

**Assessing Private Well Water Quality in Mobile and Baldwin Counties, Alabama**

by

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## **Abstract**

Approximately 43 million people in the United States rely on private well water. Lack of regulation is important due sources of contamination from geogenic and anthropogenic sources. One source of anthropogenic contamination that may impact well water quality is land use, specifically agricultural land use. Contaminants associated with agricultural land use include pesticides, herbicides and nitrate. An objective of this study was to understand if agricultural land use impacts nitrate concentration in private well water. We found a statistically significant relationship between agricultural land use and nitrate. Nitrate was also found to have an inverse relationship with pH, which was supported by interpolations, principal components analysis and a multilinear regression. Areas with lower pH can have more corrosive water which can leach toxic elements that may impact human health. Low levels of saltwater intrusion were also found in this study. In general, water quality was deemed as excellent using a Water Quality Index (WQI), which can be used to qualitatively understand water quality. Considering the vast amount of parameters affecting water quality, we determined that a more holistic approach should be taken when researching water quality.

Lack of federal regulation means that well owners are solely responsible for ensuring their water is safe. The most effective way for well owners to understand their water quality is to get it tested. Well owners can test their water by sending it to a laboratory or purchasing an at-home test kit. At-home test kits can serve as a quick and cost-effective way for well owners to understand their water quality. However, there are several different test kits and principles that citizens may use to test their water. We aimed to determine which kits and principles were the most accurate and applicable for well owners. Combination test kits were determined to be the most accurate test kits. We also found that some tests, like bacterial test have limits of detection

above the Environmental Protection Agency's Maximum Contaminant Level (EPA MCL), which may give well owners a false sense of security in their water quality. Concentration ranges and increments on comparator charts may also impact result interpretation. Though there are some limitations to using at-home test kits, at-home test kits can provide a cheap and quick way to measure water quality.

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## List of Abbreviations

AWW	Alabama Water Watch
CEnR	Community-Engaged Research
CLAS	Coastal Lowlands Aquifer System
CSMR	Chloride Sulfate Mass Ratio
<i>E.coli</i>	Escherichia Coli
EPA	Environmental Protection Agency
EPA MCL	Environmental Protection Agency Maximum Contaminant Level
fDOM	fluorescent Dissolved Organic Matter
GC-MS	Gas Chromatography Mass Spectrometry
GQI	Groundwater Quality Index
HDPE	High-density Polyethylene
ICP-MS	Inductively Coupled Plasma Mass Spectrometry
LSI	Langelier Saturation Index
MPN	Most Probable Number
MTBE	Methyl Tert-Butyl Ether
PC#	Principal Component 1, 2, 3,...
PCA	Principal Component Analysis
PCA	Principal Components Analysis
PCE	Perchloroethylene
PP	Polypropylene
PPGC	Potential to Promote Galvanic Corrosion
QAPs	Quality Assurance Programs

RESTORE Resources and Ecosystems Sustainability, Tourist Opportunities and Revived  
Economies of the Gulf Coast

RMSE Root Mean Square Error

SDWA Safe Drinking Water Act

SPC Specific Conductance

TCE Trichloroethylene

TDS Total Dissolved Solids

UN SDG United Nations Sustainable Development Goal

VOC Volatile Organic Compounds

WHO World Health Organization

WQI Water Quality Index

## Chapter 1

### Private Well Water Quality and Citizen Science in Mobile and Baldwin Counties

#### 1.1 Introduction

Clean and safe drinking water is essential to personal and community wellbeing. For people that rely on municipal water supplies, the Safe Drinking Water Act aims to ensure public water systems adhere to water quality standards established by the US Environmental Protection Agency (US EPA). The SDWA also mandates that supply systems provide citizens with information about their water through annual consumer confidence reports. However, approximately 43 million people in the United States rely on private well water as their source of drinking water (US EPA, 2023), and private well water is not regulated in the United States under the SDWA (Seltenrich, 2017; USGS, 2019), so private well users assume the responsibility of managing their own water supply.

Private well users rely on groundwater, and the groundwater quality is primarily controlled by geogenic processes, like water-rock interactions within an aquifer. There are also several anthropogenic sources of contamination that can impact groundwater quality. Anthropogenic sources of contamination include leaking underground storage tanks (Richards, 1997), sewage (Brindha et al., 2020), and applications of substances like fertilizers and pesticides on the land (Bexfield et al., 2021; Fenner et al., 2013; Lee and Murphy, 2020; Rudolph, 2015). Contaminants associated with underground storage tanks include volatile organic compounds (VOCs) and toxic trace metals (Richards, 1997). Consumption of water with elevated concentrations of these compounds can result in poor health outcomes like kidney damage and cancer (Balali-Mood et al., 2021). Pathogenic bacteria in well water like *Escherichia coli* (*E.coli*) can originate from

sewage and leaking septic systems (Murphy et al., 2020) and ingestion can result in gastrointestinal problems (Owusu et al., 2021). Widespread land applications of pesticides, herbicides, and nitrogen-rich fertilizers can result in adverse health impacts as well. Methemoglobinemia, also known as blue baby syndrome (Ward et al., 2018) and various types of cancers have been linked to high levels of nitrogen in groundwater and pediatric cancer has been linked to pesticides (Joseph and Kolok, 2022; Mathewson et al., 2020; Mendy et al., 2024). Contaminants are rarely found independently in the environment and when found together can impact health (Joseph and Kolok, 2022; Squillace et al., 2002). Well water tests are the most effective way to understand the range of contaminants that affect water quality and to select the most appropriate treatment methods when necessary.

Infrequent water testing and treatment among well owners combined with a lack of awareness of issues impacting well water quality may leave private well owners more vulnerable to water contamination than public supply users. Colley et al. (2019) conducted a literature review related to frequency and perceptions of testing in private well users in the United States and Canada and found that between 34 and 94% of well owners had tested their well once, and only 6 to 59% had tested their well in the past year. Testing rates varied by study. Malecki et al. (2017) found that in Wisconsin only 21.2% were actively treating their well water, with only 10% of well owners testing their water. Lack of testing and treatment were linked to perceptions of groundwater, so that well owners felt that since they had been using well water for a prolonged period of time with no severe health outcomes it must be safe (Malecki et al., 2017). Cost is also seen as a prohibitive factor in testing and treating well water (Morris et al., 2016). Perceived control over contamination of drinking water supply may also prevent well users from testing and treating their well water (Schuitema et al., 2020). If organoleptic properties are

satisfactory, well owners may also decide not to test and treat their water (Munene and Hall, 2019).

Well users have two main ways to test their water: sending a water sample to a commercial laboratory or purchasing an at-home test kit. Both testing routes have associated benefits and drawbacks. Sending a sample to a lab can offer lower detection limits and strict quality control and quality assurance procedures provide high confidence in the result. But, lab analyses are costly and it may take several days or weeks to receive results. Most importantly, well users must select what tests to perform, which can be overwhelming (Malecki et al., 2017). At-home test kits are cheaper, provide quicker results, and have pre-determined tests that the well owner can perform.

## **1.2 Research Questions and Hypotheses**

This research was designed to understand how anthropogenic stresses on well water quality in Mobile and Baldwin Counties, in Alabama and better understand how accurate at-home test kits are at reporting levels of contaminants. At-home well water test kits serve as an affordable way for well owners to test their wells, but we don't know how accurate kits are when compared to lab obtained analytical results. We will fill this gap in knowledge by addressing the following research questions:

**Research Question 1 (RQ1):** How does land use impact contaminant concentrations of private well water?

*Hypothesis: Wells in closer proximity to agricultural lands compared to other land use types will have higher levels of contamination because of the persistence of pollutants related to agriculture.*

**Research Question 2 (RQ2):** Do at-home test kits serve as an accurate and affordable method for citizens to quantify potential contaminants when compared to lab results?

*Hypothesis: Reported values for at-home test kits will overestimate lab-obtained results when using colorimetric test strips, similar to Ali et al. 2019 (Ali et al., 2019) and underestimate when using other test types because colorimetric test strips are more variable than other test types.*

### **1.3 Summary**

The next chapters describe how geogenic and anthropogenic sources of contamination impact private well water and how at-home test kits may be used by well owners to address private well water quality in Mobile and Baldwin counties AL. Mobile and Baldwin counties are two coastal counties in Alabama that have a high density of well users and are reliant on groundwater as the primary source of drinking water (Oltz et al., 2000). Since both counties are located on the coast, the counties are also threatened by extreme weather events that impact well water quality (Pieper et al., 2021) and saltwater intrusion (Jasechko et al., 2020). To ensure sustainable use of water resources, we must understand geogenic and anthropogenic mechanisms affecting private well water.

## Chapter 2

### Private Well Water Chemistry and Impacts from Land Use in Mobile and Baldwin Counties

#### Abstract

Previous studies suggest that agricultural land use impacts well water quality (Gosselin et al., 1997; Joseph and Kolok, 2022; Naylor et al., 2018). The results of this study indicate there is a significant relationship between agricultural land use and nitrate concentrations in private well water quality. Nitrate and pH were found to a statistically significant inverse relationship ( $\beta = -0.829$ ,  $p = 0.0051$ ) which is confirmed by interpolations of the two variables, principal components analysis and a multilinear regression. Low pH can lead to higher corrosivity which may lead to replacement of pipes and fixtures. Toxic elements may also be leached by highly corrosive water and can therefore impact human health. Additionally, this study found some level of saltwater intrusion, but saltwater intrusion was not severe enough to be a threat to human health. This study also found that generally water quality is excellent based off of a water quality index (WQI) that was constructed, with only one well owners water quality being poor. Though one well owners water quality was poor, it should be noted that the construction of WQI's is subjective and meant to be a qualitative representation of water quality. Considering the subjectivity of WQIs and the vast number of parameters affecting water quality, a holistic approach should be taken when researching water quality. The results presented in this study are not just limited to well owners living in Mobile and Baldwin counties, but also to well owners supplied by the Coastal Lowlands Aquifer. Variables impacting water quality like the

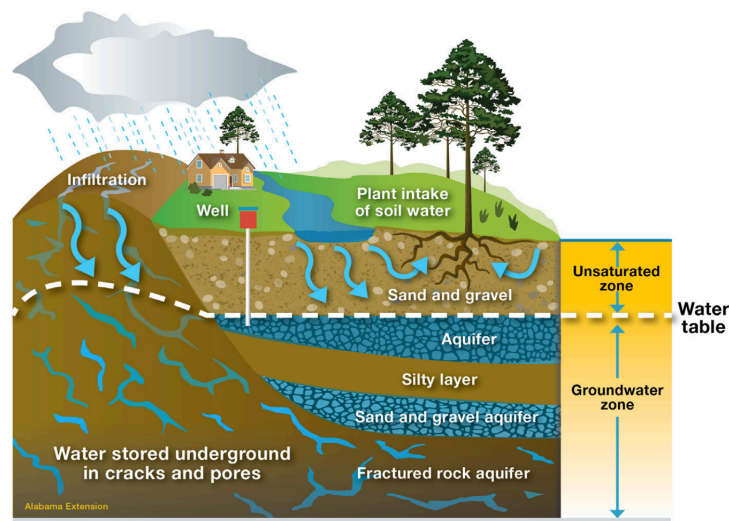
mechanisms of groundwater chemistry and potential sources of contamination are important to understand to ensure the safety of private well owners.

## 2.1 Introduction

One in five private wells (25%) host one or more contaminants at concentrations that negatively impact human health. However, the compounds of concern and the relative threat to human health varies widely across the United States (DeSimone et al., 2014). Overall, the collection of contaminants is highly dependent on the local geology and local factors that contribute to anthropogenic contamination from the surface.

### 2.1.1 Mechanisms of groundwater contamination

To understand the potential threats to groundwater quality, it is important to understand the nature of private wells and the mechanisms driving groundwater quality. Two distinct zones exist beneath the land surface: the unsaturated zone and the saturated or groundwater zone (Figure 2.1) (Curl et al., 2022). The unsaturated zone contains soil that has air and water within the pore spaces but does not contain enough water to provide a sustained water source. The



**Figure 2. 1.** Schematic of aquifer system with well (Curl et al. 2022)

boundary between the saturated and unsaturated zones is called the water table. An aquifer is the area under the water table that is saturated, and water can be pumped at reasonable yields for human use. The groundwater zone is the depth below which the earth materials contain enough water to be extracted by wells and serve as a water source. Wells are drilled, dug, or driven into the saturated zone to extract water. Wells are lined with pipe to support the structural integrity of the well; pumps are installed to withdraw water from the well.

Groundwater chemistry is primarily controlled geogenic factors that occur naturally and are the result of water-rock interactions, the reduction-oxidation (redox) potential in the aquifer, and biogeochemical processes that enhance or attenuate species in the subsurface. Aquifers composed of materials like limestone and dolomite are pH buffered by the carbonate system, resulting in generally higher pH values of the water. Aquifers composed of materials like sandstone are not buffered to such an extent, resulting in more acidic pH ranges. The speciation of contaminants like toxic metals such as copper, lead, and arsenic are affected by pH and redox conditions. Copper and lead tend to sorb onto soils when water pH is high (DeSimone et al., 2014). However, some metals like arsenic tend to desorb when pH is more alkaline and oxic, and groundwater with a reducing conditions and low pH may is likely to mobilize arsenic (Smedley and Kinniburgh, 2002). Biogeochemical processes are also controlled by pH and redox potential. For example, anoxic groundwater typically has low concentrations of nitrate due to denitrifying bacteria that convert nitrate to nitrogen gas.

Recharge potential also can impact groundwater chemistry. Recharge is what occurs when precipitation infiltrates into the subsurface and replenishes groundwater. Recharge potential is a value associated with recharge, which is impacted by factors such as the amount and type of vegetation in an area, soil types, climate, and topography (DeSimone et al., 2014). In

areas with high recharge potential, there is also a high potential for surface contamination to reach groundwater supplies. Private wells typically target shallow aquifer systems with high connectivity to the land surface, and therefore are more vulnerable to contamination compared to public wells that target deeper aquifers (DeSimone et al., 2014).

### **2.1.2 Well water contamination**

The water quality of municipal water supplies is regulated through the Safe Drinking Water (US EPA, 2004). The EPA sets primary and secondary drinking water requirements that are enforceable (primary) and non-enforceable (secondary), where the latter may affect the color or taste of the water but does not pose a human health threat. Primary standards are legally enforceable standards that public water facilities must adhere to and typically have adverse health effects. Both primary and secondary standards have a maximum contaminant level (MCL) assigned to each parameter which is the highest concentration of contaminant that is allowed to be present in drinking water. A summary of relevant MCLs in this study is presented in Table 2.1.

**Table 2. 191.**Table of EPA Maximum Contaminant Levels.

Category	Parameter	Chemical Formula	EPA MCL
Bacteria	<i>E.coli</i>	-	0 MPN
	Total coliforms	-	0 MPN
In-situ water quality parameters	pH	-	6.5-8.5
	Total dissolved solids	-	500 ppm
Trace metals and alkalinity	Iron	Fe <sub>T</sub>	0.3 ppm
	Arsenic	As	0.010 ppm
	Magnesium	Mg <sup>2+</sup>	-
	Copper	Cu <sup>2+</sup>	1.3 ppm
	Manganese	Mn <sup>2+</sup>	0.05 ppm
	Sodium	Na <sup>+</sup>	-
	Potassium	K <sup>+</sup>	-
	Lead	Pb	0.015 ppm
	Calcium	Ca <sup>2+</sup>	-
	Alkalinity	CaCO <sub>3</sub>	-
Anions	Bicarbonate	HCO <sub>3</sub> <sup>-</sup>	-
	Nitrate	NO <sub>3</sub> <sup>-</sup>	10 ppm
	Ammonium	NH <sub>4</sub> <sup>+</sup>	-
	Chloride	Cl <sup>-</sup>	250 ppm
	Fluoride	F <sup>-</sup>	2.0 ppm
	Sulfate	SO <sub>4</sub> <sup>2-</sup>	250 ppm
	Phosphate	PO <sub>4</sub> <sup>3-</sup>	-
VOCs	MtBE	C <sub>5</sub> H <sub>12</sub> O	-
	Benzene	C <sub>6</sub> H <sub>6</sub>	0.005 ppm
	Toluene	C <sub>7</sub> H <sub>8</sub>	1 ppm
	TCE	C <sub>2</sub> HCl <sub>3</sub>	0.005 ppm
	PCE	C <sub>2</sub> Cl <sub>4</sub>	-
Pesticides	Xylenes	C <sub>8</sub> H <sub>10</sub>	10 ppm
	Glyphosate	C <sub>3</sub> H <sub>8</sub> NO <sub>5</sub> P	0.7 mg/L
	Atrazine	C <sub>8</sub> H <sub>14</sub> ClN <sub>5</sub>	0.003 mg/L
	Acetohlor	C <sub>14</sub> H <sub>20</sub> ClNO <sub>2</sub>	-
	Bifenthrin	C <sub>23</sub> H <sub>22</sub> ClF <sub>3</sub> O <sub>2</sub>	-
	Diazinon	C <sub>12</sub> H <sub>21</sub> N <sub>2</sub> O <sub>3</sub> PS	-
	Fipronil	C <sub>12</sub> H <sub>4</sub> Cl <sub>2</sub> F <sub>6</sub> N <sub>4</sub> OS	-
	Malathion	C <sub>10</sub> H <sub>19</sub> O <sub>6</sub> PS <sub>2</sub>	-
Methalachor	C <sub>15</sub> H <sub>22</sub> ClNO <sub>2</sub>	-	

In contrast to regulations in place for municipal supplies, private well water quality is not regulated federally, and is infrequently regulated at the state level (Bowen et al., 2019). For

private well users, the EPA MCLs are helpful guidelines to understand water quality risks and threats to human health.

### **2.1.2.1 Agricultural contaminants in groundwater**

There is an abundance of literature on the impact of agricultural practices on private well water quality. Two contaminants associated with agricultural land use are pesticides and nitrate, which have been linked to various cancers (Joseph and Kolok, 2022; Mendy et al., 2024). Across the United States, approximately one billion pounds of pesticides are applied to the land annually (Gilliom et al., 1992). Fertilizers, a source of nitrogen, are one of the main contributors to nitrogen in the environment (DeSimone et al., 2014). As a consequence, nitrate concentrations in groundwater are elevated nationwide (DeSimone et al., 2014). Industrial leakage and urban land use has also been linked to nitrate contamination in groundwater, although to a lesser extent (Wakida and Lerner, 2005). Studies have focused on the distribution of nitrate in shallow groundwater in Iowa, North Carolina, and Nebraska (Gosselin et al., 1997; Naylor et al., 2018; Skalaban et al., 2024). Gosselin et al. (1997) found that nitrate concentrations above the EPA MCL varied across Nebraska (3 to 39%) depending on groundwater region. Skalaban et al. (2024) found that agricultural land use contributed to nitrate concentrations above the EPA MCL in 32% of wells sampled in Iowa. Similarly, Naylor et al. (2018) found nitrate concentrations varied with land use so that areas with higher average nitrate concentrations (>3.429 mg/L) also were associated with higher percentage of agricultural land compared to areas with lower average nitrate concentrations (<0.51 mg/L). A national study by Burow et al. (2010) found that out of 5,101 wells, nitrate was above the EPA MCL in 8% of wells. Though there was also no

clear spatial pattern in nitrate concentrations in wells, shallow wells near agricultural land contained the highest concentrations of nitrate.

Bexfield et al. reported in 2021 that 41% of 1,204 wells in the United States had detectable levels of pesticide compounds, with detections being most frequent in the midwestern states. Pesticide fate and transport in the environment is impacted by chemical properties and biodegradation potential in the soil (Bexfield et al., 2021; Fenner et al., 2013). While many pesticides are transported by surface runoff into surface water supplies or strongly sorb to soils, chemicals like atrazine can leach into groundwater due to its persistence in the environment (Syafudin et al., 2021). Though nitrate and pesticides have been widely studied, they are rarely studied in conjunction with other water quality parameters.

#### **2.1.2.2 Pathogenic bacteria in groundwater**

Pathogenic bacteria, like *E. coli*, can be used to determine the impact of fecal contamination (DeSimone et al., 2014). Total coliforms, though not all species are pathogenic, used as an indicator that harmful organisms may be present because a pathway for bacteria to enter the water supply exists. A study in Ohio found that 45% of wells tested were positive for total coliforms and 9% tested positive for *E. coli* (Won et al., 2013). Similarly, in a national review of water quality in the United States over the past 20 years, *E. coli* was detected in 8% of private wells (DeSimone et al., 2014). In another study examined how well construction and depth influenced pathogen contamination in Colorado and found that shallow wells (wells shallower than 199 feet) had a 71% positive rate for total coliforms (Gonzales, 2008). Though pathogenic bacteria in private wells has been studied nationwide, the relationship between pathogenic bacteria and other variables impacting water quality is still poorly understood.

### **2.1.2.3 Volatile organic compounds (VOCs) in groundwater**

VOCs mainly originate from gasoline, industrial processes, and chemical manufacturing. In national study, VOCs were detected in 61% of 2,948 well water samples (Squillace et al., 1999). VOC concentrations can also vary with land use type, with 47% of samples in urban areas having contained VOCs and only 14% in urban areas. VOCs can also co-occur with other compounds in the environment like pesticides and nitrate. For example, Squillace et al. (2002) found that mixtures of VOC, pesticides, and nitrate had a detection frequency between 2 and 19% in 1,255 private wells and 242 public supply wells. California and New Jersey have also been noted as having private wells with VOC concentrations higher than the EPA MCL (Rowe et al., 2007) which were linked to agricultural land applications and a high percentage of urban area.

### **2.1.2.4 Saltwater Intrusion**

In coastal areas, saltwater intrusion is also a threat to groundwater where saline water renders wells unsuitable for household use. Jasechko et al. (2020) found that general landward hydraulic gradient, areas where groundwater levels are lower than sea level, existed in at least 15% of the coastal wells nationally. Approximately 2.4% of wells located on the West Coast exhibit landward hydraulic gradients, and thus are at risk for salt-water intrusion. The Gulf Coast region had approximately 17.3% of wells exhibiting landward gradients. Saltwater intrusion poses a threat to private well water quality but is often treated as being an isolated contaminant source.

### **2.1.2.5 Corrosivity of groundwater**

Groundwater chemistry poses an indirect threat to human health and wellbeing. For example, corrosivity of groundwater is linked to various chemical parameters like pH, total dissolved solids (TDS), alkalinity, chloride, and sulfate, all of which are controlled by local geology (Belitz et al., 2016; DeSimone et al., 2014). Belitz et al. (2016) combined the Langelier Saturation Index (LSI) and the Potential to Promote Galvanic Corrosion indicator (PPGC) to understand corrosivity in groundwater. The LSI measures the ability for scale to form on pipes based on pH and results in 3 classifications of water: potentially corrosive, indeterminate, and scale forming. Scales in pipes provide protection for metal pipes to avoid leaching of metals into water. PPGC measures the amount of galvanic corrosion of lead in a water system that can occur when a calcium carbonate scale is not formed and results can also fit into 3 classifications based on risk of potential risk of galvanic corrosion: high, moderate, and low. Wells that were highly corrosive were located in the northeast and southeast portions of the United States (Belitz et al., 2016).

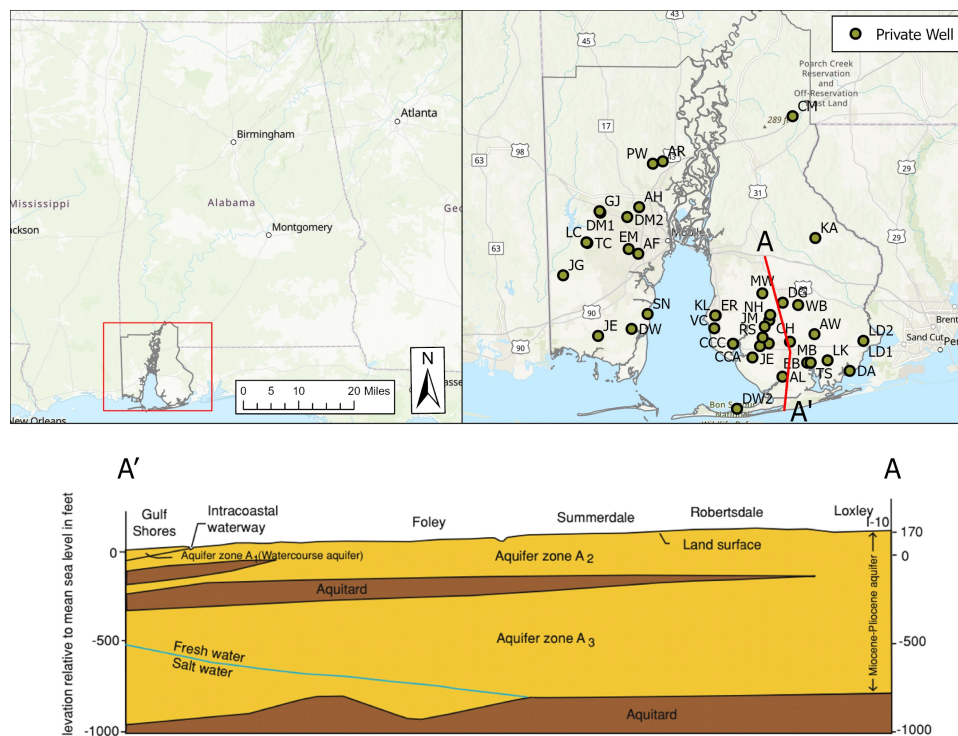
### **2.1.3 Study Motivation**

This study examines private well water quality in Mobile and Baldwin counties, two coastal counties in southern Alabama. Mobile and Baldwin counties are a part of the Coastal Lowlands Aquifer system, which supplies private well water to approximately 1.2 million people, with nearly 70,000 people relying on private well water in Mobile and Baldwin counties (Appendix 2 Section 3). Understanding mechanisms of groundwater contamination in these counties can help to ensure community sustainability for Mobile and Baldwin counties, and these results apply to many of the communities on the Gulf Coast as well. Water quality issues like nitrate and

pesticides contamination as well as saltwater intrusion has been studied in the Gulf Coast region and Coastal Lowlands Aquifer system previously (Avila Rodríguez et al., 2024; Bexfield et al., 2021; Jasechko et al., 2020) . However, mechanisms driving groundwater quality have not been widely studied in Mobile and Baldwin counties. Additionally, this study presents a holistic view of groundwater quality, which has not previously been done.

#### **2.1.4 Hydrogeologic setting of Mobile and Baldwin Counties, Alabama**

Understanding the local hydrogeology is an integral part in understanding private well water quality. Mobile and Baldwin counties are a part of the East Gulf Coast physiographic region and the Coastal Lowlands Aquifer System (CLAS) (Robinson et al., 1996). Within Baldwin and Mobile counties, the CLAS can be further divided into the Miocene-Pliocene and Watercourse aquifer systems, which contain three zones: A<sub>1</sub>, A<sub>2</sub>, and A<sub>3</sub> (Oltz et al., 2000). The Watercourse aquifer is zone A<sub>1</sub> and is unconfined, shallower, and more limited in geographic extent compared to the Miocene-Pliocene aquifer. The Miocene-Pliocene aquifer can be further divided into zones A<sub>2</sub>, and A<sub>3</sub>, with the main difference between the zones being that there is a confining clay layer between the two zones that is regionally discontinuous (Figure 2.2). The clay layer limits vertical infiltration, therefore providing better protection from contamination from the land surface. Recharge potential is an important factor to consider for surface-groundwater connectivity, and thus, potential for well water contamination. Mobile and Baldwin counties have also been found to have a high recharge potential and therefore potential for contamination based on the EPA DRASTIC model (Gutherie et al., 2022). The DRASTIC model evaluates parameters such as soil type, topography if an area, net recharge, aquifer hydraulic conductivity, depth to water table and land use, with areas classified as “well below average” having smaller recharge potentials and



**Figure 2. 1.** Study sites across Mobile and Baldwin counties and cross-section of Southern Baldwin County adapted from Murgulet and Tick 2009.

areas classified as “well above average” having larger recharge potentials. Most of both Mobile and Baldwin counties are classified as “well above average” signifying greater recharge potential and therefore, greater likelihood that private wells can be impacted by surface processes.

### 2.1.5 Previous groundwater quality studies in Mobile and Baldwin counties, Alabama

There has been little effort to assess holistic water quality for well users in Alabama, particularly the coastal counties of Mobile and Baldwin. Murgulet and Tick (2009) found that areas in southern Baldwin County exhibited elevated nitrate concentrations (ranging from 12.06 to 27.42 mg/L) which they attributed to agriculture land use. However, the authors also noted that nitrate contamination in areas of low agriculture could originate from leaking septic systems and animal waste due to higher nitrate and chloride concentrations in these areas. Groundwater nitrate in Mobile County has not been studied. Saltwater intrusion has been noted as being a potential concern in Mobile and Baldwin counties, but again, no studies have examined the

extent in both counties. In Southern Baldwin County, saltwater intrusion has been documented in the A<sub>1</sub> aquifer and is limited in the A<sub>2</sub> to areas closest to the coastline (Murgulet and Tick, 2008).

### **2.1.6 Research Questions and Hypotheses**

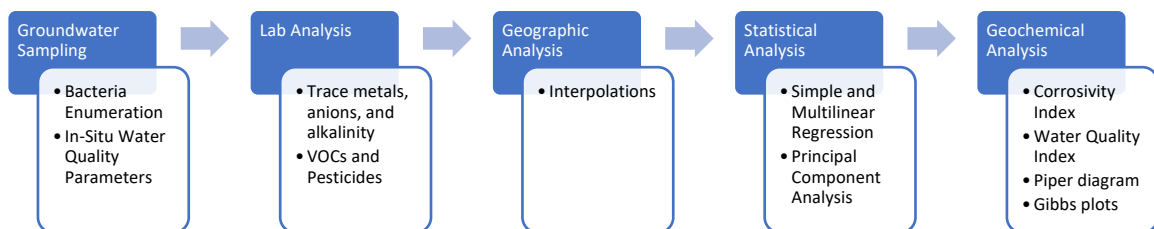
Agricultural land use has been previously linked to elevated nitrate concentrations in southern Baldwin County (Murgulet and Tick, 2008) but has not yet been examined across both Mobile and Baldwin counties to date. Previous studies have also not included compounds like pesticides to determine if agricultural land use has an impact on contaminant concentrations nor the extent to which mixtures of contaminants exist in private wells. This study presents a holistic view of water quality and investigates how water quality is impacted by land use. The overall research question and hypothesis was:

**Research Question:** How does land use impact contaminant concentrations of private well water?

*Hypothesis: Wells in closer proximity to agricultural lands compared to other land use types will have higher levels of contamination because of the persistence of pollutants related to agriculture.*

## 2.2 Methods

The general project workflow is summarized in Figure 2.3. Private well wells were sampled in Mobile and Baldwin Counties in three sampling campaigns between Fall 2022 and Fall 2023. Samples were taken from each private well and water quality parameters, such as bacteria enumeration and in-situ water quality parameters, were measured in the field. Once arriving back at the lab, samples were sent to be tested for trace metals, anions, alkalinity, VOCs and pesticides. After results for quality parameters were collected, interpolations for pH and nitrate were performed. Several simple and multilinear regressions were performed to determine relationships between nitrate and other water quality parameters. Principal component analysis was also performed to understand relationships between water quality parameters. Finally, several types of geochemical analysis were performed to understand the mechanisms behind water quality, such as a corrosivity index, water quality index, Piper diagram along with a water quality index designed for Piper diagrams, and Gibbs' plots. Methods associated with data collection and data analysis are summarized below.



**Figure 2.3.** Workflow of study methods.

### **2.2.1 Groundwater Sampling**

Sampling campaigns were conducted in September-October 2022, April-May 2023, and September 2023, with 43 total wells sampled (Figure 2.2). Upon arrival at each well, the spigot closest to the well head was identified and the wells were turned on at a high flow rate for 15 minutes to ensure that samples were representative of the groundwater quality and not impacted by factors like stagnant water in the well. Once the well was purged, five samples were taken to measure in-situ water quality parameters, pathogens, trace metals and anion, VOCs, and pesticides. All samples were taken wearing gloves and stored in a cooler at approximately 6°C until further analysis was completed.

### **2.2.2 In-situ water quality parameters and bacteria enumeration**

In-situ water quality parameters such as pH, temperature, fluorescent dissolved organic matter (fDOM), specific conductivity, turbidity, and dissolved oxygen were measured using an EXO<sup>2</sup> sonde (Yellow Springs, Ohio). The sonde and the cup used for analysis were rinsed three times with well water before measurements were taken to prevent any contamination from other samples. After rinsing the cup and sonde, the cup was filled with sample water and the sonde was placed in the cup. Prior to recording results, the sonde was allowed to stabilize. For bacteria enumeration, a 100 mL sterile high-density polyethylene (HDPE) bottle was filled and analyzed using the IDEXX Coli-ert and Quanti tray system (Westbrook, Maine). Once the sample was collected, an enzyme fluorescence powder was added and dissolved within 6 hours of sample collection. Then the sample was poured into a Quanti tray, sealed, and incubated at 35°C for at least 24 hours but no more than 28 hours. After the samples were taken out of the incubator any pod on the Quanti tray that were yellow were deemed as positive for total coliforms and any

pods that fluoresced under an ultraviolet light were deemed as positive for *E. coli*. The most-probable number (MPN) of total coliforms and *E. coli* were determined by counting the number of large and small positive pods and matched with the associated table for the Quanti-tray system.

### **2.2.3 Trace metals, anions and alkalinity**

At the well, one sample was collected in a 500 mL HDPE and used to determine metal concentration and alkalinity. The bottle was rinsed three times prior to sample collection, filled with no headspace, and transported back to the Ojeda lab. Once back at the lab 155 mL of each sample were filtered using a 10 mL syringe and 0.45  $\mu\text{m}$  cellulose acetate filter (VWR, USA). Approximately 30 mL were placed in a 60 mL HDPE bottle and acidified using 15.7 M nitric acid and analyzed by inductively coupled plasma mass spectrometry (ICP-MS) at the Auburn Geosciences ICP-MS lab following a modified version of EPA method 200.8. Concentrations of beryllium, sodium, magnesium, aluminum, potassium, calcium, chromium, manganese, iron, cobalt, nickel, copper, zinc, arsenic, selenium, molybdenum, silver, cadmium, antimony, barium, thallium, lead, thorium, and uranium were measured. Fifty milliliters of filtered, unacidified sample were frozen and sent to the University of Georgia Soil, Plant, and Water Laboratory to be analyzed for anions using ion chromatography following EPA method 300. Chloride, fluoride, phosphate, sulfate, and nitrate were quantified using this method. Twenty-five milliliters of sample were combined with a reagent powder and analyzed for ammonium using an ion selective electrode at the Ojeda lab (HACH Loveland, Colorado). Lastly, 50 mL of filtered sample was used to measure alkalinity. Bromocresol-green methyl red indicator was added to each sample if the pH was below 8.3 and then titrated using 0.009 or 0.1N sulfuric acid, depending on the

starting pH of the sample. Alkalinity was calculated following section 6.6.5.A of the USGS National Field Manual (Rounds and Wilde, 2012).

#### **2.2.4 VOCS and Pesticides**

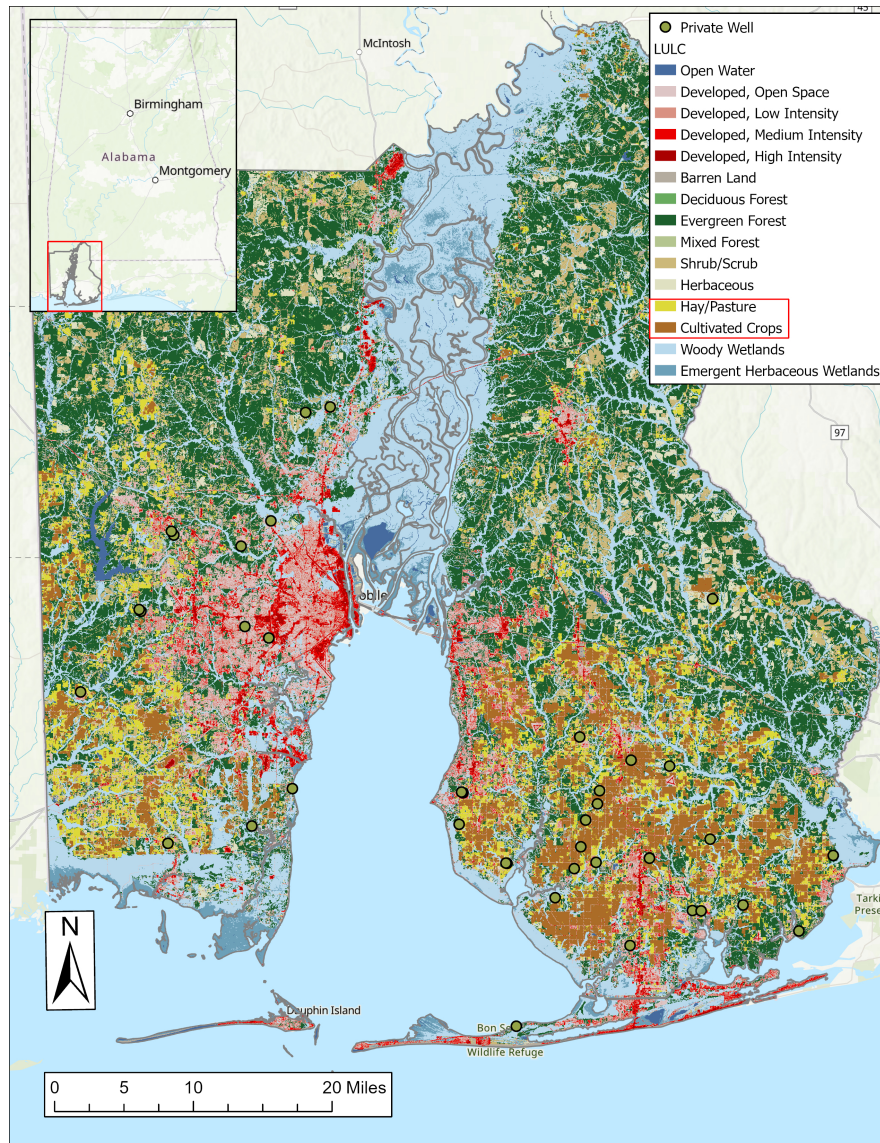
For VOCs, samples were collected under a reduced flow in a 40 mL amber glass bottle containing 25 mg of ascorbic acid and 200 mg of maleic acid following EPA method 524.3 Vials were filled with no headspace and stored in a cooler with ice prior to storage in the lab at 4 °C until analysis. VOCs were analyzed in the Ojeda lab using a purge and trap gas chromatography mass spectrometer (GC-MS). Compounds that were analyzed include methyl tert-butyl ether (MTBE), benzene, toluene, trichloroethylene (TCE), perchloroethylene (PCE), and *p*-, *m*-, and *o*-xylene. Samples for pesticide analysis were collected in a 250 mL amber bottle which was rinsed three times, then filled with no headspace. Samples were analyzed at the Pesticide Residue Laboratory in Auburn by GC-MS following EPA method 1699. Pesticides of interest included acetochlor, atrazine, bifenthrin, diazinon, fipronil, glyphosate, malathion, and metolachlor. Neither VOCs nor pesticides were found in any sample so neither parameter was included in further analysis.

#### **2.2.5 Geographic Analysis**

To understand areas within Mobile and Baldwin counties that are affected by nitrate contamination and pH interpolations were performed. Average nitrate values for wells with multiple observations were taken and for wells with left-censored values, one-half the detection limit was taken and used (Mohamed et al., 2021). The Exploratory Interpolation function within ArcGIS Pro was used to determine which interpolation method would be the best suited, with

Optimized Simple Kriging being selected due to this method having the lowest Root Mean Square Error (RMSE) with nitrate having an RMSE of 1.98 and pH having an RMSE of 0.75.

Since relationships between agricultural land use and nitrate have been previously shown, obtaining the amount of agricultural land use around each well is needed to perform further statistical analyses. Figure 2.4 shows the distribution of land cover in Mobile and Baldwin counties and the location of the wells in this study. A buffer of 500 m was created around each well based which has previously been found to be adequate and account for up-gradient flow (Johnson and Belitz, 2009) and land use values from the 2021 National Land Cover Database were extracted to each buffer zone due to little change in land use over the past 20 years (Appendix 1 Table 1) A summary of cell counts for different land use types was performed using the Summarize Categorical Raster function, and the percentage of hay/pasture and cultivated



**Figure 2. 5.** Well locations and land use types in Mobile and Baldwin counties. Land use/land cover (LULC) information was from the 2021 National Land Cover Database.

crops were recorded and used for further analysis. Both the interpolation and extraction of land use values were performed using ArcGIS Pro (v 3.2, Redlands, CA).

## **2.2.6 Data Analysis**

### **2.2.6.1 Regression Analysis**

Statistical analysis was done using R. Due to presence of concentrations that were below the detection limits of the methods, otherwise known as left-censored data, the packages NADA (“Package ‘NADA’ Title Nondetects and Data Analysis for Environmental Data,” 2022), NADA2 (Julian, 2023), and brms (“Package ‘brms’ Encoding UTF-8 Type Package Title Bayesian Regression Models using ‘Stan,’” 2023) were used. Statistical significance was evaluated at the  $\alpha = 0.05$  level. To determine if there was a direct relationship between land use and nitrate concentrations, a linear regression was performed using the percentage of agricultural land within each buffer discussed in the previous section compared to concentrations of nitrate. To check for normality of regression residuals a QQ plot for nitrate was constructed. A lognormal distribution for nitrate was determined to be the most appropriate distribution since a normal distribution appeared to be skewed. A multilinear regression was also performed to determine how other variables such as wastewater treatment, SPC, pH and recharge potential relate to nitrate. Forward selection was used to determine which model was the best, with lower AICc values preferred.

### **2.2.6.2 Principal Component Analysis**

Principal component analysis (PCA) was also performed, which clusters of parameters and samples and has been used in water quality studies previously (Joseph and Kolok, 2022; Mahapatra et al., 2012). Linear combinations of variables are made to generate new variables that explain variations in the original data set, known as principal components. Loadings for each

water quality parameter were also examined to determine how much of an influence each parameter has on each component. Clusters of samples based on counties were visualized using a biplot. Parameters were chosen to be included in the PCA based on EPA MCL exceedance or being noted as contaminants of concern in this area previously (Belitz et al., 2016; Liu et al., 2005; Oltz et al., 2000; Robinson et al., 1996). Parameters that were included in the principal component analysis were nitrate, chloride, sulfate, total coliforms, alkalinity, lead, copper, iron, arsenic, specific conductance, pH and fDOM. Data was scaled prior to analysis.

### 2.2.6.3 Water Quality Indices

LSI and PPGC were also calculated based on the average values for each well to determine the influence of corrosion of pipes. LSI measures the ability of water to form a scale on pipes, which typically protects pipes from corrosion, compares the groundwaters pH to the pH at calcite saturation (Eq.1 and 2) (Belitz et al., 2016). Wells are considered as potentially corrosive ( $LSI < -0.5$ ), indeterminate ( $-0.5 \leq LSI \leq 0.5$ ), and scale forming ( $LSI > 0.5$ ). PPGC is measured by taking the chloride to sulfate ratio and the alkalinity of a well. If the well has a CSMR value of  $< 0.2$  then the threat of corrosion is low. A well has moderate threats of corrosion if the CSMR is between 0.2 and 0.5 or if the CSMR is greater than 0.5 and alkalinity is greater than or equal to 50. Finally, a well is considered as having a high threat of potentially corrosive groundwater if the CSMR is greater than 0.5 and the alkalinity is low. By comparing the two values categories can be assigned to each well to determine overall threat of corrosive groundwater.

$$(Eq. 1) \quad LSI = pH - pH_s$$

$$(Eq. 2) \quad pH_s = (9.3 + A + B) - (C + D)$$

$$A = (\log_{10} [\text{TDS}] - 1) / 10$$

$$B = -13.12 \times \log_{10} (^\circ\text{C} + 273) + 34.55$$

$$C = \log_{10} [\text{Ca}^{2+} \text{ as CaCO}_3] - 0.4$$

$$D = \log_{10} [\text{alkalinity as CaCO}_3]$$

Finally, a water quality index was calculated for each of the wells. A water quality index measures the suitability of water for drinking. Variables to include in the water quality index were selected based on parameters previously being noted as parameters of concern in Mobile and Baldwin counties or due to their presence being above the EPA MCL in some wells (Chandler et al., 1985; Murgulet and Tick, 2008, 2009; Oltz et al., 2000). Variables were then given a weight 1 through 5 with 1 signifying that the parameter is less concerning for water quality and 5 signifying that the parameter is more concerning for water quality. A relative rank is then calculated by summing all of the individual ranks and taking the ratio of each parameter's rank to the overall rank. A quality rating is then assigned to each variable by dividing the measured value by the EPA or WHO recommended level (Eq.1). The WHO value was used in cases where there was no established EPA level. Finally, a subindex is calculated for each variable by multiplying the quality rating for each parameter by the relative weight, with the sum of the subindices being the final value for each well (Eq. 2).

$$(Eq. 3) \quad q_i = \frac{C_i}{S_i} \times 100$$

$q_i$  = quality rating for each contaminant

$C_i$  = concentration of each contaminant

$S_i$  = EPA limit of each contaminant

(Eq. 4) 
$$WQI = \sum_{i=1}^n W_i q_i$$

$W_i$  = weight of each contaminant

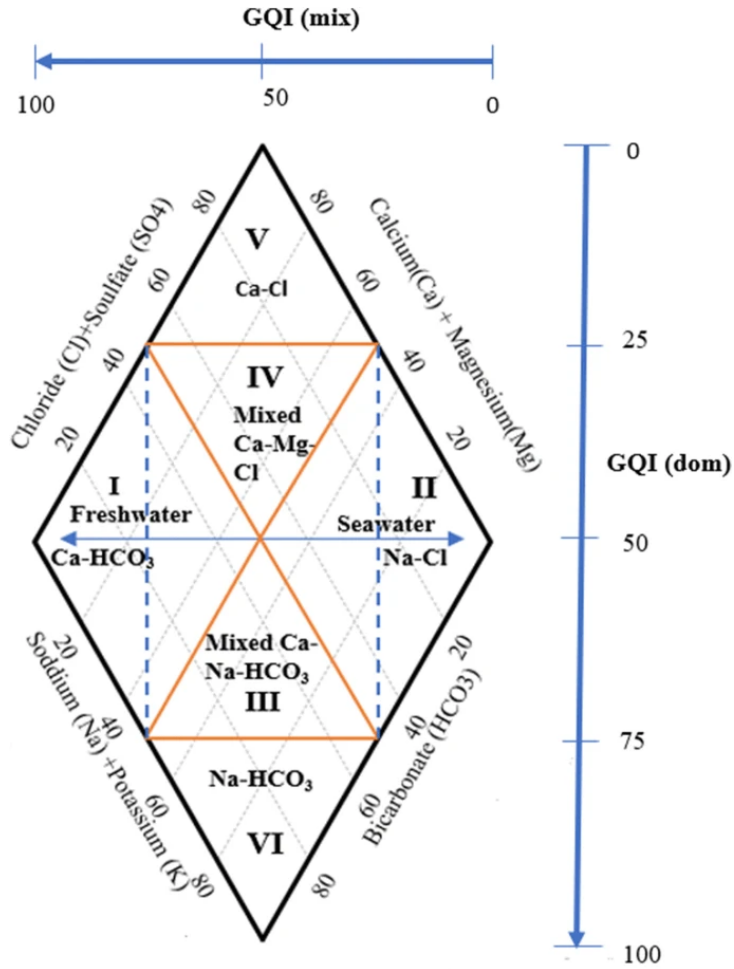
$q_i$  = quality rating for each contaminant

All subindices were added resulting in the final water quality index. Wells were classified as one of five categories: excellent (<50), good (50-100), poor (100-200), very poor (200-300), and unsuitable (>300)(Manna and Biswas, 2023; Moldovan et al., 2020; Şener et al., 2017).

### 2.2.7 Hydrochemical Facies Analysis

To determine what hydrochemical facies our samples, Piper diagrams and Gibbs plots were constructed. Piper diagrams were constructed using the Geochemists Spreadsheet function in Geochemists Workbench (v 17, Champaign, IL). Determining the relationship between the cations and anions in water samples can aid in understanding drivers of water quality (Akshitha et al., 2021; Murugesan et al., 2023).

A water quality index specifically designed for interpretation of Piper diagrams was also constructed using Eq. 5 and 6 following (Tomaszkiewicz et al., 2014). Samples are plotted in different domains, which signifies the dominant hydrochemical facies (Figure 2.5) and indicates the severity of saltwater intrusion.



**Figure 2.5.** Categorization of Piper diagram, adapted from Lotfata and Ambinakudige, 2020

$$(Eq. 5) \quad GQI_{Piper (mix)} = \left[ \frac{(Ca^{++}) + (Mg^{++})}{Total\ cations} + \frac{(HCO_3)}{Total\ anions} \right] \times 50 \text{ (in meq/L)}$$

$$(Eq. 6) \quad GQI_{Piper (dom)} = \left[ \frac{(Na^+) + (K^+)}{Total\ cations} + \frac{(HCO_3^-)}{Total\ anions} \right] \times 50 \text{ (in meq/L)}$$

Gibbs plots were also constructed to determine the main mechanisms of aquifer geochemistry (Gibbs, 1970). Precipitation data from the National Atmospheric Deposition Program was taken from four sampling points near Mobile and Baldwin counties, two in Alabama, one in Florida and one in Mississippi (NADP, 2024). Gibbs plots were constructed by

comparing total dissolved solids (TDS) to the ratio of cations and anions. Cations included are sodium and potassium and anions included are chloride and bicarbonate. Both cation and anion concentrations were converted from parts per million to milliequivalents before plots were constructed. Specific conductance was converted to TDS by multiplying specific conductance values by 0.5 (PureAqua Inc, 2024).

## 2.3 Results

### 2.3.1 General Water Quality

The water quality index is a qualitative method to understand general water quality. Water quality parameters are ranked from one to five, with one indicating the least impact to water quality while five indicates the largest impact to water quality (Table 2.2). All other parameters received were ranked relative to impacts on human health similar to previous studies (Feng et al.,

**Table 2. 255.** WQI variables and associated ranks, relative ranks, and health-based guidelines from the EPA and WHO.

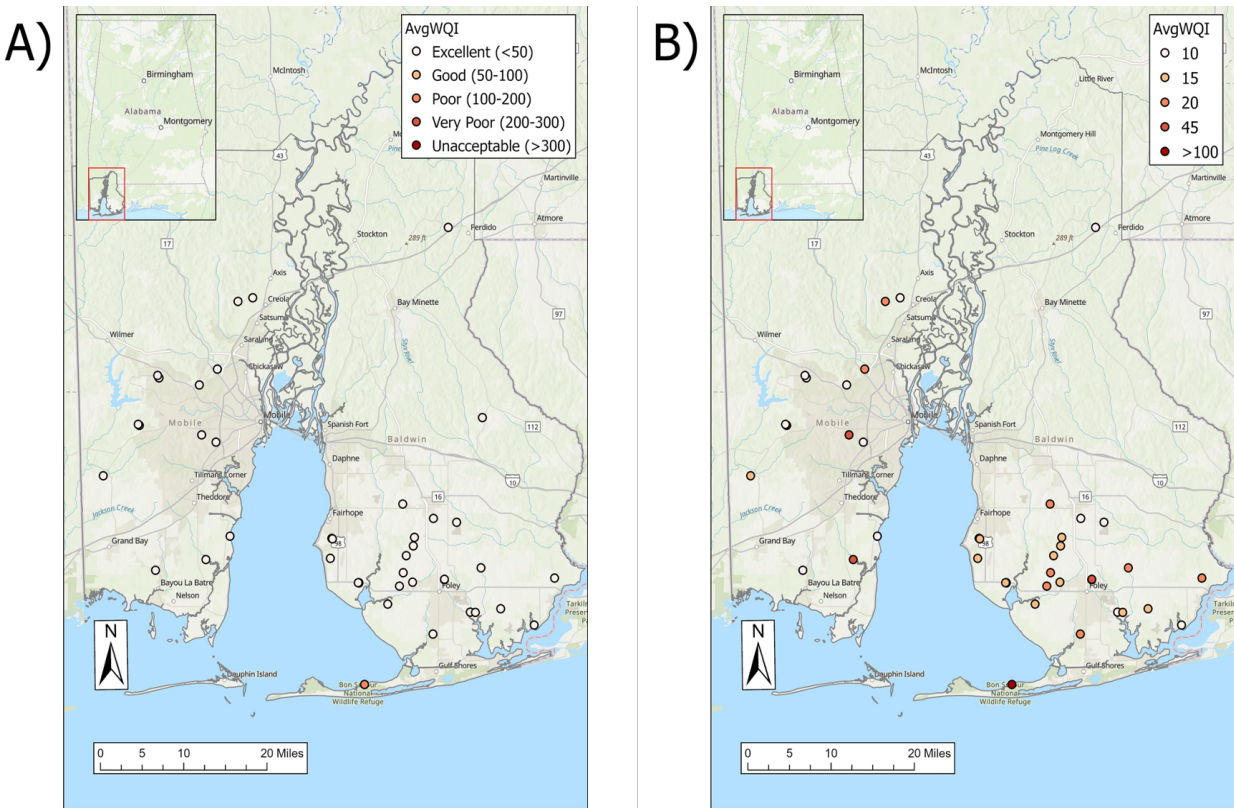
Parameter	Rank	Relative Rank	EPA <sup>b</sup> or WHO Guideline (ppm)
Pb	5	0.156	0.015 <sup>b</sup>
NO <sub>3</sub> <sup>-</sup>	4	0.125	10 <sup>b</sup>
Cl <sup>-</sup>	3	0.094	250
pH	3	0.094	8.5
Fe <sub>T</sub> <sup>a</sup>	3	0.094	0.3
TDS	3	0.094	1000
Ca <sup>2+</sup>	2	0.063	300
HCO <sub>3</sub> <sup>-</sup>	2	0.063	120
Mg <sup>2+</sup>	2	0.063	30
Mn <sup>2+</sup>	2	0.063	0.1
Na <sup>+</sup>	2	0.063	200
SO <sub>4</sub> <sup>2-</sup>	1	0.031	250

<sup>a</sup> Represents total dissolved iron

<sup>b</sup> Represents parameters where EPA Guideline differs from WHO Guideline

2020; Moldovan et al., 2020; Şener et al., 2017). Lead has been shown to impact cognitive function and therefore was ranked the highest (Balali-Mood et al., 2021). Nitrate has also been linked to negative health effects (Ward et al., 2018) (Joseph and Kolok, 2022; Mathewson et al., 2020; Mendy et al., 2024) and is the main parameter of interest in this study and was ranked the second highest (Skalaban et al., 2024).

Based on the general water quality index, all wells in both counties were classified as having “excellent” water quality except one well in southern Baldwin County that had “poor” water quality (Figure 2.6. A). Though most wells were classified as “excellent”, water quality was not homogenous. By creating a finer evaluation scheme (Figure 2.6B) (Appendix 1 Table 2), it is clear that water quality does vary, with wells exhibiting higher values (generally poorer water quality) located in southern Baldwin County and eastern Mobile County.



**Figure 2. 7.** Private wells symbolized by Water Quality Index (WQI) category (A), private wells symbolized by individual WQI values (B).

Well owners received a report detailing concentration of each parameter after each sampling campaign. Reports included measurements of each parameter, the recommended level of each parameter, health effects, sources, and treatment options for each parameter. Reports were initially constructed similar to a consumer confidence report, but due to interpretation difficulties, a stoplight system was employed for the September 2023 sampling campaign. A green light indicates that the parameter is below the EPA MCL, yellow indicates that the parameter is near (75%) the EPA MCL, and red indicates the parameter is over the MCL.

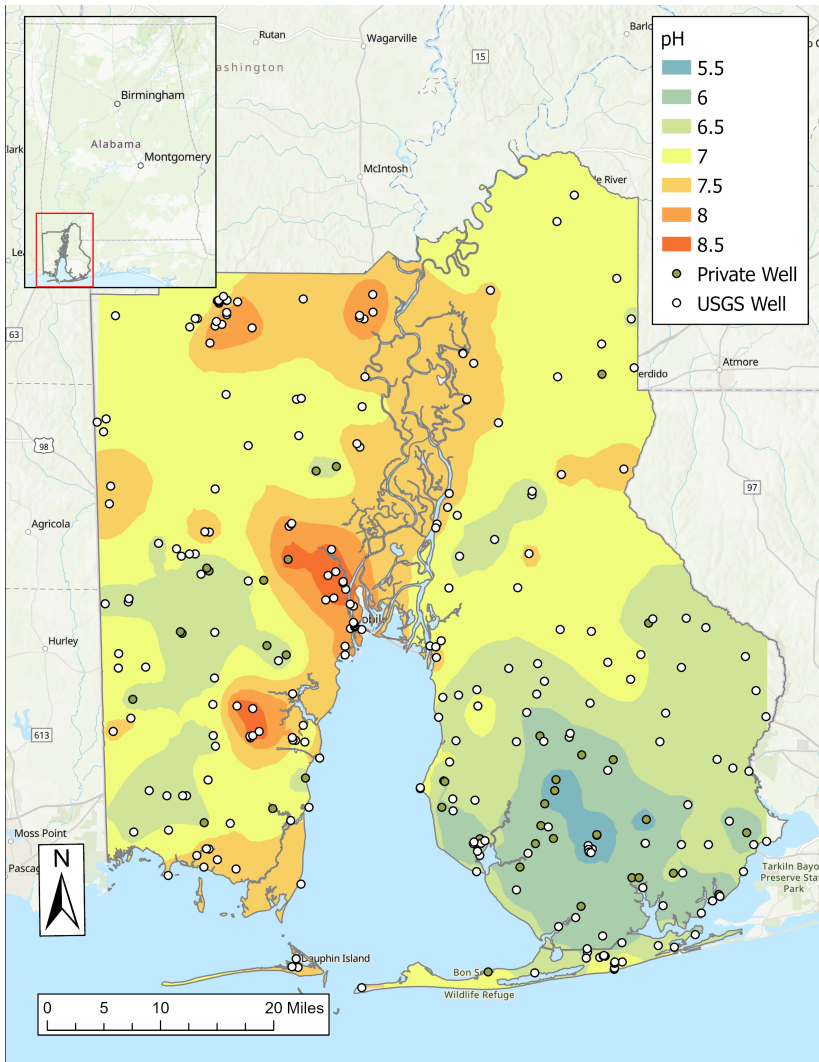
Table 2.3 is derived from the stoplight system to understand what parameters most frequently occurred that are near or exceed the EPA MCL. Total coliform most frequently exceeded the EPA MCL (25.8% of the samples) with lead and iron also notably having several samples near or above the EPA MCL (11.2 and 9%, respectively). In several samples, nitrate also exceeded the MCL (3.3%). Additionally, pH ranges were typically in the EPA recommended

range of 6.5-8.5. Arsenic, copper, and *E.coli* each were approaching or exceeded the MCL in some wells.

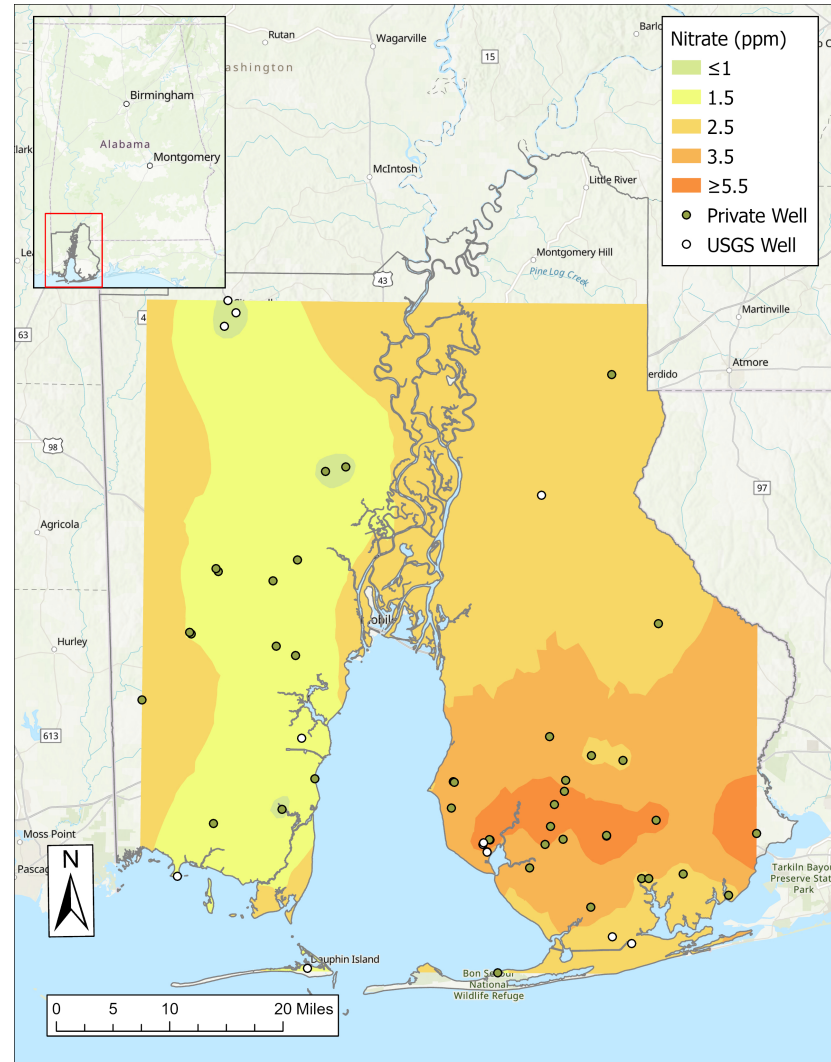
Next, the corrosivity of the groundwater was evaluated. Belitz et al. (2016) classified the state of Alabama as having potentially corrosive groundwater. The drivers of corrosion are low pH values, which impacts the values of the LSI, low sulfate, which impacts the CSMR values, and low alkalinity which impacts the overall PPGC classifications. LSI values ranged from -9.23 to -2.67 while CSMR ratios ranged from 0.5 to 79.7 (Appendix 1 Table 3). Overall, all wells in the study are influenced by groundwater conditions that are favorable for the corrosion of pipes and were classified as *very high* (42) or *high* (1) prevalence of potentially corrosive groundwater.

**Table 2. 383.** Water quality parameters proximity to the EPA MCL.

Parameter	Below EPA MCL (%)	75% EPA MCL (%)	Above EPA MCL (%)	EPA MCL (ppm)
TC	74.2	-	25.8	0
Pb	88.8	2.2	9	0.015
Fe <sub>T</sub>	91	1.1	7.9	0.3
NO <sub>3</sub> <sup>-</sup> -N	96.7	2.2	1.1	10
pH	-	7.9	-	6.5-8.5
As	98.9	0	1.1	0.010
Cu	98.9	0	1.1	1.0
<i>E.coli</i>	98.9	-	1.1	0



**Figure 2. 7.** Interpolation of pH. Green points represent private well owners and white points represent historical USGS monitoring data.



**Figure 2. 8.** Interpolation of nitrate. Green points represent private well owners and white points represent historical USGS monitoring data.

### 2.3.2 Spatial Distribution of Nitrate and pH

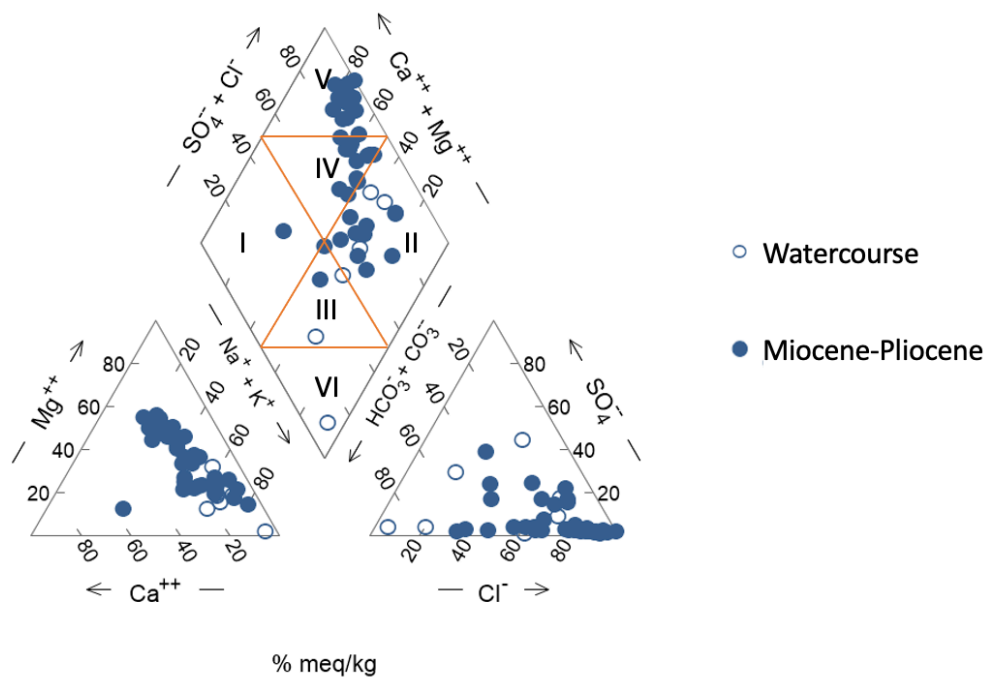
The spatial distributions of nitrate and pH were visualized through interpolations (Figure 2.7 and Figure 2.8). Optimized simple kriging was used for the interpolations and no transformations or trend removal were performed. The final root mean square error (RMSE) for nitrate and pH were 1.98 and 0.75, respectively. Nitrate and pH showed an inverse relationship, in areas with high nitrate concentrations there were low values for pH and vice versa. Murgulet and Tick (2009) found that higher concentrations of nitrate were found in southeastern portions of Baldwin County. Murgulet and Tick (2009) also found much higher concentrations of nitrate than observed in this study with maximum values ranging from 12.06 to 27.42 mg/L whereas the highest value observed here was 13.02 mg/L.

Nitrate and pH are related due through the biogeochemical processes of nitrification and denitrification (Rivett et al., 2008). Nitrification occurs when microbes convert ammonium into nitrate at a pH range of 4.5 to 7.5 (Cameron et al. 2013). Denitrification occurs when microbes transform nitrate into nitrogen gas which is then released from the subsurface. A pH range between 5.5 to 8 is favorable for denitrification processes, and if pH is outside of this range, denitrification may not proceed. The pH range of our study area is favorable for nitrification and denitrification, but the oxic nature of the groundwater suggests that denitrification is limited and therefore nitrate accumulated in the aquifer.

### 2.3.3 Groundwater Chemistry

#### 2.3.3.1 Assumptions about well depth and aquifer

Only one well user knew the depth of their well, and so interpretations of groundwater chemistry are limited because of the overall lack of well depth data. To address this issue, the most likely aquifer accessed for the private well was established based on well location and trends in the hydrochemical data. First, well locations were plotted on a map of aquifer outcrops (Oltz et al., 2000) to identify which aquifer, the Watercourse ( $A_1$ ) or the Miocene-Pliocene ( $A_2$ ), was available to access. Wells that plotted only in the Miocene-Pliocene area were assigned to

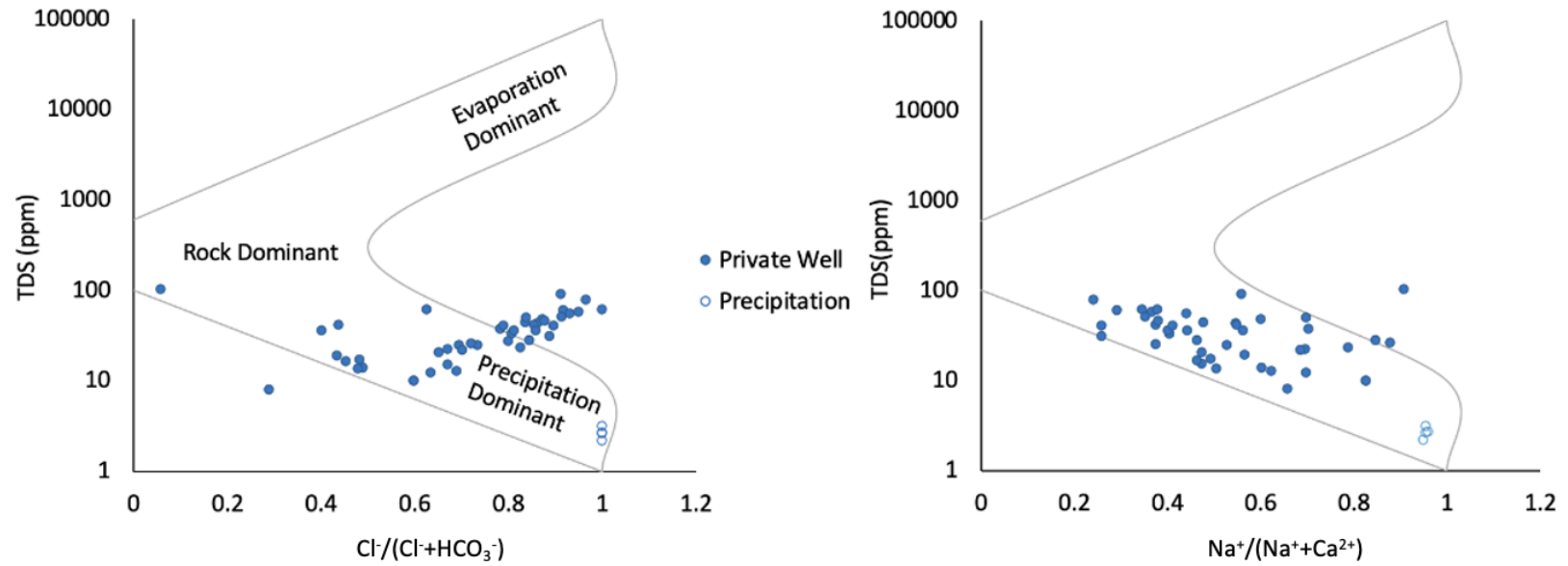


**Figure 2. 9.** Piper diagram of well water samples separated by suspected aquifer position. Open circles represent wells that were suspected to be in the Watercourse aquifer. Filled blue circles represent wells that were suspected to be in the Miocene-Pliocene aquifer. Due to lack of clustering in this analysis, all wells were treated as being a part of the Miocene-Pliocene for further analyses.

that aquifer, but those that plotted in the Watercourse have the potential to utilize either aquifer system.

In the Piper diagram in Figure 2.9, the water chemistry is compared between the wells in the Miocene-Pliocene and those that potentially use the Watercourse. The diagrams indicated that most of wells were categorized as having groundwater chemistry that belong in hydrogeochemical domains 2, 4, and 5, following a Na-Cl to Ca-Cl trend. The values of the GQI also help determine wells impacted by saltwater intrusion. Wells with  $GQI_{(mix)}$  values closer to 0 and  $GQI_{(dom)}$  values between 25 and 75 would be heavily impacted by saltwater intrusion. Wells in this study have  $GQI_{(mix)}$  values between 21.15 and 58.20 and  $GQI_{(dom)}$  values between 12.37 and 92.16 (Appendix 1 Table 4). Therefore, the effect of saltwater intrusion was minimal in these wells.

First, the lack of clustering between the well classifications indicated that the water chemistry is generally the same in all wells and following similar trends. Second, Murgulet and Tick showed that the Watercourse experiences higher degrees of saltwater intrusion compared to the Miocene-Pliocene and so the concentration of  $Cl^-$  in the aquifer can help point to the aquifer, as well. The average concentration of  $Cl^-$  in the wells in this study was  $9.2 (\pm 5)$  mg/L (max value 26.8 mg/L), which was within the same order of magnitude as observed in Murgulet and Tick (2008) (28.2 mg/L  $Cl^-$ ), but, the Watercourse showed concentrations of chloride averaging 486 mg/L, which is two orders of magnitude higher than that observed in this study. Ultimately, it was concluded that all of the wells likely utilize the Miocene-Pliocene and were treated as such in further analysis.

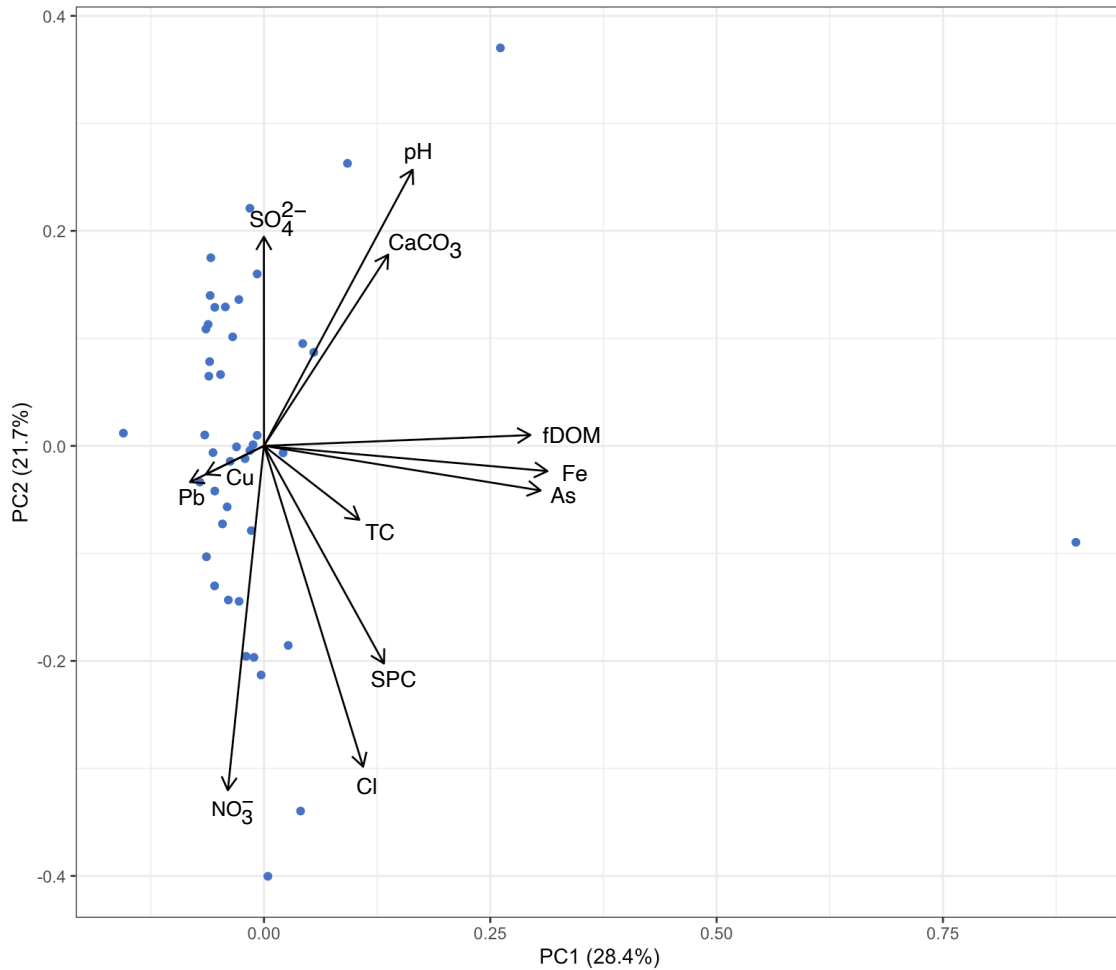


**Figure 2. 10.** Gibbs plots of private well samples treated as being in the same aquifer position. Filled circles represent private wells and empty circles represent precipitation samples taken from the National Atmospheric Deposition Program.

Gibbs plots were constructed to understand the relative impact of precipitation versus water-rock interactions on groundwater chemistry (Figure 2.10). If samples were in the lower half of the plot, then it is likely that water was dominated by precipitation and therefore surface processes likely impact water quality (Murugesan et al., 2023; Su et al., 2023)(Appendix 1 Table 5 ). However, if samples are in the top half of the plot, then the samples are more likely dominated by rock-water interactions and less by precipitation and surface processes. Water chemistry of precipitation was also plotted as a local endmember of groundwater chemistry (NADP, 2024). The Gibbs plots indicate that groundwater is heavily influenced by precipitation and reinforces the high recharge potential previously established in this area (Gutherie et al., 2022). Notably there are some areas with where samples are more calcium rich, which may be from the aquifer lithology or possibly fertilizer, since fertilizer contains numerous elements.

#### **2.3.4 Relationships between groundwater chemistry and other variables**

PCA of water quality variables was performed to understand relationships between general groundwater chemistry and those considered groundwater contaminants. Variables included were either noted as being of concern in past studies, those with elevated levels in this study, and those connected to the corrosion of pipes. PC1, PC2, PC3, PC4, and PC5 were significant following the Kaiser rules (Tabachnick and Fidell, 2007) with eigen values of 3.41, 2.60, 1.84, 1.55, 1.03, respectively. PC1 and PC2 account for 50.1% of the variance in the dataset, with PC1 accounting for 28.4% of variation and PC2 accounting for 21.7% of variation (Appendix 1 Table 7). For exploratory analysis a loading cutoff of an absolute value of 0.3 was used to understand factors that contribute to each PC. Loadings in the PCA are shown in Figure



**Figure 2. 11.** PCA of water quality parameter and private well water samples.

2.11. All variables, with the exception of copper and total coliforms meet the loading criteria for the first two principal components.

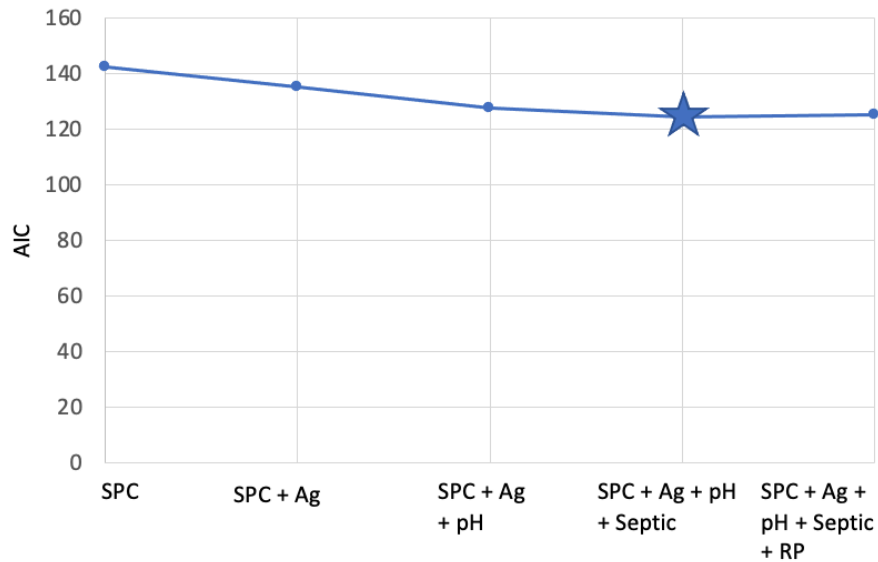
Iron, arsenic, and organic matter (as quantified by fDOM measurements) all exhibit a direct relationship, which has also been observed in other studies (Gao et al., 2016; Poulin et al., 2014; Schittich et al., 2018). Iron and arsenic having a direct relationship may be caused arsenic bonding to iron in more oxic conditions (Lee et al., 2006). Notably, the relationship between iron, arsenic, and fDOM was driven by their presence in one well in southern Baldwin County (B35\_DW2). Vectors for lead and copper cluster together, indicating that corrosion of pipe

material may be driving concentrations of those parameters in well water (Belitz et al., 2016; Harvey et al., 2016). There was an inverse relationship between nitrate and pH, which was also noted in the interpolations above.

#### **2.3.4.1 Relationships between land cover and nitrate**

Linear regression was used to evaluate the relationship between nitrate and other variables. First, simple linear regressions were created with nitrate as the dependent variable and SPC, % agricultural land, pH, wastewater system, and recharge potential as separate independent variables. Statistically significant relationships were observed ( $p < 0.05$ ) for all variables except recharge potential and septic tank usage (Table 2.4). SPC and percent agriculture showed a positive relationship with nitrate. Nitrate and pH have an inverse relationship which was, again, reflected in the PCA and interpolations. Interestingly, the use of septic systems had a strong inverse relationship with nitrate. Therefore, homes relying on municipal wastewater treatment typically exhibited higher levels of nitrate in this dataset. This is counter to literature precedent that shows that septic systems to be sources of nitrate (DeSimone et al., 2014; Wakida and Lerner, 2005).

To determine the collection of variables that best explained nitrate in a multi-linear regression, forward selection of the variables was performed with model optimization evaluated by the Akaike information criterion (AIC). SPC was chosen as the base parameter because it had the highest  $r^2$  value in the single-variable regression, then, variables were sequentially added based on the  $r^2$  value from the single-variable regressions (Table 2.4). The final multilinear model



**Figure 2. 12.** AIC graph for forward selection of regression explanatory variables. The star indicates the final model that was chosen.

**Table 2. 384.** Variables included in regression analyses

Parameter	Variable Type	$\beta$ Estimate	Standard error	p-value	$r^2$
Model 1: Each parameter is treated independently					
SPC	Continuous	0.02096	0.00467	7.10e-6	0.33
Agriculture	Continuous	0.0267	0.00764	0.00047	0.2318
pH	Continuous	-0.829	0.296	0.0051	0.1601
Septic (1=yes, 0=no)	Categorical	-0.731	0.751	0.33048	0.0223
Recharge Potential	Continuous	0.492	1.247	0.69322	0.003725

**Table 2. 385.** Forward selection of regression explanatory variables

Parameter	Rescaled Likelihood $R^2$	AIC
Model 2: Multilinear regression		
SPC	0.33	142.3873
SPC+Ag	0.4663	135.0779
SPC+Ag+pH	0.5777	127.6055
<b>SPC+Ag+pH+Septic</b>	<b>0.6286</b>	<b>124.4706</b>
SPC+Ag+pH+Septic+Recharge Potential	0.6402	125.2136

that was chosen included SPC, agricultural land use, pH and septic tank usage (Table 2.5 and Figure 2.12). The final model had the lowest AIC though it did not have the highest rescaled likelihood  $R^2$ , which is  $R^2$  used when accounting for censored data, or data that was below the detection limit of the lab used for analysis. However, the model including SPC, agricultural land use, pH, septic tank usage, and recharge potential had only a 0.0116 increase in rescaled likelihood  $R^2$  and a 0.743 increase in AIC. Since including recharge potential did not improve the model greatly, it was not included in the final model. The final rescaled likelihood  $R^2$  was 0.6286 and the final AIC was 125.2136. All variables in the final model (Table 2.6) (Appendix 1 Table 8) were significant at the  $p = 0.05$  level. Overall, the results of the multilinear regression show that there were multiple factors influencing nitrate in private well water, not exclusively agriculture.

**Table 2. 386.** Final multilinear regression model of water quality to explain nitrate in well water.

Parameter	$\beta$ Estimate	Standard error	p-value
(Rescaled Likelihood $R^2=0.6286$ , AIC= 124.4706)			
Intercept	3.19528	1.29597	0.01368
SPC	0.01962	0.00358	4.1e-8
Agriculture	0.01418	0.00614	0.02104
pH	-0.72392	0.21536	0.00078
Septic (1=yes, 0=no)	-1.07597	0.46352	0.02027

## 2.4 Discussion

### 2.4.1 Major trends in well water quality

The multitude of factors affecting well water highlight the need to understand water quality from a holistic view. The WQI (Section 6.1) indicated that the water quality was “good” to “excellent” however, a number of trends in poor water quality were observed that counter this interpretation like high corrosivity and concentrations of nitrate that are approaching or exceed the MCL. The qualitative nature of ranking water quality parameters cause this evaluation scheme to be subjective, and it could change with different parameter classifications.

A close look at the empirical water quality data can offer guidance for well users. One consideration for wells users in Mobile and Baldwin counties is the low pH values and high corrosivity which can lead to leaching of metals from pipes and fixtures. Additionally, some well water exceeded the EPA MCL for parameters such as total coliforms, lead, iron, nitrate, arsenic, and copper. With the exception of nitrate, these exceedances were on a case-by-case basis and did not display spatial trends or other widespread trends in relation to water quality. This is an important aspect to communicate because it reinforces the need for water testing across a wide array of parameters to ensure safe drinking water. Saltwater intrusion poses a threat to well water

quality in many coastal areas (Jasechko et al., 2020), but our study shows that saltwater intrusion is not severe in the Miocene-Pliocene in Alabama.

Nitrate is also a major issue across the United States (Burow et al., 2010; Nolan and Hitt, 2006). Here, interpolations show that high nitrate is most concerning in southern Baldwin County with lower concentrations present throughout Mobile County. Nitrate and pH were also shown to have an inverse relationship so that areas with high nitrate concentrations have low pH values. We also found that nitrate was also shown to have a direct relationship with the percentage of agriculture land cover. The environmental complexity was captured in the multilinear regression model so that nitrate was also shown to have a direct relationship with specific conductance and an inverse relationship pH and the presence of a septic system.

#### **2.4.2 Future of well water dependence in the study area**

Mobile County is the second largest county in Alabama based on population, and Baldwin County is among the top 5 counties that are experiencing a population increase (Oltz et al., 2000). Groundwater is one of the main sources of drinking water in both counties, along with Big Creek Reservoir serving Mobile (Oltz et al., 2000; Robinson et al., 1996, 1956). Based on a well user density model produced by Johnson et al. (2019), approximately 70,000 well users live in Mobile and Baldwin counties (Appendix 2 Section 3), and it is unclear how private well use will be affected by the increase in population. Though construction dates of most wells in this study were not available, two well owners mentioned that they had recently built their homes and installed their wells. With the growth in population, there is the potential for private well use to increase or be sustained in the future, highlighting the need to understand groundwater quality.

### **2.4.3 Implications for well water quality in the Gulf Coast**

Though water quality issues will vary by location, trends in water quality observed in Mobile and Baldwin counties are likely to apply to a broader range of well users. This study area is within the larger Coastal Lowlands Aquifer, spanning portions of Florida, Alabama, Mississippi, Louisiana and Texas (Barlow and Belitz, 2016). There are approximately 1.3 million people in the coastal lowlands aquifer that rely on private well water (Johnson et al., 2019) (Appendix 2 Section 3). Since much of the Coastal Lowlands Aquifer is in close proximity to coastal areas, saltwater intrusion may be an issue in other areas although not observed here. For example, Texas, Louisiana, and Alabama are states in the Coastal Lowland Aquifer region that have been noted as having landward hydraulic gradients. Similar lithology across the Coastal Lowlands Aquifer may also make corrosivity due to low pH a prevailing issue in the region. Nitrate across the Coastal Lowlands Aquifer was low (2% MCL exceedance) as reported by Barlow and Belitz (2016), which is generally in agreement with this study. Our areas of high agriculture land use and low pH are likely to point to these exceedances, Due to the multiple possible stressors to well water quality, it is imperative to understand well water quality from a holistic view.

### **2.5 Limitations**

This study has several limitations. First, the study lacked well depths for the samples collected. Though we have several lines of evidence based on water chemistry that suggest that the wells in the study are in the same aquifer, well depths would ensure that assumptions made in this study are accurate.

Censored data also was used in many of the analyses that we conducted. In this study, data was censored if it fell below the detection limit of the method used for analysis. For example, 20% of the samples exhibited nitrate concentration that was reported as “<0.15 ppm”. This presents an issue when values are required for data analysis techniques like interpolation or regression. A common method to handle censored data is replacing the censored value with one-half the detection limit however, it is not viewed as the best way to handle censored data (Helsel, 2012). Linear and multiple regressions do not suffer from the presence of censored data due to function in R and other programming languages having functions built to model censored data before regression. For example, Maximum Likelihood Estimation (MLE) can be used to model censored data based on the likely distribution of the data. When doing interpolations a previous study found that using one-half the detection limit for censored parameters did not alter the accuracy of the interpolation (Mohamed et al., 2021). Creating water quality indices, corrosivity indices and performing principal component analyses are other cases where using one-half detection limit may be unavoidable, but still allow valuable interpretations of the data.

Another limitation is the geographic distribution of sampling points. For example, there is a high density of well users in southwestern Mobile County where this study lacked sample points. Previous studies have included data from wells located in the Watercourse aquifer, the shallowest zone, to compare and contrast the two aquifers. This study likely lacks data from the Watercourse and so the study lacks clear differentiation between aquifer chemistries (Murgulet and Tick, 2008, 2009). Finally, the low data resolution may impact the interpretation of what seem like outlier data points. For example, one well in the northern portion of Mobile County had an average pH of 8.95, which is higher than the other wells in both counties. However,

incorporating historical groundwater data from the USGS revealed that pH's range from 7-8.5 in the surrounding area, indicating that an average pH of 8.95, though high, may not be anomalous.

Information on locations and water quality from public supply wells would also have provided another possible explanatory variable for water quality of private wells. Public supply wells are usually deeper than private wells and contain a combination of modern and pre-modern water (Levy et al., 2021). Modern water is more likely to be affected by surface processes and contamination. In an unconfined aquifer setting, heavy pumping in deeper wells causes the cone of depression to expand, causing a higher proportion of modern water to be extracted. If shallower private wells are near public supply wells, cones of depression that are caused by deeper public supply wells could draw modern contaminated water towards private wells (Levy et al., 2021). Proximity to public wells could therefore impact contaminant concentrations in private wells. There are a number of public supply wells in the Miocene-Pliocene in Baldwin and Mobile (personal communication with G. Guthrie, Geological Survey of Alabama). The impact of public supply withdraws on private well water quantity and quality is yet unknown.

## **2.6 Conclusion**

The data presented in this study indicate that there is a significant relationship between agricultural land use and nitrate concentrations in groundwater in private wells in Mobile and Baldwin counties, supporting previous studies that agriculture impacts well water quality (Gosselin et al., 1997; Joseph and Kolok, 2022; Naylor et al., 2018). The relationship between nitrate and pH was found to be inverse, which is supported by the interpolations, PCA and multi-linear regression performed. Particularly for areas of low pH, high levels of corrosion can contribute to practical home management issues like pipe and fixture replacement as well as

human health concerns if toxic elements are leached as a byproduct. These results impact well owners living in Mobile and Baldwin counties but also those living in regions where water is supplied by the Coastal Lowlands Aquifer. Another issue that is prevalent in coastal areas is the threat of saltwater intrusion. Though there was some evidence of saltwater intrusion, the level of saltwater intrusion was not a threat to human health in this study area. Overall, this study also found that water quality is generally excellent based off of the WQI constructed. However, it should be noted that WQI's are qualitative and the ranking of variables is subjective. Issues associated with the construction of WQIs again emphasize the need to take a holistic approach when researching well water quality. To ensure the safety of private well users understanding the mechanisms of groundwater chemistry and potential sources of contamination is important.

## Chapter 3

### A “First alert” for drinking water quality: commercial water quality testing kits for community-engaged research

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#### Abstract

Groundwater is a crucial source of drinking water worldwide. The 2022 UN Sustainable Development Goal (SDG) report highlighted a gap in groundwater monitoring data worldwide. One way to fill this gap is through community-engaged research (CEnR). This research identifies factors contributing to the success of CEnR programs and evaluates the practicability of tools for water quality monitoring. Specifically, we assessed the accuracy and applicability of commercial water test kits for measuring the primary standards regulated by the US Environmental Protection Agency (US EPA). We evaluated the testing principle of the commercial test kits and classified them into all-in-one and combination test kit groups. We determined that combination test kits are more accurate and reliable compared with all-in-one test and identified the most suitable kits for CEnR programs groundwater testing involving private well owners. Additionally, we discussed the importance of data quality considerations, interactions between researchers and communities, and training to ensure program success.

*Keywords: Sustainable Development Goals, water contamination, test kits, private well, groundwater, water quality.*

**Synopsis:** The combination water test kits can serve as a tool for groundwater quality monitoring in community-engaged research programs.

### 3.1 Introduction

Improving water quality is essential to protect and improve human and ecosystem health. Groundwater represents a significant portion of freshwater supplies, and the 2022 UN Sustainable Development Goal (SDG) report highlights a gap in groundwater quality monitoring data for many countries (United Nations, 2022). Moreover, the UN-Water SDG 6 Global Acceleration Framework emphasizes the role that capacity development holds for ensuring availability and sustainable management of water (Scheihing et al., 2022). Synergistically, these targets can be achieved through the community-engaged research (CEnR) framework, namely *target 6.1* access to safe drinking water and *target 6.b* participation of communities in improving water management (Fritz et al., 2019; Hegarty et al., 2021; United Nations, 2017).

The CEnR framework can occur along a continuum of leadership/participation forms starting from community-informed research, where the community is consulted about research, to community-involved, where the community members are collaborators, to community directed, where members are leading the project (Eggers et al., 2018; Flores-Díaz et al., 2018; Li et al., 2023; London et al., 2020; U.S. Environmental Protection Agency, 2015). For groundwater research, the CEnR framework benefits participants, research teams, and the larger community (Baldwin et al., 2012; Eggers et al., 2018). For the participants, it addresses direct concerns related to drinking water quality, while for researchers, it provides access to sites that are otherwise difficult to reach (Lombard et al., 2021). The outcomes of the community-based research are embedded strategies and action plans to address public concerns and promote positive change. The framework is iterative and continuous, strengthening the research questions, outcomes, and community-driven solutions (Richards et al., 1996). The CEnR framework is commonly applied to monitor water quality, but most of these efforts are focused on surface water (Baalbaki et al.,

2019; Little et al., 2016; Nath and Kirschke, 2023; Ramírez et al., 2023). For example, the Alabama Water Watch (AWW) was established in 1992 and, through the program, citizens are trained to monitor conditions and trends in local waterbodies (Dominguez, 2021). The AWW data has been used by researchers, policy makers, and other stakeholder groups to improve water quality on a state-wide scale for over 30 years. The 2023 US Volunteer Water Monitoring Network, a working group of the National Water Quality Monitoring Council, has identified similar programs in almost every state in the US (Stepenuck, 2023). Globally, FreshWater Watch is a citizen science program that collects water quality data and aims to contribute to the SDG indicator 6.3.2 “Proportion of bodies of water with good ambient water quality” (Woods et al., 2022). Notably, there is no comparable effort to monitor groundwater as emphasized by World Water Quality Alliance (World Water Quality Alliance, 2021) and UN SDG (United Nations, 2022) reports.

For CEnR, it is important to select appropriate tools for data collection that are tailored to the research question as well as the community need and ability but also that provide insights into water quality for researchers for fulfilling SDG6 (Quinlivan et al., 2020a, 2020b). Commercial water test kits for water quality can provide a useful tool, build capacity within the community, educate citizens about groundwater resources, and fill in data gaps about groundwater quality. The lowered sensitivity of the test kits and some ambiguity in the interpretations does not allow them to replace the laboratory analysis (Ali et al., 2019; Kriss et al., 2021; Reddy et al., 2020), but they can serve as a “first alert” of water quality deterioration and significantly reduce the time from sampling to receiving the result. The time lag before receiving the results is especially important during extreme weather events like flooding, where groundwater quality changes relatively quickly (Pieper et al., 2021) and microbial contamination causes waterborne outbreaks of enteric illness (Andrade et al., 2018; Mahmoodzadeh and Karamouz, 2019). On a larger scale, success of

a groundwater monitoring program also has the potential for citizens to advocate for positive change in water resource management.

Although test kits are widely available, these have not been evaluated for adoption in a CEnR framework for groundwater monitoring<sup>19,21</sup>. This study aimed to evaluate tools and practices for data collection relevant to CEnR framework for groundwater monitoring. We conducted a market analysis of test kits and assessed their performance for well water quality assessment by local communities.

## **3.2 Materials and Methods**

### **3.2.1 Test Kit Selection Process**

Commercial water quality test kits, referred to as test kits in the discussion below, are available for purchase at numerous home-improvement stores and from online vendors. Both primary and secondary drinking contaminants identified by the US EPA can be measured by simple manipulations with the test kits requiring no advanced education. Several studies evaluated the single-parameter test kits and stated the usefulness of this approach for rapid screening of lead (Kriss et al., 2021), arsenic (Das et al., 2014; George et al., 2012; Steinmaus et al., 2006), nitrate/nitrite (Nielsen et al., 2008) and pesticides (Ballesteros et al., 2003) in water. In this study we evaluated the test kits that can measure  $\geq 4$  water quality parameters. The market search of the available test kits was performed by Amazon using keywords like “water test kits”, “well water test kit”, and “drinking water test kit”. We limited our search to drinking water and well water, excluding water quality tests for spas and aquaria. The market analysis was performed from May until December 2022, and it gives an overview of the test kits available during that period.

All test kits (n=27) were classified into two major groups and were evaluated separately: 1) all-in-one test strips, where one strip contains tests for all parameters, and 2) combination test kits, where several test principals are combined in one test kit (Appendix 2 Section 1). The test kits within each group were further classified and sorted into sub-groups of unique products by the principle of analysis, concentration ranges, and the number of test parameters. Test kits were sorted into 13 groups of all-in-one and 9 groups of combination tests of unique products. All-in-one test group 13 was excluded from further analysis (Appendix 2 Table 3) because it assesses water quality parameters that are not regulated for well water by EPA (total and free chlorine, hardness, and alkalinity). Further, the parameters of all test kits were sorted into 3 categories based on US EPA standards for drinking water (United States Environmental Protection Agency, 2009): 1) primary standard; 2) secondary standard; 3) non- regulated standards. We focused on the primary standards relevant to groundwater from private wells and pH as it is an important secondary standard. We emphasized the importance of testing kits that can measure multiple parameters since communities are often exposed to a mixture of contaminants(United States Environmental Protection Agency, 2009).

To assess the sensitivity of the test kit, we examined the concentration intervals indicated on the bottle or in the instructions and compared them with the maximum contaminant levels (MCLs) set by the US EPA (details in Appendix 2 Section 2). We also noted how safe and hazardous concentrations were highlighted in the instructions and/or on the bottle/box. The test kits were then down selected based on the number of primary standards and sensitivity relative to the MCLs.

### 3.2.2 Groundwater Sampling and Analysis

Two sampling campaigns were performed in September-October 2022 and April-May 2023 in Baldwin and Mobile Counties, Alabama (n=33). The study area was tied to the funding mechanism through the Resources and Ecosystems Sustainability, Tourist Opportunities, and Revived Economies of the Gulf Coast States Act (RESTORE Act) to understand and support community sustainability in the Alabama coast. At the well, we identified the spigot closest to the wellhead to collect samples and perform kit manipulations. The well was then purged through the spigot for 15 minutes at high flow, to best collect a representative groundwater sample. Then, the flow was reduced, and the sample pH was measured in the field using an EXO2 sonde. For each sample, the calibration cup used for measurements and the sonde were rinsed three times with well water to prevent contamination from other samples. The calibration cup was then filled with well water and the sonde was placed in the cup and allowed to stabilize before measurements were recorded. Then, three water samples were collected for metals and anions, pesticides, and pathogen enumeration analysis in pre-rinsed 500-mL high density polyethylene (HDPE), 250-mL amber glass bottles, and 100-mL HDPE sterile bottles, respectively. The samples were transported on ice in the cooler and stored at 6°C until further analysis. Upon arrival at the laboratory, 500-mL samples were filtered through 0.45 µm cellulose acetate filter (VWR, USA) and split into 60-mL HDPE and 50-mL polypropylene (PP) bottles for further metal and nitrate analysis, respectively. The samples for lead and copper analysis were further acidified using HNO<sub>3</sub> (15.7 M, Supelco, USA) and analyzed by inductively coupled plasma mass spectrometry (ICP-MS) following a modified version of EPA method 200.8 (U.S. Environmental Protection Agency, 1994) at Auburn University. The samples for nitrate analysis were frozen, shipped with ice packs to University of Georgia, and analyzed by ion chromatography following EPA method 300 (Pfaff, 1993). The

samples for pesticides were delivered to Pesticide Residue Laboratory at Auburn University without pre-cleaning steps and analyzed by GC-MS following EPA method 1699. Total coliforms and *E. coli* were quantified using the Quanti-Tray<sup>®</sup> (One IDEXX Drive, Westbrook, USA). All samples were analyzed within 28 days except for total coliform and *E. coli* which were prepared within 4 hours of collection.

### **3.2.3 Community Groundwater Testing**

To evaluate the accuracy of the test kits, volunteers were recruited in collaboration with the Alabama Private Well Program through Alabama Cooperative Extension. Participants were restricted to well users located in Baldwin and Mobile counties, Alabama (30 participants total, 33 well total). Specific recruitment strategies included in-person workshops and webinars advertised through social media and the Extension webpage. During recruitment, participants that indicated interest in the study were directed to an on-line sign-up form and coordinated for well sampling campaigns. The findings of this research are valid for well water users within the Coastal Lowland Aquifer system in the US, spanning parts of Alabama, Mississippi, Louisiana, and Texas. Our estimation indicates that approximately 1.3 million private well users within the Coastal Lowland Aquifer system experience similar water quality chemistry to that observed in the Alabama cohort (details in Appendix 2 Section 3).

A team member provided the test kit to the well user and asked them to perform all manipulations described in test kit instruction to evaluate water quality. Two different test kits were used during two sampling campaigns. Participants were asked to mark corresponding values for each parameter on a reporting sheet and return the sheet to us within 2 weeks of performing the test. The reporting sheet uses the major concentration increments specified in the test kit

instruction, and additionally, we incorporated minor increments in the reporting sheet to account for circumstances where it becomes challenging to differentiate between two adjacent concentration levels. The response rate for participation (those that returned data versus all wells sampled) was 61%.

### **3.2.4 Data Processing**

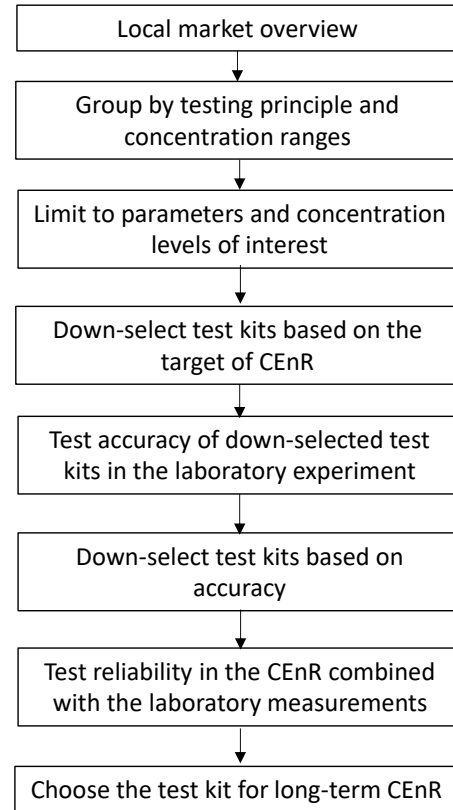
The performance of the kits was evaluated by comparing the participant reported values from test kit manipulations with the laboratory measurements of this parameter. For the colorimetric tests, the measured values were plotted over the reported values to evaluate the accuracy of the test kit. For binary tests and reagent colorimetric, the results were classified into false positive, false negative, true positive, true negative, and failed. Binary tests are used for lead and atrazine (pesticide), and the positive test result indicates that concentrations of lead and atrazine in water sample are above 15 ppb and 3 ppb, respectively. A false positive test was defined as a positive test strip result when the laboratory measurement was below 3 ppb ( $\pm 10\%$ ) for atrazine(White et al., 2004) and below 15 ppb ( $\pm 10\%$ ) for lead(Kriss et al., 2021). A false negative test was defined as a negative test strip result when the laboratory measurement was above 3 ppb ( $\pm 10\%$ ) and 15 ppb ( $\pm 10\%$ ) for atrazine and lead, respectively. The failed reported result means that the test kit strip did not show any changes in response to the contaminant. The reagent colorimetric method was used for bacteria analysis in both test kits. The Quanti-Tray<sup>®</sup> system enumerated total coliforms and *E. coli* as a most probable number (MPN), but the test kit bacterial assay as presence/absence of total coliforms. For the measured value, we classified a Quanti-Tray<sup>®</sup> result of  $<1$  MPN as negative, and  $>1$  MPN as positive. If the reported and measured values matched the test kit result is considered as true positive or true negative. When the positive reported

value corresponds to the negative measured value, the result was classified as a false positive, with the opposite being true for results classified as a false negative.

### 3.3 Results and Discussion

#### 3.3.1 Choosing Tools for Data Collection

A systematic approach can be taken to select the most appropriate test kit for a CEnR program. Program participants should evaluate key characteristics of the test kits, including water quality parameters, concentration ranges and increments, test accuracy while balancing cost and shelf-life. The selection of a test kit should be tailored to the specific requirements of CEnR programs (DeSimone et al., 2014) and consider variables such as the likely geogenic or anthropogenic compounds or elements of interest, sample type, and relevant national or regional regulatory frameworks. Other factors, including the availability of financial resources, can significantly influence the final selection of a test kit.



**Figure 3. 1.** Scheme for down-selection of the test kit

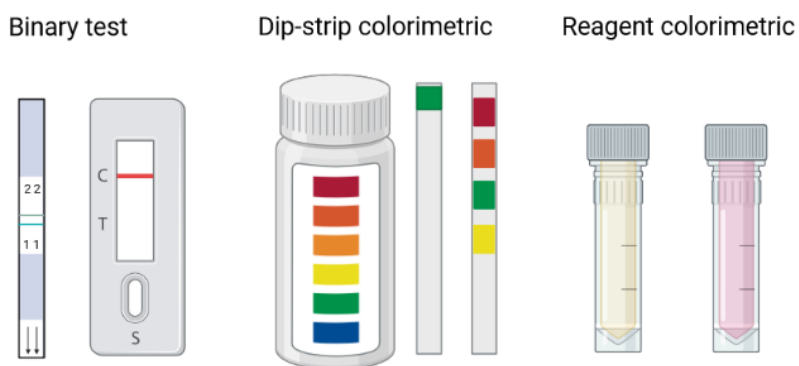
In a broader context, Figure 3.1 outlines the key decision-making steps involved in the selection of a test kit for a CEnR program. This framework includes conducting a survey of the local market, down-selecting test kits aligned with the program's specific objectives, performing laboratory validation to evaluate the accuracy and precision of the chosen test kit, and evaluating

its reliability within the CEnR framework. Matrix effects, whereby a non-target analyte interferes with quantifying the target analyte, may be relevant in some situations as seen for arsenic (Spear et al., 2006).

### 3.3.1.1 Test principal, parameters of interest, and concentration levels

The success of the CEnR relies heavily on a robust tool for data collection (Ramírez et al., 2023). In this study, we identified three main test principles in the test kits: binary tests, dip-strips,

and reagent methods (Figure 3.2). Binary tests use a form of immunoassay, and the test can be a strip or a cassette that determines the presence or absence of the target contaminants above or below



**Figure 3. 2.** Test principles overview

the MCL (White et al., 2004) by the intensities of the lines appearing on the test strips. Dip-strips and reagent colorimetric methods are based on colorimetric principles so that the testing pad or solution changes color when the target contaminant is present. The parameter value is determined by comparison of the color of the test strip pad with the comparator or by appearance/disappearance of the color. Combination test kits contain a combination of test principals in the kit: dip-strips for single parameter or a multi-pad strip to measure up to 4 parameters, binary tests for pesticides and lead and reagent colorimetric tests for pathogens and contaminants (Appendix 2 Table 2). All-in-one test kits use multi-pad dip-strip tests, where color pads (up to 16) are located on one test strip (Appendix 2 Table 1).

For CEnR, the test procedure and time spent on analysis and interpretation of the results are important factors to consider. The testing procedure should be simple and require little manipulation of the sample, while still being sensitive to detect low contaminant concentrations. In this study, we compared all-in-one-test kits, which are the simplest way to measure water quality, to combination test kits, which have more complex procedures. We found that the all-in-one test kits were not sensitive to concentrations below MCLs for most drinking water parameters (Appendix 2 Section 4). Despite the simplicity of all-in-one tests, the preliminary laboratory experiments also revealed that the all-in-one kits tested were unreliable because some color pads cross contaminated the adjacent pads, confounding our interpretations (details in Appendix 2 Section 4). The all-in-one kits were not further evaluated because of the issues described above.

Table 3.1 summarizes the evaluation of the combination test kit groups based on their sensitivity relevant to MCLs. The combination test kits showed higher sensitivity to primary standards compared to all-in-one test kits with intervals below MCLs (Appendix 2 Tables 5 and 6).

**Table 3. 1.** Evaluation of the combination test kits based on the number of measured EPA primary standards and sensitivity towards concentration below MCL

Test group	pH	Copper	Lead	Pesticides	Nitrate	Nitrite*	Fluoride*	Bacteria
1	●	●	●	●	●	●	○	●
2	●	●	●	●	●	●	○	●
3	●	●	●	○	●	●	●	●
4	●	●	●	●	●	●	○	●
5	●	●	●	●	●	●	○	●
6	●	○	○	○	●	●	○	●
7	●	○	○	○	●	○	○	●
8	●	●	●	●	●	●	○	●
9	●	●	○	○	●	○	○	●

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● – relevant to concentrations below MCL; ● – not relevant to concentrations below MCL; ○ – the test does not measure this parameter; \* – nitrite and fluoride were not measured in this study. The highlighted rows show the down-selected test kit for community testing.

The choice of test kit should align with the specific goals of CEnR. The aim of this research was to assess the reliability of test kits for evaluating groundwater quality in the Coastal Plain Aquifer within the CEnR framework. We considered several factors, including the number of test parameters, test principles, sensitivity in terms of MCL, and concentration increments. For a comprehensive evaluation of water quality, it is recommended to select a test kit that includes a variety of testing parameters and demonstrates high sensitivity. We found that test groups 1, 2, and 4 met these criteria. Since we expected low pH levels in the samples due to the regional geology and previous groundwater quality data (Montiel et al., 2019), test groups 2 and 4 were prioritized based on the wide pH range. However, test group 1 exhibited the highest sensitivity to nitrate, as evidenced by a greater number of concentrations increments below the MCL (Table Appendix 2 6). In this research, we sacrificed the sensitivity of the pH test in favor of the nitrate test's sensitivity. Consequently, we selected test kits from groups 1 and 4 for community groundwater testing in this research. This compromise may also apply in other CEnR programs, where the choice of the test kit might balance different needs within the program mission. For example, if a program primarily focuses on specific water quality parameters, a test kit tailored to those parameters should be prioritized, such as test group 3 for fluoride measurements.

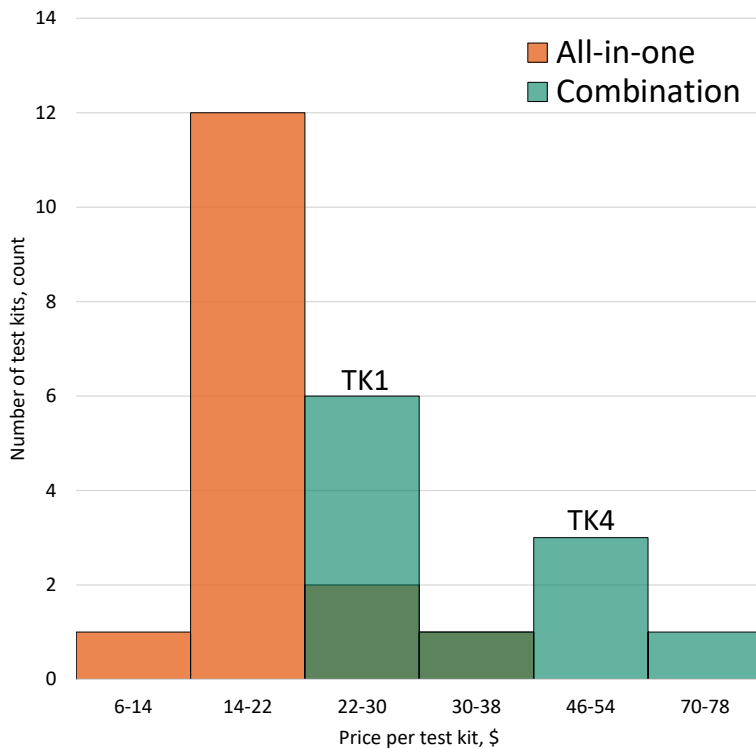
### **3.3.1.2 Indication of safe and hazardous concentrations**

Instructions are included in the test kits, guiding the users through the steps necessary to conduct the test and providing instructions for interpretations. We found the instructions were sometimes confusing or conflicting, which could present issues in CEnR projects. Some instruction packets included labels for “safe” and “hazardous” concentrations. We found that some

test kits used “hazardous” or “caution” designations that did not always align with MCLs for the parameter, e.g., all-in-one test kit groups 1 and 7 for chromium and combination test kit group 5 for copper (Appendix 2 Tables 5 and 6). Not all test kits indicate hazardous ranges of contaminants or give information about the MCLs. In the absence of clear indications of MCLs in the test kits, it is then imperative to provide support to participants to interpret the results. Using test kits with properly marked MCLs is beneficial for CEnR because it minimizes the information load to the participants. Both methods of marking only safe concentration or both safe and hazardous are acceptable. However, special attention should be paid to which concentration is marked as safe. Considering the sensitivity of the test and the concentration intervals, the concentration slightly higher than MCL can be misleadingly interpreted as safe concentration. Therefore, we advise choosing the test kits that mark MCLs concentration as hazardous for CEnR and to avoid those that provide misleading information about the safe levels.

### **3.3.1.3 Secondary criteria for the down-selection of the test kit: cost, shelf life, and storage method**

The cost of test kits is a critical parameter when considering the test kit for CEnR. As depicted in Figure 3.3, the histogram shows the price distribution for all the kits evaluated in this study. Generally, the cost of all-in-one test kits tends to be lower compared with combination test kits. Most all-in-one test kits include many test strips, resulting in an analysis cost of less than one cent. Combination test kits are designed for the analysis of a single sample, and therefore the long-term cost of use is higher. However, because the all-in-one tests were less accurate and prone to cross-contamination between color pads, the lower cost was not considered an acceptable tradeoff for use.



**Figure 3. 3.** Histogram of the price for all-in-one and combined test kit: TK1 and TK4 – combined test kits that was down selected in this research for the further tests in community-engaged part of the project.

Shelf-life and storage methods are other crucial factors to consider in the down-selection of test kits. CEnR programs are advised to utilize test kits before their expiration date and strictly adhere to storage instructions to ensure reliable results when used. The all-in-one test kits had a

shelf life of 2 years indicating both production and expiration dates. In contrast, most combination test kits only indicate an expiration date, typically within 1 year of purchase. In some cases, each test within the combination kit has its own expiration date. CEnR programs should be organized accordingly and consider the expiration date of the test. In the case of a program extending beyond this duration, additional test kits should be procured after the initial 1 or 2 years.

Storage instructions for both all-in-one and combination test kits are the same, emphasizing protection from sunlight and storage in a dry, cool place. Additional precautions are recommended for all-in-one test kits where all test strips are stored in a single bottle, requiring tight closure of

the bottle cap after removing one test strip. In contrast, combination test kits are more convenient in this regard, as each test is individually packaged and opened prior to analysis.

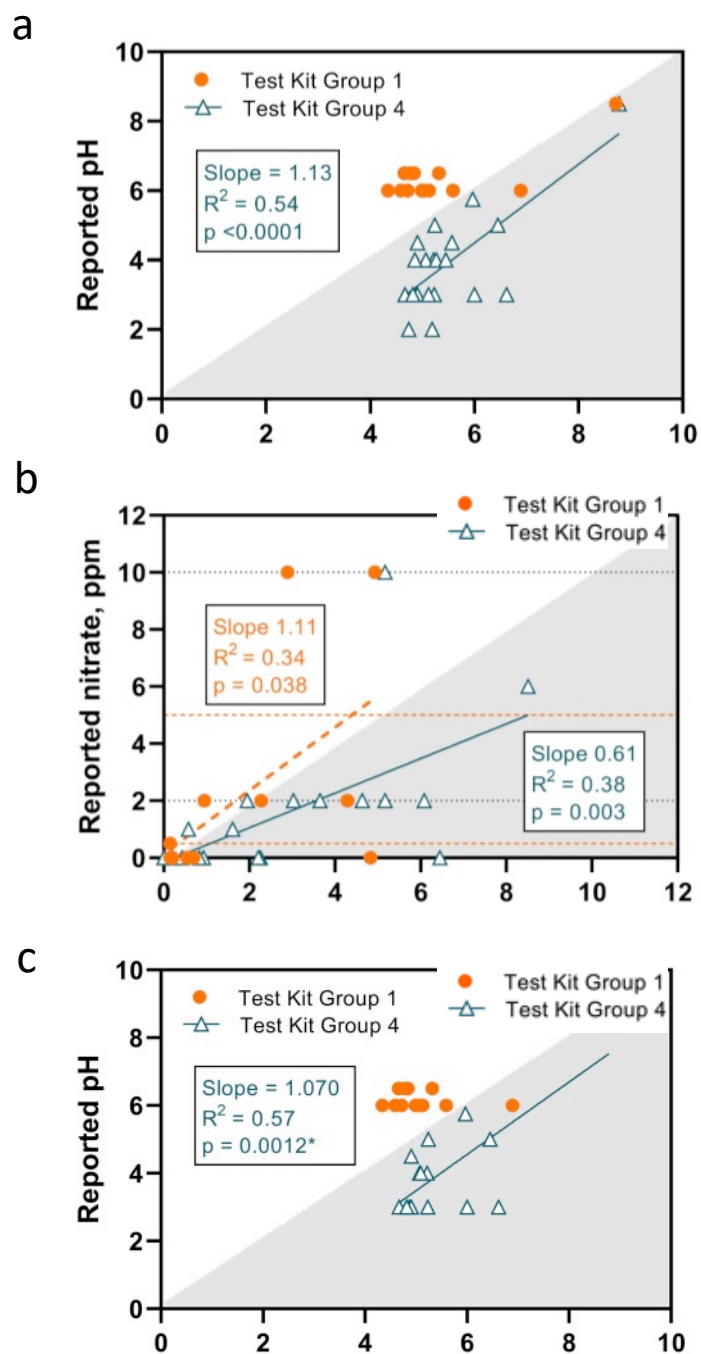
### **3.3.2 Reliability of the test kit in the CEnR program**

#### **3.3.2.1 The Importance of the Concentration Range and Increments**

The accuracy of the reported data relies on the sensitivity of the assay and the interpretation of the result by community members. The dip-strip colorimetric test principle is utilized for assessing pH, nitrate, and copper in the test kits evaluated here. Both test kits utilize the same nitrate assay with color pads changing pink when nitrate is present. In the case of pH test strips, different assays are employed for each test kit. In test kit group 1, the color pad undergoes a transition from yellow to pink for the pH range of 6-9, while in test kit group 4, the color pad changes from red to blue for the pH range 2-12 (Appendix 2 Table 4). The copper tests utilized different assays with a white-brown and white-purple color gradient in test group 1 and 4, respectively.

We found that the accuracy of the dip-strip colorimetric tests can be influenced by the concentration range and increments marked on the test kit. For example, the pH dip-strip in test kit group 1 did not cover values below the EPA recommended range of 6.5-8.5. Lower pH values are characteristic of shallow groundwater, especially in sandstone aquifers like those in the coastal plain in this study (DeSimone et al., 2014). The narrow pH range of test kit group 1 caused the well owners to overestimate pH since, generally, the pH was  $< 6$  (Figure 3.4). In contrast, test kit group 4 covers the wider pH range from 2 to 12, resulting in higher accuracy with  $|\beta|=1.13$  and a moderate  $R^2$  (0.54). The participants generally underestimated the pH values using test kit group 4. This discrepancy can be attributed not to the accuracy of the test itself, but rather to

interpretations of the colors on the test pad (Quinlivan et al., 2020a). Several participants noted challenges in distinguishing between different color shades (Appendix 2 Table 4). Enhancing the accuracy of test result interpretation can be achieved through training or providing specific instructions, such as utilizing a light background or optimizing the lighting conditions.



**Figure 3. 4.** The dip-strip colorimetric test reported data evaluation of pH (a), nitrate (b), and copper (c) in test kit group 1 and 4. The increments within the test kits are indicated by horizontal lines, with color denoting the specific increment of the test kit. Nitrate test kit group 1 has additional increments 0.5 and 5 ppm indicated. The white and grey areas represent overestimation and underestimation of the result, respectively.

The concentration increments specified in the test kit instruction also impact the interpretation of the test results. For the nitrate test, most participants reported concentration based on the major increments in the test kit instruction (Figure 3.2, horizontal lines). Despite utilizing the same assay principle and covering similar concentration range, the test kit group 1 demonstrated greater accuracy ( $|\beta|=1.11$ ) compared to the test kit group 4 ( $|\beta|=0.61$ ), which is aligned with the bigger number of concentration increments of the test kit group 1 (Appendix 2 Table 6). In general, participants tended to overestimate concentrations using test kit group 1 and underestimate the concentration using test kit group 4 where the number of major increments was smaller. The low  $R^2$  values of both test kits indicate a low level of accuracy in interpreting the test results for both tests. Previous studies reported the general agreement of nitrate/nitrite test strips with the laboratory analysis data within the concentration range of this study (Ali et al., 2019; Bischoff et al., 1996; Nielsen et al., 2008). Both overestimation (Ali et al., 2019) or underestimation (Ali et al., 2019; Bischoff et al., 1996; Nielsen et al., 2008) were reported previously and the participant's experience level (novice, experienced, expert) can influence the direction of error (Ali et al., 2019).

The copper test showed no relationship between the measured values and the reported values for both test kit groups (Figure 3.4c). Test kit group 4 had an increment greater than zero but lower than MCL (0.1 ppm Cu), and we observed that roughly half of the participants using that kit chose to report a value greater than zero, indicating some change in color when interpreting the test result. In this case, the low concentration of copper in the groundwater, and the relatively low sensitivity of the test made this a poor alert for copper.

### **3.3.2.2 The Importance of the Limit of Detection**

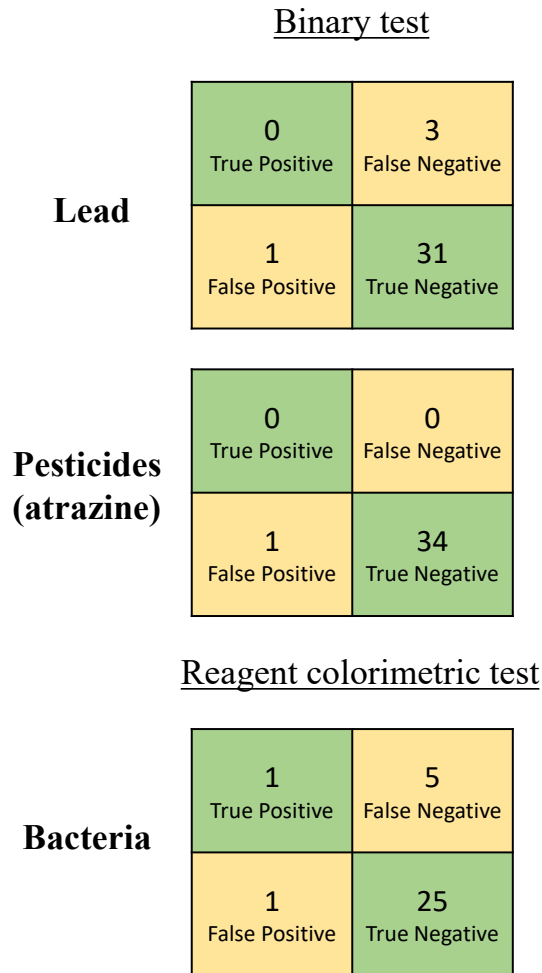
Binary tests for lead and atrazine, a widespread pesticide (Atwood and Paisley-Jones, 2017), and reagent colorimetric tests for the bacterial assay demonstrate the importance of the limit of detection for drinking water analyses. The test principle is based on immersing a dip-strip in a small volume of water and evaluating the intensities of appeared lines after 10 minutes. For each assay there is a control line to ensure the proper functioning of the assay as well as a test line to indicate the sample result. If the test line was darker than the control line, the test was negative, while a test line with equal or lighter intensity than the control line indicated a positive result. If no lines appear or the lines are faint, the test was considered failed. The test's limit of detection is an essential factor in safeguarding the safety of drinking water within this testing principle. For both the lead and pesticide tests, the detection limits aligned with the MCL values, and if properly interpreted, a successful test equates to safe drinking water.

Both the lead and pesticide tests showed a high accuracy with 86 % and 94 % of tests being true negative, respectively (Figure 3.5). Both pesticide and lead tests showed a small proportion of failed tests equal to ~3 %. Laboratory tests showed pesticide concentrations were lower than the limit of detection (0.5ppb) in all water samples, meaning there are no true positive tests in this dataset to assess. One pesticide test showed a false positive result, and although atrazine was below the limit of detection, the assay is also sensitive to simazine, which was not measured in the laboratory analysis. Similarly, only one lead test showed a false positive result. False positive results do not pose a significant threat to health, but they could trigger a follow-up laboratory analysis to confirm concentration. Conversely, false negative results that occurred to 8% of the lead tests are concerning since the participant evaluated the water safe, when in fact, it contained lead above the MCL. Kriss et al. (2021) found that adding lemon juice or vinegar to a water sample improved the ability of the test strip to detect particulate lead in addition to dissolved lead. In this

study, the laboratory tests measured dissolved lead concentrations after filtration, so the contribution of particulate lead ( $>0.45\mu\text{m}$ ) is minimized and is not a factor in evaluating the false negative results here. The laboratory experiments revealed that lead tests did not produce accurate results (Appendix 2 Section 6). The different behavior of the lead test compared to Kriss et al. (2021) could be due to different manufacturing batches or change in supplier or manufacturing

technology (Appendix 2 Section 6). The pesticides binary tests were accurate in laboratory experiments using atrazine at concentrations below, at and above the MCL (Appendix 2 Table 8).

The reagent colorimetric principle was used in both test kit groups for the bacteria assay,



**Figure 3. 5.**(Confusion matrices) Results of reported value comparison to measured values for binary and reagent colorimetric tests. Two test campaigns are grouped together due to identical tests used in the test kit group 1 and 4.

featuring a purple-yellow color transition when coliforms are present. Initially the reagent powder is added to the sample and the color turns purple. After 48hrs, a purple color indicates absence of

coliform bacteria while a transition to yellow indicates presence. The test kits showed 78% of true negative and 3% of true positive results (Figure 3.5). However, it is noteworthy that we observed 16 % false negative results and 3% false positive results. False negative results likely occur when the detection limit of the laboratory procedure is lower than that of the test kit. The test kit group 4 specifies the detection limit as 500 MPN/100 mL for total coliform (test kit manual) and was proved in the laboratory test (Appendix 2 Section 6). The Quanti-Tray® system's limit of detection is 1 MPN/100 mL (IDEXX manual). The US EPA recommends zero total coliform in drinking water (US Environmental Protection Agency, 2009), and therefore the limits of detection of the test kits significantly exceed the MCL and shift analytical window toward higher and unsafe concentrations. The high limits of detection and the occurrence of false negative tests poses a potential risk to human health by providing a false sense of drinking water safety. When developing CEnR, it is important to consider assays with detection limits that are closely aligned with the MCLs to avoid the exposure of the community to microbial contamination. In general, tests featuring binary options, such as binary tests and reagent colorimetric tests, proved more straightforward for interpretation by community members compared to dip-strip colorimetric tests. However, the binary nature of these tests, offering only "yes" or "no" outcomes, imposes limitations by not providing specific concentration information. Given the observed lower accuracy of certain dip-strip colorimetric tests and the inherent precision achieved only through laboratory analysis, it is recommended to prioritize binary and reagent colorimetric tests in the context of CEnR programs, particularly within communities lacking laboratory expertise. If this justification is used, it is additionally important that the detection limits of these tests align with the drinking water standard (either EPA or WHO) to be protective of human health.

### 3.3.3 Considerations for CEnR Program

Robust study design and volunteer retention are two key elements for a successful groundwater monitoring program. Site-specific geological and hydrological conditions, anthropogenic factors, and the expected rate of contaminant concentration change should be considered (Kumar, 2011). In some regions, certain water quality parameters may be prioritized. For example, geogenic arsenic in water is a crucial parameter for areas where arsenic rich sediment or geothermal waters influence local groundwater supplies; therefore, an arsenic test should be prioritized (Boyden et al., 2023; George et al., 2012; Reddy et al., 2020). In other regions like the US Coastal Plain Aquifer, low pH emerges as a key factor that can increase the risk of community exposure to contaminants associated with corrosion of pipes and fixtures in the home (Chidambaram et al., 2009; Degnan et al., 2020; Zhou et al., 2015). Decisions to prioritize water quality parameters should occur during the early development stage of CEnR in collaboration with the community and by assessing relevant risks from geogenic and anthropogenic sources. The test kit should be chosen based on the program's target, as previously discussed in Results and Discussions Section 1 (Figure 3.1).

Sample frequency is an important variable as groundwater quality fluctuations can occur on multiple timescales. The methodologies for effective decision-making regarding sampling schedule have been previously discussed (Johnson et al., 1996; Zhou, 1996). The frequency of sampling and the duration of the monitoring program should be optimized based on the study goals and budgetary considerations. Previous campaigns have used monthly (Zhou, 1996) to semiannual (Kumar, 2011) and annual (Johnson et al., 1996) monitoring strategies, depending on the desired outcome (Johnson et al., 1996; Zhou, 1996). The US EPA recommends testing private well water annually and increasing the frequency if needed (United States Environmental Protection Agency,

2023). For commercial test kits, the short time frame between completing the test and receiving the test results (seconds to minutes) makes test kits advantageous for a “first alert” during an extreme events like flooding, where groundwater quality changes relatively quickly (over the course of days) (Pieper et al., 2021) and waterborne outbreaks of enteric illness is a concern (Andrade et al., 2018; Mahmoodzadeh and Karamouz, 2019).

Another important consideration for groundwater monitoring programs involving private well users is the potential for unintended consequences or negative impacts of such a program (Metcalf et al., 2022). Walker et al. (2020) highlights that many benefits for participants and communities from community-driven programs are assumed rather than investigated or documented (Walker et al., 2021). In the CEnR framework proposed here, poor water quality measurements could have significant health consequences that are likely longer term than research project funding. Therefore, it is critical that groundwater monitoring programs integrate with social service programs to empower, engage, and equip users with information to address questions and concerns when they arise.

### **3.3.4 Handling uncertainty in CEnR**

Different types of uncertainty can arise during CEnR, including uncertainty and the accuracy of the tests, interpretation difficulties within the community, sample matrix effects, and challenges in sustaining participation. Measurement uncertainties lead to under- or overestimation of the contaminant concentration and may provide a false sense of threat or security for drinking water. Systematic errors caused by the limitations of the measurement instrument pose a considerable challenge as do random errors resulting from human errors in test interpretation, that can be due to differences in participant’s experience with laboratory analysis techniques,

motivation, and engagement (Ali et al., 2019). It has been noted that for some assays, particularly the binary test, it can be difficult to discern color differences and color intensity of the lines (White et al., 2004). Similarly for dip-strip tests, faint color changes (equating to low concentrations) can be difficult to detect and match with the color chart, especially if the concentration intervals on the comparator charts are large.

While complete elimination of measurement uncertainty is impossible, it can be reduced. Selecting a measuring tool that is robust, reliable, and has high sensitivity towards the target contaminant can minimize errors (Kriss et al., 2021). Here we found that specific features of the tests, like color comparator increments for dip-strips and assay measurement ranges are important considerations for test kit accuracy. Additionally, quality assurance programs (QAPs) can help reduce uncertainties in data collection and analysis. The US Volunteer Water Monitoring Network conducted a survey of 103 volunteer water monitoring programs and 40% had state QAPs while 30% have US EPA approved QAPs (Stepenuck, 2023). Critical elements of a QAP are guidance on 1) sampling, sample handling, and study design, 2) equipment maintenance, testing, and calibration, 3) training for participants, and 4) documentation, reporting, assessment, and data management.

Maintaining an ongoing dialogue with community members is essential for addressing any uncertainties in the test kits within the CEnR framework. Effective collaboration and clear communication between researchers and the community are crucial for producing high-quality data in CEnR programs (San Llorente Capdevila et al., 2020; Thornton and Leahy, 2012), particularly in the context of private well monitoring. Training and workshops discussing major water quality issues can be made available through workshops organized by scientists, integrating hydrogeological concepts into school curricula or extracurricular activities (Baalbaki et al., 2019;

Deutsch and Ruiz-Córdova, 2015; Wong and Yelderman, 2016), or participating in the local events and living among community (Wong and Yelderman, 2016). For example, in the case of the binary strips, placing the strip or cassette on a light-colored background with ample lighting can make the interpretation easier (White et al., 2004). The matrix effect, whereby non-target analytes bias the result, can also be discussed during workshops. This discussion might be relevant in cases of inaccurate test results and address possible interferences of analytes samples (Spear et al., 2006) based on laboratory analysis and the ways to mitigate it (Kriss et al., 2021). In this research project, we shared the results of laboratory water testing with the community through individual water quality reports and workshops. We used a “red light”, “yellow light”, “green light” classification system relative to the EPA MCLs to make the report more accessible. We also provided the well owners with relevant resources, such as links to database of Certified Drinking Water Treatment Units by the Public Health and Safety Organization (The Public Health and Safety Organization, n.d.).

To tackle volunteer fatigue and encourage sustained participation, the AWW program utilized various methods such as user-friendly waterbody reports, blogs, newsletters, and face-to-face meetings to highlight the positive impact of their efforts on the environment (Deutsch and Ruiz-Córdova, 2015). Private well owners are known to prioritize water security, conservation, and express environmental motivations for conservation, and they exhibit greater awareness about the water quality and supply systems compared to municipal water users (Ternes, 2018). However, the decision to test water quality relies on the well owner’s confidence in the water quality, often influenced by their satisfaction with organoleptic properties (Ternes, 2018), which may not accurately reflect the presence of some health-related contaminants.

### 3.3.5 Global prospective of drinking water quality CEnR programs

The number of groundwater citizen science programs is growing, and realization of SDG6 must be in cooperation with communities. Nath and Kirschke (2023) synthesized 33 reports of groundwater monitoring through citizen science and found the number of reports has grown since 2012, with 12/33 articles published after 2021. However, the geographic extent of the programs was limited and generally centered in North America (13 reports) and Africa (10 reports). Many of the reports were also limited to a small number of monitoring locations, a limited timeframe (<2 yrs), low sampling frequencies, and a small number of participants (<50). Extending the geographical scope of CEnR for groundwater monitoring is necessary for the realization of the SDG goals, which can be achieved through accessible tools for water quality testing and integrating science and education within middle and high schools (Haynes et al., 2019). Research should be directed to understanding participants' motivation and effective training strategies in different cultural backgrounds, and strategies for intercountry result reporting and data management.

In this research, we systematically opted for test kits available in the US market, specifically designed to exhibit sensitivity to the MCLs established by the US EPA for drinking water. Drinking water regulations vary across different countries. Most countries adhere to the World Health Organization (WHO) recommendations in the regulation of drinking water quality (World Health Organization, 2021) (Appendix 2 Section 8). Notably, the US MCLs were observed to be either more stringent or closely aligned with WHO regulations. The highly sensitive test kits chosen for CEnR in this study will be valuable for countries with regulations lower than or aligned with the WHO regulations for the evaluated parameters.

### **3.3.6 Future Research Directions**

Still, the utilization of reliable tools for measuring water quality is of primary importance for the success of the citizen science programs. This study uncovered challenges related to the sensitivity and precision of the individual tests of commercial groundwater monitoring kits. To address these issues, potential future research directions could involve developing novel assays for parameters like *E. coli* and nitrate that are relevant to groundwater concentrations. Other avenues of research include integrating the most sensitive and accurate tests into a single comprehensive kit, creating new reliable tests for groundwater monitoring, and/or testing the matrix effect on the tests in different geological settings. The development of immunoassays for a wide range of parameters within the sensitivity range of MCLs for drinking water will enhance the performance of tests in CEnR. For instance, these assay types in development for *E. Coli* (Bazsefidpar et al., 2023; Cimafronte et al., 2020) and copper (Xing et al., 2014). Easy interpretation with a yes/no option will be particularly valuable, addressing the challenges associated with result interpretation within the community.

### **SUPPORTING INFORMATION**

Additional information about the test kits and their characteristics, experimental results and details, materials, and methods, can be found in the provided supporting information.

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#### **AUTHORS' CONTRIBUTION**

CRedit: NM – conceptualization, methodology, formal analysis, investigation, visualization, writing-original draft; SM – investigation, writing – original draft, review and editing; ASO – conceptualization, methodology, writing- original draft, supervision, project administration, funding acquisition.

## Chapter 4

### Summary and Outlook

The results of this study emphasize the need to study groundwater quality from a holistic standpoint and to engage with well users about their water supply. In this study nitrate concentrations were related to the amount of agricultural land use around each well but was also seen to have a relationship with SPC, pH, and wastewater treatment type. Rarely is groundwater chemistry driven by a singular parameter, so understanding how different mechanisms control groundwater chemistry an integral part in not only understanding groundwater quality but also educating private well users about their water quality. Particularly for parameters that pose a human-health threat, laboratory analyses were superior to the commercial testing kits. Still, they are a good “first” alert for pH and lead, which are water quality issues in the Coastal Lowlands Aquifer system.

A potential argument against taking samples directly from the well head is that well users will not be using the water coming from the well head. However, understanding underlying groundwater chemistry is crucial for locating areas where water quality issues exist, especially for those with no treatment systems in place. Future work could focus on the impacts of well age, pipe material, and treatment systems on well water quality to determine the effect of the household distribution system on water quality.

For at-home test kits to be a more accessible form of well testing, emphasis should be put on developing test with more sensitive ranges, especially for tests like total coliforms and *E. coli*. Many times, well owners reported having no coliforms in their water after using an at-home test kit but analytical lab results showed that coliforms were present. Increasing sensitivity of tests

may also improve interpretation of results for well owners. Interpretation of results may also be improved by workshops designed to educate well owners about their water quality and how to use test kits. Well users often cited difficulty with interpreting results of tests due to colors on test pads not being representative of the color on the comparator chart. Difficulty with interpretation highlights the need for workshops or for the development of test kits with better color comparator charts or different test types. Notably, test kits with fewer components were typically viewed more favorably than test kits with more components. It is important that well users are not only able to accurately use at-home test kits but also do not find them difficult or inconvenient to use. Additionally, workshops may serve as an opportunity to encourage well users to continue practicing proper well stewardship practices like water testing.

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## Appendix 1

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### Table 1. Agricultural land use change

The table below shows data representing the change in land use over 20 year span. Buffers of 500 meters were created around each well and land use values were extracted to each buffer, then the percentage of agricultural lands were calculated. The values below are percentages.

Well ID	2001	2011	2021
B01_KA	43.48	35.58	35.47
B02_DA	0.31	0.47	0.47
B03_EB	5.26	5.26	5.14
B04_MB	29.94	29.71	29.71
B05_WB	19.75	12.40	12.40
B06_CCA	23.54	23.42	23.42
B07_CCB	20.87	20.30	20.30
B08_CCC	20.16	19.59	19.59
B09_VC	20.57	22.17	21.37
B13_LD1	39.04	36.19	36.19
B14_LD2	39.02	36.16	36.16
B17_DG	81.60	81.14	81.14
B19_CH	78.76	78.53	78.42
B21_LK	41.83	39.89	38.40
B22_KL	69.61	69.72	69.04
B23_AL	6.64	6.64	6.52
B26_CM	25.57	25.46	25.46
B28_JP	29.44	29.21	29.10
B30_ER	77.52	77.41	69.38
B31_TS	67.09	67.09	67.09
B32_MW	67.62	67.27	65.34
B34_AW	77.41	77.18	77.18
B35_DW2	0.00	0.00	0.00
B36_RS	89.32	89.09	86.80
B37_VM	30.97	28.34	28.23
B38_WN	66.25	66.25	66.25

B39_JE	29.74	27.10	26.98
B40_NH	63.12	53.38	52.23
B41_JM	89.11	89.11	89.11
M10_TC	42.58	42.69	42.69
M11_LC	30.94	27.97	27.97
M15_JE	54.64	48.00	47.88
M16_AF	0.11	0.11	0.11
M18_JG	63.89	55.66	55.54
M20_AH	0.23	0.23	0.23
M24_DM1	5.03	5.03	4.23
M25_EM	0.00	0.00	0.00
M27_SN	0.00	0.00	0.00
M29_AR	0.23	0.23	0.23
M33_DW1	0.00	0.00	0.00
M42_DM2	1.03	0.80	0.92
M43_GJ	2.41	2.41	2.41
M44_PW	0.92	0.92	1.37

**Table 2.** Water Quality Index data

The following table presents the raw data that was used to calculate a Water Quality Index for each well. Values were averaged when well owners were involved in multiple sampling campaigns. Cations were measured by Auburn Geoscience Department ICP-MS Lab while anions were measured at the University of Georgia Athens Ag and Environmental Services Lab. TDS, alkalinity, and pH were measured in the Ojeda Lab.

Well ID	WQI	pH	Na <sup>+</sup> (ppm)	K <sup>+</sup> (ppm)	Ca <sup>2+</sup> (ppm)	Mg <sup>2+</sup> (ppm)	Mn <sup>4+</sup> (ppm)	Fe <sub>T</sub> (ppm)	Cl <sup>-</sup> (ppm)	NO <sub>3</sub> <sup>-</sup> (ppm)	SO <sub>4</sub> <sup>2-</sup> (ppm)	Pb (ppm)	HCO <sub>3</sub> <sup>+</sup> (ppm)	TDS (ppm 500)	Alk. as CaCO <sub>3</sub> (ppm)
B01_KA	7.28	5.55	2.399	0.119	0.217	0.400	0.003	0.002	3.70	0.25	0.325	0.002	4.3	9.85	3.4
B02_DA	7.78	5.13	7.087	0.306	0.560	1.139	0.003	0.007	13.37	0.20	1.100	0.002	4.2	27.98	3.4
B03_EB	8.01	5.18	3.057	1.242	0.808	0.569	0.013	0.021	4.20	0.08	6.323	0.000	3.3	12.75	2.2
B04_MB	21.48	4.87	3.689	1.584	3.928	5.864	0.096	0.006	15.29	6.37	0.325	0.001	2.4	59.63	0.9
B05_WB	7.83	5.29	2.331	0.158	0.438	0.562	0.004	0.011	3.99	0.57	0.325	0.003	4.0	12.23	3.0
B06_CCA	12.69	5.16	3.436	0.428	2.210	2.746	0.016	0.005	7.89	3.74	0.325	0.005	3.3	32.85	2.1
B07_CCB	17.29	5.71	5.715	0.383	2.737	3.406	0.023	0.029	8.63	5.99	0.325	0.001	2.9	44.27	1.8
B08_CCC	12.48	4.82	4.59	0.37	2.29	2.64	0.01	0.01	8.29	4.04	0.325	0.01	3.3	35.95	2.5
B09_VC	12.32	5.31	7.288	2.041	2.114	3.264	0.023	0.002	15.13	2.36	6.540	0.001	3.8	47.92	2.6
B13_LD1	31.41	4.72	4.21	3.04	7.95	9.57	0.06	0.12	19.14	13.02	0.325	0.002	3.2	91.45	2.3
B14_LD2	17.34	4.94	3.55	0.86	3.34	5.25	0.01	0.03	9.97	6.72	0.325	0.02	3.3	50.2	2.4
B17_DG	9.72	5.31	2.46	0.67	0.94	0.61	0.01	0.07	3.90	0.08	2.13	0.001	7.0	13.75	5.7
B19_CH	14.35	4.62	2.355	0.647	2.943	3.206	0.016	0.018	7.13	5.40	0.325	0.001	1.5	40.60	0.5
B21_LK	10.87	6.36	5.246	0.271	8.615	1.113	0.002	0.006	9.17	0.64	0.665	0.000	29.3	41.07	24.0
B22_KL	12.11	5.42	5.771	2.615	2.086	2.942	0.023	0.003	14.02	2.27	4.475	0.001	3.9	42.90	2.4
B23_AL	22.35	5.79	6.826	1.114	1.259	2.194	0.054	0.214	9.30	3.52	1.485	0.017	4.5	37.45	3.0
B26_CM	8.08	5.22	1.673	0.673	0.815	0.907	0.007	0.006	4.63	0.79	0.325	0.002	3.9	15.20	2.1
B28_JP	30.12	4.80	3.690	3.948	5.047	7.707	0.180	0.006	19.31	8.77	0.325	0.003	1.2	78.28	0.3
B30_ER	12.07	5.42	5.519	2.480	1.988	2.874	0.022	0.006	13.84	2.23	3.860	0.002	4.1	41.55	3.0
B31_TS	11.97	5.18	2.929	0.946	1.486	2.222	0.016	0.028	7.103	2.670	0.325	0.004	3.1	27.63	2.1
B32_MW	16.80	4.86	3.877	1.385	2.680	4.000	0.047	0.025	11.42	4.927	0.325	0.009	2.7	45.7	1.6
B34_AW	19.93	4.75	5.266	0.938	4.449	5.191	0.086	0.021	16.72	5.327	0.493	0.002	1.5	58.07	0.6
B35_DW2	108.4	6.68	13.81	0.984	3.099	2.087	0.022	3.079	20.55	0.075	0.325	0.000	21.2	61.8	17.1
B36_RS	19.74	5.24	4.223	1.217	6.647	5.731	0.058	0.005	15.95	6.650	0.325	0.002	0	61.25	0
B37_VM	11.73	5.21	3.074	1.041	1.645	1.066	0.032	0.028	6.290	1.420	2.33	0.029	3.9	24.95	2.4
B38_WN	16.43	5.1	3.456	1.555	4.141	3.814	0.037	0.047	15.46	4.140	0.325	0.009	2.5	50.85	0.8
B39_JE	11.25	5.37	3.589	0.569	1.323	2.416	0.024	0.013	11.54	1.410	0.325	0.022	2.5	31.2	1.9
B40_NH	12.02	5.19	3.216	0.477	2.246	3.219	0.023	0.012	12.36	2.280	0.325	0.006	3.5	36.1	2
B41_JM	15.66	5.42	5.599	1.249	2.798	2.522	0.059	0.004	10.67	3.550	3.02	0.001	4.9	40.5	3.5
M10_TC	17.60	5.12	5.464	1.270	3.019	5.170	0.030	0.166	25.91	1.603	0.325	0.005	3.3	55.67	2.3
M11_LC	8.97	5.61	3.375	0.370	1.634	0.937	0.003	0.035	5.325	0.458	3.273	0.000	3.9	20.43	2.7
M15_JE	8.90	6.06	5.518	0.369	0.334	0.540	0.002	0.021	8.113	0.132	1.19	0.008	5.4	26	3.9
M16_AF	10.14	5.94	3.185	0.344	1.001	0.730	0.003	0.040	3.625	0.652	0.325	0.018	10.1	19.12	8.2

M18_JG	13.97	5.03	3.368	0.934	1.319	1.413	0.056	0.017	4.543	2.937	0.325	0.001	3.4	24.48	2.5
M20_AH	20.11	8.95	46.60	1.314	2.014	0.456	0.015	0.005	4.210	0.437	3.568	0.000	113.5	102.6	96.4
M24_DM1	8.66	5.44	5.463	0.295	1.046	0.686	0.004	0.008	6.680	0.840	0.325	0.009	5.6	22.35	4.3
M25_EM	43.55	6.07	4.275	0.461	0.863	0.889	0.045	1.023	7.440	0.845	0.325	0.002	5.5	21.68	4.2
M27_SN	8.19	5.11	5.244	0.667	0.613	0.783	0.009	0.014	8.265	0.420	2.81	0.000	3	23.33	2.1
M29_AR	8.04	5.84	1.964	0.364	0.451	0.246	0.002	0.011	2.323	0.075	0.575	0.000	14.5	8	5.1
M33_DW1	45.37	6.59	7.876	2.487	2.897	0.915	0.038	1.079	3.790	0.075	7.385	0.000	16.2	35.5	13.2
M42_DM2	10.22	6.84	2.093	1.161	1.320	0.613	0.002	0.014	5.350	0.930	0.325	0.001	10	13.6	8.2
M43_GJ	7.64	5.46	3.957	0.324	0.458	0.520	0.004	0.015	2.660	0.075	2.32	0.002	4.9	17.15	3.5
M44_PW	17.92	6.04	2.539	1.024	1.157	0.656	0.018	0.293	2.880	0.075	5.39	0.000	6	16.5	4.6

**Table 3.** Corrosivity index data

This table presents the data used to calculate CSMR and LSI to be able to classify wells into corrosivity categories. Headers represent individual variables from Equations 1 and 2 in Chapter 2

Well ID	Alkalinity as CaCO <sup>3</sup>	Avg. CSMR	Avg. LSI	pH	pHs	A	B	C	D
B01_KA	3.3	11.4	-7.49	5.55	13.04	0.00	2.17	-2.09	0.52
B02_DA	3.4	12.3	-7.90	5.13	13.03	0.04	2.15	-2.06	0.52
B03_EB	2.2	0.7	-7.96	5.18	13.14	0.01	2.14	-2.05	0.35
B04_MB	0.9	47.0	-8.80	4.87	13.66	0.08	2.14	-2.05	-0.09
B05_WB	3.0	12.3	-7.74	5.29	13.03	0.01	2.14	-2.05	0.47
B06_CCA	2.1	24.3	-8.08	5.16	13.24	0.05	2.15	-2.06	0.32
B07_CCB	1.8	26.5	-7.61	5.71	13.33	0.06	2.15	-2.06	0.24
B08_CCC	2.5	25.5	-8.35	4.82	13.17	0.06	2.15	-2.06	0.40
B09_VC	2.6	2.3	-7.84	5.31	13.16	0.07	2.15	-2.06	0.42
B13_LD1	2.3	58.9	-8.57	4.72	13.29	0.10	2.17	-2.09	0.36
B14_LD2	2.4	30.7	-8.26	4.94	13.20	0.07	2.15	-2.06	0.38
B17_DG	5.7	1.8	-7.46	5.31	12.77	0.01	2.15	-2.06	0.76
B19_CH	0.5	21.9	-9.23	4.51	13.74	0.06	2.16	-2.07	-0.15
B21_LK	24.0	17.4	-5.93	6.36	12.29	0.06	2.12	-2.03	1.22
B22_KL	2.4	3.1	-7.79	5.42	13.20	0.06	2.14	-2.06	0.36
B23_AL	3.0	6.3	-7.22	5.79	13.01	0.06	2.10	-2.01	0.46
B26_CM	2.1	14.2	-8.05	5.22	13.27	0.02	2.16	-2.07	0.29
B28_JP	0.3	59.4	-9.04	4.74	13.78	0.09	2.13	-2.04	-0.22
B30_ER	3.0	3.6	-7.62	5.42	13.04	0.06	2.12	-2.03	0.47
B31_TS	2.1	21.9	-8.05	5.18	13.23	0.04	2.14	-2.06	0.31
B32_MW	1.6	35.1	-8.51	4.86	13.37	0.07	2.14	-2.05	0.19
B34_AW	0.6	40.4	-8.89	4.71	13.60	0.07	2.14	-2.05	-0.03
B35_DW2	17.1	63.2	-5.52	6.68	12.20	0.08	2.07	-1.98	1.23
B36_RS									
B37_VM	2.4	2.7	-7.92	5.21	13.13	0.04	2.13	-2.04	0.38
B38_WN	0.8	47.6	-8.53	5.10	13.63	0.07	2.13	-2.04	-0.10
B39_JE	1.9	35.5	-7.85	5.37	13.22	0.05	2.12	-2.03	0.28
B40_NH	2.0	38.0	-8.07	5.19	13.26	0.06	2.15	-2.06	0.30
B41_JM	3.5	3.5	-7.54	5.42	12.96	0.06	2.12	-2.03	0.54
M10_TC	2.3	79.7	-8.15	5.12	13.26	0.07	2.16	-2.07	0.34
M11_LC	2.7	12.7	-7.54	5.61	13.15	0.03	2.15	-2.06	0.39
M15_JE	3.9	6.9	-6.67	6.25	12.91	0.03	2.15	-2.07	0.64
M16_AF	8.2	11.2	-6.67	5.94	12.61	0.03	2.14	-2.05	0.91
M18_JG	2.5	14.0	-8.11	5.03	13.14	0.04	2.14	-2.05	0.39
M20_AH	96.4	0.5	-2.67	8.95	11.62	0.10	2.14	-2.06	1.98
M24_DM1	4.3	20.6	-7.50	5.44	12.94	0.03	2.16	-2.07	0.63
M25_EM	4.2	22.9	-6.88	6.07	12.95	0.03	2.15	-2.06	0.59
M27_SN	2.1	2.9	-7.92	5.30	13.22	0.04	2.16	-2.07	0.34
M29_AR	5.1	4.6	-7.21	5.61	12.82	-0.01	2.17	-2.09	0.73

M33_DW1	13.2	0.5	-6.03	6.59	12.61	0.05	2.15	-2.06	0.95
M42_DM2	8.2	16.5	-5.72	6.84	12.56	0.01	2.13	-2.04	0.91
M43_GJ	3.5	1.1	-7.50	5.46	12.96	0.02	2.13	-2.05	0.54
M44_PW	4.6	0.5	-6.86	6.04	12.90	0.02	2.17	-2.08	0.66

**Table 4.** Groundwater quality index data

The below table shows the data used to calculate the GQI values of each well. The values for the water quality index as well as the domain that each sample was positioned is also noted.

Well ID	Ca <sup>2+</sup> (mg/L)	Mg <sup>2+</sup> (mg/L)	Na <sup>+</sup> (mg/L)	K <sup>+</sup> (mg/L)	Cl <sup>-</sup> (mg/L)	SO <sub>4</sub> <sup>-</sup> (mg/L)	HCO <sub>3</sub> <sup>-</sup> (mg/L)	GQIPiper(mix)	GQIPiper(dom)	Domain
B01_KA	0.22	0.40	2.40	0.12	3.70	0.33	4.27	33.80	54.81	2
B02_DA	0.56	1.14	7.09	0.31	13.37	1.10	4.20	21.23	43.43	2
B03_EB	0.81	0.57	3.06	1.24	4.20	6.32	3.27	26.11	41.51	2
B04_MB	3.93	5.86	3.69	1.58	15.29	0.33	2.35	42.60	15.47	5
B05_WB	0.44	0.56	2.33	0.16	3.99	0.33	3.97	37.25	48.01	2
B06_CCA	2.21	2.75	3.44	0.43	7.89	0.33	3.27	43.26	25.56	4.33
B07_CCB	2.74	3.41	5.71	0.38	8.63	0.33	2.90	38.82	27.13	4
B08_CCC	2.29	2.64	4.59	0.37	8.29	0.33	3.30	39.81	28.53	4
B09_VC	2.11	3.26	7.29	2.04	15.13	6.54	3.77	30.11	29.79	3.33
B13_LD1	7.95	9.57	4.21	3.04	19.14	0.33	3.20	45.35	13.40	5
B14_LD2	3.34	5.25	3.55	0.86	9.97	0.33	3.30	46.53	19.27	5
B17_DG	0.94	0.61	2.46	0.67	3.90	2.13	7.00	43.29	49.34	2
B19_CH	2.94	3.21	2.35	0.65	7.13	0.33	1.50	43.79	16.25	5
B21_LK	8.61	1.11	5.25	0.27	9.17	0.67	29.27	58.20	47.02	1.33
B22_KL	2.09	2.94	5.77	2.62	14.02	4.48	3.85	31.77	29.66	4
B23_AL	1.26	2.19	6.83	1.11	9.30	1.49	4.45	31.36	38.56	2
B26_CM	0.82	0.91	1.67	0.67	4.63	0.33	3.90	43.94	37.84	4
B28_JP	5.05	7.71	3.69	3.95	19.31	0.33	1.20	40.26	13.05	5
B30_ER	1.99	2.87	5.52	2.48	13.84	3.86	4.05	32.44	29.92	4
B31_TS	1.49	2.22	2.93	0.95	7.10	0.33	3.07	41.16	28.36	4
B32_MW	2.68	4.00	3.88	1.39	11.42	0.33	2.73	40.89	21.11	5
B34_AW	4.45	5.16	5.27	0.94	16.72	0.49	1.50	38.29	16.60	5
B35_DW2	3.10	2.09	13.81	0.98	20.55	0.33	21.20	35.74	51.46	2
B36_RS	3.65	5.73	4.22	1.22	15.95	0.33	0.00	37.63	12.37	5
B37_VM	1.64	1.07	3.07	1.04	6.29	2.33	3.90	36.74	35.30	4
B38_WN	4.14	3.81	3.46	1.56	15.46	0.33	2.50	40.85	17.61	5

B39_JE	1.32	2.42	3.59	0.57	11.54	0.33	2.50	35.89	25.08	4
B40_NH	2.25	3.22	3.22	0.48	12.36	0.33	3.50	42.57	21.32	5
B41_JM	2.80	2.52	5.60	1.25	10.67	3.02	4.90	36.91	31.16	4
M10_TC	3.02	5.17	5.46	1.27	25.91	0.33	3.27	37.41	19.36	5
M11_LC	1.63	0.94	3.37	0.37	5.33	3.27	3.85	36.41	36.05	3
M15_JE	0.33	0.54	5.52	0.37	8.11	1.19	5.40	22.75	53.08	2
M16_AF	1.00	0.73	3.18	0.34	3.63	0.33	10.07	47.58	54.29	2.67
M18_JG	1.32	1.41	3.37	0.93	4.54	0.33	3.43	40.54	38.87	3.33
M20_AH	2.04	0.46	46.60	1.31	4.21	3.57	113.47	48.50	92.16	6
M24_DM1	0.99	0.72	4.36	0.32	6.68	0.33	5.60	34.22	47.95	2
M25_EM	0.86	0.89	4.28	0.46	7.44	0.33	5.50	33.03	46.08	2
M27_SN	0.61	0.78	5.24	0.67	8.27	2.81	3.00	21.15	43.24	2
M29_AR	0.45	0.25	1.96	0.36	2.32	0.58	14.47	49.47	68.48	4
M33_DW1	2.90	0.91	7.88	2.49	3.79	7.39	16.15	38.70	54.11	2.5
M42_DM2	1.32	0.61	2.09	1.16	5.35	0.33	10.00	50.01	50.94	3
M43_GJ	0.46	0.52	3.96	0.32	2.66	2.32	4.90	33.05	56.38	2
M44_PW	1.16	0.66	2.54	1.02	2.88	5.39	6.00	39.34	44.36	2

**Table 5.** Precipitation data

The below table contains precipitation data from the National Atmospheric Deposition Program from stations near Mobile and Baldwin counties.

ID	Dates Active	Na <sup>+</sup> (meq/l)	K <sup>+</sup> (meq/l)	Na <sup>+</sup> /(Na <sup>+</sup> + K <sup>+</sup> )	Cl <sup>-</sup> (meq/l)	HCO <sub>3</sub> <sup>-</sup> (meq/l)	Cl <sup>-</sup> /(Cl <sup>-</sup> + HCO <sub>3</sub> <sup>-</sup> )	TDS
MS12	2010-	0.020	0.001	0.960	0.024	0.000	1.000	2.685
FL96	2013- 2016	0.015	0.001	0.950	0.018	0.000	1.000	2.173
AL02	2001- 2012	0.014	0.001	0.955	0.016	0.000	1.000	2.634
AL24	2001- 2010	0.022	0.001	0.955	0.025	0.000	1.000	2.634

**Table 6.** Principal Component scores

The table below shows the scores of each water quality parameter included in a principal component analysis. Scores that meet the criteria of |0.30| are bolded.

Variable	PC1 (28.40%)	PC2 (21.70%)	PC3 (15.32%)	PC4 (12.93%)	PC5 (8.57%)
SPC	0.22	<b>-0.33</b>	<b>0.43</b>	<b>0.37</b>	0.02
pH	0.27	<b>0.42</b>	0.2	0.28	-0.17
Fdom	<b>0.51</b>	-0.04	-0.2	-0.04	0.07
TC	0.17	-0.11	-0.13	-0.16	<b>-0.68</b>
Fe <sub>T</sub>	<b>0.48</b>	0.02	-0.21	-0.09	0.19
Cu	-0.10	-0.04	<b>-0.42</b>	<b>0.55</b>	0.12
As	<b>0.50</b>	-0.07	-0.23	-0.08	0.10
Pb	-0.13	-0.05	<b>-0.46</b>	<b>0.51</b>	-0.08
Cl	0.18	<b>-0.49</b>	0.11	0.08	0.22
NO <sub>3</sub>	-0.07	<b>-0.52</b>	0.25	0.11	-0.01
SO <sub>4</sub>	0.00	<b>0.32</b>	0.16	0.02	<b>0.58</b>
CaCO <sub>3</sub>	0.22	0.29	<b>0.37</b>	<b>0.41</b>	-0.24

**Table 7.** Regression data

The following table shows all data that was used for simple and multilinear regressions. Values with a star indicate that the value is below the labs limit of detection (censored.)

Well ID	% Agricultural Land	pH	SPC (μS/cm)	Recharge Potential	Nitrate (ppm)	Septic (1= no, 0=yes)
B01_KA	35.47	5.55	19.7	4.23	0.25	1
B02_DA	0.47	5.13	55.95	4.52	0.2	1
B03_EB	5.14	5.18	25.5	4.28	0.15*	1
B04_MB	29.71	4.87	119.3	4.36	6.37	0
B05_WB	12.4	5.29	24.47	4.46	0.57	1

B06_CCA	23.42	5.16	65.7	4.42	3.74	1
B07_CCB	20.3	5.71	88.53	4.36	5.99	1
B08_CCC	19.59	4.82	71.9	4.21	4.04	1
B09_VC	21.37	5.31	95.83	4.43	2.36	1
B13_LD1	36.19	4.72	182.9	4.44	13.02	1
B14_LD2	36.16	4.94	100.4	4.44	6.72	1
B17_DG	81.14	5.31	27.5	3.95	0.15*	1
B19_CH	78.42	4.62	81.2	4.07	5.4	1
B21_LK	38.4	6.36	82.13	4.06	0.64	1
B22_KL	69.04	5.42	85.8	4.51	2.27	1
B23_AL	6.52	5.79	74.9	4.64	3.52	1
B26_CM	25.46	5.22	30.4	4.03	0.79	1
B28_JP	29.1	4.8	156.6	4.36	8.77	0
B30_ER	69.38	5.42	83.1	4.43	2.23	1
B31_TS	67.09	5.18	55.27	4.48	2.67	1
B32_MW	65.34	4.86	91.4	4.64	4.93	1
B34_AW	77.18	4.75	116.1	4.17	5.33	1
B35_DW2	0	6.68	123.6	4.38	0.15*	1
B36_RS	86.8	5.24	122.5	3.99	6.65	1
B37_VM	28.23	5.21	49.9	4.5	1.42	1
B38_WN	66.25	5.1	101.7	4.6	4.14	1
B39_JE	26.98	5.37	62.4	3.96	1.41	1
B40_NH	52.23	5.19	72.7	4.36	2.28	1
B41_JM	89.11	5.42	81	4.15	3.55	1
M10_TC	42.69	5.12	111.3	4.7	1.6	1
M11_LC	27.97	6.33	40.7	4.56	0.84	1
M15_JE	47.88	6.06	38.57	4.51	0.61	1
M16_AF	0.11	5.94	38.23	4.42	0.94	0
M18_JG	55.54	5.03	48.97	4.39	2.94	1
M20_AH	0.23	8.95	205.3	4.07	1.16	1
M24_DM1	4.23	5.44	44.7	4.51	0.84	1
M25_EM	0	6.07	43.35	4.39	0.85	0
M27_SN	0	5.11	46.65	4.38	0.42	1
M29_AR	0.23	5.84	16	4.09	0.15*	1
M33_DW1	0	6.59	71	4.36	0.15*	1
M42_DM2	0.92	6.84	27.2	4.6	0.93	0
M43_GJ	2.41	5.46	34.3	4.51	0.15*	1
M44_PW	1.37	6.04	33	4.54	0.15*	1

## Appendix 2

### A “First alert” for drinking water quality: commercial water quality testing kits for community-engaged research

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**Section 1.** List of all test kits and grouping

Tables 1 and 2 summaries all-in-one and combination test kits, respectively, assessed in this study. All-in-one test kits were sorted into sub-groups of unique products by the principle of analysis, concentration ranges, and the number of test parameters. Combination test kits from different manufacturers were considered unique products as they contain different sets of testing principles.

**Table 1 - All-in-one test kit list and group assignments**

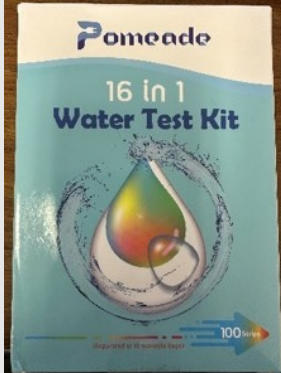
#	Test kit	Photo	Group assignment
1	Test strips 16in1		Group 1
2	AKSBTEC Drinking Water Test Strips 16in1		Group 1
3	UJOYLIFE Drinking Water Test Strips 16in1		Group 1

4 JNW Testing  
Drinking water-  
15 15-in-1 Water  
test



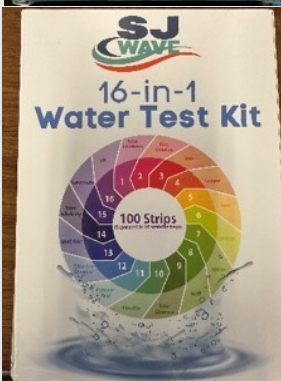
Group 2

5 Promenade 16in1  
Water Test Kit



Group 3

6 SJ Wave 16-in-1  
Water Test Kit



Group 3

7 RapiFast  
Drinking Water  
Test Strips  
16in1



Group 4

<p>8      TESP<small>ERT</small>          Drinking Water          Test Strips 16in1</p>		<p>Group 5</p>
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<p>9      Simplex Health          5-in-One Water          Test Kit</p>		<p>Group 6</p>
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<p>10     16 in 1 Drinking          Water Reagent          Strips For Water</p>		<p>Group 7</p>
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<p>11     Verify Complete          Water Test Kit          17in1</p>		<p>Group 8</p>
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12 FUNSWTM  
16in1 Drinking  
Water Test Strips



Group 9

13 Test Strips 15in1  
Reagent Strips  
for Water



Group 10

14 JNW Direct  
Heavy Metals



Group 11

15 SenSafe Water  
Metals Check



Group 12


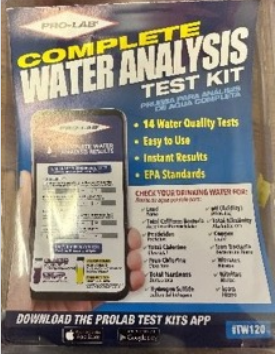


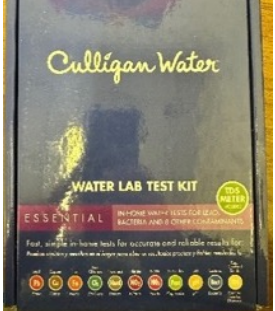

16 HACH  
AquaChek Water  
Quality Test  
Strips 5-in-1



Group 13

**Table 2 – Combination test kit list and group assignments**

#	Test kit	Photo	Test principals	Group assignment
1	Watersafe Well-Water Test Kit		<i>Bacteria</i> – reagent colorimetric; <i>lead and pesticides</i> – binary; <i>other</i> – dip-strips.	Group 1
2	LABTECH H2O OK Plus Complete Water Analysis Kit		<i>Bacteria</i> – reagent colorimetric; <i>lead and pesticides</i> – binary; <i>other</i> – dip-strips.	Group 2
3	SafeHome City Water test kit		<i>Lead</i> – binary (cassette); <i>other</i> – dip-strip.	Group 3
4	SafeHome Well Water test kit		<i>Bacteria</i> – reagent colorimetric; <i>lead</i> – binary (cassette); <i>other</i> – dip-strip.	Group 3
5	Industrial Test Systems Complete Home Water Quality Test Kit		<i>Bacteria</i> – reagent colorimetric; <i>other</i> – dip-strips.	Group 4

<p>6 Industrial Systems Water Quality Test Kit</p>		<p><i>Bacteria</i> – reagent colorimetric;  <i>lead and pesticides</i> – binary;  <i>other</i> – dip-strips.</p> <p>Group 4</p>
<p>7 Pro-Lab Complete Water Analysis Test Kit</p>		<p><i>Bacteria</i> – reagent colorimetric;  <i>lead and pesticides</i> – binary;  <i>other</i> – dip-strips</p> <p>Group 5</p>
<p>8 Health Metric Well Water Test</p>		<p><i>Bacteria</i> – reagent colorimetric;  <i>other</i> – dip-strips.</p> <p>Group 6</p>
<p>9 LaMotte Low Cost Water Monitoring Kit</p>		<p><i>All</i> – reagent colorimetric;  <i>turbidity</i> – compare with the chat.</p> <p>Group 7</p>
<p>10 Culligan Water Water Lab Test Kit</p>		<p><i>Bacteria</i> – reagent colorimetric;  <i>lead and pesticides</i> – binary;  <i>other</i> – dip-strips.</p> <p>Group 8</p>
<p>11 LaMotte Urban Water Test Kit</p>		<p><i>All</i> – reagent colorimetric.</p> <p>Group 9</p>

**Section 2.** All-in-one and combination test kit down-selection

Tables 3 and 4 summarize the test principle, color change chart of the dip-strips and concentration ranges of all-in-one and combination test kits, respectively.

**Table 3** - Concentration ranges and colorimetric principal of EPA standards in all-in-one test kits

Group	Secondary standard	Primary standard, ppm						
	pH	Copper	Lead	Mercury	Chromium	Nitrate	Nitrite	Fluoride
<b>MCL</b>	<b>6.5-8.5</b>	<b>1.3</b>	<b>0.015</b>	<b>0.002</b>	<b>0.1</b>	<b>10</b>	<b>1</b>	<b>4 (2 as secondary)</b>
1	6.2-8.4 y p	0-300 y g b	0-500 y pl	0-0.08 y pl	0-100 w pl	0-500 w p	0-80 w p	0-200 o y
2, 3, 4	6-9 y o	0-10+ y p	0-500 y r	-	-	0-500 w p	0-80 w p	0-100 pl br
5	6-9 y o	0-10+ y p	0-500 y r	-	-	0-500 w p	0-80 w p	-
6	5.5-9.5 y g	-	-	-	-	0-200 w p	0-20 w p	-
7	6-9 r g	0-5 y g b	0-0.05 y o	0-0.08 p pl	0-100 w pl	0-500 w p	0-80 w p	0-100 o y
8	6-9 r y	0-5 y g b	0-50 y o	0-0.08 p pl	-	0-500 w p	0-80 w p	0-100 o y
9	6-9 y o	0-10+ y p	0-500 y r	-	-	0-500 w p	0-80 w p	0-100 pl br
10	6-9 r g	0-300 y g b	0-500 y pl	-	-	0-500 w p	0-80 w p	0-200 o y
11	-	0-2 y g b	0-50 y o	0-0.08 p pl	-	-	-	-
12	-	Semiquantitative check for heavy metals			-	-	-	-
			o pl					

y- yellow; g- green; b- blue; p- pink; o- orange; r- red; pl- purple; w- white, - not testing.

**Table 4** - Concentration ranges and colorimetric principal of EPA standards in combination test kits

Group	Secondary standard	Primary standards, ppm							
	pH	Copper	Lead	Pesticides	Nitrate	Nitrite	Fluoride	Bacteria	Turbidity
MCLs	6.5-8.5	1.3	0.015	0.004 or 0.003*	10	1	4 (2 as secondary)	0	0
1	6-10 y p	0-5 w br	Y/N	Y/N	0-50 w p	0-10 w p	-	pl y	-
2	4-10 br b	0-3 br pl	Y/N	Y/N	0-25 w p	0-50 w p	-	r y	-
3	6-9 y o	0-10+ y p	Y/N	-	0-500 w p	0-80 w p	0-25 pl br	y g	-
4	2-12 r b	0-2 w pl	Y/N	Y/N	0-50 w p	0-3 w p	-	pl y	-
5	6.2-8.4 w g	0-5 y br	Y/N	Y/N	0-50 w pl	0-5 w pl	-	pl y	-
6	2-12 r b	-	-	-	0-50 w p	0-3 w p	-	pl y	-
7	4-10 p g pl	-	-	-	5-40 w o	-	-	r y	0-100 JTU
8	6-9 y r	0-10+ y p	Y/N	Y/N	0-500 w p	0-80 w p	-	r y	-
9	4-9 r b	0-4 r pl b	-	-	0-40 w p	-	-	r y	-

Color indications: y- yellow; g- green; b- blue; p- pink; o- orange; r- red; pl- purple; w- white, br- brown; - not testing; Y/N- binary test.

\*Atrazine MCL is 0.003 and simazine is 0.004 ppm

All-in-one test kits can measure seven EPA primary standards, including copper, lead, mercury, chromium, nitrate, nitrite, fluoride (Table 3). Test group 12 was excluded from analysis as it measures sum metal concentration in water, but the concentration of the assay is not comparable with EPA standard. The MCL levels fall within the lowest concentration range covered by all-in-one test kits. Most all-in-one test kits are not sensitive to the concentrations below MCLs for most water quality parameters, and they can only detect concentrations at or above MCLs.

Consequently, they cannot indicate exposure to low concentration or early-stage water quality deterioration. Test groups 7 and 8 exhibit higher sensitivity for copper, lead, and mercury than other all-in-one test groups. These test groups measure the largest number of primary standards in water, with seven for test group 8 and eight for test group 7. Test group 8 also can determine secondary EPA standards including chloride, sulfate, iron, manganese, and zinc; and test group 7 only iron. Hence, test groups 7 and 8 underwent further laboratory analysis.

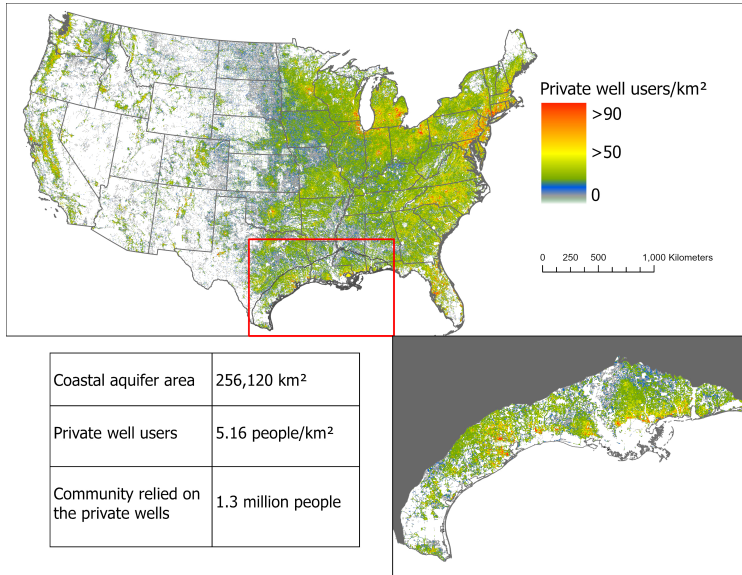
The combination test kits are subdivided into two categories based on the number of primary standards covering 3 or 6 water quality parameters (Table 4). Combination test kits are more sensitive compared to all-in-one test kits. Test groups 1 and 4 were down-selected based on selectivity and number of parameters.

**Section 3.** The estimation of the community size impacted by this research

The estimation of the community size impacted by this research were performed by utilizing the dataset and Road Enhanced Method (REM) for well user estimation (Tyler D. Johnson et al., 2019) using ArcGIS Pro 3.2. The results of this estimation are illustrated in Figure 1.

Initially, we consolidated all individual attributes labeled as "Coastal lowlands aquifer system" into a new feature (Upper Midwest Water Science Center, 2003).

Subsequently, we conducted Zonal Statistics, using the shape of the "Coastal lowlands aquifer system" as the "Input Feature Zone Data" and the REM raster as the "Input Value Raster." The chosen "Statistics Type" calculated the average well users across the entire aquifer. Following that, we

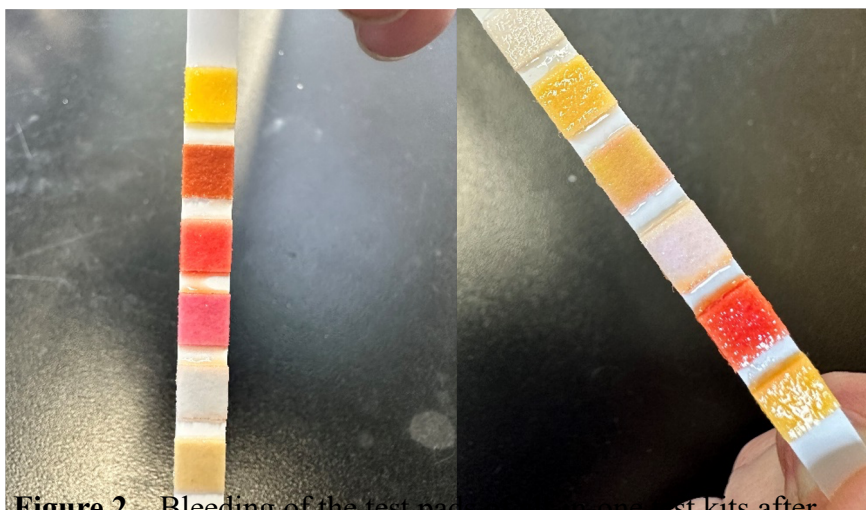


**Figure 1** – Distribution of private well users in the U.S. and coastal aquifer area, and estimation of the community impacted by this research. The figure was created using the dataset from Johnson et al., 2019.

performed summary statistics on the merged "Coastal lowland aquifer system" to determine the total area of the individual components in the aquifer system. The next step involved multiplying this sum by the average number of well users.

#### Section 4. Preliminary laboratory test of all-in-one test kits

The down-selected all-in-one test kits were tested in laboratory analysis for reliability. We analyzed the response of the test pads to the target parameter's lower MCLs. Stock solutions of single analytes were made by diluting target compound in ultra-pure water (18.2 Mohm) in a volumetric flask. We used pure powder of copper (II) sulfate (Ward's science), lead (II) nitrate (BTC), sodium nitrate (VWR), sodium nitrite (Macron), mercury chloride (J.T. Baker), sodium fluoride (VWR). The tested concentrations were 0.65 ppm as copper, 0.0075 as lead, 1 ppm as nitrate, 0.2 ppm as nitrite, 0.0014 ppm as mercury, 4.4 ppm as fluorine. We strictly followed the instruction in the manual by controlling reaction time and reading results after a certain period using stock solutions as samples. The results were recorded and compared with the dosed concentrations.



**Figure 2** – Bleeding of the test pads of all-in-one test kits after immersing into ultra-pure water. Left - colored water leaks from the pads and mixes on the surface between the test pads. Right - change in color of the nearby light pad due to bleeding of the bright pad.

The laboratory test showed that all-in-one test groups 7 and 8, down-selected as most sensitive all-in-one test kits, are not responding to the tested concentrations of nitrate, nitrite, fluoride, and mercury,

which can be explained by their low sensitivity at concentrations lower than MCL. Some color charts used several tones of the same colors making it difficult to associate the color to the color

chat. Moreover, some bright test pads (fluoride and zinc pads) are bleeding significantly and contaminate the nearest test pads (Figure 2). Therefore, it was concluded that these are significant drawbacks of all-in-one test kits, and they are not suitable for water quality monitoring at contaminant concentration lower MCL.

**Section 5.** Labeling safe and hazardous levels of contaminants on the test kits

Table 5 and 6 summarize the way information about safe and hazardous concentration levels marked in the test kits.

**Table 5** – Safe and hazardous levels marked in all-in-one test kits

Group	Secondary standard	Primary standard, ppm						
	pH	Copper	Lead	Mercury	Chromium	Nitrate	Nitrite	Fluoride
<b>MCLs</b>	<b>6.5-8.5</b>	<b>1.3</b>	<b>0.015</b>	<b>0.002</b>	<b>0.1</b>	<b>10</b>	<b>1</b>	<b>4 (2 as secondary)</b>
1	6.2, 6.8, <u>7.2, 7.8, 8.4</u>	<u>0, 1, 10</u>	<u>0, 20, 50</u>	<u>0, 0.002, 0.005</u>	<u>0, 2, 5, 10</u>	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 25, 50</u>
2	6.0, <u>6.4 - 8.2, 9.0</u>	<u>0, 0.5, 1, 3</u>	<u>0, 20, 50</u>	–	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 10, 25</u>
3	6.0, <u>6.4 - 8.2, 9.0</u>	<u>0, 0.5, 1, 3</u>	<u>0, 20, 50</u>	–	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 10, 25</u>
4	6.0, 6.4-8.2, 9.0	0, 0.5, 1, 3	0, 20, 50	–	–	0, 10, 25, 50	0, 1, 5, 10	0, 10, 25
5	6.0, 6.4-8.2, 9.0	0, 0.5, 1, 3	0, 20, 50	–	–	0, 10, 25, 50	0, 1, 5, 10	–
6	<b>5.5, 6.5-8.5, 9.0</b>	–	–	–	–	<u>0, 20, 40, 80, 160</u>	<u>0, 0.5, 1, 3</u>	–
7	6.0, 6.5-8.5, 9.0	<u>0, 0.1, 0.2, 0.4, 1, 2, 5</u>	<u>0, 0.005, 0.015, 0.03, 0.05</u>	<u>0, 0.002, 0.005, 0.01</u>	<u>0, 2, 5, 10</u>	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 4, 10, 25</u>
8	6.0, <u>6.5-8.5, 9.0</u>	<u>0, 0.1, 0.2, 0.4, 1, 2, 5</u>	<u>0, 0.005, 0.015, 0.03, 0.05</u>	<u>0, 0.002, 0.005, 0.01</u>	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 4, 10, 25</u>
9	6.0, <u>6.4 - 8.2, 9.0</u>	<u>0, 0.5, 1, 3</u>	<u>0, 20, 50</u>	–	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 10, 25</u>
10	6.0, <u>6.5-7.5, 8.0-9.0</u>	<u>0, 1, 10</u>	<u>0, 20, 50</u>	–	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 25, 50</u>
11	–	<u>0, 0.05, 0.1, 0.2, 0.4, 1, 2</u>	<u>0, 0.005, 0.015, 0.03, 0.05</u>	<u>0, 0.002, 0.005, 0.01</u>	–	–	–	–
12	–		0.01, 0.02, 0.05, 0.1, 0.2, 0.4, 1			–	–	–

Underlined – good / healthy range, bold – harmful or out-of-range. Only concentration increments around MCL are shown in this table.

**Table 6** – Safe and hazardous levels marked in combination test kits

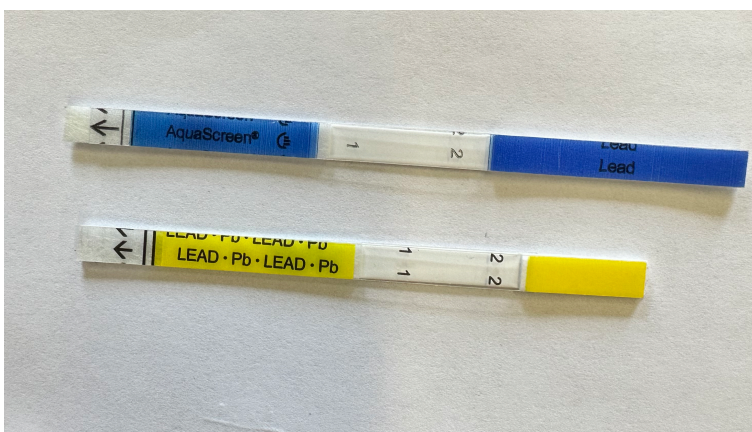
Group	Secondary standard pH	Primary standards, ppm							
		Copper	Lead	Pesticides	Nitrate	Nitrite	Fluoride	Bacteria	Turbidity
MCLs	<b>6.5-8.5</b>	<b>1.3</b>	<b>0.015</b>	<b>0.004 or 0.003*</b>	<b>10</b>	<b>1</b>	<b>4 (2 as secondary)</b>	<b>0</b>	<b>0</b>
1	<u>6.0, 6.5-8.5, 10</u>	0, 0.5, 1, 2, 5	below 0.015	Bellow or at MCL	0, 0.5, 2, 5, <b>10</b> , 20	0, 0.15, 0.3, <b>1</b> , 1.5, 3	–	Y/N	–
2	<u>4, 5, 6, 7, 8, 9</u>	<u>0, 0.3, 0.6, 1</u> , 3	below 0.015	Bellow or at MCL	<u>0, 5</u> , 10, 25	<u>0, 0.5</u> , 1, 5	–	Y/N	–
3	<b>6.0, 6.5-8.5, 9.0</b>	<u>0, 0.5, 1, 3, 10+</u>	below or at 0.002	–	<u>0, 10, 25, 50</u>	<u>0, 1, 5, 10</u>	<u>0, 1, 3, 5</u>	Y/N	–
4	2.0, 4.0, 5.0, 6.5-8.5, 9.5	0, 0.1, 0.5, <b>1, 2</b>	below 0.015	Bellow or at MCL	0, 2, <b>10</b> , 20	0, 0.2, <b>1</b> , 1.5	–	Y/N	–
5	6.2, 6.8, 7.2, 7.8, 8.4	<u>0, 1.3, 3, 5</u>	below 0.015	Bellow or at MCL	<u>0, 2, 10, 50</u>	<u>0, 0.25, 1, 5</u>	–	Y/N	–
6	2.0, 4.0, 5.0, 6.5-8.5, 9.5	–	–	–	0, 2, <b>10</b> , 20	0, 0.2, <b>1</b> , 1.5	–	Y/N	–
7	<b>4, 5, 6, 7, 8, 9, 10</b>	–	–	–	<u>5, 20, 40</u>	–	–	Y/N	<u>0, 40, 100</u>
8	6.0, 6.4-8.2, 9.0	0, 0.5, 1, 3, 10+	below 0.015	Bellow or at MCL	0, 10, 25, 50	0, 1, 5, 10	–	Y/N	–
9	4, 5, 6, 7, 8, 9	0, 1.5, 2, 4	–	–	0, 5, 20, 40	–	–	Y/N	–

Underlined – good / healthy range, bold – harmful or out-of-range. Only concentration increments around MCL are shown in this table.

\*Atrazine MCL is 0.003 and simazine is 0.004 ppm.

## Section 6. Lead/pesticides tests accuracy

The accuracy of the lead/pesticide tests from the combination test kit groups 1 and 4 was evaluated by analyzing the stock solutions with known concentrations of the target compound. The lead nitrate (BTC) was diluted in ultra-pure water to reach a concentration from 7.5 to 20 ppb. Lead tests were performed at pH varied 2.5 and 5.5 to test the pH dependency of the test results. The pH of the stock solution was adjusted by addition of a drop of HCl (3 N, VWR, USA) or KOH (3 N, VWR, USA). To evaluate the pesticide test strips, an atrazine standard (Restek, 1,000 ppm) was used, and the tested concentrations varied from 0 to 6 ppb. The tests were conducted following the procedure described in the instructions provided with the test kit.



**Figure 3** – Two types of lead test binary strips provided in the test kit groups 1 and 4

Both the lead and pesticides tests are included in the same pack, and the interior packaging is identical for both test kit groups. However, the test differed in color within the same brand (Figure 3). This difference is likely due to variations in the batches of the test kits or changes

in design or suppliers.

Our test revealed that the lead test strip had low sensitivity to the concentrations  $>MCL$  (Table 7). The test strip at 20-50 ppb showed negative results with the first line being slightly darker than the second line. When the pH was decreased to 2, the difference in line intensities became more pronounced and apparently negative. The lead test's low sensitivity to high lead

concentrations and its dependence on pH make it unreliable as a "first alert" for groundwater with low pH.

**Table 7-** Binary lead tests accuracy depending on the concentration, sample matrix, and pH (green color shows the expected result of the test)

Test result	Stock solution concentration, ppb		Groundwater Samples (pH)
	pH 5.5	pH 2	
	<MCL	>MCL	
Positive	7.5 <sup>†</sup>	N/A*	N/A
Negative	7.5	20	17.6 (5.9)
	10	25	23.6 (5.6)
	12	50	

\*N/A – no tests fell into this category, <sup>†</sup>blue test strip, green cells show accurate results.

The pesticide test strips demonstrated accurate results for atrazine at concentrations <MCL and ≥MCL (Table 8) and can be considered as reliable “first alert” tests for groundwater studies.

**Table 8 –** Pesticide tests accuracy at difference atrazine concentrations

Test result	Stock solution concentration, ppb	
	<MCL	≥MCL
Positive	0.5	3
		4
		5
		6
Negative	0	N/A*
	1	
	2	

\*N/A – no tests felt into this category, green cells show accurate results.

**Section 7. Bacteria test detection limit**

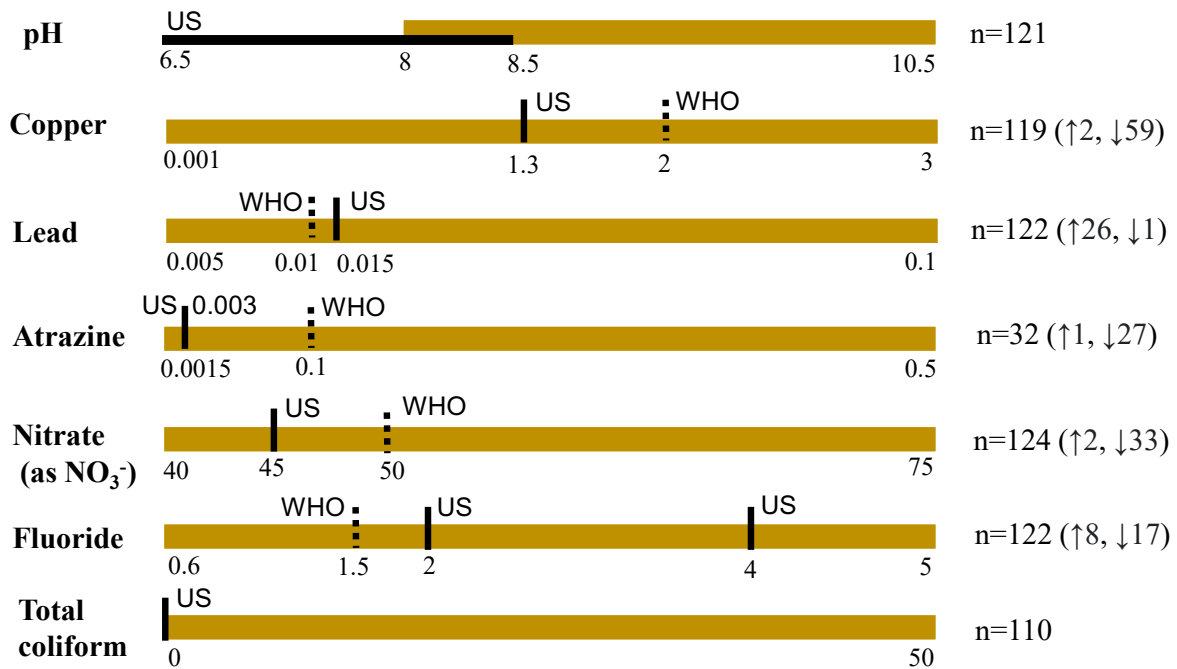
Surface water sample was collected from the local creek and then diluted using ultra-pure water to reach a final dilution ranging from 200 to 150,000 times. The diluted sample was divided into two parts and analyzed simultaneously using test kit bacteria test to determine the presence or absence of total coliform and Quanti-Tray system to quantify the total coliform count. All tests were conducted within two hours of sample collection and the results were recorded after 24-hour and 48-hour incubation period for Quanti-Tray and test kit, respectively. The minimum total coliform number that produced a positive result in the bacteria test was set as the detection limit, which was determined to be 488 MPN/100 mL (Table 9).

**Table 9** – Test kit bacteria assay detection limit (the detection limit in bold)

#	<b>Bacteria test (TK4) after 48 hours</b>	<b>Total coliform, MPN/100 mL</b>
1	Positive	1203
2	Positive	1203
3	Positive	870
4	Positive	866
<b>5</b>	<b>Positive</b>	<b>488</b>
6	Negative	236
7	Negative	236
8	Negative	87
9	Negative	11
10	Negative	< 1
11	Negative	< 1

**Section 8.** Comparison of the drinking water regulations in different countries

We conducted a comparative analysis of the Maximum Contaminant Levels (MCLs) for drinking water established by the US Environmental Protection Agency (EPA) with the regulations set forth by the World Health Organization (WHO), as well as data reported by countries worldwide. The examination of MCLs for drinking water across various countries revealed that the majority adhere to WHO standards. In Figure 4, it is evident that the US MCLs are generally lower than WHO recommendations for the evaluated parameters, with the exception of fluoride, where the US MCL is 0.5 ppm higher than the WHO recommendation. Specifically, for copper and atrazine, the majority of countries regulating these parameters exhibit standards that are more stringent than those recommended by the WHO.



**Figure 4** – Drinking water regulations in different countries as reported by WHO. All concentrations are in ppm. US- MCLs as defined by US EPA. WHO – recommended concentration by WHO. Total countries in survey: 125; n - a number of countries that regulates this water quality parameter, ↑ - number of countries with higher MCLs than WHO, ↓ - number of countries with lower MCLs than WHO.