Investigating the Impact of Land Use Composition on Water Quality of the Ala Wai Watershed

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We certify that we have read this thesis and that, in our opinion, it is satisfactory in scope and quality as a thesis for the degree of Bachelor of Science in Global Environmental Science.

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Abstract

Polluted water is a significant source of waterborne disease, specifically in urban areas where land use composition and runoff can drastically change water quality. This study investigates the relationship between land-use and water quality in the Ala Wai watershed of Honolulu, HI, focusing on the Mānoa stream during a heavy rainfall event in May 2024. Water quality parameters such as *Enterococcus* concentrations and turbidity were sampled from Mānoa Valley down through the Ala Wai Canal and out into coastal marine waters. Our analysis shows that during heavy rain events, water quality worsens in urban areas of Oʻahu with ANOVA results showing statistically significant results ($p = 0.00139$). Further, a post hoc Tukey test identified two statistically different groups, sites in dense, urban Honolulu (a), and sites furthest in Mānoa Valley less affected by urbanization (b). Poor water quality was most common around the McCully area along the Ala Wai Canal, taking approximately five days to return to baseline levels, two days after rain stopped. These findings highlight potential impacts of urban land-use on water quality and suggest that further studies with larger sample sizes are needed to support these trends in Hawaiʻi.

Keywords: Water quality, Ala Wai watershed, Enterococcus, Turbidity, Rainfall event

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1. Introduction

Ensuring the safety of water for human consumption and recreation is paramount to global public health. Around the world, concerns over water quality are rising, especially as urbanization, agricultural runoff, and environmental degradation intensify. Contamination of water sources with fecal microorganisms poses a significant risk to public health. It is estimated that each year, there are more than 120 million cases of gastrointestinal disease and over 50 million cases of severe respiratory disease from swimming in fecal-polluted coastal waters around the globe (Shuval, 2003).

The assessment of water quality and the identification of potential health hazards relies heavily on the detection of microorganisms in water. The direct measurement of specific pathogens is difficult in practice because of the abundance and variation of microbes that can appear in water quality samples. Thus, a handful of fecal indicator bacteria (FIB) are used as proxies and other infectious pathogens are assumed to be present (Hathaway, et al., 2015). Commonly used fecal indicators include Escherichia coli (*E. coli*), *Enterococcus*, and Clostridium perfringens (*C. perfringens*). The US Environmental Protection Agency (US EPA) recommends *E. coli* and *Enterococcus* as the best indicators of health risk for recreational waters (US EPA, 1985). In Hawai‘i, the Hawai‘i Department of Health (HDOH) cultures and enumerates *Enterococcus* and *C. perfringens* for water quality measurements (HDOH, 2024). The Clean Water Branch (CWB) specifies a Beach Action Value (BAV), which is the FIB level that the CWB takes further beach management action such as resampling and issuing notifications or advisories. The specified BAV level for *Enterococcus* is in accordance with EPA standards and defined as 130 CFU or MPN/100 mL. However, the HDOH’s sampling protocol does not include rain events, so water quality data under these conditions are lacking. Thus, this study aims to address this gap by investigating when water returns to baseline conditions after storm events.

Surface runoff accumulates various pollutants and is a well-known factor that affects local water quality in developed regions (Ackerman & Weisberg, 2003). The variance in types and concentrations of pollutants are related to each regions' land use (Spengler, 2018). For example, runoff from agricultural land and urban land may differ in bacterial count, turbidity, and chemical composition. The following research also investigates the relationship between predominant land use composition and FIB in Honolulu, HI.

The Ala Wai watershed is located between the Ko'olau mountains and the Ala Moana and Waikīkī shorelines. It spans across three tributaries, the Makiki, Mānoa, and Pālolo streams. The Mānoa and Pālolo streams converge mid-watershed entering the Ala Wai canal, before it reaches the ocean. Much of this watershed resides within developed, urban areas negatively impacting water quality at popular recreational beaches along the coast (Paule et. al, 2015, Goto & Yan, 2011). This study was designed to test the hypothesis that low *Enterococcus* and turbidity will be recorded in Mānoa Valley where it is less urban, and off the coast where oceanic mixing occurs. In contrast, it is anticipated that high FIB and turbidity levels are more frequent in dense urban areas. While the exact sources of fecal bacteria are unclear, studies have suggested that contamination primarily comes from non-point sources, environmental growth of FIB, and sewage (Kirs et al., 2017, Goto & Yan, 2011).

1.1 Overview of waterborne diseases

In the 19th and early 20th centuries, typhoid fever served as a prominent indicator illness of waterborne disease. Contracting severe cases of typhoid fever was common during this time as antibiotics and modern sanitation practices were not well developed. In the early 1900s, basic water treatment systems were making their debut in a handful of major American cities like Baltimore, Chicago, New Orleans, and others. The practice of simple filtration of water through sand and other porous matter reduced the rates of typhoid fever by about 46% and typhoid fever was nearly eradicated (Cutler, 2005). The high incidence and severity of waterborne disease summarizes the critical need for effective preventive measures and tools for predicting outbreaks.

Waterborne disease (WBD) continues to pose a significant threat to global public health in the 21st century, still affecting millions of people worldwide. This type of disease results from ingestion or contact with water contaminated by pathogenic microorganisms, which can lead to a wide range of health issues. Communities in areas with inadequate sanitation and clean water are devastated with outbreaks of cholera, typhoid fever, and other illnesses (Amicizia et al., 2019; CDC, 2024). Even in the 21st century, many populations still struggle with waterborne disease in both developed and developing countries (Tulchinsky, 2018). For instance, in the United States alone, about 7.15 million waterborne illnesses occur annually and result in over $3 billion in healthcare costs (Collier et. al, 2021). Climate change is projected to intensify storm events, which could further overwhelm water infrastructure, increasing the risk of contamination of drinking-water supply and WBD outbreaks (Cann et al., 2013; Tulchinsky, 2018). Despite advances in modern sanitation and infrastructure, the persistence of waterborne disease highlights the need for continued efforts to ensure safer water access and reduce outbreaks.

2. Methods

2.1 Water Quality Data and Sample Collection

Water quality samples were collected at fourteen sample sites along the Mānoa stream, Ala Wai Canal, and the nearshore waters of Waikīkī (Figure 1). Sample collections took place during a heavy rain event in May 2024 where a storm produced approximately 13 inches of rain in the back of the watershed. Sample days included were May 16th, 17th, 19th, and 21st. Field samples were collected within two hours of sunrise to reduce the risk of photo-inhibition of culturable bacteria (Sinton et al., 1999; Fujioka & Yoneyama, 2002). At each site, surface water grab samples were collected in polypropylene bottles and stored on ice with no light exposure until being processed in the lab. Analysis for *Enterococcus*, turbidity, and salinity was completed within six hours of collection. Baseline measurements were also collected to get a general idea of water quality during a non-storm period. Baseline samples were obtained during March 3, 2024, two and a half months before the heavy rain event and analyzed in the same way. *Enterococcus* concentration was analyzed in the lab using the Enterolert MPN method (IDEXX Laboratories Inc.) following the manufacturer’s protocol. Turbidity was measured using a benchtop turbidity meter (SPER Scientific) and represents the amount of suspended matter in a liquid.

Table 1. Water Quality Monitoring Site Locations

Site	Latitude	Longitude
AW1	21.328374	-157.800782
AW2	21.328176	-157.799599
AW3	21.308432	-157.809271
AW4	21.299313	-157.81364
AW5	21.283191	-157.824537
AW6	21.288225	-157.832158
AW7	21.290064	-157.834639
AW8	21.285152	-157.843317
AW9	21.282941	-157.845661
AW10	21.282506	-157.846144
AW11	21.282072	-157.844897
AW12	21.279663	-157.845444
AW13	21.276361	-157.846375
AW14	21.281202	-157.84171

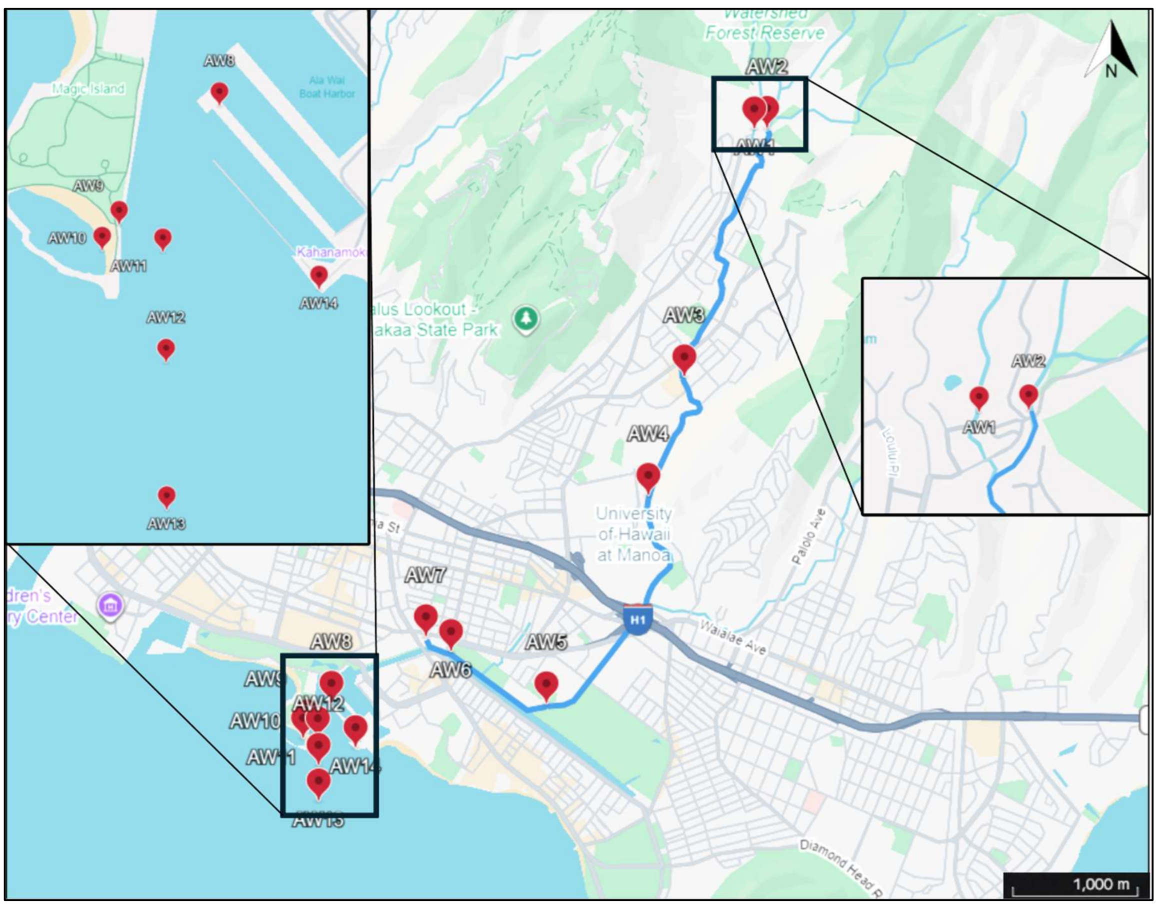

Figure 1: The Ala Wai watershed study area and the surrounding Honolulu, HI area

2.2 Geographic and Land Use Data

Geographic and O‘ahu land use data were compiled from the Hawaii Statewide GIS Program (https://geoportal.hawaii.gov). This resource is a geospatial data portal for all eight Hawaiian islands and contains maps ranging from administrative boundaries to human health & safety. For the Ala Wai watershed, zoning classifications were pulled from the Hawaii Zoning GIS dataset except for three custom classes, AW: brackish, AW: fresh, and AW: salt. These three classes were created to separate the sample sites based on water type within the Ala Wai Canal since they were treated as one zone in the Hawai‘i GIS dataset. The salinity of water samples was used to classify each sample site as brackish water, freshwater, and saltwater respectively. The other classifications are directly from the dataset and are: A-2, medium-density apartment district, R-7.5, residential district, P-1, restricted preservation zone.

2.3 Data Analysis

Data processing and analysis took place in RStudio (Version 4.4.1) using a new R Project. The packages leaflet and ggplot2 were utilized to create maps and plots. The spatial visualization helps illustrate changes in fecal indicator bacteria across different sites over time. An analysis of variance (ANOVA) was also implemented in this study to assess differences in group means and determine statistical significance of such differences. ANOVA assesses if the observed variability among groups stems from random chance or reflects meaningful differences in the data. In addition, a post hoc Tukey Test was done after ANOVA results to determine which groups’ means are different when compared with each other.

3. Results

3.1 Mānoa Stream Gauge

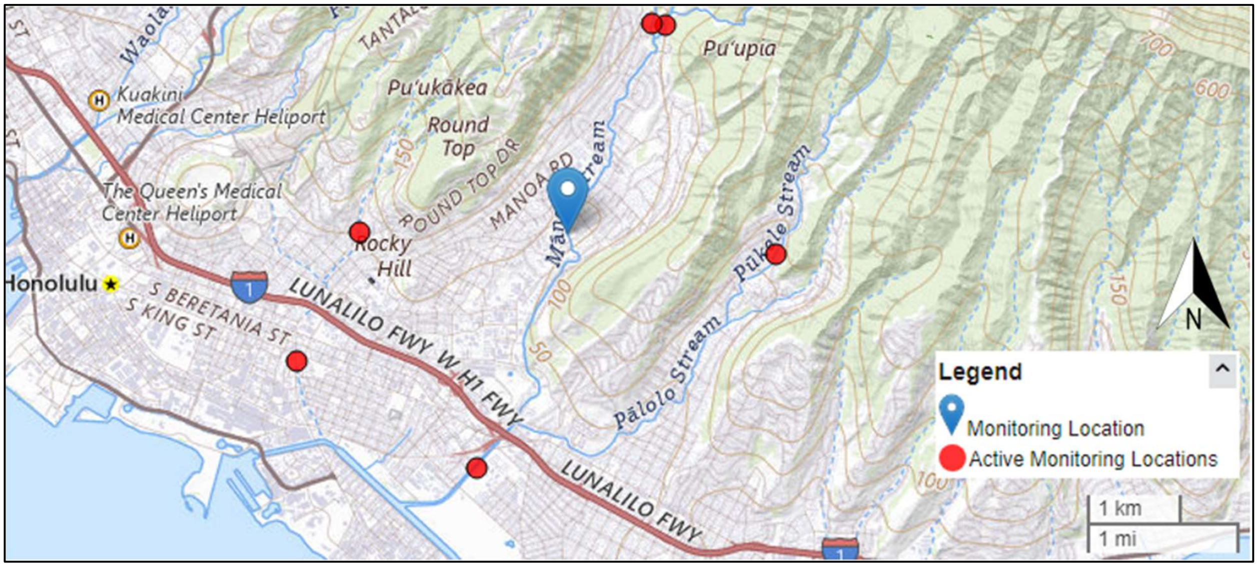

Figure 2: Location of the stream gauge along Mānoa Stream, Oʻahu.

To understand hydrological conditions in Mānoa Valley, monitoring locations have been established by the United States Geological Survey (USGS). Figure 2 shows the location of the Mānoa stream gauge (indicated by the blue marker) and other monitoring locations (indicated by red markers). Stream gauge discharge (ft^3/sec) from Mānoa Stream (#16241600) was examined during the study period. All data is available to the public via the USGS website (https://www.usgs.gov/).

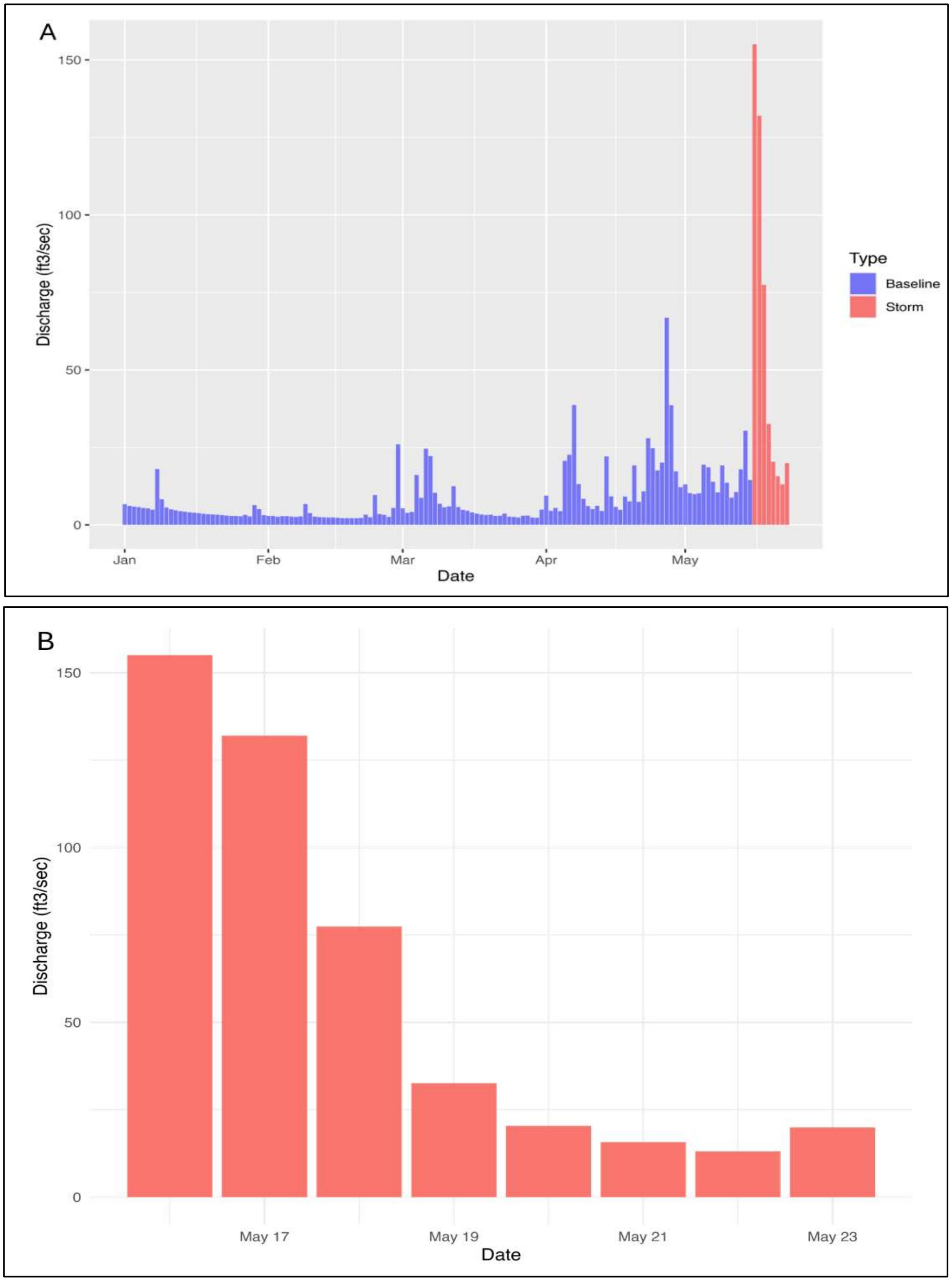

Figure 3: A) Mānoa Stream discharge from January 01, 2024 to May 23, 2024. B) Mānoa Stream discharge from the week of heavy rain: May 16-23, 2024. Taken from the USGS dataRetrieval package for RStudio.

Figure 3 presents the discharge rates for Mānoa Stream from January to May 2024. Baseline conditions shown in blue and the storm event highlighted in red. The spike in discharge on May 16 shows the sharp increase in streamflow and the elevated discharge rates in the few days after.

3.2 Time-series Maps

The following figures highlight the distribution analysis of the Ala Wai watershed and how *Enterococcus* (MPN/100 mL) concentrations changes with land use and time. MPN is a common unit used in water quality testing and stands for Most Probable Number per 100 mL. It represents the concentration of microorganisms in a sample and is done by a series of dilutions of the sample, inoculation in a growth medium, and observing the reaction. It is important to note that during high precipitation, *Enterococcus* measurements frequently exceed HDOH beach action values. A color scale is used to indicate how high *Enterococcus* concentrations were during the day of sampling where red indicates relatively high concentrations and green indicates relatively low concentrations. The same color scale was used for all figures for consistency.

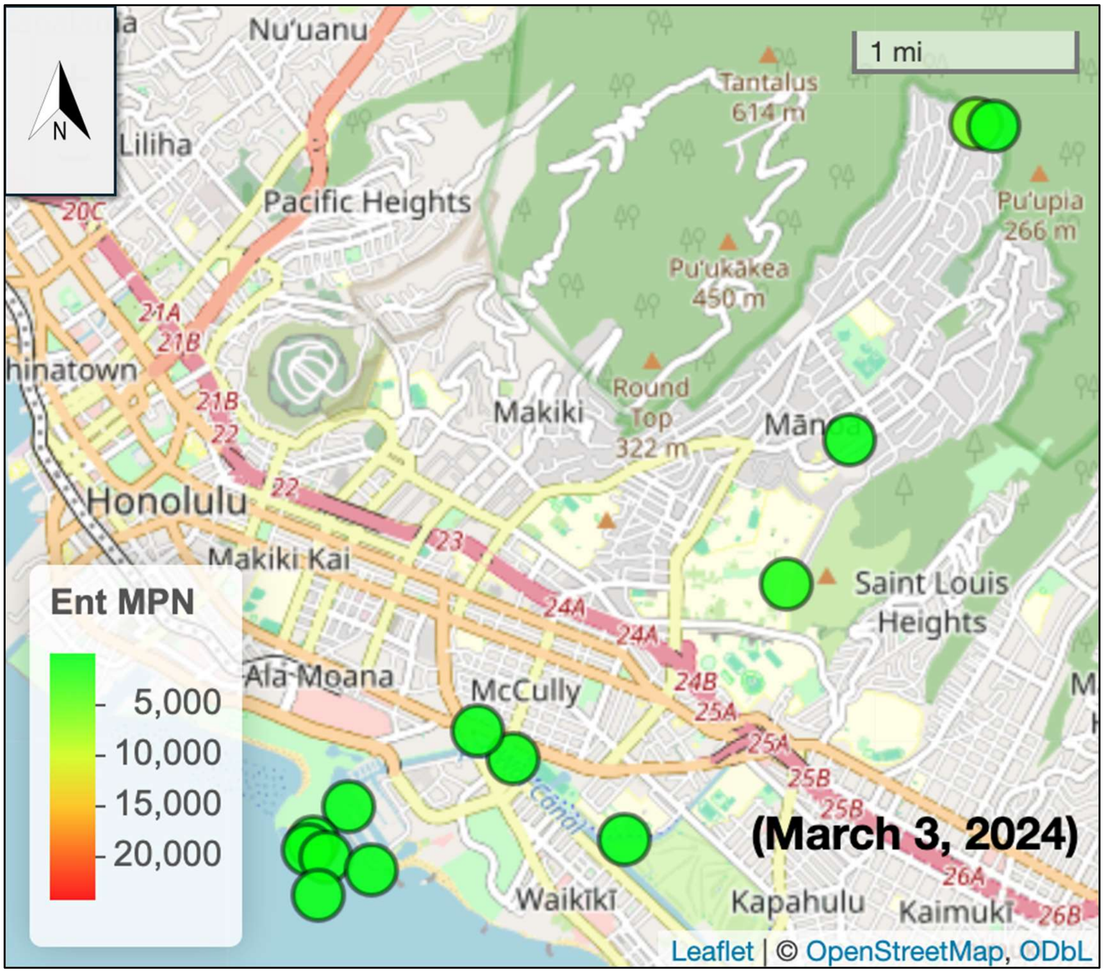

Figure 4: *Enterococcus* distribution throughout the Ala Wai Watershed on March 3, 2024, a non-rainy day.

For baseline measurements, Figure 4 shows *Enterococcus* abundance ranged from 0 MPN (AW7, AW9, AW11) – 5172 MPN (AW1). Turbidity never exceeded 2 NTU at all sites.

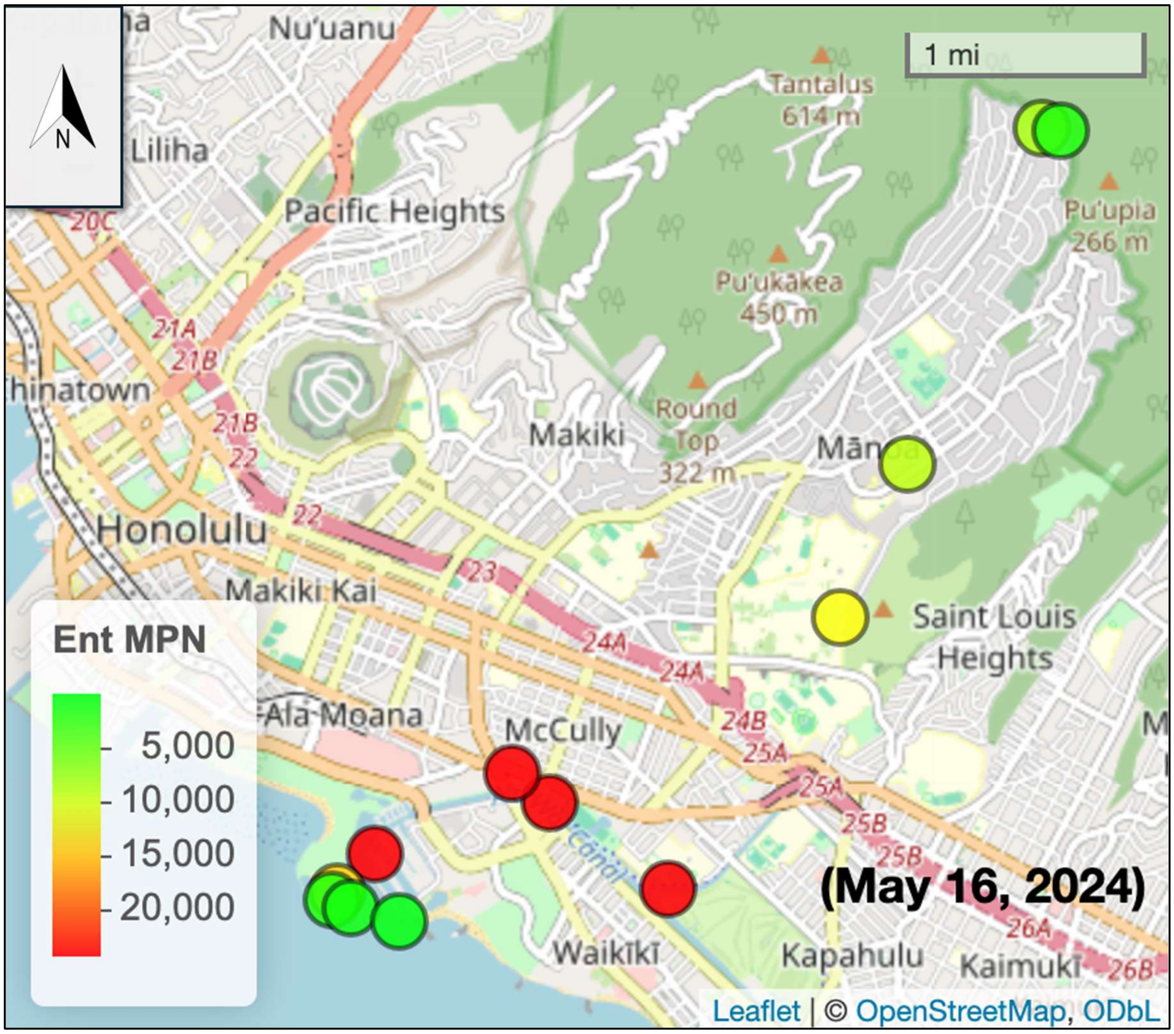

Figure 5: *Enterococcus* concentrations throughout Ala Wai Watershed on May 16, 2024 during peak precipitation.

Figure 5 presents the peak of the storm event and shows *Enterococcus* concentrations were much more variable throughout the watershed. The lowest measurement was recorded at the coast at site AW14 with a MPN reading of 299. The highest measurement was recorded in the McCully area at site AW7 with a MPN reading of 24,196. It's important to note that this value occurs multiple times during the sampling period and represents the highest possible reading from the Enterolert IDEXX test, thus the actual *Enterococcus* value is likely to be higher. Turbidity measurements were also elevated and showed increased variance. The highest

NTU recorded was at AW5 at 486 NTU and the lowest was at AW14 off Ala Wai Boat Harbor at 1.91 NTU.

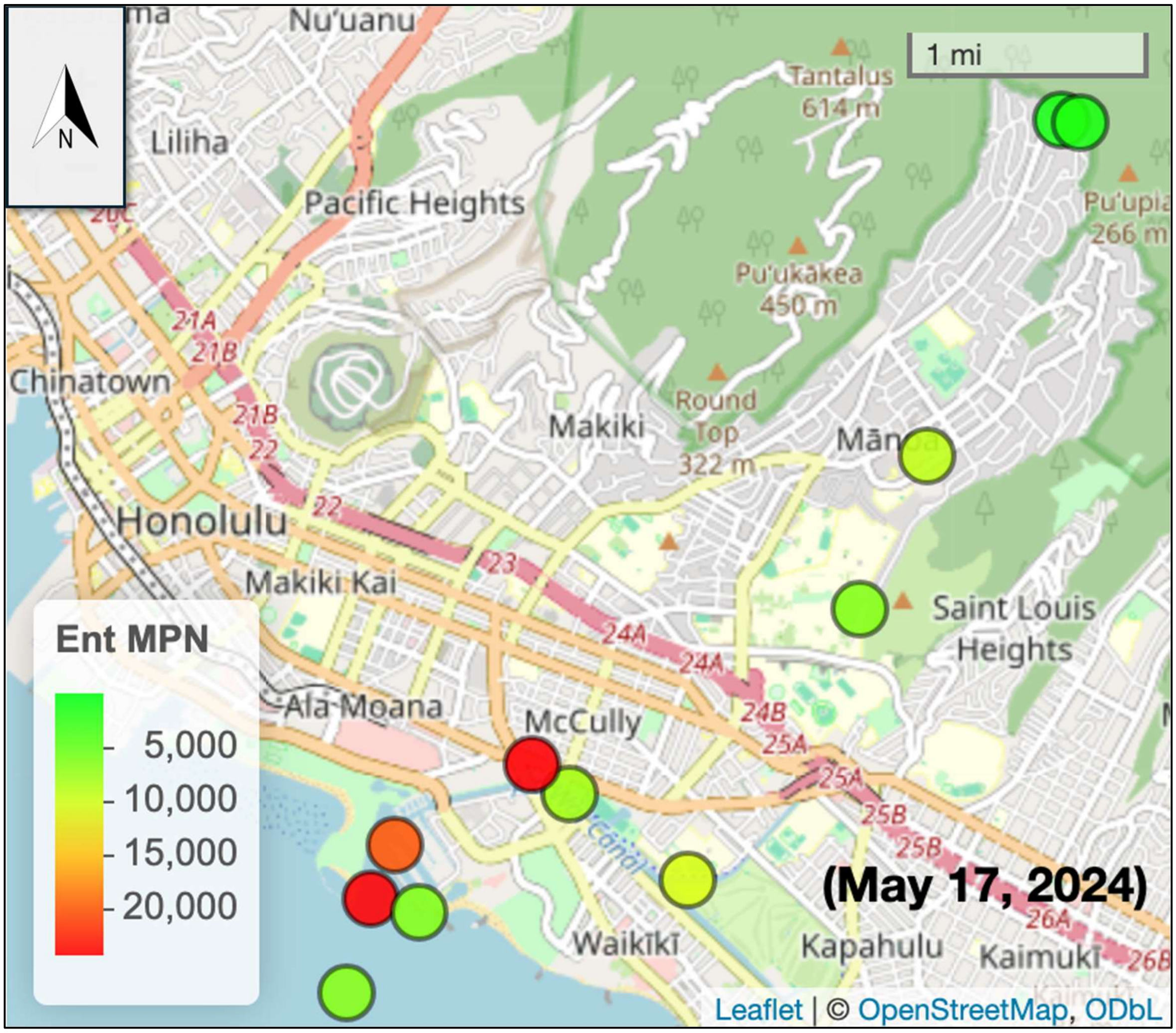

Figure 6: *Enterococcus* concentrations on May 17, 2024, one day after peak precipitation event.

Figure 6 shows that after one day, *Enterococcus* abundance decreased in the valley but remained elevated in McCully and coastal sites. High counts were still observed in the lower

McCully area and the mouth of the Ala Wai, the highest being 24,196 MPN. Turbidity levels were greatly lower overall, only reaching up to 68.00 NTU also in McCully.

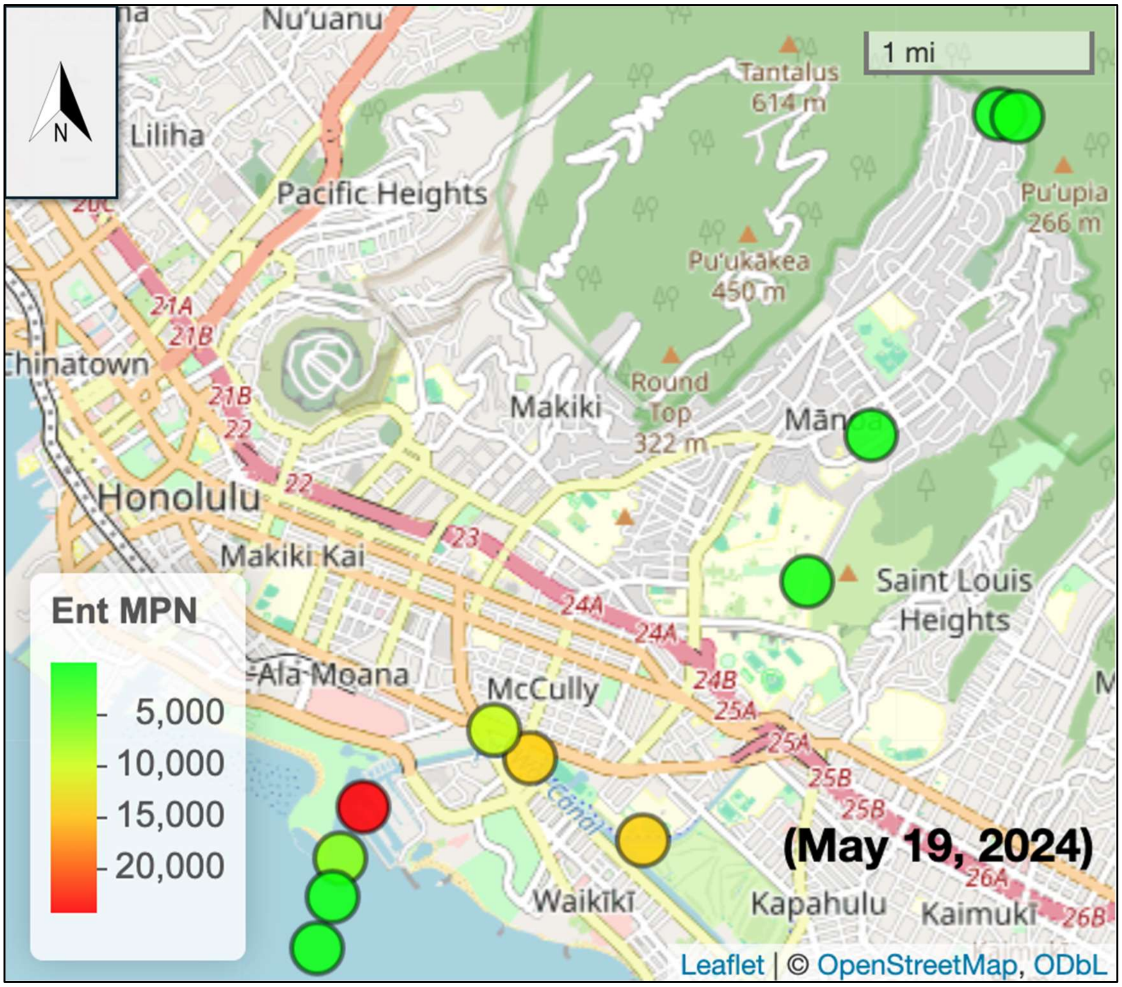

Figure 7: *Enterococcus* concentrations on May 19, 2024, three days after peak rain event.

Figure 7 shows that three days after peak rain, *Enterococcus* abundance reduced further across all sites except for site AW8 (24,196 MPN). The lowest was back in the watershed at AW2 (414 MPN). Turbidity decreased further as well, ranging from 0.00 NTU off the coast and 20.48 NTU in McCully.

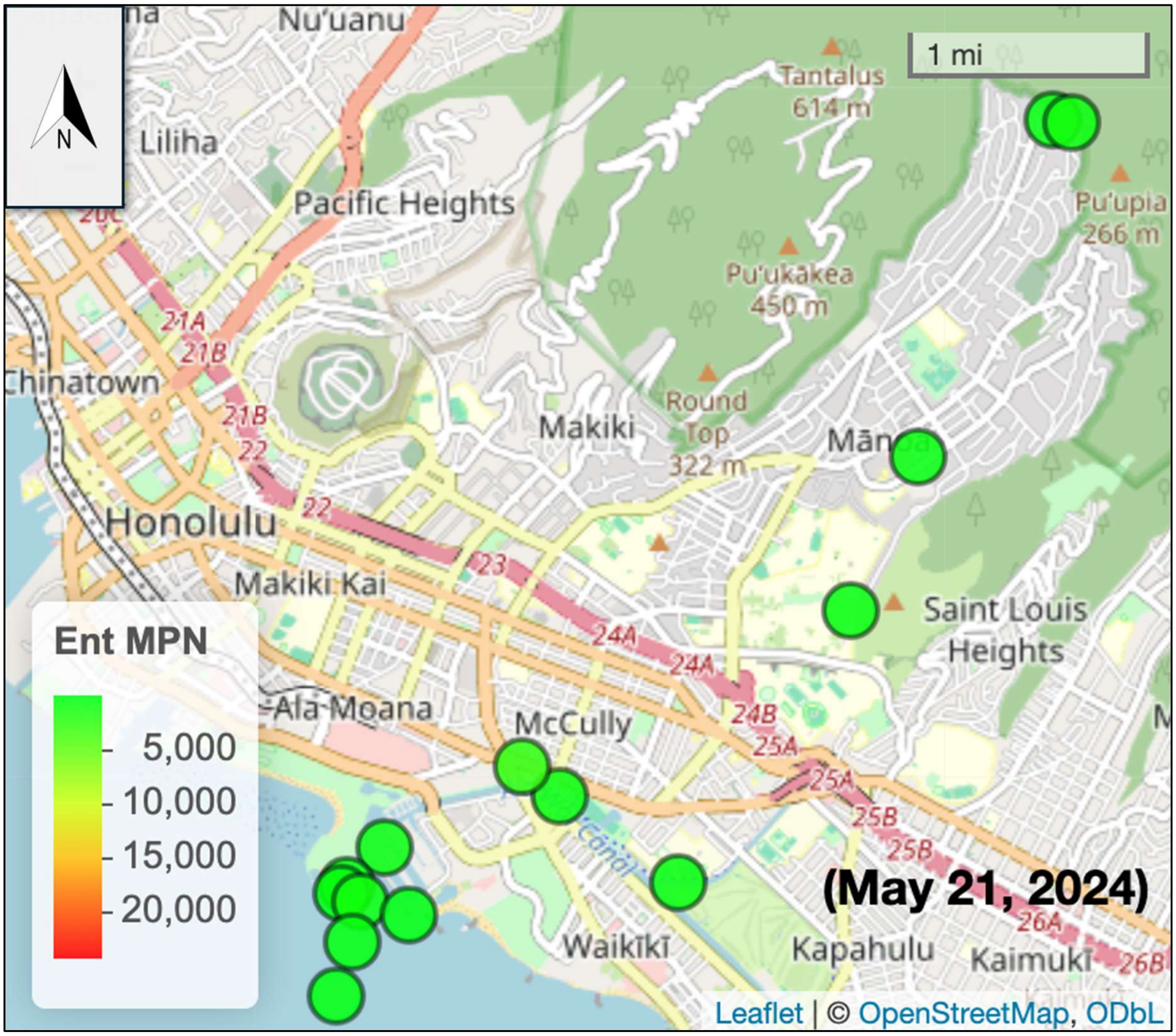

Figure 8. *Enterococcus* concentrations on May 21, 2024, five days after peak rain event.

Figure 8 shows that five days following peak rain, both *Enterococcus* and turbidity are close to baseline levels. The highest *Enterococcus* recorded was 2723 MPN in McCully and the lowest was off the coast at 10 MPN. Nearly all turbidity readings were 0 NTU, the highest recorded was 3.63 NTU.

3.3 Statistical Plots

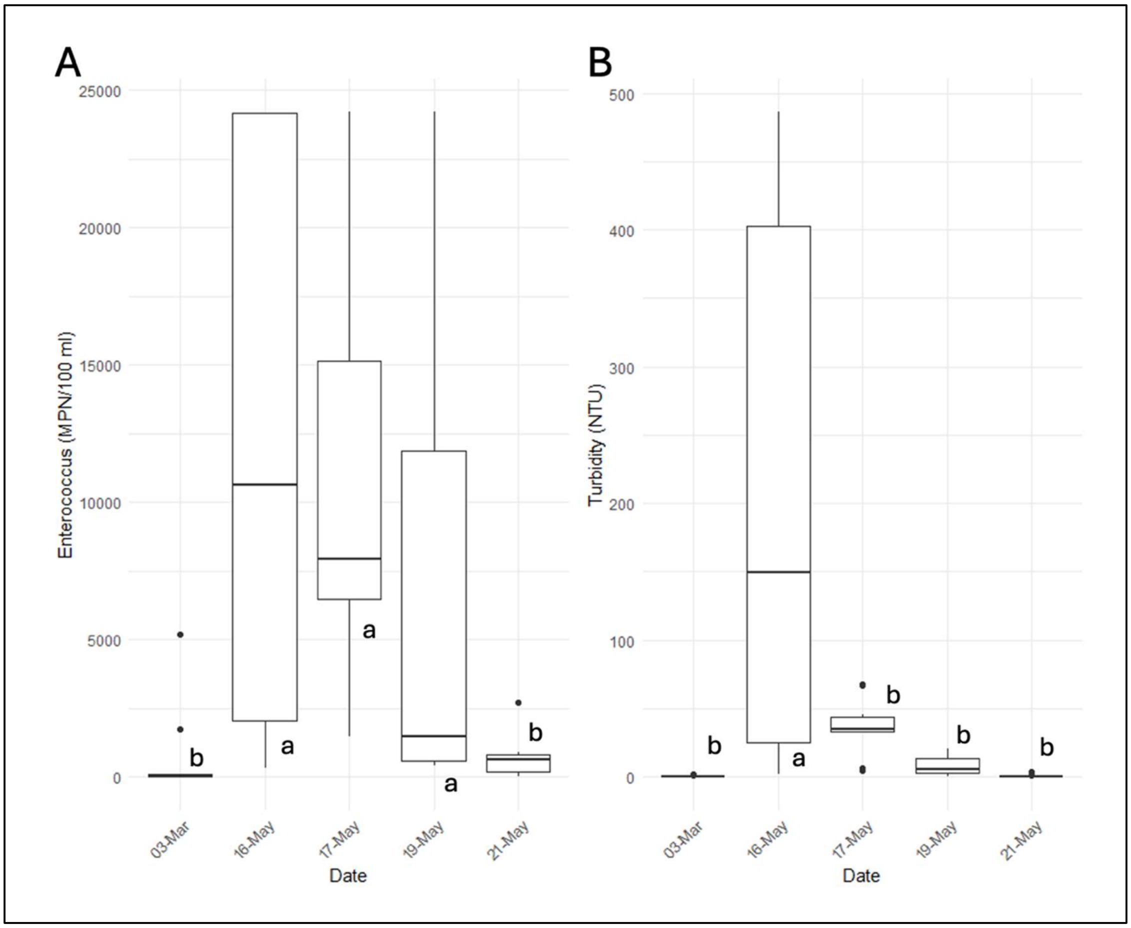

Figure 9: A) *Enterococcus* and B) turbidity distributions across all sample sites per day. March 3, 2024 is included as a baseline, dry day for comparison.

This figure displays the variability in *Enterococcus* concentrations (Figure 9A) and turbidity levels (Figure 9B) in the Ala Wai watershed before and after the May 2024 storm event. Elevated values in both parameters were observed immediately following the storm. The following days show different rates of decrease where turbidity drops at a faster rate than *Enterococcus*. By May 21, both parameters have greatly reduced, approaching levels observed as baseline conditions in March.

A one-way ANOVA was conducted to determine if there are significant differences in the log-transformed *Enterococcus* across all days of the study period (May 2024) including baseline measurements taken in March 2024. *Enterococcus* values were log-transformed to meet normal distribution standards. The F-statistic and p-value are important statistical values in an ANOVA analysis as they indicate whether the differences observed between group means are statistically significant or due to random variation. When the F-statistic is high, it suggests that the group factor (Date) has an effect on the outcome (*Enterococcus*). The p-value determines whether the F-statistic is large enough to be considered statistically significant. A small p-value (less than 0.05) suggests that it's unlikely that the observed F-statistic is due to chance. Table 2 shows results for the ANOVA analysis done between *Enterococcus* and Date. From these data, the F-statistic = 12.33 and the p-value = 5.16×10^{-7}. Residuals represent the differences between the observed data and the group means.

Post hoc analysis shows two statistically distinct groups in each plot. In Figure 9A, group a contains May 16-19 and group b contains the baseline day (March 3rd) and the last day of the study period, May 21st. In Figure 9B, the only date within group a is May 16th, the peak rain day. The other dates in group b (May 17-21) showed statistical similarity to the March 3rd turbidity measurements. For ANOVA and Tukey tests to be valid, residuals are assumed to be normally distributed. Figure 10 shows that this assumption is met in the Date group residuals.

Table 2: One-way ANOVA results for differences in log-transformed Enterococcus concentrations comparing all study dates in the Ala Wai watershed including baseline data.

ANOVA Results:

Enterococcus Levels by Zone Class

	Df	Sum Sq	Mean Sq	F-statistic	p-value
Date	4	23.92	5.981	**12.33**	**5.16E-07**
Residuals	49	23.76	0.485		

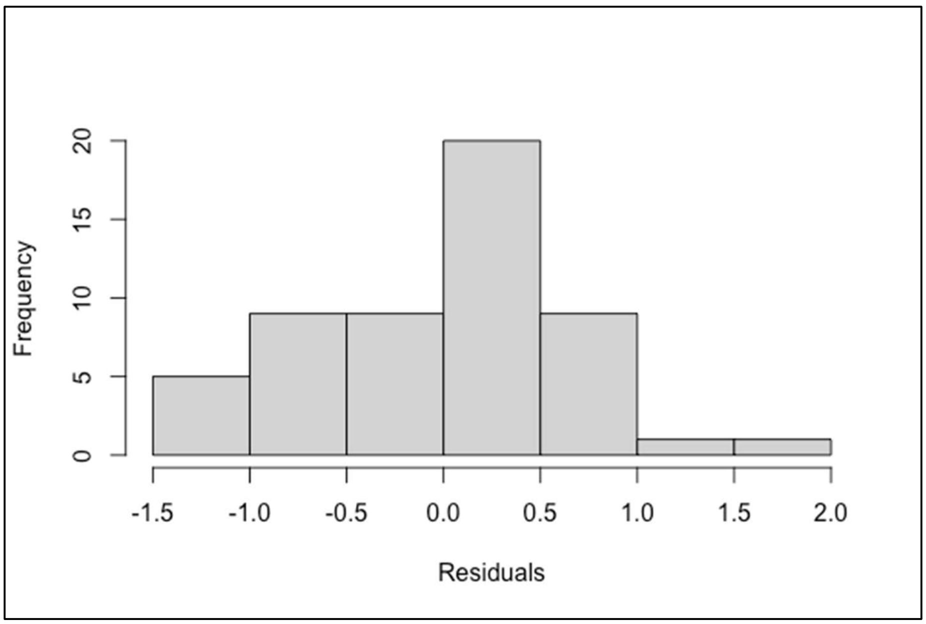

Figure 10: Distribution of residuals for Date groups from the one-way ANOVA model.

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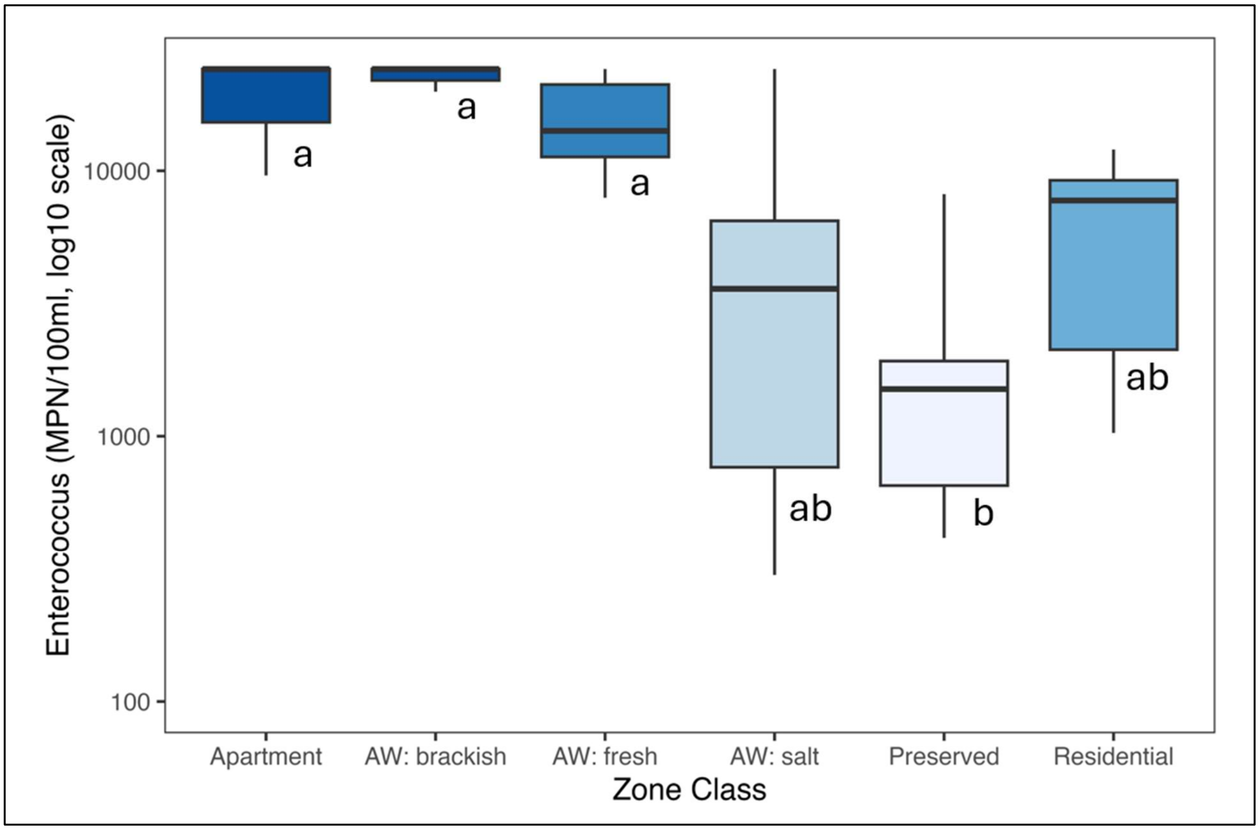

Figure 11: Boxplots comparing Enterococcus across different zone classes within the Ala Wai watershed during May 16-19, 2024. Darker shades indicate a higher median value.

Figure 11 shows water parameter boxplots for each zoning classification of our sample sites. Water quality data only from May 16th to May 19th were included to focus on the storm duration (May 16th-19th) and analyze how heavy rainfall affected each zone class individually. *Enterococcus* concentrations exhibit a high degree of variability across zones, with AW: brackish and Apartment zones having the highest median values, indicating elevated FIB in areas with high urban influence. The AW: salt zone, located where the Ala Wai meets the ocean and near the Ala Wai boat harbor, has lower median values. Similarly, the Preserved zone also shows lower levels of FIB and is located in the back of Mānoa Valley, before the residential district begins. Post hoc analysis revealed that the Preserved zone (b) was the only statistically distinct zone. In contrast, Apartment, AW: brackish, and AW: fresh zones were grouped together (a), while AW: salt and Residential zones fell into the overlapping group (ab) where statistical difference could not be determined.

Table 3: One-way ANOVA results for differences in log-transformed Enterococcus concentrations across different zone classes in the Ala Wai watershed.

ANOVA Results: Enterococcus Levels by Zone Class

	Df	Sum Sq	Mean Sq	F-statistic	p-value
zone_class	5	6.066	1.2131	**5.369**	**0.00139**
Residuals	48	6.327	0.2259		

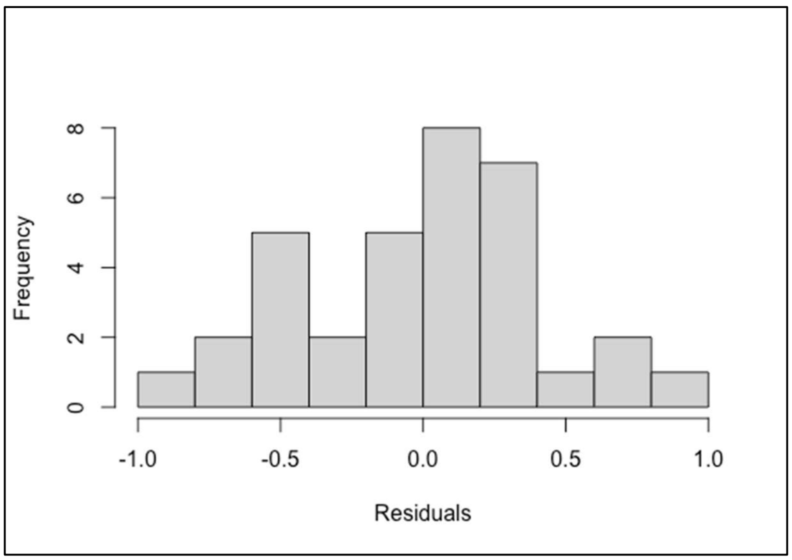

Figure 12: Distribution of residuals for zone class groups from the second one-way ANOVA model.

Another ANOVA was conducted to determine if there are significant differences in the log-transformed *Enterococcus* levels across the different zone classes in this study. Due to the large variability of *Enterococcus* between rainy and non-rainy days, only data from rainy days (May 16-19) were included. *Enterococcus* values were also log-transformed to meet normal distribution standards. Table 3 shows results for the ANOVA analysis done between *Enterococcus* and zone class. In this analysis, the F-statistic = 5.369 and p-value = 0.00139.

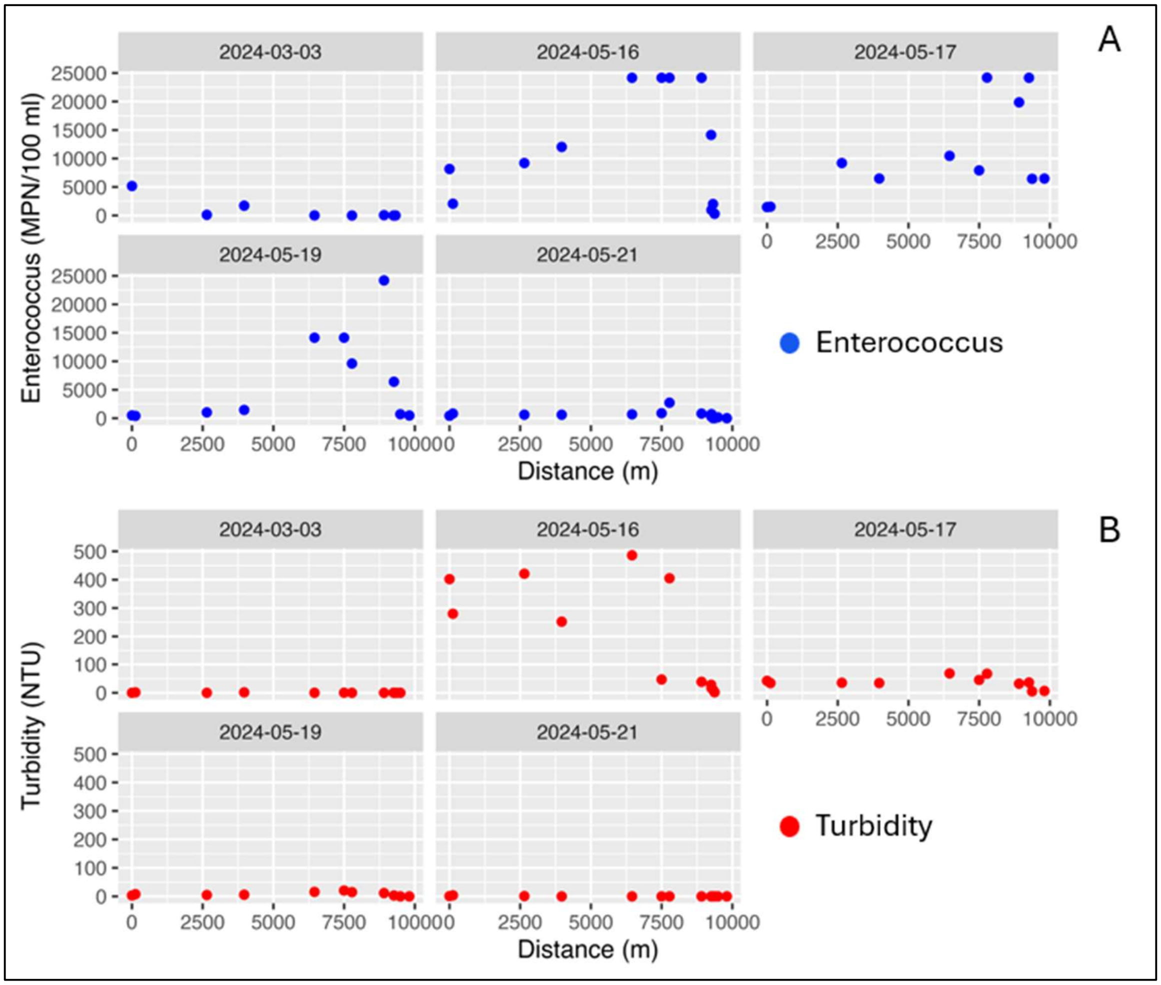

Figure 12 shows the normalcy standards were met for the zone class groups.

Figure 13: Scatter plots showing A) *Enterococcus* and B) turbidity along distances from the back of the Ala Wai watershed to the coast across each sampling date in 2024.

A stream distance analysis was done to investigate the relationship between distance from the top of the watershed and water quality parameters. Sample site AW1 was chosen as the starting point at zero meters. The distance to subsequent sample sites was determined through the measuring tool on Google Earth. In Figure 13A (*Enterococcus*) and Figure 13B (turbidity) different residence times in the watershed were observed. Figure 13B shows this contrast where turbidity spikes during peak rain (May 16) and returns to baseline levels quickly. In the *Enterococcus* plot (A), FIB levels remained consistently elevated in the Ala Wai area (6000m – 8000m), indicating these sites take longer to completely flush compared to the top of the watershed and offshore.

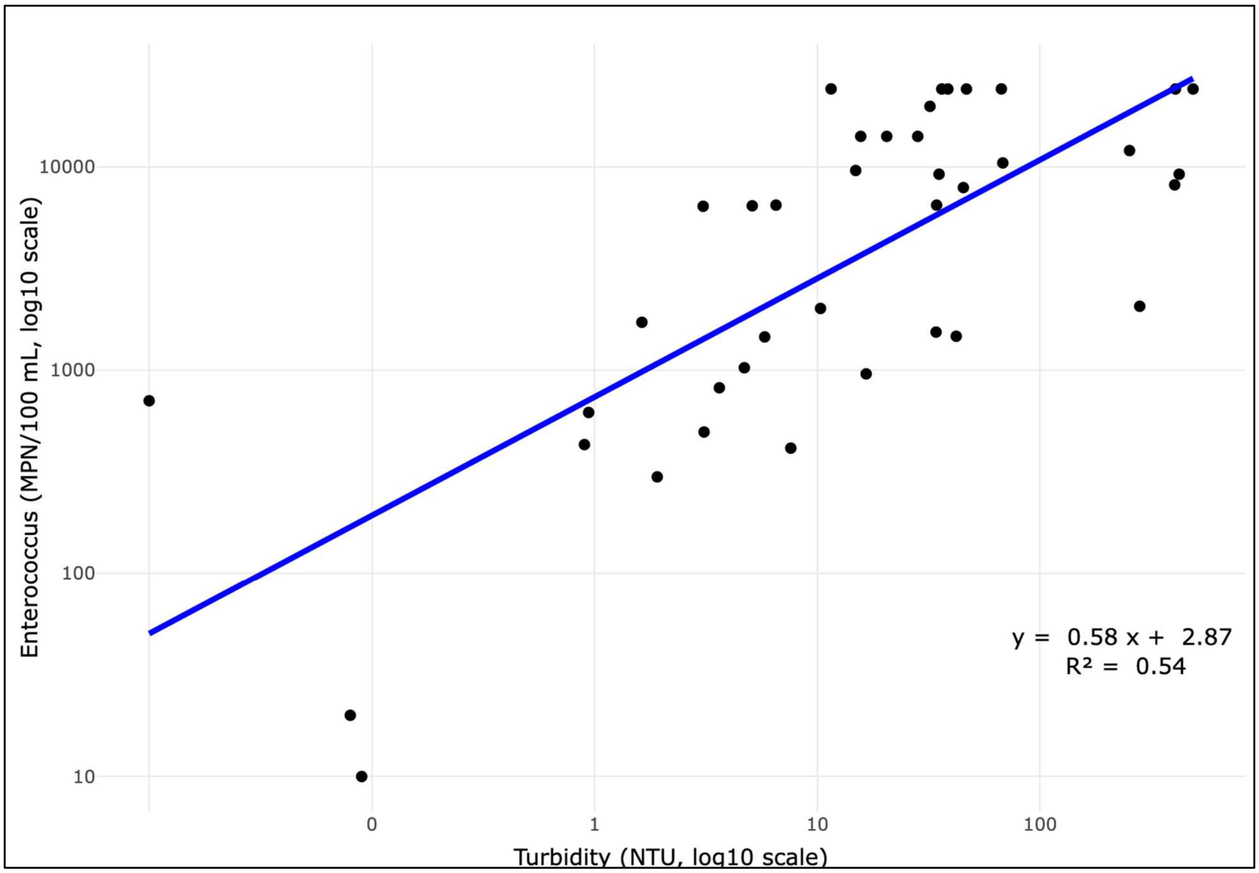

Figure 14: A linear regression between log-transformed *Enterococcus* concentrations (MPN/100 mL) and turbidity (NTU) in the Ala Wai watershed. Data used includes baseline and storm measurements.

The relationship between *Enterococcus* concentrations and turbidity was analyzed using linear regression. This revealed a positive correlation ($R^2 = 0.54$), indicating that as turbidity increases, *Enterococcus* concentrations tend to rise as well. The regression results are shown in Figure 14 which has both parameters on a log scale to normalize their distributions.

4. Discussion

4.1 Results Analysis

Heavy rainfall events are known to worsen water quality issues, primarily through stormwater runoff that transports pollutants from urban areas to nearby waters (Lapointe & Bedford, 2011; Kim et al, 2005). This study investigated surface water quality throughout the Ala Wai watershed during an extreme storm event. While the Clean Water Branch (CWB) is responsible for routine monitoring for Hawaiʻi's coastal water quality, resources and personnel often are stretched thin which results in large gaps in water quality data. This is especially true during storm events where brown water advisories are posted but the CWB cannot post physical signs on or collect samples from all impacted beaches (CWB, 2022). Thus, there is simply not enough data to disclose when water quality returns to safe levels.

In this study, the effects of land use on local water quality within an urbanized watershed in Honolulu, HI was investigated. The findings from this study support the hypothesis that urbanization negatively influences water quality. There is an increase in water pollution during a heavy rainfall event as stream water flows from less urbanized areas in Mānoa Valley toward the heavily developed McCully area. During the storm event, there is a substantial rise of FIB in McCully, peaking at 24,196 MPN (Figure 4) that persisted for several days post-storm particularly in the lower McCully area and the coast (Figures 5-6). Turbidity which reflects the amount of suspended particles in the water, also spiked from the storm with a maximum value of 486 NTU. This suggests that urban runoff not only carries bacteria like *Enterococcus* but also a high load of sediment, contributing to the degradation of water quality of Waikīkī and Ala Moana beaches (Weber, 2012).

To test for statistical significance, a one-way ANOVA was done on the log-transformed *Enterococcus* levels grouped by Date and zone class. ANOVA results (Table 2) indicated a significant effect of Date on *Enterococcus* levels ($F = 12.33$, $p = 5.16 \times 10^{-7}$). Zone class ANOVA results also indicate a significant effect of zone class on *Enterococcus* levels ($F = 5.369$, $p = 0.00139$). Both p-values from the data meets the standard $p < 0.05$ threshold so the observed differences across Dates and zone classes are determined as statistically significant. The post hoc Tukey analysis (Figure 9 & 11) provided insights as to which groups differed from each other.

In Figure 9A, *Enterococcus* levels show significant differences between sample dates, indicated by post hoc groupings (a, b). On May 16-19, *Enterococcus* levels were notably high with significant variability. These high levels likely occur from stormwater runoff during rainy days which flushes pollutants throughout the watershed. Shown in Figure 9B, turbidity exhibited a different pattern. Turbidity levels were only elevated on the initial rain day, indicated by the only statistically different group, May 16 (a). This suggests a fast flush of sediment throughout the watershed on the peak rain day. Although turbidity still remained high at some sample sites on the following day, May 17, it was not different enough to be deemed statistically different than the May 16 group (a).

In Figure 11, the Preserved zone (b) was the only zone that was statistically distinct with significantly lower FIB levels compared to other zones. This does align with the hypothesis that the Preserved zone is less influenced by urban activities and experiences less FIB. The zones Apartment, AW: brackish, and AW: fresh (a) showed the opposite effect and were grouped together due to consistent, poor water quality resulting from dense urban development. These results indicate a considerable relationship between land-use type and water quality parameters.

A key finding of this study is the delay in water quality post-storm, especially in urban areas. While Mānoa Valley showed a quicker return to baseline *Enteroccocus* and turbidity levels, the McCully area showed persistently high pollution levels up to four days after the storm event (Figure 13). This period of prolonged, poor water quality poses a risk to public health since Waikīkī is a popular water recreational area. The boxplots in Figure 9 illustrate that turbidity levels dropped rapidly after the peak on May 16, returning to baseline levels by May 19. This fast decrease of suspended particles might give the impression that the water is safe for recreational use, however, *Enterococcus* concentrations followed a different pattern and stayed elevated. While turbidity declined quickly, *Enterococcus* showed a non-linear, more variable decline (Figure 9). *Enterococcus* remained above baseline levels where turbidity returned to normal (Figure 13). Thus, water may no longer appear "brown" or "murky" but could still be contaminated with harmful pathogens. Also shown in Figure 12, a moderate R-squared value of 0.54 suggests that while there is a positive correlation between turbidity and *Enterococcus* levels, turbidity alone does not reliably predict the presence of FIB. This further indicates that visual clarity cannot be solely relied upon as an indicator of FIB contamination.

These ongoing challenges highlight the need for innovative approaches for water quality monitoring. Conventional methods rely heavily on laboratory analysis, which takes at least 24 hours to get results. By the time lab results are processed, water quality may have already returned to safe levels, leaving a window of time when water was contaminated but no advisories posted. Thus, real-time monitoring systems equipped with machine learning models offer a promising solution.

Real-time monitoring could greatly improve the timeliness and accuracy of public health advisories, saving time and manpower as well. Recent studies have demonstrated the utilization of fluorescence light at specific wavelengths to excite and detect fecal indicator bacteria in polluted samples (Offenbaume et al., 2020). Although these methods seem promising, improvement could still be made as it was also shown that other substances in a sample could trigger false positives, throwing off actual detection results. Thus, continuous monitoring systems integrated with predictive models could boost the effectiveness of these fluorescence detection systems and offer a cost-effective solution for managing water throughout the state of Hawaiʻi.

Machine learning models have been investigated in China and California and can successfully predict fecal indicator concentrations at different beaches, locations, and times (He & He, 2008; Dong et al, 2023). Selected indicators (Total coliforms, fecal coliforms, and *Enterococcus*) were correctly predicted at over 90% given a set of input variables. Neural networks and machine learning techniques could offer major improvements in understanding the complex relationships between land use, storm runoff, and pollutants. By training models on diverse sets of storm data, future studies could develop predictive tools for water quality assessment, especially with the significant leaps in modern artificial intelligence made in recent years (Harris, 2023). These models could assist in generating early warnings or advisories for the public based on real-time environmental data.

4.2 Limitations and Future Research

Although *Enterococcus* is widely used as a fecal indicator in water quality studies and recommended by the EPA, it is not without its limitations. In tropical climates like Hawaiʻi, studies have shown the *Enterococcus* can be naturally occuring (Fujioka et al., 1988; Fujioka et al., 2015). This natural occurrence could lead to the overestimation of pollution from anthropogenic sources, throwing off water quality assessment efforts. Thus, its use has been recently questioned and is currently being re-evaluated as a primary fecal indicator bacteria in the tropics. Alternative indicators have been proposed to be utilized in combination with or used as a new primary indicator. For instance, past research has suggested *C. perfringens* as a more reliable indicator for identifying sewage-specific markers in tropical areas (Fung et al., 2007; Miller-Pierce & Rhoads, 2007; Viau et al., 2011). However, the relationship between *C. perfringens* and gastrointestinal (GI) illness is not well understood and more research should be conducted to explore the risk of exposure from *C. perfringens*. (Miller-Pierce & Rhoads, 2019).

This study was limited to a single storm event in May 2024. While this provided a snapshot of how major rainfall events impact water quality, it does not account for the seasonal variability that Oʻahu experiences. The amount of rainfall, types and amounts of pollutants may vary based on factors like storm intensity and duration. To improve this, more research should include data from multiple storm events over a larger timeframe, allowing for comparisons between various storm intensities and seasonal changes (Hathaway, 2010). Additionally, our findings are focused on only one watershed out of the many on Oʻahu, Hawaiʻi. Water quality can vary greatly between watersheds depending on their land-use composition and infrastructure (Zhang et al., 2023). Expanding this study to account for comparisons across other watersheds would greatly generalize the results and provide a better understanding how urbanization impacts water quality in different areas of Oʻahu.

5. Conclusion

Improving water quality monitoring is essential for keeping our environment and communities safe. This should be especially the priority in heavily urbanized areas that are vulnerable to pollution from storm runoff. Understanding the impact of land use on water quality is crucial for the Ala Wai watershed where urban and natural landscapes intersect. In this study *Enterococcus* and turbidity levels were highest in major developed areas like McCully, Oʻahu. While baseline conditions resumed quickly in the less urban Mānoa Valley after an extreme rain event, pollution persisted in urban areas for several days. However, further research across multiple storm events and watersheds is recommended.

Current monitoring methods rely heavily on laboratory analysis, resulting in delayed results and reporting. In Hawaiʻi, storm runoff frequently impacts coastal water quality. Specifically, the Ala Wai watershed faces ongoing challenges of pollution during storm events, creating unsafe water conditions in a popular recreation area. Thus, the use of real-time monitoring systems that can predict water quality changes could significantly reduce public exposure to hazardous conditions. Such technologies is recommended to be combined with artificial intelligence learning models to further enhance Hawaiʻi's monitoring efforts. Ultimately, integrating these tools with land use management is essential for providing a safe environment for Hawaiʻi's residents and visitors.

Bibliography

Ackerman, D. & Weisberg, S. (2003). Relationship between rainfall and beach bacterial concentrations on Santa Monica bay beaches. *Journal of Water & Health*. 1(2):85-9. PMID: 15382737.

Amicizia, D., Micale, R., Pennati, B., Zangrillo, F., Iovine, M., Lecini, E., Marchini, F., Lai, P., & Panatto, D. (2019). Burden of Typhoid Fever and cholera: similarities and differences. Prevention strategies for European travelers to endemic/epidemic areas. *Journal of Preventive Medicine and Hygiene*. 60(4): E271-E285. https://doi.org/10.15167/2421-4248/jpmh2019.60.4.1333

Cann, K., Thomas, D., Salmon, R., Wyn-Jones, A., & Kay, D. (2013). Extreme weather-related weather events and waterborne disease. *Epidemiology & Infection.* 141(4): 671-686. https://doi.org/10.1017/s0950268812001653

Centers for Disease Control (CDC). (2024). *Nationally Notifiable Waterborne Diseases.* Nationally Notifiable Waterborne Diseases | Waterborne Disease and Outbreak Surveillance Reporting | CDC

Clean Water Branch, State of Hawaii. (2022). Hawaii Beach Monitoring Program. Hawaii-Beach-Monitoring-Program-Rev.1_FINAL_09.01.22.pdf

Clean Water Branch, State of Hawaii. (2024). Hawaii Beach Monitoring Program. Hawaii-Beach-Monitoring-Program-Rev.2_9-30-2024.pdf

Collier, S. A., Deng, L., Adam, E. A., Benedict, K.M., Beshearse, E.M., Blackstock, A. J…Beach, M.J. (2021). Estimate of the Burden and Direct Healthcare Cost of Infectious *Waterborne Disease in the United States. Emerging Infectious Diseases*. 27(1), 140-149. https://doi.org/10.3201/eid2701.190676

Cutler, D. & Miller, G. (2005). The role of public health improvements in health advances: the twentieth-century United States. *Demography*. 2005 Feb;42(1):1-22. https://doi.org/10.1353/dem.2005.0002

Dong, W., Zhang, Y., Zhang, L., Ma, W., & Luo, L. (2023). What will the water quality of the Yangtze River be in the future? *Science of The Total Environment*. 857(3). https://doi.org/10.1016/j.scitotenv.2022.159714

Fujioka, R., Solo-Gabriele H., Byappanahalli, M., & Kirs, M. (2015). U.S. Recreational Water Quality Criteria: A Vision for the Future. *Environmental Research and Public Health.* 12(7): 7752-7776. https://doi.org/10.3390/ijerph120707752

Fujioka, R., Tenno, K., & Kansako, S. (1988). Naturally occurring fecal coliforms and fecal streptococci in Hawaii's freshwater streams. *Environmental Toxicology*. 3(5): 613-630. https://doi.org/10.1002/tox.2540030514

Fujioka, R. & Yoneyama, B. (2002). Sunlight inactivation of human enteric viruses and fecal bacteria. *Water Science & Technology.* 46(11): 291-295. PMID: 12523768

Goto, D.K., & Yan, T. (2011). Effects of land uses on fecal indicator bacteria in the water and soil of a tropical watershed. *Microbes and Environments*. 26(3): 254-260. https://doi.org/10.1264/jsme2.me11115

Harris, L. (2023). Artificial Intelligence: Overview, Recent Advances, and Considerations for the 118th Congress. *Congressional Research Service*. R47644 (congress.gov).

He, Li-Ming & He, Zhen-Li. (2008). Water quality prediction of marine recreational beaches receiving watershed baseflow and stormwater runoff in southern California, USA. *Water Research*. 42(10): 2563-2573. https://doi.org/10.1016/j.watres.2008.01.002

Kim, L., Kang, J., Kayhanian, M., Gil, K., Stenstrom, M., & Zoh, K. (2006). Characteristics of litter waste in highway storm runoff. *Water Science & Technology.* 53(2): 225-234. http://dx.doi.org/10.2166/wst.2006.056

Kirs, M., Kisand, V., Wong, M., Caffaro-Filho, R., Moravcik, P., Harwood, V., Yoneyama, B., & Fujioka, R. (2017). Multiple lines of evidence to identify sewage as the cause of water quality impairment in an urbanized tropical watershed. *Water Research*. 116: 23-33. https://doi.org/10.1016/j.watres.2017.03.024

Lapointe, B. & Bedford, B. (2011). Stormwater nutrient inputs favor growth of non-native macroalgae (Rhodophyta) on Oʻahu, Hawaiian Islands. *Harmful Algae*. 10(3): 310-318. https://doi.org/10.1016/j.hal.2010.11.004

Miller-Pierce, M. & Rhoads, N. (2019). *Clostridium perfringens* testing improves the reliability of detecting non-point source sewage contamination in Hawaiian coastal waters compared to using Enterococci alone. *Marine Pollution Bulletin.* 144: 36-47. https://doi.org/10.1016/j.marpolbul.2019.04.053

Offenbaume, K., Bertone, E., & Stewart, R. (2020). Monitoring Approaches for Faecal Indicator Bacteria in Water: Visioning a Remote Real-Time Sensor for *E. coli* and Enterococci. *Water*. 12(9): 2591. https://doi.org/10.3390/w12092591

Paule, M., Memon, S., Lee, B., Umer, S., & Lee, C. (2014). Stormwater runoff quality in correlation to land use and land cover development in Yongin, South Korea. *Water Science & Technology*. 70(2): 218-225. https://doi.org/10.2166/wst.2014.207

Shuval, H. (2003). Estimating the global burden of thalassogenic diseases: human infectious diseases caused by wastewater pollution of the marine environment. *Journal of Water and Health*. 1(2): 53-64. PMID: 15382734.

Sinton, L., Finlay, R., & Lynch, P. (1999). Sunlight Inactivation of Fecal Bacteriophages and Bacteria in Sewage-Polluted Seawater. *Applied and Environmental Microbiology*. 65: 3605-3613. https://doi.org/10.1128/AEM.65.8.3605-3613.1999

Spengler, S., Heskett, M., & Spengler, C. (2018). Glyphosate in runoff from urban, mixed-use and agricultural watersheds in Hawaii, USA. *Water Pollution XIV*. WIT Press. 65-77. https://doi.org/10.2495/wp180081

The Hawaii State Department of Health (HDOH): Clean Water Branch. (2024). 2024 State of Hawaii Water Quality Monitoring and Assessment Report. https://health.hawaii.gov/cwb/files/2024/02/IR-2024-public-comment-draft.pdf

Tulchinsky, T. (2018). John Snow, Cholera, the Broad Street Pump; Waterborne Diseases Then and Now. *Case Studies in Public Health.* 77-99. https://doi.org/10.1016/B978-0-12-804571-8.00017-2

USEPA. (1985). Test methods for *Escherichia coli* and enterococci in water by the membrane filter procedure (Method #1103.1). EPA 600/485076. US Environmental Protection Agency, Environmental Monitoring and Support Laboratory, Cincinnati, OH.

Viau, E., Goodwin, K., Yamahara, K., Layton, B., Sassoubre, L., Burns, S., Tong, H., Wong, S., Lu, Y., & Boehm, A. (2011). Bacterial pathogens in Hawaiian coastal streams-Associations with fecal indicators, land cover, and water quality. *Water Research*. 45:3279-3290. https://doi.org/10.1016/j.watres.2011.03.033

Weber, M., Beer, D., Lott, C., Polerecky, L., Kohls, K., Abed, R., Ferdelman, T., & Fabricius, K. (2012). Mechanisms of damage to corals exposed to sedimentation. *Biological Sciences.* 109(24): E1558-E1567. https://doi.org/10.1073/pnas.1100715109.

Zhang, Y., Zhao, Y., Zhang, H., Cao, J., Chen, J., Su, C., & Chen, Y. (2023). The Impact of Land-Use Composition and Landscape Pattern on Water Quality at Different Spatial Scales in the Dan River Basin, Qin Ling Mountains. *Water*. 15(18): 3276. https://doi.org/10.3390/w15183276