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Phytoplankton blooms in Lake Erie impacted by both long-term and springtime phosphorus loading

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ABSTRACT

Harmful algal blooms in Lake Erie have been increasing in severity over the past two decades, prompting new phosphorus loading target recommendations. We explore long-term drivers of phytoplankton blooms by leveraging new estimates of historical bloom extent from Landsat 5 covering 1984–2001 together with existing data covering 2002–2015. We find that a linear combination of springtime and long-term cumulative dissolved reactive phosphorus (DRP) loading explains a high proportion of interannual variability in maximum summertime bloom extent for 1984–2015 ($R^2 = 0.75$). This finding suggests that the impacts of internal loading are potentially greater than previously understood, and that the hypothesized recent increased susceptibility to blooms may be attributable to high decadal-scale cumulative loading. Based on this combined loading model, achieving mild bloom conditions in Lake Erie (defined in recent studies as bloom areas below 600 km^2 nine years out of ten) would require DRP loads to be reduced by 58% relative to the 2001–2015 average (equivalent to annual DRP loading of 240 MT and April to July DRP loading of 78 MT). Reaping the full benefits of load reductions may therefore take up to a decade due to the effects of historical loading.

Introduction

Water quality has declined in Lake Erie's eutrophic western basin over the past two decades (Kane et al., 2014), characterized by an increasing severity in summertime harmful algal blooms and extent of hypoxic areas. This decline has prompted the revision of targets for spring total and dissolved reactive phosphorus loading in Annex 4 of the Great Lakes Water Quality Agreement (GLWQA, 2015, 2012). The revisions were based on results from a multi-model effort at explaining observed bloom severity (Scavia et al., 2016).

Despite relatively robust agreement among models about loading targets, there is ongoing disagreement about the underlying processes controlling bloom severity and the implications for system response. One question is whether the lake is becoming more susceptible to large blooms for a given amount of phosphorus loading (Obenour et al., 2014; Scavia et al., 2016), and, if so, how the underlying mechanisms impact the loading reductions necessary for, and the timescales associated with, system restoration. For example, internal phosphorus loading has recently been suggested as a possible factor in explaining bloom severity (Matisoff et al., 2016; Watson et al., 2016). As discussed in Scavia et al. (2016), additional potential factors include meteorological conditions (Michalak et al., 2013), the influence of dreissenid mussels on grazing/phosphorus recycling (Vanderploeg et al., 2001), internal loading of cyanobacteria cell inocula (Rinta-Kanto et al., 2009), co-limitation of nitrogen (Chaffin et al., 2013), and changes in the bioavailable fraction of the phosphorus load (Baker et al., 2014).

Several studies have pointed to the lack of long-term historical data on bloom severity as a limiting factor in improving understanding of underlying processes (Bertani et al., 2016; Ho and Michalak, 2015; Stumpf et al., 2016). Models used to inform recent targets for loading reductions are based on remote sensing and in situ data for 2002 to 2015 (Bertani et al., 2016; Stumpf et al., 2016; Verhamme et al., 2016). Processes operating on longer-term time scales (e.g., climate change impacts or the effects of internal loading) are especially difficult to probe without a longer period of record.

Here, we leverage historical data on phytoplankton bloom extent from Landsat 5 covering 1984–2011 (Ho et al., 2017) to supplement existing data from the MEdium and Moderate Resolution Imaging Spectrometers (MERIS and MODIS, respectively) covering 2002–2015 (ESA, 2016; NASA, 2016), in order to explore factors explaining the long-term variability in Lake Erie phytoplankton blooms. We also present implications for required loading reductions and anticipated timescales for system recovery.

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Methods

Long-term bloom records

We explore a long-term historical record of maximum summertime bloom extents for 1984 to 2015, combining remotely-sensed estimates from Landsat 5 (1984–2011), MERIS (2002 − 2011), and MODIS (2012–2015) (Ho et al., 2017; Stumpf et al., 2016, 2012; Wynne et al., 2008). The Landsat and MERIS/MODIS estimates are expected to be compatible based on an analysis of the overlapping 2002–2011 period (Ho et al., 2017).

We define a composite time series based on Landsat for 1984–2009 and 2011, MERIS for 2010, and MODIS for 2012–2015 (Fig. 1 and solid line in Fig. 2). We rely on Landsat for the period overlapping with MERIS (2002–2011) to maximize coherence with the longer preceding period (1984–2001). The exception is for 2010, when clouds obscured Landsat scenes during peak bloom activity (Ho et al., 2017). A sensitivity analysis using MERIS for 2002–2005 and 2007–2011, and Landsat for 1987–2001 and 2006 (dashed line in Fig. 2) yielded consistent conclusions. Landsat was used for 2006 in the sensitivity analysis due to data gaps in MERIS during peak bloom activity that year (see Ho et al., 2017).

Ancillary data

Observations of maximum summertime bloom extent are analyzed using discharge and phosphorus loading measurements from the Maumee River, the main tributary driving bloom severity for Lake Erie (Scavia et al., 2016). Daily total phosphorus (TP) and dissolved reactive phosphorus (DRP) concentration data are available from the Heidelberg University National Center for Water Quality Research (Heidelberg University NCWQR, 2015; Stow et al., 2015). Daily mean discharge data are available from the USGS Station at Waterville, Ohio (USGS, 2016). Total monthly loads are estimated by multiplying discharge with TP or DRP concentration and summing daily loads. Missing concentration data are imputed by taking the average of the closest 10 days of data, similar to Obenour et al. (2014).

Because recent studies have suggested that total bioavailable phosphorus (TBP) may be the strongest predictor of bloom severity (Bertani et al., 2016; Stumpf et al., 2016), we also calculate TBP as:

$$\mathrm{TBP} = \mathrm{DRP} + \theta(\mathrm{TP}-\mathrm{DRP}) \qquad (1)$$

where (TP − DRP) represents the particulate form of phosphorus (under the assumption that all dissolved phosphorus is reactive), and θ is the fraction of particulate phosphorus that is bioavailable. DRP is assumed to be 100% bioavailable (Baker et al., 2014). Two values of θ, 0.138 and 0.63, have been proposed in the literature and are considered here. The first is based on $\theta = \beta(1 - S)$, where $\beta = 0.23$ is the bioavailable fraction of particulate phosphorus and $S = 0.4$ is the fraction that settles out of the water (Stumpf et al., 2016). The second is estimated using a Bayesian hierarchical model of bloom severity that also includes several other parameters (Bertani et al., 2016).

Model development, comparison, and projection

We use multiple linear regression to model maximum summertime bloom extent as a function of TP, DRP, TBP, and/or discharge aggregated to different timescales. We limit the linear models to at most two predictors to focus only on the most parsimonious models and to avoid the possibility of over-fitting. We also perform leave-one-out cross-validation to assess model robustness (e.g., Chatfield, 2006; Obenour et al., 2014).

We consider all possible aggregations of discharge, TP, DRP, and TBP over consecutive months from January to September; we include a very broad range of months in the interest of being conservative. Given recent suggestions in the literature that internal loading may be a factor in driving bloom severity (e.g., Matisoff et al., 2016), we also include single and multiple water year aggregations of TP, DRP, TBP, and discharge, ranging from only the current water year and going back up to 20 years total. For two-predictor models (i.e. ones that include both monthly and yearly aggregations) we truncate the cumulative loading term for the current water year such that the same month does not appear in both terms. Because regular monitoring of phosphorus loading from the Maumee River began in 1975 and the bloom extent observations begin in 1984, for cumulative loading exceeding 10 years we assume that any missing years have loading equal to the average over the available years preceding a given bloom year. Additional sensitivity and robustness checks are described in the Results, Discussion, and Electronic Supplementary Material (ESM) Appendix S1.

For comparison, we also implement two existing models that have been used to guide nutrient load targets, namely the U-M/GLERL Western Lake Erie HAB model (Bertani et al., 2016; henceforth U-M/GLERL model for brevity) and the NOAA Western Lake Erie HAB model (Stumpf et al., 2016; henceforth NOAA model for brevity). For the U-M/GLERL model, we use the posterior means for the six parameters required by the model as listed in Bertani et al. (2016), which were calibrated using data for 2002–2014. The model is based on monthly TBP loading for February through June (with February receiving a lower weight than March–June) and on calendar year for modeling the long-term trend. For the NOAA model, we use published coefficients for March–July TBP loading, and weigh July twice as much as March–June but only include it for years with warm Junes, for consistency with

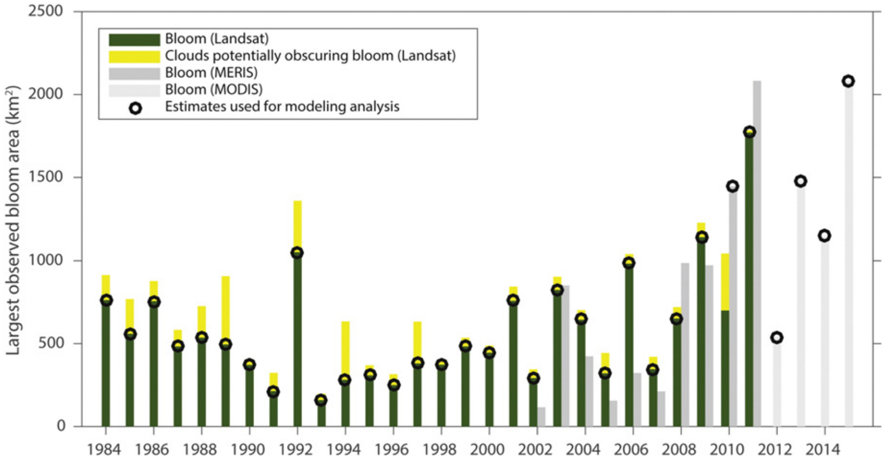

Fig. 1. Historical record of maximum summertime bloom extents from Landsat (1984–2011), MERIS (2002–2011), and MODIS (2012–2015).

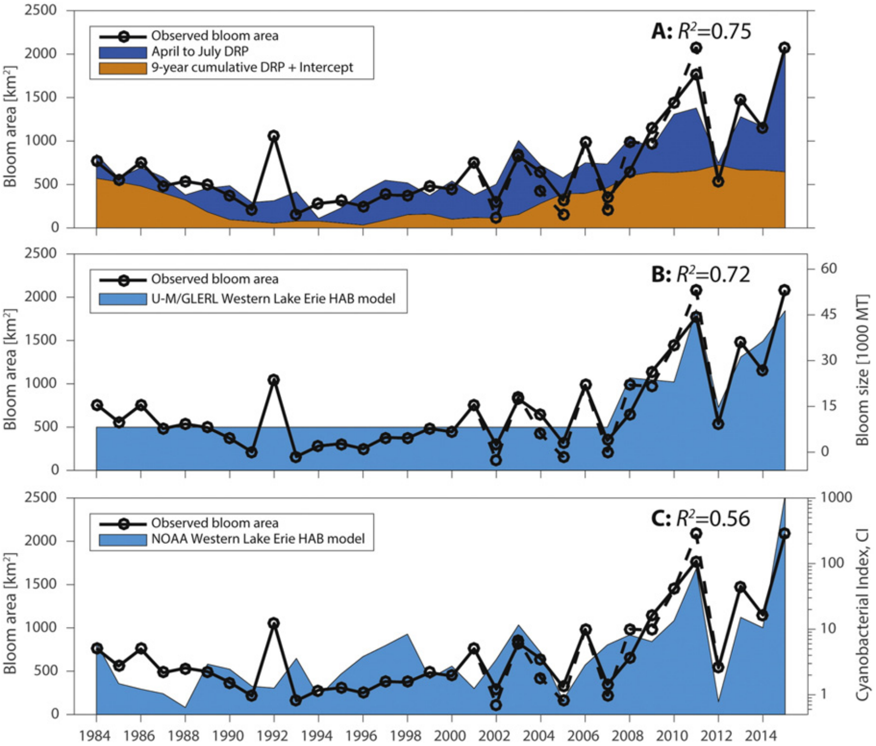

Fig. 2. (A) Contributions to predicted bloom area from April–July DRP, 9-year cumulative DRP and intercept term based on Eq. (2) fit to observed bloom areas. (B, C) Comparisons between observed bloom area [km^2] and (B) bloom size [MT] from the U-M/GLERL Western Lake Erie HAB model (Bertani et al., 2016) and (C) Cyanobacterial Index from the NOAA Western Lake Erie HAB model (Stumpf et al., 2016). Dashed line represents bloom areas used in sensitivity test.

Stumpf et al. (2016). We implement the temperature threshold for defining "warm" Junes using buoy water temperatures from National Data Buoy Center Station 45005 (NOAA NDBC, 2015) due to lack of availability of MODIS-based data prior to 1999, and use a threshold of 18.6 °C for "warm" to classify June temperatures equivalently to Stumpf et al. (2016).

Results

Comparison with historical bloom literature

The new estimates of historical maximum summertime bloom extent for 1984–2001 are generally consistent with past qualitative information from phytoplankton surveys on species abundance and distribution (Table 1). The decline in bloom area in the late 1980s and early 1990s coincides with a reduction in algal biomass and a concomitant transition from diatom-dominated blooms to sparser phytoplankton assemblages dominated by green algae. As bloom areas increase starting at the end of the 1990s and early-2000s, another transition occurs, this time from green algae dominance to blue-green algae dominance, along with increases in biomass. Overall, the Landsat record concurs with the existing literature on trends in historical phytoplankton abundance in Lake Erie across changes in the dominant phytoplankton species.

Long-term trends and drivers

We find that springtime DRP loading and long-term cumulative loading alone explain both recent (2001–2015) and historical (1984–2000) variability in maximum summertime phytoplankton bloom

Table 1
Summary of historical information about phytoplankton blooms in Lake Erie for 1984–2015. Mean bloom size and standard deviation of interannual variability are based on summertime estimates in Fig. 1.

Time period	Historical observations from phytoplankton surveys	Mean bloom size ± standard deviation [km^2]
1984–1987	Diatoms and chlorophytes (a.k.a. green algae) dominant (Makarewicz, 1993) Summer diatoms present with a mixture of phytoplankton types (Munawar and Munawar, 1999)	580 ± 250
1988–1992	Significant decreases in total phytoplankton biomass and chl-a (Leach, 1993; Makarewicz, 1993; Munawar and Munawar, 1999; Nicholls and Hopkins, 1993) Increase in algae inedible to zooplankton (Wu and Culver, 1991) Increase in chrysophyte (a.k.a. golden algae) biomass (Dahl et al., 1995) Transition to chlorophyte dominance (Munawar and Munawar, 1999)	
1993–1996	Transition from summer chlorophyte dominance (Munawar et al., 2002) to *Microcystis* cyanobacteria dominance (Charlton et al., 1999) *Microcystis* begin to appear in high concentrations (Brittain et al., 2000) 10–34% less chl-a in 1994–1996 than 1984–1986 (Charlton et al., 1999)	340 ± 110
1997–2000	Phytoplankton biomass data suggests 1998–2002 blooms were comparable to those in 1983–1989 (Conroy et al., 2005) 1998 phytoplankton biomass comparable to 1983–1988 means (Barbiero and Tuchman, 2001; Makarewicz et al., 1999)	
2001–2015	High biomass blooms with large year-to-year variability dominated by *Microcystis* cyanobacteria (Bridgeman et al., 2013; Stumpf et al., 2012; Wynne and Stumpf, 2015) Record-setting blooms occurring in 2011 and 2015 (Michalak et al., 2013; Stumpf et al., 2016)	960 ± 540

extent in Lake Erie (Fig. 2A). A linear combination of only April to July DRP loading (in metric tons [MT]) and cumulative DRP loading over nine water years (truncated at the end of March of the modeled year, see Methods) [MT] from the Maumee river together explain 75% of the variability in the maximum observed bloom area, A [km^2], over the full period of record (1984–2015):

$$A = 2.70 \cdot \mathrm{DRP}_{\mathrm{Apr-Jul}} + 0.208 \cdot \mathrm{DRP}_{9-year} - 386 \qquad (2)$$

and explains 78% of the variability over the recent period (2001–2015) (Table 2). Adding the 9-year cumulative DRP variable to the April–July DRP loading yields a highly significant improvement in explanatory power ($p = 1.14 \times 10^{-5}$, based on a standard F-test). The leave-one-out cross validation further supports the model's robustness, with the model explaining 70% of the variability in the left-out observations. Although March to July DRP has the highest explanatory power as a single variable ($r^2 = 0.53$), two-variable models that include this variable explain at most 69% of the variability.

An analysis comparing all possible combinations of two variables suggests that the combination of springtime loading and decadal-scale cumulative loading is very robust in explaining interannual variability in bloom extent, but that the available data record cannot fully distinguish between the relative value of DRP vs. TBP (based on $\theta = 0.138$) vs. discharge (ESM Table S1). For example, the two models with the highest explanatory power overall are based on April to July discharge and 9-year and 10-year cumulative DRP loading, respectively (ESM Fig. S2, Table 2), and explain 77% and 76% of the overall variability, respectively. The model in Eq. (2) has the highest explanatory power among models relying only on loading, making it more appropriate for considering management implications. Overall, the preponderance of the evidence across all two-variable models (ESM Table S1) points to springtime DRP loading (probability of 36%) or discharge (probability of 54%), together with long-term DRP loading (probability of 78%) as the best explanatory factors, based on Bayesian model averaging (Raftery et al., 1997). The presence of dreissenids and high turbidity are unlikely to be major confounding factors (see ESM Appendix S1). In addition, neither springtime nor long-term TP loading, or TBP calculated using $\theta = 0.63$, provide comparable explanatory power relative to the other variables considered. The lower explanatory power of TBP (calculated using either value of θ) could indicate changes in the historical bioavailable proportion of total phosphorus; that is, the bioavailable fractions used to estimate TBP may not apply historically.

The proposed model is also more robust and parsimonious relative to existing models. Whereas the U-M/GLERL and NOAA models provide comparable explanatory power over the current period (on which their development was based), they are less robust to the removal of outliers in 1992, 2011, and 2015, and cannot explain observed variability during the historical period (Table 2; Fig. 2). In addition, while the proposed model relies on two predictors (i.e. input variables), the NOAA model (June temperature, March to June TBP loading, July TBP loading) and U-M/GLERL model (February TBP loading, March to June TBP loading, and year) both require three. The U-M/GLERL model also relies on a relatively large number of parameters (i.e., six), while certain choices in the NOAA model are difficult to assess, such as the threshold defining a "warm" June and the assumption of a log-base-10 relationship between loading and bloom severity.

Table 2

Coefficient of determination (R^2) for selected models and time periods. The division between historical (1984–2000) and current (2001–2015) periods is selected based on the maximum observed difference in mean and standard deviation of bloom size between periods. Shading is used to denote significance level based on a standard F-test, with dark grey shading indicating $p < 0.001$; light grey $0.001 < p < 0.05$; and white $p > 0.05$. The F-test takes into account the coefficient of determination, the number of observations in each period, and the number of predictor variables for each model, which is two for the linear models, one for the individual terms, and three for the U-M/GLERL and NOAA models (see Methods).

Predictor	**Whole period (1984–2015)**	**Historical period (1984–2000)**	**Current period (2001–2015)**
All years	All	All	All
Linear model with April–July DRP and 9-year DRP	0.75	0.24	0.78
April–July DRP loading term	0.50	0.02	0.59
9–Year cumulative DRP loading term	0.43	0.24	0.30
U–M/GLERL model (Bertani et al., 2016)	0.72	N/A*	0.74
NOAA model (Stumpf et al., 2016)	0.56	0.04	0.70
Linear model with April–July discharge and 9-year DRP	0.77	0.26	0.84
Outliers removed	Removing '92, '11, '15	Removing '92	Removing '11, '15
Linear model with April–July DRP and 9-year DRP	0.71	0.78	0.62
April–July DRP loading term	0.24	0.04	0.30
9-Year cumulative DRP loading term	0.49	0.75	0.24
U–M/GLERL model (Bertani et al., 2016)	0.55	N/A*	0.50
NOAA model (Stumpf et al., 2016)	0.28	0.00	0.40
Linear model with April–July discharge and 9-year DRP	0.71	0.78	0.67

* For 1984–2001, the U-M/GLERL model defaults to the background bloom size (7910 MT), irrespective of whether we assume that the temporal trend continues prior to 2002.

Discussion

Case studies of individual blooms

The expanded bloom record and the model in Eq. (2) provide new insight into the relative size of blooms in 1984–1987. Previous vessel-based, lake-wide data had suggested that the 1986 bloom was the largest over 1983–1987 (Makarewicz, 1993), while other surface chl-a observations (ESM Appendix S1) in 1986 and 1987 had implied that these two years experienced similar blooms (EPA GLNPO, 2012). The Landsat data instead suggest that the 1984 bloom was slightly larger than the 1986 bloom, which was in turn larger than the 1987 bloom (Fig. 1). This ranking is also supported by the model (Fig. 2A), given the higher spring and cumulative loading in 1984 relative to 1986, which in turn are higher than in 1987. Together, the Landsat record and the loading-based model indicate a gradual improvement in bloom conditions in the late 1980s.

The large outlier bloom observed in 1992 is inconsistent with both the model in Eq. (2) and with other existing models, all of which predict a much smaller bloom than observed (Fig. 2, ESM Figs. S1, S2). We hypothesize that the larger observed spatial extent was driven by record wind stress (0.052 Pa in July and August versus the 1984–2015 July and August mean of 0.040 Pa) and abnormal patterns in wind direction (record-low percentage of days with northerly winds (9.6%) and the second-highest percentage of days with southwesterly wind (30%)) (ESM Appendix S1). The 1992 bloom extended north along the western shore (ESM Fig. S3), which further supports this hypothesis as the observed wind patterns would have favored moving phosphorus and phytoplankton up the western shore.

The expanded bloom record and the model also alter understanding of the 1995 bloom, previously assumed to be the first "large" bloom of the current *Microcystis*-dominated regime (Budd et al., 2001). Budd et al. (2001) had previously estimated the area of the bloom to be approximately 1000 km^2. However, the Landsat observations suggest a bloom of only 300 km^2, implying that the remainder of the bloom was less intense than the smallest Microcystis blooms of 2002–2011 on which the bloom classification threshold was developed (Ho et al., 2017). This interpretation is also consistent with the Eq. (2) model, because both springtime and cumulative loading were lower in 1995 relative to the post-2002 period (Fig. 2A).

The cumulative loading term also helps to explain observed bloom severity in 1985, 1988, 1994, and 2012 (Fig. 2A), years during which spring loading was minimal. In 2012 for example, April–July DRP loading was only 8 MT, the lowest over the whole study period, and yet a small bloom occurred. The area of the bloom is entirely consistent with the anticipated impact of cumulative loading (Fig. 2A), supporting the speculation by Matisoff et al. (2016) that the bloom was supported by internal loading. This finding also explains why the NOAA model, which relies solely on spring loading, underestimated bloom size for 2012 (Stumpf et al., 2016). Similarly, decreasing bloom extents in 1985, 1988, and 1994 (560, 536, and 282 km^2, respectively) are consistent with declining cumulative loading over that period (Fig. 2A). Cumulative loading, representative of long-term trends, thus explains bloom severity in low-loading years, which is consistent with the idea that the cumulative loading term is representative of internal phosphorus loading in the western basin of Lake Erie.

Effects of long-term phosphorus loading

Overall, our findings are consistent with the idea that internal phosphorus loading in Lake Erie is likely more important than previously considered, and may occur on timescales of up to a decade. This conclusion is consistent with observations in other lakes that have undergone reductions in inflows of nutrients (e.g., Lake Lugano: Lepori and Roberts, 2017), and implies that ecosystem recovery could be slow. For Lake Erie specifically, the importance of internal phosphorus loading was first investigated in response to events in 2012, when a drought resulted in minimal springtime phosphorus loading and yet a small bloom occurred (Matisoff et al., 2016). Measurements of internal phosphorus loading have suggested that internal diffusive loading is unlikely to trigger blooms by itself, but is sufficiently large to contribute to blooms (Matisoff et al., 2016). Our results suggest that in certain years (e.g., 2012, 1994, 1988, 1985) internal loading may be sufficient to support observed blooms almost entirely.

The timescales over which cumulative loading is observed to impact interannual variability in summertime bloom extent (Eq. (2); ESM Table S1) are substantially longer than has previously been assessed quantitatively for Lake Erie, but are consistent with speculation that internal phosphorus effects could delay the recovery of Lake Erie by 10–15 years (Watson et al., 2016). As discussed in Watson et al. (2016), residual phosphorus has been shown to delay recoveries in other lakes up to 15 years (Jeppesen et al., 2007; Phillips et al., 2005). There is also evidence for a potential reservoir of historical phosphorus for internal loading in Lake Erie sediments, with past estimates suggesting that 92% of the external phosphorus entering Lake Erie is retained (Burns, 1976), a finding supported by modeling studies showing a net accumulation of phosphorus in Lake Erie sediments (Zhang et al., 2016). Results from Lake Simcoe also showed that both long-term and short-term phosphorus can be released from sediments (Dittrich et al., 2013), suggesting that internal loading is not always made up of recently-deposited phosphorus, and thereby supporting the idea of a long-term impact of historical phosphorus.

During the historical period (1984–2000), bloom severity in fact primarily follows the long-term trend represented by the cumulative loading term, and cumulative DRP loading alone can explain 75% of the variability in historical bloom size after the removal of the outlier in 1992 (ESM Fig. S1B; Table 2). This finding is attributable to much lower year-to-year variability in spring loading during the historical period, so much so that springtime DRP loading does not provide much additional explanatory power historically (ESM Fig. S1A; Table 2). More broadly, this explains why the NOAA model, which is based primarily on spring loading, does not perform well during the historical period (Fig. 2C; Table 2), and suggests that models based primarily on springtime loading may underestimate the time required to reap the benefits of future loading reductions.

For the recent period (2001–2015), during which the interannual variability (expressed as variance) in springtime DRP loading is 7-fold higher than during the historical period, springtime DRP loading alone explains 59% of the variability in maximum summertime bloom extent, while the cumulative DRP loading term alone explains 30% (ESM Fig. S1; Table 2). Together they explain 78% of the variability, indicating that both spring and historical loading are needed to explain the interannual variability for recent blooms (ESM Fig. S1; Table 2). The influence of the increase in cumulative loading over this period (Fig. 2A) can also explain the "increased susceptibility" of Lake Erie to large blooms for a given amount of springtime loading noted in recent studies (Bertani et al., 2016; Obenour et al., 2014).

The evidence for long-term DRP or TBP (rather than TP) loading explaining bloom severity also suggests that biological mechanisms may drive the sedimentation of phosphorus available for internal loading, i.e., that biologically-assimilated-P is the primary form that is accumulated for internal recycling, rather than less labile particulate-P. DRP and TBP enter bed sediments primarily through sequestration into the food web (Sharpley et al., 2014), and settling particles and the sediment surface can act as sinks for DRP (Gächter and Mares, 1985; Williams, 1998). In the Northern Gulf of Mexico, reports of up to half of phytoplankton biomass sinking into sediment traps (Dortch 1997) suggest that phytoplankton sedimentation can be a major source of sediment nutrients. Given the timescale of historical loading effects observed here, phosphorus in Lake Erie could also be bound in sediment forms that are less labile, which might favor release over multiple years (e.g., see Sondergaard et al., 2003).

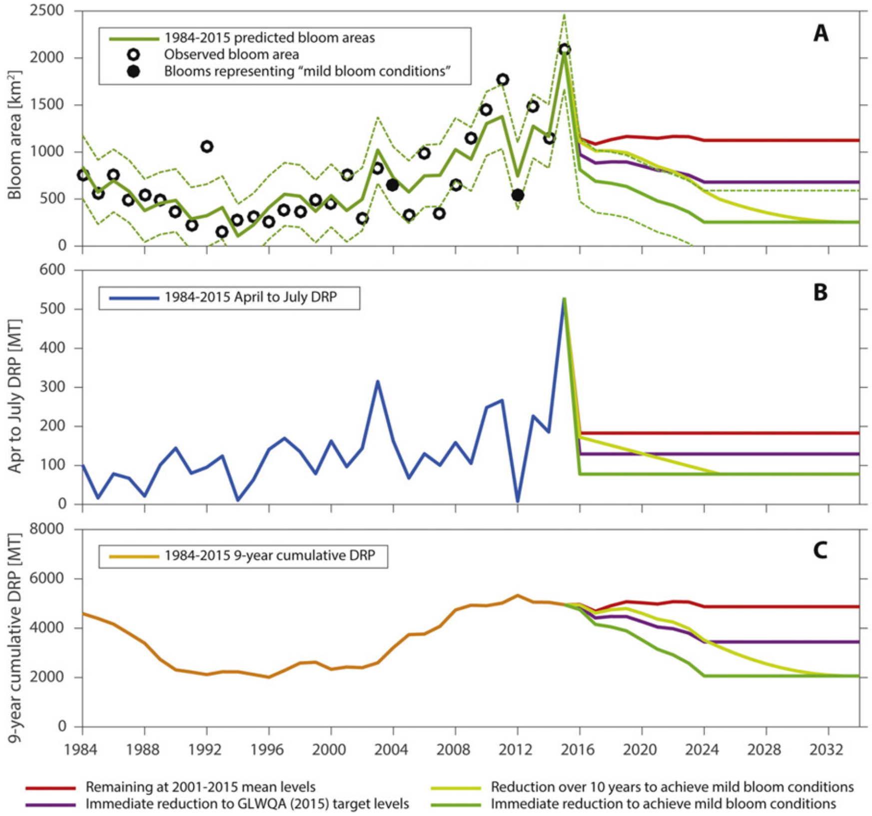

Fig. 3. (A) Predicted bloom areas based on (B) April–July DRP and (C) 9-year cumulative DRP using Eq. (2) for historical data and future loading scenarios. Dashed lines in panel (A) show 10th and 90th percentiles of the predictive uncertainty for bloom size. Filled circles in panel (A) indicate the two years (2004 and 2012) that are used to set the target for "mild bloom conditions," similar to Scavia et al. (2016).

Implications for nutrient load reduction targets

Based on the model presented in Eq. (2), we find that achieving the target laid out in GLWQA (2015), namely summertime blooms being below 2004 and 2012 bloom conditions ("mild bloom conditions" defined similarly as Scavia et al. (2016), interpreted as the average of those years' maximum bloom extents, or 600 km^2) for nine years out of 10, would require annual DRP loading to be reduced to 240 MT and April to July loading to be reduced to 78 MT (Fig. 3; Table 3). This is equivalent to a March to July loading of 112 MT, a stricter target relative to the 186 MT listed in GLWQA (2015). Discounting 1992 as an outlier leads to a slightly less stringent annual target of 280 MT, equivalent to 91 MT for April to July and 130 MT for March to July (Table 3). This projection assumes the same percentage reduction to both spring and annual loads relative to the average seasonal cycle for 2001–2015 (Table 3). We use the 90th percentile of the predictive uncertainty for bloom size as the metric for meeting future bloom size targets nine year out of ten.

If the DRP reductions were implemented immediately, the target would be achieved after a decade due to the effect of historical phosphorus; if the reduction were implemented gradually over 10 years, the target would be achieved only after close to two decades (Fig. 3). This anticipated delay in reaping the benefits of loading reductions is consistent with Lake Erie's observed recovery in the 1970s and 1980s (when TP was reduced by 50%) and also with recovery times in other lakes with residual phosphorus effects (Jeppesen et al., 2007; Phillips et al., 2005; Watson et al., 2016). These findings illustrate that while summertime blooms are likely to respond immediately to spring loading reductions, historical phosphorus loading effects could prevent the full realization of the benefits resulting from those reductions for a decade or more (Fig. 3).

The required targets are stricter than the GLWQA (2015) recommendations recently reported by Scavia et al. (2016). Applying equivalent reductions as GLWQA (2015) under the same seasonality assumptions as before (Table 3) would not return Lake Erie to mild bloom conditions using the model in Eq. (2) (Fig. 3). Instead, these reductions would

Table 3
Loading targets based on modeled projections compared to GLWQA (2015) recommended targets.

	Annual DRP load [MT]	April–July DRP load [MT]	March–July DRP load [MT]
Targets based on loading model	240[a]	78[a]	112[b]
Targets based on loading model recalibrated after excluding 1992 bloom	280[a]	91[a]	130[b]
GLWQA (2015) recommended target	–	–	186[c]
2008 loading[d]	837	158	303
2001–2015 average loading	564	183	263

[a] Determined based on the 90th percentile of predicted bloom size estimated from loading model (Eq. (2)).

[b] Calculated assuming the same percentage reduction from 2001 to 2015 as the April–July and Annual DRP load targets. Note that March–July DRP loading is not included in the loading model (Eq. (2)) but is calculated here for comparison to the GLWQA (2015) target.

[c] As reported in GLWQA (2015).

[d] Baseline for GLWQA (2015) targets.

lead to bloom sizes below 1000 km^2 nine years out of 10, similar to the 2006, 2009, and 2014 blooms rather than the 2004 and 2012 blooms.

Conclusion

In summary, we find that a linear combination of springtime and long-term cumulative DRP loading explains three quarters of interannual variability in maximum summertime phytoplankton bloom area in Lake Erie for 1984–2015 ($R^2 = 0.75$). Based on available data, we also do not find evidence of TP explaining bloom severity beyond its correlation with DRP. These results suggest that residual phosphorus effects in Lake Erie are likely more important than previously suspected, which would delay recovery following phosphorus load reductions. Results also suggest that achieving mild bloom conditions would require annual DRP loads to be reduced to 240 MT (April to July loads of 78 MT), a 58% reduction relative to the 2001–2015 average. Full recovery would only be achieved up to a decade after reductions targets are reached.

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Appendix A. Supplementary information and figures

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jglr.2017.04.001.

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