# Rainfall Effects on *E. Coli* Concentrations

# at Chicago Beaches

BY

Jordan Hepler
BS, Bowling Green State University, 2010

THESIS

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Defense Committee:

Samuel Dorevitch, MD, Chair and Advisor
Rachael Jones, PhD
Peter Scheff, PhD

## TABLE OF CONTENTS

**TABLE OF CONTENTS (continued)**

## LIST OF TABLES

## LIST OF TABLES (continued)

## LIST OF TABLES (continued)

## LIST OF FIGURES

## LIST OF ABBREVIATIONS

| | |
|---|---|
| CFU | Colony Forming Units |
| CPD | Chicago Park District |
| *E. coli* | *Escherichia Coli* |
| EPA | Environmental Protection Agency |
| K-S | Kolmogrov-Smirnov |
| OR | Odds Ratio |

## SUMMARY

Chicago has 24 beaches used for recreational swimming from May to September. Beaches are monitored daily for *E. coli* using the Colilert IDEXX culture method. The 24-hour interval between sampling and obtaining results for the Colilert method presents a significant limitation in the utility of the monitoring for protecting the public's health. Precipitation has been shown to elevate microbial concentrations in recreational swimming waters. The goal of this research is to predict the need for beach notification (swim bans or beach advisories) using prior-day *Escherichia coli* (*E. coli*) concentration (measured by culture) and precipitation information.

Beach monitoring data have been provided by the Chicago Park District (CPD) and precipitation data obtained from the National Climatic Data Center. Eight logistic regression models were used to measure the association between precipitation and beach notifications. Precipitation variables consisted of cumulative rain over 12 and 24 periods, and the presence of wet conditions defined by greater than or equal to 5 mm of precipitation over 12 and 24 hour periods. The prior day's culture results were also considered with the presence of wet or dry conditions to predict a swim advisory or closure.

During the time interval of 2003 to 2011 there were a total of 12,806 monitoring observations used to guide decision making. Presence of wet conditions was associated with elevated concentrations at 11 of 21 locations. After considering the previous day's culture results with the presence of rain, this association grew stronger. Not all Chicago beaches are affected uniformly by precipitation. Prior day culture results and precipitation information can be used to issue a beach notification without additional testing.

# I. INTRODUCTION

## A. **Background**

Chicago has 24 beaches that are used for recreational swimming from late May to early September. Traditionally the water quality of these beaches has been monitored for *Escherichia coli* (*E. coli*) using the Colilert™ culture method. This method has a 24-hour interval between sample collection and culture result. Most importantly, from a public health perspective, the time-lag may allow the beach to remain open even when the concentration is above Chicago's threshold value of *E. coli* (1000 MPN/100 mL) that triggers swim bans. Alternatively, the time-lag may result in a swim ban for the next day, when the *E. coli* concentration is actually below the standard. This problem could be reduced if more rapid methods for the analysis of indicator bacteria concentrations, such as quantitative polymerase chain reaction, were available. More rapid methods would allow a beach manager to issue an advisory or swim ban just several hours after the water sample was taken.

Statistical models, however, can predict water quality in the absence of frequent water quality measurements. Such models include a number of factors that affect the magnitude and variability of bacterial concentrations, including: rainfall, sunlight, tide, waves, wind, temperature of water, and biological bacterial sources (Boehm et al., 2008). Beginning in May 2012, the Chicago Park District (CPD) will use "real-time" models of *E. coli* to issue beach advisories. These models can provide beach managers an accurate and cost-effective solution for determining beach water quality rapidly and efficiently (Nevers et al., 2010)

In this study rainfall will be explored as the main predictor of *E. coli* concentrations at Chicago Lake Michigan beaches. Rainfall has been found repeatedly to be the most important factor that is positively associated with increased bacterial concentrations in recreational beach waters (Ackerman et al., 2003; Olyphant et al., 2004; Kleinheinz et al., 2009). Qualitative rainfall information (such as the presence or absence of a thunderstorm), and quantitative information (cumulative rain) is available immediately and can be utilized to trigger health warnings. For example, if a beach is open and a significant rain event occurs, a health warning or swim ban could be issued without water quality testing.

## B. Study Objectives

- Explore the relationship between rainfall and *E. coli* concentrations at Chicago beaches. This could potentially identify Chicago beaches that are at risk of elevated microbial concentrations due to rainfall.
- Develop a predictive model for determining the need for beach advisories and closures using (1) rainfall information and (2) the status of the beach the previous day (open versus swim advisory versus swim ban).

## II. LITERATURE REVIEW

### A. <u>Public Health and Water Quality at Beaches: Rationale for a Regulatory Framework</u>

Water-based recreation can expose individuals to a variety of pathogenic microorganisms. These waterborne pathogens are capable of causing illness, though the likelihood of illness depends upon the dose received and physical condition of the person exposed. During the late 1940s and early 1950s the United States Public Health Service (USPHS) conducted an epidemiologic study at several US beaches and found that swimmers were at significant health risk relative to non-swimmers, regardless of the levels of bacteria found in the water (Stevenson, 1953). This study, however, did not result in the promulgation of water quality criteria.

Studies initiated in 1972 by the United States Environmental Protection Agency at marine and fresh water bathing beaches affirmed that sewage-contaminated waters pose a health risk for bathers, and found that *E. coli* and *Enterococci* concentrations were most strongly correlated with swimming-associated health effects (Pearson $\rho$=.80 and $\rho$=.74, respectively). Based on these studies, EPA published criteria for bathing recreational waters in 1986 (EPA 1986). For freshwater, the EPA criteria is based on a statistically sufficient number of samples and the geometric mean for bacterial densities should not exceed 126 CFU per 100 ml for *E. coli* or 33 CFU per 100 ml for *Enterococci*. The criteria also said that no sample should exceed a one-sided confidence limit based on the frequency of use per location. For example, a designated bathing beach should follow a 75% C.L. and for a beach with infrequent use a 95% C.L. should be followed (EPA 1986).

## B. **Rainfall Effects on Beach Water Quality**

There are two mechanisms that enable rainfall to impact recreational water quality. The first occurs when there is enough rainfall to cause an overflow of combined storm water/sewer systems—excess flow that cannot be treated is then bypassed to receiving waters. The second mechanism is land-based flow that is directed to a body of water. Storm water from land-based flow can be contaminated with fecal indicator bacteria from environmental reservoirs, animals, or leaking sewage (Boehm et al. 2008).

A study published in 2003 by Ackerman and Weisberg explored the relationship between rainfall and beach bacterial concentrations at Santa Monica Bay beaches by using hourly rain data and beach bacterial data from 1995 through 2000. The relationship between rainfall volume and beach bacterial concentrations was evaluated by calculating the percentage of beaches that exceeded water quality standards as a function of rainfall amount. In order to assess the effects of a rainfall event, events were categorized by rainfall volume and days since the rain event. The researchers concluded that storms producing 6 mm or more of rainfall consistently degraded water quality enough to justify the issuance of public health warnings.

Moving from coastal waters to inland lakes, Sampson et al. (2006) assessed rainfall effects on *E. coli* levels at 15 Lake Superior beaches. During 2003 and 2004, water samples were collected from the 15 beaches within 24-hours after a rainfall of at least 6 mm. The researchers were not able to detect a significant relationship between rainfall amount and bacterial concentrations. They attributed these results to the fact that the beaches were located in a rural setting as opposed to an urban setting.

In urban areas, runoff from yards, sewage overflows, and sewage discharges during the rain events may increase the total number of microbes at the beach. Rural areas have an increased natural buffer capacity due to increased green spaces, intact wetlands, and buffer areas along riparian areas. These conditions may not be present in urban areas that possess complex storm water conveyance systems. Kleinheinz et al. (2009) studied this relationship at eight beaches located in Door County, Wisconsin. Similar to the Sampson et al. study previously mentioned, water samples were collected from beaches after rainfall events of 5 mm occurred during the previous 24-hour period. In addition to beach water samples, storm water samples were taken from outfall pipes that were adjacent to beaches that were sampled. Results indicated that six of the eight study locations showed significant impacts on the beach water *E. coli* concentrations as a result of rain events greater than 5 mm within a 24-hour period. They also found that the significance and duration of rainfall impacts to be variable between study locations.

The Sampson et al. and Kleinheinz et al. studies both suggested that each beach should be examined on its own regard with respect to rain impacts on *E. coli* concentrations in beach water. This is due to differences in E. coli source and drainage characteristics of different beaches. Chicago beaches are primarily affected by land-based flow. There are storm water outfalls spread throughout the Chicago lakeshore that drain very local drainage basins. However the majority of storm water is directed into the combined sewer system and later treated at a wastewater facility.

## III. METHODS

### A. **Study Approach**

The objectives of this study were to (1) explore the relationship between rainfall and *E. coli* concentrations at Chicago beaches and to (2) develop a predictive model to determine swim advisories and swim bans based on precipitation data and prior day beach water quality status. To accomplish the study's first objective, *E. coli* concentrations will be compared during wet and dry conditions. I hypothesize that *E. coli* concentrations at beaches will be higher during wet conditions versus dry conditions. The second objective will be met by generating several logistic regression models to produce the odds of a swim advisory or swim ban of occurring based on precipitation during 12- and 24-hour periods and the previous day beach water quality status (open, swim advisory, swim ban). Models including the status of swimming for the previous day will also be utilized in order to explore whether or not it has an effect on the next day's swimming status combined with cumulative precipitation variables. I hypothesize that rainfall affected beaches will reveal increased odds of a swim advisory or swim ban occurring.

### B. **Study Setting**

There are 20 monitoring locations that Chicago beaches along the Lake Michigan shoreline. Figure 1 indicates the monitoring locations.

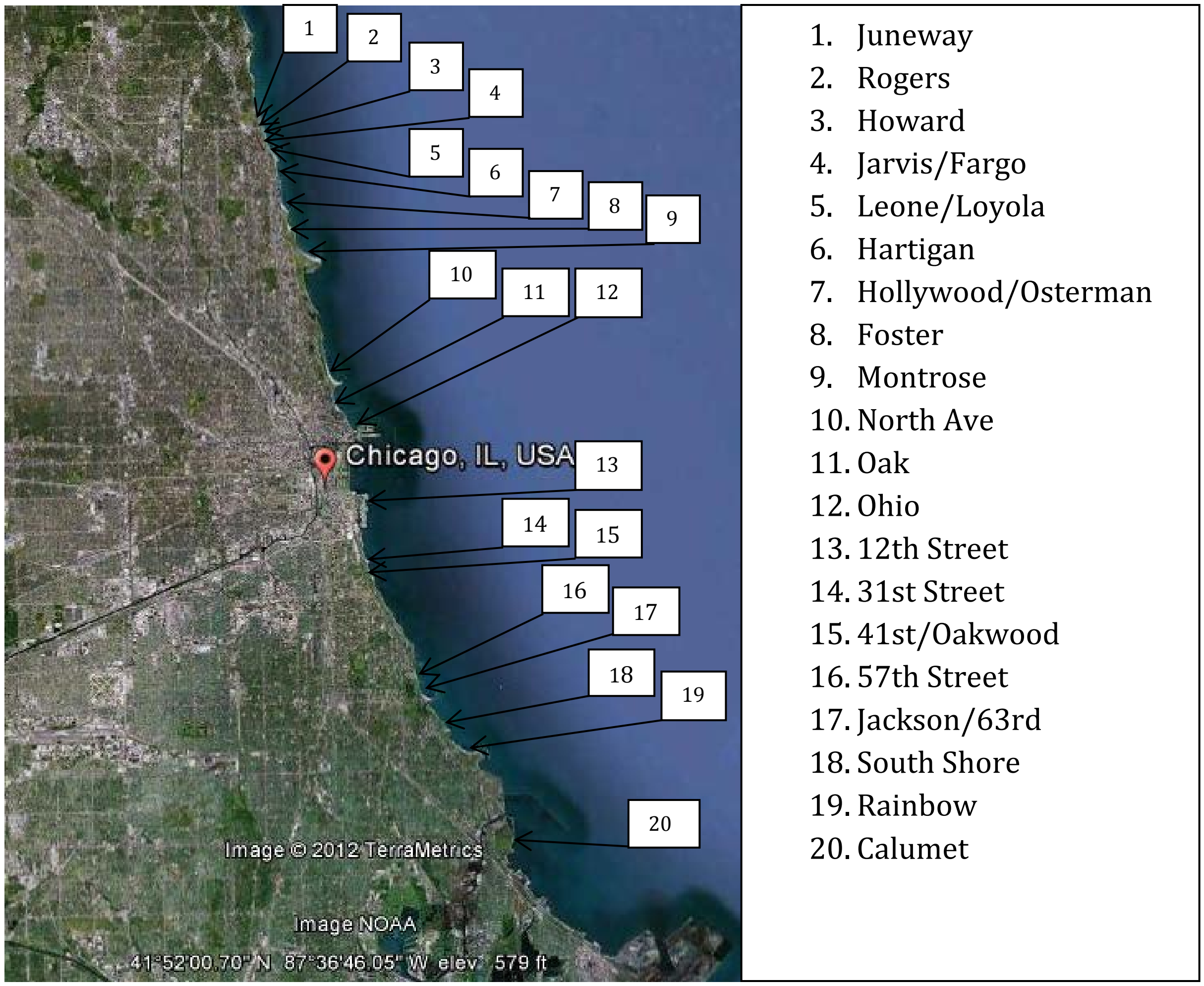


Figure 1. Map of 20 monitoring locations.

There are storm water outfalls located along Chicago's shoreline. These outfalls often drain adjacent parks and portions of Lake Shore Drive. During rain events, outfalls are considered point sources for storm water pollution and surface runoff as a non-point source. An example of one study location, Calumet, and its catchment area is shown in figures 2 and 3.


Figure 2. The map above is of Calumet Park beach and it displays three color-coded catchment areas. There are two color-coded dots that represent storm outfalls. The map was provided by the Chicago Park District.

Figure 3.  Southern outfall at Calumet Park Beach.

C. ***Escherichia coli*** **Monitoring Data**

*Escherichia coli* density data were provided by the CPD for 20 monitoring locations (Figure 1) during 2003–2011. Data were collected as specified in the EPA's 2000 (BEACH Act).

The CPD monitors a total of 21 locations representing 26 beaches along the Lake Michigan and Chicago shoreline. For the purpose of this research the CPD provided *E. Coli* monitoring data for beaches during the years 2003 to 2011.

Briefly, during the regular swim season, (late May to early September) water samples for *E. coli* analysis were collected during the weekdays, and on weekend days when further monitoring was warranted by elevated *E. coli* densities during the week. Beaches were typically sampled between 6:00 a.m. and 12:00 p.m. Sampling time was not recorded for the majority of samples. A common sampling time of 9:00 a.m. was applied to all samples and this reflects the average of sample times that were recorded.

*Escherichia coli* concentrations were enumerated by culture methods, resulting in units of colony forming units (CFU) per 100 mL of sample for 2003–2004 and most probable number (MPN) per 100 mL of sample for 2005–2011. The Colilert® method was used to calculate MPN/100 mL of undiluted sample and has a limit of detection of 0 to greater than 2419.6 MPN/100 mL. All monitoring results equaling 0 MPN/100 mL were replaced by 1 in order to permit $\log_{10}$ transformation; results equaling greater than 2419.6 MPN/100 mL were replaced by 2420.

Not every beach was monitored throughout the study period. For example, Leone and Loyola beaches were sampled separately in the beginning, but are now represented by a single sample since they are very close to each other. Since two beaches are represented by a single sample, the two beaches are referred to as the Leone/Loyola monitoring location. Similarly, monitoring efforts at Jarvis and Fargo beaches were combined due to close proximity.

## D. **Precipitation Data**

Hourly precipitation data were obtained from the Chicago Midway International Airport weather station through the NCDC. Data from this weather station were used because, of the Chicago weather stations provided by the NCDC, Chicago Midway International Airport was closest to the shoreline and therefore the beaches. The precipitation detection limit at this station is 0.254 mm (0.01”) per hour. All lagged precipitation variables are referenced to 9:00 a.m., to coincide with the average sampling time.

## E. **Statistical Methods**

Data were managed and analyzed with SAS 9.2® and Microsoft Excel®. The *E. coli* monitoring data and precipitation data were merged together by date. The first statistical step was to determine the distribution of the *E. coli* data. The *E. coli* data’s hypothesized log-normal distribution was tested using the Kolmogrov-Smirnov (K-S) goodness of fit test. The assumptions for the K-S test are that the sample is a random sample and the hypothesized distribution is continuous.

To identify beaches that are affected by rainfall, I defined wet or dry conditions for each sample collected and tested the difference in the median *E. coli* densities for wet versus dry conditions at each location. Each monitoring location was analyzed separately using wet and dry conditions. A dry condition was defined by precipitation less than 2.5 mm per 12 hours prior to sample collection and a wet condition greater than or equal to 2.5 mm per 12 hours prior to sample collection. This definition was selected because the 2009 Kleinheinz et al. study observed a change in microbial water quality immediately to 12 hours. The definition for a wet condition in Kleinheinz’s study was a rain event of 5 mm for a 24-hour period.

The second objective of the study was to develop a predictive model for swim advisories and swim bans. At first, simple linear regression was explored for the predictive modeling but since the distribution of both the *E. coli* and $\log_{10}$ transformed *E. coli* concentrations were non-normal, logistic regression was utilized. Logistic regression does not have a distribution assumption. The odds of either a swim advisory or swim ban occurring will be used to generate a predictive model. There were a total of eight different logistic regression models completed for each monitoring location. We considered two cumulative precipitation variables, $P_{12}$ (12-hour cumulative precipitation) and $P_{24}$ (24-hour cumulative precipitation) to predict the event, swim advisory or swim ban (Equation 1). Then, in the next model, we utilized a threshold of 5 mm of precipitation during the 12 and 24 hours prior to sampling and the results of the previous day's *E. coli* monitoring (Equation 2).

Equation 1. $$\ln\left[\frac{\text{p(event)}}{\text{1-p(event)}}\right] = \beta_0 + \beta_1(\text{Cumulative precipitation variable})$$

Equation 2. $$\ln\left[\frac{\text{p(event)}}{\text{1-p(event)}}\right] = \beta_0 + \beta_1(\text{Wet versus Dry variable}) + \beta_2(\text{Previous day swim advisory status}) + \beta_3(\text{Previous day swim ban status})$$

Similar to equation 1, equation 2 separately predicts the log odds of a swim advisory or a swim ban occurring. However equation 2 utilizes a dichotomous precipitation variable. We considered two dichotomous precipitation variables that define wet or dry conditions bound on rainfall in 12 and 24 hours prior to sample collection, respectively. Equation 2 also differs from Equation 1 by including two dichotomous variables representing the swimming status of the previous day. If the previous day's sample resulted in a swim advisory then a "1" was given for previous day swim advisory, if the swim advisory did not occur then a "0" was assigned and similarly for previous day swim ban status.

## IV. RESULTS

### A. **<u>Distribution of *Escherichia coli* Concentrations</u>**

The histogram in Figure 4 displays a normal distribution for $\log_{10}$ transformed *E. coli* concentrations. However after completing the K-S Test of Normality, the $\log_{10}$ transformed values were significantly non-normal, with a p less than .01. While the D statistic was reduced from 0.3240 to 0.0279 after completing the $\log_{10}$ transformation, but since 0.0279 is greater than the critical test statistic for n=13,924, the distribution was determined to be non-normal.

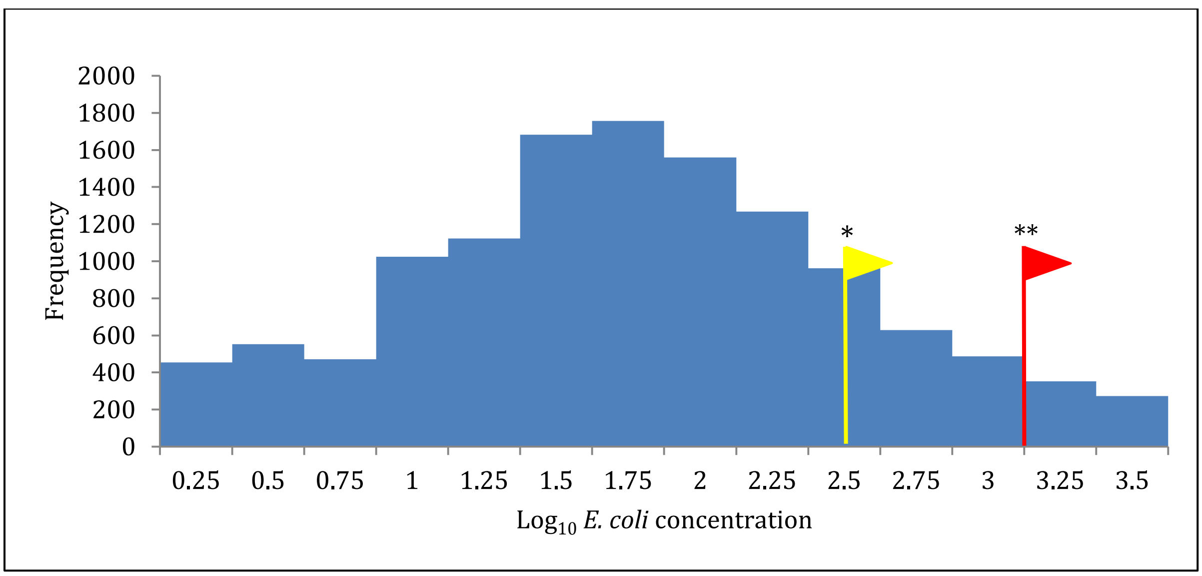


Figure 4. Histogram of *E. coli* concentrations for 20 monitoring locations in 2003–2011.

*Yellow flag is equivalent to the swim advisory threshold of 235 CFU/100 mL.
**Red flag is equivalent to swim ban threshold of 1000 CFU/100 mL.

## B. **Comparison of *Escherichia Coli* Concentrations during Dry and Wet Conditions**

The null hypothesis that the medians are equal was rejected at 10 of 20 locations (Table I). The alternative hypothesis that the population medians are not equal during wet or dry conditions is accepted for the following locations: 31st Street, Calumet, Hollywood/Osterman, Humboldt, Jackson/63rd, Montrose Ave, North Ave, Oak, Ohio, Rainbow, and South Shore.

**TABLE I**

SUMMARY OF *E. COLI* RESULTS FOR BEACHES DURING WET AND DRY CONDITIONS

| Location | Dry Conditions | | | Wet Conditions | | | Kruskal-Wallis Test |
|---|---|---|---|---|---|---|---|
| | n | Geometric mean (CFU/100mL) | Central 95% Range (CFU/100mL) | n | Geometric mean (CFU/100mL) | Central 95% Range (CFU/100mL) | p-value |
| 12th | 616 | 45 | 2–1250 | 63 | 60 | 2–2308 | 0.0975 |
| 31st | 624 | 69 | 2–2054 | 62 | 107 | 5–2418 | 0.0298 |
| 41st/Oakwood | 196 | 23 | 1–387 | 29 | 29 | 1–1062 | 0.8047 |
| 57th | 616 | 54 | 2–1724 | 62 | 81 | 3–2320 | 0.0757 |
| Calumet | 617 | 59 | 2–1891 | 64 | 120 | 4–3500 | 0.0016 |
| Foster | 610 | 43 | 1–1343 | 60 | 60 | 2–2263 | 0.0585 |
| Hartigan | 128 | 22 | 1–525 | 16 | 13 | 0–1043 | 0.4611 |
| Hollywood/Osterman | 611 | 45 | 2–1275 | 61 | 76 | 3–1963 | 0.0056 |
| Howard | 606 | 25 | 1–788 | 60 | 32 | 1–980 | 0.2796 |
| Jackson/63rd | 625 | 102 | 3–3222 | 67 | 295 | 17–5162 | <0.0001 |
| Jarvis/Fargo | 607 | 26 | 1–796 | 61 | 40 | 2–1010 | 0.0336 |
| Juneway | 606 | 26 | 1–825 | 60 | 32 | 1–1188 | 0.3173 |
| Leone/Loyola | 613 | 32 | 1–924 | 60 | 43 | 1–1218 | 0.1639 |
| Montrose | 613 | 72 | 3–1803 | 63 | 170 | 7–3985 | <0.0001 |
| North Ave | 612 | 34 | 1–843 | 62 | 60 | 3–1118 | 0.001 |
| Oak | 610 | 32 | 1–790 | 60 | 58 | 4–844 | 0.0045 |
| Ohio | 606 | 32 | 1–757 | 61 | 65 | 2–1917 | 0.0004 |
| Rainbow | 619 | 71 | 3–1869 | 64 | 148 | 5–4306 | 0.0001 |
| Rogers | 609 | 28 | 1–818 | 59 | 36 | 1–1057 | 0.2336 |
| South Shore | 616 | 65 | 2–1738 | 65 | 123 | 6–2373 | 0.0082 |

The relationship between wet conditions and densities of *E. coli* varied among the 20 monitoring locations in the study. Table I demonstrates that 85% of the study locations appeared to have elevated concentrations during wet conditions while 15% of the locations appeared to have higher concentrations during dry conditions. More importantly, 50% of the locations had statistically significant higher concentrations during wet conditions while the other 50% of the locations displayed no significant difference in concentrations during wet and dry conditions when $\alpha$=.05.

### C. <u>**Geographical Relationship between Rainfall and *Escherichica coli* Concentrations**</u>

Dividing the beaches into North and South groups using the Chicago River as the dividing line (between Oak St. and 12th St.) reveals that the Southern locations experienced larger increases in concentrations during wet conditions when only considering the statistically significant locations (Figure 5). For example, the maximum *E. coli* concentration at a south side beach increased by nearly 240 MPN/100 mL when the conditions were wet. The north grouping includes Hollywood/Osterman, North Ave, Montrose Ave, Oak St, and Ohio St Beaches while the south group contains $31^{st}$, Jackson/$63^{rd}$, South Shore, Rainbow, and Calumet Park Beaches. Due to Humboldt Park's unique property of being an inland pond it was excluded from this comparison.

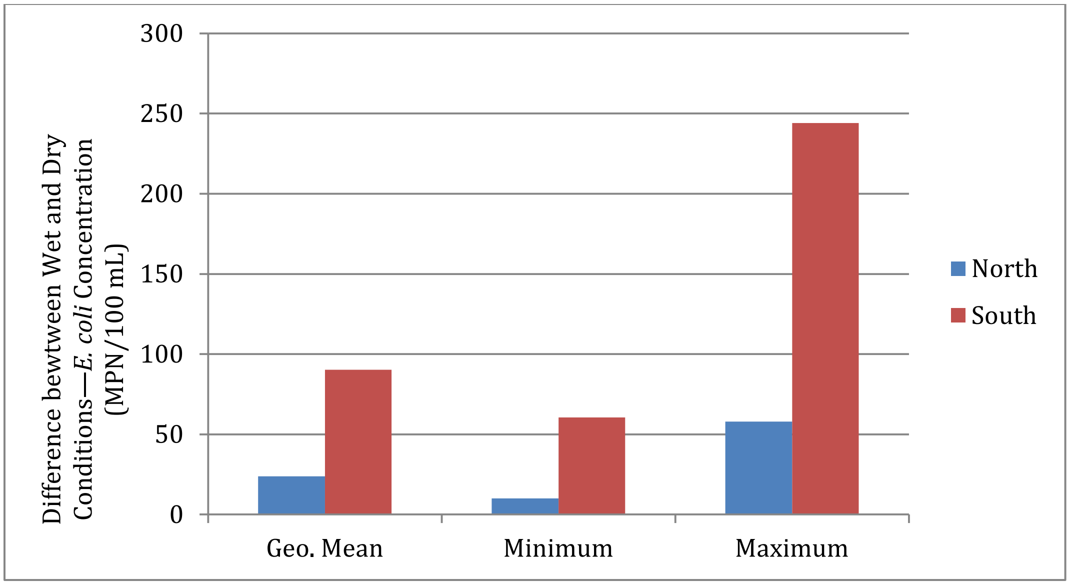


Figure 5. Difference in geometric mean, minimum, and maximum *E. coli* concentrations during wet and dry conditions and between north side and south side beaches.

## D. **Beach Action in Relation to Rain as a Continuous Variable**

### 1. **Logistic regression with cumulative amount of precipitation (in mm) as the predictor for the odds ratio of swim advisories or swim bans occurring**

Twelve-hour cumulative precipitation is associated with an increase in the odds ratio (OR) of a swim advisory at seven of 20 locations with 95% statistical significance (Table II). The ORs are small, but significant at the seven locations and should be interpreted as a percent increase in the OR per mm of precipitation during the 12-hour period prior to sample collection. Twenty-four hour cumulative precipitation is associated with an increase in the OR of a swim advisory at 9 of 20 locations with 95% statistical significance (Table II). Since 24-hour cumulative precipitation was used to produce the

ORs, they can be interpreted as percent increase in the OR of a swim advisory occurring per mm of precipitation during the 24-hour period prior to sample collection.

**TABLE II**

ODDS RATIOS FOR A SWIM ADVISORY OCCURRING PER MM OF RAIN DURING 12-HR AND 24-HR PERIODS PRIOR TO THE APPROXIMATE SAMPLING

| Location | 12-Hour Cumulative Precipitation | | 24-Hour Cumulative Precipitation | |
|---|---|---|---|---|
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12th | 1.025 | 0.996–1.056 | 1.017 | 0.994–1.039 |
| 31st | 1.031 | 1.003–1.060 | 1.015 | 0.995–1.036 |
| 41st/Oakwood | 1.011 | 0.985–1.039 | 1.007 | 0.984–1.031 |
| 57th | 1.023 | 0.994–1.053 | 1.004 | 0.982–1.028 |
| Calumet | 1.034 | 1.006–1.064 | 1.021 | 1.000–1.041 |
| Foster | 1.029 | 0.999–1.059 | 1.025 | 1.004–1.047 |
| Hartigan | 0.990 | 0.910–1.078 | 0.993 | 0.928–1.062 |
| Hollywood/Osterman | 1.029 | 1.000–1.060 | 1.027 | 1.006–1.049 |
| Howard | 1.027 | 0.995–1.060 | 1.026 | 1.002–1.050 |
| Jackson/63rd | 1.056 | 1.023–1.089 | 1.048 | 1.026–1.070 |
| Jarvis/Fargo | 1.018 | 0.985–1.052 | 1.026 | 1.004–1.049 |
| Juneway | 1.023 | 0.990–1.057 | 1.018 | 0.993–1.043 |
| Leone/Loyola | 1.018 | 0.986–1.052 | 1.023 | 1.001–1.046 |
| Montrose | 1.049 | 1.018–1.081 | 1.036 | 1.015–1.057 |
| North Ave | 1.018 | 0.984–1.052 | 1.018 | 0.993–1.042 |
| Oak | 0.998 | 0.955–1.043 | 1.013 | 0.988–1.040 |
| Ohio | 1.034 | 1.003–1.066 | 1.023 | 0.999–1.047 |
| Rainbow | 1.039 | 1.010–1.069 | 1.027 | 1.007–1.047 |
| Rogers | 1.024 | 0.991–1.058 | 1.022 | 0.998–1.047 |
| South Shore | 1.030 | 1.002–1.060 | 1.027 | 1.007–1.048 |

Twelve-hour cumulative precipitation is associated with an increase in the OR of exceeding the swim ban threshold at five out 20 (25%) locations with a 95% statistical significance (Table III). Locations listed from high to low increases in odds of a swim ban occurring: Montrose Avenue Beach (5.6% per mm of rain), Jackson/63rd Street Beach (5.4% per mm of rain), Calumet Beach (4.5% per mm of rain), 12th Street Beach (4.2% per mm of rain), and Rainbow Beach (3.9% per mm of rain).

Twenty-four hour cumulative precipitation is associated with an increase in the OR of a swim ban at three out 21 locations with a 95% statistical significance (Table III). Locations listed from high to low increases in odds of swim ban occurring: Montrose Avenue Beach (4.5% per mm of rain), Jackson/63rd Street Beach (4.2% per mm of rain), and Calumet Beach (2.8% per mm of rain).

## TABLE III

ODDS RATIOS FOR A SWIM BAN OCCURRING WITH 12IHR AND 24IHR CUMULATIVE RAIN IN MM AS THE PREDICTING VARIABLE.

| Location | 12-Hour Cumulative Precipitation | | 24-Hour Cumulative Precipitation | |
|---|---|---|---|---|
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12th | 1.042 | 1.003–1.081 | 1.020 | 0.985–1.056 |
| 31st | 0.994 | 0.941–1.050 | 0.976 | 0.930–1.024 |
| 41st/Oakwood | 1.004 | 0.934–1.080 | 1.002 | 0.939–1.069 |
| 57th | 1.035 | 0.998–1.073 | 1.016 | 0.984–1.049 |
| Calumet | 1.045 | 1.011–1.081 | 1.028 | 1.001–1.056 |
| Foster | 1.007 | 0.953–1.065 | 1.030 | 0.999–1.061 |
| Hartigan | 1.008 | 0.948–1.071 | 1.008 | 0.966–1.052 |
| Hollywood/Osterman | 1.018 | 0.971–1.067 | 1.026 | 0.995–1.058 |
| Howard | 0.985 | 0.888–1.093 | 1.011 | 0.962–1.063 |
| Jackson/63rd | 1.054 | 1.023–1.086 | 1.042 | 1.020–1.065 |
| Jarvis/Fargo | 0.993 | 0.907–1.087 | 1.024 | 0.983–1.066 |
| Juneway | 1.028 | 0.980–1.079 | 1.033 | 0.999–1.069 |
| Leone/Loyola | 1.016 | 0.965–1.070 | 1.026 | 0.994–1.060 |
| Montrose | 1.056 | 1.022–1.092 | 1.045 | 1.020–1.071 |
| North Ave | 0.994 | 0.918–1.076 | 1.025 | 0.988–1.063 |
| Oak | 0.946 | 0.819–1.093 | 1.004 | 0.956–1.054 |
| Ohio | 1.024 | 0.970–1.080 | 1.033 | 0.997–1.070 |
| Rainbow | 1.039 | 1.005–1.074 | 1.020 | 0.991–1.050 |
| Rogers | 1.006 | 0.934–1.083 | 1.016 | 0.972–1.063 |
| South Shore | 1.022 | 0.978–1.069 | 1.016 | 0.981–1.052 |

### 2. **Logistic regression with dichotomous precipitation variables and the previous day's beach status**

At 12th Street Beach, the presence of rain greater than or equal to 5 mm during 12- and 24-hour periods was not associated with a significant increase in the OR. The presence of a previous day swim advisory and previous day swim ban was associated with elevated ORs for predicting a swim advisory. For the 12-hour model, previous day swim advisory had a 95% significant OR of 2.596, while the previous day swim ban had a 95% significant OR of 3.729. The 24-hour model was similar with previous day swim advisory producing a 95% significant OR of 2.596, and previous day swim ban had a 95% significant OR of 3.558. The models with swim ban as the event did not produce significant results according to $\alpha$=.05 (Table IV).

**TABLE IV**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT 12TH STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| 12th Street Beach | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 1.863 | 0.964–3.601 | 1.445 | 0.423–4.932 |
| Previous Day Swim Advisory | 2.596 | 1.472–4.577 | 1.642 | 0.553–4.879 |
| Previous Day Swim Ban | 3.729 | 1.649–8.433 | 2.286 | 0.515–10.154 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.01 | 1.215–3.324 | 0.676 | 0.201–2.274 |
| Previous Day Swim Advisory | 2.596 | 1.471–4.581 | 1.721 | 0.581–5.100 |
| Previous Day Swim Ban | 3.558 | 1.565–8.088 | 2.348 | 0.527–10.450 |

For the 12-hour swim advisory model the presence of wet conditions increased the OR to 2.890, when there was a previous day swim advisory the OR equaled 2.138, and when there was a previous day swim advisory the OR for a swim advisory occurring was 4.284. In the presence of wet conditions, the 24-hour model was associated with a 95% significant OR of 2.192. When the prior day was a swim advisory the OR equaled 2.100 and when the prior day was a swim ban the OR equaled 4.111 (Table V).

**TABLE V**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT 31ST STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| 31st Street Beach | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.890 | 1.646–5.073 | 1.161 | 0.403–3.346 |
| Previous Day Swim Advisory | 2.138 | 1.333–3.430 | 1.457 | 0.660–3.216 |
| Previous Day Swim Ban | 4.284 | 2.355–7.795 | 2.020 | 0.758–5.379 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.192 | 1.406–3.417 | 1.184 | 0.541–2.591 |
| Previous Day Swim Advisory | 2.100 | 1.310–3.368 | 1.448 | 0.656–3.199 |
| Previous Day Swim Ban | 4.111 | 2.258–7.484 | 2.007 | 0.754–5.343 |

Table VI representing 41st Street/Oakwood Beach contains several significant parameters. In the case of predicting a swim advisory, the presence of wet conditions in a 12-hour period was associated with an elevated OR equaling 6.297 and the prior day swim advisory with an OR of 15.738. In the 24-hour model wet conditions were associated with an OR of 4.361.

**TABLE VI**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT 41ST/OAKWOOD STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| 41st Street/Oakwood Beach | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 6.297 | 1.946–20.372 | 5.269 | 0.462 |
| Previous Day Swim Advisory | 1.661 | 0.183–15.055 | <0.001 | <0.001>999.999 |
| Previous Day Swim Ban | 15.738 | 1.300–190.485 | <0.001 | <0.001–>999.1000 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 4.361 | 1.432–13.277 | 3.447 | 0.305–38.941 |
| Previous Day Swim Advisory | 1.401 | 0.157–12.497 | <0.001 | <0.001–>999.999 |
| Previous Day Swim Ban | 8.913 | 0.657–120.954 | <0.001 | <0.001–>999.999 |

In the scenario of predicting a swim advisory at the 57th Street Beach, wet conditions, previous day swim advisory and swim ban contained significant ORs. In the 12-hour model, wet conditions had an OR of 1.960, whereas the presence of a previous day swim advisory had an OR of 2.584 and previous day swim ban with an OR of 3.017. In the 24-hour model, previous day swim advisory had an OR of 2.556 while previous day swim ban had an OR of 2.997. In the next model, wet conditions were associated with swim bans with an OR of 2.556. A previous day swim ban was significant for 12- and 24-hour models, with OR's of 6.111 and 6.037 respectively (Table VII).

**TABLE VII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT 57TH STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| 57th Street Beach | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 1.960 | 1.051–3.653 | 2.556 | 1.011–6.458 |
| Previous Day Swim Advisory | 2.584 | 1.556–4.294 | 2.319 | 0.975–5.520 |
| Previous Day Swim Ban | 3.017 | 1.480–6.149 | 6.111 | 2.459–15.185 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 1.508 | 0.916–2.482 | 1.624 | 0.721–3.659 |
| Previous Day Swim Advisory | 2.556 | 1.540–4.245 | 2.293 | 0.965–5.449 |
| Previous Day Swim Ban | 2.997 | 1.472–6.102 | 6.037 | 2.439–14.947 |

At Calumet, all three parameters in both 12- and 24-hour models were associated with elevated ORs for a swim advisory occurring. For the 12-hour model, wet conditions contributed to an OR of 3.519, previous day swim advisory OR=2.256, and previous day swim ban OR=4.194. For the 24-hour model, wet conditions OR=2.631, previous day swim advisory OR=2.252, and previous day swim ban OR=3.969. Wet conditions during 12- and 24-hour periods were associated with elevated ORs for a swim ban even with ORs of 5.057

and 2.810 respectively. Prior day swim ban was also associated with a swim in the 12- and 24-hour models with ORs of 2.722 and 2.628 (Table VIII).

**TABLE VIII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT CALUMET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Calumet Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 3.519 | 2.038–6.078 | 5.057 | 2.462–10.387 |
| Previous Day Swim Advisory | 2.256 | 1.412–3.604 | 1.349 | 0.575–3.163 |
| Previous Day Swim Ban | 4.194 | 2.243–7.840 | 2.722 | 1.050–7.056 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.631 | 1.698–4.077 | 2.810 | 1.445–5.464 |
| Previous Day Swim Advisory | 2.252 | 1.410–3.595 | 1.362 | 0.585–3.168 |
| Previous Day Swim Ban | 3.969 | 2.121–7.428 | 2.628 | 1.025–6.737 |

At Foster Avenue, wet conditions were associated with swim advisories during 12- and 24-hour periods with ORs of 2.210 and 2.215. The presence of either a previous day swim advisory or ban was associated with elevated ORs for both a swim advisory and swim ban. In the 12-hour model with swim advisory as the event, previous day swim advisory OR=3.313 and previous day swim ban OR=4.239. Similarly in the 24-hour model with swim advisory as the event, previous day swim advisory OR=3.328 and previous day swim ban OR=4.051. With swim ban as the event, 12-hour model previous day swim advisory OR=3.157 and previous day swim advisory OR=6.863. For the 24-hour wet conditions OR=1.154, previous day swim advisory OR=3.180 and previous day swim ban OR=6.520 (Table IX).

**TABLE IX**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT FOSTER AVENUE WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Foster Avenue Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.210 | 1.138–4.289 | 1.482 | 0.431–5.097 |
| Previous Day Swim Advisory | 3.313 | 1.884–5.826 | 3.157 | 1.233–8.082 |
| Previous Day Swim Ban | 4.239 | 1.929–9.316 | 6.836 | 2.395–19.515 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.215 | 1.334–3.679 | 2.596 | 1.154–5.841 |
| Previous Day Swim Advisory | 3.328 | 1.888–5.864 | 3.180 | 1.236–8.183 |
| Previous Day Swim Ban | 4.051 | 1.835–8.946 | 6.520 | 2.259–18.816 |

At Hartigan, previous day swim ban was associated with elevated OR's when swim advisory was the event. The 12-hour model had an OR=34.679 and 24-hour model had an OR=40.938 (Table X).

**TABLE X**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT HARTIGAN WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Hartigan Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 1.263 | .087–18.274 | 12.857 | 0.763–216.708 |
| Previous Day Swim Advisory | 9.741 | 0.904–104.94 | <0.001 | <0.001–>999.999 |
| Previous Day Swim Ban | 34.679 | 1.546–778.139 | <0.001 | <0.001–>999.1000 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 0.866 | 0.066–11.396 | 7.818 | 0.472–129.484 |
| Previous Day Swim Advisory | 9.4 | 0.870–101.510 | <0.001 | <0.001–>999.999 |
| Previous Day Swim Ban | 40.938 | 1.846–884.233 | <0.001 | <0.001–>999.999 |

In the 12-hour model for Hollywood/Osterman, wet conditions was associated with a swim advisory with an OR of 2.512 and previous day swim advisory was associated with a swim advisory by an of OR=2.601. Twenty-four hour wet conditions was represented by an OR=2.628, and previous day swim advisory was associated with an OR of 2.504. In the event of a swim ban, previous day swim advisory in the 12-hour model OR=2.639 and previous day swim ban OR=4.207. In the 24-hour model, wet conditions OR=2.366 and previous day swim ban OR=4.088 (Table XI).

**TABLE XI**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT HOLLYWOOD/OSTERMAN WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Hollywood / Osterman Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.512 | 1.342–4.699 | 1.879 | 0.633–5.577 |
| Previous Day Swim Advisory | 2.601 | 1.477–4.581 | 2.639 | 1.044–6.672 |
| Previous Day Swim Ban | 2.065 | 0.868–4.917 | 4.207 | 1.370–12.922 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.628 | 1.625–4.251 | 2.366 | 1.068–5.244 |
| Previous Day Swim Advisory | 2.504 | 1.416 - 4.428 | 2.535 | 0.999 - 6.434 |
| Previous Day Swim Ban | 2.01 | 0.839–4.814 | 4.088 | 1.323–12.634 |

At Howard Beach, the significant associations found were in models where swim advisory was the event. For the 12-hour model, wet conditions OR=2.440, previous day swim advisory OR=4.007, and previous day swim ban OR=3.737. In the 24-hour model the wet condition OR=2.057, previous day swim advisory OR=3.966, and previous day swim ban OR=3.413 (Table XII).

**TABLE XII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT HOWARD WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| Howard Beach | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.44 | 1.169–5.0091 | 1.857 | 0.414–8.324 |
| Previous Day Swim Advisory | 4.007 | 2.076–7.737 | 3.096 | 0.863–11.107 |
| Previous Day Swim Ban | 3.737 | 1.185–11.783 | 3.446 | 0.428–27.775 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.057 | 1.143–3.704 | 2.656 | 0.923–7.649 |
| Previous Day Swim Advisory | 3.966 | 2.054–7.658 | 3.113 | 0.865–11.207 |
| Previous Day Swim Ban | 3.413 | 1.077–10.813 | 3.048 | 0.373–24.934 |

There is a strong association between 12- and 24-hour wet conditions and previous day's statuses with either a swim advisory or ban occurring at Jackson/63rd Street Beach. In the swim advisory 12-hour model, wet conditions OR=4.472, previous day swim advisory OR=3.081, and previous day swim ban OR=8.999. In the swim advisory 24-hour model, wet conditions OR=3.549, previous day swim advisory OR=2.932, and previous day swim ban OR=9.304. While in the swim ban 12-hour model, wet conditions OR=3.597, previous day swim advisory OR=2.463, and previous day swim ban OR=4.445. Lastly, in the swim ban 24-hour model, wet conditions OR=3.197, previous day swim advisory OR=2.321, and previous day swim ban OR=4.575 (Table XIII).

**TABLE XIII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT JACKSON/63RD WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Jackson / 63rd Street Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 4.472 | 2.601–7.689 | 3.597 | 1.930–6.701 |
| Previous Day Swim Advisory | 3.081 | 2.128–4.462 | 2.463 | 1.440–4.214 |
| Previous Day Swim Ban | 8.999 | 5.464–14.821 | 4.445 | 2.436–8.108 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 3.549 | 2.354–5.349 | 3.197 | 1.905–5.364 |
| Previous Day Swim Advisory | 2.932 | 2.020–4.257 | 2.321 | 1.353–3.983 |
| Previous Day Swim Ban | 9.304 | 5.636–15.357 | 4.575 | 2.504–8.360 |

At the Jarvis/Fargo sampling location and in the swim advisory 12-hour model, previous day swim advisory OR=4.985 and previous day swim ban OR=7.347. In the swim advisory 24-hour model, wet conditions OR=2.505, previous day swim advisory OR=5.130 while previous day swim ban OR=7.272. In the swim ban 12-hour model, previous day swim advisory OR=4.796 and the previous day swim ban OR=8.988. For the swim ban 24-

hour model, wet conditions OR=3.615, previous day swim advisory OR=4.925 and previous day swim ban OR=9.123 (Table XIV).

**TABLE XIV**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT JARVIS/FARGO WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Jarvis / Fargo Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.076 | 0.960–4.492 | 1.896 | 0.416–8.652 |
| Previous Day Swim Advisory | 4.985 | 2.639–9.418 | 4.796 | 1.496–15.377 |
| Previous Day Swim Ban | 7.347 | 2.647–20.393 | 8.988 | 1.839–43.941 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.505 | 1.407–4.460 | 3.615 | 1.306–10.007 |
| Previous Day Swim Advisory | 5.13 | 2.701–9.743 | 4.925 | 1.520–15.957 |
| Previous Day Swim Ban | 7.272 | 2.597–20.361 | 9.123 | 1.836–45.318 |

At Juneway, the 12-hour swim advisory model had significant associations with wet conditions with an OR=2.153, previous day swim advisory with an OR=3.336, and previous day swim ban with an OR=3.875. In the 24-hour swim advisory model wet conditions had an OR=2.203, previous day swim advisory OR=3.443, and previous day swim ban OR=3.809. The 12-hour swim ban model was associated with wet conditions with an OR=3.464 and with previous day swim ban, OR=5.061. Similarly in the 24-hour swim ban model wet conditions had an OR=4.243 and previous day swim ban OR=4.904 (Table XV).

**TABLE XV**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT JUNEWAY WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Juneway Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.153 | 1.006–4.610 | 3.464 | 1.122–10.696 |
| Previous Day Swim Advisory | 3.336 | 1.631–6.823 | 2.9 | 0.817–10.296 |
| Previous Day Swim Ban | 3.875 | 1.376–10.910 | 5.061 | 1.081–23.685 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.203 | 1.225–3.964 | 4.243 | 1.722–10.453 |
| Previous Day Swim Advisory | 3.443 | 1.678–7.063 | 3.126 | 0.871–11.222 |
| Previous Day Swim Ban | 3.809 | 1.347–10.775 | 4.904 | 1.029–23.372 |

At Leone/Loyola, the 12-hour swim advisory model had significant association with wet conditions at an OR=2.172, previous day swim advisory OR=2.923, and previous day swim ban OR=3.477. For the 24-hour swim advisory model, wet conditions OR=2.110, previous day swim advisory OR=2.868, and previous day swim ban OR=3.326. In the swim ban model 24-hour wet conditions were significant with an OR=3.100 (Table XVI).

**TABLE XVI**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT LEONE/LOYOLA WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Leone / Loyola Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.172 | 1.049–4.496 | 2.785 | 0.922–8.409 |
| Previous Day Swim Advisory | 2.923 | 1.474–5.796 | 2.092 | 0.603–7.257 |
| Previous Day Swim Ban | 3.477 | 1.345–8.989 | 3.324 | 0.732–15.093 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.11 | 1.207–3.689 | 3.1 | 1.312–7.322 |
| Previous Day Swim Advisory | 2.868 | 1.444–5.696 | 2.02 | 0.580–7.037 |
| Previous Day Swim Ban | 3.326 | 1.282–8.629 | 3.079 | 0.673–14.092 |

The swim advisory 12-hour model for Montrose Beach produced a wet conditions OR=4.099, a previous day swim advisory OR=2.322, and a previous day swim ban OR=2.449. The swim advisory 24-hour model created a wet conditions OR=3.444, a previous day swim advisory OR=2.193, and a previous day swim ban OR=2.397. In the swim ban models, wet conditions generated significant OR's in the 12-hour model with an OR=4.165 and the 24-hour model with an OR=4.496. Previous day swim advisory was associated with swim bans in both 12 and 24-hour models with OR's of 2.361 and 2.168 (Table XVII).

**TABLE XVII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT MONTROSE AVENUE WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Montrose Avenue Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 4.099 | 2.391–7.025 | 4.165 | 1.943–8.929 |
| Previous Day Swim Advisory | 2.322 | 1.481–3.640 | 2.361 | 1.143–4.880 |
| Previous Day Swim Ban | 2.449 | 1.257–4.769 | 1.918 | 0.633–5.815 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 3.444 | 2.261–5.246 | 4.496 | 2.389–8.462 |
| Previous Day Swim Advisory | 2.193 | 1.394–3.451 | 2.168 | 1.041–4.512 |
| Previous Day Swim Ban | 2.397 | 1.228–4.679 | 1.824 | 0.598–5.566 |

At North Avenue Beach, the 12-hour swim advisory model was associated with wet conditions with an OR=2.585, previous day swim advisory OR=2.306, and previous day swim ban OR=4.717. In the 24-hour swim advisory wet conditions OR=2.420, previous day swim advisory OR=2.350, and previous day swim ban OR=4.481. Previous day swim advisory was associated with swim bans in the 12-hour model with an OR=3.204. In the 24-

hour swim ban model, wet conditions were associated with an OR=4.071 and previous day swim advisory OR=3.284 (Table XVIII).

**TABLE XVIII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT NORTH AVENUE WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **North Avenue Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.585 | 1.303–5.129 | 1.92 | 0.551–6.685 |
| Previous Day Swim Advisory | 2.306 | 1.111–4.786 | 3.204 | 1.046–9.811 |
| Previous Day Swim Ban | 4.717 | 1.873–11.878 | 4.014 | 0.875–18.420 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.42 | 1.403–4.175 | 4.071 | 1.727–9.601 |
| Previous Day Swim Advisory | 2.35 | 1.131–4.885 | 3.284 | 1.058–10.197 |
| Previous Day Swim Ban | 4.481 | 1.769–11.348 | 3.588 | 0.760–16.938 |

At Oak Street Beach, the 12-hour swim advisory model concluded significant OR's with the previous day swim advisory OR=2.463 and previous day swim ban OR=5.068. The

24-hour was associated with wet conditions with an OR=2.199, previous day swim advisory OR=2.573, and previous day swim ban OR=4.920. In the swim ban models, the previous day swim advisory was associated with elevated OR's, the 12-hour OR=4.415 and the 24-hour OR=4.586 (Table XIX).

**TABLE XIX**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT OAK STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Oak Street Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 1.788 | 0.809–3.950 | 0.644 | 0.085–4.886 |
| Previous Day Swim Advisory | 2.463 | 1.148–5.285 | 4.415 | 1.571–12.404 |
| Previous Day Swim Ban | 5.068 | 2.019–12.718 | 1.883 | 0.241–14.726 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.199 | 1.235–3.914 | 1.426 | 0.474–4.291 |
| Previous Day Swim Advisory | 2.573 | 1.194–5.543 | 4.586 | 1.626–12.931 |
| Previous Day Swim Ban | 4.92 | 1.947–12.430 | 1.881 | 0.240–14.719 |

At Ohio Street Beach, the 12-hour swim advisory model was associated with wet conditions with an OR=3.193 and previous day swim advisory OR=3.279. In the 24-hour swim advisory, wet conditions OR=2.170 and previous day swim advisory OR=3.290. Finally wet conditions were associated with swim bans in the 24-hour model and had an OR=2.784 (Table XX).

**TABLE XX**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT OHIO STREET WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Ohio Street Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 3.193 | 1.652–6.170 | 2.422 | 0.686–8.552 |
| Previous Day Swim Advisory | 3.279 | 1.698–6.332 | 1.483 | 0.332–6.618 |
| Previous Day Swim Ban | 2.849 | 0.910–8.923 | 2.384 | 0.299–18.983 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.17 | 1.246–3.782 | 2.784 | 1.042–7.438 |
| Previous Day Swim Advisory | 3.29 | 1.710–6.328 | 1.438 | 0.322–6.434 |
| Previous Day Swim Ban | 2.675 | 0.856–8.357 | 2.124 | 0.263–17.139 |

At Rainbow Beach, the presence of wet conditions was significant in all four models. In the swim advisory models, the 12-hour OR=3.429 and 24-hour OR=2.522. In the swim ban models, the 12-hour OR=4.042 and the 24-hour OR=2.880. Previous day swim advisory was associated with swim advisories in the 12-hour model, OR=1.808, and the 24-hour model, OR=1.853 (Table XXI).

**TABLE XXI**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT RAINBOW WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Rainbow Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 3.429 | 2.003–5.869 | 4.042 | 1.899–8.600 |
| Previous Day Swim Advisory | 1.808 | 1.134–2.880 | 0.681 | 0.259–1.788 |
| Previous Day Swim Ban | 2.048 | 1.045–4.013 | 0.784 | 0.182–3.369 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.522 | 1.646–3.866 | 2.880 | 1.495–5.551 |
| Previous Day Swim Advisory | 1.853 | 1.166–2.944 | 0.718 | 0.275–1.871 |
| Previous Day Swim Ban | 1.939 | 0.988–3.808 | 0.723 | 0.168–3.106 |

At Rogers Beach, when swim advisory was modeled, the 12-hour previous day swim advisory OR=3.124 and the previous day swim ban OR=6.157. The 24-hour model wet conditions OR=1.872, previous day swim advisory OR=3.027, and the previous day swim ban OR=5.962. Previous day swim advisory was positively associated with an elevated odds of a swim ban occurring, 12-hour model OR=4.390. In the 24-hour swim ban model, wet conditions OR=3.072 and previous day swim advisory OR=4.121 (Table XXII).

**TABLE XXII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT ROGERS WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **Rogers Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.150 | 1.000–4.622 | 2.800 | 0.783–10.019 |
| Previous Day Swim Advisory | 3.124 | 1.533–6.367 | 4.390 | 1.390–13.864 |
| Previous Day Swim Ban | 6.157 | 2.248–16.861 | 3.310 | 0.410–26.719 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 1.872 | 1.026–3.414 | 3.072 | 1.133–8.325 |
| Previous Day Swim Advisory | 3.027 | 1.484–6.176 | 4.121 | 1.297–13.097 |
| Previous Day Swim Ban | 5.962 | 2.173–16.354 | 3.097 | 0.380–25.218 |

At South Shore Beach, the presence of a wet conditions contributed to higher odds of a swim advisory occurring, the 12-hour model produced an OR=2.422 and the 24-hour model OR=2.414. The previous day swim advisory was significant in all models, 12- and 24-hour swim advisory model ORs were 2.035 and 2.086. In the 12- and 24-hour swim ban models ORs were 3.710 and 3.756 (Table XXIII).

**TABLE XXIII**

ODDS OF SWIM ADVISORY OR SWIM BAN OCCURRING AT SOUTH SHORE WITH WET VERSUS DRY CONDITIONS AND PREVIOUS DAY'S BEACH STATUS AS PREDICTORS

| **South Shore Beach** | | | | |
|---|---|---|---|---|
| Parameter | Swim Advisory versus No Swim Advisory | | Swim Ban versus No Swim Ban | |
| | Odds Ratio | 95% Wald Confidence Limit | Odds Ratio | 95% Wald Confidence Limit |
| 12-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 12-Hour Wet versus Dry Conditions | 2.422 | 1.387–4.231 | 1.689 | 0.565–5.046 |
| Previous Day Swim Advisory | 2.035 | 1.297–3.193 | 3.710 | 1.772–7.767 |
| Previous Day Swim Ban | 2.074 | 0.934–4.608 | <0.001 | <0.001–>999.999 |
| 24-hour (Wet ≥ 5 mm of rain, Dry < 5 mm of rain) | | | | |
| 24-Hour Wet versus Dry Conditions | 2.414 | 1.560–3.735 | 1.733 | 0.727–4.127 |
| Previous Day Swim Advisory | 2.086 | 1.327–3.277 | 3.756 | 1.795–7.860 |
| Previous Day Swim Ban | 2.101 | 0.943–4.684 | <0.001 | <0.001–>999.999 |

E. **Precipitation Results**

Cumulative percentages of precipitation for hourly, 12-hour, and 24-hour periods as recorded by the National Oceanic and Atmospheric Administration (NOAA) Midway International Airport's weather station are displayed in figure 6. Approximately 16% of 12-hour precipitation events were greater than 5 mm of rain while 25% of 24-hour precipitation events were greater than 5 mm.

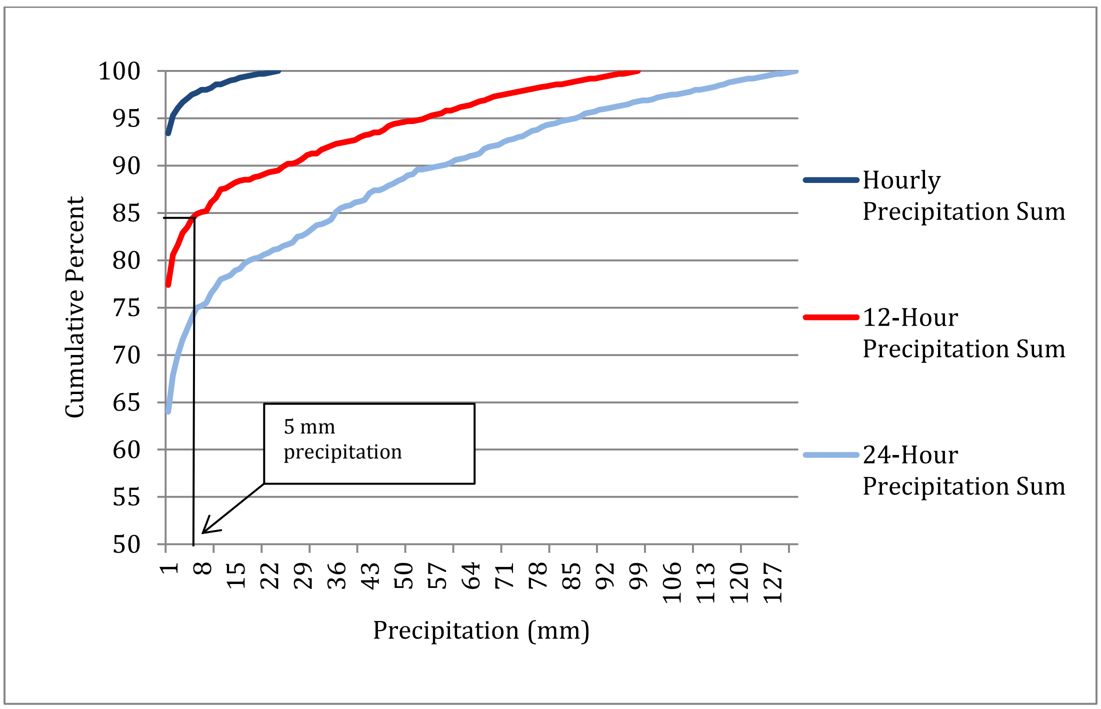


Figure 6. Cumulative percentages for different precipitation periods.

## F. Interpreting Logistic Regression for Beach Management

In efforts to develop a simple predictive model for issuing public health warnings, two different paths were explored. The first model utilized cumulative precipitation over 12 and 24 hours, while the second model took into consideration the previous day's beach status and whether or not 5 mm of rain fell during 12 or 24 hours (equation 1 and 2). The results from the first model can be interpreted as a percent increase in odds of an event occurring per mm of rain. Figure 12 and figure 13 display beaches where 12- and 24-hour cumulative precipitation was a significant factor in predicting either a swim advisory or swim ban.

There were a total of 12 beaches where either 12- or 24-hour cumulative precipitation was significant for predicting a swim advisory. Jackson/63rd St Beach recorded an increase in the odds of a swim advisory of occurring by 5.6% per mm of precipitation during the prior 12 hours. The next two largest increases were observed at Montrose Ave Beach with 4.9% per mm of rain and Rainbow Beach with 3.9% per mm of rain. When both the 12- and 24-hour cumulative precipitation variables were significant at one location, the OR associated with the 12-hour variable appeared to be higher than the OR associated with the 24-hour variable (Figure 7).

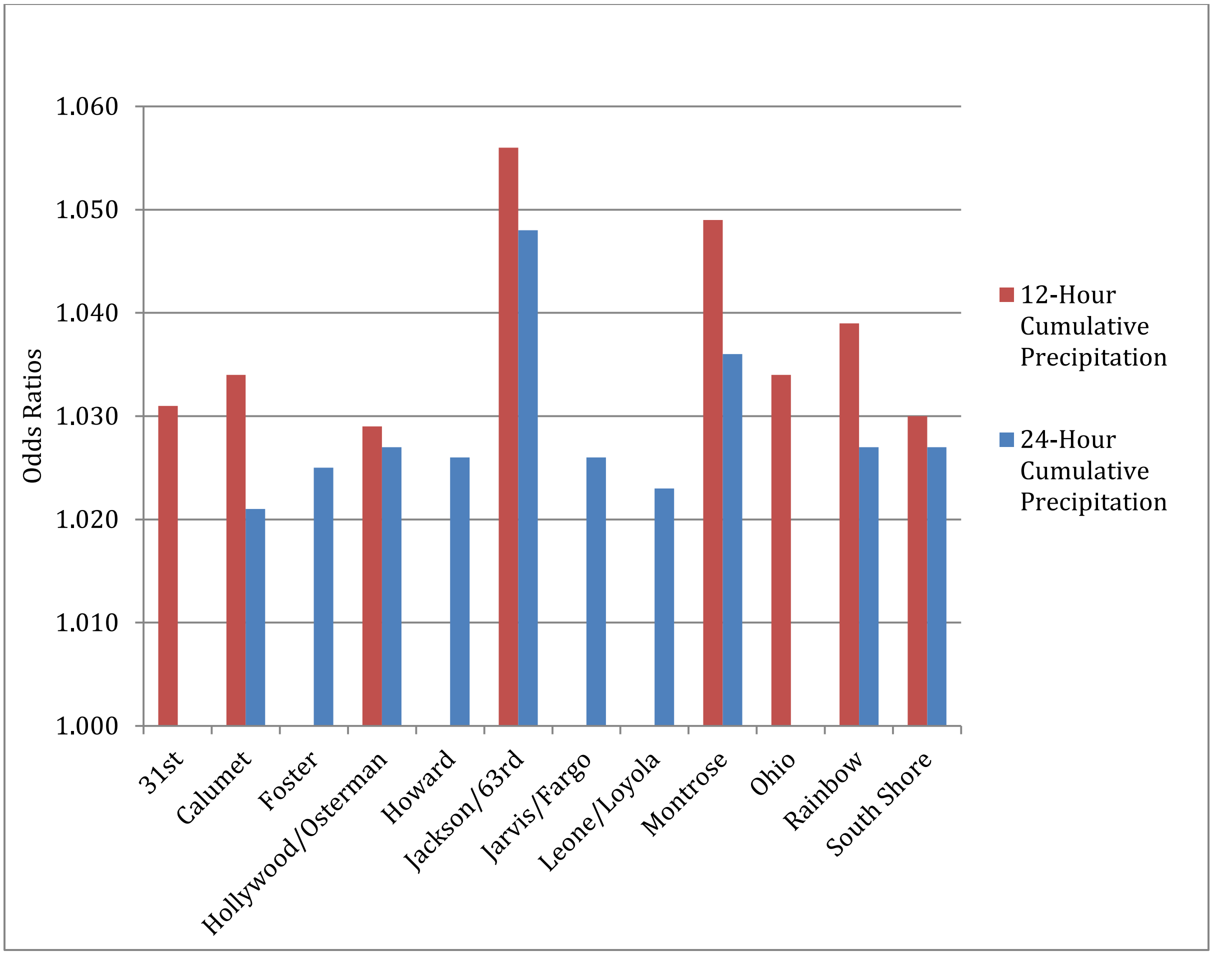


Figure 7. Predicting swim advisories with cumulative precipitation.

There were a total of five beaches where either 12- or 24-hour cumulative precipitation was significant for predicting a swim ban. Montrose Ave Beach recorded an increase in odds of a swim ban of occurring by 5.6% per mm of precipitation during the prior 12 hours. The next two highest increases occurred at Jackson/63rd St Beach with 5.4% per mm of rain and Calumet Park Beach with 4.5% per mm of rain. Also similar to figure 7, the ORs associated with 12-hour cumulative precipitation were higher than the ORs associated with the 24-hour cumulative precipitation (Figure 8).

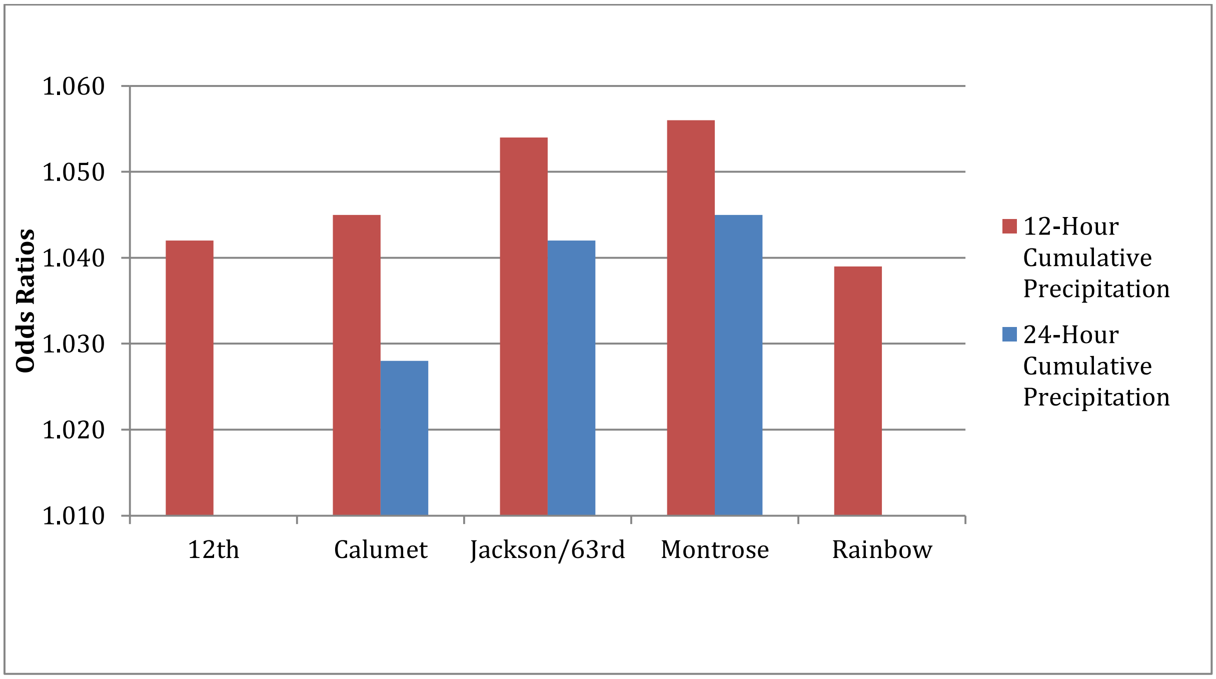


Figure 8. Predicting Swim Bans with Cumulative Precipitation.

In order to use the results from Model 1 in a predictive model, first we must know the probability of each beach status from occurring. Using Jackson/63rd St Beach as an example, when there is no precipitation, the probability of the beach being open is 67.2%, the probability of having a swim advisory is 26.0%, and the probability of having a swim ban is 7.8%. After knowing the probability of an event occurring, we can multiply that by the OR resulting in a new probability considering the effect of rain determined from Equation 1. Table XXIV and figure 9 provide an example of Jackson/63rd St Beach and how with each millimeter of rain, the probability of a swim advisory or ban increases.

## TABLE XXIV

PROBABILITY OF SWIM ADVISORY OR SWIM BAN OF OCCURRING WHEN USING 12-HOUR CUMULATIVE PRECIPITATION AT JACKSON/63RD ST. BEACH

| **Location: Jackson/63rd St. Beach** | | |
|---|---|---|
| Rain (mm) | Probability of Swim Advisory | Probability of Swim Ban |
| 0 | 26.0% | 7.8% |
| 1 | 27.5% | 8.2% |
| 2 | 28.9% | 8.6% |
| 3 | 30.4% | 9.1% |
| 4 | 31.8% | 9.5% |
| 5 | 33.3% | 9.9% |
| 6 | 34.7% | 10.3% |
| 7 | 36.2% | 10.7% |
| 8 | 37.6% | 11.2% |
| 9 | 39.1% | 11.6% |
| 10 | 40.6% | 12.0% |
| 20 | 55.1% | 16.2% |
| 30 | 69.7% | 20.4% |
| 40 | 84.2% | 24.6% |

Example:

Probability of swim advisory after 5 mm of rain = (0.26) x [(1.056 – 1.0) x 5 + 1)] = 0.333 or 33.3%

Figure 9. Interpretation of Predictive Model 1.

The example predictive model above for Jackson/63rd St. Beach was created using information obtained from logistic regression (Equation 1) and calculating the probabilities of a swim advisory or swim ban from occurring at Jackson/63rd St. Beach when there was zero 12-hour cumulative precipitation. This table can be used as a predictive model if a beach management decision was made to issue a warning when the probability of a swim advisory occurring was greater than 70%. Then, based on Table XXIV, whenever the 12-hour cumulative precipitation exceeded 30mm a swim advisory would be implemented at Jackson/63rd St. Beach. When trying to predict a swim ban, the same approach may not produce high enough probabilities to warrant a swim ban at the Jackson/63rd St. Beach.

Using cumulative precipitation is one way to develop a simple predictive model, however using a dichotomous rain variable and the prior day *E. coli* monitoring sample may simplify the model further compared to issuing a warning based on a specific threshold of rain.

## G. <u>**Predicting Swim Advisories and Swim Bans using a Dichotomous Precipitation Variable and Previous Day Beach Status**</u>

The second model in this research uses a dichotomous precipitation variable over 12 and 24 hours while also considering the prior day beach status. Interpreting the results from this model may be more intuitive as you only consider the presence or absence of 5 mm of precipitation over the last 12- or 24-hour period and whether or not the prior day *E. coli* results warranted a swim advisory or swim ban.

The ORs from the second model often increased in magnitude when there were wet conditions and a prior day swim advisory or swim ban. However it is hard to equate the need for a swim advisory or swim ban from an OR. Instead, by tabulating frequencies for each model parameter and event, probabilities of a swim advisory or swim ban of occurring can be generated. Table XV shows an example of the resulting probabilities at Jackson/63rd St. Beach. Hypothetically a beach manager could issue an advisory if the probability of an advisory of occurring is greater than 70%. In this case, an advisory would be issued when the prior day beach status was a swim ban and there was greater than or equal to 5 mm of precipitation in the last 12 hours. This example would predict an 88% chance of a swim advisory occurring (Figure 10).

**TABLE XXV**

PROBABILITY OF A SWIM ADVISORY OR SWM BAN OCCURRING AT JACKSON/63RD ST. BEACH FOR EACH MODEL PARAMETER

| Parameter | < 5 mm of rain (12-Hour) | | | | ≥ 5 mm of rain (12-Hour) | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Open | Advisory | Swim ban | N | Open | Advisory | Swim ban |
| Prior day open | 395 | 291 (74%) | 70 (18%) | 34 (9%) | 42 | 21 (50%) | 14 (33%) | 7 (17%) |
| Prior day advisory | 152 | 92 (61%) | 42 (28%) | 18 (12%) | 17 | 5 (29%) | 5 (29%) | 7 (41%) |
| Prior day ban | 78 | 27 (35%) | 34 (44%) | 17 (22%) | 8 | 1 (13%) | 4 (50%) | 3 (38%) |

Example:

88% = 50% (Probability of Swim Advisory when there was a prior day ban and ≥5 mm of rain) + 38% (Probability of Swim Ban when there was a prior day ban and ≥5 mm of rain)

Figure 10. Interpretation of Predictive Model 2.

# V. DISCUSSION

## A. **Summary of Findings**

The effects of rainfall on *E. coli* concentrations at Chicago beaches are not uniform throughout the 21 study locations. Eighteen of 21 of locations experienced higher *E. coli* concentrations after rainfall, while 11 of 21 of locations experienced statistically significant higher concentrations after rainfall greater than or equal to 5 mm during 12 hours (Table I). The magnitude of increase in *E. coli* concentrations during wet conditions differed among the 11 locations that were significantly impacted. Higher concentrations occurred at south side locations compared to north side locations. Then by comparing beaches that were significantly impacted in the south to the north reveals that southern beaches generally had higher *E. coli* concentrations and larger increases in *E. coli* concentrations during wet conditions.

The second objective of this study was to develop a predictive model for issuing swim advisories or swim bans by using information that is readily available such as precipitation data and the prior day beach's culture results. In the first model cumulative precipitation during 12- and 24-hour periods was utilized to predict the odds of either a swim advisory or swim ban occurring (Equation 1). Figure 7 shows that eight of 21 of the beaches were significantly impacted by 12-hour cumulative precipitation while 10 of 21 of the locations were impacted by 24-hour cumulative precipitation. When 12- and 24-hour cumulative precipitation both impacted a beach, 12-hour precipitation consistently had a larger impact towards the odds of a swim advisory occurring. When predicting swim bans 12-hr cumulative precipitation was significant at five out of 21 locations while 24-hr cumulative precipitation was significant at three locations. Cumulative precipitation over 12 hours was associated with higher ORs than 24-hr cumulative precipitation.

The second model used a dichotomous precipitation variable over 12- and 24-hour periods in combination with the presence or absence of a prior day swim advisory or swim ban in order to measure their association with swim advisories and swim bans (Equation 2). An increased odds of a swim advisory occurring was predicted for the 16 out of 21 locations when using the 12-hour dichotomous precipitation variable and at 19 out of 21 locations using the 24-hour variable. Increased odds of a swim ban occurred at four out of 21 locations when using the 12-hour dichotomous precipitation variable and at six out of 21 locations when using the 24-hour dichotomous precipitation.

## B. **Implications for Beach Management**

The results from this study give insight to beach managers on potential interventions that would combat fecal indicator bacteria contamination of Chicago's recreational waters and an approach for improving public notification of contaminated waters.

One potential explanation for the difference observed between north side and south side beaches is that there are designated dog beaches at north side beaches and none at the south side beaches. The presence of a designated dog beach encourages pet owners to bring their dogs to the beach and may reduce the size of the gull population at that beach, ultimately reducing the *E. coli* concentrations in the sand and near-shore water. A study conducted in Racine, Wisconsin utilized trained border collies in a gull harassment intervention with hopes of reducing the gull population and *E. coli* concentrations. The intervention was very successful as it reduced the bird population at the study site by 98% and water quality dramatically improved following the reduction in gulls (Converse et al., 2012). Chicago's designated dog beaches would have a smaller impact since they are generally placed at one side of beach and are separated from the general beach by a fence whereas the border collies were free to harass gulls across the entire beach. Chicago could implement the resource-intensive gull harassment program or introduce more designated dog beaches throughout the south side locations.

Another beach characteristic that has previously been identified to cause higher *E. coli* concentrations is the physical orientation and use of breakwaters. Breakwaters are necessary to prevent erosion and to preserve the sandy beaches along the heavily developed Chicago shoreline. In some cases, breakwaters may help trap regional contamination or help retain local contamination by creating an embayment. It is important to increase circulation in these types of waters, as it would enhance the dilution of bacteria and other pollutants (Whitman et al., 2001). In 2011, the CPD was awarded a grant by the EPA to construct a culvert through the pier on the south end of Jackson/63rd St Beach. This culvert will improve water circulation at Jackson/63rd St and should therefore reduce *E. coli* concentrations (EPA 2011). If this intervention proves successful, similar culverts should be installed where embayment conditions exist.

Using cumulative rain as the primary predictor for swim advisories may be a tool to issue protective swim advisories at beaches where precipitation heavily impacts bacterial concentrations. Evidence also suggests that cumulative precipitation alone cannot predict the need to issue a swim ban. For example, if 30 mm of rain falls within 12 hours, model 1 suggests there is a near 77% chance that the *E. coli* concentration will be above the threshold for issuing a swim advisory while there is only a 22% likelihood that the concentration is above the threshold for issuing a swim ban (Table XXIV). During our study, 30 mm of precipitation fell during the 12-hour period for 10% of the time (Figure 6).

In another simplistic approach, using a dichotomous precipitation variable and the prior day's culture results can improve public notification of swim advisories but perhaps not swim bans. Evidence from Table XXV suggests that given wet conditions during 12- and 24-hour periods in combination with the prior day's culture results greater than 1000 CFU/100 mL, there is a probability of 83.3% to 87.5% that the culture results from the day in question would yield a high enough concentration to issue a swim advisory. Using data that are easily attainable on the morning that beach notification decisions are made, a beach manager can confidently issue a protective swim advisory until monitoring results are received the next day.

## C. **Findings in Context**

To date, there has been only one other comprehensive assessment of *E. coli* concentrations for all of Chicago beaches. Whitman and Nevers (2008) obtained *E. coli* monitoring data from the CPD for the years 2000–2005. Their objectives were to relate *E. coli* concentrations among beaches along the Chicago coastline and to characterize spatial and temporal patterns of *E. coli* concentrations. When comparing descriptive statistics, the geometric means for *E. coli* concentrations from the 2000–2005 study are similar to results in this study. Their study identified Jackson/63rd St Beach to have the highest geometric mean at 140.0 MPN/100 mL with Montrose Beach having the second highest concentration on average at 76.7 MPN/100 mL. We also identified the same two beaches of having the highest geometric means for *E. coli* concentrations during wet and dry conditions. The beaches with the lowest geometric mean concentrations in their study were Ohio, Rogers, Jarvis/Fargo, Hartigan, and 49th St Beach. Although 49th St Beach was excluded from this dataset, Ohio, Rogers, Jarvis/Fargo, and Hartigan appeared to have some of lowest geometric mean concentrations during wet and dry conditions (Table I). Empirical modeling using several hydrometerological parameters were significantly correlated with *E. coli* concentrations during 2000–2004, including wind speed, air temperature, and cumulative rainfall. The authors tested both 4-hour and 24-hour cumulative precipitation variables but only 4-hour cumulative precipitation was significant in predicting *E. coli* concentrations (Nevers et al., 2005). The 4-hour variable was insignificant when there were north winds present. Their model also directly predicted *E. coli* concentrations where ours did not; this makes it difficult to compare the precipitation variables used in each study. Even though other hydrometerological parameters are significant in predicting *E. coli* concentrations; this study aims to simplify the naturally complex system in order to better protect public health.

There have been a number of studies assessing the relationship between rainfall and beach bacterial concentrations in both salt and freshwater environments. In Southern California, this relationship supported the use of a rain-based beach water quality warning system as storms larger than 6 mm consistently led to a mean fecal coliform greater than 400/100 mL. Storms with less than 2.5 mm of rain had an approximate mean fecal coliform at 100/100 mL. The runoff sources in Los Angeles County are independent storm water systems like those found along the Chicago shoreline and are not combined sewage overflows. Southern California's climate may increase the effect that rain has on beach water quality. Long dry periods allow for the accumulation of land-based contaminants until rain washes them through the storm water conveyance systems and into coastal waters, this is also known as the first flush effect (Ackerman et al., 2003). The first flush effect relationship may not be as strong in Chicago since the climate is humid and rainfall is not concentrated in any one season. When heavy rainfall does occur, storm water is directed to the combined sewer system and conveyed to a water treatment plant. Small drainage systems along the lakeshore direct rains back to Lake Michigan and can potentially impact beaches through the first flush effect.

A study assessing the effects of rainfall on *E. coli* levels at 15 Lake Superior beaches was not able to display the positive correlation between rainfall and increased bacterial concentrations. There were several possible reasons why there wasn't a positive correlation; one is that during 2003–2004, Ashland, Wisconsin only received about 77% of their normal annual precipitation. Another reason, and this is repeatedly stressed throughout recreational water quality modeling literature, is that each beach must be treated as a separate entity since individual characteristics of a beach may influence bacterial concentrations (Sampson et al., 2006). Rainfall effects were not assessed by correlation; rather the comparisons of geometric means during wet and dry conditions were utilized. Ten of the 21 study locations did not demonstrate a statistical significant higher or lower *E. coli* concentration during wet and dry conditions (Table I). The beaches that did not demonstrate a difference during wet and dry conditions may have distinct local land uses that serve as a natural buffer to storm water runoff.

Moving closer to Chicago, a study conducted at Lake Michigan beaches in Door County, Wisconsin found that rainfall greater than 5 mm over a 24-hour period significantly impacted *E. coli* concentrations in beach water at six of the eight locations where *E. coli* concentrations increased by a range of 85–500 MPN/100 mL. Also, the significance and duration of this impact was highly beach specific (Kleinheinz et al., 2009). Results indicate that the rainfall impact is not uniform across beaches in Chicago, consistent to findings of Kleinheinz et al. The logistic regression results from Equation 2 do give insight towards the relative significance of the rainfall impacts among Chicago beaches but does not characterize the duration of this impact.

## D. <u>**Limitations of Study**</u>

The limitations associated with this study are mostly limited to the precipitation and *E. coli* monitoring data. The limitation presented by the precipitation data in this study is the use of one weather station. Using one station can inaccurately extrapolate rainfall measurements from one location to the 21 locations used in this study. The study sites range in distances from 8.3 to 16.5 miles from the Chicago Midway International Airport weather station.

The *E. coli* monitoring data provided by the CPD represents one of the biggest strengths of the study but is accompanied by several limiting factors. There are two limitations intrinsic to the monitoring data. First, factors such as sampling depth, sample storage during transport, and laboratory practices can introduce error that is not well understood in this study. Samples taken from shallow depths will produce higher concentrations than samples collected from deeper depths (Kleinheinz et al., 2006). Improper sample storage or laboratory practices can lead to higher *E. coli* concentrations. In general, poor quality control can produce both inaccurate and imprecise results.

However, water samplers have been trained to be consistent in the location and depth of sample collection. The next limitation is that two different analyses were used to enumerate *E. coli.* Membrane filtration was utilized during 2003–2004 and the Colilert® method was used during 2005–2011. The use of different enumeration analyses should have minimal impact since both methods produce comparable results (Yakub et al., 2002). The next limitation was introduced after setting all sample times to 9:00 a.m. This was done since sample times were not consistently recorded in the monitoring data. When sample times were recorded they ranged from 7:00–11:00 a.m. Applying one sample time to all samples can consequently misclassify wet and dry conditions, potentially leading to weakened associations.

There were several limitations concerning the statistical methods used in this study. It was challenging to interpret ORs for predicting swim advisories and bans relative to models that predict *E. coli* concentrations directly. The wet and dry conditions defined in the study were arbitrary.

## VI. CONCLUSION

On average, precipitation negatively impacts *E. coli* concentrations at Chicago beaches. This impact was not uniform across all beaches. In fact, beaches located south of the Chicago River observed greater *E. coli* concentration differences during wet and dry conditions compared to beaches north of the Chicago River. This finding helps prioritize where future interventions should be explored in order to have the greatest impact towards better recreational water quality.

Developing an accurate predictive model to issue proactive swim warnings and bans would highly benefit beach managers. Study objective two attempted that while only using precipitation information and the results from the previous day's *E. coli* culture tests. Of the two proposed models, model two would be more practical for implementation. Before implementation, further work is needed in refining and cross validating the suggested predictive models. Analyzing various precipitation thresholds and rain periods can potentially improve model two.

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**VITA**

| | |
|---|---|
| NAME: | Jordan Thomas Charles Hepler |
| EDUCATION: | BS, Environmental Health, Bowling Green State University, Ohio, 2010 |
| | MS, Industrial Hygiene, University of Illinois at Chicago, Illinois, 2013 |
| EXPERIENCE: | Project Coordinator, Department of Environmental and Occupational Health Sciences, University of Illinois at Chicago, Illinois, 2013 |
| | Research Assistant, Department of Environmental and Occupational Health Sciences, University of Illinois at Chicago, Illinois, 2012 |
| HONORS: | National Institute of Occupational Health and Safety Trainee, University of Illinois at Chicago, Illinois, 2010–2012 |
| PROFESSIONAL MEMBERSHIP: | American Industrial Hygiene Association |