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A Simple Model for Forecasting the Effects of Nitrogen Loads on Chesapeake Bay Hypoxia

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ABSTRACT: The causes and consequences of oxygen depletion in Chesapeake Bay have been the focus of research, assessment, and policy action over the past several decades. An ongoing scientific re-evaluation of what nutrient load reductions are necessary to meet the water quality goals is needed. While models can provide insights and advice for public policy on load reduction goals, they are caricatures of nature, and it is wise to use independent modeling approaches. In this paper, we describe our simple, biophysically based model that offers a middle ground between statistical models and complex dynamic models. Our model suggests that the target total nitrogen load reduction of 35% will reduce hypoxic volumes by 36–68%, which, on average (53% or 3.4 km^3) is lower than values reported for 1950–1970 (4.2 km^3), and roughly half of the values reported for 1980–1990 (7.2 km^3). By pursuing a simple model construct, we were able to quantify uncertainty to a greater extent than is possible with the more complex numerical models. Yet, by retaining some mechanistic detail we could validate the model against state variables and process rates, an advantage over simple regressions.

Introduction

The causes and consequences of oxygen depletion in Chesapeake Bay have been the focus of research, assessment, and policy action over the past several decades (Boesch et al. 2001). During that period, this 11,000-km^2 estuary has been the subject of a series of intergovernmental agreements (EPA 1983, 1987, 1992, 2000) focused on reducing the effects (Diaz and Rosenberg 1995; Brietburg et al. 1997) of nutrient overenrichment (Malone et al. 1993) from its 167,000-km^2 watershed. The latest agreement, Chesapeake 2000 (EPA 2000), recommits the parties to nutrient reduction goals established under the 1987 agreement. The 1987 goal stipulated a 40% reduction of nitrogen and phosphorus loads relative to a baseline of the 1985 point source loading and diffuse source loading expected in an average rainfall year during the 1980s. Chesapeake 2000 also adopts the broader goal of taking sufficient action by 2010 to correct nutrient-based and sediment-based water quality problems, such that Chesapeake Bay is no longer designated as impaired under the U.S. Clean Water Act (EPA 2000). An ongoing scientific reevaluation of whether the load reduction goals are adequate to meet the water quality goals will likely be needed.

Models have played an important role in advising the public policy debate on load reduction goals (Malone et al. 1996; Boesch et al. 2001) by predicting water quality responses expected from different nutrient load reduction scenarios, by providing insights into internal dynamics affecting oxygen and nutrient concentrations, and by evaluating potential responses to changes in key drivers such as freshwater inflow. While models can provide such insights, and their use in ecological forecasting is growing (e.g., Clark et al. 2001; Valette-Silver and Scavia 2003), they must always remain caricatures of nature, subject to both known and unknown uncertainties and errors (Oreskes et al. 1994; Sarewitz et al 2000). For that reason, it is wise to use several independent models and modeling approaches for guiding important and expensive policy action. Such comparisons among multiple modeling approaches have been useful for analysis of eutrophication in other coastal systems (Scavia et al. 2004) and in the Great Lakes (Scavia and Chapra 1977; Bierman 1980).

Chesapeake Bay models for guiding policy on nutrient loading have taken a variety of forms. Some have used complex mechanistic ecological simulation models imbedded within hydrodynamic models to simulate detailed biophysical interactions and dynamics (Cerco and Cole 1993, 1994; Cerco 1995a,b). Others have used statistical approaches correlating properties of management interest, such as anoxic and hypoxic volumes and freshwater and nitrogen loads (Hagy et al. 2004). Both approaches are useful, yet both have limitations. Complex mechanistic models aid in understanding the internal dynamics of the ecosystem and in discerning

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complex effects in three dimensions. They generally involve many parameters, are difficult to calibrate, are limited in their ability to quantify uncertainties, and require very large input data sets (e.g., winds, solar radiation, river flows). The required inputs are hard to compile historically and virtually impossible to specify on the multidecadal time scales required for forecast scenarios. Evaluating a range of input conditions (e.g., wet versus dry years; Cerco 1995a,b) can provide useful bounds on forecasts; whereas essential relationships, such as the effects of hydrodynamics and nutrient loads on hypoxia have been successfully reproduced by mechanistic models, the simulations depend upon myriad assumptions about model structure and parameterizations. This is not to discount the value of simulation models, but rather to point out that mechanistic models, as they have been implemented for management for the Chesapeake Bay, have tended to be very complex because so much is asked of them.

Statistical approaches (e.g., regression), on the other hand, address relationships directly and can usually quantify the uncertainty in relationships. They are only correlative and do not represent biophysical processes.

Our approach offers a middle ground, using a simple model that is based in biophysical processes and focused directly on key variables of management interest: hypoxic volumes and nitrogen loads. With this rather simple model formulation, we can limit the number of parameters, tightly constrain the uncertainties, create functional as opposed to purely statistical relationships between the key management control variable (nutrient loads) and the expected environmental response (hypoxic volume), and apply statistical methods to quantify model uncertainty.

Each of the three modeling approaches is ultimately grounded in field observations and provides quantitative relationships among important properties. Their comparison can be instructive from both modeling and policy guidance perspectives. In this paper, we describe our simple, biophysically based model and compare its forecasts and scenarios with those of previous work and existing policy goals.

Methods

THE MODEL

The model applied in this study was originally created to simulate oxygen depletion in rivers downstream from a point source of organic matter (biochemical oxygen demand). It has been applied extensively to rivers and estuaries (Chapra 1997) as well as to hypoxia in the northern Gulf of Mexico (Scavia et al. 2003, 2004). In this particular formulation, the model simulates the downstream advection and decomposition of organic matter originating from a point source. It also simulates the oxygen consumed during that decomposition and reaeration from the atmosphere. To simplify solution of the differential equations, bottom water oxygen is expressed as a deficit from the surface layer concentration. Mass-balance equations for oxygen-consuming organic matter and dissolved oxygen (DO) deficit are:

$$dB/dt = -v\, dB/dx - aB \tag{1}$$

and

$$dD/dt = -v\, dD/dx + aB - bD \tag{2}$$

where B is the concentration in oxygen equivalents of the decomposing organic matter (mg l^{-1}), D is the DO deficit (here defined as deviation from typical surface water concentration of 5 mg l^{-1}), t is time (d), x is the distance from the point source of B (km), a and b are first-order rate constants for organic matter decomposition and vertical oxygen flux, respectively (d^{-1}), and v represents stream advection (km d^{-1}).

The steady state solutions are:

$$B = B_0 e^{-ax/v} \tag{3}$$

$$D = [a/(b-a)]B_0\left[e^{-ax/v} - e^{-bx/v}\right] + D_i e^{-bx/v} \tag{4}$$

where B_0 is the concentration in oxygen equivalents of decomposing organic matter at the point source and D_i is the oxygen deficit at the point source.

Our application to predict summer hypoxia in Chesapeake Bay assumes that there is a correspondence between the measured extent of summer hypoxia and that which would be achieved at steady state. Several other assumptions are also necessary. We assumed that: horizontal transport results from advection rather than longitudinal dispersion; Susquehanna River total nitrogen (TN) loading can be used as a surrogate for (i.e., proportional to) the load of subpycnocline biological oxygen demand; subpycnocline oxygen consumption can be modeled as a first-order process proportional to organic matter concentration; and oxygen flux across the pycnocline can be modeled as a first-order process proportional to the difference between surface and bottom layer oxygen concentrations. Tests of each of these assumptions are described below.

We applied the model to calculate summer steady state subpycnoclinal oxygen concentration profiles along the main stem of the Chesapeake Bay for each year from 1950 to 2003. In reality, the physical and biological processes relating external load of nutrients to organic matter production, transport, and fate, and to the eventual development of hypoxia, are dynamic and complex. Our resulting ability to accurately simulate interannual variability helps validate use of the point source approximation, parameterized estuarine physics, and our steady state assumption. Expanding beyond these simplifications with, for example, multilayered, time-dependent models, may add further insight, but they also require significantly more parameter estimation, calibration, and field data.

NITROGEN VERSUS PHOSPHORUS LIMITATION AND PARAMETERIZED PHYSICS

Although bioassay experiments have shown that primary production in portions of the Chesapeake Bay is sometimes limited by phosphorus (Fisher et al. 1992), empirical work (Malone et al. 1996; Hagy et al. 2004) and model simulations (Cerco 1995b) suggest that primary production and hypoxia in the middle and lower reaches are controlled principally by nitrogen. For the purposes of this modeling effort, we focus only on nitrogen. In systems with both nitrogen and phosphorus limitation, it is important to control sources of both nutrients (Paerl et al. 2004).

A controlling feature of Chesapeake Bay circulation is that in this vertically stratified estuary, surface waters flow seaward and bottom waters flow landward upstream (Fig. 1). Nitrogen enters the upper bay at the surface via the Susquehanna River, travels seaward, and is converted to phytoplankton biomass under nitrogen limitation. A portion of this production settles below the pycnocline and, as those waters travel up estuary, biomass decomposition consumes oxygen. In the parlance of the river model we use here, the organic matter that sinks from the down-estuary flowing surface production is a distributed load to the up-estuary moving bottom waters. While there are versions of this model that can incorporate distributed sources, its use would require data or parameterization of variable downstream surface production, transport, and sedimentation. Rather than add these additional details, which moves us toward the more complex eutrophication models and the attendant parameterizations and data requirements, we instead introduce the organic matter load as a single point source at the southern end of the mid Bay region (37°48′N, 76°W; c. 220 km from the Susquehanna River mouth), and model the upstream movement of subpycnocline water (Fig. 1). This approach should work well because surface layer net plankton production (e.g., Kemp et al. 1997) and chlorophyll concentrations (e.g., Harding and Perry 1997), while both stimulated by the Susquehanna River load, are considerably higher in the mid and lower Bay regions. Kemp et al. (1997, their Fig. 11) demonstrated that 92% of the annual organic matter budget for the whole Bay is from phytoplankton production. This indicates that production down Bay, rather that organic matter flowing out of the river, is the effective point source especially when one considers the distribution of primary production. Harding et al. (2002) show that euphotic zone chlorophyll *a* is 2–6 times higher in the middle and lower Bay than in the upper Bay and summer phytoplankton production (m^{-2}) is about 3-fold greater down Bay than in the upper Bay. Because the middle and lower Bays are also much larger, Kemp et al. (1997) computed that annual gross primary production in the middle and lower Bay is 29 times the annual production of the upper Bay. Only the lower Bay has positive net production, enabling it to export organic matter landward to support oxygen depletion. Deposition of organic matter to sediments in the hypoxic mid Bay region appears likely to be subsidized by net production from the lower Bay (Hagy et al. 2005).

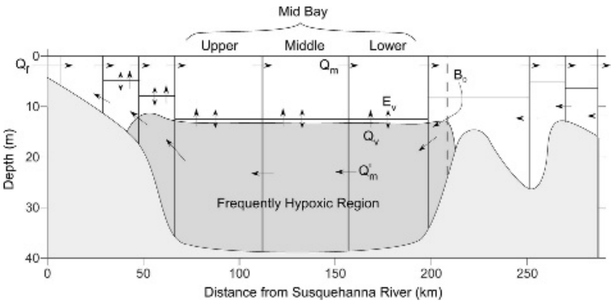

Fig. 1. Schematic of the internal flows estimated by the salt-and-water balance box model developed for Chesapeake Bay. The depth profile is a smoothed maximum depth profile. Dark gray indicates the region most frequently affected by hypoxia during summer. Arrows indicate advection; double arrows indicate vertical diffusive exchanges. The major freshwater and nitrogen source (Susquehanna River) is indicated by Q_f. One example of each type of flow (landward advection [Q'_m], seaward advection [Q_m], upwelling [Q_v], vertical exchange [E_v]) is labeled. The point where the initial biochemical oxygen demand (B_o) enters the landward flow in the oxygen model is indicated the curved arrow.

NITROGEN LOADS AND OXYGEN DEMAND

From 1945 to 1978, January-May average TN loads from the Susquehanna River at Conowingo, Maryland (Fig. 2), were computed using empirical relationships from corresponding nitrate loads at Harrisburg, Pennsylvania, as reported by Hagy et al. (2004). For 1979 to 2004, TN loads are as reported by the U.S. Geological Survey River Input Monitoring Program (USGS unpublished data). These

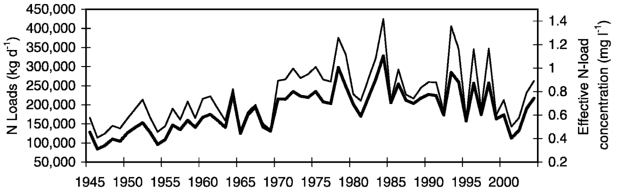

Fig. 2. Total nitrogen (TN) loads (light line) from the Susquehanna River at Conowingo, Maryland, and effective nitrogen-load concentration (bold line). Effective TN load concentration is the TN load divided by the up-estuary subpycnocline flow.

estimates are based directly on frequent measurements of Susquehanna River TN concentrations at Conowingo and were derived using the 7-parameter log-linear regression model described by Cohn et al. (1989). Although there are many tributaries to Chesapeake Bay, only the Susquehanna River and Potomac River estuaries export substantial TN loads into the main stem Bay. Boynton et al. (1995) estimated that the Potomac estuary exports 14 Gg TN yr^{-1} into the main stem. Susquehanna River TN loading accounts for ca. 80% of aggregate TN inputs to the main stem of Chesapeake Bay.

For use in the model, nitrogen load is converted to a subpycnocline concentration of oxygen demand in the following way: we divide the January–May average loading rate by the upstream flow of subpycnocline bottom waters (Hagy 2002) from the same period to obtain an estimate of average nitrogen concentration, which we assume is proportional to the concentration of oxygen demand as described below (Fig. 2).

INTERPOLATED DO PROFILES, INITIAL DEFICIT, AND HYPOXIC ZONE VOLUMES AND LENGTHS

Hypoxic volumes, defined as the volume of water with oxygen concentrations below 2 mg l^{-1}, were computed by interpolating DO observations to populate a regular grid with dimensions of 1 m in the vertical by 1 km in the horizontal. A two-step interpolation scheme was used in which interpolation proceeded first in the vertical direction, then horizontally across constant depths (Hagy et al. 2004). Hypoxic volumes were computed from gridded DO values by summing tabulated cross-sectional volumes for grid cells for which DO was less than 2.0 mg l^{-1}. Down estuary profiles of subpycnocline oxygen concentrations were also extracted from the interpolated values and used to estimate the initial oxygen deficit (for Eq. 4) and to compute the length of the hypoxic region. For years with only one summer cruise (1950–1980), we used those data for model comparisons. For years with multiple cruises (1984–2001), we used all July data for profiles and average July values for length and volume.

VERTICAL FLUX ESTIMATES

Estimates of the vertical flux of O_2 through the pycnocline were computed, for comparison to our model estimates, by estimating the summer average rate of turbulent diffusive exchange through the pycnocline for a recent period (1985–1998), then applying these rates to historical differences between surface and bottom layer O_2. Vertical exchange was estimated using a salt-and-water-balance box model, adapted from Hagy et al. (2000), and applied to Chesapeake Bay by Hagy (2002). A brief description follows. Chesapeake Bay was divided into 9 segments. All but the most upstream segment were further subdivided at the average depth of the pycnocline. Seaward advection in the surface layer from segment m to segment $m+1$ is denoted Q_m and was computed via

$$Q_m = \left(s'_{m+1} \left[\sum_{j=1}^{m} Q_{fj} + Q_r \right] + \left[\sum_{j=1}^{m} V_j \frac{ds_j}{dt} + \sum_{j=2}^{m} V'_j \frac{ds'_j}{dt} + \sum_{j=1}^{m} V_{tm} \frac{ds_{tm}}{dt} \right] \right) / \left(s'_{m+1} - s_m \right) \tag{5}$$

which is Eq. 11 in Hagy (2002, Chapter 2). Terms are defined following the convention of Pritchard (1969) and also used by Hagy et al. (2002): s_m and s'_{m+1} are the average salinity in the surface layer of segment m and in the bottom layer of segment $m+1$, respectively; Q_r and Q_{fj} are freshwater inflows from the Susquehanna River into segment 1 and from other sources into downstream segments; summation terms of the general form $\sum V(ds/dt)$ are the change in total salt content in surface layer boxes, bottom layer boxes, and tributaries and embayments adjoining the Bay along its axis. Landward and vertical advection was computed via a continuity (water balance) assumption by subtracting freshwater inflows from seaward flows. Continuity in the landward circulation also provides for computation of upwelling flows. With all the advective flows computed, vertical diffusive exchanges, E_{vm}, were computed from the salt balance for subpycnocline boxes via

$$\begin{aligned} E_{vm} = & \left(-V'_m ds'_m/dt + Q'_{m+1} s'_{m+1} \right. \\ & \left. - Q_{vm} s'_m - Q'_m s'_m \right) / \left(s'_m - s_m \right) \end{aligned} \tag{6}$$

which is Eq. 12 in Hagy (2002, Chapter 2). Q_{vm} and Q'_m are the upwelling flow within segment m and the landward advective flow from segment m to segment $m-1$, respectively. Average bottom layer salinity in segment m is s'_m; $V'_m\, ds'_m/dt$ is the corresponding rate of change of salt content.

Computed vertical exchange coefficients (E_{vm}) were divided by the pycnocline area, A, of the corresponding model segments to compute the vertical exchange rates. The vertical flux was computed as $(E_{vm}/A)\Delta O_2$ (units: g O_2 m^{-2} d^{-1}) where ΔO_2 is the difference between average O_2 in the surface and bottom layer. Volumetric fluxes (mg l^{-1} d^{-1}) and first-order exchange coefficients (b in Eq. 4; d^{-1}) were calculated by dividing the vertical flux and E_{vm}/A by the thickness of the bottom layer. Solution of Eq. 4 assumes a constant diffusion coefficient (b) from the location of the point source to each particular distance downstream. Because we know this coefficient varies over the length of the estuary, we approximated this effect by using values averaged from the location of the point source to the solution point for each calculation.

SUBPYCNOCLINE O_2 CONSUMPTION

The consumption of O_2 below the pycnocline in each of three mid Bay regions (Fig. 1) was computed by mass balance using physical transport rates obtained from the box model described above and average O_2 concentrations computed from historical observations (Hagy 2002; Hagy et al. 2004). The mass balance is described by

$$V'_m \frac{dc'_m}{dt} = Q'_{m+1} c'_{m+1} - \left(Q_{vm} + Q'_m\right) c'_m - E_{vm}\left(c'_m - c_m\right) + P'_m \qquad (7)$$

where c'_m and c'_{m+1} are the concentrations of DO in a bottom layer box and the next seaward bottom layer box, respectively, P'_m is the net production or consumption of O_2, and the other terms are as defined above. Computed rates of bottom layer O_2 consumption have units of mass per time (g s^{-1}), but were scaled by the bottom layer volume and appropriate constants to obtain values comparable to the model output (mg l^{-1} d^{-1}).

LENGTH AND VOLUME PREDICTIONS

We calculated the length of the modeled hypoxic region by determining the extent of the profile with oxygen concentrations below 2 mg l^{-1}. Predicted lengths were converted to hypoxic region volumes with the regression equation determined from observations (Fig. 3; $V = 0.00391L^2$, $r^2 = 0.97$).

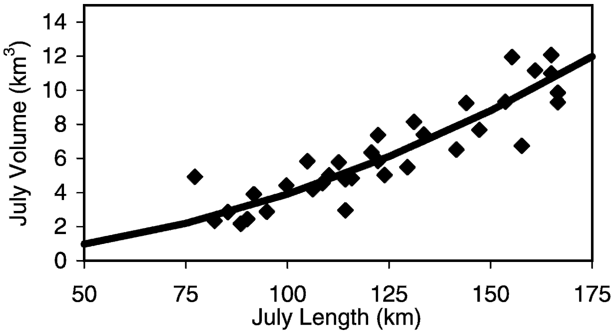

Fig. 3. Relationship between length and volume of the hypoxic region. Regression results: $V = 0.000391L^2$; $r^2 = 0.97$).

STOICHIOMETRY, SEDIMENTATION, DECOMPOSITION, CROSS-PYCNOCLINE FLUX, AND ADVECTION

We convert nitrogen entering the Bay to organic carbon via the Redfield C:N ratio (106:16 or 5.67 gC/gN), assume a proportion (f) of it settles below the pycnocline, and then convert it to a biological oxygen demand via O_2:C = 0.9, or 2.4 gO_2/gC. Clearly, not all incoming nitrogen is actually converted to algal biomass. Nitrogen that is converted is often recycled and converted several times. Similarly, not all of the organic matter is respired. Throughout this effort, we chose to use simplifying assumptions consistent with our applications, The objective is to test the assumption that organic load to the bottom waters are proportional to river nitrogen load; use of the Redfield ratio and respiration ratio provide a basis for this proportionality. We hold the first-order decomposition rate coefficient (a) constant for all segments of the Bay and across all years. The exchange coefficient (b) for cross-pycnocline flux was held constant across all years but allowed to vary along the axis of the main stem proportional to values calculated from a box model as described above. The advection term, v, represents the up-estuary flow of subpycnocline water; it was held constant for all segments of the Bay and for all years in the initial application. The coefficients v, f, a, and b were determined initially by searching systematically through ranges of their values to arrive at values that minimize the sum of squares of the difference between modeled and observed hypoxic volumes. Subsequently, v was the only model coefficient that was varied from year to year for the refined calibration. As described below, variation in the advection term required in the year-to-year refined calibration was used to test the model's ability to simulate individual years and to bound the stochastic forecasts.

Results

MODEL CALIBRATION AND TESTING

Holding all coefficients constant over all years and searching for the best fit to the data (calculated as $1 - \Sigma(P_i - O_i)^2/\Sigma(O_i - O_m)^2$, where P_i is the ith prediction, O_i is the ith observation, and O_m is the observation mean), the model explains 35% of the interannual variability in hypoxic zone volume.

These results can be compared to 37% of the variation in hypoxia volume explained by partial regression on load and time (Hagy et al. 2004).

The parameter estimation indicated that the best fit to the data results with 85% of net production settling below the pycnocline. If we convert an estimate of surface layer net plankton metabolism (= surface layer plankton production - respiration) in the mid Bay for March–April (= 1.6 $gO_2\ m^{-2}\ d^{-1}$, Table 5 in Kemp et al. 1992) to carbon with an O_2:C ratio of 2.7 (atomic O_2:C = 1.0), we obtain an estimated net production of 0.6 $gC\ m^{-2}\ d^{-1}$. There are few estimates of sedimentation flux for this physically complex system. Boynton et al. (1993) estimated March-April sedimentation flux from trap collections in the mid Bay region as 0.7 $gC\ m^{-2}\ d^{-1}$. Hagy et al. (2005) estimated sedimentation flux for the same time period and region from changes in sediment chlorophyll data as 0.5 $gC\ m^{-2}\ d^{-1}$. These sedimentation values are 80–120% of net surface production, similar to or slightly higher than our best-fit estimate of the sedimented fraction of production (85%). Considering that our value is for the entire spring–summer period, whereas this estimate is for spring, when above average deposition may be expected, the estimates are at least consistent.

While the coefficient values from the parameter estimation procedure provided the best fit to the hypoxic volume data, there were significant differences between observed and modeled down estuary oxygen profiles in many years. Even when the modeled length of the main stem profile with values below 2 $mg\ l^{-1}$ was similar to observed length, the modeled location within the Bay would be displaced relative to observed. For this reason, we explored the model further by adjusting only the advection term each year and comparing modeled and observed subpycnocline oxygen profiles (Fig. 4) and modeled and measured volumes (Fig. 5). While the model was not able to match the observed profiles in all years, given the constraints of varying only one coefficient, it improved the model such that it explained 81% of interannual variability. Even in years (e.g., 1950, 1952) where our predicted volumes are considerably below observed values, it is only because our profiles did not reach 2 $mg\ l^{-1}$; the simulated profiles were actually quite similar to the observed ones. This demonstrates the model's ability to reproduce individual years quite accurately when advection is allowed to vary year by year. The advection values obtained using this calibration exercise were between 1.8 and 8.0 $km\ d^{-1}$, similar to those measured in 1995–1999 with the mid-bay mid-channel buoy of the Chesapeake Bay Observing System (CBOS) at 18.5 m depth (1.7–6.9 $km\ d^{-1}$; Boicourt unpublished data reported in Hagy 2002).

This version of the model also performed well when compared with average cross-pycnocline flux from the mid Bay region derived from field observations for the upper, middle, and lower portions of the mid Bay region (Fig. 6). It also matched estimates of subpycnocline oxygen consumption rates derived from the same data sets. Both these model estimates and those from oxygen balance calculations are similar to, but lower than the range reported by Kemp et al. (1997). They reported sediment and lower water column oxygen consumption rates (including sulfate reduction expressed in O_2 equivalents) for the mid Bay region in 1990–1992. Combining the reported bottom water plankton respiration rates (Kemp's Fig. 3) with sediment O_2 consumption rates converted to volumetric rates assuming an average 6.5-m subpycnocline depth, we calculate a total metabolic rate between 0.08 and 0.5 $mg\ O_2\ l^{-1}\ d^{-1}$.

While the model performed well in representing year-to-year variability in down-estuary oxygen profiles and hypoxic zone volumes (Figs. 4 and 5) it is possible for models to reproduce state variables (oxygen in this case) quite accurately for the wrong reasons. This can happen most readily when process rates are all too high or too low, but compensating (Scavia 1980). The fact that our model reproduces the key state variable (DO) as well as both key flux estimates, and with advection rates similar to measured ones, lends credence to its results and confidence in its forecasts.

Forecasts and Discussion

With our model calibrated to oxygen dynamics and the key processes controlling them, we are able to provide forecasts of potential changes in hypoxic volume for a range of nitrogen loading rates. Because most uncertainty in our model is in the advection coefficient and because it is not possible to know what its value will be in the future, we provide ensemble forecasts with Monte Carlo analysis by conducting 500 simulations with the value for advection drawn from a normal distribution with mean and standard deviation (SD) of 3.6 and 0.9 $km\ d^{-1}$, a good representation of both the values used in the model calibration (Fig. 7) and observed at the CBOS station. It may be possible to take advantage of potential relationships between river inflow and up-estuary sub-pycnocline flow, but that would only be useful in refining hindcasts and simulations. Our intent here is to provide a basis for forecasts and our inability to predict changes in river flow would limit use of its relationship to advection in forecasts. Our stochastic approach allows us to estimate the mean and variability of hypoxic volume expected due to differences in the physical environment given a specified riverine

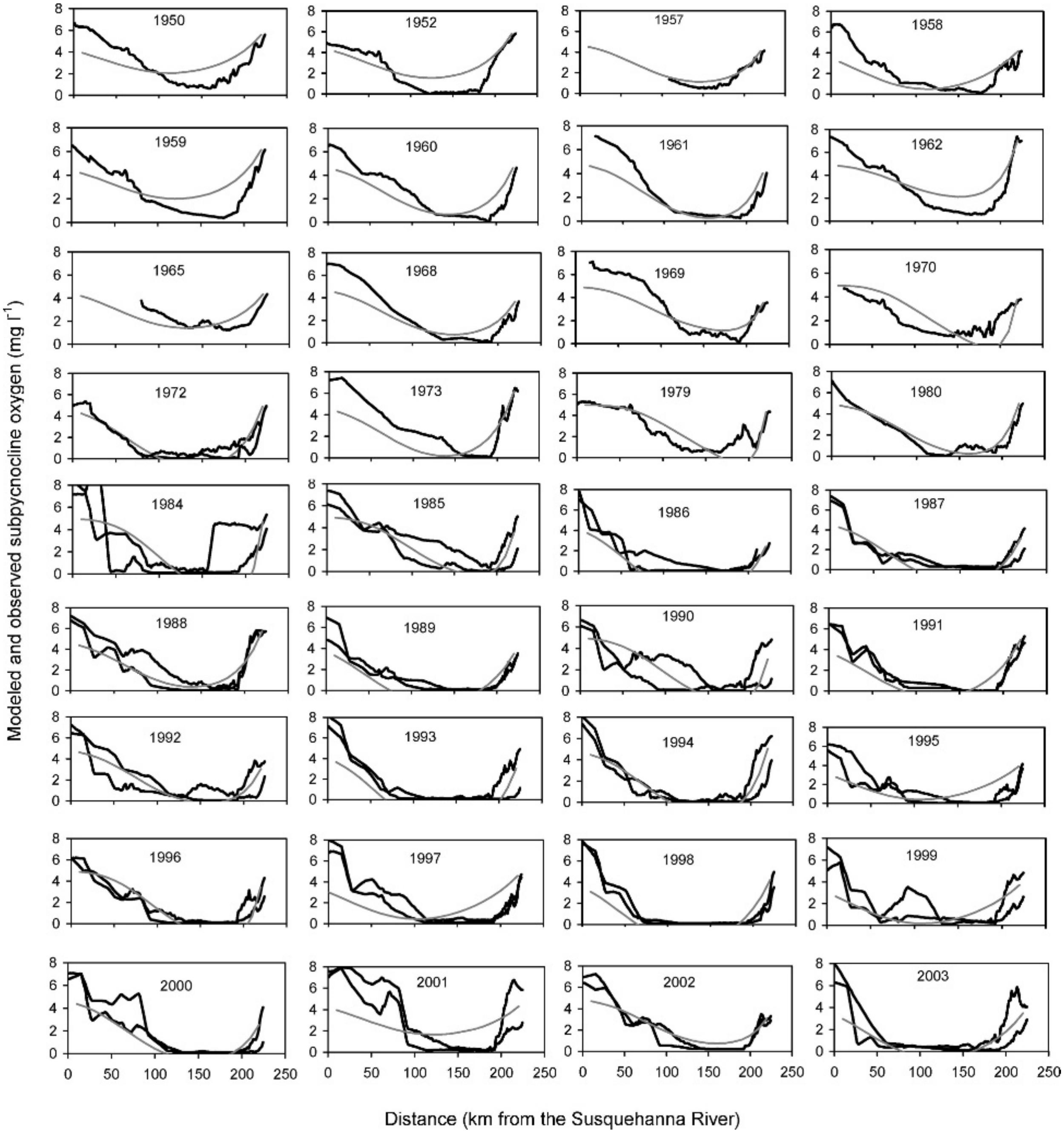

Fig. 4. Modeled and observed subpycnocline oxygen (mg l^{-1}) profiles. Light lines represent model output; dark lines represent July observations. Distance is kilometers downstream from the Susquehanna River.

nitrogen load. If we wish to achieve, on average, a specified hypoxic volume goal, the appropriate nitrogen load is that for which the mean of the Monte Carlo ensemble forecasts is the hypoxic volume goal. On the other hand, if we wish to achieve the hypoxic volume goal in most years, we must achieve the lower riverine nitrogen load for which the mean + 1 SD of the Monte Carlo ensemble forecasts of hypoxic volume is equal to the goal. In this case, the hypoxic volume in an average year will be lower than the target.

The forecast model also requires an initial oxygen deficit (deviation from 5 mg l^{-1}) at the point of the organic load. The observed deficits varied between -2.0 and 2.6 mg l^{-1} (mean = 0.9; SD = 1.1). To test for potential confounding factors related to

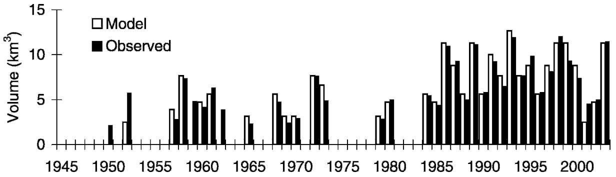

Fig. 5. Comparison of modeled (open bars) and observed (solid bars) hypoxic volume for the calibrated model with the advection term adjusted for each year.

loads and flow, we regressed the initial oxygen deficit on spring nitrogen loads and spring and annual freshwater loads. The resulting r^2 values of 0.02, 0.04, and 0.002, respectively, showed no significant correlation. That there was no clear relationship between loading or river flow and the initial oxygen deficit was somewhat surprising given the general trend toward increased hypoxia in Virginia waters in recent years (Hagy et al. 2004). The weak correlation may reflect a variable degree of increased vertical mixing of the water column at our model boundary between the Potomac and Rappahannock Rivers, which results from the rapid shoaling of the relict Bay channel (Chao and Paluszkiewicz 1991; Roman et al. 2005). In 1999, Chesapeake Bay's summer hypoxic zone was clearly bifurcated in this region by a span of normoxic bottom water (USEPA Chesapeake Bay Program unpublished data). Although one would expect that this hydrographic feature of Chesapeake Bay, referred to as the hydraulic control region, would tend to confine hypoxia and other consequences of nutrient enrichment to Maryland waters of the Bay, this tendency appears to have been overcome. Because there was no clear pattern in these values, we drew values for this factor for use in the Monte Carlo forecasts from a normal distribution with mean and SD from the observations (Fig. 7).

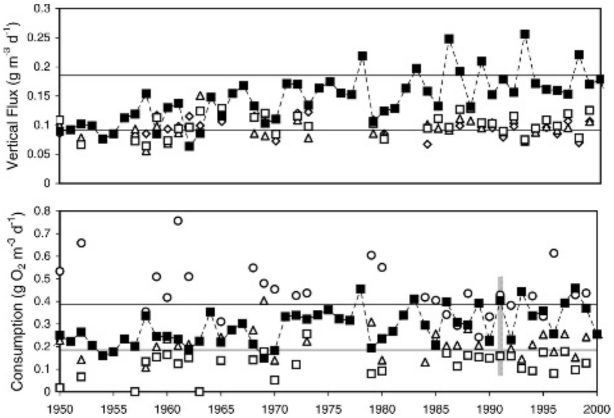

Fig. 6. Upper: Comparison of modeled vertical O_2 flux estimates with those estimated from field data. Vertical fluxes are distributed into the mean height of the lower layer, giving volumetric units. Lower: Comparison of modeled O_2 consumption with estimates from field data. Solid squares and dashed line are model values from the 70–210 km region. Horizontal lines represent mean ± one standard deviation of the model values across all years. Symbols represent the upper (diamond), middle (triangle), and lower (square) portions of the mid Bay region (Hagy 2002). Vertical bar in lower panel for 1991 represents measured oxygen consumption rates from Kemp et al. (1997).

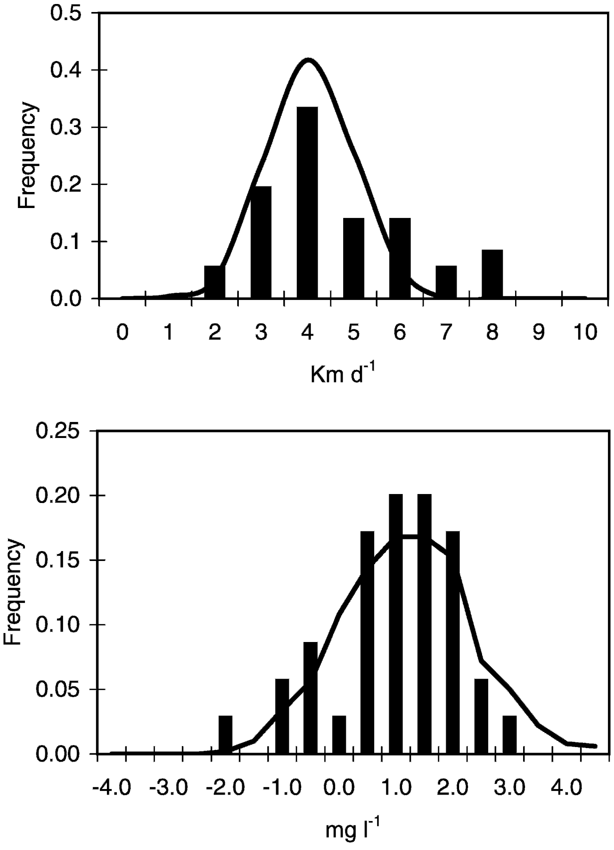

Fig. 7. Monte Carlo input frequency distributions for advection and initial oxygen deficit. Bars represent frequency distributions from advection values used in the calibrated model and oxygen deficit measured at km 220. Lines represent frequency distributions of values used in the Monte Carlo analysis.

The current Chesapeake Bay agreement (EPA 2000) recommits the signatories to reduce controllable (nonforest) sources of nitrogen by 40% from a baseline defined by the 1985 point source loads and nonpoint source loads in an average rainfall year, the same reductions agreed upon in the 1987 Chesapeake Bay Agreement (EPA 1987). The reduction translates to a 35% reduction in total load (Boesch et al. 2001; Randall 2001). To accommodate the specification of average year for nonpoint sources, in this analysis we compare all reductions to average 1980–1990 conditions; 262,881 kg N d^{-1}. A 35% reduction from these values corresponds to 170,873 kg N d^{-1}.

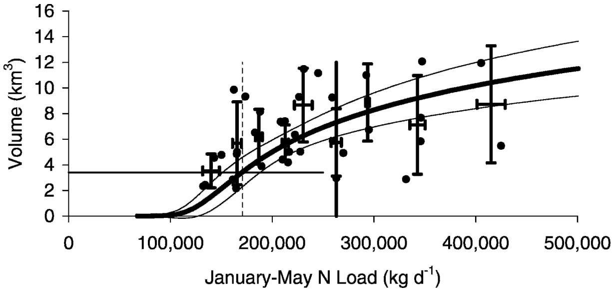

Fig. 8. Ensemble forecasts of hypoxic volume (DO $<$ 2.0 mg l^{-1}) as a function of TN loading from the Susquehanna River. Solid curves represent the mean ± one standard deviation of 500 simulations from the Monte Carlo analysis. Dots represent measured load-volume pairs from individual years. The vertical and horizontal error bars represent means ± one standard deviation of observations in discrete bins. Vertical solid line represents average river nitrogen load from 1980 to 1990; vertical dashed line represents a 35% reduction from the 1980–1990 TN load; horizontal line represents hypoxic volume corresponding to that reduction.

We looked at the requirements for, and the effects of, four benchmarks related to policy options and previous modeling efforts: the effects of the Chesapeake Bay Agreement target total load reduction of 35%, the loads required to return to conditions of 1950–1970 (c. 4.2 km^3 hypoxia), the loads required to reduce hypoxic volumes by 50% (to 3.6 km^3), and the loads required to eliminate hypoxia.

Our model results (Fig. 8) indicate that the 35% reduction called for in the Chesapeake Bay Agreement would result in hypoxic volumes averaging 3.4 km^3 in a typical year and less than 4.6 km^3 in most years, or about 53% and 36% reductions from the 1980–1990 average volumes (c. 7.2 km^3), respectively.

The 35% TN load reduction also achieves the second benchmark, reducing average hypoxic volumes to levels below those typical of 1950–1970 (4.2 km^3). To achieve that level of hypoxia or lower in most years requires a larger 53% reduction, bringing TN loading down to 150,000 kg N d^{-1} in most years. Hagy et al. (2004) concluded that a 28% load reduction would return the Bay to 1950–1970 conditions, as characterized by a lack of anoxia. That conclusion was based on a simple assumption that a return to loading conditions present in the 1950–1960s would restore oxygen status in the Bay to conditions at that time. There is evidence that a hysteretic response, arising from ecological changes in the Bay, may require larger loading reductions to achieve restoration (Hagy et al. 2004). The larger load reductions suggested here are consistent with that conclusion. In the protracted period likely needed to achieve load reductions, steady change resulting from initial progress in reduction may generate additional capacity to receive nutrient loads without adverse effects. In that case, the 28% reduction suggested by Hagy et al. may be adequate. Regardless, initial progress toward lower loads is needed.

Cerco (1995b) and Cerco and Cole (1994) also explored the effects of nutrient load reductions, but reported the results as reduced anoxic volume-days, a volume-time integration of the quantity of water with oxygen concentrations below 1 mg l^{-1}. They report that a 40% reduction in nitrogen load would decrease anoxic volume-days by about 50% (Fig. 4 in Cerco 1995b). Our model suggests that to reduce hypoxic volumes to an average of 50% of the 1980–1990 average would require a 35% load reduction. A 41% reduction would be needed to achieve the same decrease in hypoxia in most years. Our model also indicates that loads would have to be reduced by more than 73% to less than 70,000 kg d^{-1} to completely eliminate hypoxia. Of course, both this loading reduction and that water quality target are unreasonable targets for Chesapeake Bay.

Our model suggests that the target total load reduction of 35% will reduce hypoxic volumes by 36–68%, which, on average is similar to values in 1950–1970. To reduce hypoxic volumes to 50% of the 1980–1990 levels requires load reductions of 35–41%, similar to those suggested by Cerco (1995b) when taking into account interannual variability.

The fact that these results are similar to those produced by the more complex dynamic models and the statistical models, provides additional confidence that reducing nitrogen loads will produce the desired effect of decreasing hypoxic volumes. Our analysis provides additional information useful for policy development. This is the only biophysically-based model that has provided estimates of the range in hypoxic volume that can be expected given different nitrogen loading scenarios. Given the extreme natural variability in hypoxia, ecological forecasts, whether from this model or otherwise, are most useful when they provide a range of expected outcomes. We find that more aggressive loading reductions are needed to protect against recurrent incidences of more extensive hypoxia, which have the obvious potential to maintain the Bay in a less resilient, degraded state.

As we began, we noted that all models are necessarily caricatures of natural systems. Different modeling approaches offer unique combinations of strengths and weaknesses and should be selected to address a specific model objective. We suggest that this model occupies a useful intermediate position between simple empirical models (e.g., regression models) and the very complicated coupled-biological physical models that have been used for management of Chesapeake Bay. By pursuing a simpler model construct, we were able to quantify uncertainty to a greater extent than is possible with the more complex numerical models. By retaining some mechanistic detail we could validate the model against state variables and process rates, an advantage over simple regressions. Most likely, there are many other useful modeling approaches, ranging from strictly empirical, to semi-empirical simulation models, to fully-resolved models that could be developed and used to evaluate management options. We suggest that pursuing a pluralistic approach will ultimately provide the most accurate, useful, relevant, and credible scientific evaluation of policy options.

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