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Effects of land cover, topography, and built structure on seasonal water quality at multiple spatial scales

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ABSTRACT

The relationship among land cover, topography, built structure and stream water quality in the Portland Metro region of Oregon and Clark County, Washington areas, USA, is analyzed using ordinary least squares (OLS) and geographically weighted (GWR) multiple regression models. Two scales of analysis, a sectional watershed and a buffer, offered a local and a global investigation of the sources of stream pollutants. Model accuracy, measured by R^2 values, fluctuated according to the scale, season, and regression method used. While most wet season water quality parameters are associated with urban land covers, most dry season water quality parameters are related topographic features such as elevation and slope. GWR models, which take into consideration local relations of spatial autocorrelation, had stronger results than OLS regression models. In the multiple regression models, sectioned watershed results were consistently better than the sectioned buffer results, except for dry season pH and stream temperature parameters. This suggests that while riparian land cover does have an effect on water quality, a wider contributing area needs to be included in order to account for distant sources of pollutants.

1. Introduction

The effect of land development on natural systems is frequently quantified by examining the relationship between land cover and streams [1–4]. Land development, in the form of urban and agricultural land usage, increases impervious surfaces, has been found to have a negative correlation with stream health, typically increasing flash runoff and nutrient and heavy metal loads [5–9]. This association implies that without abatement efforts, increases in development can lead to decreases in water quality, which affects safe drinking water availability, recreational opportunities, floodplains, and habitat [10–13].

With this connection between land development and poor water quality, land managers are being encouraged to use geographic information systems (GISs) to identify problem areas and develop projects to improve stream health [10,11,14–16]. Spatial analysis techniques allow users to view and analyze geographic data, which includes, water quality, climate, topographic, and landscape variables, quickly and efficiently. Restoration projects or storm water retention ponds can be planned by using GIS to identify stream reaches and areas that would most benefit [17].

In humid temperate climates, where there are substantial seasonal variations in precipitation and temperature, constituent concentrations vary due to flow regimes. These seasonal regimes need to be considered when studying particulate and other pollutants' concentrations in order to account for dilution and runoff [7,15,18]. Water quality measures, such as phosphorus and stream water temperature, peak during the low flow, warm season, unlike many other parameters that fluctuate based on runoff. Studies have found that the influencing land cover for specific water quality measurements changes according to the season [15,19].

Selecting sample sites near anthropogenic or natural sources of elements such as nitrogen or phosphorus can yield valuable results [19]. Wang et al. [19] found that industrial sites along the Grand Canal in China consistently displayed higher gasoline and metal levels than samples taken elsewhere. A similar finding was reported in the study of the lower Han River basin in South Korea, where sites downstream of industrial and urban areas were found to have worse water quality than those upstream [20]. Located at the confluence of the Willamette and Columbia rivers, Portland – Vancouver's urban and industrial development has negatively impacted the first and second-order urban streams. Lower levels of DO and higher levels of nutrients and water temperatures are common in these low elevation streams [21,22].

The scale of analysis is important because it determines what area researchers use to link land cover with a stream site's chemical and physical properties. By using the watershed scale, an area

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not located along or even near the stream might be attributed to being the source of a pollutant. Including an entire stream reach might also be unreasonable, as the stream dilutes pollutants before they are sampled and may be caught up and absorbed by plants or soils along the stream [e.g. 23, 24]. Cunningham et al. [2] suggests that watershed managers focus on simple projects in riparian areas to improve water quality in the general area being targeted and downstream. Removing a parking lot next to a stream, for example, would reduce flashy flooding and allow runoff to seep into the ground before joining the stream.

Multivariate regression model allows researchers to assume a diverse array of landscape parameters in order to derive the causes of pollutants. Broad categories, such as urban or residential land covers, assume a heterogenic landscape [25,26]. These categories ignore, or do not fully incorporate changes in density or simply differences in anthropogenic development and physical geography across a space [17]. By using a spatially explicit multivariate approach, non-point sources such as agriculture as well as variables such as street density may be incorporated into a finer resolution analysis [27].

The objectives of this paper are to examine the relationship between landscape variables and water quality in the Portland, Oregon and Clark County, Washington area by answering three questions. First, does the season matter in determining what land cover has the most influence on water quality? Second, does the scale of analysis have an effect on the results, and if so, what are they? And third, does GWR, which incorporates spatial autocorrelation, offer betters predictive power than a global OLS regression model?

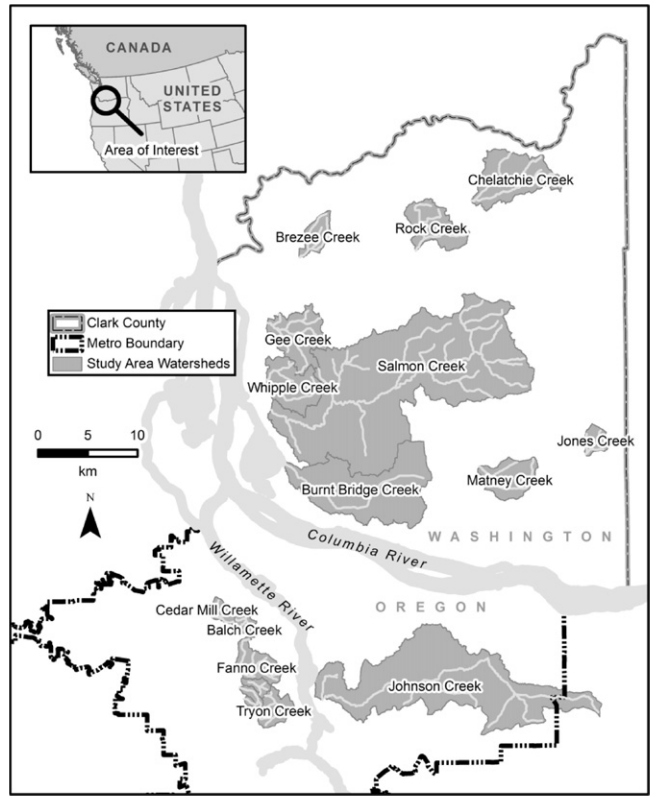


Fig. 1. Map of the study area.

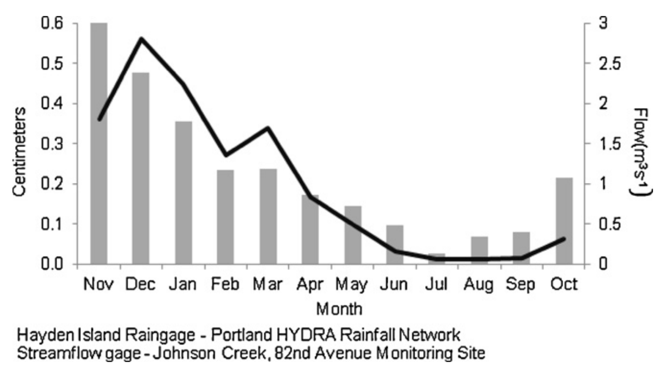


Fig. 2. Average monthly rainfall and precipitation for Portland, November 2006–April 2009.

2. Methods

2.1. Study area

The Portland Metropolitan area in Oregon and Clark County, Washington, lie on opposite sides of the Columbia River in the Pacific Northwest (Fig. 1). This region experiences a Marine west coast climate with wet, mild winters and cool, dry summers. Temperatures average 15–27 °C in the summer months, to 1–10 °C in the winter. Peak urban stream flow occurs during the wet winter months, while the dry summer months experience lower flows (Fig. 2). Individual stream's average flows vary from 0.5 to 30 m^3/s annually [28,29].

Streams in both areas are listed on the federal 303d list for water quality violations. In Portland, nearly the entire stream reaches of Tryon Creek and Johnson Creek are listed for water temperature [22]. Johnson Creek is also listed for high *E. coli* levels, and on the west side Fanno Creek is listed for toxins. In Clark County, the upper half of Burnt Bridge Creek, an urban stream running through Vancouver, is listed for multiple reasons, including water temperature, pH, and *E. coli* [30]. Portions of Salmon Creek are listed for temperature, pH, and dissolved oxygen violations. Other listed streams in the county appear for DO and temperature violations. Two watersheds, Jones Creek and Chelatchie Creek, are not listed; their primary land covers are forest and agriculture.

2.2. Stream data

We collected water quality data from several government agencies, and downloaded spatial stream data from the US Geological Survey (USGS) National Hydrography Dataset [31]. Washington water quality data was collected from Washington Department of Ecology [30], as well as Clark County Environmental Services [32]. The Portland Bureau of Environmental Services has been collecting monthly stream data at select sites consistently since 1998–2010. Twenty-one sites from Portland and 30 sites from Clark County were selected based on the available sample dates, parameters, and watershed characteristics. Each government agency collected data based their sampling methods and quality control on USEPA standards (Table 1).

Table 1
Sampling methods.

	Portland	Clark County	Burnt Bridge
EC	SM 2510 B	Electrode – on site	SM2510B
DO	SM 4500-O G	Membrane electrode – on site	On site
NN	EPA 300.0	EPA 353.2	SM4500NO3I
pH	SM 4500-H B	Glass electrode – in situ	On site
TP	EPA 365.4	EPA 365.1	SM4500PF
TS	SM 2540 B	EPA 160.3	–
Temp	SM 2550 B	Thermistor	in situ

Portland data from the Bureau of Environmental Services; Clark County data, except Burnt Bridge, via CCES; Burnt Bridge data via WADE.

Seven water quality parameters were chosen based on its importance to human and aquatic life in both Portland and Vancouver study sites. Nitrogen nitrate NO_3^+–N (NN) and total phosphorus (TP) are generally considered to be direct measures of human activity in an area, as fertilizers, vehicle emissions, and impervious surfaces increase the amount of NN and TP in their respective natural cycles [12]. Total solids (TS) can be used as a quantitative measure of aesthetics as suspended sediments in streams make the water appear cloudy. This study also used conductivity (EC), dissolved oxygen (DO), pH, and water temperature (Temp). These measurements are associated with predicting algae bloom likelihood and habitat quality for fish and other aquatic animals.

In order to account for the seasonal variation in stream flows, the data were split into wet (November–April) and dry (May–October) seasons. The seasonal data were aggregated to a geometric mean for the entire period. The geometric mean was used because it is a slightly more conservative estimate of aggregated water quality parameters than an arithmetic mean. It is also more appropriate to use a geometric mean when data are not normally distributed, which was the case for two parameters.

2.3. Independent variables

Topographic and landscape variables are shown in Table 2. The standard deviation of slope, derived here from a 10 m digital elevation model, has been used in past studies as a measure of topography complexity where the study area is relatively flat, which is the case in many of the urban watersheds [25]. The 2006 US National Land Cover Dataset was used to categorize percent urban, forest, agriculture, and wetlands in each area, with areas of less than 0.1% not included for analysis. Structural variables include single family residential (SFR) taxlots and street density. These spatial data allowed researchers a finer scale with which to examine land development within the study area. The percent area of SFR provided a measure of residential housing impact. Average building age of SFR homes built before 2010 was used as a measure of historical development. Street density provides a measure of habitat fragmentation as well as impervious surfaces. We used the 2010 taxlot and streets datasets produced by Clark County and the Portland Metropolitan Authority.

2.4. Spatial analysis

The land area associated with a sample point is often the subwatershed upstream of the sampling site [8,10,33]. The size of this area varies based on the size of the watershed and the position of the sampling point. Distant sources of pollutants, whether agriculture or urban in nature, may be diluted in the stream or stored in the soils before reaching the sample station, thereby giving an inaccurate measure of association between the land cover and water quality parameter [8]. By examining just the riparian area around a stream, delineated as a constant distance from the stream, this

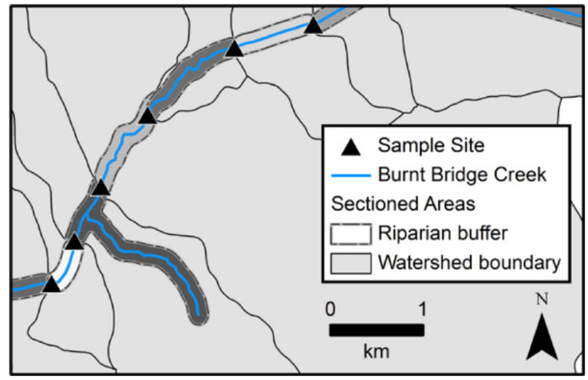


Fig. 3. Contribution watershed areas to sampling points.

issue is partly resolved. A consistent distance, however, has not been agreed on in literature and riparian buffers range from 8 m to 200 m [24,34–36].

In order to determine the association between landscape variables and water quality at each monitoring site, this study uses sectioned watersheds and riparian buffers. These sectioned zones limit the area associated with the sample site to the next site immediately upstream (Fig. 3). The riparian buffer was used to determine if the immediate environment surrounding the stream has a stronger relationship than the entire area. Watersheds were delineated from the 51 sample sites using the 10 m DEM in ArcGIS v10.0, while the riparian areas were created by buffering the streams 100 m. The downstream watersheds and riparian areas were clipped to the upstream watershed, where applicable, to create sectioned watersheds and buffers. The area of SFR was normalized to a percent coverage of the area, and the streets layer was normalized to length (m)/(1000) area (m^2). SFR house age was averaged from SFR taxlots present in the sectioned area. Land cover and topographic variables were calculated using the Spatial Analyst tools in ArcGIS.

2.5. Normalization and variable statistics

All variables were tested for a normal distribution using the one-sample Kolmogorov–Smirnov test, which tests for normality by examining the observed and theoretical distributions and determining if the difference between them is significant [37]. Of the seven seasonal water quality parameters, wet and dry for each (total 14), three were found to be skewed. The dry season NN and DO were transformed exponentially and logarithmically, respectively, while a single record was removed from the dry season EC to resolve skewness. Of the independent variables, normalization was achieved by removing records less than 10% and performing log transformations (Table 3). Soil type A was removed entirely because it was present in only two watersheds and one buffer area.

Table 2
Independent variables used in analysis.

Agency Source	Data	Derived variable	Original data
USGS	National elevation dataset (10 m)	Mean slope	Elevation
		Slope standard deviation	
		Mean elevation	
USGS	National land cover dataset (30 m)	Agriculture	Pasture, cultivated crops.
		Forest	Deciduous forest, evergreen forest, mixed forest.
		Urban	Low, medium, high intensity developed, open space.
		Wetland	Woody wetlands, emergent herbaceous wetlands.
NRCS	Soil types	ABCD hydrologic soil groups	Soil survey geographic (SSURGO) database

Table 3
Independent variable statistics.

	Buffer					Watershed				
	Min	Max	Average	Stdev	n	Min	Max	Average	Stdev	n
Urban	12.71[b]	100	73.53	27.83	48	0.89	100	58.68	31.05	51
Forest	0.1[a]	85.41	20.26	22.29	43	0.7	93.71	26.47	22.95	41
Agriculture	0.16[a]	43.14	14.31	14.12	26	0.23[a]	56.65	21.29	17.53	23
Wetland	0.01[a]	10.83	2.9	2.91	34	0.68[a]	19.39	7.22	5.19	33
Mean slope	0.31	33.5	13.07	7.85	51	1.11	33.53	10.49	7.8	51
Slope StDev	1.2	25.62	11.95	5.73	51	2.07	25.38	10.55	5.22	51
Mean elev.	10.38	546.47	114.34	93.52	51	39.69	593.85	130.18	95.68	51
Street density	0.63	15.37	6.92	4.11	51	1.04	21.84	10.45	5.04	51
%SFR	2.8	72.3	33.13	19.07	50	14.98	71.14	42.95	14.03	50
SFR age	2.8[a]	72.3	33.13	19.07	50	14.98	71.14	42.95	14.03	50
per_b	0.84[a]	100	58.84	33.76	34	–	–	–	–	–
per_c	–	–	–	–	–	1.69[a,c]	100	56.66	39.89	36
per_d	0.22[a]	100	28.14	27.8	39	0.28[a]	93.84	14.37	18.39	42

Variables before log or exponential transformation.
[a] Log 10 transformed for analysis.
[b] The 3 lowest values were removed to resolve non-normality and are not included.
[c] The 4 lowest values were removed to resolve non-normality and are not included.

2.6. Statistical analysis

Multivariate OLS regression and GWR models were developed to examine the relationship between the independent variables and the water quality parameters. Multivariate analysis filters out the significant variables across the landscape [17,19]. To find the independent variables with the strongest correlation with the water parameters, stepwise multiple linear regression (SMLR) was run in PASW Statistics 17. With seven water quality parameters, two seasons, and two scales of analysis, 28 OLS models were generated (Table 4). SMLR models run using only those independent variables identified as significant at the 95% confidence level. These variables were then used to run GWR and OLS regressions in ArcMap. An advantage of running an OLS regression in ArcMap is the output from the process includes the residual for each site, allowing the researcher to more easily test the residuals for spatial autocorrelation.

A law of geography is that things that are closer together are more likely to be related than things that are far apart. GWR captures the local variations by weighting closer observations greater than those further away. OLS models are like the following.

$$\gamma = \beta_0 + \sum_{i=1}^{p} \beta_i x_i + \varepsilon \tag{1}$$

γ represents the dependent variable, β_0 is the intercept, and $\beta_0 x_i$ are the coefficient and the independent variable. ε represents the error term, and p is the number of independent variables.

The GWR equation differs in that it incorporates the coordinates of each location.

$$\gamma_j = \beta_0(u_j, v_j) + \sum_{i=1}^{p} \beta_i(u_j, v_j) x_{ij} + \varepsilon_j \tag{2}$$

where j represents the location, the coordinates (u_j, v_j) for each location are taken and multiplied by the local independent variable x_{ij}. The model is calibrated using an exponential distance decay function.

$$W_{ij} = \exp \frac{-d_{ij}^2}{b^2} \tag{3}$$

The weight of site j as it effects site i, W_{ij}, is calculated using the distance (d) between sites i and j with b acting as the kernel bandwidth. The weight decreases rapidly when the kernel is smaller than the distance. For this study, an adaptive band was used because the density of sample sites varied across the study area. The GWR outputs include local residuals and R^2 results, as well as a global R^2 [38]. The global R^2 generated by ArcGIS is defined as the proportion of variable variance the regression model accounts for [39].

Table 4
Multivariate OLS regression models.

	Regression Model
Buffer	
Wet Season	
EC	0.974 (Urban) + 58.896
DO	1.417 (Forest) + 2.615 (SFR age) + 5.901
NN	−0.038 (%SFR) – 0.053 (Mean slope) + 3.751
pH	0.031 (StDev slope) + 0.006 (Urban) + 6.024
TP	0.042 (Urban) + 4.486
TS	0.533 (Urban) + 83.439
Temp	0.03 (Urban) – 0.089 (StDev slope) + 0.005 (Mean elevation) + 5.615
Dry Season	
EC	0.486 (Urban) – 0.124 (Mean elevation) + 139.099
DO[a]	627.083 (Mean slope) + 10,871.260 (SFR age) – 11,571.635
NN[b]	−0.003 (Mean elevation) – 0.008 (%SFR) + 0.59
pH	0.295 (SFR age) – 0.002 (Mean elevation) + 0.029 (StDev slope) + 6.963
TP	−0.017 (Mean elevation) + 0.346 (Streets) + 9.713
TS	−0.409 (Mean elevation) + 5.63 (Mean slope) – 6.176 (StDev Slope) + 186.291
Temp	−0.01 (Mean elevation) + 0.191 (StDev slope) – 0.017 (%SFR) – 0.096 (Mean slope) + 15.06
Watershed	
Wet Season	
EC	5.315 (Streets) – 2.229 (StDev slope) + 93.006
DO	0.13 (Mean slope) + 0.021 (SFR age) + 8.838
NN	0.013 (SFR age) – 0.006 (Mean elevation) – 0.022 (%SFR) + 2.816
pH	0.006 (Urban) + 6.934
TP	0.053 (Urban) + 4.024
TS	−1.728 (StDev slope) + 3.604 (Streets) + 99.903
Temp	0.152 (Streets) – 0.019 (%SFR) + 6.481
Dry Season	
EC	2.596 (Streets) – 0.193 (Mean elevation) + 155.069
DO[a]	1248.699 (StDev slope) + 186.205
NN[b]	−0.003 (Mean elevation) – 0.009 (%SFR) + 0.912
pH	−0.003 (Mean elevation) + 0.035 (StDev slope) + 7.458
TP	0.076 (Urban) + 5.72
TS	2.194 (Streets) – 0.219 (Mean elevation) + 150.29
Temp	−0.014 (Mean elevation) + 0.12 (StDev slope) + 14.961

All TP values were multiplied by 100 to accommodate software limitations.
[a] Exponentially transformed.
[b] Log 10 transformed.

The residuals may be used to test the model's accuracy at predicting local conditions by running a test for spatial autocorrelation. We used Global Moran's I for the residuals of both OLS and GWR models to test spatial dependence. Moran's *I* is calculated from the following formula.

$$I = \frac{n}{\sum_{i=1}^{n}(X_i-\overline{X})^2}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(X_i-\overline{X})(X_j-\overline{X})}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \quad (4)$$

where, X_i and X_j refer to water quality at station *i* and station *j*, respectively. $\overline{X}$ is the overall mean water quality, and W_{ij} is the weight matrix. Like correlation coefficient, *I* is positive if both X_i and X_j lie either above or below the mean, while it is negative if one station is above the mean and the adjacent stations are below the mean [40].

Global models assume that relationships between water quality and explanatory variables are the same across space. This is particularly problematic given the variation in land cover and multiple sources of pollutants. In a study of Northwest England, urban and agriculture land covers were determined to be highly correlated with NN levels [17]. Li et al. [24] found that NN was correlated with forest cover during the wet season and bare land during the dry season. With multiple sources of pollutants and patchwork landscapes, it is necessary to consider local conditions when modeling pollutant loads because pollutants can have multiple sources, both from direct point discharge and non-point sources.

3. Results

3.1. Spatial and seasonal variations of water quality

As shown in Fig. 4, there are substantial variations in water quality over space and season. Generally, higher concentrations of conductivity, NN, pH, TP, and TS are associated with low elevation urban land covers, and EC, TS, and TP values are lower during the wet periods than during the dry season (Fig. 4). Such spatiotemporal variations of water quality are related to the fact that catchment characteristics are heterogeneous in space and time. Precipitation in forested areas can dilute TS and TP concentrations in winter months [1,2,19], while in agricultural-dominant catchment, rain runoff can contribute to elevated level of nutrients and TS. During the dry season, microorganisms in the water may be absorbing more DO and NN, causing lower levels, while high TP values are due to runoff from fertilized lawns and agricultural fields [7]. In most cases, NN is higher during the wet season, probably because of runoff from impervious surfaces and the effect of dormant plants not absorbing nitrogen.

3.2. Land cover at the two spatial scales

The land cover percentages for each buffer and watershed varied across the region (Fig. 5). Portland generally had less agriculture and forest present in the watersheds. Tryon Creek (TC) and Fanno Creek (FC) have some forest present, but are mostly urban, unlike Balch Creek (BC) and the upper reaches of Johnson Creek (JC). The Salmon Creek (SC) watershed in Clark County is similar to Johnson Creek, as the upper reaches are more heavily forested and farmed than the lower reaches that pass through urban areas. The Burnt Bridge (BB) watershed also follows this gradient, with a few sites in the upper part of the watershed having some agriculture present, but mostly dominated with urban development. Other watersheds in Clark County had a mixture of land cover types, with the exception of Jones Creek, which is almost entirely forested.

Every land cover present in the watersheds was also present in the buffer areas. In almost every case, there is higher % urban land cover at the buffer scale then at the watershed scale. This is not the case for wetland or forested land covers, where wetland and forested area percentages decreased at the buffer scale in nearly every case. Agriculture land increased at the buffer scale, albeit to less than 1%.

3.3. Influence of scale and season

The landscape variables identified as being significant in predicting water quality varied depending on the scale of analysis and season. At the watershed scale, street density, a measure of impervious surfaces and landscape fragmentation, was significant in five cases (Tables 4 and 5). Likewise, forest land cover was not significant at the watershed scale, but came up as a significant variable for explaining variations in wet season DO at the buffer scale.

Out of all the predicted correlations, 11 relationships between water quality parameters and explanatory variables occurred, and the sign of the coefficients remained the same at both scales. Only one model, dry season pH, switched from negative at the watershed scale to positive at the buffer scale for standard deviation of slope. While the models were not consistent in identifying the same independent variables for each parameter in both scales, the variables' relationships with the water quality parameters remain unchanged.

Dry season results at both scales are dominated with topographic variables. Mean elevation is negatively related to dry season EC, NN, pH, TS, and TD. As shown in Fig. 6, the areas with a lower mean elevation have higher NN values. In several cases on Johnson Creek and Salmon Creek, this may be due to the higher proportion of agriculture present (Fig. 5). Both the mean and standard deviation of slope appear multiple times in dry season models. Higher standard deviations of slope is credited with increasing Temp in the dry season at both scales, and decreasing TS at the dry season buffer scale and the wet season watershed scale. Gentle slope may be acting as a literal sink for TS, slowing runoff or stopping it entirely and allowing the water to percolate through the surface. Less slope variability may be increasing stream water temperature in a similar fashion, as slow-moving water has more residence time to absorb sunlight and heat from pavement.

Structural variables – urban, percent SFR, and SFR age – appeared in multiple models at both scales. The urban variable is present in EC, pH, TP, TS, and Temp wet season buffer models, as well as the pH and TP watershed models, positively correlated. Percent SFR is negatively correlated to NN in all four models, as well as wet season buffer Temp and dry season watershed Temp.

The parameter's season with the higher concentration did not necessarily have higher R^2 values (Table 6). DO and pH had stronger models during the wet season than during the dry season at both scales, while NN and TS had higher values during the dry season than during the wet season at both scales. At the watershed scale, the wet season acted as a better predictor of water quality than the dry season except for TS and NN. At the buffer scale, the dry season data with lower flows was a better predictor for five parameters, but not for DO or pH.

3.4. Comparison of OLS and GWR models

In every case, the global R^2 value for GWR models was higher than that for the OLS models (Table 6). Improvements of over 20% occurred in 18 models, 11 at the watershed scale. Of these, half are for dry season and half for wet season models. The GWR analysis includes local R^2 values for each variable. The smallest ranges, under 0.20, occur in the buffer GWR analyses, and with the exception of three cases, the buffer models have the smallest ranges of local R^2 values. The smaller range of values implies that the local GWR model might be applied globally with the derived coefficients and constants with general consistency. Wider ranges imply that

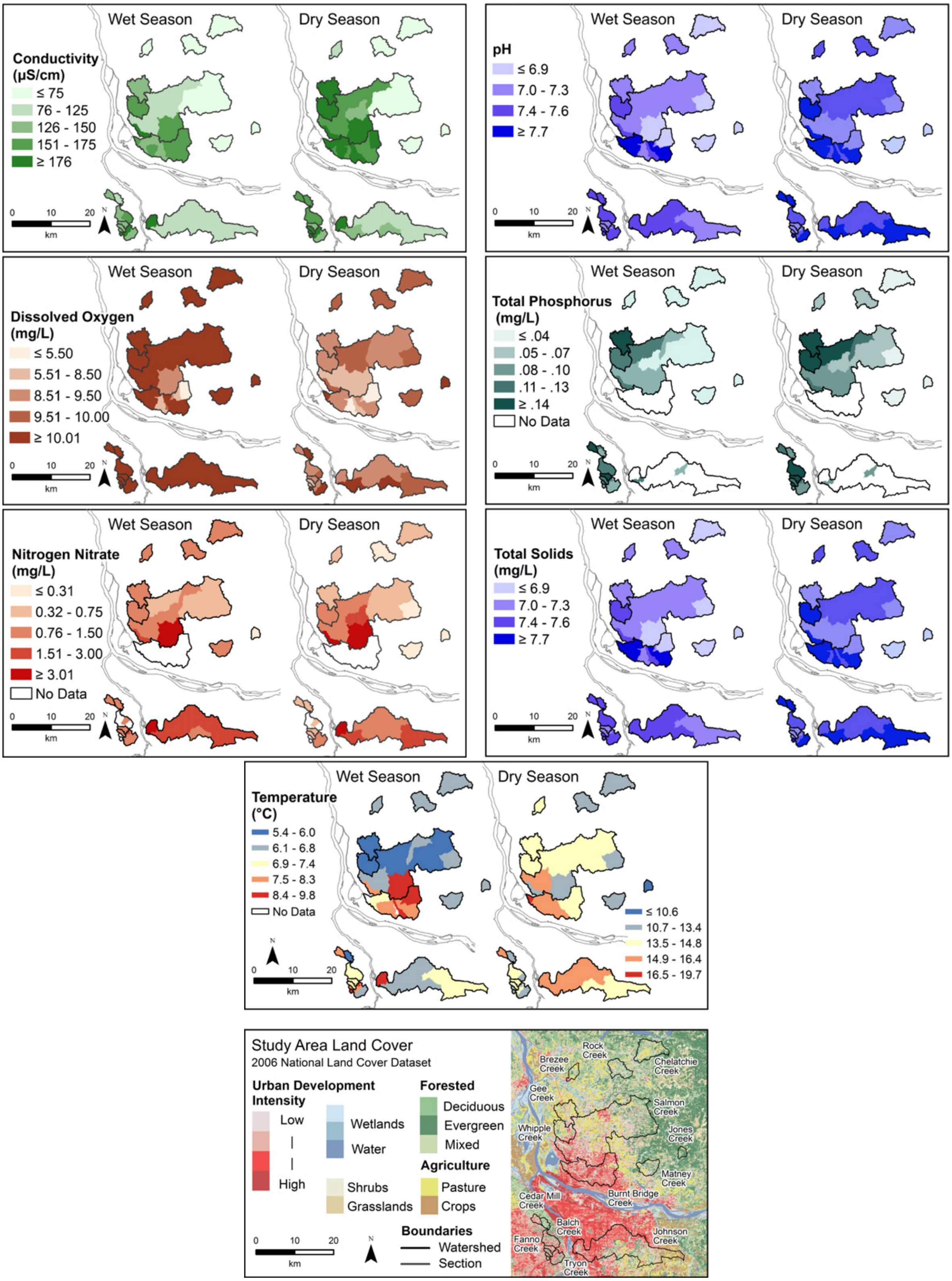


Fig. 4. Spatial variations of wet and dry season water quality.

the outlier sites have other sources of pollutants and ought to be examined more closely. The watershed scale had higher R^2 values than the buffer scale in 10 out of 14 cases, three in the dry season when runoff is less frequent or voluminous.

As described in Table 7, except the three watershed scale OLS models, wet season DO and pH and dry season Temp, the models did not have spatial autocorrelation. At these exceptions, the results were found to be positively autocorrelated, clustered at the 5% significance level. Fig. 7 maps the GWR and OLS residuals of wet season DO and pH at the watershed scale. In OLS models, similar residuals values are clustered in a few watersheds. DO residuals are clustered in Johnson Creek and Fanno Creek in Portland, while

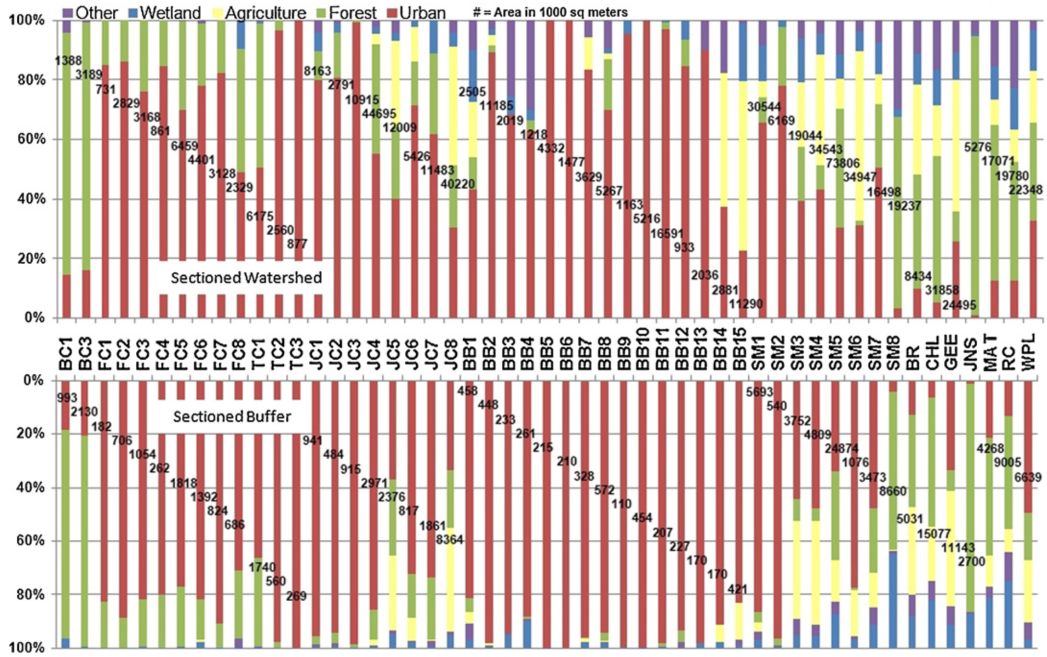


Fig. 5. Percent land cover at watershed and buffer scales.

Table 5
Regression model coefficients for explanatory variables.

			Land cover				Structure						Topographic					
			Forest		Urban		Street density		% SFR		SFR age		Mean elevation		Mean Slope		StDev slope	
			GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS	GWR	OLS
Buffer	Wet Season	EC			+	+												
		DO	+	+							+	+						
		NN							–	–					–	–		
		pH			+	+					+	+					+	+
		TP			+	+												
		TS			+	+												
		Temp			+	+							+	+			–	–
	Dry Season	EC			+	+							#	–				
		DO									+	+			+	+		
		NN							–	–			–	–				
		pH									+	+	–	–			+	+
		TP					+	+					–	–				
		TS											–	–	+	+	–	–
		Temp							–	–			–	–	–	–	+	+
Watershed	Wet Season	EC					+	+									–	–
		DO									#	+			+	+		
		NN							–	–	+	+	–	–				
		pH			#	+												
		TP			+	+												
		TS					+	+									#	–
		Temp					+	+	–	–								
	Dry Season	EC					#	+					#	–				
		DO															+	+
		NN							–	–			–	–				
		pH											–	–			+	–
		TP			+	+												
		TS					+	+					–	–				
		Temp											–	–			+	+

– indicates a negative coefficient; + indicates a positive coefficient; # indicates there is no majority positive or negative coefficient present.

Table 6
Coefficient of determination (R^2) in OLS and GWR models at two different spatial scales.

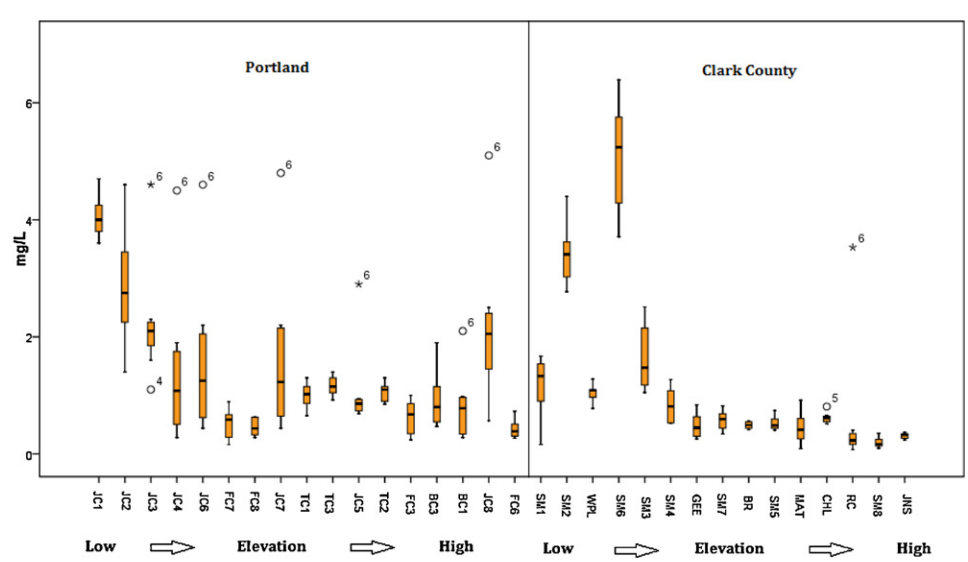
	GWR R^2 range		Buffer			Watershed		
	Buffer	Watershed	GWR	OLS	*n*	GWR	OLS	*n*
Wet season								
EC	0.12–0.9	0.35–0.83	0.69	0.48	48	0.72	0.60	51
DO	0.24–0.33	0.26–0.53	0.72	0.55	50	0.73	0.41	51
NN	0.55–0.63	0.57–0.72	0.58	0.42	32	0.59	0.51	31
pH	0.48–0.69	0.01–0.66	0.66	0.59	50	0.77	0.31	51
TP	0.16–0.51	0.07–0.49	0.38	0.24	30	0.52	0.37	30
TS	0.11–0.9	0.01–0.79	0.50	0.26	30	0.73	0.40	30
Temp	0.62–0.76	0.06–0.87	0.70	0.65	51	0.58	0.48	51
Dry season								
EC	0.04–0.9	0.05–0.74	0.72	0.28	47	0.69	0.31	48
DO	0.25–0.63	0.04–0.56	0.27	0.26	42	0.34	0.30	50
NN	0.34–0.6	0.39–0.51	0.62	0.58	32	0.67	0.63	31
pH	0.5–0.67	0–0.65	0.55	0.49	48	0.61	0.33	51
TP	0.09–0.33	0.13–0.52	0.48	0.38	27	0.44	0.29	30
TS	0.05–0.47	0.01–0.75	0.86	0.76	27	0.80	0.56	30
Temp	0.58–0.78	0.3–0.55	0.70	0.66	46	0.78	0.49	48

0 values indicate a value less than .01

Table 7
Spatial autocorrelation of residuals in GWR and OLS models.

	Buffer		Watershed	
	GWR	OLS	GWR	OLS
Wet season				
EC	−0.14	0.01	0.02	0.11
DO	−0.01	0.03	0.10	0.39
NN	−0.04	0.11	−0.24	−0.21
pH	0.01	0.12	0.01	0.24
TP	0.04	0.15	0.08	0.19
TS	0.19	0.21	0.13	0.19
Temp	−0.07	0.04	0.05	0.16
Dry season				
EC	−0.23	0.06	−0.19	−0.06
DO	0.00	0.02	−0.01	0.01
NN	0.03	0.09	0.02	0.09
pH	0.16	0.19	0.08	0.18
TP	0.05	0.10	0.06	0.07
TS	−0.17	−0.15	−0.11	0.00
Temp	0.03	0.05	0.11	0.27

Underlined values indicates the model is autocorrelated, with a $p < .05$



BC – Balch Creek, FC – Fanno Creek, TC – Tryon Creek, JC – Johnson Creek, SM – Salmon Creek, BR – Brezee Creek, CHL – Chelatchie Creek, GEE – Gee Creek, JNS – Jones Creek, MAT – Matney Creek, RC – Rock Creek, WPL – Whipple Creek

Fig. 6. Nitrogen nitrate, dry season, sorted low to high watershed mean elevation.

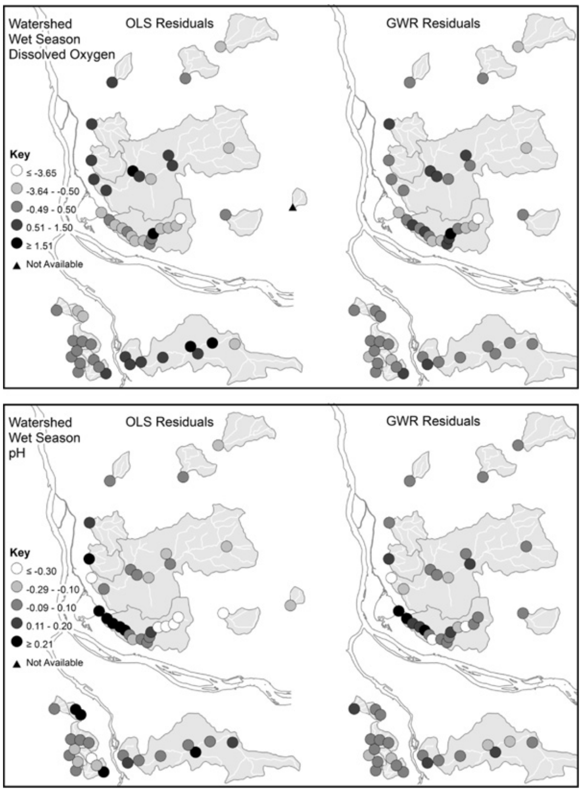


Fig. 7. Residuals of wet season dissolved oxygen and pH at the watershed scale.

pH residuals are clustered in Salmon Creek in Vancouver. With generally lower residual values, GWR model residuals, however, do not show any spatial clustering.

Fig. 8 illustrates the shift in coefficient values for EC, NN, DO, pH, TS, and Temp at both scales. The EC map is the most striking, with a clear divide between Clark County and Portland coefficient values for mean elevation. Elevation is credited as increasing the level of EC in the waters in the urban watersheds of Tryon and lower Johnson Creek, as well as the more forested Balch Creek watersheds. North of the river in Clark County, mean elevation is found to have a negative relationship with the levels of EC. Elevation is positively associated with dry season pH and DO in middle Johnson Creek, but it is negatively related to pH and Do in the rest of other study streams. e Elevation is consistently negatively associated with Temp and NN in all streams.

In the pH, TS, and Temp maps, clusters of higher R^2 values are evident in watersheds across the study area. Despite the diverse landscape present in Johnson Creek, relatively high R^2 values were still reported. In Burnt Bridge Creek, a gradient of R^2 values is evident, as R^2 values decrease from upstream forests to downstream urban areas. This may be due to the sectioned method used; perhaps the GWR model did not capture the upstream variables as thoroughly due to the distance decay built into the analysis. Additionally, downstream urban areas may contain other sources of pollutants that were not included in our models.

4. Discussion

4.1. Water quality parameters and predicting variables

Sources of TP vary. Some studies claim underlying geology in areas for high TP loads, while others believe that the decrease in TP is due to the TP attaching itself to sediment and settling into the streambed [i.e., 36, 14, 18]. Bowes, Smith, and Neal used data collected multiple times a day during high and low flow events found that TP loads increased with the rise in streamflow during a high-flow event, and speculated that the TP was trapped within the river bed sediments [41]. Although TP concentration is generally lower during the wet season in our study watersheds, in Fanno Creek, high levels of phosphorus in soils can contribute to elevated levels of TP concentrations during high flow events [42].

Forest land cover is positively associated with wet season DO at the buffer scale. This result was found in another study, where high DO levels were associated with unmanaged forest land [13]. Given that the present vegetation ought to be absorbing the oxygen in the water, this leads to speculation that the DO values might be much higher or vegetation may not be acting efficiently [7]. In Miserendino's study [13], EC was found to be positively correlated with forest land cover, however other studies found a negative relationship [11,24]. The type of plant may be affecting the water chemistry, and so a finer scale of analysis may be useful with consideration as to the type of vegetation present.

Urban land cover at the buffer scale was found to be positively correlated with EC [5,8,13]. A study in Boston found that residential land had a positive correlation with conductance however this was not seen here using the %SFR variable [38]. Urban land cover has been found to be positively correlated with a number of parameters, including EC, DO, NN, and TS [3,5,7–10,43]. This result is not unexpected, as surfaces collect particulates and chemicals that are flushed out during rain events into nearby streams. Residential land cover, however, can act as a sink for NN. This is similar to Li et al. [44] who found that NN had a negative correlation with vegetation coverage. However, the actual makeup of the residential land in this case is unknown. These areas may be completely paved over or have large, fertilized lawns. Its appearance in models for NN and Temp suggest that lawns are retaining water and allowing runoff to slow down and percolate through the soil.

The importance of topography has been noted in several other studies [15,25,34,36]. Slope can act as sinks or sources for particulates, as areas with high variability may act as sinks and steep slopes can hurry runoff to the stream, picking up particulates along the way. Besides the topographic variables, street density was found to be significant at the watershed scale in 10 models. This is likely tied to the surface of trafficked streets funneling particulate-laden runoff into streams [45].

4.2. Scale

The watershed scale of analysis clearly generated a stronger model than the buffer scale. Carter et al. [46] noted that storm water mitigation practices were not being fully exploited at the watershed scale. Instead of identifying non-point sources, direct inputs to streams were identified and mitigation projects built around them. In this study, street density, urban and residential land covers, as well as topographic variables played important roles in predicting stream water quality. The finer resolution of this data, both in terms of spatial as well as categorically, indicates that general land cover categories, i.e., urban, do not capture key variances in land uses affecting water quality. Lee et al. [8] had a similar finding, where analysis of land use patterns suffered due to poor spatial resolution and the generalization of urban land cover.

4.3. Spatial autocorrelation

The GWR models performed as expected by accounting for local variance in generating local coefficients and constants. If the residuals are autocorrelated, then it is likely that the model missed a variable that explains the variation. Several OLS models in this study had residuals that were spatially autocorrelated. The GWR models functioned correctly accounting for local variability in land

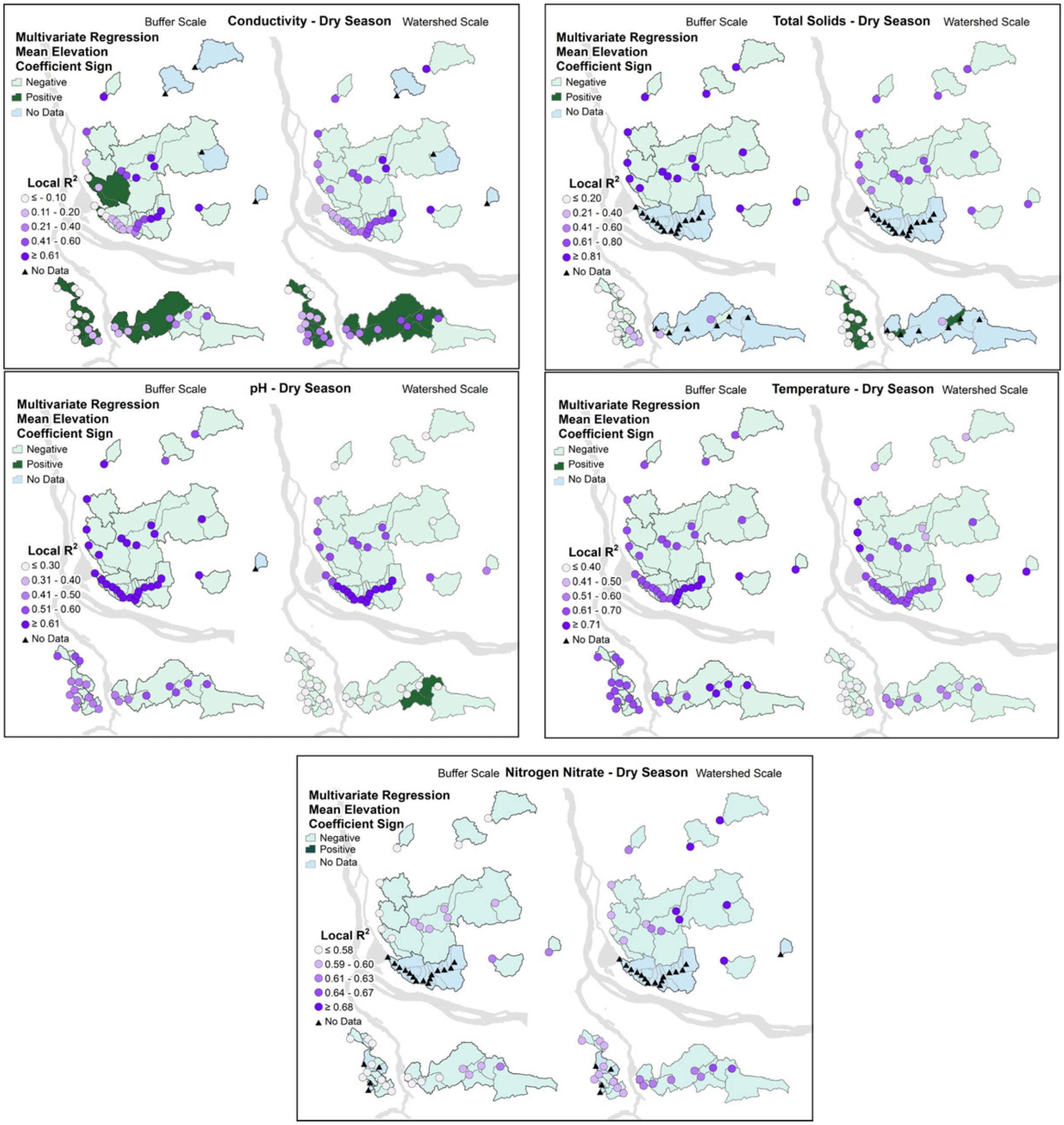


Fig. 8. Mean elevation coefficient signs and local R^2 of GWR.

cover [38]. This suggests that GWR models, by taking into account spatial autocorrelation, give higher predictive power than traditional OLS regression models. The GWR models also suggest how the relation between water quality and each explanatory variable might vary at a local scale.

5. Conclusions

This study found that depending on the type of analysis being performed, the parameter itself being examined, the season does affect the results. While selecting the time period where the water quality parameter had a higher concentration or value generally improved model strength. Topographic variables clearly appear to be important in determining water quality parameters during the dry season at both scales.

Across season and parameters, the scale of analysis did matter. Higher R^2 values were generated using sectioned watershed scale variables than the smaller buffer scale in 10 cases. Riparian restoration projects should not be discounted, nor should their impact on stream water quality be exaggerated. The cumulative effect of non-point sources across a watershed cannot be negated within a zone a set distance from a stream. Management practices must incorporate abatement projects watershed-wide instead of focusing on the stream's immediate area [11].

The GWR models did generate higher R^2 values than the OLS models, thus implying that GWR models account for more variations in local areas. However, without examining the distribution of local coefficients and independent variables, the results may be misinterpreted. Additional analysis would benefit from a wider sample pool in the watersheds and the ability to remove site outliers due to extreme land cover differences, e.g. Jones Creek. While urban land cover and other structural variables did appear as significant in several models, their presence varies greatly across the study area and also their effect. The GWR models developed in the current study can identify such local variations, which can inform managers of the role of different landscape variables affecting water quality in urban streams.

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