Spatio-Temporal Analysis of Wildfire Incidence in the State of Florida

by

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Dedication

I dedicate this thesis to my family, without whom I would not have gotten through the past two years. I especially dedicate this to my father, who listened to me and coached me through all the steps.

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Abstract

Wildfire is a growing problem in the United States that lends itself well to spatial analysis for those seeking to minimize human and environmental damages. This thesis analyzed spatio-temporal trends of wildfire in the state of Florida between the years of 1985–2014 and analyzed ecological and human demographic variables in relation to wildfire ignitions. Human population numbers, population growth, precipitation, and temperature affect the spatial distribution of wildfire. These changes can modify fire regimes in many areas, though the direction and extent of this influence is not fully understood. This research used correlation analysis to study the components of wildfire ignitions, separated into human and natural caused fires, visualized fire locations, and examined fire ignition hot spots in relation to the causes. It is hypothesized that population growth and population numbers positively influence the number of human caused wildfire ignitions, while high temperatures and low precipitation increase lightning caused fires. To create spatio-temporal maps and conduct the analysis, data on wildfire points, population counts, precipitation, and temperature were gathered and analyzed. Spatial analysis (e.g., Hot Spot Analysis (Getis-Ord Gi* statistic)) and non-spatial statistics (e.g., Pearson's correlation) were used to analyze statistically significant clustering of wildfire incidence. This thesis also used historical data to better recognize trends in wildfire occurrence and distribution. Wildfire management groups, already dealing with large fires every year, can use this information to become better prepared for future changes in wildfire incidences. The analysis revealed no significant correlations between the study variables and wildfire incidence. However, the research did reveal that there is significant clustering of wildfire ignitions due to human activity and lightning strikes.

Chapter 1: Introduction

Wildfire is a growing problem in the United States as climate change and land use changes affect fire regimes in many areas. Every year, wildfires cause devastation and costs millions in damages with no reprieve in sight. The State of Florida has many naturally fire-dependent ecosystems, yet increases in population and incursions by development into wildfire prone areas have created many population centers at high risk of devastating wildfire. Therefore, pinpointing the variables that can lead to understanding wildfire ignition and spread is important to minimize the risk to life and property as climate and land use change.

Correlation analyses, hot spot analyses, and an analysis of directional distribution trends of wildfires in Florida were the main analytical and Geographic Information System (GIS) components of this thesis. They were chosen because they allow for statistical analysis as well as cartographic visualization of the areas where wildfire has clustered around the state. Additionally, analysis found correlations between biotic and abiotic variables such as precipitation, temperature, population counts, population growth, and human and/or naturally caused fires. Analysis answered the question of whether lightning caused fires spatially and statistically correlated to periods of low precipitation and high temperatures; and if human caused fires positively correlated to absolute population numbers and population growth. To fully investigate the influence of these variables, lightning caused fires were compared to population and population growth, and human caused fires were analyzed against precipitation and temperature. Human caused wildfire ignitions were also compared spatially to nighttime lights data to see if hot spots cluster near population centers. To study the temporal changes in wildfire occurrence, an emerging hot spot analysis was also utilized across every year of the study. Finally, a directional distribution trend was calculated to see if wildfire trends are changing over time. Together, these study methods provided a clearer picture of when and where wildfires are occurring over the multi-decade (1985–2014) study period. For visualization purposes, the final year block (2010–2014) of human caused fires was overlaid with Visible Infrared Imaging Radiometer Suite (VIIRS) Nighttime Light Data from 2012. This satellite imagery captures light visible from space, indicating locations of human habitation and relative density. The VIIRS satellites also collect high quality radiometric data for digital analysis by detecting anthropogenic lightning present at the earth's surface (Elvidge et al. 2013). As VIIRS data offered many different spectral bands suitable for discrimination of different sources of light emissions, it is particularly suited for studying human night light activity. Such activity data provided strong visual clues of where humans cluster in relation to wildfire ignition. Importantly, recognizing why and where fire occurs is necessary as wildfire management is becoming an ever-growing task for both private and public entities across Florida.

1.1 Historical & Current Wildfire Policy

One major reason why wildfire is a growing problem in many parts of the United States is because of decades of fire suppression. For example, in the early 1900s, federal wildfire policy established wildfire suppression as a tool to protect natural resources from fire. This policy choice failed to focus attention on proper fuel management, thereby creating a self-defeating policy (Busenberg 2004). Because of the lack of proper fuel management, fuels like dry brush and refuse gradually accumulated over many decades in many regions of the U.S., like California and the Southeast in general, and when ignited, created massive, high intensity fires that continue to cause lasting damage (Busenberg 2004). This poor historical policy planning, coupled with today's issues of climate change, land use changes, and population growth have created the devastating fires now seen every year.

As human development continues to push into undeveloped areas, wildfire has the potential to become more common and costly. Many studies show that humans cause a majority of wildfires across the United States and the world (Romero-Calcerrada et al. 2008; Teeter 2008; Reams et al. 2005). This is especially seen within national and state forests as studies have shown a consistent trend in poorly extinguished campfires causing wildfires (Reid & Marion 2005; Cole & Dalle-Molle 1982; Prestemon et al. 2010). As humans expand further into regions long without natural fire events, fire management budgets will continue to be stretched to the brink.

As human beings continue to cause wildfires, current policy has shifted away from previous thinking; fire is now seen as an integral and important component of many ecosystems. Within the state of Florida, wildfire managers like the Florida Forest Service (FFS) and many other private forestry organizations have devised strategic plans relating to prescribed burns and their benefits. Efforts have been made to push lawmakers to recognize the importance of prescribed burning and ensure that regulations strike a balance between, for example, mitigating smoke and driver visibility concerns (Prescribed Fire in Florida, Strategic Plan 2013–2020) and ensuring enough area is control burned to prevent larger fires. Prescribed fire is now viewed as a top priority for land managers, and science-based education, training, and investment in prescribed burn procedures are being pushed to create both professional practices and healthy ecosystems.

1.2 Florida Ecosystem

Most U.S. wildfire research studies are focused on the western half of the United States, where wildfire is especially common. This focus can easily mislead a person into thinking that wildfire is not prevalent in the rest of the country. The southeast has the second highest ranking for fire activity behind the west, though the region receives little specific academic study (Flannigan, Stocks, and Wotton 2000). In particular, wildfire in Florida is a normal occurrence. This may seem surprising, as California garners the lion's share of news and funding for wildfire management. But Florida, a very densely forested state, often ranks right behind California in the number of wildfires every year, even though it is not even half as large in total area (65,755 mi^2 to California's 163, 696 mi^2).

Florida's ecosystem supports a fire regime that is characterized by frequent, low severity fires that burn the understory, but rarely the canopy, when allowed to burn via natural means and not altered by human activity (Prescribed Fire in Florida, Strategic Plan 2013–2020). The state is covered in predominately longleaf pine, a fire-adapted tree that, when in large numbers, produces an open understory that allows for the buildup of many different species of shade tolerant plants. If left unattended too long, this understory can grow extensively and when burned, it can create devastating fires that damage the ecosystem, human life, and property (Prescribed Fire in Florida, Strategic Plan 2013–2020). Figure 1 is a map of Florida with the various vegetation types across the state.

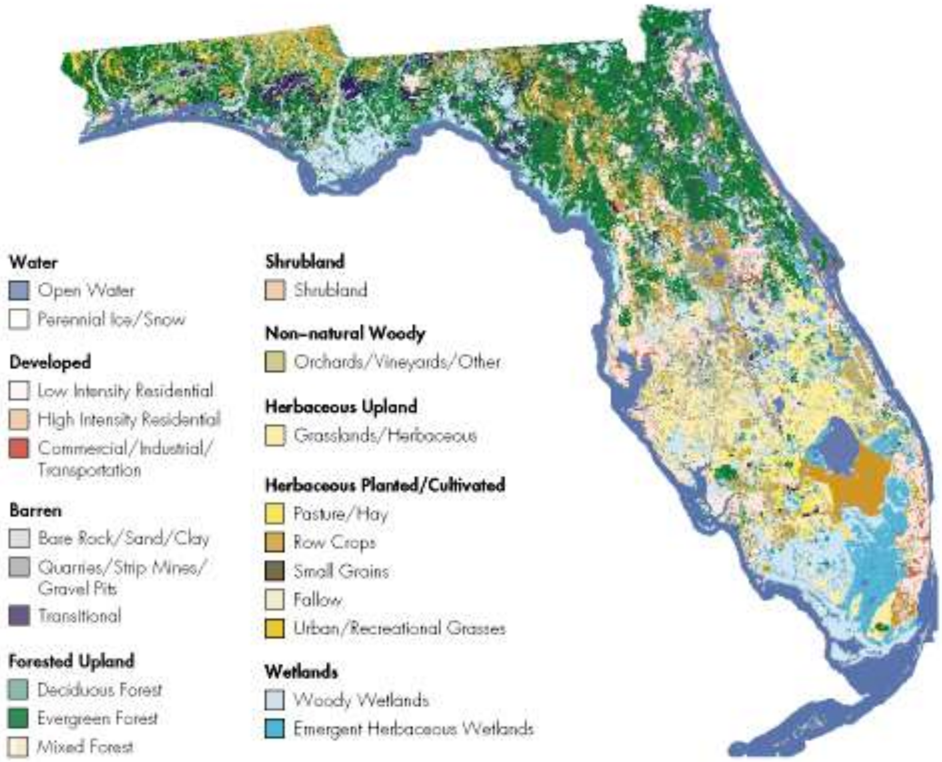

Figure 1 Map of Florida Land Cover. Source USGS.gov

Forest areas are increasingly becoming more fragmented as humans move into and develop wild areas. In addition, as population grows in Florida (now the third most populous state), regions called Wildland-Urban Interfaces (WUI) are becoming more common. These regions are transition zones between undeveloped land and human occupied regions and are rife with wildfire issues. While the scale of wildfire in the southeastern U.S. and Florida is unlikely to ever reach the scale of fire in the West, growing population and land use changes require the alteration of approaches to how, when, and where to apply prescribed burns and how to reduce the threat of wildfire.

As population continues to grow and climate changes looms ahead, it is imperative that we understand the spatio-temporal drivers of wildfire. Because many changes are highly dependent upon location due to a combination of human development and the local ecological factors, there is a continuing need to focus research on a state level to provide the most accurate data for economic and environmental groups that are planning for the future. Therefore, research of this kind inherently requires analysis of earth surface processes and interconnected spatial relationships. Analyzing the spatial pattern of wildfires in the state could yield valuable insights into how fires are being ignited, if they are spatially clustered, and what steps can be taken to minimize damages.

1.3 Fire Science

Fire science focuses on many different factors that influence wildland fire, that include fire ecology and risk management. Since Florida is heavily wooded, understanding the spatio-temporal trends of fire incidence is important for natural resource management, urban planning, and disaster relief planning. As population growth continues to rise and meteorological variables change drastically, wildfire has the potential to grow as a threat to natural ecosystems and human safety.

Fire ecology is concerned with natural processes of wildfire, its ecological effects on the environment, interactions between biotic and abiotic variables, and the role of fire within an ecosystem (DellaSala & Hanson 2015). It also covers the effects of wildfire suppression and fire as a management tool. Wildfire can significantly alter the biotic and abiotic components of an ecosystem by reducing vegetation, which in turn can change soil chemistry and fertility. Changing soil chemistry and fertility can cause alterations in the plant communities within the area, which in turn can affect wildfire susceptibility. The suppression of wildfire has historically caused unforeseen changes in ecosystems that have adversely affected plant, animal, and human communities (Minnich 1983; Keeley et al. 2005; McCollough et al. 1998; Savage and Mast 2005). For example, because plant communities are adapted to specific fire regime conditions, wildfire suppression has often augmented new selective pressures that favor non-native species that exploit the different conditions and eventually replace native species (Keeley et al. 2005).

Wildfire is also studied as a management tool. Controlled burns are often used as part of restoration and management techniques to reverse or minimize changes caused to the environment by human activities (DellaSala &Hanson 2015). While these burns are used to replicate natural fires, suppress invasive species, and restore native habitats (DellaSala &Hanson 2015), much debate over the 'level' of restoration exists. Managers must decide whether restoration means returning lands to pre-human or pre-European ecosystems, for example.

1.4 Wildland-Urban Interface

The Wildland-Urban Interface is an area of much research and analysis for scientists, land managers, and public policy makers (Bosworth 2004). As this area is the mixing of undeveloped and developed land, it is often rife with wildfire issues. The majority of the interface occurs on private land as well (Theobold and Romme 2007). In addition, this interface pattern has raised many concerns among those who oversee natural resources and forestland, as it complicates management practices and threatens the sustainability of national forests (Bosworth 2004). Urban extent is also expected to increase, from 3.1% to 8.1%, by 2050 (Nowak and Walton 2005). Therefore, understanding the fire regime types that occur in the WUI is important so that management practices can focus on both human and ecological safety inside zones.

Florida's WUI, which encompasses more than 11,000 square kilometers, is predominately characterized (75.1%) by 'high' (variable) vegetation types (Theobold and Romme 2007), which are very susceptible to wildfire. The historical fire regime before human intervention consisted of ‘low’ or ‘mixed’ severity vegetation types, which are less vulnerable to wildfires. Treatment of the high variable vegetation via thinning or low intensity prescribed burns can reduce fire hazards and restore historical forest structures back to low or mixed vegetation types (Theobold and Romme 2007).

1.5 Thesis Organization

Chapter 1 – Introduction – This chapter provides background context, an overview of the methodology, and justification for the research.

Chapter 2 – Literature Review – This chapter introduces an overview of literature related the analysis of different types of variables used in wildfire studies, the use of different research methodologies, and the use of surveys as data gathering.

Chapter 3 – Methodology – This chapter is a description of the data sets, methods and tools used to perform the analysis. The different statistical methods are introduced and the steps taken are provided in detail.

Chapter 4 – Results - This chapter presents the results of the data analysis.

Chapter 5 – Discussion - Analysis of the data provided in the results is provided in this chapter, as well as further discussion of limitations and future work.

Chapter 2: Literature Review

There are a few trends in research approaches and methodologies in the spatial and temporal study of wildfire. From analyzing causal relationships between variables to analysis of different statistical techniques, the methods of understanding the patterns of wildfire have a few recurring themes and these themes are reviewed in this section and some methods are applied further in this research.

Specifically, wildfire is studied around the world using certain relevant variables and methods. From the social and economic impacts, to meteorological effects, to their clustering patterns, wildfire variables are varied and expansive. In addition, researchers apply an assortment of research designs to include cluster analysis, surveys, and correlation methods. This review investigates the different types of variables used in the three most common research designs.

2.1 Wildfire Variables

Three major themes seen in wildfire analysis come in the form of socioeconomic variables, critical meteorological factors, and pertinent point data which are used as a means of assessing causal relationships concerning the structure and intensity of wildfire clustering. While the methodologies utilized in each study are slightly different, the variables utilized in the following reviewed studies fall into one of the three categories above. For example, socioeconomic variables like population, access to natural areas, income, age of structures, education, and employment are commonly examined. In addition, meteorological variables like precipitation, humidity, and temperature are often analyzed in wildfire studies. Point data variables focus almost exclusively on geospatial locations of wildfires. The review of research studies did reveal that socioeconomic variables were more commonly analyzed than either meteorological or point data variables.

For example, in two studies, one by Asgary, Ghaffari, and Levy (2010), and another by Corcoran et al. (2007), the spatial and temporal patterns of structure fires, which often share similar causation factors with wildfires, are investigated in Toronto, Canada, and South Wales, England respectively. The researchers aim to analyze the various causes of structure fire to determine the extent to which these data can be used as a baseline to improve fire prevention activities. By using kernel density estimation and average nearest neighbor analysis of fire events in different neighborhoods in Toronto, Asgary and colleagues find that structure fire is more common on late night weekends during the spring. In addition, they determine fire to be spatially clustered in downtown areas, along major streets, and in lower income regions. This result is similar to the findings of Corcoran et al. (2007), which argue that more affluent areas see less fire and denser regions experience more fire. These results allow fire prevention officials to focus on certain times of the day and the year within specific urban areas. Areas that are spatially more likely to have repeat fires can be focused on for both education and preventative purposes. While both papers focus on structural fires, the types of independent variables employed in the studies of structure fire have direct relevance to the study of human caused wildfire ignitions, as factors like income, employment, and others also contribute to wildfire ignition.

Socioeconomic variables can also be used to analyze wildfire along with structure fire. Feltman et al. (2012), use a geospatial approach to identify socioeconomic variables that contribute to wildfire occurrence in South Carolina. By using a hot spot analysis, the researchers create buffer zones around each fire incident and convert each feature into a weighted class. The results of the hot spot analysis reveal that the lower half of the state has more intense days of wildfire events. That region is found to be more agricultural than upper South Carolina. Additionally, high poverty rates, low education attainment, and low road densities are significant variables in predicting wildfire.

Romero-Calcerrada et al. (2008) study the socioeconomic causal factors of wildfire in the southwest of Madrid, Spain. By using the Bayesian statistic instead of a hot spot analysis, different socioeconomic variables are integrated with conditional probabilities to determine the relative importance of each variable on wildfire occurrence. The researchers also investigate spatial association between the socioeconomic variables and wildfire occurrence and create evidence maps for further study. Results from this analysis show that spatial patterns of wildfire are strongly associated with human access to nature. Unlike Feltman's (2012) team, who contend low road densities are a wildfire predictor, Romero-Calcerrada et al. (2008) assert that proximity to roads and urban areas intermixed with wild areas significantly impact wildfire clustering.

These studies reveal the extreme impact of socioeconomic factors on wildfire ignition in comparison to meteorological or point data variables, and that causation factors can be unique to human settlements. By studying many different socioeconomic variables in combination, the complex cauldron of ignition causation can be teased out so that first responders to both structure and land fires can be better equipped to minimize damages specific to their area, as different variables will influence wildfire ignitions in different regions.

Meteorological and point data variables will be identified and discussed in more detail in the following sections that investigate the most common methods used in wildfire research.

2.2 Cluster Analysis

Using cluster statistics to study wildfire with the use of socioeconomic variables is common. In addition, these straightforward approaches discussed below often use meteorological and point data variables such as aspect, slope, or climate indicators as research variables. The recurring feature of these cluster analysis studies is their reliance on spatial randomness assumptions.

Wing and Long (2015) examine whether patterns exist in the spatial and temporal distribution of large fires in Oregon and Washington over a 25-year period. These patterns and their relationship to climate variables (temperature, precipitation, etc.) are also investigated using GIS methods. The researchers perform an average nearest neighbor analysis and quadrat analysis. A hot spot analysis using the Getis Ord G* statistic and Moran's I are also used to measure the significance of clustering. The Getis Ord G* statistic determines how concentrated low or high values (cold or hot spots) are in a specific study area. This statistic, along with Moran's I, are inferential statistics and the results are analyzed within the context of a null hypothesis. Moran's I is a spatial autocorrelation measure that helps determine whether clustering or dispersion are due to random chance or because of spatial processes at work. Wing and Long's (2015) results indicate an increasing trend in fire frequency, extent, magnitude, and fire season duration over a 25-year period. In contrast to this paper's use of meteorological variables, all of the following papers compare analytical techniques to find the most accurate and realistic portrayal of wildfire clustering using only point data variables.

Spatio-temporal wildfire clustering examines the assumption of constant intensity within each fire. Hering, Bell, and Genton (2009) reanalyzed wildfire data from the St. Johns River Water Management District in northeastern Florida with an inhomogeneous version of a homogenous K-function. A homogenous K-function is a statistical tool for detecting aberrations from spatial homogeneousness. Whereas homogenous functions examine *y*, the dependent variable, inhomogeneous functions evaluate *x*, the independent variable. Along with an inhomogeneous K-function, a K-cross function is also utilized to detect relationships between points of two different types of wildfire ignitions. Simple models based on meteorological covariates, like humidity and temperature, are created from the K-cross analysis and analyzed with regression models. Once the research is completed, the researchers find that homogenous functions performed in previous studies and the K-cross functions do not realistically represent clustering. The inhomogeneous function, overall, performs better than the other functions at displaying clustering. The models utilized indicate, to a limited degree, some of the characteristics of wildfire occurrence, but more precise models are to be expected from improvements in statistical computing techniques over time.

Statistical analyses of wildfire that use K-functions are used regularly. In a study by Juan, Mateu, and Saez (2012), research is conducted to provide analytical probabilistic models that mimic the reality of wildfires to assist land managers and foresters in Catalonia, Spain. Several different techniques are used and compared. First, a homogeneous Poisson process is used to analyze spatial clustering. The Poisson model used within this study builds confidence intervals based on a corresponding K-function from several simulations under the Poisson assumption of complete spatial randomness. Within the Poisson model, the second technique studied is an inhomogeneous Thomas model that analyzes each year and cause of ignition to better fit the clustering model. This model evaluates the joint effects of covariates. The final test of spatial patterns is seen in the use of the Area-Interaction point process model. This model is chosen because it is a more inclusive spatial model that displays inhomogeneity that considers covariate trends in an infinite number of interactions. All models are then fitted with a Papangelou function to find conditional intensity and create risk maps. Of all the techniques, the

Area-Interaction model is found to best fit the behavior of wildfire for most years and causes.

The fuzzy C-means method is a data clustering technique in which a dataset is grouped into clusters with every point belonging to every cluster to a certain degree. A study by Di Martino and Sessa (2011) compares the accuracy of the fuzzy C-means algorithm against the extended fuzzy C-means (EFCM) algorithm when analyzing wildfire data from Santa Fe, New Mexico. The function begins by guessing the location of cluster centers and assigns membership values to each cluster. Through an iterative process, the function eventually moves cluster centers to a more accurate location within the dataset. The researchers argue that the EFCM algorithm is superior because of three advantages over the original FCM: robustness to noise and outliers, linear computational complexity, and automatic determination of the optimal number of hotspots (Di Martino and Sessa 2011).

The EFCM method is used when analyzing wildfire data and is found to be very stable and separated certain clusters the FCM method could not. In addition, the EFCM method is found to be sensitive to subtle changes in locational clusters and appears to be better suited to complex and dense point pattern analysis than the FCM method. The development of more robust mathematical models that utilize point data is the result of enhanced computational power of modern computers melded with highly accurate point information.

As fire is a spatially complex phenomenon, applying and comparing important statistical methods utilizing point data is paramount to building a deeper understanding of wildfire causation. Nevertheless, these methods are but a mathematical model and may not represent the true complexity of the factors that influence the initial ignition and any subsequent spread; however, as computer models become more intricate, it is possible that wildfire could be modeled with greater accuracy and precision. Such accuracy would allow for better crisis mapping and response in the future. As a caveat, it should be noted that this thesis does not perform modeling of the kind discussed above; correlations and hot spot analyses are conducted instead.

2.3 Surveys

Additional research also reviews the efficacy of various wildfire education programs for private landowners and campfire education/regulation efforts in parks and other camping regions. These particular socioeconomic variables have relevance when collected using survey instruments that measure opinion as well as knowledge, skills, and abilities. For example, Reid and Marion (2005) assess the effectiveness of three different campfire policies (outright ban, designated campfires, and unregulated campfires) as a means to protect resources in seven protected areas. The study finds that while the unregulated campfires are the worst cause of resource damage, similar to tree cutting and wildfire, the outright ban has produced negligible differences in overall damage prevention. The researchers concluded that designated campfires, along with education efforts, are the most effective means in preventing resource damage. Colle and Dalle-Molle (1982) find that where and when campfires are constructed is a longstanding issue, as well. This study recommends that since campfires are popular features of camping, minimizing areas where campfires are acceptable and enforcing regulations concerning campfire safety are important measures (contrary to the education efforts that Reid and Marion (2005) evaluate) that will help minimize campfires that get out of control.

Reams et al. (2005) discuss the challenges associated in reducing human caused wildfire incidence in the WUI. The researchers surveyed the regulatory and voluntary wildfire mitigation organizations in 25 different states. The methods and obstacles of the different programs are also discussed. Results indicate that education, homeowner assistance, wildfire risk assessments/mapping, and regulation implementation are the most common education methods used by all the wildfire mitigation organizations. While this research does not cover campfires, it still strengthens the notion that education efforts are important in reducing human caused ignitions both near the home and in the wild. However, other socioeconomic variables such as resource limitations and negative attitudes of residents are ranked as the largest obstacles in mitigating wildfire through education efforts. In addition, budgetary restraints and resistance of property owners to removal of fuel buildup are also variables that limit the success of the programs. Survey research specific to the state of Florida on regulatory and voluntary wildfire mitigation organizations was not found.

Surveys allow various organizations to target their resources and plan effectively when interfacing with the public. As homeowners and campers can have a diverse range of opinions of and knowledge concerning regulations and education efforts, surveys allow their designers to focus on the efforts that will provide the most cost benefit to the organization. As it stands, the Florida Forest Service offers wide-ranging education options available for the state overall and individual counties. Additionally, Firewise Communities are found in many communities and they provide robust education program and resource materials concerning wildfires (Firewise, 2016).

2.4 Correlation

Correlation is another common analytical method used to study wildfire activity. Correlation is used to quantify the strength of association between two variables. The correlation coefficient produced from analysis measures the linear association between two variables, and is useful when comparing wildfire variables to socioeconomic, meteorological, or other variables.

Brenner (2001) examined total acreage burned in wildfires in Florida against indices of sea surface temperatures and pressure anomalies in the Pacific Ocean during El Niño Southern Oscillation (ENSO) periods. The ENSO period provides ample wildfire study options, and is also analyzed by Chu, Yan, and Fujiuka (2002) in a similar paper about seasonal wildfires in Hawaii. Both papers conclude that there is a significant relationship between sea surface temperatures, pressure anomalies, and acreage burned by wildfires. Brenner (2001) found a relationship that indicates up to 50% of the variance in the acreage burned can be attributed to changes in Pacific Ocean meteorological conditions; Chu and associates found a positive correlation between the number of ignitions and acreage burned in the summer or spring after an ENSO event in Hawaii.

Westerling et al. (2006) also study the relationship between wildfire activity and select meteorological variables. By hypothesizing that wildfire activity has been increasing in U.S. Forests, the researchers compare large wildfire events against hydro-climatic and land surface data. Correlation results reveal that large wildfire activity increased significantly in the mid-1980s, with higher wildfire frequency, longer duration, and longer fire seasons during periods of drought. In addition, areas where human land use changes have had minimal effect on fire risks are strongly associated with increasing spring and summer temperatures and, thus, earlier fire seasons. This ties into a study by Flannigan and Harrington (1988), which investigates the correlation between meteorological variables and acreage burned by wildfire in nine Canadian provinces. However, the variables, like rainfall individually, explain only some (11–30%) of the variance in total area burned. The researchers conclude that such results indicate that bad fire months are independent of rainfall amount, but dependent instead on rainfall frequency, temperature, and relative humidity, the last of which was also identified in the Westerling's study as significant.

Unlike the studies above that use only climate variables, Mercer and Prestemon (2005) examine Florida's wildland-interface relationships using socioeconomic variables. At the county level, statistical methods like Pearson's correlation coefficient show that population and poverty are positively correlated to wildfire acreage burned, but that unemployment is negatively correlated to total ignitions. Additionally, Pew and Larsen (2001) use both climate and socioeconomic variables to investigate major trends in type of human caused wildfires, their seasonal patterns, and if the number and size of wildfire occurrences have increased over time on Vancouver Island in Canada. To determine if monthly patterns vary by wildfire cause, a Spearman rank sum test of correlation is used; results indicate that industrial practices, most notably logging, contribute to the largest fires overall. Human recreation causes the most fires in terms of number, but the fires are significantly smaller in size.

2.5 Conclusion

The literature reviewed above reveals that spatial statistics provide important insights into the behavior and distribution of both structure fires and wildfire, especially wildfire caused by humans. In the case of wildfire specifically, this body of research reviewed asserts that wildfire clusters around places frequented by people and machinery, and that the clustering can be explained by various socioeconomic variables (Prestemon et al. 2013). In fact, it could be argued that socioeconomic variables play the most significant role in wildfire ignition because humans are the largest cause of those ignitions. Also, the statistical models discussed have the potential to be useful for forest policy development and wildfire management, though their usefulness will not be analyzed in this thesis. Interestingly, very few of these studies combine a hot spot and correlation analysis together to see how they pair together as a methodology.

These statistical models shown above provide a strong theoretical framework in wildfire occurrence theories and in the development of wildfire management interventions (Prestemon et al. 2013). These models allow development of additional analytical tools that will benefit land managers as they respond to wildfire occurrences. Statistical models also help to quantify uncertainties present in older physical models and allow for more precise decision making processes (Taylor et al. 2013).

As the statistical modeling of wildfire is important, one major weakness of current spatial modeling in the United States and abroad is that there is no unified system of wildfire record keeping (Short 2014). Indeed, the research for this thesis began with a search for wildfire data in Florida. Readily available and valid fire data came only with point data for national forests – data for the entire state had to be obtained by emailing the Florida Forest Service directly. Additionally, the availability of polygon data is questionable and therefore this study relied simply on point data. Also, the method of data collection (coordinate systems, attribute data, etc.) varies dramatically with each fire management group. All the research conducted in the literature above used different formats and kinds of wildfire data, making direct comparison difficult.

Studying the spatial patterns of wildfire data also suffers from the Modifiable Areal Unit Problem (MAUP) (Dark and Bram 2007). Each study partitioned their data in different ways to suit their research purposes and by doing so the results are influenced by the boundaries of each partition. This introduces possible bias, reliability, and validity concerns into the research as the results can be modified to suit the aims of those doing the work. Unfortunately, this problem has no real remedy and must be taken into consideration when approaching any study of wildfire.

Overall, the use of spatial statistics in studying wildfire is becoming more common and methodologies more varied. As such, research provides for important policy recommendations and management techniques, continued study is necessary. With the constant advances in technology and data processing power, it is expected that the spatial and temporal study of wildfire will continue to become more precise and valuable to those who need it.

Chapter 3: Methodology

This chapter explains the boundaries of the study areas, the data sources required for this study, and the methodology used to test the hypotheses. As discussed earlier, the primary research hypothesis posits a relationship between wildfire incidence type and four different variables. Analysis using Pearson's correlation was performed to link spatial location to variables that may explain fire incidence. ArcGIS Desktop and its geoprocessing tools were the main component used to analyze the spatial location of wildfire. The Optimized Hot Spot Analysis, Emerging Hot Spot Analysis, and Directional Distribution Analysis were all used to examine potential clustering of wildfire incidence. The VIIRS Nighttime Light data revealed population clusters and was used as a visual reference for hot spot clusters and an added level of population density analysis. All of the analytical tools helped to test the hypothesis that population growth and population numbers positively influence the number of human caused wildfire ignitions, while high temperatures and low precipitation increase lightning caused fires.

3.1 Study Area and Scale of Analysis

The State of Florida was selected because it provides a wealth of information concerning wildfire incidence. Since the 1980s, the state has logged over 163,000 wildfires. Florida has an identifiable wildfire regime and an active forestry service that documents all wildfires in the state. Therefore, the wildfire data available are well maintained and can be used for cluster analysis. Florida is also a popular retirement destination choice and has steady population growth. To allow for more localized analysis for the directional distribution analysis, the state was separated into four different regions used by the Florida Forest Service (FFS) as management regions (Figure 2). Temporally, this research separated the data into five-year blocks, starting with 1985.

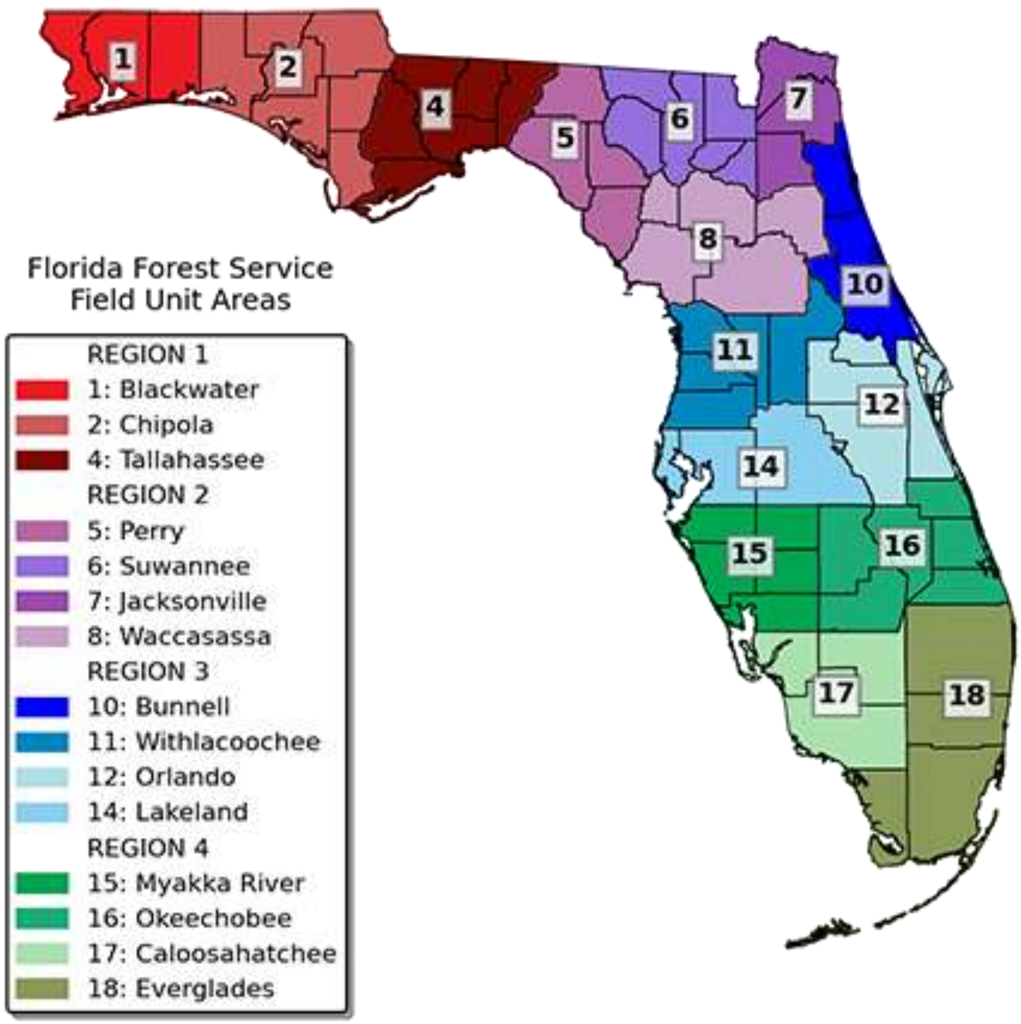

Figure 2 Map of Florida and Study Regions. Source: freshfromflorida.com

3.2 Data and Sources

Table 1 Summary of Required Data

Dataset	File Type	Data Type	Details	Source	Temporal Resolution of the Dataset
Wildfire Point Data	Shapefile	Point Feature Class	Attributes include location, date started, date ended, cause, region, and more	Florida Forest Service	January 1981 to December 2015
Population Data	Excel .xlxs	Polygon Feature Class	Incorporated, unincorporated, and county level population estimates	Florida Office of Demographic and Economic Research	1975 to 2015
Precipitation Data	Excel .xlxs	Point Feature Class	Monthly precipitation values from stations around Florida	National Oceanic and Atmospheric Administration (NOAA)	January 1985-December 2014
Temperature Data	Excel .xlxs	Point Feature Class	Monthly temperature averages from stations around Florida	NOAA	January 1985-December 2014
County Boundary	Shapefile	Polygon Feature Class	Outlines of all Florida counties	ArcGIS Online-Florida Department of Agriculture	May 2015
VIIRS Nighttime Lights	GeoTIFF	Image	Image of night time lights across the United States	NOAA	May 2012

Table 2 Summary of Required Software

Software	Manufacturer	Function	Access
ArcGIS Desktop 10.3.1	Esri	Hot Spot Analysis; Emerging Hot Spot Analysis, Directional Distribution Analysis	USC GIST Server
RStudio	R Core Team	Pearson’s Correlation Analysis	Personal desktop

The FFS maintains a detailed geodatabase containing point data about wildfires across the state. These data were available for free after an email exchange with Karen Cummins, GIS Analyst for the Florida Forest Service. The county shapefile of Florida was downloaded from ArcGIS Online. The Florida Department of Agriculture (under which the FFS operates) uploaded the information to ArcGIS Online for research analysis. The precipitation and temperature values were available on National Oceanic and Atmospheric Administration's (NOAA) website and contained X, Y coordinates that allow it to be georeferenced into ArcMap. The population data were made available by the state government of Florida and were joined to the county dataset within ArcMap. Finally, the VIIRS data were available from NOAA and was accessed on September 23, 2016 when the May 2012 data was downloaded. These data are available as a GeoTIFF and are developed into monthly cloud-free composites at a 750-meter resolution.

The wildfire incidence dataset has information dating back to 1981. The data from the 1980s uses the Public Land Survey System (PLSS), while the rest of the data uses a standard coordinate system. The use of different coordinate systems does not affect the accuracy of the hot spot analysis. The wildfire point data is also the estimated center of the fire, and while acreage burned is included in the attribute table, direction and spread of the fire is unknown. The county dataset contains simple polygon elements with no attached demographic data, though such data are available through the U.S. Census Bureau.

3.3 Methodology

Figure 3 below shows the workflow that was employed in this thesis. Several different types of data were gathered and prepared for analysis via correlation and spatial analysis in

ArcGIS. Once investigated, the data were compared against each other to reveal possible connections and correlations.

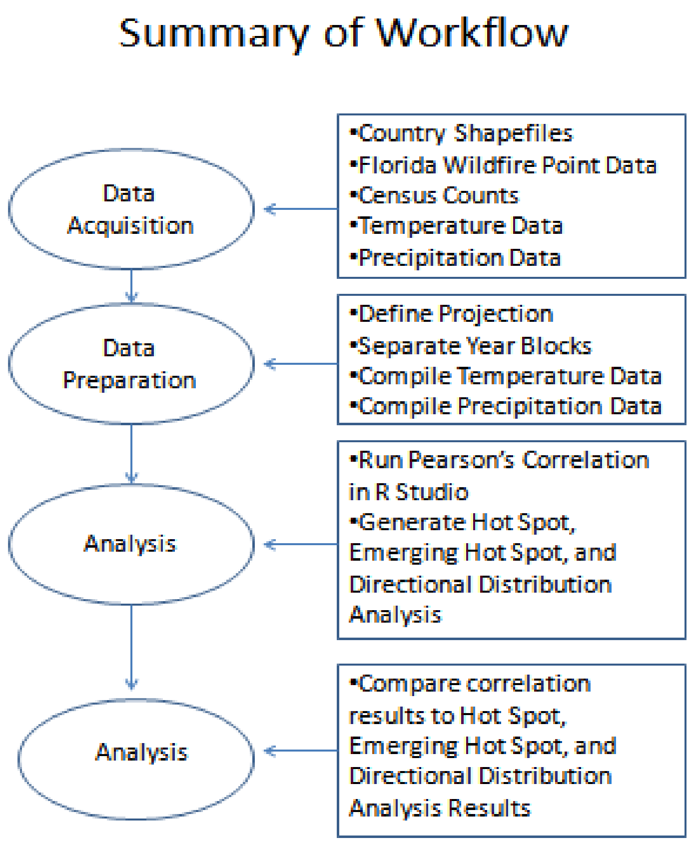

Figure 3 Summary of Workflow

3.3.1 Pearson's Correlation Analysis

The first step of analysis was to complete a correlation test on the dependent and independent variables to determine if there is a relationship. The main purpose was to test the hypothesis to see if lightning caused fires incidences increase during times of lower precipitation and higher average temperatures, and if human caused fire incidences also increase as population and population growth rate increases. Data for each five-year block was compiled in an Excel CSV document so that total human and lightning caused fires were totaled by county along with average precipitation, average temperature, population growth, and total population. Once compiled, the data were imported into RStudio and a Pearson's Product Moment Correlation analysis was performed. The year block covering 2000–2004 was also expanded into single years and correlation was run between fire causes and total precipitation for each year. This was conducted to see if the five-year blocks were masking any correlation between variables.

3.3.2 Optimized Hot Spot Analysis

Before any analysis could occur, the wildfire data for Florida was projected to an appropriate projected coordinate system. Projected coordinate systems are necessary for proper distance and/or area measurements when performing spatial analysis of the sort this research was attempting. For this investigation, the Albers Conical Equal Area projected coordinate system was used. In this coordinate system, all areas are proportional to the same areas on earth, and distance is most accurate in the middle latitudes where Florida is located.

After being projected to the appropriate coordinate system, the data were selected and separated into separate layers (and data frames) for each five-year block of analysis. Data were worked on separately for each five-year block, and then brought together for analysis at the end.

While the Optimized Hot Spot Analysis tool did the following steps automatically, they are covered in detail to provide an appropriate framework for the methodology. To begin a Hot Spot analysis, the wildfire point data must be manipulated in a few ways before being acceptable for use. The very first step the tool performed was an average nearest neighbor analysis. This analysis calculated, as described by the name, the nearest neighbor based on the average distance from each feature to its nearest neighboring feature. Five values were returned from this analysis, with the most important being the z-score and the observed mean distance. The z-score is a measure of statistical significance that indicates whether the data is clustered, random, or dispersed. The observed mean distance was used in another step of the analysis that works towards a hot spot analysis and is discussed later.

As the purpose of this initial study was to assess incident intensity instead of the spatial clustering of a specific attribute in the data, the points were simply aggregated. This was done using the Integrate and Collect Events tools. The Integrate tool maintains the integrity of shared feature boundaries by making features coincident if they fall within a specified X and Y tolerance. Once all the datasets are integrated, the point events were collected and converted to weighted point data. This was an important step, as the Hot Spot analysis required weighted points rather than individual incidents.

A Hot Spot analysis works best when certain variables can be filled in to give a more accurate picture of the spatial forces at play. One of the forces was the distance band. The distance band provided the scale of analysis and determined what features are considered neighbors. To calculate the most appropriate distance band, several steps were taken. First, Calculate Distance Band from Neighbor Count analysis was implemented. This tool finds the peak distance that ensured that each feature has one neighbor.

After finding the distance bands to ensure each feature has at least one neighbor for analytical purposes, the next step the Optimized Hot Spot Analysis implemented was the Incremental Spatial Autocorrelation analysis. This tool measured spatial autocorrelation for a series of distances and created a line graph depicting those distances and corresponding z-scores. Z-scores reflect the intensity of spatial clustering and peaks in the graph indicated distances where spatial processes that promote clustering were most pronounced. Note that the incremental distance measurement used by this tool was determined from the observed nearest neighbor distance that was created during the average nearest neighbor analysis; the starting distance was the distance band discovered using Calculate Distance Band tool. The peak distance and z-score returned from this analysis was the number used for the distance band in Hot Spot Analysis.

After determining the peak for each dataset, the Hot Spot analysis was finally utilized. An important feature of a Hot Spot analysis is the Conceptualization of Spatial Relationships, which requires the tool to specify what kind of spatial relationship is at play. The Optimized Hot Spot Analysis tool determined this relationship automatically and required no input from the user.

The data was aggregated using the aggregation scheme, COUNT_INCIDENTS_WITHIN_FISHNET_POLYGONS, which created a fishnet polygon mesh. The fishnet was positioned over each incident and points were counted within each polygon. This aggregation scheme was used because it is simple and appropriate for point feature data. For the human caused 2010–2014 block of wildfire, VIIRS Nighttime Light dataset was used to see if hot spot clusters occur near areas of light (populated areas). The VIIRS Nighttime Light Data was projected to match the Albers Conical Equal Area Projection.

3.3.3 Emerging Hot Spot Analysis

The Emerging Hot Spot tool was used to identify trends in data. The tool works to highlight new, sporadic, oscillating, intensifying, and diminishing hot and cold spots. To do so, the first step was to create space-time cubes using the Create Space Time Cube tool in the Space Time Pattern Mining toolbox. The discovery date of each wildfire was used as the time component, with the data being broken into 4 week blocks as the time step interval to replicate one year. The tool then aggregated all the points into space-time bins. These space-time bins were then used in the Emerging Hot Spot Analysis tool also located in the Space Time Pattern Mining toolbox. A hot spot analysis was performed first by the tool so that a Z-score and p-value was obtained. Then, the Mann-Kendall statistic, a rank correlation analysis, was performed on every aggregated bin. As the expected sum for each bin value is zero, any variance from zero was compared to determine if the difference was statistically significant. The location was then assigned a category type as listed above (sporadic hot spot, etc.). To better study emerging trends in wildfire activity, an Emerging Hot Spot Analysis was performed on each individual year of the study span.

3.3.4 Directional Distribution Analysis

As wildfire incidence has the potential to move in time and space due to factors like land use change affecting where wildfire can ignite, a directional distribution analysis was used to analyze whether wildfire was showing any directional trends across each of the study regions. This analytical tool also helped evaluate the primary hypothesis that population growth and population numbers positively influence the number of human caused wildfire ignitions by testing whether the fire ignitions moved closer to wildland-urban interfaces and populated areas, while high temperatures and low precipitation increase lightning caused fires. The Directional Distribution tool in the Spatial Statistics toolbox measured directional trend by calculating the standard distance in the x and y directions, thus creating an ellipse that covers the distribution of wildfire incidence. Standard deviational ellipses were plotted for the first five-year block (1985-1989) and the last (2010-2014) to show movement over time.

Chapter 4 Results

Chapter 4 documents the results of the Pearson's Correlation Analysis, Hot Spot Analysis (with VIIRS data), Emerging Hot Spot Analysis, and Directional Distribution Analysis, each of which tested critical elements of the research hypotheses that population growth and population numbers positively influence the number of human caused wildfire ignitions and that high temperatures and low precipitation increase lightning caused fires. All the exploratory variables were tested against the researched causes of fire to see if there were any statistically significant correlations. These correlations were then assessed against cluster analysis and trend distributions to see if the spatial arrangement of wildfire matched the correlation test results.

This chapter is broken into several sections to present the results of the analysis. Section 4.1 provides visualization of the independent variables used in the analyses. Section 4.2 covers the products of the Pearson's correlation testing by providing tables and scatter plots. Section 4.3 provides maps of the Hot Spot Analysis performed for each of the five-year blocks. In Section 4.4, maps and documentation are displayed with the results of the Emerging Hot Spot Analysis. Finally, Section 4.5 offers the results of the Directional Distribution Analysis.

4.1 Visualization of Data

The data used to run correlation analysis are discussed below. Tables showing the population size, density, and growth by county for each five-year analysis period, average precipitation, average temperature, and the number of fires caused by lightning and humans are included in the Appendix. However, a brief description of the data is included below.

The data revealed that Miami-Dade was consistently the most highly populated county in the state. This title persisted even with relatively low population growth within the county most years and very high population growth within other counties. Population growth, in general, was relatively high until 2010–2014, which showed a significant drop in growth across the entire state, with several counties showing population losses. Precipitation remained relatively constant across all year blocks and across the counties in general, though some counties displayed years of low precipitation in comparison to the rest of the state. For example, in the 1990–1994 block, Hillsborough County received just less than 40 inches of rain, while Martin County received just less than 74 inches. Both counties are in central-south Florida, though Hillsborough County is on the Gulf side and Martin County is on the Atlantic; weather patterns influenced by the abutting water bodies might explain the large difference in precipitation patterns.

4.2 Pearson's Correlation

The results of the Pearson's correlation coefficient are provided below in charts and scatterplots to show the p-value, correlation coefficient, and visual spread of the data. The correlation tables below detail the results from the six, five-year blocks. The results show that that correlation between certain variables was only significant during certain five-year blocks, and some variables showed no statistically significant correlation across all five-year blocks.

Table 3 Lightning Fire Correlation Coefficients and Significance

	Lightning Caused Fire Correlation with:			
	Precipitation	**Population**	**Population Growth**	**Temperature**
1985-1989	cor: 0.002010057	cor: -0.01256241	cor: 0.4561457***	cor: 0.1215951
1990-1994	cor: -0.3447747**	cor: 0.01773975	cor: 0.05532496	cor: 0.03581129
1995-1999	cor: 0.07919431	cor: 0.1137356	cor: -0.02015204	cor: 0.03835632
2000-2004	cor: -0.2103873	cor: 0.182524	cor: 0.3398065**	cor: 0.08670618
2005-2009	cor: -0.2381328*	cor: 0.1096185	cor: -0.06213862	cor: 0.0324565
2010-2014	cor: -0.1196185	cor: 0.09793746	cor: 0.06805902	cor: -0.02978265

* p<0.05; **p<0.005; ***p<0.005

Table 4 Human Fire Correlation Coefficients and Significance

	Lightning Caused Fire Correlation with:			
	Precipitation	**Population**	**Population-Growth**	**Temperature**
1985-1989	cor: -0.230888*	cor: 0.05568454	cor: -0.05357188	cor: 0.1956322
1990-1994	cor: -0.1292159	cor: 0.02714093	cor: 0.01676806	cor: 0.02800138
1995-1999	cor: 0.04073071	cor: 0.1739748	cor: -0.03839721	cor: 0.02448262
2000-2004	cor: 0.1834783	cor: 0.1370713	cor: 0.1609849	cor: 0.1213834
2005-2009	cor: 0.1102893	cor: 0.008414373	cor: 0.01731224	cor: 0.09276631
2010-2014	cor: -0.145461	cor: 0.05208139	cor: 0.006041457	cor: 0.09453123

*p<0.1

As shown, the relationship between lightning caused wildfire ignition and precipitation was only negatively correlated in two year sets, with 1990–1994 showing a moderately negatively correlation, and 2005–2009 revealing a very weak negative correlation. Ignitions caused by lightning also correlated positively with population growth in 1985–1989 and 2000–2004, with the former indicating a strong positive correlation and the latter a moderate positive correlation. Human caused wildfire ignition only showed one very weak negative correlation when compared against precipitation in 1985–1990. Scatter plots of statistically significant lightning caused wildfire ignitions and their independent variables are shown in Figures 4 and 5.

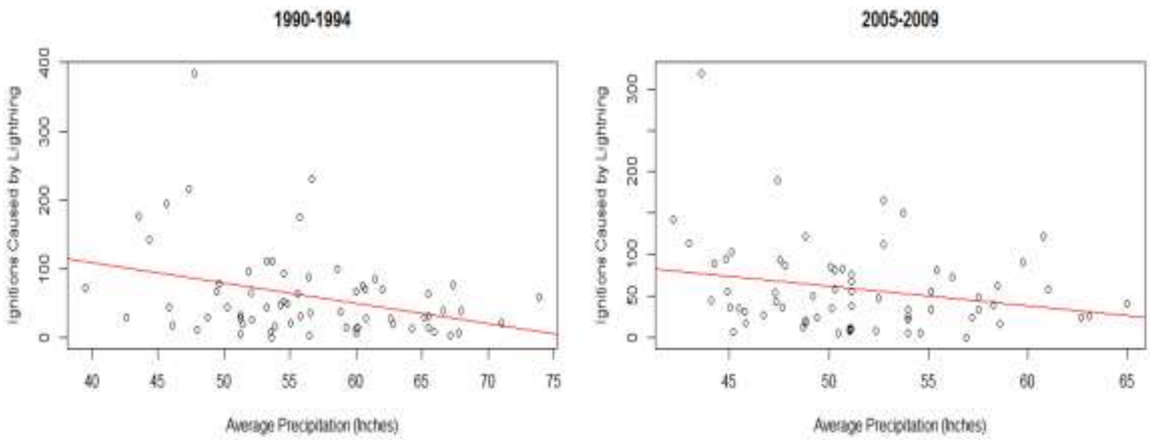

Figure 4 Scatterplot of Average Precipitation and Lighting Caused Ignitions

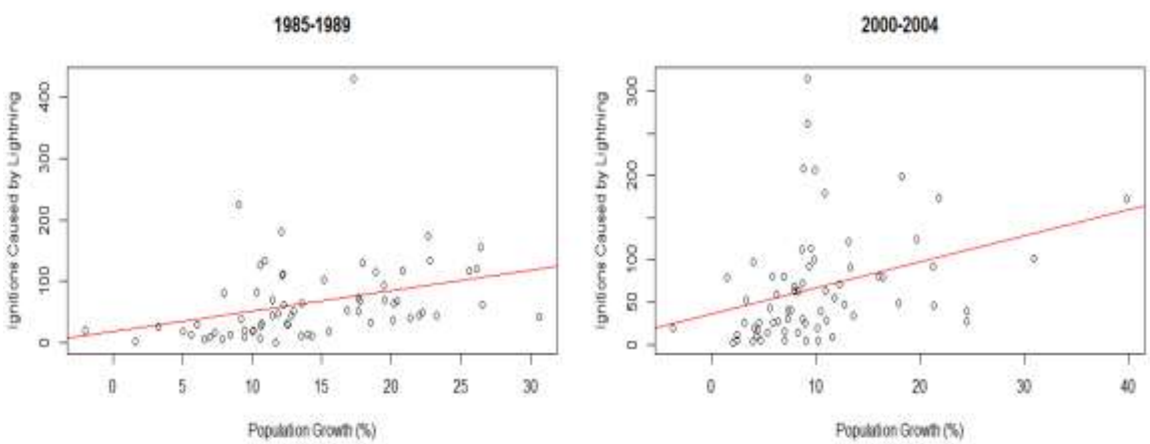

Figure 5 Scatterplot of Population Growth and Lighting Caused Ignitions

The five-year block 2000–2004 was expanded into individual years to see if the time length of the five-year blocks was hiding correlations. The results indicated that correlation were not being masked by the time frame. No statistically significant correlations existed between the different fire causes and precipitation in this five-year block (Table 5).

Table 5 Relationship between Fires Types and Precipitation

	Human Fires and Precipitation	Lightning Fires and Precipitation
2000	cor: -0.08589533	cor: -0.05336196
2001	cor: -0.05992999	cor: -0.03093068
2002	cor: -0.0390082	cor: -0.02671132
2003	cor: 0.10425353	cor: -0.1278587
2004	cor: 0.1074821	cor: 0.06861574

4.3 Hot Spot Analysis

Figure 6 displayed the results of the Hot Spot Analysis that spanned 1985–1989. As evident from the data, several large hot spot clusters existed across the entire state. There was a large, circular cluster in the northwestern panhandle, centered predominately in Santa Rosa County. Another hot spot existed in the eastern side of the panhandle inside of Suwannee County. Close to it was a large hot spot that begins in Duval, Baker, and Clay counties in the northeastern corner of the state and ran down through multiple counties to Hernando and Pasco counties in central Florida. On the central eastern coast, another cluster was in Volusia County. In the middle of central Florida, a cluster was also identified in Polk County. Finally, a large cluster existed along the Gulf of Mexico side of central Florida in Sarasota County. Central

Florida, in particular, was highly populated with large cities like Daytona Beach and Sarasota within Volusia and Sarasota counties respectively. However, Pasco County, while having a relatively large population (~272,000), did not have a major city; Hernando County was not highly populated.

The results of the Hot Spot Analysis that spans 1990 to 1994 are shown in Figure 6 as well. Like in the previous data, a hot spot cluster was localized around Santa Rosa County in the northwestern panhandle. The hot spot in Suwannee County disappeared, but the long band of clustering from Duval County in the northeast to Polk and Hernando counties was still present and stretches between Jacksonville and other small cities. The hot spot cluster in Volusia County had grown larger and covered a large portion of Flagler County above Volusia. The cluster in Polk County remained in central Florida, and the hot spot in Sarasota along the coast expanded into Lee and Charlotte counties. Miami-Dade County on the southern tip of Florida also had a small cluster that was not present in the previous figure.

Figure 7 showed the results of a hot spot analyses that covers 1995 to 1999 and 2000 to 2004. Hot spot clustering was not as prevalent in this five-year block as previous years. While the cluster in northeastern Santa Rosa remained, the large band that runs from northeast to central Florida had mostly disappeared, while a small cluster remained in Duval County in the north and Pasco in center-east. The small cluster reappeared in Suwannee County to the west of Duval. The cluster in Volusia to the east also shrank compared to years past. The cluster in Sarasota and Charlotte remained mostly unchanged, as did the cluster in Miami-Dade County.

In 2000 to 2004, as in previous years, Santa Rosa County in the northwest was still a location of hot spot clustering (Figure 7). The clustering in the northeastern panhandle grew larger since the last five-year block, and while the locations were similar to previous years, there did seem to be some slight shifting eastward of cluster locations. The clustering in Suwannee County had grown larger and spread to almost touch the clustering in Duval, Baker, and Clay counties. Volusia and Flagler counties on the east coast revealed reduced clustering activity. The clustering near central Florida that was previously located in Hernando and Pasco counties shifted to the south, in Citrus and Levy counties. Highland County, located in the middle of central Florida, showed evidence of clustering. Sarasota and Charlotte to the east remained consistent locations of hot spot activity, though there was a slight eastern movement within the counties. Miami-Dade further south remained a location of activity.

Figure 8 showed the results of the hot spot analyses performed on wildfire data ranging from 2005-2009 and 2010-2014. The cluster of hot spot activity in Santa Rosa County in the northwestern panhandle remained, but was notably smaller than in previous years. The cluster usually present near Duval County in the northeast shifted south to Putnam County, while hot spot clustering remained in Citrus and Levy counties. Volusia and Flagler counties to the east also showed clustering as in years past, though notably more than in the previous study period. While Sarasota and Charlotte remained areas of clustering, clustering also shifted east and south into Lee and Collier counties, respectively. Miami-Dade again showed activity, but the cluster appeared to have moved slightly to the south.

The 2010-2014 five-year block was quite different from the rest. While not discussed in the previous analysis, this image contained wide swathes of cold spots worth noting. A large percentage of the panhandle was covered in cold spots, and central Florida also had a large band stretching the entire width. This indicated in these areas a dispersion of ignitions that were unlikely to be the result of random chance. Hot spot activity was present in the northwestern panhandle and a large band stretched across the northeastern corner of the state as well.

Alachua, Baker, Bradford, Clay, Columbia, Duval, Flagler, Hamilton, Putnam. St. Johns, Suwannee, Union, and Volusia counties were all included in the band of hot spot clustering. To the south, clustering moved south away from Sarasota County but had noticeably diminished in size. Miami-Dade still had a small cluster in the southern portion of the county.

Lightning caused fires showed consistent hot spot clusters overall in all year blocks (Figures 9–11). In general, lightning fires clustered along the Jacksonville area on the northeastern, Atlantic coast of Florida and the Tampa/Sarasota area on the gulf side. These areas were hot spots in every single map, though the size of each hot spot did change slightly every year, while the Atlantic coast cluster appeared to grow larger over time.

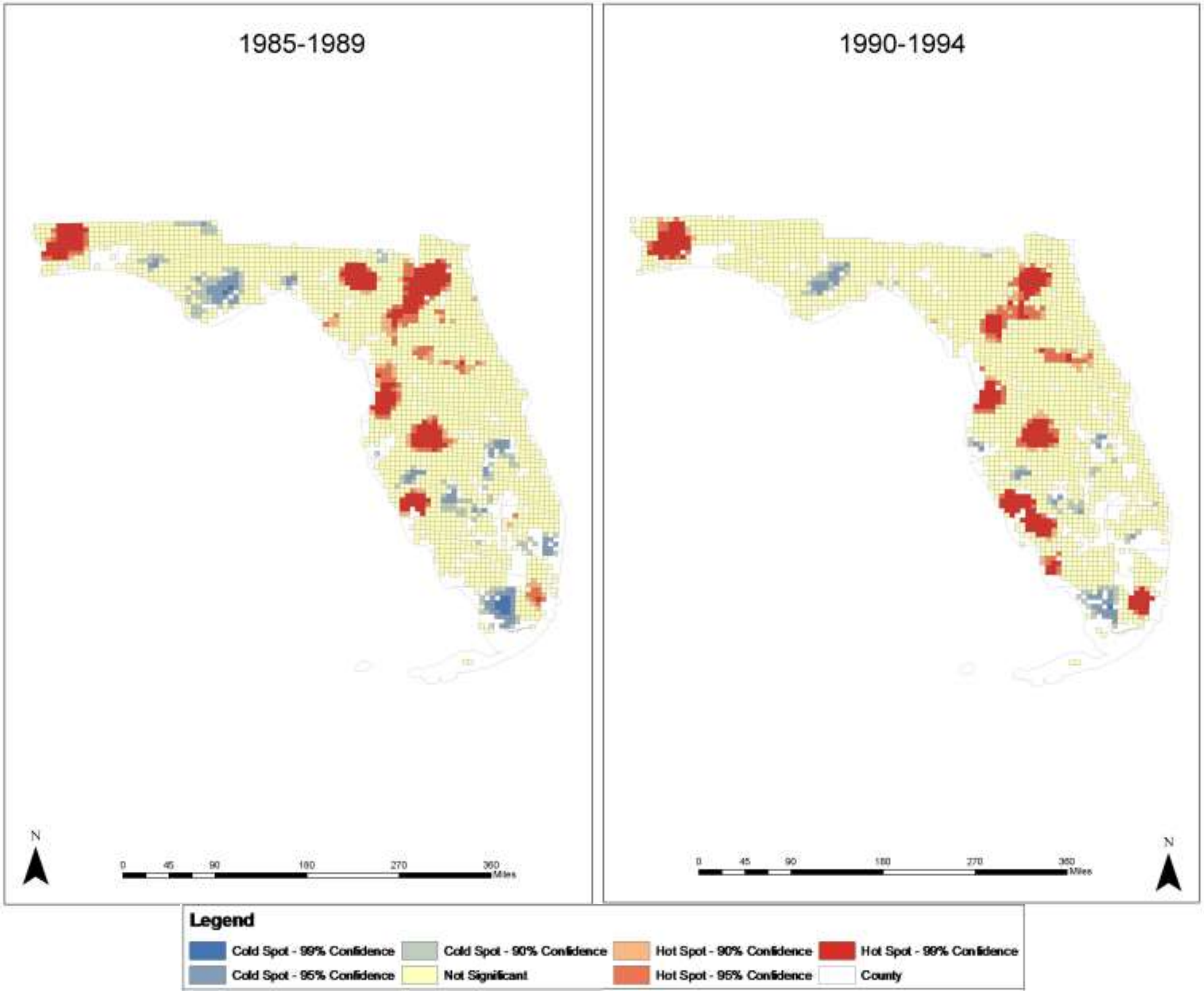

Figure 6 1985-1994 Human Hot Spot Analysis

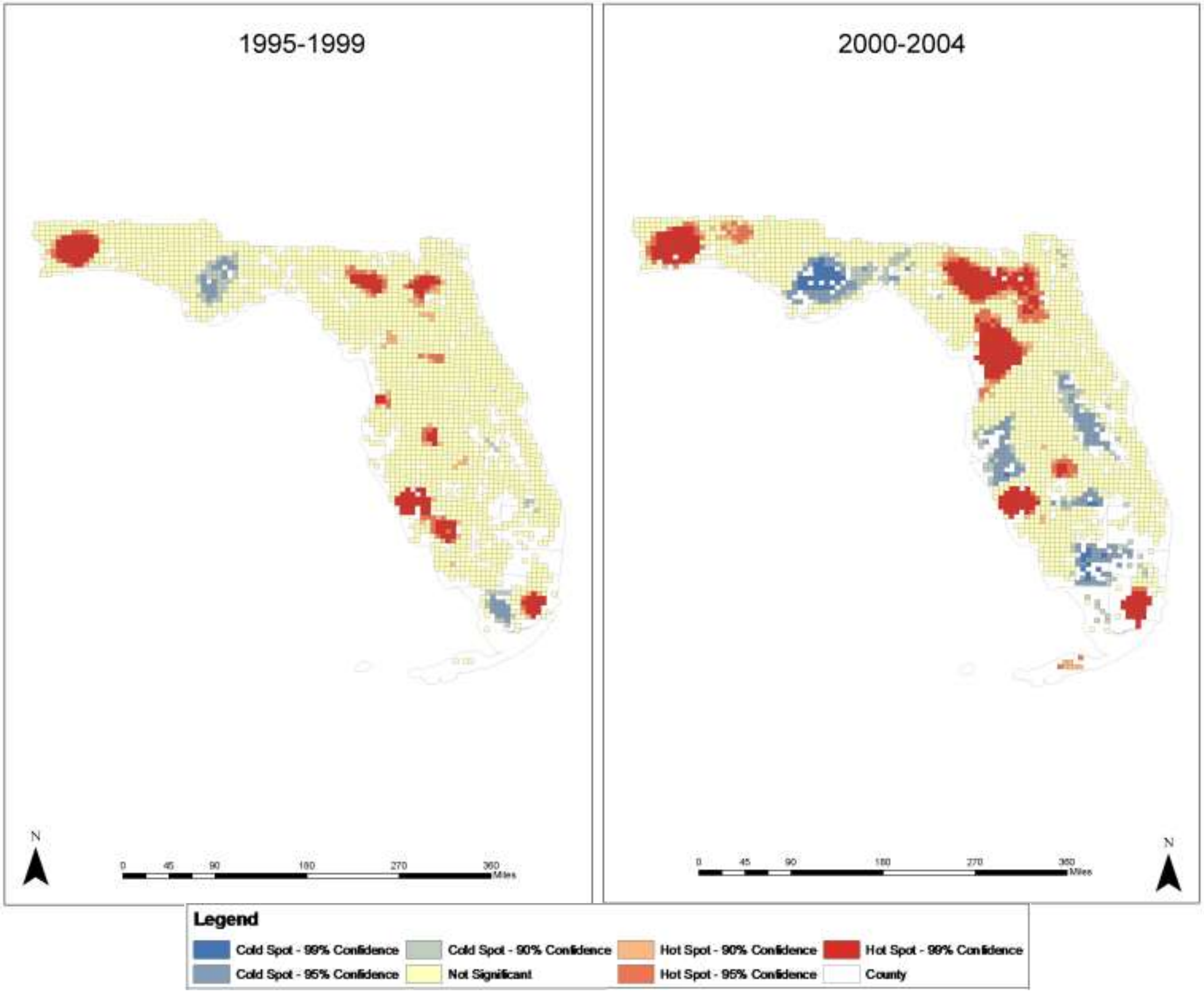

Figure 7 1995-2004 Human Hot Spot Analysis

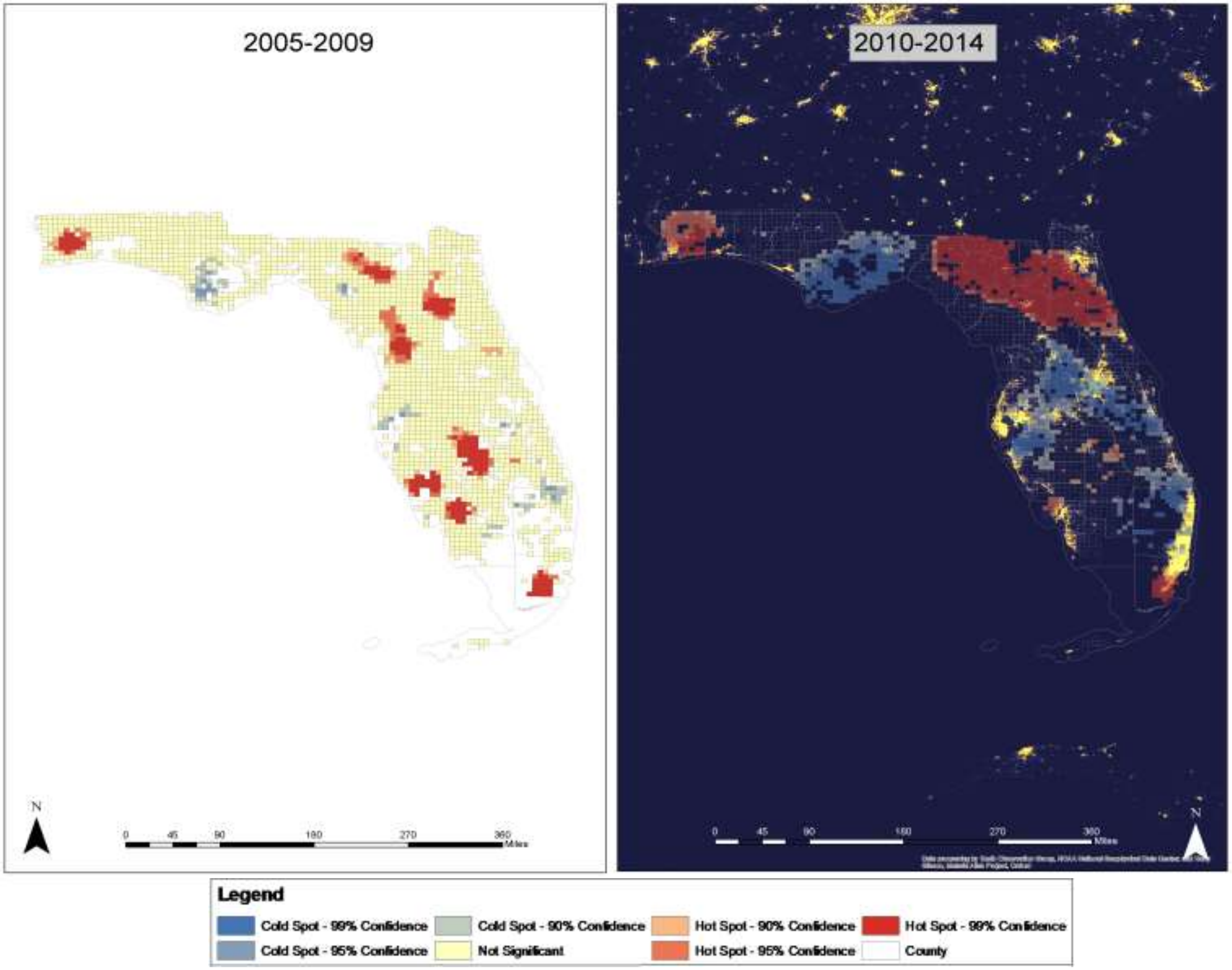

Figure 8 2005-2014 Human Hot Spot Analysis

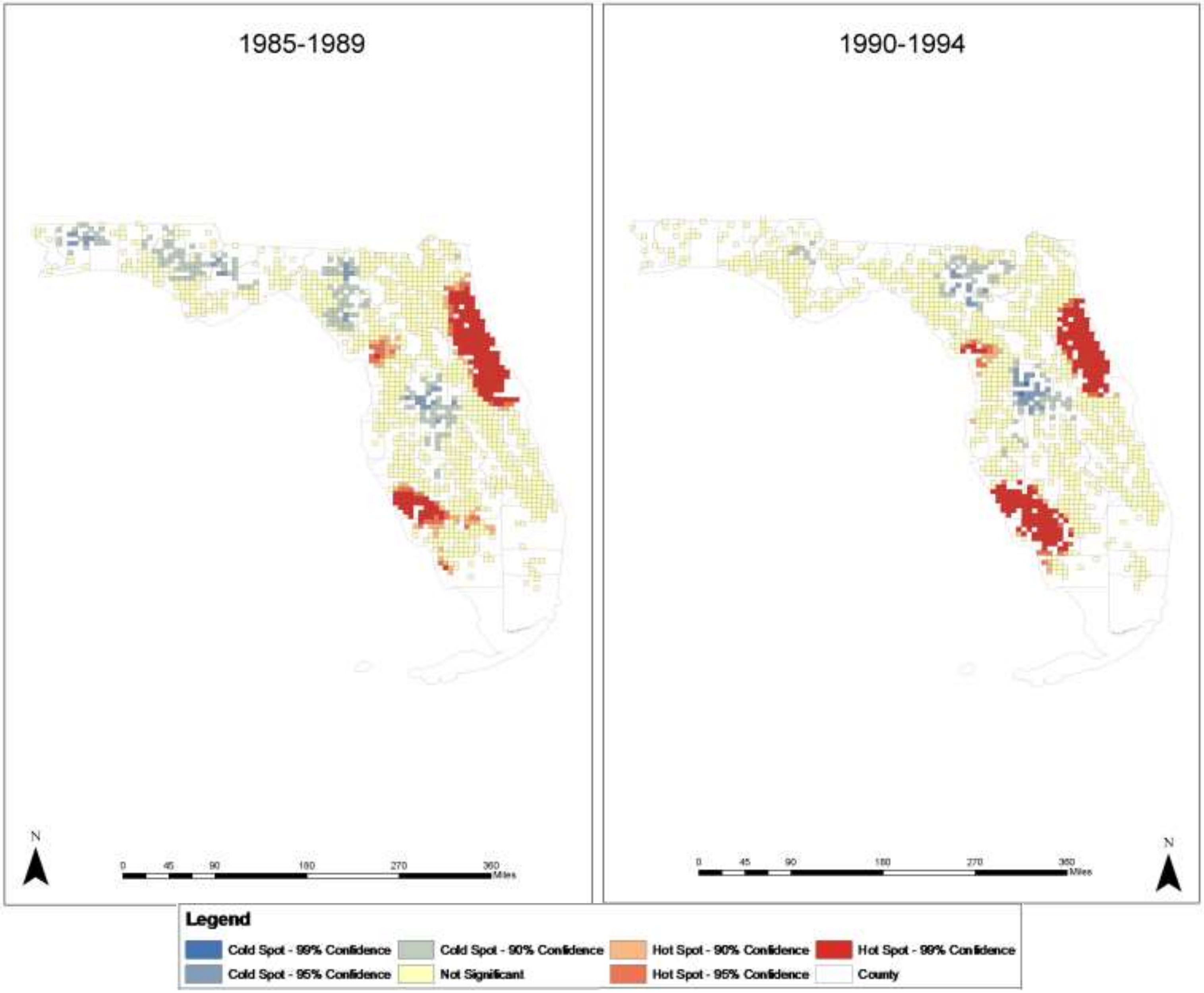

Figure 9 1985-1994 Lightning Hot Spot Analysis

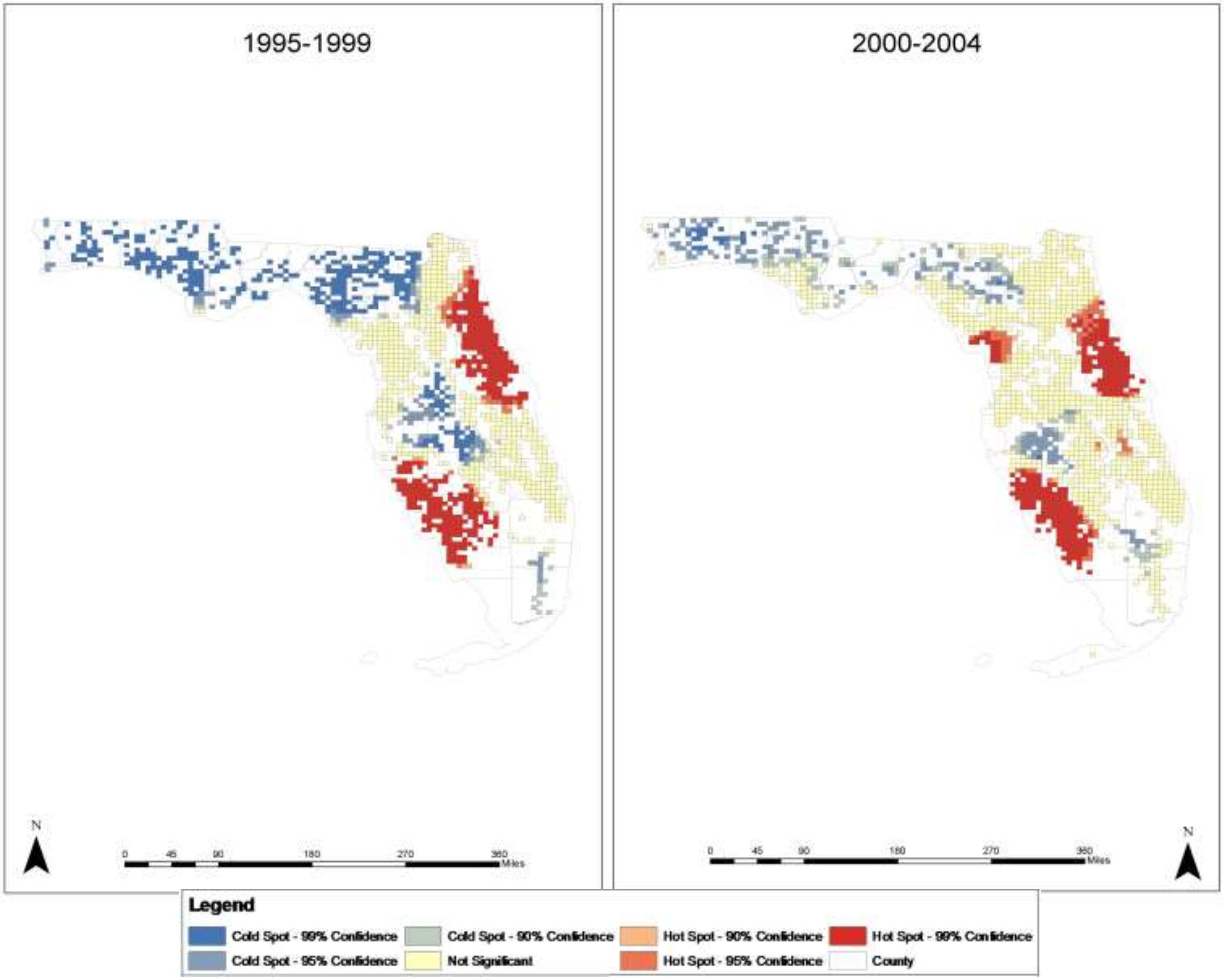

Figure 10 1995-2004 Lightning Hot Spot Analysis

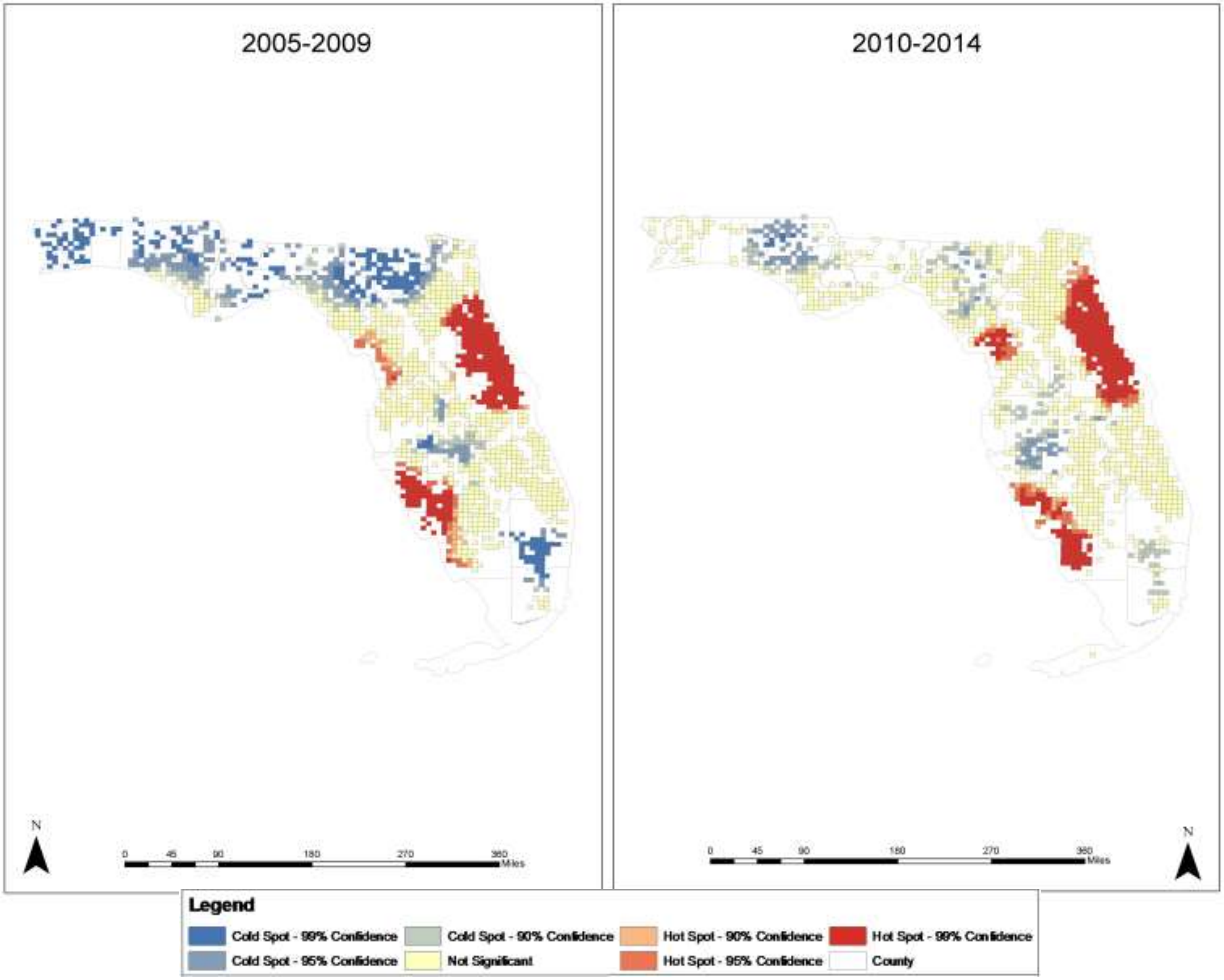

Figure 11 2005-2014 Lightning Hot Spot Analysis

4.4 Emerging Hot Spot Analysis

An Emerging Hot Spot Analysis was also performed on all the individual years of the 30-year study range. This level of analysis allowed for trends to be identified in the temporal aspect of wildfire ignition. It is possible to see how the ignition behavior acted over a time period and provided a broader picture of when ignitions are more or less common.

As every individual year was mapped out, the images were attached in the Appendix. Overall, the images indicated a large variety in the hot spot activity. Some years revealed large swathes of land with oscillating hot spots, while others years (2000, 2001, and 2014) showed no activity at all. The maps overall reveal no relationship between locations of hot spot clustering in the previous section and significant clusters in emerging maps.

4.5 Directional Distribution Analysis

The Directional Distribution analysis was performed to see if the spatial clustering of wildfire ignitions moved in trend or centroid over the study time period. The analysis was split with two, five-five-year blocks on each map (1985-1989 and 1990-1994 on one map, and so forth), so three maps are present. There were four different directional ellipses on each map to represent each region of study. The analysis was performed with both lightning and human caused fires combined into one variable.

The maps shown below all revealed similar patterning in the ellipsis location, direction, and trend. Minor variances were present in location each year, as seen in the Region 4 ellipses most predominately. In the first map showing 1985 through 1994, the directional ellipsis showed a westward movement of wildfire ignition that continued in the 1995 to 2004 map. The last map, though, revealed the direction and trend of wildfire ignition moving back towards the east slightly and away from the coast. There were similar minor variations in each of the ellipses for every region.

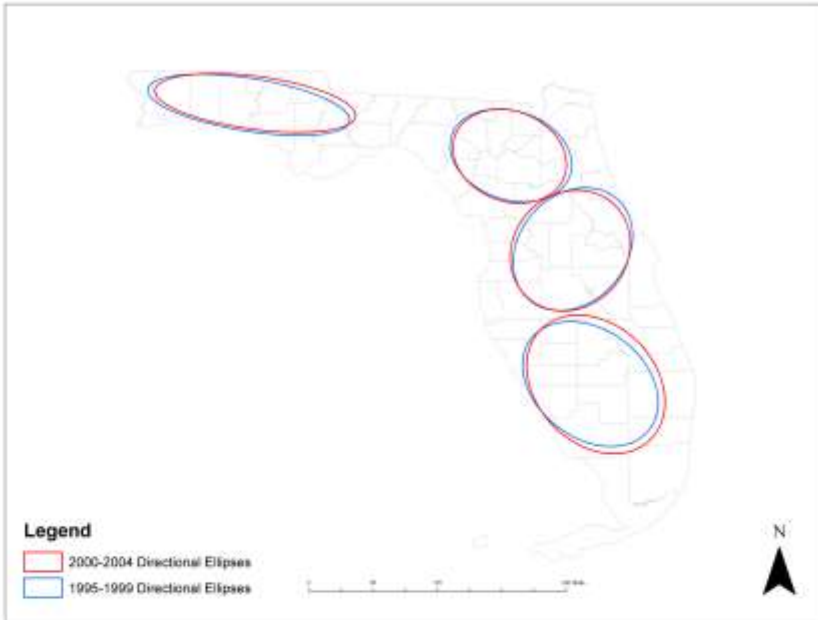

Figure 12 1985-1994 Directional Distribution

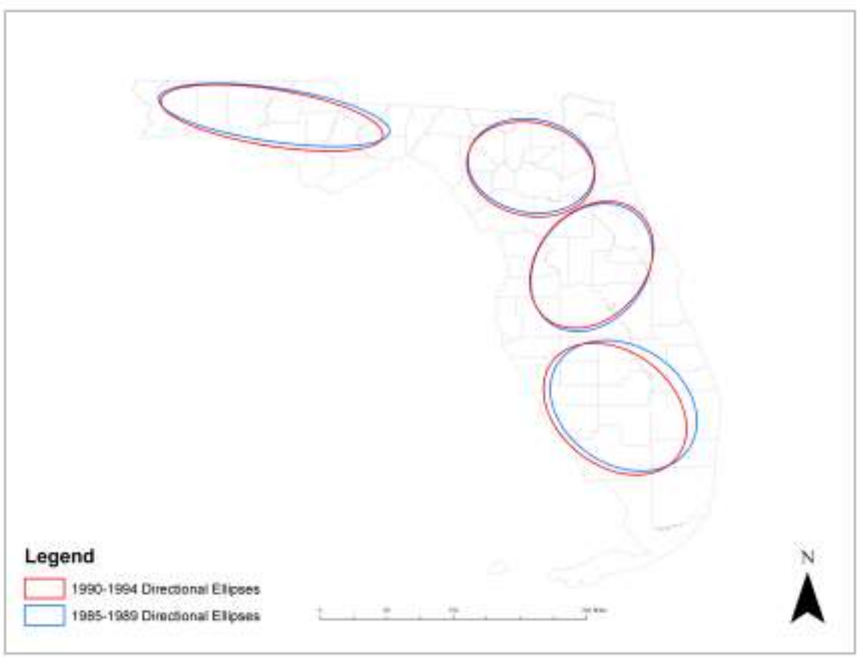

Figure 13 1995-2004 Directional Distribution

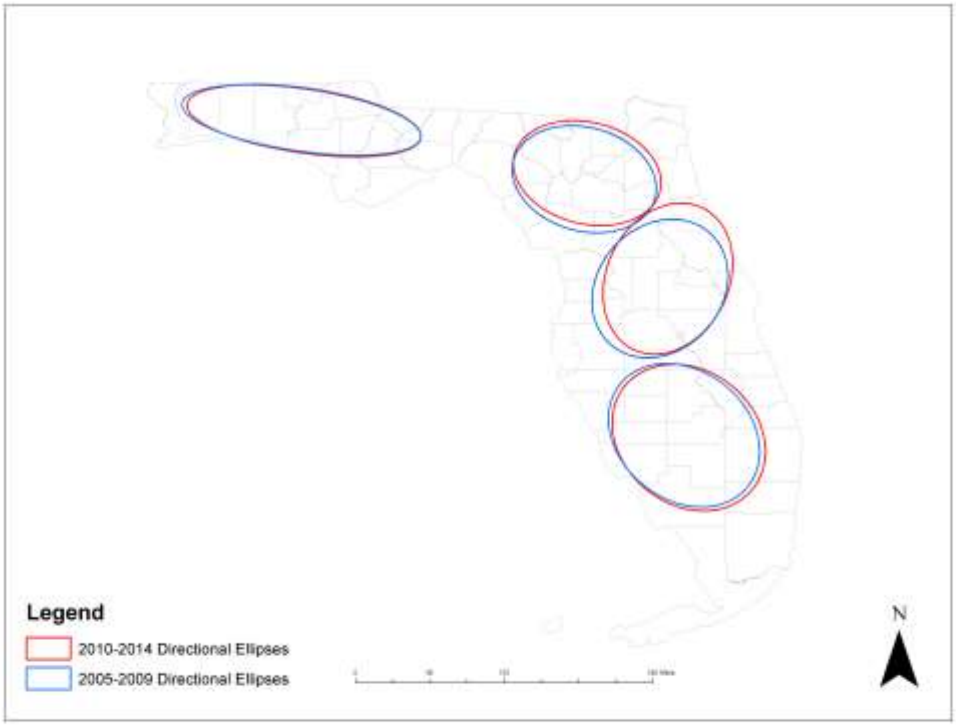

Figure 14 2005-2014 Directional Distribution

Chapter 5 Discussion

This chapter concluded this thesis and provided a discussion about the objectives of the research. This research analyzed the spatial distribution of human and lightning caused wildfires across the state of Florida from 1985 to 2014. An analysis of possible explanatory variables related to ignition was performed using correlation statistics. A spatial analysis of clusters both current and emerging was also performed to see if location correlated to the variables. Finally, a directional distribution analysis was conducted to see if the overall trend of ignition was moving in relation to human or meteorological variables. This final chapter provided a discussion of the results, their limitations, and implications for future research.

5.1 Correlation Discussion

The results of the correlation analysis did not provide sufficiently strong correlation values to conclude that there is a statistically significant relationship between any of the dependent and independent variables. Part of the main research design was to analyze part of the primary hypothesis which posited a negative correlation between lightning fires and precipitation levels across all the five-year blocks; only two time periods (1990-1994 and 2005-2009) provided weak to moderate negative correlations. Further research into correlation studies found that fire ignition often happens independently of rainfall amount, but instead depends primarily upon rainfall frequency, temperature, and relative humidity (Flannigan 1988). Results from this study suggested that temperature variables be added to the list of variables studied however, relative humidity data was not available for the study area. Unfortunately, lightning fires and temperature also provided no correlation. Discussion of explanations why no correlation was found was included in section 5.5 below.

Interestingly, the analysis of lightning caused fires in relation to population growth yielded two periods (1985-1989 and 2000-2004) of positive correlation. While investigating possible explanations, it was discovered that population growth in the WUI was rapid during the 1990s, with estimates that 60% of all homes constructed in that time being were located in a WUI (Stewart, Radeloff, and Hammer 2006). It could be that population growth in the 1980s did not coincide with intense construction of housing and amenities within the WUI, but still changed the environment in ways that produced suitable conditions for lightning ignitions. As construction of homes, roads, and amenities in the WUI during the 1990s caused habitat fragmentation and destruction, it could be hypothesized that the intense construction caused enough habitat loss to introduce other intervening variables that outweighed the correlation between lightning fires and population growth, at least temporarily. This could possibly be a cyclical event, as correlation reappeared again after the housing boom of the 1990s. Further research would be required to see if this hypothesis has merit. Another simple possibility is that the construction introduced light posts and other electrical objects that attract lightning strikes in and around the area.

Human caused fires were originally thought to be positively related to population and population growth however, human caused fires did not correlate to any of the explanatory variables. Research into why there was no correlation indicated that although the magnitude of population is important, "population distribution and, by extension, housing patterns have a much larger impact on the fire problem" (Hammer, Stewart, and Radeloff 2009, p. 778). This is because years of population decentralization resulted in suburban areas scattered amongst the wildland-urban interface. In addition, investigation into these population distribution patterns instead of raw population numbers and population growth revealed distribution patterns are more precise indicators of human presence and, thus, fire ignition (Stewart, Radeloff, and Hammer 2006). Population density numbers were also calculated and a correlation between those numbers and human caused wildfires were run to see if a relationship could be established. No statistically significant relationship was found; these results are included in the Appendix.

As no consistent correlation was found in the large five-year blocks, there was a possibility that statistically significant data was to be found by looking at individual years. The five-year block of 2000-2004 had marginally significant results so it was expanded into individual years. Both fire ignition types (lightning and human caused) were run against precipitation values for each year. Nevertheless, significant results were not produced from this analysis either. Therefore, this data supports the proposition by Flannigan (1987) that rainfall amount is a poor explanatory variable of wildfire ignition.

5.2 Hot Spot Analysis Discussion

While the correlation results proved to be insignificant in explaining wildfire ignition, the Hot Spot Analysis still provided valuable visual information about the clustering of wildfire around the state of Florida, and possibly lends credence to the studies above that listed population distribution as a predominate factor influencing ignition patterns. For example, many of the consistent hot spots areas like Sarasota County in south Florida were densely populated, and it is possible that the small location shifts over time reflect growing suburbanization; more research would need to be conducted to confirm this hypothesis. Miami also becomes a cluster over time as population grew and presumably expanded. It should be noted though, that Miami-Dade County had a very large population throughout the entire study period and yet this county was not an ignition cluster area in the first-year block. Consequently, population alone does not correlate to increased wildfire ignition. However, while the correlation results do not provide statistical backing to the cluster analysis, it is still possible to visualize trouble spots to allow for intelligent allocation of wildfire management resources.

The VIIRS NightLight data did provide visual connection for some of the hot spot clusters in the last year block. The southern end of Miami, the northwestern panhandle, and other areas showed clustering of human fire activity on the edge of the light data. This could indicate that people are traveling outside the city to more wooded areas and causing fires, though some years reveal no strong relationship between major cities and wildfire.

5.3 Emerging Hot Spot Analysis Discussion

The Emerging Hot Spot Analysis provided a vast array of information across each individual year of the study. Overall, the years were unique unto themselves and did not provide consistent results, though the 1980s showed some consistency with oscillating cold spots dominating the entire state. This trend changed in the late 1980s and early 1990s, as the last months of 1989 in particular (Figure 41, page 74) exposed almost no oscillating cold spots and instead oscillating hot spots in some areas that were consistently ignition clusters (Escambia, Sarasota counties). Oscillating hot spots made a dramatic appearance in 1991 (Figure 42, page 75) with almost the entire state covered by them. However, this trend quickly reverted to numerous areas of oscillating cold spots for the remaining years, in general. As the data across all maps seem to be unrelated to any of the hot or cold spots from the Optimized Hot Spot results, it was not prudent to draw conclusions about the importance of these results.

5.4 Directional Distribution Discussion

The ellipses generated by the Directional Distribution revealed consistent patterning across all the time blocks. While there was some minor variation in movement, overall the trend and direction of the ellipses indicated that wildfire ignitions were clustered over the same general regions across the entire span of the study. This indicated that fires are occurring in the same general area year after year. Whether the fire moves slightly in relation to population location and movement into the wildland-urban interface would require more research, and was discussed in section 5.6.

5.5 Limitations

This thesis had a few limitations that were encountered during the research process. Perhaps the biggest limitation was the accuracy and abundance of meteorological data used in the correlation research. While the data was freely available from NOAA, not every county had a weather station from which to pull data; many weather stations had to be removed entirely due to either having incomplete or inaccurate data. This limited the number of stations that could be studied; several counties had to utilize precipitation and temperature data from another county, so the analysis was not necessarily representative of actual county specific data. In the future, perhaps instead of interpolating the weather data, a different approach could be taken. Limiting the analysis of fire ignitions to only those counties with complete weather data may have produced different results. However, as this research aimed at examining the entirety of Florida, eliminated counties based on this variable was not done.

The scale of the study area could also possibly be a limitation. Such a large area could mask subtle nuances that would be apparent if the study had been conducted on a smaller scale. While the MUAP problem exists at every scale of aggregation, it could be that this scale caused disproportionate issues that hid any real correlations or statistical relationships. Focusing on counties that had multiple weather stations within their borders could have provided a more accurate and realistic display of wildfire ignition variables than the state-level scale chosen for this research.

5.6 Future Research and Implications

While the research results proved inconclusive, there is still much that could be done in the same vein of analysis. Exchanging static population numbers for population density or housing numbers, for example, could provide more precise insight into the nature of wildfire ignition in Florida when performing correlation analysis. A quick glance at the relative population densities (Table 6) shows that the counties with the highest population numbers are not always the densest; an additional variable could be added to examine population density in relation to the WUI. The same could be done for annual precipitation; exchanging it for relative humidity could be very productive.

Time scales could also be tweaked to provide different levels of analysis. As the frequency of rainfall was more important than overall total precipitation, a different project could look backwards and see if months with fewer rainfall events coincided to higher incidences of wildfire in the months that follow. As shown by Flannigan and Harrington (1988), long periods of time with minimal rainfall generally precede periods of wildfire with large burned acreage in several regions of Canada. While the Canadian study found that meteorological variables only explained 35% of the variance in total burned area each month, adding socioeconomic and point data variables into a new project could provide compelling insights into the complex nature of wildfire ignition in Florida.

Utilizing smaller analytical scales at the county/block level could also be a good opportunity to provide more exact results. While the problem of MAUP exists at any scale or aggregation type chosen, the larger the units for statistical analysis, the more likely it is that variation in data values will decrease (Dark and Bram 2007). A more thorough and detailed investigation into the WUI and other areas would be possible if the scale of the project was modified. Performing a hot spot analysis on a smaller area could yield more accurate results as to where fires are igniting the most, and the additional study of variables, like those mentioned above, could provide a more refined picture of wildfires.

By changing the variables of study, the study size, and the focus, an analysis of wildfire could provide a wealth of usable, real-world information. For fires in the WUI, there are several programs that are designed to educate and inform. The National Fire Protection Association (NFPA), a non-profit association formed to educate and eliminate death and injury due to wildfire, among other issues, has a program called Firewise Communities. The program involves homeowners in fire prone areas and provides them with tools to minimize their risk of wildfire damaging their homes. The goal is to create fire adapted communities that are built with fire resistant materials, surrounded by defensible spaces, and free of flammable material that can ignite a fire. A study of the sort described above could pinpoint which areas are at most risk so that programs such as Firewise can be finely tuned and precisely applied.

Such programs will only become more important as the WUI increases. A recent study has found that climate change is expected to harm U.S. forests (Charney et al. 2016). Recent studies have indicated that as climate change causes longer droughts and other environmental stressors, trees become more vulnerable to disease and fire outbreak (Charney et al. 2016). As the WUI becomes ever more common with population growth and climate changes, making sure homes are safe from potentially highly stressed and weakened trees is paramount to both human and structural safety.

This study did show through the hot spot analysis that wildfire clusters in the same relative areas year after year. What explains these recurring fires if fuel is being burned in the same areas repeatedly? First, most of the fires are caused by humans and are quite small, often less than an acre. These fires in Florida rarely have the destructive capacity compared to wildfires out west due to many factors like humidity, ecology, and even how the fire was ignited. Considering the thousands of acres (22 million) of ignitable land in Florida, both in the WUI and elsewhere, it is arguable that small fires can burn in the same general region every year and not clear out the majority of the fuel load.

Florida's ecology is such that regrowth is also quick, as ample rain promotes a lush, fast growing environment. Regrowth is further compounded by the current prescribed burn cycle used by the Florida Forest Service (FFS). With only two million acres being burned every year, fire-prone landscapes are seeing an 11-year fire interval, which is much longer than natural fire cycles (Prescribed Fire in Florida, Strategic Plan 2013-2020). The FFS hopes to recreate the natural fire cycle with more frequent prescribed burns as part of its future strategic plans. By increasing personnel, providing incentives to land managers to use prescribed fire more, and by using creative measures to increase the capacity of private sector burn practitioners, it is the goal of the FFS to create a fire policy that reflects natural fire cycles and protects more people and property. This research could provide a visual guideline for the FFS to see where best to place its resources and time in order to accomplish its strategic goals.

References

Asgary, Ali, Alireza Ghaffari, and Jason Levy. 2010. "Spatial and temporal analyses of structural fire incidents and their causes: A case of Toronto, Canada." *Fire Safety Journal* 45(1): 44-57.

Bradshaw, W. G. 1987. "The Urban/wildland interface fire problem. Can social science play a role?" *People and Fire at the Wildland/Urban Interface (A Source Book). USDA Forest Service, Washington, DC ed: RD Gole and HJ Cortner*.

Bosworth, Dale. 2004. "Four threats to the Nation's forests and grasslands." In *Idaho Environmental Forum*, Boise, Idaho.

Brenner, Jim. 1991. "Southern Oscillation anomalies and their relationship to wildfire activity in Florida." *International Journal of Wildland Fire* 1(1): 73-78.

Busenberg, George. 2004. "Wildfire management in the United States: the evolution of a policy failure." *Review of Policy Research* 21(2): 145-156.

Charney, Noah D., Flurin Babst, Benjamin Poulter, Sydne Record, Valerie M. Trouet, David Frank, Brian J. Enquist, and Margaret EK Evans. 2016. "Observed forest sensitivity to climate implies large changes in 21st century North American forest growth." *Ecology Letters* 19(9): 1119-1128.

Chu, Pao-Shin, Weiping Yan, and Francis Fujioka. 2002. "Fire-climate relationships and long-lead seasonal wildfire prediction for Hawaii." *International Journal of Wildland Fire* 11(1): 25-31.

Cole, David N., and John Dalle-Molle. 1982. *Managing campfire impacts in the backcountry*. US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.

Corcoran, Jonathan, Gary Higgs, Chris Brunsdon, Andrew Ware, and Paul Norman. 2007. "The use of spatial analytical techniques to explore patterns of fire incidence: A South Wales case study." *Computers, Environment and Urban Systems* 31(6): 623-647.

Dark, Shawna J., and Danielle Bram. 2007. "The modifiable areal unit problem (MAUP) in physical geography." *Progress in Physical Geography* 31(5): 471-479.

DellaSala, Dominick A., and Chad T. Hanson. 2015. *The ecological importance of mixed-severity fires: nature's phoenix*. Elsevier.

Di Martino, Ferdinando, and Salvatore Sessa. 2011. "The extended fuzzy C-means algorithm for hotspots in spatio-temporal GIS." *Expert Systems with Applications* 38(9):11829-11836.

Elvidge, Christopher D., Kimberly E. Baugh, Mikhail Zhizhin, and Feng-Chi Hsu. 2013. "Why VIIRS data are superior to DMSP for mapping nighttime lights." *Proceedings of the Asia-Pacific Advanced Network* 35: 62-69.

Feltman, Joel A., Thomas J. Straka, Christopher J. Post, and Stephen L. Sperry. 2012. "Geospatial Analysis Application to Forecast Wildfire Occurrences in South Carolina." *Forests* 3(2): 265-282.

Flannigan, Michael .D., Brian J. Stocks, and Brian M. Wotton. 2000. "Climate change and forest fires." *Science of the Total Environment*, 262: 221-230.

Flannigan, Michael. D., and J. B Harrington. 1988. "A study of the relation of meteorological variables to monthly provincial area burned by wildfire in Canada (1953-80)." *Journal of Applied Meteorology* 27(4): 441-452.

Hammer, Roger B., Susan I. Stewart, and Volker C. Radeloff. 2009. "Demographic trends, the wildland–urban interface, and wildfire management." *Society and Natural Resources* 22(8): 777-782.

Hering, Amanda S., Cynthia L. Bell, and Marc G. Genton. 2009. "Modeling spatio-temporal wildfire ignition point patterns." *Environmental and Ecological Statistics* 16(2): 225 -250.

Juan, Pablo, Jorge Mateu, and Marc Sáez Zafra. 2012. "Pinpointing spatio-temporal interactions in wildfire patterns." *Stochastic Environmental Research and Risk Assessment* 26(8): 1131-1150.

Keeley, Jon E., Melanie Baer-Keeley, and C. J. Fotheringham. 2005. "Alien plant dynamics following fire in Mediterranean-climate California shrublands." *Ecological Applications* 15(6): 2109-2125.

Loeher, Larry L. 1985. "Fire hazard: The dimension of resident's attitude." In *Conference Proceedings Living in the Chaparral of Southern California. National Foundation for Environmental Safety and USDI National Park Service. Santa Monica,* CA.

McCullough, Deborah G., Richard A. Werner, and David Neumann. 1998. "Fire and insects in northern and boreal forest ecosystems of North America 1." *Annual Review of Entomology* 43(1): 107-127.

Mercer, Evan D., and Jeffrey P. Prestemon. 2005. "Comparing production function models for wildfire risk analysis in the wildland–urban interface." *Forest Policy and Economics* 7(5): 782-795.

Minnich, Richard A. 1983. "Fire mosaics in southern California and northern Baja California." *Science* 219(4590): 1287-1294.

Nowak, David J., Jeffrey T. Walton, John F. Dwyer, Latif G. Kaya, and Soojeong Myeong. 2005. "The increasing influence of urban environments on US forest management." *Journal of Forestry* 103(8): 377-382.

Pew, K. L., and Chris. P. S. Larsen. 2001. "GIS analysis of spatial and temporal patterns of human-caused wildfires in the temperate rain forest of Vancouver Island, Canada." *Forest Ecology and Management* 140(1): 1-18.

Prescribed Fire in Florida, Strategic Plan 2013-2020. 2012. Florida Forest Service. Tallahassee, FL: Florida Department of Agriculture and Consumer Services.

Prestemon, Jeffrey P., Todd J. Hawbaker, Michael Bowden, John Carpenter, Maureen T. Brooks, Karen L. Abt, Ronda Sutphen, and Samuel Scranton. 2013. "Wildfire ignitions: a review of the science and recommendations for empirical modeling." USDA Forest Service General Technical Report SRS-171. Asheville, NC: USDA Forest Service Southern Research Station.

Reams, Margaret A., Terry K. Haines, Cheryl R. Renner, Michael W. Wascom, and Harish Kingre. 2005. "Goals, obstacles and effective strategies of wildfire mitigation programs in the wildland–urban interface." *Forest Policy and Economics* 7(5): 818-826.

Reid, Scott E., and Jeffrey L. Marion. 2005. "A comparison of campfire impacts and policies in seven protected areas." *Environmental Management* 36(1): 48-58.

Romero-Calcerrada, Raul, C. J. Novillo, J. D. A. Millington, and I. Gomez-Jimenez. 2008. "GIS analysis of spatial patterns of human-caused wildfire ignition risk in the SW of Madrid (Central Spain)." *Landscape Ecology* 23(3): 341-354.

Taylor, Steve W., Douglas G. Woolford, C. B. Dean, and David L. Martell. 2013. "Wildfire prediction to inform fire management: statistical science challenges." *Statistical Science* 28(4): 586-615.

Savage, Melissa, and Joy Nystrom Mast. 2004. "How resilient are southwestern ponderosa pine forests after crown fires?." *Canadian Journal of Forest Research* 35(4): 967-977.

Short, Keith. C. 2014. "A spatial database of wildfires in the United States, 1992-2011." *Earth System Science Data* 6(1): 1-27.

Stewart, Susan, Volker C. Radeloff., Roger B. Hammer. 2006. “The wildland–urban interface in the United States.” *Ecological Applications* 15(3): 799–805.

Theobald, David M., and William H. Romme. 2007. "Expansion of the US wildland–urban interface." *Landscape and Urban Planning* 83(4): 340-354.

Westerling, Anthony L., Hugo G. Hidalgo, Daniel R. Cayan, and Thomas W. Swetnam. 2006. "Warming and earlier spring increase western US forest wildfire activity." *Science* 313(5789): 940-943.

Wing, Michael G., and Justin Long. 2015. "A 25-Year History of Spatial and Temporal Trends in Wildfire Activity in Oregon and Washington, USA." *Modern Applied Science* 9(3): 117.

Winter, Greg, and Jeremy S. Fried. 2000. "Homeowner perspectives on fire hazard, responsibility, and management strategies at the wildland-urban interface." *Society & Natural Resources* 13(1): 33-49.

APPENDIX A: Tables and Figures

Table 6 Human Fire/Population Density Correlation Coefficients

	Human Fires and Population Density
1985-1989	cor: -0.04372439
1990-1994	cor: -0.04046809
1995-1999	cor: 0.07587163
2000-2004	cor: -0.1026769
2005-2009	cor: -0.1415845
2010-2014	cor: -0.1325636

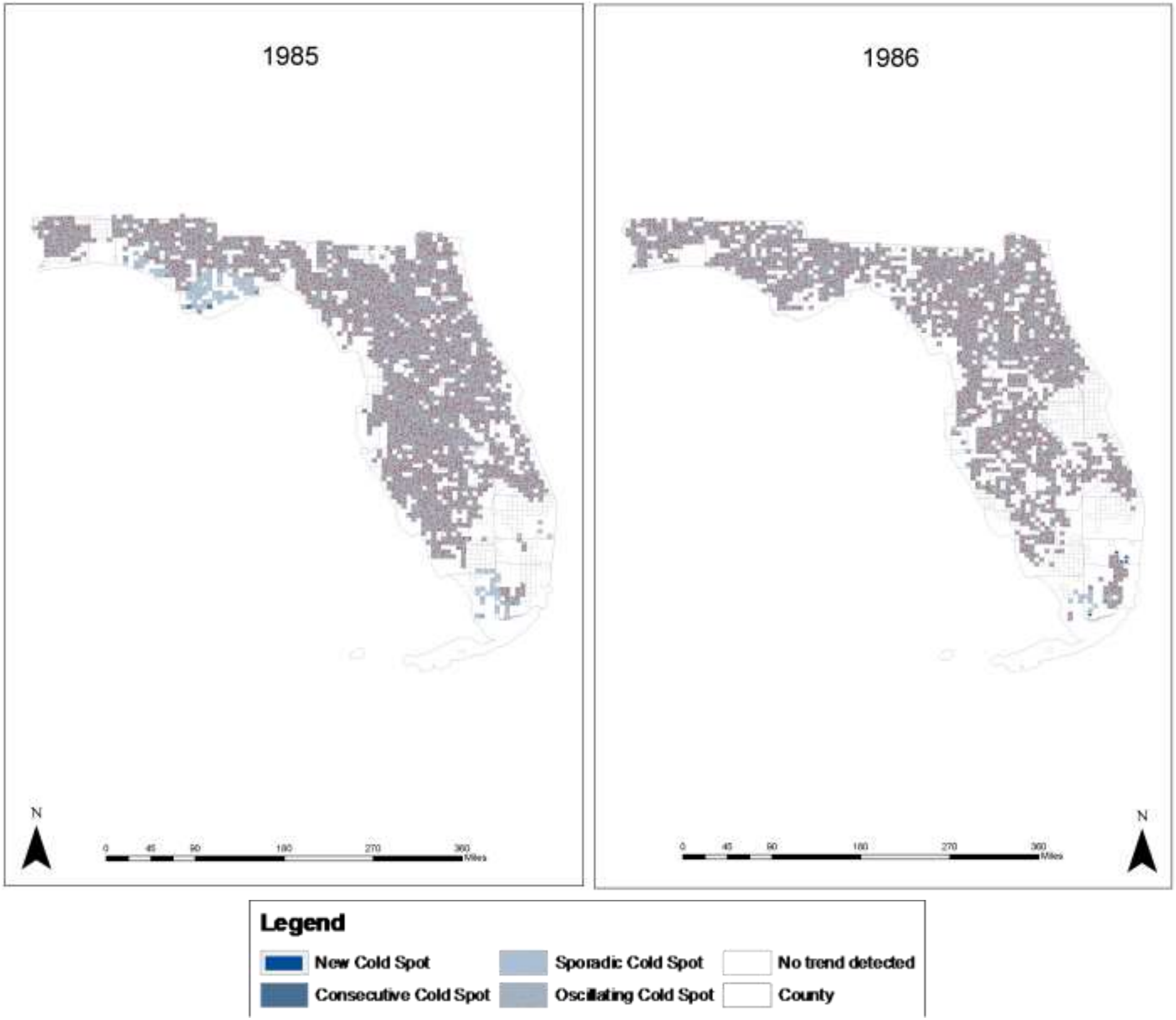

Figure 15 1985 & 1986 Emerging Hot Spot Analysis

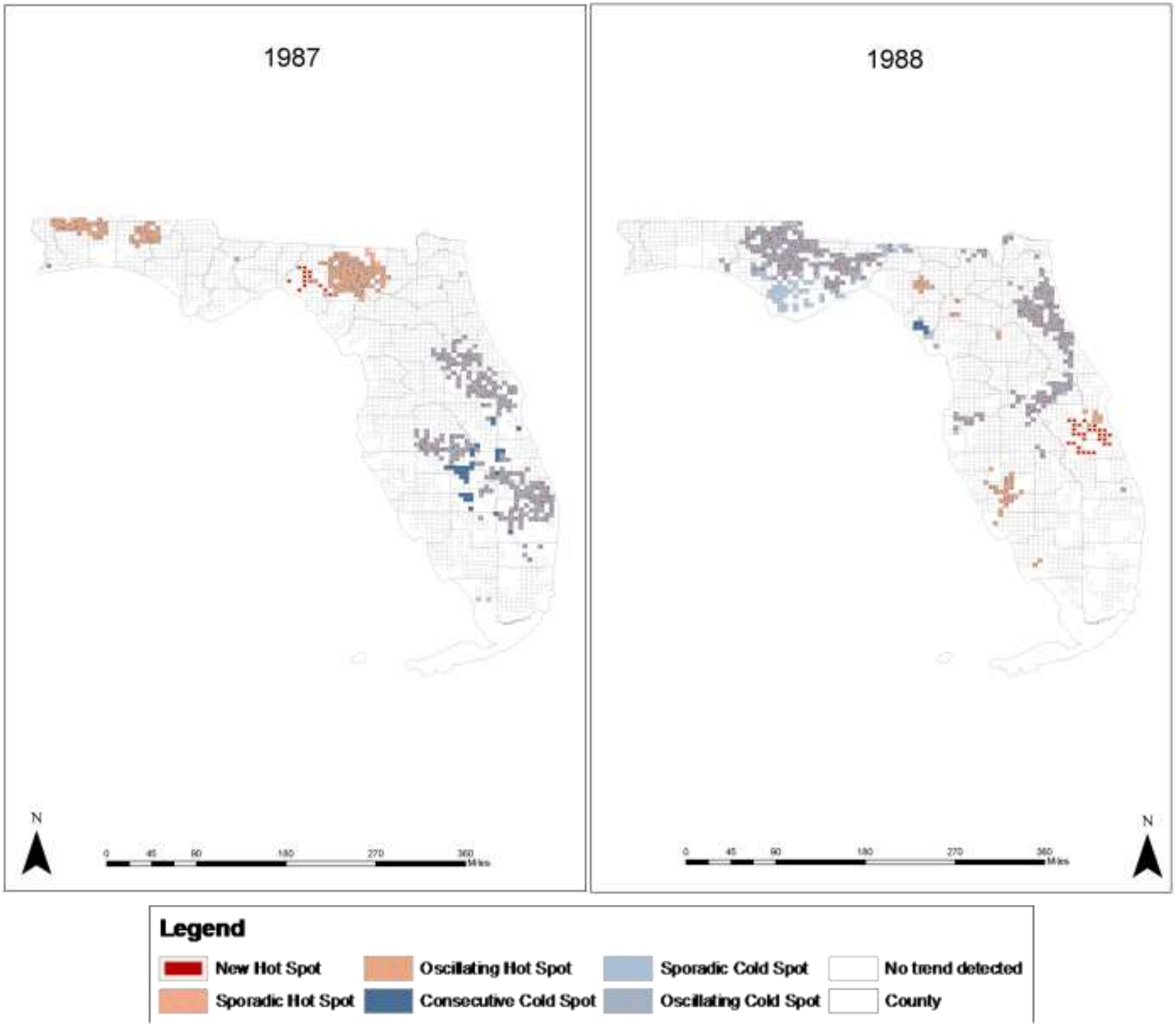

Figure 16 1987 & 1988 Emerging Hot Spot Analysis

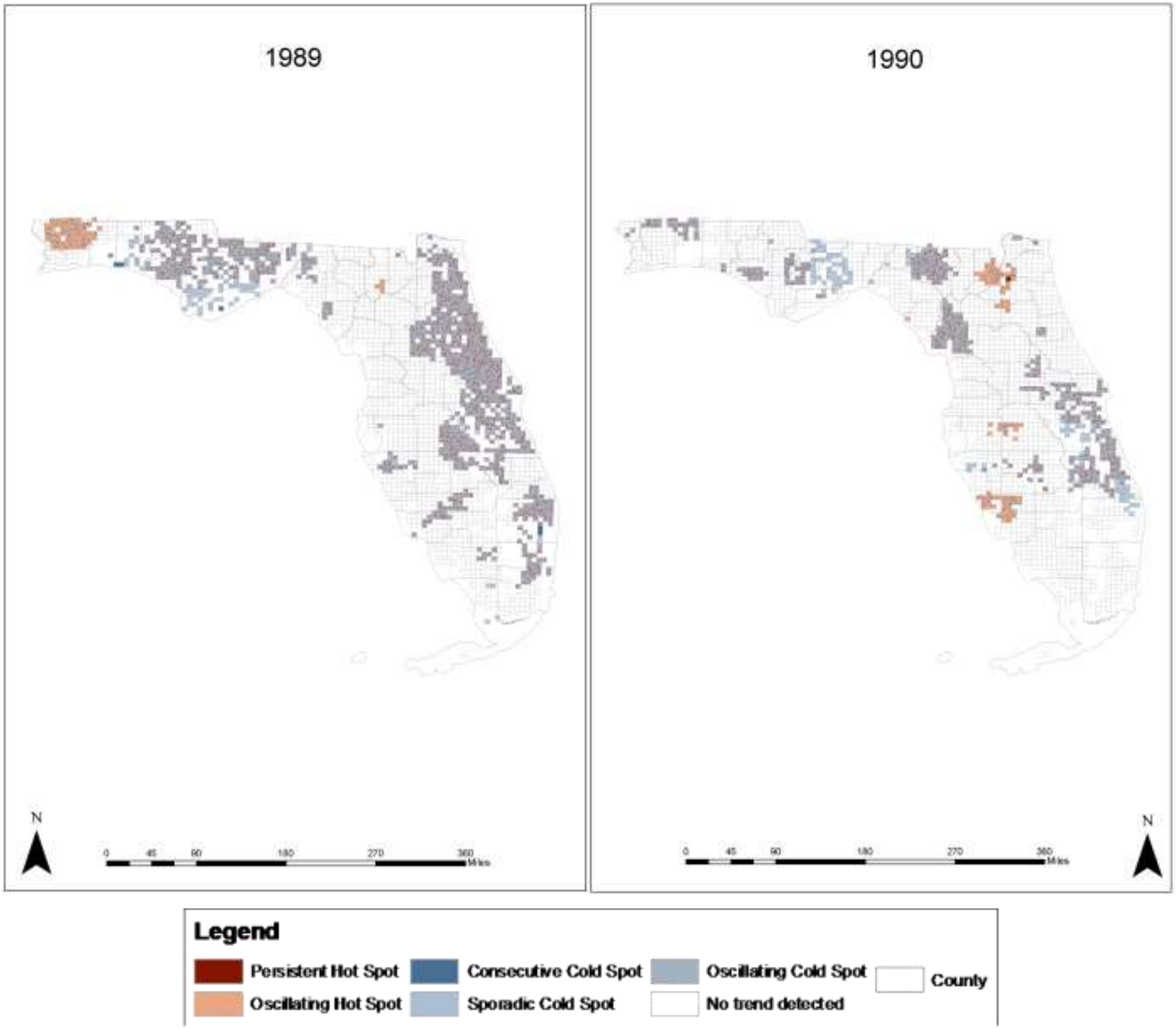

Figure 17 1989 & 1990 Emerging Hot Spot Analysis

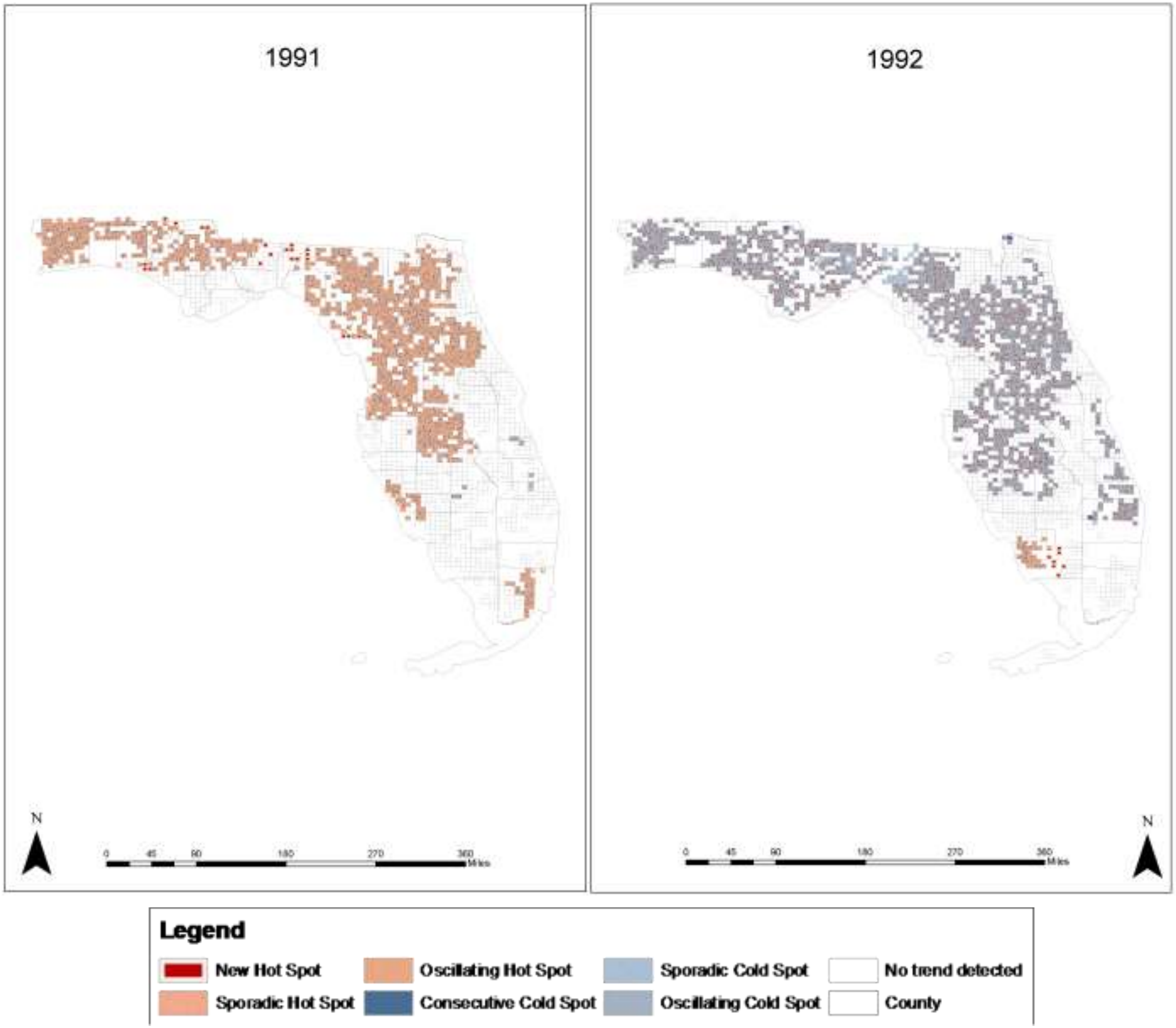

Figure 18 1991 & 1992 Emerging Hot Spot Analysis

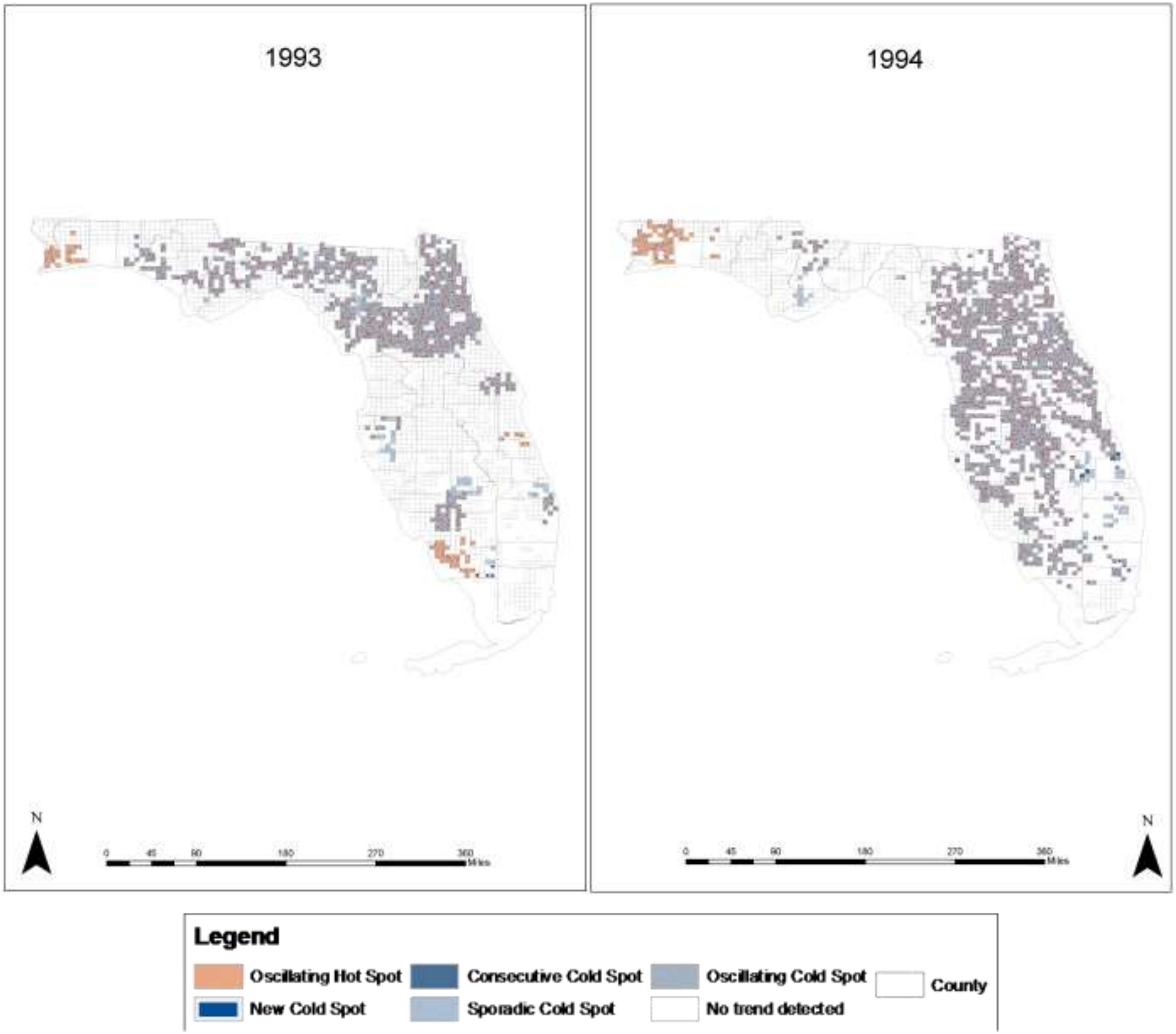

Figure 19 1993 & 1994 Emerging Hot Spot Analysis

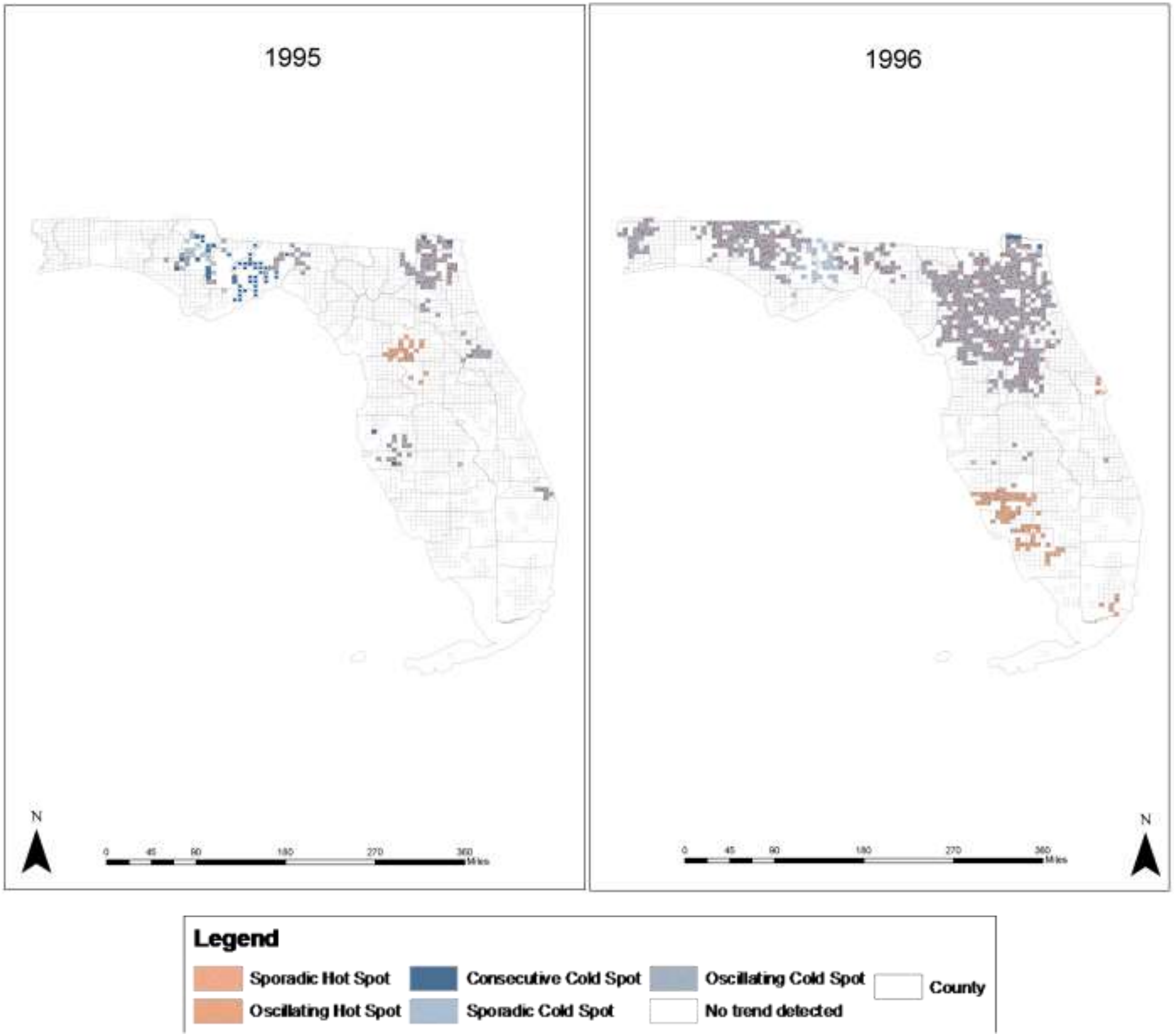

Figure 20 1995 & 1996 Emerging Hot Spot Analysis

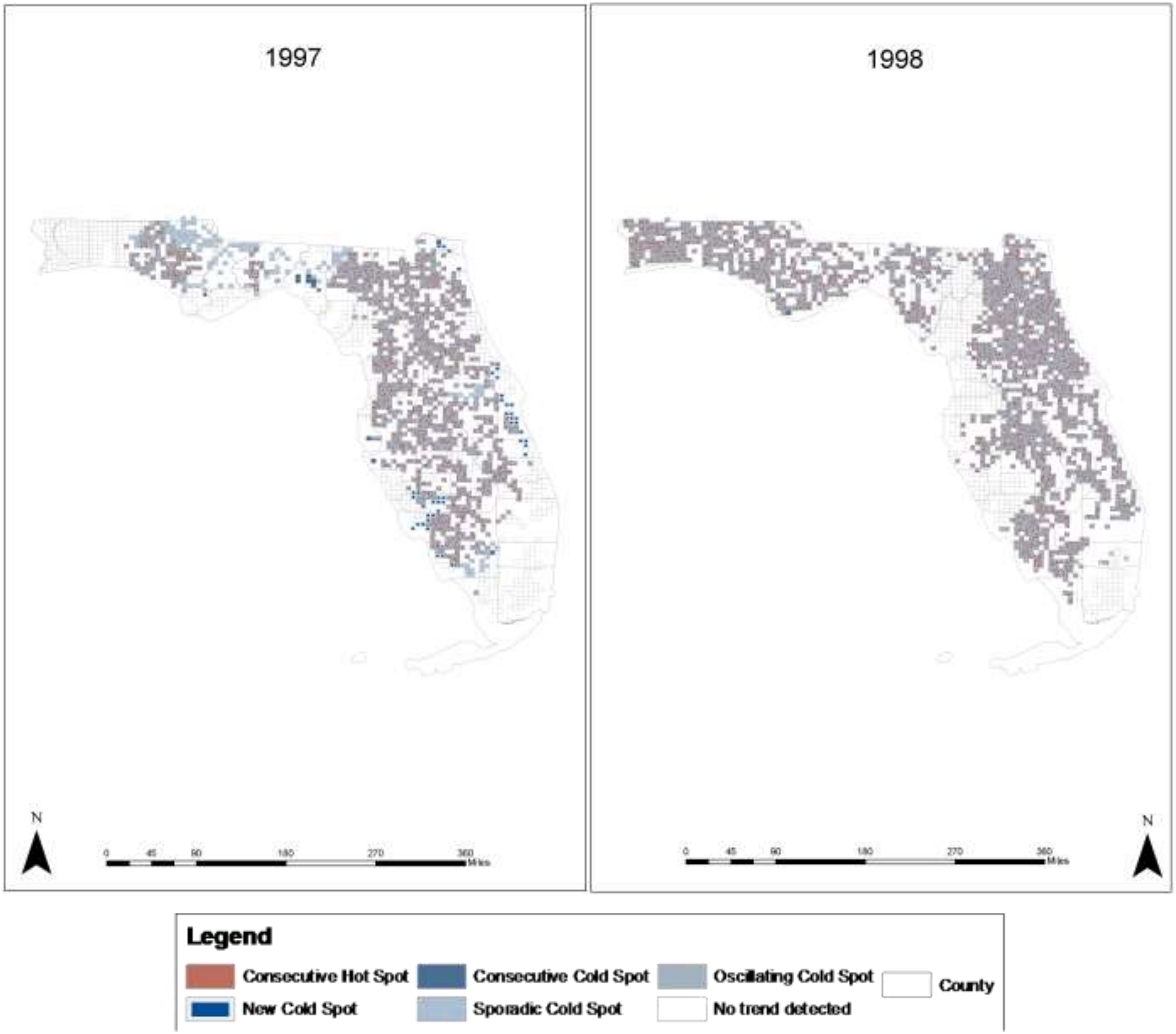

Figure 21 1997 & 1998 Emerging Hot Spot Analysis

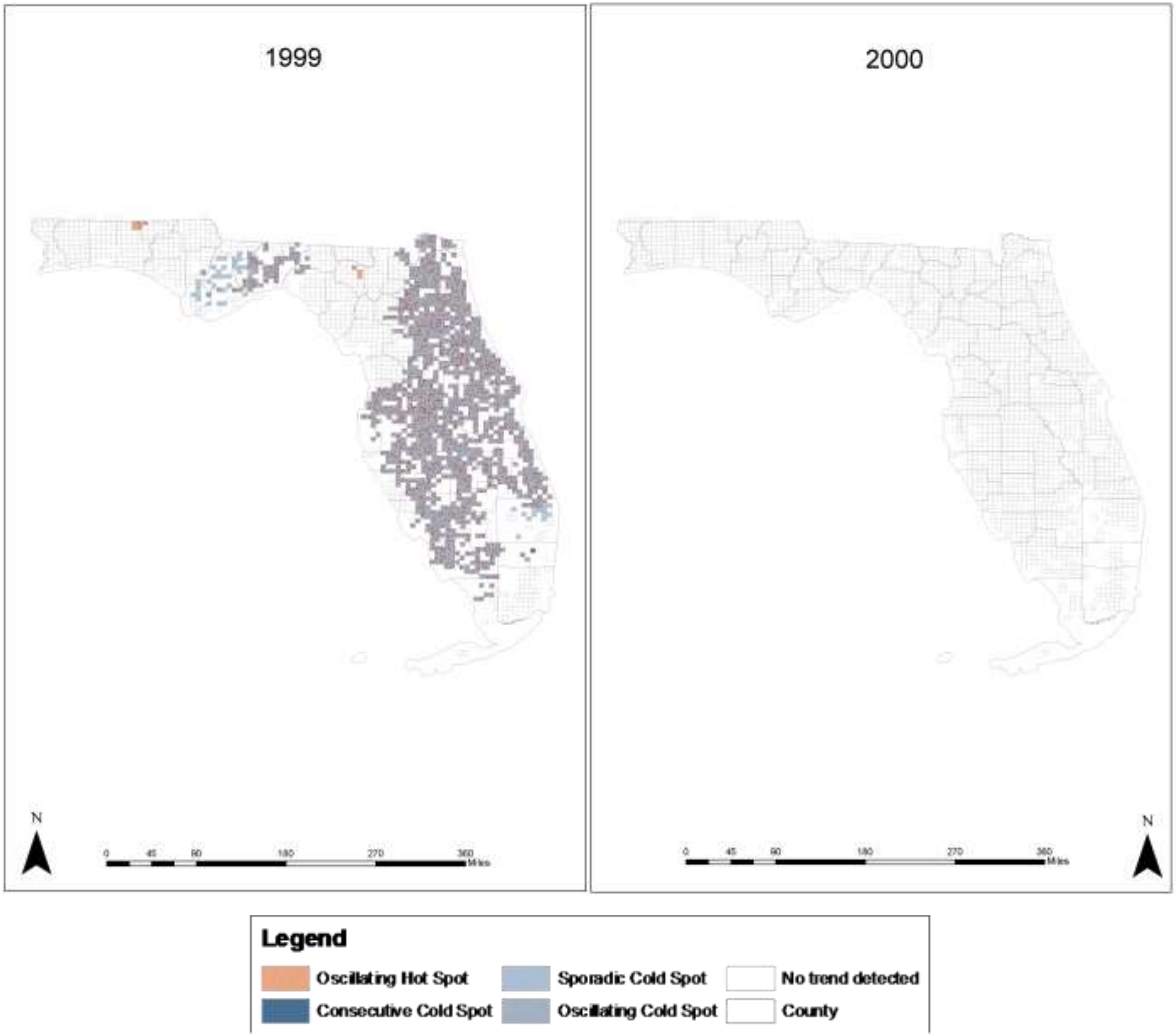

Figure 22 1999 & 2000 Emerging Hot Spot Analysis

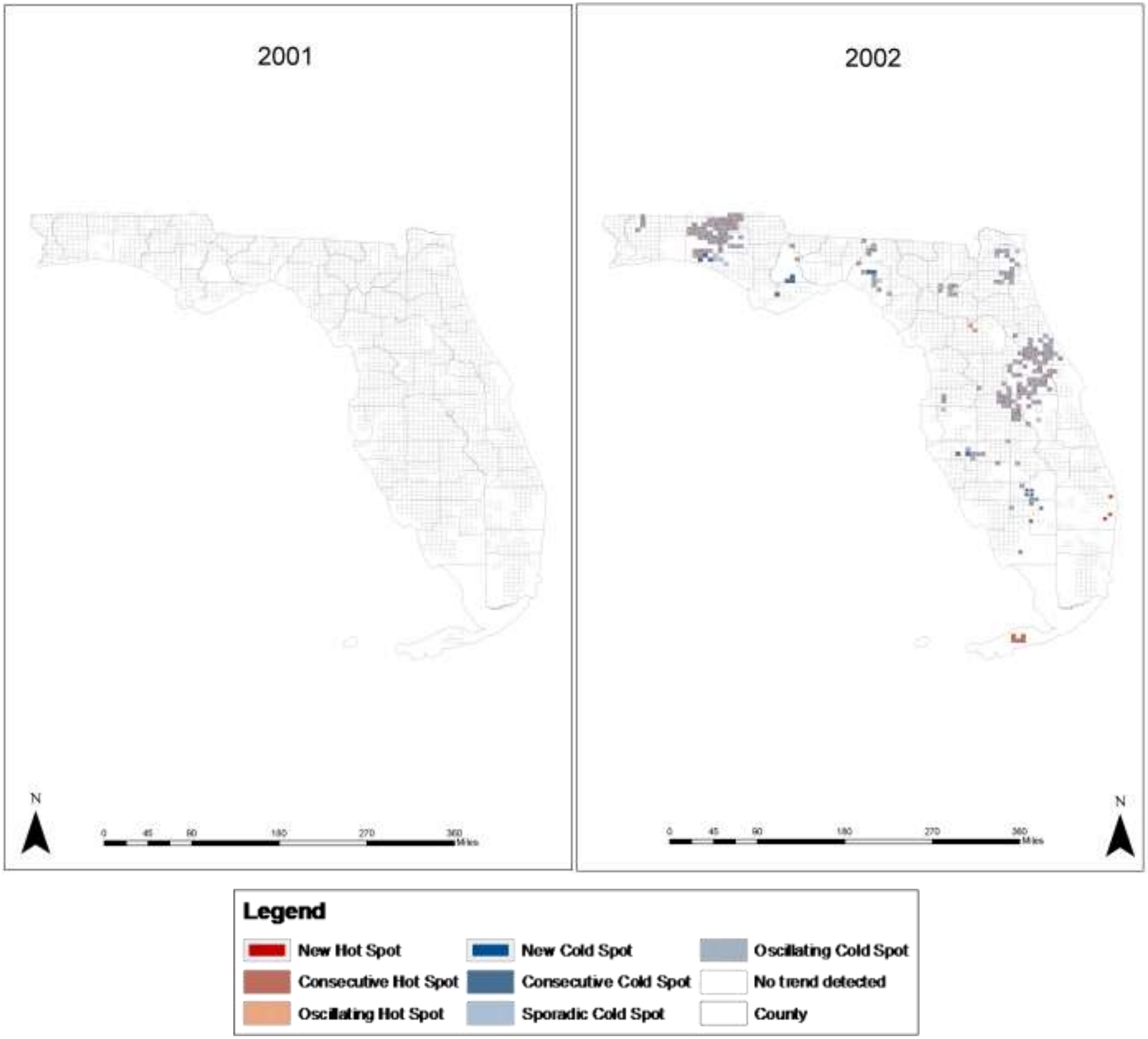

Figure 23 2001 & 2002 Emerging Hot Spot Analysis

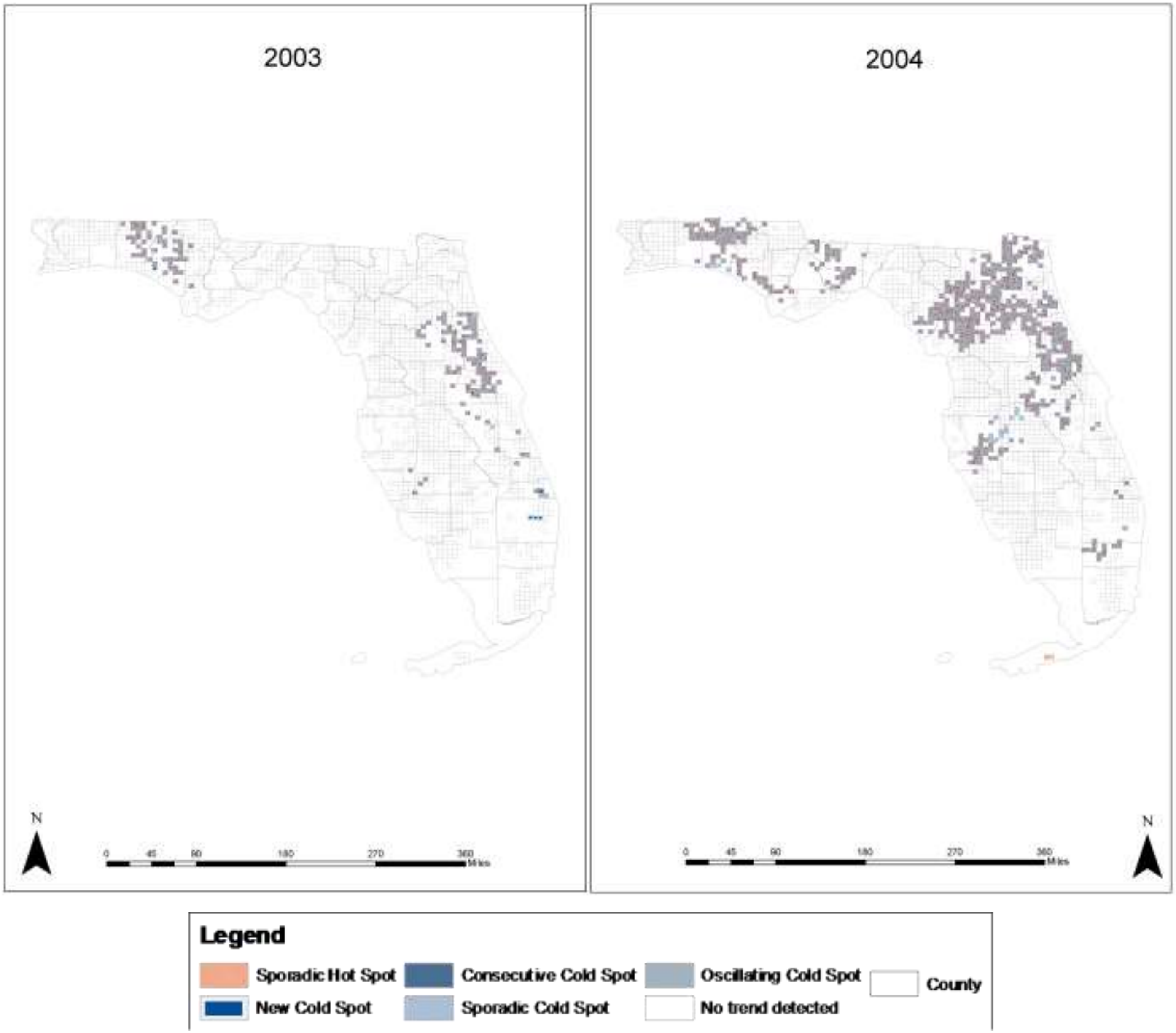

Figure 24 2003 & 2004 Emerging Hot Spot Analysis

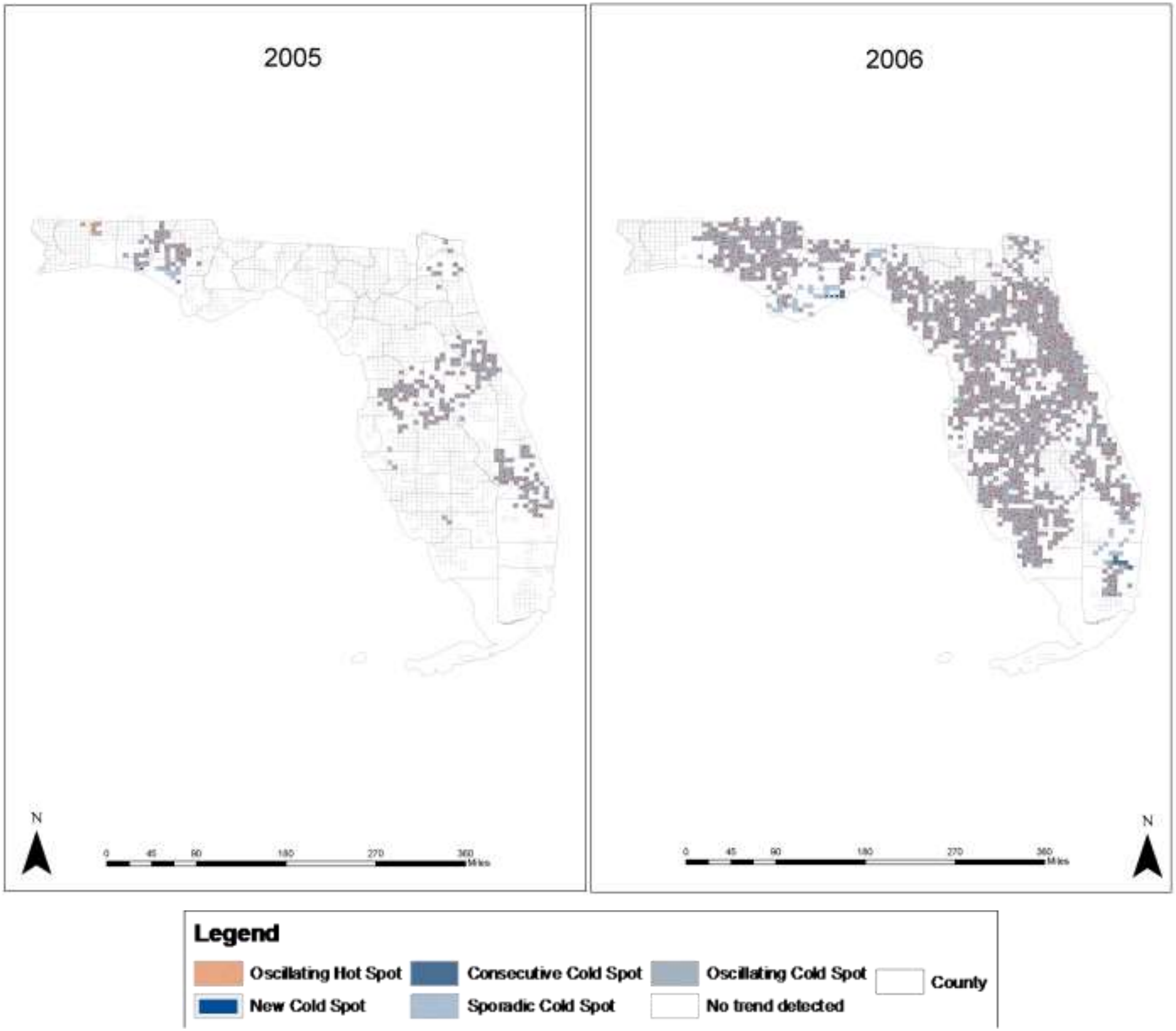

Figure 25 2005 & 2006 Emerging Hot Spot Analysis

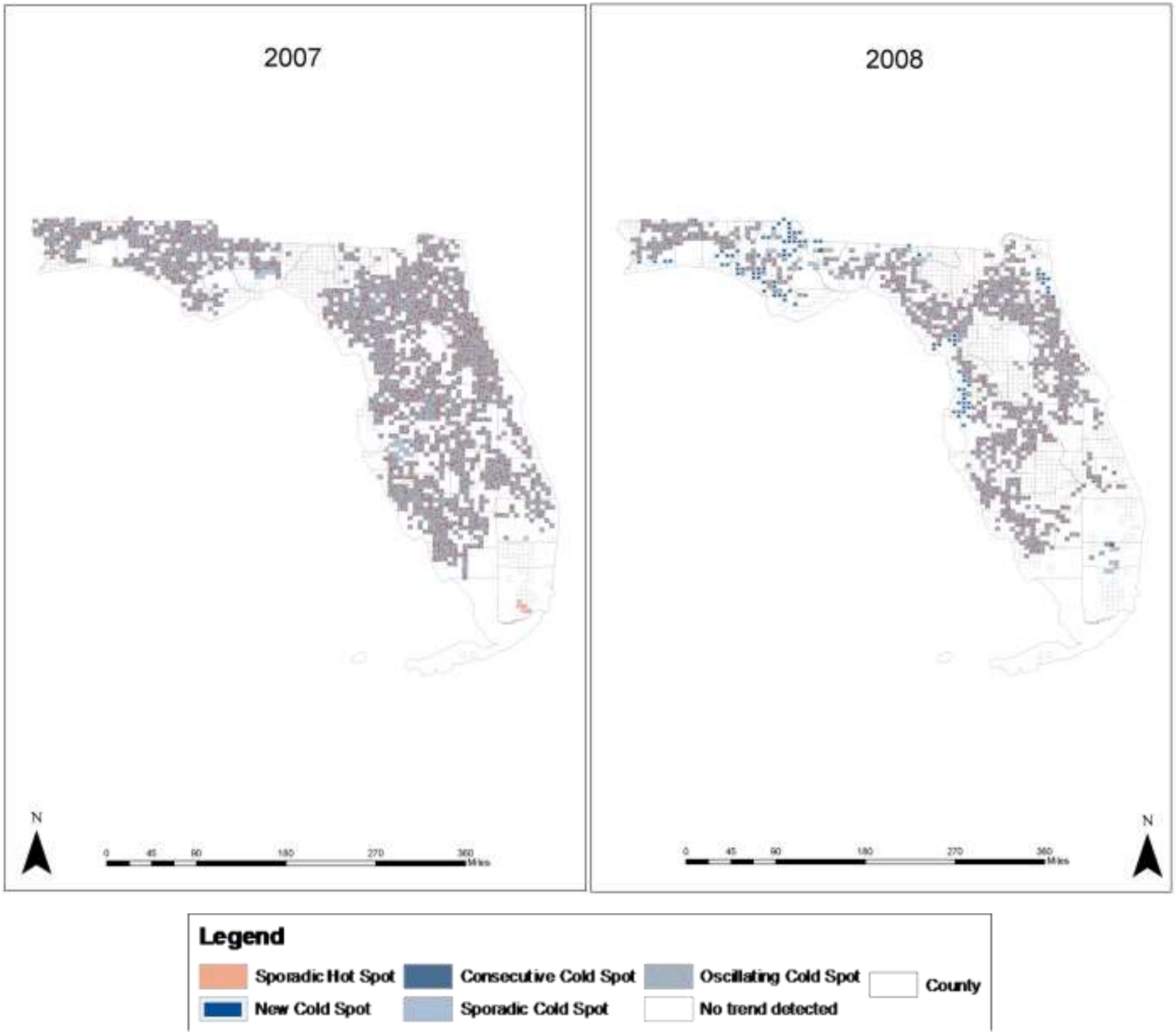

Figure 26 2007 & 2008 Emerging Hot Spot Analysis

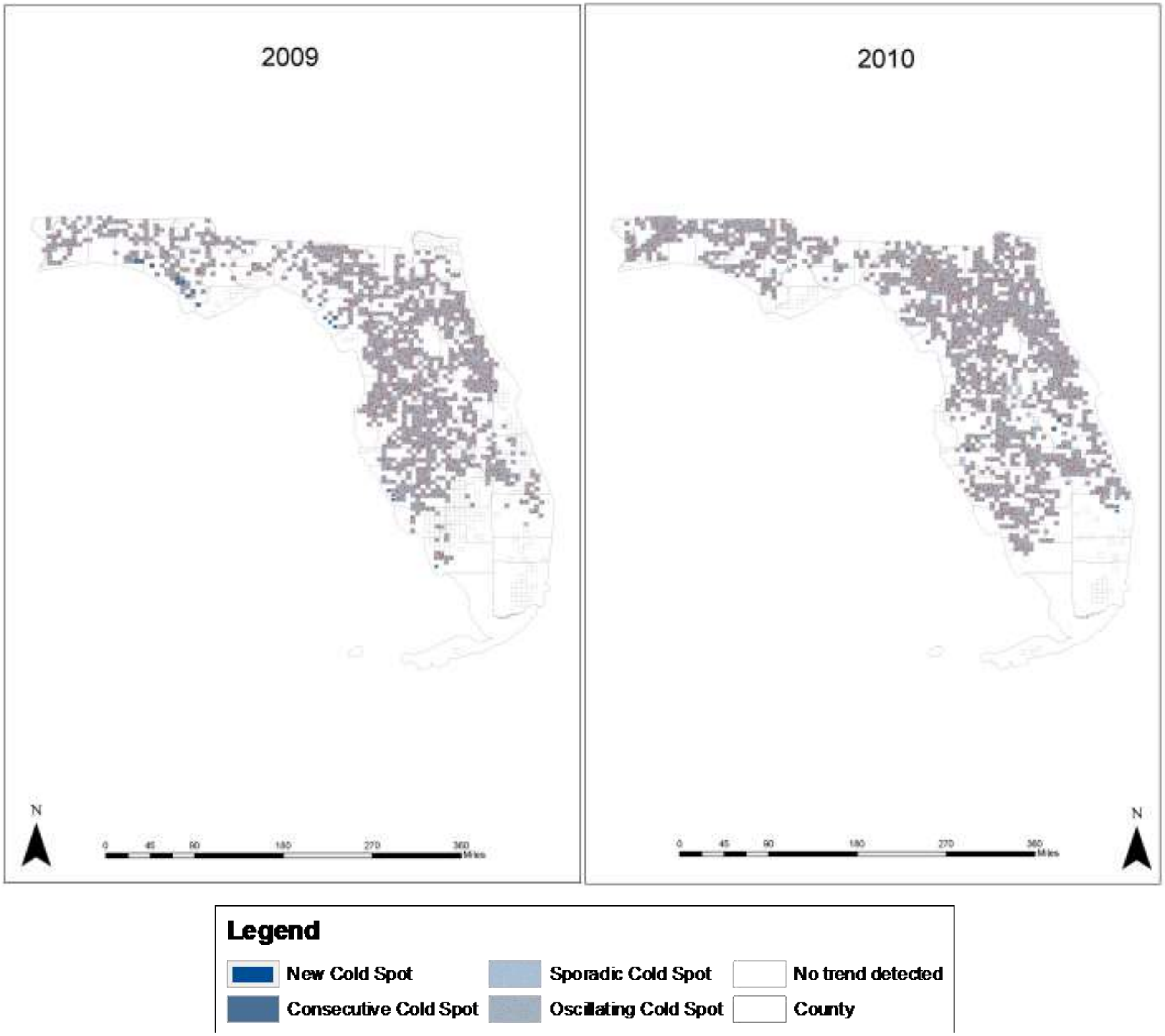

Figure 27 2009 & 2010 Emerging Hot Spot Analysis

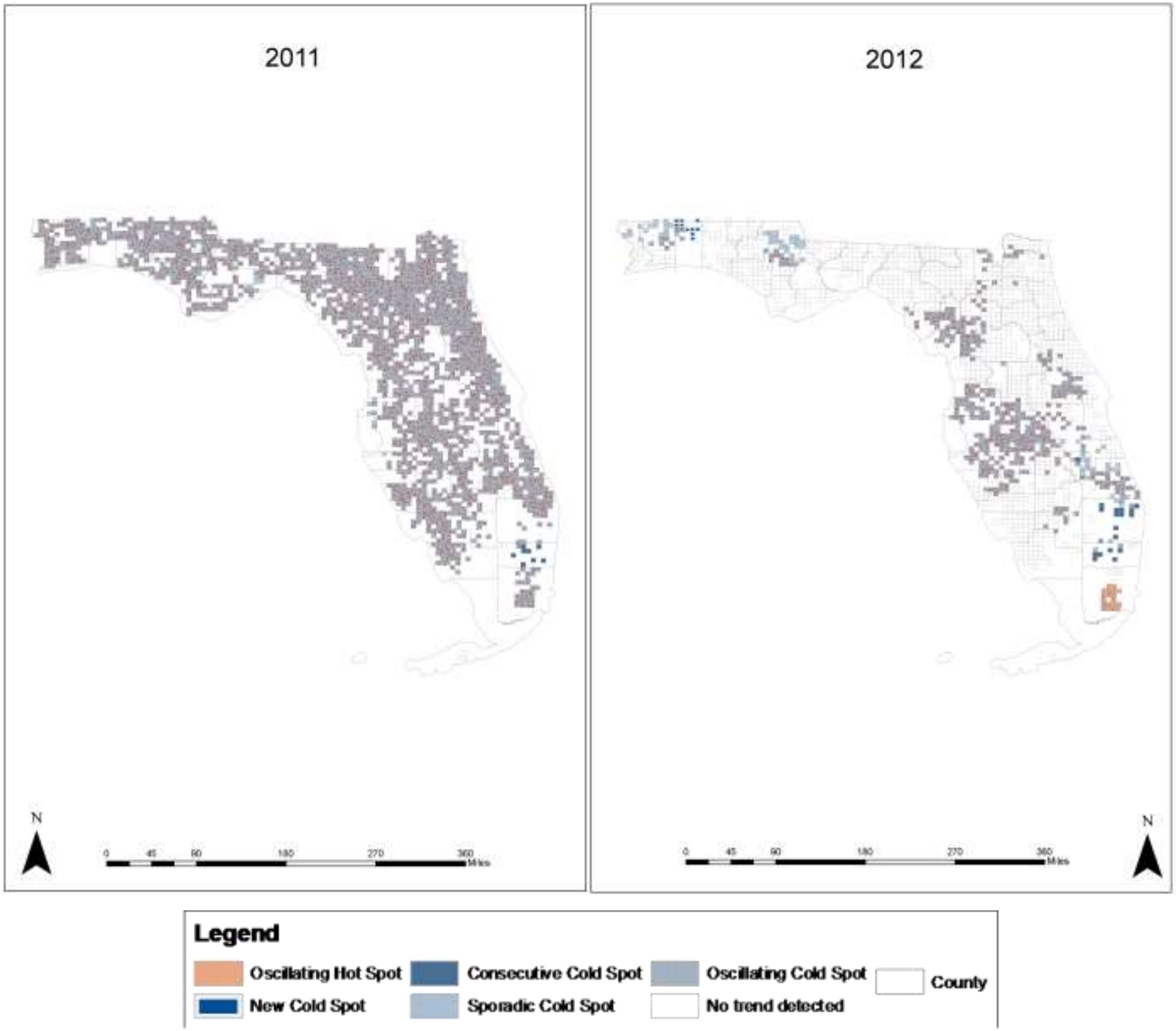

Figure 28 2011 & 2012 Emerging Hot Spot Analysis

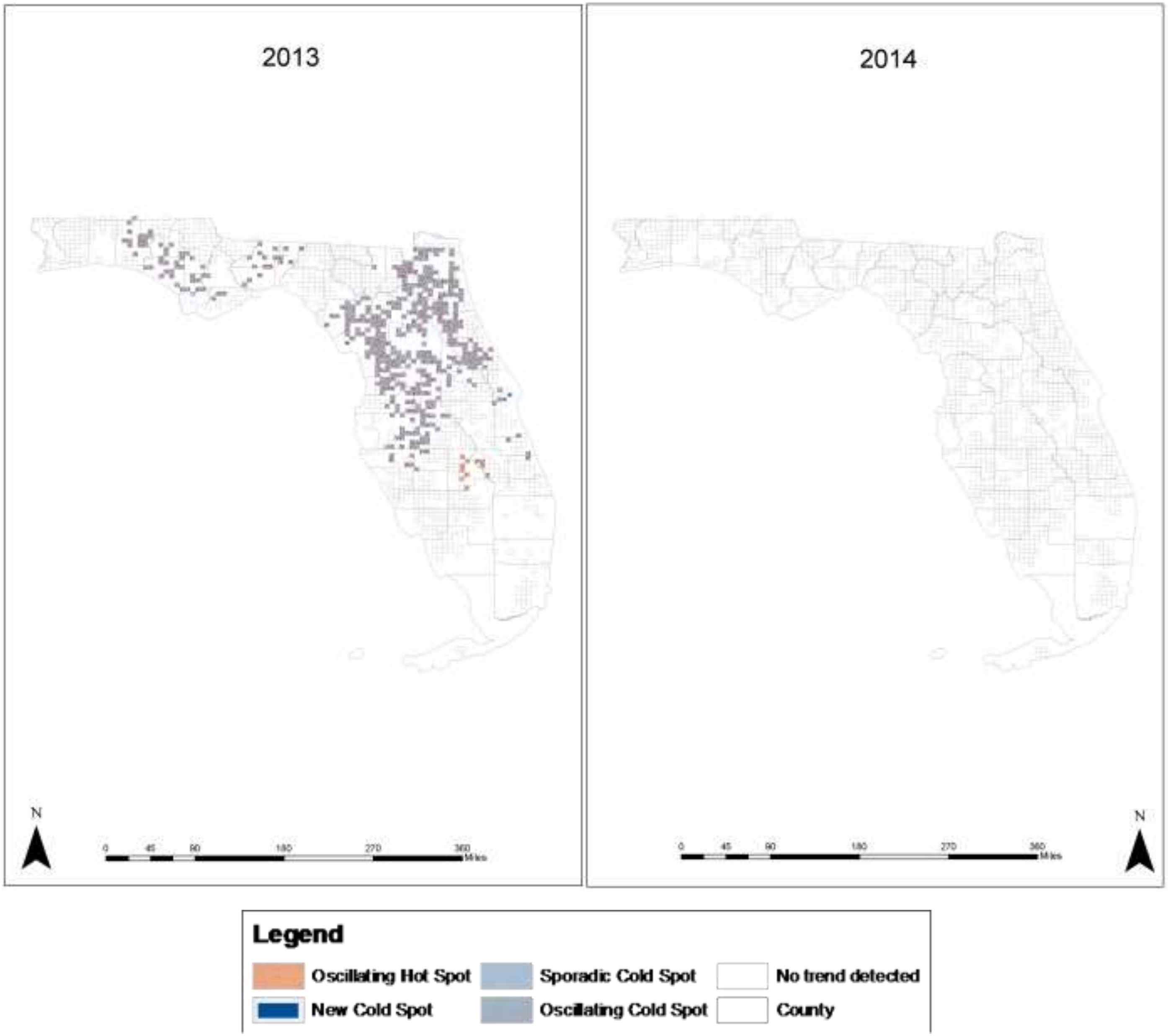

Figure 29 2013 & 2014 Emerging Hot Spot Analysis

Table 7 1985-1989 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	81	41.924	892	186772	7.99	73.436	875.02	213.4488355
BAKER	48	52.228	567	19364	11.87	70.043	585.23	33.0878458
BAY	65	54.44	476	135708	13.56	71.195	758.46	178.9257179
BRADFORD	29	51.446	403	24804	6	73.436	293.96	84.37882705
BREVARD	115	52.926	628	403500	18.86	72.178	1,015.66	397.2786169
BROWARD	8	54.02	190	1242488	10.53	74.32	1,209.79	1027.027831
CALHOUN	33	46.132	209	11268	18.54	69.303	567.33	19.8614563
CHARLOTTE	156	56.918	731	99214	26.43	71.415	680.28	145.8428882
CITRUS	63	47.092	546	91469	26.55	71.656	581.7	157.244284
CLAY	67	51.446	513	102796	20.43	70.471	604.36	170.0906744
COLLIER	117	44.81	974	144721	25.6	74.306	1,998.32	72.42133392
COLUMBIA	32	51.292	484	43553	10.66	68.995	797.57	54.60711912
DESOTO	30	50.642	235	24279	12.54	71.415	637.06	38.11100995
DIXIE	51	64.182	532	10832	17.66	72.543	705.05	15.3634494
DUVAL	69	46.732	759	686337	11.45	70.675	762.19	900.4801952
ESCAMBIA	6	52.792	564	285423	7.82	70.183	656.46	434.7911525
FLAGLER	225	53.56	435	23911	9.02	74.4	485.46	49.25431549
FRANKLIN	25	47.956	148	8678	3.23	74.75	534.73	16.22875096
GADSDEN	3	49.184	388	45639	1.6	74.61	516.33	88.3911452
GILCHRIST	19	47.848	201	7709	10	74.06	349.68	22.04587051
GLADES	111	50.562	288	7765	12.19	69.49	806.01	9.63387551
GULF	45	47.956	1206	12560	11.43	69.303	564.01	22.2691087
HAMILTON	32	45.21	196	10372	12.48	70.693	513.79	20.18723603
HARDEE	17	49.626	208	22695	7.33	69.503	637.78	35.58437079
HENDRY	103	50.664	341	26138	15.13	72.441	1,152.75	22.67447408

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	43	47.448	425	90507	30.61	74.071	472.54	191.5329919
HIGHLANDS	74	57.8	523	69089	17.61	68.435	1,016.62	67.9595129
HILLSBOROUGH	62	45.884	704	840970	12.28	73.27	1,020.21	824.3106811
HOLMES	11	64.5	267	17656	13.53	71.185	478.78	36.87706253
INDIAN RIVER	70	42.108	313	91375	19.53	71.846	502.87	181.7070018
JACKSON	10	64.5	372	4475	9.41	69.303	917.76	4.876002441
JEFFERSON	13	49.184	202	12516	8.43	69.39	598.1	20.92626651
LAFAYETTE	37	51.636	261	5404	20.12	69.176	543.41	9.944609043
LAKE	67	51.428	865	146333	17.75	70.67	938.38	155.9421556
LEE	134	50.562	668	324520	22.75	71.93	784.51	413.6594817
LEON	11	49.184	317	192578	14.27	68.633	666.85	288.7875834
LEVY	181	47.848	705	25182	12.12	71.393	1,118.21	22.51992023
LIBERTY	19	47.946	219	4757	5.01	69.303	835.56	5.693187802
MADISON	13	45.046	266	16500	5.61	73.206	695.95	23.70859976
MANATEE	52	50.656	260	192691	12.97	67.826	742.93	259.3662929
MARION	118	46.328	1162	190742	20.84	73.65167	1,584.55	120.376132
MARTIN	93	45.53	321	96636	19.44	67.09	543.46	177.8162146
MIAMI-DADE	5	54.618	733	1873078	6.54	68.33	1,897.72	987.0149442
MONROE	0	55.936	100	78966	11.65	74.74	983.28	80.30876251
NASSAU	64	52.438	384	47863	20.19	68.936	648.64	73.78977553
OKALOOSA	18	51.756	301	157517	15.51	70.01	930.25	169.3276001
OKEECHOBEE	45	51.018	341	29941	21.98	71.21	768.91	38.93953779
ORANGE	130	53.054	516	653982	17.91	70.83	903.43	723.8878496
OSCEOLA	120	51.696	617	97605	26.15	67.338	1,327.45	73.52819315
PALM BEACH	41	49.31	702	865507	21.35	75.56	1,969.76	439.3971854
PASCO	53	55.706	572	272422	16.78	70.051	746.89	364.741796
PINELLAS	9	43.72	73	855427	6.94	71.603	273.8	3124.276844

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	110	45.794	1783	410863	12.18	77.5	1,797.84	228.53146
PUTNAM	127	45.516	697	62828	10.55	72.64	727.62	86.34726918
SANTA ROSA	20	43.38	1030	69375	9.46	71.49	1,011.61	68.57880013
SARASOTA	133	48.8	413	263937	10.89	67.181	555.87	474.8178531
SEMINOLE	50	50.52	243	281049	22.23	70.343	309.22	908.8965785
ST. JOHNS	174	60.384	583	84389	22.62	70.471	600.66	140.4937902
ST. LUCIE	44	54.864	263	143214	23.21	66.58	571.93	250.4047698
SUMTER	13	48.206	171	31260	13.96	69.19	546.93	57.15539466
SUWANNEE	39	54.436	838	27688	9.2	71.36	688.55	40.21203979
TAYLOR	83	64.182	546	19710	10.33	67.276	1,043.31	18.8917963
UNION	20	49.85	134	10474	-1.98	74.06	243.56	43.0037773
VOLUSIA	430	51.428	1211	360049	17.26	72.998	1,101.03	327.0110715
WAKULLA	21	49.184	251	14485	10.08	68.33	606.42	23.88608555
WALTON	44	48.226	44	28946	12.82	71.185	1,037.63	27.8962636
WASHINGTON	27	64.5	247	16581	10.59	69.38	582.8	28.45058339

Table 8 1990-1994 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	45	50.254	595	193879	6.76	73.026	875.02	221.5709355
BAKER	29	48.788	319	19700	6.57	72.28	585.23	33.66197905
BAY	86	61.404	382	136289	7.32	71.716	758.46	179.6917438
BRADFORD	11	47.96	205	24210	7.53	73.026	293.96	82.35814397
BREVARD	111	53.208	531	436333	9.36	72.305	1,015.66	429.6053798
BROWARD	20	62.824	109	1340220	6.75	74.258	1,209.79	1107.8121
CALHOUN	31	65.442	372	11565	5.03	69.528	567.33	20.38496113
CHARLOTTE	176	43.532	638	124883	12.53	73.128	680.28	183.5758805
CITRUS	100	58.556	379	102846	9.98	71.431	581.7	176.8024755
CLAY	53	54.52	398	117779	11.13	67.345	604.36	194.8821894
COLLIER	111	53.674	824	180540	18.69	68.92	1,998.32	90.34589055
COLUMBIA	33	51.236	323	48897	14.75	73.046	797.57	61.30747144
DESOTO	20	51.432	122	26260	10.04	73.128	637.06	41.22060716
DIXIE	70	61.982	351	12150	14.78	73.316	705.05	17.23282037
DUVAL	49	54.806	448	710592	5.59	72.141	762.19	932.3029691
ESCAMBIA	7	67.762	325	277067	5.43	75.283	656.46	422.0622734
FLAGLER	216	47.346	382	35292	22.96	71.516	485.46	72.69805957
FRANKLIN	30	65.142	211	9995	11.46	72.468	534.73	18.69167617
GADSDEN	9	65.882	211	44853	9.12	73.53	516.33	86.86886294
GILCHRIST	17	53.872	179	11526	19.23	74.14	349.68	32.96156486
GLADES	71	60.71	218	8366	10.2	69.425	806.01	10.37952383
GULF	64	65.442	191	13265	15.31	69.528	564.01	23.51908654
HAMILTON	36	56.546	142	11918	9.04	68.173	513.79	23.19624749
HARDEE	9	53.524	161	22454	15.15	70.701	637.78	35.20649754
HENDRY	64	55.568	247	28686	11.3	73.253	1,152.75	24.8848406

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	44	45.838	365	114866	13.69	67.34	472.54	243.0820671
HIGHLANDS	78	49.606	414	75860	10.85	74.168	1,016.62	74.61981861
HILLSBOROUGH	72	39.532	439	879069	12.53	72.966	1,020.21	861.6549534
HOLMES	7	60.018	191	16926	7.28	75.928	478.78	35.3523539
INDIAN RIVER	47	54.314	209	97415	7.98	74.99	502.87	193.7180583
JACKSON	14	60.018	250	45421	9.78	69.528	917.76	49.49115237
JEFFERSON	15	59.288	140	13085	15.84	73.998	598.1	21.87761244
LAFAYETTE	28	51.26	130	5826	4.45	75.923	543.41	10.72118658
LAKE	65	52.03	6992	171168	12.53	72.438	938.38	182.4079797
LEE	230	56.632	799	367410	9.63	69.64	784.51	468.3305503
LEON	13	64.206	191	212107	10.19	70.525	666.85	318.0730299
LEVY	195	45.632	633	29111	12.29	74.885	1,118.21	26.03357151
LIBERTY	15	65.442	156	6538	17.39	69.528	835.56	7.824692422
MADISON	26	52.116	188	17768	14.12	72.516	695.95	25.53056972
MANATEE	31	55.796	160	228283	7.83	69.245	742.93	307.273902
MARION	77	67.36	792	217862	11.82	73.068	1,584.55	137.4914013
MARTIN	59	73.858	149	110227	9.24	74.161	543.46	202.8244949
MIAMI-DADE	3	56.492	641	1990445	2.75	70.393	1,897.72	1048.861265
MONROE	0	53.608	62	82252	5.42	71.765	983.28	83.65063868
NASSAU	44	53.26	222	47371	7.81	68.415	648.64	73.03126542
OKALOOSA	4	67.142	197	158318	10.11	73.183	930.25	170.188659
OKEECHOBEE	38	58.814	247	32325	9.11	73.533	768.91	42.04003069
ORANGE	76	60.506	316	740167	9.25	77.338	903.43	819.2853901
OSCEOLA	68	60.014	282	131111	21.71	71.671	1,327.45	98.76906851
PALM BEACH	28	60.726	295	937190	8.53	74.275	1,969.76	475.7889286
PASCO	68	49.432	431	298852	6.3	74.356	746.89	400.128533
PINELLAS	29	42.622	64	870722	2.24	73.563	273.8	3180.138787

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	96	51.856	1295	437204	7.85	70.435	1,797.84	243.1829306
PUTNAM	93	54.52	511	68980	6.01	71.858	727.62	94.80223193
SANTA ROSA	21	71.002	907	93813	14.96	69.38	1,011.61	92.73633119
SARASOTA	175	55.742	430	296002	6.56	74.006	555.87	532.5022038
SEMINOLE	39	67.974	192	316555	10.09	75.145	309.22	1023.720975
ST. JOHNS	142	44.346	433	94758	13.04	67.345	600.66	157.7564679
ST. LUCIE	28	62.642	142	166803	11.08	67.091	571.93	291.6493277
SUMTER	18	46.102	110	35189	11.44	71.338	546.93	64.33912932
SUWANNEE	21	55.062	383	29299	9.41	70.873	688.55	42.55173916
TAYLOR	88	56.414	439	17461	2.05	72.836	1,043.31	16.73615704
UNION	5	51.236	94	15534	22.26	74.14	243.56	63.77894564
VOLUSIA	385	47.756	976	396631	6.99	75.108	1,101.03	360.2363242
WAKULLA	13	64.206	176	16441	15.77	70.525	606.42	27.11157284
WALTON	39	66.616	469	31860	14.77	75.928	1,037.63	30.70458641
WASHINGTON	15	60.108	1880	18115	7.07	75.928	582.8	31.08270419

Table 9 1995-1999 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	37	56.78	419	216249	9.07	70.701	875.02	247.1360655
BAKER	47	68.291	337	21879	7.91	73.558	585.23	37.38530151
BAY	42	60.712	468	150119	7.87	74.458	758.46	197.9260607
BRADFORD	24	62.327	228	25500	4.78	70.701	293.96	86.74649612
BREVARD	98	60.27	439	474803	6.69	72.558	1,015.66	467.4822283
BROWARD	22	54.732	67	1490289	9.25	75.12	1,209.79	1231.857595
CALHOUN	24	57.934	118	14117	17.76	76.635	567.33	24.88322493
CHARLOTTE	184	57.86	790	136773	7.15	66.648	680.28	201.0539778
CITRUS	83	57.524	375	114898	8.94	72.015	581.7	197.521059
CLAY	98	68.291	401	139631	15.49	69.861	604.36	231.0394467
COLLIER	103	53.078	760	219685	17.79	74.848	1,998.32	109.9348453
COLUMBIA	26	56.011	445	56514	12.16	67.466	797.57	70.85773036
DESOTO	17	44.159	151	28438	6.75	66.648	637.06	44.63943742
DIXIE	60	62.59	275	13478	8.55	71.473	705.05	19.11637473
DUVAL	94	52.602	415	762846	6.19	73.355	762.19	1000.860678
ESCAMBIA	10	52.012	393	301613	6.67	72.95	656.46	459.4537367
FLAGLER	174	56.823	332	45818	23.84	74.265	485.46	94.38058748
FRANKLIN	17	78.07	162	10872	6.21	75.871	534.73	20.33175621
GADSDEN	4	57.468	127	51478	15.08	75.701	516.33	99.69980439
GILCHRIST	13	56.011	174	13406	12.77	70.206	349.68	38.33790895
GLADES	83	52.327	242	9867	15.39	70.28	806.01	12.2417836
GULF	61	57.934	334	14403	8.53	76.635	564.01	25.53678126
HAMILTON	18	70.22	179	14376	15.13	75.138	513.79	27.98030324
HARDEE	8	54.331	192	22594	-1.27	73.04	637.78	35.42600897
HENDRY	80	58.112	342	30552	3.58	74.88	1,152.75	26.5035784

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	38	49.313	606	127392	8.06	71.208	472.54	269.589876
HIGHLANDS	95	54.28	543	81143	5.01	69.945	1,016.62	79.81645059
HILLSBOROUGH	45	49.313	282	967511	8.36	68.168	1,020.21	948.3449486
HOLMES	6	54.68	226	18899	8.71	76.318	478.78	39.4732445
INDIAN RIVER	44	50.97	188	109579	9.29	74.071	502.87	217.9072126
JACKSON	16	57.162	270	49469	6.21	76.318	917.76	53.90189156
JEFFERSON	5	65.789	106	14424	6.77	70.623	598.1	24.1163685
LAFAYETTE	27	52.178	104	6961	6.83	72.345	543.41	12.80984892
LAKE	54	49.83	526	203863	15.22	71.598	938.38	217.2499414
LEE	238	52.327	747	417114	13.44	77.168	784.51	531.6872953
LEON	2	57.162	270	237637	9.24	75.205	666.85	356.3575017
LEVY	194	70.28	609	33408	11.95	75.26	1,118.21	29.87632019
LIBERTY	7	57.934	108	8048	17.09	76.635	835.56	9.63186366
MADISON	19	56.01	208	19632	7.02	72.653	695.95	28.20892305
MANATEE	41	59.09	146	253207	8.59	74.723	742.93	340.8221501
MARION	79	78.624	808	249433	11.05	74.443	1,584.55	157.4156701
MARTIN	67	39.78	175	121514	8.46	72.913	543.46	223.5932727
MIAMI-DADE	17	55.376	615	2126702	5.61	76.145	1,897.72	1120.661636
MONROE	1	52.71	57	87030	4.35	73.655	983.28	88.50988528
NASSAU	45	46.021	174	57381	16.8	71.558	648.64	88.46355451
OKALOOSA	18	61.25	374	179589	10.38	74.596	930.25	193.0545552
OKEECHOBEE	75	69.781	348	35510	8.08	74.618	768.91	46.182258
ORANGE	131	51.377	370	846328	11.51	73.913	903.43	936.7942176
OSCEOLA	86	54.039	286	157376	15.18	73.871	1,327.45	118.5551245
PALM BEACH	70	71.853	248	1042196	8.25	67.47	1,969.76	529.0979612
PASCO	81	52.118	357	326494	6.85	72.938	746.89	437.1379989
PINELLAS	24	52.736	51	89878	2.58	74.308	273.8	328.2615047

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	143	47.238	1126	474704	7.12	75.011	1,797.84	264.041294
PUTNAM	104	81.025	481	72883	4.84	72.996	727.62	100.1662956
SANTA ROSA	25	54.68	1046	112631	17.21	71.046	1,011.61	111.3383616
SARASOTA	211	52.73	589	321044	6.47	73.223	555.87	577.5523054
SEMINOLE	29	62.13	90	354148	9.26	70.856	309.22	1145.294612
ST. JOHNS	151	53.29	372	113941	16.04	74.265	600.66	189.6930044
ST. LUCIE	47	54.182	137	186905	9.19	75.343	571.93	326.7969856
SUMTER	20	58.174	97	50823	39.41	68.773	546.93	92.9241402
SUWANNEE	17	57.183	508	34386	12.62	74.485	688.55	49.93972841
TAYLOR	44	50.33	387	19836	8.26	75.061	1,043.31	19.01256578
UNION	22	56.011	147	13833	9.38	70.206	243.56	56.79504024
VOLUSIA	340	66.353	899	426815	5.92	74.67	1,101.03	387.6506544
WAKULLA	11	61.756	139	20648	21.42	75.205	606.42	34.04900894
WALTON	37	54.72	533	40466	21.1	76.318	1,037.63	38.99848694
WASHINGTON	11	57.162	210	22156	16.55	76.318	582.8	38.0164722

Table 10 2000-2004 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	63	50.615	413	236174	8.36	75.335	875.02	269.9069736
BAKER	41	57.255	318	23963	7.66	73.983	585.23	40.94629462
BAY	81	58.647	401	158437	6.89	74.023	758.46	208.8930201
BRADFORD	27	54.025	178	2774	6.33	75.335	293.96	9.436658049
BREVARD	114	55.456	343	521422	9.49	72.77	1,015.66	513.3824311
BROWARD	60	52.482	111	1723131	6.17	68.611	1,209.79	1424.322403
CALHOUN	26	58.647	128	13610	4.56	68.08	567.33	23.98956516
CHARLOTTE	179	53.607	54	156985	10.84	72.023	680.28	230.7652731
CITRUS	92	58.08	490	129110	9.34	71.965	581.7	221.9528967
CLAY	80	57.255	352	163461	16.08	70.966	604.36	270.4695877
COLLIER	174	56.582	532	306186	21.8	72.455	1,998.32	153.2217062
COLUMBIA	5	69.27	480	60453	6.97	70.638	797.57	75.79648181
DESOTO	26	58.412	151	34105	5.89	72.023	637.06	53.53498886
DIXIE	63	52.542	284	14928	7.96	70.971	705.05	21.17296646
DUVAL	69	59.075	287	840474	7.91	73.656	762.19	1102.709298
ESCAMBIA	10	58.6	336	307226	4.35	70.945	656.46	468.0041434
FLAGLER	172	53.385	313	69683	39.83	70.566	485.46	143.5401475
FRANKLIN	19	59.75	148	10649	-3.69	70.025	534.73	19.91472332
GADSDEN	3	60.495	155	46857	3.92	68.803	516.33	90.75010168
GILCHRIST	20	51.217	191	15900	10.13	69.441	349.68	45.47014413
GLADES	79	56.597	174	10733	1.48	68.528	806.01	13.31621196
GULF	46	58.647	242	16171	21.29	68.08	564.01	28.67147746
HAMILTON	30	66.57	262	14303	7.32	69.526	513.79	27.83822184
HARDEE	26	50.335	201	27787	3.15	72.513	637.78	43.56831509
HENDRY	53	46.335	301	37394	3.27	75.455	1,152.75	32.43895034

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	29	59.62	268	14527	11.01	77.451	472.54	30.74237102
HIGHLANDS	14	63.433	556	92057	5.37	76.75	1,016.62	90.55202534
HILLSBOROUGH	64	58.712	206	1108435	10.96	69.03	1,020.21	1086.477294
HOLMES	12	63.25	222	19012	2.41	74.57	478.78	39.70926104
INDIAN RIVER	71	51.495	182	126829	12.29	77.005	502.87	252.2103128
JACKSON	17	69.975	360	48870	4.39	74.57	917.76	53.24921548
JEFFERSON	5	62.567	129	14064	9.01	77.15	598.1	23.51446246
LAFAYETTE	41	58.307	151	7535	7.3	71.386	543.41	13.86614159
LAKE	125	59.272	471	251878	19.64	72.033	938.38	268.4179117
LEE	199	61.273	564	521253	18.23	69.4	784.51	664.4313011
LEON	5	62.567	132	263896	10.21	67.696	666.85	395.7351728
LEVY	208	62.81	662	37486	8.81	68.493	1,118.21	33.52322015
LIBERTY	5	62.567	77	7354	4.74	68.08	835.56	8.801282972
MADISON	19	50.195	193	19498	4.08	66.191	695.95	28.01638049
MANATEE	56	46.313	162	295242	11.83	75.671	742.93	397.4021779
MARION	91	64.737	833	293317	13.29	71.458	1,584.55	185.1105992
MARTIN	113	60.878	230	137637	8.61	70.263	543.46	253.2605896
MIAMI-DADE	44	53.203	612	2379818	5.61	70.416	1,897.72	1254.040638
MONROE	2	70.558	116	81236	2.07	69.7	983.28	82.6173623
NASSAU	48	55.945	208	65016	12.75	75.78	648.64	100.2343365
OKALOOSA	25	68.71	345	185778	8.96	72.433	930.25	199.7076055
OKEECHOBEE	81	45.516	329	38004	5.83	74.496	768.91	49.42581056
ORANGE	122	53.836	275	1013937	13.12	74.173	903.43	1122.319383
OSCEOLA	102	57.265	265	225816	30.91	74.496	1,327.45	170.1126219
PALM BEACH	101	64.045	292	1242270	9.82	74.605	1,969.76	630.6707416
PASCO	79	63.102	335	389776	16.43	69.013	746.89	521.8653349
PINELLAS	5	51.425	42	943640	2.4	75.84	273.8	3446.457268

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	262	61.212	1014	528389	9.19	75.926	1,797.84	293.902127
PUTNAM	98	55.862	491	73226	3.98	73.555	727.62	100.6376955
SANTA ROSA	34	67.137	787	133721	13.57	69.803	1,011.61	132.1863169
SARASOTA	207	53.29	485	358307	9.92	75.39	555.87	644.5877633
SEMINOLE	39	59.882	93	403361	10.45	73.133	309.22	1304.446672
ST. JOHNS	92	45.51	279	149336	21.28	70.966	600.66	248.6198515
ST. LUCIE	49	52.423	174	226216	17.93	74.99	571.93	395.5309216
SUMTER	40	55.575	130	66416	24.5	71.991	546.93	121.4341872
SUWANNEE	14	51.845	438	37713	8.23	71.155	688.55	54.77162152
TAYLOR	73	53.925	291	20941	8.75	75.973	1,043.31	20.07169489
UNION	30	51.217	171	14620	8.76	69.441	243.56	60.02627689
VOLUSIA	315	50.432	645	484261	9.23	72.438	1,101.03	439.8254362
WAKULLA	9	62.567	114	25505	11.56	67.676	606.42	42.05830942
WALTON	27	63.25	555	50543	24.49	74.576	1,037.63	48.71004115
WASHINGTON	15	69.975	231	22434	6.97	74.576	582.8	38.49347975

Table 11 2005-2009 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	51	49.212	351	256232	6.42	70.701	875.02	292.8298782
BAKER	37	47.668	126	25899	8.12	73.558	585.23	44.25439571
BAY	76	51.134	311	136562	4.85	74.458	758.46	180.0516837
BRADFORD	25	49.402	156	29085	3.43	70.701	293.96	98.94203293
BREVARD	93	47.532	321	555657	4.45	71.796	1,015.66	547.0895772
BROWARD	41	64.998	94	1744922	0.23	77.825	1,209.79	1442.33462
CALHOUN	38	51.134	116	14601	4.7	76.635	567.33	25.73634393
CHARLOTTE	114	42.97	382	165455	7.42	66.648	680.28	243.2160287
CITRUS	91	59.77	367	142609	7.52	72.015	581.7	245.1590167
CLAY	58	50.3	270	185208	9.19	69.861	604.36	306.4531074
COLLIER	122	48.822	388	333032	4.79	72.746	1,998.32	166.655991
COLUMBIA	34	57.512	277	66409	8.04	67.466	797.57	83.2641649
DESOTO	24	62.696	177	34792	6.7	66.648	637.06	54.61338022
DIXIE	68	51.136	241	16221	5.49	71.473	705.05	23.00687894
DUVAL	49	57.536	229	900518	4.57	73.355	762.19	1181.487556
ESCAMBIA	18	45.802	256	312980	3.08	72.95	656.46	476.7693386
FLAGLER	151	53.718	283	94901	20.71	74.265	485.46	195.4867548
FRANKLIN	26	63.084	100	12414	14.47	75.871	534.73	23.21545453
GADSDEN	5	54.59	126	50046	4.89	75.701	516.33	96.92638429
GILCHRIST	20	48.814	159	17393	7.23	70.206	349.68	49.73976207
GLADES	54	47.308	192	11311	5.42	70.28	806.01	14.03332465
GULF	56	51.134	242	16798	1.94	76.635	564.01	29.78315987
HAMILTON	17	58.598	179	14783	3.27	69.945	513.79	28.77245567
HARDEE	9	52.388	143	28333	3.66	73.04	637.78	44.42440967
HENDRY	58	61.046	222	41320	7.67	74.88	1,152.75	35.84471915

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	56	55.116	242	165048	8.79	71.208	472.54	349.278368
HIGHLANDS	74	56.208	633	99713	6.69	69.945	1,016.62	98.08286282
HILLSBOROUGH	39	58.278	220	1196892	5.77	68.168	1,020.21	1173.181992
HOLMES	5	53.984	122	19857	3.65	76.318	478.78	41.4741635
INDIAN RIVER	48	52.49	141	141634	8.91	74.071	502.87	281.6513214
JACKSON	26	53.984	318	52637	5.93	76.318	917.76	57.35377441
JEFFERSON	11	51.046	116	14677	3.12	70.623	598.1	24.53937469
LAFAYETTE	56	44.892	126	8183	2.65	72.345	543.41	15.05861136
LAKE	87	47.804	350	291993	11.02	71.598	938.38	311.1671178
LEE	122	60.802	471	615124	11.95	77.168	784.51	784.0868823
LEON	10	51.046	75	274803	1.36	75.205	666.85	412.0911749
LEVY	190	47.432	545	40674	7.08	75.26	1,118.21	36.3742052
LIBERTY	11	51.134	49	8220	8.43	76.635	835.56	9.837713629
MADISON	25	57.216	249	20333	32.3	72.653	695.95	29.21617932
MANATEE	35	50.136	133	318404	4.61	74.923	742.93	428.5787355
MARION	35	45.488	473	33044	9.37	74.443	1,584.55	20.85387018
MARTIN	89	44.252	167	143856	1.98	72.913	543.46	264.7039341
MIAMI-DADE	32	45.77	361	2472344	2.08	76.145	1,897.72	1302.797041
MONROE	0	56.918	25	77585	-5.85	73.655	983.28	78.90427955
NASSAU	34	55.13	194	72588	10.38	71.558	648.64	111.9079921
OKALOOSA	5	50.482	206	196237	3.86	74.596	930.25	210.9508197
OKEECHOBEE	86	50.108	378	39703	5.13	73.871	768.91	51.63543198
ORANGE	103	45.1	257	1108882	6.27	73.913	903.43	1227.413303
OSCEOLA	83	50.698	292	272788	16	73.871	1,327.45	205.4977589
PALM BEACH	63	58.456	165	1287344	1.69	77.55	1,969.76	653.5537324
PASCO	95	44.8	309	439786	8.08	72.938	746.89	588.822986
PINELLAS	7	45.17	29	931113	-1.75	66.893	273.8	3400.704894

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	165	52.76	856	584343	7.84	76.238	1,797.84	325.02503
PUTNAM	113	52.742	508	74608	1.14	72.996	727.62	102.5370386
SANTA ROSA	37	45.03	514	144508	5.91	71.046	1,011.61	142.8495171
SARASOTA	143	42.192	355	389320	5.83	73.223	555.87	700.3795852
SEMINOLE	45	44.058	73	423759	2.91	70.856	309.22	1370.412651
ST. JOHNS	81	50.3	254	183572	16.72	69.861	600.66	305.6171545
ST. LUCIE	27	46.718	88	272864	13.67	75.343	571.93	477.0933506
SUMTER	44	47.32	122	95326	28.73	68.773	546.93	174.2928711
SUWANNEE	12	48.694	338	40230	5.39	74.485	688.55	58.42712947
TAYLOR	81	55.434	322	23164	8.7	75.061	1,043.31	22.20241347
UNION	18	48.814	84	15576	3.52	70.206	243.56	63.95138775
VOLUSIA	319	43.568	720	507105	2.52	72.763	1,101.03	460.5732814
WAKULLA	9	51.046	1281	31791	18.33	75.205	606.42	52.42406253
WALTON	34	53.984	350	57917	8.21	76.318	1,037.63	55.81662057
WASHINGTON	22	53.984	163	24721	7.03	76.318	582.8	42.41763898

Table 12 2010-2014 Data

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
ALACHUA	60	68.712	317	250730	1.37	75.343	875.02	286.5420219
BAKER	56	66.44	209	26991	-0.46	69.48	585.23	46.12032876
BAY	50	58.578	289	170781	1.14	71.761	758.46	225.1681038
BRADFORD	23	58.702	195	27323	-4.19	75.343	293.96	92.94802014
BREVARD	105	47.476	292	552427	1.67	71.591	1,015.66	543.9093791
BROWARD	36	57.68	72	1803903	3.19	70.313	1,209.79	1491.087709
CALHOUN	18	58.578	111	14592	-0.23	73.455	567.33	25.72048014
CHARLOTTE	111	50.106	272	164467	2.8	74.178	680.28	241.7636855
CITRUS	48	51.254	233	140798	-0.31	73.02	581.7	242.045728
CLAY	69	46.03	261	197403	3.43	73.19	604.36	326.6314779
COLLIER	178	47.472	354	336783	4.75	72.43	1,998.32	168.5330678
COLUMBIA	29	52.536	298	67826	0.44	77.981	797.57	85.04081146
DESOTO	17	55.654	87	34426	-1.25	74.178	637.06	54.03886604
DIXIE	55	55.256	208	16356	-0.4	73.91	705.05	23.19835473
DUVAL	88	47.93	241	890066	2.99	72.976	762.19	1167.774439
ESCAMBIA	12	51.924	188	303907	2.11	73.061	656.46	462.9482375
FLAGLER	156	55.314	279	99121	3.58	71.051	485.46	204.1795411
FRANKLIN	29	58.578	206	11794	2.12	74.835	534.73	22.05599087
GADSDEN	8	49.388	133	48096	3.68	68.496	516.33	93.14972982
GILCHRIST	27	54.528	105	16853	-0.51	70.161	349.68	48.19549302
GLADES	71	61.244	193	12852	-0.24	70.431	806.01	15.9452116
GULF	50	58.578	109	16543	4.29	73.455	564.01	29.33104023
HAMILTON	35	68.394	230	14351	-3.03	74.685	513.79	27.93164522
HARDEE	10	44.006	96	27712	-0.06	73.801	637.78	43.45071968
HENDRY	34	48.914	156	37895	-3.18	73.513	1,152.75	32.87356322

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
HERNANDO	13	51.254	139	174955	1.26	76.001	472.54	370.2437889
HIGHLANDS	76	50.428	471	99818	1.04	77.168	1,016.62	98.18614625
HILLSBOROUGH	37	46.906	167	1301887	5.91	74.288	1,020.21	1276.097078
HOLMES	12	52.326	174	20025	0.49	76.771	478.78	41.82505535
INDIAN RIVER	45	46.804	110	140955	2.12	71.7	502.87	280.3010718
JACKSON	13	49.388	254	50231	0.97	76.771	917.76	54.73217399
JEFFERSON	6	49.012	91	14597	-1.11	69.89	598.1	24.40561779
LAFAYETTE	34	36.51	142	8696	-1.96	73.178	543.41	16.00264993
LAKE	58	49.05	250	309736	4.26	71.743	938.38	330.075236
LEE	131	60.376	395	653485	5.61	73.623	784.51	832.9849205
LEON	7	49.012	77	281292	2.11	76.216	666.85	421.821999
LEVY	187	55.256	413	40473	-0.8	72.173	1,118.21	36.19445364
LIBERTY	15	58.578	52	8668	3.62	73.45	835.56	10.37388099
MADISON	15	63.328	302	19303	0.41	66.453	695.95	27.73618794
MANATEE	29	58.128	109	339545	5.18	71.256	742.93	457.0349831
MARION	67	49.892	342	337298	1.86	74.955	1,584.55	212.8667445
MARTIN	79	64.732	196	148545	1.55	69.056	543.46	273.331984
MIAMI-DADE	24	49.442	328	2613692	4.69	70.403	1,897.72	1377.280105
MONROE	2	48.45	21	74044	1.31	71.8233	983.28	75.30306729
NASSAU	76	47.93	269	75321	2.74	76.668	648.64	116.1214233
OKALOOSA	11	45.616	151	190666	5.44	74.241	930.25	204.962107
OKEECHOBEE	67	48.186	278	39828	-0.42	68.005	768.91	51.79799977
ORANGE	129	50.438	247	1227995	7.16	71.083	903.43	1359.258603
OSCEOLA	70	48.186	183	295553	9.99	72.74	1,327.45	222.6471807
PALM BEACH	49	54.276	123	1360238	3.04	71.73	1,969.76	690.5602713
PASCO	25	50.79	176	479340	3.15	68.408	746.89	641.7812529
PINELLAS	8	60.702	14	933258	1.82	73.091	273.8	3408.53908

County	# of Lightning Fires	Average Precipitation (inches)	# of Human Fires	Population	Population Growth (%)	Average Temperature (F)	County Size (sq. mile)	Population Density (per sq. mile)
POLK	109	47.078	558	623174	3.5	75.73	1,797.84	346.6237262
PUTNAM	157	47.96	574	72523	-2.48	70.358	727.62	99.67153184
SANTA ROSA	27	48.94	448	159785	5.56	76.025	1,011.61	157.9511867
SARASOTA	87	55.98	254	387140	2.03	74.096	555.87	696.4578049
SEMINOLE	37	56.578	74	437086	3.39	75.468	309.22	1413.511416
ST. JOHNS	165	46.03	377	207443	9.16	75.19	600.66	345.3584391
ST. LUCIE	48	64.732	136	282821	1.81	76.758	571.93	494.5028238
SUMTER	19	68.22	83	111125	18.95	71.893	546.93	203.1795659
SUWANNEE	15	41.226	376	44168	6.29	71.595	688.55	64.1463946
TAYLOR	53	63.328	277	22932	1.6	77.428	1,043.31	21.98004428
UNION	16	54.528	116	15647	0.72	70.161	243.56	64.24289703
VOLUSIA	395	51.516	752	503851	1.87	74.223	1,101.03	457.6178669
WAKULLA	5	49.012	65	31285	1.65	76.216	606.42	51.58965733
WALTON	27	52.326	219	59793	8.63	76.771	1,037.63	57.6245868
WASHINGTON	13	52.326	120	24959	0.25	76.771	582.8	42.82601235