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The effects of seasonal wind regimes on the evolution of hypoxia in Chesapeake Bay: Results from a terrestrial-estuarine-ocean biogeochemical modeling system

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ABSTRACT

In this study, a terrestrial-estuarine-ocean biogeochemical modeling system (DLEM-ChesROMS-ECB) was used to investigate the impact of prevailing spring-to-summer winds on hypoxia in Chesapeake Bay. The modeling system was run continuously from 1985 to 2005 under realistic wind conditions. Correlation analysis based on the 21-year simulation results revealed that the durations of spring northeasterly winds and summer southerly winds were both positively correlated with the volume of summer hypoxia. Conversely, the duration of summer northeasterly winds was negatively correlated with hypoxia. We then conducted multiple idealized sensitivity experiments to explore the underlying mechanisms governing these relationships. The results indicated that prolonged northeasterly winds in spring promoted along-channel transport of oxygen-consuming materials from the upper to the lower Bay, leading to a higher level of oxygen consumption via water column respiration (WCR). This may have led to more severe hypoxic events in the following summer. During summer, northeasterly winds increase vertical mixing as the riverine freshwater is mostly restricted to the western bank, thereby preventing the occurrence of hypoxia. Furthermore, strengthened vertical mixing increased light availability, resulting more nutrients taken up by phytoplankton. Consequently, more dissolved oxygen was produced. When comparing the differences in mass budget terms under southerly winds, the oxygen production accounted for approximately 60% of the WCR. In contrast to previous studies that mostly examined the short-term episodic effects of wind, our study underscores the importance of the impact of prolonged seasonally variable winds and biological feedback on hypoxic volume in Chesapeake Bay, which helps in the development of appropriate nutrient management strategies in a changing climate.

1. Introduction

Hypoxia is a deficiency in the concentration of dissolved oxygen (DO) in aquatic environments. The two primary factors that lead to the development and maintenance of oceanic hypoxia are water column stratification, which inhibits the exchange of low-oxygen subpycnocline water with oxygen-rich surface water, and the microbial decomposition of organic matter in the sub-pycnocline layer, which consumes oxygen during decay (Diaz and Rosenberg, 2008). Oxygen depletion globally has resulted in negative biological impacts in many coastal waters, including the Baltic Sea, Black Sea, Gulf of Mexico, Yangtze River Estuary, and Pearl River Estuary (Sandberg, 1994;

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Daskalov, 2003; Dai et al., 2006; Fennel et al., 2011; Feng et al., 2012; Feng et al., 2014; Zhou et al., 2017; Li et al., 2020). Hypoxia has negative effects on living resources, including decreasing habitats for fish and invertebrates and shifts in trophic energy transfer and production (Breitburg et al., 2018), leading to numerous management concerns in recent years (Feng et al., 2019; Irby and Friedrichs, 2019).

Hypoxia in Chesapeake Bay was first observed in the 1930s and became more common and widespread in the late 1950s and early 1960s (Newcombe and Horne, 1938; Officer et al., 1984; Marshall and Nesius, 1996; Cronin and Vann, 2003). It has been studied extensively over the past two decades (Hagy et al., 2004; Kemp et al., 2005; Murphy et al., 2011; Li et al., 2016; Scully, 2013) and these studies have confirmed that both the extent and duration of hypoxia are positively correlated with total nitrogen (TN) loading. However, TN loading has decreased slightly since the 1980s, mainly due to the release of Clean Water ACT (Keiser and Shapiro, 2019), but the hypoxic volume in Chesapeake Bay has continued to increase (Hagy et al., 2004; U.S. Environmental Protection Agency, 2010; Murphy et al., 2011; Irby and Friedrichs, 2019; Ni et al., 2020).

Previous retrospective data analyses have demonstrated the importance of seasonal wind on hypoxic volume, in addition to nutrient loading. Scully (2010a) found that interannual variability in hypoxic volume was significantly correlated with changes in wind direction during summer. Lee et al. (2013) found a strong positive correlation between summer hypoxic volume and late winter-spring (February-April) northeasterly to southwesterly wind speed, using Chesapeake Bay Monitoring Program (CBP) data. Zhou et al. (2014) found that the ratio of the southwesterly/northeasterly wind duration from April to August, as a predictor in a multiple linear regression model, could explain more than 85 % of hypoxic volume variability. While these statistical models provided quantitative evidence for the importance of seasonal wind persistence in hypoxia, they did not provide insight into underlying mechanisms.

In this study, we used the previously built terrestrial-estuarine-ocean biogeochemical modeling system for Chesapeake Bay (DLEM-Ches-ROMS-ECB) to investigate how prolonged seasonally variable winds influence hypoxia. There have been multiple numerical studies on how wind affects hypoxia using three-dimensional coupled physical-biogeochemical models (Scully, 2010b,2013,2016; Li et al., 2015; Jiang and Xia, 2017, 2018), but their focus was limited to short-term winds. However, Wang et al. (2016) found that the relative importance of wind on hypoxia depends on wind speed and duration. Therefore, in-depth modeling of the impact of prolonged seasonally variable winds is necessary.

The remainder of this paper is organized as follows. Section 2 presents the configuration of oxygen dynamics in our land-estuarinebiogeochemistry model. Section 3 presents the results, including model validation, correlations among hypoxia and multiple external drivers in spring and summer, and dominant processes affecting oxygen and nitrogen concentrations. Section 4 summarizes the findings and discusses the limitations of the model. Finally, Section 5 discusses research implications and future research. Since DO levels typically decrease during the spring, with the onset of anoxic/hypoxic conditions occurring in May, and the February to April wind exhibits a robust correlation with summer hypoxic volume (Lee et al., 2013), we therefore designate May-August as the "summer" period and February-April as the "spring" period.

2. Materials and methods

2.1. Model Description

Our terrestrial-estuarine-ocean biogeochemical model included a terrestrial model component based on the Dynamic Land Ecosystem Model (DLEM), an estuarine-ocean physical component based on the Regional Ocean Modeling System (ROMS), and an estuarine-ocean carbon biogeochemistry (ECB) modeling component. A brief description of each component is provided below.

The hydrodynamic model was the same as that used by Scully (2016). It is based on the Chesapeake Bay Regional Ocean Modeling System (ROMS) Community Model (ChesROMS) (Xu et al., 2012; Brown et al., 2013). The domain spans the region from 77.2° W to 75.0° W and from 36° N to 40° N, covering the main stem and the nine largest tributaries of Chesapeake Bay, as well as the shelf region adjacent to the Bay (Fig. 1).

The horizontal grid spacing varies, with the highest resolution (430 m) in the northern Bay near the Chesapeake and Delaware Canals, and the lowest resolution (\sim 10 km) at the southern end of the mid-Atlantic Bight. The average grid spacing within Chesapeake Bay is 1.7 km. The model had 20 terrain-following vertical layers with higher resolution near the surface and bottom boundaries. Daily freshwater discharge data for nine major tributaries (Susquehanna, Patuxent, Potomac, Rappahannock, York, James, Nanticoke, Choptank, and Chester Rivers) from the U.S. Geological Survey (USGS) were applied at the upstream river boundaries. Tidal constituents were derived from the Advanced Circulation (ADCIRC) model, and observed water levels at Duck, NC, and Lewes, DE, from the National Oceanic and Atmospheric Administration (NOAA). Temperature and salinity data at the oceanic boundary were obtained from the World Ocean Atlas 2001 (https://www.ncei.noaa. gov/products/world-ocean-atlas). Surface atmospheric forcings, including shortwave and longwave radiation, rainfall, surface air humidity, pressure, temperature, and 10 m winds, were obtained from the National Center for Environmental Prediction (NCEP), North American Regional Reanalysis (NARR) model (https://www.ncei.noaa.gov/pr oducts/weather-climate-models/north-american-regional).

Our model is different from that of Scully (2010b, 2013, 2016) in that we coupled the physical model with the estuarine carbon biogeochemistry (ECB) model of Feng et al. (2015) rather than using a simple parameterization for oxygen. The ECB model describes a simplified nitrogen cycle with 11 state variables, including nitrate ([NO₃]), ammonium ([NH4]), phytoplankton (P), zooplankton (Z), small and large detritus (D_S and D_L, respectively), semi-labile and refractory dissolved organic nitrogen ([DON]_{SL} and [DON]_{RF}, respectively), inorganic suspended solids [ISS], chlorophyll concentration ([Chl]) and dissolved oxygen (DO) concentration ([O₂]). Da et al. (2018) and St-Laurent et al. (2020) improved the parameterizations governing the growth and fate of phytoplankton to more accurately represent the observed seasonal cycle of the Bay. This improvement involved considerations such as temperature, the photosynthesis-irradiance curve, mortality and aggregation rates, as well as light attenuation coefficient in the lower Bay. They also expanded the ECB model to include analogous variables, including dissolved inorganic carbon ([DIC]), total alkalinity ([TA]), dissolved organic carbon ([DOC]), small and large carbon detritus (DSC and DLC, respectively), and semi-labile and refractory dissolved organic carbon components ([DOC]_{SL} and [DOC]_{RF}, respectively) (St-Laurent et al., 2020). Because the focus of this study was hypoxia, only equations describing oxygen dynamics were provided. The model version was the same as that used by Feng et al. (2015), and included the full nitrogen cvcle.

Water column biochemical processes that increase DO include phytoplankton primary production and carbon-based production (which represents the carbohydrate over-production by nutrient-stressed cells, Druon et al., 2010), whereas processes that decrease DO include phytoplankton exudation, zooplankton excretion and sloppy feeding, and remineralization of small, large, and semi-labile dissolved organic nitrogen. Changes in DO as a function of time were calculated using equation (1):

$$\frac{\partial O_2}{\partial t} = Primary \ production + Excess \ based \ production - Nitrification$$
$$- Exudation - Excretion - Sloppy \ feeding - Remineralization$$
(1)



Fig. 1. (a) The Dynamic Land Ecosystem Model (DLEM) domain for the Chesapeake Bay Watersheds with major plant functional types and land cover; (b) The Chesapeake Bay model grid, bathymetry, location of EPA Chesapeake Bay Program Water Quality Monitoring Stations (red dots). The black line marked the location of trench in Figs. 3, 5, 9, 10, 12 and 14. The blue lines mark the location of cross-section in Fig. 10.

where,

$$Primary \ production = \mu_0 L_I \left(\eta_{O2:NO3} L_{NO_3} + \eta_{O2:NH4} L_{NH_4} \right) P \tag{1.1}$$

Excess based production = $\gamma_C \eta_{C:N} \mu_0 L_I (1 - L_{NO_3} - L_{NH_4}) P$ (1.2)

$$Nitrification = 2f_{NTF}n[NH_4]$$
(1.3)

 $Exudation = \eta_{O2:NH4} f_{NTF} \omega \mu_0 L_I (L_{NO_3} + L_{NH_4}) P$ (1.4)

$$Excretion = \eta_{O2:NH4} \left(l_{BM} + l_E \beta \frac{P^2}{K_P + P^2} \right) Z$$
(1.5)

Sloppy feeding =
$$\eta_{O2:NH4}(1-\beta)\lambda(1-\varepsilon)gZ$$
 (1.6)

is the Schmidt number (Wanninkhof, 1992); u_{10} is the wind speed 10 m above the sea surface; $O_{2[sat]}$ is the saturation concentration of oxygen, calculated as described by Garcia and Gordon (1992), which depends on temperature and salinity.

At the bottom of a water column, the ECB model includes an intermediate approach following that of Druon et al. (2010), which assumes that a portion (ϕ_1) of the organic matter reaching the seabed is resuspended, a portion $(\phi_2(1-\phi_1))$ is permanently buried, and the remainder $(1-\phi_2)(1-\phi_1)$ is instantaneously remineralized in the seabed through coupled nitrification and denitrification back to the ammonium pool (Boynton et al., 2023). The oxygen consumed in the bottom layer of the model by remineralization in the seabed is given by (See Feng et al., 2015):

$$\left. \frac{\partial O_2}{\partial t} \right|_{z=H} = -\eta_{O_2:NF/DNF} \frac{(1-\phi_1)(1-\phi_2)}{\Delta z} F_{TON}(1-L_{BO_2})$$
(3)

 $Remineralization = \eta_{O2:NH4} f_{NTF} (1 - \delta_N) r_{D_S} D_S - \eta_{O2:NH4} f_{NTF} (1 - \delta_N) r_{D_L} D_L - \eta_{O2:NH4} f_{NTF} r_{[DON]_{SL}} r^T [DON]_{SL} D_S - \eta_{O2:NH4} f_{NTF} (1 - \delta_N) r_{D_S} D_S - \eta_{O2:NH4} f_{NTF} (1 - \delta_N) r_{D_S$

(1.7)

In addition to processes within the water column, gas exchange across the air-sea interface that changes the oxygen concentration in the top layer of the model is represented as:

$$\frac{\partial O_{2[top]}}{\partial t} = \frac{vk_{o_2}}{\Delta z} \left(O_{2[sat]} - O_2\right) \tag{2}$$

where $vk_{O_2} = 0.31 u_{10}^2 \sqrt{660/Sc_{O_2}}$ is the gas exchange coefficient; Sc_{O_2}

The above functions were used in the state variable equations, and the biogeochemical parameters used in the equations are listed in Tables 1 and 2. It should be noted that riverine dissolved organic and inorganic nitrogen concentrations from multiple tributaries were derived from the DLEM. DLEM is a process-based model that can explicitly represent the water, carbon and nitrogen fluxes of land ecosystem. The model can plant photosynthesis, land biophysics and soil biogeochemical

Table 1

Definitions of Functions used in State Variable Equations.

Symbol	Description	Equation	Units
F _{TON}	Flux of total organic matter reaching to the bottom	$w_p P _{z=H} + w_{D_S} D_S _{z=H} + w_{D_L} D_L _{z=H}$	mmole-N m ⁻² d ⁻¹
F_{BC}	Flux of total organic carbon in the sediment	$\frac{\left[\eta_{C:N} w_p P _{z=H} + \eta_{C_B:N_B} \left(w_{D_s} D_S _{z=H} + w_{D_L} D_L _{z=H}\right)\right] \times 12 \times 365}{1000}$	g C m ⁻² yr ⁻¹
Ι	Photosynthesis available radiation	$I_0 \bullet PAR frac \bullet e^{-zK_D}$	$W m^{-2}$
L_{BO_2}	Bottom oxygen limitation factor	$\frac{K_{BO_2}\left(O_{2_{ese}} _{z=H} - O_2 _{z=H}\right)}{O_{2_{ese}} _{z=H}\left(O_2 _{z=H} + K_{BO_2}\right)}$	dimensionless
L_I	Photosynthesis-light (P-I) relationship	$\frac{aI}{\sqrt{\mu^2 + \sigma^2 I^2}}$	dimensionless
L_{NO_3}	Nitrate uptake limitation with ammonium inhibitor	$\frac{NO_3}{K_{NO_3} + NO_3} \frac{1}{1 + \frac{NH_4}{K_{res}}}$	dimensionless
L_{NH_4}	Ammonium uptake limitation	$\frac{NH_4}{K_{NH_4} + NH_4}$	dimensionless
<i>f</i> _{NTR}	Oxygen limitation for nitrification	$\frac{O_2}{O_2 + K_{min}}$	dimensionless
f_{DNF}	Oxygen limitation for denitrification	$\frac{K_{DNF}}{O_{DNF}}$	dimensionless
g	Zooplankton grazing rate	$\frac{P^2}{g_{max}}$	d ⁻¹
n	Nitrification rate	$n_{max}\left(1 - \left[0, \frac{I - I_{NTR}}{K_I + I - I_{NTR}}\right]_{max}\right)$	d-1
vk_{O_2}	Gas exchange coefficient	$vk_{O_2} = 0.31 u_{10}^2 \sqrt{660/Sc_{O_2}}$	m/s
		Sc_{O_2} is the Schmidt number (Wanninkhot, 1992) w^2 is the wind speed 10 m above the sea surface	
ϕ_1	Fraction of resuspension	u_{10} is the wind speed to in above the sea surface $\frac{\Gamma}{\Gamma}$	dimensionless
ϕ_2	Fraction of buried	$\left\{0.092 F_{BC}^{0.5797}; 0.75\right\}$	dimensionless

Table 2

Definitions of Biogeochemical Parameters Used in State Variable Equations.

Symbol	Description	Value	Units
I _{NTR}	Threshold for light-inhibition of nitrification	0.0095	$W m^{-2}$
K_{BO_2}	Half-saturation for bottom denitrification switch	26.5	mmole -O m ⁻³
K _{DNF}	Half-saturation constant for water column denitrification	1	mmole-N m ⁻³
K_I	Light intensity at which the inhibition of nitrification is half-saturated	0.1	$W m^{-2}$
K_{NH_4}	Half-saturation constant for ammonium uptake	0.5	mmole-N m ⁻³
K_{NO_3}	Half-saturation constant for nitrate update	0.5	mmole-N m ⁻³
K _{NTR}	Half-saturation constant for water column nitrification	1	mmole-N m ⁻³
K_P	Half-saturation concentration of phytoplankton ingestion	2	(mmole-N m ⁻³) ²
PARfrac	fraction of light that is available for photosynthesis	0.43	dimensionless
g _{max}	Zooplankton maximum growth rate	0.3	d ⁻¹
l_{BM}	Zooplankton basal metabolism	0.1	d ⁻¹
l_E	Zooplankton specific excretion rate	0.1	d ⁻¹
n _{max}	Maximum rate of nitrification	0.05	d ⁻¹
$r_{[DON]_{SL}}$	Remineralization of semi-labile dissolved organic nitrogen	0.00765	d ⁻¹
r_{D_L}	Remineralization of large detritus	0.2	d ⁻¹
w_L	Large detritus sinking velocity	5	m d ⁻¹
W_P	Phytoplankton sinking velocity	0.1	m d ⁻¹
Ws	Small detritus sinking velocity	0.1	m d ⁻¹
Γ_c	Critical stress	0.05	Pa
Г	Bottom shear stress	$\sqrt{ au_{b_x}^2+ au_{b_y}^2}$	Pa
α	Initial slope of the P-I curve	0.065	$W^{-1} m^2/d$
β	Zooplankton nitrogen assimilation efficiency	0.75	dimensionless
γ _C	Parameter of carbon excess-based DOC exudation	0.2	dimensionless
δ_N	Fraction of detritus solubilization to DON	15 %	dimensionless
ε	Fraction of semi-labile DON to total DON within the phytoplankton cell	0.15	dimensionless
$\eta_{C:N}$	Phytoplankton Carbon: Nitrogen ratio	106/16	mol-C/mol-N
$\eta_{C_B:N_B}$	Bottom small and large detritus Carbon: Nitrogen ratio	9.3	mol-C/mol-N
$\eta_{O_2:NO_3}$	Stoichiometry for O_2 produced when consuming 1 more of nitrate	138/16	$(mmole-O m^{-3})(mmole-N m^{-3})^{-1}$
$\eta_{O_2:NH_4}$	Stoichiometry for O_2 produced when consuming 1 more of ammonium	106/16	(mmole-O m ⁻³)(mmole-N m ⁻³) ⁻¹
$\eta_{O_2:NF/DNF}$	Stoichiometry for O_2 used when consuming 1 more of ammonium in coupled nitrification/denitrification process	115/16	(mmole-O m^{-3})(mmole-N m^{-3}) ⁻¹
$\kappa_{[DON]_{SL}}$	Temperature dependency remineralization of semi-labile DON	0.07	(°C) ⁻¹
λ	Fraction of DON to TON [DON + PON] within the phytoplankton cell	0.71	dimensionless
μ_0	Phytoplankton growth rate	2.15	d ⁻¹
ω	Phytoplankton exudation rate of labile DON	0.03	dimensionless

processes, driven by climate variability and human management (Tian et al., 2012; Yang et al., 2015a, 2015b). The hydrological model incorporated in DLEM receive water, nitrogen and carbon loading. Here, the

land model has significant improvements, including the incorporation of sewage release, the development of scale adaptive channel routing scheme and high-resolution model inputs (Pan et al., 2021). The



Fig. 2. The schematic of terrestrial-estuarine ocean biogeochemical modeling system. Internal and boundary processes included in the biogeochemical component of estuarine ocean model (ECB) were illustrated. Please refer Table A1 and A2 in Feng et al. (2015) for details of the biogeochemical model in water column and sediment (treated as the bottom layer in water column). Abbreviations: P, phytoplankton; Z, zooplankton; D_s , small detritus; D_L , large detritus; $[DON]_{SL}$, semi-labile DON; $[DON]_{RF}$, refractory DON; PON, particulate organic nitrogen; [ISS], inorganic suspended sediment; [DO], dissolved oxygen; H_2O , riverine freshwater; N_2 , nitrogen gas.

simulated water discharge and aquatic carbon constitutes has been validated by the time series data generated by U.S. Geological Survey (USGS) observation using LOADESTimator (Yao et al., 2021) (Fig. 2).

2.2. Observations

The model simulation was validated against available data from the EPA Chesapeake Bay Program (CBP) water quality monitoring program and satellite observations. CBP Data from 1985 to 2005 are publicly available for download from http://www.chesapeakebay.net/data. Between May and September, inclusive, there were typically two CBP water quality cruises per month. It is noteworthy that CBP provided measurements for $NO_2 + NO_3$, while our model only simulated NO_3 . Given the relatively small magnitude of NO_2 , we treat them equivalent in the following discussions. In addition, we used monthly composites

from GlobColour (https://hermes.acri.fr/), which provides a continuous dataset of merged L3 Ocean Color products for surface chlorophyll distribution from 1998 to 2005. For the CBP observations, model skill metrics were computed by first averaging the CBP observations and model simulations from 1985 to 2005 in three-month intervals (MarMay; Jun – Aug; Sep-Nov; Dec-Feb), and then sampling the model results at the same horizontal, vertical, and temporal locations as the observations. For satellite observations, simulated surface chlorophyll concentrations were computed by first averaging the satellite and model data from 1998 to 2005 at above three-month interval, and subsequently interpolated to the satellite pixels before calculating the skill numbers.

We used four model skill metrics to compare the model results with observations:

(1) the correlation coefficient (*r*):

$$r = \frac{\sum_{i=1}^{n} (O_i - \overline{O}) (M_i - \overline{M})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2 \sum_{i=1}^{n} (M_i - \overline{M})^2}}$$
(4)

(2) the root mean square difference (RMSD):

$$RMSD = \sqrt{\frac{\sum_{i=1}^{n} (M_i - O_i)^2}{n}}$$
(5)

(3) bias:

$$Bias = \frac{\sum_{i=1}^{n} (M_i - O_i)}{n} = \overline{M} - \overline{O}$$
(6)

(4) and the Wilmott Skill score:

$$W_{skill} = 1 - \frac{\sum_{i=1}^{n} (M_i - O_i)^2}{\sum_{i=1}^{n} (|M_i - \overline{O}| + |O_i - \overline{O}|)^2}$$
(7)

where O_i is the observation at time t_i , M_i is the model result at t_i , \overline{O} is the observation mean, and \overline{M} is the model mean. These metrics capture different aspects of model performance. The correlation coefficient measures the tendency of the predicted and observed values to covary. Bias and RMSD measure the discrepancies between model results and observations. The Willmott skill score (Willmott, 1981) is a widely used metric for quantifying the overall agreement between a model and its observations. A value of $W_{skill} = 1$ indicates perfect agreement between model results and observations, whereas $W_{skill} = 0$ indicates that the model skill is equivalent to the observational mean (Willmott, 1981). These four metrics are often used together for a comprehensive model skill assessment. Values of 0 for bias and RMSD and values of 1 for *r* and W_{skill} indicate a perfect fit to the observations.

2.3. Simulations

We first ran DLEM-ChesROMS-ECB continuously from 1985 to 2005 with realistic NARR wind forcing. In addition to comparing simulation results with the observational data list above, the long-term run was used to identify any general correlations that may exist among summer hypoxic volume and various external forcings. We then developed idealized experiments based on the correlation results and prevailing wind conditions during the 21-year period. These experiments were used for in-depth studies of the mechanisms linking wind duration and hypoxia.

For the prevailing wind conditions, we determined the proportion of time for which the wind came from each direction during spring and summer. These directions were grouped into six categories: NE-to-S (spring northeasterly to summer south), NW-to-SW, N-to-SW, NW-to-S, N-to-S, and S-to-SW. The spatial-temporal average surface wind speed was also calculated as 4.34 m/s and 3.19 m/s, respectively.

Initially, we conducted six idealized numerical experiments by maintaining a constant wind speed and direction during spring and summer according to the predominant wind conditions described above (Table S1). A constant wind configuration represents prolonged wind conditions during each season. We used the NE-to-S run as the reference run, which reflects the wind conditions observed during 2003, when hypoxia had largest volume of anoxic water largest throughout the simulated 21-year period (Lee et al., 2013, Fig. 6 in the reference work). Other surface atmospheric forcings (short/longwave radiation, rainfall, surface air humidity/pressure/temperature) and open boundary conditions were all kept the same as the realistic run in 2003. We also conducted three further experiments by keeping the spring wind northeasterly but varying the summer wind: (1) NE-to-NE. This run maintained the summer wind northeasterly instead of reversing towards

the upstream estuary (S/SW) and was compared with the realistic wind scenario to demonstrate the impact of summer southerly wind reversal on hypoxia. This can also represent the condition in which the duration of the northeasterly wind was abnormally long. The scenario (2) NE-to-high S run maintained the high wind speeds observed during spring instead of decreasing them. The experiment aimed to investigate the influence of summer wind weakening on hypoxic levels. (3) NE-to-Sinusoidal S run sinusoidally increased and decreased the summer wind speed from 0 to 6.28 m/s over a three-day period while maintaining an average wind speed of 3.19 m/s (Fig. S3). In reality, both wind speed and direction over the Bay seldom remain steady for three consecutive days; instead, they vary at synoptic timescales associated with the passage of weather systems. This scenario aimed to examine the impact of short-term episodic events on the effect of seasonal mean wind speed on hypoxia.

To highlight the role of wind, both river discharge and nitrogen loading were kept constant at 2075 (m³ s⁻¹) and 6.12 (Gg-N), respectively, which were also the 21-year averaged result from DLEM between February and August.

2.4. Mass budget analysis

To quantitatively assess the dominant process that determines variation in hypoxic volume we used the model results to investigate changes in oxygen content of a fixed control volume V. Because hypoxia is a phenomenon below the pycnocline, V was chosen to be located below a depth of 10 m in the upper-middle and lower-middle reaches of Chesapeake Bay (between the two purple dashed lines in Fig. 3a and below the dark blue in Fig. 5), which are regions most susceptible to hypoxia (Li et al., 2015, 2016). The integration of the DO equation over V yields:

$$\frac{\partial M_{O_2}}{\partial t} = F_{yady} + F_{xady+wady} + F_{vdiff} + PP + WCR + SOD$$
(8)

where M_{O_2} is the total O_2 content (kg) in V. The first term, F_{yadv} , on the right-hand side of Equation (8) is the along-channel advective flux of DO into the control volume. The second term, $F_{xadv+wadv}$, including the horizontal and vertical advection, is the cross-channel advective flux into the control volume and is called cross-channel advective flux. The third term (F_{vdiff}) represents the vertical diffusion flux. The horizontal diffusion coefficients are generally small in high resolution physical models (Riemenschneider and Legg, 2007). Therefore, are ignored here as in Li et al. (2015) and Scully (2010b, 2016).

$$F_{yadv} = \overbrace{\iiint_{V}}^{along-channel advection} (8.1)$$

$$F_{xadv+wadv} = \overbrace{\iiint_{V}}^{cross-channel advection} \left(-u\frac{\partial O_{2}}{\partial x} - w\frac{\partial O_{2}}{\partial z} \right) dxdydz$$
(8.2)

$$F_{vdiff} = \iiint_{V} \frac{\partial}{\partial z} \left(K_{v} \frac{\partial O_{2}}{\partial z} \right) dx dy dz$$
(8.3)

In addition to hydrological processes, the fourth, fifth, and sixth terms represent the oxygen produced by primary production (PP), consumed by the Water Column Respiration (WCR), and sediment oxygen demand (SOD), respectively.



Fig. 3. Observed and simulated seasonal temperature (left panels) and salinity (right panels) from 1985 to 2005. Temperature and salinity along the thalweg with background color represents the simulation and circles showing the observations. Model skill assessments are conduct by assessing the simulation results at the observational points at coincident times and locations. Panels from top to bottom, Mar-May; Jun – Aug; Sep – Nov; Dec – Feb. Purple dashed lines in Fig. 3a denote the north and south boundaries, which highlighted the upper and lower boundaries of the control volume for dissolved oxygen (DO) mass budget analysis, as well as the nitrogen fluxes in Fig. 16e.

$$PP = \iiint_{V} (Primary \, production + Excess \, based \, production) dxdydz \qquad (8.4)$$

spatial variability within any given season. Average temperatures were uniform throughout the water column and main stem of the Bay. The quantitative model skill metrics yielded: Bias = 0.51 °C; RMSD = 1.14 °C; r = 0.99; $W_{skill} = 0.99$).

$$WCR = \iiint_{V} (Nitrification + Exudation + Excretion + Sloppyfeeding + Remineralization) dx dy dz$$

(8.5)

$$SOD = \iint_{A} -\eta_{O_{2}:\frac{NF}{DNF}} \frac{(1-\phi_{1})(1-\phi_{2})}{\Delta z} F_{TON}(1-L_{BO_{2}}) dxdy$$
(8.6)

3. Results

3.1. Model validation

We first compared the simulated temperature and salinity fields with the CBP observations to ensure that the model captured the observed hydrodynamic fields well (Fig. 3). Seasonally averaged simulated temperature distributions were in good agreement with CBP observations throughout the water column. Temperature levels were higher from June to November and lower from December to May but exhibited little Seasonally averaged simulated salinity distributions successfully captured both horizontal and vertical gradients of salinity concentrations. Unlike the temperature field, the salinity field exhibited significantly stronger spatial variability than temporal variability. The point-to-point comparison yielded the model skill with Bias = 2.50 PSU; RMSD = 2.88 PSU; r = 0.97; $W_{skill} = 0.96$.

In addition to temperature and salinity, the model also effectively replicated the satellite observed surface chlorophyll concentrations (Fig. 4; Bias = 1.38 mg/L; RMSD = 2.40 mg/L; r = 0.63; W_{skill} = 0.67). During spring and summer, the model exhibited an overestimation of surface chlorophyll concentrations in the upper (4.4 mg/L) and middle (4.0 mg/L) Bay, while underestimating them in the lower Bay (1.5 mg/L). Both the model and satellite observations showed that surface chlorophyll concentrations exhibited significant seasonal variations, with higher levels from March to August and lower levels from



Fig. 4. Comparisons between 8-yr (1998 – 2005) averaged seasonal sea surface chlorophyll from satellite observations (data were retrieved from high-resolution 4km merged L3 Ocean Color products http://www.globcolour.info/; upper panels) and model simulations (lower panels). Panels from left to right, Mar-May; Jun – Aug; Sep – Nov; Dec – Feb.

September to February.

The simulated NO₃ and oxygen fields were compared with CBP observations (Fig. 5). The simulated NO₃ field successfully captured the spatial gradient and seasonal cycle of the observed CBP NO₂ + NO₃ field (Bias = 0.75 mmol N/m³; RMSD = 7.76 mmol N/m³; r = 0.95; W_{skill} = 0.97). From December to May, high NO₃ riverine waters extended seaward with low-salinity water, creating a strong vertical gradient in the upper middle Bay. From June to November, high NO₃ water was limited, mostly in the upper Bay, with a weak vertical gradient throughout most of the Bay.

Simulations and observations demonstrated that the DO below the pycnocline experienced a strong seasonal cycle with low levels from June to August (Fig. 5). The simulated DO distribution closely aligned with CBP observations throughout the water column in the upper Bay. The model successfully captured the vertical gradient in oxygen concentration in the upper middle Bay (Stations CB3.3C to CB5.1; Fig. 1b for



Fig. 5. Observed and simulated seasonal NO₃ (left panels) and DO (right panels) from 1985 to 2005. NO₃ and dissolved oxygen (DO) along the thalweg with background color represents the simulation and circles showing the observations. Model skill assessments are conduct by assessing the simulation results at the observational points at coincident times and locations. The dark blue dashed lines in Fig. 5b denoted control volume (10-m below upper and lower boundaries) for dissolved oxygen (DO) mass budget analysis.



Fig. 6. The observed (red dots) and simulated hypoxic volume using the 2 mg/L threshold (black lines) from 1985 to 2005.

station locations) during spring and summer. However, the model overestimated the DO concentration in the lower middle Bay (Stations CB5.2 CB6.3) during the summer. Again, the model and observations were in good agreement for lower Bay stations CB7.3 and CB7.4 in spring and winter, but the model overestimated DO levels in summer and fall. Overall, a quantitative skill assessment for DO yielded: Bias = 0.55 mg/L; RMSD = 1.0 mg/L; r = 0.88; $W_{skill} = 0.90$.

We compared time series of observed and simulated bottom DO concentrations at the upper (CB3.2), middle (CB4.2C and CB5.2), and lower (CB6.3) Bay stations between 1985 and 2005 (Fig. S1). The model replicated the seasonal cycle of observed bottom DO well and demonstrated its skill in predicting bottom DO for the upper and middle Bay stations, with a bias of 0.3-1.4 mg/L, correlation coefficients (r) of 0.77–0.88, RMSD of 1.7–2.7 mg/L, and Wskill exceeding 0.8. However, the model overestimated the bottom DO concentrations at the lower Bay stations. The bias of DO was as high as 2.1 mg/L at CB6.3, but our model still captured seasonal and interannual variability, with r = 0.65 (p <0.05). Bottom DO levels were lower in summer than other seasons and were abnormally low in 2003, when the hypoxic volume was the largest recorded. Potential reasons for the existing bias are discussed in the discussion section. Because our focus was on variability of hypoxia given different seasonal wind regimes, the existence of bias did not affect our subsequent discussions.

Next, we calculated daily hypoxic volume using both simulations and observations (Fig. 6). The hypoxic volume from the model was calculated by integrating the cells with DO concentrations less than 2 mg/L. DLEM-ChesROMS-ECB replicated the patterns of variation of the observed hypoxic volume, with a bias of -0.84 km^3 , a correlation coefficient of 0.66, an RMSD of 2.63 km³, and an overall skill of 0.79. Although in some years, the bias of the model can be as large as 6.68 km³, the seasonal variations in hypoxic volume are captured very well. During summer, the simulated and observed hypoxic volume was approximately 3.76 km³ and 5.17 km³, respectively, 3.63 km³ and 4.79 km³ higher than non-summer seasons. The maximum hypoxic volume differences in wet years (January-June river discharge above the 21year mean) were smaller than those in dry years (January-June river discharge below the 21-year mean). The model underestimated the hypoxic volume by 2.5 km³ for wet years, but by 4 km³ for dry years. This is not surprising, because more oxygen-consuming materials can be flushed into the lower Bay during wet years. Furthermore, both the model and observations demonstrated that hypoxic volume was largest in 2003 (Obs:5.75 km³ versus Model:6.86 km³), when Jan-Jun River discharge was the fourth largest of all simulated years and the duration of northeasterly wind in spring was the longest of all 21 simulated years.

3.2. Correlations among summer hypoxic volume and external drivers during spring and summer

We first calculated correlation coefficients among our simulated hypoxic volume during summer (May - August) and the multiple external forcings used to force the model (Table 3). This calculation was a repetition of Scully (2016) (see Table 1). Our results demonstrated that summer hypoxic volume had statistically significant positive correlations with the Jan-Jun Susquehanna TN loading (r = 0.91) and river discharge (r = 0.74), consistent with Scully (2016) and many other previous studies based on in-situ data (Hagy et al., 2004; Murphy et al., 2011). We also found that the summer hypoxic volume exhibited a statistically significant negative correlation with the duration of northeasterly wind (r = -0.51), consistent with Scully, 2016's results that r =-0.41, but mechanistic explanations were not provided in his study. We also found that the summer hypoxic volume exhibited a statistically significant positive correlation with duration of southerly wind (r = 0.44). In contrast to Scully's (2016) finding that wind speed explains most of the interannual variability in hypoxic volume, we found that summer hypoxic volume exhibited a small and non-significant negative correlation (-0.17) with summer wind speed. In addition to replicating Scully's (2016) calculation, we calculated correlation coefficients among the summer hypoxic volume and percent duration of spring (February-April) wind from eight equally spaced compass directions and demonstrated that the summer hypoxic volume was also significantly correlated with northeasterly winds in spring (r = 0.42), in contrast to the negative correlation with summer winds.

As the correlations indicate that hypoxic volume is most strongly correlated with the duration of spring and summer NE winds, as well as summer S winds, we then analyzed the idealized NE-to-S and NE-to-NE experiments in detail. Of all the idealized experiments, summer hypoxic volumes did not significantly differ between prolonged SW and S winds (Fig. S2). Therefore, we considered the S-to-SW run to be a persistent upestuary wind and compared it with persistent down-estuary and reversal winds. To explore the role of wind speed, we utilized the NE-to-high S, NE-to-sinusoidal S, and NE-to-S simulations.

3.3. Hypoxic volumes during idealized wind experiments

The simulated hypoxic volumes under various spring and summer wind conditions are shown in Fig. 7 and S2. For all simulations, hypoxic volumes started to develop in mid-March and reached a maximum in July. There was a large break in early May because the idealized experiment assumed that the spring-to-summer wind transition occurred on May 1st. Hypoxic volume exhibited strong seasonal cycles when the wind direction changed to southerly (black lines in Fig. 7) or southwesterly (red line in Fig. 7) in summer. However, the summer hypoxic volume was as high as 5.9 ± 1.2 km³ if wind was northeasterly in spring (solid black line in Fig. 7), and this was 64 % larger than the volume occurring with a southerly wind $(3.6 \pm 2.3 \text{ km}^3)$ (red line in Fig. 7). In contrast, a hypoxic volume did not develop if the wind remained northeasterly from spring to summer (light blue line in Fig. 7). The variability of hypoxic volume under idealized wind scenarios is consistent with the correlation results in Table 3, which shows that the summer hypoxic volume is positively correlated with the percentage of southerly wind in summer, but negatively correlated with the percentage of northeasterly wind in summer. Furthermore, we observed that

Table 3

Wind Variables

Correlation coefficients between the simulated average May-Aug hypoxic volumes from 1985 to 2005 and the Feb-Apr (Jan-Jun) Susquehanna River discharge and TN loading, percentage of Feb-Apr (May-Aug) winds from eight compass directions and wind speed, as shown in Scully (2016) Table 1. Significant correlations (<0.05) are denoted with asterisks.

	NARR WSPD	Northerly	Northeasterly	Easterly	Southeasterly	Southerly	Southwesterly	Westerly	Northwesterly
		Percent durati	Percent duration summer wind from						
Feb-Apr	0.37	0.01	0.42*	0.32	0.27	0.01	-0.09	-0.21	-0.55*
May-Aug	-0.17	-0.21	-0.51*	-0.33	0.03	0.44*	0.03	0.28	-0.06
River Variable	es								
	Discharge	TN loading							
Feb-Apr	0.46*	0.73*							
Jan-Jun	0.74*	0.91*							



Fig. 7. The simulated hypoxic volume at 2 mg/L threshold in idealized wind scenario experiments NE-to-S, NE-to-high S, NE-to-sinusoidal S, NE-to-NE, S-to-SW.

change in the wind speed during summer had an impact on the hypoxic volume, but not to the same extent as changes in wind direction. With higher (black dash line in Fig. 7) or oscillates (black dotted line Fig 0.7) southerly winds, hypoxic volume southerly winds was approximately 19 % (4.8 \pm 1.9 km³) and 22 % (4.6 \pm 1.5 km³) lower than the reference run, respectively.

3.4. Seasonal wind regimes and their effects on the evolution of hypoxia in Chesapeake Bay

We next investigated how the biophysical responses to wind regime transition from spring to summer. For both south and northeasterly spring and summer winds, a two-layer circulation emerged that was seaward at the surface and landward in the bottom layer due to estuarine gravitational circulation (Fig. 10 left panels). We also observed that down-estuary northeasterly summer winds strengthened the circulation (Fig. 10a and 10g), resulting in more riverine nutrients being transported seaward than with southerly wind (Fig. 10c and 10e). The high nutrients stimulated phytoplankton growth, enhancing detritus and semi-labile DON concentrations below the pycnocline in the upper and middle Bay in summer (compare the NE-to-NE and NE-to-S in Fig. 8b, f, 9c, d). We also observed the high-salinity seawater (S > 24 PSU) intruding more into the head of the Bay below the pycnocline (Fig. 10g, NE-to-NE). We expected that low-salinity freshwater would extend more seaward above the pycnocline, but this was barely observed along the vertical section because of the accumulation of freshwater in the western shoal arising from cross-channel circulation (Fig. 10g, h). This accumulation generated an eastward pressure gradient, forming a seaward jet on the western flank through geostrophic adjustment (Fig. 8e, 10h). In addition to increasing organic matter, summer northeasterly winds also resulted in a higher vertical mixing coefficient from the upper to middle Bay compared to southerly winds (compare the NE-to-NE and NE-to-S in Fig. 8c, g, 9a, b) owing to differences in lateral circulation. Under summer southerly winds, an eastward flow occurs from the surface to a depth of \sim 3 m, turns westward from \sim 3 m to \sim 18 m, and finally turns eastward again from ~ 18 m to the bottom (Fig. 10f). This creates a dipole circulation that is clockwise in the upper layer and counterclockwise in the lower layer. In contrast, the lateral circulation associated with northeasterly winds has only two layers: a westward flow from the surface to a depth of \sim 8 m, and a eastward flow from a depth of ~ 8 m to the bottom. This implies that northeasterly winds drive a uniform counterclockwise circulation cell throughout the water column. These circulation structures align with those of Li and Li (2012) and Xie et al. (2017) and were attributed to the combined effects of wind-driven lateral Ekman flow, vertical shear-induced tilt of planetary vorticity, and lateral baroclinic forcing due to sloping isopycnals. These circulation patterns significantly modify the shape of isohalines. Under

northeasterly winds, a strong westward surface flow constrains lowsalinity water on the western shore, causing isohalines to tilt upward (Fig. 10b and 10h) and increasing the overall degree of vertical mixing. In contrast, the east–west-east lateral flow under southerly winds flattens the isohalines (Fig. 10d and f), reducing the degree of vertical mixing (Fig. 8c, 8g, 9a, and 9b). As a result, bottom- and belowpycnocline DO were higher under the northeasterly wind (Fig. 8d, h, 9e, and 9f), aligning with the findings of Scully (2010b) who found with a previous version of our same model that the amount of oxygen supplied by vertical mixing by episodic southerly winds was approximately 40 % that of northern winds (see Fig. 3 and Table 2 in the reference article).

Comparisons of salinity, currents, amounts of detritus and semilabile DON, and vertical mixing coefficients between the NE-to-NE run, NE-to-S run and S-to-SW run in spring and summer, yielded similar results (Fig. 10a-d; Fig. 11a-c, g, and Fig. 12a-d). While spring northeasterly winds increased the amount of organic matter, they also significantly increased vertical mixing, preventing the occurrence of hypoxia during spring. However, in summer, the amount of detritus and semi-labile DON in the NE-to-S winds was higher than that in the S-to-SW winds (Fig. 12). As a result, the concentrations of dissolved oxygen below the pycnocline and at the bottom were lower under NE-to-S winds than under S-to-SW winds (Fig. 11d, h, Fig. 12i, and j), particularly in the upper to upper-middle Bay.

Compared with the reference run (Fig. 8a-d), higher or oscillating wind speeds resulted in stronger gravitational circulation during summer (Fig. 13a and Fig. 13e), leading to greater seaward transport of riverine NO₃, and thus higher detritus and semi-labile DON concentrations (Fig. 13b and Fig. 13f). Additionally, both higher and oscillating wind speeds increased the strength of vertical mixing (Fig. 13c and g). As a result, the concentrations of dissolved oxygen below the pycnocline and at the bottom decreased from the upper to the upper-middle Bay (Figs. 8a-8d, 13, and 14).

3.5. The DO budgets under idealized wind experiments

To better quantify the causes of temporal variability in the hypoxic volume, the DO budget below 10-m in the middle of the Bay was calculated, as shown in Fig. 5b. The daily DO source and sink terms were averaged for spring and summer under the selected wind scenarios (Table 4).

First, the three largest oxygen supply terms were vertical diffusion and cross- and along-channel advection, whereas the largest sink term was water column respiration (WCR) for all experiments. As the wind direction changed, changes in cross- and along-channel DO advection were always in the anti-phase, which is expected given that the two fluxes are related via the continuity constraint.



Fig. 8. The horizontal distribution of surface salinity and velocity (a, e); depth-averaged detritus (small and large) and semi-labile DON below 10-m depth (b, f); the logarithm of depth-averaged vertical mixing coefficient (c, g); and bottom DO (d, h) during the summer for the NE-to-S experiment (a-d) and the NE-to-NE experiment (e-h).

Second, we found that the WCR under a northeasterly wind consumed 208 kg-O₂/s in spring, which was approximately 16 % higher than that under a southerly wind (179 kg-O₂/s). In summer, oxygen consumption through the WCR under northeasterly winds remained as high as 195 kg-O₂/s, which was approximately 15 % higher than that under southerly winds (170 kg-O₂/s). This suggests that down-estuary winds tend to decrease DO by supplying more oxygen-consuming materials. Additionally, we found that the WCR in summer under the S-to-SW scenario was 140 kg-O₂/s, which was 18 % lower than that under the NE-to-S scenario. This indicates that the high WCR caused by NE winds can persist during summer. Despite the higher WCR under the NE wind, the amount of oxygen supplied by vertical mixing under the NE wind in summer was also about 83.6 kg-O₂, which was 35 % higher than that in the NE-to-S we canario. Additionally, the amount of oxygen supplied by NE winds the store of t

advection in summer was about 105.9 kg-O_2, which is 8 % higher than the S-to-SW scenario and 20 % higher than the NE-to-S scenario.

Third, our analysis revealed that summer northeasterly winds led to a significant increase in primary production of approximately 16.3 kg-O₂/s, much higher than that of southerly winds, which resulted in only 1.5 kg-O₂/s. Although the contribution of primary production was smaller than that of physical processes and WCR (~25 (194.87 – 169.44)), as the analysis was below 10 m, the impact of seasonal wind changes on DO levels was deemed important. Indeed, under continued northeasterly winds in summer, there was a notable increase of ~ 15 (16.31–1.46) kg-O₂/s through primary production, comparable to the increases seen through total advection and vertical diffusion (~17 (105.91–88.94) and ~ 22 (83.6–62.08) kg-O₂/s, respectively).

In addition, we observed that an increase in southerly wind speed in summer resulted in a 73 % larger DO supply through F_{vdiff} than that with



Fig. 9. The along thalweg (see Fig. 1 for the location) vertical distributions of (a) logarithm of vertical mixing coefficient (AKv, m^2/s); (c) oxygen consuming materials (detritus and semi-labile DON, mmole-N/m⁻³); (e) DO (mg/L) during summer from the NE-to-S experiment. Vertical distributions of the differences in AKv (m^2/s) (b); detritus and semi-labile DON (mmole-N/m³) (d); and DO (mg/L) (f) between the NE-to-S and the NE-to-NE experiment during summer.



Fig. 10. Distributions of along- (left panels) and cross- (right panels) channel currents and salinity in spring of NE-to-S (a, b); spring of S to SW (c, d); summer of NE-to-S (e, f); and summer of NE-to-NE (g, h). The location of the thalweg has been shown in Fig. 1.

regular southerly wind, whereas sinusoidal southerly wind resulted in a 45 % larger DO supply. In contrast, the decrease in DO by the WCR was only 25 % and 15 % higher, respectively. Given that the total advection

between regular S, high S, and sinusoidal S was almost equivalent, these findings demonstrated that changes in hypoxic volume resulting from the wind speed experiments were mainly due to increased DO supply



Fig. 11. The horizontal distribution of spring surface salinity and velocity (a, e); depth-averaged detritus (small and large) and semi-labile DON below 10-m depth (b, f); the logarithm of depth-averaged vertical mixing coefficient (c, g); and summer bottom DO (d, h) during the NE-to-S case (upper panels) and S to SW case (lower panels).

through vertical mixing. Furthermore, when we compared the vertical mixing term between spring and summer for the NE-to-S and S-to-SW cases, we found that the oxygen supplied by the NE wind in spring was approximately twice that in summer, and that supplied by the S wind in spring was approximately three times more than in summer. The higher source of DO through vertical mixing in spring compared with summer result in less prevalent hypoxia in spring.

To investigate the cause of the high primary production below 10 m when the wind was northeasterly in summer, we plotted concentrations of NO_3 and NH_4 , new and regenerated primary production (rate of NO_3 and NH_4 taken up by phytoplankton, respectively) along with light

intensity from February to August for the NE-to-NE and reference run, NE-to-S (Fig. 15). In both scenarios, NO₃ exhibit an exponential decrease in spring, whereas NH₄ showed a rapid increase (Fig. 15a and 15c). The abrupt change was associated with high bio-activities above 10 m, alongside with rapid advections and vertical mixing during spring. Coming to summer, the NO₃ concentration remained consistently low (\sim 1 mmol/m³), while the concentrations of NH₄ were as high as 9.6 and 12.2 mmole/m³, respectively (Fig. 15a and 15c). Greater availability of NH₄ supports a higher level of regenerated production compared to new production. We've known that vertical mixing under northeasterly winds exceeds that under southerly wind. The higher vertical mixing



Fig. 12. The along thalweg vertical distributions of (a) spring logarithm of vertical mixing coefficient (AKv, m^2/s); (c) spring oxygen consuming materials (Detritus and Semi-labile DON, mmole-N/m³); (e) summer logarithm of vertical mixing coefficient (AKv, m^2/s); (g) summer oxygen consuming materials (Detritus and Semi-labile DON, mmole-N/m³); (f) summer DO. The differences between S to SW and NE-to-S for above variables were also shown (b, d, f, h, j). The location of the thalweg has been shown in Fig. 1.

prevents the accumulation of light-attenuated materials at the surface. Consequently, the summer light intensity was 38 % higher than that under the southerly winds 10-meter below the middle Bay (Fig. 15e). As a result, the phytoplankton would uptake more NH_4 , thereby supporting higher primary production and oxygen generation. On the contrary, summer wind reversal to the south limits the amount of oxygen produced by regeneration, and the consequent positive feedback to hypoxia is comparable with WCR and physical processes.

3.6. Nitrogen flux across the north and south boundary

Our mass budget analysis indicated that WCR was the largest sink term and shows significant variability under different wind scenarios. As WCR depends on riverine materials, we compared the daily depth-averaged nitrogen fluxes across the northern and southern boundaries of the control volume under various wind scenarios (Fig. 16).

Although nitrogen fluxes vary with the tide, responses to seasonally average winds are evident. For all experiments, we observed that the seaward nitrogen fluxes in summer at the north boundary were higher than those in spring. This occurred because riverine NO3 was taken up by phytoplankton and transformed into other nitrogen pools more rapidly during the spring. At the northern boundary, the nitrogen seaward flux (negative) induced by S-to-SW was $\sim 0.12 \times 10^5$ mmol/s, which is lower than that induced by persistent down-estuary winds (NE-to-NE, 1.28×10^5 mmol/s). Under the NE-to-S wind scenario during summer, the seaward nitrogen flux was 1.0×10^5 mmol/s, which is 45 % lower than that of NE-to-NE and 50 % higher than that of S-to-SW (Fig. 16a). These results suggest that down-estuary winds are more effective than up-estuary winds in transporting nitrogen to the control

volume. At the southern boundary, the seaward nitrogen flux in summer was opposite to that at the northern boundary. The flux under a S/SW wind was $\sim 1.5 \times 10^5$ mmol/s, which is higher than that under a NE wind (0.28 $\times 10^5$ mmol/s; Fig. 16c). This indicates that more nitrogen transported to the control volume by NE winds was utilized in biological activities, resulting in less transport to the lower Bay. Overall, northeasterly winds resulted in a net influx of nitrogen of 2.2 $\times 10^5$ mmol/s, contrasting with the net outflux of nitrogen (1.0 $\times 10^5$ mmol/s) by the S-to-SW wind in summer (Fig. 16e).

We also noted that the high S and sinusoidal S winds induced seaward nitrogen fluxes of 2.0 and 1.7×10^5 mmol/s, respectively, higher than the flux induced by average southerly winds speed (1.0×10^5 mmol/s). These results suggest that high and oscillating southerly winds are more effective in transporting nitrogen to the control volume. At the southern boundary, the seaward flux induced by southerly winds during summer exceeded that induced by high S/sinusoidal southerly winds, suggesting that less nitrogen was utilized in the control volume, and more was transported to the lower Bay. Overall, both high and sinusoidal S winds resulted in a net influx of nitrogen during summer (1.8 and 1.2×10^5 mmol/s), whereas the baseline southerly winds resulted in a net outflux.

In summary, south wind speed increase or oscillation will lead to a higher transport of riverine NO_3 from the upper to the middle Bay. Phytoplankton uptake these additional NO_3 concentrations, transforming them into detritus and semilabile DON (Fig. 8b, Fig. 13b and f). Subsequently, these detritus and semilabile DON are remineralized and denitrified (see WCR in Table 4), reducing the amount being delivered to the lower Bay.



Fig. 13. The horizontal distribution of surface salinity and velocity (a, e); depth-averaged detritus (small and large) and semilabile DON below 10-m surface water (b, f); the logarithm of depth-averaged vertical mixing coefficient (c, g); and bottom DO (d, h) during the summer of NE-to-High S case (upper panels) and NE-to-Sinusoidal S case (lower panels).

4. Discussion

In this study, we first ran a Terrestrial-Estuarine-Ocean Biogeochemical Modeling System (DLEM-ChesROMS-ECB) for 21-years (1985–2005) to investigate the key factors driving hypoxic volume interannual variability in Chesapeake Bay, through correlation analysis. In comparison to a coupled physical-biogeochemistry model forced by the observed riverine nutrients from USGS, the inclusion of a terrestrial model enables a more accurate quantification of temporal variability and a reduction in the uncertainty associated with nutrient and organic matter flux delivered to the estuarine environment. This inclusion has been demonstrated to enhance the model's performance in replicating inner-bay nutrient concentrations and phytoplankton biomass (Xia and Jiang, 2016). The improved model indicate that riverine nitrogen loading is the primary factor driving the interannual variability in hypoxia in Chesapeake Bay, consistent with previous studies (Hagy et al., 2004; Murphy et al., 2011; Zhou et al., 2014). In addition, the duration of spring northeasterly winds and summer southerly winds was positively correlated with the summer hypoxic volume. However, a negative correlation was observed between hypoxic volume and Table 4



Fig. 14. The differences between NE-to-high S/NE-to-sinusoidal S and NE-to-S for the along channel vertical mixing coefficient (a, b), oxygen consuming materials (c, d) Detritus and Semi-labile DON, mmole-N/ m^3), and DO (e, f) during summer. The location of the thalweg was shown in Fig. 1.

Owngon budget in the control a	volume and humovia	volume for d	onigned idealized	wind ow	norimonto in o	nring and	
Oxygen budget in the control v	volume and hypoxic	volume for a	esigned idealized	wina ex	periments in s	pring and	summer

Unit: kg O ₂ /s	NE-to-S (Spring)	S-to-SW (Spring)	NE-to-S (Summer)	S-to-SW (Summer)	NE-to-NE (Summer)	NE-to-high S (Summer)	NE-to-sinusoidal S (Summer)
Cross-channel	17.48	-5.48	29.30	42.52	101.64	42.30	22.82
Along-channel	69.19	52.86	59.64	55.19	4.26	45.25	65.43
Total adv	86.67	47.38	88.94	97.71	105.91	85.55	88.25
Vdiff	128.69	118.43	62.08	36.70	83.60	106.78	89.68
WCR	-207.69	-178.69	-169.44	-139.76	-194.87	-211.60	-194.51
SOD	-5.13	-3.90	-1.50	-1.22	-3.96	-2.35	-2.10
PP	3.56	0.50	1.46	2.52	16.32	2.36	2.05
Hypoxic volume (km ³)	$\textbf{0.8} \pm \textbf{1.2}$	$\textbf{0.2}\pm\textbf{0.3}$	5.9 ± 1.2	$\textbf{3.6} \pm \textbf{2.3}$	1.0 ± 0.8	$\textbf{4.8} \pm \textbf{1.9}$	$\textbf{4.6} \pm \textbf{1.5}$



Fig. 15. The 10 m-below depth-averaged NO_3 , NH_4 , light intensity, new production, regenerated production, and primary production from February to August in NE-to-S (black lines) and NE-to-NE (blue lines) cases.

duration of the summer northeasterly winds. To further explore the mechanisms of spring-to-summer winds during hypoxia, we performed multiple idealized sensitivity experiments. The results showed that for cases with summer south-or southwesterly winds, the hypoxic volume differed only before July during the build-up period. The volume before July was at a maximum when the spring wind was northeasterly and at a minimum when the spring wind was southerly. However, once hypoxia was established, simulated differences in hypoxic volume were modest. In contrast, if wind was northeasterly in summer, the hypoxic volume did not develop during summer. Our results are consistent with those of

Lee et al. (2013) and Zhou et al. (2014), who found that hypoxic volume is statistically significantly and positively correlated with the average January-April NE-SW wind speed, and negatively correlated with the ratio of April-August NE-SW wind duration.

The mass budget analysis from our model revealed that spring northeasterly winds intensified gravitational circulation, leading to increased transport of oxygen-consuming materials down-estuary. This effect can lead to a higher WCR and larger hypoxic volume in summer compared to spring south winds. However, northeasterly winds in summer, while potentially resulting in higher WCR, also induce counterclockwise lateral circulation, which tilts isopycnals towards a more vertical orientation and enhances vertical mixing, which replenish the bottom DO. Moreover, a prolonged northeasterly wind during the summer would lead to a high accumulation of chromophoric dissolved organic matter (CDOM) on the left bank. Consequently, in the middle trench where hypoxia occurs, more light could penetrate down to the lower layer, resulting in higher primary production and generated more oxygen.

Though our modeling system accurately replicated observed spatiotemporal variability in temperature, salinity, nutrients, chlorophyll, and dissolved oxygen (DO) from the Chesapeake Bay Program. However, the model overestimated DO concentration in the lower Bay, with a bias as high as 2.1 mg/L at CB 6.3. Overestimation of DO is typical in coupled hydrodynamic-biogeochemical modeling of other hypoxic regions, such as the Gulf of Mexico, Changjiang River Estuary, and Pearl River Estuary (Wang et al., 2017; Zhou et al., 2017; Feng et al., 2019). A possible reason for this discrepancy is that bottom processes are not accurately represented in the model. The model assumes that as the



Fig. 16. Daily depth-averaged total nitrogen fluxes across the upper (a and b) and lower (c and d) boundary (the magenta dashed lines in Fig. 3a) of the control volume for wind direction and speed experiments. Nitrogen flux is the sum of nitrogen in the form of NO₃, NH₄, small and large detritus, phytoplankton, zooplankton, semi-labile DON. Negative values are fluxes from land to ocean; positive values are fluxes from ocean to land. Total shows the net flux across the upper and lower boundaries of control volume with positive and negative values referring to the influx and outflux, respectively. Spring and summer are highlighted by the red and blue background colors.

organic matter sinks to the bottom, it is denitrified, remineralized, resuspended, or buried instantly. The assumption result in an overestimation of SOD near the mouth of each tributary in simulation and an underestimation of SOD in the mainstem of the Bay (Fig. S1a, S1c). In reality, the decomposition of organic matter can take weeks to months. Rather than remaining in one place, organic matter is transported as fluid mud and undergoes numerous resuspension and deposition cycles. The movement and long residence of organic matter in the sediment layer results in consumption of additional oxygen when decomposed by bacteria. Efforts to describe the SOD process through seabed diagenetic model would be helpful to improve the model accuracy (Laurent et al., 2016; Moriarty et al., 2017, 2018, 2021).

Another reason for the overestimation of DO by our model could be that the model parameters were not optimized. Uncertainty in the key parameters in the model can significantly affect simulated biogeochemical processes during hypoxia. For example, the spatiotemporal distribution of particulate organic matter is highly influenced by the sinking velocity. Slow-sinking particles are first transported down the Bay and then sink to the bottom, moving up the Bay through the residual flow in the deep channel. In contrast, fast-sinking particles rapidly sink to the bottom and move directly into the deep channels in the upper Bay (Wang and Hood, 2021). Optimizing critical parameters through ensemble experiments and data assimilation techniques would assist in improving model performance.

Thirdly, our current model did not consider the tidal marshes surrounding Chesapeake Bay, which may lead to an underestimation of the amount of organic matter reaching the main stem as well (Xia and Jia, 2016). Although our model underestimated the magnitude of hypoxia, it successfully replicated seasonal and interannual variability (e.g the extreme large hypoxic volume 2003 under prolonged northeasterly wind). Therefore, our primary findings regarding the impact of prolonged seasonally variable winds on hypoxia remain robust.

Coupled physical-biogeochemical models have been used to explore the mechanisms underlying the impact of wind forcing on hypoxia in Chesapeake Bay. Scully (2010b) investigated 3-day individual events of wind from different directions and found that the dominant mechanism for oxygen provision to sub-pycnocline waters is the interaction between wind-driven cross-channel circulation and enhanced vertical mixing over shoal regions. Li et al. (2015) investigated the effects of up- and down-estuary winds on hypoxia by taking the typical year of 1989 and found that the along-channel and vertical advective fluxes are significant suppliers of DO to the bottom water. However, both these studies focused on single-episode wind events. In contrast, our study investigated the role of prolonged seasonally variable wind effects. Such an impact has been indeed noticed in previous numerical experiments. For example, Scully (2013) ran the model with January and July wind forcing, repeated monthly throughout the year, and found that hypoxia occurred when the wind conditions in January were repeated every year, but did not occur when the wind conditions in July were repeated every year. Scully (2016) simulated hypoxia from 1984 to 2013 using realistic winds and found a highly negative correlation between summer hypoxia and the duration of northeasterly winds during summer. These findings are consistent with our results. Scully (2013) proposed that the absence of hypoxia under July winds was due to a significant increase in the along-channel advective flux.

Our Terrestrial-Estuary-Ocean Biogeochemistry Modeling System (DLEM-ChesROMS-ECB) has the same physical configuration as that used by Scully (2013, 2016). However, DLEM-ChesROMS-ECB employs a full-nitrogen-based biogeochemistry model instead of simple DO dynamics with a constant respiration rate. Oxygen consumption depends largely on surface phytoplankton blooms and their subsequent benthic decay and water column in-depth consumption (Zheng and DiGiacomo, 2020). In addition to mixing and advection processes impacts on DO, wind can also transport nutrients and oxygen-consuming materials to shallow shoals or deep channel, leading to spatiotemporal differences in the rate of oxygen utilization (Malone et al., 1986). A constant respiration rate assumption has limitations in diagnosing the predominant processes in regulating the oxygen level under different wind scenarios. In our model, we determined that prolonged northeasterly winds in summer lead to increased cross-channel circulation, stronger vertical mixing, and a higher WCR. While oxygen production was relatively low compared to advection, vertical mixing and WCR under the northeasterly winds, the differences with the summer southerly wind cannot be ignored. In comparison to the southerly wind, vertical mixing and advection under northeasterly winds provided 22 and 17 kg/s more of oxygen, respectively, while WCR consumed 25 kg/s. The oxygen production through photosynthesis (PP) was as high as 15 kg/s, accounting for 60 % of the WCR. This finding underscores the importance of biological feedback on hypoxia, in addition to physical processes.

Our study found no evidence to support the proposition by Scully (2016) that summer wind speed is the most important physical variable responsible for variations in the hypoxic volume. We did not find a statistically significant correlation between the summer wind speed and hypoxic volume during our 21-year simulation. However, our findings indicate that increase or oscillation in southerly wind speed during summer results in higher transport of total nitrogen to the middle Bay, contributing to oxygen dynamics and modulating the size of the hypoxic area.

Our research focuses on examining the impacts of prolonged seasonal variable winds on hypoxia in Chesapeake Bay. We found that the reversal of summer winds to the south is critical for the occurrence of hypoxia in summer. The summer southerly wind over Chesapeake Bay is generally driven by the anti-cyclonic flow around the Bermuda High. A stronger Bermuda High would favor a more southerly wind climate (Scully, 2010). Future warming or cooling could impact the strength of Bermuda High by changing the surface air pressure gradient (Luo et al., 2021). Such climate variability's influence on hypoxia should be considered in addition to warming and sea level rise (Ni et al., 2020).

5. Concluding remarks

Our modeling study found that seasonal prevailing wind direction is important for the occurrence of hypoxia in addition to the nitrogen and phosphate levels. Comparing to previous studies discussing wind influences, which used the same physical model as ours (Scully, 2010a,2010b,2013,2016), we employed a comprehensive nitrogenbased biogeochemical model instead of an oxygen-only model. A comparison between prolonged northeasterly and southerly wind during the summer has shown that the oxygen generated from regenerated production played a significant role in addition to vertical mixing and lateral advection. The results suggested that the biological feedbacks to physical processes can't be ignored in hypoxia development, and that both the wind speed and direction changes should be considered when evaluating future climate change impact on hypoxia in Chesapeake Bay.

CRediT authorship contribution statement

Youchang Zheng: Methodology, Formal analysis, Data curation. Jingwen Huang: Validation, Formal analysis, Data curation. Yang Feng: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. Huijie Xue: Writing – review & editing. Xiaohui Xie: Writing – review & editing. Hanqin Tian: Methodology. Yuanzhi Yao: Methodology. Lin Luo: Formal analysis. Xianghui Guo: Writing – review & editing. Yonglin Liu: Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data are public avaialbe, which described in the manuscript

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pocean.2024.103207.

References

- Boynton, W.R., Ceballos, M.A.C., Hodgkins, C.L.S., Liang, D., Testa, J.M., 2023. Large-Scale Spatial and Temporal Patterns and Importance of Sediment-Water Oxygen and Nutrient Fluxes in the Chesapeake Bay Region. Estuaries and Coasts 46, 356–375. https://doi.org/10.1007/s12237-022-01127-0.
- Breitburg, D., Levin, L.A., Oschlies, A., Grégoire, M., Chavez, F.P., Conley, D.J., Garçon, V., Gilbert, D., Gutiérrez, D., Isensee, K., Jacinto, G.S., Limburg, K.E., Montes, I., Naqvi, S.W.A., Pitcher, G.C., Rabalais, N.N., Roman, M.R., Rose, K.A., Seibel, B.A., Telszewski, M., Yasuhara, M., Zhang, J., 2018. Declining oxygen in the global ocean and coastal waters. Science 359, eaam7420. https://doi.org/10.1126/ science.aam7240.
- Brown, C.W., Hood, R.R., Long, W., Jacobs, J., Ramers, D.L., Wazniak, C., Wiggert, J.D., Wood, R., Xu, J., 2013. Ecological forecasting in Chesapeake Bay: Using a mechanistic-empirical modeling approach. J. Mar. Syst. 125, 113–125. https://doi. org/10.1016/j.jmarsys.2012.12.007.

- Cronin, T.M., Vann, C.D., 2003. The sedimentary record of climatic and anthropogenic influence on the Patuxent estuary and Chesapeake Bay ecosystems. Estuaries 26, 196–209. https://doi.org/10.1007/bf02695962.
- Da, F., Friedrichs, M.A.M., St-Laurent, P., 2018. Impacts of atmospheric nitrogen deposition and coastal nitrogen fluxes on oxygen concentrations in Chesapeake Bay. J. Geophys. Res.-Oceans. 123, 5004–5025. https://doi.org/10.1029/2018jc014009.
- Dai, M.H., Guo, X.G., Zhai, W.D., Yuan, L.Y., Wang, B.W., Wang, L.F., Cai, P.H., Tang, T. T., Cai, W.J., 2006. Oxygen depletion in the upper reach of the Pearl River estuary during a winter drought. Mar. Chem. 102, 159–169. https://doi.org/10.1016/j. marchem.2005.09.020.
- Daskalov, G.M., 2003. Long-term changes in fish abundance and environmental indices in the Black Sea. Mar. Ecol.-Prog. Ser. 255, 259–270. https://doi.org/10.3354/ meps255259.
- Diaz, R.J., Rosenberg, R., 2008. Spreading dead zones and consequences for marine ecosystems. Science 321, 926–929. https://doi.org/10.1126/science.1156401.
- Druon, J.N., Mannino, A., Signorini, S., McClain, C., Friedrichs, M., Wilkin, J., Fennel, K., 2010. Modeling the dynamics and export of dissolved organic matter in the Northeastern U.S. Estuar. Coast. Shelf Sci. 88, 488–507. https://doi.org/10.1016/j. ecss.2010.05.010.
- Feng, Y., DiMarco, S.F., Jackson, G.A., 2012. Relative role of wind forcing and riverine nutrient input on the extent of hypoxia in the northern Gulf of Mexico. Geophys. Res. Lett. 39 https://doi.org/10.1029/2012gl051192.
- Feng, Y., Fennel, K., Jackson, G.A., DiMarco, S.F., Hetland, R.D., 2014. A model study of the response of hypoxia to upwelling-favorable wind on the northern Gulf of Mexico shelf. J. Mar. Syst. 131, 63–73. https://doi.org/10.1016/j.jmarsys.2013.11.009.
- Feng, Y., Friedrichs, M.A.M., Wilkin, J., Tian, H.Q., Yang, Q.C., Hofmann, E.E., Wiggert, J.D., Hood, R.R., 2015. Chesapeake Bay nitrogen fluxes derived from a land-estuarine ocean biogeochemical modeling system: Model description, evaluation, and nitrogen budgets. J. Geophys. Res.-Biogeosci. 120, 1666–1695. https://doi.org/10.1002/2015jg002931.
- Feng, Y., DiMarco, S.F., Balaguru, K., Xue, H.J., 2019. Seasonal and interannual variability of areal extent of the Gulf of Mexico hypoxia from a coupled physicalbiogeochemical model: A new implication for management practice. J. Geophys. Res.-Biogeosci. 124, 1939–1960. https://doi.org/10.1029/2018jg004745.
- Fennel, K., Hetland, R., Feng, Y., DiMarco, S., 2011. A coupled physical-biological model of the Northern Gulf of Mexico shelf: model description, validation and analysis of phytoplankton variability. Biogeosciences 8, 1881–1899. https://doi.org/10.5194/ bg-8-1881-2011.
- Garcia, H.E., Gordon, L.I., 1992. Oxygen solubility in seawater: Better fitting equations. Limnol. Oceanogr. 37, 1307–1312. https://doi.org/10.4319/lo.1992.37.6.1307.
- Hagy, J.D., Boynton, W.R., Keefe, C.W., Wood, K.V., 2004. Hypoxia in Chesapeake Bay, 1950–2001: Long-term change in relation to nutrient loading and river flow. Estuaries 27, 634–658. https://doi.org/10.1007/bf02907650.
- Irby, I.D., Friedrichs, M.A.M., 2019. Evaluating confidence in the impact of regulatory nutrient reduction on Chesapeake Bay water quality. Estuaries Coasts 42, 16–32. https://doi.org/10.1007/s12237-018-0440-5.
- Jiang, L., Xia, M., 2017. Wind effects on the spring phytoplankton dynamics in the middle reach of the Chesapeake Bay. Ecol. Modell. 363, 68–80. https://doi.org/ 10.1016/j.ecolmodel.2017.08.026.
- Keiser, D.A., Shapiro, J.S., 2019. Consequences of the Clean Water Act and the demand for water quality. Q. J. Econ. 134 (1), 349–396.
- Kemp, W.M., et al., 2005. Eutrophication of Chesapeake Bay: historical trends and ecological interactions. Mar. Ecol.-Prog. Ser. 303, 1–29. https://doi.org/10.3354/ meps303001.
- Laurent, A., Fennel, K., Wilson, R., Lehrter, J., Devereux, R., 2016. Parameterization of biogeochemical sediment-water fluxes using in situ measurements and a diagenetic model. Biogeosciences 13, 77–94. https://doi.org/10.5194/bg-13-77-2016.
- Lee, Y.J., Boynton, W.R., Li, M., Li, Y., 2013. Role of Late Winter-Spring Wind Influencing Summer Hypoxia in Chesapeake Bay. Estuaries Coasts 36, 683–696. https://doi.org/10.1007/s12237-013-9592-5.
- Li, D., Gan, J.P., Hui, R., Liu, Z.Q., Yu, L.Q., Lu, Z.M., Dai, M.H., 2020. Vortex and Biogeochemical Dynamics for the Hypoxia Formation Within the Coastal Transition Zone off the Pearl River Estuary. J. Geophys. Res.-Oceans 125, 16. https://doi.org/ 10.1029/2020jc016178.
- Li, M., Lee, Y.J., Testa, J.M., Li, Y., Ni, W.F., Kemp, W.M., Di Toro, D.M., 2016. What drives interannual variability of hypoxia in Chesapeake Bay: Climate forcing versus nutrient loading? Geophys. Res. Lett. 43, 2127–2134. https://doi.org/10.1002/ 2015e1067334.
- Li, Y., Li, M., 2012. Wind-driven lateral circulation in a stratified estuary and its effects on the along-channel flow. J. Geophys. Res.-Oceans 117, C09005. https://doi.org/ 10.1029/2011jc007829.
- Li, Y., Li, M., Kemp, W.M., 2015. A Budget Analysis of Bottom-Water Dissolved Oxygen in Chesapeake Bay. Estuaries Coasts 38, 2132–2148. https://doi.org/10.1007/ s12237-014-9928-9.
- Luo, H., Adames, A.F., Rood, R.B., 2021. A Northern Hemispheric Wave Train Associated with Interannual Variability in the Bermuda High during Boreal Summer. Journal of Climate 15, 6163–6173. https://doi.org/10.1175/JCLI-D-20-0608.1.
- Malone, T.C., Kemp, W.M., Ducklow, H.W., Boynton, W.R., Tuttle, J.H., Jonas, R.B., 1986. Lateral variation in the production and fate of phytoplankton in a partially stratified estuary. Mar. Ecol. Prog. Ser. 32, 149–160. https://doi.org/10.3354/ meps032149.
- Marshall, H.G., Nesius, K.K., 1996. Phytoplankton composition in relation to primary production in Chesapeake Bay. Mar. Biol. 125, 611–617.
- Moriarty, J.M., Harris, C.K., Fennel, K., Friedrichs, M.A.M., Xu, K.H., Rabouille, C., 2017. The roles of resuspension, diffusion and biogeochemical processes on oxygen

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- Moriarty, J.M., Harris, C.K., Friedrichs, M.A.M., Fennel, K., Xu, K.H., 2018. Impact of Seabed Resuspension on Oxygen and Nitrogen Dynamics in the Northern Gulf of Mexico: A Numerical Modeling Study. J. Geophys. Res.-Oceans. 123, 7237–7263. https://doi.org/10.1029/2018jc013950.
- Moriarty, J.M., Friedrichs, M.A.M., Harris, C.K., 2021. Seabed Resuspension in the Chesapeake Bay: Implications for Biogeochemical Cycling and Hypoxia. Estuaries and Coasts 44, 103–122. https://doi.org/10.1007/s12237-020-00763-8.
- Murphy, R.R., Kemp, W.M., Ball, W.P., 2011. Long-term trends in Chesapeake Bay seasonal hypoxia, stratification, and nutrient loading. Estuaries Coasts 34, 1293–1309. https://doi.org/10.1007/s12237-011-9413-7.
- Newcombe, C.L., Horne, W.A., 1938. Oxygen-Poor Waters of the Chesapeake Bay. Science 88:, 80–81.
- Ni, W., Li, M., Testa, J.M., 2020. Discerning effects of warming, sea level rise and nutrient management on long-term hypoxia trends in Chesapeake Bay. Sci. Total Environ. 737, 139717 https://doi.org/10.1016/j.scitotenv.2020.139717.
- Officer, C.B., Biggs, R.B., Taft, J.L., Cronin, L.E., Tyler, M.A., Boynton, W.R., 1984. Chesapeake Bay anoxia: origin, development, and significance. Science 223, 22–27. https://doi.org/10.1126/science.223.4631.22.
- Pan, S., Bian, Z., Tian, H., Yao, Y., Najjar, R.G., Friedrichs, M.A.M., et al., 2021. Impacts of multiple environmental changes on long-term nitrogen loading from the Chesapeake Bay watershed. Journal of Geophysical Research. e2020JG005826 Biogeosciences. 126. https://doi.org/10.1029/2020JG005826.
- Riemenschneider, U., Legg, S., 2007. Regional simulations of the Faroe Bank Channel overflow in a level model. Ocean Modell. 17, 93–122. https://doi.org/10.1016/j. ocemod.2007.01.003.
- Sandberg, E., 1994. Does short-term oxygen depletion affect predator-prey relationships in zoobenthos? Experiments with the isopod Saduria entomon Mar. Ecol.-Prog. Ser. 103, 73–80. https://doi.org/10.3354/meps103073.
- Scully, M.E., 2010a. The importance of climate variability to wind-driven modulation of hypoxia in Chesapeake Bay. J. Phys. Oceanogr. 40, 1435–1440. https://doi.org/ 10.1175/2010jpo4321.1.
- Scully, M.E., 2010b. Wind modulation of dissolved oxygen in Chesapeake Bay. Estuaries Coasts 33, 1164–1175. https://doi.org/10.1007/s12237-010-9319-9.
- Scully, M.E., 2013. Physical controls on hypoxia in Chesapeake Bay: A numerical modeling study. J. Geophys. Res.-Oceans. 118, 1239–1256. https://doi.org/ 10.1002/jgrc.20138.
- Scully, M.E., 2016. The contribution of physical processes to inter-annual variations of hypoxia in Chesapeake Bay: A 30-yr modeling study. Limnol. Oceanogr. 61, 2243–2260. https://doi.org/10.1002/lno.10372.
- St-Laurent, P., Friedrichs, M.A.M., Najjar, R.G., Shadwick, E.H., Tian, H.Q., Yao, Y.Z., 2020. Relative impacts of global changes and regional watershed changes on the inorganic carbon balance of the Chesapeake Bay. Biogeosciences 17, 3779–3796. https://doi.org/10.5194/bg-17-3779-2020.
- Tian, H., Chen, G., Zhang, C., Liu, M., Sun, G., Chappelka, A., et al., 2012. Century-Scale Responses of Ecosystem Carbon Storage and Flux to Multiple Environmental Changes in the Southern United States. Ecosystems 15 (4), 674–694. https://doi.org/ 10.1007/s10021-012-9539-x.

- Progress in Oceanography 222 (2024) 103207
- U.S. Environmental Protection Agency, 2010. Chesapeake Bay Total Maximum Daily Load for Nitrogen, Phosphorus and Sediment. Office of Wetlands, Oceans, and Watersheds, Washington, DC.
- Wang, J., Hood, R.R., 2021. Modeling the Origin of the Particulate Organic Matter Flux to the Hypoxic Zone of Chesapeake Bay in Early Summer. Estuaries and Coasts 44, 672–688. https://doi.org/10.1007/s12237-020-00806-0.
- Wang, B., Hu, J.T., Li, S.Y., Liu, D.H., 2017. A numerical analysis of biogeochemical controls with physical modulation on hypoxia during summer in the Pearl River estuary. Biogeosciences 14, 2979–2999. https://doi.org/10.5194/bg-14-2979-2017
- Wang, P., Wang, H., Linker, L., Hinson, K., 2016. Influence of Wind Strength and Duration on Relative Hypoxia Reductions by Opposite Wind Directions in an Estuary with an Asymmetric Channel. J. Mar. Sci. Eng. 4 https://doi.org/10.3390/ imse4030062.
- Wanninkhof, R., 1992. Relationship between wind speed and gas exchange over the ocean. J. Geophys. Res.-Oceans 97, 7373–7382. https://doi.org/10.1029/ 92jc00188.
- Willmott, C.J., 1981. On the validation of models. Physical Geography 2, 184–194. https://doi.org/10.1080/02723646.1981.10642213.
- Xia, M., Jiang, L., 2016. Application of an Unstructured Grid-Based Water Quality Model to Chesapeake Bay and Its Adjacent Coastal Ocean. J. Mar. Sci. Eng. 4 https://doi. org/10.3390/jmse4030052.
- Xie, X., Li, M., Boicourt, W.C., 2017. Baroclinic Effects of Wind-Driven Lateral Circulation in Chesapeake Bay. J. Phys. Oceanogr. 47, 433–445. https://doi.org/ 10.1175/JPO-D-15-0233.1.
- Xu, J.T., et al., 2012. Climate forcing and salinity variability in Chesapeake Bay, USA. Estuaries Coasts 35, 237–261. https://doi.org/10.1007/s12237-011-9423-5.
- Yang, Q.C., Tian, H.Q., Friedrichs, M.A.M., Hopkinson, C.S., Lu, C.Q., Najjar, R.G., 2015a. Increased nitrogen export from eastern North America to the Atlantic Ocean due to climatic and anthropogenic changes during 1901–2008. J. Geophys. Res.-Biogeosci. 120, 1046–1068. https://doi.org/10.1002/2014jg002763.
- Yang, Q., Tian, H., Friedrichs, M.A.M., Liu, M., Li, X., Yang, J., 2015b. Hydrological responses to climate and land-use changes along the North American East Coast: A 110-year historical reconstruction. J. Am. Water Resour. Assoc 51 (1), 47–67. https://doi.org/10.1111/jawr.12232.
- Yao, Y.Z., Tian, H.Q., Pan, S.F., Najjar, R.G., Friedrichs, M.A.M., Bian, Z.H., Li, H.Y., Hofmann, E.E., 2021. Riverine carbon cycling over the past century in the Mid-Atlantic region of the United States. J. Geophys. Res.-Biogeosci. 126 https://doi.org/ 10.1029/2020jg005968.
- Zheng, G.M., DiGiacomo, P.M., 2020. Linkages Between Phytoplankton and Bottom Oxygen in the Chesapeake Bay. J. Geophys. Res.-Oceans. 125 https://doi.org/ 10.1029/2019jc015650.
- Zhou, F., Chai, F., Huang, D.J., Xue, H.J., Chen, J.F., Xiu, P., Xuan, J.L., Li, J., Zeng, D.Y., Ni, X.B., Wang, K., 2017. Investigation of hypoxia off the Changjiang estuary using a coupled model of ROMS-CoSiNE. Prog. Oceanogr. 159, 237–254. https://doi.org/ 10.1016/j.pocean.2017.10.008.
- Zhou, Y.T., Scavia, D., Michalak, A.M., 2014. Nutrient loading and meteorological conditions explain interannual variability of hypoxia in Chesapeake Bay. Limnol. Oceanogr. 59, 373–384. https://doi.org/10.4319/lo.2014.59.2.0373.