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Spatio-Temporal Analysis of Malaria in Paraguay

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SPATIO-TEMPORAL ANALYSIS OF MALARIA IN PARAGUAY

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ABSTRACT: SPATIO-TEMPORAL ANALYSIS OF MALARIA IN PARAGUAY

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Malaria is a mosquito-borne disease that has afflicted humans for thousands of years. Today it is considered a re-emerging disease. Malaria is most prevalent in tropical and subtropical parts of the world. The disease has been linked to several environmental parameters, including precipitation, temperature, and deforestation. However, these relationships have mainly been studied in Africa and have not been explored in other parts of the world. The study area for this thesis was the South American country of Paraguay.

Paraguay has experienced an oscillation in malaria cases over the past 20 years, with monthly cases ranging from 0 to 1200. Additionally, the country has experienced vast amounts of deforestation and climate variations. The thesis study area was two Paraguayan departments, Alto Parana and Canindeyú. Both departments had a record of monthly malaria cases for the years of 1981-2003.

It was discovered that there was a positive correlation between malaria and temperature and vegetation strength and a negative correlation between precipitation and malaria. Spatial comparisons of deforestation maps and maps of malaria risk based on the selected environmental parameters, suggests recent deforestation increases the probably of malaria occurrence. Additionally, time series analysis provides evidence that an increase in temperature increases malaria cases every 2-3 years. The annual

oscillation of temperature, precipitation, and vegetation change from the wet and dry seasons corresponds with the low and high activity time periods for malaria case rates.

Dedicated to:

My parents, Bruce and Dawn Wayant

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My family has been very instrumental in not only my graduate school education, but also my life. Thank you for always loving me, listening to my late night phone calls, and helping me move many times over the past few years. Mom, Dad, and Clay, thanks for putting up with me and showing me what a special person I am even without all my weird degrees. Special thanks goes out to my neighbor, Janie Rowan. Janie, you will never know what a difference you made for me these past few years and I will truly miss you.

Last but not least, I would like to thank the One who made everything I have ever studied and the many things in life I will never be able to study. My purpose in life is to continue to strive to learn more about You and everything You created.

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Chapter 1
Introduction

Malaria, a disease spread by mosquitoes, has afflicted human beings for thousands of years (Suh *et al.* 2004). Although many advances have been made in mosquito control and in the treatment of the disease, malaria remains a significant public health issue, with over 247 million cases reported in the year 2006 (WHO 2008). Today malaria is being viewed as a re-emerging disease, with more people dying of malaria today, anywhere between 700,000 and 2.7 million, than 40 years ago (Patz and Olson 2006, Pattanayak *et al.* 2003, Gagnon *et al.* 2002).

Malaria is most prevalent in tropical and subtropical regions of the world, especially in South and Latin America, Africa, and Southeast and Central Asia, (WHO 2008, Pascual *et al.* 2006, Prothero 1995). Most cases occur within African nations (WHO 2008, Patz *et al.* 2005). However, the disease is of considerable importance in other parts of the world, particularly South America (Prothero 1995). Out of the 869 million individuals living in the Americas, over 260 million reside in areas prone to malaria (PAHO 2004) and approximately 41 million of these people live in an area of moderate to high risk of the disease (PAHO 2004).

Previous research has shown that climate is a key factor in explaining the incidence of malaria (Mantilla *et al.* 2009, Jones *et al.* 2007, Anyamba *et al.* 2006, Campbell-Lendrum and Woodruff 2006, Pascual *et al.* 2006, Thomson *et al.* 2006, Patz *et al.* 2005, Zhou *et al.* 2004, Hay *et al.* 2002, Gagnon *et al.* 2002, Poveda *et al.* 2001, Craig *et al.* 1999). Past studies have focused on a wide variety of climatic factors and anomalies, such as temperature, precipitation, humidity, and atmospheric pressure (Mantilla *et al.* 2009, Jones *et al.* 2007, Anyamba *et al.* 2006, Campbell-Lendrum and

Woodruff 2006, Pascual *et al.* 2006, Thomson *et al.* 2006, Patz *et al.* 2005, Zhou *et al.* 2004, Hay *et al.* 2002, Gagnon *et al.* 2002, Poveda *et al.* 2001, Craig *et al.* 1999). There is concern that global climate change over the next century may exacerbate the spread of malaria (Figure 1.1).

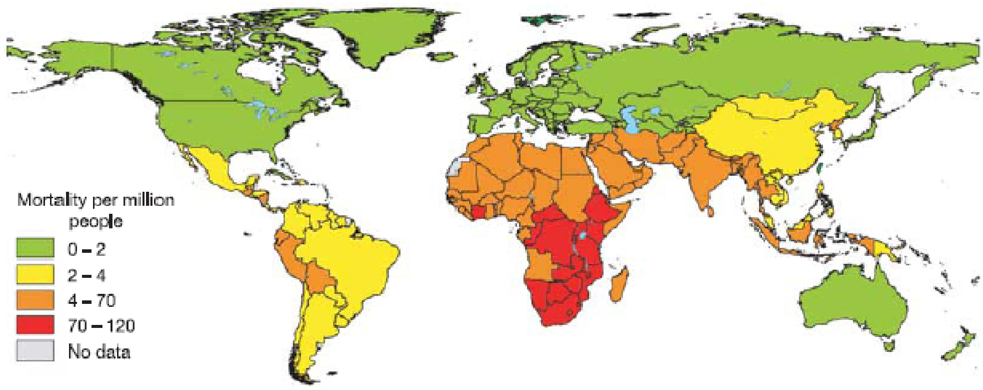


Figure 1.1: WHO estimated mortality (per million people) attributable to climate change by the year 2000 (Patz *et al.* 2005).

According to Pascual *et al.* (2006), increased temperatures can translate into a 30-100% increase in mosquito abundance (Pascual *et al.* 2006). Increased temperatures also shorten the larval development, decreasing the amount of time needed for adult mosquitoes to spread malaria and allowing for the development of more mosquitoes (Patz and Olson 2006). Land cover change, such as conversion from forest to agriculture, can exert a large impact on the microclimate of the region, increasing the mean annual average temperature (Patz and Olson 2006, Patz and Olson 2005). Treeless habitats tend to experience warmer temperatures than their forested counterparts (Patz and Olson 2005).

Precipitation also influences the incidence and transmission of malaria (Thomson *et al.* 2005, Zhou *et al.* 2004, Small *et al.* 2003, Hay *et al.* 2002). Mosquitoes require standing water in order to complete their life cycle (Olson *et al.* 2009). Although the link between precipitation and malarial incidence is not as strong as that with temperature, it has been shown that precipitation is a factor that is locally important and may also be related to land use change (Olson *et al.* 2009, Briet *et al.* 2008, Thomson *et al.* 2005, Small *et al.* 2003).

In general, inhabitants of environments that have undergone significant land use change tend to be more susceptible to mosquito-borne diseases (Norris 2004). Deforestation, for example, has been shown to greatly affect malaria case rates in varying parts of the world (Guerra *et al.* 2006, Massarani and Shanahan 2006, Vittor *et al.* 2006, Barbieri *et al.* 2005, Patz *et al.* 2005, Norris 2004, Pattanayak *et al.* 2003). Land cover change, e.g. forest to agricultural, increases the number of biting mosquitoes in a region (Guerra *et al.* 2006, Massarani and Shanahan 2006, Vittor *et al.* 2006). Cleared lands are also more prone to the development of pools of sunlit water, which provide breeding grounds for mosquitoes. Additionally, the cutting down of forests is often completed by migrant workers who have a lower immunity to malaria (Norris 2004, Pattanayak *et al.* 2003). These workers are then able to spread the disease amongst a transient population (Pattanayak *et al.* 2003). This trend of increased deforestation and malaria has been observed in South America, where more malaria cases are occurring on the borders of regions that have recently been changed from forest to agriculture (Guerra *et al.* 2006).

Within South America most malaria research has been conducted within the Amazon basin (Olson *et al.* 2009, Briet *et al.* 2008, Guerra *et al.* 2006, Massarani and Shanahan 2006, Vittor *et al.* 2006, Barbieri *et al.* 2005, Thomson *et al.* 2005, Norris 2004, Small *et al.* 2003, Pattanayak *et al.* 2003, Singh *et al.* 2002,). Considering the fact that deforestation tends to affect malaria differently in Africa, the Americas, and Southeast Asia (Guerra *et al.* 2006), it is essential to look at the association of deforestation and malaria in countries where the relationship has not been investigated.

In recent decades, it has been well demonstrated that satellite remote sensing can be a reliable source for information on land use and land cover change (Jensen 2007). Earth-observing systems such as Landsat have been used to monitor and map the land surface. However, tropical and subtropical regions of the earth are often covered with clouds, making it difficult for Landsat to monitor monthly variation in landscape, which is important when comparing to monthly cases of malaria. The Advanced Very High Resolution Radiometer (AVHRR), mounted on the National Oceanic and Atmospheric Administration (NOAA) series of satellites, has been used as an alternative to Landsat (Baldi *et al.* 2008). Although the AVHRR was designed for atmospheric rather than land surface observation, the sensor has been found to be useful for land cover assessment (AVHRR 2009, Baldi *et al.* 2008).

In most instances, data from AVHRR channels 1 (reflected red light - 0.58 to 0.68 micrometers), and 2 (reflected near infrared - 0.725 to 1.10 micrometers) are used to compute an index of vegetation "*greenness,*" the Normalized Difference Vegetation Index (NDVI). NDVI has been shown to be broadly correlated with different vegetation types (Loveland *et al.* 1991, Goward 1985, Justice *et al.* 1985, Tucker *et al.* 1985) and with several biophysical parameters such as levels of photosynthetic activity, primary production, leaf area, and albedo (Jensen 2007).

NDVI values have also been shown to be associated with precipitation and temperature (Chamaille-Jammes and Fitz 2009, Piao *et al.* 2003, Schultz and Halpert

2002, Fuller and Prince 1996). For example, Fuller and Prince (1996) found a positive correlation between NDVI and rainfall levels. Other studies have found a positive correlation between NDVI and temperature (Piao *et al.* 2003, Schultz and Halpert 2002).

Recently, Wayant *et al.* (2010), using Paraguay as a study area, found a positive relationship between AVHRR-derived NDVI and malaria. Although Wayant *et al.* (2010) demonstrated that NDVI was well correlated with incidences of malaria; the specific drivers of the observed spatio-temporal change in NDVI were not identified. More research needs to be conducted investigating the spatio-temporal drivers, such as temperature, precipitation and land cover change, of the relationship between NDVI and malaria. Additionally, time series analysis would provide needed in-depth information into the periodic behavior of malaria and its potential relationship with precipitation, temperature, and land cover.

Research Objectives

The principal objective of this research was to investigate the spatio-temporal interactions between malaria, multi-temporal AVHRR/NDVI data (as a surrogate for land use change), temperature and precipitation. Building on the previous investigation of Wayant *et al.* (2010), this research will also be conducted in Paraguay, focusing on the departments of Alto Parana and Canindeyú (Wayant *et al.* 2010). The study examined data for the time period 1983-2003.

Four specific questions were asked:

1. Will regions of high correlation between malaria and temperature and malaria and precipitation be similar to areas of correlation between malaria and NDVI?
2. Will time series analysis of the variables provide information about periodic

trends and cycles of individual variables as well as cycles of correlation?

3. By combining a selection of environmental parameters of malaria (temperature, precipitation, land cover change), will regions and times which can be highly associated with malaria incidents be discovered?
4. Does recent land cover change coincide with regions environmentally prone to malaria?

Overview of Methods

For all forms of analysis, monthly data consisting of malaria cases, AVHRR-NDVI, precipitation, and temperature, for the period 1981-2003 were used. To correct for data collection errors and prepare the data for statistical tests, the spatial datasets of NDVI, precipitation, and temperature, were smoothed using a Fourier Transform.

Time series analysis was used to determine whether or not trends and cycles existed within the malaria, NDVI (a proxy for vegetation and land cover change), temperature, and precipitation datasets. The analysis also determined if trends of correlation existed. Additionally, a lagged regression analysis was carried out to evaluate the change in malaria and its possible association with NDVI, temperature, and precipitation (Shumway and Stoffer 2006). This determined if there was a temporal relationship between malaria and precipitation, temperature, and vegetation change, and if a lag existed within that relationship. Because of the length of the time series, all analysis was completed within the frequency domain, utilizing the properties of Fourier analysis.

The temperature and rainfall data were transformed into the same length of moving windows and tested for correlation with malaria on a pixel by pixel basis.

Principal Component Analysis (PCA) was utilized to assess whether spatial and temporal patterns of malaria, rainfall and temperature were similar to patterns observed in the NDVI data observed by Wayant *et al.* (2010).

Lastly, a 1975 NASA GeoCover Landsat map of forest and non-forest areas was used to initialize the assessment of the extent of deforestation using NDVI as a surrogate of forest/non-forest change over the study period. The standard deviation of the average NDVI values for forest pixels was calculated based on the first year of the times series. Next, a map was produced of the average NDVI values for every pixel. If the average NDVI values were outside of two standard deviations (a standard statistical confidence interval (Hayter 2007)) of the original forest pixels NDVI values, it was concluded that a land cover change had occurred in the corresponding area. Since the majority of the study area was originally forest, it was assumed that any land cover change was associated with deforestation, primarily conversion to cropland.

Once the times and places of land cover change were identified, the average NDVI maps for this time period was compared to the average correlation of NDVI and malaria for that particular year. It was then determined whether or not land cover change was associated with malaria.

Thesis Outline

This thesis is organized into five chapters. The first chapter outlines the problem and establishes the overall focus and objectives of the project. Chapter 2 comprises a review of important background literature including discussion of previous research on relationships between malaria and vegetation, land use change (e.g. deforestation), precipitation, and temperature. The third chapter provides details on the data and analysis procedures used to try to address the questions outlined in the introduction. Research results are presented and discussed in Chapter 4. In chapter 5, the project is summarized and the major findings, their implications and directions for future research are identified.

Chapter 2
Background

Introduction

According to the World Health Organization (WHO) over half of the world's population is at risk to malaria transmission (WHO 2008) with 700,000 to 2.7 million people dying of the disease each year (Patz and Olson 2006, Gagnon *et al.* 2002). The Pan-American Health Organization (PAHO), the South and Latin American version of WHO, notes that worldwide, every thirty seconds a child dies of malaria (PAHO 2009). The only way to cure the disease is to begin treatment as soon as symptoms appear, usually 10 to 15 days after infection (PAHO 2009, WHO 2008). However, the individuals with the highest risk of contracting the disease also live in some of the poorest countries of the world which lack the resources to treat all of their infected citizens (PAHO 2009, WHO 2008, Pattanayak *et al.* 2003).

Previous research has focused mainly on the incidence of malaria within Africa. However, in 2008 there were over 500,000 collective cases of malaria reported in the North and South America (WHO 2008). The different strains of malaria carried by varying mosquitoes, behave differently based on its surrounding environment (Olson *et al.* 2009, Pascual *et al.* 2006, Kotwal *et al.* 2005, Zhou *et al.* 2004, Wongsrichanalai *et al.* 2002, Rab *et al.* 2001). For example, a positive relationship between malaria and precipitation has been established within the Amazon Basin (Olson *et al.* 2009) whereas a negative relationship between malaria and precipitation exists on the island of Sri Lanka (Briet *et al.* 2008).

The focus of this chapter is a literature review of past research pertaining to the relationship between malaria and temperature, precipitation, and deforestation. These particular parameters of malaria are of special importance considering the intense focus on climate change and public health. A review of journal articles portrays the importance of studying these climatic and environmental drivers of malaria on a local basis. Additionally, past research has displayed a lack of time series analysis, especially within the frequency domain, leaving a large hole in the understanding of the temporal dimensions of malaria and its environmental indicators.

Malaria

Malaria is a disease caused by a parasite belonging to the genus *Plasmodium* (CDC 2010, WHO 2008, White 2007). Although over 400 species exist, only four are known to routinely infect humans: *Plasmodium falciparum*, *P. vivax*, *P. ovale*, and *P. malariae* (White 2007). Not only does each type of parasite affect its human host differently, but each malaria parasite resides in a different geographic region. *P. falciparum* and *P. vivax* can mostly be found in the tropics and subtropics whereas *P. ovale* and *P. vivax* are more prevalent in west Africa and southeast Asia (White 2007).

Each of these strains is carried and transferred to humans by female mosquitoes that need blood to lay their eggs within shallow pools of water (CDC 2010, WHO 2008). The genus of mosquitoes that carry malaria is *Anopheles*. Of this particular genus, there are between 30-40 species of mosquitoes that are capable of carrying the disease (CDC 2010). The variation in geographic distribution of these mosquitoes and the malaria parasite they carry is thought to be related to variations in the effect of deforestation, precipitation, and temperature.

Climate and Malaria

Many studies have shown there is an association between the incidence of malaria and certain climatic variables, especially temperature and rainfall (Mantilla *et al.* 2009, Jones *et al.* 2007, Anyamba *et al.* 2006, Campbell-Lendrum and Woodruff 2006, Pascual *et al.* 2006, Thomson *et al.* 2006, Zhou *et al.* 2004, Hay *et al.* 2002, Gagnon *et al.* 2002, Poveda *et al.* 2001, Craig *et al.* 1999). However, for different countries, temperature and rainfall appeared to have varying effects on mosquito vectored diseases, which will be explained later in more detail (Olson *et al.* 2009, Briet *et al.* 2008, Thomson *et al.* 2005, Zhou *et al.* 2004, Small *et al.* 2003, Hay *et al.* 2002).

Zhou *et al.* (2004) investigated the relationship between malaria and climate in the highlands of East Africa. This investigation found a positive association between malaria outbreaks and short-term fluctuation from the annual mean of temperature and precipitation (Zhou *et al.* 2004). While the study provided insight into the general increase of malaria due to climate instability, the length of the time series data was relatively short, varying from 10-20 years for each study area, allowing no understanding of the long-term effect climate variability has had on the disease.

Additionally, the microclimate of a region can be influenced by land cover change, such as the conversion of forest to agriculture (Patz and Olson 2006, Lindblade *et al.* 2000). The change in land cover can exacerbate the effect of greenhouse-gas-induced warming and severely impact local climatic conditions (Patz *et al.* 2005). Land use change, particularly from forest to non-forest, can increase malaria incidence by increasing the temperature of the region (Patz etl al 2006, Patz *et al.* 2005, Lindblade *et al.* 2000). According to Pascual *et al.* (2006), an increased temperature of just a half-degree Celsius can significantly increase the abundance of mosquitoes, sometimes up to 100%.

The connection between land cover change and increased temperatures is pertinent to Paraguay. Since the 1970's Paraguay has undergone rapid deforestation due to land disputes among peasants, construction of large farms, ranches, and urban areas as well as small scale agriculture (Huag 2009). Considering the relationship between deforestation and climate (Pascual *et al.* 2006, Patz and Olson 2006, Lindblade *et al.* 2000, Patz *et al.* 2005), it can be hypothesized that Paraguay's local temperature should have increased, thus, escalating the risk of malaria for the region.

Rainfall has often been associated with malaria due to the creation of standing pools of water, which are prime mosquito breeding grounds (Dahal 2008, Thomson *et al.* 2005, Small *et al.* 2003). However, the relationship is non-linear and as such, there are times when rainfall appears to result in less malaria than was predicted (Thomson *et al.* 2005, Small *et al.* 2003).

While precipitation tends to be associated with an increase in mosquito breeding grounds, it has not been directly related to actual malaria cases (Olson *et al.* 2009, Briet *et al.* 2008, Thomson *et al.* 2005, Small *et al.* 2003). The relationship between precipitation and malaria is extremely complex (Briet *et al.* 2008), varying from region to region (Olson *et al.* 2009, Briet *et al.* 2008, Thomson *et al.* 2005, Small *et al.* 2003). Within the Indian island of Sri Lanka, malaria has been shown to be more prominent in the dry season than the wet season (Briet *et al.* 2008). This conclusion is based strictly on the region's mosquito that carries the disease; a mosquito which breeds in water pockets in dry river beds (Briet *et al.* 2008).

In the Amazon Basin, Olson *et al.* (2009) confirmed that precipitation drives regional malaria risk (Olson *et al.* 2009). However, precipitation had both a positive and negative association with malaria as regions with a more rugged topography experienced more malaria cases with an increase of precipitation (Olson *et al.* 2009). Low-lying areas experienced fewer malaria cases with an increase in precipitation levels (Olson *et al.* 2009).

While mosquitoes need water in order to breed and complete their life cycle (Dahal 2008, Thomson *et al.* 2005, Small *et al.* 2003), this does not always result in a correlation between rainfall and malaria. From past research, this relationship can be affected by the type of vector carrying the disease, the topography of the region, local types of vegetation, and land use and land cover change (Olson *et al.* 2009, Briet *et al.* 2008, Thomson *et al.* 2005, Small *et al.* 2003, Singh *et al.* 2002).

<u>Deforestation and Malaria</u>

It has been shown that deforestation can play an important role in malaria occurrence (Guerra *et al.* 2006, Massarani and Shanahan 2006, Vittor *et al.* 2006, Barbieri *et al.* 2005, Norris 2004, Pattanayak *et al.* 2003). In the Peruvian Amazon, regions which had experienced deforestation had 278 times more biting mosquitoes than predominately forested areas (Vittor *et al.* 2006). However, in the Mekong region of Southeast Asia, mosquitoes tend to favor densely forested regions, leaving when land cover change occurs (Guerra *et al.* 2006).

In Brazil, the city of Belém had assumed the disease had been eradicated in 1968. Vittor *et al.* (2006), however, found that deforestation in the region led to an increase and spread of malaria. Others have found that the occurrence of malaria decreases under conditions where land use is stable (Guerra *et al.* 2006, Massarani and Shanahan 2006, Patz and Olson 2006, Barbieri *et al.* 2005, Norris 2004, Pattanayak *et al.* 2003, Vittor *et al.* 2003). Therefore, it is important to identify regions and time periods of recent land use change.

Malaria research conducted by Wayant *et al.* (2010) in Paraguay found that regions of high correlation between AVHRR derived NDVI and malaria were associated with regions which had been deforested. Unfortunately, land cover data were only available for the years of 1979, 1990, and 2000. In order to gain a better understanding of how malaria relates to deforestation both spatially and temporally, land cover maps distinguishing between forest and non-forest for every individual year of a time series are required.

Remote Sensing, Land Cover Analysis and Malaria

Earth-observing satellites (e.g., Landsat) have been collecting data for more than 35 years (Jensen 2007). These data are routinely used for land cover assessment, although several practical issues have limited their usefulness for land cover mapping over sub-continental or larger areas (Jensen 2007). The large volume of data (number of scenes and number of pixels) required to cover one continent for a single date and the associated costs and complexity of data acquisition and analysis have made such analyses prohibitively expensive. As stated before, malaria-prone regions tend to be in the tropics and subtropics, which are areas that experience cloud cover throughout most of the year. Even with bimonthly (Landsat) revisit times, the generation of a cloud-free high-quality set of images entails assembling scenes acquired over several years and many seasons.

This can make it extremely difficult to determine land cover change on a yearly or monthly basis.

Because of such difficulties in using earth-observing satellites for large-area land cover assessments, recent attention has shifted to the potential application of meteorological satellite data for such ventures (Jensen 2007). Most efforts have focused on the Advanced Very High Resolution Radiometer (AVHRR), a sensor carried on the National Oceanic and Atmospheric Administration's (NOAA) series of polar-orbiting meteorological satellites. While the MODIS sensor is able to monitor large area land cover change, the length of its time series only extends back to 1999, whereas AVHRR's begins in 1981 (Jensen 2007). The AVHRR provides low-cost daily global coverage at approximately 1-km spatial resolution (Advanced Very High Resolution Radiometer-AVHRR 2009, DeFries *et al.* 2008). The high frequency of observation affords many opportunities for acquisition of cloud-free data over relatively short periods of time (e.g., 10 days) and enables one to compile information on relatively short-term changes in land-surface characteristics (Jensen 2007). Moreover, the 1-km spatial resolution produces a manageable volume of data for regional and even global applications. Although the AVHRR was designed for atmospheric rather than earth observation, the sensor has been shown useful for synoptic land cover assessment.

Of the five bands aboard the AVHRR sensor, two are significant for the short term assessment of land cover (Baldi *et al.* 2008, DeFries *et al.* 2008, Jensen 2007). Band 1 (the red portion of the spectrum) and Band 2 (the near-infrared portion of the spectrum-NIR) are often transformed to a vegetation index, most commonly the

Normalized Difference Vegetation Index (NDVI) (Rouse 1976). NDVI is a ratio of the NIR and red portions of the spectrum, in a simple equation:

$$(NIR-Red)/(NIR+Red) \qquad (2.1)$$

Using AVHRR NDVI, seasonal and inner-annual variations in vegetation growth and activity can be observed (Jensen 2007). When used in a long-term study over twenty years, NDVI can be used to help identify functional changes in ecosystems (Baldi *et al.* 2008, Hansen and DeFries 2004, Piao *et al.* 2003, Lyon *et al.* 1998). Additionally, NDVI has been shown to be positively correlated with many infectious diseases, such as malaria and rift valley fever (Wayant *et al.* 2010, Tourre *et al.* 2008, Hay el al 1998, Linthicum *et al.* 1987).

Wayant *et al.* (2010) proposed that there might be an association between land cover and malaria. They hypothesized that greenness information expressed in NDVI could be used to identify phenological cycles in vegetation that might reflect precipitation, an environmental parameter assumed to be associated with malaria (Chamaille-Jammes and Fitz 2009, Fuller and Prince 1996, Schultz and Halpert 1993). Using Paraguay as a study area, they used monthly NDVI and monthly malaria cases for 1981-2003. The NDVI data were obtained from the Global Inventory Modeling and Mapping Studies (GIMMS) data set, a calibrated AVHRR-derived dataset resampled to 8-km (NASA 2009). Non-spatial monthly malaria cases for two departments, Alto Parana and Canindeyú (Figure 2.1), were obtained from the Pan American Health Organization (PAHO).

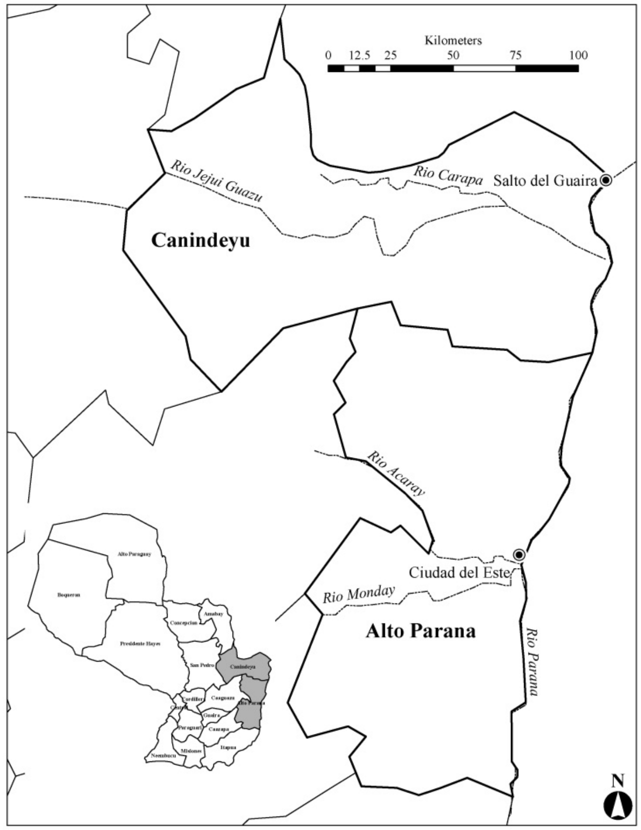
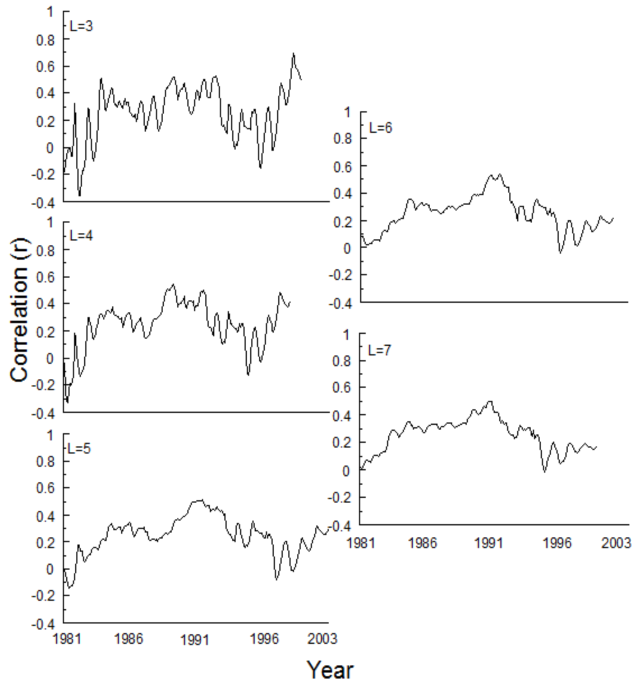


Figure 2.1: Map depicting departments of interest in Paraguayan malaria research (Wayant *et al.* 2010).

The data were placed into moving temporal windows, and malaria rates were tested for correlation on a pixel by pixel basis to NDVI data to discern spatial and temporal patterns of malaria across each of the departments, as well as the time periods when malaria was most closely correlated with NDVI (Figure 2.2). This procedure created hundreds of images depicting the spatial relationship between NDVI and malaria. Principal component analysis (PCA) was used to reduce the number of graphs and images into one map. (See Figure 2.3)

A)



B)

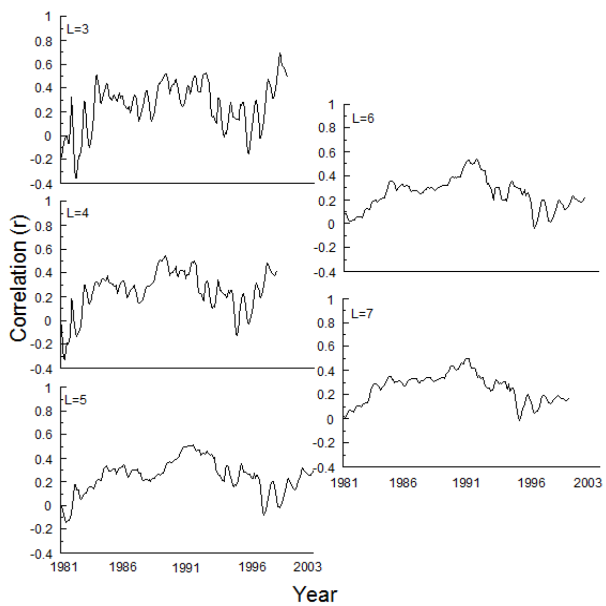


Figure 2.2: Average correlation over time for moving windows of 3-7 years for a) Alto Parana and b) Canindeyú. From these graphs, it was determined that a 4 year moving window best described the original malaria case numbers and provided the overall most accurate correlation between malaria and NDVI.

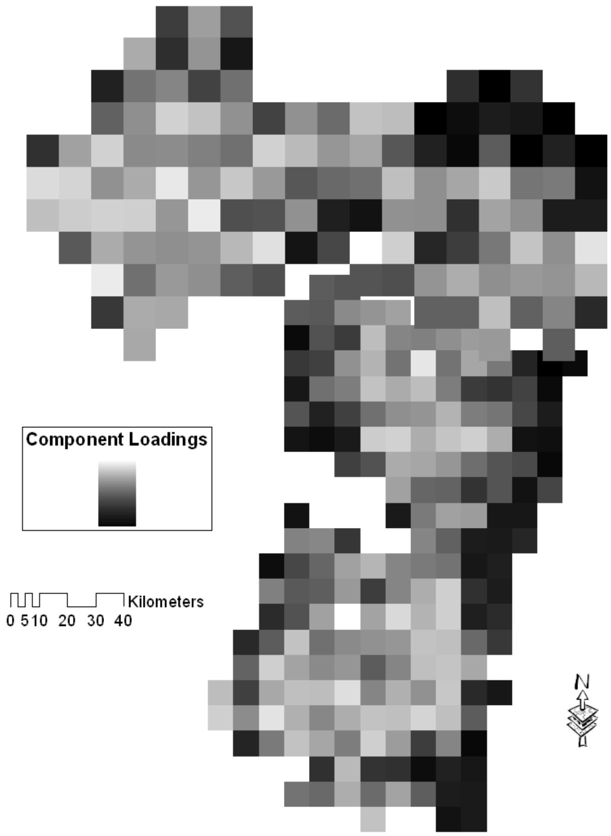


Figure 2.3: First component loading of PCA of the correlation between NDVI and malaria for both Alto Parana and Canindeyú. Regions of lighter colors depict areas of higher correlation between NDVI and malaria.

Although the research was able to portray general patterns of the relationship between malaria and NDVI, it was not possible to determine why there are high malaria correlations in certain regions or why certain time periods displayed a higher correlation. The study also did not investigate the role of additional environmental variables, such as precipitation or temperature, in the relationship of NDVI and malaria as well as in the behavior of the disease itself. Additional research is required to improve understanding of the spatial and temporal relationships between malaria and NDVI and possible interactions between malaria and precipitation, temperature, and deforestation.

Time Series Analysis

The malaria datasets used for this thesis were comprised of raw numbers of incidents for each month of each year in each of the two departments. Graphing of the datasets on the Cartesian plane does not provide any information about the long and short-term temporal behavior of the malaria case data. Many epidemiological time series, such as malaria, do not follow precise patterns throughout time. These variations are often caused by biological, physical, or environmental phenomena (Cazelles *et al.* 2007, Shumway and Stoffer 2006) and cannot be observed using descriptive statistics. Time series statistics, particularly within the frequency domain, allow for the periodic comparison of malaria to its environmental parameters (Gonzalez *et al.* 2008, Cazelles *et al.* 2007, Shumway and Stoffer 2006).

Fourier analysis, a form of spectral analysis, has often been used to investigate the complex inter-relationships between precipitation, climate and vegetation (Xu *et al.* 2004, Couteron and Lejeune 2001, Pelletier 1997, Thompson 1995, Selvam *et al.* 1992). For example, Periodic relationships were discovered, such as a three month correlation between precipitation and certain desert vegetation, which was not apparent in the raw data (Couteron and Lejeune 2001). A similar approach is important when studying epidemiological data. Studies show the spatio-temporal behavior of the disease is changing, possibly due to climate variations ((Mantilla *et al.* 2009, Jones *et al.* 2007, Anyamba *et al.* 2006, Campbell-Lendrum and Woodruff 2006, Pascual *et al.* 2006, Thomson *et al.* 2006, Zhou *et al.* 2004, Hay *et al.* 2002, Gagnon *et al.* 2002, Poveda *et al.* 2001, Craig *et al.* 1999). Understanding the temporal behavior of malaria as well as its periodic relationship to land cover change, temperature, and precipitation, will increase the spatial understanding and risk of the disease.

Summary

A review of the literature shows that climate and increasingly climate change play important roles in explaining the incidence of malaria. In many locations, increasing temperatures have been associated with an increase in malaria cases. Precipitation and malaria are also likely linked, but the linkage varies by locale and requires investigation on a regional basis.

Previous research has also shown that deforestation can increase malaria case rates as the act of deforestation creates near-perfect breeding grounds for many mosquitoes. Like precipitation, the exact relationship between deforestation and malaria is difficult to decipher and requires investigation on a location by location basis.

Lastly, time series analyses will improve understanding of the long term and periodic behavior of malaria as well as its selected environmental parameters of precipitation, temperature, and land cover change. A greater temporal understanding will be gained of these environmental variables and if they influence malaria case rates.

Chapter 3
Methods

Introduction

The overarching goal of this research project was to assess possible the spatial and temporal relationships between malaria and key environmental parameters of, temperature, precipitation, and land cover. However, since the malaria data were non-spatial and the environmental parameters were spatial. Therefore, it is difficult to determine if any kind of temporal, and especially spatial, relationships exist. Because of this, a variety of statistical, mathematical, and data manipulation techniques were utilized.

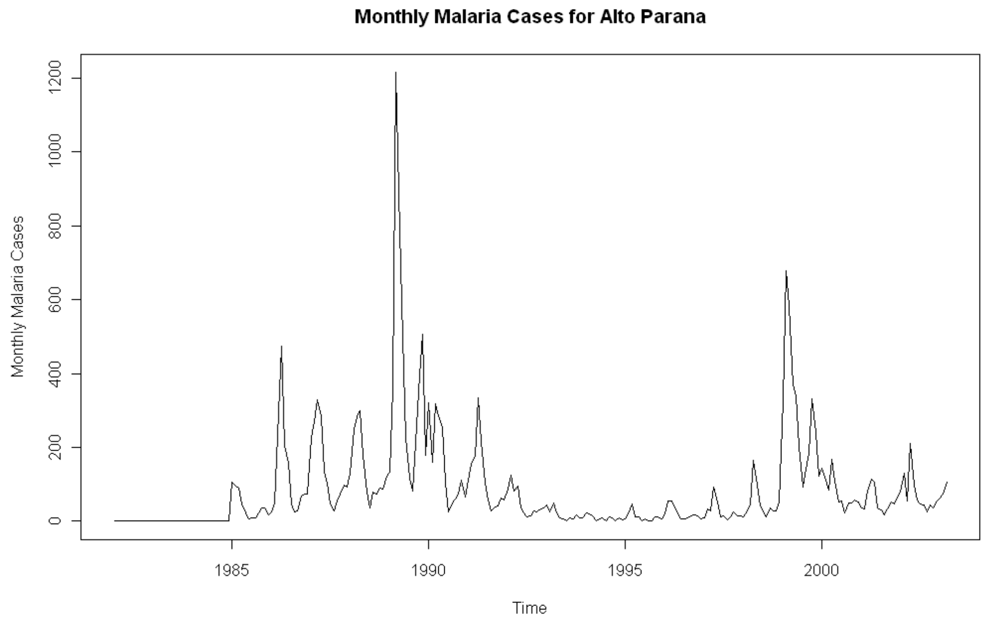
Study Area

The study area for this project included the Paraguayan departments of Alto Parana and Canindeyú (Figure 2.1). This region was selected in part because it is the same area studied in previous research by Wayant *et al.* (2010), thus allowing the results to be compared. Monthly malaria data were available for both departments for the years 1981-2003.

The departments of Alto Parana and Canindeyú are in the eastern portion of Paraguay. They belong to the region Paraneña, also known as the Orient (Hanratty and Meditz 1998). This portion of the country is relatively flat, with rolling hills in the eastern region of Canindeyú.

The graphs shown below (Figure 3.1) portray the number of raw malaria cases for each department throughout the study period. As can be observed, the number of cases for each department varies temporally and it is difficult to determine any kind of temporal pattern. For each department there appears to be two time periods, 1988 and 1999 for

Alto Parana and 1986 and 2000 for Canindeyú, where the most number of cases have been recorded. This could be attributed to climatic variations, recording errors, or even disease prevention measures made by the government.



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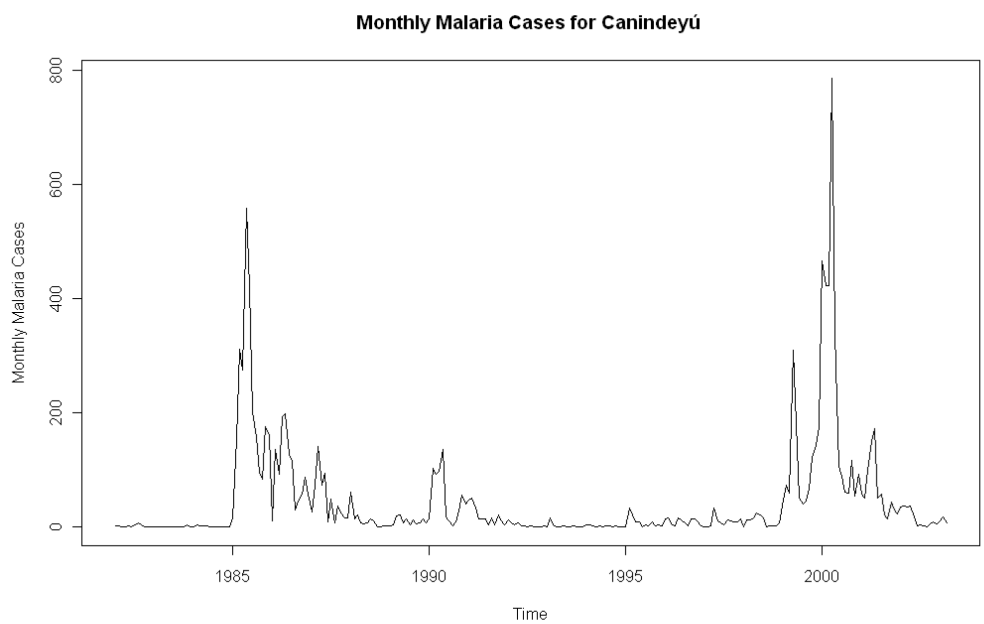


b.)

Figure 3.1: Monthly raw malaria cases for (a) Alto Parana and (b) Canindeyú.

From the graphs of malaria above, it can be observed that malaria cases were not common at the beginning of the study period. However, as time progressed there were periods of almost 1200 cases in one month compared to 0 in others.

The departments of Alto Parana and Canindeyú have undergone a relatively large population increase since the early 1980s. At the beginning of the study time period Alto Parana had a population of 188,540 and Canindeyú a population of 62,671. By 2003, the respective populations had increased to 573,575 and 144,907. This population boom is due in part to the immigrant east of Paraguayans as well as immigrants coming into eastern Paraguay from Brazil (Hanratty and Meditz 1988). Most of the immigrated population came to eastern Paraguay to convert forest into agricultural lands to develop their own farms (Huang *et al.* 2009).

Originally, the Atlantic forest, which encompasses Alto Parana and Canindeyú, has gone from a land area of 1.2 million km^2 to about 100,000 km^2 (Huang *et al.* 2009). Once home to many endemic species, the region formerly covered by forest is now predominantly farms (Biodiversity Hotspots 2011).

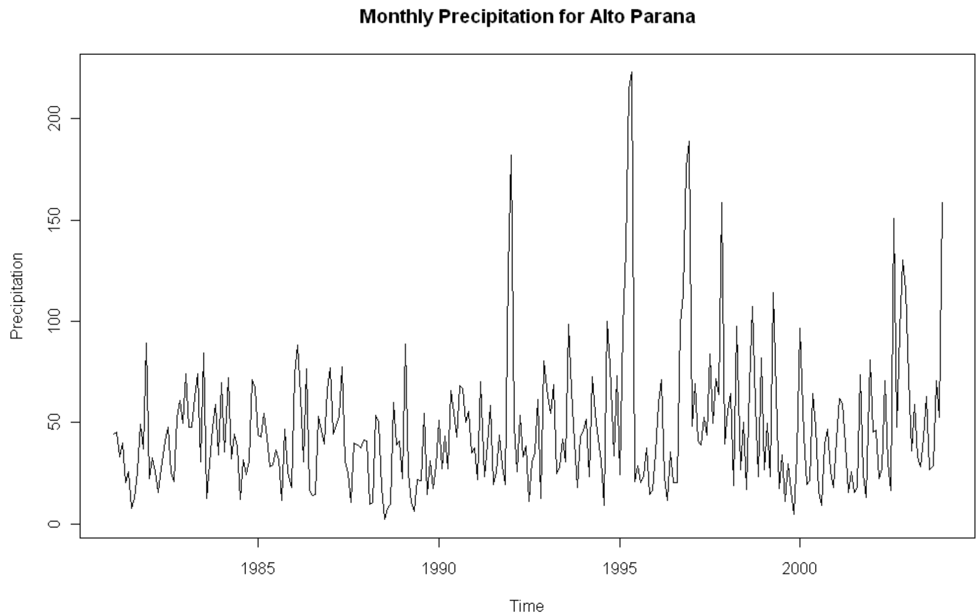
Overall, Alto Parana and Canindeyú exhibit similar annual average precipitation and temperature patterns (Figure 3.2). However, the graphs of average precipitation values for each department show that regionally more rain falls on Alto Parana than Canindeyú (Figure 3.3). Temperature values for both departments are similar throughout the study time period, although southern Alto Parana appears to be slightly cooler than Canindeyú (Figures 3.2 and 3.4). Note that, peaks of temperature variations seem to coincide with peaks in malaria case numbers.


BOLIVIA
BRAZIL
PARAGUAY
ARGENTINA
BRAZIL
PARAGUAY
PRECIPITATION

a.)

b.)

Figure 3.2: Maps of average annual (a) precipitation and (b) temperature for Paraguay (Best Country Reports 2008).



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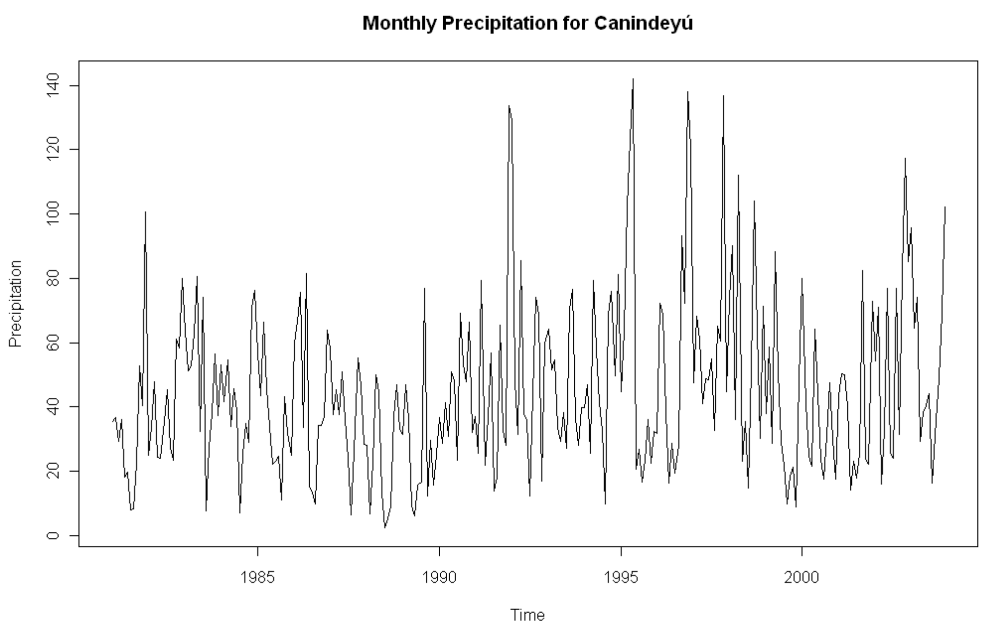
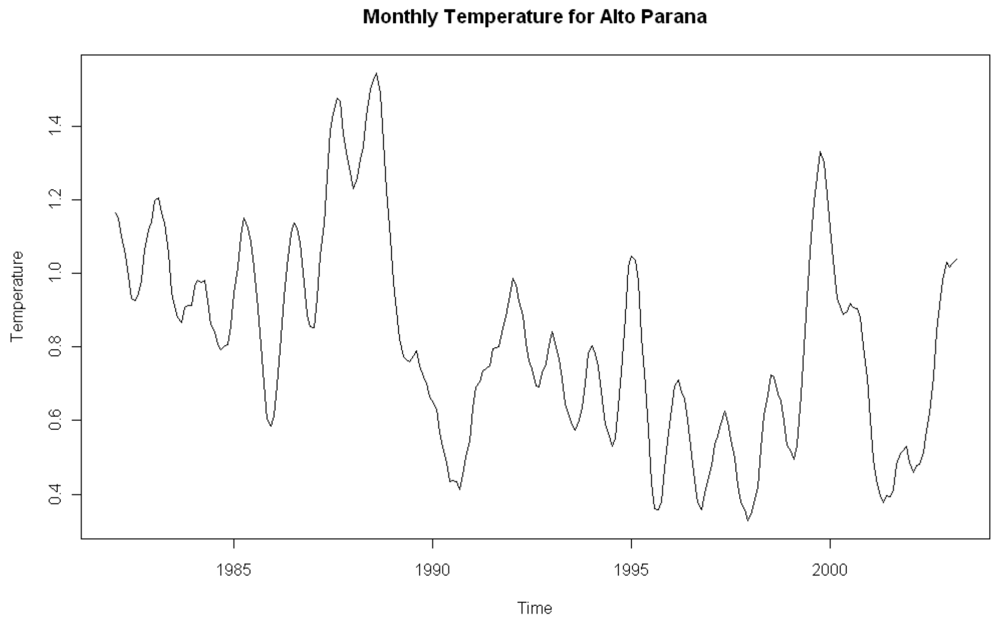


b.)

Figure 3.3: Total monthly precipitation values for (a) Alto Parana and (b) Canindeyú, measured in millimeters.



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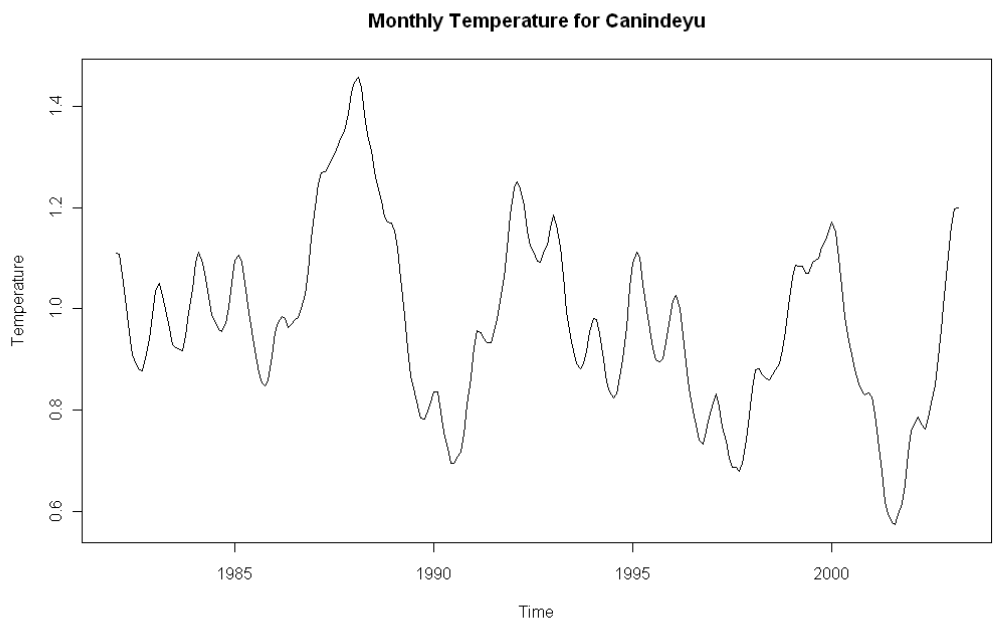


b.)

Figure 3.4: Average monthly air temperature in degrees Celsius for (a) Alto Parana and (b) Canindeyú.

Data

Climatic data were obtained from the Willmott, Matsuura and Collaborators Global Climate Resource at the University of Delaware (University of Delaware:

Willmott, Matsuura and Collaborators Global Climate Resource 2010). The temperature data were the monthly mean air temperature in degrees Celsius. The precipitation data were the monthly total precipitation values measured in millimeters. Precipitation and temperature values were measured at the Global Historical Climatology Network (GHCN2) gauge stations. However, throughout the time period of this study, gauge stations were not always active and thus sometimes did not provide precipitation or temperature measurements. When this occurred, other station records were merged to create a composite monthly station record series. When there was only one station observation for a month, it was taken as the precipitation or temperature value for that month. To create a continuous spatial dataset, climatologically aided interpolation (CAI) was utilized. In order to assure spatial accuracy, station-by-station cross validation was employed (Willmott and Matsuura, 1995). One station was removed at a time, and the precipitation or temperature value for that location was then interpolated to the removed station location from the surrounding nearby stations. The difference between the real station and the interpolated value was then calculated to determine an absolute error for the location. The spatial resolution of both precipitation and temperature datasets was 0.5 degrees.

Land cover change was estimated using GIMMS AVHRR-derived NDVI data as a surrogate (see Chapter 2 and Wayant *et al.* (2010)). The annual NDVI values were compared to a 1975 NASA GeoCover Landsat derived land cover map. This map distinguished between forest, non-forest, and water regions for the study area. Periodic NDVI values for each type of land cover were determined and used to create general maps of annual deforestation for the study period. The deforestation map for the year

2001 was tested for accuracy against a 2001 Moderate Resolution Imaging Spectroradiometer (MODIS)-derived vegetation map produced by the Global Land Cover Facility (GLCF) (Hansen *et al.* 2001).

Lastly, the monthly malaria cases for Alto Parana and Canindeyú were supplied by the Pan American Health Organization (PAHO) for the years 1981-2003 (Figure 3.1). The graphs show a wide variation of malaria cases throughout time and also portray time periods of extreme malaria activity as well as dormancy.

Procedures

Pre-Processing and Data Preparation

First, the climatic data were re-sampled from an initial resolution of 0.5 degrees to the same 8-km resolution as the AVHRR-derived NDVI. Then the climatic datasets were smoothed on a pixel by pixel basis using Fourier Transform.

Next, for the time series analysis, an average value for each month was determined for each of the spatial dataset (precipitation, temperature, and NDVI). Then the time series were analyzed to determine if they had a constant mean and standard deviation (stationary). It was that found none of the time series were stationary, meaning the raw data were not acceptable for time series analysis. All of the series were seasonally differenced to provide a constant mean and standard deviation throughout time.

Testing for Correlation and Principal Component Analysis

As mentioned before, the malaria dataset contained one case number per month for each department for the years of 1981-2003, making it impossible to test for correlation between the disease and the finer resolution on precipitation and temperature.

Additionally, the length of the time series, only 260 points in time, made it complicated to observe the effect climatic variations might have had on the disease.

To deal with this issue malaria was used to test for correlation within a four-year moving window. A four-year moving window was selected by Wayant *et al.* (2010) to analyze the spatial relationship between malaria and NDVI because it modeled the original malaria signal and produced the most accurate results of correlation between the two variables. Using this technique resulted in a set of "correlation" images of about 200 windows where each pixel had an r^2 value.

In order to efficiently analyze the hundreds of images, principal component analysis (PCA) was utilized. PCA is a non-parametric method that is often used extract information from multidimensional datasets (Slens 2005, Smith 2002, Mitra and Pesaran 1999). The results are graphs and images which are easier to analyze than the original hundreds of datasets (Mitra and Pesaran 1999). The number of components calculated equals the number of original dimensions. Typically, the first component encompasses most of the variance the dataset, describing the general behavior of the dataset (Mitra and Pesaran 1999). The first component can be observed in both a graphical and image context. The image can then be transformed into a map of the study area, enabling the visualization of possible spatial correlation. The map and graph of the first component of correlation tests between malaria and precipitation and temperature were used to classify the spatial and temporal behavior of the disease.

<u>Deforestation</u>

Ideally, land cover maps would be produced for every year of the study period based on satellite and aerial imagery and field samples. Unfortunately, data, funding, and time did not allow for such classification methods. However, GIMMS NDVI data are often used as a surrogate measure of biomass and vegetation activity (Brown *et al.* 2006, Lyon *et al.* 1998). Andres *et al.* (1994) demonstrated that a classification between forest and agricultural land can be completed using only the first and second power density frequency of a Global Vegetation Index (GVI). The power density describes how the strength of a time series is distributed through the frequency domain and is calculated by squaring the absolute value of the Fourier Transform coefficient (Mathworks 2010, Shumway and Stoffer 2006, Andres *et al.* 1994).

$$S(e^{j\omega}) = \frac{1}{2\pi N} \left| \sum_{n=1}^{N} x_n e^{-j\omega n} \right|^2 \tag{3.1}$$

Where w is in the units of radians per sample, n=[1,N], N=length of series, and $j=\sqrt{-1}$ (Mathworks 2010). The basis behind this approach is that the periodicity of vegetation aligns itself with the composition of sine and cosine waves of Fourier analysis (Shumway and Stoffer 2006, Mitra and Pesaran 1999, Andres *et al.* 1994).

This methodology was used to create annual forest/non-forest maps. The power density at the semi-annual frequency was calculated for every pixel vector of every year of the time series. Next, using a 1975 Landsat derived land cover map (Tucker *et al.* 2004), the mean and standard deviation of forested power density values were calculated for the 1982, first full year of the time series.

To determine if land cover change had occurred, a loop was run through every pixel. Based on where the pixel value fell, the following general land cover classification was made:

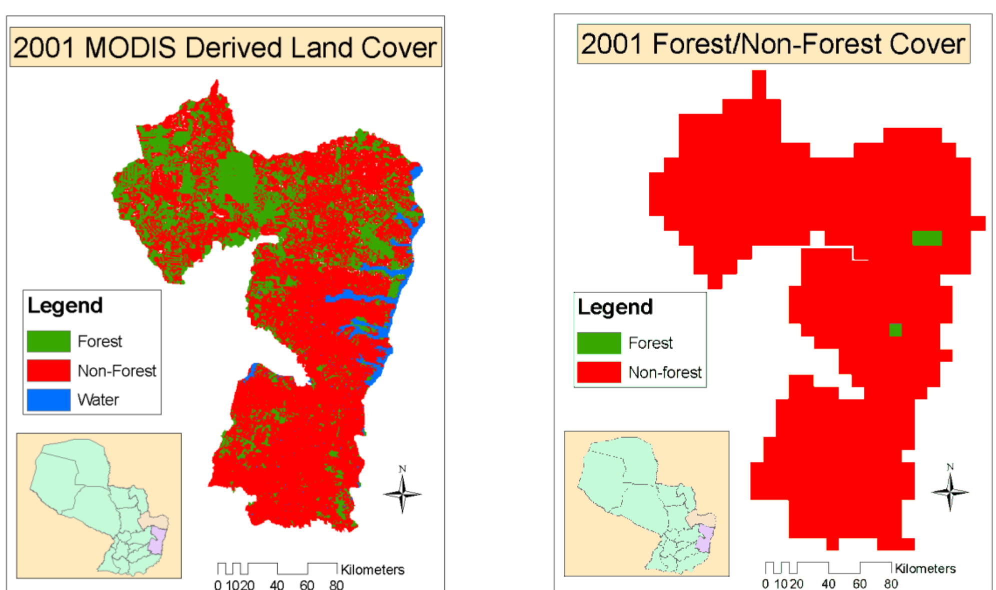
-2σ < pixel value: Non-Forest

-2σ < pixel value < 2σ: Forest

2σ > pixel value: Non-Forest

The 8-km resolution of the results was the same as the source NDVI, 8-km. From this procedure, a map of forested and non-forested regions was created for the study area for each year of the study period. (See Figure 4.8)

Next, the results were compared to a 2001 MODIS–derived vegetation map produced by the Global Land Cover Facility (GLCF) (Hansen *et al.* 2001). The spatial resolution of the MODIS product was 1-km so it had to be degraded to 8-km to match the source NDVI resolution. A pixel-by-pixel comparison showed that the GIMMS-derived classification technique produced results similar to the GLCF map for 85% of the pixels for Alto Parana and 78% of the pixels for Canindeyú.



a.) b.)

Figure 3.5: Comparison of (a)1-km resolution MODIS-derived and (b) 8-km resolution AVHRR-NDVI derived land cover maps.

Time Series Analysis

Fourier analysis techniques were used to determine the possible relationship between Paraguayan malaria and temperature, precipitation, and vegetation change (in the form of NDVI). After the time series had been prepared, analysis proceeded by looking at the behavior of all the variables over time. Non-parametric techniques were used to calculate the spectra for the time series, allowing for the investigation of dominant frequencies.

A bandwidth of 0.02682 was chosen as the kernel to complete the spectral analysis. A kernel is typically used to filter the noise out of a time series (Shumway and Stoffer 2006). This bandwidth balanced smoothing the time series and yet still maintained the smaller, faster frequencies.

Fourier analysis was used to create periodograms, a graph of the frequencies of a series, for all of the individual variables being studied: malaria, temperature, precipitation, and vegetation change. These graphs depict the strength of the frequencies of a series as a measure of their spectra value. It is important to note that frequency is the number of times something occurs over a certain period of time. For example, periodograms of precipitation depict a significant frequency at three months. This means that a three month period exists within the precipitation time series. Significant frequencies are determined by the confidence interval (Equation 3.1):

$$[2\ I(w_{j}:_{n})/\chi^{2}_{2}\ (1-\alpha/2)] \leq f(w) \leq [2\ I(w_{j}:_{n})/\chi^{2}_{2}\ (\alpha/2)] \qquad (3.2)$$

Where $I(w_{j}:_{n})$ is the periodogram value, χ^2 is the Chi-Square statistic, and α the statistically significance level (95%) (Shumway and Stoffer 2006).

Next, the cross-spectra were computed between the environmental parameters and malaria for both Alto Parana and Canindeyú. Cross-spectra, or coherence, can be thought of as a correlation indexed by frequency and can be interpreted like r^2 values (Shumway and Stoffer 2006). The results of a cross-spectra analysis are squared coherence values which measure the strength of a relationship between two time series (Shumway and Stoffer 2006). The squared coherence also represents the percent of variance of the time series at a particular frequency (Shumway and Stoffer 2006). The significance of the cross-spectrum values are determined by the confidence interval (Equation 3.2):

$$C_\alpha = \frac{F_{2,2l-2(\alpha)}}{(L-1) + F_{2,2L-2(\alpha)}} \tag{3.3}$$

Where L denotes the bandwidth, α the significance level (95%), and F represents the F-statistic.

Last, a stationary regression analysis was completed. The regression analysis extended the coherence test to look at adjacent lagged values between malaria and temperature, precipitation, and NDVI as one series. This analysis attempted to estimate an output series – malaria cases – based upon several one month lagged input series of temperature, precipitation, and NDVI. It determined if a lag existed between any of the variables, the length of the lag, and created an equation that calculates the output series (malaria) based on past values of the input series.

Chapter 4
Results and Discussion

Introduction

The goal of this research was to investigate possible spatio-temporal relationships between malaria and selected environmental parameters including temperature, precipitation, and land cover change (deforestation). This in turn may help to identify cycles of malaria outbreaks, possible environmental triggers of periodic malaria cycles, and regions environmentally prone to support malaria vectors.

Testing for Correlation and Principal Component Analysis

As described in Chapter 3, correlation tests were run for each selected environmental indicator of malaria: vegetation change, temperature, and precipitation. The tests were conducted on a pixel-by-pixel basis in a 4 year moving window time series. Principal component analysis (PCA) was employed to reduce dimensionality of the data. This section summarizes results of the PCA tests. On the graphs of the component loadings, the y-axis can be interpreted as representing r^2 values. To assist in the interpretation of results, review the map of the research study area (Figure 2.1).

Precipitation and Malaria

Regions of high correlation between malaria and precipitation appear to be exactly opposite of those discovered in previous research that has examined relationships between malaria and NDVI (Wayant *et al.* 2010). Specifically, the western portion of Canindeyú and the borders of Alto Parana were observed to have high component loadings of correlation while the other regions remain relatively low (Figure 4.1). The results suggest that there may be a negative relationship between precipitation and malaria.

First component loadings differ for each department (Figure 4.2). The first principal component captured the most variation of the relationship between rainfall and malaria, implying it represents the overall correlation between the two variables. Temporally, the relationship between malaria and precipitation is generally stable for Canindeyú until the end of the time series. However, the graph of the first principal component for Alto Parana oscillates between low or even negative component loadings to extremely high component loadings. Often the opposite of the original malaria signal, the graphs of component loadings are suggestive of a negative relationship between precipitation and malaria. The reason the first components differ so drastically could possibly be linked to the varying stability of land cover. Alto Parana, for example, has undergone more land cover change in recent decades than its northern neighbor, a topic that will be discussed further in the deforestation section of the thesis.

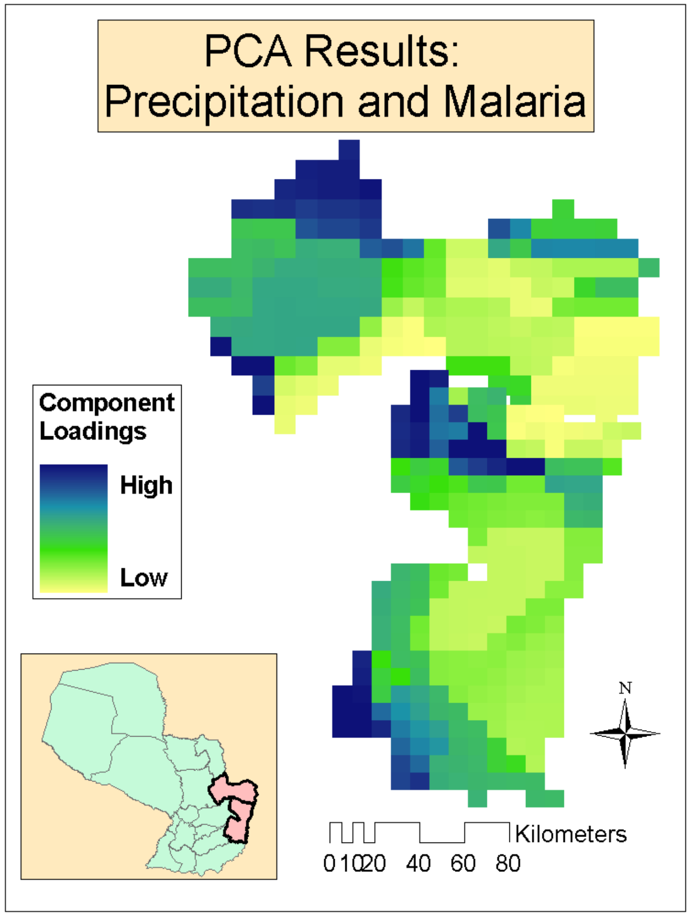
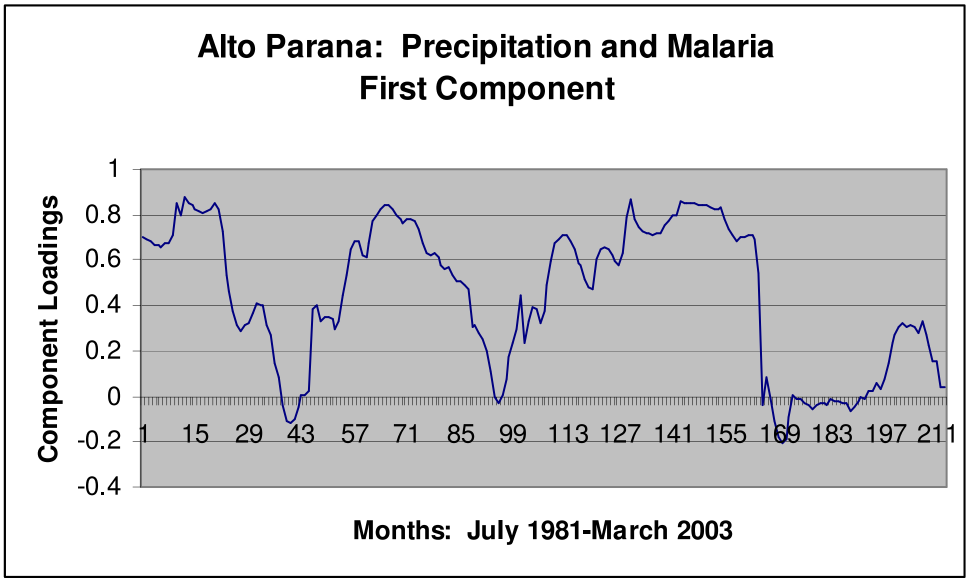


Figure 4.1: Map portraying the first principal component of the correlation test between precipitation and malaria. High component loadings designate clusters of regions with significantly high correlation values.



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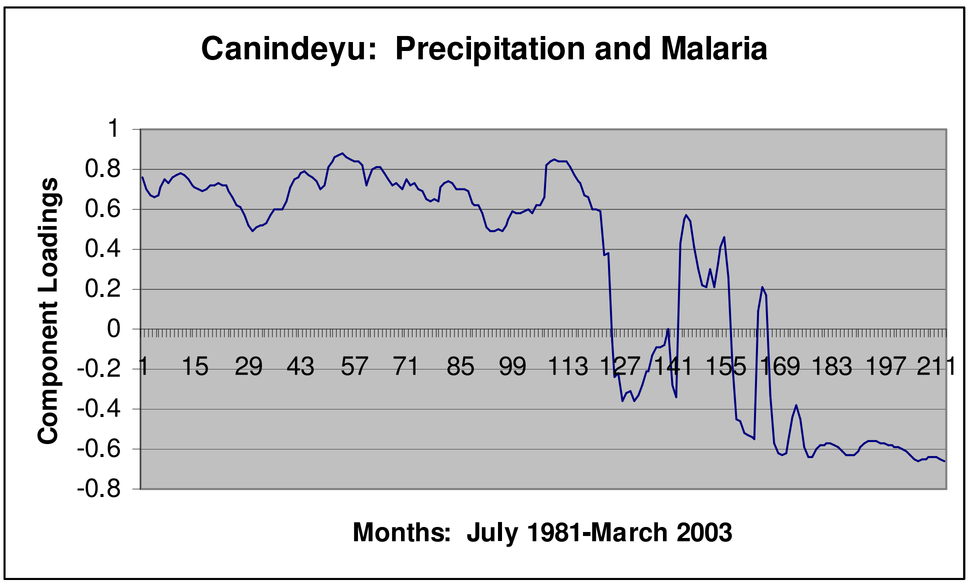


b.)

Figure 4.2: Graphs portraying the temporal relationship between precipitation and malaria for (a) Alto Parana and (b) Canindeyú. The y-axis component loadings can be interpreted as r^2 values.

Temperature and Malaria

The first principal component of the correlation between malaria and temperature captured the most variation of the analysis, implying that it represents the behavior of the correlation of the two series. The PCA results of the correlation were similar to the results testing the relationship between vegetation change and malaria found in Wayant *et al.* (2010). Regions of high correlation for the interior of Alto Parana and the northwest portion of Canindeyú were observed in both studies (Figure 4.3).

However, there are also several differences between the results of the two studies. Within Canindeyú, correlation clusters occur in the extreme northern part of the department. Similarly, there appear to be clusters of significant correlation values in the northern portion of Alto Parana. This is probably due to slight variations in temperature patterns, an artifact of land cover and most likely population distribution and migration (Hanratty and Meditz 1988).

Temporally, the first component for both departments exhibit high values of component loadings during periods of a high number of malaria cases (Figure 4.4). Additionally, the first component graphs display time periods of low component loadings during time periods of relatively low malaria. Spatially, the correlation tests between malaria and temperature are visually similar to the results of the study conducted by Wayan *et al.* (2010) which found a positive relationship between malaria and vegetation change. This suggests that both high temperatures and NDVI values are correlated with higher malaria case rates.

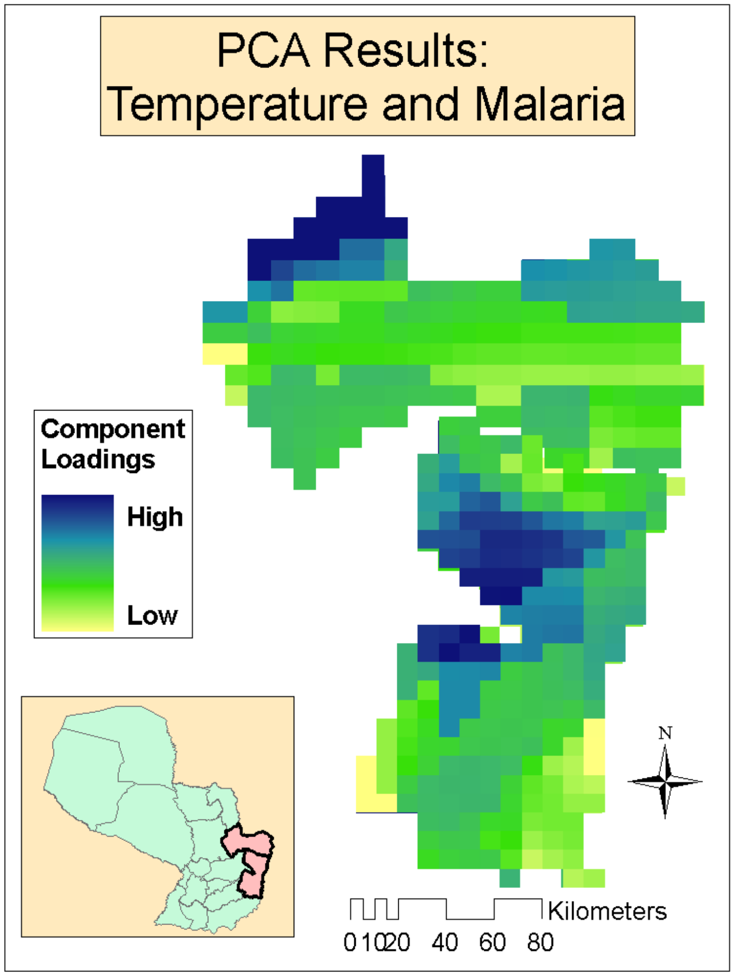
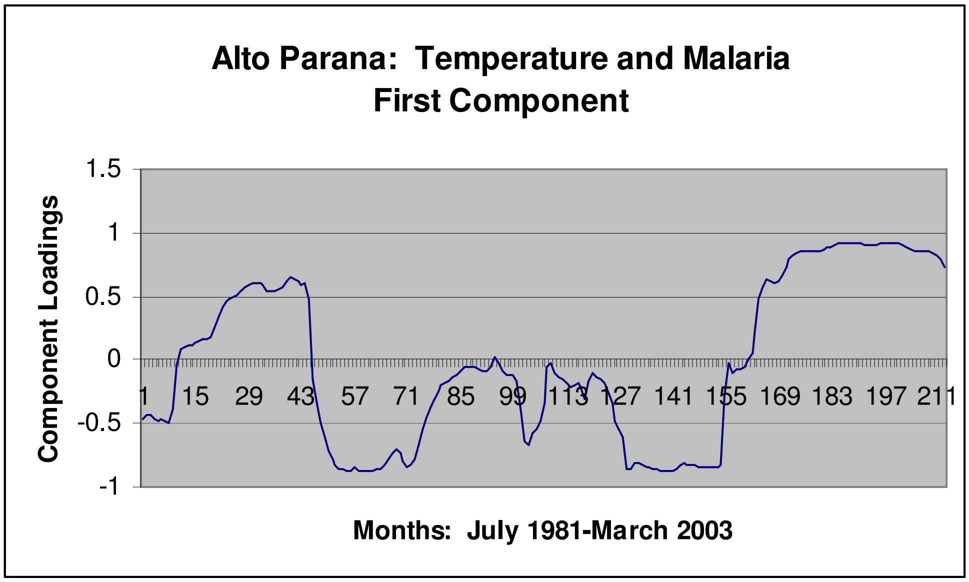


Figure 4.3: Map portraying the first principal component of the correlation test between temperature and malaria. High component loadings designate clusters of regions with significantly high correlation values.



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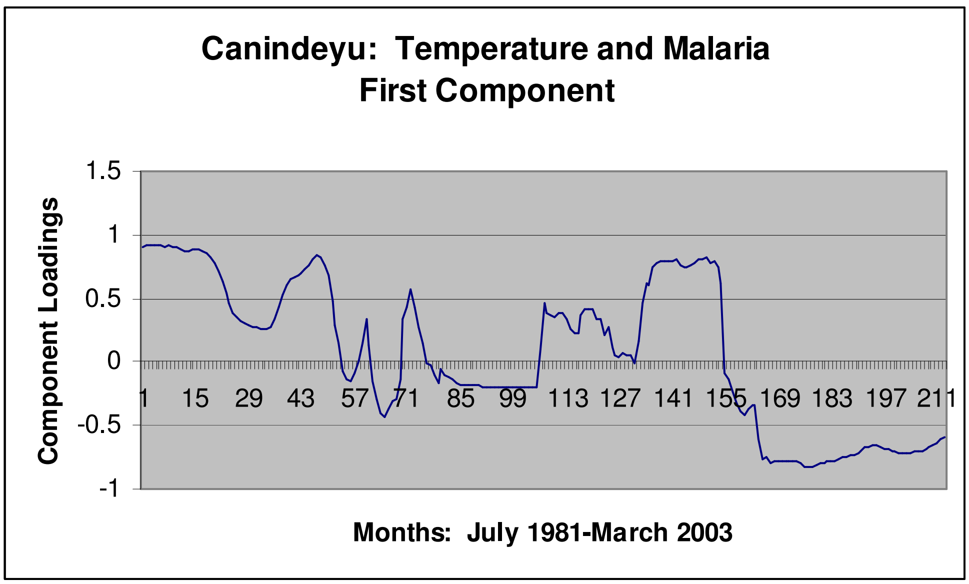


b.)

Figure 4.4: Graphs portraying the temporal relationship between temperature and malaria. The y-axis component loadings can be interpreted as r^2 values.

Research Question Explored

One of the principal goals of this thesis was to answer the following research question (Chapter 1):

- Will regions of high correlation between malaria and temperature and malaria and precipitation be similar to areas of correlation between malaria and NDVI?

The PCA of the correlation analysis produced maps and graphs detailing the temporal and spatial relationship between malaria and precipitation and temperature. Visually, regions of observed correlation between malaria and temperature were similar to the spatial correlation found with NDVI, although there are some slight differences in the northwest portion of Canindeyú. These differences may be attributed to the coarse resolution of the climatic data, which eliminates all temperature variation within an 8-km area, as well as any land cover change (Huang *et al.* 2009, Huang *et al.* 2007) toward the end of the time series. The observed positive relationship between malaria and temperature is very similar to results from other studies performed throughout the world (Pascual *et al.* 2006, Thomson *et al.* 2006, Thomson *et al.* 2005, Zhou *et al.* 2004, Small *et al.* 2003, Hay *et al.* 2002, Gagnon *et al.* 2002). That showed that higher temperature values correspond to shorter mosquito development time resulting in higher malaria case rates.

Results from the precipitation analysis showed a negative correlation between rainfall and malaria. Negative relationships between malaria and precipitation have been documented in Sri Lanka, the Amazon Basin, and Romania (Olson *et al.* 2009, Briet *et al.* 2008). This may be attributable to the changing landscape of the region from forest to agriculture (Chaves *et al.* 2008, Guerra *et al.* 2006, Massarani and Shanahan 2006), as well as the topography (Olson *et al.* 2009). The relatively flat ground combined with deforestation, created prefect breeding grounds for mosquitoes. However, rainfall would wash the breeding ground away. (Olson *et al.* 2009).

Overall, the hypothesis indicated true for temperature and false for precipitation. Correlations values between malaria and temperature corresponded to similar regions of high correlation between malaria and NDVI. While the precipitation results differed from the NDVI correlations, the spatio-temporal patterns of correlation between rainfall and malaria as well as temperature can be used to help explain the spatial relationship between NDVI and malaria.

Lagged Regression Analysis

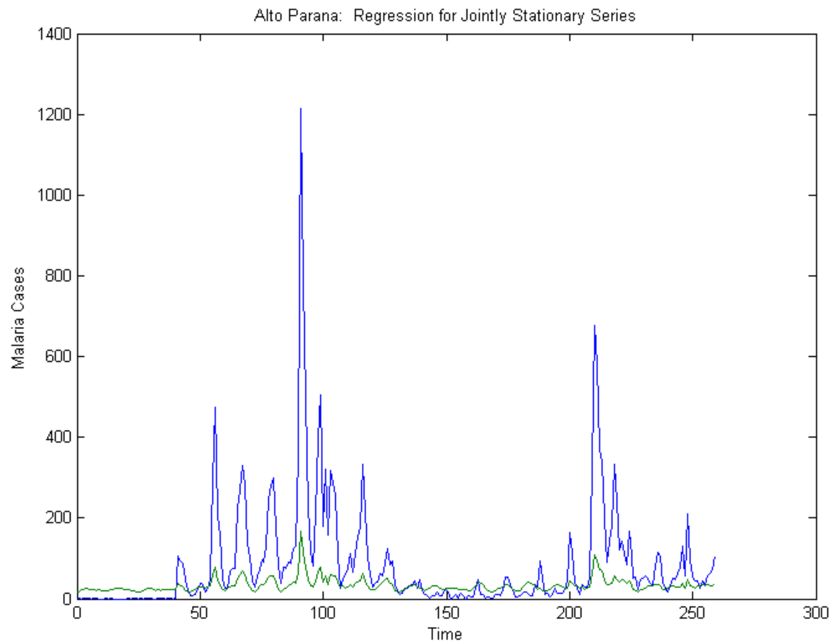
The lagged regression analysis combined all of the quantifiable variables (malaria, temperature, vegetation change, and precipitation) and tested adjacent lagged values of the input series to the output time series of malaria. Test results show there is a one month lag between malaria and any of the environmental parameters. Using this information, a possible model for malaria was developed for each department. The malaria equation models are as follows:

Alto Parana: Predicted Malaria Cases = 8.2123*NDVI + 0.3470*Precipitation + 1.666*Temperature + 0.1215*Malaria

Canindeyú: Predicted Malaria Cases = 10.5029*NDVI +0.5344*Precipitation + 2.4138*Temperature + 0.0726*Malaria

As can be observed in Figure 4.5, these equations are not perfect representations of the malaria time series. In fact, there is an 81% relative error for both departments. However, while the extreme amplitudes of the peaks are not captured, the regression model equations do an excellent job of capturing the oscillations between high and low malaria cases.

Using this information, a map of probable regions for malaria cases was created (Figure 4.6). Clusters of high component loadings are located at the northern border between the two departments, along the western border of Alto Parana, and in the western portion of Canindeyú. This could be due to the deforestation occurring in these portions of the departments. Additionally, these are areas that experienced positive correlation between temperature and malaria and negative correlation between malaria and rainfall.



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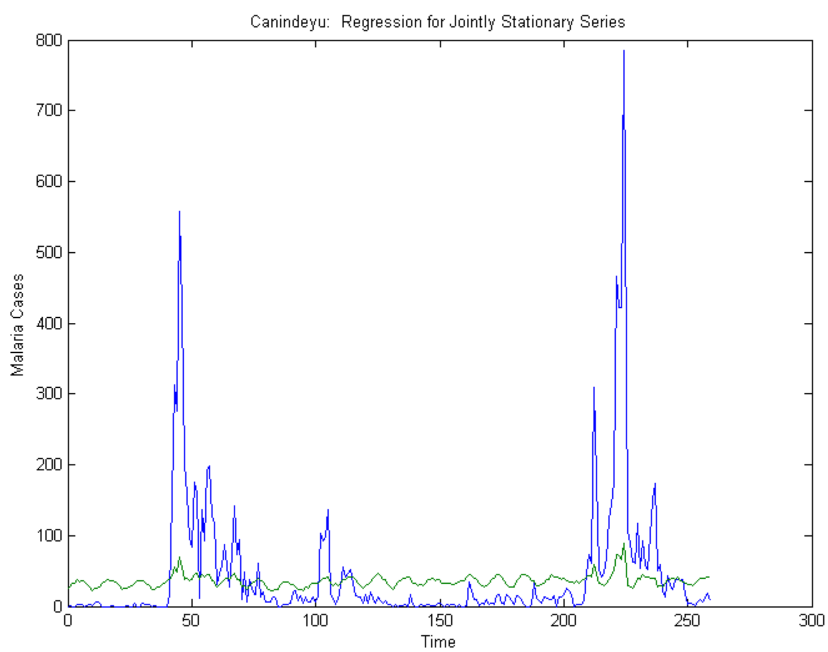


b.)

Figure 4.6: Graphs displaying the regression analysis results for (a) Alto Parana and (b) Canindeyú. Potential malaria cases are represented by a green line and recorded malaria cases by a blue line.

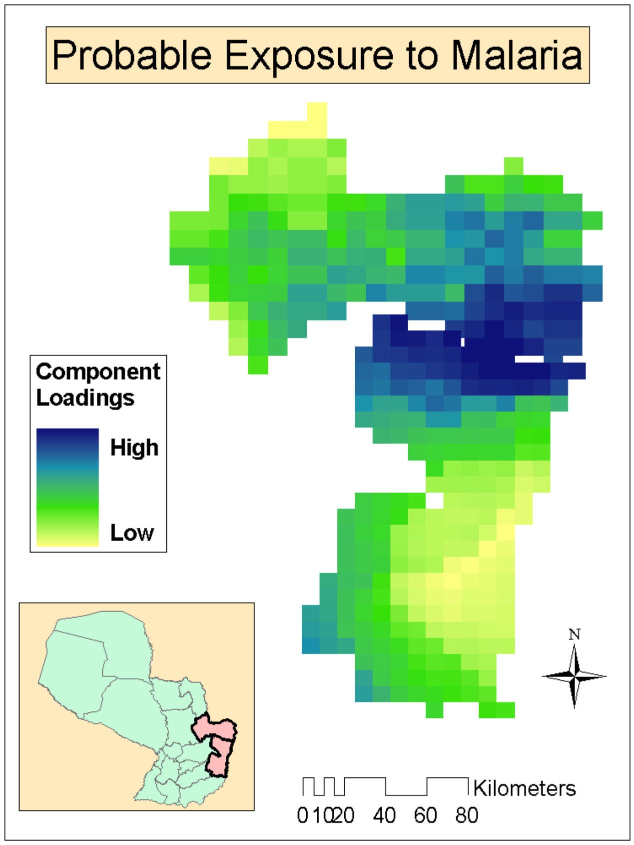


Figure 4.7: Map displaying the results of the regression analysis.

Research Question Explored

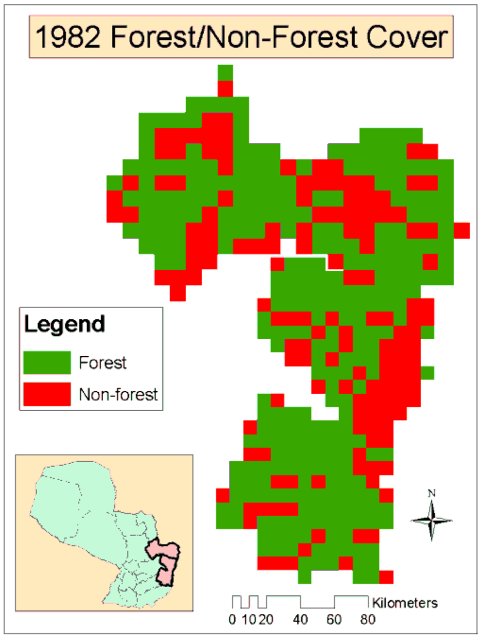
The lagged regression analysis asked the following question:

- By combining a selection of environmental parameters of malaria (temperature, precipitation, land cover change), will regions and times which can be highly associated with malaria incidents be discovered?

Although the relative error of this analysis was high, the graphs capture the overall sinusoidal behavior of malaria cases. The equation was able to correctly predict the peaks and valleys of the malaria time series, just not the amplitude of these curves. By applying the equations generated from the lagged regression analysis, the hypothesis was proven true that a map could be developed that found environmental regions that were highly associated with malaria. Additionally, the graphs of the predicted malaria cases provide a general idea of time periods when environmental parameters provide greater risk to the disease.

Deforestation

As detailed in Chapter 3, binary forest/non-forest maps were created for each year of the time series: 1982-2002 (Figure 4.8).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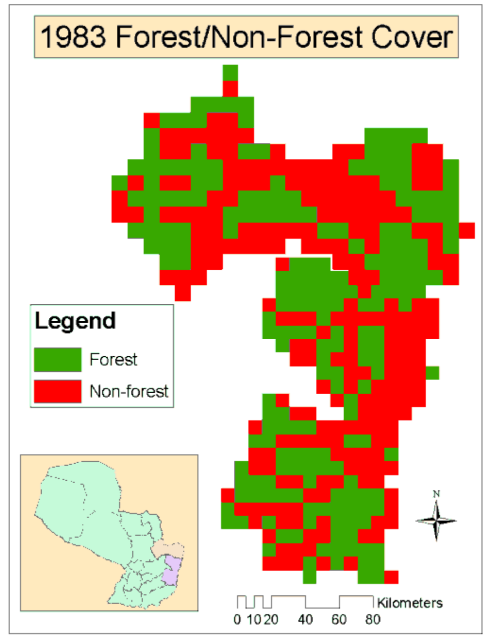
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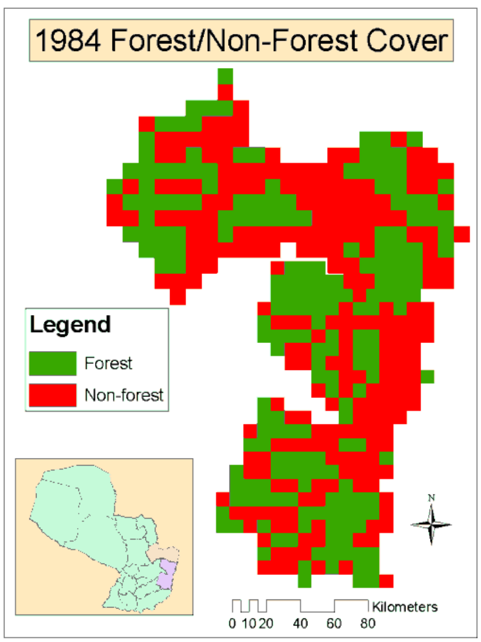
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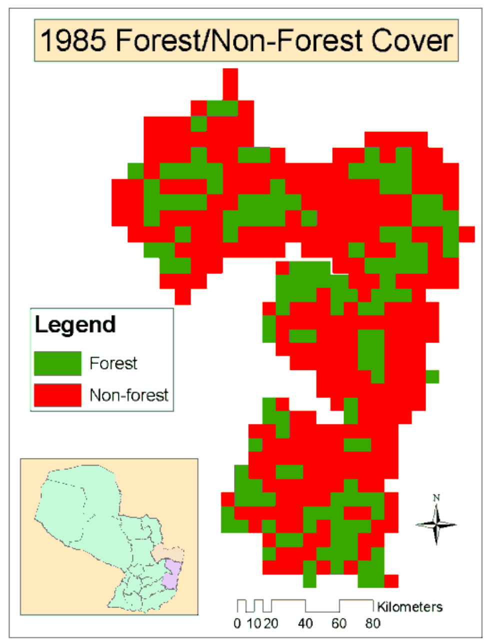
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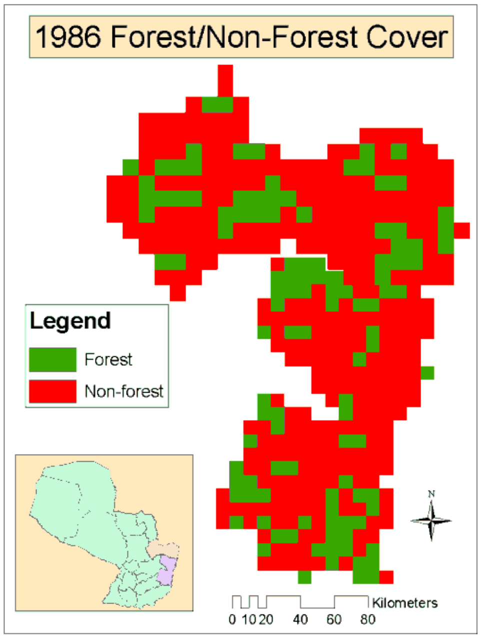
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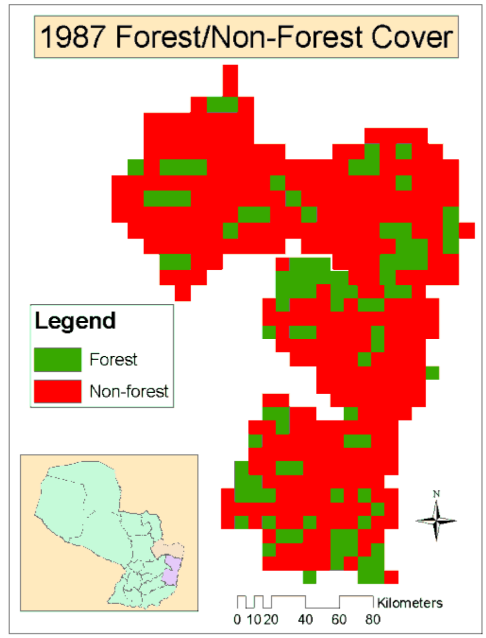
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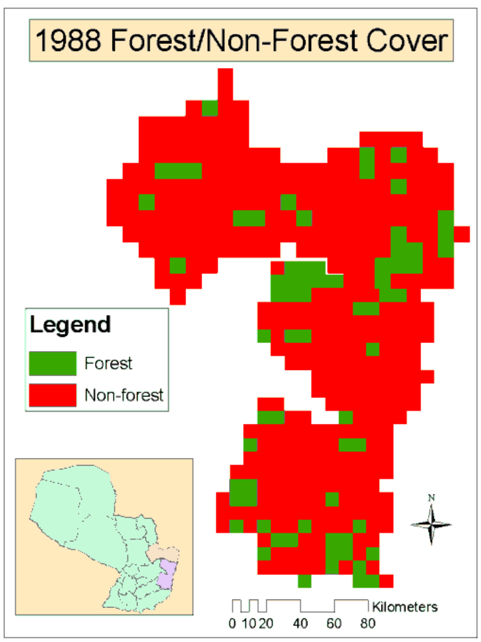
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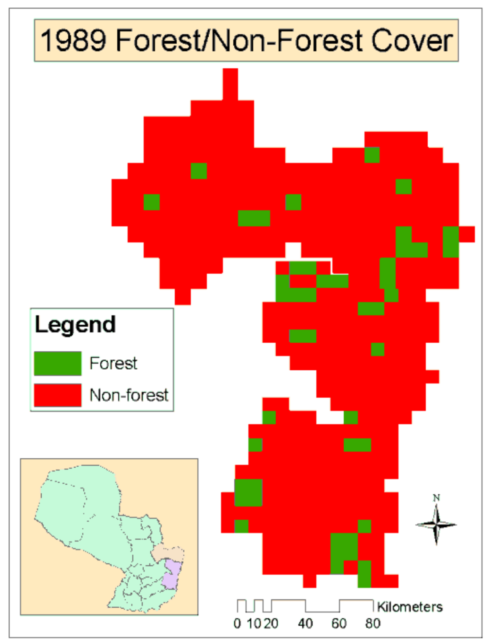
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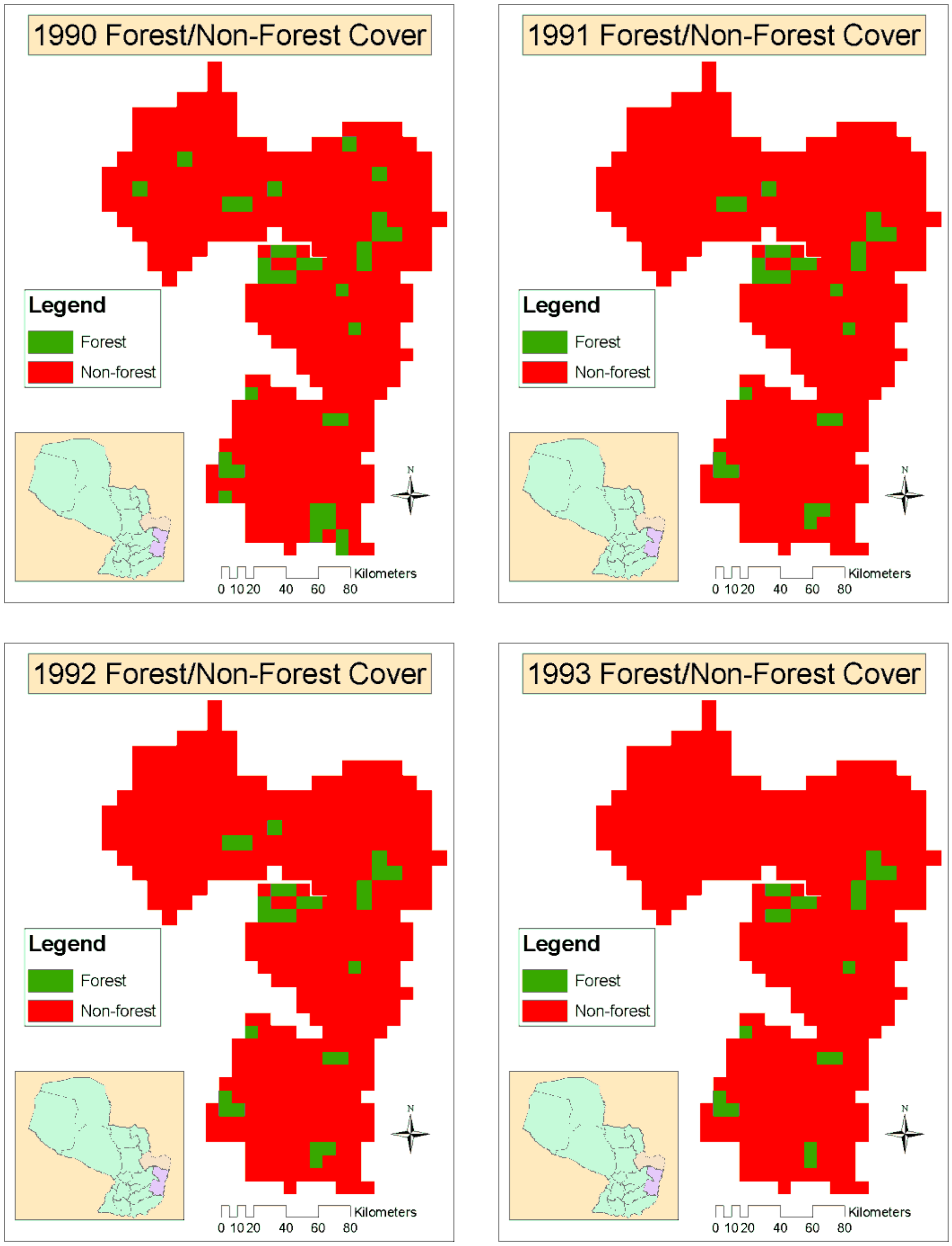
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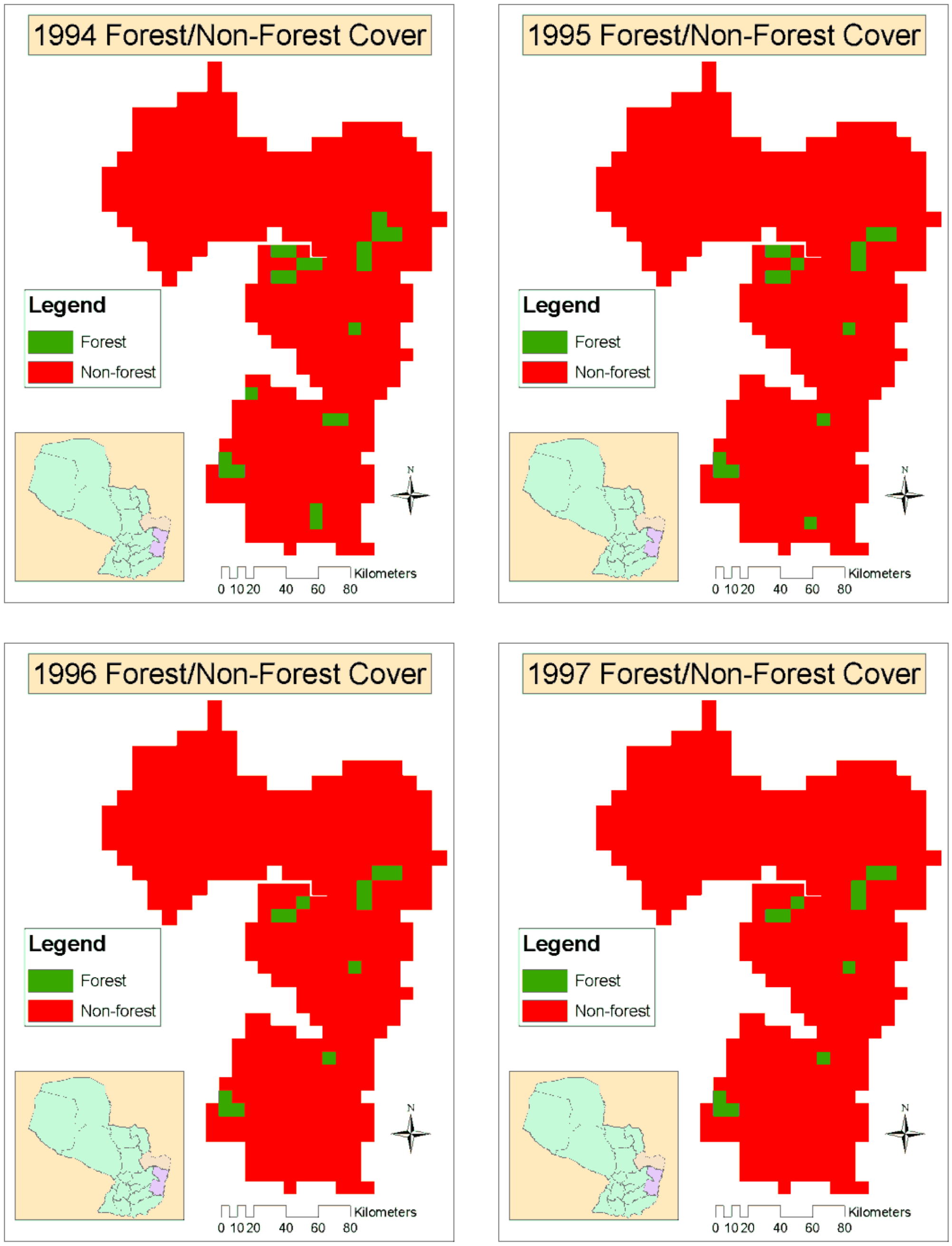
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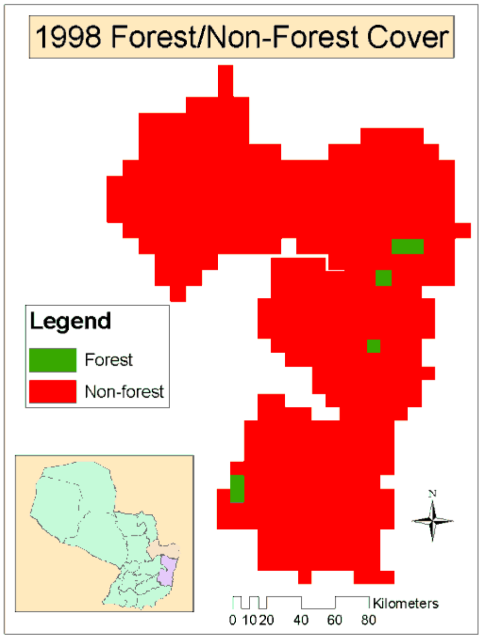
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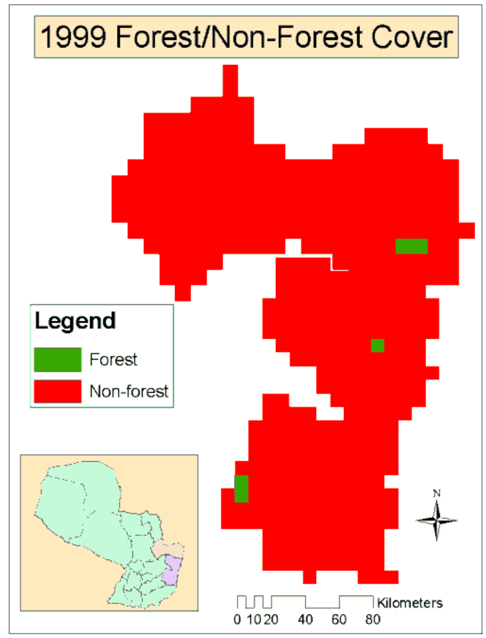
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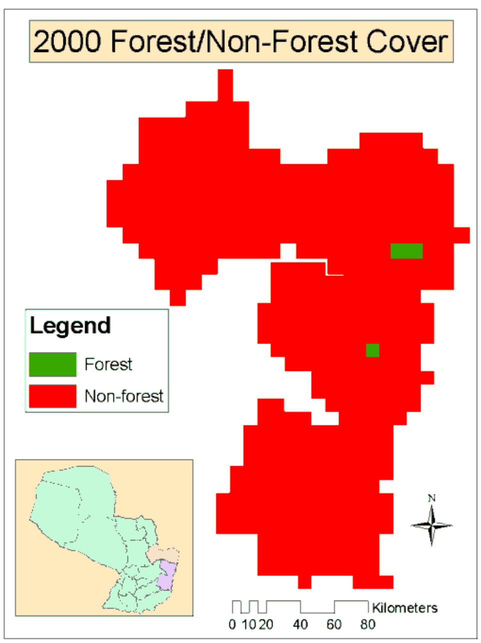
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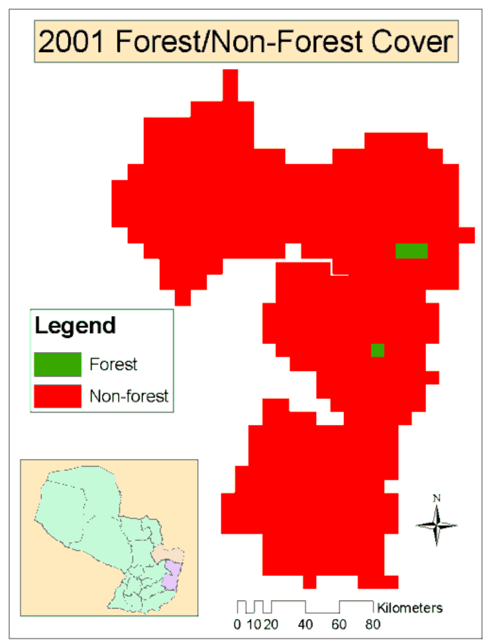
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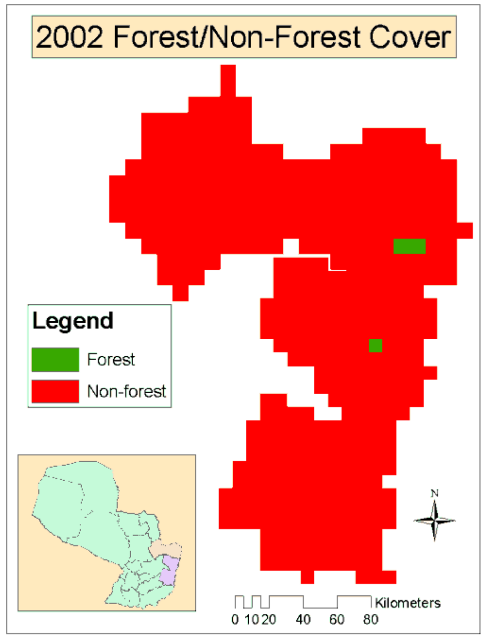


Figure 4.8: Maps displaying deforestation from 1982-2002.

The maps of deforestation display land cover change from forest to non-forest and then back to forest. Some of the land cover change can be explained by the culture of Eastern Paraguay. Until the early 1990s, slash and burn was a popular form of agriculture in Eastern Paraguay (Kammesheidt 1998, Hanratty and Meditz 1988). Additionally, starting in the 1960s and continuing into the 1990s, there was a migration of Paraguayans to the eastern departments to convert forest land into individually owned farms (Huang *et al.* 2009, Hanratty and Meditz 1988). It is important to note that while the maps of forest/non-forest cover provide an idea of where deforestation has occurred; due to the coarseness of the AVHRR-derived NDVI data (8-km) variability of land cover change within a pixel has been lost.

Comparing maps of deforestation to the map of areas more likely to support malaria transmission (Figure 4.7) it can be observed that regions that are less environmentally prone to malaria have experienced less deforestation throughout time. Additionally, times of extreme land cover change (1986-1990 and 1998-2002); coincide with periods of the most recorded malaria cases.

Research Question Explored

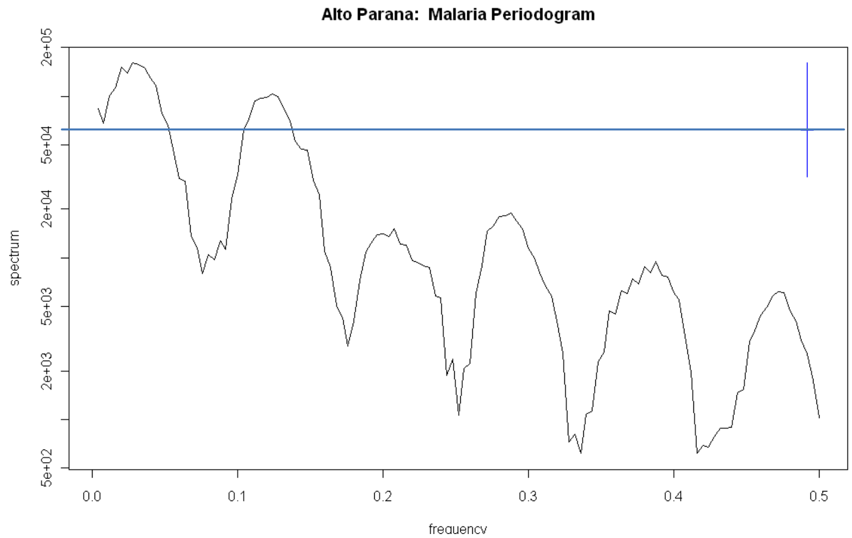
The research questioned asked was:

-Does recent land cover change coincide with regions environmentally prone to malaria?

Based on the lagged regression map of potential malaria risk, it can be observed that deforestation appears to be associated with malaria. Regions with lower probability of malaria generally coincide with lower deforestation compared to regions of higher malaria risk. Regions of deforestation are prime habitat for mosquitoes. These observations are similar to those of other researchers who have studied malaria in South America (Vittor *et al.* 2006, Barbieri *et al.* 2005, Norris 2004). Higher resolution malaria data will be required in order to confirm the relationship between malaria and deforestation.

Time Series Analysis

Time series analysis was employed to derive a better understanding of the periodic behavior of malaria and its environmental parameters. Periodograms, which are graphs of frequencies, were generated to portray the temporal behavior of each variable and the relationships between variables. Peaks above the horizontal blue represent statistically significant frequencies within the time series.



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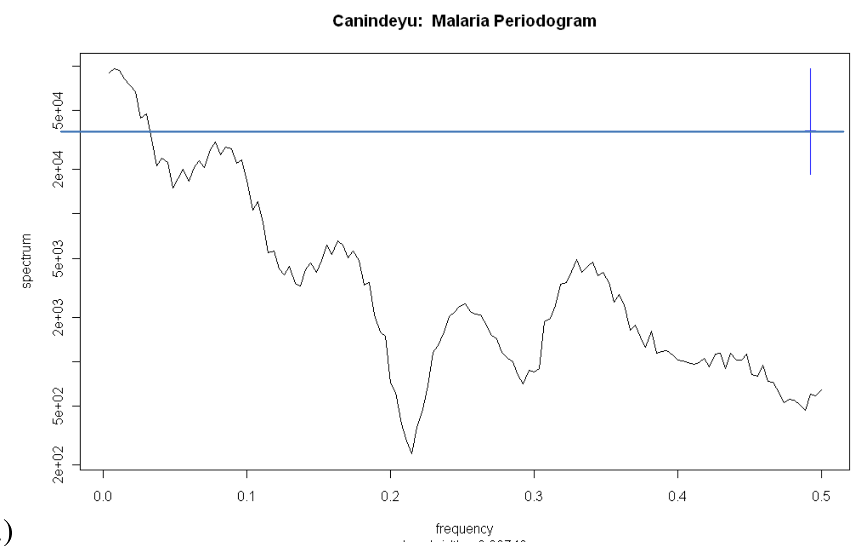
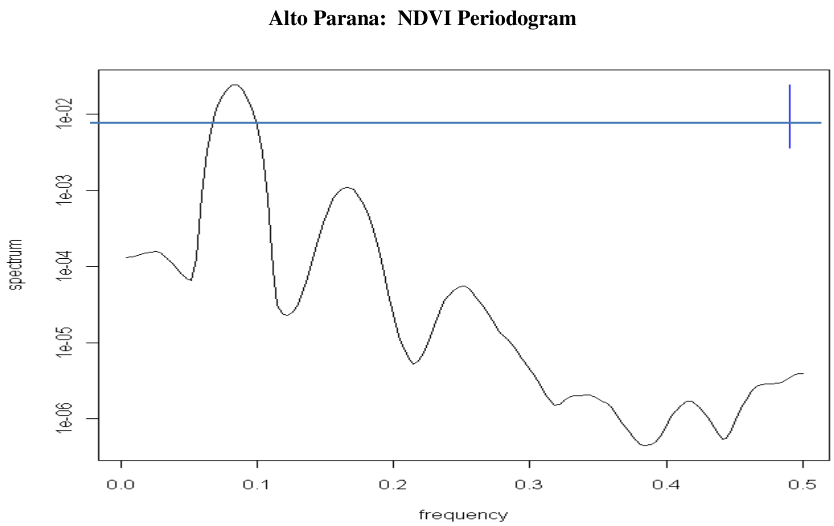


b.)

Figure 4.8: The malaria periodograms for (a) Alto Parana and (b) Canindeyú are similar**.**

The periodograms for malaria show a significant frequency of 0.0278 for both departments and an additional significant frequency at 0.125 for Alto Parana (Figure 4.8). The decimal 0.0278 translates into a fraction of 1/36 and 0.125 into a fraction of 1/8. The denominator of these fractions represents the number of months within one period, which for malaria are 36 and 8 months.



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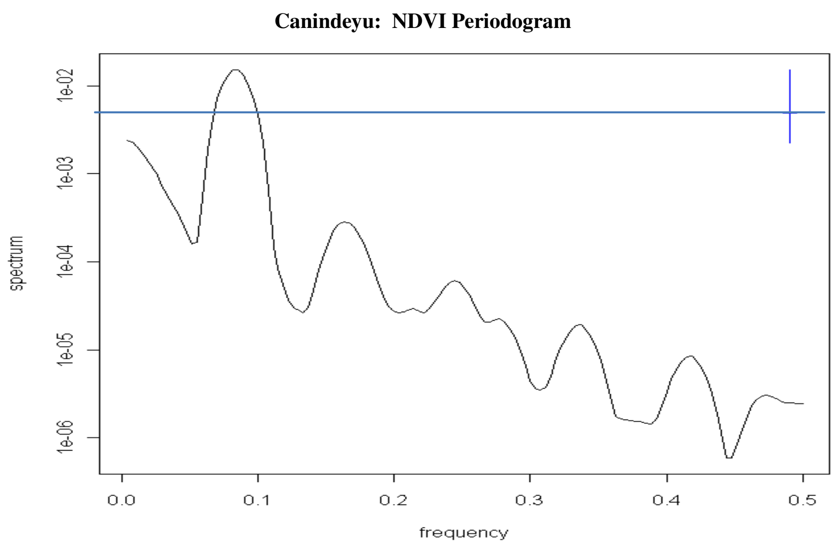
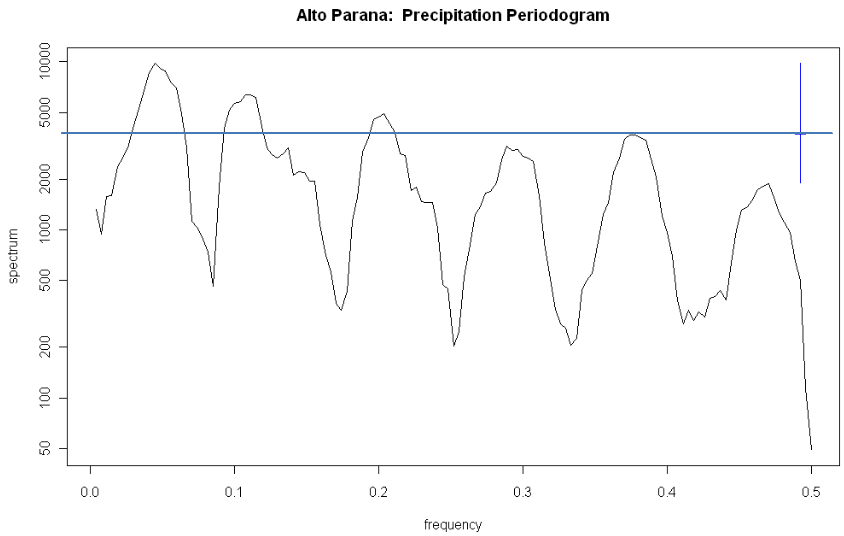


b.)

Figure 4.9: NDVI periodograms for (a) Alto Parana and (b) Canindeyú

It was also observed that there was a recurring frequency for NDVI at 0.08333 (1/12) or 12 months. (Figure 4.9) This means there is an annual cycle of NDVI values for Alto Parana and Canindeyú. While not statistically significant, it is can also be observed that there are faster frequencies of 2-6 months of NDVI values, which are weaker than the 12 month period. This would explain some of the oscillation of correlation observed in the PCA graphs.



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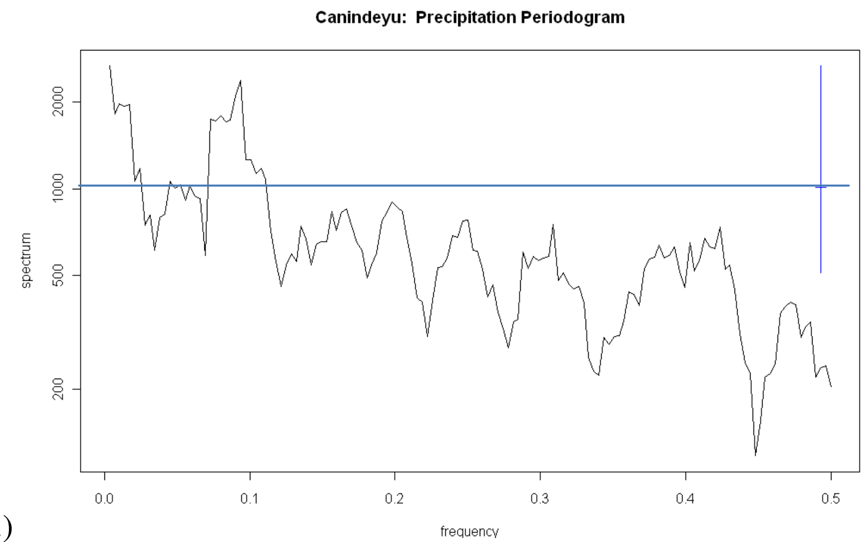
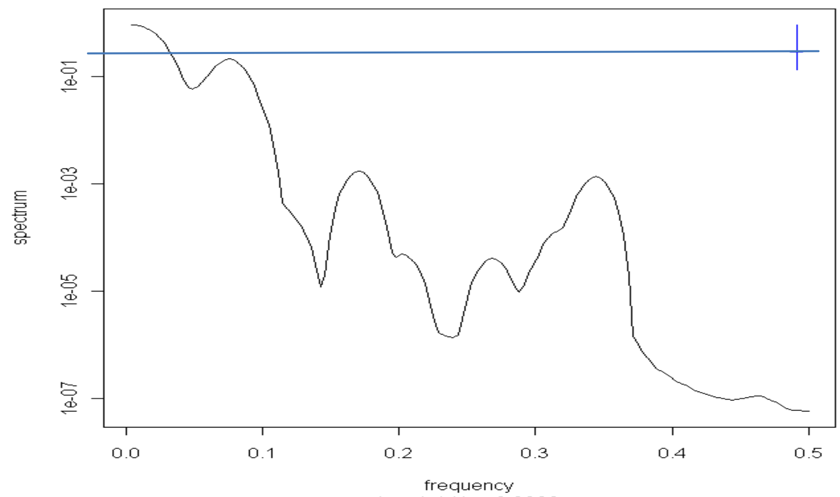


b.)

Figure 4.10: Precipitation periodograms for (a) Alto Parana and (b) Canindeyú.

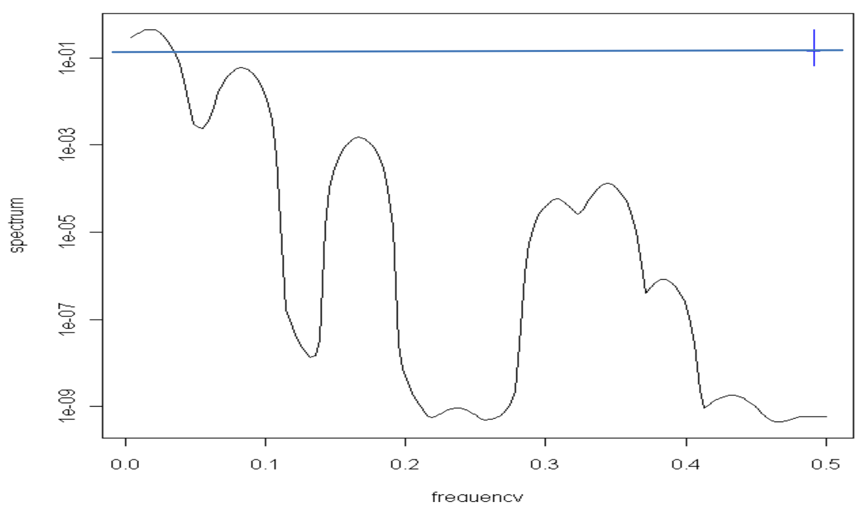
Precipitation frequencies are similar, although not the same, for each department. Significant frequencies occur at about 24, 12, 6, 4, and 3 months for Alto Parana and 24, 9, 5, and 3 months for Canindeyú. Slight differences in the periodic behavior of precipitation are to be expected due to the coarse resolution of the selected climatic data, especially in the higher faster frequencies as seen here. The resolution of the original dataset was an extremely coarse 0.5 degree, which could have allowed for regional variability to be masked. What is important to note is higher frequencies are significant for periodic behavior of precipitation, again giving evidence to the oscillations observed in the PCA correlation between rainfall and malaria.

Alto Parana: Temperature Periodgram



a.)

Canindeyu: Temperature Periodogram



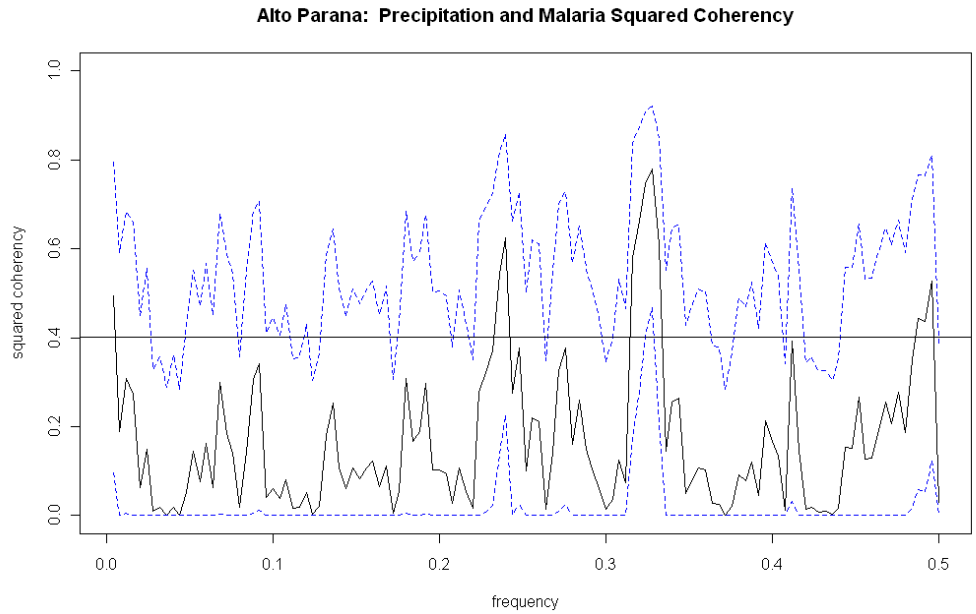
b.)

Figure 4.11: Temperature periodograms for (a) Alto Parana and (b) Canindeyú.

Peak frequencies for temperature occur at both 36 and 12 month intervals. The 12-month period is probably related to the annual variation in temperature in a typical year. Typically there are only two seasons in a year for Paraguay, wet and dry. These seasons, and their transitions, occur within a one-year time period (Hanratty and Meditz 1988). The 36-month period may be related to the El-Nino Southern Oscillation (ENSO), which occurs about every 3 to 7 years. (Xu *et al.* 2004, Gagnon *et al.* 2002, Bouma and van der Kaay 1996).

<u>Coherency Test</u>

The graphs below portray results of coherence tests between malaria and precipitation, temperature, and vegetation (NDVI). Coherency is basically a correlation indexed by frequency (Shumway and Stoffer 2006). It provides a greater understanding of the interworking relationship between two different time series. When analyzing coherency periodograms (Figure 4.12 and Tables 4.1, 4.2), the squared coherency can be associated with r^2 values in the frequency domain. Statistically significant coherency values are peaks that lie above the horizontal line drawn across the graph (See Equation 3.3).



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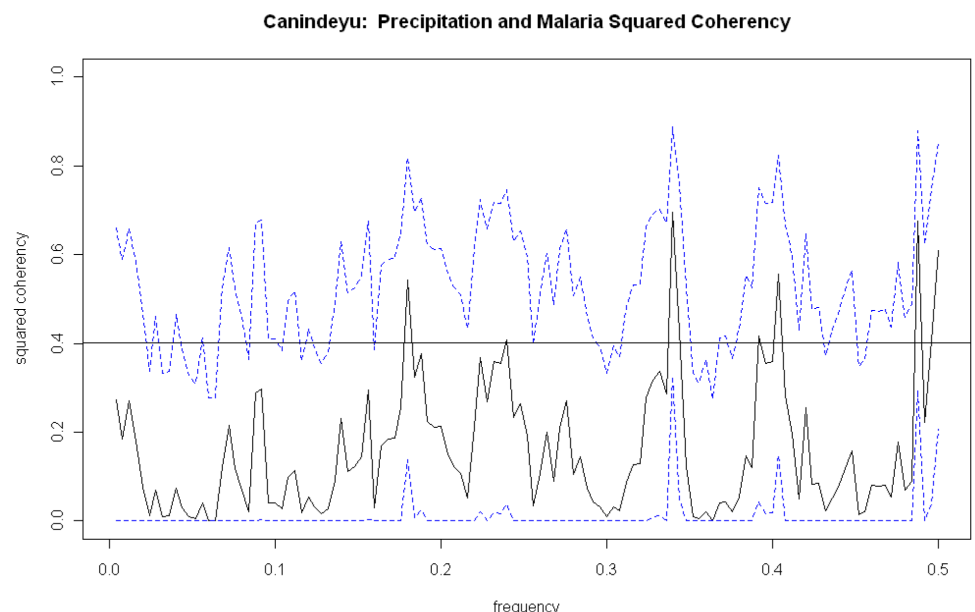


b.)

Figure 4.12: Cross-Spectra of precipitation and malaria for (a) Alto Parana and (b) Canindeyú. The coherency centers on the faster frequencies.

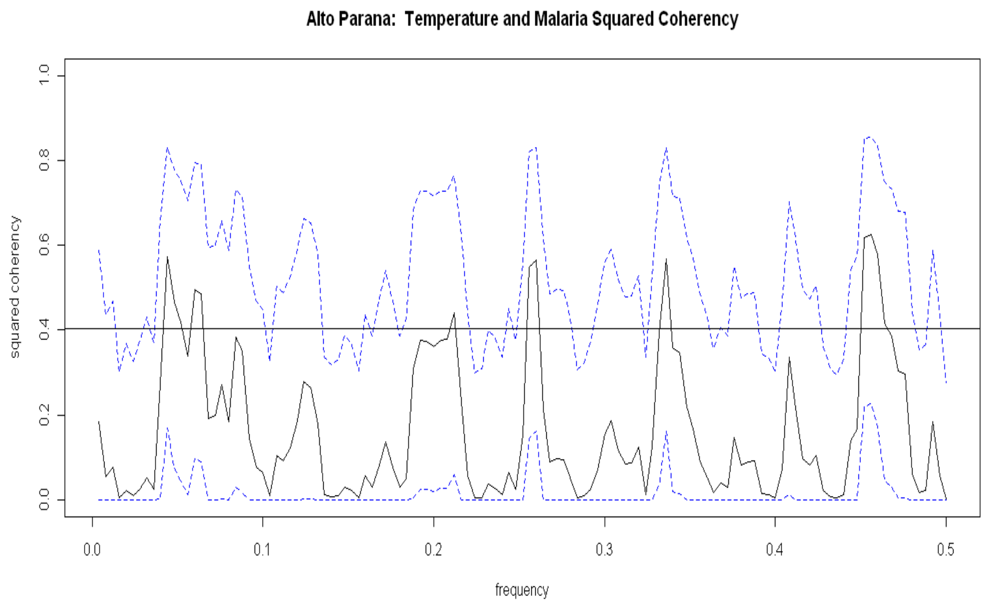
Frequency	Squared Coherence	Coherence
4	0.626	0.791
3	0.780	0.883
2	0.443	0.666

Table 4.1: Significant coherency values for Alto Parana precipitation and malaria

Frequency	Squared Coherence	Coherence
6	0.544	0.738
3	0.696	0.835
2.5	0.555	0.745
2	0.675	0.822

Table 4.2: Significant coherency values for Canindeyú precipitation and malaria

From the graph of coherency between precipitation and malaria, and the tables of significant frequencies, it can be observed there is a seasonal relationship between rainfall and malaria. All of the significant frequencies are between 2 and 6 months, meaning rainfall contributes to malaria cases on a 2-6 month period.



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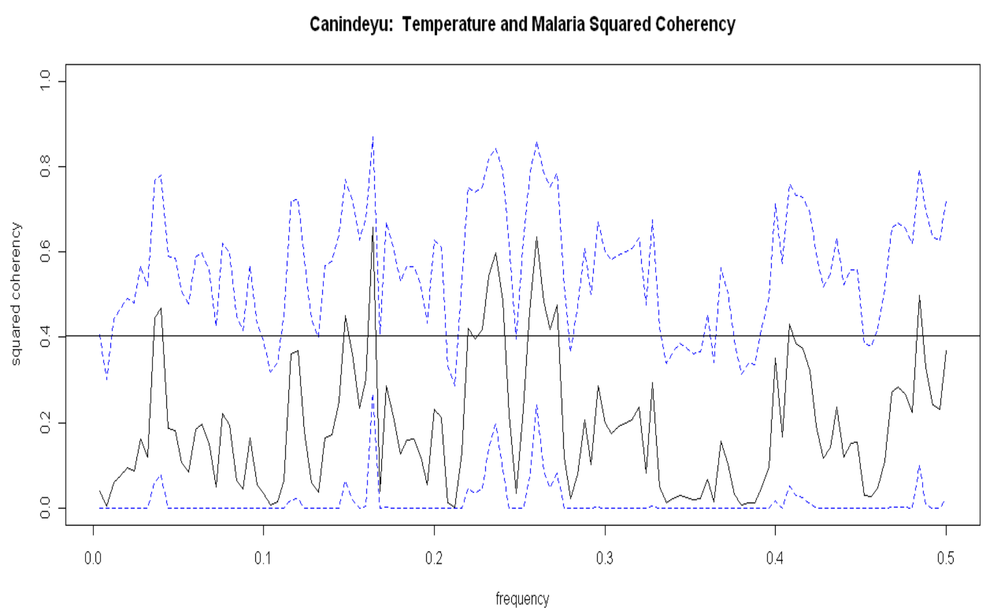


b.)

Figure 4.13: Coherence graphs of temperature and malaria for (a) Alto Parana and (b) Canindeyú.

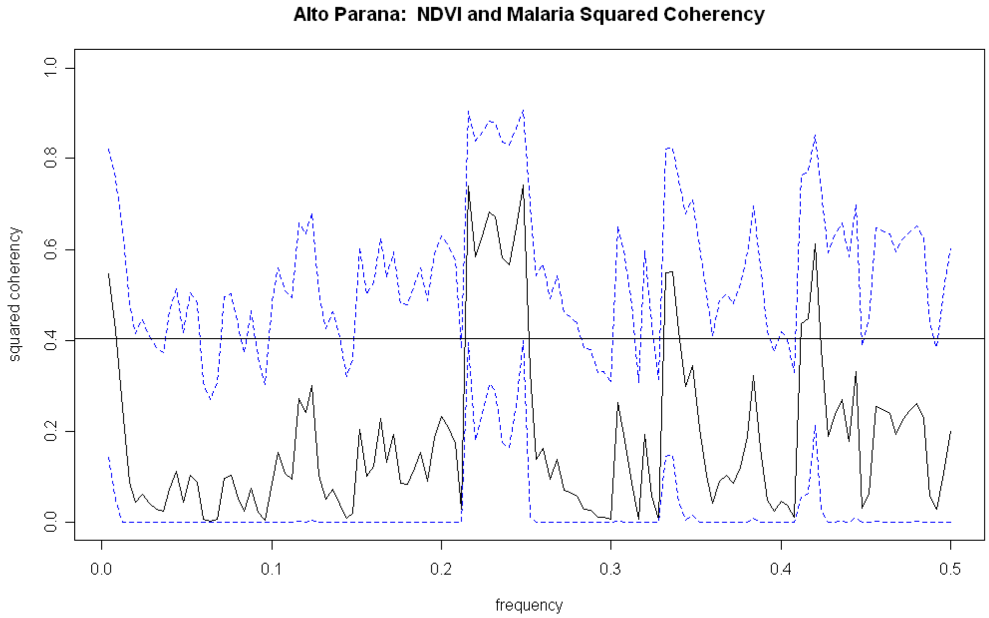
Frequency	Squared Coherence	Coherence
24	0.57	0.755
16	0.51	0.714
5	0.41	0.64
4	0.58	0.762
3	0.572	0.756
2	0.615	0.784

Table 4.3: Significant coherency values for Alto Parana temperature and malaria.

Frequency	Squared Coherence	Coherence
24	0.43	0.656
6	0.618	0.786
4	0.588	0.767
3	0.405	0.636
2	0.435	0.660

Table 4.4: Significant coherency values for Canindeyú temperature and malaria.

For temperature and malaria, there are significant coherency values at a frequency of 24 months, or every two years. Because both temperature and malaria have longer significant temporal periods (36 and 12 months), it makes sense that there would be a slow coherence frequency between the two. Additionally, the highest coherence values belong to the faster, higher frequencies (2-6 months). This suggests that temperature affects malaria case rates seasonally throughout the year every 2, 3, 5, and 6 months. The 24 month period means there is a reoccurring outbreak of malaria every two years due to temperature values.



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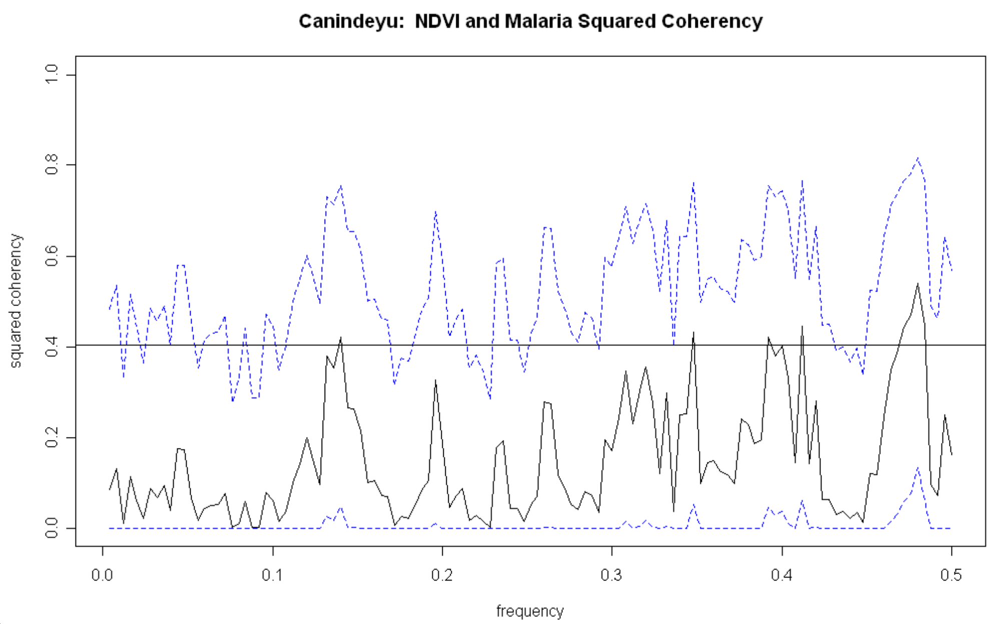


b.)

Figure 4.14: Coherency values for NDVI and malaria for (a) Alto Parana and (b) Canindeyú.

Frequency	Squared Coherence	Coherence
4.5	0.76	0.872
3	0.575	0.758
2.4	0.595	0.771

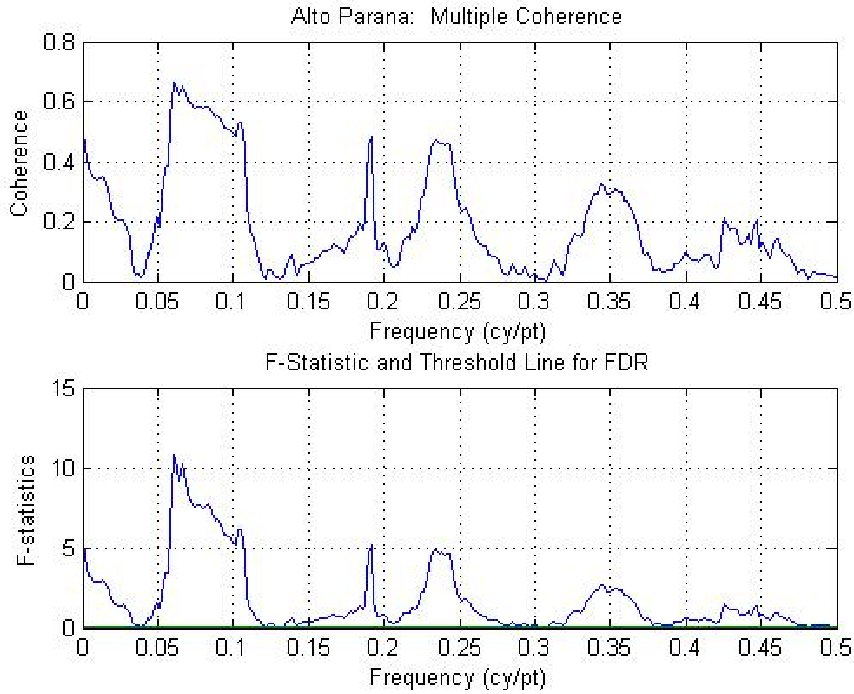
Table 4.5: Significant coherence values of Alto Parana NDVI and malaria

Frequency	Squared Coherence	Coherence
7	0.411	0.641
2.5	0.42	0.648
2	0.475	0.689

Table 4.6: Significant coherence values of Canindeyú NDVI and malaria

Significant coherency values once again center on the higher faster frequencies. Alto Parana experiences a reoccurrence of land cover change contributing to malaria values every 2, 3, and 4.5 months. Land cover change contributes to Canindeyú malaria cases every 2, 2.5 and 7 months.

The multiple coherency graphs below completed the coherency test for all of the variables, malaria, precipitation, land cover change, and temperature, as one complete system. Significant coherency values are determined by the graph of the F statistic below the multiple coherence graphs.



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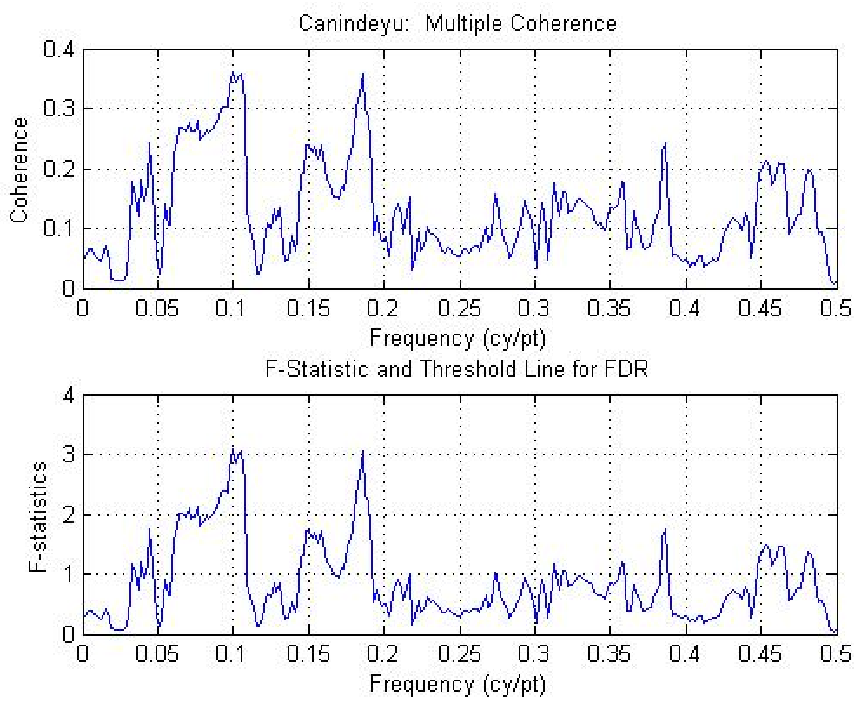

b.)

Figure 4.15: Coherency values between all of the variables for (a) Alto Parana and (b) Canindeyú.

Frequency	Squared Coherence	Coherence
18-12	0.632	0.795
5	0.495	0.704
4	0.496	0.704
3	0.35	0.592

Table 4.7: Significant frequencies for multiple coherence for Alto Parana

Frequency	Squared Coherence	Coherence
12	0.352	0.593
6	0.349	0.591
3	0.255	0.505

Table 4.8: Significant frequency for multiple coherence for Canindeyú

Every 12 months, all of the environmental variables contribute to the number of malaria cases. Additionally, the collection of environmental variables also contributes to malaria on a seasonal basis, every 3-6 months. For every coherency test, the higher faster frequencies (seasonal 2-6 months), were statistically significant. This leads to the conjecture that there is a seasonal-harmonic relationship between malaria and rainfall, temperature, and land cover change.

Research Question Explored

Time series analysis in the frequency domain provides information about the periodic behavior of a time series. Looking at the coherency between time series gives insight into the interworking relationship between two different time series. It was questioned whether:

- Will time series analysis of the variables provide information about periodic trends and cycles of individual variables as well as cycles of correlation?

It can be suggested that the answer to this question is yes. The significance tests (see Chapter 3) showed that all time series analysis results are statistically significant

(See Figures 4.9 – 4.16 and Tables 4.1-4.8). Significant coherency between malaria and temperature, vegetation change, and precipitation occurred at both low and high frequencies. The low frequency oscillations center on a 2-year (or 24-month) correlation. The higher faster frequencies tend to be between 2 to 6 months. This coherence periodicity suggests there is a seasonal or harmonic relationship between malaria and its environment.

Multiple coherency tests provided insight into the relationship between malaria and its environmental variables as one system. Significant squared coherence values between all of the environmental variables for both departments were observed. While the low frequency of 12 months (an annual cycle) was significant, the faster frequencies also displayed high coherence values. There is a harmonic, inter-seasonal relationship between malaria and selected key environmental parameters. This may explain the periodic outbreaks of malaria over the study period.

Summary

The PCA results depict a positive temporal relationship between temperature and malaria. This was reinforced spatially when it was observed that the spatial pattern of correlation between malaria and temperature was similar to the spatial pattern between vegetation change and malaria.

The temporal PCA results for precipitation and malaria were negative and the spatial results were the opposite of the pattern observed in the correlation between malaria and vegetation. There is likely a negative relationship between precipitation and malaria in eastern Paraguay. This is probably due to destruction of breeding habitats created by deforestation.

The lagged regression analysis was able to combine all of the environmental parameters of malaria: temperature, rainfall, and vegetation, into one system. An output equation of malaria cases was created based on past values of the environmental variables. The equation was able to capture the general sinusoidal behavior of malaria, capturing the peaks and valley. This equation was then applied to the spatial data and a map of malaria risk based on its environment was developed.

Deforestation maps were created for every individual year of the time series using AVHRR derived GIMMS-NDVI data. These designated between areas of forest and non-forest. When tested against a 2001 MODIS derived vegetation map (Hansen *et al.* 2003), they correctly classified the land cover about 80% of the time. By comparing these maps to the map of environmental malaria risk, it was determined that deforestation contributed malaria cases in eastern Paraguay.

Lastly, time series analysis provided information about malaria and its tested parameters that were not overly apparent in the raw data. Malaria case rates are affected by both multi-year and seasonal cycles. The discovery of multi-year cycles helps to explain the extreme peaks of the raw malaria data and the multi-year cycles of its environmental parameters give reasons for the amplitude of those peaks. Additionally, the harmonic seasonal relationship between malaria and temperature, precipitation, and vegetation change shows changes in environmental variables within a short time period can have an effect on the number of malaria cases.

Chapter 5
Summary and Conclusions

Introduction

Malaria is a mosquito-borne disease that has afflicted humans for thousands of years. Every year between 700,000 and 2.7 million people die of the disease (Patz and Olson 2006, Pattanayak *et al.* 2003, Gagnon *et al.* 2002). The disease has been linked to precipitation, temperature, and deforestation (land cover change) (Mantilla *et al.* 2009, Jones *et al.* 2007, Anyamba *et al.* 2006, Campbell-Lendrum and Woodruff 2006, Guerra *et al.* 2006, Massarani and Shanahan 2006, Pascual *et al.* 2006, Thomson *et al.* 2006, Vittor *et al.* 2006, Barbieri *et al.* 2005, Patz *et al.* 2005, Norris 2004, Zhou *et al.* 2004, Pattanayak *et al.* 2003, Hay *et al.* 2002, Gagnon *et al.* 2002, Poveda *et al.* 2001, Craig *et al.* 1999). Although most prevalent in Africa, the relationship between different vectors of malaria and their environment vary greatly around the world (Olson *et al.* 2009, Briet *et al.* 2008).

Central to this project was a time series of monthly malaria cases for the Paraguayan departments of Alto Parana and Canindeyú, from 1981-2003. Using this information, the following research questions were asked:

1. Will regions of high correlation between malaria and temperature and malaria and precipitation be similar to areas of correlation between malaria and NDVI?
2. Will time series analysis of the variables provide information about periodic trends and cycles of individual variables as well as cycles of correlation?
3. By combining a selection of environmental parameters of malaria (temperature, precipitation, land cover change), will regions and times which can be highly associated with malaria incidents be discovered.

4. Does recent land cover change coincide with regions environmentally prone to malaria?

The conclusions listed below suggest that all of these hypotheses are true, with the exception of the relationship between precipitation and malaria. As will be discussed later on in this chapter, precipitation and malaria appear to be negatively correlated.

Conclusions

The principal component analysis (PCA) results exhibited a positive correlation between malaria and vegetation change and temperature. However, a negative relationship between precipitation and malaria was also discovered. The negative correlation between malaria and rainfall may be related to the creation of breeding grounds due to deforestation which are washed away during rainfall (Olson *et al.* 2009).

Time series analysis indicated that abnormal increases in temperature raise the number of malaria cases about every twenty-four months. This may explain why there are years with almost no recorded malaria cases and years with several hundred reported malaria cases. Additionally, an atypical rise in temperature every 2-6 months increases malaria case rates. Temporally and spatially, a variation from normal temperatures corresponds with an increase in malaria case numbers.

Precipitation and vegetation change influence malaria rates on a seasonal basis, every 2-6 months. Stable vegetation cover corresponds with relatively low malaria case numbers. Within the same month, an increase in monthly precipitation (during the wet season) decreases the number of reported malaria cases. Because of the negative spatial relationship between rainfall and malaria, precipitation possibly washes away mosquito breeding pools.

The lagged regression analysis looked at the relationship between malaria and the selected environmental variables together. Even though there was an extremely high relative error of 81%, the equations developed for each department, did capture the general oscillations of the original malaria time series. The equations also displayed the strength with which land cover change, temperature, and precipitation affected malaria case rates. For both departments, the strongest environmental contributor to malaria was land cover change. Furthermore, by applying these equations on a pixel-by-pixel basis, a map was developed of probable risk to malaria (Figures 4.6 and 4.7).

Lastly, using the map generated from the lagged regression analysis, it was determined that there exists a general positive spatial and temporal relationship between malaria and deforestation. Deforestation maps distinguishing between forest and non-forest portray an increase in area designated as non-forest during time periods of increased malaria cases. Areas which have experienced less land cover change throughout time are less prone to contain malaria carrying vectors. If land cover change were to decrease, the number of malaria cases would decrease as well.

There is also a spatial association linking deforestation and malaria's relationship between precipitation and temperature. On an annual basis, regions which have experienced land cover change are similar to regions of low component loadings between precipitation and deforestation. This provides evidence towards the theory that rainfall washes away mosquito breeding grounds created by land cover change. Additionally, regions which have experienced deforestation also portray spatial similarities between malaria and deforestation. Land cover could possibly be responsible for changes in the microclimate of recently deforested areas, increasing the malaria risk of the region.

Future Research

This thesis has contributed to a better understanding of the spatio-temporal behavior of malaria and its relationship to some of its environmental parameters such as precipitation, temperature, and vegetation. However, there are several short-comings of the research results due to the coarse spatial resolution of data, research time restraints, and available demographic data.

First, the malaria data only contained raw case numbers for each month for each department from 1981-2003, making it impossible to test the results of probable correlation between malaria, precipitation, temperature, and vegetation change, as well as the lagged regression map. The resolution coarseness of the spatial datasets, 8-km, was too coarse to distinguish local variations in land cover and climatic conditions. This was especially obvious when comparing the 2001 NDVI-derived deforestation map against the 2001 MODIS-derived vegetation cover map. The 1-km resolution of the MODIS map, used to test for accuracy of the forest cover maps, was able to capture more variation in vegetation cover across the departments and thus was a more accurate representation of the land cover.

Additionally, the number of malaria cases could be considerably affected by human efforts to combat the disease (Weil 2008, Sachs and Malaney 2002, Gallup and Sachs 2001, Goodman *et al.* 2000). These efforts include but are not limited to the distribution of anti-malaria drugs and mosquito netting, the destruction of mosquito breeding grounds, and the periodic immunity of older generations to the disease. The migration of citizens around the country could also be affecting the spread of malaria (Vittor *et al.* 2006). To improve future investigations, detailed data are needed describing the spatial distribution and movement of human population, the characteristics of the population, and information on how government agencies are attempting to combat the disease.

As stated earlier, most of the time series used in this study were non-stationary, which means they did not have a constant mean and standard deviation throughout time. This is not atypical in naturally occurring series. However, in order to complete the spectral analysis the series had to be differenced to become stationary. Wavelet analysis is better able to capture the local behavior of a non-stationary time series. In the future, wavelet analysis should be examined as an alternative method for studying the temporal behavior of the variable data used to diagnosis malaria.

It would also be beneficial to test the results of this research in varying locations around the world. These locations should vary in topography, vegetation cover, and climatic conditions in order to gain a better understanding of malaria in diverse situations. Suggested locations are Afghanistan, western Paraguay, and South Korea. All of these areas are either experiencing a re-emergence of the disease (South Korea), changing malaria behavior (Afghanistan), or reside within a country where malaria research has been conducted, but not in that specific region (Kotwal *et al.* 2005, Lee *et al.* 2002).

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