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Exploring How Antecedent Precipitation Amount and the Effects of Covid-19 Affect Stormwater Runoff Quality Along Urban Gradients

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Abstract:

Stormwater runoff quality is affected by a multitude of factors including surrounding land characteristics, human activities, and antecedent precipitation amounts. We explore how seasonal and variable precipitation affect E. Coli, total suspended solids, nitrogen-nitrate, orthophosphate, lead, and zinc concentrations in Portland, OR, USA. Correlation analysis was conducted between the pollutant concentrations and antecedent rainfall each sample site received for the previous 1, 3, 5, 7, and 30 days from when the sample was taken. We ran Mann-Whitney tests to determine if the levels of the pollutants were statistically different between the wet season and the dry season. We found that the nutrients nitrate and orthophosphate saw the most instances where there were statistically significant different levels of their concentrations in the wet season versus the dry season. Additionally, we found that the heavy metals demonstrated the most statistically significant correlations with up to 7 days of antecedent precipitation. For lead, we see that as the surrounding land percent imperviousness increases there is less association of lead concentration explained by antecedent precipitation. Further exploration is needed to understand the relationship between antecedent precipitation and pollutant concentration with respect to how the surrounding level of urbanization affects them. Understanding how pollutant concentrations respond temporally to these events can give city officials insights into how to adjust stormwater management systems to best treat stormwater runoff coming from urban regions.

Introduction

1.1 Introduction

In urban areas, the highly developed landscape dictates how the stormwater runs and what it is exposed to over time. Throughout a city, its regions vary in levels along an urban gradient that can be categorized as urban, suburban, or rural. These distinct regions can expect to have different pollutant sources along with varying levels of pollutant concentrations in the catchment areas (Chen and Chang 2014). Urban catchments can see larger quantities of storm runoff during precipitation events and be more polluted as a result (Dwight et al 2011). Not only do urban lands impact the quantity of runoff, but they also observe higher volumes of runoff annually as well (Chen et al 2016). Their larger quantities in addition to the increased potential pollution sources leave stormwater runoff from urban areas susceptible to being greatly polluted which can be detrimental to public and ecological health (Fish and Jordan 2018).

The amount of precipitation an area receives is most noticeable across its wet and dry seasons. The seasons provide a macro-level time frame to observe how stormwater runoff in urban areas changes over time. Developed lands will record higher heavy metal levels in their storm runoff after the first major rain event after a long dry period (Ferriera et al 2016). Additionally, a study by Ortíz-Hernandez et al (2016) observed higher mean values for total suspended solids, lead, and zinc in the dry season than in the wet season across all sampling sites at a university in a semi-arid zone. We anticipated our study to observe extremely similar results. Namely, as the sources for heavy metals are associated with car tires and undercarriage degradation, we expected high lead and zinc levels across the entire study area and study period when driving patterns occurred normally (before covid-19 restrictions). For the rest of the pollutants which are E. Coli, total suspended solids (TSS), nitrate, and orthophosphate, we expected them to follow higher levels in the dry season and lower levels in the wet season as the majority of studies from the literature suggests.

Stormwater runoff quality can vary substantially during the same season since storm amount and duration and soil moisture conditions can affect the source, pathway, and delivery of pollutants. At smaller time scales across both seasons, The availability we explored how previous days' worth of rainfall, or antecedent precipitation, affect the concentrations of the pollutants in the runoff. We considered the precipitation of discrete previous time values going as far back as a month (i.e., 1 day, 3 days, 5 days, 7 days, and 30 days). Antecedent precipitation has been cited as a principal factor that influences the levels of pollutants in stormwater runoff (Chen and Chang, 2014; Ferreira et al, 2016; Guo et al, 2018). Antecedent precipitation provides the ground surface moisture, which is an environment that is better for the accumulation and mobilization of pollutants (Guo et al 2018). On the other hand, significant antecedent rain amounts can dilute the pollutants and lower the overall measurement of it in stormwater runoff (Ferreira et al, 2016). Thus, we see that antecedent precipitation's relationship to pollutant levels is complex. A step further, a goal of this study was to determine if areas that had a strong correlation between antecedent precipitation amounts and pollutant concentration can be attributed to various landscape variables. In other words, is there an attribute of the land's level of urbanization (e.g., percent impervious, percent developed, surrounding road length) that explains the association between antecedent rainfall and pollutant concentrations?

These time scales that we are examining may offer different explanations as to why we observe temporal differences in stormwater runoff quality and how to best respond to it. However, the major human-environmental event that was the restrictions placed as a response to the Covid-19 pandemic in 2020 saw tremendous changes in the activity of urban landscapes. According to the Oregon Department of Transportation (2021),

> After Governor Brown's stay-at-home order issued March 23, traffic volume continued to decrease, with the fewest amount of average weekday vehicles occurring the week of March 30-April 3. Since April 6, there has been a gradual increase of average weekday traffic volume on freeway. … In the late summer, traffic volumes leveled off to about 10-15% below 2019 traffic volumes (p. 4)

This undeniable shift in human activity that urban areas experienced could have impacted pollutant concentrations. We utilized the timeframe of Covid-19 to determine if the quality of stormwater runoff responded to the large decrease of human activity that we anecdotally observed for those living in highly urbanized areas. With that goal in mind, the ultimate goals of this study were to **(a)** observe if the study area saw different levels of pollutants in the wet season vs the dry season, **(b)** determine if antecedent precipitation was correlated with pollutant concentrations, then **(c)** test the surrounding land characteristics of the catchment areas to see if they can explain the antecedent precipitation and pollutant levels correlation, and lastly **(d)** analyze the effects the restrictions brought on by Covid-19 had on storm runoff quality.

Data/Methodology

2.1 Study Area

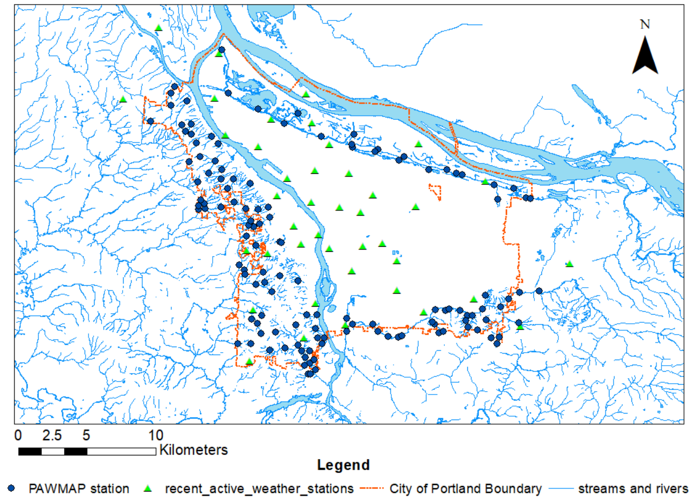


Figure 1 outlining the city limits of Portland, Oregon.

Our study area is the city of Portland, Oregon, located in the Pacific Northwest region of the United States. The city experiences its wet season from October (of the previous year) to April and the dry season from May to September. We utilized hourly rain data collected from 22 stations as part of the City of Portland HYDRA network located within the city boundaries. For water quality data, we used stormwater runoff samples taken by 131 stations that were put in place by the Portland Area Watershed Monitoring and Assessment Program (PAWMAP). The distribution of both types of monitoring stations can be seen in Figure 1. Portland's widespread rain gauge network as well as its maintenance of their water quality (PAWMAP) stations provided an in-depth record of hourly and daily precipitation going as far back as 1998 as well as storm runoff water samples starting in 2015. The availability of detailed long-term data made it possible to investigate the variability in the city's storm runoff. The city's geography contributes to the interest of its investigation. Cooley and Chang (2017) cite that studies on regional precipitation in the Pacific Northwest have been increasing in annual precipitation volume since the early 1900s. This fact along with worries that climate change can bring sporadic yet more intense precipitation can lead to higher volumes of polluted runoff in Portland. The authors go on to state that " the city has a maritime climate and receives two-thirds of its annual precipitation between November and April." (p. 3). This makes the wet season particularly important to analyze.

2.2 Data Preparation

We received raw data for this study consisting of a water quality table that had samples of stormwater runoff taken from 2015 to 2021 at the PAWMAP stations. The other raw data came in the form of hourly precipitation records of the City of Portland's Hydra network which gauged how much rain they received for every hour of the day for several years.

All sample dates had to be categorized for the seasonal pollutant variation analysis and the covid-19 analysis. For the seasonal analysis, all dates were considered to be in the wet season if the sample was collected between October and April. Dry season samples were all that were collected between the months of May and September. For covid-19 categorization, we utilized the date of March 23, 2020, quoted from the Oregon Department of Transportation (2021), as the cutoff date for samples that were taken before covid-19 restrictions went into effect. All samples after that date were considered to have been taken during covid-19 restrictions were in place.

To test the hypothesis that antecedent precipitation affects the levels of pollutants in storm runoff, we had to acquire the previous days' amounts of rain that the sample site received. The closest USGS weather station, or rain gauge, was determined for all PAWMAP stations, or water quality stations. The dates that each rain gauge had rain data for varied, so we chose stations that were sparsely located throughout the city that contained data for the samples in the water-quality table. The ultimate goal was to maximize the amount of water quality samples we had to investigate. We utilized the Python package *Pandas* to efficiently collect previous days worth of rain for all the samples that were taken at water quality stations that corresponded to a rain gauge station.

2.3 Methodology

Our study needed to quantify the differences in magnitude that our recorded samples saw by season and occurrence with respect to covid-19 restrictions. For this, we conducted the Mann-Whitney U test to determine if the pollutant concentrations were statistically different across the wet and dry season as well as before and after covid-19. The test was conducted for each pollutant individually. For samples from a water quality station to be considered in the test, the station must have had a sample taken in both periods. This reduced the data from a possible 131 water quality stations down to 89 stations for the by-season test and 48 stations for the covid-19 comparison. Next, Spearman's rank-order correlation test was used to investigate the correlation between pollutant concentrations and different days' worth of antecedent precipitation amounts. Data from all 131 stations were used to observe the correlation for each pollutant. Lastly, after the correlation analysis, we classified all samples into a quartile based on the value of a station's land attribute. The land attribute investigated in this study was the percent imperviousness of land that surrounded each water quality station in a 250-meter radial buffer zone. Then only considering the points from each station by quartile group, Spearman's correlation test displayed the impact percent imperviousness had on the relationship between pollutant concentration and antecedent rainfall amount.

Results

3.1 Seasonal differences in water quality

3.1.1 -Mann-Whitney tests results

To preface the observation of pollutant differences across the wet and dry seasons, we wanted to see how the seasons differed for our data set. Figure 2 depicts the variability of rain that all the samples saw across all 131 seasons. We see consistently the central value for each day of antecedent precipitation is higher in the wet season than in the dry season. The graph confirms the intuition that the wet season received more precipitation than the dry season in our study, as backed by Cooley and Chang (2017).

As we confirmed that the precipitation amounts varied significantly by season, we now dissect the results from comparing pollutant levels across the wet and dry seasons. It was significant to see that across all six pollutants, the Mann-Whitney test produced p-values less than 0.01 for E.coli, lead, zinc, nitrate, and orthophosphate. This measurement means that there are statistically significant differences in the pollutant's concentrations between the wet and dry seasons. Whether that change meant an increase or decrease across the seasons can be extracted from Table 1. In Table 1 we see that four out of the six pollutants saw higher mean concentrations in the wet season than in the dry season, going against what was initially expected from reading the literature. Figure 3 demonstrates boxplots that show the variation in pollutant concentrations across the seasons. The boxplots reflect the key data points from Table 1 well.

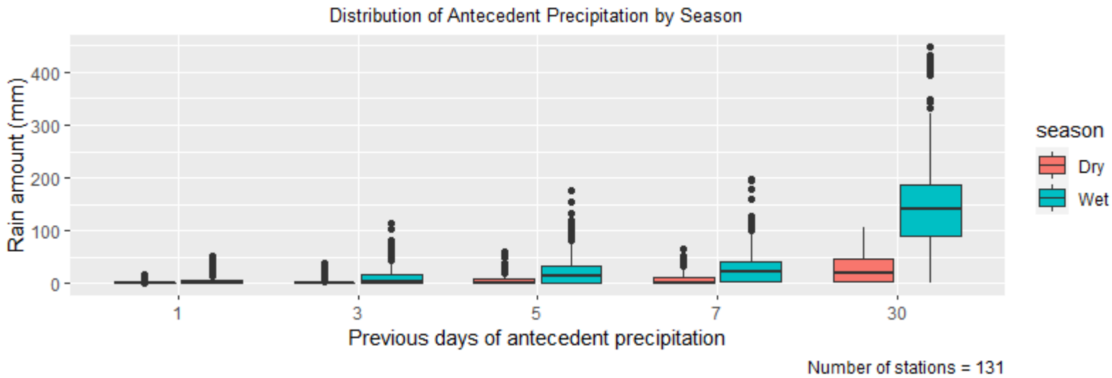


Figure 2: Box and whiskers plot for antecedent rain amounts of different days

Pollutant	**Wet Season Average**	**Dry Season Average**	**P-value**	**Number of Stations**	**Number of wet season samples**	**Number of dry season samples**
E.coli	251.4	286.6	**<0.01**	89	460	224
Lead	0.811	0.468	**<0.01**	89	460	224
Zinc	11.86	6.011	**<0.01**	89	460	224
Total Suspended Solids	20.13	9.192	**<0.1**	89	460	224
Nitrate	1.598	0.998	**<0.01**	89	460	224
Ortho Phosphate	0.0450	0.0599	**<0.01**	89	460	225

Table 1: Seasonal Difference of Pollutant Concentrations

3.1.2 - Subsection regarding Covid-19 effect on water quality

The covid-19 data had the least number of samples from all the statistical tests we conducted. Table 2 shows the number of samples that the 48 stations had available before and after the commencement of covid restrictions. In the table, we see that only total suspended solids received a statistically significant p-value for the Mann-Whitney test less than 0.05. After that, nitrate was the only pollutant below the 0.1 p-value threshold. We see the mean pollutant concentration values before and during covid and there is no common behavior among the pollutants. A distinct decrease in pollutant levels for all the pollutants is not observed here as hypothesized. Boxplots were also generated to depict the variations all pollutant concentrations saw between the two periods in Figure 4.

Pollutant	**Before covid-19 mean**	**During covid-19 mean**	**P-value**	**Number of Stations**	**Number of before covid samples**	**Number of during covid samples**
E.coli	207.1	180.3	0.25	48	333	135
Lead	0.554	0.5106	0.5	48	333	135
Zinc	9.263	8.019	0.66	48	333	135
Total Suspended Solids	13.89	9.948	**<0.05**	48	333	135
Nitrate	1.529	1.549	**< 0.1**	48	335	135
Ortho Phosphate	0.047	0.0493	0.54	48	334	135

Table 2: Pollutant Differences Between Covid-19 Periods

3.2 Relationship between precipitation and water quality

3.2.1 Correlation Analysis

Each pollutant had its concentrations plotted against the amount of precipitation that the sample received for various days going as far back as 30 days. The strength of that relationship was quantified via Spearman's rank-order coefficient. Data from all 131 stations were used to observe this relationship. All of the p-values that were generated along with the coefficients between pollutant concentrations and days of antecedent precipitation were considered statistically significant as they were below 0.05. Similar to the findings of Guo et al (2018), the highest correlation occurred for 4 out of the 6 pollutants between pollutant concentration and one day's previous rainfall amount. The pollutants associated with human activity all saw the strongest correlation with 1-day antecedent precipitation, and total suspended solids was the pollutant from more naturally occurring sources that saw the highest correlation with 1-day antecedent precipitation as well. In Table 3, you can note that most pollutants exhibit a monotonic increase or decrease across the several days of antecedent precipitation.

Table 3: Spearman Correlation Coefficient Between Pollutant & Antecedent Precipitation

Pollutant	**1 day**	3 days	5 days	7 days	**30 days**
E. coli	**0.27**	0.17	0.14	0.1	-0.14
Lead	**0.44**	0.41	0.41	0.4	0.27
Zinc	**0.38**	0.38	0.36	0.36	0.21
Total Suspended Solids	**0.29**	0.28	0.26	0.25	0.15
Nitrate	0.11	0.074	0.094	0.14	**0.26**

Ortho Phosphate	-0.081	-0.14	-0.17	-0.18	**-0.34**

Once it was determined which day caused the highest correlation coefficient, a scatter plot of the pollutant's concentration and that antecedent precipitation amount was created. We see this illustrated in Figure 5.

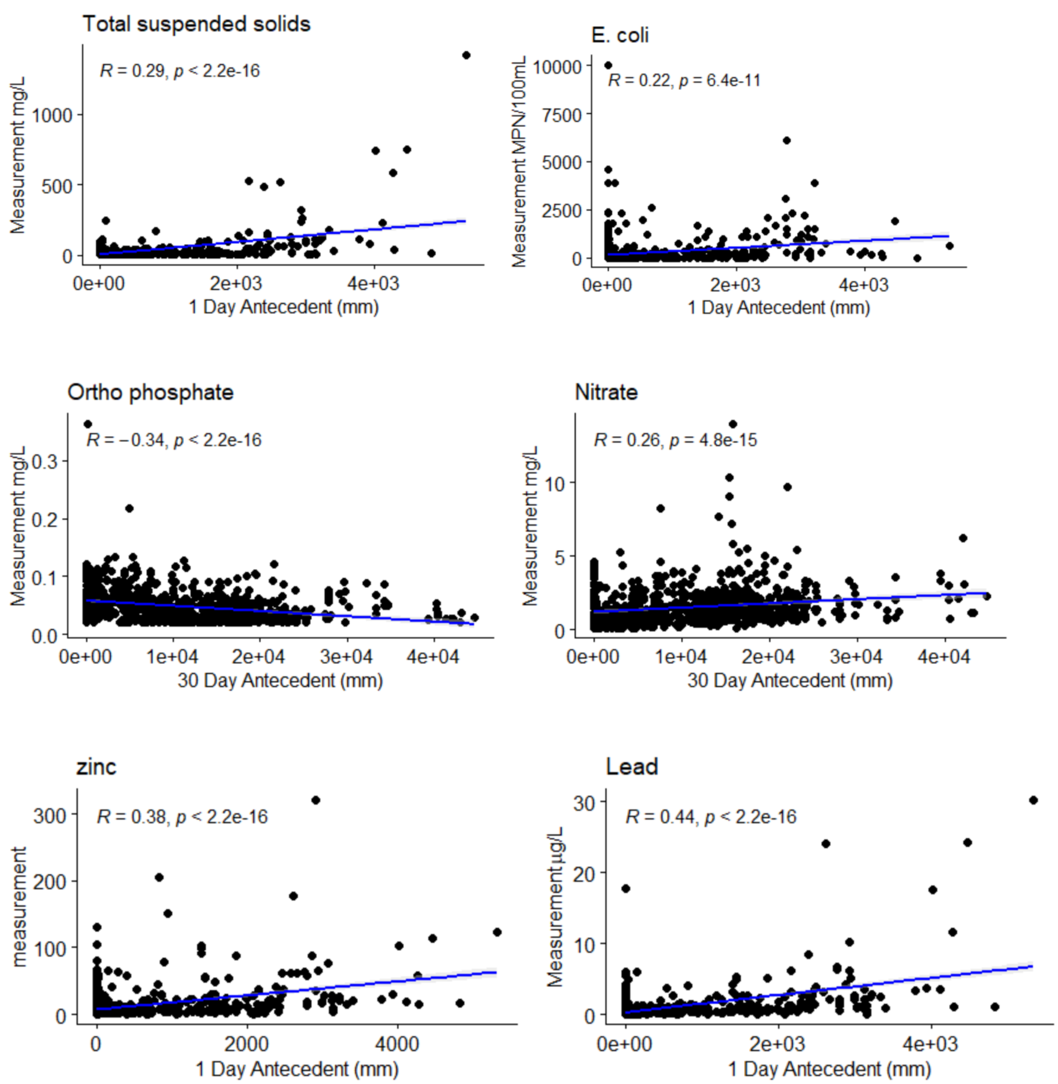


Figure 5: Pollutant Concentrations vs Antecedent Rainfall

We then picked a pollutant from the human-associated pollutants and another one from the more naturally occurring pollutants to be candidates for quantile regression. Lead and total suspended solids were thus chosen. Figure 6 shows all of the lead samples representing a quartile of stations with varying percentages of impervious surfaces that surround the sample station. Notably, Figure 7 illustrates that the stations with the lowest percent imperviousness demonstrate the strongest correlation between pollutant concentrations and 1-day antecedent precipitation. Being that lead is a human-activity-associated pollutant, the fact that stations with lower impervious surfaces is incredibly surprising. With lower impervious surfaces, such as sidewalks and roads, we expect less human activity. The low r-squared value of 0.36 tells us that further investigation is required to confirm this relationship. The same phenomena appeared with total suspended solids in Figures 8 & 9. The result was more expected again as lower impervious surfaces imply the area is surrounded by natural surface types from which TSS derives. Another low r-squared value of 0.34 suggests that percent imperviousness does not explain the entirety of variation the pollutant concentrations saw with respect to antecedent rainfall.

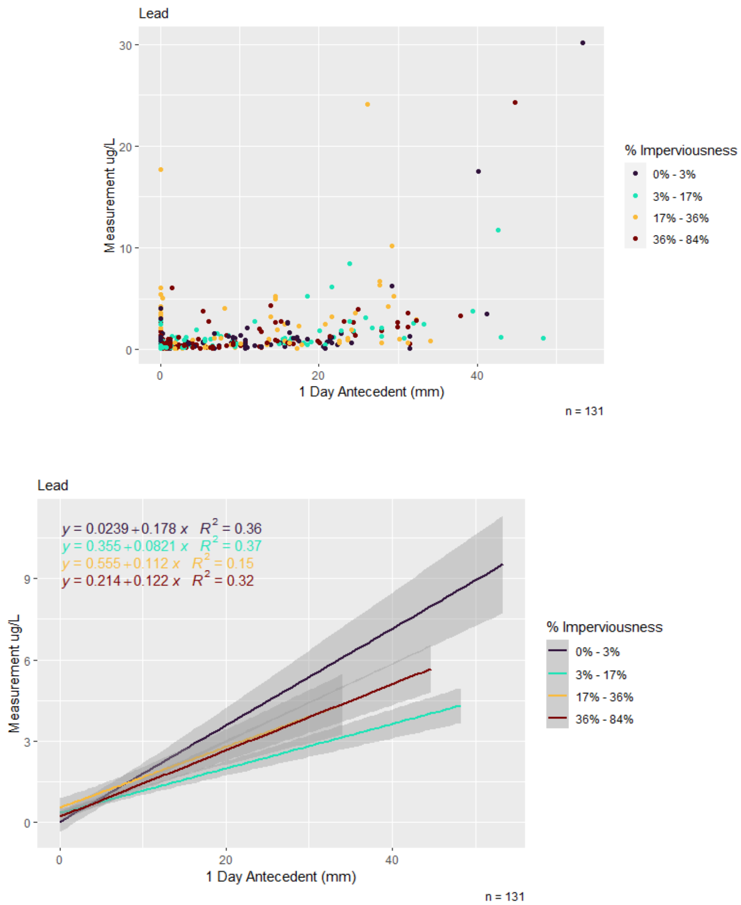


Figure 6 & 7: Lead sample points classified by sample group and their regression lines

Discussion

It was reassuring to begin our investigation by confirming that the time labeled as the wet season received the higher quantity of rain between the two seasons. However, as climate change worries continue, we might see polarization in terms of the rain disparities of the seasons. This could include even less rain during the dry season and more intense, higher volumes of rain in the wet season. Considering how our pollutants responded to the different seasons, increased changes to rainfall amounts can see extreme spikes of pollutant levels in stormwater runoff. It was unexpected to see that our pollutants did not all see lower values in the wet season than in the dry season. With the increased rain volume to possibly dilute the pollutants, one would expect lower pollutant levels. This is not the case suggesting that the increased rain amounts provided a better medium for pollutants to mobilize and thrive.

As the normal seasonal rain patterns occurred, the timeline for covid-19 interjected itself a year and a half ago. Although we anecdotally experienced huge differences in human activity, the data does not confirm any major changes to pollutant levels. The insignificant differences between samples taken in both periods might be explained by the lesser amount of stations that we had available to conduct these comparative tests. Because the PAWMAP water quality stations from our study are part of a larger network that shift being considered active, we had only 48 stations' data available across the covid periods. Additionally, the response to covid-19 varies at the state level in the United States so further studies need to be found to quantify by how much Portland saw a decrease in human activities. This along with continual monitoring of pollutant levels through the response to covid-19 should give us a better understanding of how this generational event impacted stormwater quality.

Lastly, although with low certainty, the quantile regression showed us that taking into account surrounding land characteristics surrounding the sampling station impacts the strength of the correlation between pollutant concentrations and antecedent rainfall amount. These surrounding land characteristics can be considered as explanatory variables. Percent imperviousness was the only explanatory variable studied. The next step is to branch out the quantile regression and consider the impact of other explanatory variables such as percent developed, percent forested, average road length, the standard deviation of slope, and many more. This aspect can connect the temporal aspect of our investigation with a spatial investigation. These two, when combined, give the most complete understanding of an area's water quality.

Conclusion

Stormwater quality responds to a multitude of temporal factors. All six of our pollutants saw statistically significant differences in their mean values across the seasons. Only total suspended solids saw statistically significant lower amounts after the introduction of covid-19 restrictions. One day antecedent precipitation was the most impactful amount of precipitation associated with the levels of a pollutant found in stormwater runoff. Lead and total suspended solids were the pollutants that saw the strongest correlation between 1-day antecedent rainfall and their concentrations for human-associated pollutants and naturally occurring ones, respectively. When grouping those two pollutants' samples based on the sampling station's percent imperviousness, the samples from stations that had the lowest percent imperviousness surrounding them (0-3%) showed the strongest correlation between pollutant concentration and antecedent rainfall amount with r-squared values of 0.36 and 0.34, respectively. This last point is the greatest statement that can lead to a more in-depth understanding of how the land composition affects water quality, and make connections to spatial investigations of water quality.

Appendix

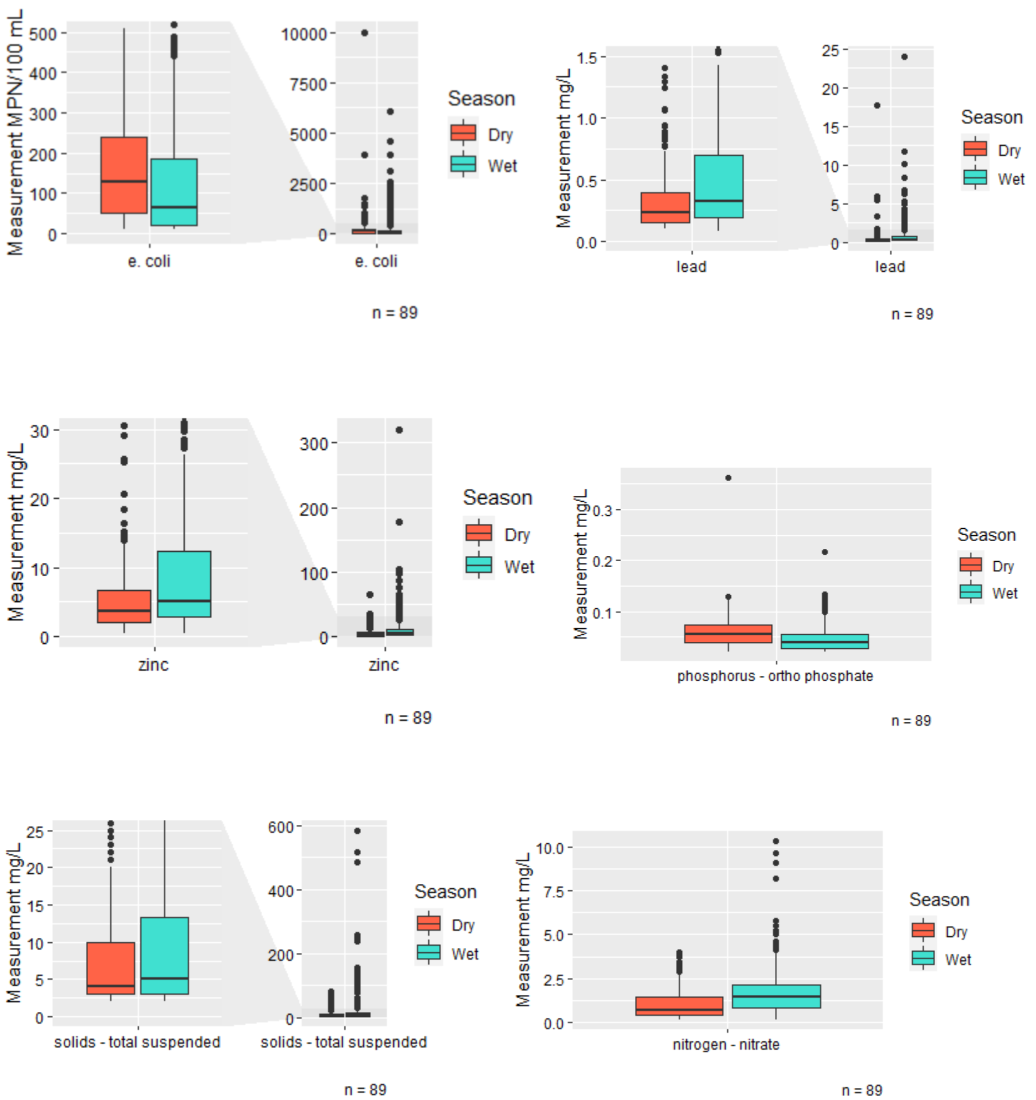


Figure 3: Boxplots showing the seasonal distribution of pollutant samples.

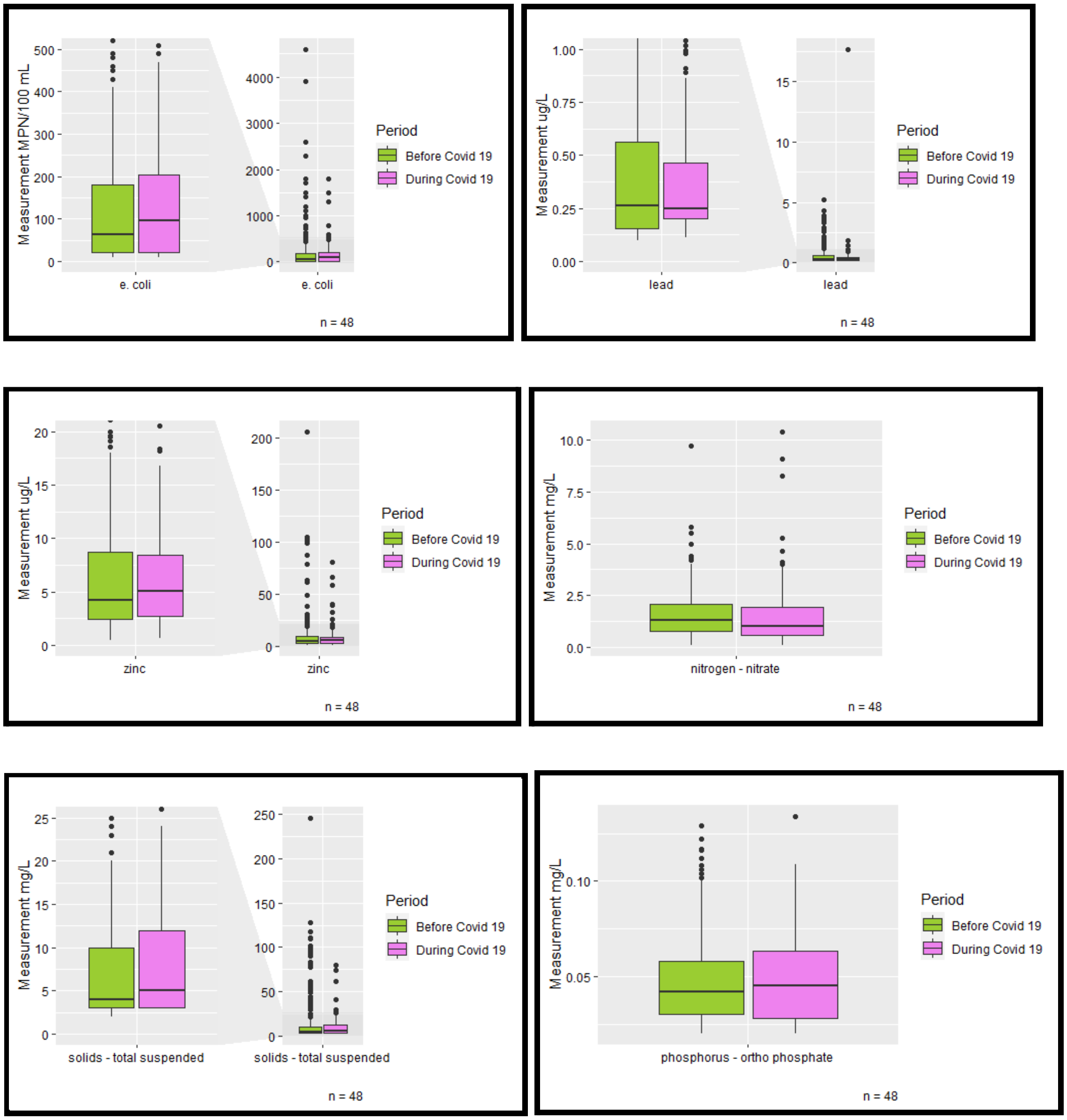
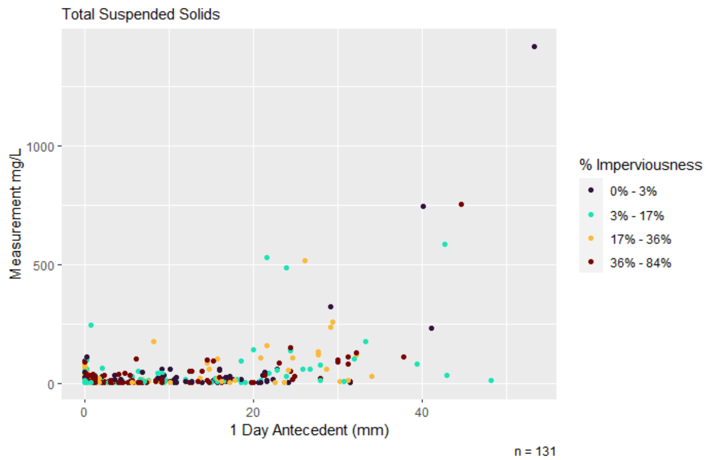
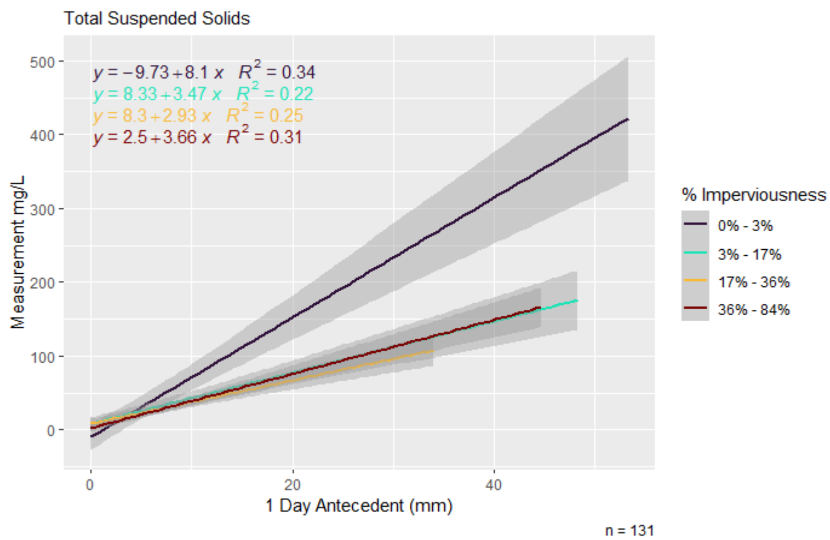


Figure 4: Showing the distribution of pollutant samples with respect to Covid-19.





Figures 8 & 9: Total suspended solids samples points classified by quartile and their regression lines

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