12-2021

Managing Water Resource and Land Use in Lower Rio Grande Valley of South Texas Using a Groundwater Vulnerability Model

Leslie Soto Sanchez
The University of Texas Rio Grande Valley

MANAGING WATER RESOURCE AND LAND USE IN LOWER RIO GRANDE VALLEY OF SOUTH TEXAS USING A GROUNDWATER VULNERABILITY MODEL

A Thesis

by

LESLIE SOTO SANCHEZ

Submitted in Partial Fulfillment of the

Requirements for the Degree of

MASTER OF SCIENCE

Major Subject: Ocean, Coastal and Earth Sciences

The University of Texas Rio Grande Valley

December 2021

MANAGING WATER RESOURCE AND LAND USE IN LOWER RIO GRANDE VALLEY OF SOUTH TEXAS USING A GROUNDWATER VULNERABILITY MODEL

A Thesis
by
LESLIE SOTO SANCHEZ

COMMITTEE MEMBERS

Dr. Chu-Lin Cheng
Chair of Committee

Dr. Jude Benavides
Committee Member

Dr. Juan Gonzalez

December 2021

ABSTRACT

Soto Sanchez, Leslie, Managing Water Resource and Land Use in Lower Rio Grande Valley of South Texas Using a Groundwater Vulnerability Model. Master of Science (MS), December 2021, 65 pp., 4 tables, 25 figures, references, 67 titles.

The Lower Rio Grande Valley includes three metropolitan statistical areas which are Brownsville-Harlingen, Laredo, and McAllen-Edinburg-Mission, the latter with a population of around 1 million people and a estimated growth rate of 62% between 2010-2018. Low precipitation rates, intensive agriculture and growing manufacturing and tourism industries have resulted in an increasing concern of scarce water supply especially as the region relies primarily on a single water source, the Rio Grande. These circumstances could potentially disrupt economic development, negatively affecting the local manufacturing industry, agriculture, and the community. With this distressing scenario it is urgent to understand the regional groundwater resources as well as its exposure to contamination. In this project the vulnerability of the selected south Texas counties was evaluated using geospatial datasets and integrating the data into a Geographic Information Systems framework. The DRASTIC method considers different parameters such as depth to water table, net recharge, aquifer media, soil media, impact of vadose zone and hydraulic conductivity.

DEDICATION

This thesis is dedicated to my beloved mother, father, and sister. Thank you for all your support and love.

ACKNOWLEDGMENTS

I would like to thank Dr. Chu-Lin Cheng for his support during this thesis. I would also like to thank my committee members Dr. Jude Benavides and Dr. Juan L. Gonzalez for their continual guidance.

I would also like to acknowledge the School of Earth, Environmental and Marine Sciences for the economic support through the completion of my master's degree as well as thanking the Gulf Coast Association of Geological Societies for the graduate student research grant.

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 Background

Groundwater is the most abundant freshwater supply except for the glaciers. It is at least 30 times more abundant than surface water and accounts for 90% of the supply of available freshwater (Arabgol et al.,2016). This resource plays a crucial role in the development of ecosystems as it provides them with water and nutrients, and in turn, these ecosystems provide a range of services for humans such as recreational activity, food, and energy productions (Velis et al., 2017). Groundwater provides for the irrigation of approximately 100 million hectares of farmland and although the use of groundwater for irrigation purposes varies from continent to continent, it is still important to notice that 40% of the global water consumption used in irrigation, relies on the withdrawal of groundwater (Siebert et al., 2010). Overall, groundwater is crucial for the development of humankind and vital for food availability and production, health, and sanitation as well as poverty reduction since the economic benefits of groundwater exceed those of surface water (Velis et al., 2017). Although the importance of groundwater is significant for human development and wellbeing, this resource has been misunderstood due to the complexity of factors that are inherent in this water source (Sophocleous, 2002). Owing to this complexity, which makes it imperceptible and complicated, groundwater is at risk of depletion and pollution. The tools for the remediation of groundwater contamination are expensive and often unreliable (Hamza et al., 2015). In addition, groundwater pollution is associated with poor water quality and an unhealthy population. Rural communities that rely on the sources of fresh water are more vulnerable than others with an adequate water infrastructure. (Velis et al., 2017). Thus, the prevention of contaminants in the groundwater supply is essential for the adequate management of water resources, benefiting all communities with impartial access to water.

The Lower Rio Grande Valley (LRGV) has three metropolitan areas. These are Brownsville-Harlingen, Laredo, and McAllen-Edinburg-Mission, with the latter being ~1 million population and estimated growth close of 62% between 2010-2018 (Arizpe y Acevedo,2012). Low precipitation, intensive agriculture as well as growth in the manufacturing and tourism industries have resulted in an increasing concern of scarce water supply. These circumstances could potentially disrupt economic development, negatively affecting the local manufacturing industry, agriculture, and the community.

It is estimated that 60% of the water usage in the state of Texas comes from groundwater (Anaya et al.,2016). Plenty of water quantity studies have been done to estimate possible water availability but little has been done regarding water quality even though water quantity and quality are linked, and water quality will have an impact on the total amount of water quantity available. One of the processes affecting groundwater quality in Texas is naturally occurring groundwater contamination. This is a process that has the potential to affect seven million Texans that rely on groundwater for water supply as well as agricultural practices which rely heavily on groundwater for irrigation. The Gulf Coast Aquifer is especially impacted by this process, with primary contaminants exceeding the Maximum Contaminant Levels (MCL) recommended by the Environmental Protection Agency (EPA). Especially worrisome is that the areas of highest risk for the exceedance of MCLs are in the southern portion of the Gulf Coast aquifer, with a higher prevalence on the subsurface located just under Hidalgo County, the most populated county in this region. The primary contaminants located in the groundwater are arsenic, gross alpha, combined radium, uranium, and total dissolved solids (Reedy et al., 2011).

To date, eight desalination plants are in the Lower Rio Grande Valley and two of them are in Cameron County. The Southmost Water Plant is one of the brackish groundwater desalination plants with a larger capacity across the state, which has a capacity of producing more than 20,000 million gallons of water per day. The brackish desalination plants are to extract groundwater to provide additional drinking water supply to meet the growing demands of the community. Understanding the hydrogeological conditions of the region becomes critical to enable better decision making and assist regional assessments for water availability, water storage capability, management, and planning for entities such as the city and several state agencies for the future.

1.2 Research Objective

The objective of this research is to evaluate the vulnerability of groundwater in the southern portion of the Gulf Coast Aquifer in South Texas, which consists of Hidalgo County and portions of Cameron and Starr counties. Two groundwater vulnerability models will be applied to examine whether geological, hydrological conditions, and human activities would threaten groundwater resources. The first model is the DRASTIC model developed by the Environmental Protection Agency (EPA). The modified model, DRASTIC-LU, is added land-use type component in addition to the original seven hydrogeological parameters. Groundwater vulnerability index maps with risk ranking will allow decision-makers to identify the zones with the greatest groundwater vulnerability potentials while urban areas continue to expand from population and economic growth and water demand continues to increase.

CHAPTER II

LITERATURE REVIEW

2.1 Groundwater Vulnerability

Since the start of civilization, groundwater has been crucial for the survival and development of human settlements (Foster et al., 2003). Currently, groundwater constitutes the predominant reservoir of freshwater, with 30% of the world's total being stored in groundwater systems (Foster et al., 2003). Estimation of groundwater ranges from 7,000,000 to 23,400,000 km3 (Nace,1971; Foster et al., 2003; Richey et al., 2015) but due to the inherent complexity of these systems, these numbers will always be open to discussion (Foster et al., 2013). Due to technological developments, groundwater has become the major raw resource exploited on the planet, being the biggest supplier of water in Europe and Sub-Saharan Africa as well as being of primordial importance for the development of agriculture in Asia (Foster et al.,2003). Because of this continual dependence on groundwater, humans have become capable of depleting entire aquifer systems, this happens because extraction is faster than natural replenishment (Schwartz et al., 2011; Wada et al.,2010). Due to the inherent surface water-groundwater interactions, intensive extraction of groundwater reservoirs also has an impact on surface water bodies (Schwartz et al., 2011), some of the unintended consequences are reduction of water flow in streams that are groundwater-fed (gaining streams) increasing the risk of desertification in areas that would normally be fed by groundwater flows (Schwartz et al., 2011).

In addition to intensive extraction, groundwater is susceptible to contamination (Pollicino et al.,2021). Anthropogenic activities such as modern agriculture which relies heavily on pesticides and fertilizers can pollute shallow aquifers, some of the contaminants associated with modern agriculture include Nitrate, Iron, and Total Dissolved Solids. Some other anthropogenic activities that heighten the risk of groundwater pollution include leakage of landfills, septic tanks, sewage, and urban run-off (Foster et al., 2003). Due to the increased industrialization of urban centers, aquifer vulnerability is expected to increase as well, impacting water quality and human health (Strauch et al.,2008).

Increases in groundwater vulnerability and degradation have led to the development of novel groundwater vulnerability assessments (Jarray et al., 2017; Allouche et al., 2016). Owing to the complexity of the hydrogeological settings and parameters and the impossibility of evaluating groundwater vulnerability out on the field, new approaches have been developed. These methods have been grouped into three categories, index-based methods, statistical methods, and simulation techniques (National Resource Council,1993).

Although there is not an internationally accepted method for the assessment of groundwater vulnerability, overlay and index methods are the most widely used (Moraru et al.,2018). Overlay and index methods make use of data involving different physical characteristics as well as hydrogeological settings. The main data source for this method involves the usage of qualitative and quantitative data interpreted found on mapped documents (Moraru et al.,2018; Jarray et al.,2017). Readily available and easy to access data, not depending on field data, as well as relatively simple procedures are some of the advantages of using overlay-index methods (Shrestha et al.,2017). Some of the most widely used overlay-index methods to evaluate groundwater vulnerability include DRASTIC (Allen et al.,1987), SINTACS (Civita et al.,1994), and GOD (Foster, 1987). The methods include a system of weights and ratings to evaluate which criteria exert the biggest influence concerning vulnerability, to create a range of vulnerability classes to later be displayed in a map format (National Resource Council, 1993; Jarray et al.,2017). However, there are disadvantages associated with the use of these methods. Since the value of the weights and rankings assigned to the different characteristics and settings is heavily influenced by the criteria of the expert developing the model, subjectivity is heavily associated with these methods (Frind et al.,2006).

Statistical methods are another approach used to assess groundwater vulnerability with Logistic Regression and Bayesian-based methods being the two techniques most used (Masetti et al., 2009). These techniques are used to determine contaminant concentration and to predict the path and route the pollutant could take (Massetti et al., 2009). These methods evaluate groundwater vulnerability using groundwater monitoring datasets which include contaminants concentrations, and water quality and quantity information as well as incorporating natural and anthropogenic factors as part of the groundwater vulnerability assessment (Bonfanti et al.,2016). These methods employ contaminant concentrations as the dependent variables and include multiple independent variables and the results of these methods will always be expressed as probabilities (National Resource Council,1993). Although these methods can be used only in specific geographic areas, incorporating readily available datasets as well as a lack of subjectivity are some of the advantages of using statistical methods to assess groundwater vulnerability (Sorichetta et al.,2012).

Process-based simulation models' methods are used to predict the flow of contaminants in the subsurface (Nobre et al., 2007). These methods are coupled with numerical approaches and robust hydrogeological data to predict contaminant transport (Burkart et al., 1999). These methods range from one-dimensional models, two-dimensional and three-dimensional transport models which attempt to predict contaminant transport at spatio-temporal scales and have been used to evaluate different physical processes such as recharge, discharge, aquifer storage, and pesticides travel times (Vu et al., 2021). One such process-based model to evaluate groundwater vulnerability is MODFLOW, which is a finite-difference flow model developed by the US Geological Survey, that has the capability of predicting contaminant transport and flow as well as other groundwater physical and chemical processes (Ghouili et al.,2020). Some of the issues with implementing process-based models for the assessment of groundwater vulnerability are the need for large datasets and a lack of hydrogeologic data at a regional scale, other disadvantages include time-consuming processes as well as calibration issues (Wachniew et al., 2006).

The concept of groundwater vulnerability was first introduced in 1968 by French hydrogeologist Jean Margat (Foster et al., 2013), where he defined it as “the possibility of percolation and diffusion of pollutants from the surface into groundwater” (Jarray et al., 2017). Other definitions that were proposed for this concept include, where the Environmental Protection Agency defined it as “the relative ease at which a contaminant (in this case a pesticide) applied on or near the land surface can migrate to the aquifer of interest under a given set of agronomic management practices, pesticide characteristics, and hydrogeologic sensitivity conditions” (National Resources Council, 1993)and even proposed a tool-box to assess this susceptibility (Allen et al.,1987). Subsequently, the concept has been broadened to include intrinsic and specific vulnerability. Intrinsic vulnerability refers to sensitivity to groundwater pollution occurring from anthropogenic activities and specific vulnerability refers to sensitivity to a particular pollutant or a group of pollutants (Bezelgues et al., 2002). Although more than 50 years have elapsed since this concept was coined, there is not a widely accepted definition and is still a cause of discussion among experts in the field (Foster et al., 2013).

2.2 Groundwater Vulnerability and Geographic Information Systems

Groundwater vulnerability can be mapped in two ways, these are intrinsic and specific. Intrinsic vulnerability is mapped taking into consideration the different hydrogeological parameters that compose a groundwater system. Specific vulnerability aims to characterize how sensitive is an aquifer to a specified pollutant (Chenini et al., 2015). Most intrinsic groundwater vulnerability mapping takes place by integrating Geographic Information Systems (GIS). GIS was developed in Canada during the 1960s, is a technology composed of different disciplines such as geography, cartography, remote sensing, and computer science, and is widely used because of its efficiency to collect, organize, manage, analyze, and display datasets and results as well as its low operational cost compared to other methods (National Research Council, 1993). Geographic data stored within GIS can be presented either as objects or fields. Objects represent real-life features as lines, polygons, and points that share geometry and topology. Meanwhile, the field presents real-life features stored as data within attribute tables (Jha et al., 2006). During the 1990s, breakthrough technological developments as well as a growing need for better natural resources management lead to the implementation of GIS as a fundamental component in natural resources management and is widely used by government agencies, universities, businesses, and the military (Lo et al., 2003). Because of the advantages, GIS has over other assessment methods and techniques, a variety of overlay and indexes have been developed to assess groundwater vulnerability. Some of the different overlay and index methods developed are DRASTIC, GOD, SINTACS, SEEPAGE, and EPIK, which were exclusively developed to evaluate groundwater vulnerability of kart systems (Shirazi et al., 2012).

2.3 DRASTIC Vulnerability Mapping

The DRASTIC model was developed by the Environmental Protection Agency in 1985 and is an overlay method that is used to assess groundwater vulnerability in the United States (Aller et al.,1987; Fritch et al., 2000; Gogu et al.,2000; Merchant,1994; Smith et al., 2017). This method takes into consideration different climates and conditions such as arid and semi-arid regions and agricultural, industrial, and coastal areas (Shirazi et al., 2012). The DRASTIC method is composed of two parts, the first component consists of mapping the different hydrogeological units that compose the model, and the second component consists of assigning weights and ranking to the hydrogeological settings to then calculate the DRASTIC index. When the DRASTIC index has been calculated, potential areas prone to groundwater contamination become easier to identify and delineate. The name of this model is an acronym of the seven hydrogeological parameters which are composed. These parameters are *Depth to Water Table, Net Recharge, Aquifer media, Soil Media, Topography, Impact to Vadose Zone, and Hydraulic Conductivity*. The description of the parameters can be found in Table 2. The DRASTIC index is calculated using the following equation:

$$DrDw + RrRw + ArAw + SrSw + TrTw + IrIw + CrCw = DI \text{ (Pollution Potential)}$$

Where:

R = Ratings

W = Weights

The DRASTIC index is calculated by multiplying each parameter rating by its weight and adding them together. Each parameter has a value ranging from 1-10 and a weight on a scale of 1-5 and the higher the value of the DRASTIC index calculated, the higher its susceptibility to contaminants.

Table 2.1 DRASTIC Parameters (Aller et al. 1987)

Factor	Description	Relative Weight
Depth to Water Table	Refers to the distance contaminants must travel to reach the water table.	5
Net Recharge	Refers to the amount of water that will infiltrate through the ground surface and represents the medium for transporting contaminants.	4
Aquifer Media	Indicates the composition of the saturated zone and can include consolidated and unconsolidated materials.	3
Soil Media	Refers to the uppermost layer above the vadose zone and exerts some control over the amount of recharge that will percolate through the ground.	2

Topography	Represents the slope and slope variability of an area.	1
Impact on Vadose Zone	Indicates the zone located at the top of the water table but below the soil media. Also known as the vadose zone, it has a major influence on the movement of contaminants.	5
Hydraulic Conductivity	Indicates the easiness to which aquifers transmit water. High hydraulic conductivity is associated with high groundwater velocity.	3

DRASTIC Weights and Rating Values for Hydrogeological Parameters													
DRASTIC Weight 5 Depth to Water Table(cm)		DRASTIC Weight 4 Recharge (mm)		DRASTIC Weight 3 Aquifer Media		DRASTIC Weight 2 Soil Media		DRASTIC Weight 1 Topography (%)		DRASTIC Weight 5 Impact to Vadose Zone		DRASTIC Weight 3 Hydraulic Conductivity (m/d)	
Range	Rating	Range	Rating	Range	Rating	Range	Rating	Range	Rating	Range	Rating	Range	Rating
0 to 152	10	0 to 51	1	Massive Shale	2	Thin or Absent	10	0-2	10	Confining Layer	1	2.10	4
152 to 457	9	51 to 102	3	Metamorphic/Igneous	3	Gravel	10	2 to 6	9	Silt/Clay	3	2.15	6
457 to 914	7	102 to 178	6	Clay	3	Sand	9	6 to 12	5	Shale	3	3.66	8
914 to 1524	5	178 to 254	8	Weathered Metamorphic/Igneous	4	Peat	8	12 to 18	3	Limestone	6		
1524 to 2286	3	254+	9	Clay and Sand	4	Shrinking Clay	7	18+	1	Sandstone	6		
2286 to 3048	2			Glacial Till	5	Sandy Loam	6			Bedded Limestone	6		
3048 +	1			Clay and Gravel	6	Loam	5			Sandstone Shale	6		
				Massive Sandstone	6	Silty Loam	4			Sand and Gravel with Significant Silt and Clay	6		
				Massive Limestone	6	Clay Loam	3			Metamorphic/Igneous	4		
				Sand and Gravel	8	Muck	2			Sand and Gravel	8		
				Basalt	9	Non-shrinking Clay	1			Basalt	9		
				Karst Limestone	10					Karst Limestone	10		

Figure 2.1. DRASTIC Parameters and Ratings Adapted

2.4 Modified DRASTIC

In addition, groundwater vulnerability will also be assessed using the modified DRASTIC-LU model. This model includes the seven parameters used in the original model and includes the addition of Land Use (LU) as the eighth parameter, to evaluate the risk anthropogenic activities could have over groundwater resources. Just as the previous parameters, Land Use contains a ranking system on a scale from 1-10 and a weight of 5. To calculate the DRASTIC-LU index, the same formula is used with only a minor modification, which is:

$$DrDw + RrRw + ArAw + SrSw + TrTw + Ir\,Iw + CrCw + LrLw = DI\ (Pollution\ Potential)$$

Where:

Lr = ratings for Land Use categories

Lw = weights assigned for Land Use

Table 2.2 Land Use Classification and Rating System (Secunda et al., 1998; Alam et al., 2012; Kumar et al., 2019)

DRASTIC-LU Weight 5	
Land Use	
Range	**Rating**
Water Bodies and Wastelands	0
Forest and Shrublands	2
Bare Areas	3
Agriculture	5
Low Density Urban Development	7
Medium Density Urban Development	8
High Density Urban Development	9

CHAPTER III

METHODOLOGY AND DATA SOURCES

3.1 Study Area

The study area for this project is situated in parts of Cameron, Hidalgo, and Starr Counties in the Lower Rio Grande Valley of South Texas. The study area is within the Rio Grande Regional Water Planning Area (Region M), Groundwater Management Area 16, and two groundwater conservation districts (Red Sands and Starr County) and underlies the southern portion of the Gulf Coast Aquifer (Texas Water Development Board, 2016). Figure 3.1 displays the location of the study area as well as the boundaries of the southern portion of the Gulf Coast Aquifer.

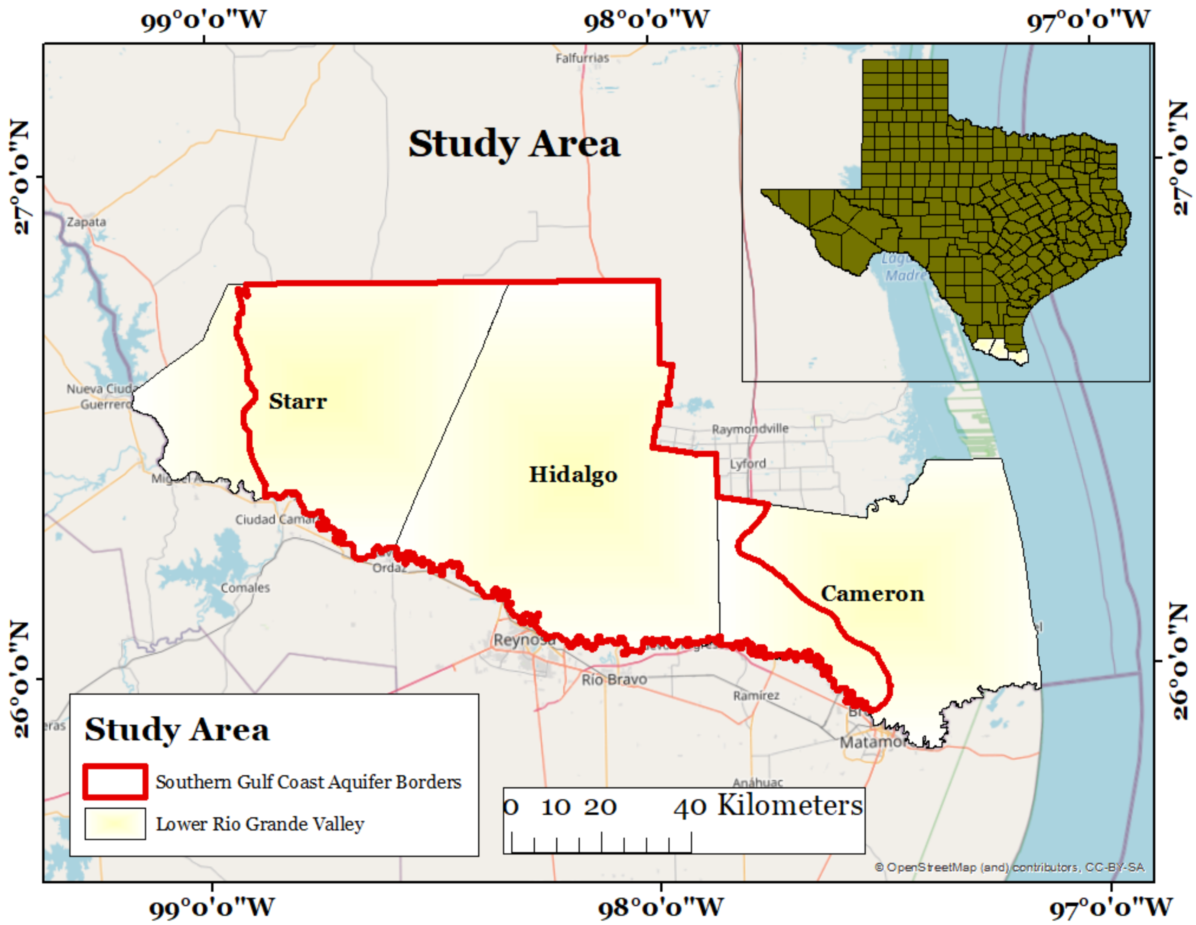

Figure 3.1 Project study area located in the boundaries of the Southern Gulf Coast Aquifer within the boundaries of the Lower Rio Grande Valley of South Texas.

The Lower Rio Grande Valley is situated in the southernmost tip of Texas, on the southern border between the United States of America and Mexico, where the Rio Grande flows and serves as a natural boundary between these two nations. This region contains two Metropolitan Statistical Areas, the Brownsville-Harlingen and McAllen-Edinburg-Mission, the latter one with approximately 1.2 million inhabitants and expected population growth of 3.05 million by the year 2050(Texas Demographic Center, 2013). The economic development of this region started with the agricultural boom of the 1920s, to this date, sugar cane, citrus and sorghum continue to be cultivated in this region (Levine, 2007). Currently, agriculture accounts for 1% of the domestic gross of the state but is the predominant economic activity for this region, with 75% of the total land area being used for agriculture and livestock (Rio Grande Regional Planning Water Group, 2021). Recently, industries such as manufacturing, commerce, and tourism have overtaken as the main economic activities of this region leading to a new influx of people (Texas Water Resources Institute, 2003). Rapid population and economic growth, as well as persistent droughts, have put under increased pressure the existing water resources of this region, exacerbating long standing water quantity and quality issues on both sides of the border (Rio Grande Regional Water Planning Group, 2021).

To implement effective water management, Regional Water Planning is mandated for the entirety of the state of Texas through Senate Bill 1 (Texas State Legislature, 1997). The study area (Cameron, Hidalgo, and Starr County) falls within the Rio Grande Regional Water Planning Area (Region M), which includes 5 other counties, these are Jim Hogg, Maverick, Webb, Willacy, and Zapata. Regional Water Planning oversees evaluating trends in population growth, water demands of this region, exploration of future water resources, and recommendations to ameliorate water scarcity problems. According to the 2021 Regional Water Plan, the major water source for Region M is the Rio Grande and is obtained via the Amistad-Falcon Reservoir System water releases. Another source of surface freshwater is the Arroyo Colorado, a distributary channel from the Rio Grande, being the principal freshwater source for the Lower Laguna Madre region. Due to existing finite water resources and to meet the ever-growing water demands of this region, since the year 2000, eight brackish groundwater desalination plants have been established (Figure 3.2), these plants provide approximately 24,000 acre-ft/year of potable freshwater, with an additional 23 desalination projects recommended for this region. Brackish desalination plants are located alongside the Nueces-River Basin, which is where the facilities dispose of the desalination concentrate, making it affordable for utility companies of the region. The cost to produce desalinated water ranges from $350- $780 per acre-ft/year (Rio Grande Regional Water Group Planning, 2021).

The Gulf Coast Aquifer is the major source of groundwater for Region M, this aquifer runs parallel to the Gulf Coast coastline and stretches from the Mexican border into the state of Florida. This is a complex and multilayered aquifer and conformed by 5 hydro-stratigraphic units: the Chicot, Evangeline, and Jasper aquifers and two confining systems, the Catahoula, and the Burkesville Formation. The Chicot, Evangeline, and Jasper aquifers are composed of sand, clay, silt, and gravel beds from Miocene to the Holocene ages. The Burkeville Formation is composed of Miocene sediments, where silt and clay predominate, making it mostly a confining unit that separates the Jasper and Evangeline aquifers. The Catahoula Formation is composed of tuff of Oligocene age, creating a confining layer at the base of the aquifer system (Texas Water Development Board, 2007). The hydraulic conductivity in this aquifer ranges from 1 ft/d in the southern portion of the aquifer to 7 ft/d in the northern part of the aquifer and the transmissivity also ranges from less than 1,000 ft^2 per day in the southern portion to 14,000 ft^2 per day in the northern portion of the aquifer (Texas Water Development Board, 2016). According to the Texas Water Development Board (2014), it is estimated that more than 275-million-acre feet of brackish groundwater of varied quality are contained in the Lower Rio Grande Valley portion of the Gulf Coast Aquifer with primary water-producing zones located across Region M. In the case of the study area, the Chicot Aquifer is the primary water-producing zone for western Cameron County and Eastern Hidalgo County. The Evangeline Aquifer is the primary water-producing zone for Cameron and Hidalgo and the Oakville Sandstone produces water for northeastern Starr County, and northwestern Hidalgo County (Rio Grande Regional Water Planning Group, 2021).

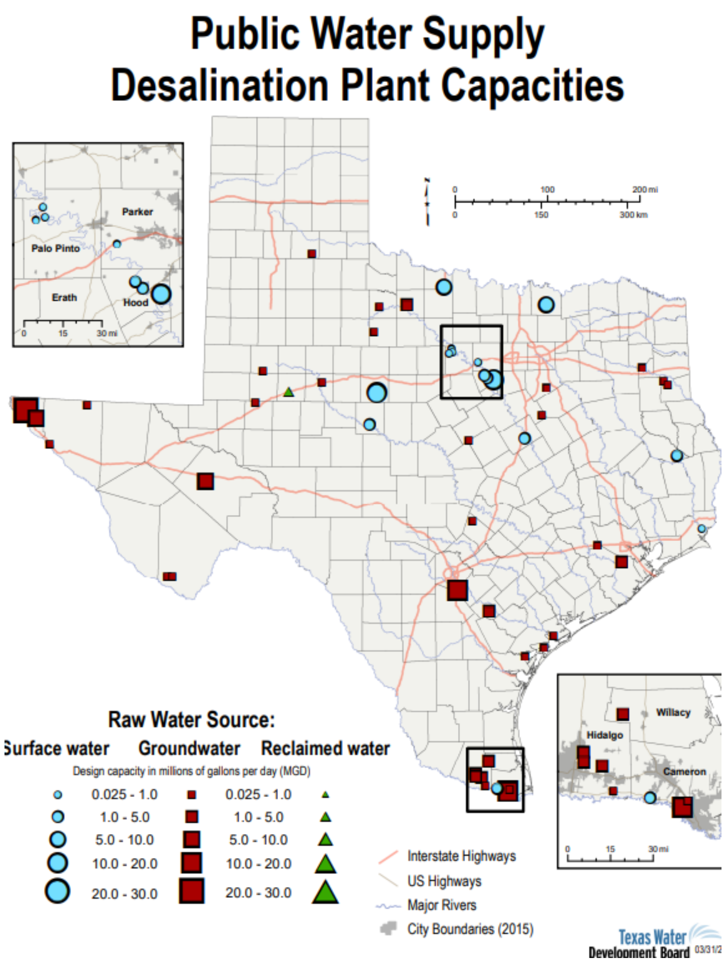

Figure 3.2. Location of Desalination Plants in Texas (Texas Water Development Board, 2021)

3.2 DRASTIC Model Method and Data Sources

As mentioned in previous chapters, groundwater resources are prone to contamination, this could be from a single pollutant or a group of pollutants, and natural or anthropogenic sources such as farming and mining. For this project, a groundwater vulnerability index developed by the US EPA was used to identify and delineate the areas more prone to groundwater contamination. For this project, ArcGIS 10.8.1 was used to create the seven layers of the DRASTIC model and to perform the needed geospatial analysis of the seven layers in raster format.

3.3 Data Processing and Analysis Methods

For this study, the Inverse Distance Weighting interpolation method was used to produce the hydraulic conductivity and aquifer media maps. The point data for the parameters was processed using this interpolation method using the default ArcGIS distance setting (distance squared). This interpolation techniques calculates the data point taking into consideration the distance of the data in relation to the cell. In this method, an average value of the data points is given. The basis of this interpolation method is that the points located closer to the cell being calculated will exert a bigger influence over the resulting interpolation whereas the cells located further will have a lesser influence over the result given (Achilleos,2011). This interpolation technique was preferred over others is because it calculates the cells values taking into consideration only the data points that fall within the range of the dataset, so extrapolation of the cells values is not possible (Doucette et al.,2000). In case the radius to calculate cell values wants to be expanded it can easily be done in the ArcGIS settings.

Since the DRASTIC model and DRASTIC-LU are overlay-index methods is necessary that the conforming layers have the same cell size and extent to get consistent results during the calculation of the final vulnerability index. For this project the selected cell size for the eight parameters that conform the model is of 200x200 m. For Depth to Water Table, Soil Media, and Topography the cell size was downsized from 368x368 meters to 200x200 meters. For Net Recharge, Aquifer Media, Hydraulic Conductivity, and Impact to the Vadose Zone the cell size was downsized from 400x400 meters to 200x200 meters. Lastly, Land Use was the only parameter where the cell size was upscaled from 30x30 meters to 200x200 meters. The 200x200 meter cell size was selected for different reasons. First, most of the data had to be converted from vector to raster format and because of this is necessary to choose a cell size that will maintain the quality resolution of the raster. Possible issues that arise from downsizing the cell size for most of the parameters is that the accuracy of the data will decrease, thus increasing the percentage of the mapping error (Congalton,1997). The second reason is because as the resolution of a raster greater storage for the data is needed as well as more processing time. Since this project was done using the desktop version of ESRI's ArcGIS in a laptop computer without the ideal Graphing Processing Unit capacity a tradeoff had to be made between the resolution and processing of the data. To ensure that the selected cell size of 200x200 meters offered enough accuracy as well as quick processing times, the vector files were converted into raster files of different resolutions such as 50x50m, 100x100m, 200x200m, 300x300m, and 400x400 m. After the conversion of different cell sizes was done, the area of each of the files was calculated to inquire which of the cell sizes offered a lesser amount of data loss due to the conversion of formats as well as to make sure that the computer had enough capacity to process the cell sizes. Although a cell size of 50x50m could be the optimal choice since it would offer more accurate data, the computer was not able to process so it was the first cell size discarded. With the 100x100 m cell size the computer was able to process the data of certain parameters but not all of them so this size was discarded as well. To choose between the remaining cell sizes as mentioned previously the area of the rasters was calculated to see which offered the lesser amount of data lost as well as to observe which also offered the lesser amount of distortion in the rasters. The calculation of the area was done using the field calculator of the attribute table. The resulting area calculations denoted that 200x200 m cell size was the one offered lesser amount of data loss as well as the computer had an easier time processing and storing this cell size.

A similar approach was used to decide the cell size of the Land Use parameter, the only layer that was upscaled, meaning that the cell size was increased. This cell size of this layer was of 30x30 m, making it the layer with the coarser resolution. The coarse resolution of this layer implicated certain issues such as the identification of certain features leading to complications when trying to classify the data, an issue that is known as the mixed pixel problem (Johnson et al., 2021). Although technological advancements had been made through the years, this issue is still prevalent to this date and different analysis had been made to dictate which is the best approach to fix this problem. One of such approaches involves the upscaling of the raster resolution and although it might not completely solve this issue it can help improve the identification and classification of features in the data (Choodarathnakara et al.,2012). Since upscaling data can also pose processing and storage issues and the computer used for this project did not have the optimal graphic processing unit, a tradeoff had to be made between using a resolution that the computer could be able to process as well as having the same cell size as the other layers used for this analysis.

To classify the data of the different parameters as well as the vulnerability index classification maps the default option in ArcGIS, Jenks Natural Breaks was used. This classification method was selected because it can show the data trends for the resulting groundwater vulnerability maps, is easier to identity possible outliers among the data as well as reducing to a minimum the possible variability of the data (Osaragi, 2002).

3.3.1 Depth to Water Table

The depths of the water table were acquired through the Soil Survey Geographic Database (SSURGO) Database. This database contains solid data collected by the National Cooperative Soil Survey through multiple sampling sites. The data contained in this database is at a scale of 1:20,000 and the database consists of georeferenced map data and attributes data. Once water table depth data was obtained, it was processed in an ArcGIS environment using the Spatial Analyst toolset. The first step consisted of merging water table depth data of the Cameron, Hidalgo, and Starr counties using the merge tool from the Data Management toolset. Once merged, the shapefile obtained was clipped following the outline of the Southern Gulf Coast Aquifer shapefile. Then, the clipped shapefile was converted to a raster format (format needed for the DRASTIC method), and once converted to a raster format, it was reclassified according to the rating system developed by the Environmental Protection Agency. Afterward, the projection of the raster was changed to Universal Transverse Mercator (UTM) projection, this was done so the linear units could be in meters. Lastly, the raster was resized using the resampling tool in the Spatial Analyst toolset, the cell size was modified from originally 368x368 meters cell size to a 200x200 meter.

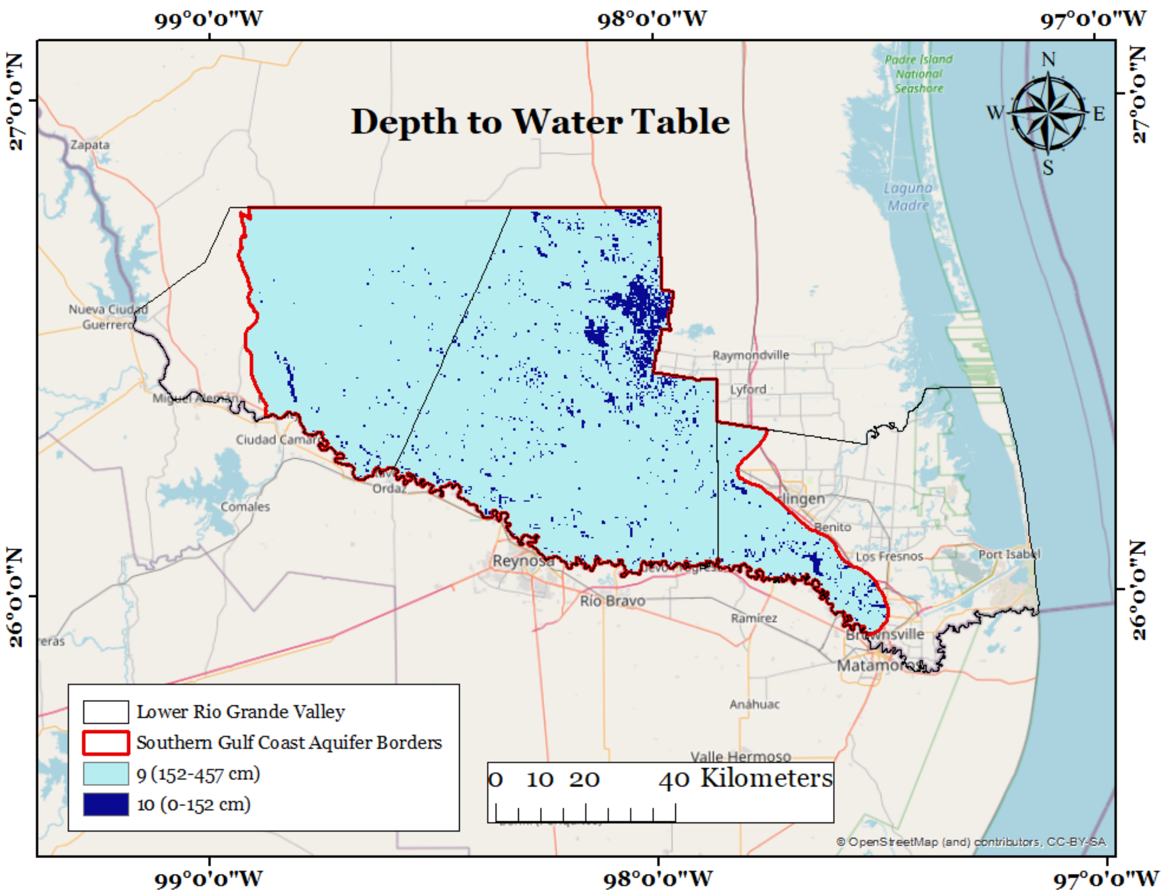

Figure 3.3. Depth to Water Table map was obtained from the Soil Survey Geographic Database. This map denotes how shallow the water table of this region is.

3.3.2 Net Recharge

Net recharge is the total amount of water that will fall into the land as well as being the medium where contaminants can travel vertically and horizontally until they reach groundwater resources (First-Ersoy et al., 2013). For this parameter recharge data was not readily available, so it had to be calculated by assigning ratings to slope, soil, and precipitation, using the following formula (Piscopo, 2001):

Net Recharge: Slope + Soil + Precipitation

The ratings for soil and slope are classified following the same rating system given to the parameters of soil media and topography and the precipitation ratings have been based on previous investigations that had to assign a ranking system to precipitation amounts. (Ahirwar et al., 2018; Maqsoom et al.,2020; Malakootian et al., 2019). The data acquiring and processing for slope and soil are explained in their respective hydrogeological parameters (Topography and Soil Media) and do not repeat information, only the data acquisition and processing for precipitation will be explained here. Precipitation data was originated by the Oregon Climate Service at Oregon State University via the GeoSpatial Data Gateway. The vector dataset consists of the 1981-2010 Annual Average Precipitation for the state of Texas and is at a scale of 250,000. The first step to process the data was to clip the precipitation shapefile following the boundaries of the Southern Gulf Coast Aquifer shapefile. After having the desired boundaries, it was converted to a raster format, and once converted it was reclassified according to the precipitation rankings developed by previous investigations. Once reclassified, the raster projection was modified to a Universal Transverse Mercator projection so the linear units could be in meters. Lastly, the cell size was modified from 400 x 400 meters to 200 x 200 meters. When the precipitation raster was finally prepared, the last step was to use the raster calculator from the Spatial Analyst toolbox to calculate the Net Recharge. To calculate it, it was necessary to input the formula mentioned before, using the slope raster, soil raster, and precipitation raster. Figure 3.3 shows the result of this raster calculation.

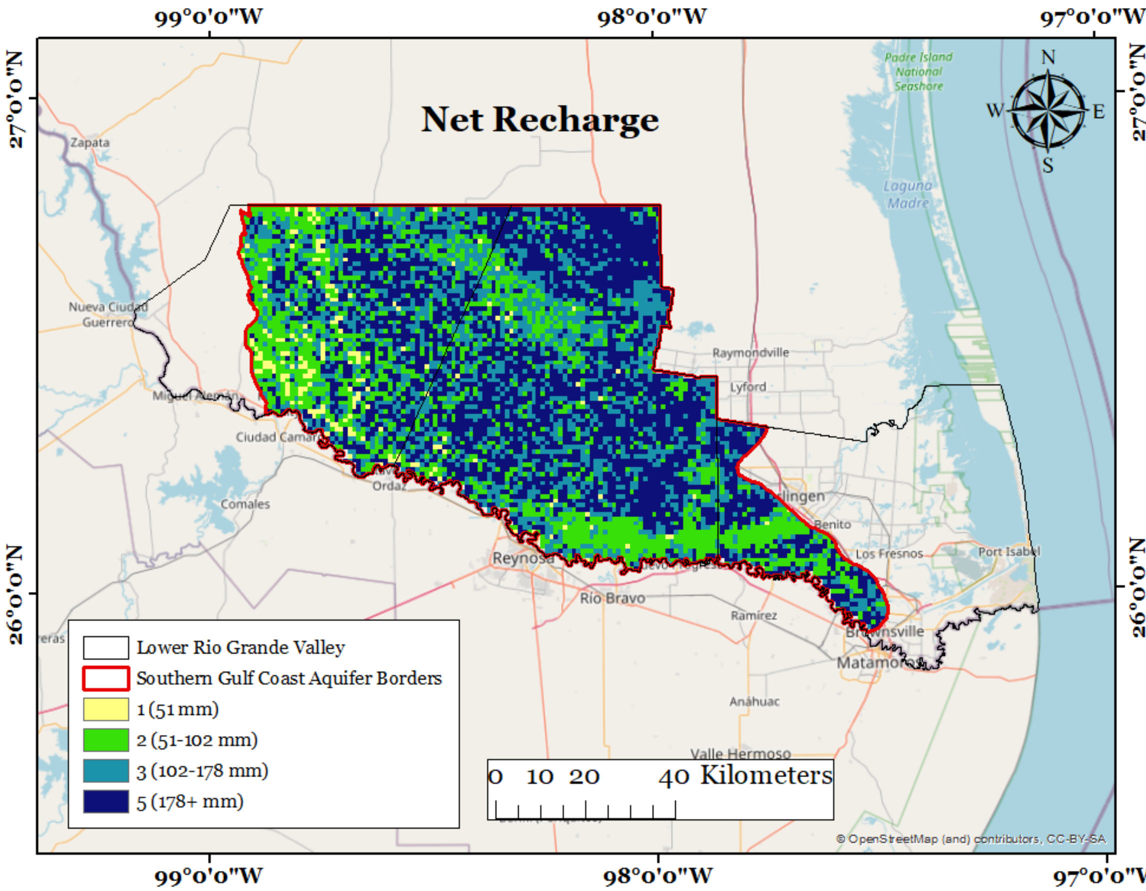

Figure 3.4. Recharge map created using data from different hydrogeological parameters. The map shows that most of the region has low to moderate infiltration rates.

3.3.3 Aquifer Media

Aquifer media represents the composition of the subsurface and has a big influence regarding the path and velocity the contaminants will have to reach groundwater resources (Abdeslam et al., 2017). Since data related to aquifer media was not available in shapefile or raster format, it had to be created. For this project aquifer media was acquired through the Texas Water Development Board Groundwater Database, this is a downloadable database through excel files and includes data about water quality and quantity as well as lithology. Something remarkable about this database is that the information is updated weekly and only the most significant well logs are included as part of the lithology. To create the aquifer media shapefile, an excel file of the lithological profiles located within the counties of South Texas was created. This file included data for 119 wells within the project study area (Figure 3.5) which included, X and Y coordinates, depth, and lithological data. Once the file was exported to an ArcGIS environment, Inverse Distance Weighting was used to interpolate the exported data, IDW was selected because there was a lack of data points in some regions, so IDW could help in determining values for the unknown areas. Once the aquifer media raster was created, the next step was to clip the raster using the Clip Raster tool, the raster was clipped based on the boundaries from the Southern Gulf Coast aquifer shapefile. After it was clipped with the desired boundaries, the values of the raster were reclassified according to the aquifer media ranking values. The next step was to change the projection of the raster to a Universal Transverse Mercator projection so the linear units could be in meters. Lastly, the cell size was modified to a 200 x 200 meters cell size.

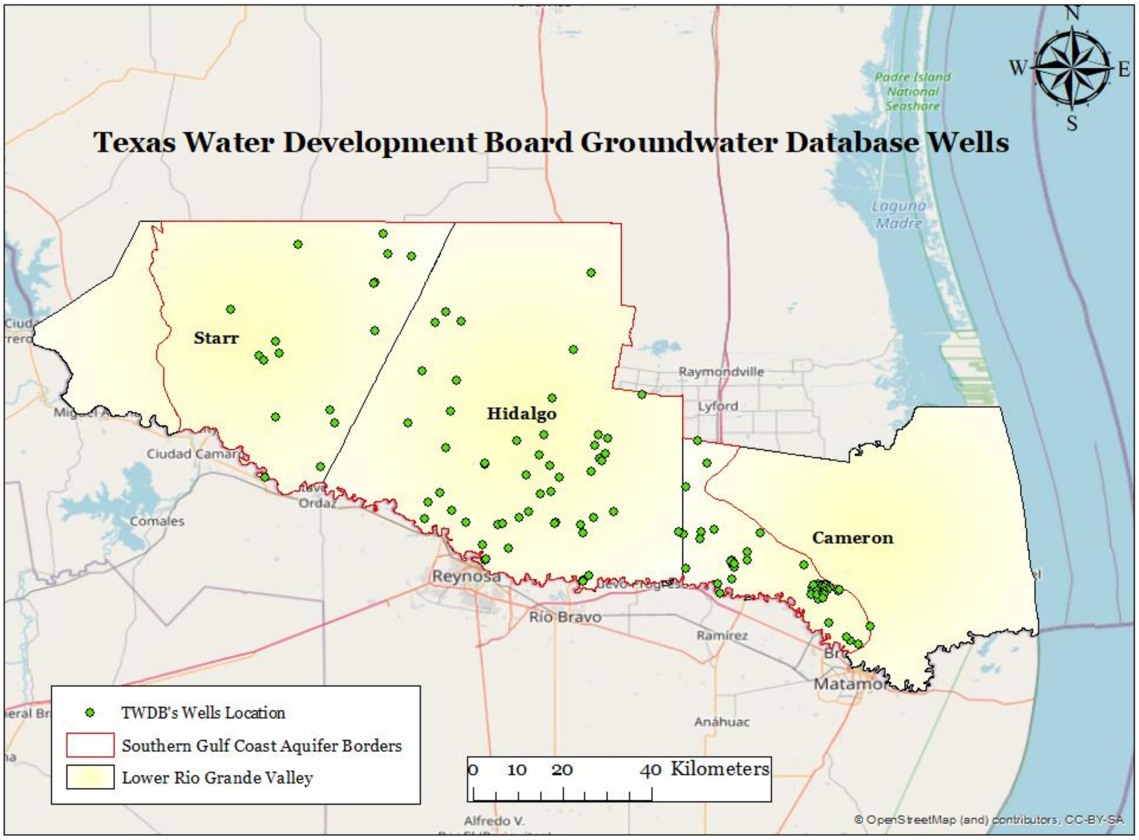

Figure 3.5. Location of the Texas Water Development Board Monitoring Wells used for the analysis of Aquifer Media and Hydraulic Conductivity.

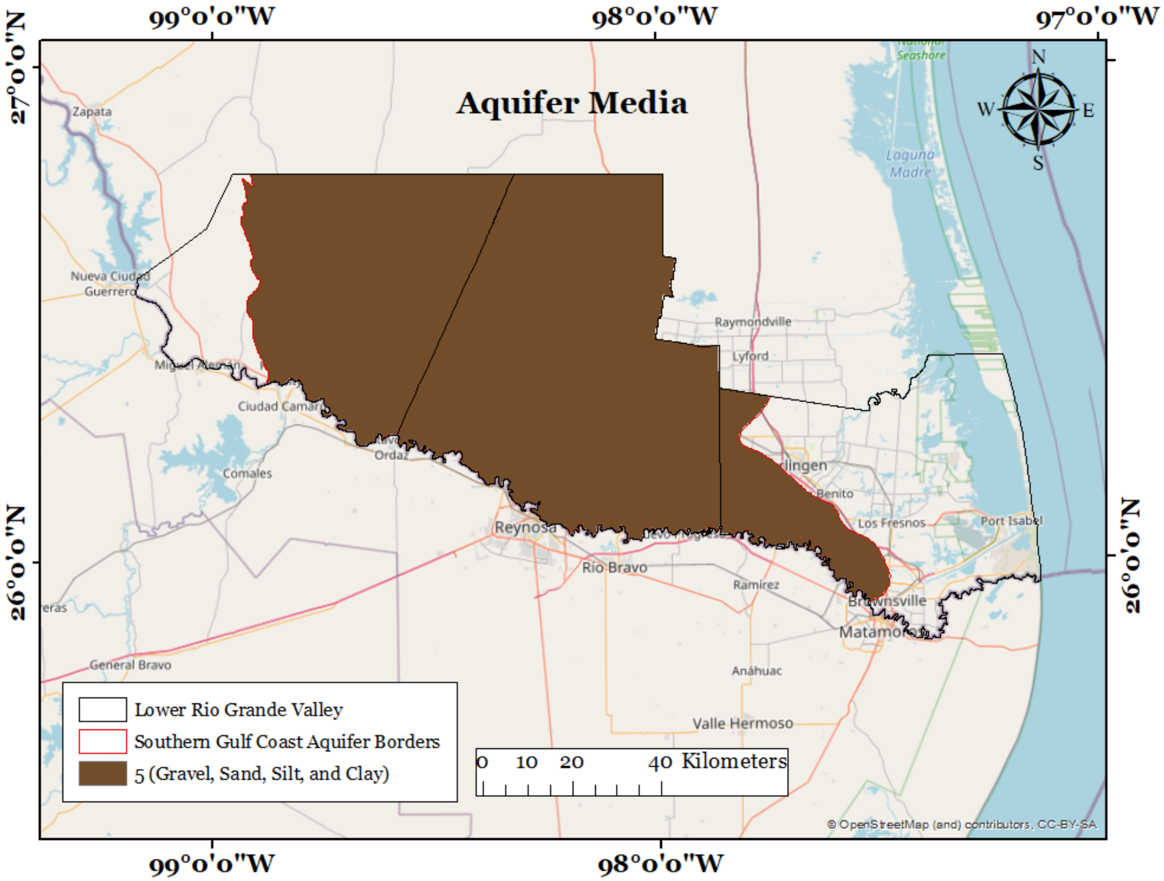

Figure 3.6. The Aquifer Media map was obtained from the Texas Water Development Board Groundwater Database as well as from their technical reports.

3.3.4 Soil Media

Soil media is the uppermost layer of the surface and is located above the vadose zone (Kumar et al., 2019). The soil data were acquired from the Soil Survey Geographic Database and contained within the soil physical properties folder as surface texture. Like previous hydrogeological parameters, the data from Cameron, Hidalgo, and Starr counties had to be merged, and once merged it was clipped based on the boundaries of the Southern Gulf Coast Aquifer shapefile. Once it had the desired boundaries, it was converted to a raster format. Once converted to a raster format, the values of it were reclassified according to the rankings of the DRASTIC model. The projection of the raster was then changed to a Universal Transverse Mercator projection, so the linear units were in meters. Lastly, the cell size was modified from 368x368 meters to 200x200 meters.

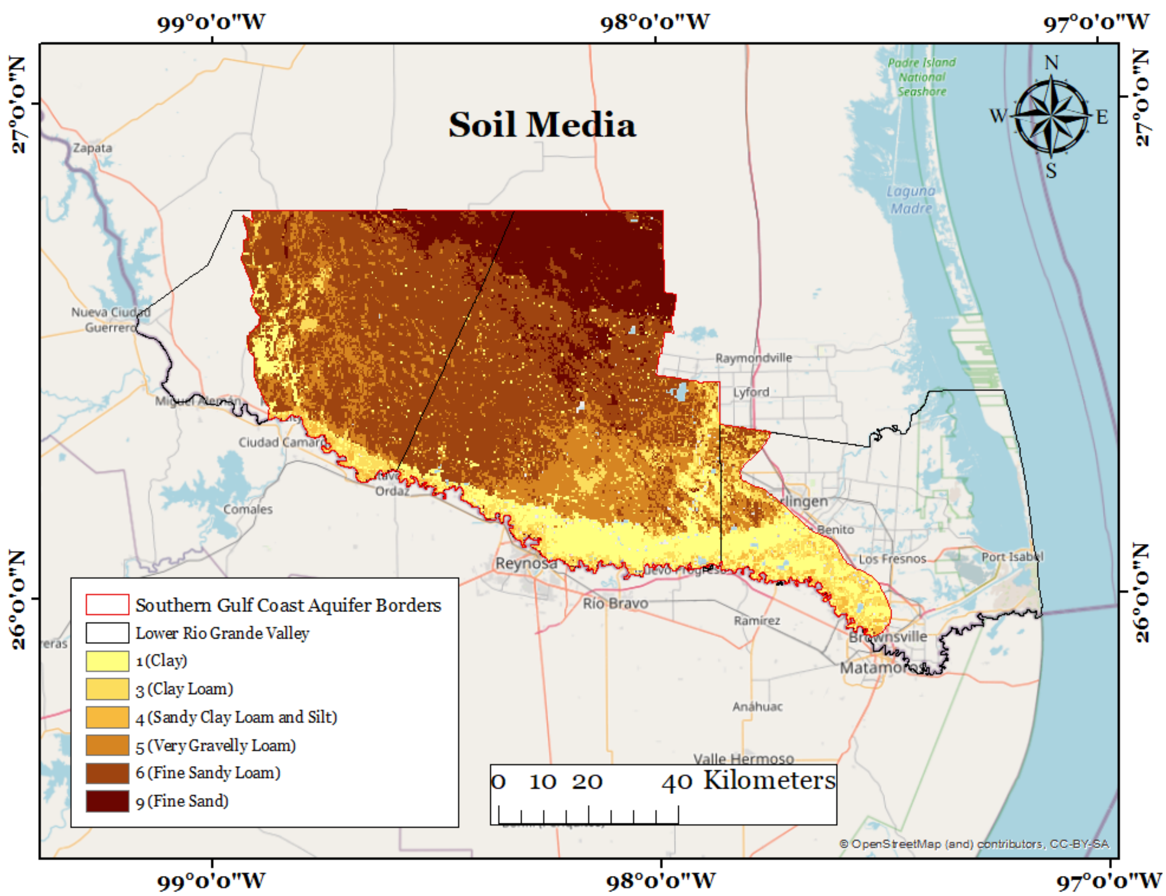

Figure 3.7. Soil Media map was obtained using the Soil Texture attribute from the Soil Survey Geographic Database.

3.3.5 Topography

Topography represents the slope of the surface, areas with low slope are associated with a greater risk of groundwater contamination since surfaces with low slope tend to have greater water storage, thus, giving more chance for water to recharge and infiltrate, resulting in contaminant transport (Colins et al., 2016). For this hydrogeological parameter, the data was acquired through the SSURGO database. The data obtained has a scale of 1:20,000 and is in a shapefile format. Following the same procedure as previous layers, the data for the counties of Cameron, Hidalgo, and Starr was merged, and later it had to be clipped according to the boundaries of the Southern Gulf Coast Aquifer shapefile. Once clipped, it was converted to a raster format and later the values of the raster were reclassified according to the rankings assigned by the DRASTIC model. Lastly, the projection of the raster was changed to a Universal Transverse Mercator projection so the linear units could be in meters and the cell size was modified using the resampling tool from the Data Management toolkit. The cell size was modified from originally a cell size of 368 x 368 meters to 200 x 200 meters.

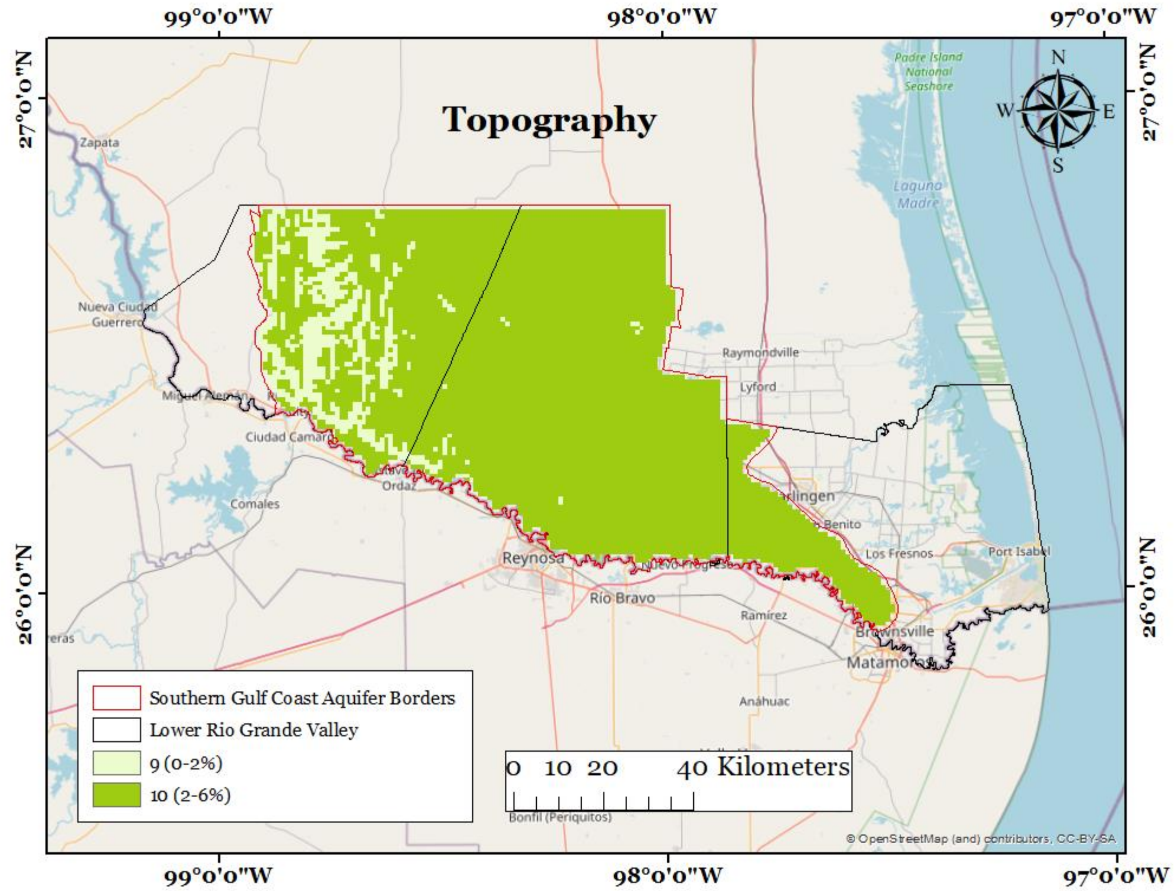

Figure 3.8. The Topography map was obtained from a Digital Elevation Model and was processed using Spatial Analyst using ArcGIS.

3.3.6 Impact of the Vadose Zone

The vadose zone also known as the unsaturated region since the pores of the sediment are not filled with water as they also contain some air, is the region located between soil media and the water table (Djemin et al., 2016). Data for this hydrogeological parameter was obtained through the United States Geological Service (USGS) Geologic Map Databases for the central states of the United States. The scales of the data range between 1:1,000,000 to 1:100,000 and can be used at scales from 1:1,000,000 to 1:500,000. The acquired data was processed through ArcGIS. The first step was to clip the geologic data based on the borders of the Southern Gulf Coast aquifer shapefile. Once the clipping was done, the shapefile was converted into raster format to later be reclassified according to the ranking system of the DRASTIC model. The next step was to change the raster to a Universal Transverse Mercator projection so the linear units could be in meters and lastly, the raster was resized using the resample tool from the Spatial Analyst toolset. The cell size was modified from 400 x 400 meters to 200 x 200 meters.

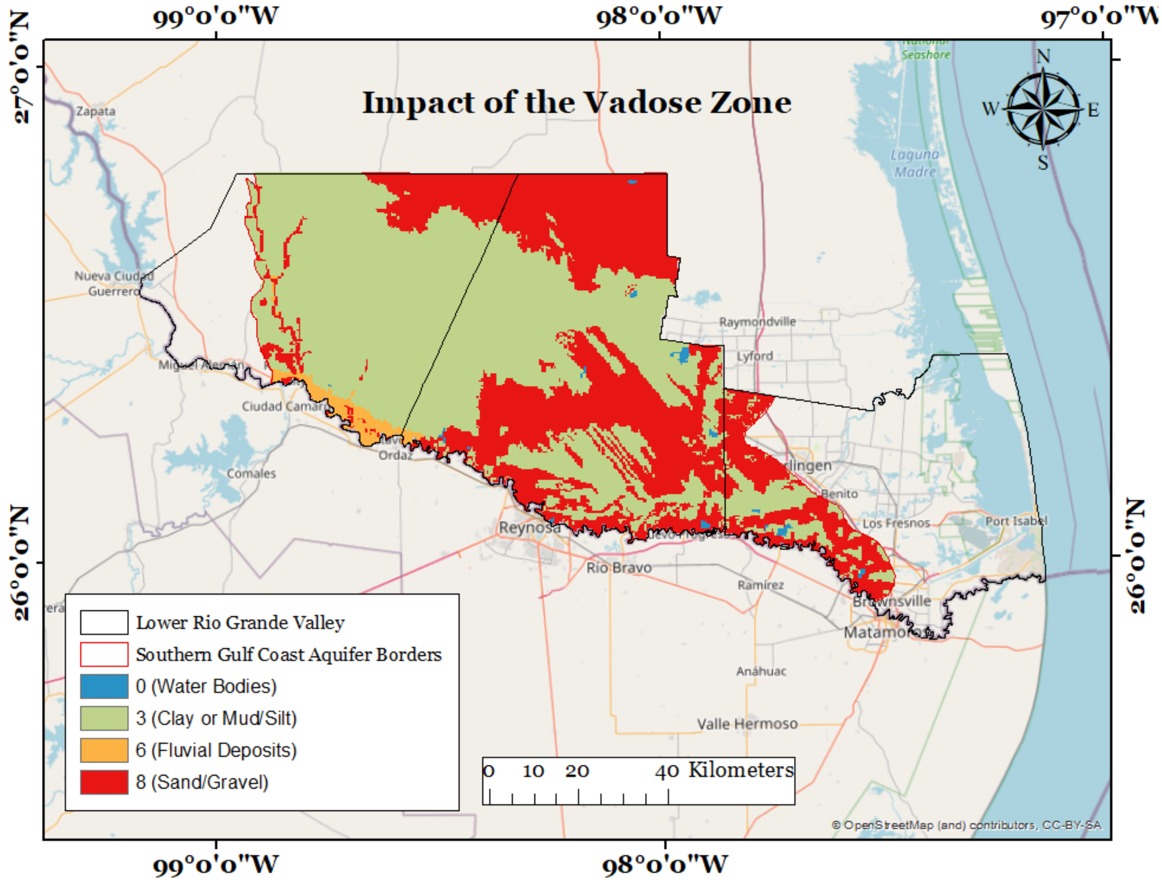

Figure 3.9. The Impact of the Vadose Zone map was obtained using data from the United States Geological Survey. The map shows the composition of the surface being a mixture of sand, gravel, clay, and silt.

3.3.7 Hydraulic Conductivity

For this project, since the data was not available in either shapefile or raster format, it had to be created. For this parameter the data was obtained from TWDB’s Groundwater Resource Evaluation and Availability Model of the Gulf Coast Aquifer in the Lower Rio Grande Valley of Texas. To have a shapefile, it first had to be generated through excel. The excel file included data for 119 data points (Figure 3.4) X, Y, and Z values and the hydraulic conductivity values from the TWDB report. The hydraulic conductivity values included in this file included the values for the counties of Cameron, Hidalgo, and Starr. Once the excel file was finalized, it was exported to an ArcGIS environment and interpolated using Inverse Distance Weighing. The next step was to clip the raster created following the boundaries of the Southern Gulf Coast Aquifer shapefile, once it had the desired boundaries the raster was reclassified following the rankings of the DRASTIC model. The next step was to change the projection of the raster to a Universal Transverse Mercator projection so the length could be measured in meters. Lastly, the cell size was modified to a 200 x 200 meters cell size.

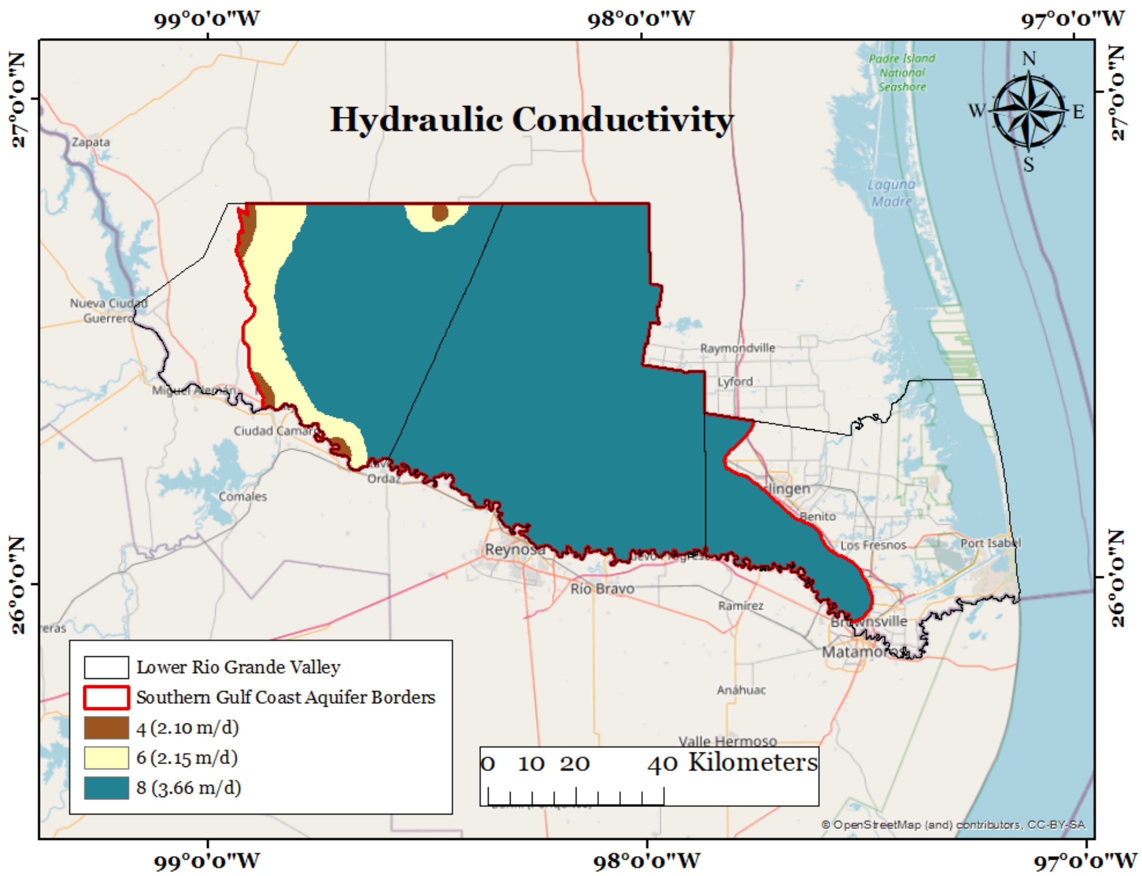

Figure 3.10. The Hydraulic Conductivity map shows the groundwater flow velocity of the study area with slower velocities in the western portion of the area.

3.3.8 Land Use

Land use has the potential to impact groundwater resources negatively, by intrusion of industrial waste, sewage, pesticides and fertilizers into the subsurface (Secunda et al., 1998). Modified DRASTIC methods that include land use patterns to evaluate groundwater contamination and assess the risk to pollution have been used in previous investigations (Alam et al., 2012; Brindha et al.,2015; Noori et al., 2018). Therefore, land use is included as part of the groundwater vulnerability assessment. Based on previous studies land use has a weight of 5 and rankings that range from 10 to 1, aiming to categorize the different land use patterns. For this parameter, data was obtained from the 2011 National Land Cover Dataset (NLCD) via the Earth Resources Observation and Science (EROS) Center. The scale of the data is 30 meters in raster format and with a Universal Transverse Mercator projection. To process the data acquired, the first step was to clip land use/land cover data based on the Southern Gulf Coast aquifer boundaries shapefile. Then, the raster was reclassified to new values according to the ranking system developed by previous investigations. Lastly, the cell size of the raster was modified from 30 x 30 meters to 200 x 200 meters, this was done so it had the same resolution as the other hydrogeological layers that conform the model.

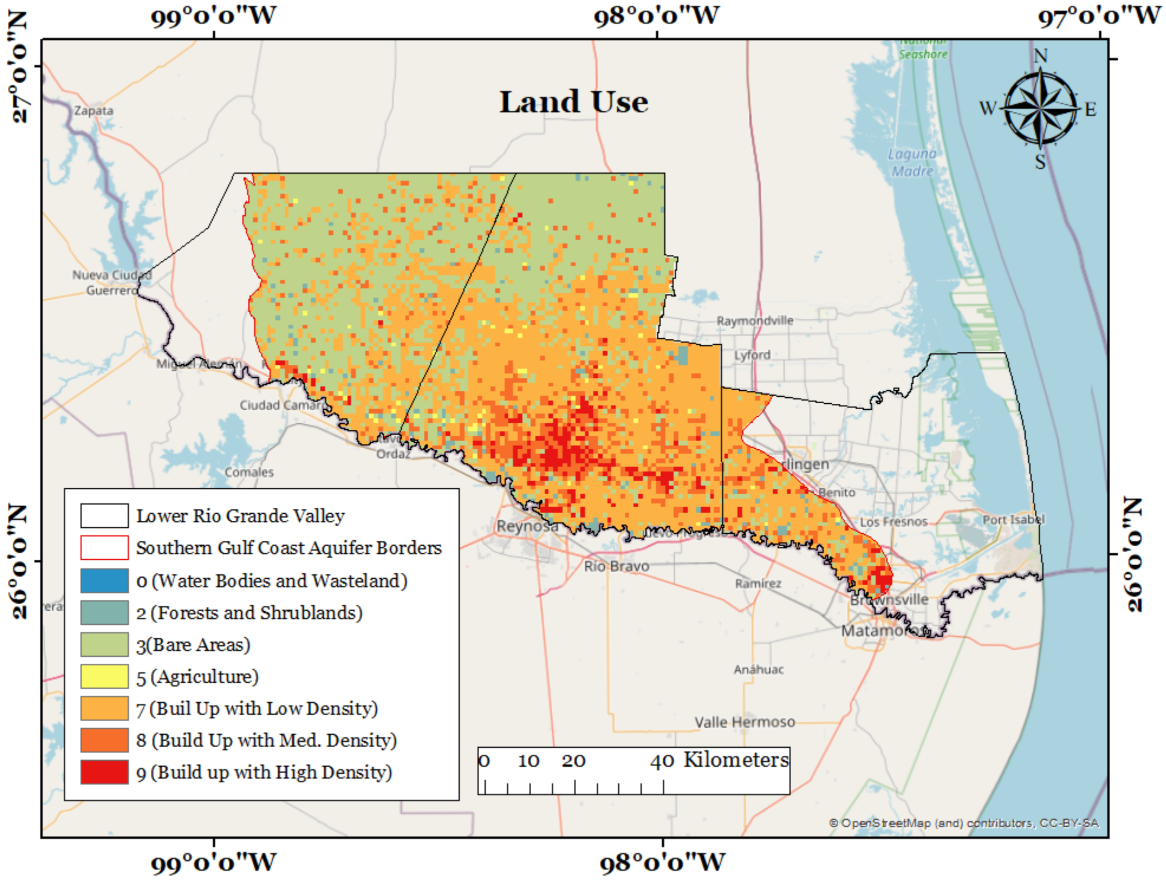

Figure 3.11. The Land Use map was obtained the 2011 National Land Cover Dataset since processing issues were present with the most recent version of this dataset.

CHAPTER IV

RESULTS AND CROSS-EXAMINATION OF DATA

4.1 Results of DRASTIC Model

The final DRASTIC vulnerability map index was created using an ArcGIS environment, with each of the seven conforming layers being rated and weighted according to the system developed by the Environmental Protection Agency. For two of the layers needed, Aquifer Media and Hydraulic Conductivity were created using interpolation and Net Recharge was created with the raster calculator tool. Once the seven layers were created, the final DRASTIC index map was determined using the raster calculator tool where the ranked rasters were multiplied with the assigned weight. Lastly, the obtained map was classified into five groundwater vulnerability index risks: Very Low, Low, Moderate, High, and Very High. The GIS model used to compute the vulnerability index is presented in figure 4, the land area and percentages are presented in table 4.1 and figure 4.1 and the resulting DRASTIC vulnerability index map is shown in figure 4.2.

The resulting index map represents the areas more and less prone to be affected by groundwater contamination. Low and moderate are the two predominant risk classes, accounting for 33% and 24% of the amount of area that falls within these two categories. Meanwhile, these two categories are followed by high and very high-risk categories, accounting for 38% of the total land area examined. It is important to notice that these two categories, although they cover less area, are located near highly populated areas such as McAllen, Harlingen, and Brownsville. Other zones located in areas with high and very high risk of groundwater contamination are the northern portions of Hidalgo and Starr counties; this zone coincides with the location of the South Texas Sand Sheet (STSS). This is not surprising since the STSS consists of coarser sediments facilitating the passage of fluids through the surface (Ahmed et al.,2021)

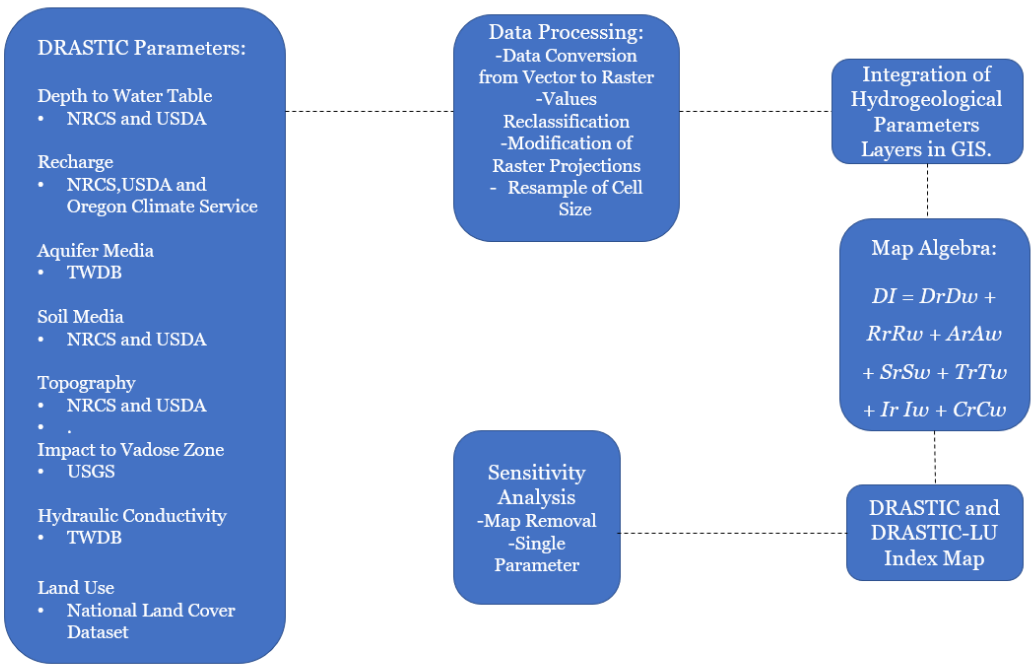

Figure 4.1. Flow Chart of the methodology followed to obtain the final DRASTIC vulnerability models.

Table 4.1. Results of DRASTIC Analysis show that most of the study area is located in areas with a moderate to very high risk of groundwater pollution.

DRASTIC Index Classification	**DRASTIC Range**	**Land Area**	**Land Area (%)**
Very Low	98-114	35,640 ha	5.25 %
Low	114-124	223,144 ha	32.87 %
Moderate	124-136	163,220 ha	24.04 %
High	136-149	115,900 ha	17.07 %
Very High	149-159	141,000 ha	20.77 %
Total Land Area		**678,904 ha**	**100 %**

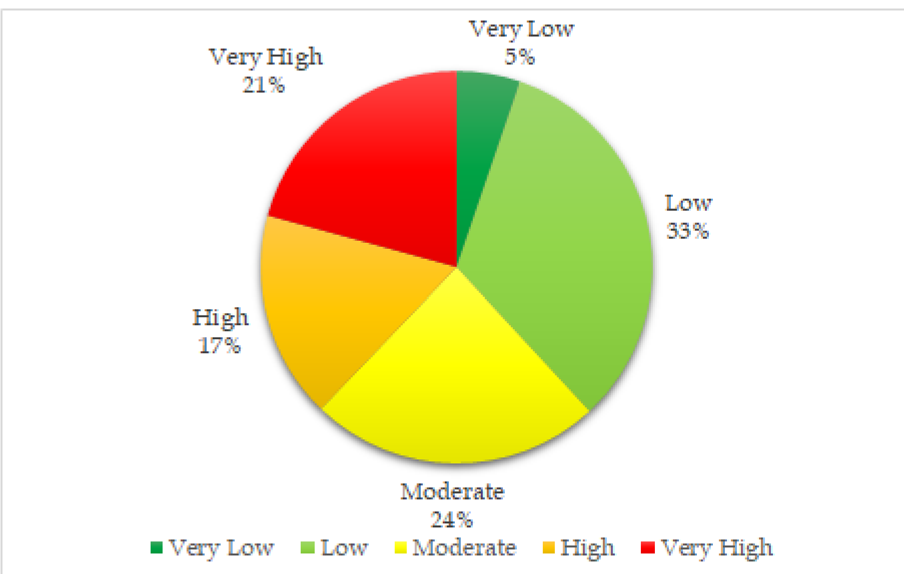

Figure 4.2. Pie Chart of the DRASTIC Vulnerability Index Results

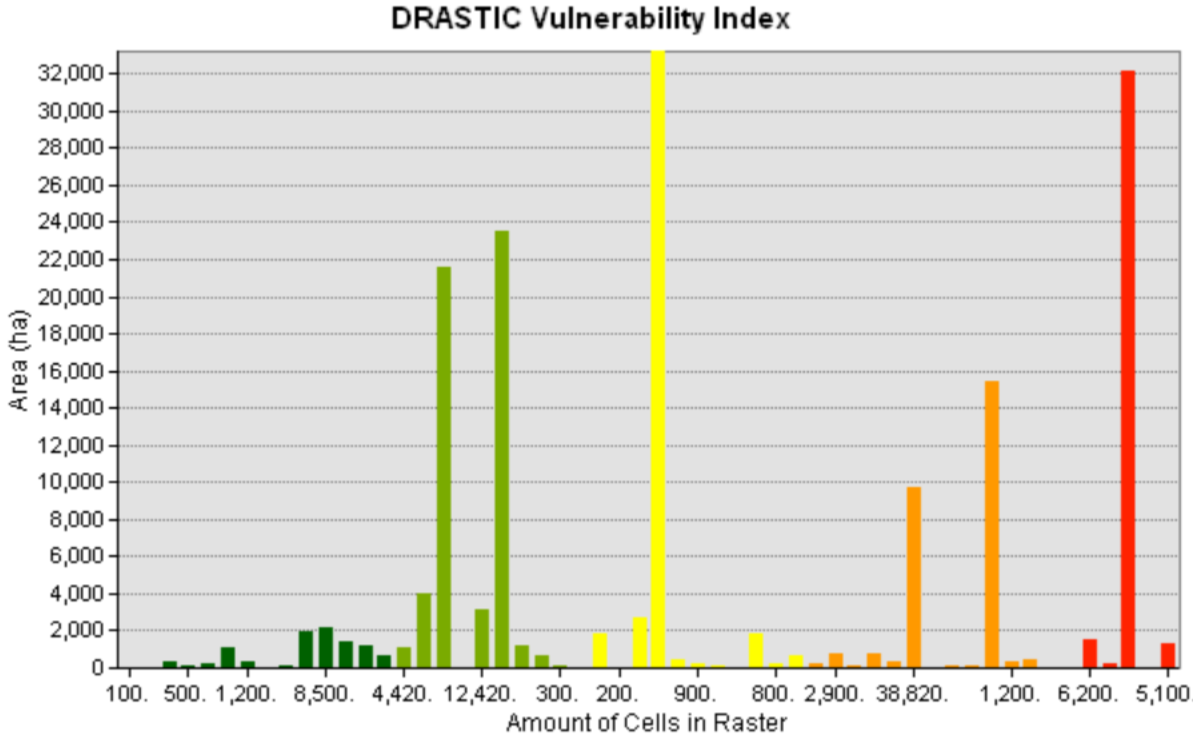

Figure 4.3. The histogram presented above shows the cell distribution of the obtained DRASTIC Index map. The X-axis is the number of cells that composed the raster, and the color of the bars denotes the vulnerability index category where each cell that compose the raster fall under. The y-axis denotes the total area (ha) for each cell size that composes the raster. For this model, most cells fall within the categories of moderate and very high.

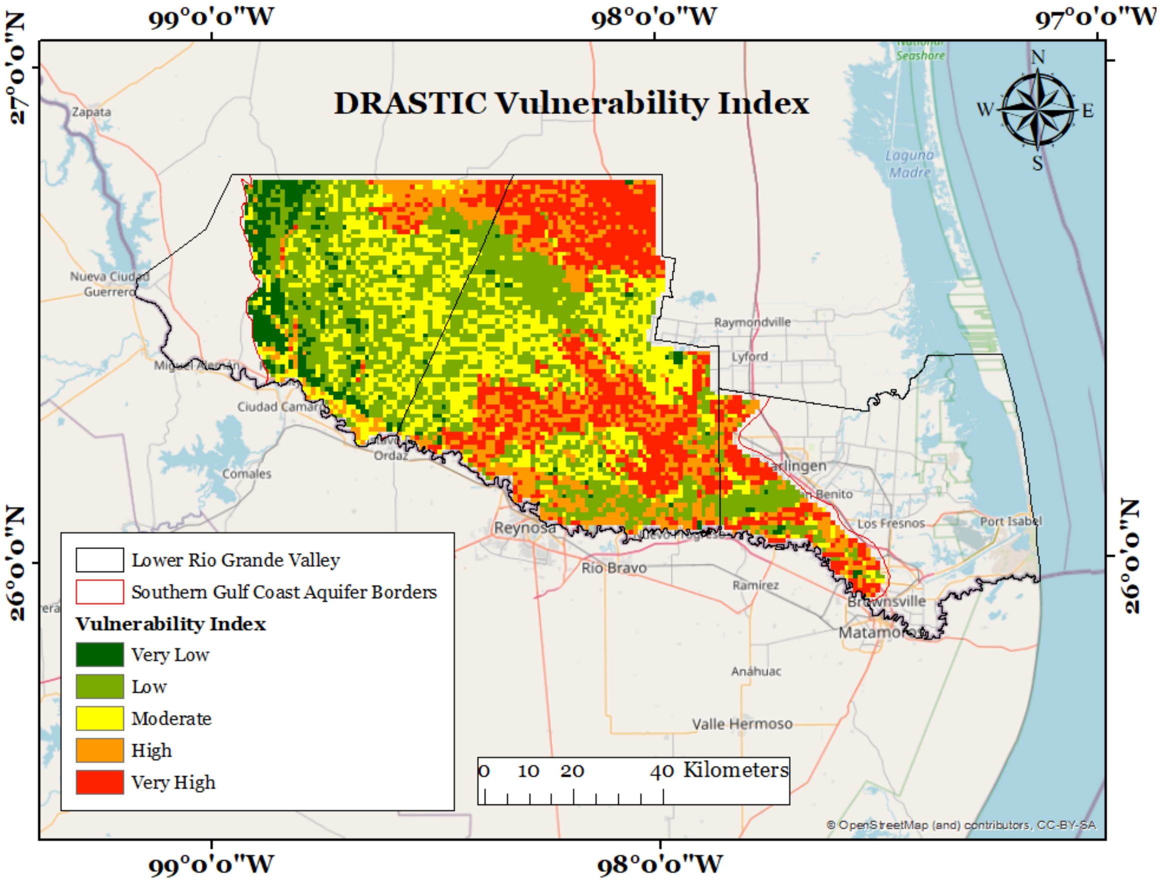

Figure 4.4. Final Vulnerability Index map obtained using the DRASTIC model by the Environmental Protection Agency. The map shows that the majority of Hidalgo County has a moderate to very high risk of groundwater contamination. Is especially worrisome since this is the most populated county in the Lower Rio Grande Valley.

4.2 Results of Modified DRASTIC Model

Since this region has a strong presence of factories as well as having a considerable amount of land being used for agricultural purposes, a modified version of the DRASTIC model was created as well, with the purpose of evaluating the potential impact that these anthropogenic activities can have over the regional groundwater resources. The DRASTIC-LU model contains the same seven hydrogeological parameters as the original DRASTIC model, the only difference is the addition of LU, which refers to Land Use, and has an effective weight of five and a ranking classification system just as the previous parameters and which can be seen in table 2.1.The resulting DRASTIC-LU map was created using the following equation:

$$DrDw + RrRw + ArAw + SrSw + TrTw + Ir\,Iw + CrCw + LrLw = DI\ (Pollution\ Potential)$$

Where L represents the LU parameter and just as the previous model presented the higher the index number, the higher the potential for groundwater contamination. The Land Use layer was obtained from the National Land Cover Dataset in raster format. Once the eight layers were obtained and ready to use, the same process to calculate the first model was executed, this means to input equation 2 in the raster calculator, where the ranked rasters were multiplied by the assigned weight. Then the resulting index map was divided into the five different risk categories. The modified GIS model is presented in figure 4 and the amount of land area and percentages of land area that fall into the five different risk categories are presented in table 4.2 and figure 4.3 Finally the resulting DRASTIC-LU vulnerability index map is shown in figure 4.4 In comparison to the results of the original DRASTIC model, the modified version shows that most of the study areas have a moderate to high risk of groundwater contamination, with 48.7 % of the land area falling within these two categories. Another cause of concern is that, although the land area with a very high risk of groundwater contamination is lesser in this model, most of it falls within the most populated Metropolitan Statistical Area of the study area, this being McAllen-Edinburg-Mission. This modified model has also lowered the potential of groundwater contamination from very high risk to mostly high and moderate to the northern portion of Hidalgo and Starr County on what is known as the STSS. Since this is a model that considers anthropogenic activities, it is apparent why the STSS has less risk of groundwater contamination in comparison to the original model since this is a mostly uninhabited area.

Table 4.2. Results of Modified DRASTIC Analysis

DRASTIC-LU Index Classification	**DRASTIC-LU Range**	**Land Area**	**% Of Land Area**
Very Low	109-142	87,560 ha	13.03 %
Low	142-156	162,544 ha	24.2 %
Moderate	156-171	183,880 ha	27.37 %
High	171-186	143,300 ha	21.33 %
Very High	186-211	94,580 ha	14.07 %
Total Land Area		**671,864 ha**	**100 %**

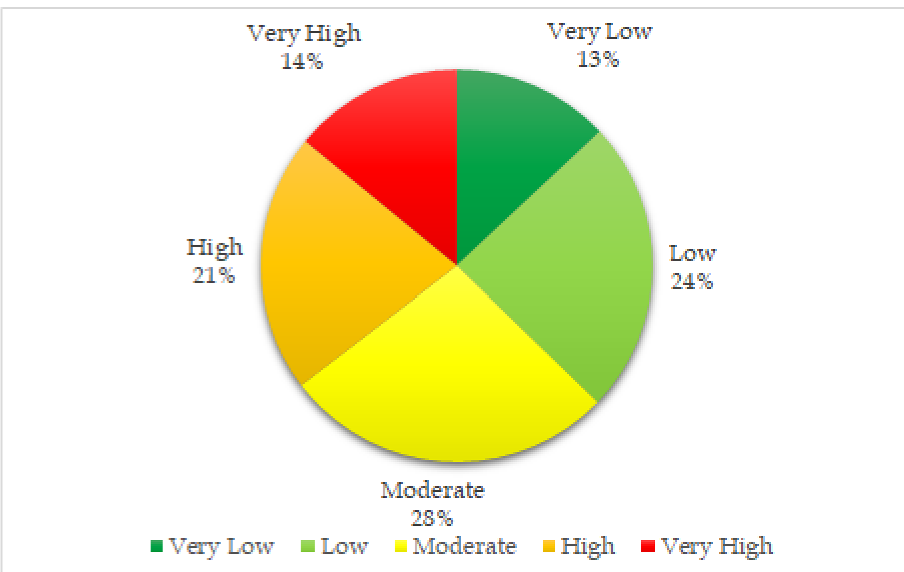

Figure 4.5. Pie Chart of the Modified DRASTIC Vulnerability Index Results

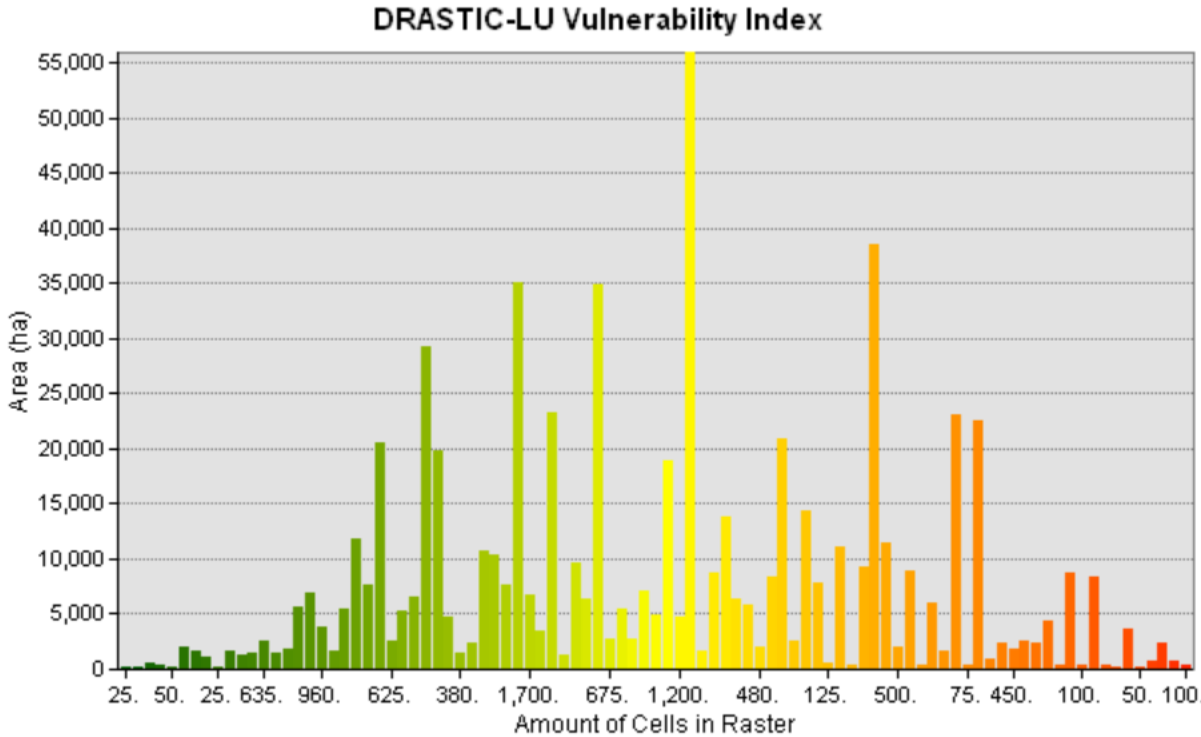

Figure 4.6. The histogram presented above shows the cell distribution of the obtained DRASTIC-LU Index map. The X-axis is the number of cells that composed the raster, and the color of the bars denotes the vulnerability index category where each cell that compose the raster fall under. The y-axis denotes the total area (ha) for each cell size that composes the raster. For this modified model, the distribution of the cells shows that most of them fall in the category of moderate and high risk.

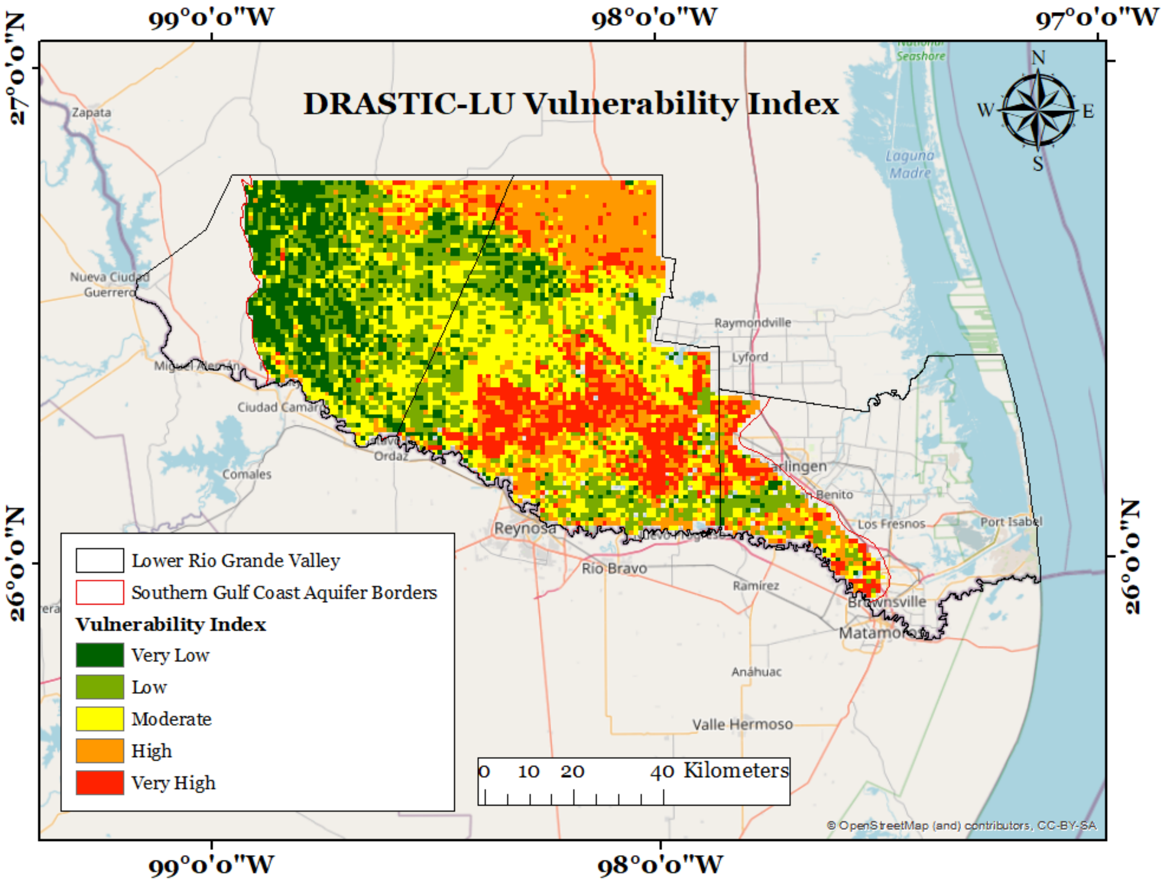

Figure 4.7 The resulting DRASTIC-LU vulnerability model lowers the risk of groundwater contamination for most of the study site. In comparison to the previous model this is because land use and anthropogenic activities are another parameter taken into consideration.

4.3 Cross-examination of DRASTIC Models with Landfills, Superfund Sites, Brownfields, Petroleum Storage Tanks, and IHWCA's

The two resulting vulnerability maps were overlayed with varied point data pertaining to the Texas Commission on Environmental Quality. The resulting cross-examination from figures 4.5 and 4.6 indicated that most of the landfills, brownfields and superfund sites within the study region are located on areas with a moderate to low risk of groundwater contamination.

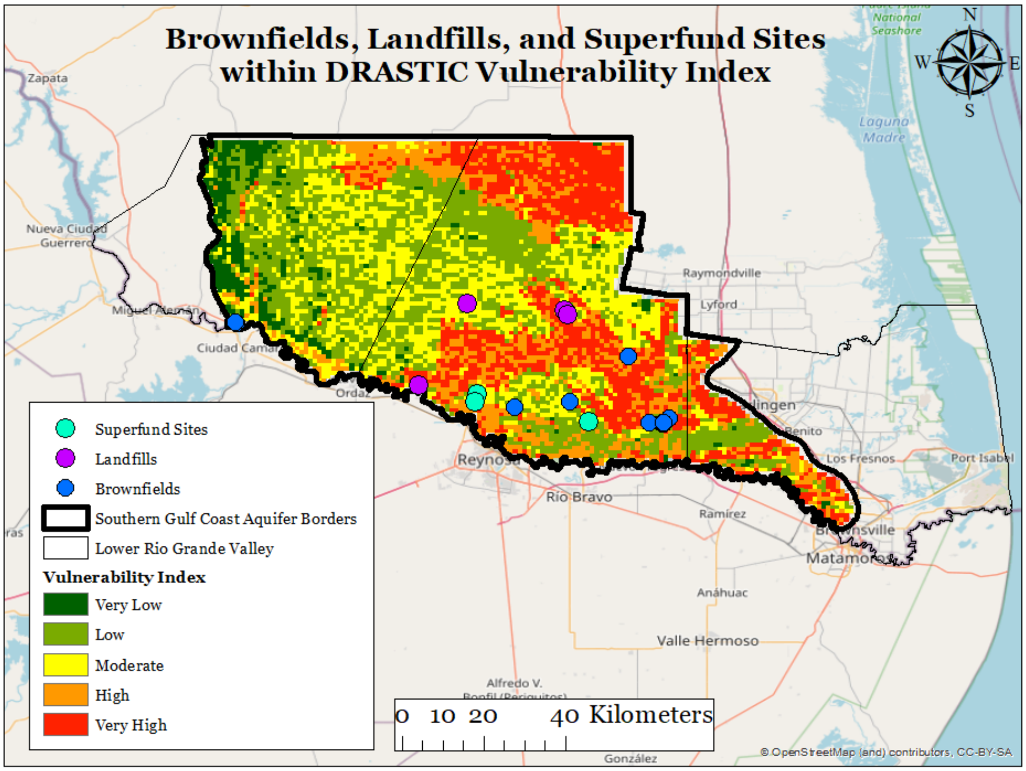

Figure 4.8. The overlay of the Texas Commission on Environmental Quality data with the resulting DRASTIC map indicated that most of these sites are in areas with a very low to moderate risk of groundwater contamination.

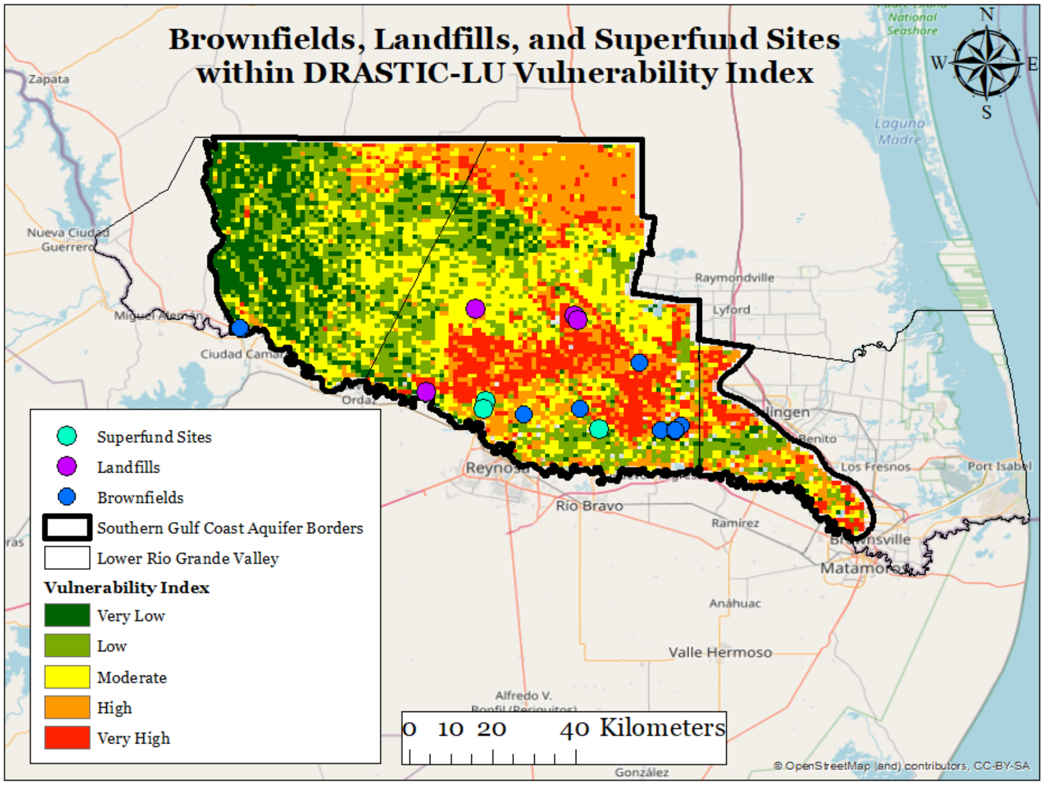

Figure 4.9. The cross-examination of the Texas Commission on Environmental Quality shows similar results as the previous figure with most of the containment sites located in areas with a very low to moderate risk of groundwater contamination.

The cross-examination shown in figures 4.7 and 4.8 consisted in overlying the obtained Vulnerability Index maps with Industrial and Hazardous Waste Corrective Actions (IHWCA)taking place inside the study area. The point data was obtained from the Texas Commission on Environmental Quality Data Hub. The resulting cross-examination denoted that most of the IHWCA occurring within the study region occur in areas with a moderate to very high risk of groundwater contamination.

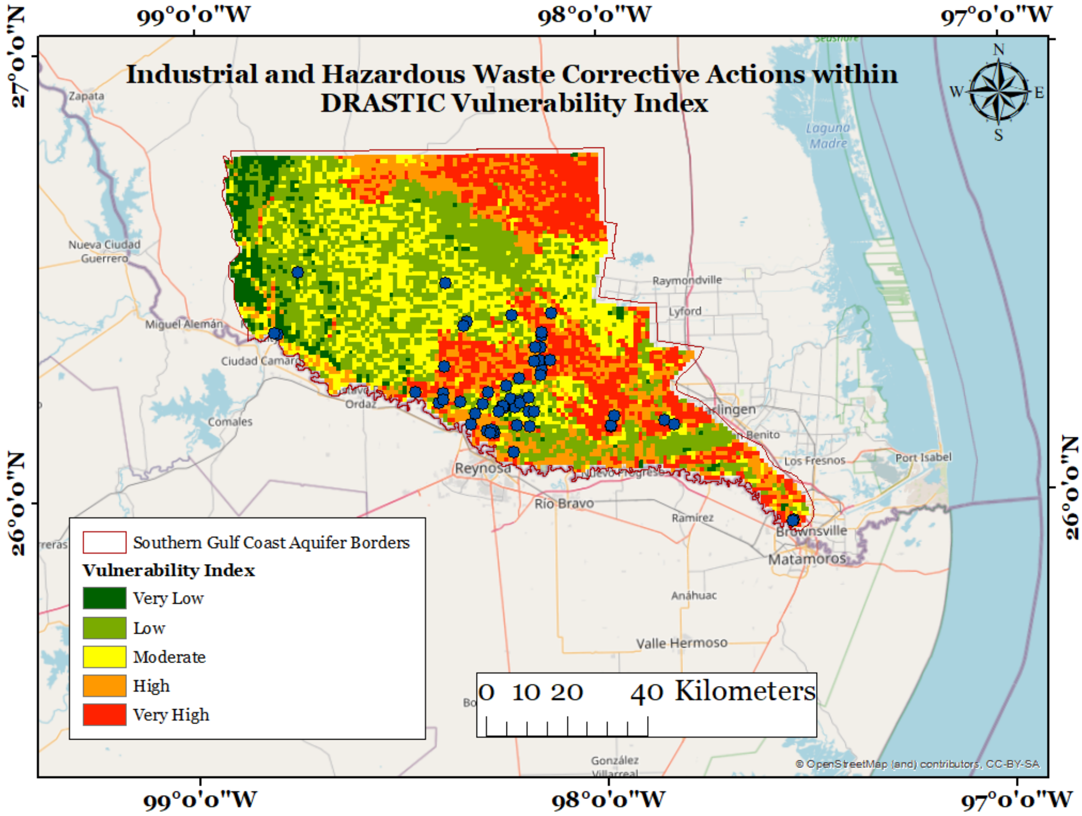

Figure 4.10. Cross-examination of IHWCA occurring within the study region occur within areas with a moderate to very high risk of groundwater contamination. Important to highlight that most of these actions are located within Hidalgo County.

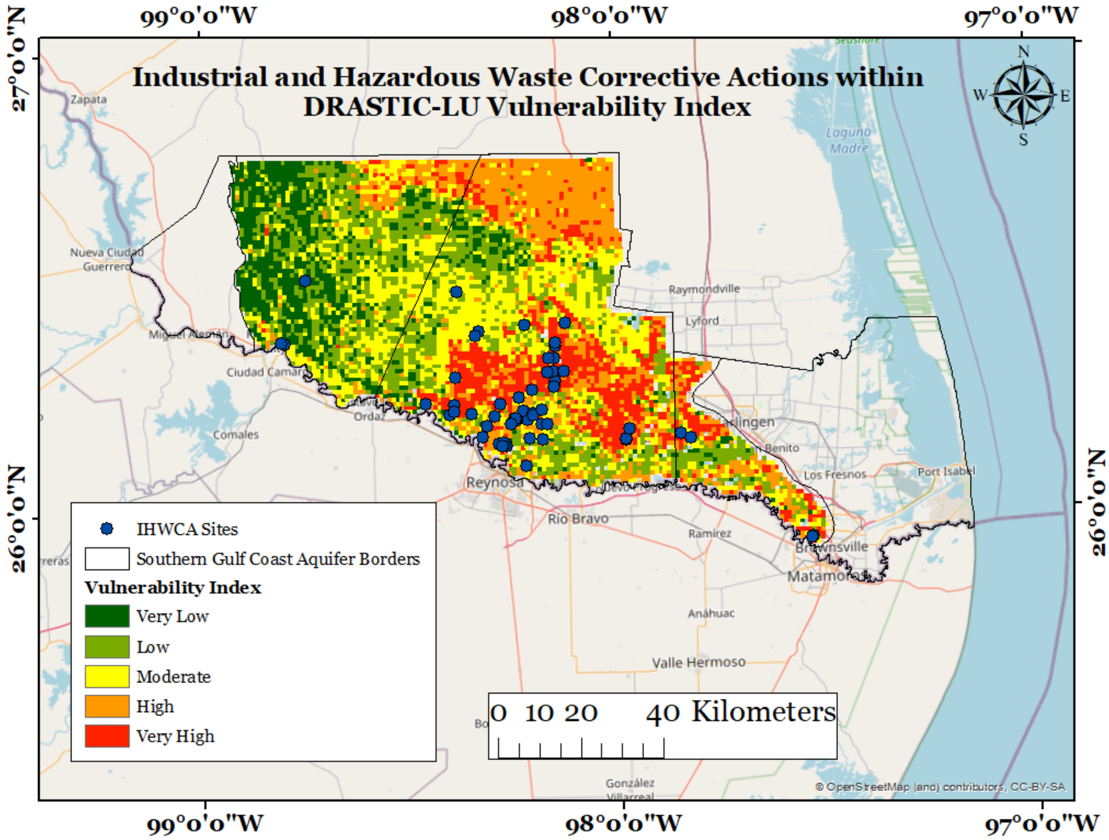

Figure 4.11. The resulting cross-examination of the IHWCA within the DRASTIC-LU map in areas with a moderate to very high risk of groundwater contamination.

The last cross-examinations shown in figures 4.9 and 4.10 consisted of overlaying both Vulnerability maps with the location of the Petroleum Storage Tanks located within the study area. The point data for the Petroleum Storage Tanks was obtained via the Texas Commission on Environmental Quality Data Hub. From the previous cross-examinations this is the most concerning because most of the Petroleum Storage Tanks are located in areas with a very high risk of groundwater contamination.

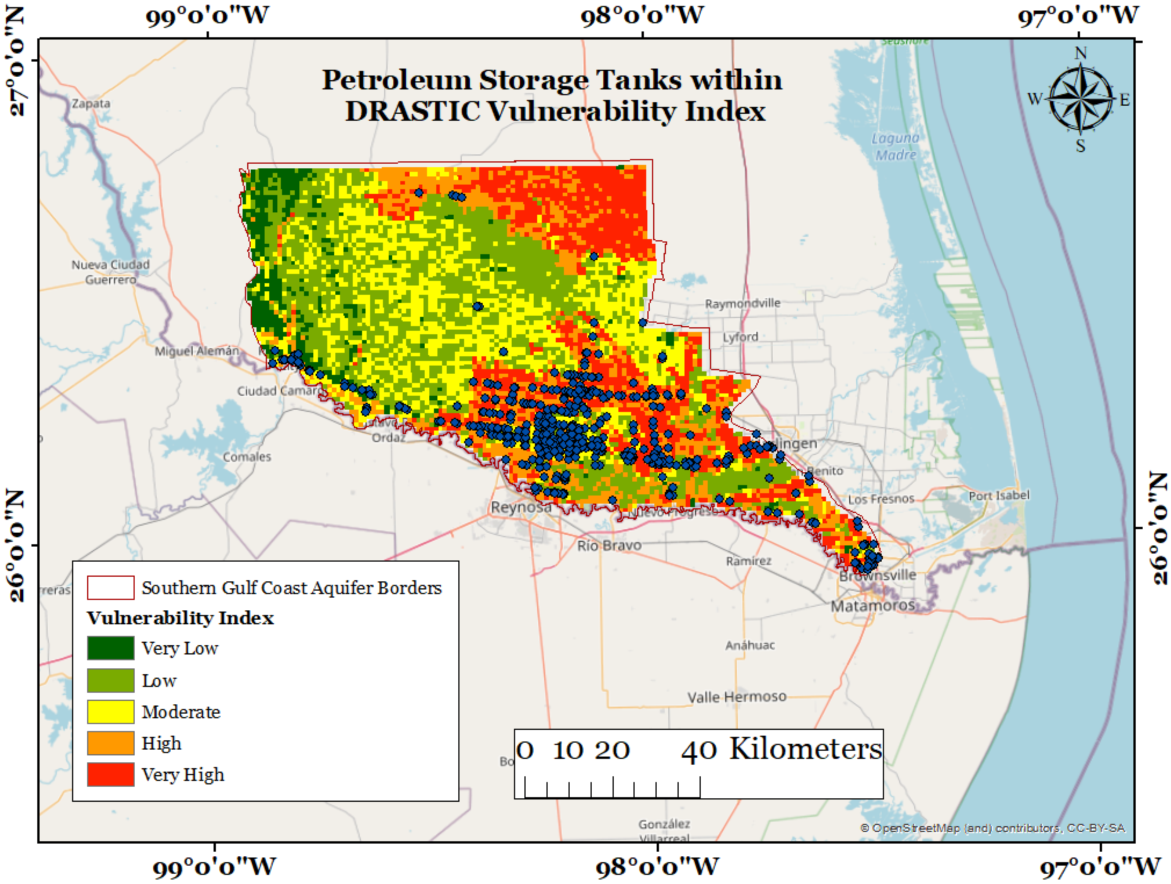

Figure 4.12. Cross-examination of the location of the Petroleum Storage Tanks with the DRASTIC vulnerability index indicated that the majority of these tanks fall within areas with a very high risk of groundwater contamination.

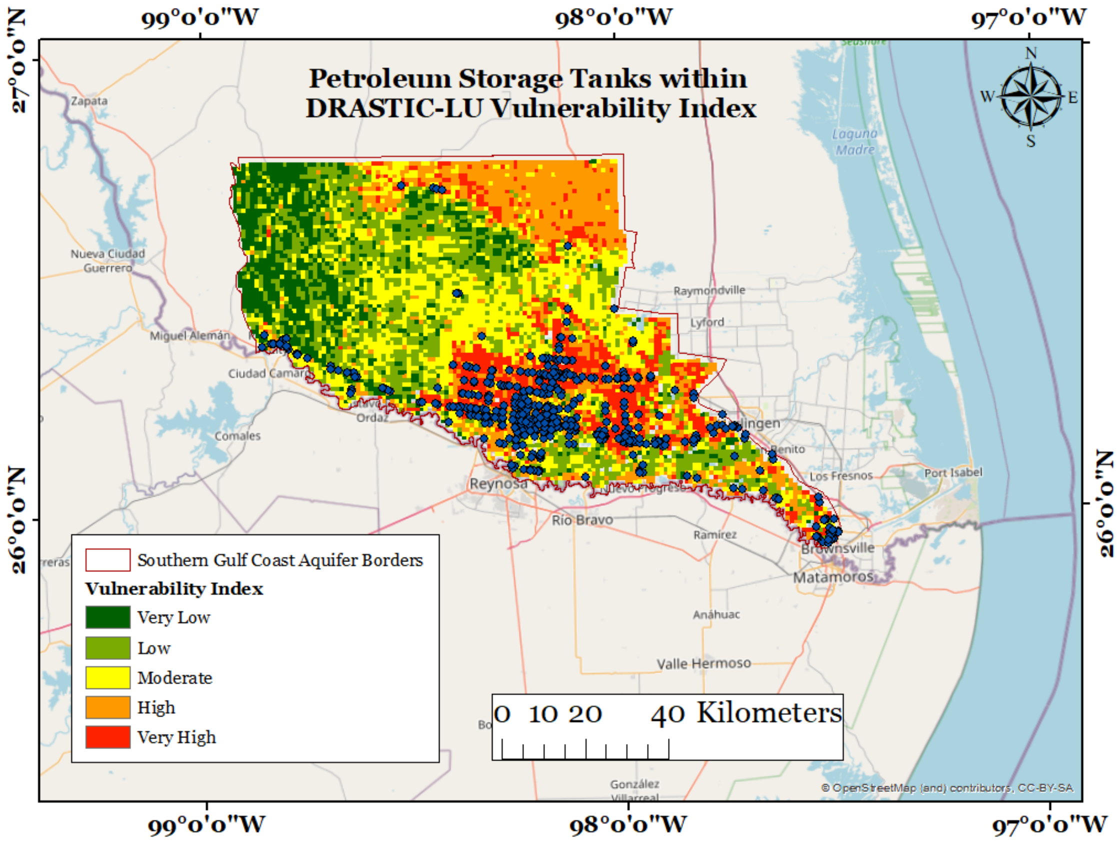

Figure 4.13. Cross-examination of the modified DRASTIC-LU map shown above illustrates that in the case of the modified DRASTIC model, the Petroleum Storage Tanks are in areas with a moderate to very high risk of groundwater contamination.

CHAPTER V

CONCLUSIONS

Groundwater has become one of the main sources of water to meet the growing demand for LRGV region. The resulting maps can serve as guidelines and assist local and state agencies in deciding what actions to take to protect local groundwater resources. The vulnerability assessments are intended to integrate complex hydrogeological data in a way that can be ready to use for the pertinent authorities as well as a tool to communicate technical data to the community. For this thesis project, two groundwater vulnerability models were used to assess how vulnerable the local groundwater resources are to contamination. It is important to highlight that publicly available dataset were used for the creation of the two groundwater vulnerability models presented in this thesis. The second model, a modified version of DRASTIC, was implemented to consider impacts from anthropogenic activities and land use. The areas that fall under each of the five vulnerability categories for the two models, DRASTIC and DRASTIC-LU, are presented in Tables 4.1 and 4.2. It is important to mention that the change in the vulnerability index range in the modified model was due to the extra parameter added. As an extra parameter (land use) was added, cell numbers in the modified DRASTIC model increased and thus the vulnerability index range. The results obtained for this model indicate that 38.12% of the study area is at a very low to low risk of groundwater contamination. The remaining 61.8% of the area has a moderate to very high risk of groundwater contamination (Table 4.1). The areas that fall within the latter category, were the areas characterized by having an aquifer media composed of coarse-grained sediments such as sands and gravels. Another critical factor was the impact of the vadose zone. The second model, DRASTIC-LU, indicated that 37.23% of the study area is at very low risk of groundwater contamination while the remaining 62.77% is in areas with a moderate to very high risk of groundwater contamination (Table 4.2). It is notable that the main difference in the results obtained from DRASTIC-LU model were that it lowered the risk of groundwater contamination to the region known as the South Texas Sand Sheet, located in the northeastern section of Hidalgo County. This reflects the limited anthropogenic activities as South Texas Sand Sheet (as known as “Wild Horse Desert”) is mostly uninhabited.

The results obtained from both models indicated a very similar distribution of the total amount of area that falls within the five categories of the DRASTIC vulnerability model. It is important to be mindful that although the resulting maps could be used as a guideline for future studies, however, there are limitations with the data implemented. One important factor possibly affecting the accuracy is the scale of the base maps. The level of details of datasets and different interpolation methods used to create DRASTIC parameter map layers can play an important role. Furthermore, future studies should implement validation methods to assess the influence that each parameter has over the resulting products to reduce possible bias since this is a qualitative model as well as to adjust the model according to the unique hydrogeological properties of this region. Finally, field investigations and ground-truthing can be a good complement to validate and ascertain the accuracy of the vulnerability rating.

REFERENCES

"2021 RIO GRANDE REGIONAL WATER PLAN." www.riograndewaterplan.org: Rio Grande Regional Water Planning Group, November 5, 2020.

Abdeslam, Ilhem, Chemseddine Fehdi, and Larbi Djabri. "Application of Drastic Method for Determining the Vulnerability of an Alluvial Aquifer: Morsott - El Aouinet North East of Algeria: Using Arcgis Environment." *Energy Procedia* 119 (July 2017): 308–17. https://doi.org/10.1016/j.egypro.2017.07.114.

Achilleos, G.A. "The Inverse Distance Weighted Interpolation Method and Error Propagation Mechanism – Creating a DEM from an Analogue Topographical Map." *Journal of Spatial Science* 56, no. 2 (December 2011): 283–304. https://doi.org/10.1080/14498596.2011.623348.

Ahirwar, Shobharam, and J. P. Shukla. "Assessment of Groundwater Vulnerability in Upper Betwa River Watershed Using GIS Based DRASTIC Model." *Journal of the Geological Society of India* 91, no. 3 (March 2018): 334–40. https://doi.org/10.1007/s12594-018-0859-0.

Alam, Fakhre, Rashid Umar, Shakeel Ahmed, and Farooq Ahmad Dar. "A New Model (DRASTIC-LU) for Evaluating Groundwater Vulnerability in Parts of Central Ganga Plain, India." *Arabian Journal of Geosciences* 7, no. 3 (December 22, 2012): 927–37. https://doi.org/10.1007/s12517-012-0796-y.

Ahmed, I.S.*, C.-L. Cheng, J., J.L. Gonzalez, J. Kang, J. Ho, and L. Soto-Sanchez, 2021, Groundwater Vulnerability Assessment of Shallow Aquifer in the South Texas Sand Sheet using a GIS-Based DRASTIC Model". Modeling Earth Systems and Environment (accepted, in press)

Aller, Linda, Truman Bennett, Jay Lehr, Rebecca Petty, and Glen Hackett. “DRASTIC: A Standardized System for Evaluating Ground Water Pollution Potential Using Hydrogeological Settings.” Environmental Protection Agency, June 1987.

Allouche, Nabila, Mohamed Maanan, Mona Gontara, Nicolas Rollo, Ikram Jmal, and Salem Bouri. “A Global Risk Approach to Assessing Groundwater Vulnerability.” *Environmental Modelling & Software* 88 (February 2017): 168–82. https://doi.org/10.1016/j.envsoft.2016.11.023.

Anaya, Roberto, Radu Boghici, Lawrence N. French, Ian Jones, Rima Petrossian, Cynthia Ridgeway, Jianyou Shi, Shirley Wade, and Andrew Weinberg. “Texas Aquifers Study.” www.twdb.texas.gov: Texas Water Development Board, December 31, 2016.

Arabgol, Raheleh, Majid Sartaj, and Keyvan Asghari. “Predicting Nitrate Concentration and Its Spatial Distribution in Groundwater Resources Using Support Vector Machines (SVMs) Model.” *Environmental Modeling & Assessment* 21, no. 1 (June 5, 2015): 71–82. https://doi.org/10.1007/s10666-015-9468-0.

Arispe y Acevedo, Baltazar. “The Geographic and Demographic Challenges to the Regional Institutionalization of the Texas Lower Rio Grande Valley.” *Norteamérica* 4, no. 2 (2012): 37–69. http://www.scielo.org.mx/scielo.php?script=sci_arttext&pid=S1870-35502009000200003.

Bezelgues, S., and E. des Garets. “Cartographie de La Vulnerabilite Des Nappes de Grande-Terre et de Marie-Galante (Guadeloupe).” Service Public du BRGM, November 2022.

Brindha, K., and L. Elango. “Cross Comparison of Five Popular Groundwater Pollution Vulnerability Index Approaches.” *Journal of Hydrology* 524 (May 2015): 597–613. https://doi.org/10.1016/j.jhydrol.2015.03.003.

Chenini, Ismail, Adel Zghibi, and Lamia Kouzana. “Hydrogeological Investigations and Groundwater Vulnerability Assessment and Mapping for Groundwater Resource Protection and Management: State of the Art and a Case Study.” *Journal of African Earth Sciences* 109 (September 2015): 11–26. https://doi.org/10.1016/j.jafrearsci.2015.05.008.

Choodarathnakara, A.L., T. Ashok Kumar, Shivaprakash Koliwad, and C.G. Patil. “Mixed Pixels: A Challenge in Remote Sensing Data Classification for Improving Performance.” *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)* 1, no. 9 (November 9, 2012): 261–71.

Chor Pang Lo, and Albert K W Yeung. *Concepts and Techniques of Geographic Information Systems*. Delhi Phi Learning Private Limited, 2014.

Chowdury, Ali, and Robert Mace. "Groundwater Resource Evaluation and Availability Model of the Gulf Coast Aquifer in the Lower Rio Grande Valley of Texas." www.twdb.texas.gov: Texas Water Development Board, June 2007.

Colins, Johnny, M. C. Sashikkumar, P. A. Anas, and M. Kirubakaran. "GIS-Based Assessment of Aquifer Vulnerability Using DRASTIC Model: A Case Study on Kodaganar Basin." *Earth Sciences Research Journal* 20, no. 1 (April 30, 2016): 1–8. https://doi.org/10.15446/esrj.v20n1.52469.

Congalton, Russell. "Exploring and Evaluating the Consequences of Vector-To-Raster and Raster-To-Vector Conversion." American Society for Photogrammetry and Remote Sensing: Photogrammetric Engineering & Remote Sensing, April 7, 1997.

Doucette, Peter, and Kate Beard. "Exploring the Capability of Some GIs Surface Interpolators for DEM Gap Fill." American Society for Photogrammetry and Remote Sensing: Photogrammetric Engineering & Remote Sensing, July 7, 2000.

Firat Ersoy, Arzu, and Fatma Gültekin. "DRASTIC-Based Methodology for Assessing Groundwater Vulnerability in the Gümüşhacıköy and Merzifon Basin (Amasya, Turkey)." *EARTH SCIENCES RESEARCH JOURNAL Earth Sci. Res. SJ* 17, no. 1 (2013): 33–40.

Foster, S. S. D., and P. J. Chilton. "Groundwater: The Processes and Global Significance of Aquifer Degradation." Edited by M. Falkenmark and C. Folke. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences* 358, no. 1440 (November 5, 2003): 1957–72. https://doi.org/10.1098/rstb.2003.1380.

Foster, Stephen, John Chilton, Geert-Jan Nijsten, and Andrea Richts. "Groundwater—a Global Focus on the 'Local Resource.'" *Current Opinion in Environmental Sustainability* 5, no. 6 (December 2013): 685–95. https://doi.org/10.1016/j.cosust.2013.10.010.

Foster, Stephen, Ricardo Hirata, and Bartolome Andreo. "The Aquifer Pollution Vulnerability Concept: Aid or Impediment in Promoting Groundwater Protection?" *Hydrogeology Journal* 21, no. 7 (July 26, 2013): 1389–92. https://doi.org/10.1007/s10040-013-1019-7.

Frind, E.O., J.W. Molson, and D.L. Rudolph. "Well Vulnerability: A Quantitative Approach for Source Water Protection." *Ground Water* 0, no. 0 (July 7, 2006): 060707065613004-??? https://doi.org/10.1111/j.1745-6584.2006.00230.x.

Fritch, Todd G., Cleavy L. McKnight, Joe C. Yelderman Jr., and Jeff G. Arnold. "An Aquifer Vulnerability Assessment of the Paluxy Aquifer, Central Texas, USA, Using GIS and a Modified DRASTIC Approach." *Environmental Management* 25, no. 3 (March 30, 2000): 337–45. https://doi.org/10.1007/s002679910026.

Ghouili, Nesrine, Faten Jarraya-Horriche, Fadoua Hamzaoui-Azaza, and Mohamed Faouzi Zaghrarni. "Groundwater Vulnerability Mapping Using the Susceptibility Index (SI) Method: Case Study of Takelsa Aquifer, Northeastern Tunisia." *Journal of African Earth Sciences* 173 (November 20, 2020).

Gogu, R. C., and A. Dassargues. "Current Trends and Future Challenges in Groundwater Vulnerability Assessment Using Overlay and Index Methods." *Environmental Geology* 39, no. 6 (April 18, 2000): 549–59. https://doi.org/10.1007/s002540050466.

Hamza, S. M., A. Ahsan, M. A. Imteaz, A. Rahman, T. A. Mohammad, and A. H. Ghazali. "Accomplishment and Subjectivity of GIS-Based DRASTIC Groundwater Vulnerability Assessment Method: A Review." *Environmental Earth Sciences* 73, no. 7 (August 23, 2014): 3063–76. https://doi.org/10.1007/s12665-014-3601-2.

Jarray, Hanen, Mounira Zammouri, Mohamed Ouessar, Fadoua Hamzaoui-Azaza, Manuela Barbieri, Ammar Zerrim, Albert Soler, and Houcine Yahyaoui. "Groundwater Vulnerability Based on GIS Approach: Case Study of Zeuss-Koutine Aquifer, South-Eastern Tunisia." *Geofisica Internacional* 56 (April 1, 2017): 157–72.

Jha, Madan K., Alivia Chowdhury, V. M. Chowdary, and Stefan Peiffer. "Groundwater Management and Development by Integrated Remote Sensing and Geographic Information Systems: Prospects and Constraints." *Water Resources Management* 21, no. 2 (June 29, 2006): 427–67. https://doi.org/10.1007/s11269-006-9024-4.

Johnson, J. Michael, and Keith C. Clarke. "An Area Preserving Method for Improved Categorical Raster Resampling." *Cartography and Geographic Information Science*, April 15AD, 2–13. https://doi.org/https://doi.org/10.1080/15230406.2021.1892531.

Kumar, Akshay, and Akhouri Pramod Krishna. "Groundwater Vulnerability and Contamination Risk Assessment Using GIS-Based Modified DRASTIC-LU Model in Hard Rock

Aquifer System in India.” *Geocarto International*, December 10, 2018, 1–30. https://doi.org/10.1080/10106049.2018.1557259.

Levine, G. “The Lower Rio Grande Valley: A Case Study of a Water Market Area.” *Paddy and Water Environment* 5, no. 4 (October 13, 2007): 279–84. https://doi.org/10.1007/s10333-007-0091-9.

Lewis, Ron. SB1, Pub. L. No. 1 (1997). https://capitol.texas.gov/billlookup/Text.aspx?LegSess=75R&Bill=SB1.

Malakootian, Mohammad, and Majid Nozari. “GIS-Based DRASTIC and Composite DRASTIC Indices for Assessing Groundwater Vulnerability in the Baghin Aquifer, Kerman, Iran.” *Natural Hazards and Earth System Sciences* 20, no. 8 (August 26, 2020): 2351–63. https://doi.org/10.5194/nhess-20-2351-2020.

Maqsoom, Ahsen, Bilal Aslam, Umer Khalil, Omid Ghorbanzadeh, Hassan Ashraf, Rana Faisal Tufail, Danish Farooq, and Thomas Blaschke. “A GIS-Based DRASTIC Model and an Adjusted DRASTIC Model (DRASTICA) for Groundwater Susceptibility Assessment along the China–Pakistan Economic Corridor (CPEC) Route.” *ISPRS International Journal of Geo-Information* 9, no. 5 (May 19, 2020): 332. https://doi.org/10.3390/ijgi9050332.

Masetti, Marco, Simone Poli, Simone Sterlacchini, Giovanni P. Beretta, and Arianna Facchi. “Spatial and Statistical Assessment of Factors Influencing Nitrate Contamination in Groundwater.” *Journal of Environmental Management* 86, no. 1 (January 2008): 272–81. https://doi.org/10.1016/j.jenvman.2006.12.023.

Mayer, John, Andrea Croskrey, Matthew Wise, and Sanjeev Kalaswad. “Brackish Groundwater in the Gulf Coast Aquifer, Lower Rio Grande Valley, Texas.” www.twdb.texas.gov: Texas Water Development Board, September 2014.

Merchant, James. “GIS-Based Gtoundwater Pollution Hazad Assessment: A Critical Review of the DRASTIC Model,” 1994.

Moraru, Constantin, and Robyn Hannigan. “Overview of Groundwater Vulnerability Assessment Methods.” *Springer Hydrogeology*, December 2, 2017, 1–16. https://doi.org/10.1007/978-3-319-70960-4_1.

Nace, Raymond L. “Scientific Framework of World Water Balance.” *Journal of Hydrology* 14, no. 3–4 (December 1971): 355–56. https://doi.org/10.1016/0022-1694(71)90053-9.

National Research Council 1993. Ground Water Vulnerability Assessment: Predicting Relative Contamination Potential Under Conditions of Uncertainty. Washington, DC: The National Academies Press. https://doi.org/10.17226/2050.

Nobre, R.C.M., O.C. Rotunno Filho, W.J. Mansur, M.M.M. Nobre, and C.A.N. Cosenza. "Groundwater Vulnerability and Risk Mapping Using GIS, Modeling and a Fuzzy Logic Tool." *Journal of Contaminant Hydrology* 94, no. 3–4 (December 2007): 277–92. https://doi.org/10.1016/j.jconhyd.2007.07.008.

Noori, Roohollah, Hooman Ghahremanzadeh, Bjørn Kløve, Jan Franklin Adamowski, and Akbar Baghvand. "Modified-DRASTIC, Modified-SINTACS and SI Methods for Groundwater Vulnerability Assessment in the Southern Tehran Aquifer." *Journal of Environmental Science and Health, Part A* 54, no. 1 (December 30, 2018): 89–100. https://doi.org/10.1080/10934529.2018.1537728.

Osaragi, Toshihiro. "Classification Methods for Spatial Data Representation," n.d. Accessed November 20, 2021.

Piscopo, Gennaro. "Groundwater Vulnerability Map Explanatory Notes." Centre for Natural Resources, August 2001.

Pollicino, Licia C., Marco Masetti, Stefania Stevenazzi, Agata Cristaldi, Chiara Righetti, and Maurizio Gorla. "Multi-Aquifer Susceptibility Analyses for Supporting Groundwater Management in Urban Areas." *Journal of Contaminant Hydrology* 238 (March 2021): 103774. https://doi.org/10.1016/j.jconhyd.2021.103774.

Reedy, Robert C., Bridget Scanlon, Steven Walden, and Gil Strassberg. "Naturally Occurring Groundwater Contamination in Texas." www.twdb.texas.gov: Texas Water Development Board, 2011.

Richey, Alexandra S., Brian F. Thomas, Min-Hui Lo, James S. Famiglietti, Sean Swenson, and Matthew Rodell. "Uncertainty in Global Groundwater Storage Estimates in a T Otal G Roundwater S Tress Framework." *Water Resources Research* 51, no. 7 (July 2015): 5198–5216. https://doi.org/10.1002/2015wr017351.

Schwartz, F. W., and M. Ibaraki. "Groundwater: A Resource in Decline." *Elements* 7, no. 3 (June 1, 2011): 175–79. https://doi.org/10.2113/gselements.7.3.175.

Secunda, S, M.L Collin, and A.J Melloul. "Groundwater Vulnerability Assessment Using a Composite Model Combining DRASTIC with Extensive Agricultural Land Use in

Israel's Sharon Region." *Journal of Environmental Management* 54, no. 1 (September 1998): 39–57. https://doi.org/10.1006/jema.1998.0221.

Shirazi, S.M., H.M. Imran, and Shatirah Akib. "GIS-Based DRASTIC Method for Groundwater Vulnerability Assessment: A Review." *Journal of Risk Research* 15, no. 8 (September 2012): 991–1011. https://doi.org/10.1080/13669877.2012.686053.

Shirazi, S. M., H. M. Imran, S. Akib, Zulkifli Yusop, and Z. B. Harun. "Groundwater Vulnerability Assessment in the Melaka State of Malaysia Using DRASTIC and GIS Techniques." *Environmental Earth Sciences* 70, no. 5 (April 10, 2013): 2293–2304. https://doi.org/10.1007/s12665-013-2360-9.

Shrestha, Sangam, Ranjana Kafle, and Vishnu Prasad Pandey. "Evaluation of Index-Overlay Methods for Groundwater Vulnerability and Risk Assessment in Kathmandu Valley, Nepal." *Science of the Total Environment* 575 (January 2017): 779–90. https://doi.org/10.1016/j.scitotenv.2016.09.141.

Siebert, S., J. Burke, J. M. Faures, K. Frenken, J. Hoogeveen, P. Döll, and F. T. Portmann. "Groundwater Use for Irrigation – a Global Inventory." *Hydrology and Earth System Sciences* 14, no. 10 (October 12, 2010): 1863–80. https://doi.org/10.5194/hess-14-1863-2010.

Smith, W. Benjamin, Gretchen R. Miller, and Zhuping Sheng. "Assessing Aquifer Storage and Recovery Feasibility in the Gulf Coastal Plains of Texas." *Journal of Hydrology: Regional Studies* 14 (December 2017): 92–108. https://doi.org/10.1016/j.ejrh.2017.10.007.

Sophocleous, Marios. "Interactions between Groundwater and Surface Water: The State of the Science." *Hydrogeology Journal* 10, no. 1 (January 11, 2002): 52–67. https://doi.org/10.1007/s10040-001-0170-8.

Sorichetta, Alessandro, Cristiano Ballabio, Marco Masetti, Gilpin R. Robinson, and Simone Sterlacchini. "A Comparison of Data-Driven Groundwater Vulnerability Assessment Methods." *Groundwater* 51, no. 6 (January 3, 2013): 866–79. https://doi.org/10.1111/gwat.12012.

Strauch, Gerhard, Monika Möder, Rainer Wennrich, Karsten Osenbrück, Hans-Reinhard Gläser, Timo Schladitz, Claudia Müller, Kristin Schirmer, Frido Reinstorf, and Mario Schirmer. "Indicators for Assessing Anthropogenic Impact on Urban Surface and Groundwater."

Journal of Soils and Sediments 8, no. 1 (June 12, 2007): 23–33. https://doi.org/10.1065/jss2007.06.234.

Stubbs, Megan, M. Edward Rister, Ronald Lacewell, John Ellis, Allen Sturdivant, John R.C. Robinson, and Linda Fernandez. “Evolution of Irrigation Districts and Operating Institutions: Texas, Lower Rio Grande Valley.” Texas Water Resources Institute, July 2003.

US EPA. “National Overview: Facts and Figures on Materials, Wastes and Recycling | US EPA.” US EPA. US EPA, October 26, 2018. https://www.epa.gov/facts-and-figures-about-materials-waste-and-recycling/national-overview-facts-and-figures-materials.

US EPA, OLEM. “Municipal Solid Waste Landfills | US EPA.” US EPA, September 13, 2018. https://www.epa.gov/landfills/municipal-solid-waste-landfills#whatis.

Vu, Tien-Duc, Chuen-Fa Ni, Wei-Ci Li, Minh-Hoang Truong, and Shaohua Marko Hsu. “Predictions of Groundwater Vulnerability and Sustainability by an Integrated Index-Overlay Method and Physical-Based Numerical Model.” *Journal of Hydrology* 596 (May 2021): 126082. https://doi.org/10.1016/j.jhydrol.2021.126082.

Wachniew, Przemysław, Anna J. Zurek, Christine Stumpp, Alexandra Gemitzi, Alessandro Gargini, Maria Filippini, Kazimierz Rozanski, Jessica Meeks, Jens Kværner, and Stanislaw Witczak. “Toward Operational Methods for the Assessment of Intrinsic Groundwater Vulnerability: A Review.” *Critical Reviews in Environmental Science and Technology* 46, no. 9 (March 10, 2016): 827–84. https://doi.org/10.1080/10643389.2016.1160816.

Wada, Yoshihide, Ludovicus P. H. van Beek, Cheryl M. van Kempen, Josef W. T. M. Reckman, Slavek Vasak, and Marc F. P. Bierkens. “Global Depletion of Groundwater Resources.” *Geophysical Research Letters* 37, no. 20 (October 2010): n/a-n/a. https://doi.org/10.1029/2010gl044571.

Zghibi, Adel, Amira Merzougui, Ismail Chenini, Karim Ergaieg, Lahcen Zouhri, and Jamila Tarhouni. “Groundwater Vulnerability Analysis of Tunisian Coastal Aquifer: An Application of DRASTIC Index Method in GIS Environment.” *Groundwater for Sustainable Development* 2–3 (August 2016): 169–81. https://doi.org/10.1016/j.gsd.2016.10.001.

BIOGRAPHICAL SKETCH

Leslie was born and raised in Matamoros, Mexico. She graduated from the University of Texas Rio Grande Valley, Brownsville Campus with an undergraduate degree in Environmental Science, with a concentration in Geology, in December 2016. She received her master's degree from the University of Texas Rio Grande Valley in the fall of 2021. She can be reached via email at leslie.a.soto93@gmail.com for any questions.