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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:

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

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

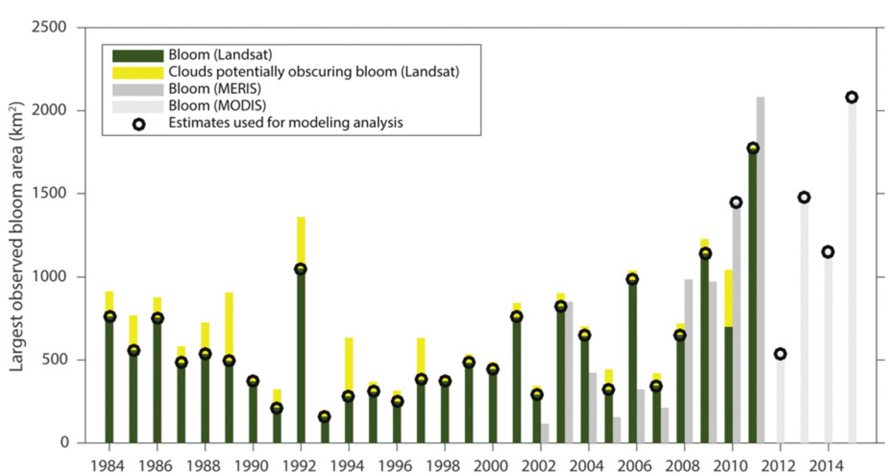

Fig. 1. Historical record of maximum summertime bloom extents from Landsat (1984–2011), MERIS (2002–2011), and MODIS (2012–2015).