WATER QUALITY TRENDS ADJUSTED FOR SEASONALITY AND STREAMFLOW USING CONTINUOUS INSTREAM DATA IN THE SUSQUEHANNA RIVER BASIN

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EXECUTIVE SUMMARY

In 2003, the Susquehanna River Basin Commission established a real-time, early warning system (EWS) network to monitor large river systems to assist drinking water suppliers with treatment processes. It was limited to large river systems and was comprised of only a few stations. In 2010, a new initiative was started as the unconventional natural gas (UNG) industry rapidly expanded in the Susquehanna River Basin and the majority of the activity was located near headwater streams. The remote water quality monitoring network (RWQMN) included 60 monitoring stations in small watersheds in the northern Pennsylvania and southern New York portions of the basin to monitor potential impacts from UNG drilling. Recently, the EWS and RWQMN were combined to create the continuous instream monitoring network (CIM). It continues to assist drinking water suppliers, but also monitors water quality in streams throughout the entire Susquehanna River Basin. Continuous water quality parameters collected at each site include pH, specific conductance, water temperature, dissolved oxygen, and turbidity. Fluctuations of these parameters may be, in part, due to the natural range of variability, changes in land use/land cover including agriculture, urban, and forest cover, potential impacts from natural gas drilling, or changes in climate and the hydrologic regime.

At the conclusion of 2021, 45 of the 70 monitoring stations had 10 or more years of data which were sufficient to conduct trend analyses. Statistical trend analyses can be used to examine trends and evaluate the rate of change, but do not provide insight in attributing a trend to a particular cause. For this reason, streamflow and seasonality need to be accounted for, in order to determine if water quality is changing over time and if those changes can be attributable to anthropogenic activities. Instantaneous streamflow data were not available for 41 out of 45 of the CIM stations; therefore, average daily flow records for each ungaged CIM station were estimated using proximal United States Geological Survey (USGS) stream gage data.

A non-linear curve fitting model, Locally Estimated Scatterplot Smoothing (LOESS), was used to define the relationship between streamflow and water quality (parameters). Residual (observed minus predicted) values from the fitted models, which describe water quality fluctuations unaffected by streamflow, were used in seasonal Mann-Kendall trend tests to detect positive or negative trends over time. Significant water quality trends ($\alpha \leq 0.05$) were noted for 75 individual parameters (33 percent) at 39 stations (87 percent). National Land Cover Datasets (USGS, 2019) were used to assess changes in land cover from 2010 to 2019 in CIM watersheds that had significant trends. No significant differences ($\alpha \leq 0.05$) between land use changes in watersheds with increasing or decreasing trends were observed.

Twenty of the stations experienced significant specific conductance trends: 16 showed increasing trends and four had decreasing trends. A significant difference between stations with increasing, decreasing, and no trend was observed in regards to percent glaciation and presence of glacial till. Turbidity trends were noted at 19 stations, 17 showing increases in turbidity and two stations showing decreases in turbidity.

Seventeen stations were found to exhibit significant pH water quality trends. The optimal pH range is between 6-9 (on a range of 0-14); therefore, an increasing pH can be both beneficial or adverse. pH is decreasing at 10 stations and increasing at seven stations. Dissolved oxygen

(DO) decreased at 13 stations, which can be detrimental, particularly for macroinvertebrate populations and coldwater species such as trout. There were six stations with significant water temperature trends: five with increasing temperatures and one with decreasing temperatures. Typically as water temperatures rises, lower DO concentrations follow; however, this is not observed in the trends at the CIM stations.

Macroinvertebrate samples were collected routinely over a 10-year period at 43 of the stream locations where CIM data are being collected. Overall PA Freestone Index of Biological Integrity (IBI) Methodology scores and assemblage structure were examined in light of flow-adjusted water quality trend results. While small differences and natural variations were observed, none of the streams showed clear evidence of biologic decline. Even those with significant trends indicating a decline in water quality did not illustrate degraded macroinvertebrate communities. It is especially important to continue frequent biologic monitoring in streams where temperature and/or specific conductivity is increasing, as those two parameters are the most likely to result in observable shifts in macroinvertebrate assemblages.

INTRODUCTION

In 2003, the Susquehanna River Basin Commission (Commission) established its first continuous instream monitoring network: Early Warning System (EWS). The network was located on large river systems in the Susquehanna River Basin to assist downstream water suppliers with their treatment processes based on changing water conditions. As unconventional natural gas extraction moved into the basin, the Commission saw the opportunity to expand the continuous instream monitoring to small watersheds underlain with shale (northern Pennsylvania and southern New York portions of the basin). In 2010, the Remote Water Quality Monitoring Network (RWQMN) was established and continued to grow through 2016. In 2016, the RWQWN expanded outside of the natural gas region of the basin to encompass watersheds in southern Pennsylvania. In 2020, the Commission integrated the EWS and RWQMN networks into one continuous instream monitoring network (CIM) comprised of 70 monitoring locations at the end of 2021 (https://www.srbc.net/continuous-instream-monitoring).

The CIM allows the Commission and stakeholders to determine if water quality conditions throughout the basin are changing over time, monitor potential impacts from human activities, and gain an overall, better understanding of water quality conditions in large and small watersheds. Out of the 70 CIM stations, 45 stations had 10 or more years of data at the end of 2021, which provided a sufficient period of record to calculate water quality trends (Figure 1). Ten years of monthly data is typically the minimum required for monotonic trend (continuous rate of change, increasing, or decreasing) analysis (Hirsch, 1982). Basin characteristics, changes in land use, and discrete water quality measurements were examined to assess the cause of increasing or decreasing water quality trends.

The CIM includes high-frequency, continuous monitoring stations that measure pH, specific conductance (conductance), water temperature, dissolved oxygen (DO), and turbidity. Trends were assessed with data from 2010-2021 (Appendix A). Longer periods of record and/or more intensive sampling frequency generally provide a greater sensitivity to detect smaller changes. Forty-three of the 45 stations considered for this study were analyzed for trends in 2016 (with three to five years of data) (Hintz and Markowitz, 2016). Results presented in this study vary from those presented in 2016, which suggests 1) a need for long-term, continuous water quality datasets, and 2) re-evaluating trends when sufficient data are available. Statistically significant trends presented in 2016 may be described more so by the variability within a limited dataset (Appendix D).

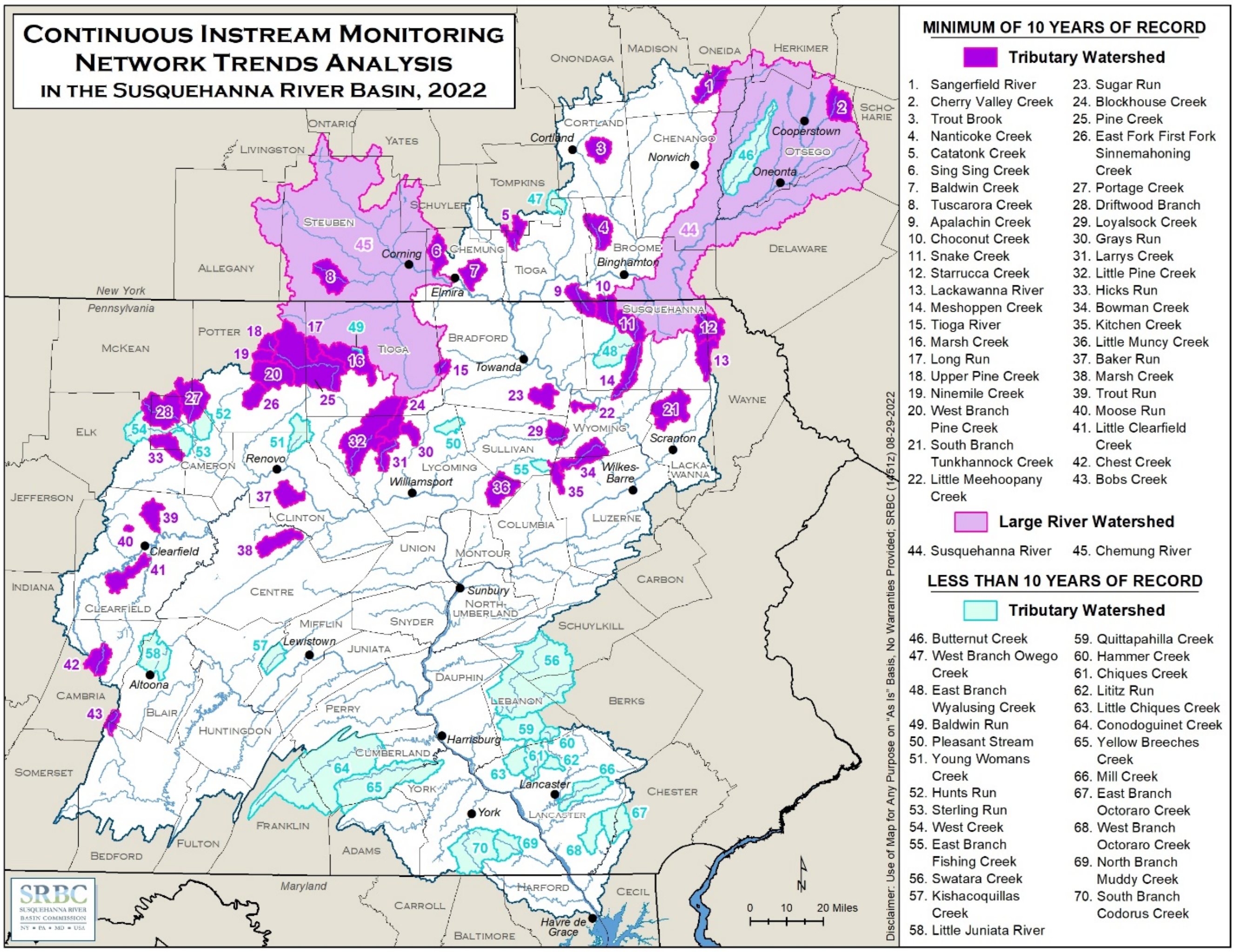

Figure 1. CIM Station Locations

Statistical trend tests can be used to detect trends and evaluate rates of change, but do not provide insight in attributing a trend to a particular cause. Other than local geology and anthropogenic activities, streamflow and seasonality tend to influence fluctuations in water quality. Intense precipitation events can lead to greater streamflows capable of scouring streambeds and banks and entraining suspended sediments, which may cause potential increases in turbidity, pH, and water temperature. Conversely, during periods of little to no precipitation, limited instream flow and higher air temperatures may lead to increases in conductivity and lower DO levels. Therefore, streamflow and seasonality need to be accounted for in order to determine if water quality is changing over time. Locally Estimated Scatterplot Smoothing (LOESS) was used to define the relationship between water quality parameters and streamflow. A seasonal Mann-Kendall trend test was performed on the residuals from LOESS regressions to examine water quality trends, independent of influences from streamflow and seasonality. The Mann-Kendall test (Mann, 1945; Kendall, 1975) is a non-parametric statistical test used for detecting upward or downward trends over a period of record.

DATA COLLECTION METHODS

Continuous pH, conductance, water temperature, DO, and turbidity data were collected at 5-minute intervals using a YSI, Inc. 6600 series data sonde from January 2010 to November 2015. In November 2015, the interval was changed to 15 minutes at stations utilizing cellular telemetry. The collection interval was not changed at stations using satellite telemetry because the data reported represent a 4-hour average; the discrete data are not reported. In 2016, the Commission began to replace the 6600 series data sonde with YSI, Inc. EXO2 and EXO3 and Eureka Manta 35+ data sondes. The replacement process was competed over four years; data intervals and transmission rates were not changed. There are 30 stations transmitting data via cellular telemetry, eight stations using satellite telemetry, and seven stations transmitted data through satellite telemetry, until mid-2015 when cellular telemetry became available in some watersheds. Appendix A indicates which stations utilize each telemetry source.

Data were stored in an Aquarius Time-Series SQL database. The Time-Series software was used to screen and correct anomalous water quality data from equipment fouling or drift (SRBC, 2021). Once the data were corrected to Commission standards, Time-Series software was used to calculate daily mean values for each parameter. These daily mean values were used in the seasonal Mann-Kendall tests to determine water quality trends.

WATER QUALITY AND BIOLOGICAL DATA

Continuous Water Quality Data

The five water quality parameters, collected on a continuous basis, influence the type of aquatic communities a stream can sustain. Conductance is the measure of how well water can conduct electricity. Conductance increases as more ions are added to the water and/or as the ions become more mobile. Geology and soils influence conductance; however, changes in conductance, such as observed within the study timeframe, are usually caused by human impacts in a watershed. Within the Susquehanna River Basin, these impacts may include abandoned mine drainage, agricultural runoff, urban runoff, and unconventional natural gas (UNG) fracking fluid spills or leaks. Aquatic life is impacted when conductance values reach 300 µS/cm in Central Appalachian streams (USEPA, 2011).

pH is the measure of a waterbody's acidity (<7) or alkalinity (>7). Pennsylvania's water quality standard for pH is 6–9. A pH value outside of water quality standards can have an adverse impact on aquatic life. While some streams can have naturally acidic conditions, a decrease in pH is more often related to human influences. Acid deposition and acid mine drainage can significantly lower pH values. Streams with low pH will begin to release metals into the stream which are detrimental to the stream health. Other human influences including agricultural and urban runoff can increase pH, causing basic conditions. In agricultural settings, runoff with excess nutrients can lead to excessive algal growth, effectively increasing the pH.

DO in a waterbody is an important component in its ability to support aquatic life. High gradient streams with turbulent riffles and plunge pools will have higher levels of dissolved oxygen compared to slower moving, pooled waterbodies. Cooler water temperatures will also increase the amount of dissolved oxygen in a waterbody. The Pennsylvania water quality standard for DO varies with the designated use of the waterbody. In order to meet water quality standards, the minimum DO level is 5.0 mg/l. An optimal DO level for smaller streams is 9.0 mg/l; when DO drops below 3.0 mg/l, it is difficult for any aquatic organism to survive.

Turbidity is the amount of particulate matter suspended in the water column, which can include sediment, microscopic organisms, or organic/inorganic compounds. Turbidity will typically increase in a waterbody during higher flows. Higher flows have a greater propensity to erode and entrain sediments from the streambanks, and re-suspend materials from the substrate. Increased and prolonged periods of turbidity increase sedimentation in a waterbody and can have adverse impacts on aquatic organisms as sediment settles on substrate, effectively burying valuable habitat for aquatic organisms. High levels of turbidity also make it difficult for water suppliers to treat drinking water.

Discrete Water Quality Data

Discrete sampling of other water quality parameters (Table 1) was conducted during various timeframes to ascertain driving mechanisms of baseline water quality and trends at each CIM station. These samples have been collected at the CIM stations intermittently from initial start-up to 2012, and seasonally (four samples per year) between 2012 and 2016. Since 2017, discrete samples were collected at all stations in the spring and collected at select stations in the summer, fall, and winter. These discrete parameters have remained largely unchanged over time; once a baseline is established for these, sampling is typically discontinued. Discrete water quality data were not used in the trends analysis. Summaries of discrete water quality parameters for each CIM station can be viewed on the Commission's Continuous Instream Monitoring (CIM) Dashboard (https://experience.arcgis.com/experience/f5b5597a6cbc48a9b6741a7d81491089).

Table 1. Discrete Water Quality Parameters

PARAMETER	PARAMETER
*Acidity	*Lithium
Alkalinity	Magnesium
*Alkalinity, Bicarbonate	Manganese
*Alkalinity, Carbonate	Nitrate
Aluminum	pH
Barium	Phosphorus
Bromide	Potassium
Calcium	Sodium
*Carbon Dioxide	Specific Conductance
Chloride	Strontium
*Gross Alpha	Sulfate
*Gross Beta	Total Dissolved Solids
Iron	Total Organic Carbon

* Parameters no longer collected after the baseline was established.

Biological Data

Macroinvertebrate data have been collected routinely over the past decade at 43 of 45 CIM sites considered in this study. Changes in water quality can be reflected in shifts in macroinvertebrate assemblages, as macroinvertebrate taxa have different water quality tolerances. The objective of the analysis was primarily to examine macroinvertebrate community metrics and assemblage structure in context to trending water quality parameters.

Macroinvertebrates were collected using the PA Freestone Index of Biological Integrity (IBI) Methodology (PADEP, 2013). Abundance data for each sample were used to calculate an IBI score which summarizes the integrity of the sampled macroinvertebrate assemblage based on six metrics that reflect different facets of richness, diversity, and tolerance values. The IBI score is a scale of 0-100 and higher scores indicate better water quality.

STREAMFLOW ESTIMATION METHODS

Continuous daily streamflow records were not available for 41 of 45 CIM stations. For these sites, an average daily flow timeseries encompassing the period of available water quality data was estimated using proximal USGS gaging station data. USGS gages used to approximate hydrologic conditions at CIM stations were identified by comparing field-measured streamflows at CIM stations with concurrent daily discharge values from nearby USGS gaging stations. Linear regressions techniques and resulting streamflow-correlation coefficients were used to assess the suitability of all possible USGS gages within a 200 mi^2 radius of each CIM station. The following criteria were also considered in the selection of USGS reference gages for each CIM station:

- Similarities in drainage area
- Regulation (diversions, reservoir operations, mining, etc.) upstream of USGS gages
- Distance between CIM and USGS gage watershed outlets
- Reference gage selections provided by the Pennsylvania Baseline Streamflow Estimator (BaSE) tool (Stuckey et al., 2012)

USGS average daily flow timeseries were adjusted to each CIM station based on the ratio of drainage areas between CIM and USGS gage locations (Equation 1). This method is commonly used to estimate streamflow and flow duration curves at ungaged assessment points (Emerson et al., 2005). Ries and Friesz (2000) indicate that the drainage area ratio method is generally as accurate as, or more accurate than, regression estimates when the drainage area ratio for ungaged sites is between 0.3 and 3 times the size of the reference gage watershed. Limitations may exist when predicting high flows, as the CIM or USGS gaging locations may be affected by local variations in the timing and duration of precipitation, infiltration, and runoff. To address this limitation, streamflow records were estimated using mean daily flows from the USGS record, rather than 15-minute data. The USGS reference gage selection(s) with associated criteria, including correlation coefficients are included in Appendix B.

Equation 1

$$Q_{ungaged} = \frac{DA_{ungaged}}{DA_{gaged}} x Q_{gaged}$$

where:
Qungaged: Flow at the ungaged location
Qgaged: Flow at surrogate USGS gage station
DAungaged: Drainage area of the ungaged location
DAgaged: Drainage area at surrogate USGS gage station

TREND TEST METHODS

Streamflow can dilute or concentrate solutes in the water column, and ultimately influence water quality fluctuations. It is therefore important to assess water quality trends independent of hydrologic conditions. Otherwise, trends may be biased towards variations in climate and hydrology, and potential impacts from land use changes may be difficult to discern. To remove the influence of streamflow on water quality measurements, the relationship between water quality parameters and streamflow must first be defined. For this study, LOESS (Cleveland, 1979; Hirsch et al., 1991), a non-linear curve fitting model, was used to describe these relationships. Daily mean concentrations of each water quality parameter and streamflow are presented in Appendix C. LOESS predictions were developed for each month, rather than combining all data from an annual period, since the relationship between water quality and streamflow can change by season (turbidity, water temperature, etc.).

Daily residual (observed minus predicted) values from the fitted models were used to describe water quality fluctuations unaffected by streamflow. Seasonal impacts from biological activity and ambient air temperatures can also influence the concentration of water quality parameters. To account for seasonality, residual values from the fitted relationships were averaged by month and compared to the same month from year-to-year, over the available period of record. The seasonal Mann-Kendall trend test, which is a non-parametric test, was used to detect positive or negative monotonic trends over time.

WATER QUALITY RESULTS

Water quality conditions for streams can change over time, and these changes can be both beneficial or have adverse impacts. Eighty-seven percent of the CIM stations had at least one water quality trend (Table 3). Trends were observed for each of the five parameters (Table 2) at various stations; however, conductance, turbidity, and pH had the highest number of sites with significant trends at 20, 19, and 17, respectively.

Table 2. Number of Water Quality Trends Using Seasonal Mann-Kendall (α≤0.05)

PARAMETER	INCREASING	DECREASING
Specific Conductance	16	4
pH	7	10
Dissolved Oxygen	0	13
Temperature	5	1
Turbidity	17	2

Table 3. Water Quality Trends and Seasonal Mann-Kendall p-values (α ≤ 0.05) (Null = No Trend)

Station	SpCond (p-value)	DO (p-value)	pH (p-value)	Temperature (p-value)	Turbidity (p-value)
Apalachin Creek					
Baker Run		Decreasing (0.008)			Increasing (0.014)
Baldwin Creek		Decreasing (0.011)	Decreasing (0.037)		
Blockhouse Creek					
Bobs Creek					Increasing (0.000)
Bowman Creek		Decreasing (0.006)			
Catatonk Creek			Decreasing (0.001)		Increasing (0.021)
Chemung River @ Elmira					Increasing (0.048)
Cherry Valley Creek	Increasing (0.000)				
Chest Creek	Decreasing (0.037)		Decreasing (0.000)		Increasing (0.044)
Choconut Creek	Increasing (0.000)			Increasing (0.046)	
Driftwood Branch		Decreasing (0.002)		Increasing (0.024)	
East Fork Sinnemahoning Creek	Increasing (0.000)	Decreasing (0.019)	Increasing (0.000)		Increasing (0.000)
Grays Run	Increasing (0.019)				
Hicks Run					
Kitchen Creek				Increasing (0.013)	
Lackawanna River	Increasing (0.000)	Decreasing (0.000)	Decreasing (0.000)		Increasing (0.000)

Station	SpCond (p-value)	DO (p-value)	pH (p-value)	Temperature (p-value)	Turbidity (p-value)
Larrys Creek	Increasing (0.002)				
Little Clearfield Creek	Decreasing (0.001)	Decreasing (0.031)	Increasing (0.020)		
Little Mehoopany Creek					
Little Muncy Creek	Increasing (0.024)	Decreasing (0.035)	Increasing (0.004)		
Little Pine Creek	Increasing (0.017)				
Long Run		Decreasing (0.022)		Increasing (0.031)	Increasing (0.022)
Loyalsock Creek	Decreasing (0.001)				Increasing (0.000)
Marsh Creek			Decreasing (0.000)		
Marsh Creek – Tioga		Decreasing (0.001)			Decreasing (0.000)
Meshoppen Creek	Increasing (0.000)				
Moose Creek			Increasing (0.000)		Increasing (0.000)
Nanticoke Creek	Increasing (0.005)				
Ninemile Run					
Pine Creek	Increasing (0.003)				Decreasing (0.000)
Portage Creek		Decreasing (0.014)	Increasing (0.011)		
Sangerfield River					Increasing (0.044)
South Branch Tunkhannock Creek		Decreasing (0.042)			
Sing Sing Creek	Increasing (0.000)		Decreasing (0.003)		Increasing (0.032)
Snake Creek	Increasing (0.001)				
Starrucca Creek			Decreasing (0.000)		Increasing (0.000)
Sugar Run	Increasing (0.012)		Increasing (0.050)	Increasing (0.044)	
Susquehanna River @ Kirkwood				Decreasing (0.021)	Increasing (0.000)
Tioga River					Increasing (0.012)
Trout Brook	Increasing (0.014)		Decreasing (0.018)		
Trout Run	Decreasing (0.002)		Increasing (0.013)		Increasing (0.000)
Tuscarora Creek	Increasing (0.000)		Decreasing (0.000)		Increasing (0.010)
Upper Pine Creek		Decreasing (0.005)	Increasing (0.006)		
West Branch Pine Creek					

Water Quality Trends and Land Use Changes

Land use and land cover changes within a watershed are some of the most likely causes for changes in water quality. Watersheds that are largely forested typically exhibit healthy water quality while developed, urban, and agricultural watersheds typically reflect degraded water quality. It is assumed that if a CIM watershed experienced a transition from forest cover to urban or agricultural cover within the study period, the stream would illustrate a negative water quality trend.

National Land Cover Datasets (USGS, 2019) were used to assess changes in land cover within each CIM watershed from 2010 to 2019. For this analysis, general land cover classes of agriculture, developed/urban, and forested were considered. To determine the change in land use from 2010 to 2019, the percentage of agriculture, developed/urban, and forested land use in 2010 was subtracted from the percentage of each in 2019. A negative percentage indicates less of that land use in 2019 compared to 2010. During this time period, urban areas increased in every CIM watershed and agriculture increased in 73 percent of the watersheds.

A one-way ANOVA (analysis of variance) was used to determine if stations with increasing trends, decreasing trends, or no trend had significantly different ($\alpha \leq 0.05$) changes in land use. A one-way ANOVA compares two or more independent groups to determine if they are significantly different from each other. The resulting data showed no significant difference between stations with increasing, decreasing, and no water quality trend (Table 4). Box plots (Figures 2–6) indicate the range, median, and quartile range of land use change (as percent) for stations with increasing, decreasing, or no trend in conductance, turbidity, pH, DO, and temperature conditions, respectively.

Table 4. One-way ANOVA p-values for Percent Land Use Change from 2010 to 2019 *($\alpha \leq 0.05$)*

Trend	WTemp p-value	DO p-value	pH p-value	SpCond p-value	Turb p-value
Forest Land Use	0.640	0.671	0.140	0.092	0.452
Development Land Use	0.758	0.992	0.404	0.712	0.965
Agriculture Land Use	0.247	0.525	0.473	0.808	0.241

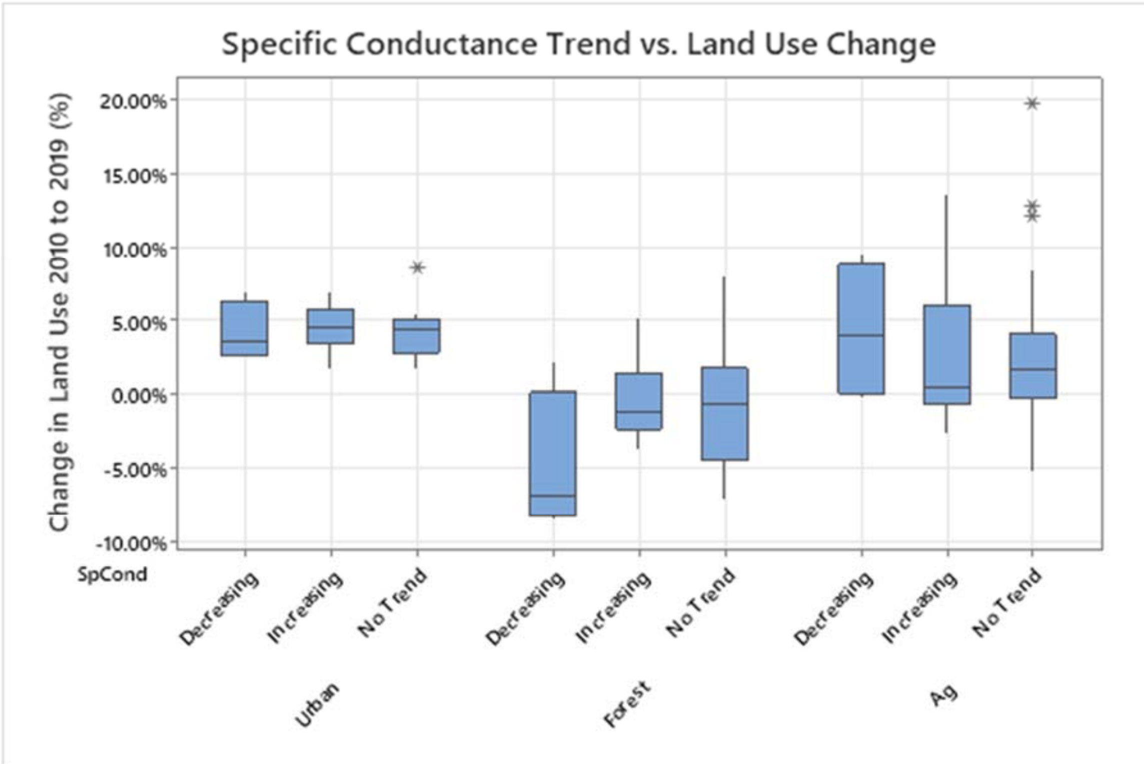

Figure 2. ***Box Plot of Specific Conductance Trends vs. Land Uses Changes***

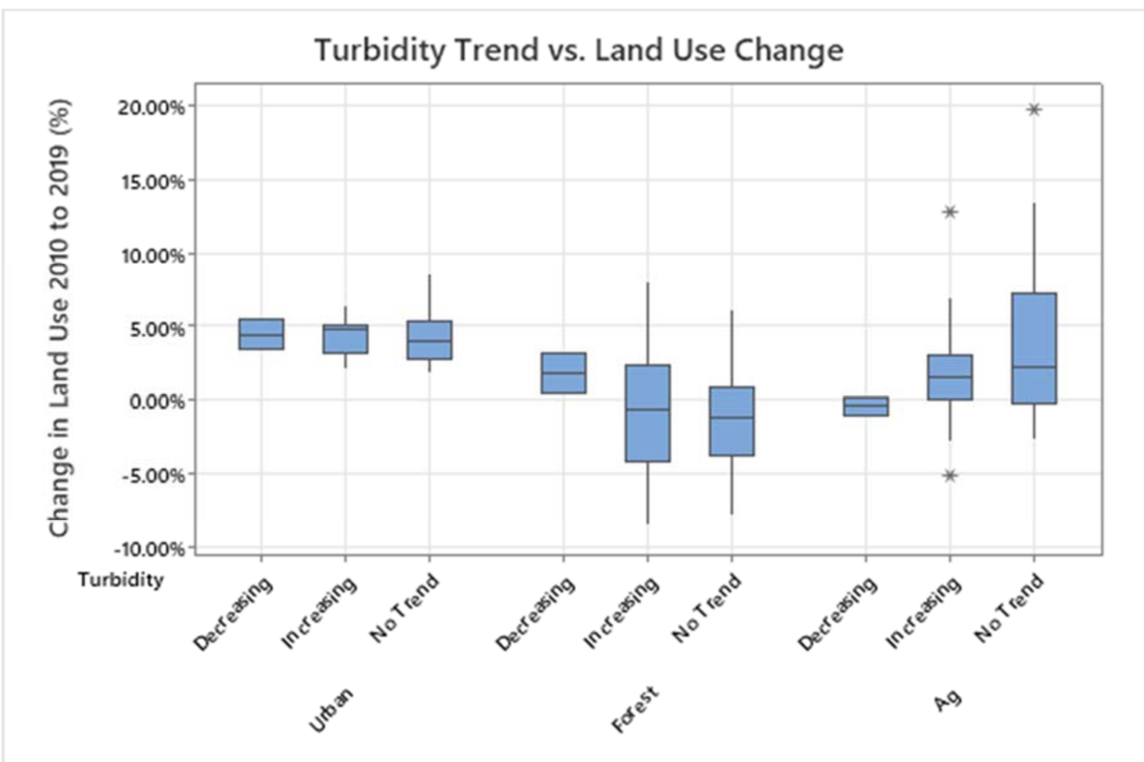

Figure 3. ***Box Plot of Turbidity Trends vs. Land Uses Changes***

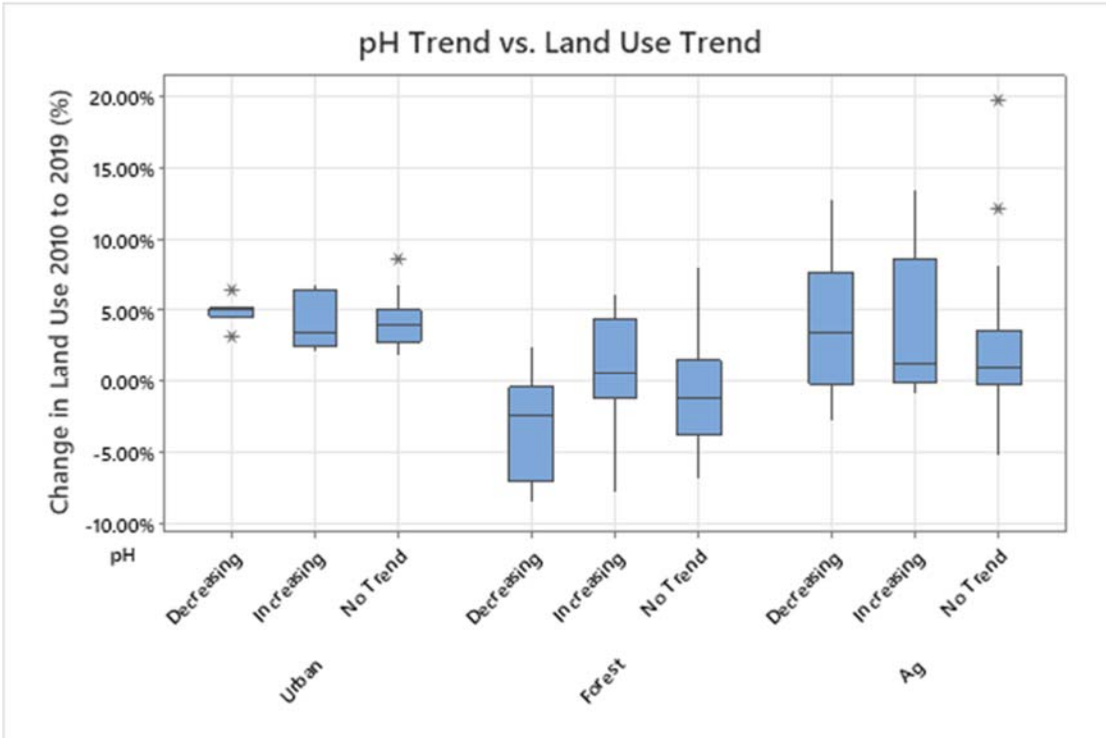

Figure 4. Box Plot of pH Trends vs. Land Uses Changes

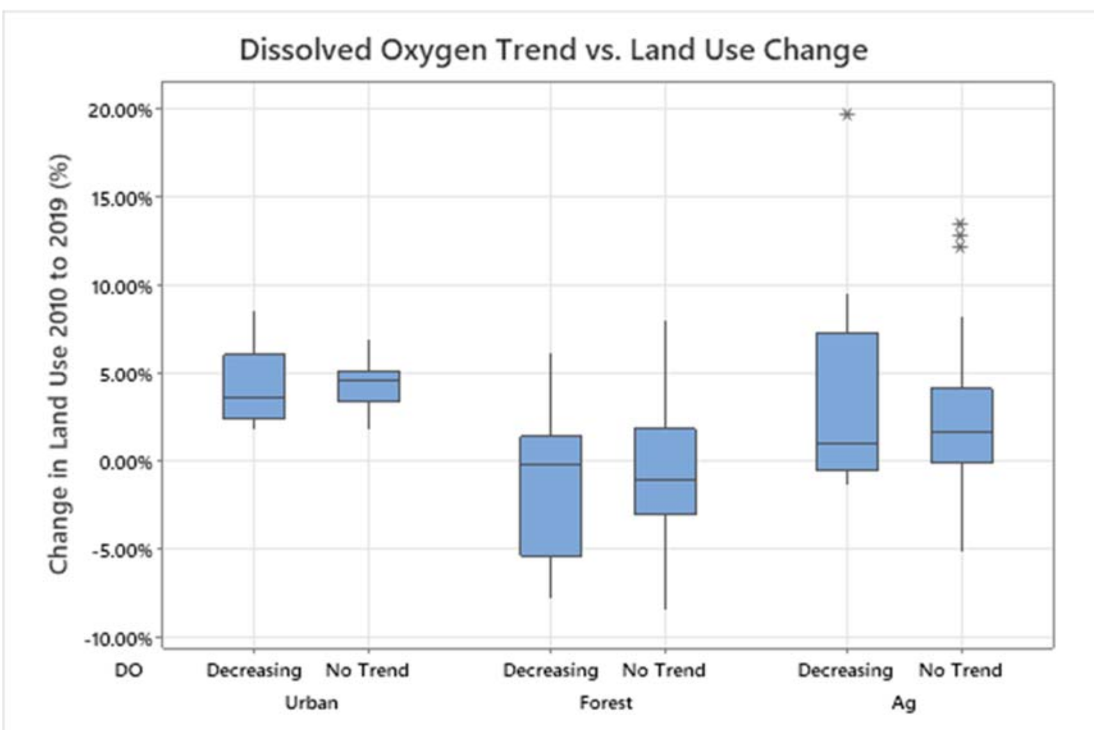

Figure 5. Box Plot of DO Trends vs. Land Uses Changes

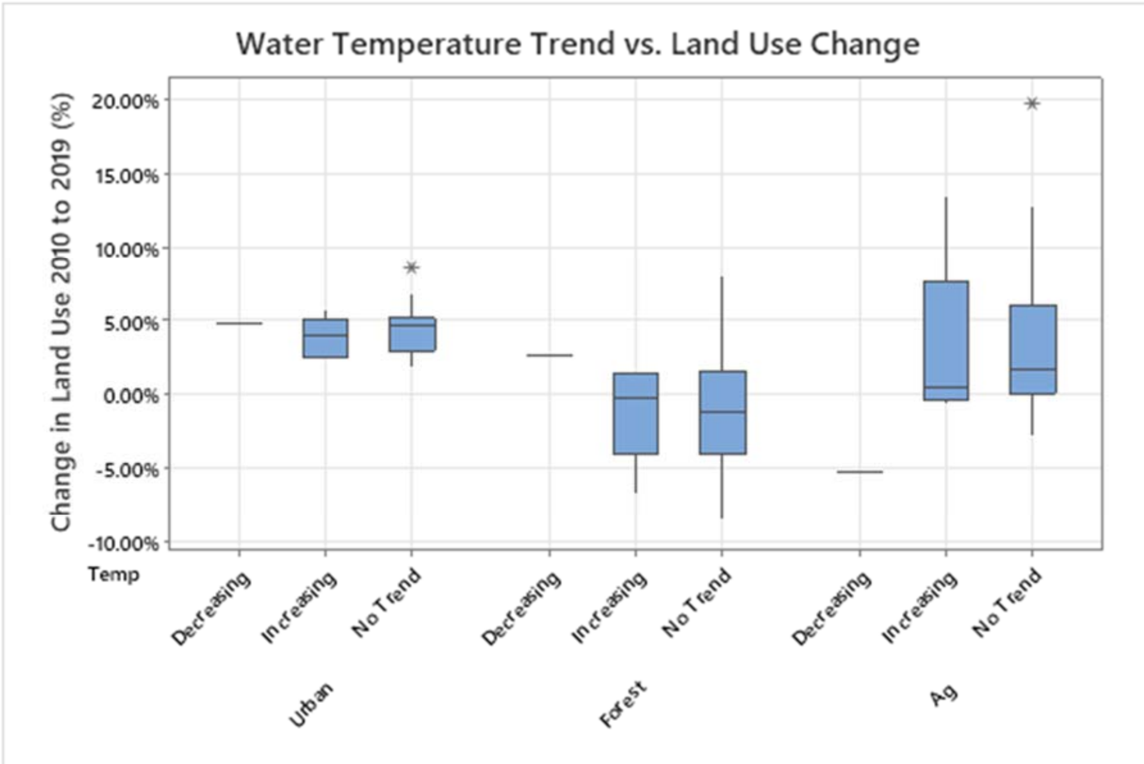

Figure 6. Box Plot of Temperature Trends vs. Land Uses Changes

Water Temperature

There are five CIM stations with increasing water temperature trends and one with a decreasing water temperature trend. Four of the stations (Driftwood Branch Sinnemahoning Creek, Kitchen Creek, Long Run, and Sugar Run) with increasing temperatures are designated as high-quality cold water fisheries. Cold water fish thrive best in water temperature less than 21 degrees Celsius. The percentage of individual readings exceeding 20 degrees Celsius were plotted by year to assess potential impacts to these cold water systems (Figure 7). The data do not show a well-correlated increase in the number of readings exceeding 20 degrees Celsius over the monitoring period (r^2 values ranged from 0.06 to 0.30). The Susquehanna River at Kirkwood (Susq-Kirkwood) CIM station illustrated decreasing water temperatures; however, the river reach is designated as a warm water fishery. This station is located on the mainstem Susquehanna River and drains over 2200 miles; the instream continuous monitoring equipment is located on the river edge and may not reflect the temperature of the entire river.

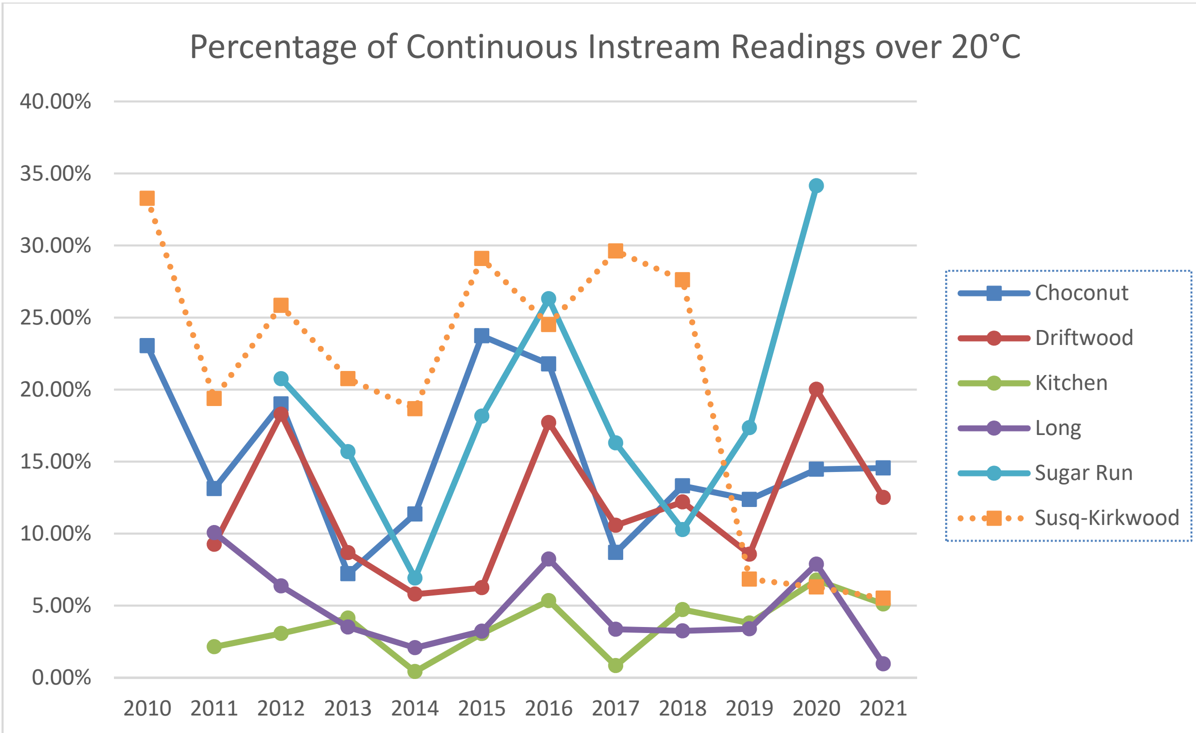

Figure 7. Percentage of Annual Reading over 20°C at Stations with Temperature Trends

Dissolved Oxygen

There are 13 stations with decreasing DO trends: Baker Run, Baldwin Creek, Bowman Creek, Driftwood Branch Sinnemahoning Creek, East Fork First Fork Sinnemahoning, Lackawanna River, Little Clearfield Creek, Little Muncy Creek, Long Run, Marsh Creek–Tioga, Upper Pine Creek, Portage Creek, and South Branch Tunkhannock Creek. Of these, Baldwin Creek, Lackawanna River, and Upper Pine Creek experienced DO levels below the minimum Pennsylvania water quality standard of 5.0 mg; adverse effects on aquatic communities at these stations may be incurred with a continuation of declining conditions.

There were no stations with increasing DO trends. Dissolved oxygen and water temperature have an inverse relationship: as water temperatures rise, DO levels decrease. However, only two of these stations with increasing water temperature trends also illustrated decreasing DO trends (Driftwood Branch Sinnemahoning Creek and Long Run).

pH

Ten stations have decreasing pH trends, while seven stations illustrated increasing pH trends (Table 5). Because the optimal range for pH is between 6 and 9, increasing or decreasing trends can be beneficial or detrimental to water quality. Four of the stations with increasing pH trends have average pH values of 7 or greater (Table 5). These increases are detrimental to stream water quality and three stations of these stations (Little Muncy Creek, Portage Creek, and

Sugar Run) experienced pH conditions exceeding the water quality standard limit of 9. East Fork Sinnemahoning Creek, Moose Creek, and Trout Run have increasing pH trends; however, on average, these sites are acidic, so an increase in pH is considered beneficial. All stations with decreasing pH trends are beneficial to water quality; seven of the 10 stations had pH conditions that exceeded the water quality limit of 9.

Table 5. Mean, Minimum, and Maximum pH Data for Stations with pH Trends

Watershed	Trend	Mean pH	Max pH	Minimum pH	Percentage of data points outside of standard (<6.0/>9.0
Baldwin Creek	Decreasing	7.46	10.21	6.20	0.0/0.3
Catatonk Creek	Decreasing	7.61	8.55	5.37	0.0/0.0
Chest Creek	Decreasing	7.29	8.93	6.13	0.0/0.0
East Fork Sinnemahoning Creek	Increasing	6.68	7.99	5.54	2.4/0.0
Lackawanna River	Decreasing	7.07	10.01	5.50	0.2/1.4
Little Clearfield Creek	Increasing	7.72	8.69	6.08	0.0/0.0
Little Muncy Creek	Increasing	7.42	9.38	5.82	0.0/0.2
Marsh Creek	Decreasing	7.33	9.69	5.35	0.1/0.1
Moose Creek	Increasing	6.40	8.00	4.88	15.4/0.0
Portage Creek	Increasing	7.26	9.84	5.86	0.0/0.7
Sing Sing Creek	Decreasing	7.73	8.92	5.97	0.0/0.0
Starrucca Creek	Decreasing	7.40	9.65	5.08	0.0/1.2
Sugar Run	Increasing	7.36	9.38	5.82	0.0/0.2
Trout Brook	Decreasing	7.73	10.21	5.66	0.0/1.2
Trout Run	Increasing	5.91	8.61	4.19	59.0/0.0
Tuscarora Creek	Decreasing	7.98	10.93	4.00	0.6/3.1
Upper Pine Creek	Decreasing	7.00	8.94	5.23	1.1/0.0

Turbidity

Nineteen stations have significant turbidity trends, with 17 indicating an increase in turbidity. Marsh Creek–Tioga and Pine Creek were the only stations to show a decrease in turbidity. These two stations both had an increase in forest cover; however, urban cover also increased. Agriculture increased in Pine Creek but decreased in Marsh Creek–Tioga. Stations with decreasing turbidity trends experienced a mix of land use changes; no definitive relationship exists between an increase in turbidity and land use change (Figure 4). While more stations with increasing turbidity trends saw an increase in agriculture, an average of about 4 percent, more stations with no turbidity trends also saw increases in agriculture at a rate of almost 6 percent.

A one-way ANOVA was used to determine if stations with increasing, decreasing, or no trend in turbidity conditions had significantly different ($\alpha \leq 0.05$) watershed characteristics (Table 6). A significant difference in percent alluvium (geologic material) was observed for stations with increasing, decreasing, or no turbidity trends (Table 6). Percent glacial till and slope, while not significantly different, had p-values of 0.068 and 0.096, respectively.

Table 6. p-values for Turbidity and Watershed Characteristics

Response:	Drainage Area	Stream Miles	Slope	% Glaciated	% Alluvium	% Glacial Till	Soil Erodibility	Soil Permeability
p-value	0.230	0.238	0.096	0.396	0.012	0.068	0.668	0.463

Specific Conductance

A total of 20 sites exhibited a water quality trend for conductance: 16 stations showed increasing conductance trends and four displayed decreasing conductance trends. Watershed characteristics were compared for watersheds with increasing, decreasing, or no conductance trends. There was no significant difference ($\alpha \leq 0.05$) in watersheds with increasing, decreasing, and no trends for conductance (Table 7). A comprehensive table of watershed characteristics compared to trend direction for all parameters is located in Appendix E.

Table 7. p-values for Specific Conductance and Watershed Characteristics

Response:	Drainage Area	Spudded UNG Wells	# Wells/mi^2	% Glaciated	% Alluvium	% Glacial Till
p-value	0.584	0.825	0.190	0.526	0.925	0.772

MACROINVERTEBRATE RESULTS AT STATIONS WITH WATER QUALITY TRENDS

Macroinvertebrate data have been collected routinely over the past decade at 43 of the 45 sites analyzed for water quality trends. Macroinvertebrate taxa have different water quality tolerances, and changes in water quality can be reflected in shifts in macroinvertebrate assemblages. The objective of this analysis was to examine macroinvertebrate community metrics as well as assemblage structure to identify any patterns or changes that may be co-occurring with water quality trends identified in the broader analysis.

Macroinvertebrates were collected using the PA Freestone IBI Methodology (PADEP, 2013). Abundance data for each sample were used to calculate an IBI score which summarizes the integrity of the sampled macroinvertebrate assemblage based on six metrics that reflect different facets of richness, diversity, and tolerance values. For each of the five continuously measured parameters, increasing, decreasing, and no trend were determined. Aggregate time series plots were used to illustrate fluctuations in IBI scores by year across trend category. The number of samples collected and which individual sites were sampled varied by year but a general pattern is evident. The range of IBI scores over time is consistent across all sites, regardless of increasing, decreasing, or no trend in water quality conditions. This suggests no change in macroinvertebrate community health at these locations (Figures 8-12).

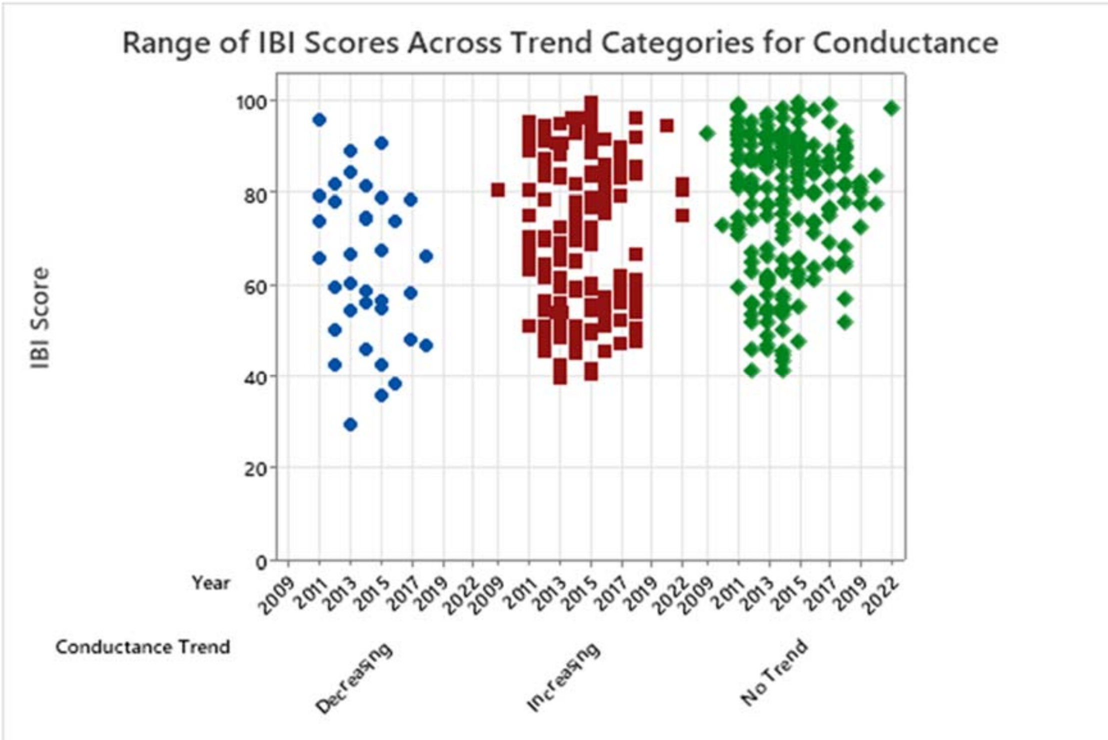

Figure 8. IBI Scores by Year and Conductance Trend Type

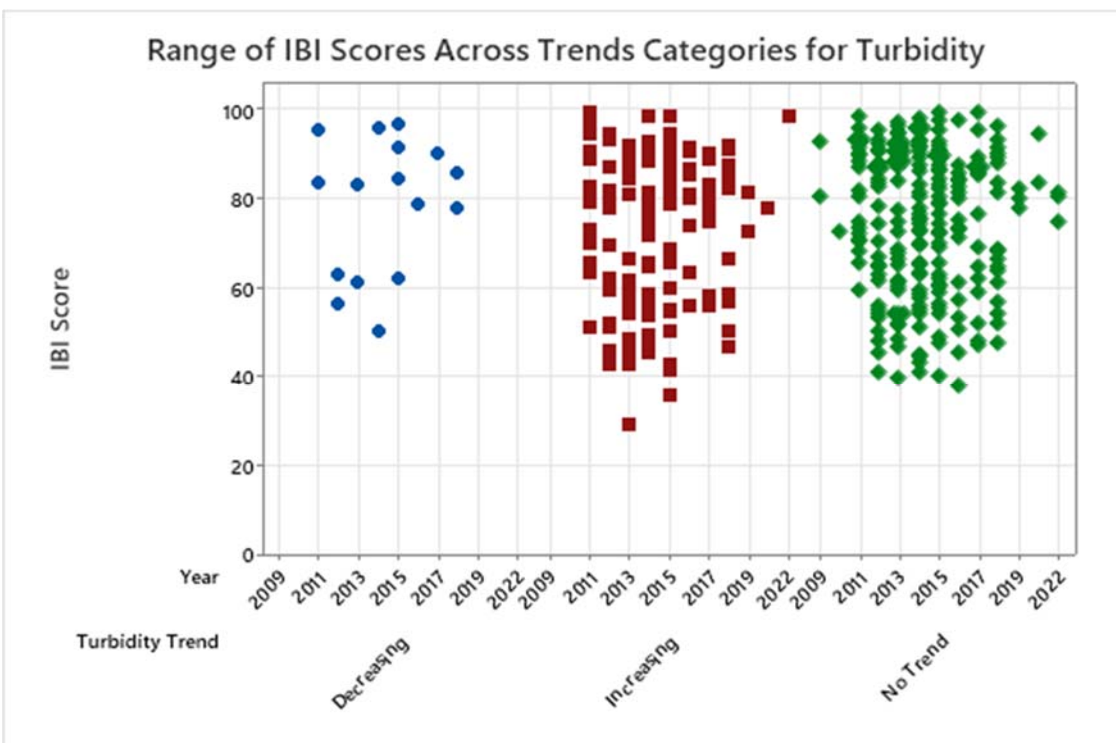

Figure 9. IBI Scores by Year and Turbidity Trend Type

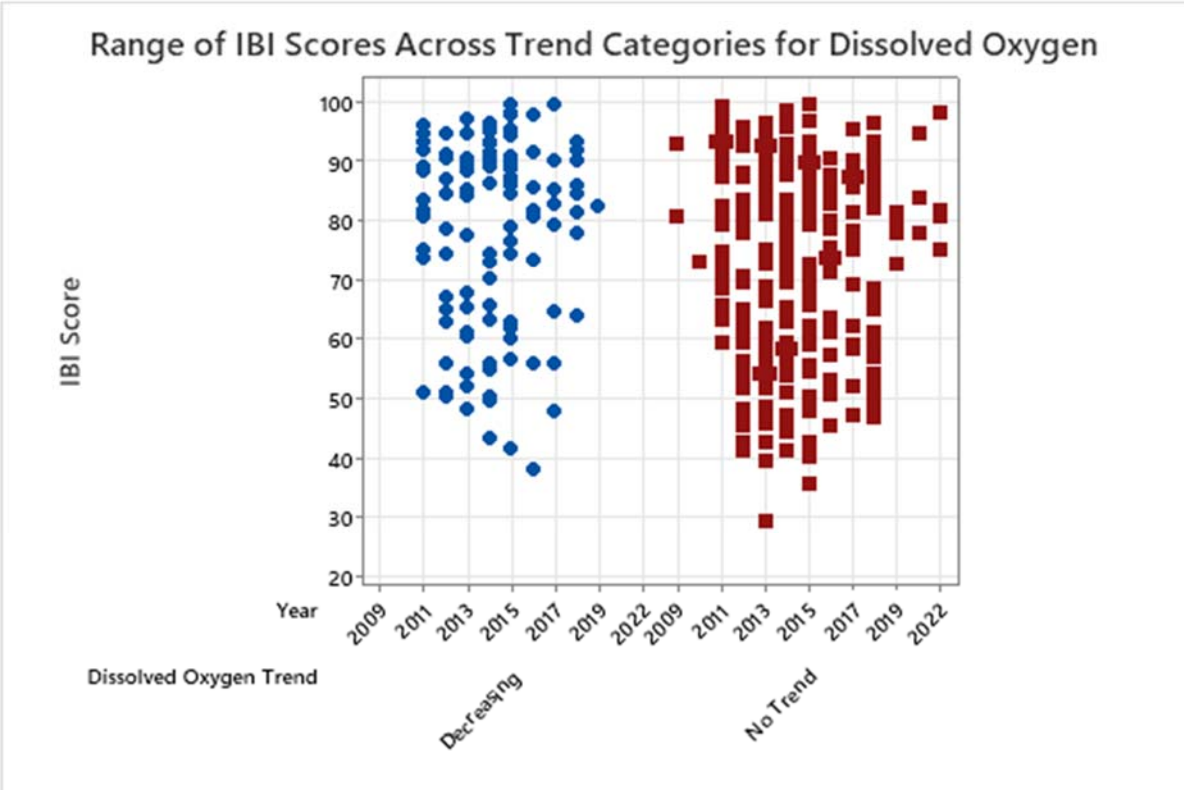

Figure 10. IBI Scores by Year and DO Trend Type

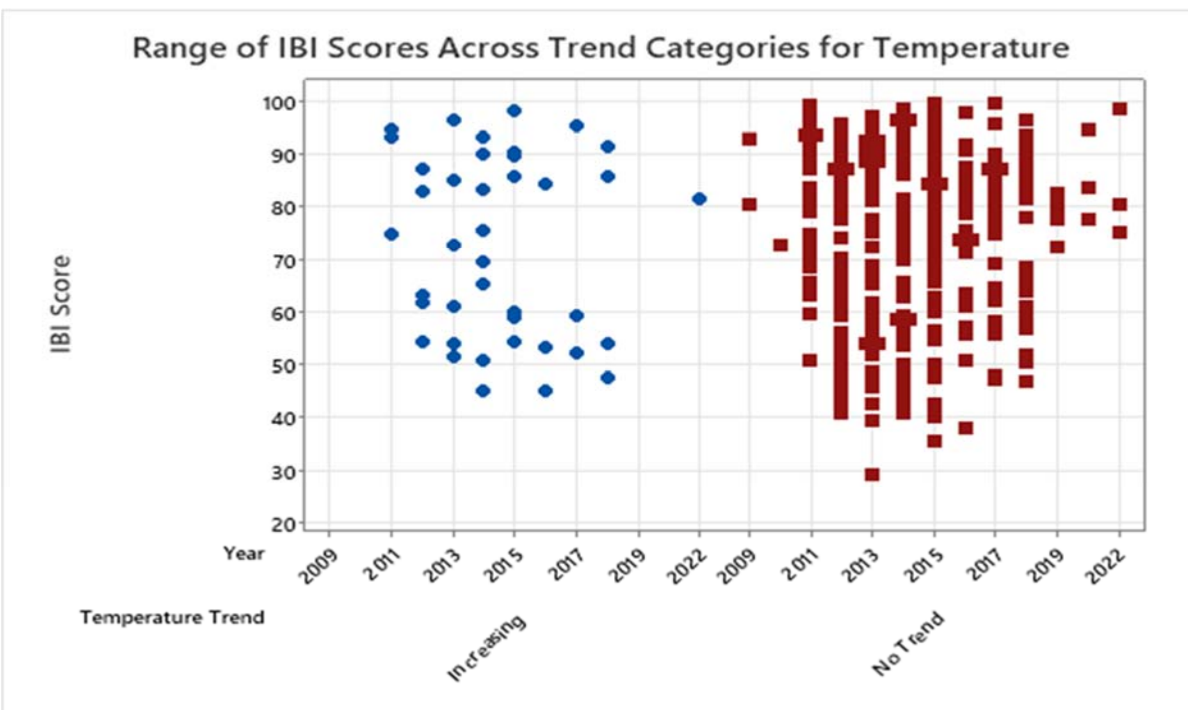

Figure 11. IBI Scores by Year and Temperature Trend Type

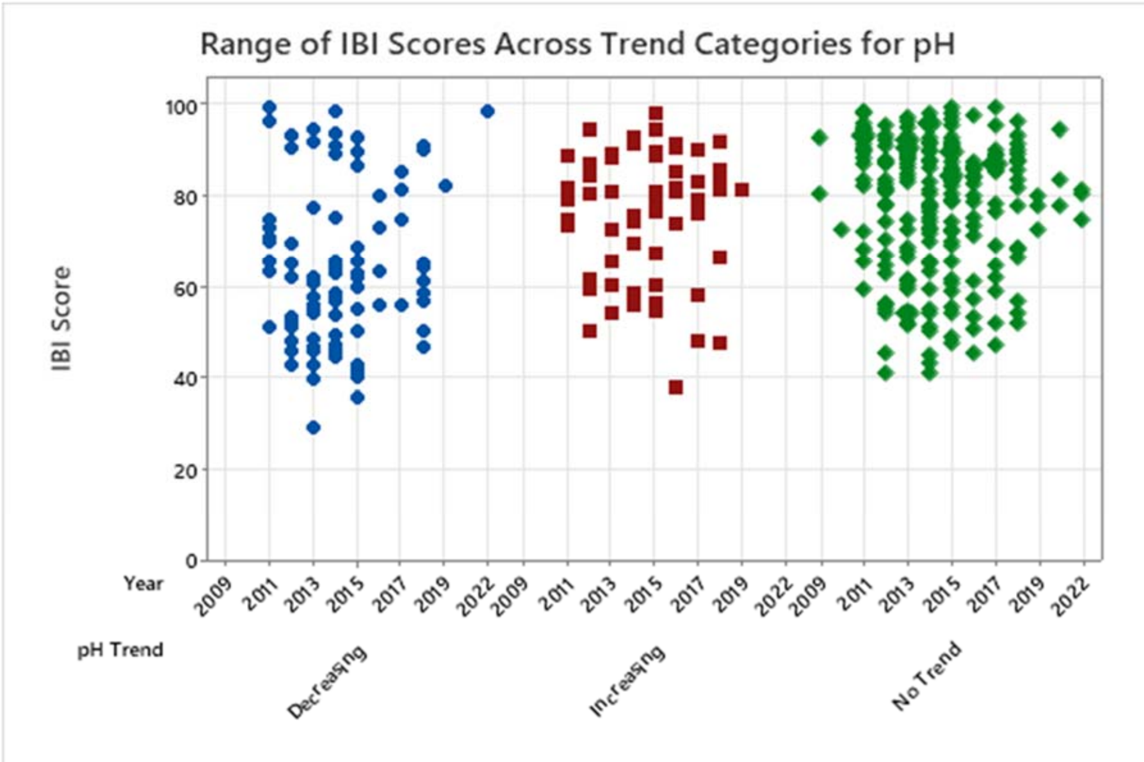

Figure 12. IBI Scores by Year and pH Trend Type

When calculating IBI scores, different combinations of macroinvertebrate taxa can result in similar IBI scores; therefore, it is important to consider changes in taxa composition. The primary method used to visualize changes in taxa composition is the resemblance-based analysis tool, nonmetric multidimensional scaling (nMDS). Each point represents an individual biological sample (in this case macroinvertebrates). Similarity is based on taxa and abundance, and the closer two points are to each other, the more similar they are. If sequential years are clustered together or the trajectory wraps back in on itself, the community may have slight annual variations but no consistent pattern of change. No adverse impacts to macroinvertebrate taxa were observed for sites experiencing water quality trends. Large scale differences were driven primarily by land use (p=0.001) and watershed size (p=0.010), not changes in water quality.

Twenty of the 43 sites had a trend for specific conductivity, four sites were significantly decreasing in conductance, and 16 sites were increasing. Increasing conductivity can be linked to almost any anthropogenic influence, including urban development, industrial discharges, agricultural uses, and natural resource extraction. Unconventional natural gas (UNG) well density (wells/square mile) is one surrogate used to examine potential UNG impacts within a watershed. Well density ranges from 0-4.3 wells/mi^2 in the 43 watersheds. Of the 13 watersheds with greater than 1.0 well/mi^2, eight of those streams showed a significant trend in specific conductivity, with seven increasing and one decreasing. However, some watersheds with no UNG development also had conductivity trends, while others with high well density showed no trends. Despite statistically significant changes in conductivity in these streams, no significant ecological shifts were observed.

A trajectory line connecting samples chronologically was added to the nMDS plot of these eight sites that have a well density >1.0 wells/mi^2 as well as a significant conductivity trend (Figure 13). Trout Run (TROT) continuous data showed decreasing conductance over the past decade and increasing conductivity was observed at the remaining seven sites. The sampling timeframe can also influence the type of taxa that are collected. For example, taxa such as blackflies and a variety of mayflies are much more common in the spring while winter stoneflies are more prevalent in the fall. In Figure 17, sites with samples collected in or around the same season grouped together for each site, which suggests seasonality contributed to the main differences in samples at the same site, rather than changing water quality.

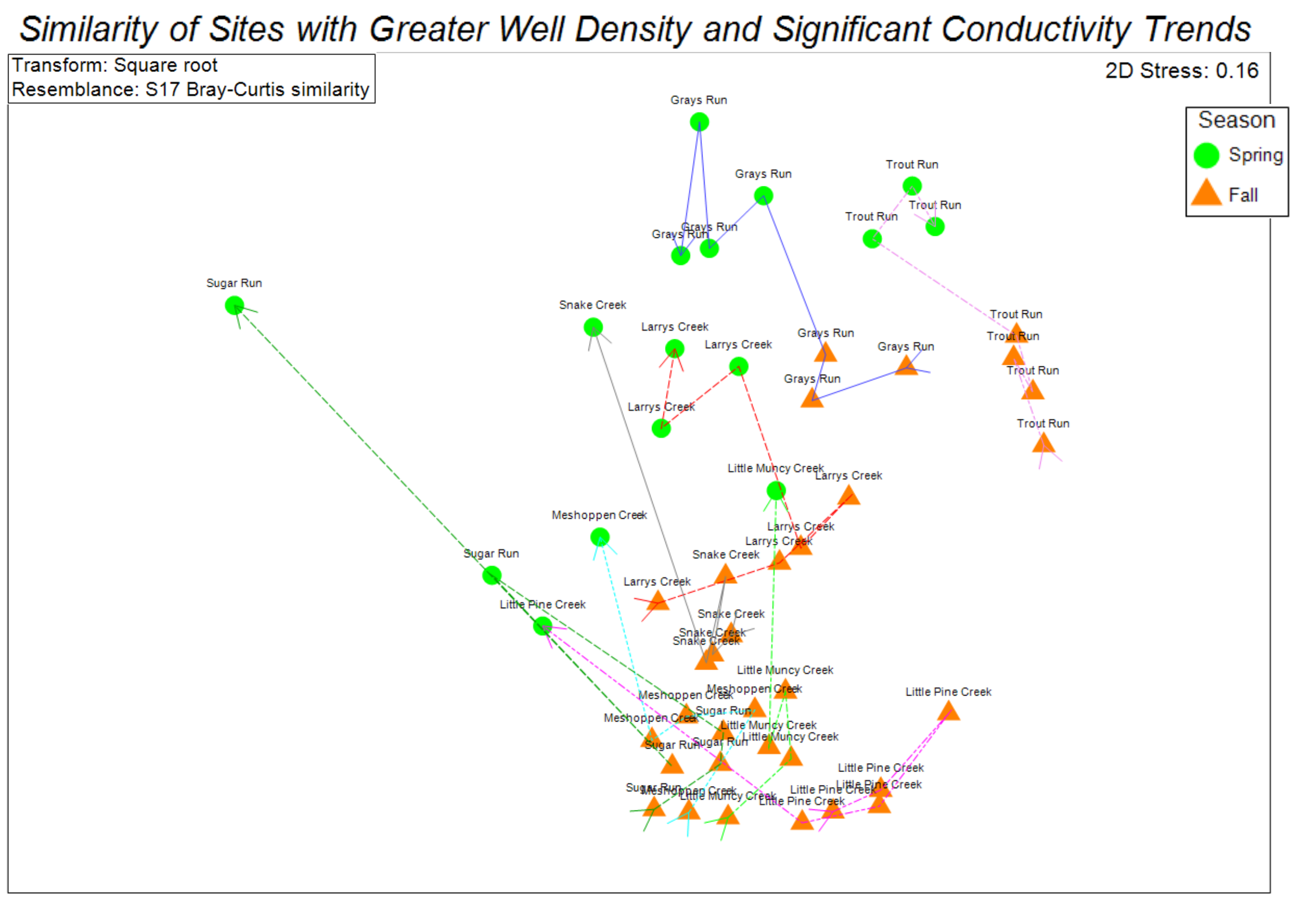

Figure 13. Sites with Greater Well Density and Significant Increasing Conductance Trends (Trout Run conductance is decreasing, while all the others are increasing)

Statistically significant (p=0.001) differences were observed between biological communities in streams that had no trend, increasing, or decreasing specific conductivity. The biggest differences were between those sites with no trend and those with a decreasing conductivity. Decreasing conductivity is generally considered a good sign for stream health.

Counter to the expected biological response, the main differences in taxa between sites with increasing and decreasing conductance was the occurrence of more sensitive taxa, such as *Ephemerella, Epeorus,* and *Paraleptophlebia* at sites with increasing conductivity.

Changes in stream temperatures could impact macroinvertebrate community structure as some taxa are generally classified as cold or cool water taxa and would not be expected to be found in warmer streams. There was no significant difference (p=0.915) between macroinvertebrate assemblages in streams that were getting warmer and those that had no temperature trend.

Dissolved oxygen can impact aquatic biological communities directly as it is required for breathing and indirectly as poorer habitat (i.e., pool instead of riffle, fine sediments instead of clean cobble) is often co-located with stream reaches with lower dissolved oxygen. No significant difference (p=0.419) was seen in any of the macroinvertebrate communities across sites with a decreasing trend or sites with no dissolved oxygen trend.

Significant differences (p=0.01) were found between macroinvertebrate communities that had no trend, increasing, or decreasing pH. The biggest differences were between sites with no trends and those with increasing pH, which were nearly 70 percent dissimilar. It appears, however, that the biggest differences in taxa are simply different genera of mayflies with very similar tolerance values in each group. For example, at sites with no trend in pH, on average, three *Ephemerella* were collected compared to one at sites where pH was rising, but at the site where pH was rising, an average of three *Epeorus* were found compared to one at sites with no trend.

A small but significant difference (p=0.001) was seen when comparing macroinvertebrate communities at streams with no turbidity trend, increasing turbidity and decreasing turbidity. However, no difference was seen between sites where turbidity was increasing and those where it was decreasing. The only taxa differences were between sites with no trend compared to increasing and decreasing turbidity, which were both about 60 percent dissimilar. However, once again the taxa differences were largely inconclusive with no obvious shifts in sensitive taxa where turbidity is increasing.

CONCLUSIONS

The Susquehanna River Basin Commission began continuous water quality monitoring in 2003 on large river systems and greatly expanded the continuous water quality monitoring in 2010 to include headwater streams in the northern half of the Susquehanna River Basin. Parameters continuously monitored include specific conductance (conductance), pH, dissolved oxygen, water temperature, and turbidity. At the conclusion of 2021, there were 45 stations with 10 or more years of continuous data to assess water quality trends. At least one trending water quality parameter was observed at 39 individual stations, with a total of 75 water quality trends (out of a possible 225) being observed (Table 8).

Table 8. Water Quality Trends by Parameter

PARAMETER	INCREASING	DECREASING
Specific Conductance	16	4
pH	7	10
Dissolved Oxygen	0	13
Temperature	5	1
Turbidity	17	2

Macroinvertebrate samples were collected routinely over a 10-year period at CIM stations. IBI scores and assemblage structure were examined in context to water quality trends. While small differences and natural variations were observed, none of the 43 streams showed clear evidence of biologic decline, despite the statistically significant water quality trends.

Several notable findings from the water quality trends and biological analyses were observed:

- Overall, increasing or decreasing water quality trends were not statistically described by changes in forest, agriculture, and or urban land use between 2010 to 2019 ($\alpha \leq 0.05$).
- There is no correlation (r^2 ranging from 0.06 to 0.30) in the percentage of water temperature readings over 20°C at stations with increasing water temperature trends.
- Dissolved oxygen and water temperature typically have an inverse relationship; however, only two stations with increasing water temperature also showed the expected decreasing dissolved oxygen concentrations (Driftwood Branch Sinnemahoning Creek and Long Run).
- Baldwin Creek, Lackawanna River, and Upper Pine Creek had decreasing dissolved oxygen concentrations, with dissolved oxygen levels below the minimum Pennsylvania water quality standard of 5.0 mg/l; these stations could be targeted for continued biological monitoring.
- pH showed increasing trends at seven stations: three of the watersheds are acidic, therefore, an increase in pH would be beneficial for the stream.
- Percent alluvium in a watershed was significantly different in watersheds with increasing, decreasing, or no turbidity trends.
- No watershed characteristics were significantly different among stations with increasing, decreasing, or no conductance trends.
- There is no significant difference in IBI scores for stations with increasing or decreasing turbidity or conductance trends. However, sites with increasing conductivity conditions had significantly ($p=0.001$) different taxa (sensitive mayflies) than those with no change in conductance; this is counter to the expected response.

- Of the 13 watersheds with greater than 1.0 well/mi^2, eight of those streams showed a significant trend in specific conductivity, with seven increasing and one decreasing. However, a number of sites with well density greater than 1.0 well/mi^2 showed no changes in any of the five parameters and sites with no drilling had multiple parameters with significant trends in both directions.

Streams are very resilient and although 10 years of monitoring leads to a robust dataset, it is critical to continue monitoring both water quality and biologic communities in these streams. It is important to note that trends are calculated using a standard measure of statistical significance. This difference may not always equate with an ecological significance to aquatic communities (i.e., a change in conductance may be mathematically significant but for the aquatic ecosystems that live in the stream, the change may be inconsequential). An additional resource highlighting the CIM water quality trends can be found at: https://storymaps.arcgis.com/stories/31b7c09d2cba43 cd9e5333752b6e1b62.

NEXT STEPS

The Commission will continue to examine water quality trends at stations as they reach the 10-year mark. For stations where water quality trends have been analyzed, they will be re-examined after each additional five-year datasets are collected. The extended timeframes will allow for more robust analyses, and also allow additional supplemental data, such as discrete water chemistry samples, to be collected in each watershed. In addition to revisiting the trends, any changes to water quality conditions will also be evaluated against the aquatic biological community data collected within the monitored watersheds. It is especially important to continue frequent biologic monitoring in streams where temperature and/or specific conductivity is increasing, as those two parameters are the most likely to result in observable shifts in macroinvertebrate assemblages. The Commission is also evaluating the location of current CIM stations and potential new stations throughout the basin. New sites may include very small headwater streams, urban streams, and nested stations within watersheds.

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APPENDIX A

Period of Data Collection and Telemetry Source by Station

Site	Stream Name	Site ID[1]	Period of Data Collection
*Apalachin Creek near Apalachin, NY	Apalachin Creek	9	12/14/2010 – 12/31/2021
+Baker Run near Glen Union, PA	Baker Run	37	9/19/2011 – 12/31/2021
*Baldwin Creek near Loman, NY	Baldwin Creek	7	12/7/2010 – 12/31/2021
*Blockhouse Creek near English Center, PA	Blockhouse Creek	24	6/4/2010 – 12/31/2021
+Bobs Creek near Pavia, PA	Bobs Creek	43	3/30/2010 – 12/31/2021
*Bowman Creek near Noxen, PA	Bowman Creek	34	4/1/2010 – 12/31/2021
*Catatonk Creek near Spencer, NY	Catatonk Creek	5	12/16/2010 – 12/31/2021
*Chemung River near West Elmira, NY	Chemung River	45	1/1/2010 – 12/31/2021
+Cherry Valley Creek near Middlefield, NY	Cherry Valley Creek	2	12/2/2010 – 12/31/2021
*Chest Creek near Patton, PA	Chest Creek	42	9/21/2010 – 12/31/2021
*Choconut Creek near Vestal Center, NY	Choconut Creek	10	1/27/2010 – 12/31/2021
*Driftwood Branch near Lockwood, PA	Driftwood Branch	28	5/19/2011 – 12/31/2021
+East Fork Sinnemahoning Creek near Logue, PA	East Fork First Fork Sinnemahoning Creek	26	5/25/2011 – 12/31/2021
*Grays Run near Gray, PA	Grays Run	30	5/5/2011 – 12/31/2021
+Hicks Run near Hicks Run, PA	Hicks Run	33	6/16/2011 – 12/31/2021
+*Kitchen Creek near Huntington Mills, PA	Kitchen Creek	35	10/30/2010 – 12/31/2021
*Lackawanna River near Forest City, PA	Lackawanna River	13	7/14/2010 – 12/31/2021
+Larrys Creek near Salladasburg, PA	Larrys Creek	31	3/30/2010 – 12/31/2021
+*Little Clearfield Creek near Dimeling, PA	Little Clearfield Creek	41	4/28/2010 – 12/31/2021
*Little Mehoopany Creek near North Mehoopany, PA	Little Mehoopany Creek	22	9/8/2010 – 12/31/2021
+*Little Muncy Creek near Moreland, PA	Little Muncy Creek	36	8/6/2010 – 12/31/2021
+*Little Pine Creek near Waterville, PA	Little Pine Creek	32	7/1/2011 – 12/31/2021
*Long Run near Gaines, PA	Long Run	17	12/17/2010 – 12/31/2021
*Loyalsock Creek near Ringdale, PA	Loyalsock Creek	29	6/3/2010 – 12/31/2021
+Marsh Creek near Ansonia Station, PA	Marsh Creek	16	6/9/2011 – 12/31/2021
*Marsh Creek near Blanchard, PA	Marsh Creek	38	6/30/2010 – 12/31/2021
*Meshoppen Creek near Kaiserville, PA	Meshoppen Creek	14	1/27/2010 – 12/31/2021
*Moose Creek near Plymtonville, PA	Moose Creek	40	5/2/2011 – 12/31/2021
*Nanticoke Creek near Maine, NY	Nanticoke Creek	4	12/16/2010 – 12/31/2021
+*Ninemile Run near Walton, PA	Ninemile Run	19	5/25/2011 – 12/31/2021
+Pine Creek near Blackwell, PA	Pine Creek	25	8/8/2011 – 12/31/2021
*Portage Creek near Emporium, PA	Portage Creek	27	8/22/2011 – 12/31/2021
*Sangerfield River near Poolville, NY	Sangerfield River	1	12/2/2010 – 12/31/2021
*Sing Sing Creek near Big Flats, NY	Sing Sing Creek	6	12/1/2010 – 12/31/2021
*Snake Creek near Lawsville Center, PA	Snake Creek	11	6/2/2010 – 12/31/2021
*South Branch Tunkhannock Creek near La Plume, PA	South Branch Tunkhannock Creek	21	7/1/2010 – 12/31/2021
*Starrucca Creek near Stevens Point, PA	Starrucca Creek	12	7/1/2010 – 12/31/2021
*Sugar Run near Sugar Run, PA	Sugar Run	23	9/21/2011 – 12/31/2021
*Susquehanna River near Kirkwood, NY	Susquehanna River	44	1/1/2010 – 12/31/2021
+Tioga River near Fall Brook, PA	Tioga River	15	6/23/2010 – 12/31/2021
*Trout Brook near McGraw, NY	Trout Brook	3	12/16/2010 – 12/31/2021
*Trout Run near Shawville, PA	Trout Run	39	4/28/2010 – 12/31/2021
*Tuscarora Creek near Woodhull, NY	Tuscarora Creek	8	12/16/2010 – 12/31/2021
+*Upper Pine Creek near Telescope, PA	Pine Creek	18	5/25/2011 – 12/31/2021
*West Branch Pine Creek near Galeton, PA	West Branch Pine Creek	20	6/3/2010 – 12/31/2021

[1]Matches ID on Figure 1
*Sites with cellular telemetry
+Sites with satellite telemetry
+*Sites started at satellite telemetry and switched to cellular telemetry in 2015

APPENDIX B

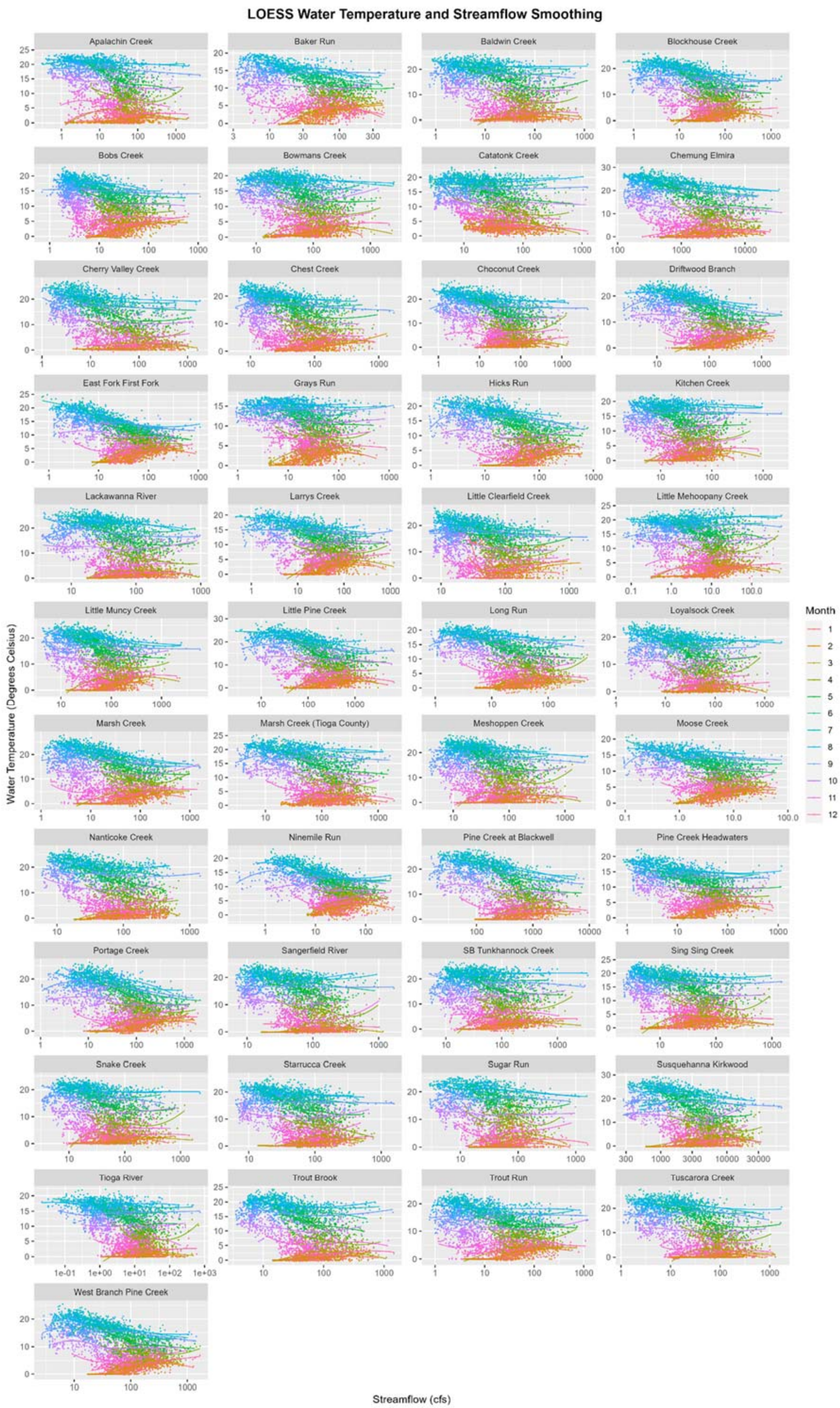
USGS Reference Gage Selection for Estimated Daily Flow Timeseries

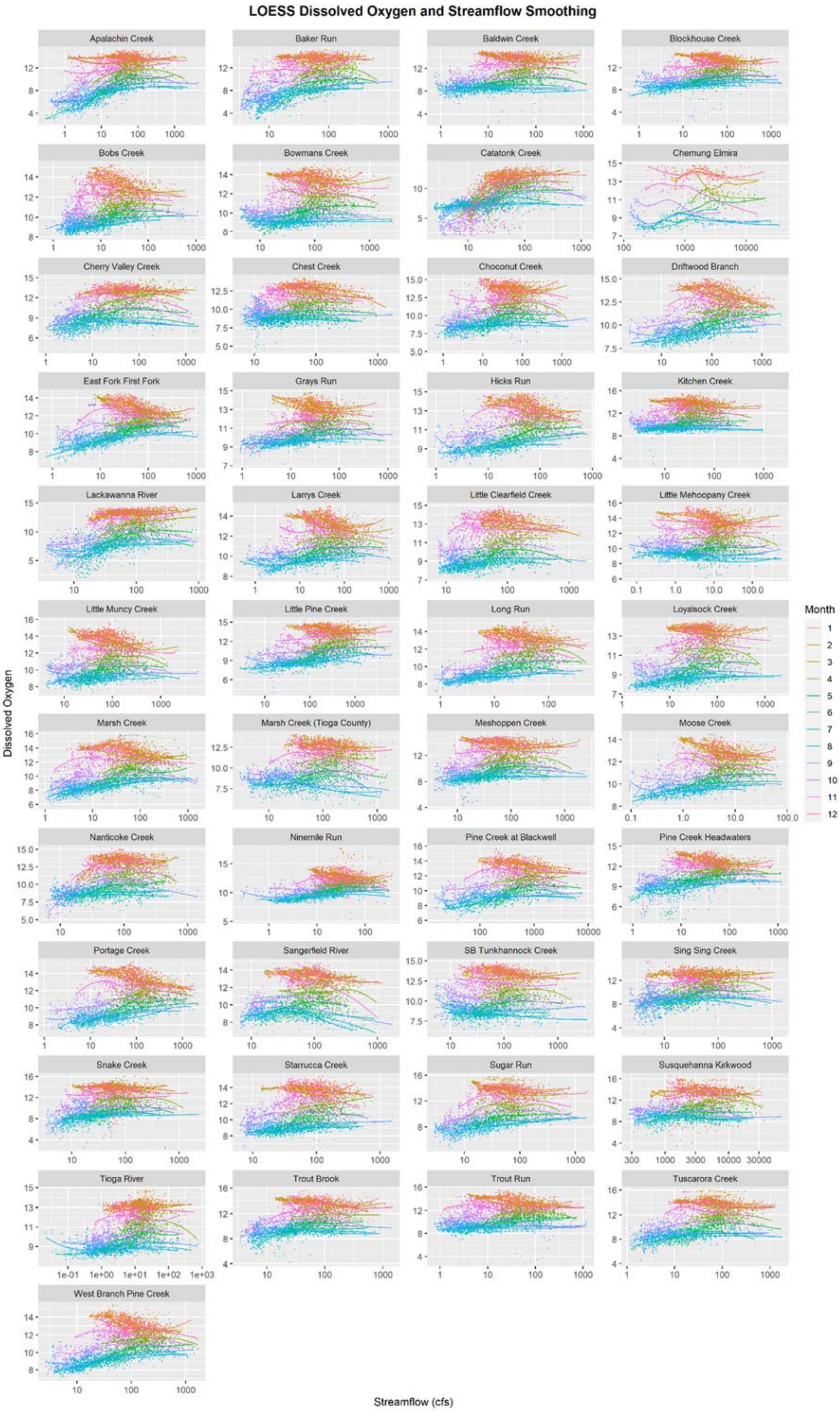
CIM Station	CIM Drainage Area (mi^2)	USGS Site Number	USGS Gage Name	USGS Gage Drainage Area	Drainage Area Ratio	Flow Correlation R^2	Distance from USGS Gage (watershed outlet) (mi)
Apalachin Creek	43	01531908	Towanda Creek Near Franklindale, PA	112	0.38	0.79	34
Baker Run	35	01547950	Beech Creek At Monument, PA	152	0.23	0.95	10
Baldwin Creek	36	01518862	Cowanesque River at Westfield, PA	91	0.39	0.86	43
Blockhouse Creek	38	01549500	Blockhouse Creek Near English Center, PA	38	1.00	0.94	0
Bobs Creek	17	01560000	Dunning Creek At Belden, PA	172	0.10	0.93	14
Bowmans Creek	54	01539000	Fishing Creek Near Bloomsburg, PA	274	0.20	0.89	32
Catatonk Creek	30	04233300	Sixmile Creek At Bethel Grove, NY	39	0.78	0.85	14
Chemung Elmira	2162	01529950	Chemung River at Corning, NY	2006	1.08	NA	12
Cherry Valley Creek	47	01349150	Canajoharie Creek Near Canajoharie, NY	60	0.78	0.76	15
Chest Creek	39	01541000	West Branch Susquehanna River At Bower, PA	315	0.12	0.94	18
Choconut Creek	38	01532000	Towanda Creek Near Monroeton, PA	215	0.18	0.82	32
Driftwood Branch	83	01543000	Driftwood Branch Sinnemahoning Creek At Sterling Run, PA	272	0.31	0.93	9
East Fork First Fork	30	01543693	East Fork Sinnemahoning Creek at Wharton Township, PA	49	0.61	0.97	4
Grays Run	20	01550000	Lycoming Creek Near Trout Run, PA	173	0.11	0.93	1
Hicks Run	34	01543500	Sinnemahoning Creek At Sinnemahoning, PA	685	0.05	0.87	8
Kitchen Creek	20	01539000	Fishing Creek Near Bloomsburg, PA	274	0.07	0.85	15
Lackawanna River	39	01534300	Lackawanna River near Forest City, PA	39	1.00	NA	0
Larrys Creek	29	01549500	Blockhouse Creek near English Center, PA	38	0.77	NA	10
Little Clearfield Creek	44	01541000	West Branch Susquehanna River At Bower, PA	315	0.14	0.94	15
Little Mehoopany Creek	11	01531908	Towanda Creek Near Franklindale, PA	112	0.10	0.87	28
Little Muncy Creek	52	01539000	Fishing Creek Near Bloomsburg, PA	274	0.19	0.90	13
Little Pine Creek	180	01549500	Blockhouse Creek Near English Center, PA	38	4.78	0.93	13
Long Run	21	01548500	Pine Creek at Cedar Run, PA	604	0.03	0.86	17

CIM Station	CIM Drainage Area (mi^2)	USGS Site Number	USGS Gage Name	USGS Gage Drainage Area	Drainage Area Ratio	Flow Correlation R^2	Distance from USGS Gage (watershed outlet) (mi)
Loyalsock Creek	27	01552500	Muncy Creek Near Sonestown, PA	24	1.13	0.86	13
Marsh Creek	44	01547700	Marsh Creek at Blanchard, PA	44	1.00	NA	0
Marsh Creek (Tioga County)	78	01548500	Pine Creek at Cedar Run, PA	604	0.13	0.72	17
Meshoppen Creek	52	01534000	Tunkhannock Creek Near Tunkhannock, PA	383	0.14	0.88	6
Moose Creek	7	01543500	Sinnemahoning Creek At Sinnemahoning, PA	685	0.01	0.83	26
Nanticoke Creek	48	01512500	Chenango River Near Chenango Forks, NY	1483	0.03	0.82	11
Ninemile Run	16	03007800	Allegheny River At Port Allegany. PA	248	0.07	0.87	27
Pine Creek at Blackwell	385	01548500	Pine Creek at Cedar Run, PA	604	0.64	NA	8
Pine Creek Headwaters	36	01518862	Cowanesque River At Westfield, PA	91	0.39	0.73	15
Portage Creek	71	01542810	Waldy Run Near Emporium, PA	5	13.47	0.96	6
Sangerfield River	53	01505000	Chenango River At Sherburne, NY	263	0.20	0.97	7
SB Tunkhannock Creek	70	01534000	Tunkhannock Creek Near Tunkhannock, PA	383	0.18	0.89	6
Sing Sing Creek	36	01516350	Tioga River Near Mansfield, PA	153	0.23	0.88	23
Snake Creek	45	01534000	Tunkhannock Creek Near Tunkhannock, PA	383	0.12	0.85	26
Starrucca Creek	52	01503000	Susquehanna River at Conklin, NY	2232	0.02	0.90	15
Sugar Run	34	01552000	Loyalsock Creek At Loyalsockville, PA	435	0.08	0.88	39
Susquehanna Kirkwood	2232	01503000	Susquehanna River at Conklin, NY	2232	1.00	NA	4
Tioga River	14	01516500	Corey Creek Near Mainesburg, PA	12	1.11	0.89	8
Trout Brook	36	01510000	Otselic River at Cincinnatus, NY	147	0.25	0.92	11
Trout Run	33	01547700	Marsh Creek At Blanchard, PA	44	0.74	0.90	39
Tuscarora Creek	53	01518862	Cowanesque River At Westfield, PA	91	0.58	0.91	13
West Branch Pine Creek	70	01548500	Pine Creek At Cedar Run, PA	604	0.12	0.90	18

APPENDIX C

LOESS Regressions for Water Quality Parameters and Streamflow


LOESS Water Temperature and Streamflow Smoothing
Apalachin Creek
Baker Run
Baldwin Creek
Blockhouse Creek
Bobs Creek
Bowmans Creek
Catatonk Creek
Chemung Elmira
Cherry Valley Creek
Chest Creek
Choconut Creek
Driftwood Branch
East Fork First Fork
Grays Run
Hicks Run
Kitchen Creek
Lackawanna River
Larrys Creek
Little Clearfield Creek
Little Mehoopany Creek
Little Muncy Creek
Little Pine Creek
Long Run
Loyalsock Creek
Marsh Creek
Marsh Creek (Tioga County)
Meshoppen Creek
Moose Creek
Nanticoke Creek
Ninemile Run
Pine Creek at Blackwell
Pine Creek Headwaters
Portage Creek
Sangerfield River
SB Tunkhannock Creek
Sing Sing Creek
Snake Creek
Starrucca Creek
Sugar Run
Susquehanna Kirkwood
Tioga River
Trout Brook
Trout Run
Tuscarora Creek
West Branch Pine Creek
Water Temperature (Degrees Celsius)
Streamflow (cfs)
Month
1
2
3
4
5
6
7
8
9
10
11
12


LOESS Dissolved Oxygen and Streamflow Smoothing
Apalachin Creek
Baker Run
Baldwin Creek
Blockhouse Creek
Bobs Creek
Bowmans Creek
Catatonk Creek
Chemung Elmira
Cherry Valley Creek
Chest Creek
Choconut Creek
Driftwood Branch
East Fork First Fork
Grays Run
Hicks Run
Kitchen Creek
Lackawanna River
Larrys Creek
Little Clearfield Creek
Little Mehoopany Creek
Little Muncy Creek
Little Pine Creek
Long Run
Loyalsock Creek
Marsh Creek
Marsh Creek (Tioga County)
Meshoppen Creek
Moose Creek
Nanticoke Creek
Ninemile Run
Pine Creek at Blackwell
Pine Creek Headwaters
Portage Creek
Sangerfield River
SB Tunkhannock Creek
Sing Sing Creek
Snake Creek
Starrucca Creek
Sugar Run
Susquehanna Kirkwood
Tioga River
Trout Brook
Trout Run
Tuscarora Creek
West Branch Pine Creek
Dissolved Oxygen
Streamflow (cfs)
Month
1
2
3
4
5
6
7
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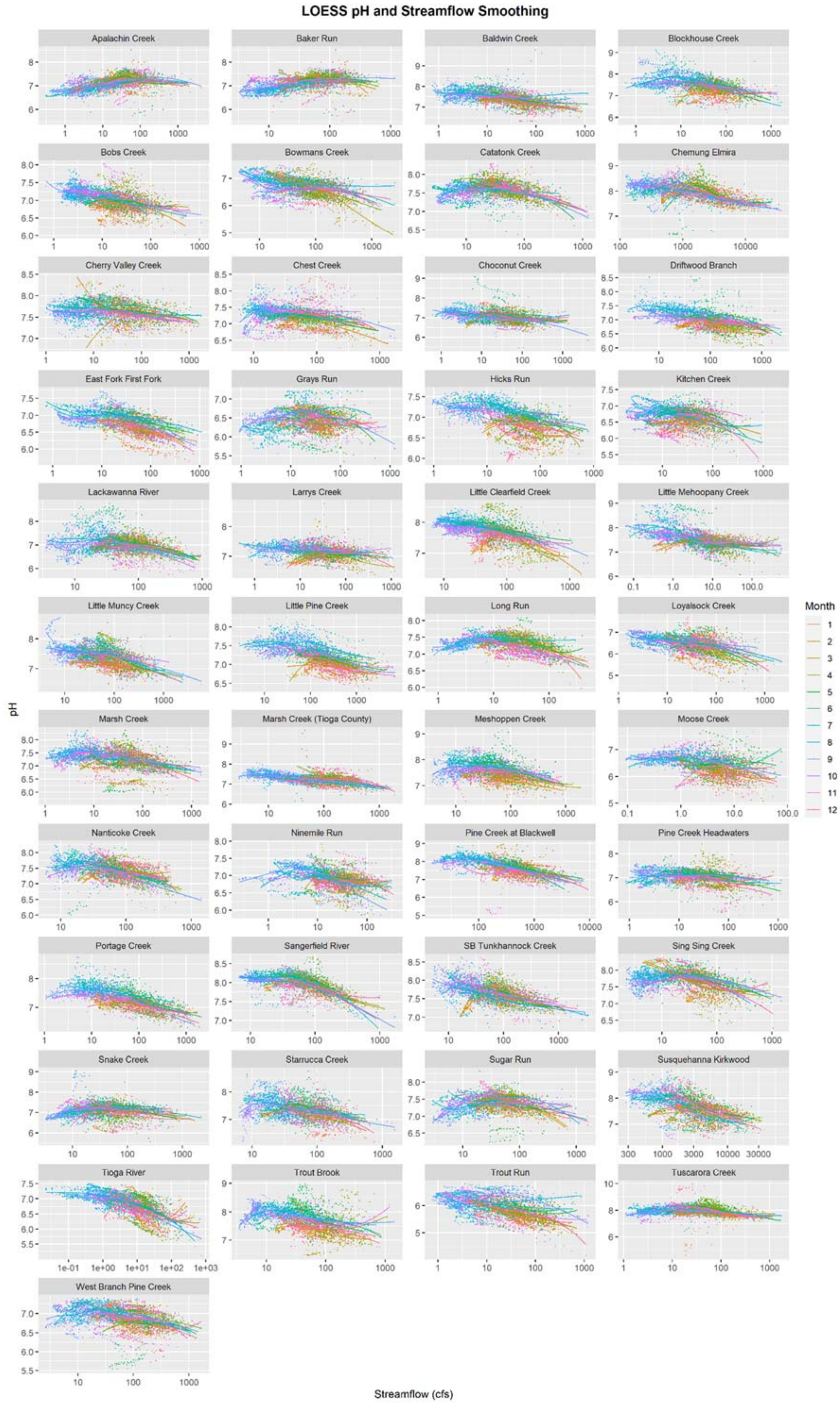
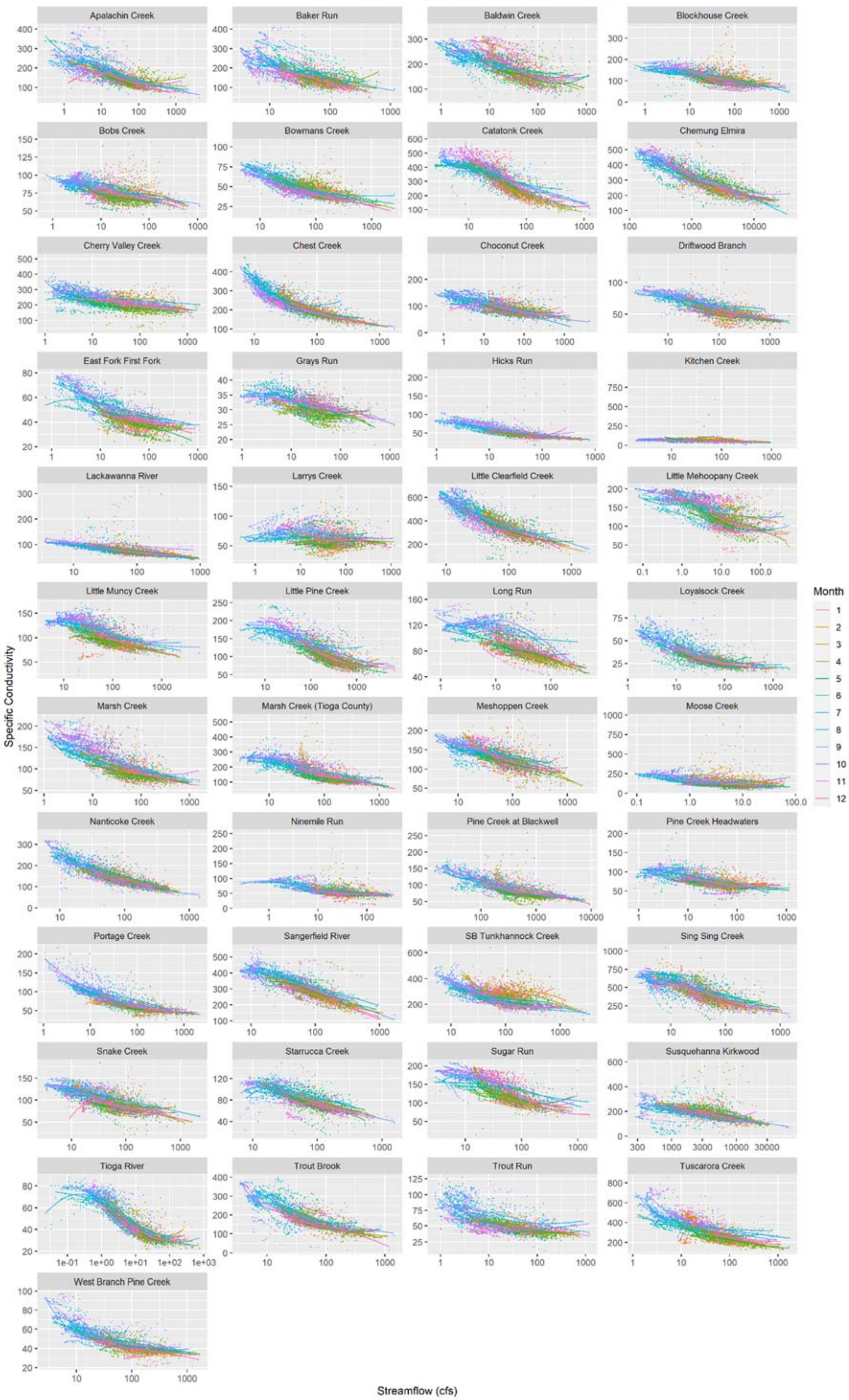
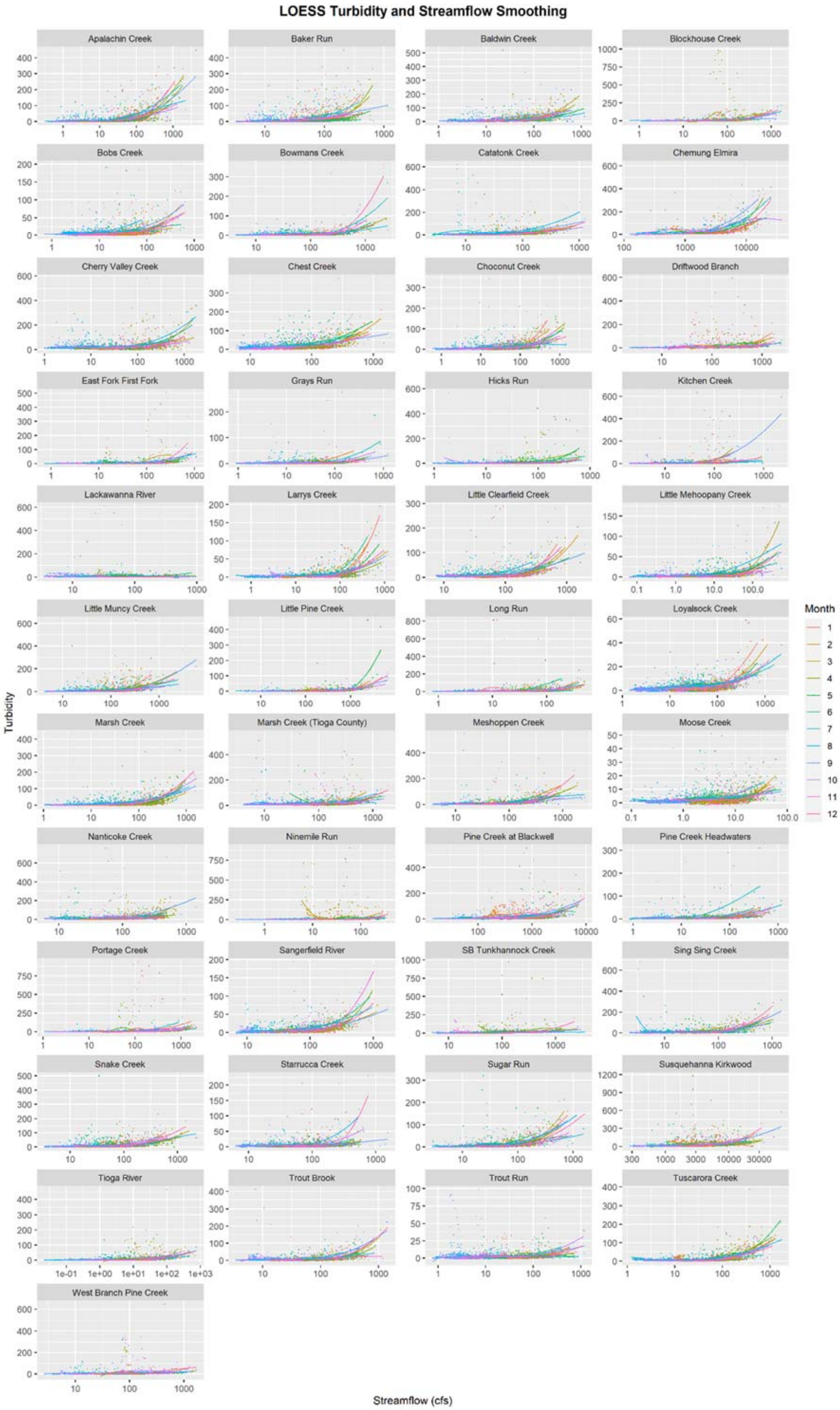
9
10
11
12


LOESS pH and Streamflow Smoothing
Apalachin Creek
Baker Run
Baldwin Creek
Blockhouse Creek
Bobs Creek
Bowmans Creek
Catatonk Creek
Chemung Elmira
Cherry Valley Creek
Chest Creek
Choconut Creek
Driftwood Branch
East Fork First Fork
Grays Run
Hicks Run
Kitchen Creek
Lackawanna River
Larrys Creek
Little Clearfield Creek
Little Mehoopany Creek
Little Muncy Creek
Little Pine Creek
Long Run
Loyalsock Creek
Marsh Creek
Marsh Creek (Tioga County)
Meshoppen Creek
Moose Creek
Nanticoke Creek
Ninemile Run
Pine Creek at Blackwell
Pine Creek Headwaters
Portage Creek
Sangerfield River
SB Tunkhannock Creek
Sing Sing Creek
Snake Creek
Starrucca Creek
Sugar Run
Susquehanna Kirkwood
Tioga River
Trout Brook
Trout Run
Tuscarora Creek
West Branch Pine Creek
pH
Streamflow (cfs)
Month
1
2
3
4
5
6
7
8
9
10
11
12

LOESS Specific Conductivity and Streamflow Smoothing




LOESS Turbidity and Streamflow Smoothing
Turbidity
Streamflow (cfs)
Month

APPENDIX D

Comparison of 2015 and 2021 Water Quality Trends

Station	2015 SpCond	2021 SpCond	2015 DO	2021 DO	2015 pH	2021 pH	2015 Temp	2021 Temp	2015 Turb	2021 Turb
Apalachin Creek	Increasing								Decreasing	
Baker Run				Decreasing	Decreasing	Decreasing				Increasing
Baldwin Creek	Increasing			Decreasing						
Blockhouse Creek	Increasing				Decreasing					
Bobs Creek					Decreasing					Increasing
Bowman Creek	Increasing			Decreasing						
Catatonk Creek			Decreasing			Decreasing	Increasing			Increasing
Cherry Valley Creek		Increasing								Increasing
Chest Creek		Decreasing				Decreasing				
Choconut Creek		Increasing	Decreasing					Increasing		
Driftwood Branch	Increasing			Decreasing				Increasing		
East Fork Sinnemahoning		Increasing		Decreasing		Increasing				Increasing
Grays Run		Increasing								
Hicks Run	Increasing				Increasing					
Kitchen Creek	Increasing							Increasing		
Lackawanna River		Increasing		Decreasing	Decreasing	Decreasing				Increasing
Larrys Creek	Increasing	Increasing								
Little Clearfield Creek		Decreasing		Decreasing		Increasing				
Little Mehoopany Creek	Increasing									
Little Muncy Creek		Increasing		Decreasing						
Little Pine Creek		Increasing	Increasing							
Long Run	Increasing			Decreasing				Increasing		Increasing
Loyalsock Creek	Increasing	Decreasing								Increasing
Marsh Creek						Decreasing				
Marsh Creek – Tioga	Increasing			Decreasing						Decreasing
Meshoppen Creek		Increasing			Decreasing				Decreasing	
Moose Creek						Increasing				Increasing
Nanticoke Creek	Increasing	Increasing							Decreasing	
Ninemile Run							Decreasing			

Station	2015 SpCond	2021 SpCond	2015 DO	2021 DO	2015 pH	2021 pH	2015 Temp	2021 Temp	2015 Turb	2021 Turb
Pine Creek		Increasing								Decreasing
Portage Creek	Increasing		Increasing	Decreasing		Increasing			Increasing	
Sangerfield River										Increasing
South Branch Tunkhannock Creek	Increasing		Increasing	Decreasing						
Sing Sing Creek	Increasing	Increasing	Increasing		Decreasing	Decreasing	Increasing			Increasing
Snake Creek	Increasing	Increasing								
Starrucca Creek			Increasing		Decreasing	Decreasing				Increasing
Sugar Run	Increasing	Increasing				Increasing		Increasing		
Tioga River	Increasing									Increasing
Trout Brook		Increasing			Decreasing	Decreasing				
Trout Run		Decreasing				Increasing				Increasing
Tuscarora Creek	Increasing	Increasing				Decreasing				Increasing
Upper Pine Creek				Decreasing	Decreasing	Increasing				
West Branch Pine Creek	Decreasing		Increasing							

APPENDIX E

Comparison of Watershed Characteristics and Water Quality Trends

Parameter	Drainage Area	Stream Miles	Stream Density	Spudded Wells	#Wells/mi^2	Slope	% Glaciated	% Alluvium	% Glacial Till	Soil Erodibility	Soil Permeability
SpCond	0.584	0.600	0.157	0.825	0.190	0.264	0.526	0.925	0.772	0.372	0.442
DO	0.360	0.363	0.850	0.384	0.262	0.027	0.090	0.476	0.965	0.686	0.669
pH	0.468	0.481	0.587	0.224	0.089	0.120	0.016	0.136	0.510	0.089	0.249
Temperature	0.000	0.000	0.486	0.183	0.838	0.743	0.924	0.557	0.489	0.540	0.318
Turbidity	0.230	0.238	0.526	0.436	0.136	0.096	0.396	0.012	0.068	0.668	0.463