Forecast of summer anoxia in the Chesapeake Bay

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Abstract

This paper presents a forecast model to predict summer anoxia in the Chesapeake Bay using preceding spring information of nitrogen and phosphorus loads, water temperature, algae concentration, and freshwater flows. It's based on a regression of over 20 years of observed data. The use of anoxic intensity, a DO-normalized anoxic volume, versus the traditional anoxic volume as the forecasting estimator is described. Anoxic volume can be influenced by partial mixing or other factors that sometimes causes a higher anoxic volume but with actually less intensity in the anoxic condition. This paper recommends using quadratic terms of separate nitrogen and phosphorus loads, and other conditions such as freshwater flows from the upper Bay and water temperature, as regressors. More than 18 regression equations with different combinations of explanatory variables were compared, and the importance of their effects on the anoxia forecast is discussed.

Introduction

The Chesapeake Bay has experienced problems of bottom water summer anoxia for several decades, which appears to be increasing in recent decades (Officer et al., 1984). The major sink of dissolved oxygen (DO) is due to the decay of organic compounds in the bottom sediment, though oxidation of sulfate and other materials also contributes the sediment oxygen demand (SOD) (DiToro, 2001). Huge amount of nutrient loads from the watershed and wastewater treatment plants feed algae blooms that subsequently settle and contribute to SOD for subsequent seasons (Officer et al., 1984). Elevated summer temperature accelerates the decay of organics. The spring freshet increases density stratification in the Bay and minimizes oxygen transfer from the surface to the deep layer (Taft et al, 1980). On the other hand, the photosynthesis of algae and aquatic plants increases DO in shallow water. Mixing with waters from the land or the ocean, the anoxic water reduces the intensity of anoxia. Wind and current promote mixing and reduce anoxia.

Within the decadal trend of anoxia, major meteorological and climatic events and

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attendant variations in runoff, nutrient loading, and wind condition have contributed to fluctuations in anoxia for a given year (Kemp et al., 1992). The managers of the Chesapeake restoration want to be in a position to anticipate summertime anoxic/hypoxic conditions in order to effectively communicate with the general public, perhaps effecting decisions of individual waterman with respect to placement of bottom traps of the crab fishing for example. A model that can predict summer anoxia in the prior spring is desired. Relationships between spring nutrient load and summer hypoxia/anoxia in the Chesapeake Bay have been documented (Hagy et al., 2004). Based on such a relationship, Jasinski et al. (2005) developed a regression model using a nutrient loading variable to predict summer anoxic volume in the mainstem Bay, which was the first forecast of anoxia (for summer 2005) for the Chesapeake Bay. The forecast methodology described here is in parallel to Jasinski's work, and focuses on data mining, regressor selection, and enhanced forecast performance.

Method

We use the relationship between observed yearly summer anoxic condition and spring total nitrogen (TN) and total phosphorus (TP) loads, chlorophyll-a concentrations, water temperature, freshwater discharge, and other factors that affect anoxia development, to predict anoxic conditions in the coming summer in the mainstem Bay. We use these factors to establish a multi-variance linear regression equation with summer anoxia as the estimator, and the influencing factors as the regressors.

An accurate estimate of summer anoxia is an important step; selection of appropriate explanatory variables (i.e., regressors) and their quantification ensures a qualified regression. This section details the calculation of these values from the observed data.

The estimator – annual summer anoxic condition

The terms of anoxia have been used in many fields, including the environmental fields, to indicate insufficient oxygen conditions. Different thresholds of DO concentration were set to delineate anoxia in different research purposes. For example, some researchers used DO=0.0 mg/l, or DO<1 mg/l (Thomann et al., 1994; Wang et al., 2006) to define anoxia, some used DO≤0.2 mg/l (CBPO, 2003). Anoxia volume is widely used to indicate anoxic problems in a water body. Jasinski et al. (2005) used it as the estimator for anoxic forecast. This paper will introduce anoxic intensity, a DO-normalized anoxic volume, as an alternative measure of anoxia.

Anoxic volume (AV). Anoxic volume is the volume of water that has DO concentration lower than a specific DO-threshold. The anoxic volume in this work is calculated based on DO observations. More than 50 long-term monitoring stations in the mainstem Bay were used. The surface area of the mainstem Bay is about 7,000 km^2. The average depth of the Bay is about 7 meters, with maximum depth of 40 meters in the deep channel. The 2001 version of the Chesapeake Bay Interpolator

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(Bahner, 2001) grid is adopted to assign measured DO to grid cells. The grid is 3-dimensional, with a 1000-meter width by 1000-meter length by 1-meter depth. The depth interval of samples is commonly in 1 meter, a similar vertical resolution to the grid. Oxygen demand of bottom sediment and re-aeration at the surface greatly influence DO in a vertical profile, while the DO concentration varies less horizontally. Dissolved oxygen in the cells lacking monitoring data is interpolated by the observed DO at a similar depth of the three nearest monitoring stations. The observed DO values are weighted based on reverse distance squares from the monitoring stations to intermediated cells.

The location of the DO probe at a given fixed monitoring station is determined by GPS instrumentation. The vertical cast of the probe often varies by two or three meters among different sampling cruises due to wind, tide, and the local bathymetry. This situation results in a mismatch between the observed depth for a cruse and the interpolator grid depth. If the observed total depth is greater than the interpolator grid column, the extra depths over 2 meters in the observation are ignored. The rest of the observation profile is adjusted to match the interpolator grid column, and DO in the observation profile are recalculated for the depths matching each cell center in the grid column. If the observed depth is shorter than the interpolator grid column, then the observation profile is stretched up to two meters longer. DO in the observation profile are recalculated then assigned to the grid cells of corresponding depths. The deeper cells in the water column, if there is any, are assigned the value of "missing". The situation of "missing values" also exists in the cells to be interpolated, if they are deeper than all nearby monitoring stations or the corresponding depths of the monitoring stations used to interpolate have "missing value". In these situations, in the calculation of anoxic volume we first look the deepest cell in a water column that is not a "missing value" and use the anoxia definition to check whether it is anoxic or not, then assign the same condition, anoxic or not, to all cells underneath.

The anoxic volume (AV) is acquired by summation of the volumes (V) from individual cells i which meet the definition of anoxia:

$$AV = \sum V_i$$

The annual summer anoxic volume is the average anoxic volume from six sampling cruises (mid June to mid September). The left half of Table 1 lists summer anoxic volume (AV) from 1985 to 2004 for three DO thresholds of anoxia.

Anoxic intensity (AI). The anoxic volumes for two stratified water bodies are regarded as being the same, as long as they have equal volumes of anoxic water. But if the average DO concentrations are different, we would say that the one with lower DO has a greater anoxic problem. An example is given here, using hypothetical but realistic observed from the Chesapeake Bay on two separate sampling cruises. In cruise A, the lower layer of water had 5-meters deep containing DO=0.1 mg/l (DO>0.2 mg/l above this layer). In cruise B, the lower layer had 7-meter deep containing DO=0.2 mg/l. The anoxic volumes in a square kilometer were 0.005 km^3 and 0.007 km^3, respectively, for waters A and B if the definition of anoxia is DO≤0.2 mg/l. Although water B has a larger anoxic volume, the degree of anoxia is not higher than water A. To overcome the above problem, here we introduce a DO concentration-normalized anoxic volume, called the anoxic intensity (AI):

$$AI = m \sum V_i / DO_i$$

where, m = 0.5 DO-threshold (in mg/l); DO_i is the DO concentration in cells i.

It is based on an assumption represented by this example: if DO=0.5 mg/l is a problem for a parcel of water, then the water of a same volume but containing DO=0.1 mg/l is 5 times the problem. The multiplier, m (a constant under a specific DO-threshold), serves for two purposes. One is to convert the unit of AI to volume equivalence (V-eqv). The other is to ensure comparability between values of AI and AV of a same DO-threshold. AI = AV if DO in the cell equals half the threshold; AI > AV if DO in the cell is lower than half the threshold; AI < AV if DO in the cell is higher than half the threshold. Thus, the unit of AI is "km^3 equivalency for DO=0.5 threshold" (briefly, km^3-eqv). In the above example, AI of DO≤0.2 mg/l are 0.005 km^3-eqv and 0.035 km^3-eqv for waters A and B, respectively. AI correctly represents the relative intensity of anoxia between waters A and B, therefore, AI is a better metric of relative intensity of anoxia. Whereas, in the AV calculation, once DO concentrations in parcels of water meet the threshold, it considers the volumes only, without comparing relative DO concentrations. Note that the anoxic volume of water B, having higher anoxic volume but lower anoxic intensity, can be generated from the water of Case A through partial mixing with higher DO water in the upper layer. However, a strong mixing can cause DO in the lower layer to be higher than the threshold, significantly reducing both anoxic volume and anoxic intensity.

Comparing anoxic volume (AV) and anoxic intensity (AI). The left half of Table 1 is annual AV and its ranks for anoxia defined by DO <0.2, ≤0.2, and ≤0.3 mg/l. Here we discuss three DO-problematic years, 1993, 1996 and 1998. At many stations the anoxic water in 1996 had much lower DO (many were 0.1 mg/l) than the anoxic water in 1998 (many were 0.2 mg/l). But in many water columns, 1998 had more cells containing DO≤0.2 mg/l than 1996. If DO<0.2 mg/l is used to define anoxia, 1996 has higher anoxic volume than in 1998. Using DO≤0.2 mg/l to define anoxia, 1998 has higher anoxic volume than in 1996. Using DO≤0.3 mg/l to define anoxia, 1998 had even higher anoxic volume than 1996, even higher than 1993, the most anoxic year during 1985-2004. It is difficult to select a suitable threshold to define anoxia.

The right half of Table 1 is annual AI and its ranks for anoxia defined by DO <0.2, ≤0.2, and ≤0.3 mg/l. The three years with the largest AI (1993, 1994 and 1996) by the three definitions of anoxia are the same. The ranks of AI among the 20 years for DO ≤0.2 and ≤0.3 mg/l, even higher such as 0.5 and 1 mg/l (not shown in the table), are almost the same, and the AI of 1996 is higher than that of 1998. This finding suggests that AI is better than AV in assessing the magnitude of anoxic problem, especially for

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this forecast task, because the prediction of anoxia is based on the relationship between high nitrogen and phosphorus load and high algae concentration, causing low dissolved oxygen.

Because the ranks of AI for DO thresholds between 0.2-1.0 mg/l are almost the same, it suggests that any of the thresholds is suitable to define AI. However, using DO-thresholds higher than or equal to 1 mg/l to define AI may involve large volumes of water that are farther away from the center of anoxia and complicate the situation. To avoid this, it is better to use DO-thresholds lower than 1 mg/l to calculate AI. On the other hand, using a low DO-threshold, such as ≤0.1 mg/l, to define AI, omits the water containing slightly higher DO (e.g., 0.2 mg/l) that is unhealthy to most aquatic species. To avoid this, it is better to use DO-thresholds greater than or equal to 0.2 mg/l. Based on the above considerations, we recommend the threshold DO ≤0.3 mg/l for calculating AI to compare relative anoxia among years in the Chesapeake Bay.

Table 1. Summer anoxic volume (AV) and anoxic intensity (AI) and their ranks (rk) for anoxia defined by DO <0.2, ≤0.2 and ≤0.3 mg/l; and the octagrade ranks (ok) for AI of DO≤0.3 mg/l.

Year	AV (km^3) by three definitions						AI (km^3-eqv) by three definitions						
	DO <0.2 mg/l		DO≤0.2 mg/l		DO≤0.3 Mg/l		DO<0.2 mg/l		DO≤0.2 mg/l		DO≤0.3 mg/l		
	AV	rk	AV	rk	AV	rk	AI	rk	AI	rk	AI	rk	ok
985	0.56	19	0.60	20	0.83	20	0.62	18	0.64	19	1.10	19	H
986	2.07	5	2.08	6	2.48	4	2.17	4	2.17	5	3.50	5	D
987	0.75	17	0.79	18	1.36	16	0.70	17	0.72	8	1.39	17	H
988	1.48	10	1.52	11	1.80	12	1.85	8	1.87	11	2.98	8	E
989	1.43	11	1.61	9	2.09	7	1.62	10	1.71	10	2.87	10	E
990	1.64	8	1.66	8	1.85	11	2.05	5	2.06	6	3.21	7	D
991	1.55	9	1.55	10	1.96	10	2.03	6	2.03	7	3.29	6	D
992	1.09	13	1.14	13	1.33	18	1.40	13	1.42	13	2.25	13	F
993	2.88	1	2.91	1	3.26	2	3.55	1	3.56	1	5.55	1	A
994	2.09	4	2.11	4	2.44	5	2.47	3	2.48	3	3.92	3	C
995	1.14	12	1.16	12	1.42	14	1.46	12	1.47	12	2.36	12	F
996	2.57	2	2.58	3	2.78	3	3.11	2	3.11	2	4.79	2	B
997	1.09	14	1.09	14	1.40	15	1.14	14	1.14	14	1.88	14	G
998	2.14	3	2.73	2	3.46	1	1.90	7	2.19	4	3.75	4	C
999	0.86	16	0.99	16	1.34	17	0.72	16	0.78	16	1.39	18	G
2000	1.72	7	1.73	7	2.03	8	1.54	11	1.54	11	2.50	11	F
2001	0.95	15	1.09	15	1.42	13	0.78	15	0.85	15	1.49	16	G
2002	0.00	20	0.67	19	1.15	19	0.00	20	0.34	20	0.81	20	H
2003	0.68	18	0.90	17	2.02	9	0.58	19	0.69	18	1.69	15	G
2004	1.79	6	2.08	5	2.43	5	1.65	9	1.79	9	2.90	9	E

Explanatory variables for anoxic estimate

N-P loads. There are three main sources of TN and TP loads to the tidal water

of Chesapeake Bay (Fig. 1): 1) fall-line (FL, i.e., at just above the head of tide) load from 9 major rivers, that is contributed by the above fall-line (AFL) point source (PS) and nonpoint source (NPS), 2) below fall-line point source (BFL_PS), and 3) below fall-line nonpoint source (BFL_NPS). The FL load was estimated by a regression model from observed data (Cohn et al., 1992; Wang and Linker, 2005). The BFL_PS load was obtained from the point source databases. The BFL_NPS load was estimated by a factor of the FL load. This factor was based on the average from the Chesapeake Bay Watershed Model of the 1985, 2000 and 2002 progress scenarios (briefly, WSM scenarios). Specifically, the BFL_NPS load was calculated by

$$(\text{monthly_FL} \frac{\text{AFL_EOS} + \text{AFL_PS}}{\text{FL}} \mid \text{monthly_AFL_PS}) \frac{\text{BFL_EOS}}{\text{AFL_EOS}},$$

where, monthly indicates the load varies monthly and is based on observed or regression from observed data, otherwise is based on average from the WSM scenarios; the "edge-of-stream nonpoint loads" (EOS), either AFL or BFL, is based on the WSM scenarios. For the basins that do not have AFL load such as Eastern Shore Virginia, Eastern Shore Maryland and Western Shore Maryland, the BFL_NPS loads were estimated by a factor of BFL_NPS of other basins, using Rappahannock, Susquehanna and Patuxent, respectively. The factors were determined by TN and TP loads in the WSM scenarios for the corresponding basins. We obtained the three main sources of TN and TP loads from 9 major tributary basins (Fig. 1).

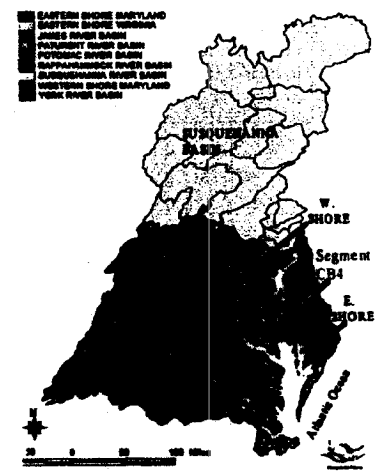

Figure 1. Mainstem and tidal tributaries of Chesapeake Bay (in white, around by land) and its watershed, and location of segment CB4 in the mainstem.

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In the anoxia forecast model, two types of N-P loads were tested: the loads from the upper Bay (i.e., the tidal Potomac River and north) and the effective loads from the whole watershed to segment CB4 (at the mid upper Bay).

Similar to the method described by Jasinski et al. (2005), the "upper Bay's load" only considers the fall-line load from the Susquehanna River and the below fall-line point sources from the upper Bay's tributaries. The reason for using the upper Bay's load is that Susquehanna is the major contributor (contributing 50% of flow) to the Bay, and it is at the upper Bay and influences the Bay's anoxic center much more than the lower tributaries. Similarly, the upper Bay's below fall-line point sources also affect the Bay's anoxic center more than the point sources from lower Bay's tributaries. The recognized limitations of this approach are: the upper Bay's load does not consider the below fall-line nonpoint sources from the upper Bay and sources from the lower Bay; the influences on anoxia from different sources in the upper Bay (by per weigh load) are considered equal. The difference from Jasinski et al. (2005) is that the Susquehanna nutrient load in this paper was estimated by an improved regression model (Wang and Linker, 2005).

The "effective load" considered all three sources from nine major tributary basins. The loads from the nine tributary basins were weighed based on their relative influences on the Bay's anoxic center, Segment CB4 (Fig. 1). The weighting factors for relative influences of TN and TP loads on CB4 by the nine tributary basins were based on the analysis from water quality models. Figure 2 shows a high correlation in anoxic intensity (AI) between CB4 and the mainstem. The recognized limitations are: the yearly change of anoxic conditions in CB4 is not exactly the same as that in the whole Bay; this method needs more load data than the upper Bay's load and requires more complicated calculations.

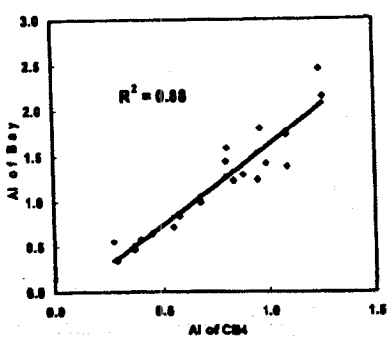

Figure 2. Correlation of anoxic intensity (AI) between segment CB4 and the entire mainstem Bay.

The spring loads used in the regression are the average from monthly loads. Total nitrogen and total phosphorus loads were separated as independent variables, either in first order or secondary order (i.e., quadratic terms). The methodology described here also used combined TN and TP loads, e.g., the nutrient index (NI, NI = TN + 10 TP), as a single loading variable (Jasinski et al., 2005).

We denote the upper Bay's TN and TP loads as U_N and U_P, respectively, and the TN and TP effective loads as E_N and E_P, respectively. The nutrient index for the upper Bay's load and the effective load are denoted U_NI and E_NI, respectively.

Other explanatory variables. Other explanatory variables were spring water temperature (sp_wt), chlorophyll-a concentration (sp_chl), flows from the Susquehanna River (sp_flw), and hypoxic condition (sp_hpx). Regressors containing summer (June, July, and August) water temperature (su_wt) and summer chlorophyll-a concentration (su_chl) were also analyzed.

The Pearson product-moment correlation coefficient (r) is a measure of the strength of linear relationship between two variables (X and Y) from a set of (M) samples. It is defined as the sum of the products of the standard scores of the two measures divided by the degrees of freedom. The following formula is used to calculate r:

$$r = \frac{\sum XY - \sum X \sum Y / M}{[(\sum X^2 - \sum X \sum X/M)(\sum Y^2 - \sum Y \sum Y/M)]^{0.5}}.$$

r values range from −1 to +1. Larger absolute values indicate stronger relationships between X and Y, either positively or negatively. Table 2 lists the r-values among AI and explanatory variables based on the 1985-2004 data. The N and P loads are the effective loads on segment CB4. N^2, NP and P^2 are quadratic terms of N and P loads.

Table 2. Pearson product-moment correlation coefficients (r) among anoxic intensity (AI) and explanatory variables.

	AI	N^2	NP	P^2	N	P	sp_wt	sp_chl	sp_flw	su_wt	su_chl	sp_hpx
AI	1.000	0.858	0.858	0.814	0.853	0.792	0.016	-0.169	0.852	0.198	0.254	0.238
N^2	0.858	1.000	0.986	0.956	0.990	0.959	-0.186	-0.060	0.956	0.224	0.233	0.237
NP	0.837	0.986	1.000	0.992	0.970	0.984	-0.205	-0.044	0.950	0.208	0.225	0.202
P^2	0.814	0.956	0.992	1.000	0.936	0.981	-0.213	-0.034	0.929	0.194	0.207	0.182
N	0.853	0.990	0.970	0.936	1.000	0.963	-0.194	-0.017	0.945	0.186	0.283	0.220
P	0.792	0.959	0.984	0.981	0.963	1.000	-0.216	0.019	0.928	0.153	0.290	0.151
sp_wt	0.016	-.186	-.205	-.213	-.194	-.216	1.000	-0.160	-0.089	0.001	-0.424	0.216
sp_chl	-.169	-.060	-.044	-.034	-.017	0.019	-0.160	1.000	-0.033	-0.093	0.390	0.412
sp_flw	0.852	0.956	0.950	0.929	0.945	0.928	-0.099	-0.033	1.000	0.110	0.305	0.379
su_wt	0.198	0.224	0.208	0.194	0.186	0.153	0.001	-0.093	0.110	1.000	-0.114	-0.149
su_chl	0.254	0.233	0.225	0.207	0.283	0.290	-0.424	0.390	0.305	-0.114	1.000	0.091
sp_hpx	0.238	0.237	0.202	0.182	0.220	0.151	0.216	0.412	0.379	-0.149	0.091	1.000

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Regression equations

Various linear regression equations with selected regressors were analyzed (Table 3). For example, using AI as the estimator the linear equation-set for Eq. 3 has the form:

$$AI = \beta_0 + \beta_1 E_N^2 + \beta_2 E_N \cdot E_P + \beta_3 E_P^2 + \beta_4 E_N + \beta_5 E_P + \beta_6 sp_wt,$$

where β_0 through β_6 are coefficients to be derived by regression.

Table 3. Regressors in 24 linear regression equations (Eq), and the adjusted R-square (adj-R^2) for regressions using anoxic volume (AV) and anoxic intensity (AI) as the estimator.

Eq.	Regressors	adj-R^2 (AV)	adj-R^2 (AI)
1	E_N, E_P	0.69	0.71
2	E_N^2, E_N·E_P, E_P^2, E_N, E_P	0.65	0.77
3	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_wt	0.76	0.81
4	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_chl	0.62	0.78
5	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_flw	0.77	0.81
6	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_hpx	0.64	0.77
7	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_wt, sp_chl, sp_flw	0.77	0.82
8	E_N^2, E_N·E_P, E_P^2, E_N, E_P, sp_wt, sp_chl, sp_flw, su_wt, su_chl	0.87	0.90
9	E_NI	0.67	0.66
10	E_NI^2, E_NI	0.66	0.68
11	E_NI^2, E_NI, sp_wt, sp_chl, sp_flw	0.76	0.67
12	U_N, U_P	0.72	0.77
13	U_N^2, U_N·U_P, U_P^2, U_N, U_P	0.69	0.79
14	U_N^2, U_N·U_P, U_P^2, U_N, U_P, sp_wt, sp_chl	0.68	0.76
15	U_N^2, U_N·U_P, U_P^2, U_N, U_P, sp_wt, sp_chl, sp_flw	0.73	0.76
16	U_NI	0.71	0.74
17	U_NI^2, U_NI	0.69	0.74
18	U_NI^2, U_NI, sp_wt, sp_chl, sp_flw	0.77	0.70
19	sp_wt	0.02	0.01
20	sp_chl	0.02	0.01
21	sp_flw	0.75	0.71
22	sp_hpx	0.10	0.07
23	sp_flw, sp_wt	0.78	0.73
24	sp_flw, sp_wt, sp_chl	0.79	0.74

Among the nutrient regressors, four types of nutrient loads were assessed: a) effective TN and TP loads on CB4 (Eqs. 1 through 8); b) nutrient index based on the effective load on CB4 (Eqs. 9, 10, and 11); c) upper Bay's TN and TP loads (Eqs. 12 through 15); d) nutrient index based on the upper Bay's nutrient load (Eqs. 16, 17, and 18).

Summer anoxic volume (AV) and anoxic intensity (AI) are used, respectively, as the estimator of anoxia in the above 18 equations. A total of 36 (=2x18) regressions were analyzed. The AV estimator used in the 18 regressions is by the threshold of DO≤0.2 mg/l, because AV of DO≤0.2 mg/l has been widely used to calculate anoxic volume for the Chesapeake Bay and was used in the recent anoxic forecast by Jasinski et al. (2005); the AI estimator is by the threshold of DO≤0.3 mg/l according to the earlier discussions.

Boynton and Kemp (2000) found that the timing of initial hypoxia in the Chesapeake was related to spring flow, temperature, and chlorophyll-a. Hagy et al. (2004) documented a high correlation of flow with anoxia (R^2=0.75). The Pearson correlation coefficients (Table 2) also indicated a high correlation between spring flow and anoxic intensity. We set up additional 6 regressions (Eqs. 19 through 24) to analyze anoxia estimates using regressors of spring flow, water temperature, chlorophyll-a, or hypoxia alone without considering nutrient loads, as also listed in Table 3.

Results and Discussions

The adjusted R-square (adj-R^2) was used to evaluate the regressions' goodness-of-fit. The left two columns of Table 3 are adj-R^2 for the 24 regressions using estimators AV and AI, respectively. In comparing goodness of two regressions using adj-R^2, we regard a 0.1 difference as significant, and a 0.03 difference as recognizable. Note: for the regressions in Table 3 the adj-R^2 are about 0.03-0.1 lower than their R^2 counterparts.

Comparing regressions with different regressors that use anoxic intensity (AI)) as the estimator

Second order versus first order of TN and TP loads. The dependence of algal growth on nitrogen and phosphorus is not a linear function, but approximates a Michaelis-Menton curve (Cerco and Cole, 1994), and the relationship between chlorophyll-a concentrations is not linear to N-P loads as illustrated from the surface analysis (Fig. 3a; Wang et al., 2002). Such a relationship also affects non-linearity of summer dissolved oxygen or anoxic volume with N-P loads (Fig. 3b; Wang et al., 2002). Consistently, the regressions of AI involving quadratic TN and TP (Eq. 2) have higher adj-R^2 than the regressions using first order TN and TP (Eq. 1). However, the adj-R^2 has no significant difference between equations 13 and 12. This may be due to less accuracy when using the upper Bay's load.

Equations 2 and 13 are comparable to the equation used in the surface analysis (Fig. 3b), and can be plot as a surface of anoxic intensity versus TN and TP load (Fig. 4). Wang et al. (2006) used Figure 3b to predict anoxic volume under a defined TN and

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TP load. Similarly, Figure 4 could be used for anoxia prediction. Please note: the anoxic volume in Figure 3b was the outputs from Water Quality Model runs that implicitly considered physical processes (such as flows, temperature, mixing, and algal growth and decay) besides the explicit TN and TP loads, therefore, resulting in a good regression (R^2=0.97); different model scenarios differed in N-P load, while the physical processes were the same, therefore, showing a good relationship between decrease of anoxic volume and decrease of TN or TP. Whereas, Equation 13 is based on observed TN and TP loads exclusively. Although the anoxic intensity decreases generally with TN or TP decreasing, such trends do not hold at low TN (Fig. 4). Therefore, other factors such as water temperature and mixing processes may play important roles on anoxia, but are not considered in the equation. Therefore, only using TN and TP as regressors (e.g., Eqs. 2 or 13) is not an optimal forecasting formula. Additional regressors will improve the regression.

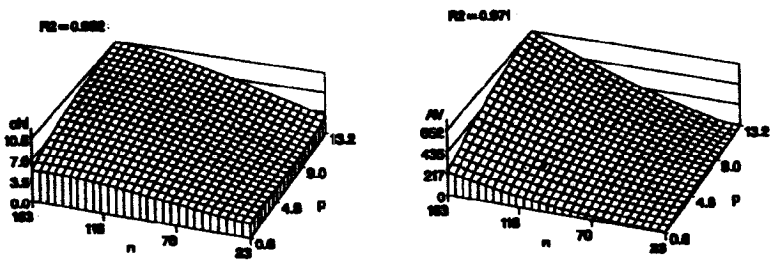

Figure 3. a) (left) Annual average spring chlorophyll-a concentration (ug/l) vs. N-P loads (k-ton) to the whole Bay; b) (right) annual average anoxic volume (km^3, cumulated over 365 days in a year for DO<1.0 mg/l) vs. N-P loads (k-ton) to the whole Bay. $AV = 0.011N^2 - 1.35P^2 + 0.266NP - 0.615N + 8.37P + 11.43$ (modified from Wang et al., 2002).

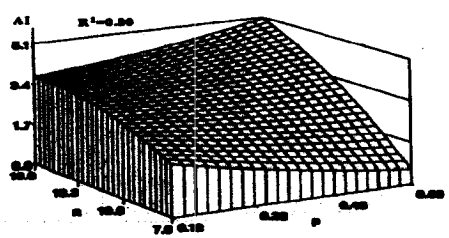

Figure 4. Surface plot of anoxic intensity (AI, km^3-eqv) versus upper Bay's TN and TP loads (k-ton). Based on Eq. 13.

Effect of summer water temperature and chlorophyll-a on summer anoxia prediction. High summer water temperature accelerates algae growth and decay, which increases DO consumption. The addition of summer temperature and chlorophyll-a as regressors significantly improves regression (Table 3, comparing adj-R^2 for Eqs. 8 and 7). However, since we are mainly using spring information to predict summer anoxia, we need to exclude summer conditions from the regressors. Nevertheless, we may use summer water temperature if it can be reasonably predicted from meteorological information, or if we want to explore summer anoxia in various summer weather scenarios. Since it is difficult to predict summer chlorophyll-a in the prior spring, therefore, summer chlorophyll-a should not be used.

Effect of spring water temperature and algae on summer anoxia prediction. Spring chlorophyll-a level reflects, to a certain extent, the availability of algae for decay in summer. Statistically, spring water temperature may reflect summer water temperature. When summer water temperature is excluded, adding regressors of spring water temperature could improves regression slightly (Table 3 for Eq. 3 versus Eq. 2). However, if summer water temperature and chlorophyll-a are used, spring temperature and chlorophyll-a become insignificant regressors, and is better to be excluded.

Effect of spring flow on summer anoxia prediction. The additional regressor of spring flow from the Susquehanna River improved the regression (Table 3, comparing Eq. 5 and Eq. 2, adj-R^2=0.81 and 0.77, respectively). This is consistent with high correlation between spring flow and summer anoxia (r=0.85, Table 2). The adj-R^2 for the AI predicted by flow alone is 0.71 (Table 3, Eq. 21), in agreement with Hagy et al. (2004). However, we cannot say that flow itself causes anoxia and simply use flow to predict summer anoxia without considering nutrient load. Flow alone without nutrient input cannot cause eutrophication and anoxia. Flow may reflect nutrient loads. This can be seen from the high correlation between flow and nutrient (r=0.93-0.96, Table 2). Spring flow may play two roles in the summer anoxia forecast. One is its effect on density stratification (Taft et al., 1980). The other is its representation of nutrient loads that compensates out the errors in the nutrient load estimate. Generally, flow observations are more frequent than nutrient observations, and flow estimate is more accurate than nutrient load estimate. Susquehanna River contributes about 50% of the freshwater from the watershed to the Bay and impacts the Bay's anoxic center significantly. Therefore, spring flow from the Susquehanna is a useful regressor.

Effect of spring hypoxia on summer anoxia. DO levels in spring may have an inherit effect on summer DO, both from the perspective of the intrinsic DO deficit at the beginning of summer and as an indication of the strength of the spring algal bloom. Monitoring data indicate that anoxia can change significantly among different sampling cruises throughout the summer, which is probably due to mixing and changes in the depth of pycnocline. The correlation between spring hypoxia and summer water temperature is r^2 = -0.15, whereas summer temperature has positive

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impact on summer anoxia (Table 2). There is no improvement by adding spring hypoxia (Table 3, comparing adj-R^2 of Eq. 6 and Eq. 2). Our final forecast model will not include spring hypoxia as a regressor, although may be worthwhile further analyzing on the role of spring hypoxia on summer anoxia.

Separate TN and TP loads versus nutrient index. The regression with separate first-order TN and TP regressors is slightly better than the regression using nutrient index by combining TN and TP loads (e.g., Eq. 1 versus Eq. 9, or Eq. 12 versus Eq. 16). It is conceivable that an optimal ratio of N and P, e.g., at the Redfield ratio (Redfield et al., 1966), in water could optimize the utilization of nutrients by algae, which further impacts DO. However, the ratios of N and P loads are different in different months and years, and the N:P ratio in the Bay's water is usually not at the Redfield ratio, therefore, separating N and P loads as individual explanatory variables will yield a better prediction of anoxia. Nevertheless, the plot of anoxic intensity versus nutrient index (Fig. 5) shows a correlation of increasing anoxia with nutrient load. The fitting line with a moderate high R^2 (=0.72) tells us that other factors besides nutrient may also be considered.

Comparing to the equation with first order nutrient index (e.g., Eq. 9 or 16), the addition of quadratic nutrient index (e.g., Eq. 10 or 17, correspondingly) does not improve anoxic forecast noticeably, in contrast to a noticeable improvement in the regression by switching from first order TN and TP loads to quadratic TN and TP loads (from Eq. 1 to Eq. 2). This further indicates that it is better to separate N and P as individual independent variables, instead of the combined one term of nutrient index.

Effective load to anoxic center versus upper Bay's load. The regression using the effective load (e.g., Eq. 7, adj-R^2=0.82) improves the anoxia estimate over the regression using the upper Bay's loads (e.g., Eq. 15, adj-R^2=0.76). Segment CB4 is in the Bay's anoxic center, and had the worst DO condition among all segments. Figure 2 shows a high correlation of the CB4's anoxia with the Bay's anoxia. However, CB4 does not fully represent the Bay's anoxic condition. We agree with Jasinski et al. (2005) that the upper Bay's load is the most important source affecting the Bay's anoxia. The calculation of effective load to CB4 requires more data and calculations. Propagation of errors in the calculation steps may cause less accuracy in load estimates. If the effective load to CB4 can be accurately estimated, then the effective load would be a better choice.

Summary. From the above discussion of various regressions for the equation using anoxic intensity (AI) as the estimator, we recommend using the regressors of quadratic terms of separate TN and TP loads, and spring water temperature, chlorophyll-a and Susquehanna flows. It is acceptable to use the effective load as the nutrient load. Therefore, Eq. 7 is recommended for forecasting summer anoxic problems. Alternatively, we may use the upper Bay's load or the nutrient index as the nutrient load for regression.

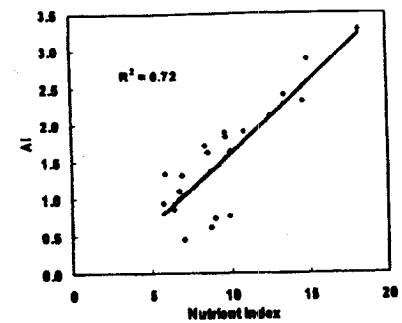

Figure 5. Relationship between summer anoxic intensity (AI) in the mainstem Bay and spring nutrient index (NI) of nutrient loads.

Comparing regressions using AV and AI as the estimator

We compare the regressions of different anoxic estimators, i.e., anoxic volume (AV) and anoxic intensity (AI), but with the same regressors for individual regression equations (Eqs. 1-18).

In the regressions using split N and P for nutrient load, especially with quadratic load terms, using AI as the estimator has slightly higher adj-R2 than using AV as the estimator (e.g., Eqs. 2 and 7). While, in the regression using the nutrient index for nutrient load, using AV usually has higher adj-R2 than using AI (e.g., Eq. 11).

Using AV as the estimator can get relatively good results for the regressions containing spring flow, such as Equations 5, 7, 11, 15, and 18, with adj-R^2 > 0.73, consistent with the above discussion that spring flow alone as a regressor can yield relatively high R^2 in the estimate of anoxia. This suggests that spring flow, besides its role on stratification, may reduce the impact by discounting DO concentration when using anoxic volume as the metric of anoxia, and the errors in the nutrient estimate may be partly compensated for by using flow as a regressor.

Since quadratic N and P loads are preferred over the nutrient index, and AI is a better metric than AV for anoxic problems, we prefer suing Equation 7 and AI as the estimator.

Exploring alternative measures of anoxic condition to be used as the estimator

The preceding sections discussed that the anoxic intensity (AI) better represents relative anoxic problems among years than the traditional anoxic volume (AV). The AI considers DO mass in anoxic water. This section explores three alternative

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measures that may represent relative DO problems among year.

DO mass or DO mass deficit. Deficit of DO mass, in reference to DO mass in full saturation, may be used to compare relative DO problems among years. The volume used to calculate DO deficit can be either the whole Bay or below a specific depth (depth-volume). However, we found that high DO deficit years and low DO deficit years are quite different for different depth-volumes and are inconsistent with other analyses of anoxic problems. DO mass in the Bay can increase due to inputs from ocean water and freshwater runoff. The input conditions vary in different sampling cruises in different years. The anoxic water in lower layers is usually affected much less by the above processes. If we have a fine time scale of sampling, the annual average DO mass could fairly represent relative DO problems. However, we only have two sampling cruises in a month. A cruise corresponding with higher runoff may overcount DO mass.

Another situation is: for two water columns that have the same amount of DO mass, the stratified water column usually has a higher difference in DO concentrations between the upper and lower layers than a better-mixed water column. Thus, the stratified one has less DO mass (or more anoxia) in the lower layer but more DO mass in the upper layer than the better-mixed one does, though their DO masses are the same. Varying spatial distributions of stratification and anoxic water cause difficulty in finding an optimal depth to calculate DO deficit.

Due to the above reasons, the method of using DO mass is not suitable in this study.

DO deficit in certain parcels of water. This is to calculate DO deficit in anoxic water defined by a specific DO threshold. The problems is: the year having more anoxic volume will have more volume to count for DO deficit, causing overcounting DO deficit in the extra volume. Certain normalization methods may make it applicable to represent intensity of anoxic problems, however, this topic is beyond the scope of this paper.

Normalization of anoxic volume by DO mass. The normalization of anoxic volume by DO mass for individual cells may express relative anoxic problems. It actually has a similar meaning as the anoxic intensity (AI) that we defined earlier and used to represent relative anoxic problems among years for the Chesapeake Bay. Please note that the normalization method is sensitive to low DO concentrations. AI could be very large if the volume is divided by very low concentrations. For this reason, we setup a quantitation limit to lump up all concentrations below that limit to the limit value. Through data mining, DO=0.07 mg/l or 0.1 mg/l were found suitable as the quantitation limit for the interpolated DO data. This work selects 0.07 mg/l as the limit and uses DO≤0.3 mg/l as the threshold of anoxia to calculate AI to be used in the forecast regression. Details can be referred to Wang et al. (in preparation).

Meanings of anoxic intensity (AI) and anoxic volume (AV) in management and anoxia forecast

This paper uses anoxic intensity as an index of anoxic problem in the Bay, and uses the AI defined by DO≤0.3 mg/l as the estimator in the regression. We adopt the commonly used anoxic volume definition of DO≤0.2 mg/l.

There is no direct comparison between AI and AV, because they are two different features. The AI is useful to compare relative DO problems among years. The AV is useful in other aspects of management. For example, given a specific species that requires DO above 0.2 mg/l, the anoxic volume (with DO≤0.2 mg/l) represents the availability of water resources to certain living creatures that require DO above the threshold.

Comparing the ranks of annual AV of DO<0.2 mg/l and DO≤0.2 mg/l, the former is more similar to the ranks of annual AI of DO≤0.2 or ≤0.3 mg/l. One of the reasons may be that, using a higher DO value as the threshold, a larger volume of water is involved, and heterogeneity among different water parcels by effects of mixing or decay of dead algae is more serious. Low DO water is usually confined in deep layers and associated more significantly with sediment oxygen demands in the summer. Therefore, it is preferred to use AV of DO<0.2 mg/l to AV of DO≤0.2 mg/l when using a non-normalized AV to compare relative anoxic problems among years. However, using DO<0.2 mg/l causes year 2002 without anoxia. Using DO≤0.2 mg/l yields nonzero anoxic volume in all years. We found that the AV forecast regressions by either AV of DO<0.2 mg/l or AV of DO≤0.2 mg/l yield similar adj-R^2. Since the threshold of DO≤0.2 mg/l has been widely used in the applications of anoxic volume (CBPO, 2003; Jasinski et al., 2005), this work uses the AV of DO≤0.2 mg/l when using AV as the estimator for the regressions in Table 3.

Importance in data mining

Our experience found that the anoxic intensity or anoxic volume forecast is sensitive to input data. Correct calculation of input data, specifically anoxic condition (e.g., anoxic volume or anoxic intensity) and N-P loads, is crucial. Errors in one of them would reduce goodness-of-fit in the regression greatly. Detailed data analysis is important before the final data utilization.

Anoxia forecast practice

The adj-R^2 in Table 3 is based on the regression using 1985-2004 data. The regressions can be used to forecast summer anoxia in 2005 or later years using spring conditions of that year. Table 4 lists predicted 2005 anoxic intensity and anoxic volume using Equation 7. Note: the 2005 loading information is from a provisional database that may be updated later. We also used 1985-2003 data to derive regression coefficients, and used 2004 spring data to predict 2004 summer anoxia as also listed in Table 4. The adj-R^2 from the regressions is still high.

There is 10-24% error in the estimates using AV as the estimator. When using AI as

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the estimator, Equation 7 yields lower errors, about 2% to 5% error in the 2004 and 2005 predictions. The average summer anoxic volume (AV) and anoxic intensity (AI) from 2005 observations are 2.68 km^3 (for DO≤0.2 mg/l) and 3.62 km^3-eqv (for DO≤0.3 mg/l), respectively, which are the third largest AV and fifth largest AI during 1985-2005 (by comparing Table 1). The forecasted 2005 summer AI by Eq. 7 is consistent with the above observations, i.e., it is the fifth largest one during 1985-2005.

Table 4. Prediction of 2004 and 2005 summer AV and AI

	Using AV (≤0.2 mg/l) as the estimator			Using AI (≤0.3 mg/l) as the estimator		
	AV (km^3)	adj-R^2	Error (%)	NV (km^3-eqv)	adj-R^2	Error (%)
2005 observed	2.68	-	-	3.62	-	-
Predicted by Eq. 7	2.04	0.76	-24	3.48	0.82	-4.9
2004 observed	2.08	-	-	2.91	-	-
Predicted by Eq. 7	1.88	0.77	-9.6	2.96	0.81	1.7

The ranking method in Table 1 is based on the values in individual years. Different ranks are assigned to different years even their values are close to each other. Considering 5-25% errors in anoxia forecast, we suggest to group values and use an octagrade system for grouping and ranking. The interval in the octagrade is determined approximately by:

(highest value – lowest value) / 8

For the AI of DO ≤0.3 mg/l in Table 1, the interval is, (5.6-0.8)/8 =0.6 mg/l. The ranges of DO concentration (mg/l) for the octagrade are: A (5.0-5.5), B (4.4-4.9), C (3.8-4.3), D (3.2-3.7), E (2.6-3.1), F (2.0-2.5), G (1.4-1.9) and H (0.8-1.3). The octagrade ranks for 1985-2004 are listed at the last column of Table 1. The forecasted 2005 anoxia is ranked the fifth worst anoxic year in 1985-2005, and ranked D in the octagrade. Note: the highest or lowest value used to calculate the octagrade interval needs not be the exact value, certain adjustments are needed for a proper division or grouping. We may expand the octagrades to include the values greater than the current maximum value or smaller than the current minimum value, and assign grades of A+ or H- correspondingly.

Future work

In the above, we were forecasting the summer anoxic problem averaged from sampling cruises in the summer. It is more complicated when individual cruises are compared. For example, the late June through early August cruises in 2005 had lower anoxic intensity than the corresponding cruises in 1993. However, the late August

and early September cruises in 2005 had higher anoxic intensity than the corresponding cruises in 1993. The above phenomenon limits the accuracy of anoxia prediction by our method. We may improve the forecast by splitting the forecasting period into two sub-periods: early summer (June and July) and late summer (August and September). For forecasting early summer's anoxia, we can still use the above procedures. For forecasting late summer's anoxia, we can add regressors of June's temperature, chlorophyll, and freshwater flow. As we had seen that adding summer temperature and chlorophyll improves regression greatly, and freshwater discharge from Susquehanna affects stratification. In July we are able to obtain June's information and have a better forecast for late summer.

In the future development, we may explore additional factors affecting summer anoxia that are not considered in this work, such as wind, salinity, cloud cover, current, stratification, other components of sediment oxygen demand, and components of TN and TP (e.g., dissolved nitrogen and dissolved phosphorus). We need to further analyze the importance of stratification on anoxia by fresh water discharge from the Susquehanna River. There are many factors affecting summer anoxia, a simple regression model may be insufficient to obtain an accurate forecast. Alternatively, a mechanistic forecast model may be pursued. Nevertheless, the current regression model could provide useful information to the water resources managers in a rather quick way, and its refinement is desirable.

Conclusions

- The anoxic volume (AV) does not fully represent the extent of the anoxic condition. The anoxic intensity (AI) is in some instances a better metric of anoxia. AI has a better correlation with nutrient loads than AV does. It is recommended to use AI as the regression estimator in forecasting summer anoxic problem.
- Anoxic volume is a useful index in aquatic living resources management, which measures volume of water available to certain species requiring a certain DO level. Fairly good prediction of anoxic volume can still be conducted by using our improved regressions.
- It is acceptable to use the upper Bay's loads as regressors. The greatest volume of anoxic waters is located in the upper middle Bay (segment CB4), is mostly affected by the loads from the upper Bay.
- The AI calculated for segment CB4 has a high correlation with the AI of the mainstem Bay. Using the effective load to segment CB4 can yield better forecasts of the Bay's anoxia than using the upper Bay's load. There is a potential improvement in anoxia forecast if the calculation of the effective load can be further improved.
- Separating N and P loads as two independent variables is better than using a single nutrient index combined from the N and P loads. When using nutrient index as nutrient loading, the upper Bay's flow should be considered in the regression so that a fairly high adj-R^2 (greater than 0.76) can be obtained.
- Algae concentrations are non-linearly related to N and P loads. Quadratic terms

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of N and P loads usually yield better regressions than using first order terms.

- Summer conditions such as temperature and chlorophyll-a have a moderate correlation with summer anoxia. However, summer conditions cannot be used for summer anoxia forecast, unless we want to predict anoxia under certain summer weather scenarios for management purposes. In this context, spring water temperature and chlorophyll-a level could become useful regressors.
- Spring freshwater discharge from the Susquehanna River has a high correlation with summer anoxia. The Susquehanna flow may represent the degree of stratification and nutrient loading, therefore is an important regressor.
- In the future development, we may explore additional factors affecting summer anoxia that are not considered in this work, such as wind, salinity, cloud cover, current, stratification, other components of SOD, and components of TN and TP (e.g., dissolved nitrogen and dissolved phosphorus). We will explore the outcomes by splitting the forecast period into finer sub-periods.

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