Universities Council on Water Resources
Journal of Contemporary Water Research & Education
Issue 176, Pages 36-49, August 2022

Total Maximum Daily Loads and *Escherichia coli* Trends in Texas Freshwater Streams

*Michael Schramm[1], Anna Gitter[2], and Lucas Gregory[1]

[1]*Texas Water Resources Institute, Texas A&M AgriLife Research, College Station, Texas*
[2]*University of Texas Health Science Center at Houston, School of Public Health, El Paso, Texas*
**Corresponding author*

Abstract: Fecal indicator bacteria are routinely used to assess surface water sanitary quality. The State of Texas uses Total Maximum Daily Loads to address water bodies that exceed the allowable fecal indicator bacteria criteria. The effectiveness of these processes in decreasing the fecal indicator bacteria concentrations has been debated due to the diversity and nature of fecal indicator bacteria sources. We assessed actual and flow-adjusted trends in measured *Escherichia coli* (*E. coli*) concentrations at 721 freshwater stream sites from 2001 through 2021. We also compared odds of statistical improvement of *E. coli* concentrations at sites before and after the adoption of Total Maximum Daily Loads (adopted from 2008 through 2014). Results indicate non-significant differences in the odds of statistically detected improvements in *E. coli* concentration between pre-Total Maximum Daily Load and post-Total Maximum Daily Load sites. Although the State of Texas and numerous watershed stakeholders have made efforts to address water quality impairments, these results join a body of evidence that water quality improvements are stagnating in the state. Furthermore, this study leverages water quality data used for state water quality standards assessment purposes and highlights that robust monitoring program design is needed to effectively assess the progress of water quality planning efforts.

Keywords: *Total Maximum Daily Load, indicator bacteria, water quality, trend test*

Elevated fecal indicator bacteria (FIB) concentrations are responsible for approximately 40% of water quality impairments in the State of Texas (TCEQ 2019). *Escherichia coli* (*E. coli*) and enterococci are non-host specific bacteria typically present in the gut of warm-blooded animals and utilized as FIB to indicate the potential for recent fecal contamination of water bodies. *E. coli* and enterococci concentrations are evaluated using numeric criteria based on U.S. Environmental Protection Agency (EPA) studies that positively correlated the incidences of gastrointestinal illnesses with concentrations of *E. coli* or enterococci at recreational beaches with known point source sewage discharges (Dufour 1984; Fujioka et al. 2015). While substantial improvements in point sources of FIB (end of pipe discharges such as municipal or other wastewater facilities) have been achieved through the Clean Water Act and its amendments, non-point sources have remained a substantial challenge (National Research Council 2001; Benham et al. 2008). Potential non-point sources of FIB are generally diffuse across a watershed and can include domestic

Research Implications

- Despite substantial efforts, only 7.4% of water quality monitoring stations had statistically decreasing *Escherichia coli* concentrations after adoption of a Total Maximum Daily Load (TMDL).
- We observed no evidence of a difference in the odds of detecting statistically decreasing *Escherichia coli* concentrations between stations before a TMDL and after a TMDL.
- Additional research is called for to understand the commonalities in successful water quality planning efforts and to identify challenges in the existing state water quality planning and implementation framework.

livestock, wildlife, septic systems, pets, and any other potential source of fecal contamination in a watershed. Furthermore, sediments and algal communities can harbor and potentially allow *E. coli* to naturalize in the environment (Ishii and Sadowsky 2008). The diffuse nature of non-point sources of FIB, background contributions from wildlife, and potential for naturalization in the environment present considerable challenges for entities involved in improving impaired waterbodies.

Federal, state, and local government agencies and stakeholders have devoted substantial resources to address the sources of these impairments. Through July 2018, the Texas Commission on Environmental Quality (TCEQ) has developed and approved 187 Total Maximum Daily Loads (TMDLs) that define the FIB load allocations for water bodies not meeting state water quality standards. In addition to TMDL development, the TCEQ and Texas State Soil and Water Conservation Board provided funding and support for the development of 34 accepted watershed-based plans by local stakeholders through July 2018. From 1998 through 2015, the U.S. Department of Agriculture contributed over $171 million in cost-share payments to Texas agricultural producers to implement best management practices that protect or improve water quality (Environmental Working Group 2016). Local and regional governmental entities are also working to address non-point source driven impairments through updated codes and design guidance that promote low impact development. Notable examples include green stormwater infrastructure design criteria adopted in Harris County, low impact design guidance from the San Antonio River Authority, and the City of Austin's watershed protection ordinance among others (Storey et al. 2011; Dorman et al. 2013; Kip 2016).

Achieving in-stream FIB reductions is challenging because of strong influences of land cover on FIB concentrations and the wide diversity of potential point and non-point indicator bacteria sources amongst watersheds (Smith and Perdeck 2004; Mallin et al. 2009). Observed improvements in non-point source degraded water quality are hindered by water quality response lag times, shifts in climate and streamflow that obscure impacts of improved land management practices, changes in land use and land cover, and the difficulty in translating site-scale runoff and pollutant reductions to watershed-scale water quality improvements (Meals et al. 2010; Tomer and Locke 2011).

TMDLs and watershed-based plans are the two primary tools available to the State of Texas for addressing water quality impairments, with the former being most used. TMDLs identify the total pollutant load that a water body can assimilate and still meet water quality standards. TMDLs also assign portions of the pollutant load to point and non-point sources. Alongside a TMDL, an Implementation Plan (I-Plan) is developed using stakeholder input to identify how TMDL allocations will be achieved (Benham et al. 2008). Historically, TMDLs were treated as desktop modelling exercises and generally considered well suited for point-source driven impairments that can be easily modeled as steady-state systems (Haith 2003). However, there are concerns about the effectiveness of the approach for non-point source dominated systems, especially in agriculturally dominated watersheds that do not fall under state or federal stormwater regulations (Laitos and Ruckriegle 2012).

One indication that collective efforts are beginning to work is a decrease in the number of FIB impaired water bodies from 320 segments in 2010 to 237 segments in 2018 (TCEQ 2019). While water body de-listings are one metric of improvement, further insight can be gleaned to provide appropriate context of the relative impacts (or lack of impacts) from TMDLs. For example, a water body that is orders of magnitude above the standard may see significant water quality improvement but remain on the list of impaired water bodies. Conversely, an unimpaired water body may see undesired increases in bacteria loads but not enough to trigger an impairment listing. Furthermore, the number of listings is a flawed metric due to administrative reasons for removal such as changes in water body classification (lengthening or shortening of the assessed water body) or changes in water quality criteria.

With nearly 200 completed TMDLs addressing bacteria impairments in the State of Texas, there is an opportunity to assess the effectiveness of TMDLs in achieving detectable water quality improvements. Trends in water quality can be masked by natural variation in precipitation and discharge because of the correlation between pollutant concentration and flow. Therefore, flow-adjustment methods can provide insight into whether pollutant concentration trends are driven primarily by changes in streamflow or on the ground practices (Helsel and Hirsch 2002; Stow and Borsuk 2003). This study intends to (1) describe actual and flow-adjusted indicator bacteria trends across the state, and (2) assess the effect of TMDLs on indicator bacteria trends.

Methods

Data

The TCEQ Surface Water Quality Monitoring (SWQM) stations and associated *E. coli* monitoring data were obtained from the Water Quality Portal (https://www.waterqualitydata.us/) using the "dataRetrieval" package in R version 4.2.1 (De Cicco et al. 2018; R Core Team 2022). Data were retrieved for all stations between January 1, 2001 through December 31, 2021. The time period was chosen to evaluate at least seven years of data before and after adoption of FIB TMDLs adopted from January 1, 2008 through December 31, 2014. A seven-year period was chosen because it aligns with the assessment period length used to evaluate compliance with water quality criteria.

Apriori power analysis by Monte Carlo simulation of *E. coli* data sets at median variance indicated that the modified Mann-Kendall test has a power of 0.63 to detect a 40% change in concentration over seven years with three samples per year and $\alpha = 0.10$ (Schramm 2021a). The statistical power increased to 0.79 with four samples per year. Here, the statistical power refers to the probability that the Mann-Kendall test rejects the null hypothesis (no-trend) when there is an actual trend in the data at a particular site and is a function of some pre-assigned significance level, effect size (percent decrease in concentration), sample size, and variance.

In order to maximize sample size, and in consideration of within site variation of annual sampling effort, we retained stations with a median three or more samples per year for analysis. Justification for this filtering criteria is further explained in the limitations section of the discussion. The actual statistical power of the modified Mann-Kendall test at an individual station will vary based on the number of samples and sample variance at that station. Schramm (2021a) provides further discussion on implications of designing monitoring approaches for stakeholders interested in detecting smaller effects.

Mean daily streamflow data from United States Geological Survey (USGS) stream gages were downloaded from the National Water Information System using the "dataRetrieval" package in R. The TCEQ SWQM stations were linked to the nearest upstream or downstream USGS streamflow gage using the NHDPlus National Seamless database (Moore and Dewald 2016) and the "nhdplusTools" package in R (Blodgett 2018). SWQM stations and data without a stream gage within 4 km on the same stream were removed from analysis. Since we assessed *E. coli* concentrations and not loads, co-located streamflow data were not necessary. The 4 km threshold was deemed adequate to capture streamflow variation for flow-adjustment procedures based on visual inspection of gages and stations in an attempt to balance maximizing stations with streamflow data and accurate streamflow data.

The locations of water bodies with FIB TMDLs adopted from 2008 through 2014 were obtained from EPA Assessment, TMDL Tracking, and Implementation System (ATTAINS) database (https://www.epa.gov/waterdata/attains) using the "rATTAINS" package in R (Schramm 2021b). Water body locations and TMDL classification were spatially linked to the NHDPlus database and SWQM station data set to classify SWQM stations as located within or outside a TMDL water body.

Trend Analysis

Prior to assessing trends in *E. coli* concentration, data were grouped into: (1) pre-TMDL stations, (2) post-TMDL stations, and (3) stations without a TMDL (no-TMDL). Pre-TMDL stations include FIB and flow data prior to TMDL adoption. Post-TMDL stations include FIB and flow data after TMDL adoption. The no-TMDL stations include stations that do not have a FIB TMDL adopted from 2008 through 2014. The data for sites without a TMDL were restricted to the seven-year period from 2015 through 2021 for appropriate comparison with post-TMDL stations. Stations that had a TMDL adopted after 2015 were excluded from this analysis.

We assessed the presence of upward or downward monotonic trends in log-transformed *E. coli* concentrations using the modified Mann-Kendall test and Sen slope at each station (Helsel and Hirsch 2002; Yue and Wang 2002). The Mann-Kendall test is a non-parametric, two-sided test, with trends considered upward or downward based on the value of the Sen Slope with a predetermined α of 0.1. Typically, substantial variance in *E. coli* concentration can be explained by natural changes in stream discharge, precipitation, and hydrology. However, decision-makers are more often concerned with human influence on changes in *E. coli* concentration. The modified Mann-Kendall test for trend can be adjusted to account for variation in streamflow by applying the test to the regression residuals between streamflow and *E. coli* concentration (Helsel and Hirsch 2002). Residuals were obtained from a Generalized Additive Model (GAM) of form:

$$log(y) = \beta_0 + tp_1(log(x)) + \varepsilon \qquad \text{(equation 1)}$$

where y is *E. coli* concentration, β_0 is the intercept, x is streamflow, and ε is the error term assumed to be normally distributed around mean zero. tp_1 is a smoothing function that utilizes reduced rank versions of thin plate splines (Wood 2003). GAMs were fit using the "mgcv" package in R which utilizes generalized cross validation to estimate the optimal splines in the smoothing function (Wood 2011). While GAMs are increasingly used for water quality assessment and trend detection, our primary interest was to obtain the residuals from the model and assess the likelihood of a monotonic improvement in flow-adjusted *E. coli* concentrations across a wide number of sites (Beck and Murphy 2017; Murphy et al. 2019).

Relationship between TMDLs and FIB Trends

A binary presence-absence outcome variable was created for each SWQM station to indicate significant improvement in *E. coli* concentration based on the modified Mann-Kendall test. The outcome variable was coded as zero if the Sen slope was positive or Mann-Kendall test p-value $\geq$ 0.1 or one if the Sen slope was negative and Mann-Kendall test p-value < 0.1. The odds ratio of the outcome variable was calculated for pre-TMDL SWQM stations and stations without a TMDL (no-TMDL) using post-TMDL streams as a reference group. This design allows comparison of SWQM stations before and after TMDLs are adopted, as well as to stations that do not have a TMDL at all. Odds ratios and 95% confidence intervals were calculated using the GLM function in R.

Results

A total of 721 SWQM stations were included in the unadjusted analysis (Table 1); however, not all stations that had TMDLs had sufficient data to be included in both pre-TMDL and post-TMDL groups. The station sample size (n = 196) decreased drastically for the flow-adjusted analysis due to fewer stations located proximate to a USGS stream gage. On average, the number of sampling events at SWQM stations with TMDLs were higher than SWQM stations without a TMDL. As expected, the *E. coli* geometric mean concentrations at SWQM stations with a TMDL were on average higher than SWQM stations without a TMDL.

Trend Analysis

Of the 164 post-TMDL stations, 7.3% showed significant decreases in *E. coli* concentrations (Figures 1, 2; Table 2). In comparison, 11% of the pre-TMDL SWQM stations and 9.2% of no-TMDL stations showed significant decreases in *E. coli* concentrations. When adjusted for flow, concentrations significantly decreased at 17.4%, 10%, and 4.7% of post-TMDL, pre-TMDL, and no-TMDL sites, respectively.

We report the results for flow-adjusted concentrations, but caution readers to limit drawing broad conclusions due to reduced sample size and possibility of selection bias. There is indication that geometric mean concentrations are typically lower at the subset of sites included in the flow-adjusted analysis compared to the full set of sites in the unadjusted analysis. Since proximity to a USGS gage is the major filter on this data, we are likely biasing selection to stations near urbanized areas or on larger tributaries and rivers that justify long-term streamflow monitoring.

Table 1. Summary statistics of SWQM stations and *E. coli* data (collected between 2001-2021). Total values do not represent the sum of the individual categories but of the total unique SWQM stations used in the analysis. Not all stations had sufficient data to include in both the pre-TMDL and post-TMDL categories.

	SWQM Stations (n)	Mean *E. coli* Samples per Station (n)	Geometric Mean *E. coli* Concentration (MPN/100 mL)	Geometric SD *E. coli* Concentration (MPN/100 mL)
Unadjusted Data				
All Stations	721	50.03	178.81	3.04
No-TMDL	552	34.55	131.77	2.62
Post-TMDL	164	63.45	409.26	2.57
Pre-TMDL	146	45.18	766.90	3.27
Flow-Adjusted Data				
All Stations	196	51.06	140.15	2.89
No-TMDL	148	40.10	97.56	2.44
Post-TMDL	46	75.70	439.59	2.37
Pre-TMDL	10	59.10	382.30	2.80

The proportion of pre- and no-TMDL stations with significant decreases in *E. coli* decreased after the flow adjustment procedure was applied (Figure 1). The proportion of post-TMDL stations with significant decreases in *E. coli* increased after the flow-adjustment procedure. This difference suggests that local changes in streamflow may have masked improvements in *E. coli* concentration in post-TMDL stations. However, a single-sided paired t-test on the unadjusted and flow-adjusted slopes at post-TMDL SWQM stations suggested an increase in mean slope when the flow-adjusted procedure was applied ($t = 6.196$, $df = 45$, p-value < 0.01). When the flow-adjustment procedure is applied, some individual stations shifted from significant decreases in *E. coli* concentration to no detectable trend (Figure 2). Again, limited conclusions can be drawn from the flow-adjusted results, but the results highlight the importance of the flow-adjustment procedure, particularly when evaluating trends at individual sites.

Relationship between TMDLs and FIB Trends

The difference in the odds of a significant improvement in *E. coli* concentrations occurring between post-TMDL and pre-TMDL SWQM stations (OR = 1.56, 95% CI [0.72, 3.49]) or between post-TMDL and no-TMDL SWQM stations (OR = 1.29, 95% CI [0.69, 2.59]) was statistically non-significant (Table 2). When adjusted for flow, the difference in odds was also statistically non-significant between post-TMDL and pre-TMDL SWQM stations (OR = 0.53, 95% CI [0.03, 3.45]) (Table 3). The difference in the odds of significant improvement in flow-adjusted *E. coli* concentrations between post-TMDL and no-TMDL SWQM stations was statistically significant (OR = 0.24, 95% CI [0.08, 0.70]).

Discussion

This work provides an exploratory analysis of the effectiveness of TMDLs within Texas for addressing FIB impairments by comparing the odds of statistically significant trends. The results indicate that the difference in the odds that significant improvements in *E. coli* concentrations were observed between post-TMDL stations and pre-TMDL stations were statistically non-significant. The odds of statistical improvement between post-TMDL and no-TMDL stations were also statistically non-significant. When adjusted for flow, significant improvements were observed in a high proportion of post-TMDL sites. The difference in the odds of improvement between the post-TMDL and pre-TMDL station categories remained statistically non-significant. However, the post-TMDL sites had statistically higher odds of *E. coli* improvements than no-TMDL sites, when adjusted for flow. The flow adjustment procedures indicate

Table 2. Cross classification table of TMDL categories and detected improvements in *E. coli* concentrations from the modified Mann-Kendall test on unadjusted *E. coli* concentrations.

	---------------------TMDL Category---------------------		
Outcome Variable	**Post-TMDL**	**Pre-TMDL**	**No-TMDL**
No Improvement	152	130	501
Statistical Improvement	12	16	51
Total	164	146	552
Odds Ratio	1	1.56	1.29
95% CI	—	(0.72, 3.49)	(0.69, 2.59)
Log Odds	0	0.44	0.25

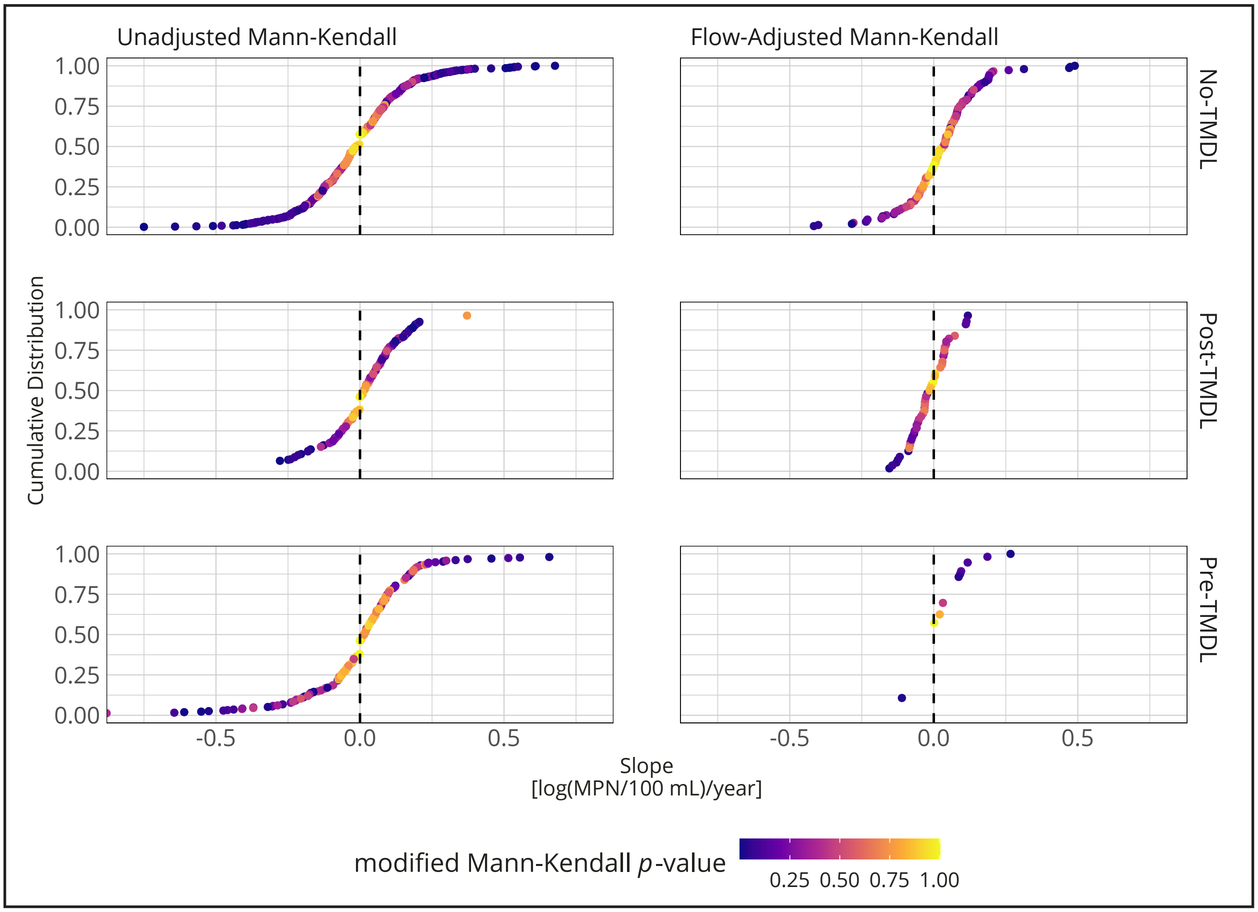

Figure 1. Cumulative distribution of Sen slope and associated p-values from the modified Mann-Kendall test on unadjusted and flow-adjusted *E. coli* concentrations at individual monitoring stations.

that changes in flow masked some improvements in *E. coli* concentrations over the sampled time period at some stations. Our expectations are that pre-TMDL stations would have significantly lower odds of improvement compared to post-TMDL stations, if broad-scale improvements in water quality occurred following TMDLs. We attempt to account for variations in flow with the flow-adjustment procedure in our analysis, but it drastically reduced the overall sample size and limits the conclusions that can be drawn. Other confounders, such as changes in land-use, variation in sources, and variance in local watershed groups are not included in this project but discussed below. Overall, this provides some evidence that improvements in *E. coli* concentrations have not been achieved at a broad scale despite TMDL efforts. While the results indicate some individual sites have seen improvement following TMDLs, the odds that they occur are not any higher than before TMDLs were implemented.

There have been limited comprehensive assessments of water quality trends in Texas for comparison. Some coastal assessments in Texas point to increasing trends of water quality exceedances or degradation. Powers et al. (2021) revealed statistically increasing rates of enterococci bacteria exceedances at Texas recreational beaches over a similar timeline. These exceedances were correlated with population increases and sea level rise that might impact the effectiveness of source-controls, such as septic systems and sanitary sewer

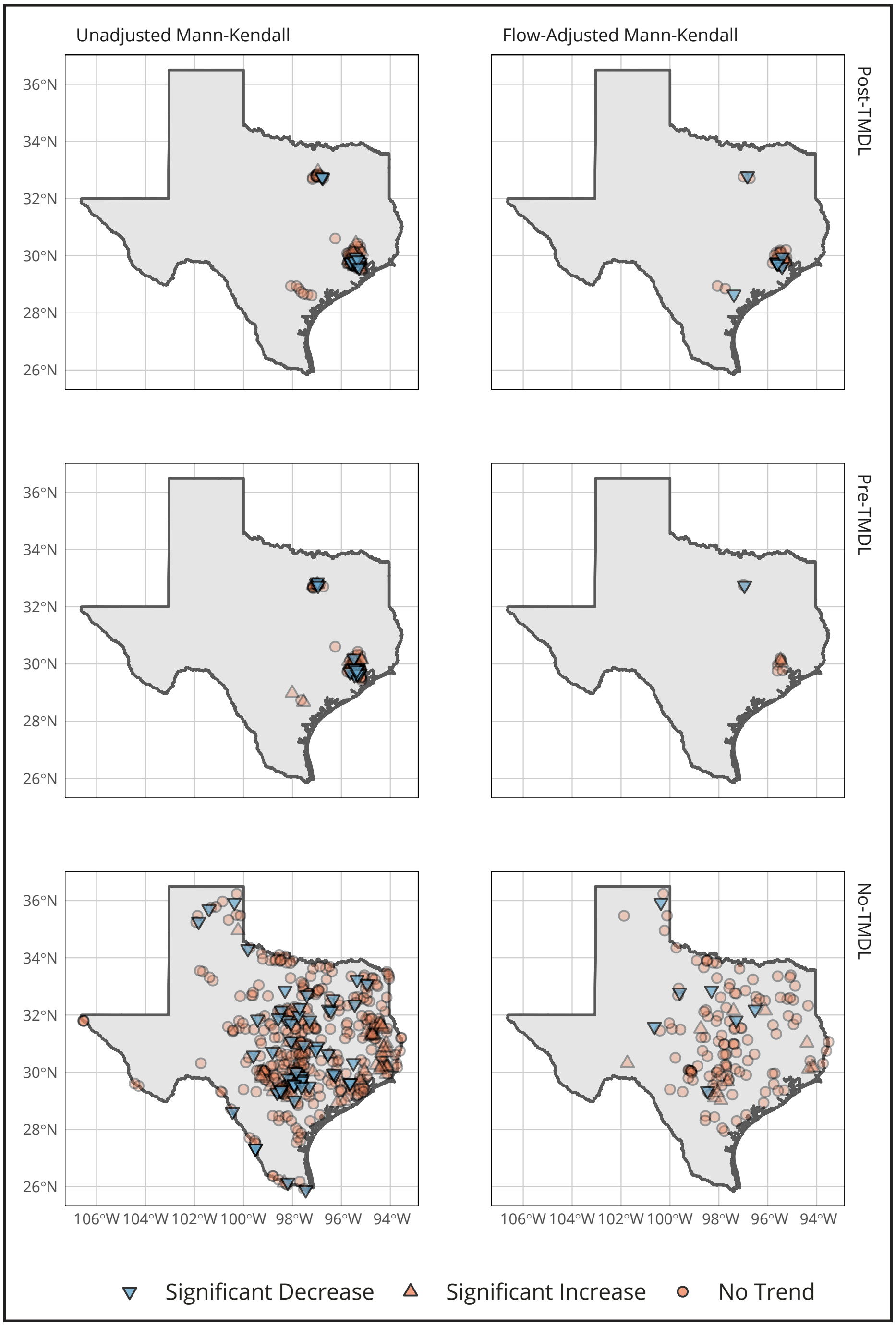

Figure 2. Map of individual monitoring stations and associated modified Mann-Kendall test results for unadjusted and flow-adjusted *E. coli* concentrations.

Table 3. Cross classification table of TMDL categories and detected improvements in *E. coli* concentrations from the modified Mann-Kendall test on flow-adjusted *E. coli* concentrations.

	---------------------TMDL Category---------------------		
Outcome Variable	**Post-TMDL**	**Pre-TMDL**	**No-TMDL**
No Improvement	38	9	141
Statistical Improvement	8	1	7
Total	46	10	148
Odds Ratio	1	0.53	0.24
95% CI	—	(0.03, 3.45)	(0.08, 0.70)
Log Odds	0	-0.64	-1.44

systems in coastal systems (Powers et al. 2021). Bugica et al. (2020) present evidence that both point and non-point sources were contributing to declining estuarine water quality and increasing risk of eutrophication on the Texas coastline between 1996 and 2016. Kuwayama et al. (2020) investigated trends in multiple water quality parameters and indices in Texas river basins and concluded that water quality improvements within the state have largely stagnated over the last 30 years. While substantial regulatory and voluntary efforts have been made to address *E. coli* and other impairments in Texas, this analysis adds to the limited but growing evidence that improvements are not being achieved on a broad scale in the state.

Many of the FIB water quality impairments and TMDLs in the state have been in and around urbanized centers such as Houston, Dallas, and San Antonio. In 2008, the first major FIB TMDL effort in the state (referred to as the Bacteria Implementation Group, or BIG) resulted in the development of 72 different TMDLs and associated I-Plans for impaired waterbodies in the Houston area (HGAC 2020). Similar groups have been formed in San Antonio, Dallas, and Austin, Texas. While these groups report on some individual successes in implementing projects and some reductions in bacteria, achievements in overall water quality goals have not been met. The negative impact of urbanization and imperviousness on hydrologic processes and water quality is well established and likely contributes to limited observations of significant improvements in *E. coli* concentrations (Handler et al. 2006; DiDonato et al. 2009; Mallin et al. 2009; O'Driscoll et al. 2010). Previous studies on fecal coliform and *E. coli* concentrations in Houston, Texas area watersheds indicated initial decreases in FIB concentration following wastewater plant improvements in the 1980s, which was followed by a period of no statistical improvements in *E. coli* concentrations coinciding with high rates of urbanization (Petersen et al. 2006; Desai et al. 2010). Within the Houston, Texas area watersheds, increased urbanization was associated with lower attenuation of wet-weather related *E. coli* concentration spikes, and relatively high *E. coli* concentrations under baseflow and stormflow conditions (compared to less developed watersheds), despite major improvements in point-source discharges. Brinkmeyer et al. (2014) found streambed and bank sediments account for up to 90% of daily *E. coli* and enterococci loads in two highly urbanized Houston, Texas waterbodies with chronically elevated FIB concentrations, and suggest that naturalized background FIB will prevent attainment of water quality goals. This evidence suggests that as urbanized centers grow in Texas, achieving water quality improvements will be increasingly difficult. In anticipation of continued land use development, improved integration of land-use planners and water managers is required to manage and plan around the interconnections between land and water (Stoker et al. 2022).

While substantial regulatory and voluntary efforts have been made to address *E. coli* impairments in Texas, we did not find broad-scale evidence that rates of improving *E. coli* concentration differ after TMDLs are implemented or from non-TMDL stations. While there are specific stations that demonstrated improvements in *E. coli* concentrations, it is beyond the extent of this project to dive into site specific data. However, we do call on a need for further research and data collection to identify the implementation efforts, funding, stakeholders, and other characteristics that might contribute to successful improvements in water quality. Previous studies indicate that the outcome of water quality planning and implementation efforts are a function of financial resources invested, stakeholder engagement, institutional capacity, and norms. Scott (2015; 2016) provides evidence that collaborative watershed management groups (like the BIG) can drive improved water quality outcomes. However, instituting a truly collaborative and effective watershed management effort is a challenge due to institutional silos, stakeholder perceptions, resource availability, and presence of cooperative networks (Lubell 2004; Imperial 2005; Koontz and Newig 2014).

Agricultural non-point sources such as livestock also contribute to FIB impairments throughout Texas and livestock management objectives are often identified in TMDL I-Plans (see HGAC 2020 for an example), presenting additional challenges for water quality planning. The agricultural associated non-point source reductions identified in I-Plans rely on voluntary implementation of best management practices achieved through outreach, education, and Farm Bill financial incentive programs. The voluntary implementation of best management practices faces major barriers such as the economic investments required of landowners, and landowners' limited trust in government programs and initiatives (Kay et al. 2008; Jordan et al. 2011; Guo et al. 2019). The mandatory implementation of agricultural best management practices is both legally and politically fraught (Laitos and Ruckriegle 2012). Due to the voluntary nature of these practices and confidentiality agreements with agencies, numerous knowledge gaps remain related to tracking and evaluating the effectiveness of agricultural best management practices implemented at the watershed scale (Batie 2009).

Partially in response to these challenges, the EPA developed guidance for the development of watershed-based plans as a local stakeholder-driven option to identify and address water quality concerns (U.S. EPA 2013). Under the watershed-based plan concept, local stakeholders drive the identification of issues and desired outcomes, increasing the likelihood of engagement, implementation, and successful outcomes (Koontz and Newig 2014). Agencies that lead these collaborative planning efforts often face difficulties shedding institutional and bureaucratic norms and enabling the flexibility required for successful collaborative governance regimes (Biddle 2017). However, agencies can also add administrative capacity and financial and technical resources, and compel participation that may lead to improved outcomes (Biddle 2017; Bitterman and Koliba 2020). Since addressing water quality challenges requires agency involvement and funding as well as strong local watershed organizations, additional research is needed in Texas to clearly identify the challenges and capacity for state institutional and local watershed groups in developing and implementing plans and projects that lead to improved water quality outcomes.

Limitations

The modified Mann-Kendall test on *E. coli* data has limited power to detect trends in *E. coli* data sets at typical monitoring frequencies (Schramm 2021a). For a station with a median population variance of *E. coli* concentration, monthly sampling is required to obtain 0.71 power for detecting a 20% change in *E. coli* concentration. Monthly sampling is the best-case scenario for most stations. Quarterly sampling is a more typical scenario for stations across the state. At four samples annually, a 40% change in *E. coli* concentration is required to achieve approximately the same power. However, for the stations in this analysis, our assumption is that most sites require relatively large percent reductions to achieve water quality standards (Table 1 indicates the overall geometric means require 67-84% reductions to meet standards, although individual sites will vary). The power of the Mann-Kendall test for detecting effects of this magnitude over seven years is sufficient with three to four samples annually.

The number of stations with adequate data limited exploratory analytic approaches, such as logistic regression, that would permit exploration of the influence of additional covariates. For unadjusted *E. coli* trends, 95 of the 134 stream assessment units with FIB TMDLS adopted from 2008 through 2014 were included in the analysis. However, for flow-adjusted *E. coli* trends, only 34 of 134 stream assessment units with FIB TMDLs were included in the analysis. SWQM stations lacking a proximate stream gage, without adequate data samples, or with only enterococci data, were excluded from analysis. This sample size restricts extending our analysis to include additional explanatory covariates such as land-use, implementation funding, and spatial dependencies that could provide desired insight. The number of SWQM stations throughout the state without a proximate stream gage severely restricted sample size, and as noted earlier, potentially introduces some sampling bias in location and stream size. Future work may consider the use of proxies for streamflow (such as precipitation) which have substantial effect on pollutant loading, and possibly allow the inclusion of more SWQM stations (Sinha and Michalak 2016). While further insights could also be gleaned by assessing financial resources invested, the types of projects implemented, and stakeholder involvement following TMDL development (Scott 2015; 2016), this data is not readily available across the study area.

The shortcomings of using changes in FIB as a metric deserve some discussion. As noted, there are numerous potential sources of FIB within a watershed and this regional level exploratory study does not parse out the possible background-level *E. coli* conditions or the feasibility of reducing *E. coli* concentrations at individual sites. We do not know if actual human health risk from water quality contact has changed following TMDL implementation. TMDLs within Texas currently do not utilize microbial source tracking (MST) to parse out potential contributors and sources of FIB within TMDLs. Nationally, efforts have been made to quantify the risks associated with FIB and integrate findings in watershed decision-making. Using FIB to assess human health risk in freshwater streams presents certain challenges. FIB can survive outside of the host and become naturalized in the environment effectively increasing baseline concentrations (Ishii and Sadowsky 2008). Furthermore, these FIB are not always host specific and may overestimate the risk relative to FIB originating from human sources, such as raw sewage, bather shedding, or treated effluent. The ability and desire to manage or mitigate non-human sources such as wildlife can be costly with uncertain effectiveness and limited impact on reducing potential risk for human health.

MST and Quantitative Microbial Risk Assessment (QMRA) are potential cost-effective frameworks that are increasingly recommended to assist resource managers with management practice selection and translation of FIB concentrations into human health risk (U.S. EPA 2014; Goodwin et al. 2017). QMRA studies have consistently indicated that FIB from non-human and non-cattle sources likely result in a lower risk for a gastrointestinal infection and illness than from FIB resulting from human sources (Schoen and Ashbolt 2010; Soller et al. 2010; Gitter et al. 2020). The presence of fecal pathogens in streams, as indicated by monitoring the FIB concentrations, can be influenced by pathogen source. A management approach that relies solely on the concentration of FIB and not the contributing sources can potentially mischaracterize the human health risk associated with recreation in a specific water body. The use of MST and QMRA provides an opportunity for regulators and stakeholders to establish goals and track progress for realistic water quality improvements based on actual human health risk, as opposed to the current single water quality criterion.

Conclusions

Our analysis indicates that there was no significant difference in the odds of statistically significant reductions of *E. coli* concentration, at an effect size broadly relevant across sites in the state, between pre- and post-TMDL stations. To an extent, sampling sizes restrict the ability of the analysis to detect smaller improvements that might be identified as relevant to local stakeholders. However, this analysis supports similar published findings that water quality improvements have largely stagnated across the state. While the state's TMDL and I-Plan efforts fulfill federal regulatory requirements, the lack of significant difference between pre-TMDL and post-TMDL trends suggests that further work is needed to identify locally successful planning mechanisms and build upon those efforts. It is likely the TMDL planning processes have evolved over time and space as response to administrative changes, stakeholder feedback, and capacity of local stakeholders to lead efforts. In-depth assessment of the processes would provide valuable insight when attempting to link outcomes to process. This study highlights the importance of a robust monitoring to assess program effectiveness and linkages to environmental outcomes, especially in light of continued efforts to develop additional TMDLs to address other impaired streams.

Data Availability Statement

Data and code generated or used during the study are available online at https://doi.org/10.5281/zenodo.4321728.

Acknowledgements

Shubham Jain and Stephanie DeVilleneuve provided comments on an early draft. We also thank two anonymous reviewers for comments that substantially improved this manuscript.

Author Bio and Contact Info

Michael Schramm (corresponding author) is a research specialist for the Texas A&M AgriLife, Texas Water Resources Institute. He provides modeling, data science, and data visualization support for the Institute's watershed planning and assessment program. He can be contacted at michael.schramm@ag.tamu.edu or 578 John Kimbrough Blvd., 2118 TAMU, College Station, Texas 77843-2260.

Dr. Anna Gitter is a post-doctoral research fellow at University of Texas Health Science Center at Houston School of Public Health. Her research is focused on the human health impacts of water quality and she specializes in quantitative microbial risk assessment. She can be contacted at anna.gitter@uth.tmc.edu.

Dr. Lucas Gregory is associate director of Texas A&M AgriLife, Texas Water Resources Institute. His research interests include: bacteria fate and transport in aquatic and soil environments, watershed assessment, planning, and management, watershed assessment tool application and development, water quality monitoring, efficient water resource utilization, implications of water policy on local watershed decision-making, and water and human health interactions. Dr. Gregory can be reached at 578 John Kimbrough Blvd., College Station, TX 77843 or LFGregory@ag.tamu.edu.

References

Batie, S.S. 2009. Green payments and the U.S. Farm Bill: Information and policy challenges. *Frontiers in Ecology and the Environment* 7(7): 380-388. DOI: 10.1890/080004.

Beck, M.W. and R.R. Murphy. 2017. Numerical and qualitative contrasts of two statistical models for water quality change in tidal waters. *JAWRA Journal of the American Water Resources Association* 53(1): 197-219. DOI: 10.1111/1752-1688.12489.

Benham, B., R. Zeckoski, and G. Yagow. 2008. Lessons learned from TMDL implementation case studies. *Water Practice* 2(1): 1-13.

Biddle, J.C. 2017. Improving the effectiveness of collaborative governance regimes: Lessons from watershed partnerships. *Journal of Water Resources Planning and Management* 143(9): 04017048. DOI: 10.1061/(ASCE)WR.1943-5452.0000802.

Bitterman, P. and C.J. Koliba. 2020. Modeling alternative collaborative governance network designs: An agent-based model of water governance in the Lake Champlain Basin, Vermont. *Journal of Public Administration Research and Theory* 30(4): 636-655. DOI: 10.1093/jopart/muaa013.

Blodgett, D. 2018. nhdplusTools: Tools for Accessing and Working with the NHDPlus. Available at: https://doi.org/10.5066/P97AS8JD. Accessed August 3, 2022.

Brinkmeyer, R., R.M.W. Amon, J.R. Schwarz, T. Saxton, D. Roberts, S. Harrison, N. Ellis, et al. 2014. Distribution and persistence of *Escherichia coli* and Enterococci in stream bed and bank sediments from two urban streams in Houston, TX. *Science of the Total Environment* 502(2015): 650-658. DOI: 10.1016/j.scitotenv.2014.09.071.

Bugica, K., B. Sterba-Boatwright, and M.S. Wetz. 2020. Water quality trends in Texas estuaries. *Marine Pollution Bulletin* 152: 110903. DOI: 10.1016/j.marpolbul.2020.110903.

De Cicco, L.A., D. Lorenz, R.M. Hirsch, and W. Watkins. 2018. dataRetrieval: R Packages for Discovering and Retrieving Water Data Available from U.S. Federal Hydrologic Web Services. U.S. Geological Survey; U.S. Geological Survey, Reston, VA. DOI: 10.5066/P9X4L3GE. Available at: https://code.usgs.gov/water/dataRetrieval. Accessed August 3, 2022.

Desai, A.M., H. Rifai, E. Helfer, N. Moreno, and R. Stein. 2010. Statistical investigations into indicator bacteria concentrations in Houston metropolitan watersheds. *Water Environment Research* 82(4): 302-318. DOI: 10.2175/106143009X12487095236595.

DiDonato, G.T., J.R. Stewart, D.M. Sanger, B.J. Robinson, B.C. Thompson, A.F. Holland, and R.F. Van Dolah. 2009. Effects of changing land use on the microbial water quality of tidal creeks. *Marine*

Pollution Bulletin 58(1): 97-106. DOI: 10.1016/j.marpolbul.2008.08.019.

Dorman, T., M. Frey, J. Wright, B. Wardynski, J. Smith, B. Tucker, J. Riverson, A. Teague, and K. Bishop. 2013. *San Antonio River Basin Low Impact Development Technical Guidance Manual*, *v1*. San Antonio River Authority, San Antonio, TX.

Dufour, A.P. 1984. Bacterial indicators of recreational water quality. *Canadian Journal of Public Health* 75(1): 9.

Environmental Working Group. 2016. EWG's Conservation Database. Available at: https://conservation.ewg.org/index.php. Accessed August 3, 2022.

Fujioka, R., H. Solo-Gabriele, M. Byappanahalli, and M. Kirs. 2015. U.S. recreational water quality criteria: A vision for the future. *International Journal of Environmental Research and Public Health* 12(7): 7752-7776. DOI: 10.3390/ijerph120707752.

Gitter, A., K. Mena, K. Wagner, D. Boellstorff, K. Borel, L. Gregory, T. Gentry, and R. Karthikeyan. 2020. Human health risks associated with recreational waters: Preliminary approach of integrating quantitative microbial risk assessment with microbial source tracking. *Water* 12(2): 327. DOI: 10.3390/w12020327.

Goodwin, K.D., A. Schriewer, A. Jirik, K. Curtis, and A. Crumpacker. 2017. Consideration of natural sources in a bacteria TMDL—Lines of evidence, including beach microbial source tracking. *Environmental Science & Technology* 51(14): 7775-7784. DOI: 10.1021/acs.est.6b05886.

Guo, T., D. Gill, T.H. Johengen, and B.L. Cardinale. 2019. What determines the public's support for water quality regulations to mitigate agricultural runoff? *Environmental Science & Policy* 101: 323-330. DOI: 10.1016/j.envsci.2019.09.008.

Haith, D.A. 2003. Systems analysis, TMDLs and watershed approach. *Journal of Water Resources Planning and Management* 129(4): 257-260. DOI: 10.1061/(ASCE)0733-9496(2003)129:4(257).

Handler, N.B., A. Paytan, C.P. Higgins, R.G. Luthy, and A.B. Boehm. 2006. Human development is linked to multiple water body impairments along the California coast. *Estuaries and Coasts* 29(5): 860-870. DOI: 10.1007/BF02786537.

Helsel, D. and R. Hirsch. 2002. *Statistical Methods in Water Resources Techniques of Water-Resources Investigations*, Book 4, chapter A3. United States Geologic Survey. Available at: http://water.usgs.gov/pubs/twri/twri4a3/. Accessed August 3, 2022.

Houston-Galveston Area Council (HGAC). 2020. Bacteria Implementation Group 2020 Annual Report. Houston, TX. Available at: https://www.h-gac.com/bacteria-implementation-group/reports. Accessed August 3, 2022.

Imperial, M.T. 2005. Using collaboration as a governance strategy: Lessons from six watershed management programs. *Administration & Society* 37(3): 281-320. Available at: https://doi.org/10.1177/0095399705276111. Accessed August 3, 2022.

Ishii, S. and M.J. Sadowsky. 2008. *Escherichia coli* in the environment: Implications for water quality and human health. *Microbes and Environments* 23(2): 101-108. DOI: 10.1264/jsme2.23.101.

Jordan, N.R., C.S. Slotterback, K.V. Cadieux, D.J. Mulla, D.G. Pitt, L.S. Olabisi, and J.-O. Kim. 2011. TMDL implementation in agricultural landscapes: A communicative and systemic approach. *Environmental Management* 48(1): 1-12. DOI: 10.1007/s00267-011-9647-y.

Kay, D., J. Crowther, L. Fewtrell, C.A. Francis, M. Hopkins, C. Kay, A.T. McDonald, et al. 2008. Quantification and control of microbial pollution from agriculture: A new policy challenge? *Environmental Science & Policy* 11(2): 171-184. DOI: 10.1016/j.envsci.2007.10.009.

Kip, N. 2016. The impact of the comprehensive watersheds ordinance on stream health in Austin, Texas. Master's thesis, University of Texas at Austin, Austin, TX. Available at: http://hdl.handle.net/2152/43590. Accessed August 3, 2022.

Koontz, T.M. and J. Newig. 2014. From planning to implementation: Top-down and bottom-up approaches for collaborative watershed management: Implementing collaborative watershed plans. *Policy Studies Journal* 42(3): 416-442. DOI: 10.1111/psj.12067.

Kuwayama, Y., S.M. Olmstead, D.C. Wietelman, and J. Zheng. 2020. Trends in nutrient-related pollution as a source of potential water quality damages: A case study of Texas, USA. *Science of the Total Environment* 724: 137962. DOI: 10.1016/j.scitotenv.2020.137962.

Laitos, J.G. and H. Ruckriegle. 2012. The Clean Water Act and the challenge of agricultural pollution. *Vermont Law Review* 37(4): 1033-1070.

Lubell, M. 2004. Collaborative watershed management: A view from the grassroots. *Policy Studies Journal* 32(3): 341-361. DOI: 10.1111/j.1541-0072.2004.00069.x.

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

Meals, D.W., S.A. Dressing, and T.E. Davenport. 2010. Lag time in water quality response to best management practices: A review. *Journal of Environment Quality* 39(1): 85. DOI: 10.2134/jeq2009.0108.

Moore, R.B. and T.G. Dewald. 2016. The road to NHDPlus advancements in digital stream networks and associated catchments. *JAWRA Journal of the American Water Resources Association* 52(4): 890-900.

Murphy, R.R., E. Perry, J. Harcum, and J. Keisman. 2019. A Generalized Additive Model approach to evaluating water quality: Chesapeake Bay case study. *Environmental Modelling & Software* 118: 1-13. DOI: 10.1016/j.envsoft.2019.03.027.

National Research Council. 2001. *Assessing the TMDL Approach to Water Quality Management*. National Academies Press, Washington, D.C. DOI: 10.17226/10146.

O'Driscoll, M., S. Clinton, A. Jefferson, A. Manda, and S. McMillan. 2010. Urbanization effects on watershed hydrology and in-stream processes in the Southern United States. *Water* 2(3): 605-648. DOI: 10.3390/w2030605.

Petersen, T.M., M.P. Suarez, H.S. Rifai, P. Jensen, Y. Su, and R. Stein. 2006. Status and trends of fecal indicator bacteria in two urban watersheds. *Water Environment Research* 78(12): 2340-2355. DOI: 10.2175/106143006X102033.

Powers, N.C., J. Pinchback, L. Flores, Y. Huang, M.S. Wetz, and J.W. Turner. 2021. Long-term water quality analysis reveals correlation between bacterial pollution and sea level rise in the Northwestern Gulf of Mexico. *Marine Pollution Bulletin* 166: 112231. DOI: 10.1016/j.marpolbul.2021.112231.

R Core Team. 2022. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Available at: https://www.R-project.org/. Accessed August 3, 2022.

Schoen, M.E. and N.J. Ashbolt. 2010. Assessing pathogen risk to swimmers at non-sewage impacted recreational beaches. *Environmental Science & Technology* 44(7): 2286-2291. DOI: 10.1021/es903523q.

Schramm, M. 2021a. Estimating statistical power for detecting long term trends in surface water *Escherichia coli* concentrations. *Texas Water Journal* 12(1): 140-150. DOI: 10.21423/twj.v12i1.7126.

Schramm, M. 2021b. rATTAINS: Access EPA ATTAINS Data. R package version 0.1.3. Available at: https://CRAN.R-project.org/package=rATTAINS. Accessed August 3, 2022. DOI: 10.5281/zenodo.3635017.

Scott, T.A. 2015. Does collaboration make any difference? Linking collaborative governance to environmental outcomes. *Journal of Policy Analysis and Management* 34(3): 537-566. DOI: 10.1002/pam.21836.

Scott, T.A. 2016. Is collaboration a good investment? Modeling the link between funds given to collaborative watershed councils and water quality. *Journal of Public Administration Research and Theory* 26(4): 769-786. DOI: 10.1093/jopart/muw033.

Sinha, E. and A.M. Michalak. 2016. Precipitation dominates interannual variability of riverine nitrogen loading across the continental United States. *Environmental Science & Technology* 50(23): 12874-12884. DOI: 10.1021/acs.est.6b04455.

Smith, J.E. and J.M. Perdeck. 2004. Assessment and management of watershed microbial contaminants. *Critical Reviews in Environmental Science and Technology* 34(2): 109-139. DOI: 10.1080/10643380490430663.

Soller, J.A., M.E. Schoen, T. Bartrand, J.E. Ravenscroft, and N.J. Ashbolt. 2010. Estimated human health risks from exposure to recreational waters impacted by human and non-human sources of faecal contamination. *Water Research* 44(16): 4674-4691. DOI: 10.1016/j.watres.2010.06.049.

Stoker, P., T. Albrecht, G. Follingstad, and E. Carlson. 2022. Integrating land use planning and water management in U.S. cities: A literature review. *JAWRA Journal of the American Water Resources Association* 58(3): 321-335. DOI: 10.1111/1752-1688.13022.

Storey, A.L., J. Blount, and M.D. Talbott. 2011. Harris County Low Impact Development & Green Infrastructure Design Criteria for Storm Water Management. Available at: https://texasriparian.org/wp-content/uploads/2013/02/Harris-County-LID-and-GI-Design-Criteria-Manual.pdf. Accessed August 3, 2022.

Stow, C.A. and M.E. Borsuk. 2003. Assessing TMDL effectiveness using flow-adjusted concentrations: A case study of the Neuse River, North Carolina. *Environmental Science & Technology* 37(10): 2043-2050. DOI: 10.1021/es020802p.

Texas Commission on Environmental Quality (TCEQ). 2019. *Second Submission of the 2018 Texas Integrated Report for Clean Water Act Sections 305(b) and 303(d)*. Austin, TX. Available at: https://www.tceq.texas.gov/waterquality/assessment/18twqi/18txir. Accessed August 3, 2022.

Tomer, M.D. and M.A. Locke. 2011. The challenge of documenting water quality benefits of conservation practices: A review of USDA-ARS's conservation effects assessment project watershed studies. *Water Science & Technology* 64(1): 300. DOI: 10.2166/wst.2011.555.

U.S. EPA. 2013. A Quick Guide to Developing Watershed Plans to Restore and Protect our Waters. EPA-841-R-13-003. U.S. Environmental Protection Agency, Washington, D.C. Available at: https://www.epa.gov/sites/production/files/2015-12/documents/watershed_mgmnt_quick_guide.pdf. Accessed August 3, 2022.

U.S. EPA. 2014. Overview of Technical Support Materials: A Guide to the Site-Specific Alternative Recreational Criteria TSM Documents. EPA-820-R-14-010. U.S. Environmental Protection Agency Office of Water. Available at: https://www.epa.gov/sites/production/files/2015-11/documents/guide-sitespecific-alternative-recreational-criteria-documents.pdf. Accessed August 3, 2022.

Wood, S.N. 2003. Thin-plate regression splines. *Journal of the Royal Statistical Society (B)* 65(1): 95-114.

Wood, S.N. 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B)* 73(1): 3-36.

Yue, S. and C.Y. Wang. 2002. Regional streamflow trend detection with consideration of both temporal and spatial correlation. *International Journal of Climatology* 22(8): 933-946. DOI: 10.1002/joc.781.