ESTIMATION OF *E. COLI* CONCENTRATIONS FROM FAILING ON-SITE WASTEWATER TREATMENT FACILITIES (OWTS) USING GIS

A Thesis

by

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ABSTRACT

Failing Onsite Wastewater Treatment Systems (OWTSs) have been identified as a significant threat to water quality, discharging significant amounts of inadequately treated sewage effluents. When developing a Watershed Protection Plan (WPP), OWTS has often been difficult to assess due to technological, institutional and economic constraints. In Texas, contamination from bacterial pathogens is the primary source in water quality concern. According to the 2012 Texas Water Quality Inventory, the Dickinson Bayou watershed is listed as "impaired", due to bacteria. Since the bacterial levels in this watershed are not meeting the State's recreation standards, actions are needed to improve the water quality. Poorly designed and maintained OWTS, along with inappropriate site characterization are major contributors of the bacteria in this watershed. The majority of the OWTS located in Dickinson Bayou are located in poorly drained soils increasing the likelihood of contaminated runoff into the surface waters. A prediction tool was developed using Geographic Information System (GIS) to assess failing OWTS and the potential *E. coli* contamination to surface waters. This tool will help identify different parameters affecting *E. coli* concentration in streams, which include: rainfall conditions, spatial connections of OWTS to stream network, age of the OWTS, and the failure rate of the OWTS.

A spatially-explicit algorithm was developed to estimate *E. coli* concentrations in watersheds resulting from failing OWTS, and implemented using ArcGIS 10. Spatial analysis of accumulated *E. coli* concentrations in streams was made possible by GIS. The algorithm was automated using python programming language, ArcPy, to simulate *E. coli* concentrations in surface waters in a coastal Texas watershed for different rainfall conditions.

This automated tool simulated potential *E. coli* loads and concentrations from failing OWTS across the Dickinson Bayou watershed in Texas. The tool was validated using observed runoff data in the Dickinson Bayou watershed. The highest potential *E. coli* loads were identified and the areas of concern were highlighted to more effectively apply Best Management Practices (BMPs). Results concluded that precipitation played a significant role in routing the *E. coli* loads to streams in the watershed. The potential *E. coli* concentration in streams decreased with increasing rainfall amount. Also, the simulation results showed the number of household size and the number of OWTS plays a major role in *E. coli* contribution in the watershed. The age of the OWTS and the hydrologic connectivity of those failing systems should be considered while simulating the *E. coli* concentrations in the stream. Regulators, planners, and watershed managers to make timely management decisions can use results from this automated tool.

DEDICATION

To my mother and father.

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Most importantly, I would like to thank my family: my parents, to whom this thesis is dedicated to, Shiraz Virani and Minaz Virani, have been a constant source of love, concern, support and strength throughout my educational journey. They never had a doubt in my capabilities and provided to me the resources to reach higher goals. My sister, Afeefa Virani, who has always encouraged me, always believed in me, always taught me to keep true, to believe in myself and to always reach higher goals. My little brother, Adam Virani, whose constant smiles and belief in me made all this hard work worth it. My aunt, Shehnaz Narula, who has supported me tremendously throughout my graduate studies like a mother. Finally, I would like to thank my best friend, Shylean Keshwani, who has helped me stay sane through these difficult years. All of their support and care helped me overcome setback and stay focused on my graduate study.

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CHAPTER I

INTRODUCTION

1.1 Introduction

Pathogens are the leading cause of impairment in US water bodies (Figure 1.1). Waterborne pathogens that cause diseases are of critical concern for water resource managers. Once pathogens enter a water body, pathogens can infect humans through skin contact, ingestion of water, and through contaminated fish and shellfish (Arnone et al., 2007). In Texas, Escherichia *coli* (*E. coli)* is used as an indicator organism of fecal contamination. When the concentration of *E. coli* exceeds the regulatory standards, the stream is listed as "impaired" as a result of fecal contamination. To address this issue of impairment in the water bodies of Texas, a simple and accurate model is needed that would simulate the bacterial load and transport for developing the Watershed Protection Plan (WPP) or Total Maximum Daily Load (TMDL). The TMDL is the maximum load of a pollutant, resulting from point and nonpoint sources within a watershed, meeting the regulatory water quality standards (TCEQ, 2009). Developing and implementing a TMDL is very costly; the average national cost per water body has been estimated around \$52,000, and can typically range from \$26,000 to more than \$500,000 depends upon the complexity and the extent of the severity (USEPA, 2001b). A substantial amount of time is also spent when developing a TMDL to identify the potential sources and allocate loads.

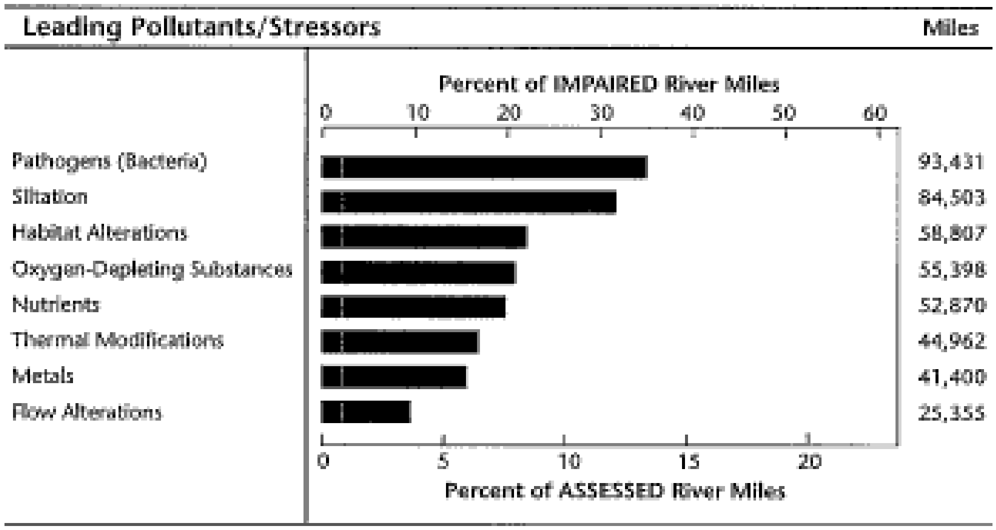

Figure 1.1 Leading pollutants/stressors in impaired rivers and streams (TCEQ, 2009).

When developing Watershed Protection Plans (WPPs) or TMDLs, On-site wastewater Treatment Systems (OWTS) have often been difficult to assess due to technological and economic constraints (Ursin et al., 2008). Onsite Wastewater Treatment Systems (OWTS) are widely used in residential areas in which houses are not connected to centralized wastewater treatment systems. Presently there are at least three types OWTS that are being used: conventional septic systems, aerobic treatment units (ATU), and the mound systems. The conventional septic system utilizes a septic tank, a soil absorption field, gravity to move wastewater through this system, and treats wastewater in the process (Gregory et al., 2013). The aerobic treatment units (ATU) have a spray distribution that pretreats the waste using aerobic digestion, settling, and disinfection to spray the treated wastewater (Gregory et al., 2013). The mound system uses similar mechanisms as the conventional system with a presence of mounding soil on the surface, which allows the drainpipes to be buried in soil. This system can be used to alleviate unsuitable conditions in the leach field (Forbis-Stokes et al., 2013). Effectiveness of these systems is highly dependent on the soil type and depth to the groundwater table (Forbis-Stokes et al., 2013).

Soil based OWTS serve between 20 and 25% of the households in the United States (US Census Bureau 2007; USEPA, 2013). If these systems are properly executed and maintained, they can prove to be a very valuable source for protecting public health, and maintaining economic vitality in the community. Unfortunately, in most cases, once systems are installed, they are generally forgotten about (USEPA, 2013). Around 7% of the housing units use OWTS in larger communities of more than 10,000 people, and the remaining 93% are connected to the public sewer. However, in small communities of less than 10,000 people, around 61% of the housing units use OWTS for their wastewater disposal (US Census Bureau, 2011).

The rise in urbanization along with improper site characterization and maintenance has resulted in failing OWTSs in several states (Carroll et al., 2005). Failing OWTSs have been identified as a significant threat to water quality, discharging significant amounts of inadequately treated sewage effluent (Meile et al., 2009). This contamination in groundwater and surface water implies direct discharge from the OWTS to the waters, or a failure in the system because of poor design, location, age, soil type, and the lack of its maintenance (Withers et al., 2011). Contamination of water resources from OWTS is of crucial concern because of the health risks they pose and the degradation of drinking and recreational water resources. This is due to the high concentrations of nutrients and potential pathogens (Reneau et al., 1989, Wilhelm et al., 1994 and Kay et al., 2008). Other effects of this contamination include surfacing effluents and mal odors. Partially treated wastewater can reach nearby streams and rivers or groundwater, resulting in contaminating source waters (Vedachalam et al., 2012).

To effectively manage risks associated with fecal contamination caused by OWTS, identifying the potential sources is crucial (Reed et al., 2001, Teague et al., 2009). A potential reason for the rise in fecal contamination in water resources in several water sources is failing OWTS. In the 1998 report of the National Water Quality Inventory (NWQI) to Congress, OWTS was the second most cited source for water contamination, citing "improperly constructed and poorly maintained septic systems are believed to cause substantial and widespread nutrient and microbial contamination to ground water" (US EPA 1998, 1999).

The use of GIS as an integrated framework for applying hydrological models has become a standard procedure tool to study the spatial variability of water (Cesur et al., 2007, Martin et al., 2005). The adaptability of GIS to process spatial data and its ability to execute analyses makes it the ultimate platform to be used in conjunction with hydrological models (Rios et al., 2013). The scope and scale of water related problems make GIS an extremely powerful tool for developing solutions (Maidment et al., 2002). The use of Geographic Information System (GIS) has become very popular in analyzing and modeling the potential contamination that OWTS may impose on the water resources.

A regression model combined with GIS was used to assess the relationship between fecal contamination and land use in a small and developed estuary near Georgetown, South Carolina. This study also showed that closer proximity of the OWTS in the study area to the hydrological network had higher fecal contamination (Kelsey et al., 2004). Rios et al. (2013) developed ArcNLET (Nitrate Load Estimation Tool), in GIS platform to stimulate nitrate loads from septic tanks to surface waters. ArcNLET is an "easy-to-use software", that can be used to conduct screening-level-analysis (Rios et al., 2013). In Alabama, GIS was used to assess the status of OWTS in the area (He et al., 2011). From the results of the study, two strategies were developed to reduce the risk on public health from the malfunction in OWTS; to expand the sewer service to cities with high-risk and to reduce costs of repairs and replacements for the system (He et al., 2011).

The Spatially Explicit Load Enrichment Calculation Tool (SELECT) was developed to help with the developing the Watershed Protection Plans (WPPs) and specifically applied to estimate potential *E. coli* loads in different watersheds in Texas (Teague et al., 2009, Borel et al., 2012b). The SELECT was automated to characterize *E. coli* loads from various point and non-point sources, including OWTS (Riebschleager et al., 2012).

SELECT is an automated Geographic Information System (GIS) tool that can be applied to a watershed of interest to assess potential *E. coli* loads and concentrations based on spatial factors such as population of different sources, suitable land use, and soil type (Teague et al., 2009, Borel et al., 2012a, Riebschleager et al., 2012). The module to estimate the potential *E. coli* contribution resulting from OWTS is not well executed and did not include all the relevant factors (Teague et al., 2009, Borel et al., 2012a, Riebschleager et al., 2012). It is therefore pertinent to develop a standalone GIS tool to estimate potential *E. coli* loads resulting from OWTS based on the location of the OWTS, population density, slope, land use, and soil type. This tool should also include the rainfall-runoff relationship to calculate the potential *E. coli* concentration within a watershed and highlight areas of concern to implement best management practices (BMPs). In addition, the automated tool developed by (Teague et al., 2009, Borel et al., 2012b, Riebschleager et al., 2012) is coded in Microsoft Visual Basic for Applications (VBA). According to ESRI, ArcGIS 10.0 is the final release of Microsoft Visual Basic for Applications (VBA), and beyond this release, they will no longer support. ESRI strongly recommends users to rewrite their programs and tools using the currently supported development language, which is Python. Therefore, development of the automated tool in this research was done using the programming language Python. The development of such an automated tool in ArcGIS 10 using ArcPy and the application of the tool to estimate potential *E. coli* loads resulting from different scenarios in a coastal Texas watershed was the main objective of this research work.

1.1. Objectives

The overall objective of the study was to develop a GIS tool to estimate potential *E. coli* loads in a watershed resulting from failing OWTS. Ultimately, when combined with a rainfall-runoff model, the concentration of *E. coli* transported into the stream can be predicted.

The specific objectives were to:

(1) develop a rainfall-runoff model in ArcGIS 10,

(2) develop a spatial tool in ArcGIS 10 to calculate the potential accumulated *E. coli* concentrations in a watershed and to validate the runoff model using observed data, and

(3) apply this GIS tool to the Dickinson Bayou watershed in Texas and run different scenarios including: different rainfall conditions and failure rates of OWTS based on the age of the OWTS.

CHAPTER II

ESTIMATING *E. COLI* CONCENTRATIONS FROM FAILING OWTS IN DICKINSON BAYOU WATERSHED

2.1. Introduction

In Texas, contamination from bacterial pathogens is the primary surface water quality concern (Teague et al., 2009; USEPA, 2008). *Escherichia coli* (*E. coli)* bacterium is used as an indicator organism to indicate fecal contamination. The *E. coli* standard set by the TCEQ for the Dickinson Bayou Tidal is 35 CFU/100mL and for the Dickinson Bayou above tidal is is 126 CFU/100 mL (TCEQ, 2014). To address *E. coli* contamination in watersheds the U.S EPA published recommendations which included identifying and characterizing the sources, assessing the contribution from each source, and estimating the *E. coli* load from each contributing source (USEPA, 2001).

Spatially Explicit Load Enrichment Calculation Tool (SELECT) is an automated Geographic Information System (GIS) tool that can be applied to a watershed of interest to assess potential *E. coli* loads and concentrations based on spatial factors such as population of different sources, suitable land use, and soil type (Teague et al., 2009, Borel et al, 2012b, Riebschleager et al, 2012). The module to estimate the potential *E. coli* contribution resulting from OWTS is not well executed. Moreover, SELECT did not include all the relevant watershed characteristics required to assess *E. coli* contamination resulting from failing OWTS (Teague et al., 2009, Borel et al., 2012b, Riebschleager et al., 2012). It is therefore pertinent to develop a standalone GIS tool to estimate potential *E. coli* loads resulting from OWTS based on the location of the OWTS, population density, slope, land use, and soil type of the each individual location of the OWTS. This tool should also include the rainfall-runoff relationship to calculate the potential *E. coli* concentration within a watershed and highlight areas of concern to implement best management practices (BMPs). In addition, the automated tool developed by (Teague et al., 2009, Borel et al., 2012b, Riebschleager et al., 2012) is coded in Microsoft Visual Basic for Applications (VBA). According to ESRI, ArcGIS 10.0 is the last release of Microsoft Visual Basic for Applications, and they will no longer support VBA beyond this release. ESRI strongly recommends users to rewrite their applications using currently supported development language, Python (Python, 2.2). Therefore, development of the automated tool in this research was done using the programming language Python. The development of such an automated tool in ArcGIS 10 using ArcPy and the application of the tool to estimate potential *E. coli* loads resulting from different scenarios in a coastal Texas watershed are presented in this manuscript.

2.2. Study Watershed: Dickinson Bayou

According to the 2012 Texas Water Quality Inventory, the Dickinson Bayou Watershed (Figure 2.1) is listed as "impaired", which means that it has elevated levels of bacteria that have been observed through consistent monitoring. Surface water samples have been collected from the Dickinson Bayou since the early 1970s, and currently, it is not meeting the TCEQ standard for bacteria levels in surface water. The State of Texas requires that Dickinson Bayou meet and maintains recreational water quality standards. Poorly designed and maintained OWTS, along with inappropriate site characterization are major contributors of the bacteria in this watershed. Majority of the OWTS located in Dickinson Bayou are located in poorly drained soils increasing the likelihood of contaminated runoff into the surface waters (TCEQ, 2012, Dickinson Bayou Partnership et al., 2012).

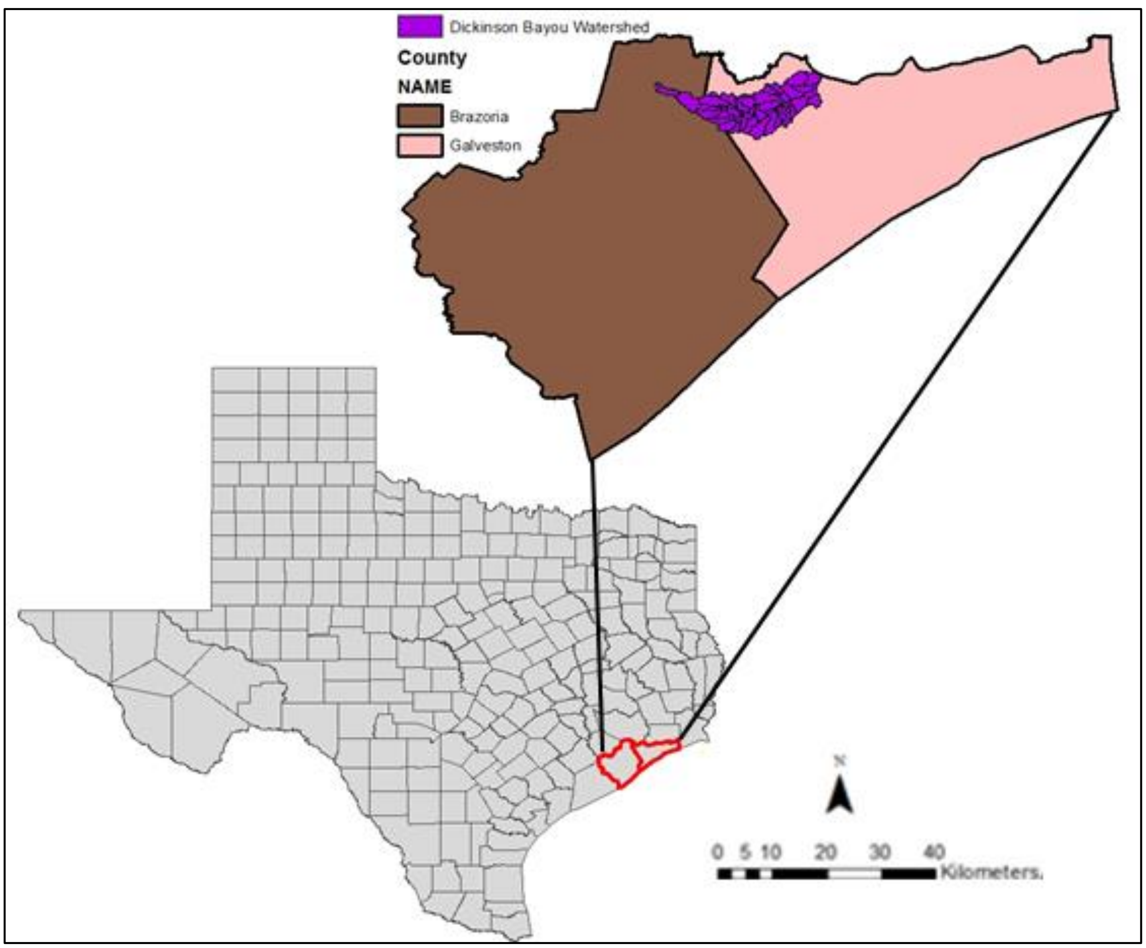

Figure 2.1 Spatial location of Dickinson Bayou watershed, Texas.

The Dickinson Bayou watershed is located southeast of Houston, Texas in the San Jacinto-Brazos Coastal Basin (Figure 2.1). Dickinson Bayou (Figure 2.2 and 2.3) is a coastal stream, which consists of tidal and non-tidal water that drains in to the Dickinson Bay. Entire cities of Algoa and Dickinson, and portions of League City, Friendswood, Texas City, Alvin and Santa Fe, are included within the Dickinson Bayou watershed (Figure 2.2). The Bayou originates north of the city of Alvin, in the northwestern Galveston County, with a latitude of 29°29' N and a longitude of 95°14' W, and the river flows to its mouth which is on Dickinson Bay and Galveston Bay, which is just south of San Leon, with a longitude of 29°28' N and latitude of 94°57' W. It has a total length of around 38.6 km with a drainage area of 258.2 km^2. It has a maximum width of approximately 11.3 km. The population density of this watershed was estimated to be 66,500 people with 29, 610 houses (U.S Census Bureau, 2010). Approximately a third of upper segment is part of the Brazoria County and consists of around 1% of the entire county area. The rest of the watershed lies in the Galveston County, which consists of 11% of the entire county area. It is important to note that even though the population of Brazoria and Galveston are close in comparison (Table 2.1), the population density of Galveston is more than three times greater than that of Brazoria and based on projections, the population in both counties are predicted to increase (TCEQ, 2012).

Table 2.1 Total population and density for the counties where Dickinson Bayou is located.

County Name	2000 U.S Census	2000 Population Density (per square mile)	2010 U.S Census	2010 Population Density (per square mile)
Brazoria	241,676	174	313,166	226
Galveston	250,158	627	291,309	732

Dickinson Bayou provides local residents with recreational activities such as fishing, boating, canoeing, water skiing, and other such water activities. The Bayou is also used for commercial shrimping and barge traffic occasionally. The distribution of population in the Dickinson Bayou is skewed towards the urban areas, mainly in the northeastern portion of the watershed, as well as the development in the southern portion near Alvin and Santa Fe (TCEQ, 2012). The average elevation of the watershed is around 11 meters above the mean sea level. The climate in the Dickinson Bayou watershed is humid, with an average annual rainfall of 122 cm (Dickinson Bayou Partnership, 2012).

This watershed has approximately 4,565 OWTS. (Figure 2.4) (Dickinson Bayou Partnership, 2012). The southern portion of the watershed has concentrated OWTS as compared to northern portion. These OWTS are mainly anaerobic systems (3,243) and ATU (1,322) (Dickinson Bayou Partnership, 2012).

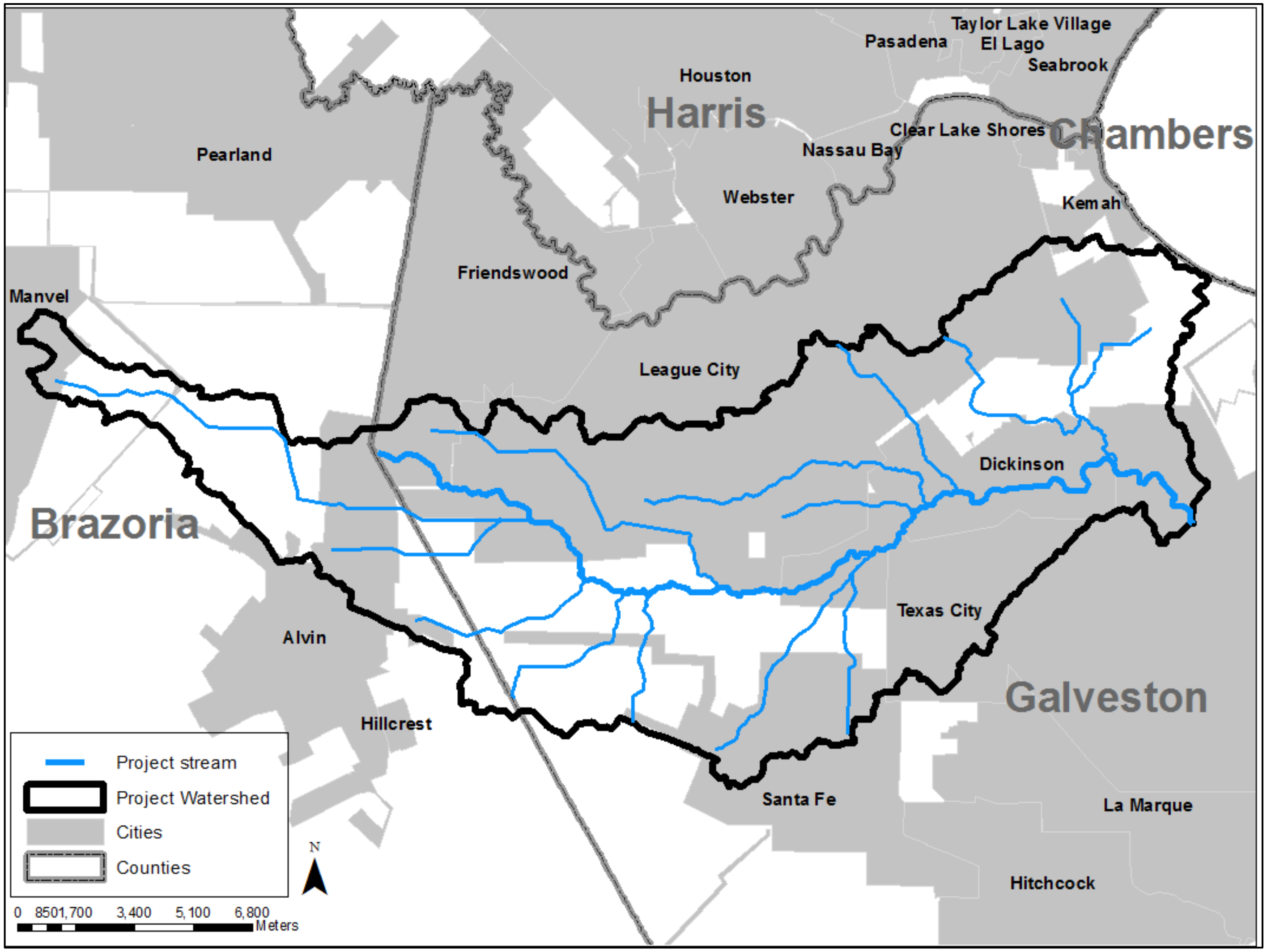

Figure 2.2 Dickinson Bayou watershed with cities, counties, and streams.

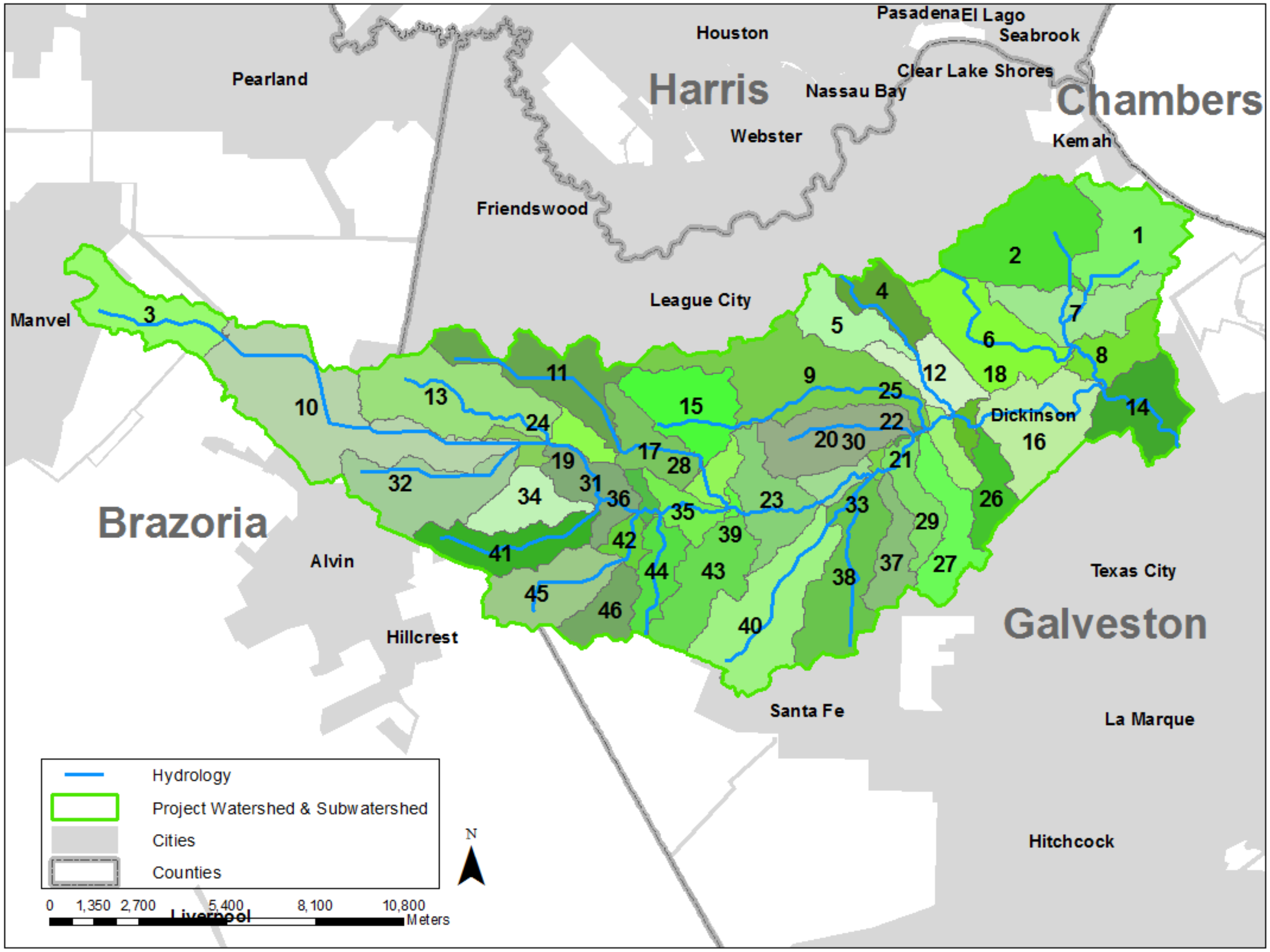

Figure 2.3 Dickinson Bayou subwatersheds delineated using BASINS along with the cities, counties, and streams.

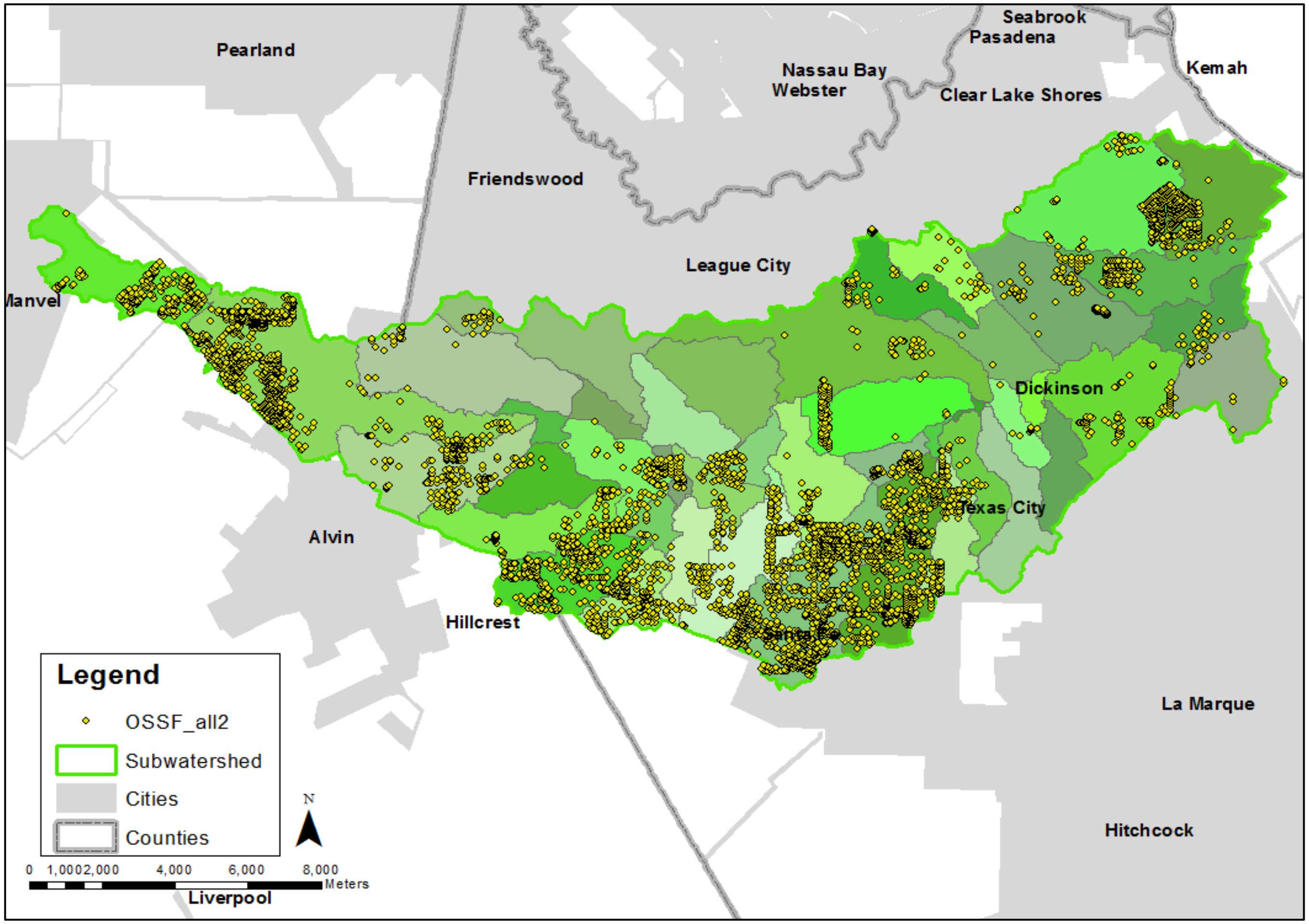

Figure 2.4 Locations of Onsite Wastewater Treatment Systems (OWTS) in Dickinson Bayou watershed (Dickinson Bayou Partnership, 2012).

Dickinson Bayou is extensively urbanized in certain areas (Figure 2.5, Table 2.2). Located in the Gulf Coast prairies and marshes ecological area of Texas, the vegetation consists primarily of Hay/Pasture, agriculture and some developed land (open space and low intensity). The development in this watershed is light to medium industrial. Agricultural uses prevail in the western portion of the watershed (Texas Stream Team River Systems Institute, 2010). The majority of the watershed's landuse is currently cultivated lands followed by low intensity developed land. Cultivated lands and grasslands account for approximately 25% and 16%, respectively (Table 2.2).

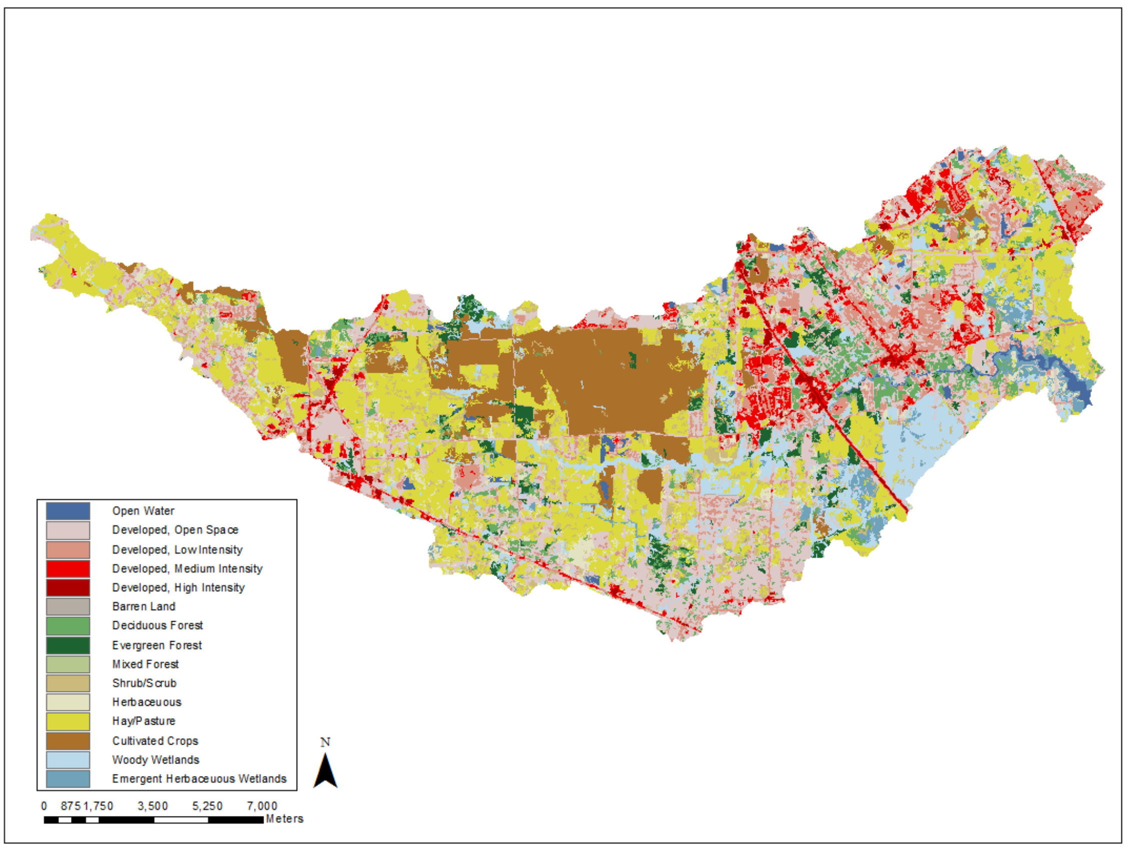

Figure 2.5 Dickinson Bayou watershed land use (NLCD, 2006).

Table 2.2 Land use distribution in Dickinson Bayou watershed.

Land Description	**Land Use #**	**Area (Square meters)**	**% Of watershed**
Cultivated Land	1	67,542,739	25.91
Developed, Low Intensity	2	58,757,752	22.54
Grassland	3	42,543,323	16.32
Developed, Open Space	4	32,011,765	12.28
Woody wetland	5	20,776,356	7.97
Developed, High Intensity	6	11,834,969	4.54
Herbaceous Wetland	7	8,550,374	3.28
Forest	8	6,517,053	2.50
Open water	9	6,282,439	2.41
Bare/Transitional Land	10	5,865,348	2.25
Total		**260,682,128**	**100%**

When precipitation occurs, the initial drops of water are intercepted by the vegetation, which is referred to as interception storage. As it continues to rain, the water that reaches the ground then infiltrates into the soil until the soil has reached its infiltration capacity. When rainfall intensity exceeds the infiltration capacity of the soil, the process of runoff occurs. One of the factors that have a direct impact on the occurrence of runoff volume is the soil type. Different soil types have different infiltration capacity based on the porosity of that particular soil. Highest infiltration occurs in sandy soils, and smaller infiltration capacity is observed in clay or loamy soils. Soils were original assigned to hydrologic soil groups (HSGs) based on their characteristics such as their porosity and their runoff potential. HSGs ranges from A to D, where soils with HSGs of A represent soils that have low runoff potential, these soils typically have 90 percent sand and 10 percent clay. Soils with HSGs of D represent soils that have high runoff potential, water movements through these soils are very restricted; these soils typically have less than 50 percent of sand, 40 percent clay and have very clay like structures. The soils in Dickinson Bayou mainly consist of HSGs of D, which causes the high surface water runoff in this watershed (Figure 2.6). Soil data were obtained from the Natural Resource Conservation Service (NRCS) Soil Survey Geographic (SSURGO) Database (2013).

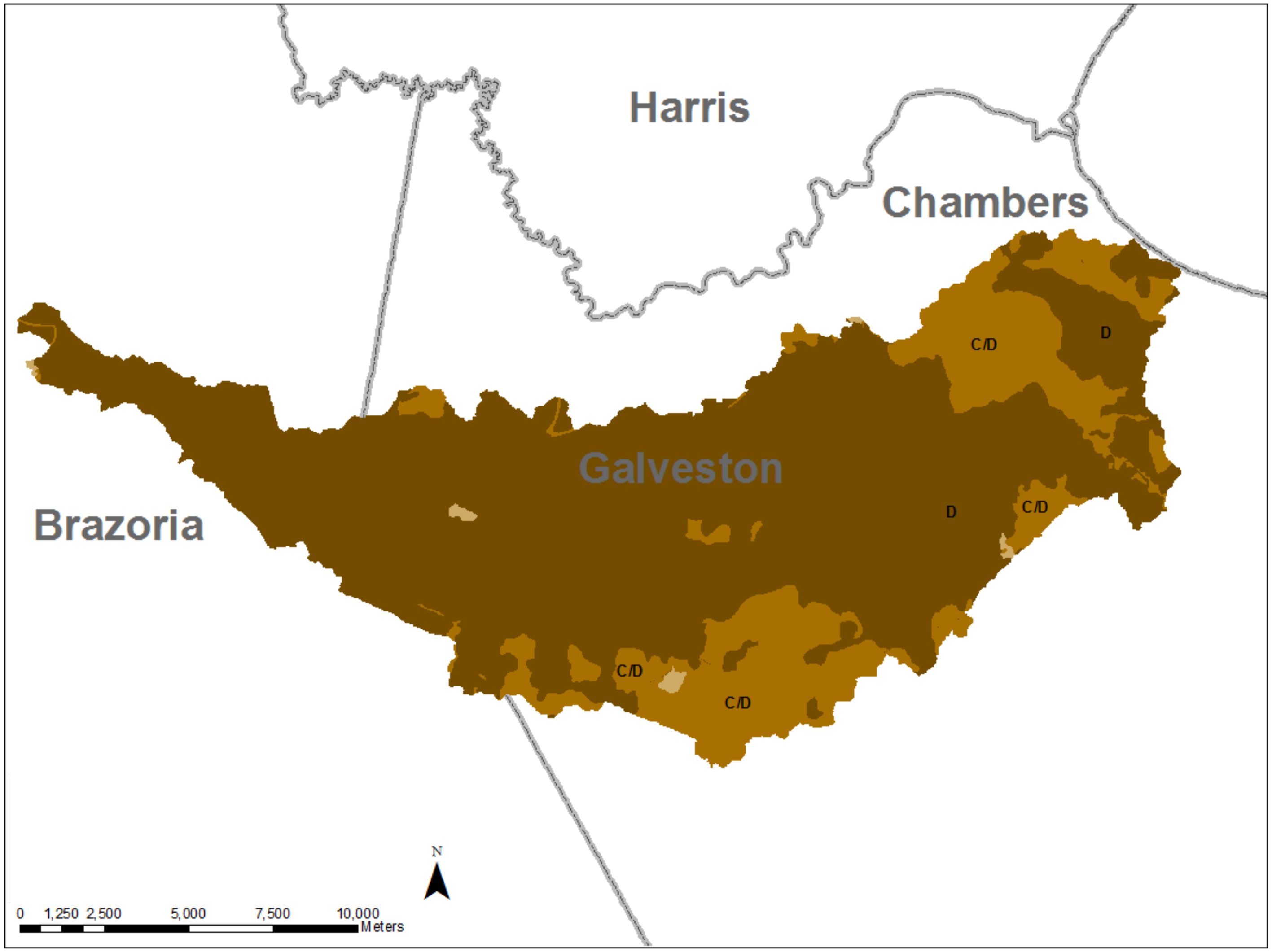

Figure 2.6 Spatial distribution of various hydrologic soil groups (A, B, C, and D) in the Dickinson Bayou watershed.

2.3. Spatially Explicit Methodology

The conceptual framework for this tool includes delineating the subwatersheds in a watershed to spatially aggregate the *E. coli* loads resulting from failing OWTS. The spatial *E. coli* loads will be estimated using the location of OWTS in the watershed, population density, rainfall amount, soil type, slope, and *E. coli* load in the untreated sewage. Once the potential *E. coli* loads are estimated, rainfall-runoff relationship will be used to calculate the *E. coli* concentration in the surface waters. The rainfall-runoff relationship will be established using NRCS Curve Number (CN) approach.

This spatial tool was developed using the Spatial Analyst extension and the ArcHydro extension within ArcGIS 10 (ESRI, Redlands, CA) in ArcPy programming language. The watershed delineation was done using the Better Assessment Science Integrating point & Non-point Sources (BASINS 4.0, USEPA, 2012). The watershed was divided into subwatersheds based on the elevation and changes along the hydrology. This was done in order for the *E. coli* loads to be aggregated to for our results (Figure 2.3). Next, the subwatersheds were divided into a raster grid of 30 m × 30 m cells. Each cell location was assigned a specific *E. coli* load based on the discharge from each failing OWTS present in that cell location. The OWTS locations (Figure 2.4) were obtained from the Dickinson Bayou Watershed Partnership, led by the Texas A&M AgriLife Extension and the Sea Grant. Land use classification (Figure 2.5) and soils (Figure 2.6) were other GIS layers required to generate the CN grid. Table 2.3 represents a summary of all the GIS layers used to do the analysis in this study to estimate the potential *E. coli* concentrations resulting from failing OWTS in the Dickinson Bayou watershed.

This automated tool provides a graphical user interface (GUI) for the users. Users can adjust parameters for different scenarios specific to their watershed of concern that include: location of the failing OWTS, Antecedent Moisture Conditions (AMC) I/II/II, precipitation amounts, population, slope, and the processing extent to which the user wants to study. This tool will simulate potential bacteria loads and concentrations based on the parameters chosen. Before using this tool, a comprehensive understanding of the watershed is necessary to assess the contribution factors that influence the potential *E. coli* concentration in the watershed.

Table 2.3 Spatial data sources and format used to predict potential *E. coli* load in Dickinson Bayou watershed

File	**Format**	**Data Source**
Digital Elevation Model (DEM)	Raster	BASINS 4.0, U.S EPA
Census block	Shapefile	U.S Census Bureau, 2010
Soils	Shapefile	SURRGO, 2013
Soil properties	Tabular	SURRGO, 2013
Landuse	Raster	National Land Cover Dataset (NLCD) 2006
OWTSs	Shapefile	Dickinson Bayou Watershed Partnership, 2013
Streams	Shapefile	National Hydrography Dataset plus, BASINS 4.0, U.S EPA

2.3.1. Estimating potential *E. coli* concentration

The potential *E. coli* concentration will be calculated using equation 2.1, developed by McElroy et al. (1976).

$$a * R * A \text{ ……………………………..} \quad (2.1)$$

Where C is the *E. coli* concentration (cfu/mL), Y is the daily *E. coli* load (CFU), R is the daily runoff (mm), a is the conversion factor (1×10^6), for the conversion from m^3 to mL, A is the grid cell area (m^2).

The *E. coli* concentration was estimated by calculating the *E. coli* load and the runoff volume resulting from a given rainfall. The analyses were conducted at a 30 m × 30 m spatial resolution. To calculate the *E. coli* load (Y); Total number of households that use OWTS were determined using census data. Census data were obtained from 2010 census block (USCB, 2010). Based on the failing OWTS location, the density of the failing OWTS was calculated per raster cell. A constant toilet water use of 56 $Lperson^{-1}day^{-1}$ (15 gal $person^{-1}$ day^{-1}) and a 10 x 10^6 CFU/100 mL of fecal coliform concentration was used to calculate the *E. coli* load resulting from failing OWTS (Table 2.4) (Teague et al., 2009, Borel et al., 2012a).

The watershed was delineated into 46 subwatersheds using BASINS (Figure 2.3) (BASINS 4.0, 2010). To convert the fecal coliform to *E. coli,* a conversion factor of 0.33 fecal coliform to *E. coli* was used based on the US EPA's regulatory standards in recreational waters. The total *E. coli* load was calculated per person per day caused by the failing OWTS which were aggregated to a subwatershed level. This spatial aggregation can be used to identify the areas of potential concern of impairment due to bacteria resulting from failing OWTS.

Table 2.4. Calculation of potential *E. coli* loads from OWTS (Teague et al., 2009, Borel et al., 2012a)

Source	***E. coli* Load Calculation**
OWTS	$EC^1 = \#OWTSs * \frac{10 * 10^6 cfu}{100\ mL} * \frac{15\ gal}{\frac{person}{day}} * \frac{Avg\ \#}{Household} * \frac{3758.2\ mL}{gal} * 0.33$ EC[1] = *E. coli* load discharged from a failing OWTS

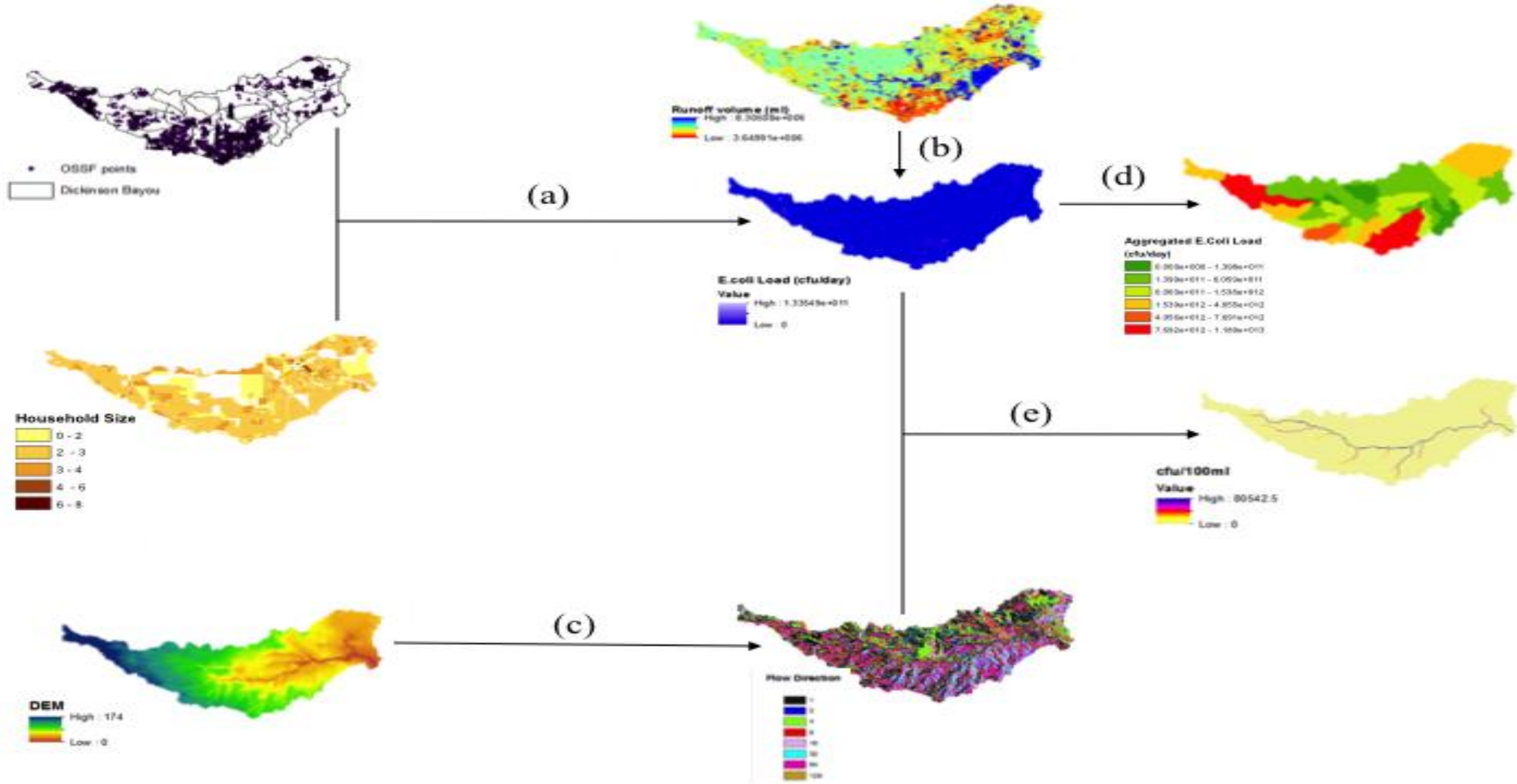

Figure 2.7 Flow chart illustrating the calculation of the contributing *E. coli* load and concentration. (a) Multiply runoff and household size to compute contributing load (b) Use equation 2.1 to calculate *E. coli* concentration (d) aggregate to subwatershed level (c) Compute flow direction (e) Compute flow accumulation using flow direction with contributing load as accumulation weight.

The inputs to calculate the *E. coli* concentrations were the previously calculated runoff volume and the DEM. The flow chart in Figure 2.7 illustrates the calculation of the contributing *E. coli* load and concentrations. Census data and the contributing load were used to calculate the contributing *E. coli* load in each OWTS (Figure 2.7 (a)). Equation 2.1 was used to calculate *E. coli* concentration (Figure 2.7 (b)). The *E. coli* load was aggregated to subwatershed level (Figure 2.7 (d)). The *E. coli* concentration was accumulated using the Digital Elevation Model (DEM) of the watershed area, resulting in accumulated runoff (Figure 2.7(c)). The resulting grid shows the accumulation of the *E. coli* concentration going through each specific cell until the outlet of the watershed (Figure 2.7(e)).

2.3.2. Estimating runoff volume in the watershed

Curve Number (CN) grid was generated for Dickinson Bayou watershed, using a combination of the soil antecedent moisture conditions (AMCII), soil type and land use. The categories used to reclassify the landuse were defined based on the watershed and study of interest. Landuse for the Dickinson Bayou watershed was reclassified into seven categories: Water, Developed – open space, Developed – low intensity, Developed – medium intensity, Developed – high intensity, Forest, and Agriculture, according to the NLCD reclassification (Figure. 2.8, Table 2.5). By the combination of the land use and hydrological soil group data, standard NRCS curve numbers were assigned. NRCS curve numbers used were based on a normal antecedent moisture condition (AMC II). The CN was calculated using the HEC-GeoHMS extension, as well as the hydro extension in

ArcGIS 10 using an NRCS Curve Number Lookup Table (Table 2.6) (Soil Conservation Service, 1986). Curve Number for this watershed ranged from 71 to 92, where 71 represents lowest runoff and 92 represents highest runoff potential (Figure 2.9). Lower curve numbers represent very permeable soil and higher curve numbers represent less permeable soil.

Table 2.5 Land use classification of Dickinson Bayou watershed (source: USGS Land Cover Institute (LCI), 2006).

Original NLCD classification		**Revised Classification (re-classification)**	
Number	*Description*	*Number*	*Description*
11	Open Water	1	Water
90	Woody wetlands		
95	Emergent herbaceous wetlands		
21	Developed, open space	2	Developed, open space
22	Developed, low intensity	3	Developed, low intensity
23	Developed, medium intensity	4	Developed, medium intensity
24	Developed, high intensity	5	Developed, high intensity
41	Deciduous forest	6	Forest
42	Evergreen forest		
43	Mixed forest		
31	Barren land	7	Agricultural
52	Scrub/Scub		
71	Grassland herbaceous		
81	Pasture hay		
82	Cultivated crops		

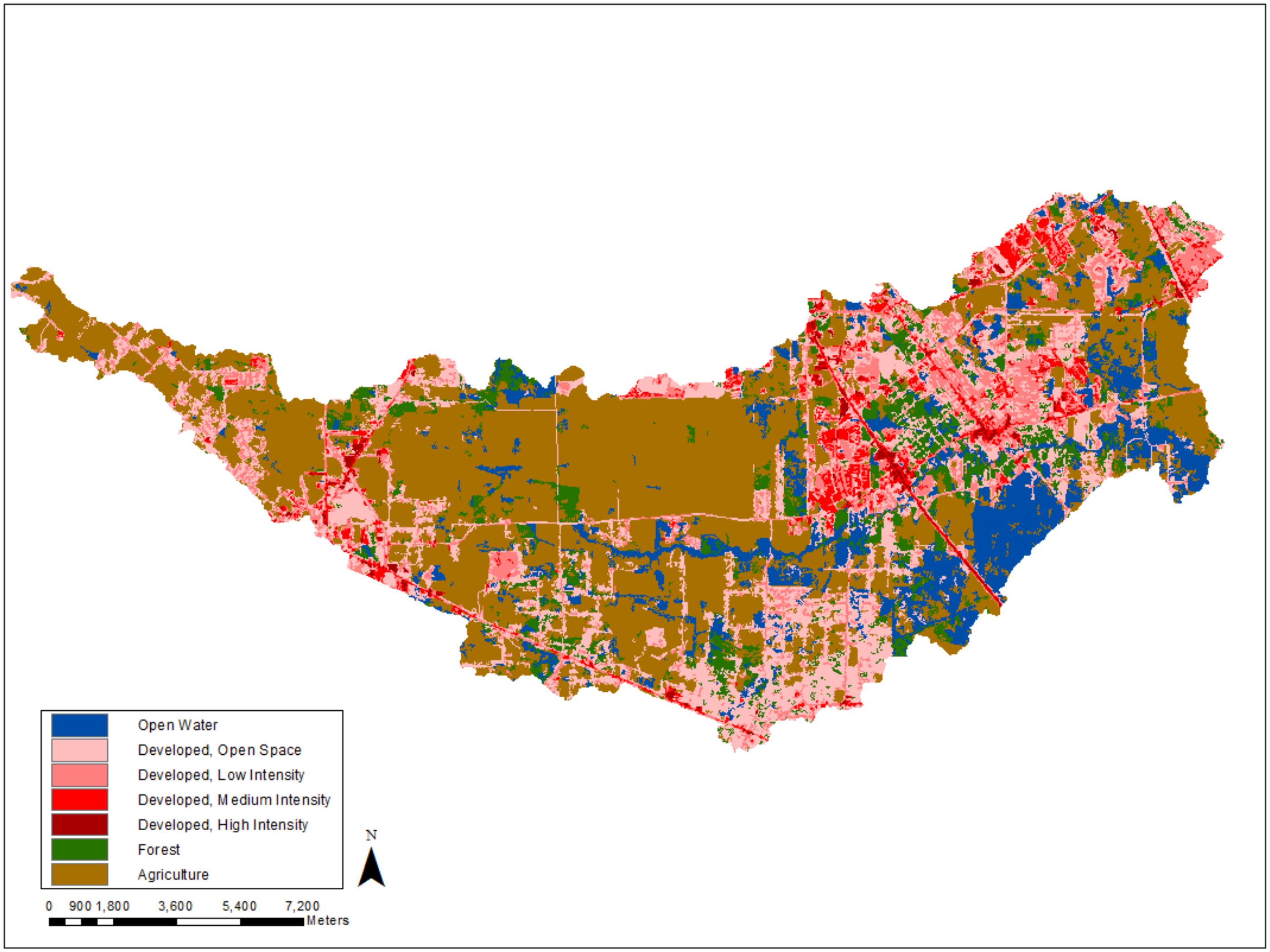

Figure 2.8 Reclassification of the landuse in Dickinson Bayou used in generating curve number grid.

Table 2.6 NRCS curve number lookup table (Soil Conservation Service, 1986)

Land Use Type	Hydrologic Soil Group	Curve Number (AMCII)
Open Water	A	NoData
	B	NoData
	C	NoData
	D	NoData
Developed, Open Space	A	39
	B	61
	C	74
	D	80
Developed, Low Intensity	A	48
	B	66
	C	78
	D	83
Developed, Medium Intensity	A	57
	B	72
	C	81
	D	86
Developed, High Intensity	A	77
	B	85
	C	90
	D	92
Forest	A	30
	B	58
	C	71
	D	78
Agriculture	A	67
	B	77
	C	83
	D	87

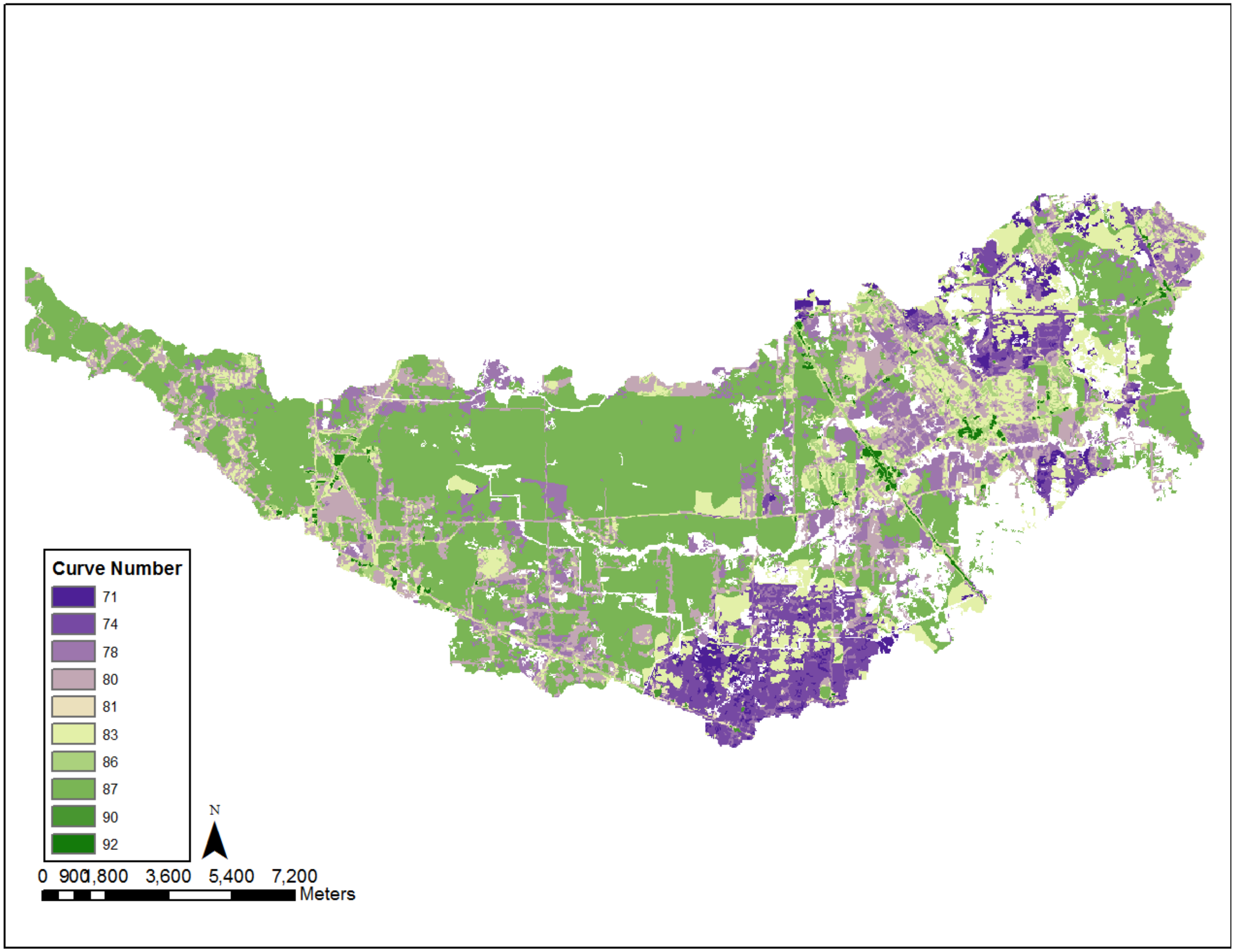

Figure 2.9 Curve number grid for the Dickinson Bayou watershed.

The maximum soil water retention parameter (S) was calculated using the CN in mm (S):

$$S \quad (2 \qquad) \ - 2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (2.2)$$

Where S is the maximum soil water retention parameter (mm) and CN is the curve number for the Dickinson Bayou watershed (Figure 2.9).

The runoff volume in the streams was calculated using an input precipitation value (Figure 2.10). An automated tool was programmed in Python within ArcGIS 10.0 to calculate the runoff volume with an input of a precipitation value, and an S grid, which is calculated using the curve number grid. Precipitation values that were greater than the minimum precipitation required to induce runoff were used to calculate the runoff volume.

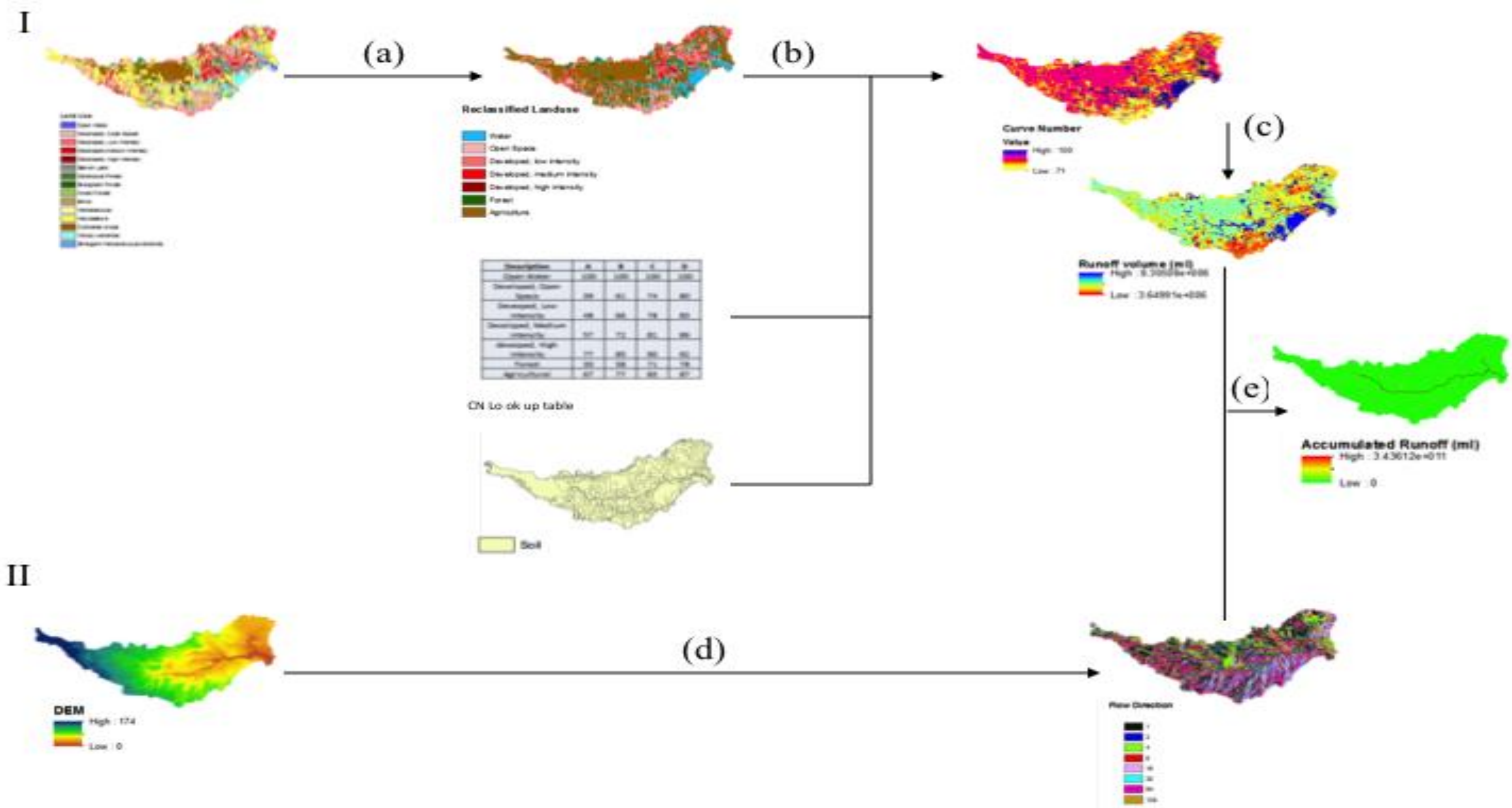

Figure 2.10 Flow chart illustrating the calculation of accumulated runoff volume. (a) Reclassify landuse grid (b) Input (a), curve number lookup table, and soil data (c) use equation 2.2 and 2.3 to convert CN grid to runoff grid, (d) Compute flow direction from DEM grid, (e) Compute flow accumulation from flow direction grid using the runoff volume grid as the accumulation weight.

The runoff volume (Figure 2.10(a-e) was calculated using SCS CN approach using the following equation:

$$(P - I_a)^2 \quad (P - I_a \quad S) \quad A \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (2.3)$$

where, Q is total runoff (m^3), P is the total precipitation (mm), I_a is the initial abstraction (stored, intercepted, and infiltrated water) (mm), S is the maximum soil water retention parameter (mm), I_a is approximated to be 0.2S, and A is the area of a grid cell (m^2).

To calculate the curve number the landuse was first reclassified (Figure 2.10 (a)). Next, the curve number grid was converted into an S grid using Equation 2.2 (Figure 2.10(b)) using the three input data: reclassified landuse, curve number lookup table, and soil data. Runoff volume was then calculated using Equation 2.3 to calculate the runoff depth in each cell. The resulting runoff depth per cell was converted into runoff volume by multiplying by the cell area, 900 m^2 (Figure 2.10(c)). Equation 2.3 requires P to exceed the 0.2 S grid, before any runoff is generated; therefore only precipitations values that were greater than the minimum precipitation required to induce runoff were used to calculate the runoff volume. The runoff was accumulated using the Digital Elevation Model (DEM) of the watershed area, resulting in accumulated runoff (Figure 2.10(d)). The resulting grid shows the accumulation of the runoff volume going through each specific cell until the outlet of the watershed (Figure 2.10(e)).

The runoff volume was calculated using different rainfall amounts (Table 2.7). The minimum amount of rainfall required to produce runoff in the watershed is S multiplied by 0.2. The automated tool was programmed into ArcGIS 10, using Python to generate a runoff grid using precipitation depths for different return periods (Table 2.7).

2.3.3. Simulation scenarios for *E. coli* concentrations resulting from OWTS

Spatial distributions of *E. coli* concentrations were estimated across the Dickinson Bayou watershed for different scenarios. The rainfall amount is the driving force in estimating potential *E. coli* concentrations in the Bayou. Age of the OWTS plays a significant role in potential *E. coli* contamination. Type of OWTS will also be a major contributing factor, however not considered in this study, due to the lack of required information on the difference between *E. coli* load discharges between the two systems. The resulting *E. coli* loads from different OWTS (ATUs vs. anaerobic systems) that are failing are not well documented.

Rainfall amount

Different rainfall conditions were used in the rainfall-runoff relationship to estimate the range of potential *E. coli* concentrations across the watershed. Rainfall amounts for different return periods used in the simulation are given in Table 2.7. Observed rainfall amounts were also used to validate the runoff model (Table 2.8).

Table 2.7 Precipitation in Dickinson Bayou watershed based on different return periods and 24 h duration (Haan et al., 1994).

Return period	Rainfall (mm)
Two-year	133.4
Five-year	180.3
Ten-year	215.9
Twenty-five year	254.0
Fifty-year	292.1
Hundred-year	330.2

Table 2.8 Measured rainfall data in a monitored site in the Dickinson Bayou watershed.

	Rainfall (mm)
10-May-13	27.7
11-Aug-13	27.9
26-Aug-13	42.7
20-Sep-13	42.9
21-Sep-13	17.5
27-Oct-13	28.2
22-Nov-13	9.9
25-Nov-13	18.0
13-Jan-14	14.2
2-Feb-14	10.7
4-Feb-14	6.6

Age of OWTS

All OWTS that is older than 30 years were assumed to be failing. Out of a total of 4,565 OWTS, 3,243 OWTS were anaerobic units and 1,322 were ATU. All the ATUs in the watershed were less then 30 years, so they were not taken into consideration, thus only anaerobic systems were compared. The anaerobic OWTS that were older than 30 years were 1132 (Figure 2.11). This resulted in a total of 35% of the anaerobic units in total.

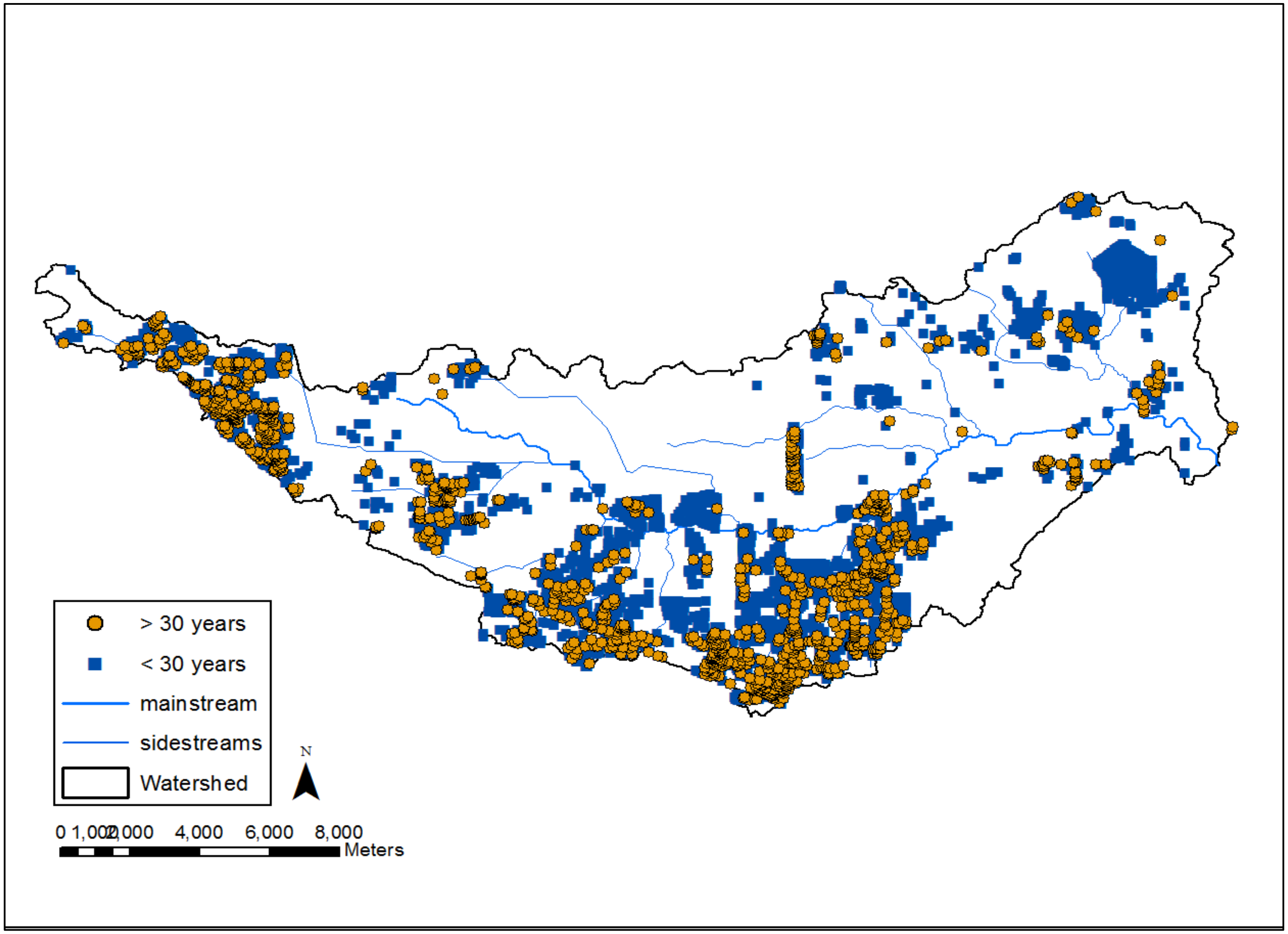

Figure 2.11 Spatial distribution of old (>30 years) and new (< 30 years) OWTS in the Dickinson Bayou watershed.

2.3.4 Statistics

The automated tool was validated by observed runoff data. Observed runoff data was obtained from the project funded by the Dickinson Bayou Project for the monitoring of *E. coli* contamination (Morrison (2015) Unpublished MS thesis). A linear regression line was plotted to represent the relationship between the model simulated runoff depth (x) and the observed runoff depth (y). Regression line can be considered as an acceptable estimation of the true relationship between the observed and predicted.

2.3.5 Monitored subwatershed

The monitored data was obtained from a small watershed with OSSFs within the Dickinson Bayou watershed (Figure 2.12 and 2.13). The monitored subwatershed is approximately 36 acres, with a total number of 28 houses. None of the houses in the w watershed are connected to a municipal sewer system. From these 28 houses, 17 houses use the anaerobic septic systems and the remaining 11 use the aerobic type of septic systems (Figure 2.13). The soil found in this subwatershed consist of Mocarey loam, Mocarey Ceino complex and Mocarey-Algoa complex, all of which are of hydrologic soil group D. The slope of this subwatershed is between 0-3 percent. The houses in this subwatershed range between 1,011 to 4,047 m^2 (0.25 to 1 ac).

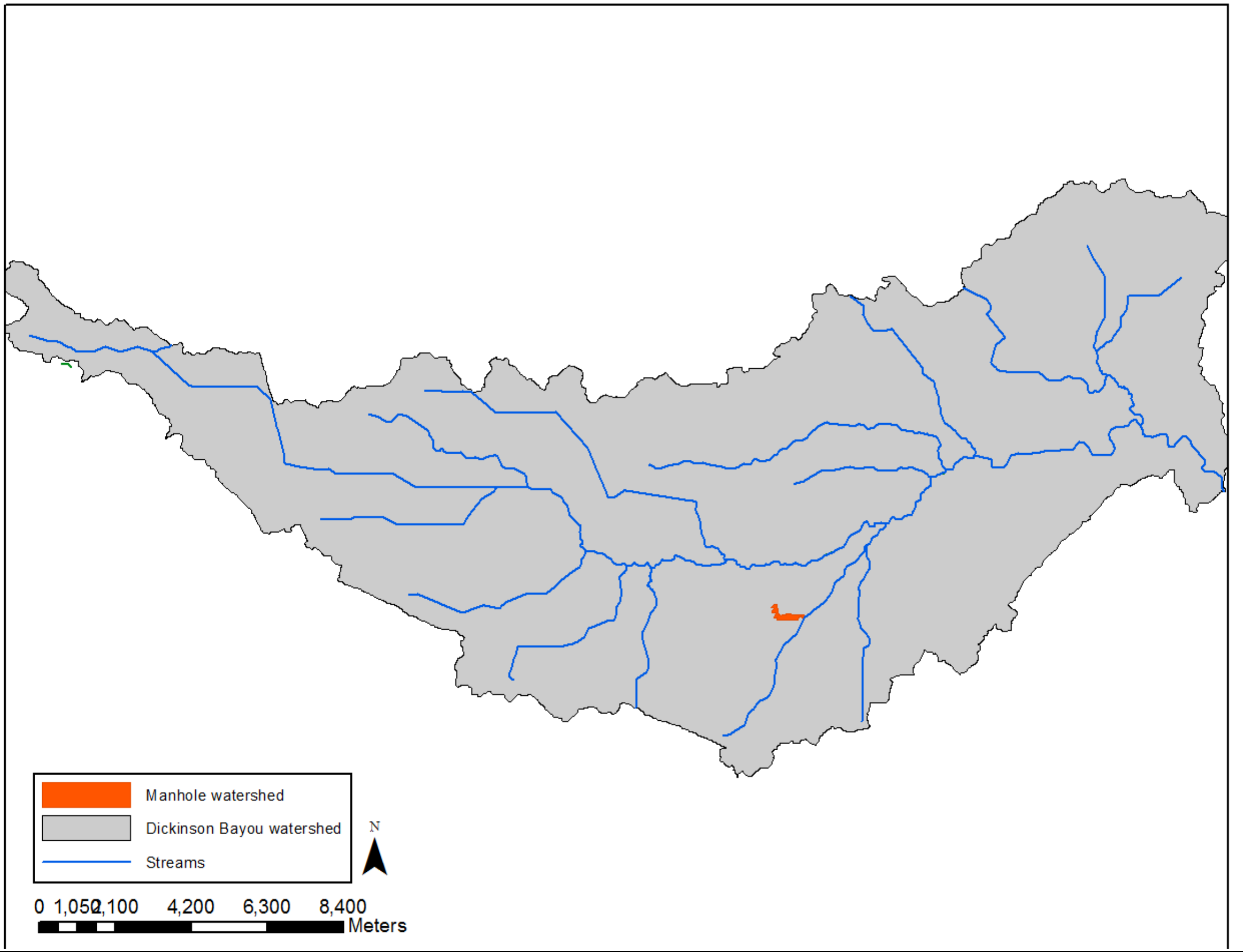

Figure 2.12 Spatial location of the monitored subwatershed within the Dickinson Bayou watershed.

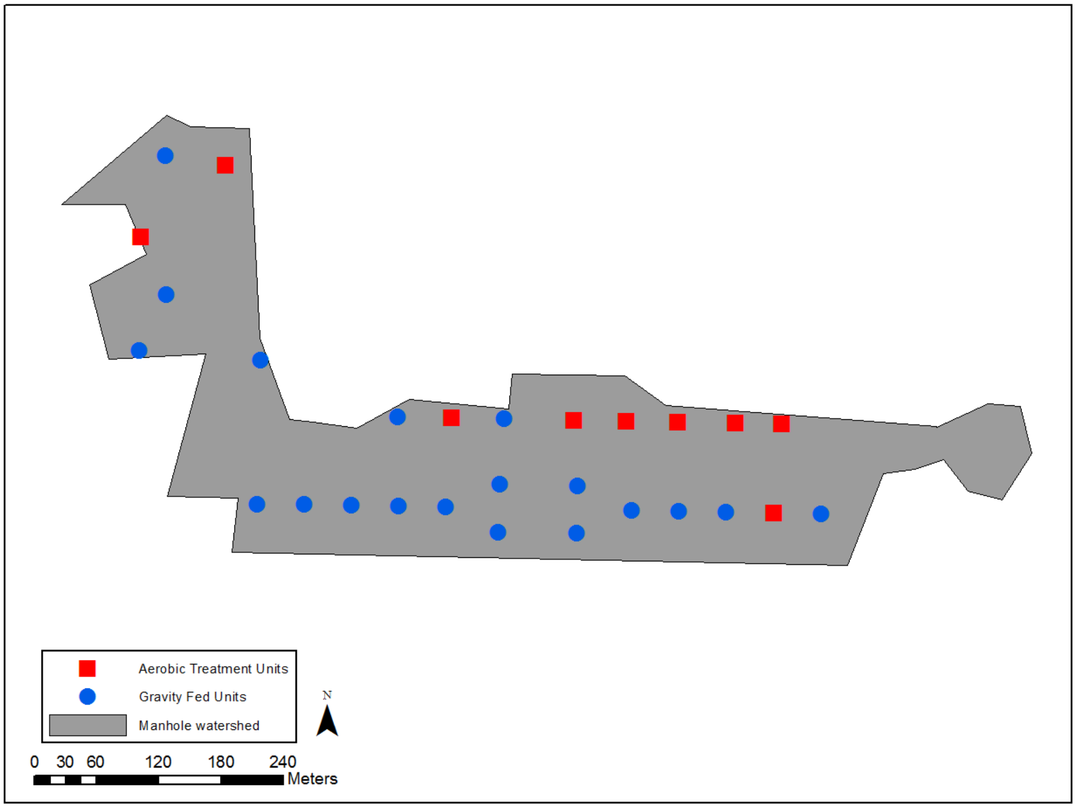

Figure 2.13 Monitored subwatershed with the spatial location of Aerobic Treatment Units (ATU) and anaerobic units in the watershed.

The model's accuracy was evaluated using the Nash-Sutcliffe Efficiency (E), root mean square error (RMSE), and RMSE-observations standard deviation ratio (RSR). In the Nash-Sutcliffe model, E is an index of agreement of disagreement between predicted and observed values (Nash-Sutcliffe Efficiency, 1970). By the application of linear regression analysis, E value evaluates the consistency of the observed values and predicted values with which they agree (Nash-Sutcliffe Efficiency, 1970). E will be computed using equation 2.4 (Nash-Sutcliffe Efficiency, 1970):

$$E = 1 - [\sum_{i=1}^{n}(O_i - P_i)^2 / \sum_{i=1}^{n}(O_i - \bar{O})^2] \quad (2.4)$$

where, O_i is the observed values, P_i is the predicted values, $\bar{O}$ is the mean of the observed values, and n is the number of samples. E values of negative infinity to 1 represent a biased model, and values of 0 to +1 represent an unbiased model (McCuen et al., 2006). According to Moriasi et al. (2007) and Parajuli et al. (2009) model efficiencies are classified as very good (E = 0.75 to 1), good (E = 0.5 to 0.74), fair (E = 0.25 to 0.49), poor (E = 0 to 0.24) and unsatisfactory (E < 0.0).

RMSE is an important error index that is used in model evaluation as the error that is indicated, will represent the units of the interested constituent (Moriasi et al., 2007). It is recommended by Legates and McCabe (1999) for a complete assesment of model performance that one must include at least one absolute error measure, *RMSE* or mean absolute error, and at least one relative error measure (R^2 or E). According to Singh, et al. (2004), *RMSE* values that are closer to 0 represent a perfect fit, however, values that are half of the stand deviation are yet considered low.

The *RMSE* equation is:

$$RMSE = \sqrt{\sum_{i=1}^{n}(O_i - P_i)^2 / n} \quad (2.5)$$

RSR is a statistic used for model evaluation, which standardizes RMSE (Equation 2.5) along with the standard deviation of the observed data (Moriasi et al., 2007). This was developed by Moriasi et al. (2007) to fill the requirement of an error index and additional data provided for using $RSME$ with the standard deviation that is recommended by Legates and McCabe (1999).

The RSR is computed by the use of equation 2.6 (Moriasi et al., 2007):

$$RSR = \left[\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}\right] / \left[\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\right] \quad (2.6)$$

RSR ranges from 0 to a large positive value. The lower values closer to 0 represent optimal values and represent a perfect model (Moriasi et al., 2007). Moriasi et al. (2007) classifies RSR values for model effiiciences as follows: RSR of 0.00 to 0.50 as very good, RSR of 0.51 to 0.60 as good and RSR > 0.70 as unsatisfactory.

Moriasi et al. (2007) states that these guidelines are applied to continuos and long term simulations, and must be adjusted based on the quantity and quality of the measured data, model calibration and the model's magnitude and scope (Moriasi et al., 2007). Moriasi et al. (2007) then states when these conditions are not met, such as a complete measured time series, and only a few samples are available per year, data might not be sufficient for analysis for statistics that is recommended.

2.4 Results and Discussion

The automated tool to estimate *E. coli* concentrations resulting from failing OWTS was developed and the code was verified for different scenarios. First runoff was estimated for different return periods assuming 24 h duration rainfall. For a 2 year 24-hour rainfall, the highest runoff resulted from developed land (medium and high intensity). This was followed by runoff from agricultural lands, and developed low intensity and open space. Forested areas generated the lowest runoff.

The model's accuracy was evaluated using the a sh-Sutcliffe Efficiency (E), root mean square error (RMSE), and RMSE-observations standard deviation ratio (RSR). The model was calibrated by comparing the model simulated data with observed data. Observed data was obtained from the TCEQ monitoring station 11467.

For a two year and fifty year 24-hour rainfall, the highest runoff resulted from developed land (medium and high intensity). This was followed by runoff from agricultural lands, and developed low intensity and open space. Forests resulted in the lowest runoff of approximately (Figure 2.14, Figure 2.15).

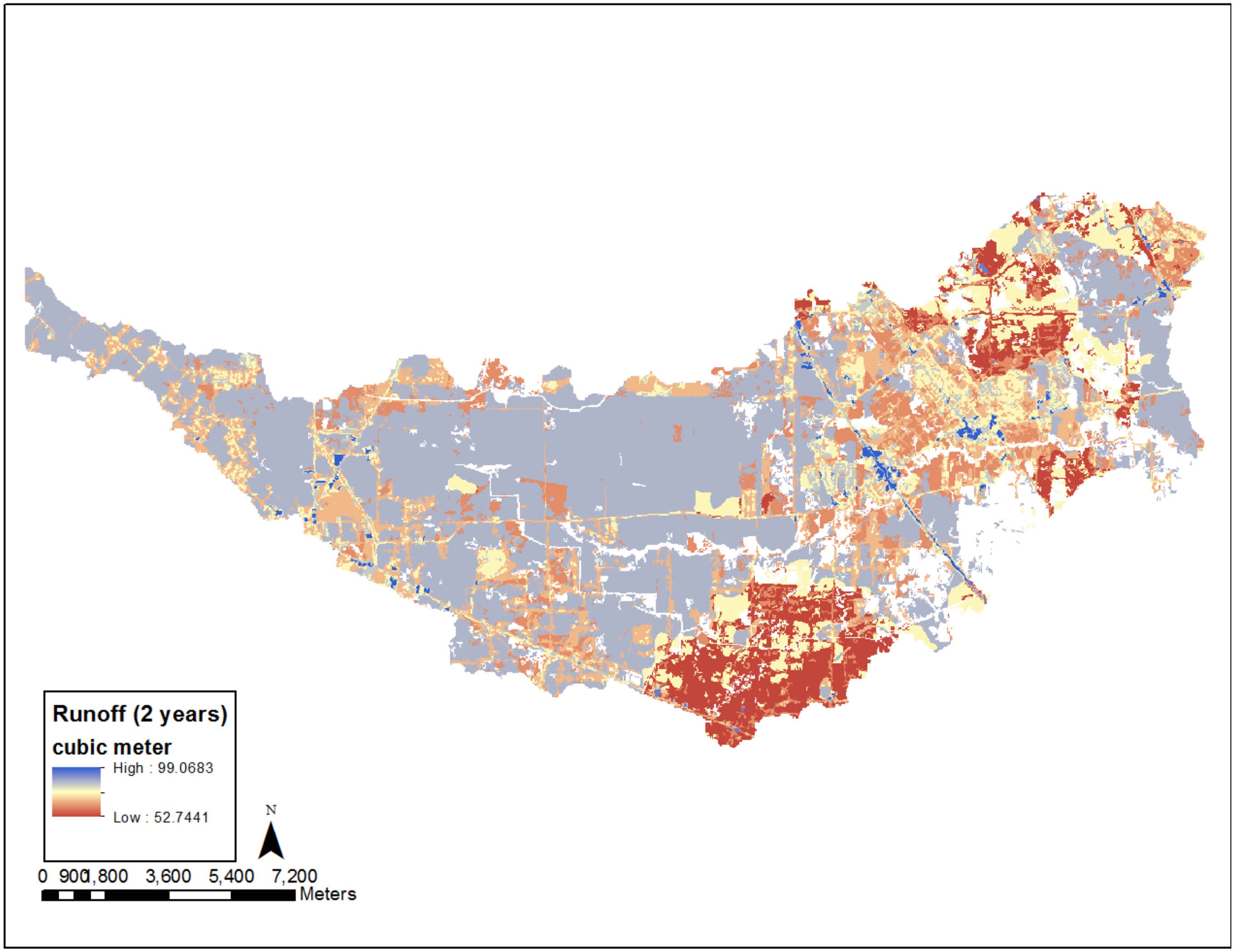

Figure 2.14 Runoff volume simulated for a two year return period in Dickinson Bayou watershed.

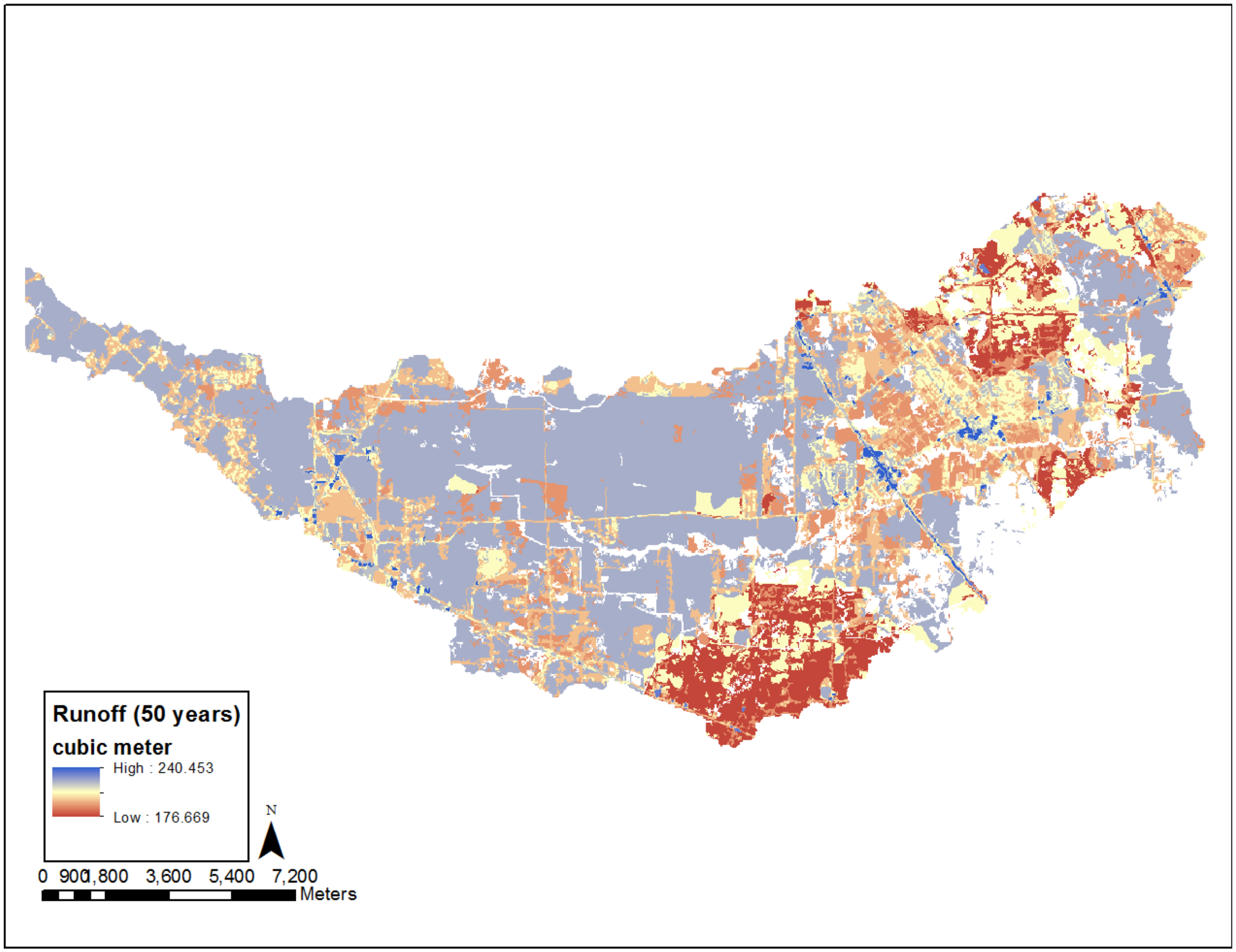

Figure 2.15 Runoff volume simulated for a fifty year return period in Dickinson Bayou watershed.

2.4.1 Spatial distribution of *E. coli* loads in Dickinson Bayou

The spatial analyses were done to highlight the subwatershed resulting in highest potential *E. coli* load contribution into the streams. The potential *E. coli* loads resulting from failing OWTS were estimated for the Dickinson Bayou watershed. A failure rate of 25% was applied on the watershed. The potential *E. coli* loads have been aggregated to subwatershed level to identify the areas of concern in the watershed. Bacteria re-growth and die-off are not accounted for in these load estimations.

From the model simulations for *E. coli* loads, subwatershed 10, 38 and 40 are located are the main sections of the Dickinson Bayou watershed that have the highest potential *E. coli* loads as a result of failing OWTS (Figure 2.16). Subwatersheds 38 and 40 are mainly characterized by developed, open space and low intensity landuse, which consists of household size of approximately between one and four people per household. The number of OWTS in watersheds 38 and 40 is significantly higher than OWTS in other subwatersheds. The combination of the high population density with the high number of OWTS in subwatershed 38 and 40 resulted in the highest potential for contributing *E. coli* load in the watershed. Agricultural lands mainly characterize subwatershed 10, along with developed, open space and low intensity land use, which consist of household size of approximately between two and four people per household. The high *E. coli* loads is a result of the high number of OWTS in the subwatershed which resulted in highest potential for contributing *E. coli* load in the bayou.

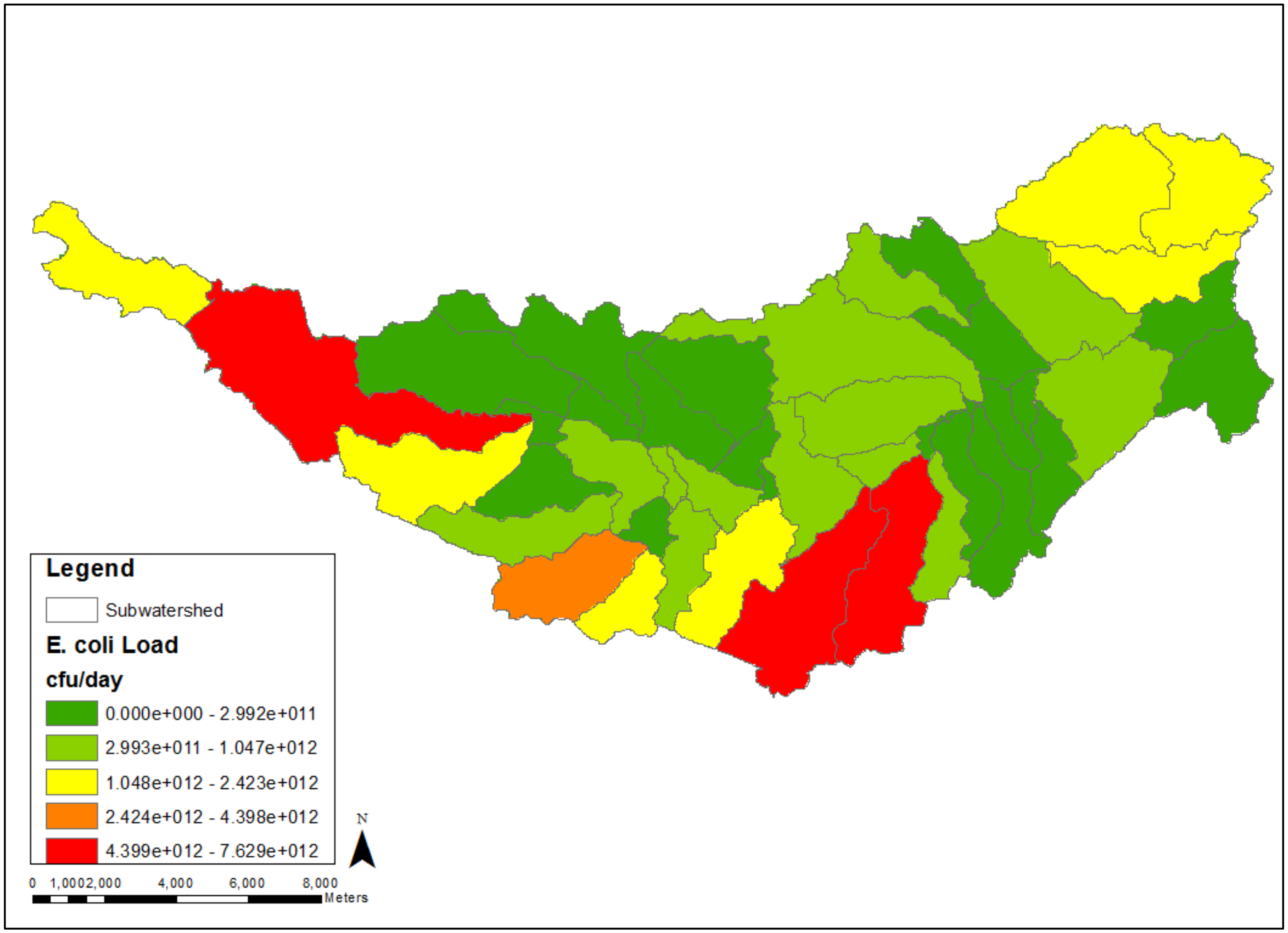

Figure 2.16 Total daily potential *E. coli* load resulting from OWTS in the Dickinson Bayou watershed aggregated to subwatershed to indicate the areas of potential concern of impairment due to bacteria resulting from failing OWTS.

2.4.2. Effects of rainfall on potential *E. coli* concentration in Dickinson Bayou watershed

Rainfall amounts (Table 2.6) for different design return periods were applied in the rainfall runoff calculation to simulate range of *E. coli* concentrations in the Dickinson Bayou watershed. Simulated *E. coli* concentrations in the bayou show that the rainfall has direct impact on the spatial distribution (Figure 2.17 - Figure 2.22). As the rainfall amount increases, the potential *E. coli* concentration in the streams decreases. During the two-year, 24-hr rainfall simulation, with a precipitation of 133.35 mm, the highest potential *E. coli* concentration getting accumulated and routed in the streams was approximately 5,519 CFU/100 mL where as it was only 1,654 CFU/100 mL for a 100-yr, 24-h storm event. Even for 100 year storm, the potential *E. coli* concentrations in the creek (1,654 CFU/100 mL) exceed the regulatory standards of 126 CFU/100 mL.

The general trend of the decreasing *E. coli* concentrations with increasing rainfall amount is because of the dilution effects in the stream for the same amount of potential *E. coli* load in the watershed. It should be noted that bacteria re-growth and die-off were not accounted for in the concentration estimations.

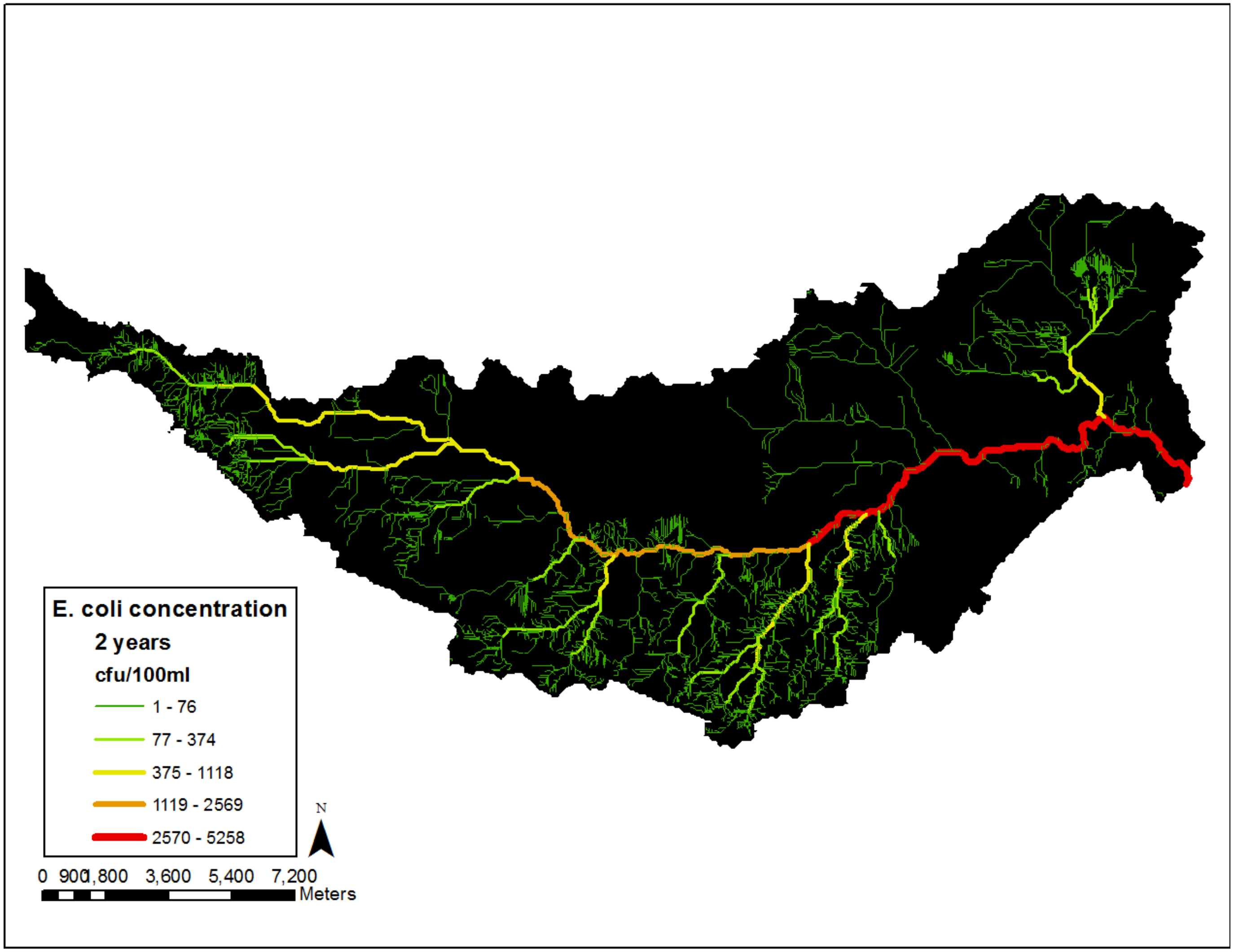

Figure 2.17 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a two year rainfall return period.

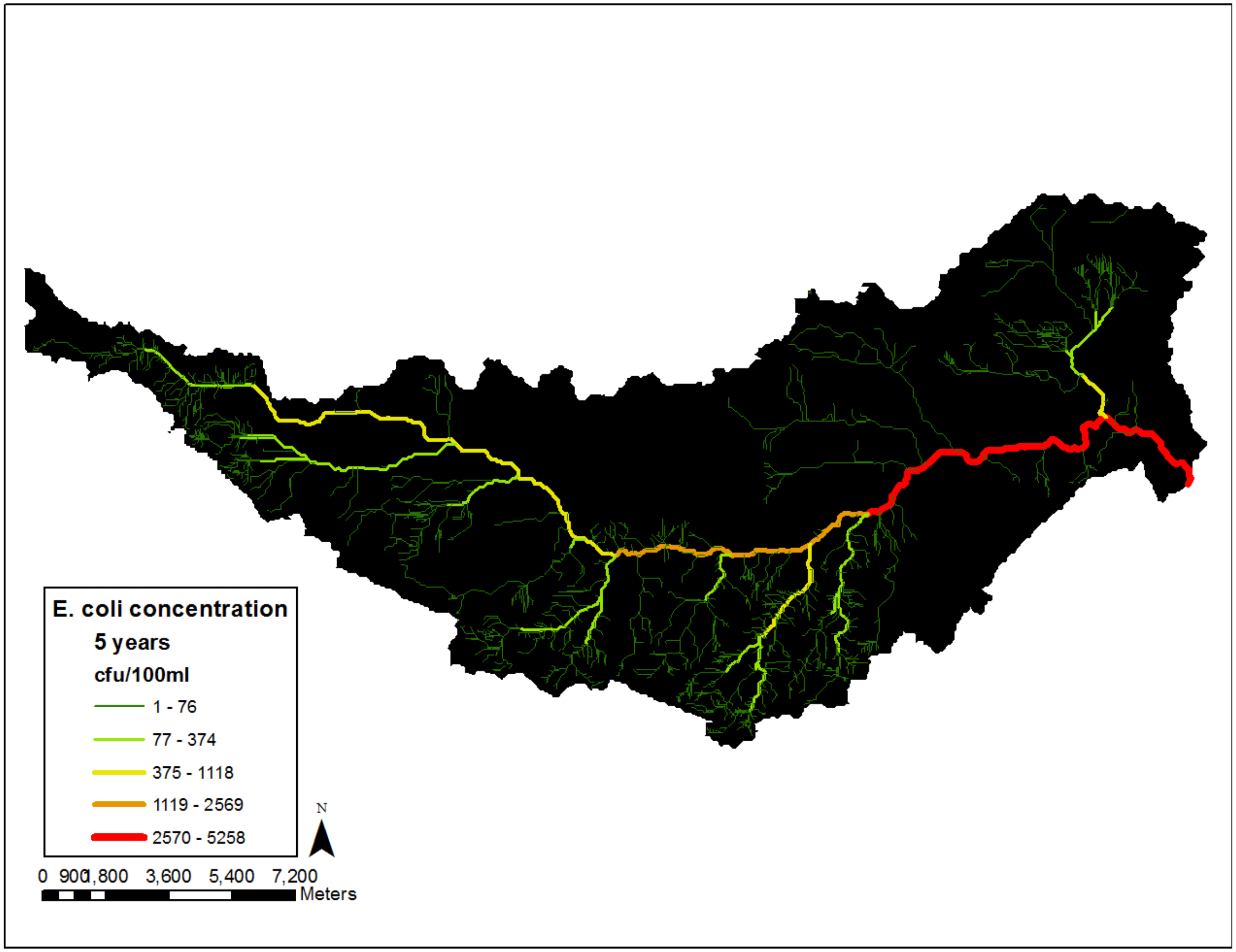

Figure 2.18 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a five year rainfall return period.

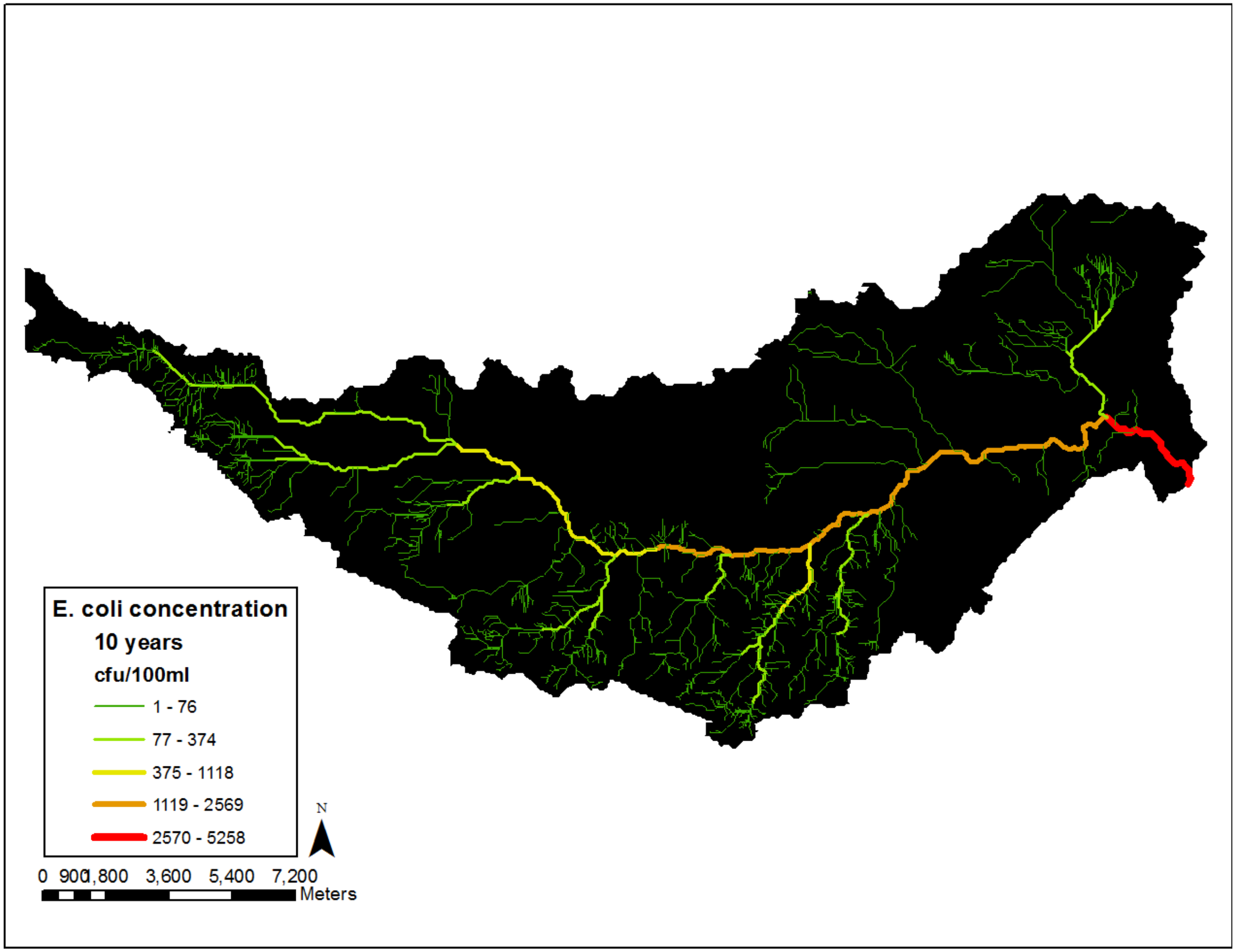

Figure 2.19 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a ten year rainfall return period.

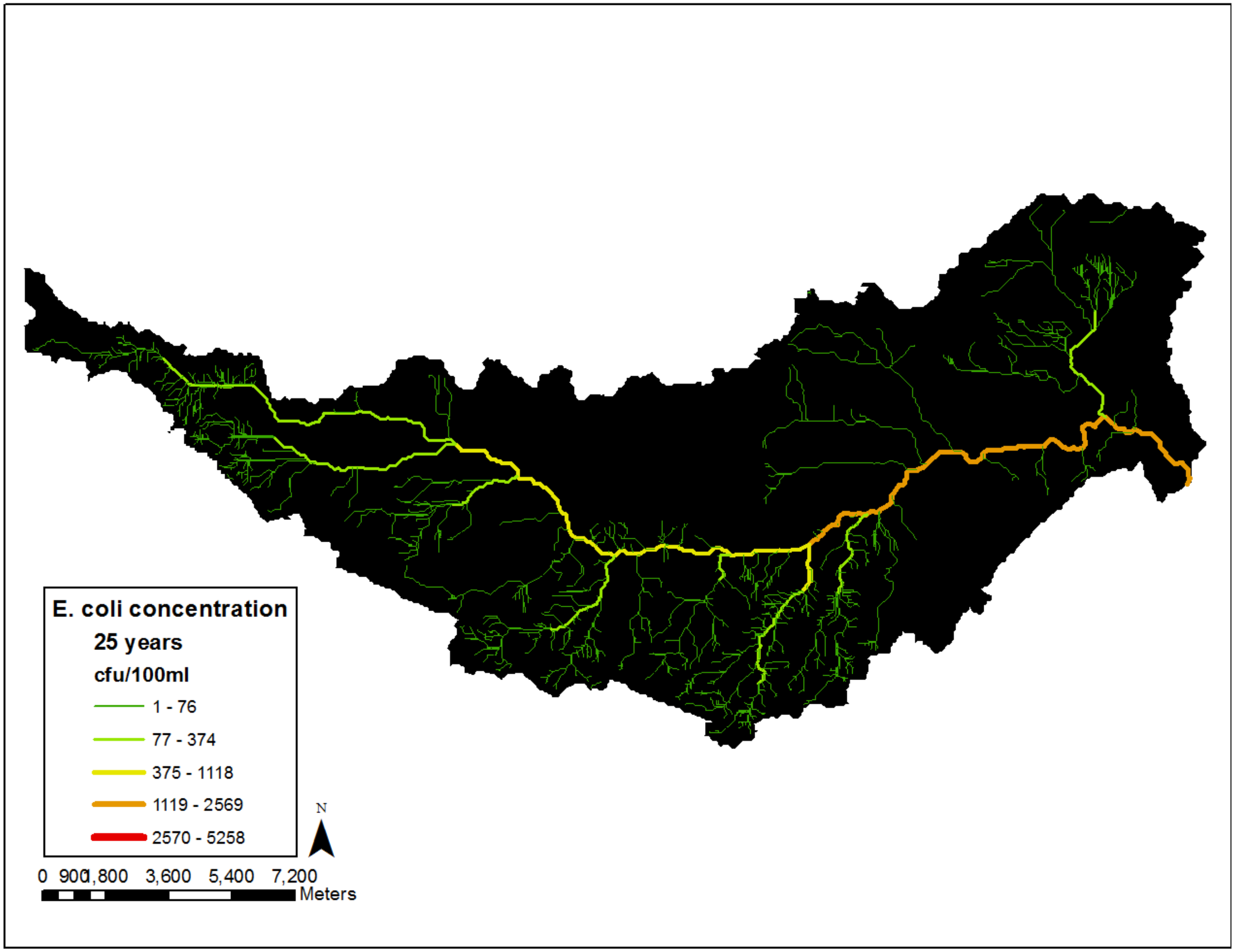

Figure 2.20 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a twenty five year rainfall return period.

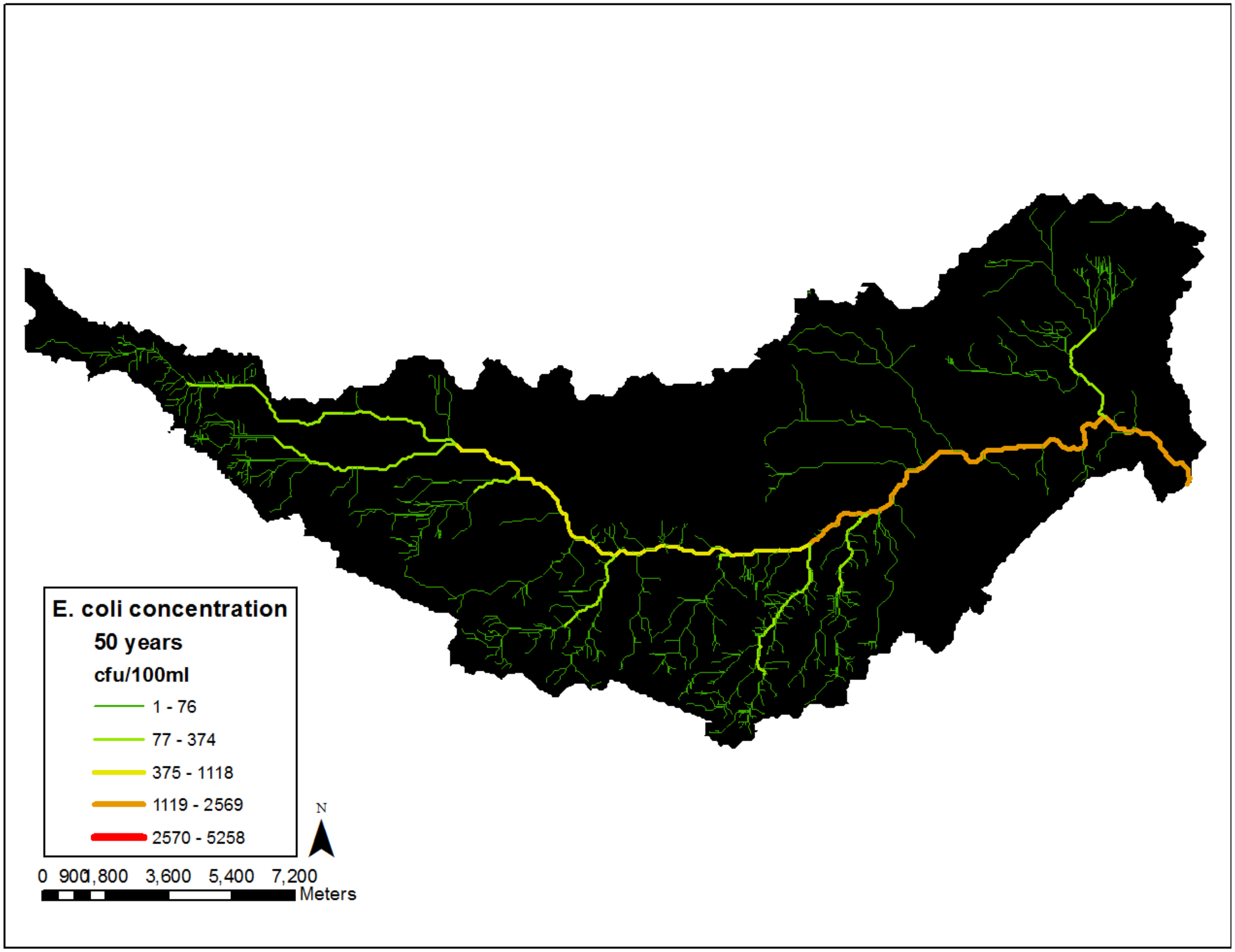

Figure 2.21 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a fifty year rainfall return period.

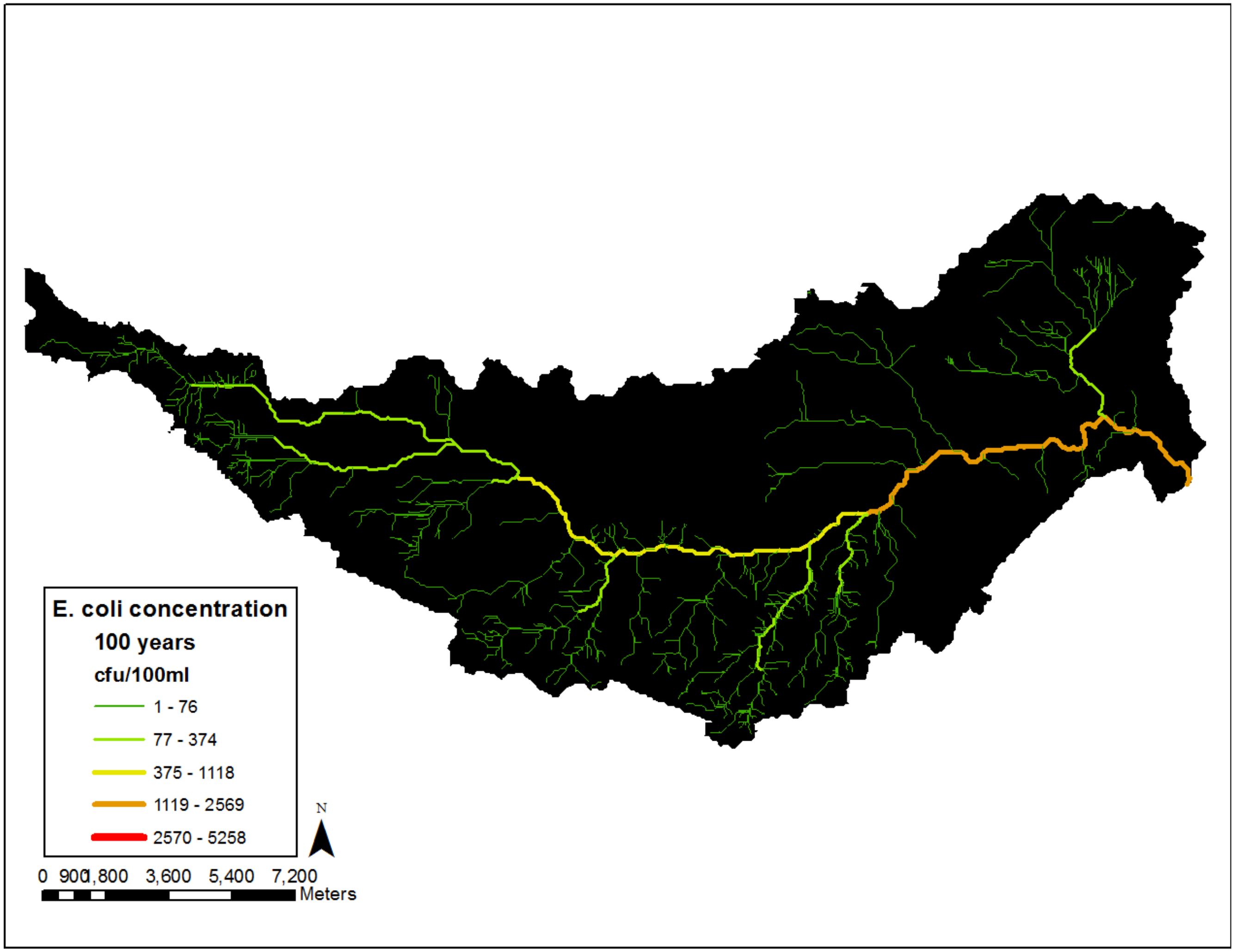

Figure 2.22 Potential *E. coli* concentrations in the Dickinson Bayou watershed for a hundred year rainfall return period.

2.4.3. Effects of age of the OWTS on potential *E. coli* concentration in Dickinson Bayou watershed

Results for the 35% failure of the anaerobic systems showed that the highest potential *E. coli* concentration estimated at the outlet of the watershed with 100% failing OWTS is 5,258 CFU/100 mL (Figure 2.24) with a 2-year return period (133.35 mm). The highest potential *E. coli* concentration estimated at the outlet of the watershed with 35% failing OWTS is 1,347 CFU/100 mL (Figure 2.23) with a 2-year return period (133.35 mm). It should be noted that even with only 35% of failing OWTS, the resulting potential *E. coli* concentration in the bayou exceeds the regulatory standards of 126 CFU/100 mL. These results verify the code: estimating higher *E. coli* concentrations for 100% failing OWTS and lower concentrations with only 35% failing systems.

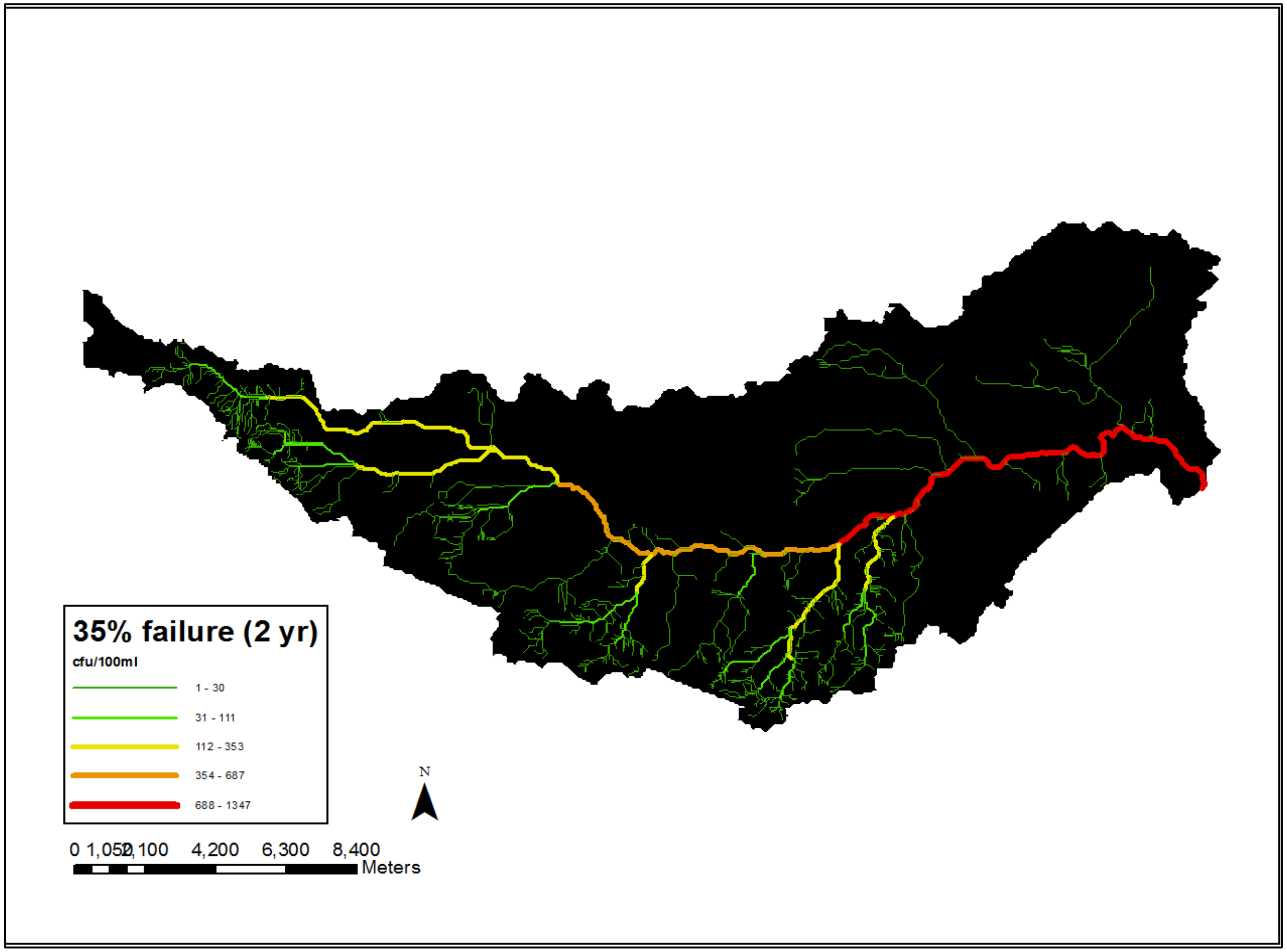

Figure 2.23 Potential *E. coli* concentrations in the Dickinson Bayou watershed for 35% failure in anaerobic systems.

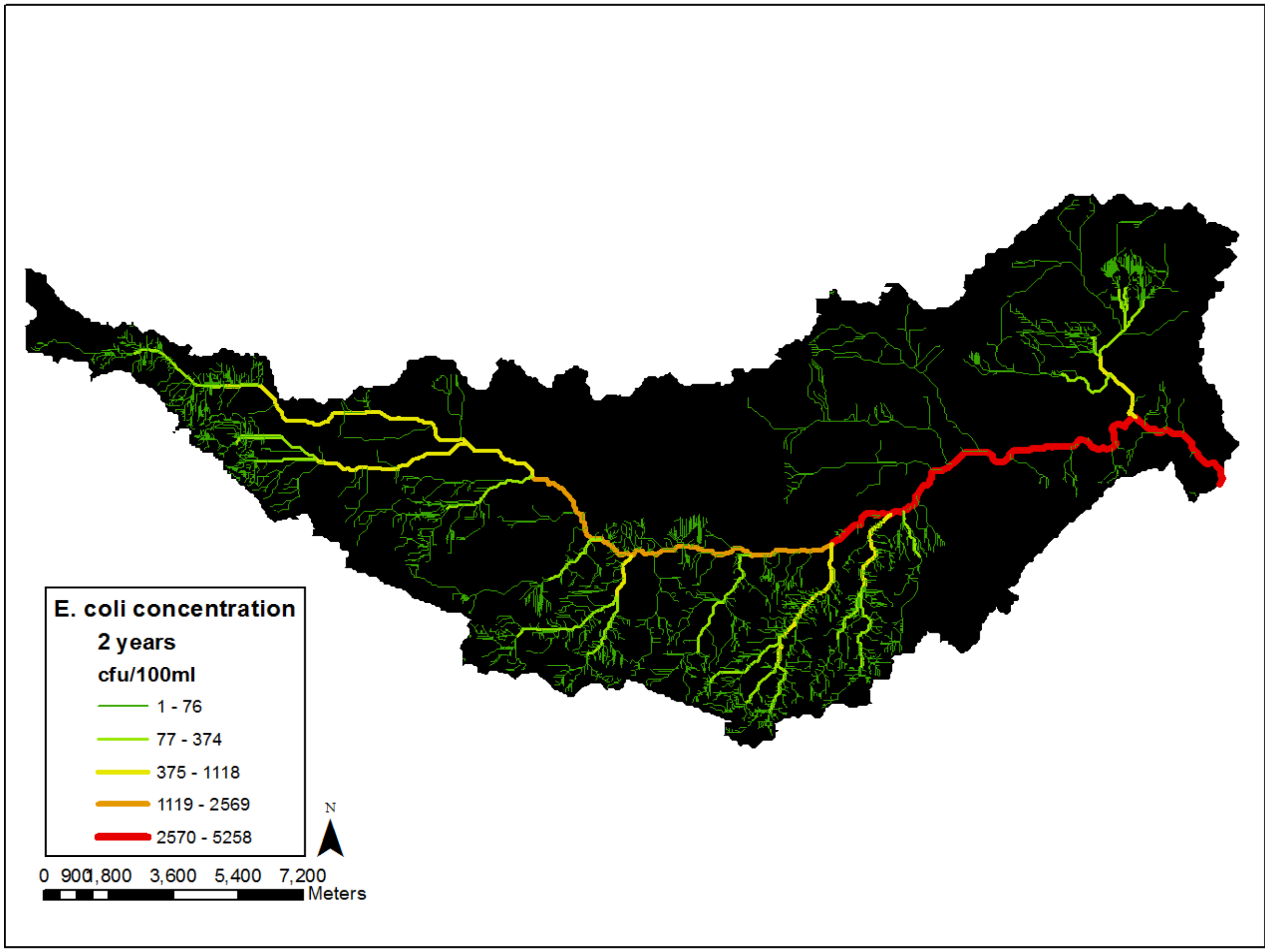

Figure 2.24 Potential *E. coli* concentrations in the Dickinson Bayou watershed for 100 % failure in anaerobic systems.

2.4.4 Simulated runoff *vs.* actual runoff

The model was validated using observed runoff depth data. Observed runoff data was obtained from the project funded by the Dickinson Bayou Project for the monitoring of *E. coli* contamination. The monitored data was collected at an outlet of subwatershed located within the Dickinson Bayou watershed (Figure 2.12 and 2.13).

2.4.5 Outlier testing

This model assumes that the rainfall occurring on the day the sample was collected caused the runoff that transports the *E. coli* to the streams. One monitored runoff value (on 11/25/13) was considered to be an outlier because of high runoff even for wet AMC conditions.. The Dixon-Thompson test was applied to test the runoff point as an outlier. The Dixon Thompson outlier test, which can be used for samples as small as three, is only valid for testing one outlier and can be applied for both low outliers as well as high outliers (McCuen, 2003). The Dixon Thompson test only tests for the largest and the smallest values in a dataset. Since the data point that is considered the outlier was the second largest runoff observed, the highest runoff was not included in the outlier test, and a sample size of 10 was used instead of 11. The equation for the Dixon-Thompson High Outlier Test Statistic is (McCuen, 2003):

$$X_n - X_{n-2} / X_n - X_3 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(2.7)}$$

where, X_n is the largest data in the dataset, and the subscripts representing the rank of the value from the smallest to the largest.

For the critical values, R_c for 5%, 2.5% and 1% levels of significance, the null hypothesis is rejected if the R is greater than R_c. The test statistic (Equation 2.7) was larger then all the R_c at 5%. 2.5% and 1% levels of significance, and therefore the largest runoff was rejected and considered as an outlier by the Dixon Thompson test. The point 11/25/13 was then removed from the data set.

2.4.6 Runoff depth

The model was able to predict the runoff at the monitored site at the Dickinson Bayou watershed with good agreement with the Nash-Sutcliffe Efficiency test (E = 0.73) (Table 2.9). Simulated runoff depth (x) versus the observed runoff depth (y) was plotted in a scatter plot. The resulting regression line had a r^2 value of 0.95 (Figure 2.25). This shows an excellent relationship between the predicted data and the observed data.

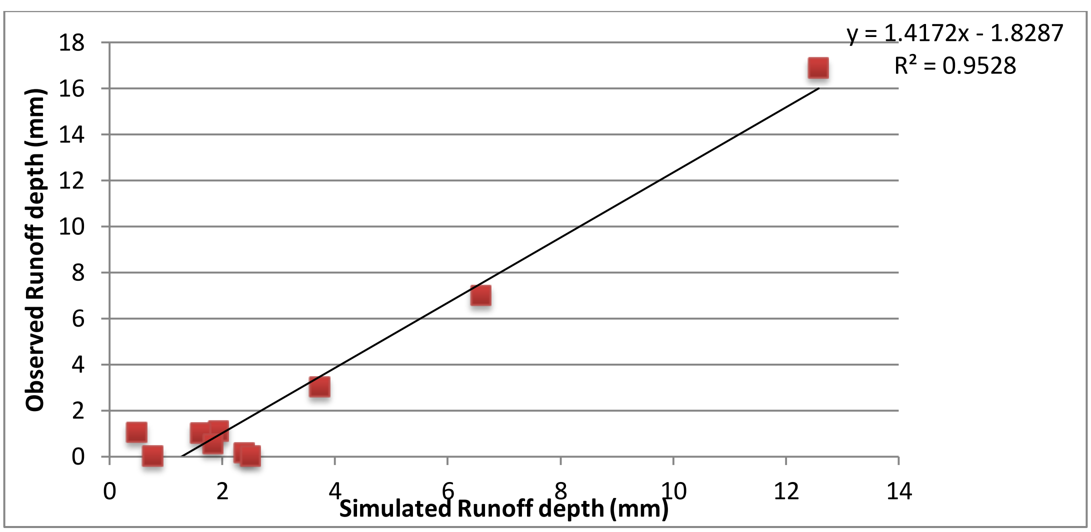

Figure 2.25 Model predicted runoff depth compared to observed runoff depth for the monitored site in the Dickinson Bayou watershed.

For the model simulated runoff, the verification of the model had good agreement (Table 2.9). The *RMSE* value is an important error index that is used in model evaluation as the error that is indicated, will represent the units of the interested constituent (Moriasi et al., 2007). The *RMSE* for the model simulated runoff depth was lower than the observed standard deviations and observed averages indicating satisfactory agreement between the standard deviation of the model predicted runoff depth and the observed runoff depth (Table 2.9). The RSR value indicated good agreement for the model simulated runoff and the observed runoff (Table 2.9).

Table 2.9. Model performance for model simulated runoff *vs.* observed runoff.

Runoff Calculation	**Statistic**	**Observed**
Model simulated	E	0.73
	RSR	0.51
	RMSE	1.79
	Observed Average	3.44
	Observed Standard Deviation	3.64

2.4.7 Uncertainty

Uncertainty is an essential issue in water quality modeling, as the results of these models are used to make important decisions in water policies, regulation and management (Beck, 1987; Sharpley et al., 2002; Harmel et al., 2006; Parajuli et al., 2009; Borel et al., 2012a). According to Coffey et al. (2010), the accuracy of accounting for all these factors that contribute to *E. coli* concentrations, both spatial and temporal, is still debatable.

Modeling bacteria may result in highest probable errors and lowest confidence as compared to nutrient or sediment modeling (Borel et al., 2012b). One potential uncertainty in modeling could be from the data inputs in GIS (Borel et al., 2012b). In this study, we used the best data available for the inputs of the spatial location of OWTS obtained from the watershed officials. In addition, other GIS data that were used such as Digital Elevation Model (DEM), soils data (SURRGO), and climate data (NOAA) were the best available data. According to Coffey et al. (2010), the uncertainty and variability that surrounds bacteria modeling can lead to large discrepancies in the results of bacterial modeling.

CHAPTER III

CONCLUSIONS AND RECOMMENDATIONS

3.1. Conclusions

A spatially explicit GIS tool was developed, automated, verified, and applied to simulate potential *E. coli* concentrations in a watershed due to failing Onsite Wastewater Treatment Systems (OWTS). This automated tool simulated potential *E. coli* loads and concentrations from failing OWTS across the Dickinson Bayou watershed in Texas. Based on the results, it was concluded that rainfall amount plays a significant role in routing the *E. coli* loads to streams in the watershed. The potential *E. coli* concentration in streams decreased with increasing rainfall amount, as a result of dilution. Hence, the 100-year storm will result in less *E. coli* concentration as compared to 2-year return period storm for a given *E. coli* in the watershed. However, it should be noted that *E. coli* attenuation factors are not considered in the simulation and the fate and transport parameters of *E. coli* in a watershed will play a significant role in estimating actual concentrations in the streams.

The model was validated using observed runoff data at a specific monitored site within the Dickinson Bayou watershed. The model was able to successfully predict the runoff occuring at the observed site. The model results were in good agreement (E = 0.73, RSR = 0.51) for the simulated runoff values. The RMSE values were less than half of the standard deviation showing a good agreement between the observed and predicted runoff depth.

This automated tool is very user-friendly and user-driven tool to conduct spatial analyses on different watersheds using varying parameters such as land use, rainfall conditions, census data, and type of OWTS. In addition, this tool can be used for technical analyses as well as for stakeholder awareness. This approach can be powerful to determine areas where attention should be focused in the watershed to implement BMPs to decrease *E. coli* pollution. This tool can be used by watershed managers to identify potential threat areas and to come up with management options.

3.2. Future Recommendations

Further investigation with *E. coli* degradation and regeneration is needed to determine the influence of time and distance on the potential *E. coli* concentration. Travel time from the OWTS to the stream should be determined to estimate *E. coli* concentrations reaching the streams. The difference between Aerobic Treatment Units (ATU) and anaerobic septic systems should be taken in to account for. The treatments for both of these systems are different and hence the contributing *E. coli* load coming from each of the failing systems must also be different. More investigation should be done to find the difference in the *E. coli* load resulting from the ATUs in order to find the difference in the contribution of *E. coli* loads and concentrations from these systems as compared to traditional anaerobic systems.

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