

# 1                    **Increasing Chlorophyll *a* Amid Stable Nutrient** 2                    **Concentrations in Rhode Island Lakes and Reservoirs**

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10                    Addressing anthropogenic impacts on aquatic ecosystems is a focus of lake management. Controlling  
11                    phosphorus and nitrogen can mitigate these impacts, but determining management effectiveness requires  
12                    long-term datasets. Recent analysis of the LAke multi-scaled GeOSpatial and temporal database for the  
13                    Northeast (LAGOSNE) United States found stable water quality in the northeastern and midwestern United  
14                    States, however, sub-regional trends may be obscured. We analyze a sub-regional (i.e., 3000 km<sup>2</sup>) trend with  
15                    the University of Rhode Island's Watershed Watch Volunteer Monitoring Program (URIWW) dataset. URIWW  
16                    has collected water quality data on Rhode Island lakes and reservoirs for over 25 years. The LAGOSNE and  
17                    URIWW datasets allow for comparison of water quality trends at regional and sub-regional extents,  
18                    respectively. We assess regional (LAGOSNE) and state (URIWW) trends with yearly mean anomalies  
19                    calculated on a per-station basis. Sub-regionally, temperature and chlorophyll *a* increased from 1993 to 2016.  
20                    Total nitrogen shows a weak increase driven by low years in the early 1990s. Total phosphorus and the  
21                    nitrogen:phosphorus ratio (N:P) were stable. At the regional scale, the LAGOSNE dataset shows similar trends  
22                    to prior studies of the LAGOSNE with chlorophyll *a*, total nitrogen, total phosphorus, and N:P all stable over  
23                    time. In short, algal biomass, as measured by chlorophyll *a* in Rhode Island lakes and reservoirs is increasing,  
24                    despite stability in total nitrogen, total phosphorus, and the nitrogen to phosphorus ratio. This analysis  
25                    suggests an association between lake temperature and primary production. Additionally, we demonstrate  
26                    both the value of long-term monitoring programs, like URIWW, for identifying trends in environmental  
27                    condition, and the utility of site-specific anomalies for analyzing for long-term water quality trends.

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## 28                    **1 Introduction**

29                    Aquatic ecosystems have been altered as the result of human activities modifying nutrient  
30                    cycling on a global scale (Vitousek et al. 1997, Filippelli 2008, Finlay et al. 2013). Because of  
31                    their position in the landscape, lakes can function as integrators and sentinels for these  
32                    anthropogenic effects (Williamson et al. 2008, Schindler 2009). Increasing nutrient inputs,  
33                    particularly of nitrogen (N) and phosphorus (P), derived from intensive agriculture and  
34                    densely populated urban areas have contributed to the eutrophication of many lakes

35 (Carpenter et al. 1998, Smith 2003). This eutrophication often leads to an increase in the  
36 frequency and severity of harmful algal blooms, greater risks for human and animal health,  
37 and potential economic costs associated with eutrophic waters (Dodds et al. 2008, Paerl  
38 and Huisman 2009, Kosten et al. 2012, Michalak et al. 2013, Taranu et al. 2015, Brooks et al.  
39 2016). To address these problems, management strategies have historically focused on  
40 reducing P inputs to lakes, but research also suggests that reducing N inputs may be more  
41 effective in certain situations (Schindler et al. 2008, Paerl et al. 2016). These studies  
42 indicate that relationships between N, P, and chlorophyll *a* exist and these relationships are  
43 spatially and temporally complex. Thus, long-term data are needed to identify trends at  
44 local, regional, and national scales.

45 Lake datasets that cover longer time periods and broader spatial scales are now becoming  
46 available. Programs such as the US Environmental Protection Agency's National Lakes  
47 Assessment (NLA) provide data that allow for continental-scale water quality analysis.  
48 These data allow for analyses that can be useful for managing water resources by  
49 developing water quality criteria for N, P, and chlorophyll *a* (Herlihy et al. 2013, Yuan et al.  
50 2014). Studying temporal trends across large spatial scales can illustrate the effects of  
51 eutrophication such as the degradation of oligotrophic systems as P increases (Stoddard et  
52 al. 2016). Broad-scale data can also be used for water quality modeling across a range of  
53 spatial scales including for predicting lake trophic state, which is indicative of ecosystem  
54 condition (Hollister et al. 2016, Nojavan et al. 2019). These trophic state models indicate  
55 that landscape variables (e.g., ecoregion, elevation, and latitude) are important and that  
56 regional trends exist. Lake-specific drivers have also been shown to be important for  
57 predicting continental-scale water quality which adds an additional layer of complexity  
58 (Read et al. 2015). Despite these challenges, it is important to study lakes at multiple  
59 spatial scales because emergent trends on regional or continental scales may or may not be  
60 present in individual lakes (Cheruvilil et al. 2013, Lottig et al. 2014).

61 Previous studies using regional data from the northeastern and midwestern United States  
62 (US) have investigated spatial and temporal water quality trends and have shown  
63 differences based on scale. Macro-scale (i.e., subcontinental) drivers of water quality trends  
64 are complex and may vary temporally (Lottig et al. 2017). This complexity can cause

65 nutrient (N and P) trends to have different drivers than ratios of the nutrients (Collins et al.  
66 2017). On a regional scale, trends of N, P, and chlorophyll *a* differ as factors such as land  
67 use and climate vary between regions, particularly when comparing the northeastern and  
68 midwestern US (Filstrup et al. 2014, 2018). Thus, it was surprising when little change in  
69 nutrients and chlorophyll *a* was reported over a 25 year period for these regions (Oliver et  
70 al. 2017). Given what is known about long-term trends in water quality within the broader  
71 region of the northeastern United States (US), we were curious if the lack of trends was also  
72 present in water quality at a sub-regional scale, using data on the 3,000 km<sup>2</sup> area that  
73 encompasses a number of Rhode Island lakes and reservoirs.

74 Examining long-term trends in Rhode Island lakes is possible because of the data gathered  
75 by University of Rhode Island's Watershed Watch (URIWW). URIWW is a scientist-led  
76 citizen science program founded in the late 1980s that has built a robust collaboration  
77 between URI scientists and a vast network of volunteer monitors. Volunteer monitors are  
78 trained and then collect *in situ* data as well as whole water samples during the growing  
79 season (e.g., May through October). The entire effort follows rigorous quality  
80 control/quality assurance protocols. These types of citizen science efforts allow for the  
81 collection of reliable data that in turn lead to crucial and frequently unexpected insights  
82 (Dickinson et al. 2012, Kosmala et al. 2016, Oliver et al. 2017). URIWW data contributed to  
83 the larger regional study by Oliver et al. (2017), and, also allowed us to examine the long-  
84 term trends specifically in Rhode Island.

85 The goals of this study were to examine ~25 years of lake and reservoir data in Rhode  
86 Island and answer two questions. First, are there state-wide trends in total nitrogen (TN),  
87 total phosphorus (TP), total nitrogen to total phosphorus ratio (TN:TP), chlorophyll *a*, and  
88 lake temperature? Second, are water quality trends in Rhode Island similar to regional  
89 trends in the northeastern United states? Another objective of this paper was to apply  
90 existing methods for examining long-term climate records (e.g., Jones and Hulme 1996) to  
91 water quality data in order to examine long-term trends. We conducted this analysis using  
92 open data from the URI Watershed Watch program and the LAke multi-scaled GeOSpatial  
93 and temporal database for the Northeast (LAGOSNE) project and the analysis in its entirety  
94 is available for independent reproduction at [https://github.com/usepa/ri\\_wq\\_trends](https://github.com/usepa/ri_wq_trends) and

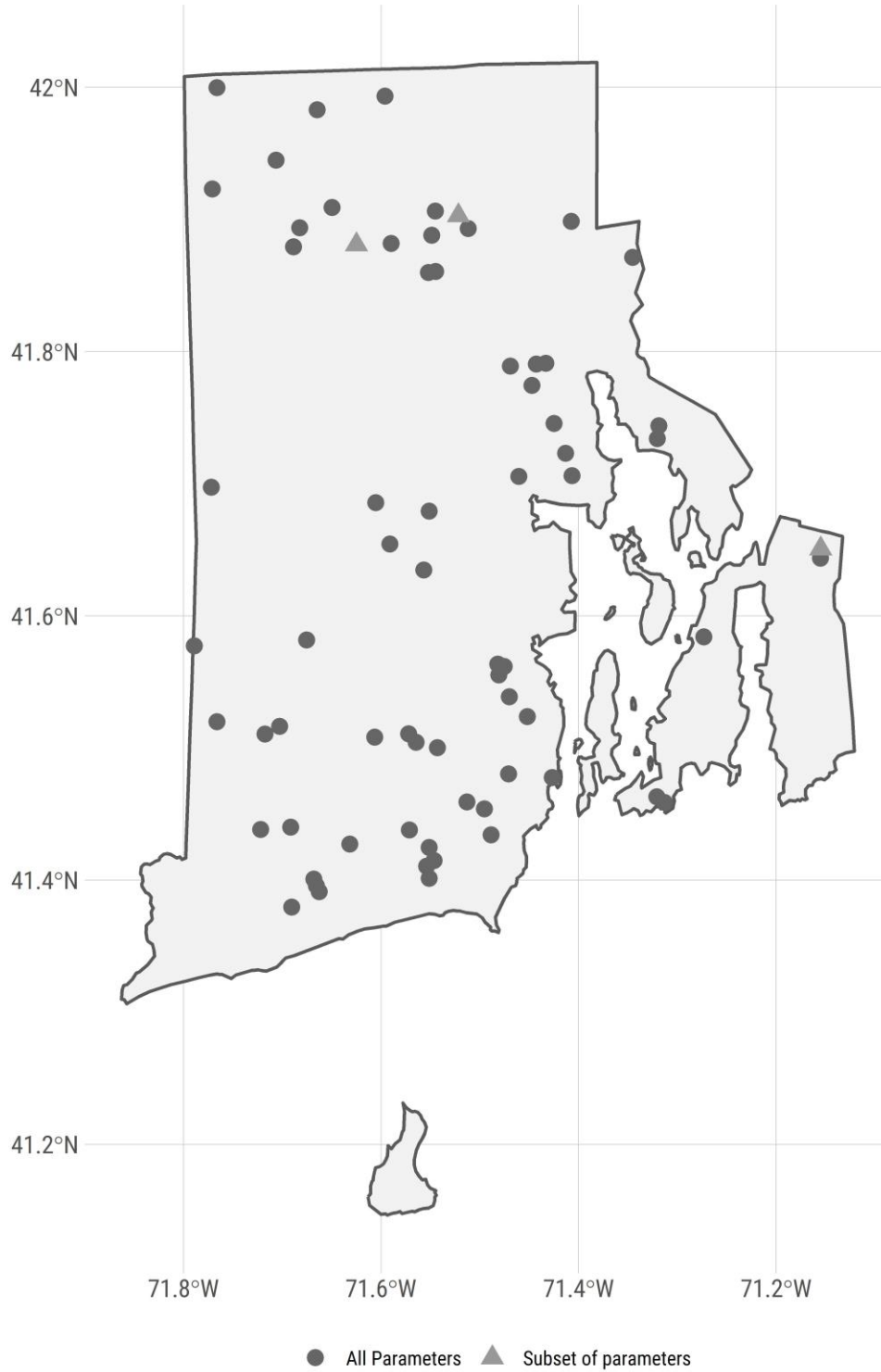
95 is archived at <https://doi.org/10.5281/zenodo.3662828> (Soranno et al. 2017, Stachelek  
96 and Oliver 2017, Hollister et al. 2019).

## 97 **2 Methods**

98 For this study, we combined a long-term dataset on water quality of lakes in Rhode Island  
99 with a trend analysis based on water quality anomalies (i.e., measured values with the long  
100 term mean subtracted) to find increasing or decreasing annual water quality trends. Details  
101 are outlined below.

### 102 **2.1 Study Area and Data**

103 The study area for this analysis includes lakes and reservoirs in the state of Rhode Island  
104 where data were collected by the University of Rhode Island's Watershed Watch program  
105 (Figure 1). The URIWW program began in 1988, monitoring 14 lakes and has now grown to  
106 include over 250 monitoring sites on over 120 waterbodies, including rivers/streams, and  
107 estuaries, with more than 400 trained volunteers. URIWW now provides more than 90% of  
108 Rhode Island's lake baseline data and is an integral part of the state's environmental data  
109 collection strategy. Data quality assurance and control is treated with paramount  
110 importance; volunteers are trained both in the classroom and the field, regular quality  
111 checks occur, and volunteers are provided with all the necessary equipment and supplies,  
112 along with scheduled collection dates. For freshwater lakes and reservoirs, weekly secchi  
113 depth and water temperature are recorded, along with bi-weekly chlorophyll *a* and in deep  
114 lakes (greater than 5 meters) dissolved oxygen. Water samples are collected three times  
115 per season (May through October) to be analyzed for nutrients and bacteria.



116

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

118 For this analysis, we were interested in trends in lake temperature, TN, TP, TN:TP, and  
119 chlorophyll *a*. In particular, we selected URIWW data that matched the following criteria:  
120 1) were sampled between 1993 and 2016, 2) were sampled in May to October, 3) and were  
121 sampled at a depth of 2 meters or less. As not all sites have data for all selected years, we  
122 further filtered the data to select sites that had at least 10 years of data for a given  
123 parameter within the 1993 to 2016 time frame. The final dataset used in our analysis  
124 included 69 lakes and reservoirs. Of these sites, our filtered dataset had approximately 67  
125 sites measured for temperature, 67 sites measured for chlorophyll *a*, 69 sites measured for  
126 TN, and 69 sites measured for TP. Of the 69 sampling sites, 66 had data for all 5  
127 parameters. The N:P ratio was calculated by dividing the mass concentrations of total  
128 nitrogen and total phosphorus and then converting to a molar ratio by multiplying by 2.21  
129 (e.g., atomic weight of P 30.974/atomic weight of N 14.007).

130 Field and analytical methods are detailed on the URIWW website at  
131 <https://web.uri.edu/watershedwatch/uri-watershed-watch-monitoring-manuals/> and  
132 [https://web.uri.edu/watershedwatch/uri-watershed-watch-quality-assurance-project-](https://web.uri.edu/watershedwatch/uri-watershed-watch-quality-assurance-project-plans-qapps/)  
133 [plans-qapps/](https://web.uri.edu/watershedwatch/uri-watershed-watch-quality-assurance-project-plans-qapps/), respectively. These methods, approved by both the state of Rhode Island and  
134 the US Environmental Protection Agency, have remained fairly consistent, although over  
135 the nearly 30 years changes did occur. When new methods were introduced, comparisons  
136 between old and new methods were conducted and in all cases no statistically significant  
137 differences were found with the new methods. Furthermore, the new methods did at times  
138 improve the limits of detection; however, this impacted a very small number (less than 1%)  
139 of measurements in this study. We did run our analyses (see **Water Quality Trend**  
140 **Analysis** section) with all data and with only those data greater than the detection limit.  
141 There was no change in the trend analysis and thus, the results we report are for all data as  
142 originally reported in the URIWW dataset. Given these results, we assume the data to be  
143 consistent across the reported time period and appropriate for a long term assessment of  
144 trends.

145 Prior studies have modeled water quality trends across a larger region of the northeastern  
146 US that included 17 states including Minnesota, Wisconsin, Iowa, Missouri, Illinois, Indiana,  
147 Michigan, Ohio, Pennsylvania, New York, New Jersey, Connecticut, Massachusetts, Rhode

148 Island, Vermont, New Hampshire, and Maine (Soranno et al. 2015, Oliver et al. 2017). We  
149 repeated our analysis (see **Water Quality Trend Analysis** section) with the same dataset  
150 used by Oliver et al. (2017), the LAGOSNE dataset (Soranno et al. 2015, 2017, Stachelek and  
151 Oliver 2017). Temperature data were not available, thus we examined trends, using our  
152 analytical methods, for TN, TP, TN:TP, and chlorophyll *a* from the LAGOSNE dataset. We  
153 used the same selection criteria on the LAGOSNE dataset as was applied to the URIWW data.

## 154 **2.2 Water Quality Trend Analysis**

155 There are many different methods for analyzing time series data for trends. Environmental  
156 data are notoriously “noisy” and one of the difficulties that is encountered with multiple  
157 sampling locations is how to identify a trend while there is variation within a sampling site  
158 as well as variation introduced by differing start years for sampling among the many sites.  
159 For instance, if long-term data on water quality were collected more frequently in early  
160 years from more pristine waterbodies, then a simple comparison of raw values over time  
161 might show a decrease in water quality, which could be misleading if later sampling  
162 occurred on both pristine and more eutrophic water bodies. Thus, it is necessary to account  
163 for this type of within-site and among-site variation, using methods similar to those used to  
164 analyze long-term temperature trends using temperature anomalies (e.g., Jones and Hulme  
165 1996). The general approach we used calculates site-specific deviations from a long-term  
166 mean over a pre-determined reference period. This allowed all sites to be shifted to a  
167 common baseline and the deviations, or anomalies, indicate change over the specified  
168 reference period. We refer to this method as “site-specific anomalies”.

### 169 **2.2.1 Summarizing site-specific anomalies**

170 Methods for calculating the site-specific anomalies and the yearly means are as follows and  
171 are presented graphically in Figure 2. Additionally, an example R script,  
172 `schematic_anomaly.R` and example dataset, `schematic.csv` to recreate and demonstrate  
173 the calculations in Figure 2 is available from at [https://github.com/usepa/ri\\_wq\\_trends](https://github.com/usepa/ri_wq_trends)  
174 and is archived at <https://doi.org/10.5281/zenodo.3662828> (Hollister et al. 2019).



	Year 1	Year 2	Year 3
<b>Station 1</b> Long-term mean = 7.06	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 5 4 8 Site and Year mean 5.67 Site and Year Anomaly 5.67 – 7.06 = <b>-1.39</b>	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 6 9 6 Site and Year mean 7 Site and Year Anomaly 7 – 7.06 = <b>-0.057</b>	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 8 9 Site and Year mean 8.5 Site and Year Anomaly 8.5 – 7.06 = <b>1.44</b>
<b>Station 2</b> Long-term mean = 3.66	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 2 3 3 4 Site and Year mean 3 Site and Year Anomaly 3 – 3.66 = <b>-0.67</b>		<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 4 3 6 Site and Year mean 4.33 Site and Year Anomaly 4.33 – 3.66 = <b>0.67</b>
<b>Station 3</b> Long-term mean = 12.44	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 11 15 Site and Year mean 13 Site and Year Anomaly 13 – 12.44 = <b>0.56</b>	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 14 Site and Year mean 14 Site and Year Anomaly 14 – 12.44 = <b>1.56</b>	<div style="border: 1px solid black; padding: 2px; display: inline-block;">data</div> 10 12 9 Site and Year mean 10.33 Site and Year Anomaly 10.33 – 12.44 = <b>-2.11</b>
<b>Mean Anomaly</b>	mean anomaly = <b>-0.50</b> s.d. anomaly = 0.98 n = 3	mean anomaly = <b>0.75</b> s.d. anomaly = 1.14 n = 2	mean anomaly = <b>0</b> s.d. anomaly = 1.15 n = 3

175

176 *Figure 2: Example calculation of the site-specific anomalies and yearly mean anomalies.*

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

- 179 1. For each site, calculate the annual means, producing a single mean value for each site  
180 and year. This step prevents bias from pseudoreplication of multiple measurements of  
181 the same site in a given year (Hurlbert 1984). The per site means across years are  
182 assumed to be independent.
- 183 2. Calculate the long-term reference mean for each site. This results in a single long-term  
184 mean for each of the sites.
- 185 3. Calculate the anomaly for each annual mean at each site by subtracting the annual and  
186 reference means.
- 187 4. Summarize by calculating the mean anomaly per year for the entire group of sites. The  
188 resultant values are analyzed for a trend over time.



## 189 **2.2.2 Linear regression on annual mean anomalies**

190 Testing for a regression slope being different than zero can be used to test for monotonic  
191 trends in water quality data (Helsel and Hirsch 2002). We used these standard procedures  
192 to test for positive or negative trends in lake temperature, chlorophyll *a*, TN, TP and TN:TP.  
193 For each parameter, we fit a regression line to the anomalies as a function of year and  
194 tested the null hypothesis that no trend existed (e.g.,  $\beta_1 = 0$ ). The slope of this line provides  
195 information on the mean yearly change of that parameter over the time period studied.  
196 Traditionally, trends would be determined by assessing “significance” but recent guidelines  
197 suggest not using arbitrary p-value cut-offs to assess significance (Wasserstein et al.  
198 2016). Our interpretation of the trends attempts to follow this advice and we assess trends  
199 with the information provided by the magnitude of the slopes, the p-values, and our  
200 understanding of the processes involved.

## 201 **2.2.3 Comparison of Rhode Island to the region**

202 Oliver et al. (2017) used hierarchical linear models and showed relatively stable water  
203 quality in the lakes of the northeastern United States. While the University of Rhode  
204 Island’s Watershed Watch data were included in this regional study, we hypothesized that  
205 in the case of Rhode Island regional trends were masking sub-regional trends. Therefore,  
206 we decided to reanalyze the LAGOSNE data to compare the trends at the regional scale to  
207 the trends at the Rhode Island state scale using the site-specific anomaly and trend analysis  
208 approach outlined above.

## 209 **3 Results**

210 During the period of 1993 to 2016, Rhode Island lakes and reservoirs in our dataset had a  
211 mean lake temperature of 21.9 °C, mean TN of 600 µg/l, mean TP of 24 µg/l, mean TN:TP  
212 ratio of 84.17 molar, and mean chlorophyll *a* of 10.1 µg/l (Table 1).

213

214

Parameter	Units	Mean	Median	Max	Std. Dev
Temperature	°C	21.9	22.2	29	1.9
Total Nitrogen	µg/l	600	475	4670	425
Total Phosphorus	µg/l	24	15	325	30
N:P	molar	84.17	71.08	827.2	57.9
Chlorophyll	µg/l	10.1	4.5	666.2	22.1

215 *Table 1: Summary statistics for URI Watershed Watch data from 1993 to 2016.*

216 For lakes and reservoirs in the larger region represented by the LAGOSNE States, mean TN  
217 was 855 µg/l, mean TP was 32 µg/l, mean TN:TP ratio was 90.37 molar, and mean  
218 chlorophyll *a* was 16.8 µg/l (Table 2).

Parameter	Units	Mean	Median	Max	Std. Dev
Total Nitrogen	µg/l	855	560	16780	1205
Total Phosphorus	µg/l	32	16	1200	54
N:P	molar	90.37	59.18	88474	1029
Chlorophyll	µg/l	16.8	6.2	696	30.4

219 *Table 2: Summary statistics for LAGOSNE data from 1993 to 2016.*

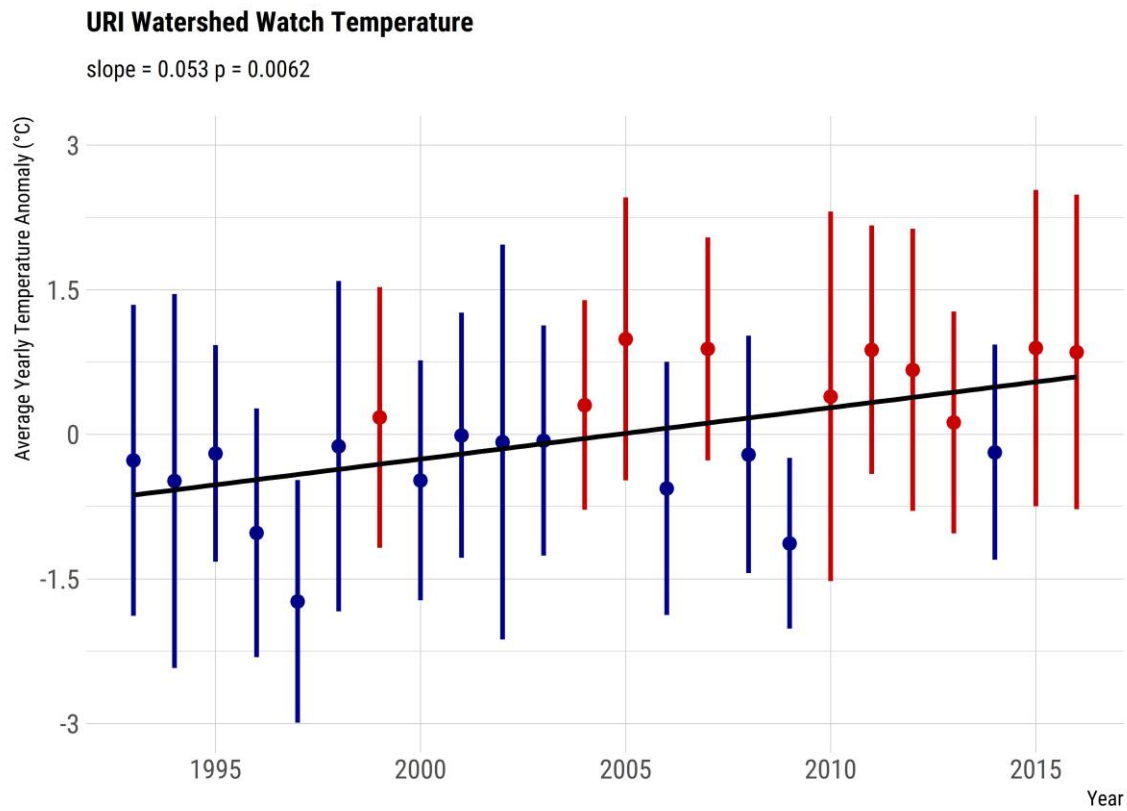
### 220 **3.1 State-wide trends in water quality**

221 Mean annual temperature anomalies in lakes and reservoirs appears to be increasing  
222 (slope = 0.053 , p = 0.0062) with the majority of years with mean temperature greater than  
223 the long-term mean occurring in recent years (Figure 3). Chlorophyll *a* is also showing an  
224 increasing trend over time (slope = 0.29 , p = 0.0000008) and with the exception of a  
225 slightly above-average year in 2003, the above-average years have all occurred in the most  
226 recent years (Figure 4A.).

227 Mean annual trends for nutrients were weaker or showed no trend over time. The data  
228 suggest a positive trend in TN (slope = 3.8 , p = 0.00022); however, that perceived trend is  
229 driven by the lower than mean TN values in 1993 and 1994 (Figure 5A.). Since 1995, the  
230 yearly trend shows a lower increase over time (slope = 2.5, p = 0.0067). TP does not show a  
231 trend over time in the yearly anomalies (slope = 0.11 , p = 0.062) and years that are over or  
232 under the mean are more evenly distributed over the years (Figure 6A.). The pattern is the  
233 same for the TN:TP ratio (slope = 0.18, p = 0.71) with little evidence suggesting a change in  
234 the concentrations of TN relative to the concentrations of TP (Figure 7A.). Data for all  
235 figures are available as a comma-separated values file, `yearly_average_anomaly.csv` from  
236 at [https://github.com/usepa/ri\\_wq\\_trends](https://github.com/usepa/ri_wq_trends) and is archived at  
237 <https://doi.org/10.5281/zenodo.3662828> (Hollister et al. 2019).

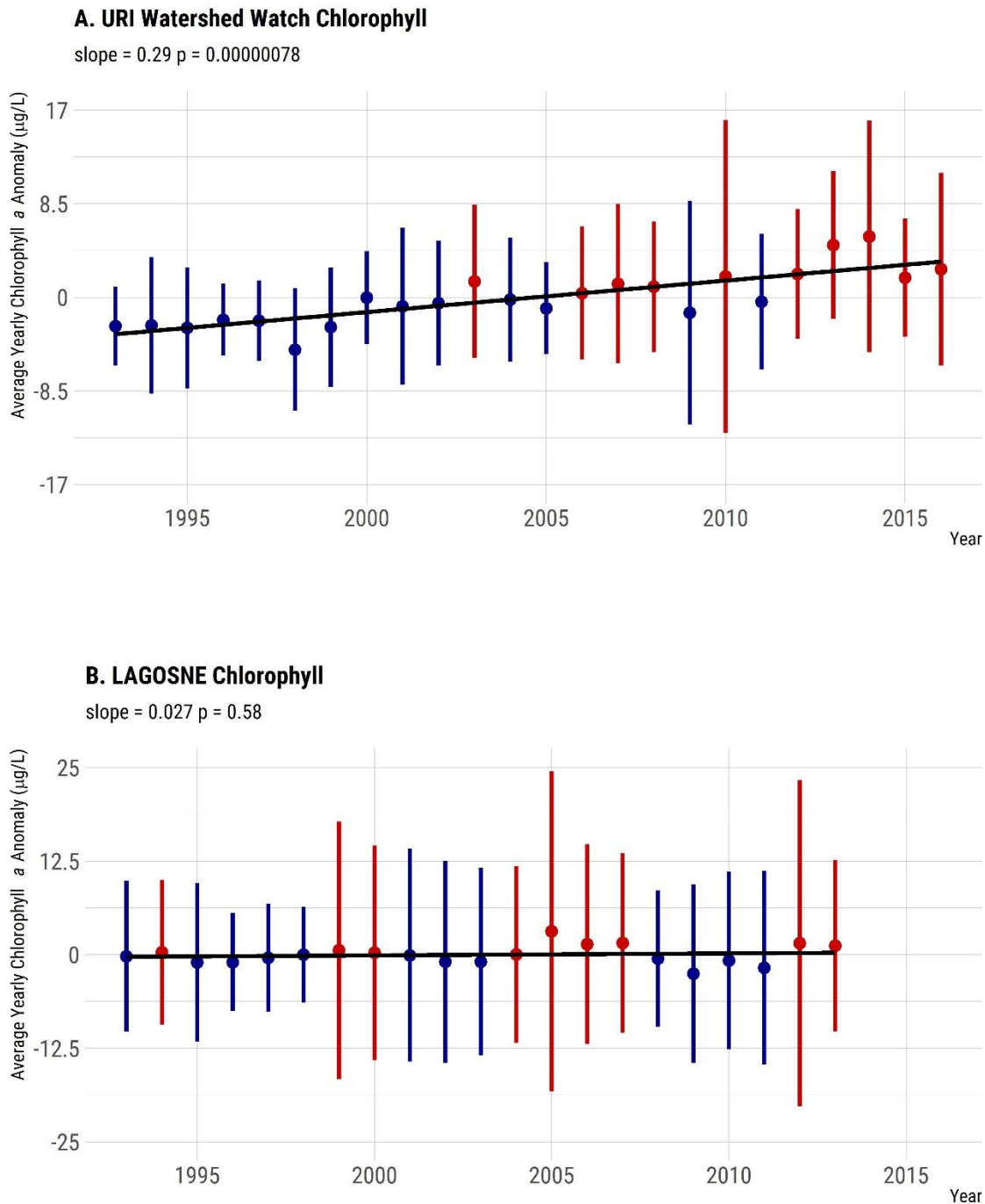
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240

241 *Figure 3: Yearly trend over 20+ years of lake temperature (mean anomaly) in Rhode Island*  
242 *lakes and reservoirs. Points are means of site-specific anomalies and ranges are standard*  
243 *deviations of site-specific anomalies. Blue indicates yearly site-specific anomalies that were,*  
244 *on average, below the site-specific long-term means. Red indicates yearly site-specific*  
245 *anomalies that were, on average, above the site-specific long-term means.*

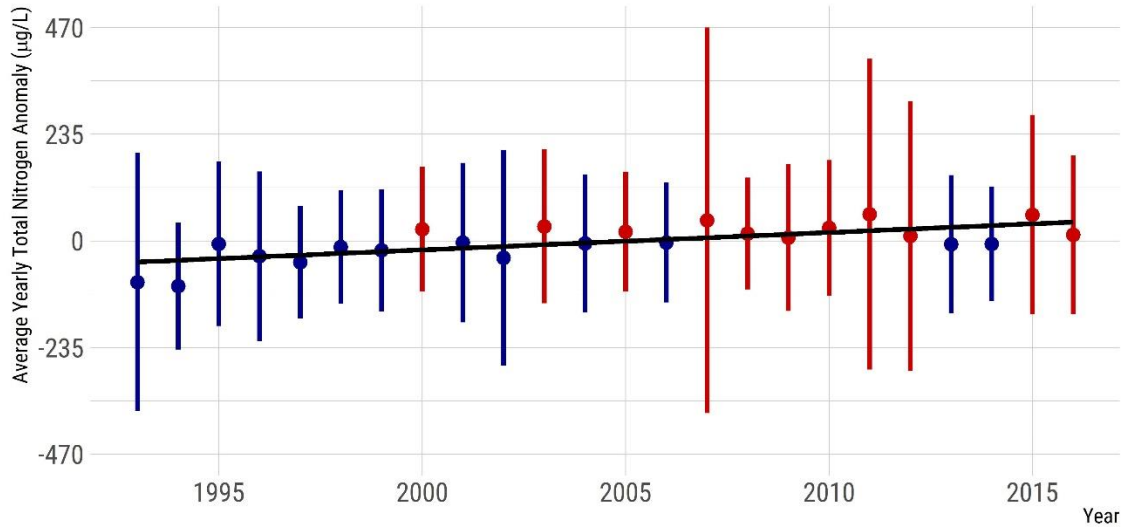


246

247 *Figure 4: Yearly trend over 20+ years of chlorophyll a (mean anomaly). Panel A. Yearly mean*  
248 *chlorophyll a anomalies from the URI Watershed Watch data. Panel B. Yearly mean*  
249 *chlorophyll a anomalies from the LAGOSNE dataset. Points are means of site-specific*  
250 *anomalies and ranges are standard deviations of site-specific anomalies. Blue indicates yearly*  
251 *site-specific anomalies that were, on average, below the site-specific long-term means. Red*  
252 *indicates yearly site-specific anomalies that were, on average, above the site-specific long-*  
253 *term means.*

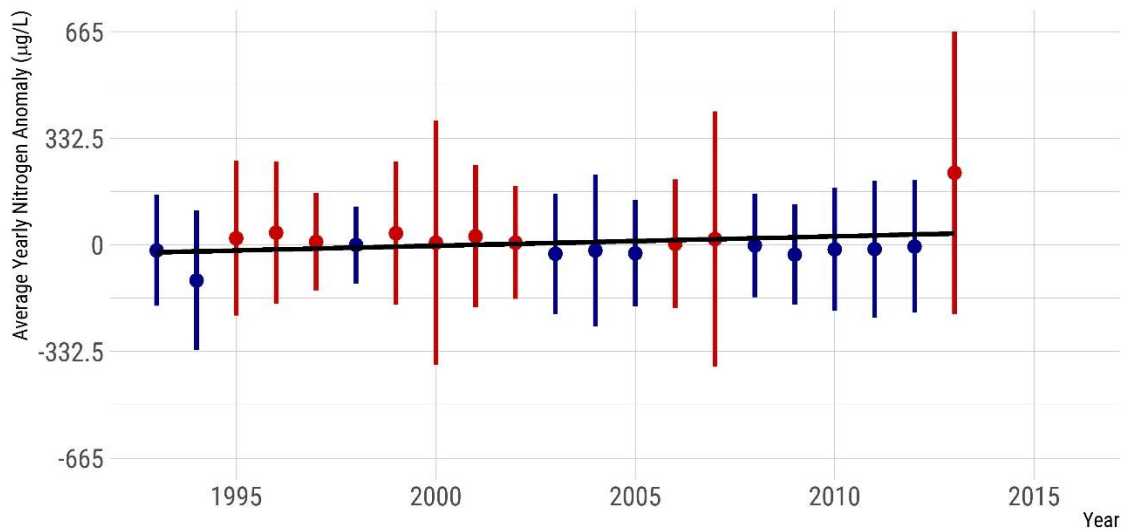
### A. URI Watershed Watch Total Nitrogen

slope = 3.8 p = 0.00022



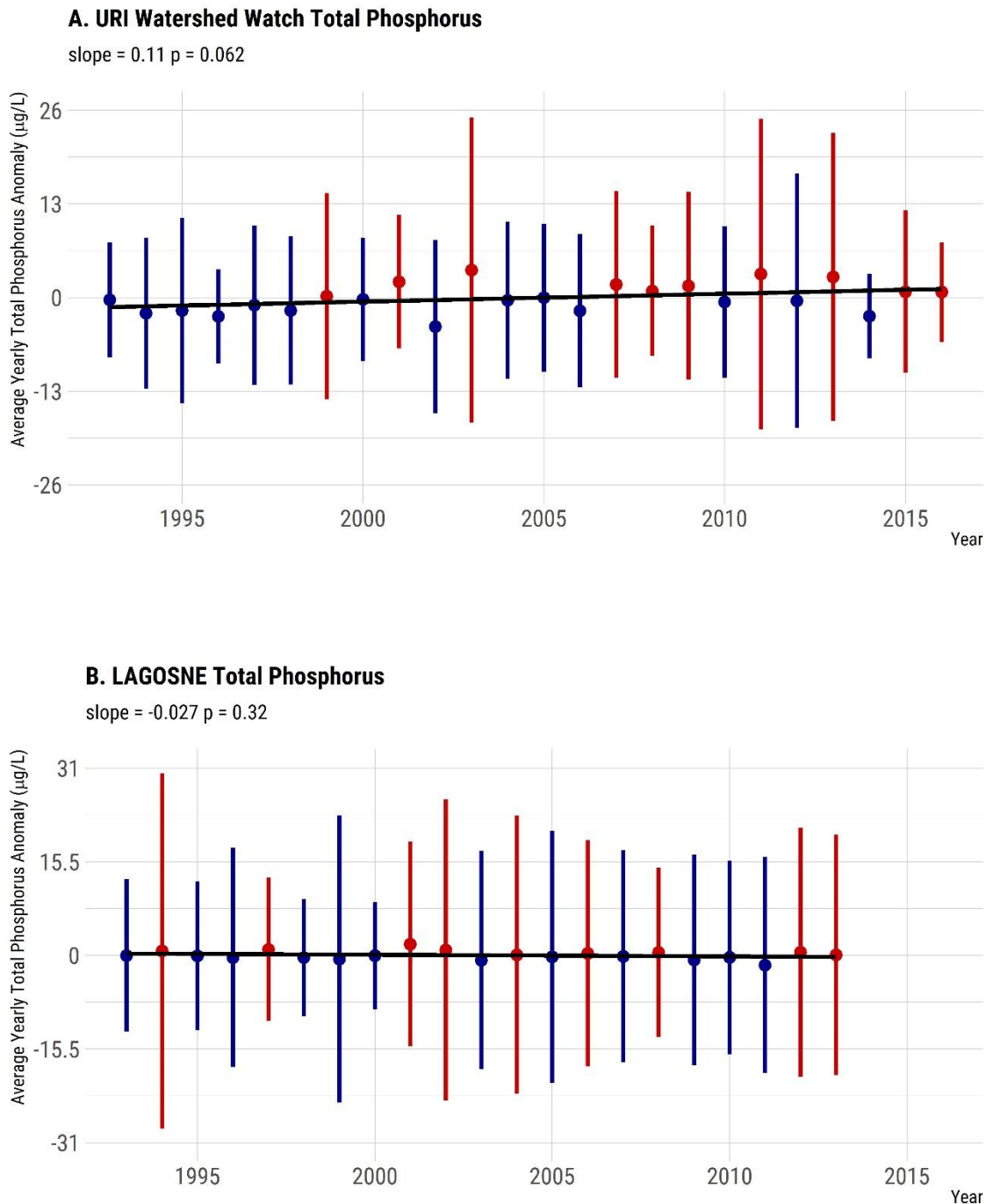
### B. LAGOSNE Total Nitrogen

slope = 2.9 p = 0.17



254

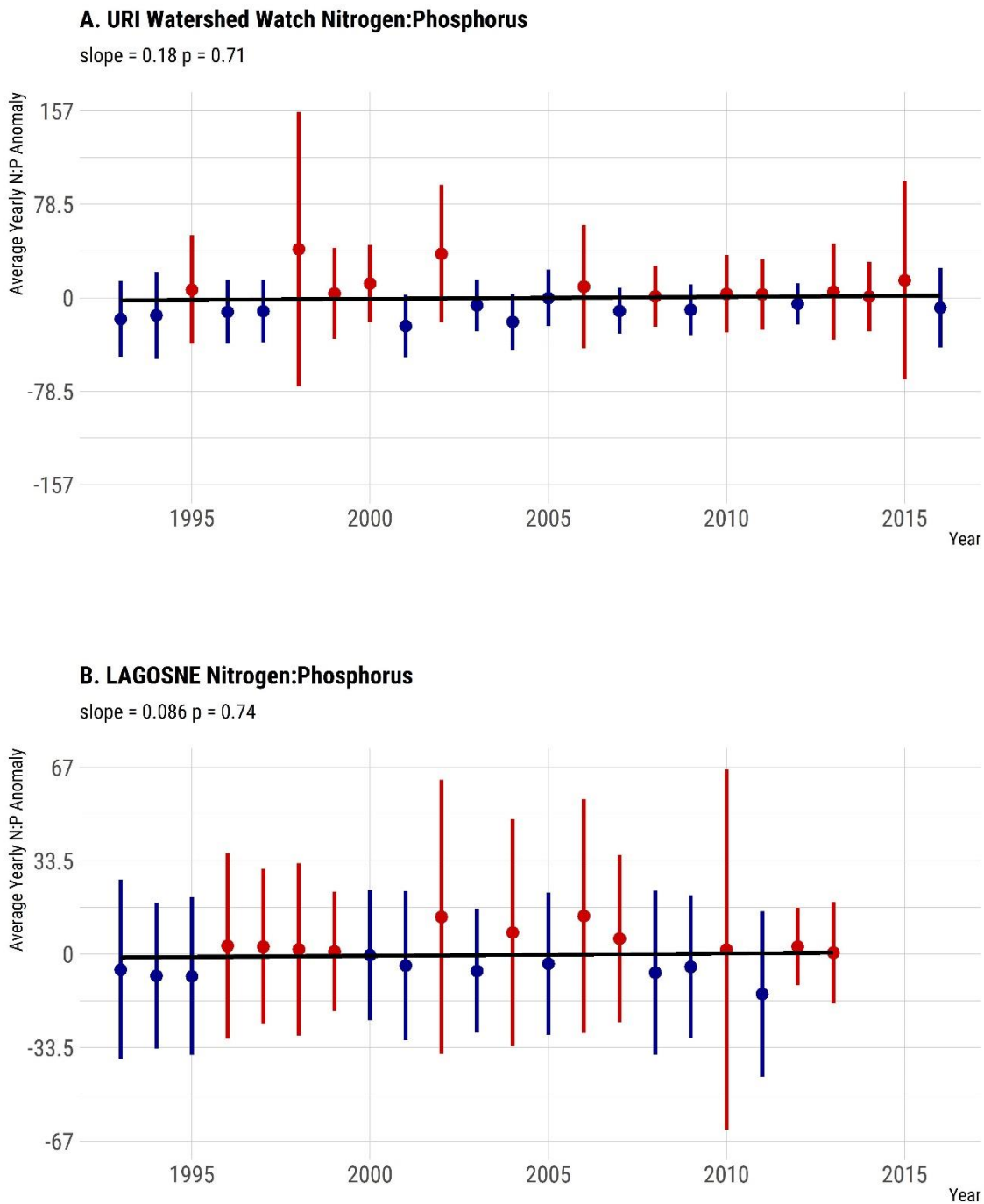
255 *Figure 5: Yearly trend over 20+ years of TN (mean anomaly). Panel A. Yearly mean TN*  
256 *anomalies from the URI Watershed Watch dataset. Panel B. Yearly mean TN anomalies from*  
257 *the LAGOSNE dataset. Points are means of site-specific anomalies and ranges are standard*  
258 *deviations of site-specific anomalies. Blue indicates yearly site-specific anomalies that were,*  
259 *on average, below the site-specific long-term means. Red indicates yearly site-specific*  
260 *anomalies that were, on average, above the site-specific long-term means.*



261

262 *Figure 6: Yearly trend over 20+ years of TP (mean anomaly). Panel A. Yearly mean TP*  
263 *anomalies from the URI Watershed Watch dataset. Panel B. Yearly mean TP anomalies from*  
264 *the LAGOSNE dataset. Points are means of site-specific anomalies and ranges are standard*  
265 *deviations of site-specific anomalies. Blue indicates yearly site-specific anomalies that were,*  
266 *on average, below the site-specific long-term means. Red indicates yearly site-specific*  
267 *anomalies that were, on average, above the site-specific long-term means.*





268

269 *Figure 7: Yearly trend over 20+ years of the TN:TP ratio (mean anomaly). Panel A. Yearly*  
270 *mean TN:TP ratio anomalies from the URI Watershed Watch dataset. Panel B. Yearly mean*  
271 *TN:TP ratio anomalies from the LAGOSNE dataset. Points are means of site-specific anomalies*  
272 *and ranges are standard deviations of site-specific anomalies. Blue indicates yearly site-*  
273 *specific anomalies that were, on average, below the site-specific long-term means. Red*  
274 *indicates yearly site-specific anomalies that were, on average, above the site-specific long-*  
275 *term means.*

## 276 **3.2 Regional trends in water quality**

277 In general, there was little evidence to suggest broad regional changes. Chlorophyll *a*  
278 showed a very weak positive trend (slope = 0.027,  $p = 0.58$ , Figure 4B.), TP showed a slight  
279 decreasing trend (slope = -0.027,  $p = 0.32$ , Figure 6B.), TN showed a slight positive trend  
280 (slope = 2.9,  $p = 0.17$ , Figure 5B.) and the TN:TP showed little change (slope = 0.086,  $p =$   
281 0.74, Figure 7B.)

## 282 **4 Discussion and conclusions**

283 Our sub-regional analysis indicates that even when nutrient regimes exhibit relative  
284 stability (i.e., neither increasing nor decreasing over time), increases in primary  
285 production, as measured by chlorophyll *a*, can occur. Over the same period we also  
286 demonstrate long-term warming of Rhode Island lakes and reservoirs. Chlorophyll has  
287 increased, on average, 0.29  $\mu\text{g/L}$  per year over the 23 years of our analysis, while  
288 temperature has increased 0.053  $^{\circ}\text{C}$  per year over the same period. This suggests that the  
289 observed increase in productivity, as measured by chlorophyll *a*, may be a result of  
290 warming waters and not a response to changes in nutrient condition. Also, geographic  
291 extent does indeed matter when trying to identify long-term water quality trends. Similar  
292 to the results of Oliver et al. (2017) our analysis shows little increasing trend in chlorophyll  
293 *a* at the regional scale (e.g., northeastern and mid-western United States). However, at the  
294 local scale of the state of Rhode Island, there is a clear increasing trend in chlorophyll *a*.

### 295 **4.1 Trends**

296 As previously mentioned, both temperature and chlorophyll *a* show increasing trends from  
297 1993 to 2016 in Rhode Island lakes and reservoirs; while total nutrients and the TN:TP  
298 ratio are all relatively stable. While TN showed a weak positive trend, that trend was  
299 largely driven by the unusually low years for TN in 1993 and 1994. With those removed the  
300 positive trends weakens considerably. The general picture in Rhode Island appears to be  
301 one of little to no change in phosphorus, a very weak positive trend in nitrogen and little to  
302 no change in the TN:TP ratio. Furthermore, it has been shown that productivity in  
303 freshwater systems is likely a function of both phosphorus and nitrogen (Paerl et al. 2016).

304 Thus, the increasing chlorophyll *a* in the face of stable TN:TP ratio suggests that the  
305 increase is being driven by something other than nutrients. We interpret these results as  
306 relative stability in nutrients in Rhode Island lakes and reservoirs.

307 Stable nutrient regimes may be partly explained by efforts to curb nutrient loadings, for  
308 example through voluntary and state wide mandatory bans on phosphates in laundry  
309 detergent which were implemented in Rhode Island in 1995 (Rhode Island State  
310 Legislature 1995, Litke 1999). However, in many lakes there are still likely sufficient  
311 nutrients present to allow for increases in chlorophyll *a*. Additionally, these results point to  
312 the fact that chlorophyll *a* and algal biomass is driven by processes operating at different  
313 scales. For instance, nutrient management is largely a local to watershed scale effort, but  
314 may also be regional as atmospheric nitrogen deposition can be a significant source of  
315 nitrogen (Boyer et al. 2002). Similarly, warming lakes are driven by broader climate  
316 patterns, yet waterbody-specific factors such as the percent of a catchment that is  
317 impervious surface and lake morphology can also impact temperature (Nelson and Palmer  
318 2007). In short, differences in regional and state level trends are driven by complex and  
319 multi-scale processes.

320 In addition to the annualized trends of the five variables we address with this study, there  
321 are other trends that may be of interest. For example, trends for water quality at finer  
322 temporal scales such as monthly or seasonal trends may be different than the annual  
323 trends we analyzed. Anecdotal evidence in Rhode Island points to warmer temperature  
324 earlier and later in the year and suggests a lengthening of the growing season.  
325 Furthermore, preliminary analysis of the URIWW data back this up with mean temperature  
326 for May 1993 to May 1995 cooler by nearly a degree than mean temperature for May 2014  
327 through May 2016. Additionally, it may be possible that the current trophic state of a given  
328 waterbody may partly explain the chlorophyll *a* changes in that lake. For instance, are  
329 oligotrophic lakes showing stronger trends than eutrophic lakes or are all lakes showing  
330 similar trends regardless of current trophic status? Lastly, changes in rainfall, extreme  
331 weather events, or other climate mediated factors can also be playing a role in increasing  
332 chlorophyll in Rhode Island lakes and reservoirs. These questions are beyond the scope of  
333 this study, but all warrant further, careful investigation.

## 334 **4.2 Management implications**

335 There are several broader management implications from the results of our analysis and of  
336 examining long-term water quality trends in general. In particular, this analysis provides  
337 much needed information about the long-term effects of current nutrient control efforts at  
338 lake-specific and sub-regional scales and identifies areas where additional information is  
339 required or a change in management approaches may be needed. First, as more long-term  
340 datasets become available, it is important for managers and stakeholders to receive  
341 feedback on long-term water quality trends at multiple spatial scales. Specifically for this  
342 study, the results provide feedback to long time volunteer monitors, highlighting the  
343 importance of volunteer monitoring programs. Second, with information on long-term  
344 trends, it is possible to adapt management approaches to address areas of concern. Our  
345 results show increasing chlorophyll *a* even though the general long-term nutrient trends  
346 have been stable. This suggests the need to further reduce nutrients to compensate for  
347 warmer water temperatures and possible longer growing seasons.

348 There are several possible approaches to further reduce nutrient loads (Yang and Lusk  
349 2018). First, nutrient load reductions may be possible through source controls and  
350 enhanced entrainment and treatment of ground and surface waters transporting nutrients  
351 to receiving waters (Kellogg et al. 2010). Green infrastructure approaches are one way to  
352 possibly achieve both goals (Pennino et al. 2016, Reisinger et al. 2019). Additionally, there  
353 is potential for within-lake approaches such as the restoration of freshwater mussels to  
354 waterbodies that historically had those species. Some studies using freshwater mussels  
355 have shown reductions in both nutrients and algal biomass (Kreeger et al. 2018).

## 356 **4.3 Data analysis approach**

357 The analysis approach we used here, site-specific anomalies, is not a novel method and  
358 does have a long history in the analysis of trends in climate (Jones and Hulme 1996, Jones  
359 et al. 1999, Hansen et al. 2006, 2010). However, using it to examine water quality trends is  
360 a new application of the technique, as we could find little evidence of using it specifically  
361 for water quality trends. We built on these methods and adapted them for use with long-  
362 term water quality trends. While other methods are valid and robust (e.g., Oliver et al.

2017), we chose mean site-specific anomalies as they can provide readily interpretable results, especially for communicating to general audiences. For instance, reporting the changes in anomalies allows us to look at changes in the original units. With our analysis, the slope of the regression line for temperature suggests a mean yearly increase of 0.053 °C and the slope of the regression line for chlorophyll *a* shows a mean yearly increase of 0.29 µg/l. Additionally, the site-specific anomalies 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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