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# Yield-per-recruit modeling of two piscivores in a Midwestern reservoir: A Bayesian approach

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ABSTRACT

Walleye *Sander vitreus* and hybrid striped bass *Morone chrysops x M. saxatilis* fisheries are supported by annual stockings in many US midwestern reservoirs. To maximize return to the angler, yield-per-recruit models are often used to evaluate expected yield and assist managers to determine which regulation to implement, generally length or bag limits. However, yield-per-recruit models are typically formulated with point estimates of life history parameters, which ignore uncertainty. Our objective was to estimate yield from yield-per-recruit models of walleye and hybrid striped bass under various harvest strategies (e.g., alternative minimum length limits and conditional fishing mortality rates) while incorporating uncertainty about the input model parameters. We estimated parameters of age and growth and weight-length models simultaneously using Bayesian inference. The full posterior distribution of these model parameter estimates were then used to estimate yield. We found that yield differed among length limits for both species at high conditional fishing mortality. We also found yield decreased for both species as minimum length limits increased for low conditional fishing mortality. Finally, we presented a probabilistic framework to determine how changing minimum length limits and conditional fishing mortality affects the probability of achieving 70–90% of the maximum yield. Our results provide insight on the expected yield under different minimum length limits and bag limits, while incorporating uncertainty in the model inputs, and add to the sparse literature on hybrid striped bass population dynamics.


## 1. Introduction

Walleye *Sander vitreus* and hybrid striped bass *Morone chrysops x M. saxatilis* fisheries are supported by annual stockings in many US midwestern reservoirs. The management of these species is often focused on modification of length limits or bag limits to maximize yield. Yield-per-recruit models are used to evaluate expected yield and assist managers determine which regulation(s) to implement. However, most growth and mortality models used to predict yield fail to incorporate uncertainty. For example, a value-per-recruit analysis of walleye using a modified Beverton-Holt dynamic pool model used point estimates for growth and mortality and found trophy and consumptive value was maximized at lengths of 559 and 457 mm (Jacobson, 1996). Similarly, Hoffman et al. (2013) used point estimates for growth parameters in a Beverton-Holt yield-per-recruit model of hybrid striped bass and concluded yield differed significantly between alternative minimum length limits when exploitation was 30% or greater. Both walleye and hybrid striped bass were modeled in an urban midwestern reservoir by Schultz and Dodd (2008), who suggested changes in length limits would produce negligible effects on yield while harvest would be decreased. In these three cases, ignoring the uncertainty in the input parameters leads to questions regarding the validity of the results, and ultimately, could impede sound management.

Yield-per-recruit models are typically formulated with point estimates of life history parameters and ignore uncertainty in these parameters (Ragonese and Bianchini, 1996; Jones and Wells, 2001; Kirchner, 2001; Colombo et al., 2007; Schultz and Dodd, 2008; Hoffman et al., 2013). Defining uncertainty in models can be done in several ways. However, the Bayesian statistical paradigm of inference is especially suited for this task. For example, this paradigm has been used to incorporate uncertainty in catch-at-age data with relative abundance indices, resulting in improved precision in population dynamics model parameters (McAllister and Ianelli, 1997). Further, Bayesian inference of a hierarchical model of abundance and mortality produced improved estimates of spatial and tem-

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poral variability in a larval walleye population abundance (DuFour et al., 2014). Thus, the use of Bayesian inference to propagate uncertainty in these models suggests the same approach could improve results in yield-per-recruit models.

Predicting expected yield while directly acknowledging the uncertainty in life history parameter estimates can help determine the best harvest strategies to improve angler success for walleye and hybrid striped bass. Our objective was to estimate yield from yield-per-recruit models for walleye and hybrid striped bass under various harvest strategies (e.g., different minimum length limits and conditional fishing mortality rates) and three levels of conditional natural mortality while incorporating uncertainty from the input model parameters. To accomplish this, we estimated age and growth (i.e., parameters of the von Bertalanffy growth model), mortality (i.e., parameters of a catch curve model), and weight-length relationships (i.e., parameters of the weight-length model) for both species using Bayesian inference and used the full posterior distribution as inputs for yield-per-recruit analysis. We expect to show that propagating uncertainty would result in yield estimates for walleye and hybrid striped bass that more fully describe our understanding of yield responses to changes in management strategies by providing a distribution of credible values compared to those based on point estimates alone.

## 2. Methods

### 2.1. Study area

We studied population dynamics of walleye and hybrid striped bass at Monroe Reservoir in south-central Indiana. Monroe Reservoir is operated by the Army Corp of Engineers as a flood control reservoir and is the largest reservoir in Indiana at 4,350 ha. The fish community consists of walleye, gizzard shad *Dorosoma cepedianum*, white crappie *Pomoxis annularis*, bluegill *Lepomis macrochirus*, yellow bass *Morone mississippiensis*, longear sunfish *Lepomis megalotis*, channel catfish *Ictalurus punctatus*, largemouth bass *Micropterus salmoides*, spotfin shiner *Cyprinella spiloptera*, and hybrid striped bass (Kittaka, 2008). Walleye fingerlings have been stocked annually since 1982 and hybrid striped bass fingerlings since 1983. Since 2000, walleye fingerlings have been stocked at an average of 92 fish per hectare and hybrid striped bass fingerlings have been stocked at an average of 17 fish per hectare. Walleye are managed with a 356 mm length limit and six fish bag limit, while hybrid striped bass are managed with no minimum length limit, 12 fish bag limit, of which no more than two can exceed 432 mm.

### 2.2. Data collection

Walleye sampling was conducted for eight years between 1994 and 2011, and hybrid striped bass sampling for seven years between 2004 and 2012. Sampling was not consistent each year. Both species were collected during September and October using nighttime pulsed DC boat electrofishing with two dippers. Thirty-two sites were sampled each year for 15 min each, creating an annual sampling effort of 8 h. Sites were based upon historical index sampling locations. All fishes collected were identified and measured for total length. Weight was recorded for up to four (when possible) individuals per 25 mm length class. Scales were removed from up to five fish per 12.7 mm length class for age and growth analysis and to provide the information necessary to generate age-length keys. Although other structures have been shown to be more precise than scales (Isermann et al., 2003), scales have historically been used by the Indiana Department of Natural Resources to estimate age and growth for the two species examined in this analysis and no other structures were available.

### 2.3. Age and growth models

Age and growth of each species was assessed by fitting a von Bertalanffy growth model to mean length-at-age (von Bertalanffy, 1938) such that:

$$y_{ij} = L_{\infty j}\left(1 - e^{-\kappa j\left(\text{age}_{ij} - t_{0j}\right)}\right) + \varepsilon_{ij},\ \varepsilon_{ij} \sim \text{normal}\left(0, \sigma^2/n_{ij}\right) \tag{1}$$

where $y_{ij}$ is average total length (mm) at age $i$ from year (or year-class) $j$, $L_{\infty j}$ is the hypothetical average maximum total length achieved for year (or year class) $j$, $\kappa_j$ is the Brody growth coefficient of year (or year class) $j$ with units $t^{-1}$, $\text{age}_{ij}$ is the age of observation $i$ from year (or year-class) $j$, $t_{0j}$ is the age when individuals would have been length 0 for year (or year-class) $j$, and $\varepsilon_{ij}$ is a random error term of observation i for year (or year class) $j$ with mean 0 and constant variance $\sigma^2$. Because age estimates based on scales are not as precise as other hard parts (Isermann et al., 2003), we extended the von Bertalanffy growth model to incorporate measurement error (Hatch and Jiao, 2016):

$$\text{age}'_{ij} = \text{age}_{ij} * e^{\varepsilon_i} \tag{2}$$

where $\text{age}_{ij}$ is the true mean age for the $i^{th}$ observation from year (or year class) j. The observed $\text{age}_{ij}$' is assumed to be lognormally distributed with mean $\log_e(\text{age}_{ij})$ and variance $\varphi^2$. Other methods are available to account for aging error using random effects (Cope and Punt, 2007). However, they require multiple readers with multiple age estimates for each individual. The historical data used in this analysis only had one recording made per individuals, precluding a random effects model. To improve convergence of the model, we followed Kimura (2008) where $L_{\infty j}$, $\kappa_j$, and $t_{0j}$ are estimated on the logarithmic scale. However, because negative values are possible for $t_0$, and by definition, would not be possible on the log scale, we added 10 to $t_{0j}$. Kimura (2008) estimated parameters using maximum likelihood approaches. However, the transformation of Kimura (2008) have also been used to estimate growth parameters of the von Bertalanffy model using Bayesian inference (Midway et al., 2015). Ten was then subtracted from the $t_{0j}$ parameter estimate when interpreting the coefficient on the original scale. We additionally treated the coefficients for hybrid striped bass year-class as a random effect as they were sampled consistently each year. This hierarchical relationship (i.e., random effects) assumes growth parameters from each year class are similar across years. This allowed us to share information among years and generate a posterior distribution for each parameter used to create the yield-per-recruit model. Because walleye were not consistently sampled, the coefficient for year of collection was treated as a random effect for this fish (i.e., synthetic cohort). Thus, each model parameter ($L_{\infty j}$, $\kappa_j$, and $t_{0j}$) was indexed for $j$ year of collection (walleye) or year class such that:

$$\ln\left(L_{\infty j}\right) \sim \text{normal}\left(\mu_1, \sigma_1^2\right) \tag{3}$$

$$\ln\left(\kappa_j\right) \sim \text{normal}\left(\mu_2, \sigma_2^2\right) \tag{4}$$

$$\ln\left(10 + t_{0j}\right) \sim \text{normal}\left(\mu_3, \sigma_3^2\right) \tag{5}$$

where $\mu_1$, $\mu_2$, and $\mu_3$ represent the overall mean $L_\infty$, $\kappa$, and $t_0$ and $\sigma_1^2$, $\sigma_2^2$, and $\sigma_3^2$ represent the global variance for the model parameters.

### 2.4. Natural mortality

Natural mortality, M, was estimated using the $\text{Hoenig}_{\text{nls}}$ model (Then et al., 2015):

$$M = a t_{max}^{b} \tag{6}$$

where $t_{\max}$ is the maximum age attained (set to maximum age observed, 10 for walleye and 13 for hybrid striped bass) and $a$ and $b$