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

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Addressing anthropogenic impacts on aquatic ecosystems is a focus of lake management. Controlling phosphorus and nitrogen can mitigate these impacts, but determining management effectiveness requires long-term datasets. Recent analysis of the LAke multi-scaled GeOSpatial and temporal database for the Northeast (LAGOSNE) United States found stable water quality in the northeastern and midwestern United States, however, sub-regional trends may be obscured. We analyze a sub-regional (i.e., 3000 km²) trend with 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. The LAGOSNE and URIWW datasets allow for comparison of water quality trends at regional and sub-regional extents, respectively. We assess regional (LAGOSNE) and state (URIWW) trends with yearly mean anomalies calculated on a per-station basis. Sub-regionally, temperature and chlorophyll *a* increased from 1993 to 2016. Total nitrogen shows a weak increase driven by low years in the early 1990s. Total phosphorus and the nitrogen:phosphorus ratio (N:P) were stable. At the regional scale, the LAGOSNE dataset shows similar trends to prior studies of the LAGOSNE with chlorophyll *a*, total nitrogen, total phosphorus, and N:P all stable over time. In short, algal biomass, as measured by chlorophyll *a* in Rhode Island lakes and reservoirs is increasing, despite stability in total nitrogen, total phosphorus, and the nitrogen to phosphorus ratio. This analysis suggests an association between lake temperature and primary production. 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 anomalies for analyzing for long-term water quality trends.

1 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 nitrogen (N) and phosphorus (P), derived from intensive agriculture and 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 (Cheruvelil 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^2 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

95 (Soranno et al. 2017, Stachelek and Oliver 2017, Hollister et al. 2019).

2   Methods

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

2.1   Study Area and Data

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

115
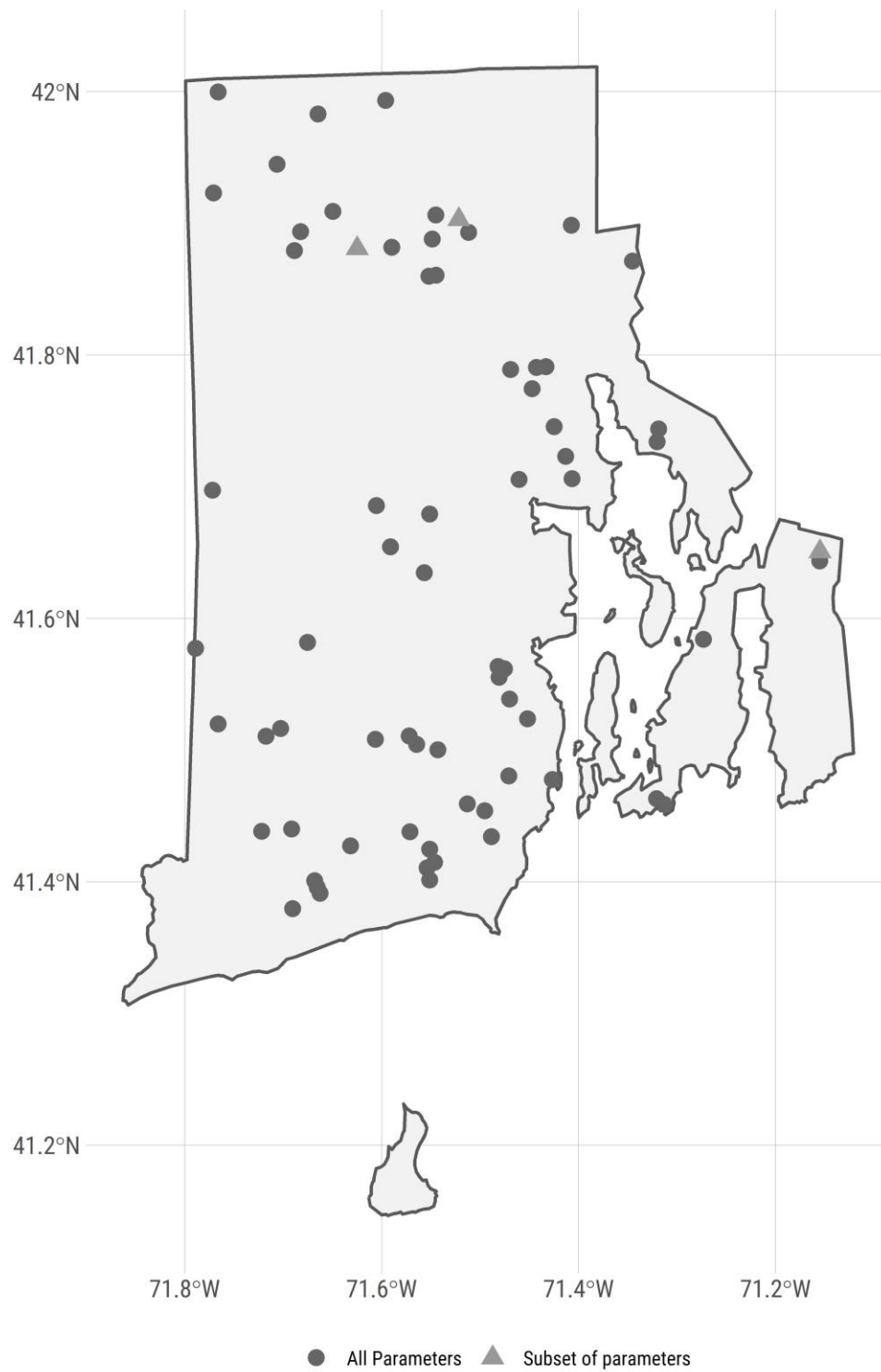
Figure 1: Map of URI Watershed Watch lake and reservoir sampling sites

117 For this analysis, we were interested in trends in lake temperature, TN, TP, TN:TP, and

118 chlorophyll *a*. In particular, we selected URIWW data that matched the following criteria:

119 1) were sampled between 1993 and 2016, 2) were sampled in May to October, 3) and were

120 sampled at a depth of 2 meters or less. As not all sites have data for all selected years, we

121 further filtered the data to select sites that had at least 10 years of data for a given

122 parameter within the 1993 to 2016 time frame. The final dataset used in our analysis

123 included 69 lakes and reservoirs. Of these sites, our filtered dataset had approximately 67

124 sites measured for temperature, 67 sites measured for chlorophyll *a*, 69 sites measured for

125 TN, and 69 sites measured for TP. Of the 69 sampling sites, 66 had data for all 5

126 parameters. The N:P ratio was calculated by dividing the mass concentrations of total

127 nitrogen and total phosphorus and then converting to a molar ratio by multiplying by 2.21

128 (e.g., atomic weight of P 30.974/atomic weight of N 14.007).

129 Field and analytical methods are detailed on the URIWW website at

130 https://web.uri.edu/watershedwatch/uri-watershed-watch-monitoring-manuals/ and

131 https://web.uri.edu/watershedwatch/uri-watershed-watch-quality-assurance-project-

132 plans-qapps/, respectively. These methods, approved by both the state of Rhode Island and

133 the US Environmental Protection Agency, have remained fairly consistent, although over

134 the nearly 30 years changes did occur. When new methods were introduced, comparisons

135 between old and new methods were conducted and in all cases no statistically significant

136 differences were found with the new methods. Furthermore, the new methods did at times

137 improve the limits of detection; however, this impacted a very small number (less than 1%)

138 of measurements in this study. We did run our analyses (see **Water Quality Trend**

139 **Analysis** section) with all data and with only those data greater than the detection limit.

140 There was no change in the trend analysis and thus, the results we report are for all data as

141 originally reported in the URIWW dataset. Given these results, we assume the data to be

142 consistent across the reported time period and appropriate for a long term assessment of

143 trends.

144 Prior studies have modeled water quality trends across a larger region of the northeastern

145 US that included 17 states including Minnesota, Wisconsin, Iowa, Missouri, Illinois, Indiana,

146 Michigan, Ohio, Pennsylvania, New York, New Jersey, Connecticut, Massachusetts, Rhode

147   Island, Vermont, New Hampshire, and Maine (Soranno et al. 2015, Oliver et al. 2017). We

148   repeated our analysis (see **Water Quality Trend Analysis** section) with the same dataset

149   used by Oliver et al. (2017), the LAGOSNE dataset (Soranno et al. 2015, 2017, Stachelek and

150   Oliver 2017). Temperature data were not available, thus we examined trends, using our

151   analytical methods, for TN, TP, TN:TP, and chlorophyll *a* from the LAGOSNE dataset. We

152   used the same selction criteria on the LAGOSNE dataset as was applied to the URIWW data.

2.2   Water Quality Trend Analysis

154   There are many different methods for analyzing time series data for trends. Environmental

155   data are notoriously "noisy" and one of the difficulties that is encountered with multiple

156   sampling locations is how to identify a trend while there is variation within a sampling site

157   as well as variation introduced by differing start years for sampling among the many sites.

158   For instance, if long-term data on water quality were collected more frequently in early

159   years from more pristine waterbodies, then a simple comparison of raw values over time

160   might show a decrease in water quality, which could be misleading if later sampling

161   occurred on both pristine and more eutrophic water bodies. Thus, it is necessary to account

162   for this type of within-site and among-site variation, using methods similar to those used to

163   analyze long-term temperature trends using temperature anomalies (e.g., Jones and Hulme

164   1996). The general approach we used calculates site-specific deviations from a long-term

165   mean over a pre-determined reference period. This allowed all sites to be shifted to a

166   common baseline and the deviations, or anomalies, indicate change over the specified

167   reference period. We refer to this method as "site-specific anomalies".

2.2.1   *Summarizing site-specific anomalies*

169   Methods for calculating the site-specific anomalies and the yearly means are as follows and

170   are presented graphically in Figure 2. Additionally, an example R script,

171   `schematic_anomaly.R` and example dataset, `schematic.csv` to recreate and demonstrate

172   the calculations in Figure 2 is available from "fill in with zenodo link" (Hollister et al. 2019).

	Year 1	Year 2	Year 3

Station 1
Long-term mean = 7.06

Year 1: data 5, 4, 8 — Site and Year mean 5.67 — Site and Year Anomaly 5.67 − 7.06 = -1.39

Year 2: data 6, 9, 6 — Site and Year mean 7 — Site and Year Anomaly 7 − 7.06 = -0.057

Year 3: data 8, 9 — Site and Year mean 8.5 — Site and Year Anomaly 8.5 − 7.06 = 1.44

Station 2
Long-term mean = 3.66

Year 1: data 2, 3, 3, 4 — Site and Year mean 3 — Site and Year Anomaly 3 − 3.66 = -0.67

Year 3: data 4, 3, 6 — Site and Year mean 4.33 — Site and Year Anomaly 4.33 − 3.66 = 0.67

Station 3
Long-term mean = 12.44

Year 1: data 11, 15 — Site and Year mean 13 — Site and Year Anomaly 13 − 12.44 = 0.56

Year 2: data 14 — Site and Year mean 14 — Site and Year Anomaly 14 − 12.44 = 1.56

Year 3: data 10, 12, 9 — Site and Year mean 10.33 — Site and Year Anomaly 10.33 − 12.44 = -2.11

Mean Anomaly

Year 1: mean anomaly = -0.50, s.d. anomaly = 0.98, n = 3

Year 2: mean anomaly = 0.75, s.d. anomaly = 1.14, n = 2

Year 3: mean anomaly = 0, s.d. anomaly = 1.15, n = 3

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

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 for each site. This results in a single long-term mean for each of the sites.

3. Calculate the anomaly for each annual mean at each site by subtracting the annual and reference means.

4. Summarize by calculating the mean anomaly per year for the entire group of sites. The resultant values are analyzed for a trend over time.

187 ### *2.2.2 Linear regression on annual mean anomalies*

188 Testing for a regression slope being different than zero can be used to test for monotonic

189 trends in water quality data (Helsel and Hirsch 2002). We used these standard procedures

190 to test for positive or negative trends in lake temperature, chlorophyll *a*, TN, TP and TN:TP.

191 For each parameter, we fit a regression line to the anomalies as a function of year and

192 tested the null hypothesis that no trend existed (e.g., $\beta_1 = 0$). The slope of this line provides

193 information on the mean yearly change of that paramter over the time period studied.

194 Traditionally, trends would be determined by assessing "significance" but recent guidelines

195 suggest not using arbitrary p-value cut-offs to assesses significance (Wasserstein et al.

196 2016). Our interpretation of the trends attempts to follow this advice and we assess trends

197 with the information provided by the magnitude of the slopes, the p-values, and our

198 understanding of the processes involved.

199 ### *2.2.3 Comparison of Rhode Island to the region*

200 Oliver et al. (2017) used hierarchical linear models and showed relatively stable water

201 quality in the lakes of the northeastern United States. While the University of Rhode

202 Island's Watershed Watch data were included in this regional study, we hypothesized that

203 in the case of Rhode Island regional trends were masking sub-regional trends. Therefore,

204 we decided to reanalyze the LAGOSNE data to compare the trends at the regional scale to

205 the trends at the Rhode Island state scale using the site-specific anomaly and trend analysis

206 approach outlined above.

207 # 3 Results

208 During the period of 1993 to 2016, Rhode Island lakes and reservoirs in our dataset had a

209 mean lake temperature of 21.9 °C, mean TN of 600 µg/l, mean TP of 24 µg/l, mean TN:TP

210 ratio of 84.17 molar, and mean chlorophyll *a* of 10.1 µg/l (Table 1).

211

212

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

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

214   For lakes and reservoirs in the larger region represented by the LAGOSNE States, mean TN

215   was 855 µg/l, mean TP was 32 µg/l, mean TN:TP ratio was 90.37 molar, and mean

216   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

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

3.1   State-wide trends in water quality

219   Mean annual temperature anomalies in lakes and reservoirs appears to be increasing

220   (slope = 0.053 , p = 0.0062) with the majority of years with mean temperature greater than

221   the long-term mean occurring in recent years (Figure 3). Chlorophyll *a* is also showing an

222   increasing trend over time (slope = 0.29 , p = 7.810^{-7}) and with the exception of a

223   slightly above-average year in 2003, the above-average years have all occurred in the most

224   recent years (Figure 4A.).

225   Mean annual trends for nutrients were weaker or showed no trend over time. The data

226   suggest a positive trend in TN (slope = 3.8 , p = 0.00022); however, that perceived trend is

227   driven by the lower than mean TN values in 1993 and 1994 (Figure 5A.). Since 1995, the

228   yearly trend shows a lower increase over time (slope = 2.5, p = 0.0067). TP does not show a

229   trend over time in the yearly anomalies (slope = 0.11 , p = 0.062) and years that are over or

230   under the mean are more evenly distributed over the years (Figure 6A.). The pattern is the

231   same for the TN:TP ratio (slope = 0.18, p = 0.71) with little evidence suggesting a change in

232   the concentrations of TN relative to the concentrations of TP (Figure 7A.). Data for all

233   figures are available as a comma-separated values file, `yearly_average_anomaly.csv` from

234   "fill in with zenodo link" (Hollister et al. 2019).

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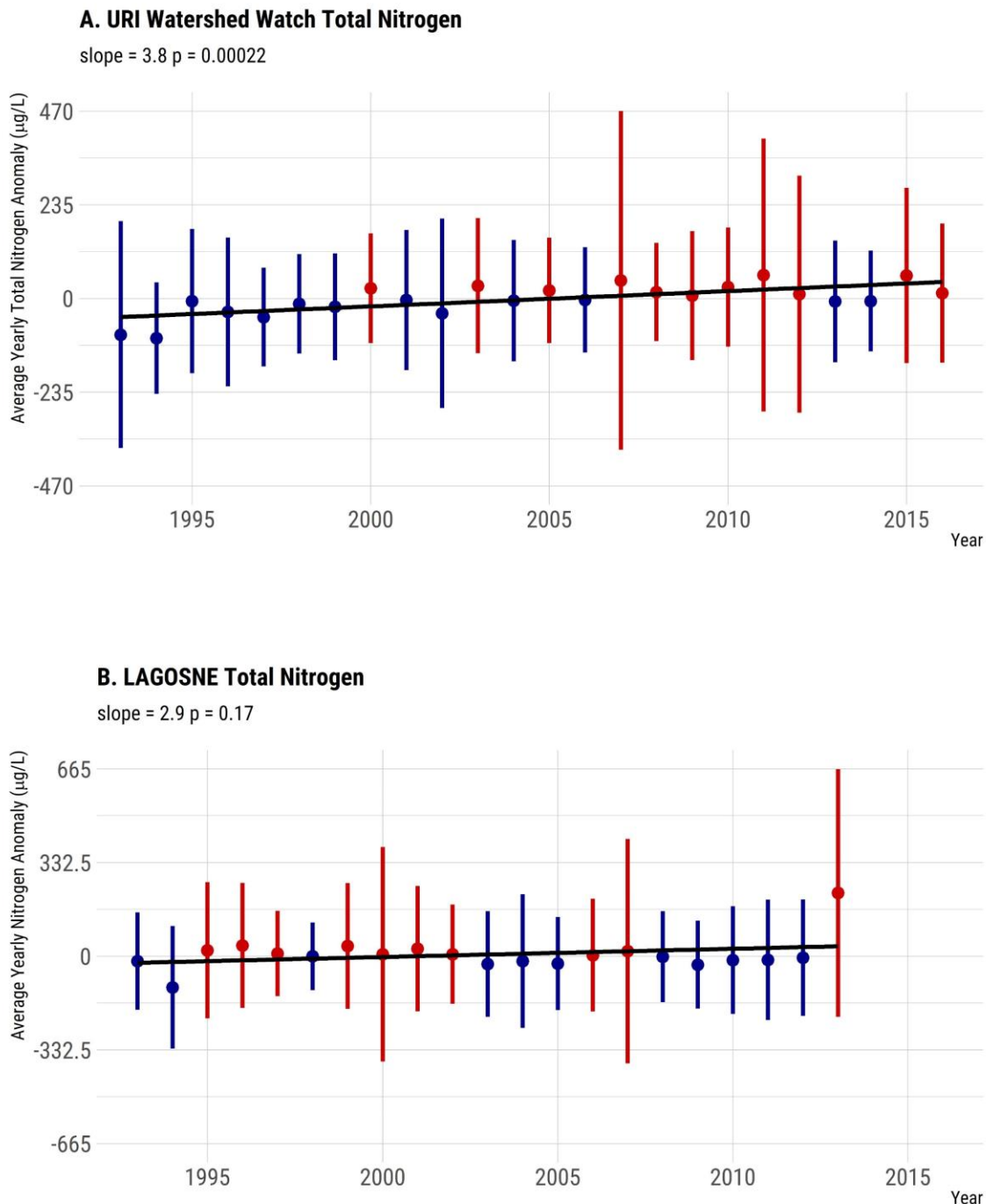**URI Watershed Watch Temperature**

slope = 0.053 p = 0.0062

237
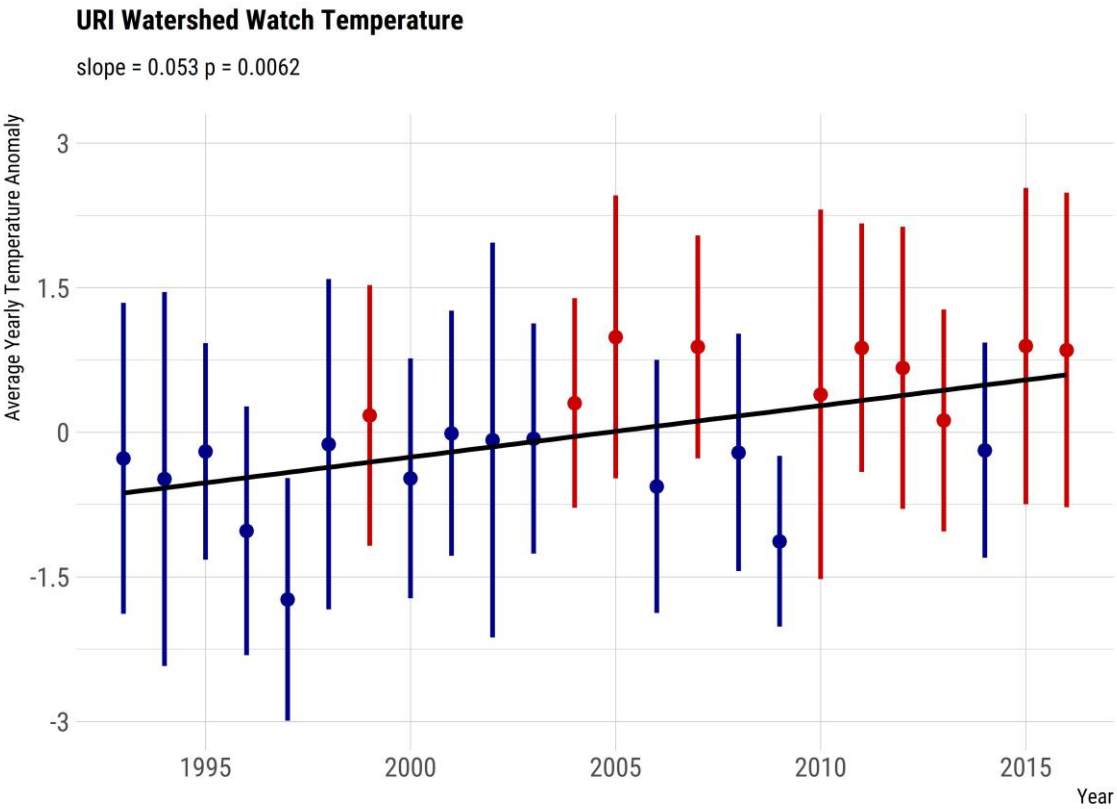
Figure 3: Yearly trend over 20+ years of lake temperature (mean anomaly) in Rhode Island
lakes and reservoirs. Points are means of site-specific anomalies and ranges are standard
deviations of site-specific anomalies. Blue indicates yearly site-specific anomalies that were,
on average, below the site-specific long-term means. Red indicates yearly site-specific
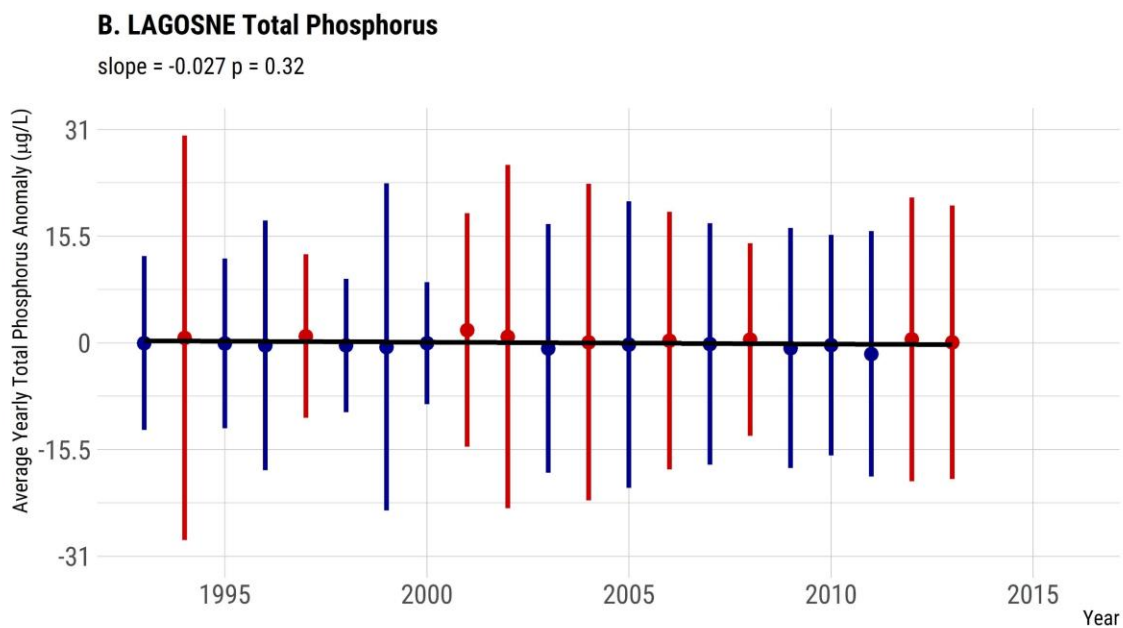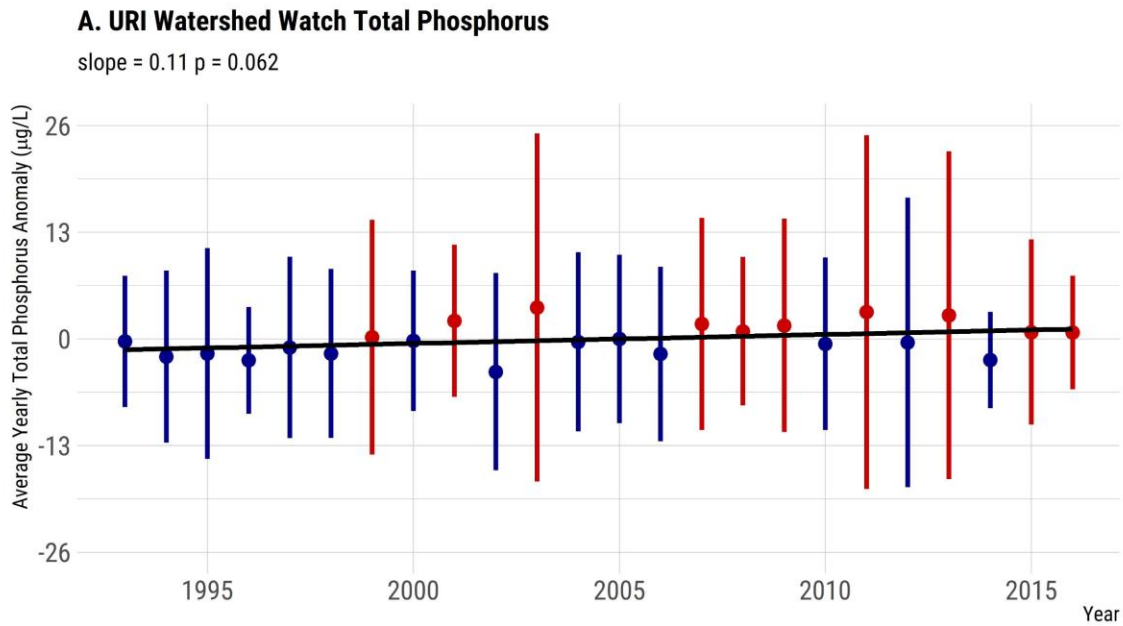*anomalies that were, on average, above the site-specific long-term means.*

243
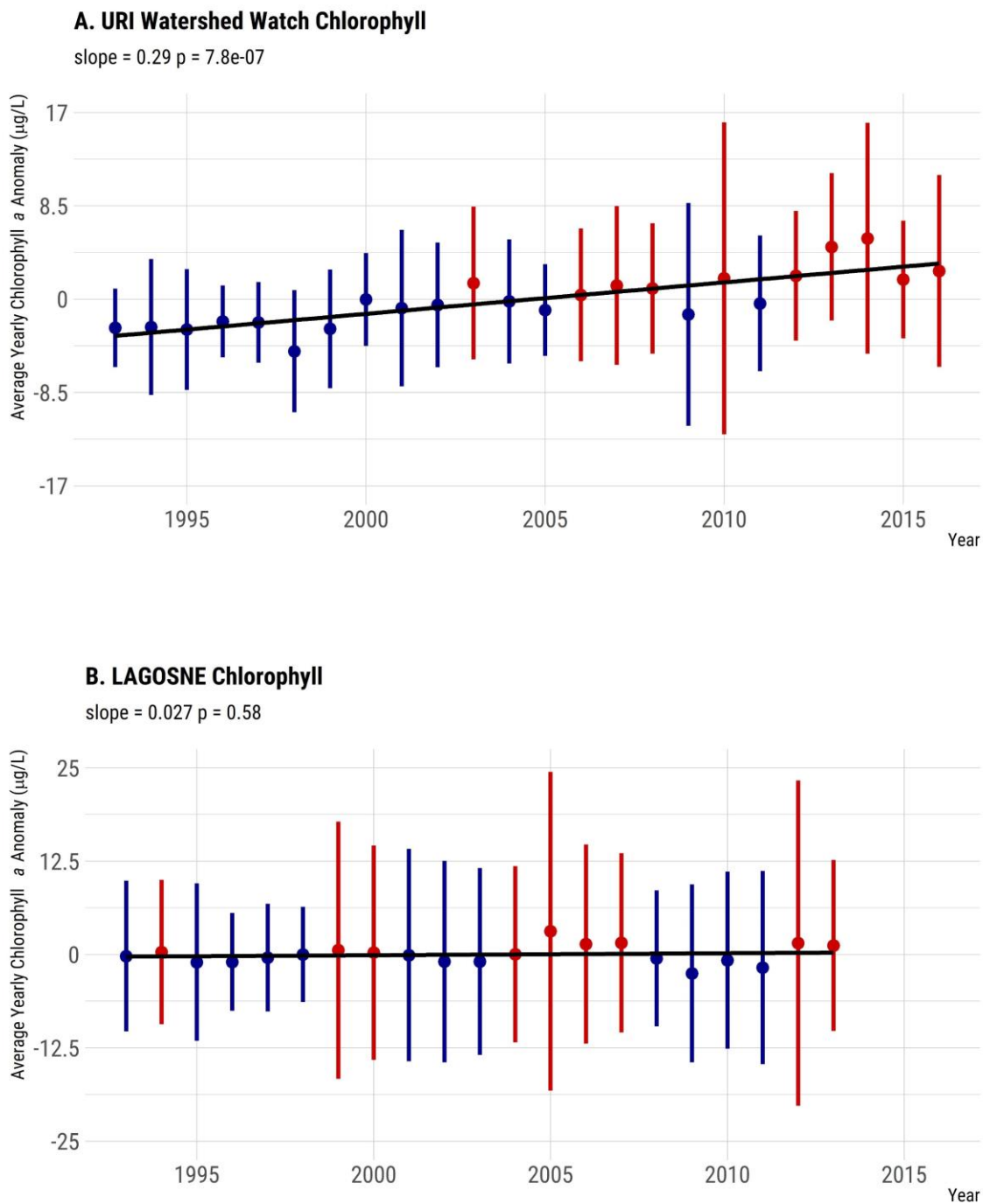
Figure 4: Yearly trend over 20+ years of chlorphyll a (mean anomaly). Panel A. Yearly mean
chlorophyll a anomalies from the URI Watershed Watch data. Panel B. Yearly mean
chlorophyll a anomalies from the LAGOSNE dataset. Points are means of site-specific
anomalies and ranges are standard deviations of site-specific anomalies. Blue indicates yearly
site-specific anomalies that were, on average, below the site-specific long-term means. Red
indicates yearly site-specific anomalies that were, on average, above the site-specific long-
term means.

A. URI Watershed Watch Total Nitrogen

slope = 3.8 p = 0.00022
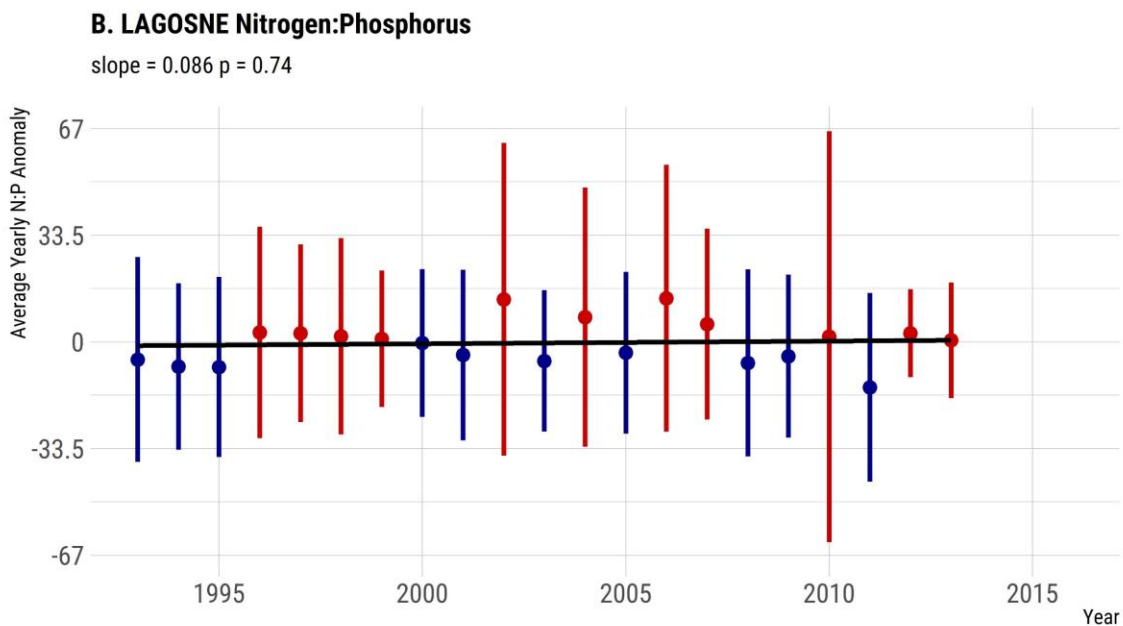
B. LAGOSNE Total Nitrogen

slope = 2.9 p = 0.17

251

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

A. URI Watershed Watch Total Phosphorus

slope = 0.11 p = 0.062
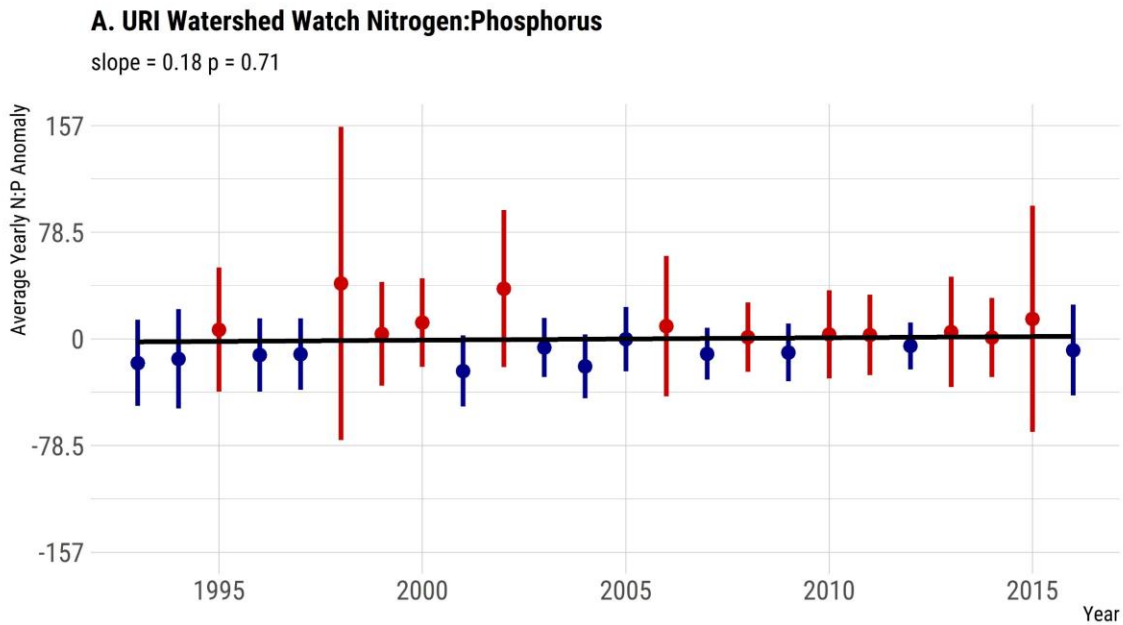
B. LAGOSNE Total Phosphorus

slope = -0.027 p = 0.32

258

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

A. URI Watershed Watch Nitrogen:Phosphorus

slope = 0.18 p = 0.71

B. LAGOSNE Nitrogen:Phosphorus

slope = 0.086 p = 0.74

265

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

3.2 Regional trends in water quality

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

4 Discussion and conclusions

Our sub-regional analysis indicates that even when nutrient regimes exhibit relative stability (i.e., neither increasing nor decreasing over time), increases in primary production, as measured by chlorophyll *a*, can occur. Over the same period we also demonstrate long-term warming of Rhode Island lakes and reservoirs. Chlorophyll has increased, on average, 0.29 µg/L per year over the 23 years of our analysis, while temperature has increased 0.053 °C per year over the same period. This suggests that the observed increase in productivity, as measured by chlorophyll *a*, may be a result of warming waters and not a response to changes in nutrient condition. Also, geographic extent 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 chlorophyll *a* 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 chlorophyll *a*.

4.1 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. While TN showed a weak positive trend, that trend was largely driven by the unusually low years for TN in 1993 and 1994. With those removed the positive trends weakens considerably. The general picture in Rhode Island appears to be one of little to no change in phosphorus, a very weak positive trend in nitrogen and little to no change in the TN:TP ratio. Furthermore, it has been shown that productivity in freshwater systems is likely a function of both phosphorus and nitrogen (Paerl et al. 2016).

301   Thus, the increasing chlorophyll *a* in the face of stable TN:TP ratio suggests that the

302   increase is being driven by something other than nutrients. We interpret these results as

303   relative stability in nutrients in Rhode Island lakes and reservoirs.

304   Stable nutrient regimes may be partly explained by efforts to curb nutrient loadings, for

305   example through voluntary and state wide mandatory bans on phosphates in laundry

306   detergent which were implemented in Rhode Island in 1995 (Rhode Island State

307   Legislature 1995, Litke 1999). However, in many lakes there are still likely sufficient

308   nutrients present to allow for increases in chlorophyll *a*. Additionally, these results point to

309   the fact that chlorophyll *a* and algal biomass is driven by processes operating at different

310   scales. For instance, nutrient management is largely a local to watershed scale effort, but

311   may also be regional as atmospheric nitrogen deposition can be a significant source of

312   nitrogen (Boyer et al. 2002). Similarly, warming lakes are driven by broader climate

313   patterns, yet waterbody-specific factors such as the percent of a catchment that is

314   impervious surface and lake morphology can also impact temperature (Nelson and Palmer

315   2007). In short, differences in regional and state level trends are driven by complex and

316   multi-scale processes.

317   In addition to the annualized trends of the five variables we address with this study, there

318   are other trends that may be of interest. For example, trends for water quality at finer

319   temporal scales such as monthly or seasonal trends may be different than the annual

320   trends we analyzed. Anecdotal evidence in Rhode Island points to warmer temperature

321   earlier and later in the year and suggests a lengthening of the growing season.

322   Furthermore, preliminary analysis of the URIWW data back this up with mean temperature

323   for May 1993 to May 1995 cooler by nearly a degree than mean temperature for May 2014

324   through May 2016. Additionally, it may be possible that the current trophic state of a given

325   waterbody may partly explain the chlorophyll *a* changes in that lake. For instance, are

326   oligotrophic lakes showing stronger trends than eutrophic lakes or are all lakes showing

327   similar trends regardless of current trophic status? Lastly, changes in rainfall, extreme

328   weather events, or other climate mediated factors can also be playing a role in increasing

329   chlorophyll in Rhode Island lakes and reservoirs. These questions are beyond the scope of

330   this study, but all warrant further, careful investigation.

4.2 Management implications

331

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

345 There are several possible approaches to further reduce nutrient loads (Yang and Lusk
346 2018). First, nutrient load reductions may be possible through source controls and
347 enhanced entrainment and treatment of ground and surface waters transporting nutrients
348 to receiving waters (Kellogg et al. 2010). Green infrastructure approaches are one way to
349 possibly achieve both goals (Pennino et al. 2016, Reisinger et al. 2019). Additionally, there
350 is potential for within-lake approaches such as the restoration of freshwater mussels to
351 waterbodies that historically had those species. Some studies using freshwater mussels
352 have shown reductions in both nutrients and algal biomass (Kreeger et al. 2018).

4.3 Data analysis approach

353

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

360 2017), we chose mean site-specific anomalies as they can provide readily interpretable

361 results, especially for communicating to general audiences. For instance, reporting the

362 changes in anomalies allows us to look at changes in the original units. With our analysis,

363 the slope of the regression line for temperature suggests a mean yearly increase of 0.053 °C

364 and the slope of the regression line for chlorophyll *a* shows a mean yearly increase of 0.29

365 μg/l. Additionally, the site-specific anomalies are robust to variations in sampling effort

366 and in the timing of inclusion of given sampling locations (e.g., added later in a time period

367 or removed). Lastly, this analysis is only possible because of the availability of sound, long-

368 term data on water quality in Rhode Island. Without the URIWW data and the commitment

369 and participation of more than 2500 volunteers over the years, our analyses would have

370 been impossible. Going forward, it is important to appreciate the role that volunteer

371 monitoring and citizen science programs can play in capturing and better understanding

372 long term environmental trends.

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