Chesapeake Bay Hypoxic Volume Forecasts

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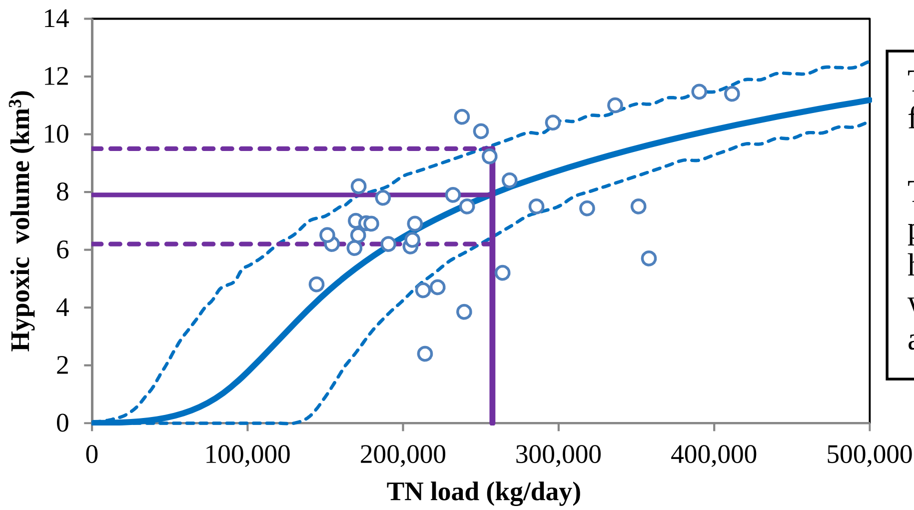
The 2018 Forecast **- Given the average January-May 2018 total nitrogen load of 257,436 kg/day, this summer's hypoxia volume forecast is 7.9 km^3, an above average size for the period of record.**



The average 2018 forecast is 7.9 km^3.

There is a 95% probability that hypoxic volume will be between 6.2 and 9.5 km^3.

Figure 1. Forecasting relationship of total nitrogen vs. hypoxic volume. The solid blue curve is the response curve (mean value) calibrated to observed values for 1985-2017 (open blue circles); dashed blue curves are response curve confidence intervals (2.5 and 97.5% values). The vertical purple line represents the 2018 Jan-May TN load of 257,436 kg/day and the horizontal lines show the forecast hypoxic volume (mean and confidence intervals) associated with this load.

Model track record– The model has been used to produce an annual forecast each year since 2007 (Figure 2). During this time, the observed hypoxic volume has been within the forecast confidence interval in 7 of the 11 years. In the remaining years, the model under predicted hypoxic volume slightly in 2011, over predicted it slightly during 2008 and substantially in 2007 and 2014. In 2014, model over prediction is attributable to the passing of Hurricane Arthur in early July and its disruption of the Bay's stratification and hypoxic layer. Extreme weather events such as hurricanes can significantly influence the average extent of hypoxic volume, but they are currently not accounted for by the model.

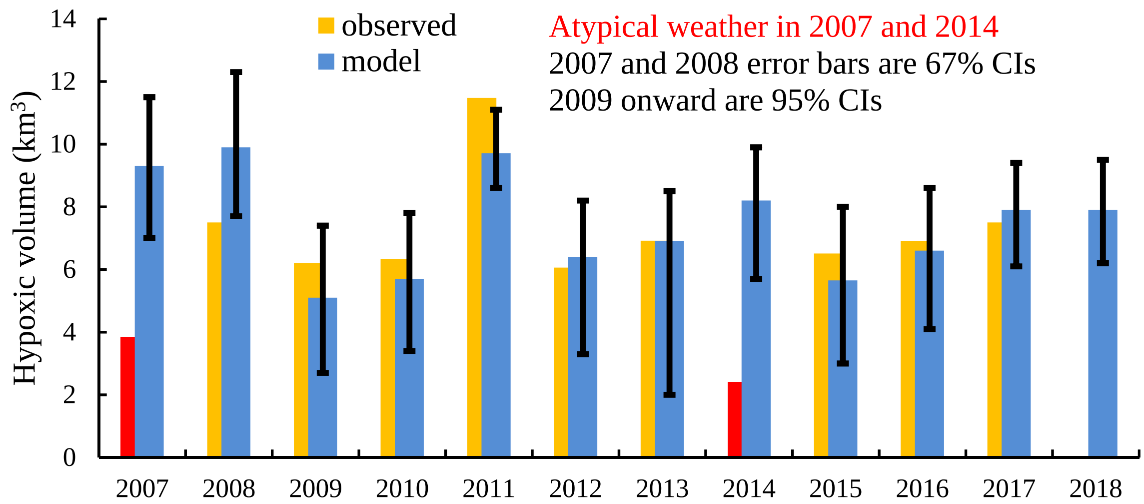


Figure 2. Model forecast and observed hypoxic volume for the years when spring forecasts have been performed. The model calibration has varied over the years. The years 2007 and 2008 used the original model calibration; 2009 used a recalibration with updated load and hypoxic volume information; in 2010-2014 a three year moving window calibration was used (Evans and Scavia 2011); 2015 through 2017 used the years 1985-2013 to calibrate the model; and in 2018 the model was calibrated using updated USGS load estimations WRTDS method for the entire time period of 1985-2017.

***Hypoxia in the Chesapeake Bay* –** The level of oxygen in the waters of the Chesapeake Bay is a critical factor in determining the health of the Bay's ecosystem.

The nitrogen load, one of the key drivers of hypoxia in the Bay has increased significantly since the 1950s but remains highly variable from year to year. The plot below shows the average Jan-May loads of total nitrogen from the Susquehanna River, the primary source of nitrogen to the main stem of the Bay.

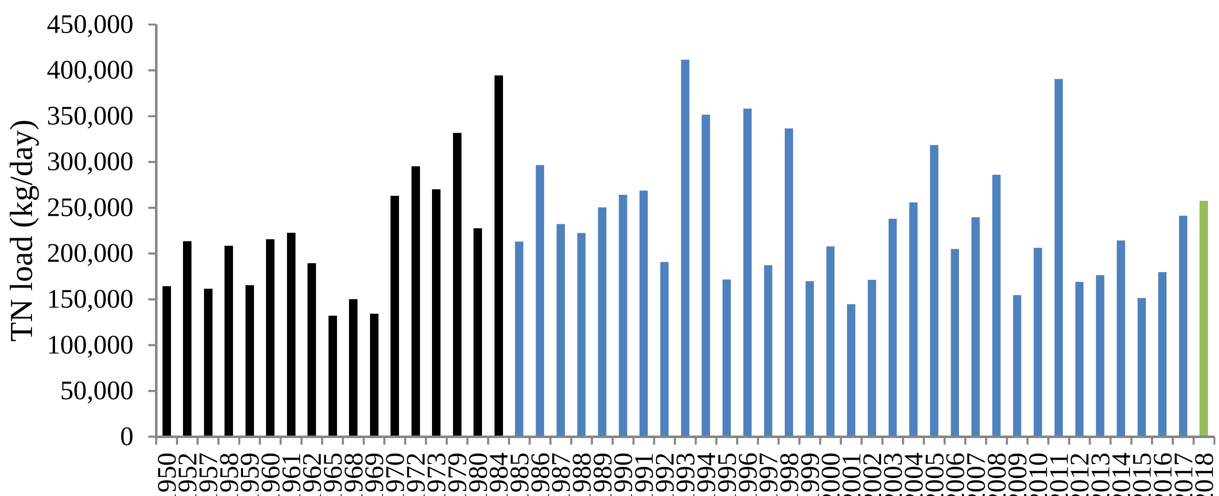


Figure 3. The average Jan-May Susquehanna River TN load (kg/day). Blue bars represent the period for which the model is calibrated, and the recently measured load for 2018 is in green.

These loads are used to forecast the volume of water with oxygen concentrations below 2 mg/l, the definition of hypoxia for the Bay. Hypoxic volume (Figure 4) has increased during this same time period, particularly through the early 1990s. The total volume of the Bay mainstem is about 51 km^3; in an average summer (hypoxic volume of 6.3 km^3), over 10% of the Bay becomes hypoxic or anoxic.

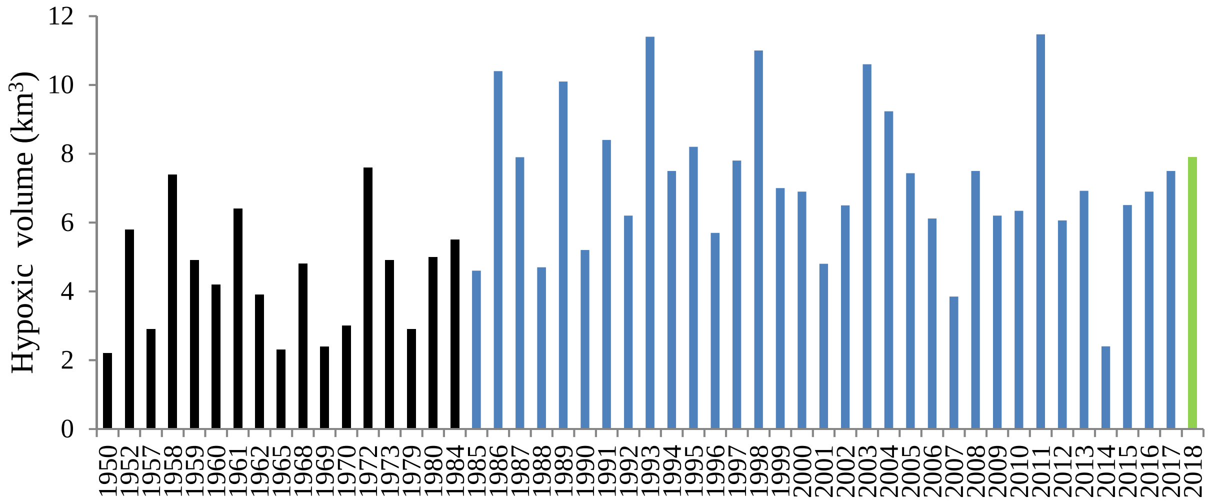


Figure 4. Observed hypoxic volume (km^3) for the period of record. Blue bars represent the period for which the model is calibrated, and the 2018 predicted volume is in green.

These two data sets were used to develop and test the model used for hypoxia scenario development and forecasts.

The model **-** The forecast is based on a model that was developed to assess the impacts of changes in nitrogen loads on Chesapeake Bay hypoxia (Scavia et al. 2006). While it was originally designed to estimate the extent of nitrogen load reduction needed to reach a particular goal for hypoxia volume, it can also be used to forecast hypoxic volumes for a given year, based on the average January-May nitrogen loads.

The model is an adaptation of a river model that predicts oxygen concentration downstream from point sources of organic matter loads using two mass balance equations for oxygen-consuming organic matter, in oxygen equivalents (i.e., BOD), and dissolved oxygen deficit. The equation for dissolved oxygen (DO), solved at steady state is:

$$DO = DO_S - \frac{k_1 BOD_u (F)}{K * k_2 - k_1} \left(e^{-k_1 \frac{x}{v}} - e^{-K*k_2 \frac{x}{v}} \right) - D_i e^{-K*k_2 \frac{x}{v}}$$

where DO = the dissolved oxygen concentration (mg/L), DO_s = the saturation oxygen concentration, k_1 = the BOD decay coefficient (1/day), k_2 = the reaeration coefficient (1/day), BOD_u = the ultimate BOD (mg/L), x = the downstream distance (km), v = stream velocity (km/day), and D_i = the initial DO deficit (mg/L). This approach to modeling coastal and estuarine hypoxia has also been used successfully for Gulf of Mexico hypoxia (Scavia et al. 2003, 2004).

Recalibration - The model calibration has varied over the years. The original model was calibrated and tested against 1950-2003 nitrogen load and hypoxic volume estimates assembled by Hagy (2002). The years 2007 and 2008 used the original model calibration, while 2009 used a recalibration with updated load and hypoxic volume information. Specifically, the Chesapeake Bay Program provided load and hypoxic volume updates for 1986-2008, and even though the new estimates varied little from the original ones (Figure 5), the model was recalibrated to the new 1986-2008 estimates. In 2010-2014 a three year moving window calibration has been used (Evans and Scavia 2011).

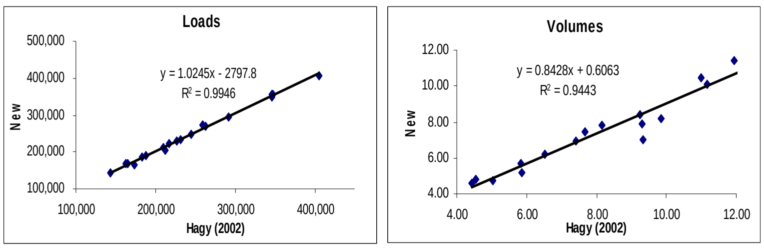


Figure 5. Comparison of Hagy (2002) and Chesapeake Bay Program (CBP) estimates of Loads and Volumes for the years 1986 – 2008.

This year's calibration uses TN load and hypoxic volume data for the years 1985-2017. TN loads for the entire period were updated with new estimates based on the Weighted Regressions on Time, Discharge, and Season (WRTDS) method from the USGS, though new estimates varied little from previous ones.

Bayesian Inference – The above hypoxic model was calibrated using Bayesian Inference, an increasingly commonly used method in environmental and ecological modeling (Reckhow 1994; Malve and Qian 2006; Arhonditsis et al. 2007; Stow and Scavia 2009) because it provides a convenient way to combine existing information and past experience with models and current observations for projecting future ecosystem response. The Markov Chain Monte Carlo (MCMC) algorithm has been applied to obtain the numerical summarization of parameters (Qian et al., 2003) in a Bayesian framework.

In the original application, most of the interannual variability was captured by varying only the calibration term, v, and initial deficit, D_i, from year to year. Currently only D_i is allowed to vary with year, using measured values, and there is no calibration term. We implemented MCMC with Gibbs sampling with WinBUGS (version 1.4.3; Lunn et al., 2000), called from R (version 2.6.0; R2WinBUGS (version 2.1-8; Gelman and Hill 2007). The MCMC sampling was carried out using four chains, each with 5,000 iterations. The first 2500 iterations were discarded after model convergence and samples for each unknown quantity were taken from the next 2500 iterations using a thin (MCMC sampling interval) equal to 10 to reduce serial correlation. Statistical inference was based on the resulting 1,000 MCMC samples.

For more information on the role and importance of oxygen in the Chesapeake, see this website from the Chesapeake Bay Program: https://www.chesapeakebay.net/state/dead_zone

For more information on this and other Chesapeake Bay ecosystem forecasts, see their Eco-check website: https://ian.umces.edu/ecocheck/

For more information on the forecasting method and comparisons to other approaches:

Evans and Scavia 2011

(http://scavia.seas.umich.edu/wp-content/uploads/2010/12/Evans-and-Scavia-2010.pdf)

Liu and Scavia 2010

(http://www.scavia.seas.umich.edu/wp-content/uploads/2010/04/Liu-and-Scavia-2010.pdf)

Scavia, Kelly, and Hagy 2006

(http://www.scavia.seas.umich.edu/scavia/wp-content/uploads/2009/11/scavia__kelly__hagy_2006.pdf)

REFERENCES

Arhonditsis, G. B., S. S. Qian, C. A. Stow, C. E. Lamon, and K. H. Reckhow. 2007. Eutrophication risk assessment using Bayesian calibration of process-based models: Application to a mesotrophic lake. Ecological Modelling, 28: 215-229.

Bierman, V. J. Jr. 1980. A comparison of models developed for phosphorus management in the Great Lakes, p. 235-258. In R. C. Loehr, C. S. Martin, and W. Rast (eds.), Phosphorus Management Strategies for Lakes. Ann Arbor Science, Ann Arbor, MI.

Boesch, D. F., R. B. Brinsfeld, and R. E. Magnien. 2001. Chesapeake Bay eutrophication: Scientific understanding, ecosystem restoration, and challenges for agriculture. *Journal of Environmental Quality* 30:303-320.

Brietburg, D. L., T. Loher, C. A. Pacey, and A. Gerstein. 1997. Varying effects of low dissolved oxygen on trophic interactions in an estuarine food web. *Ecol. Monogr.* 67:489-507.

Cerco, C. F. 1995a. Simulation of long-term trends in Chesapeake Bay eutrophication. *Journal of Environmental Engineering* 121:298-310.

Cerco, C. F. 1995b. Response of Chesapeake Bay to nutrient load reductions. *Journal of Environmental Engineering* 121:549-557.

Cerco, C. F. and T. M. Cole. 1994. Three-dimensional eutrophication model of Chesapeake Bay. Technical Report EL-94-4. US Corps of Engineers, Waterways Experiment Station, Vicksburg, MS.

Cerco. C. F. and T. M. Cole. 1993. Three-dimensional eutrophication model of Chesapeake Bay. *Journal of Environmental Engineering* 119:1006-1025

Clark, J.S., S.R. Carpenter, M. Barber, S. Collins, A. Dobson, J. Foley, D. Lodge, M. Pascual, R. Peilke, Jr., W. Pizer, C. Pringle, W.V. Reid, K.A. Rose, O. Sala, W.H. Schlesinger, D. Wall, and D. Wear. 2001. Ecological forecasts: An emerging imperative, *Science* 293:657-660.

Diaz, R. J. and R. Rosenberg. 1995. Marine benthic hypoxia: A review of its ecological effects and the behavioral responses of benthic macrofauna. *Oceangr. Mar. Biol. Ann. Rev* 33:245-303.

Environmental Protection Agency (EPA). 1983. 1983 Chesapeake Bay Agreement. US Environmental Protection Agency, Chesapeake Bay Program Office, Annapolis, MD.

Environmental Protection Agency (EPA). 1987. 1987 Chesapeake Bay Agreement. US Environmental Protection Agency, Chesapeake Bay Program Office, Annapolis, MD.

Environmental Protection Agency (EPA). 1992. Chesapeake Bay Agreement: 1992 Amendments. US Environmental Protection Agency, Chesapeake Bay Program Office, Annapolis, MD.

Environmental Protection Agency (EPA). 2000. Chesapeake 2000. US Environmental Protection Agency, Chesapeake Bay Program Office, Annapolis, MD.

Evans, M.A. and D. Scavia 2010. Forecasting hypoxia in the Chesapeake Bay and Gulf of Mexico: Model accuracy, precision, and sensitivity to ecosystem change. Environ. Res. Letters. doi:10.1088/1748-9326/6/1/015001

Hagy, J. D., 2002. Eutrophication, hypoxia and trophic transfer efficiency in Chesapeake Bay. PhD dissertation, University of Maryland at College Park, College Park, Maryland.

Malone, T. C., D. J. Conley, T. R. Fisher, P. M. Glibert and L. W. Harding. 1996. Scales of nutrient-limited phytoplankton productivity in Chesapeake Bay. *Estuaries* 19:371–385.

Malone, T. C., W. Boynton, T. Horton, and C. Stevenson. 1993. Nutrient loading to surface waters: Chesapeake case study, p 8-38. In M. F. Uman (ed.), Keeping pace with science and engineering. National Academy Press, Washington, DC.

Oreskes, N., K. Shrader-Frechette, and K. Belitz. 1994. Verification, validation, and confirmation of numerical models in the Earth sciences. *Science* 263:641–646.

Qian, S. S., C. A. Stow, and M. E. Borsuk. 2003. On Monte Carlo methods for Bayesian inference. Ecological Modelling, 159(2-3): 269-277.

Reckhow, K.H. 1994. Importance of scientific uncertainty in decision-making. Environmental Management 18: 161-166.

Sarewitz, D., R. A. Pielke, Jr., and R. Byerly, Jr. 2000. Prediction: Science, Decision Making, and the Future of Nature. Island Press, Washington, DC. Introduction, p. 1–22, 299–313.

Scavia, D. 1980. The Need for Innovative Verification of Eutrophication Models, p. 214–225. In R. V. Thomann and T. D. Barnwell (eds.), Verification of Water Quality Models. U.S. Environmental Protection Agency, Athens, Georgia.

Scavia, D. and S. C. Chapra. 1977. Comparison of An Ecological Model of Lake Ontario and Phosphorus Loading Models. *J. Fish. Res. Bd. Canada* 34:286–290.

Scavia, D., D. Justic, and V.J. Bierman, Jr. 2004, Reducing hypoxia in the Gulf of Mexico: Advice from three models. Estuaries 27(3): 419-425.

Scavia, D., E.A. Kelly, and J. D. Hagy III. 2006 A simple model for forecasting the effects of nitrogen loads on Chesapeake Bay hypoxia. Estuaries and Coasts 29(4): 674-684.

Scavia, D. N.N. Rabalais, R.E. Turner, D. Justic, and W. Wiseman Jr. 2003. Predicting the response of Gulf of Mexico Hypoxia to variations in Mississippi River Nitrogen Load. Limnol. Oceanogr. 48(3): 951-956.

Valette-Silver, N. J. and D. Scavia (eds.). 2003. Ecological Forecasting: New Tools for Coastal and Marine Ecosystem Management. NOAA Technical Memorandum NOS-NCCOS-1. 120p.