Evaluating Drivers and Sources of Pathogens to Surface Waters in Primarily Arid and Semi-Arid Tribal Lands of the United States

by

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ABSTRACT

Pathogenic contamination is a significant factor contributing to the degradation of surface water both globally and within the United States. This leads to negative economic impacts, sickness, and, in severe cases, fatalities. As the world's population grows, pollution increases, placing more stress on water resources, particularly in arid regions. The situation is made worse by climate change. The forecasted expansion of arid and semi-arid land areas and alterations in precipitation patterns could have a significant impact on those living in poverty and dry regions. This dissertation aims to investigate previously undocumented threats to water quality through understanding pathogen drivers in arid and semi-arid environments and documenting wastewater infrastructure on Tribal lands. Specifically, I first investigated how ephemeral streams (common in arid and semiarid areas) impact the presence of pathogens in surface waters by identifying the main drivers of *E. coli* concentration from a series of proposed predictors. Second, I identified unknown potential sources of water quality impairments on Tribal lands, which are mainly rural and in arid or semiarid areas, focusing on wastewater infrastructure in these systems. I specifically quantified populations served by wastewater treatment plants and then used a remote sensing approach to identify possible unpermitted wastewater lagoons that often serve as the only wastewater infrastructure in some areas. The findings revealed unique insights that could help aid water management in arid and semiarid regions as well as in rural areas.

DEDICATION

To Alberto†, Olga, Olga Marina, and Luis. None of this would have been possible without you.

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TABLE OF CONTENTS

CHAPTER Page

CHAPTER Page

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1. Background

Water is a fundamental resource for human subsistence and essential for economic and social well-being. Freshwater demands are continuously growing; however, environmental degradation is being reflected in the limited water resources of the planet, which has been one of the most affected environmental factors, putting the availability of quality water supply and development at risk. (Khan et al., 2022; WWAP (United Nations World Water Assessment Programme), 2017). In the United States (US), 24% of assessed lakes were hypereutrophic, with phosphorus and nitrogen being the most common stressors in 2017 (United States Environmental Protection Agency, 2022c). In 2014 44% of perennial river and stream miles were rated as poor quality based on benthic macroinvertebrates (United States Environmental Protection Agency, 2020), 32% of the wetland area was in poor biological condition in 2011 (United States Environmental Protection Agency, 2016b), and 15% of estuarine waters were impacted by eutrophication in 2015 (United States Environmental Protection Agency, 2021b). These assessments demonstrate a sustained need to protect water resources from pollution threats.

As development and population increase, so does the number of activities that can contaminate the water, increasing the load and number of pollutants, the number of contaminant sources, and, of course, the quantity of wastewater. Water pollution can occur from those direct and identifiable sources called point sources such as sewage treatment plants and oil refineries, or from non-point sources, those that are both diffuse in nature and difficult to define and control such as agricultural regions and land development (Dressing et al., 2016; Speight, 2020). Pollutants are categorized on different characteristics such as organic and inorganic, pathogenic or nonpathogenic, source and origin, and by their impacts on environment and human health (Madhav et al., 2020). The type of pollutants contaminating water vary depending on the type of anthropogenic activity. Runoff from agricultural fields is likely to contain high concentrations of suspended solids, dissolved salts, nutrients (mainly nitrogen and phosphorus), pesticides, organic matter, and pathogens. Water used in domestic and municipal activities is likely to contain high bacterial loads, while that used in industrial and mining activities may also contain toxic organic compounds or emerging contaminants, which for some, only a small amount can lead to detrimental contamination.

Although there is growing concern about emerging pollutants in industrial wastewater (Chowdhary et al., 2020; Rasheed et al., 2019; Wilson & Aqeel Ashraf, 2018; WWAP (United Nations World Water Assessment Programme), 2017) and the nutrients nitrogen and phosphorus, pathogens are still a major pollution concern. Waterborne pathogens and related diseases are a major public health concern because of the morbidity and, in extreme cases, the mortality they cause; the latter is estimated at 2.2 million deaths per year especially in populations of children (Ramírez-Castillo et al., 2015). They also impact the economy mainly by the high cost that represents their prevention and treatment (Habibi-Yangjeh et al., 2020). For example, some pathogens like *Cryptosporidium* spp., an intestinal parasite and a common cause of severe diarrhea especially in immunocompromised people and young children (Zahedi & Ryan, 2020), can only be killed using sophisticated and expensive water treatment methods rather than just chlorination (Gerba & Pepper, 2019). It has been suggested that waterborne diseases have an associated annual economic cost of 1 billion dollars in the US alone and 12 billion dollars worldwide (Ramírez-Castillo et al., 2015). Pathogens are one of the most reported impairments of water quality throughout the US, according to the Environmental Protection Agency (EPA). For the period 2004 to 2014 it was the top impairment reported for all assessed rivers and streams, bays and estuaries, and coastal shoreline (Dressing et al., 2016).

1.2. Waterborne Diseases

An organism causing disease to its host is called pathogen (Balloux & Van Dorp, 2017). Pathogens are a diverse group comprising viruses, bacteria, fungi, protozoa, worms, and even infectious proteins called prions, the most familiar are bacteria and viruses (Alberts, 2002). There is a vast abundance of bacteria and viruses on Earth, in fact, they inhabit all kinds of environments, it is estimated that there may be as many as $1x10^{31}$ viruses in existence (Nature Reviews

Microbiology, 2011). It is worth noting that the human body carries an average of 3.8×10^{13} bacteria, primarily in the gut (Sender et al., 2016)) and that a human adult will excrete their own weight only in fecal bacteria each year (Nature Reviews Microbiology, 2011) while the pathogen concentration in animal waste depends on the species, age, health, stress, and diet (Alegbeleye & Sant'Ana, 2020). However, it is important to acknowledge that not all these microorganisms pose a threat to our well-being.

Every living organism is affected by pathogens, a total of ~1400 known pathogens species affect humans (Nature Reviews Microbiology, 2011) which are diverse in size, shape, and content, each causing disease in a different way (Alberts, 2002). Pathogens in humans can be transmitted by direct contact —person to person, droplet spread—, or indirect contact —airborne transmission, contaminated objects, food and drinking water, animal to person, animal reservoirs, insect bites, environmental reservoirs— (Van Seventer & Hochberg, 2017). When water acts as the passive carrier of pathogens the term waterborne is used, the diseases transmitted from contaminated water are known as waterborne diseases (Leclerc et al., 2002).

A wide variety of pathogens excreted in feces are capable of initiating waterborne diseases, depending on factors such as pathogen survival, latency, ability for multiplication in the environment, and the required dose for establish infection; in theory, even a single organism is enough to cause an infection (Leclerc et al., 2002). There is a potential risk of pathogen spread into the environment wherever feces are deposited, stored, or applied to land (Alegbeleye & Sant'Ana, 2020) which can be heightened by the amount of produced feces. Manure and wastewater produced by farms and people has been estimated at 335 million tons of dry matter per year by Concentrated Animal Feeding Operations (CAFOs) and 18.1 million tons of dry matter per year by the citizens only in the US (Bradford et al., 2013). Diverse symptoms can be caused by waterborne diseases as gastrointestinal, skin, ear, respiratory, eye, neurological or bloodstream problems with the most common being diarrhea and vomiting (Centers for Disease Control and Prevention, 2023a; Minnesota Department of Health, 2022b). Children under 5 years, the elderly, pregnant women, and the immunocompromised are more vulnerable to waterborne diseases due to reduced immunity (Gaffield et al., 2003; Rhoden et al., 2021).

Outbreaks of waterborne diseases happen all around the world. According to Yang et al., (2012) from 1991 to 2008 the reported outbreaks clustered in western Europe, central Africa, north India and southeast Asia. In the United States, 82 waterborne outbreaks were reported from 32 states to the National Outbreak Reporting Systems (NORS) of the Centers for Disease Control and Prevention (CDC) during 2015 where recreational water (47), drinking water (23), other exposures (6), and unknown (6), were implicated in the outbreak (Centers for Disease Control and Prevention, 2022c). Also in the US, for the period 1971–2020 the top causes of waterborne outbreaks were *Legionella*, *Giardia*, *Norovirus* spp., *Shigella* and *Campylobacter* in drinking water (Centers for Disease Control and Prevention, 2022d), and *Cryptosporidium*, *Pseudomonas*, *Legionella*, *Shigella* and *Norovirus* spp. in recreational water (Centers for Disease Control and Prevention, 2022b).

1.3. Pathogens in Surface Water

Most of the commonly occurring waterborne pathogens in the US, such as *Cryptosporidium*, *Cyclospora spp.,* and *E. coli* O157:H7*,* typically stem from fecal waste on land, both from animals and humans (Minnesota Department of Health, 2022a, 2022c, 2022d); these pathogens can enter surface water through different channels. Other pathogens such as *Legionella* and *Naegleria fowleri*, occur naturally in waterbodies (Centers for Disease Control and Prevention, 2018, 2023b). Sources of pathogens on land impacting surface water depend on the type of developed activities in the watershed. Land use, land cover and their change can impact water quality, particularly pathogen concentration (Pandey et al., 2012). Land use can contribute to soil erosion (Nakhle et al., 2021) while land use changes in the process of urbanization, industrialization, and agriculture can change the surface characteristics of watersheds and therefore the quality and quantity of runoff (Camara et al., 2019). Precipitation may increase the concentration of pathogens in surface water due to increased surface runoff from agricultural lands and urban areas and re-suspension from sediments.

In an urban environment, where land use changed from forest or agricultural use to suburban and urban areas, the creation of impervious surfaces introduces hydraulic modifications that profoundly affect the quantity, path and therefore the quality of the stormwater runoff (Carstens

& Amer, 2019; National Research Council, 2009). During rainfall events, stormwater runoff is produced from both pervious and impervious areas, collecting pollutants such as pathogens as it passes over roads, streets, rooftops, and compacted lands (Gaffield et al., 2003; Müller et al., 2020). Additionally, during periods of intense runoff combined sewer and less likely sanitary sewer overflows can discharge contaminated water directly into waterbodies (Office of Water Programs & California State University Sacramento, 2008; United States Environmental Protection Agency, 2023f), Curriero et al., (2001) found that most waterborne disease outbreaks in the US follow large precipitation events. Other on-land sources of pathogens include Wastewater Treatment Plants (WWTPs) depending on the treatment process, when poorly operated, or when spills occur (Anastasi et al., 2012; Verburg et al., 2019), broken or leaky sewer pipes, failing or poorly sited septic systems, illicit sewer connections, urban litter, and domestic pet feces (Ahmed et al., 2018; Arnone & Perdek Walling, 2007; Benham et al., 2006).

In agricultural settings, where the commonly associated pathogens are zoonotic microbes which are capable of causing disease in both animals and humans (Bradford et al., 2013), pathogen sources include direct deposition of livestock manure to waterbodies, runoff from fields with recent manure application, grazing activities, feedlots, CAFOs and ranches (Alegbeleye & Sant'Ana, 2020; Burkholder et al., 2007). CAFOs and ranches produce considerable quantities of fecal waste, it is typical for nearby streams to contain pathogens as a result of the direct discharge of their effluents into the water, leaks from manure storage areas and ponds, the application of manure to nearby land, and accidental spills (Alegbeleye & Sant'Ana, 2020; Haack et al., 2015; Heaney et al., 2015; Hubbard et al., 2020). It is worth noting that EPA considers agriculture as one of the major pollutant sources (United States Environmental Protection Agency, 2017a). Wildlife areas where feces from animals are continuously and randomly deposited on the soil surface become potential sources of pathogens when a rainfall event occurs, potentially carrying large quantities of pathogens to rivers (Bolds et al., 2022; Cox et al., 2005; Nguyen et al., 2018).

There are other factors influencing the concentration and the fate and transport of waterborne pathogens including precipitation amount, type and location of sources on land, sediment, and the survival characteristics of individual organisms which in turn are influenced by moisture, nutrient availability, temperature, pH, salt, and sunlight (Gerba, 2015; Jokinen et al., 2012; United States Environmental Protection Agency, 2023c). The effect of temperature differs depending on the pathogenic organism species and strain, some organisms are more heat tolerant (Legionella spp.) or cold tolerant (Cryptosporidium spp.), with extreme cases called extremophiles thriving temperatures around 131 or 32 degrees Fahrenheit (hyperthermophiles or psychrophiles) respectively (D'Amico et al., 2006; Rampelotto, 2013). Generally cooler temperatures enable longer survival times and above certain temperature thresholds the survival rates typically decrease. In water bodies, water temperature, which is directly affected by air temperature, can strongly influence growth and survival rates of pathogens, and typically, the survival or growth of pathogens decreases with warmer temperatures (Islam et al., 2021; Shahid Iqbal et al., 2017; United States Environmental Protection Agency, 2023c). Watershed slope also plays an important role in water quality; under the force of gravity, water moves from higher to lower elevation with a speed and rate proportionate to the steepness and length of the slope. Many hydrological processes such as soil erosion, soil deposition, runoff, and infiltration have dependency on the speed and rate at which water moves on land, which in turn has a significant impact on surface water quality (Alberti, 2008; Lintern et al., 2018). Stream networks can also influence pathogen concentrations by influencing the water residence time and water dilution capacity (Wang et al., 2018). Flow duration is the basis for hydrologic stream classification; perennial streams flow year-round for which base flow is maintained by local or regional groundwater inflows; intermittent streams only flow continuously at certain times of the year due to a seasonal groundwater source; and ephemeral streams flow briefly during and immediately after precipitation in the vicinity (Levick et al., 2008). Flow also plays an important role in stream connectivity which controls the mobility of matter and organisms in the system (Jaeger et al., 2014; Wohl, 2017). River connectivity could explain pathogen sources and abundance —at locations with higher river connectivity increased abundance may be expected compared to sites with lower connectivity (Frick et al., 2020).

1.4. ***Escherichia coli*** **(*E. coli*) as Water Quality Indicator**

In the US, Water Quality Standards (WQS) are provisions approved by EPA describing the desired condition of a water body and the means by which that condition will be protected or achieved. WQS consist of at least three components: designated uses of a water body, Water Quality Criteria (WQC) to protect the designated uses, and antidegradation requirements to protect existing uses and high quality/high value waters (United States Environmental Protection Agency, 2023b). The WQC are those scientifically defensible characteristics to protect aquatic life and human health (Schnoor, 2014). These can be numeric, as maximum pollutant concentration levels permitted, or narrative, as the description or the desired conditions of a water body (United States Environmental Protection Agency, 2023b). EPA provides national recommended WQC, however states and authorized tribes may adopt other scientifically defensible ones where appropriate (United States Environmental Protection Agency, 2017b). For ambient waters —those open waters such as rivers, lakes, and streams (United States Environmental Protection Agency, 2023g) — EPA recommends WQC for human health, recreation, aquatic life, and nutrients among others (United States Environmental Protection Agency, 2022i). When these criteria are met, water quality will generally protect the designated use; if exceeded, the water quality may pose a human health or ecological risk, and protective or remedial action may be needed (United States Environmental Protection Agency, 2017b). Human health WQCs protect any designated uses related to ingestion of water, ingestion of aquatic organisms, or other waterborne exposure from surface waters (United States Environmental Protection Agency, 2017b, 2022p). The purpose of recreational WQCs is to safeguard recreational activities that involve direct contact with water, such as swimming, surfing, water skiing, tubing, and other similar activities that may involve immersion, ingestion, and a high level of bodily contact with water (United States Environmental Protection Agency, 2017b, 2021a, 2023d).

Those WQCs related to pathogens in ambient water use indicator organisms or surrogates given that identifying and isolating waterborne pathogens can prove to be challenging due to the difficulties and expenses involved in the testing for varieties of pathogens (Islam et al., 2021). Typically, nonpathogenic Fecal Indicator Bacteria (FIB) such as *fecal coliform*, *E. coli*, and *fecal* *streptococci* and *enterococci* serve as surrogates to detect the potential presence of fecal waste and therefore a wide variety of most commonly occurring pathogens with fecal origin (Motlagh & Yang, 2019; Pandey et al., 2014). *E. coli* and total coliforms are the most commonly used FIB (Wen et al., 2020). A useful aspect of common FIB is their prevalence in the feces of various animals, including birds, mammals, and humans making them a reliable means of identifying fecal pollution. However, the lack of host specificity makes it challenging to identify the exact source of the pollution (E. Li et al., 2021), and they are ineffective to indicate the presence of enteric viruses and protozoa from fecal waste or naturally occurring waterborne pathogens (Hussain, 2019).

E. coli are a large and diverse group of gram-negative, rod-shaped bacteria found in food, the environment, and the gastrointestinal tract and feces of warm-blooded animals (Centers for Disease Control and Prevention, 2014). The hundreds of *E. coli* strains can be grouped into commensal organisms —not causing disease and normal residents of the gastrointestinal tract, intestinal pathogens —strains causing diarrheal intestinal disease referred as diarrheagenic *E. coli*, and extraintestinal pathogens – causing diseases outside of the intestinal tract (Gerba, 2015; Poolman, 2017). Diarrheagenic *E. coli* group includes Shiga Toxin-producing *E. coli* (STEC) also referred to as Verocytotoxin-producing *E. coli* (VTEC) or Enterohemorrhagic *E. coli* (EHEC). The most commonly identified STEC strain in the US is O157:H7 (Centers for Disease Control and Prevention, 2014) that can cause abdominal cramps, severe bloody diarrhea, fever, and hemolytic uremic syndrome that can lead to kidney failure and death (Johns Hopkins Medicine, 2019).

E. coli concentrations in water are measured using different approaches such as Membrane filtration, Multiple Tube/Multiple Well, and Multiple Tube Fermentation with procedures standardized by EPA (Guidelines Establishing Test Procedures for the Analysis of Pollutants, 2020) resulting in measurement units of Colony-Forming Units per 100 milliliters (CFU/100 mL) or Most Probable Number per 100 milliliters (MPN/100mL). EPA WQC for *E. coli* is expressed in CFU/100 mL. For recreational water the recommended values are a Geometric Mean (GM) of 126 CFU/100mL and a Statistical Threshold Value (STV) of 410 CFU/100 mL, with weekly sampling to evaluate them over a 30-day period (United States Environmental Protection Agency, 2021a).

1.5. Pathogenic Impaired Waters in the US

The Clean Water Act (CWA) regulates for pathogens found in ambient water bodies in the US (United States Environmental Protection Agency, 2022h) while the Safe Drinking Water Act (SDWA) addresses pathogens in drinking water supplies (Centers for Disease Control and Prevention, 2022a). The CWA, a federal law originally enacted in 1948 with major updates in 1972, has a primary goal to achieve water quality that meets beneficial use requirements for a given waterbody. To accomplish this, the restoration and maintenance of the chemical, physical and biological integrity of the water in the country is supported by several actions mandated by this Act (United States Environmental Protection Agency, 2021e). Section 305(b) of the CWA requires states and territories to prepare and submit biennially to EPA a report including a description of the water quality of the Waters Of The US (WOTUS) in the state during the preceding years. The section 303(d) is used to identify and make a list of those waters that are polluted —impaired waters— and their causes of pollution called Clean Water Act Section 303(d) List of Water Quality Limited Segments, and to establish a priority ranking for such waters and plans to restore degradation settling a Total Maximum Daily Load (TMDL) of the related pollutants (United States Environmental Protection Agency, 2021c, 2023h). A TMDL is a calculation that determines the maximum amount of a pollutant that can enter a waterbody to meet and maintain WQSs for that specific pollutant. It identifies a target for reducing the pollutant and distributes the necessary load reductions to the source(s) responsible for the pollutant (United States Environmental Protection Agency, 2022t). To develop a TMDL it must be in accordance with the CWA regulations for waters with bacterial concentrations exceeding the WQCs; the identification of pollutant sources is fundamental, Waste Loads Allocations (WLAs) —the maximum load of pollutants allowed to be released (Minnesota Pollution Control Agency, 2022)— from those point sources as well as Load Allocation (LA) for those non-point sources should be defined (United States Environmental Protection Agency, 2022t). The point sources used to assign WLAs are all sources subject to regulation under the National Pollutant Discharge Elimination System (NPDES) program as WWTPs, stormwater discharges, and CAFOs.

According to EPA estimates, pathogens are the leading cause of impairment for 303 (d) listed waters. Since pathogens are not usually directly measured, the presence of FIB suggests the pollution is from fecal matter. Pandey et al., (2014) suggest that more than 480,000 km of rivers and shorelines as well as 2,000,000 Ha of lakes are impaired by pathogens in the US, while for the period 2004 to 2014 national totals for causes of impairments or threats to impairment obtained from this data show that at least 178,219 miles of rivers and streams, and 549,515 acres of lakes, reservoirs, and ponds are impaired by pathogens (Dressing et al., 2016). This is likely an underestimate because not all surface waters have been assessed and the spatiotemporal variability of water quality.

While the EPA has played a fundamental role in controlling point source discharges to WOTUS thanks to the establishment of the NPDES program, for some potential point sources of pollutants, especially those not discharging to a WOTUS, there is often no federal or state/local approach to regulation and monitoring. Thus, there has been no comprehensive assessment of their contributions to water quality impairments or proximity to vulnerable communities.

1.6. Drylands

There are numerous definitions regarding drylands, but a commonly accepted definition is based on the comparison of the long-term average of Precipitation (P) to the long-term average of climatic water demand, known as Potential Evapotranspiration (PET). This numerical indicator is called the aridity index (Cherlet et al., 2018). This ratio indicates the maximum amount of water vapor capable of being lost by a ground completely covered with vegetation, in a given climate, involving both the evaporation that occurs from the soil and the transpiration that takes place from the vegetation within a particular area during a specified time frame (Gaur & Squires, 2018). Based on the aridity index, drylands are the climatic zones where the ratio of long-term mean annual precipitation to potential evapotranspiration is less than 0.65, with the subtypes hyper-arid (aridity index < 0.05), arid ($0.05 \leq$ aridity index < 0.2), semi-arid ($0.2 \leq$ aridity index < 0.5), and dry subhumid ($0.5 \leq$ aridity index < 0.65) (Cherlet et al., 2018; European Commission. Joint Research Center, 2019).

Drylands are characterized by a combination of low precipitation, droughts, and heat waves inducing water scarcity (Food and Agriculture Organization of the United Nations, 2023; Gaur & Squires, 2018). In these areas, the soil is prone to erosion caused by wind and water, and there is intensive mineral weathering; additionally, the topsoil has low fertility due to limited organic matter content (Food and Agriculture Organization of the United Nations, 2023). Drylands are critical environments that cover more than 40% of the Earth land surface, where hyper-arid, arid, semiarid, and dry subhumid regions account for about 13, 31, 36, and 20% of this area, respectively (Plaza et al., 2018) and are home to around three billion people (Gaur & Squires, 2018; Mirzabaev et al., 2019). Drylands encompass round 30% of urban areas where approximately 34% of the urban population resides, and about 44% of the world's agricultural land, which produces roughly 60% of the world's food exist. (Cherlet et al., 2018). In the US, 40% of the land is considered dryland (United States Geological Survey, 2016).

The presence of ephemeral and intermittent streams is a characteristic of drylands and both are important for ecological and societal purposes (Jaeger et al., 2014). Ephemeral and intermittent headwater streams account for ~60% of total mean annual flow to all northeastern US streams and rivers, for example (Dewey et al., 2020). Ephemeral streams have characteristics that differ from perennial rivers as larger flood magnitudes compared to rivers of more humid regions, high sediment supply, and poor bank stabilization and cohesion due to the sparse or absent riparian vegetation and low presence of clay (Billi et al., 2018). Even slight variations in climate can result in significant changes in surface flows in dryland streams such as more frequent and extensive dry streambeds and reduced hydrologic connectivity particularly noticeable during prolonged droughts, that coupled with human population growth can lead them to reduce or cease flow (Jaeger et al., 2014); as well as high transport of sediments with high magnitude storm events.

E. coli can be transported in water as free cells or cells attached to particles of solids (e.g. soil and manure) affecting its fate and transport in aquatic systems (Cizek et al., 2008; Garcia-Armisen & Servais, 2009; Krometis et al., 2007; Ribolzi et al., 2016; Soupir et al., 2010). Boithias et al., (2021) found that high values of in-stream *E. coli* concentrations were predominantly driven by surface runoff and soil surface erosion. This fact could be especially important in semi-arid areas where soil erosion is considered one of the major threats (Xiong et al., 2018) and intense storms lead to high-energy flash floods (Rio et al., 2017; L. Yang et al., 2017).

1.7. Pathogens and Climate Change

Greenhouse emissions due to human activities contribute to global warming. In the period 2011-2020 an average increment of 1.09˚C with respect to the period 1850-1906 has been detected, being larger over land (1.59 ˚C) than over the ocean (0.88 ˚C); the increase has been faster in the last 50 years period (Intergovernmental Panel on Climate Change, 2023). Among the impacts of global warming are the increases in frequency and magnitude of heatwaves, heavy rainfall, droughts, tropical cyclones, and sea level rise.

As the climate continues to change, experts predict that the rise in precipitation and temperatures will only worsen issues with fecal contamination (Islam et al., 2021) increasing the challenges of water availability and exposure to unsafe water. More than 3.3 billion people live in conditions that are highly vulnerable to climate change, including those with development constraints among which are Indigenous people, small-scale food producers and low-income households (Intergovernmental Panel on Climate Change, 2023). Studies suggest that if temperature increases 1.5 ˚C, around 951 million people living in drylands, excluding hyper-arid lands, will be exposed to increasing impacts related to water such as water stress, drought intensity, and habitat degradation. The fact that drylands currently cover a big portion of the global land area and are home to more than a third of the world population, special attention should be paid to these types of lands and their water resources.

In the US it is expected that climate change includes higher temperatures and increases in the uncertainty in precipitation amount and seasonal timing (Melillo et al., 2014), especially increasing the frequency of heavy precipitation events and longer dry periods between events (United States Environmental Protection Agency, 2023c). Prein et al., (2016) found that the US Southwest has already experienced a 25% decrease in precipitation along with increased precipitation intensities in the period 1980-2010. Given the It is crucial to acknowledge the potential impacts of waterborne pathogens due to the undeniable scientific evidence supporting climate change.

The impact of climate change on waterborne pathogens will differ according to the characteristics of various watershed settings and will be influenced by local land use, water management, and other human activities that impact water sources, even though some generalizations can be identified. Expected rise in precipitation could result in similar increases in streamflow, which can impact water quality in a similar manner with the mobilization of pathogens (Wilkes et al., 2011) and resuspension from river and lake bed sediments (Garzio-Hadzick et al., 2010; Wu et al., 2009) leading to more peak concentrations. This can also occur with droughts as reduced flow volumes could result in less microbial dilution. Flooding could lead to inundation of drinking water and sewage treatment plants as well as to the increase of sewer overflow (Coffey et al., 2014). Projected increases in air and water temperatures could alter pathogen survival, replication and virulence (Levy et al., 2018) as well as human exposure to waterborne pathogens by extending the period of warm-weather recreational uses (United States Environmental Protection Agency, 2023c).

1.8. Research Objectives and Dissertation Structure

While studies have been conducted to understand the most probable factors that influence *E. coli* levels in surface waters (as previously described), the focus has been primarily in humid or temperate regions (Causse et al., 2015; Crosby et al., 2019; Xue et al., 2018), with few studies available in arid and semiarid regions, likely because temperate and humid regions support extensive agricultural production and have more water available to monitor (Azad Hossain, 2013).Thus there are still more questions that need to be answered such as how pathogen drivers differ in arid and semiarid regions, and where potential sources of contamination exist, especially in underserved areas like Tribal lands, of which approximately 80% are located on arid or semi-arid regions (United Nations Environmental Programme, World Conservation Monitoring Centre, 2019; United States Census Bureau, 2020a).

This dissertation aims to investigate previously undocumented threats to water quality through understanding pathogen drivers in arid and semi-arid environments and documenting wastewater infrastructure on Tribal lands (**Figure 1**) by addressing two major questions 1) How do ephemeral streams (common in arid and semiarid areas) impact the presence of pathogens in surface waters? and 2) What are some unknown potential sources of water quality impairments in Tribal areas? To address the first question Chapter 1 uses publicly available water quality data, specifically *E. coli* concentrations for Arizona. Arizona has both arid and semi-arid regions and therefore a significant number of ephemeral rivers typical of this type of climate, so it makes an ideal case study area. The goal of this work is to identify the main drivers of *E. coli* concentration from a series of proposed predictors. Chapter 2 focuses on Tribes with government-to-government relationships with the state and Tribal land base in the US and the WWTPs serving their populations. Information about facilities discharging to a WOTUS from an EPA database as well as race data is used to identify and categorize these facilities with the goal of assessing the current state of wastewater infrastructure in these communities. Chapter 3 is centered on developing an algorithm using publicly available remotely sensed data to detect terminal Wastewater Lagoons (WWLs). This infrastructure is commonly used to treat domestic wastewater produced by small and rural communities. This work is expected to reduce the gap of information on the locations of facilities not discharging to a WOTUS that due to their possible lack of monitoring could become a source of pathogenic contamination.

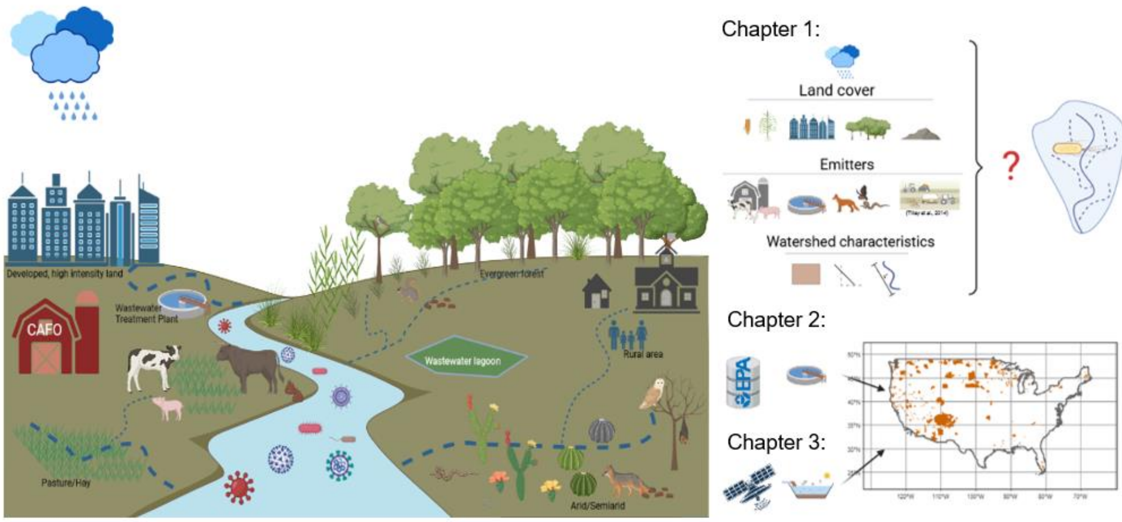


Figure 1. Dissertation sketch showing how different possible pathogenic sources interact with arid and semi-arid environments. This research aims to bring a better understanding of *E. coli* drivers and sources. Created with BioRender.com.

CHAPTER 2

ESCHERICHIA COLI DRIVERS IN SURFACE WATERS OF ARID AND SEMIARID REGIONS: A CASE OF STUDY OF ARIZONA

As discussed previously, surface water, as streams and lakes, is an important source of freshwater due to its accessibility, a characteristic that also makes it susceptible to contamination (Walker et al., 2019). Climate change will exacerbate pressures on freshwater resources in many regions of the world that are already facing water stress. In the near future, climate change may impact the already highly variable spatial and temporal patterns of rainfall in arid and semi-arid regions especially, contributing to more water stress. Both rainfall and land degradation impact water security through reductions in the reliability, quantity, and quality of water flows mainly affecting surface water (UN Water, 2020).

The challenges faced in water treatment, combined with extant and worsening water quantity concerns in arid and semiarid regions emphasizes the need to improve water quality by reducing in-stream pathogenic contamination. This requires an understanding of the combined impacts of point and non-point sources, climatic conditions, physical landscape characteristics, and anthropogenic activities on pathogen contamination at the watershed level (Pandey et al., 2012).

This research attempts to answer the question of what drivers are important in influencing *E. coli* concentrations in Arizona streams through two approaches: (1) analyzing all in-stream *E. coli* observations with respect to the type of river and antecedent moisture conditions and (2) through the aggregation of *E. coli* data to the watershed level (10-digit Hydrologic Unit Codes (HUC10s)) (United States Geological Survey, n.d.-e) and then examining the relationship to different watershed characteristics using a linear regression model.

2.1. Methods

The first objective focuses on comparing hydrologic characteristics with all observations given the uniqueness of arid and semi-arid hydrology. In the second objective, a more typical aggregated approach was applied considering as many sources and drivers as possible. All analyses were conducted using ArcGIS (Environmental Systems Research Institute (Esri), n.d.) and the statistical software R version 4.2.0 (R Core Team, 2022; RStudio Team, 2022). **Figure 2** outlines the methodological approach for both objectives of the study, with more details provided in the following sections.

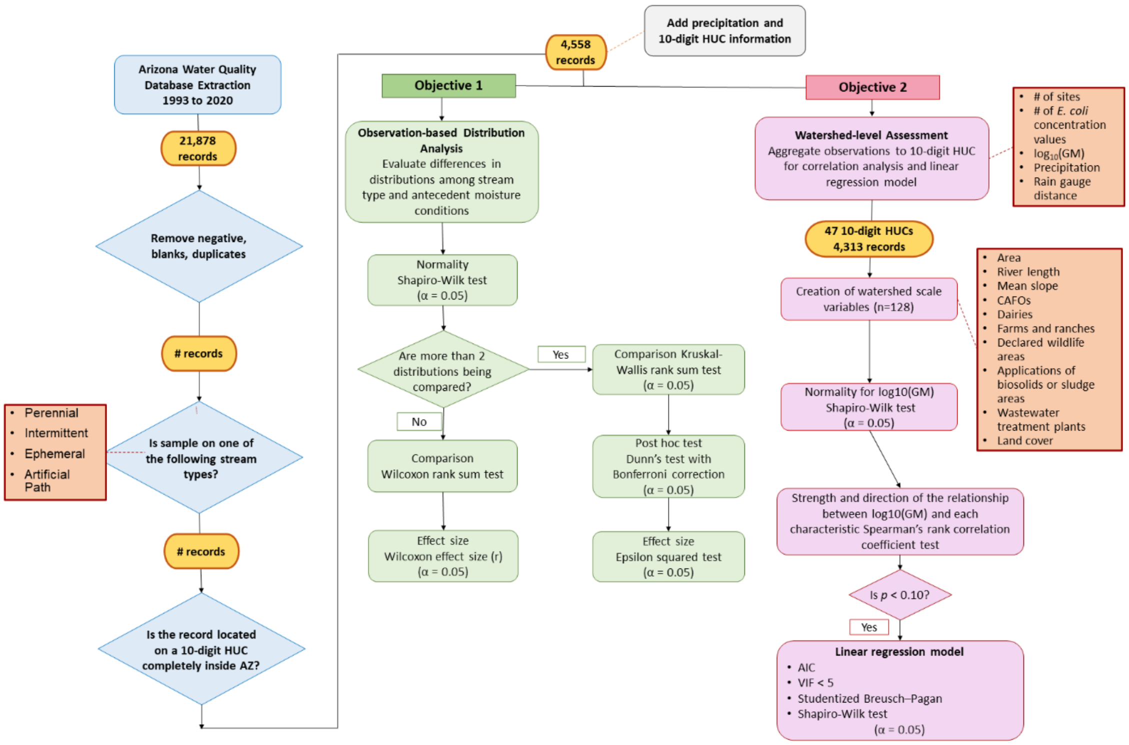


Figure 2. Methodological approach including the approach to both study objectives. Light blue color refers to the screening process, green color refers to objective 1 approach which uses all in-stream *E. coli* observations, while light purple outlines objective 2 approach that aggregates *E. coli* data to the watershed level before performing subsequent statistical analysis.

2.1.1. Study Area

The study was conducted on surface waters in Arizona, a state located in the southwest part of the US, bordering Mexico and other states of Utah, New Mexico, California, and Nevada. Arizona is the sixth largest state by land area and is characterized by arid and semi-arid climates with average annual precipitation ranging from around 3 inches in the southwest to around 40 inches in some mountain areas (Arizona State Climate Office, n.d.) leading to scarce water resources (United States Environmental Protection Agency, 2021d). In summer, May - September, monsoons cause heavy rainfall with the monsoon season in northern Arizona officially designated as June 15th to September 30th (United States Department of Commerce, n.d.). However, the onset and end of monsoonal rainfall can vary from year to year. Arizona has approximately 323,036 stream miles of which only ~1.35 % are classified as perennial, ~12.45 % intermittent, and ~86.20% ephemeral, based on the US Geological Survey (USGS) National Hydrography Dataset (NHD) for Arizona (United States Geological Survey. National Geospatial Program, 2020). Even though the NHD is the most comprehensive source on stream extent and streamflow classification, it tends to be less accurate characterizing intermittent rivers and ephemeral streams (Fritz et al., 2020; Wang & Vivoni, 2022), adding a degree of uncertainty in the indicated amounts and further classification. These designations and their impact on water quality are highly important now, as the debate over what waterbodies are included in the federal definition of “Waters of the United States” (WOTUS) has been politically charged in recent years (Keiser et al., 2022; Sullivan et al., 2019) and even in recent Supreme Court rulings. According to the Arizona Department of Environmental Quality (ADEQ), *E. coli* is the most common surface water quality impairment in Arizona in the period 2012 to 2021 in assessed surface waters focusing on perennial waters and excluding Indian reservations (Arizona Department of Environmental Quality, 2022a).

2.1.2. Data

1.1.2.1. In-Stream *E. coli* Concentration Observations. Through a search in the Arizona Water Quality Database (Arizona Department of Environmental Quality, n.d.-d) on June 2020 were downloaded 21,878 records with 38 *E. coli* related variables (listed in the supplementary information (Appendix A - SI 1.1. Table 1)), including values of *E. coli* concentration measured in CFU/100mL and MPN/100mL for water as the sample medium and for the period 1993 to 2020. This database stores surface and groundwater water quality data collected by ADEQ through the Monitoring Unit that conducts ambient monitoring of lakes and streams to assess their biological and chemical integrity to determine potential sources of pollution and provide guidance to improve their water quality conditions, and the Watershed Protection Unit that collects data in support development of TMDL; and other agencies for the state of Arizona (Arizona Department of

Environmental Quality, 2022b). The data were available across 1,186 different sites as part of various water quality monitoring programs.

Records with negative or empty values of *E. coli* concentration, records with same date and time for the specific site, and those labeled as “duplicated”, “split”, or “blank” were removed from the database except those marked as “duplicated” without another record with the same date and same or similar time. Sites were classified into 8 different categories: Perennial, Intermittent, Ephemeral, Artificial Path, Well, Intermittent Spring, Canal/Ditch, and Not identified, described in the supplementary information (Appendix A - SI 1.2. Table 2), based on its geographic location according to the NHD Flowlines shapefile from the USGS for Arizona (United States Geological Survey. National Geospatial Program, 2020) using “Type” variable and Google Earth imagery to confirm as needed. Records in the time span from 2010 to 2019 and with sites classified as Perennial, Intermittent, Ephemeral, and Artificial Path within HUC10 watersheds completely inside Arizona, were selected for this study.

2.1.2.2. Precipitation Data. Precipitation data in inches for the recorded sampling date (day 0) and for each of the 8 prior days (days 1 to 8) for each *E. coli* observation were obtained from the closest rain gauge to the site with available data for all 9 days. Three datasets were used to develop the precipitation data: the Global Historical Climatology Network – Daily (GHCN-Daily) from the National Oceanic and Atmospheric Administration (NOAA) (National Oceanic and Atmospheric Administration. National Centers for Environmental Information, n.d.), the Maricopa County Rainfall Data (Maricopa County, n.d.), and the Arizona Meteorological Network (AZMET) from the University of Arizona (The University of Arizona. The Arizona Meteorological Network, n.d.). Rain gauge locations, Station IDs, and precipitation data were accessed through their websites except for the GHCN-Daily where Station IDs and locations were extracted from the GHCND Stations layer created by NOAA National Centers for Environmental Information (NCEI) (National Oceanic and Atmospheric Administration. National Centers for Environmental Information, 2021). Precipitation for the 9 days associated with each record was also summed to create a total antecedent rainfall value. For each watershed (see next section), mean and median values for precipitation on the sampling day, one day before up to eight days before, mean and median number of days, out of 9, with and without precipitation and until precipitation, as well as mean and median distance from the sample site to the rain gauge location were computed.

2.1.2.3. Watersheds and Watershed Boundaries. To explore relationships between watershed characteristics and *E. coli* concentration values in the second objective, observations were also aggregated to the HUC10s. According to the USGS Watershed Boundary Dataset (WBD) accompanying the NHD for Arizona (United States Geological Survey. National Geospatial Program, 2020), 485 HUC10 watersheds cover Arizona and of them, 374 are located completely inside the state boundaries delineated by the USGS National Boundary Dataset (NBD) (United States Geological Survey. National Geospatial Technical Operations Center, 2021) while 77 are shared with neighboring states and 34 are shared with Mexico. Watersheds located completely inside Arizona and including more than 10 *E. coli* records were selected.

2.1.2.4. Watershed Characteristics.

2.1.2.4.1. Area. Watershed area in squared meters was determined using the USGS WBD information accompanying the NHD for Arizona (United States Geological Survey. National Geospatial Program, 2020). Specifically, the shapefile WBDHU10 was used for this purpose.

2.1.2.4.2. River Length. The length of perennial, intermittent, and ephemeral rivers, as well as artificial paths for each watershed were derived using the line features in the USGS NHD for Arizona (United States Geological Survey. National Geospatial Program, 2020), which are available in the "NHDFlowline" shapefiles. One of the code values used by the USGS NHD is the feature code ("FCode"), a five-digit integer value, the first three referring to the type of the feature and the remaining to its characteristics, that includes most of the information needed to re-create the hydrography and allows automated processing (United States Geological Survey, n.d.-g). FCode values of 46003, 46006, 46007, and 55800, refer to features with hydrographic categories of intermittent, perennial, and ephemeral stream/rivers and artificial paths, respectively, and were used in this study (United States Geological Survey, n.d.-c). Using length values, more characteristics were calculated including the total length (the length summation of all types); the sum of the lengths of artificial paths with perennial rivers as well as of intermittent with ephemeral rivers; the density (length per watershed area) for each type, the total, and the combinations of above; and the percent (length divided by the total length) for each type and the combinations.

2.1.2.4.*3. Mean Slope.* Mean slope, in degrees, for each watershed was derived from a 1/3 arc second (~10 meters) resolution Digital Elevation Model (DEM) acquired from the 3D Elevation Program (3DEP) seamless products of The National Map (United States Geological Survey, n.d.-a). Slope serves as a parameter to indicate the susceptibility to soil erosion (Nut et al., 2021).

2.1.2.4.4. Number of Potential Emitters. Number of CAFOs, dairies, farms and ranches, declared wildlife areas, and applications of biosolids or sludge areas were counted for each watershed from the ADEQ Arizona Unified Repository for Informational Tracking of the Environment (AZURITE) Places layer (Arizona Department of Environmental Quality, 2021a). WWTPs were obtained from the Enforcement and Compliance History Online (ECHO) database (https://echo.epa.gov/facilities/facility-search/results). Each of these entities has the potential to release *E. coli* or other fecal contamination into the environment. The number of CAFOs, dairies, and farms and ranches were added to account for the potential emitters related with animals in agriculture. Densities (number per watershed area) for each type and the combination were also calculated. While many factors contribute to whether or not these sources may indeed release fecal contamination, such as treatment level of WWTP, manure application locations, and total number of animals per farm, without access to detailed information for each source here the total number of emitters was used as an indicator of potential sources and contributions.

2.1.2.4.5. Land Cover. Area, in squared meters, for each category of land cover in the watersheds was derived from the USGS National Land Cover Database (NLCD) 2016 (Dewitz, 2019). The database has a 30 m spatial resolution and 16-class categorization for the Conterminous United States (CONUS). The 2016 NLCD epoch was preferred over 2011 and 2019 for being closer to the middle of the study period. To account for areas with different levels of urbanization, different types of vegetation, possible presence of wildlife and presence of water, ten combinations of land cover classes were constructed as shown in **Table 1.** Densities (land cover by watershed area) for all land cover classes and the combinations were computed.

Table 1

Combinations of Land Cover Classes Used to Account for Areas With Different Levels of Urbanization, Types of Vegetation, and Presence of Water

No	Land cover classes combination
Urbanized area	
1	Developed, high intensity + Developed, medium intensity + Developed, low intensity + Developed, open space (Developed, HI + MI + LI + OS)
2	Developed, low intensity + Developed, open space (Developed, LI + OS)
3	Developed, high intensity + Developed, medium intensity (Developed, HI + MI)
Vegetated area	
4	Grassland/herbaceous + Pasture/hay
5	Barren land (rock/sand/clay) + Shrub/scrub
6	Deciduous forest + Evergreen forest + Mixed forest
Other land classifications	
7	Barren land (rock/sand/clay) + Deciduous forest + Evergreen forest + Mixed forest + Shrub/scrub + Woody wetlands + Emergent herbaceous wetlands
8	Barren land (rock/sand/clay) + Deciduous forest + Evergreen forest + Mixed forest + Shrub/scrub
9	Woody wetlands + Emergent herbaceous wetlands
Water	
10	Open water + Woody wetlands + Emergent herbaceous wetlands

2.1.3. Data Aggregation for Watershed-Based Analysis

For each watershed the number of sites as well as the number of *E. coli* concentration values as a total and by site type were summarized. The number of samples from artificial paths and perennial river sites were added, as well as from intermittent and ephemeral sites. For the above mentioned data, densities and rates were computed, dividing the quantity by the watershed area or by the total number of samples in the watershed respectively.

The GM was calculated for the *E. coli* concentration values in each watershed using **Equation 1** where n is the number of values and x_i are the values of *E. coli* concentration; values lower than 1 were replaced with 0.9 (Arizona Department of Environmental Quality, n.d.-a; Arizona Department of Environmental Quality. Surface Water Section, 2018) and values measured in CFU/100mL and MPN/100mL were considered equivalent (Makarowski, 2020; North Carolina Department of Health and Human Services, Division of Public Health, 2022) resulting in final GM reported in CFU/100mL. Although the two methods differ in their approach, with one directly counting visible colonies of bacterial growth and the other measuring growth statistically, they have been found to be strongly positively related. In some cases, MPN values have been found to be greater than CFU values (Cho et al., 2010). GM values were log transformed using a base 10 logarithm ($\log_{10}$(GM)) and the distribution of these values was tested for normality using the Shapiro-Wilk test (α = 0.05).

$$GM = \left(\prod_{i=1}^{n} x_i\right)^{\frac{1}{n}} = \sqrt[n]{x_1 x_2 \dots x_n} \qquad (1)$$

2.1.4. Statistical Analysis

1.1.4.1. Exploratory Data Analysis Using *E. coli* Concentrations (Objective 1). Data subsets were created to obtain distributions of *E. coli* concentrations across multiple factors including site type, presence of rain, and their combinations (**Table 2**).

Table 2

Data Subsets Analyzed According to Site Type, Presence of Rain on the Sampling Date and the Eight Previous Days, and Their Combinations

No.	Subsets	Description
According to site type		
1	Artificial path	Records from artificial path sites
2	Perennial	Records from perennial path sites
3	Intermittent + Ephemeral	Records from intermittent or ephemeral sites
According to presence of rain		
4	In rain condition	Records with rainfall presence at least in the sampling date or in one of the eight previous days
5	In no rain condition	Records without the presence of rainfall in the sampling date or in any of the previous eight days
Combination		
6	Artificial path in rain condition	Records from artificial path sites with rain presence in the sampling date or at least in one of the eight previous days
7	Perennial in rain condition	Records from perennial path sites with rain presence in the sampling date or at least in one of the eight previous days
8	Intermittent + Ephemeral in rain condition	Records from intermittent or ephemeral sites with rain presence in the sampling date or at least in one of the eight previous days
9	Artificial path in no rain condition	Records from artificial path sites without the presence of rain on the sampling date or on any of the previous eight days
10	Perennial in no rain condition	Records from perennial path sites without the presence of rain on the sampling date or on any of the previous eight days
11	Intermittent + Ephemeral in no rain condition	Records from intermittent or ephemeral sites without the presence of rain on the sampling date or on any of the previous eight days

The twelve distributions in Table 2 and their logarithmic base 10 transformations, computed after adding the value 1 to all the *E. coli* concentration values to avoid undefined results, were tested for normality using the Shapiro-Wilks test. Comparison of not transformed distributions was done using the nonparametric Kruskal-Wallis rank sum test when comparing more than two distributions, otherwise the Wilcoxon rank sum test was used. Dunn's test with Bonferroni correction was used as a post hoc test and the Epsilon squared test for effect size when Kruskal-

Wallis test was applied, or Wilcoxon effect size (r) if Wilcoxon rank sum test was utilized. A significance level of 0.05 ($\alpha = 0.05$) was used to determine significance with all these analyses.

2.1.4.2. Regression Model on Watershed-Aggregated Data (Objective 2). Spearman's rank correlation coefficient test was used first to summarize the strength and direction of the relationship between $\log_{10}$(GM) values and each of the 128 watershed characteristics (either observed or derived) listed in supplementary information (Appendix A - SI 1.3. Table 3), *p*-values less than 0.10 were considered as significant. Characteristics without a significant test result were considered to have no clear relationship with *E. coli* concentration values and therefore not included in further analysis. A stepwise linear regression model was then created using backward elimination with $\log_{10}$(GM) values as the dependent variable to assess the relative impacts of the significant characteristics. Based on the results, the least significant characteristic or related characteristic(s) (e.g., perennial river length - perennial river length/total river length - perennial river length/watershed area) were discarded, and a new linear regression model was created, repeating the process. The different models were compared using the Akaike Information Criterion (AIC) values. A final model was selected when all model variables were significant at the level of 0.05. The resulting model variables were checked for multicollinearity using the Variable Inflation Factor (VIF), where values less than 5 were considered acceptable (Daoud, 2017). To evaluate the model, the adjusted coefficient of determination (R^2) was calculated, the assumptions of linearity, homoscedasticity, and normality of the residuals were checked, and the studentized Breusch–Pagan test was applied to test homoscedasticity while Shapiro-Wilks test was used to test normality, both using a significance level of 0.05.

2.2. Results

2.2.1. E. coli Data and its Variability

A total of 4,558 *E. coli* concentration records were available from 2010 to 2019 on sites classified as perennial, intermittent, ephemeral, and artificial path. They are unevenly distributed across 610 different sites in Arizona, each of which contains between 1 - 178 records as presented in **Figure 3**. 585 sites (95.90%) have less than 26 records while 8 (1.31%) have more than 100 records. 2,622 (57.53%) records are located on perennial streams, 681 (14.94%) on intermittent streams, 99 (2.17%) on ephemeral streams, and 1,156 (25.36%) on artificial paths.

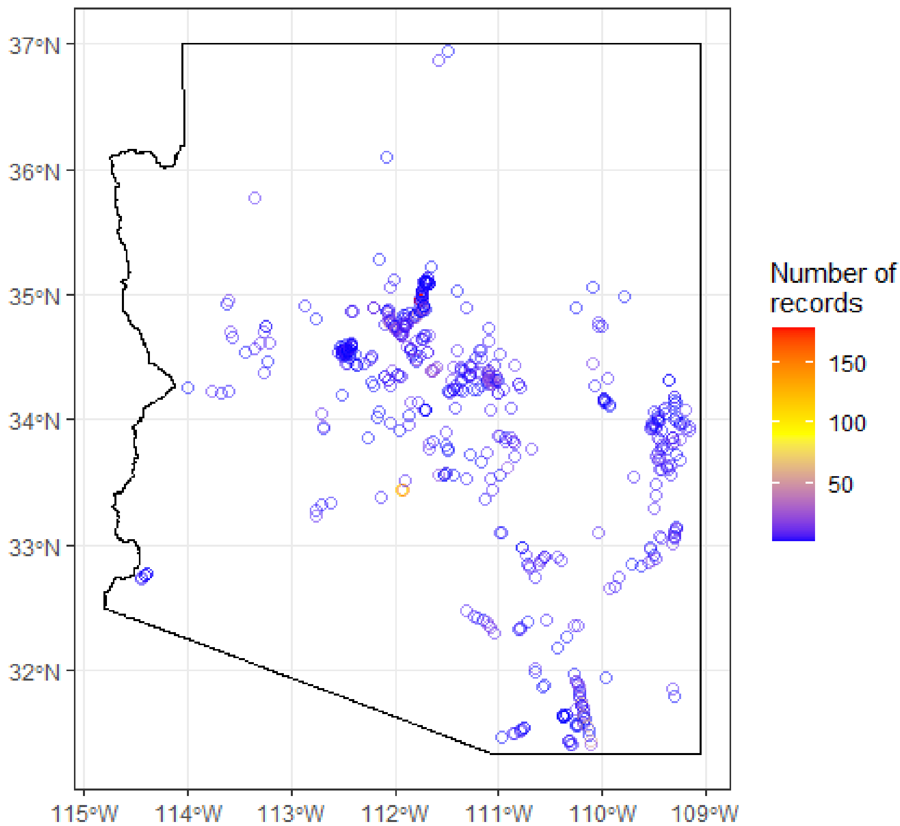


Figure 3. Spatial distribution of the 610 sites analyzed in this study. Circles represent a site while color represents the number of records from the site.

The distribution of the number of records according to the type of site across the years and months in the studied time span is presented in **Figure 4A** and **Figure 4B**. 2015 is the year with the least number of records (261) while 2013 has the most (585). Regarding the months, January has the least number of records (130), while August the most (777), followed by July (766) and June (679); this is likely due to the seasonal monsoon experience throughout much of Arizona which occurs June to August. The highest number of ephemeral records is 28 in 2019 while the lowest is 0 in 2012. By month, the number of records in ephemeral sites range from 3 to 12, indicating consistently fewer ephemeral records overall.

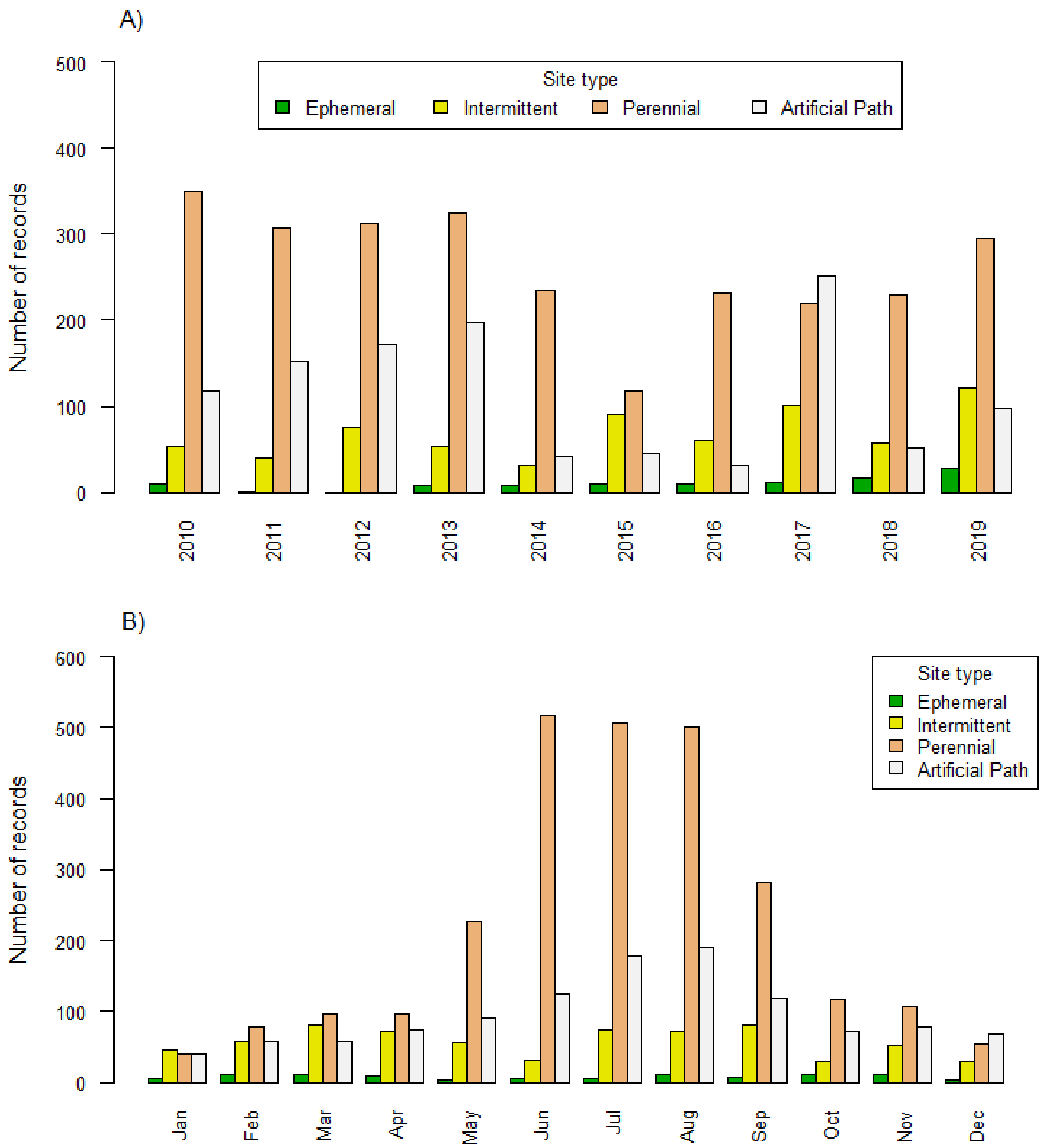


Figure 4. Concentration records. Number of *E. coli* concentration records categorized by type of site and A) year versus B) month.

Variation in *E. coli* concentrations overall, and across different stream types are provided in **Figure 5**. All distributions are skewed right. Artificial paths presented with the lowest *E. coli* median concentration (~17.50 CFU/100mL), followed by perennial streams (~25.90 CFU/100mL), and intermittent + ephemeral (~42.60 CFU/100mL) with the median of the overall dataset is of ~25.90 CFU/100mL. While there were fewer samples available in the intermittent and ephemeral category, their higher median overall warrants further study given the previously mentioned debate over what kinds of streams should be included in WOTUS.

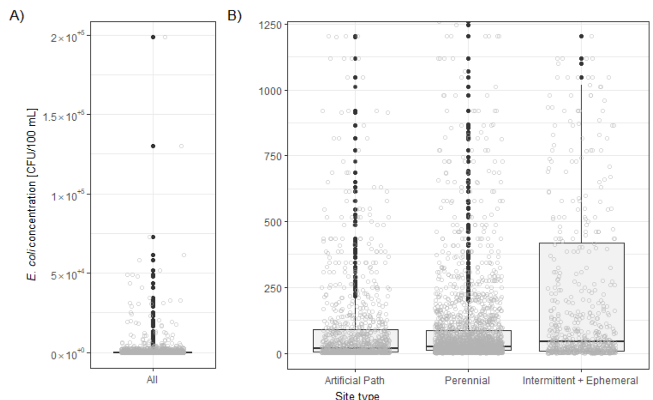


Figure 5. Concentration distributions. *E. coli* concentration distributions for A) All site types, B) Site type Artificial Path, Perennial, and Intermittent + Ephemeral. Part B is zoomed in at the interval [0, 1250] CFU/100mL for a better representation of the data in the first three quartiles.

In the studied period, monthly median and maximum values of *E. coli* concentrations generally were higher in the presence of rain (on sampling date or within previous 8 days), while peak median and maximum concentrations were seen in the summer likely due to monsoons. Median values were higher in intermittent and ephemeral rivers especially in summer (**Figures 6A** and **6B**). Time series of monthly median and maximum values of *E. coli* concentration are presented in supplementary information (Appendix A - SI 1.4. Figure 1).

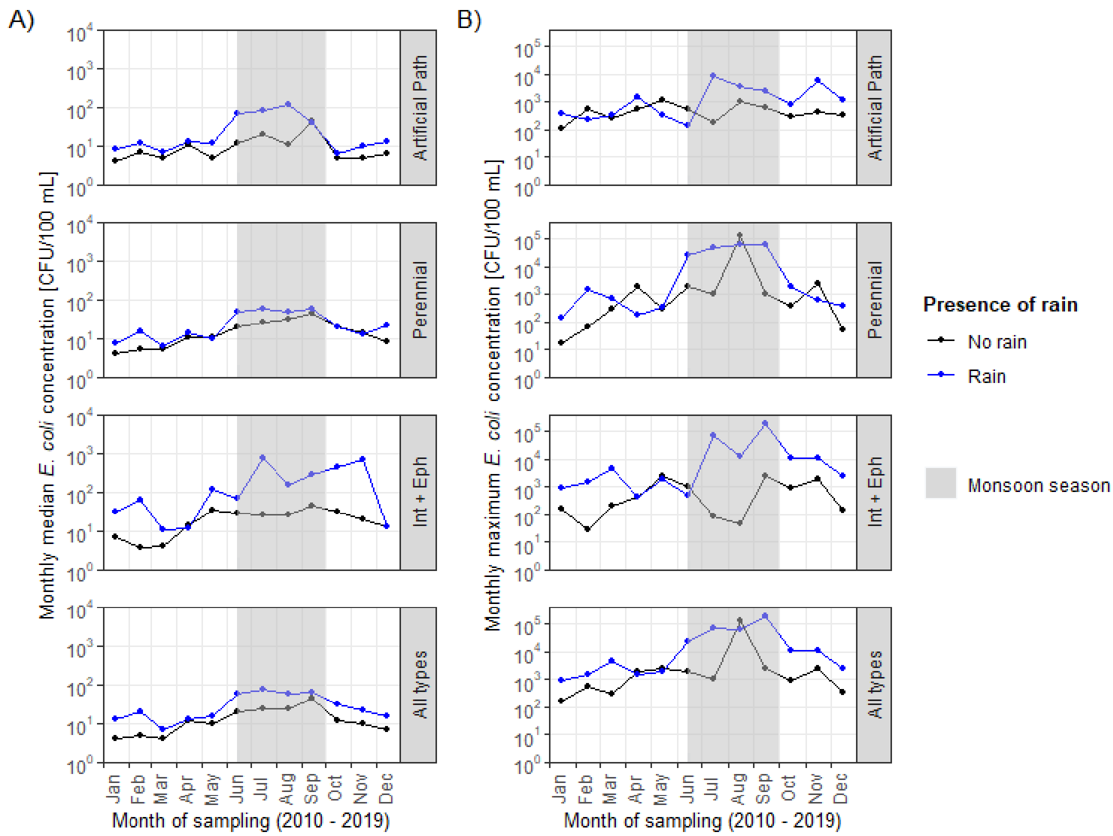


Figure 6. Median and maximum concentration values. Monthly A) median and B) maximum *E. coli* concentration values from different types of streams for the entire studied period. The blue color represents values with rain on the sampling date or at least in one of the eight previous days, while black color indicates values without antecedent precipitation.

Of the 485 HUC10 watersheds across Arizona, 106 had at least one *E. coli* record, but only 47 met the requirements of being located completely inside Arizona and including more than 10 records. These were chosen for objective 2 of the study and totaled to 4,313 records (2,504, 617, 92, and 1,100 records from perennial, intermittent, ephemeral, and artificial path sites respectively), unevenly distributed across 517 sites. In each watershed the number of sites ranged from 1 to 94 with a median value of 6. The maximum number of records within a watershed was 1,399 while the median value was 26. Resulting GM values across the watersheds ranged from ~3.91 CFU/100mL to ~336.69 CFU/100mL with a positively skewed probability density distribution (**Figure 7A**). The $\log_{10}$(GM) values ranged from ~0.59 to ~2.53 with a probability density distribution presented in **Figure 7B**, which, according to the Shapiro-Wilk test results (W = ~0.958, p = ~0.092), was normal with an alpha level of 0.05. The spatial distribution of the $\log_{10}$(GM) values along with the watersheds they represent is depicted in **Figure 7C**.

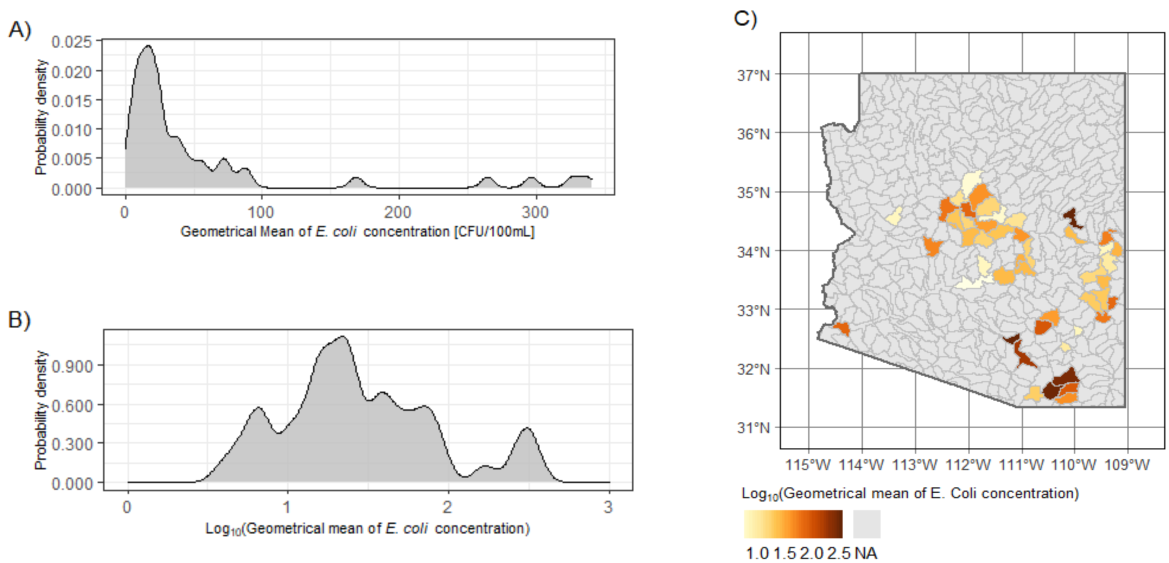


Figure 7. Geometric mean values. A) Probability density plot for Geometric mean of *E. coli* concentration values, B) Density plot for log transformed base 10 GM values, C) Spatial distribution of log base 10 transformed GM values, for 47 different HUC10s in Arizona.

2.2.2. Predictor Variables Across Sites and Watersheds

A total of 41,022 precipitation values were obtained from 205 different rain gauges ranging from ~0 to ~53 kilometers away from the sample site (**Figure 8A**). Of these, 173 rain gauges came from the GHCN- Daily dataset, 29 from the Maricopa County Rainfall dataset, and 3 from the AZMET dataset (**Figure 8B**). The rain gauge used was not always the same for a given site due to the availability of data for the specific dates in the records. Precipitation values ranged from 0 to 5.09 inches (**Figure 8C**). The 9 days accumulative precipitation from the sampling dates ranged from 0 to 9 inches, with a median of ~0.12 inches (**Figure 8D**).

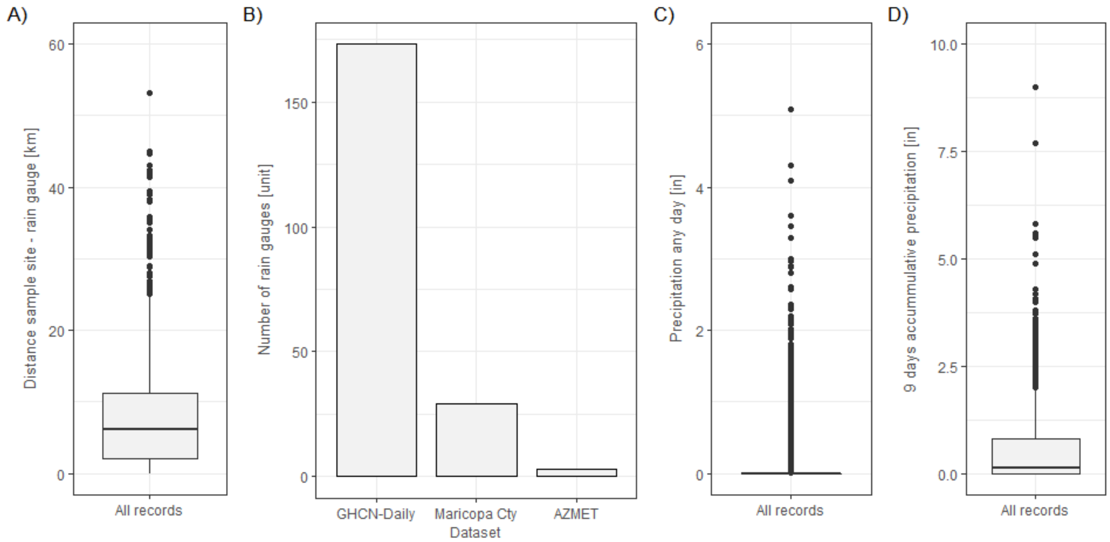


Figure 8. Rain gauges and precipitation. A) Distribution of distances, in kilometers, from the sample site to the rain gauge used to obtain precipitation values for each of the 4558 records. B) Number of rain gauges from each of the three datasets used to obtain precipitation data. C) Distribution of the 41,022 precipitation values, in inches, for the recorded sampling date (day 0) or for any of the 8 prior days (days 1 to 8). D) Distribution of the 9 days accumulative precipitation, in inches, for each of the 4558 records.

Minimum, median, and maximum values of mean precipitation in the sites of the watersheds for the sampling day are of 0 inches, 0.03 inches, and 0.29 inches, while for all nine days they were 0 inches, 0.39 inches, and 1.71 inches (**Figure 9A**). Respective median precipitation values are of 0 inches, 0 inches, 0.05 inches for the sampling day, and of 0 inches, 0.07 inches, and 0.8 inches for the nine days (**Figure 9B**). Median number of days with precipitation presence in the 9 days period for the watersheds has minimum, median, and maximum values of 0 days, 1 day, and 4 days, while the median number of days until precipitation, counted from the sampling day to the closest past day with rain presence, of 0 day, 6.5 days, and 9 days respectively (**Figure 9C**). Mean and median distances from the sample site to the rain gauge have minimum, median, and maximum values of ~1.26 kilometers, ~8.77 kilometers, ~37.46 kilometers, and ~1.31 kilometers, ~9.05 kilometers, and ~41.42 kilometers respectively (**Figure 9D**).

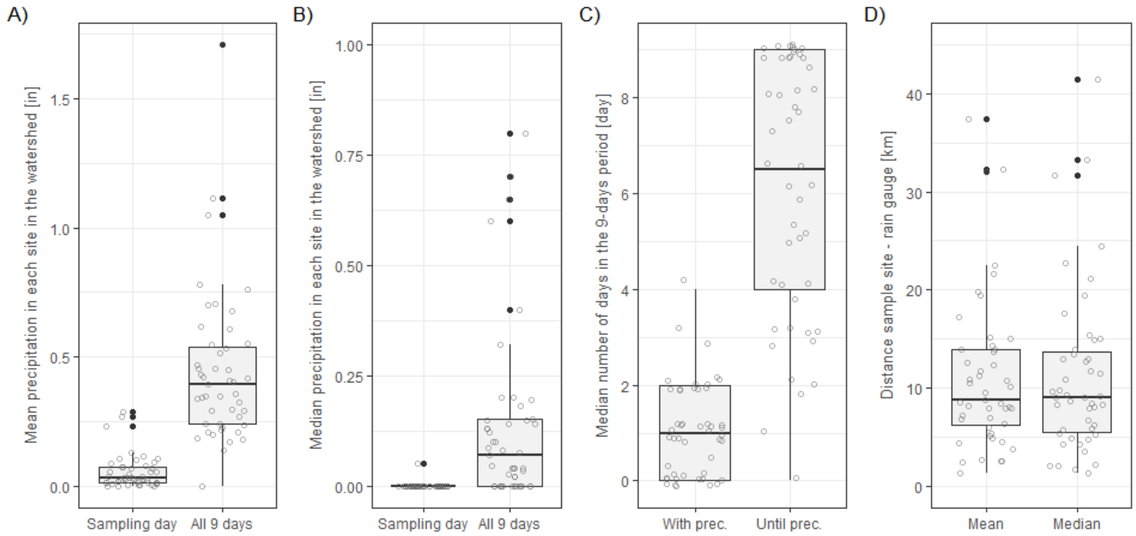


Figure 9. Precipitation. Distribution of A) mean precipitation, and B) median precipitation, measured in inches, for each site of the 47 studied watersheds, for the sampling day (day 0) and for all 9 days (days 0 to 8). C) Median number of days with precipitation presence in the 9 days period for sites in the watersheds and median number of days until precipitation, counted from the sampling day to the closest past day with rain presence. D) Distribution of mean and median distances, in kilometers, from the sample site to the rain gauge used to obtain precipitation values for all the records in each watershed.

Watershed areas range from ~2.49x10^8 m^2 to ~1.24x10^9 m^2 (**Figure 10A**) and total river length from ~4.54x10^5 m to ~3.13x10^6 m (**Figure 10B**). On average in the watersheds there are more meters of ephemeral rivers than other types (~4.18x10^4 m for artificial paths, ~4.92x10^4 m for perennial, ~1.98x10^5 m for intermittent, and ~1.28x10^6 m for ephemeral) (**Figure 10B**).Terrain in the watersheds presents differences in its mean slope, from gently sloping (~2.08 degrees) with low susceptibility to soil erosion to moderately steep (~21.36 degrees) with very high susceptibility to soil erosion (**Figure 10C**).

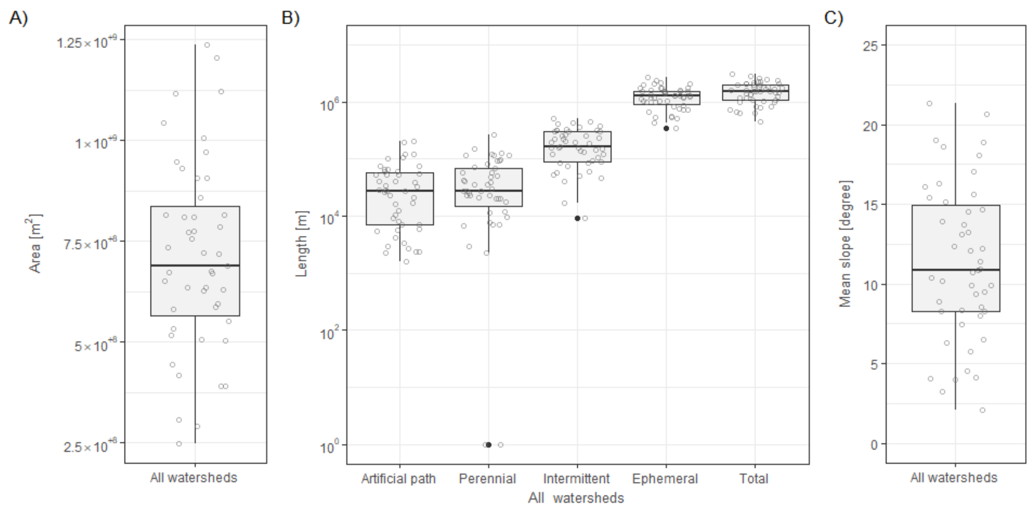


Figure 10. Watersheds and rivers. Distribution of A) area values, in squared meters, B) length, in meters, of artificial paths, perennial, intermittent, and ephemeral rivers as well as of all these classes, and C) mean slope, in degrees, for all the 47 studied watersheds.

The number of CAFOs, dairies, farms and ranches, WWTPs, declared wildlife areas, and areas with applications of biosolids or sludge in each watershed range significantly with there being more farms and ranches than other facility types in most watersheds (**Figure 11A).** The majority of the watersheds have none of these source types, however Fifteen land cover classes were identified: Open water; Developed, Open Space (OS); Developed, Low Intensity (LI); Developed, Medium Intensity (MI); Developed, Hi Intensity (HI); Barren land (rock/sand/clay); Deciduous forest; Evergreen forest; Mixed forest; Shrub/scrub; Grassland/herbaceous; Pasture/hay; Cultivated crops; Woody wetlands; and Emergent herbaceous wetland, with them the ten combinations of land cover classes in Table 1 were constructed, the distribution of the landcover and the combinations for all 47 watersheds is presented in **Figure 11B** and **Figure 11C** respectively. Majority of area is covered by Shrub/scrub land followed by Evergreen forest, or by the combination of Barren land (rock/sand/clay) + Deciduous forest + Evergreen forest + Mixed forest + Shrub/scrub + Woody wetlands + Emergent herbaceous wetlands.

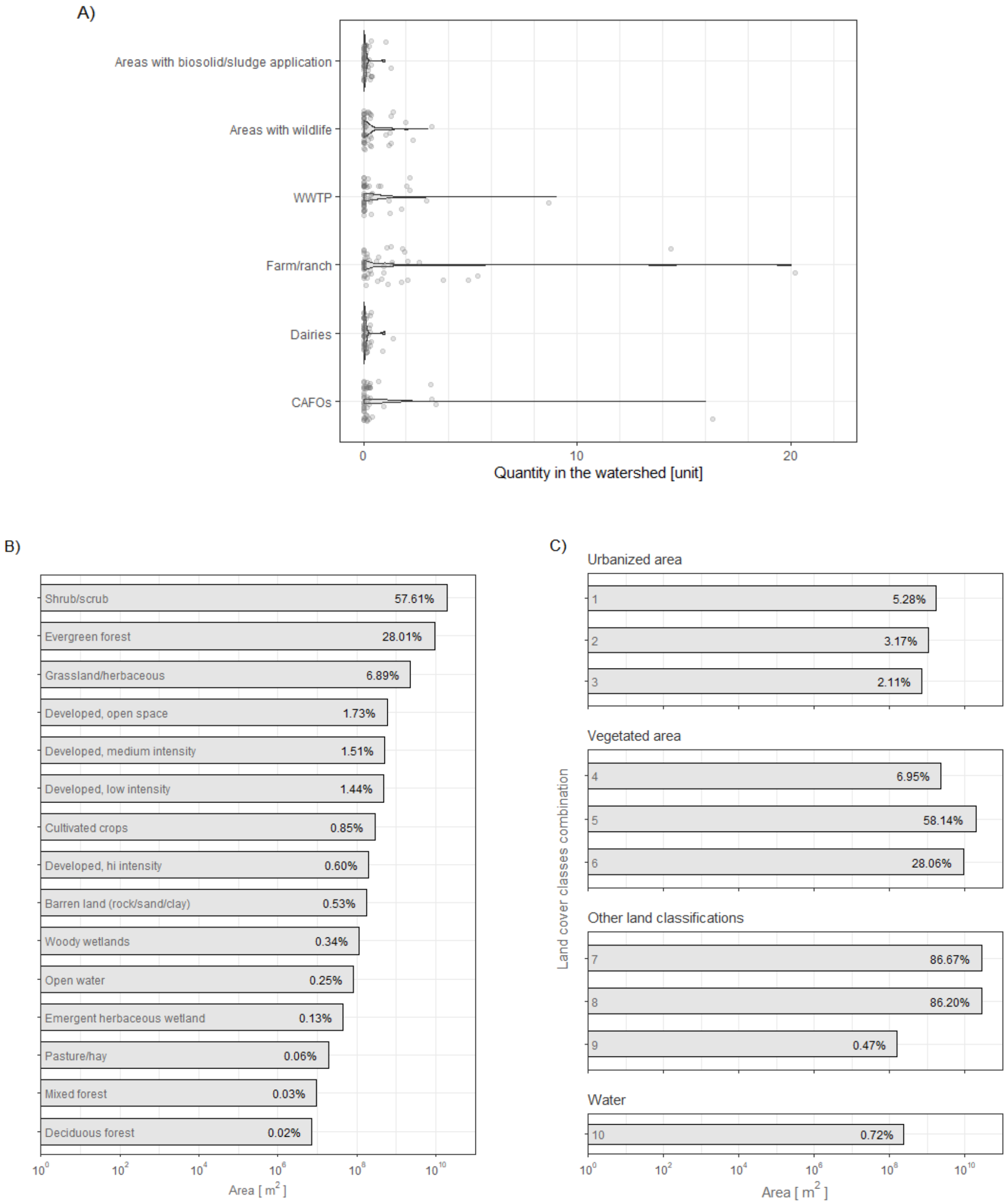


Figure 11. Emitters and land cover. A) Number of CAFOs, dairies, farms and ranches, wastewater treatment plants, declared wildlife areas, and areas with applications of biosolids/sludge in each watershed. B) Land cover distribution and C) Combination of land cover classes used to account for areas with different levels of urbanization, types of vegetation, and presence of water: 1 Developed, HI + MI + LI + OS, 2 Developed, LI + OS, 3 Developed, HI + MI, 4 Grassland/herbaceous + Pasture/hay, 5 Barren land (rock/sand/clay) + Shrub/scrub, 6 Deciduous forest + Evergreen forest + Mixed forest, 7 Barren land (rock/sand/clay) + Deciduous forest + Evergreen forest + Mixed forest + Shrub/scrub + Woody wetlands + Emergent herbaceous wetlands, 8 Barren land (rock/sand/clay) + Deciduous forest + Evergreen forest + Mixed forest + Shrub/scrub, 9 Woody wetlands + Emergent herbaceous wetlands. 10 Open water + Woody wetlands + Emergent herbaceous wetlands, as a total and as a percentage, according to the National Land Cover Dataset 2016 for all 47 studied watersheds.

2.2.3. The Impact of Site and Rainfall Characteristics on E. coli Concentrations (Objective 1)

E. coli concentration distributions for the three types of sites and their transformations were not normal. A Kruskal-Wallis rank sum test showed that stream type had a significant, yet relatively weak effect on *E. coli* concentration ($\chi2 = 91.396$, $p < 2.2\text{x}10^{-16}$, $\varepsilon^2 = 0.0201$). A post-hoc test using Dunn's test with Bonferroni correction showed significant differences between *E. coli* concentration distributions from artificial paths and intermittent + ephemeral streams ($p = \sim 8.00\text{x}10^{-21}$), artificial path and perennial streams ($p = \sim 3.37\text{x}10^{-9}$), and intermittent + ephemeral and perennial streams ($p = \sim 1.19\text{x}10^{-7}$).

With respect to antecedent rainfall, 2,766 records were classified as having antecedent rainfall, while another 1,792 records were classified as having no antecedent rainfall. Observations associated with previous rainfall had a median *E. coli* concentration of 42 CFU/100mL while records without previous rainfall had a median value of 13.6 CFU/100mL. Both distributions of *E. coli* concentration values and their log transformations were not normal. Distribution of *E. coli* concentrations between these two rainfall conditions were significantly different according to the Wilcoxon rank sum test ($W = 3388453$, $p < 2.2\text{x}10^{-16}$, moderate effect size $r = 0.311$).

Under antecedent rainfall conditions there were 619, 1,565, and 582 records classified as artificial paths, perennial, and intermittent + ephemeral sites, respectively, while for under no previous rainfall records the distribution was 537, 1,057, and 198. Median values of *E. coli* concentrations under rain conditions were 40.80 CFU/100 mL, 36.90 CFU/100 mL, and 81.45 CFU/100 mL for the previously mentioned site types and under no rain conditions these values decreased to 7.3 CFU/100 mL, 16.0 CFU/100 mL, and 15.8 CFU/100 mL. All six distributions and their respective transformations are not normal. Kruskal-Wallis rank sum tests were thus used and showed that site type and rain conditions both had a significant and relatively moderate effect on *E. coli* concentrations ($\chi2 = 499.31$, $p < 2.2\text{x}10^{-16}$, $\varepsilon^2 = 0.11$). A post-hoc test using Dunn's test with Bonferroni correction showed there were significant differences between distributions for all except between Perennial and Artificial Path under both antecedent rainfall conditions, and Perennial and Intermittent + Ephemeral under no antecedent rainfall conditions. Test results are summarized in

Table 3, resulting Dunn's test *p*-values, indicative of the statistical difference significance, for the compared distributions are presented in **Table 4.**

Table 3

Number of Records, E. coli Concentration Median Values, and Normality for the 12 Studied Distributions. Differences between groups were tested using Kruskal-Wallis rank sum test when comparing more than two distributions, otherwise the Wilcoxon Rank sum test was used

No.	Distribution	# of records	*E. coli* concentration median value [CFU/100 mL]	Normality		Comparison between population medians
				Dist.	$Log_{10}()$	
1	All	4,558	25.90	No (W = 0.073957, $p < 2.2x10^{-16}$)	No (W = 0.96174, $p < 2.2x10^{-16}$)	N/A
According to site type						
2	Artificial path	1,156	17.50	No (W = 0.32579, $p < 2.2x10^{-16}$)	No (W = 0.9455, $p < 2.2x10^{-16}$)	Significantly different, yet relatively weak effect on *E. coli* concentrations ($\chi 2$ = 91.396, $p < 2.2x10^{-16}$, ε^2 = 0.0201)
3	Perennial	2,622	25.90	No (W = 0.072193, $p < 2.2x10^{-16}$)	No (W = 0.96068, $p < 2.2x10^{-16}$)	
4	Intermittent + ephemeral	780	42.60	No W = 0.13273, $p < 2.2x10^{-16}$)	No (W = 0.96865, $p = 6.895x10^{-12}$)	
According to presence of rain						
5	In rain condition	2,766	42	No (W = 0.1054, $p < 2.2x10^{-16}$)	No (W = 0.9741, $p < 2.2x10^{-16}$)	Significantly different (W = 3388453, $p < 2.2x10^{-16}$, moderate effect size r = 0.311)
6	In no rain condition	1,792	13.6	No W = 0.014086, $p < 2.2x10^{-16}$)	No (W = 0.96395, $p < 2.2x10^{-16}$)	
Combinations						
7	Artificial path in rain condition	619	40.80	No (W = 0.41102, $p < 2.2x10^{-16}$)	No (W = 0.96962, $p = 5.034x10^{-10}$)	Significantly different and relatively moderate effect on *E. coli* concentrations ($\chi 2$ = 499.31, $p < 2.2x10^{-16}$, ε^2 = 0.11)
8	Perennial in rain condition	1,565	36.90	No (W = 0.13135, $p < 2.2x10^{-16}$)	No (W = 0.96658, $p < 2.2x10^{-16}$)	
9	Intermittent + ephemeral in rain condition	582	81.45	No (W = 0.15878, $p < 2.2x10^{-16}$)	No (W = 0.97755, $p = 8.705x10^{-08}$)	
10	Artificial path in no rain condition	537	7.3	No (W = 0.41835, $p < 2.2x10^{-16}$)	No (W = 0.91574, $p < 2.2x10^{-16}$)	
11	Perennial in no rain condition	1,057	16.0	No (W = 0.017229, $p < 2.2x10^{-16}$)	No (W = 0.96807, $p = 1.76x10^{-14}$)	
12	Intermittent + ephemeral in no rain condition	198	15.8	No (W = 0.28167, $p < 2.2x10^{-16}$)	No (W = 0.96288, $p = 4.498x10^{-05}$)	

Table 4

Dunn's Test With Bonferroni Correction p-Values for Pairwise Comparison Between Distributions of E. coli Concentration Values for Different Site Types and Rain Conditions. p-values compared to the significance level of 0.05 ($\alpha = 0.05$) tells which pair of distributions are statistically significantly different

No.	**Compared distributions**	**Difference**	**Dunn's test *p*-value**
1	Artificial path – Perennial	Significant	$\sim 3.37 \times 10^{-9}$
2	Artificial path – Intermittent + Ephemeral	Significant	$\sim 8.01 \times 10^{-21}$
3	Perennial – Intermittent + Ephemeral	Significant	$\sim 1.19 \times 10^{-7}$
Both distributions under antecedent rainfall conditions			
4	Artificial path – Perennial	Not significant	$\sim 9.15 \times 10^{-01}$
5	Artificial path – Intermittent + Ephemeral	Significant	$\sim 4.41 \times 10^{-06}$
6	Perennial – Intermittent + Ephemeral	Significant	$\sim 2.99 \times 10^{-04}$
Both distributions under no antecedent rainfall conditions			
7	Artificial path – Perennial	Significant	$\sim 5.71 \times 10^{-07}$
8	Artificial path – Intermittent + Ephemeral	Significant	$\sim 2.81 \times 10^{-02}$
9	Perennial – Intermittent + Ephemeral	Not significant	~1.00
Only the first distributions under antecedent rainfall conditions			
10	Artificial path – Artificial path	Significant	$\sim 1.82 \times 10^{-33}$
11	Artificial path – Perennial	Significant	$\sim 1.92 \times 10^{-16}$
12	Artificial path – Intermittent + Ephemeral	Significant	$\sim 1.79 \times 10^{-07}$
13	Perennial – Artificial path	Significant	$\sim 3.13 \times 10^{-58}$
14	Perennial – Perennial	Significant	$\sim 5.09 \times 10^{-38}$
15	Perennial – Intermittent + Ephemeral	Significant	$\sim 2.98 \times 10^{-12}$
16	Intermittent + Ephemeral – Artificial path	Significant	$\sim 5.60 \times 10^{-64}$
17	Intermittent + Ephemeral – Perennial	Significant	$\sim 4.64 \times 10^{-44}$
18	Intermittent + Ephemeral – Intermittent + Ephemeral	Significant	$\sim 3.20 \times 10^{-19}$

2.2.4. Watershed Characteristics Influence on E. coli Concentrations (Objective 2)

At the watershed level, Spearman's rank correlation coefficient tests were performed to determine which of the 128 variables studied and listed in supplementary information (Appendix A - SI 1.3. Table 3) had a significant relationship to the $\log_{10}$(GM) *E. coli* concentrations across watersheds. The results showed that of the 128 variables tested, 49 were significant ($p < 0.10$; **Figure 12**). Most of the variables (40) were positively related to $\log_{10}$(GM) while 9 were negatively related. Precipitation related variables had the stronger relationships to *E. coli*.

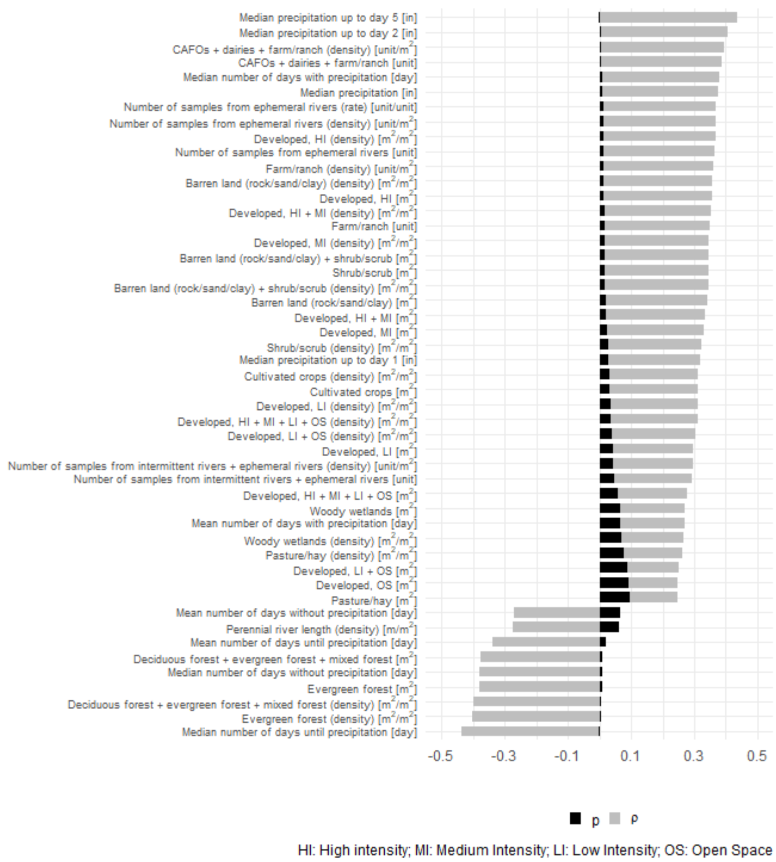


Figure 12. Significant characteristics. Characteristics with significant ($p < 0.10$) Spearman's rank correlation coefficient test results (ρ), positive and negative directions of ordinates depict positive and negative correlation between $\log_{10}$(GM) and the corresponding characteristic. Spearman's rank correlation coefficient (ρ) summarizes the strength and the direction of the relationship between $\log_{10}$(GM) values and watershed characteristics with possible values ranging from -1 to 1, the stronger the relationship the further away is ρ from zero, positive and negative values mean as one variable increases the other tends to increase or decrease respectively. The null hypothesis (*Ho*) stating no correlation between $\log_{10}$(GM) values and each watershed characteristic is rejected when the probability value (p) is lower than 0.10, accepting the alternative hypothesis (H_1) that there is a correlation.

All 49 significant variables were included in the stepwise linear regression model with backward elimination. The final regression model included five variables, those independent characteristics in the watershed which contributions to *E. coli* concentration are the most important: CAFOs + dairies + farm/ranch (density) [unit/m^2], Pasture/hay land use (density) [m^2/m^2], Median number of days out of 9 with precipitation [day], Evergreen forest (density) [m^2/m^2], Developed, high Intensity land use total [m^2], the variables Pasture/hay land use (density) and Evergreen forest (density) were not included in the linear regression model with backward elimination result but they were significant according to the Spearman's rank correlation coefficient test results. Corresponding coefficients, *p*-values, and VIF values, as well as the intercept, the adjusted R^2, overall significance and AIC values are presented in **Table 5**. Supplementary information (Appendix A - SI 1.5. Figure 2) shows the residuals of the model with no obvious patterns which supports the linearity and homoscedasticity assumptions. Studentized Breusch–Pagan test has a value of ~4.58 with 5 degrees of freedom and a *p*-value of 0.4699 suggesting homoscedasticity or that the variance of residuals is the same for any value. Shapiro-Wilk normality test result for residuals is of ~0.98 with a *p*-value of 0.5296 indicating normal distribution. By comparing the magnitude of the coefficient estimates the relative importance of the different watershed characteristics analyzed can be determined. CAFOs + dairies + farm/ranch (density) has the greatest magnitude, with orders of magnitude greater than the remaining variables indicating its main influence on the model. For four of the variables (CAFOs + dairies + farm/ranch (density), Pasture/hay (density), Median number of days out of 9 with precipitation, and Evergreen forest (density)) the sign of the coefficient estimates is the same as the sign of the correlation identified by the Spearman's rank statistics while for the variable Developed, high intensity is the opposite.

Table 5

Results of the Final Linear Regression Model That Includes the Most Relevant of the Tested Variables to Assess the Relative Impacts on E. coli Concentration Values at the Watershed Level

For the variables				
Variable	*Unit*	*Coefficient*	*p-value*	*VIF*
CAFOs + dairies + farm/ranch (density)	unit/m^2	2.166×10^{7}	6.190×10^{-3}	~ 1.55
Pasture/hay (density)	m^2/m^2	5.117×10^{1}	2.763×10^{-2}	~ 1.07
Median number of days out of 9 with precipitation	day	2.489×10^{-1}	2.04×10^{-5}	~ 1.05
Evergreen forest (density)	m^2/m^2	-7.147×10^{-1}	5.47×10^{-4}	~ 1.12
Developed, high intensity	m^2	-9.329×10^{-9}	2.591×10^{-3}	~ 1.44
For the model				
Intercept	1.312			
Adjusted R^2	0.5423			
Overall significance (p-value)	3.801×10^{-7}			
AIC value	~ 36.40			

Spearman's rank correlation test measures the strength and direction of the association between only two variables one of them the dependent variable, while the linear regression model estimates the relationship of two or more variables with a dependent variable, being the sign of each variable dependent upon which variables are included in the model and not related with the one obtained from the Spearman's rank correlation test, therefore the direction of the correlation between the five watershed characteristics included in the model and *E. coli* concentration must be taken from the Spearman's rank analysis. The two analyses combined enable making conclusions about the relationships between watershed characteristics and *E. coli* concentration and their relative importance. This model should not be used to quantitatively estimate *E. coli* concentrations. A comparison between fitted values and observed values of $\log_{10}$(GM) is presented in **Figure 13**.

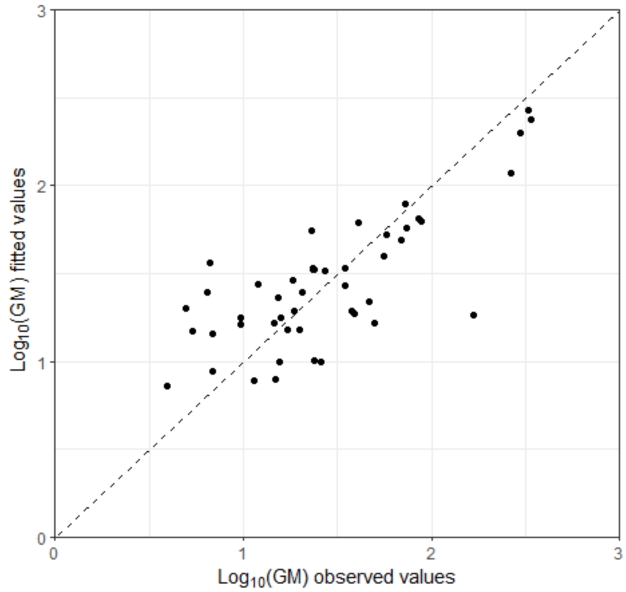


Figure 13. Comparison scatterplot. Scatterplot to compare $\log_{10}$(GM) observed values to fitted values produced by the multiple linear regression model five predictive variables (Table 5).

2.3. Discussion

E. coli concentrations from intermittent and ephemeral sites were significantly different from those in artificial paths and perennial rivers. Even though all *E. coli* concentration distributions for different stream types are right skewed, the median value for intermittent + ephemeral streams is almost 65 and 140 percent higher than those for perennial streams and artificial paths, respectively. Also, the *E. coli* concentration values between the median and the 75th percentile are almost 5 times greater. These findings indicate that intermittent and ephemeral streams, which together represent an average ~95% of the stream network of the studied watersheds, could be important drivers of pathogen loads to perennial streams and other waterbodies.

In general, rain increases the concentrations of *E. coli* in streams under antecedent rainfall conditions —*E. coli* median concentration was ~3 times higher than observations where no recent rain was observed. Since contributions from ephemeral and intermittent streams would be minimal under no local rain conditions, the similarity during these conditions is not unexpected. Higher differences between concentrations of *E. coli* under rain conditions and under no rain conditions at the beginning of the monsoon season could be due to the contributions of subsurface and surface flow, as subsurface flow increases during the monsoon season so does the *E. coli* concentration under no rain conditions, to the point where the rain does not increase in greater proportion the *E. coli* concentration at the end of the monsoon season. In intermittent and ephemeral streams there are marked differences in *E. coli* concentrations under rain and no rain conditions. Ephemeral streams flow under the direct influence of recent rain which forms runoff and erosion that can carry *E. coli* (Muirhead et al., 2006). Similarly, the flow of intermittent rivers is also affected by rain increasing the surface and subsurface components of the flow and thus *E. coli* concentration as well.

It was found that at the watershed level, five of the studied variables are the most related to the presence of *E. coli* in the streams –hereafter discussed in more detail.

CAFOs, dairies, farms, and ranches are related to the production, storage, and application of manure (Kast et al., 2019; Spiegal et al., 2022) which may contain numerous pathogens and *E. coli*. A significant positive correlation between their number and *E. coli* geometric means at the watershed scale was found. Previous research, as conducted by Hamner et al. (2014) and Heaney et al. (2015), found evidence of high concentrations of *E. coli* and the presence of specific related fecal markers in surface waters proximal to CAFOs and CAFOs liquid waste land application sites, likely due to direct discharges or surface runoff after rain events. While ADEQ issues various permits for these kinds of facilities related to the discharge of pollutants to water (e.g., the Aquifer Protection Permit) (Arizona Department of Environmental Quality, n.d.-b, n.d.-c, 2021b), the focus of these permits is typically on the protection of groundwater and contributions to ephemeral and intermittent rivers may not be a priority.

According to the NLCD, Pasture/hay is an agriculture class (Jin et al., 2019) planted on a perennial cycle, for livestock grazing or the production of seed or hay crops (Multi-Resolution Land Characteristics Consortium, n.d.). A significant positive correlation between Pasture/hay land cover and *E. coli* concentrations was observed. Cattle-grazed pastures have been found to be significant contributors of *E. coli* to surface waters in Georgia (Byers et al., 2005) and New Zealand (Donnison et al., 2004) as grazing activities increase the concentration of *E. coli* in soil and storm events mobilize it to streams, rivers, ponds and lakes. Likewise a hay area fertilized with manure was found to be a potent source of *E. coli* contamination to surface water via runoff in Vermont (Meals & Braun, 2006).

Similar to the previous analysis, precipitation (and specifically, the median number of days with precipitation) had a significant positive correlation with *E. coli* concentrations. In previous research *E. coli* and preceding rainfall events have been found to be significantly correlated. Vidon et al. (2008) studied two artificially drained agricultural watersheds in the Midwest, finding significant correlation between *E. coli* concentration and the average precipitation in the 7 days preceding measurements. Hathaway et al., (2010) found that averages of 28 days and 2 days antecedent precipitation in an urbanized watershed in North Carolina were significant, likely because the antecedent rainfall conditions affect both the amount of water and energy available for *E. coli* transport leading to substantially higher runoff, and the amount of moisture present in a watershed that is critical for *E. coli* survival (Chen & Chang, 2014; Schoener & Stone, 2019).

Evergreen forest areas are those areas where more than 20% of the total vegetation cover is dominated by tree species that maintain their leaves all year (Multi-Resolution Land Characteristics Consortium, n.d.). In this study there was a significant negative correlation between Evergreen Forest and *E. coli* concentrations. This finding is in agreement with previous studies reporting decreased fecal contamination in forested areas (Brendel & Soupir, 2017; Hubbart et al., 2022; Petersen & Hubbart, 2020; Tong & Chen, 2002). Forested areas can benefit water quality through filtering and promoting sedimentation (Anbumozhi et al., 2005).

Developed, high-intensity land cover refers to areas where high numbers of people reside or work and impervious surfaces account for 80% to 100% of the total cover (Multi-Resolution Land Characteristics Consortium, n.d.). A significant correlation was observed between this type of land cover and *E. coli* concentrations. While developed, high intensity land cover covered only ~0.60% of the total watershed area, it was still found to be a significant driver of *E. coli* concentrations, suggesting that this type of land cover even small amounts can impact the water quality in these systems. This is in accordance with the findings of Chen & Chang, (2014) who studied three watersheds with different land uses (urban, suburban, and rural) in Oregon and Washington where the urban watershed (84% urban land use) had the highest level of *E.coli.* The amount of impervious land cover area in developed areas redirects rainfall and decreases its infiltration into soil, consequently increasing surface runoff. Also, urban areas have more people and pets which can have adverse effects on stream water quality, increasing the amount of pollutants including pathogens (Crim et al., 2012; Hamid et al., 2020).

The obtained results could be improved with the implementation of Microbial Source Tracking (MST) markers which are intended to discriminate between sources of fecal contamination based on the concept that various warm-blooded animal intestinal systems have different and specific gut microbial populations that could be used in genome sequencing.

2.3.1. Limitations of the Study

This study was limited by the scope of available data. Uneven spatial and temporal distribution of sites and records may lead to misrepresentation of ephemeral and intermittent rivers, dry season, as well as watersheds, especially those located in the northern and southwestern part of the state. Further work could explore ephemeral and perennial sites in the same watershed with more intensive sampling to expand the knowledge around the contributions from ephemeral streams. Related, observational sites used in this study were classified in the four used categories according to the NHD. Misclassifications in the NHD and site coordinates could affect the obtained results.

Rain data were obtained from the closest rain gauge to the site, yet great distances could negatively impact the accuracy of site precipitation data. Additionally, in arid and semi-arid regions, where rainfall patterns can be sporadic and variable, rain in an upstream portion of a watershed could lead to intense flows at an observed site even if the closest rain gage showed no precipitation. Future work could consider larger spatial patterns of rainfall especially at upstream gages.

2.4. Conclusions

What drivers are important in influencing *E. coli* concentrations in Arizona streams were investigated using water quality data from 2010 – 2019 through two methods: first the influence of stream type and antecedent precipitation on concentrations and second watershed-level drivers of concentrations. The results suggest that *E. coli* concentrations in this semiarid region vary according to the type of river (e.g., ephemeral, perennial) and the presence of rain. *E. coli* concentrations with the highest median values are associated with intermittent and ephemeral rivers. Antecedent rainfall conditions resulted in significantly elevated presence of *E. coli* in streams, especially in ephemeral streams. Moreover, the analysis demonstrates that at the watershed level, some types of land cover, the presence of specific sources, and precipitation are still important for explaining the presence of *E. coli* in rivers. Specifically, four watershed-level variables and rain explained more than 50% of the concentration of *E. coli*, with indicators of animal agriculture being a main influence associated with higher concentrations. Overall, the results indicate that ephemeral and intermittent rivers could play a key role in the presence of *E. coli* in watersheds. The impact of ephemeral rivers is likely under-recognized given the spatiotemporal variability and frequency of the studied samples. However, the importance and influence of non-perennial streams should be considered in further sampling campaigns. The results of this study can help to inform future policy and management strategies to address elevated levels of *E. coli* in streams in arid and semiarid areas. Given recent debate over the status of ephemeral and intermittent rivers (Keiser et al., 2022; Sullivan et al., 2019), these results could inform future policy discussions given recent Supreme Court rulings (United States Environmental Protection Agency, 2022d, 2023j, 2023k). If ephemeral streams are not considered in WOTUS and polluters could theoretically emit to these waterways without regulation, we could see increases in pathogens in the future in semiarid and arid regions like Arizona.

CHAPTER 3

WASTEWATER INFRAESTRUCTURE AS POSSIBLE POINT SOURCES OF POLLUTANTS ON TRIBAL LANDS

As previously mentioned, WWTPs have the potential to be a source of pathogens and can significantly contribute to the contamination of surface water in a watershed (Kistemann et al., 2012; Sanders et al., 2013). With a total population of about one million where more than 50% are American Indian and Alaska Native alone (United States Census Bureau, 2020d) and with an area of more than 300 billion of square meters (United States Census Bureau, 2020a), Tribal lands lack of available information regarding the connectivity of Tribal communities to WWTPs. This information is important to understand current sanitation infrastructure which drives public health and community construction, knowledge of potential routes of pathogenic contamination through lack of infrastructure and/or discharging facilities. Of particular concern are the breath of wastewater treatment facilities across these rural and decentralized communities, human waste can contaminate clean drinking water sources if not properly controlled. A report from the Government Accountability Office in 2018 showed that there is a deficit of data related to American Indian communities in the US and the extent to which communities were connected to municipal wastewater treatment facilities or some basic sanitation system in general, recommending federal dollars should be invested in providing information to fill data gaps in an effort to recommend where infrastructure needs existed (United States Government Accountability Office, 2018b, 2018a, 2018c).

According to the Native American Rights Fund an Indian Tribe “was originally a body of people bound together by blood ties who were socially, politically, and religiously organized, who lived together in a defined territory and who spoke a common language or dialect” (Native American Rights Fund, n.d.). The US government currently recognizes Indian Tribes federally and by state, when the state has established such authority, and maintains a direct government-to-government relationship with 574 Federally Recognized Indian Tribes (FRITs) variously called tribes, nations, bands, pueblos, communities, colonies, rancherias, and villages, listed in supplementary information (Appendix B - SI 2.1. Table 1). A majority of FRITs are isolated and rural with 227 located in Alaska and the remaining located in 34 other states (Indian Entities Recognized and Eligible to Receive Services From the United States Bureau of Indian Affairs; Correction, 2021; Indian Entities Recognized by and Eligible to Receive Services From the United States Bureau of Indian Affairs, 2021; National Congress of American Indians, 2020; United States Department of the Interior, n.d.-b). Being federally recognized makes Indian Tribes eligible for funding and services from the Bureau of Indian Affairs and enables possession of certain inherent rights of self-government or sovereignty; FRITs may also be automatically state recognized. Additionally, there are 66 Indian Tribes that are only state recognized (National Conference of State Legislatures, 2020) and others that lack both federal and state recognition.

Federal recognition gives Indian Tribes the authority to self-govern their territory as independent nations, driven by self-determination that is protected by the trust responsibility. In doing so, the government is responsible for holding land in trust as permanent homelands for FRITs as they continue to exercise their sovereignty and provide services to their Tribal citizens that include health care, law enforcement, education, utilities, housing, infrastructure, disposal, wastewater management, and environmental management and protection (National Congress of American Indians, 2020). The federal government of the US holds titles of areas of land in trust on behalf of FRITs to be permanent Tribal homelands; these are Federal Indian Reservations (FIRs). The history of federal policies on Tribal land rights is complex as FIRs are defined by geographic boundaries that are composed of their original ancestral territories or lands from the resettlement of FRITs by the government. There are other types of lands for the use of FRITs or Tribal members including Off-reservation Trust Lands (ORTLs), Allotted lands, Restricted status, State Indian Reservations, Hawaiian home lands, and Private properties (United States Census Bureau, 2021a; United States Department of the Interior, n.d.-a). Not every FRIT has a FIR or ORTL, some have more than one, and others share. **Figure 14** depicts the number of FRITs with and without FIRs and/or ORTLs areas classified according to state.

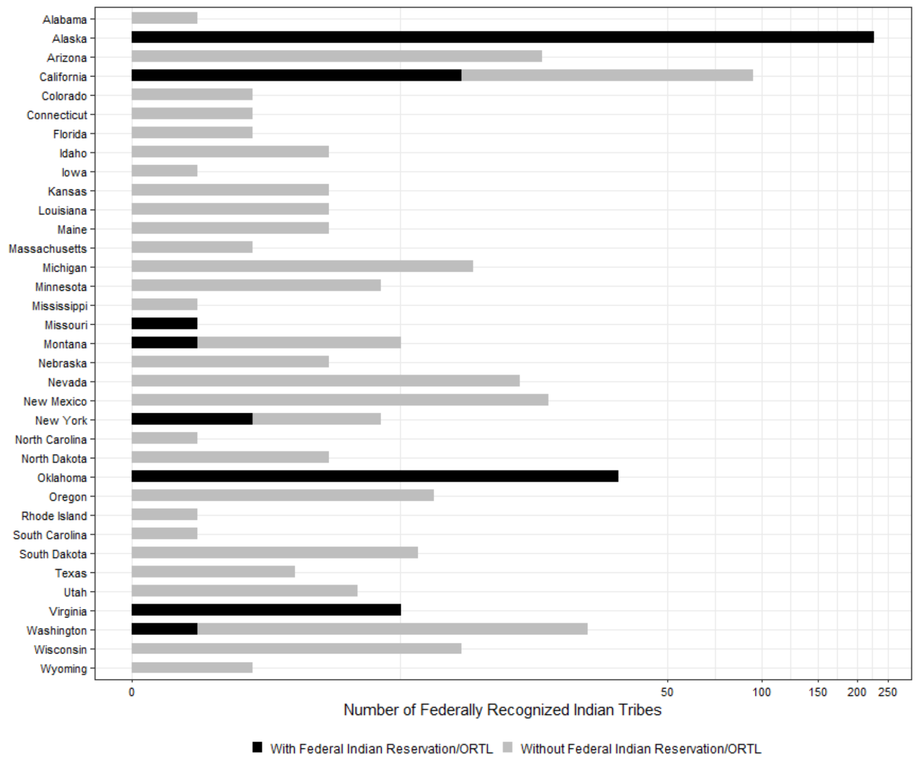


Figure 14. Number of Federally Recognized Indian Tribes with and without Federal Indian Reservations (FIRs) and/or Off-reservation Trust Land (ORTLs) areas classified according to state. FIRs and ORTLs may cross states boundaries (Indian Entities Recognized and Eligible to Receive Services From the United States Bureau of Indian Affairs; Correction, 2021; Indian Entities Recognized by and Eligible to Receive Services From the United States Bureau of Indian Affairs, 2021; United States Department of the Interior, n.d.-b).

As stated, the CWA created the NPDES permit program to address to a certain extent water pollution by regulating point sources such as WWTP that discharge pollutants to WOTUS by mandating a permit and implementing a regular monitoring system. This program authorizes some state and FRITs governments by the US EPA to extend permits that, after a thorough review and analysis, specify the facility discharge requirements (limits on what to discharge, monitoring and reporting requirements, etc.) to ensure water quality will not be impacted for specific designated uses. Permit details include limits on what pollutants they can discharge in addition to monitoring and reporting requirements. For locations where the state or FRITs government is not authorized to extend permits, US EPA Regional authorities will permit facilities. In all cases, including FRITs, the US EPA is the final regulator (United States Environmental Protection Agency, 2022u).

As sovereign nations, FRITs are still subject to environmental regulations; however, the management of public water supplies (under the SDWA) and wastewater discharge will vary if the Indian Tribe has been granted state-status under the "Treatment as State" (TAS) provision (Haider & Teodoro, 2021), also known as Tribal Primacy. TAS was enacted by the US in 1987, allowing Indian Tribes to draft and enforce their own environmental laws. At a minimum, the Indian Tribe must be federally recognized (not state), have legal authority over their natural resources, and have the ability to manage such changes (National Primary Drinking Water Regulations Implementations, 2020). To date, the Navajo Nation is the only Indian Tribe with TAS status to implement the Public Water System Supervision (PWSS) program (United States Environmental Protection Agency, 2022f) but none has this status to implement the CWA § 402 referring to the NPDES (United States Environmental Protection Agency, 2022s, 2023e). Since 1987, only ~15% of Publicly Owned Treatment Works (POTWs) have been regulated by Indian Tribes that hold Tribal Primacy status, while the remaining are overseen by state and EPA (Haider & Teodoro, 2021).

Wastewater generated on FIRs and/or ORTLs, here thereafter called Tribal lands, is managed through many types of facilities. Centralized secondary and in some cases, tertiary, wastewater treatment utilities with a sewer network serving a considerable number of people are more common near population centers. However, a significant number of wastewater facilities are decentralized, often located as close as possible to where the wastewater is generated. These decentralized systems may serve individual dwellings, single industries, or institutions and may be outhouses, lagoons, and septic systems. According to a 2019 report (Division of Sanitation Facilities Construction. Office of Environmental Health and Engineering. Indian Health Service., n.d.), over 58,000 American Indian and Alaska Native homes are deficient in safe drinking water and improved sanitation, and 5-10% of Tribal households do not have basic sanitation (Indian Health Service, 2021; United States Environmental Protection Agency, 2023a). Lack of adequate water and wastewater services has been correlated with respiratory tract and skin infections in Alaska Native populations (Hennessy et al., 2008; Wenger et al., 2010).

Information on Tribal wastewater facilities can be found in federal databases. The ECHO database at https://echo.epa.gov/ provides data on environmental regulatory compliance and enforcement for public use and program management. This website provides data focused on inspection, violation, enforcement, and penalties for the Clean Air Act (CAA), Resource Conservation and Recovery Act (RCRA), SDWA, and CWA for more than 800,000 facilities nationwide regulated through an NPDES permit (United States Environmental Protection Agency, n.d., 2022e, 2023i). ECHO includes US EPA, state, local and Tribal environmental agency compliance and enforcement records that are reported into US EPA national databases. Information on permit data, inspection and/or compliance evaluation dates and findings, violations of environmental regulations, enforcement actions, and penalties assessed are available for all permitted facilities (United States Environmental Protection Agency, n.d., 2023i). The Integrated Compliance Information System National Pollutant Discharge Elimination System (ICIS-NPDES), Facility Registry Service (FRS), Toxics Release Inventory (TRI) data, and Emission Inventory System (EIS) are some of the available datasets in ECHO (United States Environmental Protection Agency, 2023i) to allow a better analysis such as FRS contains facility identification information while ICIS-NPDES allows tracking permit compliance and enforcement status of facilities regulated by the NPDES program. Permit information including facility location and permitted features (e.g., discharge points or outfalls), limits, and discharge monitoring data are available (United States Environmental Protection Agency, 2022g, 2022m).

The goal was to achieve two objectives: first, to locate WWTPs as potential point sources of pathogens on FIRs and/or ORTLs, and second, to identify the connectivity of all 574 FRITs to WWTP facilities by identifying the number of WWTPs associated with them. To accomplish this, I reviewed NPDES permits available from EPA’s ECHO for proximity to and within spatial boundaries of Tribal lands, including those serving Tribal towns, casinos, K-12 schools, and those operated by private and Tribal utilities in addition to population race data from federal databases to develop a list of facilities located on Tribal lands and those that collect from predominantly Native American communities.

3.1. Methods

The study was conducted for the entire US to find permitted WWTPs that are located on or near FIRs and/or ORTLs areas and those serving Tribal populations. All analyses were conducted using ArcGIS (Environmental Systems Research Institute (Esri), n.d.) and the statistical software R version 4.2.0 (R Core Team, 2022; RStudio Team, 2022). The flow diagram in **Figure 15** highlights the decision tree of data, various data sources, and the number of treatment plants identified in each step of the process.

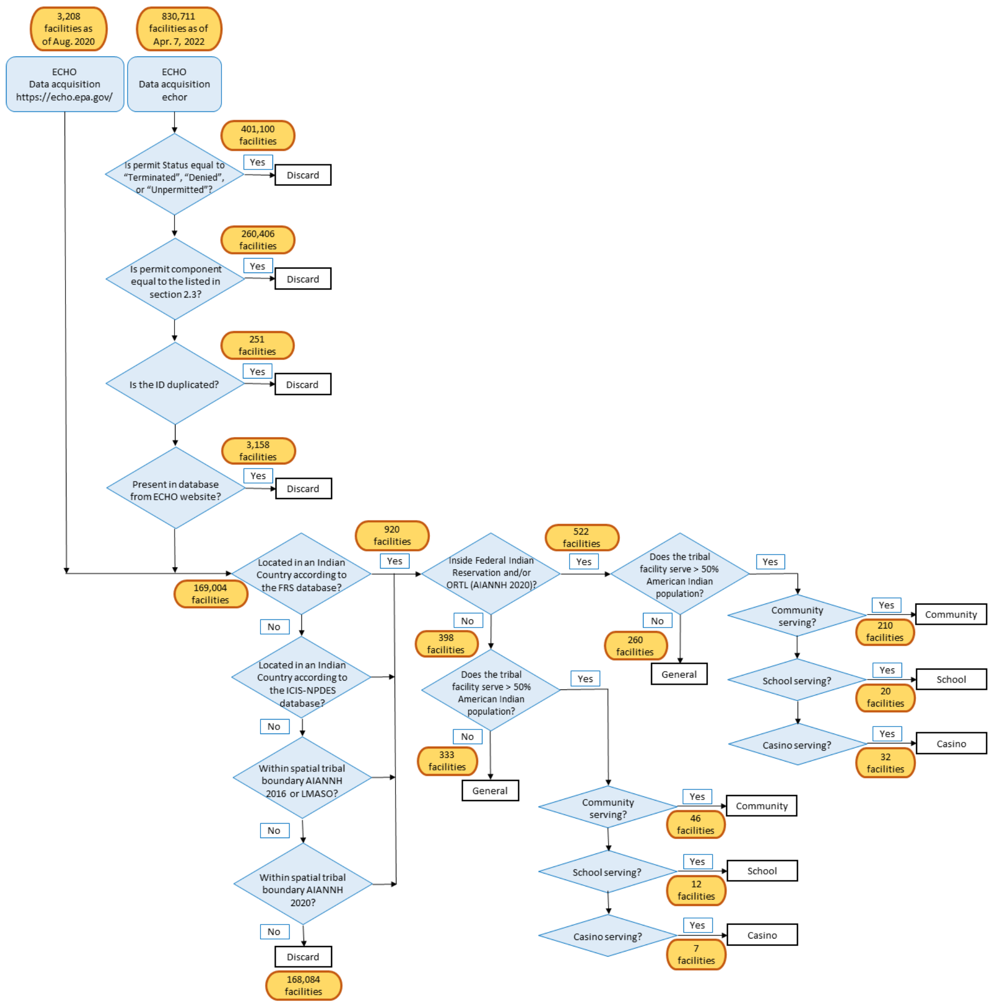


Figure 15. Followed procedure to find permitted facilities that mainly serve Tribal communities in the United States.

3.1.1. Study Area

The study was conducted on land areas in the US administered as FIRs or ORTLs. In 2020, approximately 327 land areas in the US were administered as FIRs or ORTLs by 290 FRITs (United States Census Bureau, 2020a), **Figure 16** depicts the FIRs and ORTLs for which the US Census Bureau publishes data. Supplementary information (Appendix B - SI 2.1. Table 1) lists and relates FIRs and/or ORTLs with their corresponding FRIT(s).

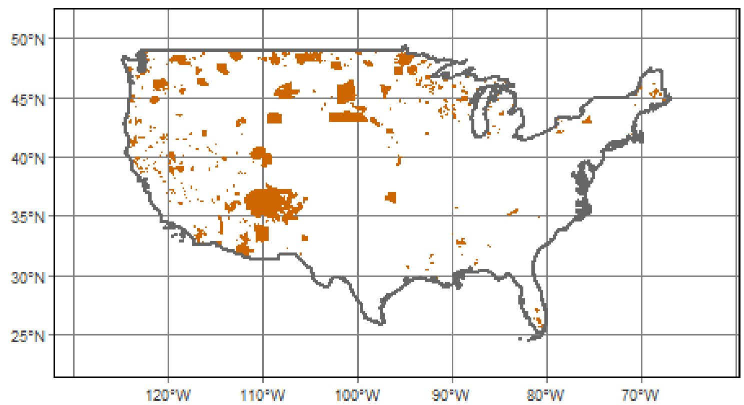


Figure 16. Distribution of Federal Indian Reservations (FIRs) and Off-reservation Trust Lands (ORTLs) along the United States. FIRs and ORTLs may cross states, counties, county subdivisions, and/or place boundaries (Environmental Systems Research Institute (Esri), 2022; United States Census Bureau, 2020a, 2020b).

3.1.2. Data Acquisition Search Criteria

A Tribal wastewater facility search was conducted in August 2020 using the search criteria listed in supplementary information (Appendix B - SI 2.2. Table 2) in EPA's ECHO database (https://echo.epa.gov/); the resultant data table was customized to include additional "Facility Information" within the results output. Selected data included the Street Address, City, State, EPA Region, FRS Tribal Land Code, ICIS Tribal Land Flag, Within Spatial Tribal Boundary, FRS Spatially Derived Tribe, Latitude/Longitude, Facility Design Flow, and Actual Average Facility Flow. No criteria were selected for other fields. The names of the resulting field headers differed between the selected search criteria, the results table, and downloaded files, corresponding values are listed in supplementary information (Appendix B - SI 2.3. Table 3) under the columns "Result page field name” and “Data download file field name” and described in accordance with the ECHO website (United States Environmental Protection Agency, 2022j). The column header “FacIndianCntryFlg” selected in the original search criteria as “FRS Tribal Land Code”, and “CWPIndianCntryFlg” as “ICIS Tribal Land Flag” refer to whether the facility is (“Y”) or is not (“N”) located in Indian Country in the FRS or the ICIS-NPDES databases, respectively. Indian Country is defined as Indian reservations, dependent Indian communities, and Indian allotments in accordance with the Title 18 § 1151 of the US Code (Crimes, 2011; United States Environmental Protection Agency, 2016a). “FacIndianSpatialFlg”, selected as “Within Spatial Tribal Boundary” in the search criteria, displays “Y” if the facility is located within a default value of ~40 km (25 miles) of a Tribal spatial boundary or “N” if the contrary, where a Tribal spatial boundary is defined using the US Census Bureau 2016 Tribal boundary layer data, also called American Indian/Alaska Native/Native Hawaiian (AIANNH) Area National Shapefile, when developing the results responses for tribes in the lower 48 United States or the Bureau of Land Management Alaska State Office (LMASO) for responses for tribes in Alaska (United States Environmental Protection Agency, 2022j, 2022l). Also, the R (R Core Team, 2022; RStudio Team, 2022) package echor (Schramm, 2021) was used on April 7, 2022 to search and download the permitted facility data from ECHO listed and described in supplementary information (Appendix B - SI 2.4. Table 4).

3.1.3. Location Update

The US Census Bureau AIANNH Area National Shapefile for the year 2016 (United States Census Bureau, 2016) used by EPA ECHO differs from that for the year 2020 (United States Census Bureau, 2020a) in the number of registers. To avoid discarding facilities inside Tribal lands identified for 2020 from the ECHO website, using “Latitude” and “Longitude” the Tribal facilities were mapped along with the 2020 shapefile using ArcGIS Desktop 10.7.1®. Those facilities located within the boundaries of a FIR and/or ORTL were labeled as “Inside Federal Indian Reservation and/or ORTL” associated with the specific FRIT, or they were labeled as “Outside Federal Indian Reservation and/or ORTL”.

3.1.4. Screening Process

For the facilities identified with the echor package, a screening process was executed consisting of discarding facilities already obtained from the ECHO website and those with same “SourceID”; “CWPPermitStatusDesc” equal to “Terminated”, “Denied”, or “Unpermitted”; “PermitComponents” equal to "Biosolids", "Biosolids, CAFO", "Biosolids, CSO", "Biosolids, Industrial Stormwater", "CAFO", "CAFO, Industrial Stormwater", "Construction Stormwater", "Construction Stormwater, Industrial Stormwater", "CSO", "Industrial Stormwater", "Industrial Stormwater, Urban Stormwater (Medium/Large MS4)", "Industrial Stormwater, Urban Stormwater (Small MS4)", "Urban Stormwater (Medium/Large MS4)", "Urban Stormwater (Medium/Large MS4), Urban Stormwater (Small MS4)", "Urban Stormwater (Small MS4)", and facilities with “FacIndianCntryFlg”, “CWPIndianCntryFlg”, and “FacIndianSpatialFlg” equal to “N” and located outside FIRs and/or ORTLs according to the US Census Bureau AIANNH area national shapefile for the year 2020. Of the remaining, facilities with Standard Industrial Classification (SIC) code values (United States Department of Labor, n.d.) listed in supplementary information (Appendix B - SI 2.5. Table 5) in “CWPSICCodes” were kept. Missing data was obtained from the ECHO website using the “SourceID” value. The facilities listed on the website and located in the same place were confirmed not to be terminated or retired.

3.1.5. Population Demographics

For this analysis, race data were evaluated from the 2010 census for the city location of each facility from the US Census Bureau (data.census.gov) (United States Census Bureau, n.d.-c). Delays in 2020 Census data and public access to the Data Explorer tool prohibited use of the newer dataset (United States Census Bureau, 2021b). Information for six racial designations were provided: White alone or in combination with one or more other races, Black or African American alone or in combination with one or more other races, American Indian and Alaska Native alone or in combination with one or more other races, Asian alone or in combination with one or more other races, Native Hawaiian and Other Pacific Islander alone or in combination with one or more other races, and Some Other Race alone or in combination with one or more other races.

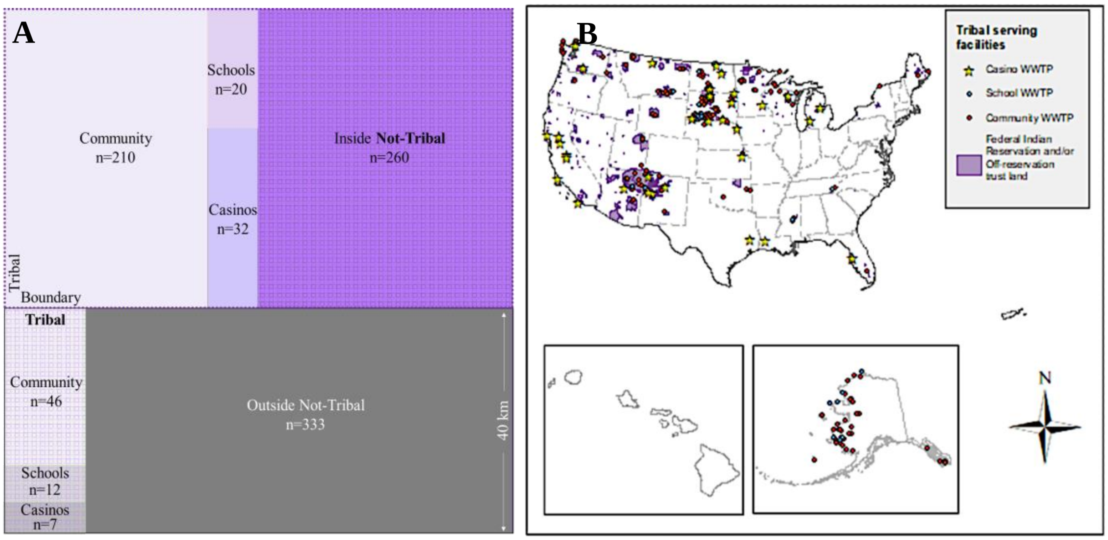
For facilities located in unincorporated communities or not census designated places, the website https://censusreporter.org/ was used, an independent project with the purpose of making US Census Bureau American Community Survey (ACS) 2019 5-Year data easier to use (Census Reporter, n.d.). Here, race data are categorized as: White, Black, Native, Asian, Islander, Other, Two or more, and Hispanic.

3.1.6. Wastewater Facility Classification

Facilities were classified in 8 different categories: 1) Not-Tribal serving, General ─ Outside Federal Indian Reservation and/or ORTL, "General" meaning the facility could serve a city, a school, a hotel, etc. and "Not-Tribal serving" meaning ≤50% of the population related were American Indian and Alaska Native alone or in combination with one or more other races (AI); 2) Not-Tribal serving, General ─ Inside Federal Indian Reservation and/or ORTL; 3) Tribal serving, Community ─ Outside Federal Indian Reservation and/or ORTL; 4) Tribal serving, Community ─ Inside Federal Indian Reservation and/or ORTL; 5) Tribal serving, School ─ Outside Federal Indian Reservation and/or ORTL; 6) Tribal serving, School ─ Inside Federal Indian Reservation and/or ORTL; 7) Tribal serving, Casino ─ Outside Federal Indian Reservation and/or ORTL; and 8) Tribal serving, Casino ─ Inside Federal Indian Reservation and/or ORTL. Casino facilities were classified as Tribal serving based on the ownership, although their services often cater to the general public.

3.2. Results

Results from the ECHO database search revealed 572 facilities in Indian Country or near/in a Tribal spatial boundary (~40 km) with an additional 70 identified by the 2020 American Indian/Alaska Native/Native Hawaiian (AIANNH) Area National shapefile, and 278 identified by using echor package, bringing the total number to 920. Spatial location (latitude and longitude) was then used to verify if facilities were inside (n = 522) or outside FRITs and/or ORTL (n= 398). Of those defined as Tribal serving (>50% AI, 327), 262 (~80%) were inside FRITs and/or ORTL, with an additional 65 locations outside. The distribution of wastewater facilities is summarized in **Figure 17A** and supplementary information (Appendix B - SI 2.6. Table 6), including the breakdown for those serving the community versus schools and casinos (**Figure 17C)**. The Tribal serving facilities are listed in supplementary information (Appendix B - SI 2.7. Table 7), and their location is shown in **Figure 17B.** Of those not-Tribal serving locations (n=593), 260 or ~44% were inside Tribal lands, while only ~16% (n=65) Tribal serving locations were outside Tribal lands.



C

574 FRITs (**587**)	290 with FIR + ORTL	97 with WWTF (**543**)	82 with only inside FIR + ORTL (**398**)	29 with only NTS (**84**)	
				28 with only TS (**57**)	17 with TS community + additional location (**44:** 0, 40, 2, 2)
					11 without TS community location
				25 with NTS and TS (**257**)	23 with TS community + additional location (**242:** 130, 92, 13, 7)
					2 without TS community location (**15:** 13, 0, 0, 2)
			3 with only outside FIR + ORTL (**3**)	1 with TS community + additional location (**1:** NA, 1, 0, 0)	
				2 without TS community location (**2:** NA, 0, 0, 2)	
			12 with inside and outside FIR + ORTL (**142**)	Inside (**124:** 33, 78, 5, 8)	
				Outside (**18:** NA, 9, 5, 4)	
		193 without WWTF			
	284 without FIR + ORTL	42 with WWTF (**44**)	34 with TS community + additional location (**36:** NA, 36, 0, 0)		
			8 without TS community location (**8:** NA, 0, 7, 1)		
		242 without WWTF			

(**Total number of facilities:** not-Tribal serving, community, school, casino)
NTS = not-Tribal serving; TS = Tribal serving; *without TS community location can include serving a school, casino, or NTS (e.g., not AI communities, lodge, mine)

Figure 17. Facilities. A) Facility classification according to those serving Federally Recognized Indian Tribe (FRIT) population. Facility distribution between Tribal and non-Tribal lands, predominantly AI serving (>50%) facilities and whether those include community, school or casino. B) Location of facilities classified as "Tribal serving" across the United States (United States Census Bureau, 2020a, 2020b, 2020c). C) Breakdown of total number of FRITs, those with a Federal Indian Reservation (FIR) and/or Off Reservation Trust Land (ORTL) and the total number of WWTP based on geographic location (inside/outside) and types of population served Tribal vs. Not-Tribal, community vs. school, vs, casino.

3.2.1. Tribal-Level Analysis

Analysis of available NPDES permits shows that 94 FRITs have at least one facility inside the boundaries of their FIR and/or ORTL. Of these 65 have at least a Tribal serving facility, either community (n=51), school (n=8), or casino (n=24). In addition, ~50% (n = 33) of those 65 also have a non-Tribal facility onsite (service to population with less than 50% AI), while another 29 FRITs have only non-Tribal serving facilities. Analyzing the location of wastewater facilities inside and outside FIRs and/or ORTLs, 110 FRITs have facilities serving their community, school, and/or casino. 86 FRITs of them have at least one community specific location, 17 have at least one school specific location and 29 have at least a casino location.

For the 210 Tribal serving wastewater treatment facilities (community serving) inside FIRs and/or ORTLs, serving 51 unique Tribes, the percentages of the estimated total AI population in the FIRs and/or ORTLs connected are shown in **Figure 18**. For example, the wastewater treatment facility serving Oneida Nation capturing > 50% AI by demographics only captures 8% of the total Tribal community living on the FIR and/or ORTL. On average, the total percentage of each AI population captured by wastewater infrastructure is 57% ± 27% (min, max, median 8, 100, 55).

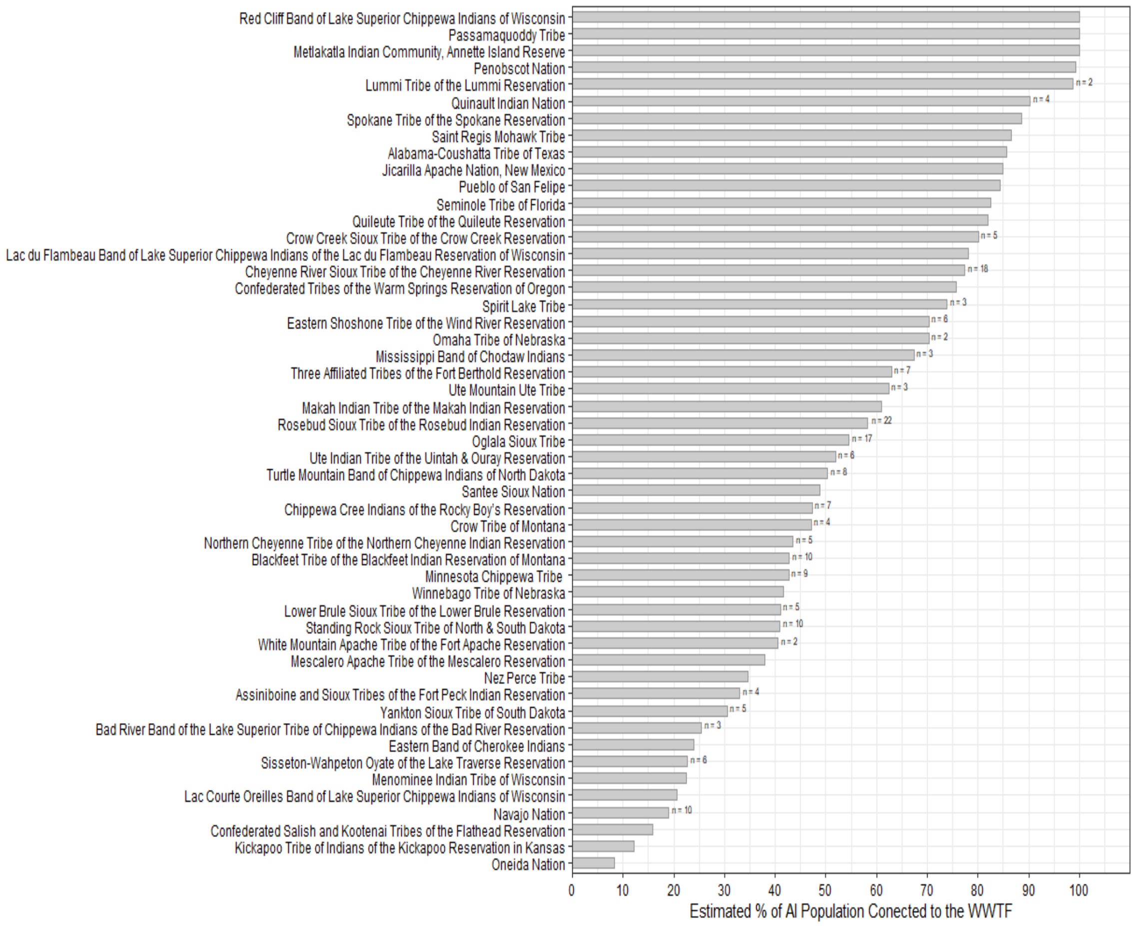


Figure 18. Connected population. List of Federal Recognized Indian Tribes with estimated percentage (%) of American Indian population on the Federal Indian Reservation and/or Off-reservation Trust Land that is connected to a community serving wastewater treatment plant (WWTP). n = number of Tribal community serving WWTP, n = 1 unless otherwise stated.

3.3. Discussion

3.3.1. Tribal Infrastructure

3.3.1.1. Basic Sanitation Assessment. This analysis identified that 94 FRITs have registered NPDES permits within FIRs and/or ORTL boundaries, of them 51 are connected to community wastewater treatment plant facilities, covering an estimated 135,000 people or 36% of Tribal members on FIRs and/or ORTLs.

However, 523 FRITs have unknown community sewage treatment practices. These could be because they 1) have on-site septic systems, 2) have sewer connections that feed into non-

Tribal or off-reservation facilities, 3) have sewer connections that feed into reservation facilities located at a distance greater than 40 km, 4) are non-discharging (terminal lagoons), 5) do not discharge into surface water but to other locations such as infiltration basins, 6) recycle their wastewater for irrigation or other purposes, or 6) do not have FIR or ORTL that would require a wastewater facility. Additional methods should be used to determine if current infrastructure exists, but information is not available via EPA ECHO the database that captures only NPDES permitted (discharging) facilities. In rural communities, often common on Tribal reservations, decentralized wastewater treatment plants are common, generally non-discharging single-cell lagoon systems (United States Environmental Protection Agency, 2022q). Previous work has highlighted the importance of non-discharging systems to the total number of collection systems on Tribal reservations, particularly in the west (Driver et al., 2022).

3.3.1.2. Opportunities for Monitoring. The delineation of facilities into communities, schools, and casinos adds a unique opportunity for monitoring. Casinos provide revenue and tourism, but visitors may act as infectious disease vectors or sources of illicit substances. Additionally, schools are incredibly important to the health of communities and may act as reservoirs of disease aiding spread from schools to isolated homes. Both of these types of facilities would be useful to community-level sentinel monitoring.

3.3.1.3. Environmental Justice Concerns. The evaluation identified 260 of 522 (~50%) WWTP on Tribal lands that serve predominantly non-Tribal populations. Of these 102 serve commercial or industrial uses (e.g., hotels, lodges, processing plants and other construction uses) that are not included here. Thus, 158 predominantly serve non-Tribal communities on Tribal lands. In fact, the majority serve ≤ 10% of a Tribal-identifying population, which calls into question how the infrastructure ended up on Tribally-administered land (**Figure 19**). The Indian Health Sanitation (IHS) Facilities Act Public Law 86-121 is intended to serve AI/AN homes and communities with adequate water, sewage, and solid waste disposal (Indian Hospitals and Health Facilities, 2004). IHS recognizes that data on Tribal housing, sanitation services, and construction needs through the Home Inventory Tracking System (HITS) and Sanitation Deficiency System (SDS) is incomplete (United States Government Accountability Office, 2018c). Additionally, WWTP consume a large land footprint, are often considered visually unappealing, fraught with noise pollution from vehicular traffic and heavy machinery, as well as odor and pollution issues (Jensen et al., 2018). The treatment facilities in this study are covered by the NPDES permit program under the Clean Water Act (1972), so all of these facilities are discharging into water bodies. NPDES permits provide limits on target pollutants, which vary geographically, however numerous studies highlight the selective pressures of low levels of these regulated pollutants in effluent, to synergistic exposures and impacts of these compounds, and the various classes of unregulated contaminants (Deblonde et al., 2011; Huggett et al., 2003; Mason et al., 2016). An analysis of ECHO's NPDES permits under the CWA demonstrated that Tribally-owned POTWs have statistically fewer numbers of inspections and more violations, further supporting environmental disparities impacting Tribal lands (Teodoro et al., 2018).

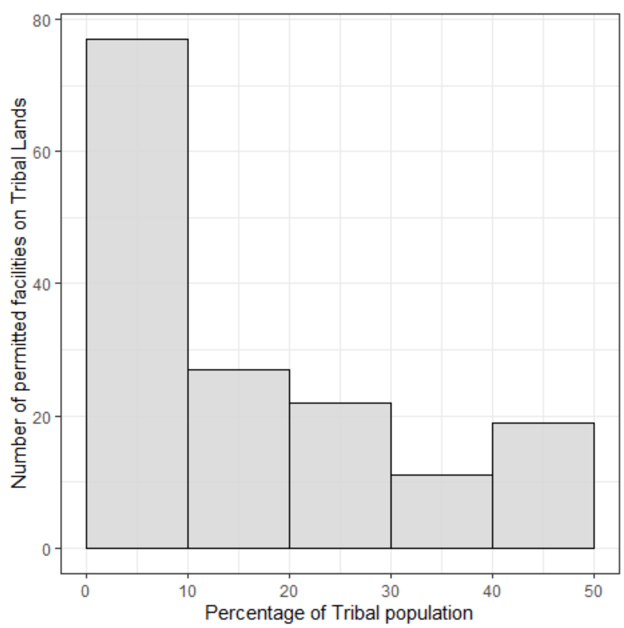


Figure 19. Number of wastewater treatment plants (WWTP) on Tribal reservations or ORTL with WWTP infrastructure that predominantly serves non-Tribal populations.

3.4. Conclusions

Publicly available permit data on federally regulated wastewater treatment facilities was successfully used to provide information on the number of FRITs administering FIRs and/or ORTL with municipal sanitation infrastructure. It was estimated that 36% or 135,000 people from 51 of 94 FRITs with wastewater infrastructure in-place are served by community WWTPs. This is considered a conservative estimate of Tribal infrastructure connectivity and identified that additional tools are necessary to assess non-discharging facilities. I identified a list of 210 Tribal communities from 54 FRITs with appropriate infrastructure to be applicable for wastewater monitoring activities.

CHAPTER 4

WASTEWATER LAGOON DETECTION ON THE UNITED STATES TRIBAL LANDS USING REMOTELY SENSED DATA

Various physical, chemical, and biological technologies, often used in combination, exist today to treat wastewater in an effort to return it to the desired level of water quality in the most economical manner. Method selection depends on several factors, such as wastewater characteristics, cost, efficiency, and required operation and maintenance (Rashid et al., 2021).

Wastewater Lagoons, also known as stabilization ponds, are designed structures where mainly physical and biological processes are carried out to treat or stabilize wastewater. The most recognized part of this infrastructure is the containment that resembles a natural lagoon called a lagoon, pond, or cell (State of Michigan. Department of Natural Resources & Environment, 2010). The size, water depth, number of ponds, and materials used in lagoon treatment systems vary according to several factors, such as the amount of wastewater to be treated, the type of pollutants to be removed, the level of treatment required, type of soil, amount of land area available, whether they are used alone or in conjunction with other wastewater treatment processes, and applicable regulations (Department of Environmental Protection. State of Maine, n.d.; United States Environmental Protection Agency, 2011).

For the US wastewater lagoons are important wastewater infrastructure; in 2011 there were over 8,000 units representing more than 50% of the wastewater treatment facilities (United States Environmental Protection Agency, 2011). They have been the main choice to treat domestic wastewater produced by small communities (Schulhof, 2022; United States Environmental Protection Agency, 2011), while cities and individual households normally treat their wastewater with more advanced technologies and septic systems, respectively (United States Environmental Protection Agency, 2022k). The concept of small community is not well defined. Muga & Mihelcic (2008) define small communities as those producing less than 5 Million Gallons per Day (MGD) or 18.9×10^3 cubic meters of wastewater, while the US EPA defines those with 10,000 or fewer people and wastewater flow less than 1 MGD on average as small communities (United States

Environmental Protection Agency, 2023a). Treatment with wastewater lagoons has many advantages including: ability to treat many sources of wastewater, operability under a wide range of climatic conditions, low maintenance, and cost-effectiveness. However, Kayira & Wanda, (2021) and Painter et al., (2020) found indications of significant pollution in a river resulting from wastewater lagoons, this because wastewater lagoons are often unable to meet some water quality requirements, becoming a potential source of adverse environmental and human impacts when the implementation of other technology is cost-prohibitive —a common situation for small communities (Schulhof, 2022).

Additionally to the ECHO database, the US EPA maintains the more specific Lagoon Inventory Dataset containing information from publicly or semi-publicly owned lagoon wastewater treatment systems where the lagoon is the main form of secondary treatment and there are not any other further steps (United States Environmental Protection Agency, 2022b). The facilities included in the Lagoon Inventory Dataset tend to serve rural communities with less than 3,000 people and those that are economically disadvantaged. Of the lagoons identified in this database, 33% of them discharge to waterbodies with an impaired status under Clean Water Act Section 303(d) and between September 2018 and September 2021, over 2,800 of the more than 4,600 lagoons in this dataset faced effluent exceedances, the most common being biological oxygen demand, total suspended solids, fecal indicator bacteria, pH, and ammonia (Schulhof, 2022). For those lagoons that do not require a NPDES permit (those that don't actively discharge —hereafter called a "terminal wastewater lagoon"), there are no such publicly available databases to locate them or get data from.

According to the US Census Bureau, rural areas comprise areas with populations less than 2,500 residents (United States Census Bureau, n.d.-b). In 2020, rural areas accounted for 97% of the total US land area, had a population of about 46 million, or ~14% of the total population (Dobis et al., 2021; Schulhof, 2022). Rural settings have unique geographic and demographic characteristics that often cause their residents to face greater economic development challenges, as well as difficulties accessing services, less developed infrastructure, and lower personal incomes which can create a challenge for wastewater treatment (Schulhof, 2022).

Lands under American Indian control comprise more than 56 million acres (National Congress of American Indians, 2020); these lands encompass many small and rural communities that may be using wastewater lagoons, and oftentimes include terminal lagoons that are not designed to discharge to WOTUS. Almost 40% of Native individuals on reservations were living in poverty compared to the national rate of 13% in 2015 (National Congress of American Indians, n.d.), which may affect the community's ability to maintain wastewater lagoon facilities, especially those that do not have the surveillance of an environmental agency, turning them into a potential source of contamination. Locating, quantifying, and evaluating lagoons within Tribal land areas could help advance wastewater management in these primarily rural areas; however, given many of the lands are rural and in arid areas, the lagoons are likely to be terminal and thus unaccounted for in existing databases.

Remotely sensed data has been proven to be useful in identifying inland water bodies using different methodologies such as water indexes (Feyisa et al., 2014; McFeeters, 1996; Z. Wang et al., 2018; Xu, 2006), single band thresholds (Klein et al., 2015), or machine learning techniques (Ghasemigoudarzi et al., 2022). Some advantages of remotely sensed data are that many are freely available and cover a large area of the world, while some disadvantages are their potentially low spatial and temporal resolutions. Synthetic Aperture Radar (SAR), known for having the advantage of operating at wavelengths not impeded by cloud cover or a lack of illumination, and multi-spectral imagery are two types of remotely sensed data that have been successfully used to map inland water bodies including flooded areas, rivers, lakes and reservoirs (Kim et al., 2021; Schmitt, 2020). At a smaller scale both Ottinger et al. (2021) and Sun et al. (2020) successfully identified aquaculture ponds using remotely sensed data opening the door to the possibility of detecting smaller inland water bodies.

The Copernicus program is an initiative of the European Commission in cooperation with partners such as the European Space Agency and the European Organization for the Exploitation of Meteorological Satellites that monitors the Earth and its environment delivering data, information, and services based on satellite and in situ data. This program is served by a constellation of dedicated satellites including the Sentinel family that hosts Sentinel-1A and 1B and Sentinel-2A and 2B which operate simultaneously (Programme of the European Union, n.d.). The satellites have a repeat cycle at the Equator between 10 to 12 days. Sentinel-1 satellites perform C-band SAR imaging providing dual polarization. Sentinel-2 satellites obtain high-resolution and multi-spectral images (13 bands) at different spatial resolutions. Both the repeat cycle and the high spatial resolution of these satellites make the use of their data highly advantageous (The European Space Agency, n.d.-a, n.d.-b, n.d.-e, n.d.-d, n.d.-f, n.d.-c). Google Earth Engine (GEE), a free cloud-based platform for geospatial analysis at the planetary scale for academic and research use, allows the access and the use of very large geospatial datasets including Sentinel-1 and Sentinel-2 based datasets by virtue of its massive cloud-based computational capabilities (Gorelick et al., 2017).

It is likely that the locations of terminal wastewater lagoons on Tribal lands can be derived using existing satellite-based methodologies for inland water detection. Knowing the location of terminal wastewater lagoons across these lands can be beneficial for infrastructure and land management, understanding demographic and environmental justice patterns, prioritizing technical and financial assistance, preventing water pollution, and monitoring of public health through wastewater-based epidemiology. Therefore, in this study I have two aims: 1) to develop an algorithm using free and publicly available input data that aids in the detection of wastewater lagoons on US federal Tribal lands, and 2) identify Tribal lands with highest potential of impacts due to wastewater lagoons.

4.1. Methods

To identify potential wastewater lagoons on Tribal lands I used a band threshold and geometry- based approach leveraging SAR, multi-spectral Surface Reflectance (SR), and several additional data sources, validating with information from an EPA database. I focused the search for lagoons on areas within Tribal lands near cities, towns, and educational institutions. I conducted satellite imagery and product processing, and the first stage of algorithm development within the GEE cloud-base analysis platform (Gorelick et al., 2017). Image and product processing, the second stage of algorithm development, validation, and spatial analyses were conducted using ArcGIS (Environmental Systems Research Institute (Esri), n.d.). Other statistical analyses were performed using the software R and RStudio (R Core Team, 2023; RStudio Team, 2023). **Figure 20** schematizes the procedure followed, and the data preparation and analysis steps are detailed in the next sections.

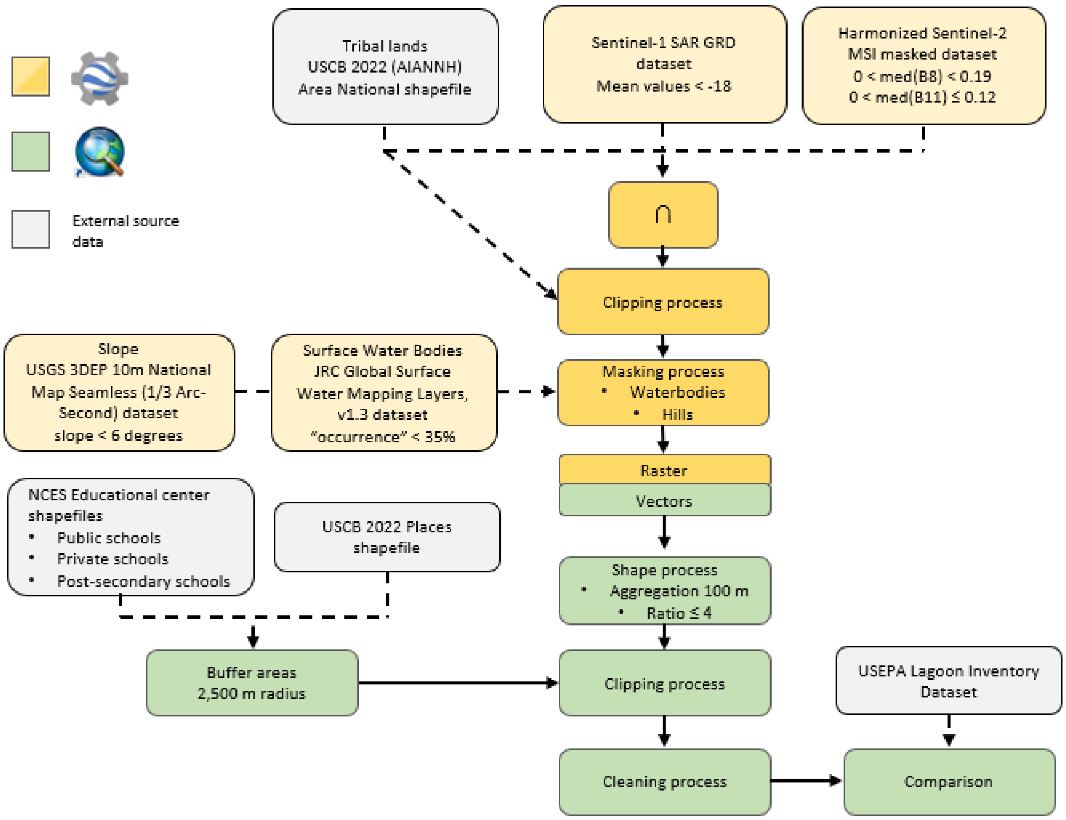


Figure 20. Flowchart depicting the general procedure to find possible terminal wastewater lagoons on Tribal lands. Yellow color refers to the stage using Google Earth Engine while green color to the Geographic Information System (GIS) stage, gray color represents data obtained from the different sources: United States Census Bureau (USCB), National Center for Education Statistics (NCES), United States Geological Survey (USGS), and United States Environmental Protection Agency (USEPA). AIANNH = American Indian/Alaska Native/Native Hawaiian; SAR = Synthetic Aperture Radar; GRD = Ground Range Detected; MSI = Multi Spectral Instrument; USGS = United States Geological Survey; 3DEP =3D Elevation Program; JRC =Joint Research Centre.

4.1.1. Study Area

The study was conducted on 484 land areas administered as FIRs, ORTLs, or joint-use areas. The total covered area is ~2.97x10^{11} m^2 distributed as follows: 313 FIRs covering ~96.5%, 168 ORTLs covering ~3.5%, and 3 joint-use areas covering ~0.002% depicted in **Figure 21A** and **21B.** The Navajo Nation administers the largest amount of land (~21.3%) while the Seminole Tribe of Florida manages the smallest area (<0.001%). These lands are distributed across 35 states and may cross state boundaries, serving 290 FRITs listed in the Supplementary information (Appendix C - SI 3.1. Table 1). Only one is in Alaska while 106 are in California; **Figure 16** in Chapter 2 depicts their distribution in the Contiguous US. The population in these areas has increased ~39% since 2000 and has the highest poverty rate in the country (~39%). Most areas are considered rural (National Congress of American Indians, 2020), thus combined with the high poverty rate indicates that Tribal lands are more likely to be served by wastewater lagoons than full-scale wastewater treatment plants.

Tribal land area data were obtained from the American Indian/Alaska Native/Native Hawaiian (AIANNH) Area National shapefile of the US Census Bureau for the year 2022 (United States Census Bureau, 2022a). Values between 0001 to 4999 of the AIANNH area Census Code (AIANNHCE) referring to FIRs, ORTLs, and joint-used areas were used, this code is a 4-character nationally unique string assigned to legal and statistical AIANNH areas (United States Census Bureau, 2022b). Individual shapefiles were created for each area, when possible related FIRs and ORTL were grouped, the resulting areas —grouped, not grouped, and joint-use areas— are referred as Tribal lands.

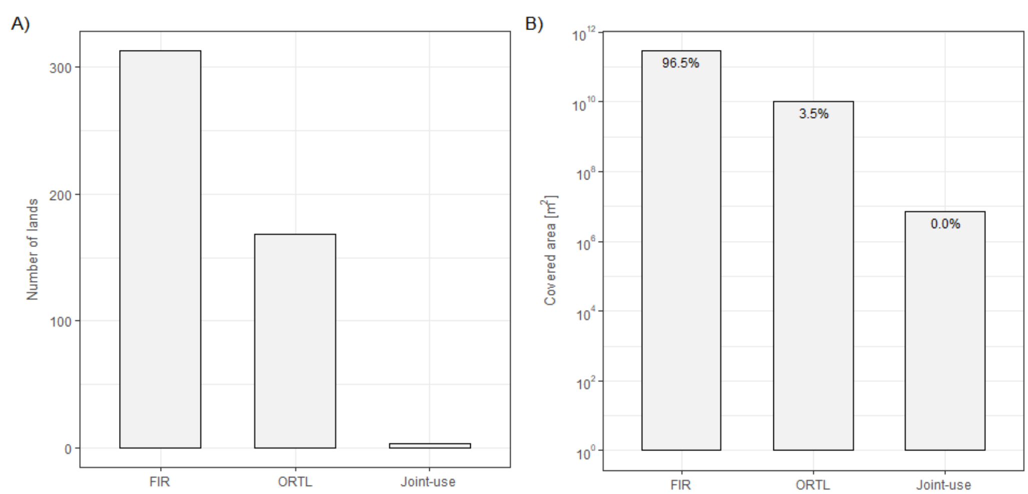


Figure 21. Tribal lands. A) Number and B) covered areas, according to the type of Tribal land. (United States Census Bureau, 2022a).

4.1.2. Study Time Period

The training and detection process was centered on one entire year to mitigate the uncertainties arising from fluctuations in wastewater levels within the wastewater lagoons. These variations could be caused by daily cycles (e.g., day and night) as well as seasonal changes (e.g., summer and winter, school year or vacation timing), and weather conditions (e.g., hot and cold temperatures). I selected the period from January 1 to December 31, 2019, which was a year prior to the start of the Coronavirus Disease of 2019 (COVID-19) pandemic. During this period, I assumed a typical trajectory of life development without the influence of the pandemic, but if the number or quality of the images was low in 2019 then years 2020 or 2021 were used instead.

4.1.3. Data Collection and Preparation

4.1.3.1. Defining Areas of Interest Within Tribal Lands. Wastewater lagoons are expected to be on or near populated places such as cities and towns or where activities occur at group settings such as educational institutions, especially in rural areas. This strategic placement ensures convenient access to the facilities and therefore the management and treatment of wastewater can be efficiently carried out. In order to analyze the data effectively, the study concentrated on the areas on Tribal lands where incorporated places, Census Designated Places (CDPs), and educational institutions are located, as well as their surrounding areas (**Figure 22**). Incorporated places are officially recognized by the states as cities, towns, villages or boroughs. CDPs are areas with a designated name but lack legal recognition from the state and have undefined boundaries. Public elementary and secondary schools, private schools, and post-secondary schools are considered educational institutions. A 2,500 meter radius around these areas was also included in the analysis. I created a shapefile with areas that encompass the recognized boundaries of incorporated places, as of January 1, 2022, and CDPs along with a 2,500-meter perimeter around them that intersected Tribal lands. This was based on the "Places" shapefile for 2022, obtained from the US Census Bureau (United States Census Bureau, 2022a, 2022b).

Point locations (latitude and longitude) of three types of educational institutions, public elementary and secondary schools, private schools, and post-secondary schools, were obtained from the shapefiles “Public School Locations – Current” (National Center for Education Statistics, 2022b), “Private School Locations – Current” (National Center for Education Statistics, 2021), and “Postsecondary School Locations – Current” (National Center for Education Statistics, 2022a). These educational institutions are included in the National Center for Education Statistics Common Core of Data, which centralizes administrative and fiscal data about public schools, school districts, and state education agencies in the US (National Center for Education Statistics, n.d.-b), and the Private School Survey, or the Integrated Postsecondary Education Data System, which gathers information from colleges, universities and technical and vocational institutions participating in the federal student financial aid programs (National Center for Education Statistics, n.d.-a). I have generated a shapefile that comprises the areas as well as a 2,500 m radius around these three types of educational institutions located on Tribal lands (**Figure 22**).

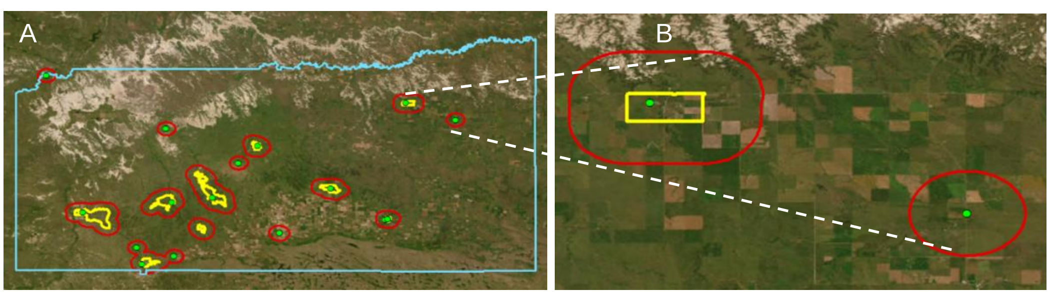


Figure 22. Areas of interest. A) Incorporated and census designated places (yellow) and educational institutions (green) including a 2,500 m surrounding area (red) within a Tribal land (sky blue). B) A close-up view of a census designated place (yellow) and two public schools (green) within the Tribal land area shown in A). The areas of interest (red) include a 2,500 meter surrounding radius. (National Center for Education Statistics, 2021, 2022b, 2022a; United States Census Bureau, 2022a).

4.1.3.2. Predictor Variables and Data. For each separate Tribal land, I compiled satellite imagery and other covariate data in GEE that I expected would aid in identifying areas with water that could be wastewater lagoons (**Table 6**). In order to identify potential wastewater lagoons, I focused on identifying areas with water, of a specific shape, and in low-sloping areas. To distinguish lagoons from waterbodies such as rivers, lakes, and lagoons, I can consider occurrence over time.

To distinguish a wastewater lagoon from natural permanent water features, I can consider their quasi-regular shape, often taking the form of rectangles or polygons. Conversely, areas that are narrow and elongated or irregular in shape are unlikely to be wastewater lagoons. Such shapes are more common in natural water accumulations. Finally I also know that wastewater lagoons have a recommended slope value between 5% to 7% (2.86˚ to 4.00˚) not exceeding 12% (6.84˚) (Arkansas Department of Health, 2007; Schultheis, 2022). Areas with high slopes are thus not suitable. Data and processing steps are described further in this section.

Table 6

Data Products and Sources Used in the Prediction of Wastewater Lagoons on Tribal Lands

Data	Source	Spatial resolution	Temporal resolution	Reason for including
VV polarization	Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar Ground Range Detected, log scaling	10 m	12 days (single satellite)	Helps to identify water
NIR Band 8, wavelength 835.1/833 nm	Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-2A	10 m	10 days (single satellite)	Helps to identify water
SWIR1 Band 11 wavelength 1613.7/1610.4 nm	Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-2A	20 m	10 days (single satellite)	Helps to identify water
Occurrence	JRC Global Surface Water Mapping Layers, v1.3	30 m	1984-2020	Identification of surface water
Elevation	USGS 3DEP 10m National Map Seamless (1/3 Arc-Second)	10.2 m N/S and variable E/W	1998-2020	To estimate slope; lagoons are suitable only on low slopes

VV = vertical transmit/vertical receive polarization, NIR = Near Infrared, SWIR = Short-wave Infrared, N = north, S = south, E = east, W = west.

4.1.3.2.1. SAR Based Imagery for Water Detection. For each Tribal land I generated a binary image where pixels with 1-values are considered related to water. The collection "Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar Ground Range Detected, log scaling" in GEE

(Google Developers, n.d.-b), was used to access Ground Range Detected (GRD) C-band SAR Images with Interferometric Wide (IW) swath instrument mode, and ascending orbit direction, originally captured by Sentinel-1 satellites, covering the Tribal land (S1). The single co-polarization, Vertical transmit/Vertical receive (VV) polarization band of these images was used to produce a reduced image by calculating the mean of all values at each pixel. The image produced was then utilized to generate a binary image clipped to the Tribal land area, having 1-values for pixels with values below -18, identifying pixels likely to be water.

4.1.3.2.2. Spectral Based Imagery for Water Detection. Near Infrared (NIR) and Short-wave Infrared (SWIR) bands are considered related to water in that it absorbs more energy in their wavelength causing low reflectance (Mondejar & Tongco, 2019). For each Tribal land I generated a binary image where pixels with 1-values are considered related to water. Spectral images of SR scaled by 10,000, originally obtained by Sentinel-2 satellites, with less than 10% of cloudy pixels covering the Tribal land (S2) were accessed from the collection "Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-2A" in the Earth Engine Data Catalog (Google Developers, n.d.-a). These images were masked for opaque and cirrus clouds using the bits 10 and 11 of the QA60 atmospheric band, downscaled dividing by 10,000, and reduced by calculating the median of all values at each pixel for all their 12 spectral bands. With the resulting image clipped to the area of the Tribal land, a binary image was created where pixels with values of 1 were those where pixels in NIR (B8) and SWIR1 (B11) bands that had values in the range $0 < B8 < 0.19$ and $0 < B11 \leq 0.12$, respectively, indicating pixels likely to be water.

4.1.3.2.3. Surface Water Bodies Image to Exclude Natural Waterbodies. To exclude areas with natural surface waterbodies I created a seamless binary image where 1-values represented areas with low frequency of water presence. To identify these areas the "JRC Global Surface Water Mapping Layers, v1.3" dataset in the Earth Engine Data Catalog (Earth Engine Data Catalog, n.d.) was used. This dataset produced by the Joint Research Centre of the European Commission under the Copernicus program with data from satellites Landsat 5, 7 and 8 of the

National Aeronautics and Space Administration /United States Geological Survey (USGS) Landsat Program and the methodology of Pekel et al., (2016). This data contains one image with 7 bands of 30 meters spatial resolution showing the location, temporal distribution, and statistics on the extent and change of surface water in the period 1984 to 2020. I applied a threshold (<35%) to the band "occurrence" to retain areas with low presence of water occurrence. This band refers to the frequency with which surface water was present in the period with values ranging from 0% to 100%. Permanent surface water has a 100% occurrence.

4.1.3.2.4. Elevation Data to Exclude High Slope Areas. To exclude steep areas where the probability that a wastewater lagoon would be located is low, I generated a seamless binary image where 1-values represent areas with slope less than 6 degrees. Slope, in degrees, was calculated from the "elevation" band, in meters, in the "USGS 3DEP 10m National Map Seamless (1/3 Arc-Second)" dataset ingested in GEE (United States Geological Survey, n.d.-b). This dataset is a seamless digital elevation model for the US, with a pixel size of 10.2 meters north/south and variable east/west, developed by the 3D Elevation Program managed by the USGS National Geospatial Program (United States Geological Survey, n.d.-b).

4.1.4. Wastewater Lagoon Algorithm Development and Evaluation

The first stage of the algorithm was performed within GEE using a threshold-based approach both in preparing that data (Table 6, and as described above) and in creating a final binary image representing areas with semi-permanent water that are low-sloping. A threshold approach is used as a primitive model for image segmentation (Dey et al., 2010), and is widely applied in remote sensing and classification problems across disciplines (Coffer et al., 2020; Thomas et al., 2019). Using the predictor data described above, I generated a binary image consisting of pixels with a value of 1 only in areas where all the predictor binary images also had a value of 1, indicating water-related, low-sloping regions. This image was exported as a raster with 0 values converted to 9999 values.

To obtain a more precise delineation of water related areas, I performed the second stage of the algorithm, which involved a geometry process using GIS software. The raster file was transformed into vectors, creating polygons with a value of 1 where pixels also had a value of 1. These were retained, aggregated within a distance of 100 meters, and further enclosed as convex hulls. The width and length of these new polygons were calculated, and the ratio of length to width was determined. Only those polygons with a ratio value less than or equal to 4 and were within previously described buffers of Places and Educational Institutions areas were retained. The final step consisted of using the imagery basemap in ArcMap to discriminate whether each remaining polygon could be a potential wastewater lagoon or not.

4.1.4.1. Model Training. In order to establish predictor variables and thresholds described above, I experimented with various data, threshold values, and their combinations on both the Navajo Nation Reservation and Off-Reservation Trust Land, and the Pine Ridge Reservation. Although the EPA databases contain geographic information for permitted wastewater lagoons, they do not include data on those that are terminal or non-discharging to a WOTUS. Thus, I visually identified possible wastewater lagoons using base imagery in ArcMap. The potential lagoons were then combined with permitted wastewater lagoons and added to a shapefile. I then used this shapefile to compare the detected areas to the previously identified potential wastewater lagoons within these regions and adjust thresholds and predictor variables used in the final algorithm described above.

4.1.4.2. Model Verification Using Permitted Wastewater Lagoons. While I cannot do a complete model validation effort since there is no wastewater lagoon database that includes both permitted and unpermitted lagoons, I still wanted to perform a verification to assess how well the algorithm worked for at least the permitted lagoons. Known wastewater lagoons on Tribal lands, publicly or semi-publicly owned, serving as the main form of secondary treatment without more advanced treatment or add-on technologies, and holding a NPDES permit that allows them to discharge pollutants into WOTUS, were obtained from the EPA Lagoon Inventory Dataset. This dataset, updated May 2022 and revised on July 2022, contains compiled information from 18 datasets about 4,537 wastewater lagoons including locations (latitude and longitude), although this dataset does not capture all wastewater lagoons in the US (United States Environmental Protection Agency, 2022r).

Of the 4,537 locations of permitted wastewater lagoons in the EPA Lagoon inventory dataset, only 174 are on Tribal lands. Of them, 6 are in the same place as other wastewater lagoons, 5 are not on or near a visually identifiable wastewater lagoon, and 8 had to be relocated using the name of the wastewater lagoon, leaving a total of 163 wastewater lagoons to possibly be detected for verification of the approach.

4.2. Results

4.2.1. Wastewater Lagoon Identification

Of the 31,732 different incorporated places and CDPs in the US, only 1,089 are at least partially located on a Tribal land area. Also, 769 of 101,662 public elementary and secondary schools, 53 of 21,572 private schools, and 43 of 6,847 post-secondary schools are located on Tribal lands.

S1 and S2 images from 2019 were obtained for 315 Tribal lands, from 2020 images for 11 Tribal lands, and from 2021 images for 1 Tribal land. A total of 23,074 S1 and 29,725 S2 images were used; the minimum, maximum, and median number of images used for a Tribal land was 10, 490, and 57 for S1 and of 7, 1,193, and 66.5 for S2. Goshute reservation was an exception because only 1 S2 image from 2019 was used due to the low quality of the other images. This resulted in 327 raster images after the first stage of the algorithm was applied. **Figures 23A** and **23B** show the S1 mean and S2 median images for one Tribal land area while **Figure 23C** depicts a close-up of the resulting binary image after the application of the first stage of the algorithm, showing the detection of water-related, low-sloping regions.

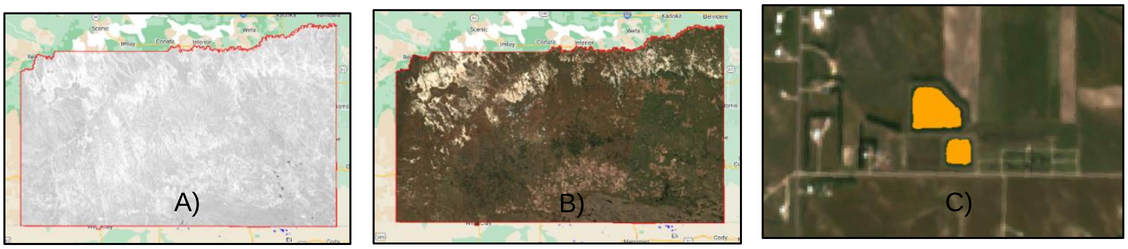


Figure 23. Created images. A) S1 mean image and B) S2 median image, for Pine Ridge reservation, delineated in red color, a Tribal land under the administration of the Oglala Sioux Tribe. C) Close-up of the resulting binary image after the application of the first stage of the algorithm showing in orange color water-related, low-sloping regions (Corresponding S2 median image is used as background for visual context).

After transformation of the raster files to vectors, 205,487 polygons with value of 1 were retained, **Figure 24A** presents six examples of these polygons. Aggregation resulted in 60,027 polygons, **Figure 24B** shows the resulting polygons after aggregation of those in Figure 24A. Convex hull enclosing generated same number of polygons of which 47,961 have the length to width ratio less than or equal to 4, **Figure 24C** shows two examples with length to width ratio of 1.94 (upper) and 5.32 (lower). Of them, 10,746 polygons overlapped Places and Educational Institutions areas. After using the imagery basemap in ArcMap to discriminate each remaining polygon, 834 (~7.8%) were identified as potential wastewater lagoon with 93 located on the same possible lagoon, 9,758 (~90.8%) were related to other kinds of water (e.g. rivers, ponds, lakes), and 154 (~1.4%) were related to other types of objects (e.g. grass, forest, asphalt).

A) B) C)

Figure 24. Created polygons. In yellow color: A) Polygons with value of 1 obtained after transformation to vectors of the raster images resulting from the first stage of the algorithm. B) Polygons after aggregation with a 100 m distance. C) Polygons after convex hull enclosing. In the upper part, a polygon with a length to width ratio value of 1.94 (length = 371.67 m, width = 191.01 m), while in the lower part a discarded polygon with a ratio value of 5.32 (length = 334.22 m, width = 62.82 m). The imagery basemap in ArcMap is used as background for visual context.

4.2.2. Verification

With the algorithm, 113 of the 163 (~69.3%) wastewater lagoons in the EPA Lagoon inventory dataset on Tribal lands were detected. Out of the remaining 50 (~30.7%), 16 (~9.8%) were detected in the first stage but discarded in the second stage. This was because 2 of them were aggregated to polygons detecting rivers, 3 had the length to width ratio larger than 4, and 11 were outside the defined areas of interest. The remaining 34 (~20.9%) were not detected in the first stage. Among them, 21 could not be detected as they were almost empty and the detection in the first stage is based on pixels related to water. Additionally, 11 were small with sizes similar to the pixel size of the used products, and 2 had a green color that is more related to vegetation than to water. **Table 7** shows the distribution of detected and not detected wastewater lagoons and the cause when not detected.

Table 7

Detection Status of 163 Wastewater Lagoons on Tribal Lands in the EPA Lagoon Inventory Dataset

Action/Cause	Subtotal	Total	%	
Detected		113		~69.3
Detected in the first stage but discarded in the second stage		16		~9.8
Aggregated with a waterbody	2		~1.2	
Length/width > 4	3		~1.8	
Outside areas of interest	11		~6.8	
Not detected in the first phase		34		~20.9
Almost empty	21		~12.9	
Small size	11		~6.8	
Green color	2		~1.2	

4.2.3. Permitted and Possible Unpermitted Wastewater Lagoons and Tribal Lands

I classified lagoons (permitted and possible unpermitted) across all Tribal lands. The 163 permitted wastewater lagoons serve on 33 Tribal lands to 35 FRITs, the minimum number serving a FRIT is 1 and the maximum 20 with a median value of 2. There are no records of permitted wastewater lagoons on 294 Tribal lands administered by 255 FRITs. With this approach, 628 possible unpermitted wastewater lagoons were identified, these are distributed on 121 Tribal lands administered by 114 FRITs, their number in Tribal lands ranged from 1 to 121 with a median value of 2, with The Osage Nation having the highest number. There are no lagoon identifications on 206 Tribal lands administered by 176 FRITs. Based on Tribal lands, 6 (covering ~3.7% of the total Tribal land area) only have permitted wastewater lagoons, while 27 (~61.3%) have both permitted and possible unpermitted, whereas 94 (~31.4%) have only possible unpermitted, and 200 (~3.7%) have no identified lagoons at all. **Table 8** shows this distribution while **Figure 25** shows the number of permitted and possible unpermitted wastewater lagoons on each FRIT listed in the Supplementary information (Appendix C - SI 3.1. Table 1) having at least one wastewater lagoon of any type.

Table 8

Number of Permitted and Possible Unpermitted Wastewater Lagoons, Tribal Lands, Federally Recognized Indian Tribes, and Tribal Land Area

Condition	# of permitted WWLs	# of possible unpermitted WWLs	# of Tribal lands	# of FRITs	Area of the Tribal lands[a]
With only permitted WWLs	20	0	6	6	~3.7%
With permitted and possible unpermitted WWLs	143	369	27	29	~61.3%
With only possible unpermitted WWLs	0	259	94	85	~31.4%
Without permitted or possible unpermitted WWLs	0	0	200	170	~3.7%
	Total	163	628	327	290

[a]With respect to the total land area administered as FIRs, ORTLs, or joint-use areas of ~2.97×10^{11} m^2.
= number, WWL = wastewater lagoon, FRIT = federally recognized Indian tribe.

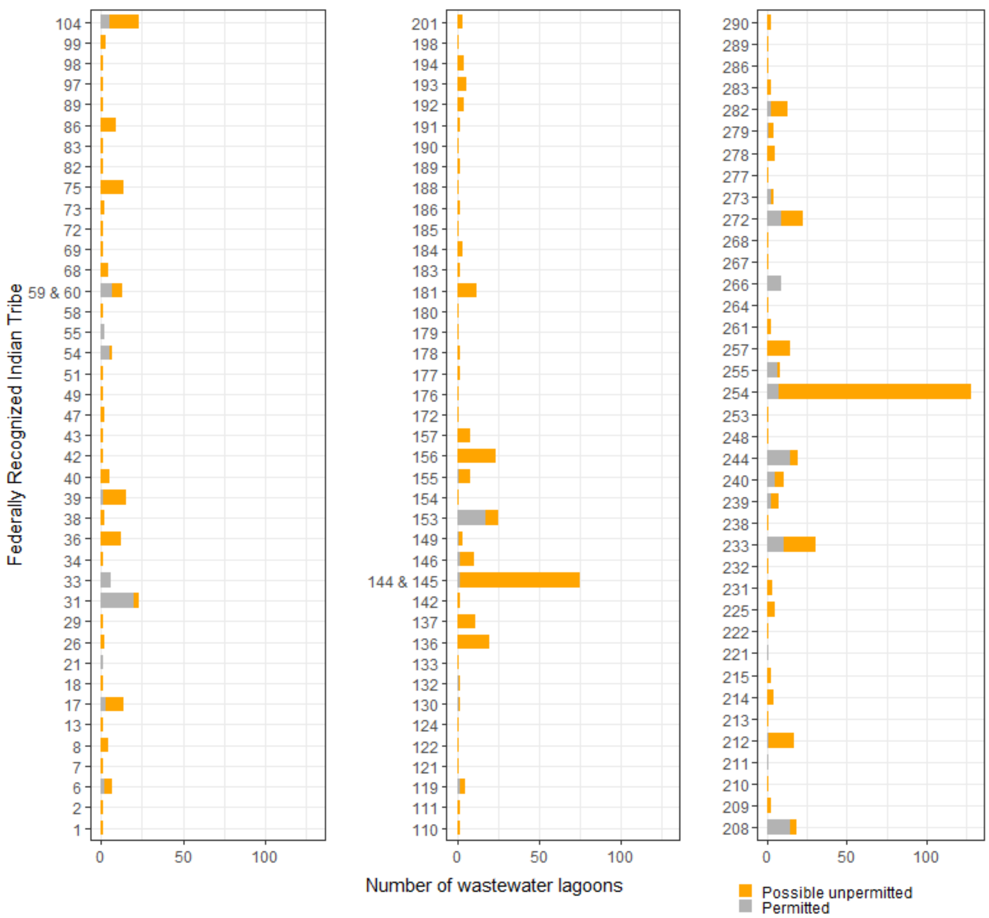


Figure 25. Wastewater lagoon quantities. Number of permitted and possible unpermitted wastewater lagoons serving Federally recognized Indian Tribes (FRITs). Numbers in y-axis refer to the FRIT number listed in Supplementary information (Appendix C - SI 3.1. Table 1). FRITs without wastewater lagoons are not depicted.

4.3. Discussion

The findings suggest that the signature of small water bodies detected from a variety of satellite image datasets can be used in the future to locate currently unknown wastewater (or other types) lagoons. This information could help reveal where the efforts should be directed to prevent environmental impacts such as pathogenic contamination of surface water as well as to prioritize support to underserved communities through technical and financial assistance efforts. Bacteria are present in the WWTP influent. They also play a crucial role in wastewater treatment as they help break down organic matter, facilitate energy flow, and biochemical cycling. However, their abundant presence can pose a risk as they may emit harmful pathogens, especially if the WWTP is poorly operated or if leaks or floods occur. For example, Oluseyi Osunmakinde et al., (2019) found bacterial pathogens in treated wastewater effluent in South Africa, while Skwor et al., (2020) identified antibiotic-resistant pathogens in populations in rivers that receive treated wastewater in Wisconsin. Even WWTPs having an NPDES permit, which guarantees good management practices, regular monitoring, and oversight by the EPA, can still exceed effluent limits and become a source of pollution. Those operating with a low budget or without governmental oversight pose an even greater risk, even if they do not directly discharge into a WOTUS. In drylands, ephemeral and intermittent rivers comprise most of the river system but are not regularly monitored. Limited data suggest that their concentration of fecal contamination is higher than perennial rivers (see Chapter 1), which is especially concerning during the rainy season when river connectivity is at its highest. Contaminants can be transported to perennial streams that serve as water sources.

The discussed approach mainly focuses on detecting WWL in domestic sewage treatment. Nevertheless, it can also be utilized to identify other similar lagoons that treat wastewater in industrial and agricultural settings, such as CAFOs and mining operations. Over the last few decades, there has been a rise in the number of CAFOs in the United States (Raff & Meyer, 2022). Despite EPA and environmental agency regulations, these facilities have been connected to low ambient water quality (Miralha et al., 2022). One contributing factor is that many of these operations use manure lagoons for biological treatment and extended animal waste storage. Depending on the state, CAFOs may be subject to regulation through an NPDES permit (Shea et al., 2022).

However, this varies by state and can make it challenging to obtain data that would aid in their effective management and monitoring. Mining operations can also pose a significant threat to ambient water conditions and the health of communities nearby. The wastewater produced by these operations is often stored in lagoons and can contain dangerous substances such as arsenic, cadmium, and chromium at high levels, which could potentially spill. In a study conducted by Santana et al., (2020), heavy metals were discovered in sediment, surface water, and groundwater samples taken from three mining areas located in a semi-arid region of Brazil. It would be highly advantageous to know the whereabouts of un- or under-regulated and abandoned mining sites in order to prevent environmental pollution.

From the observations, I found that over 98% of the polygons detected were associated with water, with only about 7.8% identified as potential wastewater lagoons. The number of polygons considered increased significantly with the resolution in the delineation of natural surface water areas. It is crucial to fully identify surface water bodies to avoid misidentification. However, it is difficult to delineate rivers, lakes, and other surface water areas at a national level. It is well-documented that water bodies such as lakes, rivers, and ponds undergo inter and intra-annual level variations due to factors such as evaporation, precipitation, and human use, affecting the area covered by water (Guo et al., 2023; Larson & Schaetzl, 2001; M. Li et al., 2016; Lin et al., 2017; You et al., 2015).Therefore, I used a publicly accessible global dataset that maps the occurrence of surface water as a proxy for surface water areas. As a result, surface water areas that are only covered for a short period were not included as part of the water body in the used image and may not be discarded. Another factor that could impact the identification of surface water in the image being used is the pixel size. If a 30-meter pixel is only partially covered by water, it may not be classified as such (Pekel et al., 2016).

The delineation of the areas of interest is another factor that affected the detection of wastewater lagoons. Certain incorporated locations and CDPs have open areas on one side and developed spaces on the other near the border, which leads to the potential areas where wastewater lagoons might exist being disregarded. Detection of possible wastewater lagoons could be improved when including location of small towns, those with less than 2500 inhabitants that are not included as incorporated places or CDPs, and casinos. Another factor is the type of terrain included in the areas of interest; the terrain of the Osage Nation contains a considerable number of small ponds that could contribute to the high number of possible unpermitted wastewater lagoons found.

Identifying smaller or less full wastewater lagoons can be a challenge since the algorithm depends on products that have restricted resolution and wavelengths specifically designed for water detection. The possible wastewater lagoons detected could be facilities not discharging to a WOTUS to be considered subject to regulations. Alternatively, they could be wastewater lagoons that were previously permitted but are no longer in operation that have not been fully dismantled yet, such as those used during construction activities, man-made ponds for other purposes, or simply natural ponds.

Tribal lands without permitted wastewater lagoons (~89.9%) could be serving their population with other types of facilities such as on-site septic systems, sewer connections that feed into more sophisticated wastewater treatment plants or recycling their wastewater for other uses. By identifying possible unpermitted wastewater lagoons, the number of Tribal lands without wastewater lagoon operations would decrease to ~52.9% considering that according to the US Census Bureau in 2010 27 Tribal lands were not populated (United States Census Bureau, n.d.-a). When assessing the wastewater infrastructure for Tribal populations, it is important to consider all populated clusters. Merely having a wastewater lagoon on a Tribal land does not necessarily mean that it's servicing the entire population due to the vast expanse of Tribal lands.

4.4. Conclusions

Wastewater lagoons, especially those that may not be regularly monitored, could pose a risk to surface water when inadequately managed. Data regarding the location of those operating without an NPDES permit that allows the government oversight can be beneficial to tackle contamination especially by pathogens. This study offers a methodology that can be applied on a broad scale to locate possible unpermitted and permitted wastewater lagoons, or other small pond or lagoon features which may be sources of contaminants. The algorithm relies on free and publicly available input data including satellite-based radar and optical imagery and other datasets such as slope and water occurrence, providing a new approach to detect small inland water features. I identified 628 possible wastewater lagoons located on 121 Tribal lands administered by 214 Federally recognized Indian Tribes. I identified that other types of technology could potentially be utilized for managing the wastewater of at least 173 Tribal lands. This information could help in the management of infrastructure and water, the understanding of demographic and environmental justice patterns, and in prioritizing technical and financial assistance and monitoring of public health through wastewater-based epidemiology.

CHAPTER 5

OUTLOOK AND FUTURE WORK

It has been previously stated that environmental degradation, particularly affecting water resources, may be driven by development and population growth. This is due to the increase in pollutants and their sources, with underrepresented communities and drylands being among the most impacted. In previous chapters, I identified ephemeral and intermittent streams as having higher concentrations of *E. coli* and summarized the wastewater infrastructure in use for these areas. In this final chapter, I will link these concepts together by exploring the links between drylands and Tribal areas, as well as links between wastewater infrastructure, ephemeral and intermittent streams, and pathogen impairment.

5.1. Relationship of Tribal Lands and Drylands

Identification and quantification of Tribal land areas with four types of drylands —hyper arid, arid, semiarid, and dry subhumid— was carried out as I previously identified unique drivers (stream type) of *E. coli* in dryland ecosystems. Dryland subtypes in the US were identified from the Drylands dataset 2007 (United Nations Environmental Programme, World Conservation Monitoring Centre, 2019). The 484 FIRs, ORTLs, and joint-use areas serving 290 FRITs in 2022 cover an area of ~297.38x10^9 m^2; of them, ~0.07% are classified as hyperarid, ~6.29% as arid, ~7.32% as dry subhumid, ~74.16% as semiarid, and the remaining ~12.16% as other (**Figure 26**). More than 85% of Tribal lands are thus classified as dryland.

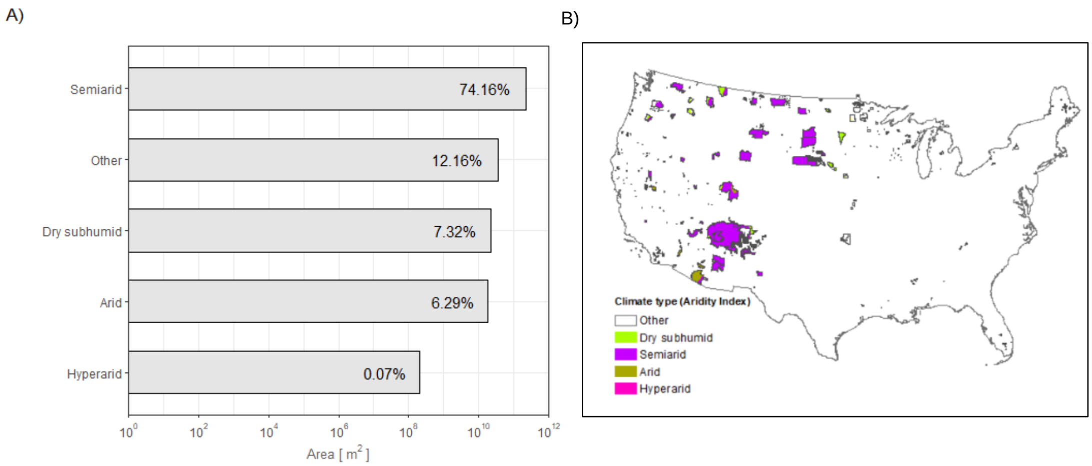


Figure 26. Arid Tribal lands. A) Quantification and B) Map of the conterminous United States of Tribal land areas with climate classification based on Aridity Index (United Nations Environmental Programme, World Conservation Monitoring Centre, 2019; United States Census Bureau, 2022a).

5.2. Tribal Population

The population living on Tribal lands could give a good indication of the potential impact on humans if surface water becomes polluted. Total population data on Tribal lands was extracted from table “P1 Race” in the Summary File 1 (SF 1) of the 2010 US Census Bureau (data.census.gov). The SF 1 includes population and housing characteristics for the total population as well as for race groups (United States Census Bureau, 2012). Of the 327 related Tribal lands 27 were not populated in 2010 according to US Census data. For the rest their population varied between 1 and 173,667 (**Figure 27**) with a total of 994,881.

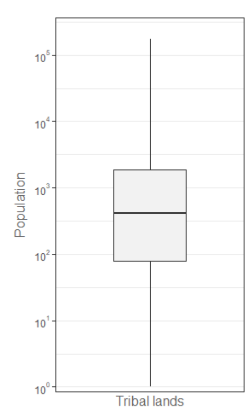


Figure 27. Population. Total population living on Tribal lands in 2010 according to the U.S. Census Bureau; 27 of 327 related Tribal lands were not populated.

5.3. Relationship of Wastewater Lagoons (Both Permitted and Possible Unpermitted) and Other Types of Wastewater Treatment Plants to Streams

It is known that wastewater treatment plants have the potential to be a source of pathogens and can significantly contribute to the contamination of surface water in a watershed (Kistemann et al., 2012; Sanders et al., 2013) depending on the treatment process, when poorly operated, or when spills occur (Anastasi et al., 2012; Verburg et al., 2019). By determining the distance between wastewater treatment plants and surface waters, I can begin to identify potential pollution risk in Tribal lands.

The shortest distance, in meters, from wastewater infrastructure (each permitted (known) and possible (identified in Chapter 3) wastewater lagoon and the wastewater treatment plants in the ECHO database (summarized in Chapter 2)) on Tribal lands to any perennial, intermittent, or ephemeral river, or artificial path nearby and to any pathogenic impaired stream segment was quantified. Information about perennial, intermittent, and ephemeral rivers, and artificial paths, was derived using the line features in the USGS National Hydrography Dataset (NHD) for all states containing Tribal lands. These features are incorporated in the “NHDFlowline” shapefiles acquired from The National Map (United States Geological Survey, n.d.-f). The Feature code (Fcode) values of 46000, 46003, 46006, 46007 and 55800, referring to stream/rivers and surrogates of flow direction in water bodies and flooding areas in rivers were used (United States Geological Survey, n.d.-d). For the 628 possible unpermitted wastewater lagoons identified in Chapter 3, the distance to the nearest river ranged between 0 and ~12,000 m with majority (~80%) within 500 m and to an intermittent river (~40%) (**Figure 28A**); furthermore ~37% are in the nearest 100 m with ~17% near to intermittent rivers (**Figure 28B**). For the 163 permitted wastewater lagoons from the EPA’s Lagoon Inventory Dataset, the nearest distance range between 0 and ~4,000 m also with majority (~88%) within 500 m and to an intermittent river (~55%) (**Figure 28C**). Moreover, ~50% are within 100 m, ~34% near to an intermittent river (**Figure 28D**). Of the 522 facilities in the EPA’s ECHO database on Tribal lands, 368 are not included in the Lagoon Inventory Dataset and for them the nearest distance is up to ~12,000 m with majority (~79%) within 500 m and to an intermittent river (~40%) (**Figure 28E**), ~30% are within the 100 m, ~14% near to an intermittent river (**Figure 28F**).

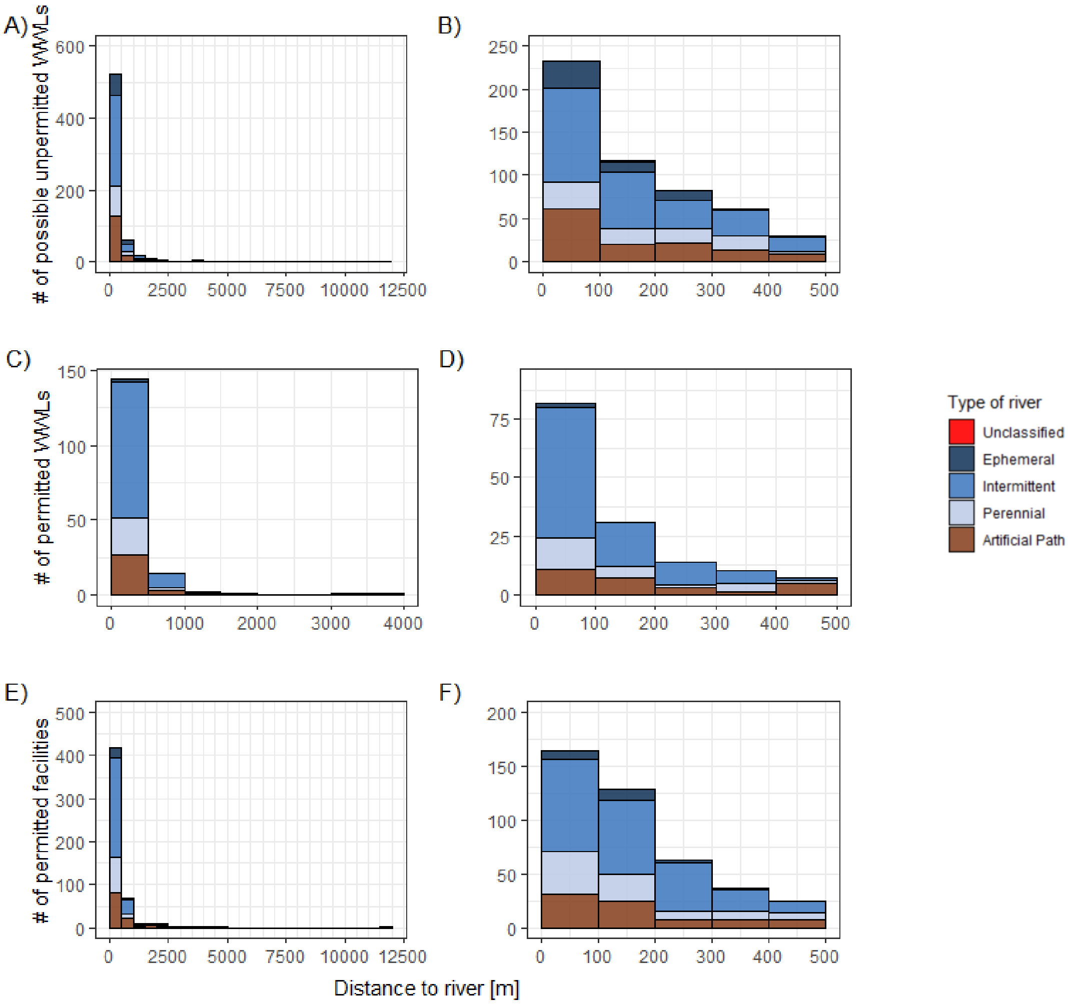


Figure 28. Distances. Nearest distance from possible unpermitted Wastewater Lagoons (A, B), permitted Wastewater Lagoons (C, D), and permitted wastewater treatment plants (E, F), with figures on the right zooming into distances within 500 m.

Location of pathogenically impaired WOTUS (**Figure 29A**) was obtained from the Assessment, Total Maximum Daily Load (TMDL) Tracking and Implementation System (ATTAINS) Geographic Information System (GIS) dataset (United States Environmental Protection Agency, 2022a). ATTAINS summarizes information about reports submitted to EPA in compliance with the CWA, sections 303(d) and 305(b). Distance to the nearest impaired WOTUS for ~34% of possible unpermitted wastewater lagoons is less than 10,000 m (**Figure 29B**) while for permitted wastewater lagoons and other types of wastewater facilities for only ~19% and ~29% respectively (**Figure 29C and 29D**).

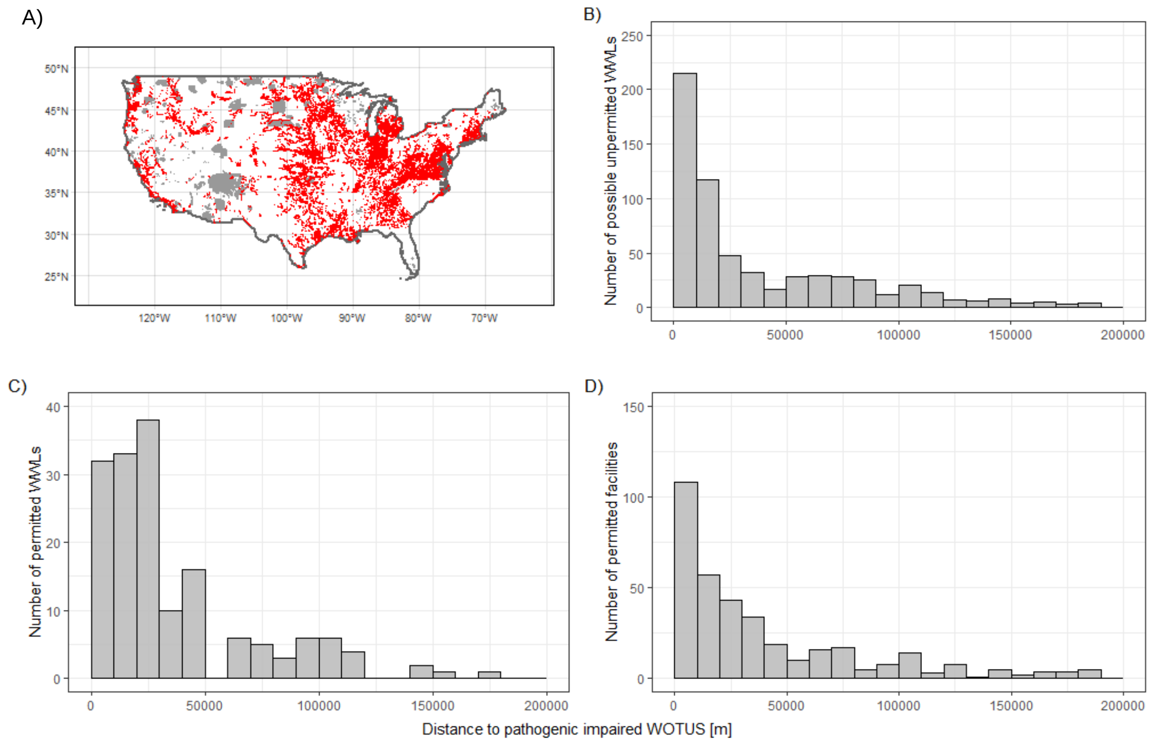


Figure 29. Pathogenic impaired Waters of the United States. A) Pathogenically impaired Waters of the United States (WOTUS) (red). (United States Census Bureau, 2022a; United States Environmental Protection Agency, 2022a). Distance to pathogenic impaired WOTUS from B) possible unpermitted, C) permitted wastewater lagoons, and D) other types of wastewater treatment plants on Tribal lands.

As previously stated, intermittent rivers rely on seasonal groundwater sources. Therefore, reducing pathogenic levels from WWTPs may be limited, resulting in elevated concentrations. Unfortunately, the CWA-mandated monitoring campaigns may not include this type of river making essential to pay close attention to drinking water supplies, towns with large populations, and recreational areas with many visitors near intermittent rivers that are within 500 meters of WWTPs.

5.4. Permitted Wastewater Treatment Plants and *E. coli* Violations

NPDES permits establish wastewater treatment plant effluent limitations to control discharges of pollutants to receiving waters based on available technology and the quality standards of the receiving water (United States Environmental Protection Agency, 2022n). Effluent self-monitoring results should be submitted to EPA through a Discharge Monitoring Report (DMR) as established in the permit (Pennsylvania Department of Environmental Protection, n.d.). Through the package echor in *R* (Schramm, 2021), *E. coli* effluent violations for quarters in the last three years were searched for the 522 permitted wastewater treatment plants on Tribal lands listed in ECHO database using the parameter code 51040 corresponding to "*E. coli*". There were records for 122 (~23.4%) wastewater treatment plants reporting one of the following "DMR Non-Receipt Reporting Violation", "Non-Reportable Noncompliance Effluent Violation", or "No Violation Identified". The first refers to when DMRs are not received within 31 days of the due date (United States Environmental Protection Agency, 2022o), the second to effluent violations that will not be included in the official report (Noncompliance and Program Reporting, 2015), and the last to the absence of violations. The total number of retrieved records was 6,567 distributed into the mentioned categories respectively as follows ~11.4%, ~7.2%, and ~81.4% (**Figure 30**). For each WWTP the number of records ranges from 2 to 117, with ~17.2% reported with all three violations and the rest with one or two violations as detailed in **Table 9**.

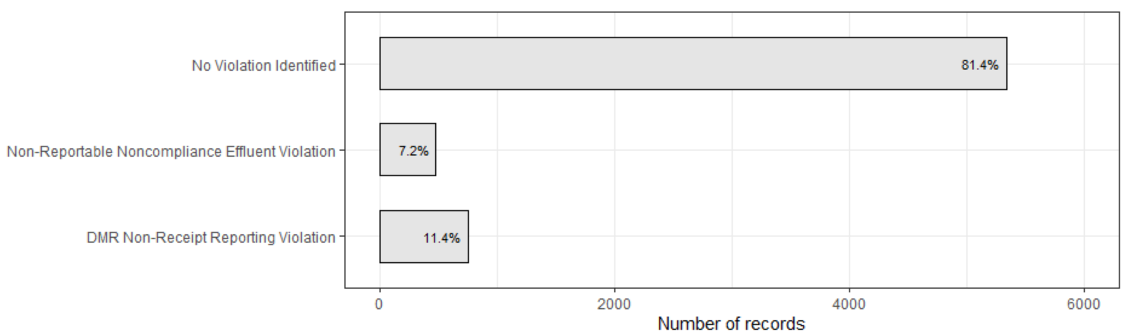


Figure 30. Number of records according to type of violation for wastewater treatment plants in ECHO database and on Tribal lands.

Table 9

Number of Wastewater Treatment Plants With One or Two Different Types of Violations Reported Quarterly in the Last Three Years

And	DMR Non-Receipt Reporting Violation	No Violation Identified	Non-Reportable Noncompliance Effluent Violation
DMR Non-Receipt Reporting Violation	4 (~3.3%)	28 (~23.0%)	0
No Violation Identified		44 (~36.1%)	25 (~20.5%)
Non-Reportable Noncompliance Effluent Violation			0

There is no information about ~76.6% of the permitted wastewater treatment plants, for those which there are, 43.4% have had delays in presenting DMRs and 73.8% have reported no violation identified at least once.

5.5. Takeaways and Final Remarks

This dissertation explored drivers and sources of pathogens on Tribal Lands through different approaches to better understand the threats to surface water in arid and semiarid lands. The results suggest that 1) Consistent monitoring of rivers over time and space is crucial for establishing a robust dataset for future analyses; 2) Monitoring of intermittent and ephemeral rivers, particularly in dry regions, is essential because they form the primary network of rivers and may contain high concentrations of *E. coli* during rainy seasons, potentially impacting perennial rivers and waterbodies; 3) It is important to identify and regulate wastewater treatment plants and other types of wastewater infrastructure that discharge to or are nearby any waterbody, whether it is considered part of WOTUS or not, as their effluents, seepage, or accidental emissions could impact perennial surface waters.

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APPENDIX A

SUPPLEMENTARY INFORMATION – *ESCHERICHIA COLI* DRIVERS IN SURFACE WATERS OF ARID AND SEMIARID REGIONS: A CASE OF STUDY OF ARIZONA

1.1. Table 1. Variables Included in the Records Downloaded from the Arizona Water Quality Database of the Arizona Department of Environmental Quality (ADEQ). Not all fields in the database were populated.

No.	Variable	No.	Variable	No.	Variable
1	Project	14	Lookup Result	27	Bottom Depth
2	Site	15	Lab Reporting Limit	28	WQX Flag
3	Trip#	16	Limit Unit	29	Last Updated Date
4	Sample#	17	Dilution Multiplier	30	Short Desc
5	Site ID	18	QA Flags	31	Type
6	Trip Type	19	Lab Notation	32	County
7	Medium	20	QA Memo	33	HUC 12
8	Sample Date	21	Comments	34	HUC 14
9	Sample Type	22	Credible Level	35	Eco
10	Protocol	23	Sample Depth	36	Stream Name
11	Result	24	Usability Code	37	Lat.
12	Result Unit	25	Usability Originator	38	Long.
13	Lab Internal No.	26	Top Depth		

1.2. Table 2. Categories Used for Site/River Classification.

No.	Category	Description
1	Perennial	Site located on a stream that always contains water[a].
2	Intermittent	Site located on a stream that contains water for only part of the year, but more than just after rainstorms and snowmelt[a].
3	Ephemeral	Site located on a stream that contains water only during or after a local rainstorm or heavy snowmelt[a].
4	Artificial Path	Site located in water bodies or flooded areas[a].
5	Well	Site located in a hole drilled into the ground to access water contained in an aquifer.
6	Intermittent Spring	Site located where a concentrated discharge of ground water flows at the ground surface only during part of the year.
7	Canal/Ditch	Site located on an artificial open waterway constructed to transport water, to irrigate or drain land, to connect two or more bodies of water, or to serve as a waterway for watercraft[a].
8	Not identified	Site located in an unidentified place.

[a] Description in accordance with the National Hydrography Dataset (NHD) User Guide. Retrieved June 2020, from https://nhd.usgs.gov/userguide.html.

1.3. Table 3. Observed and Derived Watershed Characteristics Evaluated.

No.	Variable	Description	Unit	Variable (density)			Variable (rate)		
				No	Variable/ Watershed area[1]	Unit	No	Variable/ Total of the variable	Unit
Related to sites									
1	Number of sample sites	Total number of sampling sites located on perennial rivers, intermittent rivers, ephemeral rivers or artificial paths in a watershed.	U	2	✓	U/m^2			
Related to samples									
3	Number of samples from artificial paths	Total number of samples obtained from sites located on artificial paths in a watershed.	U	10	✓	U/m^2	17	✓[2]	U/U
4	Number of samples from ephemeral rivers	Total number of samples obtained from sites located on ephemeral rivers in a watershed.	U	11	✓	U/m^2	18	✓[2]	U/U
5	Number of samples from intermittent rivers	Total number of samples obtained from sites located on intermittent rivers in a watershed.	U	12	✓	U/m^2	19	✓[2]	U/U
6	Number of samples from perennial rivers	Total number of samples obtained from sites located on perennial rivers in a watershed.	U	13	✓	U/m^2	20	✓[2]	U/U
7	Number of samples from intermittent rivers + ephemeral rivers	Total number of samples obtained from sites located on intermittent rivers or ephemeral rivers in a watershed.	U	14	✓	U/m^2	21	✓[2]	U/U
8	Number of samples from perennial rivers + artificial paths	Total number of samples obtained from sites located on perennial rivers or artificial paths in a watershed.	U	15	✓	U/m^2	22	✓[2]	U/U
9	Total number of samples	Total number of samples obtained from sites located on perennial rivers, intermittent rivers, ephemeral rivers or artificial paths in a watershed.	U	16	✓	U/m^2			
Related to rivers[3]									
23	Artificial path length	Total length of artificial paths in a watershed.	m	30	✓	m/m^2	37	✓[4]	m/m
24	Ephemeral river length	Total length of rivers classified as ephemeral in a watershed.	m	31	✓	m/m^2	38	✓[4]	m/m
25	Intermittent river length	Total length of rivers classified as intermittent in a watershed.	m	32	✓	m/m^2	39	✓[4]	m/m
26	Perennial river length	Total length of rivers classified as perennial in a watershed.	m	33	✓	m/m^2	40	✓[4]	m/m
27	Artificial path + perennial river length	Sum of the total lengths of artificial paths and rivers classified as perennial.	m	34	✓	m/m^2	41	✓[4]	m/m
28	Intermittent + ephemeral river length	Sum of the total lengths of rivers classified as intermittent and rivers classified as ephemeral.	m	35	✓	m/m^2	42	✓[4]	m/m
29	Total river length	Sum of the total lengths of rivers classified as perennial, intermittent or ephemeral and artificial paths.	m	36	✓	m/m^2			
Related to terrain									
43	Mean slope	Average degree of the terrain inclination in a watershed relative to the horizontal plane.	°						
44	Watershed area	Area of a watershed.	m^2						
Related to potential emitters									
45	Areas with biosolid/sludge application	Number of areas where biosolids or sludges are applied in a watershed.	U	52	✓	U/m^2			
46	Areas with wildlife	Number of geographically defined areas which are designated or regulated and managed to serve as a refuge or preservation area for wildlife in a watershed.	U	53	✓	U/m^2			
47	CAFOs	Number of commercial animal feeding operations (CAFOs) in a watershed.	U	54	✓	U/m^2			
48	Dairies	Number of businesses for the harvesting and/or processing animal milk in a watershed.	U	55	✓	U/m^2			
49	Farm/ranch	Number of farms or ranches in a watershed.	U	56	✓	U/m^2			
50	WWTP	Number of waste water treatment plant (WWTP) facilities installed at a site to treat and dispose of wastewater, predominantly of human origin in a watershed.	U	57	✓	U/m^2			
51	CAFOs + dairies + farm/ranch	Sum of the number of CAFOs, dairies, and farms or ranches in a watershed.	U	58	✓	U/m^2			
Related to Land use/Land cover									
59	Barren land (rock/sand/clay)[5]	Areas of bedrock, desert pavement, scarps, talus, slides, volcanic material, glacial debris, sand dunes, strip mines, gravel pits and other accumulations of earthen material. Generally, vegetation accounts for less than 15% of total cover in a watershed.	m^2	84	✓	m^2/m^2			
60	Cultivated crops[5]	Areas used for the production of annual crops, such as corn, soybeans, vegetables, tobacco, and cotton, and also perennial woody crops such as orchards and vineyards. Crop vegetation accounts for greater than 20% of total vegetation. This class also includes all land being actively tilled in a watershed.	m^2	85	✓	m^2/m^2			
61	Deciduous forest[5]	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species shed foliage simultaneously in response to seasonal change in a watershed.	m^2	86	✓	m^2/m^2			
62	Developed, high intensity (HI)[5]	Highly developed areas where people reside or work in high numbers. Examples include apartment complexes, row houses and commercial/industrial. Impervious surfaces account for 80% to 100% of the total cover in a watershed.	m^2	87	✓	m^2/m^2			
63	Developed, low intensity (LI)[5]	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 20% to 49% percent of total cover. These areas most commonly include single-family housing units in a watershed.	m^2	88	✓	m^2/m^2			

1.3. Table 3. (continued).

No.	Variable	Description	Unit	Variable (density)			Variable (rate)		
				No	Variable/ Watershed area[1]	Unit	No	Variable/ Total of the variable	Unit
64	Developed, medium intensity (MI)[5]	Areas with a mixture of constructed materials and vegetation. Impervious surfaces account for 50% to 79% of the total cover. These areas most commonly include single-family housing units in a watershed.	m^2	89	✓	m^2/m^2			
65	Developed, open space (OS)[5]	Areas with a mixture of some constructed materials, but mostly vegetation in the form of lawn grasses. Impervious surfaces account for less than 20% of total cover. These areas most commonly include large-lot single-family housing units, parks, golf courses, and vegetation planted in developed settings for recreation, erosion control, or aesthetic purposes in a watershed.	m^2	90	✓	m^2/m^2			
66	Emergent herbaceous wetlands[5]	Areas where perennial herbaceous vegetation accounts for greater than 80% of vegetative cover and the soil or substrate is periodically saturated with or covered with water in a watershed.	m^2	91	✓	m^2/m^2			
67	Evergreen forest[5]	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. More than 75% of the tree species maintain their leaves all year. Canopy is never without green foliage in a watershed.	m^2	92	✓	m^2/m^2			
68	Grassland/herbaceous[5]	Areas dominated by gramanoid or herbaceous vegetation, generally greater than 80% of total vegetation. These areas are not subject to intensive management such as tilling, but can be utilized for grazing in a watershed.	m^2	93	✓	m^2/m^2			
69	Mixed forest[5]	Areas dominated by trees generally greater than 5 meters tall, and greater than 20% of total vegetation cover. Neither deciduous nor evergreen species are greater than 75% of total tree cover in a watershed.	m^2	94	✓	m^2/m^2			
70	Open water[5]	Areas of open water, generally with less than 25% cover of vegetation or soil in a watershed.	m^2	95	✓	m^2/m^2			
71	Pasture/hay[5]	Areas of grasses, legumes, or grass-legume mixtures planted for livestock grazing or the production of seed or hay crops, typically on a perennial cycle. Pasture/hay vegetation accounts for greater than 20% of total vegetation in a watershed.	m^2	96	✓	m^2/m^2			
72	Shrub/scrub[5]	Areas dominated by shrubs; less than 5 meters tall with shrub canopy typically greater than 20% of total vegetation. This class includes true shrubs, young trees in an early successional stage or trees stunted from environmental conditions in a watershed.	m^2	97	✓	m^2/m^2			
73	Woody wetlands[5]	Areas where forest or shrubland vegetation accounts for greater than 20% of vegetative cover and the soil or substrate is periodically saturated with or covered with water in a watershed.	m^2	98	✓	m^2/m^2			
74	Barren land (rock/sand/clay) + shrub/scrub	Total of barren land (rock/sand/clay) and shrub/scrub areas in a watershed.	m^2	99	✓	m^2/m^2			
75	Barren land (rock/sand/clay) + deciduous forest + evergreen forest + mixed forest + shrub/scrub	Total of barren land (rock/sand/clay), deciduous forest, evergreen forest, mixed forest, and shrub/scrub areas in a watershed.	m^2	100	✓	m^2/m^2			
76	Barren land (rock/sand/clay) + deciduous forest + evergreen forest + mixed forest + shrub/scrub + woody wetlands + emergent herbaceous wetlands	Total of barren land (rock/sand/clay), deciduous forest, evergreen forest, mixed forest, shrub/scrub, woody wetlands, and emergent herbaceous wetlands areas in a watershed.	m^2	101	✓	m^2/m^2			
77	Deciduous forest + evergreen forest + mixed forest	Total of deciduous forest, evergreen forest, and mixed forest areas in a watershed.	m^2	102	✓	m^2/m^2			
78	Developed, HI + MI	Total of Developed, high intensity and medium intensity areas in a watershed.	m^2	103	✓	m^2/m^2			
79	Developed, LI + OS	Total of Developed, low intensity and open space areas in a watershed.	m^2	104	✓	m^2/m^2			
80	Developed, HI + MI + LI + OS	Total of Developed, high intensity, medium intensity, low intensity and open space areas in a watershed.	m^2	105	✓	m^2/m^2			
81	Grassland/herbaceous + pasture/hay	Total of grassland/herbaceous and pasture/hay areas in a watershed.	m^2	106	✓	m^2/m^2			
82	Open water + woody wetlands + emergent herbaceous wetlands	Total of open water, woody wetlands, and emergent herbaceous wetlands areas in a watershed.	m^2	107	✓	m^2/m^2			
83	Woody wetlands + emergent herbaceous wetlands	Total of woody wetlands and emergent herbaceous wetlands areas in a watershed.	m^2	108	✓	m^2/m^2			
Related to precipitation[6][7]									
109	Mean precipitation in day 0	Mean value of the amounts of precipitation in the day 0 (sampling day) for all samples in a watershed. $\left(\sum_{1}^{n} P_0\right)/n$	in						
110	Mean precipitation in day 1	Mean value of the amounts of precipitation in the day 1 (one day before the sampling day) for all samples in a watershed. $\left(\sum_{1}^{n} P_1\right)/n$	in						
111	Mean precipitation up to day 1	Mean value of the sum of the amounts of precipitations in the day 0 (sampling day) and day 1 (one day before the sampling day) for all samples in a watershed. $\sum_{1}^{n}\left(\sum_{i=0}^{1} P_i\right)/n$	in						

1.3. Table 3. (continued).

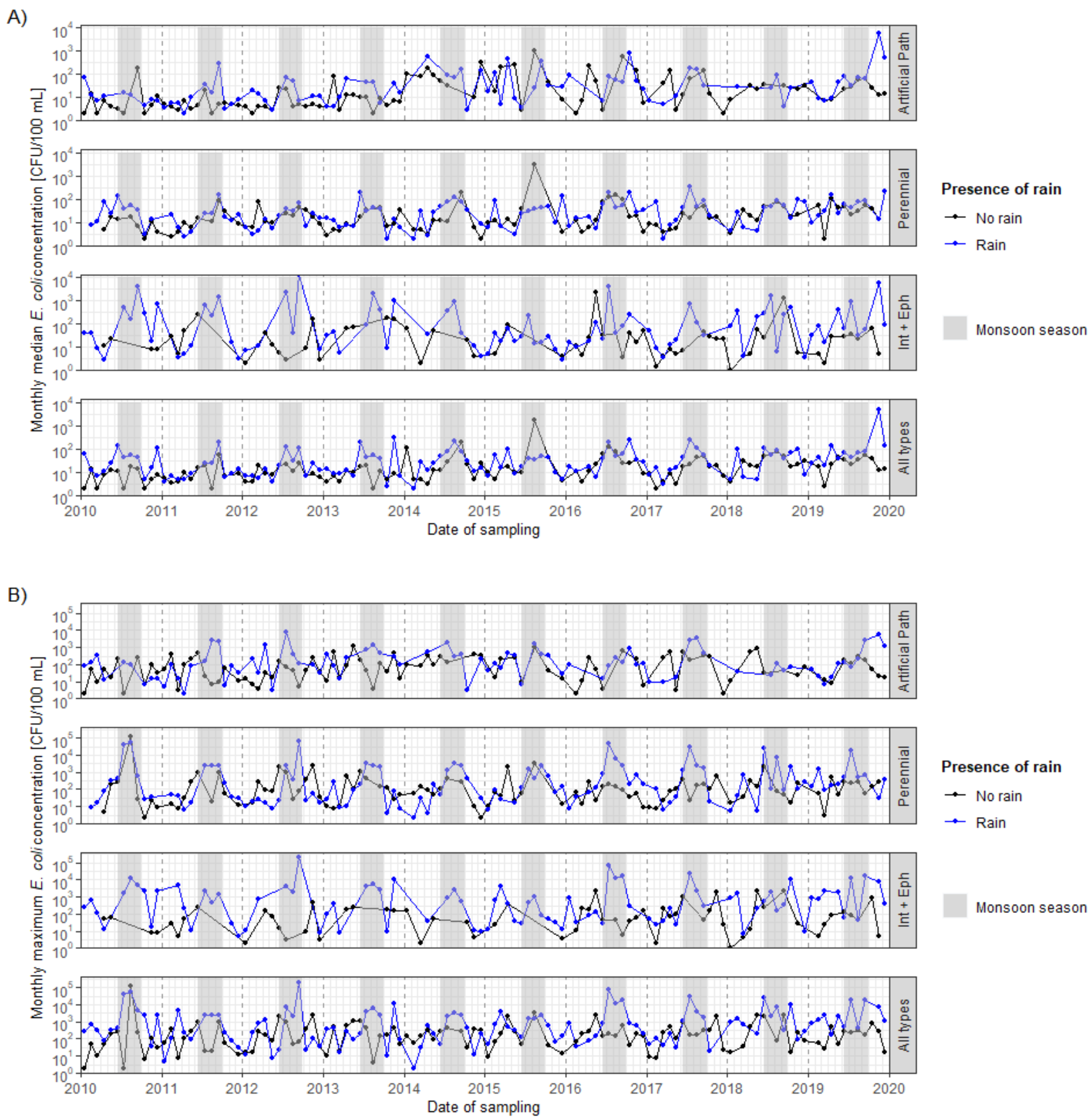
No.	Variable	Description	Unit	Variable (density)			Variable (rate)		
				No	Variable/ Watershed area[1]	Unit	No	Variable/ Total of the variable	Unit
112	Mean precipitation up to day 2	Mean value of the sum of the amounts of precipitations in the day 0 (sampling day), day 1, and day 2 (one and two days before the sampling day) for all samples in a watershed. $\sum_{1}^{n}\left(\sum_{i=0}^{2} P_i\right)\Big/n$	in						
113	Mean precipitation up to day 5	Mean value of the sum of the amounts of precipitations in the day 0 (sampling day), day 1, day 2, day 3, day 4, and day 5 (one to five days before the sampling day) for all samples in a watershed. $\sum_{1}^{n}\left(\sum_{i=0}^{5} P_i\right)\Big/n$	in						
114	Mean precipitation	Mean value of the sum of the amounts of precipitations in the day 0 (sampling day), day 1, day 2, day 3, day 4, day 5, day 7, and day 8 (one to eight days before the sampling day) for all samples in a watershed. $\sum_{1}^{n}\left(\sum_{i=0}^{8} P_i\right)\Big/n$	in						
115	Median precipitation in day 0	Median value of the amounts of precipitation in the day 0 (sampling day) for all samples in a watershed. $median\left((P_0)_1, (P_0)_2, (P_0)_3, \dots, (P_0)_n\right)$	in						
116	Median precipitation in day 1	Median value of the amounts of precipitation in the day 1 (one day before the sampling day) for all samples in a watershed. $median\left((P_1)_1, (P_1)_2, (P_1)_3, \dots, (P_1)_n\right)$	in						
117	Median precipitation up to day 1	Median value of the sums of the amounts of precipitation in the day 0 (sampling day) and day 1 (one day before the sampling day) for all samples in a watershed. $median\left(\left(\sum_{i=0}^{1} P_i\right)_1, \left(\sum_{i=0}^{1} P_i\right)_2, \left(\sum_{i=0}^{1} P_i\right)_3, \dots, \left(\sum_{i=0}^{1} P_i\right)_n\right)$	in						
118	Median precipitation up to day 2	Median value of the sums of the amounts of precipitation in the day 0 (sampling day), day 1, and day 2 (one and two days before the sampling day) for all samples in a watershed. $median\left(\left(\sum_{i=0}^{2} P_i\right)_1, \left(\sum_{i=0}^{2} P_i\right)_2, \left(\sum_{i=0}^{2} P_i\right)_3, \dots, \left(\sum_{i=0}^{2} P_i\right)_n\right)$	in						
119	Median precipitation up to day 5	Median value of the sums of the amounts of precipitation in the day 0 (sampling day), day 1, day 2, day 3, day 4, and day 5 (one to five days before the sampling day) for all samples in a watershed. $median\left(\left(\sum_{i=0}^{5} P_i\right)_1, \left(\sum_{i=0}^{5} P_i\right)_2, \left(\sum_{i=0}^{5} P_i\right)_3, \dots, \left(\sum_{i=0}^{5} P_i\right)_n\right)$	in						
120	Median precipitation	Median value of the sums of the amounts of precipitation in the day 0 (sampling day), day 1, day 2, day 3, day 4, day 5, day 7, and day 8 (one to eight days before the sampling day) for all samples in a watershed. $median\left(\left(\sum_{i=0}^{8} P_i\right)_1, \left(\sum_{i=0}^{8} P_i\right)_2, \left(\sum_{i=0}^{8} P_i\right)_3, \dots, \left(\sum_{i=0}^{8} P_i\right)_n\right)$	in						
121	Mean number of days with precipitation	Mean number of days, out of nine, with precipiation value greater than zero in a watershed. $\sum_{1}^{n}\left(\sum_{i=0}^{8} Q_i\right)\Big/n$	day						
122	Mean number of days without precipitation	Mean number of days, out of nine, with precipiation value equal to zero in a watershed. $\sum_{1}^{n}\left(9-\sum_{i=0}^{8} Q_i\right)\Big/n$	day						
123	Median number of days with precipitation	Median number of days, out of nine, with precipiation value greater than zero in a watershed. $median\left(\left(\sum_{i=0}^{8} Q_i\right)_1, \left(\sum_{i=0}^{8} Q_i\right)_2, \left(\sum_{i=0}^{8} Q_i\right)_3, \dots, \left(\sum_{i=0}^{8} Q_i\right)_n\right)$	day						
124	Median number of days without precipitation	Median number of days, out of nine, with precipiation value equal to zero in a watershed. $median\left(\left(9-\sum_{i=0}^{8} Q_i\right)_1, \left(9-\sum_{i=0}^{8} Q_i\right)_2, \left(9-\sum_{i=0}^{8} Q_i\right)_3, \dots, \left(9-\sum_{i=0}^{8} Q_i\right)_n\right)$	day						

1.3. Table 3. (continued).

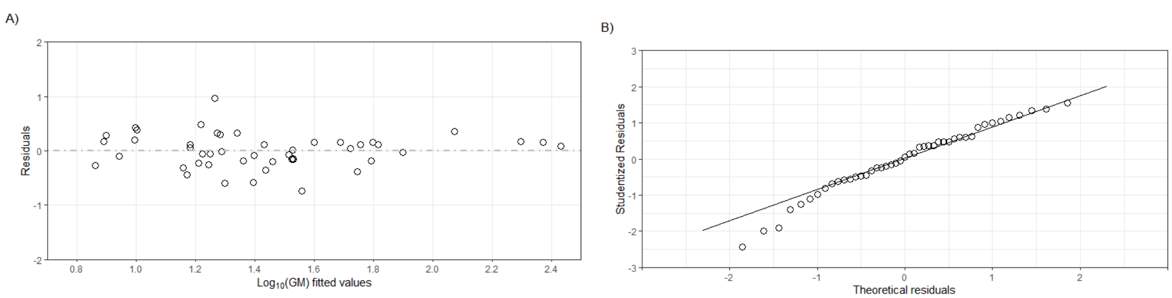
No.	Variable	Description	Unit	Variable (density)			Variable (rate)		
				No	Variable/ Watershed area[1]	Unit	No	Variable/ Total of the variable	Unit
125	Mean number of days until precipitation	Mean of the number of days without precipitation counted backwards, starting at 0, from the day of sampling until the first day with precipitation value different from zero.	day						
126	Median number of days until precipitation	Median of the number of days without precipitation counted backwards, starting at 0, from the day of sampling until the first day with precipitation value different from zero.	day						
127	Mean distance from the sample site to the rain gauge	Mean of the distances between the location of the sampling site to the rain gauge used to obtain precipitation data for the day of sampling to eight days before for all samples in a watershed $\left(\sum_{i=1}^{n} D_i\right)/n$	km						
128	Median distance from the sample site to the rain gauge	Median of the distances between the location of the sampling site to the rain gauge used to obtain precipitation data for the day of sampling to eight days before for all samples in a watershed $median(D_1, D_2, D_3, \dots, D_n)$	km						

(1) Watershed area refers to variable number 44
(2) Total of the variable is variable number 9 "Total number of samples"
(3) Classification according to the NHD 20200616 for Arizona State or Territory Shapefile Model Version 2.2.1 by the National Geospatial Program of the United States Geological Survey retrieved from https://nationalmap.gov/viewer.html
(4) Total of the variable is variable number 29 "Total river length"
(5) Name and definition according to the National Land Cover Database Class Legend and Description 2016 at https://www.mrlc.gov/data/legends/national-land-cover-database-class-legend-and-description.
(6) n = total number of samples in a watershed [unit].
P0 = Precipitation in the sampling day (day 0) [in].
P1 = Precipitation one day before the sampling day (day 1) [in].
P2 = Precipitation two days before the sampling day (day 2) [in].
P3 = Precipitation three days before the sampling day (day 3) [in].
P4 = Precipitation four days before the sampling day (day 4) [in].
P5 = Precipitation five days before the sampling day (day 5) [in].
P6 = Precipitation six days before the sampling day (day 6) [in].
P7 = Precipitation seven days before the sampling day (day 7) [in].
P8 = Precipitation three days before the sampling day (day 8) [in].
(7) Qi = 1 if Pi > 0
Qi = 0 if Pi = 0
(8) Di = Distance between the location of the sampling site to the rain gauge used to obtain precipitation data for the day of sampling to eight days before the i sample [km].

1.4. Figure 1**.** Monthly A) mean and B) maximum *E. coli* concentration values from different types of streams in all years of the studied period. Points are indicative of data existence in the considered month, blue color represents values with rain presence in the sampling date or at least in one of the eight previous days, while black color those with no presence of rain.



1.5. Figure 2. A) Residuals versus $\log_{10}$(GM) fitted values. The inexistence of no obvious pattern supports the assumptions of linearity and homoscedasticity. B) Q-Q plot of studentized residuals versus theoretical residuals. Most points approximately fall on the line suggesting residuals have a normal distribution. Residuals are the difference between predicted values using the model including the five variables: CAFOs + dairies + farm/ranch (density) [unit/m^2], Developed- High Intensity [m^2], Evergreen forest (density) [m^2/m^2], Pasture/Hay (density) [m^2/m^2] and Median number of days with precipitation in the 9 days [day] (fitted values) and observed values of $\log_{10}$(GM). Studentized residuals are the residuals fitted to a student distribution. Theoretical residuals are derived from a population following the theoretical student distribution.



APPENDIX B

SUPPLEMENTARY INFORMATION – WASTEWATER INFRASTRUCTURE AS POSSIBLE POINT SOURCES OF POLLUTANTS ON TRIBAL LANDS

2.1. Table 1. Federally Recognized Indian Tribes (FRITs) and their corresponding Federal Indian Reservations (FIRs) and/or Off-reservation trust land (ORTL).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Alabama	Poarch Band of Creeks Indians	Poarch Creek Reservation and Off-Reservation Trust Land	1
Alaska	Agdaagux Tribe of King Cove		227
	Akiachak Native Community		
	Akiak Native Community		
	Alatna Village		
	Algaaciq Native Village (St. Mary's)		
	Allakaket Village		
	Alutiiq Tribe of Old Harbor		
	Angoon Community Association		
	Anvik Village		
	Arctic Village[d]		
	Asa'carsarmiut Tribe		
	Beaver Village		
	Birch Creek Tribe		
	Central Council of the Tlingit & Haida Indian Tribes		
	Chalkyitsik Village		
	Cheesh-Na Tribe		
	Chevak Native Village		
	Chickaloon Native Village		
	Chignik Bay Tribal Council		
	Chignik Lake Village		
	Chilkat Indian Village (Klukwan)		
	Chilkoot Indian Association (Haines)		
	Chinik Eskimo Community (Golovin)		
	Chuloonawick Native Village		
	Circle Native Community		
	Craig Tribal Association		
	Curyung Tribal Council		
	Douglas Indian Association		
	Egegik Village		
	Eklutna Native Village		
	Emmonak Village		
	Evansville Village (aka Bettles Field)		
	Galena Village (aka Louden Village)		
	Gulkana Village Council		
	Healy Lake Village		
	Holy Cross Tribe		
	Hoonah Indian Association		
	Hughes Village		
	Huslia Village		
	Hydaburg Cooperative Association		
	Igiugig Village		
	Inupiat Community of the Arctic Slope		
	Iqugmiut Traditional Council		
	Ivanof Bay Tribe		
	Kaguyak Village		
	Kaktovik Village (aka Barter Island)		
	Kasigluk Traditional Elders Council		
	Kenaitze Indian Tribe		
	Ketchikan Indian Community		
	King Island Native Community		
	King Salmon Tribe		
	Klawock Cooperative Association		
	Knik Tribe		
	Kokhanok Village		
	Koyukuk Native Village		
	Levelock Village		
	Lime Village		
	Manley Hot Springs Village		
	Manokotak Village		
	McGrath Native Village		
	Mentasta Traditional Council		
	Metlakatla Indian Community, Annette Island Reserve	Annette Island Reserve	
	Naknek Native Village		
	Native Village of Afognak		
	Native Village of Akhiok		
	Native Village of Akutan		
	Native Village of Aleknagik		
	Native Village of Ambler		
	Native Village of Atka		
	Native Village of Atqasuk		
	Native Village of Barrow Inupiat Traditional Government		
	Native Village of Belkofski		
	Native Village of Brevig Mission		
	Native Village of Buckland		
	Native Village of Cantwell		
	Native Village of Chenega (aka Chanega)		

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Alaska	Native Village of Chignik Lagoon		
	Native Village of Chitina		
	Native Village of Chuathbaluk (Russian Mission, Kuskokwim)		
	Native Village of Council		
	Native Village of Deering		
	Native Village of Diomede (aka Inalik)		
	Native Village of Eagle		
	Native Village of Eek		
	Native Village of Ekuk		
	Native Village of Ekwok		
	Native Village of Elim		
	Native Village of Eyak (Cordova)		
	Native Village of False Pass		
	Native Village of Fort Yukon		
	Native Village of Gakona		
	Native Village of Gambell		
	Native Village of Georgetown		
	Native Village of Goodnews Bay		
	Native Village of Hamilton		
	Native Village of Hooper Bay		
	Native Village of Kanatak		
	Native Village of Karluk		
	Native Village of Kiana		
	Native Village of Kipnuk		
	Native Village of Kivalina		
	Native Village of Kluti Kaah (aka Copper Center)		
	Native Village of Kobuk		
	Native Village of Kongiganak		
	Native Village of Kotzebue		
	Native Village of Koyuk		
	Native Village of Kwigillingok		
	Native Village of Kwinhagak (aka Quinhagak)		
	Native Village of Larsen Bay		
	Native Village of Marshall (aka Fortuna Ledge)		
	Native Village of Mary's Igloo		
	Native Village of Mekoryuk		
	Native Village of Minto		
	Native Village of Nanwalek (aka English Bay)		
	Native Village of Napaimute		
	Native Village of Napakiak		
	Native Village of Napaskiak		
	Native Village of Nelson Lagoon		
	Native Village of Nightmute		
	Native Village of Nikolski		
	Native Village of Noatak		
	Native Village of Nuiqsut (aka Nooiksut)		
	Native Village of Nunam Iqua		
	Native Village of Nunapitchuk		
	Native Village of Ouzinkie		
	Native Village of Paimiut		
	Native Village of Perryville		
	Native Village of Pilot Point		
	Native Village of Point Hope		
	Native Village of Point Lay		
	Native Village of Port Graham		
	Native Village of Port Heiden		
	Native Village of Port Lions		
	Native Village of Ruby		
	Native Village of Saint Michael		
	Native Village of Savoonga		
	Native Village of Scammon Bay		
	Native Village of Selawik		
	Native Village of Shaktoolik		
	Native Village of Shishmaref		
	Native Village of Shungnak		
	Native Village of Stevens		
	Native Village of Tanacross		
	Native Village of Tanana		
	Native Village of Tatitlek		
	Native Village of Tazlina		
	Native Village of Teller		
	Native Village of Tetlin		
	Native Village of Tuntutuliak		
	Native Village of Tununak		
	Native Village of Tyonek		
	Native Village of Unalakleet		
	Native Village of Unga		
	Native Village of Wales		
	Native Village of White Mountain		
	Nenana Native Association		
	New Koliganek Village Council		
	New Stuyahok Village		
	Newhalen Village		

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Alaska	Newtok Village		
	Nikolai Village		
	Ninilchik Village		
	Nome Eskimo Community		
	Nondalton Village		
	Noorvik Native Community		
	Northway Village		
	Nulato Village		
	Nunakauyarmiut Tribe		
	Organized Village of Grayling (aka Holikachuk)		
	Organized Village of Kake		
	Organized Village of Kasaan		
	Organized Village of Kwethluk		
	Organized Village of Saxman		
	Orutsararmiut Traditional Native Council		
	Oscarville Traditional Village		
	Pauloff Harbor Village		
	Pedro Bay Village		
	Petersburg Indian Association		
	Pilot Station Traditional Village		
	Pitka's Point Traditional Council		
	Platinum Traditional Village		
	Portage Creek Village (aka Ohgsenakale)		
	Qagan Tayagungin Tribe of Sand Point		
	Qawalangin Tribe of Unalaska		
	Rampart Village		
	Saint George Island[e]		
	Saint Paul Island[e]		
	Salamatof Tribe		
	Seldovia Village Tribe		
	Shageluk Native Village		
	Sitka Tribe of Alaska		
	Skagway Village		
	South Naknek Village		
	Stebbins Community Association		
	Sun'aq Tribe of Kodiak		
	Takotna Village		
	Tangirnaq Native Village		
	Telida Village		
	Traditional Village of Togiak		
	Tuluksak Native Community		
	Twin Hills Village		
	Ugashik Village		
	Umkumiut Native Village		
	Village of Alakanuk		
	Village of Anaktuvuk Pass		
	Village of Aniak		
	Village of Atmautluak		
	Village of Bill Moore's Slough		
	Village of Chefornak		
	Village of Clarks Point		
	Village of Crooked Creek		
	Village of Dot Lake		
	Village of Iliamna		
	Village of Kalskag		
	Village of Kaltag		
	Village of Kotlik		
	Village of Lower Kalskag		
	Village of Ohogamiut		
	Village of Red Devil		
	Village of Sleetmute		
	Village of Solomon		
	Village of Stony River		
	Village of Venetie[d]		
	Village of Wainwright		
	Wrangell Cooperative Association		
	Yakutat Tlingit Tribe		
	Yupiit of Andreafski		
Arizona	Ak-Chin Indian Community	Maricopa (Ak Chin) Indian Reservation and Off-Reservation Trust Land	20
	Cocopah Tribe of Arizona	Cocopah Reservation	
	Colorado River Indian Tribes of the Colorado River Indian Reservation	Colorado River Indian Reservation	
	Fort McDowell Yavapai Nation	Fort McDowell Yavapai Nation Reservation	
	Gila River Indian Community of the Gila River Indian Reservation	Gila River Indian Reservation	
	Havasupai Tribe of the Havasupai Reservation	Havasupai Reservation	
	Hopi Tribe of Arizona	Hopi Reservation and Off-Reservation Trust Land	
	Hualapai Indian Tribe of the Hualapai Indian Reservation	Hualapai Indian Reservation and Off-Reservation Trust Land	
	Kaibab Band of Paiute Indians of the Kaibab Indian Reservation	Kaibab Indian Reservation	
	Navajo Nation	Navajo Nation Reservation and Off-Reservation Trust Land	
	Pascua Yaqui Tribe of Arizona	Pascua Pueblo Yaqui Reservation and Off-Reservation Trust Land	
	Quechan Tribe of the Fort Yuma Indian Reservation	Fort Yuma Indian Reservation	
	Salt River Pima-Maricopa Indian Community of the Salt River Reservation	Salt River Reservation	
	San Carlos Apache Tribe of the San Carlos Reservation	San Carlos Reservation	
	San Juan Southern Paiute Tribe of Arizona	Navajo Nation Reservation and Off-Reservation Trust Land	

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Arizona	Tohono O'odham Nation of Arizona	Tohono O'odham Nation Reservation and Off-Reservation Trust Land	
	Tonto Apache Tribe of Arizona	Tonto Apache Reservation and Off-Reservation Trust Land	
	White Mountain Apache Tribe of the Fort Apache Reservation	Fort Apache Reservation	
	Yavapai-Apache Nation of the Camp Verde Indian Reservation	Yavapai-Apache Nation Reservation and Off-Reservation Trust Land	
	Yavapai-Prescott Indian Tribe	Yavapai-Prescott Reservation	
California	Agua Caliente Band of Cahuilla Indians of the Agua Caliente Indian Reservation	Agua Caliente Indian Reservation and Off-Reservation Trust Land	105
	Alturas Indian Rancheria	Alturas Indian Rancheria	
	Augustine Band of Cahuilla Indians	Augustine Reservation	
	Bear River Band of the Rohnerville Rancheria	Rohnerville (Rancheria) Trust Land	
	Berry Creek Rancheria of Maidu Indians of California	Berry Creek Rancheria and Off-Reservation Trust Land	
	Big Lagoon Rancheria	Big Lagoon Rancheria	
	Big Pine Paiute Tribe of the Owens Valley	Big Pine Reservation and Off-Reservation Trust Land	
	Big Sandy Rancheria of Western Mono Indians of California	Big Sandy Rancheria and Off-Reservation Trust Land	
	Big Valley Band of Pomo Indians of the Big Valley Rancheria	Big Valley Rancheria	
	Bishop Paiute Tribe	Bishop Reservation	
	Blue Lake Rancheria	Blue Lake Rancheria and Off-Reservation Trust Land	
	Bridgeport Indian Colony	Bridgeport Reservation and Off-Reservation Trust Land	
	Buena Vista Rancheria of Me-Wuk Indians of California		
	Cabazon Band of Mission Indians	Cabazon Reservation	
	Cachil DeHe Band of Wintun Indians of the Colusa Indian Community of the Colusa Rancheria	Colusa Rancheria	
	Cahto Tribe of the Laytonville Rancheria	Laytonville Rancheria	
	Cahuilla Band of Indians	Cahuilla Reservation	
	California Valley Miwok Tribe		
	Campo Band of Diegueno Mission Indians of the Campo Indian Reservation	Campo Indian Reservation	
	Capitan Grande Band of Diegueno Mission Indians of California (Barona Group of Capitan Grande Band of Mission Indians of the Barona Reservation) Viejas (Baron Long) Group of Capitan Grande Band of Mission Indians of the Viejas Reservation	Barona Reservation and Off-Reservation Trust Land	
		Capitan Grande Reservation	
		Viejas Reservation and Off-Reservation Trust Land	
	Cedarville Rancheria	Cedarville Rancheria and Off-Reservation Trust Land	
	Chemehuevi Indian Tribe of the Chemehuevi Reservation	Chemehuevi Reservation	
	Cher-Ae Heights Indian Community of the Trinidad Rancheria	Trinidad Rancheria and Off-Reservation Trust Land	
	Chicken Ranch Rancheria of Me-Wuk Indians of California	Chicken Ranch Rancheria and Off-Reservation Trust Land	
	Cloverdale Rancheria of Pomo Indians of California		
	Cold Springs Rancheria of Mono Indians of California	Cold Springs Rancheria	
	Coyote Valley Band of Pomo Indians of California	Coyote Valley Reservation	
	Dry Creek Rancheria Band of Pomo Indians	Dry Creek Rancheria and Off-Reservation Trust Land	
	Elem Indian Colony of Pomo Indians of the Sulphur Bank Rancheria	Sulphur Bank Rancheria	
	Elk Valley Rancheria	Elk Valley Rancheria and Off-Reservation Trust Land	
	Enterprise Rancheria of Maidu Indians of California	Enterprise Rancheria and Off-Reservation Trust Land	
	Ewiiaapaayp Band of Kumeyaay Indians	Ewiiaapaayp Reservation	
	Federated Indians of Graton Rancheria		
	Fort Bidwell Indian Community of the Fort Bidwell Reservation of California	Fort Bidwell Reservation and Off-Reservation Trust Land	
	Fort Independence Indian Community of Paiute Indians of the Fort Independence Reservation	Fort Independence Reservation	
	Fort Mojave Indian Tribe of Arizona, California & Nevada	Fort Mojave Reservation and Off-Reservation Trust Land	
	Greenville Rancheria	Greenville Rancheria	
	Grindstone Indian Rancheria of Wintun-Wailaki Indians of California	Grindstone Indian Rancheria	
	Guidiville Rancheria of California	Guidiville Rancheria and Off-Reservation Trust Land	
	Habematolel Pomo of Upper Lake	Upper Lake Rancheria	
	Hoopa Valley Tribe	Hoopa Valley Reservation	
	Hopland Band of Pomo Indians	Hopland Rancheria	
	Iipay Nation of Santa Ysabel	Santa Ysabel Reservation	
	Inaja Band of Diegueno Mission Indians of the Inaja and Cosmit Reservation	Inaja and Cosmit Reservation	
	Ione Band of Miwok Indians of California		
	Jackson Band of Miwuk Indians	Jackson Rancheria	
	Jamul Indian Village of California	Jamul Indian Village	
	Karuk Tribe	Karuk Reservation and Off-Reservation Trust Land	
	Kashia Band of Pomo Indians of the Stewarts Point Rancheria	Stewarts Point Rancheria and Off-Reservation Trust Land	
	Kletsel Dehe Band of Wintun Indians	Cortina Indian Rancheria	
	Koi Nation of Northern California		
	La Jolla Band of Luiseno Indians	La Jolla Reservation	
	La Posta Band of Diegueno Mission Indians of the La Posta Indian Reservation	La Posta Indian Reservation	
	Lone Pine Paiute-Shoshone Tribe	Lone Pine Reservation	
	Los Coyotes Band of Cahuilla and Cupeno Indians	Los Coyotes Reservation	
	Lytton Rancheria of California	Lytton Rancheria	
	Manchester Band of Pomo Indians of the Manchester Rancheria	Manchester-Point Arena Rancheria	
	Manzanita Band of Diegueno Mission Indians of the Manzanita Reservation	Manzanita Reservation and Off-Reservation Trust Land	
	Mechoopda Indian Tribe of Chico Rancheria		
	Mesa Grande Band of Diegueno Mission Indians of the Mesa Grande Reservation	Mesa Grande Reservation	
	Middletown Rancheria of Pomo Indians of California	Middletown Rancheria	
	Mooretown Rancheria of Maidu Indians of California	Mooretown Rancheria and Off-Reservation Trust Land	
	Morongo Band of Mission Indians	Morongo Reservation and Off-Reservation Trust Land	
	Northfork Rancheria of Mono Indians of California	North Fork Rancheria and Off-Reservation Trust Land	
	Pala Band of Mission Indians	Pala Reservation	
	Paskenta Band of Nomlaki Indians of California	Paskenta Rancheria	
	Pauma Band of Luiseno Mission Indians of the Pauma & Yuima Reservation	Pauma and Yuima Reservation	
	Pechanga Band of Luiseno Mission Indians of the Pechanga Reservation	Pechanga Reservation	
	Picayune Rancheria of Chukchansi Indians of California	Picayune Rancheria and Off-Reservation Trust Land	
	Pinoleville Pomo Nation	Pinoleville Rancheria	
	Pit River Tribe, California (includes XL Ranch, Big Bend, Likely, Lookout, Montgomery Creek, and Roaring Creek Rancherias)	Big Bend Rancheria	
		Likely Rancheria	
		Lookout Rancheria	
		Montgomery Creek Rancheria	
		Pit River Trust Land	
		Roaring Creek Rancheria	
		XL Ranch Rancheria	

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
California	Potter Valley Tribe		
	Quartz Valley Indian Community of the Quartz Valley Reservation of California	Quartz Valley Reservation and Off-Reservation Trust Land	
	Ramona Band of Cahuilla	Ramona Village	
	Redding Rancheria	Redding Rancheria	
	Redwood Valley or Little River Band of Pomo Indians of the Redwood Valley Rancheria	Redwood Valley Rancheria	
	Resighini Rancheria	Resighini Rancheria	
	Rincon Band of Luiseno Mission Indians of Rincon Reservation	Rincon Reservation and Off-Reservation Trust Land	
	Robinson Rancheria	Robinson Rancheria and Off-Reservation Trust Land	
	Round Valley Indian Tribes, Round Valley Reservation	Round Valley Reservation and Off-Reservation Trust Land	
	San Manuel Band of Mission Indians	San Manuel Reservation and Off-Reservation Trust Land	
	San Pasqual Band of Diegueno Mission Indians of California	San Pasqual Reservation and Off-Reservation Trust Land	
	Santa Rosa Band of Cahuilla Indians	Santa Rosa Reservation	
	Santa Rosa Indian Community of the Santa Rosa Rancheria	Santa Rosa Rancheria	
	Santa Ynez Band of Chumash Mission Indians of the Santa Ynez Reservation	Santa Ynez Reservation	
	Scotts Valley Band of Pomo Indians of California		
	Sherwood Valley Rancheria of Pomo Indians of California	Sherwood Valley Rancheria and Off-Reservation Trust Land	
	Shingle Springs Band of Miwok Indians, Shingle Springs Rancheria (Verona Tract)	Shingle Springs Rancheria and Off-Reservation Trust Land	
	Soboba Band of Luiseno Indians	Soboba Reservation and Off-Reservation Trust Land	
	Susanville Indian Rancheria	Susanville Indian Rancheria and Off-Reservation Trust Land	
	Sycuan Band of the Kumeyaay Nation	Sycuan Reservation and Off-Reservation Trust Land	
	Table Mountain Rancheria	Table Mountain Rancheria and Off-Reservation Trust Land	
	Tejon Indian Tribe		
	Timbisha Shoshone Tribe	Timbi-Sha Shoshone Reservation and Off-Reservation Trust Land	
	Tolowa Dee-ni' Nation	Smith River Rancheria and Off-Reservation Trust Land	
	Torres Martinez Desert Cahuilla Indians	Torres-Martinez Reservation	
	Tule River Indian Tribe of the Tule River Reservation	Tule River Reservation and Off-Reservation Trust Land	
	Tuolumne Band of Me-Wuk Indians of the Tuolumne Rancheria of California	Tuolumne Rancheria	
	Twenty-Nine Palms Band of Mission Indians of California	Twenty-Nine Palms Reservation and Off-Reservation Trust Land	
	United Auburn Indian Community of the Auburn Rancheria of California	Auburn Rancheria and Off-Reservation Trust Land	
	Utu Utu Gwaitu Paiute Tribe of the Benton Paiute Reservation	Benton Paiute Reservation and Off-Reservation Trust Land	
	Wilton Rancheria		
	Wiyot Tribe	Table Bluff Reservation	
	Yocha Dehe Wintun Nation	Rumsey Indian Rancheria	
	Yurok Tribe of the Yurok Reservation	Yurok Reservation	
Colorado	Southern Ute Indian Tribe of the Southern Ute Reservation	Southern Ute Reservation	2
	Ute Mountain Ute Tribe	Ute Mountain Reservation and Off-Reservation Trust Land	
Connecticut	Mashantucket Pequot Indian Tribe	Mashantucket Pequot Reservation and Off-Reservation Trust Land	2
	Mohegan Tribe of Indians of Connecticut	Mohegan Reservation	
Florida	Miccosukee Tribe of Indians	Miccosukee Reservation and Off-Reservation Trust Land	2
	Seminole Tribe of Florida	Big Cypress Reservation	
		Brighton Reservation	
		Coconut Creek Trust Land	
		Fort Pierce Reservation	
		Hollywood Reservation	
		Immokalee Reservation	
		Seminole (FL) Trust Land	
		Tampa Reservation	
Idaho	Coeur D'Alene Tribe	Coeur d'Alene Reservation	4
	Kootenai Tribe of Idaho	Kootenai Reservation and Off-Reservation Trust Land	
	Nez Perce Tribe	Nez Perce Reservation	
	Shoshone-Bannock Tribes of the Fort Hall Reservation	Fort Hall Reservation and Off-Reservation Trust Land	
Iowa	Sac & Fox Tribe of the Mississippi in Iowa	Sac and Fox/Meskwaki Settlement and Off-Reservation Trust Land	1
Kansas	Iowa Tribe of Kansas and Nebraska	Iowa (KS-NE) Reservation and Off-Reservation Trust Land	4
	Kickapoo Tribe of Indians of the Kickapoo Reservation in Kansas	Kickapoo (KS) Reservation	
		Kickapoo (KS) Reservation/Sac and Fox Nation Trust Land joint-use area	
	Prairie Band Potawatomi Nation	Prairie Band of Potawatomi Nation Reservation	
	Sac & Fox Nation of Missouri in Kansas and Nebraska	Kickapoo (KS) Reservation/Sac and Fox Nation Trust Land joint-use area	
		Sac and Fox Nation Reservation and Off-Reservation Trust Land	
Louisiana	Chitimacha Tribe of Louisiana	Chitimacha Reservation	4
	Coushatta Tribe of Louisiana	Coushatta Reservation and Off-Reservation Trust Land	
	Jena Band of Choctaw Indians	Jena Band of Choctaw Reservation	
	Tunica-Biloxi Indian Tribe	Tunica-Biloxi Reservation and Off-Reservation Trust Land	
Maine	Aroostook Band of Micmacs	Aroostook Band of Micmac Trust Land	4
	Houlton Band of Maliseet Indians	Houlton Maliseet Reservation and Off-Reservation Trust Land	
	Passamaquoddy Tribe	Indian Township Reservation	
		Passamaquoddy Trust Land	
		Pleasant Point Reservation	
	Penobscot Nation	Penobscot Reservation and Off-Reservation Trust Land	
Massachusetts	Mashpee Wampanoag Tribe	Mashpee Wampanoag Trust Land	2
	Wampanoag Tribe of Gay Head (Aquinnah)	Wampanoag-Aquinnah Trust Land	
Michigan	Bay Mills Indian Community	Bay Mills Reservation and Off-Reservation Trust Land	12
	Grand Traverse Band of Ottawa and Chippewa Indians	Grand Traverse Reservation and Off-Reservation Trust Land	
	Hannahville Indian Community	Hannahville Indian Community and Off-Reservation Trust Land	
	Keweenaw Bay Indian Community	L'Anse Reservation and Off-Reservation Trust Land	
		Ontonagon Reservation	
	Lac Vieux Desert Band of Lake Superior Chippewa Indians of Michigan	Lac Vieux Desert Reservation	
	Little River Band of Ottawa Indians	Little River Reservation and Off-Reservation Trust Land	
	Little Traverse Bay Bands of Odawa Indians	Little Traverse Bay Reservation and Off-Reservation Trust Land	
	Match-e-be-nash-she-wish Band of Pottawatomi Indians of Michigan	Reservation Trust Land	
	Nottawaseppi Huron Band of the Potawatomi	Huron Potawatomi Reservation and Off-Reservation Trust Land	
	Pokagon Band of Potawatomi Indians	Pokagon Reservation and Off-Reservation Trust Land	
	Saginaw Chippewa Indian Tribe of Michigan	Isabella Reservation and Off-Reservation Trust Land	
	Sault Ste. Marie Tribe of Chippewa Indians	Sault Ste. Marie Reservation and Off-Reservation Trust Land	

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Minnesota	Lower Sioux Indian Community in the State of Minnesota	Lower Sioux Indian Community	6
	Minnesota Chippewa Tribe	Bois Forte Reservation and Off-Reservation Trust Land	
		Fond du Lac Reservation and Off-Reservation Trust Land	
		Grand Portage Reservation and Off-Reservation Trust Land	
		Leech Lake Reservation and Off-Reservation Trust Land	
		Mille Lacs Reservation and Off-Reservation Trust Land	
		Minnesota Chippewa Trust Land	
		White Earth Reservation and Off-Reservation Trust Land	
	Prairie Island Indian Community in the State of Minnesota	Prairie Island Indian Community and Off-Reservation Trust Land	
	Red Lake Band of Chippewa Indians	Red Lake Reservation	
	Shakopee Mdewakanton Sioux Community of Minnesota	Land	
	Upper Sioux Community	Upper Sioux Community and Off-Reservation Trust Land	
Mississippi	Mississippi Band of Choctaw Indians	Mississippi Choctaw Reservation and Off-Reservation Trust Land	1
Missouri	Eastern Shawnee Tribe of Oklahoma		1
Montana	Assiniboine and Sioux Tribes of the Fort Peck Indian Reservation	Fort Peck Indian Reservation and Off-Reservation Trust Land	8
	Blackfeet Tribe of the Blackfeet Indian Reservation of Montana	Blackfeet Indian Reservation and Off-Reservation Trust Land	
	Chippewa Cree Indians of the Rocky Boy's Reservation	Rocky Boy's Reservation and Off-Reservation Trust Land	
	Confederated Salish and Kootenai Tribes of the Flathead Reservation	Flathead Reservation	
	Crow Tribe of Montana	Crow Reservation and Off-Reservation Trust Land	
	Fort Belknap Indian Community of the Fort Belknap Reservation of Montana	Fort Belknap Reservation and Off-Reservation Trust Land	
	Little Shell Tribe of Chippewa Indians of Montana		
	Northern Cheyenne Tribe of the Northern Cheyenne Indian Reservation	Northern Cheyenne Indian Reservation and Off-Reservation Trust Land	
Nebraska	Omaha Tribe of Nebraska	Omaha Reservation	4
	Ponca Tribe of Nebraska	Ponca (NE) Trust Land	
	Santee Sioux Nation	Santee Reservation	
	Winnebago Tribe of Nebraska	Winnebago Reservation and Off-Reservation Trust Land	
Nevada	Duckwater Shoshone Tribe of the Duckwater Reservation	Duckwater Reservation	17
	Ely Shoshone Tribe of Nevada	Ely Reservation	
	Fort McDermitt Paiute and Shoshone Tribes of the Fort McDermitt Indian Reservation	Fort McDermitt Indian Reservation	
	Las Vegas Tribe of Paiute Indians of the Las Vegas Indian Colony	Las Vegas Indian Colony	
	Lovelock Paiute Tribe of the Lovelock Indian Colony	Lovelock Indian Colony	
	Moapa Band of Paiute Indians of the Moapa River Indian Reservation	Moapa River Indian Reservation	
	Paiute-Shoshone Tribe of the Fallon Reservation and Colony	Fallon Paiute-Shoshone Colony and Off-Reservation Trust Land	
		Fallon Paiute-Shoshone Reservation and Off-Reservation Trust Land	
	Pyramid Lake Paiute Tribe of the Pyramid Lake Reservation	Pyramid Lake Paiute Reservation	
	Reno-Sparks Indian Colony	Reno-Sparks Indian Colony and Off-Reservation Trust Land	
	Shoshone-Paiute Tribes of the Duck Valley Reservation	Duck Valley Reservation	
	Summit Lake Paiute Tribe of Nevada	Summit Lake Reservation and Off-Reservation Trust Land	
	Te-Moak Tribe of Western Shoshone Indians of Nevada (Four constituent bands: Battle Mountain Band; Elko Band; South Fork Band; and Wells Band)	Battle Mountain Reservation and Off-Reservation Trust Land	
		Elko Colony	
		South Fork Reservation and Off-Reservation Trust Land	
		Wells Colony	
	Walker River Paiute Tribe of the Walker River Reservation	Walker River Reservation	
	Washoe Tribe of Nevada & California (Carson Colony, Dresslerville Colony, Woodfords Community, Stewart Community, & Washoe Ranches)	Carson Colony	
		Dresslerville Colony	
		Stewart Community	
		Washoe Ranches Trust Land	
		Woodfords Community	
	Winnemucca Indian Colony of Nevada	Winnemucca Indian Colony	
	Yerington Paiute Tribe of the Yerington Colony & Campbell Ranch	Campbell Ranch	
		Yerington Colony	
	Yomba Shoshone Tribe of the Yomba Reservation	Yomba Reservation	
New Mexico	Jicarilla Apache Nation, New Mexico	Jicarilla Apache Nation Reservation and Off-Reservation Trust Land	21
	Mescalero Apache Tribe of the Mescalero Reservation	Mescalero Reservation	
	Ohkay Owingeh	Ohkay Owingeh	
	Pueblo of Acoma	Acoma Pueblo and Off-Reservation Trust Land	
	Pueblo of Cochiti	Pueblo de Cochiti	
	Pueblo of Isleta	Isleta Pueblo	
	Pueblo of Jemez	Jemez Pueblo	
	Pueblo of Laguna	Laguna Pueblo and Off-Reservation Trust Land	
	Pueblo of Nambe	Nambe Pueblo and Off-Reservation Trust Land	
	Pueblo of Picuris	Picuris Pueblo	
	Pueblo of Pojoaque	Pueblo of Pojoaque and Off-Reservation Trust Land	
	Pueblo of San Felipe	San Felipe Pueblo	
		San Felipe Pueblo/Santa Ana Pueblo joint-use area	
		San Felipe Pueblo/Santo Domingo Pueblo joint-use area	
	Pueblo of San Ildefonso	San Ildefonso Pueblo and Off-Reservation Trust Land	
	Pueblo of Sandia	Sandia Pueblo	
	Pueblo of Santa Ana	Santa Ana Pueblo	
		San Felipe Pueblo/Santa Ana Pueblo joint-use area	
	Pueblo of Santa Clara	Santa Clara Pueblo and Off-Reservation Trust Land	
	Pueblo of Taos	Taos Pueblo and Off-Reservation Trust Land	
	Pueblo of Tesuque	Tesuque Pueblo and Off-Reservation Trust Land	
	Pueblo of Zia	Zia Pueblo and Off-Reservation Trust Land	
	Santo Domingo Pueblo	Santo Domingo Pueblo	
		San Felipe Pueblo/Santo Domingo Pueblo joint-use area	
	Zuni Tribe of the Zuni Reservation	Zuni Reservation and Off-Reservation Trust Land	
New York	Cayuga Nation		8
	Oneida Indian Nation	Oneida Nation Reservation	
	Onondaga Nation	Onondaga Nation Reservation	
	Saint Regis Mohawk Tribe	St. Regis Mohawk Reservation	
	Seneca Nation of Indians	Allegany Reservation	
		Cattaraugus Reservation	
		Oil Springs Reservation	

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
New York	Shinnecock Indian Nation		
	Tonawanda Band of Seneca	Tonawanda Reservation	
	Tuscarora Nation	Tuscarora Nation Reservation	
North Carolina	Eastern Band of Cherokee Indians	Eastern Cherokee Reservation	1
North Dakota	Spirit Lake Tribe	Spirit Lake Reservation	4
	Standing Rock Sioux Tribe of North & South Dakota	Standing Rock Reservation	
	Three Affiliated Tribes of the Fort Berthold Reservation	Fort Berthold Reservation	
	Turtle Mountain Band of Chippewa Indians of North Dakota	Turtle Mountain Reservation and Off-Reservation Trust Land	
Oklahoma	Absentee-Shawnee Tribe of Indians of Oklahoma		37
	Alabama-Quassarte Tribal Town		
	Apache Tribe of Oklahoma		
	Caddo Nation of Oklahoma		
	Cherokee Nation		
	Cheyenne and Arapaho Tribes		
	Citizen Potawatomi Nation		
	Comanche Nation		
	Delaware Nation		
	Delaware Tribe of Indians		
	Fort Sill Apache Tribe of Oklahoma	Fort Sill Apache Indian Reservation	
	Iowa Tribe of Oklahoma		
	Kaw Nation		
	Kialegee Tribal Town		
	Kickapoo Tribe of Oklahoma		
	Kiowa Indian Tribe of Oklahoma		
	Miami Tribe of Oklahoma		
	Modoc Nation		
	Otoe-Missouria Tribe of Indians		
	Ottawa Tribe of Oklahoma		
	Pawnee Nation of Oklahoma		
	Peoria Tribe of Indians of Oklahoma		
	Ponca Tribe of Indians of Oklahoma		
	Quapaw Nation		
	Sac & Fox Nation		
	Seneca–Cayuga Nation		
	Shawnee Tribe		
	The Chickasaw Nation		
	The Choctaw Nation of Oklahoma		
	The Muscogee (Creek) Nation		
	The Osage Nation	Osage Reservation	
	The Seminole Nation of Oklahoma		
	Thlopthlocco Tribal Town		
	Tonkawa Tribe of Indians of Oklahoma		
	United Keetoowah Band of Cherokee Indians in Oklahoma		
	Wichita and Affiliated Tribes (Wichita, Keechi, Waco, & Tawakonie)		
	Wyandotte Nation		
Oregon	Burns Paiute Tribe	Burns Paiute Indian Colony and Off-Reservation Trust Land	9
	Confederated Tribes of Siletz Indians of Oregon	Siletz Reservation and Off-Reservation Trust Land	
	Confederated Tribes of the Coos, Lower Umpqua and Siuslaw Indians	Coos, Lower Umpqua, and Siuslaw Reservation and Off-Reservation Trust Land	
	Confederated Tribes of the Grand Ronde Community of Oregon	Grand Ronde Community and Off-Reservation Trust Land	
	Confederated Tribes of the Umatilla Indian Reservation	Umatilla Reservation and Off-Reservation Trust Land	
	Confederated Tribes of the Warm Springs Reservation of Oregon[f]	Warm Springs Reservation and Off-Reservation Trust Land	
	Coquille Indian Tribe	Coquille Reservation	
	Cow Creek Band of Umpqua Tribe of Indians	Cow Creek Reservation and Off-Reservation Trust Land	
	Klamath Tribes	Klamath Reservation	
Rhode Island	Narragansett Indian Tribe	Narragansett Reservation	1
South Carolina	Catawba Indian Nation	Catawba Reservation and Off-Reservation Trust Land	1
South Dakota	Cheyenne River Sioux Tribe of the Cheyenne River Reservation	Cheyenne River Reservation and Off-Reservation Trust Land	8
	Crow Creek Sioux Tribe of the Crow Creek Reservation	Crow Creek Reservation	
	Flandreau Santee Sioux Tribe of South Dakota	Flandreau Reservation	
	Lower Brule Sioux Tribe of the Lower Brule Reservation	Lower Brule Reservation and Off-Reservation Trust Land	
	Oglala Sioux Tribe	Pine Ridge Reservation	
	Rosebud Sioux Tribe of the Rosebud Indian Reservation	Rosebud Indian Reservation and Off-Reservation Trust Land	
	Sisseton-Wahpeton Oyate of the Lake Traverse Reservation	Lake Traverse Reservation and Off-Reservation Trust Land	
	Yankton Sioux Tribe of South Dakota	Yankton Reservation	
Texas	Alabama-Coushatta Tribe of Texas	Alabama-Coushatta Reservation and Off-Reservation Trust Land	3
	Kickapoo Traditional Tribe of Texas	Kickapoo (TX) Reservation and Off-Reservation Trust Land	
	Ysleta del Sur Pueblo	Ysleta del Sur Pueblo and Off-Reservation Trust Land	
Utah	Confederated Tribes of the Goshute Reservation	Goshute Reservation	5
	Northwestern Band of the Shoshone Nation	Northwestern Shoshone Reservation	
	Paiute Indian Tribe of Utah (Cedar Band of Paiutes, Kanosh Band of Paiutes,	Paiute (UT) Reservation	
	Skull Valley Band of Goshute Indians of Utah	Skull Valley Reservation	
	Ute Indian Tribe of the Uintah & Ouray Reservation	Uintah and Ouray Reservation and Off-Reservation Trust Land	
Virginia	Chickahominy Indian Tribe		7
	Chickahominy Indian Tribe—Eastern Division		
	Monacan Indian Nation		
	Nansemond Indian Nation		
	Pamunkey Indian Tribe		
	Rappahannock Tribe, Inc.		
	Upper Mattaponi Tribe		

2.1. Table 1. (continued).

State[a]	Federally Recognized Indian Tribe[b]	Federal Indian Reservation and/or Off reservation trust land[c]	Sub-total Federally Recognized Indian Tribes[f]
Washington	Confederated Tribes and Bands of the Yakama Nation[f]	Yakama Nation Reservation and Off-Reservation Trust Land	29
	Confederated Tribes of the Chehalis Reservation	Chehalis Reservation and Off-Reservation Trust Land	
	Confederated Tribes of the Colville Reservation	Colville Reservation and Off-Reservation Trust Land	
	Cowlitz Indian Tribe	Cowlitz Reservation	
	Hoh Indian Tribe	Hoh Indian Reservation and Off-Reservation Trust Land	
	Jamestown S'Klallam Tribe	Jamestown S'Klallam Reservation and Off-Reservation Trust Land	
	Kalispel Indian Community of the Kalispel Reservation	Kalispel Reservation and Off-Reservation Trust Land	
	Lower Elwha Tribal Community	Lower Elwha Reservation and Off-Reservation Trust Land	
	Lummi Tribe of the Lummi Reservation	Lummi Reservation	
	Makah Indian Tribe of the Makah Indian Reservation	Makah Indian Reservation	
	Muckleshoot Indian Tribe	Muckleshoot Reservation and Off-Reservation Trust Land	
	Nisqually Indian Tribe	Nisqually Reservation	
	Nooksack Indian Tribe	Nooksack Reservation and Off-Reservation Trust Land	
	Port Gamble S'Klallam Tribe	Port Gamble Reservation and Off-Reservation Trust Land	
	Puyallup Tribe of the Puyallup Reservation	Puyallup Reservation and Off-Reservation Trust Land	
	Quileute Tribe of the Quileute Reservation	Quileute Reservation	
	Quinault Indian Nation	Quinault Reservation	
	Samish Indian Nation		
	Sauk-Suiattle Indian Tribe	Sauk-Suiattle Reservation	
	Shoalwater Bay Indian Tribe of the Shoalwater Bay Indian Reservation	Shoalwater Bay Indian Reservation and Off-Reservation Trust Land	
	Skokomish Indian Tribe	Skokomish Reservation and Off-Reservation Trust Land	
	Snoqualmie Indian Tribe	Snoqualmie Reservation and Off-Reservation Trust Land	
	Spokane Tribe of the Spokane Reservation	Spokane Reservation and Off-Reservation Trust Land	
	Squaxin Island Tribe of the Squaxin Island Reservation	Squaxin Island Reservation and Off-Reservation Trust Land	
	Stillaguamish Tribe of Indians of Washington	Stillaguamish Reservation and Off-Reservation Trust Land	
	Suquamish Indian Tribe of the Port Madison Reservation	Port Madison Reservation	
	Swinomish Indian Tribal Community	Swinomish Reservation and Off-Reservation Trust Land	
	Tulalip Tribes of Washington	Tulalip Reservation and Off-Reservation Trust Land	
	Upper Skagit Indian Tribe	Upper Skagit Reservation and Off-Reservation Trust Land	
Wisconsin	Bad River Band of the Lake Superior Tribe of Chippewa Indians of the Bad River	Bad River Reservation	11
	Forest County Potawatomi Community	Forest County Potawatomi Community and Off-Reservation Trust Land	
	Ho-Chunk Nation of Wisconsin	Ho-Chunk Nation Reservation and Off-Reservation Trust Land	
	Lac Courte Oreilles Band of Lake Superior Chippewa Indians of Wisconsin	Lac Courte Oreilles Reservation and Off-Reservation Trust Land	
	Lac du Flambeau Band of Lake Superior Chippewa Indians of the Lac du Flambeau Reservation of Wisconsin	Lac du Flambeau Reservation	
	Menominee Indian Tribe of Wisconsin	Menominee Reservation and Off-Reservation Trust Land	
	Oneida Nation	Oneida (WI) Reservation and Off-Reservation Trust Land	
	Red Cliff Band of Lake Superior Chippewa Indians of Wisconsin	Red Cliff Reservation and Off-Reservation Trust Land	
	Sokaogon Chippewa Community	Sokaogon Chippewa Community and Off-Reservation Trust Land	
	St. Croix Chippewa Indians of Wisconsin	St. Croix Reservation and Off-Reservation Trust Land	
	Stockbridge Munsee Community	Stockbridge Munsee Community and Off-Reservation Trust Land	
Wyoming	Eastern Shoshone Tribe of the Wind River Reservation	Wind River Reservation and Off-Reservation Trust Land	2
	Northern Arapaho Tribe of the Wind River Reservation	Wind River Reservation and Off-Reservation Trust Land	

[a]According to the United States Department of the Interior. (n.d.). Tribal Leaders Directory. Indian Affairs. Retrieved July 19, 2021, from https://www.bia.gov/bia/ois/tribal-leaders-directory/

[b]According to Indian Entities Recognized and Eligible to Receive Services From the United States Bureau of Indian Affairs; Correction, 86 FR 18552 (2021) and Indian Entities Recognized by and Eligible to Receive Services From the United States Bureau of Indian Affairs, 86 FR 7554 (2021).

[c]According to the United States Census Bureau. (2020). 2020 TIGER/Line Shapefiles [Data file]. https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2020&layergroup=American+Indian+Area+Geography

[d]Arctic Village and Village of Venetie are part of the affiliate Native Village of Venetie Tribal Government. [e]Saint George Island and Saint Paul Island are part of the Affiliate Pribilof Islands Aleut Communities of St. Paul & St. George Islands.

[f]The relation of Celilo Village with an especific FRIT could not be determined. Most residents of Celilo Village are members of either the Confederated Tribes and Bands of the Yakama Nation or Confederated Tribes of the Warm Springs Reservation of Oregon.

2.2. Table 2. Search criteria used on the ECHO website to obtain wastewater facilities within or related to any Tribal Land with a permit in any status. Fields not listed were left as default.

Search criteria used on the ECHO website	
Search Type	Water
Community – Indian Country/Tribal Land	
ICIS Tribal Land Flag	Yes
FRS Tribal Land Code	Yes
On or Near Spatial Tribal Boundary	Within Spatial Boundary
Tribe	No Selection
Find Facilities That Match	Any Tribal Options
Facility Characteristics	
Permit Status	Effective, Expired, Administratively Continued, Pending, Retired
Permit Type	NPD - NPDES Individual Permit, GPC - General Permit Covered Facility, UFT - Unpermitted Facility
Permit Components	POTW [a]

[a]According to EPA, Facility Type is set to "POTW" if the permit has a "POTW" permit component and the linked facility has a "Facility Type of Ownership" value that is one of the following: County Government (CNG), Municipality (CTG), Municipal or Water District (MWD), Mixed Ownership (e.g., Public/Private) (MXO), School District (SDT), State Government (STF), Tribal Government (TRB).

2.3. Table 3. Description of the results fields after the search of wastewater facilities on the ECHO website using the criteria listed in supplementary information (Appendix B - SI 2.2. Table 2).

Field No.	Result page field name	Data download file field name	Description[a]
1	Facility Name	CWPName	Company or permit holder name, as maintained in the ICIS-NPDES database.
2	NPDES ID	SourceID	A unique 9-character ID assigned for each permit within the National Pollutant Discharge Elimination System (NPDES) program. The ID may contain both letters and numbers and often begins with the two-letter abbreviation for the state in which the facility is permitted.
3	Street Address	CWPStreet	Street address where facility is located, as maintained in the ICIS-NPDES database.
4	City	CWPCity	City where facility is located, as maintained in the ICIS-NPDES database.
5	State	CWPState	State where facility is located, as maintained in the ICIS-NPDES database.
6	EPA Region	CWPEPARegion	The EPA region where the facility is located.
7	FRS Tribal Land Code	FacIndianCntryFlg	Displays “Y” if a facility is flagged as being located in Indian Country, or “N” if a facility is not located in Indian Country, based on information from the EPA's Facility Registry Service (FRS).
8	ICIS Tribal Land Flag	CWPIndianCntryFlg	Displays “Y” if a facility is flagged as being located in Indian Country, or “N” if a facility is not located in Indian Country, based on information from the EPA's Integrated Compliance Information System (ICIS).
9	Within Spatial Tribal Boundary	FacIndianSpatialFlg	Displays “Y” if a facility is located within 25 miles of a Tribal spatial boundary, or “N” if a facility is not located within or near a Tribal spatial boundary, as defined by the U.S. Census Bureau Tribal boundary layer data for tribes in the lower 48 states and Bureau of Land Management Alaska State Office data for tribes in Alaska.
10	FRS Spatially Derived Tribe	FacDerivedTribes	The tribes or Tribal territories located within 25 miles of the facility's location compared to the U.S. Census Bureau Tribal boundary layer data for tribes in the lower 48 states and Bureau of Land Management Alaska State Office data for tribes in Alaska.
11	Latitude	FacLat	Displays the latitude of the facility or permit holder as maintained in the program data system.
12	Longitude	FacLong	Displays the longitude of the facility or permit holder as maintained in the program data system.
13	Facility Design Flow (MGD)	CWPTotalDesignFlowNmbr	The amount of wastewater flow, in million gallons per day (MGD), that the permitted facility is designed to accommodate, as entered in ICIS-NPDES.
14	Actual Average Facility Flow (MGD)	CWPActualAverageFlowNmbr	The actual amount of wastewater flow at the facility at the time of the permit application, in million gallons per day (MGD), as entered in ICIS-NPDES.
15	Facility Type	CWPFacilityTypeIndicator	The facility ownership classification in ICIS-NPDES.
16	NPDES IDs	NPDESIDs	Displays all NPDES IDs associated with a FRS ID.

[a]United States Environmental Protection Agency. (2022, August 9). Search Results Help—Wastewater/Stormwater/Biosolids. Enforcement and Compliance History Online. https://echo.epa.gov/help/facility-search/water-search-results-help.

2.4. Table 4. Output information from the ECHO database using the echor R package (Schramm, 2021) for permitted wastewater facilities.

Schramm, M. (2021). *Introduction to echor*. https://cran.r-project.org/web/packages/echor/vignettes/introduction.html

ColumnID	ObjectName	Description
1	CWPName	Facility or permit holder name, as maintained in ICIS-NPDES.
2	SourceID	Unique Identifier assigned by EPA.
3	CWPStreet	Facility street address
4	CWPCity	City in which the facility is located.
5	CWPState	Facility location - two-digit state abbreviation.
11	CWPEPARegion	The EPA region where the facility is located. EPA has 10 regional offices that execute programs within several states and territories.
16	FacIndianCntryFlg	Flag showing Y/N whether the facility is located in Indian Country.
17	CWPIndianCntryFlg	Displays Y if a facility is located in Indian country.
18	FacIndianSpatialFlg	Returns “Y” if a facility is located within a Tribal spatial boundary as defined by the U.S. Census Bureau 2010 Tribal boundary layer data for tribes in the lower 48 states and Bureau of Land Management Alaska State Office data for native villages in Alaska. Returns “N” if a facility is not located within a Tribal or native Alaskan village area.
19	FacDerivedTribes	The tribes or Tribal territories located within 25 miles of the facility's location.
21	CWPSICCodes	Indicates the facility's or permit's primary Standard Industrial Classification (SIC) Code.
22	CWPNAICSCodes	Indicates the facility's or permit's primary North American Industry Classification System (NAICS) Code.
23	FacLat	The latitude of the facility in decimal degrees expressed using the NAD83 horizontal datum. The coordinate comes from the FRS EPA Locational Reference Tables (LRT) file which represents the most accurate value for the facility based on the available spatial metadata.
24	FacLong	The longitude of the facility in decimal degrees expressed using the NAD83 horizontal datum. The coordinate comes from the FRS EPA Locational Reference Tables (LRT) file which represents the most accurate value for the facility based on the available spatial metadata.
25	CWPTotalDesignFlowNmbr	The amount of wastewater flow in million gallons per day (MGD) that the facility is designed for.
26	CWPActualAverageFlowNmbr	The actual amount of the facility's wastewater flow measured in million gallons per day (MGD).
27	CWPFacilityTypeIndicator	Each National Pollutant Discharge Elimination System (NPDES) permit is defined by the program office as a Major or non-major discharger. This field also indicates the permit type.
60	CWPPermitStatusDesc	The current stage/status in the NPDES permit life cycle.
65	CWPEffectiveDate	Date (MM/DD/YYYY) that the permit became effective.
66	CWPTerminationDate	Date (MM/DD/YYYY) that the permit was terminated.
69	PermitComponents	Indicates the permit component(s) associated with the NPDES Permit Program Area.
77	NPDESIDs	Clean Water Act ID from the ICIS-NPDES (Integrated Compliance Information System - National Pollutant Discharge Elimination System)
203	CensusBlockGroup	A geographic unit used by the United States Census Bureau, generally defined to contain between 600 and 3,000 people.

2.5. Table 5. Standard Industrial Classification (SIC) Code of the studied facilities.

No.	SIC Code	Description[a]
1	4952	Sewerage Systems
2	6515	Operators of Residential Mobile Home Sites
3	7011	Hotels and Motels
4	8211	Elementary and Secondary Schools
5	8221	Colleges, Universities, and Professional Schools
6	8222	Junior Colleges and Technical Institutes
7	8299	Schools and Educational Services, Not Elsewhere Classified
8	9223	Correctional Institutions
9	Blank	

[a]According to United States Department of Labor. (n.d.). Standard Industrial Classification (SIC) System Search. Occupational Safety and Health Administration. Retrieved October 4, 2022, from https://www.osha.gov/data/sic-search?field_sic_number_value=9223&title_and_body=

2.6. Table 6. Facility classification in eight categories based on location, race data, and name.

Classification		**Outside Federal Indian Reservation and/or ORTL**	**Inside Federal Indian Reservation and/or ORTL**	**Sub- total**	**Total**
Not-Tribal serving	General	333	260		**593**
Tribal serving	Community	46	210	256	**327**
	School	12	20	32	
	Casino	7	32	39	
Total		**398**	**522**		**920**

2.7. Table 7. Tribal serving facilities (Native American population > 50%) listed according to their location (inside or outside a Federal Indian Reservation and/or ORTL) and whom they serve (community, school or casino).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
1	AK0053813	Metlakatla Sewer Treatment Plant
2	AZ0023078	Unknown
3	AZ0024058	Whiteriver Sewage Lagoons
4	AZ0024589	Hon-Dah Regional WWTF
5	AZ0024619	Upper Village Of Moenkopi WWTF
6	COG587101	Towaoc Lagoon 2
7	COG587103	Towaoc Lagoon 1
8	COG651002	Towaoc Wastewater Treatment System No. 1
9	FLR10I62B	Abiaki Tribal Historic Preservation Office Building
10	ID0028347	Nez Perce Tribe - Lapwai Valley WWTP
11	KS0095206	Kickapoo Tribe In Kansas - Housing Site #1
12	ME0100773	Passamaquoddy WWTF
13	ME0101311	Penobscot Indian Nation
14	MN0025887	Usdi Bia Grnd Prtg Ind Res
15	MN0049794	Ogema
16	MN0058611	East Lake Sewage Lagoon
17	MN0059439	Ponsford WWSL
18	MN0059447	Nett Lake WWSL
19	MN0064165	Naytahwaush WWSL
20	MN0064173	White Earth WWSL
21	MN0064637	Mille Lacs WWTF
22	MN0068438	Big Rice Lake WWSL
23	MS0040924	Tucker Wastewater Treatment Facility
24	MS0043494	Standing Pine WWTF
25	MS0053503	Pearl River Wastewater Treatment Plant
26	MT0021890	Lodge Grass- Town Of
27	MT0029360	Lame Deer Lagoon
28	MT0030538	Crow Agency WTP
29	MT0030571	Wolf Point, City Of
30	MT0030597	Poplar, Town Of
31	MT0030775	Blackfeet Community Water Plant
32	MTDW0003I	Two Medicine Water Co.
33	MTG589006	Browning, Town Of
34	MTG589009	Absaalooke Water And Wastewater Authority - Crow Agency Lagoon

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
35	MTG589020	East Glacier Lagoons-Two Medicine Water
36	MTG589101	Blackfeet Utilities Commission
37	MTG589103	St. Mary Lagoons
38	MTG589104	Browning Lagoon
39	MTG589105	Last Starr WWTF
40	MTG589501	Wolf Point- City Of
41	MTG589502	Brockton, Town Of
42	MTG589601	Ashland Lagoons
43	MTG589602	Busby Lagoons
44	MTG589603	Muddy Cluster Lagoons
45	MTG589604	Birney Lagoons
46	MTG589701	Agency Lagoon
47	MTG589702	Lower Dry Fork Lagoon
48	MTG589703	Azure Lagoon
49	MTG589704	Blue Lagoon
50	MTG589705	Multi-Community Lagoon
51	MTG651005	Blackfeet Utilities, Heart Butte Lagoon
52	MTG651008	Pablo Water And Sewer District
53	MTG651009	Agency Lagoon
54	MTG651012	Browning, Town Of
55	MTG651013	Agency Wastewater Lagoon System
56	MTU000058	Town Of Pryor WWTF
57	NC0052469	Cherokee Wastewater Treatment Plant
58	ND0030970	Fort Yates WTP
59	ND0031143	Riverview Estates Wastewater Treatment Facility
60	NDG323281	Selfridge City Of
61	NDG589101	White Shield Wastewater Treatment Lagoon
62	NDG589103	Twin Buttes Wastewater Treatment Facility
63	NDG589106	Four Bears Wastewater Treatment System
64	NDG589107	Mandaree Wastewater Treatment Lagoons
65	NDG589108	New Town Water Resource Recovery Facility
66	NDG589109	Parshall Wastewater Treatment Facility
67	NDG589201	West Acres Wastewater Treatment Lagoons
68	NDG589202	St Michaels Wastewater Treatment Lagoon
69	NDG589205	Tokio Wastewater Treatment Lagoons
70	NDG589301	Mclauhglin Wastewater Treatment Facility
71	NDG589305	Porcupine Community Lagoon System
72	NDG589311	Kenel Lagoon System

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
73	NDG589312	Fort Yates Lagoon System
74	NDG589313	Bear Soldier Lagoon System
75	NDG589314	Wakpala Lagoon System
76	NDG589315	Cannonball Lagoon System
77	NDG589401	City Of Belcourt
78	NDG589402	East Dunseith Wastewater Treatment Lagoons
79	NDG589403	Green Acre Wastewater Treatment Lagoons
80	NDG589404	Sky Dancer Wastewater Treatment Lagoons
81	NDG589406	Shell Valley Wastewater Treatment Lagoons
82	NDG589407	St Marys Wastewater Treatment Lagoons
83	NDG589408	Turtle Mountain Public Utilities Commission
84	NDG589411	Belcourt Recreation Area And Manufacturing Plant Wastewater Treatment Facility
85	NE0061263	Omaha Tribal Utility Comm
86	NE0113212	Winnebago Wastewater Treatment Facility
87	NE0132641	Village Of Santee Wastewater
88	NE0138932	Village Of Walthill WWTF
89	NM0030520	Dulce Wastewater Treat.Plt.
90	NM0030660	Mescalero Apache Wastewater
91	NM0031011	San Felipe Pueblo Wastewater Treatment Plant
92	NN0020265	Chinle WWTF
93	NN0020281	Kayenta WWTF
94	NN0020290	Tuba City WWTP
95	NN0020621	Shiprock WWTF
96	NN0021555	Window Rock WWTF
97	NN0022195	Ganado WWTP
98	NN0024228	Pinon WWTF
99	NN0030325	Pinehill WWTF
100	OR0032638	Confederated Tribes Of Warm Springs - Warm Springs WWTP
101	SD0020192	Eagle Butte WWTF
102	SD0020800	Lower Brule Sioux Tribe
103	SD0021601	City Of Martin
104	SD0022004	Lake Andes, City Of
105	SD0022713	City Of Batesland
106	SD0022756	Peever - Town Of
107	SD0027537	Whitehorse WWTF
108	SD0028637	Southern Missouri Recycling & Waste Management District
109	SD0034436	Unknown
110	SD0034614	Sicangu Village WWTP

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
111	SD0034631	Lower Brule Water Trmnt Plnt
112	SDG584001	Lower Brule Rural Water Syst.
113	SDG589102	Ridgeview Wastewater Treatment Facility
114	SDG589103	Habitat For Humanity
115	SDG589104	Green Grass Wastewater Treatment Facility
116	SDG589105	Bear Creek Wastewater Treatment Facility
117	SDG589106	Blackfoot Wastewater Treatment Facility
118	SDG589107	Bridger Wastewater Treatment Facility
119	SDG589108	Cherry Creek Wastewater Treatment Facility
120	SDG589109	Iron Lightning Wastewater Facility
121	SDG589110	La Plant Wastewater Treatment Facility
122	SDG589111	Whitehorse Wastewater Facility
123	SDG589112	Thunder Butte Wastewater Treatment Facility
124	SDG589113	Swiftbird Wastewater Facility
125	SDG589114	Red Scaffold Wastewater Facility
126	SDG589115	Foxridge Wastewater Treatment Facility
127	SDG589116	Dupree Wastewater Treatment Facility
128	SDG589120	Mni Waste Elk Pasture WWTF
129	SDG589201	Big Bend Lagoon System
130	SDG589202	Crow Creek Lagoon System
131	SDG589203	Fort Thompson Lagoon System
132	SDG589204	Stephan Lagoon System
133	SDG589205	Fort Thompson-East
134	SDG589401	West Brule Lagoon North
135	SDG589402	West Brule Lagoon South
136	SDG589501	Allen Lagoon
137	SDG589502	Evergreen Lagoon
138	SDG589503	Kyle Community Lagoon
139	SDG589504	Manderson Community Lagoon
140	SDG589505	Martin Sunrise Housing WW Lagoon
141	SDG589506	Oglala Community Lagoon
142	SDG589507	Pine Ridge Community Lagoon
143	SDG589508	Potato Creek Community Lagoon
144	SDG589510	Sharp'S Corner Lagoon System
145	SDG589511	Wakpamni Community Lagoon
146	SDG589512	Wolf Creek Community Lagoon
147	SDG589513	Wounded Knee Community Lagoon
148	SDG589514	Wanblee (Osha) Lagoon

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
149	SDG589525	Porcupine Community Lagoon
150	SDG589528	Lakota Fund Housing Lagoon
151	SDG589601	Mission - Antelope Sanitation Facility
152	SDG589602	Black Pipe/Norris WWTF
153	SDG589605	Ideal Community
154	SDG589606	Okreek Community Lagoon
155	SDG589607	Parmelee Community
156	SDG589608	Rosebud Community
157	SDG589609	Spring Creek, Community Of
158	SDG589610	Soldier Creek - South
159	SDG589612	Two Strikes Community
160	SDG589616	City Of St Francis Wastewater Treatment Facility
161	SDG589617	Soldier Creek - North
162	SDG589619	Rosebud Sioux Tribe Water And Sewer
163	SDG589701	Lake Andes Housing
164	SDG589702	Marty Community Wastewater Lagoon
165	SDG589803	Old Agency Village WWTF
166	SDG589806	Long Hollow Water System
167	SDG589807	Peever Flats Housing WWTP
168	SDG589808	Enemy Swin Housing WWTP
169	SDG589809	Finley Heights Water System
170	SDG826743	Ravinia, Town Of
171	SDU000019	Two Strikes, Community Of
172	SDU000020	Springs Creek, Community Of
173	SDU000021	Parmelee, Town Of
174	SDU000024	Horse Creek, Community Of
175	SDU000025	White Horse, Community Of
176	SDU000026	Soldier Creek, Community Of
177	SDU000027	Rosebud, Community Of
178	SDU000028	Okreek, Community Of
179	SDU000030	Ideal, Community Of
180	SR0240281	St.Regis Mohawk Tribe WWTP
181	TX0052809	Alabama-Coushatta Tribe Of Tx
182	UTG589401	Fort Duchesne Wastewater Treatment Facility
183	UTG589402	Yellowstone Wastewater Treatment Facility
184	UTG589403	Sunshine Subdivision WWTF
185	UTG589404	Hilltop Sewage Lagoons
186	UTG589405	Whiterocks Sewage Lagoons

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.A. Community		
187	UTG589406	Randlett Sewage Lagoons
188	WA0023213	Makah Tribal Counsel - Makah WWTP
189	WA0023434	Quinault Indian Nation - Taholah Village WWTP
190	WA0023442	Quinault Indian Nation - Queets Village WWTP
191	WA0025585	Quinault Indian Nation
192	WA0025666	Lummi Indian Business Council - Gooseberry Point WWTP
193	WA0025704	Wellpinit Sanitation & Maint F
194	WA0026280	Quileute Natural Resources
195	WA0026603	Quinault Indian Nation - Moclips River Estates WWTP
196	WA0026727	Lummi Tribal Sewer And Water District - Kwina Road Mbr WWTP
197	WI0036544	Bad River Band
198	WI0036579	Bad River Indian Reservation
199	WI0036587	Bad River Band
200	WI0046868	Menominee Tribal Enterprise
201	WI0049727	Red Cliff Band WWTF
202	WI0073041	Lac Courte Oreilles
203	WIG012679	Lincoln Avenue Capital Site
204	WINOEIA04	Avs All In One
205	WYG589101	Fort Washakie Hotsprings Lagoon
206	WYG589102	Great Plains Lagoon
207	WYG589103	Wastewater Treatment Lagoon
208	WYG589105	Mill Creek Lagoon
209	WYG589106	Ethete Wastewater Lagoon
210	WYG589107	Beaver Creek Lagoons
1.B. School		
211	AZ0022501	Unknown
212	MTG589202	Saint Labre Indian School
213	NC0089907	Jacob Cornsilk Complex
214	ND0031160	Mha Interpretive Center
215	NDG589206	Four Winds Tate Topa Tribal School
216	NDG589307	Smee School District 15-3
217	NDG589409	Dunseith North Head Start Center Wastewater Treatment Center
218	NDG589410	Ojibwa Millennium School Wastewater Treatment Lagoons
219	SD0025453	Unknown
220	SDG589307	Smee School District #15-3
221	SDG589515	American Horse School
222	SDG589516	Crazy Horse School
223	SDG589517	Wolf Creek School WW

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.B. School		
224	SDG589518	Rocky Ford School
225	SDG589520	Little Wound School
226	SDG589521	Loneman School Corporation
227	SDG589523	Wanblee Headstart School
228	SDG589524	Porcupine Day School
229	SDG589526	Red Cloud Indian School
230	SDG589527	Oglala Lakota College
1.C. Casino		
231	CA0004009	Chukchansi Gold Resort&Casino
232	CA0005241	Dry Creek Rancheria WWTF
233	CA0050008	Santa Ynez Band/Chumash WWTP
234	CA0084280	Table Mountain Rancheria WWTP
235	CA0084284	Hollywood Casino Waste Water Treatment Plant
236	CA0084697	Thunder Valley Casino WWTP
237	CAC442169	Thunder Valley Casino WWTP
238	LA0124656	Coushatta Casino Resort WWTP
239	MI0058582	Saganing WWTP
240	MI0058661	Gun Lake Gaming/Entertainment
241	MIG960083	Gun Lake Casino WWTP
242	MTG589706	Northern Winz Casino Lagoon
243	ND0030813	Dakota Magic Casino Hotel Wastewater Treatment Facility
244	ND0031135	Prairie Knights Casino And Resort
245	ND0031178	Spirit Lake Casino WWTF
246	ND0032107	Sky Dancer Wastewater Lagoons
247	NM0030678	Casa Blanca WWTP
248	NM0031224	Tesuque Casino Wastewater Treatment Plant
249	NN0030343	Northern Edge Casino WWTF
250	NN0030344	Twin Arrows Casino Water And Wastewater Systems
251	SD0034444	Grand River Casino & Resort
252	SD0034584	Rosebud Casino And Hotel
253	SD0034746	Dakota Sioux Casino
254	SD0034752	Grand River Casino And Resort
255	SD0034760	Prairie Winds Casino WWTF
256	SDG589519	Prairie Wind Casino
257	SDG589703	Fort Randall Casino/Hotel And Travel Plaza
258	SDG589801	Dakota Sioux Casino
259	TX0127582	Alabama Coushatta Tribe Of Tx
260	WA0025062	Swinomish Indian Tribal Community - Northern Lights Casino (North End WWTP)

2.7. Table 7. (continued).

No.	SourceID	CWPName
1. Inside Federal Indian Reservation and/or ORTL		
1.C. Casino		
261	WA0026743	Yakama Nation - Yakama Nation'S Legends Casino WWTP
262	WIG012390	Wis Dot - 9130-00-00
2. Outside Federal Indian Reservation and/or ORTL		
2.A. Community		
263	AK0043427	St George, City Of
264	AK0046655	Saxman, City Of
265	AK0053376	Klawock, City Of
266	AKG570064	Nulato Sewage Lagoons
267	AKG570097	Savoonga Sewage Lagoon
268	AKG572001	Atqasuk WWTF
269	AKG572022	Hoonah WWTF
270	AKG572036	Point Lay WWTF
271	AKG572048	Wainwright WWTF
272	AKG573001	Alakanuk Lagoon
273	AKG573002	Chuathbaluk Wastewater Lagoon
274	AKG573004	Dillingham Lagoon
275	AKG573006	Emmonak Lagoon
276	AKG573008	Kongiganak Lagoon
277	AKG573011	Napaskiak Lagoon
278	AKG573012	Noatak Lagoon
279	AKG573013	Nightmute Lagoon
280	AKG573014	Pilot Station Wastewater Lagoon
281	AKG573015	Quinhagak Sewage Lagoon
282	AKG573016	St Marys Lagoon
283	AKG573017	St Michael Lagoon
284	AKG573018	Scammon Bay Lagoon
285	AKG573019	Selawik Lagoon
286	AKG573025	Togiak Village Lagoon
287	AKG573026	Upper Kalskag Lagoon
288	AKG573030	Kipnuk Community Sewage Lagoon
289	AKG573031	Mountain Village Lagoon
290	AKG573035	Noorvik Lagoon
291	AKG573036	Kiana Sewage Lagoon
292	AKG573037	Galena 2 Lagoon
293	AKG573039	New Kasigluk Sewage Lagoon_2
294	AKG573040	Shageluk Sewage Lagoon
295	AKG573041	Old Kasigluk Lagoon
296	COG587102	White Mesa Wastewater Lagoon

2.7. Table 7. (continued).

No.	SourceID	CWPName
2. Outside Federal Indian Reservation and/or ORTL		
2.A. Community		
297	NDG589308	Rock Creek Lagoon System (Bullhead Lagoons)
298	NDG589310	Little Eagle Community Lagoon System
299	NDG589405	San Haven Wastewater Treatment Lagoons
300	OK0028151	Anadarko Pwa
301	OK0030341	Stilwell Area Development Auth
302	OK0032328	Hulbert Public Works Authority
303	SDG589613	White Horse Community Of
304	SDU000022	Norris, Community Of(Black Pip
305	WI0036498	Lac Du Flambeau Indian Tribe
306	WI0071315	Keshena WWTF
307	WI0071501	Sokaogon Chippewa Wastewater Treatment System
308	WI0073059	Neopit Community Water System
2.B. School		
309	AKG572006	Barrow WWTF
310	AKG572023	Joann A Alexie Memorial School WWTF
311	AKG572025	Mcqueen School WWTF
312	AKG572026	Tuntutuliak School WWTF
313	AKG572056	Little Diomede School WWTF
314	AKG572098	Paul T Albert High School WWTF
315	AKG573034	Shishmaref School WW Treatment Plant
316	MS0057649	Conehatta School Wastewater Treatment Plant
317	NN0020800	Nenahnezad Boarding School
318	NN0020958	Wingate High School
319	NNL020800	Nenahnezad Boarding School
320	SDG589117	Takini School Wastewater Facility
2.C. Casino		
321	CA0049675	Buena Vista Casino
322	FLR10I625	Tampa Hard Rock Hotel And Casino
323	FLR10I62A	Hardrock Orient Road
324	IA0073717	Winnavegas Casino
325	KS0093777	Harrah'S/Prairie Band Casino
326	MN0061336	Prairie Island
327	NM0030686	Rio Puerco WWTP/Route 66 Casino

APPENDIX C

SUPPLEMENTARY INFORMATION – WASTEWATER LAGOON DETECTION ON THE UNITED STATES TRIBAL LANDS USING REMOTELY SENSED DATA

3.1. Table 1. Federally Recognized Indian Tribes (FRITs) and their corresponding Federal Indian Reservations (FIRs), Off-reservation trust land (ORTL), and/or joint use area.

FRIT No.	Federally recognized Indian Tribe[a]	Reservation + Off reservation trust land[b]/joint-use area
A		Celilo Village[c]
1	Agua Caliente Band of Cahuilla Indians of the Agua Caliente Indian Reservation	Agua Caliente Indian Reservation and Off-Reservation Trust Land
2	Ak-Chin Indian Community	Maricopa (Ak Chin) Indian Reservation and Off-Reservation Trust Land[d]
3	Alabama-Coushatta Tribe of Texas	Alabama-Coushatta Reservation and Off-Reservation Trust Land
4	Alturas Indian Rancheria	Alturas Indian Rancheria
5	Aroostook Band of Micmacs	Aroostook Band of Micmac Trust Land
6	Assiniboine and Sioux Tribes of the Fort Peck Indian Reservation	Fort Peck Indian Reservation and Off-Reservation Trust Land
7	Augustine Band of Cahuilla Indians	Augustine Reservation
8	Bad River Band of the Lake Superior Tribe of Chippewa Indians of the Bad River Reservation	Bad River Reservation
9	Bay Mills Indian Community	Bay Mills Reservation and Off-Reservation Trust Land
10	Bear River Band of the Rohnerville Rancheria	Rohnerville (Rancheria) Trust Land
11	Berry Creek Rancheria of Maidu Indians of California	Berry Creek Rancheria and Off-Reservation Trust Land
12	Big Lagoon Rancheria	Big Lagoon Rancheria
13	Big Pine Paiute Tribe of the Owens Valley	Big Pine Reservation and Off-Reservation Trust Land[d]
14	Big Sandy Rancheria of Western Mono Indians of California	Big Sandy Rancheria and Off-Reservation Trust Land[d]
15	Big Valley Band of Pomo Indians of the Big Valley Rancheria	Big Valley Rancheria
16	Bishop Paiute Tribe	Bishop Reservation
17	Blackfeet Tribe of the Blackfeet Indian Reservation of Montana	Blackfeet Indian Reservation and Off-Reservation Trust Land
18	Blue Lake Rancheria	Blue Lake Rancheria and Off-Reservation Trust Land
19	Bridgeport Indian Colony	Bridgeport Reservation and Off-Reservation Trust Land[d]
20	Burns Paiute Tribe	Burns Paiute Indian Colony and Off-Reservation Trust Land
21	Cabazon Band of Mission Indians	Cabazon Reservation
22	Cachil DeHe Band of Wintun Indians of the Colusa Indian Community of the Colusa Rancheria	Colusa Rancheria
23	Cahto Tribe of the Laytonville Rancheria	Laytonville Rancheria
24	Cahuilla Band of Indians	Cahuilla Reservation
25	Campo Band of Diegueno Mission Indians of the Campo Indian Reservation	Campo Indian Reservation
26	Capitan Grande Band of Diegueno Mission Indians of California (Barona Group of Capitan Grande Band of Mission Indians of the Barona Reservation) Viejas (Baron Long) Group of Capitan Grande Band of Mission Indians of the Viejas Reservation	Barona Reservation and Off-Reservation Trust Land[d] Capitan Grande Reservation Viejas Reservation and Off-Reservation Trust Land[d]
27	Catawba Indian Nation	Catawba Reservation and Off-Reservation Trust Land
28	Cedarville Rancheria	Cedarville Rancheria and Off-Reservation Trust Land
29	Chemehuevi Indian Tribe of the Chemehuevi Reservation	Chemehuevi Reservation
30	Cher-Ae Heights Indian Community of the Trinidad Rancheria	Trinidad Rancheria and Off-Reservation Trust Land
31	Cheyenne River Sioux Tribe of the Cheyenne River Reservation	Cheyenne River Reservation and Off-Reservation Trust Land
32	Chicken Ranch Rancheria of Me-Wuk Indians of California	Chicken Ranch Rancheria and Off-Reservation Trust Land
33	Chippewa Cree Indians of the Rocky Boy's Reservation	Rocky Boy's Reservation and Off-Reservation Trust Land
34	Chitimacha Tribe of Louisiana	Chitimacha Reservation
35	Cocopah Tribe of Arizona	Cocopah Reservation
36	Coeur D'Alene Tribe	Coeur d'Alene Reservation
37	Cold Springs Rancheria of Mono Indians of California	Cold Springs Rancheria
38	Colorado River Indian Tribes of the Colorado River Indian Reservation	Colorado River Indian Reservation
39	Confederated Salish and Kootenai Tribes of the Flathead Reservation	Flathead Reservation
40	Confederated Tribes and Bands of the Yakama Nation	Yakama Nation Reservation and Off-Reservation Trust Land
41	Confederated Tribes of Siletz Indians of Oregon	Siletz Reservation and Off-Reservation Trust Land
42	Confederated Tribes of the Chehalis Reservation	Chehalis Reservation and Off-Reservation Trust Land
43	Confederated Tribes of the Colville Reservation	Colville Reservation and Off-Reservation Trust Land
44	Confederated Tribes of the Coos, Lower Umpqua and Siuslaw Indians	Coos, Lower Umpqua, and Siuslaw Reservation and Off-Reservation Trust Land
45	Confederated Tribes of the Goshute Reservation	Goshute Reservation
46	Confederated Tribes of the Grand Ronde Community of Oregon	Grand Ronde Community and Off-Reservation Trust Land
47	Confederated Tribes of the Umatilla Indian Reservation	Umatilla Reservation and Off-Reservation Trust Land[d]
48	Confederated Tribes of the Warm Springs Reservation of Oregon	Warm Springs Reservation and Off-Reservation Trust Land
49	Coquille Indian Tribe	Coquille Reservation
50	Coushatta Tribe of Louisiana	Coushatta Reservation and Off-Reservation Trust Land
51	Cow Creek Band of Umpqua Tribe of Indians	Cow Creek Reservation and Off-Reservation Trust Land
52	Cowlitz Indian Tribe	Cowlitz Reservation
53	Coyote Valley Band of Pomo Indians of California	Coyote Valley Reservation
54	Crow Creek Sioux Tribe of the Crow Creek Reservation	Crow Creek Reservation
55	Crow Tribe of Montana	Crow Reservation and Off-Reservation Trust Land
56	Dry Creek Rancheria Band of Pomo Indians	Dry Creek Rancheria and Off-Reservation Trust Land[d]
57	Duckwater Shoshone Tribe of the Duckwater Reservation	Duckwater Reservation
58	Eastern Band of Cherokee Indians	Eastern Cherokee Reservation
59 & 60	Eastern Shoshone Tribe of the Wind River Reservation/Northern Arapaho Tribe of the	Wind River Reservation and Off-Reservation Trust Land
61	Elem Indian Colony of Pomo Indians of the Sulphur Bank Rancheria	Sulphur Bank Rancheria
62	Elk Valley Rancheria	Elk Valley Rancheria and Off-Reservation Trust Land
63	Ely Shoshone Tribe of Nevada	Ely Reservation

3.1. Table 1. (continued).

FRIT No.	Federally recognized Indian Tribe[a]	Reservation + Off reservation trust land[b]/joint-use area
64	Enterprise Rancheria of Maidu Indians of California	Enterprise Rancheria and Off-Reservation Trust Land[d]
65	Ewiiaapaayp Band of Kumeyaay Indians	Ewiiaapaayp Reservation
66	Flandreau Santee Sioux Tribe of South Dakota	Flandreau Reservation
67	Forest County Potawatomi Community	Forest County Potawatomi Community and Off-Reservation Trust Land
68	Fort Belknap Indian Community of the Fort Belknap Reservation of Montana	Fort Belknap Reservation and Off-Reservation Trust Land
69	Fort Bidwell Indian Community of the Fort Bidwell Reservation of California	Fort Bidwell Reservation and Off-Reservation Trust Land
70	Fort Independence Indian Community of Paiute Indians of the Fort Independence Reservation	Fort Independence Reservation
71	Fort McDermitt Paiute and Shoshone Tribes of the Fort McDermitt Indian Reservation	Fort McDermitt Indian Reservation
72	Fort McDowell Yavapai Nation	Fort McDowell Yavapai Nation Reservation
73	Fort Mojave Indian Tribe of Arizona, California & Nevada	Fort Mojave Reservation and Off-Reservation Trust Land
74	Fort Sill Apache Tribe of Oklahoma	Fort Sill Apache Indian Reservation
75	Gila River Indian Community of the Gila River Indian Reservation	Gila River Indian Reservation
76	Grand Traverse Band of Ottawa and Chippewa Indians	Grand Traverse Reservation and Off-Reservation Trust Land
77	Greenville Rancheria	Greenville Rancheria
78	Grindstone Indian Rancheria of Wintun-Wailaki Indians of California	Grindstone Indian Rancheria
79	Guidiville Rancheria of California	Guidiville Rancheria and Off-Reservation Trust Land
80	Habematolel Pomo of Upper Lake	Upper Lake Rancheria
81	Hannahville Indian Community	Hannahville Indian Community and Off-Reservation Trust Land
82	Havasupai Tribe of the Havasupai Reservation	Havasupai Reservation
83	Ho-Chunk Nation of Wisconsin	Ho-Chunk Nation Reservation and Off-Reservation Trust Land
84	Hoh Indian Tribe	Hoh Indian Reservation and Off-Reservation Trust Land[d]
85	Hoopa Valley Tribe	Hoopa Valley Reservation
86	Hopi Tribe of Arizona	Hopi Reservation and Off-Reservation Trust Land
87	Hopland Band of Pomo Indians	Hopland Rancheria
88	Houlton Band of Maliseet Indians	Houlton Maliseet Reservation and Off-Reservation Trust Land
89	Hualapai Indian Tribe of the Hualapai Indian Reservation	Hualapai Indian Reservation and Off-Reservation Trust Land
90	Iipay Nation of Santa Ysabel	Santa Ysabel Reservation
91	Inaja Band of Diegueno Mission Indians of the Inaja and Cosmit Reservation	Inaja and Cosmit Reservation
92	Iowa Tribe of Kansas and Nebraska	Iowa (KS-NE) Reservation and Off-Reservation Trust Land
93	Jackson Band of Miwuk Indians	Jackson Rancheria
94	Jamestown S'Klallam Tribe	Jamestown S'Klallam Reservation and Off-Reservation Trust Land
95	Jamul Indian Village of California	Jamul Indian Village
96	Jena Band of Choctaw Indians	Jena Band of Choctaw Reservation
97	Jicarilla Apache Nation, New Mexico	Jicarilla Apache Nation Reservation and Off-Reservation Trust Land
98	Kaibab Band of Paiute Indians of the Kaibab Indian Reservation	Kaibab Indian Reservation
99	Kalispel Indian Community of the Kalispel Reservation	Kalispel Reservation and Off-Reservation Trust Land
100	Karuk Tribe	Karuk Reservation and Off-Reservation Trust Land
101	Kashia Band of Pomo Indians of the Stewarts Point Rancheria	Stewarts Point Rancheria and Off-Reservation Trust Land[d]
102	Keweenaw Bay Indian Community	L'Anse Reservation and Off-Reservation Trust Land
		Ontonagon Reservation
103	Kickapoo Traditional Tribe of Texas	Kickapoo (TX) Reservation and Off-Reservation Trust Land[d]
104	Kickapoo Tribe of Indians of the Kickapoo Reservation in Kansas/Sac & Fox Nation of Missouri in Kansas and Nebraska[e]	Kickapoo (KS) Reservation
		Kickapoo (KS) Reservation/Sac and Fox Nation Trust Land joint-use area
105	Klamath Tribes	Klamath Reservation
106	Kletsel Dehe Band of Wintun Indians	Cortina Indian Rancheria
107	Kootenai Tribe of Idaho	Kootenai Reservation and Off-Reservation Trust Land
108	La Jolla Band of Luiseno Indians	La Jolla Reservation
109	La Posta Band of Diegueno Mission Indians of the La Posta Indian Reservation	La Posta Indian Reservation
110	Lac Courte Oreilles Band of Lake Superior Chippewa Indians of Wisconsin	Lac Courte Oreilles Reservation and Off-Reservation Trust Land
111	Lac du Flambeau Band of Lake Superior Chippewa Indians of the Lac du Flambeau Reservation of Wisconsin	Lac du Flambeau Reservation
112	Lac Vieux Desert Band of Lake Superior Chippewa Indians of Michigan	Lac Vieux Desert Reservation
113	Las Vegas Tribe of Paiute Indians of the Las Vegas Indian Colony	Las Vegas Indian Colony
114	Little River Band of Ottawa Indians	Little River Reservation and Off-Reservation Trust Land
115	Little Traverse Bay Bands of Odawa Indians	Little Traverse Bay Reservation and Off-Reservation Trust Land
116	Lone Pine Paiute-Shoshone Tribe	Lone Pine Reservation
117	Los Coyotes Band of Cahuilla and Cupeno Indians	Los Coyotes Reservation
118	Lovelock Paiute Tribe of the Lovelock Indian Colony	Lovelock Indian Colony
119	Lower Brule Sioux Tribe of the Lower Brule Reservation	Lower Brule Reservation and Off-Reservation Trust Land
120	Lower Elwha Tribal Community	Lower Elwha Reservation and Off-Reservation Trust Land
121	Lower Sioux Indian Community in the State of Minnesota	Lower Sioux Indian Community and Off-Reservation Trust Land[d]
122	Lummi Tribe of the Lummi Reservation	Lummi Reservation
123	Lytton Rancheria of California	Lytton Rancheria
124	Makah Indian Tribe of the Makah Indian Reservation	Makah Indian Reservation
125	Manchester Band of Pomo Indians of the Manchester Rancheria	Manchester-Point Arena Rancheria
126	Manzanita Band of Diegueno Mission Indians of the Manzanita Reservation	Manzanita Reservation and Off-Reservation Trust Land
127	Mashantucket Pequot Indian Tribe	Mashantucket Pequot Reservation and Off-Reservation Trust Land
128	Mashpee Wampanoag Tribe	Mashpee Wampanoag Trust Land
129	Match-e-be-nash-she-wish Band of Pottawatomi Indians of Michigan	Match-e-be-nash-she-wish Band of Pottawatomi Reservation and Off-Reservation Trust Land
130	Menominee Indian Tribe of Wisconsin	Menominee Reservation and Off-Reservation Trust Land
131	Mesa Grande Band of Diegueno Mission Indians of the Mesa Grande Reservation	Mesa Grande Reservation

3.1. Table 1. (continued).

FRIT No.	Federally recognized Indian Tribe[a]	Reservation + Off reservation trust land[b]/joint-use area
132	Mescalero Apache Tribe of the Mescalero Reservation	Mescalero Reservation
133	Metlakatla Indian Community, Annette Island Reserve	Annette Island Reserve
134	Miccosukee Tribe of Indians	Miccosukee Reservation and Off-Reservation Trust Land
135	Middletown Rancheria of Pomo Indians of California	Middletown Rancheria
136	Minnesota Chippewa Tribe (Six component reservations: Bois Forte Band (Nett Lake); Fond du Lac Band; Grand Portage Band; Leech Lake Band; Mille Lacs Band; White Earth Band)	Bois Forte Reservation and Off-Reservation Trust Land[d]
		Fond du Lac Reservation and Off-Reservation Trust Land
		Grand Portage Reservation and Off-Reservation Trust Land
		Leech Lake Reservation and Off-Reservation Trust Land
		Mille Lacs Reservation and Off-Reservation Trust Land
		Minnesota Chippewa Trust Land
		White Earth Reservation and Off-Reservation Trust Land
137	Mississippi Band of Choctaw Indians	Mississippi Choctaw Reservation and Off-Reservation Trust Land[d]
138	Moapa Band of Paiute Indians of the Moapa River Indian Reservation	Moapa River Indian Reservation
139	Mohegan Tribe of Indians of Connecticut	Mohegan Reservation
140	Mooretown Rancheria of Maidu Indians of California	Mooretown Rancheria and Off-Reservation Trust Land
141	Morongo Band of Mission Indians	Morongo Reservation and Off-Reservation Trust Land
142	Muckleshoot Indian Tribe	Muckleshoot Reservation and Off-Reservation Trust Land
143	Narragansett Indian Tribe	Narragansett Reservation
144 & 145	Navajo Nation/San Juan Southern Paiute Tribe of Arizona	Navajo Nation Reservation and Off-Reservation Trust Land
146	Nez Perce Tribe	Nez Perce Reservation
147	Nisqually Indian Tribe	Nisqually Reservation
148	Nooksack Indian Tribe	Nooksack Reservation and Off-Reservation Trust Land
149	Northern Cheyenne Tribe of the Northern Cheyenne Indian Reservation	Northern Cheyenne Indian Reservation and Off-Reservation Trust Land
150	Northfork Rancheria of Mono Indians of California	North Fork Rancheria and Off-Reservation Trust Land
151	Northwestern Band of the Shoshone Nation	Northwestern Shoshone Reservation
152	Nottawaseppi Huron Band of the Potawatomi	Huron Potawatomi Reservation and Off-Reservation Trust Land
153	Oglala Sioux Tribe	Pine Ridge Reservation
154	Ohkay Owingeh	Ohkay Owingeh
155	Omaha Tribe of Nebraska	Omaha Reservation
156	Oneida Indian Nation	Oneida Indian Nation Reservation
157	Oneida Nation	Oneida (WI) Reservation and Off-Reservation Trust Land
158	Onondaga Nation	Onondaga Nation Reservation
159	Paiute Indian Tribe of Utah (Cedar Band of Paiutes, Kanosh Band of Paiutes, Koosharem Band of Paiutes, Indian Peaks Band of Paiutes, and Shivwits Band of Paiutes)	Paiute (UT) Reservation
160	Paiute-Shoshone Tribe of the Fallon Reservation and Colony	Fallon Paiute-Shoshone Colony and Off-Reservation Trust Land
		Fallon Paiute-Shoshone Reservation and Off-Reservation Trust Land
161	Pala Band of Mission Indians	Pala Reservation
162	Pascua Yaqui Tribe of Arizona	Pascua Pueblo Yaqui Reservation and Off-Reservation Trust Land
163	Paskenta Band of Nomlaki Indians of California	Paskenta Rancheria
164	Passamaquoddy Tribe	Indian Township Reservation
		Passamaquoddy Trust Land
		Pleasant Point Reservation
165	Pauma Band of Luiseno Mission Indians of the Pauma & Yuima Reservation	Pauma and Yuima Reservation
166	Pechanga Band of Luiseno Mission Indians of the Pechanga Reservation	Pechanga Reservation and Off-Reservation Trust Land[d]
167	Penobscot Nation	Penobscot Reservation and Off-Reservation Trust Land
168	Picayune Rancheria of Chukchansi Indians of California	Picayune Rancheria and Off-Reservation Trust Land
169	Pinoleville Pomo Nation	Pinoleville Rancheria
170	Pit River Tribe, California (includes XL Ranch, Big Bend, Likely, Lookout, Montgomery Creek, and Roaring Creek Rancherias)	Big Bend Rancheria
		Likely Rancheria
		Lookout Rancheria
		Montgomery Creek Rancheria
		Pit River Trust Land
		Roaring Creek Rancheria
		XL Ranch Rancheria
171	Poarch Band of Creeks Indians	Poarch Creek Reservation and Off-Reservation Trust Land
172	Pokagon Band of Potawatomi Indians	Pokagon Reservation and Off-Reservation Trust Land
173	Ponca Tribe of Nebraska	Ponca (NE) Trust Land
174	Port Gamble S'Klallam Tribe	Port Gamble Reservation and Off-Reservation Trust Land[d]
175	Prairie Band Potawatomi Nation	Prairie Band of Potawatomi Nation Reservation
176	Prairie Island Indian Community in the State of Minnesota	Prairie Island Indian Community and Off-Reservation Trust Land
177	Pueblo of Acoma	Acoma Pueblo and Off-Reservation Trust Land
178	Pueblo of Cochiti	Pueblo de Cochiti
179	Pueblo of Isleta	Isleta Pueblo
180	Pueblo of Jemez	Jemez Pueblo
181	Pueblo of Laguna	Laguna Pueblo and Off-Reservation Trust Land
182	Pueblo of Nambe	Nambe Pueblo and Off-Reservation Trust Land
183	Pueblo of Picuris	Picuris Pueblo
184	Pueblo of Pojoaque	Pueblo of Pojoaque and Off-Reservation Trust Land
185	Pueblo of San Felipe	San Felipe Pueblo
		San Felipe Pueblo/Santa Ana Pueblo joint-use area
		San Felipe Pueblo/Santo Domingo Pueblo joint-use area

3.1. Table 1. (continued).

FRIT No.	Federally recognized Indian Tribe[a]	Reservation + Off reservation trust land[b]/joint-use area
186	Pueblo of San Ildefonso	San Ildefonso Pueblo and Off-Reservation Trust Land
187	Pueblo of Sandia	Sandia Pueblo
188	Pueblo of Santa Ana	Santa Ana Pueblo
189	Pueblo of Santa Clara	Santa Clara Pueblo and Off-Reservation Trust Land[d]
190	Pueblo of Taos	Taos Pueblo and Off-Reservation Trust Land
191	Pueblo of Tesuque	Tesuque Pueblo and Off-Reservation Trust Land
192	Pueblo of Zia	Zia Pueblo and Off-Reservation Trust Land
193	Puyallup Tribe of the Puyallup Reservation	Puyallup Reservation and Off-Reservation Trust Land
194	Pyramid Lake Paiute Tribe of the Pyramid Lake Reservation	Pyramid Lake Paiute Reservation
195	Quartz Valley Indian Community of the Quartz Valley Reservation of California	Quartz Valley Reservation and Off-Reservation Trust Land
196	Quechan Tribe of the Fort Yuma Indian Reservation	Fort Yuma Indian Reservation
197	Quileute Tribe of the Quileute Reservation	Quileute Reservation
198	Quinault Indian Nation	Quinault Reservation
199	Ramona Band of Cahuilla	Ramona Village
200	Red Cliff Band of Lake Superior Chippewa Indians of Wisconsin	Red Cliff Reservation and Off-Reservation Trust Land
201	Red Lake Band of Chippewa Indians	Red Lake Reservation
202	Redding Rancheria	Redding Rancheria
203	Redwood Valley or Little River Band of Pomo Indians of the Redwood Valley Rancheria	Redwood Valley Rancheria
204	Reno-Sparks Indian Colony	Reno-Sparks Indian Colony and Off-Reservation Trust Land[d]
205	Resighini Rancheria	Resighini Rancheria
206	Rincon Band of Luiseno Mission Indians of Rincon Reservation	Rincon Reservation and Off-Reservation Trust Land[d]
207	Robinson Rancheria	Robinson Rancheria and Off-Reservation Trust Land
208	Rosebud Sioux Tribe of the Rosebud Indian Reservation	Rosebud Indian Reservation and Off-Reservation Trust Land
209	Round Valley Indian Tribes, Round Valley Reservation	Round Valley Reservation and Off-Reservation Trust Land
210	Sac & Fox Nation of Missouri in Kansas and Nebraska	Sac and Fox Nation Reservation and Off-Reservation Trust Land
211	Sac & Fox Tribe of the Mississippi in Iowa	Sac and Fox/Meskwaki Settlement and Off-Reservation Trust Land[d]
212	Saginaw Chippewa Indian Tribe of Michigan	Isabella Reservation and Off-Reservation Trust Land[d]
213	Saint Regis Mohawk Tribe	St. Regis Mohawk Reservation
214	Salt River Pima-Maricopa Indian Community of the Salt River Reservation	Salt River Reservation
215	San Carlos Apache Tribe of the San Carlos Reservation	San Carlos Reservation
216	San Manuel Band of Mission Indians	San Manuel Reservation and Off-Reservation Trust Land[d]
217	San Pasqual Band of Diegueno Mission Indians of California	San Pasqual Reservation and Off-Reservation Trust Land[d]
218	Santa Rosa Band of Cahuilla Indians	Santa Rosa Reservation
219	Santa Rosa Indian Community of the Santa Rosa Rancheria	Santa Rosa Rancheria
220	Santa Ynez Band of Chumash Mission Indians of the Santa Ynez Reservation	Santa Ynez Reservation
221	Santee Sioux Nation	Santee Reservation
222	Santo Domingo Pueblo	Santo Domingo Pueblo
223	Sauk-Suiattle Indian Tribe	Sauk-Suiattle Reservation
224	Sault Ste. Marie Tribe of Chippewa Indians	Sault Ste. Marie Reservation and Off-Reservation Trust Land
225	Seminole Tribe of Florida	Big Cypress Reservation
		Brighton Reservation
		Coconut Creek Trust Land
		Fort Pierce Reservation
		Hollywood Reservation
		Immokalee Reservation
		Seminole (FL) Trust Land
		Tampa Reservation
226	Seneca Nation of Indians	Allegany Reservation
		Cattaraugus Reservation
		Oil Springs Reservation
227	Shakopee Mdewakanton Sioux Community of Minnesota	Shakopee Mdewakanton Sioux Community and Off-Reservation Trust Land
228	Sherwood Valley Rancheria of Pomo Indians of California	Sherwood Valley Rancheria and Off-Reservation Trust Land
229	Shingle Springs Band of Miwok Indians, Shingle Springs Rancheria (Verona Tract)	Shingle Springs Rancheria and Off-Reservation Trust Land[d]
230	Shoalwater Bay Indian Tribe of the Shoalwater Bay Indian Reservation	Shoalwater Bay Indian Reservation and Off-Reservation Trust Land
231	Shoshone-Bannock Tribes of the Fort Hall Reservation	Fort Hall Reservation and Off-Reservation Trust Land
232	Shoshone-Paiute Tribes of the Duck Valley Reservation	Duck Valley Reservation and Off-Reservation Trust Land[d]
233	Sisseton-Wahpeton Oyate of the Lake Traverse Reservation	Lake Traverse Reservation and Off-Reservation Trust Land
234	Skokomish Indian Tribe	Skokomish Reservation and Off-Reservation Trust Land[d]
235	Skull Valley Band of Goshute Indians of Utah	Skull Valley Reservation
236	Snoqualmie Indian Tribe	Snoqualmie Reservation and Off-Reservation Trust Land[d]
237	Soboba Band of Luiseno Indians	Soboba Reservation and Off-Reservation Trust Land
238	Sokaogon Chippewa Community	Sokaogon Chippewa Community and Off-Reservation Trust Land
239	Southern Ute Indian Tribe of the Southern Ute Reservation	Southern Ute Reservation
240	Spirit Lake Tribe	Spirit Lake Reservation
241	Spokane Tribe of the Spokane Reservation	Spokane Reservation and Off-Reservation Trust Land
242	Squaxin Island Tribe of the Squaxin Island Reservation	Squaxin Island Reservation and Off-Reservation Trust Land
243	St. Croix Chippewa Indians of Wisconsin	St. Croix Reservation and Off-Reservation Trust Land
244	Standing Rock Sioux Tribe of North & South Dakota	Standing Rock Reservation
245	Stillaguamish Tribe of Indians of Washington	Stillaguamish Reservation and Off-Reservation Trust Land
246	Stockbridge Munsee Community	Stockbridge Munsee Community and Off-Reservation Trust Land[d]
247	Summit Lake Paiute Tribe of Nevada	Summit Lake Reservation and Off-Reservation Trust Land
248	Suquamish Indian Tribe of the Port Madison Reservation	Port Madison Reservation

3.1. Table 1. (continued).

FRIT No.	Federally recognized Indian Tribe[a]	Reservation + Off reservation trust land[b]/joint-use area
249	Susanville Indian Rancheria	Susanville Indian Rancheria and Off-Reservation Trust Land
250	Swinomish Indian Tribal Community	Swinomish Reservation and Off-Reservation Trust Land
251	Sycuan Band of the Kumeyaay Nation	Sycuan Reservation and Off-Reservation Trust Land[d]
252	Table Mountain Rancheria	Table Mountain Rancheria and Off-Reservation Trust Land[d]
253	Te-Moak Tribe of Western Shoshone Indians of Nevada (Four constituent bands: Battle Mountain Band; Elko Band; South Fork Band; and Wells Band)	Battle Mountain Reservation and Off-Reservation Trust Land[d]
		Elko Colony
		South Fork Reservation and Off-Reservation Trust Land
		Wells Colony
254	The Osage Nation	Osage Reservation
255	Three Affiliated Tribes of the Fort Berthold Reservation	Fort Berthold Reservation
256	Timbisha Shoshone Tribe	Timbi-Sha Shoshone Reservation and Off-Reservation Trust Land
257	Tohono O'odham Nation of Arizona	Tohono O'odham Nation Reservation and Off-Reservation Trust Land
258	Tolowa Dee-ni' Nation	Smith River Rancheria and Off-Reservation Trust Land
259	Tonawanda Band of Seneca	Tonawanda Reservation
260	Tonto Apache Tribe of Arizona	Tonto Apache Reservation and Off-Reservation Trust Land[d]
261	Torres Martinez Desert Cahuilla Indians	Torres-Martinez Reservation
262	Tulalip Tribes of Washington	Tulalip Reservation and Off-Reservation Trust Land
263	Tule River Indian Tribe of the Tule River Reservation	Tule River Reservation and Off-Reservation Trust Land
264	Tunica-Biloxi Indian Tribe	Tunica-Biloxi Reservation and Off-Reservation Trust Land
265	Tuolumne Band of Me-Wuk Indians of the Tuolumne Rancheria of California	Tuolumne Rancheria
266	Turtle Mountain Band of Chippewa Indians of North Dakota	Turtle Mountain Reservation and Off-Reservation Trust Land
267	Tuscarora Nation	Tuscarora Nation Reservation
268	Twenty-Nine Palms Band of Mission Indians of California	Twenty-Nine Palms Reservation and Off-Reservation Trust Land[d]
269	United Auburn Indian Community of the Auburn Rancheria of California	Auburn Rancheria and Off-Reservation Trust Land
270	Upper Sioux Community	Upper Sioux Community and Off-Reservation Trust Land
271	Upper Skagit Indian Tribe	Upper Skagit Reservation and Off-Reservation Trust Land[d]
272	Ute Indian Tribe of the Uintah & Ouray Reservation	Uintah and Ouray Reservation and Off-Reservation Trust Land
273	Ute Mountain Ute Tribe	Ute Mountain Reservation and Off-Reservation Trust Land
274	Utu Utu Gwaitu Paiute Tribe of the Benton Paiute Reservation	Benton Paiute Reservation and Off-Reservation Trust Land
275	Walker River Paiute Tribe of the Walker River Reservation	Walker River Reservation
276	Wampanoag Tribe of Gay Head (Aquinnah)	Wampanoag-Aquinnah Trust Land
277	Washoe Tribe of Nevada & California (Carson Colony, Dresslerville Colony, Woodfords Community, Stewart Community, & Washoe Ranches)	Carson Colony
		Dresslerville Colony
		Stewart Community
		Washoe Ranches Trust Land
		Woodfords Community
278	White Mountain Apache Tribe of the Fort Apache Reservation	Fort Apache Reservation
279	Winnebago Tribe of Nebraska	Winnebago Reservation and Off-Reservation Trust Land
280	Winnemucca Indian Colony of Nevada	Winnemucca Indian Colony
281	Wiyot Tribe	Table Bluff Reservation
282	Yankton Sioux Tribe of South Dakota	Yankton Reservation
283	Yavapai-Apache Nation of the Camp Verde Indian Reservation	Yavapai-Apache Nation Reservation
284	Yavapai-Prescott Indian Tribe	Yavapai-Prescott Reservation
285	Yerington Paiute Tribe of the Yerington Colony & Campbell Ranch	Campbell Ranch
		Yerington Colony
286	Yocha Dehe Wintun Nation	Rumsey Indian Rancheria
287	Yomba Shoshone Tribe of the Yomba Reservation	Yomba Reservation
288	Ysleta del Sur Pueblo	Ysleta del Sur Pueblo and Off-Reservation Trust Land
289	Yurok Tribe of the Yurok Reservation	Yurok Reservation
290	Zuni Tribe of the Zuni Reservation	Zuni Reservation and Off-Reservation Trust Land

[a] According to the Federal Register Vol. 86, No. 18, Pages 7554-7558 (5 pages), Friday, January 29, 2021, Notices, 86 FR 7554; and the Federal Register Vol. 86, No. 67, Pages 18552-18553 (2 pages), Friday, April 9, 2021, Notices, 86 FR 18552.

[b] According to the United States Census Bureau. (2022). 2022 TIGER/Line Shapefiles [Data file]. https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2020&layergroup=American+Indian+Area+Geography

[c] Most of the people living at Celilo are enrolled as members of either the Yakama Nation or the Confederated Tribes of the Warm Springs, some are enrolled Umatilla, and some Nez Perce (https://lillianpitt.com/celilo-village-then-and-now/)

[d] Reservation and/or Off-reservation trust land without population in 2010, accordig to the United States Census Bureau

[e] Sac & Fox Nation of Missouri in Kansas and Nebraska is accounted for in FRIT No. 210