ABSTRACT

Title of Thesis: ENVIRONMENTAL IMPACTS ON FECAL INDICATOR BACTERIA IN 5 NATIONAL PARK RECREATIONAL WATER AREAS

Greg A Raspanti, Master's of Public Health, 2012

Thesis directed by: Professor Amir Sapkota
Maryland Institute of Applied Environmental Health

The National Park Service oversees 397 park units throughout the 50 states and US territories. Due to the high visitation, protecting the health of visitors is a top priority. Fecal contamination in recreational water can occur as a result of land use practices and weather related factors. The aim of this study is to investigate weather related factors and land use factors that contribute to fecal contamination in five National Park units. Overall, rainfall proved to be highly predictive of subsequent elevations in fecal bacteria. Specifically, same day rainfall and day prior to the sampling day rainfall showed the strongest association with elevated fecal bacteria levels. Seasonal variation of fecal bacteria was generally higher in the summer months. The land use variables were not highly predictive of fecal bacteria levels. The results of this study can be used by park managers to better predict variations in fecal contamination.

ENVIRONMENTAL IMPACTS ON FECAL INDICATOR BACTERIA IN 5 NATIONAL PARK RECREATIONAL WATER AREAS

By:

Greg A Raspanti

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Advisory Committee:

Professor Amir Sapkota, Chair
Professor Xin He
Professor Amy Sapkota

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List of Abbreviations

BISC – Biscayne National Park

CHAT – Chattahoochee River National Recreation Area

CHIC – Chickasaw National Recreation Area

FIB – Fecal Indicator Bacteria

GLCA – Glen Canyon National Recreation Area

GUIS – Gulf Islands National Seashore

NPS – National Park Service

NP – National Park

NRA – National Recreation Area

NS – National Seashore

I. Introduction

The National Park Service oversees and manages a total of 397 park units throughout the 50 states, District of Columbia, Puerto Rico, Guam, and other US territories (NPS, 2010). These park units can encompass large areas of natural areas, such as Yellowstone National Park, or smaller areas such as battlefields, historic buildings, and monuments. In 2011, about 278 million people visited one of these 397 National Park units totaling nearly 1.24 billion visitation hours (NPS STATS, 2011). These visitors come into direct and indirect contact with surface water bodies as part of their recreational activities, therefore understanding the determinants of various bacteria in such recreational water bodies within the National Park units are of significant public health concern.

The Office of Public Health within the National Park Service traditionally focuses on four broad areas of work: Environmental Health, Disease Detection and Response, Comprehensive Public Health Protection and Promotion, and Emergency Preparedness and Response (NPS, 2011). Within the Environmental Health focus, recreational water has been one of many areas of focus. Recreational waters are used for a variety of activities within the National Park Service. Swimming, fishing, boating, and many other recreational activities are common within park units which have surface waters. Because the National Park Service protects many natural environments, exposure to human pathogens in recreational surface waters can occur.

From January 2007 to December 2008 in the United States, a total of 134 outbreaks associated with recreational water were reported leading to an estimated 13,966 total cases (CDC, 2011). The vast majority of cases, about 87%, were identified in treated recreational water areas such as public and private pools and interactive fountains. Only 18 reported outbreaks were associated with untreated recreational waters, of which only one outbreak was etiologically confirmed with *Escherichia coli* or *E coli* (CDC, 2011). Illness associated with recreational water use has been extensively researched in both treated and untreated water (Hagedorn et al., 1999; Marion, Lee, Lemeshow, & Buckley, 2010; Soller, Bartrand, Ashbolt, Ravenscroft, & Wade, 2010; Soller, Schoen, Bartrand, Ravenscroft, & Ashbolt, 2010; Viau et al., 2011). However, few studies have focused solely on National Park units and human health risks associated with recreational water use.

One of the studies focusing on National Parks and recreational water quality was conducted in Kings Canyon, Sequoia, and Yosemite National Park which represent some of the largest parks in the nation (Derlet & Carlson, 2004). These parks are very extensive and are found in rural areas of California. Derlet and Carlson found that all positive fecal coliform samples collected were at sites downstream from known areas used by pack animals and backpackers, while all other samples did not show increased levels of coliform bacteria (Derlet & Carlson, 2004). Within this rural California area, the main contributors of fecal bacteria may be the visitors and animals within the park itself. The researchers did not specify any specific type of coliform bacteria, which makes it difficult to identify the potential human hazard associated with exposure to these bacteria in the park units; however they reported an association between the type of recreational activity, use of land within National Parks, and fecal indicator bacteria (FIB). In a second study conducted in the Sierra Nevada Mountain Range in California, Derlet et al (2008) reported that the areas of highest risk of fecal bacteria contamination were those near or downstream of cattle and pack animal areas, while contributions by humans were much lower (Derlet, Ger, Richards, & Carlson, 2008). Cattle grazing areas in California have shown that nearly 96% of surface waters contained significant FIB, suggesting that areas with high densities of cattle can lead to increased levels of FIB (Derlet, Goldman, & Connor, 2010). Similarly, areas of known human use, such as day hiking and backpacking, have shown minimal coliform levels in downstream surface waters when compared with cattle grazing areas (Derlet, 2008). Furthermore, areas designated as “wild” where humans or pack animals are not present are used to simulate the contribution of wildlife to coliform levels in the surface water. Again, minimal levels of coliform bacteria was found in these areas (Derlet, 2008). Surface waters in National Parks which have a combined use of humans and pack animals have shown increased *E coli* and total coliform levels, specifically in the summer months (Ursem, Evans, Ger, Richards, & Derlet, 2009). Land use practices within National Parks can contribute to fecal contamination of surface water; however land use in the areas surrounding the National Park can also lead to surface water contamination within the park unit.

In addition to the land use practices within National Parks, studies have shown that land use outside of National Park units may contribute to the contamination of recreational water with the park unit. Rural areas in South Carolina have shown that the highest levels of *E coli* found in the surface waters are directly downstream from riparian cattle grazing and dairy farm areas (Klott, 2007). In other rural settings the unrestricted access of cattle to streams have shown to contribute up to 86% of fecal contamination found in surface waters (Hagedorn et al., 1999). The contribution of beef cattle far exceeded the contributions by other wildlife such as deer and water fowl, which can suggest cattle density to potentially be predictive of FIB in surface water in rural settings (Hagedorn et al., 1999). Storm water runoff from urban and agricultural areas can significantly contribute to FIB levels in surface water (Parker, McIntyre, & Noble, 2010). Recreational water areas with storm water outflows cause concern (Pan & Jones, 2012). Furthermore, agricultural runoff from the application of cattle manure can also contribute to fecal bacteria in surface water. If a rainfall event takes place shortly after the application of manure to agricultural land, the amount of fecal bacteria that enters surface waters can increase by up to one order of magnitude (Ramos, Quinton, & Tyrrel, 2006). Furthermore, agricultural land use has shown to be influential on the levels of *E coli* in surface water (Stott et al., 2011; Walters, Thebo, & Boehm, 2011). In contrast, urban areas can have increased levels of FIB in surface water as well. These sources can be very difficult to identify due to the inclusion of many different environments within urban centers. Urban water runoff, mainly during storm events, can cause large increases in the FIB levels due to combined sewer outflows (Passerat, Ouattara, Mouchel, Rocher, & Servais, 2011). The non-point source contamination of surface water is difficult to trace, while point source contamination is much easier to identify.

In contrast to the aforementioned non-point source pollution, point source pollution can also impact FIB levels in recreational water. In a study conducted in two public beaches in Virginia, the source of FIB were two restrooms located on the beach (Dickerson, Hagedorn, & Hassall, 2007). Similar findings were reported by a study conducted in Florida that identified human point source water pollution from restroom facilities on public beaches to be the primary source of FIB (Korajkic, Brownell, & Harwood, 2011). Other sources such as humans or dogs have also been examined as potential contributors to FIB levels in recreational areas. Human shedding during swimming and other recreational activities does not contribute significantly to FIB levels (Wang, Solo-Gabriele, Abdelzaher, & Fleming, 2010; Zhu, Wang, Solo-Gabriele, & Fleming, 2011). The loading of FIB in surface waters can originate from a variety of sources; however the characteristics of the aquatic environment can impact survival of FIB once it reaches the surface water.

The survival of *E coli* in freshwater environments depends mainly on the sediments in the environment (Garzio-Hadzick et al., 2010). Aquatic environments that contain at least 25% clay has been shown to increase the survival of *E coli* (Burton, Gunnison, & Lanza, 1987). Furthermore, the survival of fecal bacteria has been associated with the sediment, rather than the overlaying water. The amount of organic carbon concentration and small particle size can determine the survival of fecal bacteria. Aquatic environments with high organic carbon concentration can increase the survival of *E coli* (Chandran et al., 2011). Enterococci can survive in a number of harsh aquatic environments including chlorinated swimming pools (Maier, Pepper, & Gerba, 2009). Kinzelman investigated the replication ability and the persistence of *E coli* (2004). The study indicates that *E coli* persistence is responsible for the presence of the bacteria in the water, rather than the replication of *E coli* (Kinzelman et al., 2004). Another potential reservoir for *E coli* in recreational water areas can be beach sands. Sands with moisture content between 15%-19% have been associated with higher levels of *E coli*. Also following rain events, the levels of *E coli* have increased by nearly 100 fold possibly due to contaminant loading and sand washout (Beversdorf, Bornstein-Forst, & McLellan, 2007). Furthermore, sand provides microbial protection from UV light therefore increasing the survival of *E coli* in beach environments (Beversdorf et al., 2007). Tidal cycles can pick up these bacteria from the sand and transport them into the aquatic environment (Abdelzaher et al., 2010). If large amounts of *E coli* are deposited in the sand following a significant rain event, the possibility for human exposure to *E coli* can continue for days.

The relationship between precipitation and FIB levels in water is also of importance when investigating environmental factors and FIB in National Parks. One important aspect of the relationship between rainfall and FIB levels is the lag time between rainfall events and the peak FIB levels. In a previous study, *E coli* bacteria levels found in the surface water was not associated with rainfall or the turbidity on the day of sampling (Kinzelman et al., 2004). This implies that the loading of *E coli* in surface water is not an immediate effect following rainfall. Rather, there exists some unidentified latency period following rainfall before the *E coli* can be found in surface waters. Marion et al observed that the rainfall on the day prior to sampling is associated with elevated *E coli* levels (Marion et al., 2010). Similarly, cumulative rainfall 7 days prior to sampling was also positively associated with both *E* coli and fecal coliform concentrations in recreational waters, but not for enterococci (Korajkic et al., 2011). Other studies have shown seasonality to be a strong predictor of the presence of *E coli* and other FIB, with higher concentration observed during warmer summer months with high rainfall (Coulliette, Money, Serre, & Noble, 2009). The relationship between FIB levels and air temperature may be masked by the amount of rainfall in the warmer months. In fact, milder air temperatures have been associated with an increase in *E coli* levels in surface waters (Wilkes et al., 2009; Wilkes et al., 2011). There exists large regional variation in weather patterns across the United States; therefore seasonality can be very different depending on the location of interest (Pan & Jones, 2012). Furthermore, depending on the water conditions and the activity of other microorganisms, the FIB levels in the summer months can also be quite low (An, Kampbell, & Breidenbach, 2002).

Predictive modeling of water quality based on environmental factors is being explored as an alternative to the current monitoring techniques which can take days to complete. Such models can predict the FIB levels using observed environmental conditions with varying degrees of success (Nevers & Whitman, 2011). This approach allows proactive beach closure for recreational use as soon as the conditions for contamination are met, rather than waiting for the water sample results. This preventive approach will serve to minimize the possible exposure of humans to FIB in recreational surface water.

Few studies have been conducted specifically aimed to identify environmental predictors to assess human exposure in recreational water areas in National Parks and traditionally have been focused on parks in California creating a large research gap. Furthermore, these studies have focused mainly on human activities and land use within the parks and do not consider meteorological variables or land use outside the park. The successful completion of this project will provide a more comprehensive view into the relationship between land use, meteorological influences, and fecal contamination in recreational water in a variety of National Parks across the country. The goal of this investigation is to identify the environmental factors related to FIB fluctuation in recreational waters within 5 National Park units. The parks of interest include Biscayne National Park (FL), Chattahoochee National Recreation Area (GA), Chickasaw National

Recreation Area (OK), Glen Canyon National Recreation Area (UT), and Gulf Islands National Seashore (FL/MS). This study aims to answer the following two research questions:

1. How does the level of FIB fluctuate in relation to the cattle density and agricultural land use patterns over time?
2. How do environmental factors, such as precipitation and temperature, influence FIB levels within the National Park units?

We hypothesize that parks with high percentage of surrounding agricultural land and high cattle density will experience higher amounts of FIB. The successful completion of this research project will identify the major attributes of fecal bacteria into the waterways of US National Parks. The geographical differences within these 5 park units will allow comparison between urban and rural parks, as well as regional variation. The proposed research will also provide the National Park Service (NPS) with concrete, scientifically supported information regarding the major contributors of fecal bacteria, in which the NPS can better predict the increase of these bacteria and convey potential hazards to the public. There has been little research into recreational waters specifically in National Park units and this research can act as a basis for further investigation into this topic.

II. Methods

a. Park Data

The five different park units included in this study are Biscayne National Park, Chattahoochee River National Recreation Area, Glen Canyon National Recreation Area, Gulf Islands National Seashore, and Chickasaw National Recreation Area. Biscayne NP is located off the eastern coast of Florida, near Miami, and encompasses 172,971 acres of land (NPS STATS, 2011). The park is surrounded on by the Atlantic Ocean and 476,077 people visited this park in 2011. Many park visitors engage in recreational water activities like diving, boating, or snorkeling. Chattahoochee River NRA is located outside of Atlanta, GA in densely populated Fulton County. This recreation area is centered on the Chattahoochee River in which visitors can kayak, swim, or other water related activities. The park unit covers nearly 9,800 acres and visitation reached 3 million visitors 2011.

Chickasaw NRA is located in Murray County in south central Oklahoma. This park is located in a rural area of the state. Chickasaw NRA ranks 58th in total visitation out of the 397 park units with about 1.2 million total visitors in 2011. The park unit encompasses nearly 10,000 acres of total land. Glen Canyon NRA is an extremely large park unit, about 1.2 million acres, in rural Utah. This park extends through many counties in Eastern Utah and extends slightly into Arizona where along the Colorado River in which it connects to Grand Canyon NP. In 2011, 2.27 million people visited Glen Canyon NRA. Lastly, Gulf Islands NS is a chain of islands that extend from the Western panhandle of Florida near Pensacola to off the coast of Mississippi in the Gulf of

Mexico. Encompassing about 138,000 total acres, Gulf Islands NS ranks 9th in total visitation with 5.5 million visitors in 2011 (NPS STATS, 2011).

b. Water Quality Data

The water quality data was provided from each individual National Park unit. Each of these park units has unique water quality monitoring protocol and various fecal indicators targeted for measurement. Furthermore, the exact locations of the water monitoring stations are unknown. The park units all have varying sampling frequencies, duration, and bacteria of interest, which makes direct comparison difficult. The samples were taken in accordance with Standard Methods for the Examination of Water and Wastewater, 18th Edition, Part 9060 and analyzed using membrane filtration methods. Reporting and correction methods are in accordance with the EPA's *Beaches Environmental Assessment and Costal Health Act of 2000*. Table 1 shows the number of monitoring stations in each park, the FIB measured and number of observations. It is important to note that Gulf Islands NS extends from off the Western coast of Florida to Mississippi in the Gulf of Mexico. All the water quality measurements were taken from the island off the coast of Florida. Description of water quality measurements and descriptive statistics of FIB by park unit can be found in Table 1 and Table 2.

c. Meteorological Data

Meteorological data was acquired from the National Climatic Data Center (NCDC), a branch of the National Oceanic and Atmospheric Association (NOAA) that maintains the world's largest archive of meteorological data from the past 150 years. The climate data used in this study are archived in two broad categories: DSI-3200 and DSI-

3210. The DSI-3200 database contains approximately 8,000 active stations, with up to 23,000 stations for selected years. The stations cover all 50 states plus Puerto Rico, US Virgin Islands and Pacific Island territories. The DSI-3200 data contains various weather parameters including daily maximum and minimum temperatures, snowfall and 24-hour precipitation totals. The DSI-3210 dataset represents weather monitors located in the metropolitan areas and airports across North America. In addition to the temperature and precipitation data from DSI-3200, the DSI-3210 dataset contains a much larger number of specific meteorological variables including wind speed, direction, cloudiness, sky cover, humidity, and daily sea-level pressure. For the US, there are close to 400 monitoring stations that come under this DSI-3210 category.

Each weather station was evaluated for database completeness and proximity to the body of water within the park of interest. Many weather stations were identified as being geographically closer to the park, but were disqualified for missing many years of data leaving large data gaps. The specific distance from the park to the weather station was measured using GIS software. The weather database was modified to reflect only the variables of interest, including maximum temperature and precipitation.

d. Land Use

County level data was used to estimate land use surrounding each National Park unit. Only Chickasaw NRA (Murray County, OK) is fully enclosed within one county. Therefore all calculations were made using the single county data. Also, Biscayne NP (Miami-Dade County, FL) and Gulf Islands NS (Escambia County, FL) are islands off the coast of Florida; therefore the data from the county closest to the park unit was used.

Chattahoochee River NRA land use variables were also averaged from the counties surrounding the park unit (Fulton and Cobb County, GA). The data from these counties was averaged in order to account for the land use on all sides of the park unit. Cattle density was identified by the USDA Agriculture Census by the counties which encompass the park unit for the years 1987, 1992, 1997, 2002, and 2007. This measurement is in cattle / mi^2 and used to investigate the contribution of cattle in the counties surrounding the parks.

A second land use estimate was derived from the USDA Agriculture Census. Agricultural land use in acres was divided by the total acreage of the county to create a ratio reflecting the percent of land used for agricultural purposes within each county. This secondary land use calculation will be useful to determine the relationship between the bacteria levels and agricultural practices surrounding the park units.

e. Data Analysis

All data management and data analysis was performed using SAS 9.2 (Cary, NC). In order to investigate the relationship between the weather and water quality data, the weather and water quality datasets were sorted and merged by date. This merging allowed for the creation of new variables reflecting the weather patterns of the days leading up to the sample day. Dichotomous variables were created to reflect the presence or absence of rain within 1, 3, 7, and 10 days before sampling. Furthermore, these sampling windows were created in order to calculate both the average and cumulative rainfall in the 1, 3, 7, and 10 days prior to sample days. This information was used to investigate the impact of rainfall and the levels of FIB and the latency periods which have the most impact. Also, a season variable was created in order to analyze inter-season variability. The season variable identified December-February as winter, March-May as spring, June-August as summer, and September-November as autumn.

All FIB variables were log transformed for statistical analysis purposes and checked for normality. Independent two sample t-tests were conducted to compare the mean FIB levels for the presence or absence of rainfall in the last 1, 3, 7, and 10 day windows. Furthermore, one way ANOVA, combined with Scheffe's test, was used to test for inter-season variability of the FIB levels in the recreational waters. Pearson's correlation coefficients were calculated between all land use, meteorological data, and the FIB levels (Table 3).

A linear mixed effect model was used to model the FIB as a function of land use patterns and environmental factors. This model was chosen in order to account for the relationship between repeated measurements at multiple locations taken over time. The model was altered to test the relationship between each rainfall variable and the individual bacteria measured in each park. The dependent variable is the FIB levels and the independent variables include rainfall on sampling day (prcp), rainfall on day prior to sampling (cumprcp1), 3 day cumulative rainfall (cumprcp3), 7 day cumulative rainfall (cumprcp7), cumulative 10 day rainfall (cumprcp10), maximum air temperature, cattle density per mi^2 (Cow_Dens), and percent of farm land in surrounding counties (percentfarm). The model was used for each park separately with the meteorological data and land use data as fixed variables and the water quality monitoring stations as the random variables.

$$FIB_{ij} = \beta_0 + \beta_1 RAINFALL_{ij} + \beta_2 TMAX_{ij} + \beta_3 COW\_DENS_{ij} + \beta_4 PERCENTFARM_{ij} + b_i + e_{ij}$$

In the model above, $FIB_{ij,}$ $Rainfall_{ij,}$ $TMAX_{ij,}$ Cow_Dens_{ij}, and $Percentfarm_{ij}$ represent the fecal bacteria levels, rainfall variables, maximum temperature, and land use variables during the time of the *j*-th water sample taken at the *i*-th water sampling station within each park. The rainfall variables included in the model are the same day rainfall, rainfall day prior to sample day, cumulative 3 day rainfall, cumulative 7 day rainfall and cumulative 10 day rainfall. The model is able to account for the relationship between the repeated measurements taken at a monitoring station over time. The model was run with only one of the rainfall variable included to reduce the multicollinearity effect (Table 4). Results of the linear mixed effect model can be found in Tables 5 -11.

Exceedance days were identified using the EPA's one day maximum FIB concentration for full body contact. These standards are separated by type of water and FIB. The freshwater standard for *E coli* of 235 per 100 ml was used for Chattahoochee River NRA, Chickasaw NRA, and Glen Canyon NRA. The marine water standard for enterococci of 104 per 100 ml was used for Gulf Islands NS (EPA, 1986). Since the EPA does not have standards for fecal coliform or total coliform levels, the standard used by the state of Florida for fecal coliform levels in marine waters of 400 per 100 ml was used to identify exceedance days for Biscayne NP and Gulf Islands NS (FDH, 2000). The exceedance day variable is structured as a dichotomous variable in order to apply logistic regression.

$$EXCEED_i = \beta_0 + \beta_1 RAINFALL_i + \beta_2 TMAX_i + \beta_3 COW\_DENS_{ij} + \beta_4 PERCENTFARM_{ij} + \beta_5\, YEAR_i + e_i$$

The logistic regression model includes rainfall variables, land use variables, and maximum temperature. Similarly, only one rainfall variable was included in the model per run to reduce multicolinearity issues. Results of the percentage of exceedance days by season can be found in Table 12.

III. Results

a. *E coli*

E coli was tested in three of the five park units used in this project. In all three of these parks, *E coli* mean levels were significantly higher in the presence of rainfall for each rainfall variable ($p < 0.001$). This suggests that rainfall can immediately impact *E coli* levels in recreational water and the impact can be sustained over time. The ANOVA test to investigate the relationship between *E coli* levels and season varied geographically by the park units examined. For CHAT, significantly higher mean values of *E coli* were found in the summer months, which correspond to higher rainfall during the summer months as well ($p < 0.001$). When comparing only two seasons at a time, statistical significance was found between every combination of seasons with highest means in summer and fall for *E coli* (Figure 2). The rainfall and season ANOVA test showed statistical significance between summer/fall, summer/winter, and summer/spring with the highest mean rainfall in the summer months. The increased rainfall in the summer season corresponds with the increased *E coli* levels.

No statistically significant seasonal variation was observed in CHIC (Figure 3). Conversely in GLCA, the highest mean levels of *E coli* were in the spring and lowest in the winter months (Figure 4). This is further confirmed when comparing only two seasons and *E coli* levels. More specifically, statistical significance was found in *E coli* mean levels between fall/winter, spring/winter, and summer/winter. The ANOVA test comparing seasonal variations and rainfall showed statistical significance between fall/spring, summer/winter, and summer/spring. The increased rainfall in the fall months does not correspond to the higher levels of *E coli* found in the spring. In CHAT, the strongest, positive Pearson's correlation coefficients were identified between *E coli*, same day rainfall, and 3 day cumulative rainfall (r = 0.40 and 0.38). In addition to same day and 3 day cumulative rainfall (r = 0.28 and 0.24), strong Pearson's correlation coefficients were observed in CHIC for day prior rainfall (r = 0.22), 7 day cumulative (r = 0.24), and 10 day cumulative rainfall (r = 0.29). Conversely, very weak correlations were observed in all rainfall variables in GLCA, possibly due to the large distance between the weather station and park.

The linear mixed effect model indicates a highly significant association between all rainfall variables and levels of *E coli* in all three park units. All beta coefficients were small, yet positive supporting the hypothesis of increased rainfall leads to higher *E coli* levels. Furthermore, we observed a significant association between maximum temperature and *E coli* levels. For CHAT and CHIC, the negative beta coefficient for maximum temperature indicates an inverse relationship with *E coli* levels. In combination, these results indicate that *E coli* levels in CHAT and CHIC are increased with lower temperatures. However in GLCA, a significant, positive association was found between maximum temperature and *E coli* levels. The contradictory findings suggest that the relationship between air temperature and *E coli* varies by geographic location and climatic trends.

Only in CHAT was a significant association between *E coli* the land use variables. The positive beta coefficient for the cattle density shows that the high density of cattle in Fulton and Cobb County, GA increases the FIB levels within the park unit ($p < 0.001$). Conversely, the negative relationship between percent of farmland and *E coli* levels indicates that urban areas contribute to increased *E coli* levels ($p < 0.05$). This negative association between *E coli* and percentage of farm land is also reflected in GLCA ($p <$ 0.001). CHIC followed similar trends as CHAT, but was not statistically significant for either land use variable.

b. Enterococci

Only one park unit tested for enterococci. In GUIS, the t-test revealed statistical significance in the mean levels of enterococci levels in the sampled recreational water and the presence/absence of rainfall windows (p= 0.25; p=0.003; p=0.003; p=0.02 respectively). These results indicate that rainfall can impact the levels of enterococci recreational waters. Furthermore, the one way ANOVA test for inter-seasonal variation of FIB levels did not show any statistical significant difference of mean enterococci levels (p = 0.447). The second ANOVA test comparing seasonal variations in rainfall showed statistical significance between fall and spring, with the higher mean in the fall (Figure 5). In GUIS, no statistically significant association between enterococci and any of the weather or land use variables was identified in the linear mixed effect model. Due to the short duration of sampling in GUIS, we were unable to test the land use variables because they remained constant during the sample period. However, Pearson's correlation coefficients reveal a positive relationship between enterococci levels and same day rainfall (r = 0.41), 7 day cumulative rainfall (r = 0.36), and 10 day cumulative rainfall (r = 0.33).

c. Fecal Coliform

GUIS and BISC were the only parks that measured fecal coliform levels. The state of Florida mandates that recreational waters must be tested for fecal coliform levels.

In BISC, the independent two sample t-tests used to test the mean values of fecal coliform levels in the groups representing the presence of rain in the last 1, 3, 7, and 10 days versus absence of rainfall in the same time windows showed no statistical significance (p=0.06; p=0.06; p=0.38; p=0.86 respectively). Similarly, no significance difference in mean fecal coliform levels was found in GUIS (p=0.29; p=0.47; p=0.31; p=0.25 respectively). In both park units, the ANOVA test for inter-seasonal variations of fecal coliform levels showed no significant difference in mean fecal coliform levels between seasons (Figure 1 and Figure 5). In relation to Pearson's correlation coefficients, positive correlations were observed in both BISC and GUIS between fecal coliform levels, same day rainfall (r = 0.23; r = 0.22), day prior rainfall (r = 0.30; r = 0.27), and 3 day cumulative rainfall (r = 0.29; r = 0.22).

The linear mixed effect model in GUIS identified a statistical significant association between fecal coliform levels, rainfall on the day of measurement, and cumulative rainfall 3 days prior to the sample day. Due to the short duration of sampling in GUIS, we were unable to test the land use variables because they remained constant during the sample period. In BISC, the liner mixed effect model results indicate that all rainfall windows significantly influenced the levels of fecal coliform. The positive, but small, beta coefficients indicate a positive correlation in which small amounts of rainfall can contribute to increases in fecal coliform levels. Maximum temperature did not show any significant relationship with the fecal coliform levels. Similarly, neither land use variable had statistical significance with the fecal coliform levels.

d. Total Coliform

Only CHAT measured total coliform levels and the results were very similar to the *E coli* results in CHAT (Figure 2). The results of the independent two sample t-tests to compare the mean value of total coliform levels when there was rainfall and no rainfall in 1, 3, 7, and 10 days prior to the sample day are statistically significant (p <0.001) in each of the time windows. Furthermore, the one way ANOVA test showed significant inter-seasonal variation for mean total coliform levels (p<0.001). Total coliform levels were highest in the summer months, followed by fall and lowest in the winter months. Only same day rainfall (r = 0.43) and 3 day cumulative rainfall (r = 0.42) showed a strong positive Pearson's correlation coefficient.

The linear mixed effect model revealed a highly significant association between total coliform levels and all rainfall variables (p < 0.001). As with *E coli* in CHAT, a significant negative association between maximum temperature and total coliform levels (p < 0.001) was observed.

e. Exceedance Days

Overall, the vast majority of exceedance days occurred during the summer months. In BISC, 0.62% of samples taken exceeded the Florida fecal coliform levels. No significance was found for any variables included in the logistic regression model. In CHAT, 22.7% of samples taken exceeded the EPA's *E coli* maximum one sample limit. The majority of exceedance days occurred in the summer and fall months, 31.5% and 25.5% respectively. Positive, significant associations were identified between exceedance days and same day rainfall (OR = 1.025; 95% CI 1.020-1.030; p < 0.001), 3 day cumulative rainfall (OR = 1.006; 95% CI 1.002-1.01; $p = 0.003$), and 10 day cumulative rainfall (OR = 1.003; 95% CI 1.002-1.004; $p < 0.001$). These odds ratios are not very strong, but significant never the less. Similarly, exceedance days in CHIC were identified in 22.6% of samples. The vast majority of exceedance days occurred in the summer months (76.1%). The logistic regression model indicates a positive, significant relationship between exceedance days and 10 day cumulative rainfall (OR = 1.007; 95% CI 1.003-1.010; $p = 0.0009$).

Conversely, in GLCA only 4.4% exceeded the EPA standard for freshwater *E coli* levels. Again, nearly 79% of exceedance days occurred during the summer months. The logistic regression model did not show any significance between exceedance days and any rainfall or weather variables. A positive, significant association was identified between cattle density and exceedance days (OR = 1.64; 95% CI 1.065-2.54; $p < 0.001$). Only 2.2% of fecal coliform samples taken in GUIS exceeded the Florida fecal coliform standard and 3.2% of enterococci samples taken exceeded the EPA's marine water enterococci standard. No significance was found in either fecal coliform or enterococci logistic regression models. The weak odds ratios combined with highly significant *p* values can be a result of the small number of water monitoring stations and a large number of repeated measures taken at these stations.

V. Discussion

The results of this study show that there is a clear link between rainfall and FIB levels in recreational water; however the lag time following the rainfall until the peak FIB concentrations varies and seems site specific. Every park unit, with the exception of GUIS, showed a very highly significant association between every rainfall variable and FIB levels. The largest beta coefficients were seen in the same day and day prior to sampling day rainfall totals indicating that significant rainfall can lead to an immediate rise in FIB levels, which can extend into the next day. The remaining rainfall variables (3 days, 7 days, and 10 days prior to sampling) still showed high significance, but a beta coefficient much smaller. In some cases, up to one order of magnitude smaller than the same day and 1 day rainfall variables. These results are in accordance with those found in previous studies (Kinzelman et al., 2004; Korajkic et al., 2011; Marion et al., 2010).

The other weather variables yielded interesting results in relation to FIB levels. In all but one of the statistically significant models, the FIB levels and maximum temperature of the sampling day had an inverse relationship. This indicates that the FIB levels were greatest in milder days, which support the findings from (Wilkes et al., 2009; Wilkes et al., 2011). However, the seasonal variation found in the ANOVA testing contradicts the relationships found in the linear mixed effects model. The relationship between air temperature FIB levels may be a result of the relationship between air temperature and water temperature. The cooler air temperature may not accurately reflect the water temperature, which may explain the inverse relationship observed and the seasonal ANOVA results.

The seasonal variations of both rainfall and FIB levels varied greatly within each park unit. BISC did not have any statistically different seasonal trends in FIB levels or rainfall amounts. This can be due to the subtropical environment in southern Florida in which very little variation of weather occurs. CHAT showed statistically significantly higher mean values for both rainfall and FIB levels during the summer months. The increased levels of both rainfall and FIB levels during the summer months correspond to findings from previous studies (Coulliette et al., 2009; Ursem et al., 2009). CHIC showed statistically significant increased rainfall in the fall months, but no seasonal variation in FIB levels. Conversely, GLCA experienced the highest rainfall in the fall months and highest FIB levels during the spring months. Lastly, GUIS had higher rainfall in the fall months as well, but no significant variation in FIB levels. These findings further support the relationship between FIB levels and rainfall, while also indicating specific seasonal trends in different geographical regions, water body size, and type of water. The null findings in GUIS can be due to the small sample size, while there were no water quality samples taken in CHIC during the winter months. This may be due to the colder weather in Oklahoma and the limited use of the recreational water areas. Winter and spring months showed little influence on the FIB levels possibly due to the lower rainfall and other climatic conditions.

Land use patterns also varied by each individual park unit, with much less significance found than the rainfall variables. The land use variables revealed an interesting relationship with FIB levels. In CHAT, a strong positive association was found in the cattle density and FIB levels, but an equally strong negative association with percent of farm land surrounding the park for both *E coli* and total coliform levels.

GLCA showed a strong negative association with percent farm land as well. All other park units did not show any statistical significance with the land use variables. Furthermore, we were unable to compare FIB levels and the land use variables in GUIS due to the short sampling duration and the land use variables remained constant during sampling. The results from CHAT indicate that high densities of cattle contribute to the FIB levels, but the FIB levels increase with urbanization as well. This dynamic relationship may be a result of the geographic location of the park unit near Atlanta, GA. The insignificant findings in many of the land use variables make it difficult to compare urban and rural parks.

The environmental factors leading to FIB levels to surpass federal and state standards greatly varied between parks. Overall, the majority of exceedance days occurred during the summer months. This may be explained by the increase in visitation and usage of the recreational water areas. The model showed that rainfall was associated with exceedance days in only CHAT and CHIC. Both parks showed a significant association between exceedance days and 10 day cumulative rainfall. Furthermore, same day rainfall and 3 day cumulative rainfall were also associated with exceedance days in CHAT. The only park that showed a positive, significant association with the cattle density was GLCA. No other land use variables were significant in any other park unit. The implications of these results can be beneficial to park managers to better predict environmental influences and seasonal trends in which high levels of FIB may be expected. Furthermore, park managers may increase water monitoring during the summer months, especially following heavy rain events, in order to identify potentially higher risks to visitor's health.

The strengths of this study include the geographical variation of the park units included in this study. These parks vary greatly in weather patterns, climate, land use, and other characteristics which add to the validity of the study. Furthermore, some park units have been monitoring the recreational water areas for long periods of time which provides a large sample size. Some limitations of the study stem from the secondary data analysis approach. The data provided in some cases was limited to only FIB and no other water quality measurements. Furthermore, we did not know the exact location of the monitoring sites within the park unit, in which we had to approximate the weather variables to all monitoring stations within the park. The weather stations chosen to represent the historical weather conditions in some cases were nearly 50 miles from the surface water within the park, while one weather station was within the park unit. Again, these stations were used because of the completeness of the data and the proximity to the park. Closer weather stations existed, but they were missing many years worth of data. Also, the weather data used only went up to 2008, in which all water quality data after 2008 was not included in the analysis. This created a small number of observations in BISC and GUIS park units. From information in previous studies, we only chose to focus on cattle density as the only animal contributor. We did not consider other wildlife such as water fowl or deer due to the unavailability of the specific data. The other land use variables proved to be difficult to estimate for BISC and GUIS park units. Being parks on islands, the contributions of FIB in the recreational areas may have come from a large number of sources. Therefore, the closest county estimates may not have been fully inclusive.

a. Conclusions

The clear, positive association between rainfall and FIB levels in recreational surface water is reinforced in the multiple analyses in this investigation. The consequences of these findings can be used to better anticipate high FIB levels and taking a proactive method to protecting the health of the National Park visitors. For example, if high amounts of rainfall are expected, information can be passed to the public in reference to the potential for increased FIB levels and increased risk of GI infections or other related health issues. Tracking confirmed cases of GI infections in National Park visitors can be extremely difficult for many reasons. The incubation period of GI infections can last a few days, and the visitors may have already left the park. The transient nature of the National Park visitors makes it difficult to successfully confirm cases of GI infections that may have occurred in the National Park. Therefore, it would be necessary to create a strong and protective effort to limit visitor's exposure to FIB levels during recreational activities.

Land use and animal contribution in the areas surrounding the park did not prove to be highly predictive of FIB levels in this investigation. Overall, the less agricultural land surrounding the park inferred a higher concentration of FIB in surface waters. This indicates that urban parks or urbanized areas may have higher levels of FIB for a variety of reasons such as storm water runoff or sewer overflows draining into the surface water. At this point, this relationship remains unclear and merits further investigation. The recent development of *bacteroidales* as species specific markers of the source of fecal pollution proves to be promising in conclusively identifying the specific animal or human source. This can potentially be used in the future to plan mitigation methods specific to the sources and geographical location. Furthermore, measuring caffeine as an indicator of human sourced fecal contamination has been explored. Although each individual park unit is subject to the environment in the surrounding area, this investigation can serve as a basis for further research into the impact of land use and potential fecal contributions from wildlife, domesticated animal and human sources.

Table 1: Description of Water Quality Measurements

			NUMBER OF OBSERVATIONS			
PARK	**# OF STATIONS**	**RANGE OF YEARS**	**ECOLI**	**ENTEROCOCCI**	**FECAL COLIFORM**	**TOTAL COLIFORM**
BISC	3	1996-2008			181	
CHAT	3	2000-2008	4,580			4,569
CHIC	4	2001-2008	884			
GLCA	139	1988-2008	14,805			
GUIS	5	2007-2008		655	218	

Table 2: Mean, Standard Deviation, and Median of FIB Levels in Each Park Unit

PARK	ECOLI			TOTAL COLIFORMS			ENTEROCOCCI			FECAL COLIFORM		
	MEAN	S.D.	MEDIAN	MEAN	S.D.	MEDIAN	MEAN	S.D.	MEDIAN	MEAN	S.D.	MEDIAN
BISC	-	-	-	-	-	-	-	-	-	18.58	60.7	10.0
CHAT	381.21	1,305.6	80.0	12,785.9	39,523.3	3,310.0	-	-	-	-	-	-
CHIC	233.55	344.8	131.7	-	-	-	-	-	-	-	-	-
GLCA	46.19	199.03	1.0	-	-	-	-	-	-	-	-	-
GUIS	-	-	-	-	-	-	13.53	47.5	2.0	43.57	81.9	12.0

Table 3: Pearson's Correlation Coefficients

Park	FIB	PRCP	PRCP1	PRCP3	PRCP7	PRCP 10	% FARM	RATIO	TMAX
BISC	F COLI	0.23	0.30	0.29	-0.006	-0.006	0.05	0.002	0.06
CHAT	E COLI	0.40	0.002	0.38	0.014	0.004	0.06	0.07	0.05
CHAT	T COLI	0.43	0.001	0.42	0.02	0.005	0.06	0.09	0.09
CHIC	E COLI	0.28	0.22	0.24	0.24	0.29	-0.11	-0.11	-0.1
GLCA	E COLI	-0.01	-0.01	-0.01	-0.001	-0.001	-0.12	0.13	0.001
GUIS	ENTER	0.41	0.06	0.17	0.36	0.33	-	-	0.04
GUIS	F COLI	0.22	0.27	0.22	0.09	0.09	-	-	0.29

Table 4: Correlation Matrix between Rainfall Variables

Pearson Correlation Coefficients ***P-value*** **Number of Observations**					
	PRCP	**Cumprcp1**	**Cumprcp3**	**Cumprcp7**	**Cumprcp10**
PRCP	1.00000 20147	0.87791 <.0001 20139	0.92964 <.0001 20147	0.74570 <.0001 20147	0.61788 <.0001 20147
Cumprcp1	0.87791 <.0001 20139	1.00000 20139	0.97289 <.0001 20139	0.84870 <.0001 20139	0.71715 <.0001 20139
Cumprcp3	0.92964 <.0001 20147	0.97289 <.0001 20139	1.00000 20147	0.88445 <.0001 20147	0.75326 <.0001 20147
Cumprcp7	0.74570 <.0001 20147	0.84870 <.0001 20139	0.88445 <.0001 20147	1.00000 20147	0.94957 <.0001 20147
Cumprcp10	0.61788 <.0001 20147	0.71715 <.0001 20139	0.75326 <.0001 20147	0.94957 <.0001 20147	1.00000 20147

PRCP = Same day precipitation
Cumprcp1= Cumulative rainfall 1 day prior to sampling
Cumprcp3= Cumulative rainfall 3 days prior to sampling
Cumprcp7= Cumulative rainfall 7 days prior to sampling
Cumprcp10= Cumulative rainfall 10 days prior to sampling

Table 5: Linear Mixed Effect Model Results - BISC Fecal Coliform

BISC – Fecal Coliform				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	0.7043	0.3376	0.2846
	Same Day Precipitation	0.001198	0.000318	0.0002
	Max. Temperature	0.001806	0.002127	0.3971
	Cattle Density	0.1193	0.1588	0.4537
	Percent Farmland	-0.6790	3.7408	0.8562
Model 2	Intercept	-0.4937	0.6411	0.5822
	1 Day Cumulative Precipitation	0.001522	0.000293	<.0001
	Max. Temperature	0.000538	0.002050	0.7935
	Cattle Density	-0.2051	0.2548	0.4222
	Percent Farmland	11.5172	6.6071	0.0833
Model 3	Intercept	0.5900	0.3256	0.3210
	3 Day Cumulative Precipitation	0.000789	0.000151	<.0001
	Max. Temperature	0.000691	0.002064	0.7382
	Cattle Density	0.1546	0.1533	0.3149
	Percent Farmland	1.0989	3.5781	0.7592
Model 4	Intercept	0.5630	0.3388	0.3449
	7 Day Cumulative Precipitation	0.000442	0.000117	0.0002
	Max. Temperature	0.001312	0.002135	0.5398
	Cattle Density	0.1668	0.1602	0.2994
	Percent Farmland	0.2524	3.7202	0.9460
Model 5	Intercept	0.6113	0.3435	0.3259
	10 Day Cumulative Precipitation	0.000292	0.000097	0.0031
	Max. Temperature	0.001206	0.002178	0.5806
	Cattle Density	0.1245	0.1617	0.4425
	Percent Farmland	0.8809	3.7735	0.8157

Table 6: Linear Mixed Effect Model Results – CHAT Total Coliform

CHAT – Total Coliform				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	2.2114	0.1407	0.0040
	Same Day Precipitation	0.006110	0.000170	<.0001
	Max. Temperature	0.01309	0.000596	<.0001
	Cattle Density	0.2007	0.01398	<.0001
	Percent Farmland	-10.7117	0.9156	<.0001
Model 2	Intercept	2.2051	0.1406	0.0040
	1 Day Cumulative Precipitation	0.005713	0.000183	<.0001
	Max. Temperature	0.01330	0.000615	<.0001
	Cattle Density	0.2048	0.01441	<.0001
	Percent Farmland	-11.0077	0.9444	<.0001
Model 3	Intercept	2.1835	0.1397	0.0041
	3 Day Cumulative Precipitation	0.002509	0.000067	<.0001
	Max. Temperature	0.01349	0.000590	<.0001
	Cattle Density	0.1968	0.01384	<.0001
	Percent Farmland	-10.6802	0.9063	<.0001
Model 4	Intercept	2.1120	0.1396	0.0043
	7 Day Cumulative Precipitation	0.001565	0.000040	<.0001
	Max. Temperature	0.01442	0.000582	<.0001
	Cattle Density	0.1846	0.01365	<.0001
	Percent Farmland	-10.3852	0.8930	<.0001
Model 5	Intercept	2.0802	0.1392	0.0045
	10 Day Cumulative Precipitation	0.001208	0.000032	<.0001
	Max. Temperature	0.01450	0.000592	<.0001
	Cattle Density	0.1805	0.01389	<.0001
	Percent Farmland	-9.9945	0.9080	<.0001

Table 7: Linear Mixed Effect Model Results – CHAT *E coli*

CHAT – *E coli*				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	1.3440	0.1372	0.0103
	Same Day Precipitation	0.006613	0.000164	<.0001
	Max. Temperature	0.003683	0.000573	<.0001
	Cattle Density	0.08277	0.01344	<.0001
	Percent Farmland	-2.9788	0.8812	0.0007
Model 2	Intercept	1.3382	0.1382	0.0105
	1 Day Cumulative Precipitation	0.006108	0.000178	<.0001
	Max. Temperature	0.003904	0.000598	<.0001
	Cattle Density	0.08726	0.01402	<.0001
	Percent Farmland	-3.2984	0.9191	0.0003
Model 3	Intercept	1.3149	0.1363	0.0106
	3 Day Cumulative Precipitation	0.002672	0.000065	<.0001
	Max. Temperature	0.004101	0.000570	<.0001
	Cattle Density	0.07906	0.01337	<.0001
	Percent Farmland	-2.9636	0.8758	0.0007
Model 4	Intercept	1.2428	0.1359	0.0117
	7 Day Cumulative Precipitation	0.001621	0.000039	<.0001
	Max. Temperature	0.005055	0.000568	<.0001
	Cattle Density	0.06717	0.01330	<.0001
	Percent Farmland	-2.6863	0.8706	0.0020
Model 5	Intercept	1.2122	0.1362	0.0124
	10 Day Cumulative Precipitation	0.001239	0.000032	<.0001
	Max. Temperature	0.005117	0.000581	<.0001
	Cattle Density	0.06353	0.01362	<.0001
	Percent Farmland	-2.3144	0.8908	0.0094

Table 8: Linear Mixed Effect Model Results – CHIC *E coli*

CHIC – *E coli*				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	-13.3959	9.3619	0.1863
	Same Day Precipitation	0.006463	0.000964	<.0001
	Max. Temperature	-0.00060	0.001544	0.6956
	Cattle Density	-0.03318	0.01403	0.0184
	Percent Farmland	24.1958	13.8357	0.0809
Model 2	Intercept	-13.9648	9.4531	0.1737
	1 Day Cumulative Precipitation	0.004098	0.000712	<.0001
	Max. Temperature	-0.00095	0.001557	0.5423
	Cattle Density	-0.03275	0.01417	0.0212
	Percent Farmland	24.9519	13.9707	0.0746
Model 3	Intercept	-13.8138	9.3858	0.1752
	3 Day Cumulative Precipitation	0.001764	0.000273	<.0001
	Max. Temperature	-0.00051	0.001553	0.7442
	Cattle Density	-0.03255	0.01407	0.0210
	Percent Farmland	24.6717	13.8712	0.0758
Model 4	Intercept	-14.2821	9.3909	0.1626
	7 Day Cumulative Precipitation	0.000577	0.000090	<.0001
	Max. Temperature	-0.00034	0.001560	0.8272
	Cattle Density	-0.03169	0.01408	0.0248
	Percent Farmland	25.1668	13.8789	0.0703
Model 5	Intercept	-14.5577	9.3079	0.1523
	10 Day Cumulative Precipitation	0.000428	0.000060	<.0001
	Max. Temperature	0.000120	0.001553	0.9384
	Cattle Density	-0.03127	0.01396	0.0255
	Percent Farmland	25.4061	13.7561	0.0653

Table 9: Linear Mixed Effect Model Results – GLCA *E coli*

GLCA – *E coli*				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	0.3403	0.1310	0.0096
	Same Day Precipitation	0.003363	0.000674	<.0001
	Max. Temperature	0.007675	0.000996	<.0001
	Cattle Density	0.3391	0.03796	<.0001
	Percent Farmland	-7.3398	0.2930	<.0001
Model 2	Intercept	0.3320	0.1309	0.0115
	1 Day Cumulative Precipitation	0.003776	0.000681	<.0001
	Max. Temperature	0.007797	0.000996	<.0001
	Cattle Density	0.3384	0.03795	<.0001
	Percent Farmland	-7.3553	0.2926	<.0001
Model 3	Intercept	0.3321	0.1310	0.0115
	3 Day Cumulative Precipitation	0.001272	0.000231	<.0001
	Max. Temperature	0.007808	0.000997	<.0001
	Cattle Density	0.3382	0.03795	<.0001
	Percent Farmland	-7.3638	0.2929	<.0001
Model 4	Intercept	0.3224	0.1310	0.0142
	7 Day Cumulative Precipitation	0.000614	0.000103	<.0001
	Max. Temperature	0.007927	0.000997	<.0001
	Cattle Density	0.3384	0.03794	<.0001
	Percent Farmland	-7.3908	0.2930	<.0001
Model 5	Intercept	0.3233	0.1310	0.0139
	10 Day Cumulative Precipitation	0.000431	0.000073	<.0001
	Max. Temperature	0.007897	0.000997	<.0001
	Cattle Density	0.3389	0.03794	<.0001
	Percent Farmland	-7.3893	0.2931	<.0001

Table 10: Linear Mixed Effect Model Results – GUIS Fecal Coliform

GUIS – Fecal Coliform				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	-0.4052	0.4597	.
	Same Day Precipitation	0.008269	0.003287	0.0137
	Max. Temperature	0.01843	0.005848	0.0022
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 2	Intercept	-0.5551	0.4629	.
	1 Day Cumulative Precipitation	0.004476	0.002347	0.0597
	Max. Temperature	0.02041	0.005853	0.0008
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 3	Intercept	-0.6680	0.4589	.
	3 Day Cumulative Precipitation	0.002765	0.001102	0.0139
	Max. Temperature	0.02123	0.005766	0.0004
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 4	Intercept	-0.6525	0.6137	.
	7 Day Cumulative Precipitation	0.000625	0.000373	0.0976
	Max. Temperature	0.02142	0.005882	0.0005
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 5	Intercept	-0.6646	0.4685	.
	10 Day Cumulative Precipitation	0.000639	0.000356	0.0759
	Max. Temperature	0.02136	0.005866	0.0005
	Cattle Density	0	.	.
	Percent Farmland	0	.	.

Table 11: Linear Mixed Effect Model Results – GUIS Enterococci

GUIS – Enterococci				
Model	**Predictor**	**Coefficient**	**Standard Error**	***p-value***
Model 1	Intercept	-0.03587	0.2785	0.9093
	Same Day Precipitation	0.003238	0.001635	0.0489
	Max. Temperature	0.005688	0.003028	0.0618
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 2	Intercept	-0.07328	0.2783	0.8169
	1 Day Cumulative Precipitation	0.001072	0.001372	0.4352
	Max. Temperature	0.006345	0.003037	0.0379
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 3	Intercept	-0.08496	0.2782	0.7889
	3 Day Cumulative Precipitation	0.000284	0.000544	0.6016
	Max. Temperature	0.006506	0.003027	0.0328
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 4	Intercept	-0.1399	0.2780	0.6648
	7 Day Cumulative Precipitation	0.000368	0.000176	0.0377
	Max. Temperature	0.006778	0.002988	0.0243
	Cattle Density	0	.	.
	Percent Farmland	0	.	.
Model 5	Intercept	-0.1270	0.2790	0.6937
	10 Day Cumulative Precipitation	0.000281	0.000165	0.0909
	Max. Temperature	0.006623	0.002998	0.0283
	Cattle Density	0	.	.
	Percent Farmland	0	.	.

Table 12: Exceedance Days by Season

Park	**# of Samples**	**% of Total Exceedance Days**	**% in Winter**	**% in Spring**	**% in Summer**	**% in Fall**
BISC**	1	0.62	0.0	0.0	100.0	0.0
CHAT*	927	22.7	23.3	19.7	31.5	25.5
CHIC*	138	22.6	0.0	17.4	76.1	6.5
GLCA*	569	4.4	0.0	8.3	79.0	12.8
GUIS**	2	2.2	0.0	0.0	50.0	50.0
GUIS ***	7	3.2	0.0	28.6	28.6	42.9

*= EPA Maximum, one sample limit for freshwater *E coli* – 235 per 100 ml
** = State of Florida fecal coliform standard – 400 per 100 ml
*** = EPA Maximum, one sample limit for marine enterococci – 104 per 100 ml

Figure 1: BISC Average Rainfall and Fecal Coliform Levels by Season

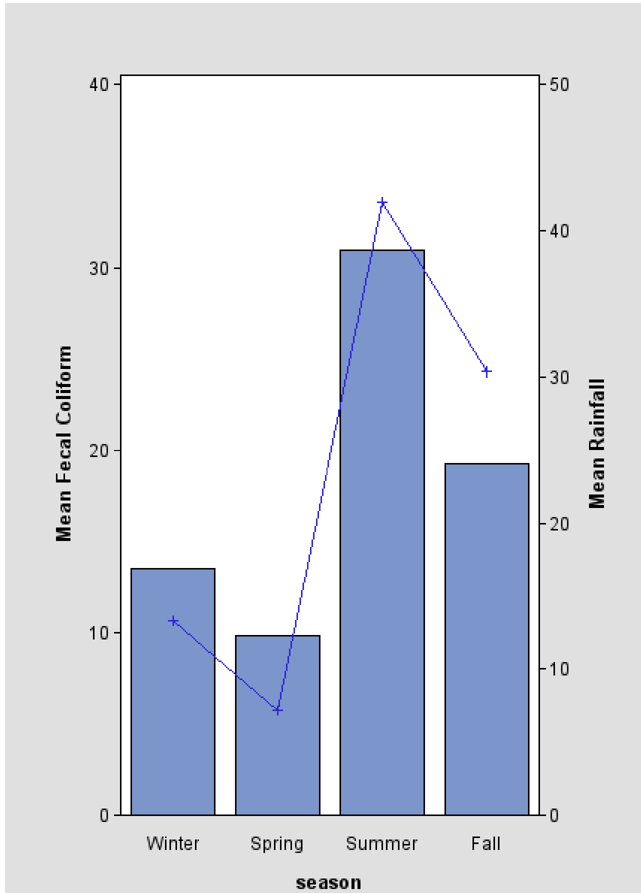


Figure 2: CHAT Average Rainfall, *E coli*, and Total Coliform Levels by Season

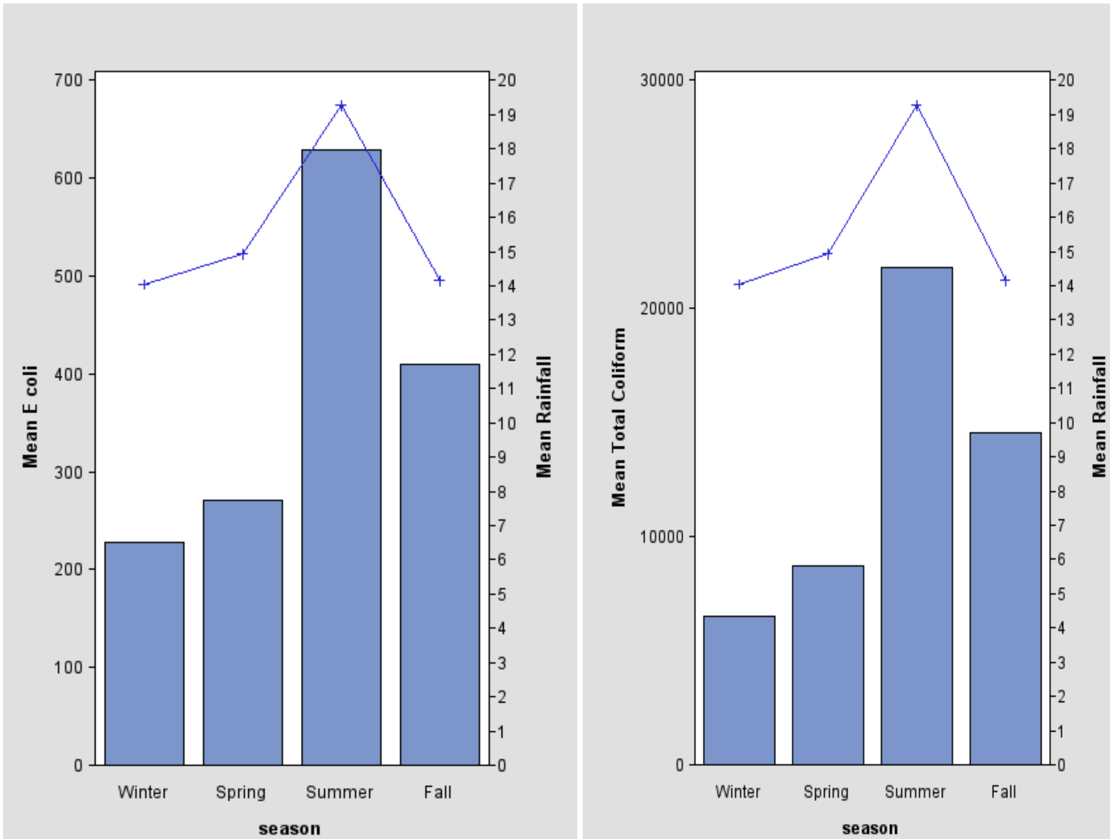


Figure 3: CHIC Average Rainfall and *E coli* Levels by Season

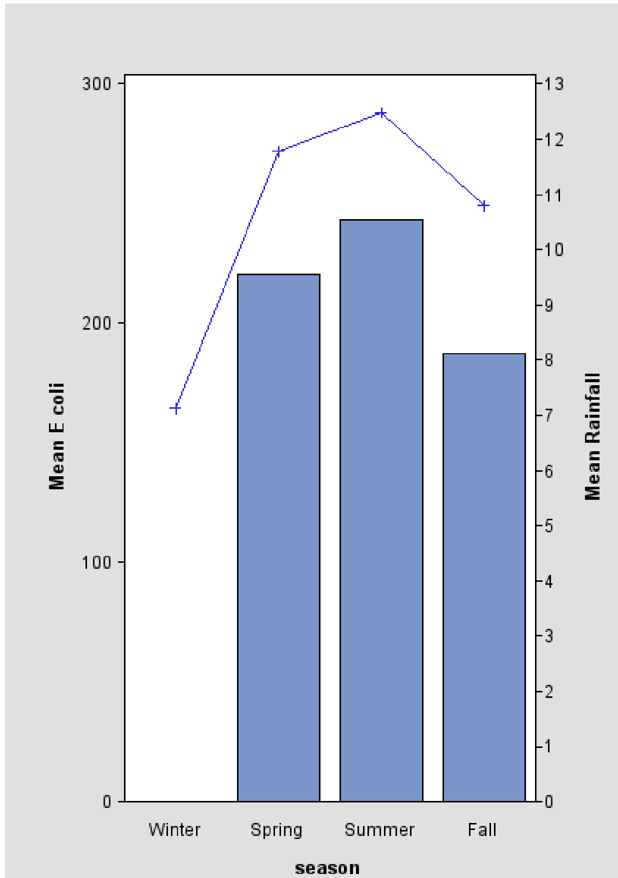


Figure 4: GLCA Average Rainfall and *E coli* Levels by Season

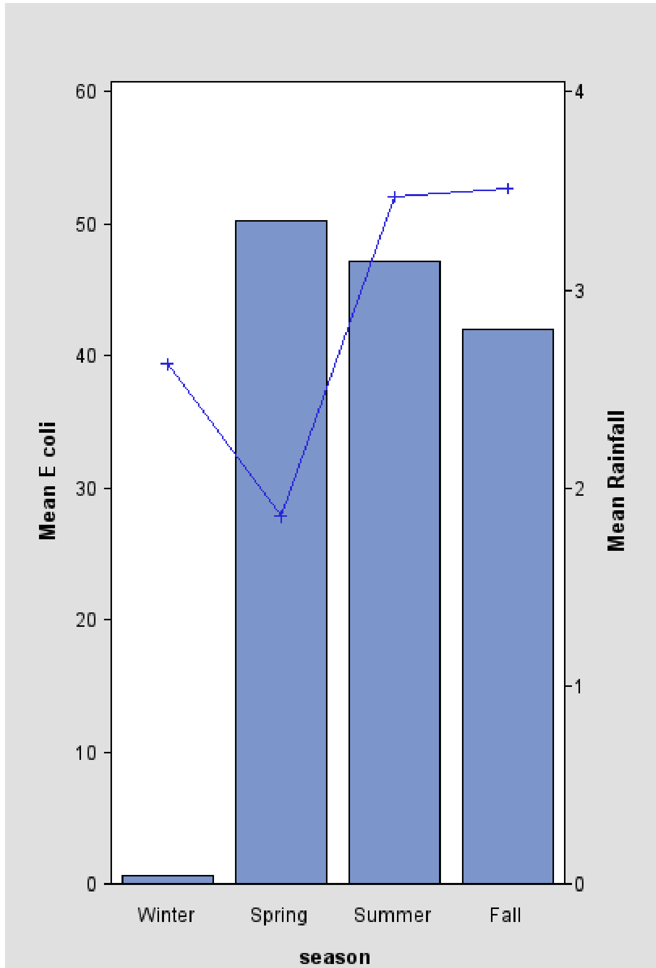
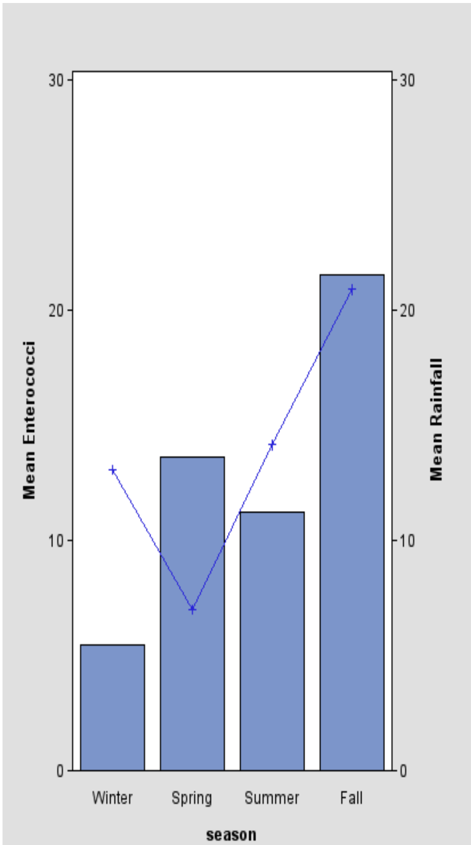
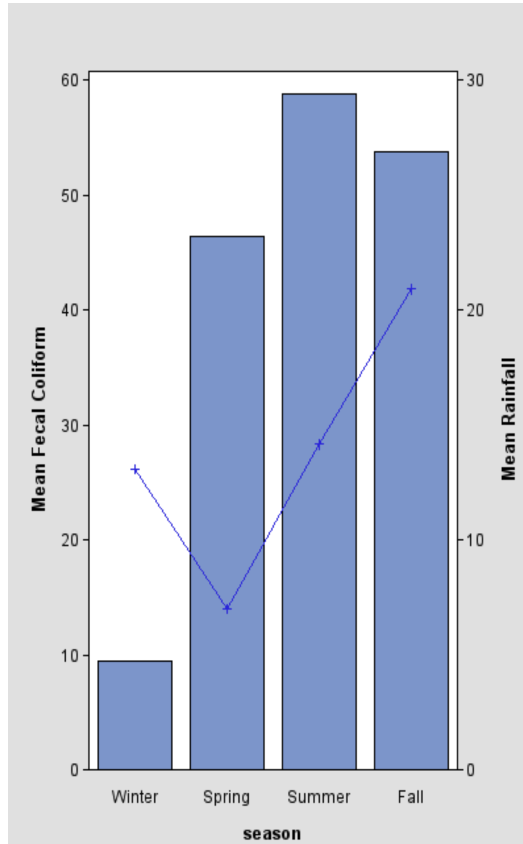


Figure 5: GUIS Average Rainfall, Enterococci, and Fecal Coliform Levels by Season





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