Chesapeake Bay Hypoxic Volume Forecasts and Results

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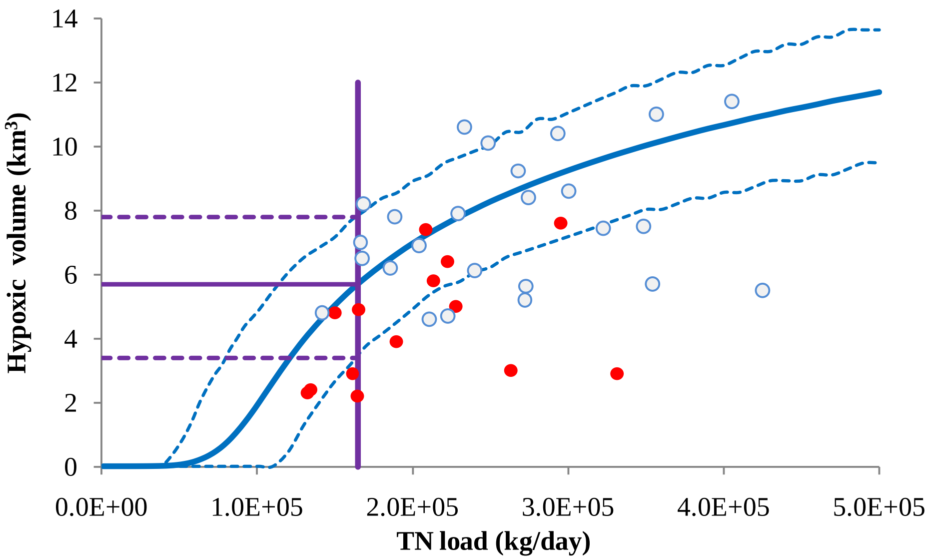
June 22, 2010

***The 2010 Forecast* - Given average Jan-May 2010 total nitrogen load of 164,624 kg/day, this summer's hypoxia volume forecast is 5.7 km^3, below average for recent years and the 6th lowest in the post-1985 period.**

The late July 2010 measured volume was * km^3 (to be published).**



- **The average forecast is 5.7 km^3.**
- **There is a 95% probability that hypoxic volume will be between 3.4 and 7.8 km^3.**

Figure 1. The forasting TN vs. Hypoxia volume. *The solid blue curve is the forecasting result (mean value); dashed blue curves are forecasting confidence intervals (2.5 and 97.5% values). The open circles are observed values for 1985-2008 and closed circels are observed values before 1985. The model was calibrated to the post-1985 period because of a regime shift around that time. The vertical line represents the 2010 Jan-May TN load of 164,624 kg/day and the horizontal lines show the forecast hypoxic volume (mean and confidence intervals) associated with this load.*

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

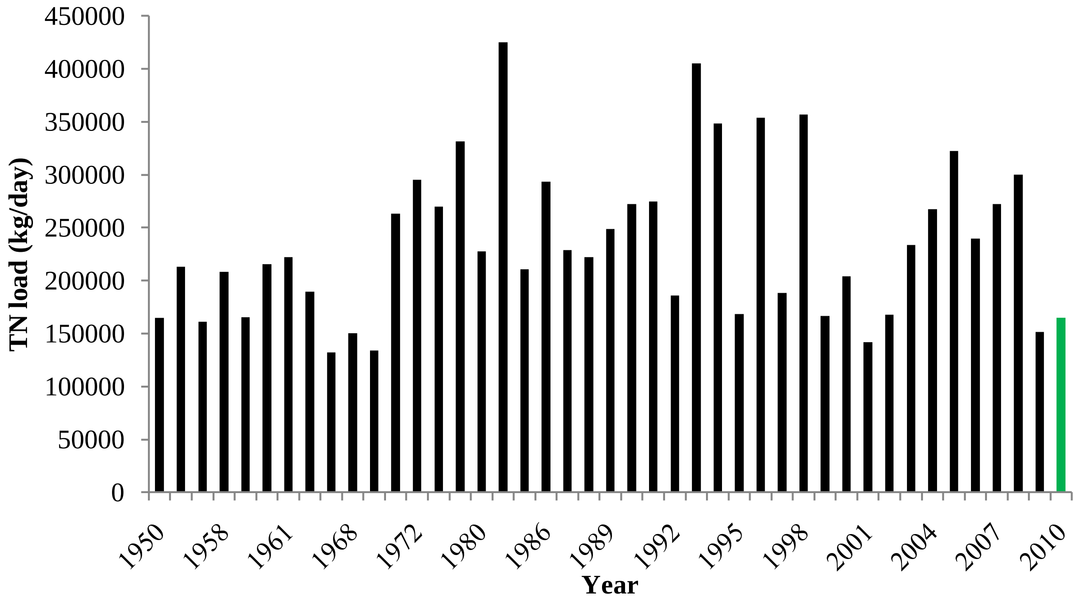


Figure 2. The Susquehana River TN Load (kg/day), the recently measured laod for 2010 is in green.

These loads have driven the increase in the volume of water with oxygen concentrations below 2 mg/l, the definition of hypoxia for the Bay. The graph below of estimates of those volumes show how it has increased during this same time period.

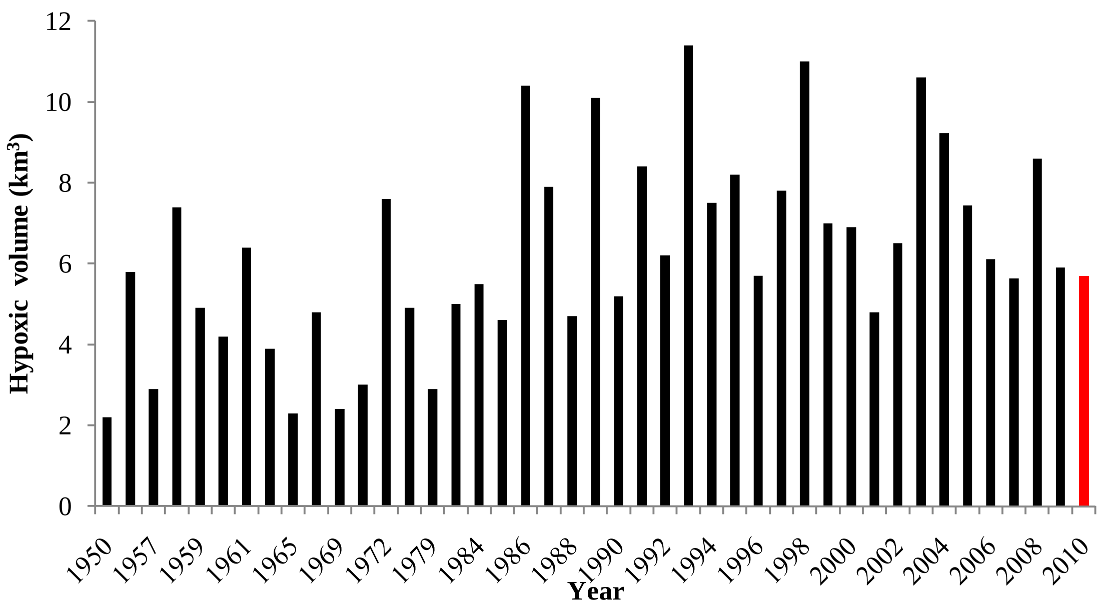


Figure 2. The observed hypoxic volume (10^3 km^3), the predicted couume in 2010 is in red.

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

The model **-** The forecast was done with 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 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). In this application, the parameter, v, is a calibration term that integrates all model and data uncertainty.

Recalibration - The original model was calibrated and tested against 1950-2003 nitrogen load and hypoxic volume estimates assembled by Hagy (2002). 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; the model was recalibrated for this application to the new 1986-2008 estimates.

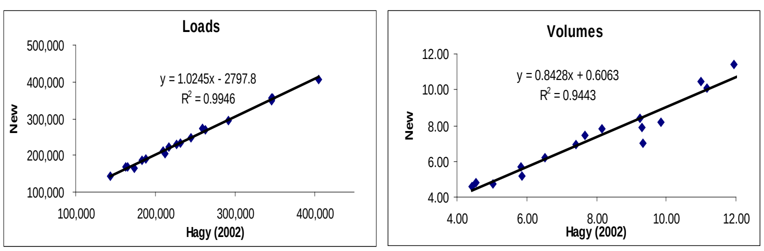


Figure 3. Comparison of Hagy (2002) and CBP estimates of Loads and Volumes

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/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.

As 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 (Figure 4). Therefore, 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

20,000 iterations (first 10,000 discarded after model convergence); and samples for each unknown quantity was taken from the next 10,000 iterations using a thin (MCMC sampling interval) equal to 40 to reduce serial correlation. Statistical inference was based on the resulting 1,000 MCMC samples.

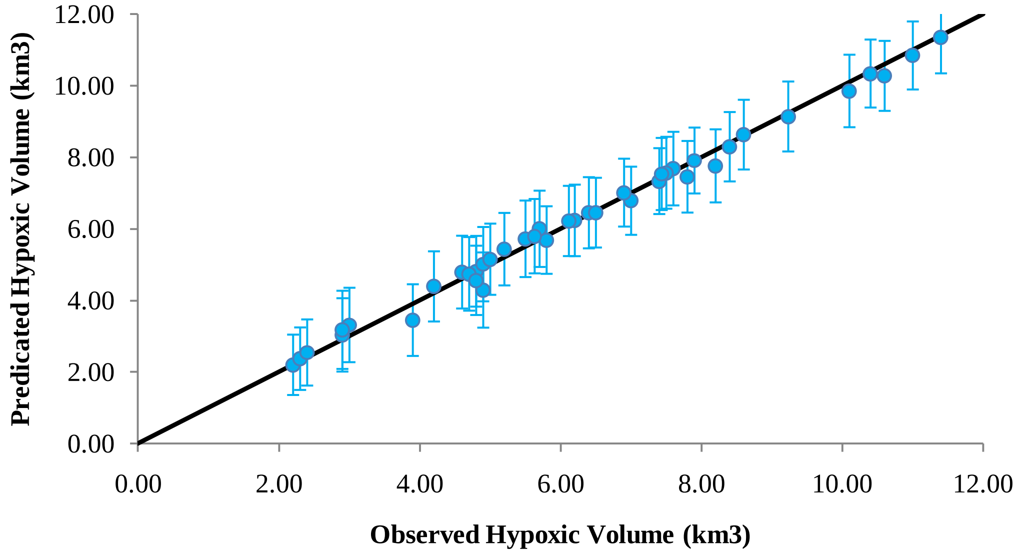


Figure 4. Bayesian Predicted vs. Observed Volume. *The error bars represent the predicated standard deviation.*

The parameters k_1, K and F used the Bayesian estimated posterior distributions from the model calibration process; v and D_i use the mean posterior distributions of the post-1985 period (please refer to the Table below) reflecting the documented regime shift in the relationship between nitrogen load and hypoxic volume.

Table 1 The parameters used for forecasting

	Mean	S.D.	2.5%	25%	50%	75%	97.5%
v	2.738	0.334	2.056	2.519	2.736	2.946	3.408
Di	1.401	0.705	0.049	0.908	1.413	1.914	2.697
K	0.636	0.039	0.555	0.614	0.637	0.660	0.715
k_1	0.152	0.034	0.088	0.130	0.151	0.173	0.224
F	0.969	0.027	0.900	0.957	0.978	0.989	0.999

For more information on the role and importance of oxygen in the Chesapeake, check out this website from the Chesapeake Bay Program:

http://www.chesapeakebay.net/dissolvedoxygen.aspx?menuitem=14654

For more information on this and other Chesapeake Bay ecosystem forecasts, check out their Eco-check website: http://www.eco-check.org/

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

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

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

[Scavia, Kelly, and Hagy 2006](http://www.snre.umich.edu/scavia/wp-content/uploads/2009/11/scavia__kelly__hagy_2006.pdf)

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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.

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. <u>Prediction: Science, Decision Making, and the Future of Nature</u>. 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.