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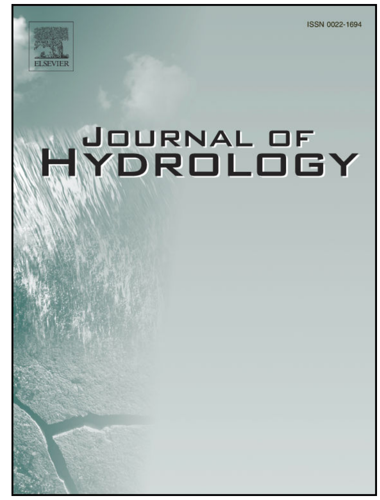

Research papers

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Volunteer science data show degraded water quality disproportionately burdens areas of high poverty

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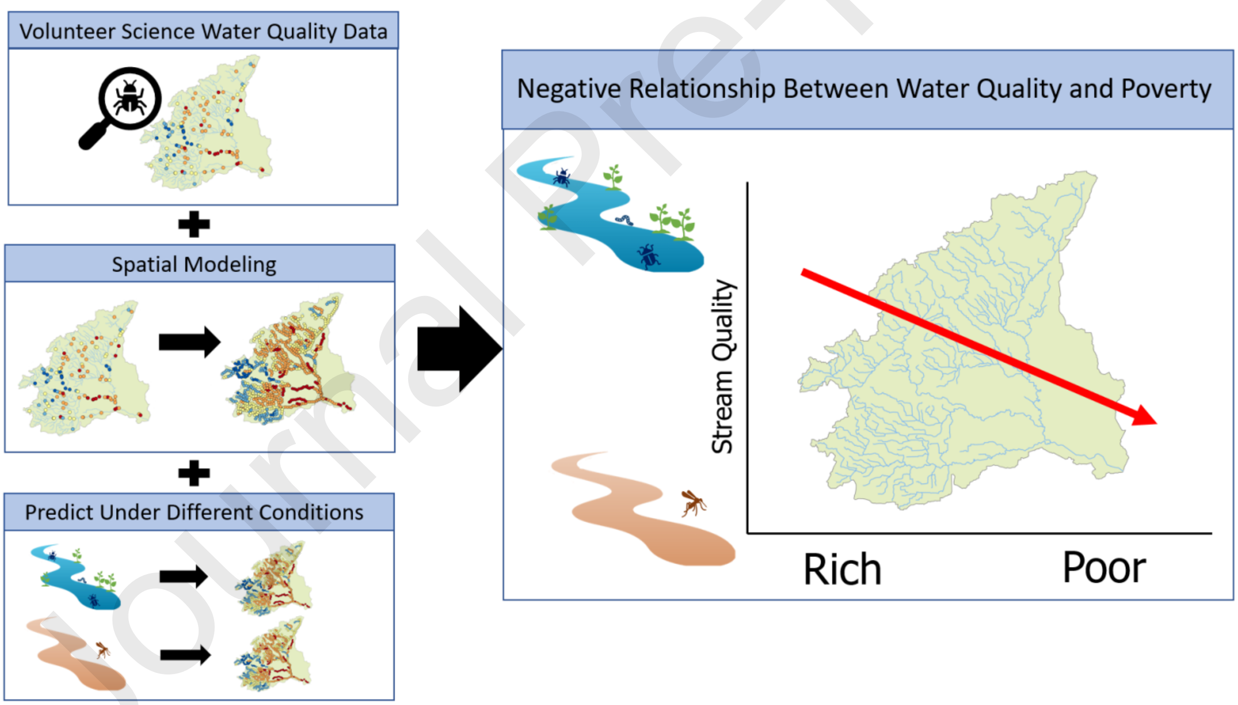
Abstract

Anthropogenic activity degrades stream water quality, especially in urban areas. Quantified connections between pollution sources, degree of water quality degradation, and the disproportionate impact of degradation on underserved communities are not yet fully explored. Here, the anthropogenic effects on water quality and the heterogeneous distribution of degraded streams were examined in the urban watershed of the Rouge River in metropolitan Detroit, Michigan. We used benthic macroinvertebrate data collected by volunteer scientists and aggregated into a Stream Quality Index (SQI) to define long-term water quality patterns. Spatial dependence of the data was assessed with spatial stream network models incorporating socio-economic and environmental predictors. The best model included poverty as an explanatory variable with a negative relationship with stream quality. SQI predictions under true watershed conditions revealed a 1% decrease in SQI with 1% increase in poverty. This work demonstrated the benefits of volunteer science and spatial modeling methods for urban stream modeling. Our finding of inequitably distributed water quality impairment in urban streams underscores the importance of focused restoration in economically oppressed urban areas.



Graphical Abstract.

Key words: Volunteer Science; Spatial Stream Network; Socio-hydrology; Urban Hydrology; Macroinvertebrates; Poverty

1. Introduction

Human activity and environmental systems are interconnected. Over one third of Earth's surface is impacted by anthropogenic landcover alterations (Vitousek, Mooney, Lubchenco, & Melillo, 1997) and these landcover changes are connected to water quality and river ecosystem health (Allan, 2004). Landcover change is a particularly important driver of water quality in urban areas. The term "urban stream syndrome" broadly defines this relationship between dense anthropogenic activity and the negative effect on stream quality and diminished ecosystem services (Booth, Roy, Smith, & Capps, 2016; Walsh et al., 2005; Withers & Jarvie, 2008). Urban streams have higher nutrient loading (Grimm et al., 2005; Meyer, Paul, & Taulbee, 2005; Wahl, McKellar, & Williams, 1997; Withers & Jarvie, 2008), biochemical oxygen demand (BOD) loading (Mallin, Johnson, Ensign, & MacPherson, 2006), highly variable flows (Blaszczak, Delesantro, Urban, Doyle, & Bernhardt, 2019) and highly variable temperature profiles (Walsh et al., 2005), contributing to hypoxia and other damaging impacts.

Causes and in-stream effects of urban stream syndrome have been broadly assessed, but less is known about how this water quality degradation is distributed within an urban watershed. Understanding disproportionate water quality degradation is essential to understand the extent and impact of urban stream syndrome. In the United States, the Environmental Protection Agency (U.S. EPA) monitors spatial connections between environmental indicators and demographic indicators through the "EJscreen" platform (United States Environmnetal Protecion Agency, 2021). Previous studies identified relationships between communities of racial minorities and economically oppressed people and environmental burdens like poor air quality (Anderson, Kissel, Field, & Mach, 2018; Miranda, Edwards, Keating, & Paul, 2011), harmful chemical exposures (Bevc, Marshall, & Picou, 2007), inequitable land use zoning, environmental regulation protections, and environmental law enforcement (Bullard, 1996). Past studies of the intersections between water and environmental justice investigated inequity in flood risk, and sought to inform just flooding infrastructure and management decisions (Maantay & Maroko, 2009; Meenar, Fromuth, & Soro, 2018). Recent work expanded this study between environmental justice and water to include quantitative assessments of the spatial distribution of socioeconomic status and stream water quality (Daneshvar, Nejadhashemi, Zhang, & Herman, 2018; Daneshvar et al., 2016; Sanchez et al., 2015, 2014). Existing models demonstrate weak correlations or inconsistent correlation directions between stream health and socioeconomic parameters (Daneshvar et al., 2018, 2016; Sanchez et al., 2015, 2014). Limitations in data availability and the need to address the complex longitudinal patterns in stream quality data present challenges towards exploring these relationships between stream quality and socioeconomic distribution of stream degradation.

The first challenge, the paucity of water quality data, is an issue because both spatially and temporally robust data are necessary to accurately represent prevailing water quality trends. This challenge was addressed in the present study with volunteer science (i.e. citizen science) data. Volunteer science programs are a widely used method to overcome the data shortage challenge (Taylor et al., 2021). Involving community members in water quality research enables more spatially and temporally robust data collection, spanning large physical distances and long time periods while promoting community engagement and education (Buytaert et al., 2014; Jollymore, Haines, Satterfield, & Johnson, 2017; Krabbenhoft & Kashian, 2020; Njue et al., 2019). However, volunteer science resources are limited, for example, safety conditions or lack of volunteers prevent uniform and ubiquitous distribution of sampling effort. For this reason, a combination of modeling and volunteer science data are necessary to achieve full spatial coverage of water quality data.

The second challenge, stream connectivity, refers to the interdependency between water quality observations on streams. Both in-stream and out of stream relationships may exist between data points, and this prevents the application of analysis methods requiring independence between points. To overcome this challenge, the spatial correlations from upstream, downstream, and near-stream relationships must be considered. Spatial stream network (SSN) models appropriately address stream connectivity by encompassing spatial correlations that exist both on flow paths and outside of flow paths into model predictions (Isaak et al., 2014; Peterson & Ver Hoef, 2014; Peterson et al., 2013; Ver Hoef, Peterson, Clifford, & Shah, 2014). When used in conjunction, volunteer science data and SSN modeling overcome challenges in data paucity and stream connectivity.

This research is a collaboration with Friends of the Rouge (FOTR), a non-profit organization that leads volunteer science data collection events in metropolitan Detroit. FOTR and their volunteer scientists voiced an interest in better understanding the relationships between socioeconomic, environmental, and water quality patterns in the Rouge River. Our goal is to address this community interest and address the prevailing lack of understanding of the distribution of water quality impairment in urban watersheds. The large area and urban setting of the Rouge River provides a range of environmental conditions and diverse communities towards addressing this question. We address the challenges of data paucity and stream connectivity analysis with volunteer science and spatial modeling. Our hypothesis is that water quality degradation in metropolitan Detroit is not distributed uniformly across communities of varying poverty levels. To test this hypothesis, benthic macroinvertebrate observations from FOTR volunteer scientists were modeled with environmental and socio-economic variables in an SSN model. Additionally, this model was used to predict water quality under varying manipulated watershed conditions to evaluate the relationship between poverty and predicted water quality.

2. Methods

2.1 Study Area

The study area was the Rouge River watershed, which contains parts of metropolitan Detroit, MI. The watershed is approximately 1200 km^2 and includes 204 km of stream segments (Figure 1). The watershed drains into the Detroit River, which within the context of the Laurentian Great Lakes, connects Lake St. Clair and Lake Erie. The Rouge River watershed is highly urbanized, with 85% developed, 4% agricultural, and 6% forested landcover (NLCD, 2019). These landcover types are spatially heterogeneous across the watershed, with a general trend of increasing urbanization towards the outlet in the southeast. From 2001 to 2019 imperviousness increased across the watershed, but the magnitude of this increase was less than 1% within ~97% of catchments. The Rouge River twenty-year mean annual discharge is 147 million m^3 $year^{-1}$ (US Geological Survey, 2016). Landcover and hydrologic conditions within the various tributaries are diverse. The relatively undeveloped and rural headwaters contain the least impacted streams. The Rouge River stream segments span all levels of anthropogenic alteration, from groundwater fed pristine segments to segments encased in concrete channels. The U.S. EPA identified the lower Rouge River as an Area of Concern under the Great Lakes Water Quality Agreement of 1987 and cited nine Beneficial Use Impairments in the watershed (Selzer, 2008).

2.2 Volunteer Science Stream Quality Index Data

Benthic macroinvertebrates are bioindicators of stream health and quality, and they are relevant in environmental impact studies near the Rouge River (Burlakova et al., 2018) and globally (Bae, Kil, & Bae, 2005; Del Arco, Ferreira, & Graca, 2012; Graham & Taylor, 2018; Patang, Soegianto, & Hariyanto, 2018). Macroinvertebrate populations are affected by environmental degradation, and their use as sentinels of water quality impact from urbanization is well documented (Del Arco et al., 2012; Kenney, Sutton-Grier, Smith, & Gresens, 2010; Vitousek et al., 1997; Walsh et al., 2005; Walsh, Sharpe, Breen, & Sonneman, 2001). Benthic macroinvertebrates are particularly good bioindicators of stream conditions, as the presence or absence of sensitive taxa reflects long-term stream conditions, rather than the "snapshot" conditions shown by grab samples and chemical analysis (Infante, David Allan, Linke, & Norris, 2009; Lenat, 1988). This relevance as a water quality proxy, as well as cheap and simple collection methods make benthic macroinvertebrates a feasible water quality indicator for volunteer science groups (Graham & Taylor, 2018). Here, we use volunteer science collected benthic macroinvertebrate data as a bioindicator of water quality.

Macroinvertebrate species and frequencies were collected by FOTR volunteers. FOTR collected benthic macroinvertebrate data with volunteer scientists participating in biannual (Spring and Fall) "bug hunts". FOTR started collecting benthic macroinvertebrate data in 2001, and data collection is ongoing. Prior to collection and identification events, volunteers were trained as "bug hunt" team leaders in workshops led by both FOTR and a local biologist. Samples were collected from a rotating subset of 122 sampling locations (Figure 1). Trained volunteer scientist leaders surveyed instream habitats for benthic macroinvertebrates (riffle, cobble, pool, overhanging vegetation, undercut banks) with "D"-frame nets (Brua, Culp, & Benoy, 2011). Macroinvertebrates were preliminarily identified in the field, to order. Four to five specimens of all but clams, mussels, snails, and crayfish were preserved in ethanol and later identified in the lab by FOTR staff and the local biologist to check field identifications and identify to family.

The sensitivity of benthic macroinvertebrates and their frequencies are converted to a Stream Quality Index (SQI) using the MiCorps' Macroinvertebrate Datasheet (Supplemental Figure 1). SQI categorizes macroinvertebrates (mainly by order) into three levels: "sensitive" "somewhat sensitive" and "tolerant," based on pollution sensitivity and rates them as rare (1-10 individuals) or common (11 or more). Common "sensitive" organisms like mayflies are scored higher than common "Tolerant" organisms. A higher SQI score reflects higher numbers of sensitive species like stonefly nymphs (*Plecoptera*) and hellgrammites (*Megaloptera*), indicating higher water quality. This study considers biannual SQI observations from 2001-2021 (n=1,655 site visits).

All FOTR volunteer science SQI collection was completed using a quality assurance project plan reviewed by the Michigan Department of Environment, Great Lakes, and Energy (EGLE), the Michigan Department of Natural Resources, the Michigan Clean Water Corps (MiCorps), the Wayne County Department of Public Services, and FOTR (Petrella, 2020). FOTR checked SQI scores year to year and flagged data points that differed from past observations. Yearly observations of SQI were also checked against local knowledge and reported biannually. A validation study found that SQI calculated in the Rouge River and nearby Clinton River by volunteer scientists produced comparable, but more conservative estimates of stream quality than quantitative data collected by professional scientists (Krabbenhoft & Kashian, 2020). The SQI is a water quality index used by monitoring groups in Michigan developed by the Michigan Department of Environmental Quality (now, Michigan EGLE) through their grant funded program to engage volunteer science groups in benthic macroinvertebrate monitoring around the state. MiCorps is a statewide network that took oversight of the state-backed volunteer science monitoring program in 2003 (“Michigan Clean Water Corps: About,” n.d.). The establishment of the SQI metric in Michigan follows the popularization of bioindicators for water quality monitoring at the state and federal level in the late 1980s due in part to guiding programs like EPA’s Rapid Bioassessment Protocol (Barbour, Gerritsen, Snyder, & Stribling, 1999; Barbour, Stribling, & Verdonschot, 2006). Indices of biological integrity similar to SQI are historically prevalent in volunteer-based water quality monitoring (Firehock, K. and West, 1995) and accepted as reliable indicators of aquatic conditions (Engel & Voshell, 2002). Further, there is a precedent for bioindicator index application in in foundational environmental justice water quality models (Daneshvar et al., 2018, 2016; Sanchez et al., 2015, 2014).

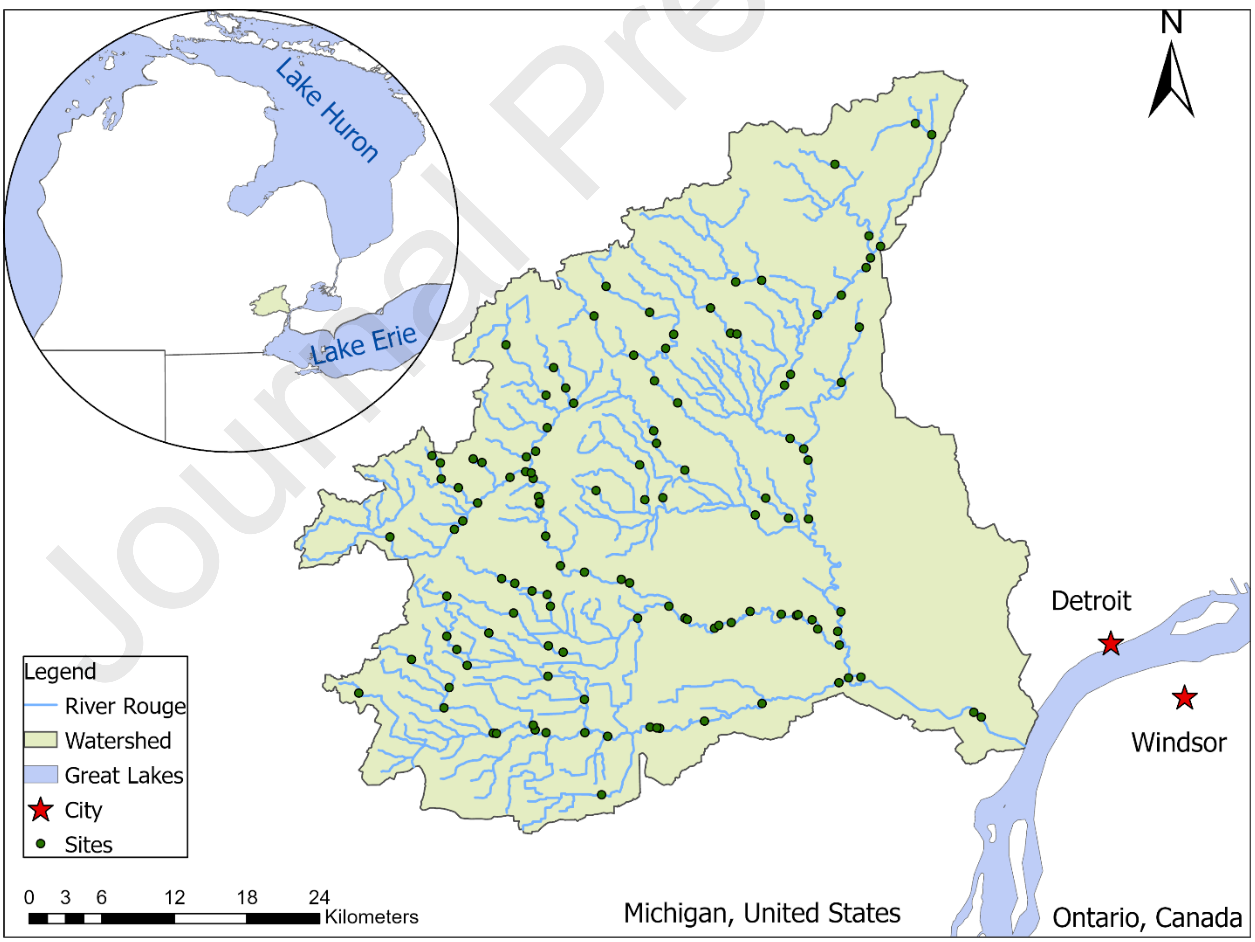


Figure 1: The Rouge River watershed. The Rouge River watershed includes parts of metropolitan Detroit and its Western suburbs. Volunteer science benthic macroinvertebrate data were collected sporadically at 122 observation sites along the Rouge River.

2.3 Stream Spatial Network

To test our hypothesis, we built an SSN model for SQI as a function of environmental and social variables. This modeling step was performed to expand the spatial coverage of SQI data. Environmental data included landcover and stream characteristics, and socio-economic data was represented by poverty distributions. Landcover is a strong driver of in-stream conditions, where anthropogenic land uses, whether urban or agricultural, degrade stream quality (Brabec, Schulte, & Richards, 2002; Carlisle, Falcone, & Meador, 2009; Chen et al., 2016; Epps & Hathaway, 2021; Tong & Chen, 2002). Degraded stream quality effects population size and diversity of benthic macroinvertebrate communities, which are sensitive to degraded stream conditions (Carlisle et al., 2009; Walsh et al., 2001; Wang et al., 2018). Thus, we used sediment regulation (lack of degradation from sedimentation) and percent imperviousness watershed area as landcover characteristics to predict invertebrate population derived SQI. These parameters were obtained from the U.S. EPA StreamCat database and were available for each individual stream segment (Hill, Weber, Leibowitz, Olsen, & Thornbrugh, 2016). Three different poverty metrics were weakly but positively correlated with another water quality index in the neighboring watershed of the Saginaw Bay basin (Sanchez et al., 2014). Poverty was obtained from the U.S. Census Bureau's 2016 American Community Survey data.

Imperviousness is a measured value indicating the mean percent of landcover that is classified as an anthropogenic surface such as pavement, roads, and buildings (Figure 2b). Our imperviousness variable is an average of the mean percent of impervious landcover within a stream segment's immediate and upstream drainage area as reported for 2001, 2004, 2006, 2008, 2011, 2013, 2016, and 2019 in the National Land Cover Database (NLCD) (Dewitz & U.S. Geological Survey, 2021).

Sediment regulation is a modeled parameter on a scale of 0 to 1 that was developed to summarize sedimentation using instream and out-of-stream parameters in the StreamCat database (Hill et al., 2016; Thornbrugh et al., 2018) (Figure 2a). Sedimentation describes inorganic particle retention and size alteration due to transport to and within streams (Flotemersch et al., 2016; Thornbrugh et al., 2018). The sediment regulation parameter was calculated considering observed values of stressors relative to maximum stress level for 5 major stressors: 1) presence and volume of reservoirs, 2) stream channelization and levee construction, 3) alteration and changes to riparian vegetation, 4) frequency of mines, frequency of forest cover loss, and density of roads, and 5) agriculture presence weighted by soil erodibility (Flotemersch et al., 2016; Hill et al., 2016; Thornbrugh et al., 2018).

Poverty associated with each stream segment reflects census-tract level percentages of households living below the poverty line, an annual household income of $31,661. (Figure 2c, U.S. Census Bureau (US Census), 2020). Poverty information was obtained as census-tract based and converted to the average poverty in the topographical boundary (catchment) of each stream segment. These catchment-level values were then averaged with upstream catchments to express the percentage of households below the poverty line in the entire upstream drainage area of each stream segment. Poverty as census-tract based measurements ranged from 0% to 91%, and when converted to upstream watershed-based, ranged from 0.2% to 24.5% of households in the catchment and upstream watershed residing below the poverty line.

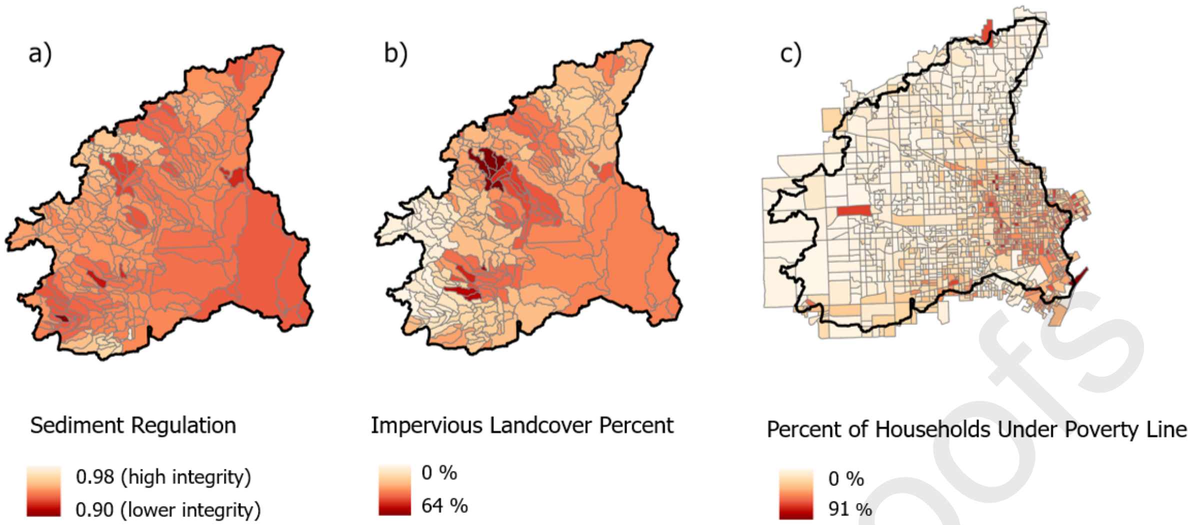


Figure 2: Relevant characteristics in the Rouge River watershed. Sediment regulation (a) is a modeled parameter from 0-1 where 0 indicates low impact of sediment within a catchment, imperviousness (b) as the average percent of landcover identified as impervious, and poverty is the percent of the population living under the poverty line (c) plotted in original data format as percentages within census tracts.

In addition to multiple explanatory variables, the SSN also considers spatial relationships between sites in models. Spatial relationships are categorized into either flow-connected or flow-unconnected relationships, based on whether there is a direct flow path connecting two sites. These relationships consider three autocovariance functions: tail-up, tail-down, and Euclidean distance. Tail-up autocovariance exists only between flow-connected sites, and they represent a weighted moving average function in the upstream direction. Tail-down autocovariance may exist under either flow-connected or flow-unconnected conditions, and they represent a weighted moving average function in the downstream direction. Euclidean distance may be considered in flow-unconnected relationships when autocovariance isn't restricted to in-channel distances between sites (Garreta, Monestiez, & ver Hoef, 2010; Isaak et al., 2014; Ver Hoef & Erin, 2010).

The weighting model for these tail-up and tail-down autocovariances can be calculated with linear, exponential, spherical, Mariah, and Epanech weights (Garreta et al., 2010; Ver Hoef & Erin, 2010). Euclidean autocovariance weighting included standard spatial covariance models: spherical, exponential, Gaussian, and Cauchy. The suitability of these various spatial autocovariances differs depending on the nature of the stream metric. For example, chemical data would be most likely to follow flow-connected tail-down autocovariance because chemical transport in a stream network is driven by transport in the channel, and in the downstream direction. However, macroinvertebrate-derived data may be represented with both flow-connected and flow-unconnected relationships since benthic macroinvertebrates have preferential travel along stream channels, but they can travel in both in upstream and downstream directions, and can also move outside of the confinement of stream channels (Isaak et al., 2014).

Our SSN was implemented by using the Spatial Tools for the Analysis of River Systems (STARS) and SSN tools in ArcMap 10.8.1, R version 3.6.1, and RStudio version 1.2.5019, respectively (Peterson & Ver Hoef, 2014; Ver Hoef et al., 2014). SSN models were made with sediment regulation, imperviousness, and poverty as independent variables. The dependent variable was log mean SQI. Mean SQI was calculated as the mean SQI observation at a site through time. Means were taken to simplify temporally diverse data, because only 9% of sites observed a linear change ($p < 0.05$) in SQI over time, and this change was mixed, with 7 sites increasing and 4 sites decreasing SQI. Mean SQIs were logged to ensure normal distribution. All explanatory variables were normalized using min-max normalization to redistribute values from 0-1 based on the ranges of these variables measured at observation sites. This was done to standardize model covariates to the same scale. SSN models were constructed with multiple combinations of tail up, tail down, and Euclidean distance autocovariances to encompass the three possible spatial relationships between observation sites (Isaak et al., 2014; Ver Hoef et al., 2014). A final SSN model was then selected by comparing models with the evaluators: Akaike information criterion (AIC), coefficient of determination (R^2), and root mean square error (RMSE) calculated from leave one out cross validation (LOOCV). The best performing SSN of SQI as a function of the environmental variables and socio-economic variables was further evaluated by comparing it to two simpler models. The first simple model omitted the spatial component of the SSN and the second simple model omitted the socio-economic variable. Additionally, SQI could decrease downstream along flowlines as a result of physical stream attributes associated with high flows and greater depth. To account for this, the best performing model was reparametrized with a random effect for stream order. Again, models with and without the stream order random effect were compared via AIC, R^2, and RMSE.

2.5 Water Quality across Potential Scenarios

To explore potential conditions within the Rouge River we predicted SQI with the best performing model at points every 800m of all stream segments in the Rouge River watershed. SQI predictions were made under 4 conditions: true (observed) conditions, and three levels of hypothetical watershed conditions – good, standard, and poor conditions (Figure 3). Each hypothetical watershed condition used manipulated values of imperviousness and sediment regulation and observed values of poverty. The values of imperviousness and sediment regulation conditions assigned to the “good”, “standard” and “poor” labels were selected to represent a range of values that are realistic for the watershed. Good conditions were defined as imperviousness at 25% of the range of imperviousness observations (18% imperviousness) and 75% of the range of sediment regulation (0.96). Standard conditions were defined as imperviousness at 50% of the range of imperviousness observations (35% imperviousness) and

50% of the range of sediment regulation (0.94). Poor conditions were defined as imperviousness at 75% of the range of imperviousness (53% imperviousness) and 25% of the range of sediment regulation (0.92). Imperviousness and sediment regulation intervals were opposite one another because increasing imperviousness is associated with poor environmental conditions, while increasing sediment regulation indicates higher integrity, or lack of impact from sedimentation, and is thus associated with better environmental conditions. These intervals were made to demonstrate the impact of poverty on SQI under different environmental conditions that were reasonable in the context of the ranges of imperviousness and sediment regulation observed in the watershed. Linear models of predicted SQI and poverty were generated based on the 4 conditions above. The slopes of these linear models were then compared.

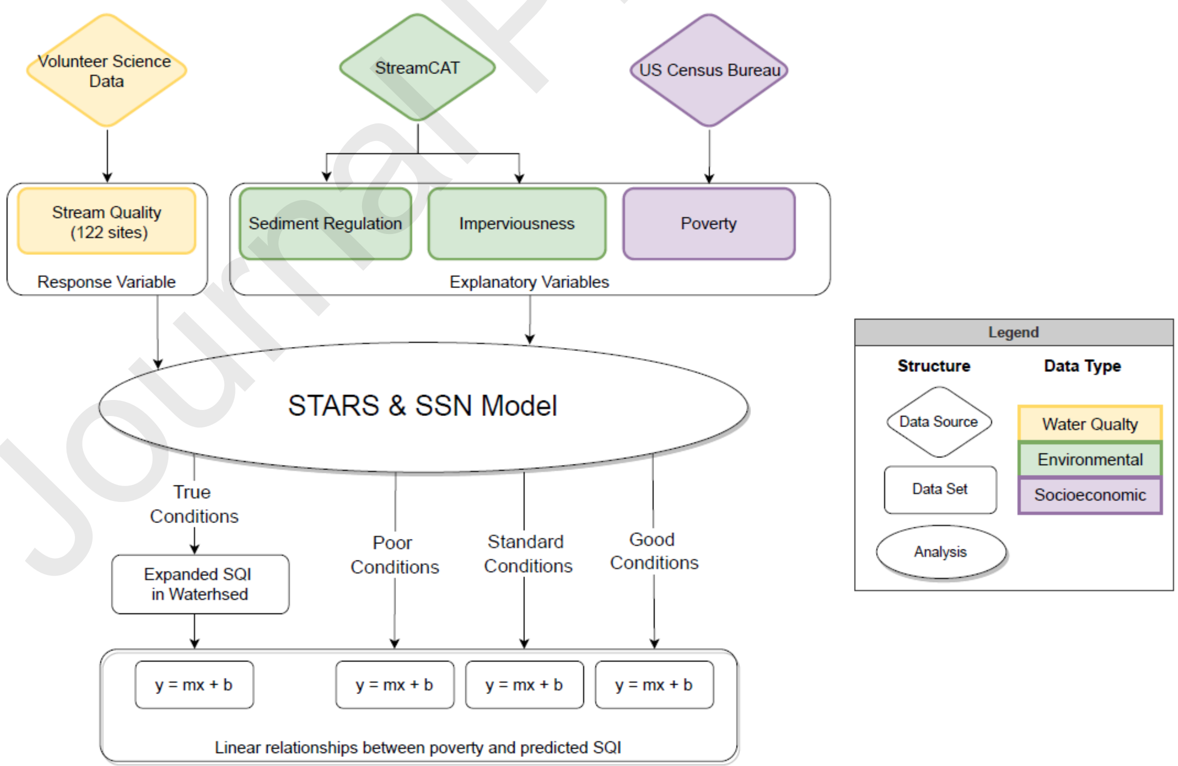


Figure 3: Flow diagram of methods, highlighting data inputs and analysis methods.

3. Results

3.1 SQI Observations

Average SQI observations ranged from 14 to 48 (Figure 4a). Stream quality was generally worse on the main branch and near the watershed outlet. However, poor quality was also observed in some headwater streams. The highest quality was observed on streams on the western edge of the watershed.

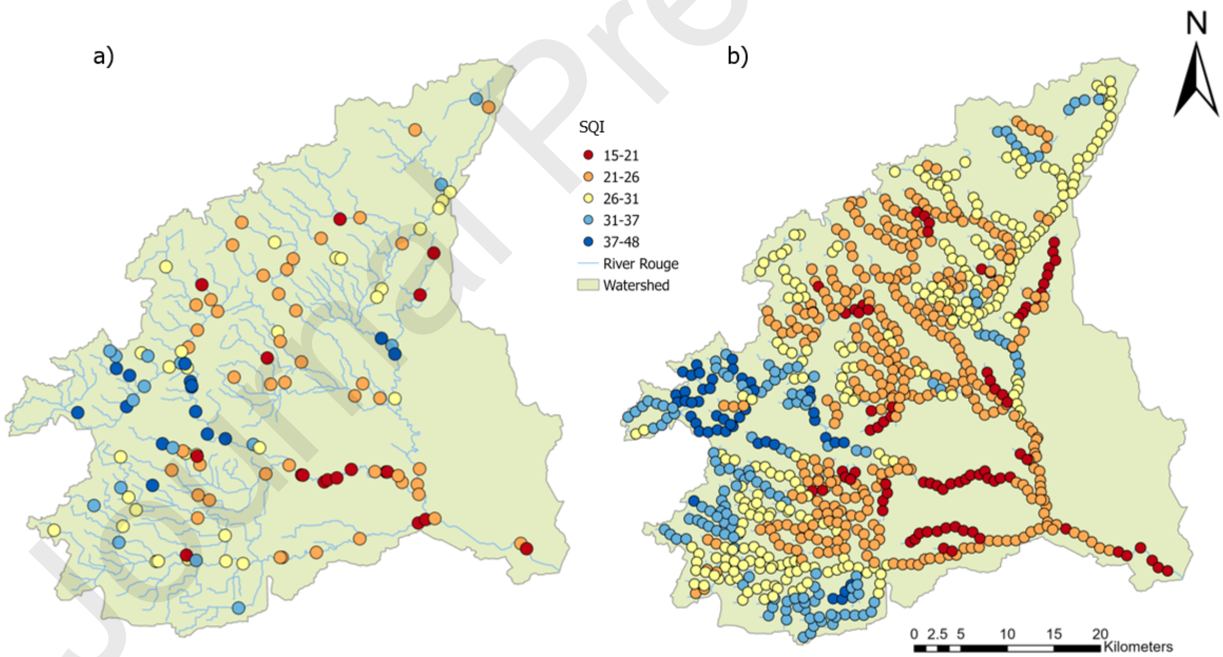


Figure 4: Observed and modeled SQI data. SQI measures were collected for sites in the Rouge River watershed by the volunteer science organization Friends of the Rouge. Observations of SQI (a) compared to modeled SQI along every 800m of stream under true conditions (b).

3.2 Spatial Model Performance

The best performing SSN model based on our model comparison metrics used sediment regulation, imperviousness, and poverty in a multivariate spatial regression model with a linear-sill tail-down autocovariance and no random effect on stream order (Supplementary Table 1). The R^2 value indicates that about 1/3 of the variability in SQI is captured in the model. The RMSE indicates that prediction error is about 3 SQI points, or about 10% of the range of observed SQI values. The explanatory variables are correlated with one another, however, variance inflation factors (VIF, Helsel & Hirsch, 1992) for sedimentation, imperviousness, and poverty were low (1.23, 1.23, and 1.16, respectively). These are close to the ideal value (VIF ~1, Helsel & Hirsch, 1992) and below the cutoff value applicable for SSN models (VIF <5, Isaak et al., 2017) thus suitable for our hypothesis testing. Imperviousness and poverty had negative relationships with SQI with model coefficients -0.28 ($p = 0.01$) and -0.23 ($p = 0.05$), respectively. Sediment regulation had a positive relationship, model coefficient 0.30 ($p = 0.07$), this is interpreted as less impact from sedimentation related to higher SQI. The linear sill tail-down autocovariance indicates that both flow-connected and flow unconnected relationships exist in the SQI data, and that these relationships are linear and point downstream. This means that between two SQI observations the downstream point is influenced by the upstream point and that relationship decreases linearly with increasing distance between the points.

This spatial socio-economic environmental model outperformed the simple model and spatial model fit with only environmental predictors. The simple model had a higher R^2 value (Supplementary Table 1), but lower AIC and RMSE (Figure 5). The spatial environmental-only model had a slightly higher AIC, lower R^2, and higher RMSE compared to the best model (Supplementary Table 1). The RMSE value especially highlights the value of modeling SQI with

SSN models, as the RMSE for the simple model was about one SQI index point higher than the RMSE for either of the spatial models, indicating a worse ability of the simple model to capture the true variability in SQI data (Figure 5). Poverty adds predictive power to the model, as demonstrated by the improvement in all model evaluators when poverty is included in the spatial model.

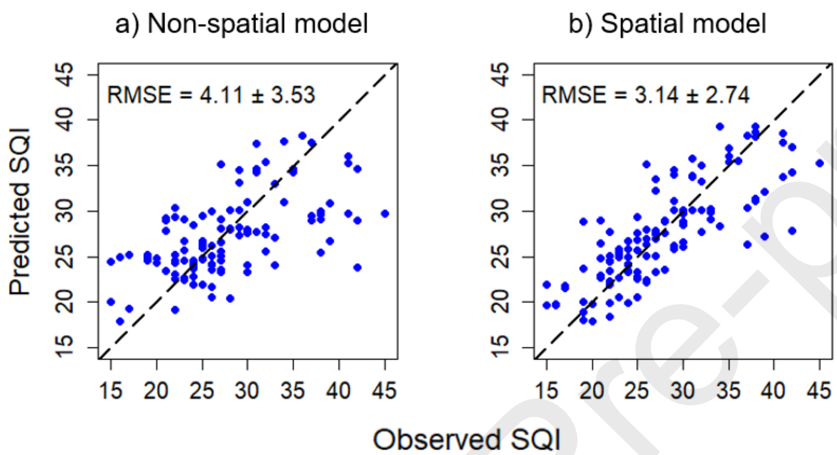


Figure 5: Leave one out cross validation (LOOCV) results compared for a non-spatial model (a) containing the same predictor variables as a spatial model with socio-economic and environmental variables (b). Root mean square error (RMSE) and the standard deviation of this calculation is printed on each plot, showing higher RMSE and standard deviation for the simple model than for the spatial model.

Adding stream order as a random effect did not improve model performance. The stream order-random effect model had a higher AIC and RMSE, and a comparable R^2 as the best performing model. This showed that the relationship between SQI and explanatory variables did not vary based on the stream order. In other words, small streams should not be modeled differently than larger branches. This provides support that stream order and associated downstream trends do not explain water quality in the watershed better than sediment regulation, imperviousness, and poverty without stream positioning information.

3.3 Predictions under Potential Scenarios

The SSN model was used to predict SQI every 800m of stream segment in the Rouge River watershed. Under true conditions in the watershed, SQI predictions ranged from 15.76 (poor) to 44.83 (good) (Figure 4b). The average prediction standard error was 1.17. The slope between poverty and predicted SQI was negative and indicated that a stream segment with 10% higher poverty in its upstream watershed drainage area would have a 3.62 lower SQI. This 3.62 change in SQI is equivalent to a 10% change in the range of water quality, or about a 1% decrease in water quality for every 1% increase in poverty.

Under manipulated watershed conditions, poverty and predicted SQI also had negative relationships (Figure 6). The magnitude of this negative relationship increased with increasingly positive watershed conditions. Under poor watershed conditions (53% imperviousness, 0.92 sediment regulation) a 10% increase in poverty would result in a decrease in SQI by 2.87. Under standard watershed conditions (35% imperviousness, 0.94 sediment regulation) a 10% increase in poverty would decrease SQI by 3.61. Finally, under good watershed conditions (18% imperviousness, sediment regulation = 0.96) a 10% increase in poverty would decrease SQI by 4.53.

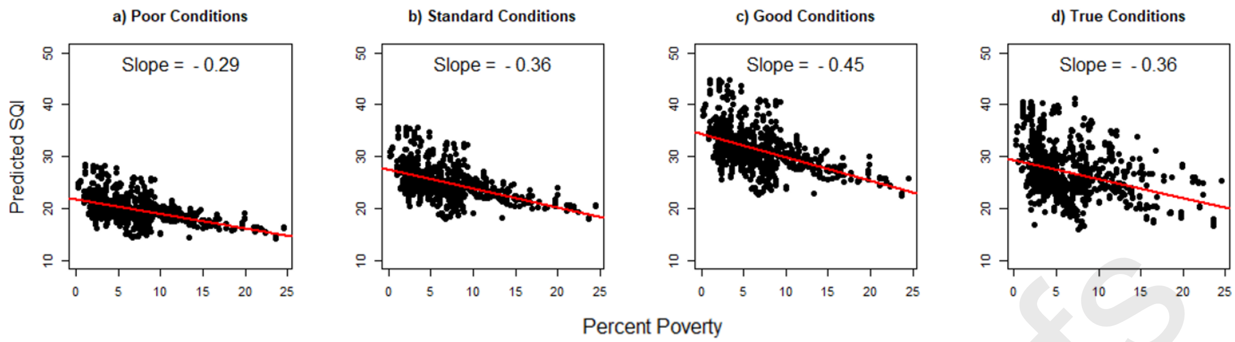


Figure 6: Relationships between predicted SQI and poverty under hypothetical poor (a), standard (b) and good (c) watershed conditions, compared to the relationship under true watershed conditions (d). The slope of the linear relationship between predicted SQI and poverty is plotted under each scenario.

4. Discussion

4.1 Degraded Water Quality in Higher Poverty Areas

The identified negative relationship between water quality and poverty provides information about spatial distribution of water quality degradation. Our SSN's negative coefficient between stream quality and poverty provides statistical evidence that stream quality is associated with socioeconomic factors, in addition to known relationships between stream quality and environmental factors like sediment regulation and imperviousness.

The observed decrease of stream quality in high poverty areas provides support that urban stream degradation is inequitably distributed. It is important to emphasize that the negative relationship does not prove a causal relationship; it provides statistical support that environmental degradation of water quality disproportionately affects impoverished communities. Explicitly, it is incorrect to interpret that high poverty causes poor water quality. While a latent cause-effect relationship may exist, our analysis does not articulate an underlying causal structure. Previous research provides support for potential casual structures. For example, inequity in access and proximity to parks has been shown for poor communities (Rigolon, Browning, & Jennings, 2018), and park land is one tool used to impede stormwater runoff from polluting streams (Cettner, Ashley, Viklander, & Nilsson, 2013).

Local knowledge and spatial setting further contextualize the relationship between poverty and water quality. The highest poverty area in the watershed is in the Southeast region of the watershed. Observations of SQI in this area included 23 sites, with an average SQI of 24, a "fair" rating. While this SQI score is relatively low, it fails to express other water quality issues in this area. The segment of the Rouge River bordering the highest density poverty area contains 21 uncontrolled combined sewer overflow (CSO) outfalls, making this area subject to flashy water levels and at risk to acute degradation events post rainfall as is true in cities with similar drainage systems, like Philadelphia, PA and Chicago, IL (Miskewitz & Uchrin, 2013; Quijano, Zhu, Morales, Landry, & Garcia, 2017). Further, tributary streams in this area are sparse, having been removed from their historical locations (Figure 7). The lack of tributary streams in this area is an example of water inequality, as this high poverty area is deprived of natural surface waters entirely.

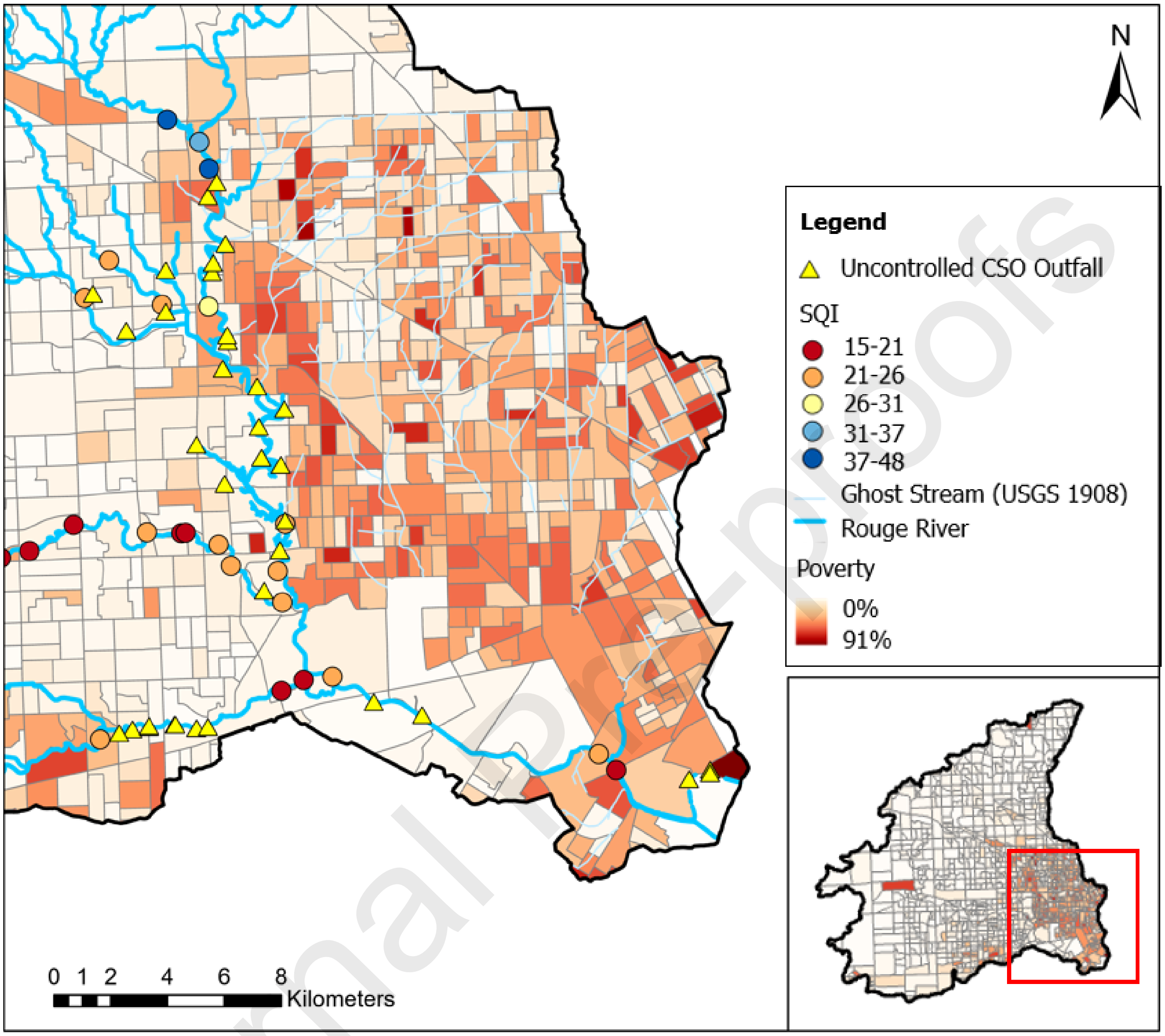


Figure 7: High poverty within the Southeast part of the Rouge River watershed, highlighting water concerns in this region including density of uncontrolled Combined Sewer Overflow (CSO) outfalls and locations of ghost streams that no longer exist.

This lack of naturally formed stream channels is also a limit of our analysis – lack of natural drainage boundaries in high poverty areas, as well as highly urbanized areas, compromise the catchment- level units of analysis. In these areas, our measurements of sediment regulation and imperviousness may not properly represent the land being drained to stream segments since stormwater infrastructure in a combined sewer system would carry stormwater to a wastewater treatment plant, or in an overflow event, may convey water to stream segments that wouldn't have naturally received that water. To estimate water quality more accurately in the high poverty area of the Rouge River, future work would need to consider conversion of naturally delineated drainage areas to those defined by stormwater infrastructure (Achleitner, Möderl, & Rauch, 2007; House et al., 1993; Tscheikner-Gratl et al., 2019).

Other limits of our poverty analysis are the quality of U.S. Census data, and the assumptions made in converting poverty data from census tract to catchment-based units. A limitation of environmental justice datasets is low survey responses and lack of internal community involvement in surveying (Lee, 2020; Mah, 2017). Increased involvement of local community members in environmental justice data collection is necessary for increased understanding of the disproportionate water quality burdens across socioeconomic groups. A second layer of potential error in U.S. Census data was introduced when we converted data from census tracts to drainage area. This conversion was made by assuming that poverty was distributed homogenously in census tracts. This assumption is an over-generalization that could lead to inaccuracy in calculating poverty rates in units of catchments. Scales of socioeconomic data resolution are influential in improving stream health modeling performance (Daneshvar et al., 2016), so future modeling efforts would benefit from a more realistic conversion of socioeconomic data from census-area to area units more conducive to water quality modeling.

4.2 Volunteer Science Data Applicability

Volunteer science collected water quality data was key to executing this work. The term volunteer science was selected intentionally over similar titles (citizen science, community science, community-based monitoring) because volunteers collected data and volunteerism was entirely unrelated to citizen status (contrary to the implication of the term citizen science), and the community was not involved in all stages of the research (as is common in community science) (Cooper et al., 2021). Our work serves as an example of a mutually beneficial partnership between formal research and volunteer science. Labor, cost, time, and local knowledge would have prevented this research without volunteer science collaboration, which provided a temporally and spatially robust dataset. For the volunteer science data collecting group FOTR, technical and resource hurdles stand in the way of the spatial model building and analysis needed to fully understand river data. This mutually beneficial partnership between scientists and the local community offers the exchange of knowledge and perspective from interested parties who come from diverse backgrounds and motivations (Taylor et al., 2021), and is one reason why volunteer science has recently become more prevalent in aquatic science and hydrology research (Kielstra, Chau, & Richardson, 2019; Krabbenhoft & Kashian, 2020; Maguire & Mundle, 2020). An additional co-benefit of FOTR volunteer science is that data collection events are used to engage volunteer scientists in the watershed, raise awareness about river conditions, and advocate for the need to clean up the Rouge River.

Despite the benefits offered to both scientists and volunteer science groups, there are obstacles that prevent the widespread use of volunteer science data. These obstacles include scientific community acceptance, data validity and governance, research problem definition, and in the case of water quality – observation tool expense and access (Buytaert, Dewulf, De Bièvre, Clark, & Hannah, 2016; Buytaert et al., 2014). The most common critique of volunteer science is data validity (Jollymore et al., 2017). Means to overcome this obstacle include volunteer scientist training, and understanding of volunteer science volunteerism motivation which increases the reliability (Alender, 2016; Buytaert et al., 2014; Jollymore et al., 2017).

In volunteer science organized by FOTR, volunteer training and internal quality assurance checks are the primary means of data quality assurance. The team leaders who collect data attend training in the classroom and field to learn sampling techniques and identification. Volunteers who want to become team leaders must first attend a sampling day as a regular volunteer. Following training, trainees are paired with an experienced team leader for their first few events and the experienced leader works with them to make sure they are sampling thoroughly and following procedures. Team leaders repeat the training every few years to stay updated. On sampling days, team leaders conduct all sample collection, and untrained volunteers assist in picking through the samples. Team leaders collect voucher specimens which are identified in the lab. Quality assurance is performed with internal checks against historical SQI observations, where any results for sites that vary greatly from past sampling are examined to determine the cause. A reliability study on FOTR volunteer science data concluded the SQI data used here is a conservative estimate of water quality as traditionally measured numerically by scientists (Krabbenhoft & Kashian, 2020). The macroinvertebrate preservation method used by FOTR may be one potential source of this discrepancy, as only 4-5 representative specimens are preserved for post-hoc identification rather than preserving all samples as recommended by other benthic macroinvertebrate sampling (Barbour et al., 1999).

4.2.1 Lessons from Friends of the Rouge

The long-term operation of volunteer science at FOTR has resulted in many learned experiences that can benefit other communities, including the scientific community. Initially, FOTR provided training and equipment and expected trainees to monitor sites on their own. This model failed to engage volunteers, and consequently FOTR altered their sampling events to group sampling days with the trainees leading untrained volunteers. This structure allows for wide community participation, with over 100 volunteers attending monitoring days. Success of this method is measured through volunteer retention, and influence of volunteering experience on community members. Many volunteers return year after year, some for as long as 20 years. Volunteers learn about stream ecology and urban rivers through their experience at sampling events. Children participate with their parents and many reported going on to pursue a degree in the sciences because of the experience.

FOTR also attributes their success to their commitment to ensure that the data is useful and made available to stakeholders. Following each monitoring event, a report is made available to all volunteers, and state and local agencies, including the communities who are now providing some of the funding to support monitoring. FOTR makes the data freely available to academic institutions for research use which has resulted in journal publications (Krabbenhoft & Kashian, 2020; Maguire & Mundle, 2020) and several Master's students theses.

Volunteer science events conducted by FOTR have also resulted in unsuspected co-benefits. Inspired by questions from volunteers about pipes while sampling, team leaders are now trained in illicit discharge elimination and have been responsible for reporting spills, sewage leaks, erosion issues, and more that might have never been noticed otherwise. Volunteers have also observed other species while working on macroinvertebrate study events. Notably, new native species have been documented including one new to the state and multiple invasive species were tracked.

4.3 Spatial Modeling

The SSN and STARS tools were useful in modeling stream water quality in the Rouge River from volunteer science water quality data, and spatial relationships in stream systems. STARS and SSN tools have been applied to a range of stream modeling applications like surface water isotope variations (McGill, Steel, Brooks, Edwards, & Fullerton, 2020), fish genetic diversity in southern France (Paz-Vinas et al., 2018), and fecal contamination in streams in Northeast Scotland (Neill et al., 2018) and central North Carolina (Holcomb, Messier, Serre, Rowny, & Stewart, 2018). SSN methods have been previously applied with volunteer science data (Kielstra et al., 2019), and macroinvertebrates in streams (Frieden, Peterson, Angus Webb, & Negus, 2014; Pond, Krock, Cruz, & Ettema, 2017). This project uniquely combines volunteer science collected macroinvertebrate data into a spatial model, which together were able to overcome challenges in data paucity and stream connectivity.

Water quality in the Rouge River was modeled with imperviousness and sediment regulation, both of which reflect some degree of anthropogenic activity; and together they show that human behavior affects stream quality through different avenues. Imperviousness is directly related to human populations and densities, where high imperviousness is associated with high human density and is known to cause increased flashiness, temperatures, and BOD; and cause streamlined pollution conveyance via stormwater (Blaszczak et al., 2019; Grabowski, Watson, & Chang, 2016; Mallin, Johnson, & Ensign, 2009). The negative imperviousness coefficient modeled here aligns with the emphasis placed on impervious sources as a key driver of water resources impacts in previous research (Arnold & Gibbons, 1996; McGrane, 2016; Salerno, Viviano, & Tartari, 2018). Sediment regulation is estimated through factors directly or indirectly driven by humans, like reservoir presence and volume, stream channelization, riparian vegetation, and agriculture weighted by soil erodibility (Thornbrugh et al., 2018). The positive coefficient associated with sediment regulation indicates an increase in sensitive benthic macroinvertebrate species associated with high sediment regulation. This relationship was expected as benthic macroinvertebrates thrive in well oxygenated water, with low proportions of fine substrate (Kaller & Hartman, 2004; Von Bertrab, Krein, Stendera, Thielen, & Hering, 2013). The use of imperviousness and sediment regulation helped to build the stream quality SSN model.

Our methodology using an SSN model builds upon existing analyses of the socioeconomic influence of stream quality. Previous analyses explored regression relationships and spatial clustering between stream environment indicators and variables describing historically disadvantaged populations. These studies found mixed correlation results, revealing negative trends between a stream health index and both household size and poverty (Daneshvar et al., 2016; Sanchez et al., 2014). The strength of correlations between socioeconomic and stream health indices was improved by applying spatial clustering (Sanchez et al., 2015) and tailoring the resolution of spatial analysis (Daneshvar et al., 2016). In general, higher resolution data produced higher correlations (Daneshvar et al., 2016; Sanchez et al., 2015). The method of parameter estimation for environmental justice modeling has also been performed with many explanatory variables categorized as ecological, socioeconomic, and physiological (Daneshvar et al., 2018). This work's methodology avoided the ambiguousness associated with correlation calculations and complexity of clustering methods by using both socioeconomic and environmental variables, and a spatial model designed for stream networks. The spatial modeling framework applied in past models was conditional autoregressive modeling, which considers spatial influence of neighboring points (Daneshvar et al., 2016; Sanchez et al., 2015, 2014). Our modeling approach with SSN expands on this consideration of neighboring points, by including relationships that exist on stream flow paths. While our model identifies weaker statistical relationships than those observed in past models (Sanchez et al., 2015, 2014), the simplicity and interpretability of our SSN model provides a straightforward means of expressing the complex relationship between socioeconomic parameters and urban stream quality. Ultimately, our work aligns with previous environmental justice models, all finding negative relationships between historically underserved groups and water quality via stream health indices.

5. Conclusion

Urban stream syndrome remains a prevalent environmental concern, and this work shows how degraded stream water quality disproportionately burdens higher poverty areas. Our results show that under similar environmental conditions, streams with higher poverty have lower stream quality. Volunteer science collected data provided a robust understanding of stream quality in the Rouge River, and spatial modeling methods enabled the incorporation of stream interdependencies in stream quality modeling. In further analyses of the socioeconomic distribution of water quality degradation, we encourage the partnership of volunteer science groups, who may have parallel interests in understanding the water quality story in their community.

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5. Bibliography

Achleitner, S., Möderl, M., & Rauch, W. (2007). CITY DRAIN (C) - An open source approach for simulation of integrated urban drainage systems. *Environmental Modelling & Software*, *22*(8), 1184–1195. https://doi.org/https://doi.org/10.1016/j.envsoft.2006.06.013

Alender, B. (2016). Understanding volunteer motivations to participate in citizen science projects: A Deeper look at water quality monitoring. *Journal of Science Communication*, *15*(3), 1–19. https://doi.org/10.22323/2.15030204

Allan, J. D. (2004). Landscapes and riverscapes: The influence of land use on stream ecosystems. *Annual Review of Ecology, Evolution, and Systematics*, *35*(2002), 257–284. https://doi.org/10.1146/annurev.ecolsys.35.120202.110122

Anderson, C. M., Kissel, K. A., Field, C. B., & Mach, K. J. (2018). Climate Change Mitigation, Air Pollution, and Environmental Justice in California. *Environmental Science and Technology*, *52*(18), 10829–10838. https://doi.org/10.1021/acs.est.8b00908

Arnold, C. L. J., & Gibbons, C. J. (1996). Impervious Surface Coverage: The Emergence of a Key Environmental Indicator. *Journal of the American Planning Association*, *62*(2). https://doi.org/https://doi.org/10.1080/01944369608975688

Bae, Y. J., Kil, H. K., & Bae, K. S. (2005). Benthic macroinvertebrates for uses in stream biomonitoring and restoration. *KSCE Journal of Civil Engineering*, *9*(1), 55–63. https://doi.org/10.1007/bf02829098

Barbour, M. T., Gerritsen, J., Snyder, B. D., & Stribling, J. B. (1999). *Rapid Bioassessment Protocols for Use in Streams and Wadeable Rivers: Periphyton, Benthic*

Macriinvertebrates, and Fish, Second Edition. EPA 841-B-99-002. Rapid Bioassessment Protocols for Use in Streams and Rivers. Washington, D. C. Retrieved from http://www.epa.gov/OWOW/monitoring/techmon.html

Barbour, M. T., Stribling, J. B., & Verdonschot, P. F. M. (2006). The multihabitat approach of USEPA's rapid bioassessment protocols: Benthic macroinvertebrates. *Limnetica*, *25*(3), 839–850. https://doi.org/10.23818/limn.25.58

Bevc, C. A., Marshall, B. K., & Picou, J. S. (2007). Environmental justice and toxic exposure: Toward a spatial model of physical health and psychological well-being. *Social Science Research*, *36*(1), 48–67. https://doi.org/10.1016/j.ssresearch.2005.11.001

Blaszczak, J. R., Delesantro, J. M., Urban, D. L., Doyle, M. W., & Bernhardt, E. S. (2019). Scoured or suffocated: Urban stream ecosystems oscillate between hydrologic and dissolved oxygen extremes. *Limnology and Oceanography*, *64*(3), 877–894. https://doi.org/10.1002/lno.11081

Booth, D. B., Roy, A. H., Smith, B., & Capps, K. A. (2016). Global perspectives on the urban stream syndrome. *Freshwater Science*, *35*(1), 412–420. https://doi.org/10.1086/684940

Brabec, E., Schulte, S., & Richards, P. L. (2002). Impervious surfaces and water quality: A review of current literature and its implications for watershed planning. *Journal of Planning Literature*, *16*(4), 499–514. https://doi.org/10.1177/088541202400903563

Brua, R. B., Culp, J. M., & Benoy, G. A. (2011). Comparison of benthic macroinvertebrate communities by two methods: Kick- and U-net sampling. *Hydrobiologia*, *658*(1), 293–302. https://doi.org/10.1007/s10750-010-0499-x

Bullard, R. D. (1996). Environmental Justice: It's More Than Waste Facility Siting. *Social Science Quarterly*, *77*(3), 493–499. Retrieved from https://www.jstor.org/stable/42863495

Burlakova, L. E., Kovalenko, K. E., Schmude, K. L., Barbiero, R. P., Karatayev, A. Y., & Lesht, B. M. (2018). Development of new indices of Great Lakes water quality based on profundal benthic communities. *Journal of Great Lakes Research*, *44*(4), 618–628. https://doi.org/10.1016/J.JGLR.2017.11.004

Buytaert, W., Dewulf, A., De Bièvre, B., Clark, J., & Hannah, D. M. (2016). Citizen Science for Water Resources Management: Toward Polycentric Monitoring and Governance? *Journal of Water Resources Planning and Management*, *142*(4), 01816002. https://doi.org/10.1061/(asce)wr.1943-5452.0000641

Buytaert, W., Zulkafli, Z., Grainger, S., Acosta, L., Alemie, T. C., Bastiaensen, J., … Zhumanova, M. (2014). Citizen science in hydrology and water resources: Opportunities for knowledge generation, ecosystem service management, and sustainable development. *Frontiers in Earth Science*, *2*(October), 1–21. https://doi.org/10.3389/feart.2014.00026

Carlisle, D. M., Falcone, J., & Meador, M. R. (2009). Predicting the biological condition of streams: Use of geospatial indicators of natural and anthropogenic characteristics of watersheds. *Environmental Monitoring and Assessment*, *151*(1–4), 143–160. https://doi.org/10.1007/s10661-008-0256-z

Cettner, A., Ashley, R., Viklander, M., & Nilsson, K. (2013). Stormwater management and urban planning: Lessons from 40 years of innovation. *Journal of Environmental Planning and Management*, *56*(6), 786–801. https://doi.org/10.1080/09640568.2012.706216

Chen, Q., Mei, K., Dahlgren, R. A., Wang, T., Gong, J., & Zhang, M. (2016). Impacts of land use and population density on seasonal surface water quality using a modified geographically weighted regression. *Science of the Total Environment*, *572*, 450–466. https://doi.org/10.1016/j.scitotenv.2016.08.052

Cooper, C. B., Hawn, C. L., Larson, L. R., Parrish, J. K., Bowser, G., Cavalier, D., … Wilson, S. (2021). Inclusion in citizen science: The conundrum of rebranding. *Science*, *372*(6549), 1386–1388. https://doi.org/10.1126/science.abi6487

Daneshvar, F., Nejadhashemi, A. P., Zhang, Z., & Herman, M. R. (2018). Assessing the relative importance of parameter estimation in stream health based environmental justice modeling. *Journal of Hydrology*, *563*(February), 211–222. https://doi.org/10.1016/j.jhydrol.2018.06.004

Daneshvar, F., Nejadhashemi, A. P., Zhang, Z., Herman, M. R., Shortridge, A., & Marquart-Pyatt, S. (2016). Evaluating stream health based environmental justice model performance at different spatial scales. *Journal of Hydrology*, *538*, 500–514. https://doi.org/10.1016/j.jhydrol.2016.04.052

Del Arco, A. I., Ferreira, V., & Graca, M. A. S. (2012). The performance of biological indicators in assessing the ecological state of streams with varying catchment urbanisation levels in Coimbra, Portugal. *Limnetica*, *31*(1), 141–154.

Dewitz, J., & U.S. Geological Survey. (2021). National Landcover Database (NLCD) 2019 Products. *U.S. Geological Survey Data Release*. https://doi.org/10.5066/P9KZCM54

Engel, S. R., & Voshell, J. R. (2002). Volunteer biological monitoring: Can it accurately assess the ecological condition of streams? *American Entomologist*, *48*(3), 164–177. https://doi.org/10.1093/ae/48.3.164

Epps, T. H., & Hathaway, J. M. (2021). Inter-Event Water Quality Variability and Intra-Event Pollutant Dynamics in Context of Effective Impervious Area. *Journal of Sustainable Water in the Built Environment*, *7*(4), 04021013. https://doi.org/10.1061/jswbay.0000953

Firehock, K. and West, J. (1995). A Brief History of Volunteer Biological Water Monitoring Using Macroinvertebrates Author (s): Karen Firehock and Jay West Source : Journal of the North American Benthological Society , Vol . 14 , No . 1 (Mar ., 1995), Published by : The University of. *Journal of the North American Benthological Society*, *14*(1), 197–202.

Flotemersch, J. E., Leibowitz, S. G., Hill, R. A., Stoddard, J. L., Thoms, M. C., & Tharme, R. E. (2016). A Watershed Integrity Definition and Assessment Approach to Support Strategic Management of Watersheds. *River Research and Applications*, *1671*(October 2015), 1654–1671. https://doi.org/10.1002/rra

Frieden, J. C., Peterson, E. E., Angus Webb, J., & Negus, P. M. (2014). Improving the predictive power of spatial statistical models of stream macroinvertebrates using weighted autocovariance functions. *Environmental Modelling and Software*, *60*, 320–330. https://doi.org/10.1016/j.envsoft.2014.06.019

Garreta, V., Monestiez, P., & ver Hoef, J. M. (2010). Spatial modelling and prediction on river networks: Up model, down model or hybrid? *Environmetrics*, *21*(5), 439–456. https://doi.org/10.1002/env.995

Grabowski, Z. J., Watson, E., & Chang, H. (2016). Using spatially explicit indicators to investigate watershed characteristics and stream temperature relationships. *Science of the Total Environment*, *551–552*, 376–386. https://doi.org/10.1016/j.scitotenv.2016.02.042

Graham, M., & Taylor, J. (2018). *Development of Citizen Science Water Resource Monitoring*

Tools and Communities of Practice for South Africa, Africa and the World.

Grimm, N. B., Sheibley, R. W., Crenshaw, C. L., Dahm, C. N., Roach, W. J., & Zeglin, L. H. (2005). N retention and transformation in urban streams. *Journal of the North American Benthological Society*, *24*(3), 626–642. https://doi.org/10.1899/04-027.1

Helsel, D. R., & Hirsch, R. M. (1992). *Statistical Methods in Water Resources*. New York, NY: Elsevier.

Hill, R. A., Weber, M. H., Leibowitz, S. G., Olsen, A. R., & Thornbrugh, D. J. (2016). The Stream-Catchment (StreamCat) Dataset: A Database of Watershed Metrics for the Conterminous United States. *Journal of the American Water Resources Association*, *52*(1), 120–128. https://doi.org/10.1111/1752-1688.12372

Holcomb, D. A., Messier, K. P., Serre, M. L., Rowny, J. G., & Stewart, J. R. (2018). Geostatistical Prediction of Microbial Water Quality Throughout a Stream Network Using Meteorology, Land Cover, and Spatiotemporal Autocorrelation. *Environmental Science and Technology*, *52*(14), 7775–7784. https://doi.org/10.1021/acs.est.8b01178

House, M. A., Ellis, J. B., Herricks, E. E., Hvitved-Jacobsen, T., Seager, J., Lijklema, L., … Clifforde, I. T. (1993). Urban drainage - Impacts on receiving water quality. *Water Science and Technology*, *27*(12), 117–158. https://doi.org/10.2166/wst.1993.0293

Infante, D. M., David Allan, J., Linke, S., & Norris, R. H. (2009). Relationship of fish and macroinvertebrate assemblages to environmental factors: Implications for community concordance. *Hydrobiologia*, *623*(1), 87–103. https://doi.org/10.1007/s10750-008-9650-3

Isaak, D. J., Peterson, E. E., Ver Hoef, J. M., Wenger, S. J., Falke, J. A., Torgersen, C. E., …

Monestiez, P. (2014). Applications of spatial statistical network models to stream data. *Wiley Interdisciplinary Reviews: Water*, *1*(3), 277–294. https://doi.org/10.1002/wat2.1023

Isaak, D. J., Wenger, S. J., Peterson, E. E., Ver Hoef, J. M., Nagel, D. E., Luce, C. H., … Parkes-Payne, S. (2017). The NorWeST Summer Stream Temperature Model and Scenarios for the Western U.S.: A Crowd-Sourced Database and New Geospatial Tools Foster a User Community and Predict Broad Climate Warming of Rivers and Streams. *Water Resources Research*, *53*(11), 9181–9205. https://doi.org/10.1002/2017WR020969

Jollymore, A., Haines, M. J., Satterfield, T., & Johnson, M. S. (2017). Citizen science for water quality monitoring: Data implications of citizen perspectives. *Journal of Environmental Management*, *200*(2017), 456–467. https://doi.org/10.1016/j.jenvman.2017.05.083

Kaller, M. D., & Hartman, K. J. (2004). Evidence of a threshold level of fine sediment accumulation for altering benthic macroinvertebrate communities. *Hydrobiologia*, *518*(1–3), 95–104. https://doi.org/10.1023/B:HYDR.0000025059.82197.35

Kenney, M., Sutton-Grier, A., Smith, R., & Gresens, S. (2010). Benthic macroinvertebrates as indicators of water quality: The intersection of science and policy. *Terrestrial Arthropod Reviews*, *2*(2), 99–128. https://doi.org/10.1163/187498209x12525675906077

Kielstra, B. W., Chau, J., & Richardson, J. S. (2019). Measuring function and structure of urban headwater streams with citizen scientists. *Ecosphere*, *10*(4). https://doi.org/10.1002/ecs2.2720

Krabbenhoft, C. A., & Kashian, D. R. (2020). Citizen science data are a reliable complement to quantitative ecological assessments in urban rivers. *Ecological Indicators*, *116*(April), 106476. https://doi.org/10.1016/j.ecolind.2020.106476

Lee, C. (2020). *A Game Changer in the Making? Lessons from States Advancing Environmental Justice Through Mapping and Cumulative Impact Strategies*. *Environmental Law Reporter* (Vol. 5). Washington D.C. Retrieved from https://www.eli.org/sites/default/files/docs/50.10203.pdf

Lenat, D. R. (1988). Water Quality Assessment of Streams Using a Qualitative Collection Method for Benthic Macroinvertebrates. *Freshwater Science*, *7*(3). https://doi.org/https://doi.org/10.2307/1467422

Maantay, J., & Maroko, A. (2009). Mapping urban risk: Flood hazards, race, & environmental justice in New York. *Applied Geography*, *29*(1), 111–124. https://doi.org/10.1016/j.apgeog.2008.08.002

Maguire, T. J., & Mundle, S. O. C. (2020). Citizen Science Data Show Temperature-Driven Declines in Riverine Sentinel Invertebrates. *Environmental Science and Technology Letters*, *7*(5), 303–307. https://doi.org/10.1021/acs.estlett.0c00206

Mah, A. (2017). Environmental justice in the age of big data: challenging toxic blind spots of voice, speed, and expertise. *Environmental Sociology*, *3*(2), 122–133. https://doi.org/10.1080/23251042.2016.1220849

Mallin, M. A., Johnson, V. L., & Ensign, S. H. (2009). Comparative impacts of stormwater runoff on water quality of an urban, a suburban, and a rural stream. *Environmental Monitoring and Assessment*, *159*(1–4), 475–491. https://doi.org/10.1007/s10661-008-0644-4

Mallin, M. A., Johnson, V. L., Ensign, S. H., & MacPherson, T. A. (2006). Factors contributing to hypoxia in rivers, lakes, and streams. *Limnology and Oceanography*, *51*(1 II), 690–701.

https://doi.org/10.4319/lo.2006.51.1_part_2.0690

McGill, L. M., Steel, E. A., Brooks, J. R., Edwards, R. T., & Fullerton, A. H. (2020). Elevation and spatial structure explain most surface-water isotopic variation across five Pacific Coast basins. *Journal of Hydrology*, *583*(July 2019), 124610. https://doi.org/10.1016/j.jhydrol.2020.124610

McGrane, S. J. (2016). Impacts of urbanisation on hydrological and water quality dynamics, and urban water management: a review. *Hydrological Sciences Journal*, *61*(13), 2295–2311. https://doi.org/10.1080/02626667.2015.1128084

Meenar, M., Fromuth, R., & Soro, M. (2018). Planning for watershed-wide flood-mitigation and stormwater management using an environmental justice framework. *Environmental Practice*, *20*(2–3), 55–67. https://doi.org/10.1080/14660466.2018.1507366

Meyer, J. L., Paul, M. J., & Taulbee, W. K. (2005). Stream ecosystem function in urbanizing landscapes. *Journal of the North American Benthological Society*, *24*(3), 602–612. https://doi.org/10.1899/04-021.1

Michigan Clean Water Corps: About. (n.d.). Retrieved June 1, 2022, from https://micorps.net/about/

Miranda, M. L., Edwards, S. E., Keating, M. H., & Paul, C. J. (2011). Making the environmental justice grade: The relative burden of air pollution exposure in the United States. *International Journal of Environmental Research and Public Health*, *8*(6), 1755–1771. https://doi.org/10.3390/ijerph8061755

Miskewitz, R., & Uchrin, C. (2013). In-Stream Dissolved Oxygen Impacts and Sediment Oxygen

Demand Resulting from Combined Sewer Overflow Discharges. *Journal of Environmental Engineering*, *139*(10), 1307–1313. https://doi.org/10.1061/(asce)ee.1943-7870.0000739

Neill, A. J., Tetzlaff, D., Strachan, N. J. C., Hough, R. L., Avery, L. M., Watson, H., & Soulsby, C. (2018). Using spatial-stream-network models and long-term data to understand and predict dynamics of faecal contamination in a mixed land-use catchment. *Science of the Total Environment*, *612*, 840–852. https://doi.org/10.1016/j.scitotenv.2017.08.151

Njue, N., Stenfert Kroese, J., Gräf, J., Jacobs, S. R., Weeser, B., Breuer, L., & Rufino, M. C. (2019). Citizen science in hydrological monitoring and ecosystem services management: State of the art and future prospects. *Science of the Total Environment*, *693*. https://doi.org/10.1016/j.scitotenv.2019.07.337

Patang, F., Soegianto, A., & Hariyanto, S. (2018). Benthic Macroinvertebrates Diversity as Bioindicator of Water Quality of Some Rivers in East Kalimantan, Indonesia. *International Journal of Ecology*, *2018*. https://doi.org/10.1155/2018/5129421

Paz-Vinas, I., Loot, G., Hermoso, V., Veyssière, C., Poulet, N., Grenouillet, G., & Blanchet, S. (2018). Systematic conservation planning for intraspecific genetic diversity. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1877). https://doi.org/10.1098/rspb.2017.2746

Peterson, E. E., & Ver Hoef, J. M. (2014). Stars: An ArcGIS toolset used to calculate the spatial information needed to fit spatial statistical models to stream network data. *Journal of Statistical Software*, *56*(2), 1–17. https://doi.org/10.18637/jss.v056.i02

Peterson, E. E., Ver Hoef, J. M., Isaak, D. J., Falke, J. A., Fortin, M. J., Jordan, C. E., … Wenger, S. J. (2013). Modelling dendritic ecological networks in space: An integrated network perspective. *Ecology Letters*, *16*(5), 707–719. https://doi.org/10.1111/ele.12084

Petrella, S. (2020). *Quality Assurance Project Plan*. Plymouth, MI. Retrieved from https://micorps.net/wp-content/uploads/2021/02/FOTR-Signed-QAPP-for-Benthic-Monitoring-11-25-2020-web.pdf

Pond, G. J., Krock, K. J. G., Cruz, J. V., & Ettema, L. F. (2017). Effort-based predictors of headwater stream conditions: comparing the proximity of land use pressures and instream stressors on macroinvertebrate assemblages. *Aquatic Sciences*, *79*(3), 765–781. https://doi.org/10.1007/s00027-017-0534-3

Quijano, J. C., Zhu, Z., Morales, V., Landry, B. J., & Garcia, M. H. (2017). Three-dimensional model to capture the fate and transport of combined sewer overflow discharges: A case study in the Chicago Area Waterway System. *Science of the Total Environment*, *576*, 362–373. https://doi.org/10.1016/j.scitotenv.2016.08.191

Rigolon, A., Browning, M., & Jennings, V. (2018). Inequities in the quality of urban park systems: An environmental justice investigation of cities in the United States. *Landscape and Urban Planning*, *178*(January), 156–169. https://doi.org/10.1016/j.landurbplan.2018.05.026

Salerno, F., Viviano, G., & Tartari, G. (2018). Urbanization and climate change impacts on surface water quality: Enhancing the resilience by reducing impervious surfaces. *Water Research*, *144*, 491–502. https://doi.org/10.1016/j.watres.2018.07.058

Sanchez, G. M., Nejadhashemi, A. P., Zhang, Z., Marquart-Pyatt, S., Habron, G., & Shortridge, A. (2015). Linking watershed-scale stream health and socioeconomic indicators with spatial clustering and structural equation modeling. *Environmental Modelling and Software*, *70*, 113–127. https://doi.org/10.1016/j.envsoft.2015.04.012

Sanchez, G. M., Nejadhashemi, A. P., Zhang, Z., Woznicki, S. A., Habron, G., Marquart-Pyatt, S., & Shortridge, A. (2014). Development of a socio-ecological environmental justice model for watershed-based management. *Journal of Hydrology*, *518*(PA), 162–177. https://doi.org/10.1016/j.jhydrol.2013.08.014

Selzer, M. D. (2008). *The Michigan Department of Environmental Quality Biennial Remedial Action Plan Update For the Rouge River Area of Concern*. Lansing, MI. Retrieved from https://www.michigan.gov/documents/egle/wrd-aoc-rap-rouge_665199_7.pdf

Stream Macroinvertebrate Datasheet. (n.d.). *MiCorps*. Retrieved from https://micorps.net/wp-content/uploads/2021/01/old-VSMP-Macro-OrderLevel-Datasheet-1.pdf

Taylor, J., Graham, M., Louw, A., Lepheana, A., Madikizela, B., Dickens, C., … Warner, S. (2021). Social change innovations, citizen science, miniSASS and the SDGs. *Water Policy*, *00*(0), 1–10. https://doi.org/10.2166/wp.2021.264

Thornbrugh, D. J., Leibowitz, S. G., Hill, R. A., Weber, M. H., Johnson, Z. C., Olsen, A. R., … Peck, D. V. (2018). Mapping watershed integrity for the conterminous United States. *Ecological Indicators*, *85*(December 2017), 1133–1148. https://doi.org/10.1016/j.ecolind.2017.10.070

Tong, S. T. Y., & Chen, W. (2002). Modeling the relationship between land use and surface water quality. *Journal of Environmental Management*, *66*(4), 377–393. https://doi.org/10.1006/jema.2002.0593

Tscheikner-Gratl, F., Bellos, V., Schellart, A., Moreno-Rodenas, A., Muthusamy, M., Langeveld, J., … Tait, S. (2019). Recent insights on uncertainties present in integrated catchment water quality modelling. *Water Research*, *150*, 368–379. https://doi.org/10.1016/j.watres.2018.11.079

U.S. Census Bureau (US Census). (2020). *Understanding and Using American Community Survey Data: What All Data Users Need to Know*. Washington, DC. Retrieved from https://www.census.gov/content/dam/Census/library/publications/2020/acs/acs_general_handbook_2020.pdf

United States Environmnetal Protecion Agency. (2021). EJSCREEN. Retrieved February 9, 2022, from https://www.epa.gov/ejscreen

US Geological Survey. (2016). National Water Information System. https://doi.org/http://dx.doi.org/10.5066/F7P55KJN

Ver Hoef, J. M., & Erin, E. P. (2010). A moving average approach for spatial statistical models of stream networks. *Journal of the American Statistical Association*, *105*(489), 6–18. https://doi.org/10.1198/jasa.2009.ap08248

Ver Hoef, J. M., Peterson, E. E., Clifford, D., & Shah, R. (2014). SSN: An R Package for Spatial Statistical Modeon Stream Networks. *Journal of Statistical Software*, *56*(3). https://doi.org/10.18637/jss.v056.i03

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science*, *277*(5325), 494–499. https://doi.org/10.1126/science.277.5325.494

Von Bertrab, M. G., Krein, A., Stendera, S., Thielen, F., & Hering, D. (2013). Is fine sediment deposition a main driver for the composition of benthic macroinvertebrate assemblages? *Ecological Indicators*, *24*, 589–598. https://doi.org/10.1016/j.ecolind.2012.08.001

Wahl, M. H., McKellar, H. N., & Williams, T. M. (1997). Patterns of nutrient loading in forested and urbanized coastal streams. *Journal of Experimental Marine Biology and Ecology*, *213*(1), 111–131. https://doi.org/10.1016/S0022-0981(97)00012-9

Walsh, C. J., Roy, A. H., Feminella, J. W., Cottingham, P. D., Groffman, P. M., & Morgan, R. P. (2005). The urban stream syndrome: Current knowledge and the search for a cure. *Journal of the North American Benthological Society*, *24*(3), 706–723. https://doi.org/10.1899/04-028.1

Walsh, C. J., Sharpe, A. K., Breen, P. F., & Sonneman, J. A. (2001). Effects of urbanization on streams of the Melbourne region, Victoria, Australia. I. Benthic macroinvertebrate communities. *Freshwater Biology*, *46*(4), 535–551. https://doi.org/https://doi.org/10.1046/j.1365-2427.2001.00690.x

Wang, Q., Roß-Nickoll, M., Wu, D., Deng, W., Wang, Z., Yuan, X., & Zhang, Y. (2018). Impervious area percentage predicated influence of rapid urbanization on macroinvertebrate communities in a southwest China river system. *Science of the Total Environment*, *627*, 104–117. https://doi.org/10.1016/j.scitotenv.2018.01.231

Withers, P. J. A., & Jarvie, H. P. (2008). Delivery and cycling of phosphorus in rivers: A review. *Science of the Total Environment*, *400*(1–3), 379–395. https://doi.org/10.1016/j.scitotenv.2008.08.002

Appendix A. Supplemental Material

MiCorps Site ID#:________________

Michigan Clean Water Corps

IDENTIFICATION AND ASSESSMENT

Use letter codes [**R** (rare) = 1-10, **C** (common) = 11 or more] to record the approximate numbers of organisms in each taxa found in the stream reach.

*** Do NOT count empty shells, pupae, or terrestrial macroinvertebrates***

Group 1: Sensitive

____ Caddisfly larvae (Trichoptera)
EXCEPT Net-spinning caddis
____ Hellgrammites (Megaloptera)
____ Mayfly nymphs (Ephemeroptera)
____ Gilled (right-handed) snails (Gastropoda)
____ Stonefly nymphs (Plecoptera)
____ Water penny (Coleoptera)
____ Water snipe fly (Diptera)

Group 2: Somewhat-Sensitive

____ Alderfly larvae (Megaloptera)
____ Beetle adults (Coleoptera)
____ Beetle larvae (Coleoptera)
____ Black fly larvae (Diptera)
____ Clams (Pelecypoda)
____ Crane fly larvae (Diptera)
____ Crayfish (Decapoda)
____ Damselfly nymphs (Odonata)
____ Dragonfly nymphs (Odonata)
____ Net-spinning caddisfly larvae
(Hydropsychidae; Trichoptera)
____ Scuds (Amphipoda)
____ Sowbugs (Isopoda)

Group 3: Tolerant

____ Aquatic worms (Oligochaeta)
____ Leeches (Hirudinea)
____ Midge larvae (Diptera)
____ Pouch snails (Gastropoda)
____ True bugs (Hemiptera)
____ Other true flies (Diptera)

STREAM QUALITY SCORE

Group 1:
____ # of R's * 5.0 = ____
____ # of C's * 5.3 = ____
Group 1 Total = ______

Group 2:
____ # of R's * 3.0 = ____
____ # of C's * 3.2 = ____
Group 2 Total = ______

Group 3:
____ # of R's * 1.1 = ____
____ # of C's * 1.0 = ____
Group 3 Total = ______

Total Stream Quality Score = _______
(Sum of totals for groups 1-3; round to nearest whole number)

Check one:
____ Excellent (>48)
____ Good (34-48)
____ Fair (19-33)
____ Poor (<19)

Identifications made by:____

Rate your confidence in these identifications: Quite confident 5 4 3 2 1 Not very confident

Figure A1: SQI calculation sheet developed by the Michigan Clean Water Corps from their Macroinvertebrate Datasheet (pre 2020) ("Stream Macroinvertebrate Datasheet," n.d.).

Supplemental Table 1: Model selection parameters for the best performing model and parallel models excluding spatial modeling methods, socio-economic data, and including stream order.

Spatial Relationship	Variables	Random Effect	AIC	R^2	RMSE
-	Imperviousness Sediment Regulation Poverty	-	-48.01	0.40	4.11
Linear Sill Tail-down	Imperviousness Sediment Regulation	-	-83.33	0.31	3.16
Linear Sill Tail-down	Imperviousness Sediment Regulation Poverty	Stream Order	-81.77	0.36	3.16
Linear Sill Tail-down	Imperviousness Sediment Regulation Poverty	-	-83.77	0.36	3.14

CRediT Author Statements:

Isabelle R Horvath: Formal analysis, Investigation, Writing, Visualization. **Anthony J Parolari**: Supervision, Writing – Review & Editing. **Sally Petrella**: Conceptualization, Resources, Data Curation, Writing – Review & Editing. **Craig Stow**: Writing – Review & Editing, Supervision, Project administration, Funding acquisition. **Casey Godwin**: Writing – Review & Editing, Supervision, Project administration, Funding acquisition. **Timothy J. Maguire**: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing, Visualization, Supervision, Funding acquisition.

Figure Captions

Figure 1: The Rouge River watershed. The Rouge River watershed includes parts of metropolitan Detroit and its Western suburbs. Volunteer science benthic macroinvertebrate data were collected sporadically at 122 observation sites along the Rouge River.

Figure 2: Relevant characteristics in the Rouge River watershed. Sediment regulation (a) is a modeled parameter from 0-1 where 0 indicates low impact of sediment within a catchment, imperviousness (b) as the average percent of landcover identified as impervious, and poverty is the percent of the population living under the poverty line (c) plotted in original data format as percentages within census tracts.

Figure 3: Flow diagram of methods, highlighting data inputs and analysis methods.

Figure 4: Observed and modeled SQI data. SQI measures were collected for sites in the Rouge River watershed by the volunteer science organization Friends of the Rouge. Observations of SQI (a) compared to modeled SQI along every 800m of stream under true conditions (b).

Figure 5: Leave one out cross validation (LOOCV) results compared for a non-spatial model (a) containing the same predictor variables as a spatial model with socio-economic and environmental variables (b). Root mean square error (RMSE) and the standard deviation of this calculation is printed on each plot, showing higher RMSE and standard deviation for the simple model than for the spatial model.

Figure 6: Relationships between predicted SQI and poverty under hypothetical poor (a), standard (b) and good (c) watershed conditions, compared to the relationship under true watershed conditions (d). The slope of the linear relationship between predicted SQI and poverty is plotted under each scenario.

Figure 7: High poverty within the Southeast part of the Rouge River watershed, highlighting water concerns in this region including density of uncontrolled Combined Sewer Overflow (CSO) outfalls and locations of ghost streams that no longer exist

Highlights

- Citizen science data was used to build a spatial stream network model
- Stream quality was modeled with a combination of environmental and socio-economic variables
- Stream quality is lower in urban streams with high poverty rates