Increasing Productivity Amid Stable Nutrient Regimes in Rhode Island Lakes and Reservoirs

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Addressing anthropogenic impacts on aquatic ecosystems has long been the focus of lake management. Controlling phosphorus and nitrogen can mitigate the impacts of eutrophication, but to determine the effectiveness requires long-term datasets. A recent analysis of the LAke multi-scaled GeOSpatial and temporal database (LAGOSNE), found stable water quality in the Northeast and Midwestern regions of the United States; however, trends at smaller scales may be masked. We address this by analyzing the University of Rhode Island’s Watershed Watch Volunteer Monitoring Program (URIWW) dataset. URIWW has collected water quality data on Rhode Island lakes and reservoirs for over 25 years. These data, included in LAGOSNE, allow for comparison of water quality trends at regional and state extents. We assess for trends with z-scores (i.e. scaled anomalies) calculated on a per-station basis and examine yearly averages. Temperature and chlorophyll *a* are increasing. Total nitrogen (TN) shows a weak increasing trend driven by low years in the early 1990s. Total phosphorus (TP) and the total nitrogen:total phosphorus ratio (TN:TP) are stable. Applying the site-specific z-score approach to LAGOSNE found similar trends to prior studies with chlorophyll *a*, TN, TP, and TN:TP. In short, productivity in Rhode Island lakes and reservoirs is increasing, in spite of stable nutrient regimes. Although not causal, this analysis suggests an association between lake temperature and productivity. Additionally, we demonstrate both the value of long-term monitoring programs, like URIWW, for identifying trends in environmental condition, and the utility of site-specific z-scores for analyzing for long-term trends.

# Introduction

Aquatic ecosystems have been altered as the result of human activities modifying nutrient cycling on a global scale (Vitousek et al. 1997, Filippelli 2008, Finlay et al. 2013). Because of their position in the landscape, lakes can function as integrators and sentinels for these anthropogenic effects (Williamson et al. 2008, Schindler 2009). Increasing nutrient inputs, particularly of N and P, derived from intensive agriculture and densely populated urban areas have contributed to the eutrophication of many lakes (Carpenter et al. 1998, Smith 2003). This eutrophication suggests an increase in the frequency and severity of harmful algal blooms, greater risks for human and animal health, and potential economic costs associated with eutrophic waters (Dodds et al. 2008 , Paerl and Huisman 2009, Kosten et al. 2012, Michalak et al. 2013, Taranu et al. 2015, Brooks et al. 2016). To address these problems, management strategies have historically focused on reducing P inputs to lakes, but research also suggests that reducing N inputs may be more effective in certain situations (Schindler et al. 2008, Paerl et al. 2016). These studies indicate that spatial differences and relationships between N, P, and chlorophyll *a* exist and that long-term studies are needed to identify trends at local, regional, and national scales (I’m confused about this sentence- not sure how to edit. Let’s discuss it). Maybe… These studies indicate that relationships between N, P, and chlorophyll *a* exist and these relationships are spatially complex; long-term studies are needed to identify trends at local, regional, and national scales.

Attempts to explore these spatial dyanmics are available (my attempt at intro sentence for paragraph). Programs such as USEPA’s National Lakes Assessment (NLA) provide data that allow for continental-scale water quality analysis. These analyses can be used for managing water resources by developing water quality criteria for N, P, and chlorophyll *a* (Herlihy et al. 2013, Yuan et al. 2014) (I’m not sure how this NLA fits into this. Again, let’s chat). Studying trends across large spatial scales can evaluate the effects of eutrophication such as the degradation of oligotrophic systems as P increases(Stoddard et al. 2016). Broad-scale data can also be used for water quality modeling across a range of spatial scales including for predicting lake trophic state, which is predictive of ecosystem condition (Hollister et al. 2016, Nojavan et al. 2019). These trophic state models indicate that landscape variables (i.e. ecoregion, elevation, and latitude) are important and that regional trends exist. Lake-specific drivers are also important for predicting continental-scale water quality which adds an additional layer of complexity (Read et al. 2015). Despite these challenges, it is important to study at multiple spatial scales because emergent trends on regional or continental scales may not be evident when studying individual lakes (Cheruvelil et al. 2013, Lottig et al. 2014). (thought- Maybe this paragraph just needs a introduction sentence. )

Previous studies using regional data from the Northeastern and Midwestern (I don’t actually think these should be capitalized, but they are elsewhere in the paper) United States have investigated spatial and temporal water quality trends and have shown differences based on scale. Macro-scale (i.e. subcontinental) drivers of water quality trends are complex and may vary temporally (Lottig et al. 2017). This complexity can cause nutrient (N and P) trends to have different drivers than ratios of the individual nutrients (Collins et al. 2017). On a regional scale, trends of N, P, and chlorophyll *a* differ as factors such as land use and climate vary among regions, particularly when comparing the Northeastern and Midwestern US (Filstrup et al. 2014, 2018). Thus, it was surprising when stasis was reported over a 25 year period for these regions (Oliver et al. 2017). Given what is known about long-term trends in water quality within the broader region of the northeastern United States, we were curious if those trends were also present in water quality in Rhode Island lakes and reservoirs.

Examining long-term trends in Rhode Island lakes is possible because of the data gathered by University of Rhode Island’s Watershed Watch (URIWW). URI’s Watershed Watch is a citizen science program founded in the late 1980’s that has built a robust collaboration between URI scientists and a vast network of non-expert volunteer monitors. Volunteer monitors are trained and then collect *in situ* data as well as whole water samples during the growing season. These efforts have been ongoing in some waterbodies since 1988. These types of citizen science efforts allow for the collection of reliable data that in turn lead to crucial and frequently unexpected insights (Dickinson et al. 2012, Kosmala et al. 2016). Here specifically, URIWW data contributed to not only the larger regional study by Oliver et al. (Oliver et al. 2017), but also allowed us to examine the long-term trends in Rhode Island.

Thus, the goals of this study were to examine approximately 25 years of lake and reservoir data in Rhode Island and answer two questions. First, what are the state-wide trends in total nitrogen (TN), total phosphorus (TP), total nitrogen to total phosphorus ratio (TN:TP), chlorophyll *a*, and lake temperature. Second, are water quality trends in Rhode Island similar to regional trends in the Northeastern United states. Another focus of this paper was to apply existing methods for examining long-term climate records (e.g., (Jones and Hulme 1996)) to water quality data in order to examine long-term trends. Finally, this analysis has also been done using open data from the URI Watershed Watch program and the LAGOSNE project and the analysis in its entirety is available for independent reproduction at <https://github.com/usepa/ri_wq_trends> (Soranno et al. 2017, Stachelek and Oliver 2017).

# Methods

For this study, we combined a long-term dataset on water quality of lakes in Rhode Island with a trend analysis based on centered and scaled water quality values (i.e. z-scores) to find increasing or decreasing annual water quality trends. Details are outlined below.

## Study Area and Data

The study area for this analysis includes lakes and reservoirs in the state of Rhode Island where data were collected by the University of Rhode Island’s Watershed Watch (URIWW) program (Figure 1). The URIWW is a volunteer monitoring program that has been collecting water quality data from Rhode Island lakes and reservoirs for over 25 years. The program began in 1988, monitoring 14 lakes and has now grown to include over 250 monitoring sites on over 120 waterbodies, including rivers/streams, and estuaries, with more than 400 trained volunteers. URIWW now provides more than 90% of Rhode Island’s lake multi-year baseline data (^I don’t know what this means- is a common knowledge I’m missing? If so, ignore), and is an integral part of the state’s environmental data collection strategy. Data QA/QC is treated with paramount importance; volunteers are trained both in the classroom and the field, and are provided with all the necessary equipment and supplies, along with scheduled collection dates. For freshwater lakes and reservoirs, weekly secchi depth and water temperature are recorded, along with bi-weekly chlorophyll *a* and dissolved oxygen. Water samples are collected three times per season (May through October) to be analyzed in the EPA-certified laboratory.

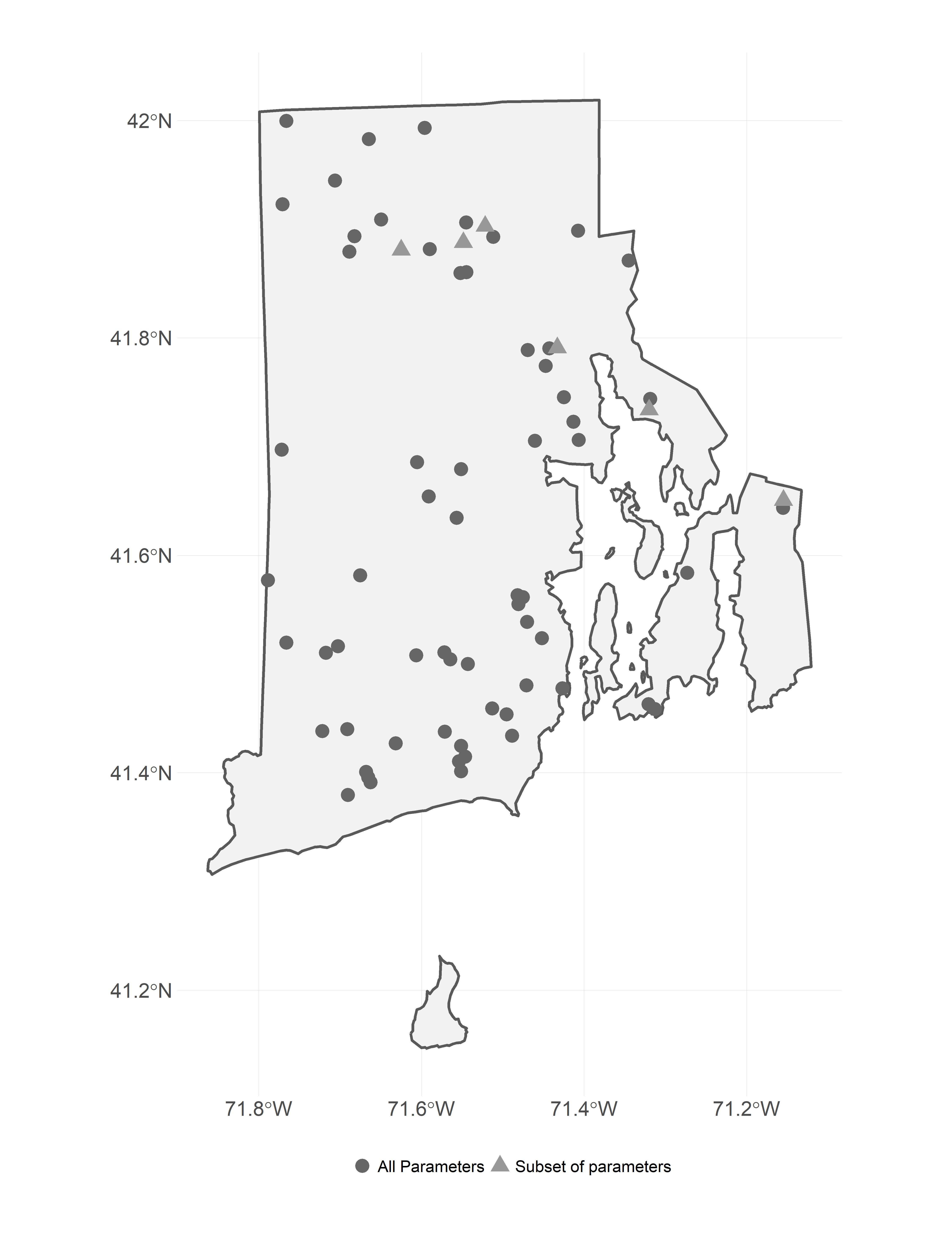


Figure 1: Map of URI Watershed Watch lake and reservoir sampling sites

In particular, we selected URIWW data that matched the following criteria: 1) were sampled between 1990 and 2016, 2) were sampled in May to October, 3) and were sampled at a depth of 2 meters or less. For this analysis, we were interested in trends in lake temperature, TN, TP, TN:TP, and chlorophyll *a*. For each of these parameters, we further filtered the data to select sites that had at least 10 years of data for a given parameter within the 1990 to 2016 timeframe. The final dataset used in our analysis included 69 lakes and reservoirs which had approximately 67 samples for temperature, 67 samples for chlorophyll *a*, 65 samples for TN, 66 samples for TP. Of the 69 sampling sites, 63 had data for all 5 parameters.

Additionally, prior studies have looked at water quality trends across a larger region of the Northeastern United states that included 17 states including Minnesota, Wisconsin, Iowa, Missouri, Illinois, Indiana, Michigan, Ohio, Pennsylvania, New York, New Jersey, Connecticut, Massachusetts, Rhode Island, Vermont, New Hampshire, and Maine (Soranno et al. 2015, Oliver et al. 2017). The authors found little change in water quality trends across this region (Oliver et al. 2017) . We repeated our analysis (see **Water Quality Trend Analysis** section) with the same dataset used by (Oliver et al. 2017), the LAGOSNE dataset (Soranno et al. 2015, 2017, Stachelek and Oliver 2017). Temperature data were not available, thus we examined trends, using our analytical methods, for TN, TP, TN:TP, and chlorophyll *a* from the LAGOSNE dataset.

## Water Quality Trend Analysis

There are many different methods for analyzing time series data for trends. Environmental data are notoriously “noisy” and one of the difficulties that is encountered with multiple sampling locations is how to identify a trend while there is variation within a sampling site as well as variation introduced by differing start years for sampling among the many sites. For instance, if long-term data on water quality were collected more frequently in early years from more pristine waterbodies then a simple comparison of raw-values over time might show a decrease in water quality, which could be misleading if later sampling occurred on both pristine and more eutrophic water bodies. Thus, it is necessary to account for this type of within-site and among-site variation, using methods similar to those used to analyze long-term temperature trends using temperature anomalies (e.g., (Jones and Hulme 1996)). The general approach is to calculate site-specific deviations from a long-term mean over a pre-determined reference period. This allows all sites to be shifted to a common base line and the deviations, or anomalies, show change over the specified reference period.

### Z-score

Anomaly analysis works best with a single measure (e.g., temperature) or with multiple measurements that are on the same scale. The water quality parameters that we explored have different scales and thus the anomaly alone is difficult to interpret across metrics. For instance, temperature in Rhode Island lakes during the growing season ranges from approximately 15 degrees Celsius to a high of 30 degrees Celsius, whereas phosphorus might range from near zero ug/l to ~900 ug/l. To standardize these values, we used the common approach of dividing each anomaly by the standard deviation for the reference period (e.g., (Jones and Hulme 1996)). The resultant value is commonly referred to as a z-score. We used these z-scores to examine each water quality parameter for a trend over the time period of 1993 to 2016. Furthermore, since we are interested in water quality trends over time at individual sites, z-scores were calculated over the reference period, 1993-2016, for each site. We refer to this approach as the site-specific z-scores.

### Summarizing site-specific z-scores

Methods for calculating the site-specific z-scores and the yearly averages are as follows and are presented graphically in Figure 2. Additionally, an example R script, schematic.R and example dataset, schematic.csv to recreate and demonstrate the calculations in Figure 2 is available from (**???**).

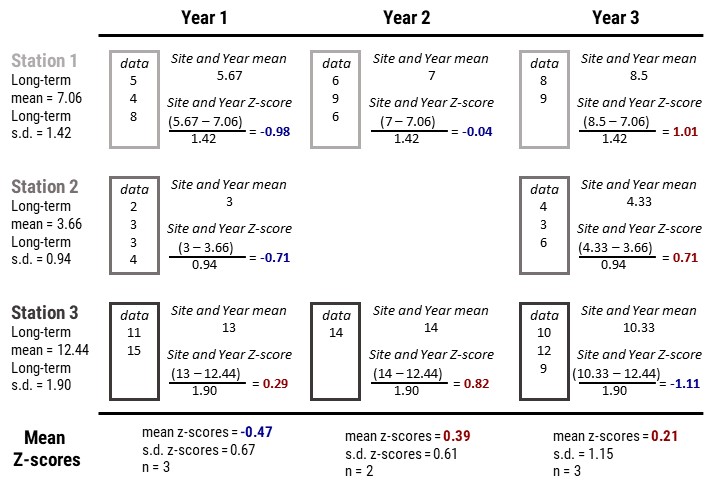


Figure 2: Example calculation of the site-specific z-scores and yearly mean z-scores.

The general steps, outlined in Figure 2 and listed below, are repeated for each of the water quality parameters.

1. For each site, calculate the annual means, producing a single mean value for each site and year. This step prevents bias from pseudoreplication of multiple measurements of the same site in a given year (Hurlbert 1984). The per site means across years are assumed to be independent.
2. Calculate the long-term reference mean and reference standard deviation for all sites. This results in a single long-term mean and standard deviation for each of the sites.
3. Calculate the z-score for each annual mean at each site by subtracting the reference mean and dividing by the reference standard deviation.
4. Summarize by calculating the mean z-score per year for the entire group of sites. The resultant values are analyzed for a trend over time.

### Linear regression on annual means

Testing for a regression slope being different than zero can be used to test for monotonic trends in water quality data (Helsel and Hirsch 2002). We used these standard procedures to test for positive or negative trends in lake temperature, chlorophyll *a*, TN, TP and TN:TP. For each parameter, we fit a regression line to the z-scores as a function of year and tested the null hypothesis that no trend existed (e.g. 1 = 0).

### Comparison of Rhode Island to the Region

Prior studies have shown relatively stable water quality in the lakes of the Northeastern United Sates (Oliver et al. 2017). While the University of Rhode Island’s Watershed Watch data were included in that regional study, we were curious if regional trends were masking local trends in Rhode Island and thus, wanted to compare the trends at the regional scale to the trends at the state scale. The analysis conducted by Oliver et al. (2017) is a robust approach; however, to make direct comparisons between Rhode Island and the region, we re-analyzed the same dataset used by Oliver et al. (2017) but using the trend analysis approach outlined above.

# Results

During the period of 1990 to 2016, Rhode Island lakes and reservoirs in our dataset had a mean lake temperature of 21.93 celsius, mean TN of 606.56 µg/l, mean TP of 24.44 µg/l, mean TN:TP ratio of 41.56 , and mean chlorophyll *a* of 10.13 µg/l (Table 1).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Parameter | Units | 25th Percentile | Mean | Median | 75th Percentile | Max | Std. Dev |
| temp | celsius | 21.07 | 21.93 | 22.20 | 23.08 | 29.00 | 1.88 |
| total\_n | µg/l | 364.38 | 606.56 | 475.00 | 703.33 | 10742.50 | 494.98 |
| total\_p | µg/l | 10.50 | 24.44 | 15.00 | 24.00 | 664.00 | 33.74 |
| np\_ratio |  | 24.35 | 41.56 | 32.50 | 43.09 | 1063.74 | 46.28 |
| chla | µg/l | 2.21 | 10.13 | 4.51 | 10.47 | 666.23 | 22.07 |

*Table 1: Summary statistics for URI Watershed Watch data from 1990 to 2016.*

For lakes and reservoirs in the larger region represented by the LAGOSNE States, mean TN was 854.14 µg/l, mean TP was 31.66 µg/l, mean TN:TP ratio was 40.89 , and mean chlorophyll *a* was 16.8 µg/l (Table 2).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Parameter | Units | 25th Percentile | Mean | Median | 75th Percentile | Max | Std. Dev |
| total\_n | µg/l | 346.00 | 854.14 | 560.00 | 923.33 | 16778 | 1205.11 |
| total\_p | µg/l | 9.50 | 31.66 | 15.50 | 30.00 | 1200 | 53.70 |
| np\_ratio |  | 18.12 | 40.89 | 26.78 | 39.60 | 40033 | 465.77 |
| chla | µg/l | 3.20 | 16.80 | 6.20 | 17.22 | 696 | 30.35 |

*Table 2: Summary statistics for LAGOSNE data from 1990 to 2016.*

## State-wide trends in water quality

Average annual scaled temperature in lakes and reservoirs appear to be increasing (slope: 0.038 , p-value: 0.00755) with the majority of years with average temperature greater than the long-term average occurring in the years since 2000 (Figure 3). Chlorophyll *a* is also showing an increasing trend over time (slope: 0.058 , p-value: 0) and with the exception of a slightly above-average year in 2003, the above-average years have all occurred since 2010 (Figure 4A.).

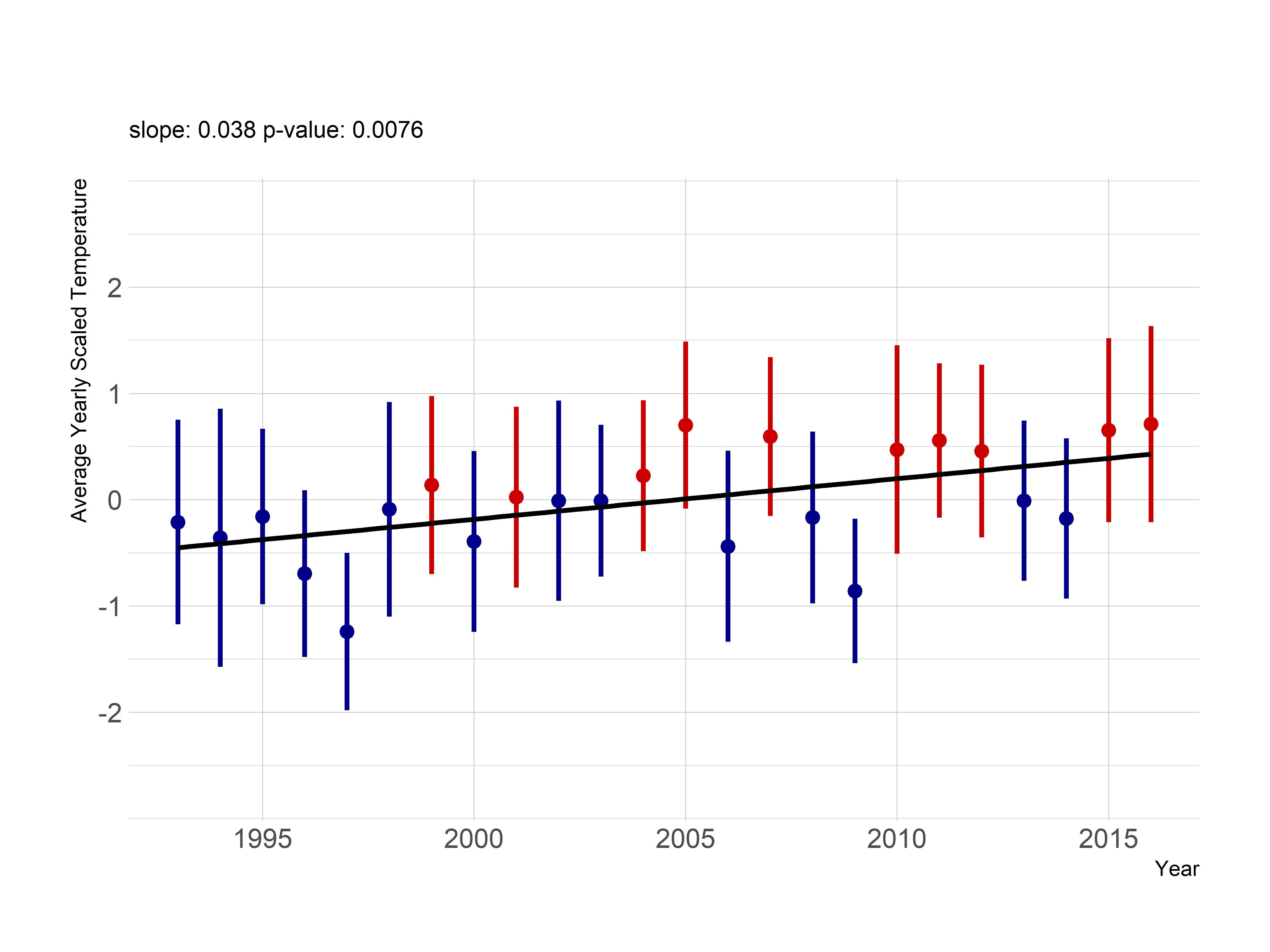


Figure 3: Yearly trend over 20+ years of lake temperature in Rhode Island lakes and reservoirs. Points are averages and ranges are standard deviations with blue indicating an average below the long-term mean and red indicating an average above the long-term mean.

* Reminder- need to add “a” to figure titles

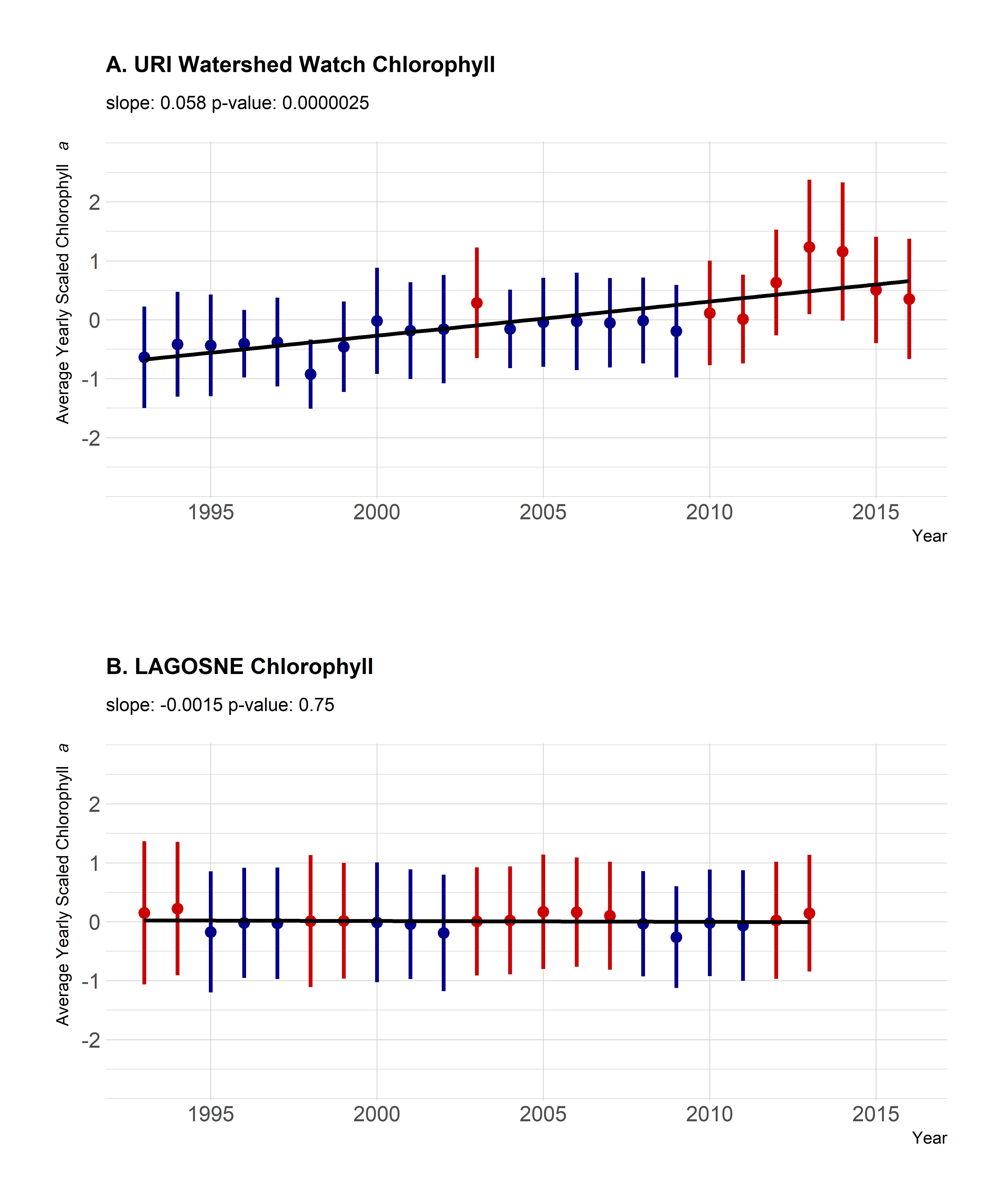


Figure 4: Yearly trend over 20+ years of chlorphyll \*a\* (average z-score). Panel A. Yearly averaged chlorophyll \*a\* z-scores from the URI Watershed Watch data. Panel B. Yearly averaged chlorophyll \*a\* z-scores from the LAGOSNE dataset. Points are averages and ranges are standard deviations with blue indicating an average below the long-term mean and red indicating an average above the long-term mean.

Mean annual trends for nutrients were weaker or showed no trend over time. The data suggest a positive trend in TN (slope: 0.023 , p-value: 0.00148); however, that perceived trend is driven by the lower than average TN values in 1993 and 1994 (Figure 5A.). Since 1995, the yearly trend is shows much lower increase over time (slope: 0.011, p-value: 0.04177). TP does not show a trend over time in the yearly z-scores (slope: 0.023 , p-value: 0.00148) and years that are over or under the average are evenly distributed over the years (Figure 6A.). The pattern is the same for the TN:TP ratio (slope: 0.012, p-value: 0.278) with little evidence suggesting a change in the concentrations of TN relative to the concentrations of TP (Figure 7A.). Data for all figures are available as a comma-separated values file, yearly\_average\_z.csv from (**???**).

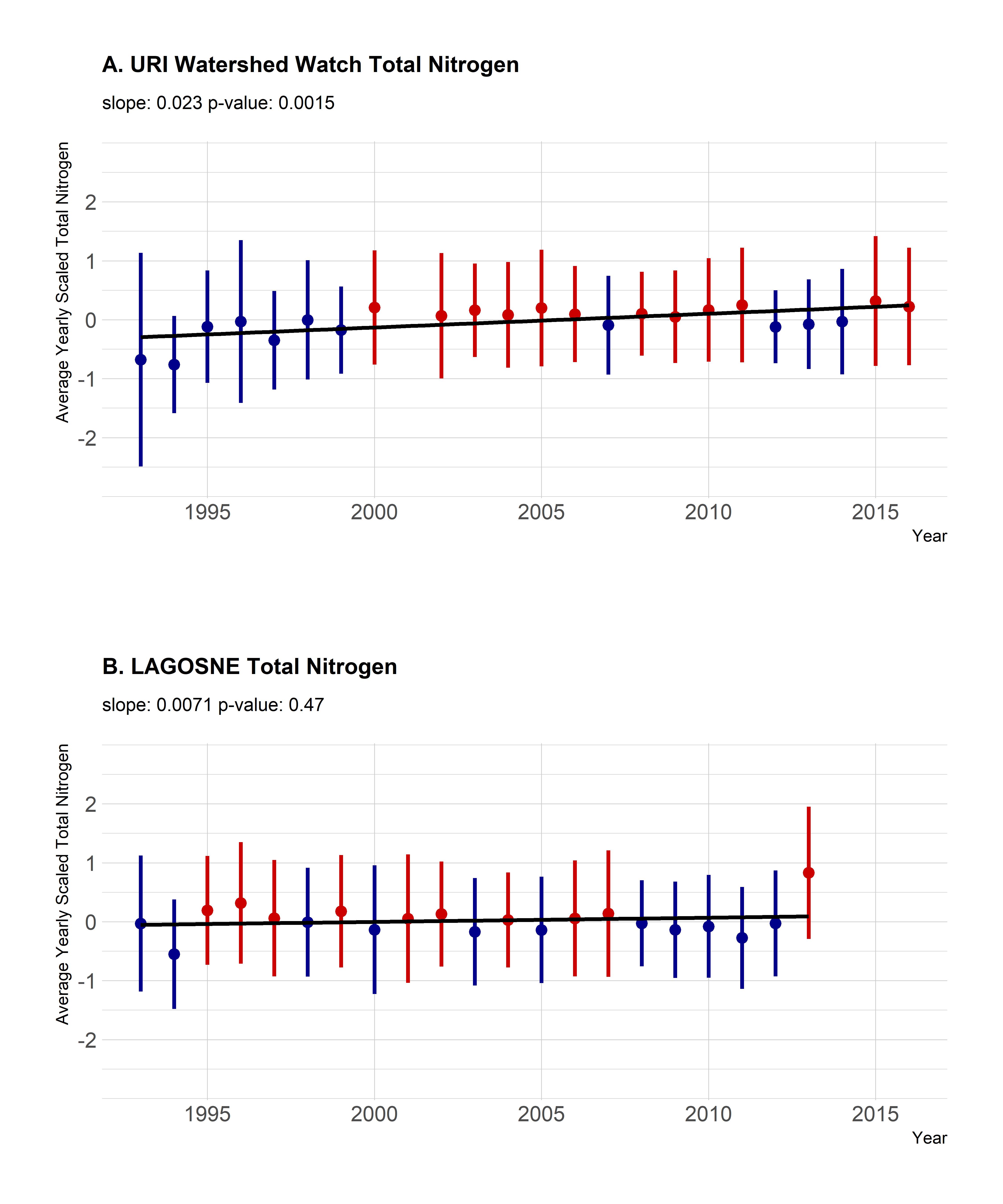


Figure 5: Yearly trend over 20+ years of TN (average z-score). Panel A. Yearly averaged TN z-scores from the URI Watershed Watch dataset. Panel B. Yearly averaged TN z-scores from the LAGOSNE dataset. Points are averages and ranges are standard deviations with blue indicating an average below the long-term mean and red indicating an average above the long-term mean.

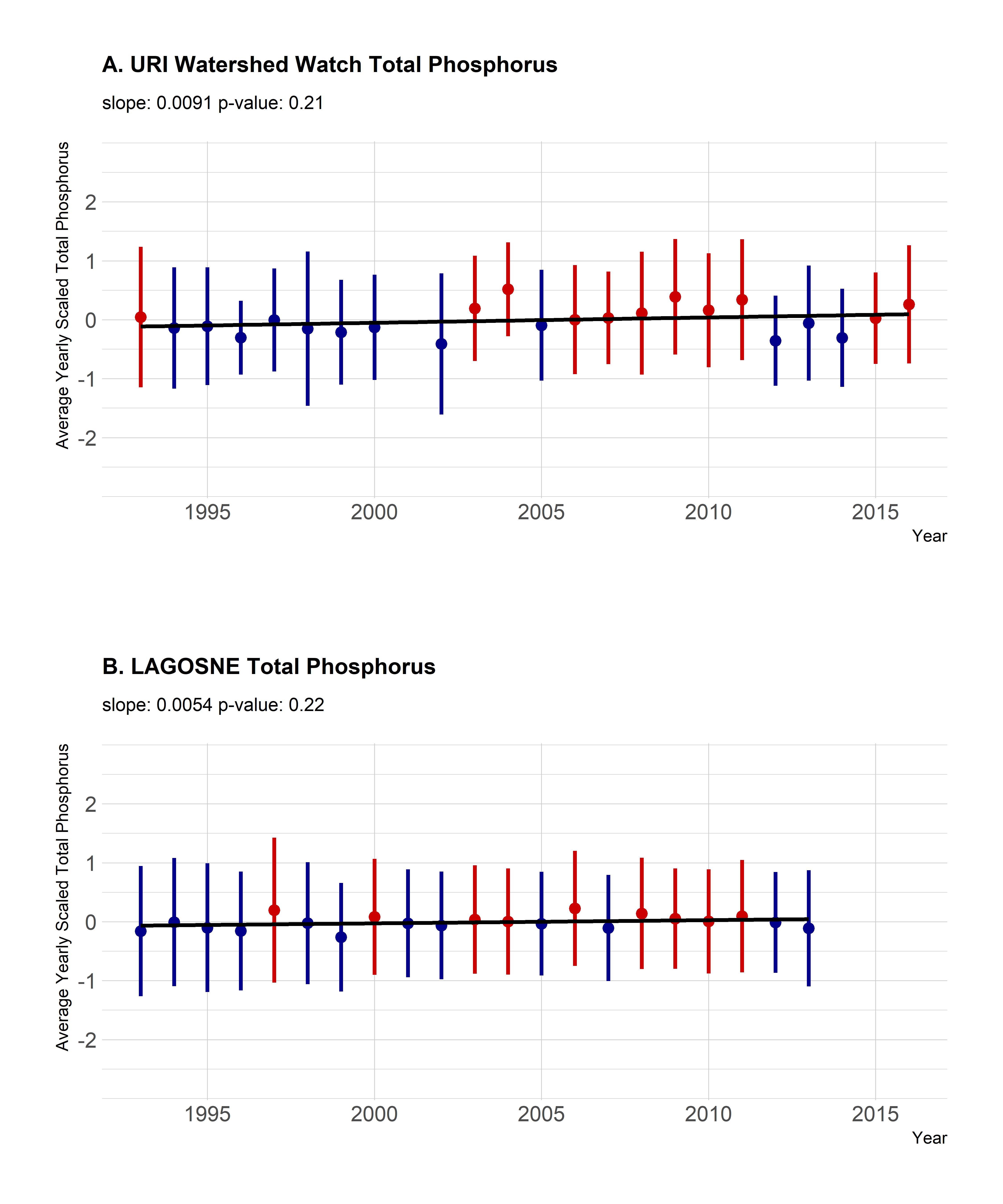


Figure 6: Yearly trend over 20+ years of TP (average z-score). Panel A. Yearly averaged TP z-scores from the URI Watershed Watch dataset. Panel B. Yearly averaged TP z-scores from the LAGOSNE dataset. Points are averages and ranges are standard deviations with blue indicating an average below the long-term mean and red indicating an average above the long-term mean.

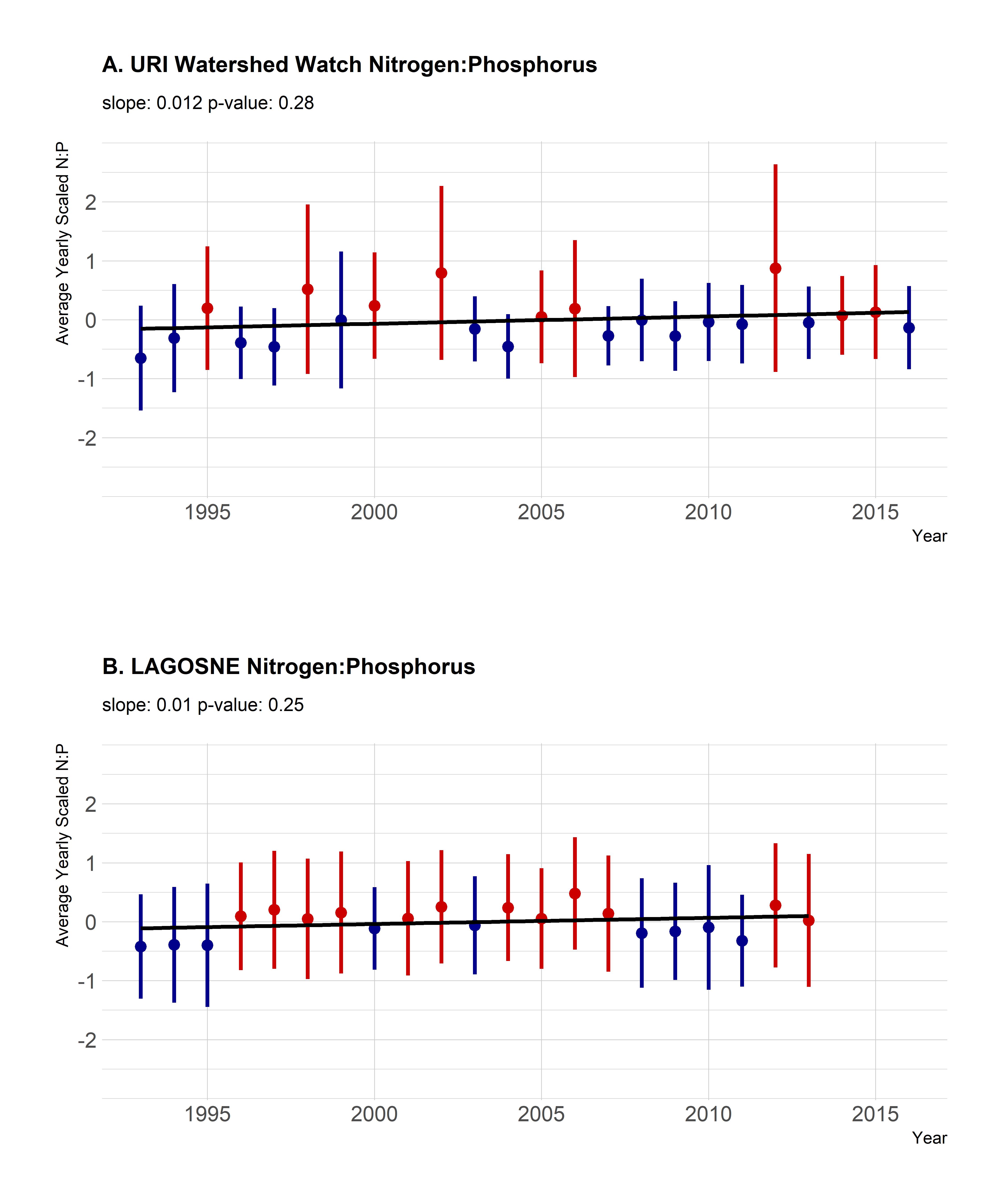


Figure 7: Yearly trend over 20+ years of the TN:TP ratio (average z-score). Panel A. Yearly averaged TN:TP ratio z-scores from the URI Watershed Watch dataset. Panel B. Yearly averaged TN:TP ratio z-scores from the LAGOSNE dataset. Points are averages and ranges are standard deviations with blue indicating an average below the long-term mean and red indicating an average above the long-term mean.

## Regional trends in water quality

In general, there was little evidence to suggest broad regional changes. Chlorophyll *a* showed a very weak negative trend (slope: -0.001, p-value: 0.75122, Figure 4B.), TP showed a slight increasing trend (slope: 0.005, p-value: 0.2157, Figure 6B.), TN showed a slight negative trend (slope: 0.007, p-value: 0.46615, Figure 5B.) and the TN:TP ratio was also flat (slope: 0.01, p-value: 0.24931, Figure 7B.)

# Discussion and conclusions

Our analysis indicates that even when nutrient regimes exhibit relative stability (i.e. neither increasing nor decreasing over time), increases in productivity, as measured by chlorophyll *a*, occur. One possible explanation is the long-term warming of Rhode Island lakes and reservoirs as also indicated by our analysis. Also, scale does indeed matter when trying to identify long-term water quality trends. Similar to the results of Oliver et al. (2017,) our analysis shows little increasing trend in productivity at the regional scale (e.g. Northeastern and Mid-western United States). However, at the local scale of the state of Rhode Island, there is a clear increasing trend in productivity.

## Trends

As previously mentioned, both temperature and chlorophyll *a* show increasing trends from 1993 to 2016 in Rhode Island lakes and reservoirs; while total nutrients and the TN:TP ratio are all relatively stable. These stable nutrient regimes may be partly explained by efforts to curb nutrient loadings (e.g., [EQIP at USDA (QK will provide), ]). Additionally, these results point to the fact that productivity is driven by processes operating at different scales. For instance, nutrient management is largely a local to watershed scale effort, but may also be regional as atmospheric nitrogen deposition can be a significant source of nitrogen [Boyer et al. 2002]. Similarly, warming lakes are driven by broader climate patterns, yet waterbody-specific factors such as catchment percent impervious and lake morphology can also impact temperature [Nelson & Palmer, 2007]. Differences in regional and state level trends are driven by complex processes.

In addition to the annualized trends we address with this study, there are other trends that may be of interest. For example, what are the trends for water quality at finer temporal scales such as monthly or seasonal trends? Anecdotal evidence in Rhode Island [SHOULD REFERENCE THIS SOMEHOW - let’s ask Elizabeth] points to greater increases in temperature earlier and later in the growing season and suggests a lengthening of the growing season. Furthermore, preliminary analysis of the URIWW data back this up with mean temperature for May 1993 to May 1995 cooler by nearly a degree than mean temperature for May 2014 through May 2016. Additionally, are trends influenced by the current state of a given waterbody? For instance, are oligotrophic lakes showing stronger trends than eutorphic lakes or are all lakes showing similar trends regardless of current trophic status? These questions are beyond the scope of this study, but all warrant further, careful investigation.

## Management Implications

There are several broader management implications from the results of our analysis and of examining long-term water quality trends in general. In particular, this analysis provides much needed information about the long-term effects of current nutrient control efforts and identifies areas where additional information is required or a change in management approaches may be needed. First, as more long-term datasets become available, it is important for managers and stakeholders to receive feedback on long-term water quality trends. Specifically for this study, the results provide feedback to long time volunteer monitors, highlighting the importance of volunteer monitoring programs. Second, with information on long-term trends, it is possible to adapt management approaches to address areas of concern. Our results show increasing productivity even though the general long-term nutrient trends have been stable, suggesting the need to further reduce nutrients to compensate for warmer water temperatures, a longer growing season and associated higher productivity.

There are several possible approaches. First, nutrient load reductions may be possible through source controls and enhanced entrainment and treatment of ground and surface waters transporting nutrients to receiving waters. Green infrastructure approaches are one way to possibly achieve both goals [see notes]. Additionally, within-lake approaches may also be used. A promising approach is the restoration of freshwater mussels to waterbodies that historically had those species. Some studies have shown reductions in both nutrients and algal biomass [see notes].

## Data Analysis Approach

The analysis approach we used here, site-specific z-scores, is not a novel method, but using it to examine water quality trends is novel as we could find few examples of using it specifically for water quality trends [NEED TO DO THIS LIT SEARCH]. This approach, and in particular non-scaled anomalies, does have a long history in the analysis of trends in climate (Hansen et al. 2006 pp. hansen2010global, @jones1996calculating, @jones1999surface). We simply built on these methods and adapted them for use with long-term water quality trends. While other methods are valid and robust (e.g. (Oliver et al. 2017)), we chose averaged site-specific z-scores as they can provide readily interpretable results, especially for communicating to general audiences. In addition, the site-specific z-scores are robust to variations in sampling effort and in the timing of inclusion of given sampling locations (e.g., added later in a time period or removed). Lastly, this analysis is only possible because of the availability of sound, long-term data on water quality in Rhode Island. Without the URIWW data and the commitment and participation of more than 2500 volunteers over the years, our analyses would have been impossible. Going forward, it is important to appreciate the role that volunteer monitoring and citizen science programs can play in capturing and better understanding long term environmental trends.

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