A SPATIAL-TEMPORAL ANALYSIS OF VEGETATION CHANGE, LAND COVER CHANGE, AND HEALTH IMPACTS IN FLORIDA

By

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To my family and friends, who, always support me

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The present dissertation contributes to the overall better understanding of vegetation change; land cover and land use change and health impacts in Florida, but would also have implications and significance beyond just Florida. By using the Normalized Difference Vegetation Index (NDVI) as vegetation representation, a time-series approach is applied in order to assess vegetation dynamics across the state from 1982-2006. In addition, the response of vegetation to climate variability and land cover is investigated with remote sensing based land cover classification data. At last, the impacts of land cover and land use change on air quality is examined. Overall, three conclusions can be drawn from this dissertation. First, there is an increasing NDVI value during winter months from 1995 onward and this phenomenon could be explained by the Atlantic Multidecadal Oscillation (AMO) switched into its warm phase around 1995. The result also corresponding with an increased winter rainfall proportion has been found from a previous study. Second, precipitation and land cover types both influence NDVI behavior. The NDVI responds to precipitation is found to be stronger in natural land cover like estuarine wetlands than in human manipulated land cover such as

developed land. Third, air pollution is highly correlated to weather conditions especially precipitation. Future research opportunities are plenty based on the findings from this dissertation.

CHAPTER 1
INTRODUCTION

A quote from President Obama's inaugural speech, "For the world has changed, and we must change with it" points out that the global environment was changed dramatically and human beings need to face the challenges resulting from these changes. The global environment is changing due to human and natural causes (GLP 2005) and human causes have been recognized as a major contributor to global environment changes (Vitousek et al. 1997, Dale 1997, Foley et al. 2005, GLP 2005).

A conceptual model of how human alterations to the Earth system operate through interacting processes is developed by Vitousek and colleagues in 1997. They argue that the growth of human population and growth in the resource base used by humanity is maintained by a suite of human enterprises such as agriculture, industry, fishing, and international commerce (Meyer and Turner 1992). These enterprises transform the land surface (through cropping, forestry, and urbanization), alter the major biogeochemical cycles (Kalnay and Cai 2003, Foley et al. 2005, Bala et al. 2007, Bonan 2008, Grimm et al. 2008, McCarthy et al. 2010, Lambin et al. 2003, Davidson and Janssens 2006, Pongratz et al. 2009), and alters species and genetically distinct populations in most ecosystems (O'Reilly et al. 2003, Harveson 2006). Many of these changes are substantial, are well quantified, and all are ongoing. These well-documented changes cause further alteration to the functioning of the Earth system, most notably by driving global climatic change (Dale 1997, Bounoua et al. 2002, Feddema et al. 2005, Ebi and McGregor 2008, Jacob and Winner 2009) and causing irreversible losses of biological diversity (Vitousek et al. 1997, Lambin et al. 2001, Foley et al. 2005, Moss et al. 2010).

Realizing human activities are responsible for the majority of changes on Earth across a variety of spatial and temporal scales, there is a need to understand the interaction between humans and the environment and the way these have affected, and may yet affect, the sustainability of the Earth System (GLP 2005). Much of the international global change research is facilitated by four programmes, including the International Geosphere-Biosphere Programme (IGBP), the International Human Dimensions Programme on Global Environmental Change (IHDP), DIVERSITAS (an international programme of biodiversity science) and the World Climate Research Programme (WCRP). In 2005, the Global Land Project (GLP) Science Plan and Implementation Strategy was built upon the extensive heritage of the joint IGBP-IHDP project on land use and land-cover change (LUCC) and worked on improving the understanding of land system dynamics in the context of Earth System functioning (GLP 2005).

Numerous researchers collaborated and contributed observations, study results, experiments and modeling techniques to improve the ability to explain and predict global environmental changes (Turner et al. 1990, Lambin et al. 2001, Tilman et al. 2001, O'Reilly et al. 2003, Oerlemans 2005, Janssen et al. 2006, Rosenzweig et al. 2008). Recently, an integrated "Land Change Science (LCS)" has emerged as a foundational element of global environment change and sustainability science. The focus of LCS requires the integration of social, natural, and geographical information sciences (Rindfuss et al. 2004). Researchers of LCS utilize environmental, human, and remote sensing/geographical information system (GIS) science to solve various questions about land-use and land-cover changes. They also study the impacts of these

changes on humankind and the environment as an integrated science (DeFries et al. 1999, Lambin et al. 2001, Bounoua et al. 2002, Gutman et al. 2004, Rindfuss et al. 2004, Southworth et al. 2006, Turner et al. 2007). Satellite-based observations of the Earth have provided a spatially and temporally consistent picture of the state of global land cover and it has been used in LCS as a valuable resource (Townshend et al. 1991, Bartholome and Belward 2005, Lambin and Geist 2006, Herold et al. 2008, Friedl et al. 2010). Integration of Geographical Information Systems (GIS) and Global Positioning Systems (GPS) with advanced remote sensing techniques improves the ability and efficiency in assessing land cover change than by remote sensing data only (Xiao et al. 2006, Shalaby and Tateishi 2007, Friedl et al. 2010).

However, the challenge of thoroughly understanding the complexity of global environment changes remains (Lambin and Geist 2006). As the world population approaches 10 billion in the next ninety years (UN 2010), the intensity and extent of human alterations to the Earth system as well as their interacting processes are only expected to increase. Additionally, the Earth system responds to changes at different speeds and extents and that varies greatly through time and from place to place (Turner et al. 1990, Vitousek et al. 1997, Steffan 2004, Rockstorm et al. 2009). Thus, a more detailed investigation is needed across different time (short-term and long-term) and spatial scales (global, regional, community) to provide explicit monitoring, analyzing, and problem solving strategies, and to link changes across systems, such as changes in climate to resultant vegetation, or changes in climate on human health.

As a regional scaled investigation, the southeast US has drawn more attention from researchers across diverse disciplines. Sohl and Sayler (2008) pointed out the

southeast US has experienced massive land-use change since European settlement and continues to experience extremely high rates of forest cutting, significant urban development, and changes in agricultural land use. Based on a report from the U.S. Global Change Research Program (USGCRP 2009), the southeast US has also experienced an increase in annual average temperature by 2°F since 1970. There has been a 30 percent increase in fall precipitation over most of the region since 1901 but a decrease in fall precipitation in South Florida. The decline in fall precipitation in South Florida contrasts strongly with the regional average. However, there has been an increase in heavy downpours in many parts of the region (Keim 1997, Karl and Knight 1998), while the percentage of the region experiencing moderate to severe drought increased since the mid-1970s. Additionally, sea-level rise and the likely increase in hurricane intensity and major hurricane frequency with associated storm surge pose a severe risk to the southeast US (Mulholland et al. 1997, Esterling et al. 2000, Pielke et al. 2005). Furthermore, as the population of Florida more than doubled during the past three decades and it receiving over 80 million visitors every year, the overall ecosystem is under an elevated pressure caused by its dwellers. From 2000 to 2010, there was a 17.6 percent increase of Florida's population (US Census Bureau, 2011) which is almost double the nation's population increase rate of 9.7 percent. The increased population coupled with an increase in societal demand is a big contributor to agricultural development, land cover change/urbanization and air pollution in Florida (Samet et al. 2000, Solecki and Walker 2001, USGS 2004, Hu et al. 2008, Zanobetti and Schwartz 2009). However, anthropogenic activities have not only transformed the landscape of the Florida peninsula, but also altered the regional climate (Marshall et al.

2004, Pielke and Niyogi 2010) and potentially the sustainability of Florida ecosystems (Harwell et al. 1996, Solecki 2001).

The characteristics of the southeast US make Florida a desirable study region. A long term spatial and temporal variability analysis is needed to provide insights into the dynamic ecological and societal system (Magnuson et al. 1991). Climatologically, Florida is experiencing changes in weather patterns and precipitation tends to be a big factor influencing the natural landscape/vegetation. Ecologically, Florida is confronting a massive land cover change with aggressive anthropogenic activities coupled with adverse environmental and health impacts like air pollution. The present dissertation research utilizes advanced remote sensing and geographical information system (GIS) techniques to analyze the changes in Florida in terms of its vegetation cover, climate variability, land cover and land use with associated health impacts especially on air pollution as well as the associated linkages/exchanges among these different variables.

The overarching object of this present dissertation is to contribute the overall better understanding of vegetation change; land cover and land use change and health impacts in Florida, but would also have implications and significance beyond just Florida. The order of main chapters is organized by three research papers. The first paper apply the normalized difference vegetation index (NDVI) to investigate long term vegetation trend and the spatial and temporal variations of vegetation cover (as represented by NDVI) within the landscape which are influenced by different climate variables, in particular precipitation and large scale circulation patterns such as the Atlantic Multidecadal Oscillation (AMO). The second paper analyzes the responds of NDVI to climate variability and land cover and how the responds varied spatially by

using the wavelet analysis. The third paper combined the results from both previous papers with an emphasis on the associated air pollution impacts for developed areas in Florida.

CHAPTER 2
SPATIAL PERSISTENCE AND TEMPORAL TRENDS IN VEGETATION COVER ACROSS FLORIDA, 1982-2006

2.1 Background

As modern advanced remote sensing techniques have been proven to provide an efficient tool to provide a spatially and temporally consistent picture of land surface conditions (Curran 1989, Gould 2000, Stow et al. 2004, Townshend et al. 1991, Bartholome and Belward 2005, Lambin and Geist 2006, Herold et al. 2008, Friedl et al. 2010), they have been increasingly used to monitor and detect patterns and variations in vegetation worldwide(Gao 1996, Gould 2000, Wu et al. 2009, Tang et al. 2010)

In order to enhance our understanding of intra- and inter-annual variations in vegetation, time series approach of analyzing continuous Earth Observation (EO) based estimates of vegetation are being adapted by many scholars (Myneni et al. 1998; Eklundh & Olsson 2003; Olsson et al. 2005; McCloy et al. 2005; Anyamba & Tucker 2005, Jeyaseelan et al. 2007, Helldén & Tottrup 2008, Fensholt et al. 2009, Neeti et al. 2011). The Advanced Very High Resolution Radiometer (AVHRR) on board the National Oceanic and Atmospheric Administration (NOAA) satellite series provides an excellent opportunity to employ time series approaches to vegetation research because of its consistent fine spatial and temporal coverage.

Florida is well known of its diverse ecosystems and natural resources (Brockway et al. 1998, Gentile et al. 2001, Menges et al. 2009). Its vegetation cover is influenced by numerous factors not the least of which is the 600 percent increase in population since 1940. Land cover and land use change resulting from global climate change/variability are big concerns in terms of its indirect and direct impacts on vegetation cover. Vegetation structure and pattern in Florida has been studied

intensively in several regions such as Everglades National Park (Huang et al. 2008, Todd et al. 2010, Gaiser et al. 2011), South Florida (LaRoche and Ferriter 1992, Menges et al. 2001, Ross et al. 2009); or in specific ecosystems (Sitch et al. 2003, Smith et al. 2009, Haile et al. 2010). Less recognized, however, is a determination of the overall vegetation pattern and trend across the state. During the twentieth century, the natural landscape of the Florida peninsula was transformed extensively by agriculture, urbanization, and the diversion of surface water features (Marshall et al. 2004). Therefore, it is necessary to evaluate the statewide spatial and temporal trends of vegetation cover in order to enhance our understanding of a long term vegetation changes that may be as background information for future research.

This study applies advanced remote sensing techniques especially the use of Normalized Difference Vegetation Index (NDVI) derived from AVHRR in order to assess a long term time series study on vegetation cover in Florida from 1982-2006. NDVI is a sufficient and the most commonly used vegetation index to monitor the healthiness of vegetation (Anyamba and Eastman 1996, Carlson and Ripley 1997, Li and Kafatos 2000, Gurgel and Ferreira 2003, Jarlan et al. 2005, Pettorelli et al. 2005, Barbosa et al. 2006, Philippon et al. 2007, Meng et al. 2011, Begue et al. 2011). Therefore, NDVI is reasonable and applicable means of representing vegetation in this study. Pickup and Foran (1987) developed a mean-variance analysis by utilizing a graphical analysis of a dynamical system to describe the motion or trajectory of states through time. Later on Zimmermann et al. (2007) and Washington-Allen et al. (2003 & 2008) applied the mean-variance analysis on their research. From their results, they concluded that mean-variance analysis is an effective method to describe the seasonal and interannual

response of vegetation to climate and disturbance. Therefore, the mean-Variance analysis is employed to describe the trajectory of the state of vegetation across the 25 year time period in terms of the mean NDVI, characterizing the overall amount of vegetation, and its simultaneous spatial variance, describing the spatial heterogeneity, in a two-dimensional plane. The persistence analysis is applied to assess changes in NDVI from 1982-2006 in a spatially explicit manner. Based on the value of every pixel, two spatial persistence analyses are performed. One of them is based on a logic of NDVI is increase/decrease to the next time step and another one is based on calculating the absolute amount of NDVI value changes through time. Statistical tests are performed in order to characterize vegetation patterns and trends more objectively.

Overall, this study proposes a unique method by which to explicitly detect vegetation cover patterns and trends both spatially and temporally. The results provide valuable information and enhance the understanding of statewide temporal changes in vegetation cover change. Additionally, the results from this study will also fed into further investigations of land cover change combining climate variability of Florida.

2.2 Methods

2.2.1 AVHRR-Vegetation Indices

Satellite-derived vegetation indices have proven to be an efficient way to characterize explicitly surface vegetation conditions (Gutman 1991 & 1999, Huete et al. 2002, Anyamba and Tucker 2005, Fensholt et al. 2009, Meng et al. 2011, Begue et al. 2011). Analysis of the seasonal and interannual vegetation dynamics and trends in Florida is based on the normalized difference vegetation index (NDVI) data derived from measurements made by the Advanced Very High Resolution Radiometer (AVHRR) sensor aboard the National Oceanic and Atmospheric Administration (NOAA) polar

orbiting satellite series (NOAA-7, 9, 11, 14, 16 and 17). The AVHRR sensor was originally designed as a weather satellite. However from the early 1980s, AVHRR data have found increasing use to monitor the type and condition of land vegetation. Therefore there is a large archive of AVHRR data, providing a very rich source of information for multi-temporal studies (Warner and Campagna 2009).

NDVI is a vegetation index commonly used in remote sensing research whose signal response is a function of absorbed radiation by chlorophyll in the red band and scattering by cellulose in the near-infrared (NIR) and it has been widely accepted as an indicator for providing vegetation properties and assessing ecological response to environmental changes for large scale geographic regions (Anyamba and Eastman 1996, Carlson and Ripley 1997, Li and Kafatos 2000, Gurgel and Ferreira 2003, Jarlan et al. 2005, Pettorelli et al. 2005, Barbosa et al. 2006, Philippon et al. 2007, Meng et al. 2011, Begue et al. 2011). NDVI is a variant of simple ratio of near-infrared and red band, which is defined:

NDVI = (Near Infrared-Red)/(Near Infrared+Red).

However, by constructing the ratio as the difference of the two wavelengths over the sum of the two wavelengths, NDVI is normalized, so that the range falls between -1 and +1. Furthermore, NDVI is designed such that high values of the ratio (closer to +1) indicate abundant green vegetation, and values near zero or less indicate an absence of vegetation (Warner and Campagna 2009). The AVHRR NDVI record is calculated based on its red band (band 1 covered the 0.58 to 0.68 μm radiation) and infrared band (band 2 covered the 0.72 to 1.10 μm radiation).

AVHRR GIMMS (Global Inventory Modelling and Mapping Studies) NDVI dataset is available from July 1981 to December 2006 and has been used for numerous regional to global scale vegetation studies (Los et al. 1994, Hogda et al. 2001, Tucker et al. 2005, Anyamba et al. 2005, White and Nemani 2006, Fensholt et al. 2009, Milesi et al. 2010, Raynold et al. 2012). AVHRR GIMMS NDVI dataset has been corrected for residual sensor degradation and sensor intercalibration differences; distortions caused by persistent cloud cover globally; solar zenith angle and viewing angle effects due to satellite drift; volcanic aerosols; missing data in the Northern Hemisphere during winter using interpolation due to high solar zenith angles; and low signal to noise ratios due to sub-pixel cloud contamination and water vapor. The spatial resolution is 8 km and the data record is based on 15-day composites in order to construct cloud-free views of the Earth with the maximum NDVI during regularly spaced intervals.

According to its intensive 25-year monthly coverage, AVHRR GIMMS NDVI dataset has been chosen in this study. The Florida state boundary covering the domain 25~30°N, 79~87°W was subset from the dataset for the period January 1982-December 2006. Since the AVHHR GIMMS NDVI dataset is constructed based on 15-dat maximum composites, so for every month, there are two 15-day composites. For this study, the statewide higher NDVI value composite is chosen from those two 15-day composites at a monthly basis to represent the NDVI value for the month.

2.2.2 NOAA CCAP Land Cover Classification Data

Florida land cover classification data are available from the Coastal Change Analysis Program (C-CAP) developed by the National Oceanic and Atmospheric Administration (NOAA) with collaborations of the Department of Commerce (DOC), National Ocean Service (NOS) and NOAA Coastal Services Center (CSC). Current

production of the Coastal Change Analysis Program (C-CAP) land cover datasets is accomplished through closely coordinated efforts with the U.S. Geological Survey (USGS) as it produces the National Land Cover Dataset (NLCD).

C-CAP data are developed, primarily, from Landsat Thematic Mapper (TM) satellite imagery. The smallest feature size (spatial resolution) that can be mapped is 30 meter pixels (1/4 acres) on the ground. Current C-CAP datasets are available for Florida in the years 1996, 2001, and 2006 by 23 classes. In order to simplify for the following analysis, 23 classes were regrouped into 10 classes based on their classification scheme (Table 2-1).

2.2.3 Mean-Variance Analysis

In order to characterize the spatio-temporal behavior of NDVI, the NDVI values derived from AVHRR GIMMS NDVI dataset are analyzed using a mean-variance approach. A mean-variance analysis is developed in late 1980s by Pickup and Foran (1987) to characterize the spatiotemporal behavior of a remotely sensed vegetation index (VI) and researchers utilize it to describe the seasonal and inter-annual response of vegetation to climate and disturbance at several regions across the globe (Wachington-Allen et al. 2003 and 2008, Zimmermann et al. 2007).

The mean can be interpreted as vegetation presence or the overall amount of vegetation within the landscape and the variance is representative of the degree of landscape heterogeneity. Figure 2-1 shows the hypothetical relationship between mean-variance and vegetation status (Washington-Allen et al. 2008). Each quadrant demonstrates a relative measurement of heterogeneity (variance) and vegetation status (mean). Quadrant 1 (low mean and low variance) can be considered as the most degraded landscape because the amount of vegetation is relatively low and

homogeneous. Quadrant 2 (low mean and high variance) indicates that a greater proportion of the landscape tend to be bare ground and thus high susceptibility to disturbance. Quadrant 3 (high mean and low variance) shows a relatively higher vegetation cover with lower vegetation variability. Quadrant 4 (high mean and high variance) indicates the landscape has higher vegetation cover with a higher variability of vegetation cover.

The approach is employed to describe the trajectory of vegetation state across the 25 year time period in terms of the mean NDVI characterizing the overall amount of vegetation and the simultaneous variance of NDVI describing the heterogeneity by a two-dimensional plane.

Three temporal scales are examined in order to depict trend and pattern if any. First, the annual total NDVI value is cumulated by summing up all NDVI value from January to December for a specific year. Second, the seasonal NDVI value is represented by two non-overlapped seasons, winter (October, November, December, January, February, March) and summer (April, May, June, July, August, September). Winter NDVI value is calculated by summing up all NDVI value from the defined winter months and summer NDVI value is calculated by summing up all NDVI value from the defined summer months. A special note here is winter NDVI value is named based on the year of January-March, for instance, winter 1983 is calculated by summing up the NDVI value from October 1982 through March 1983. Third, a monthly NDVI value is derived from the monthly composite that chosen from AVHRR GIMMS NDVI dataset for the period January 1982 to December 2006 to represent the maximum NDVI for a particular month.

2.2.4 Spatial Persistence

The concept of persistence analysis is to detect changes based on the value of every pixel. Total two spatial persistence analyses are performed; one of them is based on a logic of NDVI is increase/decrease to the next time step and another one is based on calculating the absolute amount of NDVI value changes through time.

The persistence analysis is applied to assess NDVI change from 1982-2006 in a spatially explicit manner on a monthly basis. The spatial persistence layers characterize the direction of change and the absolute amount of change of NDVI value during successive years on a pixel basis.

The direction of change of NDVI value is determined using the following nomenclature:

$$t > t_{i+1} = -1$$

$$t_i = t_{i+1} = 0$$

$$t_i < t_{i+1} = +1$$

Where the NDVI, t, in year I,s t_i and t_(i+1) is the value in the following year, e.g. t_i=October NDVI in 1982, then t_(i+1)=October NDVI in 1983. A value +1 is assigned to pixels which have had an increase in successive values of NDVI; value -1 is assigned to pixels which have had a decrease in NDVI, and zero indicating no change.

However, theoretically, there is an infinitesimally very small chance that two successive NDVI values are truly identical as NDVI is a continuous variable. Limiting by the AVHRR GIMMS NDVI dataset structure, NDVI value are stored and scaled from -1000 to +1000, which means there are only three decimal places if it is scaled back to the original theoretical NDVI range -1 to +1. In order to handle the occasional issue a

zero change, a neighborhood evaluation of GIS technique is applied. A 5*5 window is placed on pixels that returning a value of zero value from the above nomenclature, a new value either -1 or +1 is assigned based on the majority value from the neighborhood. For example, if the majority of the neighboring pixels return values of +1, this pixel itself is assigned a new value +1 instead of the original value zero. This adjustment had to be made in order to overcome the issue of data truncation in the AVHRR GIMMS NDVI dataset.

The absolute change of NDVI is calculating by subtracting successive values. Thus if a pixel, returns an NDVI value of 0.647 in January 1982 and 0.691in January 1983 ; the persistence analysis for direction of change will assign this pixel a value of +1 and the analysis for absolute amount of change will yield a value of +0.044;. Retain the convention that positive values of both variables imply an increase in NDVI. There are 24 time steps maps for the persistence analysis procedure for each month, for a 25-year record. By summing up each of the individual maps, , one persistence layer representing the cumulative direction of change and one representing the absolute amount of change in NDVI are produced for each month.

2.2.5 Statistical Test for Persistence Analysis

No appropriate statistical test of significance exists for these two variables. However, if NDVI values in the absence of any trends or jumps induced by climate change/variability or land use change, are assumed to be normally distributed and serially independent (Independent and identically distributed, aid, random variable), then this condition can provide the “null” conditions against which observations may be compared, and from which critical values of the persistence variables may be derived via simulation. On a purely theoretical basis, the assumption of normality runs into

difficulties as NDVI is a bounded variable (-1 to +1), and because it is computed as a ratio of two negatively correlated variables, it will become increasingly negatively (positively) skewed, as the mean values of NDVI approach the upper (lower) end of the scale. However, empirical evidence drawn from pixels whose land use categories remained constant, suggests that, the assumption of normality, for LULC types found in Florida is not totally unreasonable, and may at least provide a reasonable set of null conditions. Similarly, in the absence of any climate change/variability and LULC change, the phenomena that we are trying to identify, it is also reasonable to assume serial independence from one month to the same month in the next year.

2.2.5.1 Persistence analysis of direction of change

The persistence analysis of direction of changes in NDVI from 1982 to 2006 (25 years) yields a possible range of -24 to +24. Under the null hypothesis, if one specific pixel's NDVI value in January 1989 is right at the long-term mean, the probability of a positive change in direction in 1990, is +1 If the January 1990 value is exactly one standard deviation greater than the mean, then the probability of a positive step to January 1991 has now dropped to 0.16. The persistence measures used here therefore are not analogous to a standard random walk process (see for example, Wilson and Kirkby, 1980) as the probabilities of successes/failures (positive steps/negative steps) is not fixed with every iteration or transition but is controlled by the magnitude of the preceding observation. Therefore the likelihoods of smaller (larger) directional sums – positive or negative - increases (decreases) in comparison to the random walk.

For the persistence analysis of direction of change in NDVI, 10,000 sequences of normally distributed data, each of 25 observations are simulated and analyzed using the same methodology to yield a relative frequency count of the sums of directional change

under conditions of the null hypothesis. A comparison of this simulated distribution with the cumulative persistence layer result is conducted to examine which pixel yields unusually high (positive or negative) observed frequencies. As the directional variable is by definition a discrete variable, and because of the number of transitions involved, only possible to take on even numbers or zero, traditional significance values (e.g. 0.05) cannot be used. However the simulated distributions do allow approximations to these values. In this case, values of +/-6, represent 4.3% of the area under the distribution in either tail, and will be used as critical values of the variable throughout.

2.2.5.2 Persistence analysis of absolute amount of change

As the absolute change variable requires a magnitude term in addition to the sign of the change, the establishment of the null conditions becomes more difficult. However regardless of the observed values of mean and variance of NDVI (for instance, Developed Land, compared to Forest) each distribution could itself be reduced to a standard normal distribution. Simulations and computations can then be carried out and appropriate critical values determined based upon the mean and variance of the original data set. It is well known that the sum (Z) of variables drawn from two Normal distributions (X and Y) is itself normally distributed with mean (Z) = mean (X) + mean (Y), and variance (Z) = variance (X) + variance (Y). In this study, there are 25 independent observations from 1982 to 2006, the sum, Z, can be extending to $Z=X1+X2+X3+\ldots+Xn-1+Xn$, for n=25 with mean (n. mean(X)) and variance (n. variance(X)). Then confidence bounds could be set up based on the standard normal distribution at any interested level such as 10% to identify extreme values in the distribution. However, as in the case of the directional variable, the definition of this variable does not match the established theory. It is the differences in NDVI from the

previous value that are being summed not the values e.g NDVI themselves. Extension of the previous 10,000 simulated series allows the computation of the distribution of values of this variable under the null conditions. It was found that the sums themselves approximated to a normal distribution, with a mean of zero and a standard deviation of 1.41 (based on the standard normal distribution employed in the simulation). These properties can them be applied to the observed sum of magnitudes derived from a set of data with a specific mean and variance by multiplying the observed variance by 1.41. Under null conditions the most likely sum of changes was zero

This approach presents the problem of identifying the expected variance, which was not important in computations for the directional change variable. This could only be done by observing typical values of variance in pixels that appeared to meet the conditions of the hull hypothesis. Guided initially by the results from the analysis of directional changes, pixels were also selected that met the following criteria:

- It should stay the same land cover type (1982-2006); and
- The land cover type should dominant at least 50% within this NDVI pixel's spatial resolution 8 km square.

Examples, if they existed, were also to be drawn separately from each of the 6 NOAA climate divisions of the state in order to avoid establishing unrealistic null conditions resulting from spatial variations in annual and monthly rainfall totals across the region. Accompany with NOAA CCAP land cover classification data at three dates 1996, 2001, and 2006 (spatial resolution 30 meter square), selecting criteria for a particular pixel including:

- It should stay the same land cover type; and
- It can be found across the state from climate division 1 to climate division 6; and

- The land cover type should dominant at least 50% within this NDVI pixel's spatial resolution 8 km square.

The series of NDVI values for these land cover/ month/climate division type are derived from the AVHRR GIMMS NDVI dataset from 1982 to 2006 and utilized for comparative purpose and to provide the basic variance measures to be used in establishing significance levels. Examples from three land cover types; developed land, agricultural land, and palustrine wetlands were found in each of six climate divisions.

2.3 Results

2.3.1 Mean-Variance Analysis

For the annual temporal scale that have been examined (Figure 2-2), the NDVI values from January to December are summed to produce only one single mean and variance of NDVI for a specific year. A grand mean and a grand variance are marked in the plot as a vertical straight line and a horizontal straight line. For a convenient visualization purpose, 1980s (1982-1989) are marked as purple colored circles, 1990s (1990-1999) are marked as green colored squares, and 2000s (2000-2006) are marked as yellow colored triangle. As a result, an increasing trend in mean NDVI (represent vegetation presence) tends to been seen after 1995 in quadrant 3 (higher mean, lower variance) and quadrant 4 (higher mean, higher variance) except 1999.

For the seasonal temporal scale that have been examined (Figure 2-3 and Figure 2-4), the NDVI values from October to March are summed to produce a winter total NDVI and the NDVI values from April to September are summed to produce a summer total NDVI. The same plotting scheme is applied to these seasonal temporal results. As a result, winter NDVI are showing a very clear clustered pattern after 1995 in quadrant 4

(higher mean, higher variance) except 1999. However, summer NDVI do not have a clear pattern and the values are more spread out in the plot.

For the monthly temporal scale that have been examined (Figure 2-5), NDVI values are plotted following the same plotting scheme. The months from October to March are showing an increasing trend in mean NDVI after 1995. In general, the grand mean NDVI values (vertical straight line) are higher during the summer months (April to September) and lower during the winter months (October to March).

2.3.2 Spatial Persistence with Statistical Test

2.3.2.1 Persistence analysis of direction of change

Total twelve persistence layers are produced to represent the summation of direction of change from January to December 1982-2006. Only January and August are shown in Figure 2-6 (a) as examples. Green gradient colors represent positive summation values (+1 to +24) and red gradient colors indicate negative summation values (-1 to -24). Gray colors present zero summation values. Numbers in each possible classes (-24 to +24) are extracted for each month and served as observed value and then compare to the simulated normally distributed data mentioned before (Figure 2-7).

The comparison results are plotted in Figure 2-8. For each plot, the black dashed line represents the cumulated frequencies for the simulated normally distributed data (null hypothesis), and the black dots with connecting red line represents the cumulated frequencies for the observed data from the direction of change persistence results for each month. If the null hypothesis (black dashed line) describes the actual process then the black dots with connecting red line should fall right along the clack dashed line. As

a result, the null hypothesis could not be rejected in March and May and it looks dubious in November.

In addition, the plots are also representing a degree of upward/downward trend form the data. If the red line plots up above the black dashed line (like April), there are probably more negative classes than one would expect (downward trend in NDVI). If the red line plots below the black dashed line (like November) then there are more positive classes than expected (upward trend in NDVI). This upward trend in NDVI can also been seen in the months September, October, November, January and February.

Figure 2-9 are examples of areas that are identified above or below the cumulative direction of critical change classes +6 and -6 in January and August respectively. The areas that have been marked should be interpreted as areas that experience a significant increasing (green gradient) or a decreasing trend (red gradient) in NDVI from 1982-2006. A further investigation of why these areas experience either increased or decreased trends of NDVI is needed. In general, these may be areas in which climate has changed over the study period or more specifically really, pixels' land cover classification trajectory may have been altered dramatically by human activity.

2.3.2.2 Persistence analysis of absolute amount of change

Total twelve persistence layers are produced to represent the summation of absolute amount of change from January to December 1982-2006. Only January and August are shown in Figure 2-6 (b) as examples. Green gradient colors represent positive summation values (above zero) and red gradient colors indicate negative summation values (below zero).

A confidence bound has been set up at 10% (5% at either tail) by climate division and by month in order to identify areas that may experience an increased or decreased

trend in terms of the absolute amount of change in NDVI value for three land cover type (developed land, agricultural land, and palustrine wetlands). Figure 2-10 represents the confidence bounds for developed land. Places that below 5% is represented in red color while upper 95% is represented in green color. For each month, three dates NOAA CCAP land cover classification data are examined by these three land cover type.

Additionally, a series maps are produced in order to show the distribution of percentage of either tails (lower 5 and upper 95) by climate divisions (Figure 2-11, Figure 2-12 and Figure 2-13) for three land cover classification dates. The benchmarks which is the null hypothesis of totally random (stationary) changes is true, then 5% of the pixels in each division are expected to fall into these two categories (lower 5 and upper 95) purely by chance. On the maps, the colored circles represent the actual percentage of pixels in that division/month that fell into each category. Green color is assigned to the lower 5 category while red color indicates the upper 95 category. Each vertical arrangement of circles represents the time of land cover classification data are utilized (1996, 2001 and 2006). The proportional circles have a radius equal to the square root of the observed percentage and powered down proportionate to the radius used to represent 5%. In this way, the size of the circles is actually displaying the percentage.

Since developed land does not have difference between three land cover classification dates in terms of the percentages in either tails, only one date data are present here (Figure 2-11). Agricultural land and palustrine wetlands are both presented for all three dates (Figure 2-12 and Figure 2-13).

Generally speaking, despite of different land cover types, all the winter months (October to March) especially October and November are showing larger green circles than in the summer months (April to September). This result imply a greener trend occurs during winter months and it matches with the mean-variance analysis results which also reveal that the mean NDVI is increasing during winter months after 1995.

2.4 Discussion and Summary

The results from mean-variance analysis and persistence analysis (both direction of change and absolute amount of change) have shown a consistent pattern from 1982-2006 in vegetation trend of Florida. The consistent pattern of vegetation trend is illustrated by overall higher NDVI values are observed during the winter months, October to March. The results are coincident with Waylen and Qiu (2008) unpublished work. Waylen and Qiu conduct their work on winter rains to annual precipitation totals in Florida based on selected stream flow data from 1979-2000. The conclusion from their work indicates that winter rainfall proportion to annual precipitation totals in Florida is increasing during the studied period.

A possible physical explanation of this found pattern can be drawn based on the Atlantic multidecadal oscillation (AMO). The AMO is an ongoing series of long-duration changes in the sea surface temperature of the North Atlantic Ocean, with cool and warm phases that may last for 20-40 years at a time and a difference of about 1°F between extremes. These changes are natural and have been occurring for at least the last 1,000 years (NOAA, 2011). According to Enfield et al. (2001), During AMO warming's most of the United States sees less than normal rainfall, including Midwest droughts in the 1930s and 1950s. Between AMO warm and cool phases, the inflow to Lake Okeechobe varied by 40%. They concluded that the geographical pattern of

variability is influenced mainly by changes in summer rainfall. The winter patterns of interannual rainfall variability associated with ENSO are also significantly changed between AMO phases.

According to the monitoring data from National Oceanic and Atmospheric Administration (NOAA), there are many impacts of the AMO to air temperatures and rainfall in Florida. First of all, rainfall in central and south Florida becomes more plentiful when the Atlantic is in its warm phase and droughts and wildfires are more frequent in the cool phase. As a result of these variations, the inflow to Lake Okeechobee changes by 40% between AMO extremes. In northern Florida the relationship begins to reverse - less rainfall when the Atlantic is warm. Secondly, during warm phases of the AMO, the numbers of tropical storms that mature into severe hurricanes is much greater than during cool phases, at least twice as many. Since the AMO switched to its warm phase around 1995, severe hurricanes have become much more frequent and this has led to a crisis in the insurance industry.

Compare this to the results from mean-variance and persistence analysis of NDVI, it is reasonable to assume that the increasing vegetation trend during winter months is driven by the increased rainfall while AMO is switched to warm phase after 1995. However, rainfall variability may not be the only driver of vegetation trend. Florida is experiencing a massive land cover change and anthropogenic influences because its population is increasing by 600 percent since 1940 (Schmidt et al. 2001). With the growth in population and increased societal demands during the twentieth century, the natural landscape of the Florida peninsula was transformed extensively by agriculture, urbanization, and the diversion of surface water features (Marshall et al. 2004).

Therefore, human-induced land cover change is another important factor while examining vegetation trend over time and space.

Coupling the climate variability and anthropogenic influences, Florida's vegetation dynamic is more complex and rich for scientific research. A further investigation of climate variability with land cover change analysis is needed in order to gain more deep understanding of the drivers of vegetation dynamics in Florida.

Table 2-1. CCAP Land Cover Classification

Original Value	Class	Regroup Value	Class
0	Background		
1	Unclassified		
2	Developed, High Intensity	1	Developed Land
3	Developed, Medium Intensity		
4	Developed, Low Intensity		
5	Developed, Open Space		
6	Cultivated Crops	2	Agricultural Land
7	Pasture/Hay		
8	Grassland/Herbaceous	3	Grassland
9	Deciduous Forest	4	Forest Land
10	Evergreen Forest		
11	Mixed Forest		
12	Scrub/Shrub	5	Scrub Land
13	Palustrine Forested Wetland	7	Palustrine Wetlands
14	Palustrine Scrub/Shrub Wetland		
15	Palustrine Emergent Wetland		
16	Estuarine Forested Wetland	8	Estuarine Wetlands
17	Estaurine Scrub/Shrub Wetland		
18	Estaurine Emergent Wetland		
19	Unconsolidated Shore	9	Barren Land
20	Bare Land	6	Barren Land
21	Open Water	10	Water and Submerged Lands
22	Palustrine Aquatic Bed		
23	Estuarine Aquatic Bed		

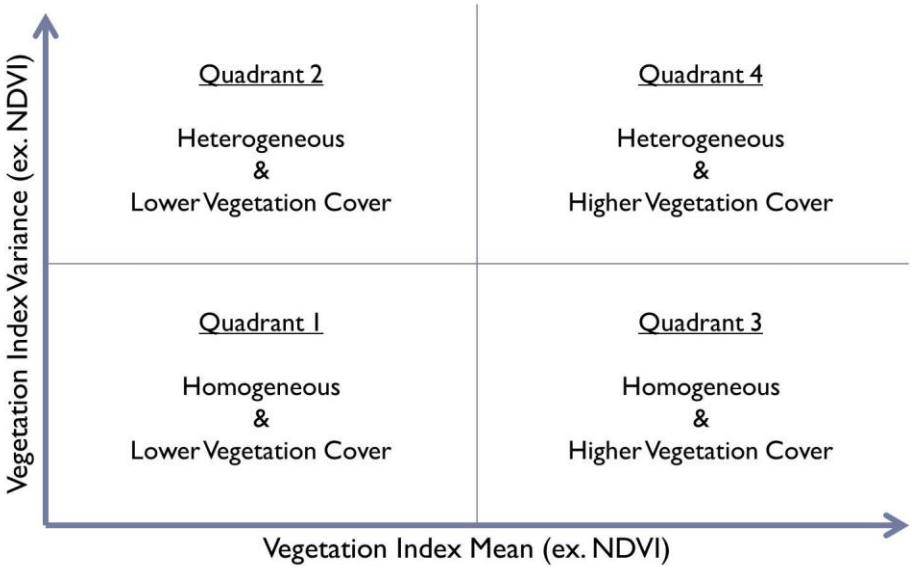


Figure 2-1. Hypothetical relationship between mean-variance and vegetation status, [Adapted from Washington-Allen, R. A. Ramsey, R., West, N. E. and B. E. Norton, B.E. (2008) Quantification of the ecological resilience of drylands using digital remote sensing. Ecology and Society 13, pp. 33.]

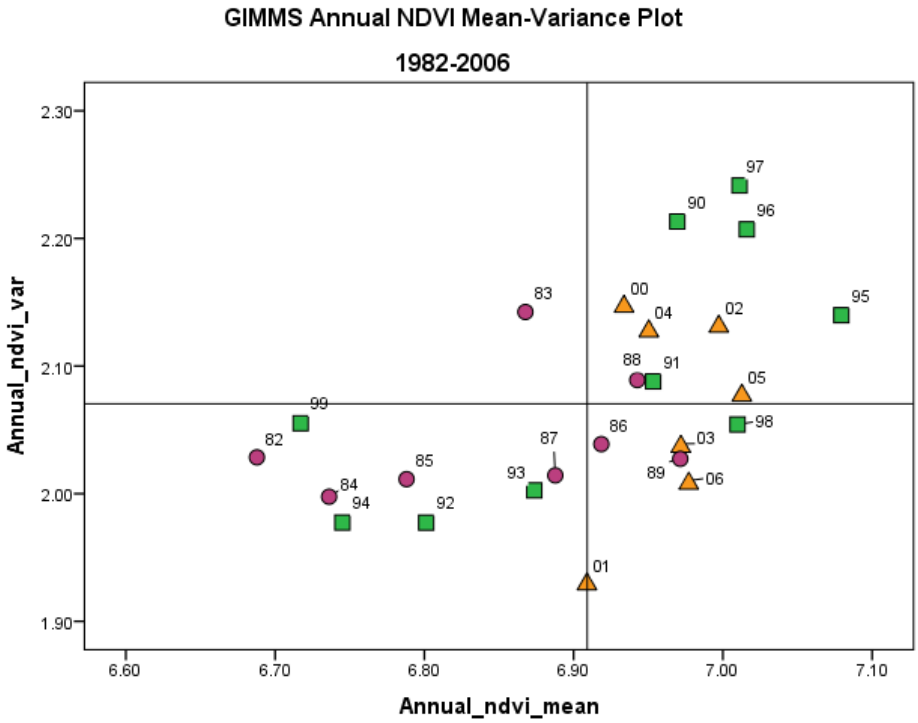


Figure 2-2. Mean-Variance plot for annual NDVI

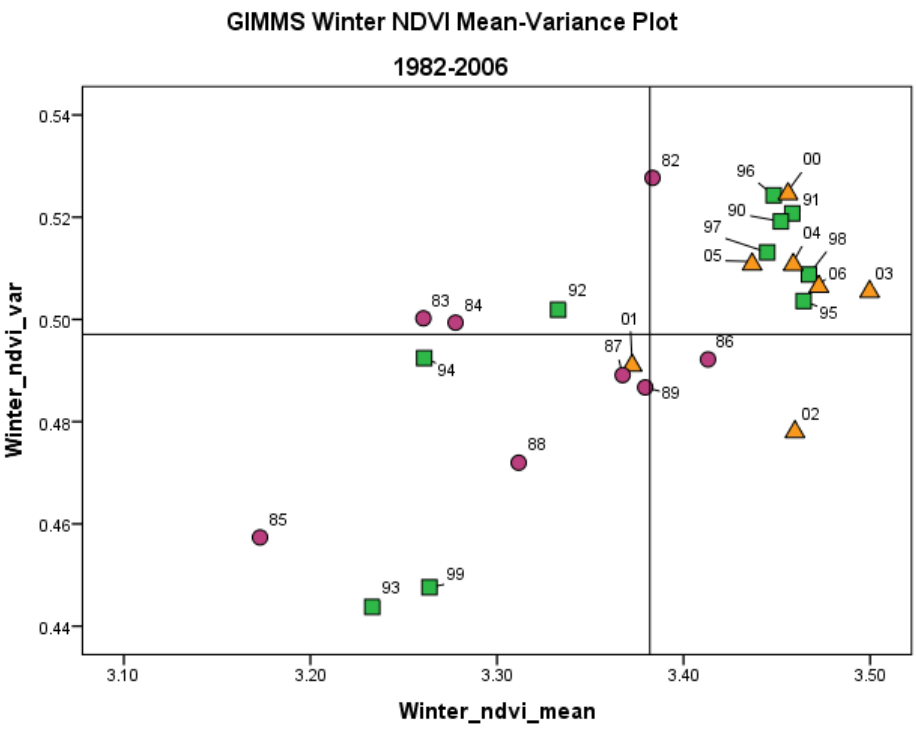


Figure 2-3. Mean-Variance plot for winter NDVI

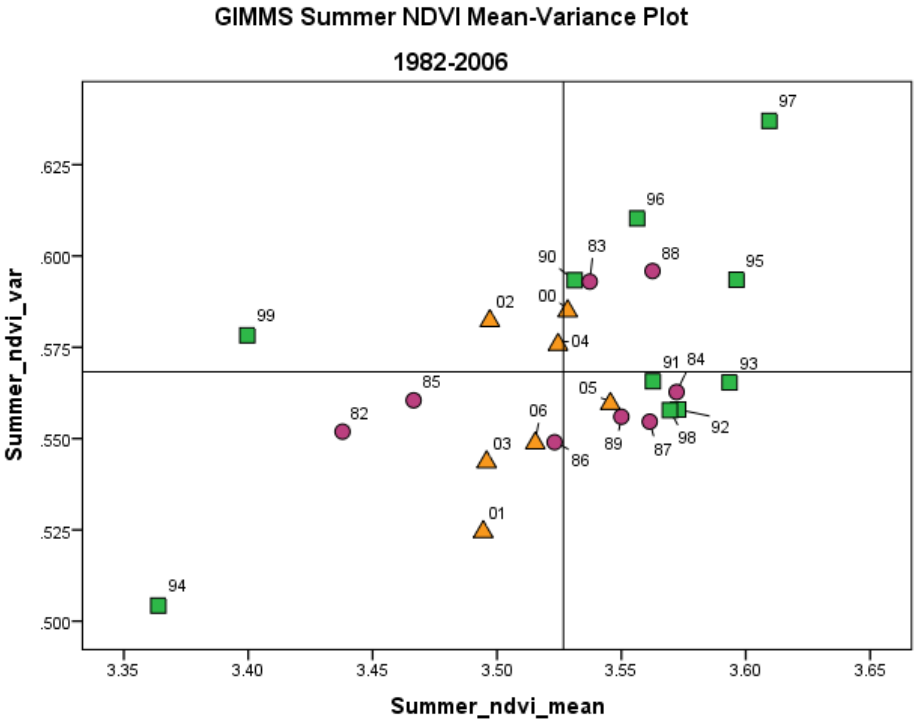


Figure 2-4. Mean-Variance plot for summer NDVI

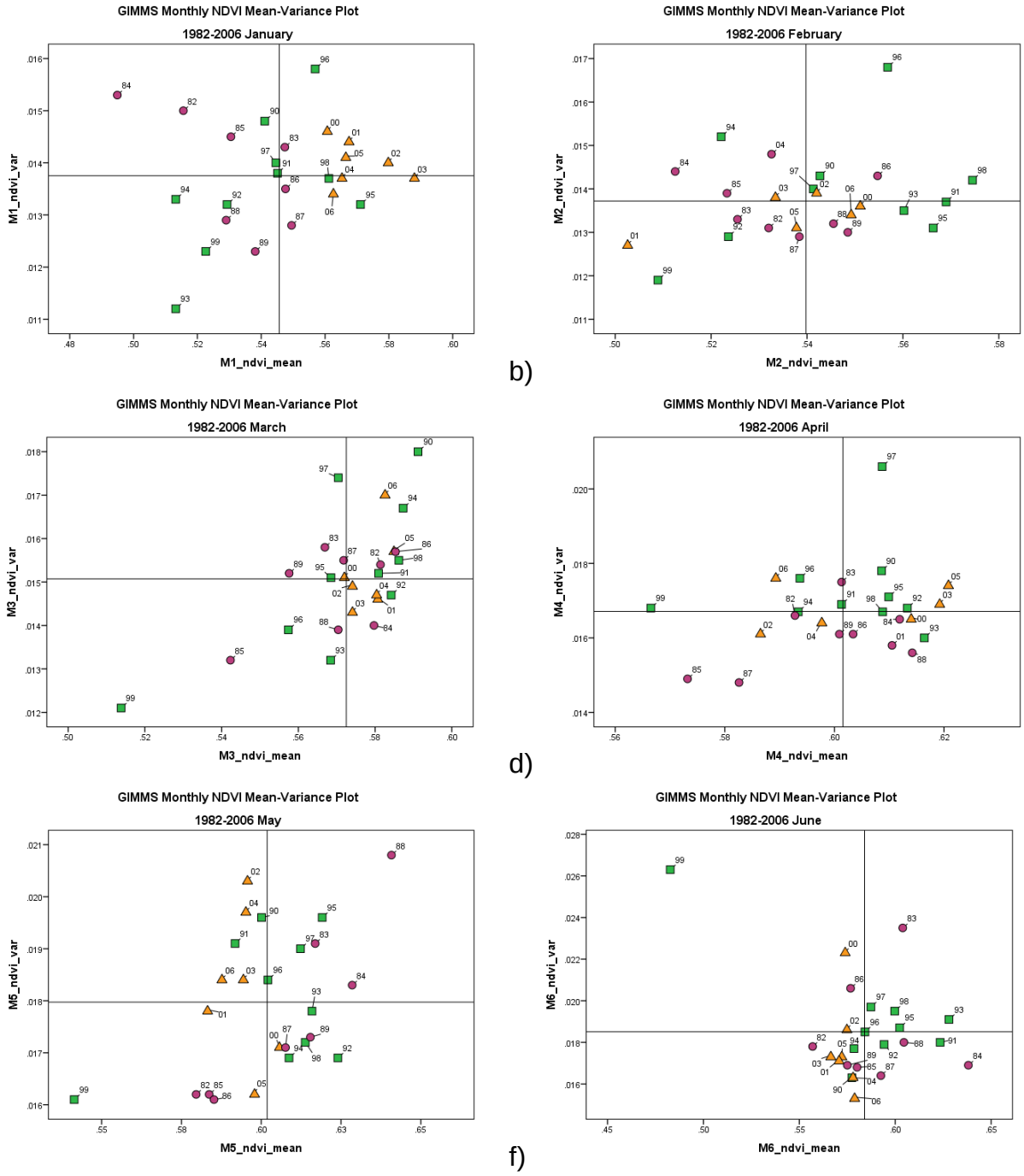
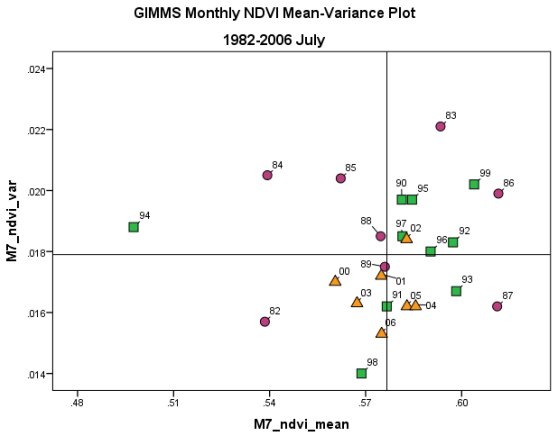
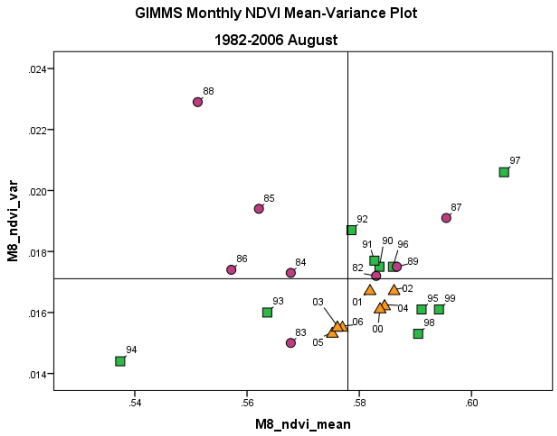


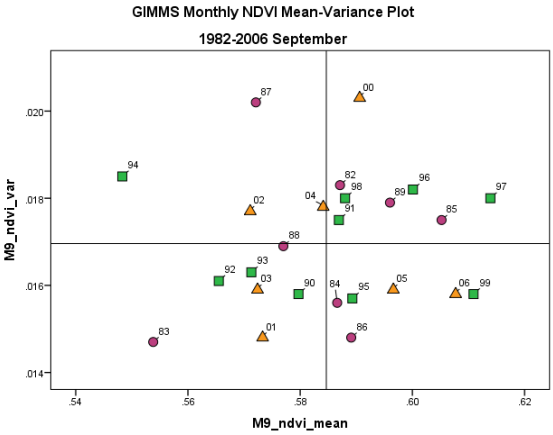
Figure 2-5. Mean-Variance plot for monthly NDVI a) to l) represents January to December



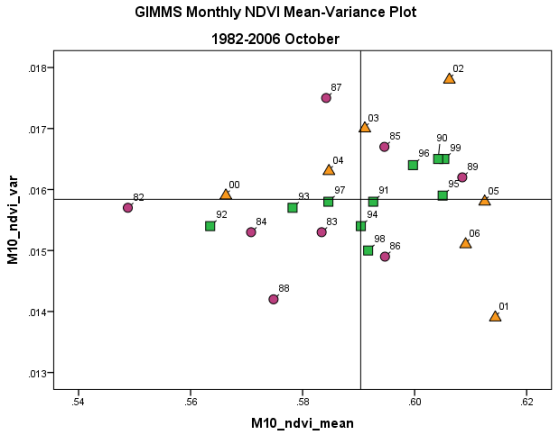
g)



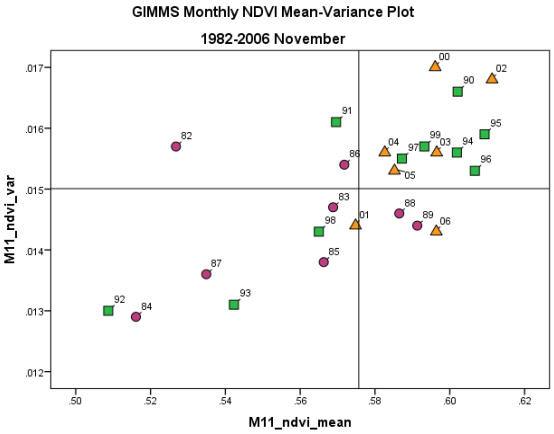
h)



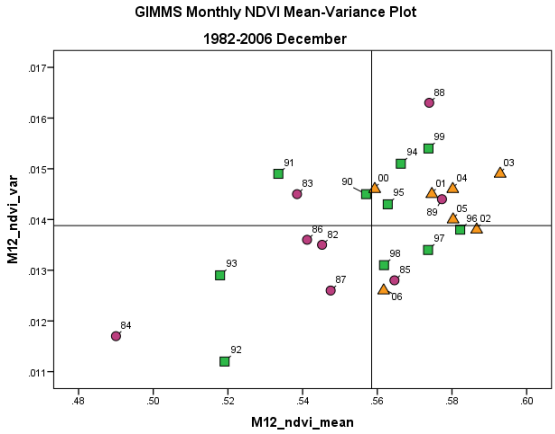
i)



j)



k)



l)

Figure 2-5. Continued.

a) b)

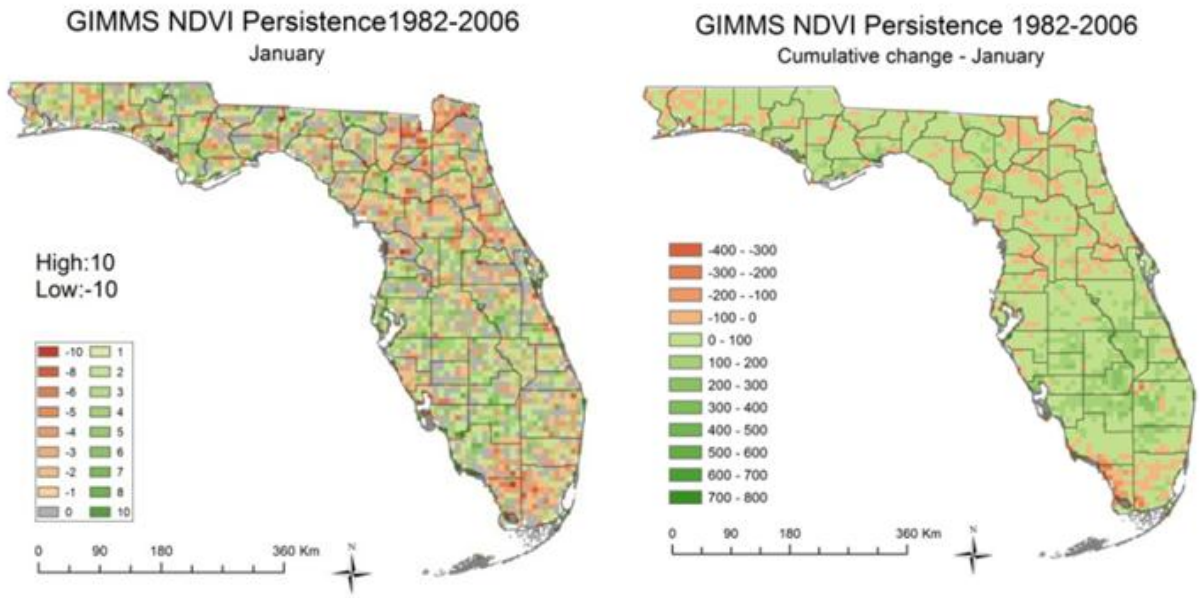


Figure 2-6. Example maps for persistence analysis of a) direction of change of NDVI.in January from 1982 to 2006 and b) absolute amount of change of NDVI in January from 1982 to 2006

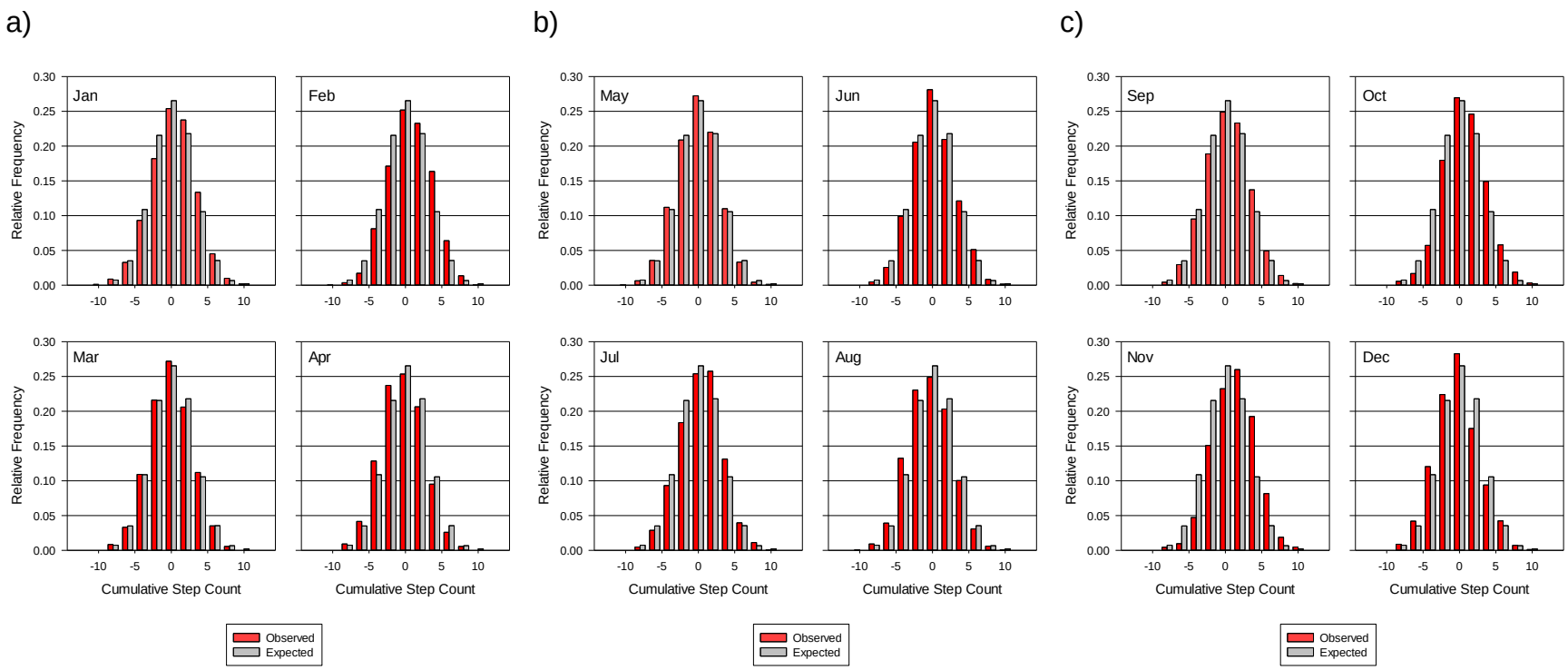


Figure 2-7. Comparison of observed value from persistence analysis direction of change with simulated normal distribution result a) January to April b) May to August and c) September to December

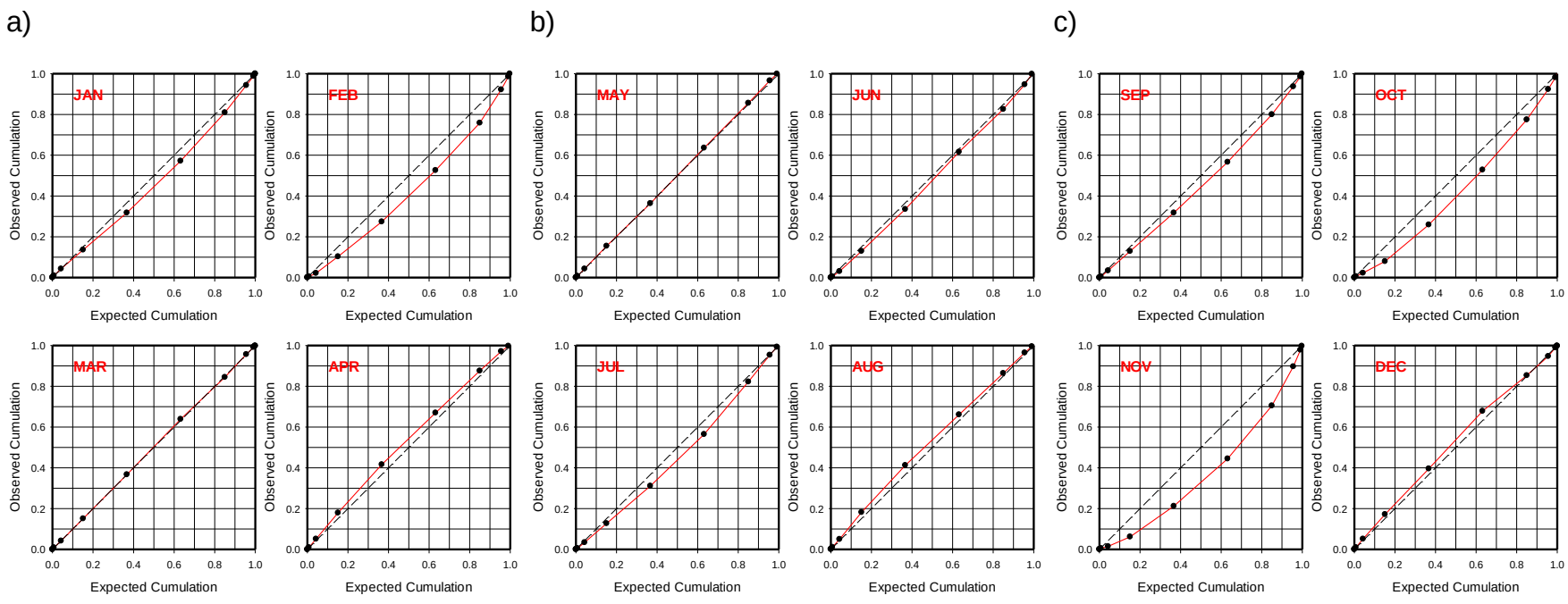


Figure 2-8. Cumulative frequency plots for comparison of observed value from persistence analysis direction of change with simulated normal distribution a) January to April b) May to August and c) September to December

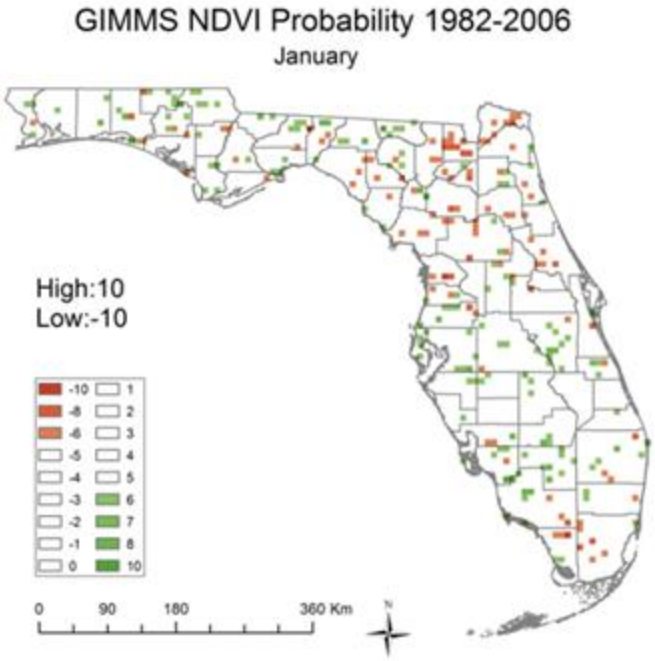


Figure 2-9. Example of areas that identified by above or below critic classes

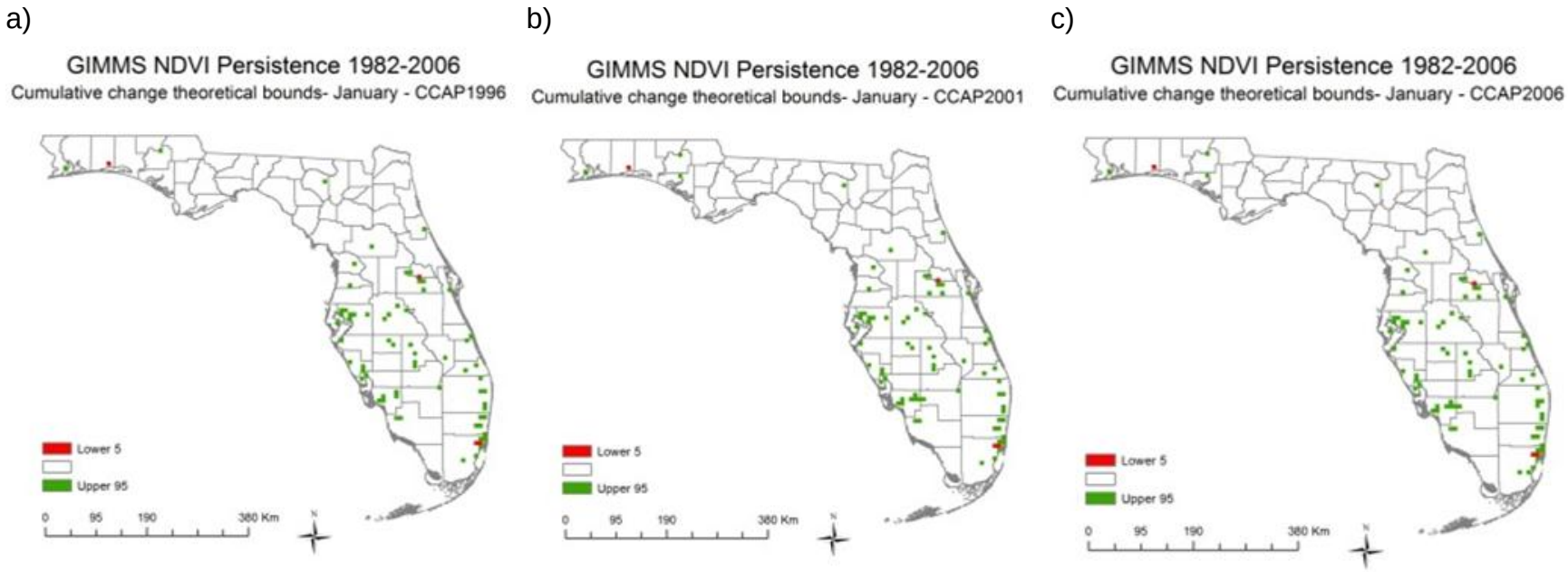


Figure 2-10. Example for developed land confidence bounds maps in January. a) 1996 land cover classification b) 2001 land cover classification and c) 2006 land cover classification

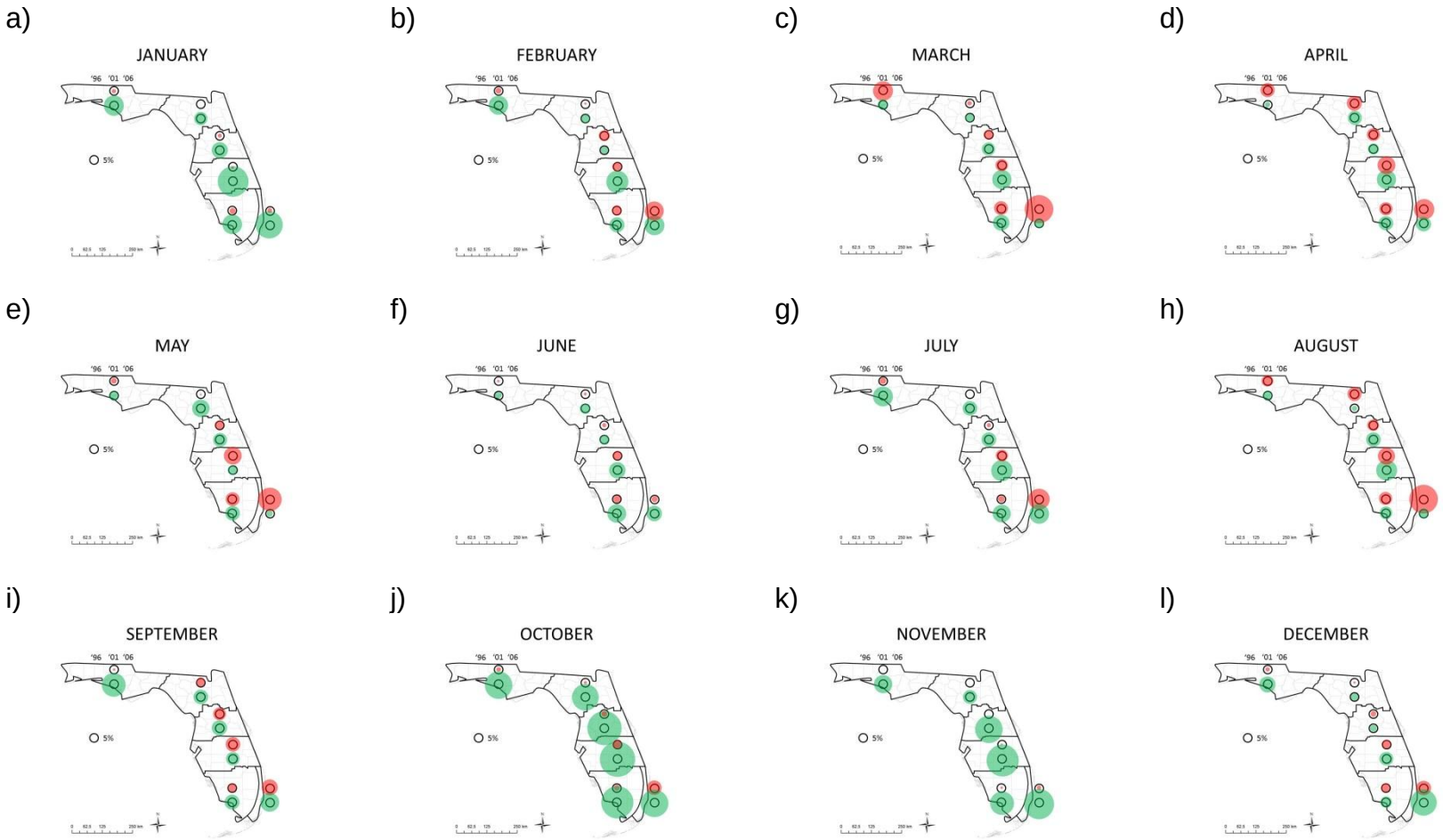


Figure 2-11. Developed land confidence category percentage maps a) to l) represents January to December

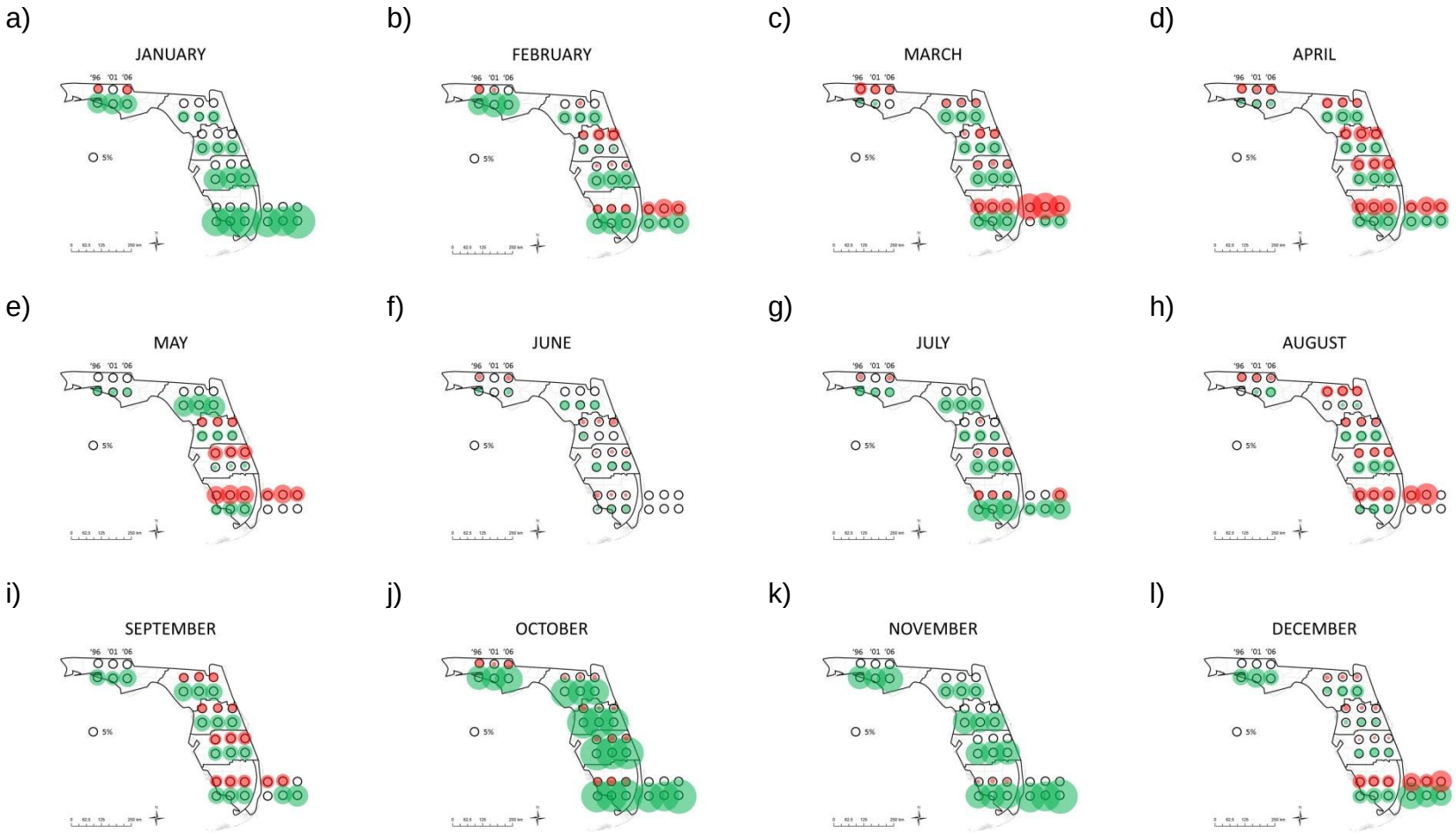


Figure 2-12. Agricultural land confidence category percentage maps a) to l) represents January to December

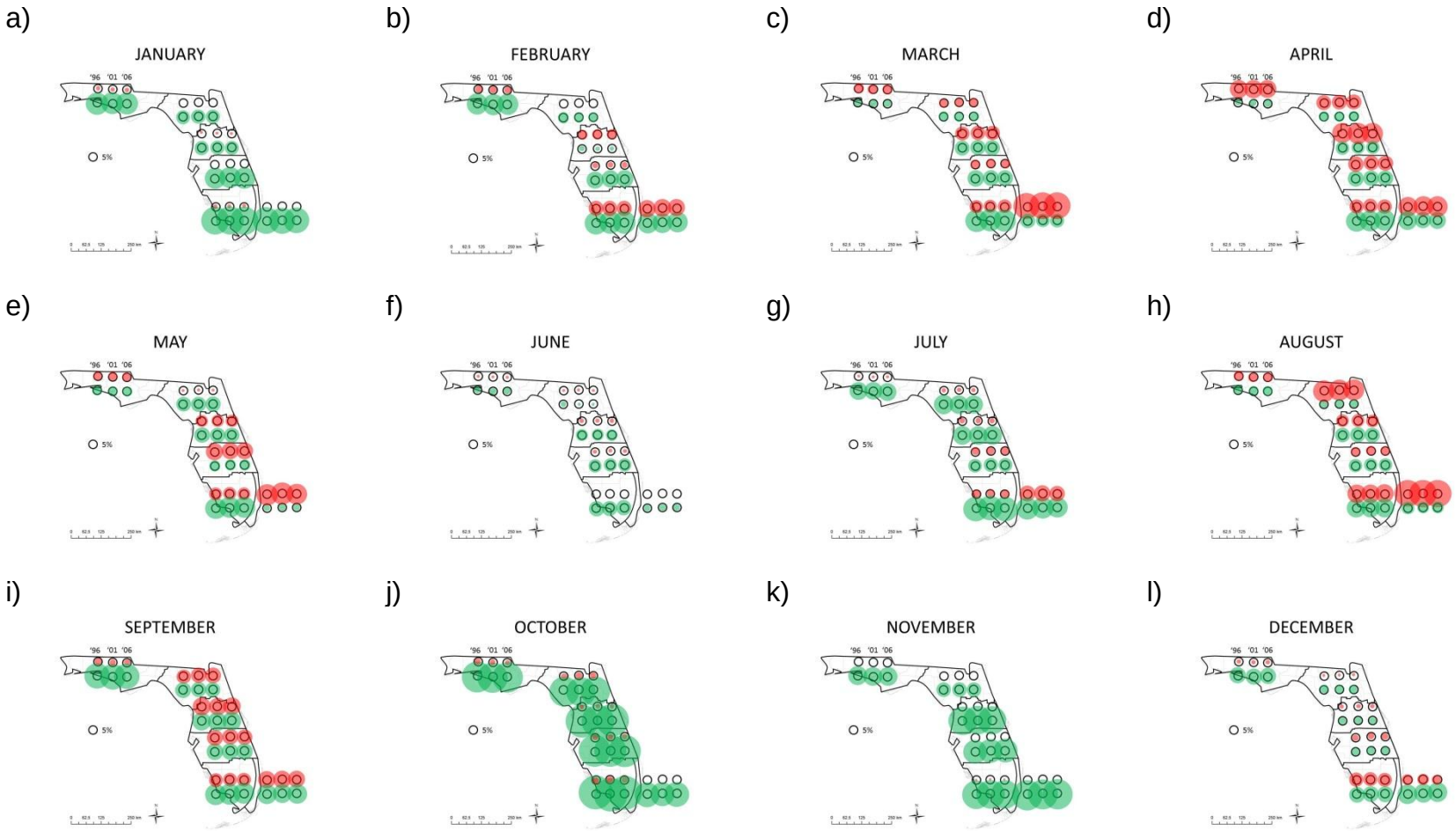


Figure 2-13. Palustrine wetlands confidence category percentage maps a) to l) represents January to December

CHAPTER 3
NDVI, CLIMATE VARIABILITY AND LAND COVER IN FLORIDA

3.1 Background

As a regional scaled investigation, the southeast US has drawn more attention from researchers across diverse disciplines. Sohl and Sayler (2008) pointed out the southeast US has experienced massive land-use change since European settlement and continues to experience extremely high rates of forest cutting, significant urban development, and changes in agricultural land use. The subtropical and tropical climate makes Florida an ideal place for agriculture, tourism, water recreation, industry, etc. On the other hand, Florida appears to be a particular vulnerable environment subject to major changes due to climate variability and anthropogenic influences. Much evidence has been presented regarding climate variability and anthropogenic influences impacting Florida's ecosystems at different rates and scales (Duever et al. 1994, Schmidt et al. 2001, Enfield et al. 2001, Cronin 2002), however, a broad picture of the dynamics in Florida's vegetation coupled with climate variability still remains unclear.

The potential impacts of climate variability such as the El Nino-Southern Oscillation (ENSO) phenomena in Florida have been evaluated by many researchers. From an agricultural aspect, Hansen et al. (1998) found that during the winter season (months) in Florida, quarterly yields, prices, production, and value for crops such as tomato, bell pepper, sweet corn, and snap bean are related to ENSO phase and its relationship to rainfall, temperature, and solar radiation. From a more hydrological aspect, Schmidt et al. (2001) analyzed the influence of ENSO on Florida's seasonal rainfall and river discharge from 1950-98 and report that Florida does not respond as a

uniform region to ENSO, particularly with respect to precipitation in the Panhandle and the southernmost areas of Florida.

Additionally, anthropogenic influences in Florida have been amplified since 1940 due to a 600 percent increase in population (Schmidt et al. 2001). From 2000 to 2010, these was a 17.6 percent increase in Florida's population (US Census Bureau, 2011), which is almost twofold to the nation's population increase rate of 9.7 percent. With the growth in population and increased societal demands during the twentieth century, the natural landscape of the Florida peninsula was transformed extensively by agriculture, urbanization, and the diversion of surface water features (Marshall et al. 2004). According to the National Resources Inventory (NRI) from the USDA Natural Resources Conservation Service (2001), the largest increases in US developed areas between 1982 and 1997 were in the south and Florida was one of the top three states with the largest average annual additions of developed area (Alig et al. 2004).

Furthermore, anthropogenic activities have not only transformed the landscape of the Florida peninsula, but also altered the regional climate (Marshall et al. 2004, Pielke and Niyogi 2010) and potentially the sustainability of Florida's ecosystems (Harwell et al. 1996, Solecki 2001). They concluded that there was a 9% decrease in rainfall averaged over south Florida with the 1973 landscape and an 11% decrease with the 1993 landscape, as compared with the model results when the 1900 landscape is used. Marshall et al. (2004) present a numerical model to study the possible impacts of land cover change on the warm season climate. Their results are in reasonable agreement with an analysis of observational data that indicates decreasing regional precipitation and increasing daytime maximum temperatures during the twentieth century.

Although the relationship between NDVI variability and climate variability has been examined at varied spatial and temporal scales globally (Nicholson et al. 1990, Farrar et al. 1994, Richard and Poccard 1998, Lotsch et al. 2003, Fensholt et al. 2004) and the relationship between precipitation and NDVI has been well established. For Florida, there still missing a statewide analyze of NDVI with climate variability. Thus, coupling the climate variability and anthropogenic influences, we ask, what are the changes in Florida's vegetation cover and thus ecosystems? How do they respond to climate variability? And what are the dominant human-induced land cover conversions Impacting the state?

In order to get more insight of the vegetation response to climate variability and land cover and land use, this study utilizes NDVI derived from Global Inventory Modeling and Mapping Studies (GIMMS) group as vegetation presence indicator and applies a time-series approach by performing the wavelet analysis in order to study the how NDVI respond to precipitation across different locations and different land cover type.

3.2 Study Area

The state of Florida (25~30°N, 79~87°W) is located in the southeastern USA (Figure 3-1) with a geographical area of approximately 1,398,600 square kilometers and population densities of around 135 persons per square kilometer in 2010 (U.S. Census Bureau 2011).

Climate to Floridians is undisputed as being very important from its well-known official nickname "The Sunshine State" (Henry et al. 1994). In general, there are couple chief factors that govern Florida's climate, which include latitude, land and water distribution, prevailing winds, storms, pressure systems and ocean currents. Most of the

State lies within the extreme southern portion of the Northern Hemisphere's humid subtropical climate zone, noted for its long hot and humid summers and mild and wet winters. The southernmost portion of the State is generally designed as belonging to the tropical savanna region, which is sometimes called the wet and dry tropics (NCDC 2011).

The annual average precipitation is approximately 1371.6 mm with high peak during the summer time (Figure 3-2, NCDC 2011). The panhandle and southeastern Florida are the wettest parts of the state (Figure 3-3, Fernald and Patton 1984). The driest portions are the Florida Keys and the offshore bar of Cape Canaveral. The principle precipitation generating mechanisms operating in Florida are varied across space and time. The panhandle receives rainfall during winter when the fronts pass through and during summer when convective rain falls. Frontal influence is reducing southward for the state (Jordan 1984, Henry 1994). Additionally, the position and intensity of Azores-Bermuda High Pressure system also exerts a powerful influence on peninsular Florida's weather during the winter. During summer, the primary rainfall is associated with convective activity for the whole state. Florida's summer rainy season normally begins in the southeastern part in late April and the moves northward. The fall dry season begins in North Florida in September, and spreads southward, arriving in extreme South Florida in mid-November. Moreover, tropical storms play an important role in the summer rainfall and it can also postpone the arrival of the dry season. On average, the hurricane season reaches its peak in September, and the length of coastline of Florida makes it more prone to hurricane impacts and landfalls than other states.

According to the National Climate Data Center, Florida is divided into seven climate divisions: Northwest, North, North Central, South Central, Everglades and Southwest Coast, Lover East Coast, and Keys (Figure 3-4). The present study will exclude the Keys because its relatively small land mass. Spatial variations are expected to be seen in each climate division. The influence of frontal is stronger up north and weaker when it moves southward. As a result, climate division 1 and 2 are influence by frontal activities the most and division 5 and 6 may not get a pronounced effect from frontal activities.

Depending on the location, the influences of the low-frequency climate phenomena, such as the ENSO and the Atlantic Multidecadal Oscillation (AMO), Quasi-Biennial Oscillation (QBO), North Atlantic Oscillation (NAO), Pacific North America pattern (PNA), Pacific Decadal Oscillation (PDO), Madden-Julian Oscillation (MJO) have been identified with aggregate annual or seasonal rainfall variations in Florida (Enfield et al. 2001, Kwon et al. 2009). Among those large-scale atmospheric circulations, the relationship between Florida's climate and ENSO has been studied extensively (Hansen et al. 1998, Schmidt et al. 2002, Gubler et al. 2001, Cronin et al. 2002). ENSO is a physical phenomenon that occurs in the equatorial Pacific Ocean where the water temperature oscillates between being unusually warm (El Nino) and unusually cold (La Nina). These two oceanic events shift the position of the jet streams across the North America continent, which act to steer the fronts and weather systems. During El Nino, it typically brings 30 to 40 percent more rainfall and cooler temperatures to Florida in the winter, while La Nina brings a warmer and much drier than normal winter and spring. According to that, La Nina is frequently a trigger to periodic drought in

Florida (NCDC 2011). Table 3-1 is the summary of El Nino and La Nina impacts for the southeast part of the US.

3.3 Methods

3.3.1 Remote Sensing Data

NDVI is calculated from the visible red waveband (RED) and near-infrared (NIR) waveband reflected by vegetation as equation below (Eidenshink 1992).

NDVI = (NIR-RED)/(NIR+RED)

This relatively simple algorithm produces output values in the range of -1.0 to 1.0. Increasing positive NDVI values indicate increasing amounts of healthy green vegetation. NDVI values near zero and decreasing negative values indicate non-vegetated features such as barren surfaces (rock and soil) and water, snow, ice, and clouds (USGS 2010).

The Global Inventory Monitoring and Modeling System (GIMMS) group Normalized Difference Vegetation Index (NDVI) dataset was used in this study. The GIMMS dataset is a NDVI product available for a 25 year period spanning from 1981 to 2006 with its spatial resolution 8 km. The dataset is derived from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the NOAA satellite series 7, 9, 11, 14, 16 and 17. The GIMMS data set has been corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation change. The GIMMS data set is composited at a 15-day time step. For each month, the first composite is the maximum value composite from the first 15 days of the month and the second is from days 16 through the end of the month. For each month, the highest NDVI value composite is chosen as the NDVI for the month because it represents the maximum NDVI value for the month.

The time-series of NDVI value are extracted for Florida from July 1981 to December 2006 and processed in ERDAS 2011 and ESRI ArcGIS 10 software.

3.3.2 Precipitation Data

Precipitation data were gathered from the PRISM Climate Group, Oregon State University. PRISM stands for parameter-elevation regression on independent slopes model, which is a climate mapping system developed by Dr. Christopher Daly, PRISM climate group director. The PRISM model allows for the incorporation of expert knowledge about the climate and can be particularly useful when data points are sparse. With this method, one can explicitly account for the effects of coastal influences, terrain barriers, temperature inversions, and other factors on spatial climatic patterns (Daly et al. 2002). PRISM data sets are recognized world-wide as some of the highest-quality spatial data sets currently available (Hijmans et al. 2005, Hamann and Wang 2005, Wang et al. 2006, Daly 2006, Loarie et al. 2009) and is the USDA's official climatological data. All monthly precipitation data were downloaded from the PRISM website for the study area from 1981 to 2006 for the state of Florida (Figure 3-7).

3.3.3 Climatic Divisions

The climate divisions represent regions within states that are considered to be climatically homogeneous (Karl and Riebsame 1984). Although extreme climate variations can occur in areas of complex terrain, such as mountainous areas (Karl and Riebsame 1984), in the case of Florida's flat terrain, it should not be a major concern.

According to the National Climate Data Center, Florida is divided into seven climate divisions: Northwest, North, North Central, South Central, Everglades and Southwest Coast, Lower East Coast, and Keys (Figure 3-4). For audience's convenience, Northwest division will be denoted as division 1; North division will be

denoted as division 2; North Central will be denoted as division 3; South Central will be denoted as division 4; Everglades and Southwest Coast will be denoted as division 5; Lower East Coast will be denoted as division 6 and Keys will be excluded because it has relatively small land mass and vegetated area (Figure 3-4).

Time-series of NDVI value and precipitation data by each of the climate divisions are created for further analysis (Figure 3-7).

3.3.4 Land Cover Data

Florida land cover classification data are available from the Coastal Change Analysis Program (C-CAP) developed by the National Oceanic and Atmospheric Administration (NOAA) with collaborations of the Department of Commerce (DOC), National Ocean Service (NOS) and NOAA Coastal Services Center (CSC). Current production of the Coastal Change Analysis Program (C-CAP) land cover datasets is accomplished through closely coordinated efforts with the U.S. Geological Survey (USGS) as it produces the National Land Cover Dataset (NLCD).

CCAP land cover classification data are developed, primarily, from Landsat Thematic Mapper (TM) satellite imagery. The smallest feature size (spatial resolution) that can be mapped is 30 meter pixels (1/4 acres) on the ground. Current C-CAP datasets are available for Florida in the years 1996, 2001, and 2006 by 23 classes (Figure 3-5). In order to simplify for the following analysis, 23 classes were regrouped into 10 classes based on their classification scheme (Table 2-1).

CCAP land cover classification data for the years 1996, 2001, and 2006 were analyzed under a superimposed GIMMS NDVI pixel grid, which is an 8km squared grid. Then for each grid, the proportions of each land cover type (regrouped 10 classes) are recorded. Practically, there is no single one grid that only has solo land cover type.

According to that and in order to find a proper NDVI time series to represent a typical land cover type, a determine process was proposed as follows.

First of all, the land cover type need to be consistent from 1996 through 2006 (land cover classification stay the same). Second, we determined the land cover type occupied more than 70 percent of a grid can represent a typical behavior of NDVI for this specific land cover type. The determine process just as the climate zones are thought to exhibit patterns representative of the climate region it is found in.

As a result, seven land cover types were selected as they met the criteria (Figure 3-6). These seven land cover types are developed land, agricultural land, forest land, scrub land, palustrine wetlands, estuarine wetlands and water and submerged lands. The detailed classification scheme can be found in Table 3-2.

Time-series of NDVI value and precipitation data by each of the seven land cover types are created for further analysis (Figure 3-7).

3.3.5 Time-Series Approach and Wavelets

The decomposition of time series into time–frequency space permits not only the identification of the dominant modes of variability, but also the determination of how these modes vary in time. This can be done by using either windowed Fourier transform or wavelet transform (Coulibaly 2006). Fourier transform has traditionally been used to analyze relationship between oscillating time series and decomposes time series into their different periodic components (Klvana et al. 2004). This method was initially developed for the analysis of physical phenomena but is not always appropriate when dealing with complex biological and climatic time series (Chatfield 1989). A major shortcoming of standard Fourier transform is that it does not provide an accurate time–frequency localization of dynamical processes (Coulibaly 2006).

Figure 3-8 illustrates the main difference of time-frequency windows usage between Fourier transform (FT), windowed Fourier transform (WFT) and wavelet transform (WT). In some way, WT is a generalized form of FT and WFT (Gabor 1946). The Fourier transform uses sine and cosine base functions that have infinite span and are globally uniform in time. For a stationary time-series with a pure sine-wave signal, its FT is a line spectrum (Figure 3-8, left panel). FT does not contain any time dependence of the signal and therefore cannot provide any local information regarding the time evolution of its spectral characteristics. In a WFT, a time-series is examined under fixed time-frequency window with constant intervals in the time and frequency domains. The middle panel in Figure 3-8 shows when a wide range of frequencies is involved, the fixed time window of the WFT tends to contain a large number of high-frequency cycles and a few low-frequency cycles or parts of cycles. One big disadvantage of WFT is it often results in an overrepresentation of high-frequency components and underrepresentation of the low-frequency components. A WT uses generalized local base functions (wavelets) that can stretched and translate with a flexible resolution in both frequency and time (Figure 3-8, right panel). As a result, high precision in time localization in the high-frequency band can be achieved at the expense of reduced frequency resolution (Lau and Weng 1995).

Wavelet analysis is notably free from the assumption of stationary and offers several advantages (Daubechies 1990, Lau and Weng 1995, Torrence and Campo 1998, Cazelles et al. 2008, Martinez and Gilbert 2009). It overcomes the problems of non-stationary in time-series by performing a local time-scale decomposition of the signal, i.e., the estimation of its spectral characteristics as a function of time (Lau et al.

1995, Torrence and Campo 1998). Through this approach one can track how the different scales related to the periodic components of the signal change over time and represent time-series into a finer scale-time domain without a window with arbitrary limited length (Coulibaly 2006). Detailed reviews of wavelet analysis can be found from Daubechies 1990, Farge (1992), Meyers et al. (1993), Weng and Lau 1994, Lau and Weng (1995), an Torrence and Compo (1998).

Many softwares such as Interactive Wavelets, MATLAB®, TimeStat, and R all have wavelets-related packages. This present study adapted the MATLAB® codes developed by Drs. Christopher Torrence and Gilbert P. Compo (Torrence and Compo 1998) to perform wavelet analysis in MATLAB® environment.

3.4 Results

A time-series of NDVI and precipitation data is analyzed for the whole state of Florida (Figure 3-9 and Figure 3-12). This is done to provide information as a controlled baseline. Upon this controlled baseline, it would be easier to detect the changes and fluctuations at different scales - climate divisions and land cover types. Furthermore, a more informative analysis from comparisons among different spatial scales provides insight of ecosystems functions.

Figure 3-9 represent the wavelet analysis of NDVI for the whole state of Florida. The upper panel is the time series data. The middle left panel present the wavelet power spectrum in a contour map. Areas below the curved black line indicate the region of cone of influence (COI), where zero padding has reduced the variance. Which means the areas below the curved black line should not be considered into analysis.

The bold black contour line is the 10% significance level using a red-noise (autoregressive lag1) background spectrum. In the global wavelet spectrum (lower

panel on the right), blue line represent the overall wavelet power at each period and the dashed line is the significance for the global wavelet spectrum assuming the same significance level and background spectrum. Any blue line come cross the dashed line indicate the power at the specific period is significant.

Generally speaking, reading the results from the wavelet analysis need to pay more attention to two parts. First, is the significant period (above the dashed line in global wavelet spectrum); second, is the time of this significant period in the power spectrum (bold black contour line in wavelet power spectrum). For all the analysis, the significant period are extracted and present in a tabulation form with value 1 represents significant. The timing of significant are also present in a tabulation form with value 0 represents not significant and value 1 represent significant.

Form the wavelet analysis, this study propose a hypothesis that if two time-series data have identical significant period, it is reasonable to assume that these two time-series data have similar periodic pattern/cycle and can be a driven relationship between these two. For example, if the wavelet analysis of NDVI in climate division 3 is having identical significant period pattern/cycle with the rainfall in climate division 3, it is demonstrating that the rainfall in climate division 3 is an important driver for the NDVI. However, the timing of significant period/cycle needs to be examined between NDVI and rainfall time-series as well in order to identify a more clear relationship in time.

3.4.1 Climate Divisions

The results from wavelet analysis for climate divisions are shown in Figure 3-10 and Figure 3-13. The significant period and the timing of significant period in the power spectrum are shown in Table 3-3 and Table 3-4. From Table 3-4, climate division three and four are showing identical significant periods of NDVI and rainfall (2.46 month, 5.84

month, and 11.69 month). For a convenience expression purpose, 2.46 month can be considered as 3 month; 5.84 month can be considered as 6 month and 11.69 month can be considered as 12 month.

Generally speaking, a 2.5-3 month (2.46-2.92 month) period pattern/cycle is seen in rainfall across all climate divisions. A 6 month (5.84 month) period pattern/cycle appear in rainfall from division 1 to 5 but not seen in division 6. An annual 12 month (11.69 month) period pattern/cycle appears in divisions 2 to 6. There are spatial variation exist in NDVI across climate divisions. The NDVI in climate division 1 and 2 are identical. Additionally, the NDVI in climate division 3 and 4 are also identical. However, NDVI in division 5 and 6 are not similar.

3.4.2 CCAP Land Cover Types

The results from wavelet analysis for land cover types are shown in Figure 3-11 and Figure 3-14. The significant period and the timing of significant period in the power spectrum are shown in Table 3-3. From Table 3-3, only estuarine wetlands are showing identical significant periods of NDVI and rainfall (2.46 month, 4.13 month, and 11.69 month). This can be intepret that the NDVI in estuarine wetlands are mainly driven by its rainfall. Agricultural land, forest land, scrub land and palustrine wetlands are showing significant periodic pattern/cycle at about 6 month (5.84 month) for both NDVI and rainfall. Almost all land cover types shown an annual 12 month (11.69 month) period pattern/cycle. A 2.5-3 month (2.46-2.92 month) cycle in rainfall can be seen at all land cover types.

3.5 Discussion

Many researchers have pointed out precipitation is a primary control on vegetation dynamics in many tropical and subtropical biomes (Nicholson et al. 1990, Li and Kafatos

2000, Wang et al. 2001, Ichii et al 2002, Gurgel and Ferreira 2003, Lotsch et al. 2003, Jarlan 2005, Phillippon et al. 2007, Neeti et al. 2012). Climate induced disturbances in both the frequency and timing of precipitation result in observable ecosystem responses (Knapp and Smith 2001). However, the variability in precipitation regimes at seasonal and longer time scales strongly influences ecosystem dynamics and is varied by location.

Additionally, many researchers found out other than precipitation, land cover type is also responsible for vegetation dynamics. For example, Yang et al. (1997) use 1-km multitemporal AVHRR-derived NDVI data to examine the eco-climatological relations in Nebraska, U.S.A. from 1990-1991.They conclude that NDVI-precipitation and NDVI-potential evapotranspiration relations exhibited time lags, although the length of lag varied with land cover type, precipitation, and soil hydrologic properties. Moreover, they find that NDVI response to precipitation was stronger in natural grasslands and grassland/wet meadows than in areas of irrigated cropland and mixed crop/ grass.

Florida is experiencing a massive land cover alteration due to its increasing population and climate variability has been a big concern raised by global climate change. Therefore, the main goal of this study is to investigate the vegetation dynamics with precipitation and land cover variations in Florida by performing the wavelet analysis.

From Figure 3-9 and Figure 3-12, the wavelet power spectrums of Florida's NDVI and precipitation (controlled baseline), it is clearly to see a strong activity present at 6 month (5.84 month) and 12 month (11.69 month) cycle for both. However, a 2.5month (2.46 month) cycle can only be found in rainfall. However, the pattern and timing of

black contour line (10% significance level) does not match with each other. This can be explained by two reasons. First, since Florida has a big north –south variation of precipitation pattern, mixing precipitation information may result in an averaged presentation in the power spectrum. Secondly, the NDVI-precipitation relationship is not a perfect linear trend, more information such as soil moisture, land cover types, temperature need to be considered.

For climate divisions, the analysis is done based on averaging the NDVI and rainfall within each division. As a result, spatial variations can be seen from its significant periodic pattern/cycle (Table 3-4) and especially pronounced on rainfall pattern. The rainfall pattern in climate division 1 is explainable by its expected influences by frontal activities during winter time and convective rainfall during summer time. However, the NDVI in climate division 1 are not having exactly identical significant period with rainfall. Non-identical situation also happen in climate division 5 and 6 which suggest that the rainfall may not be the only driver that influence the performance of NDVI. According to this climate division subgroup are mixing all the land cover types within climate divisions, it is reasonable to discover a mixing signal of NDVI from a diverse land cover types. Thus, the response from NDVI to precipitation is more complicated.

For different land cover types, only estuarine wetlands have identical significant periodic/cycle between NDVI and rain. Theoretically, it is reasonable to assume that if land cover type is not manipulated by human and maintain its more natural state, the relationship between NDVI and rain should be directly related and showing identical periodic pattern/cycles from wavelet analysis results. For instance, in estuarine

wetlands (Figure 3-11 (e)), the NDVI pattern and rainfall pattern on its global wavelet spectrum are very similar in terms of the shapes. Additionally, their significant period results are also showing identical cycles as well (Table 3-3).

If land cover type is manipulated by human, the relationship between NDVI and rain may not be found directly related, as a result, the periodic patterns/cycles are expected to be found different between NDVI and rain. For example, in agricultural land (Figure 3-11 (b)), a very strong 12 month cycle (11.69 month) is a strong evidence of human manipulation. In developed land, the NDVI patterns are very scattered and it suggest that even within one single land cover type, spatial variation also plays a role. This part of analysis is based on the same land cover group, however, the same land cover can be found from different location. Thus, the spatial variation is not been reflected.

3.6 Summary and Finding

The NDVI-precipitation relationship has not previously been investigated explicitly in Florida. The present study applies wavelet analysis to monthly NDVI and precipitation data from July 1981 to December 2006 and links the inter-annual and intra-annual variability of precipitation to the NDVI responses accordingly. Additionally, considering anthropogenic influence is a big factor contributing to ecosystem dynamics, different land cover types are analyzed to examine the response in terms of NDVI and precipitation variability.

The wavelet analysis appears to be an efficient technique to depict periodic patterns/cycles from a time series data. The results from this study provide strong evidences that NDVI and precipitation are related in terms of its period patterns. However, spatial variations are present from the results. Additionally, land cove types

play an important role of NDVI pattern. We found out that NDVI response to precipitation was stronger in estuarine wetlands than in areas of agricultural land.

The present study present a novel time-series approach to investigate the relationships between precipitation and NDVI variability with explicit consideration of land cover types. We conclude that spatial variations exist on NDVI and precipitation in Florida and they both have strong influences on the behavior of NDVI.

Table 3-1. El Niño/La Niña Impacts across the Southeast U.S. (Source: Florida Climate Center 2011)

Phase	Region	Oct-Dec	Jan-Mar	Apr-Jun	Jul-Sep
El Nino	Peninsular Florida	Wet & cool	Very Wet & cool	Slightly dry	Slightly dry to no impact
	Tri-State Region	Wet	Wet	Slightly wet	No impact
	Western Panhandle	No impact	Wet	Slightly Dry	No impact
	Central and North Ala. & Ga.	No impact	No impact	No impact	Slightly Dry
La Niña	Peninsular Florida	Dry & slightly warm	Very dry & warm	Slightly wet	Slightly cool
	Tri-State Region	Slightly dry	Dry	Dry	No impact
	Western Panhandle	Slightly dry	Dry	Dry	No impact
	Central and North Ala. & Ga.	Dry	Dry in the south, wet in NW Ala.	No impact	Wet in NW Ala.
Neutral	All Regions	No impact	No impact	No impact	No impact

Table 3-2. Selected C-CAP Land Cover Classification Scheme (Source: NOAA 2011)

Class name		Description
Developed Land	Developed, High Intensity	contains significant land area is covered by concrete, asphalt, and other constructed materials. Vegetation, if present, occupies < 20 percent of the landscape. Constructed materials account for 80 to 100 percent of the total cover. This class includes heavily built-up urban centers and large constructed surfaces in suburban and rural areas with a variety of land uses.
	Developed, Medium Intensity	contains areas with a mixture of constructed materials and vegetation or other cover. Constructed materials account for 50 to 79 percent of total area. This class commonly includes multi- and single-family housing areas, especially in suburban neighborhoods, but may include all types of land use.
	Developed, Low Intensity	contains areas with a mixture of constructed materials and substantial amounts of vegetation or other cover. Constructed materials account for 21 to 49 percent of total area. This subclass commonly includes single-family housing areas, especially in rural neighborhoods, but may include all types of land use.
	Developed, Open Space	contains areas with a mixture of some constructed materials, but mostly managed grasses or low-lying vegetation planted in developed areas for recreation, erosion control, or aesthetic purposes. These areas are maintained by human activity such as fertilization and irrigation, are distinguished by enhanced biomass productivity, and can be recognized through vegetative indices based on spectral characteristics. Constructed surfaces account for less than 20 percent of total land cover.
Agricultural Land	Cultivated Crops	contains areas intensely managed for the production of annual crops. Crop vegetation accounts for greater than 20 percent of total vegetation. This class also includes all land being actively tilled.
	Pasture/Hay	contains areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle and not tilled. Pasture/hay vegetation accounts for greater than 20 percent of total vegetation.

Table 3-2. Continued.

Class name		Description
Forest Land	Deciduous Forest	contains areas dominated by trees generally greater than 5 meters tall and greater than 20 percent of total vegetation cover. More than 75 percent of the tree species shed foliage simultaneously in response to seasonal change.
	Evergreen Forest	contains areas dominated by trees generally greater than 5 meters tall and greater than 20 percent of total vegetation cover. More than 75 percent of the tree species maintain their leaves all year. Canopy is never without green foliage.
	Mixed Forest	contains areas dominated by trees generally greater than 5 meters tall, and greater than 20 percent of total vegetation cover. Neither deciduous nor evergreen species are greater than 75 percent of total tree cover. Both coniferous and broad-leaved evergreens are included in this category.
Scrub Land	Scrub/Shrub	contains areas dominated by shrubs less than 5 meters tall with shrub canopy typically greater than 20 percent of total vegetation. This class includes tree shrubs, young trees in an early successional stage, or trees stunted from environmental conditions.
Palustrine Wetlands	Palustrine Forested Wetland	includes tidal and nontidal wetlands dominated by woody vegetation greater than or equal to 5 meters in height, and all such wetlands that occur in tidal areas in which salinity due to ocean-derived salts is below 0.5 percent. Total vegetation coverage is greater than 20 percent.
	Palustrine Scrub/Shrub Wetland	includes tidal and non tidal wetlands dominated by woody vegetation less than 5 meters in height, and all such wetlands that occur in tidal areas in which salinity due to ocean-derived salts is below 0.5 percent. Total vegetation coverage is greater than 20 percent. Species present could be true shrubs, young trees and shrubs, or trees that are small or stunted due to environmental conditions.
	Palustrine Emergent Wetland (Persistent)	includes tidal and nontidal wetlands dominated by persistent emergent vascular plants, emergent mosses or lichens, and all such wetlands that occur in tidal areas in which salinity due to ocean-derived salts is below 0.5 percent. Total vegetation cover is greater than 80 percent. Plants generally remain standing until the next growing season.

Table 3-2. Continued.

Class name		Description
Estuarine Wetlands	Estuarine Forested Wetland	includes tidal wetlands dominated by woody vegetation greater than or equal to 5 meters in height, and all such wetlands that occur in tidal areas in which salinity due to ocean-derived salts is equal to or greater than 0.5 percent. Total vegetation coverage is greater than 20 percent.
	Estuarine Scrub / Shrub Wetland	includes tidal wetlands dominated by woody vegetation less than 5 meters in height, and all such wetlands that occur in tidal areas in which salinity due to ocean-derived salts is equal to or greater than 0.5 percent. Total vegetation coverage is greater than 20 percent.
	Estuarine Emergent Wetland	Includes all tidal wetlands dominated by erect, rooted, herbaceous hydrophytes (excluding mosses and lichens). Wetlands that occur in tidal areas in which salinity due to ocean-derived salts is equal to or greater than 0.5 percent and that are present for most of the growing season in most years. Total vegetation cover is greater than 80 percent. Perennial plants usually dominate these wetlands.
Water and Submerged Lands	Open Water	include areas of open water, generally with less than 25 percent cover of vegetation or soil.
	Palustrine Aquatic Bed	includes tidal and nontidal wetlands and deepwater habitats in which salinity due to ocean-derived salts is below 0.5 percent and which are dominated by plants that grow and form a continuous cover principally on or at the surface of the water. These include algal mats, detached floating mats, and rooted vascular plant assemblages. Total vegetation cover is greater than 80 percent.
	Estuarine Aquatic Bed	includes tidal wetlands and deepwater habitats in which salinity due to ocean-derived salts is equal to or greater than 0.5 percent and which are dominated by plants that grow and form a continuous cover principally on or at the surface of the water. These include algal mats, kelp beds, and rooted vascular plant assemblages. Total vegetation cover is greater than 80 percent.

Table 3-3. Significant period – CCAP land cover class. The significant period are represented in star mark

Land Cover/ period	1_Developed Land		2_Agricultural Land		4_Forest Land		5_Scrub Land		7_Palustrine Wetlands		8_Estuarine Wetlands		10_Water and Submerged Lands		Florida	
	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain
2.07																
2.46		*		*	*			*		*	*			*		*
2.92	*					*										
3.47													*			
4.13											*	*				
4.91													*			
5.84	*		*	*	*	*	*	*	*	*				*	*	*
6.95																
8.26																
9.83					*											
11.69	*	*	*	*		*	*	*	*	*	*	*	*	*	*	*

Table 3-4. Significant period – Climate Division. The significant period are represented in star mark

Climate Division / period	1		2		3		4		5		6		Florida	
	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain	NDVI	Rain
2.07														
2.46					*	*	*	*		*		*		*
2.92		*		*										
3.47											*			
4.13												*		
4.91														
5.84	*	*	*	*	*	*	*	*	*	*			*	*
6.95														
8.26														
9.83									*					
11.69	*		*	*	*	*	*	*		*	*	*	*	*

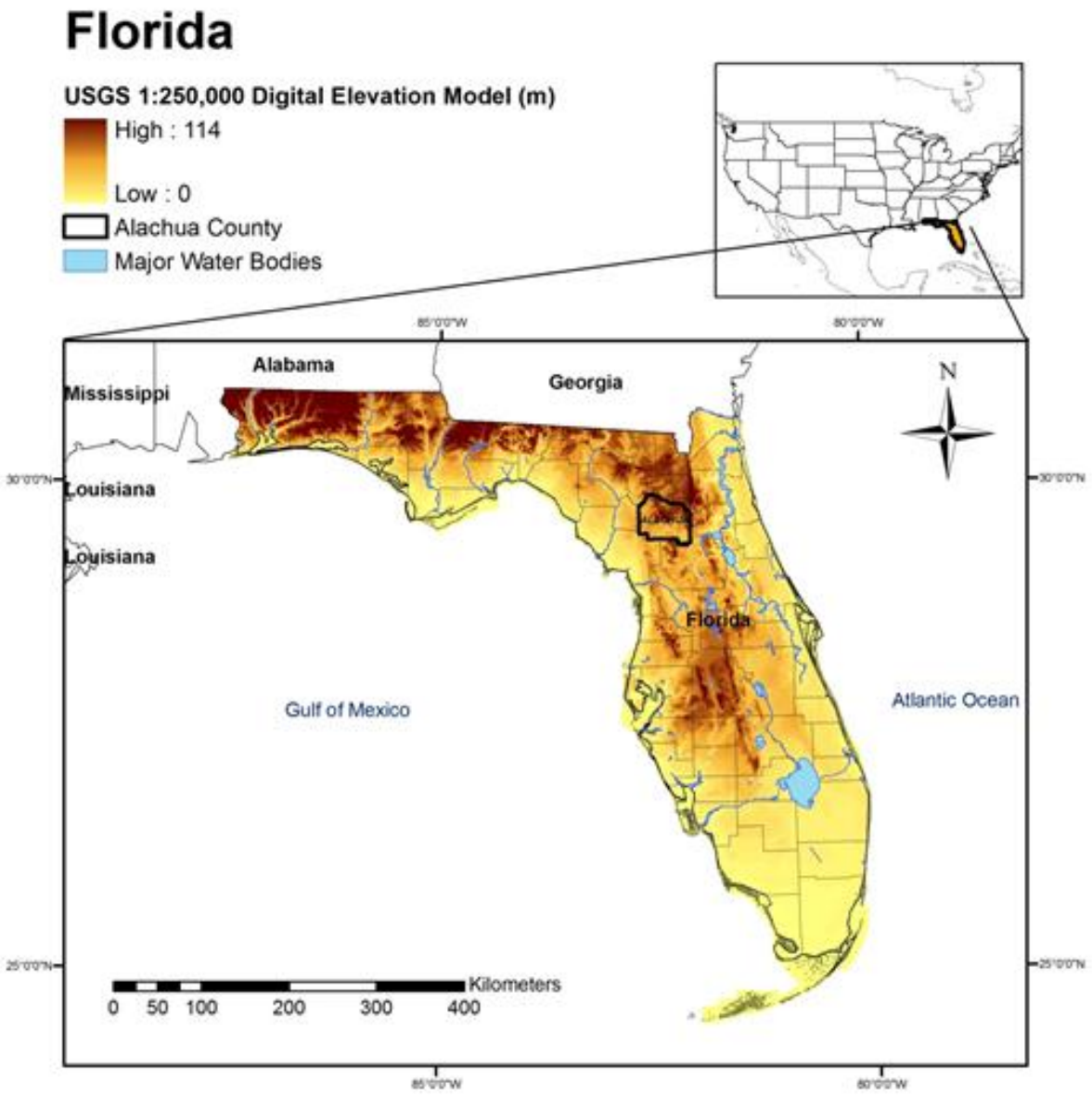


Figure 3-1. Study area: Florida State, U.S.A.

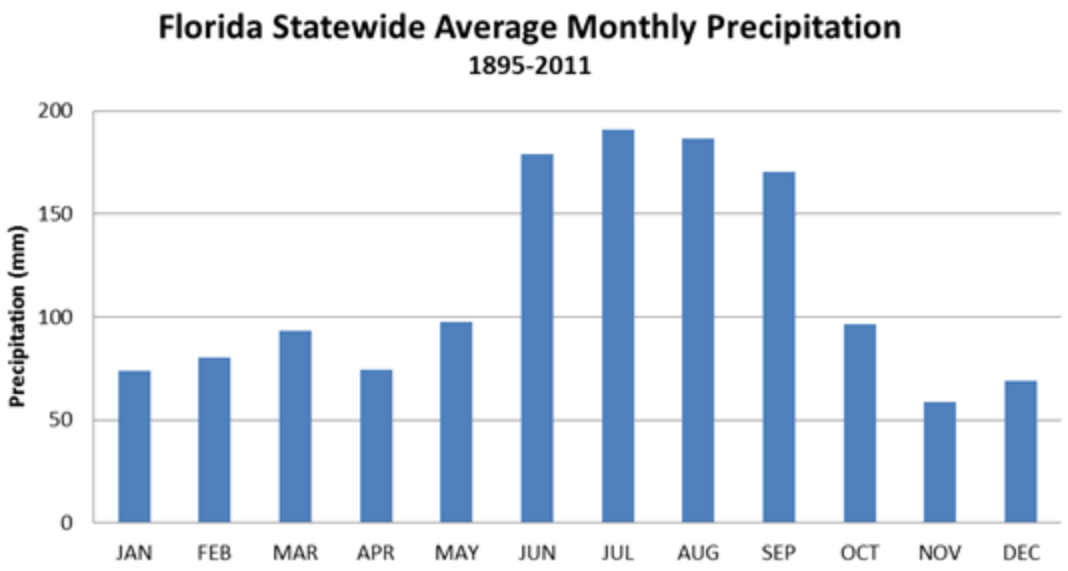


Figure 3-2. Florida statewide average monthly precipitation (Source: NCDC 2011)

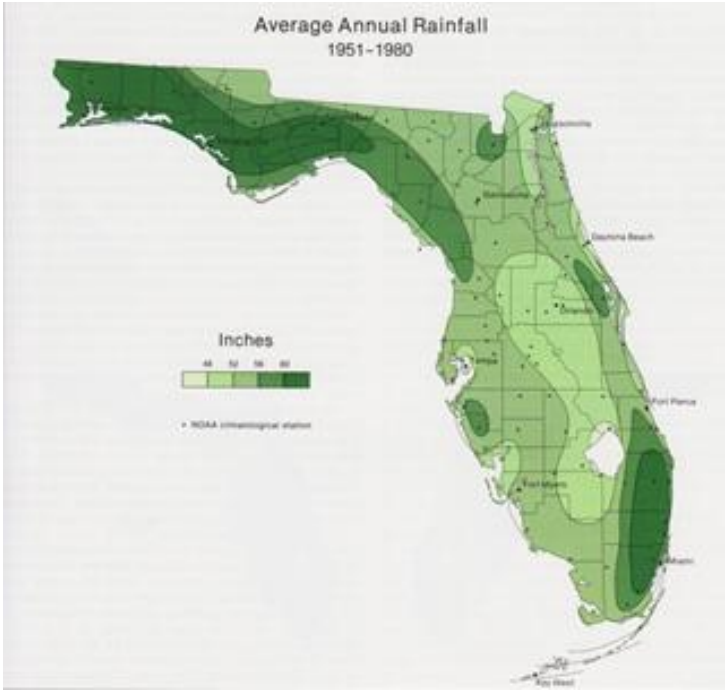


Figure 3-3. Florida statewide average monthly precipitation and distribution [Adapted from Fernald, E. A. and Patton, D. J. 1984. Water resources atlas of Florida (Page 121, Figure 3-1). Florida State University, Florida.]

Figure 3-4. Climate divisions in Florida (Source: NCDC 2011)

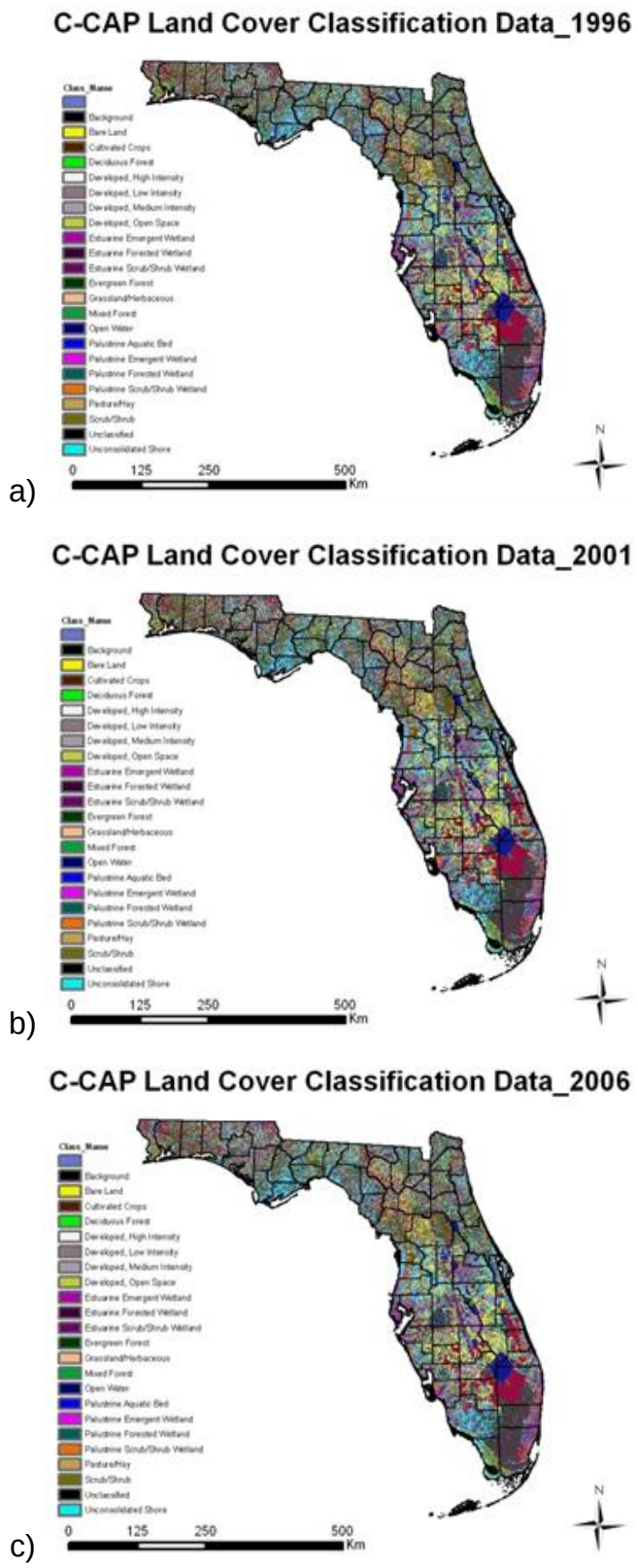


Figure 3-5. Land cover classification data from C-CAP for the year a) 1996, b) 2001, and c) 2006 (Source: NOAA 2011)

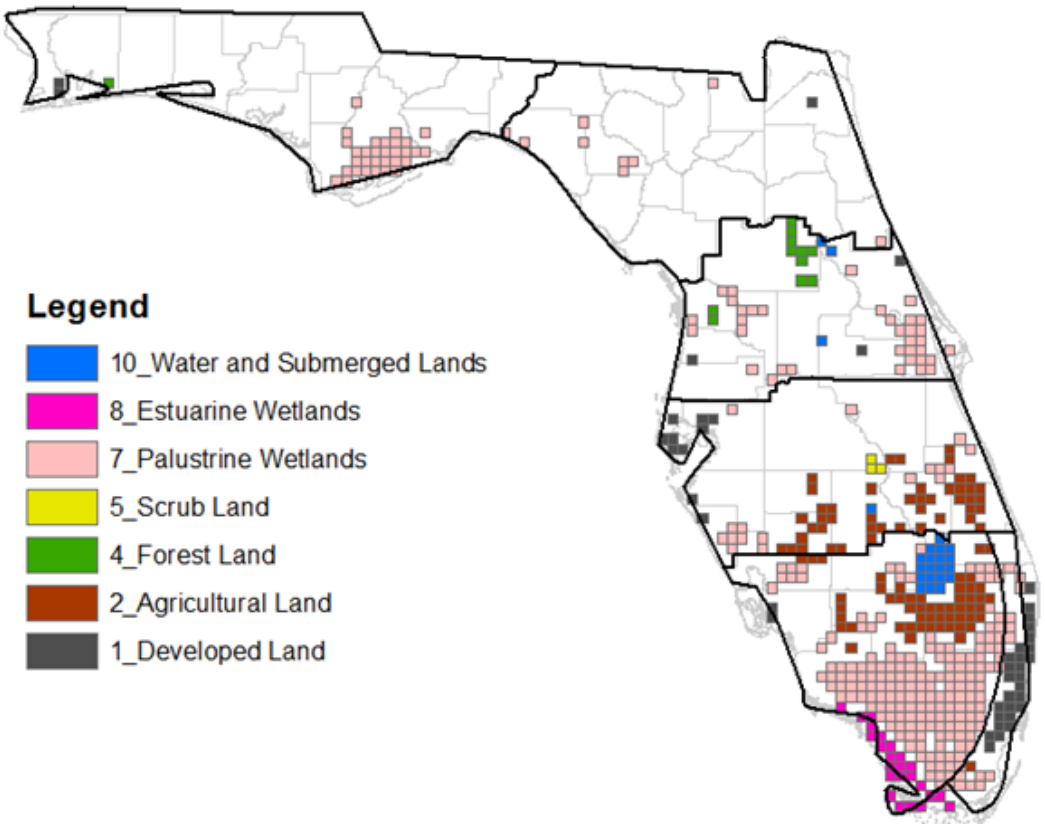
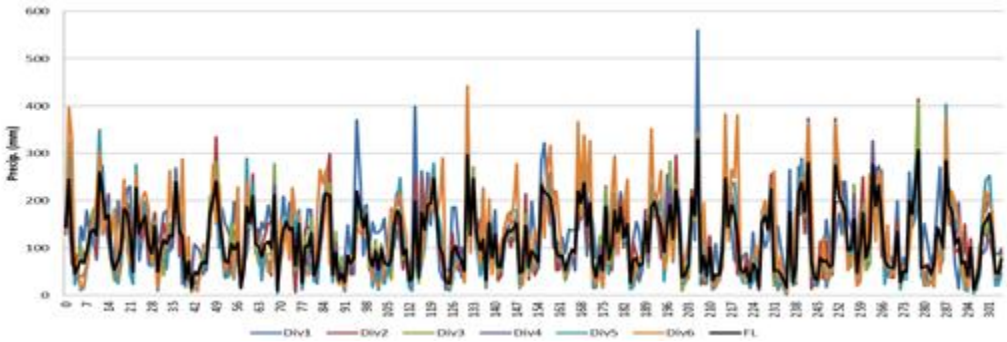
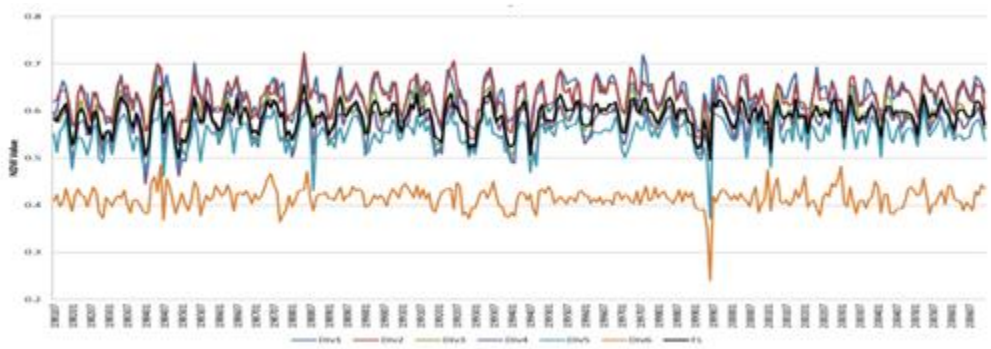


Figure 3-6. Dominant land cover types at different percentages (superimposed black line: climate divisions)

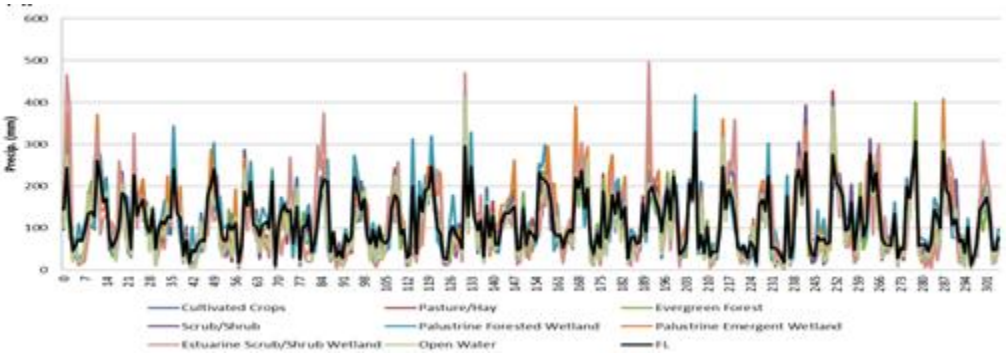
(a)



(b)



(c)



(d)

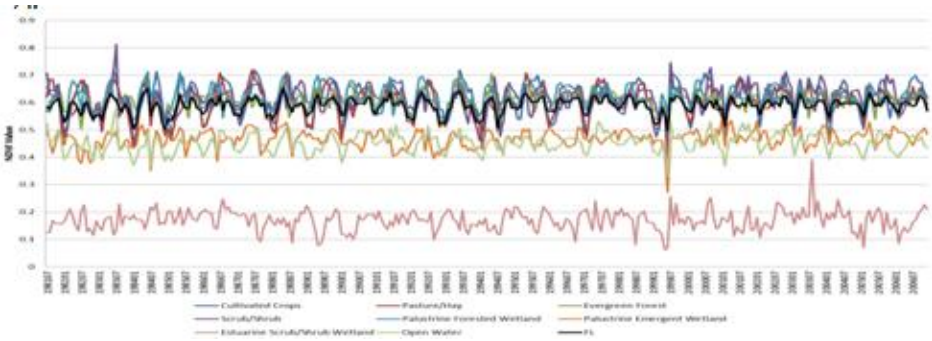


Figure 3-7. Precipitation and NDVI time-series present in monthly order July 1981 to December 2006. (a) Precipitation for climate divisions and Florida; (b) NDVI for climate divisions and Florida. . (c) Precipitation for land cover types and Florida; (d) NDVI for land cover types and Florida.

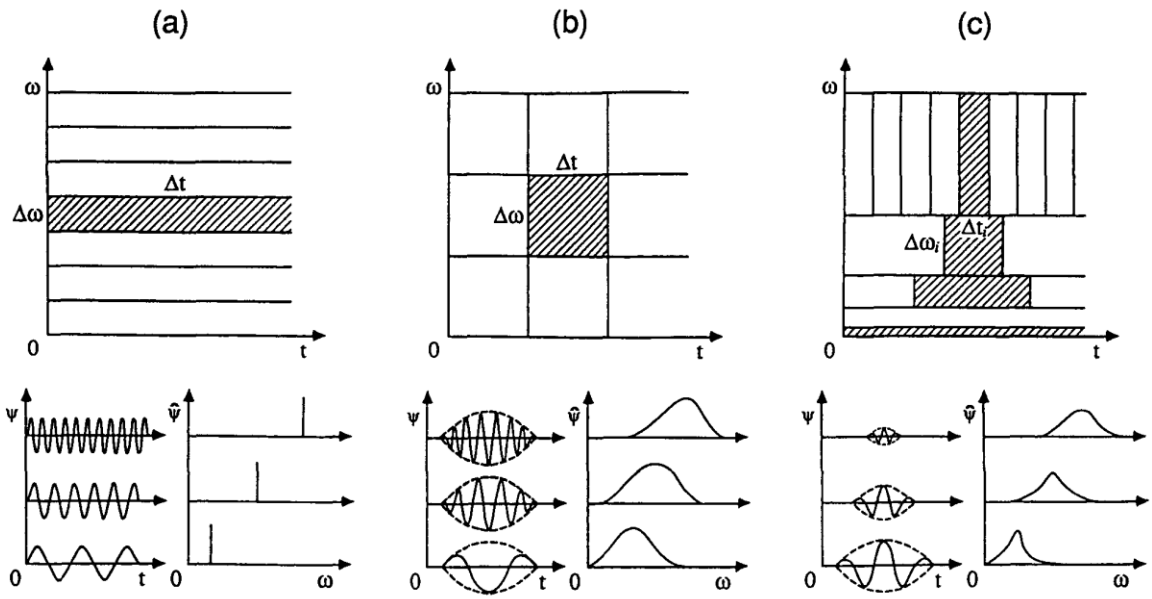


Figure 3-8. Time (Δt)-frequency(ΔCO) window used in (a) Fourier transform (FT), (b) a windowed Fourier transform (WFT), and (c) a wavelet transform (WT), and their time series represented in time space and frequency space. (Source: Lau and Weng 1995)

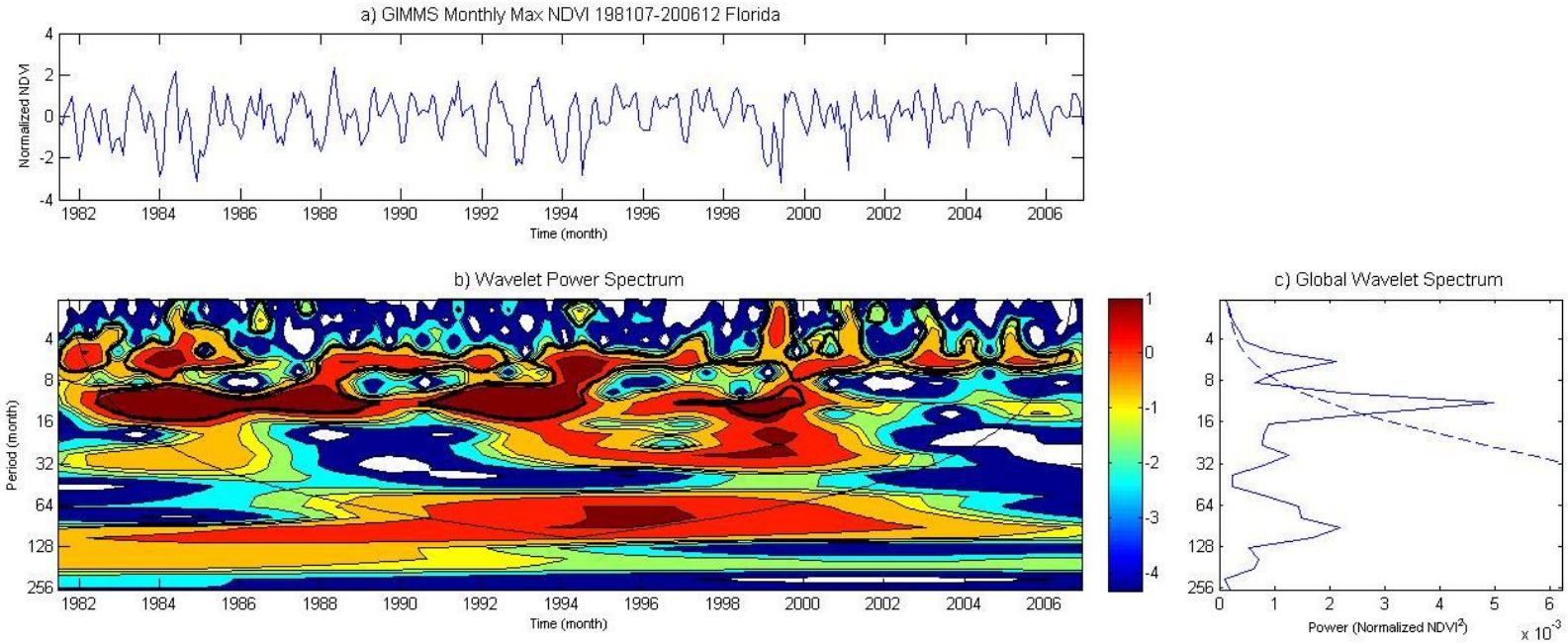


Figure 3-9. Wavelet analysis of Florida's NDVI: a) NDVI Data. b) The wavelet power spectrum. The cross-hatched region is the cone of influence, where zero padding has reduced the variance. Black contour is the 10% significance level, using a red-noise (autoregressive lag1) background spectrum. c) The global wavelet power spectrum (black line). The dashed line is the significance for the global wavelet spectrum, assuming the same significance level and background spectrum as in b).

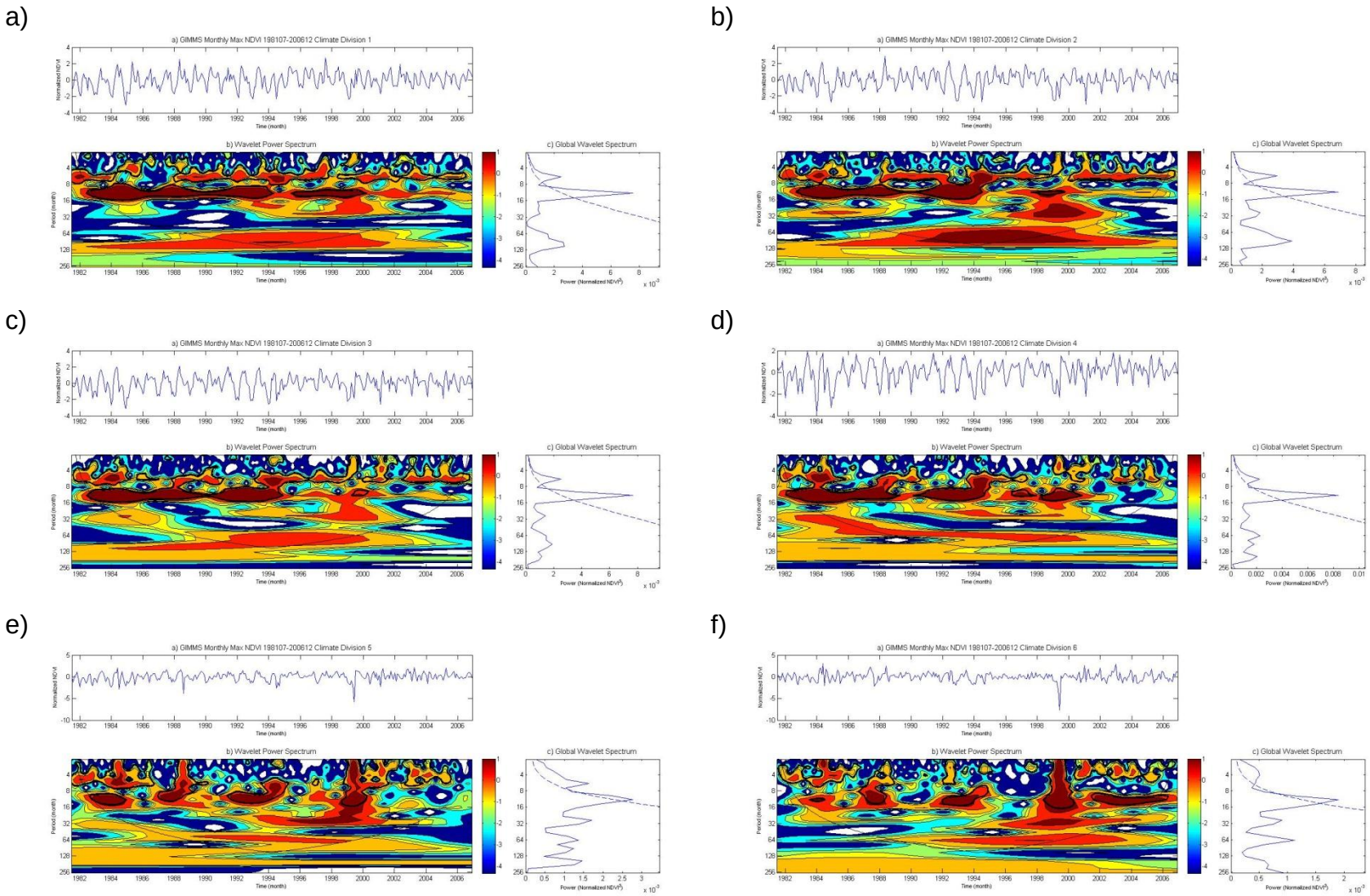


Figure 3-10. Wavelet analysis of NDVI for Florida climate divisions. a) climate division 1 to f) climate division 6

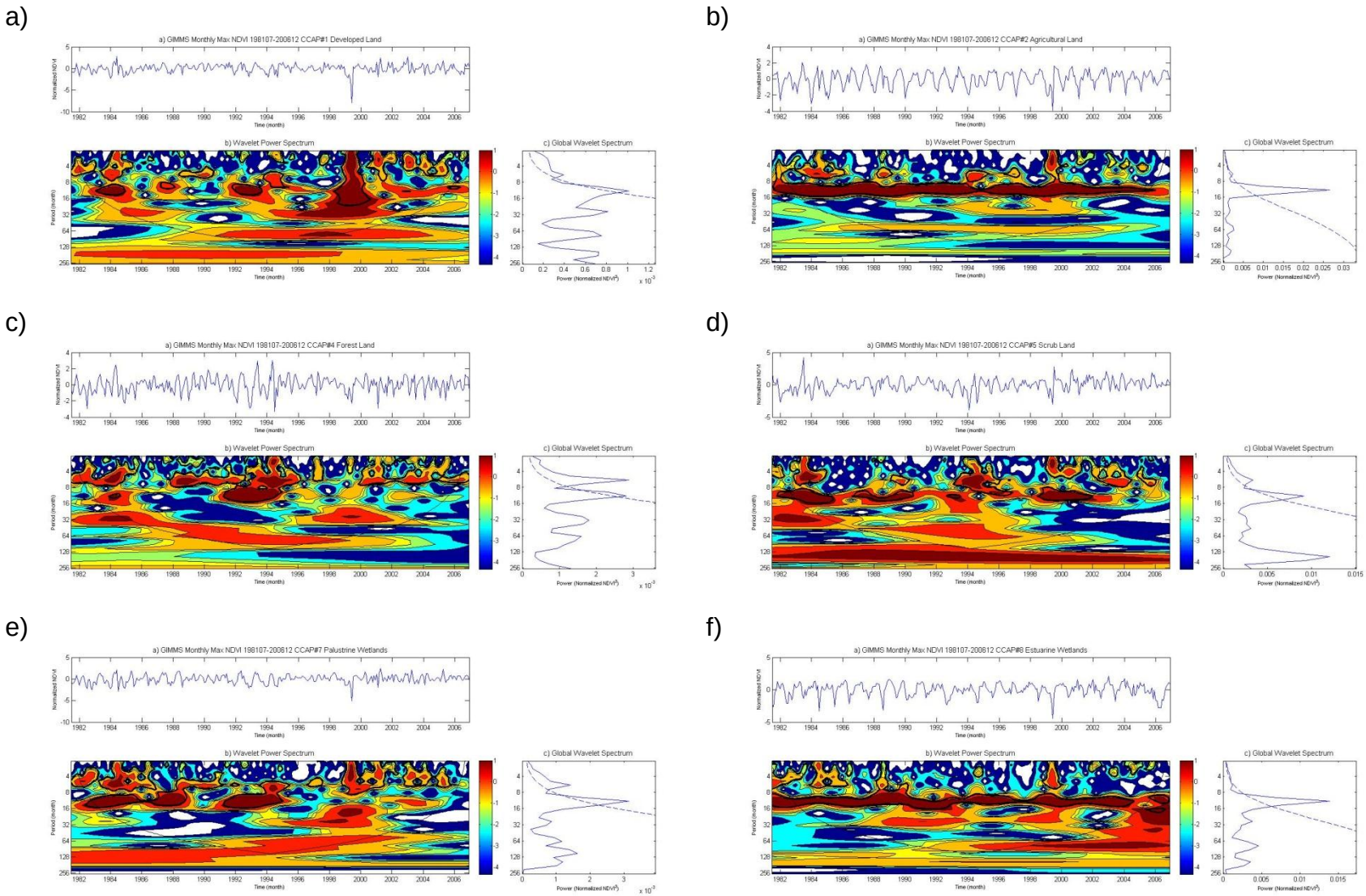


Figure 3-11. Wavelet analysis of NDVI for different land cover types. a) developed land b) agricultural land c) forest land d) scrub land e) palustrine wetlands f) estaurine wetlands

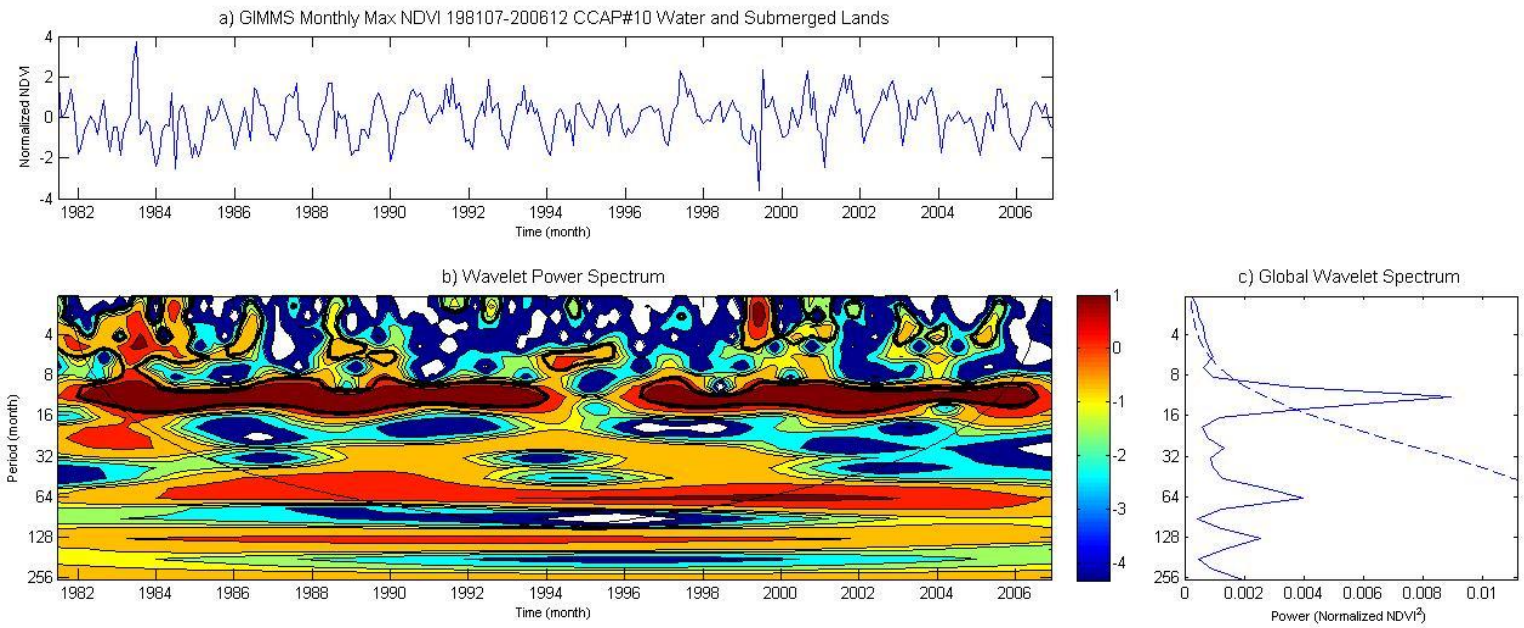


Figure 3-11. Continued. Wavelet analysis of NDVI for water and submerged land

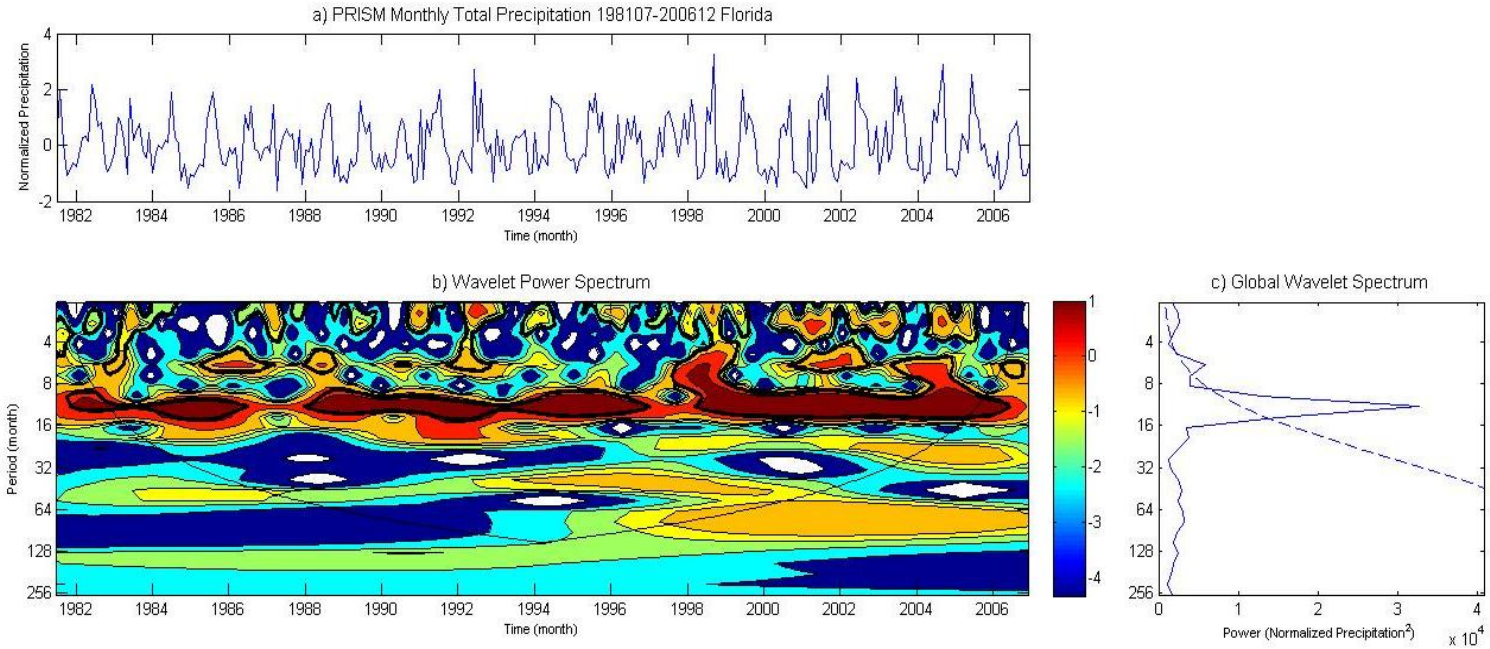


Figure 3-12. Wavelet analysis of precipitation of Florida: a) Precipitation data. b) The wavelet power spectrum. The contour levels are chosen so that 75%, 50%, 25%, and 5% of the wavelet power is above each level, respectively. The cross-hatched region is the cone of influence, where zero padding has reduced the variance. Black contour is the 10% significance level, using a red-noise (autoregressive lag1) background spectrum. c) The global wavelet power spectrum (black line). The dashed line is the significance for the global wavelet spectrum, assuming the same significance level and background spectrum as in (b).

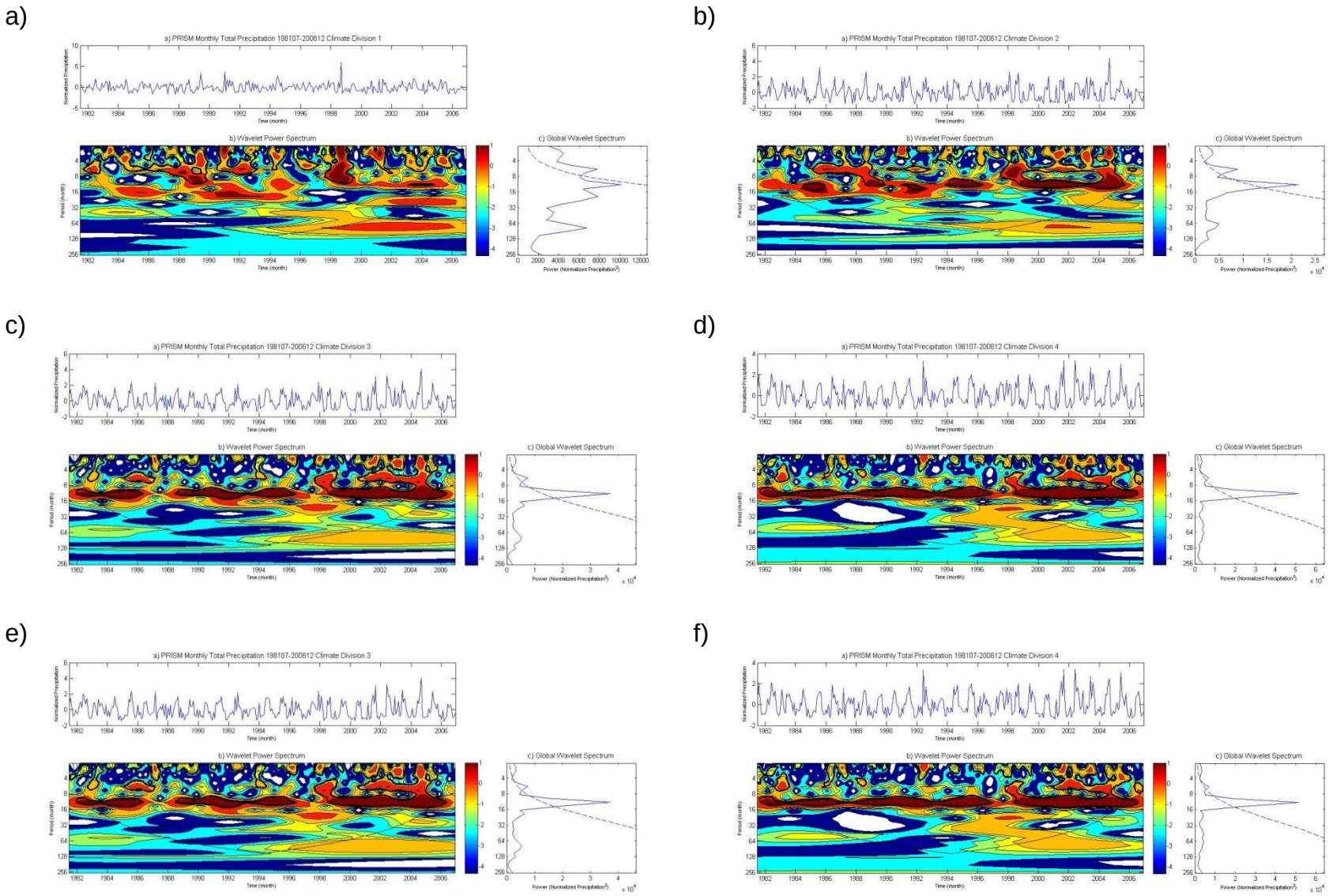


Figure 3-13. Wavelet analysis of precipitation for Florida climate divisions. a) climate division 1 to f) climate division 6

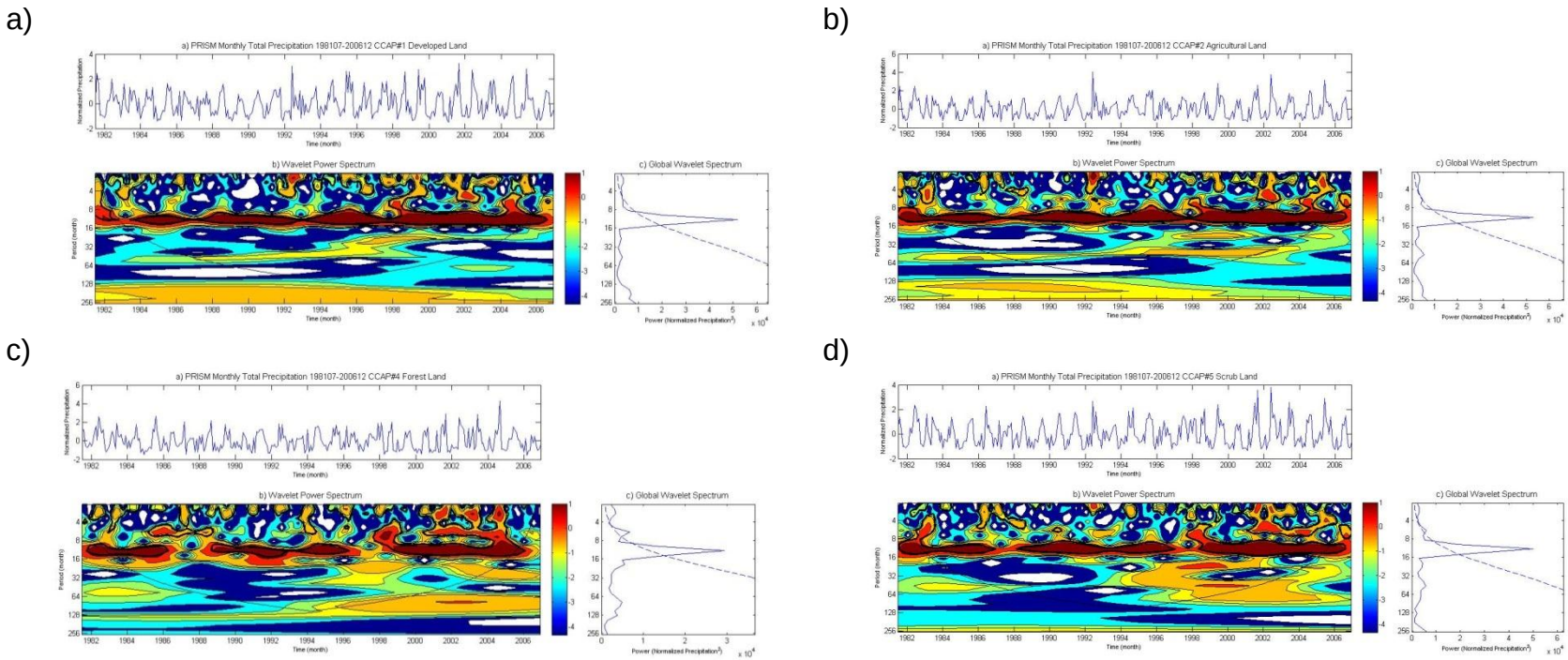
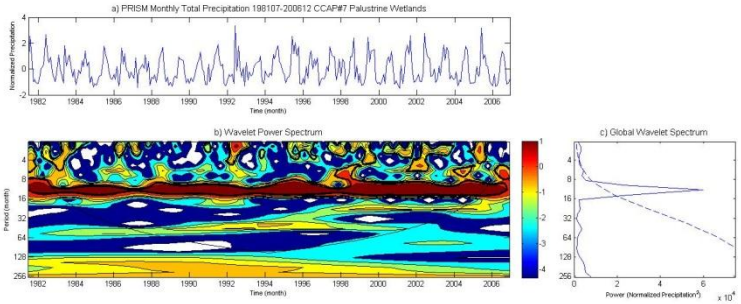


Figure 3-14. Wavelet analysis of precipitation fordifferent land cover types. a) developed land b) agricultural land c) forest land d) scrub land

e)



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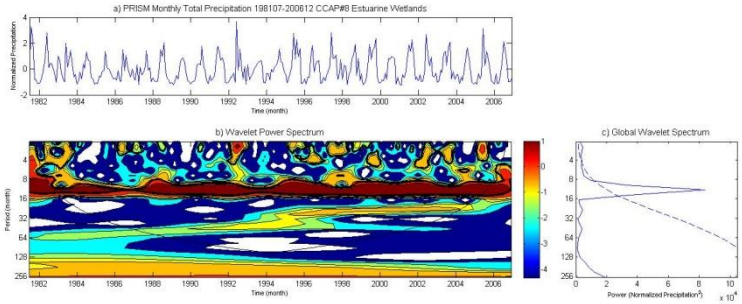


g)

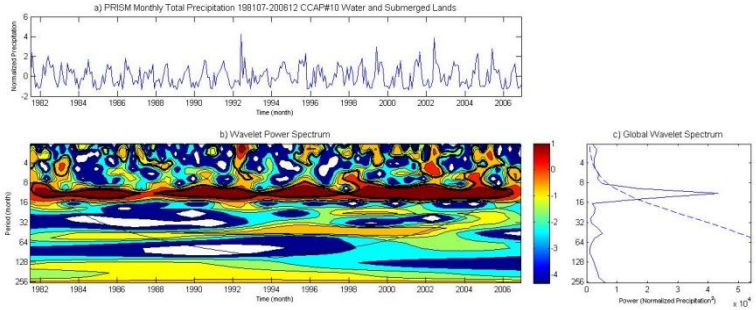


Figure 3-14. Continued. Wavelet analysis of precipitation for different land cover types. e) palustrine wetlands f) estaurine wetlands and g)water and submerged land

CHAPTER 4
IMPACTS OF LAND COVER AND LAND USE ON AIR QUALITY IN FLORIDA

4.1 Background

The impacts of land cover and land use are studied intensively from many aspects (Lambin et al. 2001, Patz et al. 2005, Felet et al. 2005, Lambin et al. 2006). Utilizing modern techniques with concentration on assessing public health issues become a hot topic in academic (Gimms et al. 2008, Zhou et al. 2011). Air quality concerns have been raised according to the degree of land cover change coupled with consequences from anthropogenic influences (Kinney 2008, Yuan 2008, Jacob et al. 2009).

Florida is experiencing a massive land cover and land use change during the twentieth century (Marshall et al. 2004). From 2000 to 2010, there was a 17.6 percent increase of Florida's population (US Census Bureau, 2011) which is almost double the nation's population increase rate of 9.7 percent. The increased population coupled with an increase in societal demand is a big contributor to agricultural development, land cover change/urbanization and air pollution in Florida (Samet et al. 2000, Solecki and Walker 2001, USGS 2004, Hu et al. 2008, Zanobetti and Schwartz 2009). In general, air pollution contributing factors include emissions from vehicles, industrial facilities, electric utilities like power plants and other combustion sources. All those factors are exaggerated by increased population and land cover change.

Particulate matter (PM) and ground level ozone (O_3) are two of the six common air pollutants that have adverse effects on human and environmental health. Of the six pollutants, particle pollution and ground level ozone are the most widespread health threats (US EPA 2012). Fine particles, or so called $PM_{2.5}$, are defined as particle diameter less than 2.5 micrometers. $PM_{2.5}$ can be directly emitted from sources such as

forest fires, or they can form when gases emitted from power plants, industries and automobiles react in the air (US EPA 2012). Ground level ozone sometimes referred as “bad ozone” is not emitted directly into the air, but is created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC) in the presence of sunlight. Common emission sources of NOx and VOC are from industrial facilities and electric utilities, motor vehicle exhaust, gasoline vapors, and chemical solvents. O_3 pollution is becoming a concern during summer months especially in many urban and suburban areas throughout the United States (US EPA 2012). $PM_{2.5}$ and O_3 have been continued monitored by EPA since 1999 and 1980s, respectively.

In addition, since Florida is characterized by humid tropical climate for a majority state with the southernmost part by tropical savanna climate (NCDC 2011), climate variability also plays an important role in terms of its effects on air quality. According to the previous studies about vegetation and precipitation variability, evidences are found across the state indicating that Florida is a place that having very active interactions between environmental factors and human-induced factors. Therefore, understanding the impacts of land cover change and the relationship between air pollutants becoming an important issue when a lot of complicate factors all contributing to the amount of air pollutants.

Therefore, it is important to understand the relationship between pollutants and their interaction with environmental factors (such as rainfall and temperature) and human-induced factors (such as land cover and land use change) in Florida. In this study, Pearson’s correlation analysis is applied to investigate the relationship between land cover and land use with air pollutants, $PM_{2.5}$ and ground level O_3. A more detailed

correlation analysis on pollutants measurements from different land cover types is also investigated in this study.

4.2 Data and Methods

4.2.1 Particulate Matter ($PM_{2.5}$)

Particulate matter, also known as particle pollution or PM, is a complex mixture of extremely small particles and liquid droplets. Particles that are 10 micrometers in diameter or smaller can pass through the throat and nose and enter human's lungs and affect human health by influencing heart and lungs functions with associated serious health problems (US EPA 2011). People with heart or lungs diseases, children and older adults are the most likely to be affected by particle pollution exposure (US EPA 2011, Brook et al., 2010, Ebi and McGregor 2008, Harrison and Yin, 2000).

As well as PM affecting human health, the environmental effects of PM are also enormous such as reducing visibility, making lakes and streams acidic, changing the nutrient balance in coastal waters, damaging sensitive forests and farm crops, and affecting the diversity of ecosystems (US EPA 2011). Furthermore, air pollution concentrations are the result of interactions among local weather patterns, atmospheric circulation features, wind, topography, human activities (i.e., transport and coal-fired electricity generation), human responses to weather changes (i.e., the onset of cold or warm spells may increase heating and cooling needs and therefore energy needs), and other factors (Ebi and McGregor, 2008).

In order to reduce the impacts of air pollution, the Clean Air Act Amendments, the law that aims to protect and improve the nation's air quality and the stratospheric ozone layer was enacted by Congress in 1990. Under the Clean Air Act, EPA sets and reviews national air quality standards (NAAQS) for wide-spread pollutants like PM (Table 4-1).

Using a nationwide network of monitoring sites, EPA has developed ambient air quality trends for particle pollution. Although average PM concentrations have decreased over the years nationally (US EPA 2011), geographic variations play an important role on public health (Harrison and Yin, 2000).

Daily $PM_{2.5}$ data are derived from US EPA Air Quality System (AQS) and subset to the geographical area of Florida for the year 2001 and 2006. Monitor sites are selected based on its data quantity and quality. Total twenty-four monitor sites are selected for $PM_{2.5}$ data source and $PM_{2.5}$ values are aggregated at monthly basis in order to match with other materials (Figure 4-1).

4.2.2 Ozone (O_3)

Ozone is one of the air quality concerns that have been set as one of six common air pollutants by the United States Environmental Protection Agency (EPA). Ozone can be found in two regions of the Earth's atmosphere – one in the upper regions of the atmosphere called stratosphere and the other one at ground level. Ozone in both layers is containing the same chemical composition (O_3). However, while the upper atmospheric ozone (sometimes referred to as "good ozone") is providing a protection to the Earth from harmful rays from the sun (biologically damaging ultraviolet sunlight), the ground level ozone is the main component of smog and has been referred to as "bad ozone" because the harmful effect to human health. According to the negative health effect, the ground level ozone standards has been set up by EPA guided by the Clean Air Act Amendments since 1997 in order to reduce ozone air pollution and protect human/environment health.

The ground level ozone is created by chemical reactions between oxides of nitrogen (NOx) and volatile organic compounds (VOC). Thus, ozone concentration

elevated on hot sunny days in urban environments and could be transported long distances by wind which means during a hot sunny day ground level ozone are more likely to reach unhealthy levels. Therefore, the ground level ozone is focused in this study and states as ozone (O_3) only.

Very similar to PM, O_3 also affects both sensitive human population and environment. Vegetation and ecosystems including forests, parks, wildlife refuges and wilderness areas experience higher exposure to ozone can have adverse impacts including loss of species diversity and changes to habitat quality and water and nutrient cycles.

Daily O_3 data are derived from US EPA Air Quality System (AQS) and subset to the geographical area of Florida for the year 1996, 2001 and 2006. Monitor sites are selected based on its data quantity and quality. Total twenty-one monitor sites are selected for O_3 data source and ozone values are aggregated at monthly basis in order to match with other materials. The arithmetic mean value and the maximum value of O_3 are extracted for analysis (Figure 4-1).

4.2.3 Normalized Difference Vegetation Index (NDVI)

NDVI is calculated from the visible red waveband (RED) and near-infrared (NIR) waveband reflected by vegetation as equation below (Eidenshink 1992).

$$NDVI = (NIR-RED)/(NIR+RED)$$

This relatively simple algorithm produces output values in the range of -1.0 to 1.0. Increasing positive NDVI values indicate increasing amounts of healthy green vegetation. NDVI values near zero and decreasing negative values indicate non-vegetated features such as barren surfaces (rock and soil) and water, snow, ice, and clouds (USGS 2010).

The Global Inventory Monitoring and Modeling System (GIMMS) group Normalized Difference Vegetation Index (NDVI) dataset was used in this study. The GIMMS dataset is a NDVI product available for a 25 year period spanning from 1981 to 2006 with its spatial resolution 8 km. The dataset is derived from imagery obtained from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the NOAA satellite series 7, 9, 11, 14, 16 and 17. The GIMMS data set has been corrected for calibration, view geometry, volcanic aerosols, and other effects not related to vegetation change. The GIMMS data set is composited at a 15-day time step. For each month, the first composite is the maximum value composite from the first 15 days of the month and the second is from days 16 through the end of the month. For each month, the highest NDVI value composite is chosen as the NDVI for the month because it represents the maximum NDVI value for the month.

The monthly NDVI value are extracted for Florida for the year 1996, 2001 and 2006 based on the locations of $PM_{2.5}$ and ozone monitor sites.

4.2.4 Precipitation and Maximum Temperature Data

Precipitation and Maximum Temperature data were gathered from the PRISM Climate Group, Oregon State University. PRISM stands for parameter-elevation regression on independent slopes model, which is a climate mapping system developed by Dr. Christopher Daly, PRISM climate group director. The PRISM model allows for the incorporation of expert knowledge about the climate and can be particularly useful when data points are sparse. With this method, one can explicitly account for the effects of coastal influences, terrain barriers, temperature inversions, and other factors on spatial climatic patterns (Daly et al. 2002). PRISM data sets are recognized world-wide as some of the highest-quality spatial data sets currently available (Hijmans et al. 2005,

Hamann and Wang 2005, Wang et al. 2006, Daly 2006, Loarie et al. 2009) and is the USDA's official climatological data. Monthly precipitation and maximum temperature data were downloaded from the PRISM website and extracted for each monitor sites for the year 1996, 2001, and 2006.

4.2.5 NOAA CCAP Land Cover Classification Data

Florida land cover classification data are available from the Coastal Change Analysis Program (C-CAP) developed by the National Oceanic and Atmospheric Administration (NOAA) with collaborations of the Department of Commerce (DOC), National Ocean Service (NOS) and NOAA Coastal Services Center (CSC). Current production of the Coastal Change Analysis Program (C-CAP) land cover datasets is accomplished through closely coordinated efforts with the U.S. Geological Survey (USGS) as it produces the National Land Cover Dataset (NLCD).

C-CAP data are developed, primarily, from Landsat Thematic Mapper (TM) satellite imagery. The smallest feature size (spatial resolution) that can be mapped is 30 meter pixels (1/4 acres) on the ground. Current C-CAP datasets are available for Florida in the years 1996, 2001, and 2006 by 23 classes. For this study, the original 23 classes are kept in order to analysis the relationship between pollutants with more detailed land cover and land use.

Additionally, 1 km and 5 km buffers are created for each $PM_{2.5}$ and ozone monitor sites. The percentages of developed land area (four levels of developed intensity, Table 3-2 and Figure 4-2) within each buffer are recorded in order to analysis the relationship between pollutants and monitor site's surrounding area.

According to Xian and Crane (2005), a strong relationship has been found between impervious surface area (ISA) and urban land use. ISA is usually defined as

roofs, roads, parking lots, driveways, and sidewalks (Xian 2007), thus this study proposed that the developed land classification of NOAA CCAP land cover classification dataset can be considered as a substitute variable to represent ISA. More specifically, based on the classification scheme, the developed high intensity class has constructed materials account for 80 to 100 percent of the total cover, so the level of ISA is the highest among other developed land cover classes. The medium intensity class has constructed materials account for 50 to 79 percent of the total cover, so it can be considered as the second highest ISA level. The low intensity class has constructed materials account for 21 to 49 percent of the total cover, so it can be considered as the third highest ISA level. The open space has constructed materials account for less than 20 percent of the total cover, so it is the lowest ISA among others.

4.2.6 The Person's Correlation Analysis

The Person's correlation analysis is applied to analysis relationship between land cover and land use on air quality. First of all, the relationship between air pollutants ($PM_{2.5}$ and O_3) with NDVI, rain, and maximum temperature are examined. Then $PM_{2.5}$ and O_3 monitor sites are categorized by their land cover type in order to evaluate land cover and land use influences on air pollutant variation. In this step, the percentages of developed land area within 1 km and 5 km buffers are included. Theoretically, the pollutants sources of $PM_{2.5}$ and O_3 include emissions from vehicles, industrial facilities, electric utilities like power plants and other combustion sources. This study propose a hypothesis that surrounding areas that contain more constructed areas (higher percentage) may have a higher chance to contribute air pollutants. Additionally, the timing of the year may have a function in terms of pollutants concentration and the

interaction between pollutants with climate variables. Therefore, all the variables are organized again in order to investigate the relationship by month.

4.3 Results and Discussion

Figure 4-3 presents the results from the Pearson's correlation analysis for $PM_{2.5}$, O_3 (arithmetic mean and maximum) with NDVI, rain, and maximum temperature. Significant statistical negative correlations are found between $PM_{2.5}$ with rain and O_3 with rain. From many literatures (Querol et al. 2001, Pillai et al. 2002, Hien et al. 2002, Latha and Badarinath 2005), it is reasonable to expect a removal process like washout and rainout. The relationship between NDVI with $PM_{2.5}$ and O_3-arithmetic mean are not significant related. However, O_3-maximum is found significantly positively related to NDVI and maximum temperature. Maximum temperature is found significantly positive related to O_3-max which can be explained by O_3 concentration are more likely to increase during a hot sunny day due to its active photochemical reaction.

Figure 4-4 shows categorized monitor site by land cover type and their relationship with NDVI, rain and maximum temperature. Rainfall again is found significantly negative related to almost all $PM_{2.5}$ and O_3 monitor sites' concentration. The relationship between NDVI and pollutants are more fluctuated by the land cover classes of the monitor sites.

For monitor sites located in developed high intensity location (Figure 4-5), NDVIs are found to be negative related to pollutants which can be interpret that the higher the NDVI the lower the pollutant concentration ($PM_{2.5}$ and O_3-arithemetic mean). For monitor sites located in developed medium intensity location, NDVIs are found to be positive and significant related to pollutants concentration ($PM_{2.5}$ and O_3-arithmetic mean). This could be understandable if in this particular land cover, there are a lot of

contributions sources like electric facilities or vehicles emissions level are elevated through commute. For monitor sites located in developed low intensity location, NDVIs are found to be negative related to pollutants but not significant. This could be reasonable to assume that in this low intensity area; it is commonly includes single-family housing areas especially in rural neighborhoods, there are sparse sources that would contribute to air pollution (Figure 4-6 and Figure 4-7).

According to almost monitor site measure $PM_{2.5}$ and O_3 are located in developed land classes (and in different intensity level), the further analysis is focus on the relationship between pollutants with developed land. Additionally, O_3 maximum concentration has shown more clearly relationship with pollutants, so from now on the analysis is concentrate on O_3 maximum instead of O_3 arithmetic mean.

First of all, the relationship of pollutants with NDVI, rain and maximum temperature are examined by simple charts visually. In general, rainfall in all monitor sites located in developed land classes is reaching its maximum during summer time (Jul to Sep) and its minimum during late winter (Mar to Apr). Maximum temperature in all monitor sites reaches its highest during summer time and minimum during winter time. However, NDVI value stay pretty consistent does not matter what time of the year. It can be explained by human maintaining system are mainly controlling the landscape of developed land.

For $PM_{2.5}$, the concentration reaches its highest point in May with minimum during late fall (Oct-Dec). For O_3-max, the concentration reaches its highest point in May and minimum in Nov to Feb. A seasonal variation can be expected since the weather obviously influences the pollutants. Variation can also been seen between observations

years for pollutants, it can be assume that regional and local weather patterns, as well as anthropogenic sources, play a significant role to pollutants' concentration.

Seasonal variation can be found from the monthly correlation analysis (Figure 4-7). For the overall $PM_{2.5}$ (including all land cover classes), rainfall has been shown a constant negative correlation with pollutants with a stronger correlation in May and Sep. Maximum temperature appears to be negative correlated with pollutants from Aug to Feb and positive from May to July. It could be considered that during May to July, the temperature is generally higher and the usage of air conditions is expected to be higher. As a result, the more the air conditions' usage, the more demands on electricity, then the higher chance for power plant to generate more contribution to $PM_{2.5}$.

For O_3, the relationship with meteorological parameters, rain and maximum temperature are more complex to explain. However, there are more significant positive correlation be found In O_3-max with maximum temperature which can be understandable from its photochemical process relationship.

Figure 4-8 represents the relationship between pollutants and monitor site's buffer area. As a result, rainfall has shown a significant negative relationship with pollutants. The high intensity land cover has negative relationship with pollutants at 5 km buffer but not 1 km buffer (weak positive correlation). The medium intensity land cover has presented a constant negative relationship with pollutants in both 1 km and 5km buffer. The low intensity land cover has shown a positive correlation with $PM_{2.5}$ and O_3-arithmetic but negative correlation with O_3-max. The open space land cover holds consistent positive correlation with pollutants. Figure 4-8 represents the correlation coefficients of pollutants with the percentage developed lands cover (different

intensities) within 1 km and 5 km buffers. The single star indicates correlation is significant at the 0.05 level (2-tailed) and double stars indicate correlation is significant at the 0.01 level (2-tailed).

4.4 Summary and Finding

The analyses of patterns and results reveal that air pollutants levels in Florida exhibit strong seasonal variations. However, NDVI with pollutants cannot be found a strong correlation in this study. Couple possible reasons including the limitation of monitor site's location are mainly concentrated in urban area is responsible for the failure of establish relationship. Additionally, the data quality is another issue with air pollutants monitor system. From the process of data collection, a significant amount of missing data situation is been found constraining the further investigation. Furthermore, the spatial resolution of GIMMS AVHRR NDVI and CCAP land cover classification data are much coarser than the point observation of air pollutants monitor sites. It could be also an issue of lacking more detailed local information due to its pixel size.

In this study, an inverse relationship between rainfall and pollutants-$PM_{2.5}$ and O_3 are found. It provides strong evidences that weather conditions play an important role in ambient air quality regardless land cover types. However, future study and further investigation are needed in order to understand the pollutants spatial pattern and what are the spatial variations of the relationship between pollutants with environment conditions.

Table 4-1. National ambient air quality standards (NAAQS) (source: EPA. (2011). National ambient air quality standard. from http://www.epa.gov/air/criteria.html)

	Primary Standards		Secondary Standards	
Pollutant	Level	Averaging Time	Level	Averaging Time
Particulate Matter ($PM_{2.5}$)	15.0 µg/m3	Annual (Arithmetic Average)	Same as Primary	
	35 µg/m3	24-hour	Same as Primary	
Ozone (O_3)	0.075 ppm	8-hour	Same as Primary	

Figure 4-1. Florida air monitor site location for particulate matter ($PM_{2.5}$)and ozone (O_3) with climate division boundary embedded

Figure 4-2. Florida air monitor site location for particulate matter ($PM_{2.5}$)and ozone (O_3) that locate in developed land use category

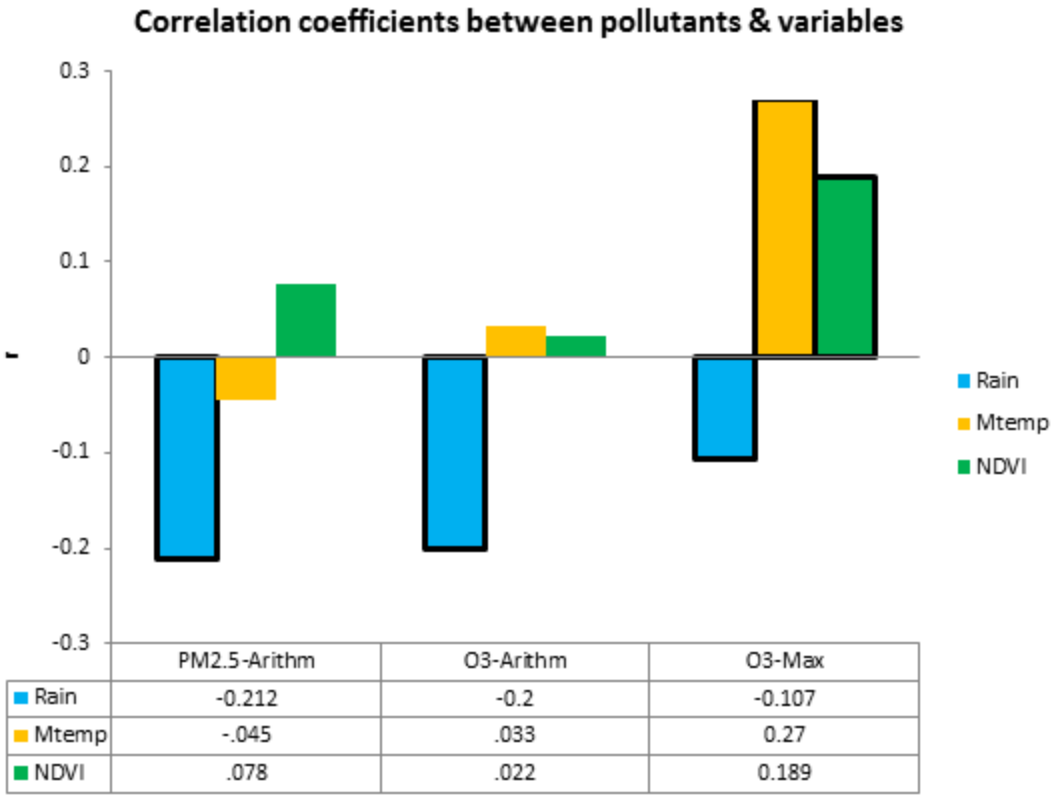


Figure 4-3. The correlation coefficients between $PM_{2.5}$ and O_3 with rain, maximum temperature and NDVI for all monitor sites. Bar with solid black boundary indicates the correlation is significant at the 0.01 level (2-tailed)

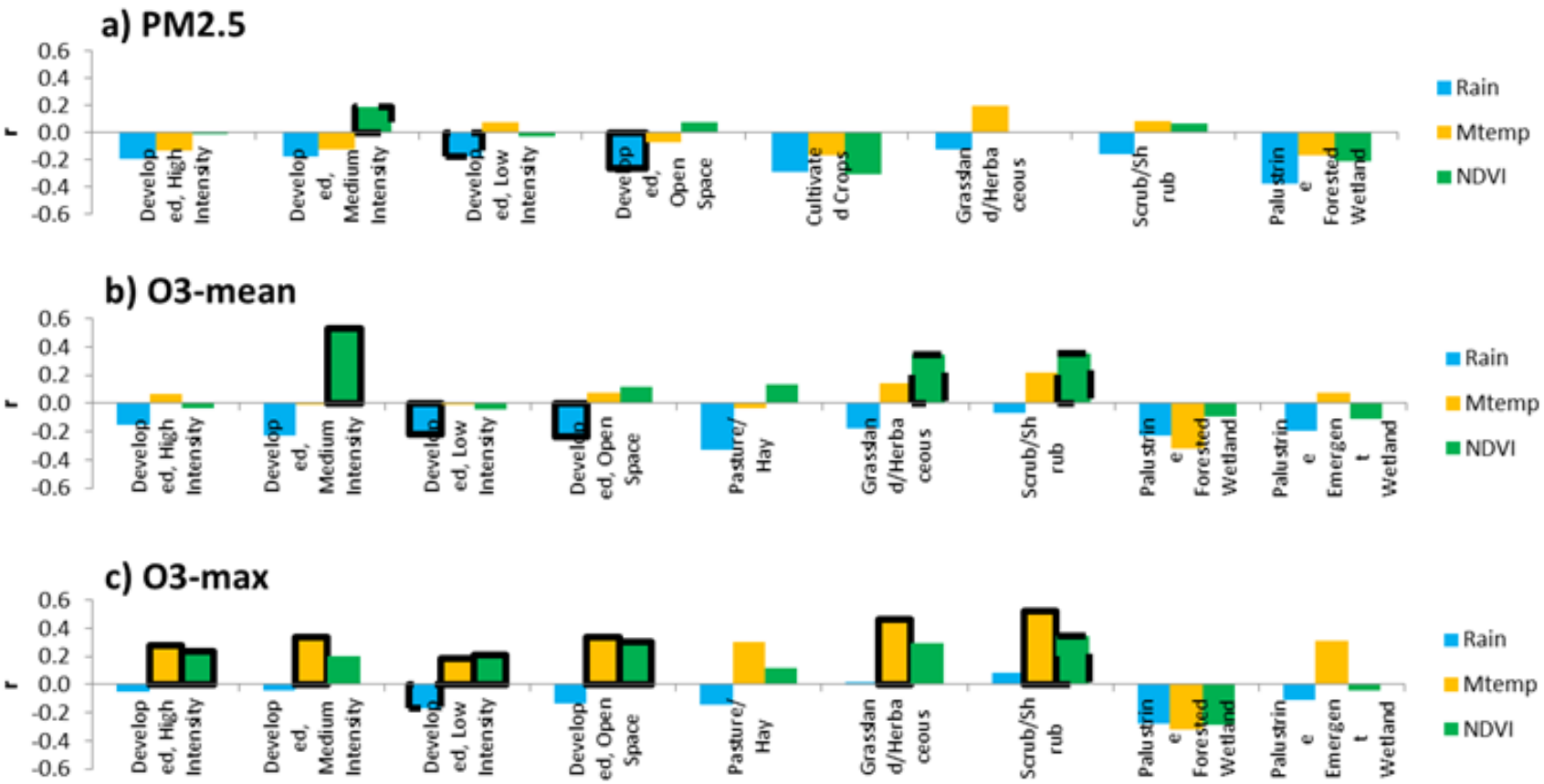


Figure 4-4. The correlation coefficients between a) $PM_{2.5}$, b) O_3 mean and c) O_3 maximum with rain, maximum temperature and NDVI for all monitor sites by land cover types. Bar with solid black boundary indicates the correlation is significant at the 0.01 level (2-tailed). Bar with dashed black boundary indicates the correlation is significant at the 0.05 level (2-tailed)

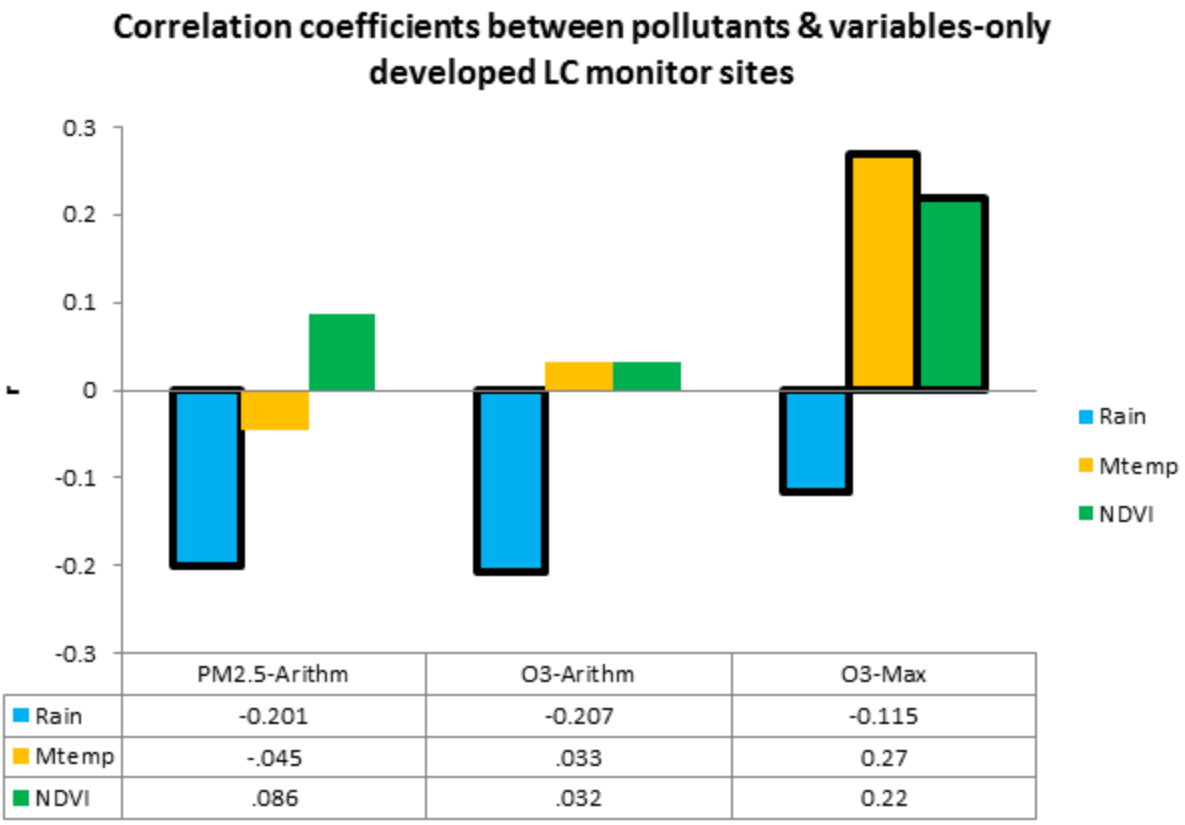


Figure 4-5. The correlation coefficients between $PM_{2.5}$ and O_3 with rain, maximum temperature and NDVI for all monitor sites. Bar with solid black boundary indicates the correlation is significant at the 0.01 level (2-tailed)

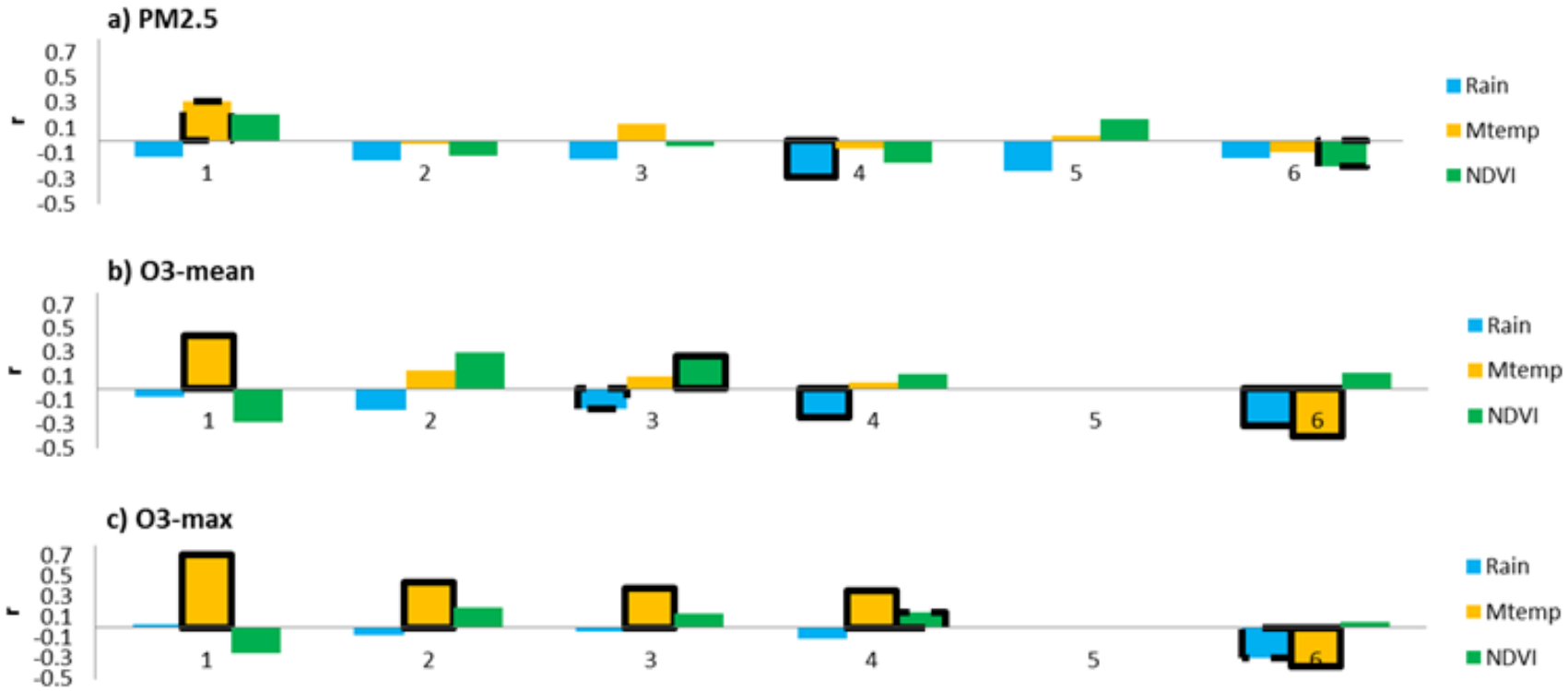


Figure 4-6. The correlation coefficients between $PM_{2.5}$ and O_3 with rain, maximum temperature and NDVI for all monitor sites by climate divisions. Bar with solid black boundary indicates the correlation is significant at the 0.01 level (2-tailed). Bar with dashed black boundary indicates the correlation is significant at the 0.05 level (2-taile)

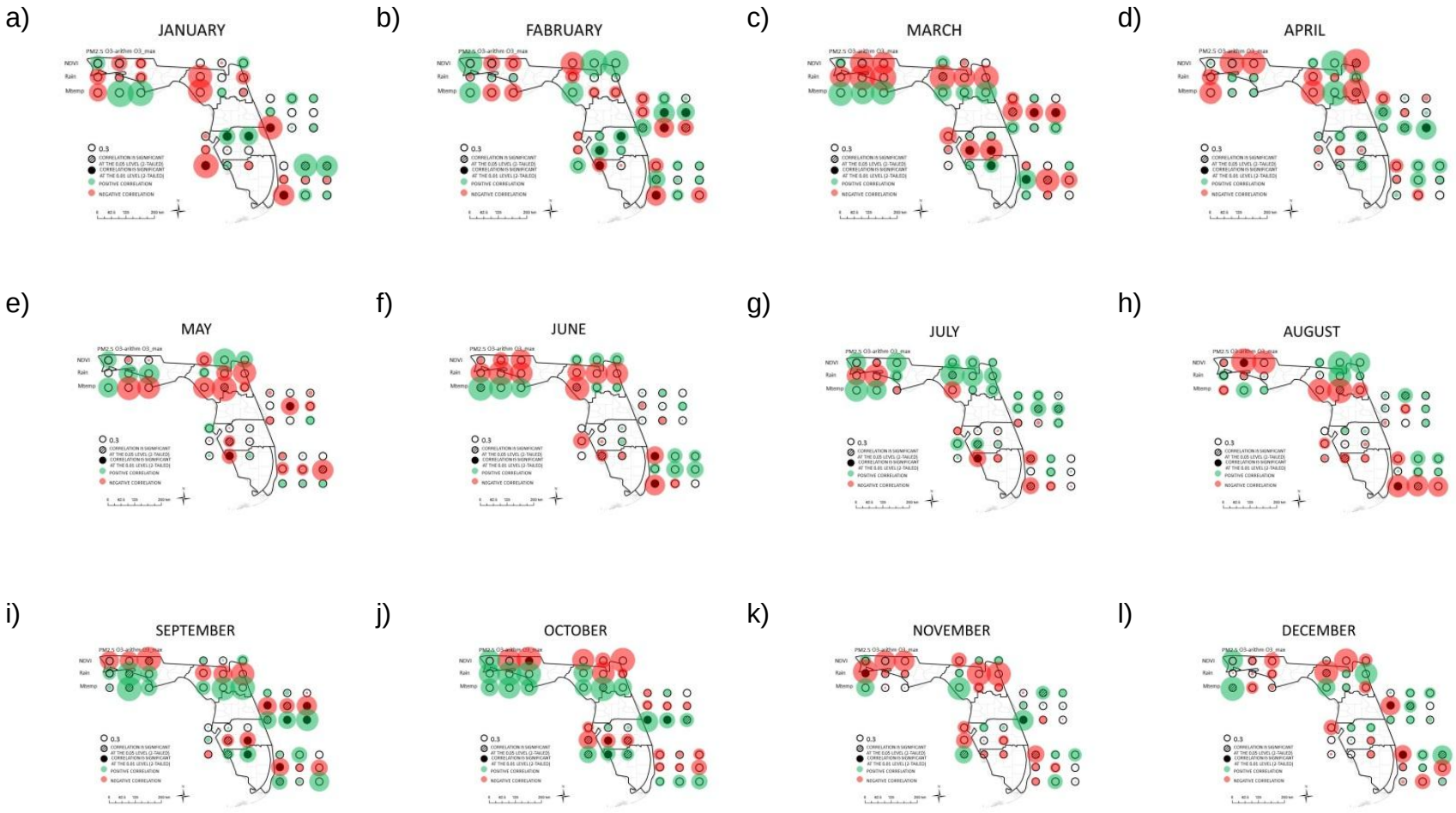
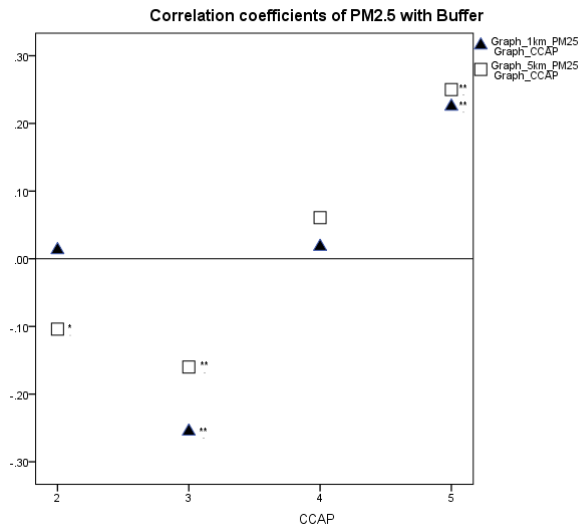
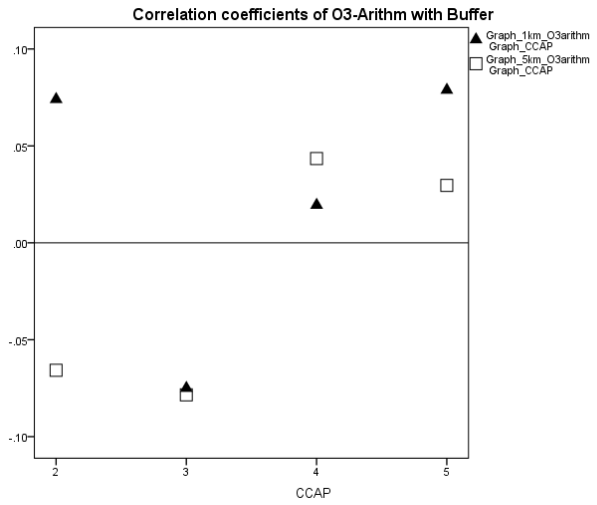


Figure 4-7. Seasonal variation of the correlation coefficient by climate divisions. a) to l) represents January to December. The size of black hollow circle represents the correlation coefficient equals 0.3. The circle with upward diagonal indicate the correlation is significant at the 0.05 level (2-tailed) and the solid black circle indicate the correlation is significant at the 0.01 level (2-tailed). Green color circle represents positive correlation and red color circle represents negative correlation

a)



b)



c)

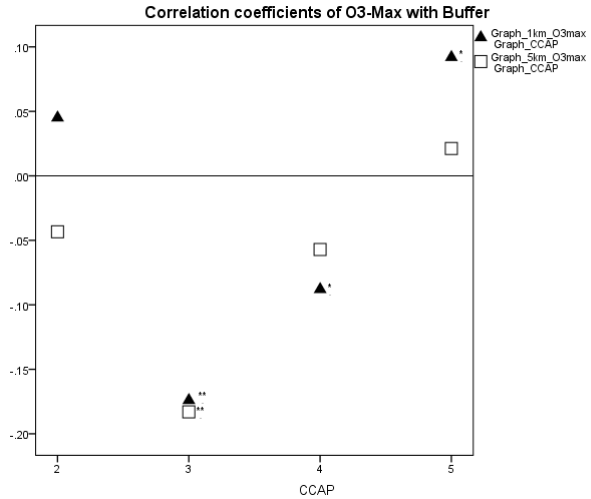


Figure 4-8. Correlation coefficients of pollutants with Buffer. a) $PM_{2.5}$ b) O_3 mean and c) O_3 maximum

CHAPTER 5
CONCLUSION

The overarching object of this present dissertation is to evaluate the overall vegetation trend/change; land cover and land use change and health impacts especially on air pollution in Florida from 1982 to 2006. Numerous evidences have been pointed out that Florida is experiencing big challenges such as the effects of global climate change and anthropogenic activities (Mulholland et al. 1997, Esterling et al. 2000, Pielke et al. 2005, USGCRP 2009). According to that, an overall evaluation of the environmental changes including vegetation trend, land cover and land use, and associated impacts on air pollution is needed for Florida.

First of all, by using the Normalized Difference Vegetation Index (NDVI) as vegetation representation, a time-series approach is applied in order to assess vegetation dynamics across the state from 1982-2006. We argue that there is an increasing NDVI value during winter months from 1995 onward and this phenomenon could be explained by the Atlantic Multidecadal Oscillation (AMO) switched into its warm phase around 1995. This result also corresponding with an increased winter rainfall proportion has been found from a previous study.

In addition, the response of vegetation to climate variability and land cover is investigated with remote sensing based land cover classification data. From the wavelet analysis result, it provide evidence that the NDVI responds to precipitation is found to be stronger in natural land cover like estuarine wetlands than in human manipulated land cover such as developed land.

Moreover, the impact of land cover and land use on air pollution is evaluated. The results point out there are seasonal variations exist in air pollution. However, air

pollution is found highly correlated to weather conditions especially an inverse relationship with precipitation.

Future research opportunities are plenty based on the findings from this dissertation. This dissertation recommends that since modern remote sensing satellites like MODIS (start at 2000) provides a better spatial resolution than AVHRR; it could be beneficial to use a finer spatial scaled data when the records are sufficient to support a long term investigation. Areas that have been identified having extreme increasing/decreasing NDVI can be another interesting research topic if considering its associated land cover change over time. Additionally, air pollution assessment can be improved if the monitored data can be gathered at low cost in the place of interest or the analysis could apply the other satellite-based air pollutants information.

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BIOGRAPHICAL SKETCH

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