12-2021

A GIS-Based Model to Assess On-Site Sewage Facility (OSSF) Contamination Risk to Local Water Resources

Alvaro Garcia
The University of Texas Rio Grande Valley

A GIS-BASED MODEL TO ASSESS ON-SITE SEWAGE FACILITY (OSSF) CONTAMINATION RISK TO LOCAL WATER RESOURCES

A Thesis

by

ALVARO GARCIA

Submitted in Partial Fulfillment

of the Requirements for the Degree of

MASTER OF SCIENCE

Major Subject: Agriculture, Environmental, and Sustainability Sciences

The University of Texas Rio Grande Valley

December 2021

A GIS-BASED MODEL TO ASSESS ON-SITE SEWAGE FACILITY CONTAMINATION

RISK TO LOCAL WATER RESOURCES

A Thesis
by
ALVARO GARCIA

COMMITTEE MEMBERS

Dr. Jude A. Benavides
Chair of Committee

Dr. Chu-Lin Cheng
Committee Member

Dr. Owen Temby
Committee Member

December 2021

ABSTRACT

Garcia, Alvaro, A GIS-Based Model to Assess On-site Sewage Facility (OSSF) Contamination Risk to Local Water Resources. Master of Science (MS), December, 2021, 63 pp., 6 tables, 25 figures, references, 30 titles.

In a collaborative effort between Texas Water Resources Institute (TWRI), Cameron County Public Health (CCPH), Texas A&M AgriLife Extension (TAMAE), and the University of Texas Rio Grande Valley (UTRGV), a GIS database that includes relevant OSSF information, such as location, system age, lot size, and other important parameters was created.

This OSSF database, along with publicly available GIS data, was used to create an integrative GIS-based risk assessment model where OSSF risk parameters were assigned a risk factor and combined into a spatial contamination risk for surrounding areas and their receiving waterbodies. Parameters were broken down into two categories: environmental factors and OSSF system factors. *Environmental parameters* included soil type, land slope, floodplain, surface water proximity, drinking water supply proximity, and groundwater recharge areas. OSSF *system parameters* included system age and OSSF density. A model sensitivity analysis was then conducted using map removal sensitivity analysis and single parameter sensitivity analysis. A limited bacterial assessment was also conducted by enumerating *E. coli* in low and high risk waterbodies to provide a framework for future model calibration and validation.

DEDICATION

I dedicate this thesis to my loving parents

Juan A. Garcia and Sandra Garcia

ACKNOWLEDGMENTS

I would like to thank my major advisor Dr. Jude A. Benavides, and committee members Dr. Chu-Lin Cheng, and Dr. Owen Temby for their wisdom and encouragement throughout this project. I would also like to thank Mr. Jaime Flores, Dr. Gabriele Bonaiti, the Arroyo Colorado Watershed Partnership, Cameron County Public Health, Brownsville Public Utilities Board, TCEQ, and UTRGV as this project would have not been possible without them.

Thank you to all the people who assisted me academically, financially, and emotionally during one of the hardest, yet most exciting journeys of my life. Thanks to all my family, for their continued support and for always believing in me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Page

CHAPTER I

INTRODUCTION

In Texas, it is estimated that 20% of homes use OSSFs to properly treat their wastewater, and that 20,000 to 30,000 new OSSF permits are issued every year (TGPC, 2019). With this number of new systems being installed each year, it is becoming more important to explore the potential public and environmental health impacts of OSSFs. Using OSSF permitting information from our local health department, a GIS-based model that assessed OSSF contamination risk to local waterbodies was created. A limited bacterial assessment was then conducted by enumerating E. coli in low and high-risk waterbodies using Colilert-18/Quanti-tray method (Colilert 18- IDEXX US, n.d.). The sensitivity of the model was also assessed using map removal sensitivity analysis and single parameter sensitivity analysis. Results from this study have the potential to inform policy implementation and bring awareness to nonpoint source pollution in our local waterbodies.

Purpose

The purpose of this research is not only to advance the body of local knowledge regarding OSSFs and their risks to public health and the environment but to encourage long-term collaboration and knowledge-sharing between local regulatory entities, scientists, and stakeholders. The results of this research can be used to inform policy decisions by local OSSF governance authorities and bring additional awareness to a critical pollutant in the Lower Rio Grande Valley. Furthermore, this research complements recent and existing watershed protection planning and characterization efforts in the Lower Rio Grande Valley, such as the Arroyo Colorado Watershed Protection Plan. This particular plan has cited OSSFs as prime contributors to degrading water quality in the area (Flores et al., 2017).

Objectives

Improperly managed OSSFs and challenging environmental conditions can increase the risk of OSSF contamination to waterbodies, and thus the risk of bacteria exposure to the public. This emphasizes the importance of assessing contamination risk to avoid potentially deleterious public health consequences. As part of the initial groundwork for mitigating OSSF contamination, this research aims to satisfy the following objectives:

1. Develop a GIS-based model that considers relevant OSSF risk parameters to assess OSSF contamination risk to surrounding areas and potential receptor waterbodies, such as resacas, drainage ditches, and groundwater, within Cameron County.
2. Perform a model sensitivity analysis using single parameter sensitivity analysis and map removal sensitivity analysis.
3. Complete an initial, albeit basic model performance evaluation. This will be accomplished through a limited bacterial assessment that enumerates E. coli in low and high-risk waterbodies as determined by the OSSF risk model.

CHAPTER II

LITERATURE REVIEW AND BACKGROUND

On-Site Sewage Facilities (OSSFs)

OSSFs, if properly designed, installed, operated, and maintained, can provide long-term and cost-effective wastewater treatment where centralized water systems are not readily available. These decentralized wastewater systems can provide rural, often small communities with many economic, environmental, and public health benefits. OSSFs can effectively reduce the risk of disease transmission, remove contaminants from residential water, recharge the treated water back into the environment, and reduce the large infrastructure costs associated with wastewater collection and treatment (EPA, 2018).

OSSFs function by storing and treating wastewater through a combination of physical, chemical, and biological processes. A conventional septic tank works by first taking in wastewater from a residence through gravity driven flow, and then storing it in a large holding tank. In this septic tank, denser solids are allowed to settle and anaerobic microbial digestion of bacteria takes place. After this first phase of treatment, the effluent then flows towards a distribution system known as a leach field. The leach field consists of perforated pipes that allow the effluent to slowly percolate, or leach into surrounding soils. These perforated pipes are surrounded by a gravel media filter, while a geotextile membrane separates loamy soil above the drain field from the perforated pipes (TAMAE, 2008). The soils then further filter organic matter and solids while soil microbes digest bacteria and pathogens found in the effluent (TAMAE, 2008). Refer to Figure 1 for an illustrated diagram of a conventional septic system.

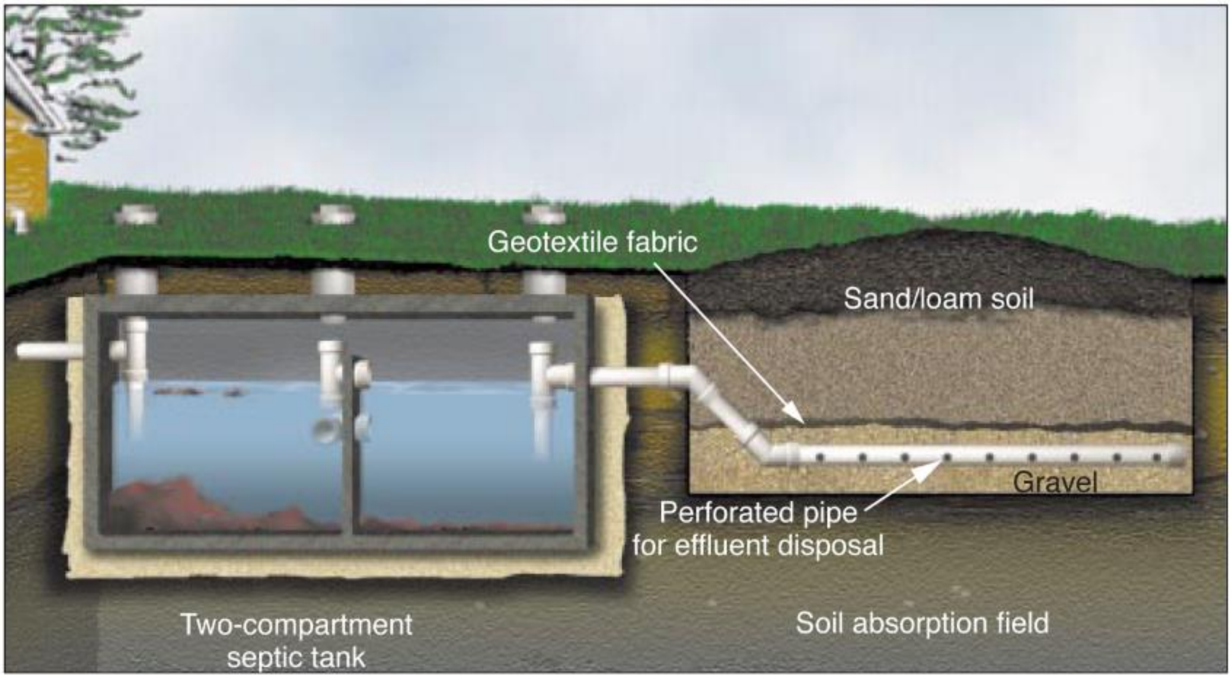

Figure 1. Conventional OSSF: A conventional septic tank and soil adsorption system (TAMAE, 2008).

OSSF Risk to Local Waterbodies

Watersheds

Two of the primary watersheds located within Cameron County are the Lower Laguna Madre/Brownsville Ship Channel Watershed and the Arroyo Colorado Watershed. The Arroyo Colorado Watershed incorporates the northern portions of the county, with areas such as San Benito, Harlingen, and the Rio Hondo falling within its bounds. The Lower Laguna Madre Watershed is found on the southern area of the county, and includes the Brownsville, Port Isabel, Rancho Viejo, and Los Indios areas. A third watershed, known as the North Floodway, covers a smaller area of the northwestern corner of the county. This watershed includes the Santa Rosa area. Figure 2 below illustrates the watersheds present within Cameron County.

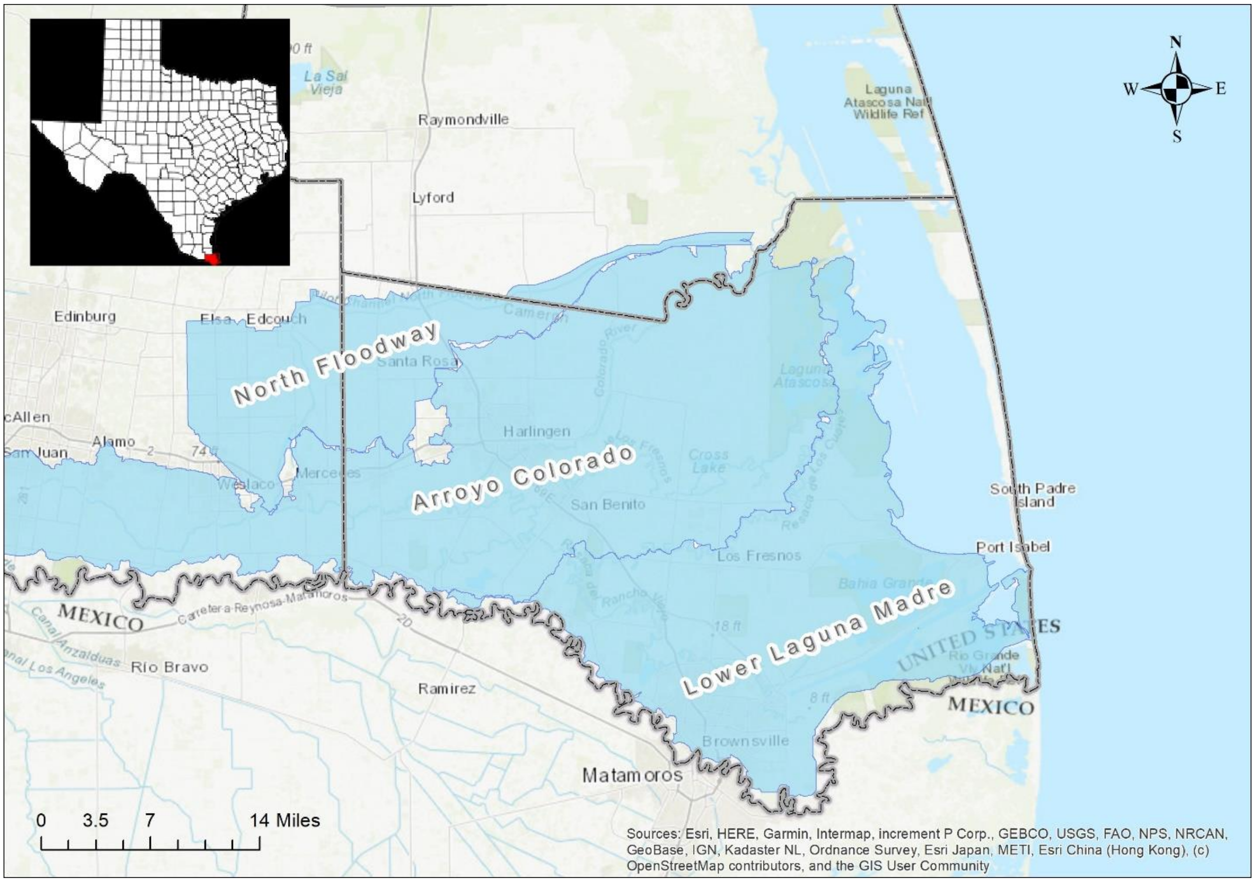

Figure 2. Map of Watersheds Located in Cameron County: The North Floodway, Arroyo Colorado, and Lower Laguna Madre/Brownsville Ship Channel watersheds within Cameron County.

Cameron County resides in the Lower Rio Grande river delta, which exhibits a complex, dense network of irrigation ditches, canals, and ancient distributary channels and their ox-bows (Figure 3) known locally as “resacas.” Historically, these distributary channels diverted and drained floodwaters during periods of high flow in the natural flood cycle of the Rio Grande river. As interest for farming and ranching grew in the early 1900s, the delta’s hydrology was altered to meet irrigation and flood prevention needs (Knight, 2009). This led to the creation of a dense hydrological system composed of irrigation canals, ditches, dams, drains, weirs, and pumps.

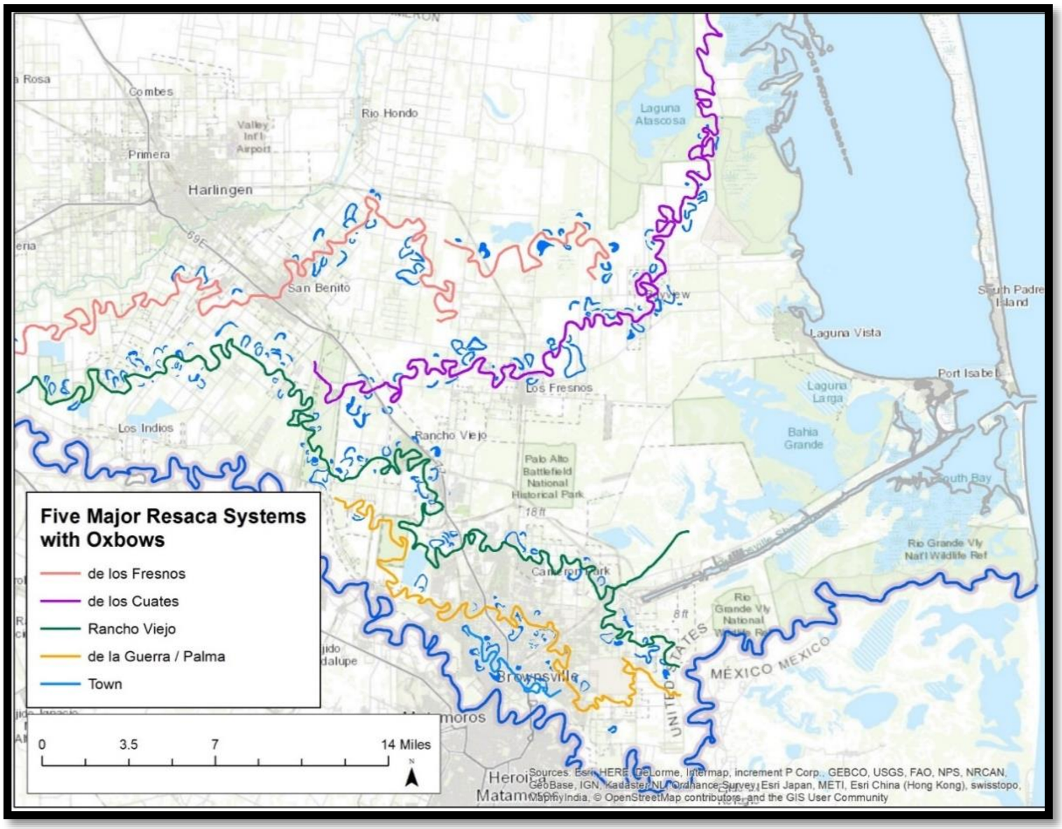

Figure 3. Map of Resacas and Ox-bows: Ancient distributaries of the Rio Grande with their respective ox-bows, known locally as "resacas," play an important, and poorly researched, role in the hydrology of the area.

Currently, the heavy urbanization of the Lower Rio Grande Valley is shifting the role of this hydrologic system into one of flood and irrigation water storage and conveyance (Lower of Laguna Madre/Brownsville Ship Channel Characterization Report, 2018). More urban resacas have been repurposed as reservoirs for flood control, irrigation water storage, and stormwater management, while rural resacas rely on periodic inundation from rainfall and more often resemble marsh like environments (Lower Laguna Madre/Brownsville Ship Channel Characterization Report, 2018). Both urban and rural resaca systems receive overland flow from their narrow watersheds and likely interact with groundwater to some degree. However, these surface-groundwater interactions are not well-understood due to very limited studies that focus on this issue. It should also be noted that at times, resaca systems do not exhibit traditional outflows, with their historical outlets being closed due to sedimentation, urban development, or agricultural activities. Despite these cases, the majority of resacas, irrigation canals, and ditches drain into the Lower Laguna Madre, a shallow hypersaline lagoon bordering the Texas coastline (Figure 4).

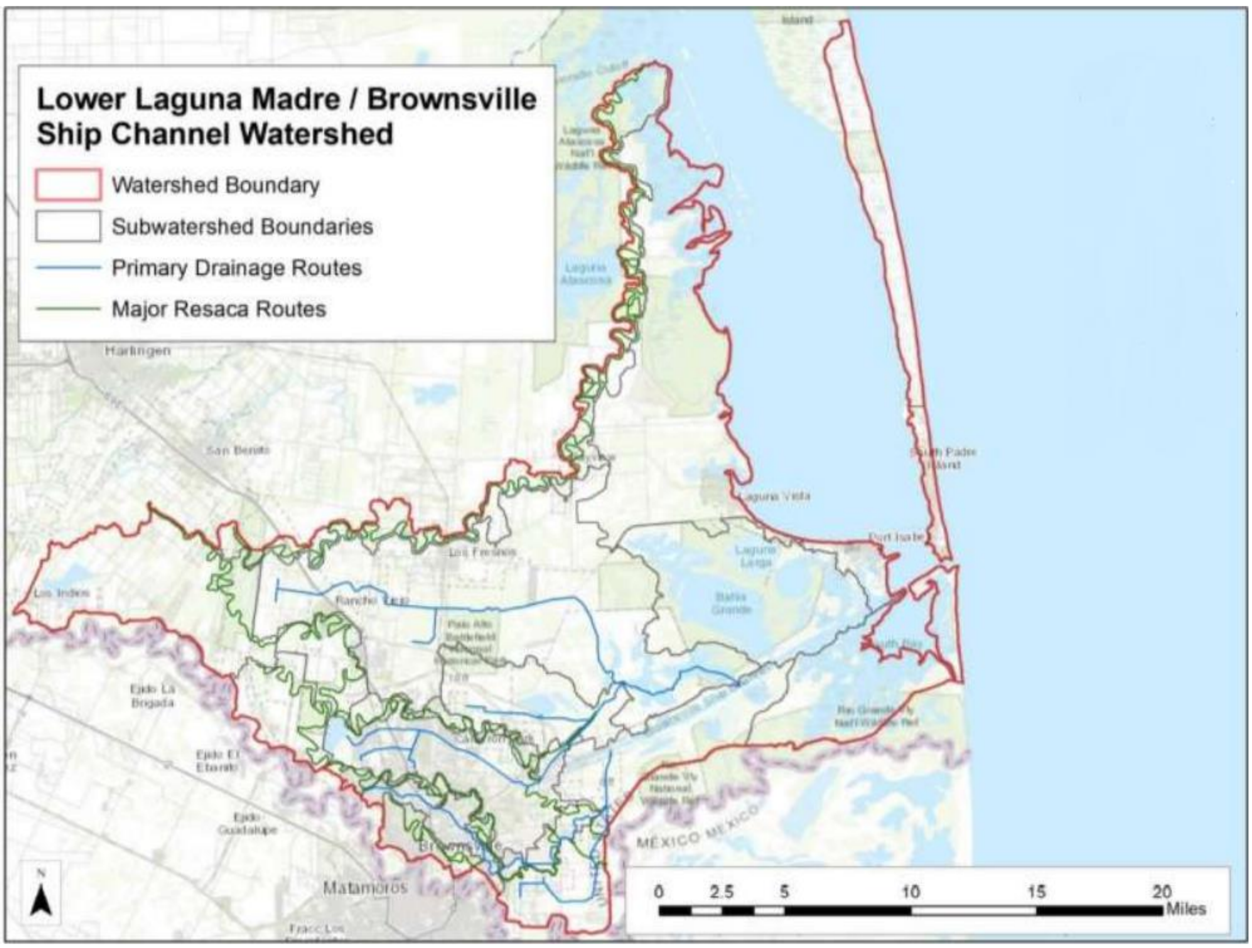

Figure 4. Lower Laguna Madre/Brownsville Ship Channel Watershed. The alternating arrangement of the resaca and interstitial drainage ditch network are potential transport mechanisms of OSSF discharge into the Laguna Madre (Lower Laguna Madre/Brownsville Ship Channel Characterization Report, 2018).

Resacas

The hydrological features of the resaca and drainage ditch network are of interest to OSSF contamination as both resacas and drainage ditches can function as potential storage and transport mechanisms for OSSF discharge. However, there are notable differences between these two drainage features. Resaca systems can be viewed as a network of linear pools separated by weirs. During dry periods, there is minimal or no water exchange between pools because water levels are often below the height of the weir, resulting in an impoundment and long-term storage of water. In this case, weirs act as small dams that prevent water from accumulating at the most downstream pools. Due to the depositional nature of the ancient Rio Grande, resacas often exhibit a clay pan at the bottom that causes low infiltration rates to groundwater. The restriction of longitudinal flow by weirs and low infiltration rates caused by clay pans lead to high residence times during dry periods. In this manner, high residence times can lead to higher risk of public exposure to bacteria. On the other hand, resacas can also function as transport mechanisms during wet periods because high runoff causes water levels that are sufficiently high enough to overtop weirs and induce downstream flow. It should also be noted that some resacas are manually pumped with water to induce flow on occasion. Other resacas are constantly pumped and have continuous flow year round. Depending on the hydrological flow regimes of resaca systems as seen in Figure 5 below, resacas can function as OSSF contaminant storage during periods of low flow and as transport mechanisms during high rainfall events.

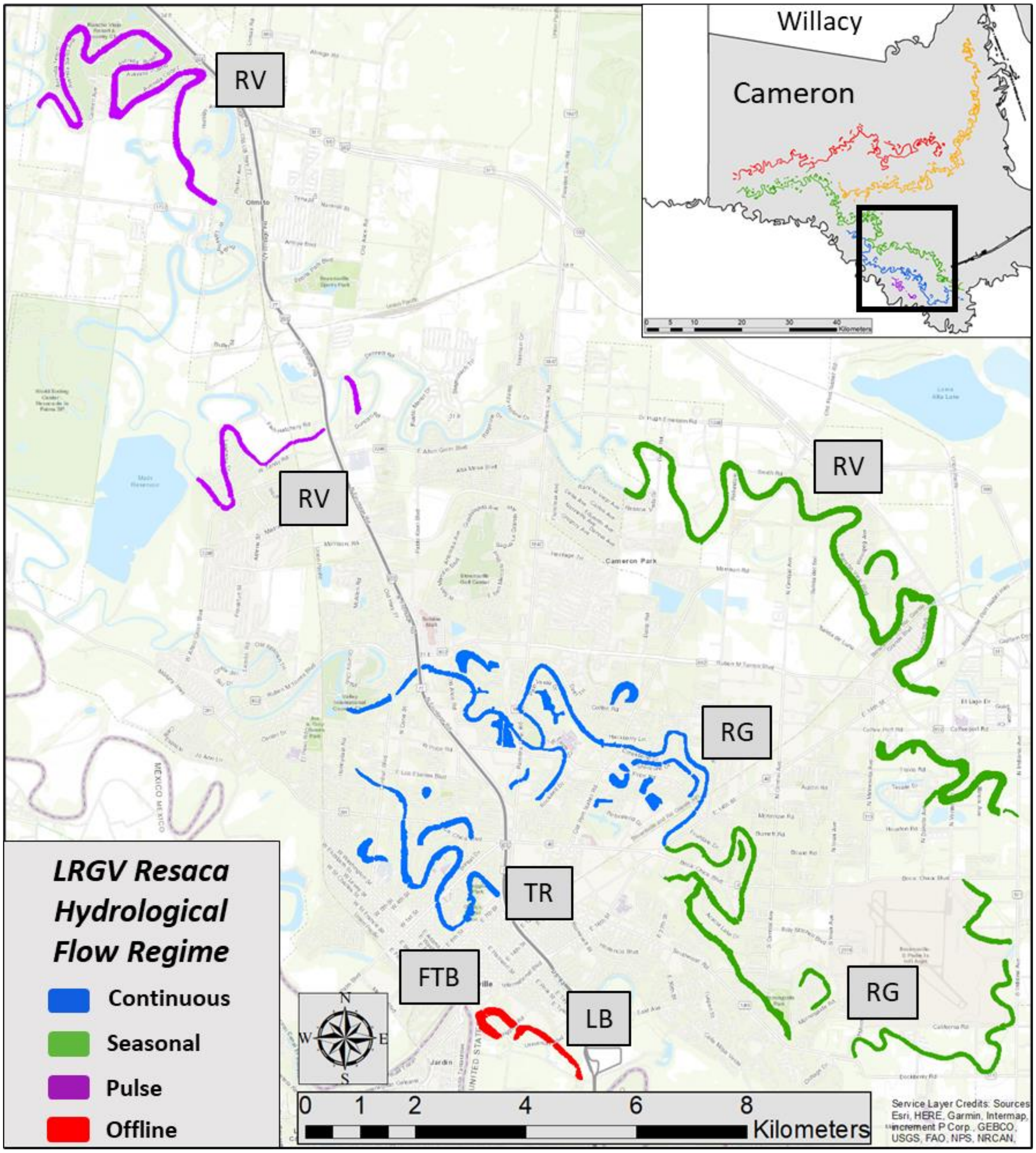

Figure 5. LRGV Resaca Hydrological Flow Regimes. There are differences in the hydrological flow regimes of resaca systems (Lecusay, 2021) which have impacts on contaminant transport and storage. Resacas with continuous flow exhibit flow at all times while resacas with seasonal flow have periodic flow when flow is associated with a cause other than filing the resaca, such as irrigation conveyance. Resacas with pulse flow are filled periodically for the main purpose of increasing/maintaining resaca levels. Figure provided by David Lecusay Jr.

Drainage Ditches

Drainage ditches function primarily as transport for OSSF discharge when runoff that flows through areas of high-risk for OSSF contamination ends up in the storm water system. When rain falls outside of the narrow resaca watersheds, it is directed towards drainage ditches via a storm water system. Despite lower infiltration rates, some parts of drainage ditches are perennially filled with water from past rainfall events, effectively functioning as temporary storage for OSSF contamination. During high rainfall events, potentially contaminated storm water does drain into the LLM. Unlike resacas, drainage ditches have lower residence times because the absence of weirs causes uninterrupted longitudinal flow.

Groundwater

Although groundwater in the LRGV is heavily under-studied, some reports have tried to characterize the groundwater system in the LRGV. Hutchison and others (20XX) developed a numerical groundwater model for TWDB in order to estimate impacts of brackish groundwater pumping on water availability. A similar groundwater availability model (GAM) was also developed by TWDB in order to estimate groundwater levels after well pumping (Chowdhury and Mace, 2007). However, models such as these tend to focus on water availability and impacts due to pumping, and lack information on groundwater transport processes and surface water-groundwater interactions (Hutchison, 2017). Generally, groundwater in the LRGV follows surface topography with the highest elevations coming from the northwestern and western portions of the delta (Hutchison, 2017), roughly 5-10ft below surface depending on location. These elevation patterns are dictated by the depositional nature of the resaca distributary network, as seen by LIDAR maps of the area (Figure 6). Resacas exhibit natural levee systems that were created when the historical Rio Grande river would flood the river delta, overflowing the distributary systems and depositing materials on their banks. The influence of these terrain modifications by resacas on surface water-groundwater interactions is poorly understood due to a lack of studies on the topic.

Near surface groundwater-surface water interactions have the potential to be major transport mechanisms between OSSFs and surface waterbodies. Although there is a lack of substantive data regarding the interactions between groundwater and surface waters, the water table generally follows surface topology. Depending on the elevation of the water table, there could be exchanges between groundwater and surface waterbodies and thus possible OSSF contaminant transport.

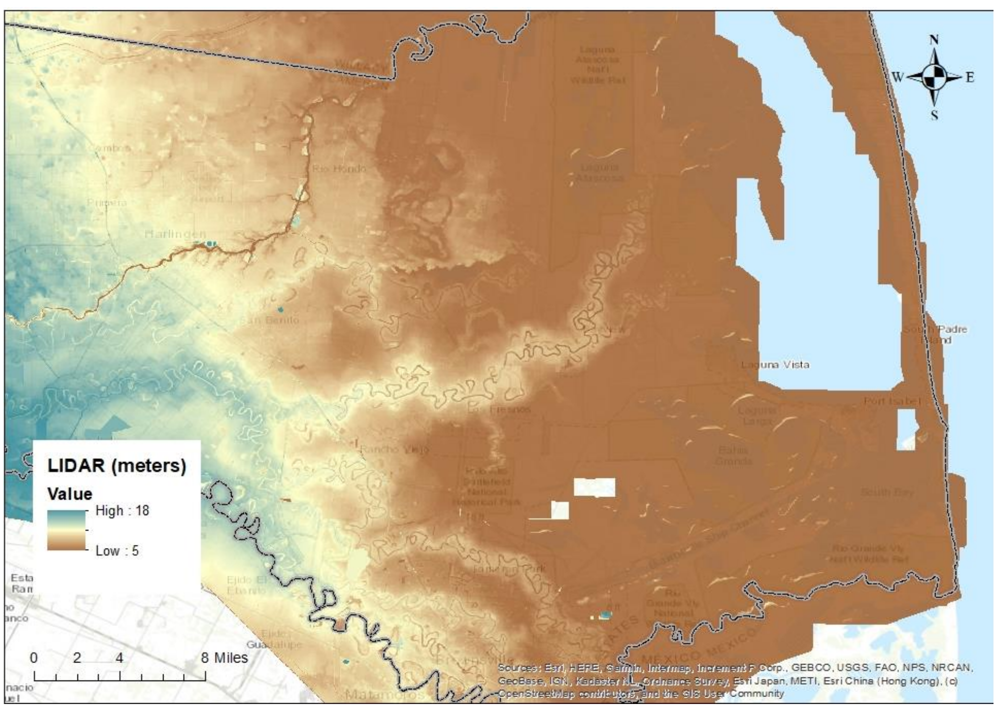

Figure 6. Cameron County LIDAR. LIDAR data demonstrates that elevation patterns are heavily influenced by the depositional nature of resaca systems. This is evidenced in this figure as the natural resaca levees are higher in elevation than surrounding areas.

Coastal Waterbodies

As mentioned before, many of the more inland hydrological features drain into coastal waterbodies such as the Lower Laguna Madre, the Bahia Grande, surrounding estuaries, and ultimately into the Gulf of Mexico. This is of special concern as many of the coastal receiving waterbodies have already been listed as impaired due to elevated bacteria levels by the 2020 Texas Integrated Report of Surface Water Quality as seen in Figure 7 below. Elevated bacterial levels in these coastal waterbodies pose serious threats to public health, the environment, and the economy. Consequences such as disease outbreaks, cultural eutrophication, and a decline of tourism can occur if contamination is left unchecked. These concerns have led to extensive watershed protection planning and to the creation of task forces, such as the Arroyo Colorado Watershed Partnership. As cited within the Arroyo Colorado Watershed Protection Plan, OSSFs contribute to pollutant loading of the Arroyo Colorado and to the Laguna Madre. Proposed action to mitigate the potential consequences of OSSFs include the development of an OSSF database, inspecting and replacing failing OSSFs, conducting OSSF education programs, and extending wastewater service to areas with high OSSF density (Flores et. al., 2017).

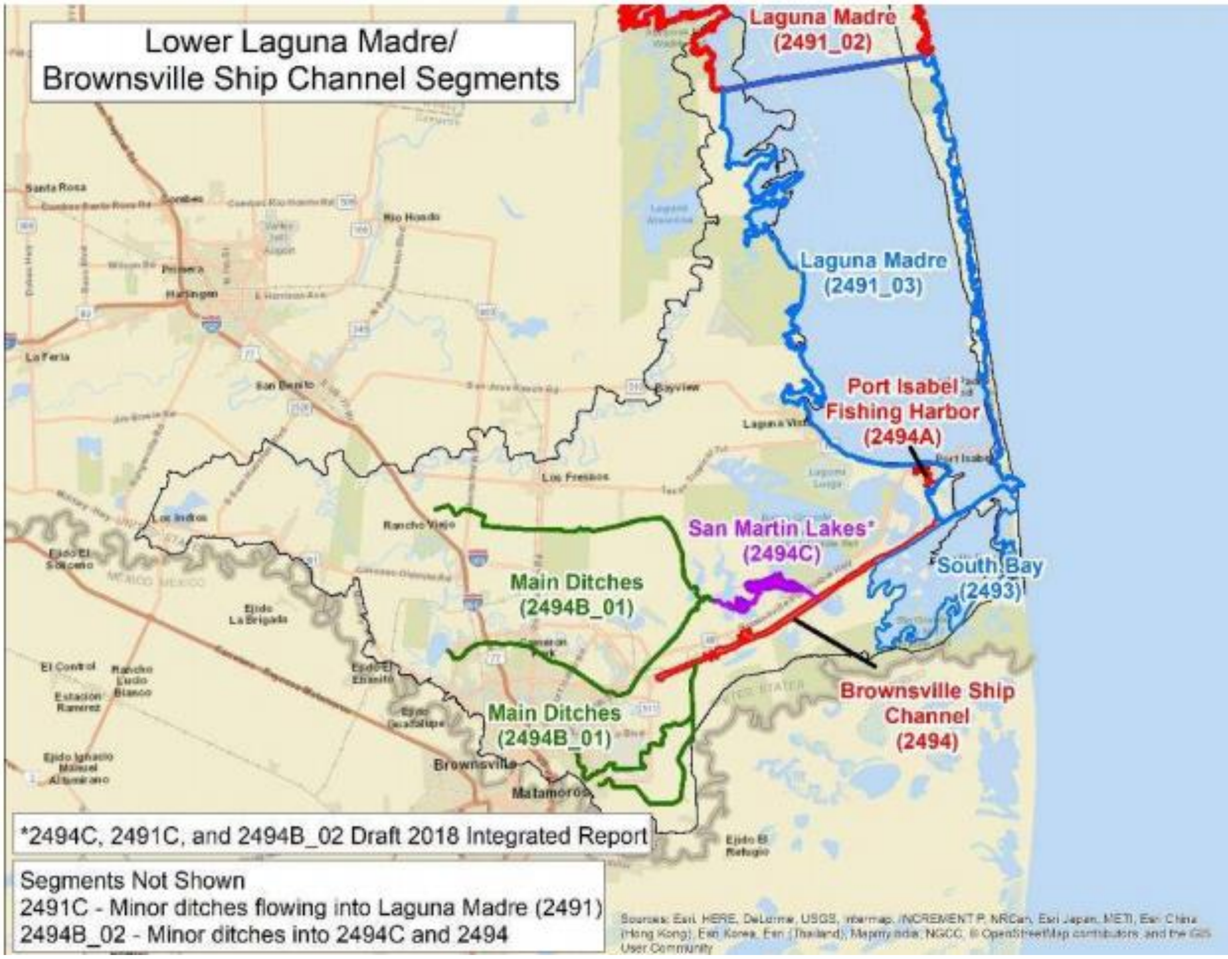

Figure 7. Lower Laguna Madre/Brownsville Ship Channel Segments. TCEQ segments that have been listed as impaired due to elevated bacteria levels are highlighted in red (Lower Laguna Madre Watershed Characterization, 2018).

OSSFs and Environmental Health

Various studies have documented how OSSFs can pose significant danger to both the environment and public health. Failing OSSFs can discharge harmful pathogens into our waterbodies, which can then make contact with the public. An example of this was seen in the Yukon Territory of Canada, where a restaurant's water supplied by a groundwater well was contaminated by a failing OSSF (Beller et al. 1997). This resulted in a viral gastroenteritis breakout that affected 54 people, of which 6 were hospitalized. Another incident happened in northeastern Wisconsin, where the employees of a restaurant suffered from acute gastroenteritis because they ingested contaminated water from the restaurant's water well (Borchardt et al., 2010). OSSFs have also been linked to large scale municipal water supply contamination (O' Reilly, 2004) and bacteria-related beach closures (Flanagan et. al., 2019). It is also well known that OSSFs have the potential to discharge nutrients into the environment (Beal et al., 2005), which can accelerate cultural eutrophication and also pose a human health risk (Chand et al., 2011). As showcased by various case studies, failing OSSFs can have potentially harmful consequences for both public health and the environment.

The potential impacts associated with OSSFs are important in Cameron County as recreation and ecotourism are common in the area. Waterbodies such as the Arroyo Colorado have contact recreation as a designated use (TCEQ, n.d.) and kayaking, fishing, wading, motor boating, and occasionally swimming occur in many of the county's waterbodies. Ecotourism in the Lower Laguna Madre is also commonplace, with bird watching being very popular in the area. This is of particular concern because waterbodies in the area, such as the Arroyo Colorado and parts of the Lower Laguna Madre, have been classified as impaired with elevated bacteria levels.

OSSF Risk Assessment and Geographic Information Systems (GIS)

Risk-based models can aid in the proper management and prevention of OSSF contamination (Carrol et al., 2006). There have been numerous risk-based approaches that have assessed OSSF impacts to the surrounding environment and public health. However, recent

OSSF risk models are starting to take advantage of spatial technologies such as Geographic Information Systems (GIS). Although GIS has traditionally been used for other types of overlay analysis, such as habitat suitability, novel approaches are developing OSSF contamination risk models with the use of GIS.

Hazard modeling, where the characteristics of a site or region are rated to provide an overall indicator of the likelihood of environmental contamination, has proven to be very useful in assessing the potential impacts of OSSFs (Vieritz et al., 2006). This modeling approach can also consider the importance of potential receptors and their geographic separation distance from OSSFs. With the use of GIS, high-risk areas can be efficiently mapped and hot spots can be determined.

A notable example of this type of modeling approach can be seen in Oosting and Joy (2011). Oosting and Joy developed a GIS-based risk model that analyzed OSSF system and environmental parameters to predict OSSF contamination risk in the rural township of Huron-Kinloss in Ontario. Environmental parameters included soil type, land slope, floodplain, and groundwater intrinsic susceptibility index while OSSF system design parameters included lot size, surface water proximity, system age, and water supply proximity. These attributes were combined to map cumulative risk from OSSFs to both ground and surface waterbodies. The final risk map created was then shared with local OSSF governance authorities and high-risk areas were confirmed by local experts.

Carrol and others also followed a similar approach by creating an integrated risk framework that consisted of OSSF siting and design risk, environmental risk, and public health risk for the more urban, slightly larger Gold Coast region in Queensland, Australia. Their approach also included the use of stakeholder workshops and focus groups to identify OSSF hazards within these categories (Carrol et. al., 2006). Attributes such as soil's ability to renovate effluent, lot size, slope, setback distances from groundwater wells and surface water, and the floodplain were taken into consideration for determining OSSF siting and design risk (Carrol et. al, 2006). Public health and environmental health risk were calculated by using data from already established monitoring stations. Thresholds for nitrogen and phosphorous were used for determining environmental risk while fecal coliforms and *E. coli* thresholds were used for calculating public health risk.

Another example of hazard modeling was demonstrated by the On-site Sewage Risk Assessment System (OSRAS) risk framework developed in New South Wales, Australia. This larger scale risk framework integrated three types of hazards: natural hazard, sewage export hazard, and environmental susceptibility and receptor hazard (Kenway, 2001). "Natural hazard" involved the environmental attributes of the site that allow the proper assimilation of effluent into the environment (Kenway, 2001). This hazard is assessed using soil, landform, and climate spatial data in order to map and classify natural hazard. "Sewage export hazard" was the likelihood of sewage being exported by the OSSF and is determined by combining natural hazard with site characteristics such as lot size (Kenway, 2001). "Environmental susceptibility and receptor hazard" identifies and classifies different pathogen sensitivities and thresholds for different types of waterbodies. For example, raw water supplies for drinking and waterbodies used to farm seafood are more sensitive to bacterial contamination than second contact recreation areas because bacteria thresholds are much smaller for raw drinking water supplies; thus, raw drinking water supply had a higher risk classification. The OSRAS framework is currently being implemented and expanded across the coastal watersheds in New South Wales as state agencies, councils, and consultants are being trained to efficiently implement the system (Kenway, 2001).

These studies highlight the complexity of designing hazard models and their limitations, as these type of models can be designed with different data inputs, contaminant thresholds, and spatial scales in mind. The different ways a risk assessment can be designed and modified can prove challenging when trying to evaluate, calibrate, or validate these models especially when quantitative data is limited.

Bacterial Assessment and Resacas

E. coli has been frequently used as an indicator bacteria to test for the presence of fecal contamination and other pathogens in waterbodies. Of the five classes of fecal coliforms, E. coli is the only one that is not naturally found in the environment, making it an excellent indicator bacteria. Previous standard methods involved the multiple-tube (most probable number) method, but that standard has been withdrawn by the International Organization for Standardization (ISO) and has replaced it with Colilert-18/Quanti-Tray (ISO 9308-2:2012). In this method, the nutrient indicator 4-methylumbelliferyl-β-D-glucuronide (MUG) found in their proprietary reagent is metabolized by *E. coli* to create fluorescence (IDEXX, n.d.). First, 100 ml samples are collected and then the reagent is added into the sample. This mixture is then added into the IDEXX Quanti-Tray (Figure 8) which is then heat-sealed and placed in a 35°C ± 0.5°C incubator for 18 hours. Finally, yellow/fluorescent wells are counted and then referred to the Most Probable Number (MPN) table, which links number of positive wells with the most probable number of colony forming units per 100 ml.

Figure 8. IDEXX Quanti-Tray. Quanti tray system uses nutrient indicators to quantify coliform and *E. coli*.

The IDEXX method will be used for testing low and high-risk resaca pools as designated by the OSSF risk assessment model. However, it’s important to highlight some of the resaca pool characteristics that can have impacts on E. coli enumeration. Despite the larger scale trends mentioned, each individual resaca pool functions somewhat uniquely depending on its surrounding environment, both natural and man-made. Residence times can greatly influence the concentration of fecal contamination per resaca pool. Residence time can be calculated using the equation below:

$$\tau = V/Q$$

τ = Residence time (sec)

V = Volume (ft^3)

Q = Flow rate (ft^3/sec)

For example, the presence/absence of storm drains and/or weirs can have significant impact on flow and residence times. This can lead to higher bacteria levels in resacas that have longer residence times and lower bacteria levels in resacas with shorter residence times. This means individual resaca pools with higher flows can primarily function as contaminant transport while resacas with lower flows function as storage. Furthermore, some resaca pools have seasonal pulse flow while others function more like lakes, adding a time dimension to their possible interactions with OSSF contamination. Another factor is the presence of either domestic or wild animals, as they could have effects on bacterial loading. All of these factors could also interact with each other and have cumulative effects when it comes to fecal contamination. In the case of resacas with storm drains, stormwater runoff contaminated by domestic animals could spike bacteria levels in an individual pool regardless of whether OSSF contamination was present in the area.

CHAPTER III

METHODOLOGY

The methodology followed in this research can be broken down into five sections:

1. Study Area
2. OSSF Inventory
3. Risk Assessment Model
4. Model Sensitivity Analysis
5. Model Performance Evaluation

Study Area

Cameron County was the selected study area because the area has high environmental and public health risks, OSSF GIS data is readily available, and there is a socioeconomic need for wastewater management in the area. Specifically, Cameron County's boundary was chosen as the geographic study feature because the main OSSF permitting authority is the Cameron County Public Health Department. The jurisdictional bounds for their permitting authority are the county lines. However, it is to be noted that the county has issued OSSF permits for properties located within city jurisdictions. These permits originate from areas that were previously county jurisdiction and were then incorporated into cities. Currently, there is no state method to track already existing OSSF properties that were later incorporated into sewer networks, which proves challenging to locating active OSSF systems (TGPC, 2019).

OSSF Inventory

The first major project to take inventory of OSSFs in Cameron County was the Texas Coastal OSSF Inventory as part of the Coastal Zone Reauthorization Amendments (CZARA). OSSF locations and permit information were recorded for areas that fall within the Texas General Land Office's defined Coastal Zone. The project was completed in October 2017 and around 63,374 OSSFs were located in all 19 coastal counties (Bonaiti et. al., 2017).

The Coastal Zone OSSF project then later led to more localized efforts to take inventory of OSSFs within all of Cameron County. While the Texas Coastal OSSF Inventory and Arroyo Colorado Watershed Protection Plan were being developed, Texas A&M AgriLife Extension and TWRI partnered to develop preliminary OSSF estimate maps for Cameron County. Sewer service maps and Cameron County 911 addresses were used to estimate OSSFs in this project. Areas that fell outside of the sewer service maps were assumed to contain OSSFs in these preliminary estimate maps.

The partnership between TWRI and Texas AgriLife Extension then expanded to include Cameron County Public Health and UTRGV in order to create a more detailed Cameron County OSSF Inventory. Permit spreadsheets and information were obtained from the Cameron County Health Department and permit information was linked to the Cameron County Appraisal District and 911 address GIS maps in order to verify permit locations (Figure 9).

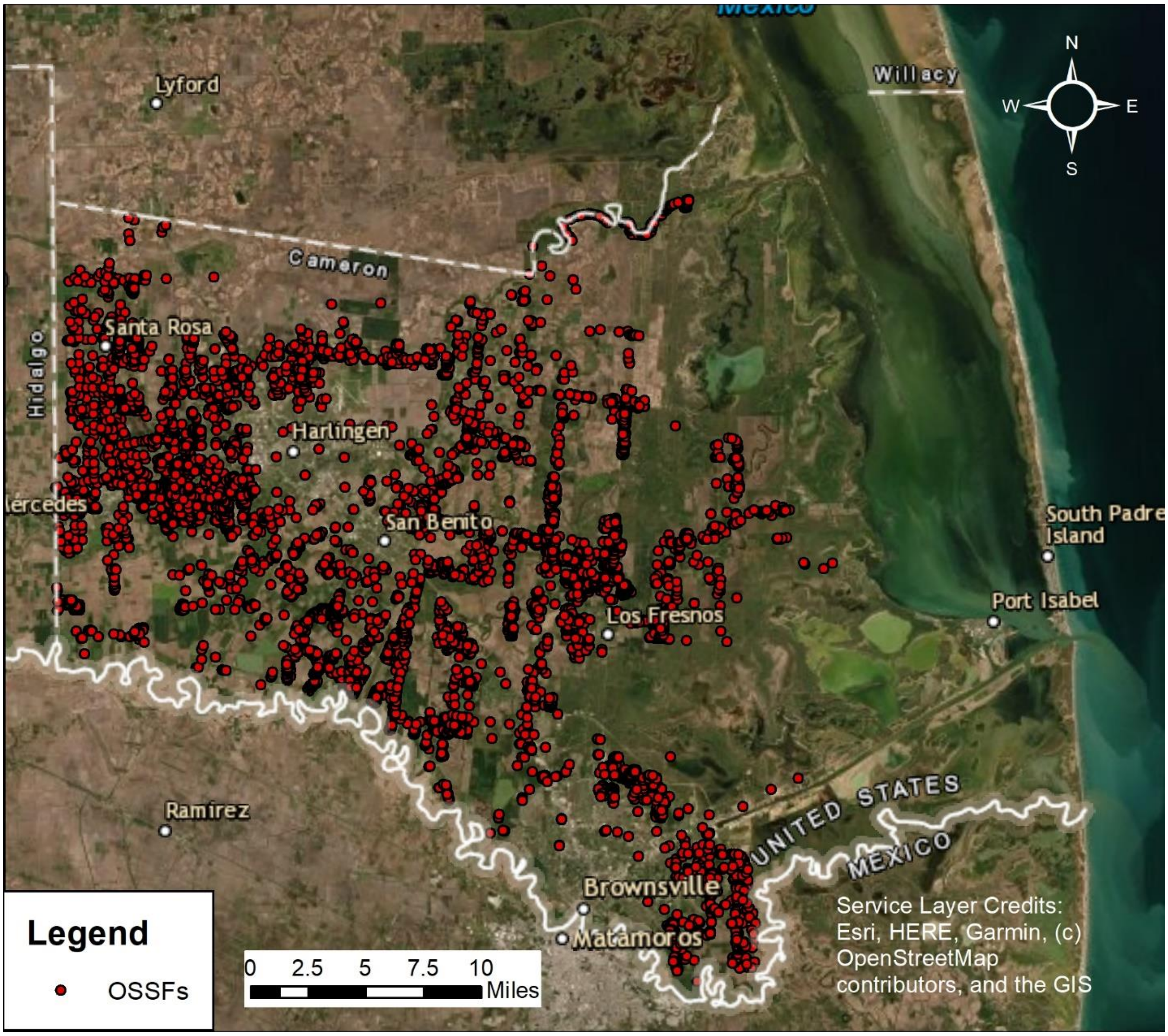

Figure 9. OSSF Inventory. This map demonstrates the current OSSF database as of summer 2021.

The current phase of the project involves further digitization, location, and inventory of physical paper OSSF permits from the Cameron County Public Health. The physical copies are scanned into PDFs and stored in Cameron County's database management software, which stores address information, soil type, OSSF installation dates, and other relevant permit information. Because the address located in the permit is not always the OSSF site address, the legal description of location must be verified in order to finalize a permit location. This is done by manually linking a property ID from Cameron County Appraisal District maps with a permit number. Challenges to managing this database include missing permits, double counting when systems are upgraded or replaced, permits with missing location, and legibility of paper copies.

OSSF Risk Assessment Model Methods

Methods from Oosting and Joy were adapted to develop a GIS-based risk assessment model. Under this methodology, risk parameters assessed the cumulative risk an area presented to contaminating local water resources. It is important to note that this model did not attempt to determine which OSSFs are failing, but rather aimed to define high contamination risk areas relative to one another. Although the central methodology was based on Oosting and Joy's model, the GIS-based model used for Cameron County was modified to be more representative of the study area.

Cell Size

In order to assign risk to an area, a survey grid spanning all of Cameron County was created within GIS. As different cell sizes can significantly impact a model's results (Vieux and Needham, 1993), careful attention was given to the cell size of the survey grid. Similar sizes used in Oosting and Joy's model were chosen for comparison. Survey grids of 100 meter by 100 meter cell size, 250 meter by 250 meter cell size, and 750 meter by 750 meter cell sizes were compared to determine the optimal cell size for the model. Preliminary models using the cell sizes mentioned above were created. When comparing these cell sizes, it was observed that large areas could receive high-risk scores even though a small component of the area met the condition, thus overgeneralizing risk from a spatial perspective. Furthermore, a smaller cell size was deemed more appropriate as larger cell sizes could include various risk classes of surface water proximity and drinking water proximity as seen in Figure 10 below. Due to these reasons, a 100 meter by 100 meter cell size was chosen for this study, which resulted in a total of 237,091 cells.

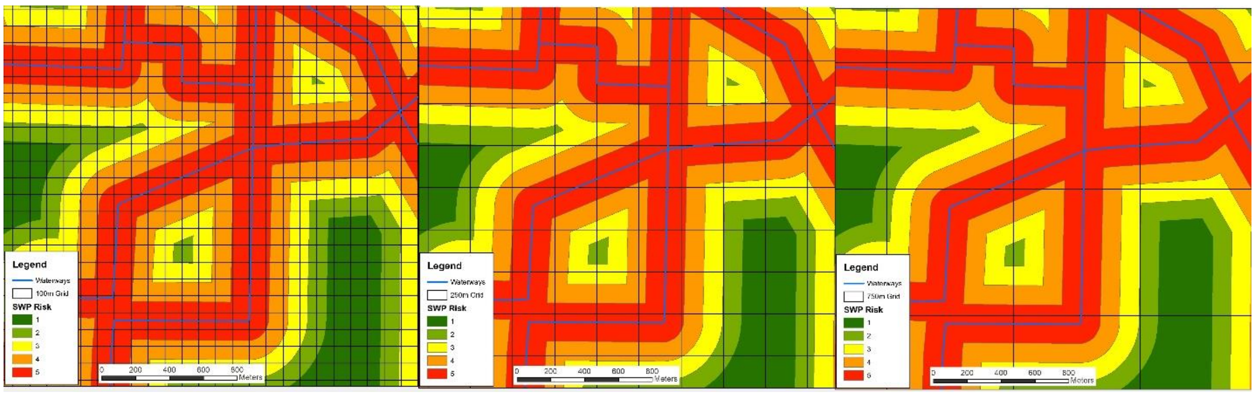

Figure 10. Cell Size Selection. Cell sizes of 100m x 100m, 250m x 250m, and 750m x 750m, respectively, were considered for this study. As seen on the 750m x 750m grid, many surface water proximity risk class buffers are found within one cell while the 100m x 100m grid tends to have one risk category per cell. Distances for surface water proximity and drinking water supply can be found in the Risk Parameters section below. A total of 237,091 cells were used in the 100m x 100m grid.

Risk Parameters

Cumulative contamination risk from OSSFs was determined by first creating an environmental risk map using environmental parameters and then combining that map with OSSF system risk, which is a measure of risk associated with OSSF location and OSSF properties. Environmental parameters included:

- Soil Type
- Land Slope
- Floodplain
- Groundwater Recharge Areas

- Surface Water Proximity
- Drinking Water Supply Proximity

An OSSF System risk parameter was created by calculating an OSSF system density and weighing that by system age. Adapted from Oosting and Joy (year), the summary of classification criteria used can be found in Table 1 below.

Table 1. Summary of Classification Criteria Used to Assign Contamination Risk

Risk Parameter Classification Table					
Risk Parameter	**1**	**2**	**3**	**4**	**5**
Soil	Class B	--	Class C	--	Class A and Class D
Slope	<5%	5-10%	10-15%	15-20%	>20%
Floodplain	Outside 100 year floodplain	--	--	--	Within 100 year floodplain
Groundwater Recharge Areas	Outside estimated recharge areas	--	--	--	Within estimated recharge areas
Surface water Proximity	Beyond 1500 ft.	1125 ft. - 1500 ft.	750 ft. - 1125 ft.	375 ft. - 750 ft.	Within 375 ft.
Water Supply Proximity	Beyond 3000 ft.	2250 ft. - 3000 ft.	1500 ft. - 2250 ft.	750 ft. - 1500 ft.	Within 750 ft.
OSSF System Risk (OSSFs per 28 km^2)	0 - 30	30 - 91	91 - 177	177 - 300	300 - 520

Environmental Risk Factors:

- Soil Type: The physical properties of the soil on site have a significant impact on contaminant transport and contaminant attenuation, as they determine infiltration rates for the effluent. (Dawes and Goonetilleke 2003; Oosting and Joy, 2011). Soil classification GIS data from USDA's National Resource and Conservation Service was used. Specifically, SSURGO data, which is optimized for county scale analysis, was employed for this study. Hydrologic Class was used to designate a risk rating. Extremely low or high hydraulic conductivities, represented by Hydrologic Class D and A respectively, were assigned high-risk ratings. In the case of multiple soil classifications within a cell, risk scores for each risk category present were averaged.

- Land Slope: Land slope can heavily influence runoff and erosion patterns (U.S. EPA, 2002) and thus the proper dispersion of effluent into the ground. As recommended by the EPA, maximum slopes should generally be around 10-20% while anything greater than 20% poses a severe risk of contamination (U.S. EPA, 2002). The National Elevation Dataset from NRCS at 10 meter resolution was used to calculate the slope of the land. Calculated slopes were then split into ranges and assigned a risk score. The average slope was used per cell. As Cameron County resides in a relatively flat terrain, this might not be a major factor for the area.

- Floodplain: Floods are major pathway for contaminant transport to the public and other waterbodies (Kuhlers et al, 2009; Taylor et al, 2010). The 100-year floodplain was used to assess contamination risk due to floods. Specifically, SFHAs within Standard Digital

Flood Insurance Maps (DFIRMs) were employed to determine areas at risk of a 100-year flood. Areas inside the 100-year flood zone received a high-risk rating of 5 while areas outside the floodplain received a low-risk rating of 1. In the case of partial inclusion of a floodplain within a cell, high-risk designation was given if the floodplain intersected the cell. While the 100-year floodplain poses serves as a great metric to assess flood risk, future models could expand to include other flood periods, such as 25-year or 50-year flood zones. This model could also benefit from more detailed floodplain data from ongoing flood studies, such as Flood Improvement Projects funded by TWDB and City of Brownsville flood study (TWDB, n.d.).

- Groundwater Recharge Areas: Significant groundwater recharge areas provide a pathway for surface water to make its way into the water table. As this data is not readily available, potential recharge areas were estimated using SSURGO data. Specifically, a threshold factor for infiltration and sand percentage was used to select soil textures that were then classified into significant groundwater recharge areas. Soil textures that fell into this classification included “Very fine sandy loam,” “Loamy fine sand,” “Fine sandy loam,” and “Fine sand.” Areas found within the specified recharge areas received a risk score of 5 while areas outside received a low-risk score of 1. In the case of partial inclusion of a groundwater recharge area within a single cell, high-risk designation was given if the groundwater recharge area intersected the cell. This environmental risk factor potentially spatially correlates with soil type, as areas with high infiltration rates, such as Class A, also tend to be areas with high sand percentages.

- Surface Water Proximity: Horizontal setback distances are frequently used by most governing codes regarding OSSFs. A combination of the National Hydrography Dataset (NHD), TCEQ water quality segments, and delineated resacas was used to determine surface waters in the area. In Texas, a setback distance of 75 feet is used for streams, ponds, lakes, rivers, and creeks. Safety factors were employed to create risk classes. Relative risks were assigned in multiples of 5 to obtain a more generalized map. The highest risk of 5 was designated to areas that fall within 375 feet (safety factor of 5) of surface waterbodies while the lowest risk was assigned to areas that fell beyond 1500 feet (safety factor of 20) of surface waterbodies. In the case of multiple cells with different surface water proximities within a cell, the mean was used to represent the overall risk within a cell.

- Water Supply Proximity: Proximity to public water supplies is an important risk factor to consider to avoid harmful consequences for public health. TCEQ's Source Water Assessment was used to determine public water supplies. According to OSSF setback regulations in Texas, a setback distance of 150 feet from public water supplies is recommended. Safety factors were employed to create risk classes. Relative risks were assigned in multiples of 5 to obtain a more generalized map. The highest risk of 5 was designated to OSSFs that fell within 750 feet (safety factor of 5) while the lowest risk was assigned to OSSFs that fell beyond 3000 feet (safety factor of 20). In the case of multiple systems with different water supply proximities within a cell, the mean was used to represent the overall risk within a cell.

OSSF System Risk Factor:

- OSSF System Risk: OSSF system risk is a measure of potential contamination risk that is based on OSSF system location and OSSF system properties. This was calculated by weighing OSSF system density by system age. A point-density analysis within GIS was conducted using a circle neighborhood with a radius of 9,842 meters and system age was used as a weight field. The Jenks classification method within GIS was used to represent relative risk brackets. This method of classification aims to reduce the variance within classes and increase the variance between classes (Jenks, 1967). High-risk scores were given to areas with the highest OSSF densities and system ages.

Model Sensitivity Analysis Methods

A sensitivity analysis was conducted to measure the variation or uncertainty in the model's output results. Specifically, map removal sensitivity analysis (Lodwick et al., 1990) and single parameter sensitivity analysis (Nappolitano and Fabbri, 1996) were implemented. These types of sensitivity analysis aid in understanding the impact of individual parameters on the final risk map by manipulating input parameters and observing the changes in the final output risk map.

The impact of individual parameters on the final OSSF risk map is best assessed by single parameter sensitivity analysis. Single parameter analysis determines the effective weight a single parameter exhibited on the final map in comparison to its theoretical weight (Nappolitano and Fabbri, 1996). The equation for effective weight is as follows:

$$Sp = (Rp \times Rw / A) \times 100$$

Sp = effective weight (%)

Rp = rating of individual parameter

Rw = weight of individual parameter

A = ultimate susceptibility index

The sensitivity of operations between map layers is better assessed by map removal sensitivity analysis (Lodwick et al., 1990). In this analysis one or more input parameters are removed in order to calculate a variation index percent. The equation for variation index percent is as follows:

$$S = [(V/N - V'/n)/V] \times 100$$

S = sensitivity measure
V = unperturbed vulnerability index
V' = perturbed vulnerability index
N = number of layers used to compute V
n = number of layers used to compute V'
The output of these analysis will be discussed in further detail in the Results section below.

Model Performance Evaluation Methods

Bacterial Assessment

E. coli was enumerated in 11 of Cameron County's resacas using the Colilert-18/Quanti-tray standard method. Although other types of waterbodies exist within the study area, perennial resacas were chosen as the waterbody type to sample due to their relatively long residence times, their substantial role as potential transport and storage mechanisms for OSSF contamination, and they are relatively easy to access and sample.

Resacas sample sites were selected by performing a spatial zonal analysis within GIS. This consisted of creating 200-meter buffers around each resaca and using the zonal statistics tool within GIS to obtain a mean OSSF risk for resacas. The resacas were then split into low and high-risk classes using the mean risk score for all resacas. Based on ease of access, 4 high-risk resaca pools, 5 low-risk resaca pools, and 2 urban resaca pools without OSSFs were selected for sampling. The resaca sites were sampled in triplicate per sampling run for *E. Coli* using the Colilert-18/Quanti-tray method. Resaca sampling sites can be seen in Figure 12 below.

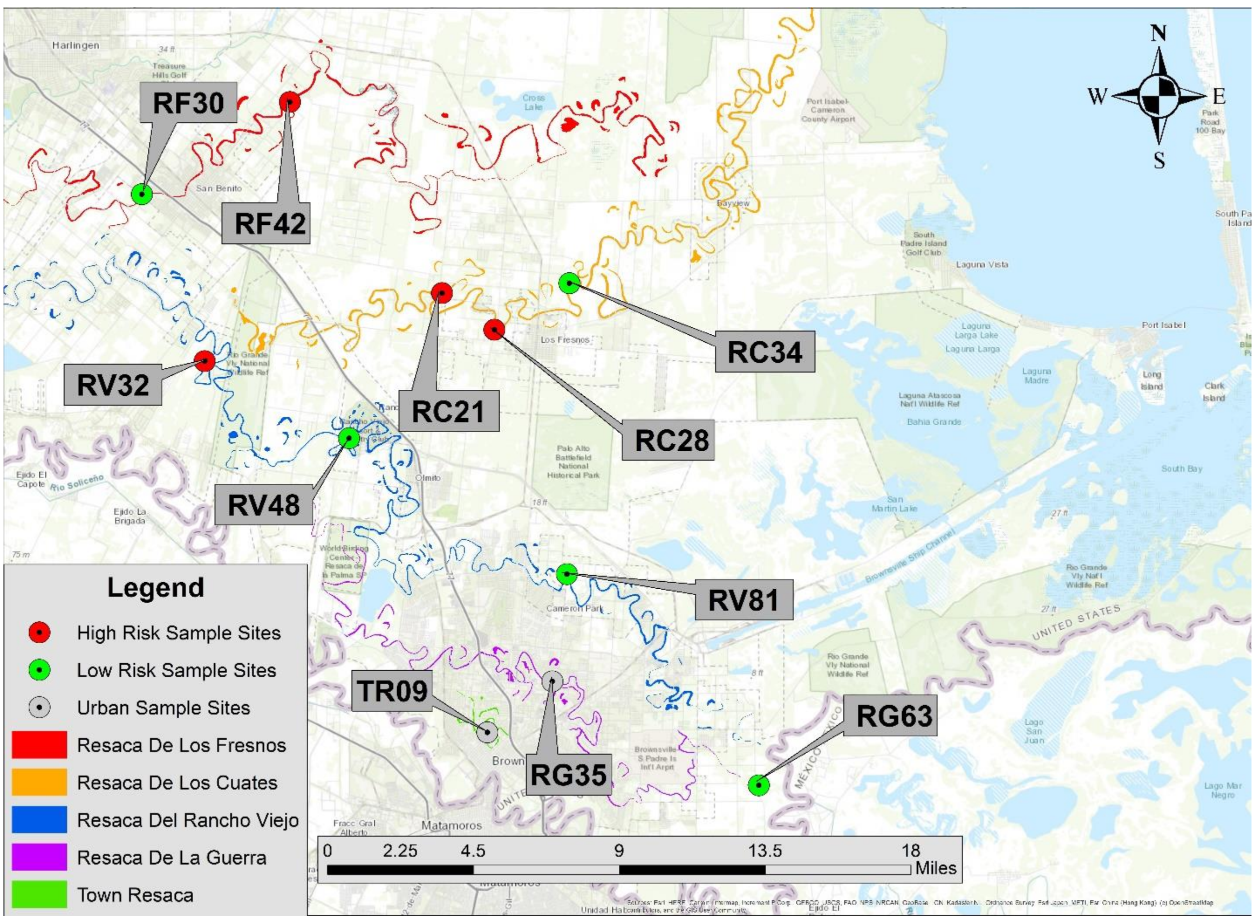

Figure 11. Resaca Sampling Sites. This map demonstrates resaca water sampling sites all across Cameron County. The first two letters indicate the name of the resaca system while the last two numbers represent the code number of individual resaca pools and their relative positions upstream/downstream. Lower numbers indicate a more upstream location.

Model Performance Evaluation Matrix

A model performance evaluation matrix was then created to relate the OSSF risk assessment's resaca pool risk class to E. coli enumeration results as seen in Table 2 below.

Model Performance Evaluation Matrix	Predicted High from Risk Assessment Model	Predicted Low from Risk Assessment Model
Observed High from E. coli Testing	Possibly Correct – BST recommended to confirm	Calibration Suggested – BST recommended to confirm
Observed Low from E. coli Testing	Calibration Suggested – Investigate temporal patterns	Possibly Correct – Investigate temporal patterns

Table 2. Model Performance Evaluation Matrix.

In order to relate E. coli testing results to the OSSF risk assessment model, the geometric mean of sampling runs was calculated and compared to the primary contact recreation standard of 126 MPN/100 ml. The model performance evaluation matrix serves as a means of evaluating the OSSF risk model's prediction of whether high or low E. coli levels would be observed per resaca pool. For example, if a resaca pool was classified as high-risk using the OSSF risk assessment model, then it was expected that the resaca pool would exceed the primary contact recreation standard once sampled. Likewise, it would be expected for low-risk resaca sites to not violate the primary contact recreation standard. These two scenarios mentioned would indicate that the OSSF risk assessment model successfully predicted the observed E. coli levels for that resaca pool. However, it is important to note that E. coli enumeration does not conclusively determine the source of the bacteria and thus Bacterial Source Tracking (BST) is recommended to confirm whether high bacteria levels originate from failing OSSFs nearby. It's also important to investigate temporal patterns to conclusively determine whether or not E. coli levels are consistently low year-round. In the case that the risk assessment model's risk prediction did not match the observed E. coli levels, then further calibration of the risk assessment model is needed. How exactly the model performance evaluation matrix was applied will be covered in greater detail in further sections.

CHAPTER IV

RESULTS

OSSF Risk Assessment Model Results

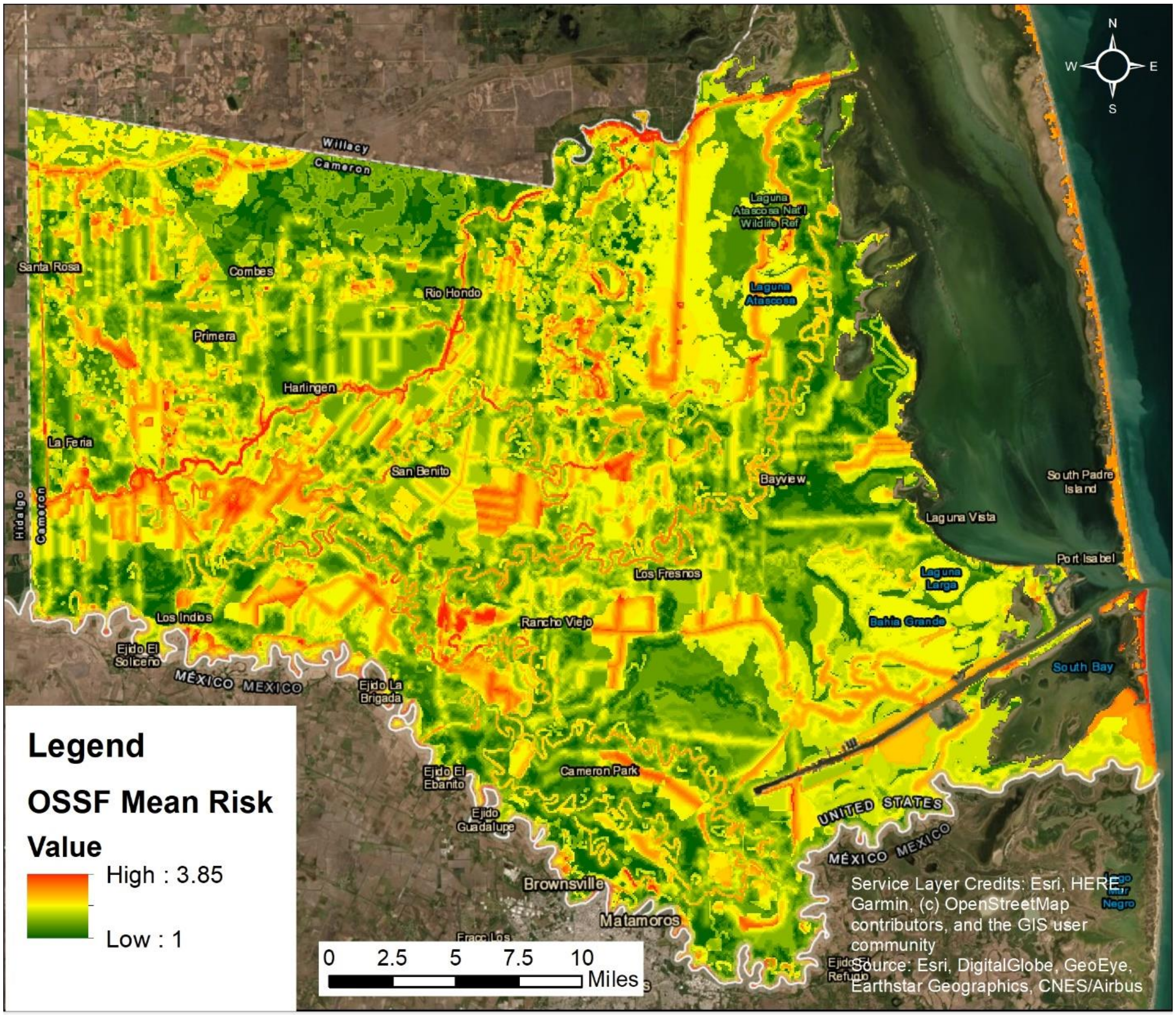

Figure 12. Mean OSSF Risk. Final mean OSSF risk demonstrates high-risk areas relative to low-risk areas once all risk parameters have been combined.

In total, 236,091 100 m^2 cells were used to assess OSSF contamination risk to surrounding areas and their receiving waterbodies. Figure 13 above illustrates the resulting mean risk of combining all 8 OSSF risk parameters. The resulting map had a mean risk score of 1.97, a minimum risk score of 1, a maximum risk score of 5, and a standard deviation value of 0.46. Overall 50.5% of the study area received an OSSF mean risk score between 1-2, 47.9% received an OSSF mean risk score between 2-3, and 1.8% received an OSSF mean risk score higher than 3.

In terms of the spatial distribution of risk, high-risk areas were found near major waterbodies, with a notable example being the Arroyo Colorado. A particularly large high-risk area near the Arroyo Colorado can be found in between the cities of La Feria and Harlingen. The high-risk in this area is primarily attributed to the clay soils (Class D) found on the southern border of the Arroyo Colorado in this area. The high-risk clusters found in the northern border of the Arroyo Colorado in this area are caused more by a higher density of OSSF systems with old ages. Resacas and drainage ditches also experienced high mean risk scores, especially when they were found in areas with high OSSF system risk scores. This can be seen in Figure 13, as resacas and drainage ditches with yellow colors are located in less environmentally sensitive areas while a more red coloration indicates these waterbodies are found in either more environmentally sensitive areas or in areas with high OSSF system risk scores. An example of this can be seen in the drainage ditch east of Rancho Viejo, where a drainage ditch found in the 100-year floodplain briefly exits the floodplain and re-enters it again as it heads east. The coast also received high mean risk scores, with areas such as South Padre Island, the ship channel, and areas near Laguna Atascosa displaying high-risk scores. The high sand percentages (Class A), the 100-year floodplain, and groundwater recharge areas were contributed to the high-risk designations in these areas. As expected, the lower-risk areas were found in areas without major waterbodies.

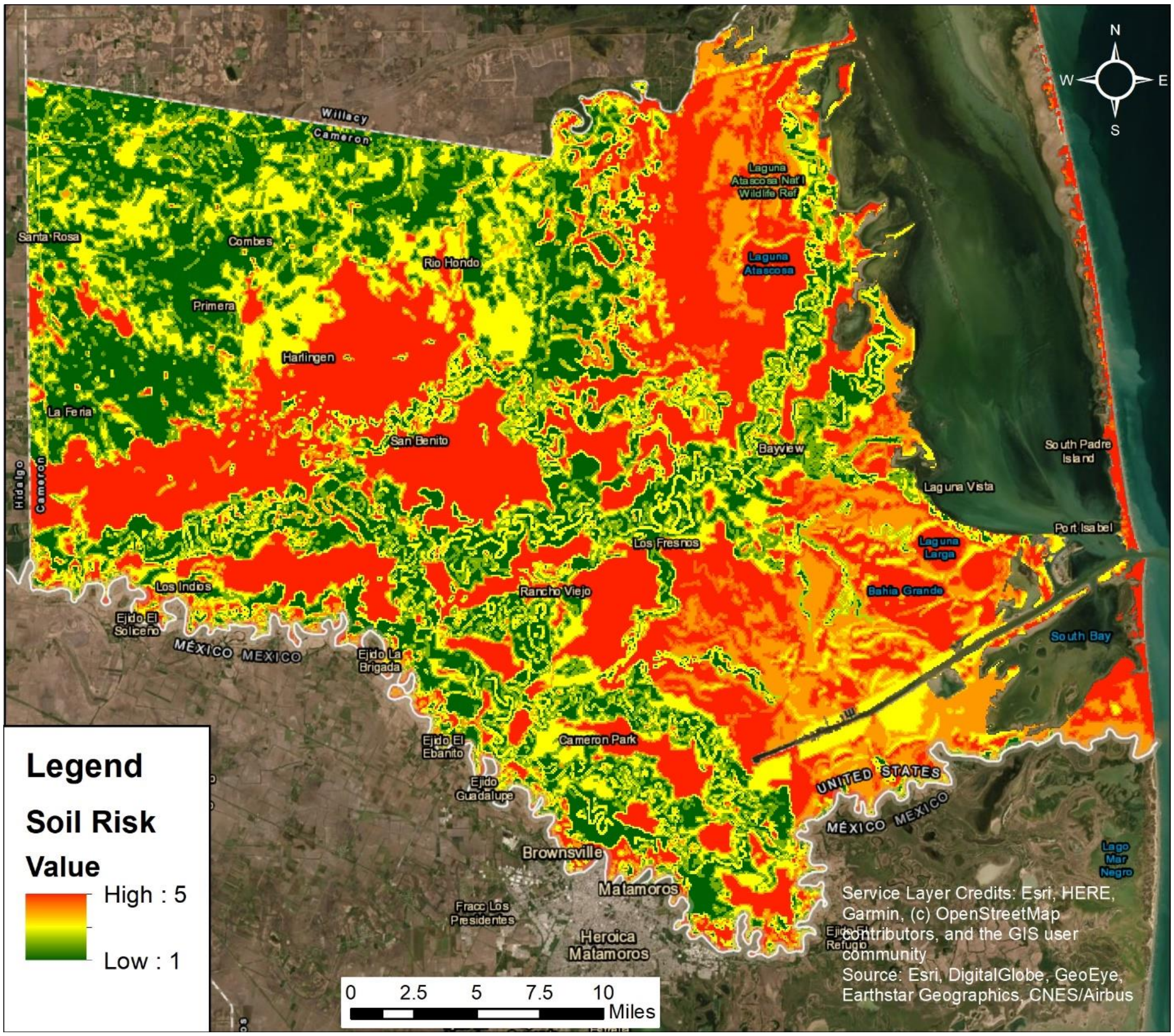

Figure 13. Soil Risk. This map demonstrates the relative risk the hydrologic class of soils contributes to potential OSSF contamination.

Soil risk, which was assessed by hydrologic soil group, had large areas dominated by high-risk. The depositional nature of resacas is evident here, with resaca watersheds being composed primarily of generally silty clay loam and silty clay (Class B and Class C respectively). Large clay (Class D) areas were found in between resacas, which contributed very high-risk scores. The coast also received high soil risk scores mainly due to sandy soils (Class A). The soil risk map had a mean risk score of 3.24, a minimum risk score of 1, a maximum risk score of 5, and standard deviation value of 1.47

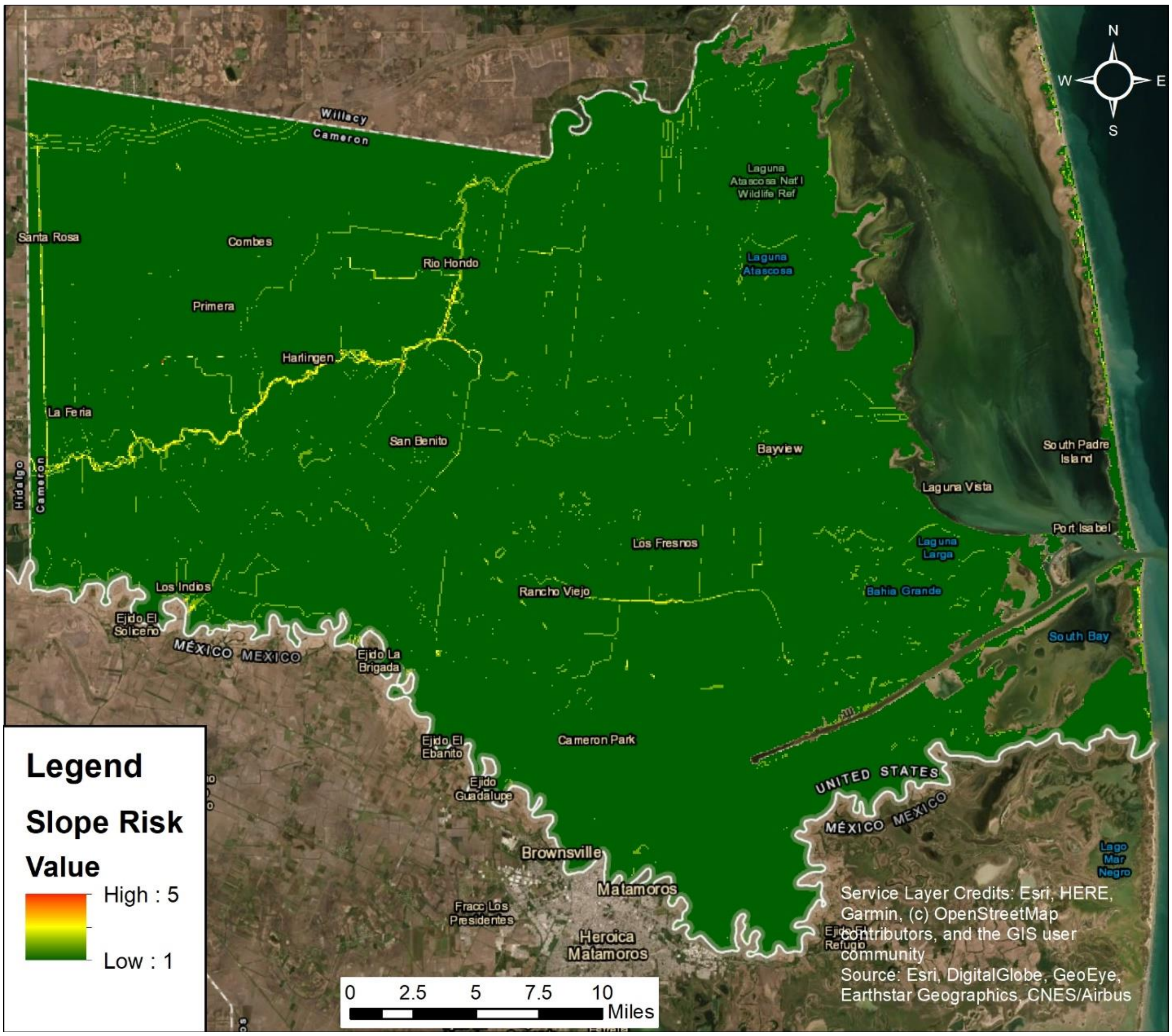

Figure 14. Slope Risk. This map demonstrates the relative risk the land slope contributes to potential OSSF contamination.

Compared to other risk factors, slope had significantly smaller total area with high-risk. Only few distinct areas, such as the Arroyo Colorado and certain drainage ditches, yielded moderate risk scores. These values properly represent the generally flat terrain of Cameron County. The slope map had a mean of 1.03, a minimum of 1, a maximum of 5, and a standard deviation of 0.19.

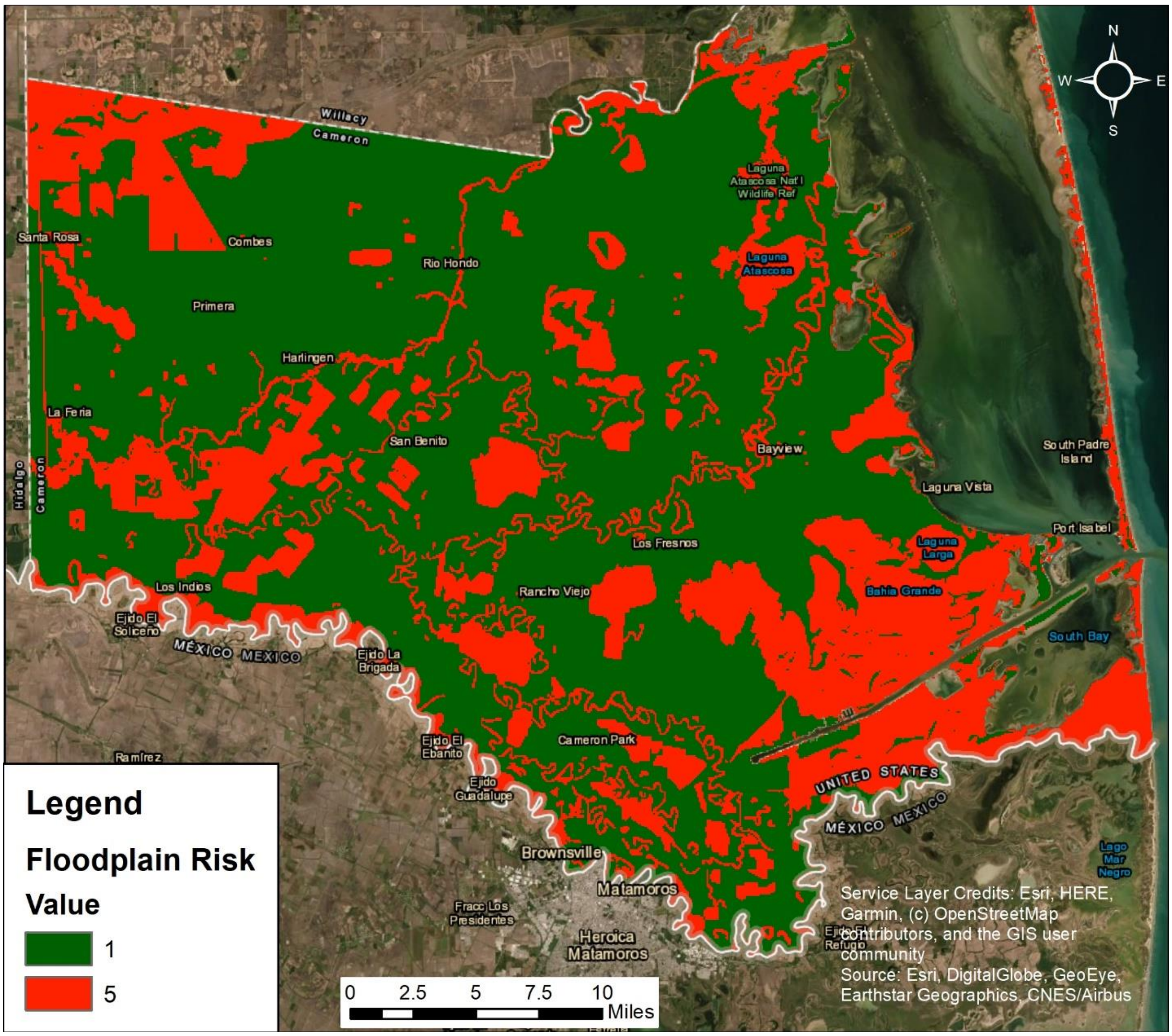

Figure 15. Floodplain Risk. This map demonstrates the relative risk the 100-year floodplain contributes to potential OSSF contamination.

Overall, floodplain risk was high across a large area of the county. As seen in Figure 16, much of the coast and the northwestern part of the county experienced very high-risk floodplain scores. Resacas were also found within the 100 year flood zone and thus received a high-risk floodplain score. The floodplain risk map had a mean risk value of 2.30, a minimum value of 1, a maximum value of 5, and a standard deviation of 1.87.

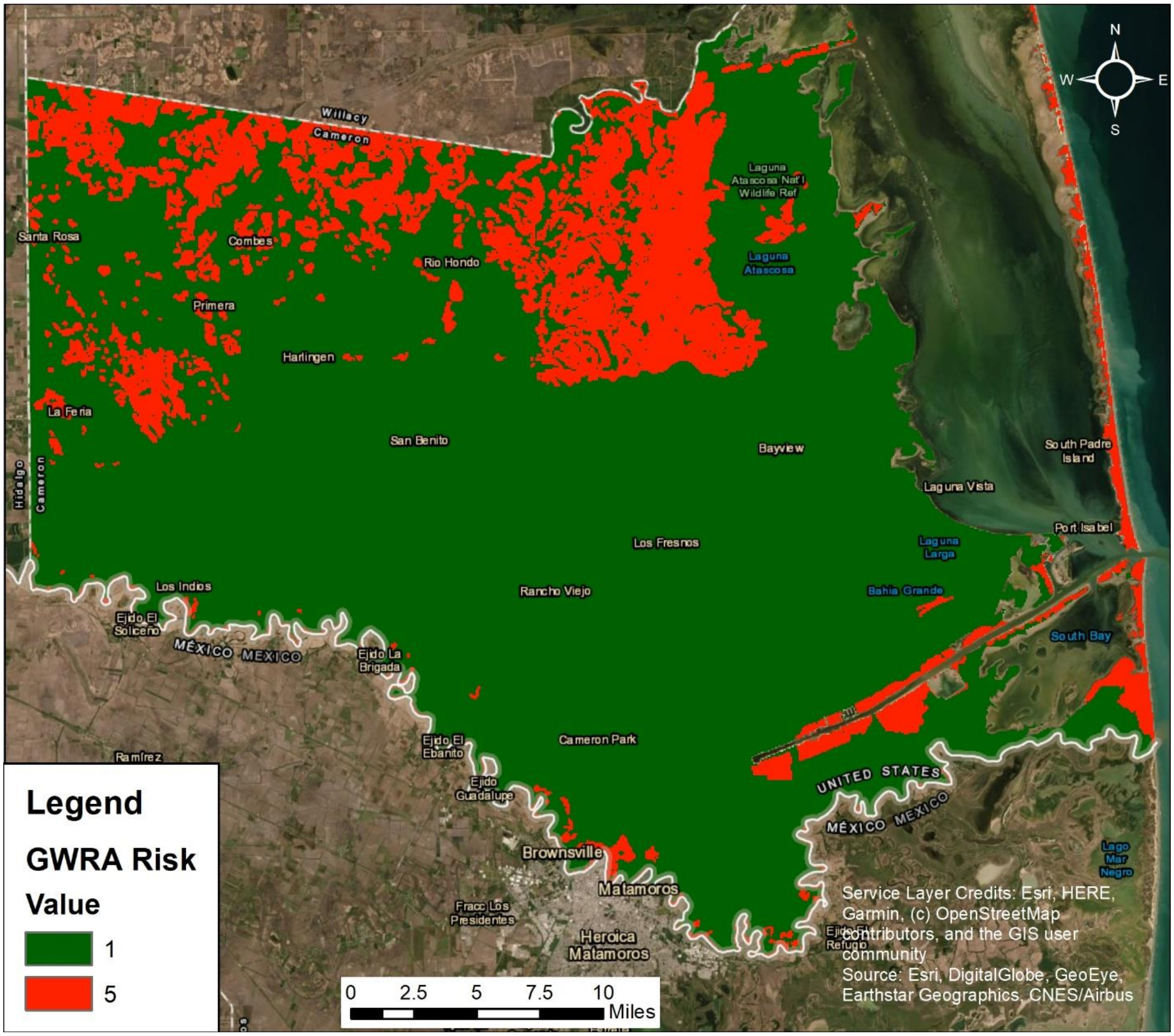

Figure 16. Groundwater Recharge Area Risk. This map demonstrates the relative risk groundwater recharge areas contributes to potential OSSF contamination.

GWRA risk also had large areas that presented a high-risk. Notable high-risk areas include the northern portion of the county spanning from Santa Rosa to the outskirts of Laguna Atascosa. Some areas near the coast also displayed high-risk, such as the Brownsville Ship Channel and South Padre Island. The GWRA risk map had a mean risk score of 1.71, a minimum of 1, a maximum of 5, and a standard deviation of 1.53.

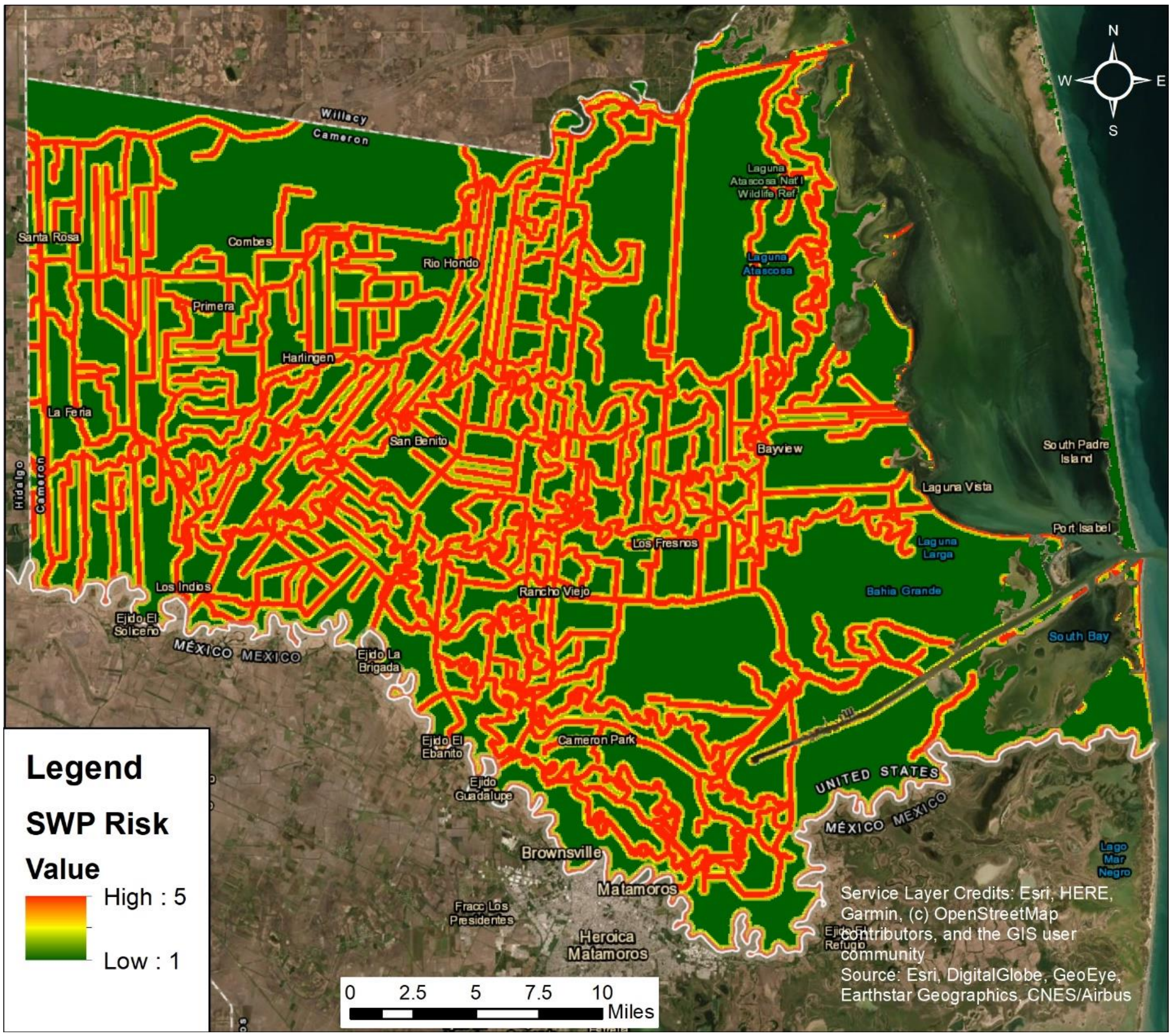

Figure 17. Surface Water Proximity Risk. This map demonstrates the relative risk surface water proximity contributes to potential OSSF contamination.

Due to the dense hydrological system present in the area, SWP risk covered much of Cameron County with a high-risk score. Much of the risk was associated with the resaca and drainage ditch network and associated setback distances. It is important to note that some coastal waterbodies were masked out due to the availability of data for other risk parameters. Areas such as the Laguna Madre and South Bay were filtered out as not only did they significantly increase the mean risk while having no OSSFs nearby, but no data existed for the other risk parameters in these large-area waterbodies. The SWP risk map had a mean risk score of 2.57, a maximum of 5, a minimum of 1, and a standard deviation of 1.52.

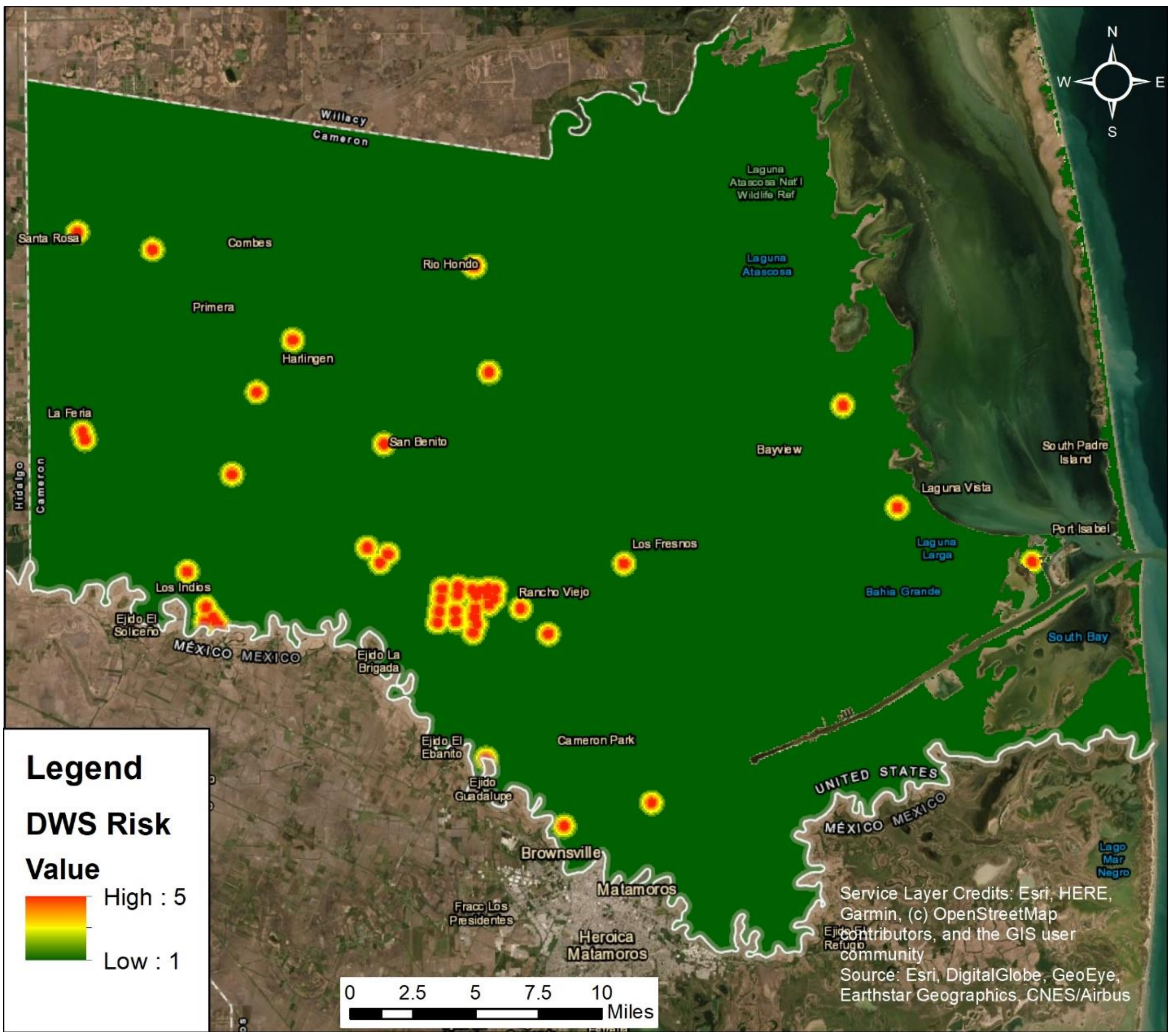

Figure 18. Drinking Water Supply Risk. This map demonstrates the relative risk public drinking water supply proximity contributes to potential OSSF contamination.

Unlike other risk parameter maps, not many areas demonstrated a high-risk for drinking water supply. Most of the map received a low-risk score of 1 while high-risk areas were found in small clusters, such as the area west of Rancho Viejo, which is associated with Brownsville Public Utility Board's brackish groundwater desalination plant well field. The DWS risk map had a mean risk of 1.07, a maximum of 5, a minimum of 1, and a standard deviation of 0.41.

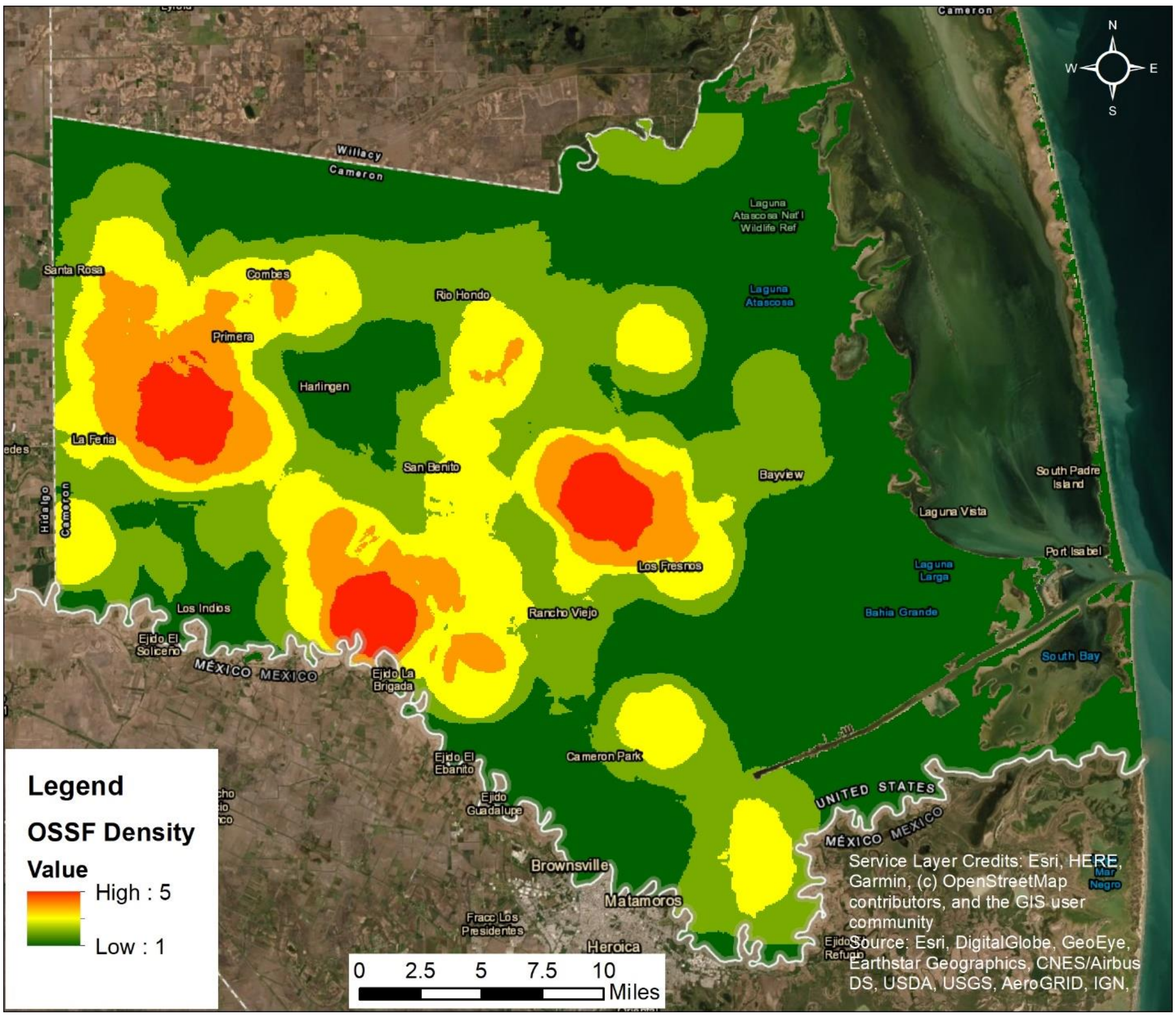

Figure 19. OSSF Density Risk Map. This demonstrates the relative risk OSSF density contributes to potential OSSF contamination.

The OSSF density risk map illustrated three high-risk hotpots: one found west of the city of Rancho Viejo, another located north and northwest of the city of Los Fresnos, and one more found in between the cities of La Feria and Harlingen. The OSSF density risk map had a mean risk score of 1.97, a maximum of 5, a minimum of 1, and a standard deviation of 1.11.

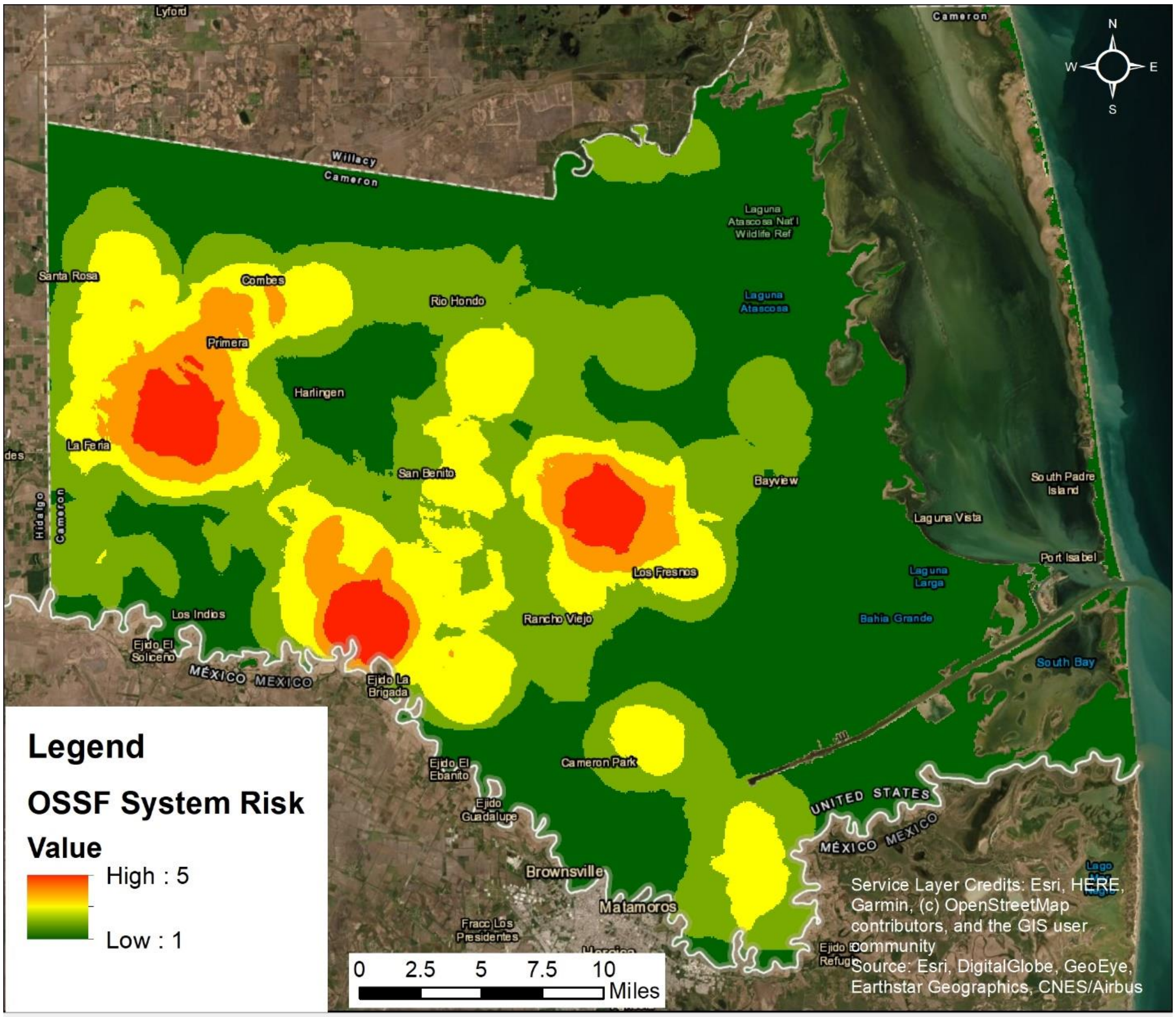

Figure 20. OSSF System Risk. This demonstrates the relative risk OSSF density weighted by system age, or OSSF system risk, contributes to potential OSSF contamination.

Once OSSF density was weighted by system age, there were substantial changes in the spatial risk distribution. One of the more notable ones is how the OSSF density map demonstrated areas closer to the city of Santa Rosa as having higher risk when system age was not considered. The OSSF system risk map illustrated a shift of higher risk towards the city of Primera, as the area has septic systems with higher ages. The OSSF system risk map had a mean risk score of 1.86, a maximum of 5, a minimum of 1, and a standard deviation of 1.05.

Model Sensitivity Analysis Results

Single Parameter Sensitivity Analysis

Results from single parameter sensitivity analysis demonstrate that soil and surface water proximity had the highest mean effective weights as seen in Table 3 below. When compared to their theoretical weight, soil and surface water proximity were highly impactful to the overall final OSSF risk assessment. More moderately impactful risk parameters include floodplain, OSSF system, and groundwater recharge areas, which had mean effective weights closer to their theoretical weight. Parameters that were of low impact to the risk assessment model included drinking water supply and slope, as these parameters demonstrated mean effective weights way below their theoretical weights.

Table 3. Summary of Results From Map Removal Sensitivity Analysis.

		Effective Weight (%)			
Parameter	**Theoretical Weight**	**Mean**	**Min**	**Max**	**SD**
Soil	14.20%	23.48	4.32	45.18	10.18
SWP	14.20%	18.25	4.41	45.18	9.86
Floodplain	14.20%	15.55	4.41	45.18	10.79
OSSF System	14.20%	13.83	3.82	45.18	7.8

Table 3. (Cont.)

GWRA	14.20%	12.22	3.82	45.18	10.01
DWS	14.20%	8.02	3.68	42.59	3.09
Slope	14.20%	7.77	3.68	28.4	2.04

Map Removal Sensitivity Analysis

According to the map removal sensitivity analysis results, the OSSF risk assessment model was particularly sensitive to the removal of soil. As seen in Table 4, the removal of soil resulted in a mean variation index of 1.9, which indicates there is substantial variation between an aggregate final risk map without soil risk and one with soil risk. The risk assessment model was least sensitive to the removal of OSSF system, slope, and drinking water supply as these risk parameters had low mean variation index values of 1.06, 1.07, and 1.09, respectively.

Table 4. Summary of results from map removal sensitivity analysis.

Parameter Removed	Mean	Min	Max	SD
Soil	1.9	0	5.19	1.29
Floodplain	1.54	0	5.19	0.95
SWP	1.46	0	5.19	1.01
GWRA	1.41	0	5.19	0.93
DWS	1.09	0	4.76	0.35
Slope	1.07	0	2.38	0.33
OSSF System	1.06	0	5.19	0.74

Model Performance Evaluation Results

Bacterial Assessment

A trend highlighted by the bacterial assessment was that urban resaca pools had higher *E. coli* levels as discussed earlier. Potential reasons for this include the presence/absence of domestic and wild animals and/or the storm sewer network draining into urban resacas. The fact that urban resacas often have storm water systems means that storm events may bring new bacterial inputs from other sources while rural resacas receive inputs primarily from their narrow subwatersheds. This difference between direct pipe flow and overland flow not only means urban resacas with storm water systems receive more pollutant runoff but they also receive it faster and with less natural mitigation. Using the geometric mean of all samples, 5 out of the 11 resacas sampled exceeded the primary contact standard.

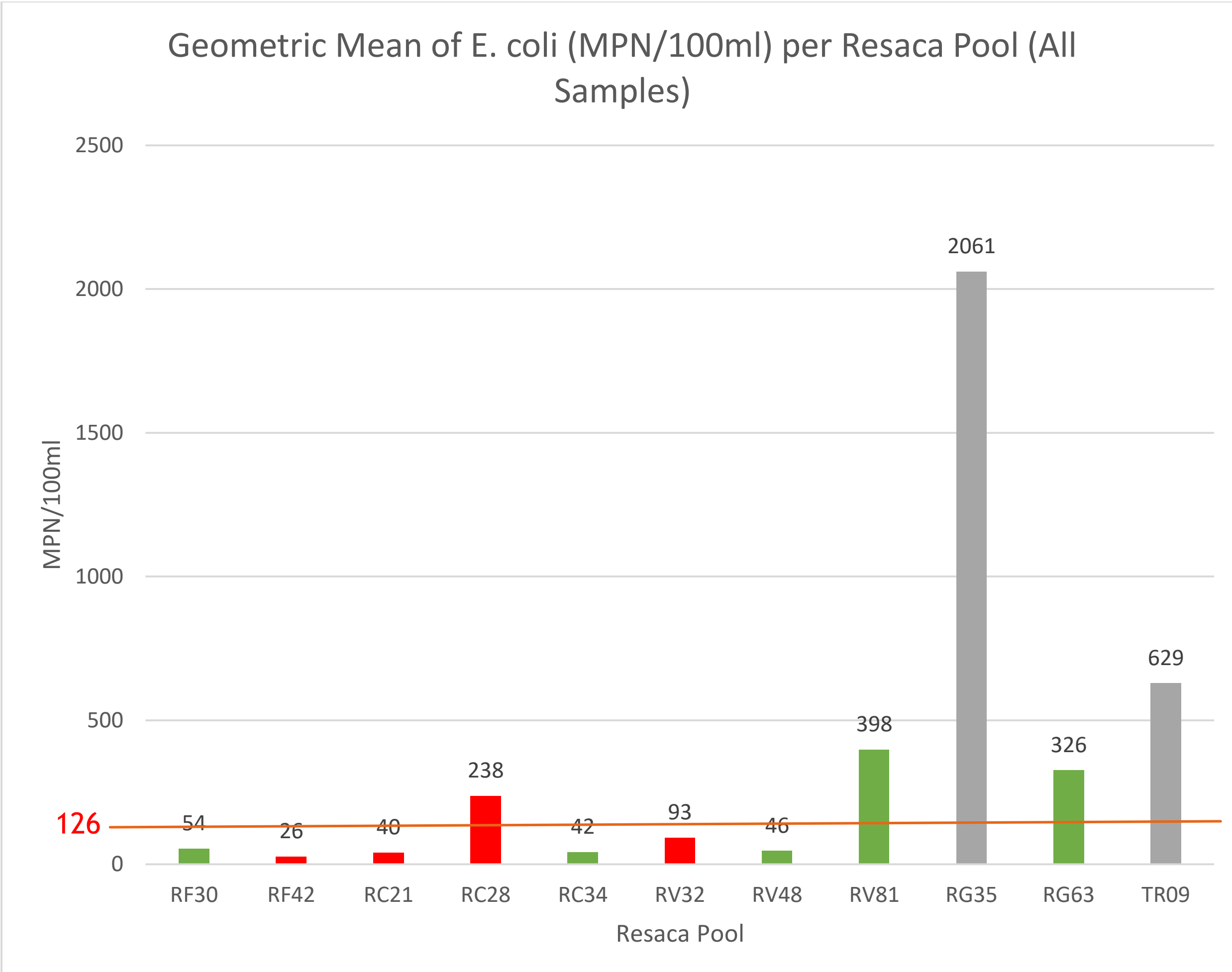

Figure 21. Geometric Mean of E. coli per Resaca Pool for All Samples. The geometric mean of E. coli per resaca pool is shown. Risk classifications of resacas (low and high) are denoted by green and red, respectively. Resaca pools are organized from north to south (left to right) and then by upstream to downstream with higher resaca code numbers indicating a location further downstream. These represent the geometric mean of all 9 samples taken per resaca pool during 3 discrete sampling events with 3 samples taken per event per resaca pool.

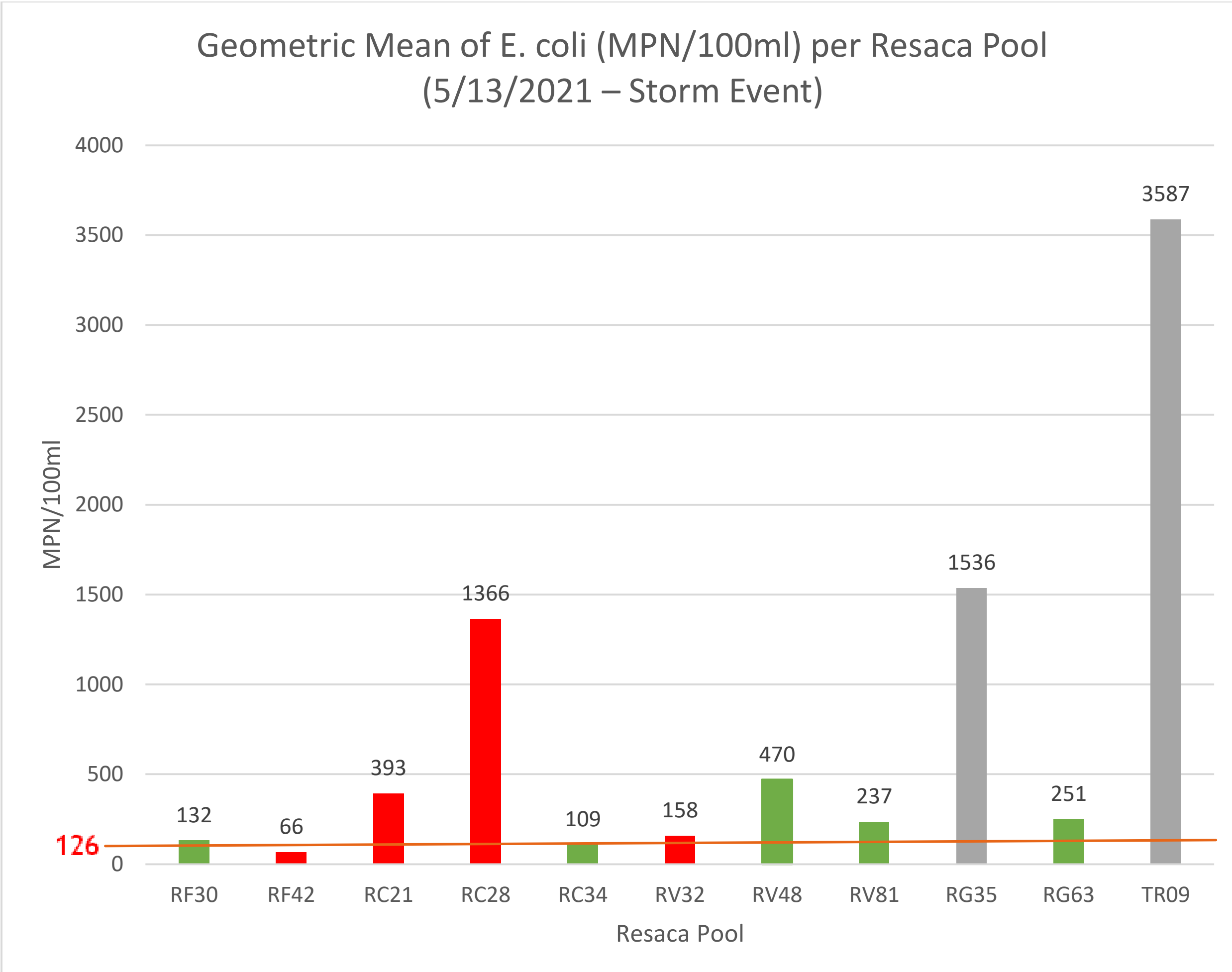

Figure 22. Geometric Mean of E. coli per Resaca Pool (5/13/2021). The geometric mean of E. coli per resaca pool for sampling run conducted on 5/13/2021 is shown.

Both urban resaca pools in the first sampling run had much higher levels of bacteria when compared to other pools for this sampling period. This sampling event was conducted 24 hours after a storm period, and especially high levels of bacteria in urban resaca pools might be influenced by inputs from storm drains. RC28 was of special concern as, seen below in Figures 24 and 25, had relatively higher MPN/100 ml when compared to other sampling events. This might mean that bacteria levels might fluctuate substantially depending on the time when sampling occurred. During this sampling event, 9 out of the 11 resacas sampled had a geometric mean higher than the primary contact recreation standard.

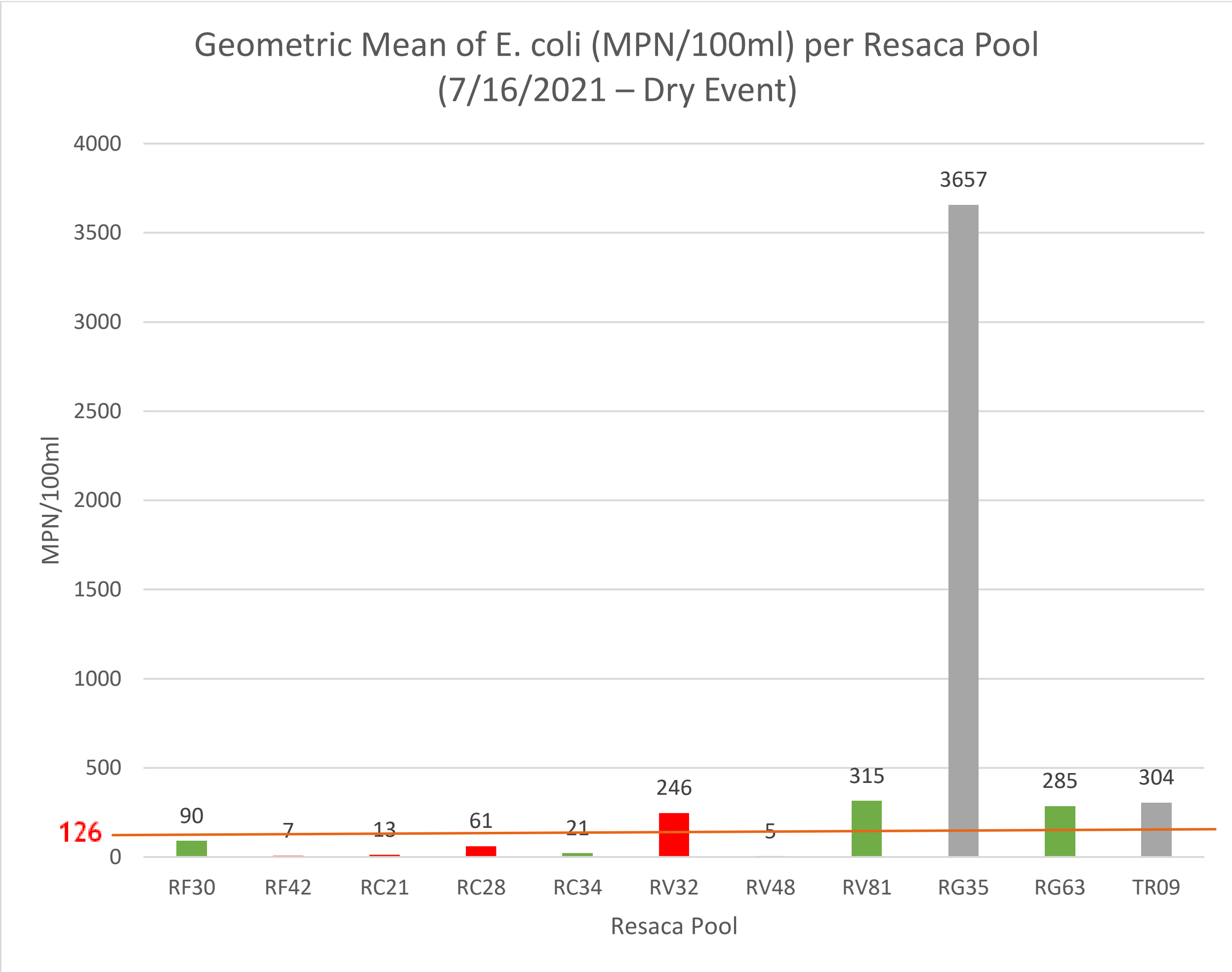

Figure 23. Geometric Mean of E. coli per Resaca Pool (7/16/2021). The geometric mean of E. coli per resaca pool for sampling run conducted on 7/16/2021 is shown.

The urban resaca pool RG35 had substantially higher MPN/100 ml when compared to the other resaca pools. However, it was observed when sampling that this particular resaca pool has a high incidence of waterfowl, which might offer an explanation for the high value. During this sampling event, 5 out of 11 resaca pools did not meet primary contact recreation standards.

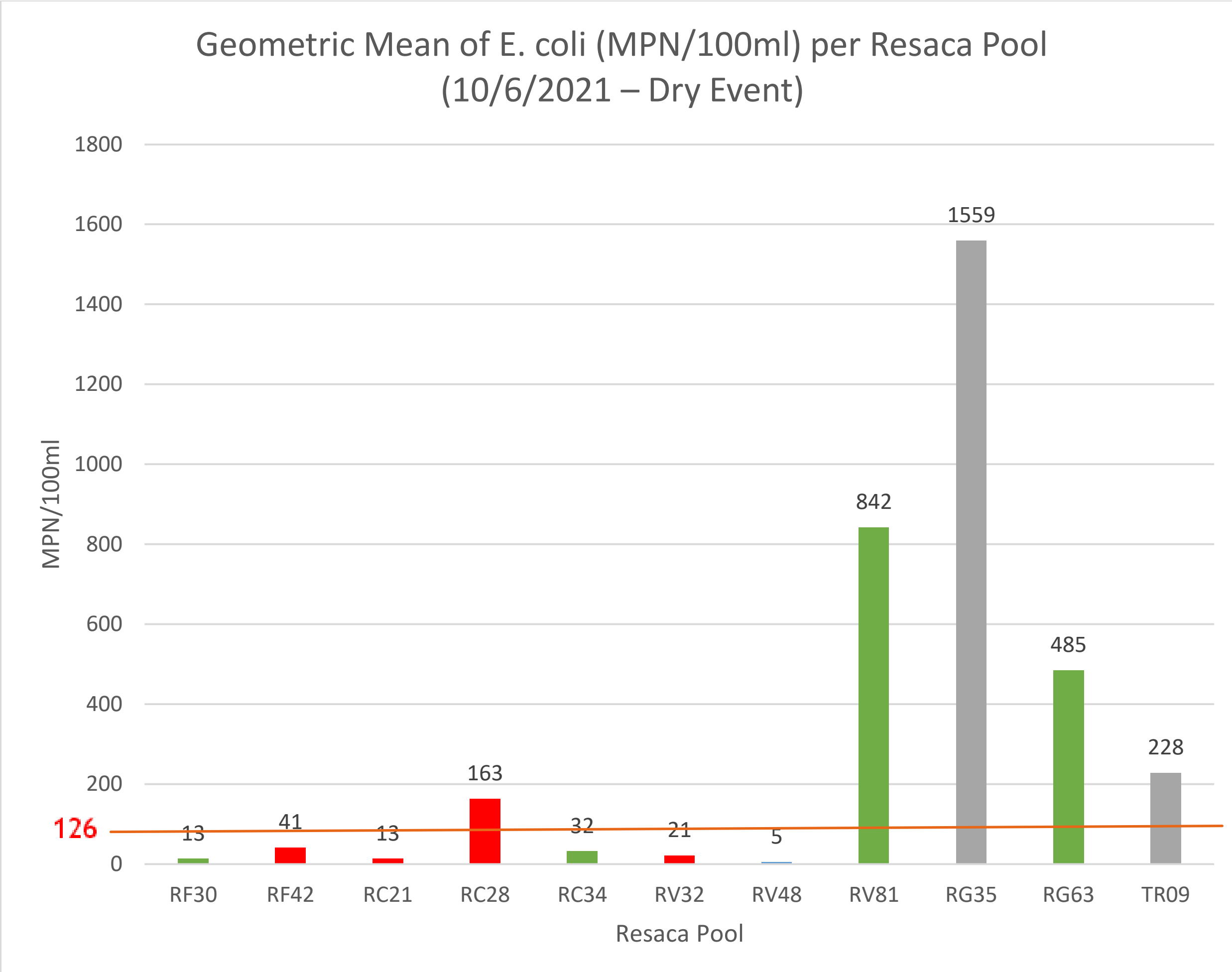

Figure 24. Geometric Mean of E. coli per Resaca Pool (10/6/2021). The average MPN per 100 ml for sampling run conducted on 10/6/2021 is shown.

The sampling run conducted in October was marked by having especially low MPN/100 ml for most resaca pools. Only 5 out of 11 resaca pools did not meet the primary contact recreation standard. However, there was an especially high spike in RV81 that had not been observed during the other two sampling events. This may be attributed to a high incidence of waterfowl observed in that resaca pool that day. RG35 remained consistent with its previous high MPN/100 ml from other sampling events.

Model Performance Evaluation Matrix

As mentioned earlier, the results of E. coli testing were related to the model's predictions using a model performance evaluation matrix. Based on whether the geometric mean of resaca pools exceeded the primary contact recreation standard of 126 MPN/100 ml, the observed bacteria levels were determined high or low. Then this information was related to whether the OSSF risk assessment model predicted the resaca pool to be of high-risk or low-risk. If high-risk was predicted by the OSSF risk assessment model and observed E. coli levels exceeded the primary contact recreation standard, then the model in that area is possibly correct but Bacterial Source Tracking (BST) is suggested to exclude/confirm OSSF contamination in those waterbodies. Likewise, if the risk assessment model predicted low-risk and E. coli levels were below the primary contact recreation standard then the model is possibly correct but temporal patterns of E. coli must be investigated to confirm constant low E. coli levels. However, if the risk assessment prediction and observed E. coli values do not match, then the model is possibly incorrect and must be calibrated. The results for all resaca pools and their sampling periods can be found in Table 5 below. Overall, the OSSF risk assessment was possibly correct 16 out of 36 times. It's important to note urban resaca pools were not assessed by the OSSF risk assessment model as they were assumed to be in a sewer area.

Table 5. Model Performance Evaluation Table By Sampling Event and Average of All Samples. This table demonstrates how the model performance matrix and E. coli sampling results were conjunctively used to evaluate the model's performance.

Model Performance Evaluation				
Resaca Pool	All Samples	5/13/2021	7/16/2021	10/6/2021
RF30	Possibly Correct	Calibration Suggested	Possibly Correct	Possibly Correct
RF42	Calibration Suggested	Calibration Suggested	Calibration Suggested	Calibration Suggested
RC21	Calibration Suggested	Possibly Correct	Calibration Suggested	Calibration Suggested
RC28	Possibly Correct	Possibly Correct	Calibration Suggested	Possibly Correct
RC34	Possibly Correct	Possibly Correct	Possibly Correct	Possibly Correct
RV32	Calibration Suggested	Possibly Correct	Possibly Correct	Calibration Suggested
RV48	Possibly Correct	Calibration Suggested	Calibration Suggested	Possibly Correct
RV81	Calibration Suggested	Calibration Suggested	Calibration Suggested	Calibration Suggested
RG35	Urban Resaca Pool	Urban Resaca Pool	Urban Resaca Pool	Urban Resaca Pool
RG63	Calibration Suggested	Calibration Suggested	Calibration Suggested	Calibration Suggested
TR09	Urban Resaca Pool	Urban Resaca Pool	Urban Resaca Pool	Urban Resaca Pool

The OSSF risk assessment model was possibly correct 44% of the time while calibration was suggested 56% of the time according the model performance evaluation matrix. The model was able to more successfully predict low bacteria levels than high bacteria levels as seen in Figure 26 below by a higher percentage for the "Observed Low, Predicted Low" category. Although calibration was suggested more, bacterial source tracking is suggested to conclusively determine if OSSF contamination is present in an area. For example, resaca pools that exhibited low-risk predictions but observed high E. coli levels may have E. coli inputs specifically from wildlife and not failing OSSFs nearby. The additional information of E. coli origin could then potentially increase the percentage the risk assessment model was correct in its predictions. Factors such as presence/absence of storm drains, wildlife, pets, lack of riparian habitat, and temporal patterns affect E. coli enumeration results, which makes evaluating the OSSF risk assessment model challenging.

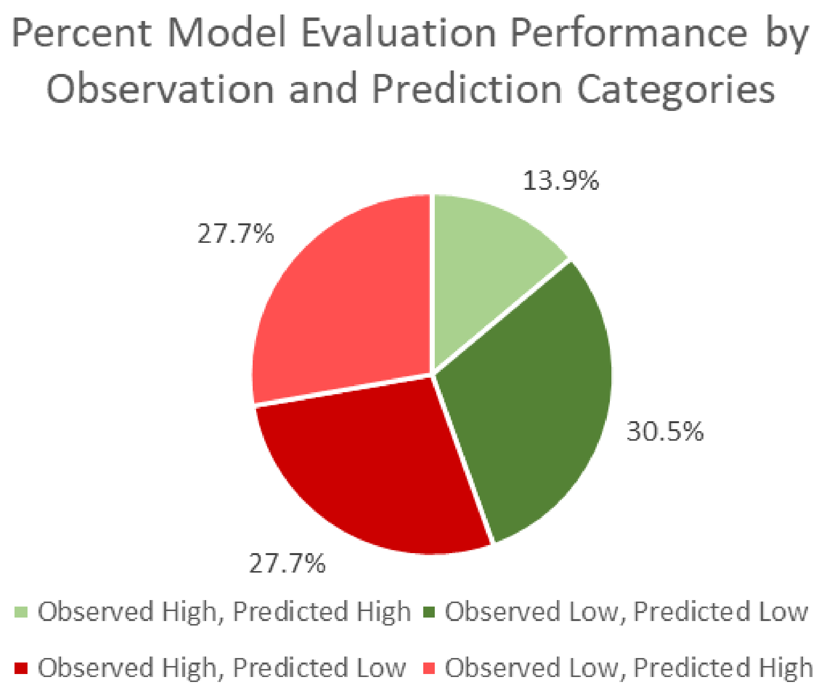

Figure 25. Percent Model Evaluation Performance by Observation and Prediction Categories. This figure illustrates the percentage of each possible outcome in the model performance evaluation matrix.

CHAPTER V

DISCUSSION

OSSF Risk Assessment Model

Table 6. Statistics of Mean OSSF Risk Map.

Parameter	Mean	Min	Max	SD
Soil	3.24	1	5	1.47
SWP	2.57	1	5	1.52
Floodplain	2.3	1	5	1.87
OSSF System	1.86	1	5	1.05
GWRA	1.71	1	5	1.53
DWS	1.07	1	5	0.41
Slope	1.03	1	5	0.19
Mean Risk	1.97	1	3.85	0.46

In accordance with Table 6 above, the risk parameters responsible for the largest high-risk areas within the final risk map were soil, surface water proximity, and floodplain. This is supported by single parameter sensitivity analysis as soil, surface water proximity, and floodplain had the highest mean effective weights of 23.48%, 18.25%, and 15.55%, respectively.

This means these 3 risk parameters contributed significantly to high-risk areas in the final OSSF risk assessment map. The dominance of soil, surface water proximity, and floodplain is also evident in the map removal sensitivity analysis results, as the OSSF risk assessment model was most sensitive to the removal of soil from the aggregate risk assessment map. This is consistent with the current understanding of the study area's hydrological and depositional patterns. For example, in the case of soil risk, large clay areas with especially low infiltration rates can be observed in the floodplain in between resaca systems. These clay areas were created when the ancient Rio Grande would flood the Rio Grande delta system, layering out distributaries on top of the clay and depositing heavier material such as silt on its banks while lighter material would be carried farther inland. These depositional patterns also influence the location of high floodplain risk, with low-lying areas with particularly high clay content usually being designated as part of the 100 year flood zone between the resaca systems. The areas with the highest risk were found in areas that had high OSSF system risk, were a flood zone, with tightly clustered waterways, and soils with high runoff potential (class D soils). These areas present a challenge to the proper functioning of OSSFs as they can effectively reduce an OSSF's capacity to properly filter contaminants but can also easily transport potential contamination to other nearby areas and water features.

Other parameters that also had a more moderate influence on the OSSF risk assessment model included OSSF system risk and groundwater recharge areas. Three hotpots for OSSF system risk were found north from the city of Los Fresnos, west of the city of Rancho Viejo, and in the area in between the cities of La Feria and Harlingen. All of these areas received high-risk scores in the aggregate OSSF risk map, as these areas also were environmentally sensitive as many environmental parameters observed high-risk in these areas as well, such as high soil risk north of the city of Los Fresnos. Groundwater recharge areas were mostly found along the coast and near Laguna Atascosa, yet still contributed a moderate amount of risk to the overall OSSF risk assessment model. As new information regarding surface-groundwater interactions is uncovered, the groundwater recharge areas could expand to include resaca systems, as studies regarding their interactions or exchanges with groundwater system are very limited. Another potential factor that would benefit the groundwater assessment of the OSSF risk assessment model could be the inclusion of a depth to water table risk map (i.e., vadose zone).

Drinking water supply and slope, as expected, had a lower impact on the overall risk assessment model. This was expected due to the area's generally flat terrain and because there's a limited amount of drinking water supplies in the study area. However, drinking water supplies could be expanded in future work to include irrigation water wells.

Model Sensitivity Analysis

The combination of single parameter sensitivity analysis and map removal sensitivity analysis yielded some important information about the overall impact of individual risk parameters and map operations on the final vulnerability index. Results from single parameter sensitivity analysis are consistent with the results from the OSSF risk assessment model. Large, high-risk spatial trends caused by large area risk parameters such as soil, surface water proximity, and floodplain have the highest mean effective weights. This means these risk factors exerted the greatest impact on which areas were determined as high risk or not.

Results from map removal sensitivity analysis also support the high impact on OSSF mean risk that soil, surface water proximity, and floodplain had as individual factors. The highest variation index values were observed when these particular parameters were removed. For example, the removal of soil risk resulted in a mean variation index value of 1.9 when compared to the mean variation index value of 1.07 for slope. On another note, the OSSF system risk was the least sensitive parameter despite having a relatively higher mean effective weight and mean risk than drinking water supply and slope. This may be due to the spatial distribution of OSSF system risk in relation to other risk parameters. Exploring the spatial distribution of risk with regards to sensitivity analysis is recommended as mean variation index does not take into account where risk is spatially distributed.

Model Performance Evaluation

Although the bacterial assessment conducted is insufficient to definitively conclude whether there is OSSF contamination within an area as it enumerates all sources E. coli regardless of origin, it does provide key insights that can be investigated with future work. As mentioned before, it is important to consider that each individual resaca pool, for the most part, functions somewhat uniquely due to the nature of flow, human-made structures particularly storm drains, surface-groundwater interactions, and the presence/absence of wildlife. These factors add an immense amount of uncertainty to conclusively attributing high *E. coli* levels in a resaca pool to failing OSSF systems nearby, and thus increase the complexity of properly evaluating the risk assessment model. However, the model performance evaluation does establish that some resacas at certain times, regardless of whether bacteria originate from OSSFs, do violate primary contact recreation standards and thus present a public health hazard. In order to evaluate the risk assessment model properly, bacterial sourcing of samples is necessary in order to identify the origin of the bacteria and thus determine if OSSFs are failing nearby.

CHAPTER VI

CONCLUSION

Ultimately, the OSSF risk assessment model was able to successfully predict around 44% of E. coli observations in resaca pools. This suggests further calibration is needed in order for the OSSF risk assessment model to more accurately assess risk to nearby waterways from OSSFs.. Moving forward, more detailed monitoring and bacterial sourcing of samples is necessary to further evaluate, calibrate, and validate the model. Bacterial sourcing can give insight into the origin of bacteria and thus determine if failing OSSFs are nearby.

Possible future work includes the development of a point-risk assessment model, as was explored early on this research. In this type of model, OSSF systems would be rated based using the risk parameters used in this study and/or other new risk parameters, such as type of OSSF system, how many people the OSSF system serves, or whether the system is for residential or commercial use. In this way, risk would be assigned to an OSSF system instead of an area, and thus the likelihood of an OSSF failing and contaminating nearby areas could be determined.

This study highlights that the current understanding of the hydrology of the area is not enough to properly characterize contaminant transport. More studies on groundwater-surface water interactions are needed. The effects of "sewershed" and urbanization on hydrological patterns, and the nature of *E. coli* transport within the area's hydrological system also are needed. With additional information in place, risk assessment models such as this can be further updated and improved.

REFERENCES

Beal D., Gardner, E. A., & Menzies, N. W. (2005). Process, performance, and pollution potential: A review of septic tank - soil absorption systems. *Soil Research, 43*(7), 781. doi:10.1071/sr05018

Beller, M. (1997). Outbreak of viral gastroenteritis due to a contaminated well. *Jama, 278*(7), 563. doi:10.1001/jama.1997.03550070055038

Bonaiti G., R. Gerlich, A. Karimov, and A. Jantrania. (2017) "OSSF Inventory and Analysis Report," Final Report submitted to TCEQ for the CZARA 319 Grant Project.

Borchardt A., Chyou, P., Devries, E. O., & Belongia, E. A. (2003). Septic system density and infectious diarrhea in a defined population of children. *Environmental Health Perspectives, 111*(5), 742-748. doi:10.1289/ehp.5914

Carroll, Goonetilleke, A., Thomas, E., Hargreaves, M., Frost, R., & Dawes, L. (2006). Integrated risk framework for onsite wastewater treatment systems. *Environmental Management, 38*(2), 286-303. doi:10.1007/s00267-005-0280-5

Chand, Ashif, Y. M., & Ayub M. (2011). Nitrate Pollution: A Menace to Human, Soil, Water and Plant. *Journal of Environmental Research and Technology, 1*, 22-32.

Chowdhury, A., & Mace, R. (2007). *Groundwater Models of the Gulf Coast Aquifer of Texas*. Retrieved December 5, 2021, from https://www.twdb.texas.gov/publications/reports/numbered_reports/doc/R365/ch10-GulfCoastModelingPaper.pdf

Colilert 18 - IDEXX US. (n.d.). Www.idexx.com. https://www.idexx.com/en/water/water-products-services/colilert-18/

Dawes, & Goonetilleke, A. (2003). An investigation into the role of site and soil characteristics in onsite sewage treatment. *Environmental Geology, 44*(4), 467-477. doi:10.1007/s00254-003-0781-6

EPA. (2002). Onsite Wastewater Treatment Systems Manual. EPA/625/R-00/008. 367 pp

EPA. (2018). Septic Systems Overview. Retrieved from https://www.epa.gov/septic/septic-systems-overview

Flanagan, K., Dixon, B., Rivenbark, T., & Griffin, D. (2019). An integrative GIS approach to analyzing the impacts of septic systems on the coast of Florida, USA. *Physical Geography*, 1–26. https://doi.org/10.1080/02723646.2019.1671297

Flores, J., Wagner, K., Gregory, L., Benavides, J. A., & Cawthon, T. (2017). *Update to the Arroyo Colorado Watershed Protection Plan* (Rep. No. 504).

Hutchison, W. (2017). *Conceptual Model Report: Lower Rio Grande Valley Groundwater Transport Model* https://www.twdb.texas.gov/groundwater/models/research/lrgv_t/LRGV_ConceptualModelReport_final.pdf

Jenks G., (1967). The Data Model Concept in Statistical Mapping. International Yearbook of Cartography 7. 186-190

Knight, L. (2009). *A Field Guide to Irrigation in the Lower Rio Grande Valley* (Rep. No. 2009-01). Buda, TX: Knight and Associates.

Kenway, S., R. Irvine, and R. Moorhead. (2001). The onsite sewage risk assessment system. R. A. Patterson, and Jones M. J. (eds.), Proceedings of Onsite '01 Conference: Advancing Onsite Wastewater Systems, Armidale, pp 227– 234.

Kühlers, Bethge, E., Hillebrand, G., Hollert, H., Fleig, M., Lehmann, B., . . . Wölz, J. (2009). Contaminant transport to public water supply wells via flood water retention areas. *Natural Hazards and Earth System Sciences, 9*(4), 1047-1058. doi:10.5194/nhess-9-1047-2009

Lecusay, D. (2021). *Assessment and monitoring of deltaic wetlands: refining and validating a multimetric index of ecosystem health* [Review of *Assessment and monitoring of deltaic wetlands: refining and validating a multimetric index of ecosystem health*].

Lodwick, W. A., Monson, Svoboda, L. (1990). Attribute error and sensitivity analysis of map operations in geographical informations systems: suitability analysis. *International Journal of Geographical Information Systems*, *4*(4), 413–428. https://doi.org/10.1080/02693799008941555

Lower Laguna Madre/ Brownsville Ship Channel Watershed Characterization (2018). Retrieved December 5, 2021, from https://arroyocolorado.org/media/zqjpi1e0/llm_wc_102618_forstakeholderreview.pdf

Napolitano, P., Fabbri, A.G., (1996). Single-parameter sensitivity analysis for aquifer vulnerability assessment using DRASTIC and SINTACS. Application of Geographic Information Systems in Hydrology and Water Resources Management (Proceedings of the Vienna Conference, April 1996). IAHS Publ. no. 235, 559-566

Oosting, & Joy, D. (2011). A GIS-Based model to assess the risk of on-site wastewater systems impacting groundwater and surface water resources. *Canadian Water Resources Journal / Revue Canadienne Des Ressources Hydriques, 36*(3), 229-246. doi:10.4296/cwrj3603882

O'reilly E., Bowen, A. B., Perez, N. E., Sarisky, J. P., Shepherd, C. A., Miller, M. D., . . . Lynch, M. F. (2007). A waterborne outbreak of gastroenteritis with multiple etiologies among resort island visitors and residents: Ohio, 2004. *Clinical Infectious Diseases, 44*(4), 506-512. doi:10.1086/511043

TCEQ. (n.d.). Arroyo Colorado: Surveying recreational uses. Retrieved August 10, 2020, from https://www.tceq.texas.gov/waterquality/tmdl/87-arroyobacteria.html

TGPC. (2019). How Is Groundwater Quality Affected by Failing On-Site Sewage Facilities. Retrieved July 13, 2020, from https://tgpc.texas.gov/gwissues/white_papers/OSSFwhitepaper16Jan2019.pdf

TWDB. (n.d.) Flood Infrastructure Fund (FIF).www.twdb.texas.gov http//www.twdb.texas.gov/financial/programs/FIF/index.asp

Texas A&M AgriLife Extension Service. (2008). “Onsite Wastewater Treatment System: Conventional Septic Tank/Drainfield,” EL-5234

Vieritz, A., Beavers, P., Gardner, E., Beal, C., Doherty, J., Baisden, J., & Turner, T. (2006). *RISK ASSESSMENTS FOR IMPACTS FROM NON-SEWERED SUBDIVISIONS*. https://research-repository.griffith.edu.au/bitstream/handle/10072/39807/70564_1.pdf%3bsequence=1

Vieux E., & Needham, S. (1993). Nonpoint-Pollution model sensitivity To Grid-Cell Size. *Journal of Water Resources Planning and Management, 119*(2), 141-157. doi:10.1061/(asce)0733-9496(1993)119:2(141)

BIOGRAPHICAL SKETCH

Alvaro Garcia obtained his B.S. in Environmental Science from the University of Texas Rio Grande Valley in December 2019. After graduating from the University of Texas Rio Grande Valley in December 2021 with a M.S. in Agriculture, Environmental, and Sustainability Sciences, Alvaro is currently working as a GIS analyst with a focus on environmental science at Halff Associates. He can be contacted at alvaro.garcialm10@gmail.com.