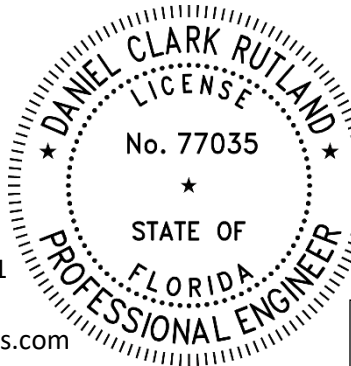


2022 Annual Groundwater Monitoring and Corrective Action Report: OUC Stanton Energy Center CCR

PREPARED FOR: Orlando Utility Commission
PREPARED BY: CH2M HILL Engineers, Inc.
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Purpose

On April 17, 2015, the United States Environmental Protection Agency (EPA) published the final rule for the Coal Combustion Residuals (CCR) Rule, Subtitle D of 40 Code of Federal Regulations (CFR) 257. The CCR Rule established national minimum criteria for CCR disposal and became effective October 19, 2015. The Orlando Utilities Commission (OUC) must comply with this rule when managing the disposal of CCR material generated at Stanton Energy Center (SEC). This technical memorandum fulfills the reporting requirements associated with the annual groundwater monitoring and corrective action report, Section 257.90 (2)(e), CFR.

The CCR Rule includes: deadlines for the establishment of a groundwater monitoring system, sampling and analysis of groundwater requirements, the statistical analysis of the groundwater quality data, and specifying corrective actions (if necessary) for facilities disposing of CCR. The CCR Groundwater Monitoring and Corrective Action program is described in Sections 257.90 through 257.98 of the CCR Rule:

- Applicability (§257.90)
- Groundwater Monitoring Systems (§257.91)
- Groundwater Sampling and Analysis Requirements (§257.93)
- Detection Monitoring Program (§257.94)
- Assessment Monitoring Program (§257.95)
- Assessment of Corrective Measures (§257.96)
- Selection of Remedy (§257.97)
- Implementation of Corrective Action Program (§257.98)

Monitoring requirements for compliance are included in §257 sub-sections. How OUC met the requirements of the CCR program is described in the first annual report (CH2M 2018). The 2017 annual report contained the results of the Groundwater Monitoring and Corrective Action program from July 2015 through December 2017. Subsequent OUC SEC annual reports were intended to only describe the status of the program for the given year in accordance with §257.90(e) (Table 1). This technical memorandum provides the required 2022 documentation to demonstrate the OUC SEC's compliance with the CCR Rule annual groundwater monitoring and corrective action report.

Table 1. Annual Groundwater Monitoring and Corrective Action Report (§257.90(e))

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

Requirement	Response
A map, aerial image, or diagram showing the CCR unit and the background (or up-gradient) and downgradient monitoring wells, to include the well identification numbers, that are part of the groundwater monitoring program for the CCR unit.	These are shown in Figures 2 and 3 in the background section
Identification of any monitoring wells that were installed or decommissioned during the preceding year, along with a narrative description of why those actions were taken.	No changes to the wells during this period
In addition to the monitoring data obtained under §257.90 through §257.98, a summary including the number of groundwater samples that were collected for analysis for each background and downgradient well, the dates the samples were collected, and whether the sample was required by the detection monitoring or assessment monitoring programs.	See results section
A narrative discussion of any transition between monitoring programs (e.g., the date and circumstances for transitioning from detection monitoring to assessment monitoring in addition to identifying the constituent(s) detected at a statistically significant increase [SSI] over background levels).	See discussion section
Other information required to be included in the annual report as specified in §257.90 through §257.98.	Part of discussion and conclusions

Background and Setting

SEC is located 12 miles southeast of Orlando, Florida. OUC has been operating SEC since 1987 and dry-managing CCRs in landfills on the west side of the property. The original, now closed, landfill received CCR from July 1987 through August 28, 2015. From the period of May 28 through August 15, 2015, the CCR directed to the closed landfill was used to form part of the landfill cap. The cap was completed with 2 feet of soil and then sodded to stabilize the soil. The old landfill is closed (hereinafter "closed landfill") and is undergoing post-closure monitoring under OUC's Conditions of Certification with the Florida Department of Environmental Protection (FDEP). The closed landfill has a 6.42-megawatt solar power generation farm installed over its top. The closed landfill is exempt from the CCR Rule because it ceased operations prior to the rule's implementation.

The new landfill (hereinafter "active landfill") began receiving CCR on May 28, 2015 as a monofill that receives CCR produced by the SEC coal-fired power generating process. The new landfill is positioned immediately west of and adjacent to the closed landfill and immediately east of the road Innovation Way, which is the approximate SEC western property boundary (Figure 1). The Orange County Landfill for municipal solid waste is immediately west of SEC. The design standards for the active landfill are compliant with Florida's municipal solid waste landfill requirements under Chapter 62-701, Florida Administrative Code. The active landfill is fully double-lined and does not discharge into the surficial groundwater.

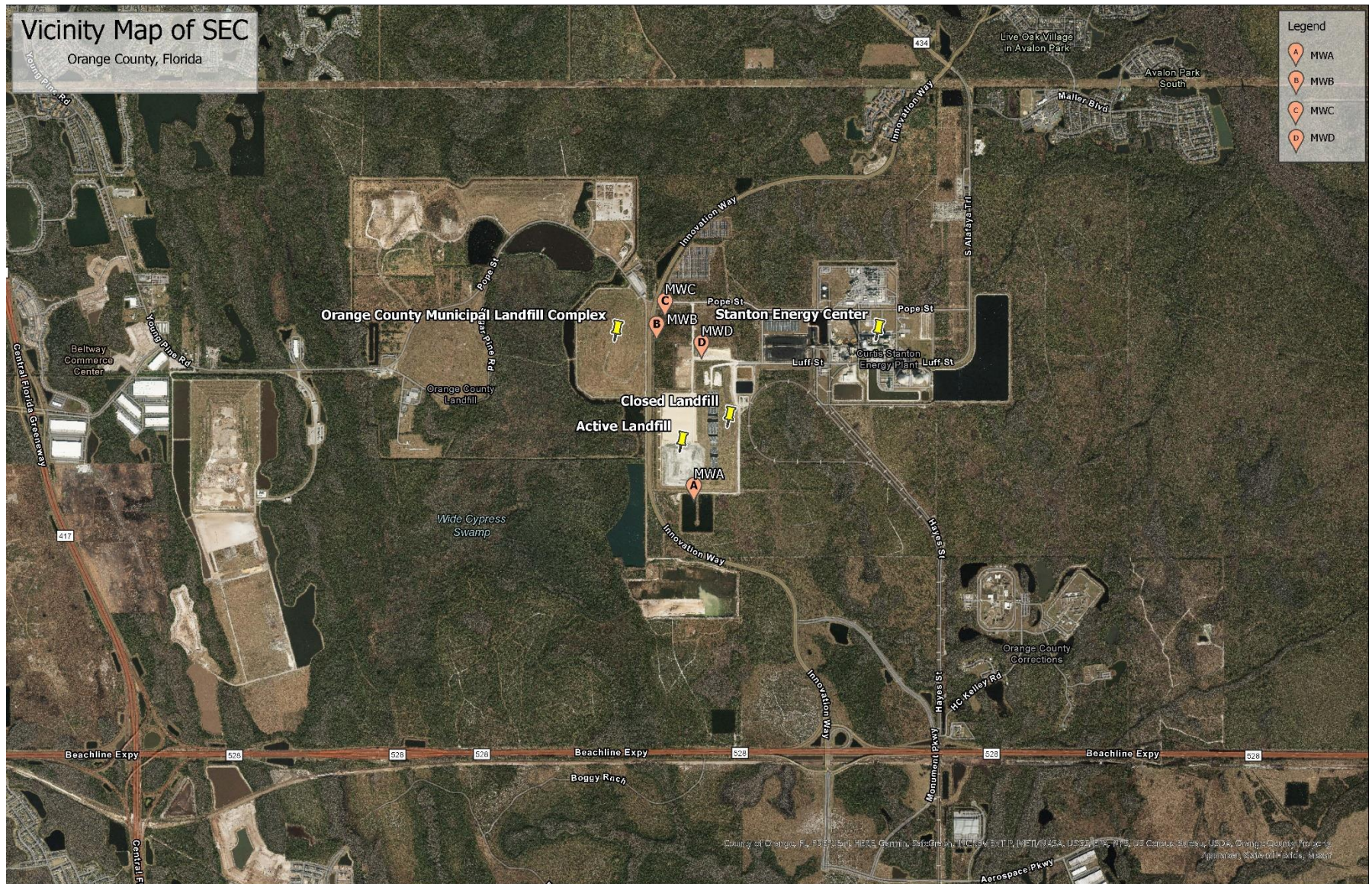


Figure 1. General Vicinity Map of OUC SEC and Landfills
2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

Groundwater conditions at SEC are regulated under two separate programs: the FDEP Power Plant Siting Act and the U.S. Environmental Protection Agency (EPA) CCR Rule. The FDEP monitoring program has been active since August 1986, while the CCR monitoring program began in October 2015. OUC has made a conscious effort to keep these programs separate because different regulatory requirements, different groundwater quality standards, and different monitored constituents. However, the groundwater under the two adjacent landfills is common.

CCR monitoring well locations were selected based on the groundwater gradient characteristics, the positions of the active and closed landfills, and were also constrained by the western site boundary. The physical constraints, the history of FDEP's groundwater monitoring and other investigation results were used to locate the monitoring wells for the CCR program. The western property boundary is the regional groundwater up-gradient edge at the SEC site (Figures 2 and 3). The surficial aquifer groundwater near the SEC CCR active landfill is generally flowing outward from an apparent local groundwater level high under the adjacent closed coal residual landfill (this is especially evident at the end of the wet season in Figure 3). Even though the surficial groundwater gradient is toward the southwest initially from this local high, the overall groundwater gradient is still toward the east and northeast. Consequently, the groundwater quality conditions near the active landfill that are monitored for the CCR program do not represent unaffected background conditions. The CCR Rule groundwater data represent conditions since the beginning of the CCR monitoring program.

Key program activities for 2022 were to continue with CCR detection monitoring and prepare an annual report by January 31, 2023 and upload the document to the OUC CCR website within 30 days of placing this information in the operating record.

CCR Groundwater Data Screening and Decision Process through the Assessment Monitoring Program

The groundwater data and screening and decision process was derived from §257.90 through §257.98 of the CCR Rule. A summary of the monitoring process is:

1. Collect CCR period background water quality data, Appendix III and IV constituents. This step occurred between September 9, 2015 and July 20, 2017 at SEC and is completed.
2. Identify method(s) to evaluate the data for statistically significant trend changes for each well and constituent for Appendix III and IV constituents by well. This step was completed and documented in an October 2017 report (CH2M 2017a).
3. Quantify criteria that define the limits for statistically significant change from background for each Appendix III and IV constituent by well. This was completed and documented in the 2017 annual report and has been updated for the 2022 monitoring year and is included for reference in Appendix A.
4. Establish a groundwater protection standard for each Appendix IV constituent [§257.95(h)] detected in groundwater. Note that the CCR Rule does not list Appendix III constituents to establish groundwater protection standards. This was completed and documented in the 2017 annual report.
5. Collect detection program water quality data, Appendix III constituents (§257.94). The previous detection monitoring program sampling results are presented in the 2017 through 2021 annual reports.

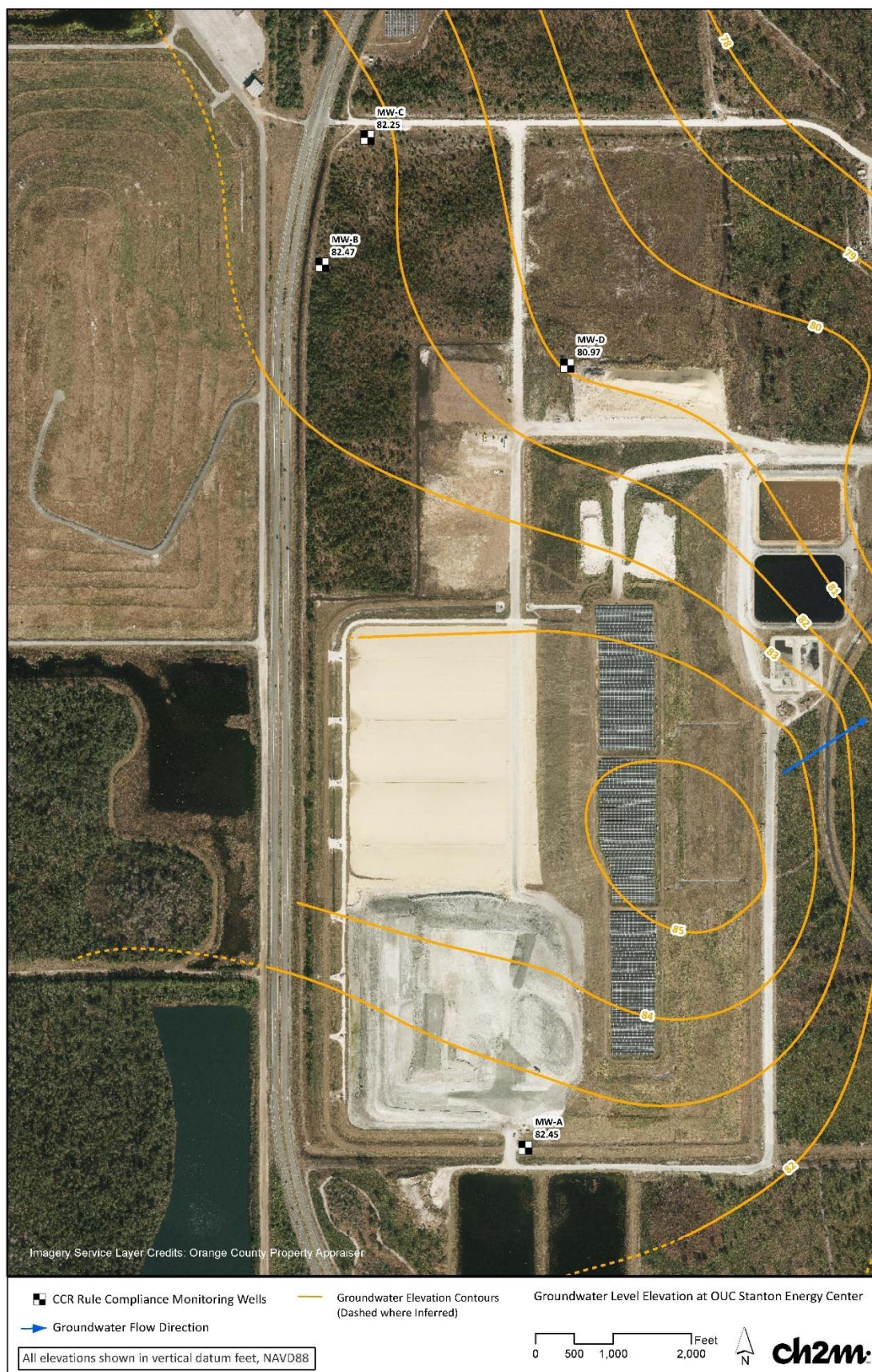


Figure 2. 2022 First Semi-Annual Event Groundwater Levels
2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

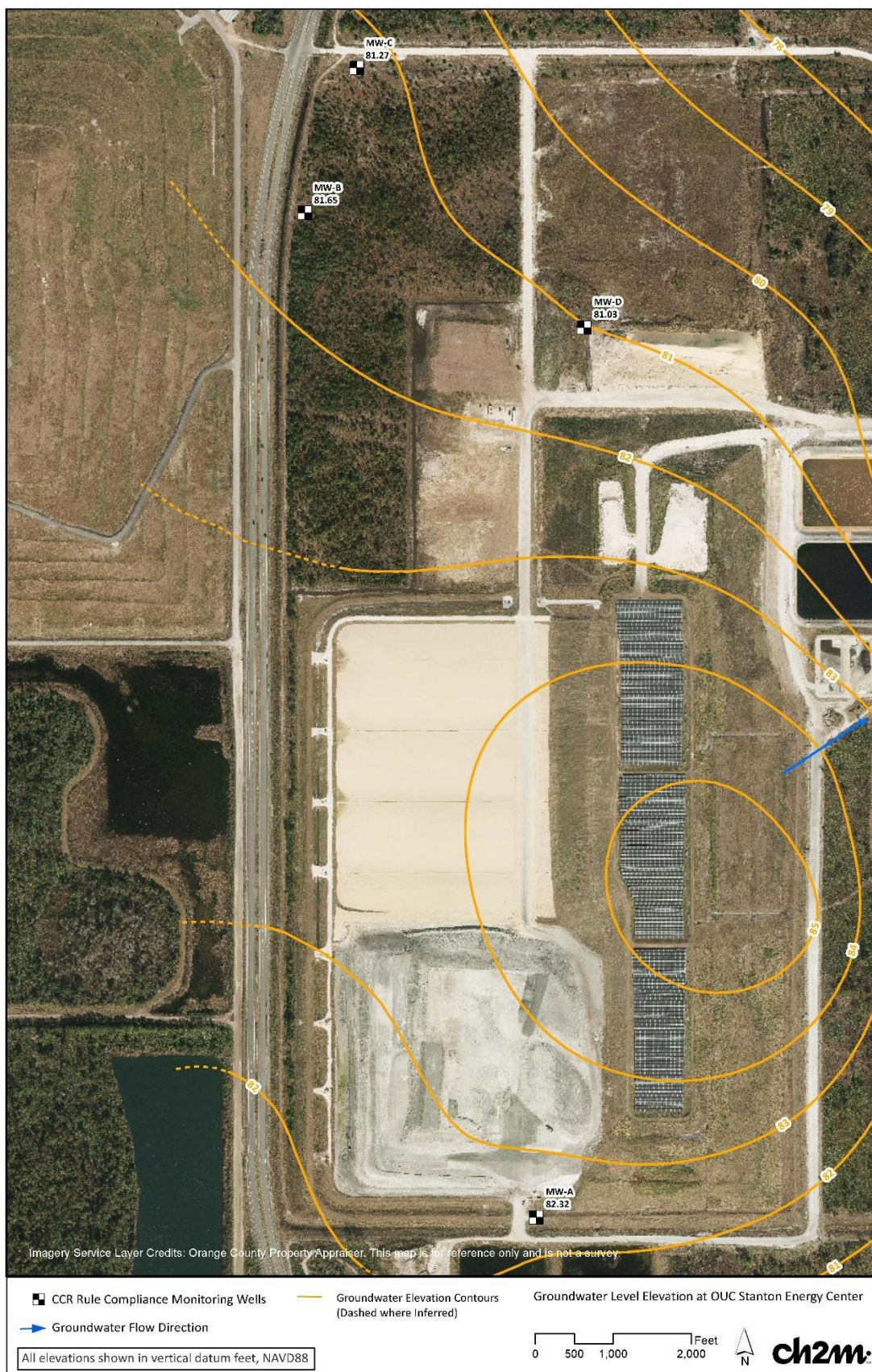


Figure 3. 2022 Second Semi-Annual Event Groundwater Levels
 2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

6. Assess groundwater flow direction and rate. The previous detection monitoring program sampling results are presented in the 2017 through 2021 annual reports.
7. Compare detection program water quality data to the statistical trend criteria to evaluate for no significant trend change, or a significant trend change, from the background water quality data.
 - a. If the result is no significant trend change then continue with detection program monitoring
 - b. If the result is a significant trend change may be indicated, then resample within 90 days
 - i. Compare data to the statistical criteria for no significant trend change or significant trend change
 1. If the result is no significant trend change then continue with detection program monitoring
 2. If the result is significant trend change of one or more constituents at the waste boundary [§257.94(e)]
 - a. Establish an assessment monitoring program and post a notification on the CCR Web site that an assessment monitoring program has been established, or
 - b. Demonstrate that a source other than the CCR unit caused the significant increase within 90 days. Continue with the detection monitoring program.
 - c. After approximately 3 years of detection program monitoring reassess the statistical analyses of the groundwater water quality trends against the background data to identify if changes are needed. The 2015 through 2021 dataset was statistically reanalyzed to update baseline conditions and more accurately represent groundwater quality trends for each constituent. The analysis of new baseline concentrations and prediction intervals is included in Appendix A.
8. Assessment monitoring program (§257.95)
 - a. Within 90 days of establishing an assessment monitoring program sample the groundwater for Appendix IV constituents, and then sample annually thereafter.
 - b. The number of samples, N, needs to be sufficient to support the statistical evaluation of the data [§257.93(e)]. The owner may demonstrate that an alternative sampling frequency is necessary during the active life and post-closure of the CCR unit based on site conditions; however, sample no less frequently than annually.
 - c. After obtaining the results from the above, within 90 days sample all wells for Appendix III and IV constituents, at least semi-annually. The number of samples, N, needs to be sufficient to support the statistical evaluation of the data [§257.93(e)].
 - i. Establish groundwater protection standards consistent with [§257.95(h)] as described in Item 4, above.
 - ii. If the sampling results for the Appendix III and IV constituents are below the established groundwater protection standards for two consecutive sampling events, the monitoring program may return to detection monitoring (Appendix III constituents). Notification that the detection monitoring program is resuming must be posted on the CCR Web site.

- iii. If concentrations of one or more constituents are above background but below the groundwater protection standard continue with the assessment monitoring program.
- iv. If concentrations of one or more constituents are statistically significant concentrations above the groundwater protection standard, post a notification on the CCR Web site [§257.95(g)] and characterize the nature of the release [§257.95(g)(1)].

Results of the Detection Monitoring Program – 2022

Monitoring Wells

The SEC CCR active landfill groundwater monitoring system consists of four surficial aquifer monitoring wells. These wells are named MW-A, MW-B, MW-C, and MW-D. The monitoring wells are about 20 to 25 feet deep into the surficial aquifer. MW-A has an approximate 10-foot deeper installation depth because the land surface elevation at its location is approximately 10 feet higher than at the other wells. The horizon for the monitoring interval for MW-A is the same as the interval for MW-B, MW-C, and MW-D. MW-A is considered the regional up-gradient well and the other wells are downgradient based on local groundwater levels.

Groundwater Levels and Flow

Groundwater levels in the monitoring wells were collected with each sampling event and groundwater level elevation maps were prepared. Table 2 presents the well location and water level data. Figure 4 shows a chart of the semi-annual groundwater elevations. The semi-annual groundwater level maps are provided in Figures 2 and 3. In general, there are no major changes in groundwater levels and flow patterns across the site since 2015. The 2018 values were like those measured in 2016, while 2017 showed some larger variations. The 2019 levels were about 0.3- to 0.7-foot higher than 2018 levels for the dry and wet seasons, respectively. Water levels in October 2021 were the highest recorded to date after a very wet summer. These levels were similar to the fall 2017 and fall 2020 levels and within the range monitored during the entire program, since 2015 (Figure 4). Overall, there is no substantial trend in groundwater levels as the fall 2022 levels were similar to the fall 2017 and fall 2021 levels (less than 0.4-foot difference).

Table 2. Background and Operations Period Groundwater Levels – MW-A, MW-B, MW-C, and MW-D, OUC Stanton Energy Center

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

DATE	Well	Florida State Plane East Zone (901)		Elevation TOC ¹ (feet, NAVD88)	Depth to Water (feet)	Water Level Elevation (feet, NAVD88 ²)
		Northing (feet)	Easting (feet)			
10/30/2015	MW-A	1504260.1	597643.8	95.77	13.6	82.17
4/29/2016					13.96	81.81
10/31/2016					13.53	82.24
4/25/2017					15.64	80.13
10/31/2017					13.31	82.46
4/27/2018					15.16	80.61
10/30/2018					14.20	81.57
4/29/2019					14.82	80.95
10/31/2019					13.94	81.83

**Table 2. Background and Operations Period Groundwater Levels – MW-A, MW-B, MW-C, and MW-D,
OUC Stanton Energy Center**

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

DATE	Well	Florida State Plane East Zone (901)		Elevation TOC ¹ (feet, NAVD88)	Depth to Water (feet)	Water Level Elevation (feet, NAVD88 ²)
		Northing (feet)	Easting (feet)			
4/29/2020	MW-A	1504260.1	597643.8	95.77	15.28	80.49
10/29/2020					13.35	82.42
3/17/2021					14.47	81.30
10/13/2021					13.39	82.38
4/19/2022					13.32	82.45
10/25/2022					13.45	82.32
10/30/2015	MW-B	1508750.3	596609.8	86.05	4.86	81.19
4/29/2016					5.20	80.85
10/31/2016					4.90	81.15
4/25/2017					7.25	78.80
10/31/2017					4.41	81.64
4/27/2018					6.17	79.88
10/30/2018					5.59	80.46
4/29/2019					5.74	80.31
10/31/2019					4.72	81.33
4/29/2020					6.54	79.51
10/31/2020					4.21	81.84
3/17/2021					5.60	80.45
10/13/2021					3.79	82.26
4/19/2022					13.32	82.45
10/25/2022					4.4	81.65
10/30/2015	MW-C	1509397.7	596841.6	86.84	6.22	80.62
4/29/2016					6.56	80.28
10/31/2016					6.14	80.70
4/25/2017					8.36	78.48
10/31/2017					5.67	81.17
4/27/2018					7.35	79.49
10/30/2018					6.90	79.94
4/29/2019					6.95	79.89
10/31/2019					5.94	80.90
4/29/2020					7.80	79.04
10/31/2020					5.50	81.34
3/17/2021					6.98	79.86
10/13/2021					5.19	81.65
4/19/2022					4.59	82.25
10/25/2022					5.57	81.27

Table 2. Background and Operations Period Groundwater Levels – MW-A, MW-B, MW-C, and MW-D, OUC Stanton Energy Center

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

DATE	Well	Florida State Plane East Zone (901)		Elevation TOC ¹ (feet, NAVD88)	Depth to Water (feet)	Water Level Elevation (feet, NAVD88 ²)
		Northing (feet)	Easting (feet)			
10/30/2015	MW-D	1508237.4	597858.3	85.10	4.89	80.21
4/29/2016					5.58	79.52
10/31/2016					5.14	79.96
4/25/2017					7.44	77.66
10/31/2017					3.96	81.14
4/27/2018					5.79	79.31
10/30/2018					5.43	79.67
4/29/2019					5.65	79.45
10/31/2019					4.60	80.50
4/29/2020					5.85	79.25
10/29/2020					3.97	81.13
3/17/2021					4.45	80.65
10/13/2021					3.79	81.31
4/19/2022					4.13	80.97
10/25/2022					4.07	81.03

1 TOC - Top of casing

2 NAVD88 - North American Vertical Datum of 1988

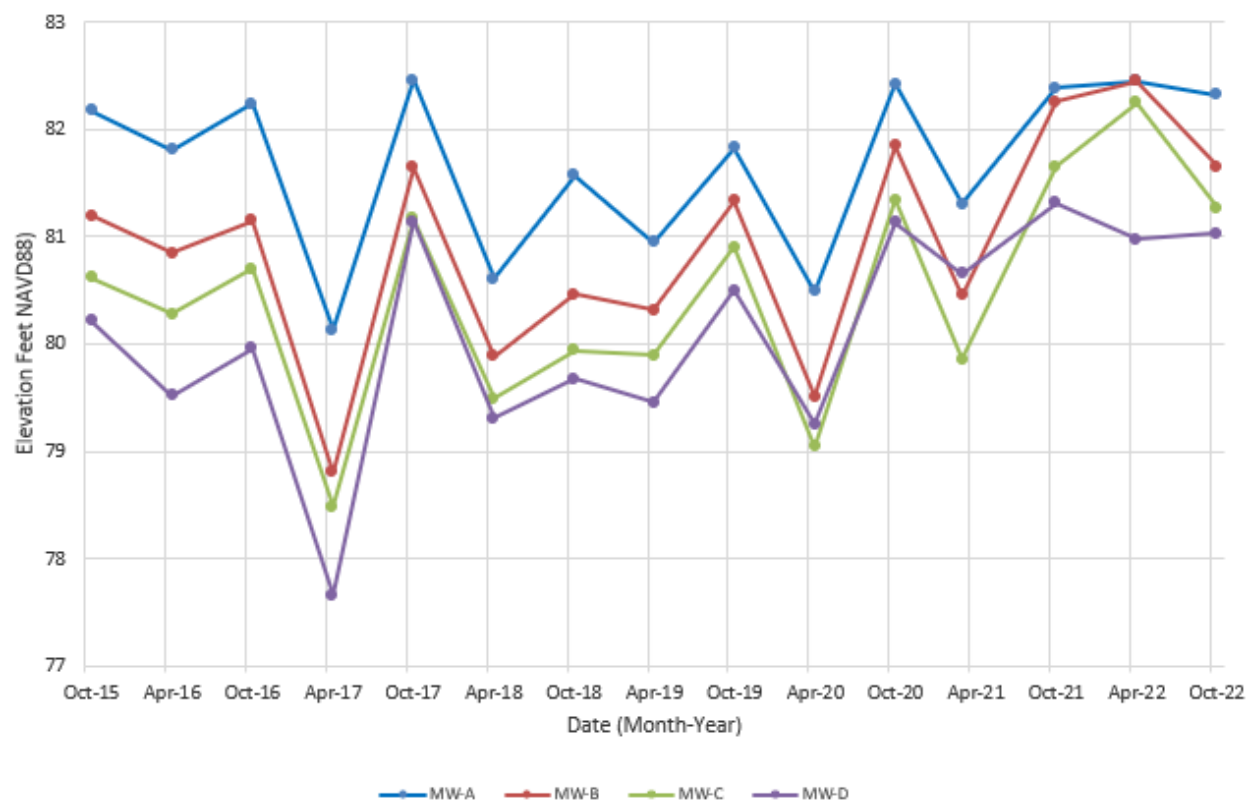


Figure 4. Semi-Annual Groundwater Levels

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

Groundwater Sampling and Laboratory Analysis

The detection monitoring program began with establishing background groundwater quality conditions that consisted of collecting and analyzing quarterly samples between September 2015 and July 2017 for Appendix III and IV constituents. Sampling events to establish background water quality conditions were completed by October 17, 2017 in accordance with §257.94(b). MW-A is the background well and MW-B, MW-C, and MW-D are the three wells to monitor for compliance with the CCR.

Several parameters being monitored had trends noted during the CCR background period. In the past, the upper probability limits (UPL, and lower probability limit [LPL] for pH) were tested by modifying the baseline UPL/LPL with the trend parameter. This made the limits slope with time, and in some instances the limits approached zero - which is not feasible. Because it was difficult to see the change over time when both the observed data and probability limits vary, starting with the 2019 annual report the UPL/LPL were held constant and the observed data were adjusted by the trend parameters (that is, “detrended” by applying the slope parameter to the observed data as shown by example on the bottom of Table 3). Time series plots were created to show the change in the observations over time against a constant limit. These plots are discussed further in the next section.

The 2022 semi-annual sampling results are shown in Table 4 (and Appendix B). The following results are noted:

- The March 22, 2022 CCR monitoring sampling event resulted in the identification of potential SSIs for constituents at 1 well. For constituents that resulted in potential SSIs relative to detrended UPL, resampling was completed on May 10, 2022 and constituents with the following results:
 - Well MW-D for calcium, chloride, sulfate, and total dissolved solids (TDS). The detrended retest values were similarly outside of their respective probability limits.

- The September 13, 2022 CCR monitoring sampling event resulted in the identification of potential SSIs of similar constituents at 2 wells. For constituents that resulted in potential SSIs relative to detrended UPL, resampling was completed on November 9, 2022 for the following wells and constituents:
 - Well MW-C was retested for fluoride. The fluoride concentration of the retest was below the UPL and resulted in an unconfirmed SSI. Note that the statistical analysis for fluoride at MW-C is based on historical measurements at the lowest result that can be routinely quantified and reported by the laboratory. As a result, minor fluctuations in fluoride concentration about this limit will indicate a potential SSI.
 - Well MW-D for calcium, chloride, fluoride, sulfate, and TDS. While the boron, calcium, chloride, and fluoride observed values were lower in the spring sampling event, for the fall sampling event sulfate was lower and TDS remained approximately the same. The retest values were higher than originally collected, except for TDS, which was lower.

Table 3. Detection Monitoring Parameters Tolerance Limits and Trend Parameters*2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report*

Well	Constituent	UPL ¹	LPL ²	Unit	Limit Trend Slope	Detrended ⁴
MW-B	Boron	69		µg/L ³	0.02	Y
	Calcium	25,800		µg/L		
	Chloride	101,000		µg/L	-7.74	Y
	pH	4.80	4.14	pH Units		
	Fluoride	211		µg/L		
	Sulfate	66,200		µg/L	-3.72	Y
	TDS	280,000		µg/L	-17.54	Y
MW-C	Boron	21		µg/L		
	Calcium	8,200		µg/L	0.58	Y
	Chloride	11,100		µg/L	3.76	Y
	pH	5.59	4.76	pH Units		
	Fluoride	110		µg/L		
	Sulfate	3,350		µg/L		
	TDS	58,200		µg/L	9.92	Y
MW-D	Boron	31		µg/L		
	Calcium	56,800		µg/L		
	Chloride	85,200		µg/L	13.71	Y
	pH	5.63	4.41	pH Units	-0.13	Y
	Fluoride	440		µg/L		
	Sulfate	13,500		µg/L		
	TDS	320,00		µg/L	16.76	Y

1 UPL - upper probability limit/tolerance level

2 LPL - lower probability limits/tolerance levels.

3 µg/L = micrograms per liter

4 Detrended means that the data need to be adjusted for the trend. The trend is applied to the days since the baseline period began (9/9/2015) to the observed data. The trend's case is opposite when applied to the data; for example, boron March 22, 2022 adjustment is $-0.02 \times 2,450 \text{ days} = -49 \text{ ug/L}$. The detrended March 2022 boron value is $121 - 49 = 72 \text{ ug/L}$.

Table 4. Summary of the 2022 Annual Data Detection Monitoring Results

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

Well	Constituents	Units	LPL ³	UPL ²	Trend	First Semi-Annual Sampling Event on 3/22/2022 & Retesting on 5/10/2022						Second Semi-Annual Sampling Event on 9/13/2022 & associated Retesting on 11/9/2022							
						Observed Value	Detrended / Observed Value	Within Probability Limits	Is Retesting Required?	Retest Values	Detrended Retest Value	SSI ⁴	Observed Value	Detrended / Observed Value	Within Probability Limits	Is Retesting Required?	Retest Values	Detrended Retest Value	SSI ⁴ Confirmed
MW-B	Boron	µg/L ¹		69.0	Y	121.0	-13.0	Yes	No				97.0	-47.0	Yes	No			
	Calcium	µg/L		25,800		4,000	4,000	Yes	No				5,670	5,670	Yes	No			
	Chloride	µg/L		101,000	Y	16,700	67,232	Yes	No				24,900	79,139	Yes	No			
	pH	pH Units	4.14	4.80		4.62	4.62	Yes	No				4.49	4.49	Yes	No			
	Fluoride	µg/L		211		70	70	Yes	No				100	100	Yes	No			
	Sulfate	µg/L		66,200	Y	34,300	58,572	Yes	No				30,000	56,052	Yes	No			
	TDS	µg/L		280,000	Y	106,000	220,612	Yes	No				121,000	244,019	Yes	No			
MW-C	Boron	µg/L		21.0		10.0	10.0	Yes	No				12.0	12.0	Yes	No			
	Calcium	µg/L		8,200	Y	9,340	5,526	Yes	No				10,100	6,007	Yes	No			
	Chloride	µg/L		11,100	Y	26,300	1,727	Yes	No				26,800	425	Yes	No			
	pH	pH Units	4.76	5.59		5.19	5.19	Yes	No				5.08	5.08	Yes	No			
	Fluoride	µg/L		110		100	100	Yes	No				130	130	No	Yes	100	100	No
	Sulfate	µg/L		3,350		340	340	Yes	No				650	650	Yes	No			
	TDS	µg/L		58,200	Y	102,000	37,223	Yes	No				99,000	29,472	Yes	No			
MW-D	Boron	µg/L		31.0		27.0	27.0	Yes	No				49.0	49.0	No	Yes	76.0	76.0	Yes
	Calcium	µg/L		56,800		1,380,000	1,380,000	No	Yes	1,300,000	1,330,000	Yes	1,450,000	1,450,000	No	Yes	1,600,000	1,600,000	Yes
	Chloride	µg/L		85,200	Y	3,570,000	3,537,279	No	Yes	3,740,000	3,740,000	Yes	4,390,000	4,293,845	No	Yes	5,300,000	5,201,705	Yes
	pH	pH Units	4.41	5.63	Y	4.39	5.23	Yes	No				4.41	5.31	Yes	No			
	Fluoride	µg/L		440		380	380	Yes	No				570	570	No	Yes	2,900	2,900	Yes
	Sulfate	µg/L		13,500		270,000	270,000	No	Yes	2,810,000	2,810,000	Yes	363,000	363,000	No	Yes	410,000	410,000	Yes
	TDS	µg/L		320,000	Y	10,600,000	10,560,015	No	Yes	11,000,000	10,959,194	Yes	12,900,000	12,782,498	No	Yes	11,000,000	10,879,883	Yes

1 µg/L = micrograms per liter
2 UPL - upper probability limit/tolerance level
3 LPL - lower probability limits/tolerance levels.
4 SSI – Statistically Significant Increase Requiring Alternate Source Demonstration

Data Discussion

Sample results from the first semi-annual sampling event conducted on March 22, 2022 required retesting for identified potential SSIs at well MW-D for calcium, chloride, sulfate, and total dissolved solids. After checking the results with the lab and retesting on May 10, 2022, the potential SSIs were confirmed at MW-D for calcium, chloride, sulfate, and TDS. Detrended concentrations for these parameters were orders of magnitude different from the baseline data.

The results of second semi-annual sampling event conducted on September 13, 2022 also indicated potential SSIs for boron, calcium, chloride, fluoride, sulfate, and TDS at MW-D. Retesting results collected on November 9, 2022 identified potential SSIs for boron, calcium, chloride, sulfate, and TDS. It was determined that the elevated concentrations at MW-D for boron, calcium, chloride, sulfate, and TDS could not be explained by statistical analysis alone. Detrended concentrations for these parameters were orders of magnitude different from the baseline data. The fluoride concentration at MW-D was higher than the statistical upper limit. However, because of high dissolved solids, it is possible that fluoride may not be accurately represented by laboratory analysis when measured in low concentrations.

Considering the original baseline and the 2017 through 2021 data, the original trends/non-trends estimated on the smaller background dataset seemed to be inaccurate for some constituents, especially at MW-B for boron, pH, and sulfate. The 2015 through 2021 dataset was statistically reanalyzed for all wells for each constituent to update baseline limits and to improve accuracy in representing groundwater quality trends (Appendix A). Figure 5 shows the detrended data over time using the new analysis. Accurate time series plots of the detrended data should be relatively flat, like it is for MW-C pH and sulfate. A few parameters had trends during the original baseline period but now have better consistency over the entire period (including boron, chloride, and TDS in MW-B). Similarly, pH and calcium now have no trend adjustment required but sulfate now does. It is probable that the original baseline trend analysis over a shorter time was not representative and this new 2022 baseline will be used going forward.

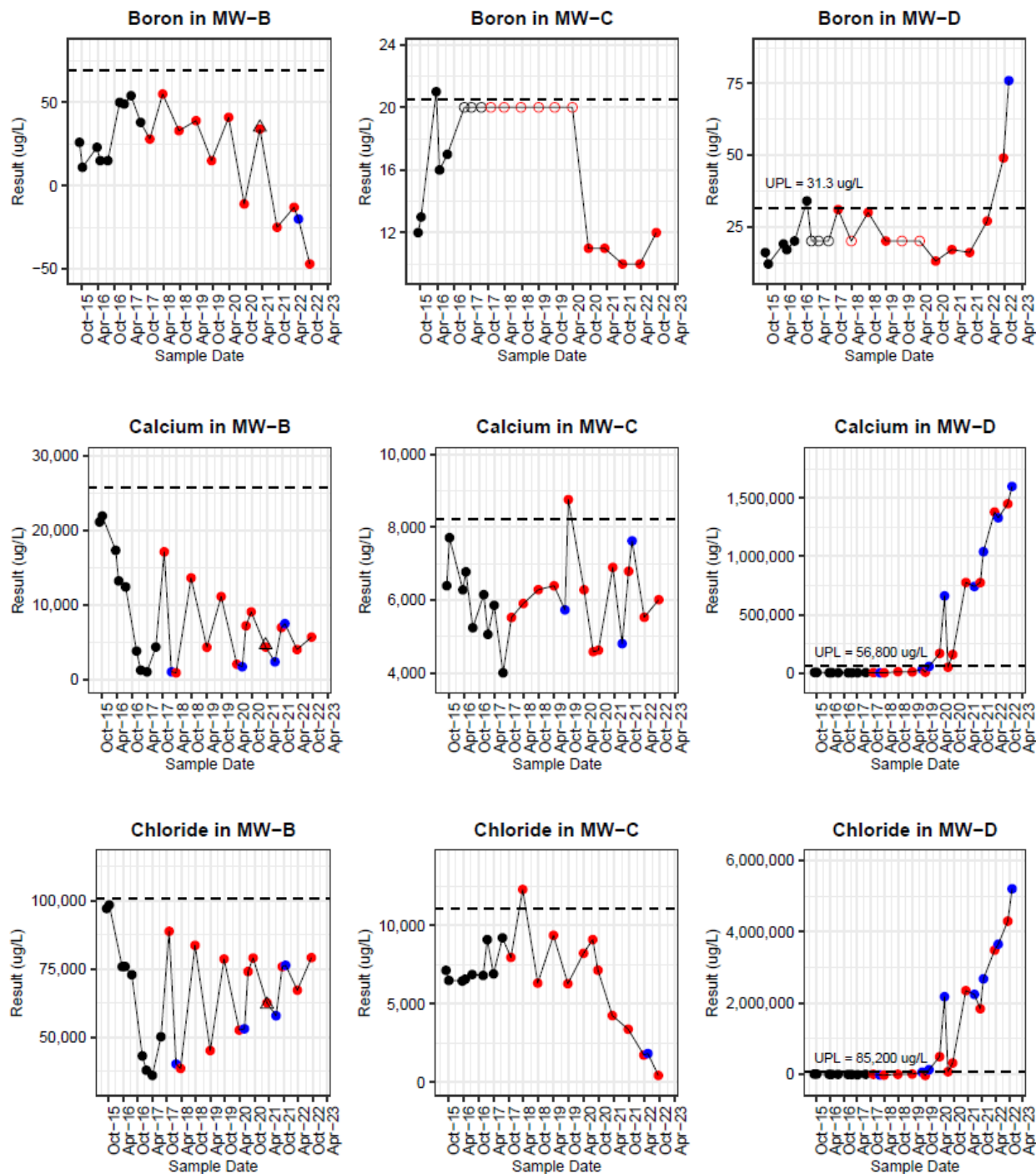
For some data, the new time series plots indicated that there could have been a change occurring around 2017 at MW-D. The chloride, calcium, sulfate, and TDS concentrations started to rise greatly in MW-D by 2018 (Figure 5). However, during 2020 there was a significant increase in these four parameters which indicated that there is a potential new source or introduction of inorganic minerals in the shallow groundwater. The previous annual reports and alternative source evaluation demonstrated a likely alternative source and concluded that detection monitoring should continue.

Potential Alternative Sources Review

The 2017 and 2018 results and analysis indicated that calcium, chloride, pH (low) and TDS from MW-B, and calcium and chloride from MW-D fell outside the statistical confidence intervals. This did not mean that there was a problem, but continued scrutiny was needed to assess site conditions. Continued detection monitoring proceeded. SSIs for chlorides, calcium, sulfate, and TDS were observed in MW-B, MW-C, and MW-D in the 2019 and 2020, and 2021 results. In accordance with the CCR rule requirements, a closer review of the potential alternative sources was conducted during 2020 and 2021 (CH2M 2020b and CH2M 2021b). These reviews indicated that the source was not from the CCR-regulated landfill and detection monitoring could continue.

Additionally, the statistical baseline and trend analysis was repeated in 2022 (Appendix A) to update the original trend estimates that were made with the limited initial data set, as required by the CCR Rule, and in accordance with EPA recommendations (EPA 2009b). The results of this 2022 analysis provided updated UPL and LPL (for pH) that characterize each well over a longer period (September 2015 to September 2021). The updated baseline trend analysis resulted in revised thresholds for UPLs that

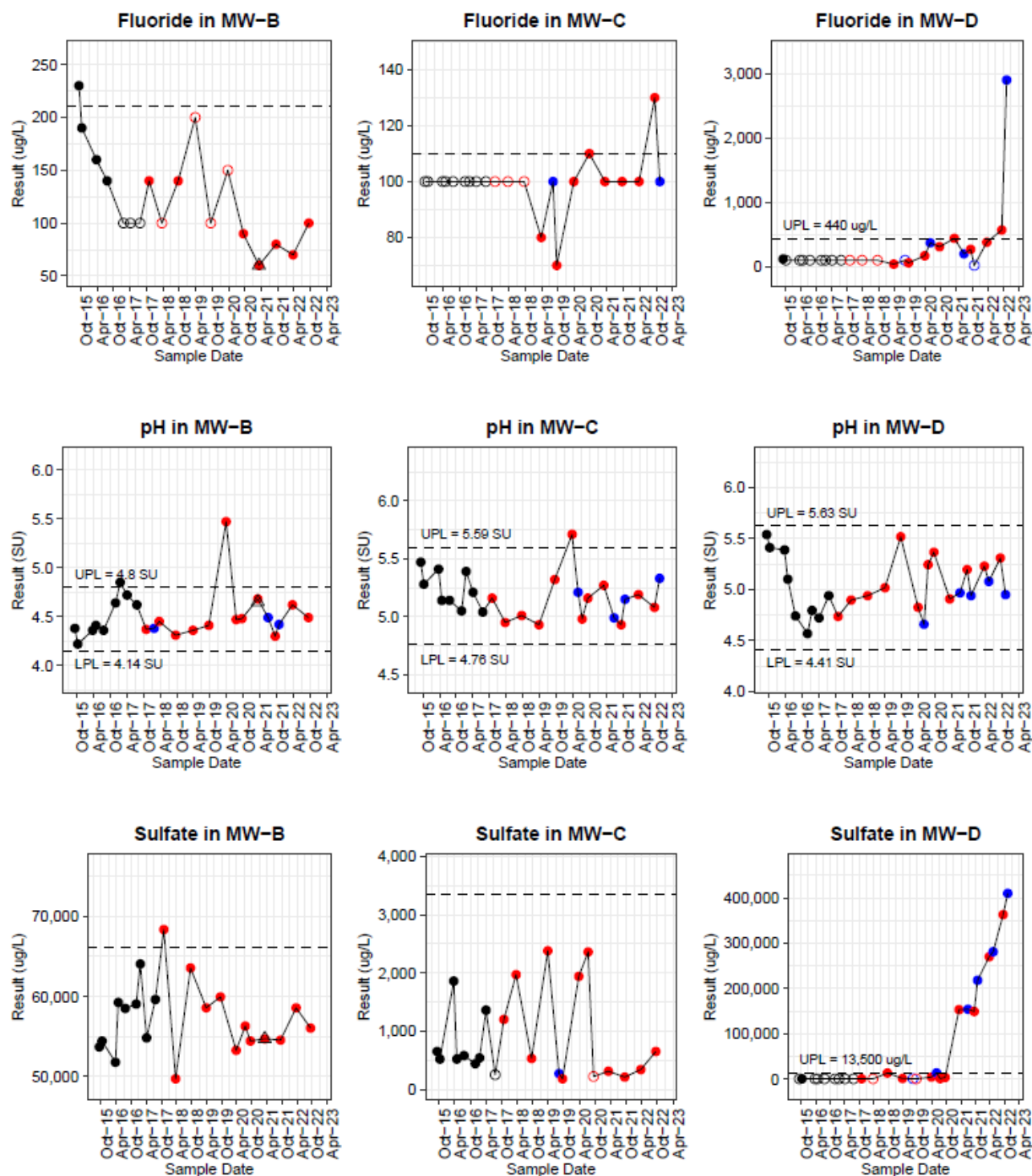
would have eliminated SSI categorization for previous sampling data for calcium, chloride, pH, and TDS in MW-B and MW-C. The same analysis would have eliminated SSIs at MW-D for pH and fluoride. The statistical analysis completed for the 2022 data shows similar concentrations as in recent years but with identified SSIs only at MW-D for boron, calcium, chloride, sulfate, and TDS.



Black dots are background data; red dots are detection data; blue dots are resampled data

Figure 5. Well-Constituent Results

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Black dots are background data; red dots are detection data; blue dots are resampled data

Figure 5 (Continued). Well-Constituent Results

2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

As a result of the updated statistical baseline analysis that better characterizes the historical data and trends at each well in the CCR monitoring program, MW-B and MW-C seem to have no consistent SSIs. MW-B and MW-D are not close to the new, double-lined CCR landfill subject to this regulation. MW-B is approximately 3,125 linear feet and MW-D is approximately 2,600 linear feet from the CCR regulated landfill. MW-C is even further north. MW-B is closer to the western boundary of the property than MW-D and the water level elevation in MW-B is consistently about 0.2- to 1.0-foot higher than the elevation in MW-D (Table 2 and Figure 4). Consequently, the high concentrations in MW-D do not appear to be coming from the west or northwest.

The rise in calcium, chloride, sulfate, and TDS concentrations measured in MW-D started in mid-2017, approximately 780 days from the initiation of storing CCR material in the active landfill. The calculated groundwater flow rate in the western part of the site is between 0.105 and 0.405 feet per day under the typical groundwater gradient measured on site. The groundwater travel time from the northern edge of active cell of the active landfill to any compliance monitoring well is expected to be greater than 17 years (CH2M 2021b). In accordance with the recommendations outlined in the alternative source demonstration conducted in 2021, additional field investigations to identify the source influencing water quality at MW-D have been initiated and field work has been completed but not all laboratory results have been received. The analysis of collected data will be completed and included in the 2023 Annual Groundwater Monitoring and Corrective Action Report.

Additional groundwater samples from the four CCR MWs have been collected since July 13, 2020 for a suite of major anions and cations for a geochemical analysis to identify if the groundwaters at the MWs are from different sources. These parameters for geochemical pattern analysis included: bicarbonate/carbonate (HCO_3/CO_3), chloride (Cl), sulfate (SO_4), calcium (Ca), magnesium (Mg), potassium (K), and sodium (Na).

Geochemical Pattern Analysis

During sampling events starting in July 2020, OUC has sampled the four CCR MWs for a suite of major ions for geochemical pattern analysis using the method described by Piper (1944). The results of the March 2022 sampling are presented in Table 5. The results from the September 2022 sampling are shown in Table 6. The low percent difference between the total cations and anions indicate that the basic geochemistry constituents are in balance at each MW and suitable to use for the pattern analysis.

Piper's graphical method plots the equivalent concentration results (milliequivalents per liter, meq/L) of the sampled common water ions over a diamond grid. Sample results that plot close to one another are geochemically similar indicating a possible common source; sample results that do not plot close to one another are geochemically dissimilar indicating different sources.

The equivalent ion concentrations were plotted (percent meq/L) and aligned to a geochemical facies pattern. The overlay of the OUC CCR results and the facies pattern are presented in Figures 6 through 9 for MW-A, MW-B, MW-C, and MW-D, respectively. The data were very similar between sampling events, except for MW-D. The results of the procedure show that the position of the MW-D groundwater (as indicated by the triangles in Figures 6 through 9) have slowly migrated toward similar cation and anion distributions as MW-A. The results indicate that groundwater at MW-D is similar to the groundwater at MW-A.

Table 5. March 22, 2022 Geochemical Sampling Results with Ion Balances

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Well	Anions			Cations			
	HCO ₃	SO ₄	Cl	Na	Ca	Mg	K
	Concentration (mg/L)						
MW-A	2.4	1,040.0	19,500.0	5,630.0	6,250.0	3.8	1,620.0
MW-B	2.4	34.3	16.7	12.0	4.0	2.4	11.2
MW-C	18.3	0.3	26.3	11.1	9.3	1.0	1.6
MW-D	2.4	270.0	3,570.0	874.0	1,380.0	25.1	146.0
Well	Concentration (mEq/L)						
MW-A	0.0	21.7	550.0	244.9	311.9	0.3	41.4
MW-B	0.0	0.7	0.5	0.5	0.2	0.2	0.3
MW-C	0.3	0.0	0.7	0.5	0.5	0.1	0.0
MW-D	0.0	5.6	100.7	38.0	68.9	2.1	3.7
Well	Concentration Percentage of mEq						
MW-A	0%	4%	96%	41%	52%	0%	7%
MW-B	3%	58%	38%	43%	17%	16%	24%
MW-C	29%	1%	71%	45%	43%	8%	4%
MW-D	0%	5%	95%	34%	61%	2%	3%
Well	Ion Balance						
Well	Sum Anion	Sum Cations	Ion Balance				
AW-A	571.7	598.5	2.3%				
MW-B	1.23	1.20	-0.9%				
MW-C	1.05	1.07	1.1%				
MW-D	106.36	112.68	2.9%				

Notes:

Bicarbonate (HCO₃), carbonate (CO₃), chloride (Cl), sulfate (SO₄), calcium (Ca), magnesium (Mg), potassium (K), and sodium (Na)

mg/L= milligram per liter; meq/L = milliequivalents per liter

Percentage meq is the percent of the sum of the four anions/cations listed

The ion balance was calculated (in meq/L) as the total dissolved-anions concentration minus the total dissolved-cation concentration divided by the total concentration of ions

Table 6. September 13, 2022 Geochemical Sampling Results with Ion Balances
2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

Well	Anions			Cations			
	HCO ₃	SO ₄	Cl	Na	Ca	Mg	K
	Concentration (mg/L)						
MW-A	1.2	1,160.0	19,600.0	5,330.0	5,790.0	3.5	1,560.0
MW-B	4.9	30.0	24.9	18.1	5.7	2.2	3.8
MW-C	18.3	0.7	26.8	10.2	10.1	0.9	1.0
MW-D	1.2	363.0	4,390.0	1,060.0	1,450.0	26.0	223.0
Well	Concentration (mEq/L)						
MW-A	0.0	24.2	552.8	231.8	288.9	0.3	39.9
MW-B	0.1	0.6	0.7	0.8	0.3	0.2	0.1
MW-C	0.3	0.0	0.8	0.4	0.5	0.1	0.0
MW-D	0.0	7.6	123.8	46.1	72.4	2.1	5.7
Well	Concentration Percentage of mEq						
MW-A	0%	4%	96%	41%	52%	0%	7%
MW-B	6%	44%	50%	58%	21%	14%	7%
MW-C	28%	1%	71%	42%	48%	7%	2%
MW-D	0%	6%	94%	37%	57%	2%	5%
Well	Ion Balance						
Well	Sum Anion	Sum Cations	Ion Balance				
AW-A	577.0	561.0	-1.4%				
MW-B	1.41	1.35	-2.1%				
MW-C	1.07	1.05	-1.1%				
MW-D	131.40	126.31	-2.0%				

Notes:

Bicarbonate (HCO₃), carbonate (CO₃), chloride (Cl), sulfate (SO₄), calcium (Ca), magnesium (Mg), potassium (K), and sodium (Na)

mg/L= milligram per liter; meq/L = milliequivalents per liter

Percentage meq is the percent of the sum of the four anions/cations listed

The ion balance was calculated (in meq/L) as the total dissolved-anions concentration minus the total dissolved-cation concentration divided by the total concentration of ions

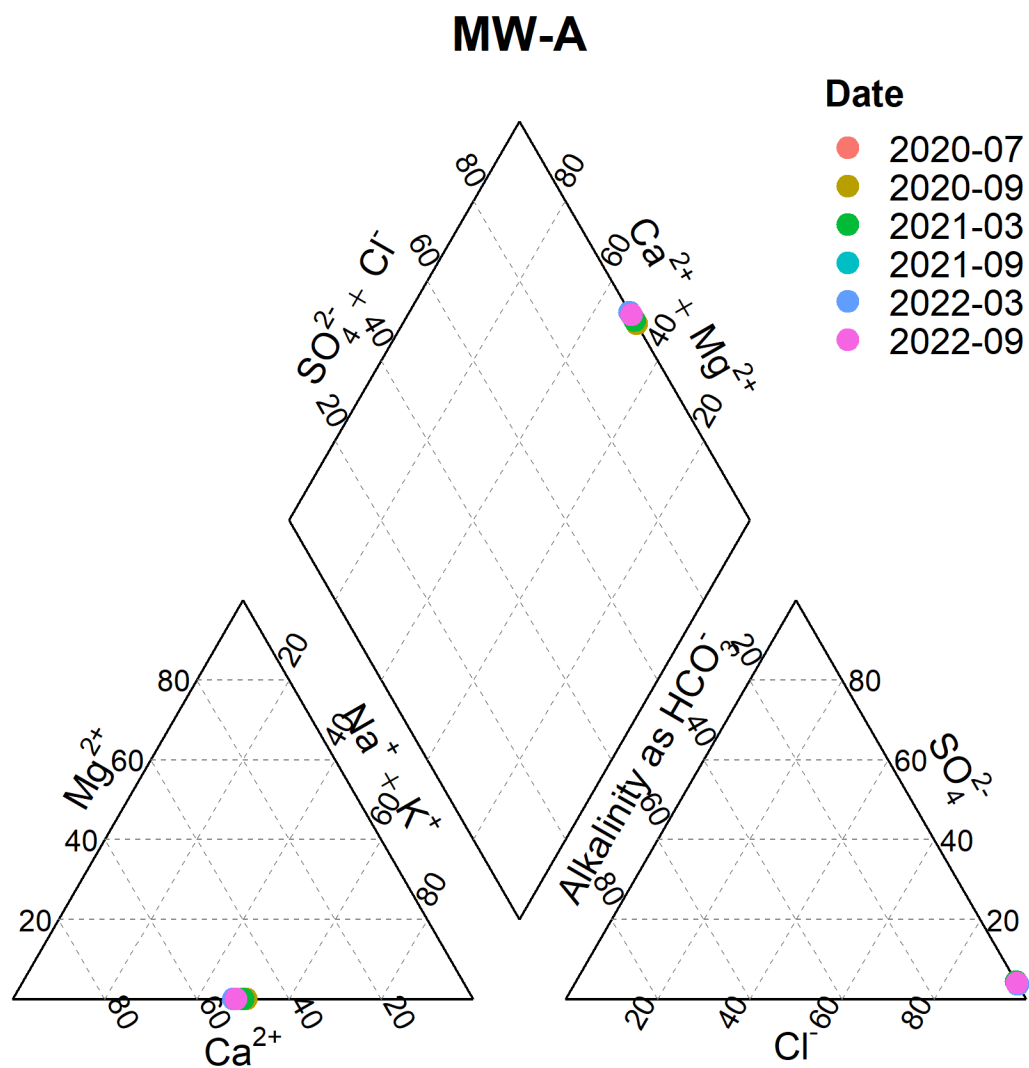
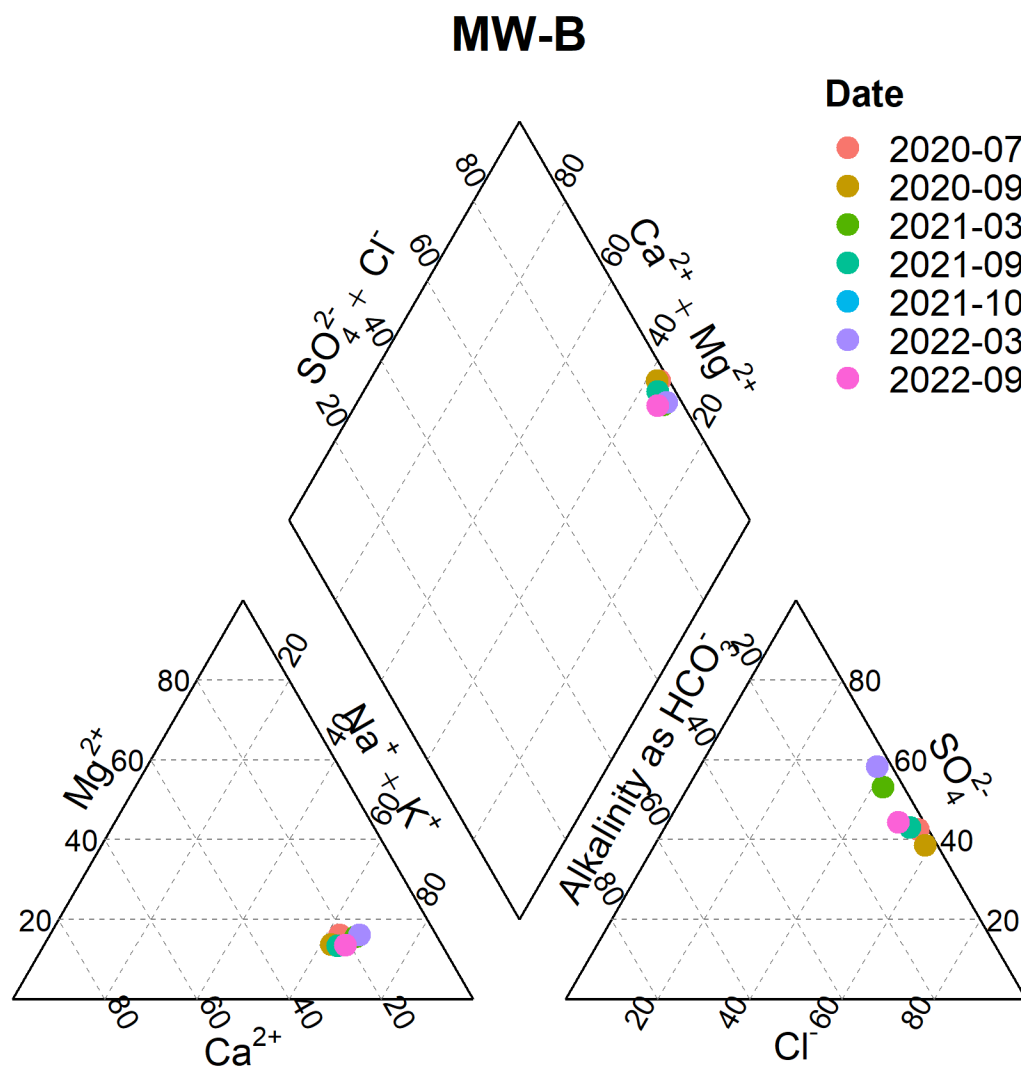
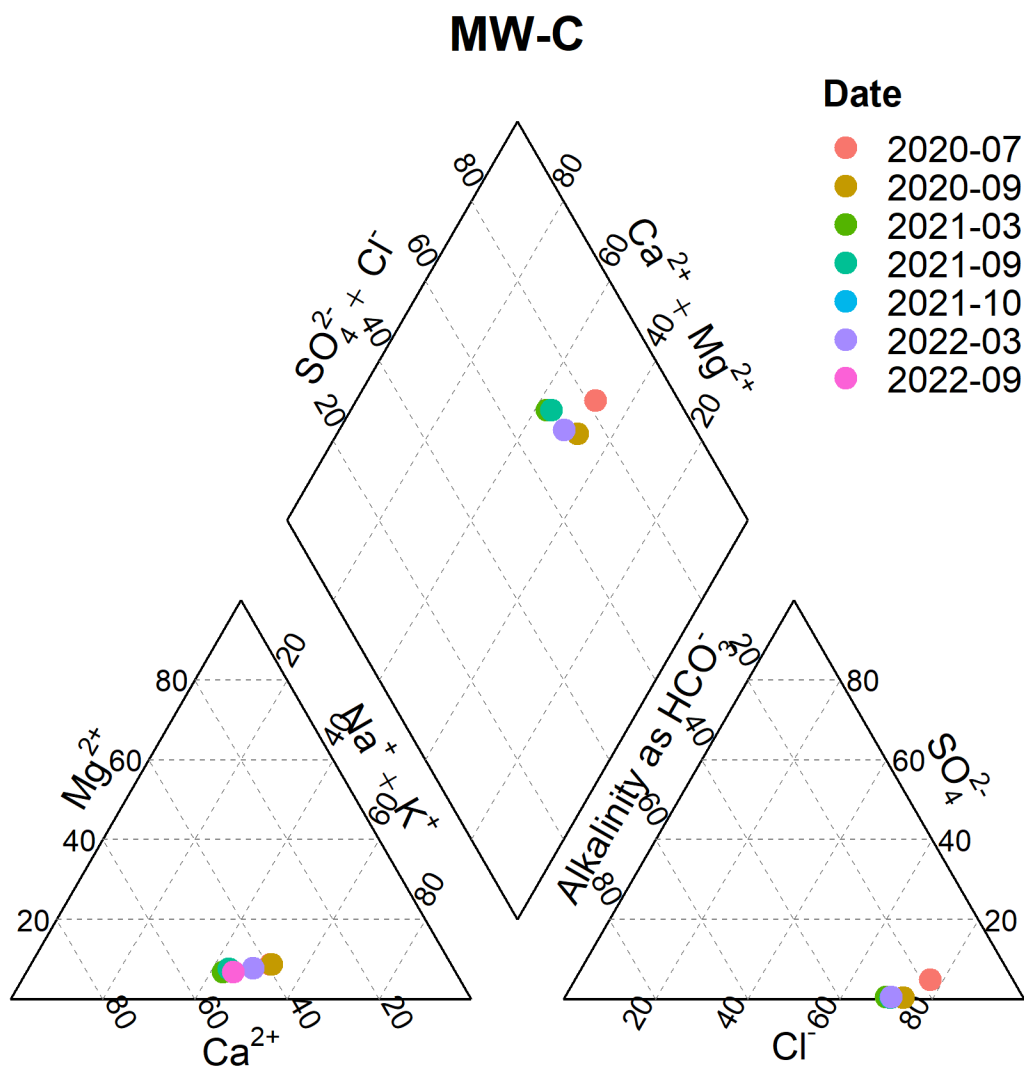


Figure 6. MW-A Results of Geochemical Facies Pattern and Analysis Results
 2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report



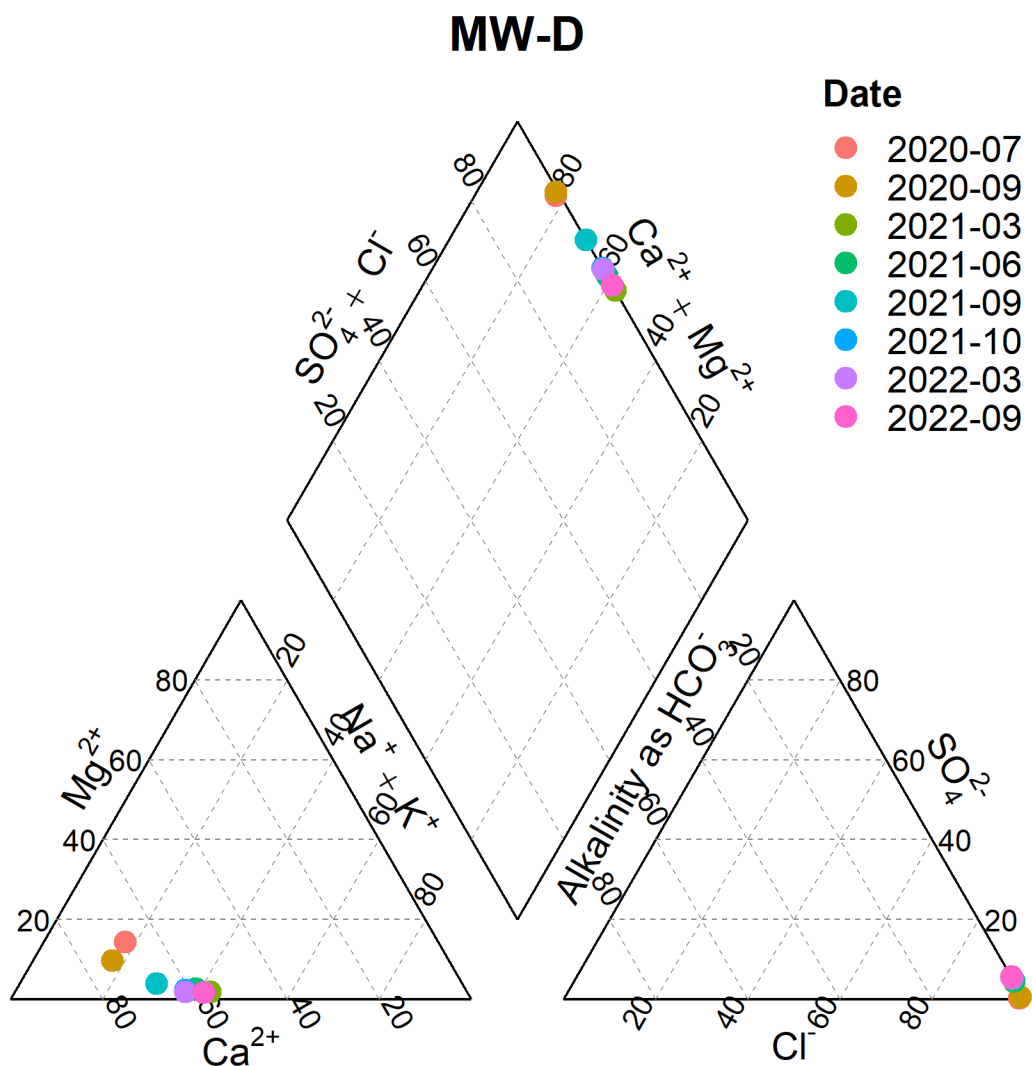
Note that data points overlap and may not be seen.

Figure 7. MW-B Results of Geochemical Facies Pattern and Analysis Results
 2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report



Note that data points overlap and may not be seen.

Figure 8. MW-C Results of Geochemical Facies Pattern and Analysis Results
 2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report



Note that data points overlap and may not be seen.

Figure 9. MW-D Results of Geochemical Facies Pattern and Analysis Results
 2022 Coal Combustion Residuals Annual Groundwater Monitoring and Corrective Action Report

General Site Conditions

The 2021 Annual Groundwater Monitoring and Corrective Action Report detailed the location and history of a nearby stockpile of material, including crushed limestone (also called limerock) and sand. This stockpile area was removed in 2022 and the area has been returned to normal ground.

During Hurricane Ian travel over Central Florida on September 28th and September 29th, approximately 13.1 inches of rain was recorded at the nearby Orlando International Airport rainfall station (NOAA Station Number USW00012815). Antecedent conditions indicate that approximately 7 inches of rainfall fell in the two weeks prior Hurricane Ian. During the hurricane, the northwest berm of Cell 2 was compromised, ultimately discharging water into the adjacent stormwater ditch. The berm was immediately repaired, and the FDEP was notified. This event and resolution will be further documented in the Annual Landfill Inspection Report.

Conclusion

The general purpose of the 2022 annual report is to document the results of the CCR detection monitoring conducted at OUC SEC. The results indicated that analyses of several parameter fell outside the expected statistical prediction limit based on the original background analysis of the CCR data. These SSIs are derived from a comparison of the results to a statistical analysis of a limited number of background readings.

The statistical baseline and trend analysis was repeated in 2022 (Appendix A) to update the original trend estimates that were made with the initial limited-sized dataset. The results of this analysis provided updated UPL and LPL (for pH) that characterize each well over a longer period (September 2015 to September 2021). As a result, the updated statistical baseline analysis better characterizes the historical data and trends at each well in the CCR monitoring program.

The updated baseline trend analysis resulted in revised thresholds for UPLs that have eliminated SSI categorization for previous sampling data for calcium, chloride, pH, and TDS in MW-B and MW-C. The same analysis has eliminated SSIs at MW-D for pH and fluoride. The statistical analysis with the revised baseline completed for the 2022 data identified SSIs at MW-D for boron, calcium, chloride, sulfate, and TDS.

If a potential SSI is verified using the detection monitoring program, the site assessment monitoring program must be initiated for all monitoring wells within 90 days and continue at semiannual frequency. Alternately, the owner of the facility must demonstrate that a source other than the CCR unit is responsible for the increase. The CCR landfill is relatively new (7 years old) and located away from downgradient CCR monitoring wells. Groundwater does not move very quickly along the low gradient landscape at OUC SEC. Additional site investigations were completed as part of an Alternative Source Analysis in 2021 (CH2M 2021b). This analysis focused on the hydrogeologic conditions on the western portion of the site between MW-D and the active landfill and found that groundwater travel time from the northern edge of the active landfill cell to MW-D is expected to be greater than 17 years. Results of this analysis indicated that the groundwater quality at MW-D cannot yet be influenced by the new CCR landfill and that an alternate source is responsible for the water quality at MW-D.

Based on the review of the data against projected trends and analysis of groundwater flow potential at the site, it is concluded that SSIs of constituents are not verified to be from the CCR and it is not appropriate to proceed to assessment monitoring. There is reasonable documentation that the high concentration of dissolved ions is from an alternative source and that continued Detection Monitoring is recommended with additional ionic groundwater data collection so groundwater conditions can continue to be reviewed.

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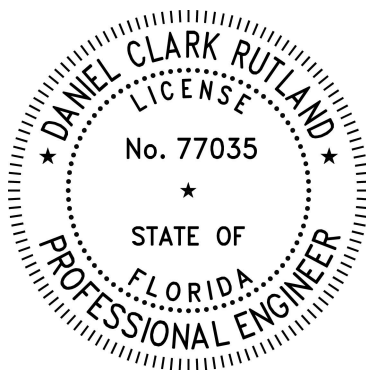
Appendix A
Update of Background Water Quality Concentrations for
the OUC SEC CCR Landfill Detection Monitoring Program

Update of Background Water Quality Concentrations for the Orlando Utilities Commission Stanton Energy Center CCR Landfill Detection Monitoring Program

PREPARED FOR: Orlando Utility Commission
PREPARED BY: CH2M HILL Engineers, Inc.
DATE: January 28, 2022
PROJECT NUMBER D3292400

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This report has been digitally sealed by Daniel C. Rutland, P.E. on the date adjacent to the seal.

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Objective

This technical memorandum (TM) documents the analysis to update the existing groundwater quality background limits used at the Orlando Utilities Commission (OUC) Stanton Energy Center (SEC) by incorporating the detection monitoring data collected since the last background water quality was established in 2017. The objective of this work is to develop appropriate statistical methods so that the future detection monitoring samples can be tested against limits that best represent the current background conditions.

Background

The Coal Combustion Residuals (CCR) Rule created three phases of groundwater monitoring that include: detection, assessment, and corrective action. The main objective of this report is to update background values for the detection monitoring phase. The detection monitoring phase assumes that groundwater is clean or not impacted under the CCR Rule. The main objective of detection monitoring is to determine if a statistically significant increase (SSI) greater than background concentrations for Appendix III constituents have been observed. Therefore, detection monitoring continues until an SSI above background is observed. An observed SSI must be large enough to account for the inherent uncertainty and variability in the data.

The detection monitoring consists of the seven constituents listed in Appendix III of the CCR Rule. Specifically, detection monitoring is performed for the following constituents:

- Boron
- Calcium
- Chloride
- Fluoride
- pH
- Sulfate
- Total Dissolved Solids (TDS)

The focus of background development and detection monitoring is limited to the selected detection monitoring constituents. Monitoring data for other constituents may be collected and reported, but they are not directly incorporated into the formal CCR Rule detection monitoring assessment. By limiting the statistically evaluated constituents to the most useful indicators, the overall number of statistical tests can be reduced to help meet the site-wide false-positive rate (SWFPR). Fewer tests also imply a lower single test false negative error rate, and therefore an improvement in statistical power.

The basic assumption in detection monitoring is that the facility is not impacting groundwater unless statistically demonstrated otherwise. Statistical comparisons are made between background and downgradient detection wells (interwell comparisons), or over time in a single well (intrawell comparisons), to identify significant changes in groundwater quality that may be caused by the facility.

The initial step in developing a detection monitoring program is establishing background concentrations for the required constituents. Appropriate and representative background data is the single most important factor to a successful statistical groundwater monitoring program (EPA 2009). Representative background data show numerical characteristics closely matching those arising from the site-specific aquifer being evaluated. Background data must also be appropriate to the statistical test. All detection monitoring tests involve comparisons of detection point data against the established background limits. A minimum of 8 to 10 independent background samples are generally required for most parametric statistical tests, but as many background data points as possible are preferable to provide adequate statistical power to control false-positive and false-negative errors. Unlike parametric statistical tests, the nonparametric statistical tests require a large sample size to meet the false-positive and false-negative requirements (EPA 2009).

Because of natural temporal changes in ambient groundwater quality and the need for sufficiently large sample sizes for statistical analysis, background data should not be regarded as a single fixed quantity. If natural groundwater conditions change over time during the collection of detection monitoring data, comparisons against previously established backgrounds may not be appropriate. EPA (2009) recommends that background should be updated periodically.

Review of the Existing Data

EPA (2009) recommends that all observations designated as background should be evaluated periodically (2 to 3 years for semi-annual sampling) to ensure that they still adequately reflect the current natural or baseline groundwater conditions to help establish appropriate and representative background limits. In general, the set of new observations is statistically compared to the existing background data, as appropriate. If the data are found to be comparable, then the new data set is combined with the existing background data set to re-establish the statistical background limits. If the data are shown to be significantly different, then

the data will be reviewed to evaluate the cause of the difference. Absence evidence of a release, the new data should be considered more representative of present-day groundwater conditions and used for background. Thus, to update the background limits, both the initial background data and the detection data were reviewed so that an updated background data set representing the current conditions can be established. The available data comprised of:

- The OUC SEC CCR groundwater monitoring network is comprised of 4-wells, one upgradient well MW-A, and three downgradient wells (MA-B, MW-C, and MW-D). The background data consists of the data collected from the three downgradient wells.
- 9 rounds of initial background data collected over approximately 2 years (September 2015 to July 2017) from three detection monitoring wells in the network per the CCR Rule requirements, and
- 9 rounds of detection monitoring data collected over approximately 4 years (Oct. 2017 to September 2021).

Table 1 presents the basic descriptive statistics of the available data set (Sept. 2015 to Oct. 2021) for all 4-wells of the OUC groundwater monitoring network.

Summary of Alternative Source Demonstrations

After identification of an exceedance during each detection monitoring event, additional statistical evaluations were conducted to prepare alternate source demonstrations. A brief summary of the most recent alternative source demonstrations is given below:

- During the CCR detection monitoring history a stockpile of crushed limestone (also called limerock) to support landfill operations was placed near MW-D. Over time the stockpile grew and the position of the northwest corner of the stockpile came within approximately 75 feet of MW-D. It was hypothesized that stormwater runoff from the pile could have impacted surficial groundwater quality at MW-D through direct infiltration and groundwater transport, or overland flow then infiltration and groundwater transport around the general area. An alternative source demonstration was completed and found that the limerock stockpile was a potential alternative source for SSIs at MW-D and MW-B (CH2M 2020).
- The stockpile was removed in January 2020 (CH2M 2021). The spike in TDS-related data occurred in 2020, so it is possible that there was a residual influence of the near-surface groundwater from the stockpile, or perhaps, the removal efforts mixed limerock into the surface soil causing the spike in calcium, chloride, and TDS concentrations. The concentrations of calcium and chloride dropped in September of 2020 nearly as precipitously as they increased but returned to high levels in March and September of 2021.
- Additional site investigations were completed as part of an Alternative Source Analysis in the 2021 monitoring year (CH2M 2021). As part of this alternate source demonstration, additional groundwater data were collected in September 2021 to evaluate hydrogeologic conditions in the surficial aquifer. This additional analysis was focused on the hydrogeologic conditions on the western portion of the site between MW-D and the active landfill. New groundwater percolation data were collected near the MWs. The results of this investigation found that groundwater travel time from the northern edge of active cell of the new landfill to either monitoring well is expected to be greater than 17 years. Because the CCR active landfill cell is relatively new (6 years old) and located

Table 1: Summary Statistics (Before removal of Outliers)*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	Units	Total Samples	Detect Results	Nondetect Results	Detect Frequency (%)	Minimum Nondetect	Maximum Nondetect	KM Mean	KM Standard Deviation	KM CV	Minimum Detect	Maximum Detect	Mean Detect	Median Detect	Standard Deviation Detect	CV Detect
MW-A	Boron	mg/L	18	12	6	67	0.4	0.4	0.272	0.245	0.9	0.0575	1.01	0.32	0.352	0.283	0.885
MW-A	Calcium	mg/L	19	19	0	100	---	---	3787	977.9	0.258	2220	5580	3787	3830	977.9	0.258
MW-A	Chloride	mg/L	19	19	0	100	---	---	14670	2622	0.179	9730	18400	14670	14700	2622	0.179
MW-A	Fluoride	mg/L	18	1	17	6	0.1	100	1.182	3.421	2.895	12	12	12	12	---	---
MW-A	pH	SU	19	19	0	100	---	---	4.061	0.19	0.0467	3.81	4.52	4.061	4.01	0.19	0.0467
MW-A	Sulfate	mg/L	19	19	0	100	---	---	1119	214.2	0.192	674	1550	1119	1130	214.2	0.192
MW-A	TDS	mg/L	18	18	0	100	---	---	29517	8014	0.272	17100	45600	29517	28750	8014	0.272
MW-B	Boron	mg/L	18	18	0	100	---	---	0.078	0.0381	0.489	0.0133	0.147	0.078	0.0819	0.0381	0.489
MW-B	Calcium	mg/L	23	23	0	100	---	---	8.058	6.689	0.83	0.879	21.9	8.058	6.95	6.689	0.83
MW-B	Chloride	mg/L	23	23	0	100	---	---	41.96	25.96	0.619	13	97.7	41.96	33.7	25.96	0.619
MW-B	Fluoride	mg/L	18	9	9	50	0.1	1	0.113	0.0492	0.434	0.06	0.23	0.137	0.14	0.0541	0.396
MW-B	pH	SU	22	22	0	100	---	---	4.507	0.264	0.0586	4.22	5.47	4.507	4.415	0.264	0.0586
MW-B	Sulfate	mg/L	19	19	0	100	---	---	47.65	8.98	0.188	32.2	60.4	47.65	49.8	8.98	0.188
MW-B	TDS	mg/L	22	22	0	100	---	---	163.1	49.03	0.301	99	250	163.1	151	49.03	0.301
MW-C	Boron	mg/L	18	9	9	50	0.02	0.02	0.0144	0.00519	0.362	0.01	0.0324	0.0159	0.0133	0.00704	0.443
MW-C	Calcium	mg/L	22	22	0	100	---	---	7.802	1.671	0.214	5.09	11.2	7.802	7.48	1.671	0.214
MW-C	Chloride	mg/L	19	19	0	100	---	---	17.11	7.149	0.418	6.82	27.3	17.11	16.2	7.149	0.418
MW-C	Fluoride	mg/L	19	7	12	37	0.1	0.1	0.0821	0.0128	0.156	0.07	0.11	0.0943	0.1	0.014	0.148
MW-C	pH	SU	22	22	0	100	---	---	5.177	0.198	0.0383	4.93	5.71	5.177	5.155	0.198	0.0383
MW-C	Sulfate	mg/L	20	18	2	90	0.22	0.25	0.911	0.756	0.83	0.18	2.38	0.99	0.56	0.778	0.786
MW-C	TDS	mg/L	21	21	0	100	---	---	74.05	21.8	0.294	35	107	74.05	73	21.8	0.294
MW-D	Boron	mg/L	18	12	6	67	0.02	0.02	0.0187	0.0062	0.331	0.0123	0.0341	0.0203	0.0178	0.00724	0.357
MW-D	Calcium	mg/L	25	25	0	100	---	---	181	323.6	1.788	1.79	1040	181	7.93	323.6	1.788
MW-D	Chloride	mg/L	25	25	0	100	---	---	532.3	935.6	1.758	6.74	2760	532.3	29.2	935.6	1.758
MW-D	Fluoride	mg/L	22	9	13	41	0.02	0.1	0.113	0.123	1.089	0.04	0.44	0.22	0.2	0.138	0.627
MW-D	pH	SU	22	22	0	100	---	---	4.633	0.404	0.0871	4.05	5.54	4.633	4.565	0.404	0.0871
MW-D	Sulfate	mg/L	23	12	11	52	0.25	0.65	31.01	64.31	2.074	0.3	218	59.2	8.61	82.67	1.396
MW-D	TDS	mg/L	23	23	0	100	---	---	1558	2610	1.675	36	7320	1558	110	2610	1.675

Notes:

KM Mean = Corrected mean value using the Kaplan-Meier mehod

KM Standard Deviation = Corrected standard deviation value using the Kaplan-Meier mehod

% = percent

mg/L = milligrams per liter

SU = standard units

Update of Background Water Quality Concentrations for the Orlando Utilities Commission Stanton Energy Center CCR Landfill Detection Monitoring Program

far away from the compliance MWs, it is highly unlikely that the groundwater at MW-B, MW-C, and MW-D is from the active cell of the CCR landfill. Therefore, continued Detection Monitoring was recommended.

The above findings support the recommendation to periodically review the background concentration values using the background and detection data sets to see if they can be combined, creating a larger background sample size. To update the background limits, the initial background data, and the newly collected data (that is, the detection monitoring data) were combined to provide better statistical power to control false positive and false negative error rates.

Managing Duplicate Data

Duplicate groundwater samples have been collected from the CCR monitoring wells at the SEC for quality assurance and quality control (QA/QC) purposes. For statistical analysis of parameters with duplicate sample results, only the parent sample was used for statistical comparisons, assuming that review of all QA/QC data indicated that the original parent sample result was valid.

Data Qualifiers

Estimated concentrations (constituent concentrations denoted with the "J" qualifier) for the background groundwater monitoring data were treated as qualified detected concentrations for statistical analysis. No rejected data through analytical data validation were identified in the data set; therefore, no data were rejected from the data set that was used for statistical evaluation.

Statistical Evaluation

A stepwise approach was used for evaluating the OUC Landfill background groundwater monitoring data to determine its suitability for statistical analysis. These steps include data compilation, exploratory analysis and descriptive statistics, statistical outlier detection, evaluation of data independence and stationarity, and testing for parametric behavior. Unless stated differently, statistical tests conducted during the exploratory data evaluation stage were performed using a significance level of 5 percent (0.05). If the calculated probability from a test is below this significance level, a conclusion is drawn to reject the null hypothesis and instead determine that a significant test result exists. A significance level of 5 percent is often used to provide strong evidence against the null hypothesis. Using this significance level, there is a probability that 5 percent of the cases would be significant simply from random variability (false positives).

It is important to make sure that the data set used to determine background levels is representative of the site-specific anthropogenic background data set. Thus, before conducting statistical analysis for establishing background levels, it is desirable to determine if the background data set that represents a "single" population and possibly without any outliers.

Testing for Outliers According to the Unified Guidance

Statistical outliers are observations considered not from the same population set as the rest of the samples and violate the basic statistical assumption of identically and independently distributed measurements. The Unified Guidance (EPA 2009) recommends that testing for outliers be performed on background data, but that data generally should not be removed

unless some basis for a likely error or discrepancy is identified. As management of potential outliers carries both positive and negative risks, the Guidance suggests that these risks should be carefully understood while deciding removal of potential outliers. If a potential outlier is not removed from background prior to statistical testing, it may substantially raise the magnitude of both parametric and nonparametric background limit values. A subsequent compliance well test against this background limit will be much less likely to identify an exceedance, lowering the statistical power of the method and the overall quality of the statistical monitoring program. According to the Unified Guidance (USEPA 2009) and ProUCL Technical Guide (USEPA 2015), the presence of outliers distorts most statistics of interest [e.g., mean, standard deviation, upper confidence limits (UCLs), upper prediction limits (UPLs), and upper tolerance limits (UTLs)]. Because of these concerns, it may be advisable at times to remove high-magnitude outliers in background even if the reasons for these apparently extreme observations are not known (USEPA 2009). The overall impact of outlier removal will tend to improve the power of background limits, and thus result in a more environmentally protective program. While estimating the background limits, it is implicitly assumed that the background data set represents a single statistical population. Therefore, it is desirable to compute decision statistics based upon data sets representing the main population and not to compute distorted statistics by accommodating a few outlier results that have a low probability of representing natural variation (USEPA 2015).

Thus, prior to the calculation of background, the groundwater monitoring data were visually inspected for potential outliers using graphical presentations of the entire potential background data set, as previously described. Statistical outliers also were evaluated using Dixon's outlier test (1953). Dixon's test is valid for data sets with up to 25 observations and is recommended by EPA (2009) for outlier identification. The probability values (p-values) provided for Dixon's test were compared with a significance level of 0.05 (the most common significance level in most statistical works, including environmental statistics [EPA 2009]). A calculated probability lower than the significance level of 0.05 is defined as "statistically significant." Conversely, a calculated probability higher than or equal to the significance level of 0.05 is defined as "statistically insignificant."

Dixon's outlier test assumes that the data values (aside from those being tested as potential outliers) are normally distributed. Because environmental data tend to be right skewed, a test that relies on an assumption of a normal distribution may identify a relatively large number of statistical outliers. Thus, statistical outliers were further evaluated by applying a logarithmic transformation of the data to improve adherence to normality (EPA 2009). For data sets that do not comply with the normality assumption, interquartile range (IQR) and median absolute deviation (MAD) scores (Wilcox 2010) were calculated and used to assist in outlier identification. The EPA (2009) defines any observation that falls from 1.5 times to 3 times the IQR above the 3rd quartile or below the 1st quartile as a "mild" outlier and any value more than 3 times the IQR above the 3rd quartile or below the 1st quartile as an "extreme" outlier.

Attachment 1 presents scatter plots of the raw data by plotting observation numbers versus the observation values along with IQR and MAD score lines for each well-analyte pair. Based on the IQR and MAD scores, the identified outliers for various well-analyte data sets are also shown on these scatter plots. These preliminary identified outliers were candidates for further analyses using the parametric outlier tests. Table 2 presents results of outlier analyses showing p-values of the Dixon's test conducted using raw and log-transformed data along with the IQR and MAD scores for all well-analyte pairs. As the Dixon's test identify only a single outlier at a time, this

Table 2: Outlier Identification (Raw Data)*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	Sample Date	Result	Next Closest Value	Units	RPD	IQR Score	MAD Score	Dixon's Test P-Value	LogDixon's Test P-Value	Data normally distributed after removal of outlier(s)?
Statistical High Outliers											
MW-B	Boron	3/7/2021	0.147	0.134	mg/L	8.84	0.87	2.08	0.35	0.22	Yes
MW-B	Calcium	10/12/2015	21.9	21.1	mg/L	3.65	0.86	1.92	0.46	0.95	No
MW-B	Chloride	10/12/2015	97.7	97.1	mg/L	0.61	0.82	2.94	0.20	0.60	No
MW-B	Fluoride	4/27/2016	0.5	0.23	mg/L	54.00	3.37	6.07	0.00	0.25	No
MW-B	pH	3/25/2020	5.47	4.85	SU	11.33	3.92	11.86	0.00	0.00	Yes
MW-B	Sulfate	10/30/2017	60.4	59	mg/L	2.32	0.41	1.30	0.70	0.71	Yes
MW-B	TDS	9/9/2015	250	242	mg/L	3.20	0.48	2.02	0.90	0.94	No
MW-C	Boron	11/29/2016	0.0324	0.0205	mg/L	36.73	6.28	Inf	0.00	0.01	No
MW-C	Calcium	10/26/2021	11.2	11.1	mg/L	0.89	1.73	3.14	0.64	0.55	Yes
MW-C	Chloride	7/13/2020	27.3	26	mg/L	4.76	0.27	1.15	0.98	0.98	Yes
MW-C	Fluoride	9/14/2020	0.11	0.1	mg/L	9.09	0.50	Inf	0.70	0.66	No
MW-C	pH	3/25/2020	5.71	5.47	SU	4.20	1.66	2.77	0.08	0.11	Yes
MW-C	Sulfate	3/28/2019	2.38	2.36	mg/L	0.84	0.76	3.66	0.62	0.67	No
MW-C	TDS	3/7/2021	107	102	mg/L	4.67	0.26	1.09	0.74	0.84	Yes
MW-D	Boron	11/29/2016	0.0341	0.031	mg/L	9.09	1.50	2.44	0.66	0.85	No
MW-D	Calcium	10/26/2021	1040	776	mg/L	25.38	5.64	119.81	0.32	0.95	No
MW-D	Chloride	10/26/2021	2760	2420	mg/L	12.32	6.31	82.15	0.63	0.98	No
MW-D	Fluoride	3/7/2021	0.44	0.37	mg/L	15.91	2.63	Inf	0.18	0.03	No
MW-D	pH	9/9/2015	5.54	5.4	SU	2.53	2.73	4.24	0.66	0.71	Yes
MW-D	Sulfate	10/26/2021	218	154	mg/L	29.36	24.68	734.10	0.24	0.95	No
MW-D	TDS	10/26/2021	7320	6960	mg/L	4.92	4.62	68.49	0.78	1.00	No
Statistical Low Outliers											
MW-B	Boron	10/12/2015	0.0133	0.0261	mg/L	96.24	0.53	2.19	0.76	0.72	Yes
MW-B	Calcium	3/22/2018	0.879	1.01	mg/L	14.90	0.12	0.78	1.00	0.90	No
MW-B	Chloride	6/28/2021	13	16.6	mg/L	27.69	0.19	0.95	0.90	0.61	No
MW-B	Fluoride	1/18/2017	0.05	0.06	mg/L	20.00	0.02	0.67	1.00	1.00	No
MW-B	pH	10/12/2015	4.22	4.3	SU	1.90	0.63	2.19	0.61	0.58	No
MW-B	Sulfate	9/14/2021	32.2	34.3	mg/L	6.52	0.47	2.16	0.70	0.64	Yes
MW-B	TDS	6/28/2021	99	106	mg/L	7.07	0.28	1.06	0.88	0.76	No
MW-C	Boron	1/18/2017	0.01	0.011	mg/L	10.00	0.00	NA	1.00	1.00	No
MW-C	Calcium	7/20/2017	5.09	5.74	mg/L	12.77	1.04	2.02	0.71	0.76	Yes
MW-C	Chloride	10/12/2015	6.82	7.12	mg/L	4.40	0.30	0.97	0.93	0.71	Yes
MW-C	Fluoride	9/9/2015	0.05	0.07	mg/L	40.00	0.00	NA	1.00	1.00	Yes
MW-C	pH	3/28/2019	4.93	4.95	SU	0.41	0.34	1.12	0.97	0.96	Yes
MW-C	Sulfate	9/14/2020	0.11	0.125	mg/L	13.64	0.16	0.84	0.98	0.93	No
MW-C	TDS	10/12/2015	35	50	mg/L	42.86	0.45	1.22	0.41	0.14	No
MW-D	Boron	1/18/2017	0.01	0.0123	mg/L	23.00	0.00	0.77	1.00	1.00	No
MW-D	Calcium	3/22/2018	1.79	1.81	mg/L	1.12	0.01	0.71	1.00	0.98	No
MW-D	Chloride	9/9/2015	6.74	6.78	mg/L	0.59	0.01	0.68	1.00	1.00	No
MW-D	Fluoride	10/26/2021	0.01	0.04	mg/L	300.00	0.37	Inf	0.75	0.67	No
MW-D	pH	5/29/2020	4.05	4.15	SU	2.47	1.20	2.24	0.79	0.75	No
MW-D	Sulfate	9/9/2015	0.125	0.13	mg/L	4.00	0.00	0.67	1.00	1.00	No
MW-D	TDS	4/4/2017	36	37	mg/L	2.78	0.01	0.70	1.00	1.00	No

Notes:

mg/L = milligram per liter

IQR = interquartile range

MAD = median absolute deviation

mg/L = milligrams per liter

P-Value = probability of rejecting the null hypothesis when it is true

RPD = relative percent difference

SU = standard units

^(a) Detected concentration consistent with other results and within the expected range of variability.

Table 3: Outliers Removed*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	Sample Date	Result	Units	Outlier Removed
MW-B	Fluoride	4/27/2016	1	mg/L	Yes
MW-B	Fluoride	11/29/2016	1	mg/L	Yes
MW-B	pH	3/25/2020	5.47	SU	Yes
MW-C	Boron	11/29/2016	0.0324	mg/L	Yes
MW-D	Calcium	3/25/2020	168	mg/L	Yes
MW-D	Calcium	5/29/2020	661	mg/L	Yes
MW-D	Calcium	9/14/2020	159	mg/L	Yes
MW-D	Calcium	3/7/2021	776	mg/L	Yes
MW-D	Calcium	6/28/2021	742	mg/L	Yes
MW-D	Calcium	9/14/2021	775	mg/L	Yes
MW-D	Calcium	10/26/2021	1040	mg/L	Yes
MW-D	Chloride	3/25/2020	556	mg/L	Yes
MW-D	Chloride	5/29/2020	2240	mg/L	Yes
MW-D	Chloride	9/14/2020	387	mg/L	Yes
MW-D	Chloride	3/7/2021	2420	mg/L	Yes
MW-D	Chloride	6/28/2021	2320	mg/L	Yes
MW-D	Chloride	9/14/2021	1920	mg/L	Yes
MW-D	Chloride	10/26/2021	2760	mg/L	Yes
MW-D	Sulfate	3/7/2021	153	mg/L	Yes
MW-D	Sulfate	6/28/2021	154	mg/L	Yes
MW-D	Sulfate	9/14/2021	149	mg/L	Yes
MW-D	Sulfate	10/26/2021	218	mg/L	Yes
MW-D	TDS	3/25/2020	1590	mg/L	Yes
MW-D	TDS	5/29/2020	4710	mg/L	Yes
MW-D	TDS	9/14/2020	1090	mg/L	Yes
MW-D	TDS	3/7/2021	6450	mg/L	Yes
MW-D	TDS	6/28/2021	6960	mg/L	Yes
MW-D	TDS	9/14/2021	5980	mg/L	Yes
MW-D	TDS	10/26/2021	7320	mg/L	Yes

Notes:

mg/L = milligrams per liter

SU = standard units

test is repeated for datasets obtained after removing the confirmed outliers until the test results are negative (i.e., Dixon's test the $p\text{-value} \geq 0.05$).

A list of statistical outliers identified at the 5 percent significance level is provided in Table 3. Dixon's test was performed for all constituent/well combinations having their detection frequency greater than or equal to 50 percent. Based on outlier analysis, a total of 29 outliers (2 observations of fluoride and 1-observation of pH at MW-B, 1-observation of boron at MW-C, and 7-observations of calcium, chloride, and TDS each, and 4-observations of sulfate at MW-D) were confirmed as outliers and removed from the dataset before conducting further statistical analyses.

Summary Statistics and Graphical Presentation of the OUC Landfill Established Background Data

The dataset obtained after removing the confirmed statistical outliers is the established updated background data set. Summary statistics for the Appendix III constituents after removing 29 outliers are provided in Table 4. This table includes the total number of samples, frequency of detection, and the minimum and maximum concentrations for detected observations. Graphical presentations of the Appendix III constituents are generated using various statistical plotting methods to provide added insight (e.g., existence of extreme observations, data distributions and patterns, mixture populations, and visual comparison of two or more groups) into data sets that are not possible to visualize and understand by reviewing descriptive and test statistics and tabulated data. Graphical representation of the analysis is provided in attachments to this report, as referenced in the discussion below.

Statistical plotting methods include box-and-whisker plots, histograms, and probability plots as shown in Attachments 2 and 3. Box-and-whisker plots show the central tendency, degree of symmetry, range of variation, and potential outliers of a data set. The upper value of the box represents the 75th percentile for the data and the lower value of the box is the 25th percentile for the data. Thus, 50 percent of the data fall within the box. The top of the whisker represents the 75th percentile plus 1.5 times the interquartile range (IQR), where the IQR is the 75th percentile minus the 25th percentile. The bottom of the whisker is the 25th percentile minus 1.5 times the IQR. Any value outside of this range is considered a potential statistical outlier, which is represented by a dot on the plot.

The outlying concentrations of box-and-whisker plots only serve the definition of falling relatively far from the middle 50 percent of the data. If the data are drawn from a highly skewed distribution, or a symmetrical one with long tails, multiple observations of this type are expected. Although it is common vernacular to refer to these observations as outliers, they should not be confused with the outlier definitions described earlier in this report as part of the outlier evaluation discussion.

Normal probability plots show the ordered sample results versus the corresponding quantiles of a theoretical data distribution, such as the normal distribution, and is described as a quantile–quantile, or Q–Q, plot (e.g., normal Q–Q plot). Since quantiles are associated with cumulative probabilities, Q–Q plots are also referred to as probability plots. A normal probability plot is used to evaluate the normality of the distribution of a variable (i.e., whether, and to what extent, the distribution of the variable follows the normal distribution). If the data are not normally distributed, they will deviate systematically from a straight line. Variability in the data will cause the data to scatter randomly around the normality line, but the data will still appear to follow a single straight line. Outliers may also be evident in this plot. In addition to these plots, separate Q–Q plots showing the Shapiro-Wilk and Lilliefors normality test results are included in Attachment 3.

A histogram is a visual representation of the data collected into groups. The data range is divided into several bins, or classes, and the data is sorted into the bins. A histogram is a bar graph conveying the bins and the frequency of data points in each bin. Histograms provide a visual method of accessing location, shape, and spread of the data; the shape of a histogram helps determine whether the distribution is symmetric or skewed. The visual impression of a histogram is sensitive to the number of bins selected. A large number of bins will increase data detail, while fewer bins will increase the smoothness of the histogram.

Table 4: Summary Statistics (After removal of Outliers)*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	Units	Total Samples	Detect Results	Nondetect Results	Detect Frequency (%)	Minimum Nondetect	Maximum Nondetect	KM Mean	KM Standard Deviation	KM CV	Minimum Detect	Maximum Detect	Mean Detect	Median Detect	Standard Deviation Detect	CV Detect
MW-B	Boron	mg/L	18	18	0	100	---	---	0.078	0.0381	0.489	0.0133	0.147	0.078	0.0819	0.0381	0.489
MW-B	Calcium	mg/L	23	23	0	100	---	---	8.058	6.689	0.83	0.879	21.9	8.058	6.95	6.689	0.83
MW-B	Chloride	mg/L	23	23	0	100	---	---	41.96	25.96	0.619	13	97.7	41.96	33.7	25.96	0.619
MW-B	Fluoride	mg/L	16	9	7	56.25	0.1	0.2	0.113	0.0492	0.434	0.06	0.23	0.137	0.14	0.0541	0.396
MW-B	pH	SU	21	21	0	100	---	---	4.461	0.157	0.0351	4.22	4.85	4.461	4.41	0.157	0.0351
MW-B	Sulfate	mg/L	19	19	0	100	---	---	47.65	8.98	0.188	32.2	60.4	47.65	49.8	8.98	0.188
MW-B	TDS	mg/L	22	22	0	100	---	---	163.1	49.03	0.301	99	250	163.1	151	49.03	0.301
MW-C	Boron	mg/L	17	8	9	47.06	0.02	0.02	0.0133	0.00288	0.217	0.01	0.0205	0.0138	0.0129	0.00356	0.258
MW-C	Calcium	mg/L	22	22	0	100	---	---	7.802	1.671	0.214	5.09	11.2	7.802	7.48	1.671	0.214
MW-C	Chloride	mg/L	19	19	0	100	---	---	17.11	7.149	0.418	6.82	27.3	17.11	16.2	7.149	0.418
MW-C	Fluoride	mg/L	19	7	12	36.84	0.1	0.1	0.0821	0.0128	0.156	0.07	0.11	0.0943	0.1	0.014	0.148
MW-C	pH	SU	22	22	0	100	---	---	5.177	0.198	0.0383	4.93	5.71	5.177	5.155	0.198	0.0383
MW-C	Sulfate	mg/L	20	18	2	90	0.22	0.25	0.911	0.756	0.83	0.18	2.38	0.99	0.56	0.778	0.786
MW-C	TDS	mg/L	21	21	0	100	---	---	74.05	21.8	0.294	35	107	74.05	73	21.8	0.294
MW-D	Boron	mg/L	18	12	6	66.67	0.02	0.02	0.0187	0.0062	0.331	0.0123	0.0341	0.0203	0.0178	0.00724	0.357
MW-D	Calcium	mg/L	18	18	0	100	---	---	11.32	16.83	1.488	1.79	56.8	11.32	3.64	16.83	1.488
MW-D	Chloride	mg/L	18	18	0	100	---	---	39.18	51.87	1.324	6.74	185	39.18	13.2	51.87	1.324
MW-D	Fluoride	mg/L	22	9	13	40.91	0.02	0.1	0.113	0.123	1.089	0.04	0.44	0.22	0.2	0.138	0.627
MW-D	pH	SU	22	22	0	100	---	---	4.633	0.404	0.0871	4.05	5.54	4.633	4.565	0.404	0.0871
MW-D	Sulfate	mg/L	19	8	11	42.11	0.25	0.65	2.064	4	1.938	0.3	13.5	4.556	2.21	5.582	1.225
MW-D	TDS	mg/L	16	16	0	100	---	---	108.6	123.8	1.14	36	476	108.6	58	123.8	1.14

Notes:

KM Mean = Corrected mean value using the Kaplan-Meier method

KM Standard Deviation = Corrected standard deviation value using the Kaplan-Meier method

% = percent

mg/L = milligrams per liter

SU = standard units

Spatial Variability

Spatial variability refers to statistically identifiable differences in mean and variance levels across the well network. In the absence of any spatial variation, it is expected that each constituent in the monitoring well network should have approximately the same population mean and variance.

A nonparametric analysis of variance (ANOVA) method, the Kruskal-Wallis test, was applied to the data to test for spatial variability. This test considers the locations of monitoring wells as the relevant statistical factor. While the parametric ANOVA method is a statistical procedure used to determine whether there are statistically significant differences in mean concentrations among wells, the Kruskal-Wallis method tests for differences among average population ranks equivalent to the medians. Under the null hypothesis of no difference in concentrations among wells, the observations are assumed to arise from identical distributions with equal population variances. When the calculated probability (p-value) is greater than or equal to the common significance level of 0.05, the null hypothesis of no significant difference between wells is assumed. When the probability is below 0.05, a significant difference between the central tendency of at least one of the wells and the other multiple-well groups is suggested. The Levene test was conducted to test the underlying assumption for equality of variance for the validity of the Kruskal Wallis results. When the assumption for equality of variance was not met the Welch-F Test was used as an alternative test to the Kruskal-Wallis test.

Table 5 presents result of the spatial variability analysis obtained using the Kruskal-Wallis test. The results indicate that the background groundwater monitoring constituents exhibit significant spatial variation. This is shown graphically in the overlapping time series and box plots included in Attachment 4.

Temporal Variability

A stationary statistical distribution is one whose population characteristics do not change over time or space. A nonstationary distribution infers that either the mean, variance, or both are changing over time in any given well. Temporal variability exists when the distribution of measurements varies with the times at which sampling or analytical measurement occurs. The EPA (2009) distinguishes temporal variations from trends or seasonal effects by the lack of a regular or identifiable pattern.

The Kruskal-Wallis test was applied to the data to test for temporal variability for each well-analyte pair considering the sampling events as the relevant statistical factor. Table 6 presents the results of the temporal variability analysis using the Kruskal-Wallis test. The obtained results indicate that the background groundwater monitoring constituents do not exhibit significant temporal variation.

Table 5: Results of Spatial Variability Analysis*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Parameter	Levene P-Value	KW P-Value	WF P-Value	Conclusion
After Outliers are removed (All Wells)				
Boron	0.00	0.00	0.00	Significant
Calcium	0.00	0.00	0.00	Significant
Chloride	0.00	0.00	0.00	Significant
Fluoride	0.00	0.00	0.00	Significant
pH	0.00	0.00	0.00	Significant
Sulfate	0.00	0.00	0.00	Significant
TDS	0.00	0.00	0.00	Significant
After Outliers are removed (DG Wells)				
Boron	0.00	0.00	0.00	Significant
Calcium	0.00	0.23	0.68	Insignificant
Chloride	0.00	0.00	0.00	Significant
Fluoride	0.00	0.16	0.02	Significant
pH	0.00	0.00	0.00	Significant
Sulfate	0.00	0.00	0.00	Significant
TDS	0.00	0.00	0.00	Significant

Notes:

KW = Kruskal-Wallis Test

Levene = Levene Test for testing variance

NDs = nondetects

WF = Welch-F Test

P-Value = probability of rejecting the null hypothesis when it is true

Table 6: Results of Temporal Variability Analysis*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	KW P-Value	Conclusion
MW-B	Boron	0.22	Insignificant
MW-B	Calcium	0.15	Insignificant
MW-B	Chloride	0.13	Insignificant
MW-B	Fluoride	0.36	Insignificant
MW-B	pH	0.48	Insignificant
MW-B	Sulfate	0.12	Insignificant
MW-B	TDS	0.19	Insignificant
MW-C	Boron	0.94	Insignificant
MW-C	Calcium	0.37	Insignificant
MW-C	Chloride	0.54	Insignificant
MW-C	Fluoride	0.34	Insignificant
MW-C	pH	0.78	Insignificant
MW-C	Sulfate	0.38	Insignificant
MW-C	TDS	0.24	Insignificant
MW-D	Boron	0.57	Insignificant
MW-D	Calcium	0.34	Insignificant
MW-D	Chloride	0.54	Insignificant
MW-D	Fluoride	0.30	Insignificant
MW-D	pH	0.49	Insignificant
MW-D	Sulfate	0.43	Insignificant
MW-D	TDS	0.35	Insignificant

Notes:

KW = Kruskal-Wallis Test

NDs = nondetects

P-Value = probability of rejecting the null hypothesis when it is true

Seasonality Analysis

For each well-analyte pair, the observed data was divided into two seasons: data collected during January through June of each year was considered as the first season (normally dry), whereas the data collected during July through December in any year was considered as the second season (normally wet). Using this data and the Kruskal-Wallis test, seasonality was tested whether there are statistically significant seasonal effects in the data. Table 7 presents the results of seasonality analysis for all well-analyte pairs. Except for 4 well-analyte pairs (calcium, chloride, and TDS at well MW-B and sulfate at MW-C) from the total 21 well-analyte pairs, no other well-analyte pair shows significant seasonality effects at the 5 percent significance level. As the majority of the well-analyte pairs do not indicate any seasonal effects, it was decided not to make any seasonality corrections to the 4 well-analyte pairs that have indicated seasonal effects. It is unusual to have seasonal effects only for a few well-analyte pairs. It is possible the identified seasonality may be an artifact of some other unknown phenomenon.

Table 7: Results of Seasonality Analysis*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Constituents	Levene P-Value	KW P-Value	WF P-Value	Seasonality
MW-B	Boron	0.40	0.13	0.24	No
MW-B	Calcium	0.51	0.01	0.01	Yes
MW-B	Chloride	0.33	0.00	0.02	Yes
MW-B	Fluoride	0.20	0.15	0.10	No
MW-B	pH	0.11	0.18	0.15	No
MW-B	Sulfate	0.80	0.62	0.61	No
MW-B	TDS	0.40	0.01	0.01	Yes
MW-C	Boron	0.20	0.91	0.69	No
MW-C	Calcium	0.43	1.00	0.83	No
MW-C	Chloride	0.93	1.00	0.89	No
MW-C	Fluoride	0.91	0.96	0.99	No
MW-C	pH	0.25	0.51	0.38	No
MW-C	Sulfate	0.17	0.03	0.04	Yes
MW-C	TDS	0.81	0.53	0.45	No
MW-D	Boron	0.03	0.28	0.14	No
MW-D	Calcium	0.00	0.02	0.06	No
MW-D	Chloride	0.01	0.14	0.08	No
MW-D	Fluoride	0.12	0.59	0.34	No
MW-D	pH	0.91	0.25	0.29	No
MW-D	Sulfate	0.57	0.73	0.74	No
MW-D	TDS	0.08	0.08	0.15	No

Notes:

KW = Kruskal-Wallis Test

Levene = Levene Test for testing variance

NDs = nondetects

WF = Welch-F Test

P-Value = probability of rejecting the null hypothesis when it is true

Secular Trend Analysis

A secular trend at a well location indicates that the mean is not stationary but is changing over time. Secular trend analysis was performed using the nonparametric Mann-Kendall test (Gilbert 1996). As a nonparametric procedure, the Mann-Kendall test does not require the underlying data to follow a specific distribution. The test compares the relative change of sample data over time rather than the magnitude of data values. Non-detects were used by assigning them a common value that was less than the lowest measured value in the data set (EPA 2009).

The Mann-Kendall test statistic (S) is found by counting the number of "concordant observations", where the later-in-time observation has a larger value for the series and subtracting the number of "discordant observations", where the later-in-time observation has a smaller value for the series. This is done for all pairs of observations in the data set. The total difference is denoted by S. Positive values of S indicate an increase in constituent concentrations over time, whereas negative values indicate a decrease in constituent concentrations over time. The strength of the trend is proportional to the magnitude of S (i.e., the larger the absolute value of S, the stronger the evidence for a real trend).

The results for the Mann-Kendall test for each well-constituent pair are shown in Table 8. This table includes the calculated probability for a single-tailed test, which represents the probability that an observed trend would occur purely by chance (given the variability and sample size of the data set). Attachment 5 presents the trend plots for all well-analyte pairs. A significance level of 0.05 was used for comparisons with this probability and the resulting decisions are reported as significantly increasing or decreasing trends or a non-significant result (no trend).

Table 8: Mann-Kendall Trend Evaluation*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	No. of Samples	No. of Detects	Units	Detect Freq. (%)	MK Test Statistic (S)	MK p-value	TS Slope (per year)	Trend Analysis Result
MW-B	Boron	18	18	mg/L	100	111	0.000	0.02	Increasing
MW-B	Calcium	23	23	mg/L	100	-61	0.113	0.00	No Trend
MW-B	Chloride	23	23	mg/L	100	-123	0.001	-7.74	Decreasing
MW-B	Fluoride	16	9	mg/L	56	-38	0.080	0.00	No Trend
MW-B	pH	21	21	SU	100	25	0.467	0.00	No Trend
MW-B	Sulfate	19	19	mg/L	100	-105	0.000	-3.72	Decreasing
MW-B	TDS	22	22	mg/L	100	-132	0.000	-17.54	Decreasing
MW-C	Boron	17	8	mg/L	47	-29	---	0.00	---
MW-C	Calcium	22	22	mg/L	100	132	0.000	0.58	Increasing
MW-C	Chloride	19	19	mg/L	100	148	0.000	3.76	Increasing
MW-C	Fluoride	19	7	mg/L	37	91	---	0.01	---
MW-C	pH	22	22	SU	100	-67	0.062	0.00	No Trend
MW-C	Sulfate	20	18	mg/L	90	-22	0.495	0.00	No Trend
MW-C	TDS	21	21	mg/L	100	150	0.000	9.92	Increasing
MW-D	Boron	18	12	mg/L	67	-10	0.728	0.00	No Trend
MW-D	Calcium	18	18	mg/L	100	45	0.096	0.00	No Trend
MW-D	Chloride	18	18	mg/L	100	115	0.000	13.71	Increasing
MW-D	Fluoride	22	9	mg/L	41	91	---	0.01	---
MW-D	pH	22	22	SU	100	-120	0.001	-0.13	Decreasing
MW-D	Sulfate	19	8	mg/L	42	62	---	0.13	---
MW-D	TDS	16	16	mg/L	100	52	0.022	16.76	Increasing

Notes:

--- = values were not calculated due to Detection frequency < 50%

% = percent

Detect Freq. = frequency

MK = Mann-Kendall

TS Slope = slope of the fitted regression line using the Theil-Sen nonparametric procedure

p-value = probability value

Trend analysis performed using Mann Kendall single-tailed test at 0.05 significance level.

Of the 21 cases evaluated with the Mann-Kendall test, there were 10 cases (about 48 percent) with a significant calculated trend, 4 of them representing significantly decreasing trends and 6 significantly increasing trends. In 7 cases (33%), there were no trends and 4 cases couldn't be evaluated due to their detection frequencies being less than 50 percent.

Correcting for Linear Trends

If a data set exhibits a linear trend, the sample will exhibit temporal dependence. The Unified Guidance (USEPA 2009) recommends that these data sets should be detrended. The easiest way to detrend observations with a linear trend is to compute a linear regression on the data and then use the regression residuals instead of the original measurements for background calculations. Equation 1 is used to obtain the detrended data:

$$x_i^{\text{detrended}} = \alpha + [x_i - (\alpha + \beta t)] = x_i - \beta t \quad \text{Equation 1}$$

where, x_i represents the raw data, $x_i^{\text{detrended}}$ represents the detrended data, α is the regression line intercept, β is the slope (unit per year) of the fitted regression line, and t is time in years since September 2015. Table 8 includes the values of Theil-Sen slope for all well-constituent pairs. Using this information, the data sets for all well-constituent pairs identified for significant trends were detrended and background values were determined using the detrended data.

Goodness-of-Fit Testing

Determining the nature of the underlying population from which samples are drawn is important as it governs whether a parametric test procedure should be employed in subsequent statistical analyses. The ability to apply parametric statistical tests conveys higher statistical power, a lower false-positive error rate, and more robust conclusions overall.

Goodness-of-fit tests were performed to determine the probability that a particular background data set could have come from the tested distribution. Because a data set can pass a goodness-of-fit test for more than one distribution, the following hierarchy was used to choose a parametric distribution to calculate the background statistics:

- A normal distribution is used when a dataset passes the test for normality. Normal distribution was always selected over a lognormal or a gamma distribution.
- A gamma distribution is used when a dataset fails the test for normality but passes the test for the gamma distribution. A gamma distribution was always preferred over a lognormal distribution for background determination, if justified.
- A lognormal distribution is used when a dataset is neither normal nor gamma but passes the test for lognormality.
- Nonparametric methods are used when a dataset exhibited no discernible distribution, then the distribution-free nonparametric method is used to determine the background statistics.

EPA (2015) warns that use of a parametric lognormal distribution on a lognormally distributed data set may yield impractically large background values, especially when the standard deviation of the log-transformed data becomes greater than 1.0 for small data sets (less than 30 to 50 measurements). Because environmental data sets typically can be modeled by a gamma distribution, gamma distribution limits are given preference over lognormal distribution limits, where appropriate.

If the data do not appear to be normally distributed, the data may be transformed mathematically such that the transformed data follow a normal distribution; alternatively, a nonparametric method may be used. However, because nonparametric methods generally require large data sets to maintain an adequate low SWFPR, parametric methods are preferred. For mildly skewed, nonparametric data sets with a standard deviation of the log-transformed data less than 0.5, a normal distribution-based background estimation method was considered (EPA 2015). The results of the goodness-of-fit testing are provided in Table 9. All four cases, normal, gamma, lognormal, and nonparametric, exist in the updated background data.

Detection Monitoring Background Determination

Selection of Statistical Method

The CCR Rule specifically lists four methods acceptable for background determination. These methods are listed below and described in the following paragraphs.

- Tolerance or prediction interval procedure in which an interval for each parameter is established from the distribution of the background data, and the level of each parameter in each monitoring well is compared to the upper tolerance or prediction limit.

Table 9: Goodness-of-Fit Test Results*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Parameter	No. of Samples	P-Value for Normality	P-Value for Lognormality	P-Value for Gamma	Do data appear to be approximate normal?	Do data appear to be approximate gamma?	Do data appear to be approximate lognormal?	Approximate distribution of data
MW-B	Boron	18	0.19	---	---	Yes	---	---	Normal
MW-B	Calcium	23	0.02	0.09	0.20	No	Yes	Yes	Gamma
MW-B	Chloride	23	0.11	0.06	0.08	Yes	Yes	Yes	Normal
MW-B	Fluoride	9	0.76	0.61	0.74	Yes	Yes	Yes	KM Normal
MW-B	pH	21	0.05	0.07	0.06	Yes	Yes	Yes	Lognormal
MW-B	Sulfate	19	0.35	0.58	0.50	Yes	Yes	Yes	Normal
MW-B	TDS	22	0.15	0.11	0.13	Yes	Yes	Yes	Normal
MW-C	Boron	22	---	---	---	---	---	---	Nonparametric
MW-C	Calcium	22	0.87	0.94	0.96	Yes	Yes	Yes	Normal
MW-C	Chloride	19	0.21	0.07	0.17	Yes	Yes	Yes	Normal
MW-C	Fluoride	19	---	---	---	---	---	---	Nonparametric
MW-C	pH	22	0.13	0.19	0.17	Yes	Yes	Yes	Normal
MW-C	Sulfate	18	0.00	0.14	0.06	No	Yes	Yes	KM Lognormal
MW-C	TDS	21	0.68	0.44	0.54	Yes	Yes	Yes	Normal
MW-D	Boron	12	0.05	0.26	0.16	No	Yes	Yes	KM Gamma
MW-D	Calcium	18	0.00	0.01	0.00	No	No	No	Nonparametric
MW-D	Chloride	18	0.00	---	---	No	---	---	Nonparametric
MW-D	Fluoride	18	---	---	---	---	---	---	Nonparametric
MW-D	pH	22	0.19	0.26	0.23	Yes	Yes	Yes	Normal
MW-D	Sulfate	22	---	---	---	---	---	---	Nonparametric
MW-D	TDS	16	0.00	0.22	0.34	No	Yes	Yes	Gamma

Notes:

p = probability value

- Control chart approach that gives control limits for each parameter.
- Parametric ANOVA followed by multiple comparisons procedures to identify statistically significant evidence of contamination.
- Nonparametric ANOVA based on the ranks of the data followed by multiple comparisons procedures to identify statistically significant evidence of contamination.
- Additional statistical test that meets the performance standards listed in 40 CFR 297.93(g).

Parametric and Nonparametric ANOVA

The use of ANOVA assumes stringent assumptions that both background and detection monitoring data sets have similar distributions and equal variances, a condition that rarely occurs in practice. ANOVA procedures do not adjust for multiple comparisons due to multiple well-constituent combinations. Because the CCR Rule mandates a minimum Type I error of 0.05 for multiple comparisons (0.01 for individual monitoring well comparisons) when using ANOVA, it would be difficult to maintain EPA's (2009) recommended annual SWFPR of 10 percent for detection monitoring. Additionally, EPA (2009) reports that ANOVA is more sensitive to spatial variability than contamination. Spatial variability affects mean concentrations but typically not the variance; hence, small yet consistent differences will achieve statistical significance (Gibbons et al. 2009). In contrast, contamination affects both variability and mean concentration; therefore, a much larger effect is required to achieve statistical significance. While spatial variation is also a problem for prediction limits and tolerance limits for single future measurements, it is not nearly as severe a problem as for ANOVA because the distribution of the individual measurements is considered and not the more restrictive distribution of the sample mean. Based on these considerations, EPA (2009) does not recommend the use of ANOVA for detection monitoring.

Control Charts

Control charts are a viable alternative to parametric prediction limits for testing groundwater detection monitoring. Because control charts are a parametric method (there is no current nonparametric alternative), the data or transformed data must be normally distributed, and the frequency of non-detects (NDs) is less than 50 percent. The statistical performance (i.e., false-positive rates and statistical power) of control charts is not well understood because the control limit used to identify potential releases to groundwater is not based on a formula incorporating a desired false positive rate. Unlike prediction limits, the control limit cannot be precisely set to meet a pre-specified SWFPR unless the behavior of the control chart is modeled via Monte Carlo simulation; the same is true for assessing the statistical power (ability to detect a release if one occurs). Control charts usually provide less flexibility than prediction limits in designing a statistical monitoring program (EPA 2009).

Tolerance Limits

Although the construction of a tolerance limit is nearly identical to that of a prediction limit, tolerance limits lack the statistical properties that allow practitioners to modify the tests to control the SWFPR. As multiple comparisons of detection monitoring sample results are made to the background levels, the chance of falsely declaring a statistically significant release at the site increases when using tolerance limits. While simultaneous prediction limits consider the actual number of comparisons in defining exact false positive error rates, tolerance limit approaches

utilize an approximate and less precise pre-selected low level of probability. Thus, EPA (2009) recommends the use of prediction limits compared to tolerance limits for detection monitoring.

Prediction Limits

Of the statistical test methods listed in the CCR Rule, EPA (2009) recommends prediction limits for detection monitoring for their proven use of retesting strategies and ability to define an exact false positive error rate while maintaining high statistical power. The mathematical basis of retesting with prediction limits is well established, while those for retesting with tolerance limits or control charts are not. In contrast, to control charts, nonparametric prediction limits can be constructed as an alternative to parametric prediction limits for data exhibiting nonnormality.

Based on these reasons, prediction limits will be used as the preferred statistical method for detection monitoring at the OUC Landfill. Prediction intervals can be used for both interwell and intrawell comparisons. At sites where natural geochemical differences in groundwater quality exist between monitoring locations, the probability increases that statistically significant differences reported between upgradient, and downgradient locations are the result of spatial and/or hydrogeologic variability rather than the facility. In these situations, intrawell statistical methods minimize the likelihood that spatial variability will contribute to invalid statistical limits, assuming there has been no previous release.

For monitoring of the OUC Landfill, intrawell comparisons are used due to the statistically significant spatial variability that exists within the monitoring well network. The OUC Landfill CCR background monitoring program is comprised of 3 background detection monitoring wells: MW-B, MW-C, and MW-C. The step-by-step general procedure for background determination is as follows:

- For constituents composed of 100 percent NDs, the Double Quantification Rule (EPA 2009) will be evaluated by the following quasi-statistical rule: "A confirmed exceedance is registered if any well-constituent pair in the "100 percent ND" group exhibits quantified measurements (i.e., at or above the reporting limit [RL]) in two consecutive samples and resample events."
- For constituents exhibiting an ND frequency greater than 50 percent, a nonparametric upper prediction limit (UPL) was computed.
- For data sets containing at least 50 percent or fewer NDs, the detected results were used to attempt a fit to a distribution. If a reasonable fit was found, a prediction limit was calculated based on the estimated mean and standard deviation adjusted for the presence of left-censored values using the Kaplan-Meier (KM) product-limit estimator (Kaplan and Meier 1958).
- For constituent data sets that do not naturally fit a normal, a gamma, or a lognormal distribution, data were transformed using an appropriate transformation to comply with the normality assumption so that a parametric prediction limit could be constructed. The goal of data transformation is to find a transformation to approximate a normal distribution. The Box-Cox transformation technique is used to transform the dataset that does not fit any well-known distribution functions (EPA 2009).
- For constituents that could not be transformed to comply with normality assumption, a nonparametric prediction limit was computed.

Parametric Upper Prediction Limit

Assuming the background data are normally distributed or can be transformed to fit a normal distribution, the parametric upper prediction limit (UPL) is calculated using the following equation:

$$UPL = \bar{x} + Ks \quad \text{Equation 2}$$

where:

$\bar{x}$ = mean concentration of the background data set

s = standard deviation of the background data set

K = multiplier based on the characteristics of the site and the statistical test

Values for K are chosen to maintain the annual SWFPR at 10 percent. If data are transformed prior to determining the prediction limit, back-transformation in the original units should be performed to facilitate comparisons against detection point data. The K values selected for this location are discussed further below.

For pH, a lower prediction limit (LPL) and an upper prediction limit (UPL) is required; the following equation is used:

$$LPL, UPL = \bar{x} \pm Ks \quad \text{Equation 3}$$

Nonparametric Prediction Limit

Nonparametric prediction limits were considered when the background data were not normally distributed or could not be transformed to fit a normal distribution. A nonparametric UPL is constructed by setting the limit as a large order statistic selected from the background data (e.g., the maximum or second-largest background value). Unlike parametric limits, the confidence level for nonparametric limits is not adjustable but is fixed. To increase the confidence level, the number of future values to be predicted needs to be decreased or the number of background observations increased (EPA 2009).

The confidence probability for a prediction limit on one future measurement is equal to:

$$\text{Confidence} = (1 - \alpha) = j/(n + 1) \quad \text{Equation 4}$$

where:

α = false positive rate

n = sample size

j = rank of the prediction limit value

If the background maximum is taken as the UPL, the confidence level thus becomes $n/(n+1)$. Davis and McNichols (1999) developed a general formula to determine the confidence probability when the jth order statistic is taken as the UPL:

$$\text{Confidence} = (1 - \alpha) = \frac{(j+m-1) \cdot (j+m-2) \cdot \dots \cdot (j+1) \cdot j}{(n+m) \cdot (n+m-1) \cdot \dots \cdot (n+2) \cdot (n+1)} \quad \text{Equation 5}$$

To construct a prediction interval with sufficiently high confidence, more background observations are needed for a nonparametric prediction limit compared to a parametric-based limit. Parametric prediction intervals do not require as many background measurements because the form of the underlying distribution is assumed to be known.

Sitewide False Positive Rate and Statistical Power

EPA (2009) recommends an annual SWFPR of 10 percent, which is distributed equally among the total number of sampling events. An SWFPR of 5 percent is targeted for each semiannual sampling event. EPA also requires demonstration that the statistical methodology selected for a facility will provide adequate statistical power to detect a release, should one occur. EPA recommends a statistical power of at least 55 percent at 3 standard deviations and 80 percent at 4 standard deviations above the background mean.

Retesting Strategy

Retesting is an integral part of the statistical methodology for control of the SWFPR when multiple monitoring locations and parameters are being evaluated. EPA (2009) recommends that prediction limits be combined with retesting for maintaining a sufficiently low false-positive rate with the ability to detect a release if it occurs. Generally, a one-of-two or one-of-three retesting strategy is used to verify that an apparent detection exceeds the background. With this retesting approach, an apparent SSI cannot be confirmed until the retesting results have been obtained. If the initial detection result does not exceed the UPL, then no retesting is needed. If the initial detection result does exceed the UPL, then a retest should be conducted before the next regularly scheduled sampling event at the monitoring well(s) and for the constituent(s) exceeding the UPL. Resampling occurs after adequate time has elapsed to ensure physical independence between the initial sample and the resample. If a constituent-well combination passes the detection test based on the resampling results, detection monitoring continues. Otherwise, the owner must conduct further investigations to evaluate the reason for the potential SSI.

K-Multiplier Values

The K-multipliers for the prediction limits were computed using the EnvStats (Millard 2013) library run within the R language and environment for statistical computing (R Core Team 2014). The EPA (2009) includes R-code files for calculating exact K-multipliers and per-test false positive error rates. The exact K-multipliers were then verified using the K-multiplier tables in Appendix D of the Unified Guidance (EPA 2009). Values for K were chosen to maintain the annual SWFPR at 10 percent (EPA 2009), and are dependent upon the following:

- Number of detection wells (three at SEC)
- Number of constituents being evaluated (7 per the Appendix III list)
- Size of the background data set (ranges from 16 to 23)
- Number of statistical evaluations performed per year (2 for semiannual sampling)
- Retesting strategy

In general, the false positive rate increases in direct proportion to the number of comparisons being made, so a larger number of comparisons will increase the probability that a release will be indicated even though no release has occurred. Several options are available for limiting the SWFPR of a facility where multiple comparisons are made: (1) limit the number of comparisons, (2) decrease the per-test false positive rate, or (3) allow retesting in cases where statistical exceedances are noted.

The EPA (2009) recommends that detection monitoring programs be developed using a SWFPR of 10 percent over a 1-year period of testing. Using this criterion, the yearly SWFPR is fixed at

10 percent, and as such, the semiannual SWFPR is fixed at 5 percent. The magnitude of the per-test significance level (α -test) varies with the number of statistical tests required per semiannual evaluation. A cumulative false positive error rate α_{cum} is calculated as the probability of at least one statistically significant outcome for a total number of tests n_T in a calendar year at a single false positive error rate α -test using the properties of the Binomial distribution:

$$\alpha_{cum} = 1 - (1 - \alpha_{test})^{n_T} \quad \text{Equation 6}$$

By rearranging to solve for α -test and substituting the 10 percent design SWFPR for α -cum, the needed per-test false positive error rate is calculated as:

$$\alpha_{test} = 1 - (0.9)^{1/n_T} \quad \text{Equation 7}$$

The design of the retesting strategy is based on an assessment of its ability to meet the power standards provided by EPA (2009). In addition to specifying the annual SWFPR, the EPA (2009) also requires facilities to achieve adequate statistical power to detect a release, should one occur. More specifically, the EPA (2009) recommends a power of approximately 55 percent to 60 percent when concentration levels are 3 standard deviations above the background mean, or approximately 80 percent to 85 percent power at 4 standard deviations above the background mean.

Results of the power analysis for the intrawell parametric UPLs are shown in Table 10, as are the K-multipliers calculated for each background sample size. Sample sizes for the updated background data set ranged from 18 to 23 for the detection wells. As shown in Table 10, a one-of-two retesting strategy meets the recommended minimum power requirements as specified by the EPA (2009). The per-test significance level (α) is achieved based on how parametric prediction limits are developed. This is not necessarily the case for nonparametric prediction limits.

Table 10: Parametric Intrawell Prediction Limit Power Analysis

Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program

No. of Samples	Rule	Retesting Strategy	Tails	K Multiplier	Power at 3 SD	Power at 4 SD	Power Rating	Total Samples
23	k.of.m	1-of-2	1	1.87	0.92	1	Good	4
22	k.of.m	1-of-2	1	1.89	0.92	1	Good	4
21	k.of.m	1-of-2	1	1.9	0.91	1	Good	4
20	k.of.m	1-of-2	1	1.91	0.91	1	Good	4
19	k.of.m	1-of-2	1	1.93	0.9	1	Good	4
18	k.of.m	1-of-2	1	1.95	0.9	0.99	Good	4
17	k.of.m	1-of-2	1	1.97	0.89	0.99	Good	4
16	k.of.m	1-of-2	1	1.99	0.88	0.99	Good	4
22	k.of.m	1-of-2	2	2.11	0.86	0.99	Good	4
21	k.of.m	1-of-2	2	2.13	0.85	0.99	Good	4

Notes:

No. = number

SD = standard deviations

EPA (2009) recommends at least 55 to 60 percent annual power for detecting a 3 standard deviation increase and at least 80 to 85 percent annual power for detecting a 4 standard deviation increase above the true background mean.

Calculation of Prediction Limits

An intrawell UPL (and LPL for pH) was calculated for each of the Appendix III detection monitoring constituents at the three downgradient detection monitoring wells (MW-B, MW-C, and MW-D). Table 11 presents the prediction limits and supporting summary statistics, including the number of samples, the number of detections, and the percentage (frequency) of detection; the minimum and maximum detected values and the minimum and maximum reporting limits for non-detects; and the mean, median, standard deviation, and coefficient of variation along with corrected mean and standard deviation values using the KM method for datasets having less than 50 percent NDs. Also included in the table are the distributional assumptions used to calculate the prediction limits.

Future Background Updating

The basic assumption in detection monitoring is that the facility is not impacting groundwater unless statistically demonstrated otherwise. For intrawell testing, statistical comparisons are made over time at each detection well to identify significant changes in groundwater quality that may be caused by the facility.

Appropriate and representative background data is the most important factor for a successful statistical groundwater monitoring program. Representative background data show numerical characteristics closely matching those arising from the site-specific aquifer being evaluated. Background data must also be appropriate to the statistical test. All detection monitoring tests involve comparisons of detection point data against the established background limits. Due to temporal changes in ambient groundwater quality, background data should not be regarded as a single fixed quantity (that is, static). If natural groundwater conditions change over time during the collection of detection monitoring data, comparisons against previously established background may not be appropriate.

The EPA (2009) recommends that background data should be updated periodically so detection samples can be tested against data that best represent the current background conditions. There are however no firm rules on how often to update background data. The Unified Guidance (EPA, 2009) adopts the general principle that updating should occur when enough new measurements have been collected to allow a two-sample statistical comparison between the existing background data and a potential set of newer data. With quarterly sampling, at least 4 to 8 new measurements should be gathered to enable a two-sample statistical comparison; this implies that updating would take place every 1 to 2 years. With semi-annual sampling, the same principle would call for updating every 2 to 3 years assuming appropriate alternative source demonstrations are conducted for the confirmed SSIs. In cases when an SSI is confirmed and no alternative source demonstration is conducted, the background should not be updated; instead, appropriate regulatory action at the site will be taken.

Table 11: Intrawell Prediction Limits for Appendix III Constituents (Detection Monitoring)*Update of Background Water Quality Concentrations for the OUC CCR Landfill Detection Monitoring Program*

Well	Constituent	Units	Frequency of Detection			Minimum Values		Maximum Values		KM Mean	KM Standard Deviation	CV	Updated Background Values			
			Total Samples	Detect Results	Detect Freq. (%)	Non-Detect	Detect	Non-Detect	Detect				Trend Removal	LPL	UPL	Distribution
MW-B	Boron	mg/L	18	18	100	---	-0.0246	---	0.055	0.0273	0.0215	0.789	Yes		0.0692	Normal
	Calcium	mg/L	23	23	100	---	0.879	---	21.9	8.058	6.689	0.83	No		25.8	Gamma
	Chloride	mg/L	23	23	100	---	36.04	---	98.4	64.95	19.53	0.301	Yes		101	Normal
	Fluoride	mg/L	16	9	56	0.1	0.06	0.2	0.23	0.113	0.0492	0.434	No		0.211	KM Normal
	pH	SU	21	21	100	---	4.22	---	4.85	4.461	0.157	0.0351	No	4.14	4.8	Lognormal
	Sulfate	mg/L	19	19	100	---	49.71	---	68.35	57.3	4.62	0.0806	Yes		66.2	Normal
	TDS	mg/L	22	22	100	---	164.5	---	276.6	213.7	35.31	0.165	Yes		280	Normal
MW-C	Boron	mg/L	17	8	47	0.02	0.01	0.02	0.0205	0.0133	0.00288	0.217	---		0.0205	Nonparametric
	Calcium	mg/L	22	22	100	---	4.003	---	8.752	6.073	1.128	0.186	Yes		8.2	Normal
	Chloride	mg/L	19	19	100	---	3.373	---	12.27	7.349	1.966	0.267	Yes		11.1	Normal
	Fluoride	mg/L	19	7	37	0.1	0.07	0.1	0.11	0.0821	0.0128	0.156	---		0.11	Nonparametric
	pH	SU	22	22	100	---	4.93	---	5.71	5.177	0.198	0.0383	No	4.76	5.59	Normal
	Sulfate	mg/L	20	18	90	0.22	0.18	0.25	2.38	0.911	0.756	0.83	No		3.35	KM Lognormal
	TDS	mg/L	21	21	100	---	34.1	---	59	45.19	6.823	0.151	Yes		58.2	Normal
MW-D	Boron	mg/L	18	12	67	0.02	0.0123	0.02	0.0341	0.0187	0.0062	0.331	No		0.0313	KM Gamma
	Calcium	mg/L	18	18	100	---	1.79	---	56.8	11.32	16.83	1.488	No		56.8	Nonparametric
	Chloride	mg/L	18	18	100	---	-33.35	---	128	9.694	38.73	3.996	Yes		85.2	Nonparametric
	Fluoride	mg/L	22	9	41	0.02	0.04	0.1	0.44	0.113	0.123	1.089	---		0.44	Nonparametric
	pH	SU	22	22	100	---	4.568	---	5.54	5.019	0.288	0.0573	Yes	4.41	5.63	Normal
	Sulfate	mg/L	19	8	42	0.25	0.3	0.65	13.5	2.064	4	1.938	---		13.5	Nonparametric
	TDS	mg/L	16	16	100	---	0.56	---	406.3	75.66	109.8	1.452	Yes		320	Gamma

Notes:

"---" = not applicable

% = percent

CV = coefficient of variation

Detect Freq. = frequency

KM Mean = Corrected mean value using the Kaplan-Meier method

KM Standard Deviation = Corrected standard deviation value using the Kaplan-Meier method

LPL = lower prediction limit

mg/L = milligrams per liter

SU = standard units

UPL = upper prediction limit

UPLs were calculated using an annual Site-Wide False Positive Rate of 10 percent and a one-of-two retesting strategy.

Summary of Updated Background Set and Prediction Limits

Groundwater monitoring relies on comparing the results of sampling to statistically justified prediction limits derived from a set of background data. These limits need to be revisited periodically to remain current (EPA 2009). While updating the limits used for assessing potential SSI, the new observations must be statistically compared to the existing background data, as appropriate. If the data are found to be comparable, then the new data is to be combined with the existing background data set to re-compute the statistical background limits. If the data are shown to be different, then the data will be reviewed to evaluate the cause of the difference. Absence evidence of a release, the more recent data will be considered more representative of present-day groundwater conditions and used for the background.

This procedure was completed for the OUC SEC CCR Rule monitoring wells with monitored data collected through 2021. New trend analyses and UPL (and LPL for pH) were developed. Table 11 provides a summary of the new updated limits that will be applied going forward (starting in 2022). Some data will require trend adjustment prior to evaluation, as documented in Table 8. If there is an exceedance, then a resample will be collected prior to the next regularly scheduled event.

This background data set may be updated again in the future, in accordance with EPA guidance (EPA 2009).

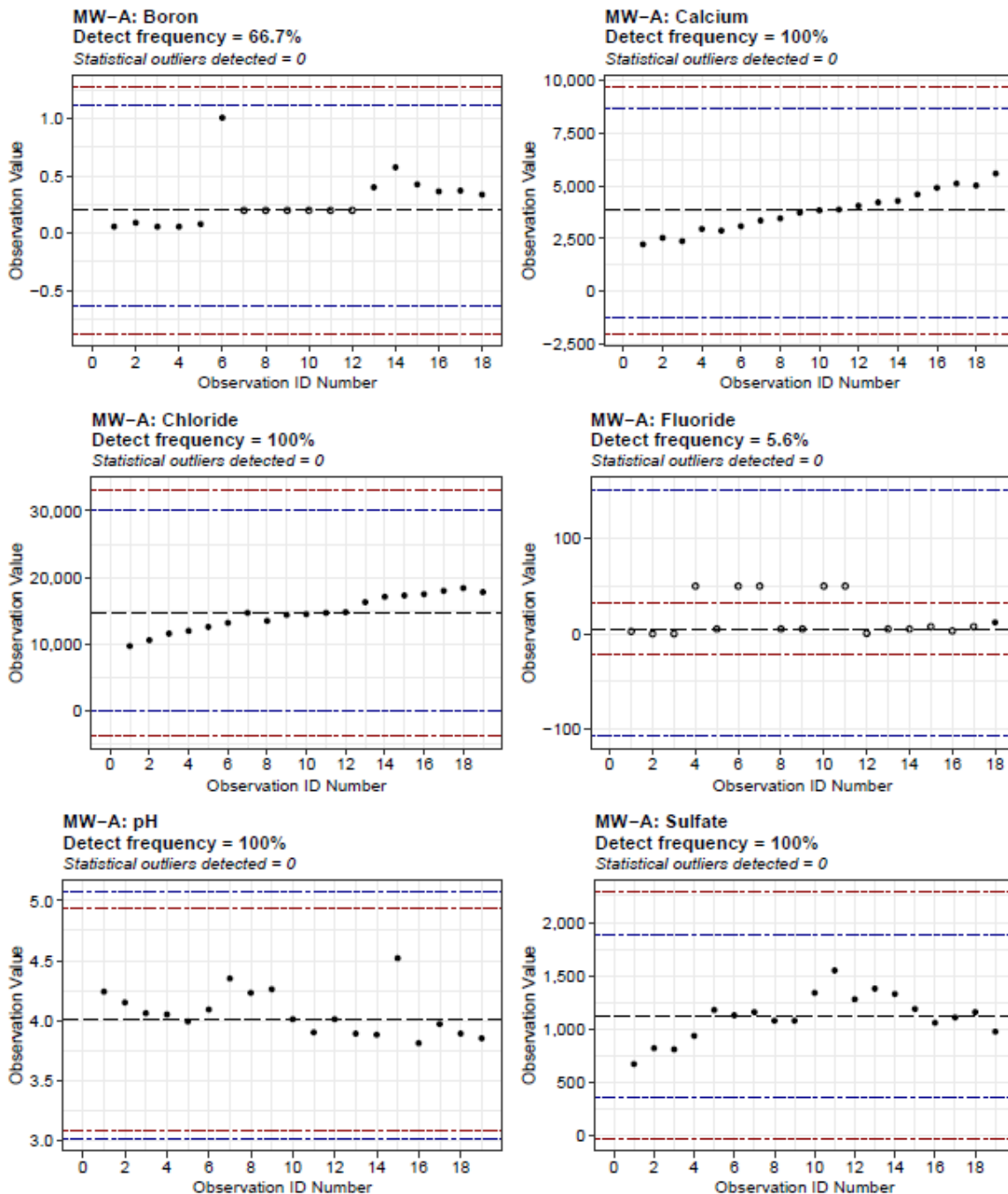
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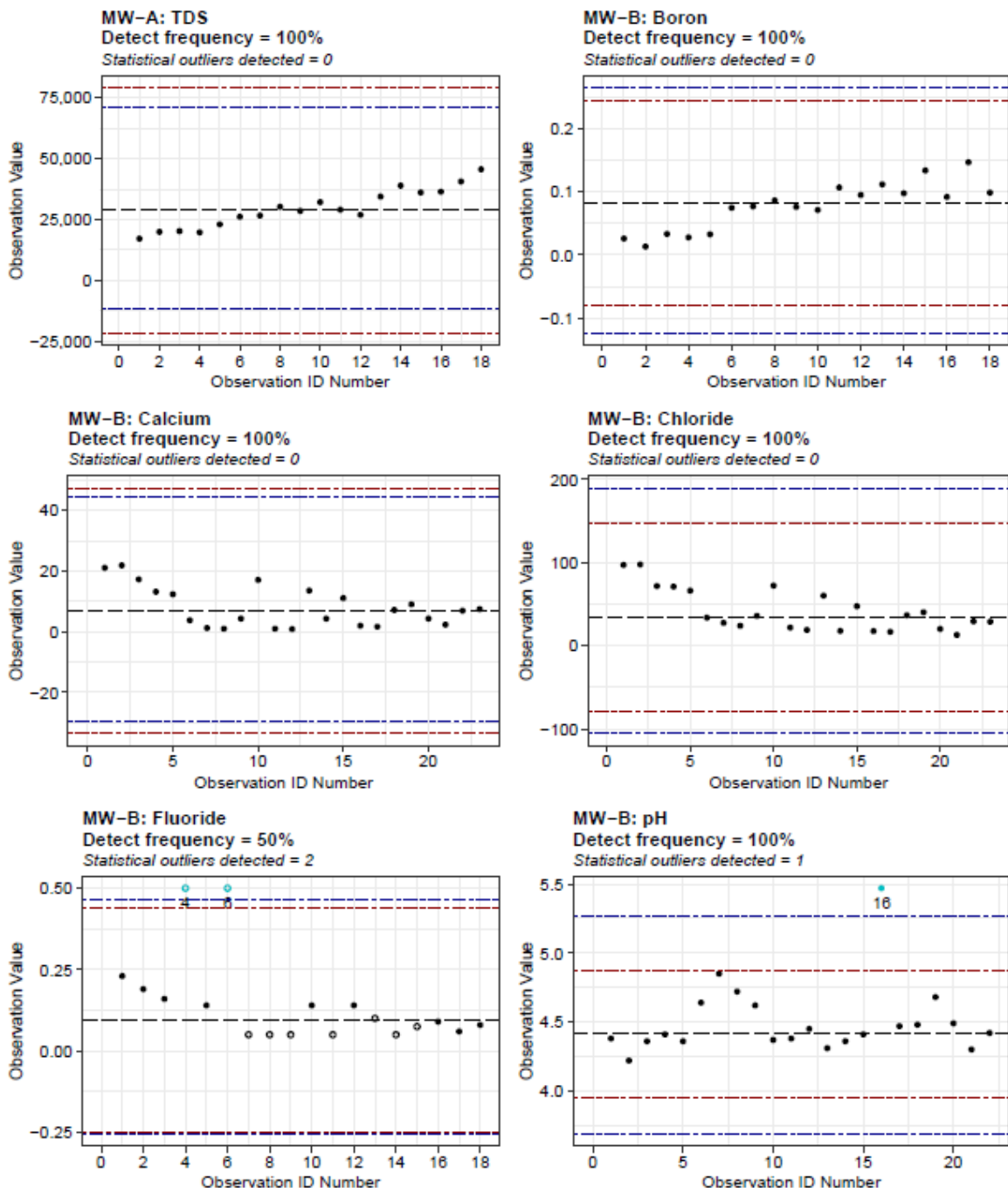
Attachment 1

Outlier Plots

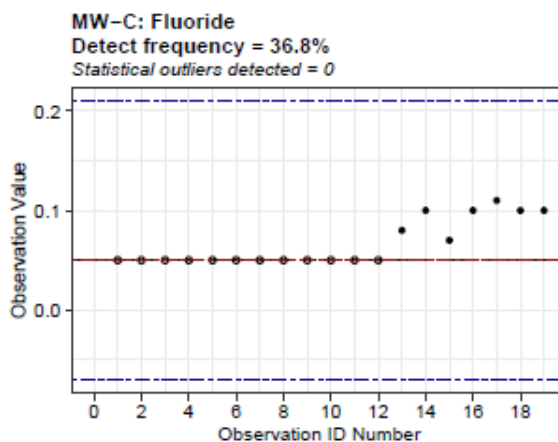
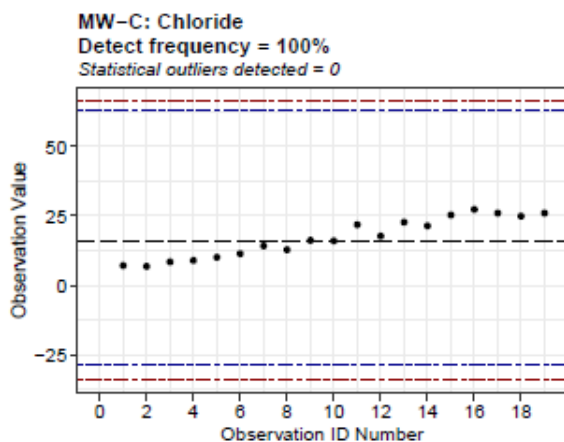
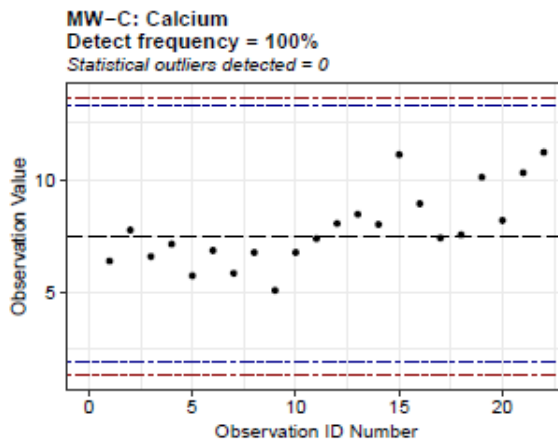
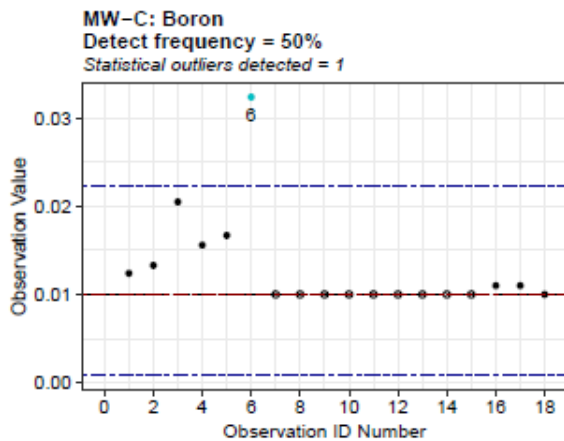
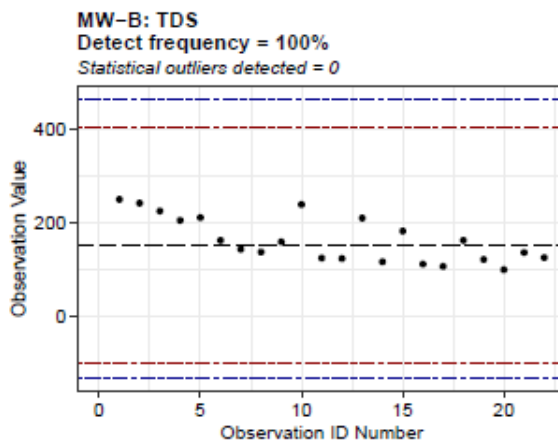
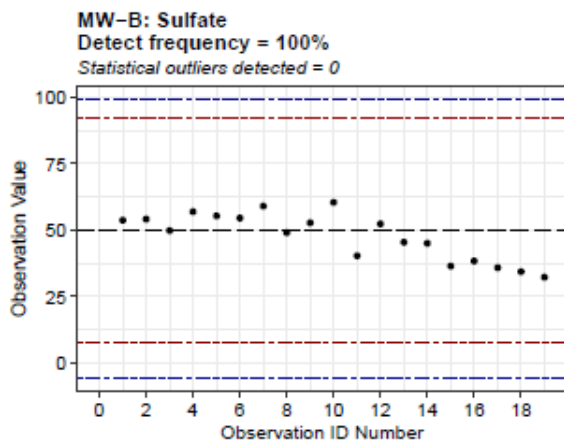
Outlier Plots for OUC Alluvium Data
 (lines represent median value [black], MAD limits [red], and IQR limits [blue])
 (nondetects are shown as open circles at MDL/2)



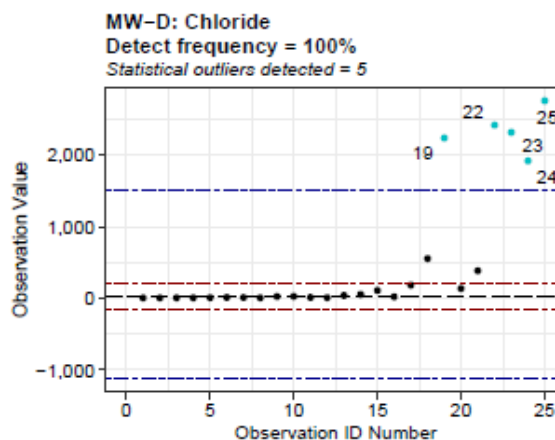
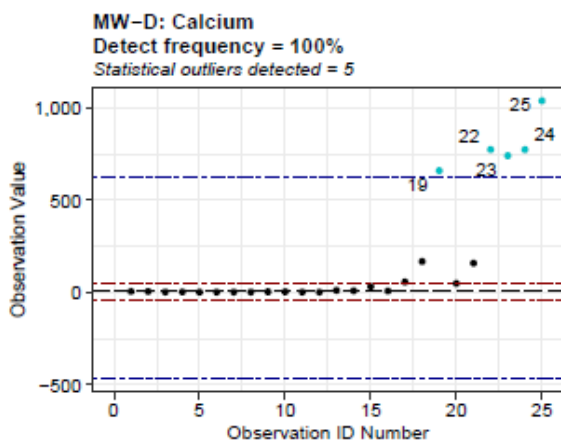
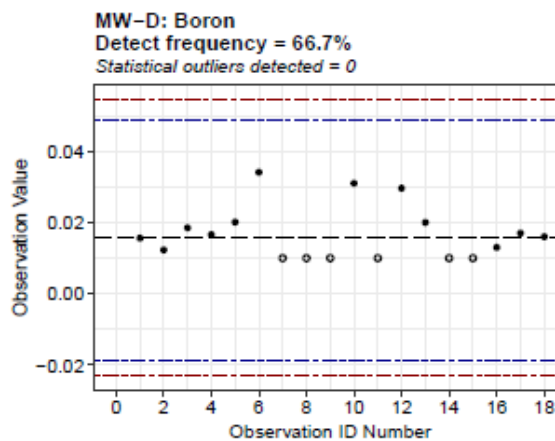
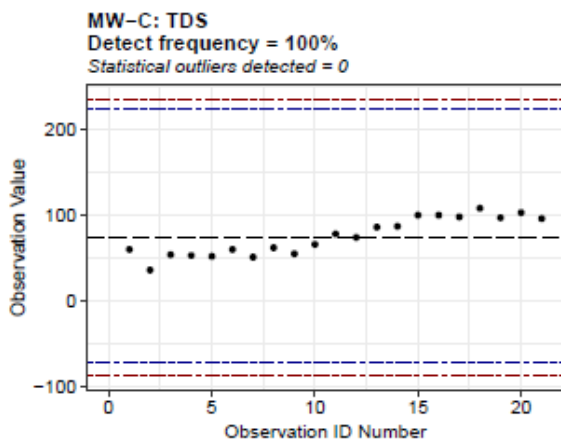
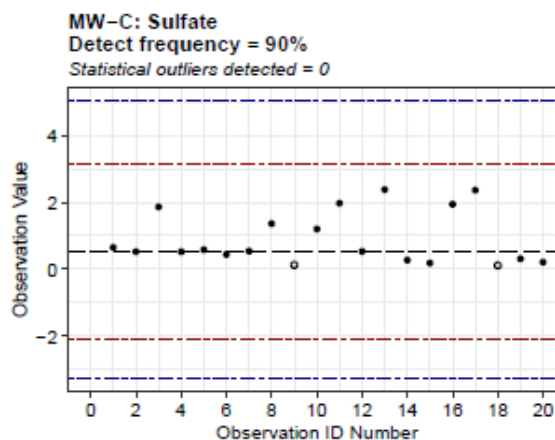
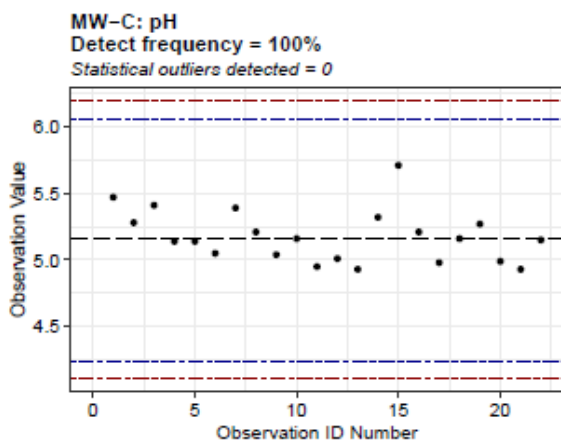
Outlier Plots for OUC Alluvium Data
 (lines represent median value [black], MAD limits [red], and IQR limits [blue])
 (nondetects are shown as open circles at MDL/2)



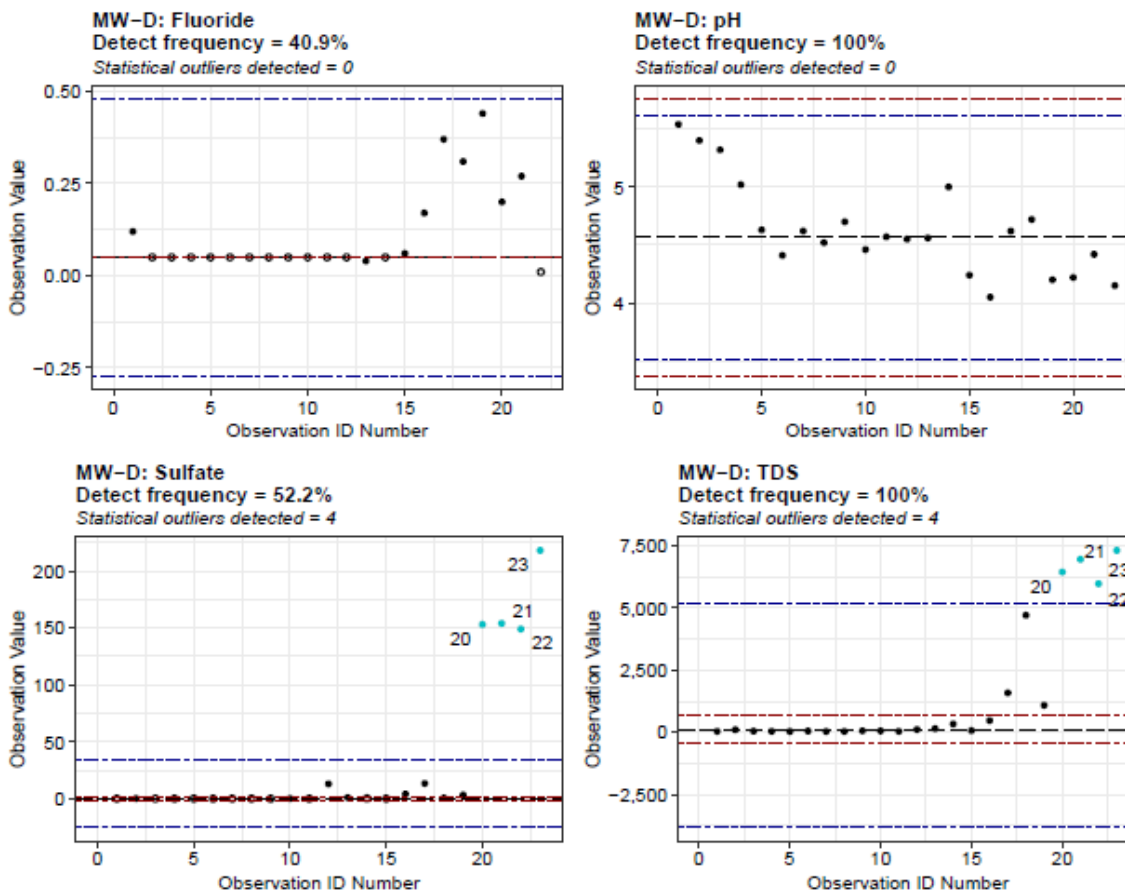
Outlier Plots for OUC Alluvium Data
 (lines represent median value [black], MAD limits [red], and IQR limits [blue])
 (nondetects are shown as open circles at MDL/2)



Outlier Plots for OUC Alluvium Data
 (lines represent median value [black], MAD limits [red], and IQR limits [blue])
 (nondetects are shown as open circles at MDL/2)



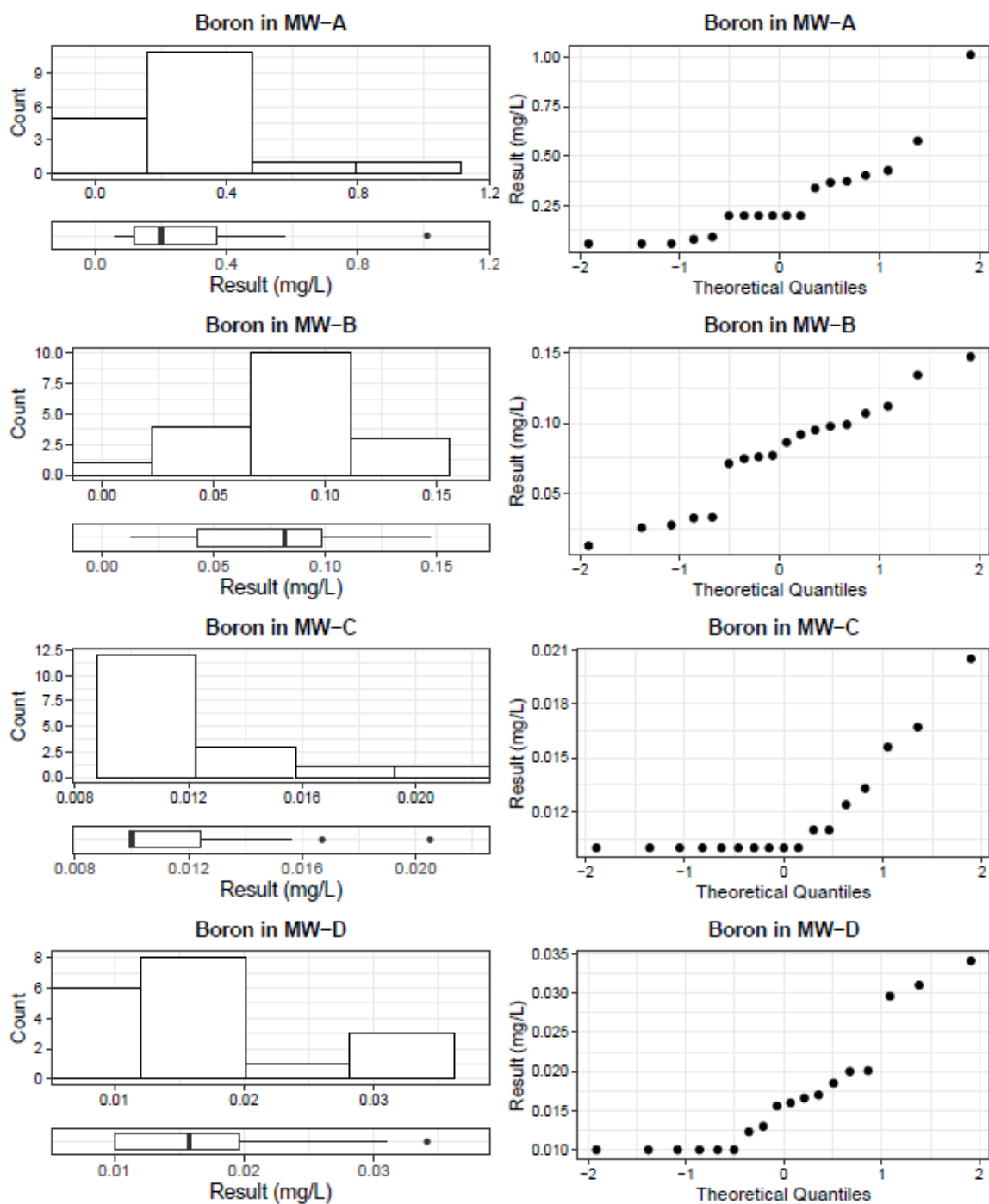
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 (lines represent median value [black], MAD limits [red], and IQR limits [blue])
 (nondetects are shown as open circles at MDL/2)



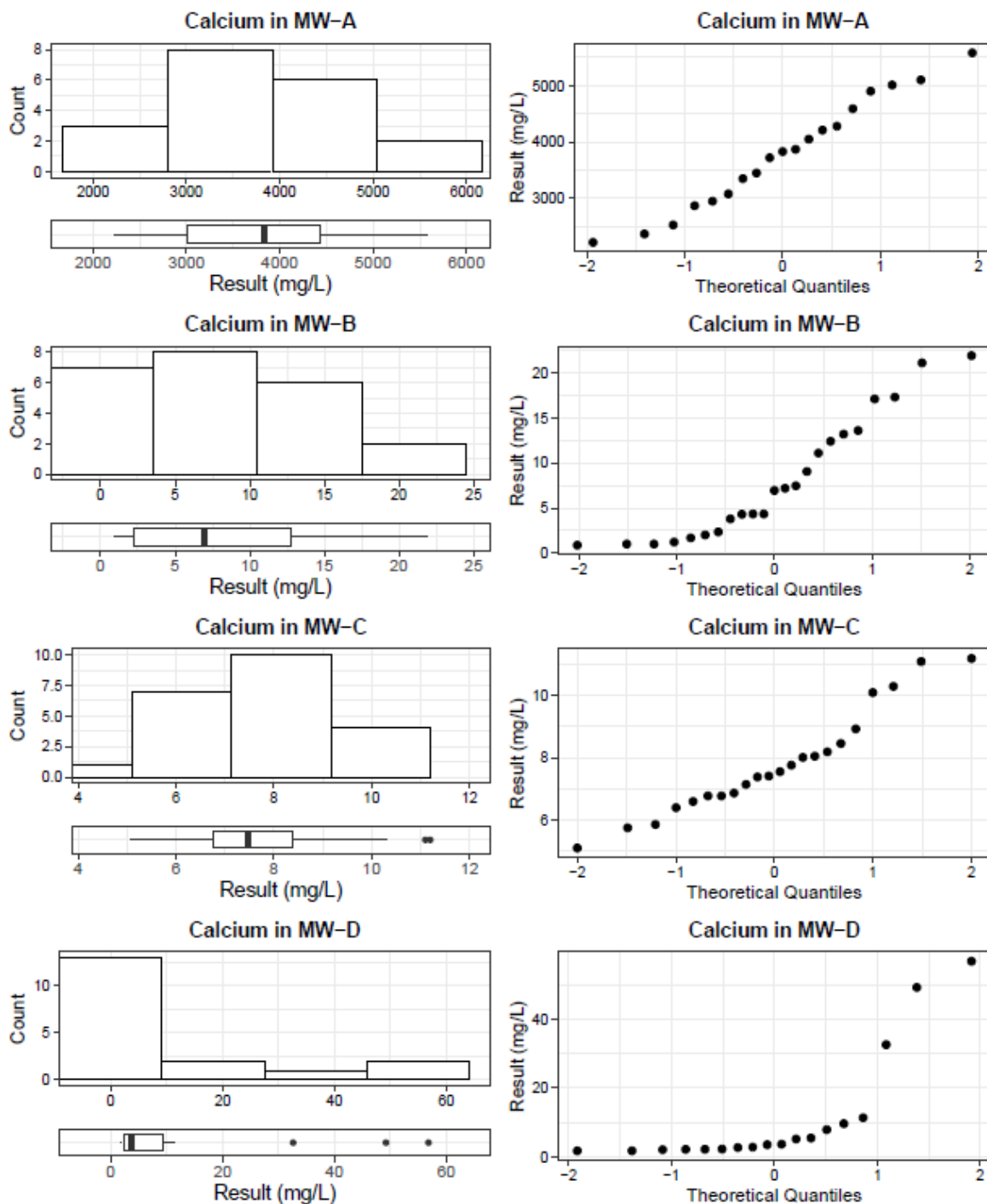
Attachment 2

Histograms, Bow Plots, and QQ Plots

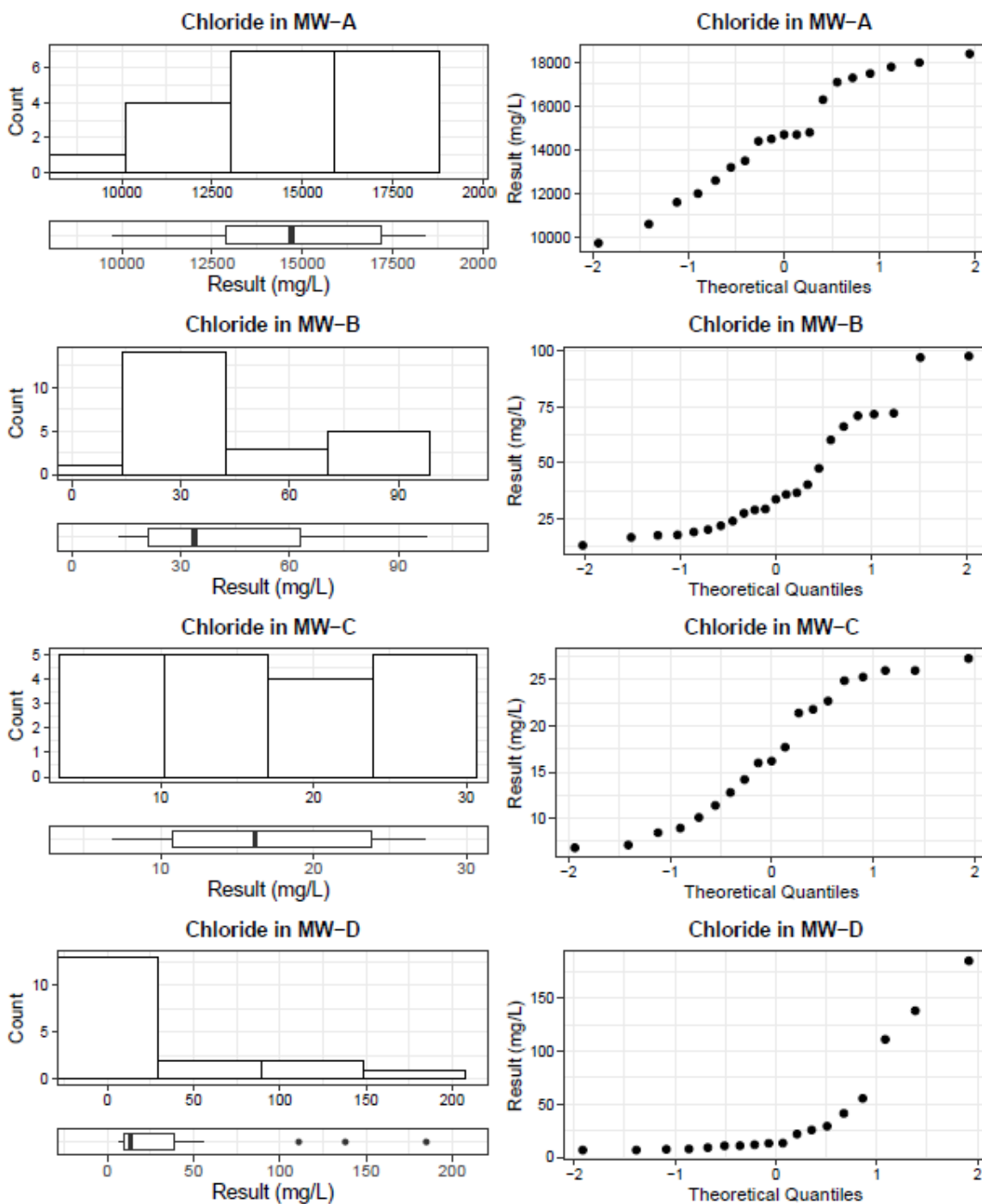
OUC Landfill Histogram, QQ, and Box-Whisker Plots after Outlier Removal (nondetects assumed equal to one-half the MDL)



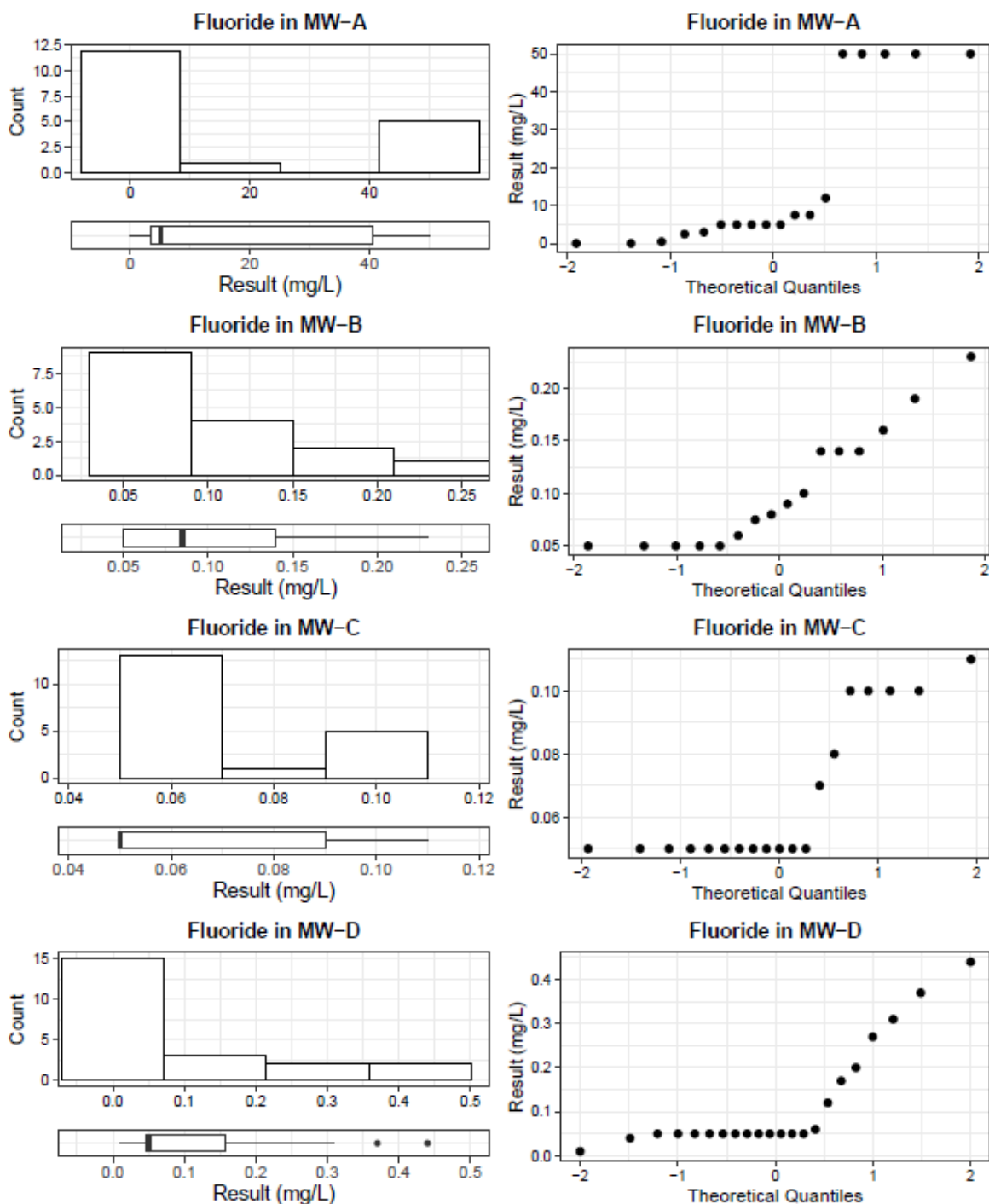
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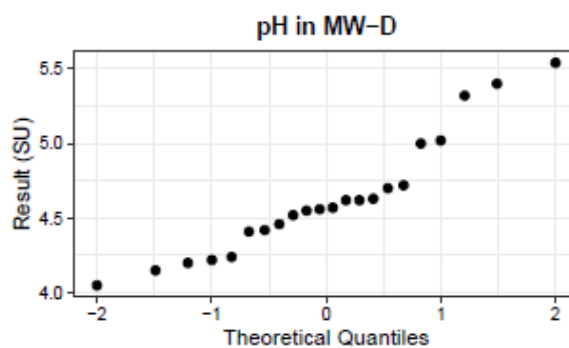
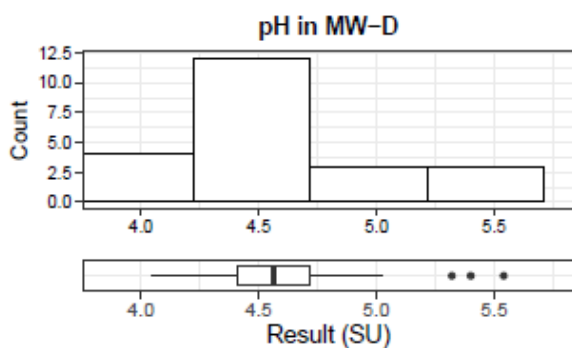
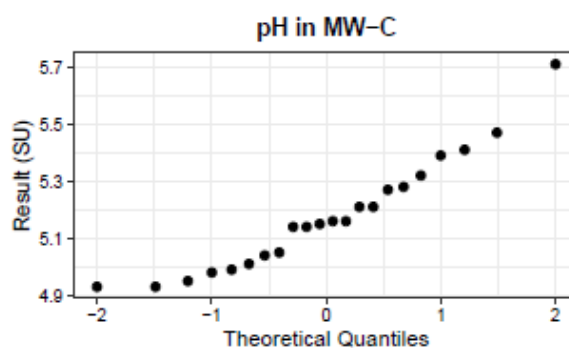
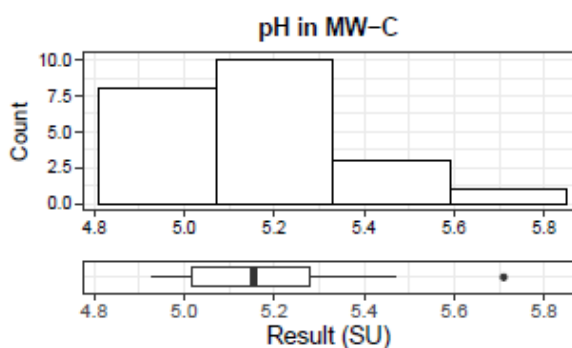
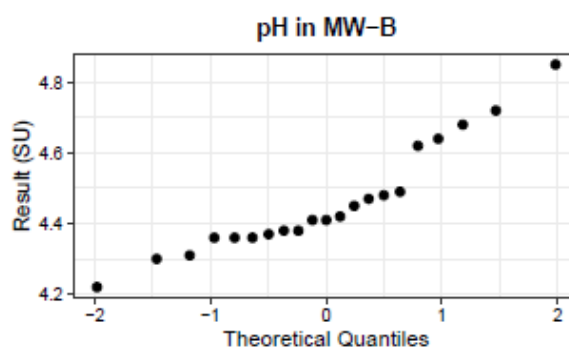
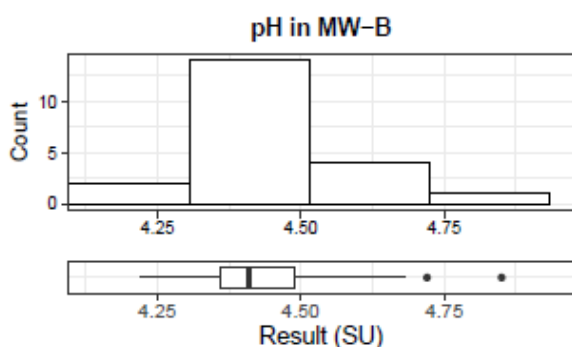
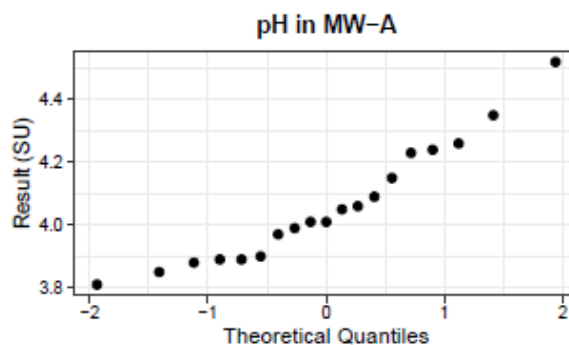
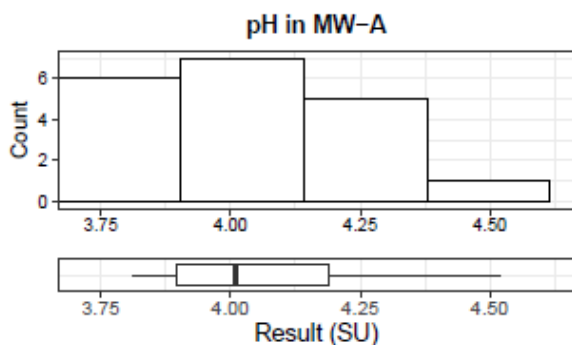
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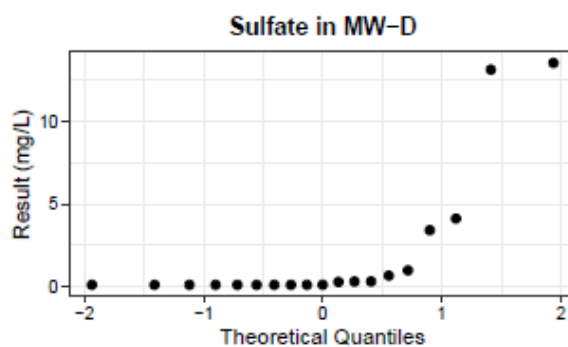
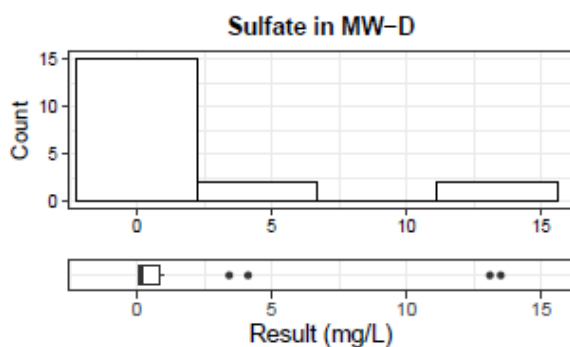
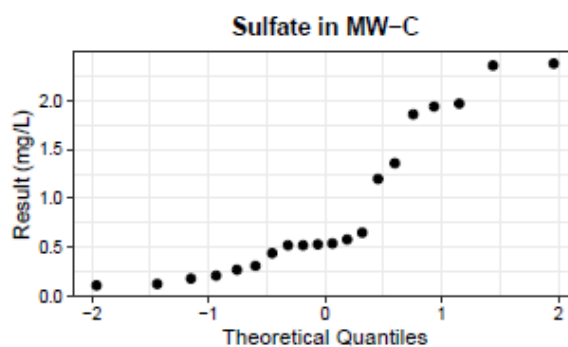
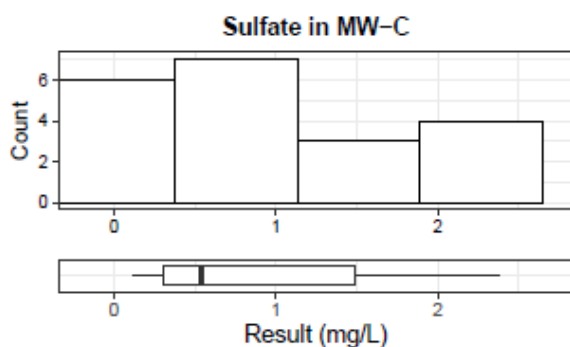
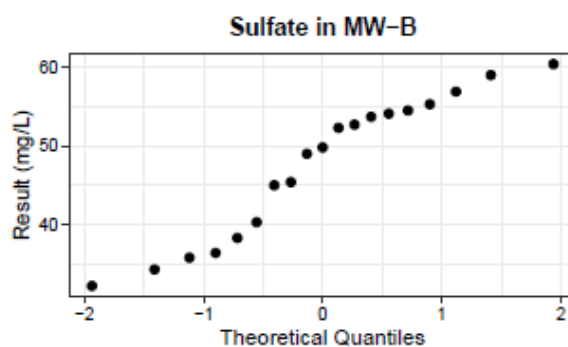
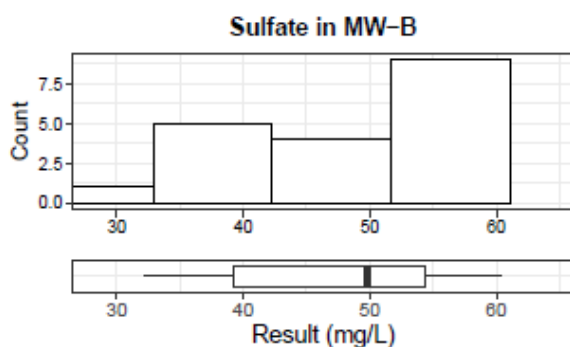
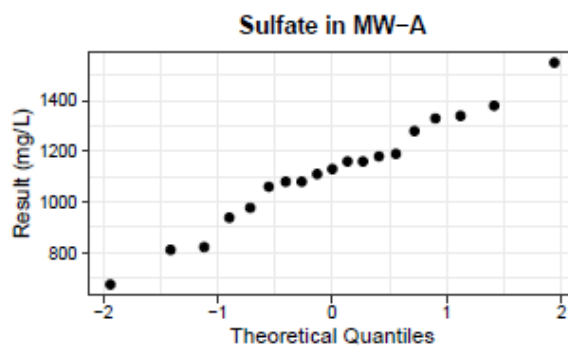
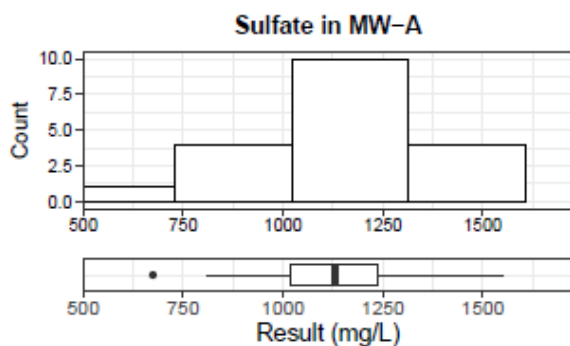
OUC Landfill Histogram, QQ, and Box-Whisker Plots after Outlier Removal (nondetects assumed equal to one-half the MDL)



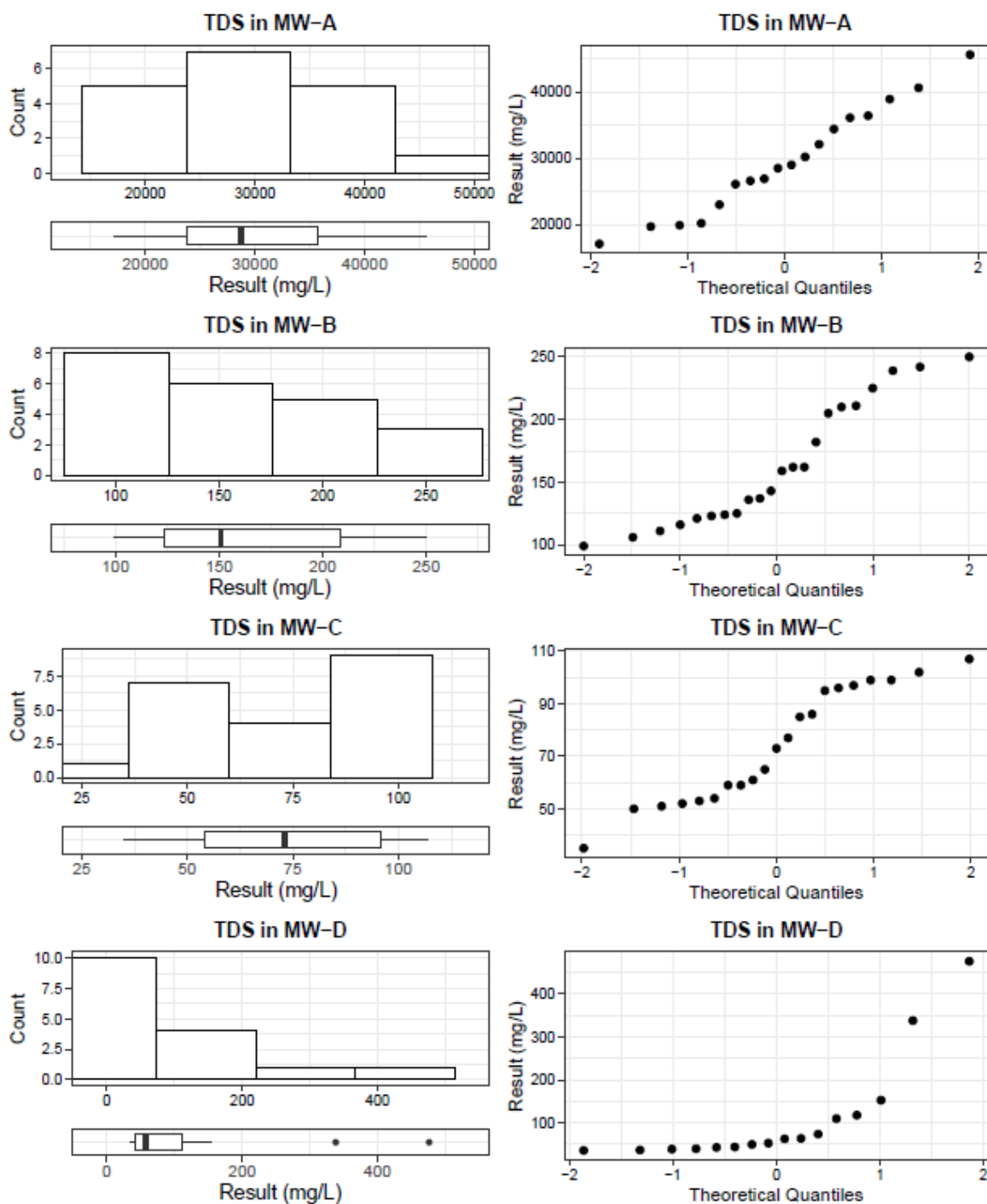
OUC Landfill Histogram, QQ, and Box-Whisker Plots after Outlier Removal (nondetects assumed equal to one-half the MDL)



OUC Landfill Histogram, QQ, and Box-Whisker Plots after Outlier Removal (nondetects assumed equal to one-half the MDL)



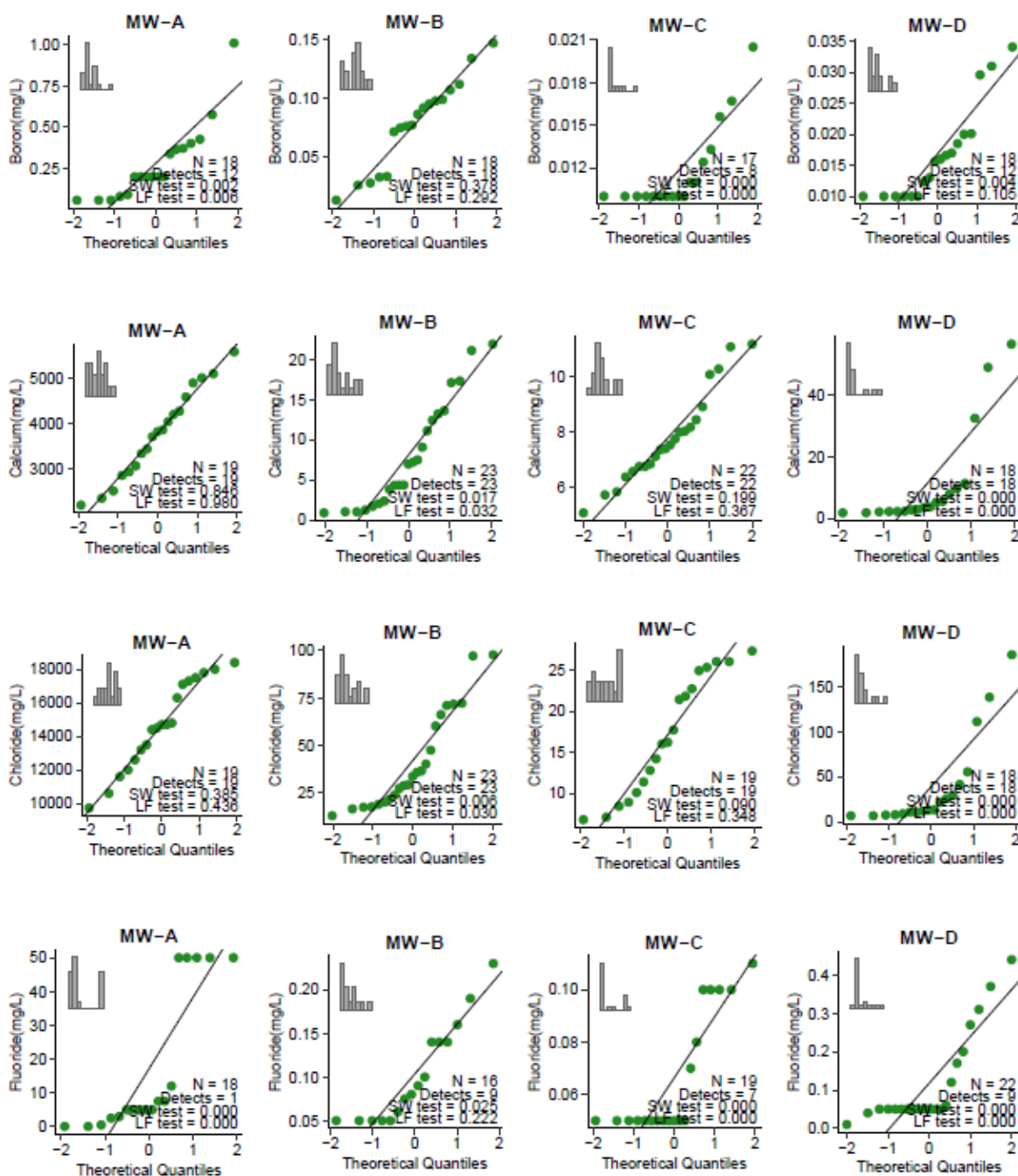
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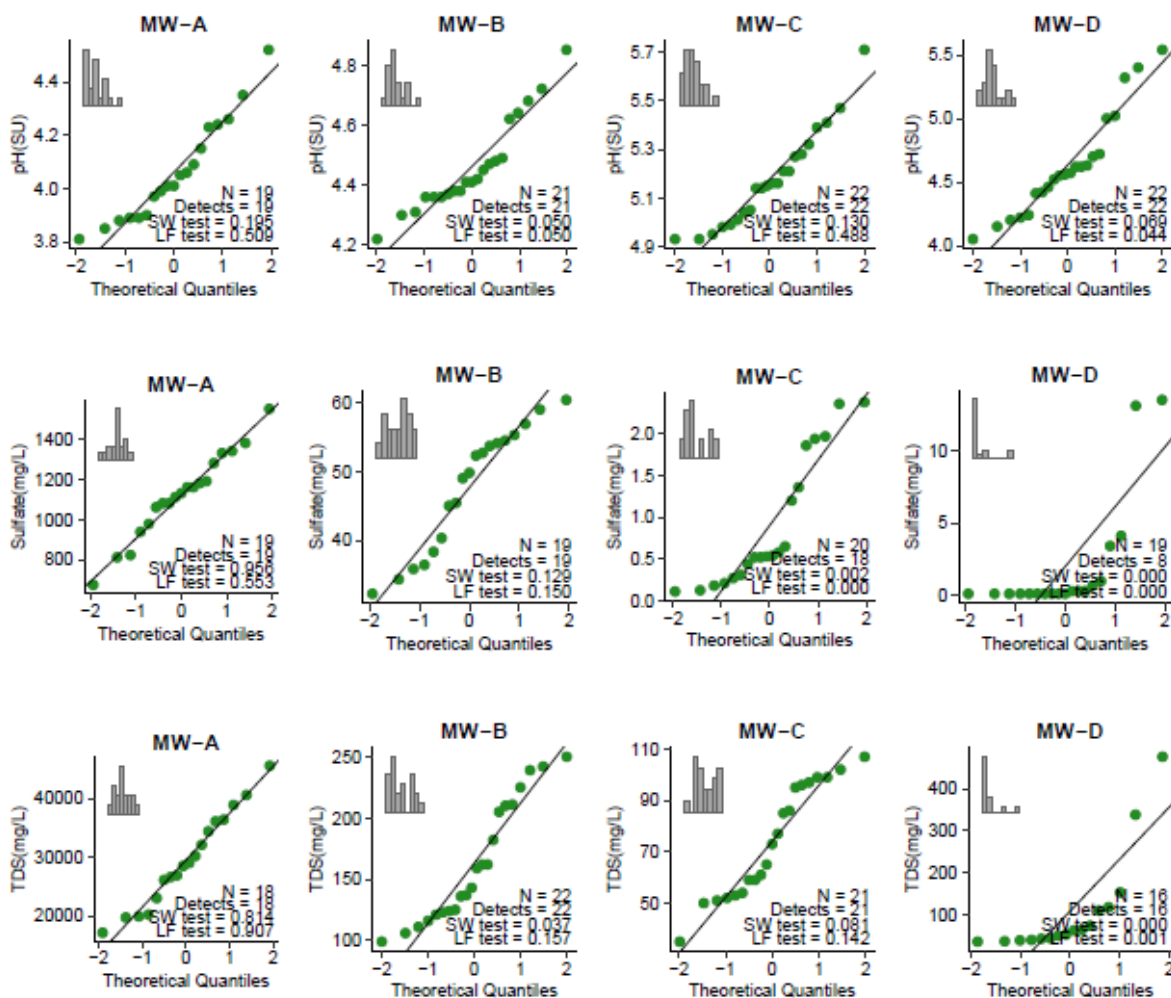
Attachment 3

QQ Plots with Normality Tests

Q-Q Plots, OUC Data
(nondetects assigned one-half the MDL)



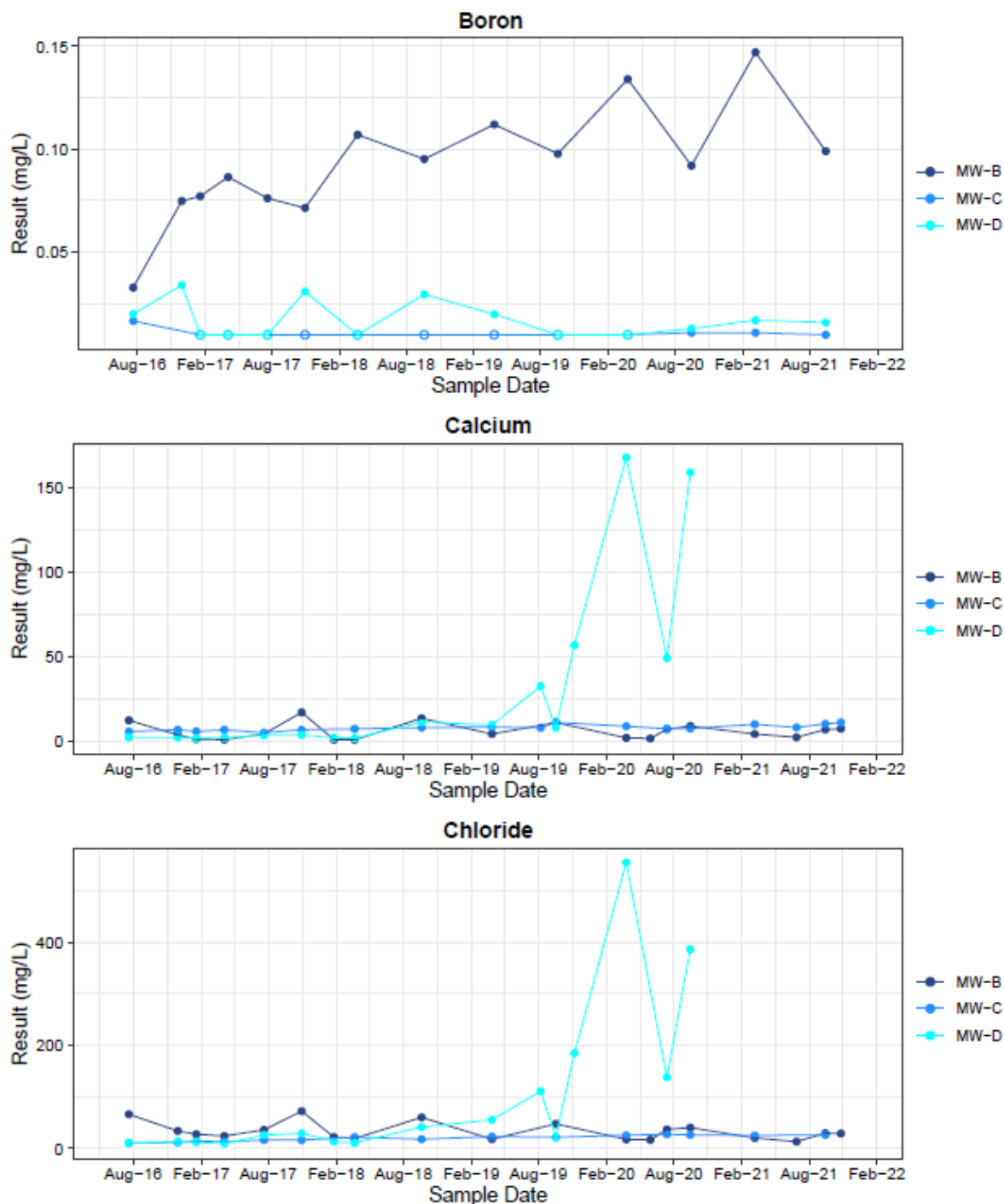
Q-Q Plots, OUC Data
(nondetects assigned one-half the MDL)



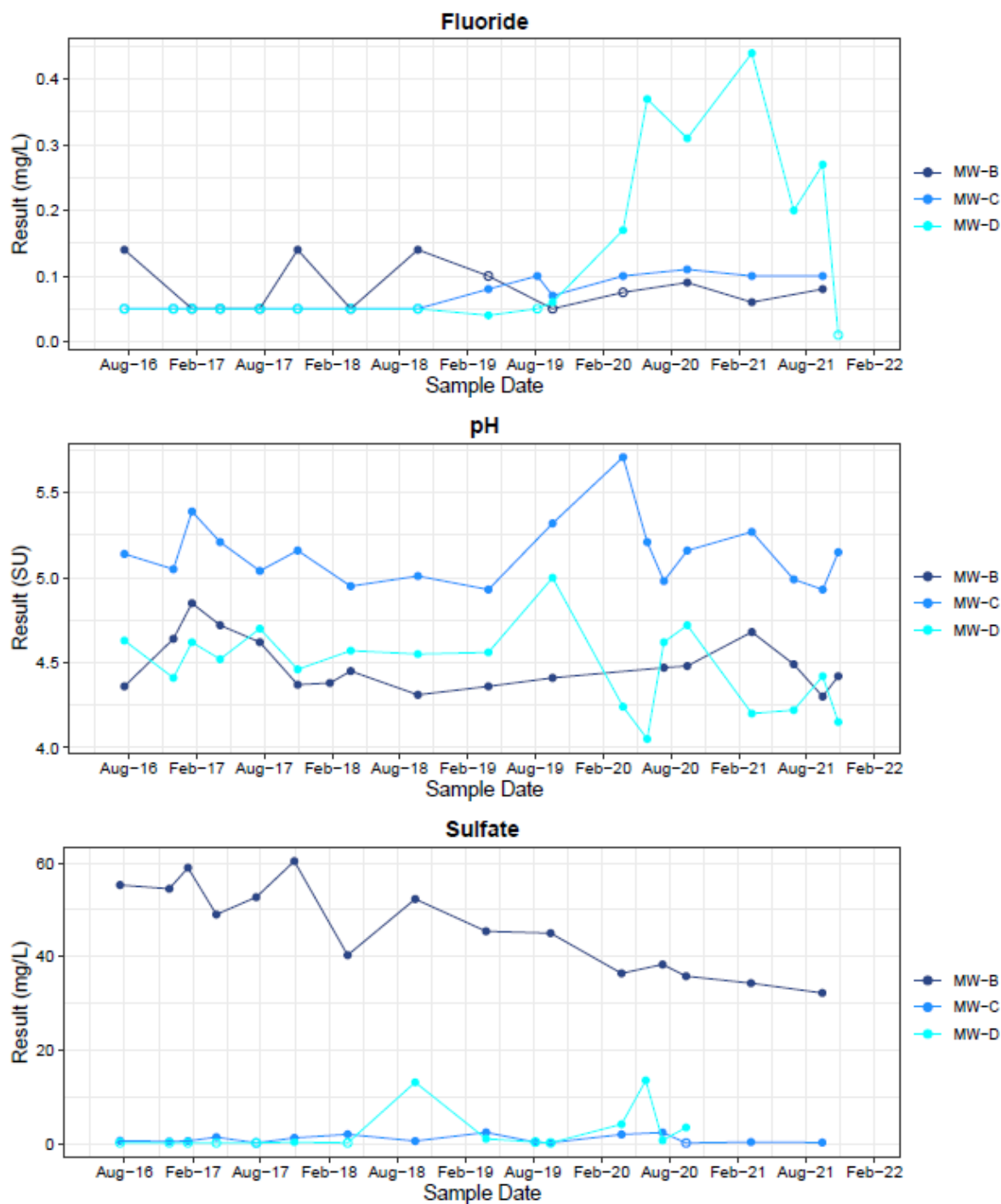
Attachment 4

Overlapping Timeseries Plots

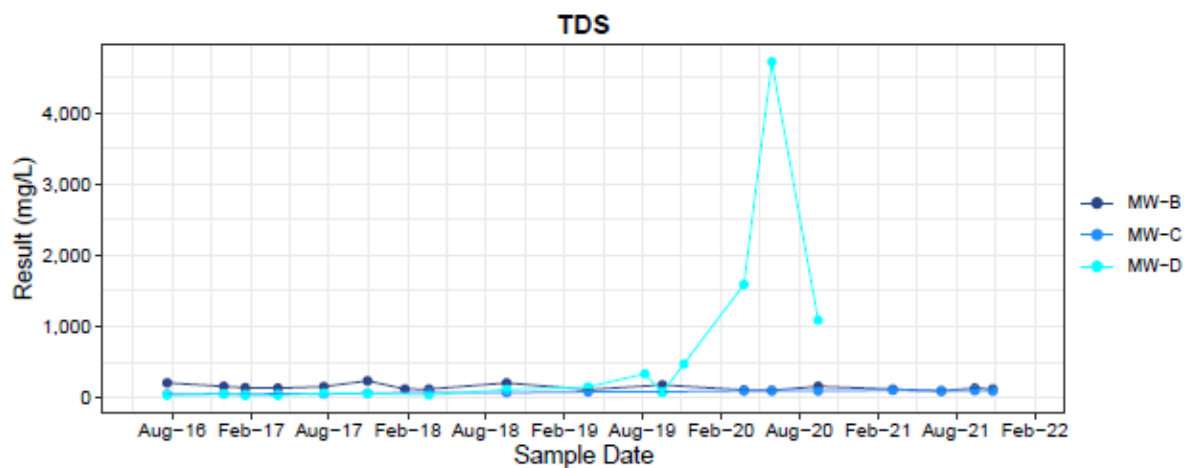
Overlapping Time Series Plots for OUC Landfill
(nondetects plotted using open symbols at one-half the reporting limit)



Overlapping Time Series Plots for OUC Landfill
(nondetects plotted using open symbols at one-half the reporting limit)



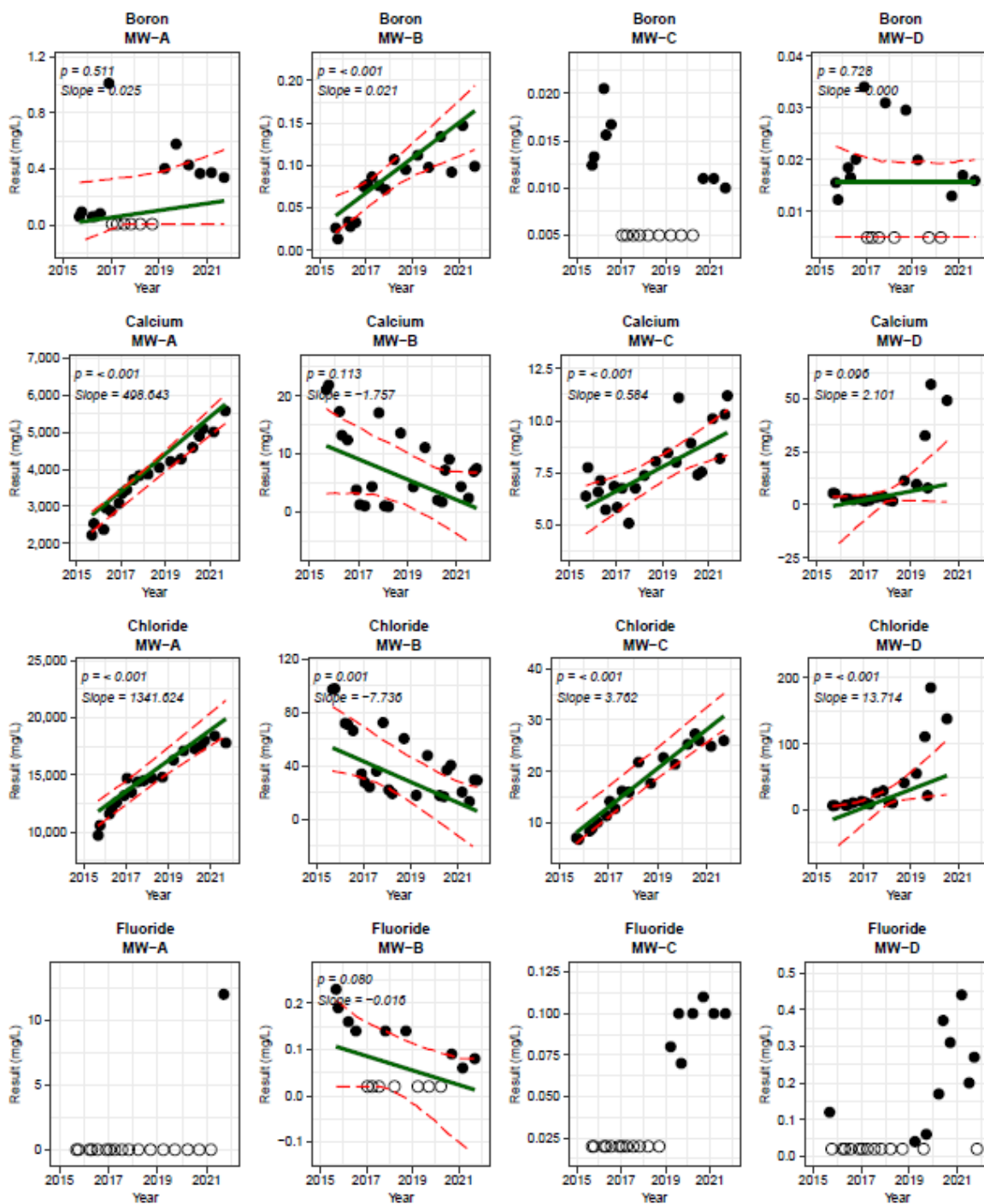
Overlapping Time Series Plots for OUC Landfill
(nondetects plotted using open symbols at one-half the reporting limit)



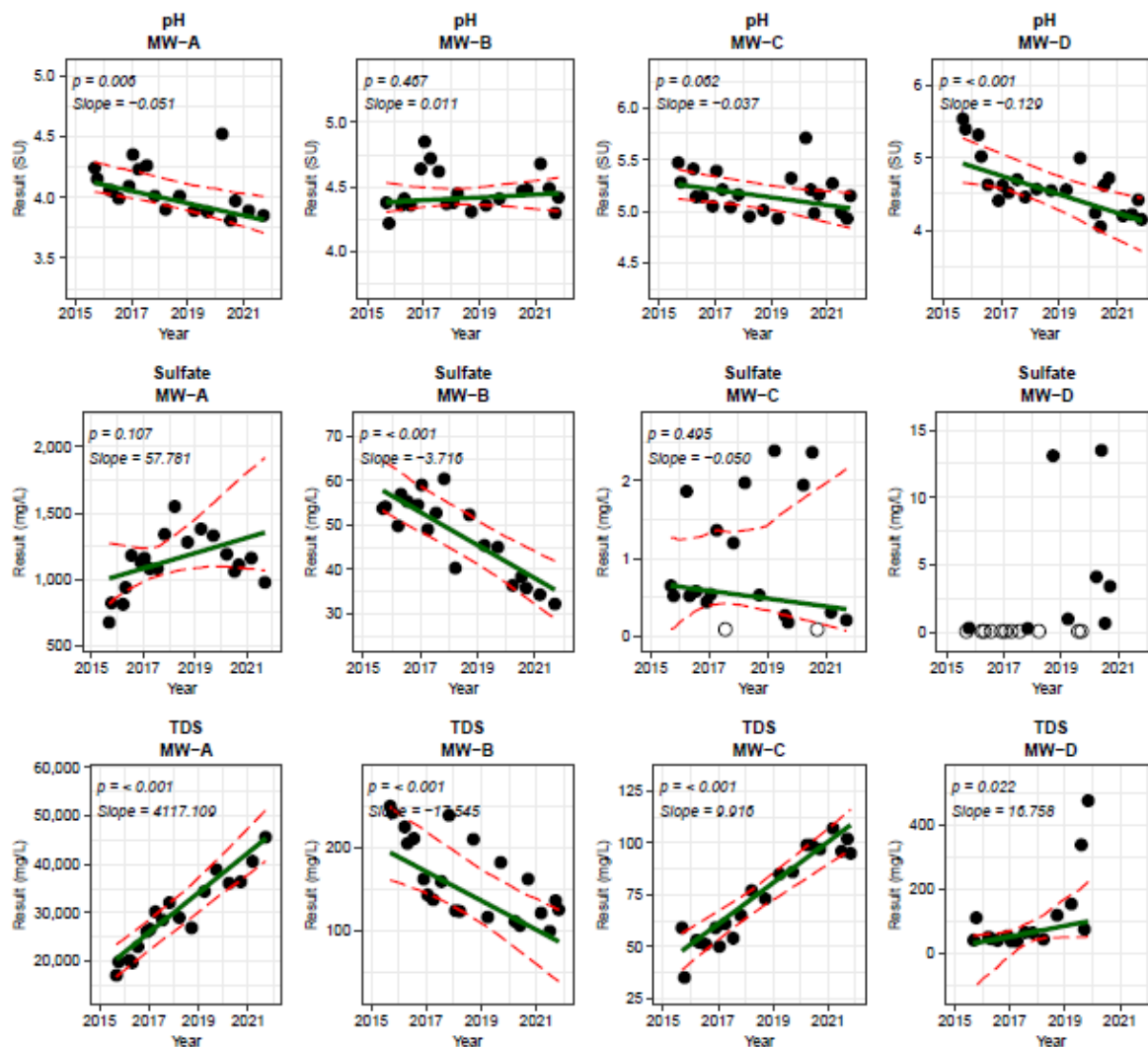
Attachment 5

Theil-Sen Trend Plots

Theil-Sen Trend Plots



Theil-Sen Trend Plots



Appendix B

Laboratory Analysis Results

OUC Stanton CCR Monitoring Well Results, 2022								
Location ID	Sample Date	Parameter Name	MCL	Final Result Text	Final Result Units	Final Reporting Limit	Final Detection Limit	Qualifier Flag
MW-B	3/22/2022	Boron		121	µg/L	5	2	
MW-B	3/22/2022	Calcium		4,340	µg/L	500	50	
MW-B	3/22/2022	Chloride	250,000	16,700	µg/L	1,000	110	
MW-B	3/22/2022	Fluoride	4,000	70	µg/L	100	20	I
MW-B	3/22/2022	pH	6.5 to 8.5	4.62	pH Units			
MW-B	3/22/2022	Sulfate	250,000	34,300	µg/L	2,320	780	
MW-B	3/22/2022	TDS	500,000	106,000	µg/L	5,000	5,000	
MW-B	9/14/2021	Boron		97	µg/L	5	2	
MW-B	9/14/2021	Calcium		5,670	µg/L	500	50	
MW-B	9/14/2021	Chloride	250,000	24,900	µg/L	1,000	110	
MW-B	9/14/2021	Fluoride	4,000	100	µg/L	100	20	I
MW-B	9/14/2021	pH	6.5 to 8.5	4.49	pH Units			
MW-B	9/14/2021	Sulfate	250,000	30,000	µg/L	2,320	780	
MW-B	9/14/2021	TDS	500,000	121,000	µg/L	5,000	5,000	
MW-C	3/22/2022	Boron		10	µg/L	5	2	
MW-C	3/22/2022	Calcium		9,340	µg/L	500	50	
MW-C	3/22/2022	Chloride	250,000	26,300	µg/L	1,000	110	
MW-C	3/22/2022	Fluoride	4,000	100	µg/L	100	20	
MW-C	3/22/2022	pH	6.5 to 8.5	5.19	pH Units			
MW-C	3/22/2022	Sulfate	250,000	340	µg/L	460	160	I
MW-C	3/22/2022	TDS	500,000	102,000	µg/L	5,000	5,000	
MW-C	9/14/2021	Boron		12	µg/L	5	2	
MW-C	9/14/2021	Calcium		10,100	µg/L	500	50	
MW-C	9/14/2021	Chloride	250,000	26,800	µg/L	1,000	110	
MW-C	9/14/2021	Fluoride	4,000	130	µg/L	100	20	
MW-C	9/14/2021	pH	6.5 to 8.5	5.08	pH Units			
MW-C	9/14/2021	Sulfate	250,000	650	µg/L	460	160	I
MW-C	9/14/2021	TDS	500,000	99,000	µg/L	5,000	5,000	
MW-C	11/9/2022	Fluoride	4,000	100	µg/L	100	20	
MW-D	3/22/2022	Boron		27	µg/L	10	4	
MW-D	3/22/2022	Calcium		1,380,000	µg/L	20,000	2,000	
MW-D	3/22/2022	Chloride	250,000	3,570,000	µg/L	100,000	11,000	
MW-D	3/22/2022	Fluoride	4,000	380	µg/L	100	20	
MW-D	3/22/2022	pH	6.5 to 8.5	4.39	pH Units			
MW-D	3/22/2022	Sulfate	250,000	270,000	µg/L	46,500	15,500	
MW-D	3/22/2022	TDS	500,000	10,600,000	µg/L	5,000	5,000	
MW-D	5/10/2022	Calcium		1,330,000	µg/L	25,000	2,500	
MW-D	5/10/2022	Chloride	250,000	3,740,000	µg/L	100,000	11,000	

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MW-D	5/10/2022	Sulfate	250,000	281,000	µg/L	46,500	15,500	
MW-D	5/10/2022	TDS	500,000	11,000,000	µg/L	5,000	5,000	
MW-D	9/14/2021	Boron		49	µg/L	5	2	
MW-D	9/14/2021	Calcium		1,450,000	µg/L	20,000	2,000	
MW-D	9/14/2021	Chloride	250,000	4,390,000	µg/L	200,000	22,000	
MW-D	9/14/2021	Fluoride	4,000	570	µg/L	100	20	
MW-D	9/14/2021	pH	6.5 to 8.5	4.41	pH Units			
MW-D	9/14/2021	Sulfate	250,000	363,000	µg/L	46,500	15,500	
MW-D	9/14/2021	TDS	500,000	12,900,000	µg/L	5,000	5,000	
MW-D	11/9/2022	Calcium		1,520,000	µg/L	50,000	5,000	
MW-D	11/9/2022	Chloride	250,000	5,300,000	µg/L	500,000	55,000	
MW-D	11/9/2022	Fluoride	4,000	2,900	µg/L	10,000	2,500	I
MW-D	11/9/2022	Sulfate	250,000	410,000	µg/L	46,500	15,500	
MW-D	11/9/2022	TDS	500,000	11,000,000	µg/L	5,000	5,000	

Flags: U = Results below method detection limit; I = The reported value is greater than or equal to the laboratory method detection limit but less than the laboratory practical quantitation limit.