Specified Input Values for a Stochastic Simulation Model for Yellow Perch in Southern Lake Michigan

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Prepared by:

Brian J. Irwin[1], Michael J. Wilberg[2], James R. Bence[1], and Michael L. Jones[1]

[1]Quantitative Fisheries Center and Department of Fisheries and Wildlife, 13 Natural Resources, Michigan State University, East Lansing, MI 48824-1222.

[2]Chesapeake Biological Laboratory, University of Maryland Center for Environmental Science, P.O. Box 38, Solomons, MD 20688.

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Summary

This Quantitative Fisheries Center Technical Report provides initial parameter values used in a stochastic simulation model for yellow perch *Perca flavescens* in southern Lake Michigan. The stochastic simulation model was developed, in large part, from previous stock assessment models (Wilberg et al., 2005). The stochastic simulation model was used to evaluate performance of alternative harvest polices and is described in more detail in Irwin et al. (in press). Additionally, Wilberg et al. (in press) used the simulation model to explore alternative cases of source-sink dynamics. In total, these efforts are aimed at providing information to fisheries managemers as they consider alternate management strategies for the yellow perch fishery.

This report is organized into three sections. In Section 1, parameter definitions and equations used in the various population sub-models described in Irwin et al. (in press) are provided in Tables 1 and 2. Initial parameter values, standard errors, and correlation coefficients for this base model are provided in appendix A. Section 2 briefly describes modifications for an analysis evaluating the consequences of alternative source-sink scenarios (Wilberg et al., in press) on harvest policy performance, with relevant modifications to starting parameters provided in appendix B. Lastly, Section 3 summarizes some analyses used to estimate stock-recruitment parameters, which were then used to represent alternative states of nature (recruitment hypotheses) as part of the overall harvest policy evaluation for yellow perch in southern Lake Michigan.

Section 1: Parameter definitions and equations

The initial parameter values and corresponding standard errors and correlation coefficients provided here correspond to the model described in detail in Irwin et al. (in press), with an overview of that description also provided here. The model was stochastic and projected the age-, sex-, size-, and spatial-dynamics of the yellow perch population in the southern basin of Lake Michigan. Harvest policies represented combinations of levels of instantaneous fishing mortality and control rules (constant-F and two state-dependent rules). The operating model included uncertainties that can be roughly grouped as (a) model uncertainty – uncertainty about the nature of the stock-recruitment relationship, (b) parameter uncertainty – given a stock-recruitment relationship, uncertainty about parameter values for that relationship, (c) process uncertainty – given the model parameters, uncertainty about what specific process errors will occur during a given simulation, and (d) assessment and implementation uncertainty – uncertainty arising during a given simulation because of errors in population assessment and policy implementation.

The model represented abundance of yellow perch in eight age groups ranging from age 2 through an age-9 "plus" group that was an aggregate group including ages 9 and older. All simulations began with the same initial abundance-at-age values (A.1), and recruitment during year one was specified as the average recruitment from stock assessment models for 1999-2002 (A.2). Recruitment was defined as the number of age-2 yellow perch entering the population annually and was generated for each management area, with an equal sex ratio at recruitment (equation T.2.1). We included a separate recruitment model for the area-specific ("area"; equation T.2.2) and mixed-stock ("mixed"; equation T.2.3) recruitment hypotheses, within which two additional alternative hypotheses for future recruitment potential were represented ("recent" and "variable" recruitment hypotheses). Depending on the recruitment hypothesis, log-scale Ricker model parameters were drawn from different multivariate normal distributions (i.e., these parameters varied across simulations) with variances and covariances equal to the asymptotic variance-covariance matrix derived from fitting Ricker models to stock-assessment model estimates of spawning stock biomass (SSB) and recruitment time series (A.3-A.7; see Section 3 for additional details on estimation). A multiplicative lognormal error was applied to median recruitment each year (i.e., recruitment was stochastic over time). The log of the standard deviation of the recruitment errors was drawn from a normal distribution; the standard deviation of this distribution was estimated as part of fitting the Ricker models.

For the case of "recent" productivity, Ricker parameters were based on spawner-recruit patterns from stock assessment models for the 1993-2002 year classes (A.3-A.4; see Section 3). For the case of "variable" productivity, parameters for two recruitment regimes were identified by classifying year classes as either "high" or "low", regardless of the year, and fitting Ricker models to these subsets of data assuming a common density-dependent term (A.5-A.6). For a given simulation of the variable recruitment hypothesis in the model, the selected Ricker α parameter was scaled downward (c in equations T.2.2-T.2.3) for years designated to have "low" recruitment. The designation of either a "high" or "low" recruitment regime for a given year was determined by a random Bernoulli variable. The parameter of the Bernoulli distribution (probability of "high" recruitment) was drawn for each simulation from a uniform distribution, U[0.1, 0.25]. For area-recruitment hypotheses, recruitment errors were correlated among areas for a given year to replicate the high correlation in observed recruitment across areas (equation T.2.2; A.7). Alternatively, the recruitment errors for the mixed-recruitment scenarios were applied to total recruitment (equation T.2.3), and total recruits were then allocated among the four management areas, with expected proportions of total recruits in an area derived from stock assessment models from 1996-2004 (A.8). Process error was included by considering the proportions of returning recruits to be a random draw from a multinomial distribution with a sample size of 100 so that the expected proportions mimicked the variation in proportional recruitment seen in the stock assessments. In connection with the implemented recruitment uncertainty, area-specific maximum-recruitment levels (A.8) were imposed at four times the maximum estimated recruitment because simulations without this limit produced a few cases of unbelievably high recruitment that strongly influenced the performance statistics.

The abundance of individual cohorts decreased over time as they aged and were exposed to sources of mortality that depended upon management area, year, age, and sex (equations T.2.1, T.2.4). In all simulations, we assumed an instantaneous natural mortality rate of 0.37 yr^{-1} that was held constant across age, sex, area, and time as was the case for the assessment models (Wilberg et al., 2005). Fishing mortality was scaled by age- and sex-specific selectivity that varied over time and among areas (equation T.2.5), although length-based selectivity was constant over sex, area, and time (Wilberg et al., 2005). The length-based selectivity pattern was the average selectivity for the recreational fishery in Wisconsin and Illinois (Wilberg et al., 2005). Age-based selectivity was the weighted average of the length-based selectivities with weights equal to the numbers at length for a given age (equation T.2.6). Thus, variation in growth across sex, area, and time led to the variation in age-based selectivity. Fishery harvest was calculated within each management area, and total annual harvest was used as one of the performance statistics (equation T.2.7). Modest movement of yellow perch among management areas occurred at the end of the year and was based on a migration matrix that was parameterized using mark-recapture data (Glover, 2005; equation T.2.1; A.9), with the annual amount of emigration for any one area not exceeding 20%.

Growth was represented using a form of the incremental von Bertalanffy growth model that included density dependent and independent components (equations T.2.8-T.2.9; A.10-A.12). Increments in mean length from one age to the next in the following year were projected by management area and sex (equations T.2.8-T.2.9) so that female yellow perch grew faster and achieved a larger maximum total length than males. Density dependence was represented by modeling the intercept of the increment in mean length versus initial mean length relationship for each sex and area as a linear function of total abundance in that management area (equation T.2.9). Density-independent variation in growth was incorporated by modeling the slope of the same relationship by a first-order autoregressive process (AR(1); equation T.2.9; $\rho_{\varphi} = 0.118$ and $\sigma_{\varphi} = 0.144$). For all autoregressive processes, the first value of the autocorrelated time series was drawn from a distribution, defined as $N\left(0, \frac{\sigma^2}{1-\rho^2}\right)$, where σ and ρ are the parameters of the AR(1) process (e.g., σ_{φ} and ρ_{φ} for equation T.2.9). Parameters of the growth models were estimated from mean-length-at-age data for each management area (Wilberg et al., 2005). However, these parameters estimates produced unreasonably large or small length-at-age values in the simulation model for population sizes that were outside those used in the estimation. Therefore, we adjusted the parameter values of the density-dependent component so that growth would be reasonable for population sizes outside those used to estimate model parameters while still being consistent with available data. A multivariate normal distribution was then used to generate parameter values $(\gamma_0, \gamma_1, \text{and } \bar{b}_1)$ for the growth submodel for each simulation (A.11). Next, annual size distributions for a given management area and sex were generated by allocating fish from each age class into thirty-one length bins ranging from <9 cm to ≥38 cm, in 1 cm increments. Allocation among length bins was done assuming normally distributed length-at-age for each sex, with mean lengths-at-age from the von Bertalanffy model and corresponding CVs (Wilberg et al., 2005; equation T.2.10; A.13). All simulations began with the same initial length-at-age values (A.14).

SSB was calculated based on abundance by length categories of females at the start of the year (reproduction is in spring before growth or substantial mortality), mass-at-length, and the proportion mature at length (equation T.2.11). Mass-at-length was calculated for the mid-point of each total-length bin, and the relationship between length and mass was constant over time (Wisconsin Department of Natural Resources, unpublished data; equation T.2.12; A.15). Female maturity-at-length followed a constant logistic function (equation T.2.13; A.15) based on a relationship determined for yellow perch collected in Indiana waters of Lake Michigan (Ball State University, unpublished data; also see Wilberg et al., 2005). A description of harvest policies and the assessment and implementation errors associated with these policies (equations T.2.14-T.2.18; A.16) is provided in Irwin et al. (in press).

Table 1. Symbols and descriptions of variables used in the stochastic forecasting model (Table 2). Structural parameters and parameters associated with stochastic errors are identified as constant over simulations and time ("constant"), randomly drawn for a given simulation ("sim") or randomly drawn for each year ("year").

Symbol	Description
	Index variables
y	Year
m	Management area (WI, IL, IN, MI)
g	Sex (male = 1, female = 2)
a	Age (2-9+)
l	Length bin (≤9, 9-10, …,37-38, ≥38 cm)
r	Recruitment hypothesis indicator
	State and control variables
N	Actual abundance
$\hat{N}$	Assessed abundance
R	Recruits
SSB	Actual spawning stock biomass (kg, females)
$\hat{SSB}$	Assessed spawning stock biomass (kg, females)
B_0	Unfished spawning stock biomass (kg, females)
$\dot{T}$	Transition matrix for post-recruitment movement
b_0	Intercept for density-dependent growth increment
b_1	Slope for density-dependent growth increment
L	Mean length (cm)
W	Mass-at-length (kg)
Mat	Maturity-at-length
T_{B_0}	Biomass threshold for state-dependent harvest policy
F^*	Asymptotic maximum target F
F	Actual instantaneous fishing mortality rate
$\tilde{F}$	Target F given estimated SSB
$\hat{F}$	F applied to N that would produce same catch as $\tilde{F}$ applied to $\hat{N}$
Z	Instantaneous total mortality rate
C	Catch in numbers (harvest)
$\tilde{C}$	Target catch that would result from applying $\tilde{F}$ to $\hat{N}$
$\dot{p}$	Proportions at length for each age
s	Fishery selectivity
	Structural parameters
α	Ricker stock-recruitment parameter (sim)
β	Ricker stock-recruitment parameter (sim)
c	Ricker stock-recruitment parameter (sim)
R_{max}	Cap used to limit maximum recruitment (constant)

p	Proportion of recruits allocated to an area (year)
$\overline{b}_1$	Mean slope for density-dependent growth increment (sim)
τ_0	Intercept for density-dependent length at age 2 (constant)
τ_1	Slope for density-dependent length at age 2 (constant)
γ_0	Intercept for growth model intercept (sim)
γ_1	Slope for growth model intercept (sim)
CV_a	Coefficient of variation of length-at-age (constant)
$\dot{a}$	Mass-at-length parameter (constant)
b	Mass-at-length parameter (constant)
m_1	Maturity-at-length parameter, slope (constant)
m_2	Maturity-at-length parameter, half-saturation (constant)
M	Instantaneous natural mortality rate (constant)
	Distributional parameters and associated stochastic errors
ρ_φ	Autocorrelation coefficient for error in b_1 (constant)
ρ_ϕ	Autocorrelation coefficient of assessment error (constant)
ε	Recruitment deviation (year)
ζ	Error for mean length at age 2 (year)
δ	Error in b_1 (year)
φ	Error for δ (year)
ψ	Assessment error (year)
ϕ	Error for ψ (year)
v	Implementation error (year)
Σ_ε	Variance-covariance matrix for correlated ε among m (sim)
σ_ε	Standard deviation for ε (sim)
σ_ζ	Standard deviation for mean length at age 2 errors (constant)
σ_φ	Standard deviation for b_1 errors (constant)
σ_ϕ	Standard deviation for assessment errors (constant)
σ_ς	Standard deviation for implementation errors (constant)

Table 2. Equations used in stochastic simulation model.

Population model equations	#
$N_{y,m,g,a} = \begin{cases} \frac{R_{y,m}}{2} & \text{if } a = 2 \\ \sum_i \dot{T}_{m,i} N_{y-1,i,g,a-1} e^{-Z_{y-1,i,g,a-1}} & \text{if } 2 < a \le 8 \\ \sum_i \dot{T}_{m,i} \left(\left(N_{y-1,i,g,a-1} e^{-Z_{y-1,i,g,a-1}}\right) + \left(N_{y-1,i,g,a} e^{-Z_{y-1,i,g,a}}\right)\right) & \text{if } a = 9+ \end{cases}$ sums over $\{i =$ WI, IL, IN, MI$\}$	T.2.1
"Area" recruitment $R_{y,m} = \alpha_{r,m} \text{SSB}_{y-2,m} e^{\left(-\beta_{r,m} \text{SSB}_{y-2,m}\right)} e^{\varepsilon_{y-2,m}}$; $\underline{\varepsilon}_y \sim MVN(0, \Sigma_\varepsilon)$; where $\alpha_{r,m} = \begin{cases} \alpha_{\text{"recent"},m} \\ \alpha_{\text{"variable-high"},m} \\ \alpha_{\text{"variable-low"},m} = e^{\left(\log\left(\alpha_{\text{"variable-high"},m}\right) - c_m\right)} \end{cases}$	T.2.2
"Mixed" recruitment $R_{y,m} = p_m \alpha_r \text{SSB}_{y-2} e^{\left(-\beta_r \text{SSB}_{y-2}\right)} e^{\varepsilon_{y-2}}$; $\varepsilon_y \sim N(0, \sigma_\varepsilon^2)$ where $\alpha_r = \begin{cases} \alpha_{\text{"recent"}} \\ \alpha_{\text{"variable-high"}} \\ \alpha_{\text{"variable-low"}} = e^{\left(\log\left(\alpha_{\text{"variable-high"}}\right) - c\right)} \end{cases}$	T.2.3
$Z_{y,m,g,a} = M + F_{y,m,g,a}$	T.2.4
$F_{y,m,g,a} = F_{y,m} s_{y,m,g,a}$	T.2.5
$s_{y,m,g,a} = \sum_l \dot{p}_{y,m,g,a,l} s_l$	T.2.6
$C_y = \sum_m \sum_g \sum_a \frac{F_{y,m,g,a}}{Z_{y,m,g,a}} \left(1 - e^{-Z_{y,m,g,a}}\right) N_{y,m,g,a}$	T.2.7

$$L_{y,m,g,a} = \begin{cases} \tau_{0m} + \tau_{1m}\left(\dfrac{\sum_g \sum_a N_{y-1,m,g,a}}{1\,000\,000}\right) + \zeta_{y,m}; \quad \zeta_{y,m} \sim N(0,\sigma_\zeta^2) & \text{if } a = 2 \\ L_{y-1,m,g,a-1} + \Delta L_{y,m,g,a} & \text{if } a > 2 \end{cases} \tag{T.2.8}$$

$$\Delta L_{y,m,g,a} = b_{0\,y,m,g} + b_{1\,y,m,g} L_{y-1,m,g,a-1}$$

where

$$b_{0\,y,m,g} = \gamma_{0m,g} + \gamma_{1m,g}\left(\frac{\sum_g \sum_a N_{y-1,m,g,a}}{1\,000\,000}\right) \tag{T.2.9}$$

$$b_{1\,y,m,g} = \bar{b}_{1m,g} e^{\delta_{y,m}}; \quad \delta_{y,m} = \rho_\varphi \delta_{y-1,m} + \varphi_{y,m}; \quad \varphi_{y,m} \sim N(0,\sigma_\varphi^2)$$

$$\dot{p}_{y,m,g,a,l} = \Phi\left(\frac{l+1-L_{y,m,g,a}}{CV_a L_{y,m,g,a}}\right) - \Phi\left(\frac{l-L_{y,m,g,a}}{CV_a L_{y,m,g,a}}\right) \tag{T.2.10}$$

where Φ is the normal cumulative distribution function

$$\text{SSB}_{y,m} = \sum_l W_{y,m,2,l} Mat_{y,m,2,l} N_{y,m,2,l} \tag{T.2.11}$$

$$W_l = \dot{a}(l+0.5)^b \tag{T.2.12}$$

$$Mat_l = \frac{1}{\left(1+e^{(-m_1(l-m_2))}\right)} \tag{T.2.13}$$

<u>Observation and policy implementation</u>

$$\tilde{F}_{y,m} = \begin{cases} (F^*)\dfrac{\left(\hat{\text{SSB}}_{y,m} / B_{0\,m}\right)}{T_{B_0}} & \text{if } \hat{\text{SSB}}_{y,m} / B_{0\,m} < T_{B_0} \\ F^* & \text{for constant - F or if } \hat{\text{SSB}}_{y,m} / B_{0\,m} \ge T_{B_0} \end{cases} \tag{T.2.14}$$

$$\hat{N}_{y,m,g,a} = N_{y,m,g,a} e^{\psi_{y,m}}; \; \hat{\text{SSB}}_{y,m} = \text{SSB}_{y,m} e^{\psi_{y,m}}$$
$$\psi_{y,m} = \rho_\phi \psi_{y-1,m} + \phi_{y,m}; \; \phi_{y,m} \sim N(0,\sigma_\phi^2) \tag{T.2.15}$$

$$\tilde{C}_{y,m} = \sum_g \sum_a \frac{\tilde{F}_{y,m,g,a}}{\tilde{Z}_{y,m,g,a}}\left(1-e^{-\tilde{Z}_{y,m,g,a}}\right)\hat{N}_{y,m,g,a} \tag{T.2.16}$$

where $\tilde{Z}_{y,m,g,a} = M + \tilde{F}_{y,m,g,a}$

$$\widetilde{C}_{y,m} = \sum_{g}\sum_{a}\frac{\hat{F}_{y,m,g,a}}{\hat{Z}_{y,m,g,a}}\left(1-e^{-\hat{Z}_{y,m,g,a}}\right)N_{y,m,g,a}$$

$$\text{where } \hat{Z}_{y,m,g,a} = M + \hat{F}_{y,m,g,a} \qquad \text{T.2.17}$$

$$F_{y,m} = \hat{F}_{y,m}e^{\nu_{y,m}}\ ;\ \nu_{y,m} \sim N\left(0,\sigma_{\varsigma}^{2}\right) \qquad \text{T.2.18}$$

Note that some equations (T.2.2, T.2.3, T.2.8, T.2.9) are presented in greater detail with respect to the parameter values provided in the appendices here than was the case for a more simplified presentation in Irwin et al. (in press), which previously did not fully describe how some specific parameter values were incorporated into equations (e.g., scaling adjustments).

Appendix A. Specified input values needed for simulations. These are parameters used in Table 2 that were constant over simulations or the mean or median (indicated with a "bar" e.g., $\overline{\beta}$), standard deviations, and correlations needed to define the distribution for parameters that were drawn randomly and varied among simulations or over time.

Table A.1. Starting values for abundance at age ($N_{y=0,m,g,a}$) by management area and sex.

Sex	Area	Age							
		2	3	4	5	6	7	8	9+
Male	Wisconsin	260 848	180 096	22 745	0	6 741	272 663	17 503	20 553
Male	Illinois	1 140 220	400 798	275 172	3 344	6 056	668 175	30 496	43 334
Male	Indiana	2 485 943	1 888 723	1 300 506	126 464	211 814	1 773 538	177 182	363 094
Male	Michigan	1 336 354	1 135 873	766 568	54 727	265 593	636 881	59 415	145 262
Female	Wisconsin	260 848	180 063	22 526	0	6 541	259 973	16 817	12 644
Female	Illinois	1 140 220	400 591	263 970	2 960	4 929	526 955	26 307	27 213
Female	Indiana	2 485 943	1 887 766	1 285 007	120 771	191 246	1 504 553	142 310	333 373
Female	Michigan	1 336 354	1 134 796	749 266	51 543	243 831	576 270	53 872	192 797

Table A.2. Number of initial recruits.

Area	$R_{y=1,m}$
Wisconsin	171 250
Illinois	600 127
Indiana	3 405 594
Michigan	2 118 778

Table A.3. Median and log-scale standard deviation for "recent" recruitment parameters by management area and for mixed-pool (Mixed) stock-recruitment models. The parameters $\log(\alpha)$ and β were drawn from a multivariate normal distribution with means and σ shown below, correlations are provided in Table A.4. "Standard deviations" are approximately equal to coefficient of variation for $\log(\alpha)$, β, and σ_ε.

Area	$\log(\bar{\alpha})$	σ_α	$\bar{\beta}$	σ_β	$\bar{\sigma}_\varepsilon$	$\sigma_{\sigma_\varepsilon}$
Wisconsin	1.872	0.612	1.05E-05	0.920	1.715	0.18
Illinois	1.422	0.800	2.95E-06	1.209	1.327	0.18
Indiana	1.847	0.344	5.37E-07	0.638	0.792	0.18
Michigan	1.978	0.282	9.79E-07	0.493	0.696	0.18
Mixed	1.999	0.310	3.26E-07	0.553	0.773	0.18

Table A.4. Correlation of α and β for "recent" recruitment by management area and for mixed-pool (Mixed) spawning stocks. Correlations between σ_ε and either α or β were zero and are not shown. These correlation parameters reflect that the "recent" recruitment parameters were drawn (see A.3) to be correlated among areas.

Area	$\rho_{\alpha,\beta}$
Wisconsin	0.696
Illinois	0.829
Indiana	0.801
Michigan	0.801
Mixed	0.801

Table A.5. Median and log-scale standard deviation for "variable" recruitment parameters by management area and for mixed-pool (Mixed) stock-recruitment models. The parameters $\log(\alpha)$, β, and c were drawn from a multivariate normal distribution with means and σ shown below, correlations are provided in Table A.6. "Standard deviations" are approximately equal to coefficient of variation for $\log(\alpha)$, β, c, and σ_ε.

Area	$\log(\bar{\alpha})$	σ_α	$\bar{\beta}$	σ_β	$\bar{c}$	σ_c	$\bar{\sigma}_\varepsilon$	$\sigma_{\sigma_\varepsilon}$
Wisconsin	6.499	0.227	2.87E-05	0.306	4.472	0.331	1.653	0.18
Illinois	5.124	0.229	9.79E-06	0.315	2.970	0.351	1.328	0.18
Indiana	4.233	0.144	1.19E-06	0.22	2.084	0.266	0.679	0.18
Michigan	3.902	0.13	1.81E-06	0.193	1.729	0.266	0.564	0.18
Mixed	4.414	0.129	6.79E-07	0.193	2.127	0.242	0.632	0.18

Table A.6. Correlation of α , β , and c for "variable" recruitment by management area and for mixed-pool (Mixed) spawning stocks. Correlations between σ_ε and other parameters were zero and are not shown. These correlation parameters reflect that the "recent" recruitment parameters were drawn (see A.5) to be correlated among areas.

Area	$\rho_{\alpha,\beta}$	$\rho_{\alpha,c}$	$\rho_{\beta,c}$
Wisconsin	0.843	0.753	0.552
Illinois	0.839	0.589	0.306
Indiana	0.845	0.651	0.397
Michigan	0.845	0.651	0.397
Mixed	0.845	0.651	0.397

Table A.7. Correlation matrix for recruitment errors for annual recruitment variability.

Area	Wisconsin	Illinois	Indiana	Michigan
Wisconsin	1.000	0.885	0.846	0.924
Illinois	0.885	1.000	0.935	0.806
Indiana	0.846	0.935	1.000	0.811
Michigan	0.924	0.806	0.811	1.000

Table A.8. Proportion of unfished spawning stock biomass (USSB), proportion of total recruits from mixed-pool recruitment that return to each management area (p_m), and area-specific cap used as a limit on maximum recruitment in an area for a given year (in millions, $R_{max,m}$).

Area	Proportion USSB	p_m	$R_{max,m}$
Wisconsin	0.22	0.035	50
Illinois	0.27	0.091	70
Indiana	0.32	0.526	270
Michigan	0.20	0.348	110

Table A.9. Transition matrix $(\dot{T})$ specifying post-recruitment migration among the four management areas. Each cell represents the proportion of the population moving from an area (column) to another area (row). Values along the diagonal represent the proportion of an area's population that does not migrate.

Area	Wisconsin	Illinois	Indiana	Michigan
Wisconsin	0.92	0.10	0.03	0.01
Illinois	0.05	0.80	0.10	0.05
Indiana	0.02	0.08	0.80	0.10
Michigan	0.01	0.02	0.08	0.84

Table A.10. Mean and standard deviations for parameters for determining length at age two $\left(L_{y,m,g,2}\right)$ by management area.

Area	$\tau_{0,m}$	$\tau_{1,m}$	$\sigma_{\zeta,m}$
Wisconsin	12.3	-0.12	0.5
Illinois	15.6	-0.25	0.5
Indiana	16.4	-0.16	0.5
Michigan	12.6	-0.17	0.5

Table A.11. Mean and standard deviation parameters for density-dependent von Bertalanffy growth model by sex and management area. The parameters $\gamma_{0,m,g}$, $\gamma_{1,m,g}$, $b_{1,m,g}$ and were drawn from a multivariate normal distribution with means and σ shown below, correlations are provided in Table A.12.

Sex	Area	$\bar{\gamma}_{0,m,g}$	$\sigma_{\gamma_0,m,g}$	$\bar{\gamma}_{1,m,g}$	$\sigma_{\gamma_1,m,g}$	$\bar{b}_{1,m,g}$	$\sigma_{b_1,m,g}$
Male	Wisconsin	-0.050	0.016	8.70	0.80	-0.323	0.06
Male	Illinois	-0.028	0.007	8.75	0.80	-0.323	0.05
Male	Indiana	-0.001	0.0002	3.35	0.30	-0.113	0.02
Male	Michigan	-0.004	0.001	6.30	0.60	-0.274	0.04
Female	Wisconsin	-0.045	0.015	11.40	1.05	-0.336	0.04
Female	Illinois	-0.030	0.008	11.60	1.10	-0.387	0.05
Female	Indiana	-0.004	0.001	6.30	0.60	-0.181	0.03
Female	Michigan	-0.008	0.002	6.45	0.60	-0.173	0.03

Table A.12. Correlation matrices for parameter values for a density-dependent von Bertalanffy growth model by management area and sex. M = males, F = females.

Area		γ_0 M	γ_0 F	γ_1 M	γ_1 F	b_1M	b_1F
Wisconsin	γ_0 M	1.000	0.062	-0.583	-0.031	0.302	0.003
	γ_0 F	0.062	1.000	-0.006	-0.680	-0.022	0.253
	γ_1 M	-0.583	-0.006	1.000	0.042	-0.909	-0.057
	γ_1 F	-0.031	-0.680	0.042	1.000	-0.038	-0.797
	b_1M	0.302	-0.022	-0.909	-0.038	1.000	0.069
	b_1F	0.003	0.253	-0.057	-0.797	0.069	1.000
Illinois	γ_0 M	1.000	0.007	-0.489	-0.026	0.297	0.029
	γ_0 F	0.007	1.000	-0.022	-0.602	0.022	0.378
	γ_1 M	-0.489	-0.022	1.000	0.071	-0.964	-0.077
	γ_1 F	-0.026	-0.602	0.071	1.000	-0.072	-0.950
	b_1M	0.297	0.022	-0.964	-0.072	1.000	0.079
	b_1F	0.029	0.378	-0.077	-0.950	0.079	1.000
Indiana	γ_0 M	1.000	-0.019	-0.685	0.001	-0.060	0.020
	γ_0 F	-0.019	1.000	0.018	-0.797	-0.008	0.057
	γ_1 M	-0.685	0.018	1.000	0.006	-0.652	-0.030
	γ_1 F	0.001	-0.797	0.006	1.000	-0.008	-0.600
	b_1M	-0.060	-0.008	-0.652	-0.008	1.000	0.022
	b_1F	0.020	0.057	-0.030	-0.600	0.022	1.000
Michigan	γ_0 M	1.000	0.011	-0.690	-0.008	-0.086	-0.005
	γ_0 F	0.011	1.000	-0.016	-0.778	0.009	-0.198
	γ_1 M	-0.690	-0.016	1.000	0.026	-0.640	-0.017
	γ_1 F	-0.008	-0.778	0.026	1.000	-0.026	-0.424
	b_1M	-0.086	0.009	-0.640	-0.026	1.000	0.029
	b_1F	-0.005	-0.198	-0.017	-0.424	0.029	1.000

Table A.13. Parameter values for coefficient of variation for length at age (CV_a) by sex.

Sex	Age							
	2	3	4	5	6	7	8	9+
Males	0.23	0.18	0.14	0.12	0.12	0.12	0.12	0.12
Females	0.25	0.2	0.15	0.12	0.12	0.12	0.12	0.12

Table A.14. Starting values for mean length ($L_{y=0,m,g,a}$) at age by management area and sex.

Sex	Area	Age							
		2	3	4	5	6	7	8	9+
Male	Wisconsin	12.00	17.08	21.52	23.62	25.08	26.21	26.95	27.26
Male	Illinois	12.73	15.38	17.28	18.61	20.34	22.73	24.51	25.72
Male	Indiana	13.60	15.10	16.40	17.60	18.60	19.60	20.50	21.30
Male	Michigan	11.20	14.50	16.80	18.40	19.60	20.80	21.60	22.00
Female	Wisconsin	12.00	19.52	24.96	27.55	29.59	31.30	32.18	32.49
Female	Illinois	12.73	19.12	23.15	25.84	27.91	29.32	30.89	32.21
Female	Indiana	13.60	17.50	20.70	23.20	25.30	27.00	28.40	29.60
Female	Michigan	11.20	15.80	19.50	22.50	25.10	27.80	30.10	31.20

Table A.15. Parameters for calculating mass at length (W_l) and maturity at length (Mat_l).

Parameter	value
$\log(\dot{a})$	-12.68
b	3.41
m_1	1.26
m_2	14.08

Table A.16. Standard deviation and autocorrelation coefficient for either assessment error or recreational fishery implementation error.

	σ	ρ
Assessment error (ϕ)	0.22	0.7
Implementation error (ς)	0.08	0.0

Section 2: Implementation of the model to explore source-sink dynamics

The source-sink model (Wilberg et al., in press) used the "mixed" version of the stochastic Ricker model for stock-recruitment dynamics as described in Section 1 (equation T.2.3). However, basin-wide recruitment was produced from spawning stock biomass (SSB) of a single management area for the various source-sink scenarios. The Ricker parameters for the "recent" recruitment hypothesis were based on analysis of a recruitment and SSB time series from 1993-2002, whereas parameters for the variable recruitment hypothesis were based on analysis of a time-series for 1986-2002, where each year was assigned to one of the two regimes (see Section 3). Parameters were estimated by fitting models of total estimated recruitment in southern Lake Michigan to SSB estimates for each management area. Recruitment and SSB were estimated using updated versions of models in Wilberg et al. (2005) for Illinois and Wisconsin and similar unpublished models for Indiana and Michigan. Parameter uncertainty was estimated on a log-scale by asymptotic standard errors and correlations obtained from regression. In the simulation models, the log-scale stock recruitment parameters used in individual simulations were then drawn from a multivariate normal distribution with medians and standard deviations (B.1 and B.2), and correlations (B.4 and B.5) for the variable and recent stock recruitment models, respectively.

Appendix B. Specified input values needed for source-sink simulations. These are parameters used in Table 2 that were constant over simulations or the mean or median (indicated with a "bar" e.g., $\bar{\beta}$), standard deviations, and correlations needed to define the distribution for parameters that were drawn randomly and varied among simulations or over time.

Table B.1. Median parameter values and log-scale standard deviations for the variable stock recruitment model.

Management area	$\log(\bar{\alpha})_m$	$\sigma_{\alpha,m}$	$\bar{\beta}_m$	$\sigma_{\beta,m}$	$\bar{c}_m$	$\sigma_{c,m}$	$\bar{\sigma}_{\varepsilon,m}$	$\sigma_{\sigma_{\varepsilon},m}$
Illinois	8.248	0.07	2.06E-05	0.16	2.509	0.22	0.619	0.18
Indiana	6.619	0.09	7.21E-06	0.22	1.954	0.27	0.670	0.18
Michigan	5.053	0.11	1.27E-06	0.19	2.117	0.24	0.631	0.18
Wisconsin	5.529	0.10	2.02E-06	0.19	2.117	0.24	0.631	0.18

Table B2. Median parameter values and log-scale standard deviations for the recent stock recruitment model.

Management area	$\log(\bar{\alpha})_m$	$\sigma_{\alpha,m}$	$\bar{\beta}_m$	$\sigma_{\beta,m}$	$\bar{\sigma}_{\varepsilon,m}$	$\sigma_{\sigma_{\varepsilon},m}$
Illinois	5.697	0.10	1.02E-05	0.49	0.878	0.18
Indiana	4.349	0.15	3.58E-06	0.57	0.756	0.18
Michigan	2.612	0.24	6.04E-07	0.55	0.771	0.18
Wisconsin	3.096	0.20	9.76E-07	0.55	0.771	0.18

Table B3. Correlation matrices for parameters in variable model. Correlations between σ and α, β, and c were zero and are not shown.

Management area	$\rho_{\alpha,\beta}$	$\rho_{\alpha,c}$	$\rho_{\beta,c}$
Illinois	-0.84	-0.75	0.55
Indiana	-0.84	-0.59	0.31
Michigan	-0.85	-0.65	0.40
Wisconsin	-0.85	-0.65	0.40

Table B4. Correlation of α and β parameters in recent model. Correlations between σ and α and β were zero and are not shown.

Management area	$\rho_{\alpha,\beta}$
Illinois	-0.70
Indiana	-0.83
Michigan	-0.80
Wisconsin	-0.80

Section 3. Estimating stock-recruitment parameters for YPDA model

One of the more challenging parts of the Lake Michigan yellow perch decision analysis (YPDA) project was the estimation of stock-recruitment parameters for the model. This section outlines the methods used to estimate these parameters.

Stock and Recruitment Time Series

Stock (as spawning stock biomass [SSB]) and recruitment time series were estimated from 1986-2005 for Wisconsin, 1986-2004 for Illinois, and 1996-2004 for Indiana and Michigan waters of southern Lake Michigan (Figures 1 and 2) using updated versions of the Wilberg et al. (2005) assessment models for Wisconsin and Illinois and newly developed assessment models (following similar methods to Wilberg et al. 2005) for Indiana and Michigan. There was a large degree of correspondence between the recruitment time series among states (Figure 1). Therefore, synthetic estimates of recruitment for Indiana and Michigan were produced for 1986-1995 using linear relationships between annual recruitment in Michigan and Indiana versus average annual recruit for Wisconsin and Illinois based on recruitment estimates available from the assessment models during 1996-2004 (Figure 3).

Estimated time series of SSB were quite similar for Wisconsin and Illinois and for Indiana and Michigan. However, patterns between models with longer time series and shorter time series were quite different, with Indiana and Michigan showing an almost monotonous decline since 1996. We believe that the Wisconsin and Illinois estimates are better estimates given the qualitative patterns in catches and perceptions by the managers during the past 20 years are matched by these estimates as well as the data used in the Wisconsin and Illinois models are, for the most part, more complete and more precise. Because we concluded that the overall pattern was wrong in the Indiana and Michigan time series, we took a different approach to estimating the SSB time series than we did for the recruitment time series. To generate synthetic SSB time series for Michigan and Indiana, we rescaled the average SSB time series in Wisconsin and Illinois so that they had the same mean during 1996-2004 as the Michigan or Indiana model estimates (Figure 4).

Stock Recruitment Models

We considered two alternative hypotheses with regard to how recruits mix and two with regard to future productivity, which led to four stock-recruitment models. The mixing hypothesis was that each state's SSB solely contributes recruits to that state's waters. In this hypothesis, each state's waters are essentially closed for the purpose of stock-recruitment. The alternative mixing hypothesis was that recruits from each of the four states mix in a common pool before settling out in each state. The first productivity hypothesis stated that the system has fundamentally changed and will follow stock recruitment patterns since 1993 (i.e., "recent" recruitment hypothesis). The alternative productivity hypothesis was that the system still retains the capacity to have large recruitment events (i.e., "variable" recruitment hypothesis). When these two alternatives for mixing and productivity were crossed, this led to four stock recruitment models: 1) individual stocks by state with recruitment dynamics similar to 1993-2004, 2) individual stocks by state with recruitment dynamics that maintain the capacity to have high recruitment in the future, 3) recruitment mixing among states with recruitment dynamics similar to 1993-2004, and 4) recruitment mixing among states with the capacity for high recruitment in the future.

Individual State Models

To estimate the parameters of the variable recruitment models, ANCOVAs were fitted to the data shown in Figures 5 and 7 to estimate the good and bad regime parameters of the variable recruitment hypothesis (Figure 8). Specifically, the model was

$$\log\left(\frac{R_{y,m}}{SSB_{y-2,m}}\right) = \log\alpha_{r,m} - \beta_{r,m}SSB_{y-2,m} - c_m D,$$

where R is recruitment and D is a dummy variable that describes whether the year is in the good or bad regime, and α, β , and c were estimated parameters. Years were classified as good or bad by eye, by looking at the plots in figure 5 and separating years into good or bad years. Good or bad classifications for a given year were the same across states, so a given year was either good across all states or bad across all states.

To estimate the parameters of the models that presumed that recruitment dynamics would remain consistent with the lower productivity seen during 1993-2002, simple Ricker models (as above without the dummy variable) were fitted to the data shown in Figures 6 and 7. The models predicted quite different responses in recruitment to changes in SSB (Figure 8). The good regime allowed for substantially higher productivity than the poor regime, and dynamics during the last decade allowed for somewhat higher recruitment than the bad regime.

Individual state – recent recruitment

Parameters for each state were drawn each simulation from a multivariate normal distribution with variances and covariances equal to the asymptotic variance-covariance matrix and covariances among states were assumed to be zero. Each year a correlated (among areas) lognormal error was applied to the median recruitment. Correlation coefficients (r) among recruitment residuals of states (during 1996-2004) ranged from 0.81 to 0.93.

Individual state – variable recruitment

Parameters for each state were drawn for each simulation from a multivariate normal distribution with variances and covariances equal to the asymptotic variance-covariance matrix. Covariances among states are assumed to be zero. The regime of a given year was a random Bernoulli variable, where the probability of a good year is *p*. The parameter *p* was randomly drawn at the beginning of each simulation from a uniform distribution (0.1-0.25). This distribution was based on an analysis of z-transformed relative recruitment from the 1950s to the present, and the proportion of years with "above average" recruitment was about 0.2.

Mixed pool – recent recruitment

Parameters for each state were drawn for each simulation from a multivariate normal distribution with variances and covariances equal to the asymptotic variance-covariance matrix. Total SSB across states was calculated and total recruitment was predicted. The predicted recruitment was multiplied by a lognormal error, and the recruits are reapportioned to the four states. The proportion of total recruits that return to a state was random (calculated from a random sample from a multinomial distribution with a sample size of 100) with means based on the proportion of total estimated/synthetic recruits that were found in that state's waters during 1986-2004.

Mixed pool – variable recruitment

Parameters for each state were drawn each simulation from a multivariate normal distribution with variances and covariances equal to the asymptotic variance-covariance matrix. Total SSB across states was calculated and recruitment was predicted. The regime of a given year is a random Bernoulli variable as above. The predicted recruitment was multiplied by a lognormal error, and the recruits were reapportioned to the four states based on a proportion that return to each state as above.

Figure 1. Estimated recruitment time series by state for yellow perch in southern Lake Michigan.

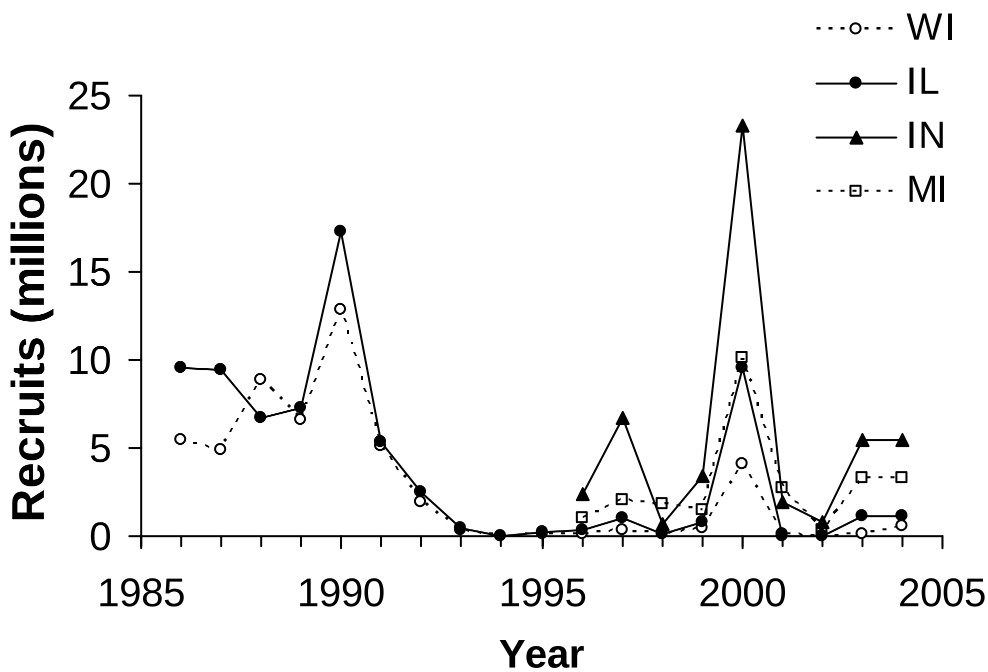


Figure 2. Estimated spawning stock biomass (kg) of yellow perch by state in southern Lake Michigan.

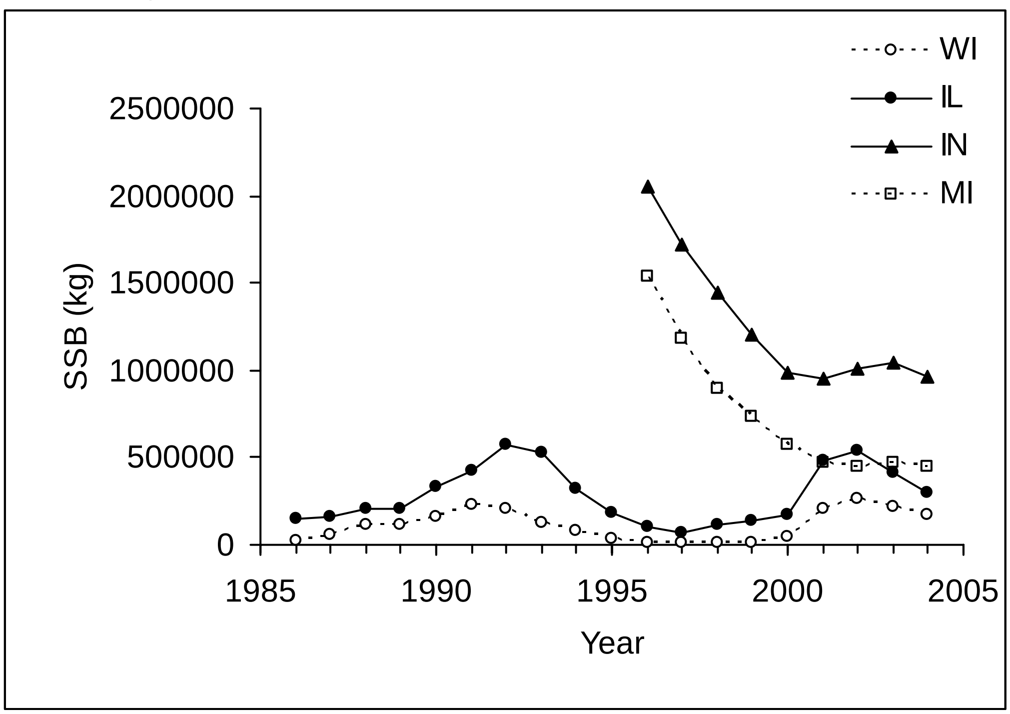


Figure 3. Observed and synthesized time series of recruitment for yellow perch in southern Lake Michigan by state. Values for Indiana and Michigan during 1986-1995 were synthesized using linear relationships between recruitment in each state and average recruitment in Illinois and Wisconsin.

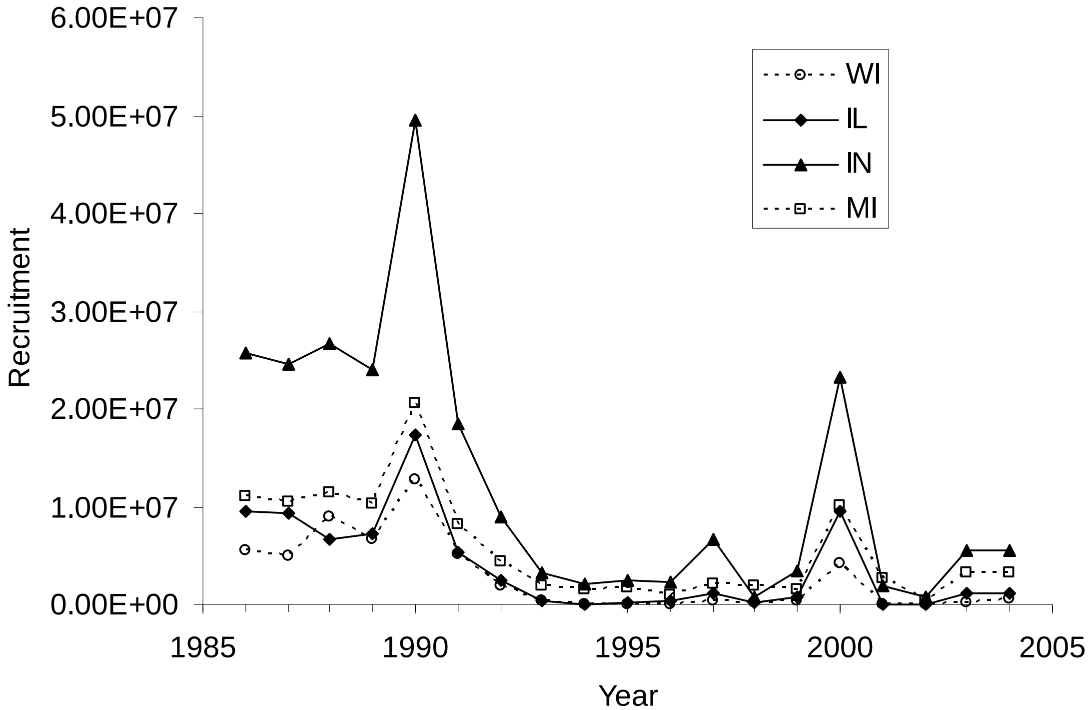


Figure 4. Observed and synthesized estimates of spawning stock biomass (SSB) for yellow perch in southern Lake Michigan. Values for Indiana and Michigan were synthesized by rescaling the average SSB time series for Illinois and Wisconsin so it has the same mean as the Indiana or Michigan SSB time series.

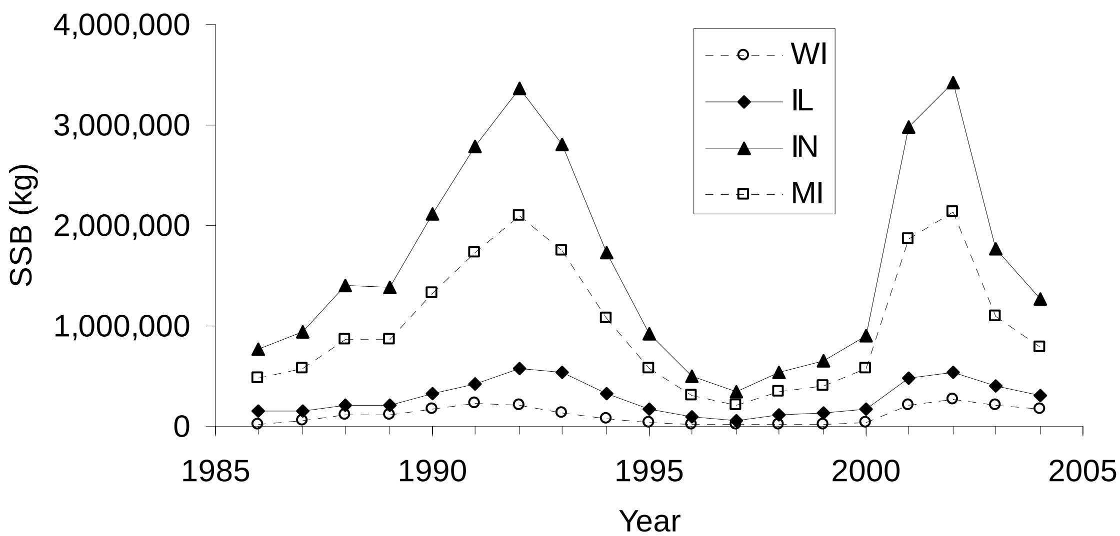


Figure 5. Plots of log(recruits/kg SSB) for yellow perch in southern Lake Michigan for each state. Ellipses (fit by eye) on the graphs indicate what might be separate regimes for recruitment.

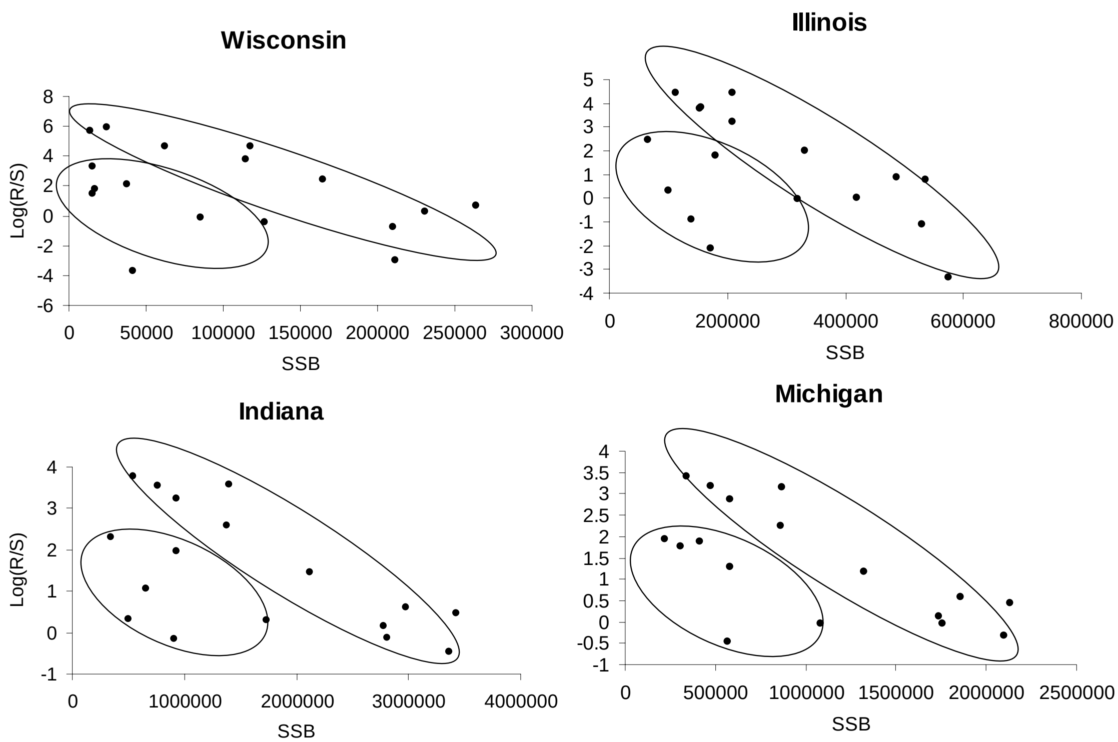


Figure 6. Plots of log(recruits/kg SSB) for yellow perch in southern Lake Michigan for each state for the 1993-2002 cohorts.

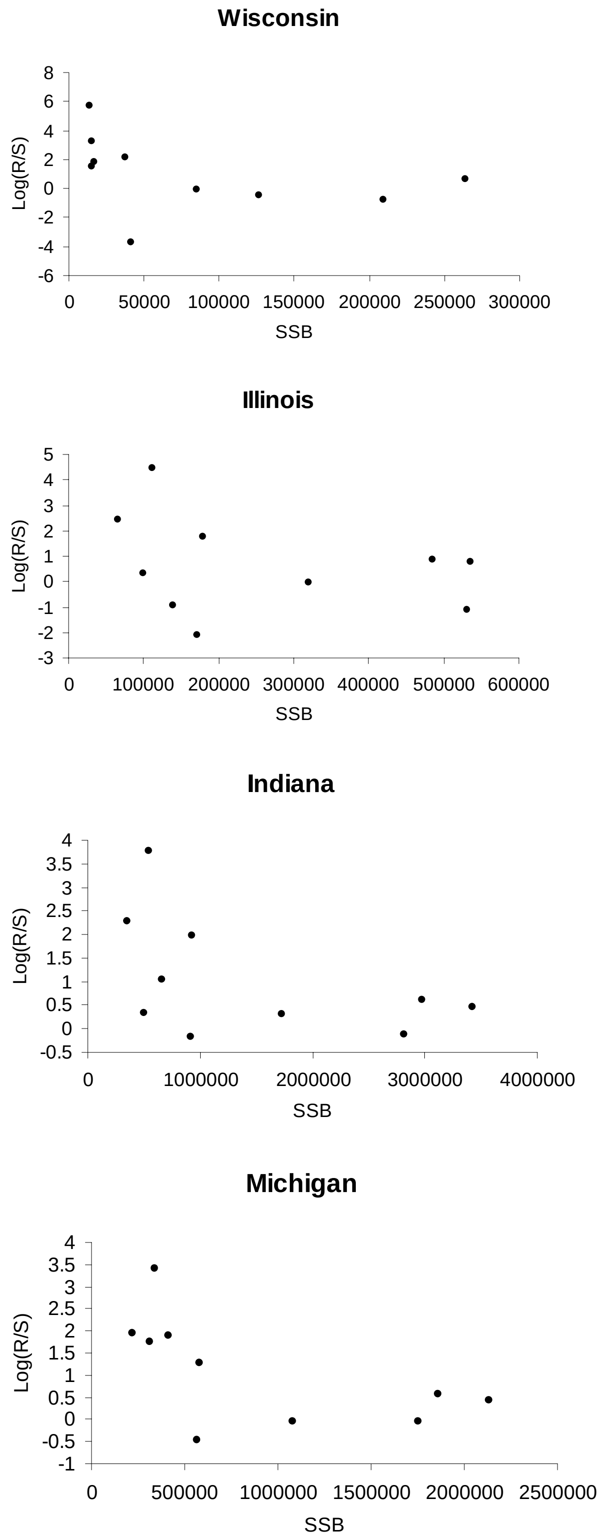
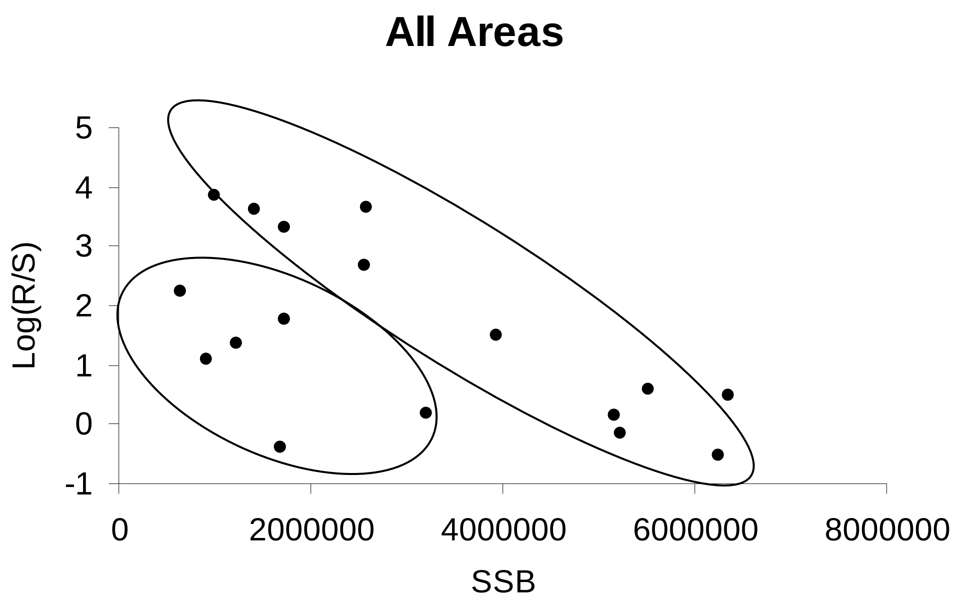


Figure 7. Plots of log(recruits/kg SSB) for yellow perch in southern Lake Michigan for the Mixed stock model for all cohorts (1986-2002) and just the 1993-2002 cohorts.



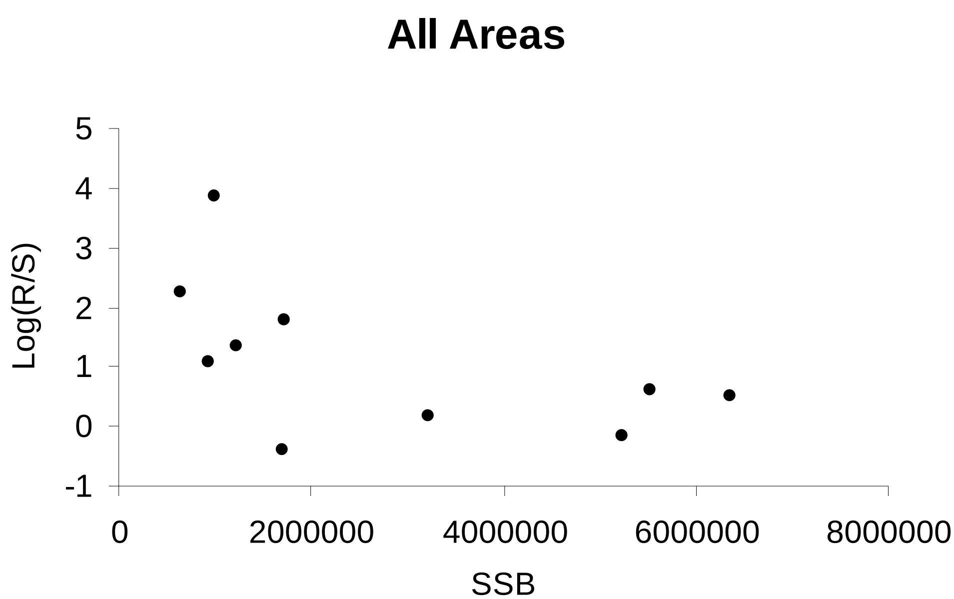
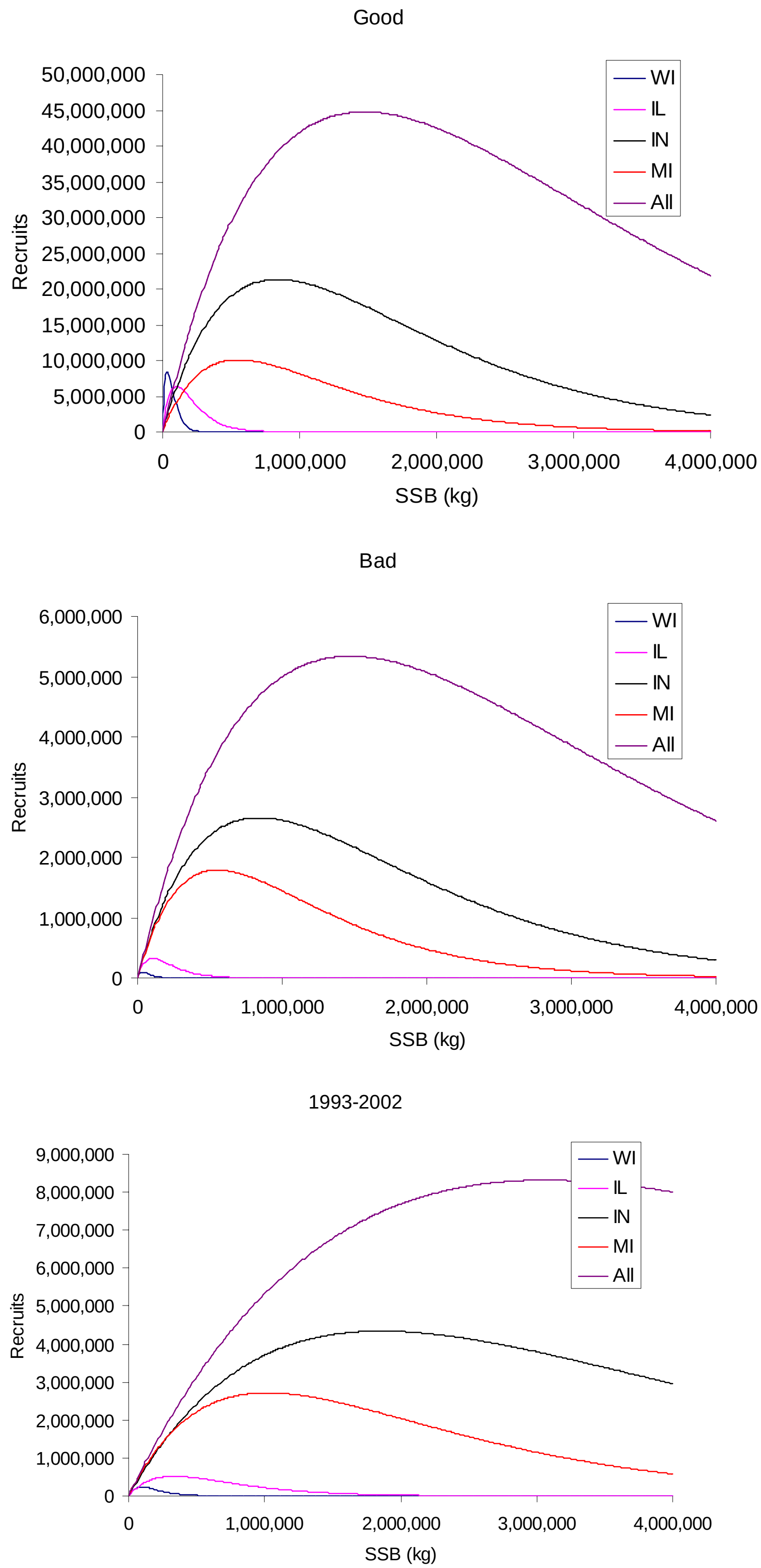


Figure 8. Estimated stock-recruitment curves for the good regime, bad regime, and during 1993-2002.



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