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Review

Trends in nutrient-related pollution as a source of potential water quality damages: A case study of Texas, USA

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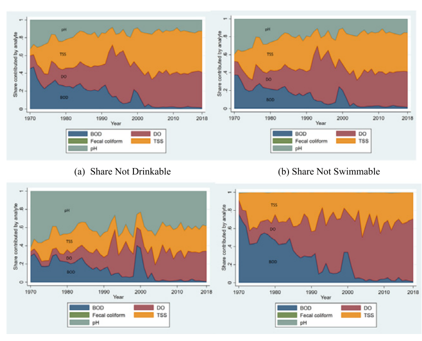
HIGHLIGHTS6

- We examine nutrient-related trends in surface water quality in Texas, USA.
- Trends may tend toward degradation for DO, TN, TP and chlorophyll *a* statewide.
- Trends vary by river basin and depend on the parametric or nonparametric test used.
- Gains in meeting pollution thresholds for human uses have flattened since the 1990s.
- The role of DO and TSS in non-attainment of human use designations has increased.

GRAPHICAL ABSTRACT



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ABSTRACT

We examine long-run trends in surface water quality in Texas, USA, with a focus on nutrient pollution and its potential economic impacts. Using >2 million observations of total nitrogen, total phosphorous, dissolved oxygen, and chlorophyll *a* concentrations from water quality monitors in the state's 23 river sub-basins, we find that nutrient pollution may be a growing problem that is essentially statewide in scope. In addition, because economic impacts of nutrient pollution depend not just on observed water quality, but also on the typical uses of surface water resources that people value, we quantify the share of the state's surface water resources that does not meet common definitions of quality suitable for boating, fishing, swimming, and drinking, as well as the share that does not meet state regulatory standards for their designated uses. This analysis indicates that water quality improvements relative to human uses have stagnated over the last three decades and that nutrient pollution represents a much greater relative threat to attainment of designated uses than it did in the 1970s. We conclude that nutrient pollution is likely taking a toll on the economic value of Texas' water resources.

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Contents

1. Introduction

The major sources of ambient surface water quality impairment in the United States have shifted over time, from primarily point-source concerns (such as industrial pollution) toward nonpoint source concerns (such as agricultural runoff) (U.S. GAO, 1999). As in many other industrialized countries, U.S. water quality regulation under the framework of the 1972 Clean Water Act (CWA) focused primarily on limiting effluent from point sources, has only recently begun to target nonpoint source pollution, and is limited in its capacity to do so, especially with respect to agricultural sources (Olmstead, 2010). While both point and nonpoint source pollution remain important causes of impairment in specific areas, recent U.S. Environmental Protection Agency (EPA) data rank nutrients as the third most frequent cause of impairment in U.S. rivers and streams, second for lakes and rivers, and second for bays and estuaries (EPA, 2020). The United States is not alone in this trend; eutrophication due to excessive anthropogenic nutrient loading is a global phenomenon in both inland and coastal waters (Doney, 2010; Le Moal et al., 2019). Eutrophic waters experience reductions in clarity, may smell and look bad, and may also experience harmful algal blooms (HABs) that can be dangerous for humans and animals (Gámez et al., 2019; Patiño et al., 2014). Reported hypoxic or anoxic "dead zones," in which aquatic life that cannot escape the low-oxygen zone cannot be supported, doubled worldwide between 1995 and 2008 to >400 zones and increased to 515 sites in 2011 (Rabotyagov et al., 2014). Addition of nitrogen is typically an important driver of eutrophication in coastal marine systems, while addition of phosphorus often plays this role in freshwater systems (National Research Council, 2000).

While the impacts of nutrient pollution and HABs on ecosystem health have been the focus of significant attention in the scientific literature, these phenomena have more recently prompted research by economists concerned with quantifying damages to human health, recreational uses, property values, and commercial fishing. The magnitude of economic damages from nutrient pollution depends strongly on the degree to which water quality impairment is likely to affect human uses such as drinking water supply, swimming, fishing, wildlife watching, beachgoing, and boating. The benefits of water quality for some of these activities are capitalized in markets, and others have primarily non-market value. All of them can be monetized using state-of-the-art economic and econometric methods (Freeman III et al., 2014).

The economic impacts of nutrient pollution depend not just on observed water quality, but on the typical uses of surface water resources that people value. For example, recreators may enjoy swimming, boating, and fishing at beaches on the Gulf of Mexico, but would be less likely to expect to do so at major ports, where economic value may come primarily from industrial activities such as shipping and the disposal of treated wastewater. The water quality conditions needed to support these different uses vary in obvious ways. Waters used by humans for primarily industrial purposes are still aquatic ecosystems, and pollution creates damages therein that might be monetized. However, the magnitude of economic damages in waters used for purposes like drinking water supply and recreation is likely to be higher than that of damages in primarily industrial areas, for a given level of pollution, because the literature confirms that human health effects are valued highly in comparison to other types of pollution damages (Keiser et al., 2019).

In this paper, we examine long-run trends in nutrient pollution and demonstrate that it increasingly constrains the capacity of surface water resources to support major human uses, suggesting that it is also likely an increasing source of economic damages associated with impairment. Our analysis focuses on surface water resources in Texas, USA, including all of the state's 23 river sub-basins at the hydrological unit code (HUC)-8 level (Fig. 1), along with associated coastal waters.

The availability of a rich set of data on surface water quality between 1970 and 2018 motivates our choice of study area, along with the fact that Texas surface water quality is likely to reflect U.S. and global trends in nutrient pollution driven by population growth, urbanization, and increased agricultural output. For example, Texas' population increased by >50% from 1970 to 2017 (Texas State Library and Archives Commission, 2019), and its net farm income more than quadrupled between 1970 and 2015 (Gleaton and Robinson, 2016).[1] In 2018, seven of the 15 fastest-growing cities in the United States were located in Texas (U.S. Census Bureau, 2018). When these trends are paired with common low-streamflow conditions, treated wastewater is a dominant contributor to surface water flows in some Texas basins, particularly during dry periods (Brooks et al., 2006). The climate in the state ranges from arid to semi-arid in western river basins, to humid and sub-tropical in the east; rivers like the Rio Grande that flow from one end of the state to the other move through this entire range of climates (TWDB, 2012).[2] The northwestern Gulf

[1] In contrast to net farm income, the amount of land in cropland, pastureland and rangeland has fallen a bit over time – about 6.8% from 1982 to 2015 (USDA, 2018). Some intensification has also taken place; for example, the number of head of cattle in Texas in 2015 was about the same as it was in 1970, despite the small decrease in pastureland and rangeland area (USDA, 2015).

[2] Evaporation exceeds precipitation in most of the state (TWDB, 2012), so our results may be particularly applicable to other areas with semi-arid climates, on average.

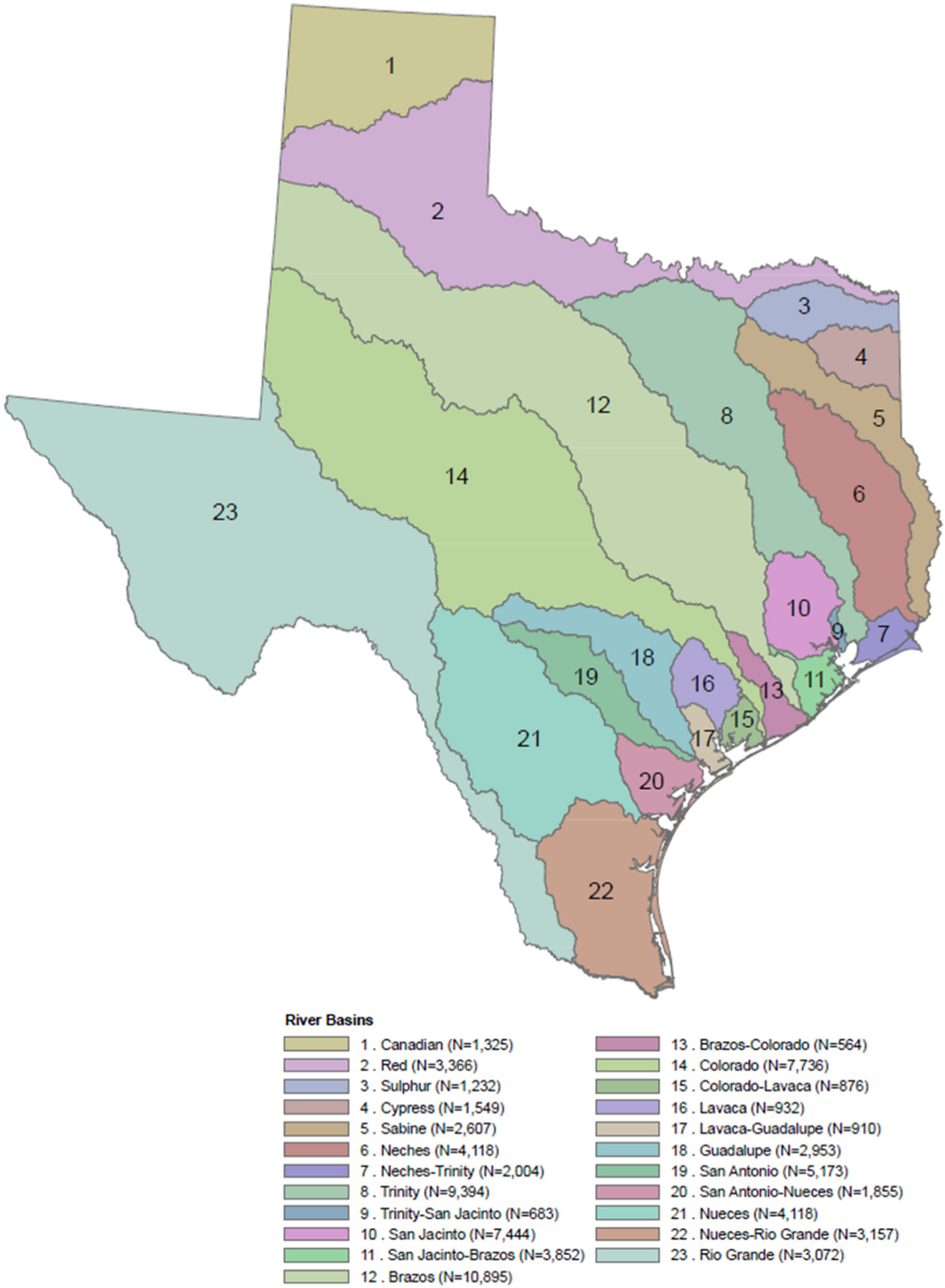


Fig. 1. River basins in Texas. Notes: Shapefiles for basins are from the Texas Water Development Board. Number of water quality monitoring stations in each basin is reported in parentheses in the legend, calculated using latitude/longitude of station location from Water Quality Portal and Texas Commission on Environmental Quality.

now has "among the highest diversity of toxic algal boom events in North America" (Swanson et al., 2010), and Texas is designated as a "hotspot" for fish kills among all U.S. coastal states (Thronson and Quigg, 2008). This setting offers a useful opportunity to observe the degree to which nutrient pollution trends over time impair human uses of water.

2. Literature review

The scientific literature contains many studies of nutrient pollution in Texas river basins, especially coastal basins.[3] For example, a study of the San Antonio River watershed concludes that of nine water quality parameters studied in 2004–2005, only turbidity and nitrate-nitrogen exceeded Texas Commission on Environmental Quality (TCEQ) or federal limits (Anderson et al., 2007). Scott et al. (2019) find that nutrient concentrations (and other water quality concerns such as bacteria) from centralized wastewater treatment plant discharge and onsite septic systems are causes of impairment in 2014 in Dickinson Bayou, an urban estuary in Galveston County, TX, and that dissolved oxygen (DO) levels fall below state standards at some sites and in some periods. Wetz et al. (2016) find high nutrient and chlorophyll *a* concentrations in the Oso Bay estuary in 2011–2013, resulting in periodically low DO concentrations, due in part to wastewater treatment plant discharge.

Eutrophication also favors HAB formation in Texas river basins. Golden algal blooms, which can produce toxins lethal to fish (James et al., 2011), were first reported in Texas in the 1980s, but blooms have expanded significantly since 2001 in reservoirs on the Brazos, Colorado, and Red Rivers (Patiño et al., 2014). The causes of this rapid expansion are not well understood, though salinity, DO, temperature, and pH are potential drivers (Patiño et al., 2014). Blue-green algae (also known as cyanobacteria) produce harmful toxins and cause the majority of freshwater HABs in Texas (Gámez et al., 2019). This type of HAB is clearly related to nutrient pollution and eutrophication, as well as warm temperatures and lack of rainfall, which can increase stagnation in surface water (Michalak et al., 2013).

The prior papers cited above focus on specific drivers of changes in water quality over a few months or a few years, relying on water quality measurements from specific waterbodies, often obtained through investigator-led sampling. While U.S. government assessments of water quality regularly report on nationwide trends (U.S. EPA, 2017), peer-reviewed studies describing and analyzing trends at large geographic scale are relatively uncommon (Smith et al., 1987; Keiser and Shapiro, 2019). Analysis at a broad geographic scale is critical, because water quality regulation happens at a broad geographic scale – either at the state or federal level in the United States, for example. Without assessment of trends at these levels, it can be difficult to assess the benefits and costs of regulation, retrospectively or prospectively, and may also be impossible to identify important pollution sources and challenges that might be addressed through new or revised regulation. Assessing long-run trends is particularly important for nutrient pollution, due to the natural wide variation in waterbodies' trophic status (Bachmann et al., 2012).

Our analysis fills this gap, relying on publicly-available water quality monitoring data collected from 1970 to 2018 in every river basin in Texas. Thomas et al. (2019) take a similar approach to ours, though they study only the Nueces River Basin and focus on streamflow and climate trends rather than water pollution. Jones and van Vliet (2018) examine the impacts of drought on water quality using data from 66 monitoring stations distributed across the Southern United States, including all major Texas river basins, over a 10-year period. However, the authors focus on specific conductance, rather than nutrients. Wetz et al. (2017) use both long-term observational data similar to those used in our study and investigator sampling to show that high nutrient and chlorophyll *a* concentrations in Baffin Bay are related to the large, repeated brown tide blooms observed in that estuary since 1990. Reisinger et al. (2017) use remotely-sensed reflectance data to estimate total suspended solids (TSS) over a 13-year period at a 500-meter resolution in Corpus Christi Bay. Other studies focus on explaining heterogeneity in water quality across multiple Texas river basins or estuaries over time (Konapala et al., 2017; Montagna et al., 2018; Jones and van Vliet, 2018). We do not examine specific drivers of the patterns we describe in our statewide database, leaving this for future research.

Economists use a variety of methods to estimate the value of water quality changes, including those related to nutrient pollution (Freeman III et al., 2014). Recent work in Michigan, USA, demonstrates that toxic cyanobacteria blooms increase the incidence of low birth weight, identifying a potentially important link between infant health and ambient nutrient pollution in the United States (Jones, 2019).[4] The impacts of nutrient pollution on property prices (Boyle et al., 1999; Leggett and Bockstael, 2000; Poor et al., 2007; Walsh et al., 2017; Wolf and Klaiber, 2017; Kuwayama et al., 2019) and recreation demand (Phaneuf, 2002; von Haefen, 2003; Phaneuf et al., 2008; Egan et al., 2009; Parsons et al., 2009; Abidoye and Herriges, 2012; Abidoye et al., 2012; Kuwayama et al., 2019) have also been monetized. None of these studies monetizing impacts on health, recreation or property values have focused on water pollution in Texas. However, the vast majority of these studies find that water pollution creates economic damages, thus, the trends we identify in Texas could be economically important.[5]

3. Data description

3.1. Geospatial data

In order to represent geographic variation in nutrient pollution trends in Texas, we rely upon a geospatial shapefile dataset delineating the major river basins of Texas as defined by the Texas Water Development Board (TWDB). Texas is divided into 23 major river and coastal basins at the HUC-8 level (Fig. 1). In reporting results throughout the paper, we combine each of the eight relatively small coastal river basins in Fig. 1 with its nearest non-coastal basin, resulting in 15 river basin areas. We use latitude and longitude to match each water quality monitoring station in our sample to the river sub-basin shapefile that contains the station.

3.2. Water quality and weather data

To comprehensively track levels and changes in key water pollutants across space and over time, we draw upon two publicly-available data sources. The first of these is the Water Quality Portal (WQP), an online data service sponsored by the U.S. Geological Survey (USGS), the EPA, and the National Water Quality Monitoring Council (NWQMC). It integrates publicly-available water quality data from the USGS National Water Information System (NWIS), the EPA STOrage and RETrieval (STORET) Data Warehouse, and the U.S. Department of Agriculture's Sustaining The Earth's Watershed–Agricultural Research Database System (STEWARDS). The WQP data include observations from 5524 Texas monitoring stations with surface water quality samples for the nutrient-related analytes we examine.[6]

The second source of water quality data we rely on is the Surface Water Quality Monitoring Information System (SWQMIS) provided by TCEQ.[7] We developed an R script to download data for all identified water body segments in the application. The raw TCEQ data include

[3] While our study focuses on surface water, a related literature examines trends in groundwater quality, including some longer-term studies tracking nitrate concentrations in Texas groundwater (Dörnhöfer and Oppelt, 2012).

[4] The human health impacts of nitrate in *drinking water* are well studied (Ward et al., 2018), though to our knowledge have not been monetized using economic methods.

[5] Water pollution can also affect commercial fishing. Economists have estimated significant impacts of hypoxia on the market for Gulf of Mexico shrimp through declines in shrimping effort (Purcell et al., 2017) and impacts on shrimp landings (O'Connor and Whitall, 2007) and prices (Smith et al., 2017). In 2008, Texas coastal oyster beds were closed due to the presence of toxins that are harmful to human health, a phenomenon related to HABs (Swanson et al., 2010).

[6] Based on WQP definitions of site types, we selected monitoring sites in aggregate surface water use, estuaries, lakes, reservoirs, impoundments, oceans, springs, rivers/streams and wetlands.

[7] TCEQ makes SWQMIS data publicly available through a map application at: https://www80.tceq.texas.gov/SwqmisPublic/index.htm.

observations from 3327 stations on 1018 unique water body segments (or sub-segments) over the sampling period, 1968–2019. The full suite of raw data we pull from TCEQ includes over 10 million water quality observations, a rich source of data for future research. In this paper, we focus on four primary indicators of nutrient pollution: total nitrogen (TN), total phosphorus (TP), DO, and chlorophyll *a*.

We clean these data as follows. First, we keep only data observed in calendar years 1970 through 2018. Data collected in the 1960s exist for some analytes but tend to be sparse. Second, we drop missing values in the raw data, testing the sensitivity of results to this step in the Supplemental Material. Third, we combine TCEQ and WQP data, dropping any overlapping samples from the two databases and converting measurements to standard units as necessary. Fourth, we drop the top and bottom 0.25% of the observations for each analyte to remove outliers. In total, we obtained >2 million water quality observations for the four nutrient-related water quality parameters after combining the WQP and TCEQ data.

TN is the sum of organic nitrogen, ammonia, nitrate, and nitrite (University of Maryland Center for Environmental Science, 2020). WQP and TCEQ collect monitoring data on these analytes individually and collectively. For instance, some TCEQ monitoring stations collect data on total Kjeldahl nitrogen (TKN), which is the combination of organic nitrogen, ammonia, and ammonium. To generate measures of TN, we first combine all data on nitrogen. We use latitude and longitude information to define a monitoring station and use the sampling date to define each monitoring event at the station. We then sum the relevant nitrogen measures (above) to calculate TN for each monitoring event. This process yields 353,101 monitoring events that report nitrogen data, with a mean TN concentration of 0.82 mg/L during our study period (Table 1).

We obtained data on TP concentrations directly from the WQP and TCEQ websites. Fewer monitoring events report TP than for TN. From 1970 to 2018, 217,894 TP samples are reported in the two sources combined. The mean TP concentration is 0.44 mg/L (Table 1).

Declining DO is a key indicator of nutrient over-enrichment and eutrophication, and DO is among the most common measures of water quality used in existing research on water pollution's economic impacts (Keiser and Shapiro, 2019). DO is critical for fish survival, and water quality that meets the criteria for fish also meets the criteria for most other beneficial water uses and is often of good ecological status (Environmental Protection Agency, 2001). Higher DO levels indicate better water quality; areas with low DO may suffer from reduced fish catch or the presence of algae mats. Our data include 445,778 monitoring events that report DO, with a mean concentration of 7.37 mg/L (see Table 1). DO concentrations exhibit daily and seasonal fluctuation due to changes in water temperature and other factors (Baumann and Smith, 2018), so we take this into account in our methods. While DO can increase with nutrient loading and the resulting algal production, decreasing DO over time has been used in prior work as a measure of eutrophication in coastal settings (Baumann and Smith, 2018; O'Boyle et al., 2013) as well as inland rivers (Flynn et al., 2015; Justus et al., 2019) and lakes/reservoirs (Crossman et al., 2019).

Chlorophyll *a* concentrations are indicative of algae growing in water (EPA, 2020). Our data include far fewer samples that measure chlorophyll *a* concentrations (145,654) compared to the other three nutrient-related parameters we examine. The mean chlorophyll *a* concentration in our data is 12.84 μg/L (Table 1).

Our analysis relies on four additional water quality indicators: biochemical oxygen demand (BOD), TSS, fecal coliform, and pH. These other indicators are components of the "water quality ladder" (WQL), a commonly-used scale for determining whether waterbodies meet established thresholds for human uses (Mitchell and Carson, 1981), which we employ in the paper. Thus, Table 1 also provides summary statistics for these analytes.[8]

Table 2 shows that the statewide mean concentrations of TN and chlorophyll *a* in 2010–2018 both increased significantly from their average values in 1970–1979. In contrast, the statewide mean TP and DO concentration decreased slightly between the two periods. We break these state-level trends down to the basin level in Section 4 and include a table of mean comparisons by basin across the study period as Table S.2 in the Supplemental Material. Note, for example, that while Table 2 reports a small, statistically significant decrease in DO concentrations statewide from the 1970s to the 2010s, Table S.2 reveals that DO declined significantly in seven basins, was approximately unchanged in three, and increased in five.

Finally, in some of our models, we use daily minimum and maximum temperature data on the day that each analyte concentration is observed. We obtain these data from the National Oceanic and Atmospheric Administration (NOAA) Global Historical Climatology Network (Menne et al., 2012). We download temperature readings from all Texas weather stations from 1970 to 2018 and spatially join stations with county boundaries. We then calculate the mean maximum temperature and mean minimum temperature for each county on each day (January 1, 1970–December 31, 2018), and merge the temperature data with our water quality data, using the county location for each water quality monitor and the date of each sample. In the models using these temperature data, we drop about one-tenth of the original observations, due to missing temperature data.

3.3. Methods

3.3.1. Nonparametric analysis of water quality trends over time

In addition to the raw mean comparisons described above, we implement several tests to evaluate whether the TN, TP, DO and chlorophyll *a* concentrations in Texas river basins have changed over time. First, we take a non-parametric approach, applying the seasonal Mann-Kendall test, widely used to test for trends in environmental parameters (Hirsch and Slack, 1984; Oelsner et al., 2017), to a time series of monthly median observations for the four analytes in each of the 15 condensed river basin regions. The basic Mann-Kendall test analyzes the sign of the difference between later-measured data and earlier-measured data, where each later-measured value is compared to all values measured earlier. A seasonal Kendall test statistic is computed by performing a Mann-Kendall calculation for each season, then combining the results for each season. There are several advantages to using this test statistic to identify long term trends, given the nature of our water quality data. First, the statistic controls for seasonality that could affect naïve percent change estimates if observations are collected more heavily at certain times of the year in one decade relative to others. In addition, the seasonal Kendall test statistic allows for missing

Table 1
Summary statistics for WQP and TCEQ water quality data.

	Count	Mean	Std. Dev.	Min.	Max.
Dissolved oxygen (mg/L)	445,778	7.367	2.63	0	15.8
Chlorophyll *a* (μg/L)	145,654	12.835	19.147	0.2	233
Total nitrogen (mg/L)	353,101	0.823	1.542	0	51.1
Total phosphorous (mg/L)	217,894	0.435	0.808	0	7.34
Biochemical oxygen demand (mg/L)	67,465	3.78	4.545	0.05	49.8
Total suspended solids (mg/L)	253,150	47.784	130.004	0.8	2150
Fecal coliform (CFU/100 mL)	136,208	4020.46	21,064.8	0	400,000
pH	585,735	7.763	0.544	0	14
N	2,204,985				

[8] Table S.1 in the Supplementary Material lists these same summary statistics at the more detailed river basin level.

Table 2
Summary statistics by decade.

Analyte	Mean 1970–1979	N 1970–1979	Mean 2010–2018	N 2010–2018	Mean Diff.
Total nitrogen (mg/L as N)	0.802	50,631	1.055	92,297	0.253***
Total phosphorous (mg/L as P)	0.480	14,654	0.430	79,458	−0.049***
Dissolved oxygen (mg/L)	7.499	37,194	7.449	129,338	−0.049***
Chlorophyll *a* (μg/L)	13.814	11,572	14.172	49,655	0.359***

Notes: Asterisks in the last column indicate significant difference in means between the two groups, according to a *t*-test for difference in means.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

observations in the case that there were no observed measures of an analyte in a given river basin in a given month.

A common concern while analyzing water quality data is the treatment of censored data. Data from our two sources very rarely indicate that a concentration is below detection limits (BDL).[9] Thus, censoring may be a concern with either missing observations, observed concentrations at zero, or both. The Kendall test statistic is robust to censoring that may result from pollutant concentrations being BDL because the test relies on rank correlation. Moreover, because the time series to which we apply the seasonal Kendall test statistic consists of monthly medians of water quality observations, and these medians are well above detection limits, these tests will be robust to censoring limits that may have changed over time due to changes in detection limits in our monitoring data.

3.3.2. Parametric analysis of water quality trends over time

Next, we use a set of panel-data regressions, estimating Eq. (1) separately for TN, TP, DO, and chlorophyll *a*.

$$WQ_{icyt} = \beta X'_{icy} + \delta T'_{it} + \alpha_y + \gamma_i + \varepsilon_{icyt} \tag{1}$$

The dependent variable, WQ_{icyt}, is the concentration of the analyte (DO, chlorophyll *a*, TN or TP) from monitoring site *i*, during hour (0–24) and calendar day (1–365) *c*, in year *y*, on day *t*. X'_{icy} is a vector of variables including: an indicator for observations that are missing time of day, along with cubic polynomials in hour of day (0–24) and in day of year (1–365). The time-of-day and day-of-year effects control for any potential daily and seasonal fluctuations in analyte concentrations unrelated to pollution loading. T'_{i_t} comprises the daily minimum and maximum temperature at weather stations in water quality monitor *i*'s county on the day (*t*) each sample was drawn, accounting for inter-annual changes (such as those due to climate change) not addressed by X'_{icy}.[10] γ_i is a monitoring station fixed effect that controls for all time-invariant characteristics that are unique to a monitoring site. The coefficients of interest, α_y, represent yearly changes in average concentrations relative to the first year (1970), which is omitted from the regression.[11] Unlike the Mann-Kendall tests, this approach controls comprehensively for daily fluctuations in water quality parameter concentrations, as well as time-invariant average conditions at each monitoring site. Also unlike the Mann-Kendall tests, Eq. (1) does not impose monotonicity on any estimated trends in water quality. Standard errors in this and all of our other regression models are clustered at the river basin level. Like the Mann-Kendall tests, Eq. (1) controls for seasonality by comparing observations across years within specified time periods.

Unlike the seasonal Kendall test statistic, implementation of Eq. (1) requires explicit consideration of censored data. With the exception of TN, none of our water quality parameters have fractions of missing observations that exceed one-tenth of 1%. About 8% of TN observations are missing. Zeros are slightly more common than missing observations in our data. Zeros are reported for chlorophyll *a* and TP in <1% of observations, and are reported for TN in about 1.25% of observations. About 7% of DO observations are zeros. Unfortunately, we cannot determine which, if any, missing or zero values are actually positive concentrations that are BDL. In the main results reported in the paper, we drop missing observations and treat zeros as true zeros. In the Supplemental Material, we implement sensitivity analyses to account for the possibility that censoring could influence our results. We re-estimate Eq. (1) as follows: (1) replacing missing values with ½ the lowest detected level by analyte-year (Helsel, 2005) but treating zeros as true zeros, and (2) replacing zeros and missing values with ½ the lowest detected level by analyte-year.[12] In the first approach, the lowest detected level by analyte-year includes zeros (which are assumed to be true zeros). In the second approach, we take 1/2 of the lowest detected non-zero concentration to replace missing and zero values.

3.3.3. Analysis of trends relative to human use thresholds for water quality

While informative, trends in surface water quality indicators provide only a partial picture of the implications of water quality changes for Texas residents and visitors. As noted in Section 2, the economic impacts from water pollution depend not just on observed water quality, but on the typical uses of surface water resources that people value. The idea that waterbodies are used for different purposes is reflected in the CWA, which requires that water quality standards be met consistent with waterbodies' designated uses. As a result, the State of Texas classifies waterbodies as having appropriate uses such as public drinking water supply, support of exceptional aquatic life, and recreation.

We take two approaches to describing trends in water quality impairment that account for the typical uses of specific water resources. First, we estimate trends in the share of the state's surface water resources that do not meet common definitions of quality suitable for boating, fishing, swimming, and drinking. We then track changes in attainment of these thresholds over time. We calculate these shares by comparing the water quality data we collected from the WQP and TCEQ to the WQL, which defines minimum numeric criteria consistent with each waterbody use across five water quality parameters: fecal coliform, DO, BOD, turbidity, and pH (Mitchell and Carson, 1981). The criteria for each use designation are reported in Table 3. These are not

[9] In rare cases, observed concentrations are recorded as "greater than" detection limits; we treat these few right-censored cases as if they are observed at the limit.

[10] Ideally, we would control for water temperature and salinity when and where each sample was drawn in order to account for variation in DO with these factors. However, water temperature and salinity appear too infrequently along with the DO samples in our data to support this approach.

[11] Note that if minimum detection levels have fallen over time for any of the analytes we examine, this could introduce an upward bias in estimated trends for all four analytes. This would make our estimates conservative for DO, but have the opposite effect for TN, TP and chlorophyll *a*. In response to a comment from a referee, we did look for trends in detection limits over time and found no evidence that this is an important concern in our data.

[12] To calculate 1/2 the lowest detected TN concentration, we take ½ the lowest detected concentration for each component of TN (organic N, ammonia, nitrate, nitrite, and TKN), and then sum these component halves.

Table 3
Parameter thresholds for water quality ladder use designations.

Use designation	Fecal coliforms	DO	5-day BOD	TSS	pH
Boatable	≤2000/100 mL	≥3.5 mg/L	<4.0 mg/L	<100 mg/L	≥4.25
Fishable	≤1000/100 mL	≥4.0 mg/L	<3.0 mg/L	<50 mg/L	≥7.25
Swimmable	≤200/100 mL	≥6.5 mg/L	<1.5 mg/L	<10 mg/L	≥7.25
Drinkable	0/100 mL	≥7.0 mg/L	0 mg/L	<5 mg/L	≥7.25

Notes: Parameter thresholds taken from Mitchell and Carson (1981), substituting TSS for turbidity as in Keiser and Shapiro (2019).

enforceable standards for all waterbodies, but rather measures of whether or not Texas waters meet common thresholds for human use, applied in economic and regulatory analysis. The WQL thresholds were established in the early 1980s (Mitchell and Carson, 1981) and have been used since then in peer-reviewed economic evaluations of the CWA (Keiser and Shapiro, 2019; Carson and Mitchell, 1993) as well as in regulatory impact analyses at EPA (Griffiths et al., 2012).[13]

The WQL standards are increasingly stringent across rungs, ranging from boating (least stringent) to drinking (most stringent). Following Keiser and Shapiro (2019), we use TSS instead of turbidity, given that TSS data are much more readily available in our setting. One challenge in our context is that TN and TP are not included in the set of WQL parameters that determine whether waterbodies meet thresholds for human uses. Thus, we consider DO, which is included, as a key parameter related to eutrophication. TSS is a secondary related parameter included in the WQL, given the known propensity of sediments to act as "nutrient carriers" (Paudel et al., 2019). Note, however, that while TSS is a significant source of water quality impairment (EPA, 2020), and sediments and nutrients have many common sources (such as agricultural and urban stormwater runoff), increasing TSS concentrations are not always related to nutrients.

To visualize trends over time in the share of the state's surface water resources that fail to meet established standards for drinkable, swimmable, fishable, and boatable water quality, we first limit our samples to those collected on days on which at least one water quality parameters were sampled. Then, following Keiser and Shapiro (2019), we regress an indicator variable for whether the water quality observation meets the standard for each of the five pollutants on a set of additional indicator variables: a set of year fixed effects (where we take 1970 as the reference year), a set of monitoring station fixed effects, a day-of-year cubic polynomial, and an hour-of-day cubic polynomial, estimating Eq. (2).

$$1\left[WQ_{icy} \geq WQLthreshold\right] = \beta' X_{icy} + \alpha_y + \gamma_i + \varepsilon_{icy} \tag{2}$$

The dependent variable is an indicator equal to 1 if the WQL parameter threshold is met for a sample drawn at monitor i during hour (0–24) and calendar day (1–365) c, in year y. Aside from the fact that the dependent variable is binary, Eq. (2) is identical to Eq. (1). The goal of this analysis is to show how shares of Texas surface water quality observations that fail to meet each WQL threshold have trended over time, controlling comprehensively and flexibly for time-invariant attributes of sampling locations that can influence average concentrations, and for when during the year and during the day each sample is drawn. Eq. (2) is a linear probability model in which the coefficients of interest, α_y, can be interpreted as the changes in the share of waters failing to meet the relevant WQL threshold each year 1971–2018, compared to 1970.[14] When we include a constant in the regression, this is interpreted as the baseline (1970) share of waters failing to meet each threshold. We then graph the sum of the constant plus each α_y to sketch out trends over time. Along these same lines, we also examine trends in the "constraining pollutants" for meeting WQL thresholds over time. We first calculate the total number of instances in which each designated use standard is not met each year, and the number of instances in which each analyte did not meet its portion of each designated use standard each year. We then divide the number of instances that an analyte (e.g., DO) did not meet a standard (e.g., fishable) by the total number of "not fishable" occurrences in that year to calculate the contribution of each water quality parameter.

Finally, we assess trends over time in whether Texas waters meet the differential regulatory standards set by the TCEQ for each water quality parameter based on established human use classifications. For example, regulatory standards for lakes, reservoirs and river segments designated for drinking water supply or primary contact recreation are more stringent than those for other uses. For this analysis, we first match our water quality monitoring data to the corresponding 2018 segment-level Texas surface water quality standards for two of our parameters: DO and chlorophyll *a*. Numeric chlorophyll *a* standards only exist for 39 reservoirs in Texas, so this part of the analysis is only relevant to reservoirs; DO standards, in contrast, are widespread across all waterbody types.[15] We only use data from the TCEQ SQWMIS for this last analysis, as these are the data that are officially used to determine compliance with water quality standards in Texas. We then determine whether individual pollution monitor readings are above or below the standard and calculate the proportion of readings in each calendar year that meet the standard, tracking changes over time.

4. Results: long-run trends in nutrient pollution in Texas river basins

Table 4 presents results from the application of the seasonal Kendall test statistic to monthly medians of the four water quality parameters in each river basin, calculated using the "Kendall" R package (McLeod, 2015). More river basins exhibit deteriorations in chlorophyll *a* and TP conditions than improvements, while there are about equal numbers of positive and negative trends for DO. More basins show improvement in TN, but many of the improvements are not statistically significant. The seasonal Kendall test statistics indicate that no basins experienced water quality improvements across all four parameters during this period, while the Nueces and Rio Grande Basins exhibit declines in water quality across all parameters, most of them statistically significant.

We provide a visual representation of the trends indicated in Table 4 in a set of maps (Fig. 2). The panels in Fig. 2 illustrate the τ test statistic value from our seasonal Mann-Kendall tests of TN, TP, DO, and

[13] A related method would use the WQL parameter values to construct a continuous water quality index, so that the worst individual water quality parameter does not determine the use classification in a lexicographic manner. This is the way in which the WQL is now used in regulatory analysis at EPA (Griffiths et al., 2012). We do not use this method because it requires readings for all five water quality measurements at the same time from the same water quality monitor. Even with our rich dataset, the sample size is reduced dramatically when we constrain the data in this way.

[14] An alternative approach to the linear probability model is a conditional logit model for panel data. The main advantage of this approach would be that it constrains the estimated shares to between zero and 1. The linear probability model generally does a reasonable job estimating marginal effects, and requires fewer potentially problematic assumptions about the error structure (Angrist and Pischke, 2009). In response to a referee comment, we did implement conditional (fixed-effects) logit models, but these models do not converge if we include the monitoring site fixed-effects, which are essential components of our approach to minimizing omitted variables bias. Thus, we retain the linear probability approach.

[15] Like most U.S. states, Texas historically had narrative nutrient criteria in its surface water quality standards; numeric criteria for chlorophyll *a* were developed in 2010 in response to an EPA mandate. Through 2018, EPA had approved the state's numeric criteria for only 39 reservoirs. In the state's approach, chlorophyll *a* is the primary indicator of nutrient-impaired waters; reservoirs that do not meet numeric chlorophyll *a* standards are then assessed for TN and TP, which have screening levels as part of this process, but no numeric standards. The surface water quality standards for DO and chlorophyll *a* can be found at https://texreg.sos.state.tx.us/fids/201800575-5.pdf and https://texreg.sos.state.tx.us/fids/201800575-10.pdf. Because criteria for chlorophyll *a* are fewer in number and defined relative to both specific segments and monitoring stations, these data are far sparser data than for DO.

Table 4
Seasonal Kendall test statistics by river basin.

Basin name	Dissolved oxygen	Chlorophyll *a*	Total nitrogen	Total phosphorus
Brazos	−0.020	0.056*	−0.010	−0.012
	(0.494)	(0.056)	(0.714)	(0.671)
Canadian	−0.051*	0.047	−0.063**	−0.116***
	(0.087)	(0.144)	(0.030)	(0.000)
Colorado	−0.184***	0.095***	−0.064**	0.069**
	(0.000)	(0.001)	(0.024)	(0.020)
Cypress	0.046	0.198***	0.140***	0.014
	(0.124)	(0.000)	(0.000)	(0.649)
Guadalupe	−0.048*	−0.261***	−0.042	0.144***
	(0.097)	(0.000)	(0.140)	(0.000)
Lavaca	0.127***	−0.070**	−0.038	0.199***
	(0.000)	(0.049)	(0.212)	(0.000)
Neches	0.343***	0.078***	0.113***	0.159***
	(0.000)	(0.010)	(0.000)	(0.000)
Nueces	−0.093***	0.105***	0.224***	0.106***
	(0.001)	(0.000)	(0.000)	(0.000)
Red	−0.030	0.063**	−0.146***	0.009
	(0.297)	(0.063)	(0.000)	(0.772)
Rio Grande	−0.139***	0.099***	0.037	0.099***
	(0.000)	(0.001)	(0.199)	(0.001)
Sabine	−0.016	0.302***	−0.034	0.016
	(0.577)	(0.000)	(0.232)	(0.618)
San Antonio	0.113***	−0.191***	0.254***	0.119***
	(0.000)	(0.000)	(0.000)	(0.000)
San Jacinto	0.097***	0.028	−0.073**	−0.287***
	(0.001)	(0.365)	(0.010)	(0.000)
Sulphur	0.130***	0.075**	−0.066**	−0.121***
	(0.000)	(0.034)	(0.028)	(0.000)
Trinity	0.181***	0.092***	−0.296***	−0.448***
	(0.000)	(0.002)	(0.000)	(0.000)

Notes: τ values from the seasonal Mann-Kendall tests by basin and analyte are reported in each cell, with associated *p*-values in parentheses below. Asterisks indicate significant increasing or decreasing trends according to the calculated test statistic.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

chlorophyll *a* at the river basin level between 1970 and 2018. As noted in Section 3, for ease of visualization, we combine each of the eight relatively small coastal basins along the Texas coast with its nearest non-coastal river basin, resulting in the 15 river basin areas presented in the maps in Fig. 2 rather than the original 23 basins as shown in Fig. 1.[16] Values of τ can take the range $[-1, 1]$ and are interpreted similarly to correlation coefficients. A τ between zero and one (zero and negative one) indicates a monotonically increasing (decreasing) trend. Note that increases in nutrient pollution and associated eutrophication would be consistent with *increasing* concentrations of TN, TP, and chlorophyll *a*, and *decreasing* concentrations of DO. Accordingly, we have flipped the color scheme for the map illustrating changes in DO concentrations (Fig. 2, panel c) so that it can be more easily compared to the maps for other parameters.

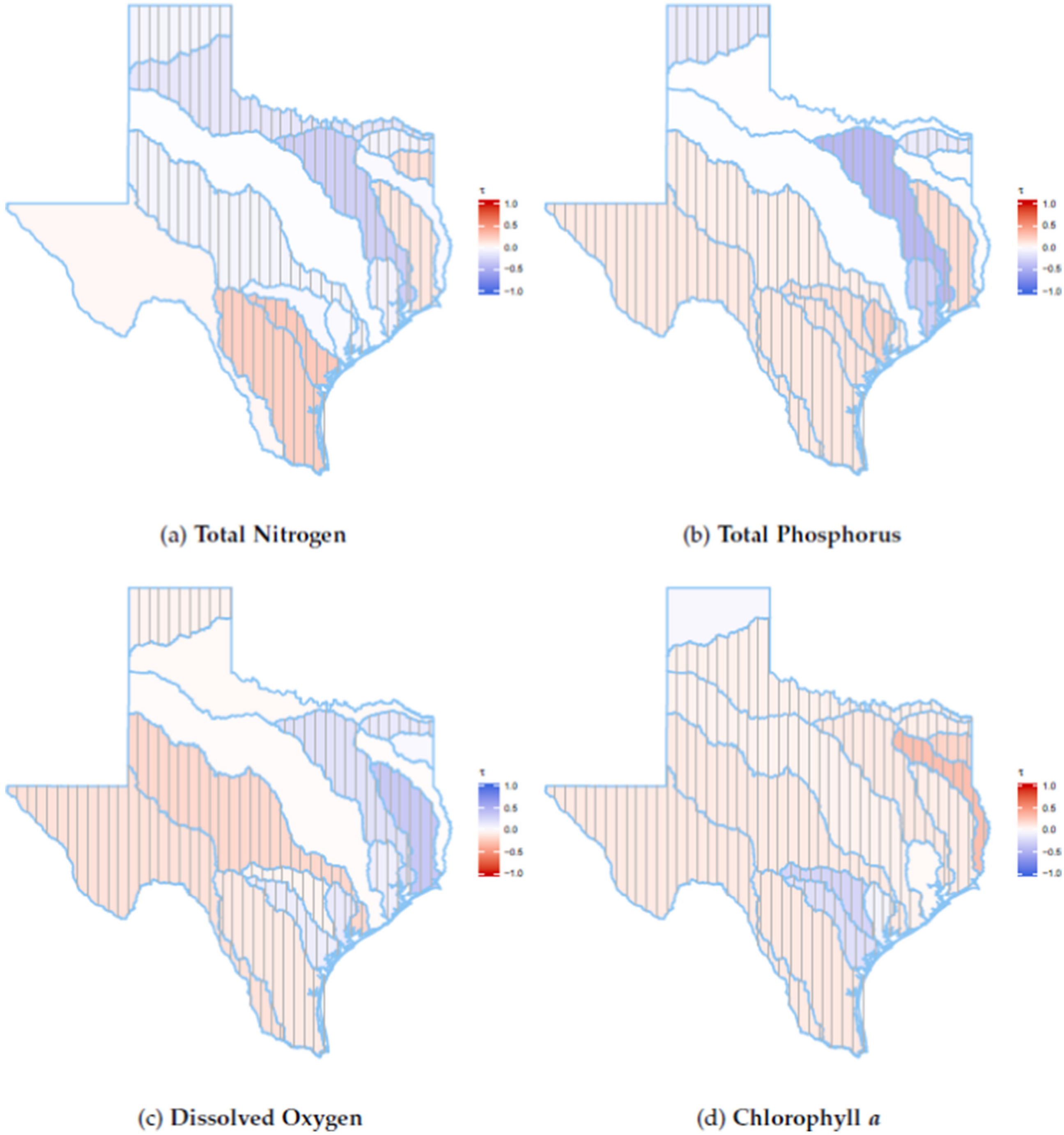
Fig. 2, panel a shows that concentrations of TN exhibit increasing trends in some river basins, with particularly large increases in the Cypress, Neches, Nueces and San Antonio Basins. The Canadian, Colorado, Red, San Jacinto, Sulphur and Trinity exhibit statistically significant decreasing trends. TP, in contrast, has increased significantly in seven river basins (Colorado, Guadalupe, Lavaca, Neches, Nueces, Rio Grande, and San Antonio) and has declined significantly in four of the remaining eight (Fig. 2, panel b).

DO concentrations exhibit decreasing trends across a large chunk of Texas during our study period (Fig. 2, panel c), a potential concern for the health of the state's aquatic ecosystems. Decreases in average DO concentrations have been largest in the Colorado Basin, with smaller but significant declines observed in the Canadian, Guadalupe, Nueces, and Rio Grande Basins. DO exhibits increasing trends in most of the state's eastern river basins from the Trinity to the Gulf Coast.

The seasonal Mann-Kendall tests show an increasing trend in chlorophyll *a* concentrations in most of the state over time (Fig. 2, panel d). The only statistically significant decreasing trends we observe in this water quality indicator occur in the Guadalupe and San Antonio Basins. Interestingly, some of the eastern river basins that experienced increases in DO concentrations have also experienced increases in chlorophyll *a* concentrations.

Taken together, the changes observed in Fig. 2 and Table 4 suggest that nutrient pollution is a growing problem that is essentially statewide in scope. Given the scientific literature on risks to aquatic ecosystem health from eutrophication, as well as evidence from the economic literature of impacts on recreation and property values in other parts of the United States, the economic damages associated with these trends could be significant. At the same time, even basin-specific trends may not relate to economic impacts of nutrient pollution in a straightforward way. Increases in pollution are more likely to be socioeconomically relevant in large river basins, such as the Brazos, the largest river basin in Texas, where average flow is over 30 times greater than that in the smallest basin, the Canadian. Moreover, the number of individuals living in Texas river basins varies greatly, and negative pollution trends in river basins with high population are more likely to result in significant economic impacts. Similarly, waterbodies supporting critical habitat could have high economic value, even if small. Prior literature shows that recreation demand, in particular, may respond differently to water quality parameters; for example, one study suggests that TP concentration is the single most influential parameter in determining site visitation among Iowa lakes (Abidoye and Herriges, 2012),

[16] The Texas Surface Water Quality Standards define two additional segments in addition to the 23 primary basins: a "bays and estuaries" category for coastal observations, and a final category for monitoring stations further out in the Gulf of Mexico. For the basin-by-basin trends presented here, we match observations from the "bays and estuaries" category to the closest of the 23 primary basin categories, and we drop data from the Gulf of Mexico category. We retain data from this category for other analysis in this paper. All analyses are robust to dropping estuary observations from the data (see Table S.3 in the Supplemental material).



(a) Total Nitrogen

(b) Total Phosphorus

(c) Dissolved Oxygen

(d) Chlorophyll *a*

Fig. 2. τ values from seasonal Mann-Kendall tests for nutrient indicators from 1970 to 2018. Notes: Each panel indicates the calculated τ value from our series of seasonal Mann-Kendall tests by river basin. Values of τ closer to 1 indicate a strong increasing trend, and values closer to −1 indicate a strong decreasing trend. Basins in which the estimated trend is statistically significant are vertically-hatched.

and another identifies Secchi depth as the most significant driving factor, with TP also influential (Egan et al., 2009).[17] The four nutrient-related water quality measures in Fig. 2 may be strongly correlated in terms of pure science, but they may still differ in importance from the perspective of human uses such as boating, fishing and swimming.[18]

Fig. 3 graphs the coefficient estimates, α_y, plus a constant, from Eq. (1) in Section 3. (The constant is the baseline average analyte concentration in 1970), for DO, chlorophyll *a*, TN and TP. Once we control for the covariates in Eq. (1), and allow each year its own change relative to 1970, DO concentrations statewide trend notably upward in the early 1970s, with little change since then. Chlorophyll *a* concentrations show no obvious trend over time in Fig. 3. While TN concentrations vary significantly year-to-year, there is little or no average difference between 2018 concentrations statewide and those in the early 1970s. TP varies less than TN in Fig. 3, and shows no obvious trend over time. Using this more flexible approach to describing changes over time and our comprehensive set of controls, the

[17] Neither of these studies include DO. Chlorophyll *a* is either unimportant (Egan et al., 2009), or even positively correlated with visitation (Abidoye and Herriges, 2012). TN is less important for visitation than TP in both studies.

[18] We do not test hypotheses regarding the potential drivers of water quality changes. Potential explanations include differential changes in land use (e.g., agricultural expansion, oil and gas development), population, and climate.

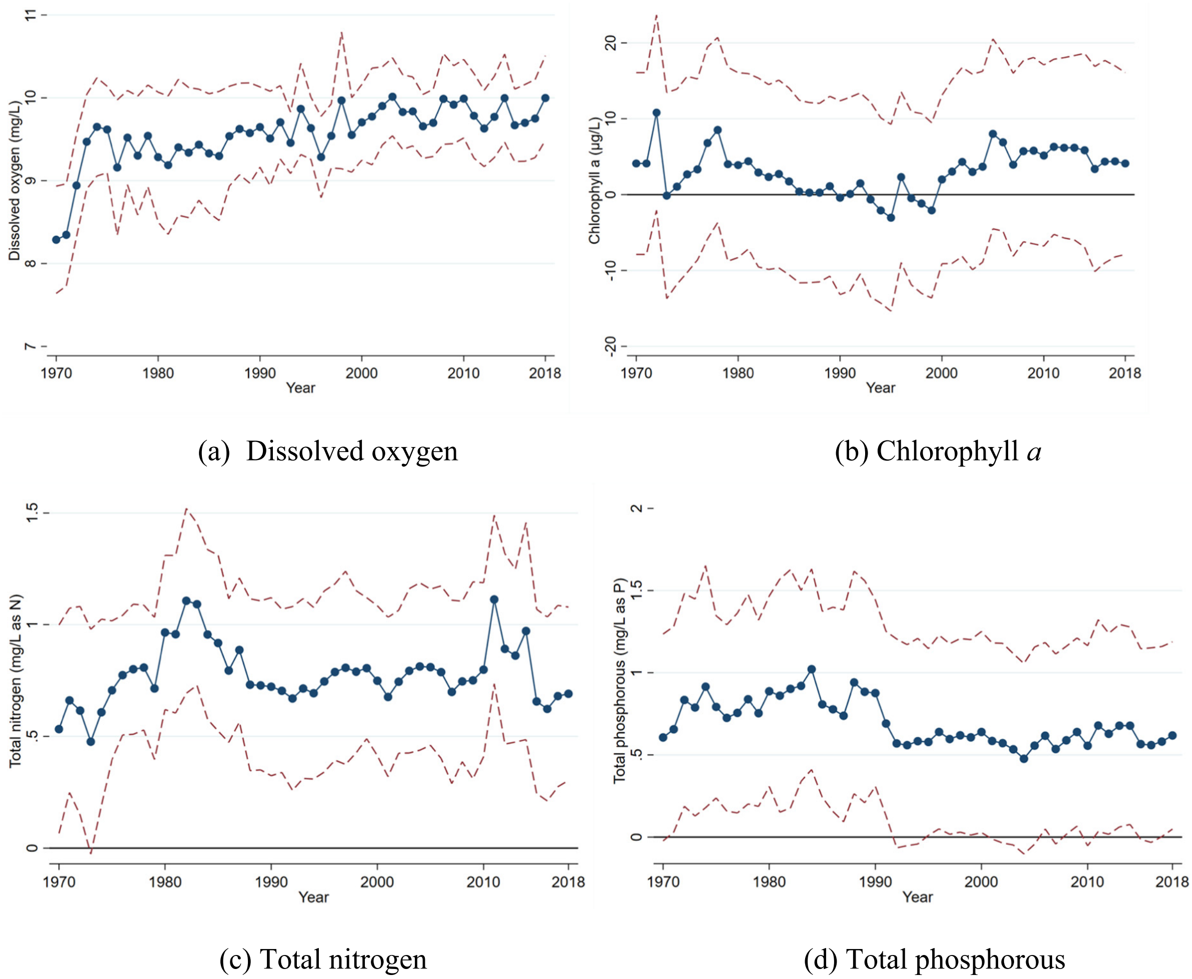


Fig. 3. Panel regression-estimated trends in surface water quality in Texas, 1970–2018. Notes: Graphs show year fixed effects plus a constant from regressions that control for monitoring station fixed effects, a day-of-year cubic polynomial, and an hour-of-day cubic polynomial following Keiser and Shapiro (2019), as well as controls for daily minimum and maximum temperature on the day each sample was drawn. Blue connected dots show yearly values and red dashed lines show the 95% confidence interval for year fixed effect estimates. 1970 is the reference year. Standard errors are clustered by river basin.

negative water quality trends identified with the Mann-Kendall approach in Fig. 2 and Table 3 do not carry over to Fig. 3. In Figs. S.1 and S.2 in the Supplemental Material, we reproduce Fig. 3 with the two different approaches to censoring described in Section 3. Fig. S.1 replaces missing values with ½ the lowest detected level by analyte-year (Helsel, 2005) but treats zeros as true zeros. Fig. S.2 replaces zeros and missing values with 1/2 the lowest detected level by analyte-year. The results of both approaches are indistinguishable from those reported in Fig. 3.

5. Results: long-run trends in water quality impairment relative to human uses

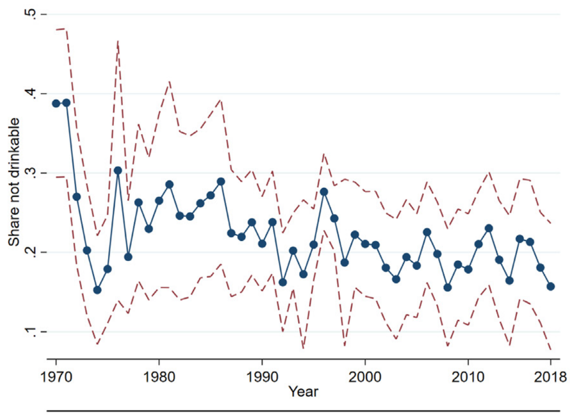
5.1. Trends relative to water quality ladder thresholds

This section summarizes the results of our analysis of trends in Texas waters' capacity to meet the WQL thresholds for drinking, swimming, fishing and boating. Fig. 4 graphs the coefficient estimates (α_y) plus the constant term from Eq. (2) in Section 3 (the constant term is the baseline share of waters meeting the relevant WQL threshold in 1970). The blue dots (connected by a line), thus capture the trend over time in the share of waters not meeting the relevant WQL threshold. We also plot each estimate's 95% confidence interval noted in dotted red lines, for drinkable (Fig. 4, panel a), swimmable (panel b), fishable (panel c), or boatable (panel d) water quality.

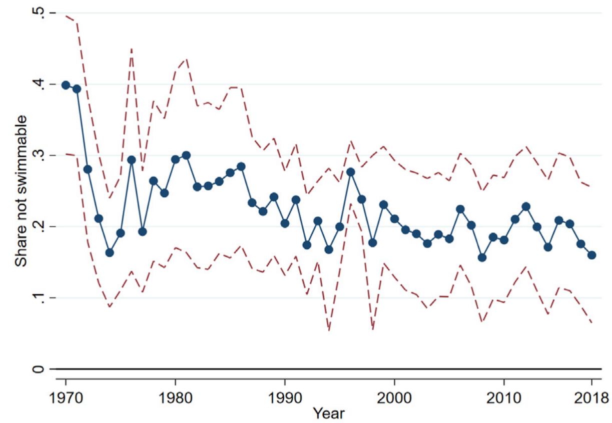
We find that the share of waters that do not meet each of these standards in Texas has fallen over time since 1970. Starting with the least stringent standard—suitability for boating—the share of observations that do not meet this threshold has fallen from about 10% in 1970 to <4% in 2018. The share of waters not fishable has fallen from about 15% in 1970 to about 7% in 2018. The share not swimmable has fallen from about 40% in 1970 to <20% in 2018. The share not drinkable has, similarly, fallen from about 40% in 1970 to <20% in 2018, though again, the difference is not statistically significant. For the fishable and boatable standards, these changes are not significant, as the confidence intervals for the two endpoint years in Fig. 4 overlap.

In all four cases, we observe a fairly rapid decline in failure to meet the threshold starting in 1970 to around 1990, but little continued progress over the subsequent 30 years. That is, the trend in shares not meeting each threshold flatten out around 1990, remaining fairly stable through 2018.

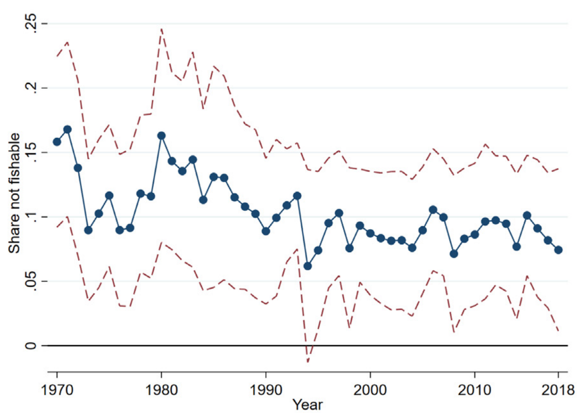
Fig. 5 illustrates the degree to which failure to meet designated uses for waterbodies is driven by each of the five WQL water quality parameters, as described in Section 3. Several trends are notable. First, we observe that fecal coliform is never a driver of Texas waterbodies' failure to attain designated uses; as a result, it is not visible in the figure. Note that this does not necessarily indicate that pathogens are a small water



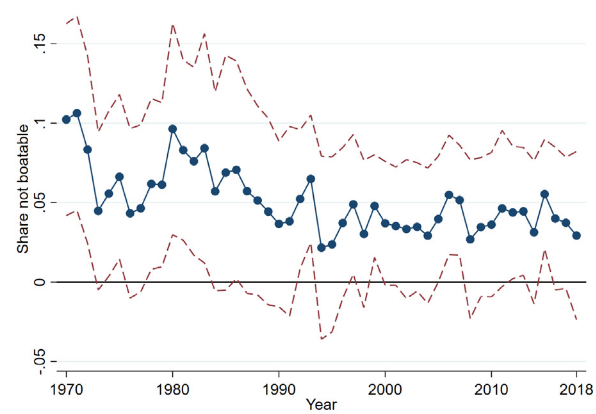
(a) Share Not Drinkable



(b) Share Not Swimmable



(c) Share Not Fishable



(d) Share Not Boatable

Fig. 4. Trends in Water Quality Ladder threshold non-attainment in Texas, 1970–2018. Notes: Graphs show year fixed effects plus a constant from regressions that control for monitoring station fixed effects, a day-of-year cubic polynomial, and an hour-of-day cubic polynomial following Keiser and Shapiro (2019). Blue connected dots show yearly values and red dashed lines show the 95% confidence interval for year fixed effect estimates. 1970 is the reference year. Standard errors are clustered by river basin.

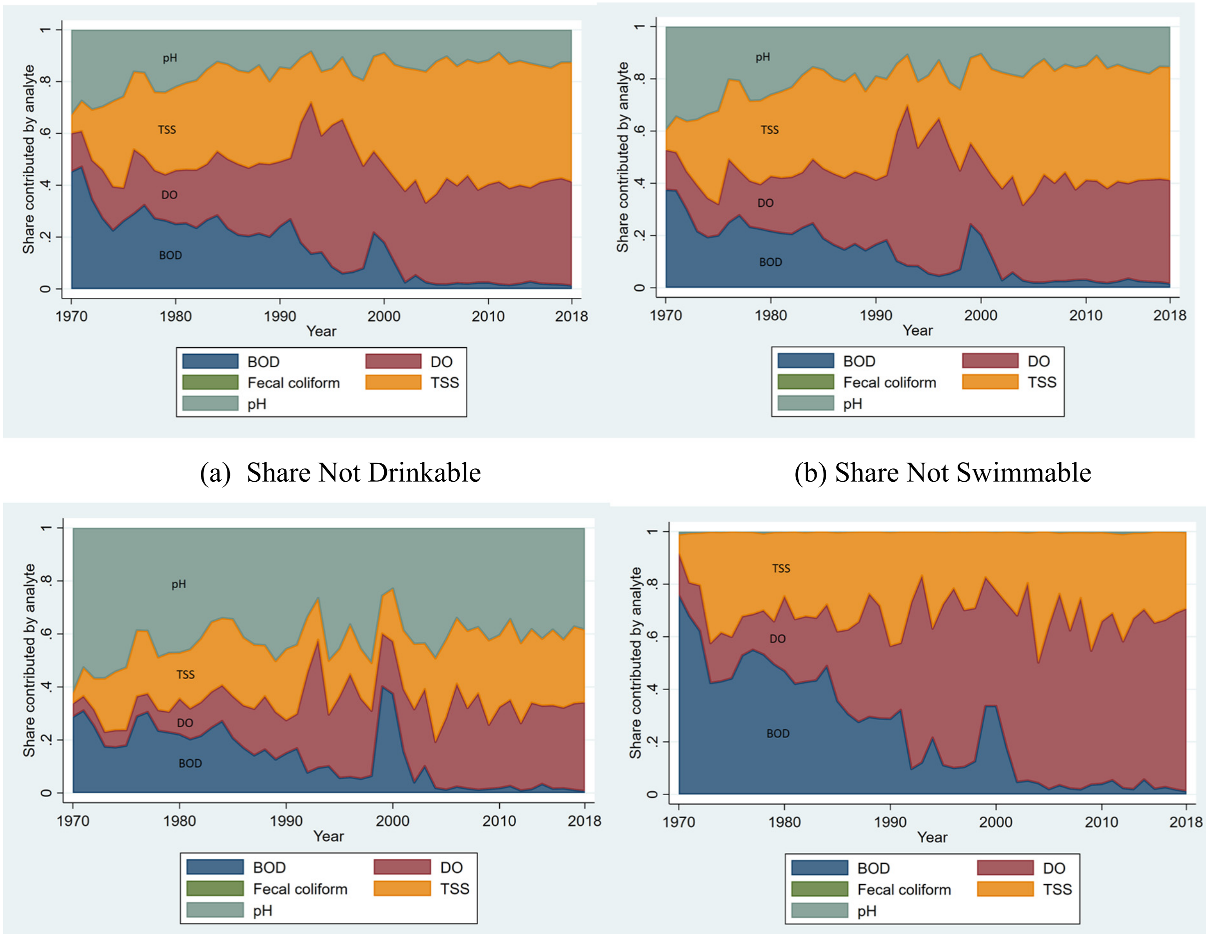
quality concern; since 2000, Texas state standards based on EPA guidance are now set for *E. coli* (freshwater) or enterococci (saltwater), not fecal coliform (though we still observe fecal coliform concentrations in the data for the entire sample period). Since the WQL uses fecal coliform, it may not be a good tool for understanding trends in pathogen-related impairment after 2000. Second, the share of observations that fail to achieve a given use that is attributable to BOD declines dramatically between 1970 and 2018 for all designated uses, though the combined contributions of BOD and DO (which are likely to be coupled) do not exhibit a clear trend over our time period of analysis.[19] Consistent with nationwide trends of declining point-source industrial pollution and improved municipal wastewater treatment, potentially associated with the CWA (Keiser and Shapiro, 2019), the contribution of BOD to non-attainment of designated uses starts out at between 30 and 75% in 1970 and declines to a negligible share for all four use designations by 2018. The contribution of pH to non-attainment of the drinkable, swimmable, and fishable thresholds has also generally declined over time, though unlike BOD, it is still an important driver of non-attainment at the end of the study period, especially for the fishable threshold.

Third, and most importantly for this study, the combined roles of DO and TSS in Texas waters' failure to meet the WQL's designated use thresholds grows dramatically between 1970 and 2018. The joint contribution of these two parameters to non-attainment starts out at about 20% for the drinkability and swimmability thresholds in 1970, but grows to about 80% by 2018. Similarly, the two parameters' joint contribution to failure to meet the fishability threshold is negligible in 1970 but rises to almost 60% by 2018. Impacts on boatability are even larger, where almost 100% of non-attainment in 2018 can be attributed to DO and TSS (especially DO).[20] Subject to the caveat that the WQL may not be designed to appropriately capture pathogen-related impairment, this growth in the role of DO and TSS is notable; these two pollutants represent a much greater relative threat to attainment of designated uses in Texas than they did in the 1970s.

In light of the trends shown in Fig. 4 that water quality improvements relative to human uses have stagnated over the last three decades, we conclude that few gains can be achieved in meeting the

[19] Note that decreases in the contribution to WQL non-attainment by one analyte (like BOD) and increases in the contribution by another analyte (like DO) don't necessarily mean that the two analytes are trending in opposite directions in terms of concentration. This merely indicates that one analyte is triggering non-attainment more often than the other over time.

[20] Note that, unlike in Figure 3, censoring at zero (from concentrations that are BDL) is not a real concern in Figures 4 and 5, because we examine the share of waters meeting the WQL thresholds, which are all well above detection limits (Table 3). The small exceptions would be in the "drinkable" category (panel a in both figures), for which the fecal coliform and BOD thresholds are both zero.



(a) Share Not Drinkable

(b) Share Not Swimmable

(c) Share Not Fishable

(d) Share Not Boatable

Fig. 5. Contribution to Water Quality Ladder non-attainment by parameter, 1970–2018.

WQL thresholds without seriously addressing nonpoint source pollution—a fact not lost on regulators. For example, in a 2000 study of the CWA, the EPA concluded that even if all U.S. point sources of water pollution were to achieve zero emissions, only 10% of the nation's river and stream miles would rise a step or more on the WQL, given the primary role now played by nonpoint source pollution in impairing U.S. water quality (Bingham et al., 2000).

One concern with Fig. 5 might be that the relative sampling frequency for each of the five WQL parameters may have changed over time. This would affect our ability to conclude that changing shares of responsibility for the failure to meet each threshold are due to changes in the relative severity of pollution. To address this concern, in Fig. S.3 in the Supplemental Material, we weight each parameter's share of the responsibility for failing to meet the WQL thresholds by the ratio of that parameter's number of observations to the total number of observations across all parameters. The story is qualitatively similar; controlling for changing frequency of observation, the share of failures to meet each WQL threshold for human use has grown substantially for the nutrient pollution-related parameters, though BOD plays a more prominent role in contributing non-attainment.

5.2. Trends relative to segment-specific state standards for human uses

In Section 5.1, we assessed trends over time in the capacity of Texas surface waters to meet human use thresholds in the WQL; these are well-accepted standards, but not enforceable regulations. This section examines trends over time in whether Texas waters meet state regulatory standards, enforced by the TCEQ, that are specific to each waterbody (e.g., a lake or river segment).[21] We then determine whether individual pollution monitor readings are above or below the standard and calculate the proportion of readings in each calendar year that meet the standard.

Fig. 6 reports as solid lines the proportion of observations that meet these waterbody-specific standards each year for DO and chlorophyll *a*, accompanied by 95% Wilson score confidence intervals represented with dashed lines. Recall from Section 3 that numeric chlorophyll *a* standards exist only for 39 reservoirs in the state, while DO standards are ubiquitous across waterbody types. Because we apply the 2018 state water quality standards for the entire study period, the figure does not reflect changes in the standards themselves, either as a whole or for specific waterbody segments. Holding the standards constant at 2018 levels allows us to interpret changes in compliance with state standards as true changes in water quality, unless the location and timing of monitoring are correlated with water quality. Considering this possibility, we calculated the correlation between mean decadal DO concentrations (sample decade 1, 1970s vs. sample decade 5, 2010s) at the waterbody segment level (the same segments defined by TCEQ for the Fig. 6 results). Cleaner waters appear slightly more likely to receive additional monitors over time. If empirically important, given the

[21] As noted in Section 3, this analysis can only be done for DO and chlorophyll *a*, because there are no enforceable TCEQ standards for TN or TP in surface water.

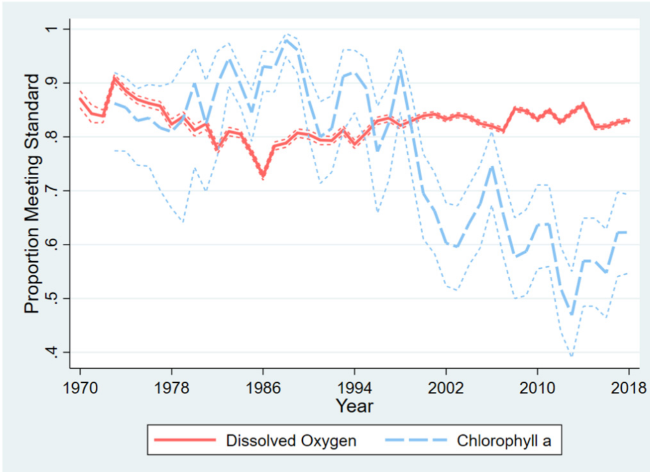


Fig. 6. Compliance with TCEQ 2018 surface water quality standards for DO and chlorophyll *a*, 1970 to 2018. Notes:DO series represents the yearly proportion of observations in the TCEQ data only that exceed the segment- level DO standard as prescribed by the 2018 revisions to the Texas water quality standards (n = 742,642). Chlorophyll *aseries* represents the proportion of observations in the TCEQ data only below the segment and station-level chlorophyll *a* standards (n = 5668). Dashed lines represent 95% Wilson score intervals.

relatively low correlation, this would tend to impair our ability to detect negative water quality trends over time, making the DO results conservative.[22]

The proportion of water quality samples meeting Texas state DO standards for their waters' designated uses falls from the early 1970s until the mid-1980s. After the mid-1980s, the trend is reversed, with a gradual increase in the share of observations in compliance with state standards, though by 2018 the proportion is still lower than what it was in the early 1970s. Fig. 6 also indicates that the share of observations meeting the 2018 standards for chlorophyll *a* fluctuates between 80 and 100% until the mid-1990s, after which the share declines sharply down to the 50 to 60% range by the end of the study period. This reduction in the share of samples compliant with chlorophyll *a* is consistent with the patterns shown in the map in Fig. 2, panel d. The wider confidence intervals for chlorophyll *a* relative to those for DO are driven by the smaller number of available chlorophyll *a* observations. Nonetheless, the share in compliance in 2018 is statistically significantly lower than the share in 1970.

6. Conclusions

This paper harnesses a very large quantity of data available from public sources but, to our knowledge, never before compiled and analyzed in one place, to survey major trends in Texas surface water quality from 1970 to 2018, a period of almost 50 years in which Texas has seen large changes in many key drivers of water quality: population, land use, urban and agricultural development, industrial development (including oil and gas), and weather and climate. Some of these trends mirror those elsewhere and have been identified as major contributors to the growing problem of eutrophication.

The analysis also demonstrates that fairly rapid improvements in meeting key thresholds for human uses from 1970 to 1990 have been followed by 30 years of approximate stasis, for reasons about which we can only speculate. Subsequent analysis shows that most of the remaining failures of waterbodies in the state to meet human use designation thresholds can be attributed to DO and TSS (among the set of parameters included in the WQL), and that this share has grown so much in the past few decades that it may be difficult to make further gains in achieving human use designations without addressing the problem of nonpoint source pollution, especially nutrient loading. Similarly, the share of the state's waters meeting state-designated, spatially-specific use standards for chlorophyll *a* concentrations (established for 39 of the state's reservoirs) has fallen dramatically since the mid-1990s.

Our analysis of general trends in nutrient pollution as measured through DO, TN, TP and chlorophyll *a* concentrations produces results that are less sharp. Monotonic, seasonally-adjusted trends identified using nonparametric approaches tend toward water quality degradation statewide, though the trends vary by river basin. Estimates from parametric regressions with comprehensive controls are not consistent with some of the trend results from the nonparametric Mann-Kendall tests. This is not necessarily unexpected, since the nonparametric and parametric approaches are very different, especially in the assumptions regarding monotonicity of the trends and the ability to control for intertemporal variation in factors such as temperature and precipitation.

Future research that explains why attainment of water quality thresholds for human uses has stagnated would be valuable and highly policy relevant. Some potential explanations include long-term changes in related environmental conditions such as air and water temperature, which may correlate with the water quality measures we observe, or socioeconomic drivers such as population growth or changes in state regulations. Nonetheless, given the results regarding designated use attainment, nutrient pollution is likely taking a toll on the economic value of Texas' water resources. The economics literature links reductions in DO, and subsequent effects on water's appearance and odor, suitability for aquatic organisms, and human recreation, with impacts on property values, recreation demand, and other economic outcomes. Economic valuation methods for monetizing these impacts are well-developed, especially for urban areas, and particularly at or near the coast. However, due to the lack of published studies valuing nutrient-related water quality damages in Texas, we do not attempt to estimate the economic impacts of the water quality changes we observe in this study. As we describe in Section 2.2, existing studies on the value of water quality improvements demonstrate that society is willing to pay significant sums for local water quality improvements. For example, literature on the nationwide benefits of water quality improvements attributed to the CWA produces benefit estimates on the order of billions of U.S. dollars per year, even when limited to benefits tied to recreational water use and those capitalized in housing markets (Carson and Mitchell, 1993; Freeman III et al., 2014; Keiser and Shapiro, 2019). Thus, further research on the economic impacts of water quality changes in Texas would make novel contributions to the academic literature, and to important policy debates about water pollution regulation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[22] We first estimate the mean DO concentration by decade for each TCEQ waterbody segment, and sort segments into quintiles by decade. We do the same for the number of water quality monitors picking up DO, sorting each segment into decadal quintiles of monitoring intensity. Then we calculate the directional change in quintiles for both DO and monitors from decade 1 to decade 5. For example, if a segment was in quintile 1 in decade 1 and quintile 5 in decade 5, the change is positive. We then calculate the correlation between the changes in DO quintile and changes in monitoring quintile from decade 1 to decade 5. The overall calculation is 0.21 and significant. Conditional on water quality improvement, the correlation is 0.31 and significant. Conditional on water quality degradation, the correlation is −0.12 and insignificant.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.137962.

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