.02 DN, but this is predominantly in the latter half of the study (1997-2005). Wayne County also experienced some of the lowest annual variance, with DN values ranging only 0.04. Of the entire study region, Long County experienced the least total variance, with DN values differentiating only 0.03. Some counties, Effingham, Long, Camden, and Chatham, saw value declines in the initial years, only to have stronger recoveries from 1997 forward. These counties experienced different rates of total greenness and also different rates of return. The most consistent item from the PCA

winter assessment is that NDVI is the controlling predicate for change detection, and the accumulated county values are the most positive for any season within the time-series.

There were three large positive-change polygons for the winter season and include (the): 1) Effingham-North, 2) Interior West, and 3) Northeast Coast. So far as variability, winter change values were concentrated primarily along the north study zone, extending into the Effingham area. Winter was a season in which values from the North Okefenokee region did not experience positive change. This is noteworthy because of the relatively healthy tendency of the swamp barrier. This barrier remains healthy, but does not change dramatically (Figures 19, 20).

Positive correlations also correspond to an increasing trend with NDVI throughout the study period. Values were highly correlated with NDVI healthiness over time (Tables 3, 4). Winter is the only season that experienced the strength of positive change and NDVI growth in each of the high-change polygons (Figure 23).

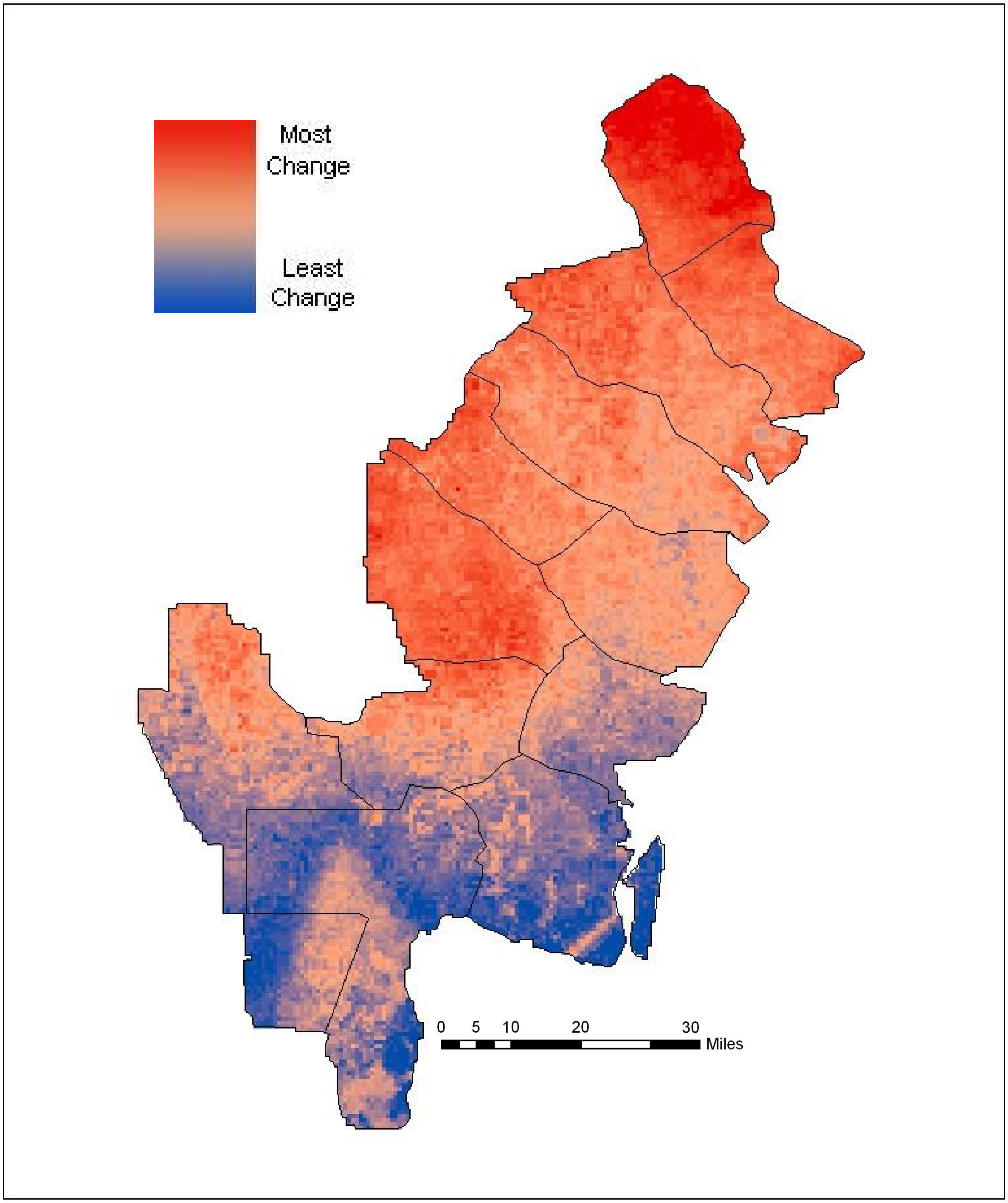

Figure 19, Winter PC2-Change Image (Time)

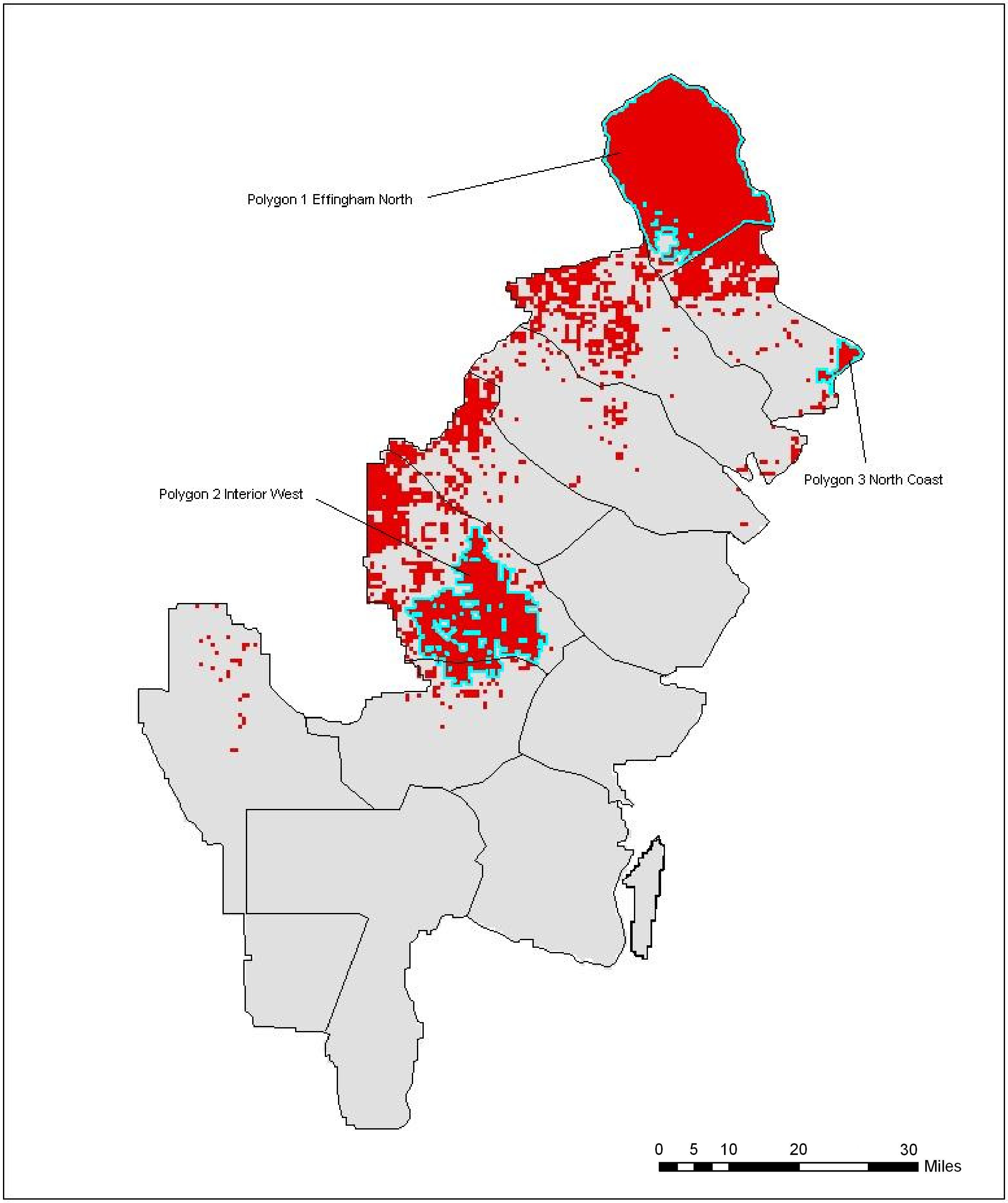

Figure 20, Winter Extreme-Variability Polygons

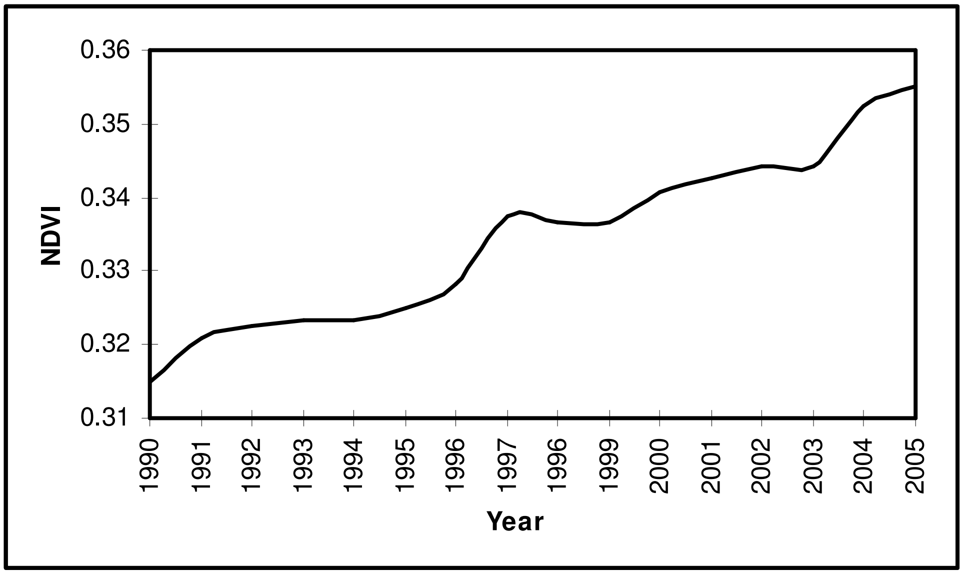

Figure 21, Winter NDVI Results

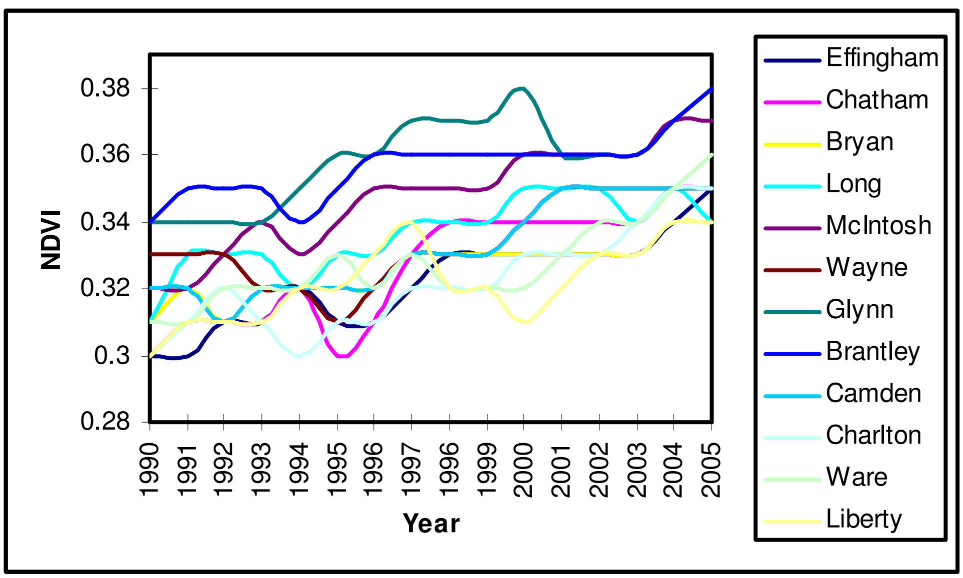

Figure 22, Winter NDVI Results by County

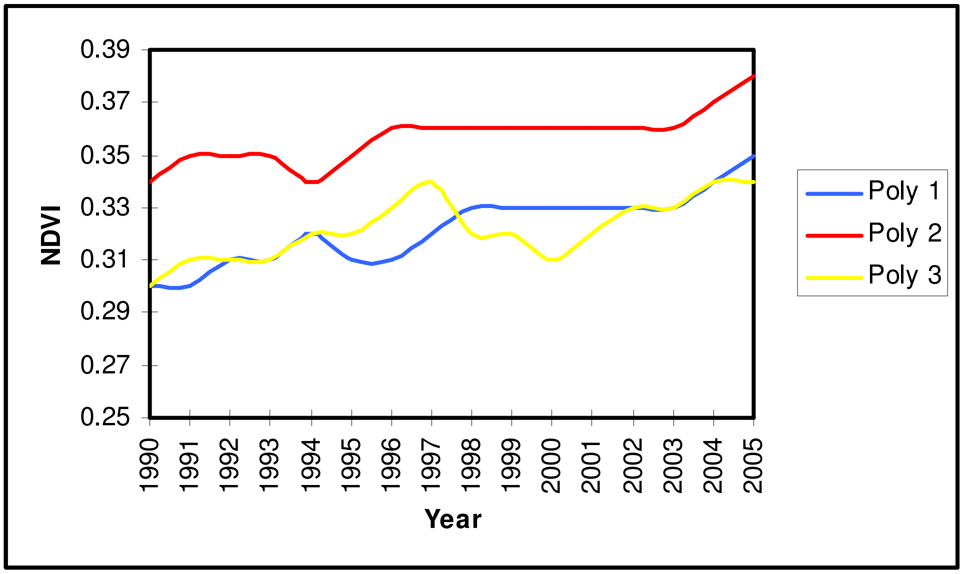

Figure 23, Mean Winter NDVI Values for High-Change Areas

3.3.3 Spring

The spring assessment returned NDVI healthiness values that diminished along a central growth corridor, and were at peak levels over the entire study region, and throughout the entire time-series (Figures 26, 27). DN values ranged between -0.05 to 0.01. There was actually a cumulative net decrease in total DN of 0.11. Spring values, as noted from the literature, showed high levels of above-ground biomass at peak greenness values (0.5-0.6).

Yearly NDVI averages were steadily on the decline and resulted in having few years of continued growth throughout the entire time-series. Cumulatively, the worst years for mean decreases were 1992 and 2002; the decrease for 1992 never sufficiently rebounded for the rest of the study region. The best years for growth were 1995-6 and in 2005. The correlation testing confirmed a negative correlation when examining seasonal NDVI growth. This correlation at -.350 was significant at the 0.05 level.

Part of the reason that aggregate growth was down was due primarily to three coastal counties along the northernmost stretch of the study area. A net loss of 0.11 NDVI value does not mean that counties did not experience growth, but instead, they did not grow enough to overcome declines in counties with sizable losses. Chatham, Bryan, and Liberty Counties all experienced total NDVI losses of 0.05 - 0.03 DN, while Effingham, Brantley, and Camden Counties experienced neither growth nor loss (+/- 0). Glynn and Ware Counties also experienced losses on par with the growth of Long, McIntosh, and Wayne Counties at 0.01 DN.

Some counties' losses could be explained through variance. Ware County, for example, had annual values fluctuated between 0.5 and 0.49 the entire time series and ended with 0.49 DN. The indication is loss, though the true result is that values were steady over the entire duration. In fact, this is true for all of the counties with the exception of Chatham, Bryan, and

Liberty counties, where declines were fairly constant. The most annual variation can also be attributed to Chatham and Bryan counties where values peaked (1990) near 0.6 DN and averaged declines in stages.

Spring values have also remained fairly similar during the entire sixteen-year study period. Save declining rates for Chatham, Bryan, and Liberty counties along the northern coast – average values have remained fairly steady over this period.

High-Change polygons for the spring include (the): 1) North Okefenokee, 2) Interior West, and 3) Northeast Coast (Figures 24, 25). High positive change along the PC2 image is consistent with high NDVI values in each of the major change areas (Figure 28). This is especially the case for the north Okefenokee, canopy barrier. This area revealed the highest change values coupled with the largest area of healthy vegetated land throughout the study region. Similarly, the interior west and north coast recorded high change values with aligned vegetation differences.

There were segments running north to south along the outset of the central corridor which did not show much spring change throughout the study period. The aforementioned high change areas did respond to healthiness increases with the exception of polygon two, where aggregate vegetation values are healthy, but slightly declined in the study period. The north coast returned the least positive (yet significant) correlation between change and NDVI, however, this growth to raw NDVI is nominal (less than 0.1). There was more variability in spring with polygon two's (interior west) return of negative correlations by year. As far as raw values are concerned, the difference in NDVI is nominal, however.

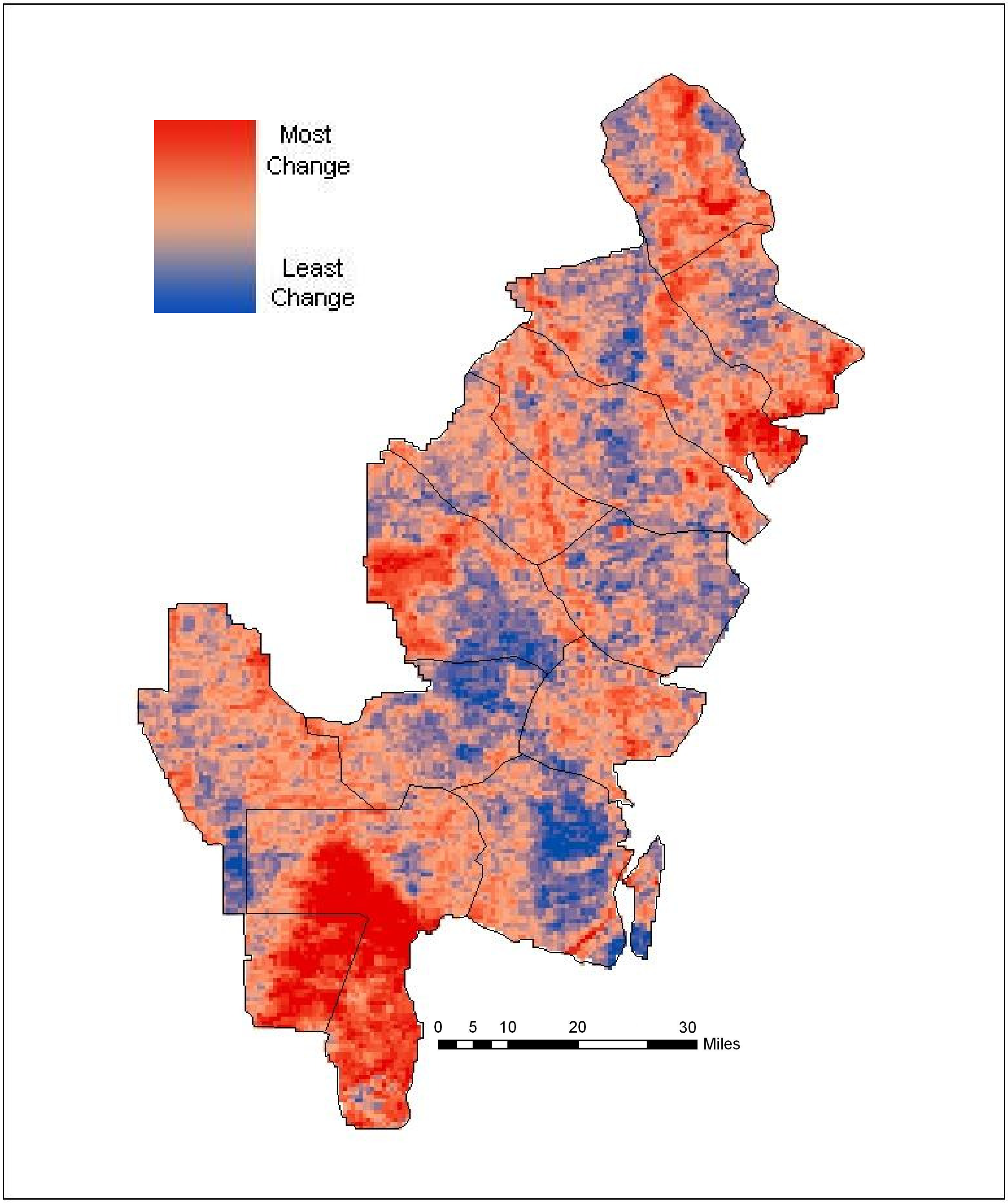

Figure 24, Spring PC2-Change Image (Time)

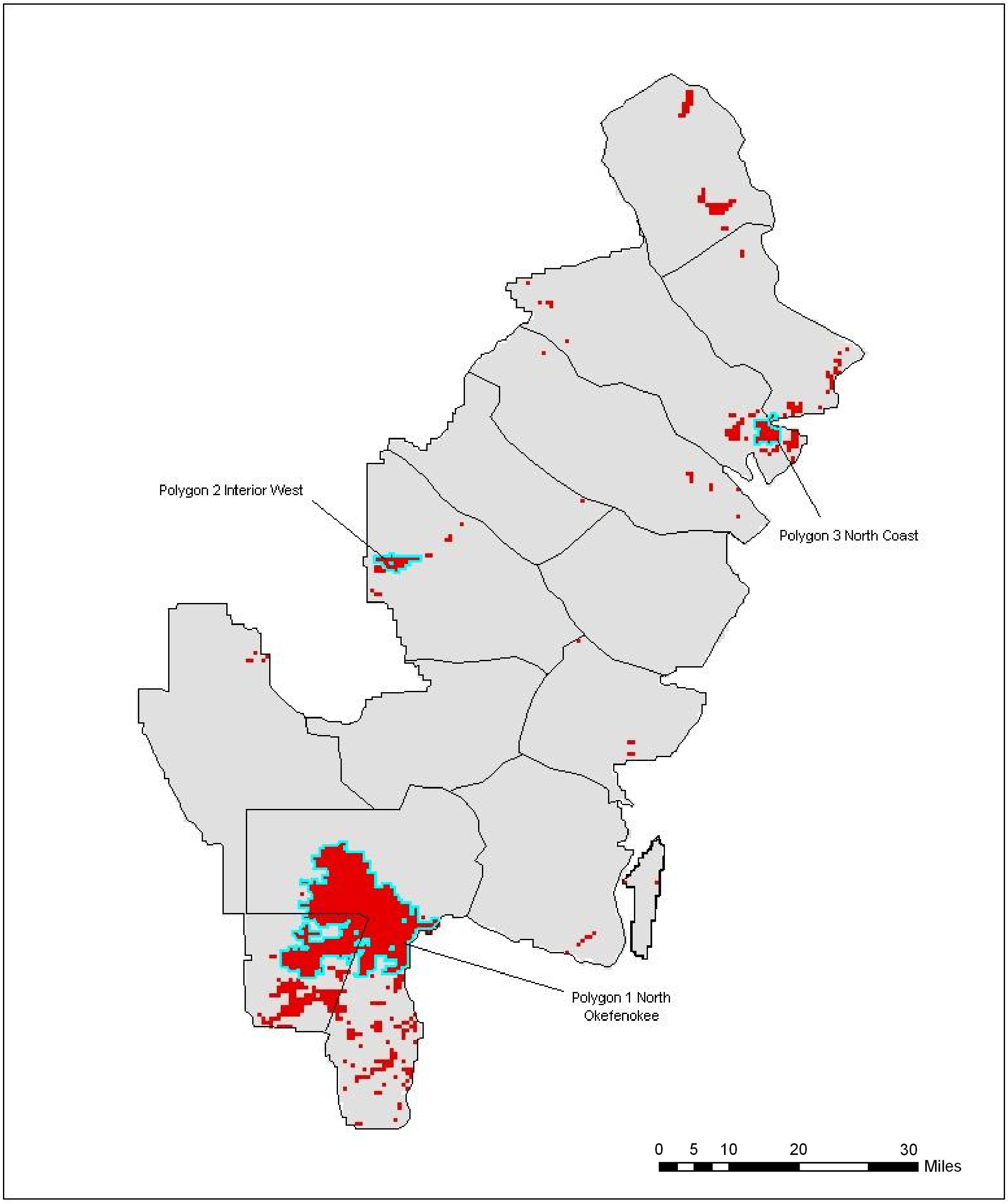

Figure 25, Spring Extreme-Variability Polygons

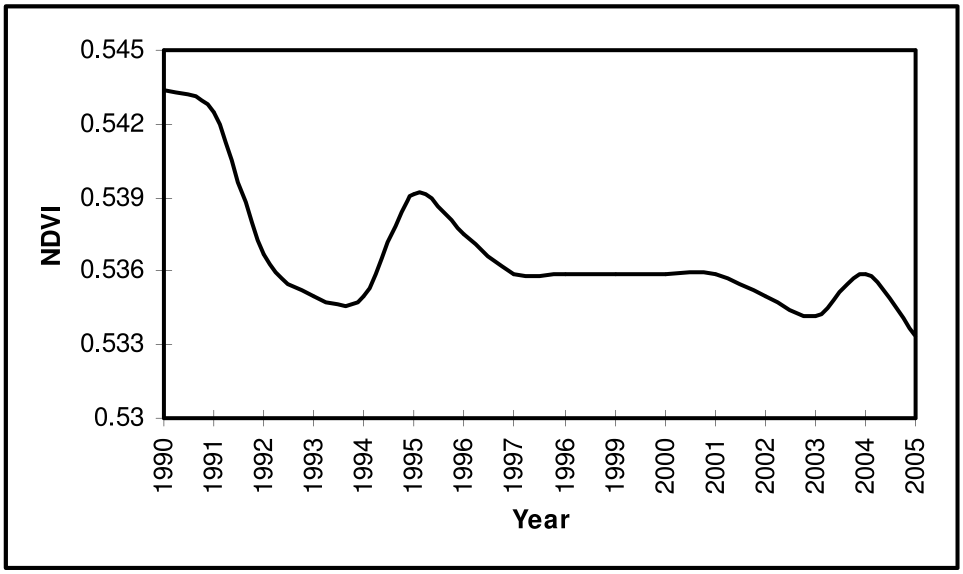

Figure 26, Spring NDVI Results

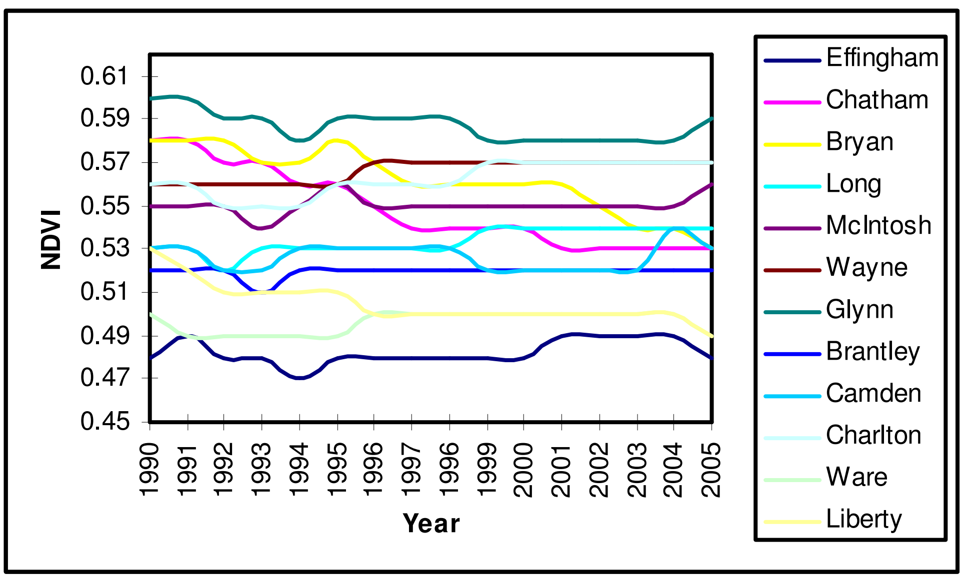

Figure 27, Spring NDVI Results by County

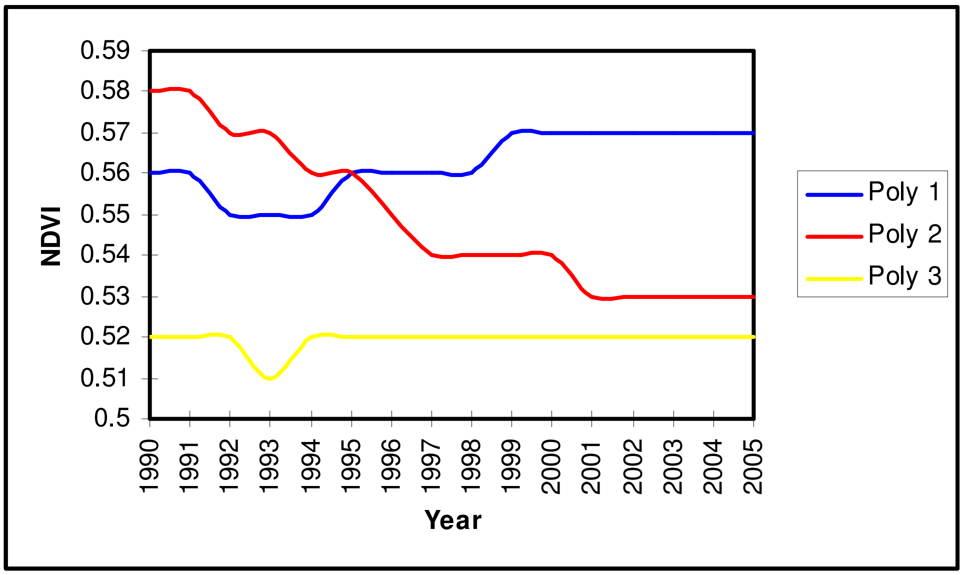

Figure 28, Mean Spring NDVI Values for High-Change Areas

3.3.4 Summer

Summer results returned relatively moderate gains in overall NDVI seasonal value (Figures 31, 32). NDVI values were steadily on the rise for summer months between 1990 and 2005. This growth was aggregately quicker in the earlier portion of the study period (1990-96) but stabilized for the most part onward (2000-2005).

There was an across the board increase (including for each county) in the net DN-NDVI value accumulation. Positive DN values ranged between 0.01 and 0.04. There was an NDVI increase of 0.22 DN for the total study area during the time-series duration. This reveals a net increase of 0.02 DN per county.

The correlation testing revealed strong positive NDVI growth that was correlated throughout the time-series (.944 at 0.05). For summer, growth was highly constant per year. Counties with the highest increases included Wayne, Long, and McIntosh (0.04-0.03), while counties like Chatham, Ware, and Glynn recorded more moderate greenness values (0.02-0.01). The summer gains were neither isolated to inland counties, nor separated to ocean borders. In fact, the gaining trend was clumped in the central coast with Wayne, Long, and McIntosh counties. Between them, they were responsible for nearly half (0.1 DN of the total 0.22) of the net DN gain. The trend for summer, unlike for spring, was that a gaining trend was seen in all counties instead of just a few. Every year produced a net NDVI value gain with the exceptions of 1997 and 2001.

Polygons for summer include (the): 1) North-Okefenokee, and 2) Hinesville-Fort Stewart (Figures 29, 30). Variability in the summer season was primarily confined to the bottom half of the study region. These high positive change values corresponded with increasing NDVI trends for summer (Table 4). Values for the region were especially high in the north Okefenokee

region, indicating healthiness in the barrier groundcover. There were similar findings in the south central corridor extending up toward Hinesville, indicating vegetation increases with NDVI. These increase were, however, slight to moderate (Figure 33). The increased values did not fall outside two standard deviations from the mean, so their values were not included in within the high-change image. Both summer high-change areas returned increasing trends, but again, summer experienced mostly growth as NDVI values suggest.

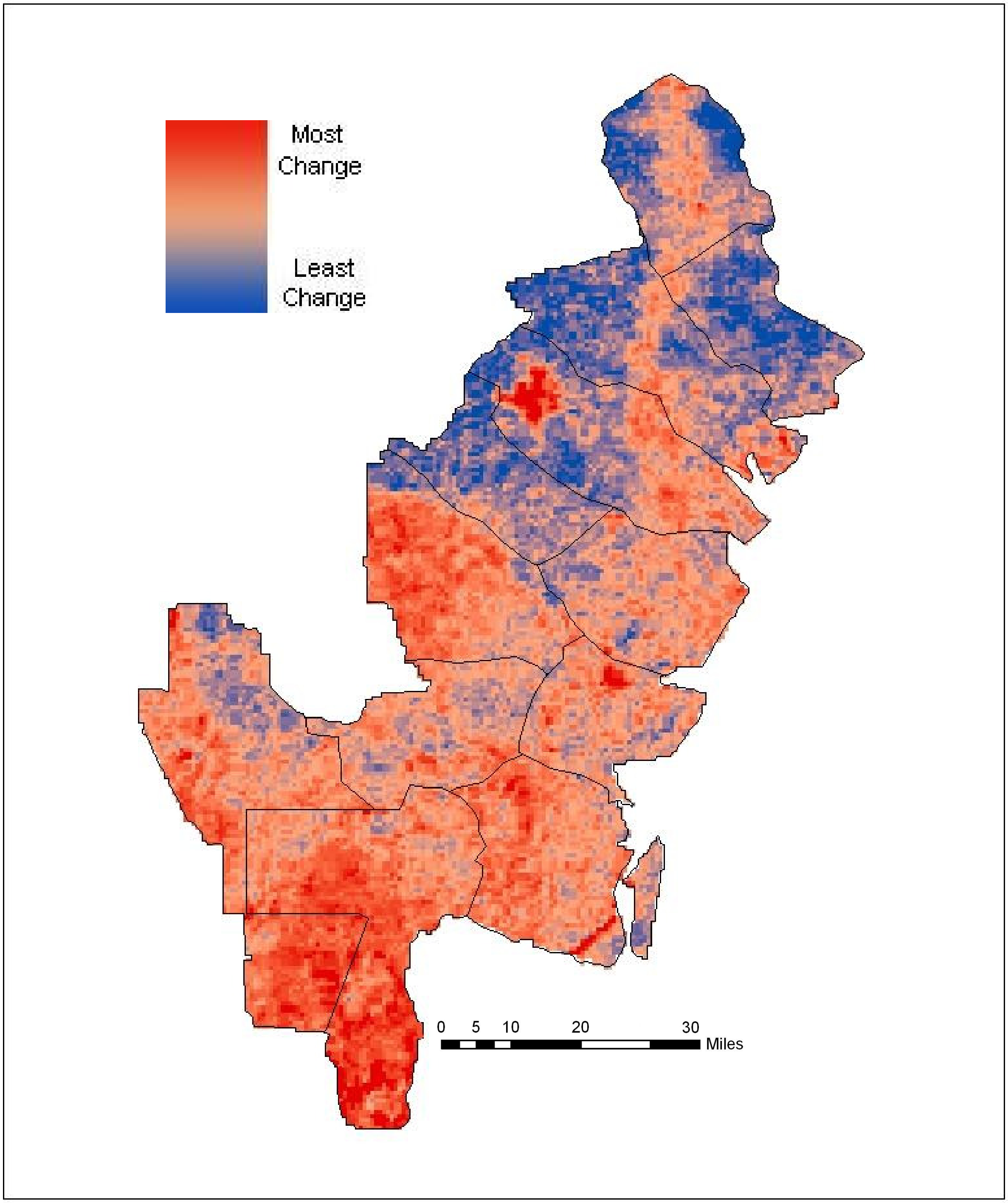

Figure 29, Summer-PC2 Change Image (Time)

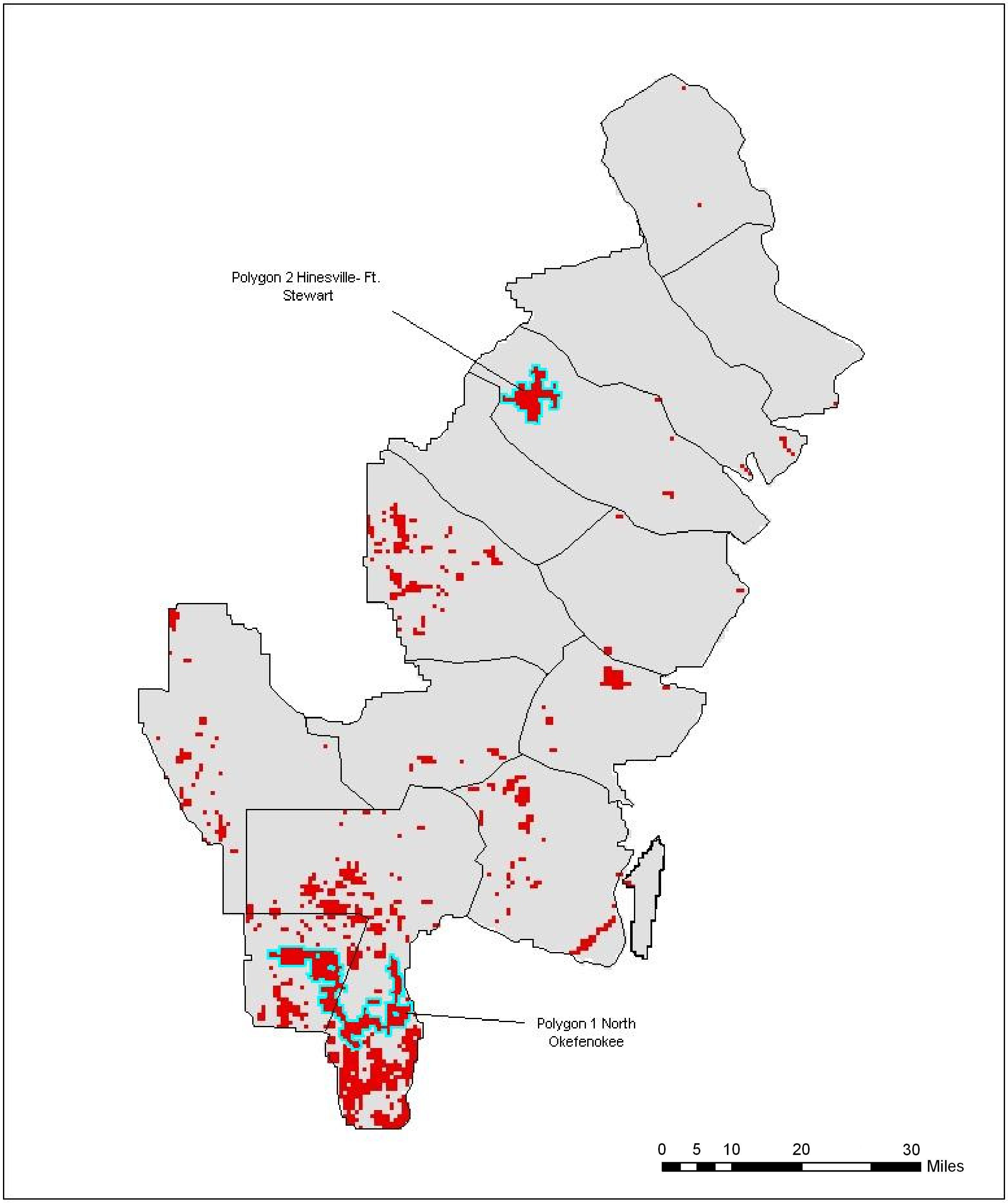

Figure 30, Summer Extreme-Variability Polygons

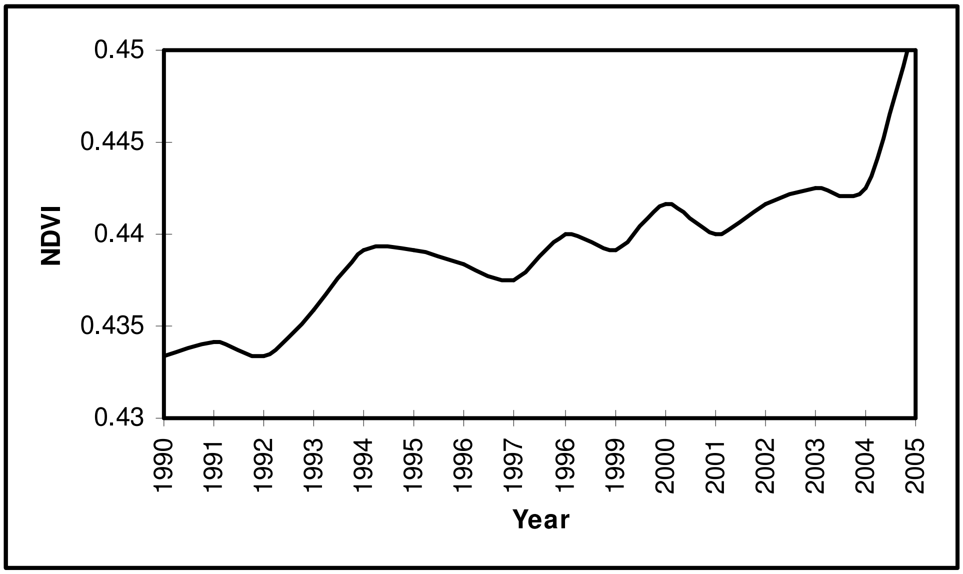

Figure 31, Summer NDVI Results

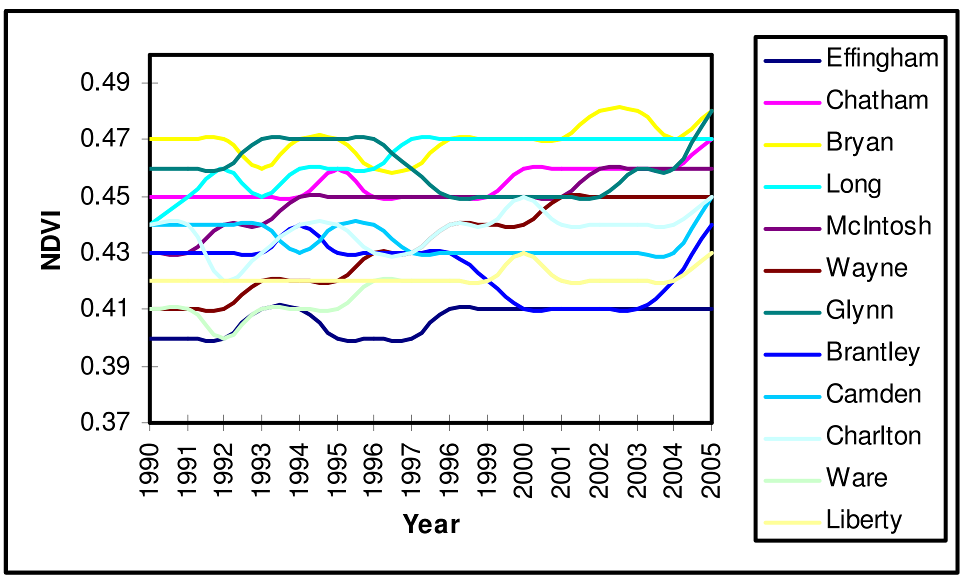

Figure 32, Summer NDVI Results by County

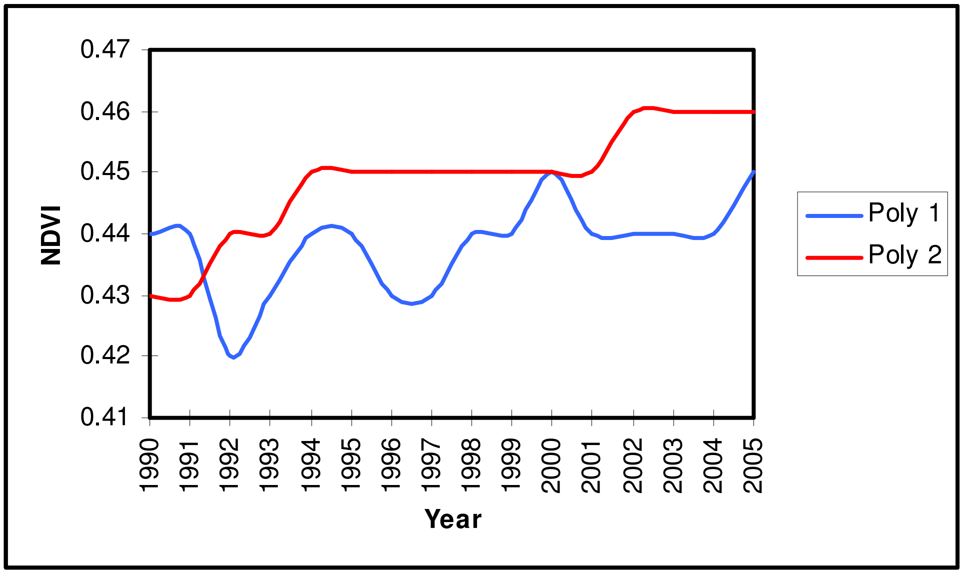

Figure 33, Mean Summer NDVI Values for High-Change Areas

Table 3, Regional NDVI-Time Series Correlation by Season

Winter	Spring	Summer	Fall
.989*	-.350*	.944*	-.878*

* Values Significant at the 0.05 level (one-tailed)

Table 4, High Change Area NDVI-Time Series Correlation by Season

Winter	Spring	Summer	Fall
1) .974* 2) .899* 3) .749*	1) .842* 2) -.975* 3) .053	1) .506* 2) .927*	1) -.016 2) -.938* 3) -.694* 4) -.891*

* Values Significant at the 0.05 level (one-tailed)

Winter Polygon Zones: 1) Effingham-North
2) Interior West
3) Northeast Coast

Spring Polygon Zones: 1) North Okefenokee
2) Interior West
3) Northeast Coast

Summer Polygon Zones: 1) North Okefenokee
2) Hinesville-Fort Stewart

Fall Polygon Zones: 1) North Okefenokee
2) Hinesville-Fort Stewart
3) Northeast Coast
4) Interior West

3.4 Climatic Variability

3.4.1 Fall

Temperature and precipitation values with the coastal study zone show strong interannual transition (Figures 34, 35). The range for each variable is in flux more so than what was seen with soil moisture levels (which to some degree is dependent upon both temp and precip). What is more interesting about temperature and precipitation is that neither revealed significant correlations with NDVI during the time series. There were insignificant weak correlations (both positive and negative) for the seasons, but the larger determining climatic factor responsive to NDVI was soil moisture. The forthcoming results for soil moisture only seek to confirm this. Fall correlations for temperature and precipitation were particularly weak (Tables 5, 6). This is the case for the remaining seasons, which is why soil moisture will be discussed in more detail.

Soil moisture values (from the outset) resemble similar findings to seasonal NDVI. Volumetric readings (mm) for the fall season show a diminishing trend (Figure 36). Total volume readings decreased during fall from 2.8 mm (measured in 1990) to 2.5 mm (measured in 2005). There is an annual variability for soil moisture concentrations that has been as high as 0.4 mm (potentially 15 percent increase/decrease annually). Fall soil moisture values were aggregately declining (save variability) and terminally did so to the effect of 12 percent.

The fall correlation testing revealed strong positive correlations between NDVI values and soil moisture concentrations. In fact, all of the years were significantly correlated at the 0.05 level. As fall NDVI values decreased, soil moisture concentrations were similarly decreasing. For fall, the highest anomaly occurred in the years from 1995-1998, peaking in 1996. This hike is primarily the result of heightened mean precipitation coupled with lower mean temperatures.

In the case of fall, precipitation was at the highest point while temperature was at the lowest for their respective measurements.

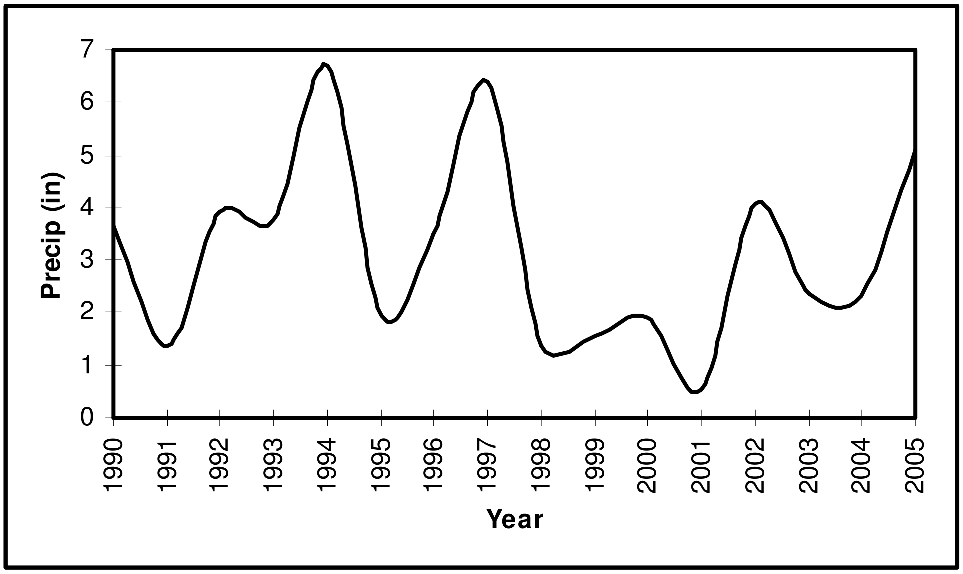

Figure 34, Mean Fall Precipitation

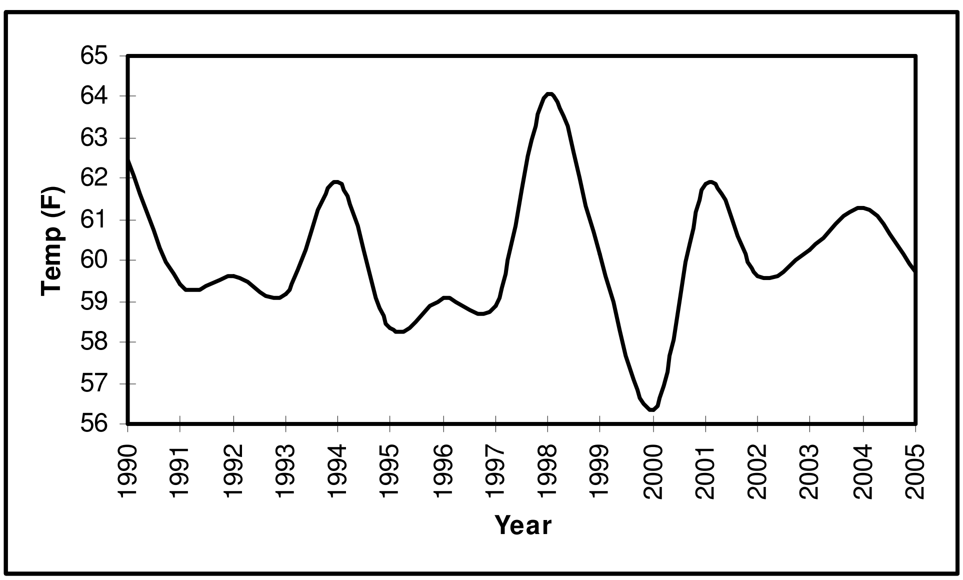

Figure 35, Mean Fall Temperature

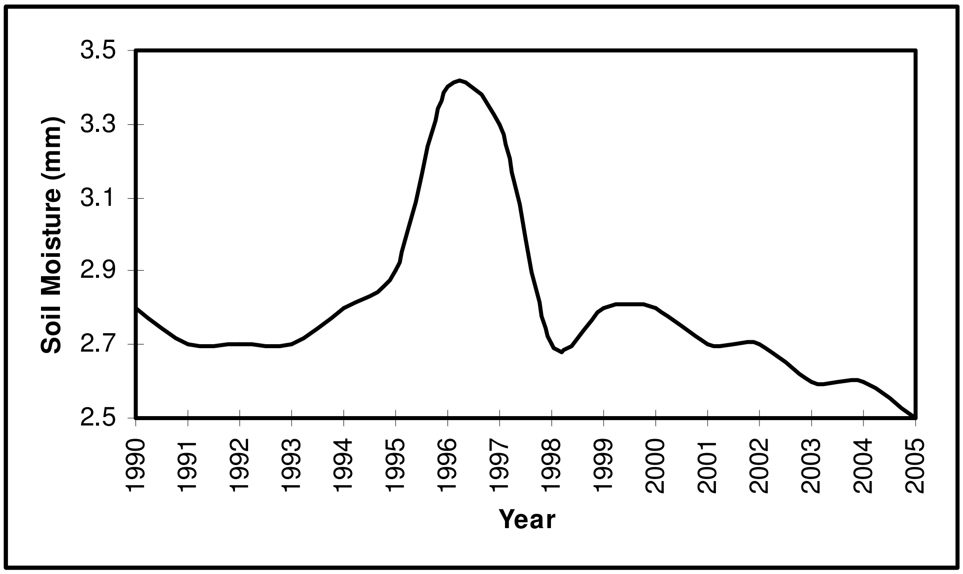

Figure 36, Mean Fall Soil Moisture

3.4.2 Winter

Temperature and precipitation showed constant transitions (Figures 37, 38). These climatic devices were variable in nature, but did not show significant correlations to describe NDVI fluctuations (Tables 5, 6). Therefore, temperature and precipitation are not significant indicators to explain winter vegetation.

Winter was a period that experienced some of the highest soil moisture content for any period (Figure 39). Total moisture volume increased in winter from 3.1 mm (1990) to 3.9 mm (2005). Annual soil moisture variability was as high as 0.4mm (16 percent increase/decrease annually). Winter soil moisture values were cumulatively on the rise, and terminally rose 21 percent by the end of the study period. Values for winter were just as highly correlated as fall values had been. All years were significantly correlated at the 0.05 level. Therefore, soil moisture content and NDVI were highly correlated in winter. Winter values for all three change polygons were negatively correlated for both temperature and precipitation. Soil moisture, as a demonstrated correlated variable, showed strong correlations for all four seasons (Tables 5, 6).

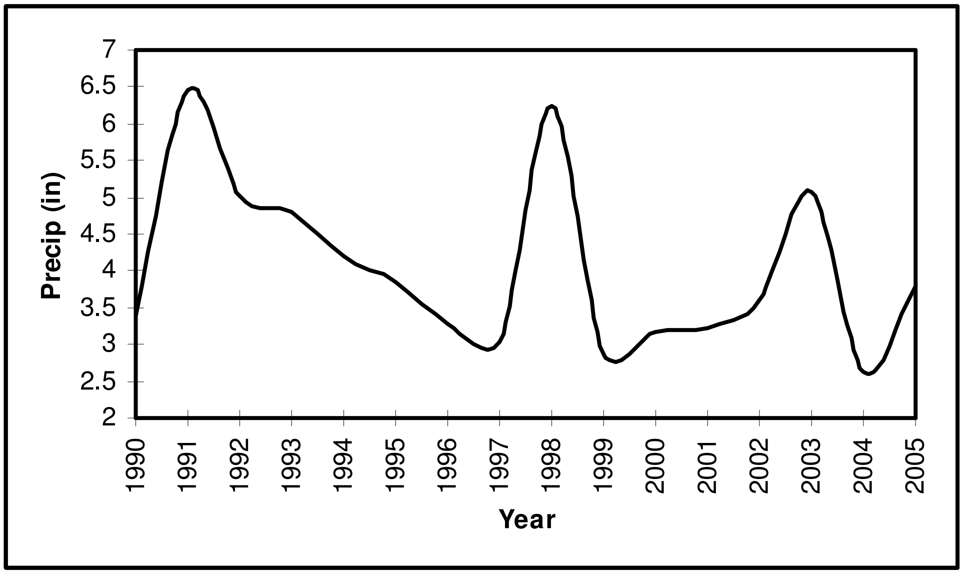

Figure 37, Mean Winter Precipitation

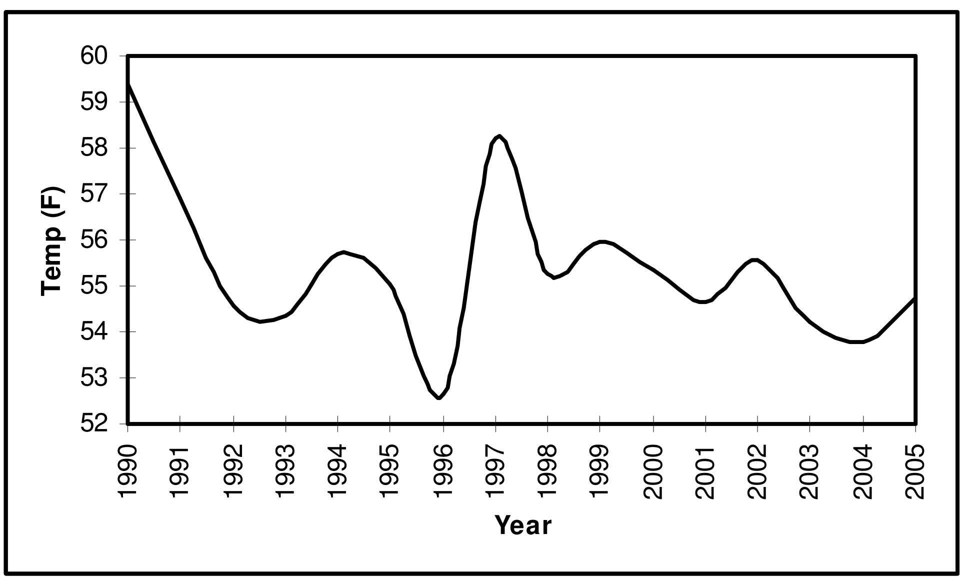

Figure 38, Mean Winter Temperature

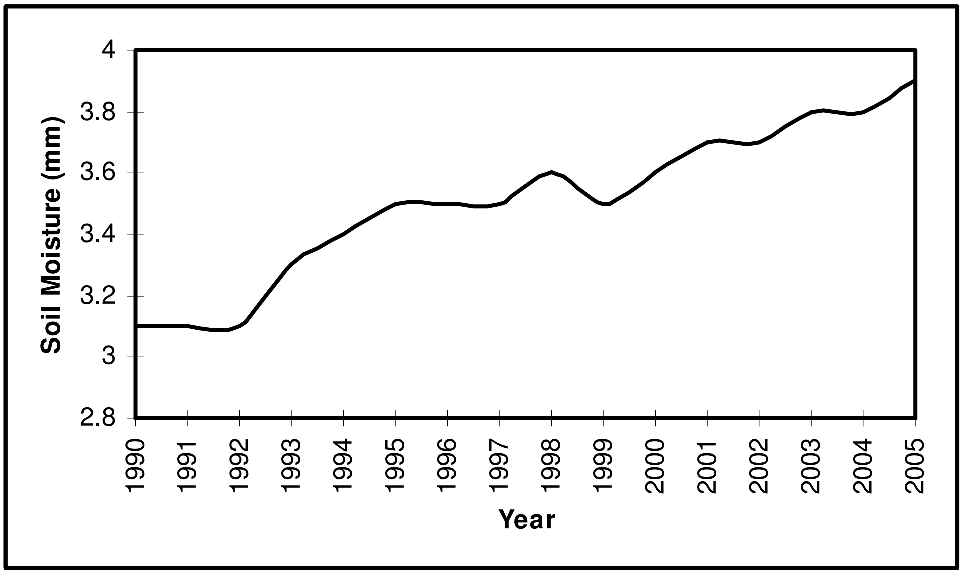

Figure 39, Mean Winter Soil Moisture

3.4.3 Spring

Temperature and precipitation showed constant transitions (Figures 40, 41). These climatic devices were variable in nature, but did not show significant correlations to describe NDVI fluctuations (Tables 5, 6). Therefore, temperature and precipitation are not significant indicators to explain winter vegetation. The relationship with soil moisture as a correlated variable for both regional and high-change areas was highly significant (Tables 5, 6).

There was an ebb and flow to the spring period that was unlike any other in context to soil moisture levels (Figure 42). Total soil moisture levels were the second highest for any season within the study. Total moisture content increased in spring from 3 mm (1990) to 3.1 mm (2005). However, the annual moisture variability was also lower than in any other season, ranging as much as 0.2 mm (6 percent increase/decrease annually). The terminal range would indicate that moisture content was on the rise, but the mean value (3.06mm) compared with the annual variability actually reveals nominal to no additional moisture. Moisture values for spring were not, however, different from the other seasons when correlated with NDVI values. Again, these correlations occurred significantly at the 0.05 level, and the positive correlation was .622 from 1990-2005. In total, values were highly correlated.

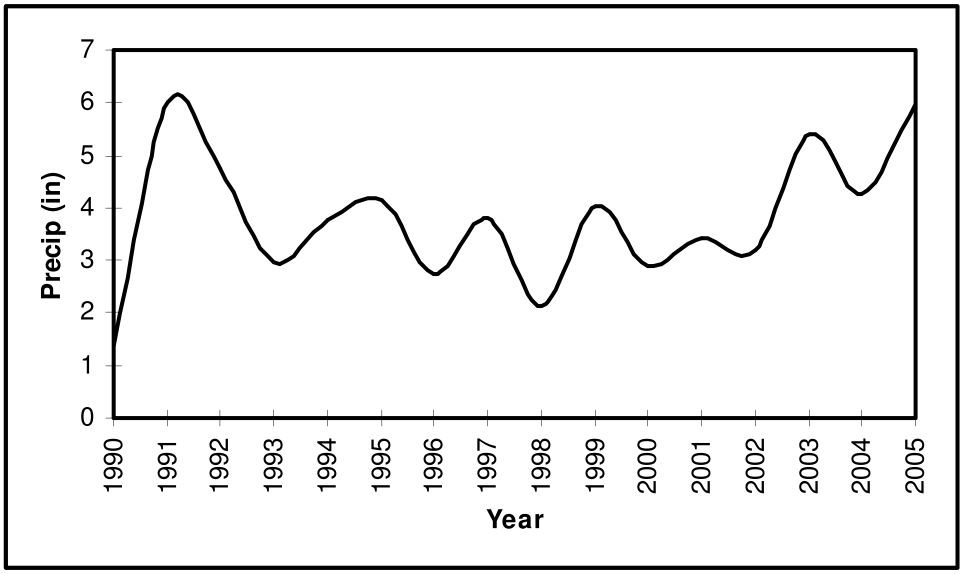

Figure 40, Mean Spring Precipitation

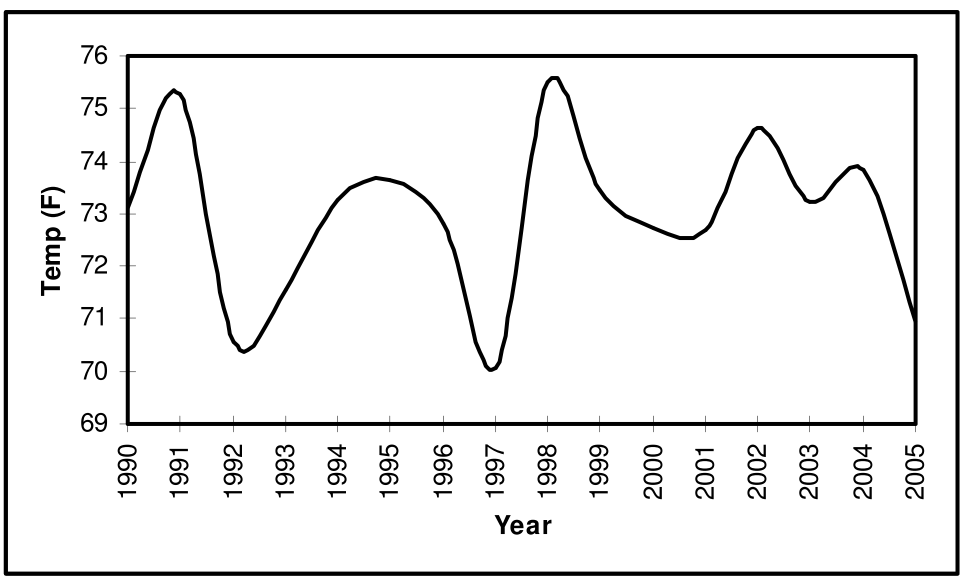

Figure 41, Mean Spring Temperature

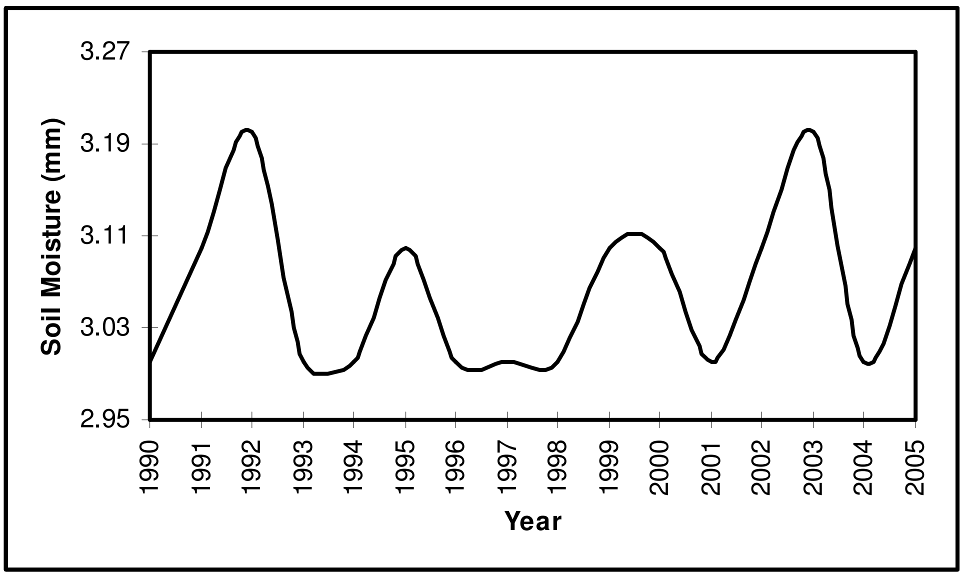

Figure 42, Mean Spring Soil Moisture

3.4.4 Summer

Temperature and precipitation values (Figures 42, 43) for the summer season were not significantly correlated with vegetated growth values (Table 5). The soil moisture levels were much more consistent with NDVI findings (Figure 44). Aggregately, for high-change and regional areas alike (Table 6), soil moisture has proven to be a superior measure in context to controlling climate variables.

Summer soil moisture volume showed steady advances. Summer values were some of the highest of any season with a mean of 3.42 mm. Total soil moisture content increased in summer from 2.4 mm (1990) to 2.7 mm (2005). Summertime moisture variability was potentially as high as 0.3 mm (12 percent increase/decrease annually) – the second lowest variability among the seasons. The most significant summer finding was that values on the latter half of the study were partially greater than those on the prior half. In fact, summer soil moisture content increased by an average of 15 percent from 2000 onward. The summer moisture values were consistently correlated with NDVI. Like each other season, values were correlated at the 0.05 significance level. The correlation was .617 for the study period.

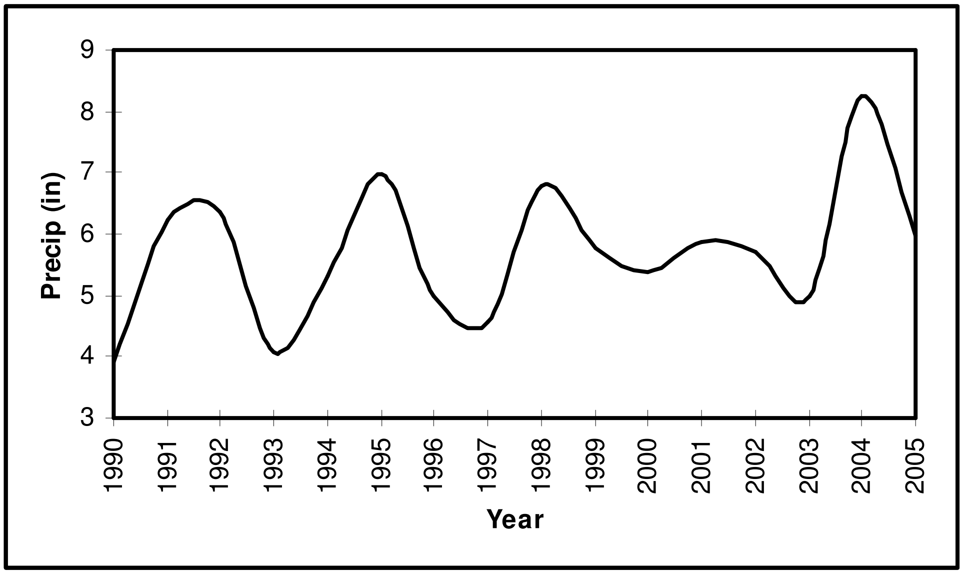

Figure 43, Mean Summer Precipitation

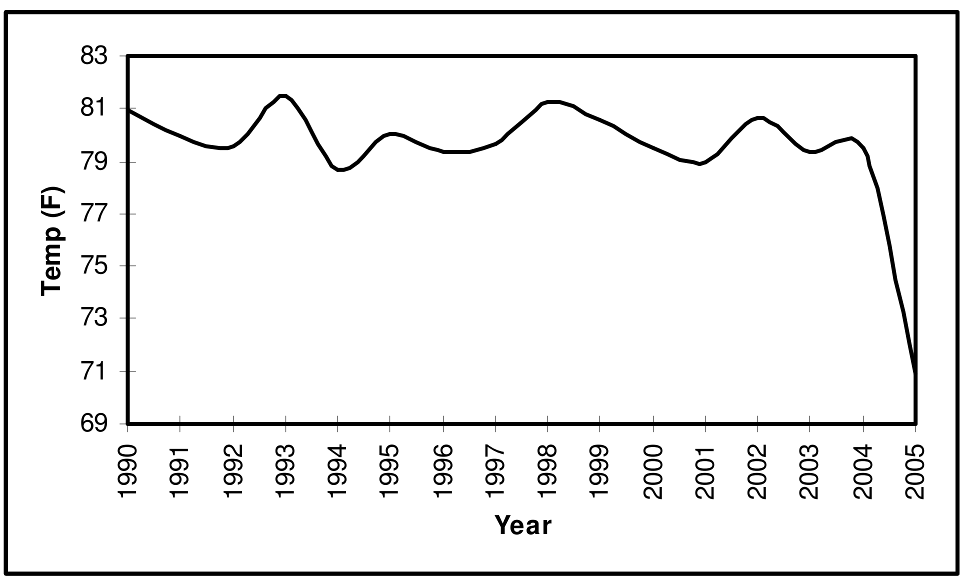

Figure 44, Mean Summer Temperature

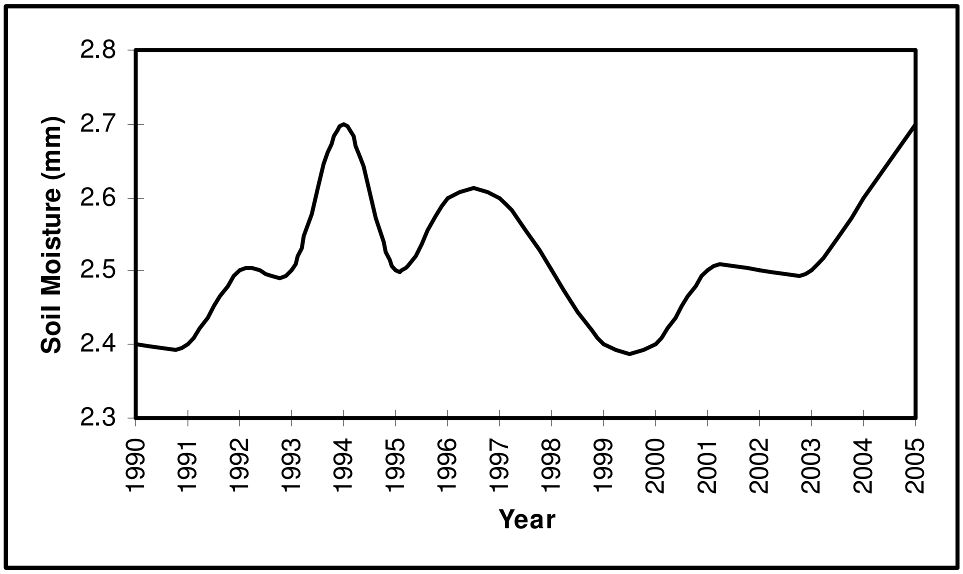

Figure 45, Mean Summer Soil Moisture

Table 5, Coastal-NDVI Study Zone Correlation by Season

	Winter	Spring	Summer	Fall
Precip (inches)	.108	-.133	.206	-.187
Temperature (F)	-.151	-.014	-.210	-.125
Soil Moisture	.686*	.622*	.617*	.660*

* Values Significant at the 0.05 Level (one-tailed)

Table 6, High-Change Area Climate-Correlation by Season

	Winter	Spring	Summer	Fall
Precip (inches)	1) -.369 2) -.450 3) -.353	1) -.168 2) -.155 3) .196	1) .255 2) .235	1) -.368 2) .072 3) -.206 4) .109
Temp (F)	1) -.267 2) -.367 3) -.304	1) .166 2) -.026 3) .252	1) -.267 2) -.419	1) -.180 2) -.096 3) -.299 4) -.239
Soil Moisture	1) .508* 2) .645* 3) .678*	1) .687* 2) .718* 3) .633*	1) .597* 2) .669*	1) .683* 2) .544* 3) .510* 4) .501*

* Values Significant at 0.05 Level (one-tailed)

Winter Polygon Zones: 1) Effingham-North
2) Interior West
3) Northeast Coast

Spring Polygon Zones: 1) North Okefenokee
2) Interior West
3) Northeast Coast

Summer Polygon Zones: 1) North Okefenokee
2) Hinesville-Fort Stewart

Fall Polygon Zones: 1) North Okefenokee
2) Hinesville-Fort Stewart
3) Northeast Coast
4) Interior West

CHAPTER FOUR

DISCUSSION

4.1 Spatial Variations in Above-Ground Biomass

The principal components analysis reconfirmed much of what the literature suggested in using such a statistical preliminary for landcover vegetation analysis. It demonstrated the most usefulness in context to data reduction. Pixel analysis confirmed how each component could be brought out to assess both vegetation healthiness and change over time. The use of these components would again affirm the quality of inputs and processing, as Mora and Merchant had suggested (Roberts et al. 1994, Mora et al. 1996). In this case, a limited mean variance was attributed to additional components and NDVI scores were fortified as the majority indicator for vegetation changes.

Vegetation healthiness experienced varying outcomes per each season, especially fall. Healthiness in fall contained the widest variability (over any subsequent season) across the study region. Fall vegetation values were also relatively low (0.36-0.39), which is not unexpected. This is to say that downturns continuing from summer result in lower fall values. The healthiest areas include the North Okefenokee barrier. Values in this area score higher because of the persistence of broadleaf vegetation, the bordered protection zone, and access to higher rates of soil moisture. Protection in this area is vital to the persistence of vegetation because of neighboring agricultural deforestation – which would lower NDVI values leading up to the border of the swamp. This directly connects to available soil moisture sources as well because of the bordering lands utilization and supplementation of ground water sources. The available soil moisture sources are primarily the result of lesser elevations and dense canopy which block some

of the solar radiation from reaching the ground. Some of the least healthy areas include major urban sites, and sites comprised of swamp/wetland with low canopy density. These are typical of low-scoring sites because of heavily saturated/flooded soils that do not support forest diversity. The difference in these areas related to soil moisture is that many vegetated species thrive in high soil moisture concentrations, though not as many thrive in inundated flood zones.

Winter experienced the lowest aggregate NDVI values (0.3-0.35) of any season. There was, however, less variability to winter growth than experienced in fall. This is to say that winter values were both more evenly distributed and also that the range between high and low values was not as extreme. Positive winter values persisted over the North Okefenokee area, while negative values persisted in urban areas and in the heavily flooded south swamp. This is primarily because of soil moisture retention and species biodiversity.

Spring experienced values that were the highest average NDVI scores (0.48-0.57) for any season. There was also more variability than experienced in winter, or again in summer. The range of healthiness supported lower values in urban areas and flooded wetlands. Moderate values, which were comparatively more common in summer, persisted in areas with mixed, but where diversity was lower. Spring and summer were periods when, because of heightened total vegetation healthiness, distinguished values for forest types were more detectable. This includes being able to witness when separate types of coniferous forest reflected differently from one another. In this case, loblolly-mixed hardwood forests (at similar densities) reflect more efficiently (fNIR) than do isolated longleaf forests. The reason for this is primarily attributed to the biodiversity of constituents within the forest. Longleaf stands tend to occur in primarily dry areas with open understories. Loblolly-mixed hardwood forests contain a variability of different

understories (and trees) which may include an abundance of broadleaf vegetation – and will thusly reflect to a higher degree (Via 2004).

Summer values (0.41-0.48) were lesser than those from spring, but remained higher than those for fall and winter. Summer values also experienced a lesser variability than values in spring or fall. In this way, during climate peaks in summer and winter, values were more muted in context to high-low variability. Lesser scores occurred in urban areas, combined urban-low diversity species areas, and in flooded/swamp zones. Heightened areas (North Okefenokee, SC Interior) occurred with abundant forest density and with forest diversity.

4.2 Temporal Variability in Above-Ground Biomass

Over the breadth of the study period, NDVI values for winter and summer were collectively on the rise. All eleven counties in the coastal ecoregion experienced significant growth in winter, and slight to moderate growth in summer. The average winter growth was slightly higher than 0.3 DN, which, over the time and spatial gamut, translates to a total greenness increase of slightly more than 13 percent. Summer results were more moderate, but nonetheless demonstrated an enhancing greenness trend. Summer values demonstrated an average increase of 0.18 DN (seven percent).

Spring values, upon first glance, seem to be in a period of recession; but this is not the case. With the subtraction of three northern coastal counties (Chatham, Liberty, Bryan), DN values are more or less stagnant. The addition of the counties brings mean greenness values down by 20 percent. The omission of those areas produces a change of less than negative one percent. Values are still at their highest points during the spring, which means that vegetation is

as healthy in this time of year as any. However, spring has not experienced growth at the same rates as have other seasons.

Fall is the only season that experienced truly negative greenness growth. NDVI values collectively dropped at a similar consistency to the positive winter values. NDVI decreased on average of eight percent, although there was a year to year variance for each of the counties. Nonetheless, aggregate values extending to the end of the study period outpaced values at the outset.

There is not a statistical significance along the coastal region to connect high-change areas with temperature and precipitation. There are positive and negative correlations, but their values in connecting seasonal trends are intermittent and inconsistent. In addition, these values are not statistically sufficient enough to conclude that resulting NDVI changes occurred as a result of temperature and precipitation fluctuations. The only consistent trend in the high-change areas is the same correlation over the breadth of the entire study region. Strong correlations suggest that changing soil moisture signals shifts to coastal vegetation healthiness. The importance of examining high change areas in this way (and the most significant finding) is that temperature and precipitation are not likely causes for coastal biomass change (in and of themselves). The relationship between the two, in the retention of soil moisture, is a much more meaningful connection.

One of the essential physiographic variables for unlocking exactly how greenness values shift has been soil moisture. This study found results that only confirmed what the literature concluded about strong correlations between the two (Adegoke et al. 2002, Lozano-Garcia et al. 1991). It is important to note that raw soil-moisture and NDVI values are not always synonymous. Each variable is in a constant state of flux, so it is difficult to connect the two at a

radiometric level. Instead, the correlation suggests that when one variable is lessened, the other variable will similarly show parallel effects. In this study, this happened whenever there was a dip in NDVI. In these cases there was an analogous dip in mean soil moisture, and the correlation values only confirm this. This reaffirms the findings that soil moisture anomalies are driven by precipitation, and their insistence and duration are driven by lesser evaporation rates caused by low temperature (Huang et al. 1996). This relationship can also be tracked through the increase in winter NDVI and in soil moisture levels alike. Nonetheless, the correlation figures only confirm that when soil moisture is down, greenness is down as well (and vice versa).

Over the 16 year study period, two major results are generated from this soil moisture-NDVI research. 1 –Vegetation greenness and availability (pixels) is steady, and, 2 – as long as vegetated areas have adequate soil moisture they will remain healthy. Changes to this relationship, lumped with time, can be attributed to any number of factors including anthropogenic activity and climatic devices. A good deal of this land occurs in wetlands, government sanctuaries, marshes, and barrier islands; so it stands to reason that a nominal percentage of change could have occurred due to growth activities.

4.3 Spatio-Temporal Vegetation/Landcover Changes

There are a number of consistent trends concerning loadings for NDVI and for change along the coastal study zone. These trends can be explained through climatic devices to an extent, meaning anthropogenic causes are primarily responsible for a good deal of change.

Urban impacts are responsible for explaining some values in the coastal area. Indeed, there is a causal nature to urban expansion and vegetated biomass loss (Singh et al. 2006). This is, in part, due to differentiating urban densities. This is to say that overall biomass is dependent

upon the capacity for an area (land) to support it. Urban areas, defined by an increased density of human structures and beings, determine the total capacity for vegetated space by density. The influence of larger impervious surfaces in urban areas signals a lack of vegetation, and greater urban expansions in the area. Values in these urban areas are low, but are determinant, however, on the total biomass capable of proliferation in densely impervious areas.

The first of these trends is lower loading values in the central corridor – that is Long, McIntosh, Wayne, and Liberty counties. Primary component loadings are diminished in this region throughout the study zone. Values have increased and decreased interannualy, but aggregate values are lower than many others during similar seasons. Landcover data in the central corridor supports two reasons for this trend. Firstly, there is a great percentage of this land that is cultivated hay, barren, and pasture. There is also a good deal more cypress-gum swamp, and wetland (Altamaha River basin). In each of these cases the expectation is for diminishing NDVI values over time because those areas do not contain as much photosynthetically active biomass responsive to NDVI (Tucker et al. 1985). Secondly, the corridor contains urban expansion from Ft. Stewart (Hinesville). Fort Stewart, which now encompasses land from five surrounding counties, is one of the largest military bases in the state – and is continuing to expand (Liberty, Long, Tattnall, Evans and Bryan). In addition to urban growth, the base has partnered with The Nature Conservancy (TNC) in an effort to revitalize longleaf pine stands in the coastal plain (TNC 2008). Fort Stewart has the largest remaining stand of longleaf pine forest in the state – and these values for pines are typically lower than for rich, leafy biomass (Brown 2001). Conversely, fall and winter values in the Hinesville area are higher toward the end of the study period. In this Fort Stewart area, this was primarily the reason due to conservation efforts. Values may be collectively diminished in the growing season

because of urban growth and differentiating growth types, yet fall and winter values are vastly improved due to expansion of *some* additional vegetated landcover. The accumulation of urban growth and changing biomass types are the primary reasons from which to examine changes in this corridor.

The second trend within the coastal study zone concerns diminishing biomass in north Chatham, east Glynn, and in south McIntosh counties (Northeastern Coast). These values are expressly lower than surrounding areas, as the change images demonstrate. Primarily, this is the result of expanding urban districts in Savannah, Brunswick, and Darien. Coupled with mixed-level urban development is the expansion of Hunter Army Airfield in Savannah. Also, these areas are more closely positioned to bare land, wetland, and consequently water – all of which exhibit very low NDVI reflectance. Increases in the areas of east Effingham, east Bryan, and east Wayne counties (Interior West) are part of an inland push where values are very high for each growing season. These values are additionally responsible for bringing up means throughout the entire county. This increase (winter) can also be seen in north Effingham county. The reasons for this growth are three-fold and include: diversity of mixed forest species (Pine, Hardwood, Deciduous, Evergreen), limited exposure to urban growth, and most importantly, lands placed under TNC control for conservation and restoration. In total, more than 100,000 acres have been placed under TNC conservation authority in the coastal plain, and this includes 12,000 acres since 1988 (within the coastal study zone) for conservation and restoration efforts (TNC 2008).

Additionally, there have been diminishing NDVI values in south Charlton and Brantley counties similar to those near Hinesville (Liberty County). This is due in part from urban expansions at nearby Kings Bay Naval Base, but is primarily caused by landcover taxonomy.

There are large concentrations of the longleaf pine, cypress gum swamp, and mixed wetlands in this area. This trend only continues further west as the area is positioned near the Okefenokee Swamp. The inclusion of water, non-leafy biomass, and urban growth are the chief reasons that landcover is changing in these areas.

Perhaps the greatest change throughout all seasons is by examining the North-Okefenokee swamp area. The upturned “V” is present in every change image and scored highly in every season except winter (although winter values for the region were the healthiest throughout the study zone). What is more intriguing in context to aggregate biomass is that this area is healthy. The Okefenokee Swamp is bordered by mainly agricultural lands and loblolly-mixed pine forest. The “V” is formed by a barrier of thick canopy that clearly demarcates the protected lands. This edge that appears so healthy is a natural barricade of bottomland and xeric hardwood, cypress trees, leafy biomass, and some invasive species like pine. The healthiness increases in this area are chiefly the work of environmental protection including natural soil moisture sources. This area is removed from urban growth, and as long as there is ample access to moisture (which should not be too difficult – low lying drainage basin extending to southern swamp) healthiness should remain steady.

The North Okefenokee healthiness is the result of several devices designed to promote forest and swamp protection. Since 1937, the swamp has been protected to preserve a refuge and breeding ground for migratory birds and indigenous wildlife species. The Okefenokee Wildlife Reserve is a zone within management from the U.S. Forest Service and the U.S. Fish and Wildlife Service. In 1974, separate previsions for spatial protection zones were established by the U.S. Forest Service to reinstitute and protect the inland swamp portions (National Wilderness Area) and the forest buffer zone bordering the swamp. The strengthening of this zone since 1974

(and extending into this study period) is due, in part, to the enactment of protections and restoration in the forest border zone.

CHAPTER FIVE

CONCLUSION

Since 1990, there have been several fluctuations to the above-ground biomass along coastal Georgia. There have been areas for both positive and negative biomass accumulations. The Georgia coast provided an interesting dynamic for study because of the range in diversity and in urban growth in the area. There is a dichotomy to growth in the study region, with urban expansion in the cities (Savannah, Brunswick, Hinesville, Waycross, Darien) and broadening forest restoration throughout the region. Coastal topography is relatively flat and ranges concerning the taxonomy in above-ground biomass. This means that because of the biological diversity, the area has a wide range of possibility concerning NDVI values. Though as has been determined, lesser yielding NDVI values do not mean an absence of vegetation, or necessarily an expansion of urban areas (i.e. Okefenokee Swamp, Altamaha Basin).

The findings of this research concerning NDVI rely on the fact that aggregate values are either increasing or remaining constant. Areas where there are value declines are transposed against conservation and restoration efforts intermingled with protected forest/beach sanctuaries, swamps, and marine environments. The likelihood that values will remain constant is solely dependent on two criteria. These criteria include the rate of urban expansion versus the perpetuation and maintenance of protected lands, and the climatic variations leading to the persistence of soil moisture levels. This includes land where NDVI declines are continuing to occur (values nominal from biodiversity type).

Vegetated lands, as has been demonstrated, are contingent upon the maintaining of soil moisture levels. Seasonal NDVI values are highly correlated with soil moisture levels

independent from other variables. As far as seasons are concerned, the relationship between vegetated biomass and healthiness is directly tied to the available soil moisture. Soil moisture has been shown to be a major control of NDVI over time. As drought, summertime depletion of groundwater resources, and poor water management continue, this relationship will continue to demonstrate that a decline in one variable will signal a decline in the other.

A material finding also lies within the uniqueness of two areas including the north Okefenokee and Ft. Stewart zones – where values are increasing and decreasing, respectively. The north Okefenokee increases are salient because of protection, maintenance, and climate trends including increased soil moisture. The Ft. Stewart decreases are prominent because of high urban levels of construction, lesser soil moisture, and the supplanting of vegetated areas with invasive species.

This study has shown that NDVI coupled with a PCA can perform an accurate landcover-vegetation assessment that is focused on change. The most conclusive findings are that aggregate coastal NDVI values are annually either steady or increasing, and soil moisture serves as a major NDVI control over time. Part of the significance in understanding this is that these findings can be specific to a few key variables (soil moisture, urban growth), and connecting responsive greenness to these variables is the material element in answering how vegetation healthiness acclimates from season to season.

The range of forested and vegetated lands is in a constant state of flux. There are a number of factors that influence the prevalence of reflective landcover over our dynamic planet. This research has designated a finite area where these landcover dynamics are in a persistent transition from anthropogenic activity and environmental reinstitution. It is the hope that this research will benefit and supplement continuing environmental and remote sensing inquiry for

the betterment of understanding landcover-vegetation changes. These changes are relentless, albeit human or environmentally induced. It is fundamental, as this research suggests, to recognize, analyze, and evaluate changes to our planet, as to ensure its hospitable and renewable nature for generations beyond.

Perhaps the best area for continued research within this vein is to focus more closely on one of the identified major change areas with (more spatially/radiometrically enhanced) a wide array of sensors. This may very well be a point from which areas within the coastal study zone could be evaluated at larger scales – the central corridor for example. It would be useful to examine particular counties for an enhanced specificity in both reflective NDVI tendency and in taxonometric phenology. This process is well performed using enhanced algorithms with highly resolved (spatially) imagery.

It would also highly improve this, and other studies, if some seasonal radiometric calibration algorithm could be determined between AVHRR-NDVI values and certain climatic-physiographic variables. Currently, no algorithms exist (even on a regional level) that connect specific values to measured levels – even those which are normalized. This makes it impossible to argue a substantive relationship for the expectation of said variables and measured reflectance. Thusly, quantitative measurements rely on strictly statistical preliminaries (correlation, regression) that deduce relationships instead of conclusivity. It would highly benefit these studies to evaluate regional variables with derived values for modeling purposes.

Additionally, research connecting supplementary climatic and physiographic variables with implemented sensor algorithms (using the AVHRR) could serve as the agent for landcover-vegetation modeling that has yet to be realized in coastal studies. Using these methods, an

adaptation of the coastal PCA could indicate areas of potential change using aligned models with highly specific indicator variables.

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APPENDIX A
Mean NDVI Values by County (Winter, Spring, Summer, Fall)

	1990	1991	1992	1993	1994	1995	1996	1997	1996	1999	2000	2001	2002	2003	2004	2005
Effingham	0.3	0.3	0.31	0.31	0.32	0.31	0.31	0.32	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.35
Chatham	0.3	0.31	0.31	0.31	0.32	0.3	0.31	0.33	0.34	0.34	0.34	0.34	0.34	0.34	0.35	0.35
Bryan	0.31	0.32	0.31	0.32	0.32	0.32	0.32	0.33	0.33	0.33	0.33	0.33	0.33	0.33	0.34	0.34
Long	0.31	0.33	0.33	0.33	0.32	0.33	0.33	0.34	0.34	0.34	0.35	0.35	0.35	0.34	0.35	0.34
McIntosh	0.32	0.32	0.33	0.34	0.33	0.34	0.35	0.35	0.35	0.35	0.36	0.36	0.36	0.36	0.37	0.37
Wayne	0.33	0.33	0.33	0.32	0.32	0.31	0.32	0.33	0.33	0.33	0.34	0.35	0.35	0.35	0.35	0.35
Glynn	0.34	0.34	0.34	0.34	0.35	0.36	0.36	0.37	0.37	0.37	0.38	0.36	0.36	0.36	0.37	0.38
Brantley	0.34	0.35	0.35	0.35	0.34	0.35	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.36	0.37	0.38
Camden	0.32	0.32	0.31	0.32	0.32	0.32	0.32	0.33	0.33	0.33	0.34	0.35	0.35	0.35	0.35	0.35
Charlton	0.3	0.31	0.32	0.31	0.3	0.31	0.31	0.32	0.32	0.32	0.33	0.33	0.33	0.34	0.35	0.35
Ware	0.31	0.31	0.32	0.32	0.32	0.33	0.32	0.33	0.32	0.32	0.32	0.33	0.34	0.34	0.35	0.36
Liberty	0.3	0.31	0.31	0.31	0.32	0.32	0.33	0.34	0.32	0.32	0.31	0.32	0.33	0.33	0.34	0.34

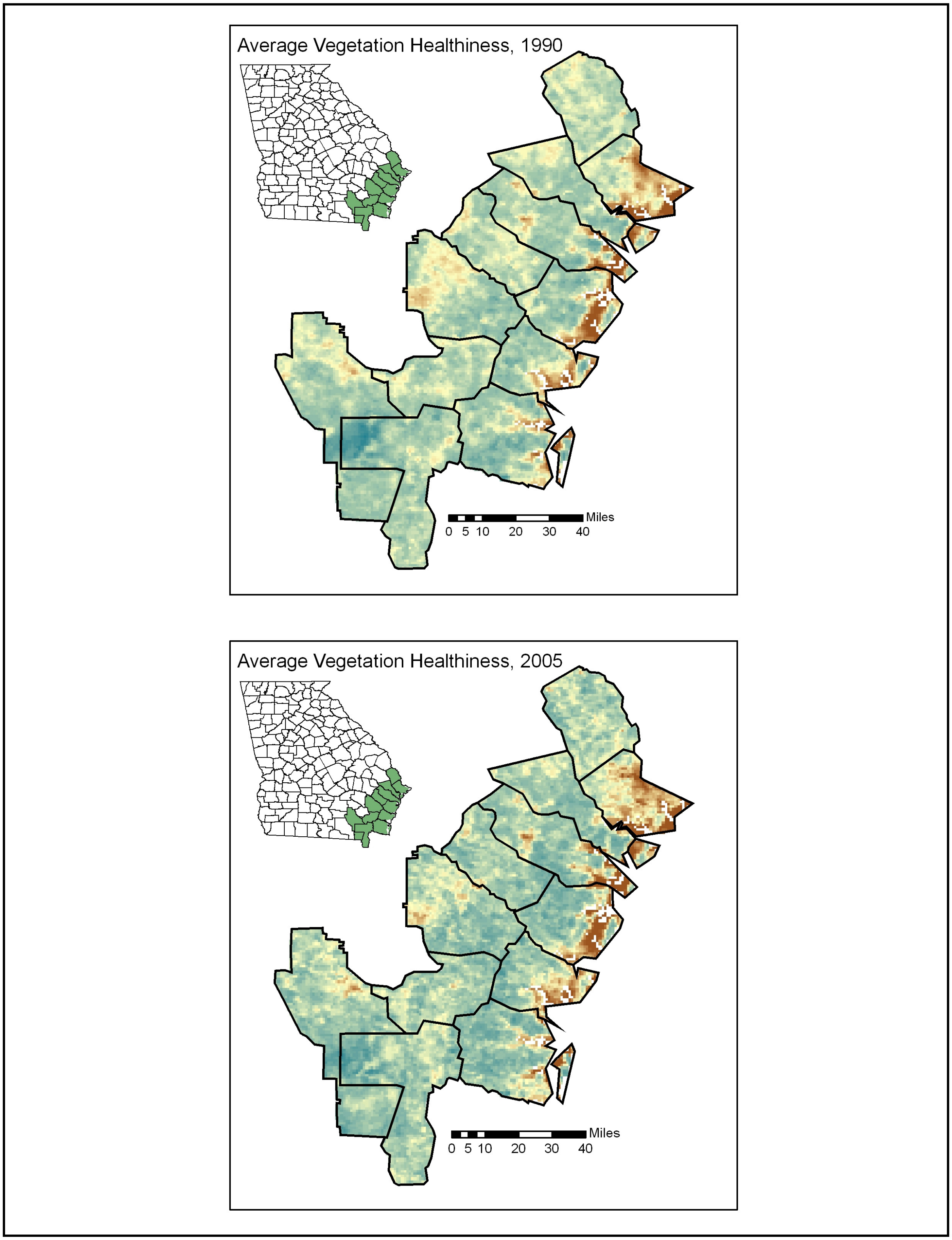
	1990	1991	1992	1993	1994	1995	1996	1997	1996	1999	2000	2001	2002	2003	2004	2005
Effingham	0.48	0.49	0.48	0.48	0.47	0.48	0.48	0.48	0.48	0.48	0.48	0.49	0.49	0.49	0.49	0.48
Chatham'	0.58	0.58	0.57	0.57	0.56	0.56	0.55	0.54	0.54	0.54	0.54	0.53	0.53	0.53	0.53	0.53
Bryan'	0.58	0.58	0.58	0.57	0.57	0.58	0.57	0.56	0.56	0.56	0.56	0.56	0.55	0.54	0.54	0.53
Long	0.53	0.53	0.52	0.53	0.53	0.53	0.53	0.53	0.53	0.54	0.54	0.54	0.54	0.54	0.54	0.54
McIntosh	0.55	0.55	0.55	0.54	0.55	0.56	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.55	0.56
Wayne	0.56	0.56	0.56	0.56	0.56	0.56	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Glynn	0.6	0.6	0.59	0.59	0.58	0.59	0.59	0.59	0.59	0.58	0.58	0.58	0.58	0.58	0.58	0.59
Brantley	0.52	0.52	0.52	0.51	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52	0.52
Camden	0.53	0.53	0.52	0.52	0.53	0.53	0.53	0.53	0.53	0.52	0.52	0.52	0.52	0.52	0.54	0.53
Charlton	0.56	0.56	0.55	0.55	0.55	0.56	0.56	0.56	0.56	0.57	0.57	0.57	0.57	0.57	0.57	0.57
Ware	0.5	0.49	0.49	0.49	0.49	0.49	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.49
Liberty'	0.53	0.52	0.51	0.51	0.51	0.51	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.49

	1990	1991	1992	1993	1994	1995	1996	1997	1996	1999	2000	2001	2002	2003	2004	2005
Effingham	0.4	0.4	0.4	0.41	0.41	0.4	0.4	0.4	0.41	0.41	0.41	0.41	0.41	0.41	0.41	0.41
Chatham	0.45	0.45	0.45	0.45	0.45	0.46	0.45	0.45	0.45	0.45	0.46	0.46	0.46	0.46	0.46	0.47
Bryan	0.47	0.47	0.47	0.46	0.47	0.47	0.46	0.46	0.47	0.47	0.47	0.47	0.48	0.48	0.47	0.48
Long	0.44	0.45	0.46	0.45	0.46	0.46	0.46	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47	0.47
McIntosh	0.43	0.43	0.44	0.44	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.45	0.46	0.46	0.46	0.46
Wayne	0.41	0.41	0.41	0.42	0.42	0.42	0.43	0.43	0.44	0.44	0.44	0.45	0.45	0.45	0.45	0.45
Glynn	0.46	0.46	0.46	0.47	0.47	0.47	0.47	0.46	0.45	0.45	0.45	0.45	0.45	0.46	0.46	0.48
Brantley	0.43	0.43	0.43	0.43	0.44	0.43	0.43	0.43	0.43	0.42	0.41	0.41	0.41	0.41	0.42	0.44
Camden	0.44	0.44	0.44	0.44	0.43	0.44	0.44	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.43	0.45
Charlton	0.44	0.44	0.42	0.43	0.44	0.44	0.43	0.43	0.44	0.44	0.45	0.44	0.44	0.44	0.44	0.45
Ware	0.41	0.41	0.4	0.41	0.41	0.41	0.42	0.42	0.42	0.42	0.43	0.42	0.42	0.42	0.42	0.43
Liberty	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.42	0.43	0.42	0.42	0.42	0.42	0.43

	1990	1991	1992	1993	1994	1995	1996	1997	1996	1999	2000	2001	2002	2003	2004	2005
Effingham	0.36	0.36	0.36	0.35	0.35	0.35	0.37	0.35	0.35	0.35	0.35	0.35	0.35	0.34	0.34	0.33
Chatham	0.39	0.39	0.38	0.39	0.38	0.39	0.4	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.38	0.37
Bryan	0.37	0.37	0.37	0.37	0.37	0.37	0.42	0.39	0.39	0.39	0.39	0.38	0.37	0.37	0.37	0.36
Long	0.37	0.36	0.36	0.36	0.36	0.36	0.38	0.36	0.36	0.36	0.36	0.36	0.36	0.35	0.35	0.34
McIntosh	0.39	0.39	0.38	0.37	0.37	0.38	0.41	0.39	0.38	0.38	0.38	0.38	0.37	0.37	0.37	0.36
Wayne	0.37	0.37	0.37	0.35	0.35	0.35	0.37	0.35	0.35	0.35	0.35	0.34	0.34	0.34	0.34	0.34
Glynn	0.4	0.4	0.39	0.39	0.39	0.39	0.36	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37	0.37
Brantley	0.36	0.36	0.36	0.35	0.35	0.35	0.35	0.34	0.34	0.34	0.34	0.33	0.33	0.33	0.33	0.32
Camden	0.36	0.36	0.36	0.36	0.36	0.36	0.37	0.35	0.35	0.35	0.34	0.33	0.33	0.33	0.33	0.33
Charlton	0.39	0.38	0.38	0.37	0.38	0.38	0.38	0.37	0.37	0.36	0.36	0.35	0.35	0.35	0.35	0.34
Ware	0.35	0.33	0.33	0.33	0.33	0.33	0.35	0.34	0.34	0.34	0.33	0.33	0.33	0.33	0.33	0.32
Liberty	0.35	0.34	0.33	0.34	0.34	0.34	0.37	0.36	0.36	0.35	0.34	0.34	0.33	0.33	0.33	0.32

APPENDIX B

Average Coastal Vegetation Increase 1990-2005 (USGS 2008)



APPENDIX C
Coastal Forest Coverage Types (NARSAL 2006)

Land Cover Type	Code	Description
Forested Urban - Deciduous	201	Low intensity urban areas containing mainly deciduous trees.
Forested Urban - Evergreen	202	Low intensity urban areas containing mainly evergreen trees.
Forested Urban - Mixed	203	Low intensity urban areas containing mixed deciduous and evergreen trees.
Hardwood Forest	412	Mesic to moderately mesic forests of the lower Piedmont and Coastal Plain. Includes non-wetland floodplain forests of yellow-poplar and sweetgum, ravines of oaks and American beech, and many upland oak-hickory stands.
Xeric Hardwood	413	Dry hardwood forests found throughout the state, although most common in the mountain regions, and progressively more rare southward. Includes areas dominated by southern red oak, scarlet oak, post oak, and blackjack oak.
Live Oak	420	Forests dominated by live oak. Most common in maritime strands along the Atlantic Coast. Also may occur in strip along southern border into southwest Georgia.
Xeric Mixed Pine-Hardwood	432	Dry mixed forests found throughout the state, although most common in the mountain regions, and progressively more rare southward. Includes areas dominated by a mix of pines (most frequently shortleaf or Virginia in the mountains, and shortleaf or longleaf elsewhere) and hardwood species such as southern red oak, scarlet oak, post oak, and blackjack oak.
Mixed Pine-Hardwood	434	Mesic to moderately dry forests of mixed deciduous and evergreen species found throughout the state at lower elevations. May include areas dominated by sweetgum, yellow-poplar, various oak species, and loblolly or shortleaf pine.
Loblolly-Shortleaf Pine	440	Found from the upper Coastal Plain northward (rare in the Blue Ridge except at the lowest elevations). Includes many stands heavily managed for silviculture as well as areas regenerating from old field conditions.
Loblolly-Slash Pine	441	Found on the lower Coastal Plain. Includes many heavily managed stands as well as a few natural areas.

Longleaf Pine	620	Open, savanna-type stands. Heavily managed plantations would likely be classed with 440 or 441. Most common on the lower Coastal Plain, although found up to the lower Piedmont and historically in the Ridge and Valley.
Cypress-Gum Swamp	890	Regularly flooded swamp forests mainly found on the Coastal Plain. May include either riparian or depressional wetlands. Usually dominated by pond or baldcypress and/or tupelo gum.
Bottomland Hardwood	900	Less frequently flooded wetland forests found throughout the state, but most common on the Coastal Plain. To the north, may be dominated by sweetgum, elms, and red maple. To the south, wetland oaks (water oak, willow oak, overcup oak, swamp chestnut oak), black gum, and even spruce pine become more common.
Evergreen Forested Wetland	990	Restricted to the Coastal Plain. Includes forests dominated by bay species, wet pine forests (typically slash or pond pine), or Atlantic white cedar.

APPENDIX D
Summary Table of Georgia Ecoregion Characteristics (EPA, Western Ecology Division 2000)

SOUTHERN COASTAL PLAIN Level IV Ecoregion		Physiography		Geology	Soil			Climate			Potential Natural Vegetation	Land Use and Land Cover
	Area (square miles)		Elevation / Local Relief (feet)	Surficial and bedrock	Order (Great Groups)	Common Soil Series	Temperature/ Moisture Regimes	Precipitation Mean annual (inches)	Frost Free Mean annual (days)	Mean Temperature January min/max; July min/max, (F)		
75e. Okefenokee Plains	2285	Flat plains on lightly dissected marine terraces; swamps and bays, low gradient streams with sandy and silty substrates.	95-270 / 10-75	Pleistocene and Pliocene sand and gravel.	Spodosols (Alaquods, Alorthods); Ultisols (Paleaquults, Paleudults)	Mascotte, Sapelo, Leon Pelham, Surrency, Leefield, Mandarin	Thermic / Aquic, some Udic	49-53	240-250	38/62 69/92	Southern mixed forest.	Evergreen forest / pine plantations, forested wetland.
75f. Sea Island Flatwoods	3934	Flat plains on lightly dissected marine terraces; swamps, low gradient streams with sandy and silty substrates.	10-220 / 5-75	Pleistocene and Pliocene marine sand, silt, and clay.	Ultisols(Paleaquults, Paleudults, Albaquults); Alfisols (Endoaqualfs); Spodosols (Alaquods, Alorthods)	Ellabelle, Bladen, Pelham, Brookman, Leefield, Mandarin, Mascotte, Leon	Thermic / Aquic, some Udic	48-53	240-260	38/62 70/92	Southern mixed forest.	Evergreen forest / pine plantations, forested wetland.
75g. Okefenokee Swamp	695	Flat plain with swamps, islands, and lakes.	110-135 / 5-20	Holocene swamp deposits of muck, peat, fine sand, and silt; Pleistocene sand and clay.	Histosols (Haplosaprists, Haplohemists), Spodosols (Alaquods, Alorthods)	Dasher, Croatan, Leon, Lynn Haven, Mandarin, Mascotte, Pamlico	Thermic / Aquic	50-53	240-255	39/63 69/92	Southern floodplain forest.	Forested wetland, non-forested wetland; wildlife habitat, mostly public land (Okefenokee National Wildlife Refuge).
75h. Bacon Terraces	1842	Flat plains on dissected marine terraces; low gradient streams with sandy and silty substrates.	80-290 / 20-100	Pleistocene and Pliocene sand and gravel, some Miocene sand, clay, and gravel near major streams.	Ultisols (Paleudults, Kandiudults, Paleaquults); Spodosols (Alaquods); Entisols (Quartzipsamments)	Leefield, Pelham, Mascotte, Surrency, Tifton, Carnegie, Clarendon, Fuquay, Kershaw	Thermic / Udic, Aquic	46-50	230-240	37/61 69/92	Southern mixed forest.	Cropland with corn, cotton, soybeans, tobacco, blueberries; pine plantations, forested wetland.
75i. Floodplains and Low Terraces	286	Major river floodplains and associated low terraces; low gradient streams with sandy and silty substrates, oxbow lakes, ponds, swamps.	1-80 5-25	Holocene alluvial gravelly sand, alluvial silt and clay.	Alfisols (Albaqualfs); Inceptisols (Endoaquepts, Dystrudepts); Entisols (Udifluvents)	Meggett, Chastain, Tawcaw, Chewacla, Congaree	Thermic / Aquic	48-52	240-260	38/62 70/91	Southern floodplain forest.	Forested wetland, deciduous forest.
75j. Sea Islands / Coastal Marsh	1295	Barrier islands, dunes, beaches, lagoons, estuaries, tidal marshes.	0-30 / 5-20	Holocene saline marsh deposits of silt, sand, peat, and clay; Holocene beach and dune sand; Pleistocene beach and near-shore marine sand.	Inceptisols (Humaquepts), Spodosols (Alorthods, Alaquods), Entisols (Sulfaquents, Psammaquents, Quartzipsamments)	Mandarin, Rutlege, Chipley, Cainhoy; Fripp and Duckston near beaches; Bohicket, Capers in tidal marshes.	Thermic / Aquic	50-52	260-285	39/60 72/90	Live oak-sea oats, cordgrass-saltgrass-rushes.	Marsh, forested wetland, evergreen forest, urban, wildlife habitat, beaches, recreation, fish and shellfish production.