2015

The Effect of Precipitation on the Spread of Mosquito-Borne Diseases: A Case Study of Florida Counties

Marvin Osbourne
University of Central Florida

THE EFFECT OF PRECIPITATION ON THE SPREAD OF MOSQUITO-BORNE DISEASES: A CASE STUDY OF FLORIDA COUNTIES

by

MARVIN ERROL OSBOURNE
B.A. University of the West Indies, 1996
B.S. Instituto Superior Politécnico "José Antonio Echeverría", 2003

A thesis submitted in partial fulfillment of the requirements
for the degree of Master of Science
in the Department of Modeling and Simulation
in the College of Graduate Studies
at the University of Central Florida
Orlando, Florida

Summer Term
2015

Major Professors: Ram Mohapatra
Zhisheng Shuai

ABSTRACT

The state of Florida is the third most populous state in the United States of America, with six (6) of its metropolitan areas dubbed as the fastest growing in the entire country. A mosquito bite may mean the transmission of a virus or disease which might be fatal. Hence, there is a need for the state to control mosquitoes through the various Departments of Mosquito Control in each of its sixty-seven (67) counties. Six locally acquired mosquito-borne viruses which affect humans and animals in the state of Florida were considered. This thesis used statistical methods to examine data for rainfall, population estimate, as well as, the data on six (6) arboviruses, over the course of thirteen (13) years, namely 2002 to 2014. The first hypothesis that was tested, was that greater precipitation increased the likelihood of a greater number of arbovirus cases. It was important to also examine the relationship that this growing human population had with mosquito-borne diseases, and so the second hypothesis that was tested, was that, an increase in the human population would increase the likelihood of a greater number of arbovirus cases. Subsequently, an analysis was done for eleven (11) of Florida's 67 counties with the greatest cumulative occurrence of human and animal arbovirus cases combined. Of the eleven counties, seven exhibited a weak associated between the size of the human population and the spread of animal and human arbovirus cases; three exhibited a somewhat moderate association; and one – Osceola County – had a strong negative association. This indicated that, as the size of the human population increased in Osceola County, the combined number of human and animal arbovirus cases decreased, which refuted the second hypothesis of this thesis. A linear regression model for the data for Osceola County was derived and that model was used to simulate what will occur in future years with the use of population projection data. In each simulated year, the number of combined human and arbovirus

cases was negative. This prediction meant that, as the projected population increased from year to year, then the number of cases should be zero in each year. The reliability of these predictions are questionable, since Osceola County does not exist in a vacuum and it cannot be isolated from the surrounding counties which may be experiencing an outbreak of arboviruses.

This research study is dedicated to my mother, Euphema Scott; the remaining members of my family, and friends, whose unwaning support has fueled me and encouraged me to strive for excellence. Thank you.

ACKNOWLEDGMENTS

I would like to acknowledge Dr. Ram N. Mohapatra, my thesis advisor and committee chair, who has been a guiding light throughout my graduate studies; just like a lighthouse that guides a ship through a stormy night. Also, I would like to thank Dr. Zhisheng Shuai, who agreed to be co-chair on my committee, for his expertise and guidance in the field of arboviruses. Dr. Peter Kincaid, as a member of my thesis committee, has been very supportive and has made himself available to me when he was extremely busy.

I would also like to acknowledge, Terry Torrens, Director of the Mosquito Control Section in Osceola County, for taking time out of her busy schedule to grant me an interview and for leading me to additional resources which have helped to shape this research paper. Lastly, but by no means the least, I would like to extend my deepest gratitude to Sabrina Kalish, Coordinator of the Modeling and Simulation Graduate Program, whose dedication and selflessness to help students seems boundless.

To all these individuals, I thank you.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE: INTRODUCTION

The coming of spring is synonymous with new life for both flora and fauna. New life in the mosquito species is no exception. This insect brings about much unpleasantness for the residents of the state of Florida. To this end, there is a need for the state to control mosquitoes through the various Departments of Mosquito Control in each of its sixty-seven (67) counties. This is done not only because of the discomfort which residents may experience from a mosquito bite, but also from the possibility that while a mosquito is feeding on a human, it may also be simultaneously transmitting a virus or disease which might be fatal. There are over 2,800 species of mosquitos in the world, over 80 of which are found in Florida. The female of the species bites and sucks blood from humans and animals and may lay anywhere from 100 to 300 eggs, depending on the species of mosquito ("Mosquito Control," 2015).

Six locally acquired arboviruses (mosquito-borne viruses) which affect humans and animals in the state of Florida will be considered, namely the West Nile Virus (WNV), the Eastern Equine Encephalitis Virus (EEEV), the Chikungunya Virus (ChikV), Dengue Fever (Dengue), the St. Louis Encephalitis Virus (SLEV) and the Highlands J Virus (HJV). None of these has a vaccine available. In the case of EEEV, which also affects horses, there is a vaccine available for horses. Generally, vector-borne diseases are among the most complex of all the infectious diseases to prevent and control. ("About DVBD", 2014). This is mainly due to the fact that it is often difficult to determine the size and location of mosquito habitats. Arboviruses account for hundreds of thousands of human illnesses worldwide, some even resulting in death; therefore, the spread of these viruses is a major health concern. Not only does it affect the quality of life and health of individuals, it also carries a huge financial burden to the public. Controlling these pests reduces the number of cases of individuals afflicted with these viruses. It saves lives, mitigates suffering and relieves the financial burden ("About DVBD", 2014).

A huge part of controlling mosquitoes is to be able to properly evaluate the conditions under which mosquitoes thrive, and in so doing, plan accordingly on how to eradicate or minimize the problem. Mosquitoes lay their eggs in wet habitats and as such, it stands to reason that if there is more rainfall, then that will increase the number of wet habitats, which will encourage mosquitoes to breed more, which will lead to a bigger mosquito population and may therefore, cause an increase in the number of cases of transmission of mosquito-borne viruses and diseases. This thesis seeks to use statistical methods to examine this data on the six aforementioned arboviruses over the course of thirteen (13) years, from 2002 to 2014, for thirty-two (32) counties in Florida. This will be done in order to ascertain if there is any kind of trend or correlation between the amount of rainfall and the spread of mosquito-borne viruses and diseases. In formal terms, the first hypothesis being tested, is that greater precipitation increases the likelihood of a greater number of arbovirus cases. Also, if there does exist a correlation, this thesis will seek to ascertain a mathematical model and use this model to predict what may happen in a future year. The radar rainfall data will be accessed from the St. John's River Water Management District (SJRWMD), as well as the Southwest Florida Water Management District (SWFWMD) websites; and the data recording the number of arbovirus activity in each county in the state of Florida, will be retrieved from the Florida Department of Health Surveillance site (http://www.floridahealth.gov/diseases-and-conditions/mosquito-borne-diseases/surveillance.html). Only locally acquired cases in the state of Florida will be considered; any cases acquired in other states or imported cases from other countries will not be considered for this study.

The state of Florida has replaced New York as the third most populated state in the U.S., with six (6) of its metropolitan areas dubbed as the fastest growing in the entire country due to an influx of new residents. One of these metropolitan areas, The Villages in Sumter County, has been recognized as the fastest growing in the entire nation. From July 1, 2013 to July 1, 2014; a 5.4% increase in population was recorded in this area (Holland, 2015). As the population in Florida increases, it is paramount to examine the relationship that this growing human population has with mosquito-borne diseases, since there may be a need for greater control of mosquito vectors. As humans move to Florida counties and take their domestic and farm animals with them, it stands to reason that if there is a greater human and animal presence, then that will increase the chances of mosquitoes biting a warm-blooded host, which may result in the transmission of mosquito-borne viruses and diseases. Further, biting a host may encourage mosquitoes to breed more, which will lead to a bigger mosquito population, and this may also cause an increase in the number of cases of transmitted mosquito-borne viruses and diseases. Statistical methods will be used to examine the data on the six aforementioned arboviruses over the course of thirteen (13) years – 2002 to 2014 – for thirty-two (32) counties in Florida. This will be done in order to ascertain if there exists any kind of trend or correlation between the size of the human population and the spread of mosquito-borne viruses and diseases. In formal terms, the second hypothesis being tested, is that, an increase in the human population increases the likelihood of a greater number of arbovirus cases. Consequently, if there does exist a correlation in any of the counties, this thesis will seek to ascertain a mathematical model and use that model to predict what may happen in a future year within the county. The population data will be accessed from the United States Census Bureau website (http://www.census.gov/popest/data/historical/index.html), and the data recording the number of arbovirus activity in each county in the state of Florida, will be retrieved from the Florida Department of Health Surveillance site. Subsequently, case studies will be conducted in seven (7) of Florida's 67 counties with the greatest cumulative occurrence of arbovirus cases by considering each individual year. Only locally acquired cases in the state of Florida will be considered; any cases acquired in other states or imported cases from other countries will not be considered for this study. Also, the data reflects the number of reported cases, and not necessarily the number of cases which actually existed.

The remainder of the thesis is divided into four (4) additional chapters: *Chapter Two: Literature Review* will detail previous research that was done on this topic. *Chapter Three: Methodology* will outline the methods used in the research of this paper; as well as how the data was collected and organized. *Chapter Four: Data Analysis and Results* will outline how the data was analyzed; in addition to the outcomes or results of these analyses. Lastly, *Chapter Five: Conclusions and Recommendations* will depict the conclusions that can be drawn from the results of the analyses and further, recommendations will be made on how to improve any models which result from the data.

CHAPTER TWO: LITERATURE REVIEW

As mentioned in Chapter One, six (6) mosquito-borne viruses which affect humans and animals will be considered. These are: the West Nile Virus (WNV), the Eastern Equine Encephalitis Virus (EEEV), the Chikungunya Virus (ChikV), Dengue Fever (Dengue), the St. Louis Encephalitis Virus (SLEV) and the Highlands J Virus (HJV). The first three viruses – WNV, EEEV and ChikV – will be discussed in this chapter.

2.1 West Nile Virus

Presently, West Nile Virus (WNV) is the leading domestically acquired arbovirus in the United States (U.S.) with 2,469 reported cases within the U.S. in 2013 (Lindsey, Lehman, Staples, & Fischer, 2014). The first outbreak in the U.S. was in the late summer of 1999, in the state of New York, which affected fifty-nine (59) individuals and resulted in seven (7) deaths (Martindale & MacIas Konstantopoulos, 2012; Mostashari et al., 2001). This virus infects mainly birds, but can also infect horses, dogs, cats and humans. It is spread when infected migratory birds are bitten by the female mosquito of the *Culex* genus – that is, it involves more than one species. These mosquitoes then bite other uninfected birds, animals and humans, and transmit the virus to them (Kenkre, Parmenter, Peixoto, & Sadasiv, 2005). Some of the manifestations in humans include fever, headache, an altered mental status, profound fatigue, coma and in some cases death. Symptoms can last for months or years. Birds will often die when infected with WNV (Kenkre et al., 2005; Martindale & MacIas Konstantopoulos, 2012; Mostashari et al., 2001).

The research done on WNV since its initial outbreak in 1999 has been extensive. Most, however, look into issues like the public health impact of the virus, the range of illnesses caused by the virus, or risk factors for infection (Martindale & MacIas Konstantopoulos, 2012; Mostashari et al., 2001). Kenkre et al., 2005, proposed a mathematical model using differential equations similar to the Abramson-Kenkre (AK) model of the Hantavirus. However, since this research was conducted in 2005 – six years after the initial outbreak of WNV – there was not sufficient data, according to the authors, to properly explain the data. It also places emphasis on how the illness is spread through the cross infection between mosquitoes and birds or through vertical transmission – from parent to offspring.

In this thesis, thirteen (13) years of data will be considered to identify any correlations between precipitation and the number of cases of WNV, along with other arboviruses, which may be used to make predictions about what may be seen in a future year. Other models describe aspects such as the evolution of the virus and seek to find parameters that can demonstrate the eradication of the virus (Thomas & Urena, 2001), but do not offer a method of calculating the number of cases which may be present.

2.2 Eastern Equine Encephalitis Virus

The Eastern Equine Encephalitis Virus (EEEV) is characterized as the most dangerous endemic – natural – arboviral disease in the U.S. It first appeared in 1933 in horses in New Jersey and Virginia, and can cause fatalities to both humans and horses. Presently, most cases are reported in Florida, New Jersey, Georgia and Massachusetts (Kelen, Downs, Unnasch, & Stark, 2014; Zacks & Paessler, 2010). From 2004 to 2013 there were eighty-five (85) reported cases of EEEV in humans, resulting in thirty-four (34) deaths which accounts for a 40% mortality rate of this illness within these years (“Eastern equine encephalitis virus disease cases and deaths reported to

CDC by year and clinical presentation , 2004-2013," 2013). The transmission cycle of this virus primarily includes the mosquito vector – *Culiseta melanura*, among other mosquito species; the avian host – passerine songbirds – and possibly reptiles (Kelen et al., 2014). EEEV is perpetuated through mosquito vector species which feed primarily or exclusively on birds. Humans, horses and other mammals become involved in the transmission cycle when bridge vectors – mosquitoes that feed on both birds and mammals – that are infected with the virus, bite a human, horse or other types of mammals (Jacob et al., 2010; Kelen et al., 2014; Unnasch et al., 2006). Signs and symptoms of persons infected with the EEEV may include fever, muscle pain, a headache that increases in severity, vomiting, coma may occur and, as mentioned before, even death. Survivors of an infection generally suffer mild to severe neurological damage and sometimes may require long-term medical care (Estep, Burkett-Cadena, Hill, Unnasch, & Unnasch, 2010; Zacks & Paessler, 2010). There is no effective treatment or vaccine available to humans; however, there is a vaccine available for horses (Kelen et al., 2014).

To date, previous research highlights on how mosquito vector species of EEEV interact with their avian hosts, especially the young (Unnasch et al., 2006) which tests the hypothesis that these mosquito vectors feed more successfully during times when avian offspring are produced. This model predicted that the abundance of avian young established and encouraged the outbreak of EEEV. Other studies have been used to develop models which predict the transmission risk for horses throughout the state of Florida (Kelen et al., 2014). This study also states that the model can be adapted to human cases of EEEV, but has not predicted the number of both human and animal cases which may occur in various types of arboviruses. Geographic Information System (GIS) modeling is used by Jacob et al., 2010, to determine the distribution of vector and host in

Tuskegee, Alabama; stating that this information may be used in the prediction of EEEV transmission.

2.3 Chikungunya Virus

The Chikungunya Virus (ChikV) first emerged in 1953 in Tanzania, until it resurfaced in 2004 in Kenya, followed by outbreaks in and around the Indian Ocean, to which it was not endemic, in 2005 (Liu & Stechlinski, 2014). It has recently been appearing in different countries around the world, including the U.S.A., Australia, and parts of Europe, due to people traveling and the transportation of goods between countries (Moulay, Aziz-Alaoui, & Cadivel, 2011). These recent outbreaks have sparked a new interest in research into ChikV.

ChikV is normally spread by the *aedes aegypti* mosquito, however, its re-emergence was associated with a mutation in the virus, which allowed the *aedes albopictus* mosquito to be a new vector of this disease (Thiberville et al., 2013). The name ‘chikungunya’ translates to ‘that which bends up’ which is characteristic of this disease, that is, it causes arthritic symptoms in individuals afflicted with the disease (Moulay et al., 2011). Other symptoms include fever, headache, muscle pain, joint swelling and nausea. ChikV does not often result in death, however the number of individuals needing medical attention is higher than that of other common arboviruses (Thiberville et al., 2013). The transmission cycle starts when a mosquito bites an infected human or animal. After the incubation period, the mosquito is able to pass on the virus to humans or animals after biting them. The mosquito is able to continue infecting humans until it dies (Moulay et al., 2011).

Previous research uses differential equations to model the relationship between the mosquito population and the transmission of ChikV to the human population (Moulay et al., 2011).

Moulay et al also considered a model which examined the changes in the vector without a constant population size, as well as the contact rate among humans that depends on the vector population size. This study concentrated on the outbreak which occurred on the island of Réunion in 2005, and did not consider other arboviruses. Other studies tried to improve on the research of Moulay et al by analyzing time-varying parameters and impulsive control (Liu & Stechlinski, 2014). That study used Lyapunov functions to investigate the conditions under which ChikV could be eradicated or guarantee persistence; and also concentrated on the Réunion Island outbreak. Other studies specifically were used as a review of ChikV using clinical data and epidemiological reports to highlight the cause and development of the disease, as well as treatment options (Thiberville et al., 2013).

CHAPTER THREE: METHODOLOGY

In order to investigate the relationship between precipitation and the spread of arboviruses and that of population growth and the spread of arboviruses, it was necessary to retrieve arbovirus data (that is, data related to the spread of mosquito-borne viruses and diseases). This data was made available through the Osceola County Mosquito Control Section, as well as, from the Florida Health Surveillance site ("Surveillance | Florida Department of Health," 2015). The Osceola County Mosquito Control Section – similar to the other mosquito control departments within the state of Florida – is responsible for controlling the diseases carried by mosquitoes ("Mosquito Control," 2015) by monitoring and controlling the size of the mosquito population within Osceola County. They control the size of the mosquito population through educating its residents and the public at large about the importance of not encouraging mosquito habitats which require the presence of water. Residents can do this by properly disposing of, or properly monitoring any water receptacles around the home, like flower pot saucers, old tires, empty food cans and even plants that can hold rain water and encourage mosquitoes to breed. Residents are also encouraged to cover up when outdoors, as well as to apply an appropriate mosquito repellant containing diethyltoluamide (DEET). The Mosquito Control Section also exercises control by larviciding and adulticiding. Larviciding is described as the killing of immature or juvenile mosquitoes by applying various agents or larvicides in order to control mosquito larvae and pupae; while adulticiding is described as controlling the adult mosquito population entirely with the use of pesticides (Connelly & Carlson, 2009). Adulticiding takes on two (2) forms in Osceola County: Ground Adulticiding – spraying with trucks – and Aerial Adulticiding – spraying with aircraft. The use of adulticides in the environment is a method of last resort (Terry Torrens, Director, Mosquito Control Section, Osceola County; personal interview, April 08, 2015) due to its effect on the environment.

Osceola County's Mosquito Control Section tries to monitor the mosquito population size by encouraging the residents of Osceola County to contact them if they have, or suspect that they have a mosquito infestation; and also by performing inspections and surveillance. In 2014, they employed two (2) inspectors who conducted 632 inspections and treated over 350 acres of ditches and other breeding sites (Terry Torrens, Director, Mosquito Control Section, Osceola County; personal interview, April 08, 2015). Surveillance is done with the use of the CDC (Centers for Disease Control and Prevention) Light Trap (See Figure 1).

Figure 1: CDC Light Trap Used by Osceola County's Mosquito Control Section

Source: Mosquito Control 2014 Update. PowerPoint Presentation. Terry Torrens, Director, Mosquito Control Section, Osceola County.

This apparatus is set up in predetermined locations, based on the complaints from residents, or if they want to carry out an investigation, such as trying to determine the presence of a virus or multiple viruses. The trap consists of a container of dry ice – carbon dioxide (CO_2) in its solid state – and a collecting chamber. When the dry ice melts, it transforms directly into its gaseous state, that is, it does not have a liquid state; it then enters the tube, which leads into the collecting chamber. This simulates the breathing of birds or mammals. The female mosquitoes, which are attracted to the CO_2 gas and the light source, are forced into the collecting chamber by a fan; the fan also prohibits them from escaping. The mosquitoes that are collected can then be counted and classified into their respective species; they are also tested for the presence of arboviruses. This information can give an idea of the size of the mosquito population in a particular area, which can then be used to determine if there is an eminent danger of an arbovirus or mosquito-borne disease to humans and animals. Control measures, like larviciding and adulticiding, can then be utilized to reduce the size of the mosquito population. ("Mosquito Light Traps - Adult Disease Surveillance - WUVCD," n.d.).

Figure 2: A Sample of Mosquitoes Collected From the CDC Light

Source: Mosquito Control 2014 Update. PowerPoint Presentation. Terry Torrens, Director, Mosquito Control Section, Osceola County.

As mentioned before, the arbovirus data used in this thesis was also retrieved from the Florida Health Surveillance site (“Surveillance | Florida Department of Health,” 2015). In Osceola County, similar to other counties, they receive reports of humans who have tested positive for the presence of antibodies of different viruses. They also test various animals, if they receive reports from animal owners. The Fish and Wildlife Conservation Commission (FWC) collects reports of dead birds, which can be an indication of arbovirus circulation in an area (“Surveillance | Florida Department of Health,” 2015). The counties also place chickens, referred to as sentinels, at strategic locations in cages. If these chickens are bitten by an infected mosquito, the virus is passed on to the chicken, then the tests are performed on the chicken, which indicate the presence of arbovirus activity. Each county provides this data to the Florida Department of Health (DOH) on a weekly basis and at the end of the year, the Florida DOH compiles the information in its annual report, the ‘Mosquito-Borne Disease Summary’. A part of one of the sections of the 2014 annual report is illustrated in Figure 3.

2014 Arbovirus Activity by County	
County	**Arbovirus Activity**
Alachua	EEEV: 3 horses (6/17, 6/20, 7/4); 11 sentinels (6/9, 6/30, 7/7, 7/14, 7/21, 7/28, 10/20) HJV: 2 sentinels (8/4, 10/20) WNV: 1 human (August); 15 sentinels (8/12, 8/18, 8/25, 9/16, 9/22, 9/29, 10/13, 10/20, 11/3, 11/10)
Baker	EEEV: 3 horses (3/13, 7/10, 7/16)
Bay	EEEV: 2 horses (6/15, 9/22); 6 sentinels (4/28, 5/6, 5/13, 5/22, 5/30) HJV: 1 sentinel (2/18) WNV: 18 sentinels (8/19, 8/26, 9/2, 9/9, 9/16, 9/23, 11/21)
Brevard	WNV: 1 horse (8/1); 31 sentinels (7/17, 8/8, 8/15, 8/20, 8/29, 9/5, 9/11, 9/12, 9/17, 9/18, 9/19, 9/26, 10/2, 10/8, 10/9, 10/10, 10/15, 10/16, 10/22, 10/31)
Broward	Chikungunya: 1 human (July)
Charlotte	WNV: 1 sentinel (9/12) SLEV: 2 sentinels (9/26, 10/24)
Citrus	EEEV: 16 sentinels (3/24, 3/31, 5/12, 5/26, 6/2, 6/30, 7/7, 7/14, 7/21, 8/4, 8/11, 9/8) HJV: 9 sentinels (2/17, 2/24, 8/11, 8/18, 9/29, 10/20, 12/1) WNV: 20 sentinels (1/2, 9/2, 9/15, 9/22, 9/29, 10/13, 10/20, 10/27, 11/10, 12/8)

Figure 3: Florida DOH Compiled Data

Source: http://www.floridahealth.gov/diseases-and-conditions/mosquito-borne-diseases/_documents/2014/week53ArbovirusReport-1-3-15.pdf

For the purposes of this thesis – and to test the first hypothesis, a Temporal Average Study was conducted with data from the 2002 to 2014 reports for thirty-two (32) counties of interest: Alachua, Baker, Bradford, Brevard, Charlotte, Citrus, Clay, DeSoto, Duval, Flagler, Hardee, Hernando, Highlands, Hillsboro, Indian River, Lake, Levy, Manatee, Marion, Nassau, Okeechobee, Orange, Osceola, Pasco, Pinellas, Polk, Putnam, Sarasota, Seminole, St. Johns, Sumter, and Volusia. The number of arbovirus activity – both human and animal cases – for each of the thirty-two counties was tallied from the data in the report and put in an Excel spreadsheet.

Subsequently, the number of annual arbovirus activity for each county was summed to give an annual total for these counties combined from 2002 to 2014 (See Table 1).

Table 1: Total Yearly Rainfall Compared to Total Annual Number of Arbovirus Activity in Thirty-two (32) of Florida's Counties.

	Total Yearly Rainfall (inches)	**Total Annual Number Of Arbovirus Activity**
2002	1652.83	1484.00
2003	1692.62	1108.00
2004	1720.56	365.00
2005	1868.75	761.00
2006	1664.40	99.00
2007	1218.50	107.00
2008	1474.98	173.00
2009	1628.65	278.00
2010	1638.64	575.00
2011	1437.18	300.00
2012	1535.08	445.00
2013	1624.45	444.00
2014	1664.75	641.00

These counties were chosen because their rainfall data was readily available via the St. John's River Water Management District (SJRWMD) and the Southwest Florida Water Management District (SWFWMD) websites. The yearly radar rainfall total, in inches, for each of the thirty-two counties was retrieved from the sites via an Excel worksheet. These totals were then summed to give a yearly total for all 32 counties combined, and this sum was placed in a table along with the total annual arbovirus data (See Table 1). Various graphs and plots were generated to analyze if there was a visible relationship between the amount of annual rainfall and the number of annual arbovirus activity for the 32 counties combined, which will be further discussed in *Chapter Four: Data Analysis and Results*.

As mentioned before, Statistical Methods were used to evaluate the data being researched. The input variable (x) represented by the data, was the annual rainfall for each year in the 32 counties combined, while the output variable (y) represented by the data, was the annual number of human and animal arbovirus cases combined for each year. This data was entered in a Texas Instruments TI-84 Plus C Silver Edition calculator and the scatter plots, regression lines and diagnostics for these plots were used for analysis. This data which has been organized using Microsoft Excel, was also used to generate scatter plots and regression lines for further verification.

For the purposes of this thesis – and to test the second hypothesis, a Spatial Average Study was be conducted for the thirty-two (32) aforementioned counties by summing the number of human and animal arbovirus activity for each county, for the 13 years, and taking this total to compare with its population size in the year 2014 – 2014 being the most recent year. Further, case studies were carried out with data from the 2002 to 2014 reports for seven (7) counties of interest: Alachua, Hillsborough, Nassau, Osceola, Orange, Putnam, and St. Johns. The number of arbovirus activity – both human and animal cases – for each of the seven counties will be tallied from the data in the reports and put in an Excel spreadsheet. Subsequently, the number of annual arbovirus activity for each county was summed to give a cumulative total for each county from 2002 to 2014. From the Spatial Average Study, the six (6) counties with the most arbovirus activity were chosen to compare this data with their population growth over the 13 years. Osceola County was also included because that was the initial county of interest, and an interview had been done with the Osceola County Mosquito Control Section.

The population data for these 7 counties was readily available via the United States Census Bureau website. This data was downloaded by year – 2002 to 2014 – and compiled in an Excel worksheet. The population data, along with the arbovirus cases data, was placed in a table for ease of organization and analysis. A table was created for each county separately (See Table 2).

Table 2: Compilation of Population Estimate and Total Number of Arbovirus Activity by Year for Osceola County, Florida.

	Annual Population Estimate (Osceola County)	**Total Annual Number Of Arbovirus Activity**
2002	190,844	60
2003	202,687	41
2004	216,541	15
2005	228,026	23
2006	242,081	3
2007	253,722	5
2008	261,746	7
2009	265,267	1
2010	269,811	14
2011	278,755	0
2012	288,970	2
2013	299,498	0
2014	310,211	1

Various graphs and plots were generated from each table to examine if there was a visible relationship between the human population growth and the number of annual arbovirus activity for the 7 counties. These graphs and plots will be further discussed in the following chapter, *Chapter Four: Data Analysis and Results*.

The input variable (*x*), represented by the data, was the human population for each year in the 7 counties; while the output variable (*y*), represented by the data, was the annual combined number of human and animal arbovirus cases for each year. This data was entered in a Texas Instruments TI-84 Plus C Silver Edition calculator and the scatter plots, regression lines and diagnostics for these plots were used for analysis. This data was organized using Microsoft Excel, which was also used to generate scatter plots and regression lines for further verification.

Subsequently, with the use of population projection data available on Florida's Office of Economic and Demographic Research's (EDR) website (http://edr.state.fl.us/Content/population-demographics/data/index.cfm), the model in this thesis was tested, by entering the projected population to simulate the number of human and animal arbovirus cases occurring in future years.

CHAPTER FOUR: DATA ANALYSIS AND RESULTS

In this chapter, different plots have been drawn, based on the data, in order to explore the correlation or relationship between rainfall and arbovirus activity, as well as, population and arbovirus activity. Subsequently, a scatter plot will be used to determine the extent of the correlation between the data and; if the correlation is linear, then the linear regression diagnostics will be determined. If the correlation coefficient which measures the strength of the association between the data, r – determined by the Texas Instruments TI-84 Plus C Silver Edition calculator – is close to 1 or -1, the stronger the association. A value of zero (0) means there is no association and values close to zero would mean little association (Gould & Ryan, 2014; pgs. 139 - 140). Further, if the relationship is linear, the coefficient of determination, r^2 will be used to calculate how much of the data is explained by the linear regression model (Gould & Ryan, 2014; pgs. 165 - 166).

4.1 Temporal Average Study

A temporal average study was done for each of the 13 years – 2002 to 2014. This study was used to investigate the correlation between precipitation and arbovirus activity in each year by summing the number of human and animal arbovirus activity for all counties, for a particular year and taking its total to compare with the rainfall for that year. For a general view of whether or not our data is related, that is, if rainfall relates to arbovirus activity, both datasets are plotted on a single graph (Figure 4). The upper graph, represented by the blue plot, illustrates the yearly rainfall from 2002 until 2014 in the 32 selected counties in the state of Florida. This plot shows a fluctuation between a minimum value of 1218.5 inches of yearly rainfall which occurred in 2007 and a maximum value of 1868.75 inches which occurred in 2005. The average annual rainfall, based on the data, is 1601.65 inches.

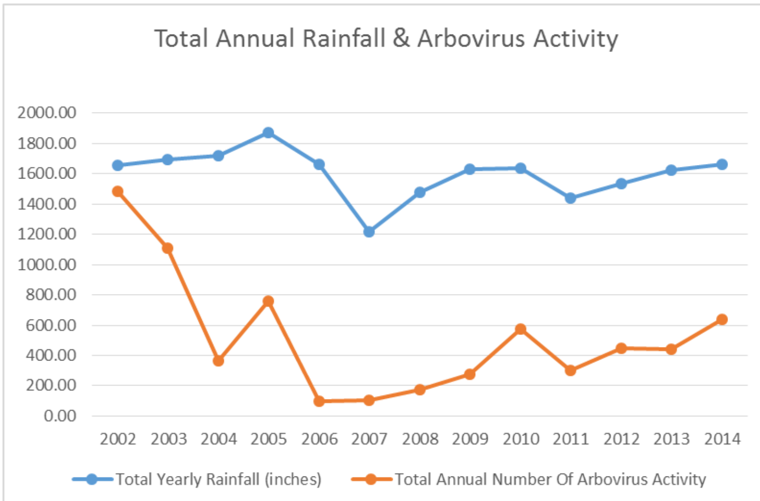

Figure 4: Total Annual Rainfall vs Total Annual Number of Arbovirus Cases.

Similarly, the lower graph, represented by the orange plot, illustrates the annual number of arbovirus cases from 2002 until 2014. This plot shows a fluctuation between a minimum value of 99 human and animal cases combined which occurred in 2006, and a maximum value of 1484 human and animal cases combined which occurred in 2002. The average number of human and animal cases combined, based on the data, is 522 – the calculated value is 521.538.

4.1.1 Modeling the Trend from 2002 to 2014

Based on the data, over thirteen years (2002 – 2014), the general shape or form of the scatter plot (Figure 5) is linear with a weak positive trend. The association is considered weak because there are a substantial number of outliers to the data, namely in the years 2002 and 2003.

This positive trend would suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

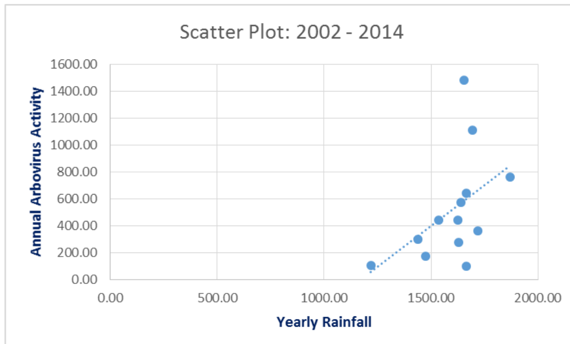

Figure 5: Scatter Plot of Yearly Rainfall against Annual Arbovirus Cases (2002 - 2014).

The linear regression diagnostics (Figure 6) indicate that the correlation coefficient of the data, *r* is 0.478. The closer *r* is to 1 or -1, the stronger the association

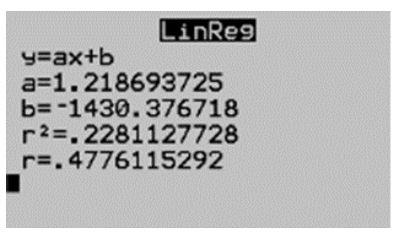

Figure 6: Linear Regression Diagnostics (2002 - 2014).

Further, the linear regression equation for this data is given by

$$y = 1.219x - 1430.377.$$

The slope of this equation is 1.219. Also,

$$Slope = \frac{Output}{Input} = \frac{Annual\ Arbovirus\ Cases}{Annual\ Rainfall} = \frac{1.219}{1}.$$

The slope in this instance may be interpreted to mean that for every 1,000 inches of rain, there will be an increase of 1,219 human and animal cases – combined – of arboviruses. Moreover, the *y*-intercept (i.e., when $x = 0$) is given by negative 1430.377. Therefore, this is interpreted as meaning that when there is no rainfall, there will be a negative number of arbovirus cases which essentially means no cases. Also, the coefficient of determination, r^2 is 0.228, which means that 22.8% of the data is explained by the linear regression line.

Although there is some correlation between the data, this is not to be considered a good model, because not many data points are represented by it – only 22.8%, and the association is weak. It must however, be reiterated that the general behavior of the trend line does suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

4.1.2 Modeling the Trend from 2003 to 2014

Based on the data, over twelve years (2003 – 2014), the general shape or form of the scatter plot (Figure 7) is linear with a weak positive trend. The association is considered weak because there are a substantial number of outliers to the data, even though one outlier – 2002 – has been omitted. This positive trend would suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

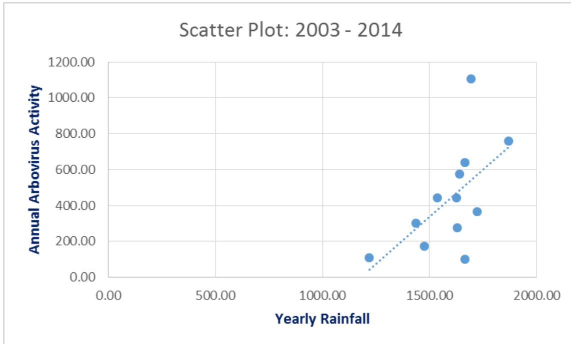

Figure 7: Scatter Plot of Yearly Rainfall against Annual Arbovirus Cases (2003 - 2014).

The linear regression diagnostics (Figure 8) indicate that the correlation coefficient of the data, *r* is 0.587. The closer *r* is to 1 or -1, the stronger the association

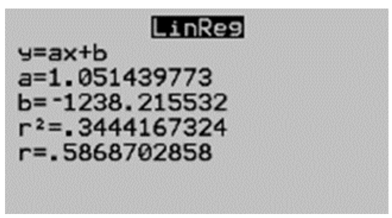

Figure 8: Linear Regression Diagnostics (2003 - 2014).

Further, the linear regression equation for this data is given by

$$y = 1.051x - 1238.216.$$

The slope of this equation is 1.051. Also, again

$$Slope = \frac{Output}{Input} = \frac{Annual\ Arbovirus\ Cases}{Annual\ Rainfall} = \frac{1.051}{1}.$$

The slope in this instance may be interpreted to mean that for every 1,000 inches of rain, there will be an increase of 1,051 human and animal cases – combined – of arboviruses. This is a similar result when the trend was modelled from 2002 to 2014. Moreover, the *y*-intercept (i.e., when x = 0) is given by negative 1238.216. Therefore, this is interpreted as meaning that when there is no rainfall, there will be a negative number of arbovirus cases which essentially means no cases. Also, the coefficient of determination, r^2 is 0.344, which means that 34.4% of the data is explained by the linear regression line.

Although there is some correlation between the data, this is not to be considered a good model, because not many data points are represented by it – only 34.4%, and the association is weak. It must however, be reiterated that the general behavior of the trend line does suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

4.1.3 Modeling the Trend from 2004 to 2014

Based on the data, over eleven years (2004 – 2014), the general shape or form of the scatter plot (Figure 9) is linear with a moderate to fairly strong positive trend. The association is considered fairly strong because there are not a substantial number of outliers to the data. This positive trend would suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

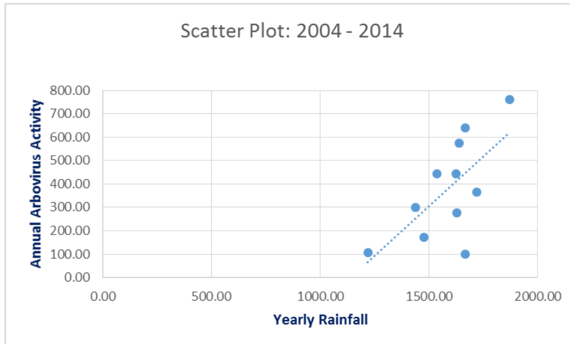

Figure 9: Scatter Plot of Yearly Rainfall against Annual Arbovirus Cases (2004 - 2014).

The linear regression diagnostics (Figure 10) indicate that the correlation coefficient of the data, *r* is 0.662. The closer *r* is to 1 or -1, the stronger the association

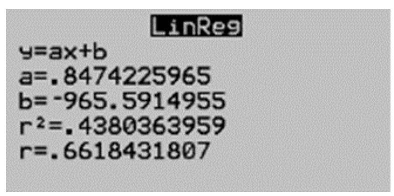

Figure 10: Linear Regression Diagnostics (2004 - 2014).

Further, the linear regression equation for this data is given by

$$y = 0.847x - 965.592.$$

The slope of this equation is 0.847. Also, again

$$Slope = \frac{Output}{Input} = \frac{Annual\ Arbovirus\ Cases}{Annual\ Rainfall} = \frac{0.847}{1}.$$

The slope in this instance may be interpreted to mean that for every 1,000 inches of rain, there will be an increase of 847 human or animal occurrence of an arbovirus. Moreover, the *y*-intercept (i.e., when $x = 0$) is given by negative 965.592. Therefore, this is interpreted as meaning that when there is no rainfall, there will be a negative number of arbovirus cases which essentially means no cases. Also, the coefficient of determination, r^2 is 0.438, which means that 43.8% of the data is explained by the linear regression line.

Based on these results, one can say there exists a correlation between the rainfall and arbovirus data, and as such it may be considered a representative model of the given data, because almost 44% of the data may be represented by it and the association is fairly strong. It must be stated that the correlation between the data does not necessarily imply causation (Gould & Ryan, 2014; pg. 161), that is, one cannot state that rainfall causes arboviruses. However, the general behavior of the trend line does suggest that as the amount of rainfall increases, then so do the number of human and animal arbovirus cases.

4.2 Spatial Average Study

A spatial average study was done for each of the 32 counties in question. This study took into consideration that over the 13 years – 2002 to 2014, the total annual precipitation was almost the same year-over-year. So then, precipitation will be treated as constant in this section. The spatial average study was used to investigate the correlation between arbovirus activity and the population size of each geographic location (i.e., county). This was done by summing the number of human and animal arbovirus activity for each county, for the 13 years, and taking this total to compare with its population size in the year 2014 – 2014 being the most recent year.

The scatter plot of the population versus the total number of human and animal arbovirus cases – over the thirteen years (2002 – 2014) – based on the 2014 population size of each county (Figure 11), indicates some trend or linear correlation between the data (r = 0.61; r^2 = 37%). However, the relationship is moderate and increasing, with 37% of the data being represented by the linear regression. This moderate linear relationship would suggest that, the human population in 2014 is directly proportional, to the combined number of human and animal arbovirus cases for each county over the 13 years. That is, as the human population grows, the annual number of arbovirus cases increases.

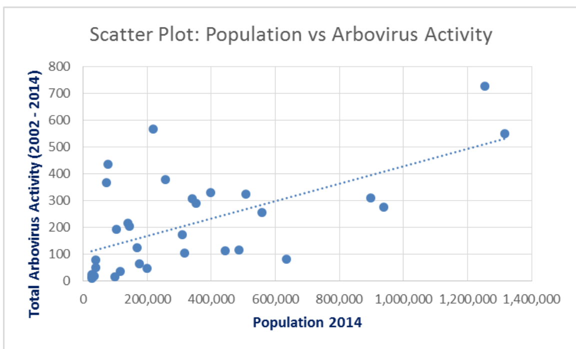

Figure 11: Scatter Plot of Population (year: 2014) against Total Arbovirus Activity for each County (2002 - 2014).

It must be stated that the correlation between the data does not necessarily imply causation (Gould & Ryan, 2014; pg. 161), that is, one cannot state that increasing population size causes an increase in the number of arbovirus cases. However, the general behavior of the trend line does suggest that as the human population increases, then the number of human and animal arbovirus cases also increases.

Further, it is possible to derive a linear model to represent this data as shown in the linear regression diagnostics in Figure 12.

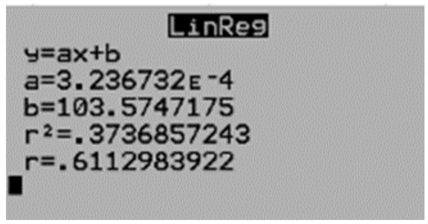

Figure 12: Linear Regression Diagnostics for Population (year: 2014) against Total Arbovirus Activity for each County (2002 - 2014).

Now, the linear regression equation for this data is given by

$$y = 0.000324x + 103.575.$$

The slope of this equation is 0.000324. Also,

$$Slope = \frac{Output}{Input} = \frac{Annual\ Arbovirus\ Cases}{Human\ Population\ in\ 2014} = \frac{0.000324}{1} = \frac{3.24}{10000}.$$

The slope in this instance may be interpreted to mean that for 1,000,000 persons included in the population in 2014, there will be an increase of 324 human or animal occurrences of an arbovirus. Moreover, the *y*-intercept (i.e., when $x = 0$) is given by positive 103.575. Therefore, this is interpreted to mean that if there is no-one living in a given county, there will be 104 arbovirus cases; which essentially means there will only be animal cases occurring. This is not to be considered a good model, since a lot of data is not represented by the linear regression. Moreover, the relationship between the data is of moderate strength.

4.3 Case Studies

For a general view of whether or not our data is related, that is, if human population growth relates to arbovirus activity, both datasets have been plotted on two separate graphs for each of the 7 counties. The first, represented by the blue plot, will illustrate the yearly human population count from 2002 until 2014 for each respective county. This plot will show any trend in population growth from year to year. Similarly, the second graph, represented by the orange plot, will be used to illustrate the annual number of arbovirus cases from 2002 until 2014 in each county.

4.3.1 Modeling Results for Orange County

Over the thirteen year period being considered, Orange County, Florida; had a total of 727 arbovirus cases; 4 of which were human cases and the remaining 723 cases were animal cases. Figure 13 illustrates the yearly human population from 2002 until 2014 for Orange County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 14 illustrates the annual number of arbovirus cases from 2002 until 2014 in Orange County. In 2002 and 2003, there were a total of 157 and 113 human and animal arbovirus cases respectively. These were the highest in all the years. In the following year, 2004, there was a significant drop in the number of cases – 28. It could have been that the mosquito control department embarked on an aggressive campaign to use larvicides and adulticides to control the insects, as well, they may have tried to increase awareness of mosquito-borne viruses. From 2004 to 2014, the trend in the number of cases is linear positively increasing. The highest number within this period occurred in 2014 – 78 – which coincidentally, also had the highest population count of all 13 years.

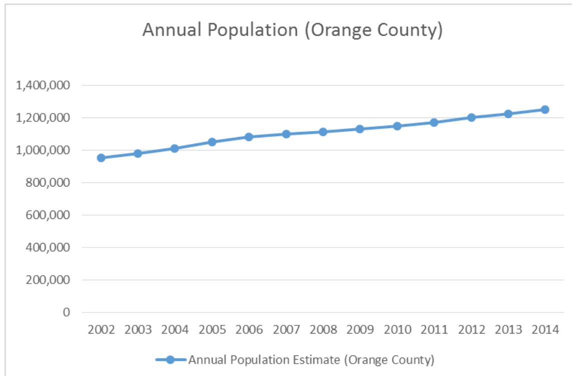

Figure 13: Population Estimates for Orange County, 2002 – 2014.

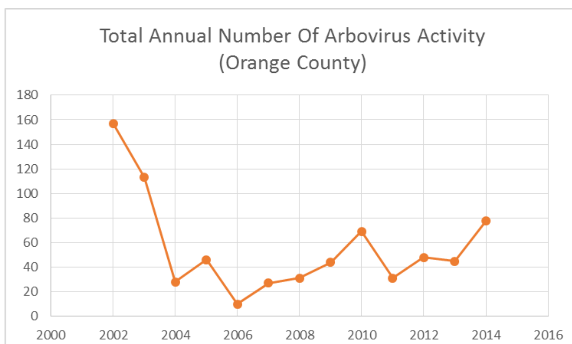

Figure 14: Annual Arbovirus Activity for Orange County, 2002 – 2014.

The scatter plot (Figure 15) over the thirteen years (2002 – 2014), indicates some trend or linear correlation between the data (r = - 0.41; r^2 = 17%). However, the relationship is weak and decreasing, with only 17% of the data being represented by the linear regression. This weak negative linear relationship would suggest that generally, the human population in Orange County is indirectly proportional, to the combined number of human and animal arbovirus cases. Moreover, the linear model to represent this data would not be a good one. If the two outliers – the years 2002 and 2003 – were omitted, then the linear relationship would be stronger and an even better model could be derived. Notwithstanding, a model for the period of 13 years is what is being sought.

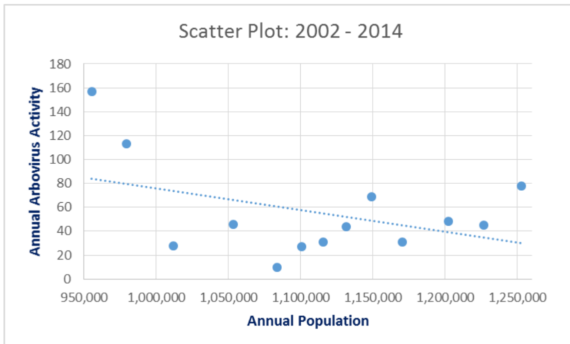

Figure 15: Scatter Plot of Annual Population against Annual Arbovirus Activity for Orange County (2002 - 2014).

4.3.2 Modeling Results for St. Johns County

Over the thirteen year period being considered, St. Johns County, Florida; had a total of 567 arbovirus cases; 1 of which was a human case and the remaining 566 cases were animal cases. Figure 16 illustrates the yearly human population from 2002 until 2014 for St. Johns County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 17 illustrates the annual number of arbovirus cases from 2002 until 2014 in St. Johns County. There is no discernable trend in this plot; it is mostly erratic in behavior.

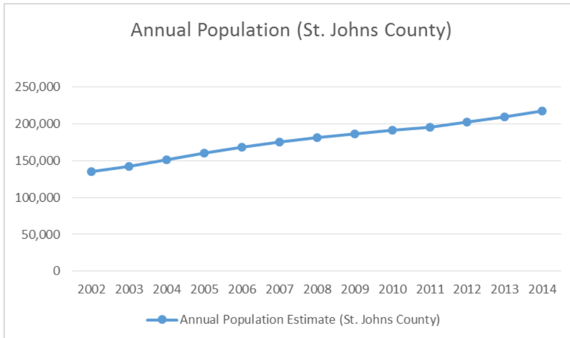

Figure 16: Population Estimates for St. Johns County, 2002 – 2014.

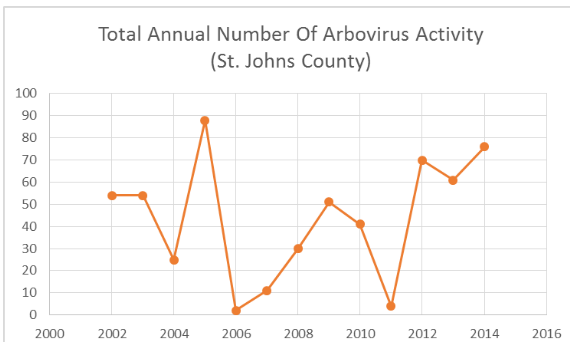

Figure 17: Annual Arbovirus Activity for St. Johns County, 2002 – 2014.

The scatter plot (Figure 18) over the thirteen years (2002 – 2014), indicates no trend or linear correlation between the data (r = 0.13; r^2 = 1.7%). The relationship is weak. This weak linear relationship would suggest that, the human population in St. Johns County is not directly nor indirectly proportional, to the combined number of human and animal arbovirus cases. Moreover, there is no good linear model to represent this data.

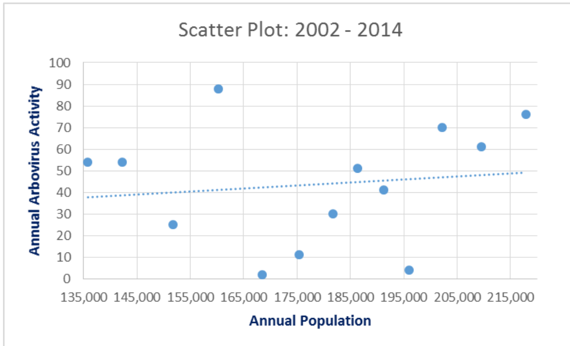

Figure 18: Scatter Plot of Annual Population against Annual Arbovirus Activity for St. Johns County (2002 - 2014).

4.3.3 Modeling Results for Hillsborough County

Over the thirteen year period being considered, Hillsborough County, Florida; had a total of 549 arbovirus cases; 10 of which were human cases and the remaining 539 cases were animal cases. Figure 19 illustrates the yearly human population from 2002 until 2014 for Hillsborough County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 20 illustrates the annual number of arbovirus cases from 2002 until 2014 in Hillsborough County. There is no discernable trend in this plot; it is mostly erratic in behavior.

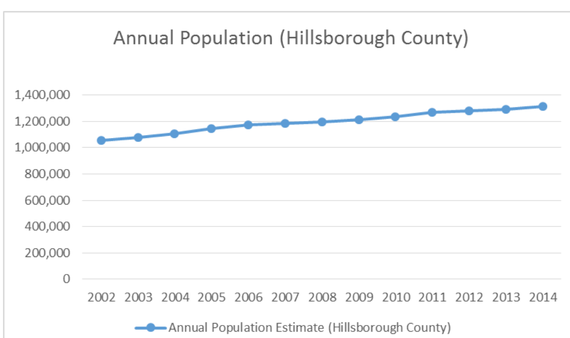

Figure 19: Population Estimates for Hillsborough County, 2002 – 2014.

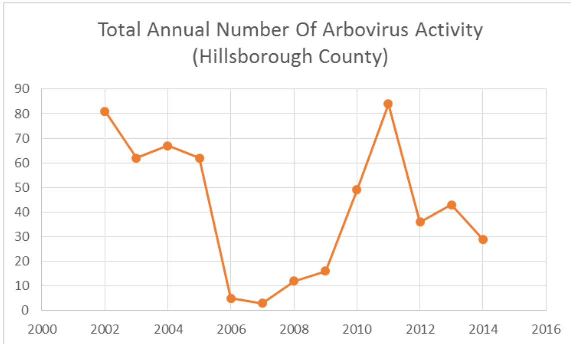

Figure 20: Annual Arbovirus Activity for Hillsborough County, 2002 – 2014.

The scatter plot (Figure 21) over the thirteen years (2002 – 2014), indicates a weak, negative association or linear correlation between the data (r = - 0.31; r^2 = 9.8%). Only approximately 10% of the data being represented by the linear regression. This weak linear relationship would suggest that, the human population in Hillsborough County is somewhat indirectly proportional, to the combined number of human and animal arbovirus cases. Moreover, this is not a good model to represent this data.

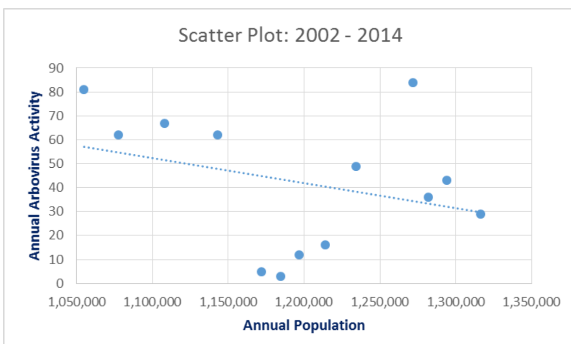

Figure 21: Scatter Plot of Annual Population against Annual Arbovirus Activity for Hillsborough County (2002 - 2014).

4.3.4 Modeling Results for Nassau County

Over the thirteen year period being considered, Nassau County, Florida; had a total of 436 arbovirus cases; 2 of which were human cases and the remaining 434 cases were animal cases. Figure 22 illustrates the yearly human population from 2002 until 2014 for Nassau County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 23 illustrates the annual number of arbovirus cases from 2002 until 2014 in Nassau County. There is no discernable trend in this plot; it is mostly erratic in behavior.

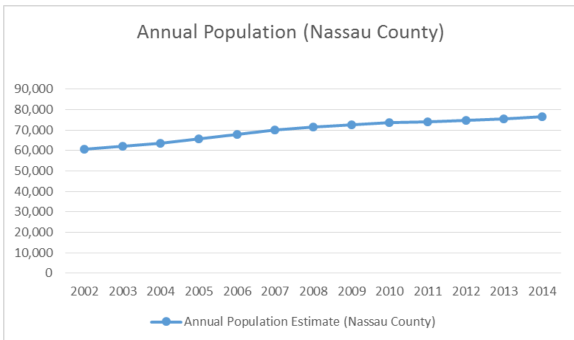

Figure 22: Population Estimates for Nassau County, 2002 – 2014.

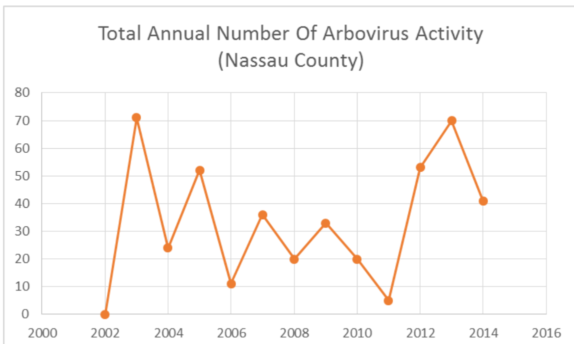

Figure 23: Annual Arbovirus Activity for Nassau County, 2002 – 2014.

The scatter plot (Figure 24) over the thirteen years (2002 – 2014), indicates no trend or linear correlation between the data (r = 0.13; r^2 = 1.7%). The relationship is weak. This weak relationship would suggest that, the human population in Nassau County is not directly nor indirectly proportional, to the combined number of human and animal arbovirus cases. Moreover, there is no good linear model to represent this data.

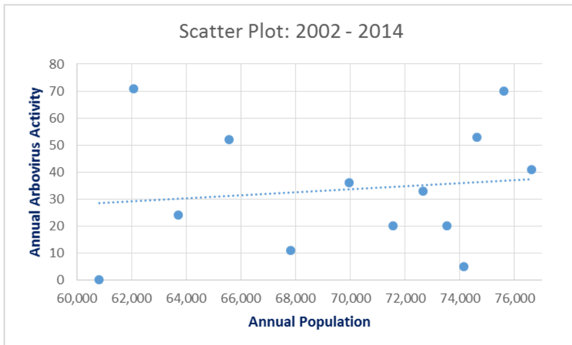

Figure 24: Scatter Plot of Annual Population against Annual Arbovirus Activity for Nassau County (2002 - 2014).

4.3.5 Modeling Results for Alachua County

Over the thirteen year period being considered, Alachua County, Florida; had a total of 379 arbovirus cases; 6 of which were human cases and the remaining 373 cases were animal cases. Figure 25 illustrates the annual human population from 2002 until 2014 for Alachua County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 26 illustrates the annual number of arbovirus cases from 2002 until 2014 in Alachua County. The general trend in this plot; seems to be negatively decreasing in behavior.

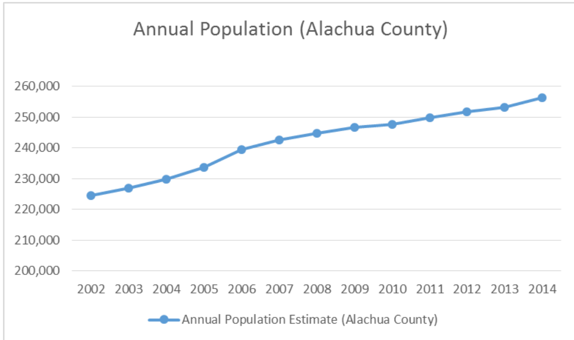

Figure 25: Population Estimates for Alachua County, 2002 – 2014.

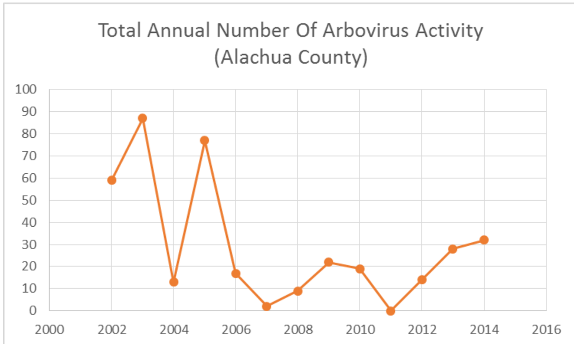

Figure 26: Annual Arbovirus Activity for Alachua County, 2002 – 2014.

The scatter plot (Figure 27) over the thirteen years (2002 – 2014), indicates a negative association between the data (r = - 0.59; r^2 = 35.2%). The relationship is moderate. This moderate, negative association would suggest that, the human population in Alachua County is indirectly proportional, to the combined number of human and animal arbovirus cases. However, this is not a good model to represent this data, since only slightly higher than 35% of the data would be represented by such a model.

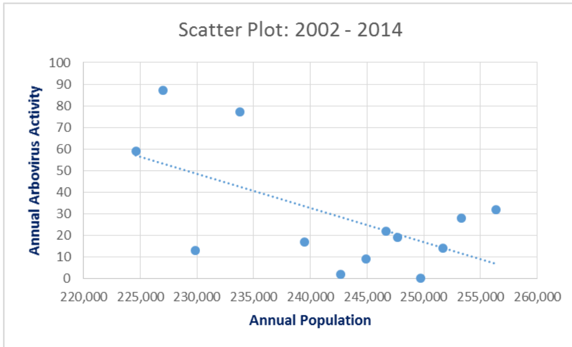

Figure 27: Scatter Plot of Annual Population against Annual Arbovirus Activity for Alachua County (2002 - 2014).

4.3.6 Modeling Results for Putnam County

Over the thirteen year period being considered, Putnam County, Florida; had a total of 365 arbovirus cases; all of which were animal cases. Figure 28 illustrates the yearly human population from 2002 until 2014 for Putnam County. This plot shows a concave downward graph with a maximum population count of 75,107 persons in the year 2007. Since 2007, there has been a steady decline in the population growth from year to year. This might have been due to the economic recession which occurred in the U.S., starting in 2007; residents might have moved out of the county to seek jobs elsewhere. Figure 29 illustrates the annual number of arbovirus cases from 2002 until 2014 in Putnam County. There is no discernable trend in this plot; it seems mostly erratic in behavior.

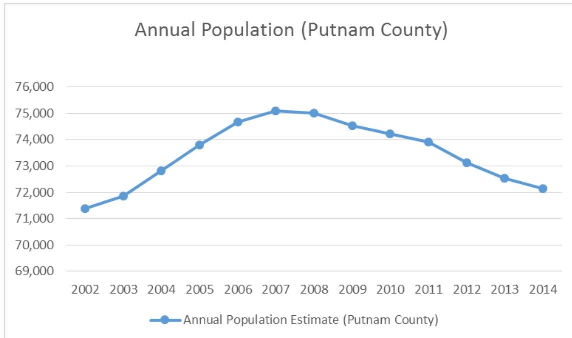

Figure 28: Population Estimates for Putnam County, 2002 – 2014.

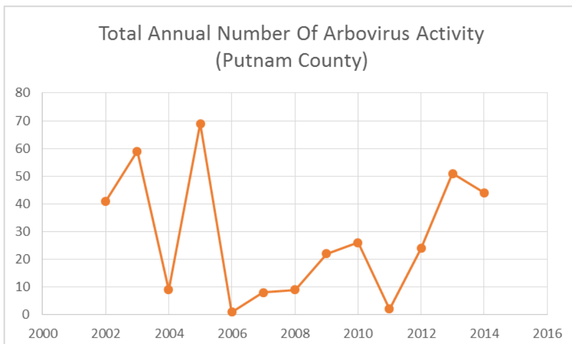

Figure 29: Annual Arbovirus Activity for Putnam County, 2002 – 2014.

The scatter plot (Figure 30) over the thirteen years (2002 – 2014), indicates a moderate negative association between the data (r = - 0.61; r^2 = 37.3%). This moderate, negative association would suggest that, the human population in Putnam County is indirectly proportional, to the combined number of human and animal arbovirus cases. However, this is not a good model to represent this data, since only slightly higher than 37% of the data would be represented by such a model.

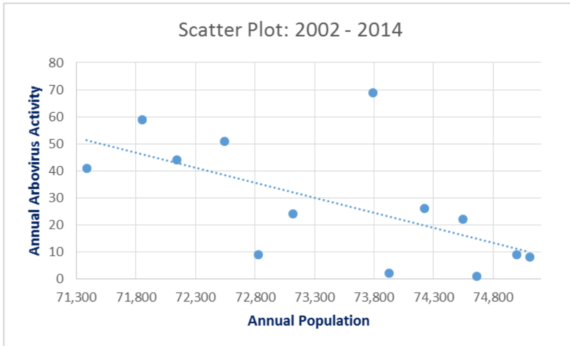

Figure 30: Scatter Plot of Annual Population against Annual Arbovirus Activity for Putnam County (2002 - 2014).

4.3.7 Modeling Results for Osceola County

Over the thirteen year period being considered, Osceola County, Florida; had a total of 172 arbovirus cases; 2 of which were human cases and the remaining 170 cases were animal cases. Figure 31 illustrates the yearly human population from 2002 until 2014 for Osceola County. This plot shows a steady increase in population growth from year to year. Similarly, Figure 32 illustrates the annual number of arbovirus cases from 2002 until 2014 in Osceola County. Generally, there seems to be a decreasing trend in the number of cases over the years.

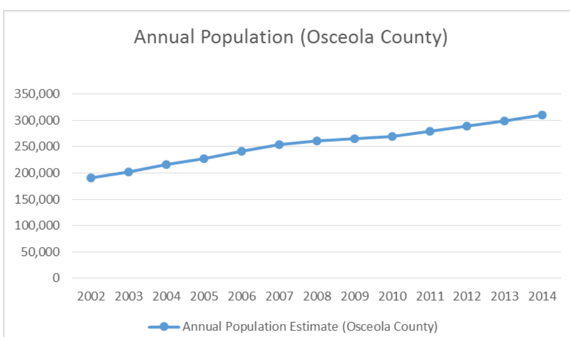

Figure 31: Population Estimates for Osceola County, 2002 – 2014.

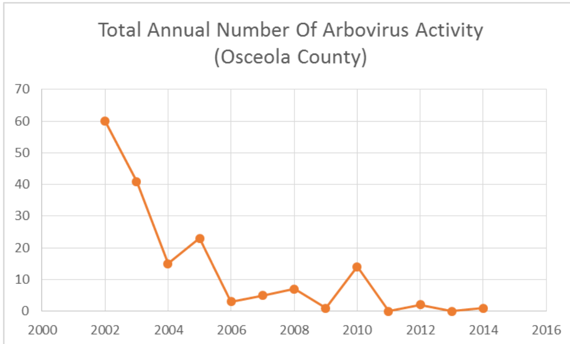

Figure 32: Annual Arbovirus Activity for Osceola County, 2002 – 2014.

The scatter plot (Figure 33) over the thirteen years (2002 – 2014), indicates a negatively associated linear correlation between the data (r = - 0.83; r^2 = 0.69). The relationship is strong. This strong negative linear relationship would suggest that, the human population in Osceola County is indirectly proportional, to the combined number of human and animal arbovirus cases. That is, as the human population grows, the annual number of arbovirus cases diminishes. This may be due to the vigilance of the Osceola County Mosquito Control Section, in making sure that there is regular monitoring of the presence of mosquitoes, as well as, the use of sentinel chickens to test for the presence of arboviruses. Also, spraying is regularly done, and residents are informed on how to properly dispose of standing water. It must be reiterated that the correlation between the data does not necessarily imply causation (Gould & Ryan, 2014; pg. 161), that is, one cannot state that increasing population causes a decrease in the number of arbovirus cases. However, the general behavior of the trend line does suggest that as the human population increases, then the number of human and animal arbovirus cases decreases.

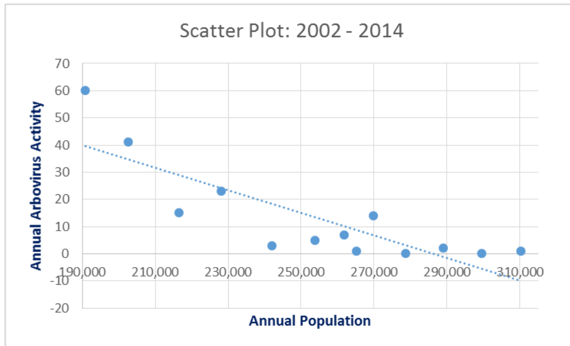

Figure 33: Scatter Plot of Annual Population against Annual Arbovirus Activity for Osceola County (2002 - 2014).

Further, it is possible to derive a good linear model to represent this data with almost 70% of the data being represented by it, as shown in the linear regression diagnostics in Figure 34.

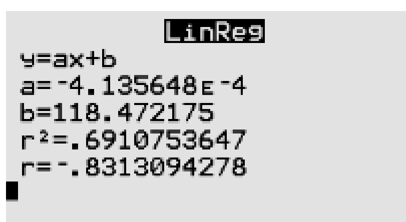

Figure 34: Linear Regression Diagnostics for Osceola County Data (2002 - 2014).

Now, the linear regression equation for this data is given by

$$y = -\,0.000414x + 118.472.$$

The slope of this equation is - 0.000414. Also,

$$Slope = \frac{Output}{Input} = \frac{Annual\ Arbovirus\ Cases}{Annual\ Human\ Population} = \frac{-0.000414}{1} = \frac{-4.14}{10000}.$$

The slope in this instance may be interpreted to mean that for 1,000,000 persons included in the population annually, there will be an annual decrease of 414 human or animal occurrences of an arbovirus. Moreover, the *y*-intercept (i.e., when *x* = 0) is given by positive 118.472. Therefore, this is interpreted as meaning that if there is no-one living in Osceola County, there will be 119 arbovirus cases; which essentially means there will only be animal cases occurring.

4.3.7.1 Simulation Using the Model

With the use of population projection data available from Florida's Office of Economic and Demographic Research's (EDR) website (http://edr.state.fl.us/Content/population-demographics/data/index.cfm), this model was able to be tested and data was put in an Excel table. In the simulation shown in Table 3, random years were chosen and the projected population for each year was input in the derived model, in order to ascertain the total annual number of human and animal arbovirus cases which will occur in that particular year.

Table 3: Simulation Using the Projected Population for Specific Years to Predict the Total Annual Number of Human and Animal Arbovirus Cases.

	Annual Projected Population (Osceola County)	**Total Annual Predicted Number Of Arbovirus Activity**
2015	306,924	-9
2016	317,418	-13
2017	328,191	-17
2020	360,478	-31
2025	409,138	-51
2030	452,651	-69

The negative number of predicted human and animal arbovirus cases means that as the projected population increases from year to year, then the number of cases should be zero (0) in 2015, zero (0) in 2016, etcetera. Therefore, if Osceola County continues to monitor the mosquito population, spray larvicides and adulticides when necessary, and continue to educate its residents, then this county should eradicate the incidence of mosquito-borne diseases.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

In this research paper, the hypotheses that were being tested was that, greater precipitation would increase the likelihood of having a greater number of arbovirus cases; and secondly that, an increase in the human population would increase the likelihood of a greater number of arbovirus cases. The former was done through a Temporal Average Study, while the latter was done using a Spatial Average Study and case studies. The conclusions and recommendations based on the findings of this study are presented in this chapter.

The Temporal Average Study revealed that the linear regression model derived from the data used for the periods 2002 – 2014 and 2003 – 2014, were not good models due to a weak association. However, after omitting the years 2002 and 2003 which were outliers to the data, the linear regression model for the time period 2004 – 2014 was fairly strong, and this correlation supported the first of the two hypotheses being tested. So, it may be concluded that, based on the data considered for the 32 counties from 2004 to 2014, more rainfall would indeed increase the likelihood of a greater number of human and animal arbovirus cases. Similarly, the Spatial Average Study revealed that the correlation between the total number of arbovirus cases from 2002 to 2014 and the population in 2014 was of moderate strength. It did support the second hypothesis being tested, but not strongly. The association indicated that as the population increased, so do the number of human and animal arbovirus cases. This yielded a model which was not representative of the majority of the data, and as such, could not be considered as a good one.

To further investigate the second hypothesis, case studies were done for seven of the thirty-two counties that had been considered. Of the 7 counties included in these case studies, all except one showed a steady increase in the size of the human population over the thirteen year time period, namely from 2002 to 2014. Putnam County was the only one which showed a decline in the size of the human population since 2007 which could have been due to the economic recession experienced in the U.S., starting in 2007. Prior to 2007, that county was experiencing a gradual increase in the size of its human population. Of the seven counties, 4 exhibited a weak association between the size of the human population and the spread of animal and human arbovirus cases; 2 exhibited a somewhat moderate association; and one – Osceola County – was strongly associated. This strong negative association indicated that, as the size of the human population increased in Osceola County, the combined number of human and animal arbovirus cases decreased, which refutes the hypothesis of this thesis. From these results it is possible to conclude that the increasing population size in Osceola County, has allowed the Mosquito Control Department to work hard to eradicate the occurrence of arboviruses. They regularly monitor mosquito habitats and use sentinel chickens to test for the presence of arboviruses, they have a sizeable budget that is dedicated to spraying regularly, and they inform their residents on how to properly dispose of standing water.

Being the only county with a strong association, it was possible to explore a linear regression model for the data and use that model to simulate what will occur in future years with the use of population projection data available from Florida's Office of Economic and Demographic Research's (EDR) website. The projected population data retrieved from this site indicated that there will be a steady increase in the size of the human population from year to year. In each simulated year, the number of combined human and arbovirus cases was negative. This prediction means that, as the projected population increases from year to year, the number of cases each year should be zero (0). The reliability of these predictions are questionable since Osceola County is landlocked and located next to Orange County. The research shows that the human population in Orange County has a weak association with the combined number of human and animal arbovirus cases; and that, as the former increases, the latter decreases. Since humans, animals and mosquitoes are traveling freely across the borders of these counties, it may prove difficult to completely contain arboviruses to Orange County and prohibit the spread to Osceola County. Based on the findings of the Spatial Average Study and the case studies, it is inconclusive as to whether or not an increase in the human and animal population would lead to a greater number of arbovirus cases.

After having completed this study, the recommendations are that Osceola County should continue to do what they are currently doing to control the mosquito population. Moreover, if the counties do not collaborate extensively to eradicate mosquito-borne viruses and disease, they should start to do so immediately. Especially those counties with the higher numbers of human and animal cases, may need to adopt what the counties, like Osceola County, with less or a decreasing number of cases are presently doing to get rid of these viruses and diseases. It is also recommended that more surveillance to collect more data for future studies should be done. The size of the mosquito population data could be used to investigate how this affects the spread of arboviruses. Most of the data used was based on animal cases, so looking at the animal population in isolation is a good idea – but it may prove to be difficult. Other factors which affect the spread of arbovirus diseases, such as temperature and humidity may also be considered to see how they are correlated. Statistical methods should be used in further studies. For a future study, other methods like sensitivity analysis could be used. Differential Equations models may be used as more data on interactions among different factors is available.

To remain vigilant and to continue the existing practice are very important to prevent mosquito-borne diseases.

LIST OF REFERENCES

About DVBD | Division of Vector-Borne Diseases (DVBD) | NCEZID | CDCAbout DVBD | Division of Vector-Borne Diseases (DVBD) | NCEZID | CDC. (2014). Retrieved April 27, 2015, from http://www.cdc.gov/ncezid/dvbd/about.html. (2014). Retrieved April 27, 2015, from http://www.cdc.gov/ncezid/dvbd/about.html

Connelly, C. R., & Carlson, D. B. (Eds. . (2009). *Florida Mosquito Control: The state of the mission as defined by mosquito controllers, regulators, and environmental managers*. *Florida Coordinating Council on Mosquito Control*. Vero Beach, FL: University of Florida, Institute of Food and Agricultural Sciences, Florida Medical Entomology Laboratory. Retrieved from http://mosquito.ifas.ufl.edu/Documents/Florida_Mosquito_Control_White_Paper.pdf

Eastern equine encephalitis virus disease cases and deaths reported to CDC by year and clinical presentation , 2004-2013. (2013). Retrieved from http://www.cdc.gov/EasternEquineEncephalitis/resources/EEEV-Cases-by-Year_2004-2013.pdf

Estep, L. K., Burkett-Cadena, N. D., Hill, G. E., Unnasch, R. S., & Unnasch, T. R. (2010). Estimation of dispersal distances of Culex erraticus in a focus of eastern equine encephalitis virus in the southeastern United States. *Journal of Medical Entomology*, *47*(6), 977–986. http://doi.org/10.1603/ME10056

Gould, R. (University of C., & Ryan, C. (California L. U. (2014). *Essential Statistics: Exploring the World through Data*. Pearson Education, Inc.

Holland, J. J. (2015). Florida has 6 of the nation's fastest-growing metro areas. Retrieved June 28, 2015, from http://www.pbs.org/newshour/rundown/florida-6-nations-fastest-growing-metro-areas/

Jacob, B. G., Burkett-Cadena, N. D., Luvall, J. C., Parcak, S. H., McClure, C. J. W., Estep, L. K., … Unnasch, T. R. (2010). Developing GIS-based eastern equine encephalitis vector-host models in Tuskegee, Alabama. *International Journal of Health Geographics*, *9*, 12. http://doi.org/10.1186/1476-072X-9-12

Kelen, P. Vander, Downs, J. A., Unnasch, T., & Stark, L. (2014). A risk index model for predicting eastern equine encephalitis virus transmission to horses in Florida. *Applied Geography (Sevenoaks, England)*, *48*, 79–86. http://doi.org/10.1016/j.apgeog.2014.01.012

Kenkre, V. M., Parmenter, R. R., Peixoto, I. D., & Sadasiv, L. (2005). A theoretical framework for the analysis of the west nile virus epidemic. *Mathematical and Computer Modelling*, *42*(3-4), 313–324. http://doi.org/10.1016/j.mcm.2004.08.012

Lindsey, N. P., Lehman, J. A., Staples, E. J., & Fischer, M. (2014). West Nile Virus and Other Arboviral Diseases — United States, 2013. *Centers for Disease Control and Prevention: Morbidity and Mortality Weekly Report*, 521–526. Retrieved from http://www.cdc.gov/mmwr/preview/mmwrhtml/mm6324a1.htm

Liu, X., & Stechlinski, P. (2014). Application of control strategies to a seasonal model of Chikungunya disease. *Applied Mathematical Modelling*, *39*(12), 3194–3220. http://doi.org/10.1016/j.apm.2014.10.035

Martindale, J. L., & MacIas Konstantopoulos, W. L. (2012). Locally acquired west nile encephalitis. *Journal of Emergency Medicine*, *43*(6), e435–e438. http://doi.org/10.1016/j.jemermed.2011.05.054

Mosquito Control. (2015, February 16). Retrieved March 30, 2015, from http://www.osceola.org/agencies-departments/community-development/offices/community-resources/mosquito-control/

Mosquito Light Traps - Adult Disease Surveillance - WUVCD. (n.d.). Retrieved May 10, 2015, from http://www.wumcd.org/surveillance/lighttraps.html

Mostashari, F., Bunning, M. L., Kitsutani, P. T., Singer, D. a., Nash, D., Cooper, M. J., … Campbell, G. L. (2001). Epidemic West Nile encephalitis, New York, 1999: Results of a household-based seroepidemiological survey. *Lancet*, *358*(9278), 261–264. http://doi.org/10.1016/S0140-6736(01)05480-0

Moulay, D., Aziz-Alaoui, M. a., & Cadivel, M. (2011). The chikungunya disease: Modeling, vector and transmission global dynamics. *Mathematical Biosciences*, *229*(1), 50–63. http://doi.org/10.1016/j.mbs.2010.10.008

Surveillance | Florida Department of Health. (2015). Retrieved May 10, 2015, from http://www.floridahealth.gov/diseases-and-conditions/mosquito-borne-diseases/surveillance.html

Thiberville, S. D., Moyen, N., Dupuis-Maguiraga, L., Nougairede, A., Gould, E. a., Roques, P., & de Lamballerie, X. (2013). Chikungunya fever: Epidemiology, clinical syndrome, pathogenesis and therapy. *Antiviral Research*, *99*(3), 345–370. http://doi.org/10.1016/j.antiviral.2013.06.009

Thomas, D. M., & Urena, B. (2001). A model describing the evolution of West Nile-like encephalitis in New York City. *Mathematical and Computer Modelling*, *34*(7-8), 771–781. http://doi.org/10.1016/S0895-7177(01)00098-X

Unnasch, R. S., Sprenger, T., Katholi, C. R., Cupp, E. W., Hill, G. E., & Unnasch, T. R. (2006). A dynamic transmission model of eastern equine encephalitis virus. *Ecological Modelling*, *192*(3-4), 425–440. http://doi.org/10.1016/j.ecolmodel.2005.07.011

Zacks, M. a., & Paessler, S. (2010). Encephalitic alphaviruses. *Veterinary Microbiology*, *140*(3-4), 281–286. http://doi.org/10.1016/j.vetmic.2009.08.023