The King County Conundrum: Spatial-Temporal Stream Water Quality Trends with Increasing Urban Development

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Abstract

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King County, Washington State, has monitored stream and river water quality monthly at 75 sites for over 40 years for an average of > 23,000 samples collected for each constituent. This sampling was conducted during a time when the population has almost doubled, and conventional wisdom predicts a decline in water quality due to increased urban development. The database includes nitrate, ammonium, and total nitrogen (N), phosphate and total phosphorus (P), alkalinity, pH, conductivity, dissolved oxygen (DO), turbidity, total dissolved solids (TSS), and fecal coliform bacteria (FCB). I quantified long-term trends, contemporary statistical relationships between catchment land-cover and water quality, and seasonal variability in constituent concentrations. The long-term trend analysis showed nitrate-N, ammonium-N, total N, phosphate-P, FCB, TSS, and DO concentrations significantly declined ($p < 0.01$) in King County streams during the sampling period. Conversely, alkalinity, conductivity, and stream temperature significantly increased. Turbidity, pH, and total P showed no clear temporal trends. Stream water quality data from 2016-2022 was fit to catchment land-cover regression models. Conductivity (r^2 = 0.56), phosphate-P (r^2 = 0.55), alkalinity (r^2 = 0.53), FCB (r^2 = 0.48), total P (r^2 = 0.44), temperature (r^2 = 0.39), total-N (r^2 = 0.37), nitrate-N (r^2 = 0.26), DO (r^2 = 0.24), and pH (r^2 = 0.21) multiple-regression models had significant fits ($p < 0.01$) with land-cover characteristics. Turbidity, total suspended solids, and ammonium-N had insignificant model fits. Developed land was the most important land-cover category for every constituent. Deciduous forest cover was an important secondary variable for total-N, nitrate-N, conductivity, and alkalinity. Agricultural land-cover (largely pasture) was an important secondary variable for the phosphate-P, total-P, and FCB models. The temperature and pH models had no important second variables. Wetlands were an important secondary variable for DO. In general, developed, deciduous forest, and agricultural landcover resulted in higher constituent concentrations, whereas wetlands and open water usually resulted in lower concentrations. The results of this study are paradoxical because the expected stream water quality trends with urban development were observed, whereas dissolved and total N, dissolved P, suspended sediment and fecal bacteria concentrations declined during a multi-decadal period when the population of King County nearly doubled.

Introduction

Since the mid-20th century, urban environments have grown rapidly, with the world urban population surpassing the rural population in 2009 (Brockerhoff, 2018). It is important to understand the effects of urbanization on stream ecosystems and how to best ameliorate their negative impacts. Streams in urbanized catchments have been found to display common patterns of degraded conditions, including elevated contaminant concentrations, altered channel morphology, flashier hydrographs, and degraded biotic communities (Walsh et al. 2005, Wenger et al. 2009). This suite of symptoms, which has been dubbed “the urban stream syndrome”, has many complex and interrelated causes, but a primary driver is thought to be stormwater runoff (Meyer et al. 2001, Walsh et al. 2005). Undisturbed natural catchments typically have low hydraulic conductivity and soils with high infiltration capacity which dampens and delays hydrograph peaks by allowing more runoff to infiltrate the soils and follow a subsurface pathway to stream channels (Booth et al. 2002). Conversely, urbanization results in large impervious areas due to compacted and paved surfaces, roofs, etc., thereby reducing stormwater infiltration. To reduce flood risk, municipalities also use stormwater conveyance systems to rapidly divert runoff to adjacent stream channels, resulting in large volumes of water quickly routing to streams (Meyer et al. 2001, Booth et al. 2002, Walsh et al. 2005).

In undisturbed catchments, the riparian zone can act as a buffer for nutrients, sediment, and contaminant transport. However, stormwater conveyance systems bypass this buffer as runoff is discharged directly to the stream channel (Booth et al. 2002). Riparian buffers also affect stream temperature, channel morphology, and nutrient transport in intensely developed catchments (May et al. 1998). Intact riparian buffers are typically heavily vegetated, which provides shade for the channel and regulates in-stream temperature. Additionally, riparian forests are the primary source of in-stream woody debris, which increases channel complexity and provides habitat for fish and invertebrates (May et al. 1998, Groffman et al. 2003). A healthy riparian buffer also attenuates sediment and nutrient transport into stream channels as sediments are held in place by organic matter, vegetation, and root systems and nutrients are taken up by vegetation (Ranalli & Macalady 2010). Both declining riparian buffer width and increasing fragmentation are correlated with urban development, so it is difficult to separate the consequences of disturbance of the immediate riparian corridor from overall catchment urbanization (May et al. 1998).

Urbanization often leads to profound changes in the stream flow regime. The increased hydraulic conductivity caused by impervious surfaces and conveyance systems results in a much flashier and erosive hydrograph, with a shorter lag between precipitation and discharge peaks (Walsh et al. 2005). The peak flows are also much higher due to larger volumes of water moving through the system during a shorter time interval. Additionally, the rising and falling limbs of the hydrograph are much steeper and more erosive (Walsh et al. 2005, Booth et al. 2016). Since small precipitation events are not infiltrated into pervious soils, peak flow events are more frequent (Paul and Meyer, 2001). These flow characteristics were the historical focus of human mitigation efforts since they result in increased flood risk. To mitigate this risk, best management practices (BMPs) have been designed to reduce peak flows to pre-development levels (Booth et al. 2002). The most common BMPs are detention and retention ponds which are designed to slow the rate of runoff into streams and infiltrate runoff, respectively. Detention ponds successfully reduce and delay peak flows, but only have a minimal impact on water quality and can introduce a separate suite of problems by increasing peak flow duration (Booth et al. 2002). Retention ponds mimic characteristics of an undisturbed catchment by capturing and infiltrating urban runoff, and have additional benefits for water quality, as nutrients, contaminants, and sediments are attenuated during subsurface transport. However, the practicality of retention ponds in urban environments is often limited by the soil infiltration capacity and available surface area (Booth et al. 2002).

Basin urbanization can significantly alter channel morphology by, for example, causing channel incision. This can be exacerbated by human intervention, such as straightening of stream channels or paving of riparian buffers (Paul and Meyer, 2001, Walsh et al. 2005). Thus, morphological change is often a consequence of the altered flow regime. Larger and more frequent peak flow events increase scour, which widens and deepens the steam as sediment is eroded from the stream channel (Walsh et. al, 2005). Mitigation strategies designed to reduce peak flows are often used to control channel erosion. However, they do little to reduce the frequency of high flow events, which do just as much if not more damage to the channel (Booth et al. 2002).

Urban development can also significantly alter stream chemistry. This primarily manifests as higher toxicant and nutrient concentrations, higher electrochemical conductivity, and elevated fecal bacteria counts (Wenger et al. 2009, Carey et al. 2013). These contaminants may come from overland flow directed to streams via stormwater conveyance systems, groundwater leachate via subsurface transport, or atmospheric deposition. Nutrients from excessive lawn fertilizer usage, erosion from construction sites, and fecal bacteria from pet waste, wildlife waste, and combined sewer overflows (CSO's) are all carried by stormwater runoff (Carey et al. 2013). Several toxicants come from road runoff, such as 6-PPDQ, a transformation product of an anti-ozonate in tire rubber that was discovered to be fatal to salmonids (Tian et al. 2021). Additionally, ions that increase conductivity come from road runoff, especially where road salts are used for de-icing (Wenger et al. 2009). Leachates from failed onsite sewer systems can also contaminate streams with bacteria, excess nutrients, and salt (Walsh et al. 2005).

It is well established that urban streams often have elevated nutrient concentrations compared to undisturbed catchments (Paul & Meyer. 2001, Brett et al. 2005, Walsh et al. 2005, Wenger et al. 2009, Booth et al. 2016). Elevated nutrient concentrations increase the risk of eutrophication, resulting in algal blooms, some harmful, which can shade out competing macrophytes and reduce oxygen availability within intergravel pore spaces (Walsh et al. 2005, Carey et al. 2013). This is detrimental to benthic invertebrates, particularly *Ephemeroptera*, *Plecoptera*, and *Tricoptera* (EPT), that depend on the oxygen-rich intergravel pore spaces for food and habitat. Wastewater treatment plant (WWTP) effluent may represent an acute nutrient source in some urban catchments, though this is less common in more developed areas where outfalls are usually routed away from streams or WWTPs implement advanced removal technologies (Carey et al. 2013, Booth, et al. 2016). However, in arid regions in the US and elsewhere, WWTP effluent may constitute a substantial fraction of stream flow (Kolpin et al. 2002). Additional nutrient sources include sediment export from construction sites which can carry significant amounts of phosphorus that was previously bound in the soil. Disturbed soils can export nutrients in stormwater for years after construction is completed, until the soil is revegetated and covered by organic matter (Chen et al. 2009, Carey et al. 2013). Stormwater runoff may contain large quantities of both nitrogen and phosphorus from onsite sewer system (OSS) failures, lawn fertilizers, and pet waste (Wenger et al. 2009). Nitrogen, which is more mobile than phosphorus, is capable of transport to streams via groundwater and can also originate from atmospheric deposition (Decina et al. 2019). Fertilizer, OSS leaks, and landfill leachate can transport nitrate to groundwater, increasing baseflow nitrogen concentrations. Urban areas also have large amounts of combustion activity from automobiles. Until the late 20th century, vehicle emissions contained various nitrogen oxide gases, which were a cause of acid rain and a direct source of nitrate (NO_3^-). Since the widespread adoption of catalytic converters, automobiles emit nitrogen as NH_3, leading to increased wet deposition of nitrogen near roadways (Bernhardt et al. 2008, Carey et al. 2013).

Baseline electrochemical conductivity varies with the biogeochemistry of catchments, but there is a consistent increase associated with urban development (Walsh et al. 2005). Runoff from roads, particularly those using road salt as a deicer, is a major source of ions entering streams.

Elevated conductivity is not usually a water quality concern but can be a useful measure of human disturbance in the catchment and can be indicative of other water quality issues. In some cases, high in-stream concentrations of chloride from road salt runoff have been found to produce both acute and chronic toxicity in aquatic organisms (Wenger et al. 2009, Corsi et al. 2010).

The myriad of effects from catchment urbanization greatly reduce the amount of suitable habitat for benthic invertebrates, leading to changes in species composition. Both macroinvertebrates and fish show a consistent pattern of reduced species diversity in urban streams, with a decline in sensitive species (e.g., EPT), and a rise in resistant species (e.g. Chironomidae and Oligochaeta) (Walsh et al. 2005, Paul & Meyer. 2001). Bacteria are more abundant in urban streams, especially fecal coliforms, whose concentrations spike during storms, as these bacteria are transported with combined sewer overflows (CSO's) or runoff carrying human and animal waste (Paul & Meyer. 2001). The algal response to stream disturbance is highly dependent on the community composition, nutrients, tree cover, discharge, and contaminants present. Overall biomass sometimes increases, as discussed earlier. Other times there will be no change in biomass. Compositional changes are highly variable, and there is not a consistent increase or decrease in algal species richness associated with stream eutrophication (Walsh et al. 2005).

This study analyzed water quality data collected from 1979-2022 for 75 stream and river monitoring sites across King County, Washington. During this time, most streams were sampled monthly. Twelve water quality parameters were recorded: nitrate/nitrite-N (henceforth referred to as nitrate-N), ammonia/ammonium-N (referred to as ammonium-N), total nitrogen, phosphate-P, total phosphorus, fecal coliform bacteria, total suspended solids, turbidity, total alkalinity, specific conductivity, pH, dissolved oxygen, and temperature. The stream sizes varied from small creeks (e.g. < 0.03 m^3/s) to major rivers (e.g. 30 m^3/s). As far as I am aware, this is one of the most extensive water quality records with regard to temporal length and spatial scale for urban streams. It is also an unprecedented opportunity to characterize water quality in an area that has rapidly urbanized. Two statistical analyses were performed on the stream water quality data: 1) quantification of long-term trends, and 2) fitting multivariate models to water quality using land-cover characteristics.

Study Area

Development and Demographic Characteristics

Spanning approximately 5700 km^2, King County is the most populous county in Washington State. It is home to Seattle, the largest city in Washington State and county seat, as well as 4 of the state's 10 largest cities. According to the 2019 USGS National Land Cover Database (NLCD) 61% of the King County is forested, 23% is developed, and about 2.5% is agricultural (Clark and Walls, 2023). Urban development is concentrated around Seattle and its suburbs along the I-5 corridor and east of Lake Washington, giving way to rural development and forest cover in the eastern half of the county. Over the last half-century, the population of King County has doubled, totaling over 2.2 million as of 2020 (density of 380/km^2) (Clark and Walls, 2023).

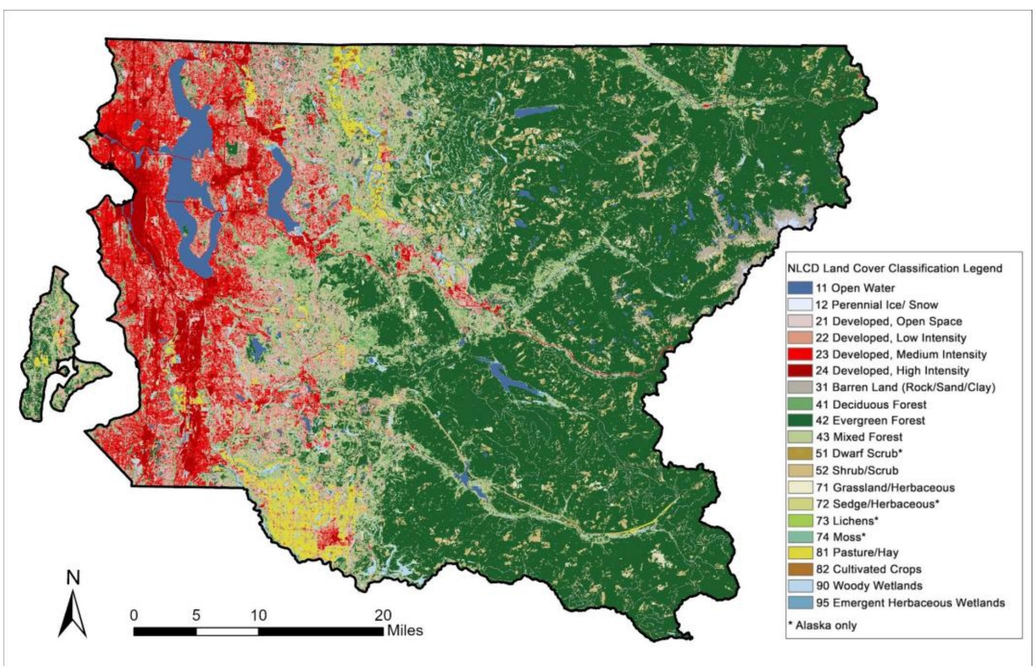

Figure 1. A map of land cover categories across King County using data from the 2019 NLCD (Clark and Walls, 2023).

King County has a wet climate with an average precipitation of 0.76 m/yr in the developed western Puget Sound lowlands and up to 3.8 m/yr in the forested mountainous eastern Cascade Mountains, with an overall average of 2.0 m/yr. Runoff averages 50% of precipitation in the lowlands up to 66% in the Cascades (USGS, 1968). King County is also home to a large number of streams and rivers, ranging from small urban streams to major rivers draining mountain catchments. These streams and rivers are ecologically, recreationally, and economically important to the region. The Tolt River and Cedar River supply drinking water to King County and the Green River is the water source for Pierce County to the south. Many of the smaller streams feed into Lake Washington and Lake Sammamish (Fuerstenberg et al. 2012), and many of these streams are spawning habitat for ecologically and economically important *salmonid* species, including sockeye and kokanee salmon (*Oncorhynchus nerka*), chinook salmon (*O. tshawytscha*), pink salmon (*O. gorbuscha*), coho salmon (*O. kisutch*), and steelhead trout (*O. mykiss*) as well as resident cutthroat trout (*O. Clarkii*) (May et al. 1998).

KC Streams Monitoring

In 1958 a voter-approved citizen initiative authorized the formation of the Municipality of Metropolitan Seattle (Metro), which was tasked with creating a regional wastewater treatment system because of the severe eutrophication of Lake Washington due to discharges of nutrient rich secondary WWPT effluents (Edmonson, 1984). In 1994 Metro merged with King County, which assumed responsibility for monthly stream sampling at 40 sites established in the late 1970's and expanded to 58 sites by 1999. Between 2008 and 2013 more than half of monitoring sites were either temporarily or permanently inactive, due to funding cuts during the Great Recession of 2008. Since 2013, more sites have been added than were initially active (Walls and Clark, 2023). The water quality constituents monitored include dissolved and total nutrients, suspended solids, turbidity, dissolved oxygen, temperature, fecal coliform bacteria, alkalinity, conductivity, and pH.

Legacy Logging and Alnus rubra

The logging industry in Washington started in the mid-19th century and was mainly driven by demand for lumber in California boomtowns. Through the late 19th century and early 20th century, nearly all old growth forests in the Puget Lowlands were cleared and replaced by urban development near Seattle and second growth forest in eastern King County (Clark and Walls, 2023). West of the Cascade Mountain range, previously logged areas have a greatly increased incidence of red alder (*Alnus rubra)* (Compton et al. 2003). Red alder is a short-lived (less than 100 years), early successional deciduous species, which is much less prevalent in mature forests where it gets shaded out by taller, late successional species such as Douglas-fir (*Pseudotsuga menziesii*), western hemlock (*Tsuga heterophylla*) and western red cedar (*Thuja plicata*) (Kruckeberg, 1991). Red alder is particularly important to watershed biogeochemistry because it is capable of nitrogen fixation via a symbiotic association with rhizobacteria, which also affects soil chemistry.

Regulatory Efforts

Washington State passed the Growth Management Act in 1990, which was intended to control the rate of sprawl and protect ecologically critical areas from development (Hepinstall-Cymerman et al. 2011). This law required governments in relevant counties to develop comprehensive plans to address urban growth, part of which was to designate zones in which development would be concentrated. This would, in theory, encourage urban densification in already developed municipalities and reduce encroachment into forested areas (Hepinstall-Cymerman et al. 2011).

In 2011, the Washington State legislature passed a bill that banned the application and sale of turf fertilizer containing phosphorus. This ban was narrow as it only applied to turf fertilizer, and many exceptions were made, namely fertilizer for establishing or repairing grass during a growing season or for adding phosphorus to lawns with deficient P levels (Miller, 2012).

The first stormwater manual published by the WA department of Ecology was released in 1992 as part of the Puget Sound Water Quality Management Plan. It marked a shift in statewide stormwater management practices from solely focusing on flood control to additionally protecting water quality (Washington Dept of Ecology, 1992). This manual served as a library of Best Management Practices (BMPs) with the dual objectives of controlling runoff discharge and reducing pollutant loads. The Ecology stormwater manual now applies to the entire state and has undergone several revisions since its first publication.

Data

Water Quality

All water quality data came from the King County streams monitoring program and was obtained by querying the county's Socrata database (https://kingcounty.socrata.com). This study assessed 13 water quality parameters: Nitrate-N, Ammonium-N, Total Nitrogen, Soluble Reactive Phosphorus (Phosphate-P), Total Phosphorus, Fecal Coliform Bacteria, Conductivity, Alkalinity, pH, Total Suspended Solids, Turbidity, Temperature, and Dissolved Oxygen concentrations. Data from the beginning of the program in 1979 to December 2022 were used in this study. In some cases, monitoring sites within streams changed during the sampling period, e.g, to avoid an active construction site. Several streams and rivers also contained multiple active monitoring sites. In these cases, the most downstream site with the most complete record was used, and the duplicate sites were not included in the analysis.

Figure 2. Map of all past and present routine streams monitoring sites in King County (Clark and Walls, 2023). Most monitored streams are in the Lake Washington Watershed (WRIA 8). Several of the sites with the longest records are in the Green River/Duwamish watershed (WRIA 9).

More than 90 sites have been monitored during the study period, with 75 active as of 2022 (**fig. 2**). These sites are concentrated in western King County, with the highest concentration of sites in the Lake Washington, Green/Duwamish, and Snoqualmie River watersheds. Several sites were added to Vashon Island in 2007.

Stream samples were typically collected once a month usually on a Monday, Tuesday or Wednesday in the first or second week of the month, though some sites were sampled more frequently during special projects. All samples were collected between 8:00AM and 4:00PM, regardless of weather, and it was noted whether the samples were collected during a storm event. Due to budget constraints and program changes, the number of sites and parameters sampled over the years varied, so the record for all sites and parameters is incomplete (Clark and Walls, 2023).

Temperature, DO, pH, and Conductivity were collected using a Yellow Springs Instruments EXO3 Sonde field probe. Dissolved and total nutrients, TSS, and Fecal Coliform samples were brought to the King County Environmental Lab (KCEL) for analysis using Standard Methods for the Examination of Water and Wastewater (Baird et al. 2017). Nitrate-N was determined using automated cadmium reduction (SM4500-NO_3 F). Ammonium-N was determined using the automated phenate method (SM4500-NH3 G). Total phosphorus and soluble reactive phosphorus were determined using automated filtered persulfate digestion and ascorbic acid reduction (SM4500-P B,F, & SM4500-P F). Total Nitrogen was determined using automated sulfuric acid digestion (SM4500-N C). TSS was determined using gravimetric filtration (SM2540 D). Turbidity was determined using the nephelometric method (SM 2130 B). Fecal coliform were determined using membrane filtration and plate counting (SM 9222 D). Total Alkalinity was determined using colorimetric titration to pH 4.5 (SM2320-B)(Baird et al. 2017). A new technique for preparation of total nutrients samples was implemented in 1998, and equipment used for analysis of dissolved nutrients was upgraded in 2007. Both changes significantly altered results for nutrient analysis, so correction factors were implemented to ensure that long-term trend analyses were possible (Clark and Walls, 2023).

The raw water quality data were used to create both monthly and annual time series. To create monthly time series, the records for each site were binned into monthly arithmetic means to create an evenly spaced time series, which removed cases where sites were sampled multiple times in a month. An annualized data set was obtained by first taking the median value for each year from the monthly dataset. Any year with less than seven months of observations was excluded to avoid seasonal bias.

Stream Flow

Discharge data used in this study came from various stream gages around King County. Many of the older gages are maintained by the USGS (https://waterdata.usgs.gov/nwis), while most stream gages installed in the 1990's and beyond are maintained by the King County Hydrologic Monitoring program (https://green2.kingcounty.gov/hydrology). The only hydrologic parameter collected was daily average discharge. Much like the water quality sampling, the flow record is incomplete over the study period as many gages were recently added. The hydrologic and stream monitoring programs are run separately, so many water quality monitoring sites are not paired with gage data. Currently, only 26 stream gages that have at least 20 years of flow data are located near water quality monitoring sites.

Land Cover Data

The watershed boundaries were drawn around all upstream channels of water quality monitoring sites with Arc Hydro Tools in ArcGIS Pro 2.8.3 (Clark and Walls, 2023). Land cover data were obtained from the 2019 USGS National Land Cover Database. Sixteen land cover classes were characterized in the study area: high intensity development, medium intensity development, low intensity development, developed open space, barren land, mixed forest, deciduous forest, evergreen forest, shrubland, grassland, pasture/hay, cultivated crops, woody wetlands, herbaceous wetlands, open water, and perennial ice and snow. From these, several aggregate categories were created, e.g., total developed (which encompasses the high, medium, low, and open space development types), total forested (which encompasses mixed, deciduous, and evergreen forest), agricultural land (which merges pasture/hay and cultivated crops), and wetlands (which merges the herbaceous and woody wetland categories).

Methods

Long Term Trends

The first goal of this analysis was to describe long term trends in stream water quality. Using the R *Tidyverse* packages, the annual time series data were used to calculate linear trends by compressing two intervals into single points and calculating the slope between them. The recent point was defined as the centroid of the 2013 – 2022 data, and the “baseline” point was defined as the centroid of the first 10 years of data in the 35 years of data collected prior to the recent period. The time span of the baseline period could vary from site to site because field sampling was initiated at the sites at different times, although most were started in 1979. Some sites may not have been active in the baseline period or were discontinued before the recent period. These, and any monitoring sites with less than 5 years of data in either interval were removed from the analysis. Between 36 and 41 monitoring sites met the inclusion criteria depending on constituent. The long-term trends were quantified as change in concentration per decade and percent change per decade and the distribution of these slopes were tested for significance using the Wilcoxon Ranked Sign Test ($\alpha = 0.01$).

$$Trend = \frac{C_{recent} - C_{baseline}}{Year_{recent} - Year_{baseline}} * 10\frac{years}{decade}$$

To ensure this result was not the product of idiosyncratic “data-torturing”, the analysis was repeated with differing baseline and recent windows and minimum data requirements. The number of sites included varied from 31 to 72. The long-term trends changed only slightly for the different scenarios, but the overall trends were the same for each water quality constituent. To additionally validate the results of the long-term trend analysis, the annual time series for the same roughly 40 monitoring sites (depending on constituent) were normalized to their stream and constituent specific Z-scores. Z-scoring is performed by subtracting each individual value (x_i) from its mean (μ) and dividing by the standard deviation (σ).

$$z_i = \frac{x_i - \mu}{\sigma}$$

Z-scores put the long-term data in terms of standard deviations from the sample mean. This makes it possible to compare the long-term trends for different constituents and streams on a common basis. Z-scores within each stream were calculated, then binned by year for all streams for a particular constituent. The Z-scores for each year were visualized using box and whisker plots for over the 44-year observation window, and regression trends based on the annual median z-scores were calculated.

Modeling Recent Water Quality Using Land Cover Characteristics

This analysis examined whether the general findings of the *Brett et al. (2005)* study could be replicated with a more extensive data set. The original study used linear regression models to fit phosphorus and nitrogen concentrations, turbidity, and total suspended solids data from 1990 to 1999 for 17 streams along an urban to forested gradient in King County to land-cover data gathered in 1998. The current analysis was expanded to 58 sites with more granular landcover categories and made use of multivariate linear regression. A series of one, two, and three variable generalized linear models (25 total) were generated with basin landcover as independent variables, and the water quality constituents as response variables. The approach was done to reduce covariance within the water quality predictor variable matrix.

A key assumption of multivariate linear regression is that independent variables are not related to one another. By comparing the correlation coefficients of all composite categories and their sub-groups (**table 1**), it was apparent that most land cover types were strongly to moderately correlated ($r > 0.50$) with the total developed grouping. Therefore, five land cover categories were selected as variables for the multi-linear regression models.

- **Total Developed:** Composite of all developed land cover types. Impervious surface coverage varies from 20%-100% and includes suburban single-family homes to highly urbanized lots. It is also the most widespread cover type (median = 56.0%) and has an approximately uniform distribution. This category has a nearly one-to-one inverse relationship with the *Forested* category (r = -0.98), so in general a less developed land coverage tends to have high forested coverage and vice versa.
- **Deciduous Forest**: A subset of the forested category with more than 75% coverage of deciduous trees. This category is useful as many riparian zones and recently disturbed forest are dominated by nitrogen-fixing red alder stands.
- **Agricultural**: Although this is a composite category, most agricultural land in King County is pasture/hay, which is grown for the purposes of livestock grazing or seed production. Only a few basins have a significant amount of row crop agriculture.
- **Wetlands**: Areas where forest or shrubland vegetation account for more than 20% of vegetative cover and the soil or substrate is periodically saturated or covered with water. Though sparse in King County, wetlands can act as important buffer zones for streams.
- **Open Water**: Areas of open water, generally with less than 25% cover of vegetation or soil and include small ponds. Although this is a fairly uncommon land cover type, open water can act as an important sink for nutrients and sediments.

The arithmetic mean water quality constituent concentration for the years 2016-2022 from annualized water quality time series was used as the response variable. This provided 7 years of data, centered on 2019, with one data point per monitoring site for each constituent. Any site with less than 4 years of data within this window was not included in the analysis, leaving 58 monitoring sites. The resulting models were assessed for R-squared, root mean squared error (RMSE), corrected Akaike Information Criterion (AIC_c), and AIC weight (AIC_{wt}), with the different models ranked by their

AIC weights (Wagenmakers & Farrel, 2004). Lastly, the significance of the best models were determined using the F-test for overall significance ($\alpha = 0.01$).

The Akaike Information Criterion is a common method for comparing the quality of multiple statistical models fit to the same independent variable, with lower the AIC indicating a more favorable balance of goodness of fit and simplicity. AIC is valid only for large data sets, so for smaller sample sizes ($n/V < 40$), an additional correction must be applied. The equation below is the formula for calculating the AIC_c. *Log(L)* is the log likelihood, *V* is the number of model parameters, and *n* is the sample size. More parameters result in a higher AIC_c, meaning the performance of the model is penalized for potential over-fitting. AIC_{wt} is a method for comparing the relative performance of multiple models. It is based on the relative likelihood of each model compared to the model with the lowest AIC_c. The total AIC_{wt} for a group of models is normalized to 1, which allows a relative comparison of the performance of each model (Wagenmakers & Farrel, 2004).

$$AICc = -2\log(L) + 2V + \frac{2V(V+1)}{(n-V-1)}$$

Table 1. The median, 10th, and 90th percentile of land coverage of each NLCD category in drainage basins sounding streams monitoring sites. As well as their correlation coefficient to either the Total Developed or Total Forest composite categories.

	10th percentile	Median % Coverage	90th percentile	r (Developed, Total)	r (Forest, Total)
Developed, Total	**6.9**	**56.0**	**91.4**	**1**	**-0.98**
Developed, Low Intensity	2.4	20.9	33.6	0.91	-0.89
Developed, Open Space	2.9	10.2	24.0	0.35	-0.36
Developed, Medium Intensity	0.4	7.8	39.1	0.86	-0.83
Developed, High Intensity	0.1	2.0	13.1	0.69	-0.68
Forest, Total	**5.7**	**34.5**	**79.5**	**-0.98**	**1**
Mixed Forest	1.8	13.3	32.5	-0.57	0.56
Evergreen Forest	1.1	12.6	61.4	-0.83	0.86
Deciduous Forest	1.0	2.6	7.6	-0.13	0.17
Wetlands, Total	**0.2**	**2.3**	**5.8**	**-0.1**	**0.01**
Woody Wetlands	0.2	1.7	4.6	-0.14	0.06
Herbaceous Wetlands	0.0	0.2	1.1	0.07	-0.14
Shrub/Scrubland	**0.1**	**1.2**	**6.3**	**-0.73**	**0.69**
Grasslands	**0.0**	**0.5**	**2.4**	**-0.77**	**0.72**
Agriculture, Total	**0.0**	**0.4**	**4.8**	**-0.32**	**0.16**
Pasture/Hay	0.0	0.4	4.7	-0.32	0.16
Cultivated Crops	0.0	0.0	0.1	-0.16	0.09
Open Water	**0.0**	**0.3**	**1.9**	**-0.15**	**0.12**
Barren Land	**0.0**	**0.1**	**1.0**	**-0.38**	**0.36**
Perennial Ice/Snow	**0.0**	**0.0**	**0.0**	**-0.22**	**0.23**

Comparison of Developed, Forested and Agricultural Landcover

To more clearly differentiate the influence of developed, forested and agricultural landcover on stream water quality, we selected streams that best represented each of these landcover types. Of the 57 streams and rivers with contemporary (2016 – 2022) water quality data, we selected a subset of systems that were almost entirely developed or forested landcover. We also included the streams that had the highest proportion of agricultural landcover. These groups were also selected to minimize overlap in landcover composition. For example, the "developed" and "forested" stream groups were selected so that they had very little agricultural landcover. Because agricultural landcover is not prevalent in King County, it was not possible to select a subset of streams that were almost entirely agricultural so in this case the streams that had the highest proportion of agricultural landcover were selected. This resulted in eight streams that represented the developed category and six streams each for the forested and agricultural categories. The developed group included streams which all had > 90% total developed landcover (with an average of 93 ± 2%; mean ± 1 SD), with 5.3 ± 2.1% total forest landcover and 0.3 ± 0.4% total agricultural landcover. The forested group had an average of 78 ± 9% total forested landcover, and 6.8 ± 5.5% and 0.4 ± 0.5% developed and agricultural landcover, respectively. The agricultural group had an average of 17 ± 10% total agricultural landcover, and 20 ± 4.3% and 53 ± 13% developed and forested landcover, respectively.

Results

Long Term Temporal Changes

More than half (7 of 13) of the water quality constituents showed significant ($p < 0.01$) long-term declines relative to baseline concentrations (**Table 2, Fig. 3**). Fecal coliform bacteria showed both the greatest share of monitoring sites decreasing (35 of 36), and the greatest median relative decline of -20%/decade. All three nitrogen constituents (TN, NO_3-N, NH_4-N) as well as PO_4-P had median long-term declines varying between -8% per decade to -10% per decade. Dissolved oxygen had the smallest relative decrease, -0.82% per decade, over the study period. Of the 39 monitoring sites, oxygen concentrations decreased in 28, showed no change in 1, and increased in 10.

There were 3 constituents that significantly increased relative to baseline concentrations, i.e. stream temperature, conductivity, and total alkalinity. Conductivity showed the greatest median increase at 3.8% per decade, while alkalinity and temperature had similar increases of 1.4% per decade and 1.8% per decade (0.19°C per decade), respectively.

Evaluating the significance of trends in the z-scored data had results which supported the long-term trend results in native units for all but two constituents. Total alkalinity had a significant positive trend in native units ($p = 0.003$) but did not have a significant trend ($p = 0.011$) when z-scored. Temperature has a significant positive trend in native units ($p < 0.001$) but also had no significant trend ($p = 0.057$) when z-scored. FCB, NO_3-N, NH_4-N, TN, and DO had significant negative trends in native units and when z-scored. Conductivity had a significant positive trend in native units and z-scores. Turbidity, pH, and TP did not have significant trends in either native units or z-scores.

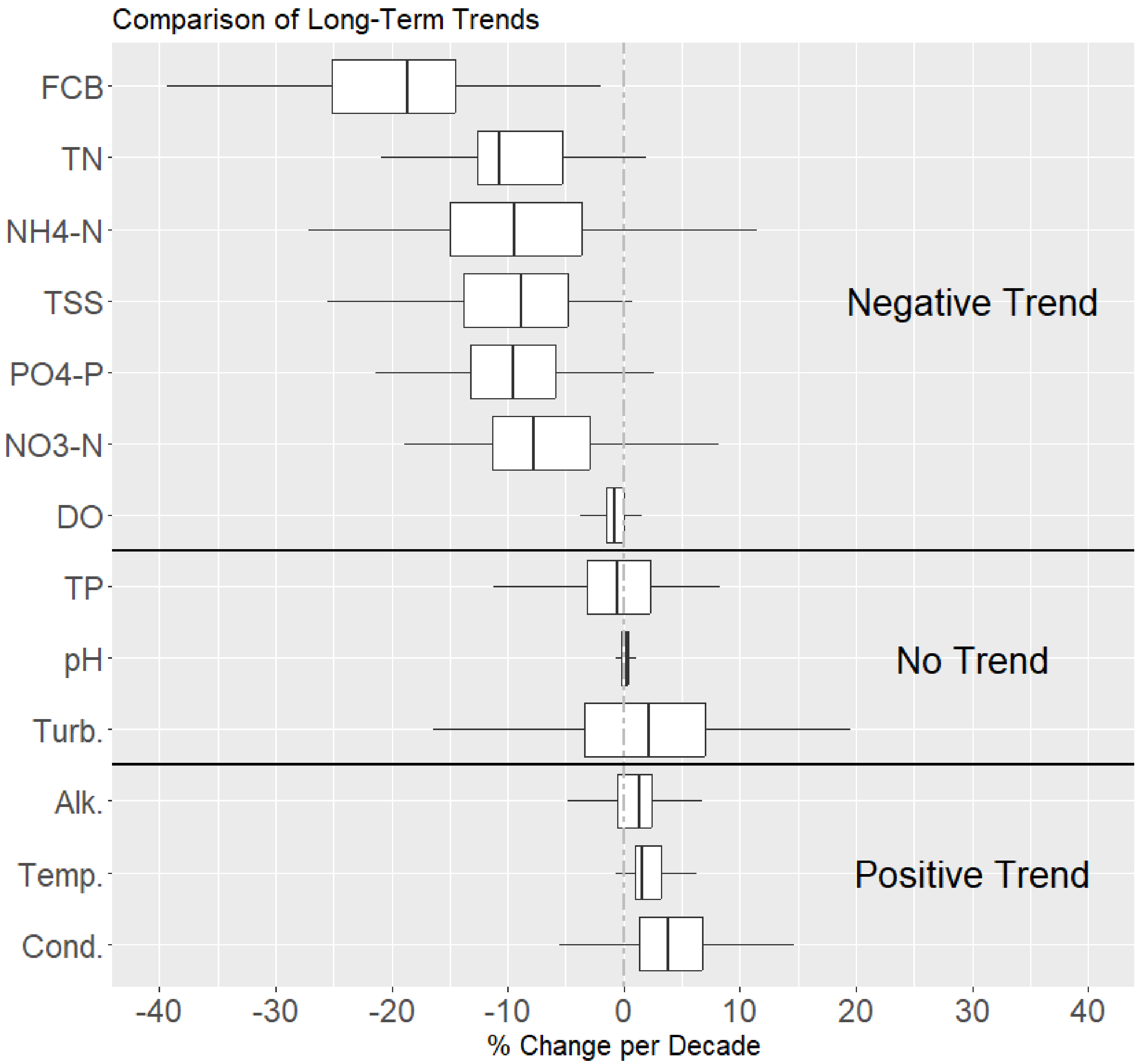

Figure 3. Box plots of the long-term trend distributions in ascending order of median change over time. Sample sizes vary between constituents. FCB: n = 36, TN: n = 39, NH_4-N: n = 39, TSS: n = 41, PO_4-P: n = 41, NO_3-N: n = 39, DO: n = 39, pH: n = 39, TP: n = 41, Turb: n = 39, Alk: n = 41, Temp: n = 39, Cond: n = 41. All constituents are normalized to % change per decade. The center of the box is the 50th percentile, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR.

Table 2. Long term trends for each constituent. The Constituents are in ascending order of median long-term trend (in % Chane per decade). N is the number of monitoring sites used to calculate each trend.

Constituent	N	Slope Units	Median Slope	Percentiles (25^{th} | 75^{th})	p-value
Negative Trend					
Fecal Coliform	36	CFU/100mL/decade	-37	(-75.2 | -16.11)	<0.001
Total-N	39	µg/L/decade	-113.4	(-157.9 | -55.5)	<0.001
Ammonium-N	39	µg/L/decade	-1.8	(-3.4 | -0.8)	<0.001
TSS	41	mg/L/decade	-0.4	(-0.9 | -0.2)	<0.001
Phosphate-P	41	µg/L/decade	-2.7	(-3.8 | -1.3)	<0.001
Nitrate-N	39	µg/L/decade	-51.7	(-102 | -22)	<0.001
Dissolved O_2	39	mg/L/decade	-0.086	(-0.159 | 0.003)	<0.001
No Trend					
Total-P	41	µg/L/decade	0.3	(-1.8 | 1.7)	0.430
pH	39	pH/decade	0.02	(-0.02 | 0.03)	0.054
Turbidity	39	NTU/decade	0.07	(-0.09 | 0.18)	0.150
Positive Trend					
Total Alkalinity	41	mg CaCO3/L/decade	0.9	(0.03 | 2.28)	0.003
Temperature	39	deg. C/decade	0.19	(0.11 | 0.37)	<0.001
Conductivity	41	µmhos/cm/decade	5.8	(1.8 | 9.0)	<0.001

Multiple Linear Regression using Landcover Characteristics

The models predicting contemporary concentrations (2016 – 2022) of stream water quality constituents were significant ($p \leq 0.01$) in all but three cases. The non-significant constituents were NH_4-N, TSS, and turbidity. The most important independent variable for every constituent with significant models was developed land (**Tables 3-6**). The one exception was NO_3-N, for which deciduous forest was the most important predictor variable, and total developed land was the second most important. These constituents could be divided into three groups based on their second most important independent variables: models based on deciduous forest, agricultural land, or neither of these.

Conductivity, alkalinity, and TN all included deciduous forest as the secondary predictor variable, while NO_3-N included it as the primary predictor. Models for conductivity had the strongest fits for these constituents. The top model for conductivity (AIC_{wt} = 0.40; r^2 = 0.59) included open water as a tertiary predictor variable. This model indicated that stream conductivity concentrations increased with the proportion of developed land and deciduous forest and decreased with the proportion of open water. The top three conductivity models accounted for 87% of the total AIC weight. The total alkalinity models had similar fits compared to conductivity models. The best alkalinity model (AIC_{wt} = 0.32; r^2 = 0.53) included only the two land cover types as independent variables which predicted increasing concentrations with the proportion of basin coverage for both total developed cover and deciduous forest cover. The top four alkalinity models accounted for 95% of the total AIC weight.

The models predicting TN and NO_3-N had weaker fits. The best model for total nitrogen (AIC_{wt} = 0.73; r^2 = 0.37) included total developed land cover and deciduous forest with agricultural land as a third independent variable. The model indicated that TN increased with developed land, deciduous forest, and agricultural land, and the top two models for TN accounted for 86% of the total AIC weight. The best NO_3-N model (AIC_{wt} = 0.39; r^2 = 0.26) included deciduous forest and total developed land with open water as the tertiary independent variable. This NO_3-N model predicted increasing concentrations with greater deciduous forest and developed land coverage, and lower concentrations with greater open water coverage. The top four models accounted for 89% of the total AIC weight.

Models for total phosphorus, PO_4-P, and fecal coliform bacteria included developed land as the most important and agricultural land as the second most important independent variable. PO_4-P had the strongest-fitting models of the group. The best model (AIC_{wt} = 0.45; r^2 = 0.55) included deciduous forest as a tertiary variable and estimated that phosphate concentrations increased with the proportion of all three land cover types and the top 3 PO_4-P models comprised 91% of the total AIC weight. The best model (AIC_{wt} = 0.33; r^2 = 0.44) for TP included developed and agricultural land, with deciduous forest as a tertiary variable. This model also predicted that concentrations increased with the proportion of basin coverage for all three land cover types, with the top three TP models accounting for 84% of the total AIC_{wt}. Unlike other water quality constituents, FCB data were log-transformed to approximate a log-normal distribution prior to fitting the land cover models. The top model (AIC_{wt} = 0.41; r^2 = 0.48) included developed and agricultural land with open water as the third independent variable. This model predicted that FCB increased with greater coverage of developed and agricultural land, and FCB decreased with greater open water area. The best three FCB models accounted for 81% of total AIC_{wt}.

The models for contemporary median annual stream temperature using land cover type as a predictor had moderate fits. The most important independent variable was total developed land, and there was no consistent secondary independent variable. The model with the greatest AIC_{wt} (0.25) was a univariate model that had an r^2 of 0.39 and predicted increasing stream temperatures with greater developed land coverage. The top five models accounted for 69% of the total AIC_{wt}. The top four dissolved oxygen models had weak fits (r^2 = 0.21 – 0.24) to land cover and collectively accounted for 90% of the AIC_{wt}. The primary predictor variable was developed land, and the secondary predictor was wetlands. The best model (AIC_{wt} = 0.33; r^2 = 0.24) included developed, wetlands, and deciduous forest as independent variables. Unlike models estimating the other water quality constituents, this model predicted that DO concentrations decreased with proportion of basin coverage for all three land cover types. Models predicting pH used developed land as a primary independent variable but did not have consistent secondary variables. The top model (AIC_{wt} = 0.18; r^2 = 0.21) included open water as the second variable and predicted that pH increased with developed land and decreased with open water. This model accounted for 18% of the total AIC weight, and the top five models accounted for 64% of the AIC_{wt}.

Table 3. Land cover multiple regression models that include deciduous forest cover as an important variable. Lists the categories used for each model and their coefficients in order of importance of each land cover category. The models listed for each constituent collectively account for either 80% or more of the AIC weight or are the five models with the most AIC weight.

	Coef. Units	Cat. 1 / β_1	Cat. 2 / β_2	Cat. 3 / β_3	R^2	RMSE	AICwt	p-value
	Deciduous Forest							
Conductivity	**µmhos/cm/% Coverage**	Developed 1.66	Deciduous Forest 5.28	Open Water -6.41	0.59	46.5	0.40	<0.001
		Developed 1.69	Deciduous Forest 5.66	- -	0.57	47.5	0.32	<0.001
		Developed 1.73	Deciduous Forest 5.60	Agriculture 0.70	0.57	47.3	0.15	<0.001
Total Alkalinity	**mg CaCO3/L/% Coverage**	Developed 0.62	Deciduous Forest 1.78	- -	0.53	18.7	0.32	<0.001
		Developed 0.64	Deciduous Forest 2.06	Wetlands 1.57	0.54	18.4	0.26	<0.001
		Developed 0.61	Deciduous Forest 1.68	Open Water -1.67	0.54	18.5	0.20	<0.001
		Developed 0.64	Deciduous Forest 1.80	Agriculture 0.35	0.53	18.6	0.17	<0.001
Total Nitrogen	**µg/L/% Coverage**	Developed 7.23	Deciduous Forest 44.1	Agriculture 20.6	0.37	352	0.73	<0.001
		Developed 5.80	Deciduous Forest 42.6	Open Water -52.3	0.33	363	0.13	<0.001
Nitrate Nitrogen	**µg/L/% Coverage**	Deciduous Forest 37.7	Developed 4.66	Open Water -59.3	0.26	383	0.39	<0.001
		Deciduous Forest 41.2	Developed 4.97	- -	0.22	394	0.22	0.001
		Deciduous Forest 40.3	Developed 5.61	Agriculture 11.4	0.24	388	0.18	0.002
		Deciduous Forest 38.0	Developed 4.70	Wetlands -17.6	0.23	392	0.10	0.003

Table 4. Land cover models that include agricultural cover as an important variable. Lists the categories used for each model and their coefficients in order of importance of each land cover category. The models listed for each constituent collectively account for either 80% or more of the AIC weight or are the five models with the most AIC weight.

	Coef. Units	Cat. 1 / β_1	Cat. 2 / β_2	Cat. 3 / β_3	R^2	RMSE	AICwt	p-value
	Agriculture							
Phosphate Phosphorus	**µg/L/% Coverage**	Developed 0.37	Agriculture 0.93	Deciduous Forest 0.71	0.55	10.26	0.45	<0.001
		Developed 0.34	Agriculture 0.92	Open Water -1.81	0.55	10.31	0.33	<0.001
		Developed 0.35	Agriculture 0.96	- -	0.51	10.67	0.13	<0.001
Fecal Coliform	**Ln(CFU/100 mL)/% Coverage**	Developed 0.018	Agriculture 0.044	Open Water -0.102	0.48	0.63	0.41	<0.001
		Developed 0.019	Agriculture 0.047	- -	0.45	0.65	0.21	<0.001
		Developed 0.018	Agriculture 0.050	Wetlands -0.056	0.47	0.64	0.19	<0.001
Total Phosphorus	**µg/L/% Coverage**	Developed 0.68	Agriculture 1.68	Deciduous Forest 1.12	0.44	23.11	0.33	<0.001
		Developed 0.65	Agriculture 1.73	- -	0.42	23.56	0.29	<0.001
		Developed 0.64	Agriculture 0.64	Open Water -2.42	0.44	23.23	0.22	<0.001

Table 5. Land cover models that have statistically significant fits, but do not fit into groups listed in tables 3 and 4. The models listed for each constituent either collectively account for 80% or more of the AIC weight, or the top five if their AIC weight accounts for less than 80% of the total.

	Coef. Units	Cat. 1 / β_1	Cat. 2 / β_2	Cat. 3 / β_3	R^2	RMSE	AICwt	p-value
	Other Significant Models							
Temperature	**°C/% Coverage**	Developed 0.019	- -	- -	0.39	0.742	0.25	<0.0001
		Developed 0.019	Deciduous Forest 0.023	- -	0.40	0.736	0.15	<0.0001
		Developed 0.019	Open Water 0.030	- -	0.39	0.741	0.10	<0.0001
		Developed 0.019	Wetlands 0.022	- -	0.39	0.741	0.10	<0.0001
		Developed 0.019	Agriculture 0.002	- -	0.39	0.742	0.09	<0.0001
Dissolved O_2	**mg/L/% Coverage**	Developed -0.016	Wetlands -0.22	Deciduous Forest -0.051	0.24	1.03	0.33	0.002
		Developed -0.014	Wetlands -0.18	- -	0.21	1.05	0.31	0.002
		Developed -0.015	Wetlands -0.18	Agriculture -0.015	0.22	1.04	0.14	0.004
		Developed -0.014	Wetlands -0.18	Open Water -0.033	0.21	1.044	0.12	0.005
pH	**pH/% Coverage**	Developed 0.004	Open Water -0.034	- -	0.21	0.26	0.18	0.002
		Developed 0.004	- -	- -	0.17	0.27	0.16	0.001
		Developed 0.004	Open Water -0.032	Wetlands -0.016	0.22	0.26	0.11	0.004
		Developed 0.004	Wetlands -0.018	- -	0.19	0.26	0.10	0.003
		Developed 0.004	Deciduous Forest 0.008	- -	0.19	0.26	0.09	0.004

Table 6. The top land cover models for water quality constituents that did not have any significant fits.

	Coef. Units	Cat. 1 / β_1	Cat. 2 / β_2	Cat. 3 / β_3	R^2	RMSE	AICwt	p-value
	Not Significant							
Turbidity	**NTU/% Coverage**	Developed 0.02	Agriculture 0.07	Deciduous Forest 0.09	0.18	1.71	0.22	0.012
Total Suspended Solids	**mg/L/% Coverage**	Developed 0.02	Agriculture 0.09	- -	0.15	1.71	0.26	0.012
Ammonium Nitrogen	**µg/L/% Coverage**	Developed 0.13	- -	- -	0.04	22.4	0.14	0.158

Developed Land vs Forested and Agricultural Comparison

The three stream groups were tested for differences with a one-way ANOVA using the stream ranks (Kruskal-Wallis test). Stream ranks were used for the statistical analysis instead of the raw water quality averages because there were a few outlier values, mostly within the developed group, thus violating the equal variance assumption for parametric statistical analyses. Of the 13 water quality parameters, nine were very strongly statistically different ($p < 0.001$) between the groups (i.e., TP, PO_4-P, TN, NH_4-N, alkalinity, conductivity, temperature, turbidity and FCB), three were strongly different ($p < 0.01$) (i.e., NO_3-N, DO, and TSS), and pH was not different ($p = 0.154$).

Table 7. The average ± 1 SD percent landcover and stream water quality for the forested, agricultural and developed stream systems. The reported P-values are for a non-parametric one-way ANOVA based on the ranks for the stream concentrations. A Kruskal-Wallis test was used because there were several outlier stream average constituent concentrations that caused the equal variance assumption to be violated. The forested sites used for this analysis were Griffin Creek, Tolt River, Cherry Creek, Raging River, Ravensdale Creek, and Cedar River. The agricultural sites were Boise Creek, Fisher Creek, Ames Creek, Judd Creek, Patterson Creek, and Newaukum Creek. The developed streams were Idylwood Creek, Springbrook Creek, Juanita Creek, Venema Creek, Forbes Creek, McAleer Creek, Longfellow Creek, and Thornton Creek.

	Units	Forested	Agricultural	Developed	p-value
Tot. Forested	% LC	78 ± 9.0	53 ± 13	5.3 ± 2.1	-
Tot. Agricultural	% LC	0.4 ± 0.5	17 ± 10	0.3 ± 0.4	-
Tot. Developed	% LC	6.8 ± 5.5	20 ± 4.0	93 ± 2.0	-
Total Phosphorus	µg/L	12 ± 5.0	57 ± 18	79 ± 44	<0.001
Phosphate Phosphorus	µg/L	3.5 ± 1.9	28 ± 11	37 ± 14	<0.001
Total Nitrogen	µg/L	405 ± 106	1045 ± 339	1018 ± 287	<0.001
Nitrate Nitrogen	µg/L	301 ± 85	723 ± 298	744 ± 340	0.002
Ammonium Nitrogen	µg/L	4.4 ± 0.9	19 ± 16	36 ± 43	<0.001
Total Alkalinity	mg $CaCO_3$/L	22 ± 10	48 ± 11	85 ± 12	<0.001
pH	$-Log_{10}[H^+]$	7.4 ± 0.1	7.4 ± 0.4	7.6 ± 0.3	0.154
Conductivity	µS/cm	62 ± 25	126 ± 27	229 ± 31	<0.001
Temperature	°C	9.5 ± 0.5	9.5 ± 0.6	11.1 ± 0.5	<0.001
Dissolved Oxygen	mg/L	11.4 ± 0.4	10.5 ± 1.1	9.8 ± 1.8	0.002
Total Suspended Solid	mg/L	1.8 ± 0.5	4.9 ± 1.4	4.7 ± 2.4	0.004
Turbidity	NTU	1.3 ± 0.3	3.7 ± 1.3	4.3 ± 2.8	<0.001
Fecal Coliform	CFU/100mL	2.8 ± 0.6	4.3±0.3	4.7 ± 0.8	<0.001

When comparing the ratios of the group medians (e.g., median of developed systems/median of forested systems), TP concentrations were ~ 6 times higher in developed streams compared to forested streams. Similarly, PO_4-P was ~ 10 times higher in developed streams, TN and NO_3-N were ~ 2.5 times higher, NH_4-N was ~ 5 times higher, alkalinity and conductivity were ≈ 4 times higher, and TSS and turbidity were ~ 3 times higher. On average (e.g., median of developed systems - median of forested systems) the developed streams were 1.2 °C warmer than the forested streams, they had 1.6 mg/L less dissolved oxygen, and they had 2 times higher FCB concentrations in $\log_{10}$ units.

In the agricultural stream group, median stream temperatures were very similar to those of the forested stream group. However, the other water quality parameters were quite elevated compared to the forested group, except for DO which was 0.9 mg/L lower in agricultural streams. Median NH_4-N, alkalinity and conductivity concentrations in the agricultural streams were 50-60% of those of the developed group; TP, PO_4-P, turbidity and FCB were 70-90% of the developed group average; and TN, NO_3-N and TSS concentrations were very similar (≈ 100%) to the developed group.

Discussion

The Conundrum

The population of King County has nearly doubled during the 40 years that this study monitored stream water quality, and during this time total and dissolved nitrogen and dissolved phosphorus, fecal coliform bacteria, and suspended sediments have broadly declined. However, when comparing contemporary concentrations to contemporary land cover data, most constituents, aside from TSS and NH_4-N, show clearly decreasing water quality in more developed catchments. Additionally, King County has developed and changed during the study period. This is the basis of the "King county Conundrum": from the literature on the urban stream syndrome (Walsh et al. 2005) we would expect nutrients, bacteria, and sediments to increase over time as the population density and urban development increased, but the long-term trends in the King County database are the opposite of these expectations.

Overall, the King County stream water quality dataset is extremely robust (>22,000 observations per constituent) and diverse. It includes: 1) systems that have stabilized or even recovered from early intense development, 2) systems that have recently transitioned from primarily forested to suburban development, 3) systems that have transitioned from agricultural to intense urban development, and 4) systems that have been dominated by forest landcover during the entirety of this study. All of this occurred during a time of rapid change in land development and stream water quality best-professional-practices. This study will summarize the most salient features of the stream responses to environmental stressors.

Beginning in the early 1990's, regional agencies placed greater emphasis on managing the water quality impacts of nonpoint sources, such as stormwater runoff and onsite sewer systems (septic tanks) (Puget Sound Water Quality Authority, 1987). The first stormwater manual for the Puget Sound Basin, published in 1992, recommended a variety of Best Management Practices (BMP's) for runoff from municipal separate storm sewer systems (MS4s), new and re-development projects, and roadways. These BMP's included erosion controls, riprap, streambank revegetation, infiltration basins, and biofiltration swales, (WA Dept of Ecology, 1992). While the water quality benefits of stormwater BMPs are well-understood, there is not a comprehensive record of BMP installation dates within King County, making quantification of their collective impact on stream water quality difficult. Replacement of failing septic systems with centralized wastewater treatment could be a factor driving water quality changes in some streams. Most of the active monitoring sites were within catchments with significant sewer main access, though 10% of county-wide onsite sewer systems (OSSs) are in areas with centralized wastewater treatment services. There are no data documenting how access to centralized wastewater treatment has expanded during the study window, or whether the number of OSS's within sewer districts has declined. Aside from structural changes, there have also been several nonstructural efforts to improve local water quality. In 2011, the Washington State legislature banned the use of phosphorus in residential lawn fertilizers, and most municipalities throughout the region have attempted to reduce pollution from pet wastes and private car washing. The general improvement in King County stream water quality during a time of rapid urban development may be the inverse of the common analogy "death by a thousand cuts". Instead, King County streams seem to have experienced a gradual recovery due to many different interventions and BMP's.

Agriculture and Stream Water Quality

The presence of even a relatively small proportion of agricultural land cover within a drainage basin had a pronounced effect on stream water quality. When comparing streams within predominantly forested, agricultural and developed catchments, degradation of water quality was greatest in developed streams while agricultural streams showed similar or somewhat less degradation. However, an average of only 17 ± 10% total agricultural landcover degraded stream water quality equivalently (e.g., TN, NO_3-N and TSS) or nearly as much (e.g., NH_4-N, alkalinity, conductivity, TP, PO_4-P, turbidity and FCB) as did 93 ± 2% total developed landcover. Fitting the data to multilinear models using land cover as independent variables also showed developed land cover strongly influenced all constituents while agricultural land strongly influenced several (e.g.PO_4-P, TP, FCB). The model coefficients for total agriculture in were nearly twice as large as those for developed land for PO_4-P and TP, and slightly larger for FCB. This indicates that in the streams sampled for this study, agricultural landcover had a much more negative effect on stream water quality than did developed landcover per unit area. This inference is somewhat confounded by the fact that none of the streams included in this study, or in King County as far as we are aware, had catchments that were primarily comprised (e.g., 80-90%) of agricultural landcover. The most agricultural stream catchments in this study were a mixture of agricultural, developed and forested landcover. This was somewhat mitigated by including total agricultural cover as one of several variables in multilinear regression. However, only six out of the 58 stream catchments had more than 5% agricultural land cover.

Agriculture has declined in King County during the last half century. In most places agriculture was probably replaced with urban development, but long-term landcover data documenting this transition is sparse. However, two monitoring sites are excellent examples of the transition from agriculture to urban land cover: Springbrook Creek in Renton, WA, and its tributary, Mill Creek in Kent, WA. Both sites are in the Green River/Duwamish basin and were heavily agricultural in the 1940's to 1970's, but more recently had intense urban development in their catchments (**figs. 4 & 5**). According to the most recent land cover data, Springbrook and Mill Creeks have 91.2% and 81.3% total developed landcover. Based on arial photography, much of the contemporary development appears to be warehouses. Springbrook Creek had the largest long-term decline in PO_4-P, TP, NH_4-N, Turbidity, TSS, and Alkalinity of the ~40 streams in the long-term trend analysis, as well as the fourth greatest decline in FCB. Mill Creek had the greatest long-term decline in FCB, and the second greatest declines in PO_4-P, TP, and NH_4-N. Yet, while both streams have shown massive water quality improvements, they still have among of the worst water quality of all of the streams in this study. Springbrook Creek has the highest contemporary PO_4-P, TP, and NH_4-N, the second highest turbidity, the fourth highest FCB, and the lowest DO. Meanwhile, Mill Creek has the highest contemporary turbidity, the second highest TSS and TP, the fourth highest NH_4-N, and the second lowest DO of the 58 streams included in this analysis. It is possible that the large overall improvement was driven by a decrease in agricultural runoff as the catchments became urbanized. Conversely, the very poor contemporary water quality in these streams is due to the intense urban development. However, because land use change data are sparse, it is difficult to fully define the trajectory of land use change and the water quality response in these catchments.

Springbrook and Mill creeks are also distinct from the other catchments in this study because they have very different soils than other streams in King County. These soils are also the reason why this area was favorable for agriculture. These catchments are dominated by the Puyallup soil series which are well suited for agriculture and are deep, well-drained, highly productive, fine sandy loam soils formed in low gradient (0 – 3%) recent alluvium in floodplains and terraces of the Green River basin (Snyder et al. 1973). (This soil type also occurs in the Sammamish River basin.) Conversely, about 85% of King County is dominated by the Alderwood soil series which are less productive soils formed in glacial drift and are usually 1 m deep to a highly compacted glacial till layer formed by previous glacial events. Alderwood soils are moderately well drained and have slopes of 0 – 65% on glacially modified valleys and foothills and are poorly suited for agriculture (Snyder et al. 1973).

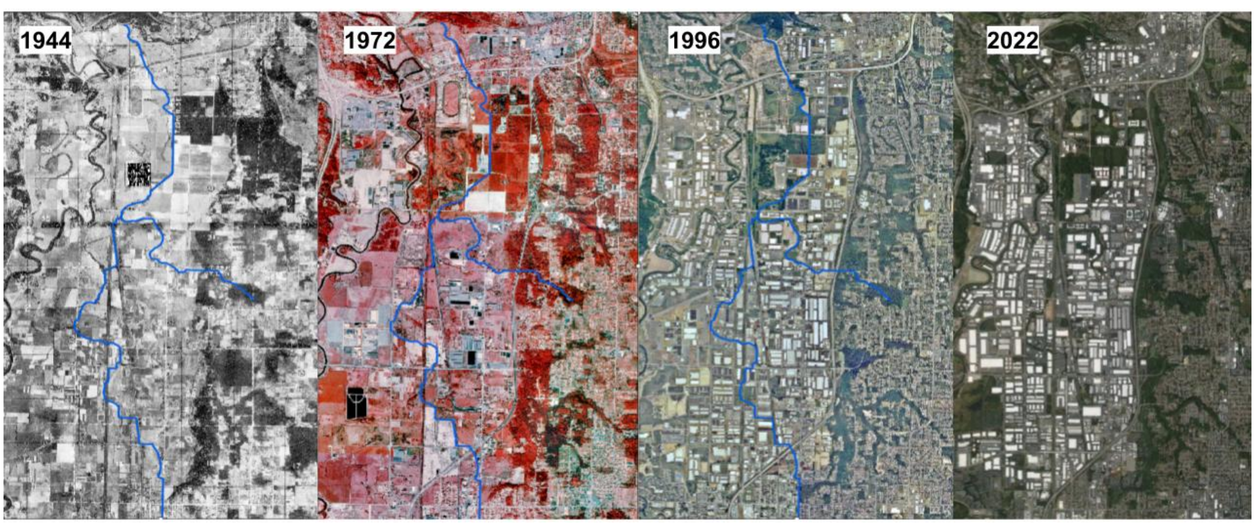

Figure 4. Ortho imagery of the Springbrook Creek catchment through time. Using Ariel photography, then satellite imagery. There is a massive change in land cover between 1972 and 1996, as more and more industrial buildings are built throughout the watershed.

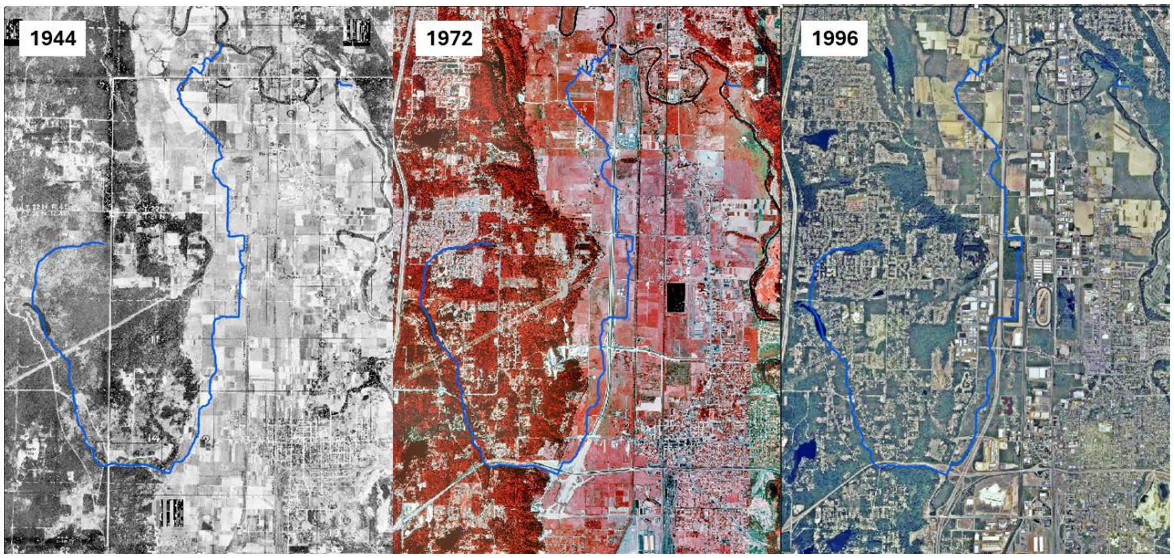

Figure 5. Ortho imagery of Mill Creek in 1944, 1972, and 1996. There is a large increase in development between 1972 and 1996, where previously agriculture land has become housing and business developments.

The Red Alder and Stream Nitrogen

Red alder (*Alnus Rubra*) are one of the most common deciduous trees in the Pacific Northwest of North America. This species grows in recently disturbed soils and is capable of nitrogen fixation, making it very important for watershed biogeochemistry. Stands of red alder act as ammonium-N sources, which are oxidized to nitrate in the soil and then leached into stream runoff (Bechtold et al. 2003). Stream NO_3-N concentrations in Pacific Northwest forests have been found to be strongly correlated with broad-leaf tree cover, of which red alder is a major constituent. This relationship is present throughout the entire drainage basin, not just the riparian buffer (Compton et al. 2003, Steinberg et al. 2011). The regression models showed that deciduous forest landcover was the most important predictor of in-stream NO_3-N concentrations, and the second most important predictor for TN concentrations. Additionally, contemporary stream NO_3-N concentrations averaged 70% of TN concentrations, and the two constituents had a nearly one-to-one relationship between streams (r =

0.97). This suggests that, while not the only driver, red alders are indeed an important source of nitrogen in the monitored streams.

Conductivity and total alkalinity were the two other constituents that included deciduous forest as a significant independent variable. The concentrations of these constituents were likely influenced by nitrification-driven cation mobilization in soils (Edmondson 1994, Compton et al. 2003). Alkalinity and conductivity also had increasing long-term trends, which could be driven by changes in the abundance of red alder. However, an increased influence of red alder is unlikely as this would theoretically coincide with greater nitrate concentrations in streams, which actually decreased over time (-8.1% per decade).

Chemical Weathering, Alkalinity and Conductivity

Our analyses have shown that stream alkalinity and conductivity concentrations are related to land cover characteristics. Average contemporary alkalinity and conductivity stream concentrations were also very highly correlated ($r = 0.97$) suggesting they were measuring similar aspects of stream chemistry. Multiple regression models showed that alkalinity and conductivity concentrations increased with the proportion of total developed, deciduous forest (a stand in for red alder), wetland, and agricultural land covers while alkalinity and conductivity decreased with the proportion of open water. The most important independent variables were developed land and deciduous forest. Both alkalinity and conductivity increased about three times as much with each unit change in deciduous forest cover (Alkalinity: 1.68 – 2.06 mg $CaCO_3$/L/% Deciduous Forest, Conductivity: 5.28 – 5.66 µS/cm/% Deciduous Forest) compared with developed cover (Alkalinity: 0.61 – 0.64 mg $CaCO_3$/L/% Total Developed, Conductivity: 1.66 – 1.73 µS/cm/% Total Developed). Overall, the most heavily forested monitoring sites had a contemporary mean alkalinity of 22 ± 10 mg

$CaCO_3$/L and mean conductivity of 62 ± 25 μS/cm, while the most developed monitoring sites had a mean alkalinity of 85 ± 12 mg $CaCO_3$/L and mean conductive of 229 ± 31 μS/cm.

Catchment urbanization has been shown to lead to alkalinization of fresh waters through chemical weathering of impervious surfaces, especially those built using calcium-rich materials like concrete (Glasser et. al. 2008, Kaushal et. al. 2017). Any increase in alkalinity should coincide with increased conductivity, as the latter is a measure of the concentration of all ionic charges in the water. This development-driven freshwater alkalinization may be seen in the few streams with catchments that have seen significant recent growth, e.g. Rock Creek (LSIN1) in Black Diamond, Washington had a long-term trend in alkalinity of 25 mg $CaCO_3$/L per decade, and a long-term trend in conductivity of 47.1 μS/cm per decade. However, both alkalinity and conductivity have broadly increased in King County Streams since consistent monitoring began in 1998, with a median long-term trends of 0.9 mg $CaCO_3$/L per decade and 5.8 μS/cm per decade, though increasing alkalinity (conductivity was not measured) has been noted in tributaries of Lake Washington since the mid 1960's (Edmondson 1994). Additionally, most streams have not seen large changes in catchment land cover during the monitoring period while they became more alkaline.

Another explanation for the increase in both stream alkalinity and conductivity could be increased partial pressure of atmospheric CO_2 leading to rainwater with a higher concentration of carbonic acid (Bogan et. al. 2008). The slightly more acidic rainwater may have increased chemical weathering of human-built impervious surfaces as well as calcite and other carbonate minerals in soils. However, the carbonate content of soils in King County is not well known, and modern concrete mixes are designed to be weather-resistant (Glasser et. al. 2008). Direct comparison of the annual time series (**fig. 6**) for the most heavily urbanized sites against the available rural sites with longer records showed that the intensely developed group had higher stream alkalinity over the entire time series, and both groups had similar median long-term trends (1.10 mg $CaCO_3$/L/decade for intensely developed, 1.13 mg $CaCO_3$/L/decade for lightly developed). The nearly equivalent increase in alkalinity suggests a common cause, but more focused research is needed to make definite conclusions. This may be due to more extensive ionization of calcium magnesium acetate-based deicers in this region.

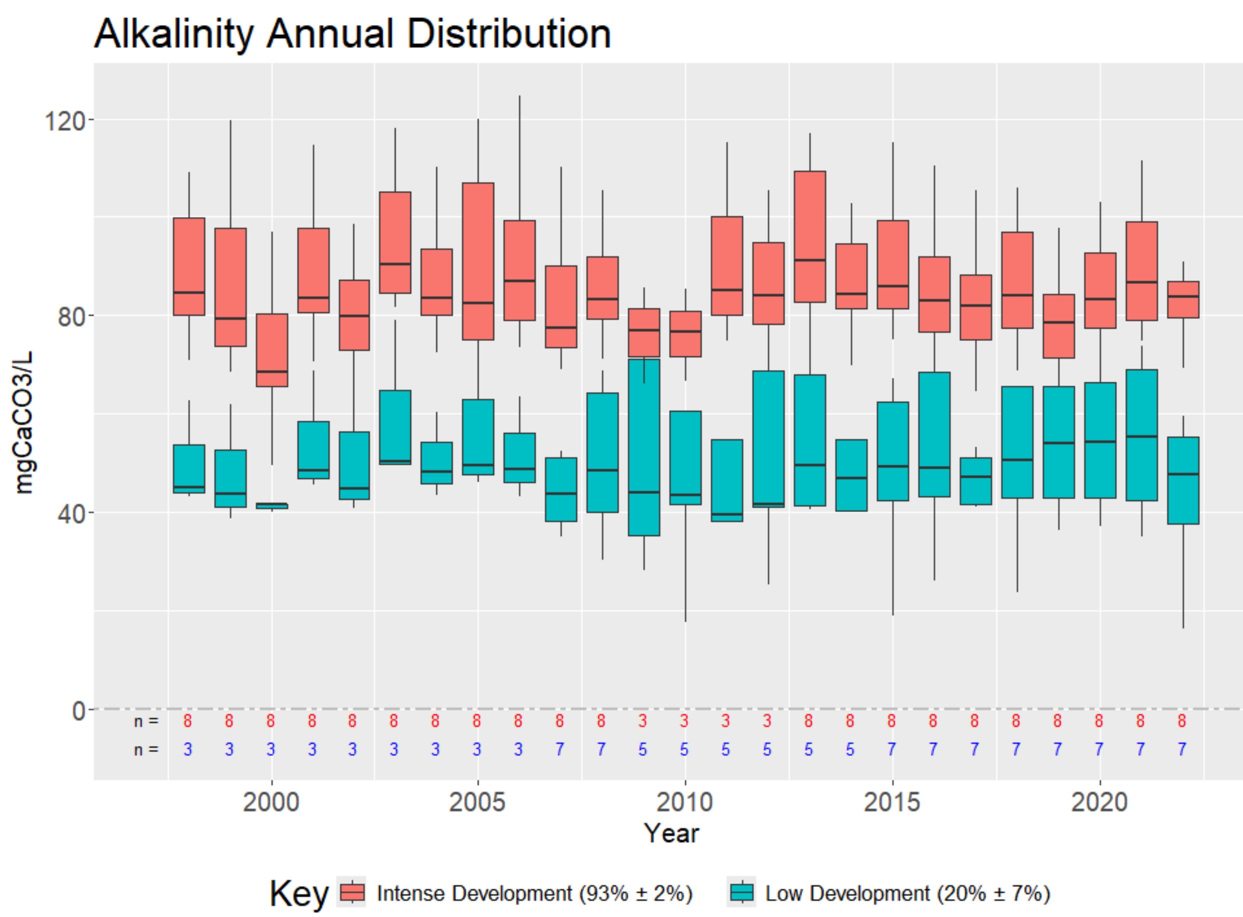

Figure 6. Annual boxplots of total alkalinity for the monitoring sites with the highest total development and the lowest total development. Sites were only used if they met the requirements for long-term trend analysis. Because most of the longest-recorded sites are in the urban core, there are much less "Low Development" sites with adequately long records. The center of each box is the 50th percentile. The sides of each box are the 25th and 75th percentile. The whiskers are 1.5 IQR. The numbers at the bottom are the number sites in each box plot. Red is the "Intense Development" group, blue is the "Low Development" group.

Road salts have seen increasing usage in King County during the study period (Heffter 2008). While some mixes contain calcium. The most common ingredient, sodium chloride, does not change stream alkalinity but does increase conductivity. Road salt is used during the coldest part of the year and causes large increases in conductivity as salt is carried into streams via rain or melting snow (Corsi et al. 2010). The acute rise in conductivity does not show up in the streams monitoring data (**fig. 7**), likely because monitored streams are only sampled once per month which makes it difficult to track short events. However, use of road salts could be another cause of increasing conductivity in King County streams, as frequent application can salinize soil and groundwater, leading to long-term increases in conductivity (Corsi et al. 2010).

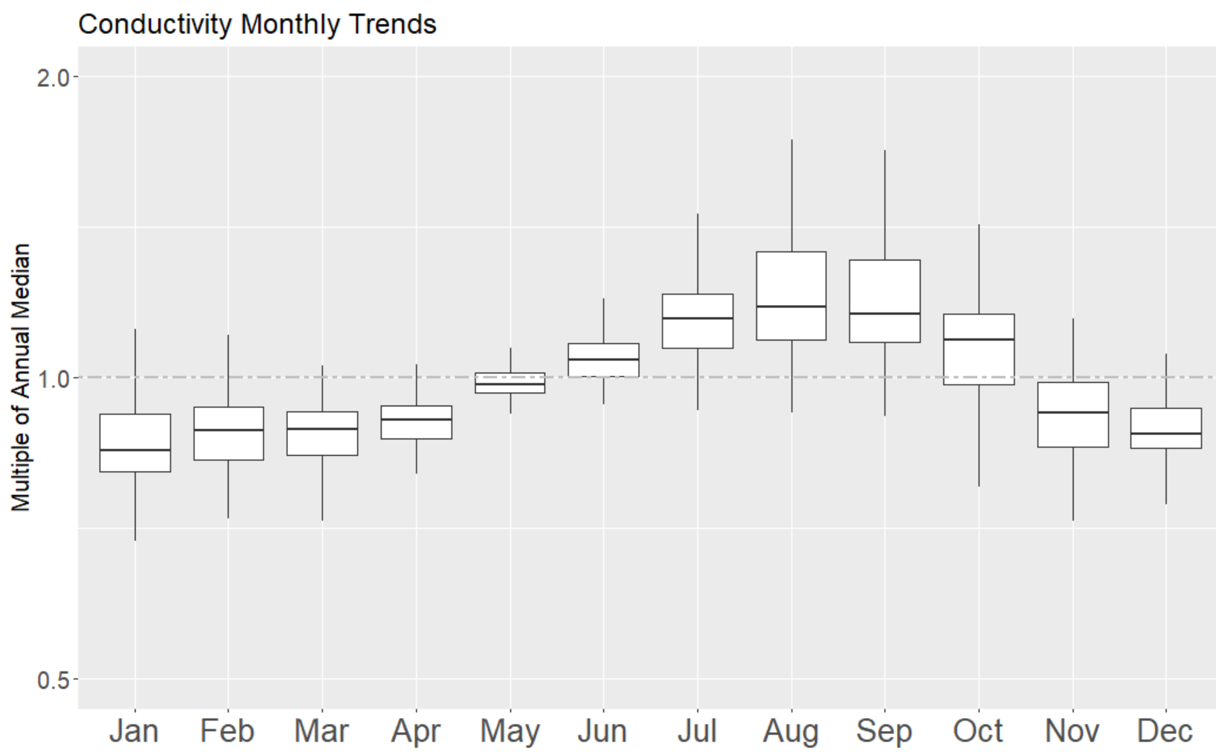

Figure 7. Monthly boxplots of conductivity in terms of relative deviation from the site and year median. The center of each box is the 50^{th} percentile. The sides of each box are the 25^{th} and 75^{th} percentile. The whiskers are 1.5 IQR. This shows the general seasonal trend in conductivity, over all sites and the entire time series n = 66. Conductivity in most monitoring sites is below the annual median during the coldest months, e.g. Dec-Feb, though the whiskers do extend above the median.

Temperature and dissolved oxygen

As expected with a warming atmosphere, annual median stream temperatures have increased at a rate of 0.19 ^{0}C per decade over the study period. Annual median dissolved oxygen has decreased by -0.086 mg/L per decade, which is similar to the decline in solubility predicted by Henry's Gas Law for water that is ~0.4°C warmer (Tromans, 2000). This means that DO has declined less than expected compared to the overall temperature increase. This is possibly due to the decline in FCB and nutrients leading to a reduced in-stream biochemical oxygen demand (BOD) from microbial restoration. This constituent, however, was not tested in streams monitoring program. The peak summer months are the only time of the year likely to be stressful for salmonid fish, so we performed a landcover regression analysis using data of the two months with the highest streams temperatures, July and August. The expectation was that this analysis would result in relatively well-fitting models. Surprisingly, this was not the case. Models for July-August temperatures fit much worse (max r^2 = 0.10) than regression models for median annual temperatures (max r^2 = 0.41). The Sammamish River/Slough (especially at the outflow from Lake Sammamish) had the highest summer temperatures in the data set, followed by Rock Creek. Both streams are downstream of large open water bodies, e.g. Sammamish River drains Lake Sammamish and Rock Creek flows through wetlands. They were also relatively slow-flowing and had little channel shading. The two streams with the lowest summer temperatures were Crisp Creek and Cochran Springs Creek, both of which originate from groundwater springs. This suggests that maximum stream temperatures are likely influenced by factors not characterized by the land cover data used for this study, such as ground water inputs, stream depth, velocity, or riparian buffer quality as opposed to land cover averaged over the entire catchment.

Future Studies

This is one of the longest and most extensive data sets of water quality tracking urban streams, with many possibilities for future studies. Future analyses would benefit from the use of additional, non-water quality data i.e. climate data such as precipitation and air temperature, stream discharge, effects on in-stream biotic integrity, or change in land cover over if possible. Other than climate data, these data sets should be more available going forward. The USGS recently began publishing an annual national land cover database, King County installed several stream gages in the last decade, and their biotic integrity monitoring program is in the process of integrating with the streams monitoring program. Studies exploring causative links would require a more focused experimental design, likely over a smaller area. Analysis of the routine streams monitoring data identified a few interesting starting points. Improvement in urban stream water quality is likely influenced by improved management of stormwater runoff, and a study that tracked the installation and type of BMP's over time in a single watershed could establish a link between the two. Possible causes of increasing stream alkalinity and conductivity could be investigated by sampling runoff in a highly urbanized catchment and a heavily forested catchment, to determine if a greater portion of alkalinity is coming from impervious surfaces, or soil. King County has encouraged the replacement of septic tanks with centralized sewer service, and a study could track decommissioning of septic tanks in a single catchment and measure changes in water quality, especially fecal coliform bacteria. Lastly, a few sites have notable concentrations of one or more constituents, i.e., Springbrook Creek's historical improvement along with its ongoing water quality problems or the cause of Cochran Springs Creek's increasing nitrogen, alkalinity, and pH. It would be enlightening to perform in-depth studies of these steams to better understand what makes them unique for the region, and how that knowledge could be applied to stream management.

Conclusion

The results showed a decline of NO_3-N, NH_4-N, TN, and PO_4-P, as well as FCB, TSS, and DO concentrations from their historic baselines in most monitoring sites used in this study. Additionally, a majority of monitoring sites had increasing stream temperatures, specific conductivity, and total alkalinity. There was no significant positive or negative trend for pH, turbidity, or total phosphorus. Analysis also showed that contemporary stream concentrations of all water quality constituents except for turbidity, TSS, and NH_4-N had statistically significant regression models using land cover characteristics as independent variables. Not unexpectedly, DO was the only constituent that decreased with greater total developed land cover. The remaining nine constituents showed higher concentrations with a greater proportion of developed land. Total alkalinity, specific conductivity, TN, and NO_3-N all increased with greater deciduous forest land cover, likely due to the influence of red alder. TP, PO_4-P, and FCB increased with agricultural land cover. DO decreased with greater wetlands coverage. The results of these analyses have a myriad of possible causes, some local, some regional. Further research using a focused data set would be required to determine a causative link between the trends found here and their potential drivers. However, the observations gathered over 40 years provide an excellent data set to identify macro-scale trends and identify individual sites for future in-depth studies.

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Appendix 1: Scatterplot Matrices

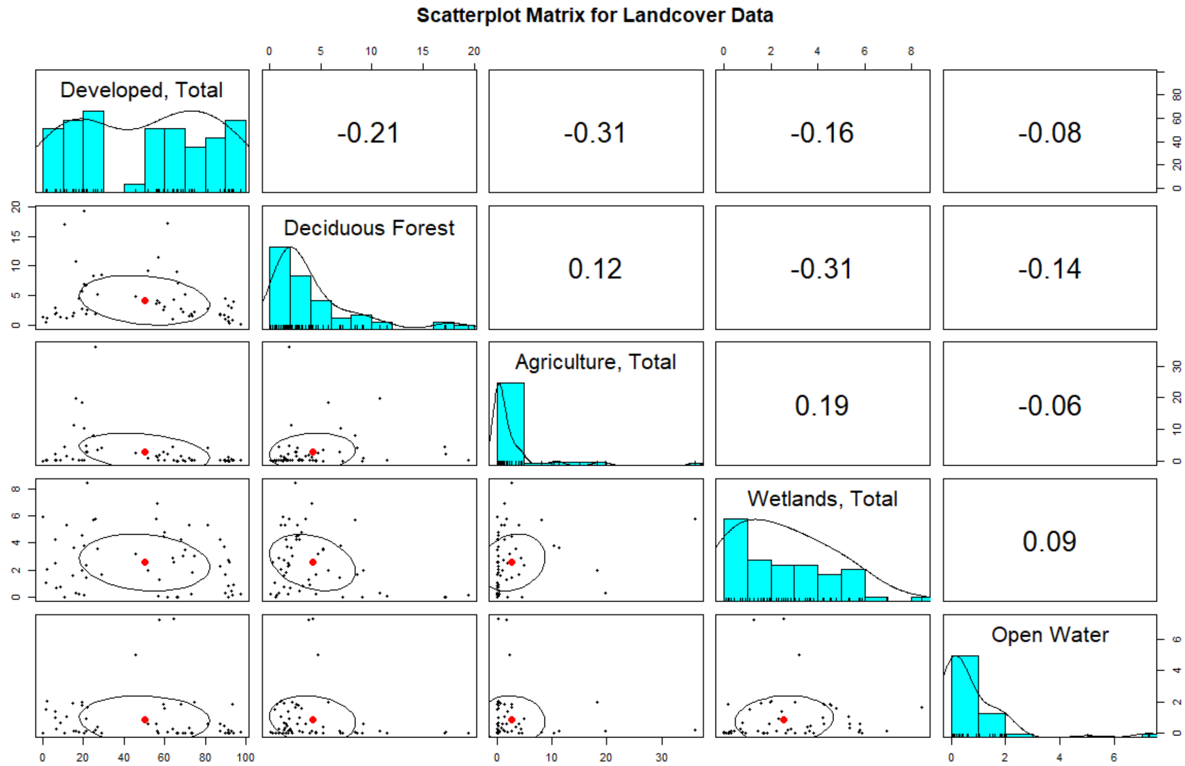

Figure 8. Scatterplot matrix of the five land cover categories used in multiple regression analysis.

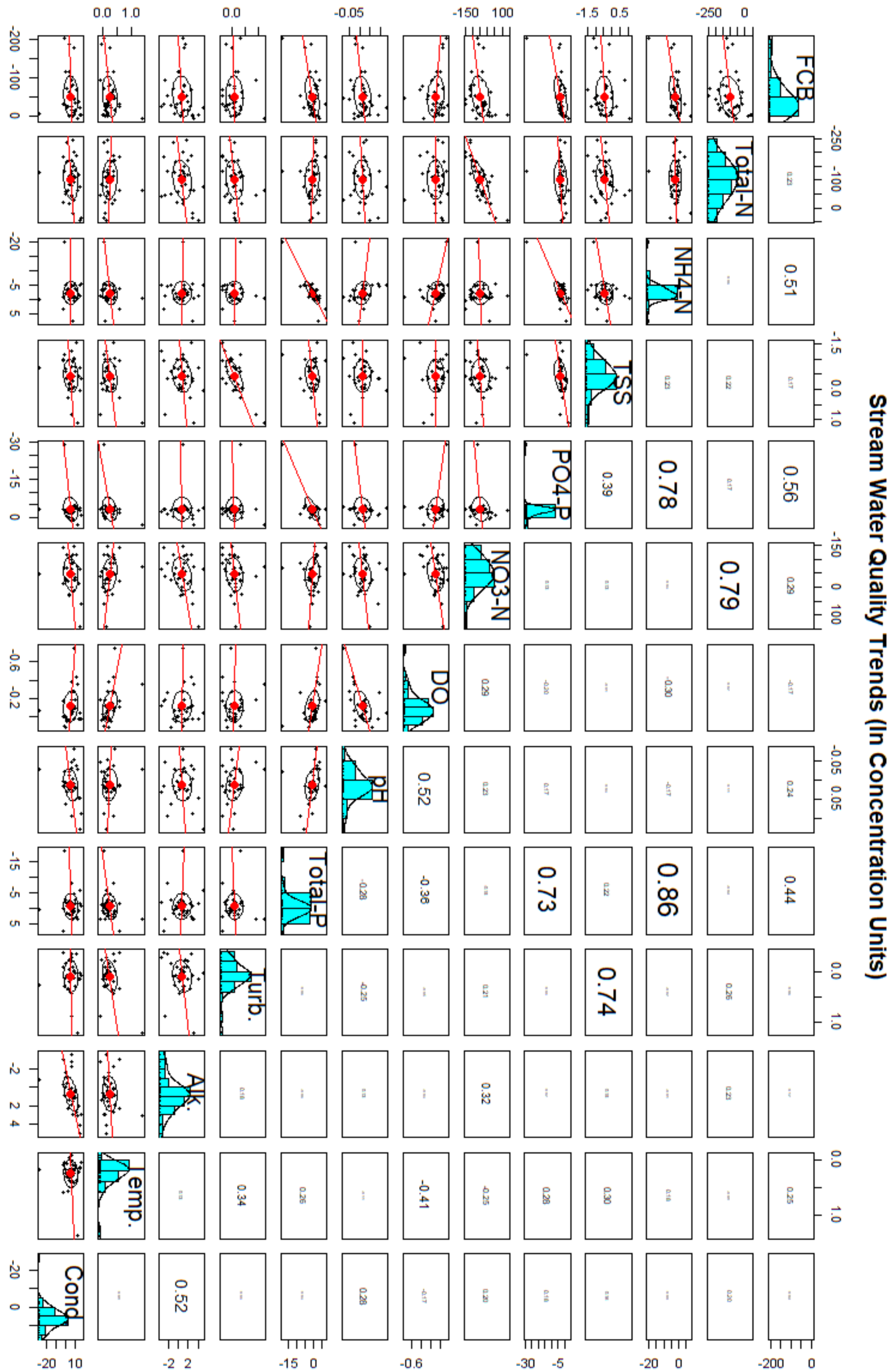

Figure 9. Scatterplot matrix of long-term trends for all 13 water quality constituents. Note: Springbrook Creek (0317) has been removed from this plot as it heavily influenced the correlation coefficients. Diagonal is a histogram of constituent long term trends. Scatterplots are below the diagonal, with centroids and regression lines. Correlation coefficients are above the diagonal, higher coefficients are larger to emphasize related constituents.

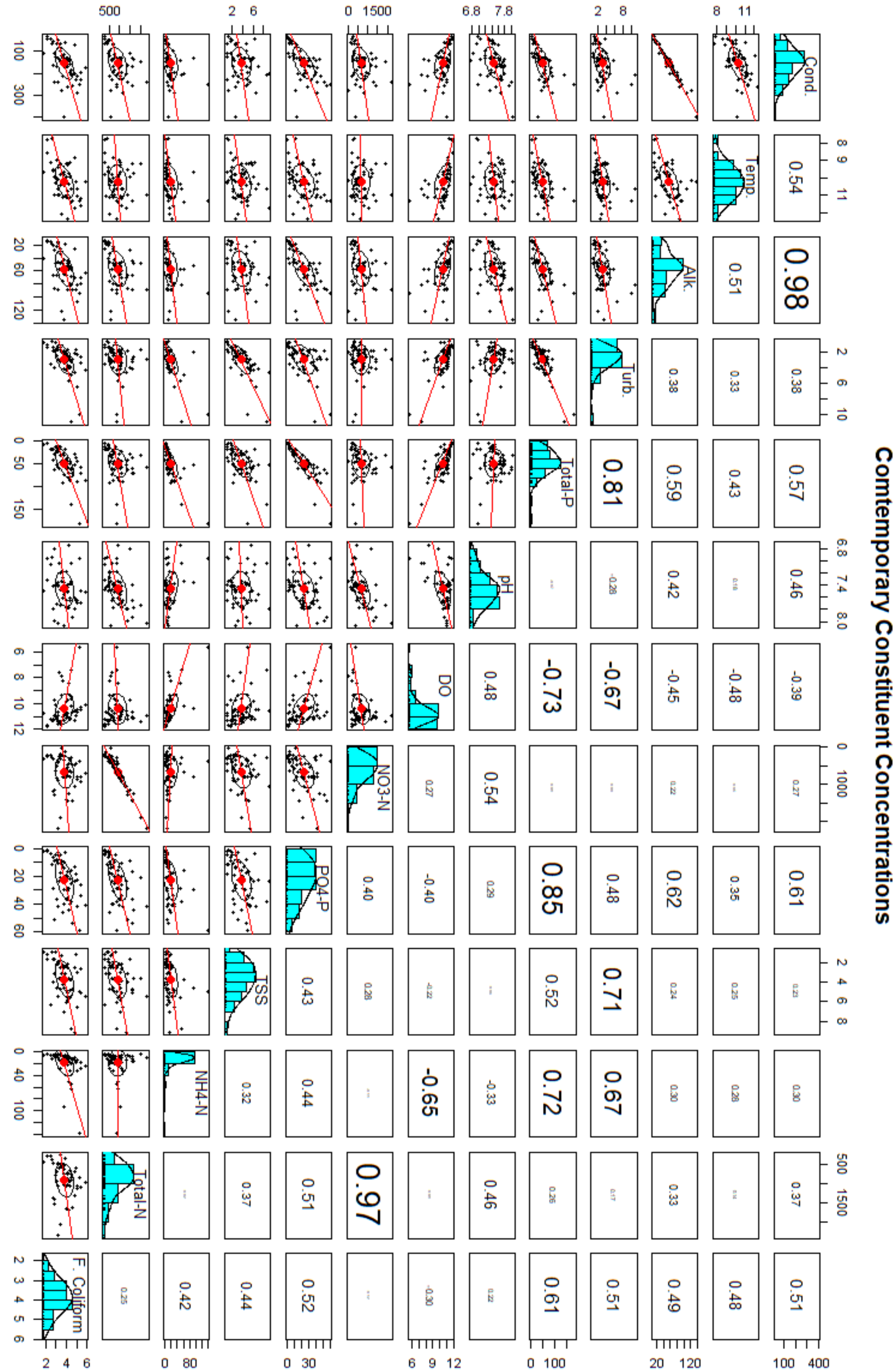

Figure 10. Scatterplot matrix of average concentrations of the years 2016-2022 for every water quality constituent. On the diagonal are histograms of constituent concentrations. Scatterplots are below the diagonal, with centroids and regression lines. Correlation coefficients are above the diagonal, higher coefficients are larger to emphasize related constituents.

Appendix 2: Long-Term Trend Distributions

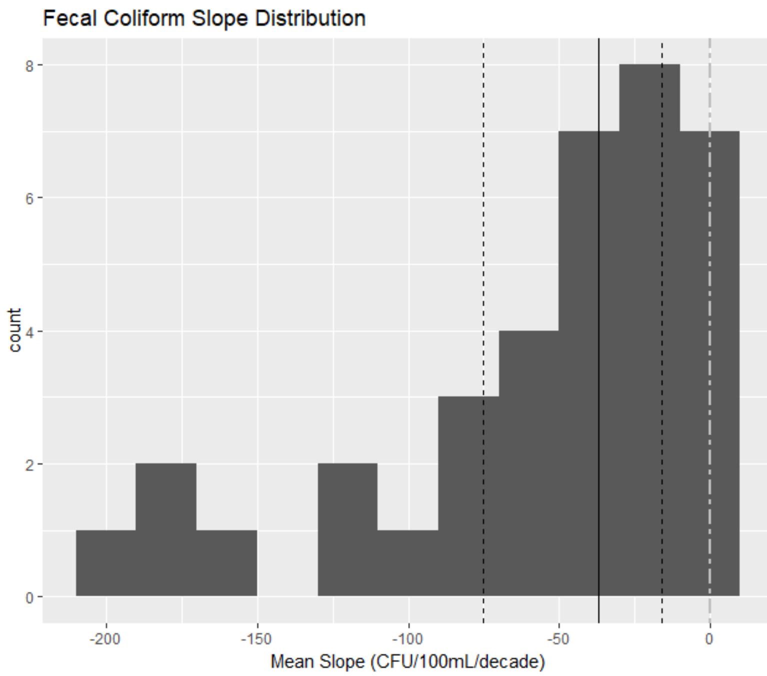

Figure 11. Histogram of long-term trends for FCB. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

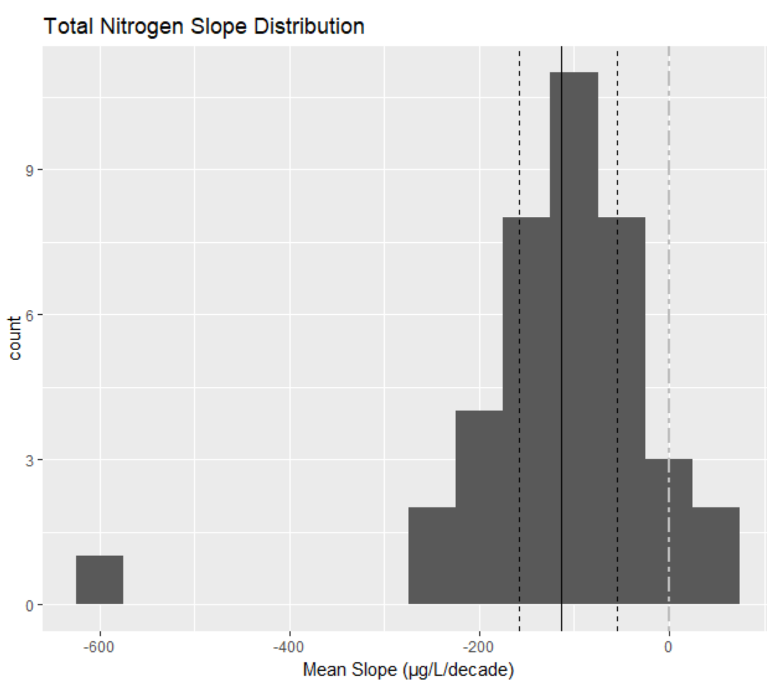

Figure 12. Histogram of long-term trends for TN. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

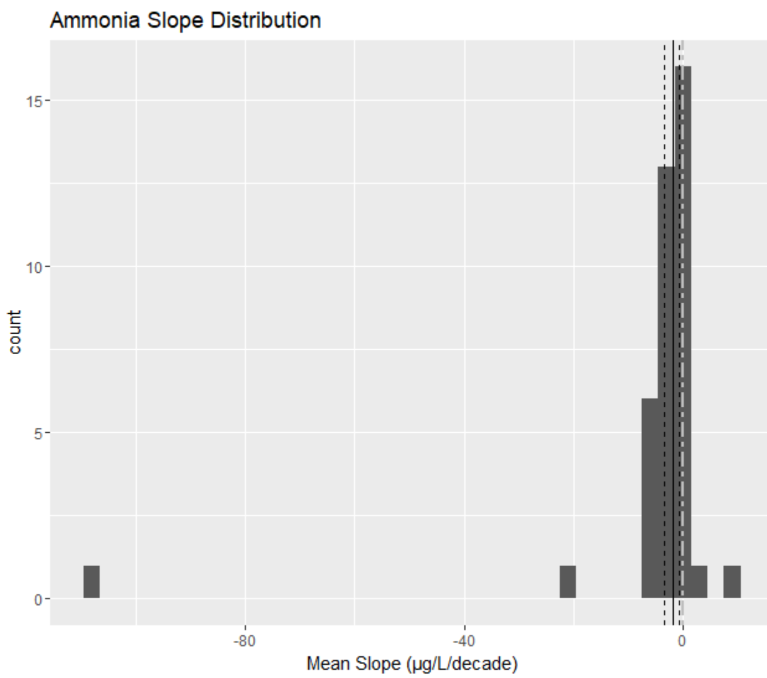

Figure 13. Histogram of long-term trends for NH_4-N. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

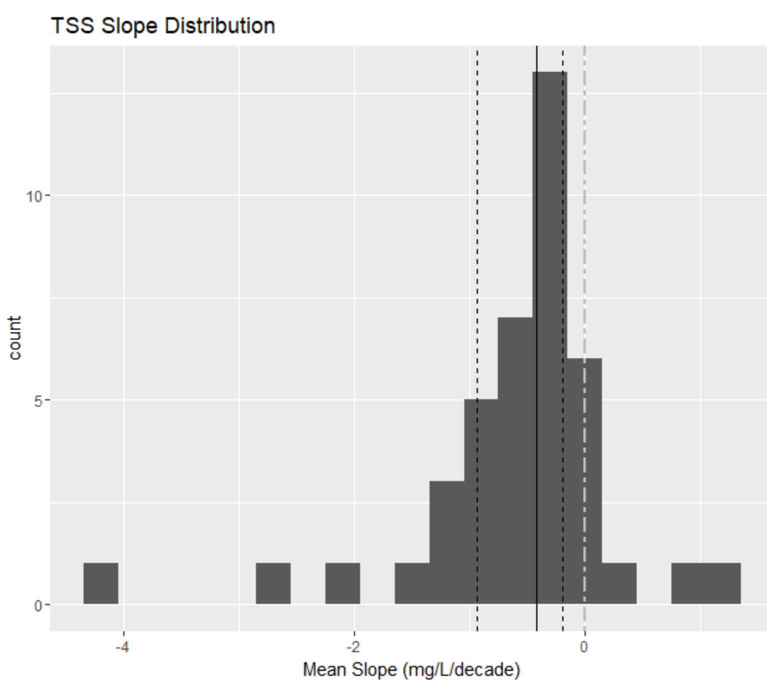

Figure 14. Histogram of long-term trends for TSS. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

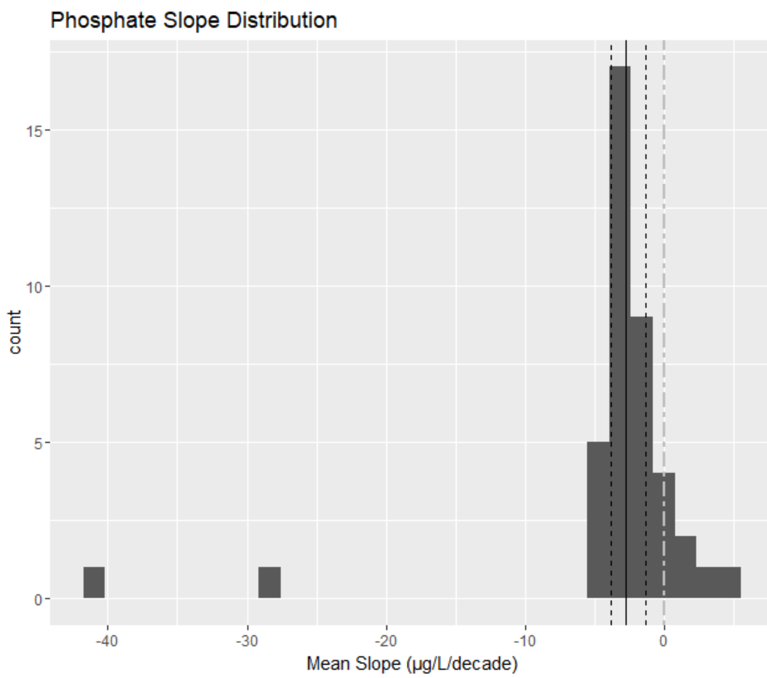

Figure 15. Histogram of long-term trends for PO_4-P. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

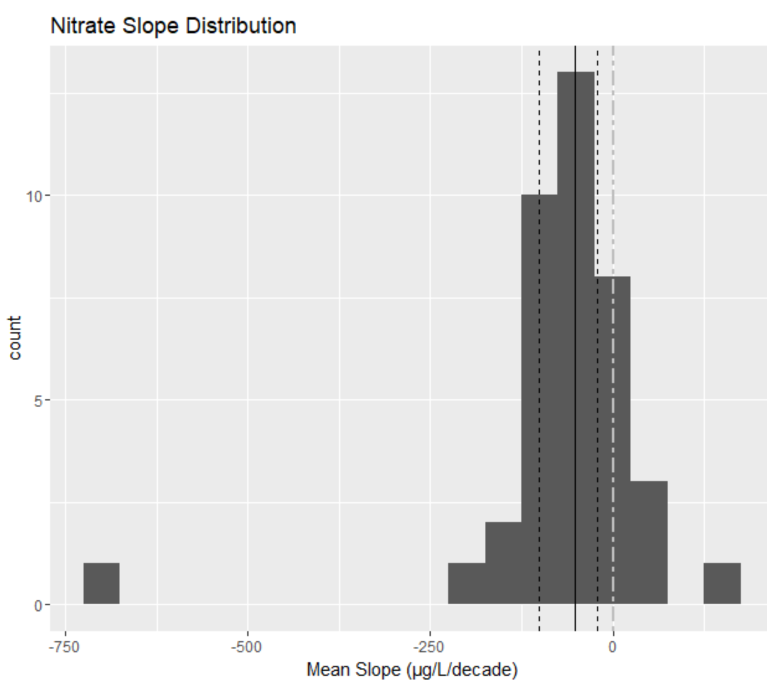

Figure 16. Histogram of long-term trends for NO_3-N. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

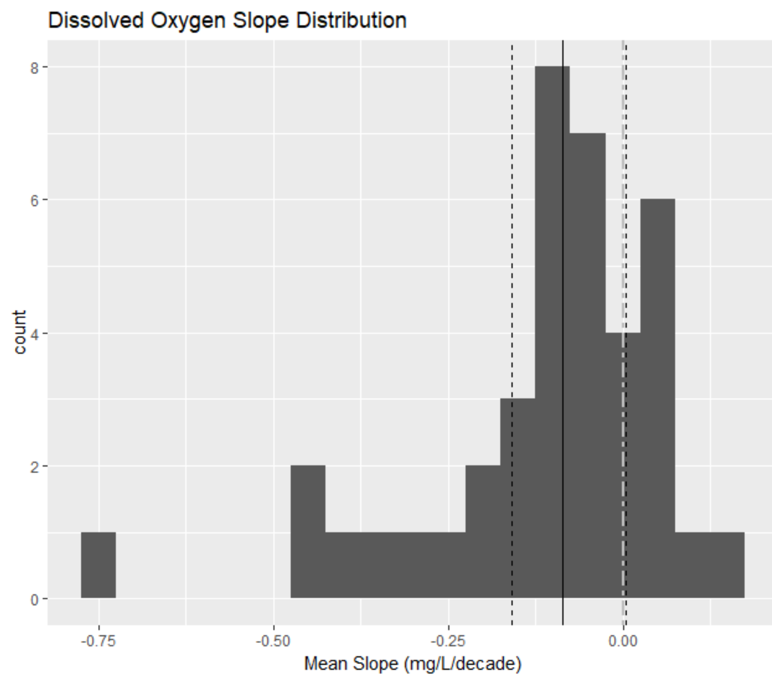

Figure 17. Histogram of long-term trends for DO. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

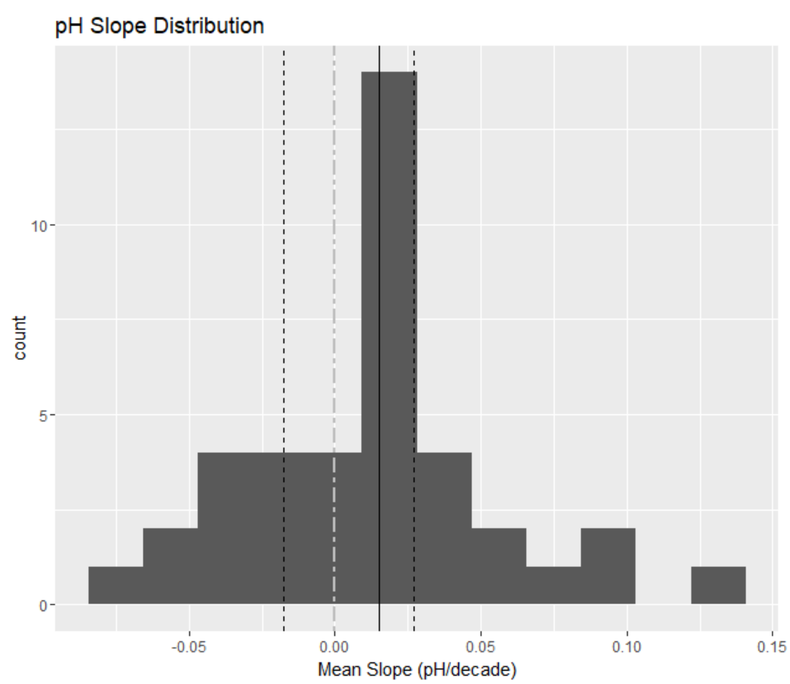

Figure 18. Histogram of long-term trends for pH. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

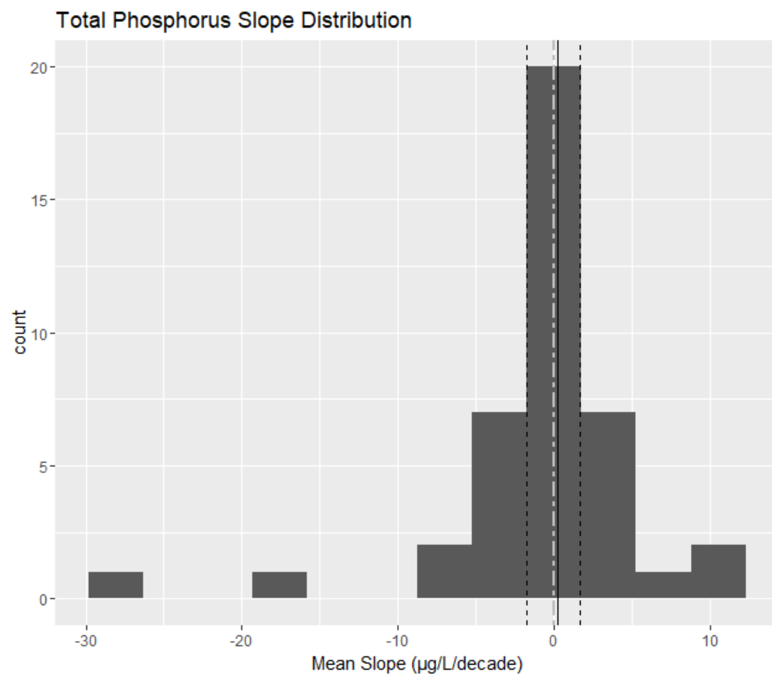

Figure 19, Histogram of long-term trends for TP. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

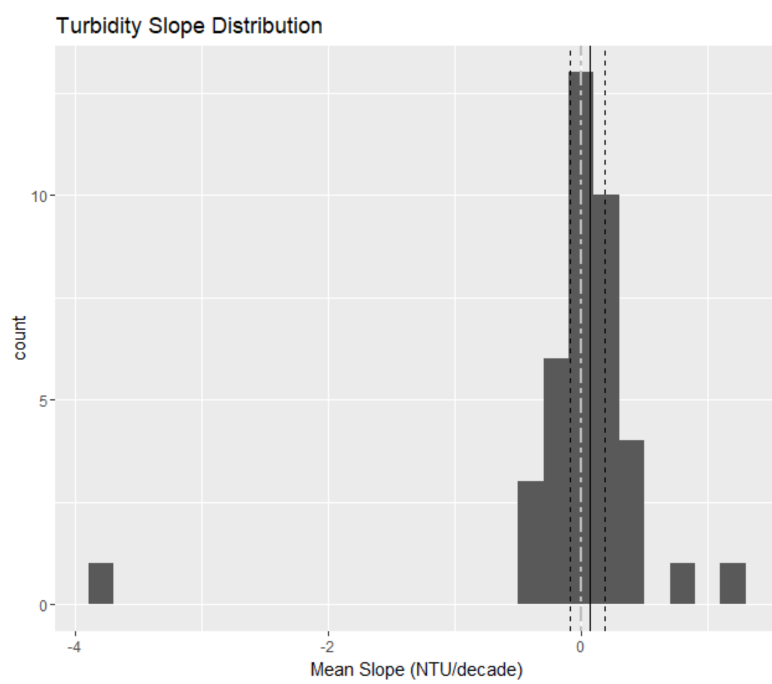

Figure 20. Histogram of long-term trends for turbidity. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

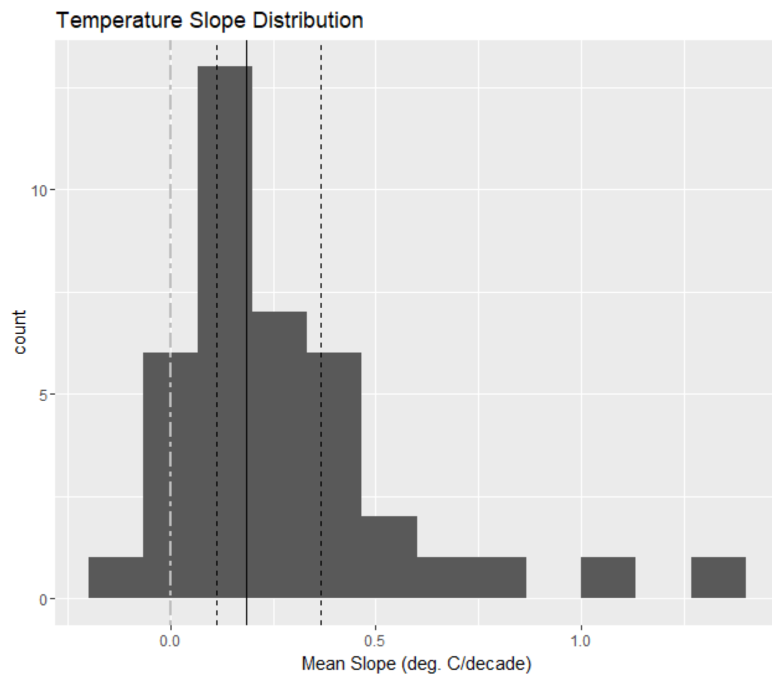

Figure 21. Histogram of long-term trends for temperature. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

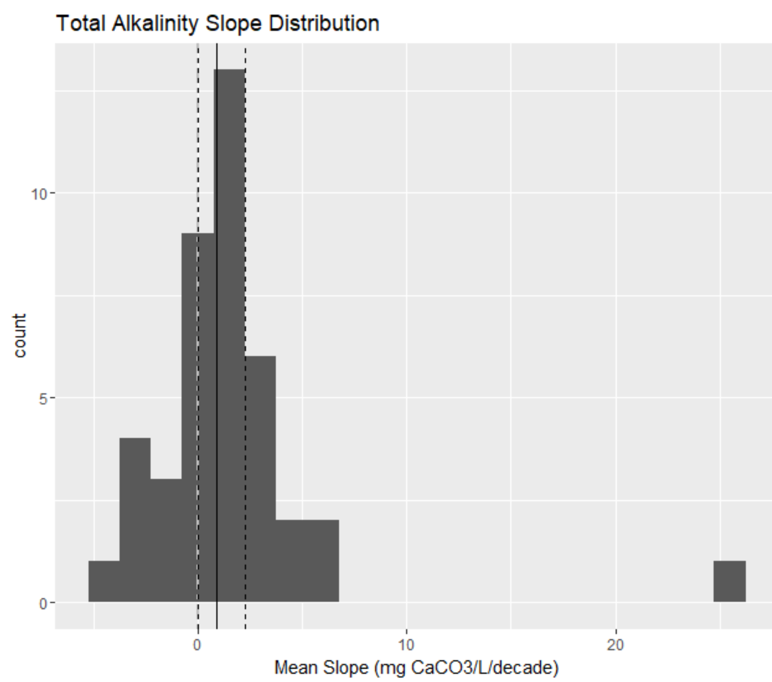

Figure 22. Histogram of long-term trends for alkalinity. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

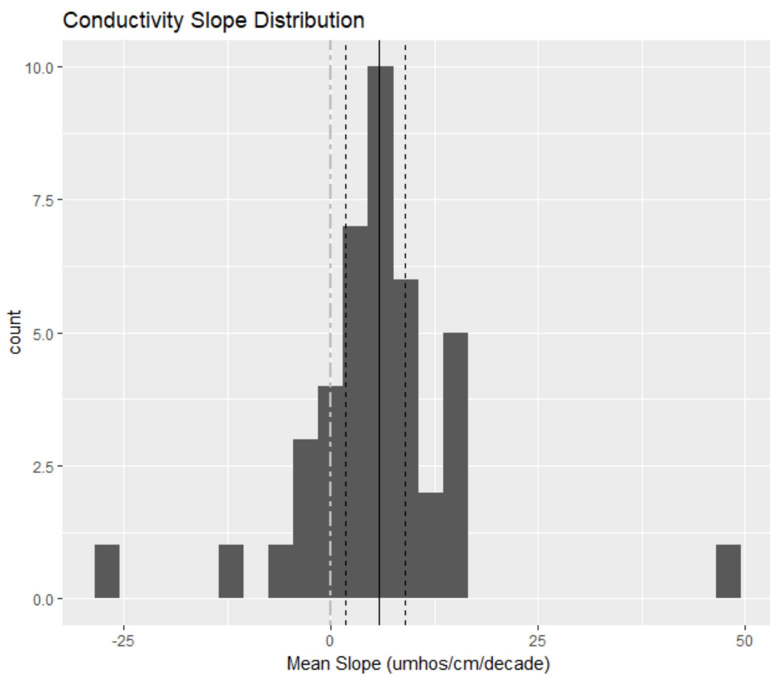

Figure 23. Histogram of long-term trends for specific conductivity. The solid black vertical line is the median. The black dotted lines are the 25th and 75th percentiles. The grey dotted line is zero.

Appendix 3: Long-Term Trend Z-Score Timeseries

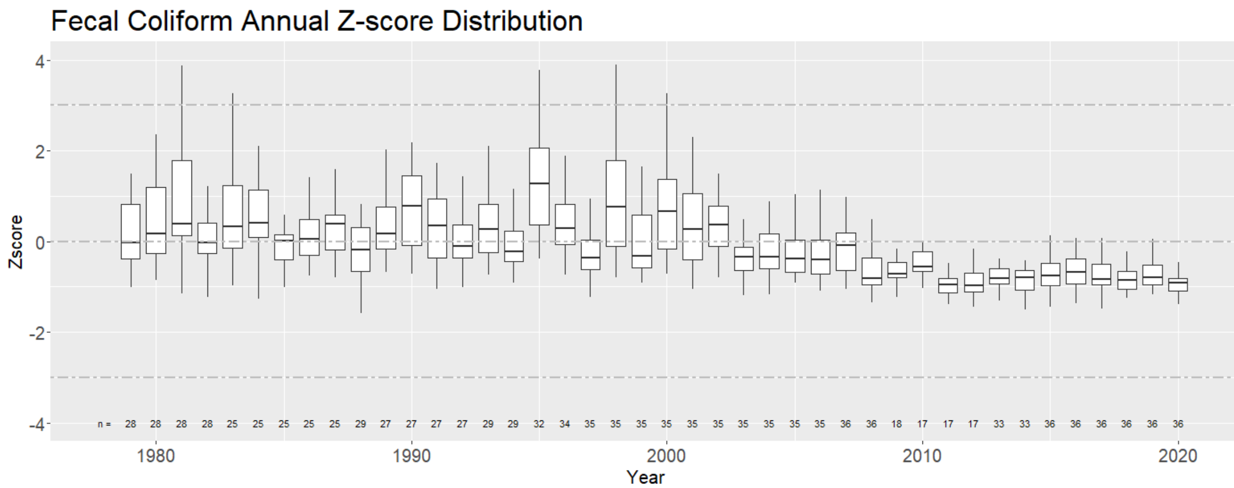

Figure 24. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$

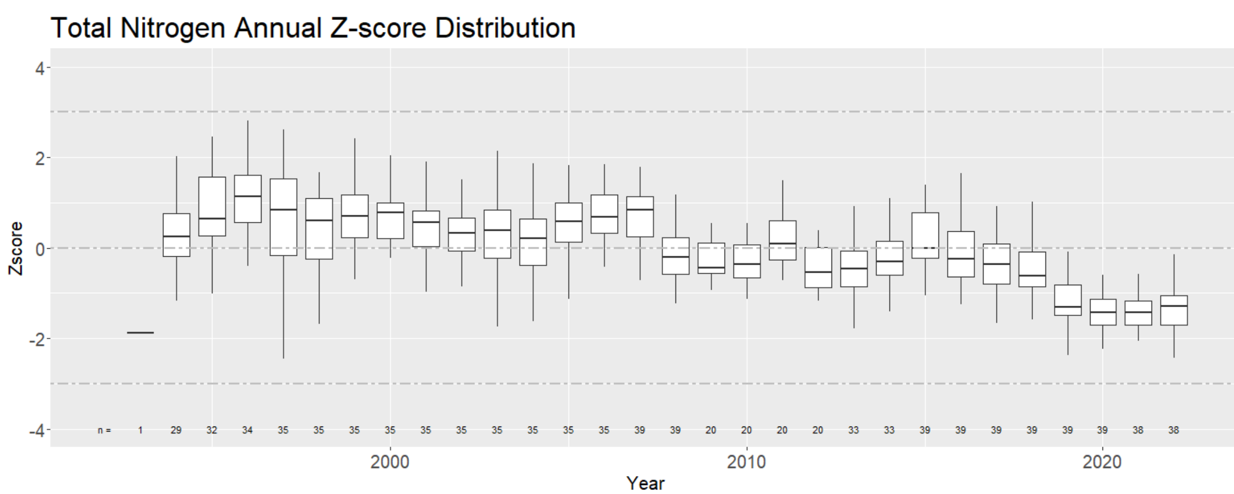

Figure 25. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$

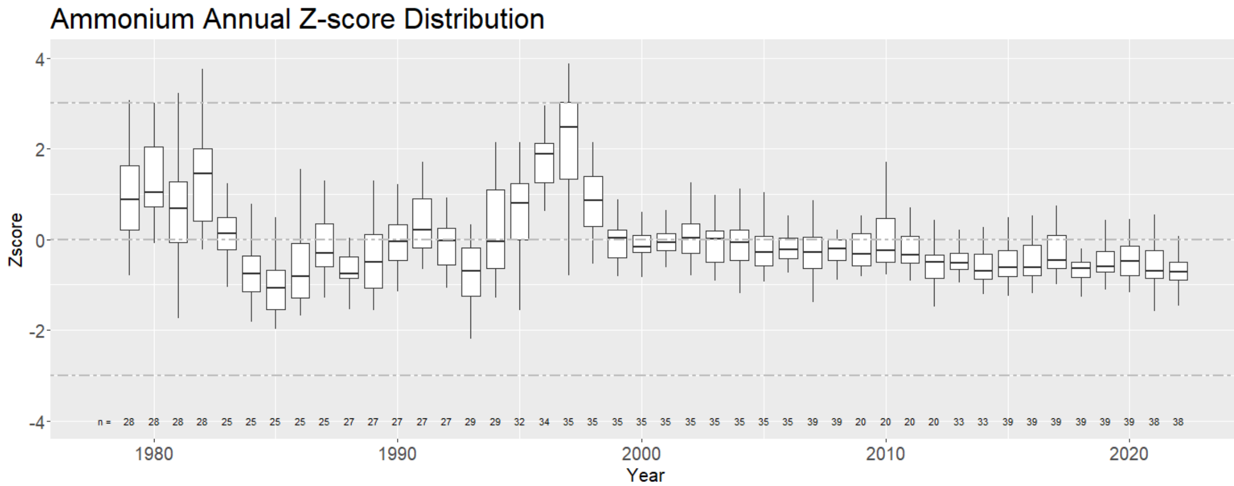

Figure 26. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p = 0.01$

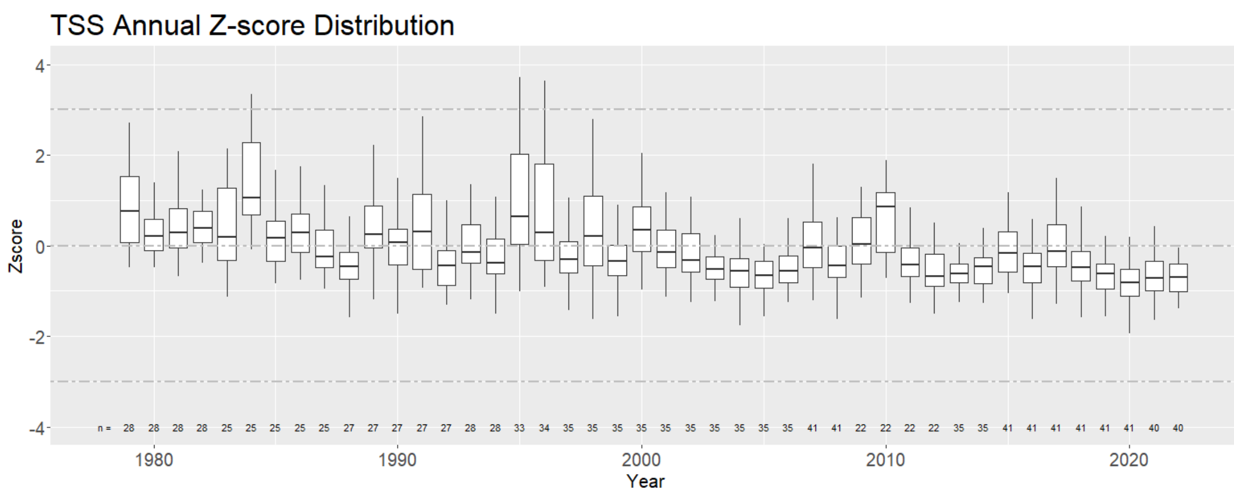

Figure 27. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$

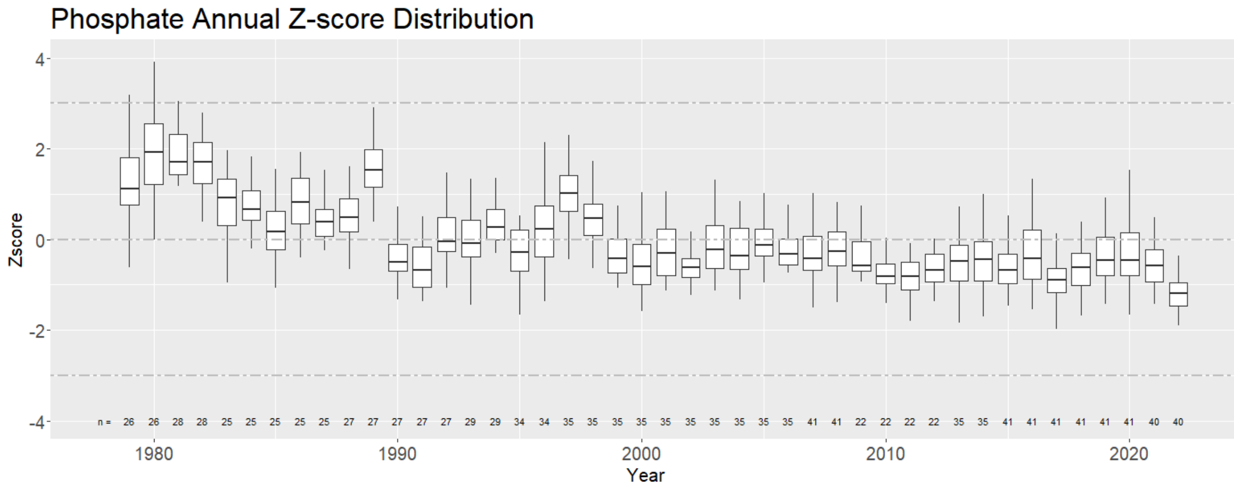

Figure 28. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$

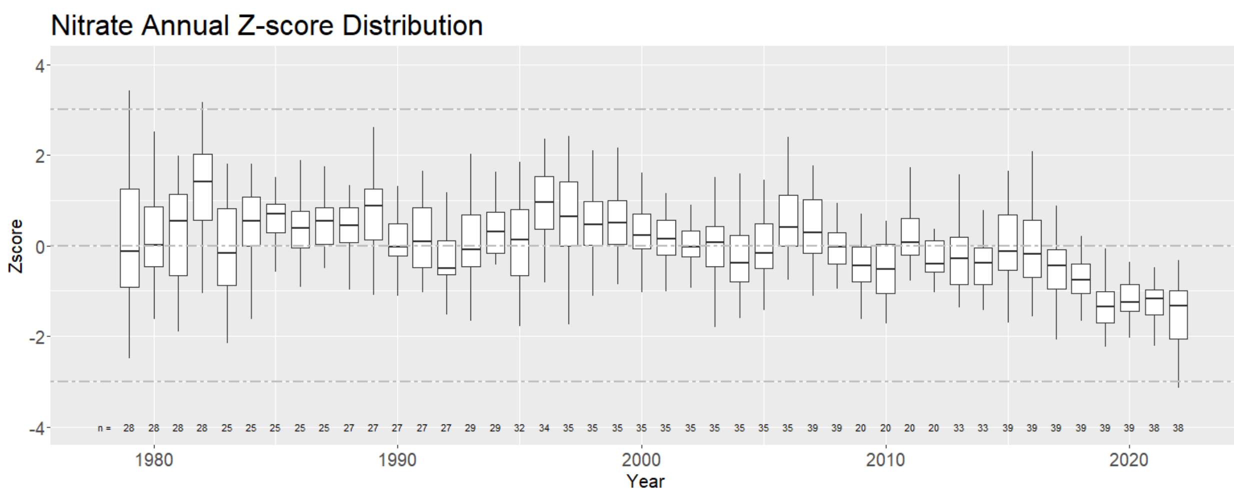

Figure 29. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$

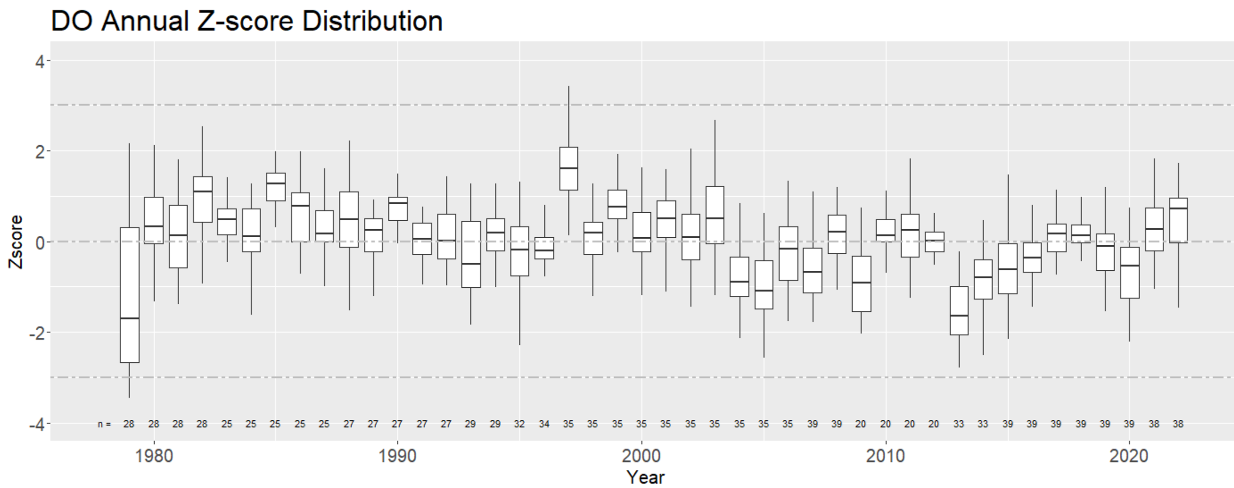

Figure 30. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.004

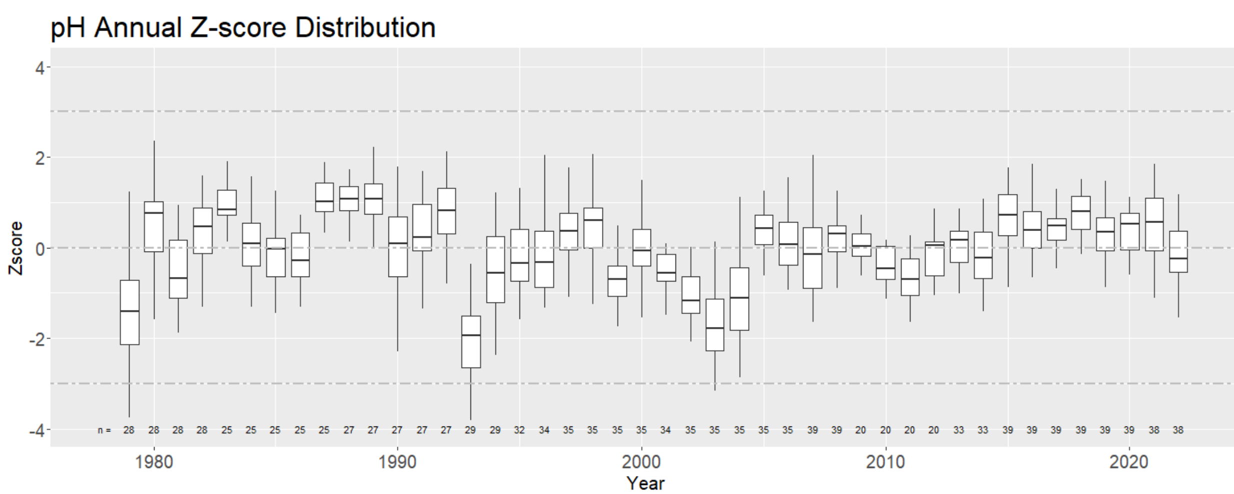

Figure 31. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.895

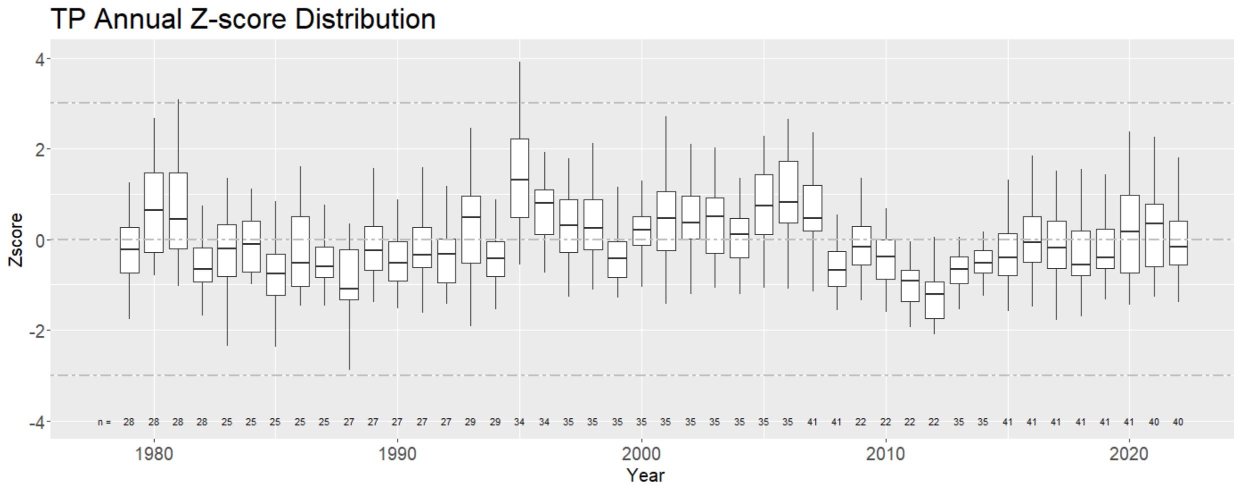

Figure 32. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.783

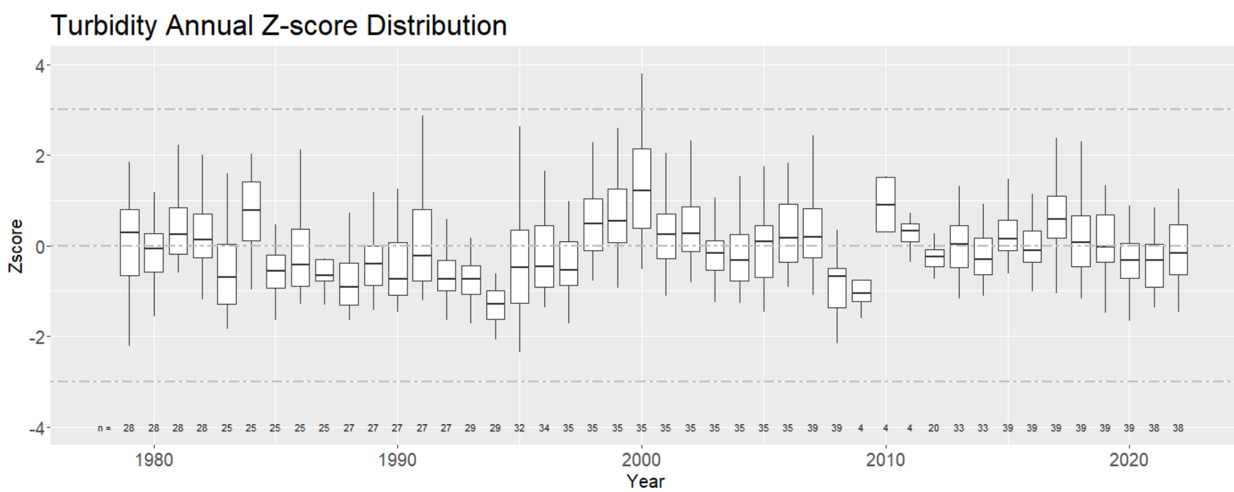

Figure 33. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.190

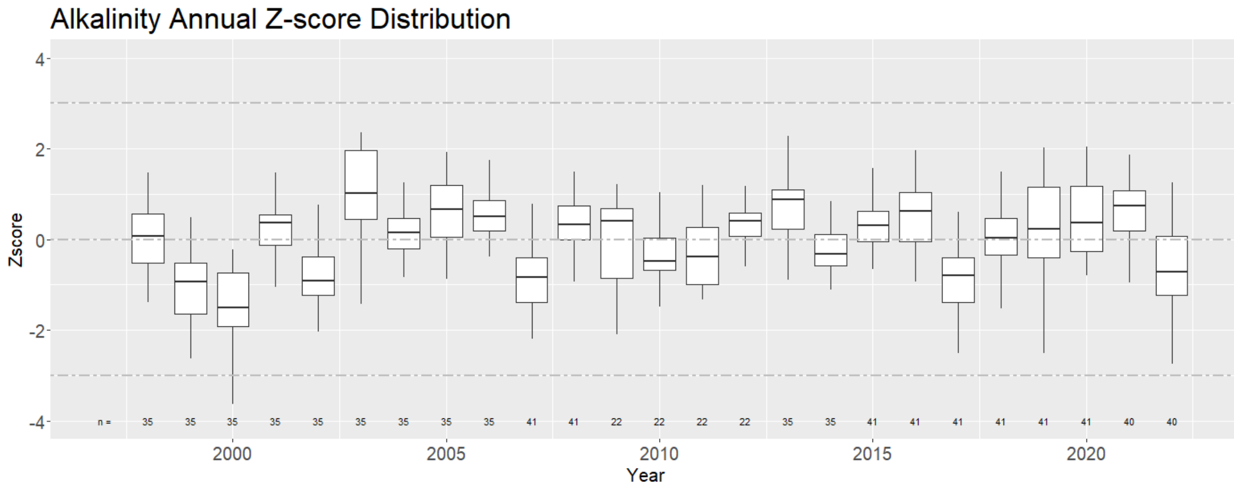

Figure 34. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.341

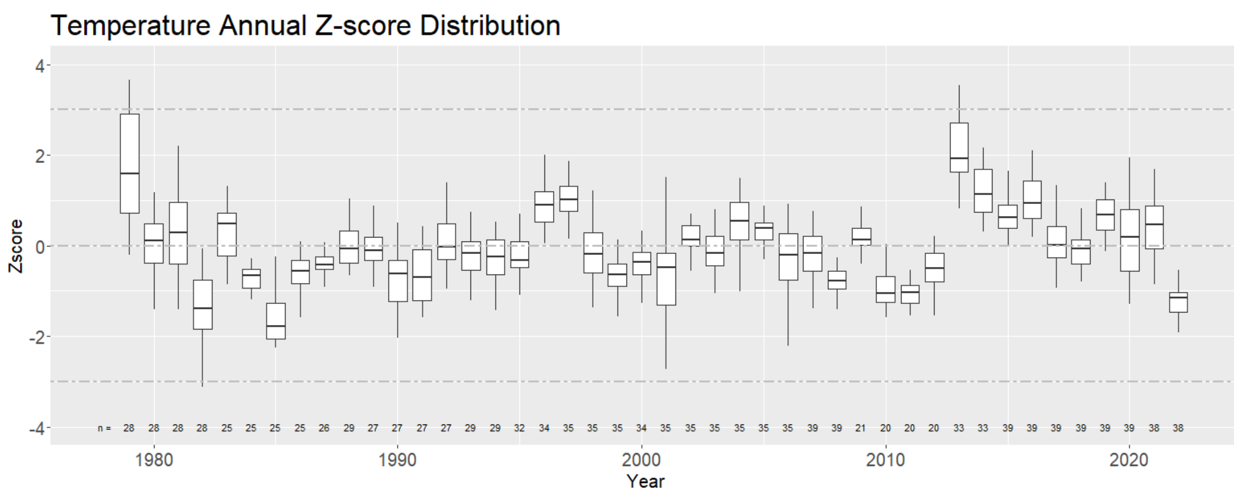

Figure 35. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: p = 0.057

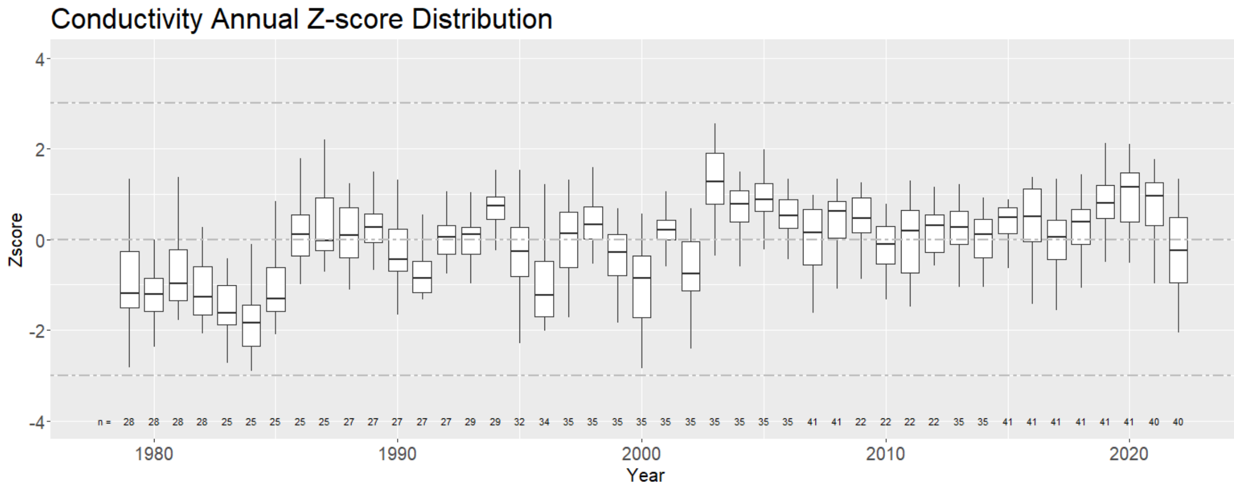

Figure 36. An annual distribution of z-scores for stream fecal coliform concentrations. The center of the box is the median, the outer borders of the box represent the 25th and 75th percentile, and the whiskers are 1.5 the IQR. The number of samples in each box and whisker plot is listed above the x-axis. Linear regression: $p < 0.001$