2022 Western Lake Erie Harmful Algal Bloom (HAB) Forecast

Donald Scavia and Yu-Chen Wang

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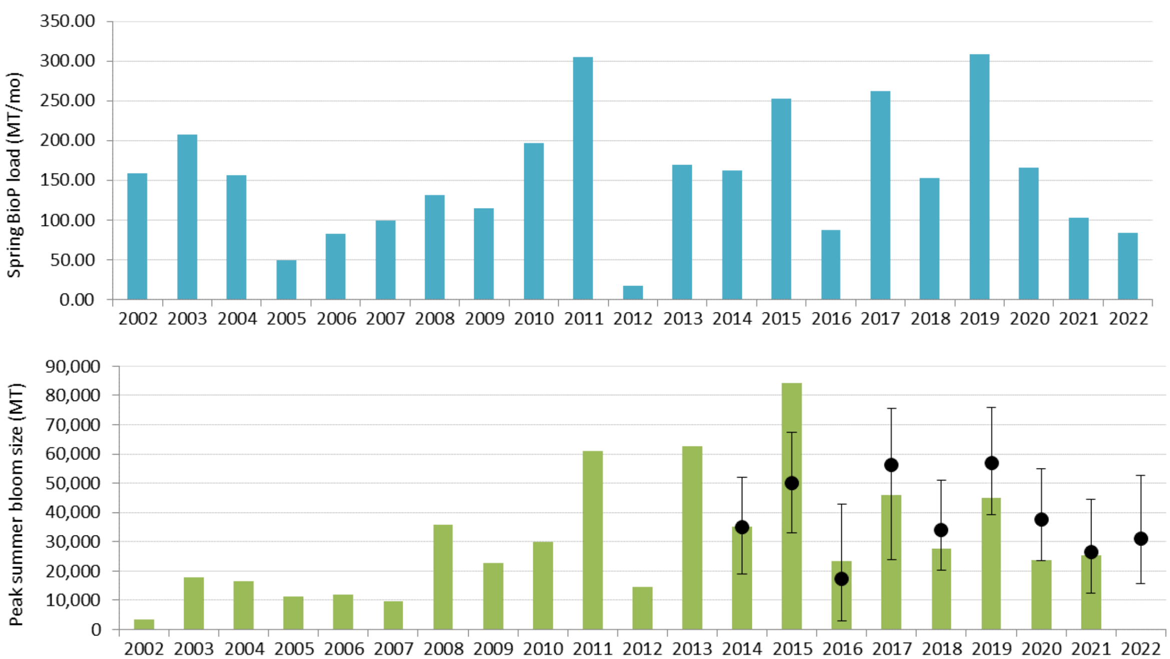
<u>Forecast summary</u>: A Harmful Algal Bloom of 31,230 metric tons (MT) is predicted for the western basin of Lake Erie in 2021, with a 95% predictive interval of 15,813 – 52,719 MT. This forecast is roughly comparable to the 2002-2021 average, and about one-third of the 2015 maximum. This forecast is a contribution to NOAA's ensemble bloom prediction.

This year's forecast is based on a new model that includes estimates of the impact of internal phosphorus recycling by including the bioavailable phosphorus load from previous years, similar to that used by Ho and Michalak (2015). This linear, segmented model predicts HAB extent as a function of the load with slopes before and after a model-estimated change point. The model, calibrated with three independent estimates of the 2002-2020 HAB observations and loading of bioavailable phosphorus, explained 77% and 85% of the interannual variability when using loads through June or July, respectively. It also explained 69% of the interannual variability in a leave-one-out cross validation, and 75% of the variability in blind forecasts.

The spring bioavailable phosphorus loads and bloom forecasts compared to observed historical blooms are shown below:



Spring phosphorus loads (top) and mean bloom observations with forecasts (bottom). Error bars represent 95% predictive intervals.

Phosphorus loads: Daily TP and DRP loads were downloaded from Heidelberg University's National Center for Water Quality Research (https://ncwqr.org/monitoring/data/), and aggregated to monthly loads. Bioavailable P was estimated as DRP plus a fraction of particulate P (TP-DRP), where the faction was determined during model calibration.

HAB extent estimates: The HAB model was calibrated using three sets of HAB estimates for 2002-2021. HAB extent as dry weight biomass was derived from two satellite-derived estimates (Stumpf et al. 2016; Manning et al. 2019) and a geostatistical estimate based on *in situ* observations (Fang et al. 2019). The Stumpf cyanobacteria index is based on processing satellite image spectra specific for cyanobacteria, whereas the Manning biomass estimates are based on chlorophyll-specific spectra (Sayers et al. 2016) that give similar results for relatively high chlorophyll concentrations. Both are constrained to near-surface observations. The Fang estimates are based on *in situ* chlorophyll observations, which are relatively sparse, but provide full water-column estimates. Stumpf estimates are for the full lake, whereas the other two estimates only determine bloom size within the western basin. So, the Stumpf estimates were clipped to the western basin as described by Fang et al. (2019).

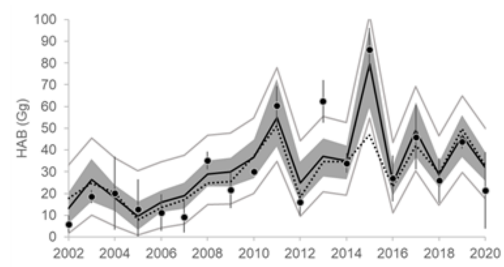


Figure 1. Calibrated HAB model. Mean and standard deviation of observations (boxes), prediction (solid line) with 95% credible intervals for parameter error (shade) and parameter error plus prediction error (grey line). Dotted line is prediction for the model calibrated with loads through June.

HAB model calibration:. Calibration was based on Bayesian inference using a Markov Chain Monte Carlo (MCMC) sampling algorithm implemented within WinBUGS interfaced with the R package, R2WinBUGS (Lunn et al., 2000; R Core Team, 2015; Sturtz et al., 2005). Detailed information on the MCMC algorithm settings, chain convergence evaluation, and parameter prior distributions can be found in Obenour et al. (2014) and Bertani et al. (2016). A new response curve was developed for the revised model based on parameter estimates and model-specific spring loads.

References

Bertani, I., D. R. Obenour, C. E. Steger, C. A. Stow, A. D. Gronewold, and D. Scavia (2016), Probabilistically assessing the role of nutrient loading in harmful algal bloom formation in western Lake Erie. *J. Great Lakes Res.*, 42(6), 1184-1192.

Bridgeman, T. B., J. D. Chaffin, and J. E. Filbrun (2013), A novel method for tracking western Lake Erie *Microcystis* blooms, 2002–2011. *J. Great Lakes Res.*, 39(1), 83-89.

Fang, S., D.D. Giudice, D. Scavia, C.E. Binding, T. B. Bridgeman, J. D. Chaffin, M. A. Evans, J. Guinness, T. H. Johengen, D. R. Obenour. A Space-time geostatistical model for probabilistic estimation of harmful algal bloom biomass and areal extent. Science of the Total Environment https://doi.org/10.1016/j.scitotenv.2019.133776

Ho, J.C., Michalak, A.M., 2015. Challenges in tracking harmful algal blooms: a synthesis of evidence from Lake Erie. J. Great Lakes Res. 41, 317–325.

Lunn, D.J., Thomas, A., Best, N., Spiegelhalter, D., 2000. WinBUGS—a Bayesian modelling framework: concepts, structure, and extensibility. Stat. Comput. 10, 325–337.

Manning, N.F., Y.C. Wang, C. M. Long, I. Bertani, M. J. Sayers, K. R. Bosse, R. A. Shuchman, D. Scavia. 2019 Extending the Forecast Model: Predicting Harmful Algal Blooms at Multiple Spatial Scales. J. Great Lakes Res. 45:587–595 https://doi.org/10.1016/j.jglr.2019.03.004

Obenour, D. R., A. D. Gronewold, C. A. Stow, and D. Scavia,(2014), Using a Bayesian hierarchical model to improve Lake Erie cyanobacteria bloom forecasts. *Water Resour. Res.*, 50(10), 7847-7860.

R Core Team, 2015. R: A Language and Environment for Statistical Computing

Sayers, M., Fahnenstiel, G.L., Shuchman, R.A., Whitley, M., 2016. Cyanobacteria blooms in three eutrophic basins of the Great Lakes: a comparative analysis using satellite remote sensing. Int. J. Remote Sens. 37, 4148–4171.

Scavia, D., Y-C Wang, D. R. Obenour, A. Apostel, S. J. Basile, M. M. Kalcic, C. J. Kirchhoff, L. Miralha, R. L. Muenich, A.L. Steiner. 2021 Quantifying uncertainty cascading from climate, watershed, and lake models in harmful algal bloom predictions. Sci. Total Environ. https://doi-org.proxy.lib.umich.edu/10.1016/j.scitotenv.2020.143487.

Stumpf, R. P., T. T. Wynne, D. B. Baker, and G. L. Fahnenstiel (2012), Interannual variability of cyanobacterial blooms in Lake Erie, *PLOS ONE*, 7, e42444.

Sturtz, S., Ligges, U., Gelman, A., 2005. R2WinBUGS: a package for running WinBUGS from R. J. Stat. Softw. 12, 1–16