

# Gulf of Mexico Hypoxia: Exploring Increasing Sensitivity to Nitrogen Loads

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Hypoxia is a critical issue in the Gulf of Mexico that has challenged management efforts in recent years by an increase in hypoxia sensitivity to nitrogen loads. Several mechanisms have been proposed to explain the recent increase in sensitivity. Two commonly cited mechanisms are bottom-water reducing conditions preventing nitrification and thus denitrification, leading to more N recycling and production of oxygen-consuming organic matter, and carryover of organic matter from previous years increasing oxygen demand, making the system more sensitive. We use models informed by these mechanisms and fit with Bayesian inference to explore changes in Gulf of Mexico hypoxia sensitivity. We show that a model including an annually fit parameter representing variation in the fraction of nutrient loading and recycling contributing to bottom water oxygen demand provides a good fit to observations and is not improved by explicit inclusion of organic matter carryover to subsequent years. Both models support two stepwise increases in system sensitivity during the period of record. This change in sensitivity has greatly increased the nutrient reduction needed to achieve the established hypoxia goal. If the Gulf remains at the current state of sensitivity, our analysis suggests a roughly 70% reduction of spring TN loads from the 1988–1996 average of 6083 ton/day may be required.

## Introduction

The Gulf of Mexico contains one of the largest human caused hypoxic zones in the United States (1) and the world (2). The midsummer hypoxic area (bottom water oxygen  $\leq 2$  mg/L) has varied between 40 and 22,000 km<sup>2</sup> since 1985, when systematic mapping began (ref 3; Rabalais, *personal communication*). This seasonal hypoxia causes deleterious ecological effects (4) and receives considerable scientific and policy attention (e.g. refs 5–8). Action Plans in 2001 and 2008 call for reducing the 5-year running average hypoxic zone to less than 5000 km<sup>2</sup> by 2015 (9, 10).

Two principal factors leading to development and maintenance of hypoxia are river discharge and organic matter decomposition (4). Freshwater discharge enhances vertical water stratification, limiting oxygen diffusion. It also carries nutrients that stimulate production of phytoplankton, which

settle into deeper waters as a main source of organic matter for oxygen consumption. Because little can be done to control freshwater discharge, reducing nutrient loads via river concentration reduction must be addressed to achieve the hypoxia goal.

Managing hypoxia by nutrient load reduction is complicated by nonlinear shifts in sensitivity to nutrients. In recent years, such shifts have been observed in many systems, including estuaries and coastal areas (3, 11–15). For example, Hagy et al. (12) found that, for a given nitrogen load, the 1980–2001 hypoxic volume in Chesapeake Bay was over two times greater than that of 1950–1979, suggesting a threshold had been reached. Multiple mechanisms can cause shifts in sensitivity including shifts between alternative stable states and changes in other drivers. Distinguishing among these mechanisms can require extensive time series, modeling, or experimental data (11). Regardless of mechanism, shifts in sensitivity to nutrient supply imply that disproportionately larger nutrient load reductions may be required to bring hypoxia under control now compared to several decades ago (3, 11–15).

Multiple lines of evidence indicate that a change in Gulf sensitivity to nitrogen load occurred in the early 1990s. However, its timing and mechanism are currently subjects of debate. A breakpoint in 1993 was proposed because of significant flooding in that year (6). An abrupt shift after 1993 was also supported by regression models between loads and hypoxia (16). In contrast, Turner et al. (3) assessed four periods based on the ratio of July Hypoxic Zone/May Nitrogen Load and found that the same May nitrogen load in 1999–2004 yielded a hypoxic zone about twice as large compared to 1981–1988.

Several mechanisms have been proposed to explain these shifts (15): (a) nitrogen recycling is increased because bottom-water reducing conditions prevent nitrification and thus denitrification, and this recycled N further stimulates production (1, 13, 17); (b) carryover of organic matter from previous years increases oxygen demand, making the system more sensitive to nitrogen loading in subsequent years (3, 18); (c) recent increases in organic matter inputs from sources other than the Mississippi basin (15); (d) phosphorus inputs are breaking the relationship with nitrogen loading (15); and (e) climate change has altered system processes to increase system sensitivity (17). It is possible that more than one of these mechanisms contributes to the shift in sensitivity and that they are interrelated. However, previous studies show that mechanisms c and d are unlikely to be strong contributors (15). As has been done for analysis of ecological shifts in other ecosystems (11, 19–21), and in our previous study in Chesapeake Bay (22), we use a simple biophysical model incorporating insights and mechanisms from a, b, and e to assess changes in Gulf of Mexico hypoxia sensitivity.

We use the one-dimensional Streeter-Phelps dissolved oxygen model, which has been used previously to model hypoxia in Chesapeake Bay (23) and the Gulf of Mexico (24–26). The model was modified to reflect additional mechanisms and then recalibrated using Bayesian inference (27) to combine existing information/past experience (priors) with model output and current observations (likelihood) (28). We then analyze temporally varying parameters as a measure of changes in internal or external processes that may explain the shift in sensitivity.

While there is evidence that both phosphorus and nitrogen are important drivers of current-day hypoxia (29–32), our earlier work (26) indicates that the long-term change in hypoxia has been driven by increased nitrogen loads. So, for

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this analysis of sensitivity change and implications for long-term, large-scale hypoxia reduction, we focus on nitrogen.

## Materials and Methods

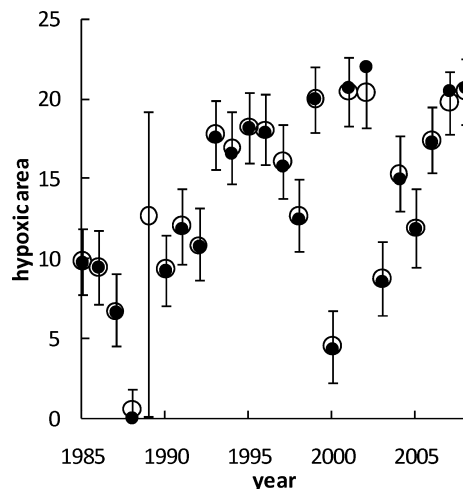
**Nutrient Flux and Hypoxia Data.** Nitrogen loads were taken from USGS adjusted maximum likelihood methods for nitrate plus nitrite (referred to herein as  $\text{NO}_3$ ) and total Kjeldahl nitrogen (33). We use daily May–June total nitrogen (TN) loads as the primary driver of summer hypoxia. Hypoxia spatial extent estimates are from shelf-wide cruises conducted between mid-July and mid-August since 1985 (excluding 1989) (ref 34; Rabalais *personal communication*).

**Hypoxia Model.** The model is an adaptation of the Streeter–Phelps river model which predicts oxygen concentrations downstream of point source organic matter loads (35). The model places the Mississippi River point source at the origin of the model’s spatial domain and the Atchafalaya source 220 km downstream. We assume 50% of the Mississippi source and 100% of the Atchafalaya source is entrained in the westward flowing plume at locations 0 km and 220 km, respectively (24, 26). The steady state solution for a given point source, ignoring longitudinal dispersion and assuming no upstream oxygen deficit can be written

$$DO = DO_s - \frac{k_d \cdot BOD_u \cdot F}{k_r - k_d} (e^{-k_d x/v} - e^{-k_r x/v}) \quad (1)$$

where  $DO$  = dissolved oxygen (mg/L),  $DO_s$  = oxygen saturation (mg/L),  $k_d$  = BOD decay coefficient (1/day),  $k_r$  = reaeration coefficient (1/day),  $BOD_u$  = ultimate BOD (mg/L),  $x$  = downstream distance (km),  $F$  = fraction of BOD sinking below the pycnocline (unitless), and  $v$  = net downstream advection (km/day). Each parameter can be fit as constant across years or fit as a calibration term for each year. If a parameter is fit as a calibration term, in addition to indicating the value of the process it models, it also represents all unmodeled processes. For our application,  $k_r$  represents DO flux across the pycnocline and  $BOD_u$  is approximated by the nitrogen load times the C:N (5.67 gC/gN) and  $\text{O}_2$ :C (2.4  $\text{gO}_2$ /gC) ratios, divided by water flux. This would assume that all of the primary production settles below the pycnocline and that nitrogen is used only once. Because not all production settles and N can cycle, we introduce  $F$  as a simplified representation that parametrizes both the fraction of net surface organic matter production that settles below the pycnocline and the effect of nitrogen recycling and loosely refer to  $F$  as an efficiency measure. The model, previously calibrated and justified in other applications (24–26), simulates average DO concentration below the pycnocline as a function of distance from the point sources. Simulated hypoxic area,  $A$  ( $\text{km}^2$ ), is determined from the length ( $L$ , km) of the profile with hypoxic concentrations and an empirical regression:  $A = 38.835 \cdot L$  (26).

**Parameter Estimation.** Bayesian inference is used because of its ability to assist uncertainty analysis and decision making (36, 37). We implemented a Markov Chain Monte Carlo (MCMC) algorithm with Gibbs sampling in WinBUGS (version 1.4.3 (38)), called from R (version 2.6.0; R2WinBUGS, version 2.1–8 (39)). The MCMC sampling was carried out using four chains, each with 20,000 iterations; samples were taken from the final 10,000 iterations of each chain using a thin of 40 to reduce serial correlation. Statistical inference was based on the resulting 1000 samples (27, 28). A potential scale reduction factor,  $Rhat$ , produced in R2WinBUGS, is used to determine model convergence (at convergence,  $Rhat = 1.0$  (39)). The overlap of 95% credible intervals (C.I.) with observations and the coefficient of determination ( $R^2$ ) between observed and predicted values were used to test model results (39). Bayesian approaches generate predictive



**FIGURE 1. Modeled hypoxic area (open circles,  $10^3 \text{ km}^2$ ) and observations (closed circles,  $10^3 \text{ km}^2$ ). Error bars represent the 2.5% and 97.5% C.I. of the estimates.**

distributions; so calculation of  $R^2$  is a non-Bayesian (“point”) assessment of the model performance (40).

The four parameters in the model ( $v$ ,  $k_r$ ,  $k_d$ , and  $F$ ) were estimated simultaneously using Bayesian fitting to observed hypoxic area. We estimate constant values for  $v$ ,  $k_r$ , and  $k_d$  across years and allow  $F$  to vary for each year.  $F$  is allowed to vary using a hierarchical structure assuming that it is normally distributed with mean 0.50, standard deviation 0.25, and restricted to be between 0 and 1 (e.g.,  $N(0.50, 0.25)I[0, 1]$ , where ‘ $I(\sim)$ ’ denotes censoring to remove values outside the range specified) (41). Other than the restriction to being between 0 and 1, this is a fairly noninformative prior. Test runs of the model without the restricted 0–1 range produce very similar patterns of variation in  $F$  and do not impact our conclusions. The following informative priors are used for the other parameters based on our previous modeling studies (24, 26, 41):  $k_d \sim \text{Uniform}(0.001, 0.01)$ ,  $k_r \sim N(0.01, 0.005)I[0, \infty]$  and  $v \sim N(0.5, 0.5)I[0, \infty]$ . In these previous studies, parameters were hand calibrated (24, 26); variability about these values was estimated at approximately twice the variance of posterior estimates for a similar Bayesian model of Chesapeake Bay using noninformative priors (41).

## Results and Discussion

Estimating fixed values for  $v$ ,  $k_r$ , and  $k_d$ , and allowing  $F$  to vary among years, results in a good fit to observations (Figure 1;  $R^2 = 0.99$ ) and identifiable parameter values. Our estimate for  $k_d$  is larger than that of Scavia and Donnelly (ref 26, Table 1), but their value is within our 95% C.I. Our  $k_r$  and  $v$  estimates are close to the value and mean value, respectively, used earlier (26).

The extent to which TN load produces oxygen-consuming bottom-water organic material ( $F$ ) is highly correlated through time with the ratio of hypoxic area to spring TN load (Figure 2). This strong correlation indicates that  $F$ , fit in the context of this model, is a good measure of system sensitivity to TN load. Consistent with other empirical evidence (3, 6),  $F$  differs among three time periods (Figure 3a): relatively low in 1985–1991, increasing in 1992–1997, and higher again in 1999–2008. Its interannual variability is relatively low in 1985–1991 and 1992–1997 but higher in 1999–2008. Outlier  $F$  estimates in years 1998 and 2003 (Figure 3a) result from matching uncharacteristically low hypoxic areas in those years (given the nitrogen load). Compared to other years, the hypoxic layer in 1998 was much thicker, resulting in the hypoxic volume being concentrated in a smaller area (4), a property our model is unable to capture. In 2003, storms

**TABLE 1. Bayesian Estimated Parameters Values in the SP Model**

parameters	mean	SD	2.5%	25%	50%	75%	97.5%	Scavia and Donnelly (26)
$k_d$ (1/day)	0.006	0.002	0.003	0.005	0.006	0.008	0.010	0.003
$k_r$ (1/day)	0.011	0.002	0.006	0.009	0.011	0.013	0.016	0.010
$v$ (km/day)	0.66	0.127	0.42	0.56	0.67	0.76	0.90	varied by year, with mean 0.56 and SD 0.19
$\sigma_A$ ( $10^3$ km <sup>2</sup> )	0.823	0.185	0.213	0.762	0.883	0.952	0.995	–

disrupted stratification during the month of the mapping cruise, reducing the size of the measured hypoxic zone (42). These outlier years do not impact the posterior distributions of  $v$ ,  $k_r$ , or  $k_d$  (data not shown). Thus, we conclude that the model provides good fits to available data and is sensitive to both system changes and extreme events beyond the scope of the model.

**Modeled Rate Processes.** To test the model at process levels, we compared modeled and empirical rate estimates. Modeled cross-pycnocline oxygen flux averages 0.045 g/m<sup>3</sup>/day (95% C.I.: 0.024–0.068), consistent with observed fluxes of 0.039 (July) and 0.049 g/m<sup>3</sup>/day (August), assuming an average 10-m subpycnocline depth (43). Modeled bottom layer respiration rate is 0.0291 g O<sub>2</sub>/m<sup>3</sup>/day (95% C.I.: 0.0170–0.0428), consistent with July estimates (0.0161 and 0.0799 g O<sub>2</sub>/m<sup>3</sup>/day), based on mass-balances assuming an average 10-m subpycnocline depth (44) and with the measure range of 0.019 to 6.96 g/m<sup>3</sup>/day (45).

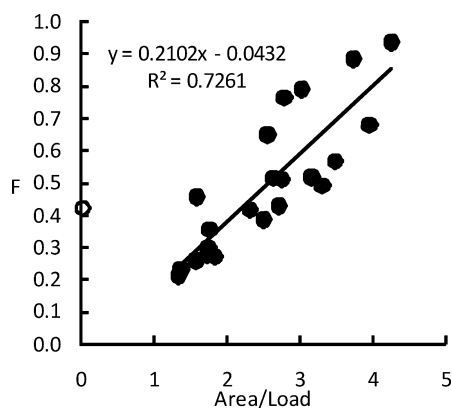
**Expanded Model.** The carryover of oxygen consuming organic matter from prior years has also been proposed as a mechanism for increasing Gulf of Mexico sensitivity. We tested an expanded version of our model that explicitly incorporates residual organic matter from previous years.

For the expanded model, we assume the current year's hypoxia is affected by the current year's spring loads and accumulated organic matter from the previous two years. For year  $i$ , eq 1 was expanded such that

$$DO[i] = DO_s - \frac{k_d((1-\alpha-\beta) \cdot F[i] \cdot BOD_o[i] + \alpha \cdot F[i-1] \cdot BOD_o[i-1] + \beta \cdot F[i-2] \cdot BOD_o[i-2])}{k_r - k_d} \left( e^{-k_r \cdot \Delta t} - e^{-k_d \cdot \Delta t} \right) \tag{2}$$

where  $\alpha$  and  $\beta$  represent the fractions of organic matter produced in year  $i-1$  and  $i-2$  that are respired in year  $i$ . Equation 1 is a special case of eq 2 for 1989, we used the predicted hypoxic area from Scavia and Donnelly (10,098 km<sup>2</sup> (26)) for modeling years 1990 and 1991. This value is close to others estimated for 1989 (i.e., 8086 km<sup>2</sup> (46)).

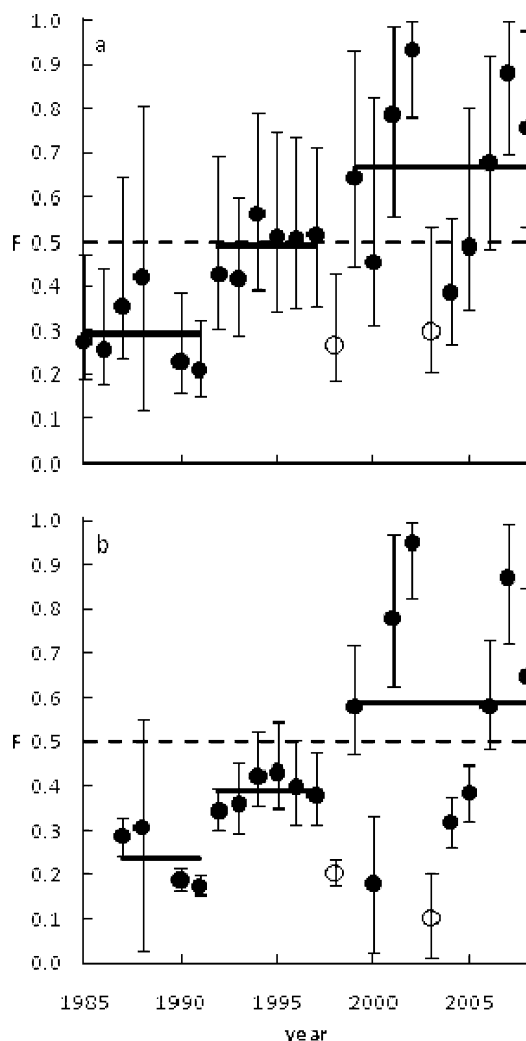
We assume normal priors for  $\alpha$  (N(0.1,0.05)I[0,]) and  $\beta$  (N(0.01,0.033)I[0,]) and estimate them along with the other parameters (Table 2; Figure 3b). The complexity of this model



**FIGURE 2.  $F$  vs hypoxic area/TN load for all years. Regression is calculated for all years except 1988 (open circle) when a drought resulted in extremely low load and hypoxic area.**

poses two challenges for model fitting. First, the underlying distribution of some parameters appears bimodal with an ecologically unrealistic mode near 0. Second, there are correlations between some parameters that impede convergence. To generate ecologically meaningful fits, we set  $v = 0.66$  (its value from fitting eq 1) and imposed cutoffs excluding the unrealistic lower modes: ( $k_r$ , N(0.01, 0.005)I[0.007,]) and  $k_d$  Uniform(0.006, 0.01).

On average, 12.6% of the preceding year's ( $i-1$ ) load and 3% of the second preceding year's ( $i-2$ ) load contribute to the current year's hypoxia. Modeled rate processes are still consistent with observed rates: cross-pycnocline flux



**FIGURE 3. Estimated  $F$  values. Error bars represent the 2.5% and 97.5% C.I. of the estimates. Dashed horizontal line is the value used in ref 26. Solid horizontal lines are the average values through the periods 1985–1991 (1987–1991 in panel b), 1992–1997, and 1999–2008; the outlier years (1998 and 2003, indicated by open circles) are not included in the calculation of average  $F$ . (a) For the model with no year to year carryover of organic matter ( $\alpha = \beta = 0$ ). (b) For the model with organic matter carryover ( $\alpha, \beta > 0$ ).**

**TABLE 2. Bayesian Estimates When Adding  $\alpha$  and  $\beta$  in the SP Model**

parameters	mean	SD	2.5%	25%	50%	75%	97.5%
$k_d$ (1/day)	0.007	0.0006	0.006	0.006	0.007	0.007	0.008
$\alpha$	0.126	0.043	0.042	0.096	0.128	0.157	0.211
$\beta$	0.026	0.019	0.001	0.011	0.021	0.037	0.070
$k_r$ (1/day)	0.008	0.0004	0.007	0.008	0.008	0.008	0.009
$\sigma_A$ ( $10^3$ km <sup>2</sup> )	0.36	0.10	0.15	0.30	0.39	0.45	0.50

(0.036 g/m<sup>3</sup>/day; 95% C.I.: 0.003–0.042) and bottom layer respiration (0.0208 g O<sub>2</sub>/m<sup>3</sup>/day; 95% C.I.: 0.0019–0.0248) and resulting  $F$  patterns (Figure 3b) are similar to the base model (eq 1): lower values and low variability in 1987–1991, increased  $F$  and low variability in 1992–1997, and higher  $F$  and increased variability after 1998. Adding  $\alpha$  and  $\beta$  to the model results in only a small decrease in the difference in average  $F$  between the first and last periods (0.38 vs 0.35); however, including organic matter carryover is not sufficient to substantially reduce shifts in  $F$ , nor did it improve model fit. In addition, we tested a version of our model that explicitly included organic matter carryover from the prior 4 years (data not shown). Resulting variability in  $F$  was approximately the same as in the model with two prior years, and the percent organic matter carried over from years  $i-3$  and  $i-4$  was of the same order of magnitude (~3%) as that from year  $i-2$ . Thus, the explicit inclusion of organic carbon carryover did not substantially improve model performance.

In both models,  $F$  follows a step pattern with three periods as described above. This pattern supports the importance of internal dynamics over the direct action of a more gradual external change, such as climate change, in determining system sensitivity. However, it should be noted that a gradual external change can act in concert with internal dynamics to generate breakpoints in system behavior (11). Thus our analysis does not rule out climate change or other external impacts on hypoxia response to N-loading and more work in this area is needed.

**Nitrogen Recycling and Bottom-Water Oxygen.** Factors that could influence  $F$  include the following: changes in phytoplankton sinking due to changed cell size, cell density, or water column mixing; changes in recycling of bottom water organic matter; and changes in vertical mixing. Mixing is strongly influenced by freshwater discharge, and there has been no significant trend in this over the period of study (slope  $p = 0.42$ , not shown). Long-term trends have been observed in Gulf phytoplankton species composition; however, these are in the direction of smaller and less silicified cells (43), potentially leading to decreased sinking rates and  $F$ , rather than the increase which we observe.

A relationship between bottom DO concentrations and N recycling has been observed in the Chesapeake Bay (12) and the Baltic Sea (17). Under reducing conditions, nitrification and denitrification are reduced such that N<sub>2</sub> production is diminished, and NH<sub>4</sub> and NO<sub>3</sub> are recycled and made available for algal production (2, 13, 15). In addition to the direct impact of low water column DO, sediment redox state can be strongly impacted by the movement of sediment macrofauna. Thus hypoxia-driven decreases in these macrofauna can amplify the relationship between DO at the sediment interface and reducing conditions in the sediments. This mechanism could even be augmented by organic matter carried over from previous years causing either increased respiration within the sediment or increased sediment accumulation rates, thus leading to a mechanistic link between the organic matter carryover and N recycling hypotheses.

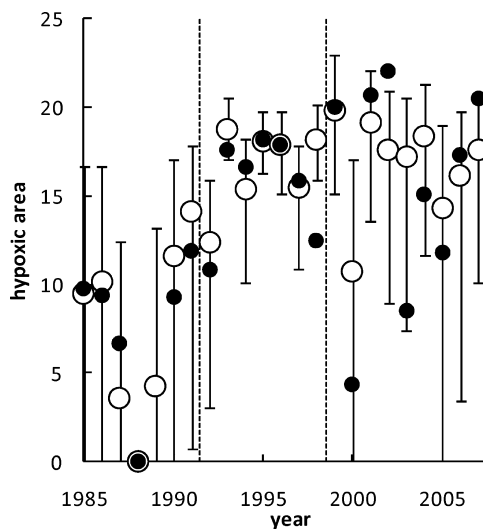
Independent observations in the Gulf of Mexico hypoxic area demonstrate that potential denitrification is reduced to ~1/2 its maximum rate at DO concentrations below 1 mg/L,

possibly leading to decreased loss of N<sub>2</sub>, increased residence time of bioavailable N (ref 47 as modified in ref 48), and thus increased N recycling efficiency. More work is needed to determine the relationships among recycled bottom-water N, its delivery to upper water-column phytoplankton, and other processes including the carryover of organic matter, increased organic matter loading from land, or control of organic matter production by P loading.

**Scenarios, Forecasts, and Policy Implications.** A version of this model has been used previously to predict impacts of nutrient load scenarios in the northern Gulf (24–26). In those applications, the model was calibrated to the full data set, irrespective of the now apparent shifts in sensitivity to TN. Here we revise this analysis using this new information.

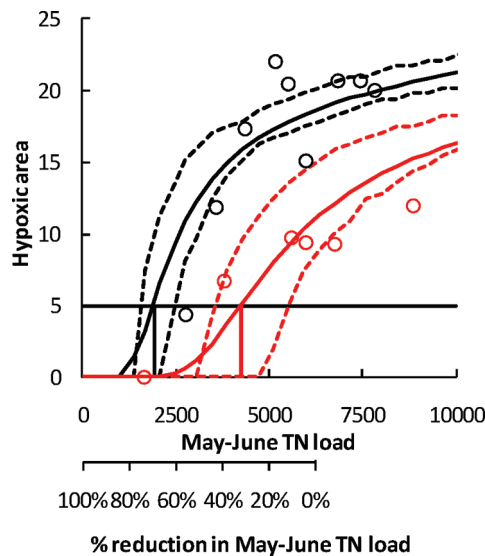
To test model robustness, we hindcast hypoxic area for before 1992, 1992–1998, and 1999–2008 using parameter distributions taken from the above calibration (Table 1 and Figure 3a) and year-specific loads.  $F$  was assigned its mean value for each period (0.29, 0.49, and 0.67, respectively). The hindcasts (Figure 4) are robust, providing a good fit (observed area is within the 95% C.I.) to observations for all but one year in each of the 1992–1998 and 1999–2008 periods. One of these is also our outlier year (1998).

Using this calibration we forecast hypoxic area vs TN load under two scenarios: assuming the system remains in its altered post-1998 state and assuming reduced loads return the system to the original pre-1992 state. For each scenario,  $F$  values were drawn from a normal distribution with mean and variance taken from the posterior distribution of the period having that state. We assume the ratio of Mississippi to Atchafalaya loads remains stable at the current average of 2.6. As in prior scenario analyses done in the context of long-range planning (24), we bound our forecasts by the 50% C.I. to more directly approximate system response in average years.



**FIGURE 4. The hind-casting results of the hypoxia area (open circles,  $10^3$  km<sup>2</sup>) and observations (closed circles,  $10^3$  km<sup>2</sup>). Error bars represent the 2.5% and 97.5% C.I. of the hind-casting estimates.**





**FIGURE 5.** Hypoxic area ( $10^3$  km<sup>2</sup>) vs May-June TN load (ton/day) and % TN load reduction (relative to the average 1980–1996 May-June TN load of 6083 ton/day, alternate x-axis). Solid curves are the predicted mean relationships with the red curve for pre-1992 conditions and the black curve for post-1998 conditions. Dashed lines indicate the 25% and 75% C.I. Open circles (red and black) are the observed values (pre-1992 and post-1998, respectively). The horizontal line is the target hypoxic area (5000 km<sup>2</sup>), and vertical lines indicate the average May-June river nitrogen load, or % reduction, needed to attain this goal under each state.

Our results (Figure 5) indicate that if the Gulf of Mexico were still in the pre-1992 state or if it returned to that state, it would only require a 34% TN load reduction (50% C.I.: 17%–46%) from the average 1988–1996 spring TN load of 6083 t/day to achieve the Action Plan goal. However, if the system remains in the new, more sensitive state, a 71% TN load reduction (50% C.I.: 62%–76%) is needed. Scheffer et al. (49) and Scheffer and Carpenter (11) provide theoretical and empirical evidence for hysteresis in such responses and describe why recovery from an altered state can take one of several paths and returning to an original state may require loads substantially below those that were in place in that original state. Thus the load reduction estimates required to achieve the Action Plan goal could be greater than simply returning to the loads of the past, and greater than those recommended in the 2001 and 2008 Action Plans (ref 9 (30%), ref 10 (45%)) or from previous assessments (e.g., 40 to 45% (16, 24, 26)). The additional uncertainty in system response due to hysteresis and state changes is a major challenge in the management of hypoxia (15). We tested the scenarios for the two extreme states (pre-1992 and post-1998) observed thus far. Between 1992 and 1998 the system was in an intermediate state and this, or a different intermediate state, could also be possible during recovery. Our TN load reductions thus are boundary estimates that bracket loading rate reduction required to meet Action Plan goal.

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