FORECASTING AND QUANTIFYING WATERBORNE PATHOGEN RISK TO IMPROVE PUBLIC HEALTH IN GALVESTON BAY, TEXAS

A Dissertation

by

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ABSTRACT

The primary public health concern related to fecal waste contamination in recreational waters is exposure to pathogens. Noroviruses, a viral pathogen, are a leading cause of illness outbreaks in recreational waters and presence of *Campylobacter* spp. has risen globally. Primary contact recreation including body immersion, head immersion, and splashes to the face increase exposure to contaminated water at coastal recreational beaches. In addition, the public is vulnerable to pathogenic illnesses during and after extreme weather events since flood waters are contaminated with pathogens.

A forecasting model framework was developed and assessed against the persistence method of beach management currently used at Sylvan Beach. Forecast model's sensitivity was at least 10% better than the persistence method for 12 of 15 models. All models, except the 2015 recreational season, had specificity greater than 80%. 87% of models were determined to be greater than 30% sensitivity. Based on a threefold assessment criterion, 71% of models passed validation. The use of forecasting models can reduce management uncertainty at Sylvan Beach.

Site-specific QMRA was performed to estimate total probability of illness for scenarios based on the population exposed, microbial source, recreational period, type of recreation, and ambient or elevated microbial conditions. Total probability of median illness was highest for primary contact during the recreational beach season. The 100% human source loads consistently accounted for highest illness probability. Predicted probability of illness for child scenarios was marginally elevated compared to adult scenarios suggesting risk may not differ between the two populations. Lastly, elevated scenarios had higher overall total illness probabilities compared to

ambient scenarios. However, the human load sources did not differ substantially between the ambient and elevated scenarios.

Potential health risk during extreme weather was estimated utilizing forecasting and QMAR models. The results suggest that overall total probability of illness is higher for event scenarios compared to expected typically ambient conditions. Concentrations of ENT were shown to be elevated during wet years compared to dry years. This could have negative repercussions on human and environmental health as the region is expected to be impacted intensifying rain events.

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All work for the dissertation was completed independently by the student. There are no outside funding contributions to acknowledge related to the research and compilation of this document.

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CHAPTER I

INTRODUCTION AND LITERATURE REVIEW

Introduction

The Lower Galveston Bay Watershed, predominantly situated in the Texas Gulf Coastal zone, encompasses a portion of the nine county Metropolitan Statistical Area (MSA) known as the Houston-Galveston region. The Houston-Galveston MSA is home to 6,490,180 (U.S. Census 2010) people mostly residing within the City of Houston; the fourth largest U.S. city by population. The Galveston Bay Watershed contains nine percent of the state's land area - including the Dallas-Fort Worth metroplex - which drains to Galveston Bay, the largest Texas estuary. The western and northern shores of Galveston Bay are highly developed while the eastern watersheds encompass rural agricultural lands and small municipalities.

Galveston Bay harbors productive oystering and seafood fisheries that account for one-third of the state's commercial fishing revenue (Lester and Gonzalez 2011). Based on the 2014 Texas Integrated Report of Surface Water Quality (formerly Texas Water Quality Inventory and 303(d) List) of impaired waterbodies, 39% of stream segments in the Lower Galveston Bay Watershed are impaired for contact recreation due to elevated levels of bacterial indicators (Figure 1). Portions of nine Galveston Bay segments are currently closed for direct to market oyster harvesting because contamination conditions pose a significant risk to public health (TCEQ 2014).

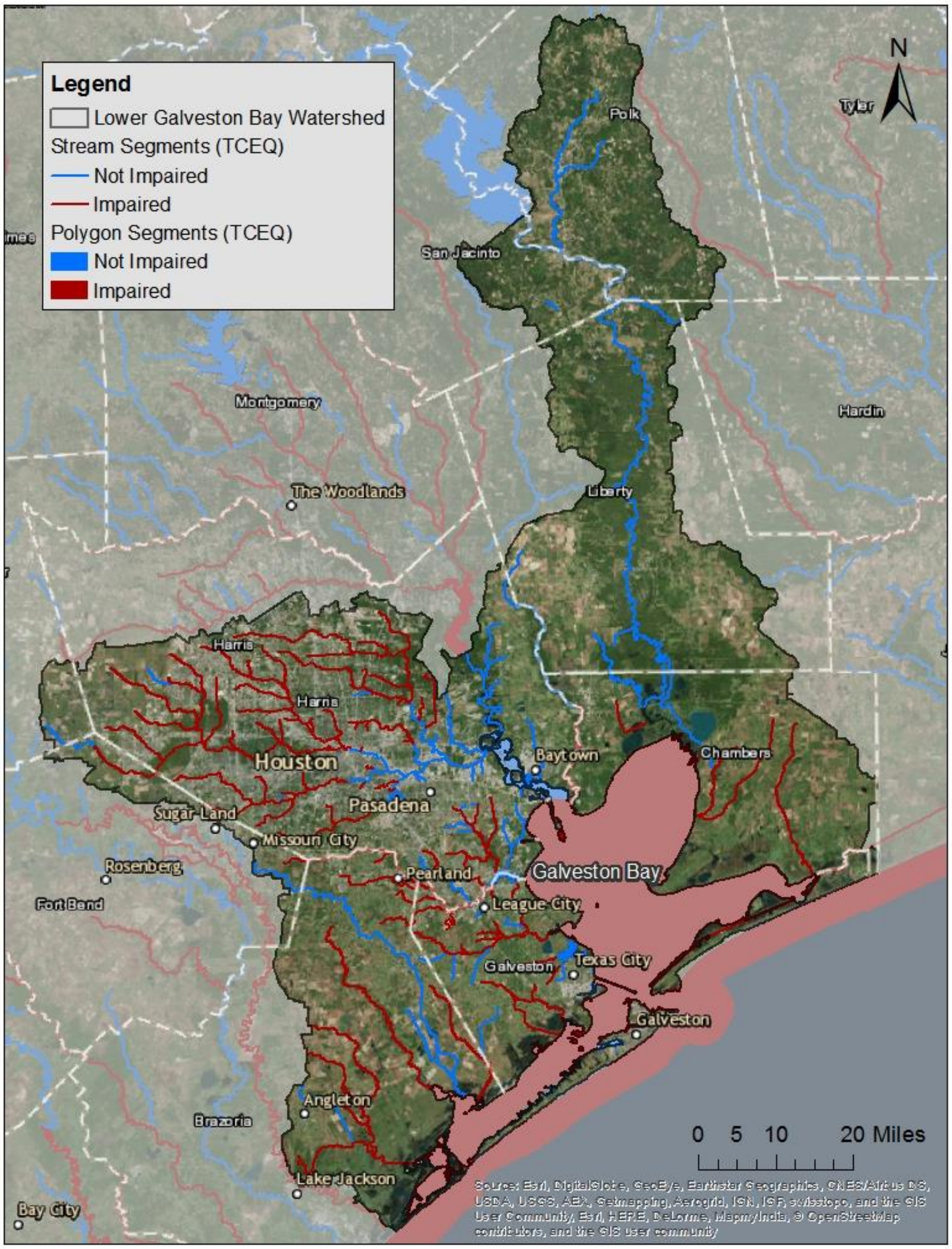

Figure 1 Lower Galveston Bay Watershed contact recreation and oyster waters impairments.

In U.S. surface waters, outdoor recreational activities such as swimming, boating, and fishing have been estimated to account for four billion recreational contact events annually (DeFlorio-Barker et al. 2018). The popularity of water-related outdoor recreation, in part due to increased ecotourism, is an economic driver for coastal and lakeside communities supporting jobs and commerce (Houston 2013). However, an estimated ninety million contact events result in the contraction of a gastrointestinal, respiratory, ear, eye, or skin related infection or illness ranging from mild to severe (DeFlorio-Barker et al. 2018). Indirect exposure, such as secondary contact recreation, also contributes to an elevated risk of gastrointestinal illness (Dorevitch et al. 2012). The primary human health concern related to fecal waste contamination in recreational waters is exposure to pathogens, such as bacteria (e.g., Campylobacter and Salmonella), protozoa (e.g., Cryptosporidium and Giardia), and viruses (e.g., noroviruses and adenoviruses) (Castro-Hermida et al. 2009, Gibson 2014, Hellein et al. 2011, Sinclair et al. 2009).

High concentrations of pathogens in surface water where recreational activity occurs has significant economic implications (DeFlorio-Barker et al. 2017, Johnson et al. 2008, Machado and Mourato 2002, Rabinovici et al. 2004, Ralston et al. 2011, Remoundou and Koundouri 2009, Shuval 2003), as well as detrimental consequences to public health (Dorevitch et al. 2012, Given et al. 2006, Ralston et al. 2011, Schwab 2007). Waterborne pathogen infections incurred by recreationists results in an estimated $2.2 to $3.7 billion encumbrance per year in national health care costs (DeFlorio-Barker et al. 2018). Furthermore, the number of direct exposure events resulting in illness at U.S. beaches is estimated to be greater than five million costing nearly $300 million per year (Ralston et al. 2011).

The Beaches Environmental Assessment and Coastal Health Act of 2000 (BEACH Act) amended the Clean Water Act (CWA) to require pathogen and pathogen indicator monitoring, the establishment of associated criteria for contact recreation, and development of state beach monitoring programs to reduce public exposure to microorganism contamination in coastal recreational waters (U.S. Congress 2000). According to the U.S. Environmental Protection

Agency (U.S. EPA), enterococci (ENT) are the preferred indicator bacterium in marine and estuarine coastal waters used for recreation (U.S. EPA 2012). Samples of ENT are interpreted to determine the level of public health risk from fecal waste contamination (U.S. EPA 2012). The Texas General Land Office's (TGLO) Beach Watch Program has installed 164 routine monitoring stations covering 62 recreational beaches along the Texas coast (Figure 2) (TGLO 2018). Public contamination advisories are issued for beaches when fecal indicator bacteria (FIB) are detected at concentrations higher than the recommend single sample maximum primary contact criterion of 104 MPN/100 mL (TGLO 2018). The persistence method of beach management which associates public health risk to the concentration of the last collected ENT sample is most utilized for recreational beach management (U.S. EPA 2007).

Figure 2 Texas Beach Watch Program at Sylvan Beach Park.

However, public contamination advisories, based on the persistence method, are reactionary opposed to preventative due to a one to several day lag time between sample collection, processing, and reporting (Brooks et al. 2016, U.S. EPA 1997). At Texas beaches, FIB samples are collected once per week during the recreational season and bi-weekly the remainder of the year (exception for Spring Break when additional samples are collected). If a sample exceeds the recreational beach standard, daily sampling is conducted until a non-exceedance is detected (TGLO 2018). However, differences in FIB concentrations at daily and weekly time intervals are large and highly variable (Boehm 2007); indicating the need for a less patchy temporal framework to guide beach management and public health decisions. A preemptive framework implemented prior to exposure could better serve illness prevention by advising the public to not recreate when beach water quality has a higher probability of impairment.

Fecal Indictor Bacteria

FIB are utilized to monitor the level of potential public health risk in recreational waterbodies because they are known to be associated with pathogens that can cause gastrointestinal disease, respiratory, ear, eye, or skin related illness (Byappanahalli et al. 2012). Indicator bacteria such as ENT are an effective alternative monitoring strategy because they are enteric in nature, residing in the gastrointestinal tract of warm-blooded animals, and therefore are capable of alerting resource managers that associated harmful pathogens may be present in the environment (Byappanahalli et al. 2012). Since the 2000 adoption of *Escherichia coli* (*E. coli*) and ENT in the Texas Administrative Code Title 30, Chapter 307, Texas Surface Water Quality Standards, these bacterial indicators have been favored over conventional fecal coliforms because they were shown to more strongly correlate with and have a higher sensitivity to potential pathogens (McElyea

2003). The Texas Commission on Environmental Quality (TCEQ) began modern FIB (*E. coli* and ENT) monitoring during the early 2000's. In 2003, the TGLO Texas Beach Watch Program was launched to provide targeted recreational beach bacteria monitoring (ENT) along the Texas coast and in select coastal bays (TGLO 2018). In 2018, the State of Texas single sample primary recreation contact criterion was updated from 104 MPN/100 mL to 130 MPN/100 mL (Texas Administrative Code, Title 30, Chapter 307 §307.7).

Enterococci

A large body of work has been generated describing environmental sources, fate, transport (Byappanahalli et al. 2012, Gao et al. 2013, Hack et al. 2003), and virulence (Betancourt et al. 2014, Jett et al. 1994, Molale and Bezuidenhout 2016) of the genus ENT. There are five distinct groups of Gram-positive *Enterococcus* spp. consisting of *E. faecalis*, *E. faecium*, *E. avium*, *E. gallinarum*, and *E. cecorum* (Byappanahalli et al. 2012). The *E. faecalis* and *E. faecium* species groups are of concern to recreational public health because they are often the major ENT species detected in surface water (Byappanahalli et al. 2012, Hack et al. 2003). Their tendency to be found in surface waters places *E. faecalis* and *E. faecium* in the direct path of humans recreating in Galveston Bay and surrounding watersheds. However, ENT are thought to decrease in concentration or deactivate the longer they are outside of their animal host.

A primary environmental ENT inactivation pathway is ultraviolet (UV) light exposure (Kay et al. 2005a, Maraccini et al. 2016). UV light is absorbed by ENT DNA which renders ENT inactive, preventing replication (Byappanahalli et al. 2012, Fujioka et al. 1981, Sassoubre et al. 2012). In addition, inactivation is a function of starvation, predation, competition, diurnal sag, seasonal variance, disinfection, and unfavorable physical and chemical water quality conditions which can lead to reduced survival time of ENT in the environment (Byappanahalli et al. 2012, Rochelle-Newall et al. 2015).

However, suspended solids (i.e. particles) in the water column provide shading and protection from sunlight for suspended as well as particle-attached bacteria (Anderson et al. 2005, Graml et al. 2014). Deposition of particle attached ENT to bottom sediments has been well documented (Fries et al. 2006). Bottom sediments are an important reservoir and source of ENT during storm events or other physical disturbances that cause their resuspension into the water column (Bai and Lung 2005, Fries et al. 2006, Yamahara et al. 2009). Presence of organic matter in the form of fecal waste is also thought to increase the rate of ENT survival in the marine environment (Byappanahalli et al. 2012). However, ENT are known to survive longer at lower salinities typical of estuarine and freshwater environments rather than at the average 35 ppt salinity of open ocean seawater (Anderson et al. 2005).

ENT bacteria are not only indicators of potential health risk; they can cause infection. Most enterococcal infections are caused by *Enterococci faecalis* (80-90%) and a majority of the rest by *Enterococcus faecium* (Jett et al. 1994). This is a concern because *E. faecalis* and *E. faecium* can comprise a majority of the ENT community isolated in surface and waste water, 20% and 63.5% respectively (Said et al. 2015). Direct human illnesses caused by ENT include urinary tract and abdominal infections, wound infections, gastrointestinal distress, and endocarditis (Arias and Murray 2012, Byappanahalli et al. 2012, Jett et al. 1994). Due to the ability of ENT to persist on the hands of health care workers, many of these infections are nosocomial. ENT are increasingly becoming more resistant to antibiotics (Arias and Murray 2012, Macedo et al. 2011), making the presence of ENT and associated fecal waste in the estuarine environment a principle concern for contact recreational use (Ahmad et al. 2014, Santiago-Rodriguez et al. 2013). Humans who were randomly assigned to bathe in ENT-contaminated marine waters, reported an increase in gastrointestinal, respiratory, and skin illnesses when compared to non-bathers (Fleisher et al. 2010).

Quantitative Microbial Risk Assessment

Despite the ramifications of misidentifying risk, current beach management protocols do not effectively characterize pathogen based public health risk with the probability of contracting an illness. The implementation of a Quantitative Microbial Risk Assessment (QMRA) beach management approach could more effectively serve to estimate the public health risks related to specific pathogens resulting in enhanced management measure implementation and better protection of public health (Ashbolt et al. 2010, Olivieri et al. 2014). At its core, QMRA is a tool used to estimate risk associated with contracting an infection from a microorganism.

More specifically, QMRA is a risk-based approach that can be applied to derive a risk probability of acquiring an illness or infection when recreating in pathogen impaired waterways by taking into consideration exposure duration and dose. The QMRA approach is commonly applied to determine primary contact recreation risk in recreational waters and can be used to determine site-specific risk-based water quality standards. The QMRA process can be attributed to four phases, including problem formulation, exposure assessment, dose response, and risk characterization. These processes combined can characterize the contamination source, determine a probability of swimming associated risk, and provide pathogen specific insight. These endpoints can more effectively inform beach and natural resource managers when making public health advisory decisions (Ashbolt et al. 2010).

The first phase of the QMRA identifies and characterizes the hazard and pathogens of interest. It is common for risk managers to select a package of reference pathogens and the QMRA might consist of multiple exposure pathways. Reference pathogens are typically used because they represent the worst-case scenario of infection. The second phase, exposure assessment, consists of determining the pathogen dose received by recreationists under a predetermined exposure scenario and subsequently determining the rate at which the dose is ingested. Phase three defines a dose response relationship per each reference pathogen selected in phase one. The dose response helps to define the exposure characteristics. The fourth and final phase serves to aggregate the tasks performed in the first three phases to determine risk characterization. Risk characterization provides an estimation of risk as total probability of infection. The beneficial and improved qualities of QMRA can be highlighted through an examination of relevant case studies.

Kundu et al. (2013) applied QMRA to estimate the risk associated with environmental concentrations of adenovirus in a mixed-use coastal watershed. Despite the QMRA process requiring several assumptions to determine model variables, the authors were successful in determining that a QMRA framework can be applied to protect public health in recreational waters (Kundu et al. 2013). Ashbolt et al. (2010) applied QMRA to describe its potential to provide beach managers with a higher level of detailed information to protect recreationists from fecal waste pollution. Betancourt et al. (2014) utilized QMRA to identify water-based recreation risks and pollution sources associated with *Cryptosporidium* and *Giardia* in tropical marine waters. This paper provided evidence that QMRA can be applied to better understand risk probabilities, distribution, and ecology of two specific waterborne pathogens associated with sewage (Betancourt et al. 2014). However, adequate pathogen monitoring data is rarely available to conduct a site specific QMRA; some studies have used ENT geometric mean criterion (35 MPN/100 mL) as a static estimate of risk (Schoen and Ashbolt 2010, Soller et al. 2010b) while others coupled a randomized ENT concentration, ingestion rate, and exposure time to determine the dose (Lim et al. 2017, Tseng and Jiang 2012) and used different fecal sources to calculate daily ENT geometric means across four recreational beaches.

These are important findings because the results indicate that QMRA techniques inform management decisions such as prioritizing specific beaches for management measures implementation to reduce risk. Management of coastal systems where people are exposed to waterborne pathogens through recreation and consumption of commercial seafood could be improved by performing QMRA to mitigate risk and inform public health management. As coastal populations continue to grow, and climate change increases uncertainty, more accurate quantification of microbial risk will be required to ensure surface water quality is suitable for drinking and recreation.

Study Site

The study site is Sylvan Beach, a popular recreational beach park that offers swimming and fishing opportunities. The site is located on the northwest shore of Upper Galveston Bay in the urbanized North Bay Watershed (Figure 3). The watershed has a total area of 64.3 km^2; as of 2011 15.6 km^2 (24%) of the watershed is impervious ground cover (Homer et al. 2012). Based on 2010 Coastal-Change Assessment Program (C-CAP) land use data, 31.5 km^2 (49%) of the watershed is developed land cover, 4.3 km^2 (7%) remains forested, with 10.2 km^2 (16%) of predominantly palustrine wetlands (NOAA 2010). The main stream segment, the only of significance, is the tidally influenced Little Cedar Bayou, which empties to Upper Galveston Bay, 1.3 km from the study site. Based on the 2014 Texas Integrated Report, Little Cedar Bayou is not impaired for contact recreation. The North Bay Watershed is hydraulically connected to the Galveston Bay system which is hydrodynamically described as a shallow micro-tidal impoundment that is heavily influenced by wind and freshwater inflows from the Trinity and San

Jacinto Rivers (Rayson et al. 2015). The bay exhibits a high degree of temporal and spatially variable salinity; over a 5-year period from 2007 to 2012 salinity ranged from 15-35 psu at the Bolivar Peninsula inlet and from 0-30 psu in Trinity Bay (Rayson et al. 2015).

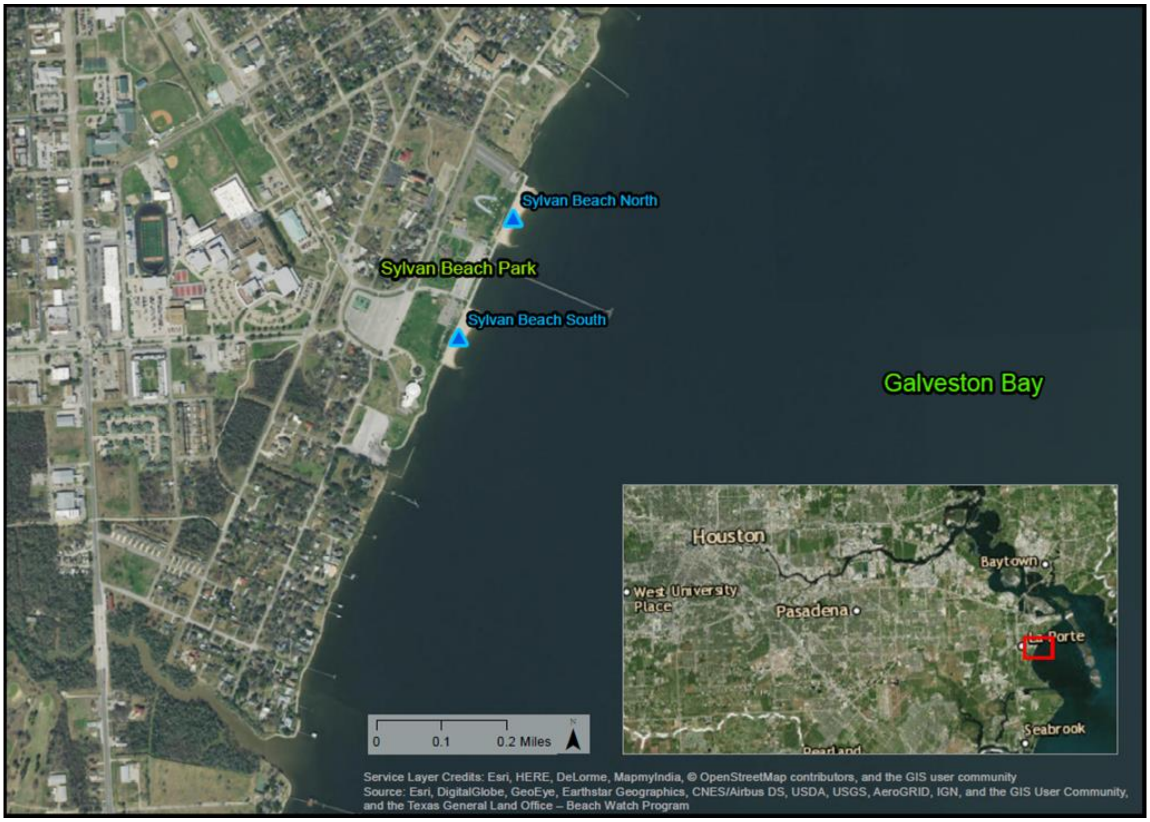

Figure 3 Sylvan Beach Park North and South on Galveston Bay near Houston, Texas.

As part of the Beach Watch Program – two bacteriological monitoring stations are located at Sylvan Beach, one at the Northern and one at the Southern swim beaches (Figure 4). ENT (MPN/100 mL) are routinely monitored at North and South Sylvan Beach stations once per week during the recreational beach season (May to September) and bi-weekly throughout the remainder of the year. Samples are collected at a depth of 0.61 meters to best represent knee height; a common depth recreationists may be exposed to pathogens (TGLO 2018). If an exceedance of the primary recreation contact standard (104 MPN/100 mL) is detected, monitoring is conducted daily until the ENT concentration falls below the criterion.

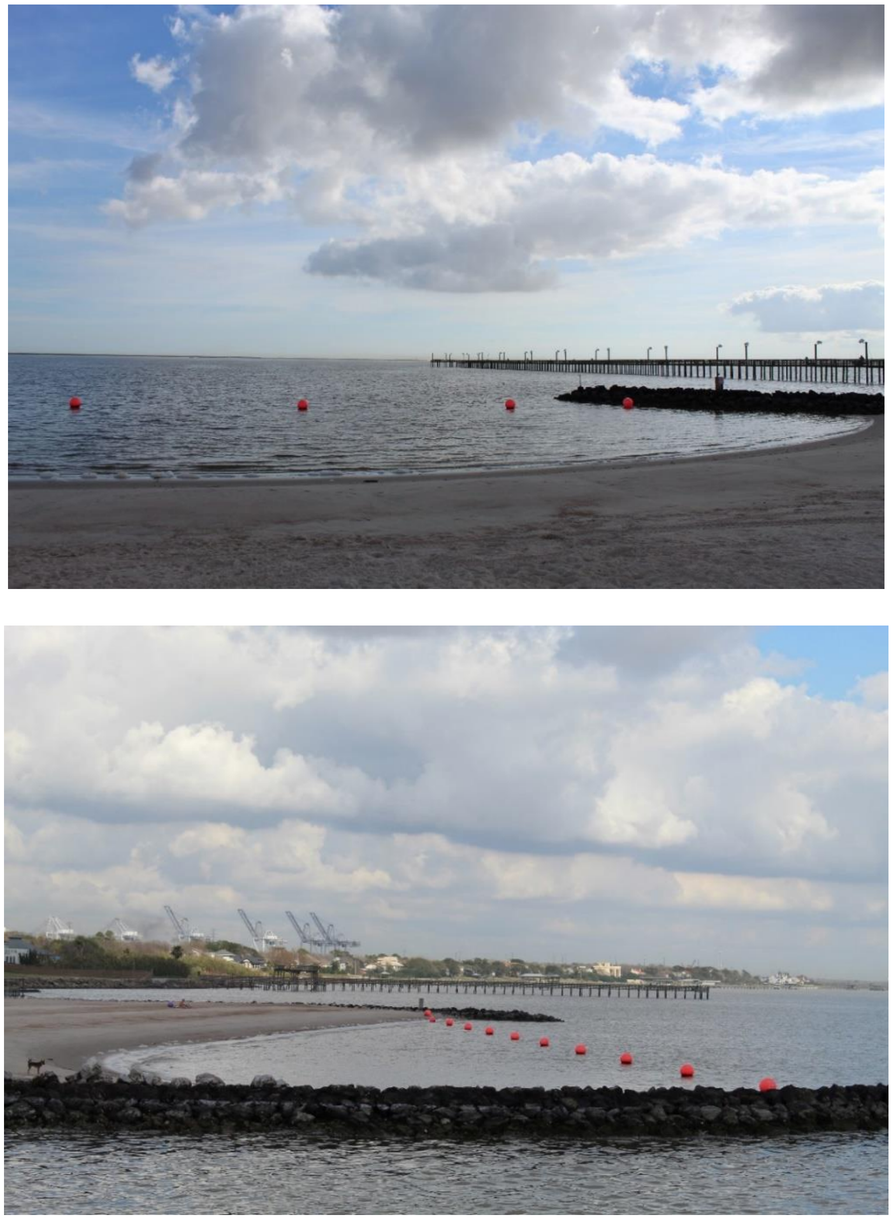

Figure 4 Sylvan Beach North (above) and South (below) swim beaches where ENT samples are collected; A dog is present on the southern swim beach.

In the North Bay Watershed fecal waste contamination stems from two primary mechanisms known as nonpoint and point sources of pollution. Point sources directly release pathogens into receiving waterways of the watershed from Wastewater Treatment Facility (WWTF) effluents, sanitary sewer overflows, and boater waste discharge events. Nonpoint sources stem from indirect sources such as stormwater runoff containing pet, wildlife, and agricultural waste as well as malfunctioning on-site septic systems (OSSF). In the heavily industrial and residential North Bay Watershed, potential mechanisms for dispersion of pathogens include nonpoint sources of pollution, typically associated with the urban environment such as human (OSSF), wildlife (seagull), and domestic animals (dogs) (Figure 5). Most of the watershed is serviced by wastewater collection infrastructure therefore a limited number of OSSF are present which does not exceed 30 per square mile. Permitted WWTF outfalls are located within the watershed, which represent a potential point source of pollution.

Figure 5 Evidence of dog presence and seagulls at Sylvan Beach Park.

The author conducted a site visit to Sylvan Beach Park on 01/08/2019; dogs and high concentrations of gulls were observed. At the study site dogs were observed on the beach, in the waters of the swim area, and in surrounding residential neighborhoods in proximity to the swim park. The neighborhoods are serviced by open vegetated roadside swales which is a concern because stormwater drainage systems can serve as conduits transporting nonpoint sources of fecal bacteria (Falbo et al. 2013). The direct presence of dogs at the study site is a concern because a source characterization study at a subtropical marine recreational swimming beach near Miami, Florida identified dogs to be the largest contributor of animal microbial load to beach waters (Wright et al. 2009). In addition, dog fecal events contribute substantially to beach microbial load compared to birds; at an equivalent factor of one dog fecal event to 7,000 bird fecal events (Wright et al. 2009). Furthermore, a microbial source tracking study conducted in a California coastal watershed concluded that dogs were a significant, yet manageable, source of fecal waste at a marine recreational beach (Ervin et al. 2014).

In addition to dogs, common wildlife sighted in proximity to the beach, on the beach, and in near-shore waters within the swim zone includes a high concentration of seagulls. The presence of gulls at the beach degrades water quality due to the high density of FIB and potential pathogens contained in their fecal waste and a positive association between animal presence and increased FIB concentration (Converse et al. 2012, Fogarty et al. 2003, Shibata et al. 2010). The contribution of ENT, by groups of birds such as gulls and pigeons ranked second, to dogs, of six categories at a beach in Miami-Dade County, Florida. (Wright et al. 2009).

The morning after the 01/08/2019 site visit two ENT samples were collected by the TGLO Beach Watch Program at Sylvan Beach Park North and South monitoring stations. The two samples resulted in exceedances of the primary contact recreation standard of 104 MPN/100 mL, as reported by the Beach Watch Program. Rainfall had not occurred in the last four days prior to sample collection (on 01/05/2019 at 0.44 inches) indicating that localized sources likely have a bearing on the concentration of FIB and associated pathogens present in swim waters at Sylvan Beach.

In the North Bay watershed, a WWTF discharges effluent via an external outfall to Little Cedar Bayou upstream from Sylvan Beach. Between 01/31/2016 to 04/30/2019 the facility released detectable concentrations of ENT with a daily maximum geometric mean of 6.7 and a daily average ranging from 1 to 5.8 MPN/100 mL (35 MPN/100 mL limit) (data obtained from EPA's Enforcement Compliance History Online database (EPA ECHO)). In addition, the facility has had at least one noncompliance violation for exceedance of the daily maximum ENT limit (104 MPN/ 100 mL) (EPA ECHO).

Detectable concentrations of ENT are an indication that norovirus could be present because wastewater treatment process may imperfectly remove norovirus (Hewitt et al. 2011). Furthermore, viruses have a higher resistance than bacteria to secondary treatment (Garcia-Aljaro et al. 2018). Although, norovirus is frequently detected in treated effluent, releases from raw or untreated wastewater pose substantial public health concerns (Eftim et al. 2017, Garcia-Aljaro et al. 2018, Haramoto et al. 2018, Hewitt et al. 2011, Kitajima et al. 2014, Qiu et al. 2015). Potential loads from human derived bather shedding is not a significant source of concern at Sylvan Beach because dogs and birds generate a higher microbial load even during crowded beach usage days (Zhu et al. 2011).

Expected Results

This dissertation research addresses one of the most pervasive coastal threats to humans and the environment (Quigg et al. 2009). Our understanding of waterborne pathogen contamination's impacts to coastal resources, economies, and public health is evolving. This research seeks to contribute to the present state of knowledge by further developing an understanding of how extreme weather events affect human health risk and by associating human health to pathogen concentrations in the Galveston Bay system. This dissertation is expected to provide enhanced resilience planning insights while highlighting the need of reducing nonpoint and point source contributions of fecal waste.

This research could have impacts beyond the local population and economy due to the export of commercial oyster fisheries catch and the large influx of tourists who visit the Houston-Galveston region on an annual basis. In addition, this project seeks to reduce the vulnerability of coastal communities to natural hazards and extreme weather events with respect to pathogen distribution and human health. This dissertation is expected to provide resource managers with results to enhance the protection of human, environmental, and economic health within coastal regions.

CHAPTER II

IMPROVING TEMPORAL RESPONSE TO WATERBORNE PATHOGEN IMPAIRMENT IN A COASTAL ESTUARY

Introduction

To overcome challenges associated with the persistence method, the use of alternative management strategies such as forecasting models has increased (Brauwere et al. 2014). Forecasting models are a quick and cost-effective way to predict FIB concentrations when compared to time intensive direct monitoring (Brooks et al. 2013, Francy 2009, Gonzalez et al. 2012, Gonzalez and Noble 2014, U.S. EPA 2007). Forecast models have been developed that outperform the persistence method of beach management (Brooks et al. 2013, Francy and Darner 2007, Frick et al. 2008). Despite prevalence of risk, there is no FIB forecasting system in Galveston Bay, or the Texas coast, to inform recreationists of potential human health concerns prior to exposure with contaminated recreational waterways and beaches.

The objective of this Chapter was to develop and assess the feasibility of applying a forecasting model that can outperform the persistence method of beach management at Sylvan Beach Park on Galveston Bay, Texas. To meet this objective, best fit regression models were identified by two variable selection techniques and integrated with multiple linear regression (MLR). A validation framework comprised of threefold assessment criteria was utilized to verify results and determine the practicality of implementing a beach management forecasting system at Sylvan Beach Park.

Methods

Study Site

The study site, Sylvan Beach Park, was selected based on the availability of continuous data sources, a seven-year historical record of bacteriological data, and because it is a popular recreational location that offers contact opportunities at a recreational swimming beach. The site is located on the northwest shore of Upper Galveston Bay in the urbanized North Bay Watershed (Figure 6). The watershed has a total area of 64.3 km^2; as of 2011 15.6 km^2 (24%) of the watershed is impervious ground cover (Homer et al. 2012). Based on 2010 Coastal-Change Assessment Program (C-CAP) land use data, 31.5 km^2 (49%) of the watershed is developed land cover, 4.3 km^2 (7%) remains forested, with 10.2 km^2 (16%) of predominantly palustrine wetlands (NOAA 2010). The main stream segment is the tidally influenced Little Cedar Bayou which drains to Upper Galveston Bay, 1.3 km from Sylvan Beach Park. The North Bay Watershed is hydraulically connected to the Galveston Bay estuary which can be hydrodynamically described as a shallow micro-tidal estuary heavily influenced by wind and freshwater inflows from the Trinity and San Jacinto Rivers (Rayson et al. 2015).

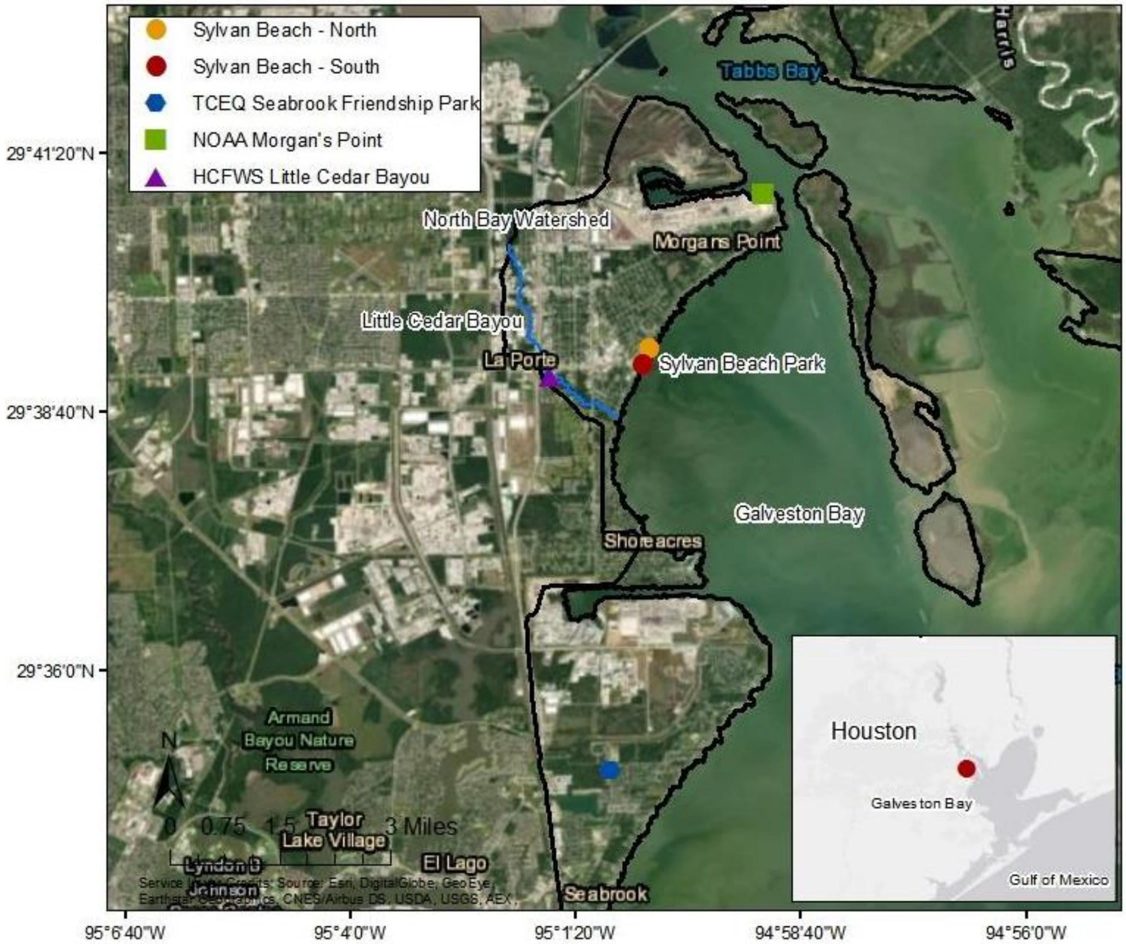

Figure 6 Sylvan Beach Park and locations of monitoring gages used to acquire data for model development.

Data Sources

Historical bacteriological, meteorological, physiochemical water quality, and physical oceanographic data were obtained for the study period (01/01/2011-12/31/2017). Variables of interest were acquired from quality assured local, state, and federal data sources in proximity to Sylvan Beach (Figure 6). The TGLO Beach Watch Program database was queried for ENT (MPN/100 mL) at two monitoring stations, North and South Sylvan Beach monitoring stations (TGLO Beach Watch Program Manager, personal communication). The Texas Beach Watch

Program collects ENT samples at 0.6 meters (m) in depth to represent recreational contact at knee height and samples are enumerated using EPA method 1600 (TGLO 2018, U.S. EPA 2006). Wind direction (degree[º]), speed (meter per second [m/s]), and peak gust (m/s), atmospheric pressure (hectopascals [hPa]), air temperature (degree Celsius [°C]), water temperature (°C), conductivity (millisiemens per centimeter [mS/cm]), water level (m), tide prediction (m), and tide stage (high/low) were downloaded from the National Oceanographic and Atmospheric Association's (NOAA) Tides and Currents Morgan's Point Station (8770613). The Harris County Flood Warning System Little Cedar Bayou at 8th Street gage provided daily 15-minute rainfall (millimeter [mm]). The daily regional clear sky ultraviolet index (UVI) archived during the solar noon hour for the City of Houston was downloaded from the National Weather Service (NWS). Lastly, solar radiation (langley per minute [ly/min]) was acquired from the TCEQ Houston Regional Office maintained Seabrook Friendship Park weather monitoring station (EPA site 482011050). Data processing, validation, and management was conducted in Microsoft Office Professional Excel ® 2016 prior to import into statistical software.

Variable Computations

Seven variables were generated from raw 15-minute rainfall data obtained from the Harris County Flood Warning System: 1, 2, 3, 5, and 7 total daily rainfall accumulation prior to day of ENT sample collection, number of prior days since last rain event (DSLR), and pre-sample rainfall (total rainfall on sample day up to time of ENT collection). A categorical variable was created from solar noon UVI data by assigning Low, Moderate, High, Very High, and Extreme identifiers based on an interval scale (Farouk et al. 2012). A second binary categorical variable was assigned to records dependent on collection in the recreational (May-September) or non-recreational (October-April) beach season. A new variable consisting of estimated salinity was generated from associated water temperature and conductivity based on a conductivity ratio to practical salinity conversion algorithm (Fofonoff and Millard 1983). In addition, two study variables were derived from TCEQ hourly solar radiation measured in ly/min: 1) maximum solar radiation on the day prior to ENT sample collection and 2) solar radiation related to time of ENT sample collection. Lastly, wind direction, wind speed, and gust speed from the NOAA Morgan's Point monitoring station were utilized to generate two meteorological components containing four variables: 1) alongshore (A) wind/gusts and 2) offshore/onshore (O) wind/gusts. A 35° angle was utilized to represent the orientation of Sylvan Beach for the component calculations with *D* and *S* defined as direction and wind/gust speed, respectively (Cyterski et al. 2013):

$$Wind/Gust\ A = -S * cosine\left((D - 35°) * \frac{3.1416}{180}\right)$$

$$Wind/Gust\ O = S * sine\left((D - 35°) * \frac{3.1416}{180}\right)$$

The remaining candidate variables not requiring computation were selected for analysis by pairing the closest data point (6-minute, 15-minute, or 1-hour time interval) to time of ENT sample collection. The reported procedures resulted in a study database containing 584 records and twenty-five candidate variables.

Statistical Procedures

The study database comprised of 584 records was developed for model building and statistical analysis. All statistical analysis was performed using JMP Pro 14.1.0. Prior to model development, candidate variables were determined to have linear relationships with the dependent variable (ENT) through a multivariate scatterplot matrix assessment. Records containing an observed value of zero for the dependent variable (ENT) along with candidate variables NOAA wind speed and NOAA wind gust were $\log_n(x+1)$ transformed (Bradshaw et al. 2016, Telecha et al. 2009). Sea level pressure was $\log_n$ transformed to reduce skewness. To determine interannual variability, seven years of historical ENT data were compared across groups using a nonparametric Kruskal-Wallis test with significance determined at 95% confidence (α=0.05). A Mann-Whitney test (95% confidence α=0.05) was performed to statistically investigate whether data between North and South monitoring stations could be utilized to generate one prediction output or if independent models per each station should be developed. Additional Mann-Whitney tests were performed to compare ENT across groups of recreational/non-recreational beach season and wet/dry sampling day. The number and percent of exceedances for each dataset were calculated based on the primary recreation contact criterion of 104 MPN/100 mL.

Model Building

Dataset Creation

It is known that optimum forecasting models can be achieved by limiting the temporal period of data used for calibration (Frick et al. 2008, Gonzalez et al. 2012) and by grouping based on bi-phase seasonal aggregations (Brooks et al. 2013, Francy and Darner 2007, Thoe et al. 2015). In addition, early results from this study suggested that bi-phase models can yield models with increased prediction performance and reduced error threshold. A bi-phase attribute was assigned to each record using the binary recreational/non-recreational categorical variable. The overall study database (584 records) was subdivided amongst recreational (347 records) and non-recreational (237 records) beach seasons. Datasets were further refined by creating annual bi-phase aggregations based on recreational and non-recreational beach season. The recreational/non-recreational identifier served as a proxy for separating seasonal influence of varying meteorological, physiochemical, and oceanographic conditions on ENT abundance, at the study site, reducing inter-annual and sub-annual variability. The studies sub-annual datasets are representative of beach management best practice which bases forecasting models on rolling short term calibration periods to make near term FIB predictions (Frick et al. 2008). The restructuring of the overall database resulted in seventeen datasets for use in model calibration and validation. The overall model was calibrated with 71% (5 years) while 29% (2 years) of the study dataset was withheld for validation.

Variable Selection

To identify independent explanatory variables for inclusion in model development, stepwise regression and all best model variable selection procedures were compared. Prior to variable selection, candidate variables determined to be collinear were withheld from further assessment. The JMP stepwise regression platform enables evaluation of Forward Selection, Backward Elimination, and Mixed Effect directions. Multiple stopping rules for variable selection were considered for each direction. An F-test at *p*-value threshold of <0.25 (Mixed Effect only), minimum Bayesian Information Criterion (BIC), and minimum Akaike Information Criterion corrected (AICc) were applied as rules. The resultant best fit model for each direction, rule, and dataset were compared amongst themselves and against best fit models selected by the all best variable selection procedure.

The generation of all best models was applied using a ten-term limit. The three best models with one to ten independent variables were evaluated. The best fit models were selected when adjusted R^2 was maximized while AICc and RMSE were minimized. The adjusted R^2 was utilized over R^2 because this metric allows for cross-model comparison and does not inflate with an increased number of model terms. AICc was utilized for model selection because bias is reduced providing an improved representation of model optimism compared to the classical AIC (Kletting and Glatting 2009, Murtaugh 2009). In addition, AICc is appropriate for models with limited sample sizes (Hurvich et al. 1998). RMSE is a valuable model selection criterion because it is representative of predictive performance. The all best model platform was determined to be optimal for selection of candidate variables because this procedure consistently resulted in equivalent or improved models compared to stepwise variable selection. These procedures allowed seventeen best fit models, representing overall, overall bi-phase, and annual bi-phase subsets, to be selected for inclusion in MLR.

Multiple Linear Regression

MLR was performed for each best fit model from overall, overall bi-phase recreational/non-recreational, and annual bi-phase recreational/non-recreational beach season subsets. The Variance Inflation Factor (VIF) provided a secondary screening for collinear terms. A VIF greater than ten indicated further evaluation was required (Belsley et al. 2005). If determined to be unacceptable the collinear term(s) were forced from the model based on highest VIF, lowest log worth, and least degree of significance. Variables with low log worth, non-significant terms, or unrealistic representations of functional relationships with the dependent variable were also considered for exclusion. Once model terms were finalized, a twofold assessment was undertaken. First, regression diagnostics including adjusted R^2 (goodness-of-fit), RMSE (predictive capability), and AICc (model optimism) were evaluated (Kletting and Glatting 2009, Murtaugh 2009). Secondly, residual by predicted plots and residual normal quantile (Q-Q) plots were assessed to assure model assumptions were supported. In addition, actual by predicted plots provided graphical insight further illustrating the model's predictive performance. Once models were determined satisfactory MLR equations were used to compute predictions per each database record along with 95% prediction intervals for use in validation.

Validation

Several studies have advocated for the use of beach forecasting evaluation criteria frameworks consisting of specificity (%) (true negatives/observed and predicted ENT indicate a beach advisory should not be issued), sensitivity (%) (true positives/observed and predicted ENT indicate a beach advisory recommendation should be issued), and total correct predictions (%) (sum of sensitivity and specificity divided by total number of samples) (Brooks et al. 2016, Brooks et al. 2013, Francy 2009, Gonzalez et al. 2012, Telecha et al. 2009, Thoe et al. 2014, Thoe et al. 2015). Thoe et al. (2014), suggested a threefold assessment matrix to determine practicality of applying forecasting models in a beach management system: 1) model sensitivity greater than 30%, 2) model sensitivity 10% greater than the persistence method, and 3) model specificity above 80%. To determine model error, false positives (predicted ENT exceedance/observed ENT non-exceedance) and false negatives (predicted ENT non-exceedance/observed ENT exceedance), are a frequently utilized. In order to derive validation criteria, observed ENT and predicted ENT values for the overall model validation period (29% - 2 years) were cross-compared. Similarly, overall bi-phase models were validated by cross-comparing predicted ENT and observed ENT values corresponding to recreational/non-recreational records in the validation period. Predicted ENT values from annual bi-phase models were validated against observed ENT values from the subsequent year of data corresponding to the correct recreational/non-recreational period, except for the study year 2017 which utilized observed ENT 2016 records for hindcast validation. The indicators of validation success were calculated independently of calibration datasets used in model development.

To allow comparison between the current and proposed beach management strategies the persistence's method sensitivity (%) was calculated for each study dataset by cross-comparing observed ENT with the subsequent sampling days observed ENT value. The average percent sensitivity for all persistence periods was 20% and the overall persistence model sensitivity was found to be 26%. Although, sensitivity of the persistence method at the study site tended to be lower than 30%, the sensitivity criterion of 30% was kept as a conservative estimate of forecast success. Specificity (%), total correct predictions (%), false positives (%), and false negatives (%), were also calculated based on the persistence method. Thirteen and fourteen samples were withheld from overall recreational and overall non-recreational validation computations, respectively, as a result of temporal breaks causing non-consecutive data points.

Results

Nonparametric

A one-way analysis nonparametric Kruskal-Wallis test, significance determined at 95% confidence (α=0.05), was conducted to discern differences of ENT amongst sample years (Figure 7). The Chi-Square Approximation rejected the null hypothesis that all group ENT medians are equal (p=<0.0001); triggering post hoc testing that utilized nonparametric comparisons for each year level under the Wilcoxon method. Ten levels of twenty-one were determined to be significantly different (α=0.05); sample years 2016 & 2011 (<0.0001), 2016 & 2012 (0.0001), 2016 & 2013 (0.0007), 2016 & 2014 (<0.0001), 2015 & 2011 (0.0100), 2015 & 2012 (0.0173), 2015 & 2013 (0.0356), 2015 & 2014 (0.0003), 2017 & 2014 (0.0074), and 2017 & 2016 (0.0077). A one-way analysis Mann-Whitney test (95% confidence α=0.05) was applied to compared ENT concentration between North and South groups resulting in a failure to reject (p=0.6120) the null hypothesis that group means are equal. This result indicated that ENT data from the two stations could be combined and utilized to generate one prediction output. A one-way analysis Mann-Whitney test (95% confidence α=0.05) for ENT across recreational and non-recreational beach seasons was performed. No difference in median concentrations of ENT was detected between the recreational and non-recreational beach seasons (p=0.1320). However, wet sampling days were determined to have greater ENT concentrations than dry sampling days (p=<0.0001) by an order of 1.65 to 2.97 ($\log_{10}$ MPN/100 mL) (α = 0.05).

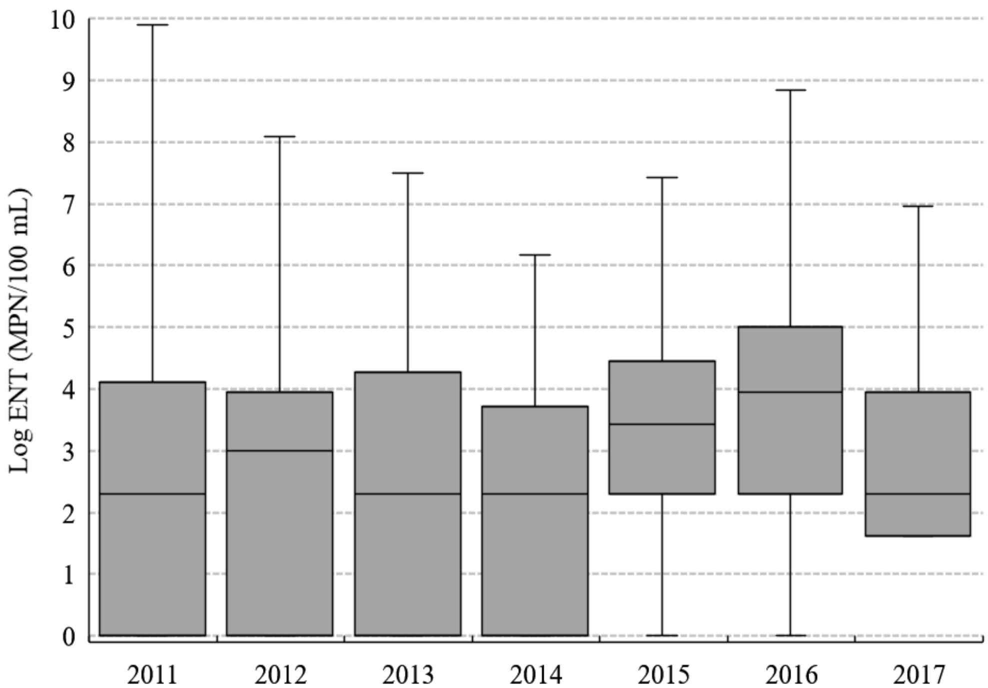

Figure 7 Boxplot of interannual ENT variability across seven study years at Sylvan Beach Park. Boxplots represent 25th, 50th (median), and 75th percentiles while whiskers are 0 (minimum) and 100th (maximum) percentiles of ENT concentration.

Model Performance

The best fit models resulted in the inclusion of five to ten terms. As expected, the overall model and overall bi-phase models performed poorly indicated by high RMSE, low adjusted R^2, and high AICc (Table 1). Due to an increase of sampling during the recreational season recreational models were calibrated with a higher number of records. However, an increased number of records was not associated with improved model performance. Model RMSE ranged from a minimum of 0.86 in the non-recreational period of 2017 to a maximum of 1.9 during the recreational season of 2011. Adjusted R^2 peaked in the 2013 non-recreational model (0.84) and was the lowest in the 2017 recreational model (0.19). The models were able to explain between 19% and 84% of ENT variance; the least amount of ENT variance was described by the overall models 21%, 23%, and 33%, except for the 2017 recreational period (19%). The 2011 non-recreational model had the lowest AICc (105.75) while the overall model had the highest (1,663.23). However, all models were significant at 95% confidence (α=0.05).

Table 1 Regression diagnostics including RMSE, Adjusted r^2, AICc, Prob>F, and the number of records (n) by temporal period for recreational (rec) and non-recreational (non-rec) forecasting models.

Temporal Period	Model	RMSE	Adjusted r^2	AICc	Prob > F	n	No. of Terms	Terms*
2011	Rec	1.90	0.36	215.86	0.0005	49	7	SR Sample, Wind A, Water Temp, Air Temp, Water Level, DSLR Prior, Clear Sky UVI
	Non-rec	0.94	0.68	105.75	<0.0001	30	9	7 Day, Conductivity, Wind O, 1 Day, Log[Sea Level Pressure], 3 Day, SR Sample, Clear Sky UVI, SR Max Day Prior
2012	Rec	1.47	0.48	175.07	<0.0001	44	8	5 Day, Log[NOAA Gust Speed], Clear Sky UVI, SR Sample, 1 Day, Wind A, Water Temp, SR Max Day Prior
	Non-rec	0.91	0.76	110.03	<0.0001	33	9	Wind A, Air Temp, DSLR Prior, Wind O, SR Sample, Water Temp, SR Max Day Prior, Water Level , 1 Day
2013	Rec	1.43	0.57	179.64	<0.0001	46	8	Water Level, DSLR Prior, SR Sample, Conductivity, Log[Sea Level Pressure], Log[NOAA Gust Speed], Clear Sky UVI, Water Temp
	Non-rec	0.88	0.84	113.61	<0.0001	34	10	Tide Prediction, Log[Sea Level Pressure], Clear Sky UVI, 5 Day, Wind O, Conductivity, 7 Day, Log[NOAA Gust Speed], 1 Day, 3 Day
2014	Rec	1.28	0.58	163.90	<0.0001	46	5	1 Day, Log[Sea Level Pressure], Tide Prediction, Log[NOAA Wind Speed], DSLR Prior
	Non-rec	1.30	0.47	110.02	<0.0001	29	5	2 Day, Air Temp, 7 Day, Conductivity, Wind A
2015	Rec	1.32	0.57	207.05	<0.0001	56	9	SR Sample, Conductivity, 7 Day, Wind O, 1 Day, SR Max Day Prior, 2 Day, Log[Sea Level Pressure], Water Level
	Non-rec	0.96	0.85	119.82	<0.0001	38	7	Pre-sample, 1 Day, 3 Day, Water Level, Wind O, SR Sample, Log[Sea Level Pressure]
2016	Rec	1.66	0.50	239.90	<0.0001	58	9	Pre-sample, Water Level, Wind A, Wind O, Clear Sky UVI, DSLR Prior, Tide Prediction, Conductivity, Air Temp
	Non-rec	1.37	0.71	143.78	<0.0001	37	7	Air Temp, 2 Day, Clear Sky UVI, 3 Day, Wind O, Log[NOAA Gust Speed], Log[Sea Level Pressure]
2017	Rec	1.03	0.19	148.88	0.0480	45	9	Air Temp, SR Sample, 1 Day, Wind O, Tide Prediction, SR Max Day Prior, 3 Day, 7 Day, Wind A
	Non-rec	0.86	0.69	106.84	<0.0001	36	7	5 Day, Wind A, 3 Day, Pre-sample, Wind O, Water Level, Conductivity
Overall	Rec	1.89	0.23	1002.01	<0.0001	242	5	1 Day, SR Sample, 2 Day, Pre-sample, Log[Sea Level Pressure]
	Non-rec	1.72	0.33	941.27	<0.0001	237	7	1 Day, SR Sample, Tide Prediction, Water Level, Pre-sample
	All	1.89	0.21	1663.23	<0.0001	403	5	Pre-sample, 1 Day, Conductivity, Air Temp, 3 Day, 7 Day, SR Max Day Prior

* Listed by Log Worth Rank

Validation

Model sensitivity ranged from 0% (no observed or prior sample primary contact recreation criterion exceedances were correctly forecasted) for 2013 and 2016 non-recreational forecast models as well as 2011 recreational and 2017 non-recreational persistence models to 100% (all observed or prior sample primary contact recreation criterion exceedances were correctly forecasted) for 2012, 2014, and 2016 non-recreational forecast models (Figure 8). Model sensitivity was greater for the forecasting method in all cases except for the study years 2015, 2016, the overall recreational, and the overall model. In one instance, 2013 non-recreational forecast and persistence were equivalent at 0% sensitivity.

Specificity ranged from a minimum of 68%, which indicated that observed or prior sample primary contact recreation criterion non-exceedances were correctly forecasted, for the 2015 non-recreational persistence model to 100% (all observed or prior sample primary contact recreation criterion non-exceedances were correctly forecasted) for the overall recreational and non-recreational models (Figure 8). Percent specificity was greater for forecasting compared to persistence in all cases except for the 2015 recreational model (77% forecast to 87% persistence).

The percentage of total correct predictions, an indication of model success, was greater for the forecasting models in all cases except for the 2015 and 2017 recreational periods. The highest percentage of false negatives was recorded for the 2014 non-recreational persistence model (26%). Similarly, the 2014 persistence model for recreational and non-recreational periods had the highest false positive rate (21%). The forecasting models performed exceedingly well generating predictions with a low percentage of false positives ranging from 0% to 7% except for the 2015 recreational and non-recreational models which scored 18% and 16%, respectively (Figure 8).

The forecast model's sensitivity was at least 10% better, indicating a higher rate of correctly predicted exceedances, than the persistence method for 12 of 15 models (Table 2).

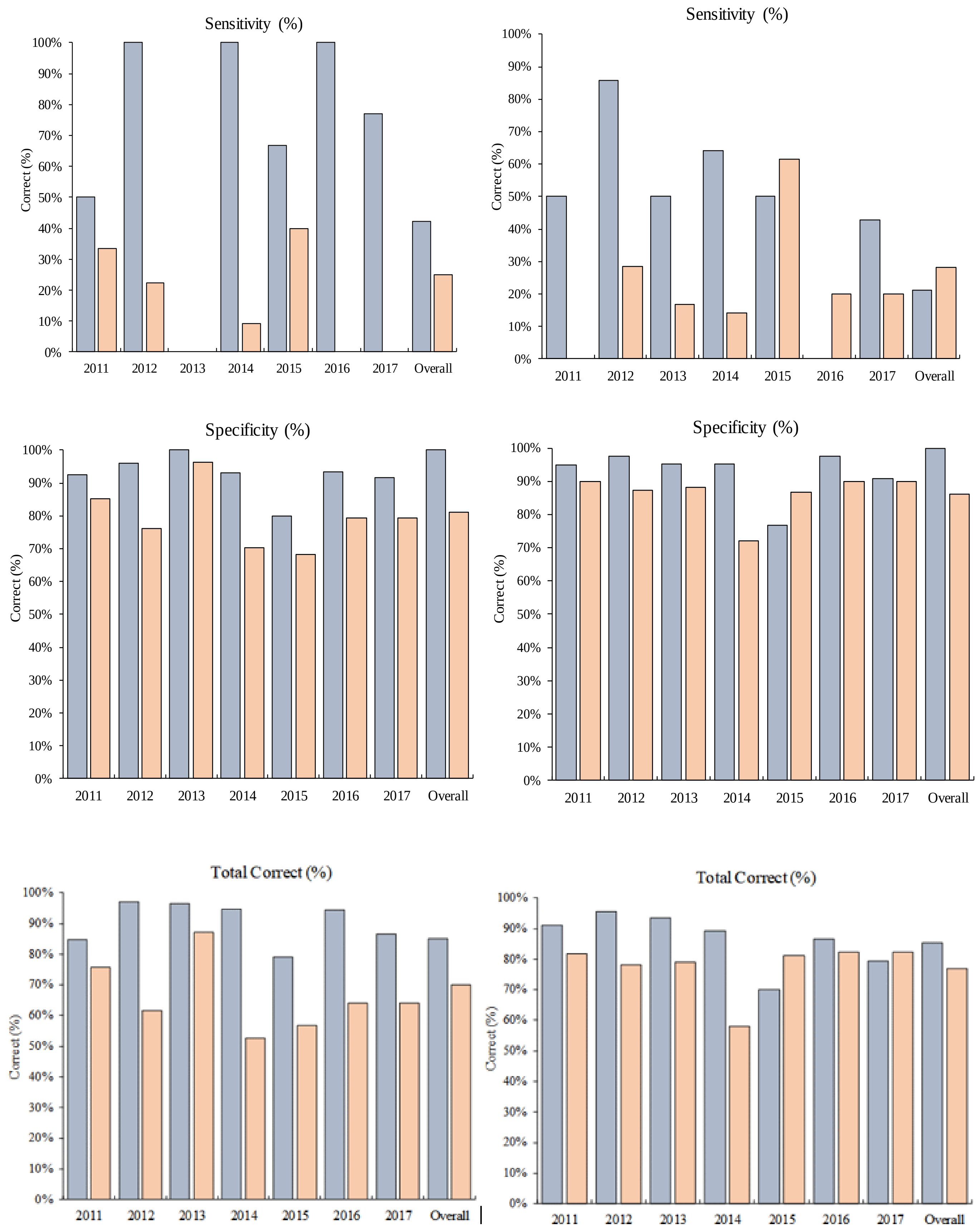

Figure 8 Non-recreational and recreational validation results (sensitivity specificity, and total correct predictions) for forecasting and persistence models

All models, except the 2015 recreational model (77% specificity), had specificity greater than 80%. The percent sensitivity for 13 of 15 models was determined to be greater than 30%. Based on the threefold assessment criteria utilized as a decision matrix, 12 of 17 models (71%) passed validation.

Table 2 Final status of validated models based on the threefold assessment matrix.

Temporal Period	**Model**	**plus 10% sensitivity**	**Specificity > 80%**	**Sensitivity > 30%**	**Pass/Fail**
2011	Rec	Yes	Yes	Yes	Pass
	Non-rec	Yes	Yes	Yes	Pass
2012	Rec	Yes	Yes	Yes	Pass
	Non-rec	Yes	Yes	Yes	Pass
2013	Rec	Yes	Yes	Yes	Pass
	Non-rec	No	Yes	No	Fail
2014	Rec	Yes	Yes	Yes	Pass
	Non-rec	Yes	Yes	Yes	Pass
2015	Rec	No	No	Yes	Fail
	Non-rec	Yes	Yes	Yes	Pass
2016	Rec	No	Yes	No	Fail
	Non-rec	Yes	Yes	Yes	Pass
2017	Rec	Yes	Yes	Yes	Pass
	Non-rec	Yes	Yes	Yes	Pass
Overall	Rec	No	Yes	No	Fail
	Non-rec	Yes	Yes	Yes	Pass
	All	No	Yes	No	Fail

Discussion

Most FIB modeling studies have been conducted in freshwater environments (Brooks et al. 2016, Brooks et al. 2013, Francy 2009, Francy and Darner 2007, Frick et al. 2008, Heberger et al. 2008, Nevers and Whitman 2005, 2011, Paule-Mercado et al. 2016, Telecha et al. 2009, Zhang et al. 2018). Fewer forecasting models have been developed for marine coastal environments (Bedri et al. 2016, Hou et al. 2006, Shibata et al. 2010, Thoe et al. 2014, Thoe et al. 2015, Zhang et al. 2012) and even less for estuarine coastal environments (Gonzalez et al. 2012, Gonzalez and Noble 2014). As a result, forecast systems to alert the public of potential health risk have been largely developed for swimming beaches on freshwater bodies such as the Great Lakes. A limited number of estuarine models (Gonzalez et al. 2012) are available and no forecasting models have been successfully developed at Texas coastal beaches. Variability of physiochemical water quality, geomorphological, and hydrological abiotic processes in estuarine coastal waters influences pathogens and, therefore, the associated microbial health risk, differently than marine and freshwater beaches. It is important to reduce uncertainty related to public health risk in estuarine waters because tourists and residents alike are drawn to swimming, fishing, boating, and engaging in water-related recreational activities in Texas coastal bays due to their abundant natural resource features.

Explanatory Variables

Limiting the included number of candidate variables was not a primary concern in this study because all study data can be obtained at minimal cost by automating data retrieval; rather, models with stronger prediction power were preferred to align with the study's objectives. Nineteen of 25 candidate variables were selected for model development in at least one forecasting model. The selected explanatory variables included macro-ambient and physical meteorological, oceanographic, and water quality conditions. Various computations of precipitation, wind direction and speed, wave height, water level, tide type, water temperature, salinity/conductivity, dissolved oxygen, turbidity, air temperature, cloud cover, and solar insolation have been included in the calibration of FIB forecasting models (Francy 2009, Gonzalez and Noble 2014, He and He 2008, Jennings et al. 2018, Nevers and Whitman 2011). Many of these variables are publicly available because state environmental quality and federal agencies including NOAA, NWS, and the United States Geological Survey (USGS) collect the data as part of routine monitoring networks.

The three most often included variables were total rainfall per day prior to ENT sample collection (1 Day), solar radiation (SR Sample), and offshore or onshore wind (Wind O) at the time of ENT sample collection. Wet weather events can result in elevated concentrations of ENT in nearshore waters due to stormwater runoff (Thompson et al. 2012). A primary environmental ENT inactivation pathway is solar deactivation from ultraviolet (UV) light exposure (Kay et al. 2005b, Maraccini et al. 2016, Zhu et al. 2011). UV light is absorbed by ENT DNA preventing replication (Byappanahalli et al. 2012, Fujioka et al. 1981, Sassoubre et al. 2012). Wind is a predominate influence linking coastal physical processes that governs the processes controlling ENT fate and transport such as increased wave activity (Feng et al. 2013). Bottom sediments are an important reservoir and source of ENT during storm events or other physical disturbances that cause their resuspension into the water column (Bai and Lung 2005, Fries et al. 2006, Yamahara et al. 2009). Suspended solids (i.e. particles) in the water column provide shading and protection from sunlight for suspended as well as particle-attached bacteria (Anderson et al. 2005, Graml et al. 2014). The influential process, one day total rainfall, solar radiation, and offshore/onshore prevailing winds, highlighted by this study play principle roles in determining ENT fate and transport.

Model Performance

The interannual variability of ENT concentration detected between study years diluted performance of the overall models. To overcome interannual variability, the study database was aggregated to bi-phase sub-annual bins. This data processing step greatly enhanced model performance due to increased uniformity amongst individualized subsets. This association was particularly distinct for non-recreational beach season group models which consistently performed better than recreational season models, except for the study year 2014. The recreational models associated with study years 2015 and 2016 resulted in two of three failures for the sub-annual bi-phase models. Study year 2015 was found to have statistically significant differences between concentrations of ENT compared to four of six study years (2011, 2012, 2013, 2014) while 2016 had significant differences amongst ENT for all study years (2011, 2012, 2013, 2014, and 2017) except 2015 (Figure 7). This is an important distinction because the recreational periods of these two years contained the highest amount of rainfall, 104 mm in 2015 and 86 mm in 2016, except for the 2017 recreational period (164 mm) due to Hurricane Harvey. The annual and bi-phase subdivision of the study database allows for a high degree of resolution that could be applied to hindcast potential health risk during extreme weather events corresponding to a specific model's calibration period whence the event occurred by applying the regression equation to recreate event conditions.

The third model to receive a fail rating was the non-recreational period of 2013. However, this failure was caused by a minute variation between observed (4.98 log MPN/100 mL) and predicted (4.42 log MPN/100 mL) ENT values; resulting, in 0% sensitivity because this period had a single primary contact recreation criterion (4.64 log MPN/100 mL) exceedance. The majority (70.6%) of forecasting models outperformed the persistence method despite elevating percent sensitivity by a 10% correction factor and using a conservative 30% sensitivity benchmark. The results of this study can be interpreted to mean that forecasting models are able to more accurately predict a true exceedance of the contact recreation criterion indicating a beach advisory or action should be issued. Forecasting models were also less likely to produce a false negative or false positive than the persistence method for the same temporal period. Recreational beach closure due to issuance of a public health risk advisory is estimated to cause a net economic loss of $1,274 to $37,030 per day to local communities as a result of missed recreationist opportunity (Rabinovici et al. 2004). Although recreation is not restricted at Texas beaches, the issuance of a false public contamination advisory could still have negative economic impacts on the surrounding communities.

The all best variable selection and MLR forecast models calibrated for this study had a RMSE ranging from 0.86 to 1.9 and adjusted R^2 between 0.19 and 0.85. Other studies that developed MLR forecasting models in coastal marine or estuarine environments produced a RMSE of 0.75 and an adjusted R^2 of 0.64 (Gonzalez et al. 2012), adjusted R^2 ranging from 0.89 to 0.90 and RMSE 0.89 to 0.82, respectively, (Gonzalez and Noble 2014), and an R of 0.48 and a RMSE of 0.50 (Thoe et al. 2014). Although most models in this study are well within the range of performance indicators for models developed in marine and estuarine environments, there is room to improve the performance of forecast models at Sylvan Beach, due to the limitation of site-specific data. The collection of additional and/or site-specific explanatory variables, not able to be included in this study, such as turbidity can enhance model performance (Frick et al. 2008, Telecha et al. 2009). Turbidity has a significant effect on controlling irradiance (Kay et al.

2005b) and is a proxy representing resuspension of particle associated ENT (Fries et al. 2008). These factors could substantiality influence the presence of waterborne pathogens at Sylvan Beach Park; ultimately, explaining more variation and reducing uncertainty of model outputs.

Management Applications

This study suggests that forecasting FIB concentrations and, therefore, the potential public health risk at Sylvan Beach is feasible. The models produced by this study were calibrated using readily available inputs in proximity to the study site. All data sources are continuously collected and could be acquired in real-time through an automated program interface to support the operation of a beach management system at Sylvan Beach Park. The implementation of a Sylvan Beach forecasting model could improve beach safety for recreationists compared to the persistence method. This Chapter detailed data sources, model development and selection procedures, and a model validation framework that could form the bases of a beach management forecasting system. To mitigate interannual variability and poor performance of multi-year models, a rolling calibration period, including up-to-date data, for the most current or previous recreational or non-recreational period, should be utilized to develop future models. The generation of a daily health risk estimate could more effectively reduce exposure with pathogen-contaminated water because recreationists would be notified prior to exposure. Due to the high rate of ENT and associated pathogens natural variability, health risk estimates could be formulated for multiple daily periods such as morning and afternoon. This Chapter determined that monitoring data from Sylvan Park's North and South swimming beaches could be combined to derive one forecast. In addition, model usefulness was improved by reducing temporal bins to sub-annual bi-phase aggregations resulting in refined models compared to comprehensive models developed with seven years of data. If the collection of weekly or bi-weekly ENT samples by the TGLO were to continue in conjunction with a forecast model beach management system, the samples could be used to cross-validate forecast outputs for days when observed monitoring occurs.

Conclusion

Despite prevalence of public health risk, feasibility testing had not been conducted prior to this study to determine if a FIB forecasting model could improve beach management and reduce public exposure to pathogens in the Houston-Galveston region. This study collected readily available historical data to develop and evaluate eight sets of models split between recreational and non-recreational beach seasons and an overall model. The studies ENT forecasting models can reduce uncertainty at Sylvan Beach Park by outperforming risk estimates made by collecting weekly or bi-weekly grab samples, known as the persistence method. Overall, most FIB forecasting models developed by this study performed better than the persistence method. Beach managers should consider adopting a forecasting model-based management system because models have the potential to improve the issuance of erroneous public health contamination advisories and serve as an early warning system reducing public pathogen exposure. Based on the methodology developed in this study, additional sites along the Texas coast should be evaluated for forecasting feasibility. The potential economic and public health implications of recreating in pathogen contaminated waters at Texas coastal beaches remains unknown but is expected to be substantial.

CHAPTER III

QUANTITATIVE MICROBIAL RISK ASSESSMENT TO ENHANCE RECREATIONAL BEACH MANAGEMENT IN A COASTAL ESTUARY

Introduction

The primary pathogen-related pollutant of concern in recreational waters is fecal waste, which may contain infectious agents such as bacteria (e.g., *Campylobacter* and *Salmonella*), protozoa (e.g., *Cryptosporidium* and *Giardia*), and viruses (e.g., noroviruses and adenoviruses) (Castro-Hermida et al. 2009, Gibson 2014, Hellein et al. 2011, Sinclair et al. 2009). Noroviruses are a leading cause of illness outbreaks in recreational water due to a high potential to survive environmental stressors and remain infectious, and a high likelihood of causing infection in the human population (Fong and Lipp 2005, Gibson 2014, Seitz et al. 2011, Sinclair et al. 2009). In addition, contamination resulting in infection from *Campylobacter* spp. has been on the rise globally (Kaakoush et al. 2015). Potential infection risk from *Campylobacter* spp. is suggested to be on the rise because the pathogen was detected in 60% of river water samples (Savill et al. 2001). The daily risk for a gastrointestinal illness (GI) per individual from *Campylobacter jejuni* was found to be higher than *Giardia* and *Salmonella* in a freshwater environment (Sunger et al. 2018).

Norovirus presence is an indication of fecal waste contamination from human sources such as faulty WWTF effluent, malfunctioning OSSF, and direct boater discharge events. Norovirus from human sources can remain viable in stormwater runoff from urban watersheds which can negatively impact nearshore water quality (Soller et al. 2017). As a result, viruses are a predominate driver of risk in recreational waters where wastewater is a contamination source of concern (Farkas et al. 2018, Sunger et al. 2018). In addition, two sources - birds and dogs -

which are commonly present near recreational beach waters, can be major contributors of fecal waste and associated pathogens including *Campylobacter* spp. posing a risk to public health (Ervin et al. 2014, Hatch 1996, Shibata and Solo-Gabriele 2012, Wright et al. 2009). In marine and estuarine coastal waters, the FIB (ENT) are monitored because they are known to be associated with pathogens that can cause gastrointestinal disease (Byappanahalli et al. 2012, Wade et al. 2010). According to the U.S. EPA, ENT are the preferred indicator bacterium to determine the level of public health risk from fecal contamination in marine and estuarine coastal waters used for recreation (U.S. EPA 2012).

Primary contact recreation including body immersion, head immersion, and splashes to the face results in an increased exposure for ingesting contaminated water (Colford et al. 2012, Suppes et al. 2014). Primary contact recreation (direct exposure such as swimming or surfing) at 65 California beaches was estimated to result in 689,000 to 4 million GI and 693,000 respiratory illness per year with a higher summer rate of infection due to increased bather presence (Brinks et al. 2008). Indirect exposure in pathogen contaminated waters (secondary contact recreation) also contributes to an elevated GI risk (Dorevitch et al. 2012). At the sub-coastal scale a regional assessment revealed that cases of GI were estimated to range from 627,800 to 1.48 million per year with economic implications up to $51 million (Given et al. 2006). In addition, local recreational beach exposure to coastal waters impaired by fecal waste has been estimated to cause hundreds of thousands of illnesses per year resulting in an approximate $3.3 million economic setback to public health (Dwight et al. 2005).

QMRA can enumerate contact recreation risk when epidemiological data are lacking and pathogenic microbial contamination stems from point or nonpoint sources (Schoen and Ashbolt 2010, Soller et al. 2015, Soller et al. 2017, Soller et al. 2010b, Soller et al. 2014, U.S. EPA

2010). The probability of acquiring an infection or illness when recreating in pathogen impaired waterways is a common QMRA endpoint. Human derived pathogens typically result in a higher proportion of risk to the target population, compared to agricultural and wildlife sources, with the exception of cattle (Schoen and Ashbolt 2010, Soller et al. 2010a, Soller et al. 2010b, Soller et al. 2014). Current beach management protocols based on the persistence method do not effectively associate risk with health endpoints. The application of a QMRA framework to inform risk-based decision-making can result in enhanced management measures promoting microbial protection of public health (Ashbolt et al. 2010, Olivieri et al. 2014). The objective of this Chapter was to perform site-specific QMRA for human and nonhuman sources of fecal waste at Sylvan Beach Park on Galveston Bay, Texas. Total probability of risk, defined as the probability of gastrointestinal infection and subsequent illness, for adults and children engaging in primary and secondary contact recreation, during recreational and non-recreational beach seasons was estimated for a variety of exposure scenarios.

Methods

Study Site

The study site, Sylvan Beach Park, was selected due to it being a popular recreational swimming beach that offers secondary contact opportunities including pier fishing, wading, and non-motorized boating. To initiate the QMRA, source characterization included a site visit, investigative research, and quantitative analysis of historical ENT data (01/01/2011-12/31/2017) from two monitoring stations at Sylvan Beach. In the heavily industrial and residential North Bay Watershed, predominant mechanisms for dispersion of pathogens are those typically associated with the urban environment. Potential human sources of microbial contamination that may influence pathogen concentrations at Sylvan Beach Park are WWTF effluent, boater waste discharge events, sanitary sewer overflows (SSO), and bather shedding. The composition of non-human sources includes a domestic animal represented by dogs (*Canis lupus familiaris*) and wildlife e.g. seagulls (laughing gull [*Larus atricilla*]). During the site visit, dogs and direct evidence of dog presence was observed on the swim beaches in proximity to the shoreline. Similarly, a high number of seagulls were observed near the swim beach, directly on the swim beach, and in the water within the designated swim zone (Figure 9). Direct deposition of fresh fecal waste from seagulls and dogs at Sylvan's swim beaches is a significant microbial contamination pathway of concern.

Figure 9 Seagulls present at Sylvan Beach Park representing a potential source of microbial contamination.

Dose Conversion

Direct pathogen monitoring data are not available at Sylvan Beach, so ENT concentration was converted to a reference pathogen dose. The TGLO Beach Watch Program database was queried for ENT (MPN/100 mL), between 01/01/2011 and 12/31/2017, at two Sylvan Beach monitoring stations North and South (TGLO Beach Watch Program Manager, personal communication). The Texas Beach Watch Program collects ENT samples at 0.6 meters (m) in depth to represent recreational contact at knee height and samples are enumerated using EPA Method 1600 (TGLO 2018, U.S. EPA 2006). A conversion equation based on concentration of a FIB to pathogen dose was developed by (Schoen and Ashbolt 2010, Soller et al. 2014) and modified by (Gitter et al. 2016).

$$D_{RP}^{S} = \frac{C_{ENT} * F^{s}}{R_{ENT}^{S} \times 100} \times R_{RP}^{S} \times P_{RP}^{S} \times I_{RP}^{S} \times V$$

For this study, reference pathogen dose (D_{RP}^{S}) was derived based on the following coefficients: specified source (S), concentration of ENT (C_{ENT}), fraction of ENT from specified source (F^{s}), concentration of ENT in source waste (R_{ENT}^{S}), wet mass concentration of reference pathogen in source (R_{RP}^{S}), prevalence of reference pathogen to source (P_{RP}^{S}), infectious potential of reference pathogen in humans (I_{RP}^{S}), and ingested volume of water (V) (Table 3). To estimate risk during ambient and elevated periods of exposure, ENT concentration was repeatedly sampled from a uniform probability distribution ranging from the 5th to the 90th (ambient) and from the 90th to 100th (elevated) percentiles.

The elevated scenario represents periods of heightened risk, such as wet weather events or a concentrated release of fecal waste. For the elevated scenario (90th to 100th percentile) ENT concentration ranged from 216 to 19,863 MPN/100 mL (recreational) and from 267 to 24,196 MPN/100 mL (non-recreational). To allow for comparisons between elevated and ambient levels of microbial contamination, the QMRA was repeated by substituting ENT concentrations ranging from the 5th to 90th percentile: 0 to 216 MPN/100 mL (recreational) and from 0 to 267 MPN/100 mL (non-recreational). All percentile ranges were calculated from the seven-year ENT study dataset by recreational and non-recreational beach season. The ratio of contributing source (F^{s}) was estimated based on three source load scenarios: 1) 100% human derived microbial load, 2) 100% non-human derived microbial load (Schoen and Ashbolt 2010), and 3) microbial load derived from a composite mixture of sources including 25% human (raw/treated sewage) and 75% domestic animal and wildlife (dogs/seagulls) (Soller et al. 2010b, Soller et al. 2014).

Table 3 Nonhuman and human load computational variables by scenario, unit values, and distribution reported in the literature as utilized in the dose conversion calculations.

Variable	Scenario	Input Data	Unit/Comment	Distribution	Citation
Volume of Water Ingested	Adult (Primary/Secondary)	12.4/3.73	mL/hour	Point estimate	Dufour et al. 2017, Dorevitch et al. 2011
	Child (Primary/Secondary)	51.3/11.25	mL/2-hours	Point estimate	Suppes et al. 2014, Dorevitch et al. 2011
ENT to Source	Gull	4.3-8.4	CFU/g	Log_{10} Uniform	Fogarty et al. 2003
	Dog	4.76-8.4	CFU/g (dry weight)	Log_{10} Uniform	Wright et al. 2009
	Treated	0.13-0.92	CFU/100 mL	Log_{10} Uniform	Montazeri et al. 2015
	Raw	4.59-5.5	Copies/L	Log_{10} Uniform	
Reference Pathogen to Source	Gull	3.3-7.08	CFU/g	Log_{10} Uniform	Levesque et al. 2000
	Dog	3 -8	Copies/g	Log_{10} Uniform	Chaban et al. 2010
	Treated	0-3.76	CFU/100 mL	Log_{10} Uniform	Kitajima et al. 2014
	Raw	4.02-6.08	Copies/L	Log_{10} Uniform	
Prevalence of Infection	Gull	0.279-0.366	Percent	Uniform	Broman et al. 2002
	Dog	0.56-0.97	Percent	Uniform	Chaban et al. 2010
	Treated	0.75	Percent	Point estimate	Kitajima et al. 2014
	Raw	1	Percent	Point estimate	
Rate of Infection	Norovirus	1	Percent	Point estimate	Seitz et al. 2011
	Campylobacter spp.	0.4-0.6	Percent range	Uniform	Tribble et al. 2010
Dose-Response Values	Norovirus	$\alpha = 0.04$, $\beta = 0.05$	Point estimate	Beta-Binomial	McBride et al. 2013
	Campylobacter spp.	$\alpha = 0.145$, $\beta = 7.59$	Point estimate	Beta-Poisson	Medema et al. 1996, Soller et al. 2017, Sunger et al. 2018, Teunis et al. 2005

Infectivity

Two types of infectious potential are required as inputs in the reference pathogen dose equation; prevalence of infection from reference pathogen to source and infectious potential of reference pathogen in humans. Prevalence of norovirus (genogroup I and II) from human sources of fecal waste was determined to be 100% in WWTF influent (raw sewage) and 75% in effluent (treated sewage) (Kitajima et al. 2014). *C. jejuni* detection ranges from 27.9% to 36.6% prevalence in black-headed gulls with no statistically significant difference amongst age (Broman et al. 2002). *Campylobacter* spp. was detected ranging from 56% to 97% prevalence in dog feces, depending on whether the individual animal was healthy or unhealthy (Chaban et al. 2010). To capture variability of *Campylobacter* spp. prevalence in gull and dog feces a uniform distribution was assigned ranging from 27.9% to 36.6% for gulls and from 56% to 97% for dogs. In addition, the infectious potential of norovirus in humans for five of six groups challenged was found to be 100% despite storage in groundwater for up to 61 days (Seitz et al. 2011). An assumed 100% norovirus human infection rate aligns with QMRA studies published in the literature (Soller et al. 2010b, Soller et al. 2014). The infectious potential of *Campylobacter* spp. exhibits a higher degree of natural variability, in part, depending on the dose. In the current study *Campylobacter* spp. was assumed to have a medium rate of infectivity (40 to 60%) (Tribble et al. 2010). The potential presence of fresh concentrated sources in the swim zone could raise the risk threshold, although, recreationists likely receive a lower diluted dose. To accommodate variability of *Campylobacter* spp., infectious potential upper and lower bound estimates were utilized in a uniform probability distribution to generate infectious potential within the percent range (40% to 60%).

Ingestion

Ingestion via the fecal-oral route was considered the principle waterborne pathogen exposure route and transmission pathway, respectively. Recreationists who engage in swimming are substantially more likely to contract an illness because risk is positively associated with exposure from body immersion, head immersion, and swallowed water (Colford et al. 2012). The development of separate ingestion assumptions was required because adults and children behave differently when engaging in primary or secondary contact recreation (Dufour et al. 2017). Children make contact more often for longer durations and are more likely to engage in immersion, ingesting about four times as much water (Dufour et al. 2017, Schets et al. 2011). In addition, children are more likely to ingest higher amounts of water from splashes to the face during primary contact (Suppes et al. 2014). Wave action, in coastal beach environments, could increase the frequency of splashes to the face.

The recreational activity being pursued such as surfing vs. swimming can have a bearing on illness risk due to potential volume of water ingestion being higher compared to less intensive activities (Tseng and Jiang 2012). Furthermore, capsizing during canoeing or kayaking significantly increases the chance for and volume of ingestion (Dorevitch et al. 2011). The types of secondary contact recreation occurring at Sylvan Beach characterized by this study are based on the availability of recreational opportunities, i.e. launching a kayak from the boat ramp, pier and shore fishing, and wading in the swim zone without immersion.

Average hourly water ingestion rates for the adult population during primary contact recreation have been found to range from 3.5 to 12.4 mL (Dufour et al. 2017, Suppes et al. 2014). Average hourly ingestion rates for children engaging in primary contact recreation of water range from 23.9 to 25.7 mL (Dufour et al. 2017, Suppes et al. 2014). The maximum average ingestion rates, 12.4 mL adult (Dufour et al. 2017) and 25.7 mL child (Suppes et al. 2014) rates per hour, were selected to represent the upper mean threshold of ingestion for the primary contact scenarios. The child primary ingestion rate was doubled to represent prolonged chance of exposure from a 2-hour period of recreational activity. Ingestion for secondary contact recreation in coastal surface waters including canoeing, kayaking, motorized boating, fishing, rowing, and wading has been determined to range from 3 to 4 mL per hour, depending on the associated activity (Dorevitch et al. 2011). The ingestion volumes reported for secondary contact activities assumed to occur at the study site were averaged resulting in a 3.73 mL per hour estimate. The 3.73 mL per hour secondary contact ingestion rate was doubled resulting in an ingestion rate of 7.5 mL per a two-hour secondary contact interval compared to the 3.73 mL per hour adult rate (McBride et al. 2013).

Exposure Scenarios Modeled

Multiple exposure scenarios were modeled based on contamination derived from 100% human, 100% nonhuman, or a mixture (25% human/75% nonhuman) and whether the recreationist engaged in primary or secondary contact during the recreational or non-recreational beach season (Table 4). The human scenarios assumed a composite norovirus load stemming from 80% treated and 20% raw sewage. The nonhuman *Campylobacter* spp. scenarios assumed a 70% contribution from gulls and 30% from dogs. Each scenario was modeled for adult and child populations. The ingestion route was the predominant exposure pathway in all risk assessment scenarios. Monte Carlo simulations (10,000) were conducted using RiskAMP Monte Carlo Simulation Engine® add-in for Microsoft Office Professional Excel® 2016. The total probability of gastrointestinal illness from human and nonhuman sources per each temporal period and adult/child populations was estimated as cumulative risk from each reference pathogen. Exposure scenarios were conducted based on bi-phase seasonal aggregations for recreational and non-recreational swim seasons to align with beach management protocols and to increase assumption accuracy, such as primary contact is less likely to occur in the non-recreational season. Recreational period (May through September) risk assessments were conducted based on primary and secondary contact and the non-recreational period (October through April) was based on secondary contact exposure.

Table 4 Exposure scenario models by source, period, population, and type of contact.

Source	Period	Population	Contact
Human/Nonhuman	Recreational	Adult	Primary/Secondary
		Child	Primary/Secondary
	Non-recreational	Adult	Secondary
		Child	Secondary
Human	Recreational	Adult	Primary/Secondary
		Child	Primary/Secondary
	Non-recreational	Adult	Secondary
		Child	Secondary
NonHuman	Recreational	Adult	Primary/Secondary
		Child	Primary/Secondary
	Non-recreational	Adult	Secondary
		Child	Secondary

Reference Pathogens

Norovirus, primarily a human pathogen, was selected to represent exposure to contamination from fecal waste in treated and raw sewage. The utilization of norovirus as a reference pathogen captures a majority of gastrointestinal risk and represents the etiologic agent of highest concern (McBride et al. 2013, Soller et al. 2010a, Soller et al. 2010b, Soller et al. 2014). The reference pathogen for two nonhuman associated sources, seagull and dog feces, is *Campylobacter* spp. (Table 5) (Schoen and Ashbolt 2010, Soller et al. 2010b, U.S. EPA 2010). *C. jejuni*, *C. coli* and *C. lari* are commonly present in the environment (Converse et al. 2012). *C. jejuni* and *C. coli* can account for 80 to 90% of human infections and are considered primary bacterial pathogens of concern from animal waste (Ketley 1997, U.S. EPA 2010). It has been estimated that 18% to 46% of healthy adult volunteers became ill with fever or diarrhea after ingesting a range of doses inoculated with two different strains of *C. jejuni* (Black et al. 1988).

Table 5 Potential sources of human and nonhuman microbial load to the surface waters of Sylvan Beach represented by reference pathogens.

	Source	Reference Pathogen	Citation
Human	WWTF, SSO, boater waste discharge, bather shedding	Norovirus	McBride et al. 2013, Soller et al. 2010a, Soller et al. 2010b, Soller et al. 2014
Nonhuman	Domestic animal (dog) Wildlife (seagull)	*Campylobacter* spp.	Schoen and Ashbolt 2010, Soller et al. 2010b, USEPA 2010

Dose-response Relationships

A best-fit norovirus dose-response model that can be universally applied to enumerate risk for a variety of exposure scenarios has yet to be identified (Abel et al. 2017). Whether or not to assume the aggregation or disaggregation of viruses is one assumption preventing the application of a single dose-response model because the media will vary according to the exposure scenario in question. Studies recommending noroviruses be aggregated (Sunger et al. 2018), disaggregated (McBride et al. 2013, Schoen and Ashbolt 2010, Soller et al. 2010a), or the utilization of both aggregated and disaggregated models to capture a range have been proposed (Abel et al. 2017). However, Abel et al. (2017), acknowledges that most studies assume disaggregation in surface water. Therefore, the disaggregated dose is assumed to stem from the ingestion of single virions and not an aggregate mixture. This study used a disaggregated beta-Binomial norovirus dose-response curve with model parameters $\alpha = 0.04$ and $\beta = 0.055$ to estimate risk (McBride et al. 2013). This QMRA assumed *Campylobacter* spp. to follow a beta-Poisson dose-response model with model parameters $\alpha = 0.145$ and $\beta = 7.59$ (Medema et al. 1996, Soller et al. 2010b, Soller et al. 2014). To translate infection to probability of illness, risk estimates were multiplied by a morbidity factor of 0.6 for norovirus (Soller et al. 2017, Sunger et al. 2018) and 0.28 for *Campylobacter* spp. (Medema et al. 1996, Soller et al. 2017, Sunger et al. 2018, Teunis et al. 2005).

Results

Total Probability of Illness

This QMRA estimated adult and child risk as total probability of gastrointestinal illness, based on three different microbial load scenarios: 1) 100% human (norovirus), 2) 100% nonhuman (*Campylobacter* spp.), and 3) a representative composite mixture of human and nonhuman sources (norovirus and *Campylobacter* spp.). The results are reported as percentiles at 95% confidence (5^{th}, 25^{th}, 50^{th},75^{th} and 95^{th}) and comparisons of predicted total probability of illness are made using the median value. Results are provided equating to total illness probability at a rate of 100 exposed recreationists or the probability of an individual contracting an illness. Graphs are provided for 5^{th} to 90^{th} (ambient) and 90^{th} to 100^{th} (elevated) percentiles of ENT concentration by adult and child populations.

In the elevated adult recreationist scenario, the total predicted median probability of illness ranged from 0.31 (100% nonhuman recreational secondary) to 0.56 (100% human recreational primary) (Figure 10). The highest predicted total probability of median illness for the adult population is from 100% human sourced microbial loads while engaging in primary contact during the recreational beach season (0.56) followed by secondary contact in the non-recreational season (0.55), and secondary contact during the recreational period (0.54). The total probability of illness for 100% human load had a low degree of variation across the three recreational scenarios and total risk was within the same magnitude. Exposure to 100% nonhuman microbial loads had the most variable median probability of illness between the primary and secondary recreational scenarios. For all three scenarios, estimated total probability of illness for secondary contact during the non-recreational beach season was slightly elevated compared to the recreational season. The interjection of a human norovirus load component in the mixed scenarios elevated the median probability of illness over the 100% nonhuman source loads. However, median probability of illness for mixed sources was less than half of the human scenario.

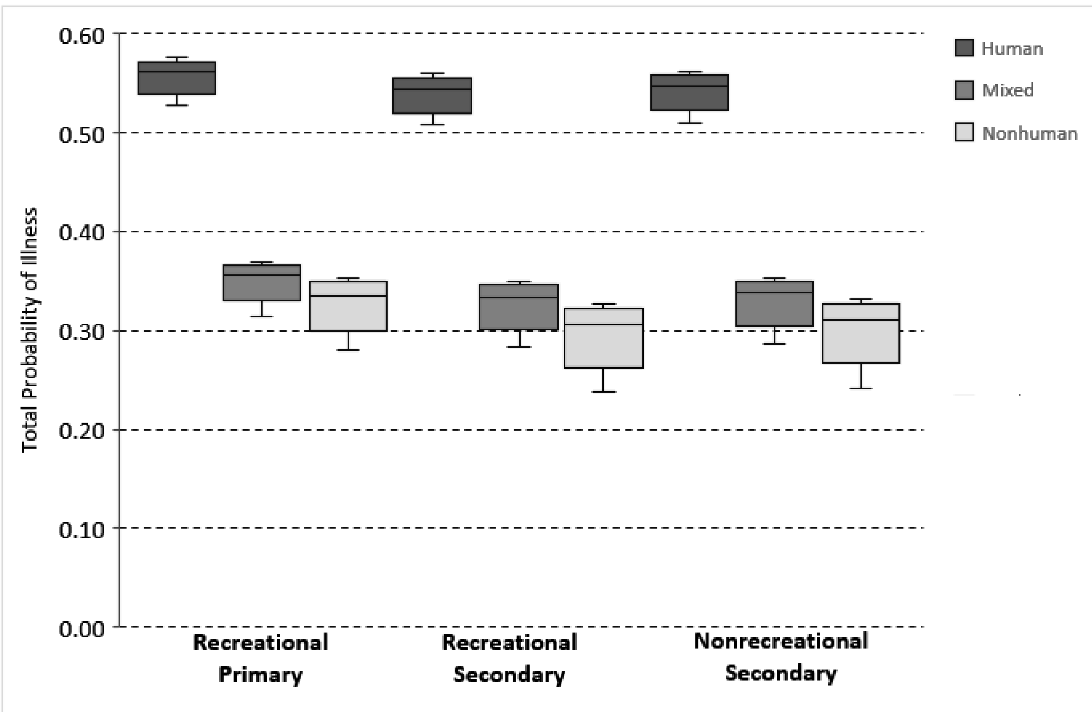

Figure 10 Predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for adult recreationists engaging in an hour of primary or secondary contact during the recreational and non-recreational beach seasons assuming 90th to 100th (elevated) ENT concentration. The upper and lower whiskers represent the 95th and 5th percentiles, respectively, while the box displays 25th, 50th (median), and 75th percentiles.

Under the 5^{th} to 90^{th} percentile ENT dose calculation, the range of predicted total probability of illness had higher variability; median illness probability ranged from 0.13 (100% nonhuman recreational secondary) to 0.49 (100% human recreational primary) (Figure 11).

However, total median probability of illness remained high for the 100% human microbial load scenarios. The greatest median probability of illness (0.48) occurs during primary recreation with microbial loads present from 100% human sources. The 100% human load recreational secondary and non-recreational secondary had higher intra-scenario variance, ranging from a total illness probability of 0.34 to 0.42, compared to the recreational primary scenario.

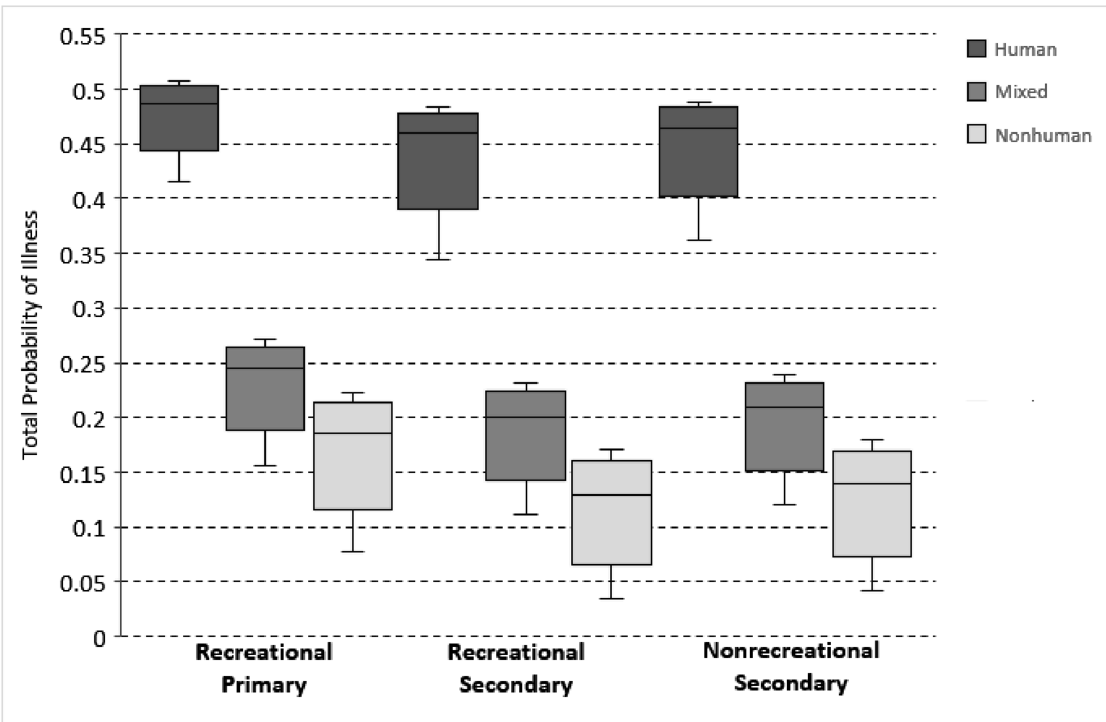

Figure 11 Predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for adult recreationists engaging in an hour of primary or secondary contact during the recreational and non-recreational beach seasons assuming 5th to 90th (ambient) ENT concentration.

Predicted total probability of illness in the child population exhibited similar patterns as the adult population (Figure 12). The total median probability of illness ranged from 0.32 (100% nonhuman recreational secondary) to 0.58 (100% human recreational primary). The 100%

human load QMRA resulted in minimal variance of predicted total illness probability across type and season of contact; however, total median risk was highest for primary contact in the recreational season (0.58). The lowest probability of median illness occurs under the 100% nonhuman load assumption for all types of recreation season and contact with lowest total probability of illness occurring during secondary contact in the recreational season. The primary contact recreational season mixed source scenario had low variance of total illness probability while total probability of illness had the highest variance in the recreational and non-recreational secondary 100% nonhuman load scenario.

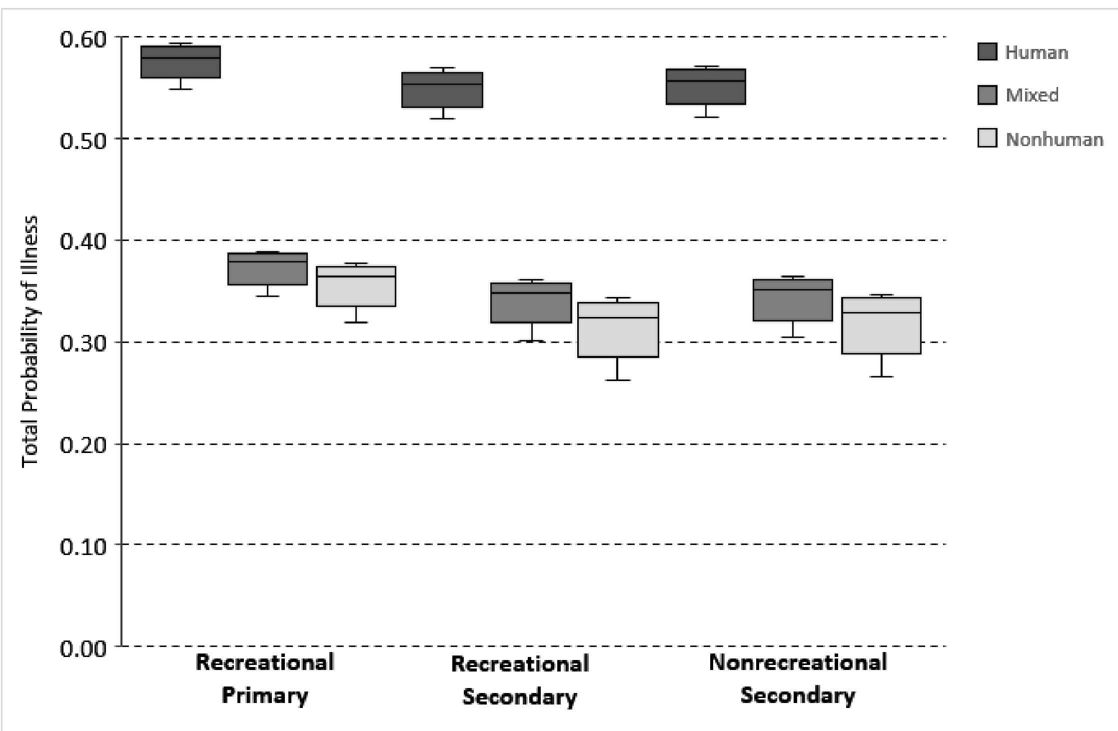

Figure 12 Predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for child recreationists engaging in two hours of primary or secondary contact during the recreational and non-recreational beach seasons assuming 90th to 100th (elevated) ENT concetration.

The total probability of median illness remained elevated for the 5th to 90th percentile ENT concentration dose calculation for 100% human load recreational primary, recreational secondary, and non-recreational secondary scenarios but was significantly lower for the mixed (0.23) and 100% nonhuman (0.09) load scenarios (Figure 13). The highest median probability of illness occurs during the recreational season from 100% human load (0.51) followed by the non-recreational (0.48) and recreational (0.48) beach seasons. The 100% nonhuman scenario had the largest difference between the recreational primary and recreational secondary/non-recreational secondary scenarios.

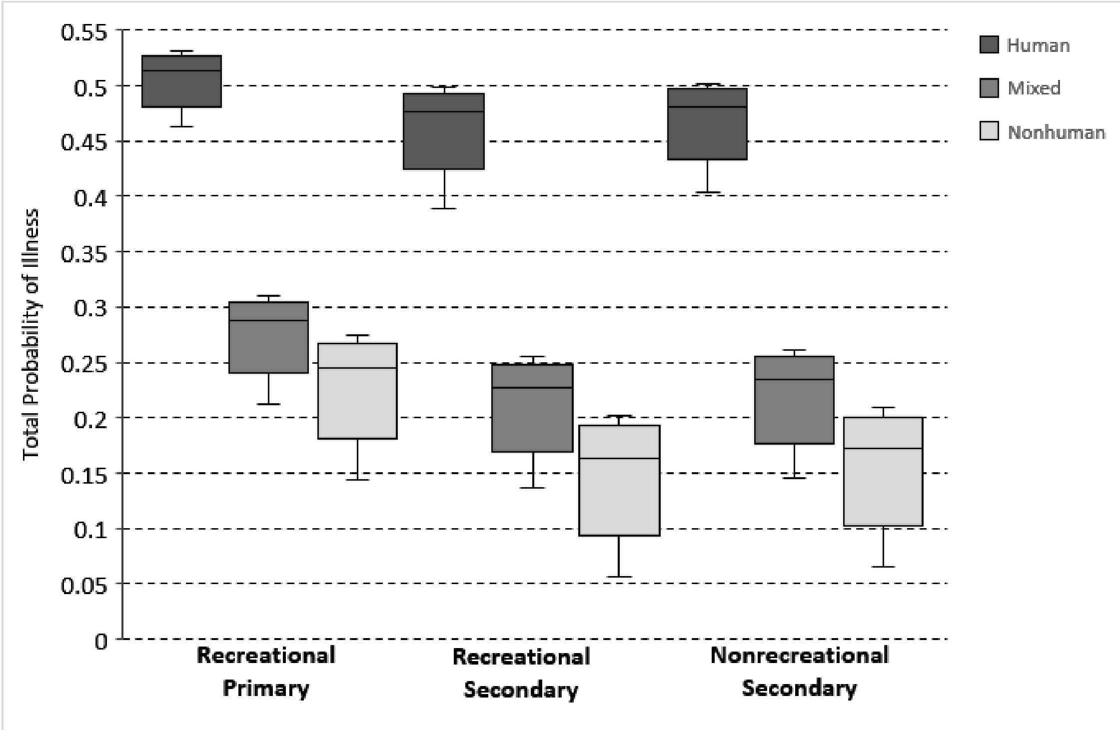

Figure 13 Predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for child recreationists engaging in two hours of primary or secondary contact during the recreational and non-recreational beach seasons assuming 5th to 90th (ambient) percenitle ENT concetration.

Discussion

This QMRA is unique because assumption-based scenarios utilized a uniform probability distribution to factor natural variability of ENT in dose conversion equation inputs. The ambient scenario of this study repeatably sampled (10,000 iterations) lower and upper bound ENT concentrations based on site specific observed ENT values from 0 to 216 MPN/100 mL (recreational) and 0 to 267 MPN/100 mL (non-recreational) while the elevated scenario ranged from 216 to 19,863 MPN/100 mL (recreational) and 267 to 24,196 MPN/100 mL (non-recreational). Previous QMRA studies held FIB concentrations constant at the U.S. recommended criteria for recreational marine waters (35 cfu/100 mL) and derived total probability of illness reflective of dry or average conditions (Soller et al. 2015, Soller et al. 2010b, Soller et al. 2014). In this QMRA scenarios were designed to compare total probability of illness between 1) recreational and non-recreational beach periods, 2) human and non-human sources, 3) child and adult recreationists, and 4) ambient and elevated microbial conditions.

Total Probability of Illness

Recreational and Non-Recreational Beach Seasons

The total probability of median illness was highest for primary contact that occurred during the recreational beach season when the beach is impaired by 100% human contamination for the adult and child populations under both ambient and elevated scenarios. During the recreational season, a higher number of patrons are more likely to engage in primary recreation as their main activity, further increasing public health risk (Brinks et al. 2008). In addition, a higher rate of ingestion for primary over secondary contact was assumed in this study (Dorevitch et al. 2011). Total probability of median illness for secondary contact in both populations was nearly equal between the recreational and non-recreational beach seasons for all three load scenarios. The sub-tropical climate allows for secondary recreation activities such as kayaking, canoeing, or fishing to be sustained throughout much of the year although activity is likely limited during the winter (December, January, and February) months. Although recreationists engaging in secondary contact are less likely to become infected via ingestion, the concentration of ENT and potentially associated pathogens is elevated during the non-recreational season compared to the recreational season resulting in comparable risk profiles for secondary contact recreation (calculated in Chapter II). The total probability of median illness for secondary contact remains comparable during the recreational and non-recreational beach season.

Human and Nonhuman Sources

The 100% human source scenarios consistently produced the highest total probability of median illness ranging from 0.46 to 0.56 while the 100% nonhuman source scenarios resulted in the lowest (0.13 to 0.30). A composite mixture of 25% human and 75% nonhuman load resulted in total probability of median illness ranging from 0.20 to 0.35. The microbial loads stemming from dogs and gulls were expected to have lower infection risk compared to human associated norovirus as supported by the high likelihood of norovirus presence resulting in illness, as observed in this study (Soller et al. 2010b, U.S. EPA 2010). Norovirus dominated the risk profile despite ingestion of a less concentrated dose as represented by the 5th to 90th percentile scenario.

The contribution of nonhuman microbial load was assumed to stem from two primary sources, dogs and gulls, based on direct observations, a cursory land use/land cover analysis, and a literature review. Dogs are known hosts of *Campylobacter* spp. including *C. upsaliensis*, *C. canis*, *C. jejuni*, and *C. coli* (Chaban et al. 2010, U.S. EPA 2010). *C. upsaliensis* has been identified as an important cause of enteric infection amongst humans and is the primary *Campylobacter* spp. detected in and associated with dog feces (Bourke et al. 1998, Chaban et al. 2010, Figura 1991, Martinez-Anton et al. 2018). Unhealthy dogs were found to harbor a significantly higher diversity of *Campylobacter* spp. compared to healthy individuals, in most cases (Chaban et al. 2010). Despite findings that suggest dogs have a substantial impact on ENT concentration within hours in localized conditions a limited number of QMRA studies have included dogs as a potential source (Zhu et al. 2011).

In addition to dogs, common wildlife sighted in proximity to the beach, on the beach, and in near-shore waters within the swim zone includes a high concentration of seagulls. Fecal matter from concentrated flocks of gulls pose a substantial risk to human health because gulls carry high concentrations of *C. jejuni* and *C. coli* which are associated with gastroenteritis in humans (Hatch 1996). *C. jejuni* has been found to comprise 95.5% of *Campylobacter* spp. isolated from black-headed gulls (Broman et al. 2002). Localized sources, including gulls and dogs, have the potential to impair the water quality of Sylvan Beach during dry weather conditions. Deposition on the beach - or within the swash zone - can result in prolonged exposure, even after source loading has ceased because wetted beach sands provide refuge and protection increasing survival time of pathogens (Halliday and Gast 2011, Hassard et al. 2016).

Norovirus presence in recreational water poses potential risk to human health and is an indication of fecal waste contamination from partially treated WWTF effluent, malfunctioning OSSF, direct boater discharge events, SSO, and bather shedding (Campos and Lees 2014, Haramoto et al. 2018, Qiu et al. 2015). In urban watersheds, norovirus can remain viable in stormwater runoff negatively impacting nearshore water quality (Soller et al. 2017). As a result of point and nonpoint source pollution, viruses are a predominant driver of risk in receiving waters, particularly when wastewater is a contamination source of concern (Farkas et al. 2018, Hassard et al. 2016, Qiu et al. 2015, Sunger et al. 2018).

Child and Adult Recreationists

Duration of recreational contact was less sensitive between the adult (1-hour) and child (2-hour) populations for norovirus compared to *Campylobacter* spp. due to the low dose of norovirus required to achieve infection illness (Ong 2013, Teunis et al. 2008). Despite scenarios assuming a longer duration of recreational activity resulting in an elevated dose, the predicated probability of median illness from a human load for children engaging in primary recreation (0.51) was not significantly elevated compared to adults (0.49) under the ambient or the elevated scenarios 0.58 (child) to 0.56 (adult). In addition, the high infection rate of norovirus resulted in minor variation of total illness probability across recreational periods.

Ambient and Elevated Conditions

The elevated scenarios resulted in reduced variability of total illness compared to the ambient scenarios. Across all three recreational periods and both adult and child populations the total median probability of illness is substantially higher in the elevated scenario compared to the ambient. However, the adult and child total probability of illness from human sources during primary contact recreation did not substantially differ between the ambient and elevated scenarios. This result suggests that a maximum condition is reached where additional human derived pathogen input does not increase the risk threshold. During ambient beach conditions represented by the 5^{th} to 90^{th} percentile ENT concentrations, human health risk from gulls and dogs remains low. In addition, concentrations of *Campylobacter* spp. have been found to be associated with gull colonies, but water ingested during recreation contaminated by gull fecal waste had a low infection threshold (Levesque et al. 2000). The infectious potential of *Campylobacter* spp. exhibits a higher degree of natural variability than norovirus, in part, dependent on dose. *C. jejuni* strain 81-176 doses of 10^5 and 10^7 CFU resulted in a 40% to 60% illness rate while a dose of 10^9 CFU caused a 92% illness rate for a population of young adults (Tribble et al. 2010). Furthermore, an infection rate ranging from 50% to 100% was associated with an 800 to 1,000 CFU dose, respectively (Black et al. 1988). However, at a maximum detected concentration potentially more than 11 MPN/100 mL of *Campylobacter* spp., an ingested volume of approximately 7.3 liters is needed to consume 800 cells resulting in a 50% infection probability (Savill et al. 2001). However, a concentrated delivery of fresh fecal material from gulls and dogs as represented by the greater than 90^{th} percentile ENT scenario could have an impact on public health resulting in a total probability of median illness ranging from 0.32 to 0.36 for children and 0.31 to 0.34 for adults.

These QMRA results indicate that norovirus dominates the risk profile, driving total probability of illness, for two of the three scenarios when the human-specific pathogen - norovirus - was included. This aligns with a recent study that concluded total risk probability is driven by the most infectious pathogen present (regardless of the microbial load) stemming from human or a mixture of human and nonhuman sources (Soller et al. 2014). In this study, the human load component has the potential to cause elevated risk during recreation when the microbial load is derived from mixed sources compared to the nonhuman load component despite the nonhuman proportion of 75%. In a mixed human and nonhuman load scenario, the median probability of GI illness was not dependent on the proportion of source, rather, risk was higher from gull fecal waste compared to poorly treated sewage only when gulls contributed 98% of the load (Schoen and Ashbolt 2010). Soller et al. (2014), concluded that waters predominantly impacted by nonhuman sources may pose lower recreational risk than waters with comparable concentrations from human sources. The risk associated with nonhuman contamination sources such as gull, chicken, and pig fecal waste has been found to be lower than human sources, as supported by this study (Soller et al. 2010b).

Management Applications

The management of coastal systems where the public can be exposed to pathogens during recreation and consumption of commercial seafood, could be improved by using QMRA results to inform public health decisions, policy, and pollution management (Ashbolt et al. 2010, Olivieri et al. 2014). This QMRA concluded that the current recreational contact standard may not be adequate to support public health safety when the proportion of microbial load at Sylvan

Beach is dominated by human sources. In the human load scenario, risk estimated as total median probability of illness occurs when the reference pathogen dose, repeatedly sampled from a uniform probability distribution, ranges from 0 to 216 or 267 MPN/100 mL depending on the recreational period. In the event of direct release of human derived pollution, beach managers may need to intervene by issuing a public health contamination advisory, even if the primary contact recreation standard has not been exceeded (Sinclair et al. 2009). However, further microbial characterization of the waters surrounding Sylvan Beach should be conducted to fully investigate and validate transient risk to the human population.

The prioritization of management measures geared toward remediating human sources of pollution likely has the highest potential to alleviate public health risk at Sylvan Beach. However, low cost solutions such as prohibiting dogs from beach access and employing scare tactics to displace gulls could help to reduce nonhuman contributions of microbial load to the waters of Sylvan Beach (Converse et al. 2012, Ervin et al. 2014, Goodwin et al. 2016). Success has been reported in controlling microbial load at a recreational beach impacted by nonpoint source pollution stemming from dogs by educating homeowners about the role dogs play in degrading water quality (Ervin et al. 2014). A similar outreach and educational campaign targeted to residents in the North Bay Watershed (particularly along Little Cedar Bayou) could prove successful at reducing microbial load to Sylvan Beach. The reduction of gulls, through active management, could improve beach water quality because *Campylobacter* spp. and FIB have been detected at a higher frequency prior to implementation of best practices (Converse et al. 2012, Goodwin et al. 2016). The use of dogs as an active measure to scare gulls from swim beaches has reported success in controlling the amount of gulls present and therefore reducing the associated microbial load (Jordan et al. 2019).

Limitations

It was assumed that children engage in recreation more often and for longer periods of time and are, therefore, exposed to higher doses, but did not account for potential higher susceptibility of children to infection (Wade et al. 2008). Gulls were considered a primary contributor to microbial load, but a high density of other coastal water bird species were observed. Limited data are available to support the inputs required for the dose conversion equation including concentration of ENT to source waste and wet mass concentration of reference pathogen in source for other bird species, which prevented their use in the formation of a risk estimate. Another limitation of this study is the inference that a pathogen dose can be derived based on the association of ENT is debated in the literature. However, direct associations among ENT presence, exposure, and resultant illness have been identified (Wade et al. 2010). These relationships are necessary to assume because coastal waters have limited direct pathogen monitoring data available and no studies are available that conducted direct pathogen monitoring within Galveston Bay or along the Texas coast. Relationships between FIB and associated pathogens differ in high-energy coastal waters compared to inland freshwaters; additionally, pathogen monitoring in coastal waters can reduce the uncertainty surrounding these parameters (Tseng and Jiang 2012).

Conclusion

The estimated total probability of infection and subsequent illness was calculated under three exposure scenarios that considered the population exposed, sources of microbial load, the recreational period during which exposure occurred, and ambient compared to elevated microbial conditions. The total probability of median illness was highest for primary contact that occurred during the recreational beach season when the largest number of recreationists have the potential to be exposed. For both populations and all recreational periods, the 100% human source loads consistently accounted for the highest total predicted probability of illness while the 100% nonhuman scenarios resulted in the lowest. Predicted probability of illness for the child scenarios where recreational contact occurred for a prolonged two-hour interval was marginally elevated compared to the one-hour adult contact scenarios suggesting that risk may not differ between the two populations. Lastly, elevated scenarios had higher overall total illness probabilities compared to ambient scenarios. However, the human load sources did not differ substantially between the ambient and elevated scenarios. The current recreational contact standard may not be adequate to support public health safety when the proportion of microbial load at Sylvan Beach is dominated by human sources because risk was elevated when the reference pathogen dose is assumed to range from 0 to 216 or 267 MPN/100 mL depending on the recreational period.

CHAPTER IV

QUANTITATIVE MICROBIAL RISK ASSESSMENT FRAMEWORK FOR THE ESTIMATION OF HUMAN HEALTH RISK DURING EXTREME WEATHER

Introduction

The prevention of immediate safety issues, during extreme weather events, including drowning and high-water rescues, take precedent over secondary concerns of pathogenic illnesses (Hunter 2003). However, the public is vulnerable to pathogenic illnesses since flood waters can inundate WWTF and sanitary sewer systems causing raw sewage and pathogen contamination (Man et al. 2014). In emergency situations following extreme weather events the public undergoes forced contact with contaminated flood waters during evacuation. Extreme weather events accelerate coastal physical processes that transport contaminated flood waters into communities where residents are exposed to heightened pathogenic risk (Hofstra 2011, Rochelle-Newall et al. 2015). Further compounding uncertainty, little information is available in the Houston-Galveston region regarding how climatic conditions such as an increased intensity of storm events affect the concentration of waterborne pathogens.

Following extreme weather events governmental agencies are unable to conduct routine bacteriological water quality monitoring, creating a lapse of information, when it is needed most to protect public health. This lack of knowledge exposes the region to risk uncertainty and raises concerns in the face of more frequent extreme storm events (Hofstra 2011, Rose et al. 2001). The quantification of risk and identification of pollution emitters is becoming increasingly important because the more fecal waste in the environment, the less resilient the coastal system will be to increasing storm events (Malham et al. 2014). Precipitation is a primary driver of costal physical processes that govern the fate, transport, and waterway concentration of environmental ENT and pathogens driving associated outbreaks (Curriero et al. 2001, Thompson et al. 2012). The impact of increased frequency and strength of wet weather and flood events on the concentrations of environmental ENT and associated pathogens needs to be determined. These changing coastal processes could dampen economic activity and deteriorate public health by increasing the number of primary contact recreation exceedances, oyster water impairments, and expose the public to infection during natural hazard events (Malham et al. 2014, Man et al. 2014).

The Houston-Galveston region has undergone several extreme weather events in recent years including the 2011 drought, flood events in 2015 and 2016, and Hurricane Harvey in 2017. Little information is available to characterize differences in pathogen infection probability between excessively wet and dry years or during extreme events which can result in hazardous waterborne pathogen conditions. The objective of this phase is to utilize the models developed in Chapter II and III to generate estimates of potential health risk during extreme weather events. This objective hindcasts the potential human health risk at Sylvan Beach during extreme weather event scenarios by retrospectively recreating event conditions with data mined from the corresponding temporal period.

Methods

This study performed scenario analysis for a range of extreme weather events when ENT sampling could not be conducted in real time. To compare years, characterized by excessive drought and rainfall, ENT was estimated for two annual periods 01/01/2011-12/31/2011 (dry drought period) and 01/01/2015-12/31/2015 (wet high rainfall period) (rainfall data from Harris County Flood Control). The 2015 Memorial Day flood (05/25/2015-05/26/2015) and the 2016 Tax Day flood (04/18/2016) were utilized as event scenarios. The prediction equation from the best fit models developed in Chapter II, corresponding to the year and recreational period, were applied to estimate ENT concentration. Input datasets for prediction were compiled consisting of explanatory variables selected for the corresponding model of best fit during Chapter II of this dissertation research. Daily ENT estimates were made at a set time point of 10 AM to align with the time ENT samples are typically collected at the study site. The QMRA modeling procedure developed in Chapter III of this dissertation research was applied to establish a quantitative measure of risk and determine the total probability of contracting a gastrointestinal illnesses from contact with pathogen impaired waters for three event scenarios with varied concentrations of ENT: 1) observed ENT concentration collected two days after the 04/18/2016 flood event, 2) ENT at the maximum detectable concentration (24,196 MPN/100 mL), and 3) a hypothetical ENT concentration ranging from 100,000 to 125,000 MPN/100 mL representing heightened microbial contamination. Scenarios were generated assuming primary and secondary contact for adult and child populations during the recreational beach season.

Study variables consisted of the following: wind direction (degree[°]), speed (meter per second [m/s]), and peak gust (m/s), atmospheric pressure (hectopascals [hPa]), air temperature (degree Celsius [°C]), water temperature (°C), conductivity (millisiemens per centimeter [mS/cm]), water level (m), were downloaded from the National Oceanographic and Atmospheric Association's (NOAA) Tides and Currents Morgan's Point Station (8770613). The Harris County Flood Warning System Little Cedar Bayou at 8th Street gage provided daily 15-minute rainfall (millimeter [mm]). The daily regional clear sky ultraviolet index (UVI) archived during the solar noon hour for the City of Houston was downloaded from the National Weather Service (NWS). Lastly, solar radiation (langley per minute [ly/min]) was acquired from the TCEQ Houston Regional Office maintained Seabrook Friendship Park weather monitoring station (EPA site 482011050). Records with one or more null values were removed. To validate the estimated

ENT concentrations dates when ENT samples were collected at Sylvan Beach Park were cross-referenced to the prediction estimates. The average concentration of ENT between Sylvan Beach North and South stations was utilized. Data processing, validation, and management was conducted in Microsoft Office Professional Excel® 2016.

The TGLO utilizes relative percent difference (RPD) as a data quality indicator to interpret precision of field duplicate ENT samples. Due to the natural variability of ENT in surface waters the TGLO considers a RPD between duplicate field samples of less than or equal to sixty percent as acceptable (TGLO 2018). As a measure of estimated ENT precision, the RPD was calculated for all dates with an estimated and observed ENT value. RPD was calculated as the absolute value of paired estimated minus observed ENT records divided by the average of the estimated and observed values. To assess model performance the data quality indicator threshold of sixty percent was applied and interpreted as an acceptable error rate. Temporal scenarios were explored by simulation using the regression model and QMRA frameworks. This will help identify sensitive time periods when warnings, beach closures, and additional precautionary actions may be required (Liao et al. 2016).

Results

Estimates

During the 05/01/2015 to 05/31/2015 analysis period five observed ENT samples align with estimated ENT samples. However, 80% (4/5) of the paired samples had an RPD greater than 60% and no samples had an RPD less than 10%. In addition, 40% (2/5) of the estimated ENT values resulted in false positive errors which occurred on 05/15/2015 and 05/28/2015. The model tended to overestimate the concentration of ENT when compared to observed ENT values and exceedance of the primary recreation contact screening level (log 4.64 MPN/100 mL) (Figure 14).

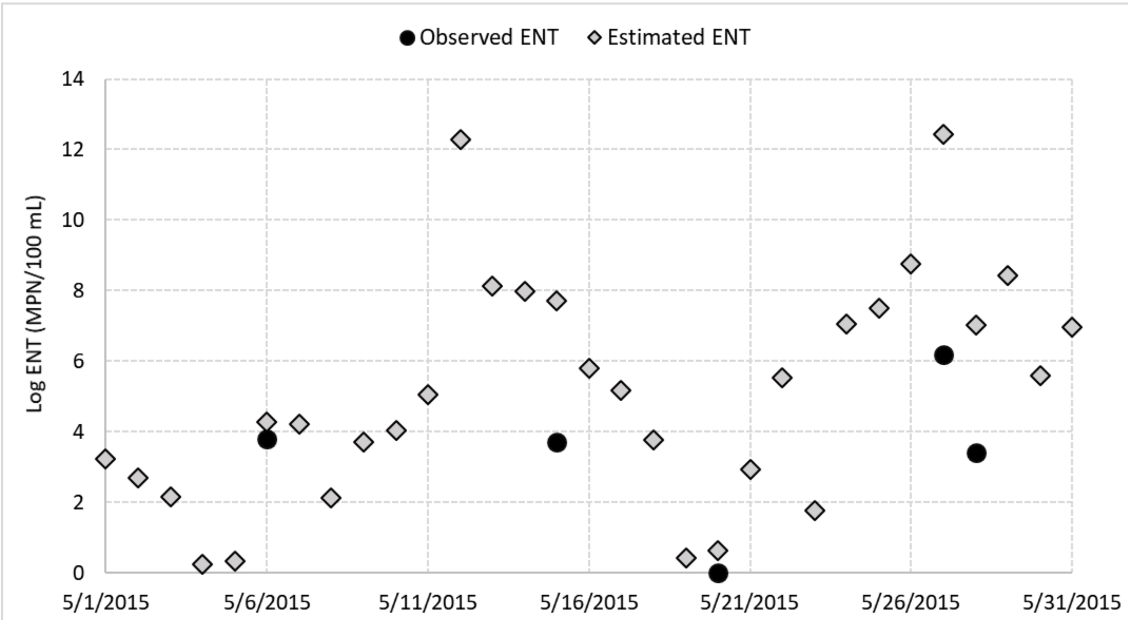

Figure 14 Observed and estimated ENT values for the temporal period 05/01/2015 to 05/31/2015.

During the analysis period of 04/01/2016 to 04/31/2016 seven paired observed and estimated ENT records are available (Figure 15). The maximum RPD occurred on 04/01/2016 (50%); no paired samples had an RPD greater than 60%. The lowest RPD was 11% corresponding to the 4/20/2016 estimated and observed samples. An error rate of 43% occurred because three of seven matched records resulted in over or under predictions. Two false positives were generated by the model resulting in an overestimation of ENT and one false negative occurred underestimating ENT.

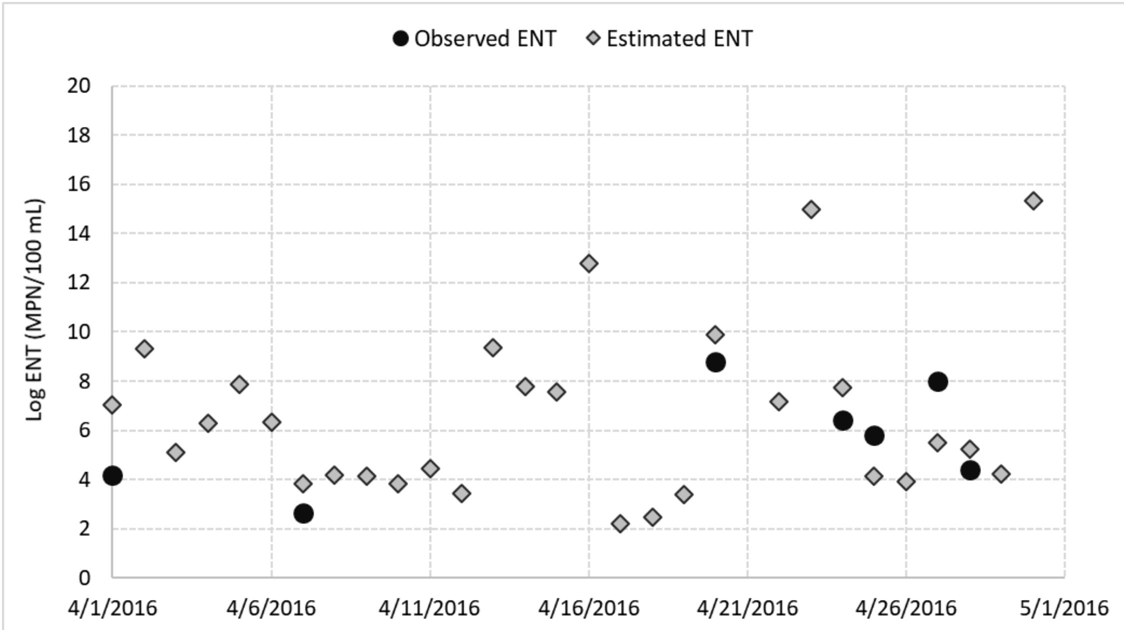

Figure 15 Observed and estimated ENT values for the temporal period 04/01/2016 to 04/31/2016; to improve clarity of the graph one estimated ENT value of 78.29 on 4/21/2016 was left off.

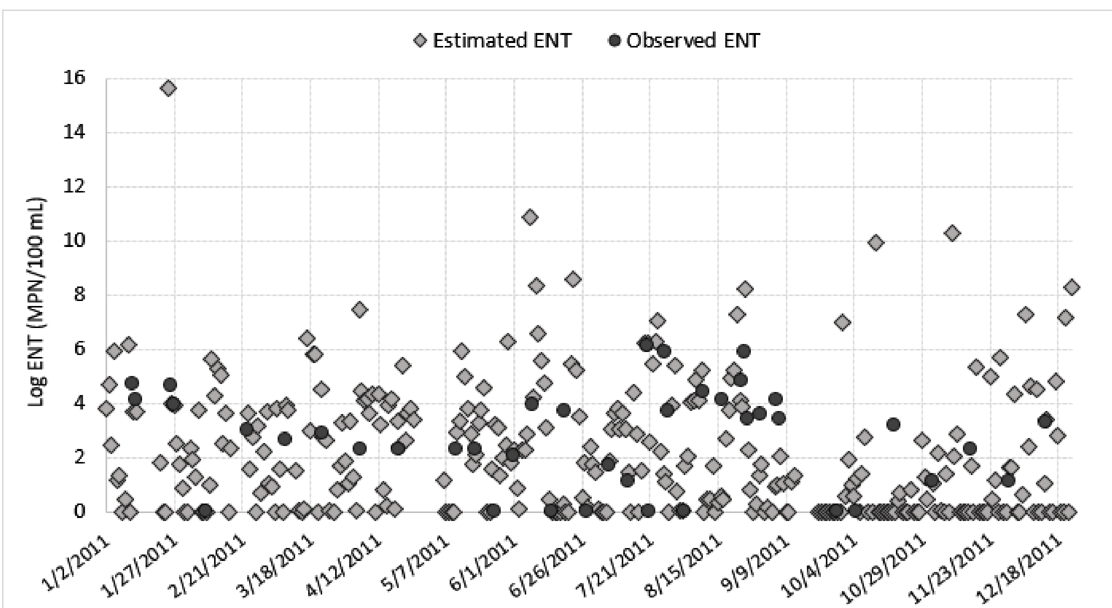

Figure 16 Overall estimated and observed ENT values for the annual period 1/01/2011 to 12/31/2011.

The regression equations for the recreational and non-recreational periods of 2011 were applied to generate predications for the analysis period 01/01/2011 to 12/31/2011 which was the driest year in state history (Figure 16). Over the course of the year 40 observed ENT samples aligned with an estimated ENT value. Comparing paired samples, 35% (14/40) had an RPD greater than 60% and 12 of 40 (30%) had an RPD of less than or equal to 10%. When paired samples where compared to the primary recreation contact screening level of log 4.64 MPN/100 mL 4 of 40 (10%) samples resulted in a false negative error were the observed ENT resulted in an exceedance, but the estimated ENT did not; no false positives were detected (Figure 17).

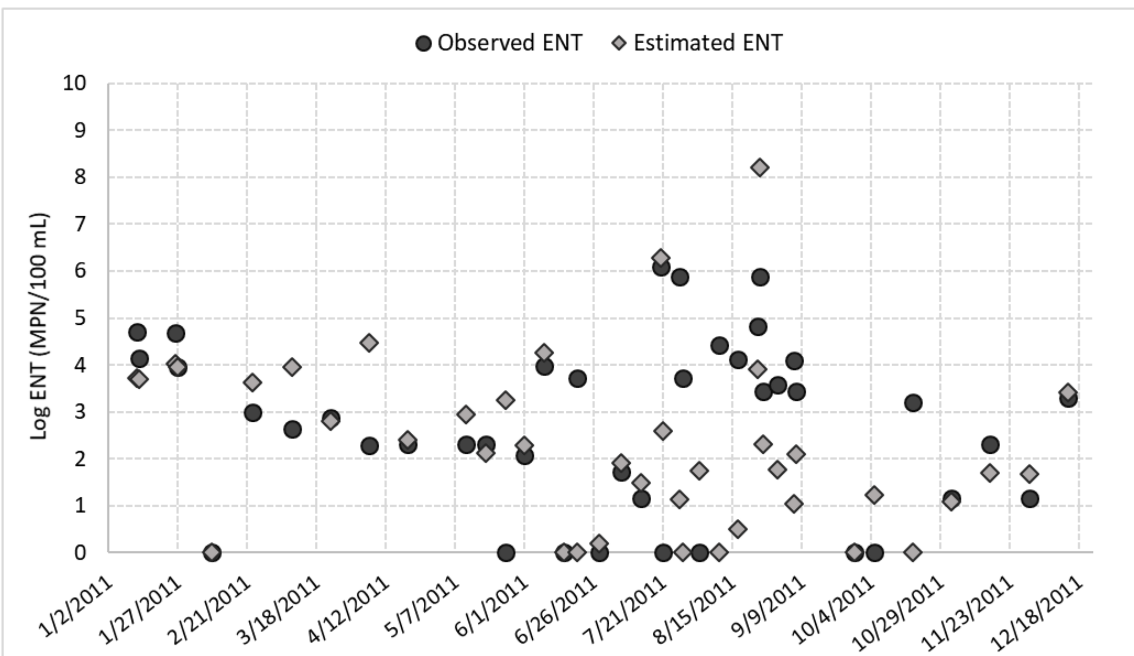

Figure 17 Paired observed and estimated ENT values for the temporal period 01/01/2011 to 12/31/2011.

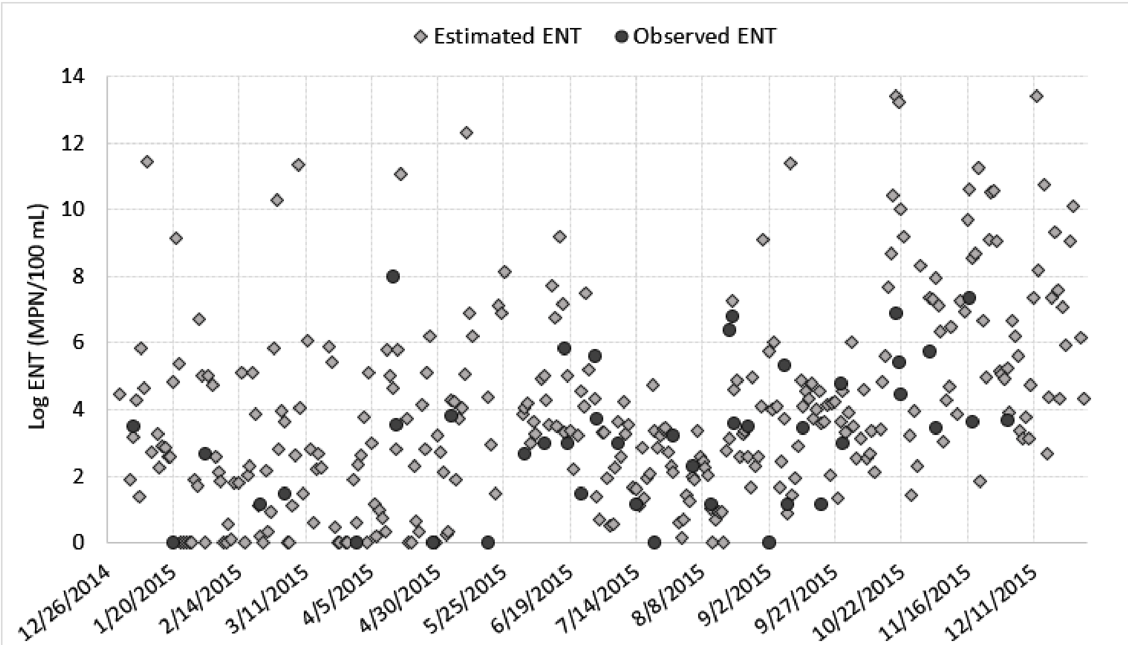

Figure 18 Overall estimated and observed ENT values for the annual period 1/01/2015 to 12/31/2015.

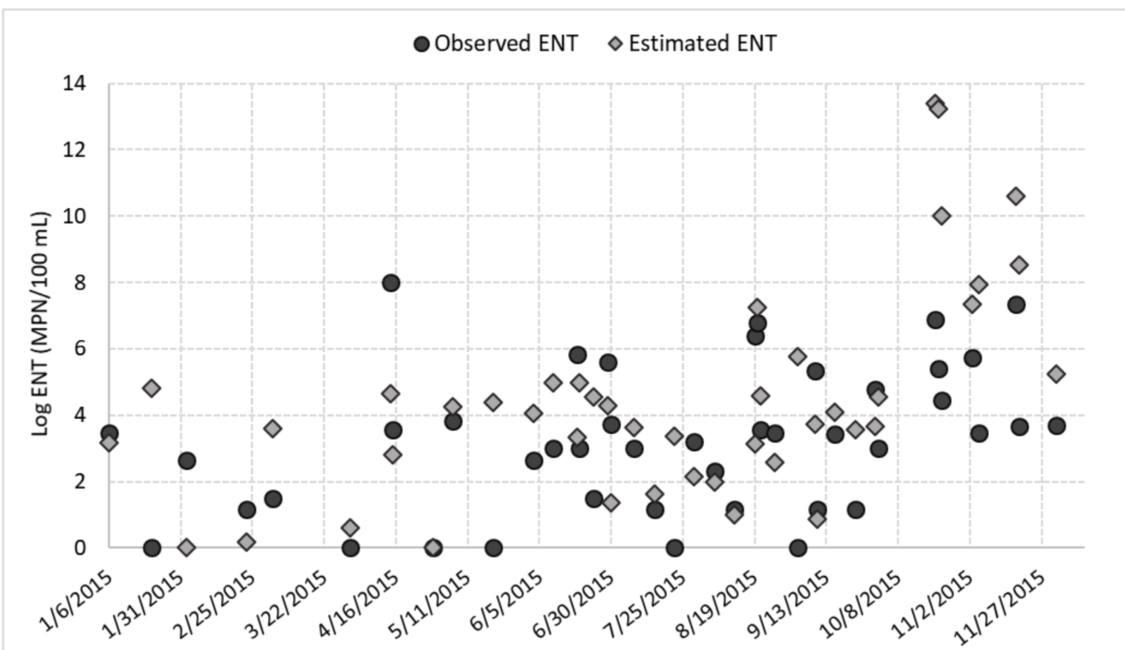

Figure 19 Paired observed and estimated ENT values for the temporal period 01/01/2015 to 12/31/2015.

The regression equations developed for 2015 recreational and non-recreational periods were applied to generate estimates for the 01/01/2015 to 12/31/2015 analysis period (Figure 18). Over the course of the year 43 records had an observed ENT sample with a corresponding estimated ENT value. Comparing observed and estimated results 40% (17/43) records had an RPD greater than 60% and three records had an RPD less than 10%. The predicted estimates resulted in a 30% (13/43) error rate (Figure 19). The model overestimated the concentration of ENT more often than underestimated. Eight false positives and five false negatives were detected when paired observed and estimated ENT values were compared to the primary recreation contact screening level.

Relative Percent Difference

To calculate an overall RPD paired estimated and observed ENT values for all analysis periods were combined and evaluated. The resultant dataset contained 90 records which were cross validated to discern an error threshold. Of the 90 records 31 (34%) had an RPD greater than the 60% threshold. However, the largest proportion of estimated and observed records (59) were found to be within the acceptable variance threshold of 60%.

QMRA

The first QMRA scenario modeled observed ENT from the study site that was collected on 04/20/2016 two days after the 04/18/16 flood event. The ENT concentration at Sylvan Beach Park ranged from 6,488 MPN/100 mL at the North site to 6,867 MPN/100 mL at the South site. The observed ENT concentrations at the study sites were utilized as the upper and lower bounds of a uniform probability distribution to generate a random coefficient incorporated in the dose conversion equation to represent total probability of risk resultant from the 04/18/16 event.

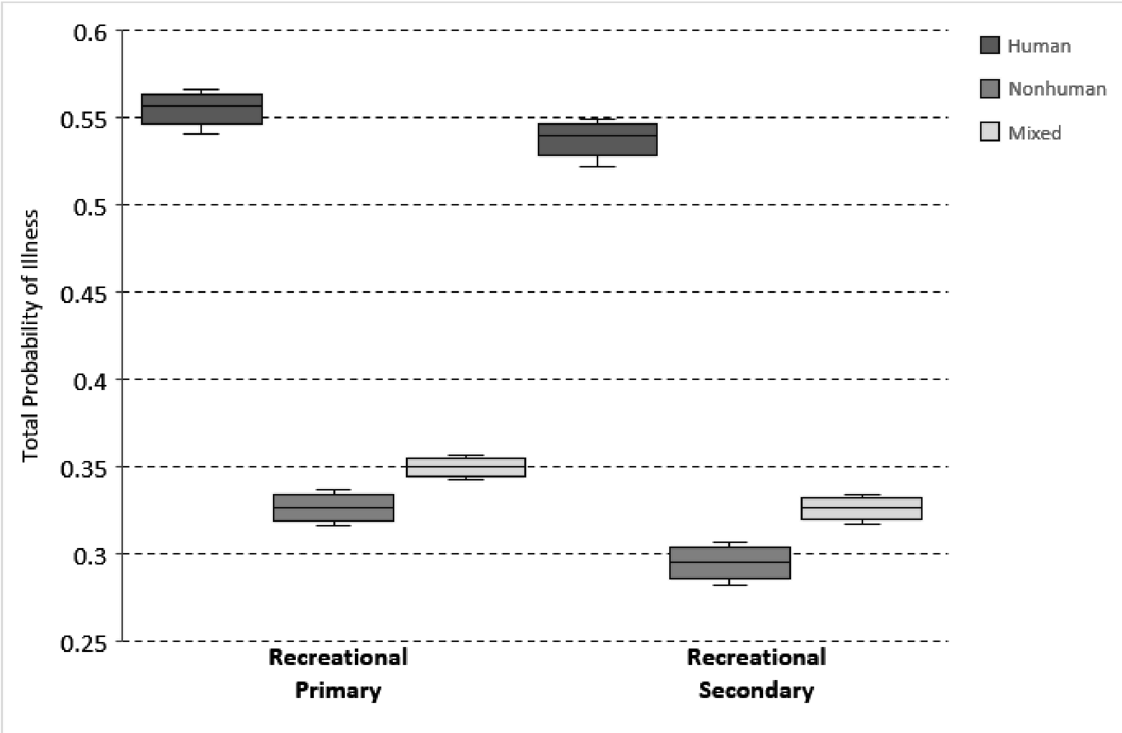

Figure 20 Scenario one - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for adult recreationists engaging in an hour of primary or secondary contact based on the 04/18/16 event conditions (6,488-6,867 MPN/100 mL).

In scenario one the total predicted median probability of illness for the adult population ranged from 0.30 (100% nonhuman secondary contact) to 0.56 (100% human primary contact) (Figure 20). The primary contact scenarios resulted in overall higher median probability of illness compared to secondary contact. The primary contact median probability of illness from mixed and nonhuman sources was 0.35 and 0.33, respectively. The total predicted median probability of illness to the adult population during secondary contact assuming the microbial load was derived from 100% human sources is 0.54. Secondary contact median probability was 0.33 for mixed and 0.3 for nonhuman scenarios. The total predicted median probabilities of illness for the child population were slightly elevated compared to the adult population (Figure

21). The median probability of illness for the 100% human load component remained high for primary and secondary contact, at 0.58 and 0.55, respectively. The 100% nonhuman load for secondary contact resulted in the lowest median probability of illness (0.32). The mixed secondary contact load scenario resulted in a median probability of illness of 0.34. The mixed (0.38) and nonhuman (0.36) scenarios for primary contact had higher median values but lower variance compared to secondary contact scenarios.

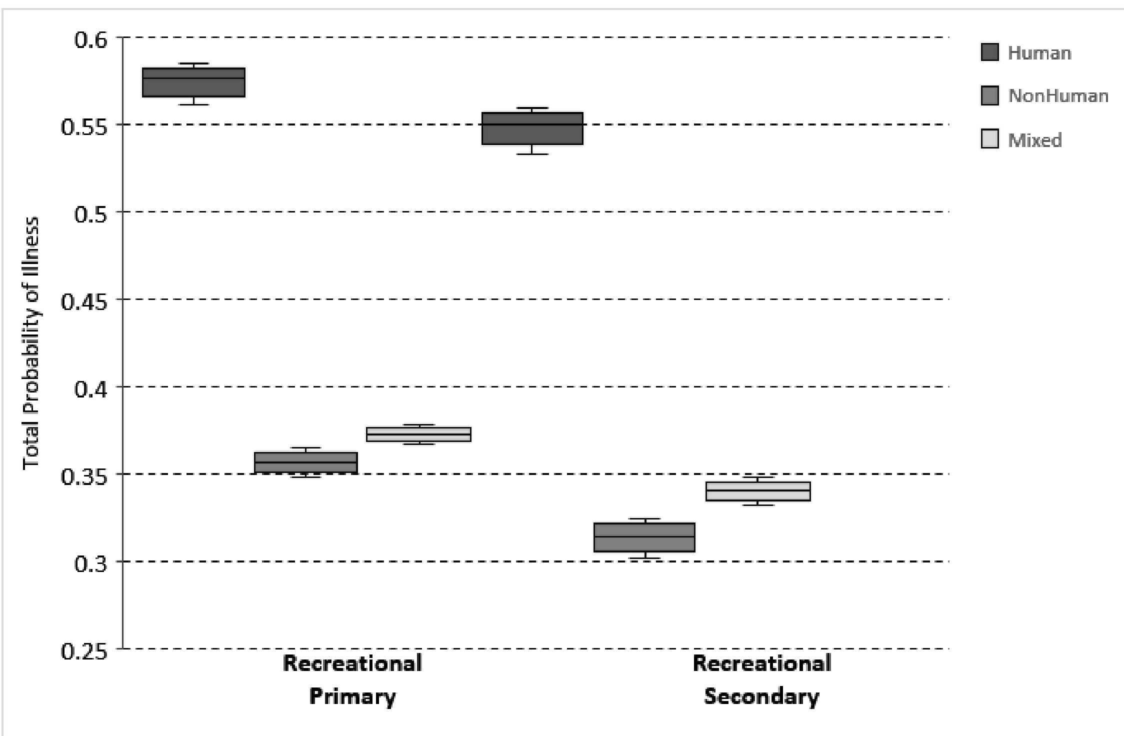

Figure 21 Scenario one - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for child recreationists engaging in an hour of primary or secondary contact based on the 04/18/16 event (6,488-6,867 MPN/100 mL).

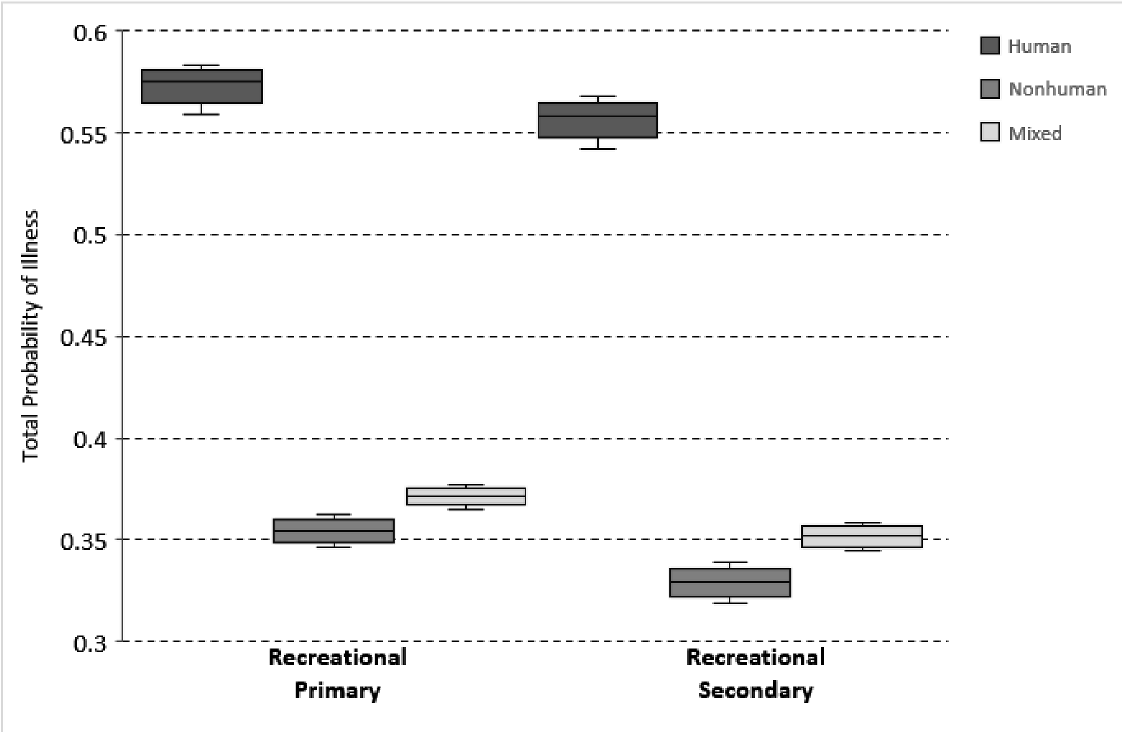

Figure 22 Scenario two - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for adult recreationists engaging in an hour of primary or secondary contact based on the maximum detectable ENT concentration (24,196 MPN/100 mL).

The second QMRA scenario modeled total probability of illness at the maximum detectable observed ENT concentration of 24,196 MPN/100 mL. Despite a fourfold increase in the modeled ENT concentration the maximum total probability of illness for the primary contact adult human load scenario increased marginally to 0.57 from 0.56 (scenario one) (Figure 22). The adult secondary contact human load scenario resulted in an elevated median probability of illness of 0.56. The median probability of illness for the secondary contact mixed (0.35) and primary contact nonhuman (0.36) load scenarios were nearly equal. The lowest median probability of illness was the nonhuman load component of the secondary contact scenario at 0.33. The child population for scenario two exhibited similar patterns compared to the adult scenario but had higher overall median probability of illnesses ranging from 0.34 (secondary contact nonhuman) to 0.59 (primary contact human) (Figure 23). The range between nonhuman primary and mixed secondary median risk contact scenarios was wider than the adult population.

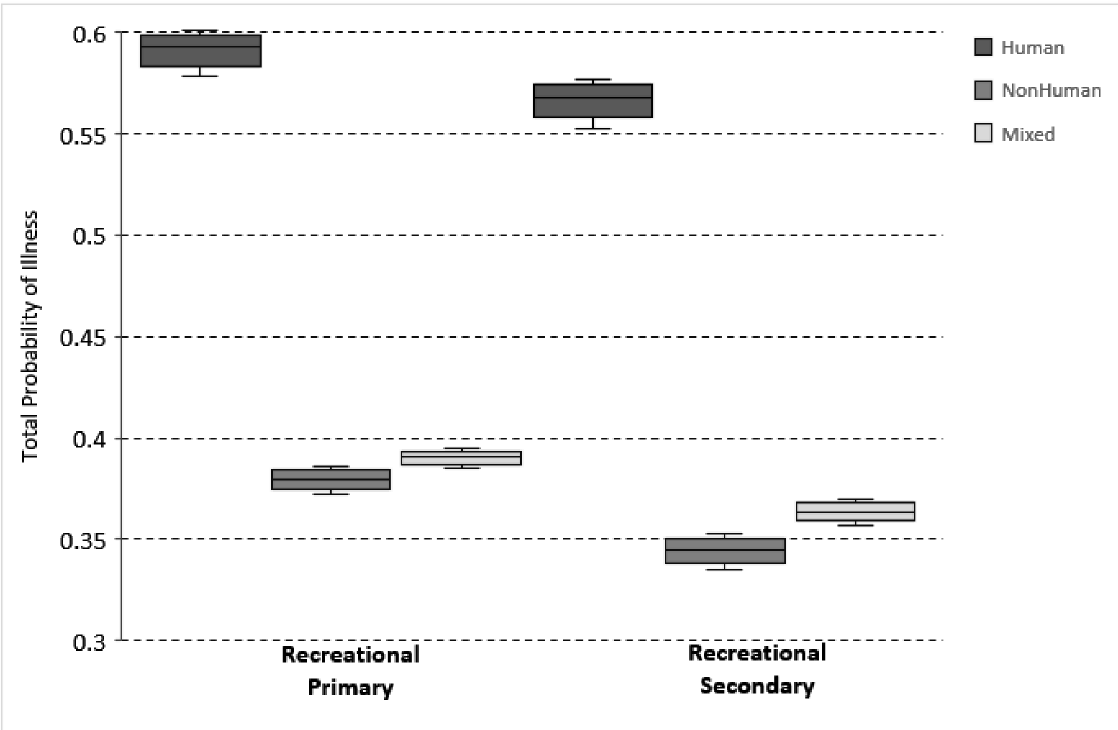

Figure 23 Scenario two - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for child recreationists engaging in an hour of primary or secondary contact based on the maximum detectable ENT concentration.

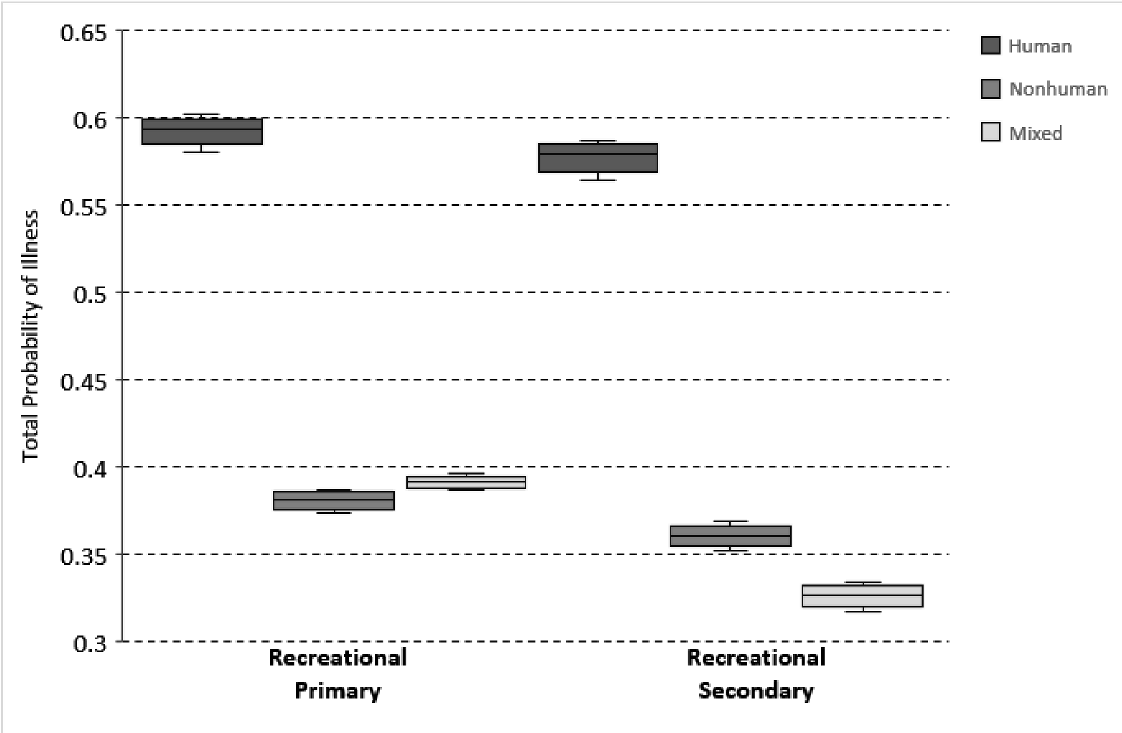

Figure 24 Scenario three - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for adult recreationists engaging in an hour of primary or secondary contact based on a theoretical extreme event ENT concentration.

The third QMRA scenario model total illness probability at a theoretical ENT concentration ranging from 100,000 to 125,000 MPN/100 mL to simulate extreme microbial conditions. The median probabilities from the human load components were slightly elevated compared to scenarios one and two; however, variance was reduced for the mixed and nonhuman primary and secondary scenarios. The maximum median probability of illness for the adult (0.59) (Figure 24) and child (0.61) (Figure 25) populations occurred under the primary contact human load scenario, as expected. Secondary contact human load scenario also resulted in elevated median probability of illness for the adult (0.58) and child (0.58) populations. In this scenario median risk from the primary recreation scenarios was nearly equal, which is a departure from the expected result that child risk tended to be elevated comparted to adults. The child scenarios resulted in reduced variance compared to the adult population for the all scenarios occurring during primary and secondary contact.

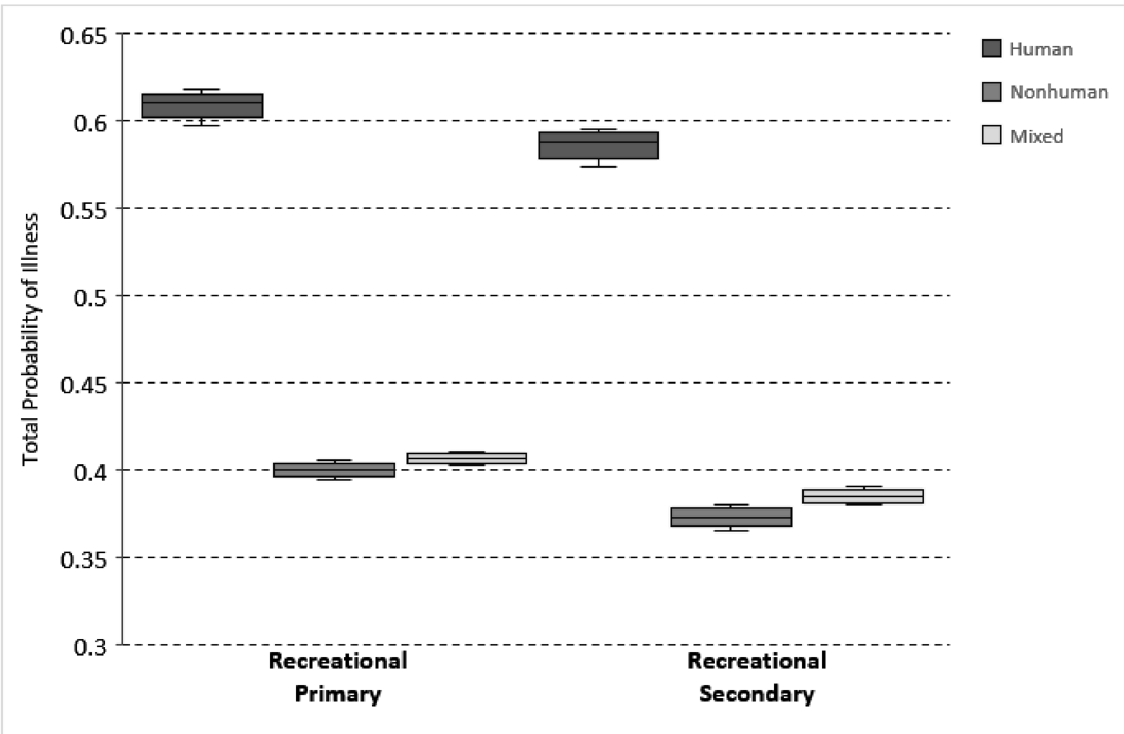

Figure 25 Scenario three - predicted total probability of illness from 100% human, mixed, and 100% nonhuman microbial loads for child recreationists engaging in an hour of primary or secondary contact based on a theoretical extreme event ENT concentration.

Discussion

This study applied regression equations to estimate ENT concentration for two annual, 2011 and 2015, and two event analysis periods, 2015 Memorial Day Flood and the 2016 Tax Day Flood. In addition, a quantitative measure of total illness probability was estimated for three event scenarios: 1) observed ENT concentration collected two days after the 04/18/2016 event,

2) ENT concentration at the maximum detectable limit, and 3) a theoretical ENT concentration ranging from 100,000 to 125,000 MPN/100 mL representing heightened microbial contamination. The study year 2015 was an exceptionally wet year with higher rainfall compared to 2011. The year 2011 was the single driest in recorded Texas State history with only 57 cm of annual rainfall while 2015 received three times the rainfall totaling 220 cm.

Regression Estimates

The maximum ENT prediction from the 2015 annual model was log 32 MPN/100 mL on 10/25/2015 while the annual 2011 model predicted one value of log 55 MPN/100 mL on 10/10/2011. The maximum values from observed ENT samples were log 6.1 MPN/100 mL in 2011 and log 8 MPN/100 mL in 2015. The geometric mean of predicted ENT values for 2015 was log 2.53 MPN/100 mL compared to the observed geometric mean of log 2.92 MPN/100 mL. A difference of log 0.39 MPN/100 mL. The geometric mean of predicted ENT in the study year 2011 was log 1.4 MPN/100 mL compared to the observed ENT concentration of log 2.15 MPN/100 mL; a log 0.75 MPN/100 mL difference. Although both annual models resulted in the prediction of outliers the overall concentrations of observed and estimated ENT were comparable for each study year. In addition, ENT concentrations for 2011 were lower than the 2015 concentrations. In Chapter II observed ENT concentrations between study years 2011 and 2015 were determined to be statistically different (α=0.05) under the nonparametric Wilcoxon method. The observed concentration of ENT in 2011 is significantly less than 2015. This pattern was reflected in the 2011 and 2015 regression models based on estimated ENT concentrations.

In addition, to estimating annual periods predictions were made for two short term periods (05/01/2015 to 05/31/2015 and 04/01/2016 to 04/30/2016) containing the 2015 Memorial Day (05/25/2015-05/26/2015) Flood and the 2016 Tax Day Flood (04/18/2016). The maximum estimated ENT concentration from the Memorial Day period was 12.44 log MPN/100 mL on 5/27/2015 compared to the observed maximum of 6.2 log MPN/100 mL which was collected on the same date. Although the model tended to overestimate the concentration of ENT it correctly predicted the maximum value which corresponds with the observed maximum on the day after the flood event. Because the precipitation variable with the highest resolution was 1-day rainfall the model was able to capture a potential high concentration of ENT one day post storm event. The maximum estimated ENT value from the Tax Day Flood period was an extreme outlier of 78 log MPN/100 mL predicted on 04/21/2016 while the actual maximum observed value was 8.8 log MPN/100 mL collected on 04/20/2016. Despite generating a high outlier, the model was able to make a comparable estimate of ENT two days after the 04/18/2016 flood event. On 04/20/2016 the model estimated a log ENT value of 9.9 MPN/100 mL compared to the 8.8 log MPN/100 mL observed value. The lowest level rainfall variable included in this model was for a 2-day period resulting in a lag between the storm event (04/18/2016) and the comparable observed/estimated ENT record.

The 2011 non-recreational model resulted in the selection of 1, 3, and 7-day rainfall as explanatory variables while the recreational model, which represents May through August, did not contain any variables describing rainfall except for the number of days since last rain event. In comparison, the 2015 non-recreational model resulted in the selection of pre-sample rainfall, as well as 1 and 3-day rain as explanatory variables. The 2015 recreational model contained 1, 2, and 7-day rainfall. Interestingly, the 2011 models contained more variables describing solar radiation and the ultraviolet index compared to the 2015 models. These results suggest that rainfall has less influence on the concentration of ENT at Sylvan Beach Park during a drought year; especially during the hottest part of the year. In drought years solar radiation is a primary influence on ENT while in years with above average rainfall the amount of precipitation is a key driver.

Bacteriological samples are typically collected as part of long-term monitoring programs on a quarterly and routine basis by State agencies such as the TCEQ. Likewise, the TGLO collects Beach Watch samples on a routine schedule, unless an exceedance is detected in which case sampling is continued until the ENT concentration is below the primary recreation contact criterion. Due to current monitoring protocols relatively few storm event ENT samples are available for use in model development and training. This causes two issues in terms of estimating ENT concentrations: 1) there are not enough ENT samples collected during or shortly after extreme weather events that can be included in model development and 2) there aren't enough observed ENT values available to validate model estimates associated with storm events. The maximum detection of ENT is limited to 24,000 MPN/100 mL which excludes the numeration of higher ENT concentrations. Additional sampling and special studies are needed to target and quantify the true upper threshold of ENT during high rainfall periods to gather better information for model development and validation corresponding to large events which can improve performance of predictive models.

QMRA

The highest estimate of total median illness probability (0.61) occurred under the high scenario for the child population from human microbial loadings during primary recreation. The lowest estimate of median total illness probability (0.30) was generated under the low scenario for adult secondary recreationists when microbial contamination is a result of nonhuman sources i.e. dogs and seagulls. All QMRA scenarios in this Chapter were generated with a significantly higher dose than the assumed ambient conditions of the QMRA in Chapter III. These results suggest that a threshold is reached, and illness probability does not increase exponentially with dose. Another pattern evident in the QMRA results is the inverse relationship between the simulated ENT dose and variability of total illness probability which decreases indicating that uncertainty of achieving illness is reduced at higher dose concentrations. The mixed load high scenario for the child population had the lowest variability with a total illness probability range of 0.02 and an interquartile range of 0.003. Conversely, the highest variability was recorded for the adult secondary recreation human load with a range of 0.023and interquartile range of 0.008. Overall the human load scenarios had greater variability compared to the nonhuman and mixed scenarios.

As seen in Chapter III the total probability of illness is driven primarily by the high rate of infection associated with norovirus. This potency results in the 100% human load scenarios having substantially elevated illness probability compared to the nonhuman and mixed scenarios. As described by Soller et al. (2014) the QMRA results of this study suggest that total illness probability is driven by the type and magnitude of source load; higher risk can be ascribed to human derived loads, while risk is substantially reduced from mixed and nonhuman sources of fecal waste. However, during event conditions represented by QMRA scenarios in this Chapter and the elevated scenario in Chapter III nonhuman and mixed loadings can contribute to total illness probability.

In Veldhuis et al. (2010) urban flood waters impacted by sanitary sewer overflows and combined sewer discharges were sampled for FIB and pathogens to quantify microbial risk. The pathogen *Campylobacter* spp. was positively detected in 5/5 samples while ENT ranged from a concentration of 500,000 to 3,700,000 cfu 100 mL^{-1}. At Sylvan Beach Park observed ENT samples were collected on 5/27/2015 that averaged 6.20 log MPN/100 mL one day after the

Memorial Day flood and on 04/20/2016 two days after the Tax Day flood event averaging 8.8 log MPN/100 mL. These concentrations suggest that Sylvan Beach may have been impacted by raw sewage contamination containing human fecal waste during flood events. However, the Memorial Day event had a longer duration and higher intensity of rainfall compared to the Tax Day episode. The greater volume of rainfall could lead to dilution in the dose associated with the Memorial Day event as evidenced by the lower concertation of ENT collected at Sylvan Beach.

Although, the QMRA scenario assumptions for this Chapter were generated to be representative of recreational contact during or shortly after extreme rain events additional monitoring needs to be conducted to improve estimates of infection risk related to high intensity weather events. To generate results with reduced uncertainty and higher degree of accuracy pathogens such as norovirus and *Campylobacter* spp. should be collected from flood waters following periods of intensive rainfall in the Houston-Galveston region.

Conclusion

Under normal conditions non-human or mixed microbial scenarios likely approximate the microbial burden at Sylvan Beach, but during extreme weather events a heighted human load is feasible. Sylvan Beach is likely vulnerable to nonpoint and point source pollution and localized high concentrations of ENT and associated pathogens after rain events, but total probability of illness likely does not increase exponentially with dose. This QMRA suggests that the overall total probability of illness is higher for event scenarios that represent heightened periods of microbial contamination compared to expected typically ambient conditions with lower ENT concentrations. Similarly, observed and estimated concentrations of ENT were shown to be elevated during wet years compared to dry years. The 2015 annual model resulted in higher geometric mean ENT concentrations while increased solar radiation has potential to influence

ENT during drought years. This could have negative repercussions on human and environmental health as the region is expected to be impacted by more intense and frequent rain events.

CHAPTER V

SUMMARY AND CONCLUSIONS

Summary

In U.S. surface waters, outdoor recreational activities such as swimming, boating, and fishing have been estimated to account for four billion recreational contact events annually (DeFlorio-Barker et al. 2018). High concentrations of pathogens in surface water where recreational activity occurs has significant economic implications (DeFlorio-Barker et al. 2017, Johnson et al. 2008, Machado and Mourato 2002, Rabinovici et al. 2004, Ralston et al. 2011, Remoundou and Koundouri 2009, Shuval 2003), as well as detrimental consequences to public health (Dorevitch et al. 2012, Given et al. 2006, Ralston et al. 2011, Schwab 2007). The primary pathogen-related pollutant of concern in recreational waters is fecal waste, which may contain infectious agents such as bacteria (e.g., *Campylobacter* and *Salmonella*), protozoa (e.g., *Cryptosporidium* and *Giardia*), and viruses (e.g., noroviruses and adenoviruses) (Castro-Hermida et al. 2009, Gibson 2014, Hellein et al. 2011, Sinclair et al. 2009). Noroviruses are a leading cause of illness outbreaks in recreational water due to a high potential to survive environmental stressors and remain infectious, and have a high likelihood of causing infection in the human population (Fong and Lipp 2005, Gibson 2014, Seitz et al. 2011, Sinclair et al. 2009). In addition, contamination resulting in infection from *Campylobacter* spp. has been on the rise globally (Kaakoush et al. 2015).

Despite prevalence of public health risk, feasibility testing had not been conducted prior to this study to determine if a FIB forecasting model could improve beach management and reduce public exposure to pathogens in the Houston-Galveston region. Chapter II of this dissertation resulted in the collection of readily available historical data to develop and evaluate eight sets of regression models split between recreational and non-recreational beach seasons as well as an overall model. The ENT forecasting models can reduce uncertainty at Sylvan Beach Park by outperforming risk estimates made by collecting weekly or bi-weekly grab samples, known as the persistence method.

Overall, most FIB forecasting models developed during this dissertation performed better than the persistence method. Beach managers should consider adopting a forecasting model-based management system because models have the potential to improve the issuance of erroneous public health contamination advisories and serve as an early warning system reducing public pathogen exposure. Based on the methodology developed, additional sites along the Texas coast should be evaluated for forecasting feasibility. The potential economic and public health implications of recreating in pathogen contaminated waters at Texas coastal beaches remains unknown but is expected to be substantial (Figure 26).

Figure 26 Recreational swimming zone at a Texas coastal beach park.

In Chapter III the estimated total probability of infection and subsequent illness was calculated under three exposure scenarios that considered the population exposed, sources of microbial load, the recreational period during which exposure occurred, and ambient compared to elevated microbial conditions. The total probability of median illness was highest for primary contact that occurred during the recreational beach season when the largest number of recreationists have the potential to be exposed. For both populations and all recreational periods, the 100% human source loads consistently accounted for the highest total predicted probability of illness while the 100% nonhuman scenarios resulted in the lowest. Predicted probability of illness for the child scenarios where recreational contact occurred for a prolonged two-hour interval was marginally elevated compared to the one-hour adult contact scenarios suggesting that risk may not differ between the two populations. Lastly, elevated scenarios had higher overall total illness probabilities compared to the ambient scenarios. However, the human load sources did not differ substantially between the ambient and elevated scenarios. The current recreational contact standard may not be adequate to support public health safety when the proportion of microbial load at Sylvan Beach is dominated by human sources. In the human load scenario, risk estimated as total median probability of illness occurs when the reference pathogen dose, repeatedly sampled from a uniform probability distribution, ranges from 0 to 216 or 267 MPN/100 mL depending on the recreational period.

In Chapter IV regression equations were utilized to estimate ENT concentration for two annual and two flood event analysis periods. The overall concentrations of observed and estimated ENT were found to be comparable for each study year. In addition, ENT concentrations for the drought year 2011 were lower than concentrations from the excessively wet year 2015. The models successfully characterized patterns displayed by observed samples and were able to generate comparable estimates of ENT concertation shortly after the Memorial and Tax Day flood events. The 2015 annual model resulted in higher geometric mean ENT concentrations while increased solar radiation has potential to influence ENT during drought years. This could have negative repercussions on human and environmental health as the region is expected to be impacted by more intense and frequent rain events.

In addition, a quantitative measure of total illness probability was estimated for three event scenarios: 1) observed ENT concentration collected two days after the 04/18/2016 event, 2) ENT concentration at the maximum detectable limit, and 3) a theoretical ENT concentration ranging from 100,000 to 125,000 MPN/100 mL representing heightened microbial contamination. Sylvan Beach is likely vulnerable to nonpoint source pollution and localized high concentrations of ENT and associated pathogens after rain events, but total probability of illness does not increase exponentially with dose. This QMRA suggests that the overall total probability of illness is higher for event scenarios that represent heightened periods of microbial contamination compared to expected typically ambient conditions with lower ENT concentrations.

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