Community Based Monitoring Programs – Data analysis of a water quality monitoring program in the California Central Valley

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Abstract

Community based monitoring (CBM) programs, specifically ones focused on water quality, engage stakeholders and community members in watershed protection and enhancement efforts (Addy et al., 2002). Cities and communities have developed CBM programs to engage their stakeholders in efforts of environmental monitoring. The City of Lodi developed a water quality CBM program called Storm Drain Detectives (SDD). The SDD program has been monitoring the Lodi-area waterbodies since 2001, providing open-source data, and engaging with students within the community on a variety of water quality related issues. In an attempt to understand what affect the City of Lodi's SDD program has had on overall water quality in the Lower Mokelumne Watershed, a data analysis of turbidity with two key sites was conducted. Findings of this data analysis found a significant difference between the sites in question, showing that the City of Lodi has an effect on overall turbidity values. Although the data does not convey the SDD program has increased overall water quality, other positive effects are that thousands of students have learned the importance of being a good stakeholder, importance of clean water, and the effects that citizens can have on their waterbody.

Keywords: Community Based Monitoring, water quality, turbidity, watershed, stakeholders, stewardship practices

Hypothesis

The City of Lodi’s Community Based Monitoring (CBM) program, Storm Drain Detective (SDD), monitors Lodi Lake and the Mokelumne River in Lodi, CA. As part of this program, the water quality data is made publicly available for anyone to review, analyze, and access. While many different water quality parameters are measured as part of this program, turbidity will be the main variable examined in this data analysis. Turbidity values will decrease following the implementation of the CBM program, SDD, due to an increase of education on personal effects on water quality, a core focus of the SDD program.

Introduction

The Clean Water Act, henceforth CWA, is a federal policy that aims at regulating the Waters of the United States (WOTUS). The first major U.S. law to address water pollution was the Federal Water Pollution Act of 1948 (P.L. 80-845), which provided "state and local governments with technical assistance funds to address water pollution problems, including research" (Copeland, 2016, pg. 2). Issues associated with the Federal Water Pollution Act of 1948 were the lack of authority to regulate WOTUS. Major amendments were established in 1972, with the Federal Water Pollution Control Act Amendments (P.L. 92-500) laying the groundwork for the present-day CWA. "Mounting frustration over the pace of pollution cleanup efforts… along with increased public interest in environmental protection, set the stage for the 1972 amendments" (Copeland, 2016, pg. 2). The 1972 amendments declared a clear objective related to water quality and water resource management: "restoration and maintenance of the chemical, physical, and biological integrity of the nation's waters"… where goals of zero discharge of pollutants by 1985 and water quality in the U.S. that is to be both “fishable and swimmable" by mid-1983 (Copeland, 2016, pg. 2).

The Environmental Protection Agency (EPA) was outlined in the CWA as a regulator of this specific policy. As part of the CWA, the EPA's major regulation is the National Pollutant Discharge Elimination System (NPDES). This NPDES program "controls water pollution by regulating point sources that discharge pollutants into the [WOTUS]" (SWRCB, National Pollutant…). As part of the NPDES permit, there is a MS4 (Municipal Separate Storm Sewer System) permit where permittees must implement a comprehensive Storm Water Management Plan (SMWP) (EPA, Municipal Separate Storm…). In California, the State Water Resources Control Board (SWRCB) oversees the implementation of NPDES permits. As part of the requirements of MS4/SWMP permits, the permitter must implement outreach to their constituents.

The City of Lodi's CBM program, SDD, was established to prevent a fine from the SWRCB. In 1998, the City of Lodi's wastewater facility was fined $20,000 for high chlorine levels in their discharge. The Public Works Director for the City of Lodi asked the SWRCB if "$10,000 of the fine [could] remain in Lodi to develop a water-quality education program" (Western City, 2017). As part of this agreement with the SWRCB, SDD was created in 2001. The SDD program now meets requirements for the Phase II MS4 General Permit of outreach.

CBM programs are a way to involve stakeholders and the community in environmental work. CBM "makes a valuable contribution to environmental management and construction of active societies for sustainable future" (Burgos et al., 2013). CBM has shown that "the hands-on activities of environmental monitoring using simple equipment and techniques are a tremendous motivation for participation" (Deutsch et al., 2001, pg. 195). The SDD program follows this outline for CBM, where hands-on activities engage a broad audience. Not only is CBM beneficial for environmental management, but CBM has also been shown to aid in decision-making (Wilson et al., 2018). Wilson et al. (2018) found that "data quality and credibility, trust and legitimacy and relevance to decision contexts are key to mobilizing CBM data in relevant decision-making processes" (Wilson et al., 2018). "Citizen-science" is frequently considered irrelevant science; however, researchers have shown that trust in CBM data is crucial to decision-making. For example, SDD data was utilized, in the decision-making process, when the City of Lodi began to plan out its Surface Water Treatment Plant located on Lodi Lake. Ultimately, the data was used to determine the water treatment plant's specifications (Western City, 2017). Therefore, trust in the data originating out of CBM is crucial.

The "degradation of water quality creates water scarcity and limits its availability for human use and ecosystem and thereby impacts the optimum management of water resources" (Rao and Mamatha, 2004, pg. 946). As Rao and Mamatha (2004) showed, water quality can significantly affect overall water levels and ecosystems. Parameters for water quality are essential in determining overall water quality. Gorde and Jadhav (2013) outlined lake water monitoring parameters that should be tested which include pH, conductivity, alkalinity, phosphorus, nitrogen, light transmission, Dissolved Oxygen (D.O.), turbidity/transparency (Secchi Disk), plankton, and chlorophyll-a. As lake ecosystems vary widely, the SDD program monitors the majority of these outlined parameters **(Table 3)**.

The City of Lodi is located in the Lower Mokelumne River Watershed (LMR), which stretches from the base of the Camanche Dam to the confluence of the Consumes and Mokelumne Rivers (Lower Mokelumne River Stewardship Steering Committee, 2012). The SDD program monitors five sites around the City of Lodi, which provides a comprehensive view of the City of Lodi's effects on overall water quality. The water quality parameters that the SDD program monitors include pH, D.O., turbidity, nitrates, bacteria, Electrical Conductivity (E.C.), and visual observations **(Figure 1 and 3)**. As turbidity can have significant effects on ecosystems, including aquatic life, this parameter will be the focus of the study. Defined, turbidity is the measure of relative clarity of a liquid and measured based on the amount of light scattered by material in the water (USGS, Turbidity and Water). In addition, the common measurement of turbidity is ntu, or nephelometric turbidity units.

Water quality trend analysis can be conducted in many different ways. Researchers convey that conducting a Kendall test is an effective way to analyze water quality trends (Hirsch et al., 1982). The seasonal Kendall test is a "nonparametric test for trend applicable data sets with seasonality, missing values, or values reported as 'less than'" (Hirsch et al., 1982). Researchers have also outlined additional ways to conduct water quality trends for watersheds: (1) quadratic trend models; (2) linear models; where "It was observed that for most of the sites and water uses quadratic trend models were a better fit than the linear models" (Khan, Husain, and Lumb, 2003). Khan et al. (2003) and Gorde and Jadhav (2013) outlined a Water Quality Index (WQI) as a test for overall water quality health. Other researchers convey that Systat 10.2, "which is a well-known program for performing a range of statistical analyses," was helpful when analyzing stormwater monitoring programs (Lee et al., 2007, pg. 4187).

Analysis and Methods

Both quantitative and qualitative analyses were conducted when looking at the specific case-study of CBM – SDD. Program data is open-source, therefore the general public can access the data collected. The SDD dataset used for analysis was in the date range of 2001-01-04 to 2021-09-28 with 755 sampling points were analyzed as part of this dataset **(Table 1)**.

For quantitative analysis, the main focus will be on differences between Site 1 and Site 9 turbidity variables. First, understanding the locations of both sites will be helpful in understanding the data **(Figure 2)**. Site 1 is located up-stream before the first City of Lodi storm-drain outfall (50-feet above) **(Figure 19)**. This site is located on personal property where the program is in collaboration with the property owner to sample at that particular location. Site 9 is located after the City of Lodi storm-drain outfalls underneath a Woodbridge (WID) Dam **(Figure 20)**. Site 9 encompasses a combined effect of the 16 storm-drain outlets where untreated stormwater enters the water system. These two sites were chosen for analysis as they could provide an understanding of the effects on water quality by the City of Lodi.

For qualitative analysis, the provided information will aid in creating better understand of the effects that SDD has on the community. A key part of the program is education outreach as SDD brings together students from the Lodi area to test the water quality. The education goals of the program are education of monitoring skills, educating responsible living that minimize effects on water quality, and connecting data collected to the affects the City of Lodi may have. As part of the education aspect of the program, there is a multiplier effect where students will convey to their parents and friends what they are learning from their experience during their monitoring. In turn, educating others indirectly involved in the program. The goal of the program is to curate responsible stewards in the LMR to reduce human effects on the water system.

A. Quantitative Analysis

Various programs were used to analyze the data, ultimately the use of different programs was determined based on ease of use **(Table 2)**. Detailed steps for data analysis were taken to ensure proper and effective diagrams and visualizations **(Workflow 1)**. In order to compare Site 1 and Site 9 a statistical difference was required between the two sites, therefore a t-test was utilized. Using Excel functionality, a t-test was conducted where a p-value (two-tail) was determined to be 0.0440489 **(Figure 3)**. Therefore, with the p-value less than .05 (our stated p value) the null hypothesis was rejected (no difference in the means). Therefore, Site 1 and Site 9 are statistically different, which allows for statistical analysis. Another test for statistical difference is a Kolmogorov-Smirnov (KS) test. Considerations for this test were done based on water quality trend analysis research conducted in the literature review process. This test was conducted within RStudio, where a p-value was 0.00323 **(Figure 4)**. This test further conveys the statistical difference between Site 1 and Site 9.

Outliers were statistically determined using Excel and statistical methods. Although there are outliers included in the figures**,** descriptive statistics, and t-tests, removing these outliers would remove important datapoints **(Figures 5, 6, 7, 8, and 9)**. For example, a datapoint of 53.2 ntu (with an associated grade of D) would be removed, however this particular datapoint conveys a high turbidity event due to a high-flow rain event **(Figure 21)**. Therefore, visualizations, analysis, and conclusions are based on the dataset without removed outliers. In regard to data validity (QA/QC), this particular datapoint would have been removed through a data scrubbing process, however there was no instances of this occurrence in the particular data range.

Descriptive statistics was conducted using XLSTAT, a statistical software for Excel, for both Site 1 and Site 9 **(Figure 10)**. An interesting statistic from this is the averages of turbidity for the sites: Site 1 average = 3.851; Site 9 average = 4.914. The average difference between Site 9 and Site 1 is 1.063 ntu, where Site 9 has on average 1.063 higher turbidity reading across the dataset. Histograms were created to determine the overall distribution of turbidity values for Site 1 and

Site 9 **(Figures 11 and 12)**. Both histograms were skewed right, where high outliers (e.g., 53.2 ntu) are skewing the average and other descriptive statistics higher.

Visualizations are a good tool to understand trends and patterns within a large dataset (Stark, 2020). Therefore, visualizations were used to determine trends and patterns between areas of interest. The main areas of interest related to the turbidity data and time-period was: (1) overall yearly turbidity; (2) turbidity trends confounded by the CA drought – pre, intra, and post; and (3) turbidity trends confounded by wet and dry seasonality. Two visualizations were created for yearly turbidity values **(Figures 13 and 14)**, where one was constructed with the average turbidity values of each year, and another was created with the average medians of the turbidity values. Trends in both average and median figures reflect a period of overall lower turbidity readings from years 2011 to 2015. Spikes in both averages and medians are seen primarily with Site 9, with a total of 10 years that have at least one ntu difference between the sites. Although Site 9 seems to have a higher average overall, there are some instances of Site 1 having a higher yearly average turbidity than Site 9: 2010 and 2019. Further analysis of the data would have to be done to explain the difference in trends for 2010 and 2019.

Furthermore, two visualizations were created for CA drought, where the dataset collected encompassing data from pre, intra, and post data frames throughout the CA drought **(Figures 15 and 16)**. Based on the turbidity averages with Site 1 and Site 9 separated, the pre-drought averages are higher than intra- and post-drought. This trend is interesting as it has been shown that droughts generally decrease water quality – higher salinity, pollution, and decreased DO (deoxygenation) (Mosley, 2014). Further data analysis of other water quality parameters (e.g., DO, EC, nitrates) would be necessary to conclude overall effects and trends of water quality.

Lastly, one figure was created of turbidity averages broken up by wet and dry seasons for the watershed [wet season = October 15 to March 15; dry season = March 16 to October 14] **(Figure 17)**. Overall averages of wet season are higher than dry seasons seen in both Site 1 and Site 9. This difference is expected as higher rainfall is seen during the wet season, allowing for pollutants to runoff into the water system. Site 9 saw a higher difference between the seasons – over a 2.5 ntu difference (2.65 ntu). This difference can possibly be explained by the cumulative pollution runoff from the City of Lodi’s storm drain outlets. To conclusively convey cause and effect, further research would have to be conducted to determine the effects of difference between the sites.

B. Qualitative Analysis

As part of the SDD program, students are educated on monitoring techniques and good stewardship practices. As part of the SDD program, students compile the previous year’s data and present at a town-hall event to the general public. This town-hall event allows students an opportunity to teach the general public about the parameters tested, procedure of testing, and about good stewardship practices. In addition to this yearly event, the SDD program and the students also participate in local events to teach the general public. For example, before COVID-19 began, SDD leaders and students ran a yearly booth at a science festival in the local area (2016 to 2019). The topics taught at this yearly booth vary from year to year based on students’ interests, but primarily focus on water quality and good stewardship practices. In addition to these events, the program coordinates with the Lodi News Sentinel in creating a yearly special-edition newspaper where students can share what they have learned in the SDD program (2016 to current). This newspaper allows for students to further communicate their knowledge with the general public. The newspaper distributes over 20,000 copies per year to schools, newspaper subscribers, the general public, and is additionally published online.

There are on average 150-180 students who participate in the SDD program each year. Over the program's 21-year run there have been over 3,000 students to monitor Lodi Lake and the surrounding water system. By the very nature of the program, there is a multiplier effect of education, where students will educate their friends, family, and general public of the knowledge they learn in the program.

C. Future Study

Further quantitative research should be done to explore the effects that CBM can have on overall water quality. As the SDD program collects variables other than turbidity, further trend analysis could be done on these other variables (e.g., DO, EC, and bacteria). Additional quantitative studies can examine the effects of clean-up events at Lodi Lake on water quality. Every year since 2004, the SDD and City of Lodi has sponsored a clean-up including the general public at Lodi Lake. Therefore, trends in water quality after clean-up events would be an important factor to consider. Additional confounders that could be analyzed would include effects of runoff using USGS HUC as a tool for analysis. Other data collected as part of the SDD program is Secchi Disc clarity testing which is done once-a-year **(Figure 18)** (Grant, 2021). This would provide an opportunity to analyze trends in another variable measuring variable turbidity. Other programs should be considered to ensure applicability of the data analysis related to other water quality trends. Systat 10.2 has specifically been shown by researchers to be a useful tool and could be utilized to complete additional analysis of the dataset.

Gaps in current qualitative research could be addressed by analyzing education effects. For example, surveys of community members could be done to determine knowledge of the program, involvement in community, and good stewardship practices. In addition, surveys could be administered with the current students and teachers pre and post program participation to see if they adapted their behavior to increase good practices in stewardship. Additional qualitative research would be to determine point and non-point pollution sources that could possibly affect the sites. This research could also become quantitative as there could be numerical tests to determine specific pollutants. Further analysis of additional CBM programs should be done to determine trends of water quality over a wider set of variables, environments, and locations.

Conclusions

Findings from the analysis of water quality data from SDD suggests that there has not been significant difference between the averages of turbidity from 2001 to present-day (2021). The hypothesis that turbidity values will decrease following the implementation of SDD was disproved. Although there was not a statistical change for turbidity readings since the implementation of SDD, significant changes and impacts can be seen within the community. Findings from additional analysis within the dataset suggest there are statistical differences between both sites (1 and 9) within wet and dry seasons. Averages of wet season turbidity compared to dry season turbidity values were found to be on average 1.629 ntu higher. This difference in turbidity values can be explained with higher levels of pollutants contained in the run-off during wet seasons. The CBM programs cultivate scientific discovery and curiosity in the general public adding to its importance. Interested parties can conduct analysis of data collected from the SDD program.

In summary, the importance of CBM programs is immense: enables scientific discovery of general public, brings stakeholders to monitor their systems, and enables community members to be a part of the science within their areas. Beyond SDD, CBM programs should be adopted as part of their investment in their community outreach. Hands-on involvement with community members can foster a trust in science, an understanding of their environmental systems, and foster good stewardship practices.

APPENDIX A:

Tables, Workflow, & Abbreviations

Table 1. Dataset description used for analysis

Dataset	Date_Start	Date_End	Sampling_Points
SDD_Data_Turbidity	2001-01-04	2021-09-28	755

Table 2. Programs used for analysis

Analytical Method	Program	Description
Data organization	Excel	Manual and automated process within Excel
Descriptive statistics	Excel – XLSTAT	XLSTAT within Excel
T-Test	Excel – Analysis ToolPak	Analysis ToolPak within Excel
KS Test	RStudio	RStudio Programming
Data Visualization	Excel – Chart Function	Chart Function within Excel
Outlier Calculation	Excel	Equation and filter tools used within Excel
Outlier Removal	Excel	Equation and filter tools used within Excel

Table 3. Measured Water Quality Parameters in SDD Program

Parameter	Units	QA/QC
DO meter	mg/L (milligrams per liter)	Manual calibration every monitoring day
DO CHEMet	mg/L (milligrams per liter)	Ensure that CHEMets test ampoules is not passed use by date
pH meter	N/A	Manual calibration every monitoring day
pH test strip (paper)	N/A	Ensure that test strip is not passed use by date
EC meter	µS (microsiemens)	Manual calibration every monitoring day
Nitrate test strip (paper)	ppm (parts per million)	Ensure that test strip is not passed use by date
Temperature	°C (degrees Celsius)	Calibration with correction done by lab
Turbidity meter	ntu (Nephelometric Turbidity unit)	Manual calibration every monitoring day
Bacteria	col/100mL (coliform per 100 milliliters)	N/A

Workflow 1. Procedure for Data Analysis

1. Retrieve data from City of Lodi datafiles
2. Populate particular data from dataset into an Excel file
    a. Date of collection
    b. Site Number
    c. Turbidity Value
    d. Associated Grade
    e. Notes associated with data collection or site
3. Organize and separate data using both manual and excel filter and sort functionality
4. Conduct descriptive statistical analysis on dataset, particularly looking at the sites separately
5. Analyze if there is a statistical difference between Site 1 and Site 9 using a t-test
6. Use Excel tools to average areas of interest
7. Use data visualization tools to see visual observations between dataset
8. Separate particular areas of interest within dataset to allow for data visualization
    a. Yearly averages of turbidity
    b. Drought event in CA (pre-, intra-, and post-drought)
    c. Wet season vs Dry season (based on watershed seasonality for dataset)
9. Analyze for outliers and remove for visualization of distribution

Abbreviations

CBM	Community Based Monitoring
NPDES	National Pollutant Discharge Elimination System
SDD	Storm Drain Detectives
SWMP	Storm Water Management Plan
SWRCB	State Water Resources Control Board
WID	Woodbridge Irrigation District
WOTUS	Waters of the United States

APPENDIX B:

Figures

Figure 1. Field Data Sheet (credit: City of Lodi)

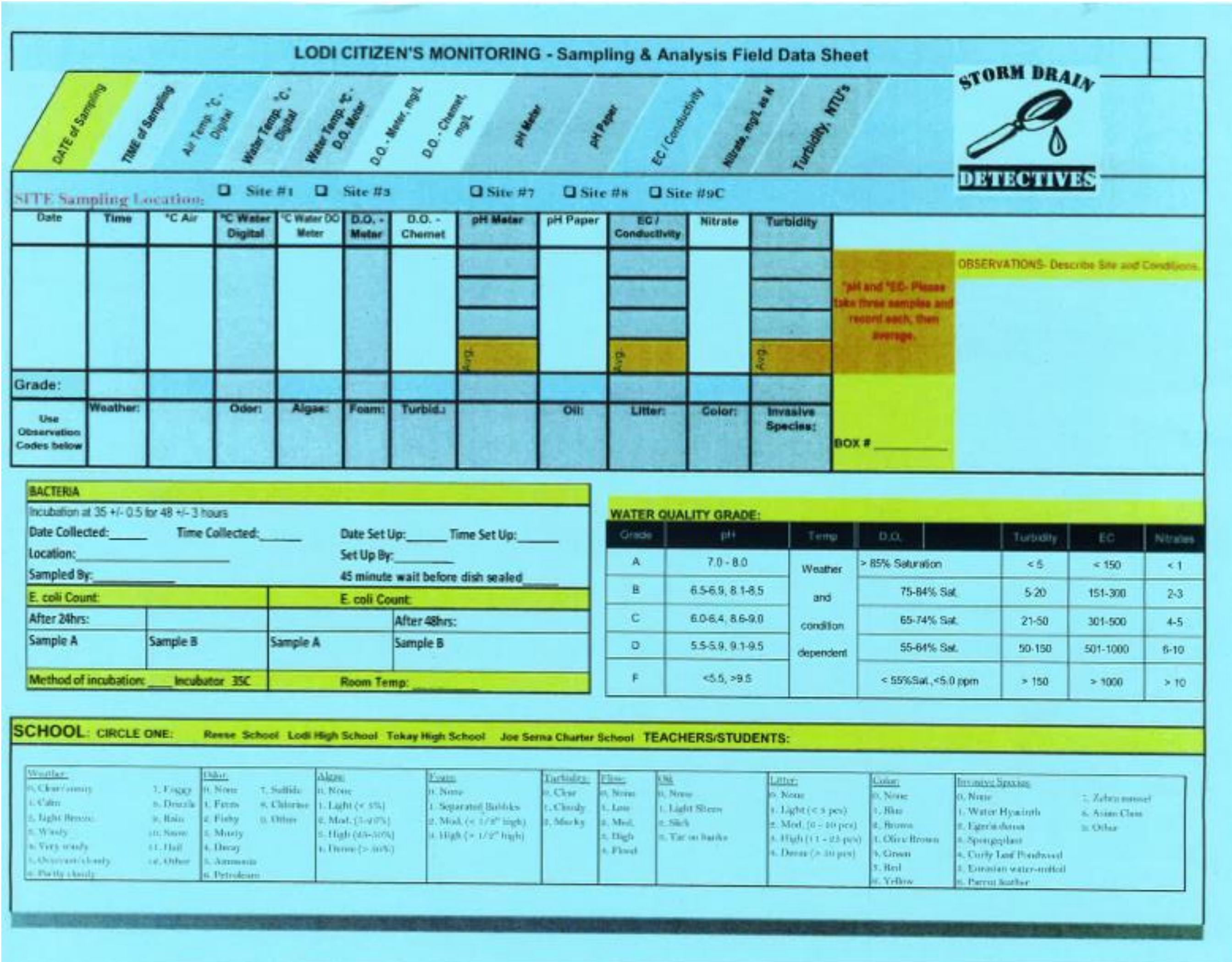

Figure 2. Site Map (credit: City of Lodi)

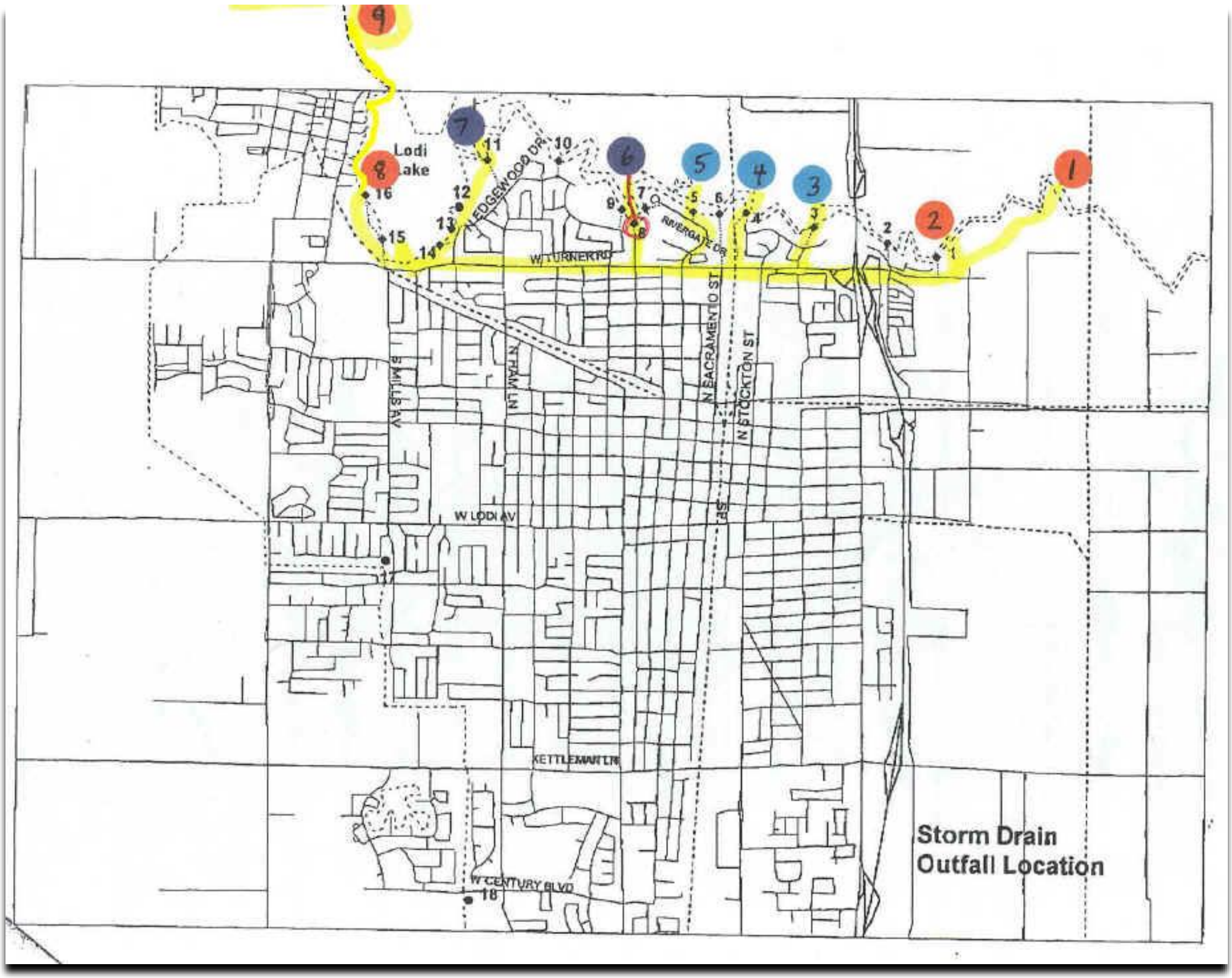

Figure 3. T-test for data with Outliers

1	**t-Test: Two-Sample Assuming Unequal Variances (with Outliers)**		
2		Site 9	Site 1
3		*Variable 1*	*Variable 2*
4	Mean	4.9142154	3.8511549
5	Variance	58.461798	34.67364
6	Observations	325	355
7	Hypothesized Mean Difference	0	
8	df	607	
9	t Stat	2.0178259	
10	P(T<=t) one-tail	0.0220244	
11	t Critical one-tail	1.6473678	
12	P(T<=t) two-tail	0.0440489	
13	t Critical two-tail	1.9638798	

Figure 4. KS Test (RStudio)

```
	Two-sample Kolmogorov-Smirnov test

data:  data$`Site 1` and data$`Site 9`
D = 0.13764, p-value = 0.00323
alternative hypothesis: two-sided

Warning message:
In ks.test(data$`Site 1`, data$`Site 9`, alternative = c("two.sided",  :
  p-value will be approximate in the presence of ties
> # Reject H0 if D > critical value (p-value).
  Therefore, based on these values the null
  hypothesis (diistributions are the same) is
  rejected... meaning that the distributions are
  not the same.
```

Figure 5. Descriptive Statistics without Outliers

Descriptive statistics (Quantitative data) without Outliers:		
Statistic	Site 1	Site 9
Nbr. of observations	328	328.000
Minimum	0.000	0.600
Maximum	7.500	9.500
1st Quartile	1.700	1.900
Median	2.390	2.900
3rd Quartile	3.700	4.300
Mean	2.719	3.347
Variance (n-1)	2.027	3.776
Standard deviation (n-1)	1.424	1.943

Figure 6. T-test for data without Outliers

1	**t-Test: Two-Sample Assuming Unequal Variances (without Outliers)**		
2			
3		*Site 9*	*Site 1*
4	Mean	3.347006803	2.718593272
5	Variance	3.776254491	2.027097402
6	Observations	294	327
7	Hypothesized Mean Difference	0	
8	df	533	
9	t Stat	4.553783688	
10	P(T<=t) one-tail	3.26757E-06	
11	t Critical one-tail	1.647717487	
12	P(T<=t) two-tail	6.53514E-06	
13	t Critical two-tail	1.964424727	

Figure 7. Calculation of Outliers

IQR = Q3 - Q1	
Q3 + (IQR x 1.5) = high outlier	
Q1 - (IQR x 1.5) = low outlier	
Site 1	**Value**
IQR	2.365
IQR x 1.5	3.548
High outlier	7.648
Low Outlier	-1.813
Site 9	**Value**
IQR	3.000
IQR x 1.5	4.5
High outlier	9.500
Low Outlier	-2.500

Statistic	Site 1	Site 9
Nbr. of observations	755	755.000
Minimum	0.000	0.600
Maximum	70.000	104.900
1st Quartile	1.735	2.000
Median	2.500	3.100
3rd Quartile	4.100	5.000
Mean	3.851	4.914
Variance (n-1)	34.674	58.462
Standard deviation (n-1)	5.888	7.646

Figure 8. Site 1 Histogram without Outliers

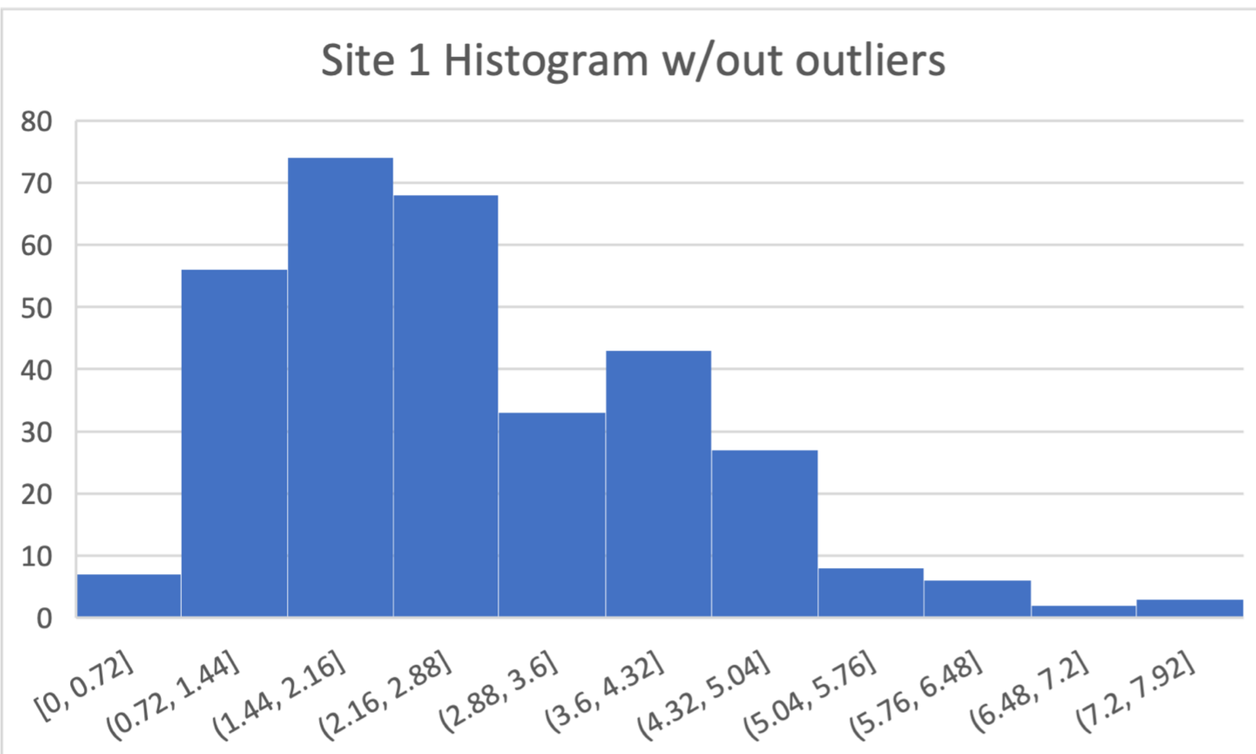

Figure 9. Site 9 Histogram without Outliers

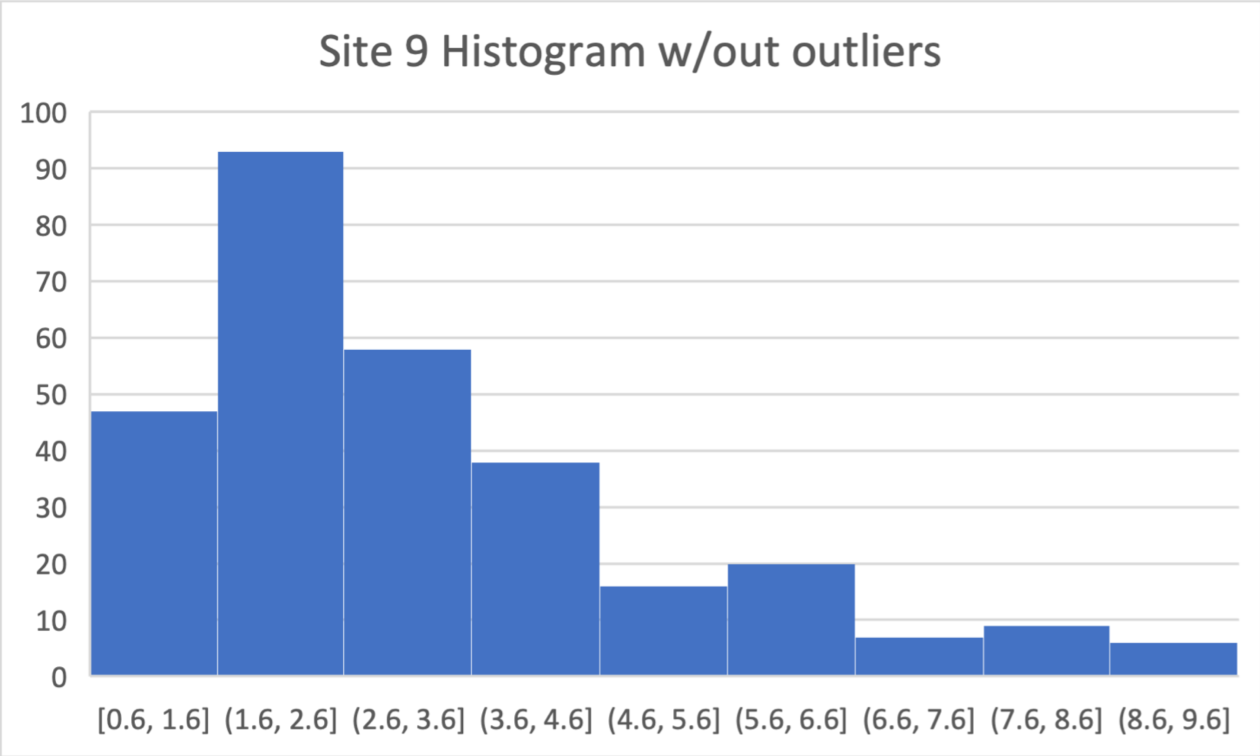

Figure 10. Descriptive Statistics with Outliers

Descriptive statistics (Quantitative data) with Outliers:

Statistic	Site 1	Site 9
Nbr. of observations	755	755.000
Minimum	0.000	0.600
Maximum	70.000	104.900
1st Quartile	1.735	2.000
Median	2.500	3.100
3rd Quartile	4.100	5.000
Mean	3.851	4.914
Variance (n-1)	34.674	58.462
Standard deviation (n-1)	5.888	7.646

Figure 11. Site 1 Histogram with Outliers

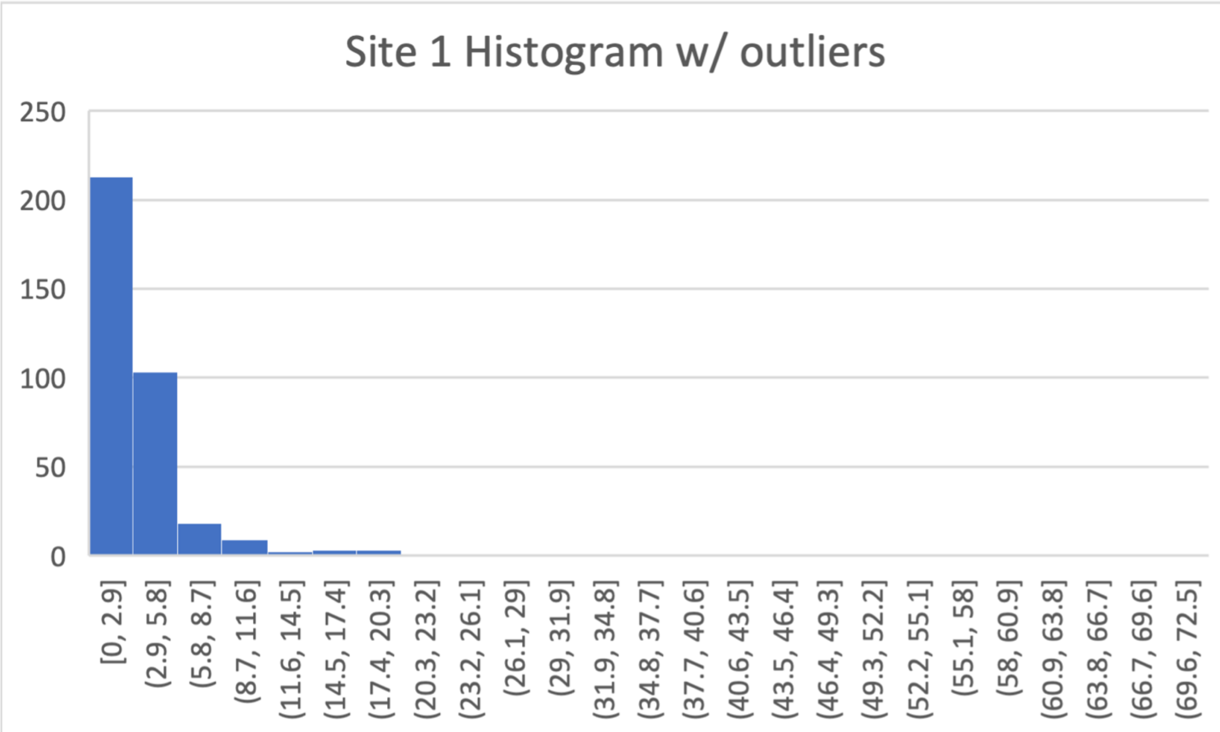

Figure 12. Site 9 Histogram with Outliers

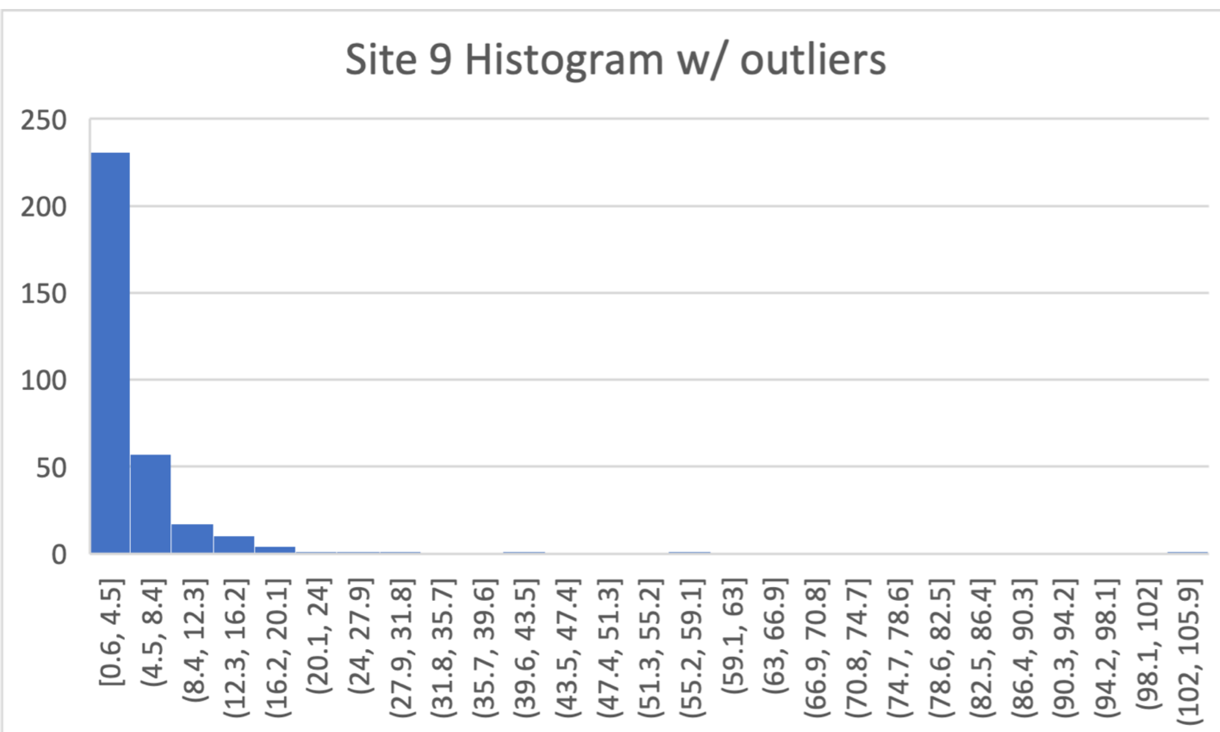

Figure 13. Yearly Turbidity Averages for Site 1 and Site 9

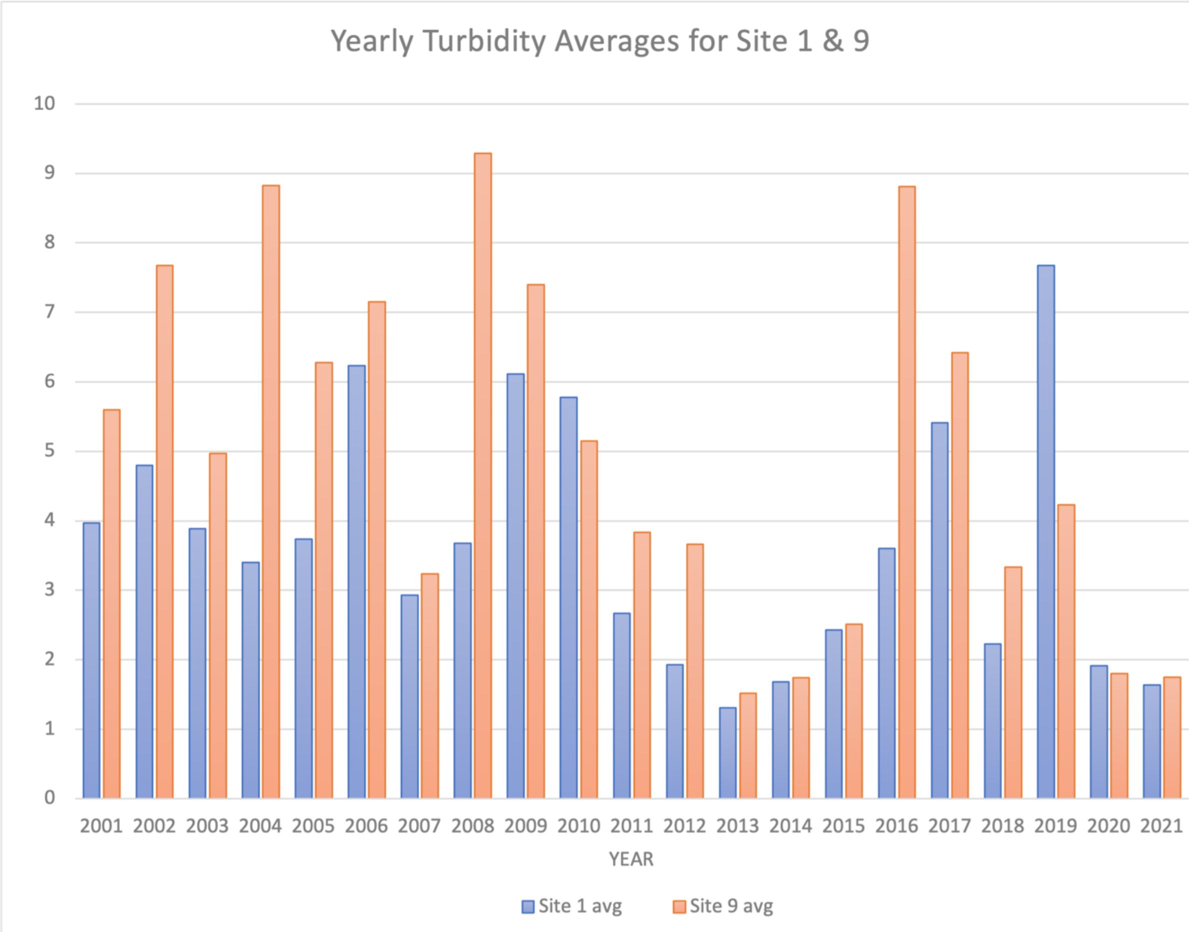

Figure 14. Yearly Turbidity Average Medians for Site 1 and Site 9

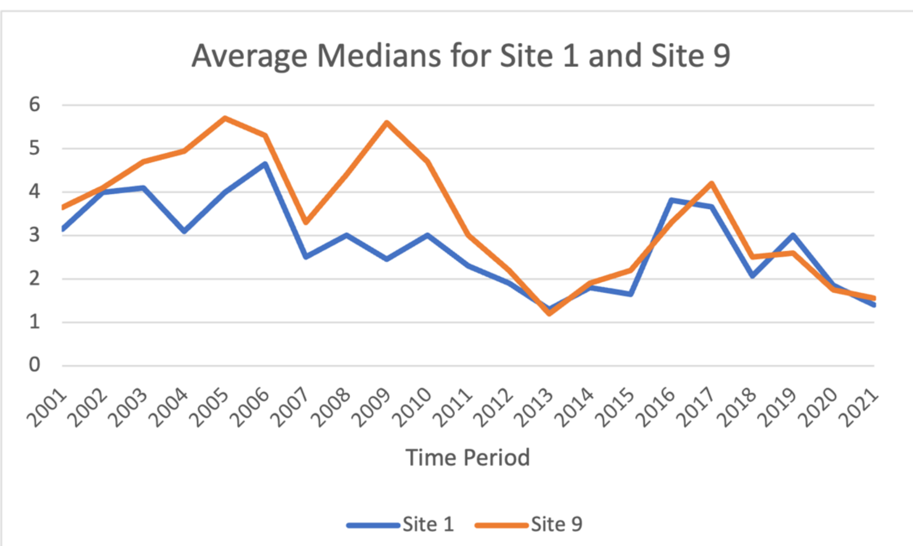

Figure 15. Turbidity Averages for Sites Broken-up by CA Drought

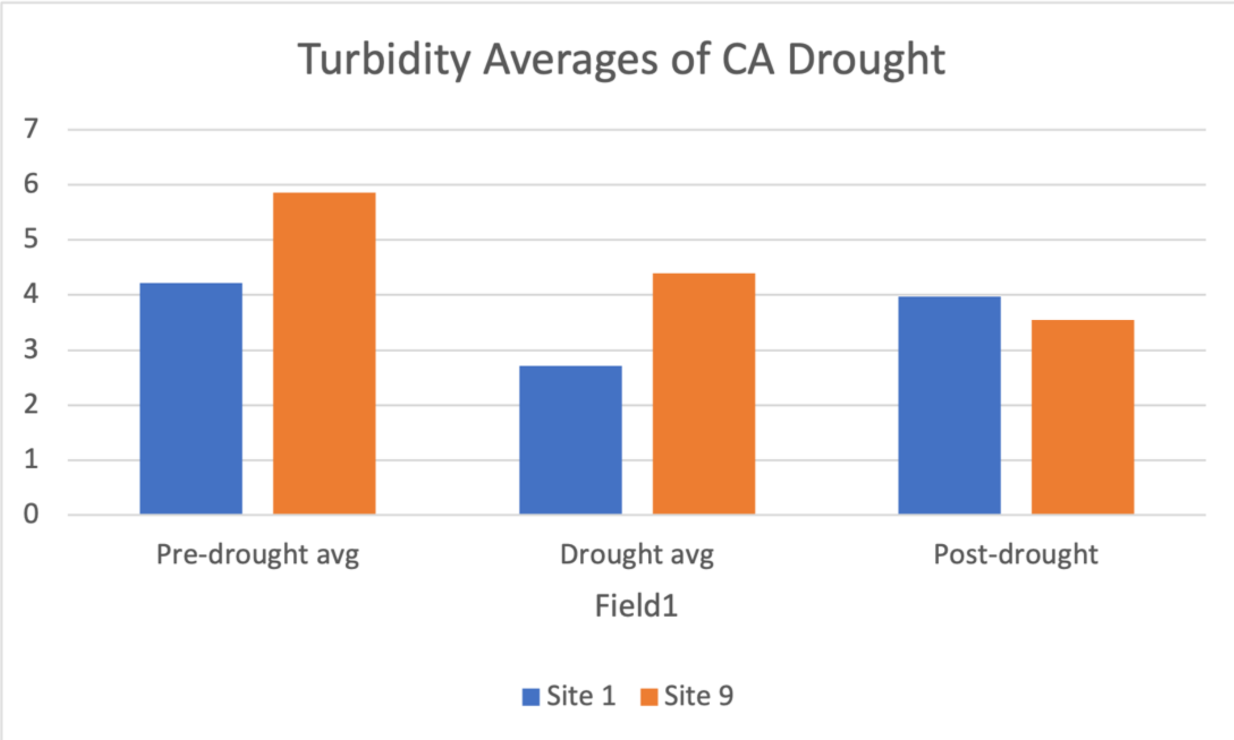

Figure 16. Overall Turbidity Averages Broken-up by CA Drought

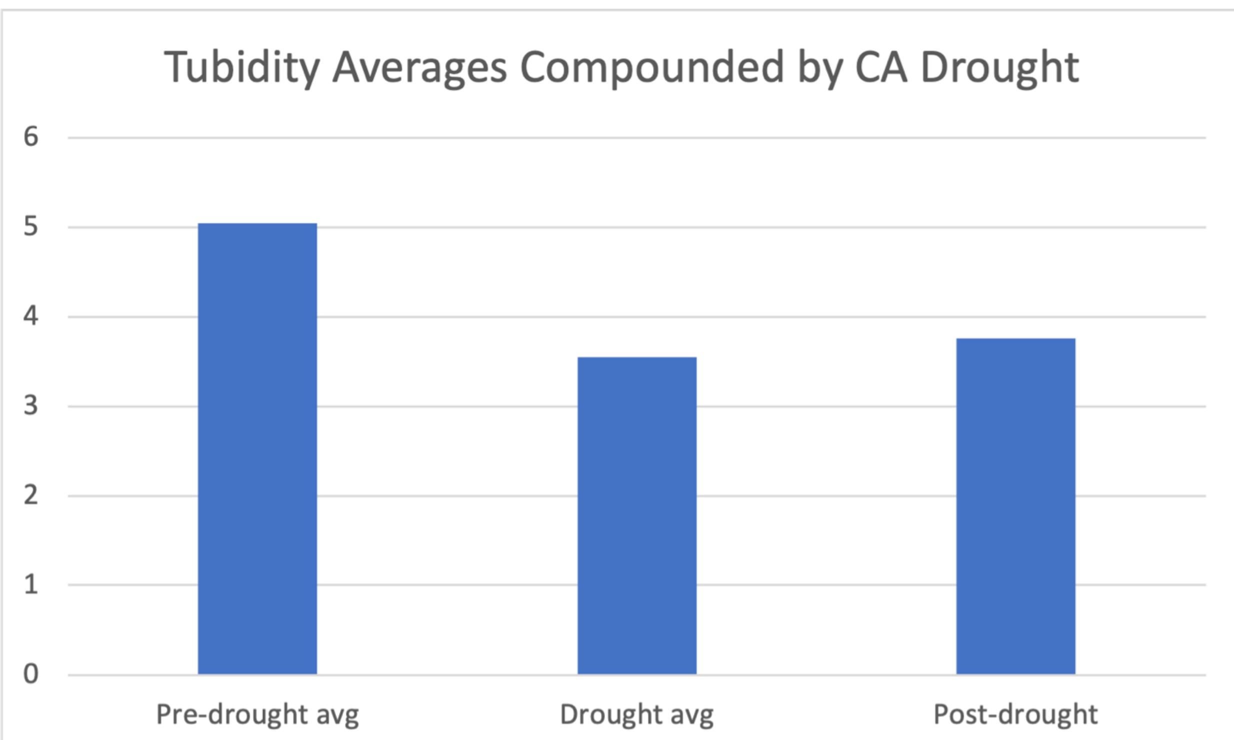

Figure 17. Overall Turbidity Averages Broken-up by Wet and Dry Seasons

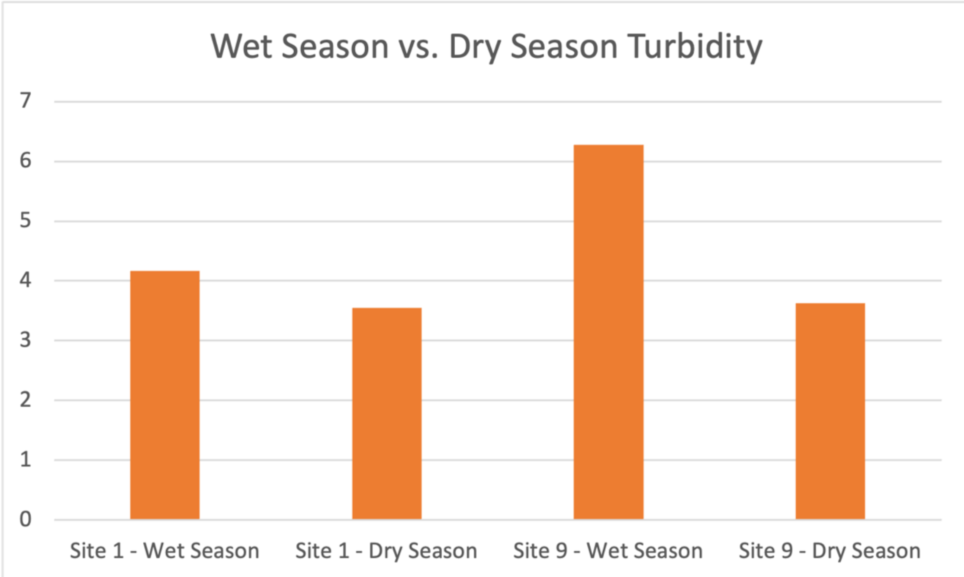

Figure 18. Secchi Disc Monitoring Diagram (credit: City of Lodi – Press Release)

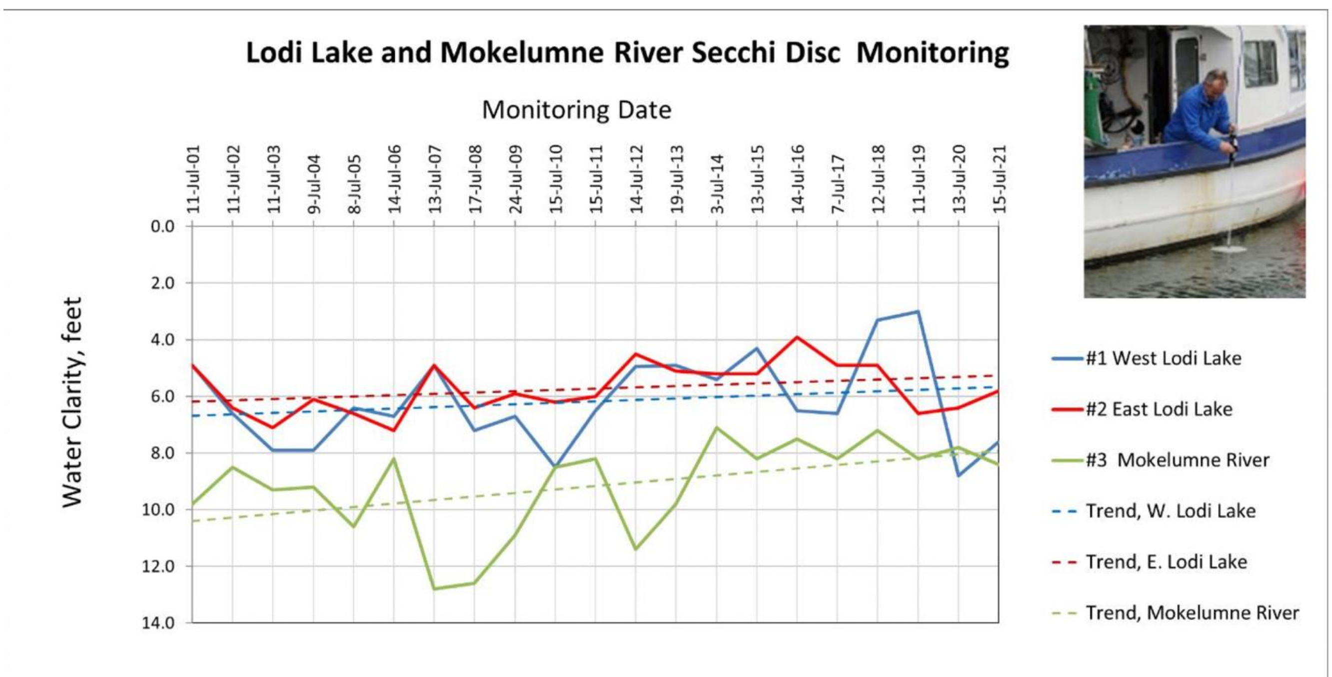

Figure 19. Site 1 Image (photo date unknown – credit: Kathy Grant)

Figure 20. Site 9 Image (July 15th, 2021 – credit: Kathy Grant)

Figure 21. High turbid event at Lodi Lake (February 26th, 2019 – credit: Dylan O'Ryan)

APPENDIX C:

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