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Spatial Analysis of Landscape Characteristics, Anthropogenic Factors, and Seasonality Effects on Water Quality in Portland, Oregon

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Abstract

Urban areas often struggle with deteriorated water quality as a result of complex interactions between landscape factors such as land cover, use, and management as well as climatic variables such as weather, precipitation, and atmospheric conditions. Green stormwater infrastructure (GSI) has been introduced as a strategy to reintroduce pre-development hydrological conditions in cities, but questions remain as to how GSI interacts with other landscape factors to affect water quality. We conducted a statistical analysis of six relevant water quality indicators in 131 water quality stations in four watersheds around Portland, Oregon using data from 2015 to 2021. Indiscriminate of station location, water quality is slightly negatively correlated with distance to nearest GSI. Spatial lag and spatial error models best explain variations in water quality using a distance band weights matrix; when accounting for spatial autocorrelation, up to 43% of variation in water quality can be explained by selected landscape and anthropogenic variables. Spatial dependence is present especially for zinc and orthophosphate, indicating a need for spatial filtering approaches. Future studies should include multi-level analysis at the census block group scale to include sociodemographic variables that demonstrate whether benefits from GSI are equally distributed. Our findings provide valuable insights to city planners and researchers seeking to improve water quality in metropolitan areas by implementing GSI.

1. Introduction

Increasing urbanization in metropolitan areas poses a threat to water quality by increasing impervious land cover and rerouting water flow to traditional pipe systems (“gray” infrastructure), which results in increased risk for flooding, sewer overflow, and heightened pollutant transport (Baker et al., 2019; Liu et al., 2015; O’Donnell et al., 2020). Furthermore, the resulting land use changes associated with urbanization interact with pre-existing landscape and seasonal factors such as land cover, geomorphology, and weather to produce secondary effects on water quality, many of which are poorly understood (Guo et al., 2019; Lintern et al., 2018).

Green stormwater infrastructure (GSI; used interchangeably with green infrastructure (GI) in this paper) such as green roofs, permeable pavement, bioswales, rainwater cisterns, and detention ponds have been introduced as a strategy to reinstate pre-development hydrological conditions in cities (Chini et al., 2017; McPhillips & Matsler, 2018). While GSI was first introduced primarily as a stormwater overflow mitigation strategy, numerous studies have also demonstrated GSI can decrease pollutant loads through bioretention or other measures and improve water quality (Liu et al., 2016, 2017; Reisinger et al., 2019). However, because of the multivariate spatiotemporal interactions between GSI types, location, age, and the surrounding environment, questions remain as to how GSI affects water quality. Cities in the United States have increasingly introduced GSI in recent years, but benefits have not been as large or quick to manifest as once thought (Liu et al., 2017), requiring better understandings of how GSI interact with the landscape. Furthermore, in the United States, white and wealthy residents have historically benefited disproportionately from green infrastructure installations, inciting recent research and planning initiatives to prioritize equitable distribution of GSI and other green infrastructure practices (Garcia-Cuerva et al., 2018; Wolch et al., 2014).

This study examines relationships between water quality, anthropogenic and landscape factors, and seasonality in Portland, Oregon, a city with abundant GSI installations and robust research surrounding GSI innovation, efficacy, and barriers to implementation (eg. Baker et al., 2019; Chan & Hopkins, 2017; Everett et al., 2018; McPhillips & Matsler, 2018; O'Donnell et al., 2020). We conducted a statistical analysis of six relevant water quality indicators in 131 water quality stations in four watersheds around the city of Portland, Oregon from 2015 to 2021. Using linear correlation, exploratory regression, and spatial regression analysis, we addressed the following research questions:

1) How do selected water quality parameter concentrations vary between the wet and dry seasons?
2) Which landscape variables explain variations in water quality between the wet and dry season?
3) How does the presence and proximity of GSI affect variations in water quality across stations?

1.2 Literature Review

Many studies have examined spatial relationships of water quality patterns and landscape or anthropogenic factors, and concluded that the ability of land use metrics to explain water quality depended largely on which spatial scale was used. Mainali & Chang 2018 found that a 100-meter scale and one-kilometer upstream scale best explained variation in water quality, while Shi et al. 2017 found varying abilities of catchment, riparian, and reach scales to explain degraded water quality (Mainali & Chang, 2018; Shi et al., 2017). However, few studies examined relationships between water quality and landscape variables at a microscale within an urbanized region.

Water quality as a whole is dependent on many parameters, including the presence of pollutants, both aqueous and particulate (Lintern et al., 2018). Lead and zinc are pollutants of concern especially in metropolitan areas, where the degradation of car tires, brake pads, and other automotive parts results in heavy metal-rich road dust entering urban streams via stormwater runoff (Huber et al., 2016; Hwang et al., 2016). Previous literature has observed strong seasonal differences in traffic-related heavy metal runoff, with road icing practices highly influencing runoff concentrations in the winter (Hilliges et al., 2016). In contrast, Hallberg et al.'s 2007 study of a major urban highway found no significant seasonal differences in lead or zinc runoff (Hallberg et al., 2007).

Escherichia coli, a fecal coliform that inhabits the intestinal tract of animals and humans, commonly contaminates water sources in areas of high population density, thus posing public health risks for urbanized areas (Jang et al., 2017). A 2018 evaluation by the City of Portland Bureau of Environmental Services concluded that *E. coli* is the main pollutant that exceeds water quality standards in Portland streams and rivers, with the highest recorded *E. coli* concentrations occurring in the summer and during storms. This is in contrast to McKee et al. 2020, whose study of recreational areas and the surrounding watershed in Atlanta, Georgia found that *E. coli* concentrations were highest during the winter (McKee et al., 2020). Spatial differences were also observed in Portland watershed *E. coli* as well; *E. coli* levels were found to be "significantly lower in the Willamette Streams and Columbia Slough than in most of the other watersheds" (Fish & Jordan, 2018). In a similar vein, Vitro et al. 2017 examined how "land use and stormwater management policies" affect fecal coliform levels at a multi-watershed scale (Vitro et al., 2017).

Phosphorus and nitrogen are organic nutrients that occur naturally in vegetation and soil, but excess amounts in water bodies can lead to eutrophication and subsequent water body impairment, among other ecosystem problems (Smith et al., 1999). Although phosphorus and nitrogen excesses are popularly known as resulting from agricultural runoff, they are also important pollutants in urbanized watersheds as well (G & J, 1997; Withers et al., 2014; Yu et al., 2012). Hobbie *et al*. 2017 found that urbanized watersheds of St. Paul, Minnesota experienced major pollution from household nitrogen and phosphorus runoff (Hobbie et al., 2017).

"Green infrastructure" (GI) is an umbrella term for best management practices (BMPs) and low impact development (LID) strategies. GI seeks to mitigate the harmful effects of or in some cases, replace entirely, gray infrastructure (Liu et al., 2015; O'Donnell et al., 2020). Institutional support for green infrastructure may hinge on stormwater runoff control, ignoring potential multi-benefits such as improvements in water quality and urban climate resilience (Kabisch et al., 2016; O'Donnell et al., 2020). Portland, Oregon is considered a leader in green infrastructure, having begun its first GSI installation efforts in the 1990s (O'Donnell et al., 2020). Baker et al. 2019 and Chan & Hopkins 2017 found that in Portland, GSI appears to be equitably distributed in terms of median income, racial minority group, and education level (Baker et al., 2019; Chan & Hopkins, 2017). A rich body of literature exists on the implementation and evolution of GSI in Portland, allowing for more rigorous review of water quality problems in the context of green infrastructure in Portland. However, our literature review returned few studies centering Portland that examined water quality at the multi-watershed scale while considering GSI as an explanatory variable.

2. Materials and methods

2.1 Study area

This study was conducted in the metropolitan area of Portland, Oregon, a large city that has recently undergone accelerated population growth and urbanization. The city uses a partially combined sewer system, but since the 1990s has made consistent efforts to introduce green stormwater infrastructure to prevent overflow events, and now boasts one of the largest collections of GSI installations in the world (Baker et al., 2019; O'Donnell et al., 2020). The region's climate consists of relatively dry and warm summers and wet, cool winters. Average annual precipitation is approximately 1400 mm (Velpuri & Senay, 2013). Soil types vary between clay, silt, silt/loam, and gravel, impacting "infiltration rate of flow" (Baker et al., 2019). Most of the city is in low-lying foothills, situated between the Columbia and Willamette Rivers (O'Donnell et al., 2020). Forest Park, a largely undeveloped, slightly higher elevation conservation area popular with hikers and bicyclists, comprises much of the western side of the study area. The Columbia Slough, a flat, low-elevation, slow-moving water body, comprises the northern side of the study area (Fig. 1). The City of Portland, in partnership with private organizations, has undertaken hundreds of rivershed restoration projects since 1990 (O'Donnell et al., 2020).

2.2 Data origin

Water quality data was obtained from the City of Portland Bureau of Environmental Services' Portland Area Watershed Monitoring and Assessment Program (PAWMAP) (*Portland Area Watershed Monitoring and Assessment Program (PAWMAP) | Environmental Monitoring | The City of Portland, Oregon*, n.d.). The data originated from 131 water quality monitoring stations located on the outskirts of the Portland metropolitan area (Fig. 1), situated within the Willamette River, Columbia Slough, Johnson Creek, and Balch Creek watersheds.

Generally, water quality measurements were taken for at least one monitoring station at least once a month by the City of Portland from July 2015 through May 2021. The PAWMAP program routinely rotates stations; as such, the completeness of data varied, with some station records containing data for multiple years, and others for less than one year. Furthermore, no station data was documented from March through most of May of 2020, most likely due to the onset of the COVID-19 pandemic in the United States in March 2020 which temporarily prevented field work (*Impacts of Covid-19 on Traffic, Portland Region | Oregon State Library*, n.d.).

Six water quality parameters of physical, chemical, and biological importance were selected for this study: *E. coli* (MPN/100 mL), lead (ug/L), nitrate (mg/L), orthophosphate (mg/L), total suspended solids (mg/L) and zinc (ug/L). Nitrate and orthophosphate were chosen because they were measured more frequently compared to other forms of nitrate and phosphorus. The data available to us measured *E. coli* directly as opposed to fecal coliform levels as a proxy, providing an uncommon opportunity to measure a water quality parameter of direct relevance to human health (Vitro et al., 2017).

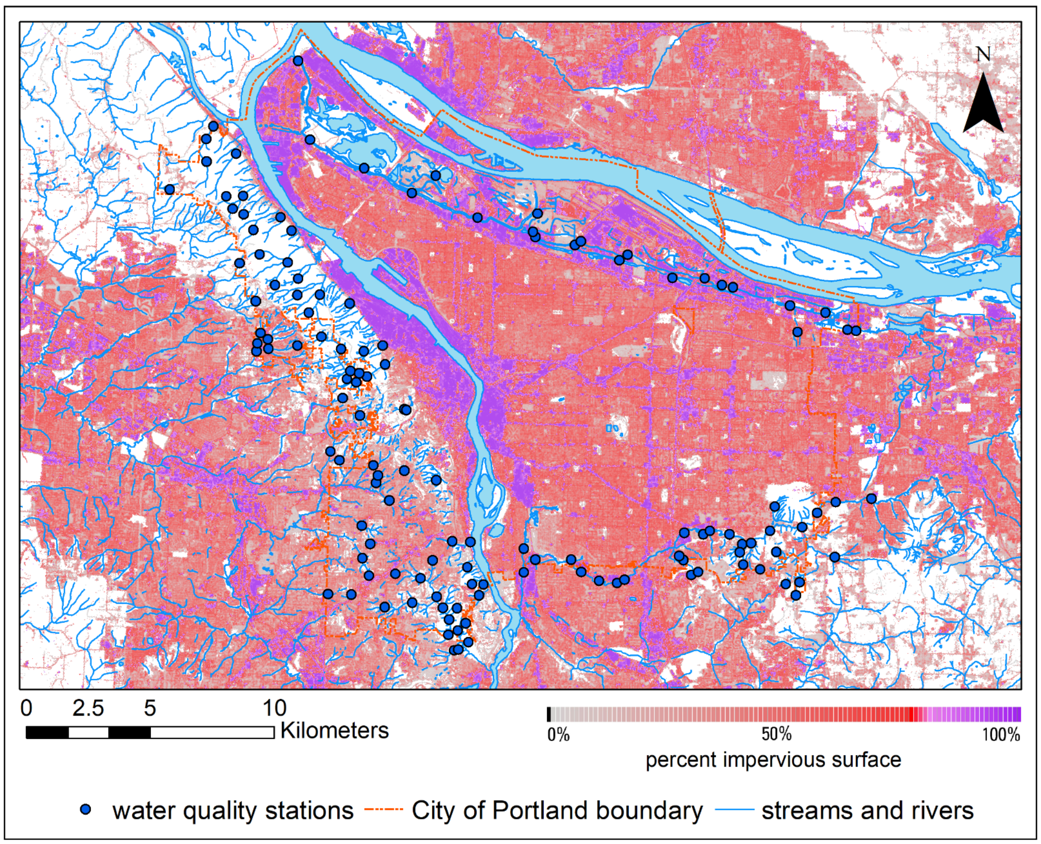


Fig. 1. Distribution of 131 PAWMAP water quality station locations around the Portland metro area

2.3 Explanatory spatial variables

Explanatory spatial variables were chosen by weighing the current literature with considerations of the data that were available to us (Table 1).

Table 1. Landscape characteristics selected as potential explanatory variables and summarized literature review of variable relationships with water quality

Variable	Relationship with water quality	Supporting literature	Data source
Land cover			
imperviousness (%)	(+)	(Brabec et al., 2002; Salerno et al., 2018)	NLCD (2019)
Developed (%)	(+)	(Brabec et al., 2002)	NLCD (2019)
Forested (%)	(-)	(Shi et al., 2017)	NLCD (2019)
Infrastructure			
Distance to nearest GI (meters)*	(+)	(McPhillips & Matsler, 2018)	City of Portland (2015)
Pipe length (meters) †	Significant	(Meierdiercks et al., 2017)	Oregon Metro rlisdiscovery.oregonmetro.gov/
Road length (meters)	(+)	(Hallberg et al., 2007; Huber et al., 2016)	Oregon Metro rlisdiscovery.oregonmetro.gov/
Soil and geomorphology			
Hydrologic soil group C (sandy clay loam) (%)	(-)	(Phillips et al., 2019; Wilson et al., 2015)	USDA NRCS gSSURGO Database (2019)
Mean slope (meters)	(+) (undeveloped) (-) (developed)	(Lintern et al., 2018)	City of Portland (2007)
Standard deviation in slope (meters)	See above	(Lintern et al., 2018)	City of Portland (2007)
Mean elevation (meters)	(+) (undeveloped) (-) (developed)	(Kim et al., 2015; Lintern et al., 2018)	City of Portland (2007)
Standard deviation in elevation	See above	(Lintern et al., 2018)	City of Portland (2007)
Stream order*	(+)	(Lintern et al., 2018)	Derived from 3-foot DEM from the City of Portland (2007)

*Evaluated from station XY coordinates without consideration of buffer area

† Evaluated only at the 250-meter scale due to data resolution

We initially defined a circular buffer area of 100 meters in diameter around each water quality station to spatially relate selected water quality parameters to selected explanatory variables (Table 1) derived at the 100-meter scale. The 100-meter distance was chosen to avoid spatial overlap in buffer area between stations that are in close proximity to one another, and the circular buffer area was chosen because of the relatively flat, urban land cover of the areas surrounding the water quality stations. However, some explanatory variables, road length and pipe length, became irrelevant at the 100-meter scale. Therefore, a 250-meter diameter circular buffer scale was introduced, with the added benefit of allowing for a multiscalar analysis at the microscale by comparing the 100-meter scale to the 250-meter scale.

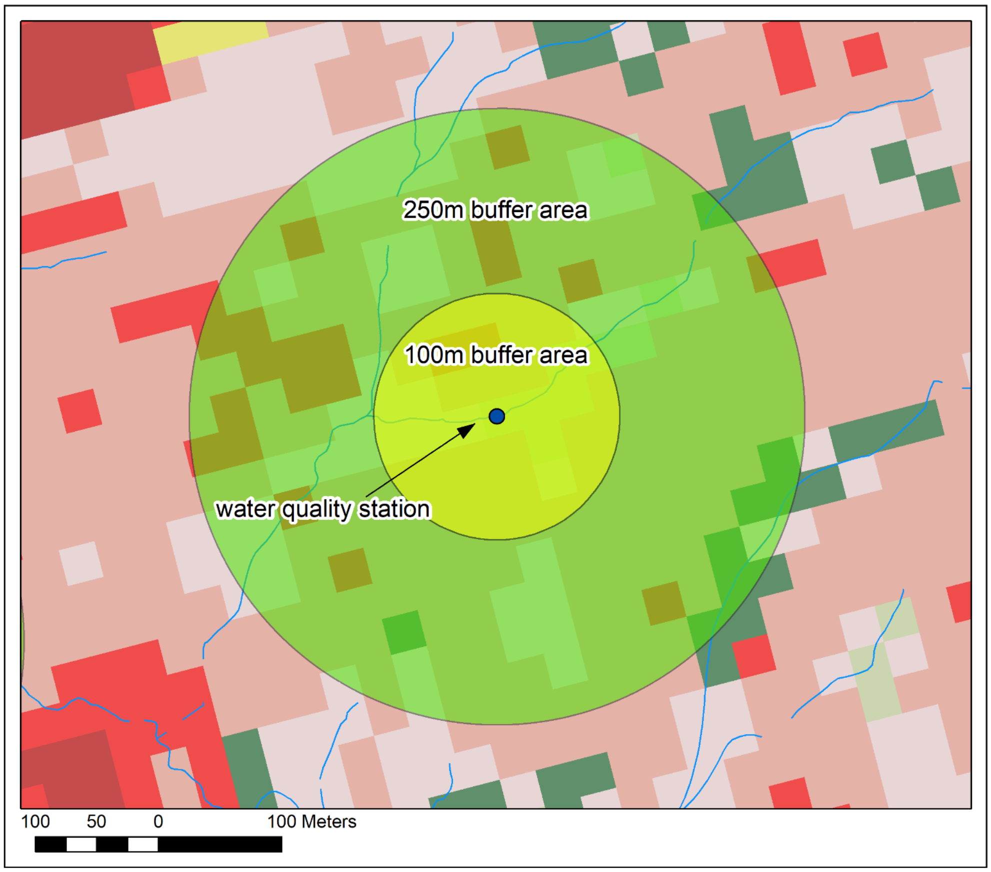


Fig. 2 Microscale delineation at the 100-meter and 250-meter scale around each water quality station through which explanatory variable metrics were calculated.

We defined *wet season* measurements as any data recorded in October through April, and *dry season* measurements as any data recorded in May through September.

2.4 Statistical analysis
Using R version 4.1 in RStudio 1.17, we employed correlation tests using a 95% confidence interval to test for significance between explanatory and dependent variables. All correlation tests used the Spearman method as a non-parametric test to account for possible non-linear trends in water quality measurements (Shrestha & Kazama, 2007). Heatmaps were then generated for each season at the 100-meter and 250-meter scales for visual comparison.

We introduced multiple linear regression to evaluate the influence of multiple landscape factors on To rule out auto-correlated explanatory variables when determining the model that best explains variations in water quality parameter concentrations, we employed the Exploratory Regression Tool in ArcGIS Desktop 10.7.1, which takes a shapefile input and applies the Global Moran's 1 spatial autocorrelation test to models that fit certain criteria such as minimum R^2 value and minimum Jarque-Bera p-value. When conducting exploratory regression for the dry season water quality measurements, we excluded stations that did not have any measurements taken in the dry season, even though they did have wet season measurements. We recorded the best model for each pollutant in both the wet and dry seasons based on highest R^2, lowest Akaike Information Criteria, and IF value less than 10.

We created two weights matrices, one using stations with non-NA wet season measurements (n= 131), and the other using stations with non-NA dry season measurements (n= 89) for the water quality stations in GeoDa with the distance band method, using the software's default bandwidth value. Using the best model detected by exploratory regression in ArcMap, we input that model into GeoDa 1.18.10's Regression tool, running the tool twice more to incorporate the weights matrix for the spatial lag and spatial error models (Matthews, 2006). From the results output, we formatted the variable coefficients into multiple linear regression equations (Table 3).

3. Results

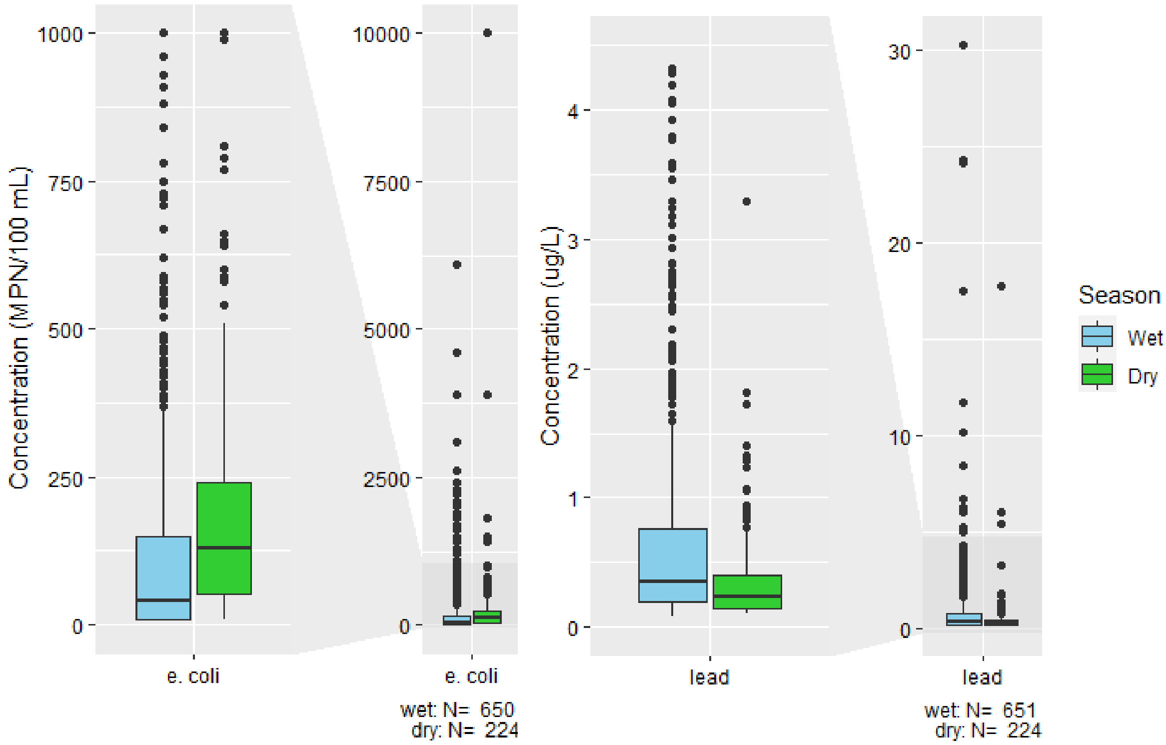
3.1 Seasonal variation
Examining all samples without considering particular sampling stations, there were clear seasonal differences in average (median and mean) and maximum water quality parameter concentrations. For lead, nitrate, total suspended solids, and zinc, average wet season concentrations exceeded dry season concentrations, a trend that was also reflected in maximum concentrations across seasons. For *E. coli* and orthophosphate, average dry season concentrations exceeded wet season concentrations, also reflected in maximum concentrations across seasons.

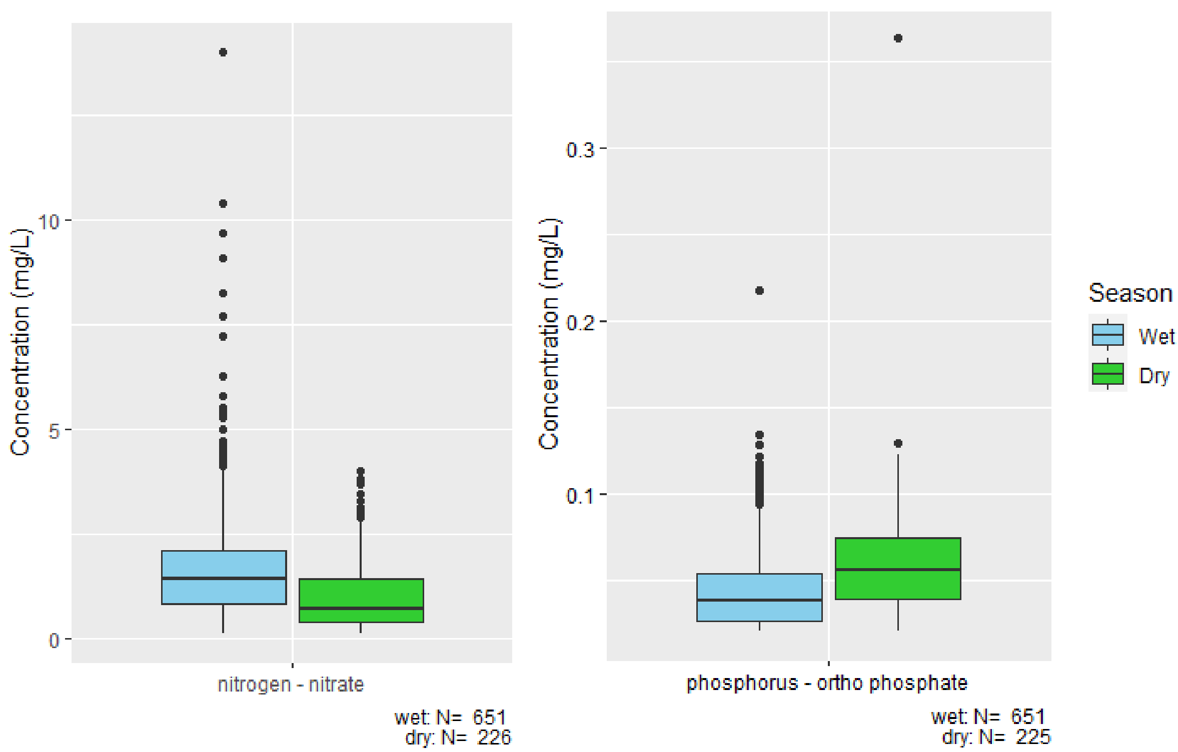
Table 2. Statistics summary for all water quality stations between the wet and dry seasons

pollutant	max	min	median	mean	standard deviation
E. coli - *wet* (MPN/100 mL)	6100	10	41	204.64	510.19
E. coli - *dry* (MPN/100 mL)	10000	10	130	287.67	791.73
lead - *wet* (ug/L)	30.2	0.08	0.34	0.90	2.20
lead - *dry* (ug/L)	17.7	0.1	0.24	0.47	1.31
nitrate - *wet* (mg/L)	14	0.1	1.4	1.67	1.32
nitrate - *dry* (mg/L)	4	0.1	0.68	1.00	0.83
orthophosphate - *wet* (mg/L)	0.22	0.02	0.04	0.04	0.02
orthophosphate - *dry* (mg/L)	0.36	0.02	0.06	0.06	0.03
total suspended solids - *wet* (mg/L)	1420	2	6	25.15	85.62
total suspended solids - *dry* (mg/L)	80	2	4	9.15	12.46
zinc - *wet* (ug/L)	321	0.5	5.02	12.99	24.24
zinc - *dry* (ug/L)	66.5	0.5	3.67	6.01	8.32

Wet season: n = 3916; dry season: n = 1341

Across all years and stations, mean water quality measurements tended to surpass median measurements, evidently due to large outliers that skewed the mean upwards. Most measurements were concentrated in the lower ranges of each water quality parameter (Table 2, Fig. 3).


Concentration (MPN/100 mL)
1000
750
500
250
0
10000
7500
5000
2500
0
e. coli
e. coli
wet: N= 650
dry: N= 224
Concentration (ug/L)
4
3
2
1
0
30
20
10
0
lead
lead
wet: N= 651
dry: N= 224
Season
Wet
Dry


Concentration (mg/L)
10
5
0
nitrogen - nitrate
wet: N= 651
dry: N= 226
Concentration (mg/L)
0.3
0.2
0.1
phosphorus - ortho phosphate
wet: N= 651
dry: N= 225
Season
Wet
Dry

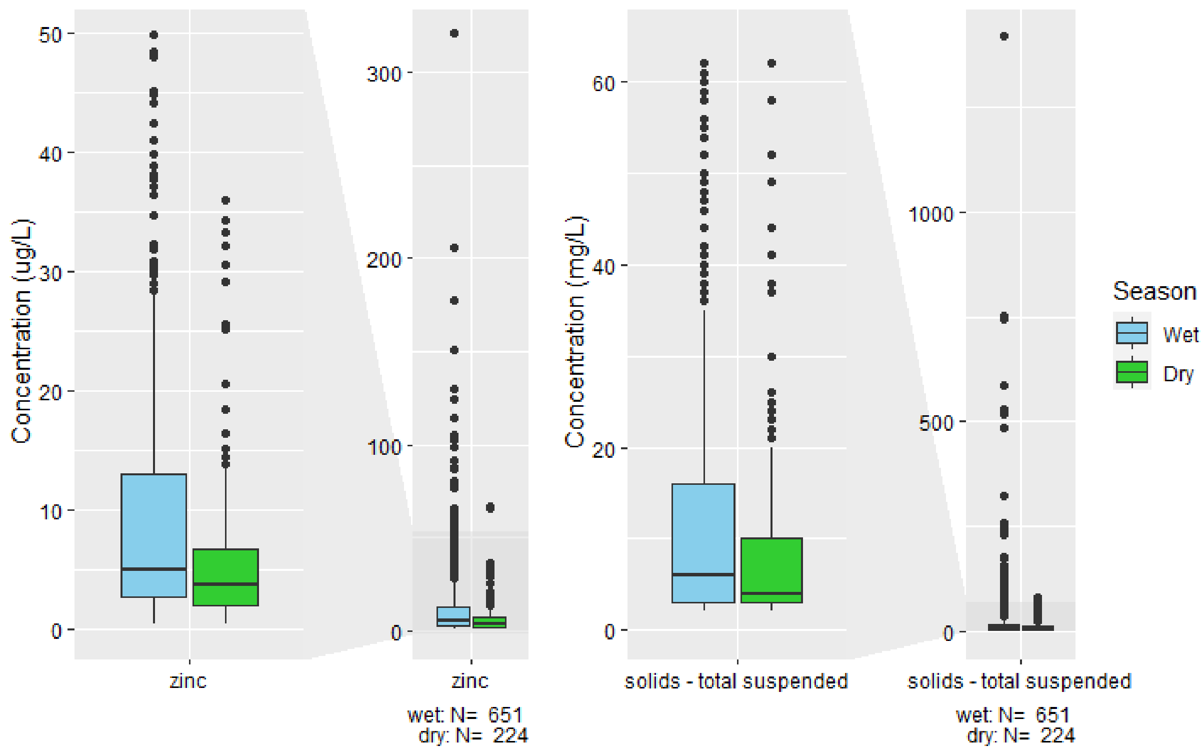
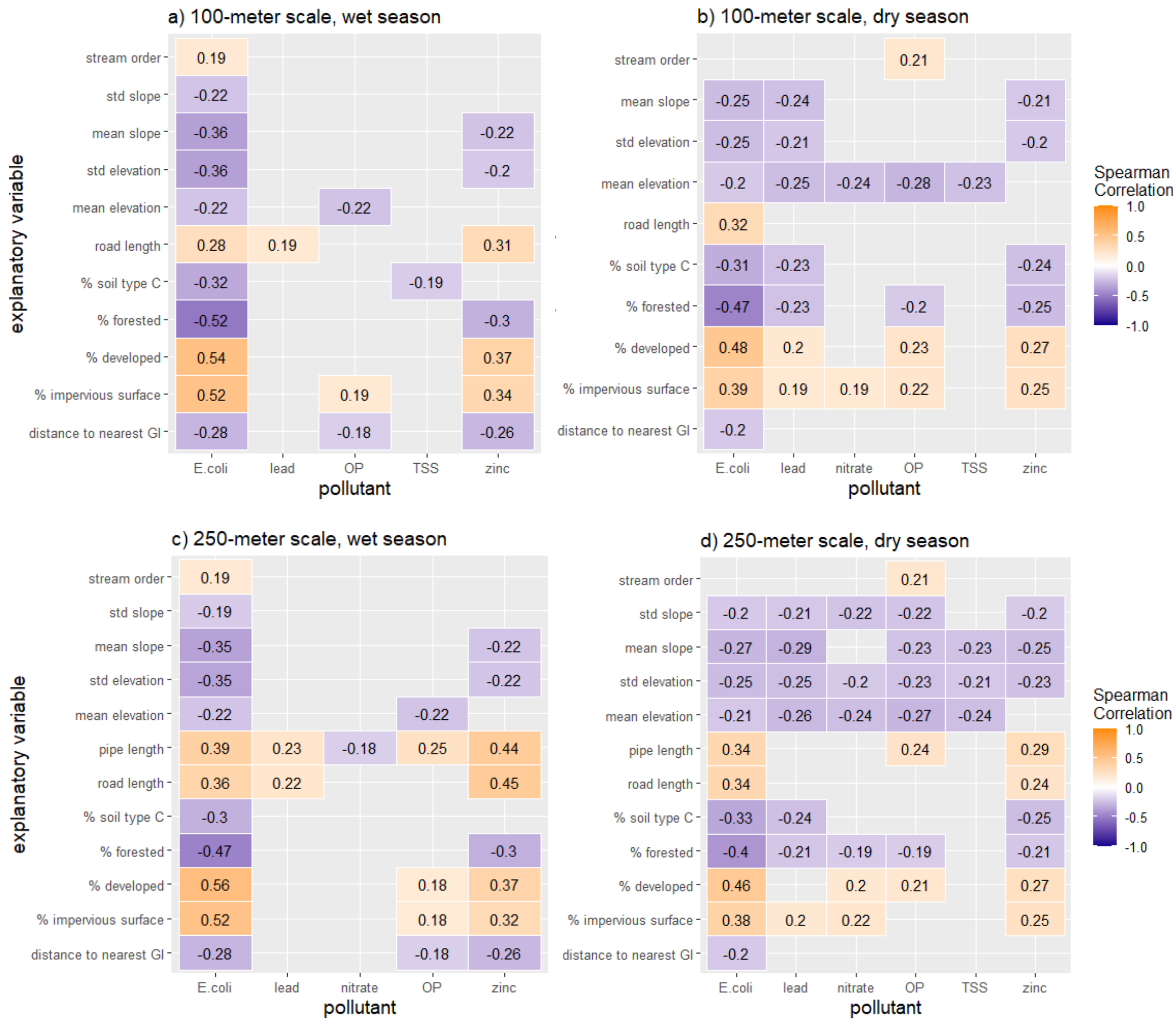


Fig. 3. Box and whisker plots for each water quality parameter in each season. Plots with two y-axis extents are adjusted to a smaller scale for ease of viewing all quartiles.

3.2 Correlation analysis

In the wet season at both scales, *E. coli*, followed by zinc, was associated with the highest number of explanatory variables at the 0.05 significance level (Figs. 2a and 2c). The strongest correlation coefficient in the wet season occurred between *E. coli* and percent developed (+), followed by percent imperviousness (+) and percent forested (-) at both scales. Zinc was correlated with percent developed (+), road length (+), and pipe length (+), but only at the 250-meter scale. Orthophosphate was most strongly correlated with pipe length (+), followed by mean elevation at both scales. Interestingly, *E. coli*, orthophosphate, and zinc were all negatively correlated with distance to nearest GI, and pipe length was positively associated with all dependent variables except nitrate, which showed positive correlation. Lead was only significantly correlated with road length and pipe length in the wet season, the latter only at the 250-meter scale. Only weak correlations occurred for nitrate and total suspended solids in the wet season.



Figs. 2a-d Correlation coefficient heatmaps for the 100-meter and 250-meter scales in the wet and dry seasons. Only values of statistical significance ($p<0.05$) are shown. OP = orthophosphate; TSS = total suspended solids. Nitrate is omitted from a) and total suspended solids is omitted from c), because no significant correlations were found with any of the spatial variables. Standard deviation of slope (std slope) is omitted from b) because no significant correlations were found with any of the water quality parameters.

Somewhat different explanatory variables were correlated with water quality parameters in the dry season than in the wet season, though the correlation coefficients were in general weaker than in the wet season. None of the associations between variables changed in direction between the wet and dry season. While *E. coli* continued to demonstrate the highest number of significant associations with explanatory variables, lead demonstrated far more significant associations compared to the wet season (Figs. 2b and 2d). Distance to nearest GI, pipe length, and road length were less significant overall in the dry season than in the wet season, while imperviousness, percent developed, and most slope and elevation variables were more significant in the dry season than in the wet season.

More explanatory variables, especially road length, were significantly correlated at the 250-meter scale than at the 100-meter scale. Slope and elevation measures became more significant at the 250-meter scale, especially in the dry season. In the dry season, nitrate and total suspended solids were significantly correlated with more variables at the 250-meter scale than at the 100-meter scale. In the wet season, orthophosphate was significantly correlated with more variables at the 250-meter scale than at the 100-meter scale.

3.3 Exploratory regression analysis

The exploratory regression tool returned a wide range in the number of models between seasons. For all pollutants, more models were available in the wet season than in the dry season (Table 2), most likely owing to lower sample sizes in the dry season. Neither *E. coli* or lead were found to have any suitable models in the dry season, despite *E. coli* having nearly 200 possible models for the wet season. *E. coli*, followed by zinc, had the highest R^2 value overall.

Table 2. Summary of the number of multiple ordinary least squares regression models found for each water quality parameter in each season using the *Exploratory Regression* tool

	E. coli	Lead	Nitrate	Orthophosphate	Total suspended solids	Zinc
Wet season						
# of models	198	13	16	128	9	102
highest R^2	0.38	0.10	0.13	0.14	0.04	0.22
Dry season						
# of models	0	0	12	30	1	3
highest R^2	*na*	*na*	0.14	0.13	0.06	0.05

"*na*" for E. coli and lead in the dry seasons indicates that the exploratory regression tool did not find any suitable models for those parameters.

3.3 Spatial regression

Even though there were fewer models detected by the exploratory regression tool for the dry season than the wet season, for nitrate and total suspended solids, the most reliable dry season models had higher R^2 values than the wet season values (Table 3).

The models for *E. coli* had the highest R^2 values out of all pollutants, with a maximum R^2 = 0.43 for both the SL and SE models (Table 3). Relatively low spatial dependence was observed, with an R^2 improvement of 13% from the OLS model.

Lead was primarily explained by road length; however, R^2 values for all models are relatively low and there were no models found for the dry season. Distance to nearest GI was slightly negatively associated with lead, reflecting similar results from our correlation analysis that showed negative correlation between distance to nearest GI and E. coli, orthophosphate, and zinc.

Nitrate demonstrated relatively low spatial dependence and had similar, relatively low explanatory power for all models in both seasons, but different explanatory variables took precedence between seasons. In the wet season, percent forested dominated, while in the dry season, percent impervious surface at the 100 meter scale dominated.

The R^2 values for orthophosphate in both the wet and dry models more than doubled after incorporating the weights matrix, demonstrating strong spatial dependence. For both wet and dry OLS models, percent hydrologic soil group C was the most significant explanatory variable, but for spatial regression, topographic variables became most significant (for the wet season, the most significant explanatory variable was mean elevation; for the dry season, it was mean slope, both at the 250-meter scale).

Models for TSS had low R^2 values and relatively high AIC values, with a maximum R^2 = 0.10 in the dry season and maximum R^2 = 0.06 in the wet season. The most significant explanatory variable in the wet season was percent imperviousness at the 250-meter scale across all models. In the dry season, standard elevation at the 100-meter scale and mean slope at the 250-meter scale were most significant.

Six explanatory variables best explained variations in zinc in the wet season: percent developed, percent imperviousness, percent hydrologic soil group C, standard deviation in elevation, standard deviation in slope, and road length, all at the 250-meter scale (except for percent imperviousness). These variables alone explained 22% of the variance in zinc concentrations in the wet season; when the spatial weights matrix was incorporated, 34% of the variance was explained. In the dry season, percent developed and percent impervious at the 100-meter scale alone explained 5% of variance; when the spatial weights matrix was added, 17% of variance was explained.

Table 3. Ordinary least squares and spatial regression results for each parameter in each season

E. coli	**Model**	$\mathbf{R^2}$	**AIC**	**Equation**
wet season	OLS	0.38	1537.74	32.9632*std_slope_250m - 12.3561*m_slope_100m + 1.04931*dev_250m - 0.614266*soil_100m + 0.069723*near_GI + 34.1373
	SL	0.43	1535.38	32.4904*std_slope_250m - 11.7446*m_slope_100m + 0.898652*dev_250m - 0.501536*soil_100m + 0.294953*W_ecoli_wet + 0.0585237*near_GI + 9.7942
	SE	0.43	1534.64	31.6529*std_slope_250m - 11.3928*m_slope_100m + 1.03914*dev_250m - 0.6086*soil_100m + 0.301888*LAMBDA_ecoli_wet + 0.0679093*near_GI + 33.9033
Lead	**Model**	$\mathbf{R^2}$	**AIC**	**Equation**
wet season	OLS	0.10	227.25	0.583142 + 0.00111162*road_100m - 0.00614092*imperv_100m - 0.000312861*near_GI
	SL	0.16	225.28	0.00105028*road_100m + 0.38686 + 0.310186*W_lead_wet - 0.00513985*imperv_100m - 0.000273207 *near_GI
	SE	0.16	223.01	0.594271 + 0.00109736*road_100m + 0.337799*LAMBDA_lead_wet - 0.00631127*imperv_100m - 0.000295845*near_GI
Nitrate	**Model**	$\mathbf{R^2}$	**AIC**	**Equation**
wet season	OLS	0.13	388.48	0.015898*forest_250m + 0.0166524*imperv_100m + 0.609113
	SL	0.17	387.38	0.014305*forest_250m + 0.0157788*imperv_100m + 0.25038*W_nitrate_wet + 0.28997
	SE	0.17	385.79	0.0152091*forest_250m + 0.0156673*imperv_100m+ 0.642436 + 0.26443*LAMBDA_nitrate_wet
dry season	OLS	0.14	223.94	1.54345 + 0.0239495*imperv_100m - 0.0142028*dev_100m - 0.111942*std_slope_100m
	SL	0.21	222.82	1.29953 + 0.0208239*imperv_100m - 0.0132173*dev_100m - 0.114364*std_slope_100m + 0.268292*W_nitrate_dry
	SE	0.20	221.39	1.61844 - 0.0136931*dev_100m + 0.0209373*imperv_100m - 0.126265*std_slope_100m + 0.278636*LAMBDA_nitrate_dry
Orthophosphate	**Model**	$\mathbf{R^2}$	**AIC**	**Equation**
wet season	OLS	0.14	-670.93	0.0305144 + 0.00014007*soil_250m - 0.000201478*m_elev_250m+ 0.00393391*std_slope_100m + 0.000106377*dev_250m - 0.00122012*m_slope_250m
	SL	0.32	-689.17	0.529979*W_ortho_wet + 0.016131 - 0.000150447*m_elev_250m + 0.00315226*std_slope_100m - 0.00104903*m_slope_250m+ 5.95354e-005*dev_250m + 5.94702e-005*soil_250m
	SE	0.33	-690.60	0.627171*LAMBDA_ortho_wet + 0.0462815 - 0.000148635*m_elev_250m + 0.00234779*std_slope_100m +-0.00100489*m_slope_250m + 6.12477e-005*dev_250m - 1.7542e-005*soil_250m
dry season	OLS	0.13	-400.07	0.0439167 + 0.000210837*soil_250m - 0.00274148*m_slope_250m - 0.000401247*imperv_250m + 0.000257691*dev_100m + 0.00548286*std_slope_100m
	SL	0.28	-407.22	0.401282*W_ortho_dry + 0.0258279 - 0.00221973*m_slope_250m + 0.000135132*soil_250m - 0.000320797*imperv_250m + 0.000207573*dev_100m + 0.00438827*std_slope_100m
	SE	0.25	-405.98	0.0506066 + 0.392953*LAMBDA_ortho_dry - 0.00184514m_slope_250m - 0.000327478*imperv_250m + 0.000201342*dev_100m +

0.000127233*soil_250m + 0.00363597*std_slope_100m

TSS	Model	R^2	AIC	Equation
wet season	OLS	0.04	964.34	12.1846 - 0.105128*imperv_250m + 0.00854033*pipe_250m
	SL	0.06	966.34	12.1259 - 0.104867*imperv_250m + 0.00852938*pipe_250m + 0.00486111*W_tss_wet
	SE	0.06	964.34	12.1934 - 0.10531*imperv_250m + 0.00853639*pipe_250m + 0.0178566*LAMBDA_tss_wet
dry season	OLS	0.06	640.77	11.7025 - 0.957524*m_slope_250m + 3.51414*std_elev_100m - 0.0805961*imperv_250m
	SL	0.10	642.57	12.4448 + 3.45958*std_elev_100m - 0.931406*m_slope_250m - 0.0840512*imperv_250m - 0.0871126*W_tss_dry
	SE	0.09	640.73	11.6007 + 3.43977*std_elev_100m - 0.923449*m_slope_250m - 0.0810322*imperv_250m - 0.0415502*LAMBDA_tss_dry
Zinc	**Model**	**R2**	**AIC**	**Equation**
wet season	OLS	0.22	986.81	0.162909*dev_250m - 0.214092*imperv_100m + 0.0848211*soil_250m - 1.5984*std_elev_250m + 2.07607*std_slope_250m + 0.00244958*road_250m - 6.62428
	SL	0.34	976.79	0.435474*W_zinc_wet + 0.132214*dev_250m - 0.162396*imperv_100m + 0.0663968*soil_250m - 1.40205*std_elev_250m + 2.02224*std_slope_250m - 8.73609 + 0.00204144*road_250m
	SE	0.34	976.48	0.492464*LAMBDA_zinc_wet + 0.149472*dev_250m + 1.97116*std_slope_250m - 0.154133*imperv_100m + 0.0747333*soil_250m - 1.24135*std_elev_250m - 6.60824 + 0.00185552*road_250m
dry season	OLS	0.05	567.29	3.9502 + 0.0688963*dev_100m - 0.103906*imperv_100m
	SL	0.17	561.94	0.382471*W_zinc_dry + 0.0584738*dev_100m - 0.0813602*imperv_100m + 1.85672
	SE	0.17	559.71	0.402597*LAMBDA_zinc_dry + 3.59011 +0.06496*dev_100m - 0.083674*imperv_100m

No dry season models are reported for *E. coli* or lead because none were found in the exploratory regression analyses for those parameters (see Section 3.2). TSS = total suspended solids; AIC = Akaike Information Criteria, OLS = Ordinary least squares, SL = Spatial lag, SE = spatial error; W_*parameter_ season*= spatial lag coefficient; LAMBDA_*parameter_season* = spatial error coefficient. Table adapted from Mainali & Chang, 2018 (Mainali & Chang, 2018). Wet season: n = 131; dry season: n = 89

4. Discussion

4.1 Seasonal variations in water quality

Wet season increases in lead, zinc, and total suspended solid concentrations are likely due in part to the first flush effects of heavy metal runoff from roads during storm events in the wet season (Li et al., 2012). For total suspended solids, erosion and increased sediment transport is more likely to occur during larger precipitation events that are more common in the wet season. Nitrate and orthophosphate concentrations are associated both with total suspended solids concentration and vegetation growth cycles (Högberg et al., 2017; Satchithananantham et al., 2019), but have different uptake and deposition mechanisms, which may explain their opposite seasonal trends. Qualitatively, pollution levels especially for E. coli and zinc tended to worsen in the southwestern portion of the study area, which may be due to downstream accumulation effects, but possibly also the overlap of natural areas popular for hiking (*E. coli*) and the proximity of the Interstate-5 highway, a major trucking route (zinc) (Figs. 3a and 3b).

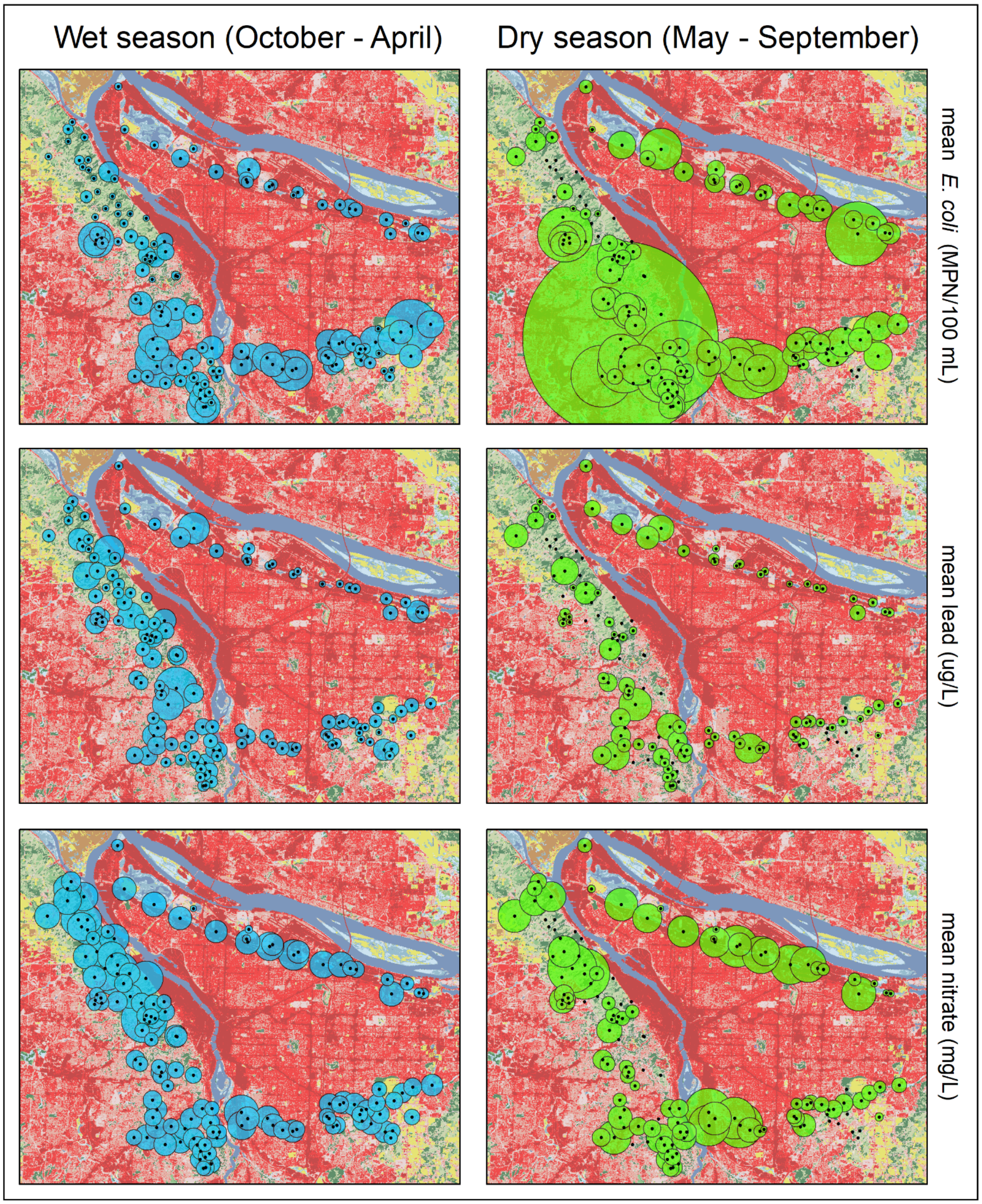


Fig. 3a. Relative proportions of mean *E. coli*, lead, and nitrate concentrations for each water quality station with background NLCD land cover classification (*National Land Cover Database 2019 (NLCD2019) Legend*, n.d.). Larger circles correspond to higher mean concentrations.

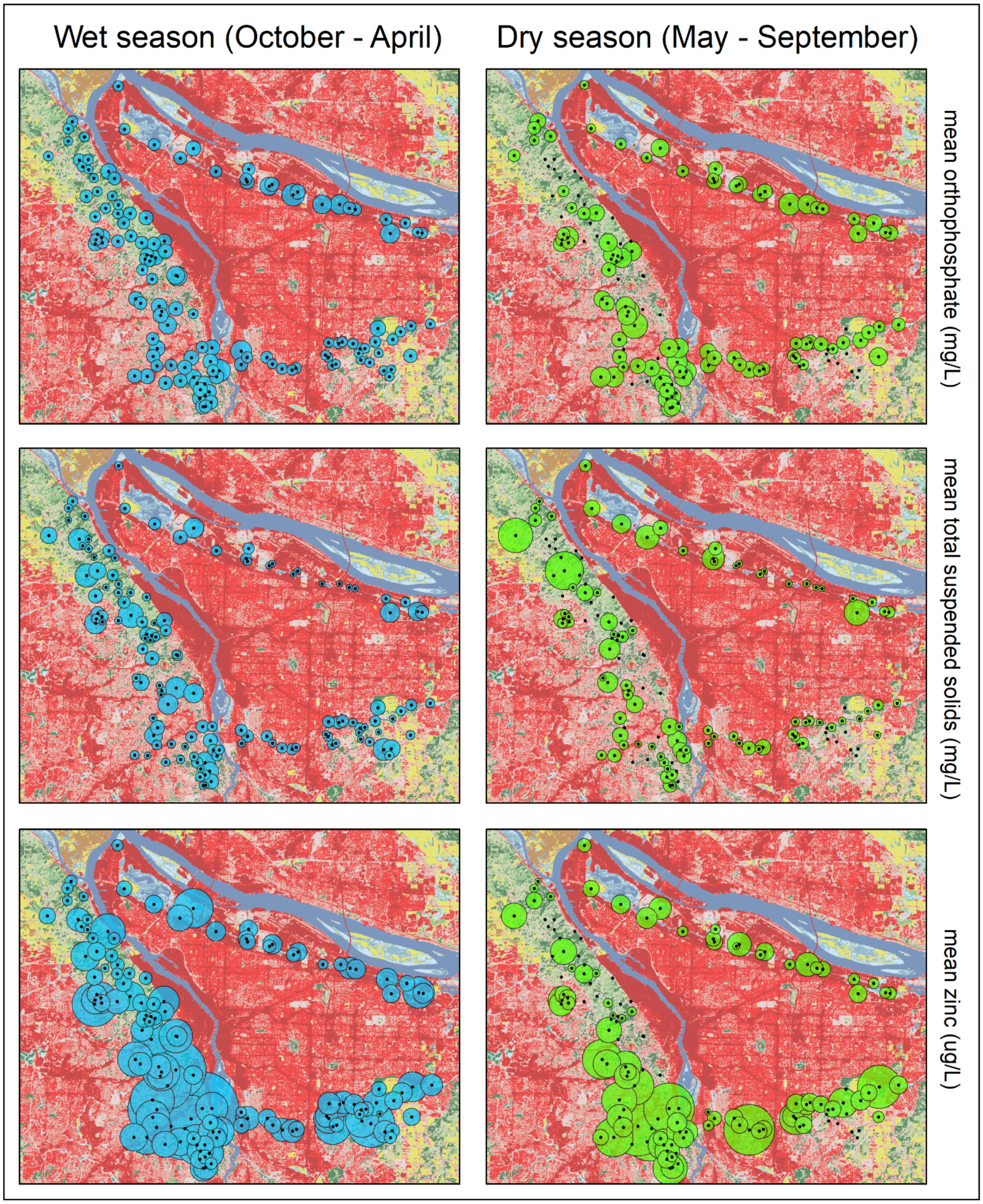


Fig. 3b. Relative proportions of mean orthophosphate, total suspended solids, and zinc concentrations for each water quality station with background NLCD land cover classification (*National Land Cover Database 2019 (NLCD2019) Legend*, n.d.). Larger circles correspond to higher mean concentrations.

4.2 Correlation analysis

The 250-meter scale produced a higher number of significant correlations and higher correlation coefficients between water quality parameters and explanatory variables in both seasons, suggesting that a larger microscale is more indicative of water quality than a more immediate microcale, at least using a circular buffer.

E. coli and zinc were significantly correlated with a high number of explanatory variables in both seasons, which may be due to secondary effects of the interactions between explanatory variables, or possibly the nature of the Spearman correlation method, which provides value rankings instead of ranking the values directly. Percent developed, percent imperviousness, and percent forested had the highest correlation coefficients, demonstrating the importance of land cover on water quality variability.

Negative correlations between the distance to nearest GI and water quality parameters was likely due in part to multicollinearity between distance to nearest GI and impervious or developed land cover in a highly urbanized area. In other words, water quality was somewhat lower when green infrastructure was present because green infrastructure tends to be situated in urbanized environments with mostly impervious surfaces. Pipe length and road length became less correlated with water quality in the dry season, which aligns with seasonal differences in pollutant averages and the role of storm runoff in affecting water quality in the wet season (Table 2).

4.3 Spatial regression analysis

For all pollutants, the spatial lag and spatial error models offered higher explanatory power than the ordinary least squares model, suggesting that there is spatial autocorrelation present in the data. However, the amount of increase in explanatory power varied between pollutants, with orthophosphate and zinc displaying the highest increases in R^2 value and thus the highest spatial dependence. Other water quality parameters such as *E. coli*, lead, and nitrate exhibited much less spatial dependence in terms of R^2 values, although *E. coli* had relatively higher AIC values for all models. No regression models were found for the dry season for *E. coli* or lead, implying that there may not have been enough variability in dry season measurements for those particular variables.

Unexpectedly, distance to nearest GI is slightly negatively associated with lead, although it is positively associated with *E. coli*. This may be due to spatial autocorrelation between GI installments and imperviousness that interacts with spatial dependence between water quality monitoring stations for lead and *E. coli* to produce opposite associations. Nevertheless, this finding warrants further investigation.

Regression models for E. coli were the most powerful, which implies that our selected explanatory variables do better at explaining variations in *E. coli* concentrations than any other selected water quality parameter. Slope variables are the most significant and positively associated with *E. coli*, which may align with documented trends in associations between slope and total suspended solids, nitrate, and phosphorus in developed areas (see Table 1). This relationship may also have to do with the steeper topography within western Portland's Forest Park area, which saw relatively high concentrations of *E. coli* compared to more low-lying areas. Possible spatial autocorrelation with high foot traffic in the area may also be present. There were no dry season models found for *E. coli*, implying that there may be very different driving factors of *E. coli* variability in the dry season compared to the wet season that our model was unable to detect.

Road length primarily explains lead variations. However, R^2 values are relatively low and there were no models found for the dry season, implying that there are hidden variables that are key to explaining lead variation in both seasons. Negative associations of lead with distance to nearest GI may be due to the relative placement of GI near roads or in highly urbanized areas with high amounts of impervious surface.

Although nitrate and orthophosphate displayed roughly the same R^2 values for the OLS model, improvements in R^2 from SL and SE model implementations were not as great for nitrate as they were for orthophosphate, indicating less spatial dependence for nitrate, but less ability to explain nitrate variations with spatial autocorrelation. Land cover variables percent forested and percent imperviousness best explained nitrate in the wet season, but were both positively associated with nitrate. While water quality as a whole may tend to be higher in forested areas, negative associations of percent forested with nitrate may be explained by the role of vegetation in nitrogen deposition, particularly in the fall and winter when decaying plants release nitrogen into the surrounding soil and waters (Högberg et al., 2017; Melillo et al., 1984).

For orthophosphate, the explanatory power of both wet and dry season ordinary least squares models were comparable, and not much seasonal difference in explanatory variables was observed. This is somewhat surprising . However, the explanatory power of both models more than doubled when adapted to the spatial lag and spatial error models, indicating that there is strong spatial dependence among neighboring water quality stations for orthophosphate in particular (Mainali et al., 2019). Percent soil group C was the most significant explanatory variable, reflecting the importance of geochemical processes on phosphorus uptake and deposition, but this variable became less important when spatial dependence was considered (Satchithanantham et al., 2019).

Variation in total suspended solids remained largely unexplained, with poor R^2 values suggesting that there are significant hidden variables that explain the majority of the pollutant's variation. When considering the higher explanatory power of selected explanatory variables for orthophosphate, the results for total suspended solids are somewhat expected, models for orthophosphate is somewhat unexpected, as orthophosphate molecules are often attached to suspended solids when transported in water bodies (L.-H. Kim et al., 2003; Lintern et al., 2018).

Zinc was positively associated with percent developed, but negatively associated with percent imperviousness with similar levels of significance for both seasons. The reasons for this unexpected relationship with percent imperviousness are unclear, but could have to do with a hidden variable that is strongly correlated with impervious land cover and less correlated with developed land cover, or vice versa.

Relatively low R^2 values for all pollutants in the dry season could be due to lower sample size and thus data availability, with only 89 water quality monitoring stations out of a total of 131 having measurements taken in the dry season.

5. Conclusion

Correlation and regression analyses were conducted for samples of six pollutants originating from 131 water quality stations around the Portland, Oregon metropolitan area from 2015 to 2021. We examined the ability of various land cover, infrastructure, and soil and geomorphological factors to act as explanatory variables at the microscale across the wet and dry seasons. We found that there were clear seasonal differences in water quality parameters that reflected established relationships found in the literature. Correlation results demonstrated high potential for associations between explanatory variables and *E. coli* and zinc in both seasons, especially for explanatory variables derived at the 250-meter scale. Spatial regression analysis determined that up to 43% of variation in water quality parameters can be explained by selected explanatory variables, with varying levels of spatial autocorrelation present. Using a distance band weights matrix, spatial lag and spatial error models best explain variations in water quality, indicating that spatial dependence is present especially for zinc and orthophosphate. In addition to land cover variables, topographic variables such as elevation and slope held surprising explanatory power for certain pollutants (orthophosphate and zinc) even in the dry season, highlighting the need to incorporate filtering approaches that remove spatial autocorrelation in future analyses (Mainali et al., 2019). Unexpected negative correlations were found between distance to nearest GI and *E. coli*, orthophosphate, and zinc, but for spatial regression analysis, this unexpected negative relationship between GI distance and water quality shifted to lead, warranting further investigation into the ability of GSI to reduce the transport of lead and other heavy metals into surrounding water bodies (Liu et al., 2017)**.**

The next phase of this study will be to transform the water quality parameters, firstly attempting a log transformation, to attempt to make the data more normally distributed. This will allow us to better justify using linear correlation and regression tests. The spatial error and spatial lag models should also be tested for significance to determine which model is more reliable for our data. Much fewer measurements were taken in the dry season than in the wet season, resulting in fewer available regression models for all pollutants; for *E. coli* and zinc, no suitable dry season models were found. In future analyses, we may consider separating seasons further into summer/fall/winter/spring categories to be able to produce better models that explain water quality variability across seasons (Mainali & Chang, 2018).

Because we conducted analysis at the microscale, we were unable to incorporate sociodemographic factors as explanatory variables in our analysis of water quality. Another important next step of this research is to perform a multi-level analysis at the census block group scale and evaluate how income, race, education, and other socioeconomic variables are associated with water quality parameters (Baker et al., 2019; Chan & Hopkins, 2017; Garcia-Cuerva et al., 2018). Another study (Ramirez 2021) using the same dataset and incorporating local precipitation data ran concurrently with this research examined temporal changes in water quality in terms of antecedent precipitation. Ideally, our study's spatial findings will be combined with the temporal analyses of the other study to examine broader spatiotemporal water quality trends.

This research adds to the rich body of knowledge surrounding local hydrology, green infrastructure, and ecosystem services in Portland, Oregon (eg. Baker et al., 2019; McPhillips & Matsler, 2018; O'Donnell et al., 2020). Facing unprecedented environmental and social changes from climate change, city planners hoping to improve water quality in metropolitan areas by implementing GSI can utilize this study to better understand how pollutant concentrations vary in a large city with a robust GSI network. Researchers in the field can use findings from this study as a stepping stone in the large task of understanding how anthropogenic and natural variables interact to affect water quality across space and time.

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