A Generalized Assessment Model to Obtain Consistent Management Advice from Diverse Data

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Stock Assessment Goals

- What harvest policy is sustainable and provides balance between preventing overfishing and attaining maximum fishing opportunities?
- Does current level of fishing (F) exceed that policy?
- Has abundance (B) been so reduced by past fishing as to put the stock and ecosystem at risk?
- What future catch would implement the policy?

Assessment Data and Situations

DATA

- Catch only
- Catch and stock abundance
- Catch, abundance and/or composition
- Add ecosystem/ climate/ habitat factors

SITUATIONS

- Short time series vs. long-term series containing contrast
- High F vs. low F
- Stable biology vs. environ/eco driven changes in process
- Degree of stock fluctuations (M + sigmaR)
- Degree of spatial viscosity

Assessment Approaches

- Catch Only
  - Time series, no biology
- Biomass Dynamics
  - Simple tuning factor
  - Time series tuning
  - STATISTICS: measurement vs. process error
- Age and/or Size Structured
  - Noisy data with gaps
  - Full catch-at-age
  - STATISTICS: Penalized pseudo-likelihood, Integration across random effects, Kalman filter
- Multi-Species with M and/or technological linkages

Added Features:
Spatial
Multi-species
Covariates

Biomass vs. Age Model Dichotomy

Biomass Dynamics
r, K parameters

Age-Structured
Empirical Reconstruction;
Then Spawn-Recruit

F_{msy} gives B_{msy}
near 0.5*K

≠

F_{msy} gives B_{msy} near 0.3*K,
or lower.

- Use 3-parameter forms that align these approaches;
- Don't ignore effects on SSB when using F_{max} as F_{msy} proxy

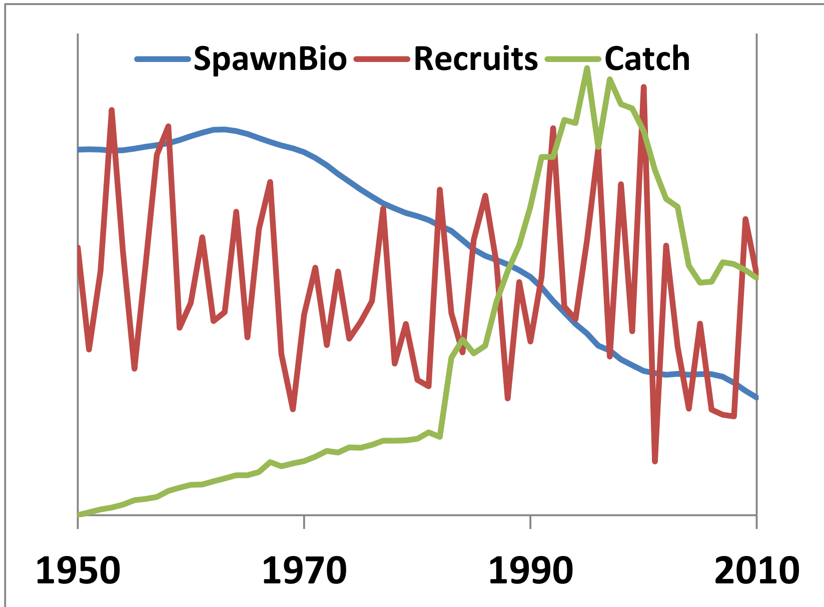
Desirable Model Characteristics

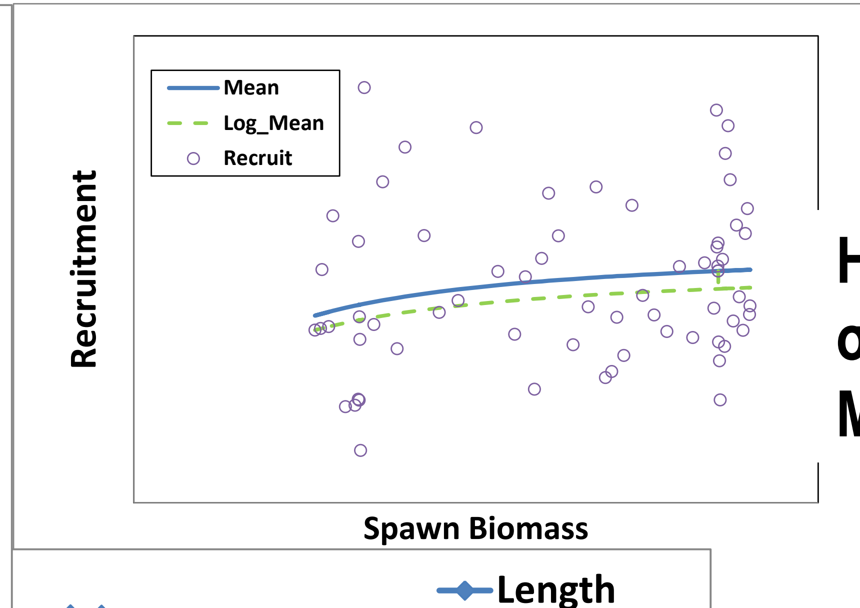
- Measures F, B, and productivity
- Estimates reference points and does forecasting
- Assimilates diverse types of data
- Consistency (no dichotomy as on previous slide)
- Statistically rigorous
- Biologically realistic
- Responsive to time-varying ecosystem/environmental processes
- Easy to use; includes A.I. to guide good usage practices
- Spatial
- Multi-species

How do Data Influence Assessment Results in a Generalized Model – Stock Synthesis?

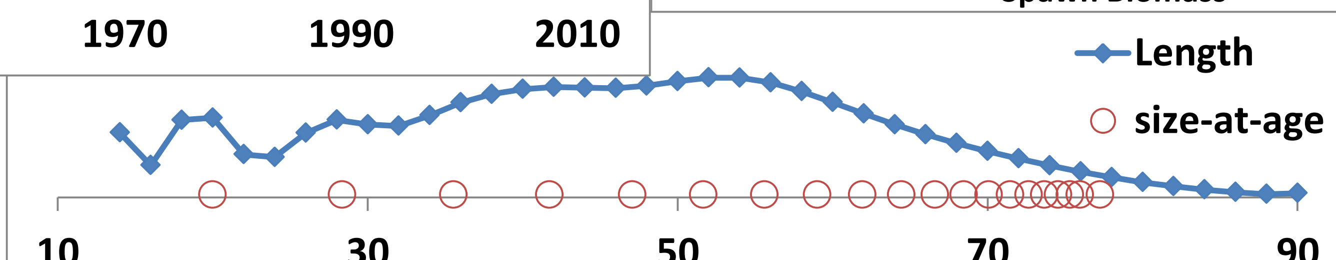
- Consider three data situation
  1. Scalar observation at end of time series
     - Mean length
     - Current F
     - $B_{current}$ / B_0
  2. Time series of relative abundance
  3. Composition data
     - Perfectly precise ages
     - Ages with ageing imprecision
     - Lengths

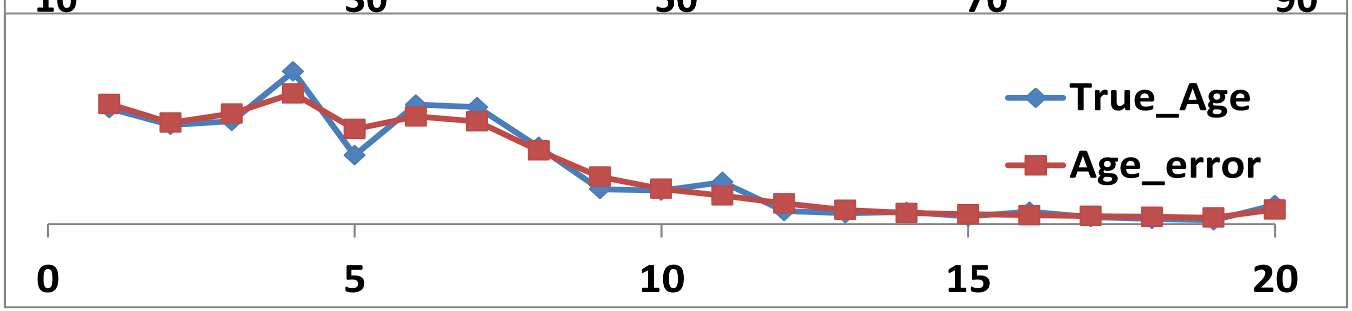
Example Simulated Population



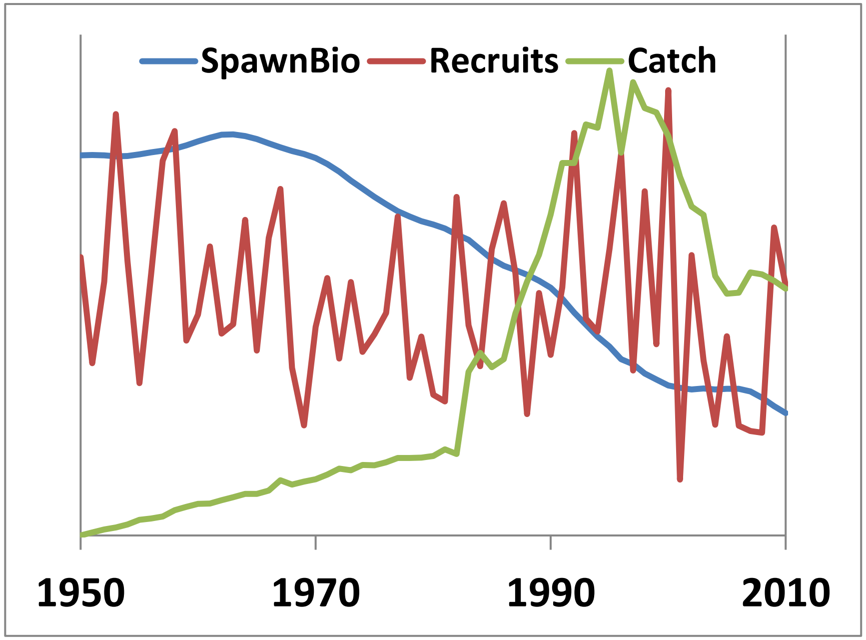


$H=0.7$; $\sigma_R=0.4$; $M=0.2$





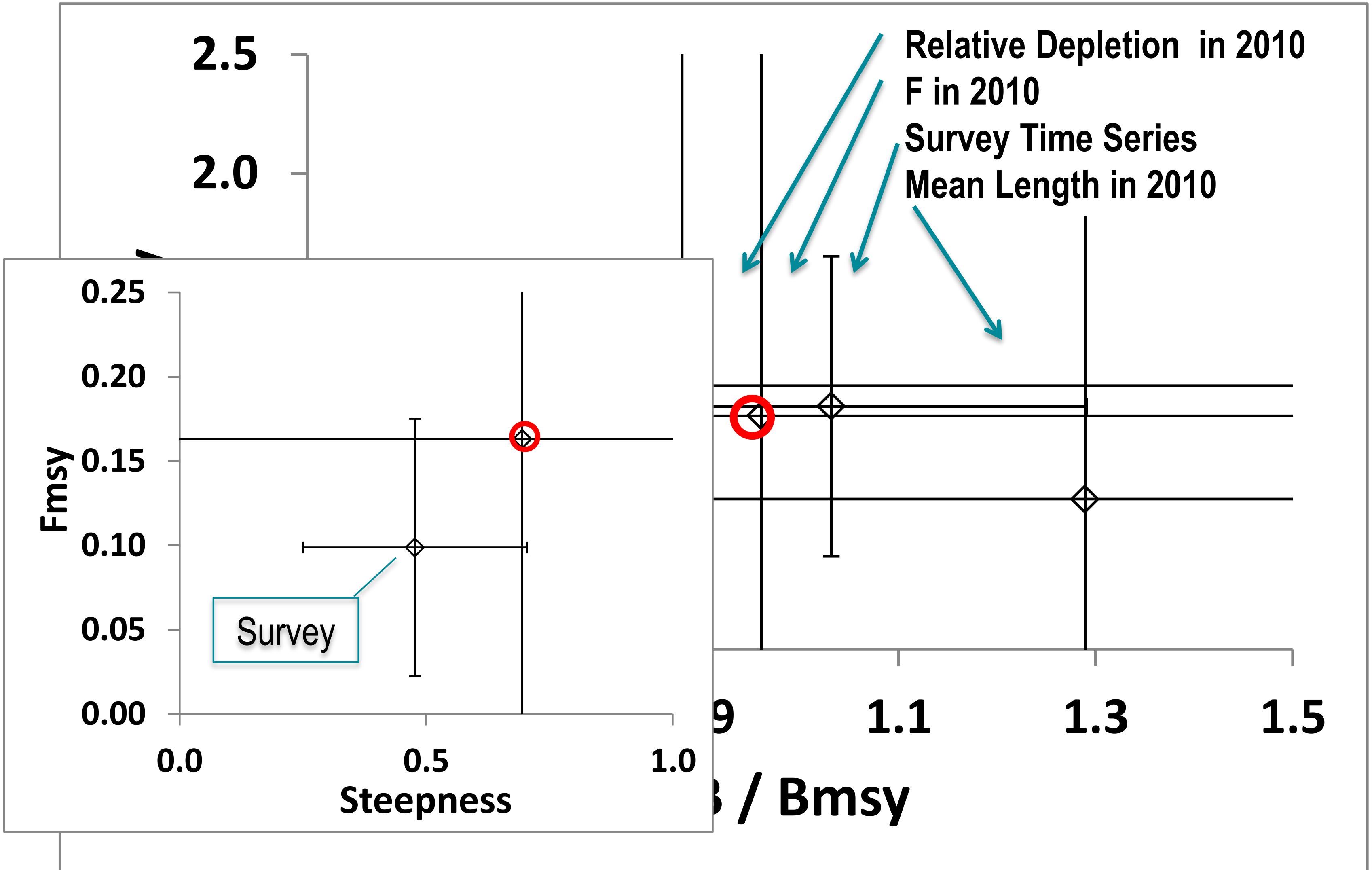
Generate and Analyze Simulated Data Using Stock Synthesis



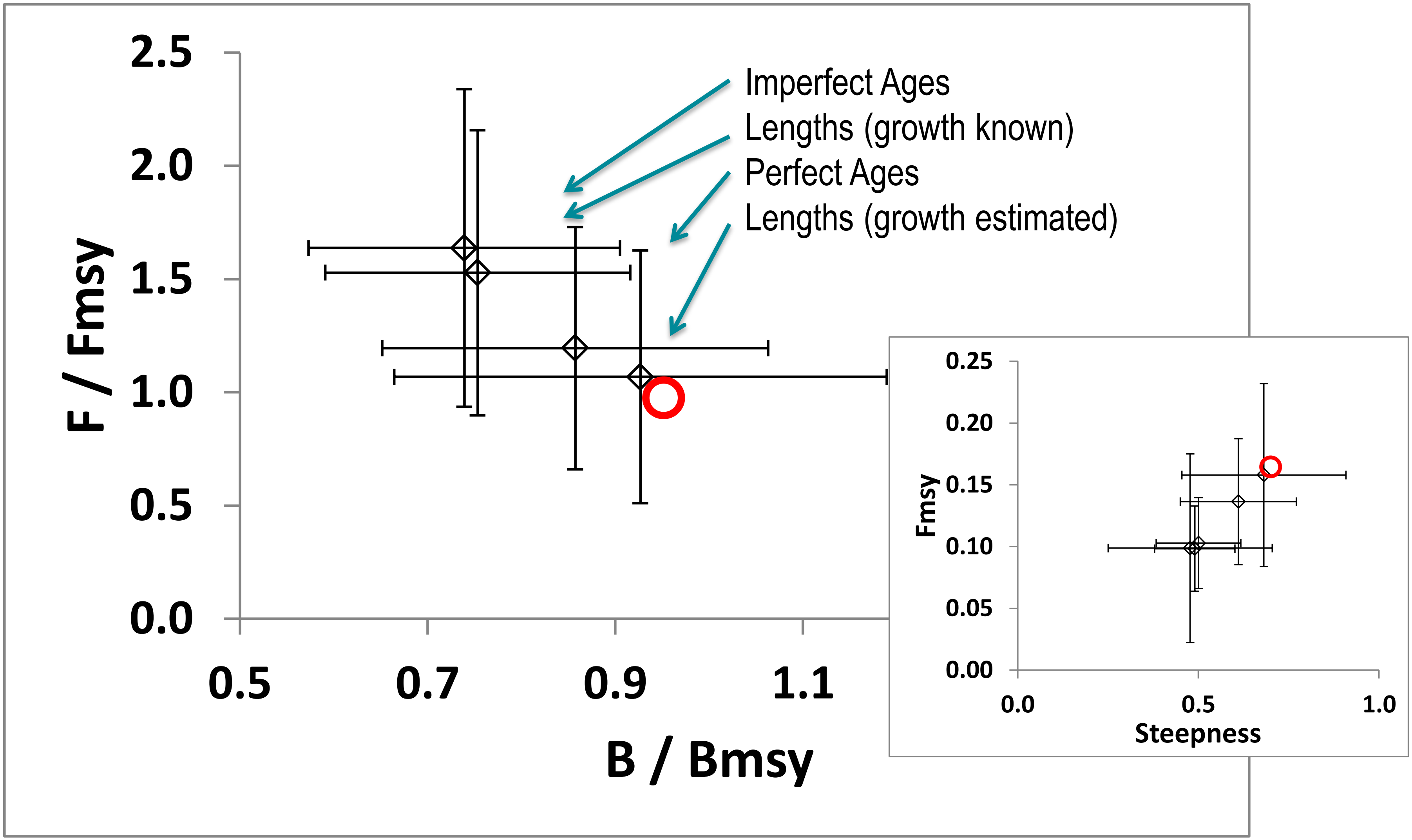
- Fishery age, length, and imperfect ages beginning in 1971
- Survey of spawning biomass beginning in 1981
- Various scalar measures in 2010

- Analyze each data scenario using Stock Synthesis (SS)
- Allow estimation of some or all of:
  - Steepness
  - Selectivity
  - M
  - Recruitment deviations
  - Growth
- Use informative priors in a penalized likelihood framework
- Focus on variance of model results

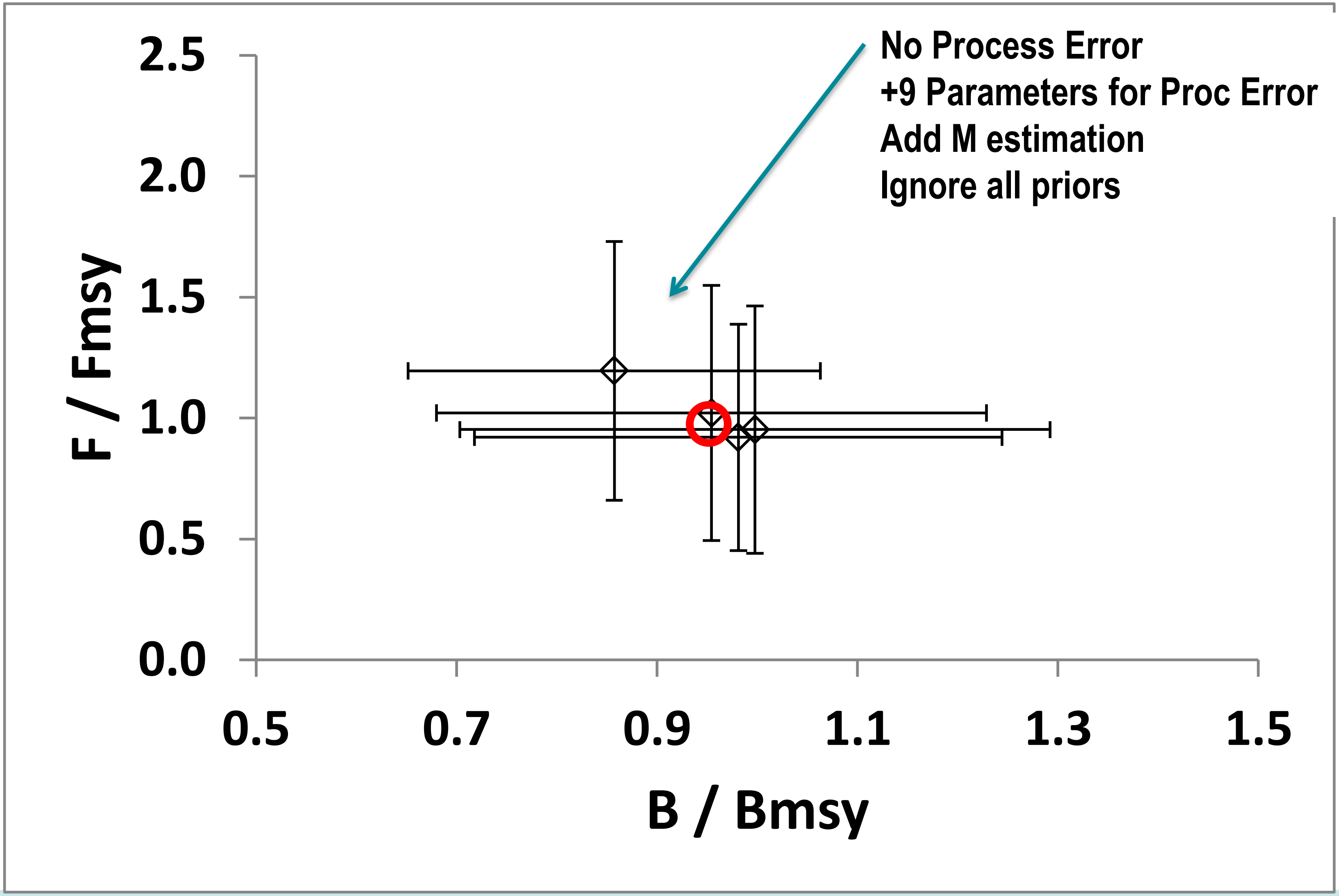
Results with Simple Data



Results with Composition and Survey Data



Age Data and Survey; Est. Selec. Process Error



Simulation Summary

- Catch time series plus some simple indicator of F is highly informative
- Three types of composition data ~ equally informative
  - Truly random data
  - Repeated observations of each cohort
- Adding process error in estimation did not greatly degrade precision

- **A generalized model enables blending information from diverse data and making comparisons such as this**
- **Lightly informative priors are important part of approach**
- **Real data must be much worse than random measurement error**

Other Simulation Studies

- Fidelity of M and h estimation in assessment models (Lee, Piner, Maunder, Methot)
- Recruitment lognormal bias adjustment protocol to obtain consistent results in Max Likelihood estimation (Methot and Taylor)
- Effect of spatial structure on performance of assessment models (various)
- Reports from the UW team to be presented today

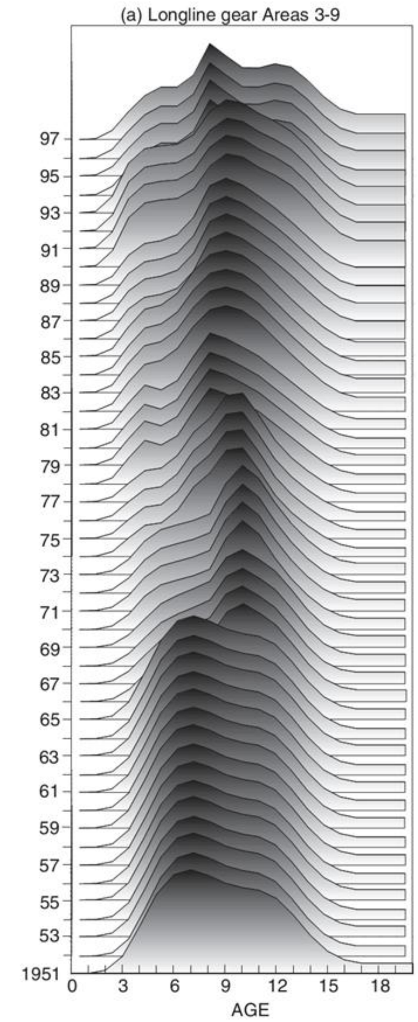
Parameter Priors and Linked Assessments

- Meta-analysis: Two recent papers by Thorson, Taylor, Stewart and Punt develop a mixed effects model to integrate results across SS applications for several west coast species
  - Estimate life history ratio: M/K
  - Estimate coherence in recruitment deviations
- Survey Q, F, survey process errors, and other factors are amenable to derivation of informative priors by linking assessments of multiple, co-occurring species

Are We Estimating the Right Factors?

Some Common Practices

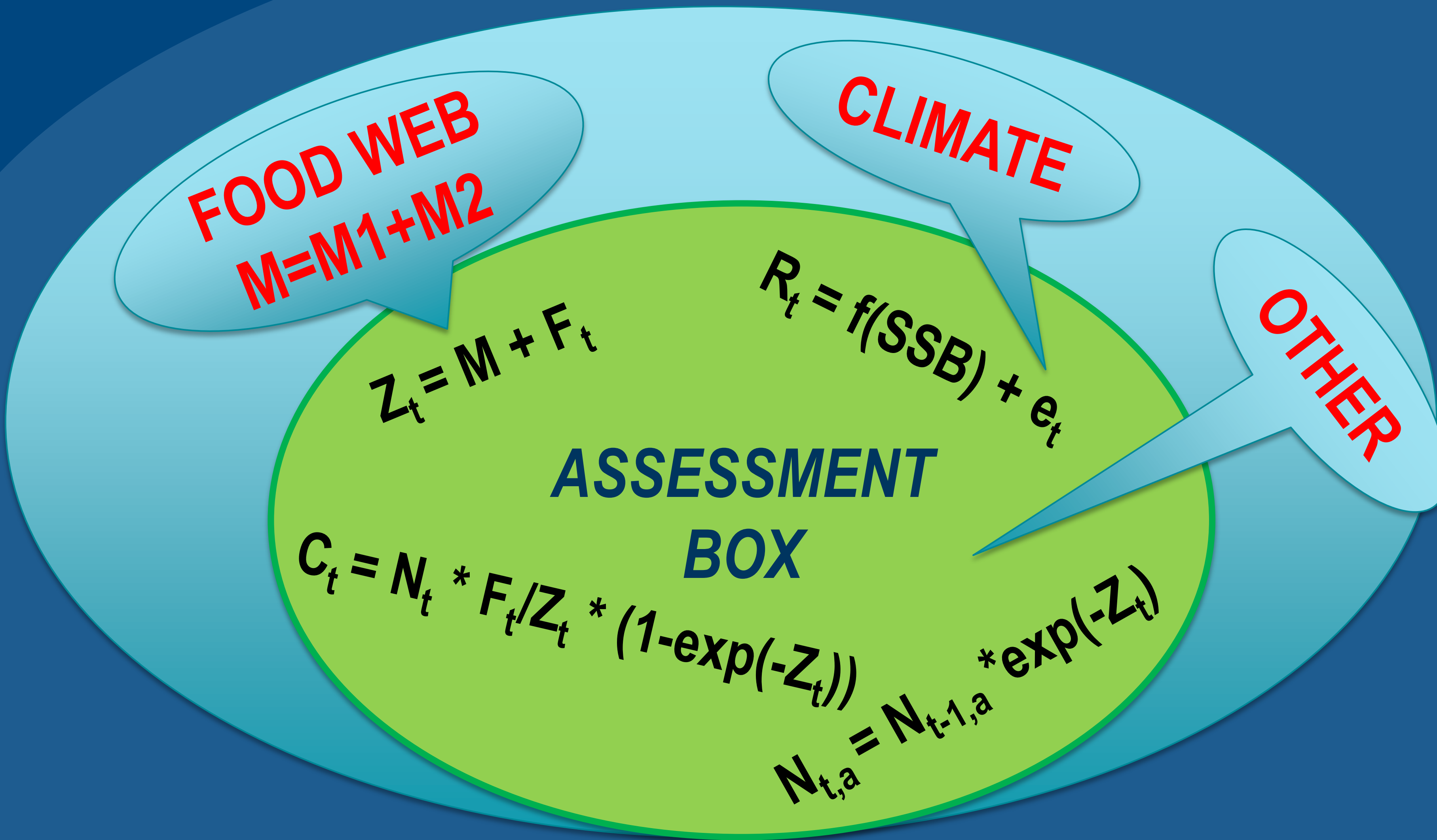
- Hold M constant, but contemporary M is among the least known factors!
- Put parametric, or complex non-parametric (right), statistical constraints on selectivity of fisheries
- Use age-specific surveys, so each has fully independent Q
- Treat survey Q's as having only uninformative priors
- Estimate population conditioned on above, but many degrees of freedom in the age composition data go into the selectivity estimation



What Could We Do Differently?

- Gear experiments, tagging studies and spatial distribution studies to make direct measurement of selectivity, or linkage of Q between ages in survey; include goodness of fit to selectivity data in models
- Gear experiments and and spatial distribution studies to put priors on overall survey Q
- With information on Q and selectivity; M estimation becomes more feasible

Ecosystem and Assessment Models



Three Approaches

1. Deterministic: Expand system so that $M_t = f(E_t)$ is now inside the system
   - Multi-species models take this approach (Curti et al)
   - Also recruitment driven by environmental time series
2. Random Effects: Treat M_t as a random process and integrate over the range of possible values to obtain an estimate of the average performance of the system, and its variance. The posterior distribution of **M** is determined by the prior on **M** and the information in the conventional “inside the system” data. **E** remains outside the model system.
3. **E** as **DATA**, like a survey of the state variable **M**.

External Factors as Data Regarding Deviations

- Expected value of factor E_t is a function of state variable M_t. Same logic as expected value of a survey is a function of the state variable $Biomass_t$.
- Model includes the logL from deviations $(E_t - e(E_t))$ in the objective function
- Example:
  - Recruitment as a random process with annual values R_t
  - A survey, O_t, of young fish is considered a measure, with sampling error, of R_t, so $e(O_t)=f(R_t)$
  - This survey could have been an annual measure of some environmental factor. From the assessment model's perspective it is just a datum that is informative about R_t
  - The estimates of the R_t will depend upon the conventional data, e.g. age compositions and young fish surveys, ***and*** the new ecosystem/ environmental data
- Stock Synthesis provides this approach for the recruitment process, and soon other random processes

SUMMARY

- Generalized assessment models can provide consistent results from a diversity of data types
  - Need best practices guide and good A.I. in model interface
- Simulation studies are key to understanding model performance in face of diverse data and structural situations
  - Must build process error generation into these studies

LOOKING FORWARD

- Meta-analysis across species will improve informative priors
- Environmental data and ecosystem model outputs will routinely be used as “data” about time-varying model processes
- Direct studies on selectivity and catchability will provide better estimation of M and the population
- A protocol for consistent derivation of reference points and harvest policies when vital rates are time-varying or ecosystem linked, including detection of regime shifts, will be developed
- Models that include spatial sub-structure will be applied in relevant situations
- Perceived boundary between single species and multi-species models will disappear; just more code and more to review
- Assessment results are imprecise and will feed into MSE evaluated management procedure, not simple control rule: C=F*B .

Challenges for fisheries stock assessment: illustrated with absolute abundance estimation

Mark Maunder
Inter-American Tropical Tuna Commission (IATTC)
Center for the Advancement of Population Assessment Methodology (CAPAM)

Preliminaries

- First, I would like to thank the organizers for inviting me here and giving me the opportunity to present and ISSF for financial support
- It is an honor to be in the same session as Sydney Holt, one of the pioneers of modern stock assessment
- However, it is disappointing how little progress we have made since Beverton and Holt published their stock assessment manual in 1957.

Major advances

- Age-structured models
  - VPA, Cohort analysis
  - Pope, Shepherd, Laurec
- Generalized production model
  - Pella and Tomlinson 1969
- Integrated analysis and the software to implement it
  - Fournier and Archibald 1982
  - CAGEAN, Deriso, Quinn, and Neal 1985
  - Fournier's AD Model Builder
  - General models
    - Coleraine, MULTIFAN-CL, CASAL, Gadget
    - Stock Synthesis – Methot (Keynote)
  - Length-structured models
    - Punt
- Bayesian analysis
  - University of Washington
    - Hilborn, Punt, McAllister
  - In the 1990's Bayesian statisticians were impressed with the complexity of Fishery Bayesian applications
- Management Strategy Evaluation
  - International Whaling Commission; De la Mare
  - Butterworth, Punt, Sainsbury, Smith, …
  - Bentley (Keynote)

Basics: Data and information

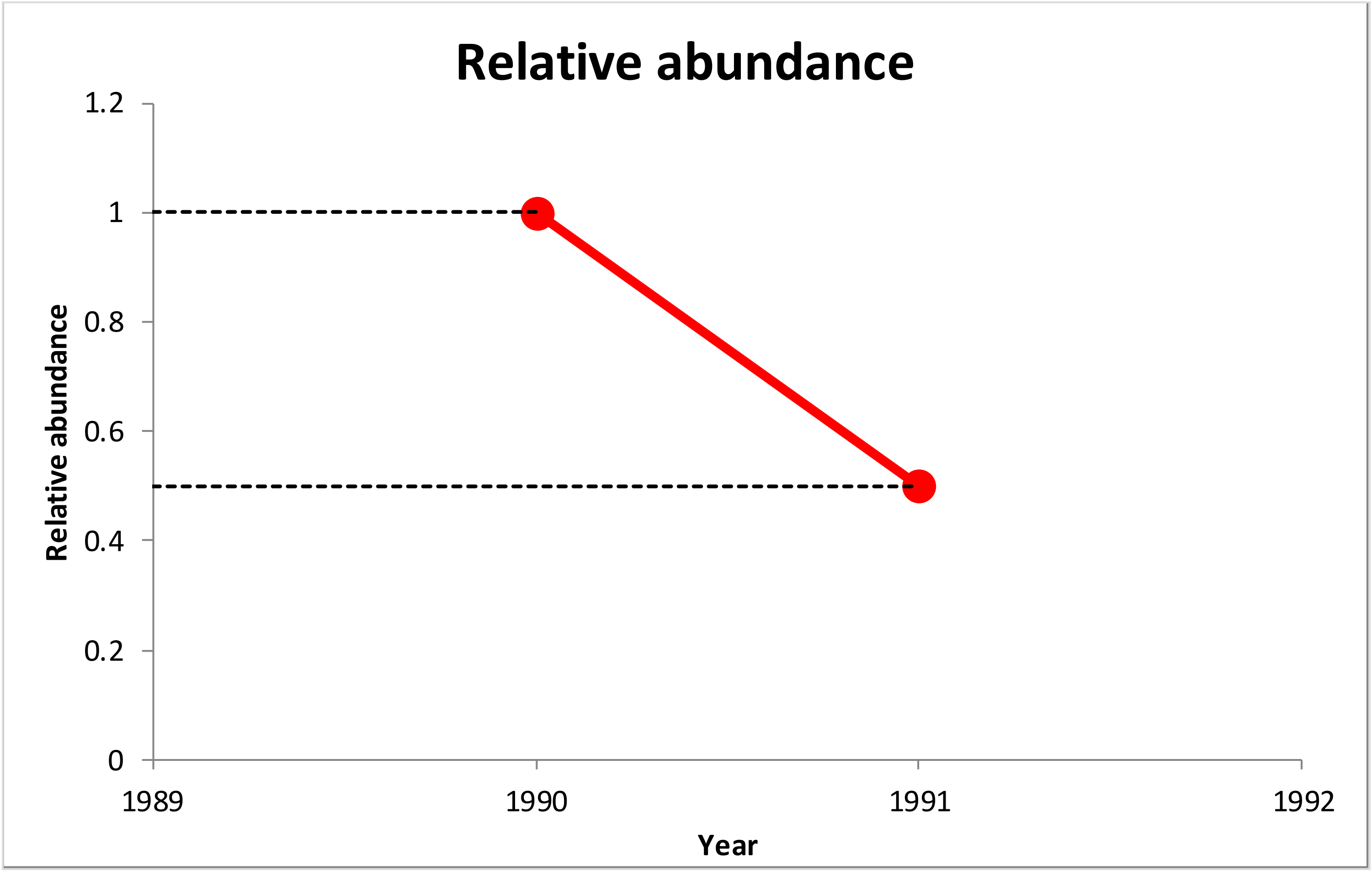
- Data
  - Typical data
    - Catch
    - Index of relative abundance
    - Age and length composition data
  - Other data
    - Tagging
- Information needed
  - Absolute abundance
  - Abundance trends
  - Biological processes
    - Natural mortality
    - Growth
    - Recruitment
  - Fishing processes
    - Selectivity

Basics: Absolute abundance

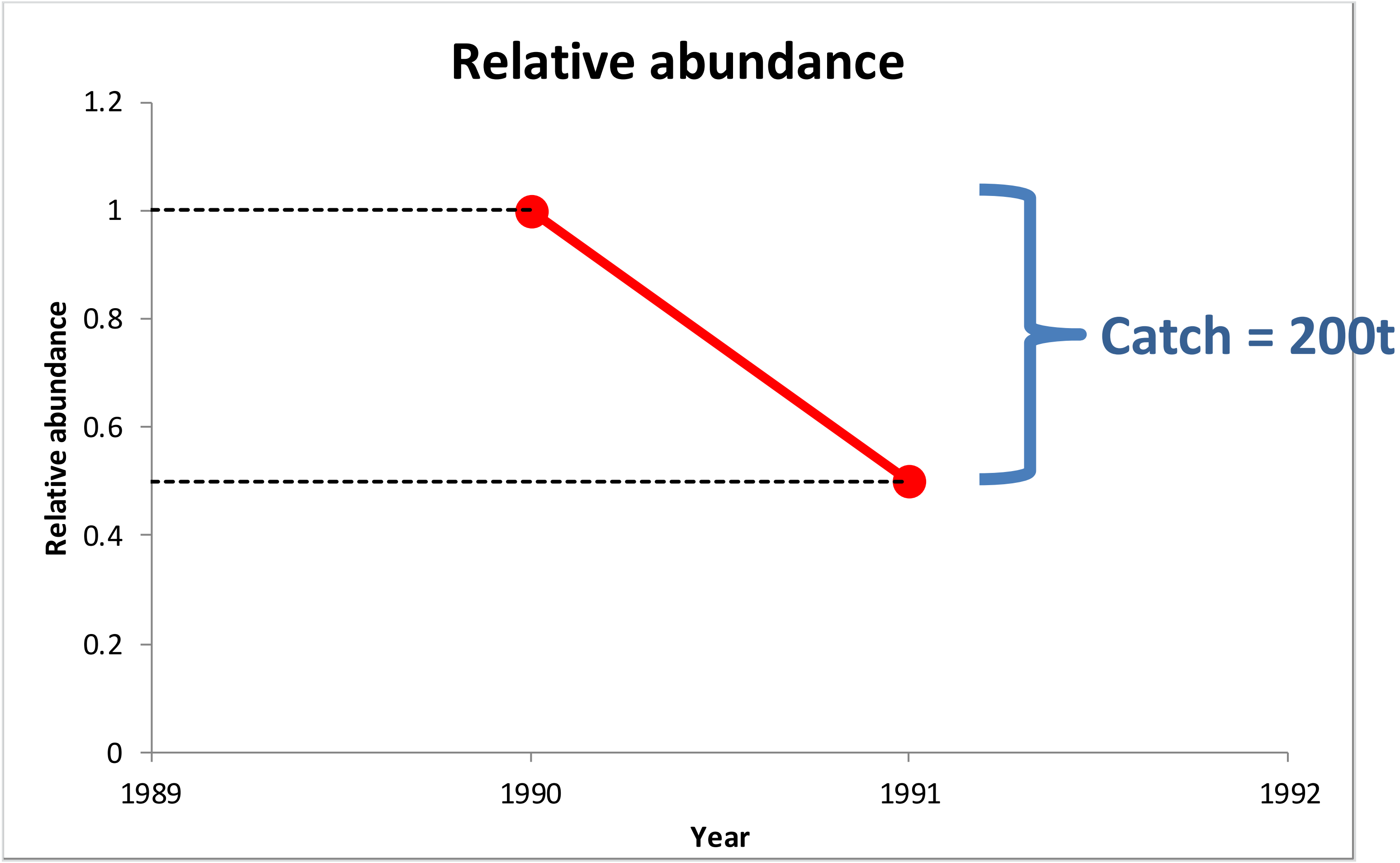
- Importance
  - TAC = harvest rate * abundance
- Information
  - Index of relative abundance
  - Age and length composition data
  - Tagging data if you are very lucky!

Index of relative abundance

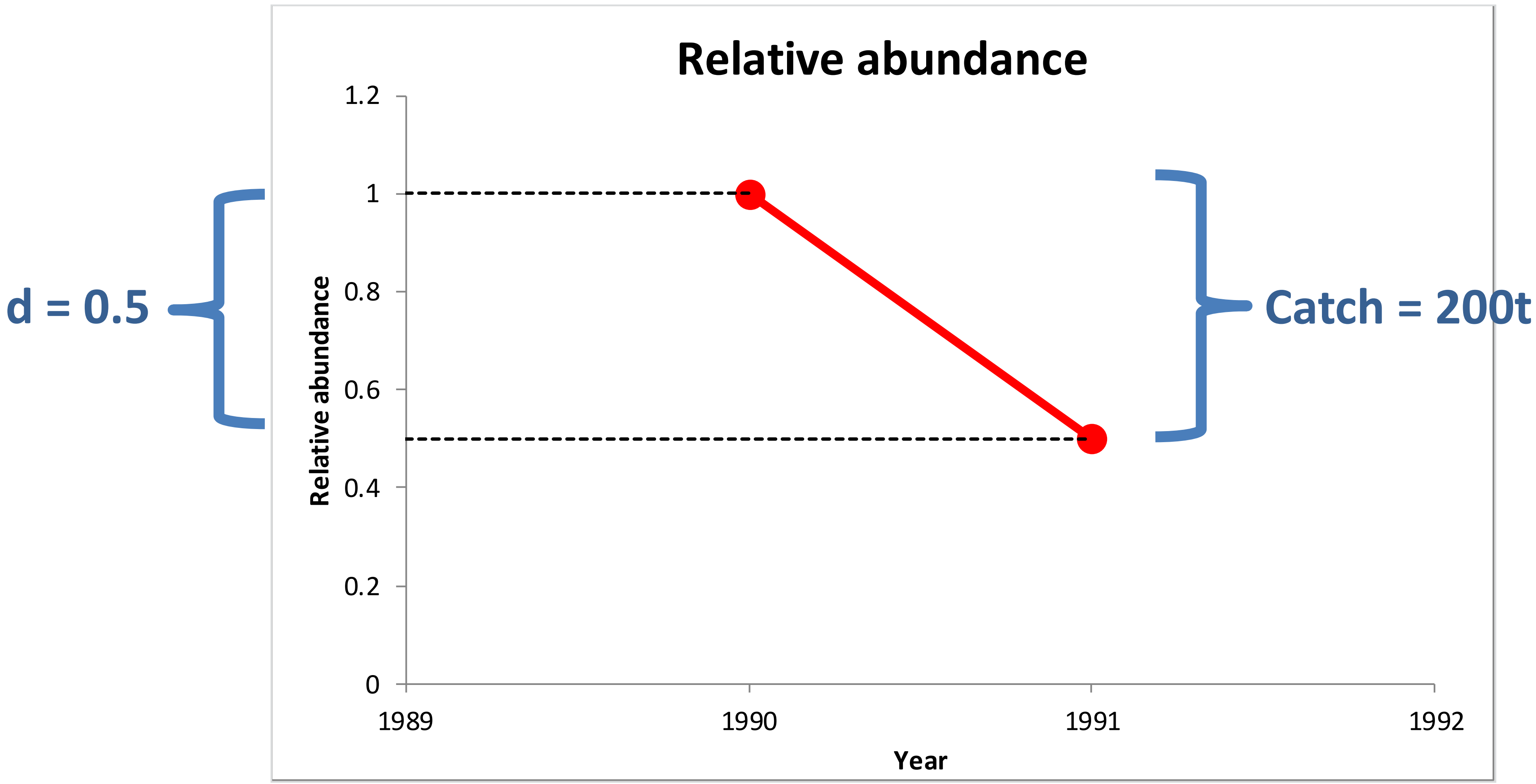
Depletion plot



Depletion plot



Depletion plot



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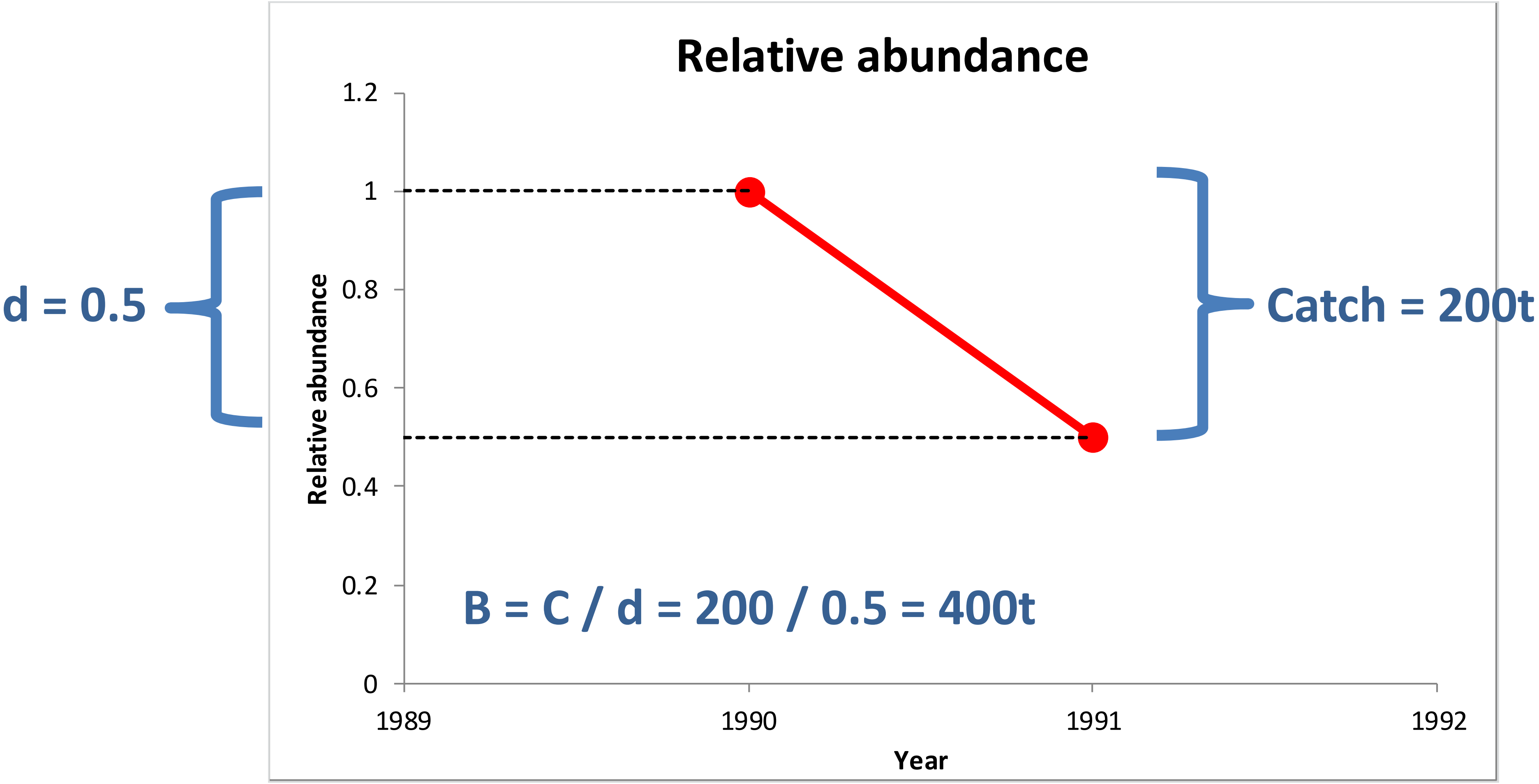

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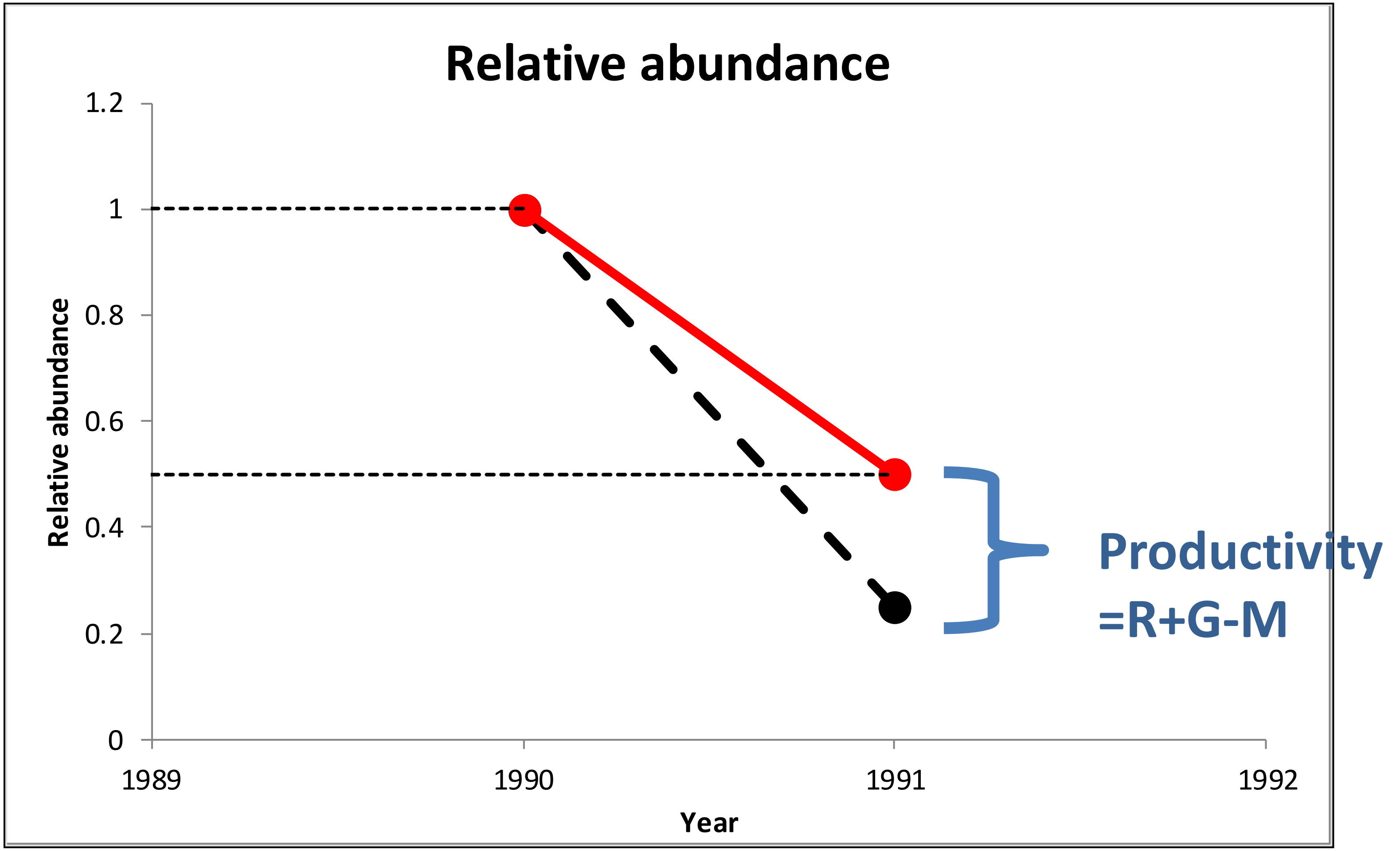

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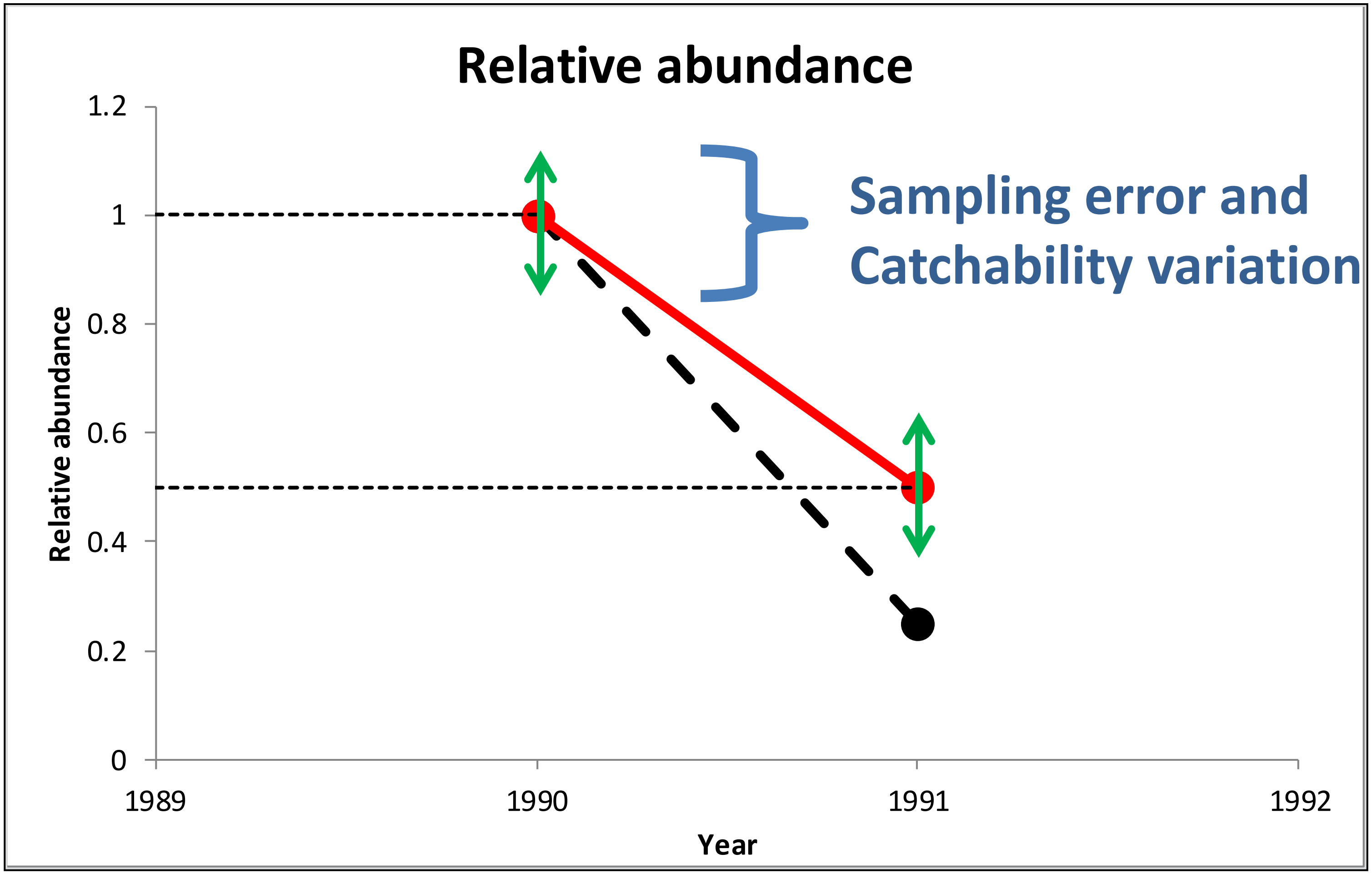


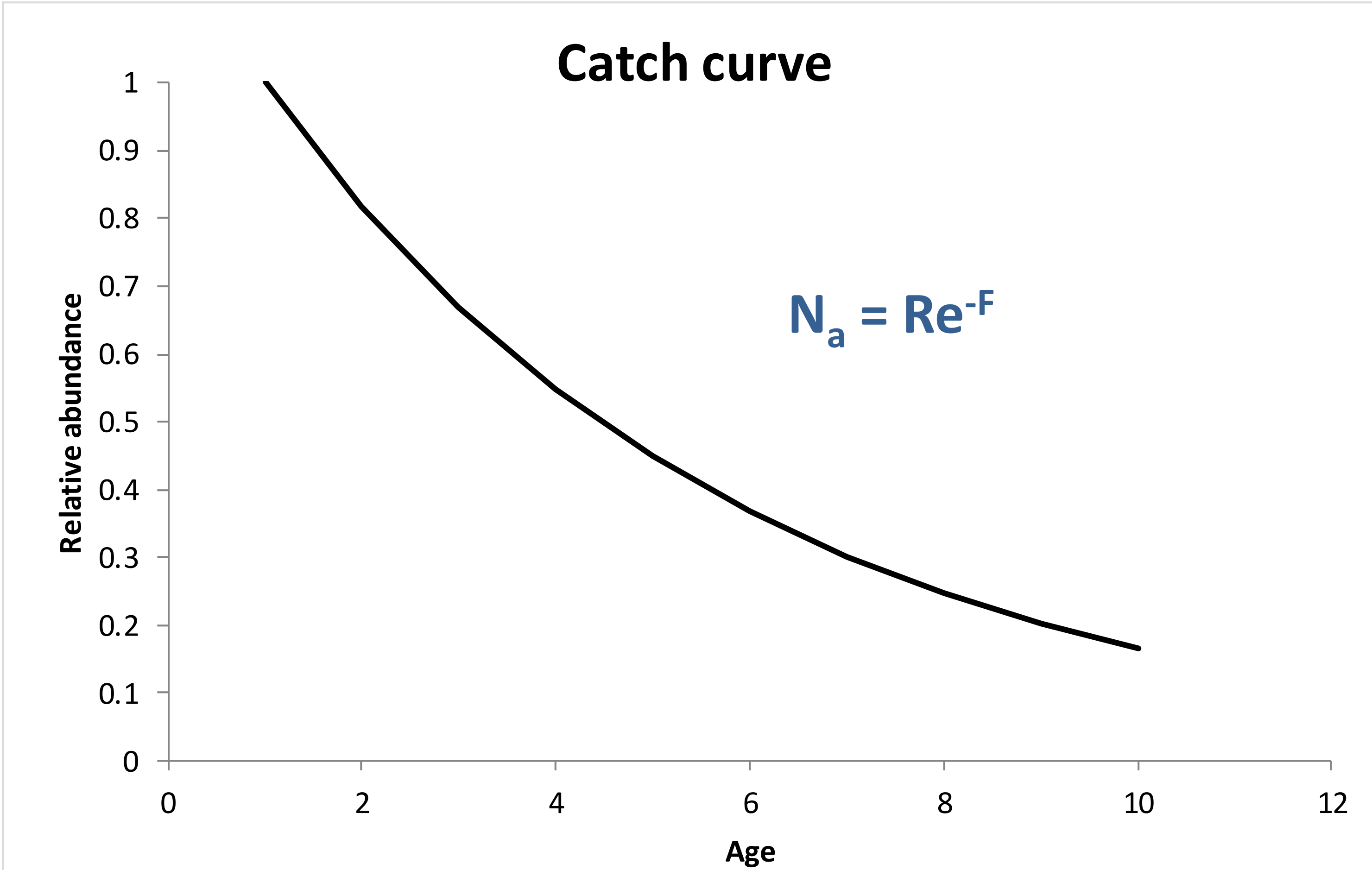
Age composition data

Age composition data

$B \approx C/F$

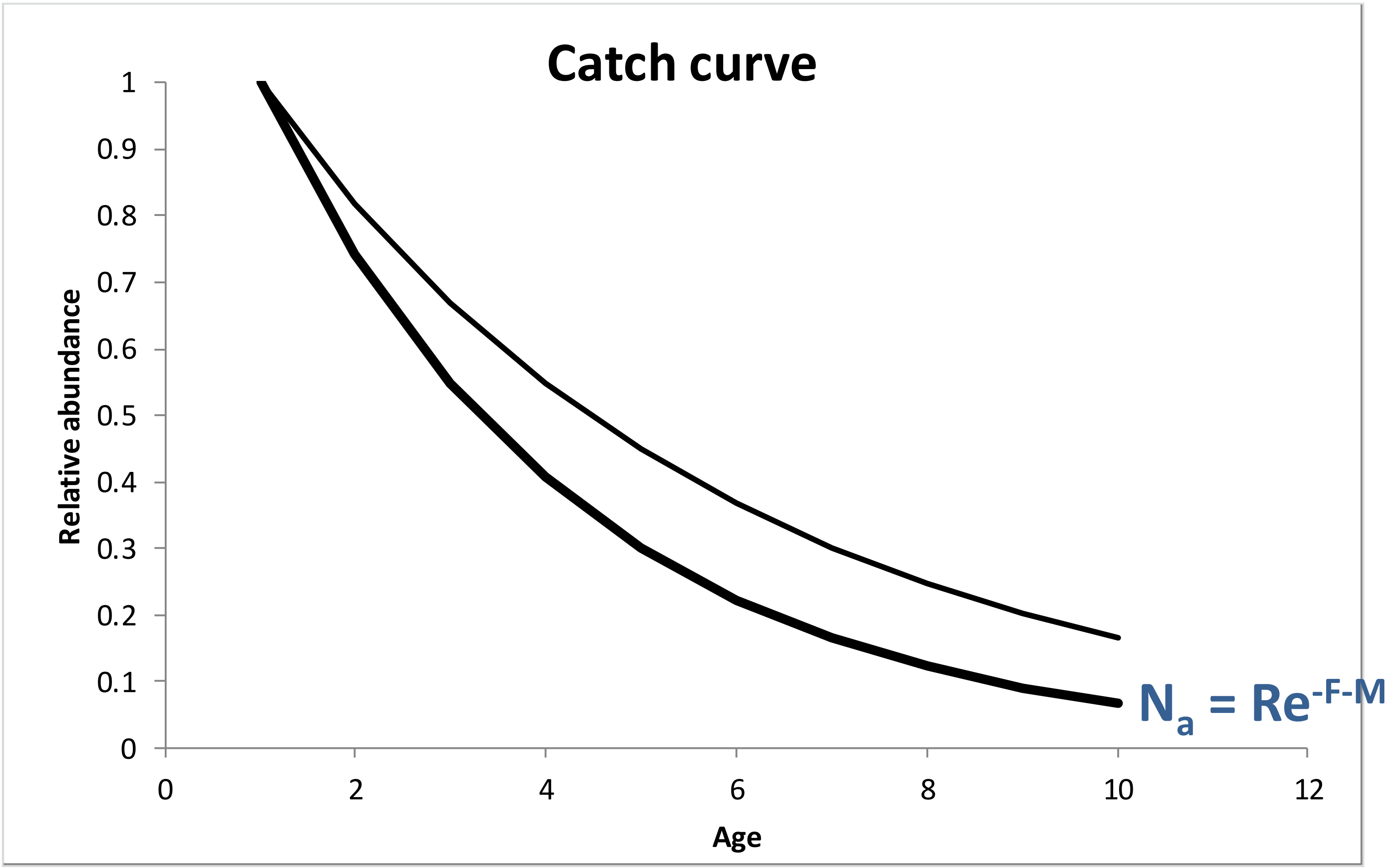
Concept: If you can estimate fishing mortality and you know catch, then you can estimate abundance

Catch curve

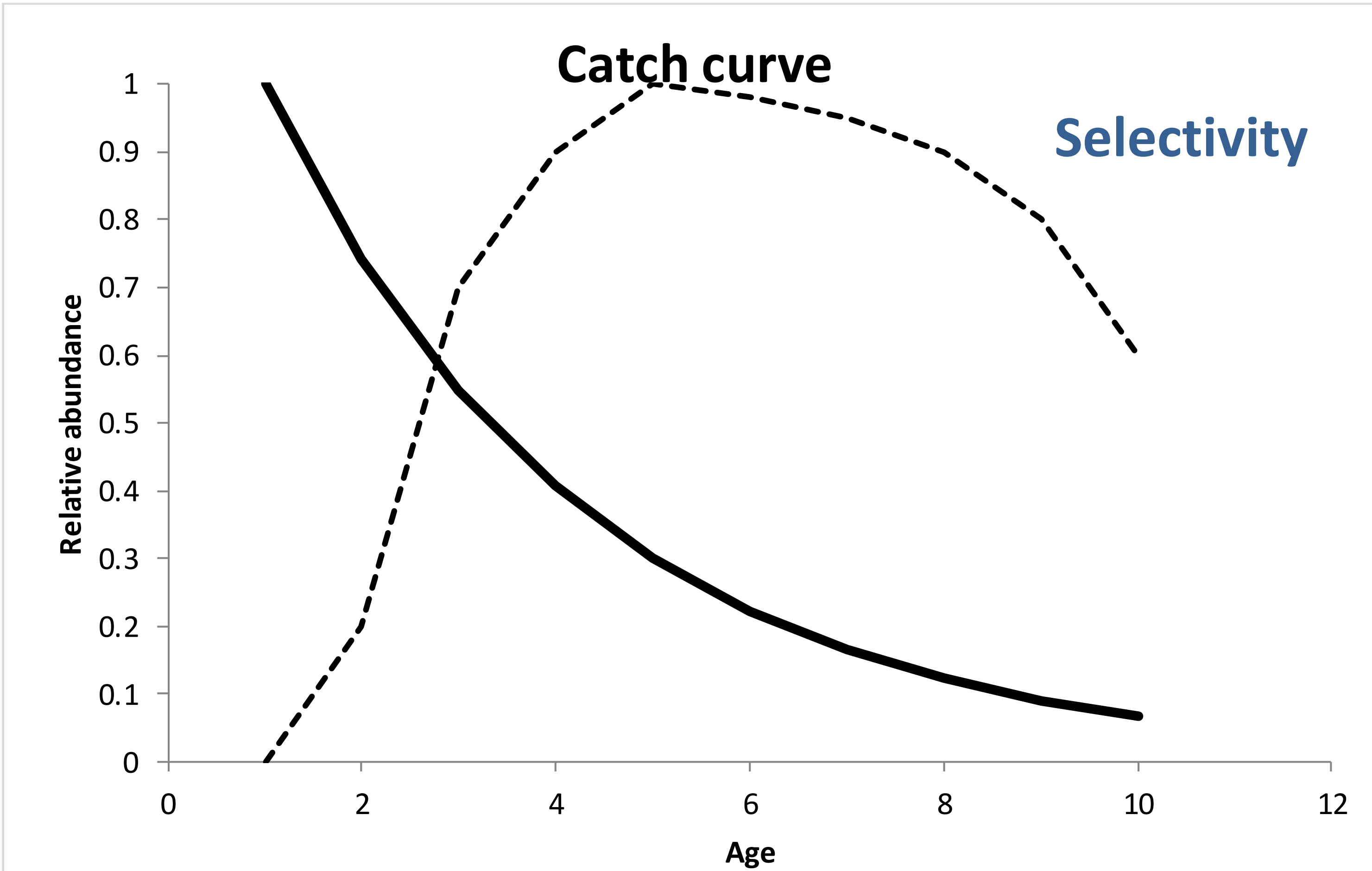


Catch curve
Relative abundance
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
0
2
4
6
8
10
12
Age
$N_a = Re^{-F}$

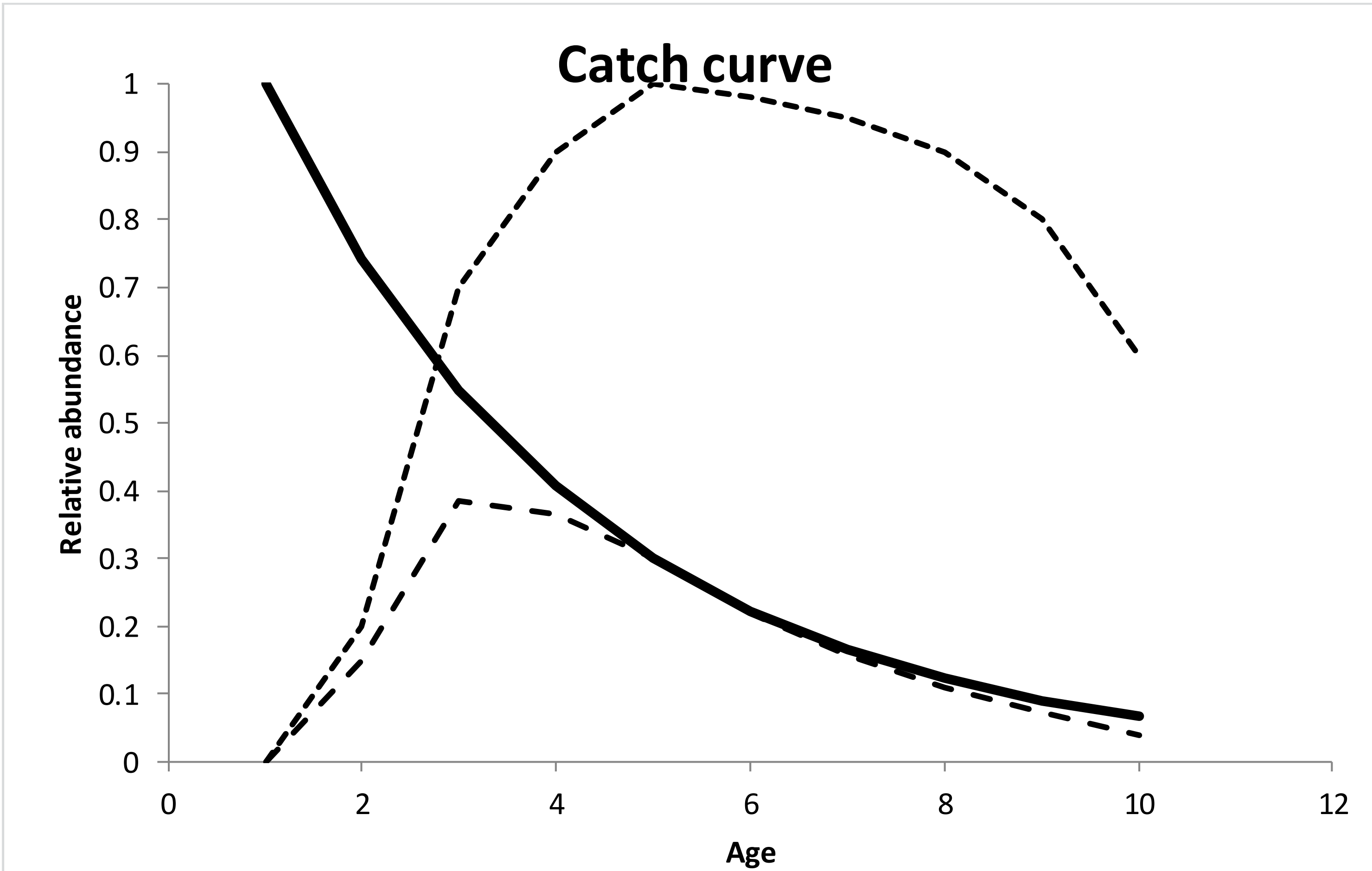
Catch curve: natural mortality



Catch curve: selectivity



Catch curve: selectivity

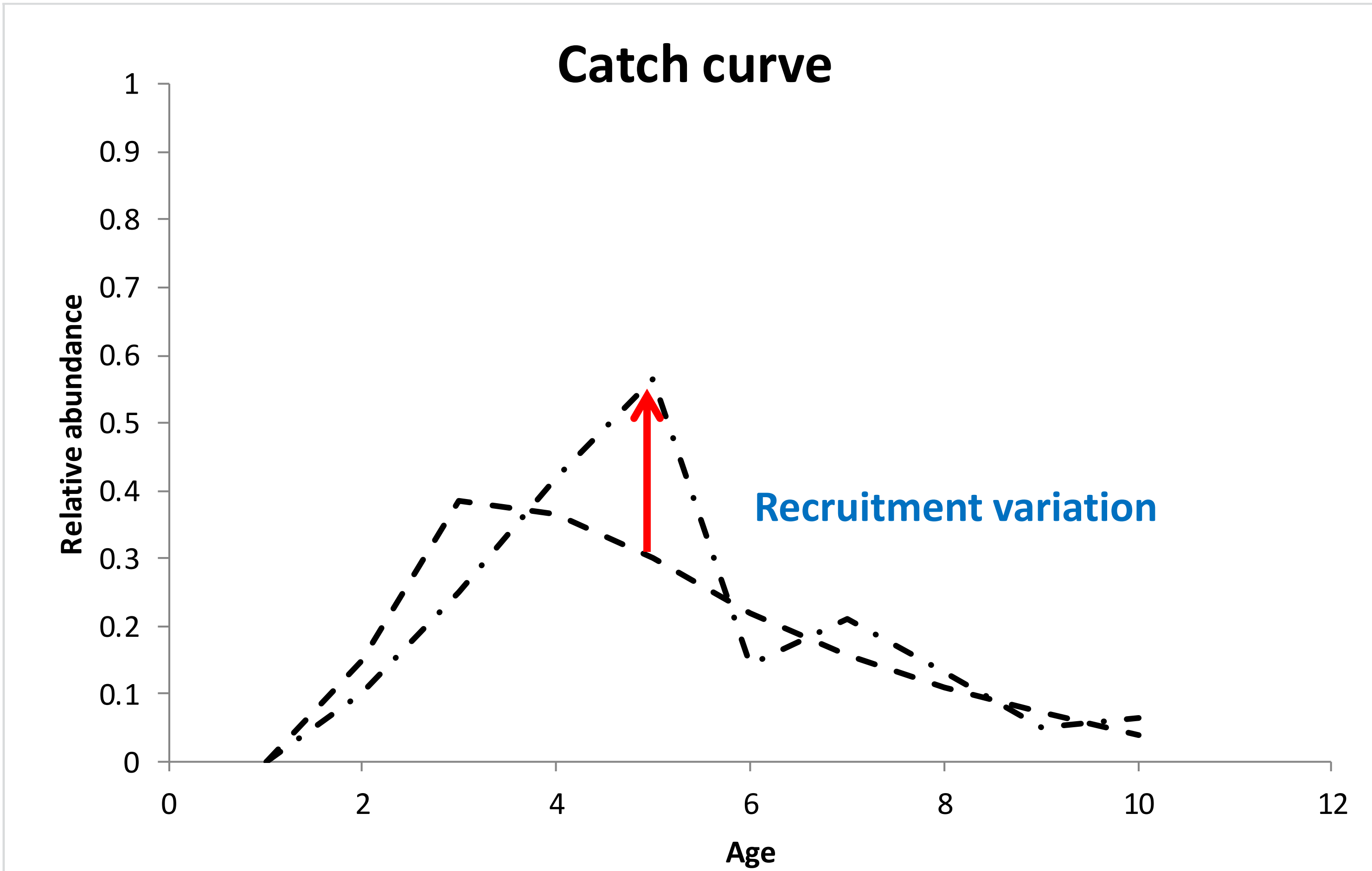


Catch curve: selectivity

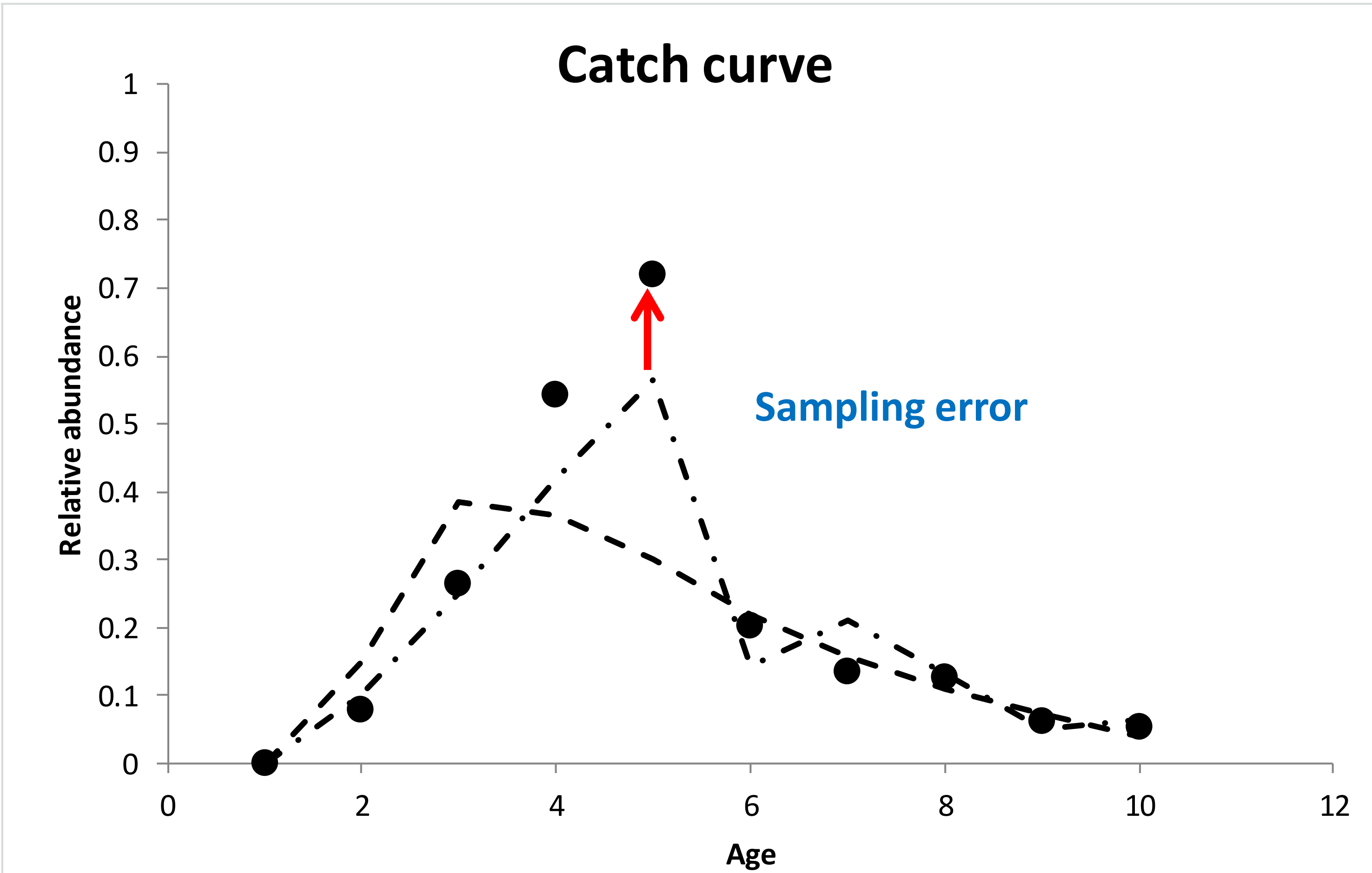
- What you observe
- What F each age experiences

- F also varies over time

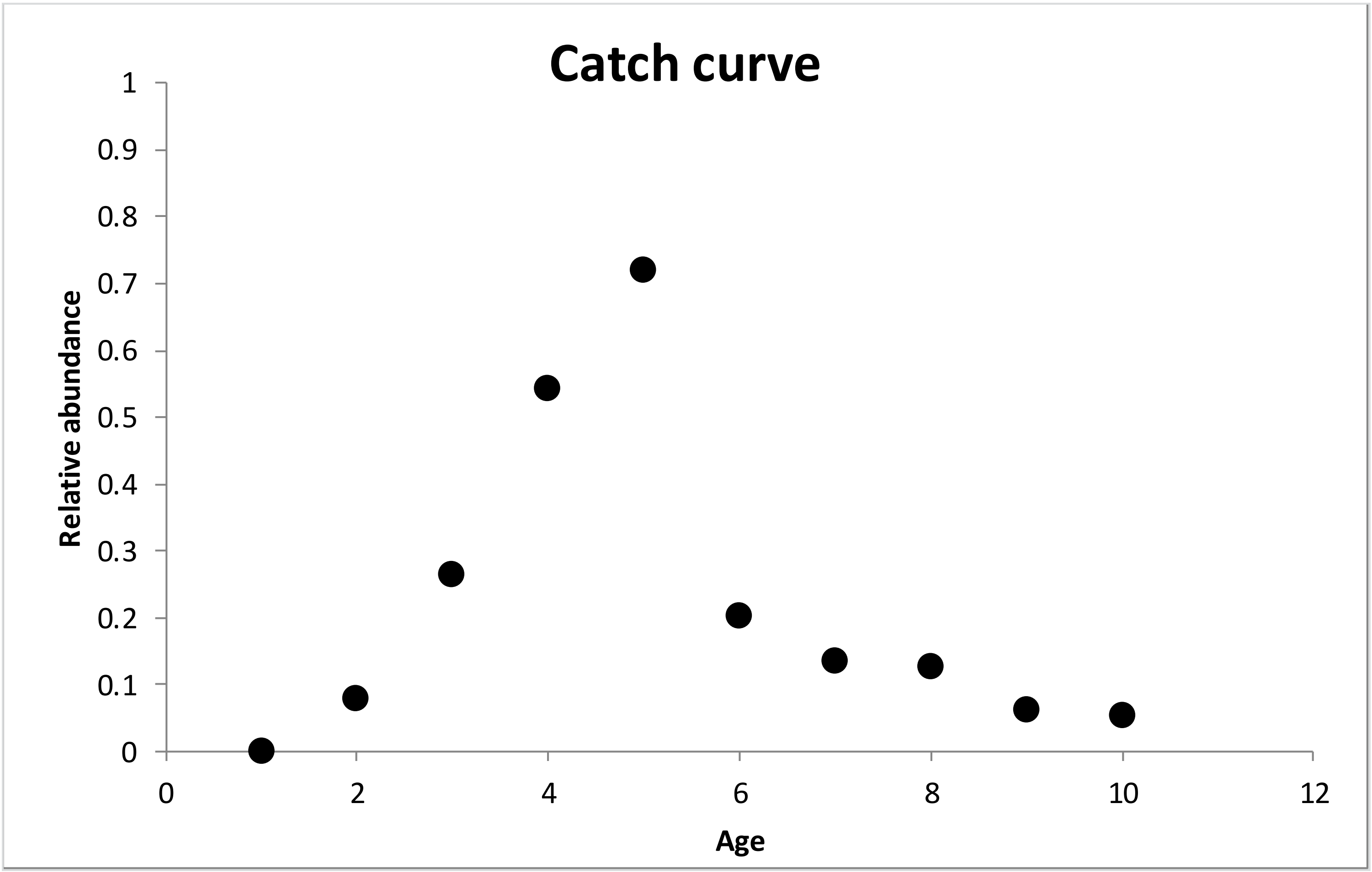
Catch curve: recruitment variation



Catch curve: sampling error



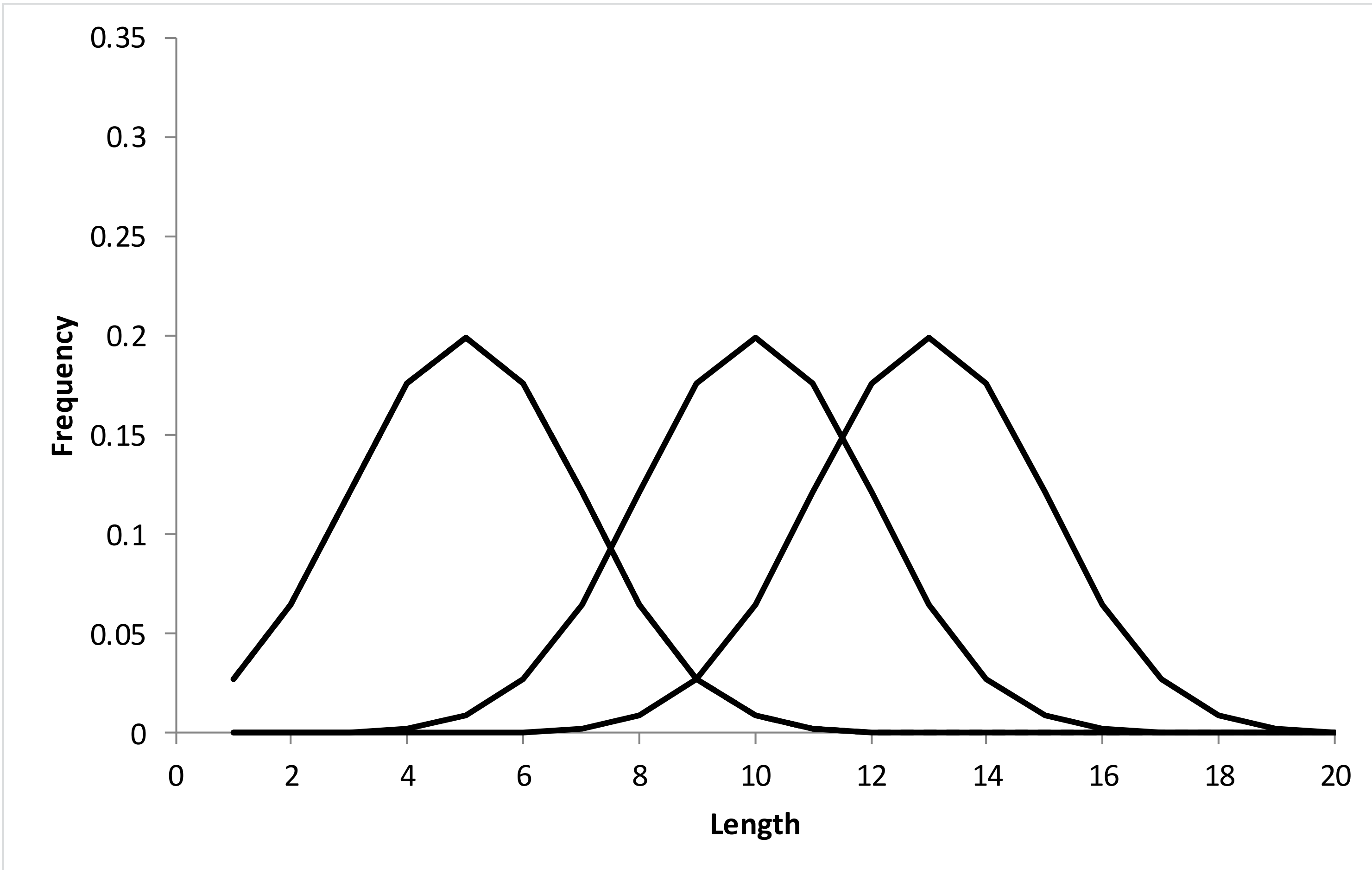
Catch curve: what you see



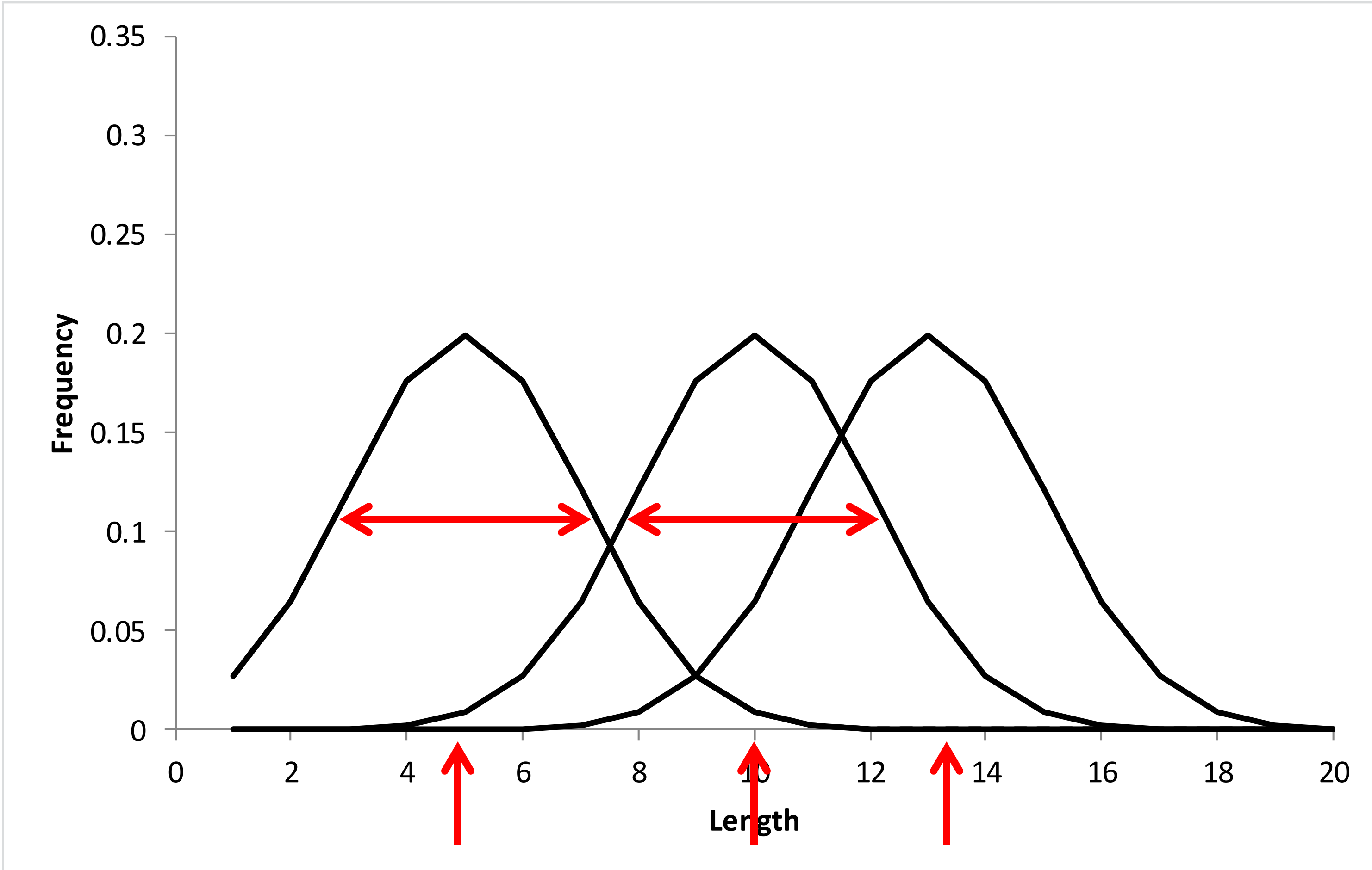
Length composition data

An additional complication for catch curves

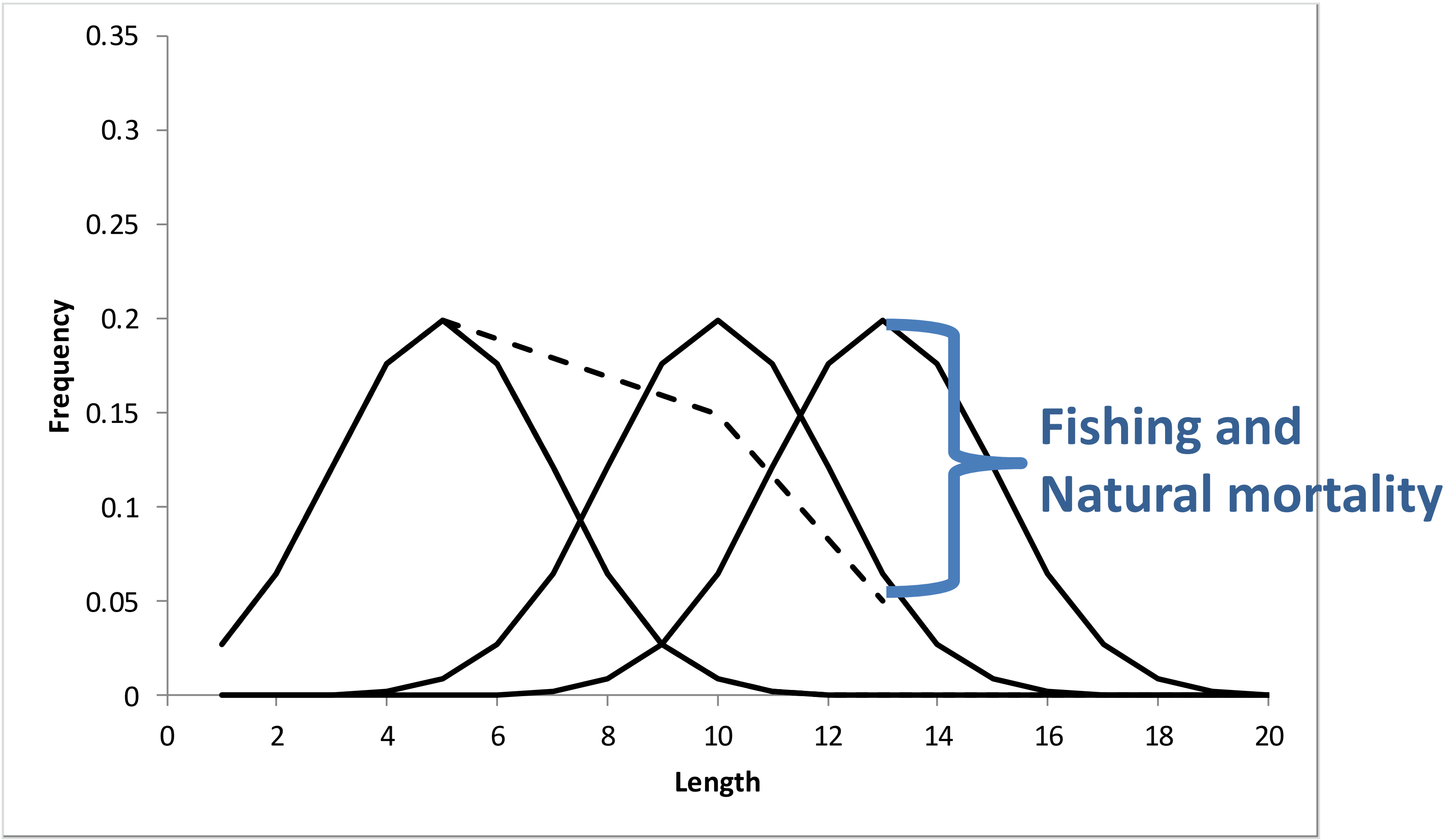
Length composition



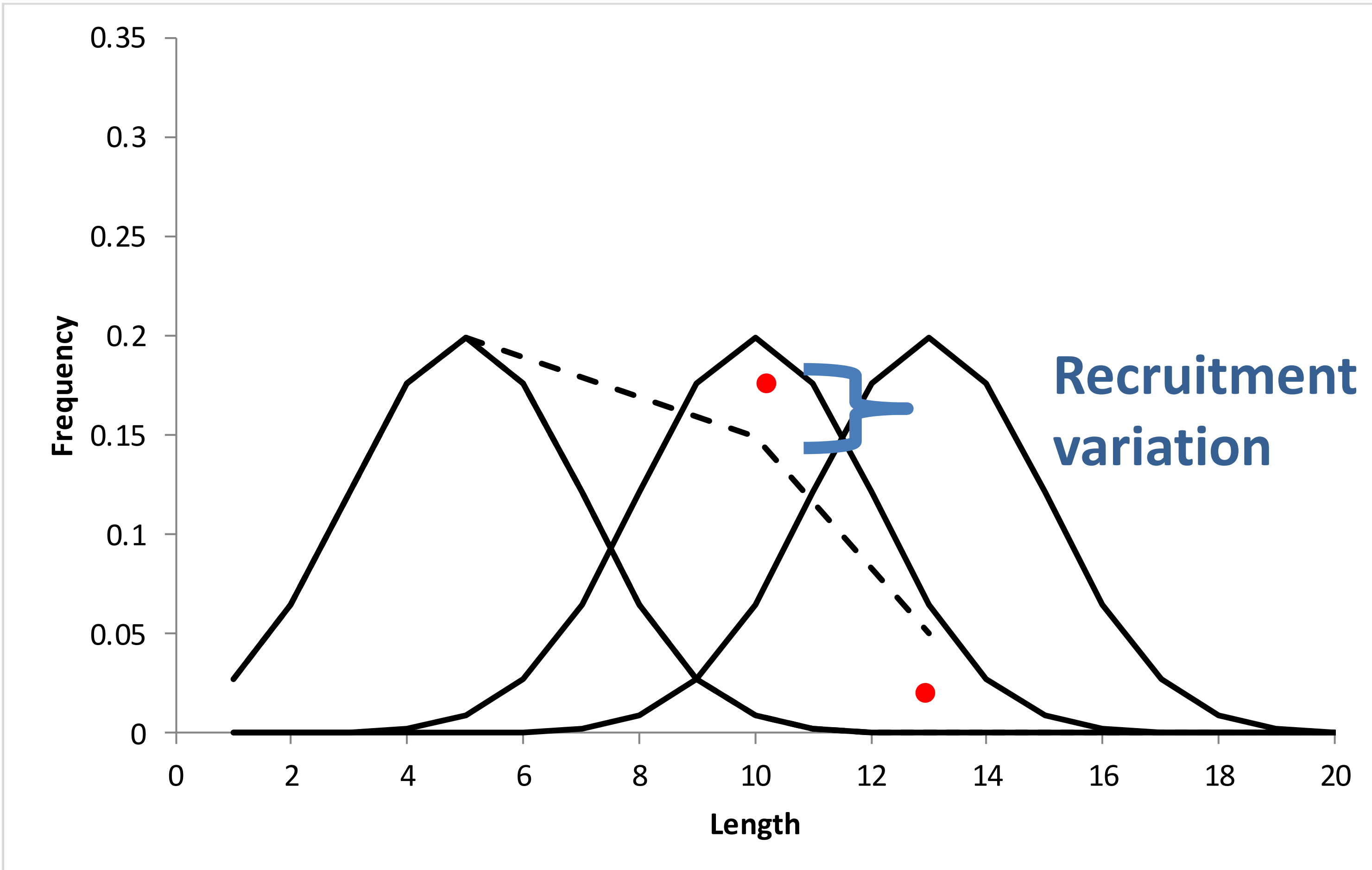
Length composition



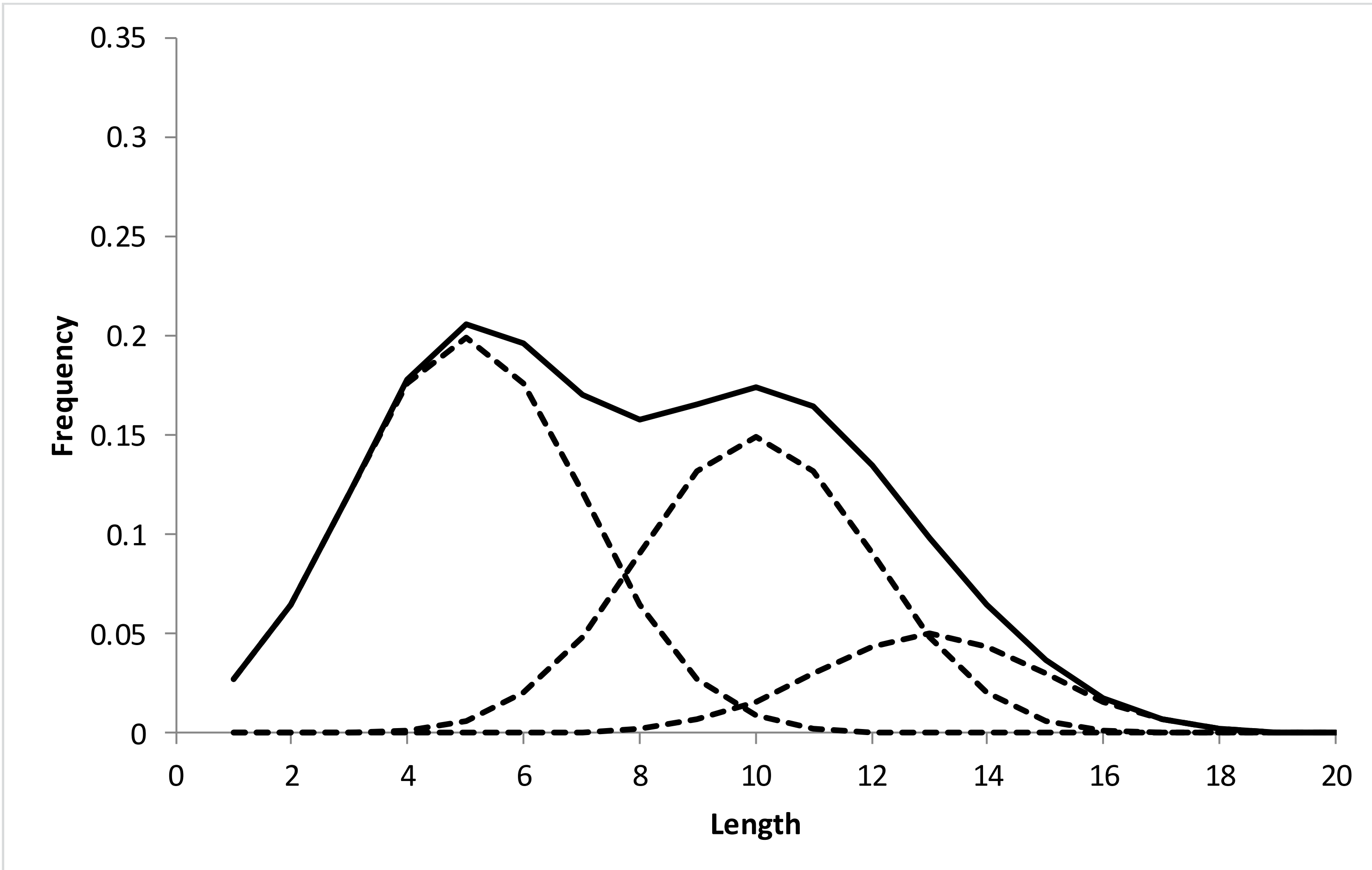
Length composition: mortality



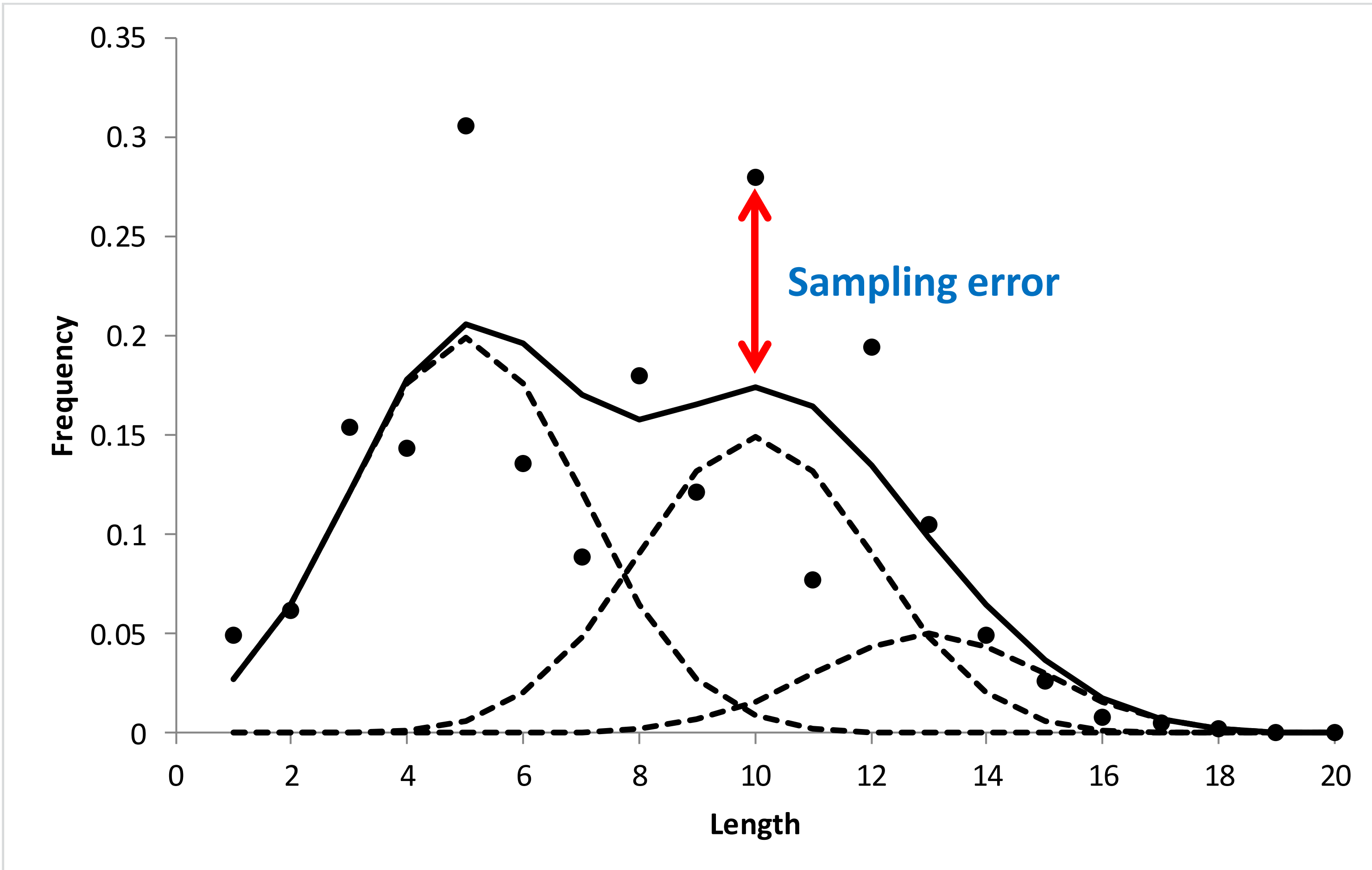
Length composition: recruitment



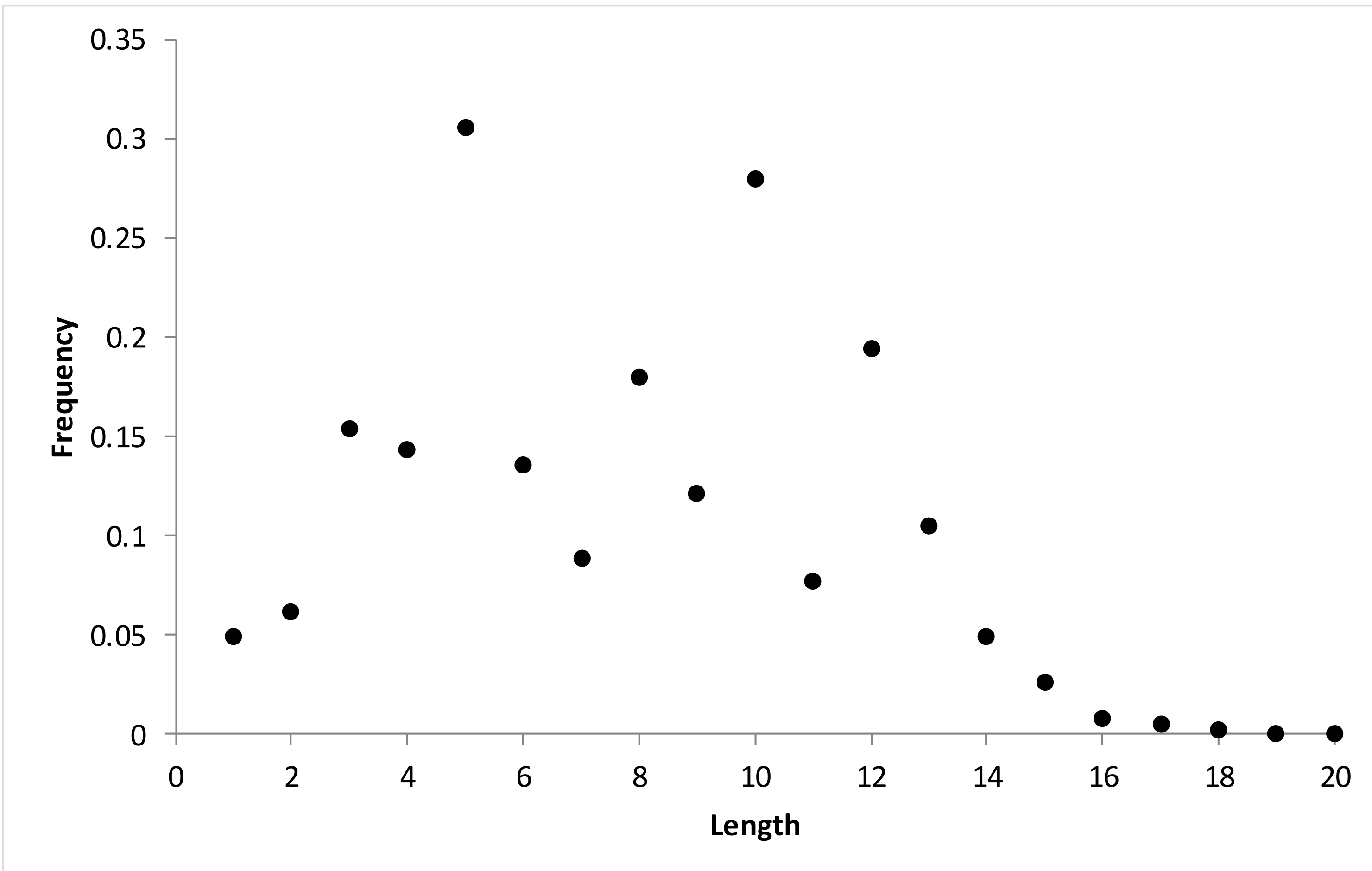
Length composition



Length composition: sampling error



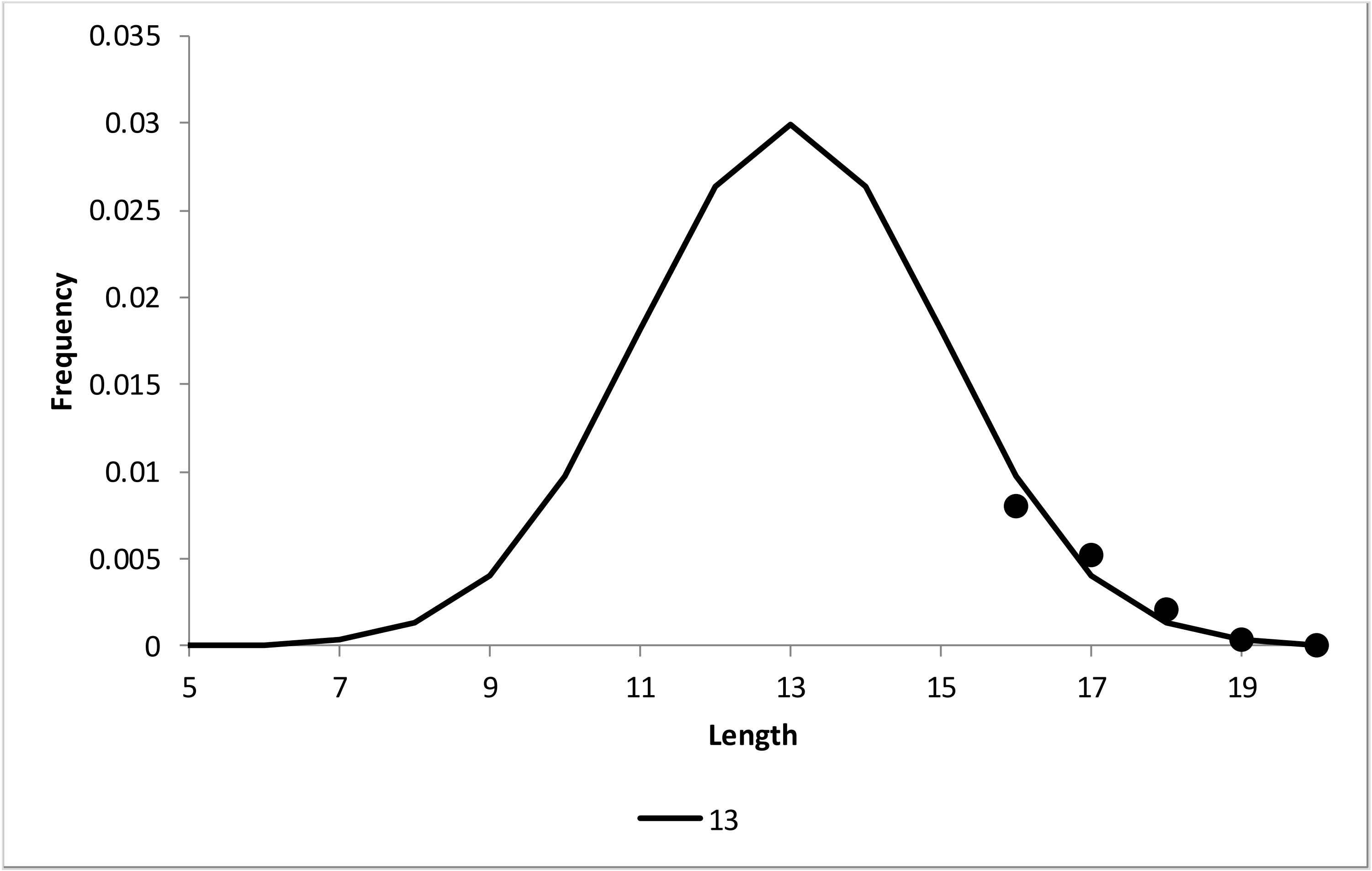
Length composition: what you see



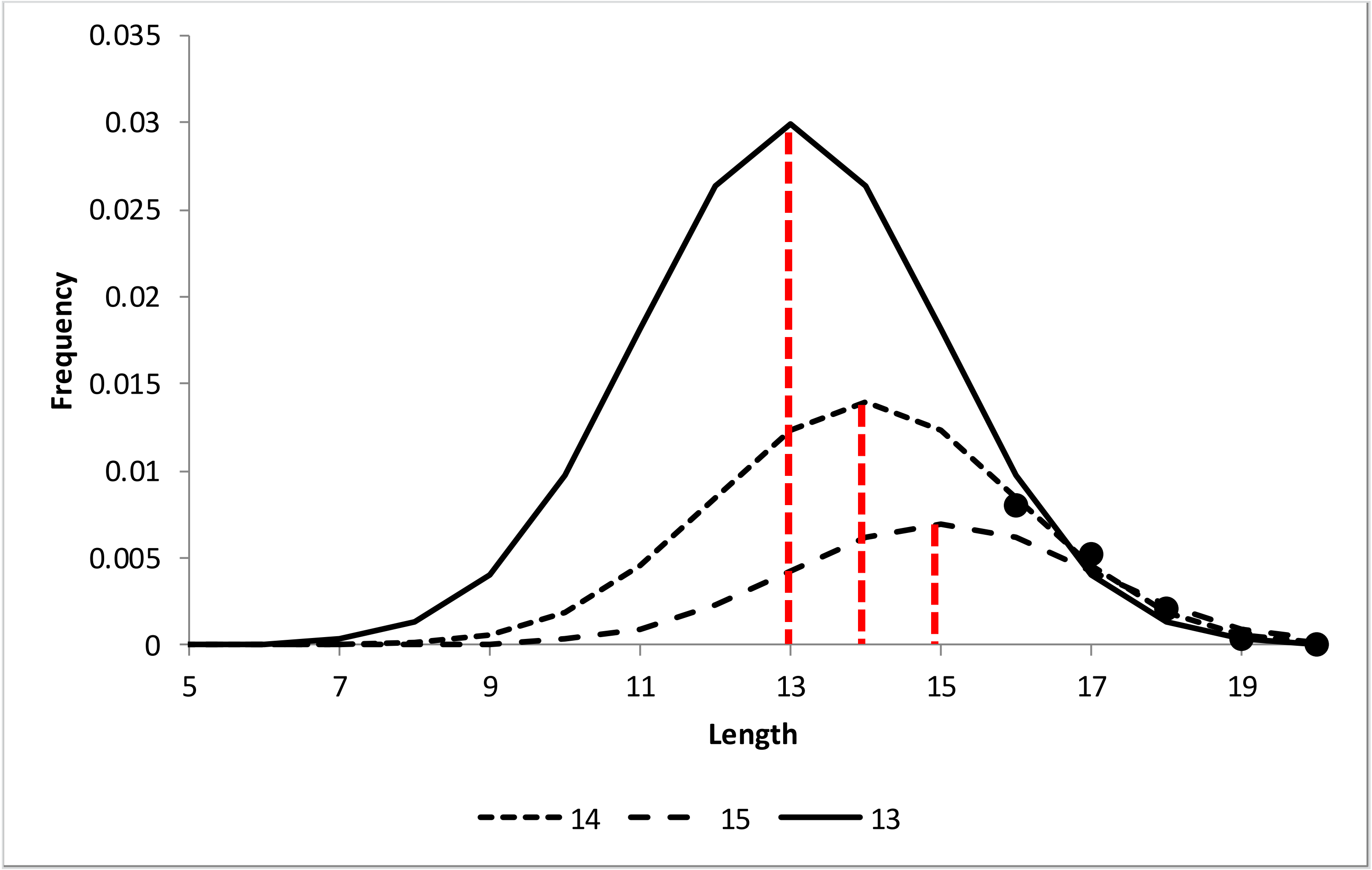
Length composition: major problem

- Asymptotic length

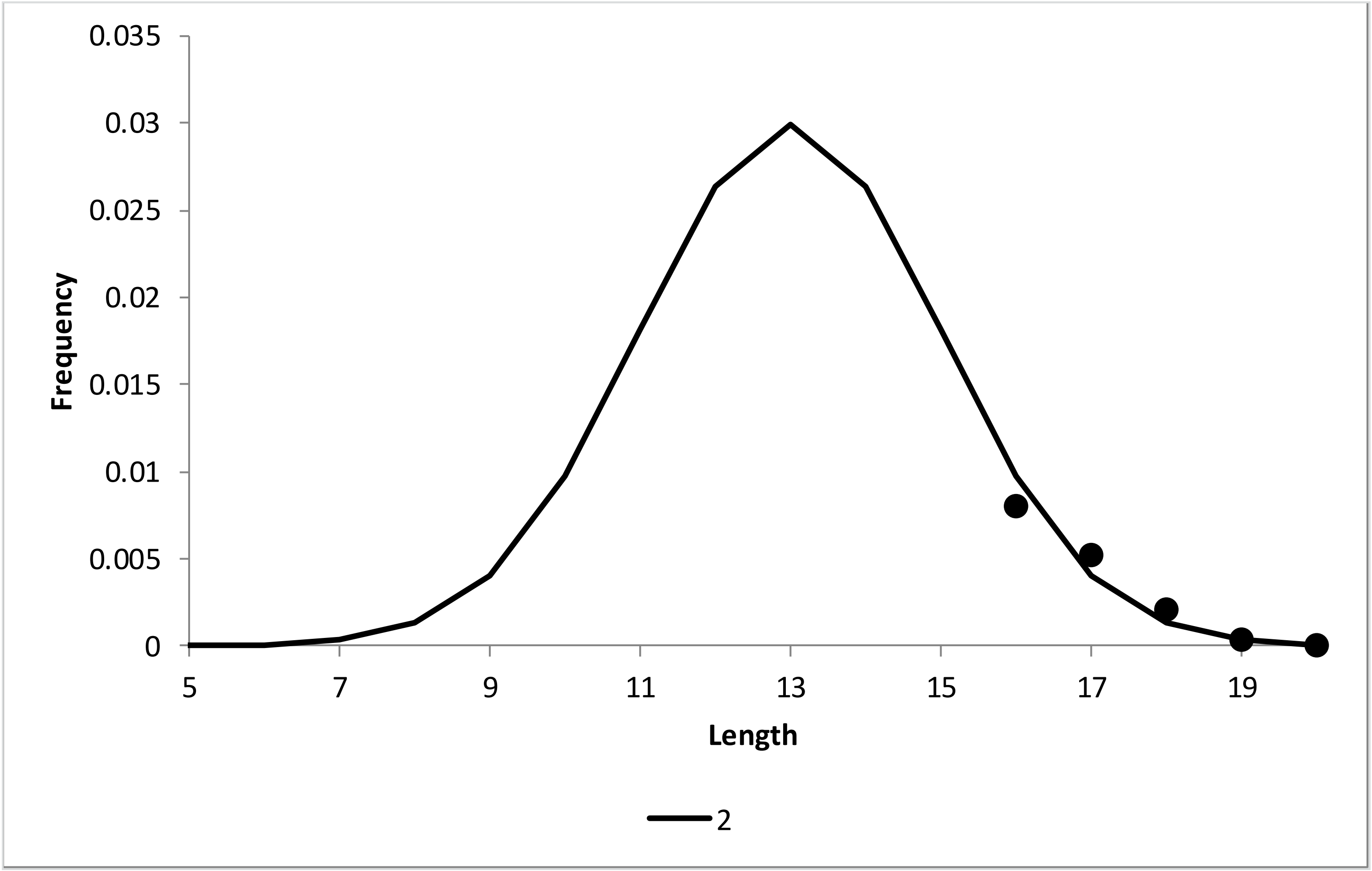
Length composition: asymptotic length



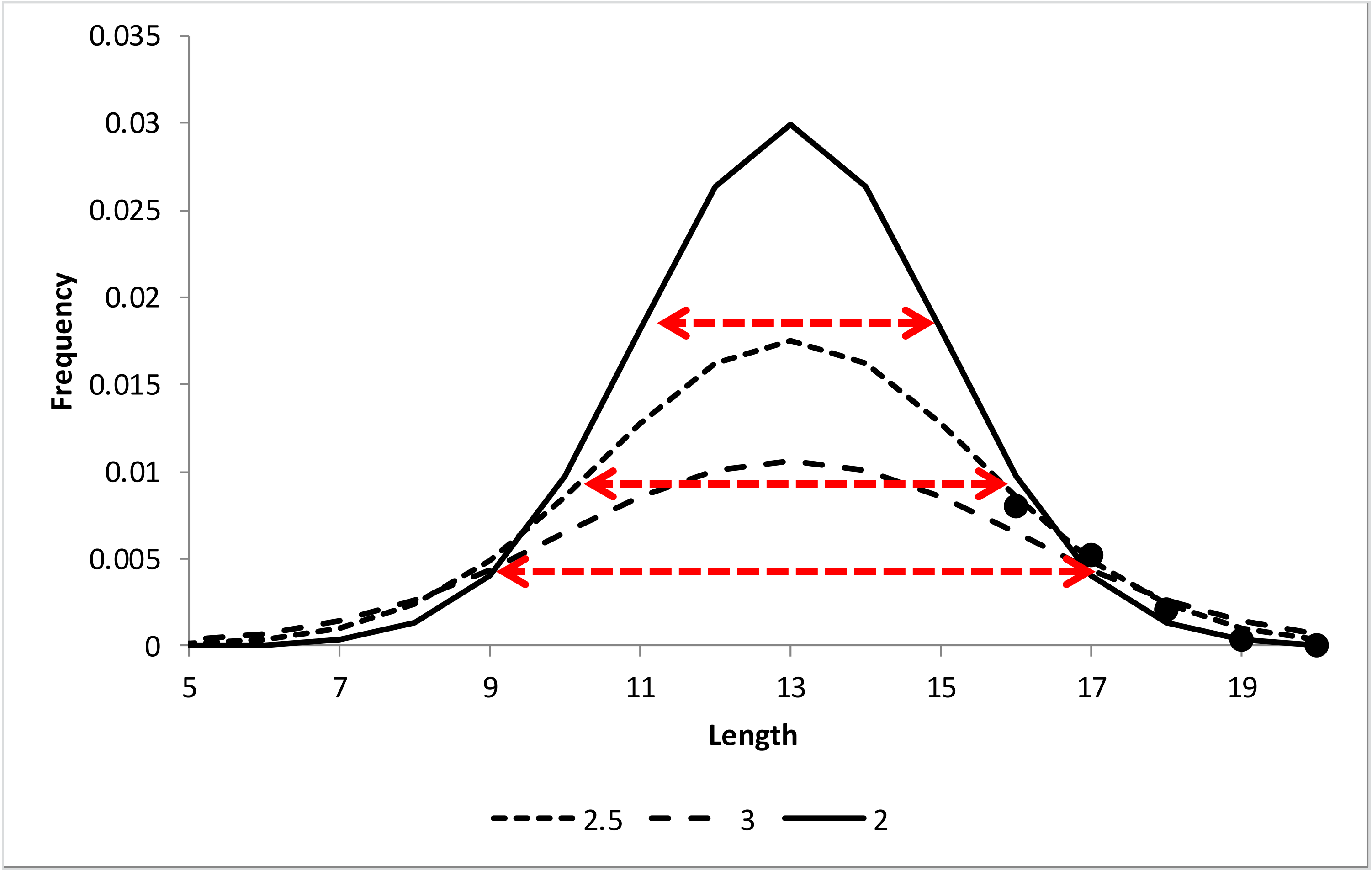
Length composition: asymptotic length



Length composition: Variation of length-at-age



Length composition: Variation of length-at-age



Management: Biology on Bmsy/B0

M	K		
	0.10	0.20	0.30
$h = 1.00$			
0.10	0.27	0.23	0.19
0.20	0.26	0.22	0.17
0.30	0.23	0.11	0.15
$h = 0.75$			
0.10	0.33	0.31	0.29
0.20	0.32	0.30	0.29
0.30	0.31	0.30	0.28
$h = 0.50$			
0.10	0.39	0.38	0.36
0.20	0.39	0.38	0.37
0.30	0.38	0.37	0.36

Maunder, M.N. (2003) Is it time to discard the Schaefer model from the stock assessment scientist's toolbox? Fisheries Research, 61: 145-149.

Management: selectivity

Fishing method	MSY	S/S_0	Effort multiplier
Current mixture	248	0.23	1.19
Longline	425	0.26	66.47
Dolphin associated	337	0.26	3.06
Free-swimming schools	199	0.14	4.72
Floating objects	144	0.13	7.60

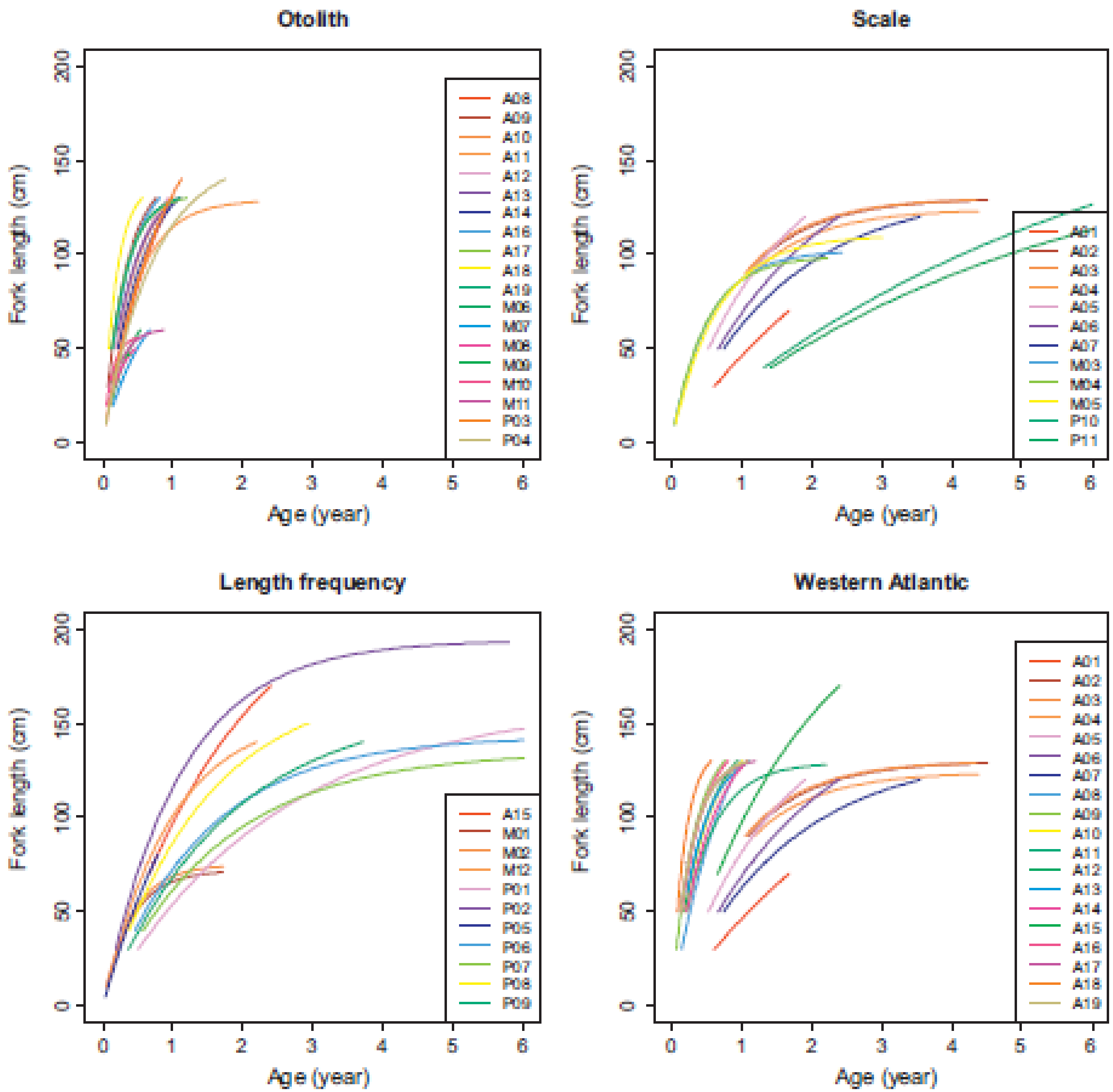
Maunder, M.N. (2002). The relationship between fishing methods, fisheries management and the estimation of MSY. Fish and Fisheries, 3: 251-260.

Requirements for Interpreting data

- Natural mortality
- Recruitment
  - Stock-recruitment relationship
  - Annual variation
- Growth
- Selectivity
- Sampling error

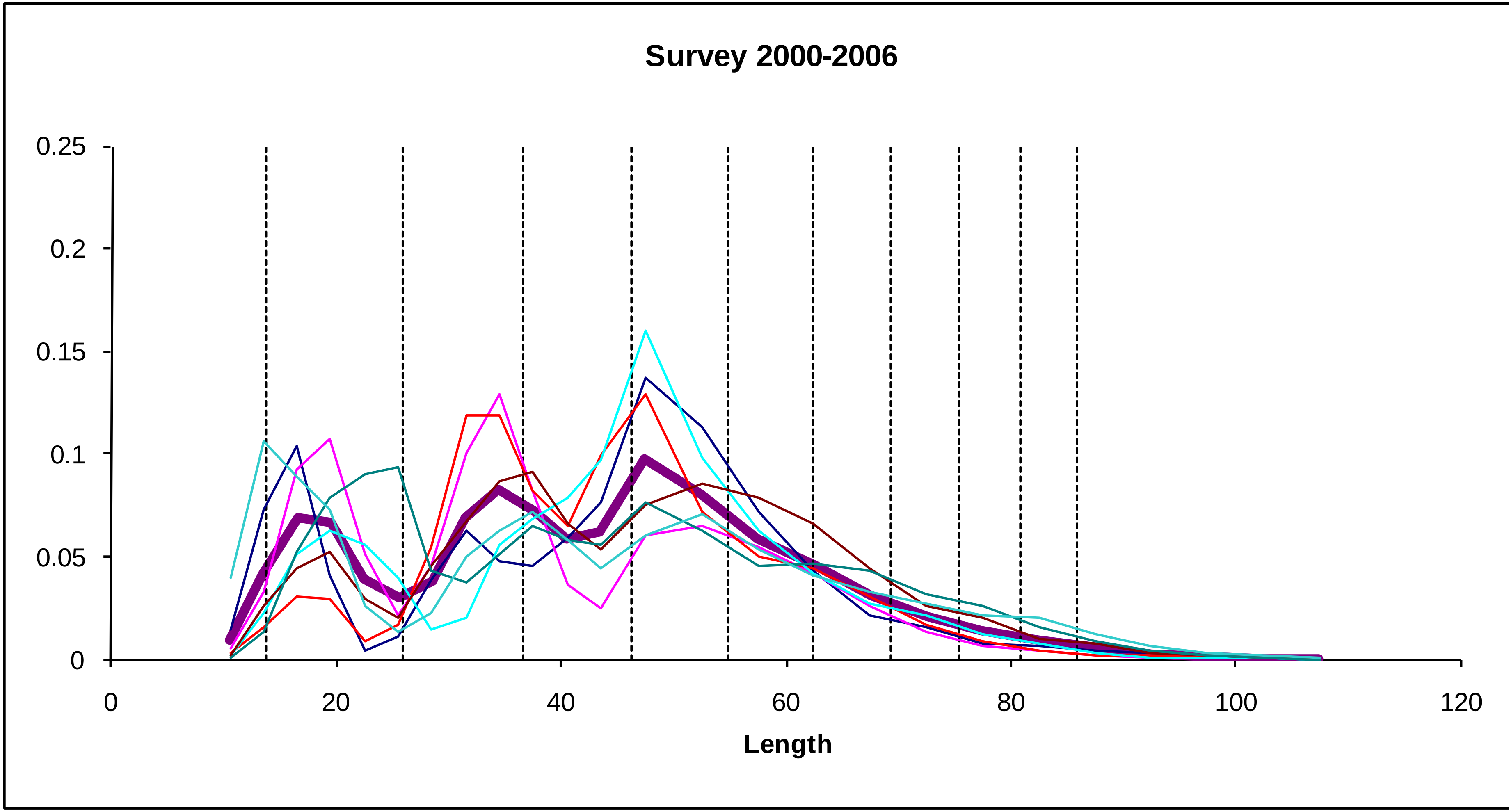
Growth

Uncertainty in growth estimates

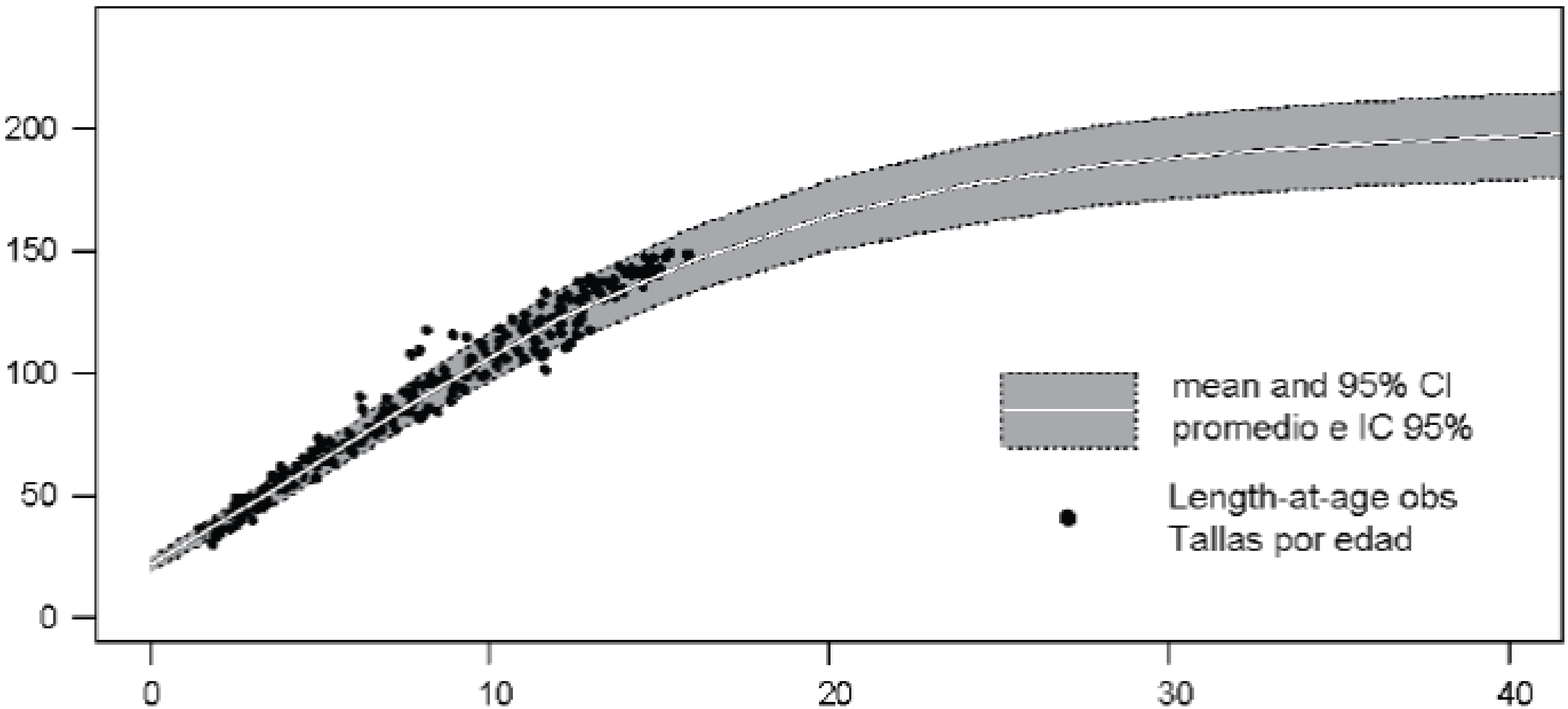


Chang, S-K. and Maunder, M.N. (2012) Aging material matters in the estimation of von Bertalanffy growth parameters for dolphinfish (Coryphaena hippurus). Fisheries Research 119-120: 147– 153.

Modes in length frequency data differ from otolith aging.

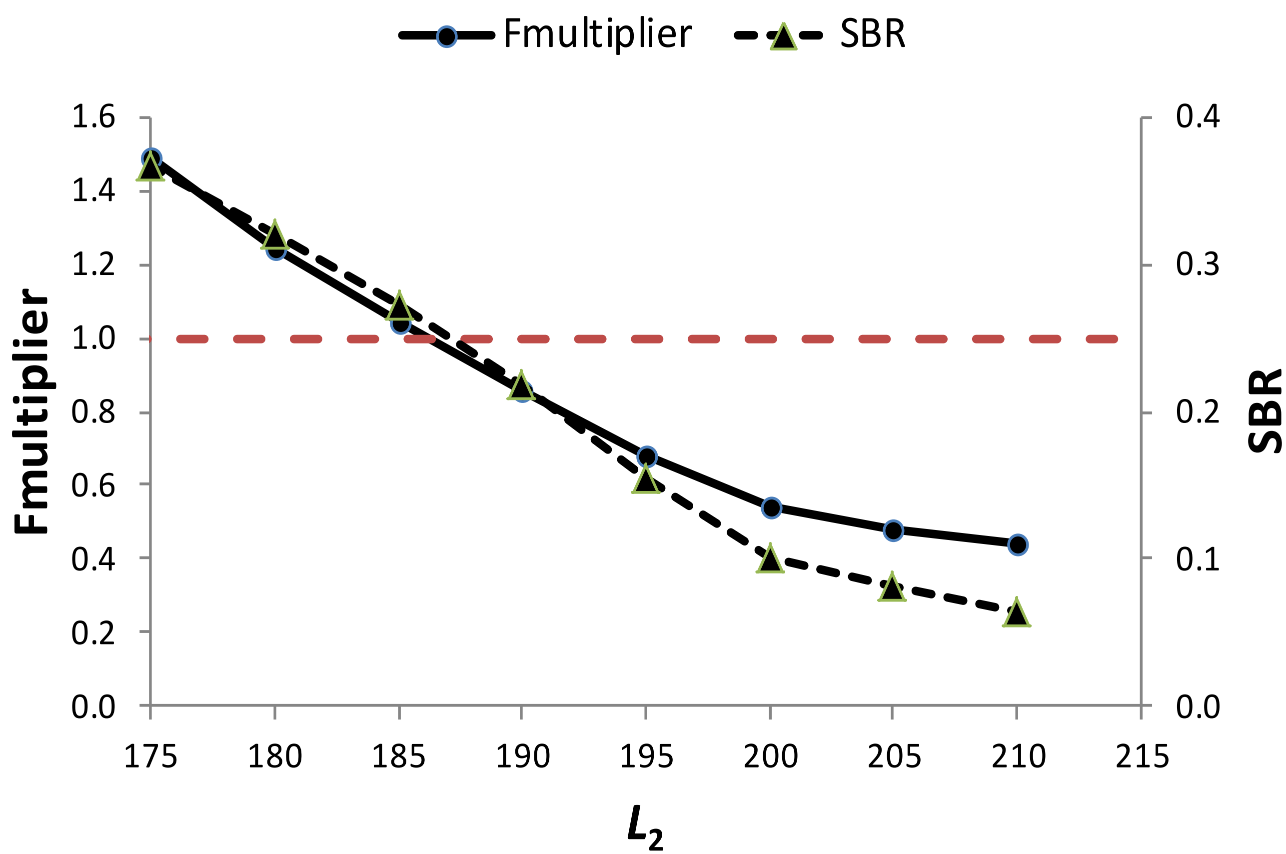


Tropical tuna aging



Aires-da-Silva et al. (submitted) Improved growth estimates from integrated analysis of direct aging and tag-recapture data: an illustration with bigeye tuna (Thunnus obesus) of the eastern Pacific Ocean with implications for management. Fisheries Research.

BET growth (get L2 sensitivity analysis estimates)



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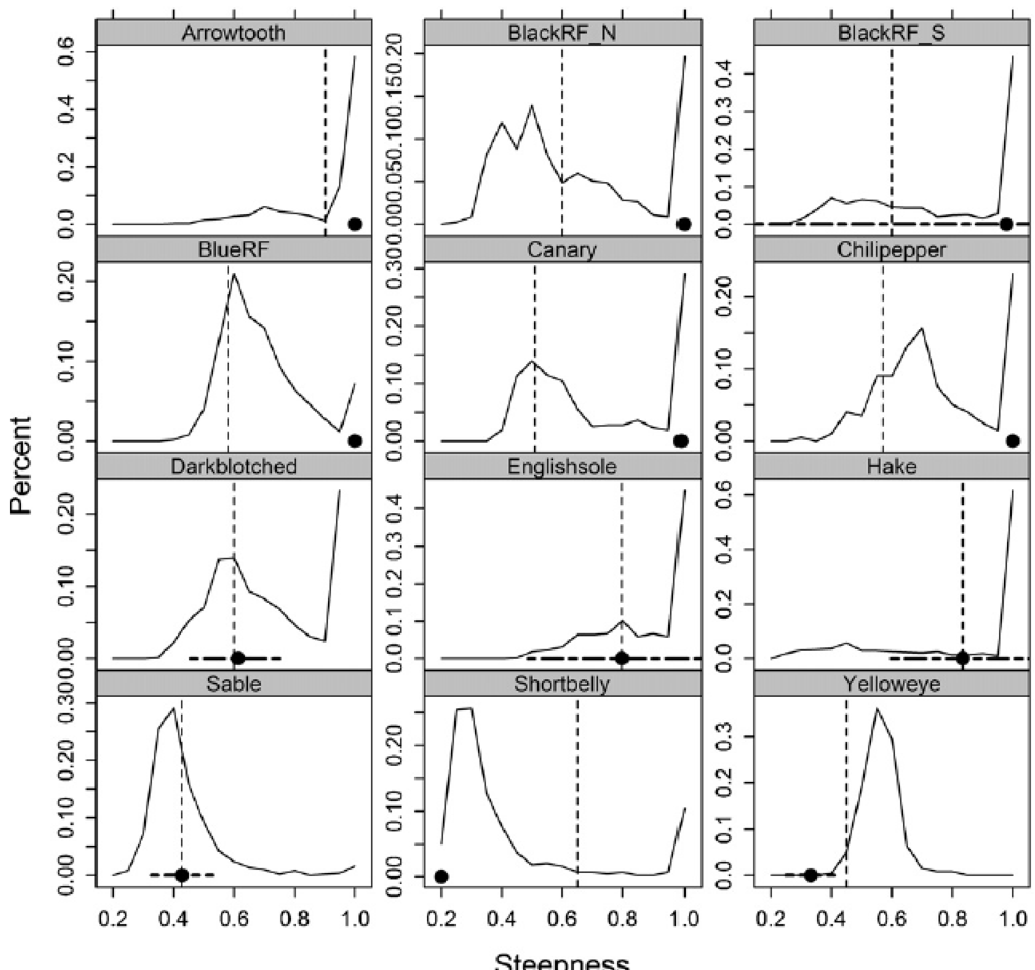
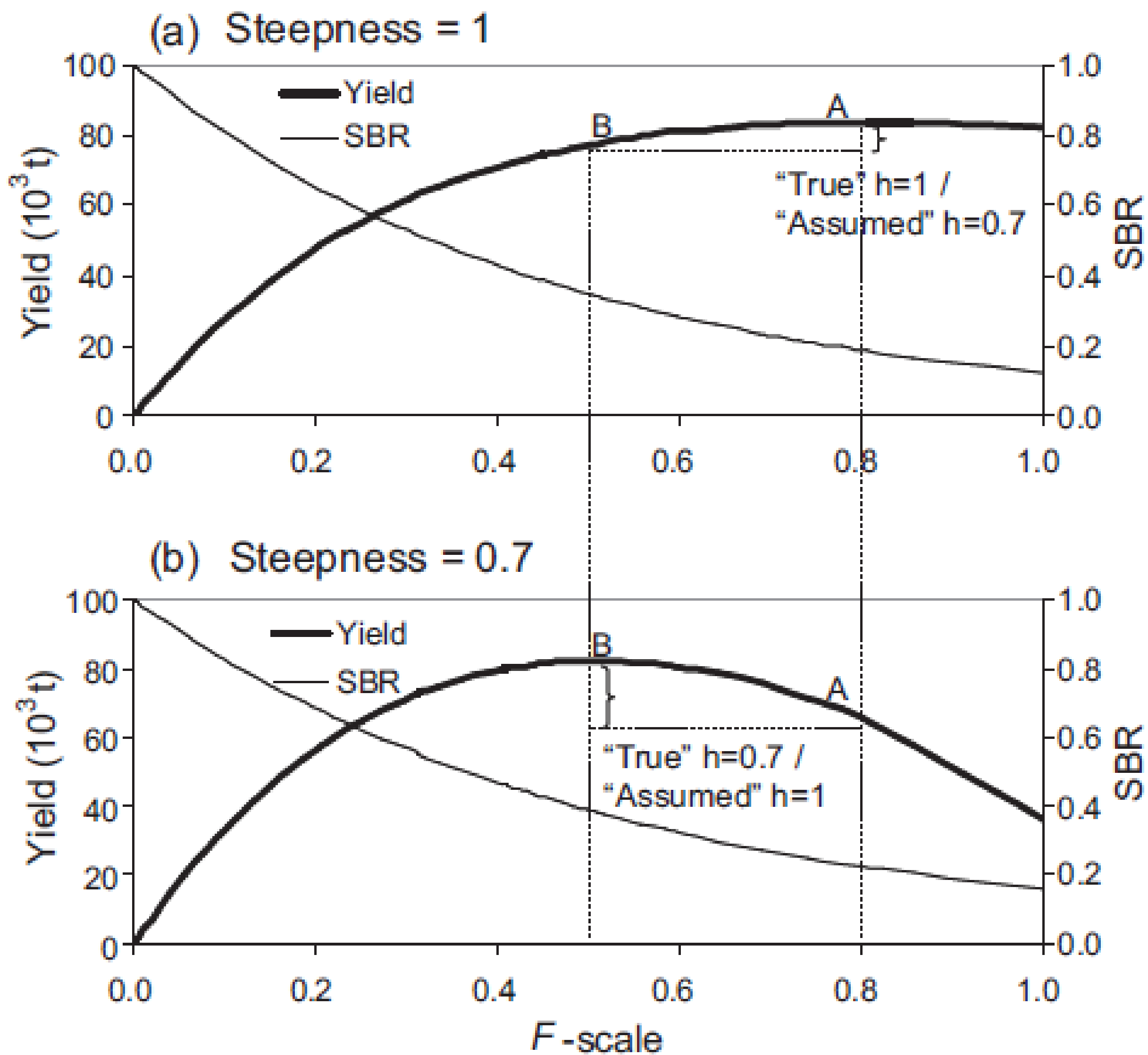
Stock-Recruitment

Bias in estimating steepness



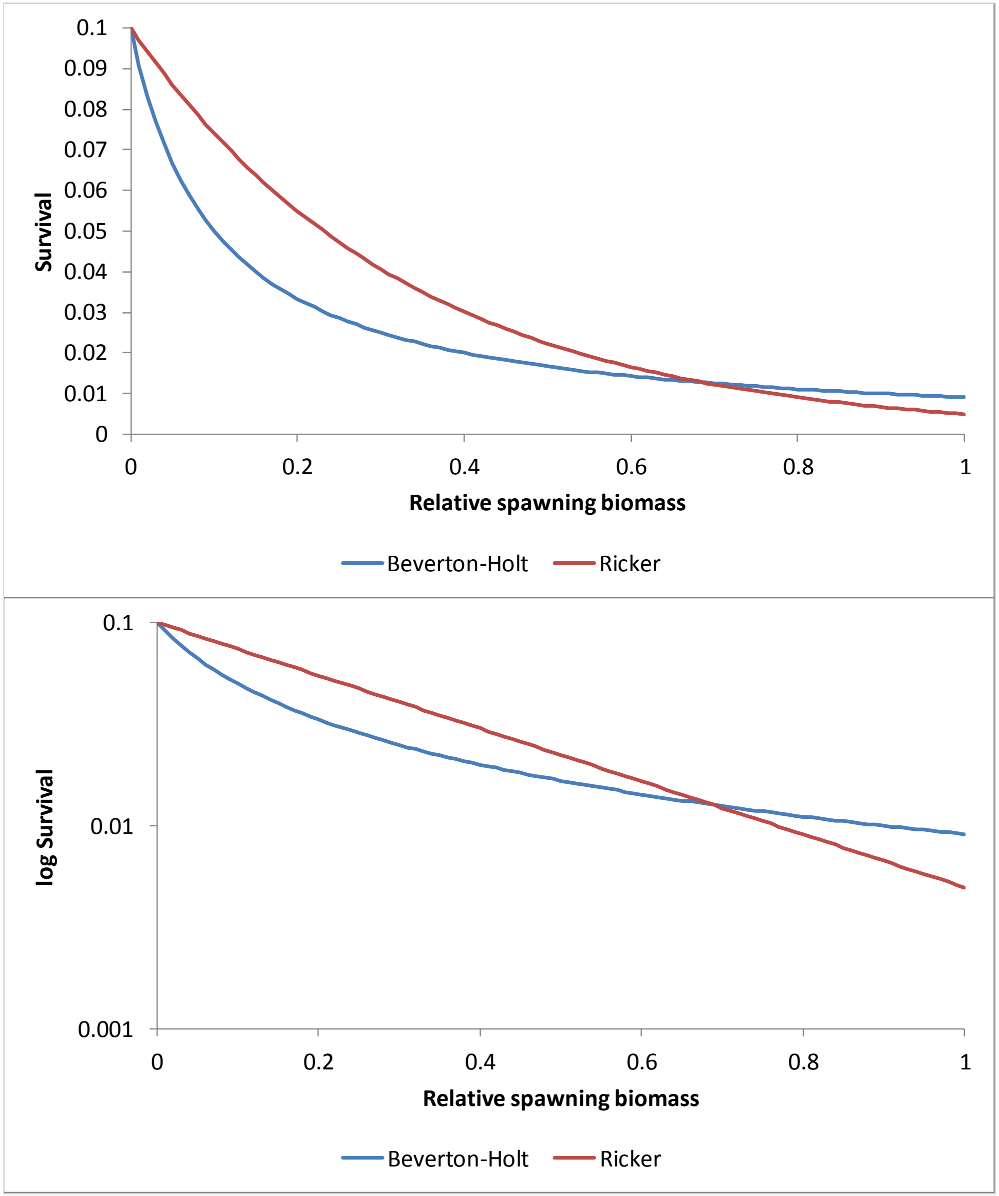
Lee et al. (2012) Can steepness of the stock-recruitment relationship be estimated in fishery stock assessment models? Fisheries Research 125-126: 254-261.

Robust steepness assumptions

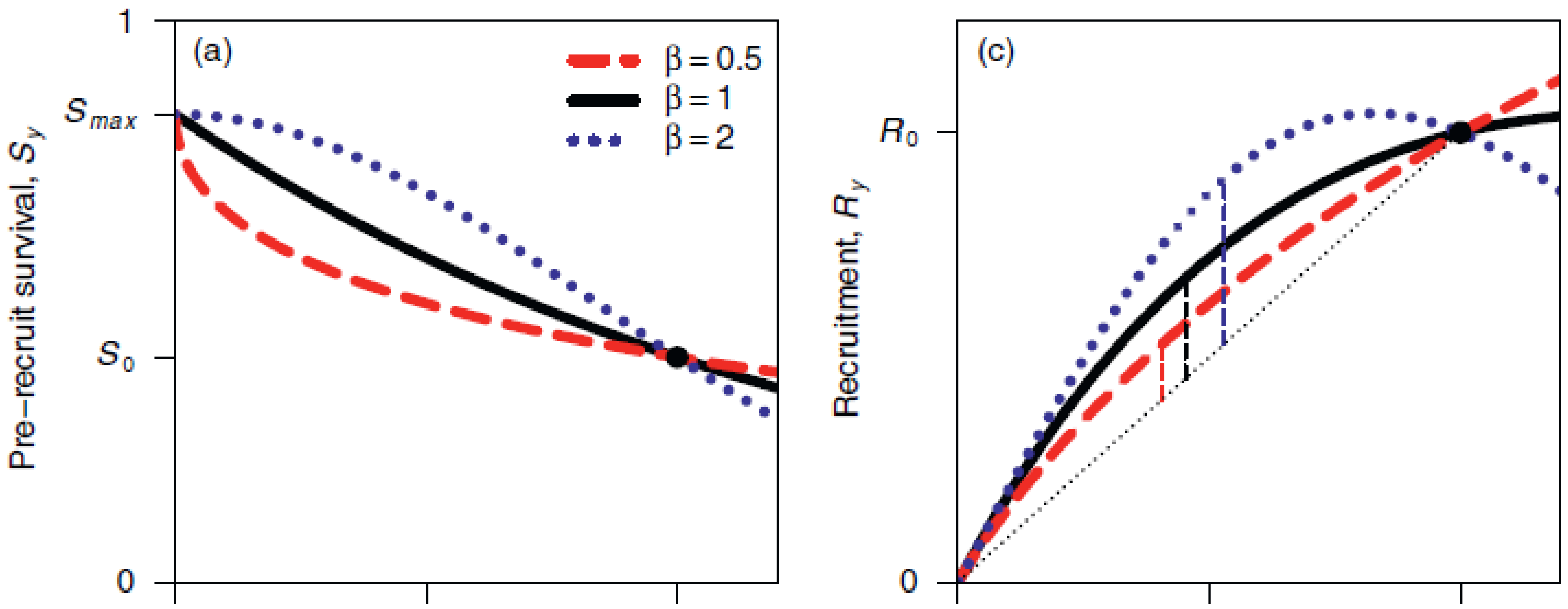


Zhu et al. (2012). Implications of uncertainty in the spawner-recruitment relationship for fisheries management: an illustration using bigeye tuna (Thunnus obesus) in the eastern Pacific Ocean. Fisheries Research 119– 120: 89– 93.

Survival implications of the Beverton-Holt and Ricker models



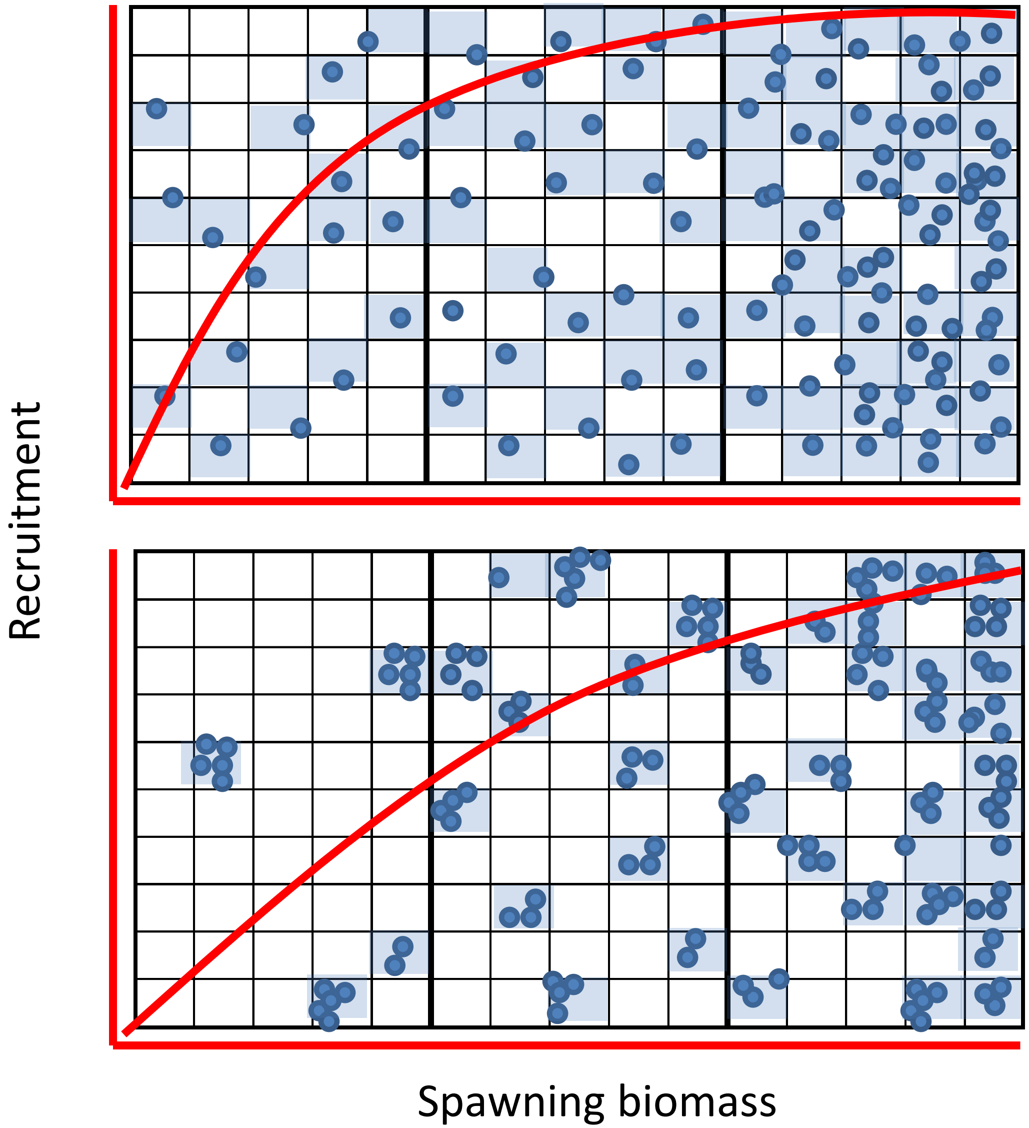
The MTM Low fecund stock-recruitment relationship



Spawning biomass

Taylor et al. (2013) A stock-recruitment relationship based on pre-recruit survival, illustrated with application to spiny dogfish shark. Fisheries Research 142: 15– 21.

A stock–recruitment model for highly fecund species based on temporal and spatial extent of spawning



Maunder, M.N. and Deriso, B.R. (2013) A stock–recruitment model for highly fecund species based on temporal and spatial extent of spawning. Fisheries Research 146: 96–101.

Natural mortality

Summer flounder natural mortality

- Value used not based on data or any reasonable rationale
- Obvious sex differences in M
- Changing the assumed male M from 0.2 to 0.3 changed the recommendations from closing the fishery to increasing the TAC

M.N. Maunder, R.A. Wong. 2011. Approaches for estimating natural mortality: Application to summer flounder (Paralichthys dentatus) in the U.S. mid-Atlantic. Fisheries Research 111, 92– 99.

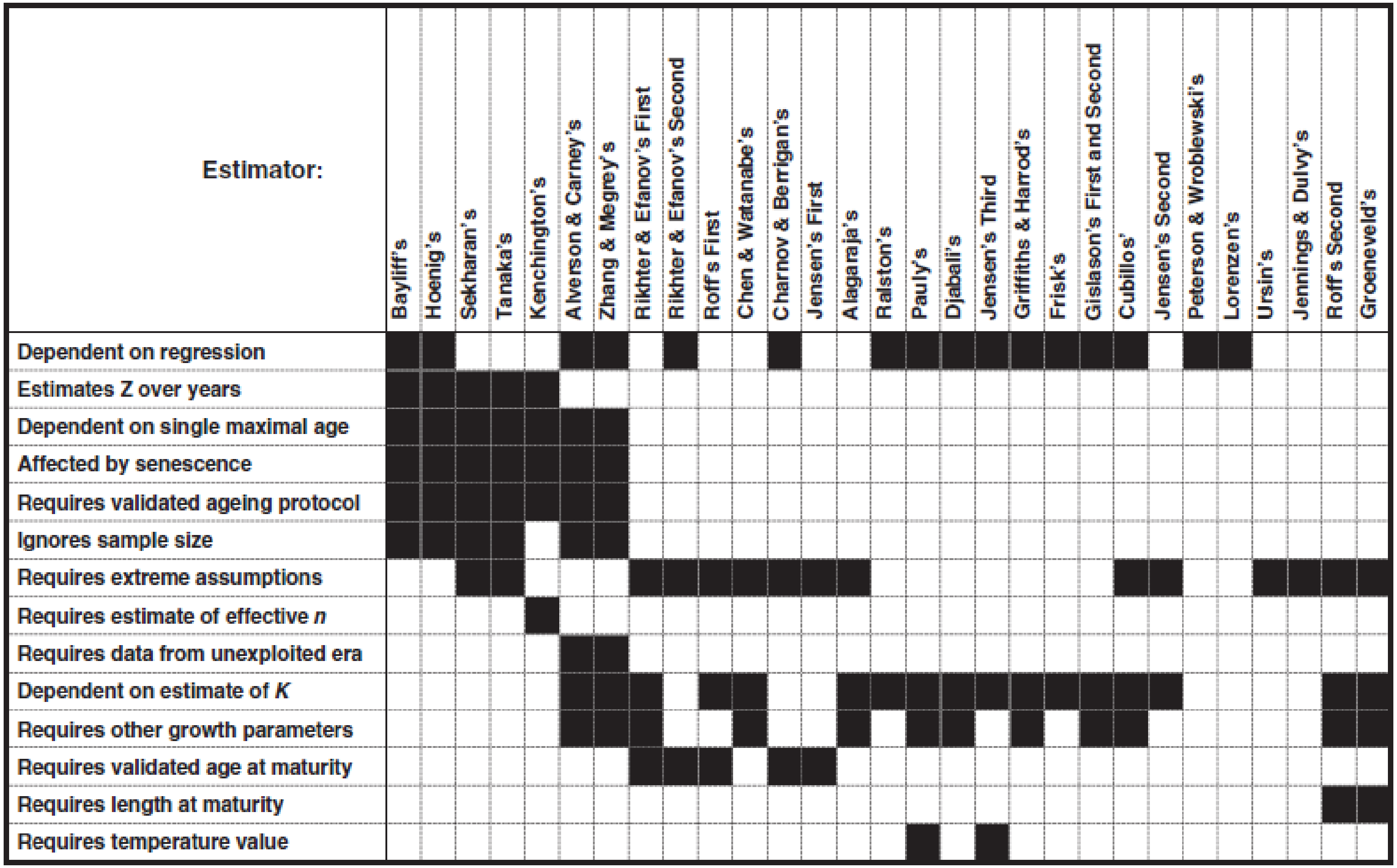
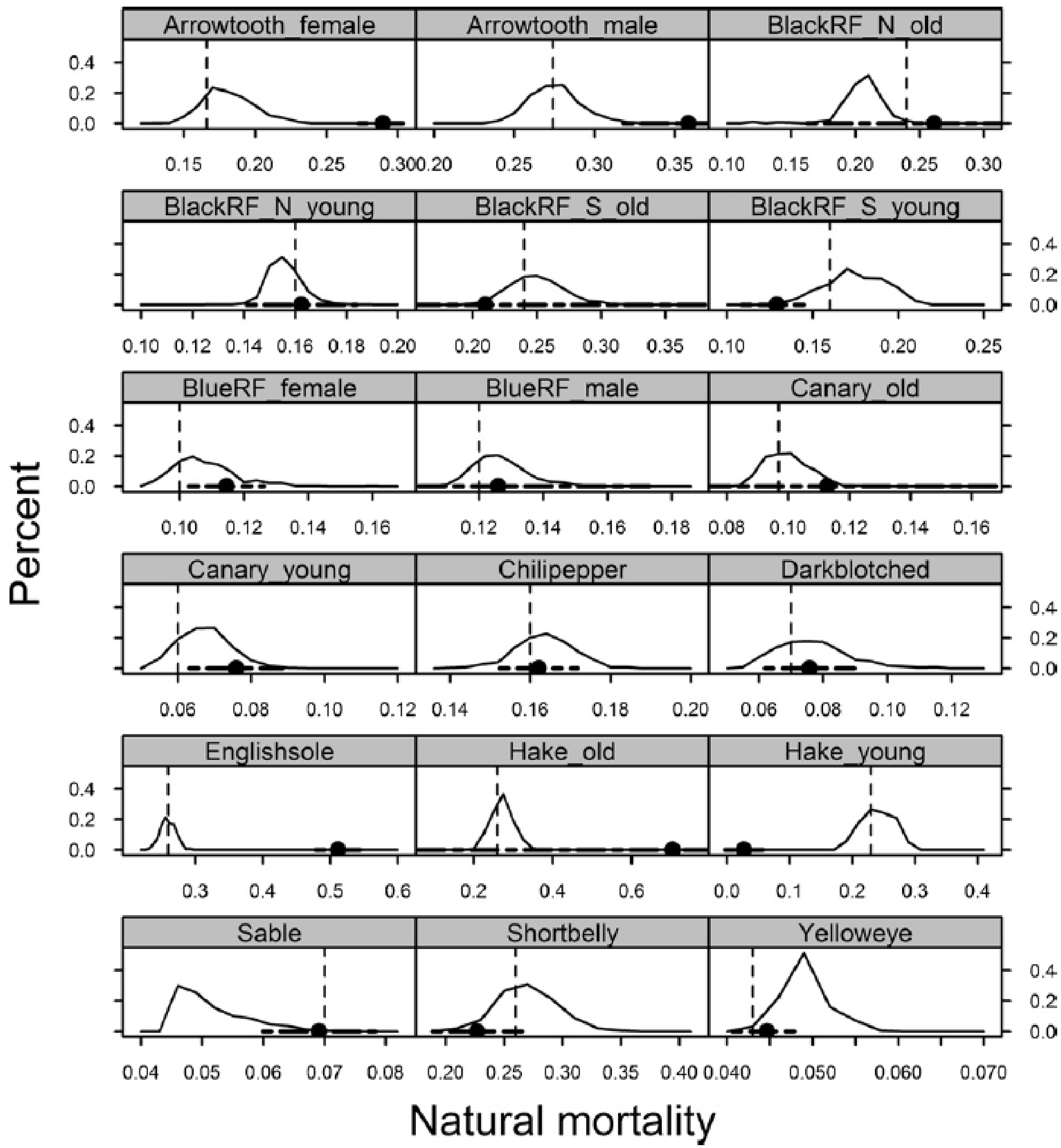


Figure 1 Summary of some limitations of, and challenges confronting application of, the *M* estimators. The fourteen limitations and challenges are explained in the text, primarily under the first of the estimators concerned. Shading indicates that a named estimator is affected by the specified issue.

"None of the 30 can provide accurate estimates for every species, and none appears sufficiently precise for use in analytical stock assessments, while several perform so poorly as to have no practical utility" (Kenchington 2013).

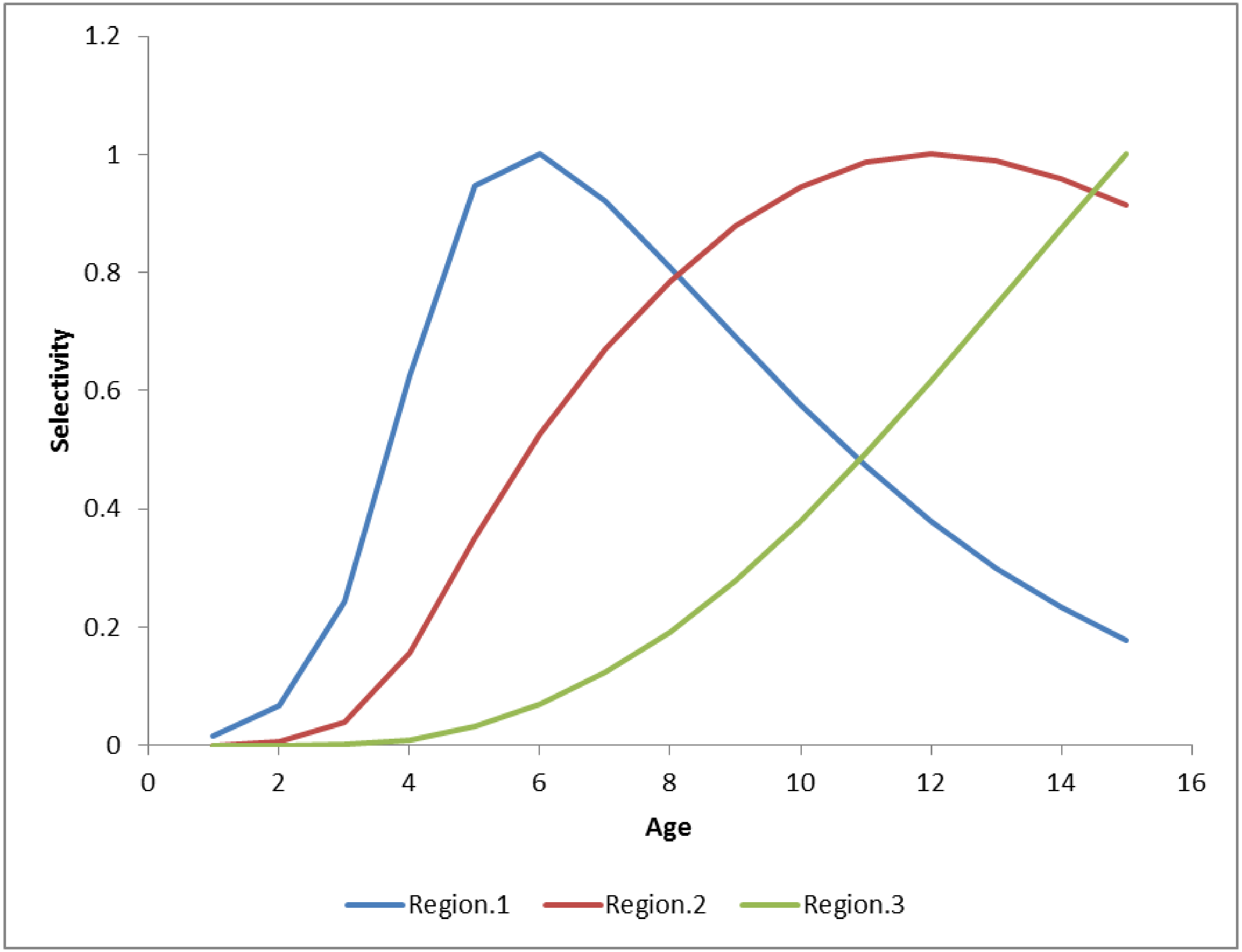
Kenchington, T.J. (2013) Natural mortality estimators for information-limited fisheries. Fish and Fisheries x: **x-x**



Lee et al. (2011) Estimating natural mortality within a fisheries stock assessment model: an evaluation using simulation analysis based on twelve stock assessments. Fisheries Research, 109: 89–94.

Selectivity

Selectivity



Waterhouse et al. (in prep) Fisheries Research.
Also see Sampson and Scott (2011) Canadian Journal of Fisheries and Aquatic Sciences 68:1077-1086.

Catchability = 1

- Consistently proved to be an incorrect assumption

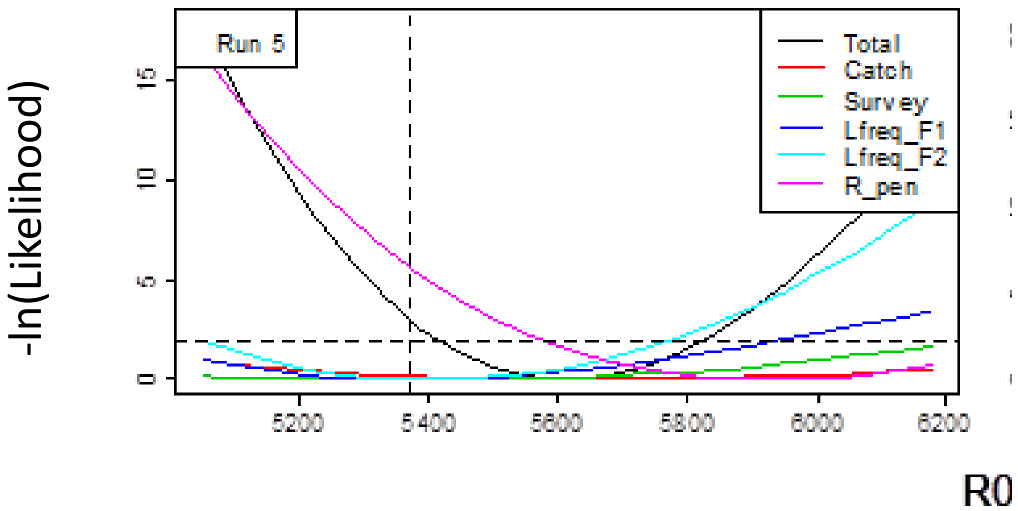
Sampling error

- Effective sample size for correlated composition data
- Modeling process error
  - Assumed in the observation error
  - Temporal variation in growth, M, selectivity, catchability
- Data weighting

Abundance diagnostics

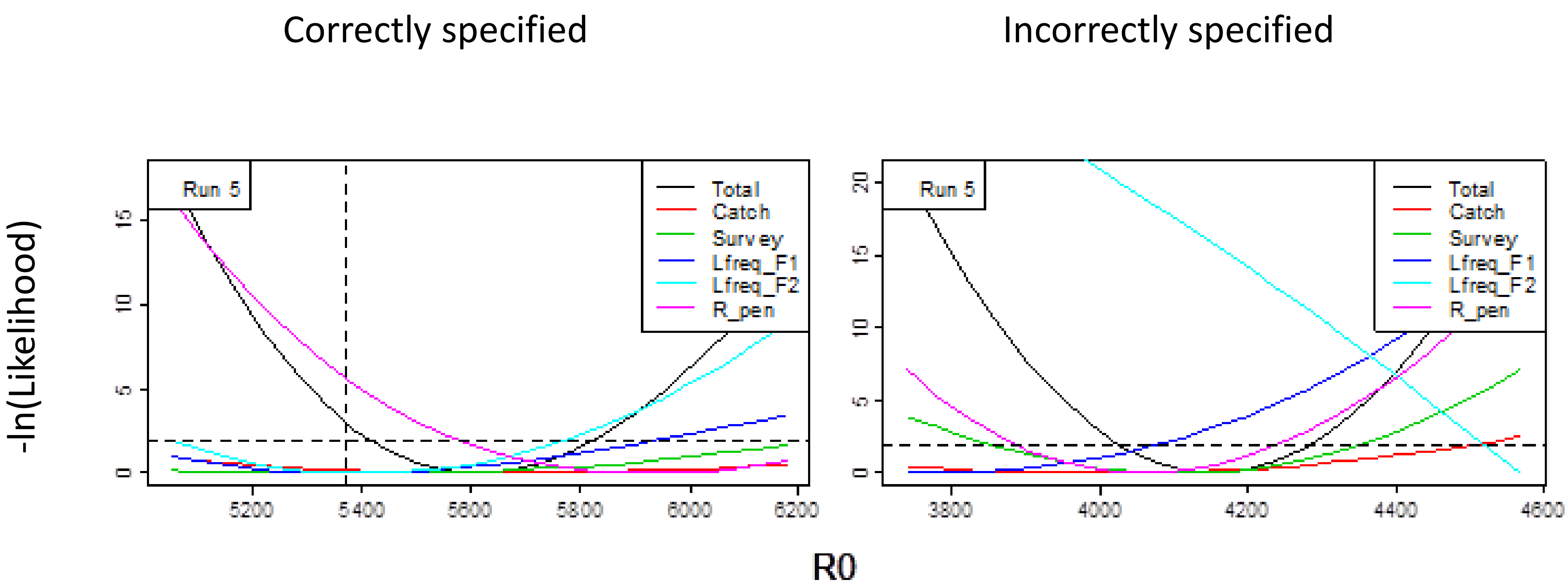
R0 likelihood component profile

Correctly specified



Wang et al. (in prep) R0 profiling as a diagnostic for selectivity curve structure in integrated stock assessment models. Fisheries Research.

R0 likelihood component profile

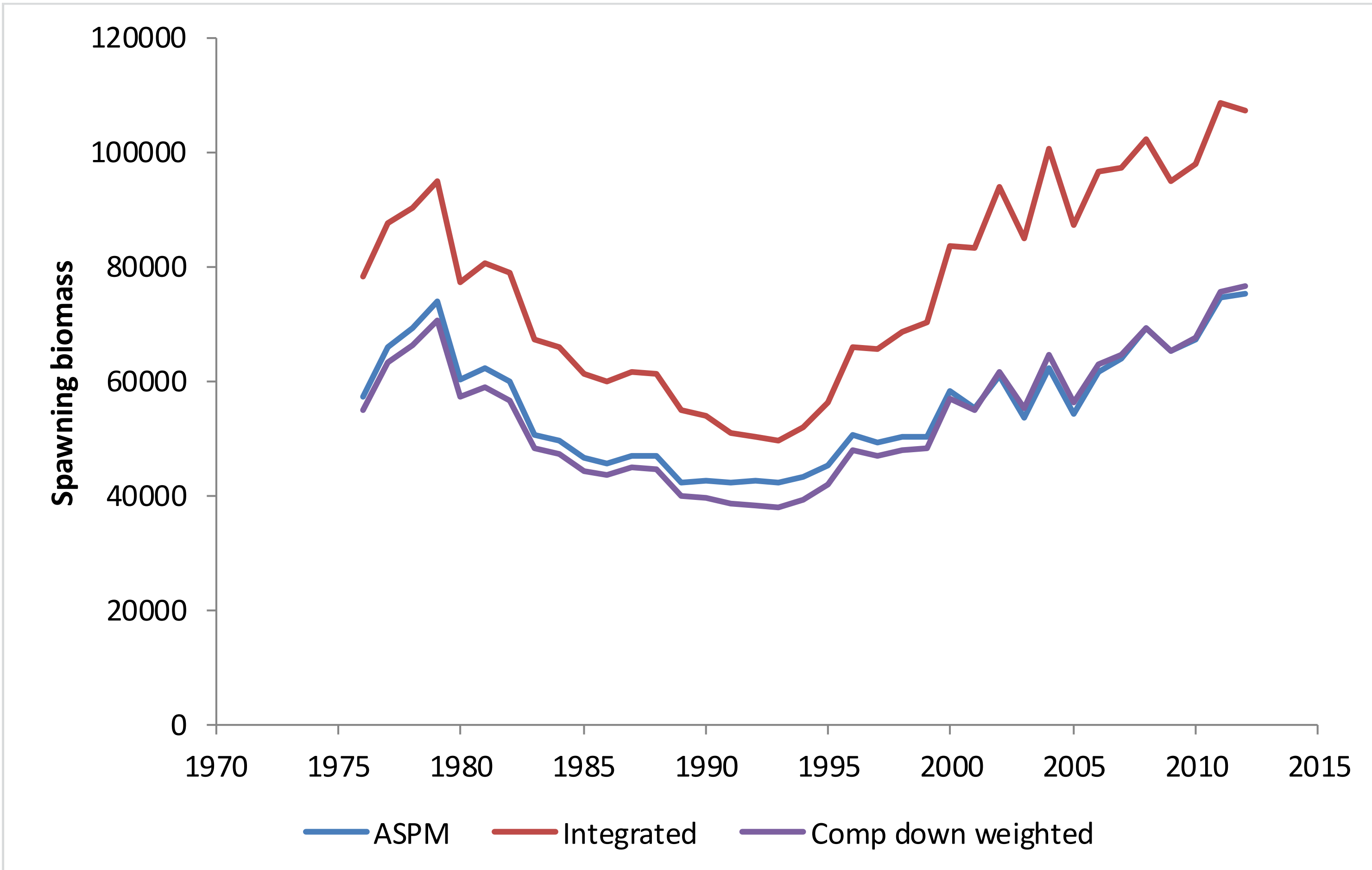


Wang et al. (in prep) R0 profiling as a diagnostic for selectivity curve structure in integrated stock assessment models. Fisheries Research.

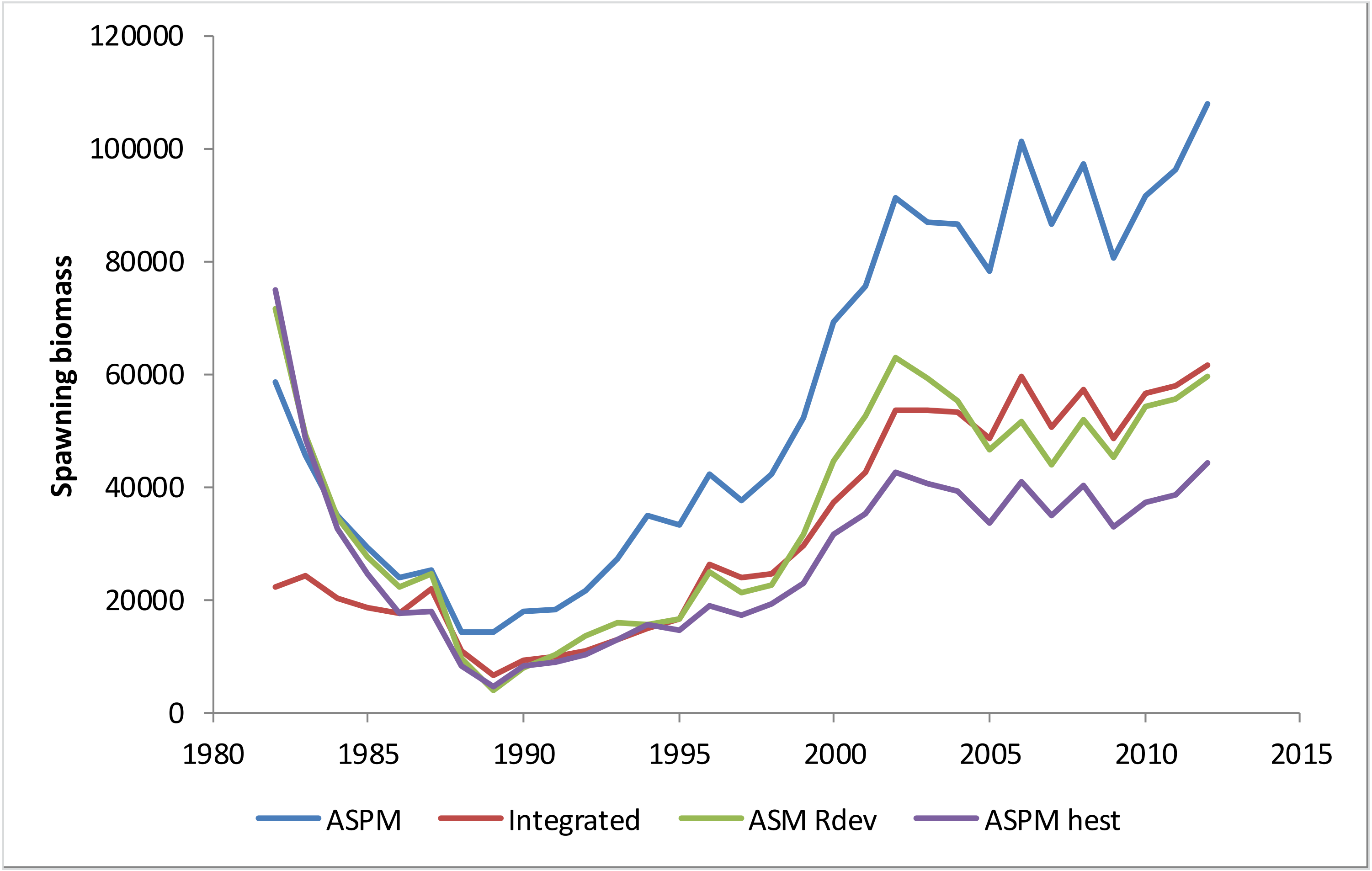
Age-structured Production Model Diagnostic

- Index consistent with dynamics and catch
- Influence of composition data
- Recruitment variation or regime changes

Hypothetical example 1: composition influence



Hypothetical example 2: mispecified steepness



Research impediments: why we have not made progress

- Rogue academics seeking fame and funding
- Trendy “soft” science for fisheries management: climate change, ecosystem based management, marine protected areas, environmental correlations
- Focus on easy publications (e.g. the first to put an archival tag on a species)
- Lack of assessment scientists
- Assessment scientists have to do assessments and not research
- More assessments requested (e.g. result of ACL’s)

Summary

- We don’t know much about
  - Growth, recruitment, natural mortality, and selectivity
- These are vital for interpreting data and providing management advice
- It is difficult to do research on these topics for a number of reasons
- We either need to prioritize this research or apply management that is robust to uncertainty (not just be conservative)

Acknowledgements

- Conference organizers
- ISSF for funding
- Numerous researchers for stimulating conversations and ideas
  - CAPAM members and Advisory Panel
  - Kevin Piner
  - Andre Punt

The end

An evaluation of some alternative flexible approaches to age-structured modeling of fish stocks

James Ianelli

July 2013

Boston MA

Overview

- Which assessment details and process-error* assumptions matter most?
  - Selectivity
  - Natural mortality
  - Catchability
    - Survey and CPUE

- Application and developments

*Process errors are time-specific

Why is accounting for process errors important?

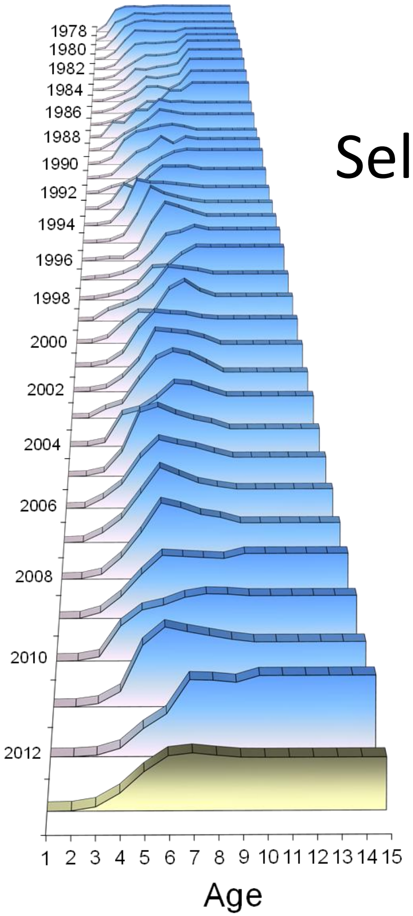
For appropriate **uncertainty** estimation

- In Alaska some FMP control rules require "**reliable**" estimate of uncertainty
- Nationally, ACLs formally depend on scientific uncertainty

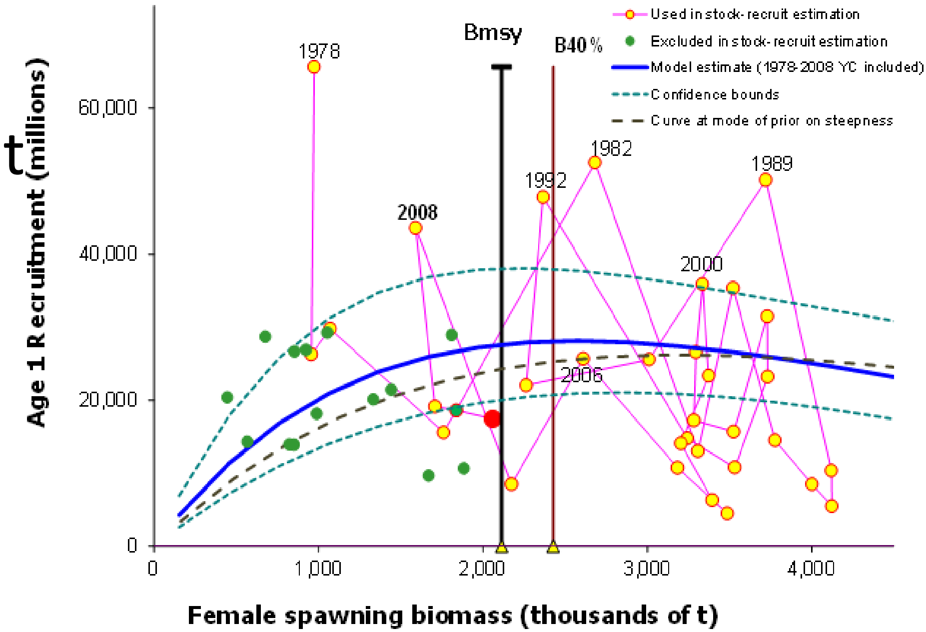
and…the expected value never happens

Sources of uncertainty in pollock F_{MSY}

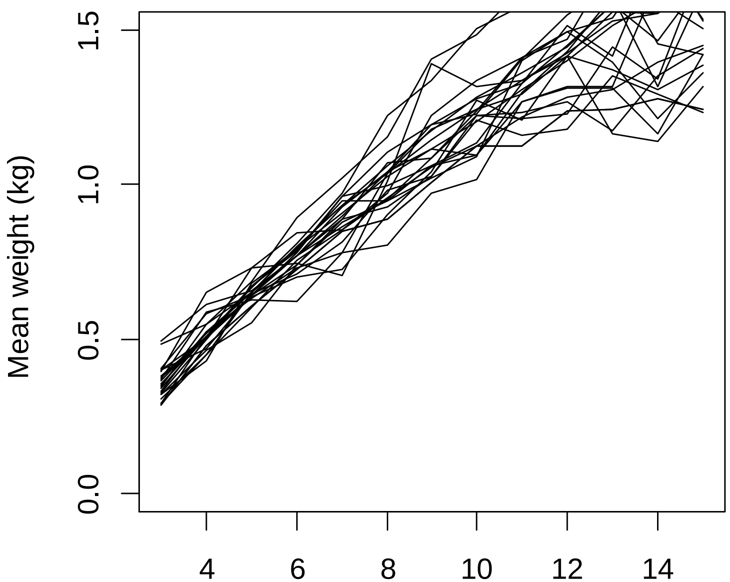
Selectivity

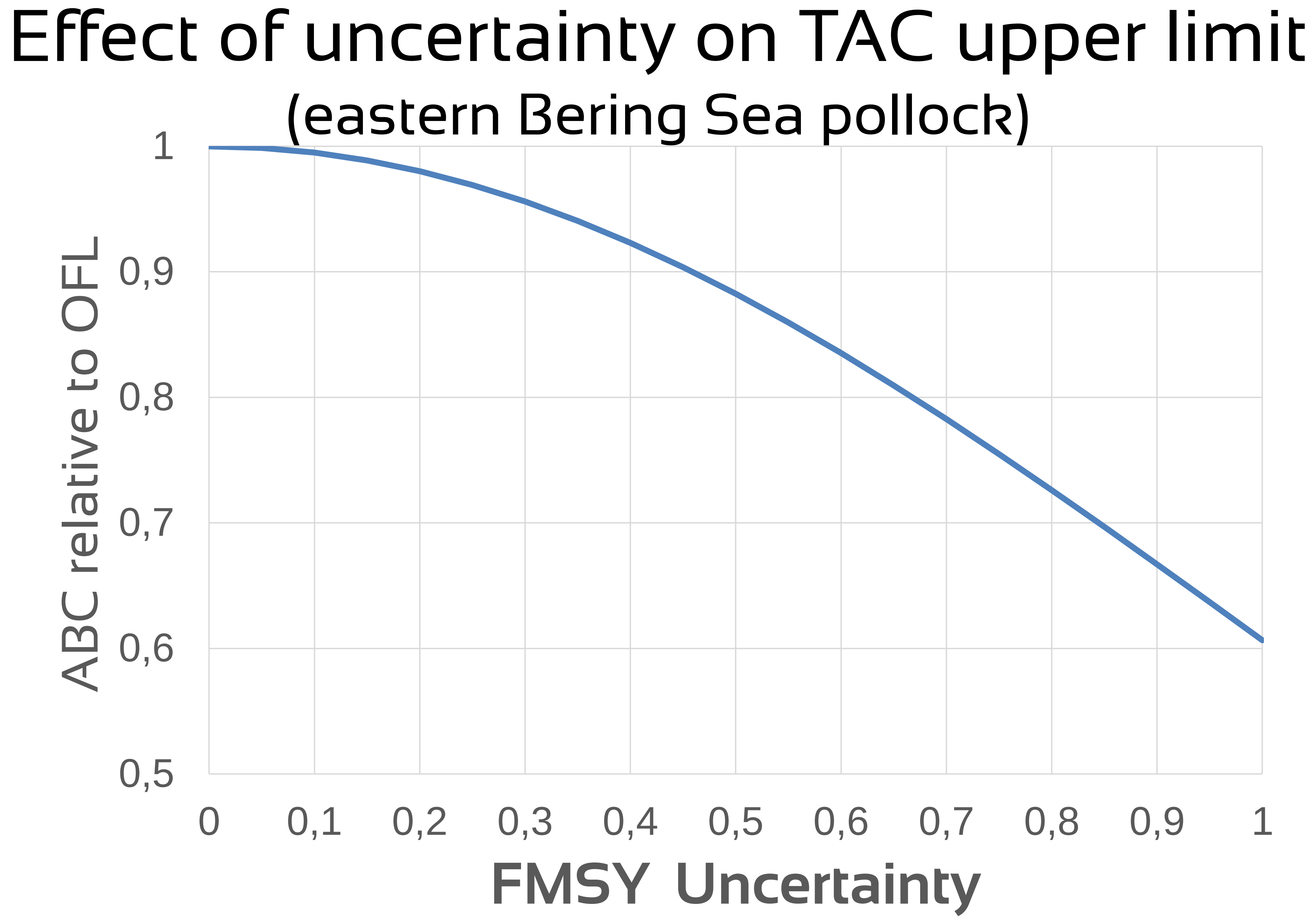


Stock recruitment



Wt-at-age




Effect of uncertainty on TAC upper limit
(eastern Bering Sea pollock)
ABC relative to OFL
1
0,9
0,8
0,7
0,6
0,5
0
0,1
0,2
0,3
0,4
0,5
0,6
0,7
0,8
0,9
1
FMSY Uncertainty

General process-error implementation details

- Bayesian
- Non-stationarity allowed
- Takes advantage of unallocated arrays (ADMB feature)
- Intermediate to full random-effects (SAM)
  - But possibly with better intuitive properties?

FAST, ACCURATE, STABLE OPTIMIZATION

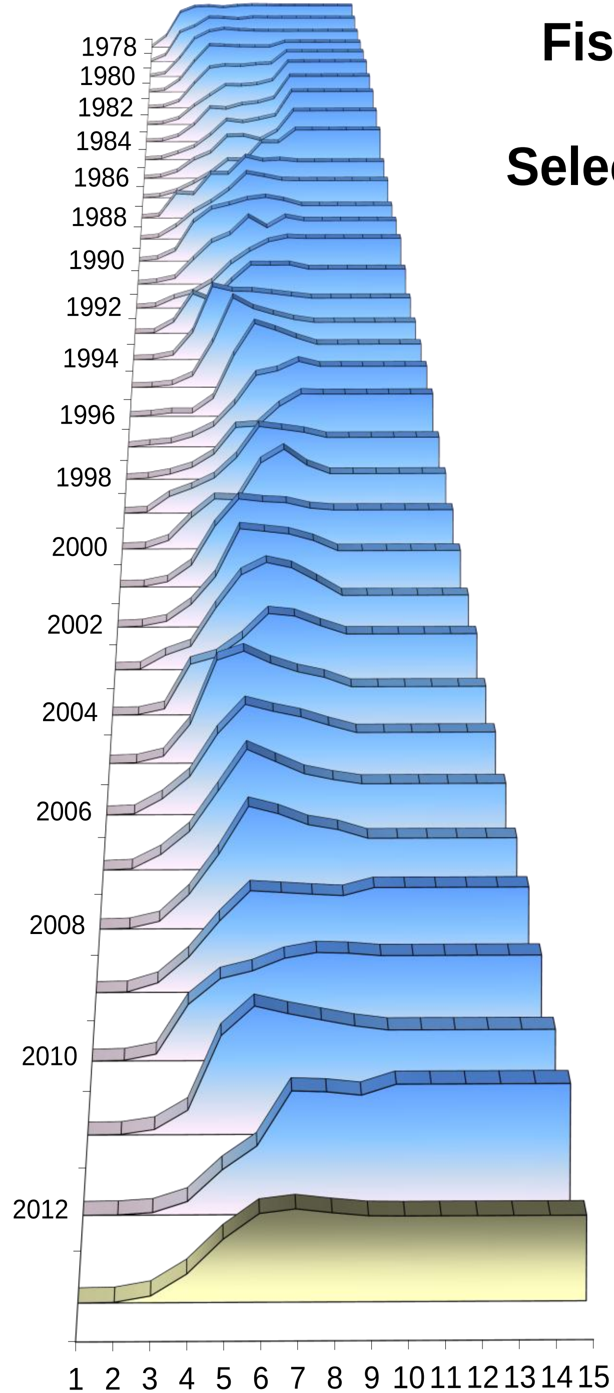
Overview

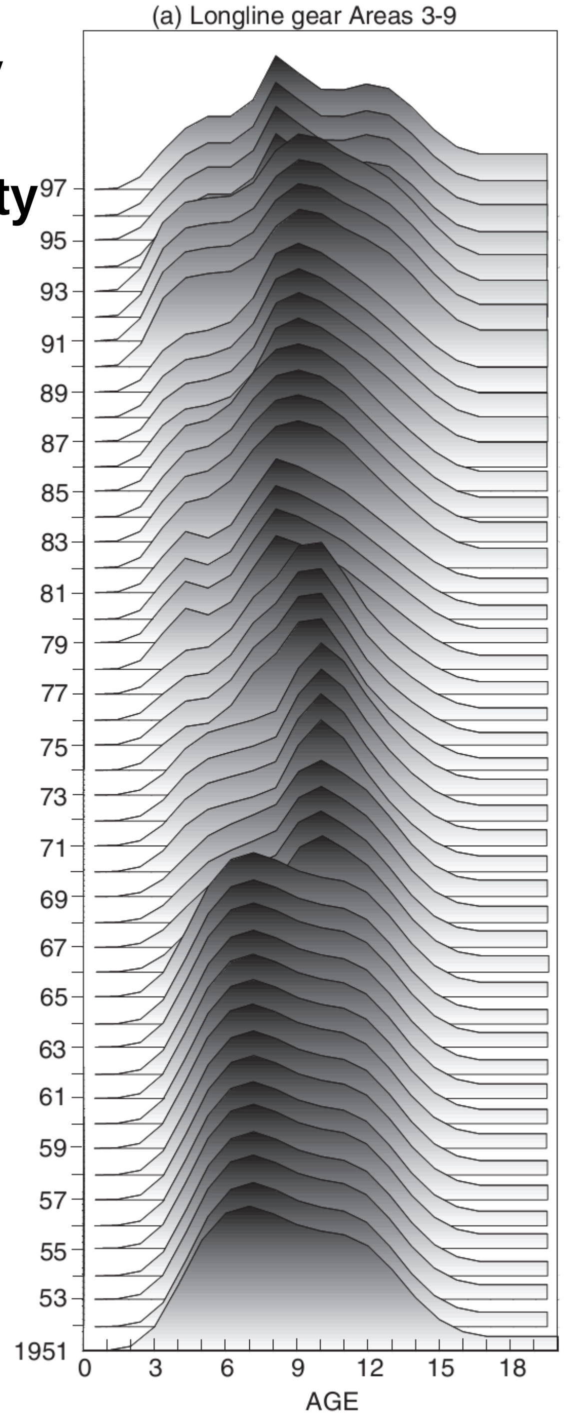
- Which assessment details and process-error assumptions that matter the most?
  - Selectivity
  - Natural mortality
  - Catchability
    - Survey and CPUE

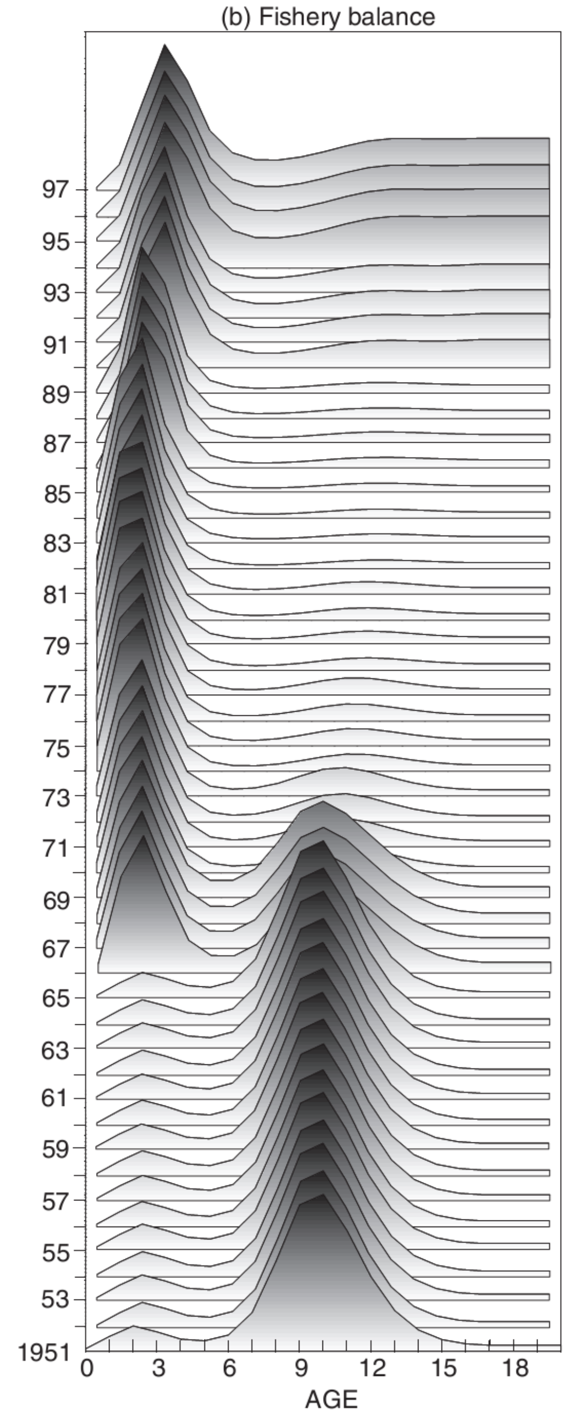
Selectivity estimation

- Can affect population scale
  - Surveys/indices
  - Fs
- Time-varying method
  - Penalized likelihood
- How to objectively set year-to-year variability?

Fishery Selectivity





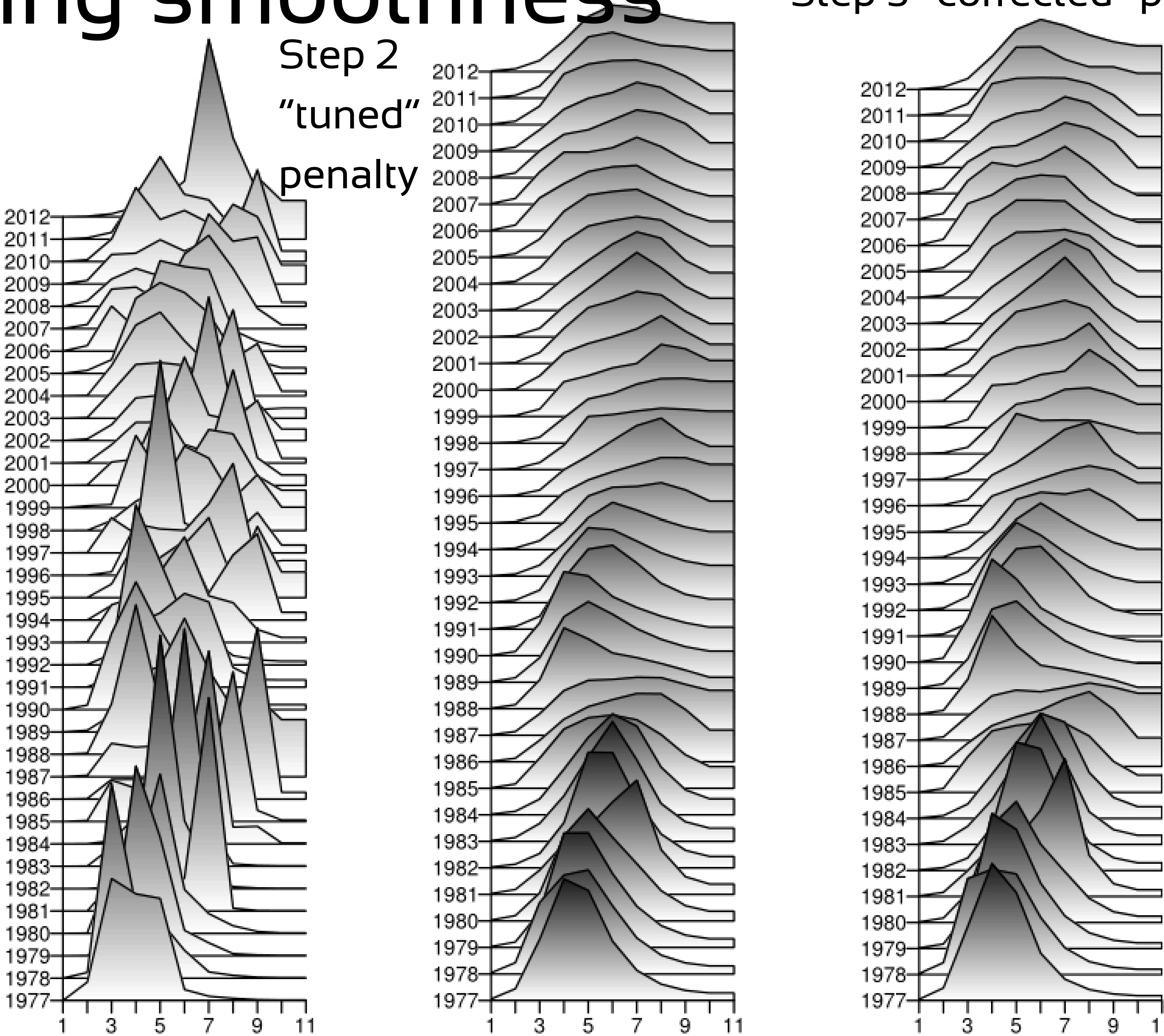


Tuning smoothness

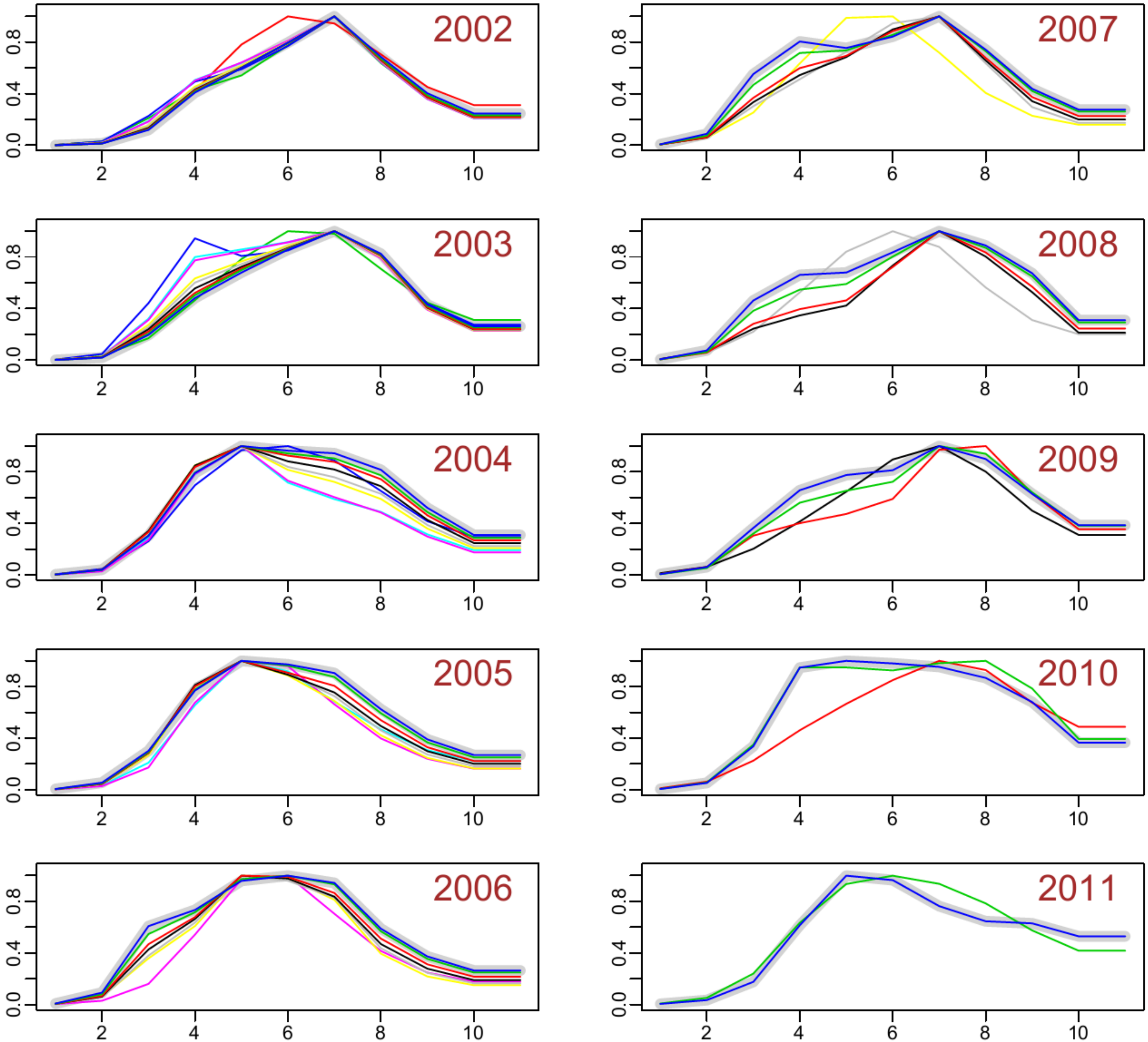
Step 1
tiny
penalty

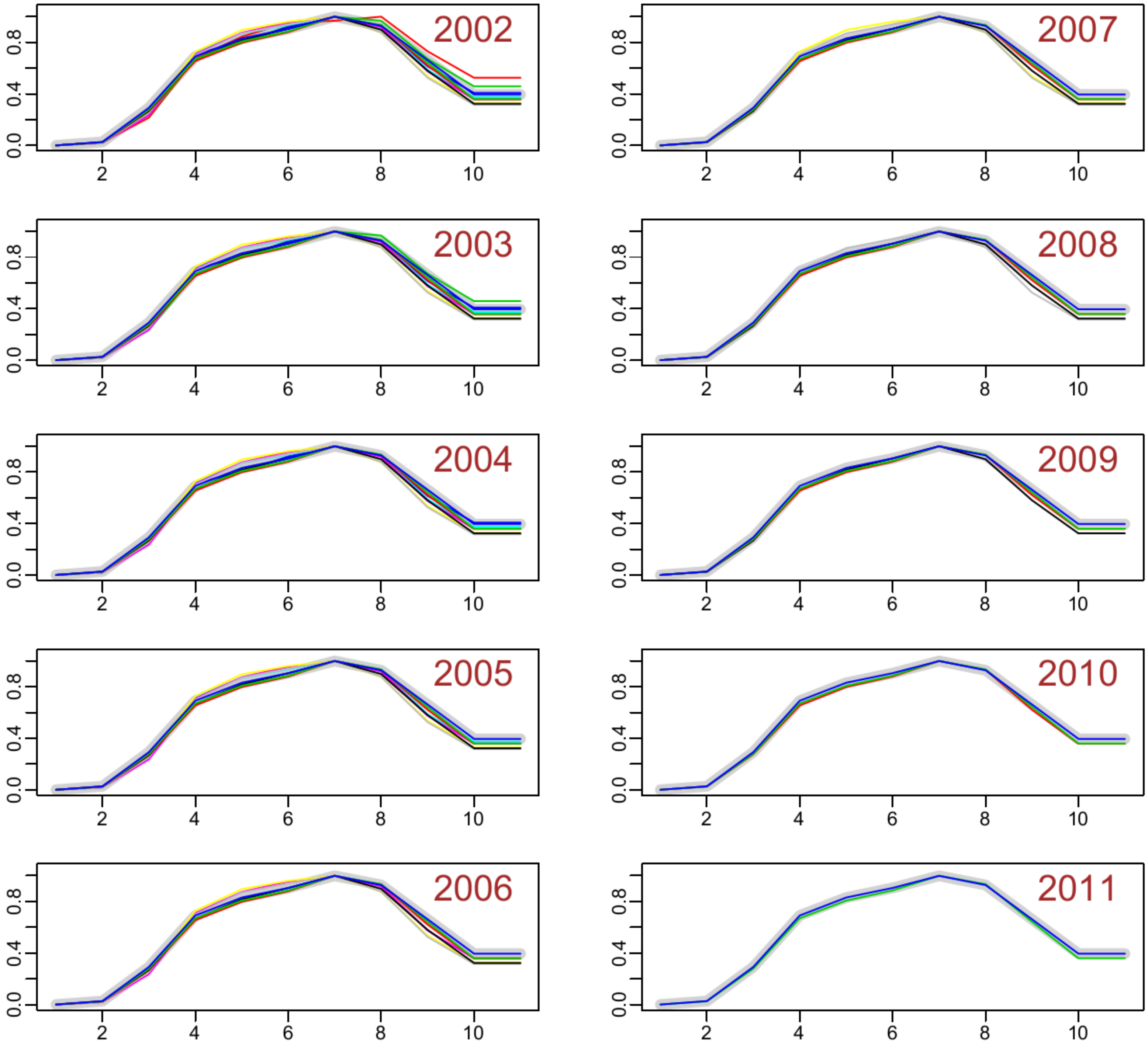
Step 2
“tuned”
penalty

Step 3 “corrected” penalty



Diagnoses on retrospective patterns


2002
2007
2003
2008
2004
2009
2005
2010
2006
2011
0.0
0.4
0.8
2
4
6
8
10


2002
2007
2003
2008
2004
2009
2005
2010
2006
2011

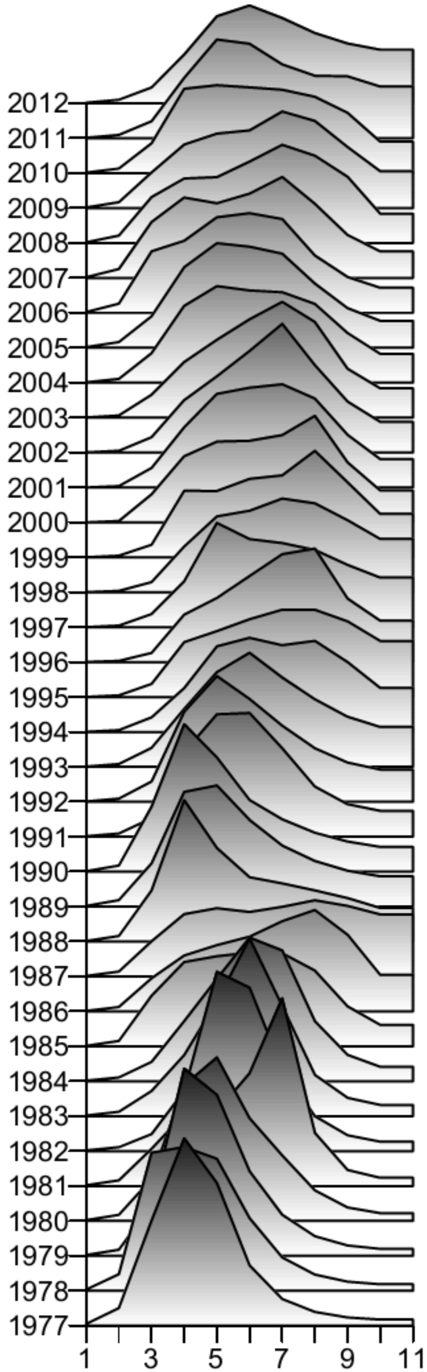
Alternative reduced-parameter approach…

Triple-separability

Attributed to Dmitri Vasilyev TISVPA—adds a cohort effect to year and age

Trick is in normalizing

- Consider 10 ages and 30 years…time-varying selectivity **HIGHLY** parameterized…
- **Can be reduced along three axes:**
  - Parameters by age, by year, and cohort



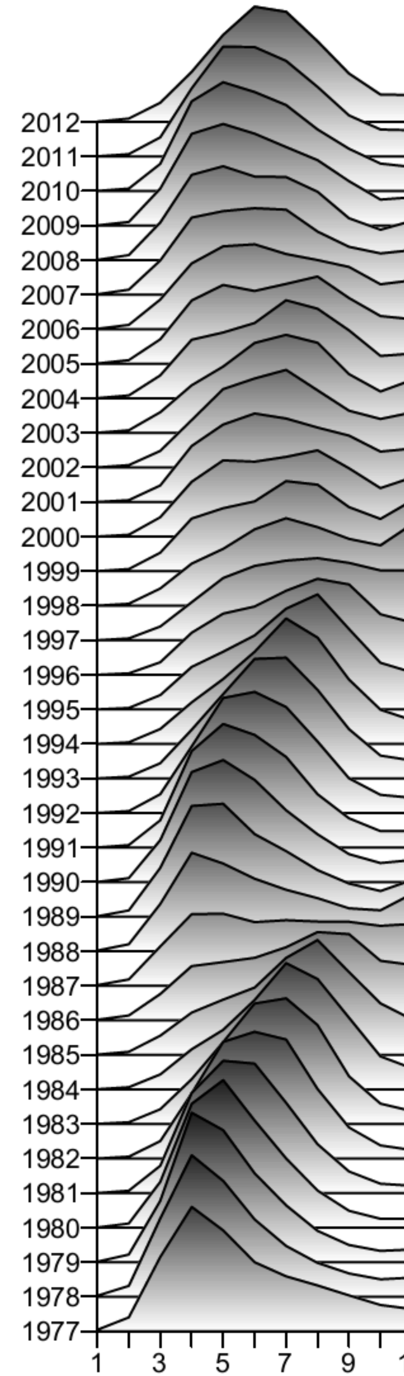
Time-varying versus cohort effect (triple-separable)

487

parameters

versus

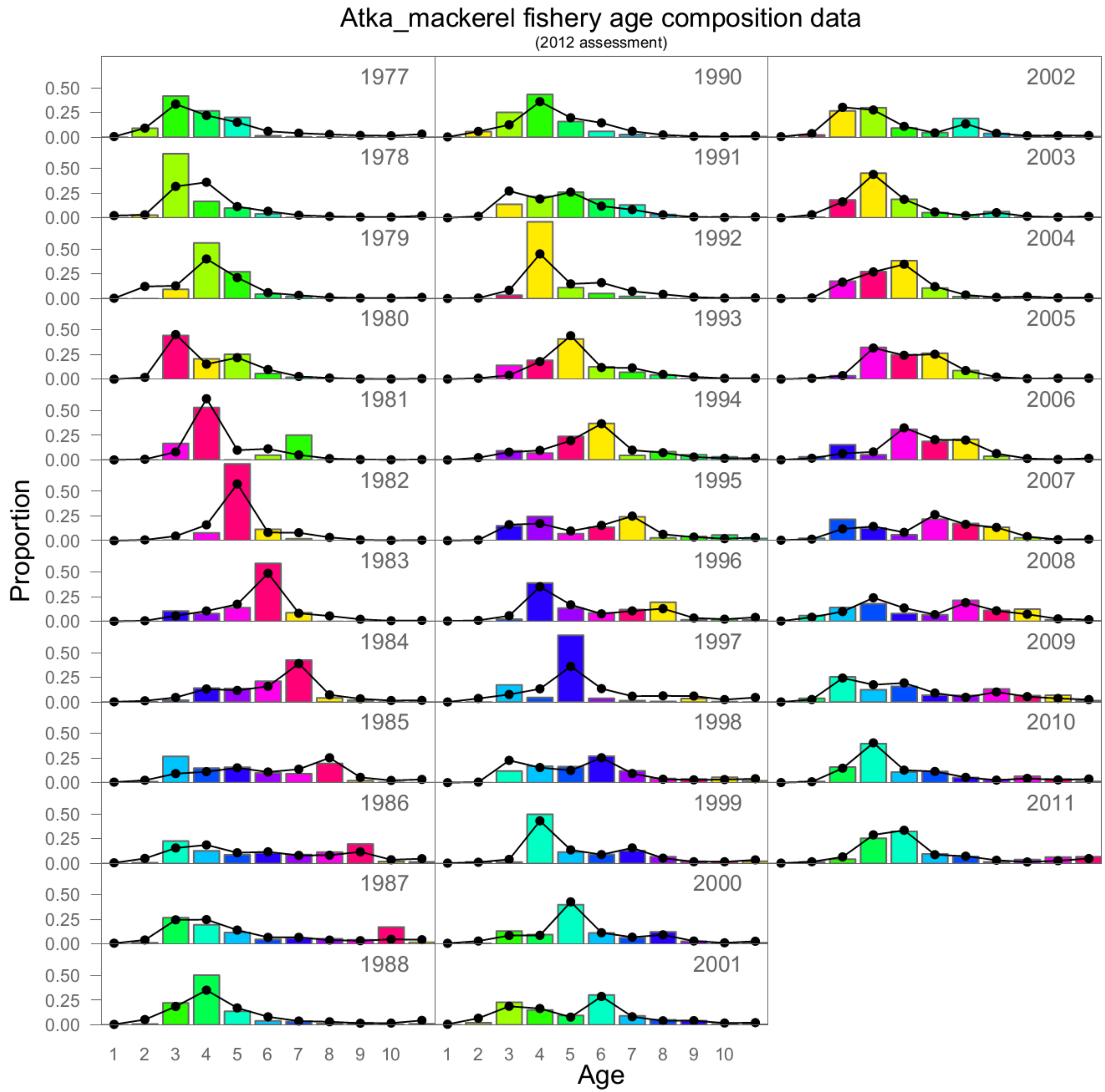
184



Triple-separable

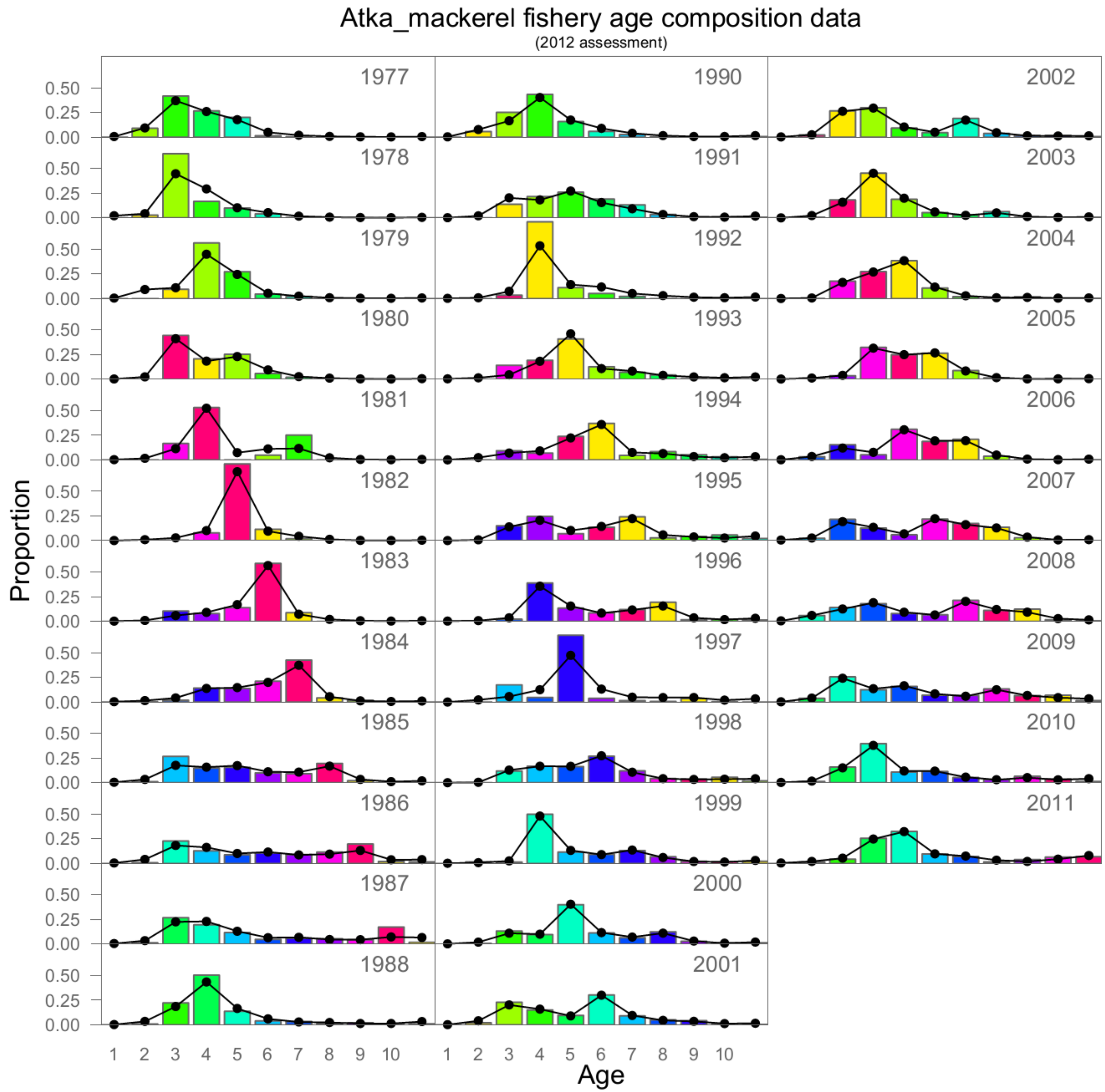
-lnLike

171

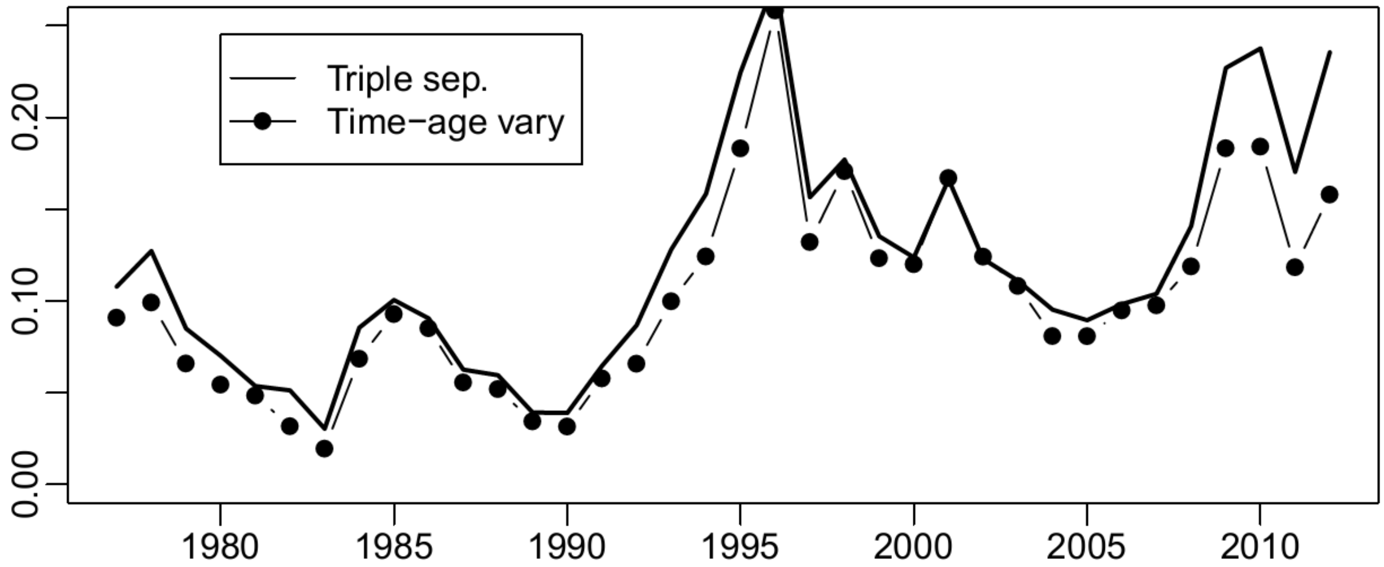


Time-age varying

-lnLike 106

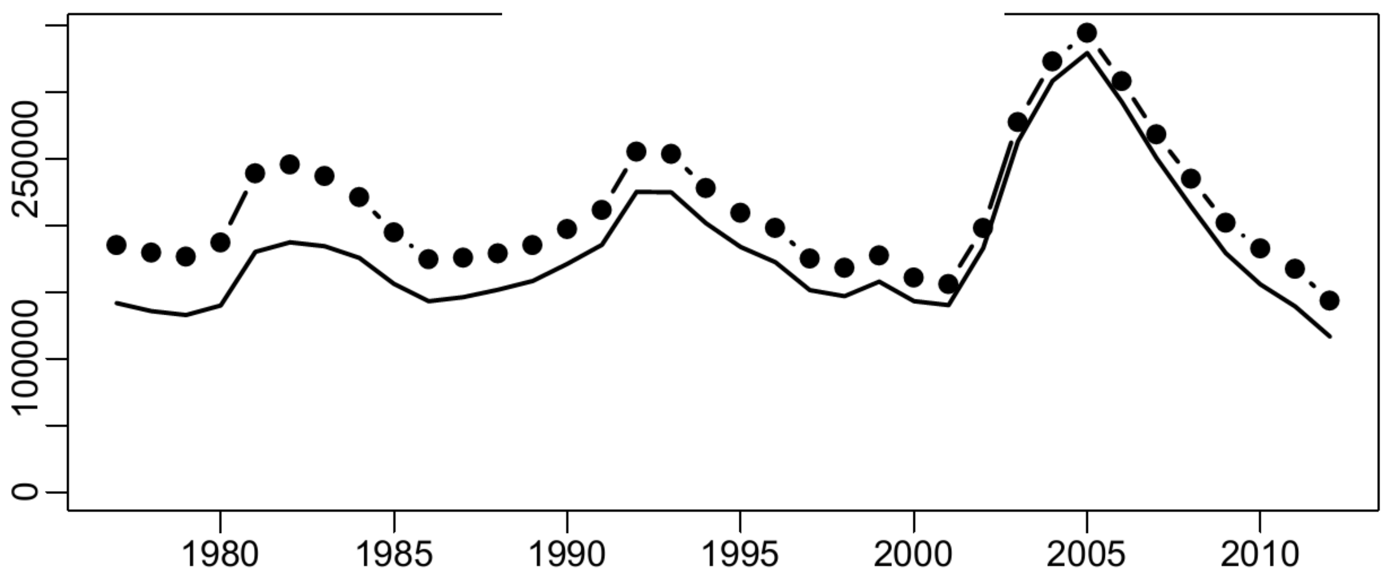


F_{bar}



Triple sep.
Time−age vary
0.00
0.10
0.20
1980
1985
1990
1995
2000
2005
2010

SSB



0
100000
250000
1980
1985
1990
1995
2000
2005
2010

Overview

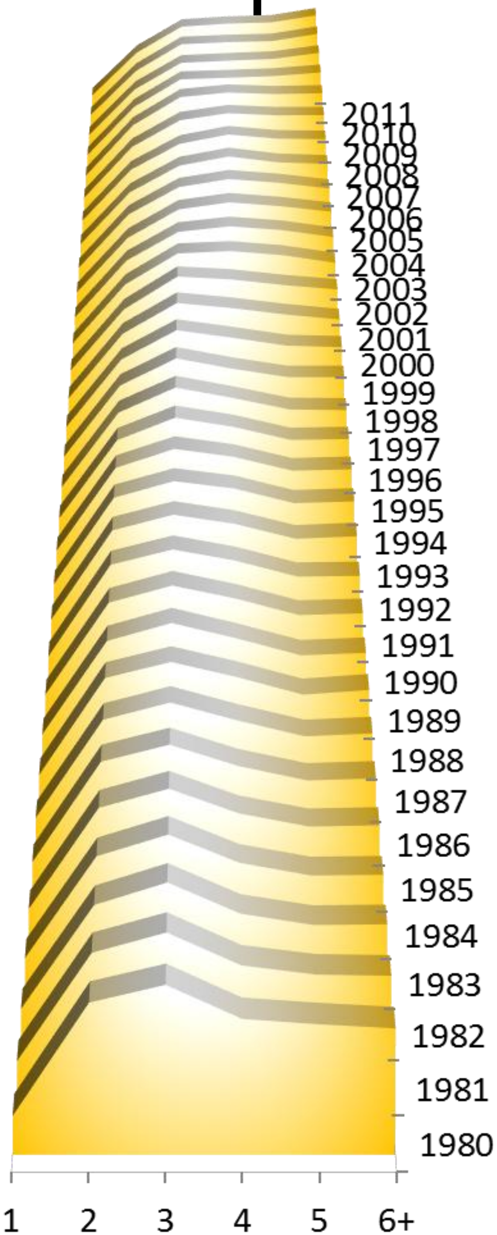
- Which assessment details and process-error assumptions that matter the most?
  - Selectivity
  - Natural mortality
  - Catchability
    - Survey and CPUE

- Application and developments

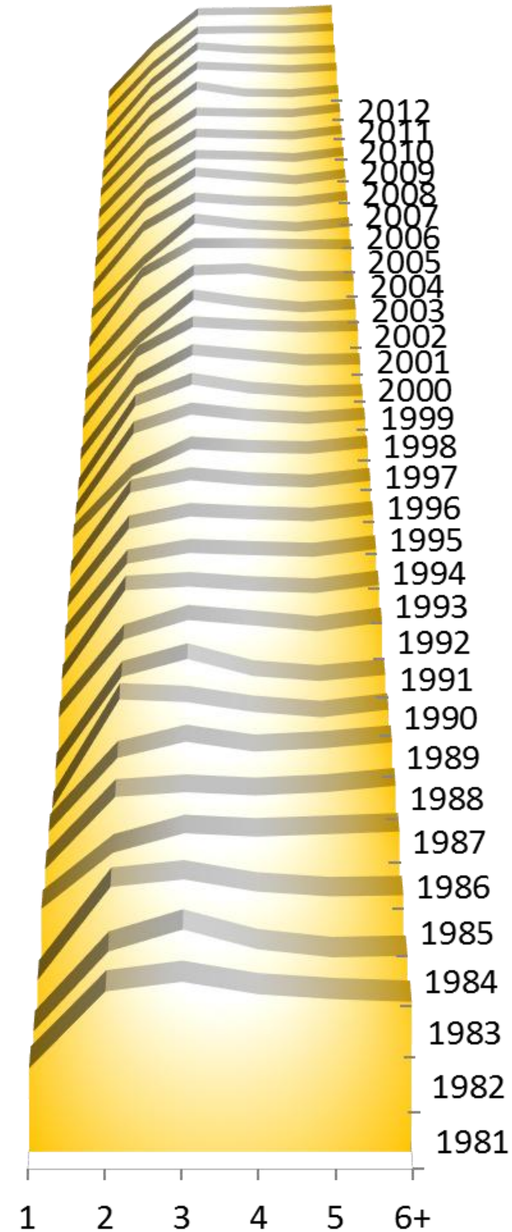
North Sea cod with random walk in M

State-space RE (SAM)

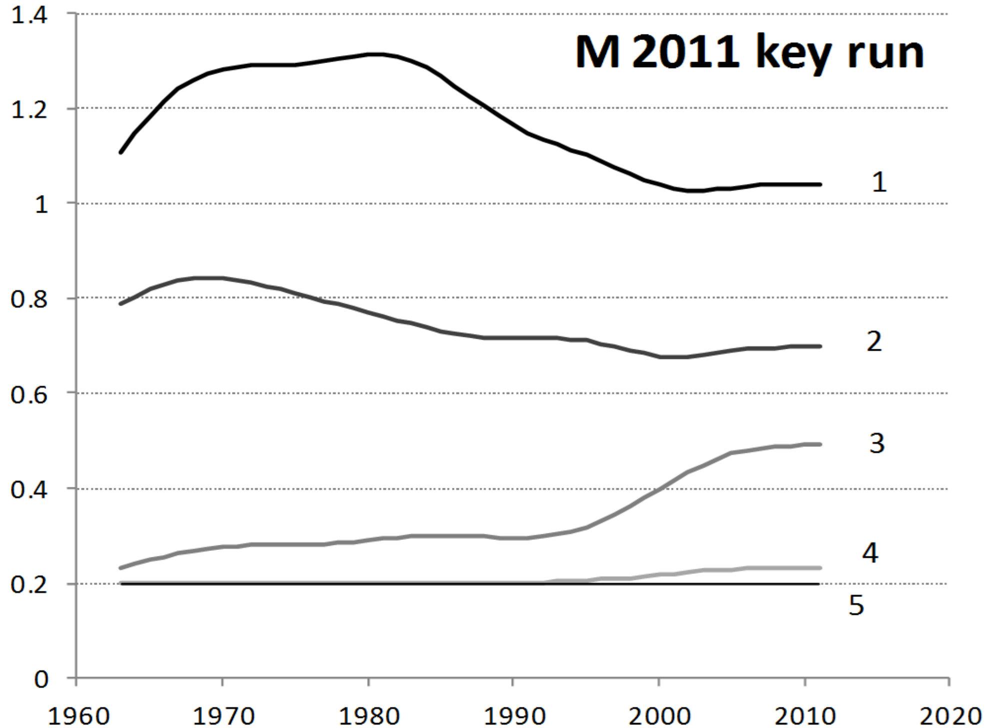
AMAK



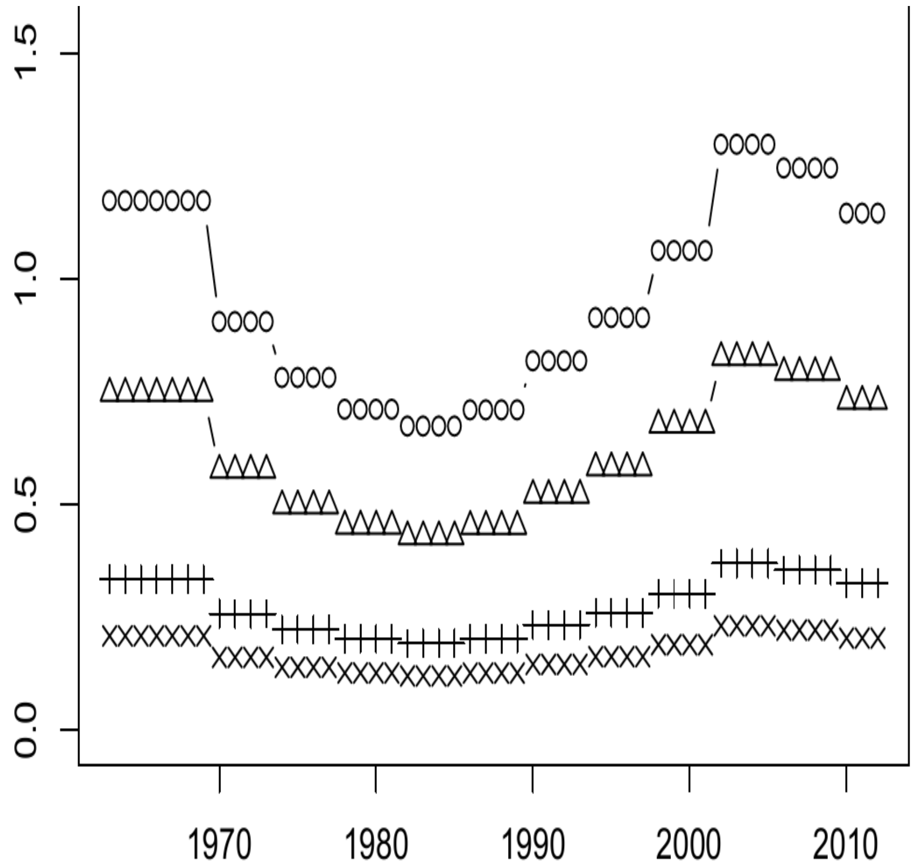
Selectivity over time



North Sea cod with random walk in M

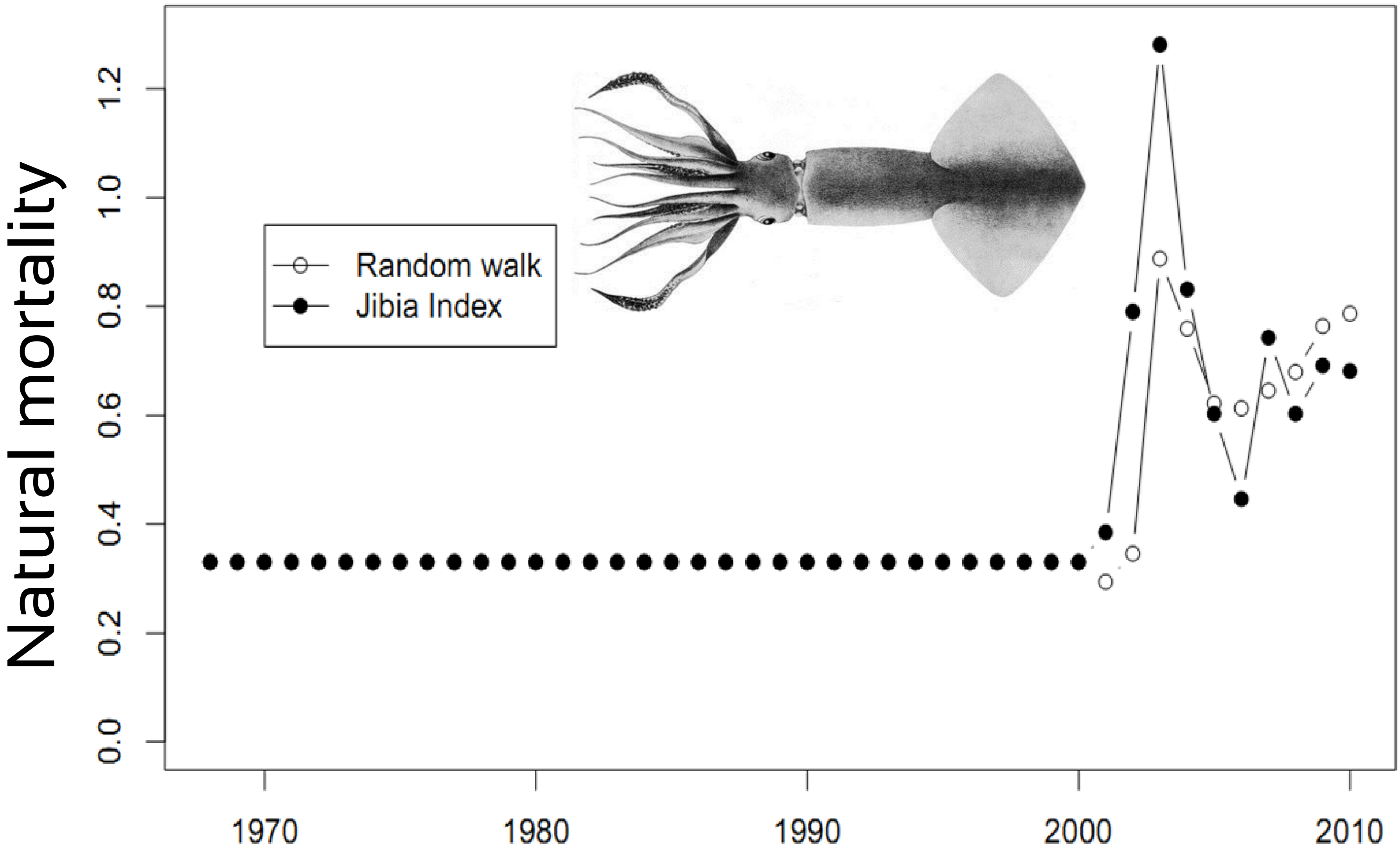


Multi-species model



Random walk

Chilean Common hake (*Merluccius gayi*)



Gatica-Molina et al. (In prep.) INPESCA, Talcahuano, Chile

Conclusions

- Accounting for process errors should be included for management parameters
  - Either directly (e.g., formally risk-averse) or
  - Developing operating model for management strategy evaluation
- Objective methods for model selection should include retrospective (including cross-validation) evaluations
- Approach here useful for quick evaluation of information content of data
  - E.g., if there is a reflection of ecosystem effects

Thanks!

A survey/exploitation vector autoregressive model for use in marine fishery stock assessment

Grant Thompson

Alaska Fisheries Science Center

Two problems

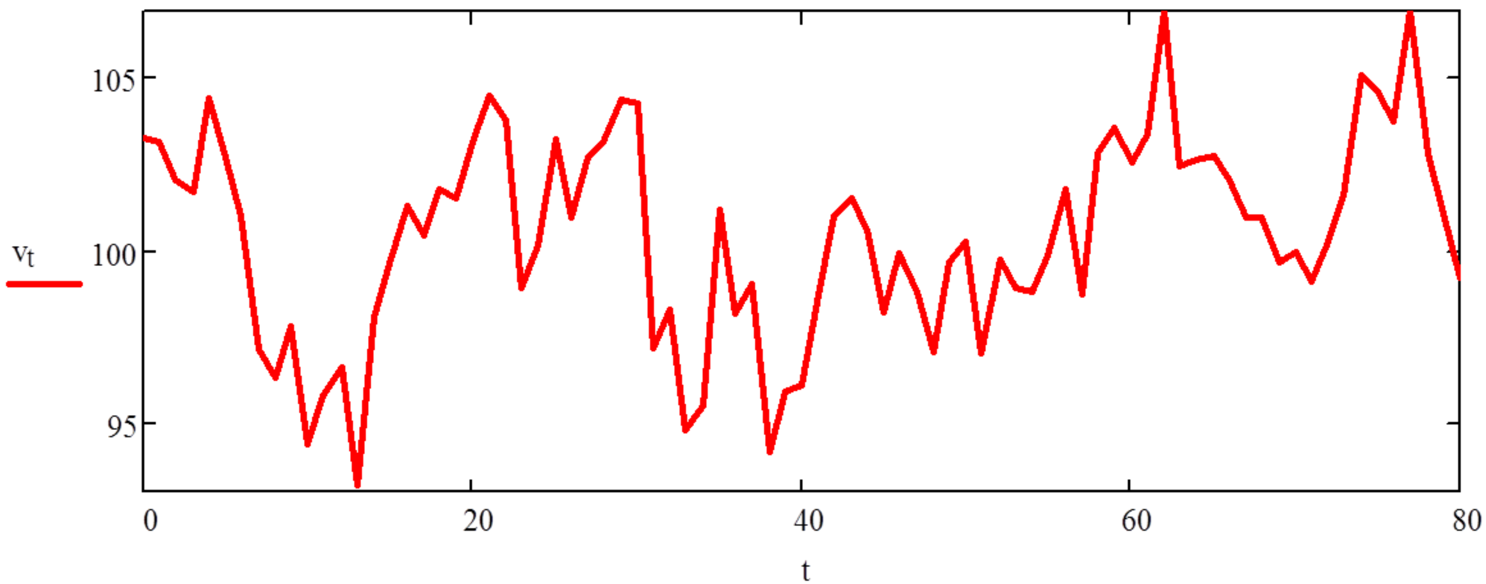
- Conventional "data-rich" assessment models contain some notoriously hard-to-estimate parameters, e.g.:
  - Natural mortality rate (M)
  - Survey catchability
  - Stock-recruitment "steepness"
- Conventional "data-moderate" assessment methods often imply some very strong assumptions, e.g.:
  - Exploitable biomass = survey biomass
  - Projected expl. biomass = current expl. biomass
  - $F_{MSY} = M$

A possible answer to both problems: SEVAR

- Stands for "survey/exploitation vector autoregressive"
- Uses survey index (b) and catch (c) data only
- Linear time series with p lags in two state variables:
  - Relative biomass $r \equiv b/b_{ave}$
  - Exploitation rate $u \equiv c/b$
- Even though survey index may be relative, absolute catch recommendations can be developed, using:
  - $c = b \times (c/b)$
- u_{MSY} estimated, no parameter values assumed

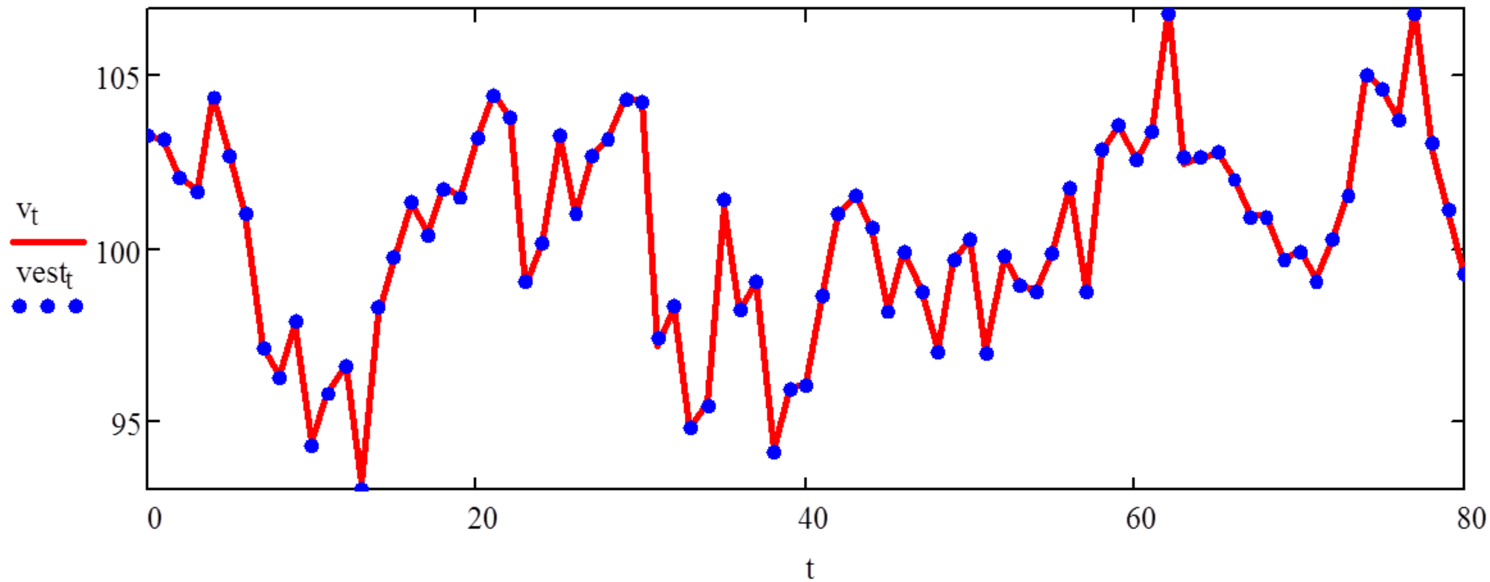
“But population dynamics are nonlinear”

- Here is a time series of stock sizes from a model with randomly varying exploitation rate, a Ricker SRR, and no process error or observation error:



Can a linear model mimic nonlinear dynamics?

- Here is the fit to the same data from a linear model with an optimized number of lags (=3, by AIC):



- $R^2 = 0.999$

State-space form, part 1

- Transition equation:

$$\begin{bmatrix} r_t \\ u_t \end{bmatrix} = \sum_{k=1}^{p} \left(\Gamma_k \cdot \begin{bmatrix} r_{t-k} \\ u_{t-k} \end{bmatrix} \right) + \phi + \varepsilon pro_t$$

  - where

$$\varepsilon pro_t \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Sigma pro \right)$$

  - and where $\Gamma_k = 2 \times 2$ matrix, $\phi = 2 \times 1$ vector, and $\Sigma pro = 2 \times 2$ matrix

Develop r isocline from transition equation

- If r is in equilibrium, transition equation for r becomes:

$$r_{equ} = \left(\sum_{k=1}^{p} (\Gamma_k)_{1,1} \right) \cdot r_{equ} + \left(\sum_{k=1}^{p} (\Gamma_k)_{1,2} \right) \cdot u + \phi_1$$

- Solving the above for r_{equ} gives a linear isocline in u:

$$r_{equ}(u) = \frac{\left(\sum_{k=1}^{p} (\Gamma_k)_{1,2} \right) \cdot u + \phi_1}{1 - \sum_{k=1}^{p} (\Gamma_k)_{1,1}}$$

- Meaning: $r_{MSY} = r_0/2$, $u_{MSY} = u_{ext}/2$; like Schaefer

State-space form, part 2

- Observation equation:

$$\begin{bmatrix} robs_t \\ uobs_t \end{bmatrix} = D_t \cdot \begin{bmatrix} r_t \\ u_t \end{bmatrix} + \varepsilon obs_t$$

  - where

$$\varepsilon obs_t \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \Sigma obs_t \right)$$

  - and where $D_t = 2\times2$ identity matrix or 2×2 zero matrix, and $\Sigma obs_t = 2\times2$ matrix

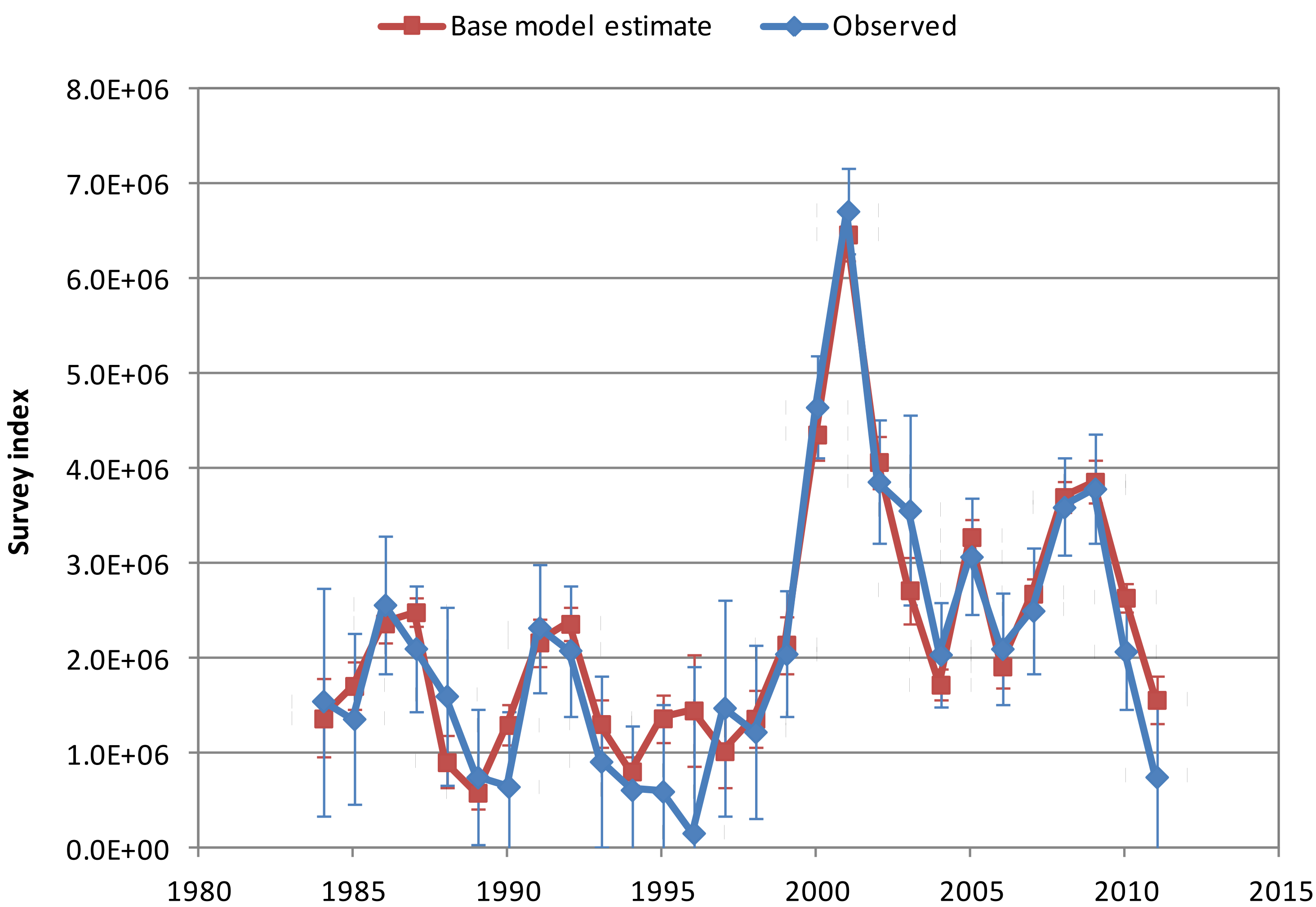
Parameters

- Total number of parameters = $4 \times (p+1)$
  - $\Gamma \rightarrow 2 \times 2 \times p$, $\phi \rightarrow 2$, $\Sigma pro \rightarrow 2$
  - Off-diagonal elements of Σpro assumed = 0
- Number of lags p is a “pseudo-parameter”
  - Fixed for a given run, profile across runs
  - Choose optimal value by BIC
- Observation error covariance Σobs_t assumed known
  - Follows from standard errors of observed c and b and the relationship between b and c/b

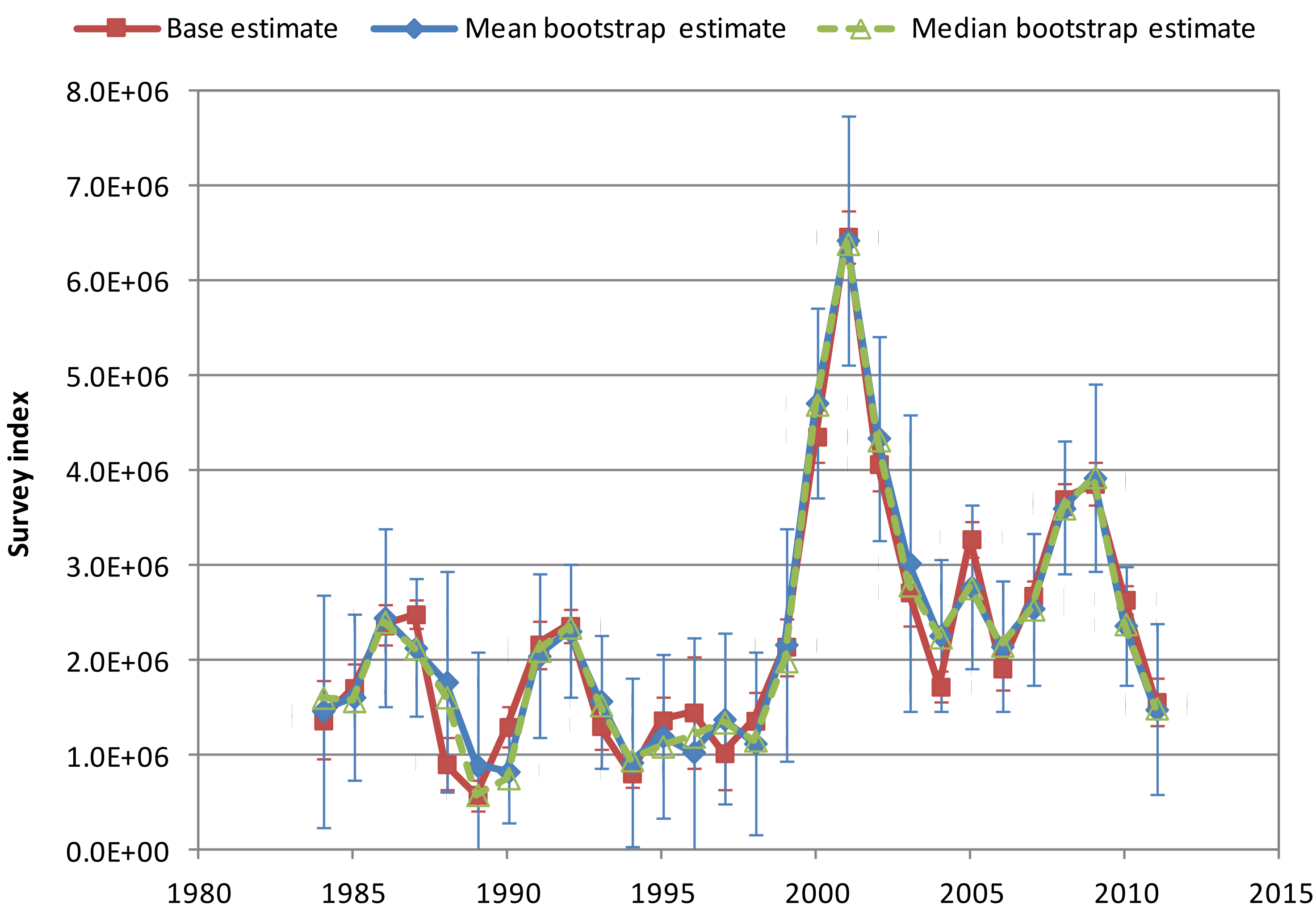
Estimation

- Problem: estimation of parameters in state-space models can be difficult
  - Combination of process *and* observation error
- For a linear model with only one lag ($p=1$), the Kalman filter gives the correct marginal likelihood after the states have been integrated out
  - But we are allowing $p>1$
- A neat trick: by stacking and augmenting matrices in a certain way, the 2-dimensional state space model with p lags can be transformed into a $2p$-dimensional model with only *one* lag, with the same number of parameters

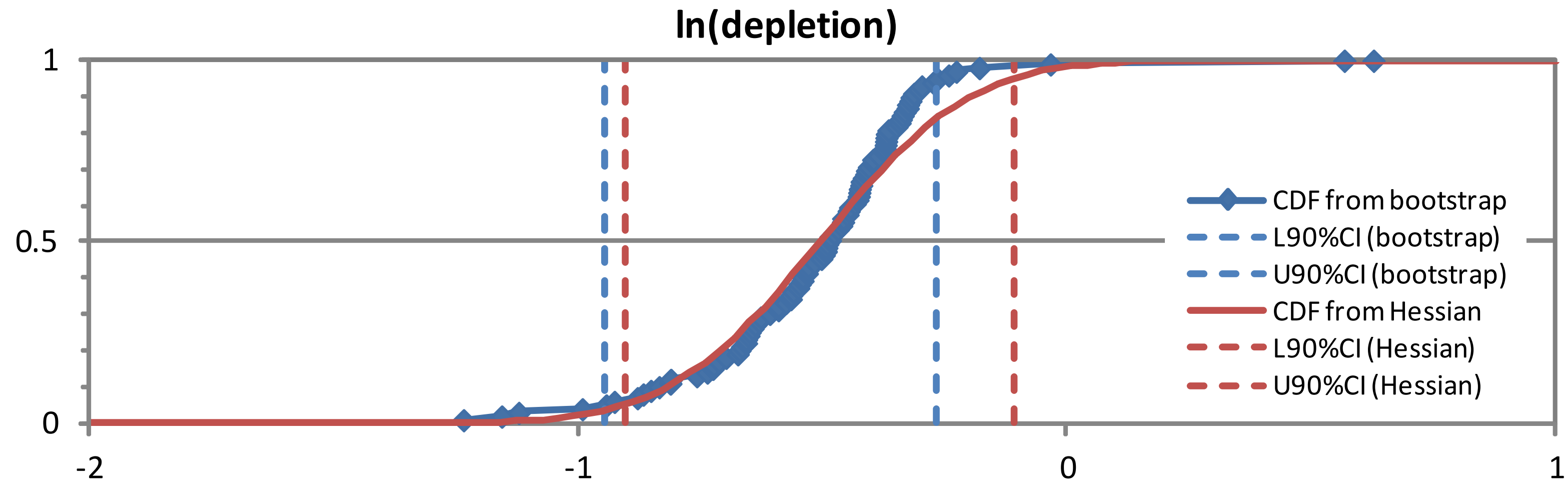
South African anchovy: fit to survey index

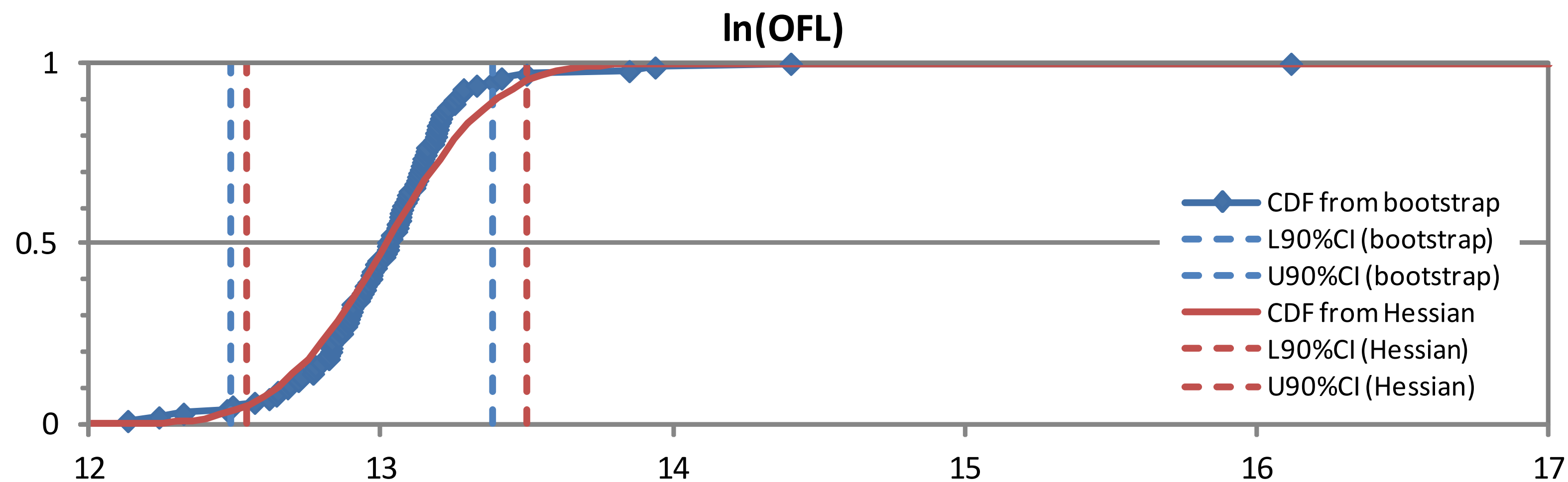


SA anchovy: observation error bootstrap



SA anchovy: CDFs of ln(depletion) and ln(OFL)





Future directions

- Need to determine whether it actually works
  - Simulations conducted so far (with *very* small sample size) indicate that SEVAR works at least as well as a full age-structured model
  - Seemed to perform about as well as most age-structured models at the SISAM workshop
- Include routines for model averaging (across p)
- Allow parameters to change between time blocks
- Make the code usable by other people

Addressing challenges in single species assessments via a simple state-space assessment model.

Anders Nielsen & Casper W. Berg
an@aqua.dtu.dk

DTU Aqua
National Institute of Aquatic Resources

Features of deterministic models

+ Super fast to compute
+ Fairly simple to explain the path from data to stock numbers (especially VPA)
– Difficult to explain why it works (converges), and what a solution mean
– These algorithms contain many ad-hoc settings (e.g. shrinkage, tapered time weights) that makes them less objective
– No quantification of uncertainties within model
? What exactly is the model
    - The assumptions are difficult to identify and verify
    - With no clearly defined model more ad-hoc methods are needed to make predictions
– No framework for comparing models (different settings)

Features of full parametric statistical models

+ Acknowledges observation noise
+ All model assumptions are transparent
+ Different model assumptions can be tested against each other (e.g. is $F_5 = F_6$?)
+ Different data sources can be included and correctly and objectively weighted
+ Estimation of uncertainties are an integrated part of the model

– Trade-off between the number model parameters and flexibility of the model (e.g. $F_{a,y}$ vs. $F_{a,y} = S_a f_y$)
– Too often ad-hoc solutions are needed (e.g. fixing variance parameters, or setting fixed penalties)
– More advanced software needed (ADMB!)

State-space assessment models

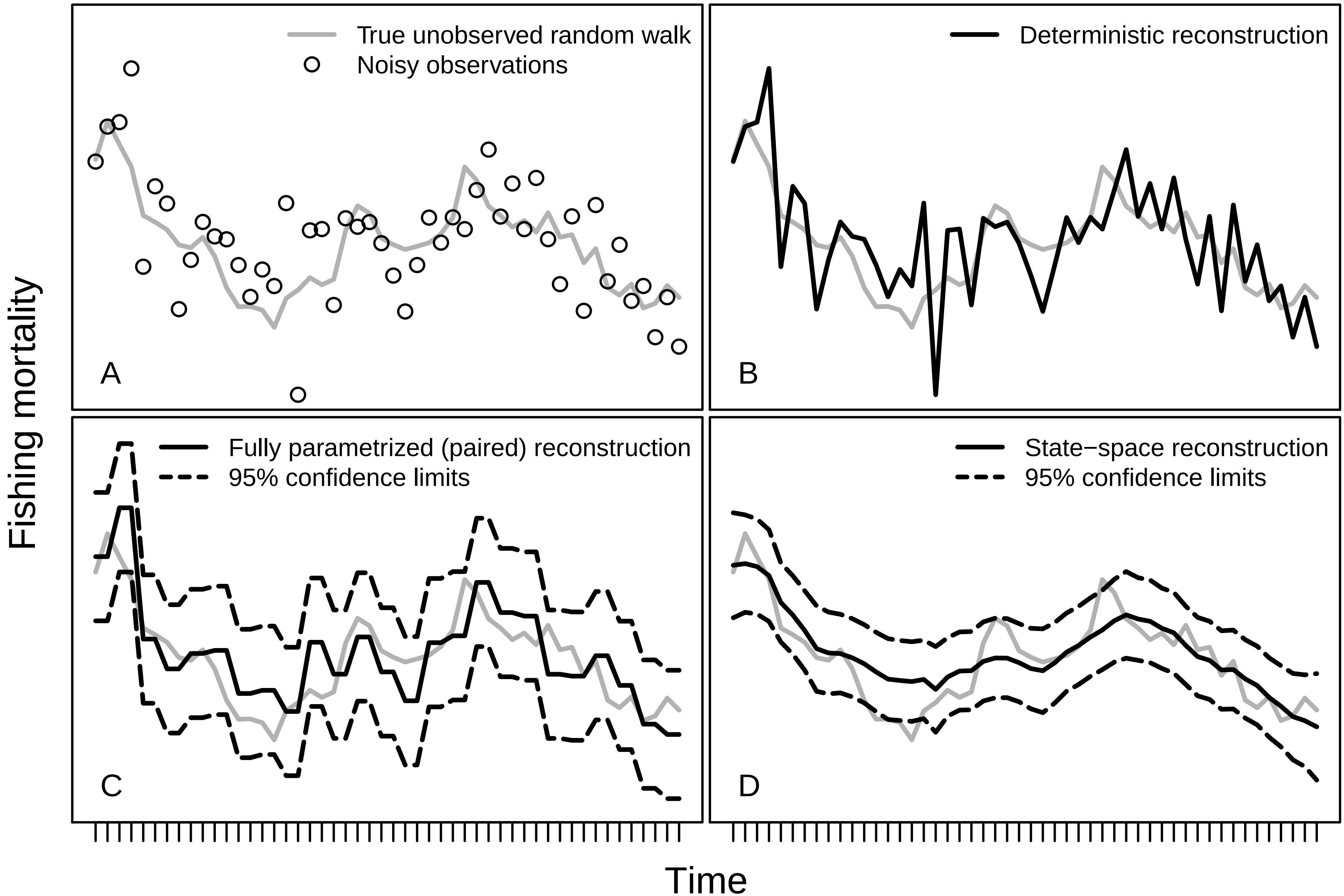
- This model class[a] is used in most other quantitative fields
- It is a very useful extension to full parametric statistical models.
- Introduced for stock assessment by Gudmundsson (1987,1994) and Fryer (2001).
- The reason state-space models have not been more frequently used in stock assessment is that software to easily handle these models has not been available
- Can give very flexible models with low number of model parameters
- For instance we can include things like:

$$F_{3,y} \text{ is a random walk with yearly variance } \sigma^2$$

- Importantly σ^2 is a model parameter estimated in the model.

[a] a.k.a. random effects models, mixed models, latent variable models, hierarchical models, ...

Illustration of the three types of models



Model

States are the random variables that we don't observe ($N_{a,y}$, $F_{a,y}$)

$$\begin{pmatrix} \log(N_y) \\ \log(F_y) \end{pmatrix} = T \begin{pmatrix} \log(N_{y-1}) \\ \log(F_{y-1}) \end{pmatrix} + \eta_y$$

Observations are the random variables that we do observe ($C_{a,y}$, $I^{(s)}_{a,y}$)

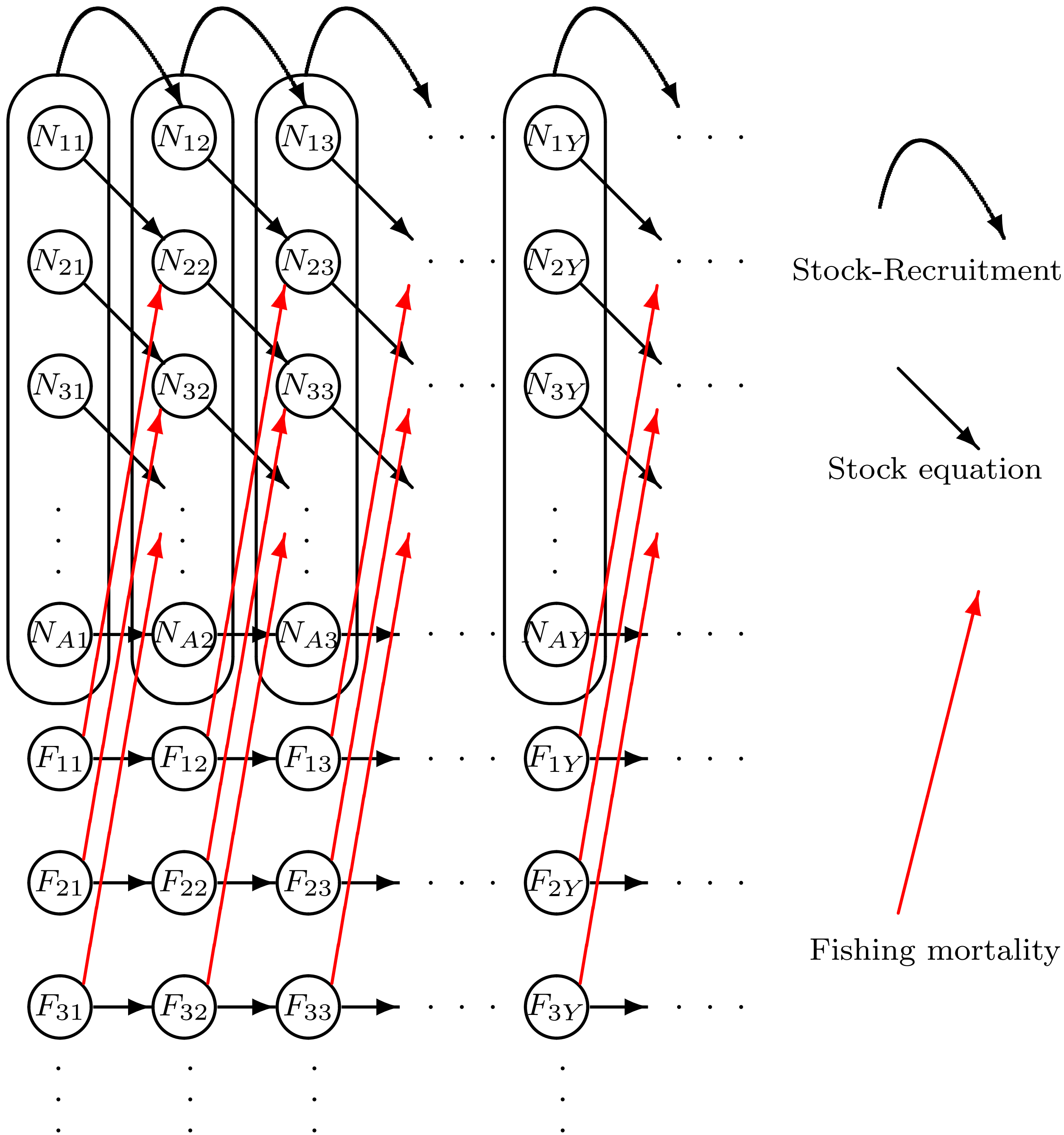
$$\begin{pmatrix} \log(C_y) \\ \log(I^{(s)}_y) \end{pmatrix} = O \begin{pmatrix} N_y \\ F_y \end{pmatrix} + \varepsilon_y$$

Model and parameters are what describes the distribution of states and observations through T, O, η_y, and ε_y.

Parameters: Survey catchabilities, S-R parameters, process and observation variances.

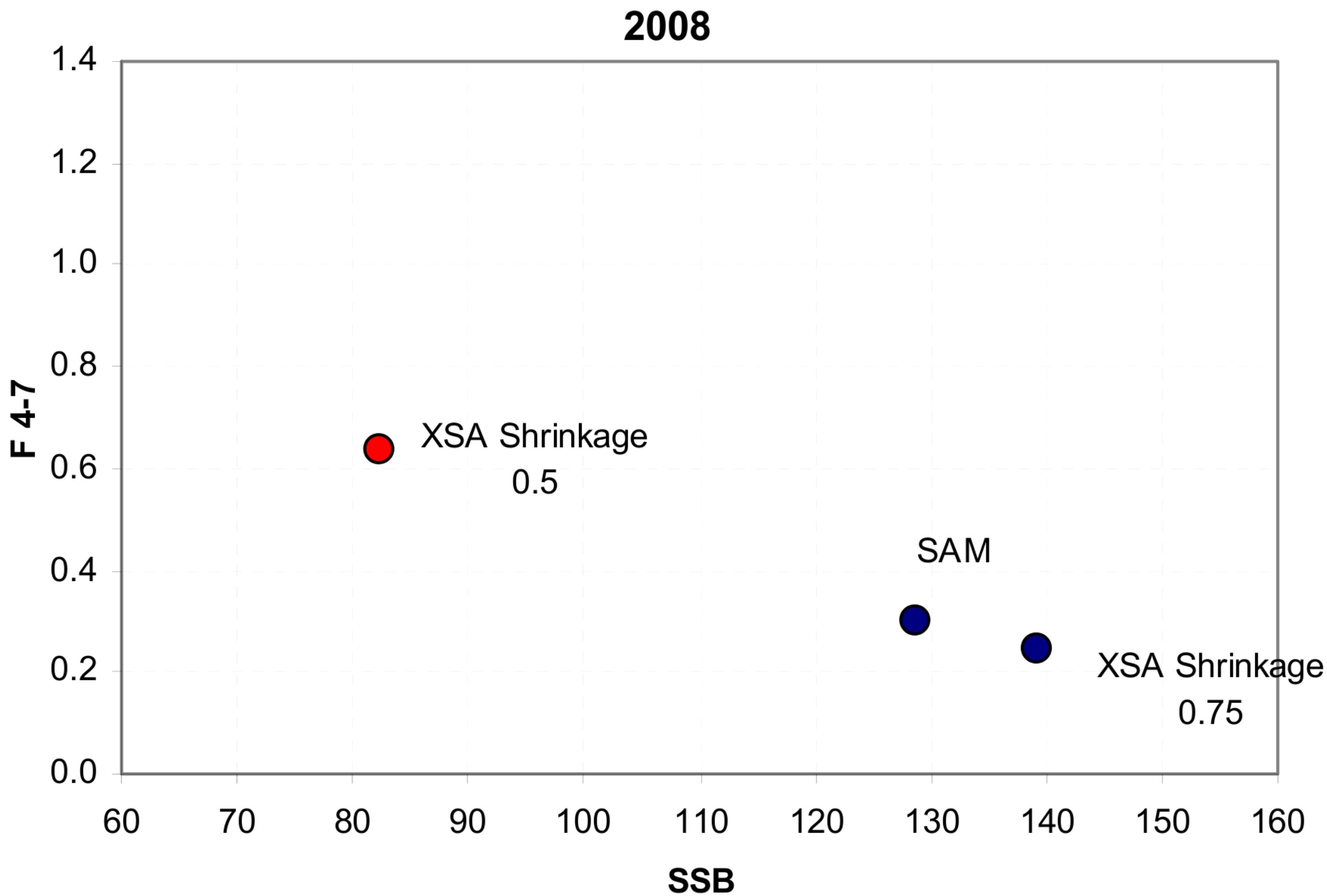
All model equation are as expected:

- Standard stock equation
- Standard stock recruitment (B-H, Ricker, or RW)
- Standard equations for total landings and survey indices



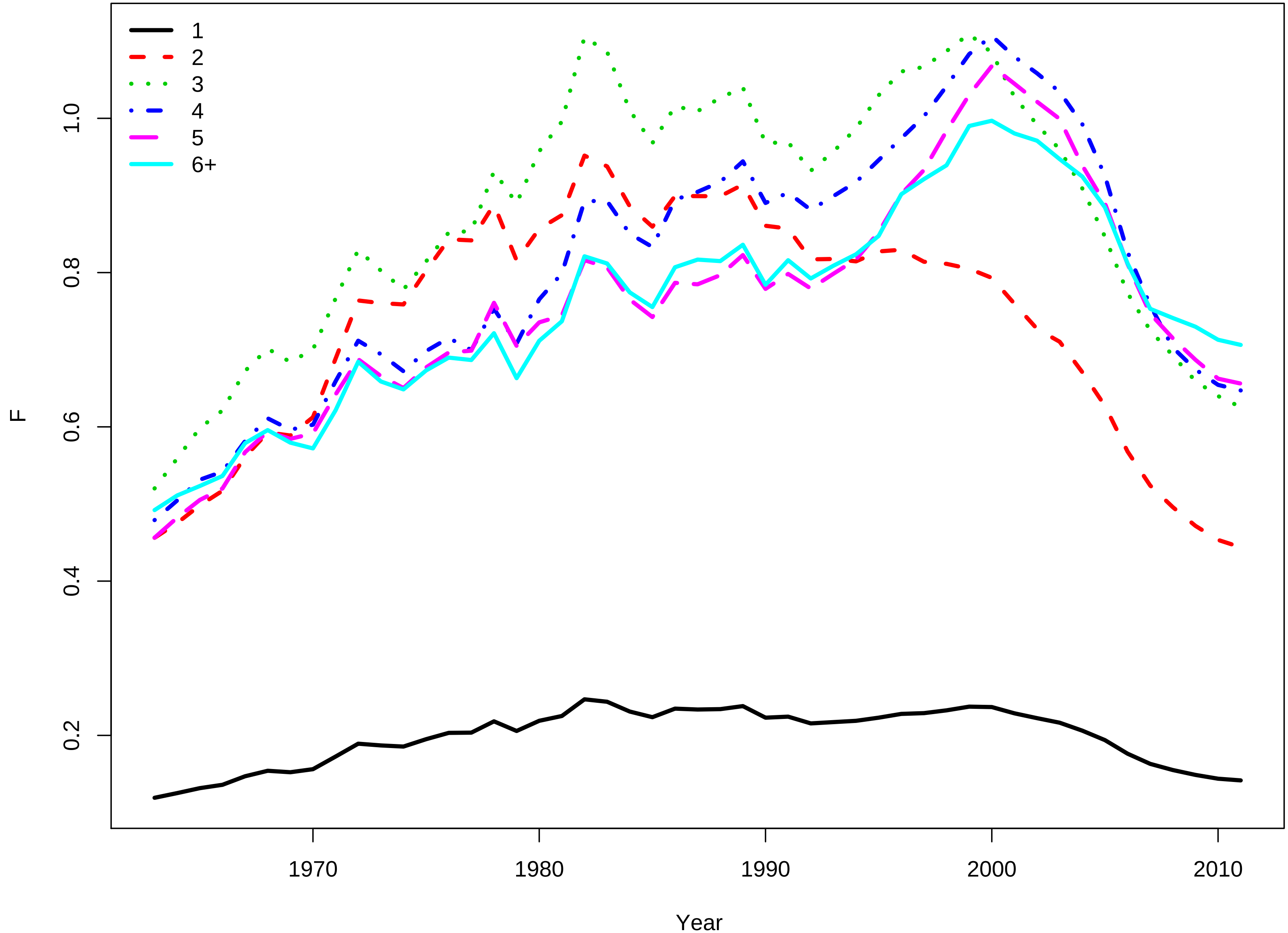
N_{11} N_{12} N_{13} N_{1Y}
N_{21} N_{22} N_{23} N_{2Y}
N_{31} N_{32} N_{33} N_{3Y}
N_{A1} N_{A2} N_{A3} N_{AY}
F_{11} F_{12} F_{13} F_{1Y}
F_{21} F_{22} F_{23} F_{2Y}
F_{31} F_{32} F_{33} F_{3Y}
Stock-Recruitment
Stock equation
Fishing mortality

Avoiding ad-hoc choices — Eastern Baltic Cod



- Using the State-space Assessment Model (SAM) gives us an objective criteria

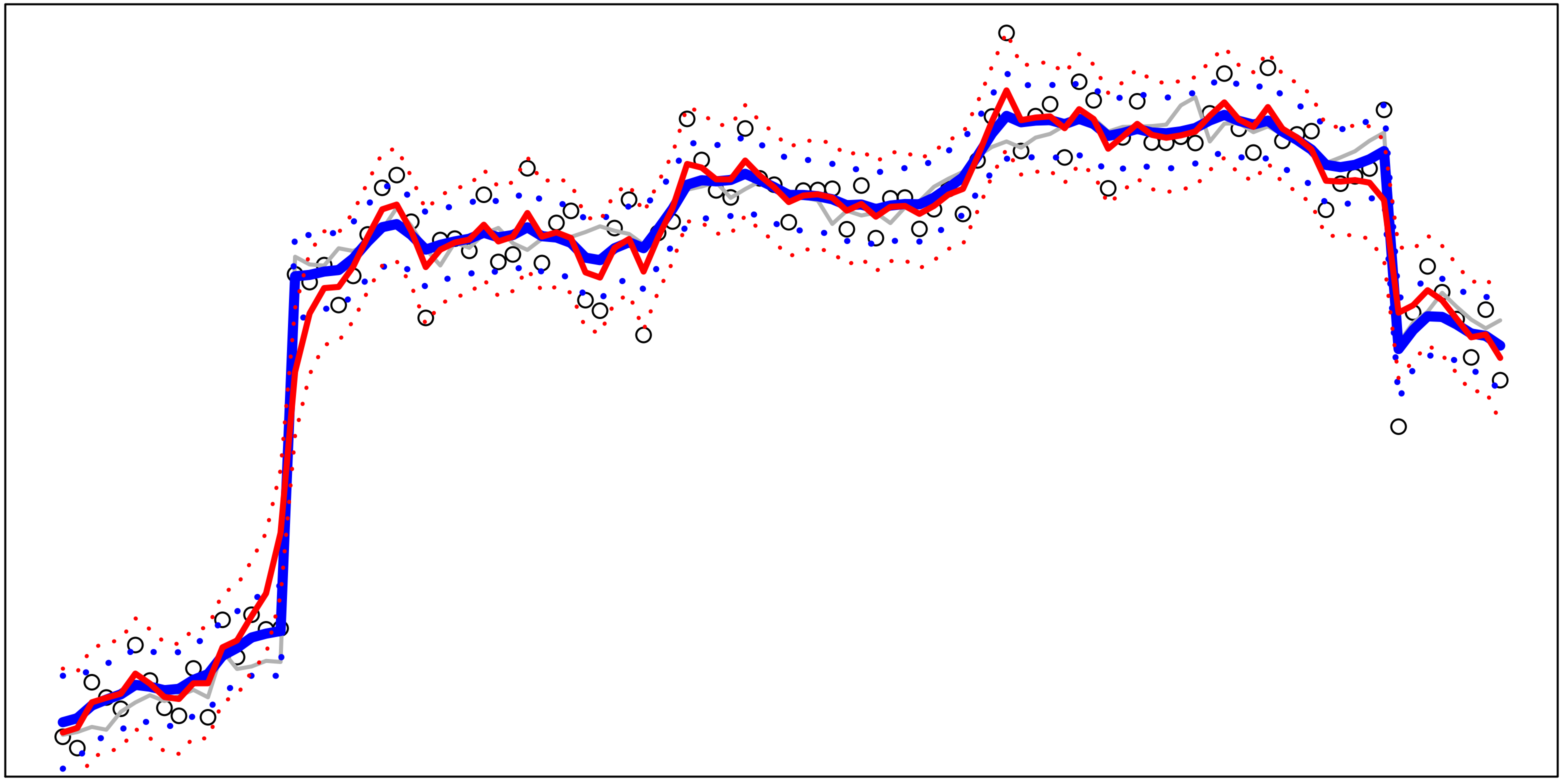
Evolving selectivity — North Sea Cod



From Fryer's listed disadvantages

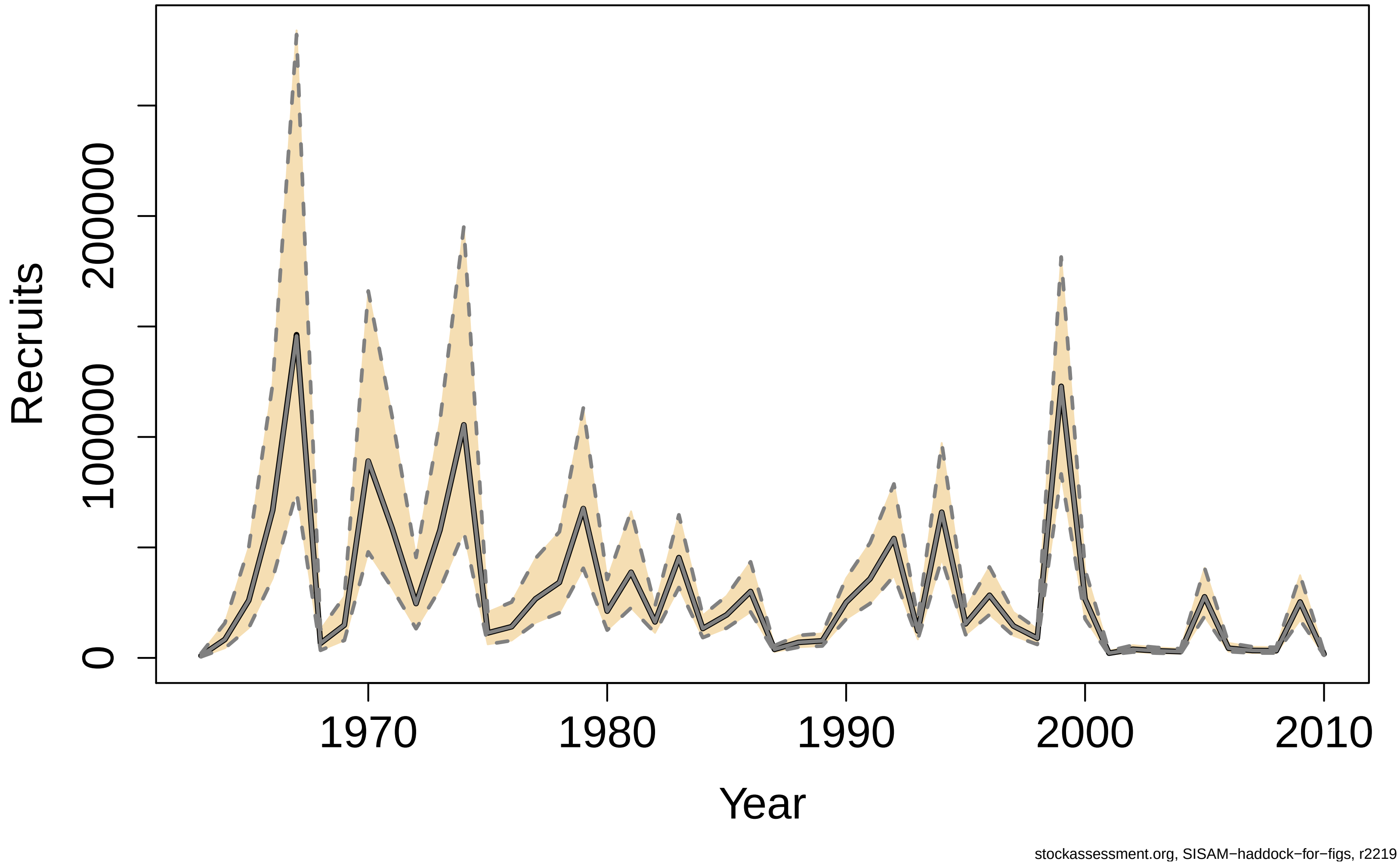
- Requires normally distributed errors. **No, but they are still convenient.**
- Requires linear approximation of non-linear equations. **Not anymore.**
- There is some arbitrariness in the starting values. **Not anymore.**
- The likelihood can be very flat. **No change.**
- Maximum likelihood estimation can take a long time. **1-2 minutes on my laptop.**
- Initial coding is hard. **ADMB makes it easier**
- Favours status quo.

Robustifying



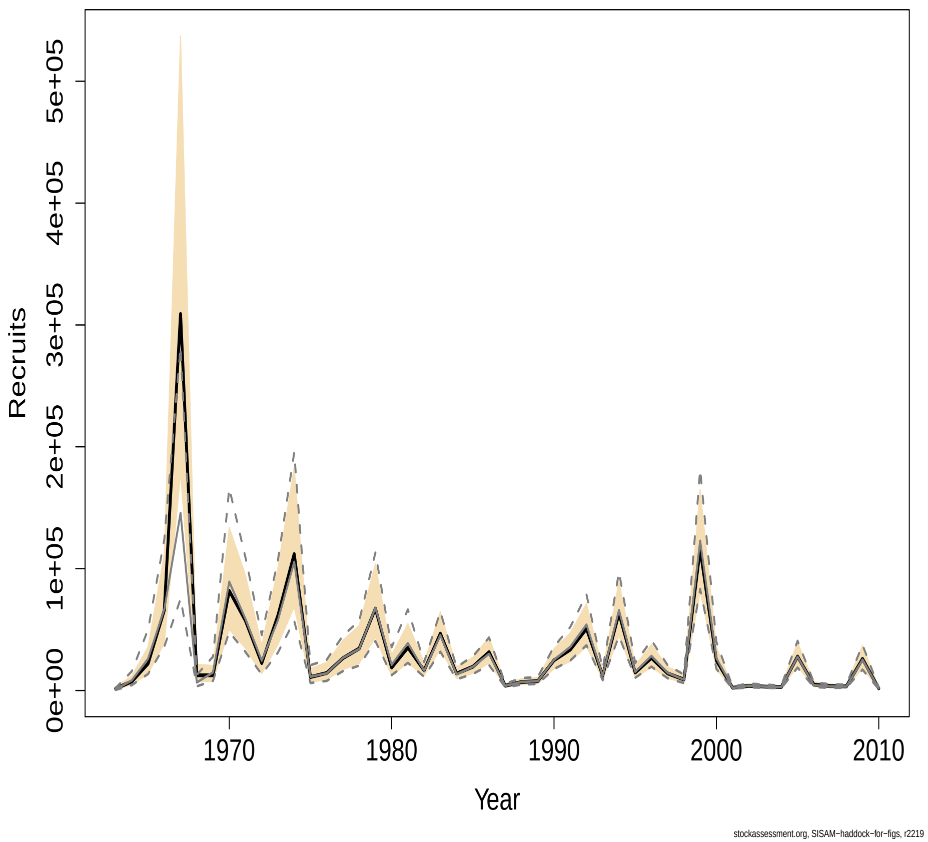
- In the standard model $\Delta \log F_y = \log F_y - \log F_{y-1}$ is assumed Gaussian
- Instead use a mixture, such as: $\Delta \log F_y \sim (1-p)\mathbf{N}(.,.) + p\mathbf{t}_1(.,.)$
- Same technique can be used to robustify w.r.t. observation outliers or recruitment spikes.

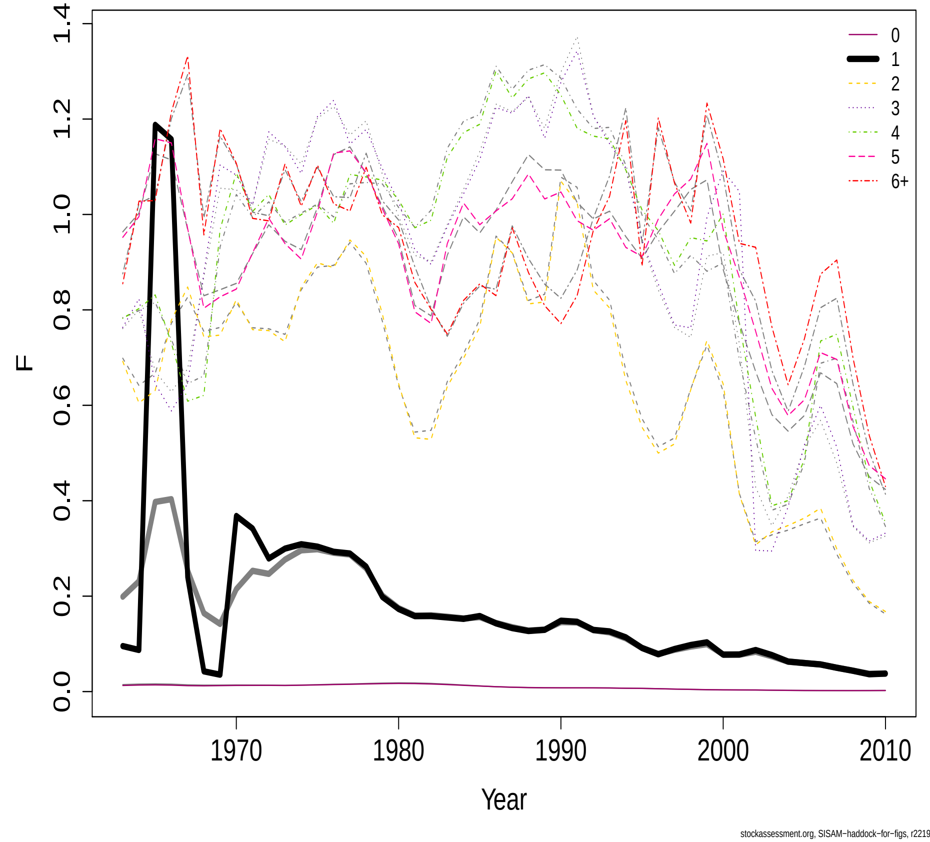
Robustifying w.r.t. recruitment spikes (Haddock)



- Comparing Gaussian (gray) with robust - no visual difference.
- Gaussian process assumptions were not restricting recruitment.

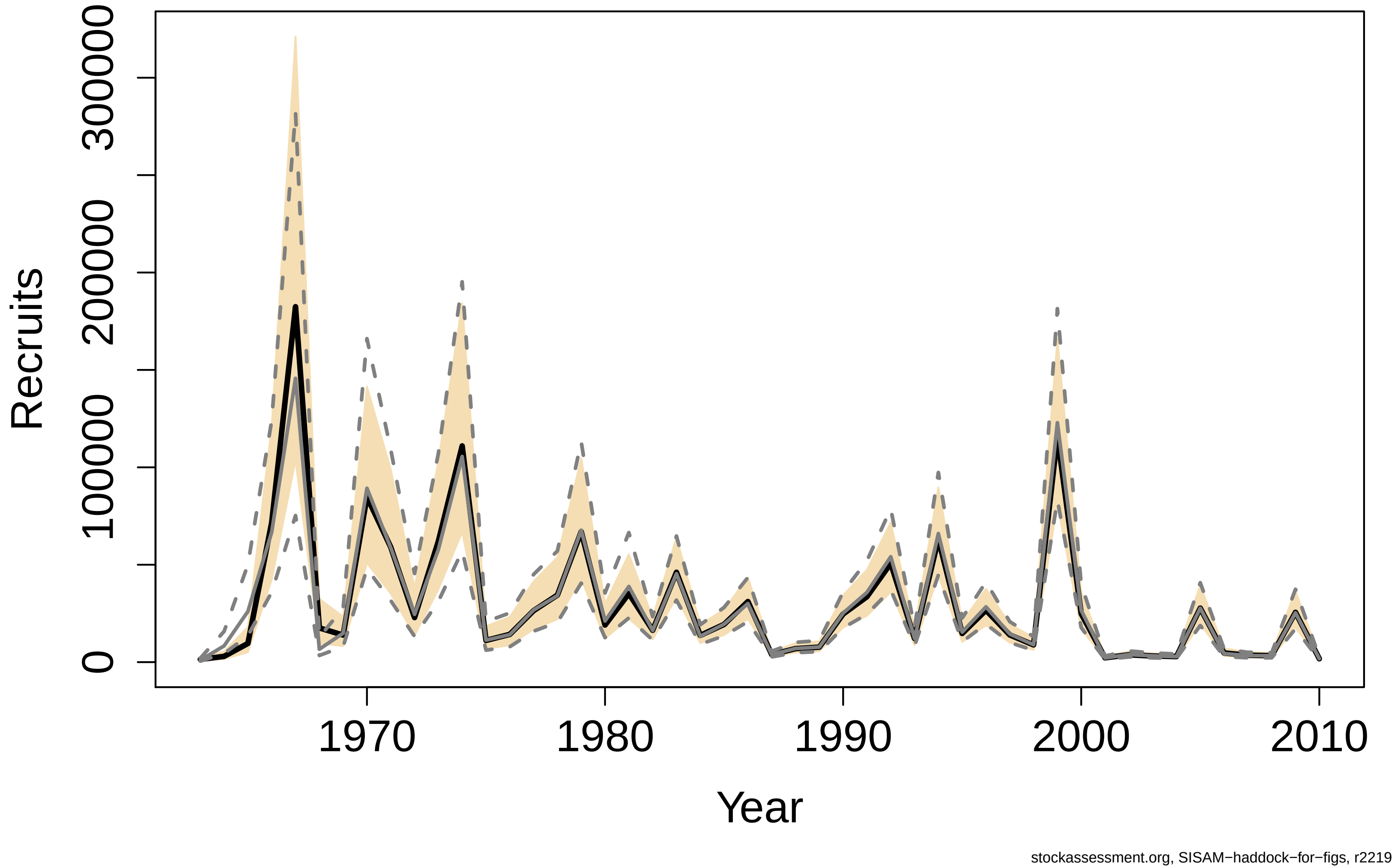
Robustifying w.r.t. Fishing mortality (Haddock)





- Implies a big change in one years recruitment
- To accommodate the change in R, $F_{a=1}$ changed a lot in those years

Robustifying w.r.t. observed catch (Haddock)



- Makes the model tolerant of outliers

Summary

- State-space assessment model is a valid alternative when:
  - Catches cannot be considered know without error
  - Quantification of uncertainties are needed
  - Ad-hoc specifications are problematic
  - Parametric structures are considered too rigid
  - The number of model parameters are worrying
- Robustifying is a useful techniques for:
  - Making the model tolerant w.r.t. outliers
  - Identifying problematic model assumptions
  - Allowing "big jumps"

1.06 Evaluating predictive power of VPA and SCAA models when natural mortality is non-stationary

Sean Cox
Sch. of Res & Environmental Mgmt
Simon Fraser University
Burnaby, BC Canada

Doug Swain
Gulf Fisheries Centre
Fisheries and Oceans Canada
Moncton, NB Canada

Non-stationarity in natural mortality rates of Atlantic cod: contrasting estimation performance of virtual population and statistical catch-age models

Sean Cox
Sch. of Res & Environmental Mgmt
Simon Fraser University
Burnaby, BC Canada

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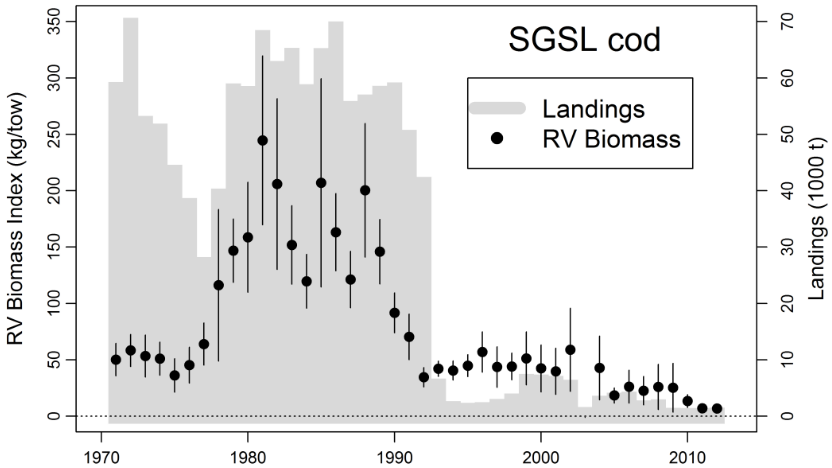
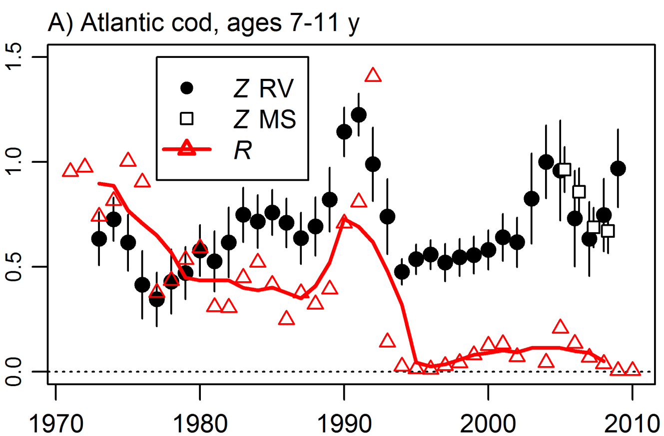
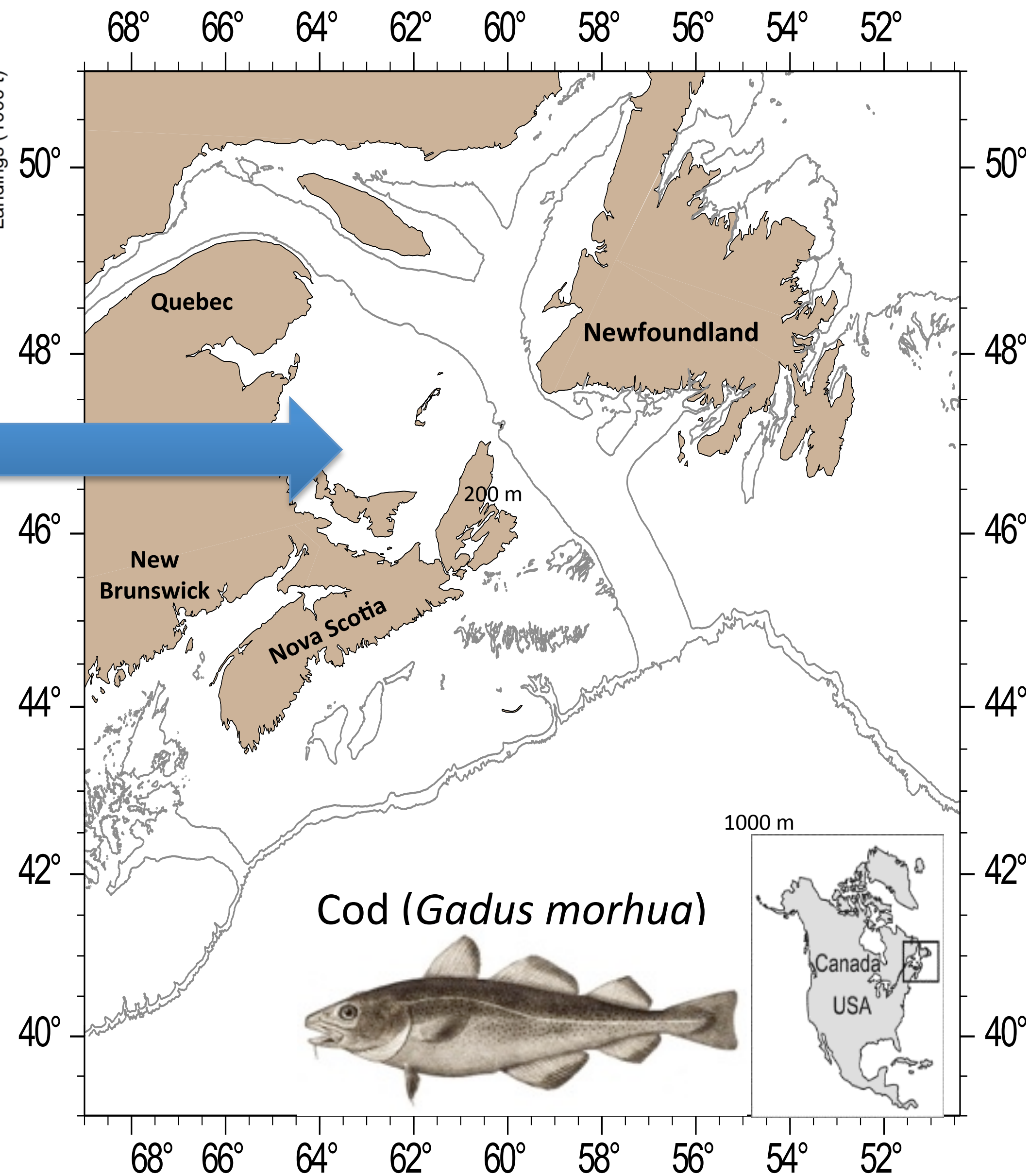
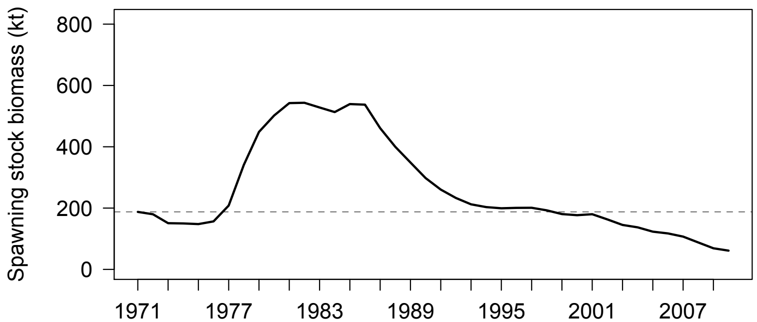


S. Gulf of St Lawrence

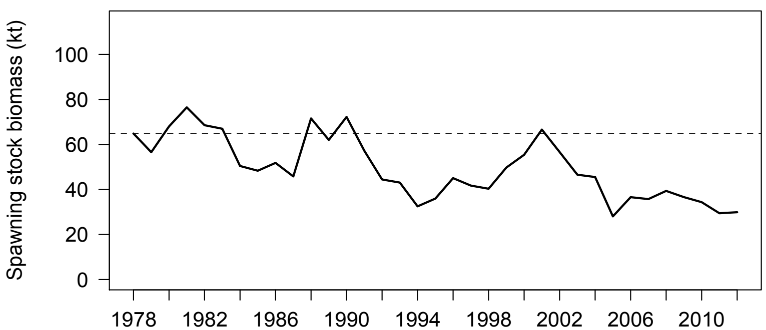




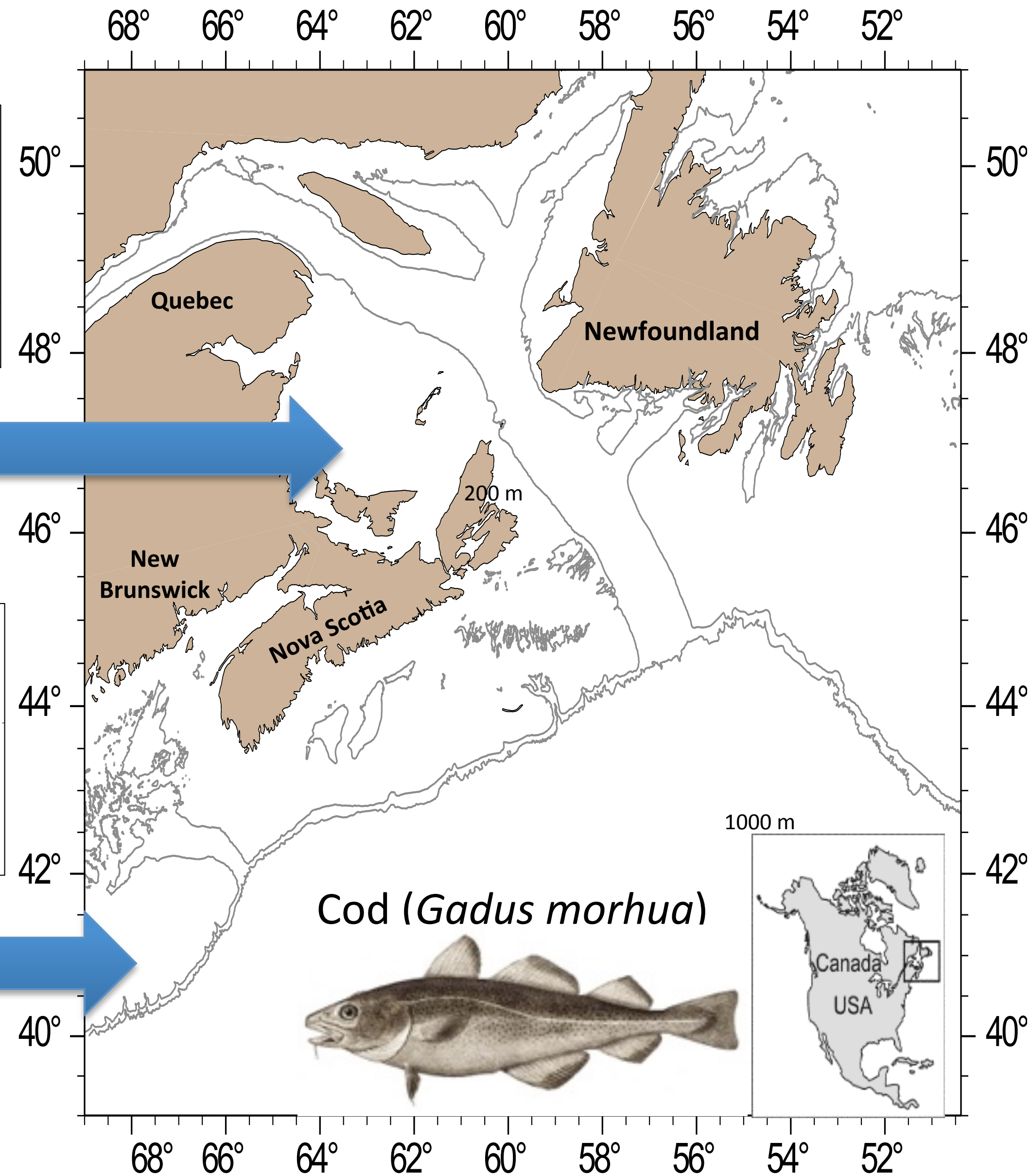
Study populations: SGSL and EGB cod



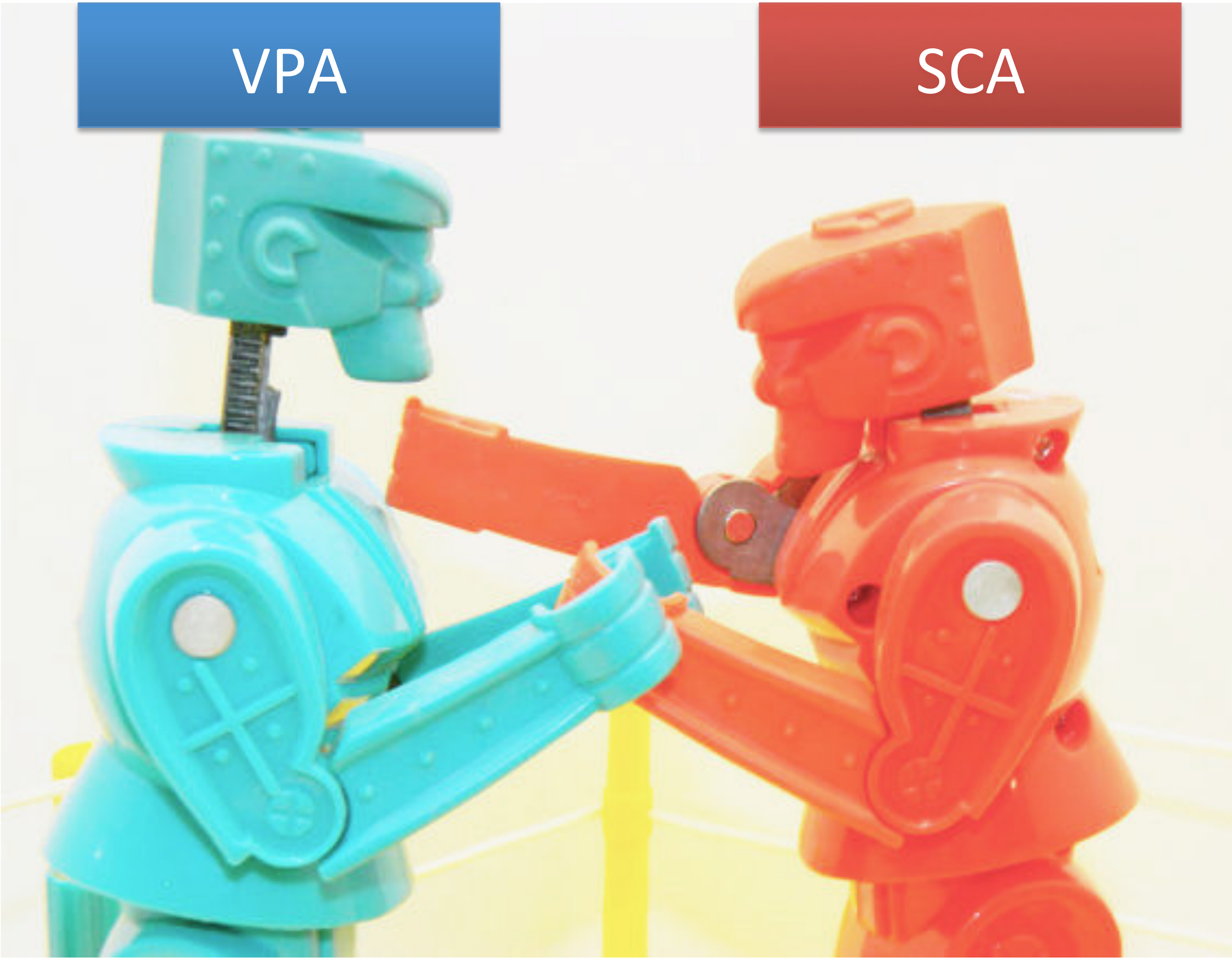
S. Gulf of St Lawrence



Eastern George's Bank



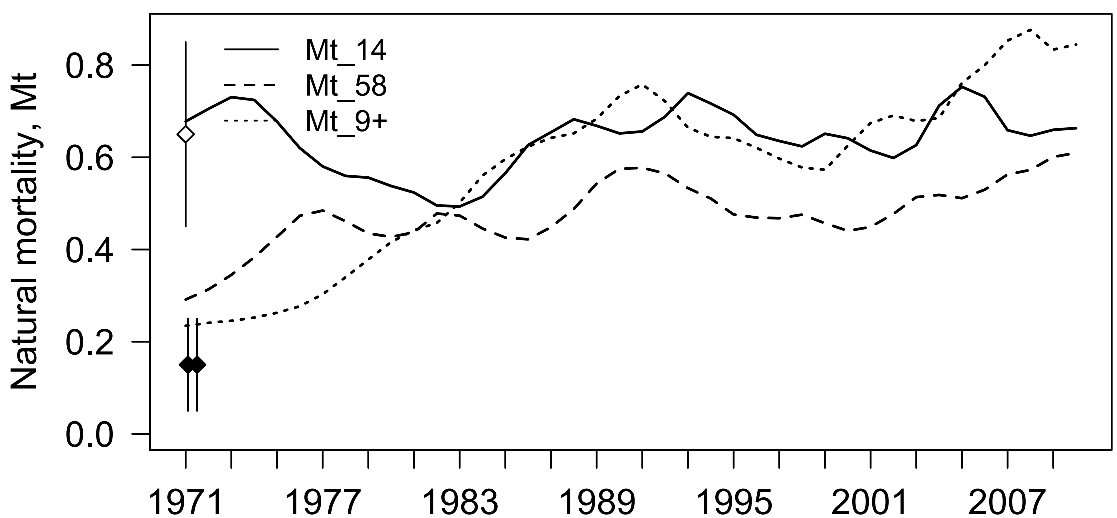
Rock'em sock'em stock assessments!



Model for non-stationary M

$$\log M_{t,a} \sim Normal\left(\log M_{t-1,a}, \sigma_M^2\right)$$

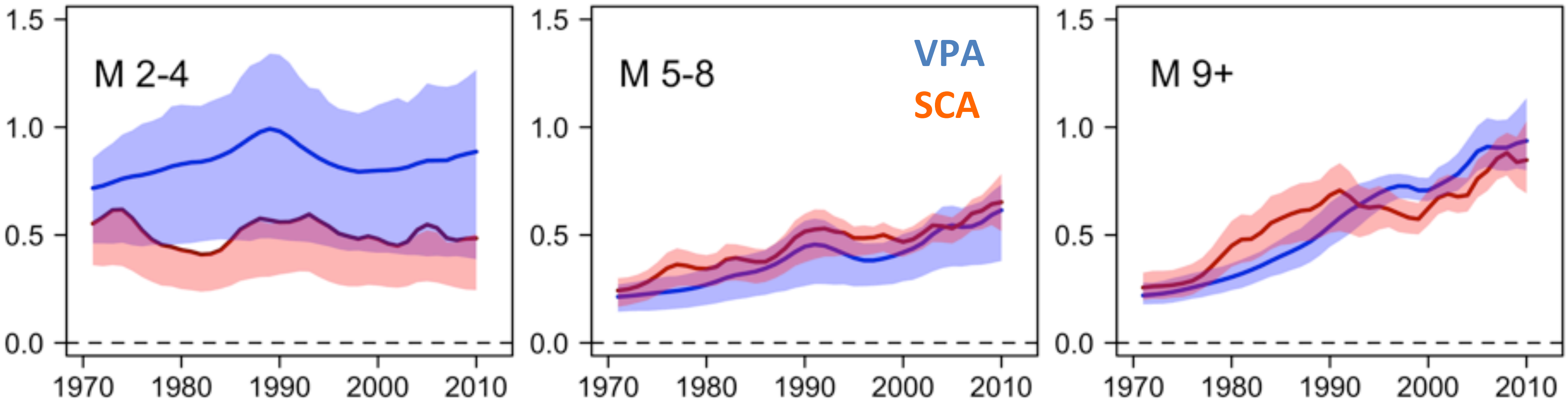
$$M_{1,a} \sim Normal\left(\mu_M, \tau_M^2\right)$$



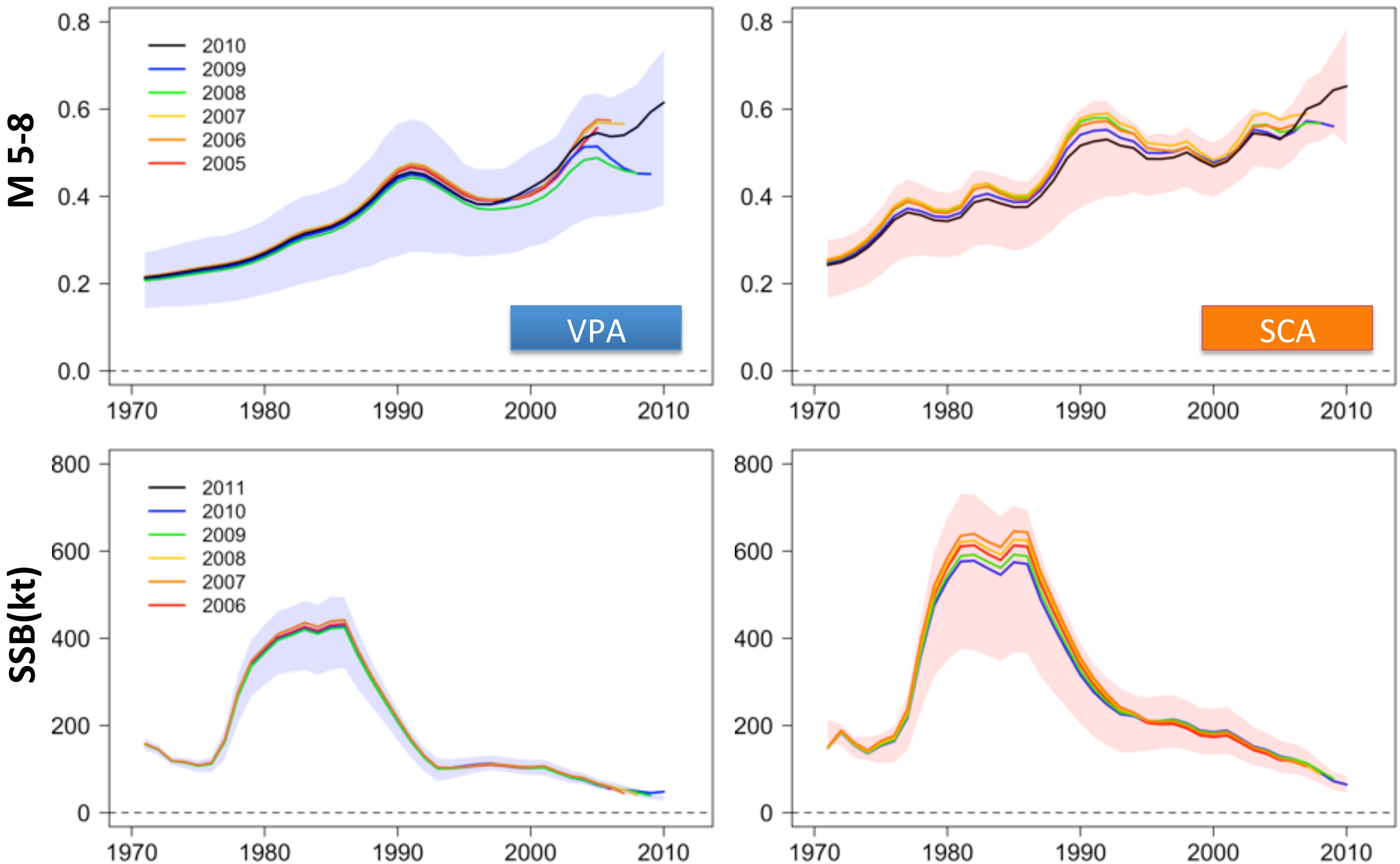
Input age-composition:

	S. Gulf St Lawrence		E. George's Bank	
Fishery	1971-2010 (**0.55**)	age 2-11	1978-2011 (**0.49**)	age 1-10
DFO/Industry	RV: 1971-2010 (**0.32**) MS: 2003-2010 (**0.38**) LL 1995-2010 (**0.22**)	age 2-11 age 2-11 age 5-11	RV: 1986-2011 (**0.71**)	age 1-8
NMFS			NMFS_S1: 1978-1981 (**0.81**) NMFS_S2: 1982-2011 (**0.58**) NMFS_F: 1978-2011 (**0.79**)	age 1-8 age 1-8 age 1-5
Weight-age	1971-2010		1978-2011	

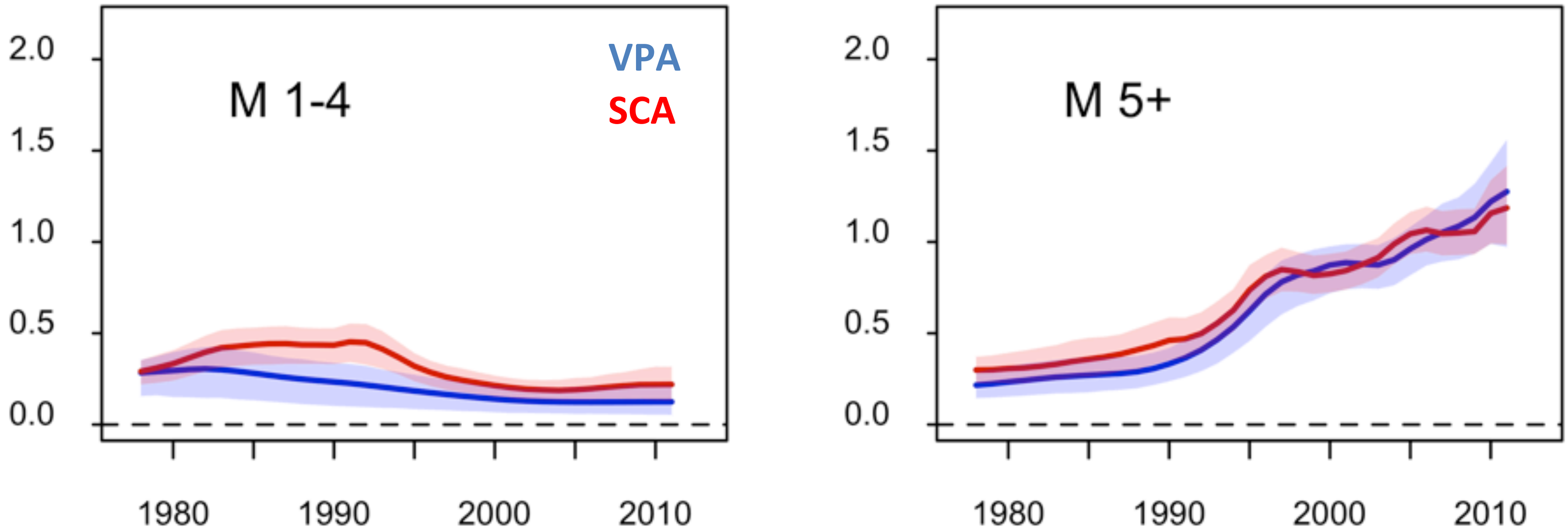
SGSL cod: M trends



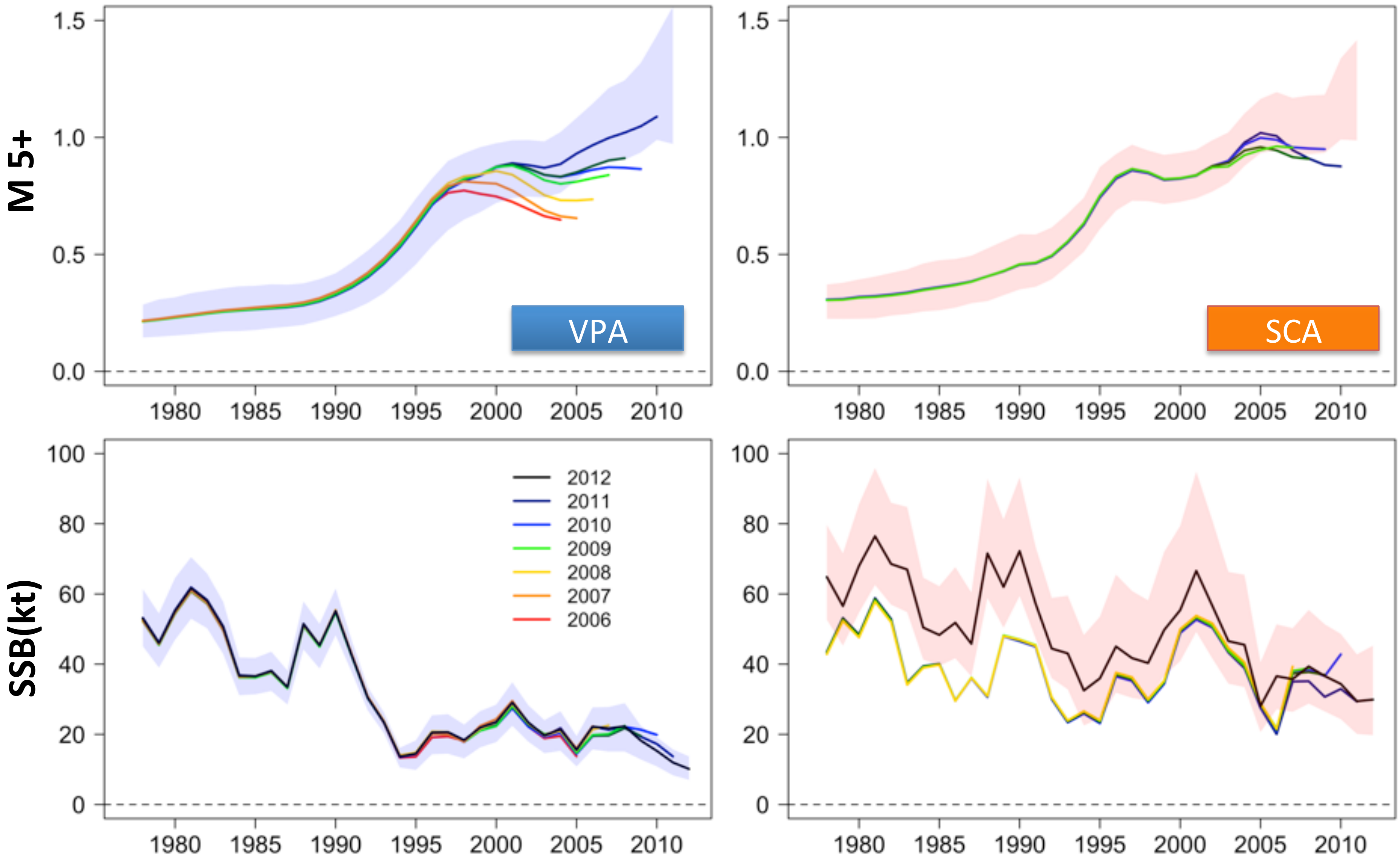
SGSL cod: M5-8 and SSB



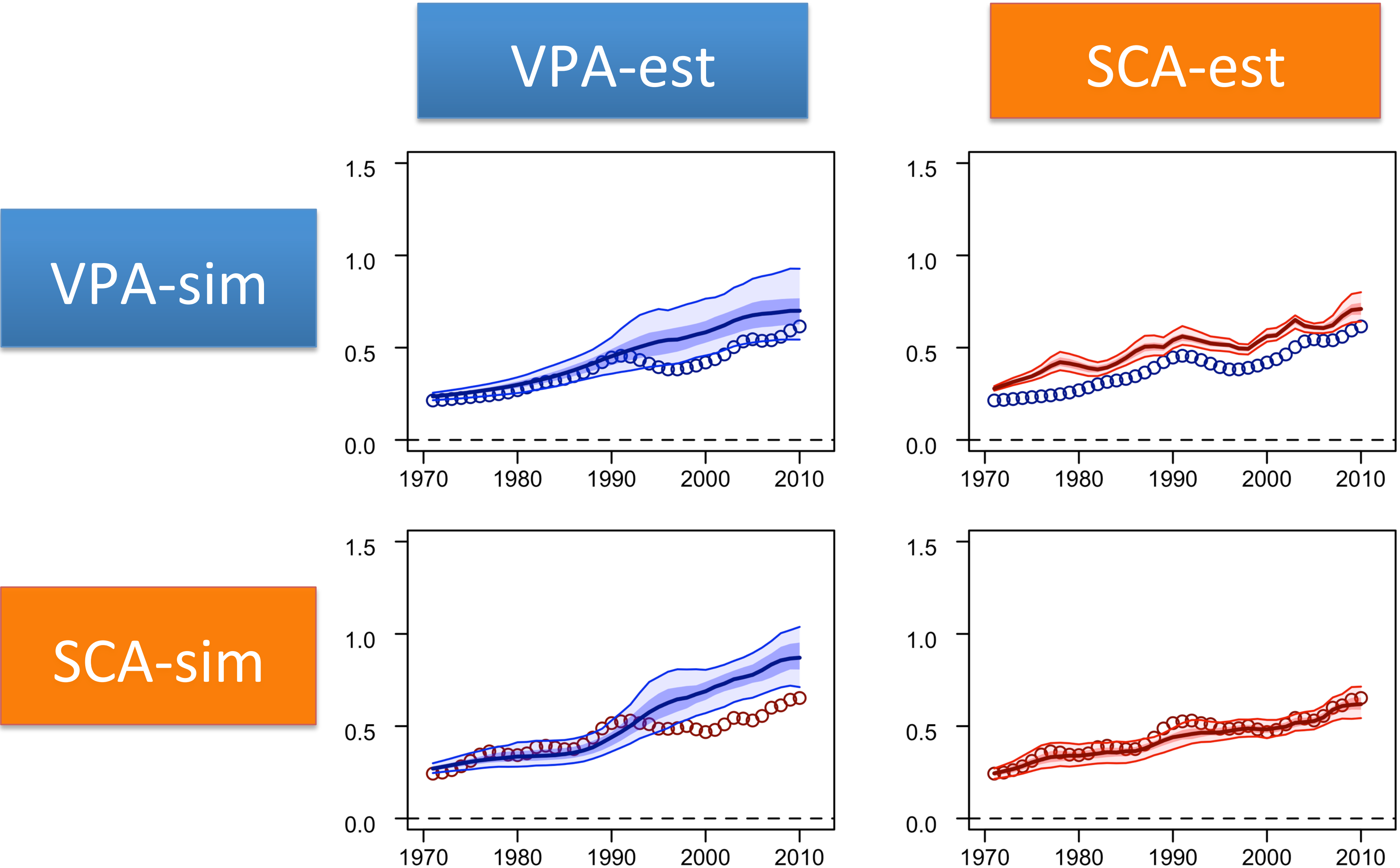
EGB cod: M trends



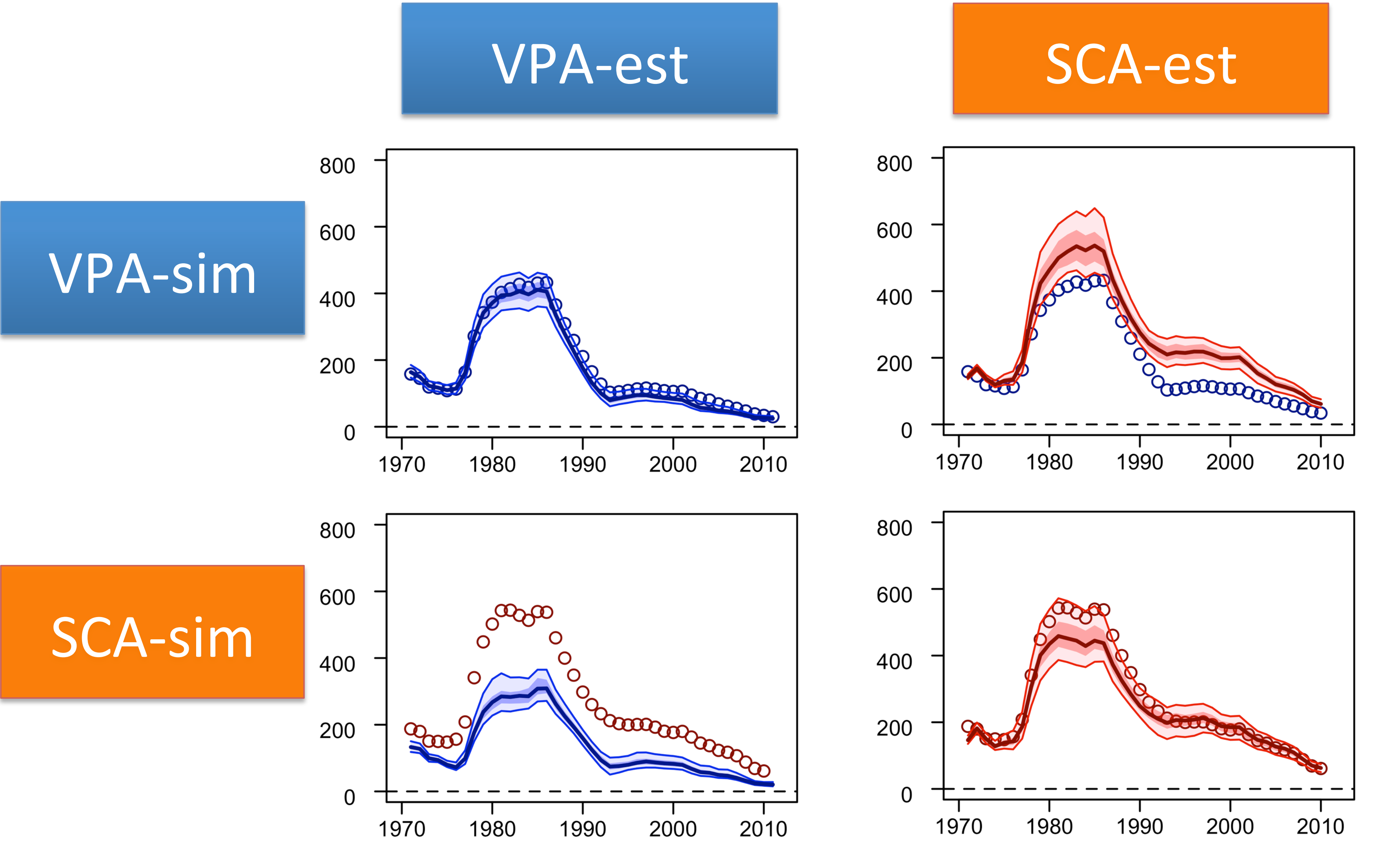
EGB cod: M5+ and SSB



SGSL simulation tests: M 5-8

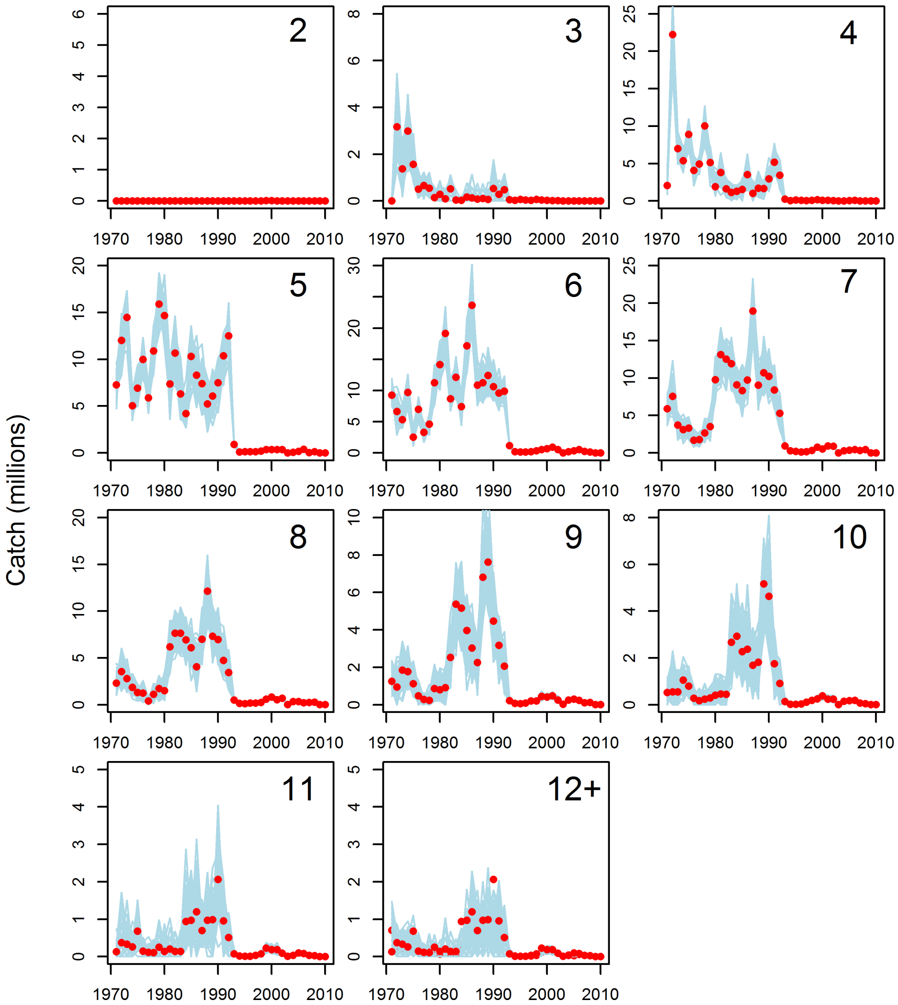


SGSL simulation tests: SSB

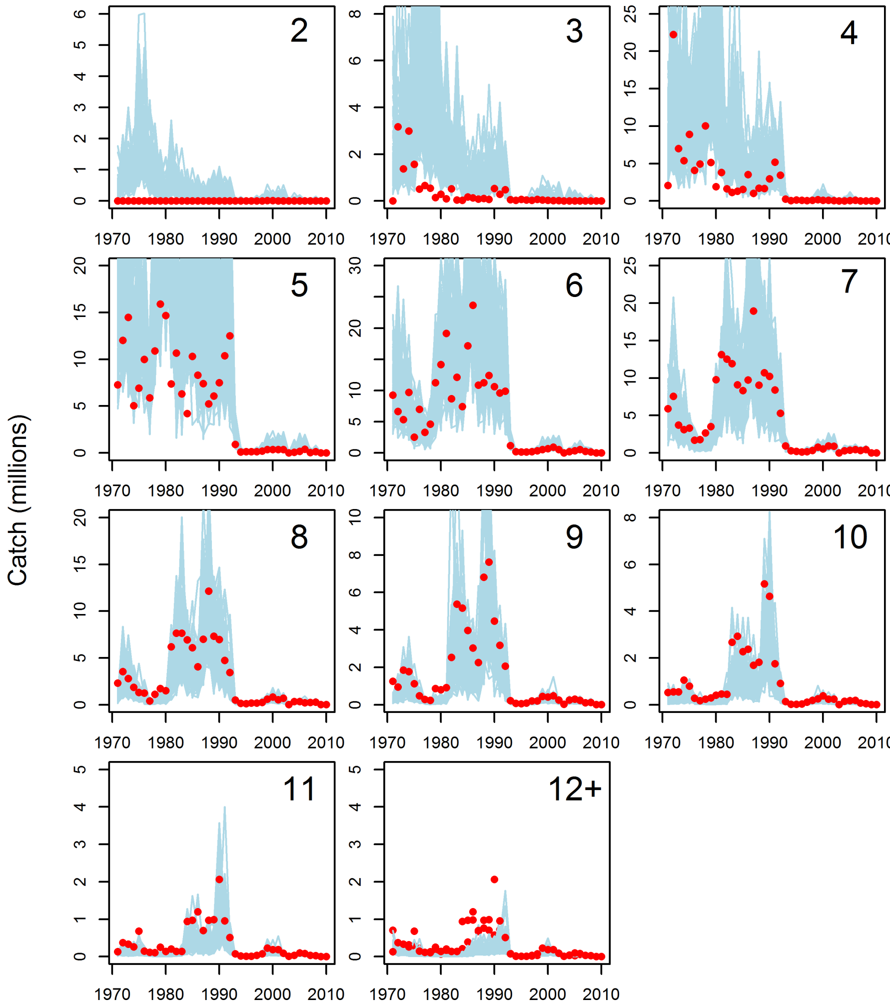


SGSL cod: Simulated **Fishery** catch-at-age

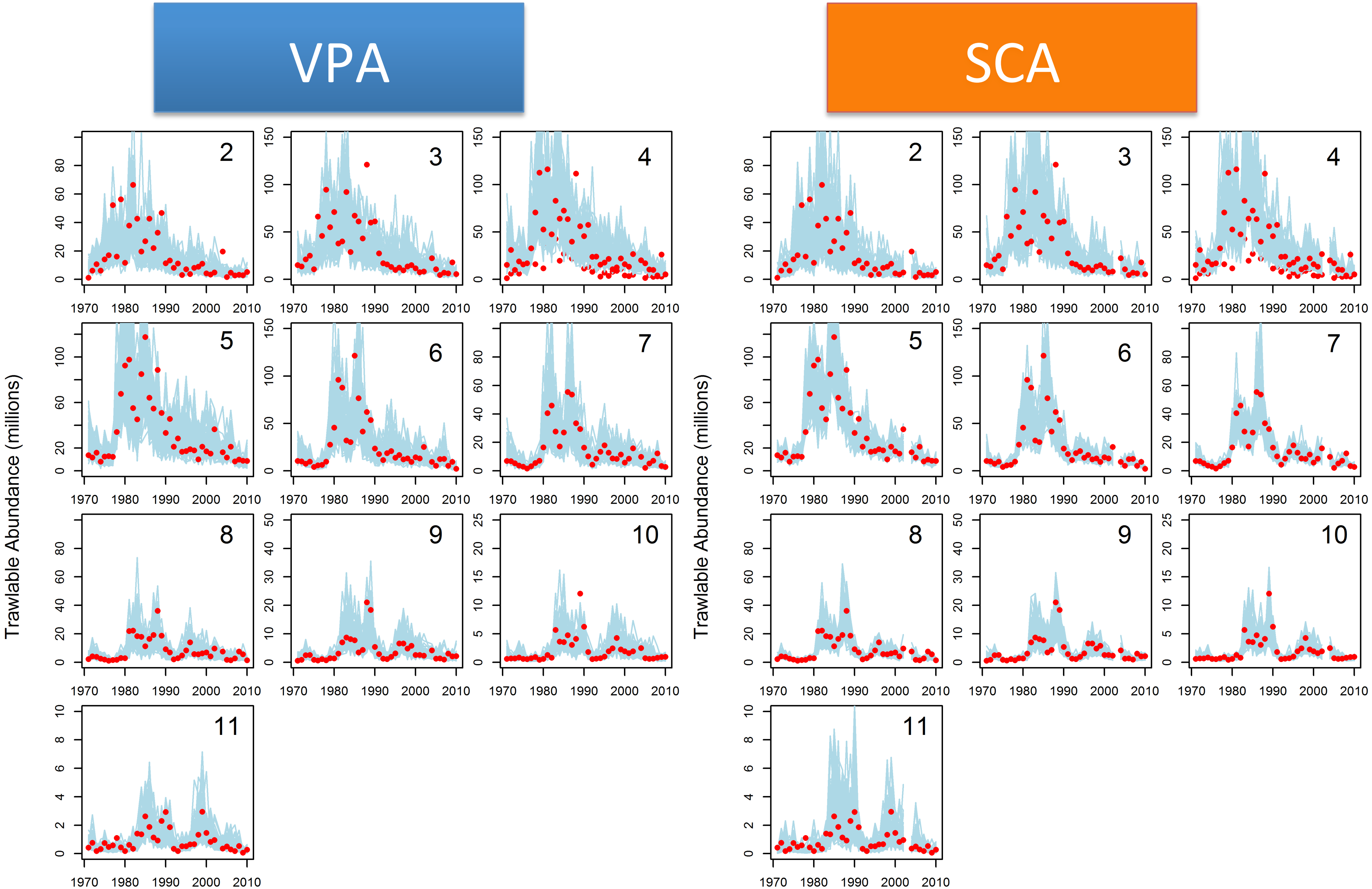
VPA



SCA



SGSL cod: Simulated **Survey** catch-at-age



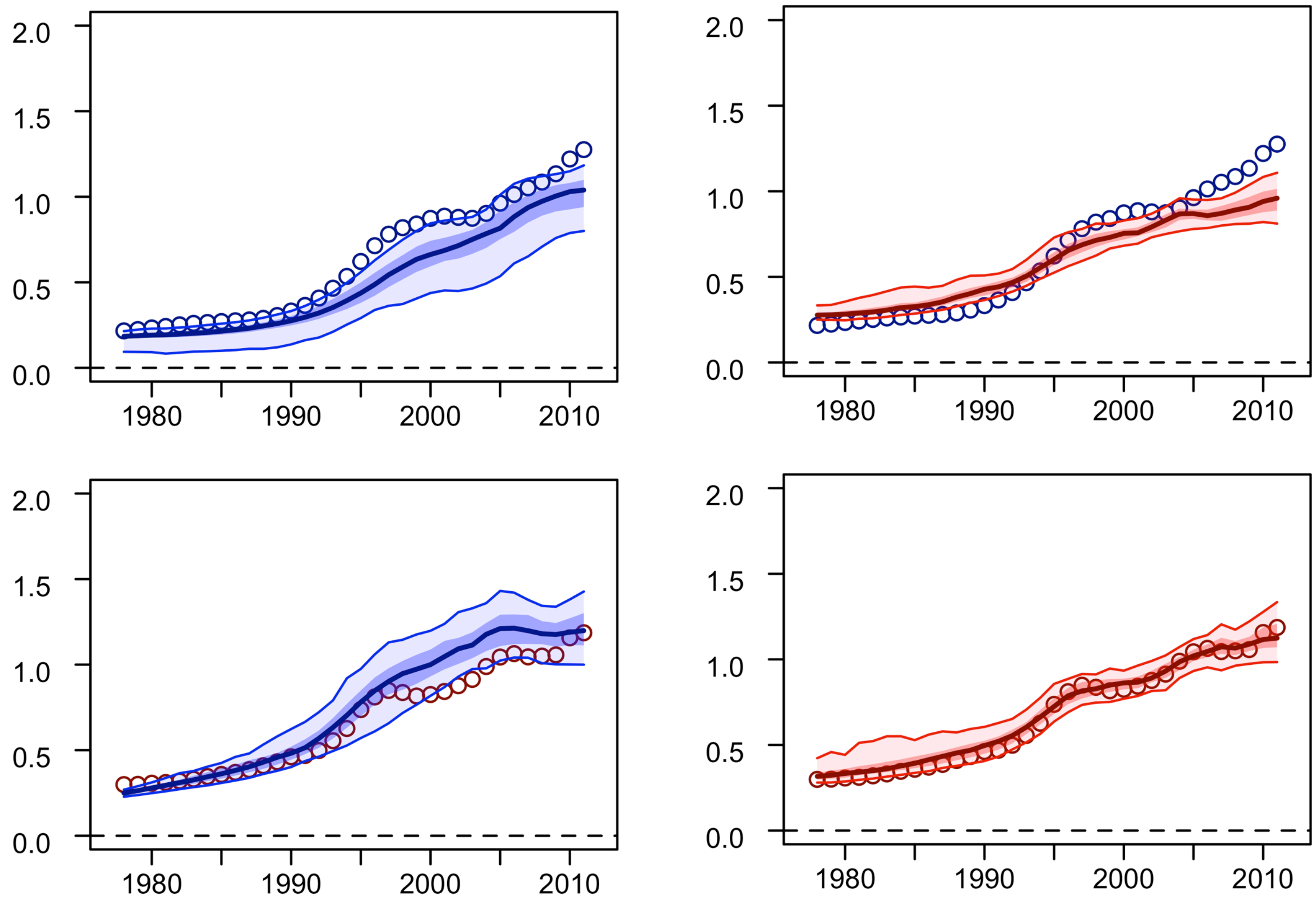
EGB simulation tests: M 5+

VPA-est

SCA-est

VPA-sim

SCA-sim

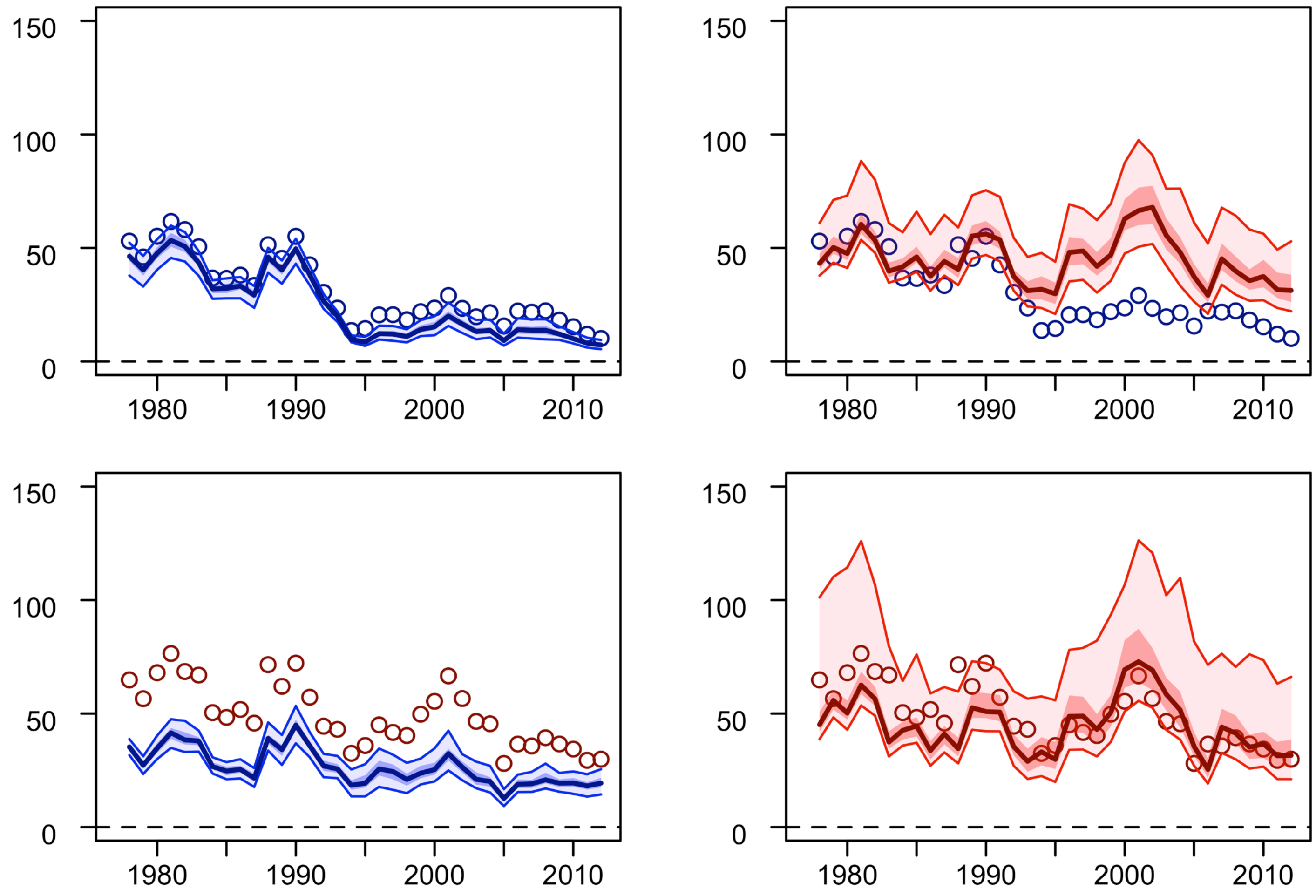


EGBsimulation tests: SSB

VPA-est | SCA-est

VPA-sim

SCA-sim



Conclusions

1. Non-stationary M trends comparable for fully-recruited age classes, but some differences may be important

2. SCA appears better for M trends, but over-estimates SSB for both cod stocks

3. VPA inconsistent for M, but always under-estimated SSB

4. Investigating potential causes for changing M should consider the stock assessment model used

Selectivity: theory, estimation, and application in fishery stock assessment models

Workshop Overview

P. R. Crone, M. N. Maunder, B. X. Semmens, J. L. Valero, and J. D. McDaniel

Center for the Advancement of
Population Assessment Methodology (CAPAM)
NOAA/IATTC/SIO
8901 La Jolla Shores Drive
La Jolla, CA 92037, USA

CAPAM – Selectivity Workshop

Presentation outline

- CAPAM background
- Workshop statistics
- Results
  - Keynote speaker presentations
  - Major findings/high priority research areas
- Current and Future work

CAPAM background

- Established Fall 2012 under NOAA-SWFSC, IATTC, UCSD-SIO

- Infrastructure includes principal investigators, post-docs, research associates, collaborators, visiting scientists, advisory panel, and administrative support staff

- Needs identified in Reauthorization of the Magnuson-Stevens FCMA (2007)

- Mission is **research**, education, and outreach that addresses animal population dynamics, models, and assessments associated with marine fishery resources

- Objectives
  - Evaluate/improve methods used in fish stock assessment model development and application
  - Afford educational and training opportunities to prepare competent researchers in fishery science
  - Deliverables include research papers, workshops, short-courses, classes, and stock assessments

- Main programs and specific projects
  - ***Good practices in stock assessment modeling*** (*selectivity, growth, data/likelihood weighting, diagnostics, etc.*)
  - ***SIO/NOAA education and training for next generation of fishery assessment scientists*** (*classes, graduate thesis collaboration, stock assessments, etc.*)
  - ***White sea bass assessment***

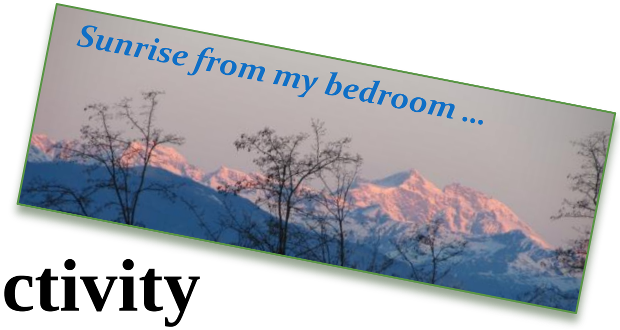
- Funding is obtained from formal RFPs, as well as direct contributions

Workshop statistics

- Held from March 11-14, 2013 at the SWFSC in La Jolla, CA
- Funded by NOAA, SIO, and ISSF
- 75 participants (USA, Canada, Japan, China, Taiwan, S. Africa, Spain)
- 35 participants via remote access available online (WebEx)
- Agenda
  - 4 keynote presentations under major sub-topics of selectivity
    - Underlying processes - **D. Sampson**
    - Specification and estimation - **J. Ianelli**
    - Model selection and evaluation - **A. Punt**
    - Impacts on management - **D. Butterworth**
    - Group discussions
  - 21 research presentations
  - 2 work sessions
    - Modeling selectivity/simulation methods using SS - I. Taylor, H-H. Lee, J. Valero
    - Developing ADMB software libraries using selectivity examples - S. Martell, A. Whitten, M. Supernaw
  - Deliverables
    - Interactive and efficient forum for training and information exchange
    - Archive of selectivity manuscripts from historical literature
    - Workshop report
    - Special issue in professional journal (*Fisheries Research*)

CAPAM – Selectivity Workshop

- **Results (keynote presentations)**
  - ❖ Underlying processes (D. Sampson)



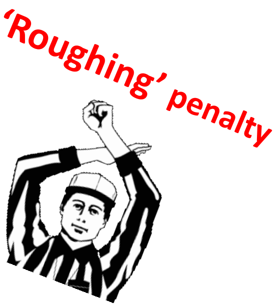
Factors Influencing Selectivity

- **Gear selection**
  - Fish species, sex, age, size, behavior, etc. affect which fish contact and are caught/retained by a specific type of fishing gear
- **Spatial locations of the fish and fishing operations**
  - Fishing gear operates at a local (fish) scale and can only catch fish that are near/contact the gear
  - At a broader (stock-wide) scale, population selection depends on the spatial distribution of fishing operations relative to the spatial distribution of the fish
- **Mixture of fishing gears**
  - When there are multiple gear types with different selection properties, the relative catch by each gear type determines the population-level selectivity

CAPAM – Selectivity Workshop

- **Results (keynote presentations)**
  - ❖ **Specification and estimation (J. Ianelli)**

Functional forms (splines) and 'smoothing'



Non-parametric smooth selectivity

Pros

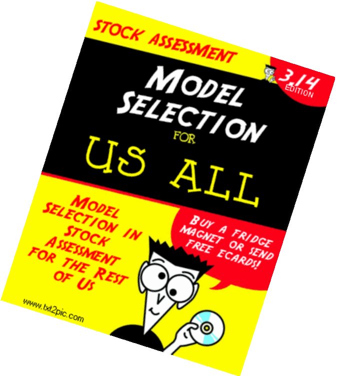
- Robust estimation
- Flexible
- Easy check
- Rarely headache (few surprises)
- Performance in MCMC
- Extends easily to time-varying

Cons

- Knowing magnitude of 'tension'
- Optimal frequency/location of knots
- May perform poorly at tails
- Confounds re-weighting
- Should be tested further
- Objective criteria needed for 'smoothing' penalties

CAPAM – Selectivity Workshop

- **Results (keynote presentations)**
  - **Model selection and evaluation (A. Punt)**



Simulation ↔ Selectivity

- The structure of most (perhaps all) operating models is too simple and leads to simulated data sets looking "too good"
  - *Andre's suggestion*: if you show someone 99 simulated data sets and the real data set, could they pick it out?
- Future simulation studies should
  - Include model and fleet selection
  - Focus on length-structured models
  - Examine whether selectivity is length- or age-based

- **Results (keynote presentations)**
  - **Impacts on management (D. Butterworth)**

Selectivity at older ages

- Issues arise from the relative paucity of older/larger fish in catches and/or surveys, for which heavy *F* at those ages/lengths is not the only possible explanation
- Analyses ubiquitously point to at least some selectivity doming, with the underlying mechanisms not always clear
- This can sometimes have important implications for BRPs and associated management advice
- Those BRPs are unlikely to be robust to alternative explanations of domed selectivity, higher *M*, or increasing *M* at older ages

"… this is not about the best assessment model, but about the best management."

CAPAM – Selectivity Workshop

Results (major findings/high priority research areas)

- Contact selectivity and availability
- General selectivity specification and estimation
- Asymptotic or dome-shape selectivity
- Size- or age-based selectivity
- Fleets as proxies for spatial processes
- Constant or time-varying selectivity
- Poor composition data
- Management strategy evaluations
- Survey selectivity
- Model selection and diagnostics

CAPAM – Selectivity Workshop

Current and Future work

- Continue with selectivity research, including splines, data/selectivity type: length vs. age, data weighting, VPA - spatial *F*/selectivity form
  - Establish working group / begin synthesis and documentation related to *Good Practices Guide*
  - Visiting scientist research

- Begin related research projects for *GPG* (e.g., modeling growth in stock assessments)
  - Prepare for growth workshop (late 2014)

- Conduct classes/short courses—SIO and international

- Build on momentum to link with institutions/programs involved in similar research (regionally, nationally, and internationally)
  - Stock assessment modeling issues
  - SISAM model setup contributions
  - Collaborative work for WCSAM (natural mortality, data quality, retrospective bias)
  - ADMB Project
  - SS model development
  - Joint workshops (national and international)
  - *Next generation of stock assessment scientists*
- Visit **www.CAPAMresearch.org**

CAPAM – Selectivity Workshop

Thanks …

The Boston Globe

VOLUME 280
NUMBER 144
Suggested retail price
$1.00

TUESDAY, JULY 17, 2013

WEATHER
TODAY: Sun, some clouds, possible T-storms.
High 88-91. Low 79-81.
TOMORROW: Very warm, afternoon showers.
High 92-95. Low 80-83.

WCSAM IS ON AND WORLD TUNES IN

In the news

Celtics shake-up roster and now to leave Boston, for of all places …
Sports, Page C1

Fountain of Youth is in FL and restores youth not by drinking, but of all things …
Health, Page E1

Unifying theory and our existence finally solved, and by of all people …
Science, Page D1

SEAPORT DISTRICT WELCOMES STOCK ASSESSMENT FORUM

WCSAM draws much public and media attention around Seaport Hotel & World Trade Center. Scientists from all over the world will be focusing this week on the application and future of stock assessment methods, critical steps for developing sustainable fishery management advice and good resource stewardship.
Local, Page B1

Growth workshop to be held late 2014 in La Jolla, CA

CAPAM will be hosting a workshop next year on modeling growth in stock assessments and registration is expected to be brisk, if not frenzied. Organizers are encouraging scientists to get their research efforts underway soon and not be left behind for this important event. Further details available online by late summer. Visit www.CAPAMresearch.org.
Page A2

Additional data and more complex assessments – do these provide improved fishery management advice?

Helena Geromont and Doug Butterworth

MARAM (Marine Resource Assessment and Management Group)
Department of Mathematics and Applied Mathematics
University of Cape Town, Rondebosch 7701, South Africa

Fisheries management

Key management questions:

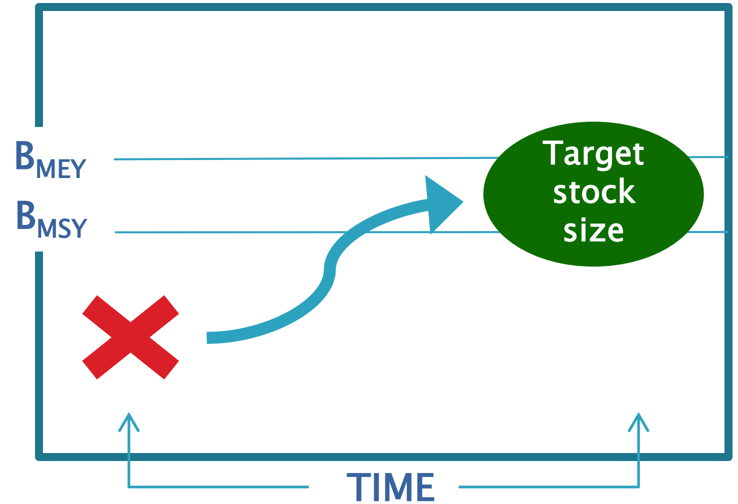
Where are we?
- Stock assessment

Where do we go?
- Policy decision

How do we get there?
- Complex annual assessments

  or
- Empirical Management Procedures

  (simple harvest control rules)



Why?

- Management advice currently based on complex annual assessments
- Typically require regular survey and large ageing programmes
- Costly
- Need to explore simpler and cheaper alternatives

- Examples: North Sea Sole,

  Gulf of Maine/ Georges Bank Witch Flounder and Plaice

Basic approach to comparison

- Retrospective analyses: go back 20 years.
- Project forward with a simple empirical MP.
- For a common basis for comparison, tune the MPs to achieve (at some %-ile) the same final spawning biomass as in assessment.
- Compare performance (catches, variability, etc.) to what was achieved in practice by the combination of complex assessments linked to management approaches as applied over that period.

Management Procedures

(I = index of abundance available annually)

Constant catch MP

$$TAC_{y+1} = TAC^{target}$$

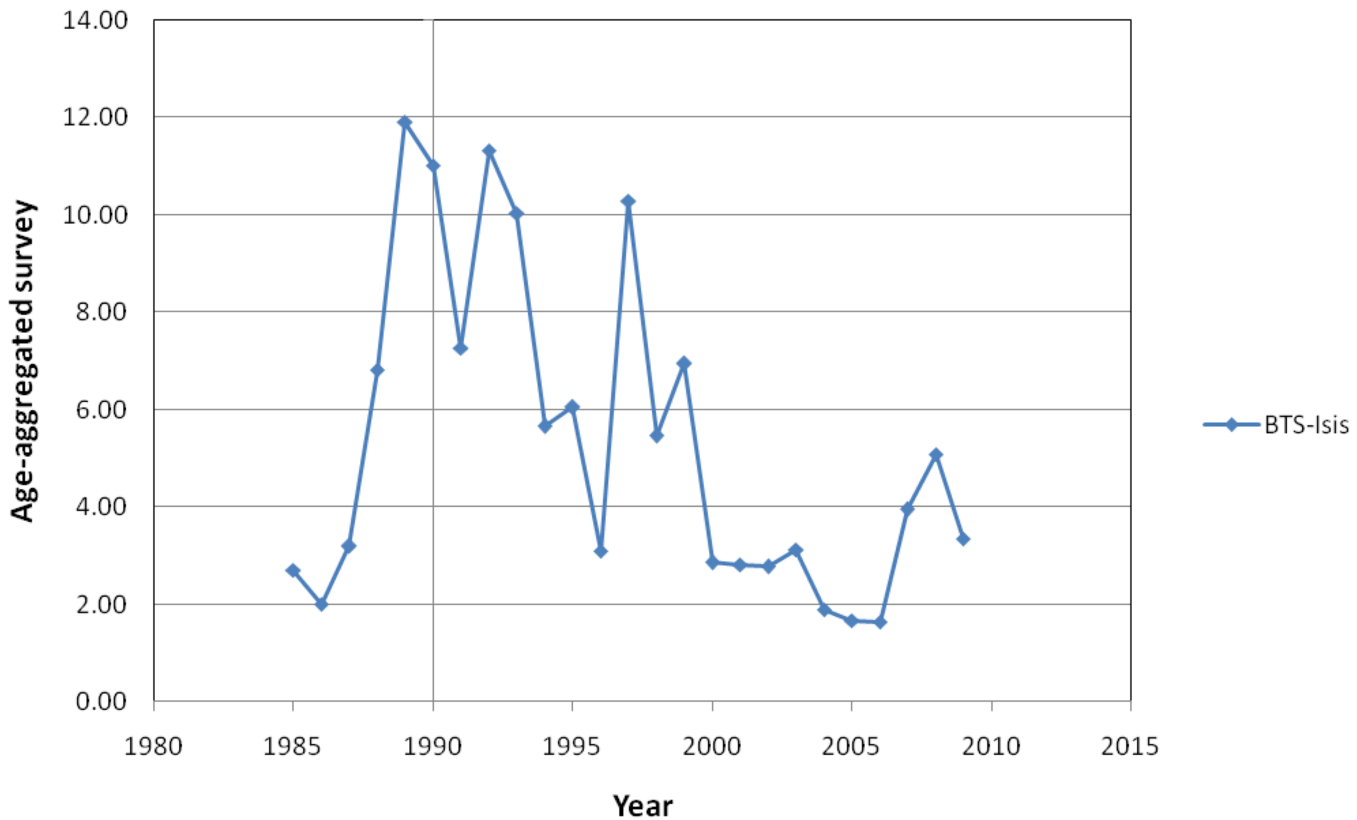
Survey slope based MP:

$$TAC_{y+1} = TAC_y(1 + \lambda s_y) \quad s_y = \text{trend in } I$$

Target based MP:

$$TAC_{y+1} = TAC^{target}\left[w + (1-w)\left\{\frac{I^{recent} - I^0}{I^{target} - I^0}\right\}\right]$$

Data: Survey Index
North Sea Sole (Subarea IV)

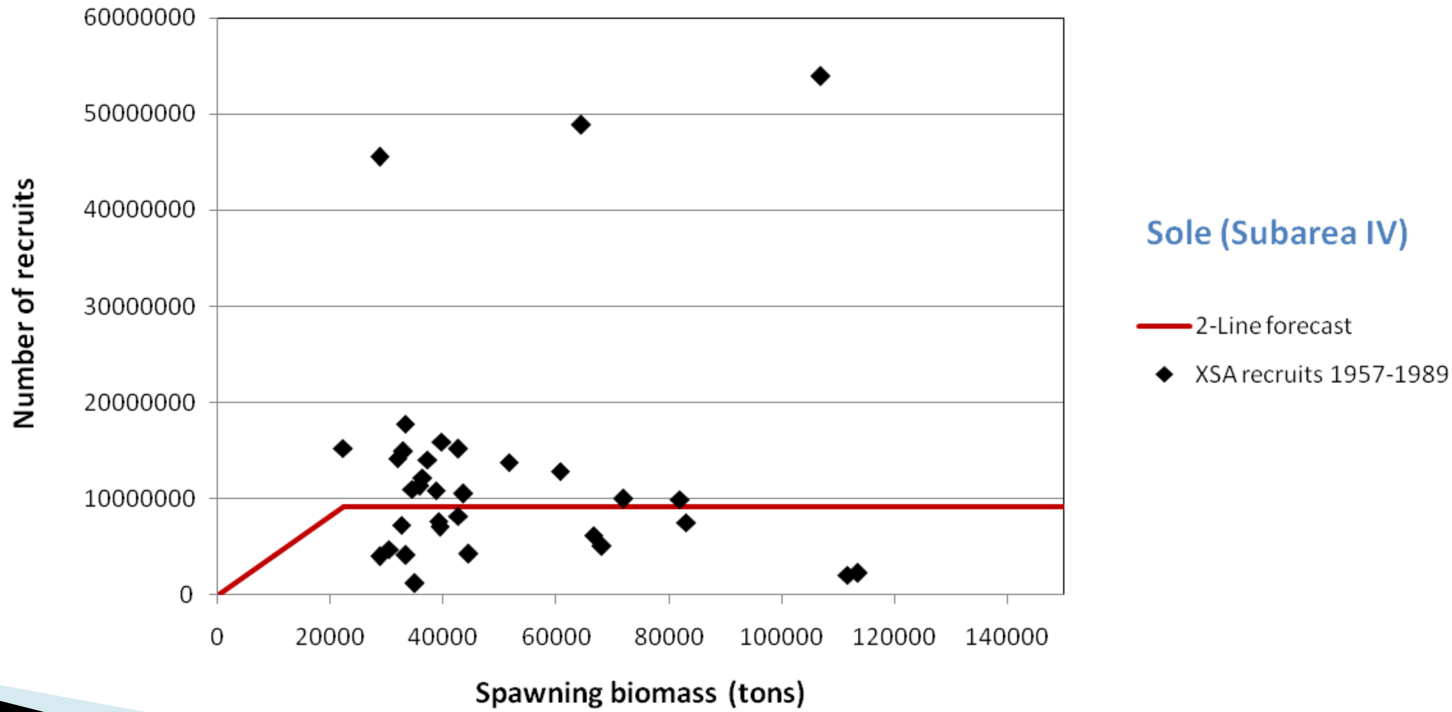


Projections: Stock-recruitment relationship

2-Line (hockey stick):

$$B^{sp}_{y-1} > B^0 \rightarrow R_y = \alpha e^{\varsigma_y}$$

$$B^{sp}_{y-1} < B^0 \rightarrow R_y = \alpha (B^{sp}_{y-1} / B^0) e^{\varsigma_y}$$



Projections: Stock-recruitment relationship

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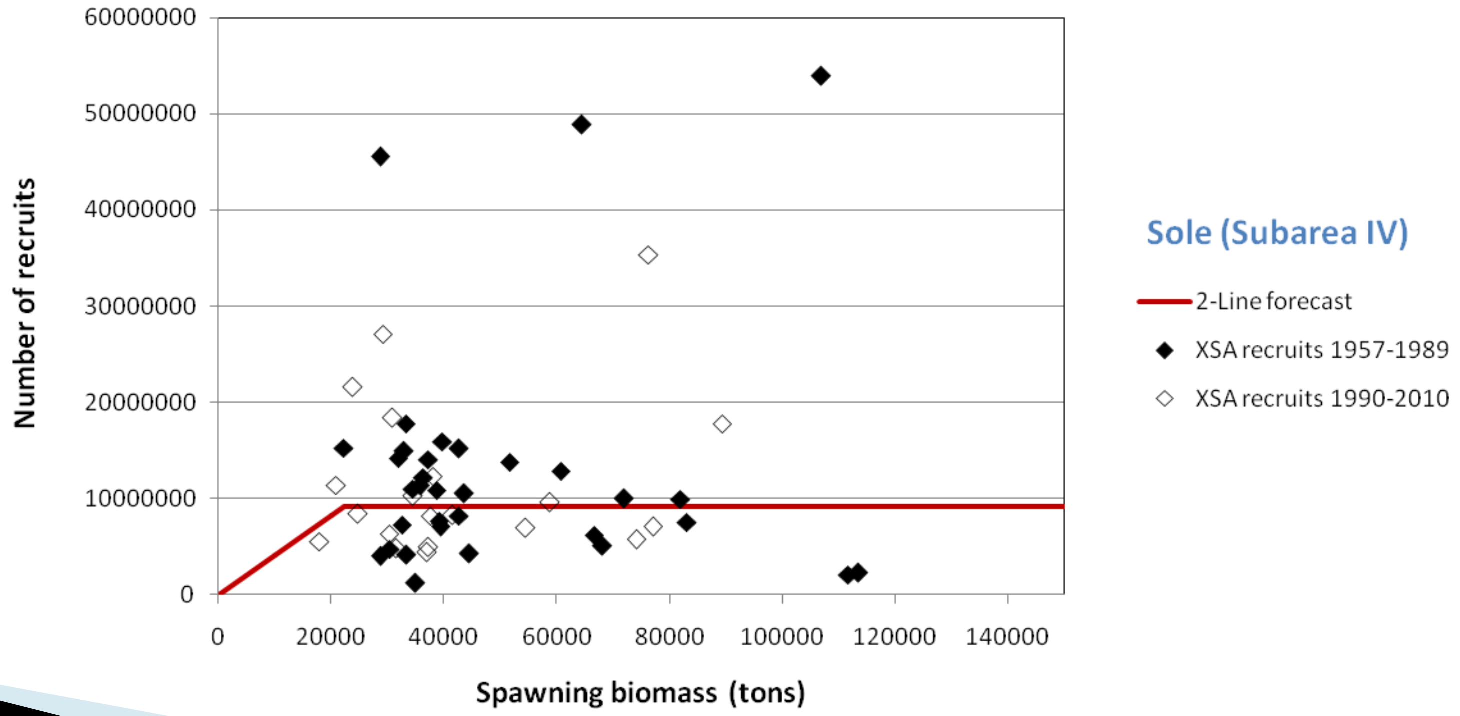


Three steps in projections

1. Deterministic "hindsight" projections

MP tuned to reach final spawning stock biomass estimated in assessment (2009 for sole)

Key assumptions:

- Same selectivity-at-age vectors
- Same S/R residuals
- Same survey index of abundance residuals

as assessment

Three steps in projections

1. Deterministic "hindsight" projections:

2. Stochastic "forecast" projections:

MP tuned so that lower 2.5%-ile reaches current biomass estimated in assessment

Generate future:

- Selectivity and weight-at-age vectors: re-sample from past
- Stock-recruitment log-normal residuals (σ^R=0.8 for sole)
- Survey log-normal residuals (σ^i=0.2 for sole)

Three steps in projections

1. Deterministic "hindsight" projections:
2. Stochastic "forecast" projections:
3. Deterministic "hindsight" projection of "forecast" MP:

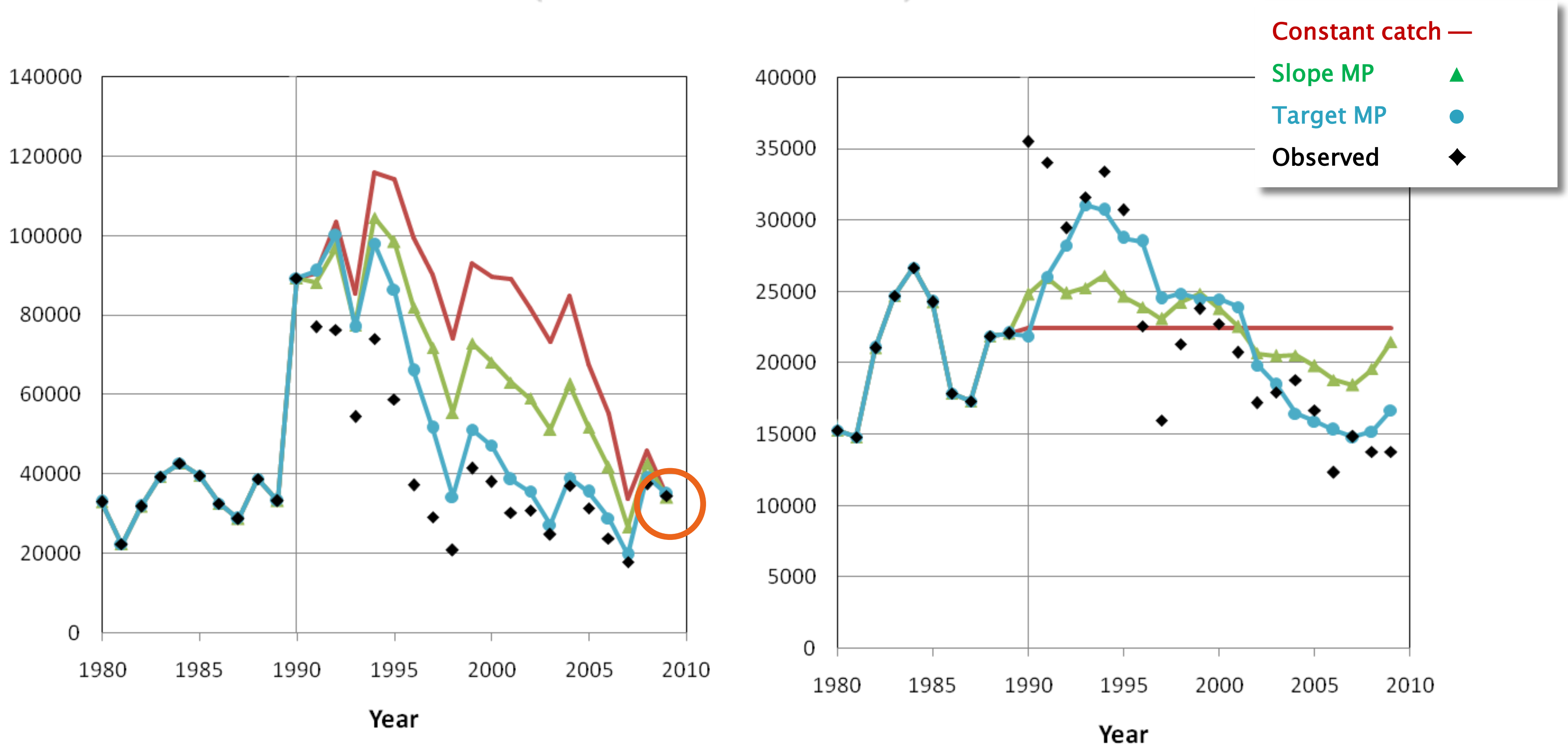
   Use best performing MP obtained in step 2 in deterministic projection

Key assumptions:

- Same selectivity-at-age vectors
- Same S/R residuals
- Same survey index of abundance residuals

as assessment

Step 1. Deterministic hindsight projections
North Sea Sole (Subarea IV)

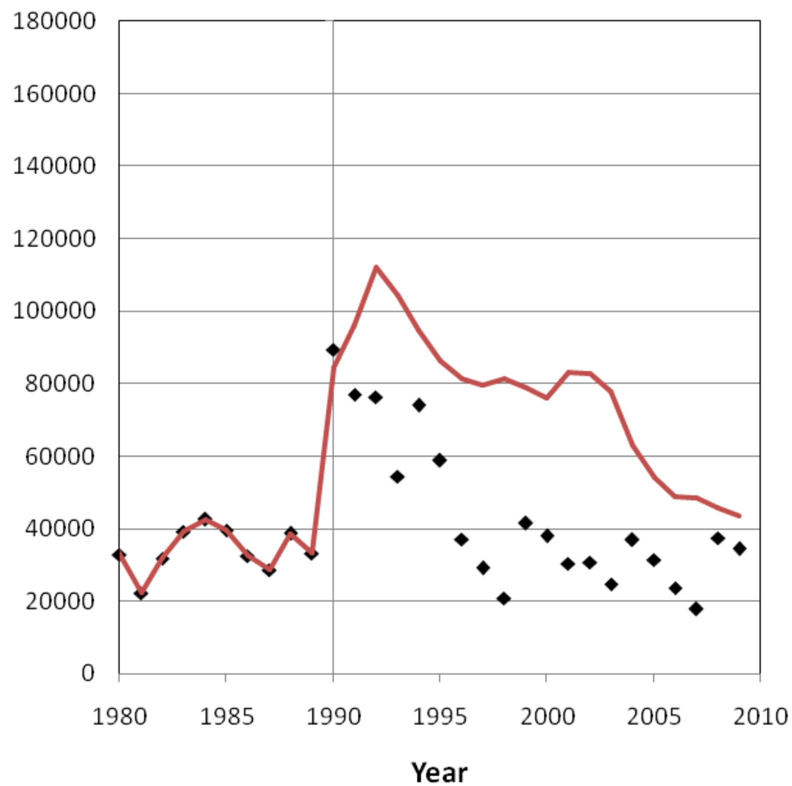


Spawning biomass (tons)

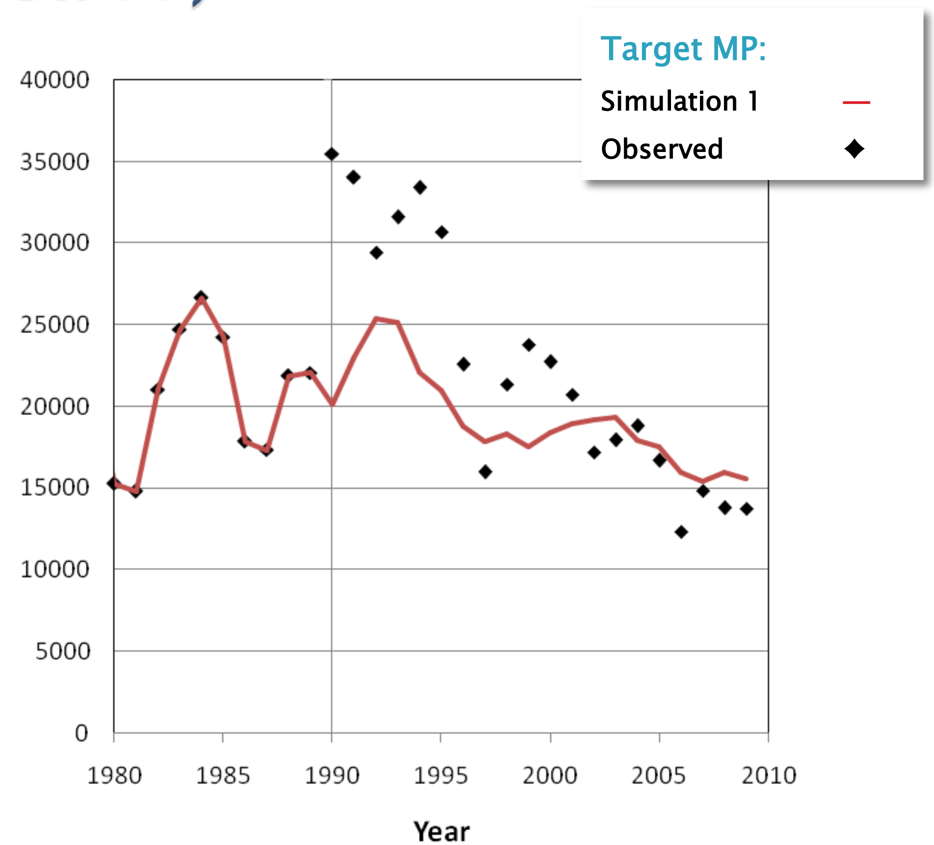
Annual catch (tons)

MARAM

Step 2. Stochastic forecast projections: North Sea Sole (Subarea IV)

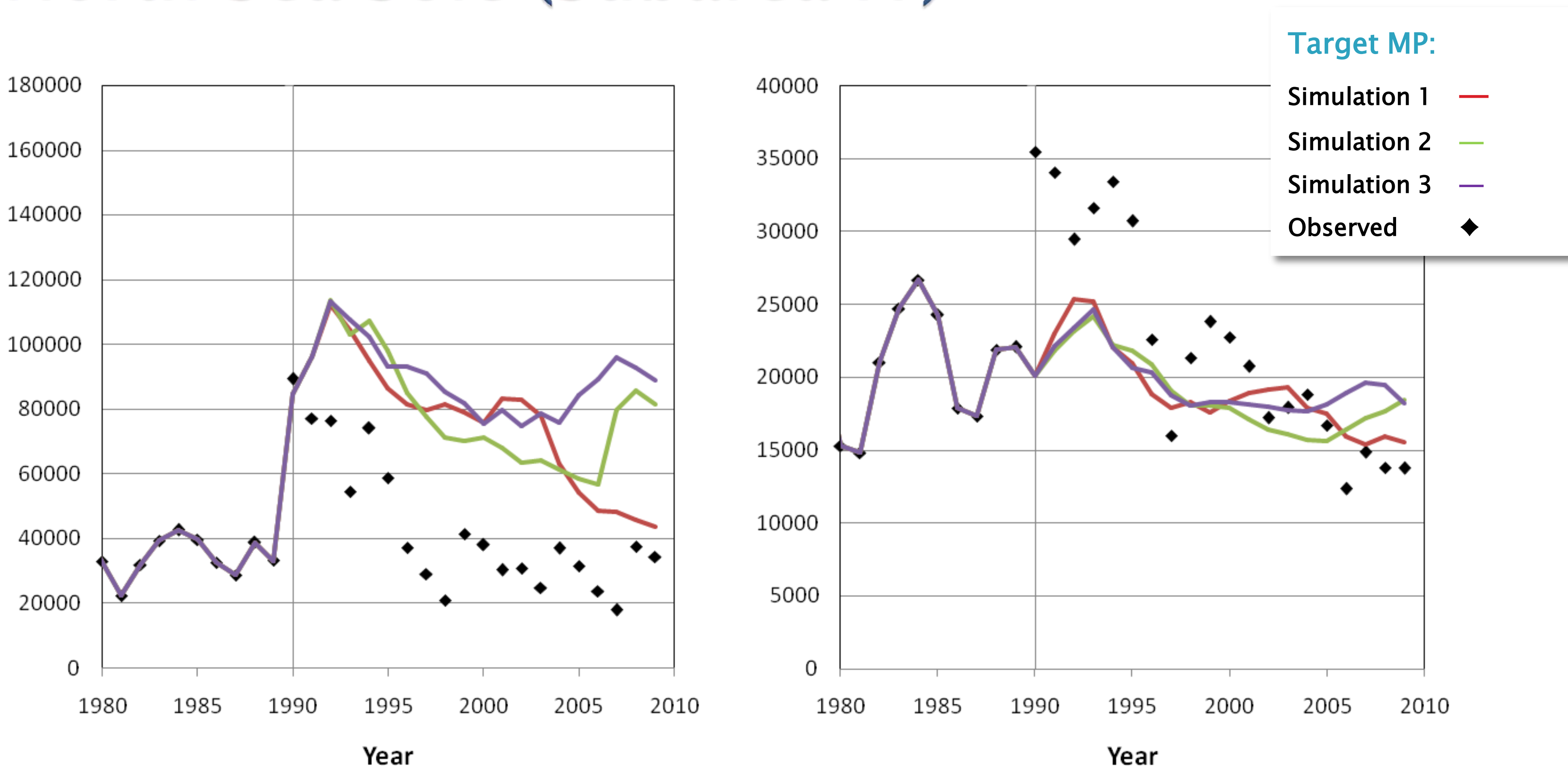


Spawning biomass (tons)



Annual catch (tons)

Step 2. Stochastic forecast projections:
North Sea Sole (Subarea IV)

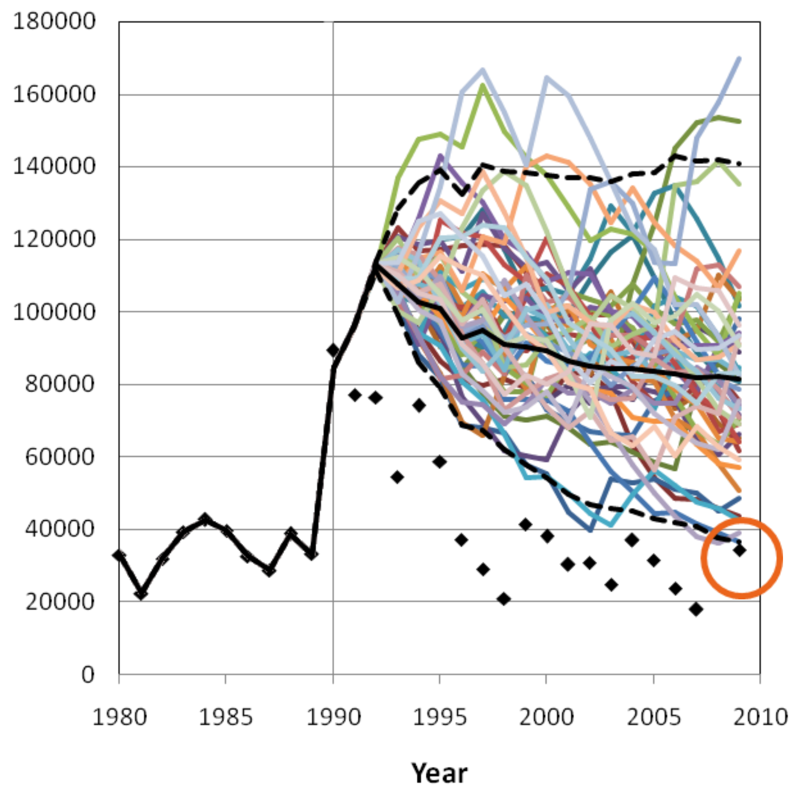


Spawning biomass (tons)

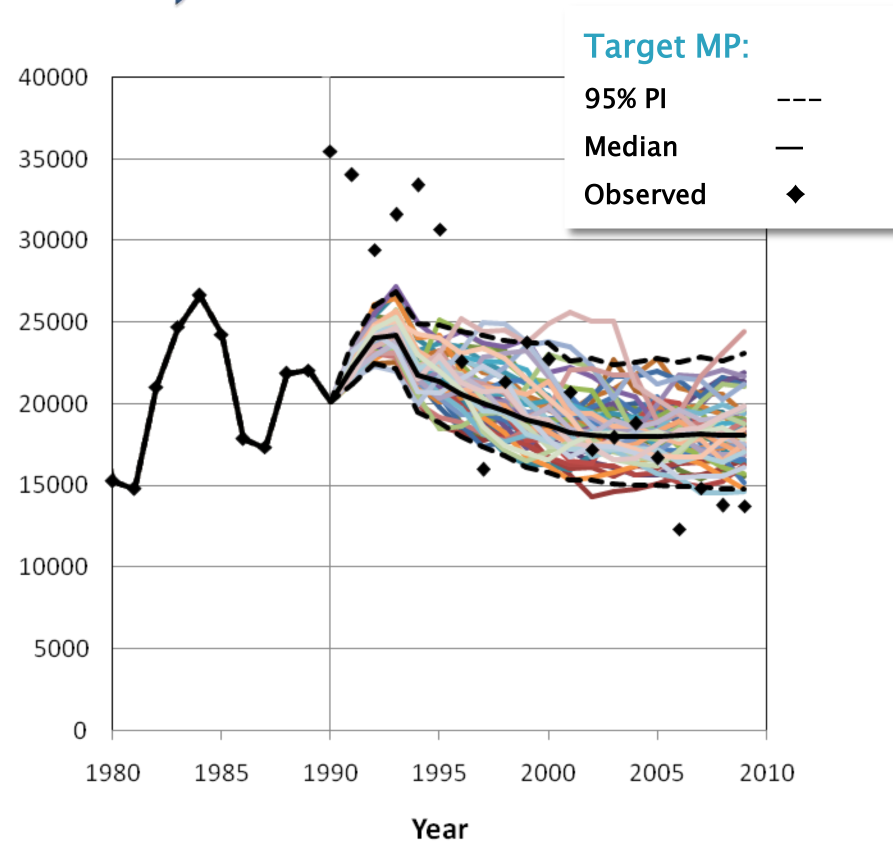
Annual catch (tons)

MARAM

Step 2. Stochastic forecast projections:
North Sea Sole (Subarea IV)



Spawning biomass (tons)

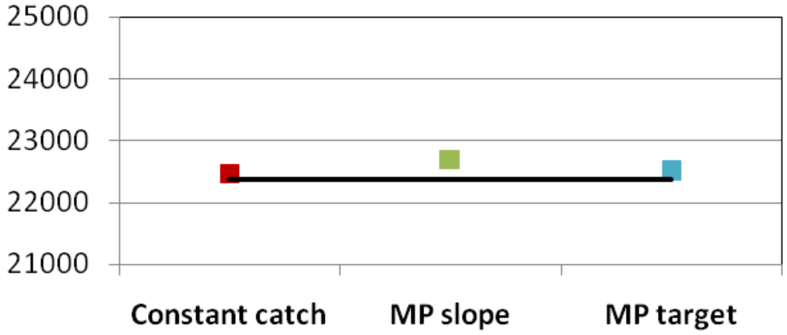


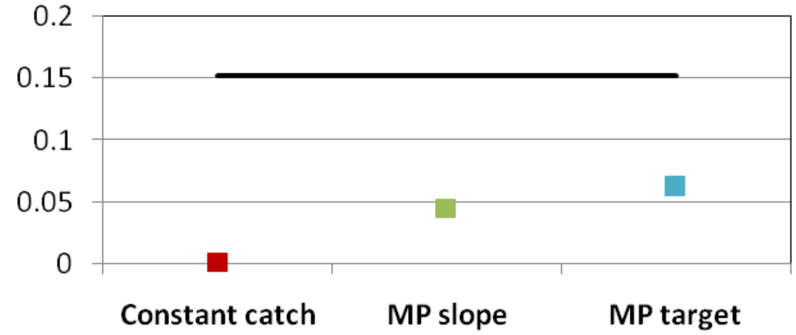
Annual catch (tons)

MARAM

Step 1. Deterministic hindsight projections
North Sea Sole (Subarea IV)

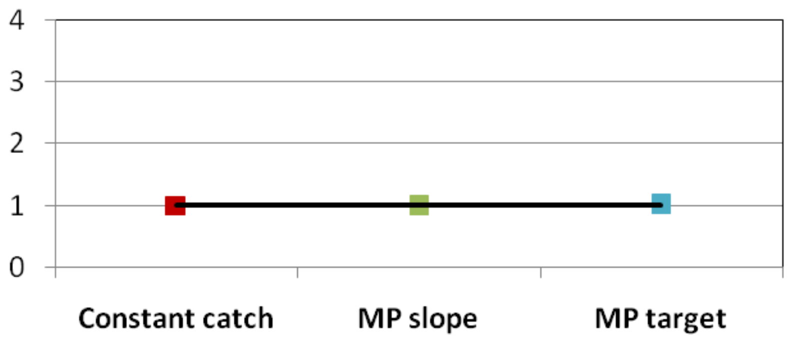
Observed —

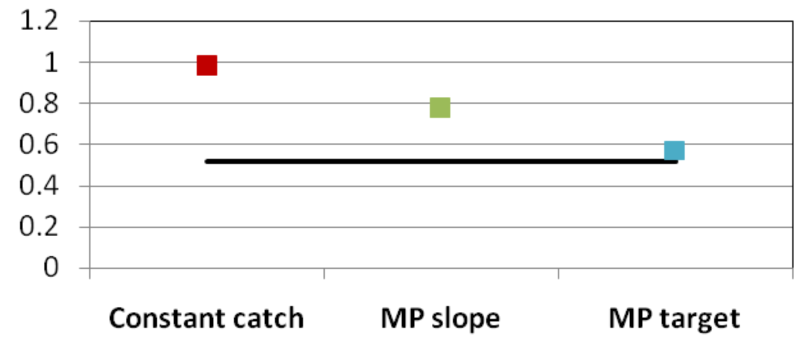




Annual average catch (tons)

Average change in catch





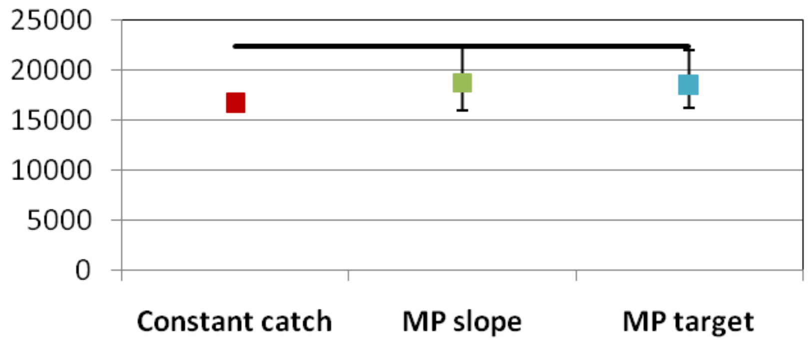
2009 SSB/SSBtarget

min SSB/SSB target

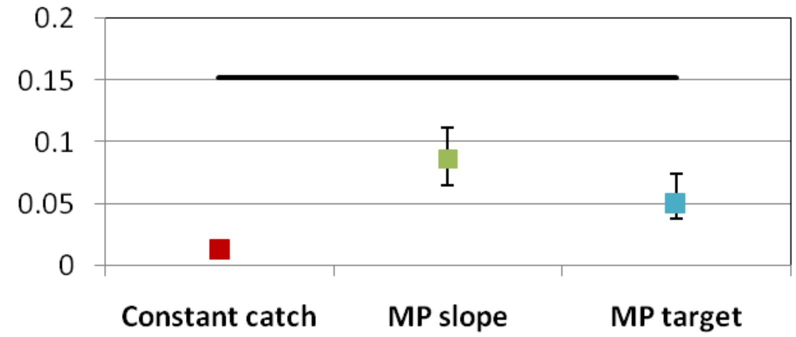
MARAM

Step 2. Stochastic forecast results:
North Sea Sole (Subarea IV)

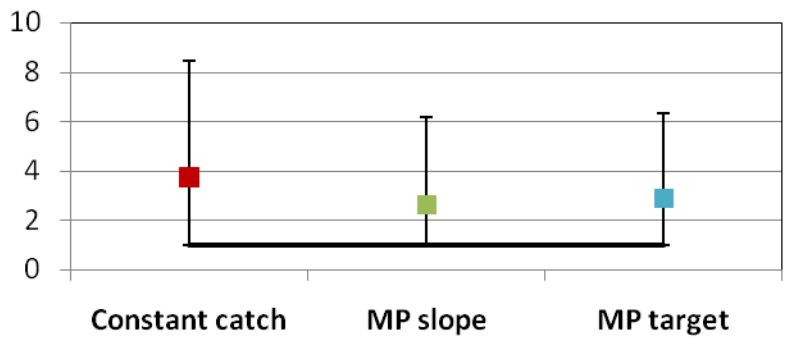
Observed —



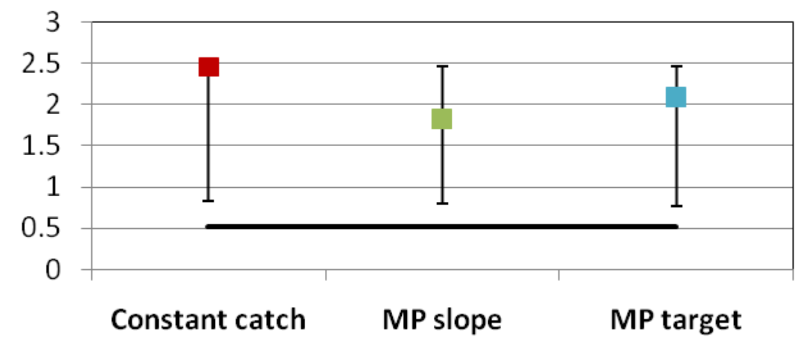
Annual average catch (tons)



Average change in catch



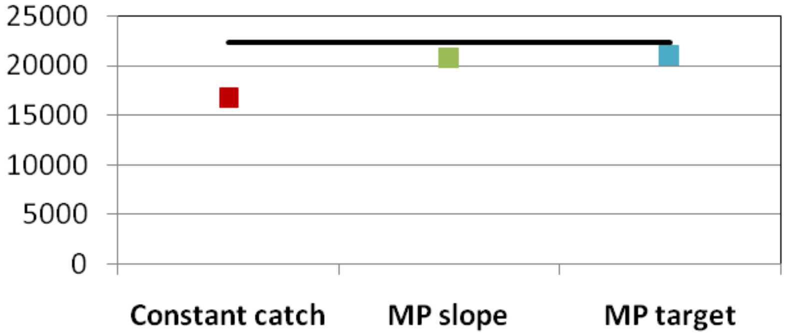
2009 SSB/SSBtarget



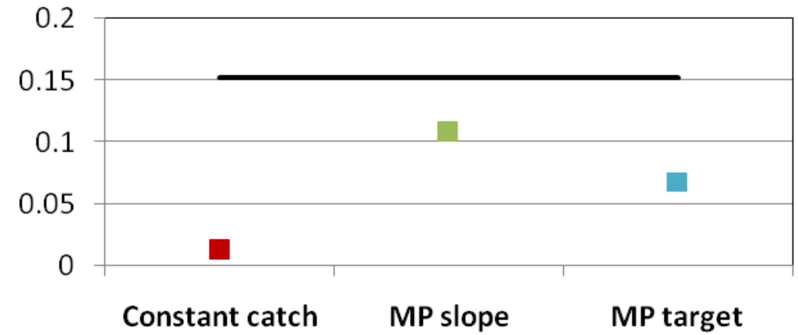
Min SSB/SSBtarget

Step 3.Hindsight projection of forecast MP
North Sea Sole (Subarea IV)

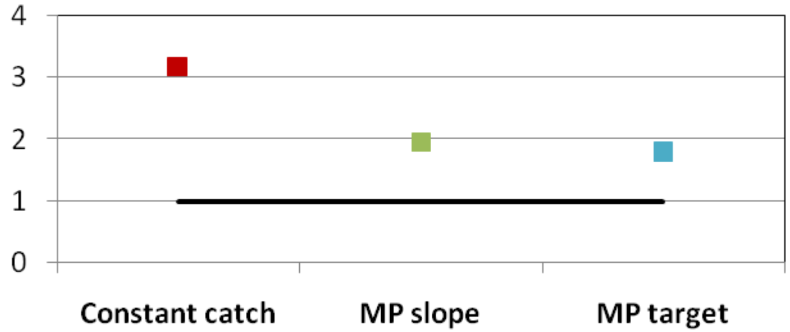
Observed —



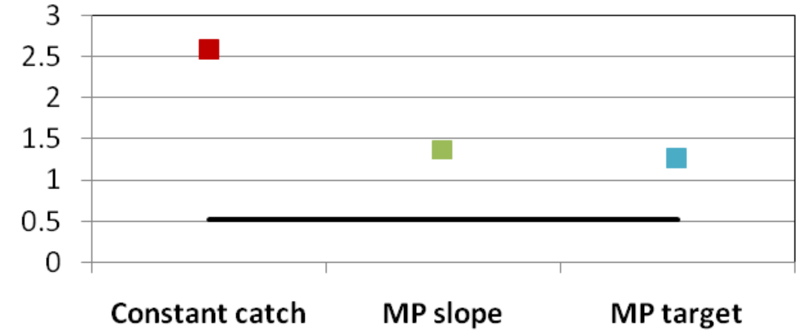
Annual average catch (tons)



Average change in catch



2009 SSB/SSBtarget

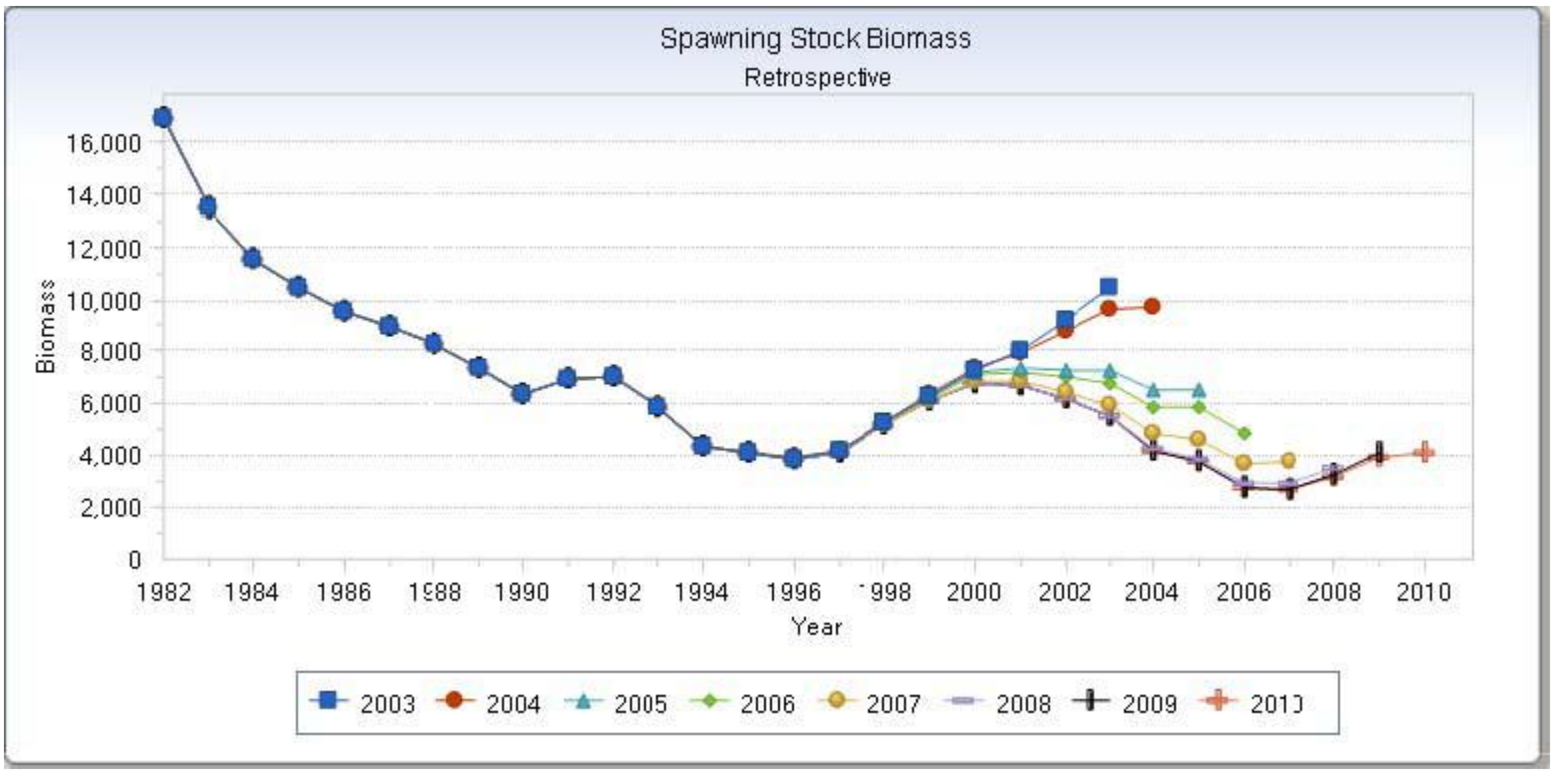


min SSB/SSB target

New England Groundfish

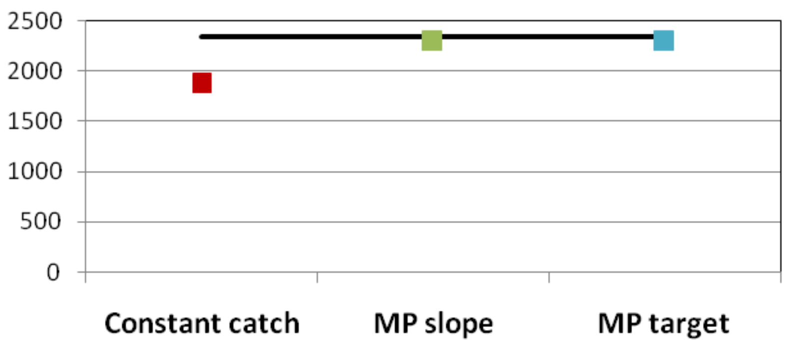
!! Retrospective patterns!!

Assessments: Retrospective patterns
Gulf of Maine Witch Flounder

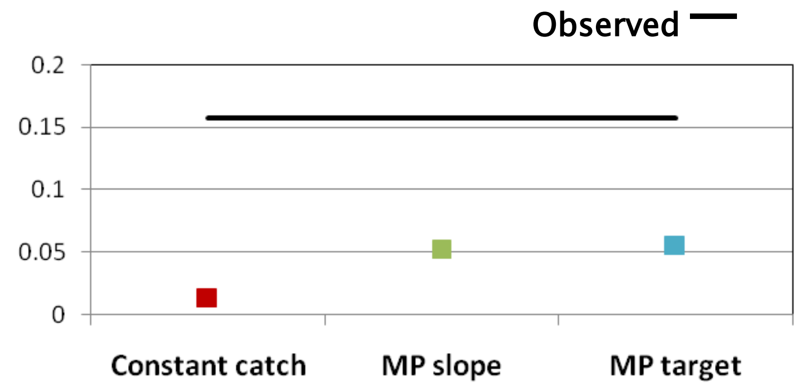


Plot copied from F. Witch Flounder by S.E. Wigley and S. Emery. February 2012

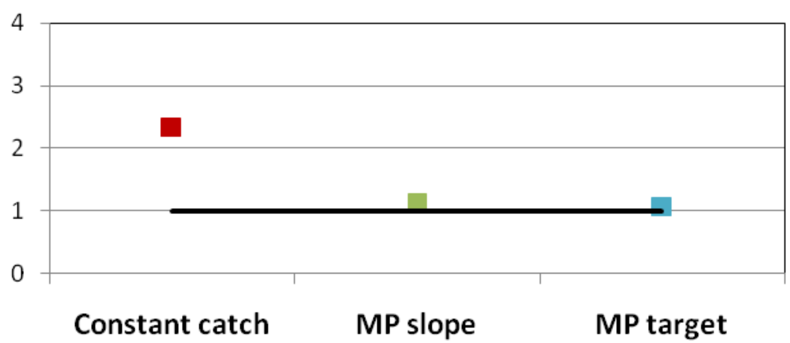
Step 3.Hindsight projection of forecast MP
Gulf of Maine Witch Flounder



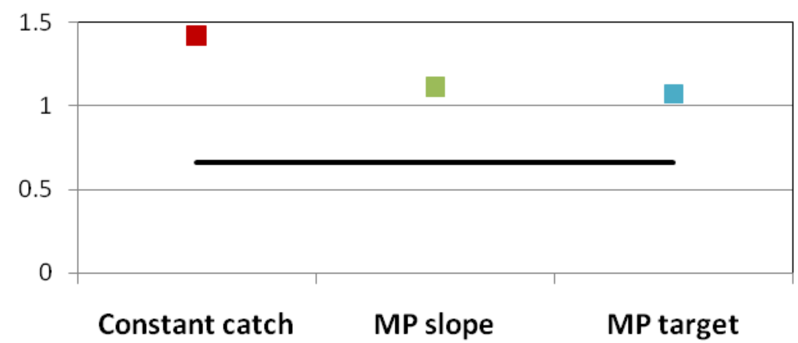
Annual average catch (tons)



Average change in catch



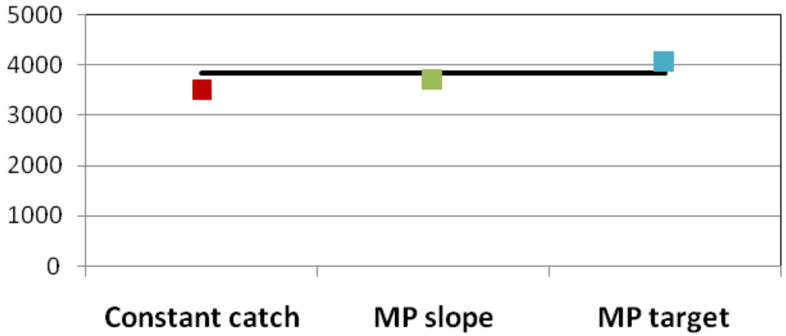
2010 SSB/SSBtarget



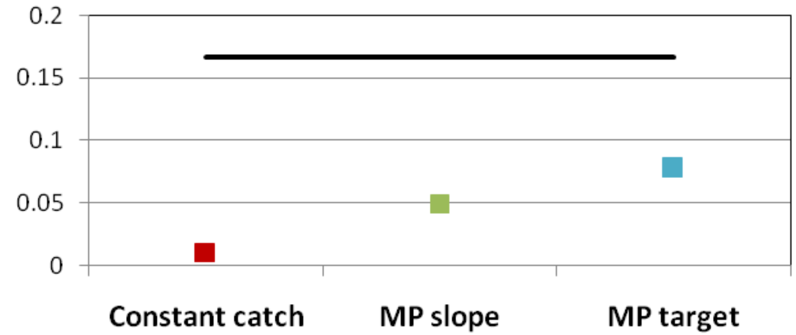
min SSB/SSB target

Step 3.Hindsight projection of forecast MP
Gulf of Maine/Georges Bank Plaice

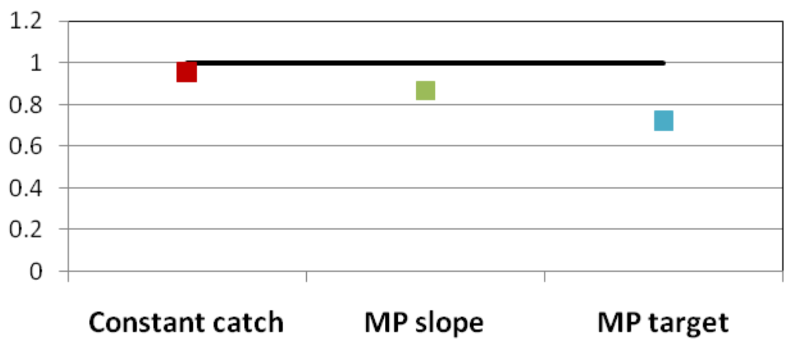
Observed —



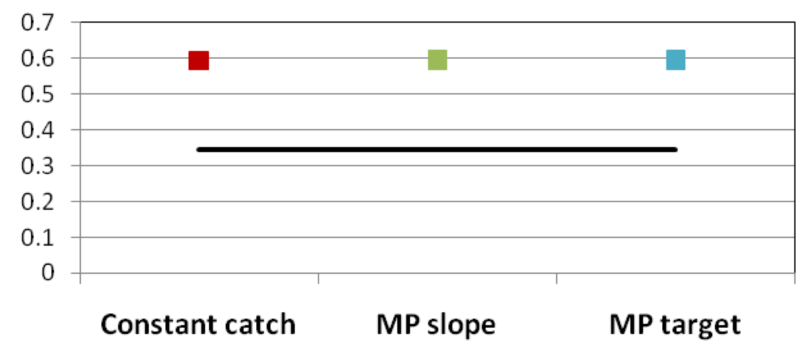
Annual average catch (tons)



Average change in catch



2010 SSB/SSBtarget



min SSB/SSB target

MARAM

Initial conclusions

- MPs perform as well or better than what occurred (based on annual complex assessments)
- Annual assessment based management add unnecessary variation to management measures without reducing resource risk
- Changed role for complex assessments: provide operating models at multi-year intervals for simulation testing of these simpler MPs
- Saving on resources otherwise needed for monitoring (e.g. ageing of catch need not be annual)

Future work

- Apply to more stocks (including tricky assessments)
- Comprehensive robustness tests (e.g. include implementation error)
- Performance given reviews after shorter MP application periods

Paul Rago on …

New England retrospective problem

"Anyone who can solve our retrospective problem deserves the Nobel prize"

Initial conclusions

- MPs perform as well or better than what occurred (based on annual complex assessments)
- Annual assessment based management add unnecessary variation to management measures without reducing resource risk
- Changed role for complex assessments: provide operating models at multi-year intervals for simulation testing of these simpler MPs
- Saving on resources otherwise needed for monitoring (e.g. ageing of catch need not be annual)
- MP approach seems to be able to handle cases with relatively strong retrospective patterns

Paul Rago on …

New England retrospective problem

"Anyone can solve our retrospective problem deserves the Nobel prize"

Paul – are you drafting our nomination yet?

Thank you for your attention

We thank José de Oliveira, Charlie Edward and Laurie Kell, for assistance in providing the ICES assessment data we have used.

Financial support of the National Research Foundation (NRF) of South Africa is gratefully acknowledged.



What generates retrospective patterns in statistical catch-at-age assessment models?

A lot of people[1,2,3,4]

[1] University of Washington, School of Aquatic and Fishery Sciences
[2] CAPAM, Center for the Advancement of Population Assessment Methodology
[3] Simon Fraser University
[4] University of British Columbia

Authors

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Outline

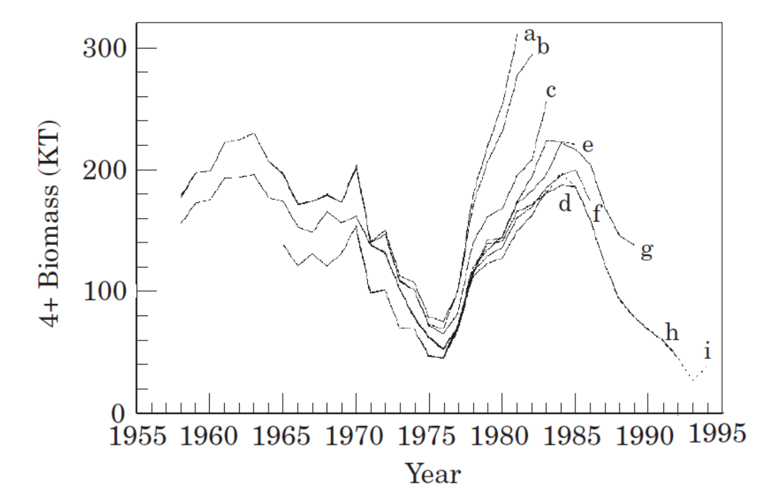


Figure 1. Retrospective pattern of 4+biomass for eastern Scotian Shelf cod from various analyses 1982–1995. a, Maguire et al., 1982; b, Gagne et al., 1983; c, Gagne et al., 1984; d, Sinclair and Gavaris, 1985; e, Sinclair and Annand, 1986; f, Sinclair and Smith, 1987; g, Fanning and MacEachern, 1990; h, Mohn and MacEachern, 1992; i, Fanning et al., 1995.

Mohn, 1999

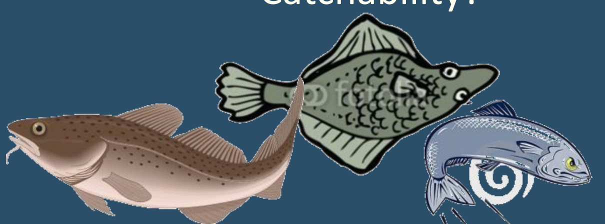
What is a retrospective bias

What factors produce retrospective patterns

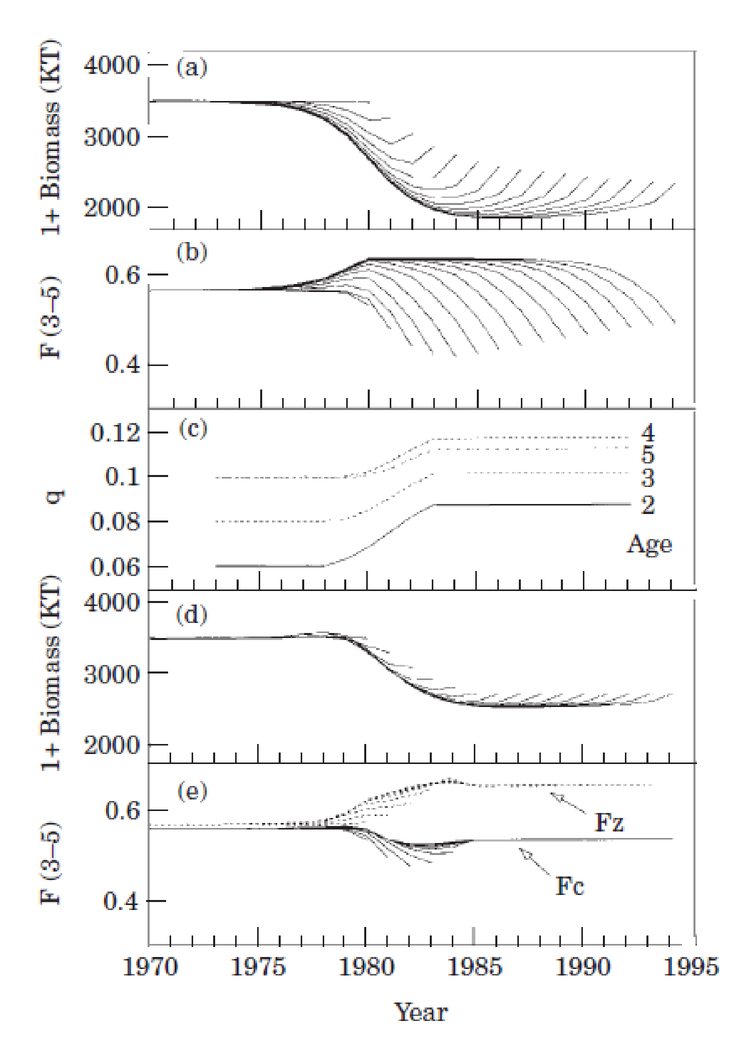
Are there generalities across these factors?

Conclusions and future work

¿ Selectivity?
Natural mortality?
Growth?
Catchability? ?



What is a retrospective pattern?



"The retrospective problem is a systematic inconsistency among a series of estimates of population size, or related assessment variables, based on increasing periods of data."

Mohn, 1999

"There are severe implications for both managers and the stock itself when stock assessments exhibit strong retrospective patterns. Management advice will be biased and could lead to continued overfishing of the stock, inability to achieve rebuilding targets, and loss of potential yield."

Legault, 2008

Previous studies have explored retrospective patterns and identified some of the factors causing them

ICES Journal of Marine Science, 56: 473–488. 1999
Article No. jmsc.1999.0481, available online at http://www.idealibrary.com on IDEAL

The retrospective problem in sequential population analysis: An investigation using cod fishery and simulated data

R. Mohn

Northeast Fisheries Science Center Reference Document 09-01

Report of the Retrospective Working Group

January 14-16, 2008, Woods Hole, Massachusetts

by Christopher M. Legault, Chair

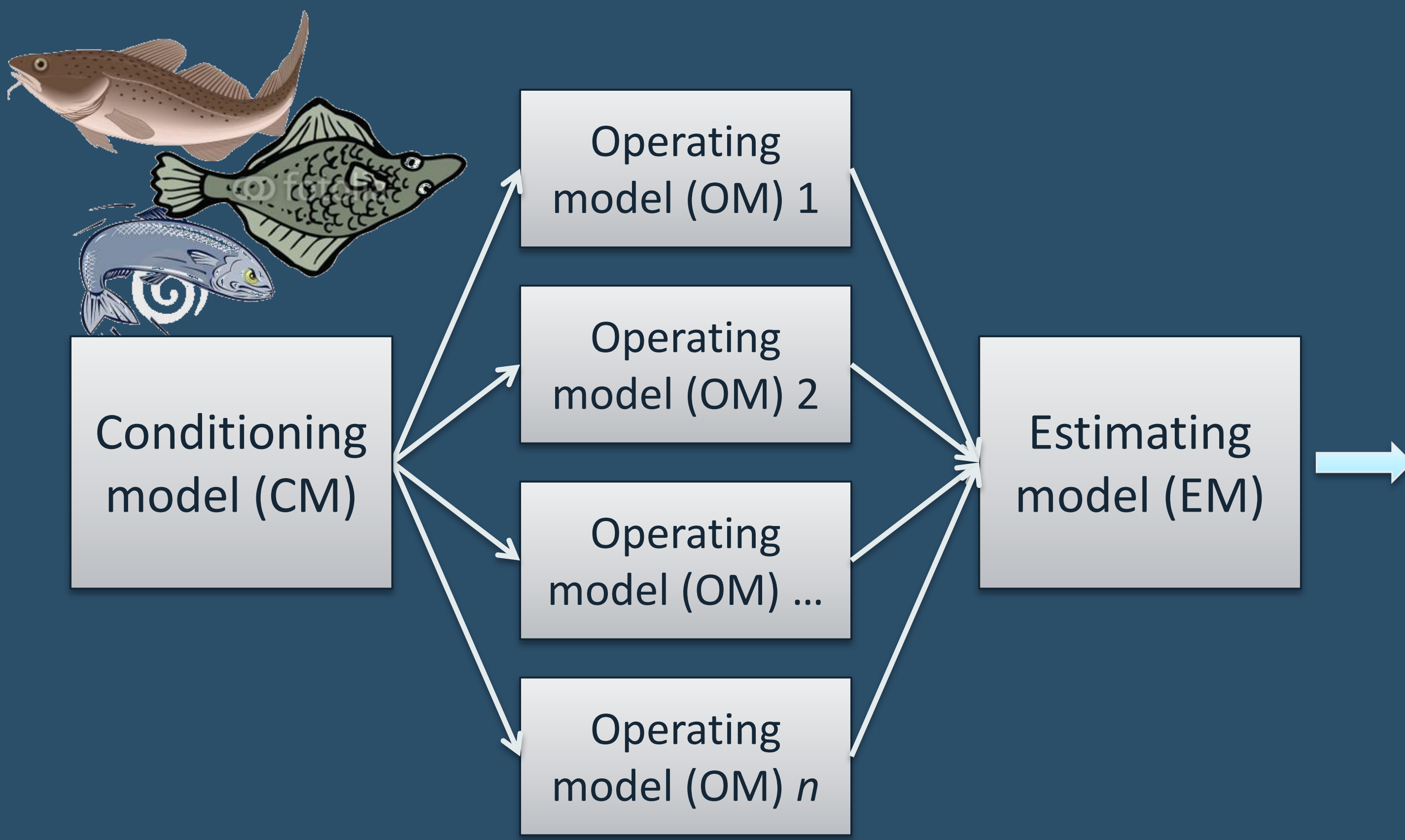
Can be caused by a number of factors, but all require a change in parameter value or assumed model value over time.

- Natural mortality
- Catch series
- Survey catchability
- Closed areas

Main questions

- What processes generates retrospective patterns? Can we generate them in catch-at-age models?
- What is the magnitude of these patterns for different processes?
- Is the use of time-varying selectivity to address these patterns appropriate?

This project uses a stock assessment evaluation framework



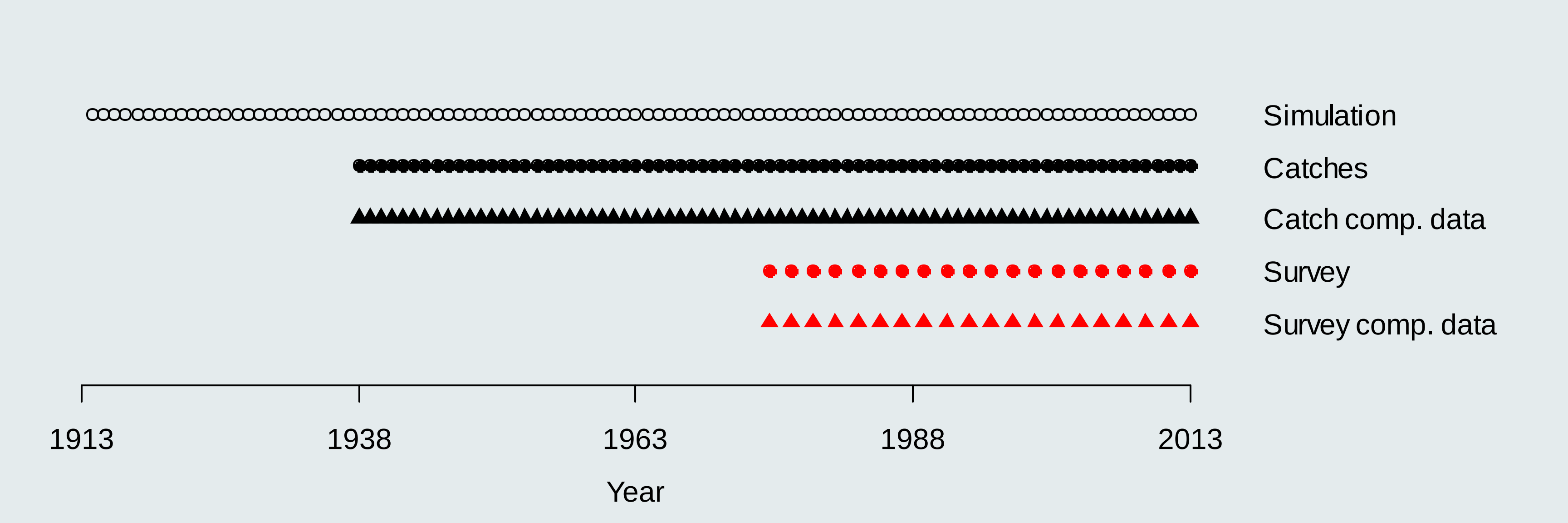
Performance measures

- Biomass
- F
- Recruitment
- Mohn's ρ

$$\rho = \overline{\left(\frac{X_{(y1:y),y} - X_{(y1:y2),y}}{X_{(y1:y2),y}}\right)}$$

All these steps are done using **Stock Synthesis** as the simulation and estimation platform

A more detailed description of the model



Parameters

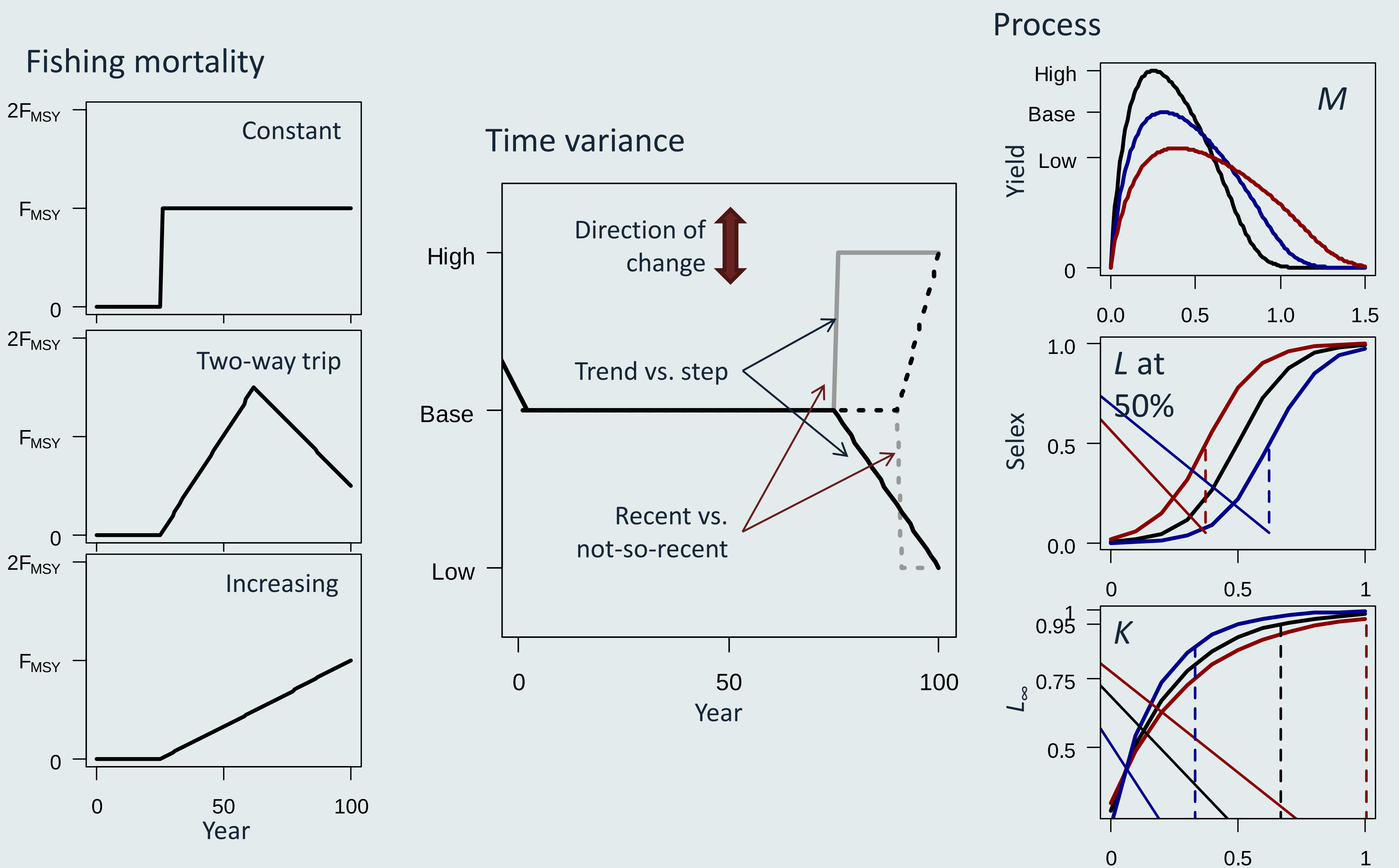
Estimated:
- Growth (K, L_∞, CV)
- R_0
- Rec. deviations
- Selectivity parameters
- Q

Fixed:
- M
- Steepness
- σ_R

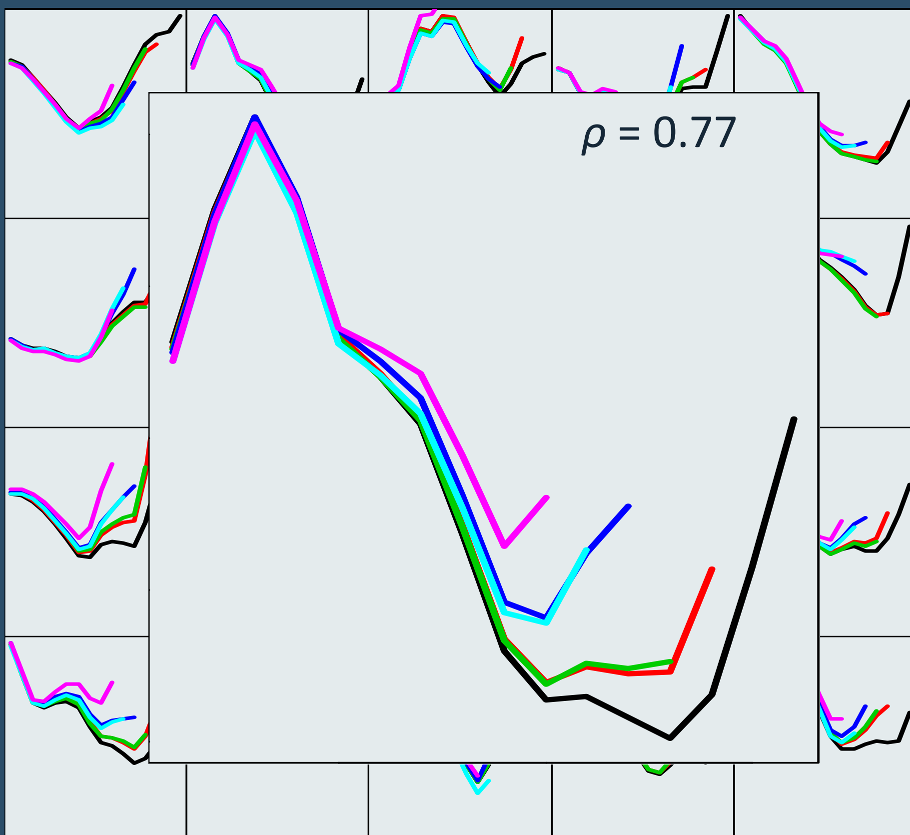
Retrospective runs

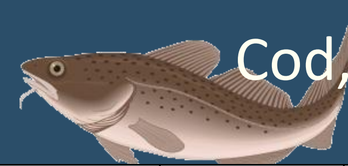
5-year retrospective analysis

Experimental design: 3 fishing patterns, 3 types of change, and 3 processes

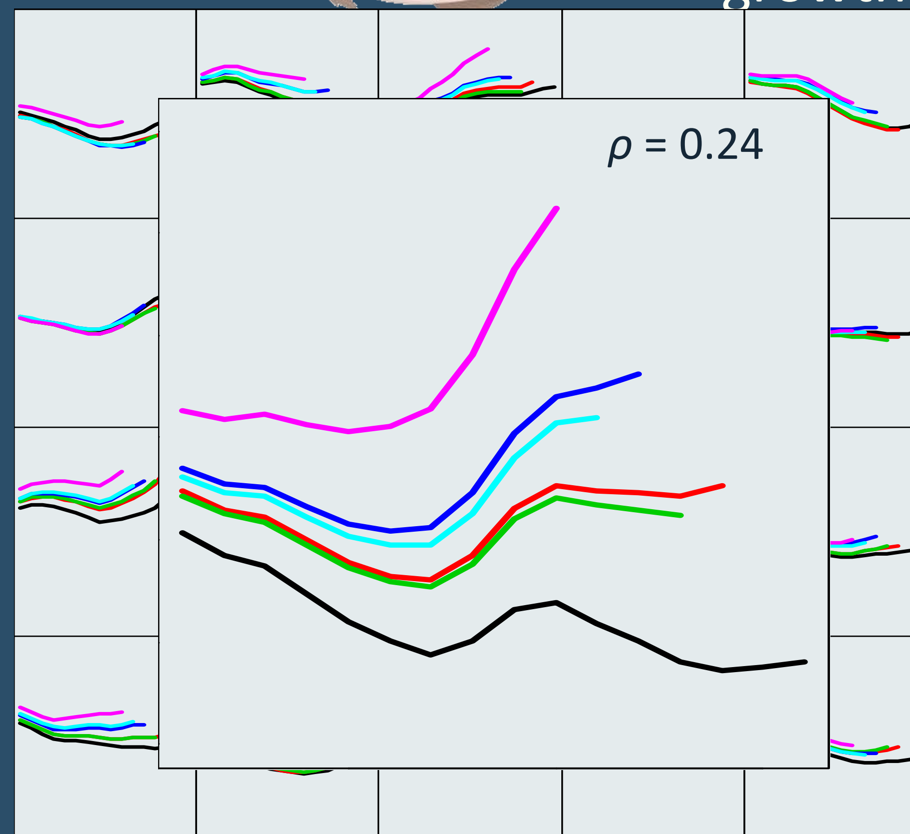


Retrospective patterns can be generated when there is model misspecification



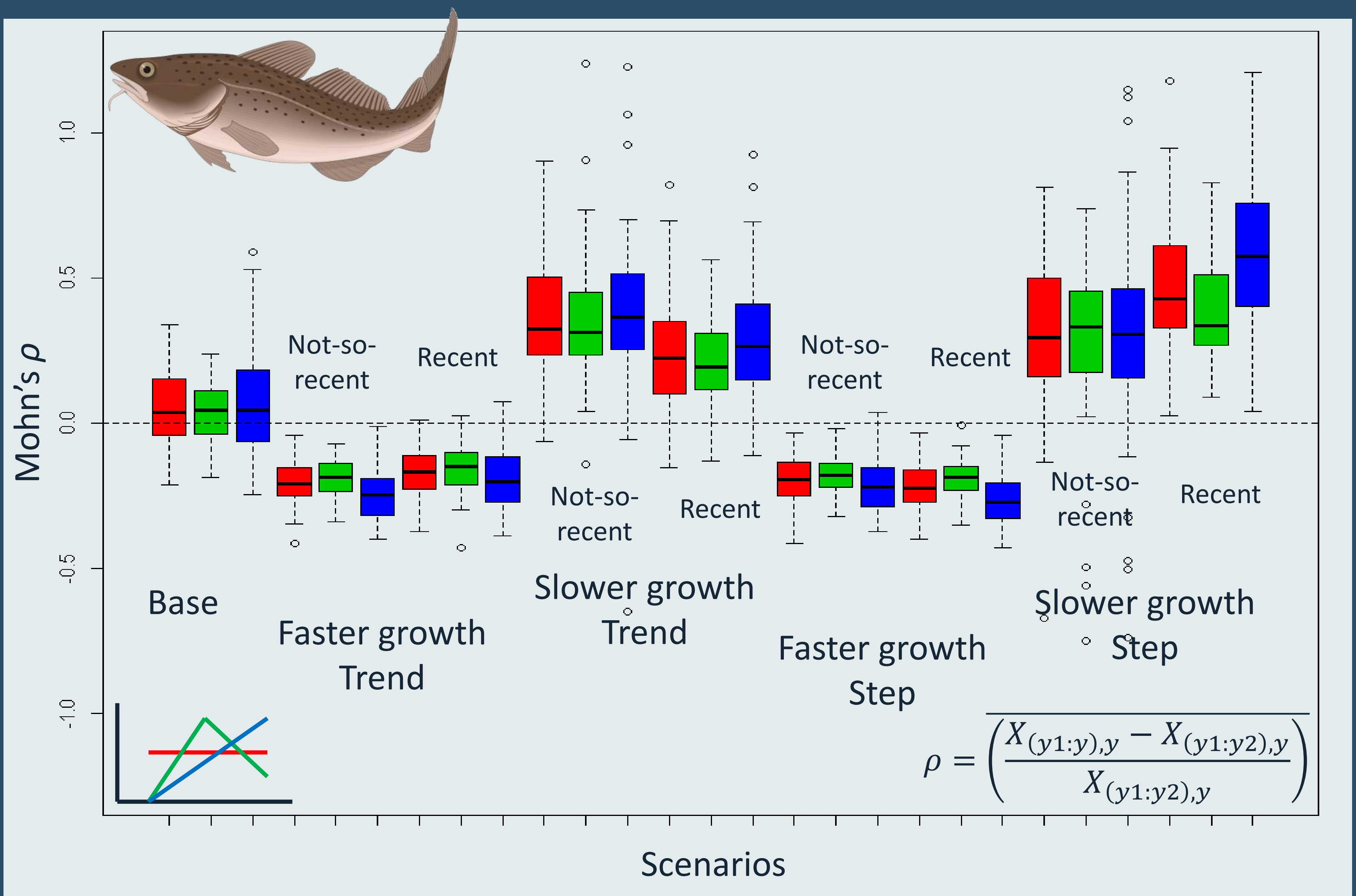


Cod, time varying growth

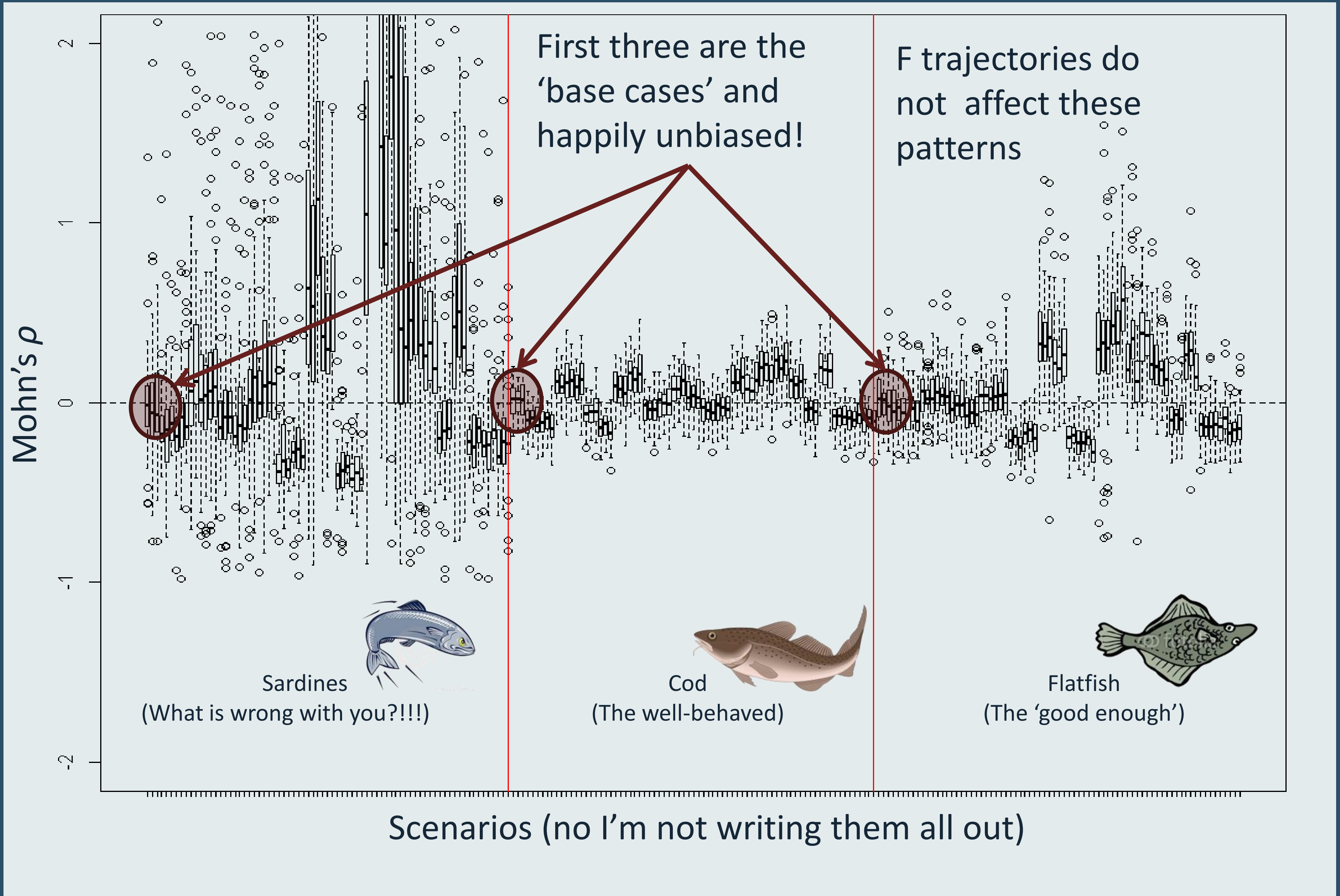


Flatfish, time varying selectivity

Mohn's ρ statistic allows to evaluate retrospective patterns across scenarios



Different factors have a different effect depending on the life history type



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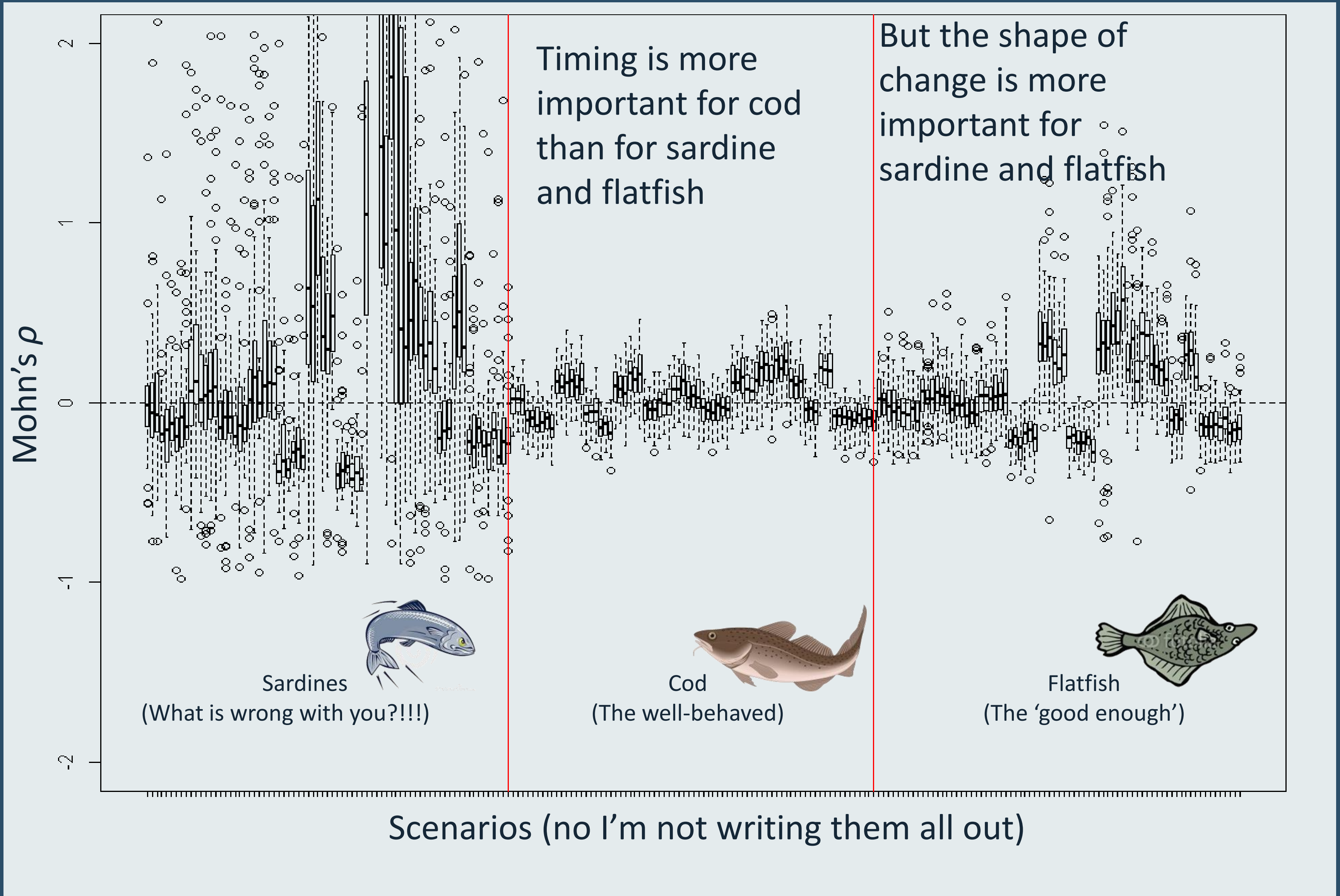
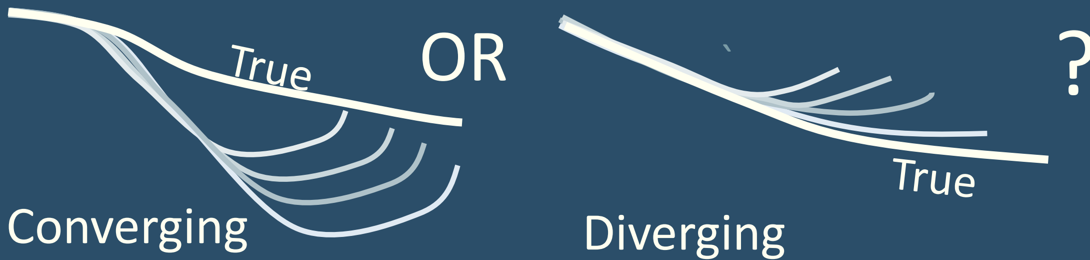
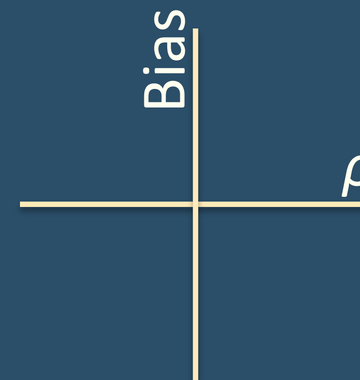
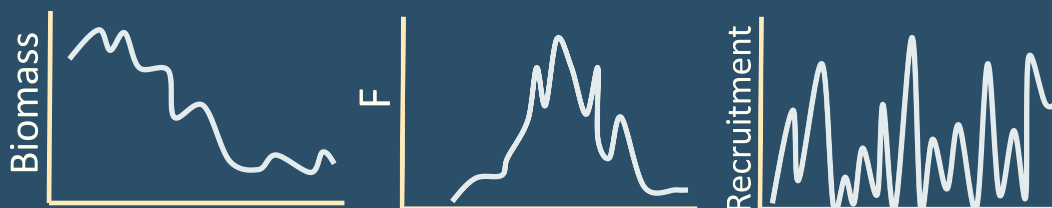


What comes next?

1. 



2. 

Parameter estimates

NMDS

3. 

4. What happens when these patterns are "corrected" using time-varying selectivity?

Conclusions

- Retrospective patterns were generated by all the factors explored.
- What factors affect retrospective patterns the most seem related to life history.
- Direction and magnitude of a retrospective pattern are affected by the direction and magnitude of the change.
- Higher variability in the data generate higher variability in the Mohn's ρ statistic.

THANK YOU

Acknowledgements:
Andre Punt, Jim Ianelli, Rick Methot, Ian Taylor, Jim Thorson

UNIVERSITY of WASHINGTON
CENTER FOR STUDIES IN DEMOGRAPHY AND ECOLOGY

Partial support for this research came from a *Eunice Kennedy Shriver* National Institute of Child Health and Human Development research infrastructure grant, R24 HD042828, to the Center for Studies in Demography & Ecology at the University of Washington

One Model ... or Three

The use of model averaging to streamline the stock assessment process

Colin Millar
Ernesto Jardim
Richard Hillary
Ruth King

European Commission
Joint Research Center

Context

This has all been developed within the a4a framework

The Problem

There are often several plausible assessment models

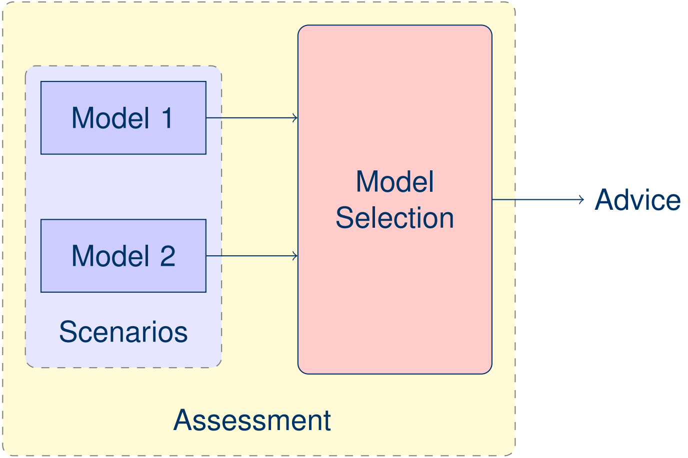
Solutions

- Choose one model
- Present several models
- Hierarchical modelling
- Combine models

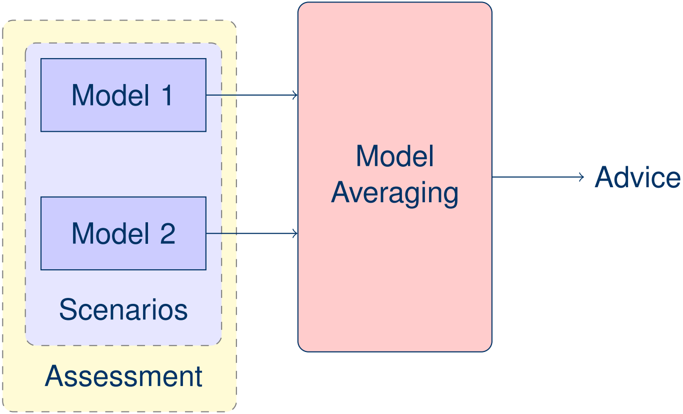
Solutions

- Choose one model
- Present several models
- Hierarchical modelling
- Combine models

An Assessment Process



Model Averaging



Model Choices in a4a

With a linear model you can fit

- linear and smooth functions of age and year
- seperable models
- partially seperable
- non-seperable
- step changes (in level, in smoother form)
- covariates (smoothed and linear)

These can be applied to log **F**, log **catchability**, **stock recruit** parameters, observation **variance.**

Model Choices in a4a

For example in selectivity

$$\log Q \sim \overbrace{\text{log Contact Selectivity}}^{\text{offset}} + \underbrace{\text{log Availability}}_{\text{formula}}$$

Model Selection in a4a

- likelihood based
  - **AIC** (Akaike Information Criterion)
  - **BIC** (Bayesian or Schwarz Information Criterion)
- Posterior model probabilities
  - **HME** (Harmonic Mean Estimator)
  - **BMA** (Bayesian Model Averaging)

All these balance complexity and fit.

Model Choices

(log) fishing mortality

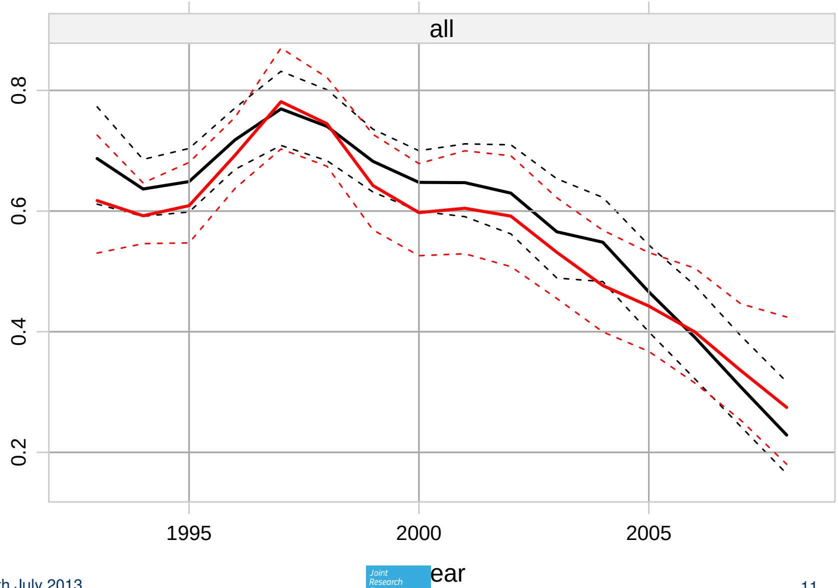
```
fmodel1 <- ~ s(age, k = 4, by = breakpts(year, c(199
+ s(year, k = 8)
fmodel2 <- ~ te(age, year, k = c(4, 8))
```

(log) survey catchability

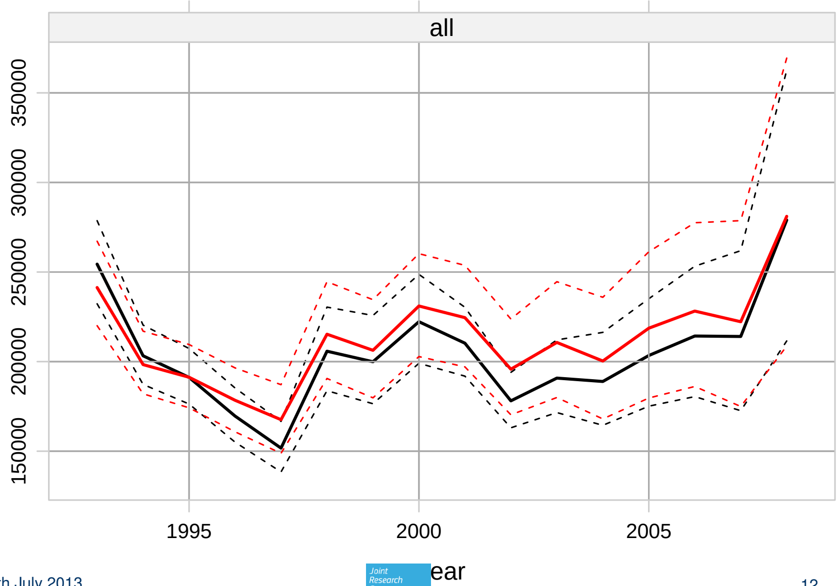
```
qmodel1 <- ~s(age, k = 4)
qmodel2 <- ~poly(age, 2)
```

AIC	fmodel1	fmodel2
qmodel1	317.238	316.506
qmodel2	317.174	316.0118

Model Fits: Fbar



Model Fits: SSB



Approaches to Model Averaging

- weighted simulation schemes
  - AIC
  - posterior model probability (HME)
- Full model averaging schemes
  - smooth AIC (bootstrap)
  - RJMCMC

Approaches to Model Averaging

- weighted simulation schemes
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Approaches to Model Averaging

We want to sample from:

$$P(\text{model, model parameters} \mid \text{data})$$

Weighted simulation schemes do:

1. simulate: $\tilde{P}(\text{model} \mid \text{data})$
   $\tilde{P}(\text{parameters} \mid \text{model})$

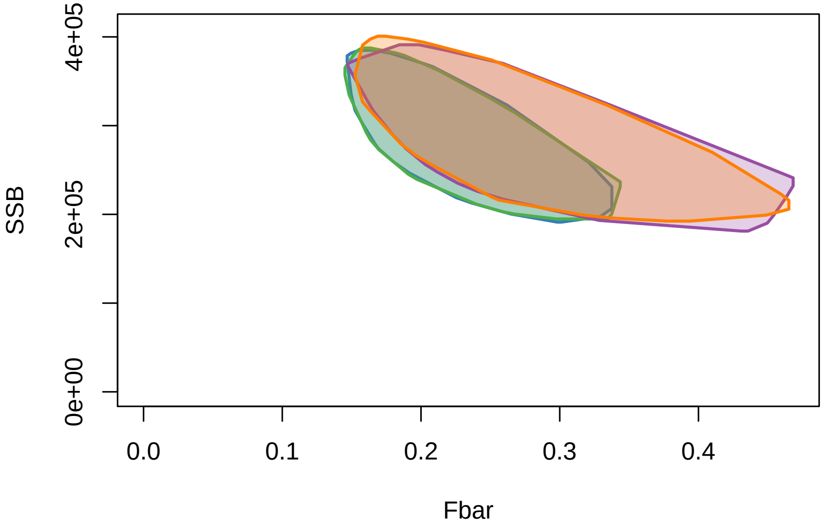
Approaches to Model Averaging

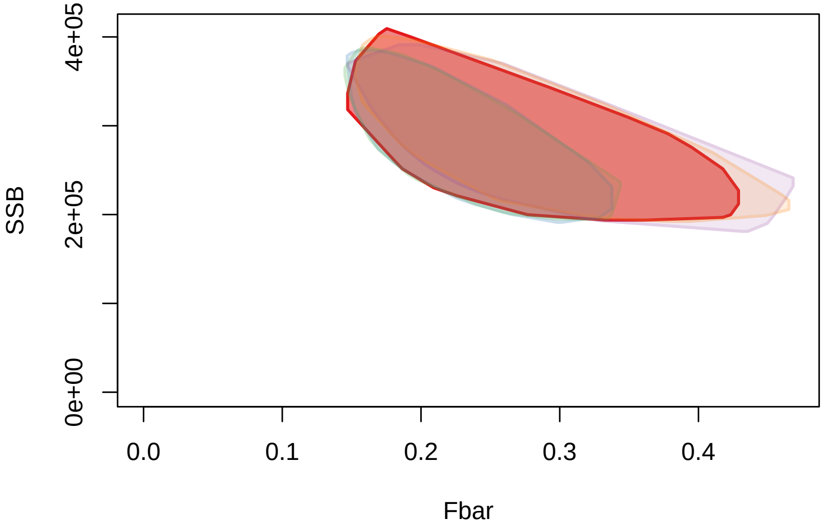
We want to sample from:

$$P(\text{model, model parameters} \,|\, \text{data})$$

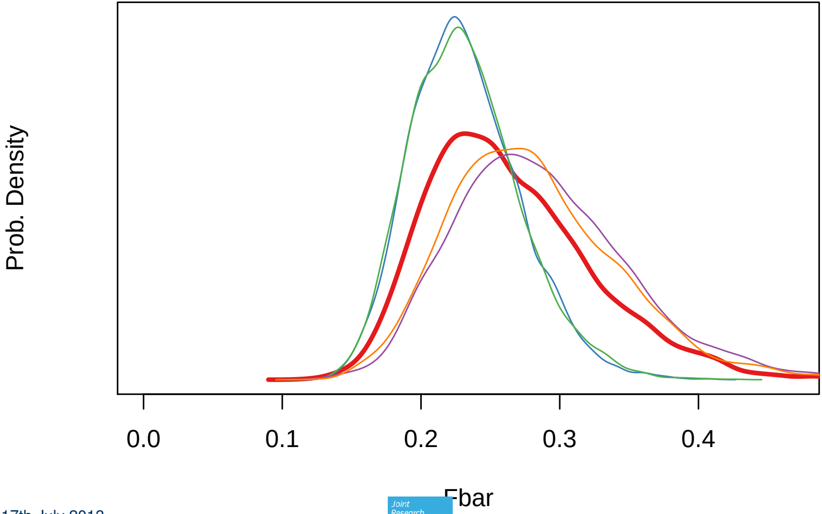
Full model averaging schemes do:

1. simulate: $\tilde{P}(\text{model, model parameters} \,|\, \text{data})$


SSB
4e+05
2e+05
0e+00
0.0
0.1
0.2
0.3
0.4
Fbar


SSB
4e+05
2e+05
0e+00
0.0
0.1
0.2
0.3
0.4
Fbar

Final year Fbar



Final thoughts

With model averaging

- We **incorporate uncertainty** from scenario choice
- It removes the need for model selection
- moves focus onto specifying **plausible** scenarios
- we can simulate, Fbar, reference points, current state w.r.t. ref points




Better data yields better yields ?
Why the type, quantity and quality of data matters in fisheries stock assessments

Fish 600 group

Wed July 17rd 2013

CAPAM

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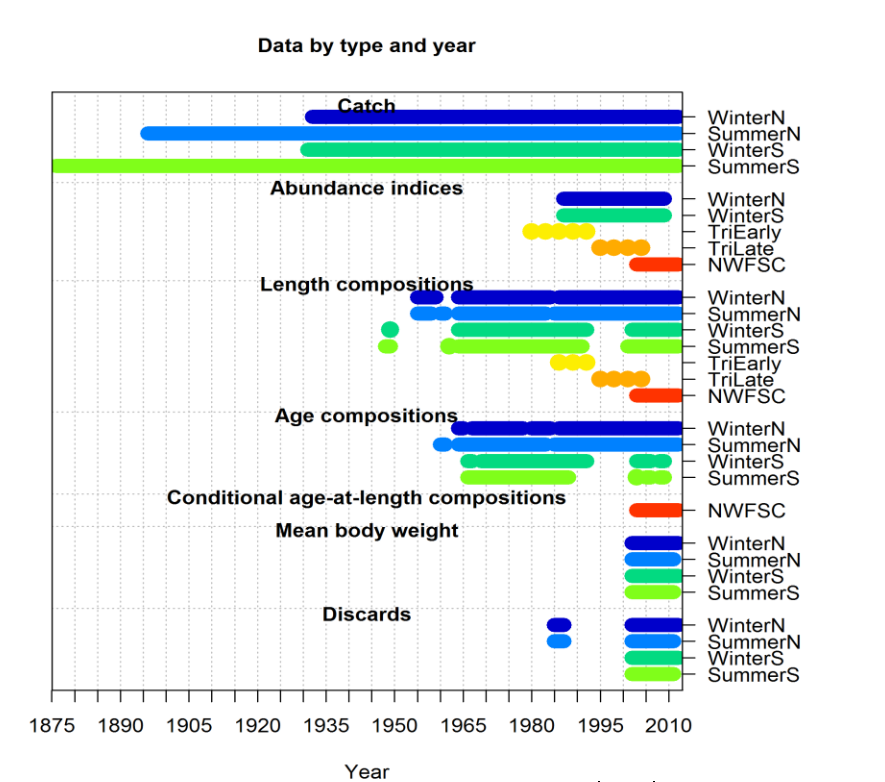
- Sean Anderson[3]
- Roberto Licandeo[4]

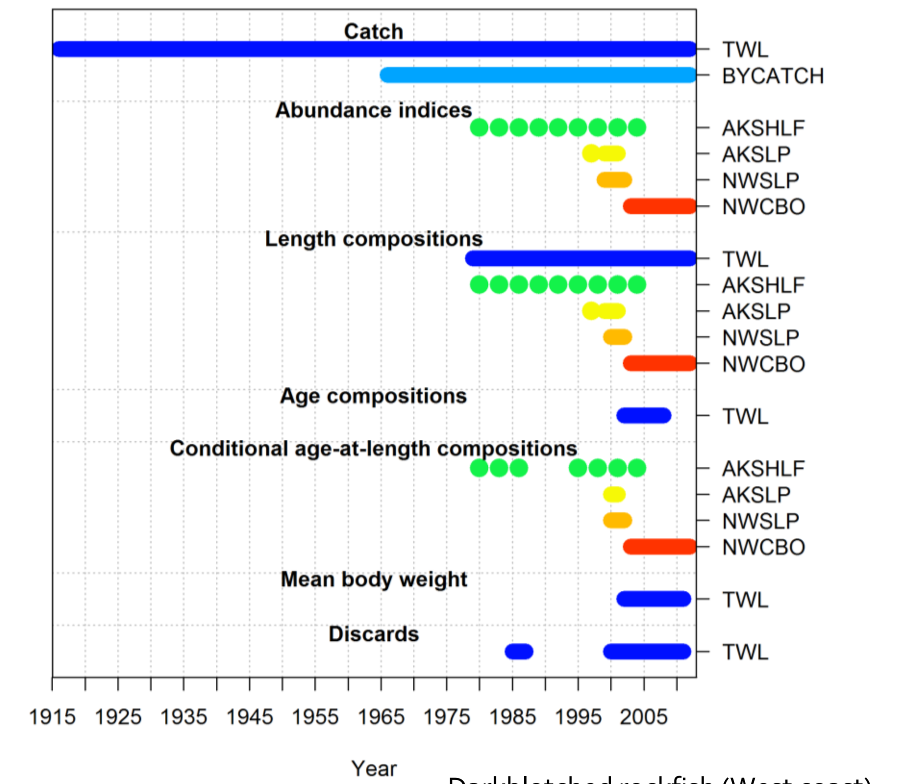
[1] University of Washington, School of Aquatic and Fishery Sciences
[2] CAPAM, Center for the Advancement of Population Assessment Methodology
[3] Simon Fraser University
[4] University of British Columbia

Background

- Not all data available for a stock assessment



Petrale sole (West coast)



Darkblotched rockfish (West coast)

Background

of

North American Journal of Fisheries Management 24:865–879, 2004

Bias and Precision of Es
Assessment Progra

Performance of a fisheries catch-at-age model (Stock Synthesis) in data-limited situations

What makes fisheries data informative?

Arni Magnusson[1,2] *& Ray Hilborn*[1]

[1]School of Aquatic and Fishery Sciences, University of Washington, Box 35520, Seattle, WA 98195, USA; [2]Marine Research Institute, Skulagata 4, PO Box 1390, 121 Reykjavik, Iceland

Background

- Not all data available for a stock assessment

→What is important for estimating quantities of interest?

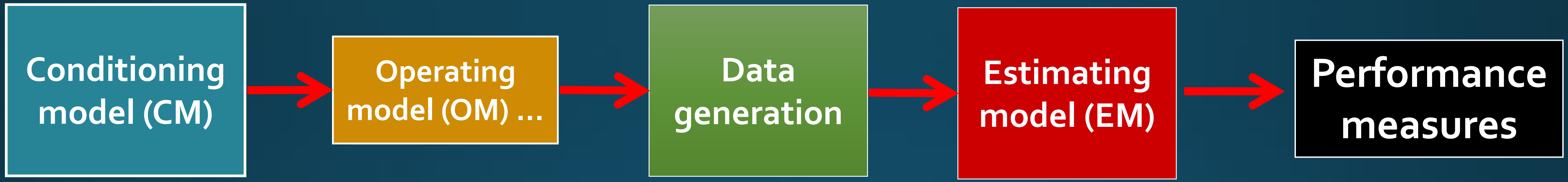
- Several studies have examined this issue

- This study expands the above by investigating the importance of composition data across three life history types using Stock Synthesis, a statistical catch at age model

Objectives

- Importance of quantity and quality of composition data between life-history types
  - Quantity: sample size, sampling frequency (number of years and spacing)
  - Quality: survey *vs* fishery composition data

Method: simulation design



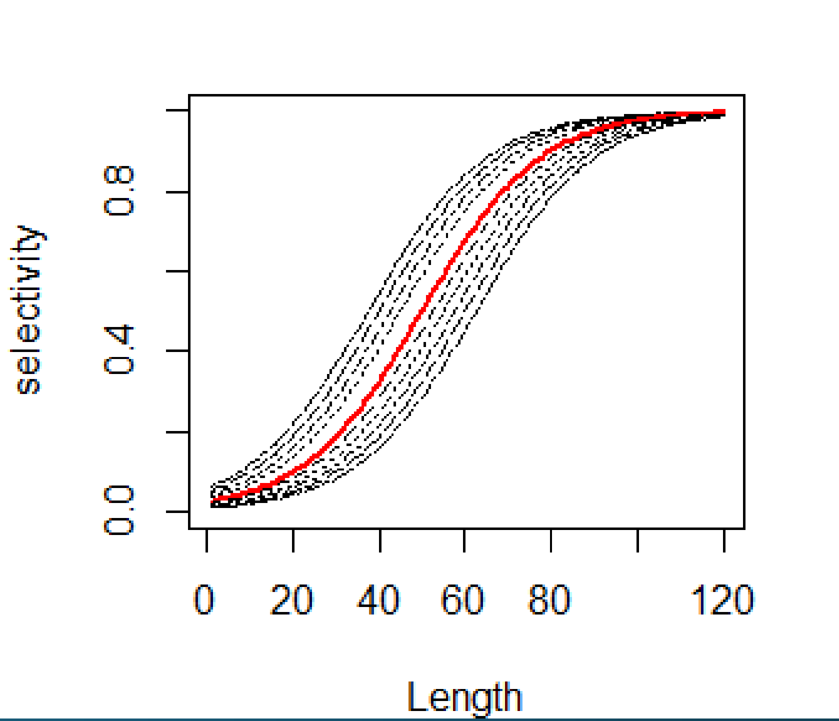
- Cod-type
- Flatfish-type
- Sardine-type

- survey data
- age composition
- length composition
- frequency
- sample size

- Biomass ratio
- MSY
- Growth parameter

All these steps are done using **Stock Synthesis** as the simulation and estimation platform

Method: model assumptions



Operating Model

- All parameters constant over time except: fishery selectivity

→asymptotic with time varying $L_{50\%}$

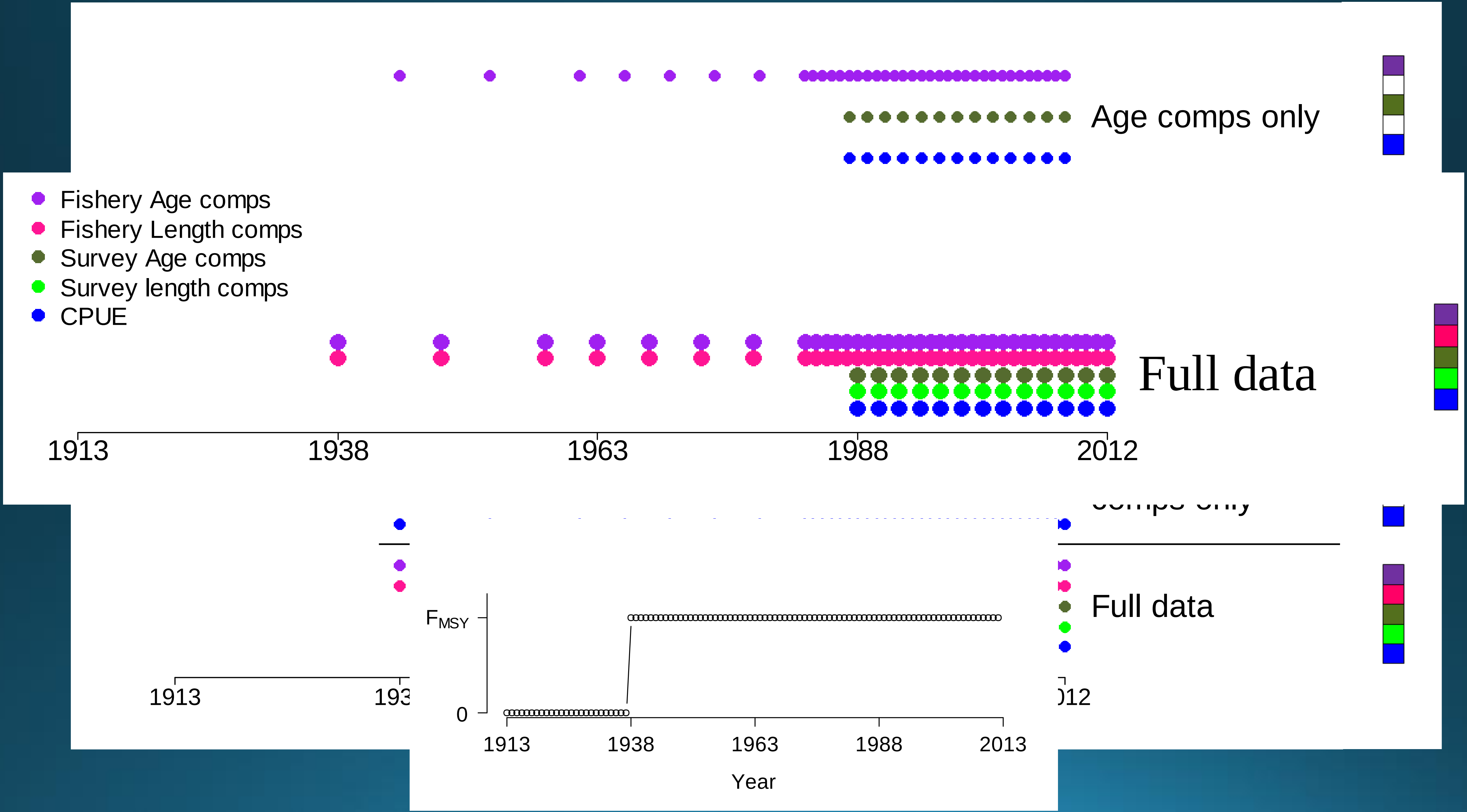
- Survey samples = Multinomial
- Fishery samples = Dirichlet (overdispersion)

Estimation Model

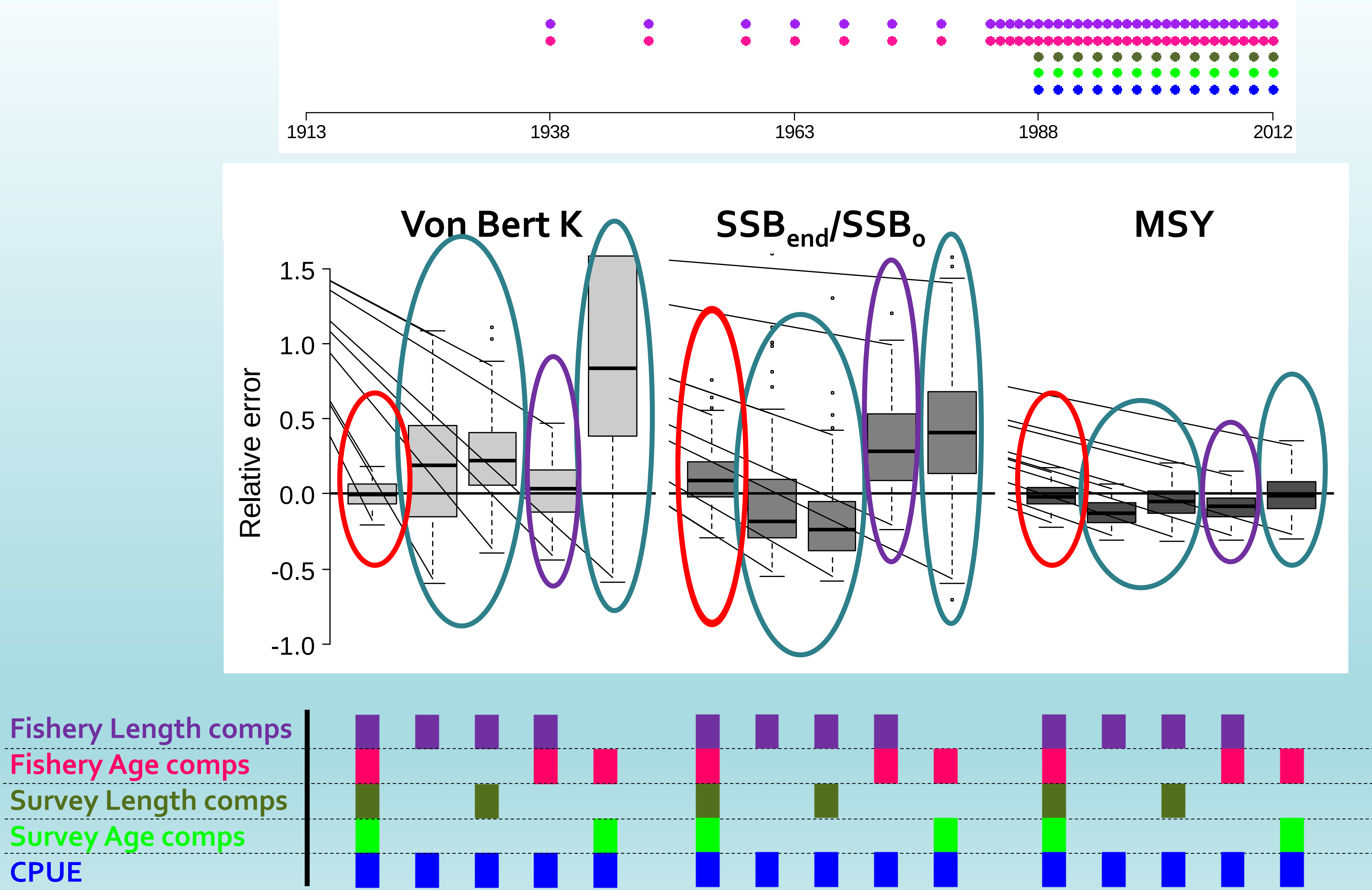
- *M* and *h* are assumed to be known without error
- Estimate growth (except the CVs of growth), catchability, R_0, recruit. devs
- Estimate NON time varying fishery selectivity

Objective 1: Importance of the different composition data types

- **Hypothesis**: Without both the age and length compositions data, growth is harder to estimate, therefore affecting other parameter estimates



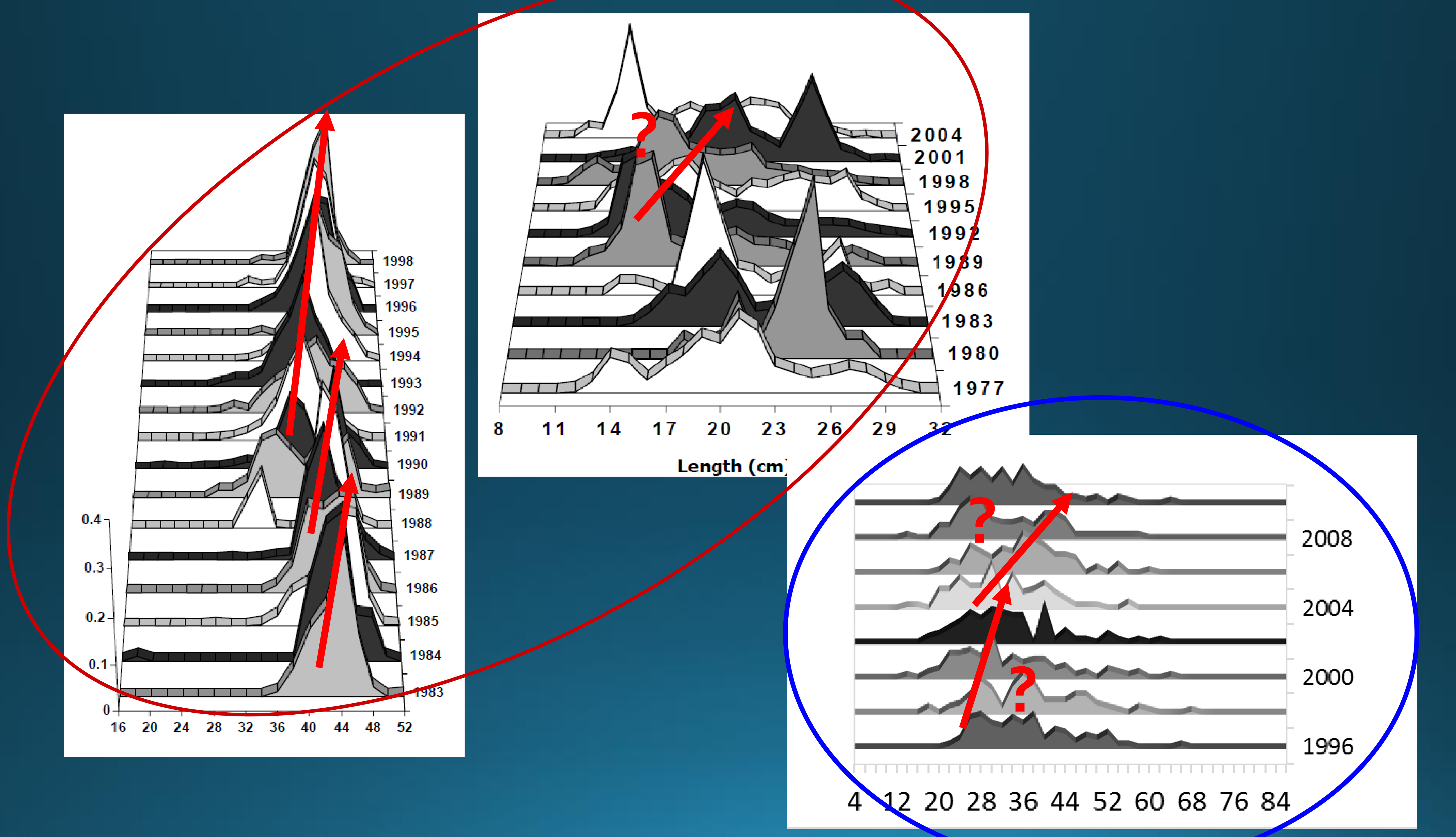
Age comps only
Fishery Age comps
Fishery Length comps
Survey Age comps
Survey length comps
CPUE
Full data
1913
1938
1963
1988
2012
Full data
1913
2012
F_MSY
0
1913
1938
1963
1988
2013
Year



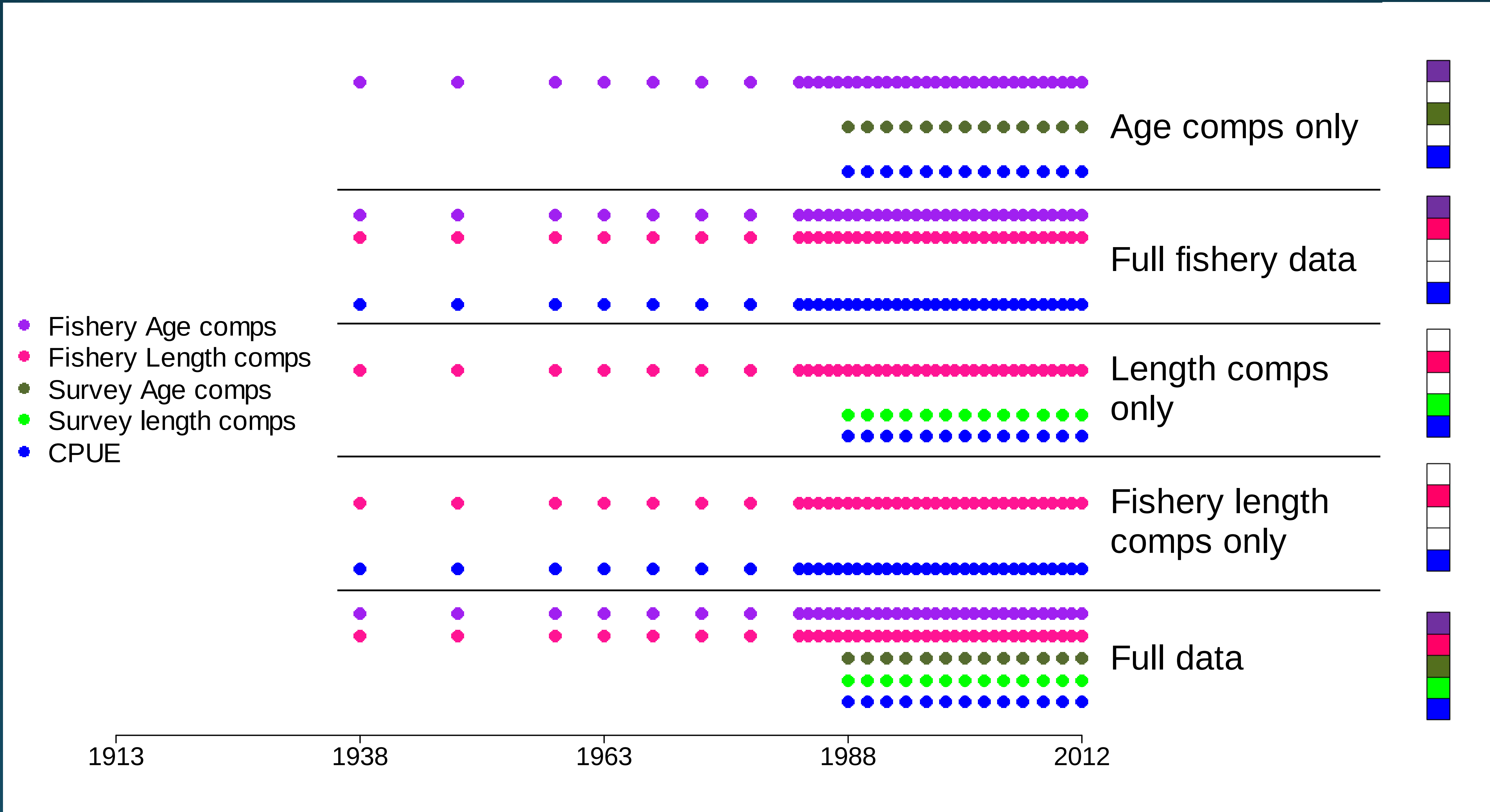
1913
1938
1963
1988
2012
Von Bert K
SSBend/SSBo
MSY
Relative error
1.5
1.0
0.5
0.0
-0.5
-1.0
Fishery Length comps
Fishery Age comps
Survey Length comps
Survey Age comps
CPUE

Objective 2: How does the importance of length and age composition data vary between life-history types?

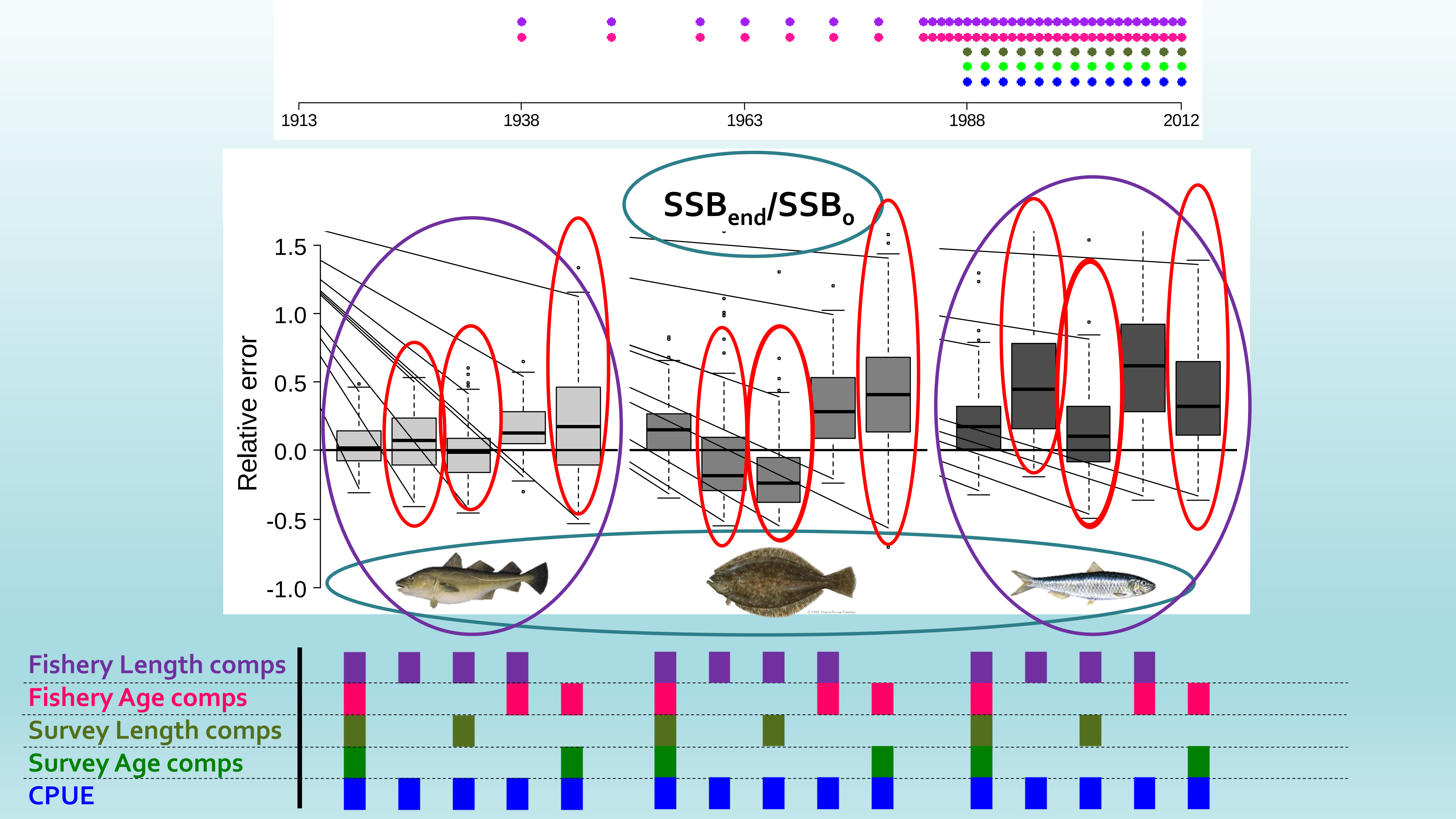
- **Hypothesis**: For some life history types, we can more easily track the cohorts hence we can better estimate growth and other parameters



1998
1997
1996
1995
1994
1993
1992
1991
1990
1989
1988
1987
1986
1985
1984
1983
0.4
0.3
0.2
0.1
0
16 20 24 28 32 36 40 44 48 52
2004
2001
1998
1995
1992
1989
1986
1983
1980
1977
8 11 14 17 20 23 26 29 32
Length (cm)
?
2008
2004
2000
1996
4 12 20 28 36 44 52 60 68 76 84
?
?



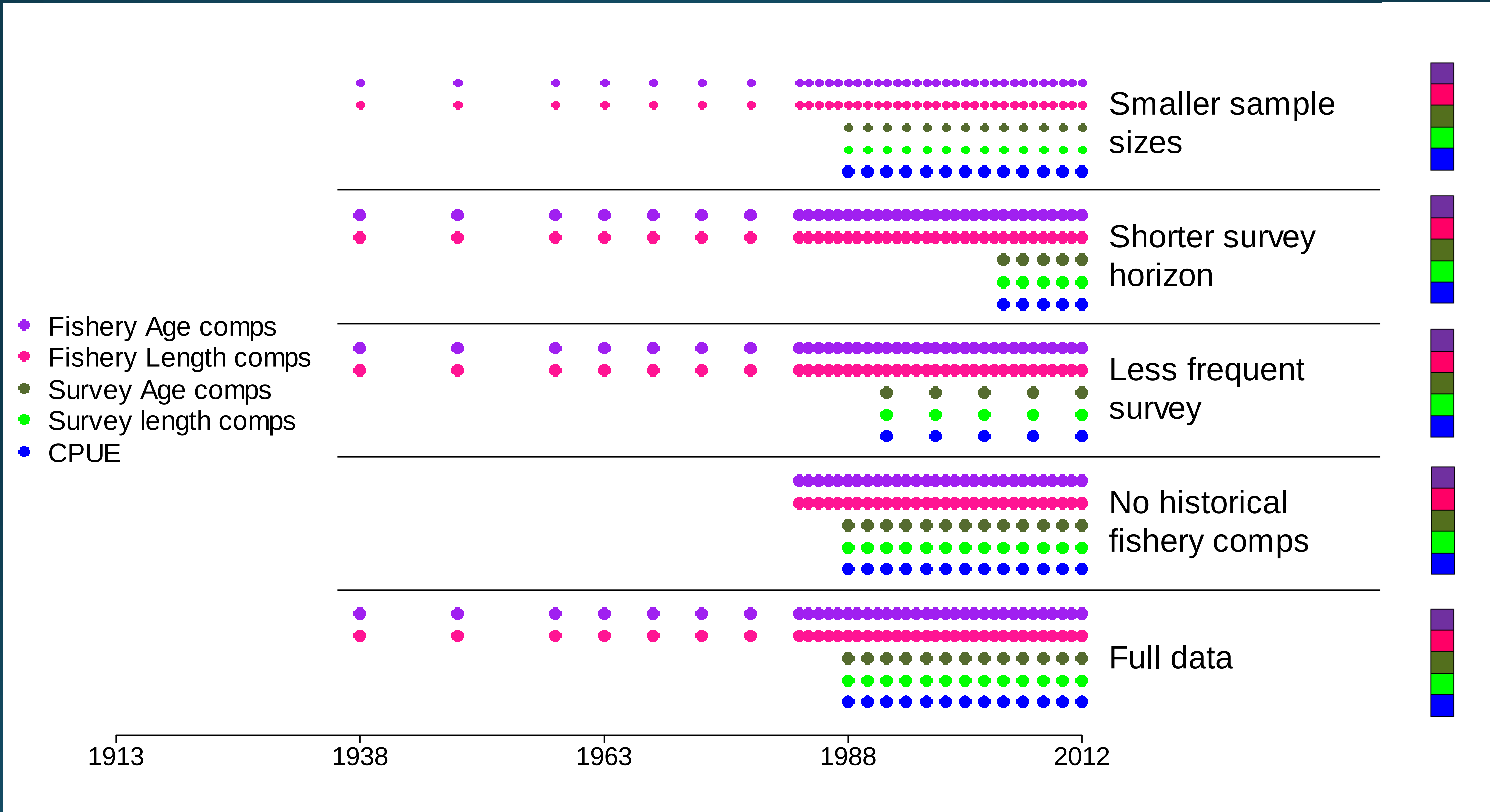
Fishery Age comps
Fishery Length comps
Survey Age comps
Survey length comps
CPUE
Age comps only
Full fishery data
Length comps only
Fishery length comps only
Full data
1913
1938
1963
1988
2012

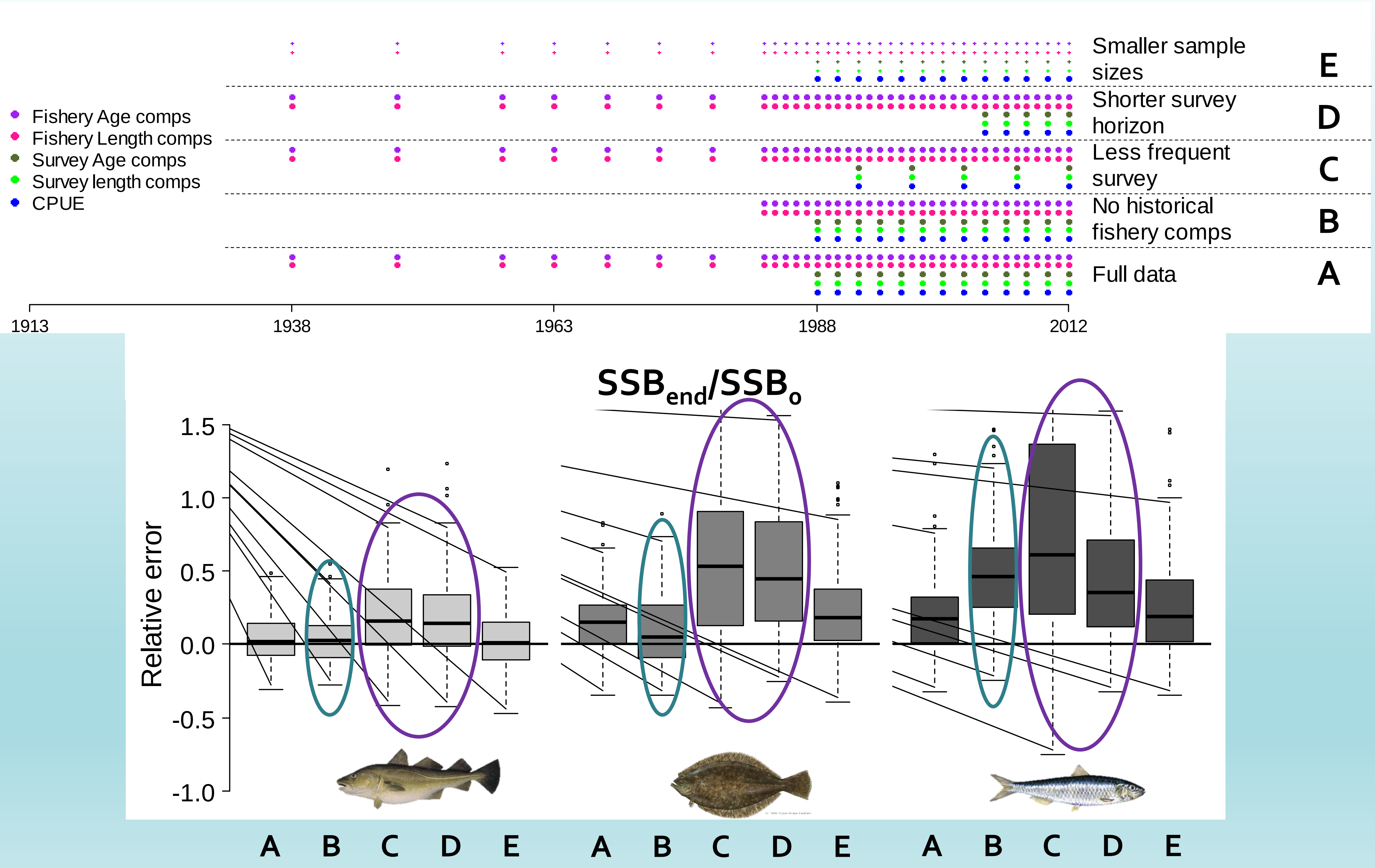


1913
1938
1963
1988
2012
SSB_{end}/SSB_o
Relative error
1.5
1.0
0.5
0.0
-0.5
-1.0
Fishery Length comps
Fishery Age comps
Survey Length comps
Survey Age comps
CPUE

Objective 3: Importance of quantity and quality of composition data among life history types

- **Hypothesis**: With less composition data, parameter estimates will be more biased and more variable but its importance depends on the life-history types


Fishery Age comps
Fishery Length comps
Survey Age comps
Survey length comps
CPUE
Smaller sample sizes
Shorter survey horizon
Less frequent survey
No historical fishery comps
Full data
1913
1938
1963
1988
2012



Smaller sample sizes
E
Shorter survey horizon
D
Less frequent survey
C
No historical fishery comps
B
Full data
A
Fishery Age comps
Fishery Length comps
Survey Age comps
Survey length comps
CPUE
1913
1938
1963
1988
2012
SSBend/SSBo
Relative error
1.5
1.0
0.5
0.0
-0.5
-1.0
A B C D E A B C D E A B C D E

Conclusion/Discussion

MOST important

LEAST important

Cod-like species

Length comps

- survey comps
- Longer survey time period OR more frequent

Age comps

Flatfish-like species

Length comps & Age comps

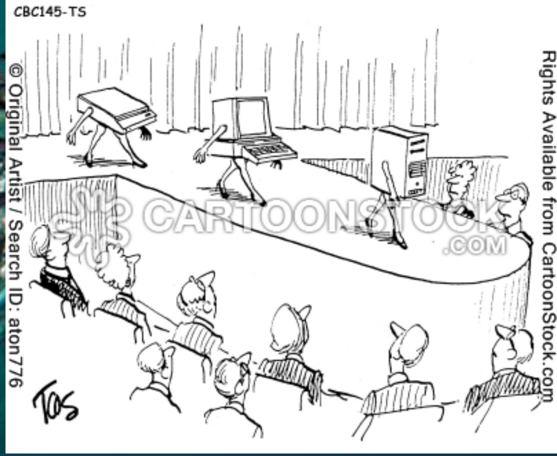
- survey comps
- Longer survey time period OR more frequent

Sardine-like species

Length comps

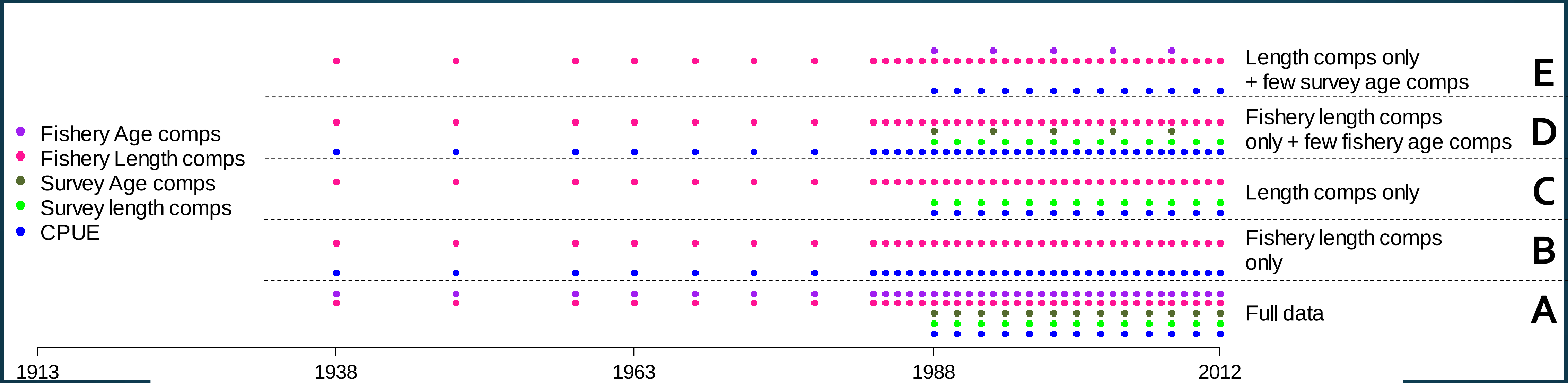
- survey comps
- more frequent survey
- longer comps coverage

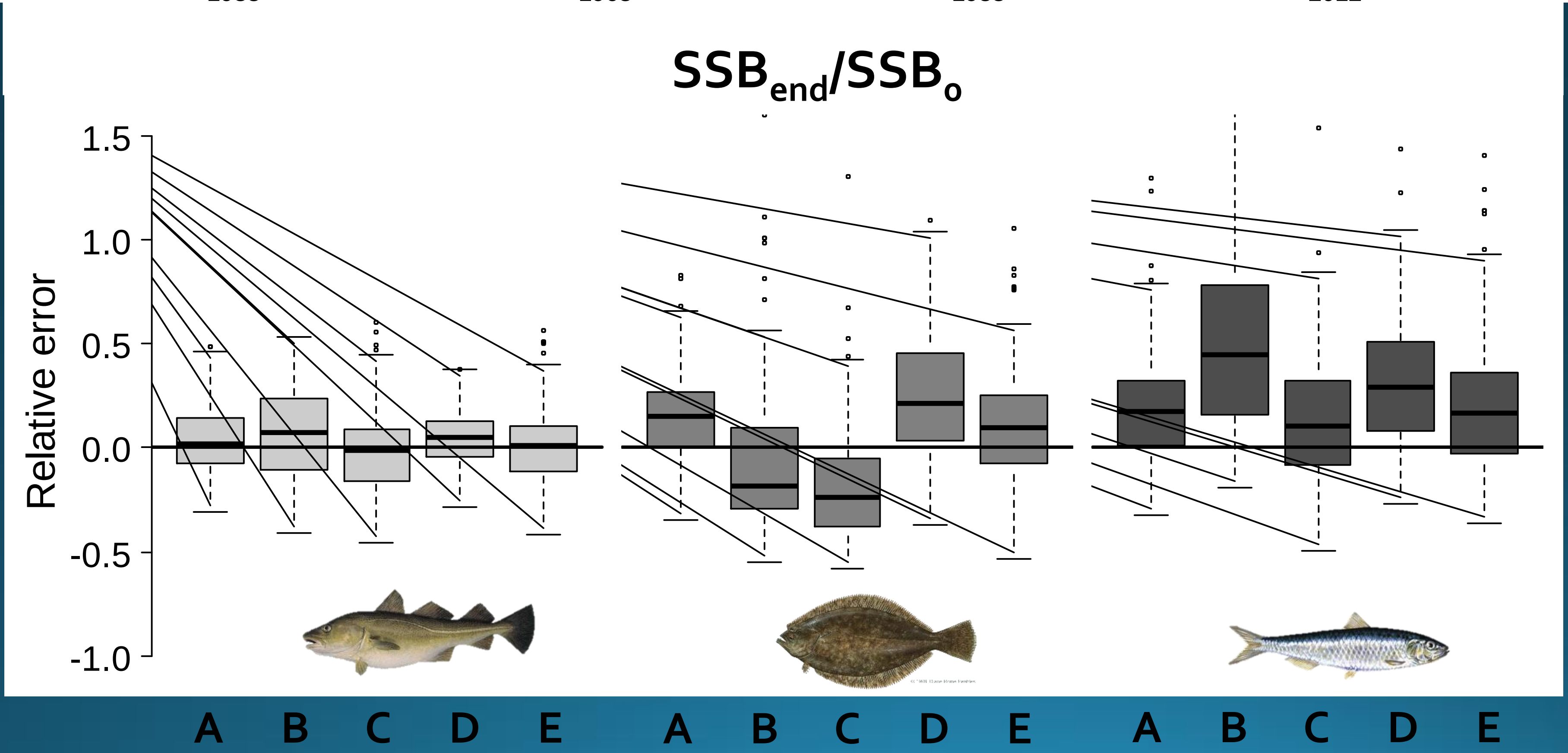
Age comps



THANK YOU!

CAPAM


Fishery Age comps
Fishery Length comps
Survey Age comps
Survey length comps
CPUE
Length comps only
+ few survey age comps
E
Fishery length comps
only + few fishery age comps
D
Length comps only
C
Fishery length comps
only
B
Full data
A
1913
1938
1963
1988
2012


SSB_{end}/SSB_o
Relative error
1.5
1.0
0.5
0.0
-0.5
-1.0
A B C D E
A B C D E
A B C D E

Conclusion/Discussion

- **Importance of the different composition data types by life-history types**
  - length comps is more important than age comps for sardine and cod (especially from survey). Equally important for flatfish
  - Survey comps is important across life history types
  - Sardine type fish tend to overestimate SSB depletion

- **Importance quantity and quality of data**
  - Increasing the survey frequency and coverage important for ALL species (not as much for cod)
  - Increasing survey sampling frequency is important than coverage for sardine, equally important for flatfish and cod

Conclusion/Discussion

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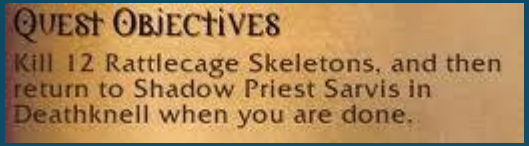
  - Increasing survey sampling frequency is more important than coverage for sardine, equally important for flatfish and cod

Outline

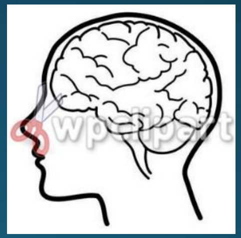
- Background

- Objectives


Quest Objectives
Kill 12 Rattlecage Skeletons, and then return to Shadow Priest Sarvis in Deathknell when you are done.

- Methods

Vs



or

- Results/discussion

Using simulation analysis to evaluate the use of cubic spline selectivity in integrated stock assessments

J. L. Valero[1], I. G. Taylor[2], M. N. Maunder[1,3] and P. R. Crone[1,4]

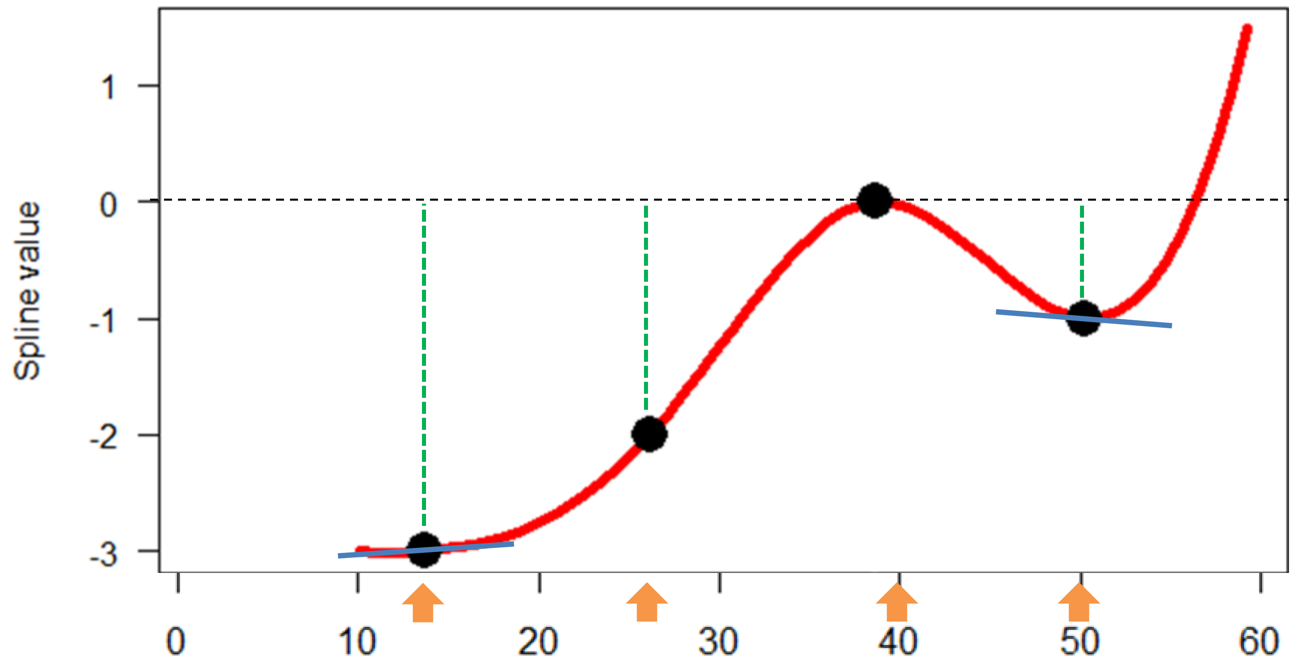
July 17, 2013 WCSAM

[1]**Center for the Advancement of Population Assessment Methodology (CAPAM)**
[2]NOAA, Northwest Fisheries Science Center, Seattle, WA, USA
[3]IATTC, La Jolla, USA
[4]NOAA, Southwest Fisheries Science Center, La Jolla, CA, USA

admb
FAST, ACCURATE, STABLE OPTIMIZATION

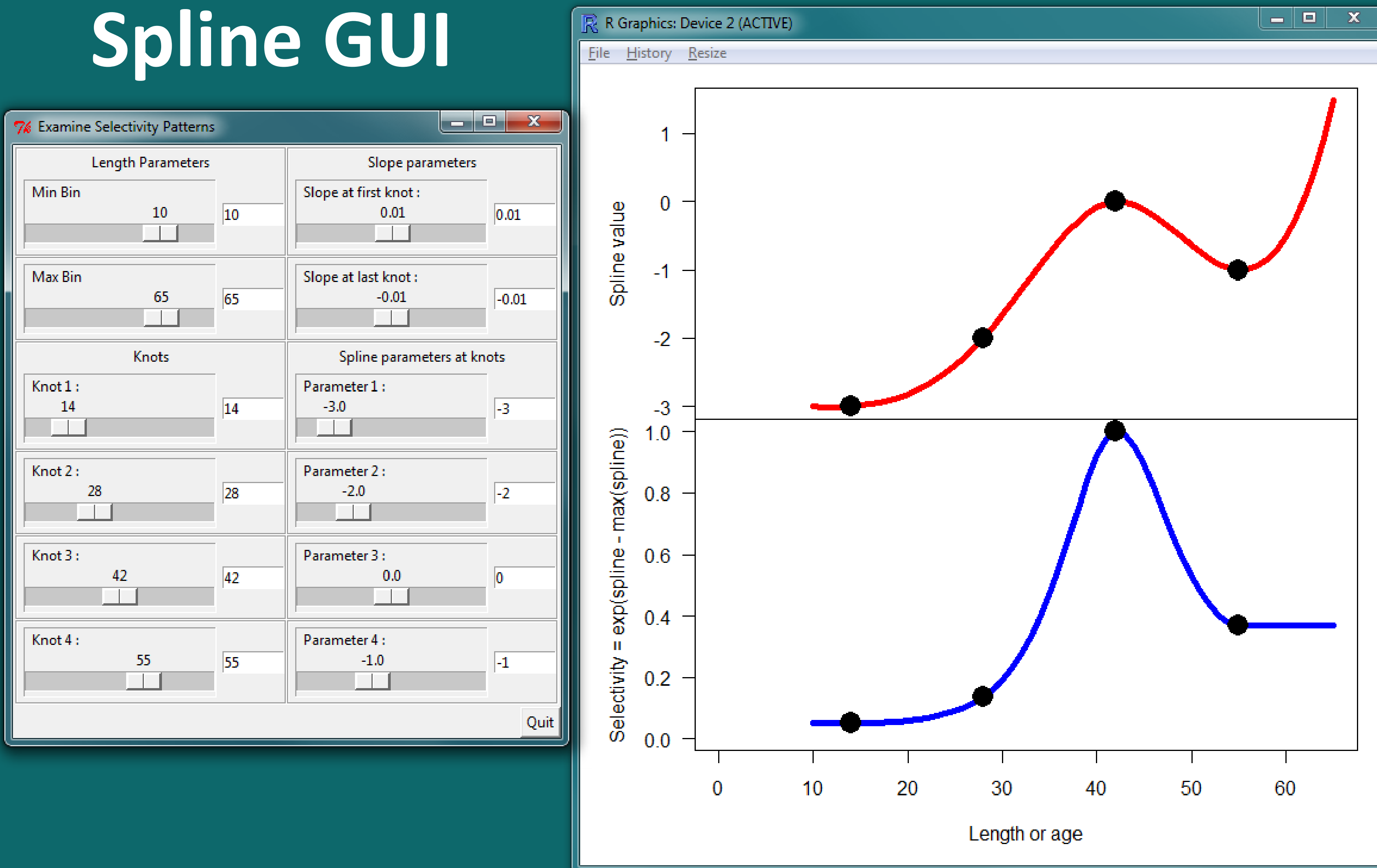
What are cubic splines?

- Smooth piece-wise polynomial functions.
- Need to specify **number and position** of knots, estimate the **value** at these knots and the **slope at the ends**



From splines to spline selectivity

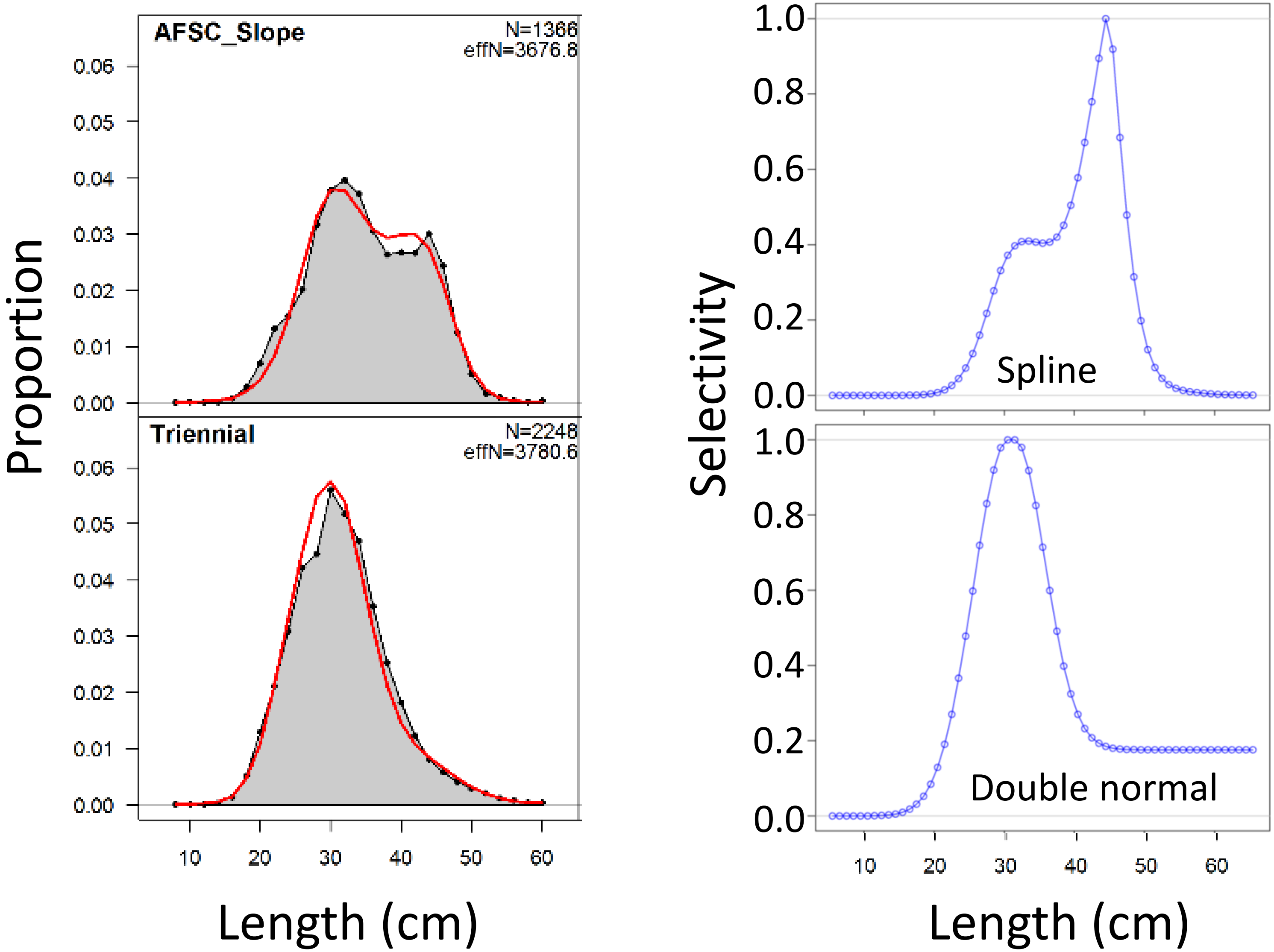
Spline GUI



Why cubic spline selectivity?

- Parametric forms may not be flexible enough

  - e.g. Dover sole assessment (Hicks and Wetzel, 2011)



Understanding splines in ADMB

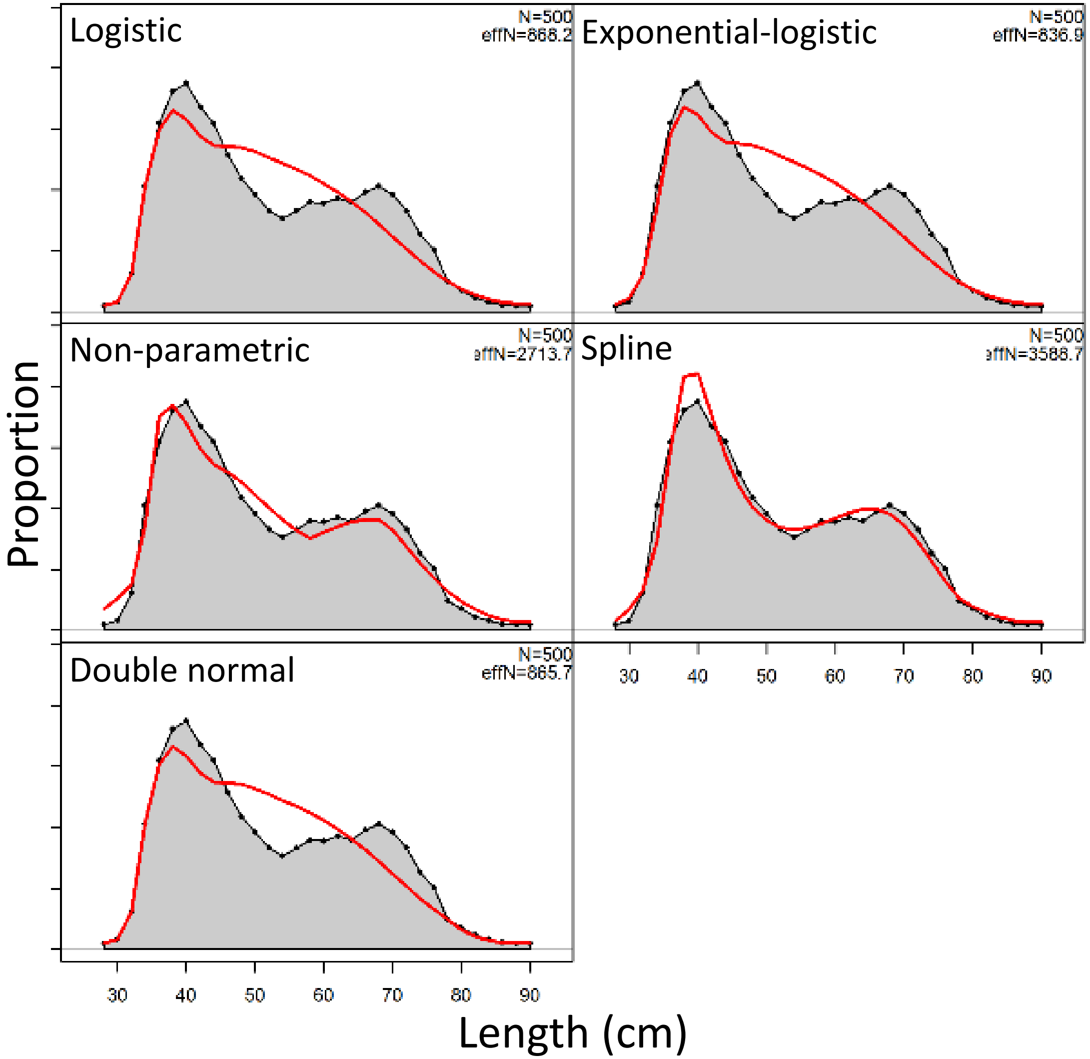
- Splines have long existed in ADMB, but not widely used for stock assessment selectivity
- Implemented in Multifan-CL in 2005
  - Several tuna assessments
- Implemented in Stock Synthesis in 2011. Only used in a few formal stock assessments based on SS:
  - Dover sole (Hicks and Wetzel, 2011)
  - Sablefish (Stewart et al., 2011)
  - Skipjack Tuna (Sharma et al., 2012)
  - Pacific Bluefin Tuna assessment (Iwata et al., 2012)

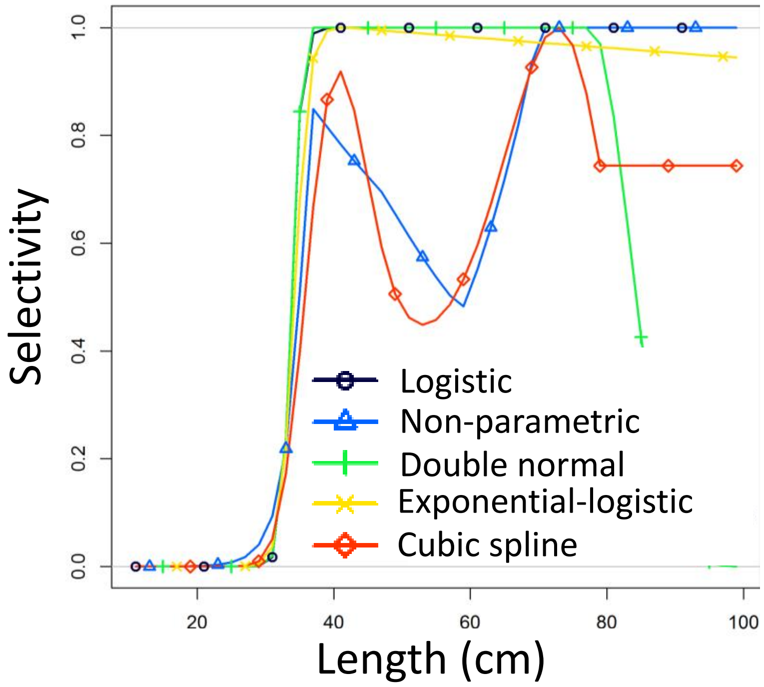
Spline selectivity in Stock Synthesis

- Current options in SS
  - User-specified number of knots (at least 3)
  - User-specified or auto placement of knots (equally spaced)
  - User-specified slope at the ends

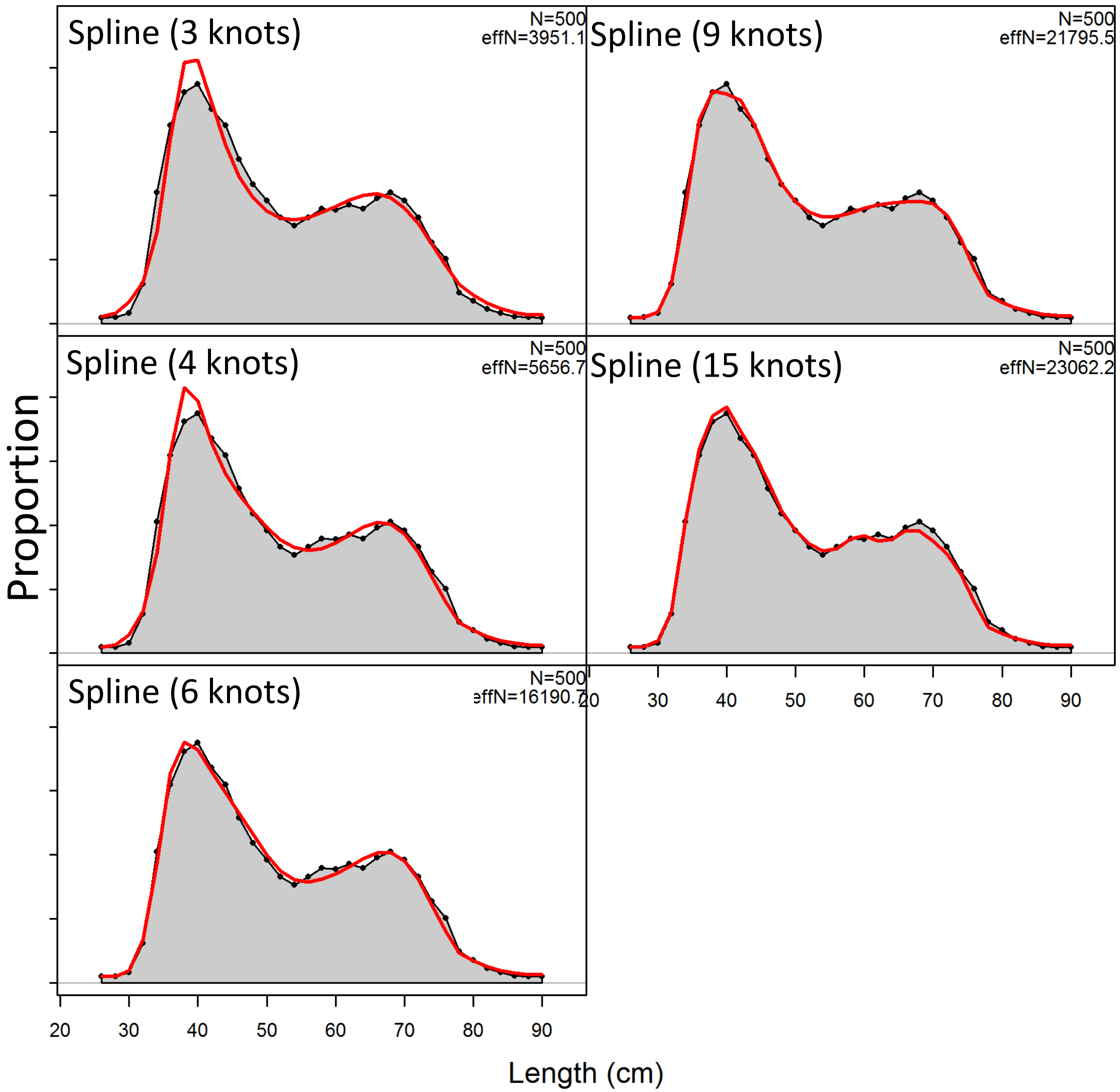
- Alternatives
  - Model selection for number of knots (e.g. use AIC)
  - Alternative knot placement
    - e.g. knots in regions where $f(x)$ change is rapid
    - e.g. knots in regions with poor fit to the combined composition data

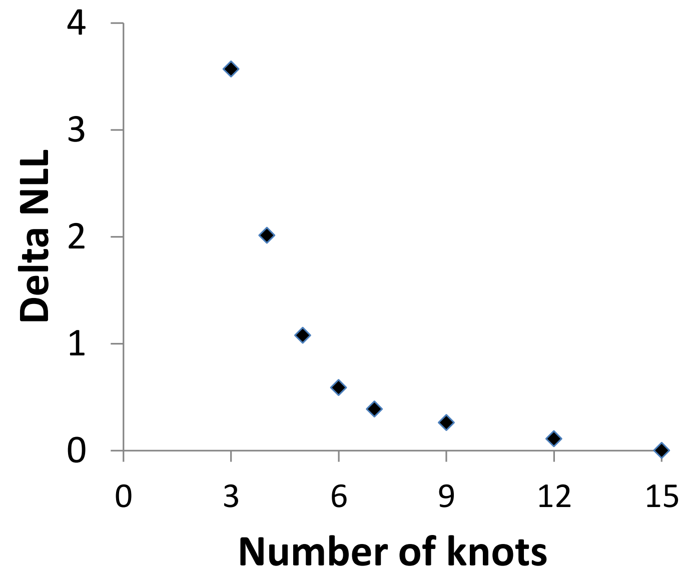
Toy model: What shape?



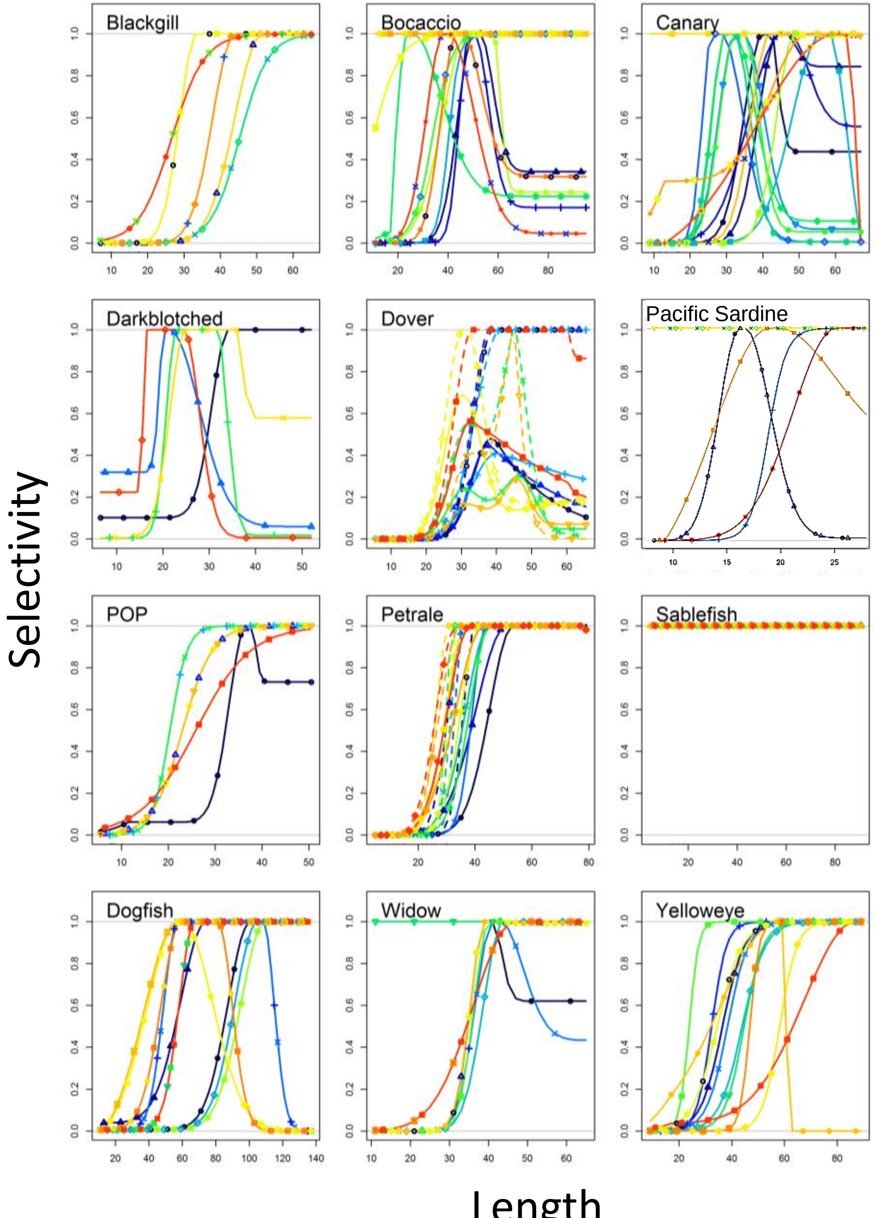


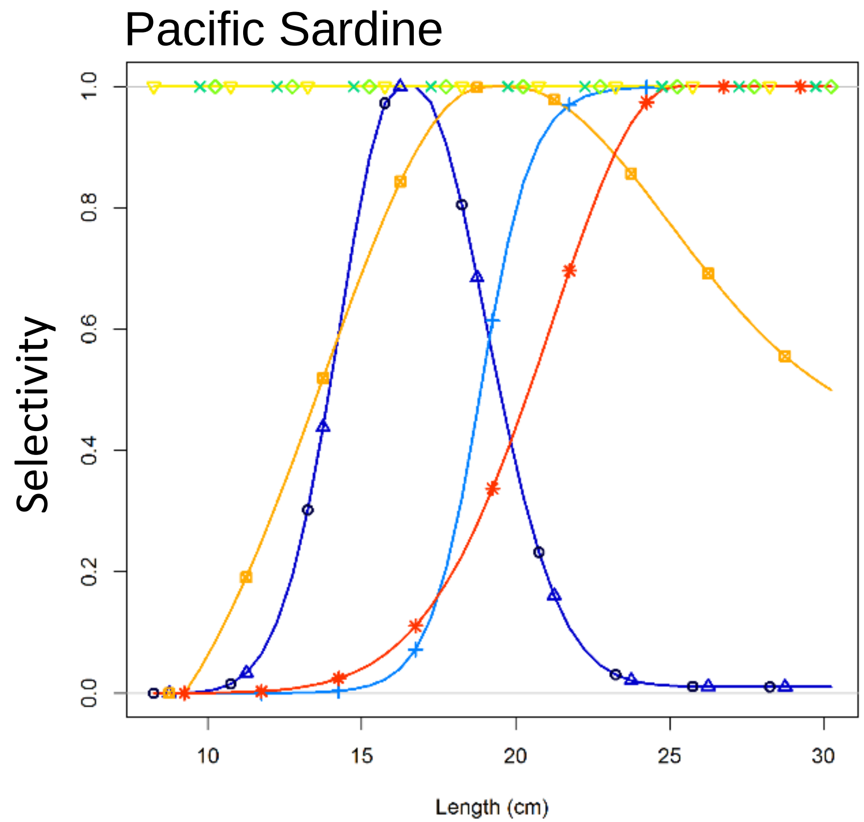
Toy model: How many knots?

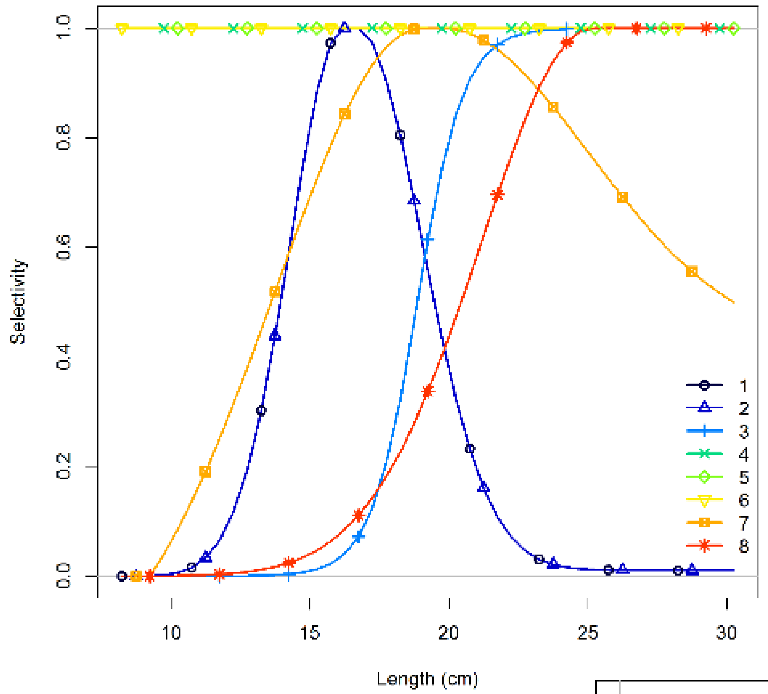


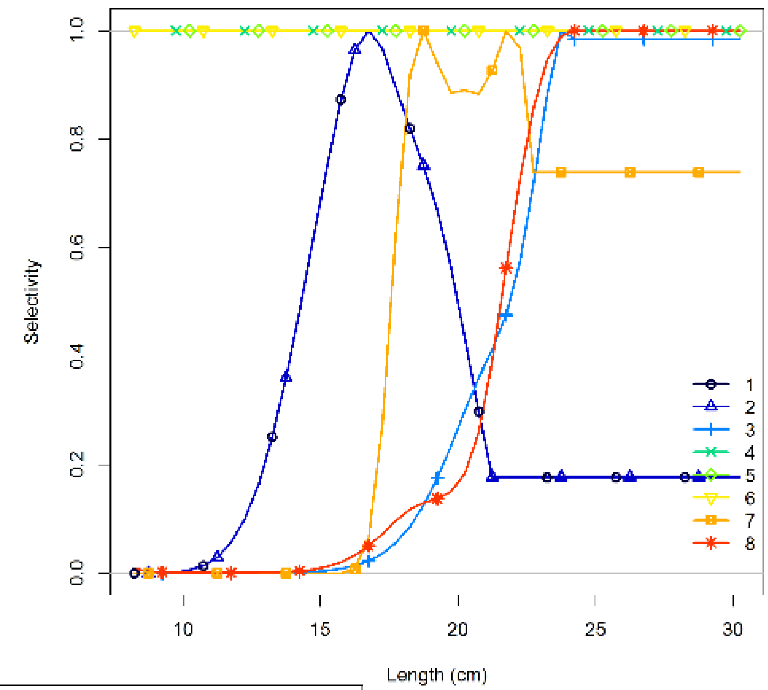


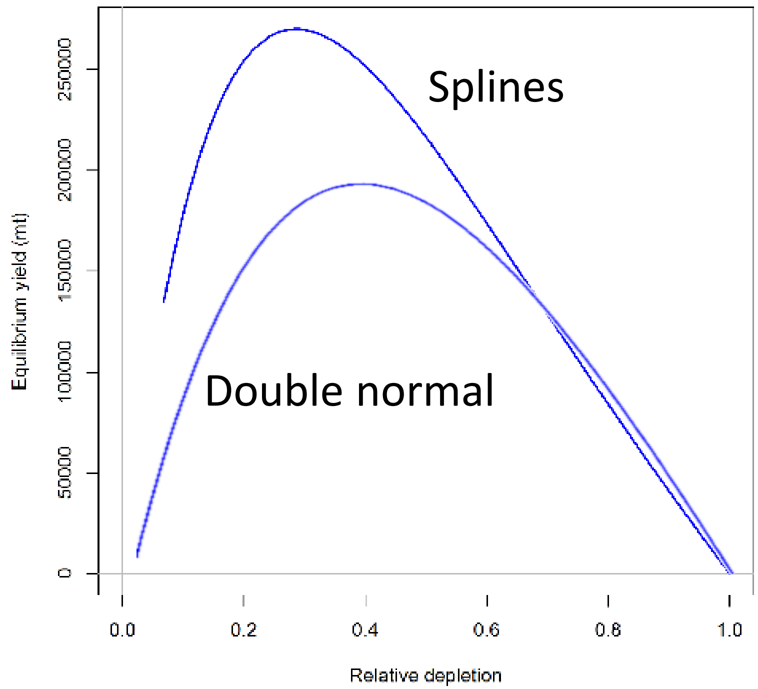
From toy model to complex models






Selectivity
1.0
0.8
0.6
0.4
0.2
0.0
10
15
20
25
30
Length (cm)
1
2
3
4
5
6
7
8


Selectivity
1.0
0.8
0.6
0.4
0.2
0.0
10
15
20
25
30
Length (cm)
1
2
3
4
5
6
7
8


Equilibrium yield (mt)
250000
200000
150000
100000
50000
0
0.0
0.2
0.4
0.6
0.8
1.0
Relative depletion
Splines
Double normal

Current and future work

- Test current and alternative methods for spline setup
  - Preliminary results show that the current method performs well, compared to alternatives
- Use simulation-estimation approach in SS to evaluate the performance of spline selectivity across different life-histories, data availability and selectivity shapes
  - Performance metrics
    - MSY, SPB, etc
- Provide guidance on good practices for using spline selectivity

NOAA FISHERIES

Northwest Fisheries Science Center

A method for calculating a meta-analytical prior for the natural mortality rate using multiple life-history correlates

Owen Hamel

July 2013

The natural mortality rate (*M*) is an important parameter in most stock assessments.

- Beverton and Holt (1957) citing Russell (1931): Four primary factors control changes in biomass in a closed population:
    - Recruitment (into the exploited phase)
    - Growth of individuals
    - Capture by fishing
    - *M*

In the assessment context, *M* is simplified

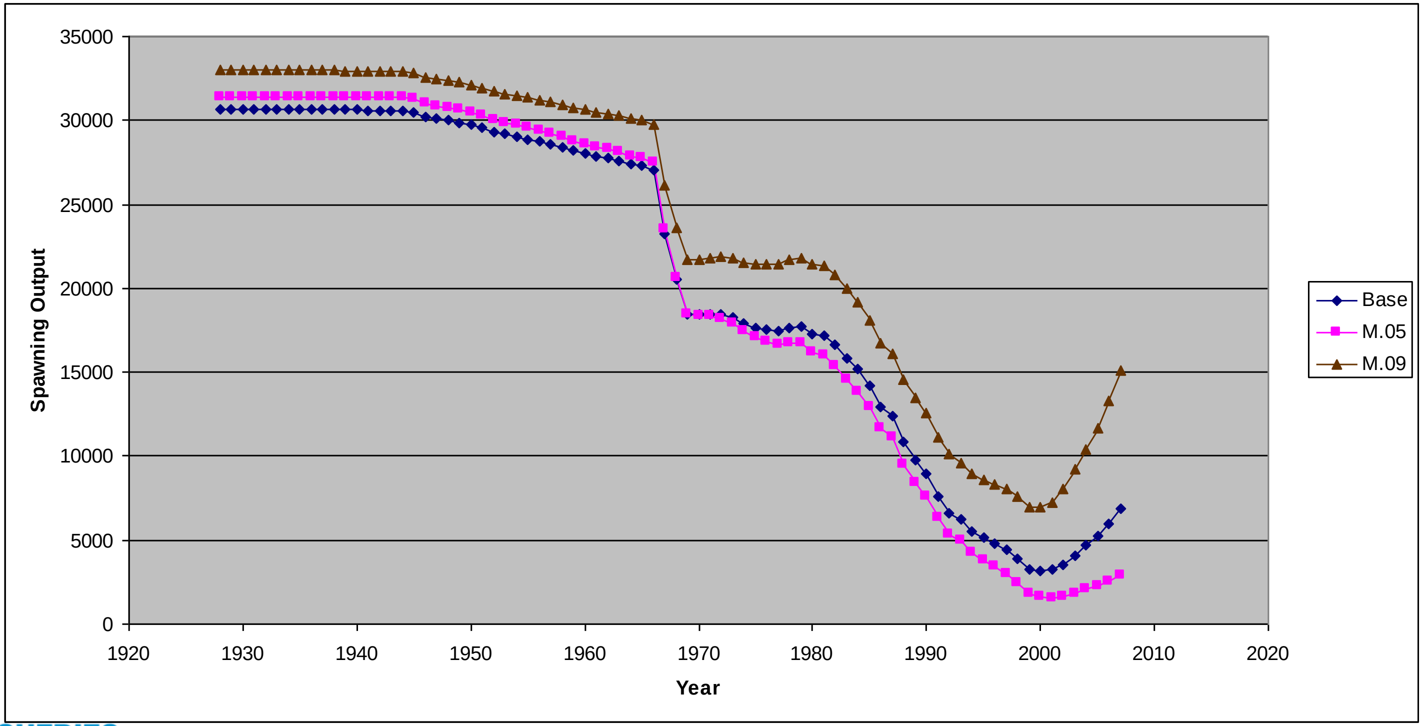
- *M* varies by age, size, gender and with time, inter- and intra-specific densities, temperature and other environmental factors.
  - Most, if not all, of these factors are usually ignored in estimation of *M* for use in stock assessment (or for estimation of *M* within stock assessments).

Estimation of *M* within stock assessment models

- Difficulties:
  - Correlation with other parameters, including
    - Stock-recruitment relationship including steepness (*h*)
    - Catchability and selectivity
      - Fisheries
      - Surveys
    - Ageing error
  - Dependent upon various assumptions in the model

What if estimate of *M* is wrong?

- Depends on model, but can have large impact on stock size and status estimation
- e.g. 2007 U.S. west coast darkblotched rockfish assessment (Base *M* = 0.07)



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Life History Invariants

- Beverton and Holt (1959)
  - von Bertalanffy k and L_∞, age and size of maturity (A_m and L_m), and M (or A_{max}).
  - $MA_m = C_1$
  - $M/k = C_2$ or $kA_{max} = C'_2$
  - $L_m/L_\infty = C_3$

Considered five published meta-analyses on *M*

1. Hoenig (1983): *M* vs. Maximum age (A_{max})
2. Pauly (1980): *M* vs. *k*, temperature (*T*) and asymptotic size (L_∞ or W_∞)
3. Jensen (1996): *M* vs. *k*
4. Gunderson (1997): *M* vs. gonadosomatic index (GSI)
5. McCoy and Gillooly (2008): *M* vs. *T* and W_∞

Re-analysed each of these data sets.

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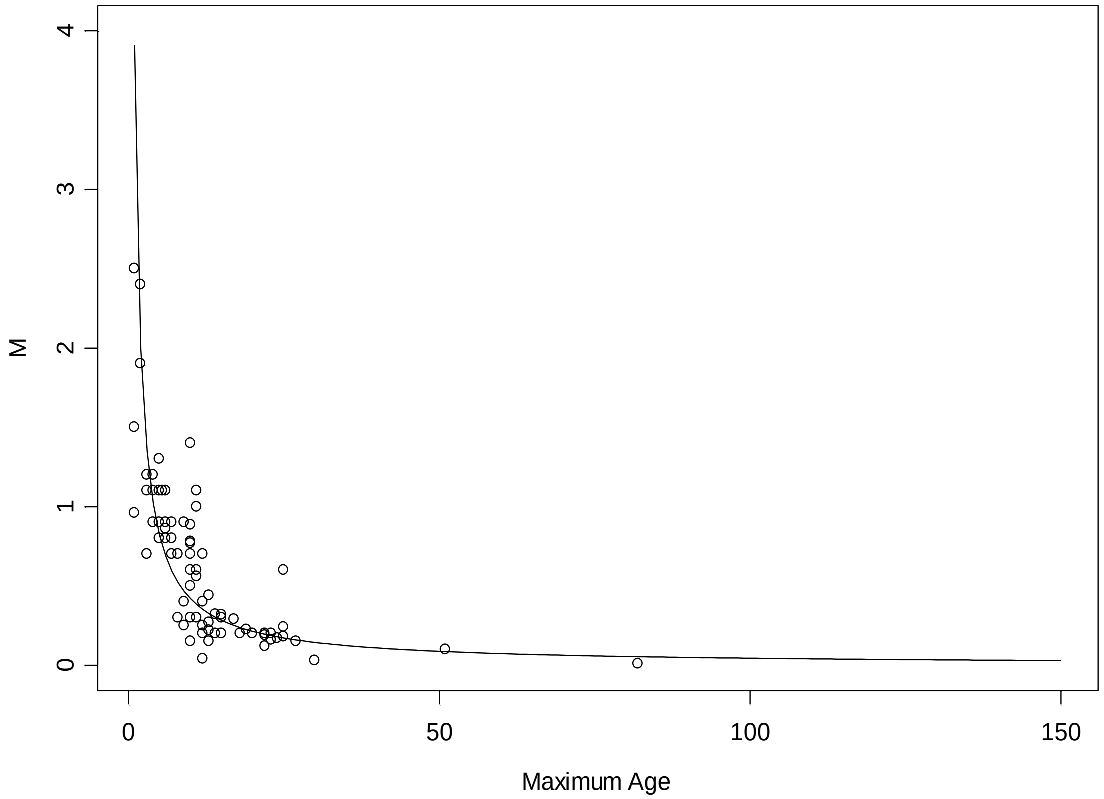
Hoenig 1983

- Used log-log regression on maximum age data from fish, cetaceans and mollusks.

- Fish only: $\ln(Z) = 1.46 - 1.01 \ln(A_{max})$
  - All: $\ln(Z) = 1.44 - 0.982 \ln(A_{max})$

Hoenig 1983 – Max Age



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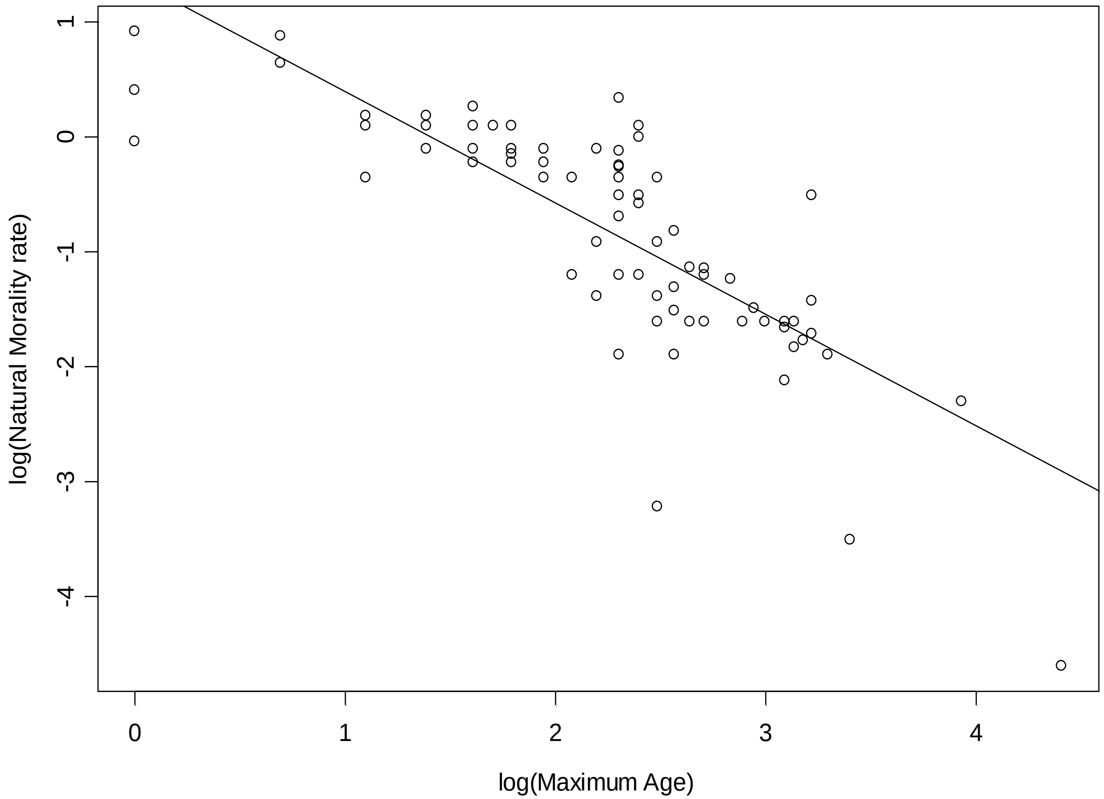
Hoenig 1983

Log-Log relationship between Maximum Age and M



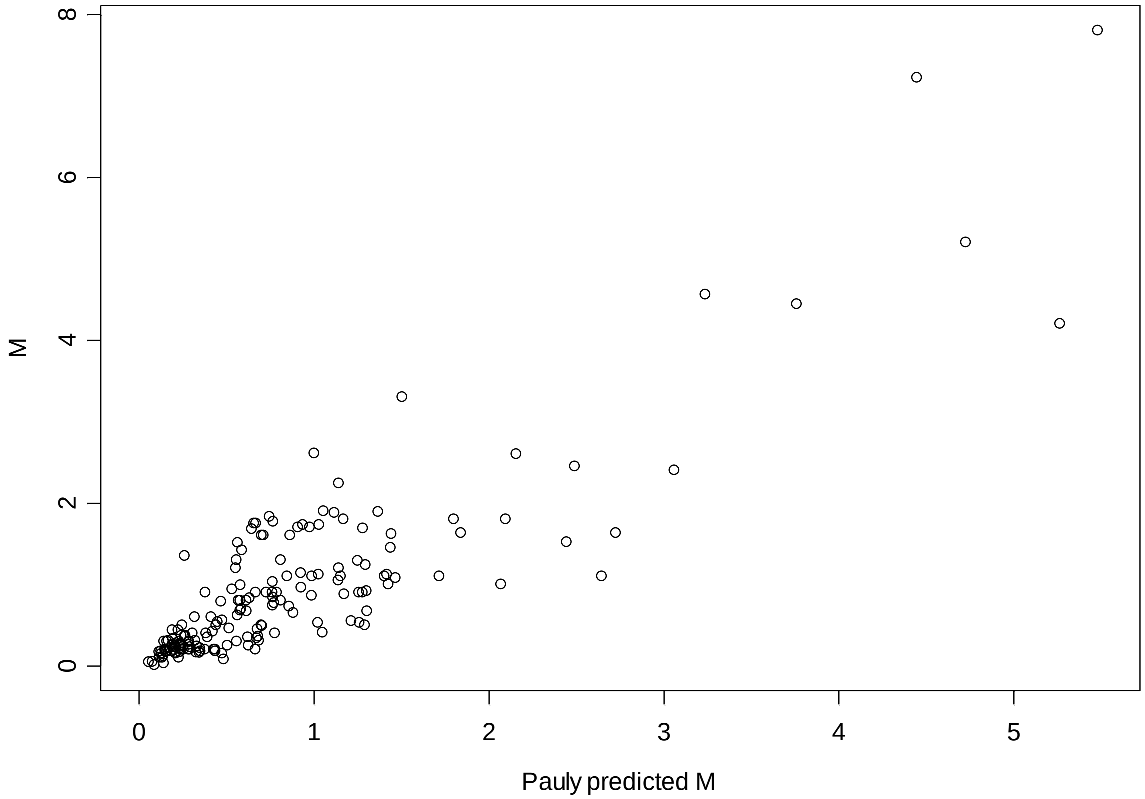
Note: forced slope to be -1

Pauly 1980

- 175 data points of *M* vs. size, *k* and Temp.
- $\log M = -0.0066 - 0.279 \log L_\infty + 0.6543 \log k + 0.4634 \log T$
- $\text{Log M} = -0.2107 - 0.0824 \log W_\infty + 0.6757 \log k + 0.4627 \log T$

- But regression coefficients for fish in general may not apply to some taxa – e.g. Beverton's (1992) comparison of *Sebastes* to long-lived large mammals, they may have lower coefficients and thus lower M. (Applies also to Jensen and McCoy and Gillooly 2008 – see below)

Pauly 1980 - W, T and k



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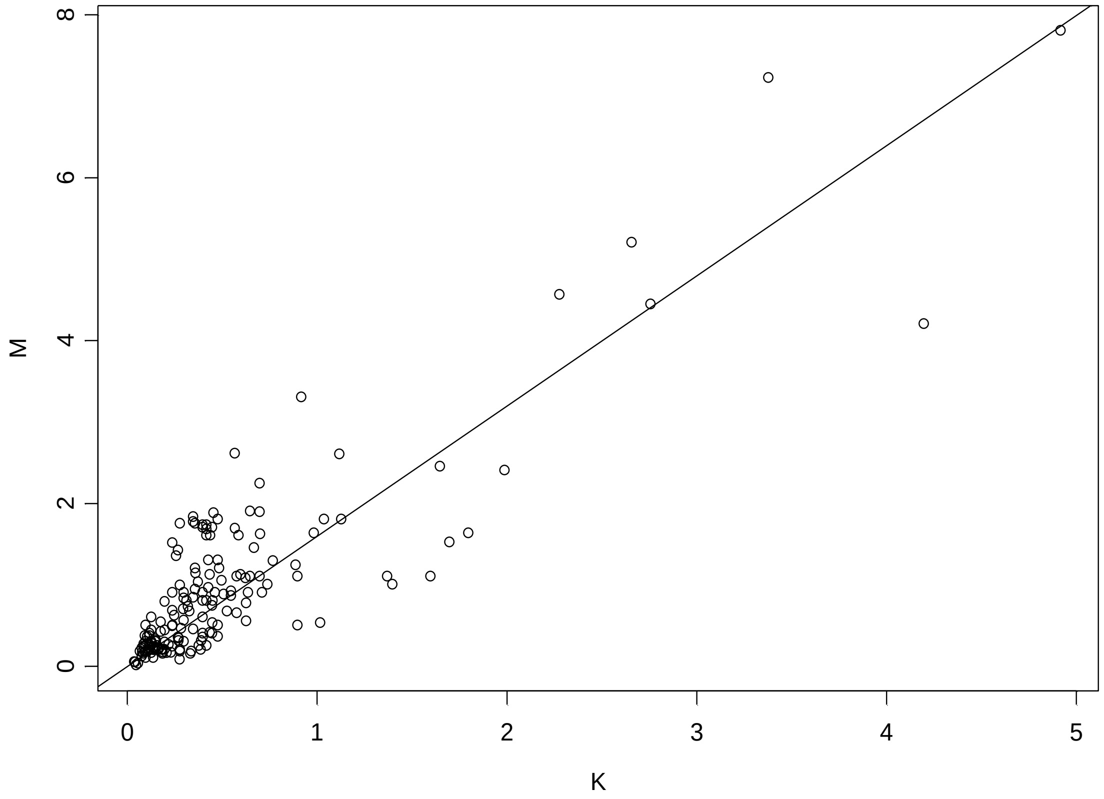
Jensen 1996

- Thought that because his R^2 for M vs. k was larger than Pauly's R^2 for log M vs. log k, log T and log L_∞, that his model was just as good, and the information on temperature and size was not important.
  - Found M = 1.5 k (based on optimal life history theory), or
  - M = 1.6 k (based on Pauly's data)
  - Also: $M = 1.65/A_{mat}$

- Others (Roff 1984, Beverton 1992) found less consistent or tight relationship between k and M.

Jensen 1996 - k

Force regression through the origin



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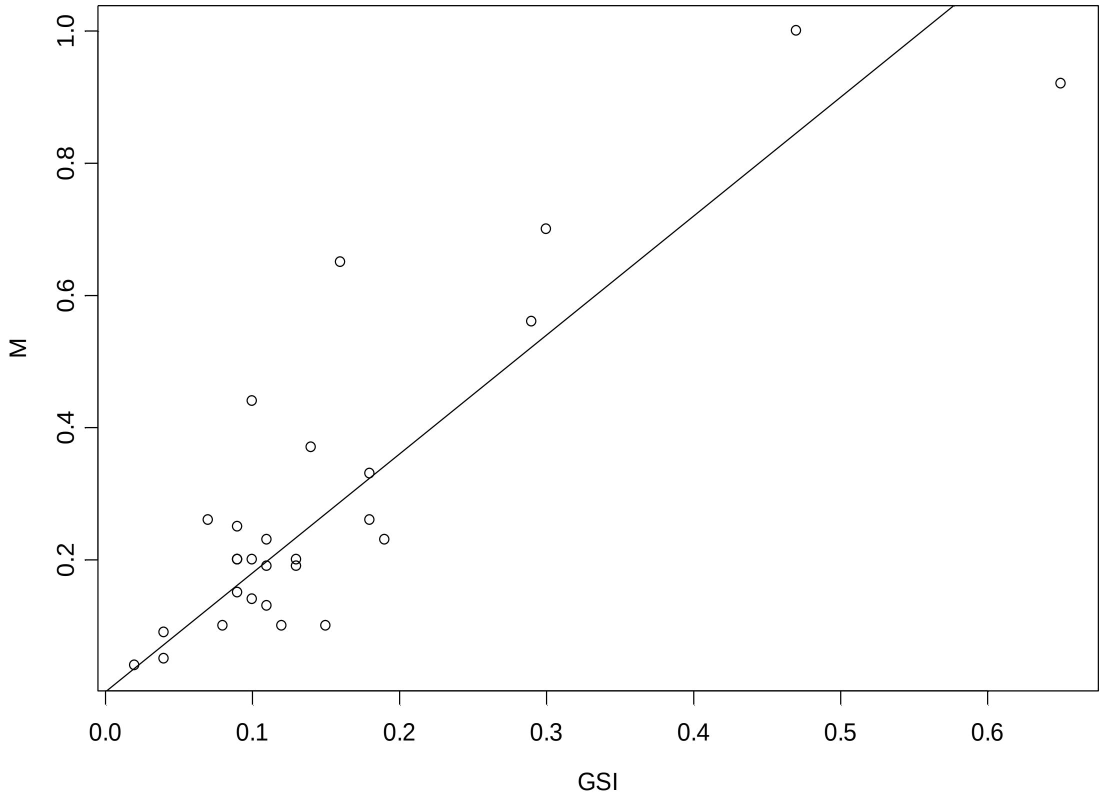
Gunderson 1997

- Gonadosomatic index (GSI) is a measure of relative reproductive effort.
- $M = 1.8 * GSI$

Gunderson 1997 - GSI

Force regression through the origin



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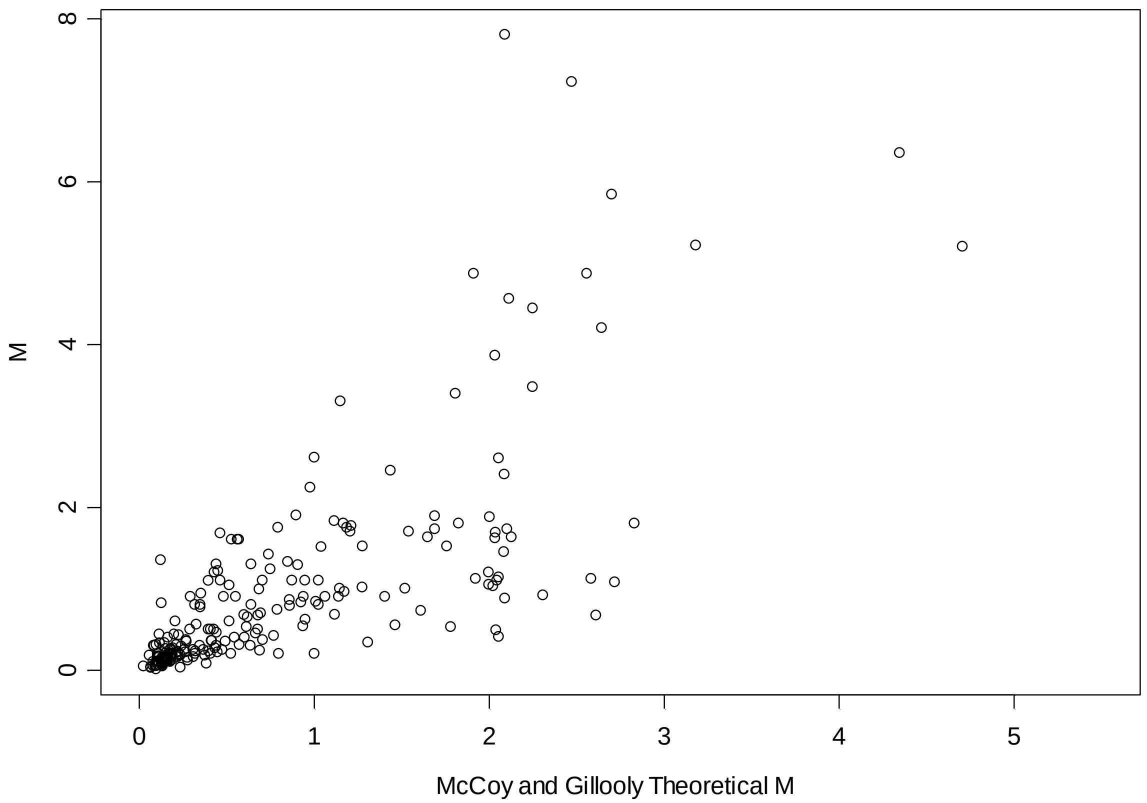
McCoy and Gilloolly 2008

- Relate dry mass *m* and temperature *T* to biological rate process – *M* should show same dependence on *m* (dry wt grams) and *T* (Kelvin).

- *Theoretically* $M = Cm^{-.25}e^{-7540(1/T - 1/293)}$

- C is taxon dependent
  - On average is about 0.4
  - For fish is about 3

McCoy and Gilloly 2008



Previous approaches to combining meta-analyses

Hewitt et al. 2007

- Looked at 8 meta-analytical methods and given uncertainty in covariates and, in some cases, uncertainty in coefficients, to get a range of *M* for each method.
  - Did not consider uncertainty in relationship in a strict statistical manner

Gunderson et al. 2003

- Used confidence intervals to create uncertainty intervals for *M* using *k* and GSI
  - These confidence intervals did not overlap

Confidence Intervals vs. Prediction Intervals

- 95% confidence interval for regression:

$$s^2(\bar{y}_h) = MSE\left[\frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2}\right]$$

- 95% prediction interval for regression:

$$s^2(y_{h(new)}) = MSE\left[1 + \frac{1}{n} + \frac{(X_h - \bar{X})^2}{\sum (X_i - \bar{X})^2}\right]$$

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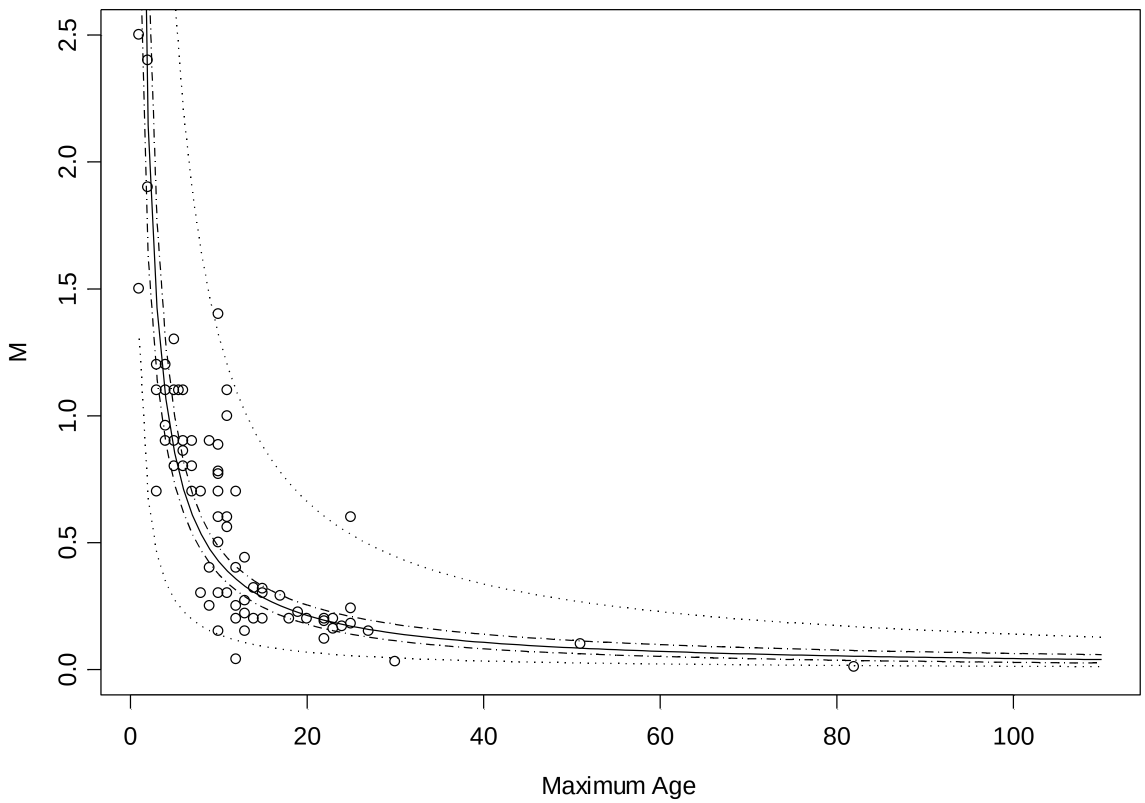
Which is correct to use?

- Confidence intervals are correct if all of the variation is due to observation error (and there is negligible error in the observation of *x*).

- Prediction intervals are correct if all of the variation is due to actual variability in the relationship.

- The truth is in between – *somewhere*, and is complicated by likely bias in estimates.

Hoenig: prediction intervals



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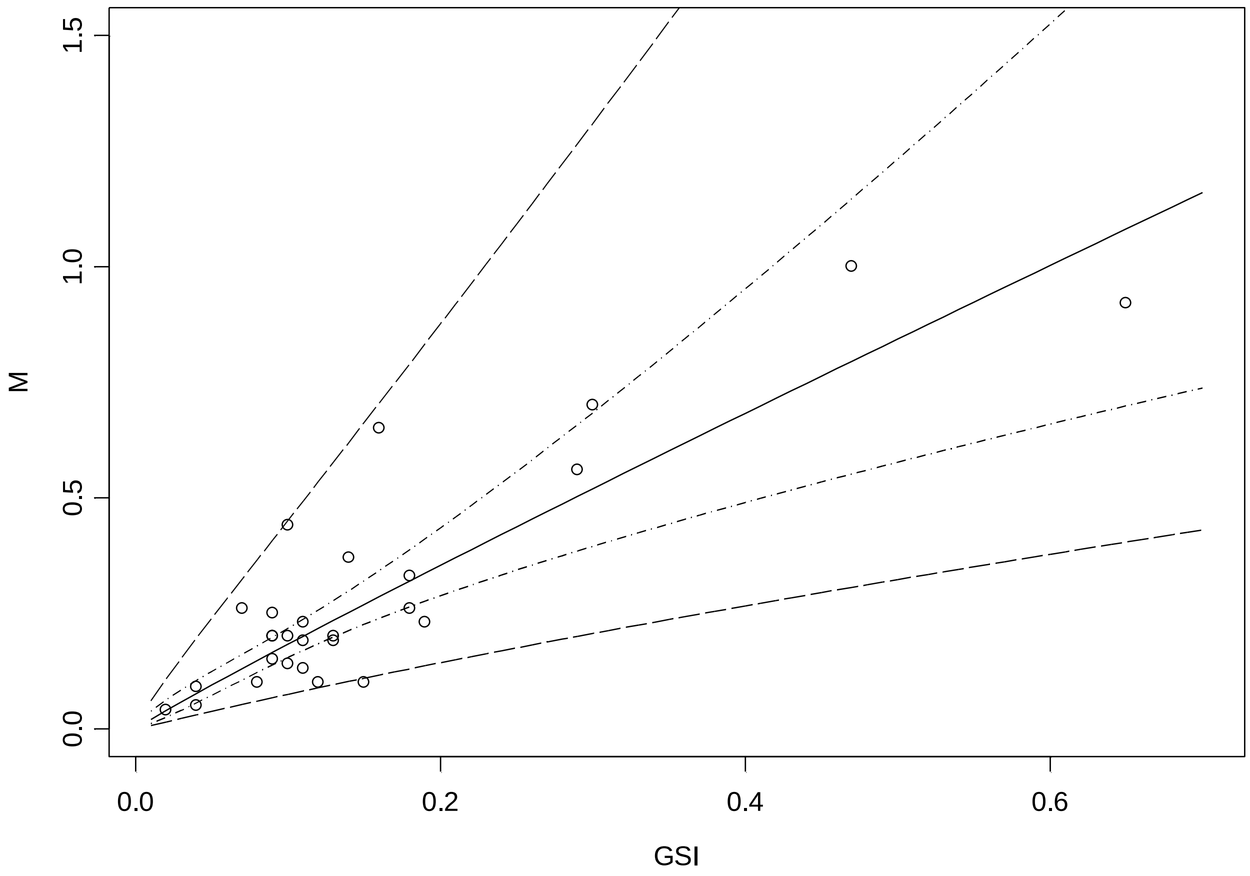
Gunderson: GSI prediction intervals



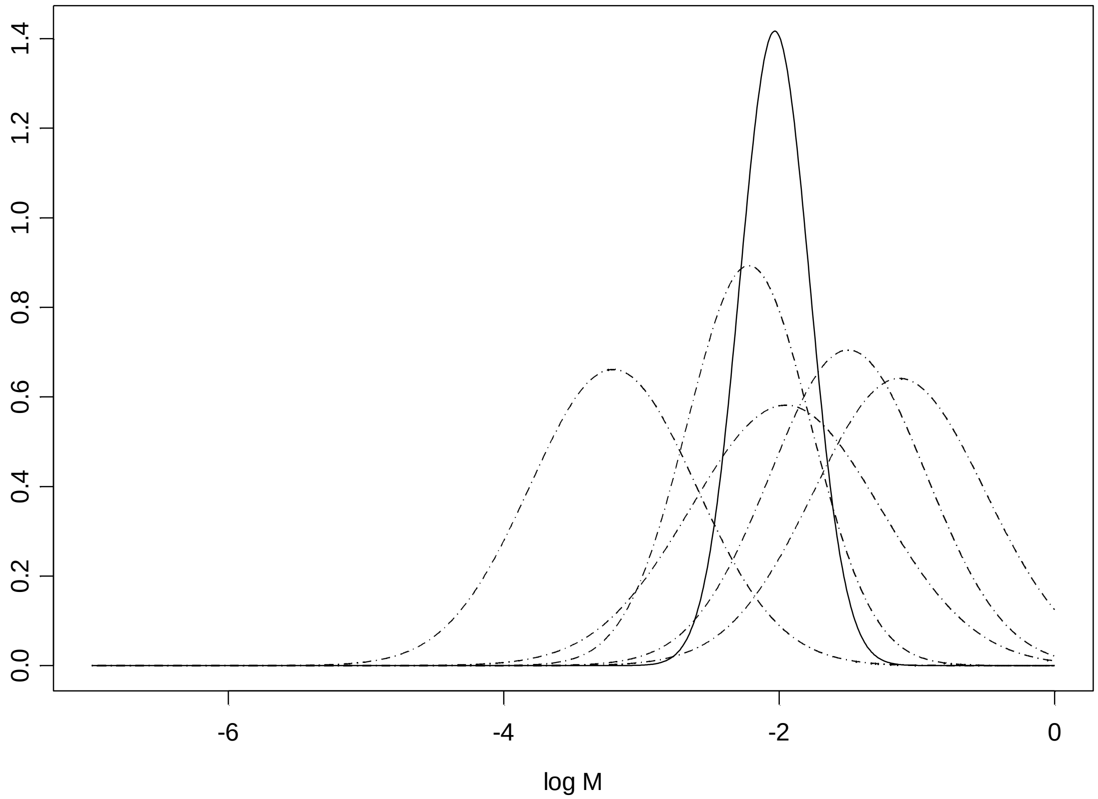
Approach

- Use log-normal distributions assuming sigma calculated from prediction intervals
  - Use variance-covariance matrix for Pauly, McCoy and Gillooly meta-analyses in calculating prediction intervals.
- Combine these log-normal distributions to get a prior distribution for *M*

Example: darkblotched rockfish (2007)

Method	Point Estimate	Lower 95% PI	Upper 95% PI
Hoenig Max Age	0.041	0.012	0.135
Jensen *k*	0.324	0.095	1.107
Pauly Size, *k*, *T*	0.223	0.073	0.683
M-G *W* and *T*	0.142	0.037	0.548
GSI	0.109	0.043	0.272

Combine priors



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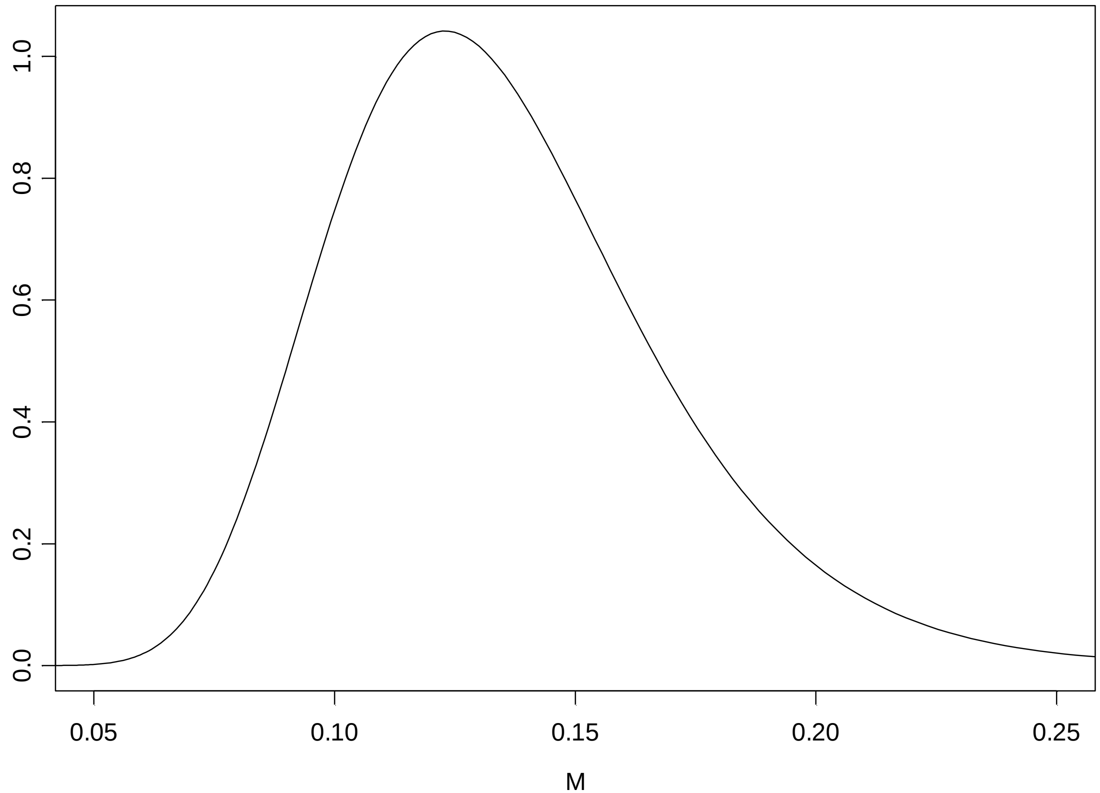
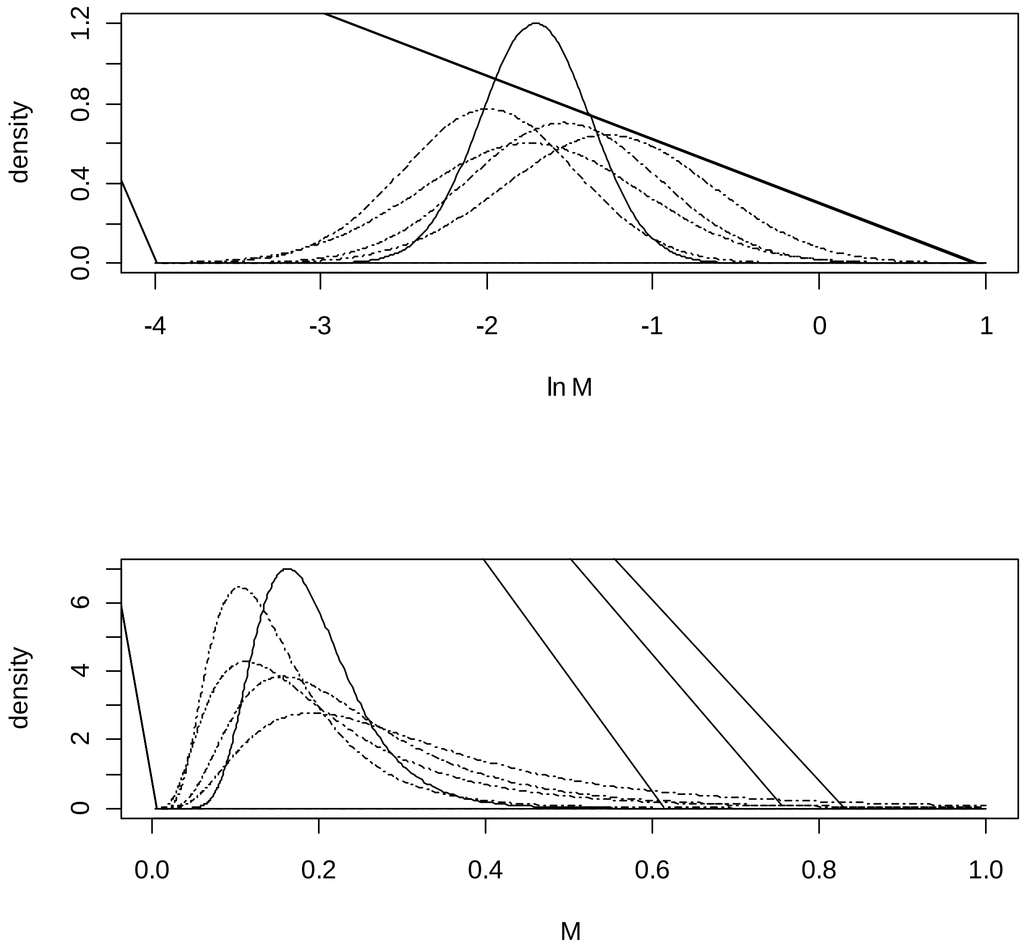
Prior on M



Prior on *M* for Petrale sole (females)



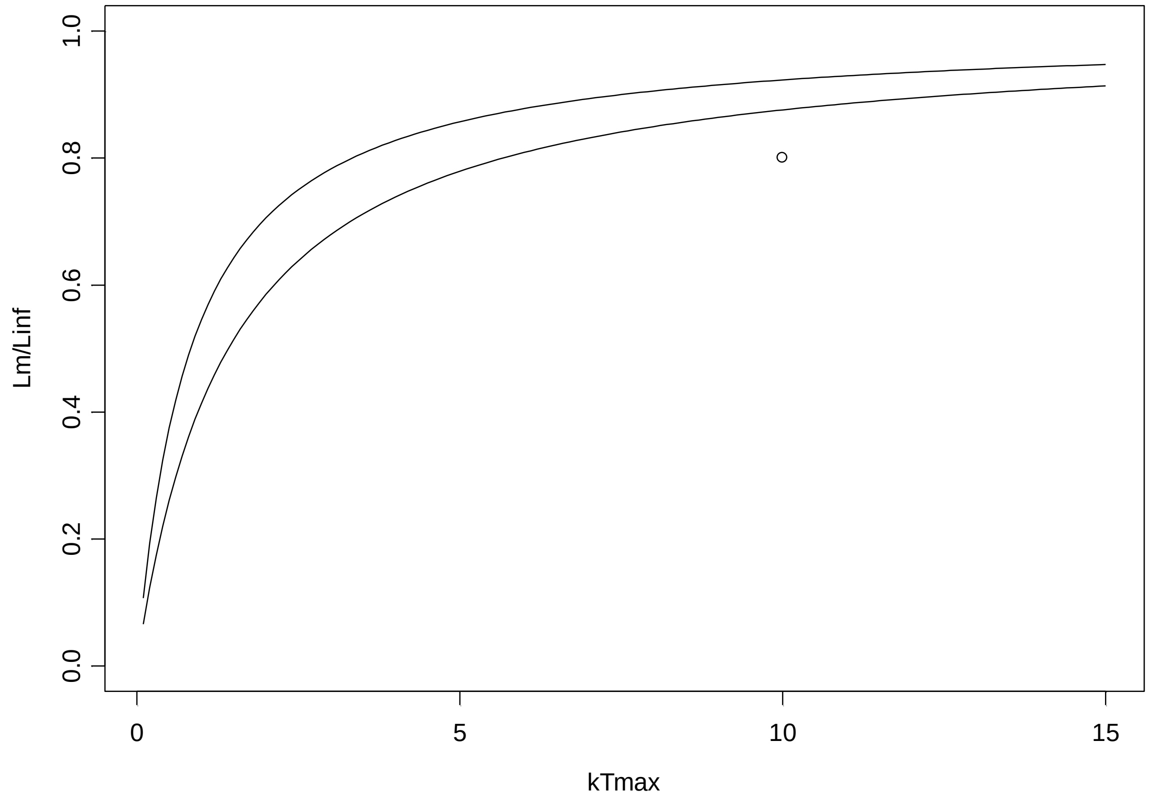
Issues

- How to combine priors when not independent (commonality/overlap of data)?
  - One solution is to down-weight those meta-analyses that share data.
- How do we weight these in general and for different taxa?
  - e.g. when we know *Sebastes* are not typical?
- Are we comfortable with the assumptions of the regression analysis?
- How good are the estimates of the covariates?
  - Values used in the original meta-analyses should be updated.

Beverton 1992

- Growth-Maturity-Longevity (GML) plots based on life history invariants:
  - Longevity and growth parameters determine optimal age and length at maturity (see Roff, 1984).
  - Relationship between k and Amax (and thus M) are taxon dependent.
  - In particular, *Sebastes* live long relative to growth rate, so M = 0.3k not 1.6k (Jensen).

GML plot



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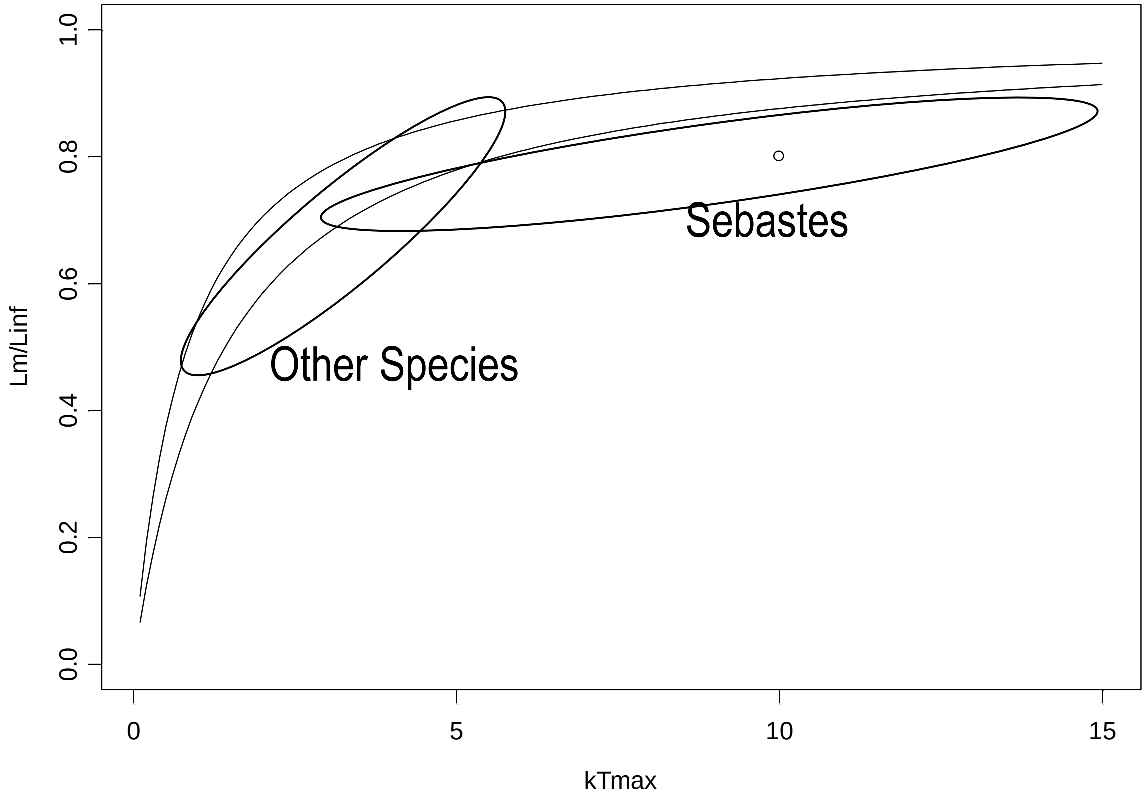
GML plot



NOAA FISHERIES

Time-varying natural mortality in fisheries stock assessment models: identifying a default approach.

Kelli Johnson [1], Cole Monnahan [1], Carey McGilliard [1], Katyana Vert-Pre [1], Athol Whitten [1], Juan Valero [2], Cody Szuwalski [1], Sean Anderson [3], Kotaro Ono [1], Felipe Hurtado-Ferro [1], Curry Cunningham [1], Melissa Muradian [1], and Roberto Licandeo [4]

[1]University of Washington, Seattle, WA
[2]Center for the Advancement of Population Assessment Methodology
[3]Simon Fraser University, Burnaby, Canada
[4]University of British Columbia, Vancouver, Canada

July 17, 2013

Hypotheses for time-varying natural mortality

- Environmental variation;
- Early maturation; and
- Predator prey dynamics.

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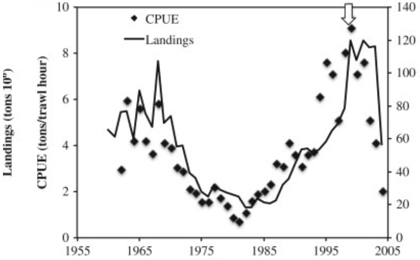
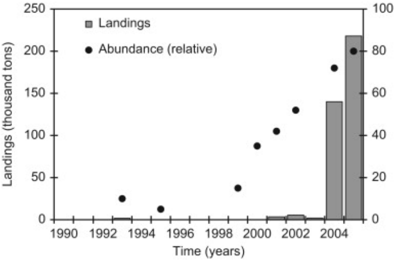
Chilean hake



Jumbo squid

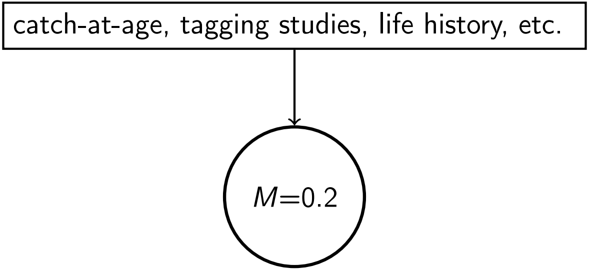


(Neiraa and Arancibiaa 2013)

Alternatives to a single constant M

catch-at-age, tagging studies, life history, etc.

Alternatives to a single constant M



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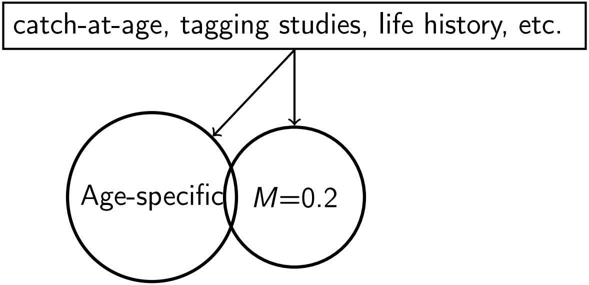

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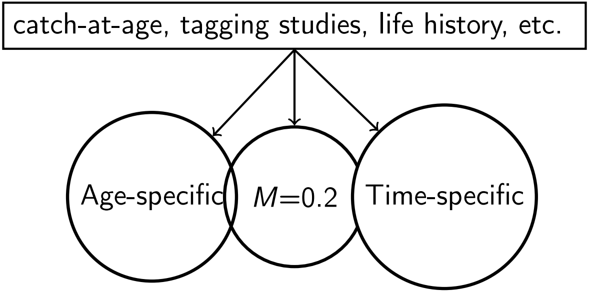

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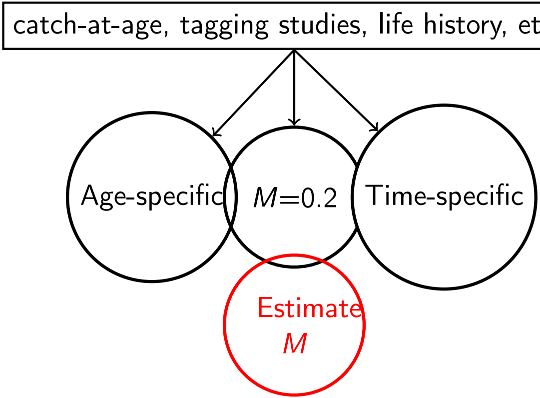

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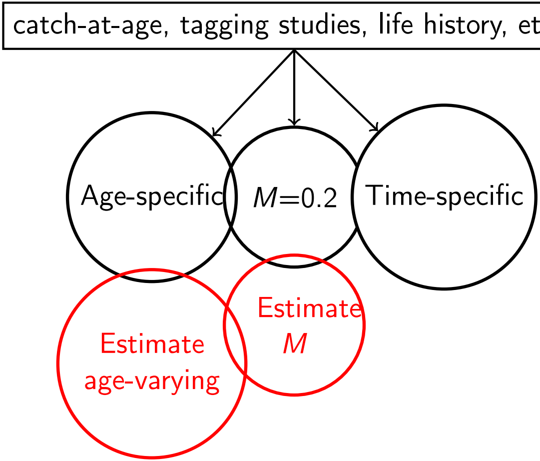

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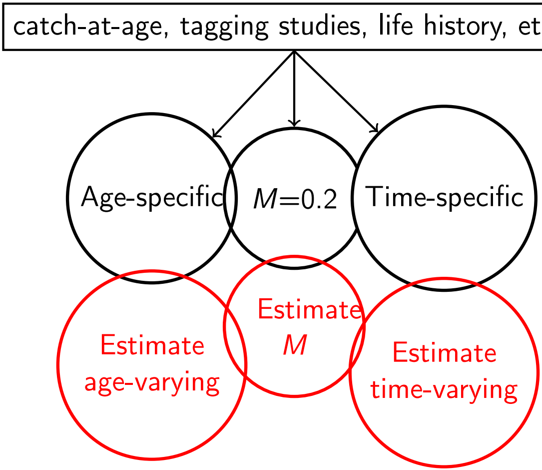

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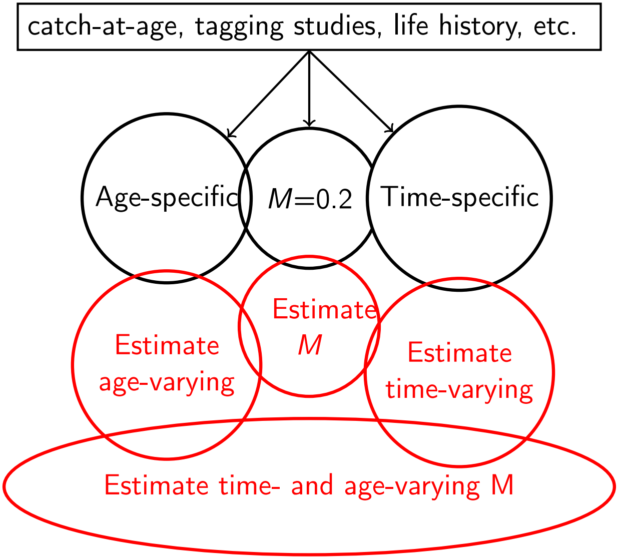

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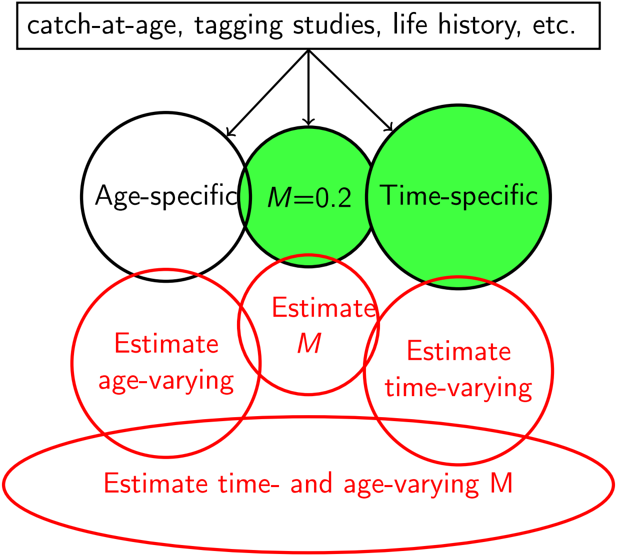


Goal of the simulation

Determine the

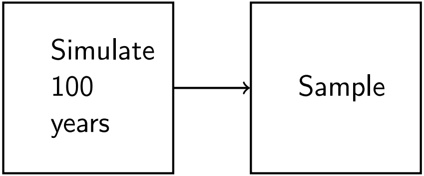
min max solution if you suspect M is time-varying but you

cannot estimate time-varying M.

General design

Simulate
100
years

General design



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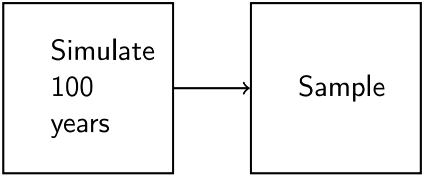

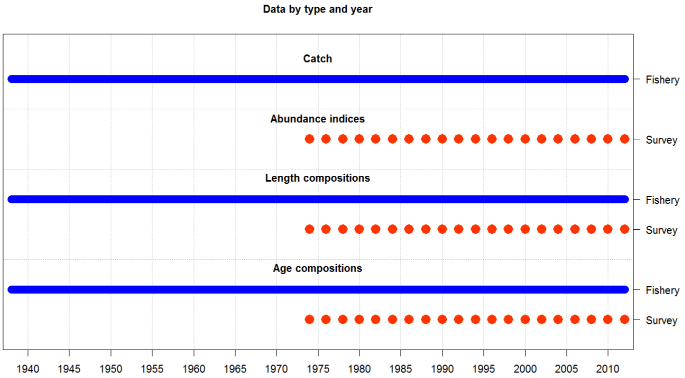

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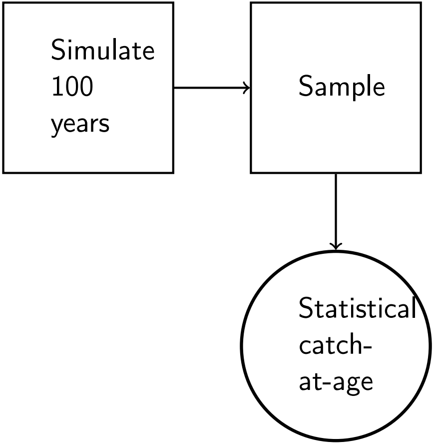

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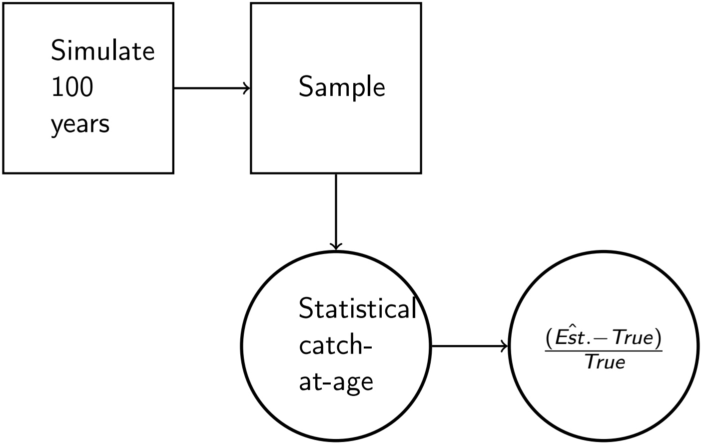

General design

Operating Model

- Fleet=1, beginning in year 1938 (25/100);
- Sex=1;
- Area=1;
- Logistic selectivity; and
- Beverton Holt stock recruit relationship

Estimating Model

- Growth parameters;
- Log of virgin recruitment (R_0);
- Logistic selectivity parameters;
- Survey catchability;
- Fishing mortality; and
- Recruitment deviations.

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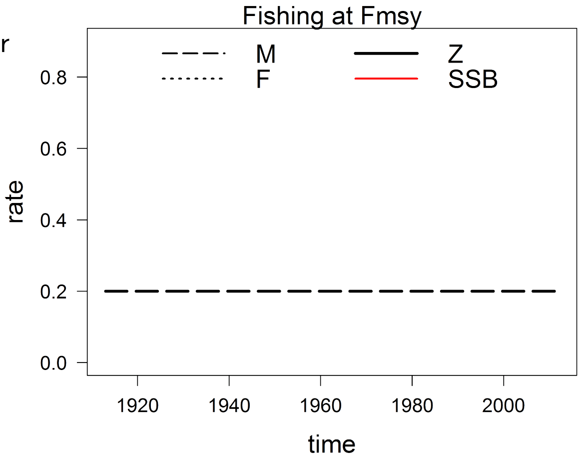
- Recruitment deviations.

Time-varying M in the operating model

- Constant;
- Linear $\Downarrow$;
- Linear $\Uparrow$;
- Step $\Downarrow$; or
- Step $\Uparrow$.

Time-varying M in the operating model

- Constant;
- Linear ⇓;
- Linear ⇑;
- Step ⇓; or
- Step ⇑.



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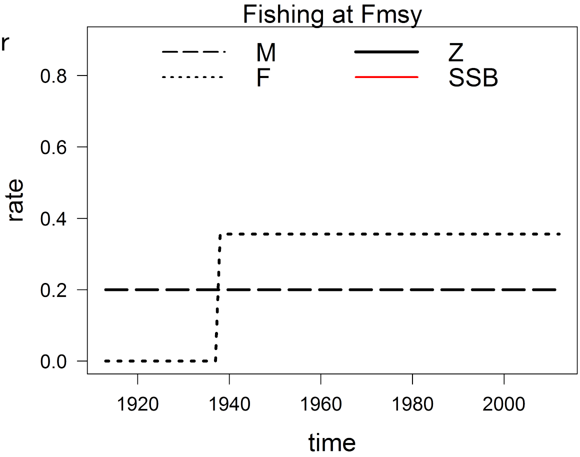

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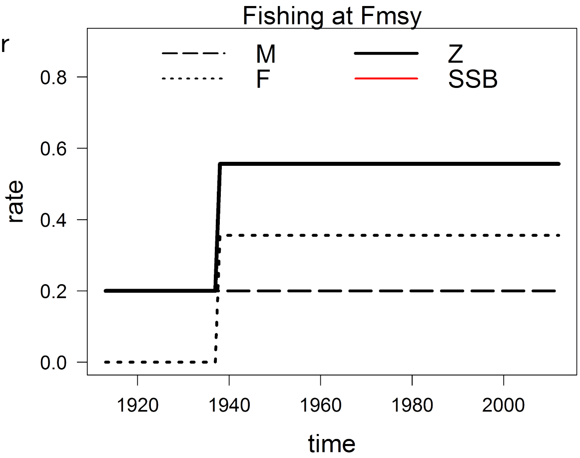

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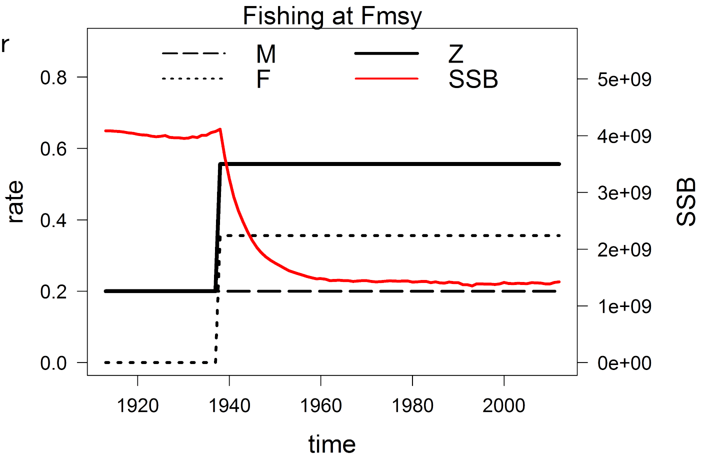

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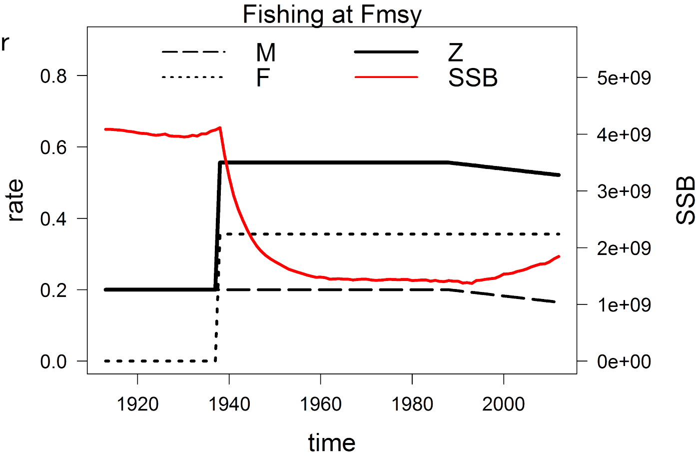

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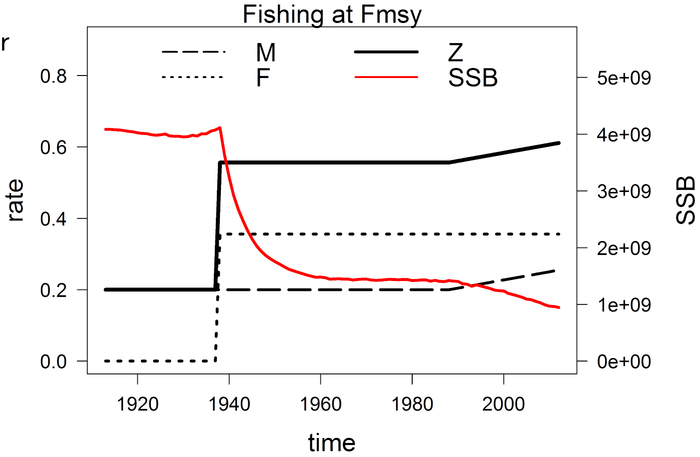

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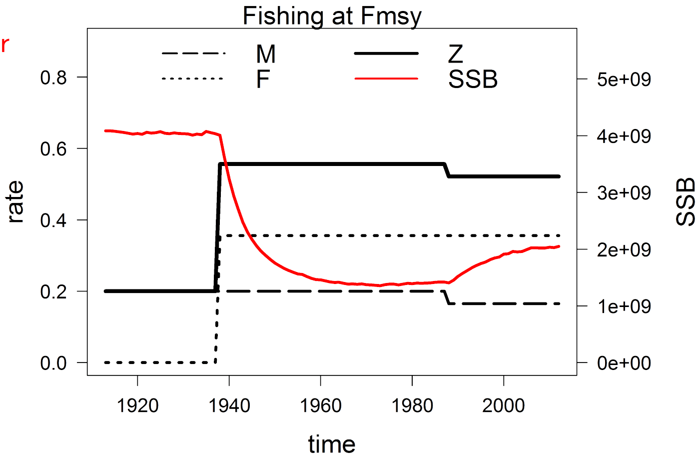

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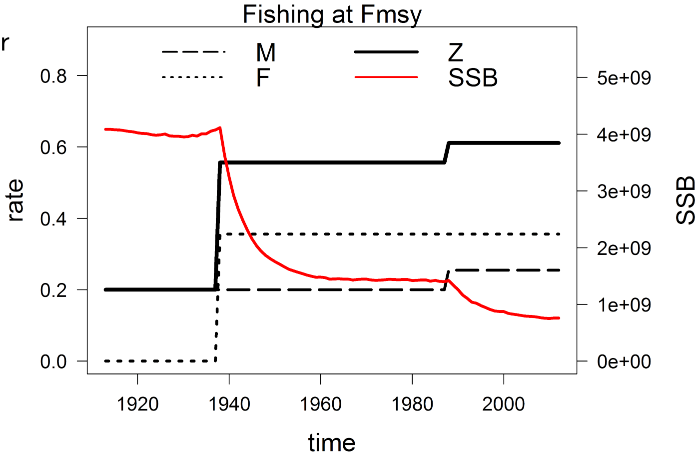
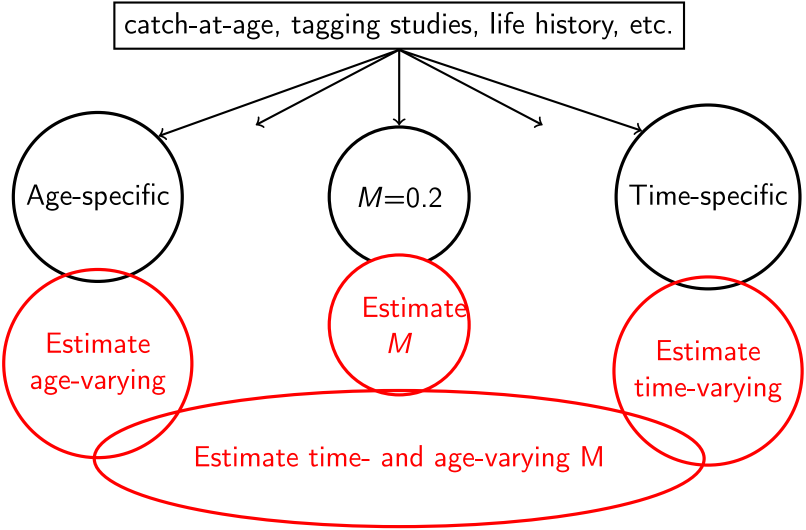


Estimating model



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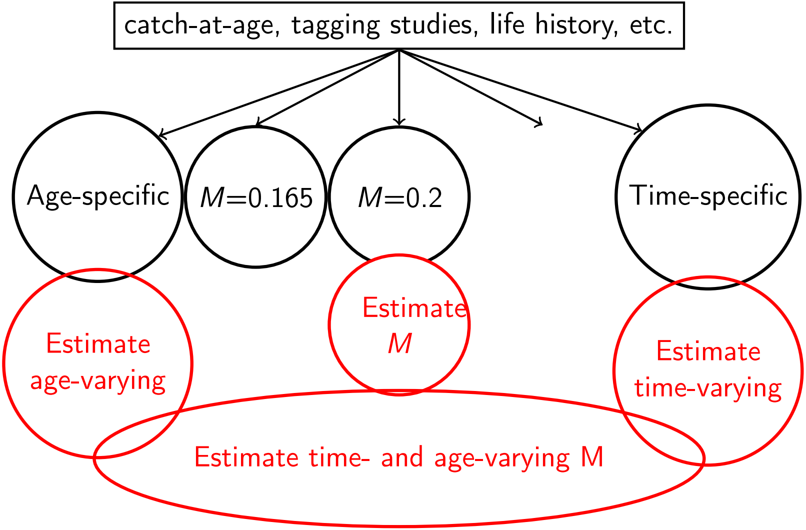

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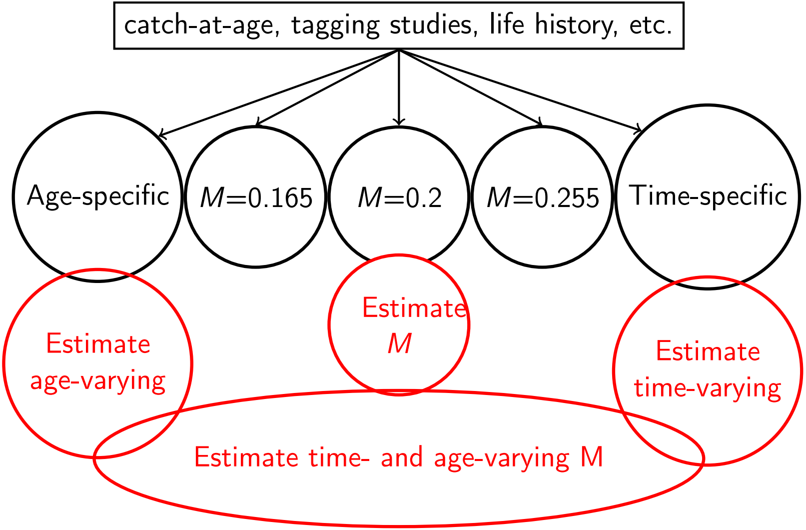

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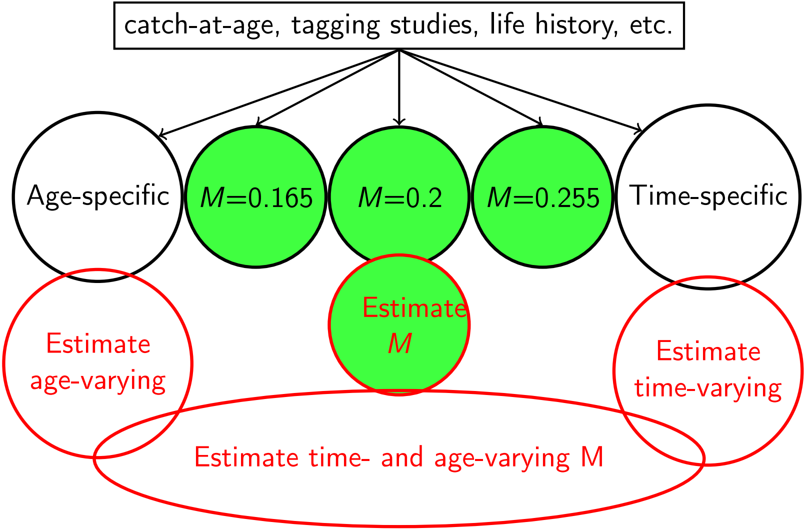
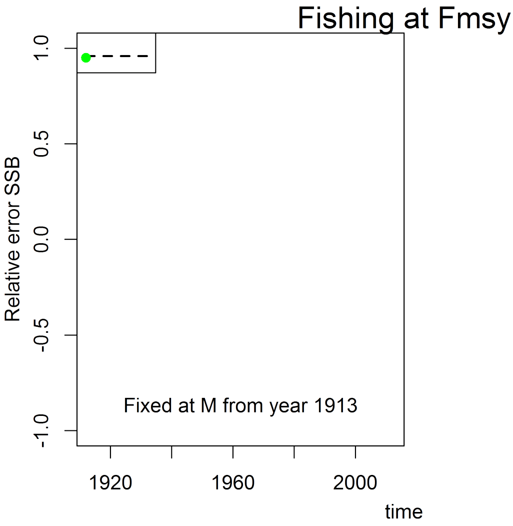


Model validation



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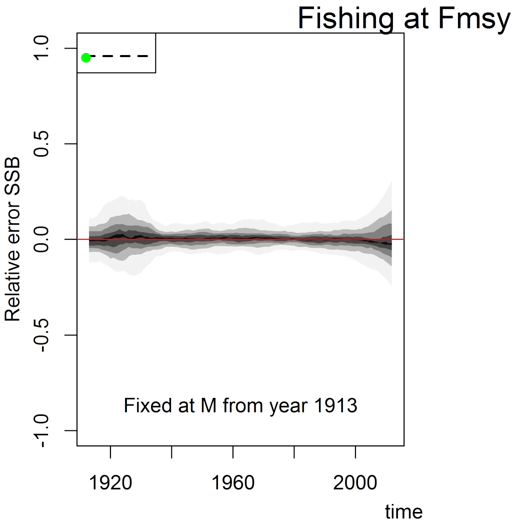

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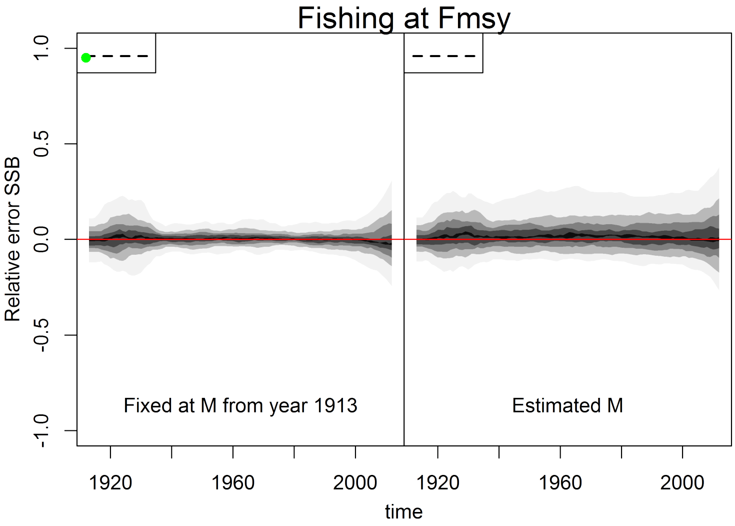
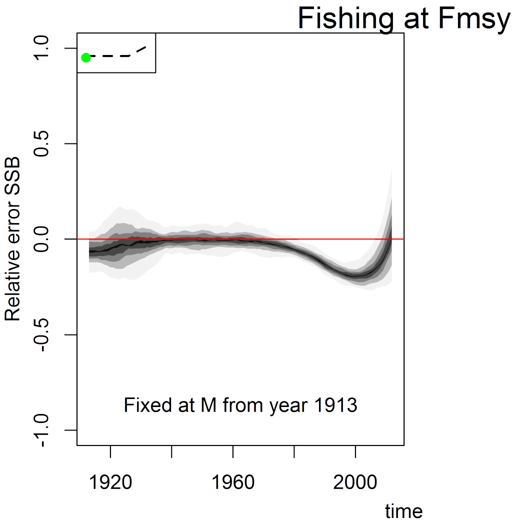


Linear increase in M - M fixed at the current M



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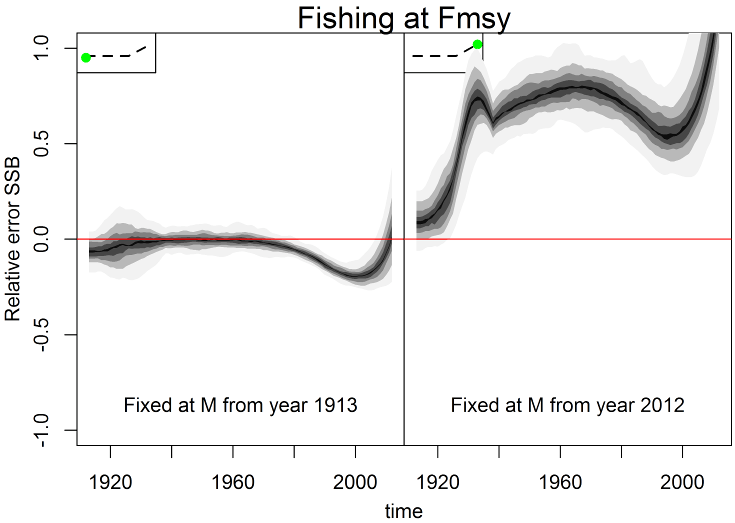
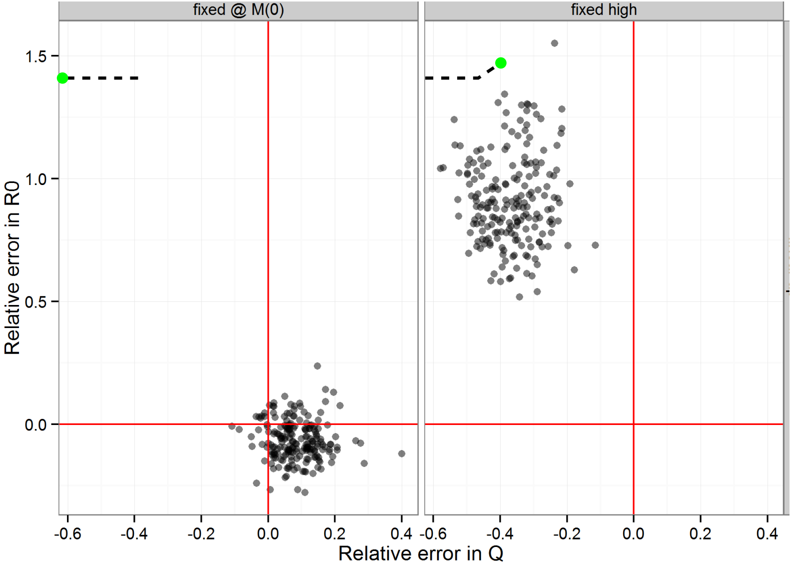
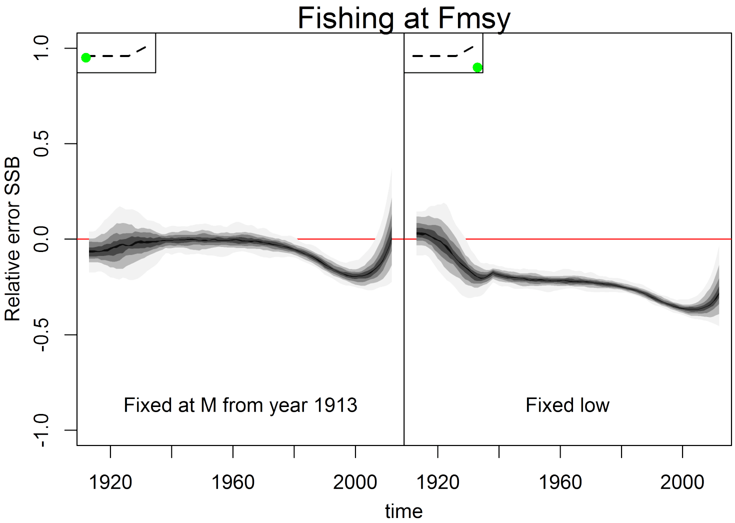


Parameter correlation: Ro and Q



Linear increase in M - Fixed at a low value



Minmax solution without estimating time-varying M

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

	Constant	Linear $\Downarrow$	Linear $\Uparrow$	Step $\Downarrow$	Step $\Uparrow$

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

	Constant	Linear $\Downarrow$	Linear $\Uparrow$	Step $\Downarrow$	Step $\Uparrow$
Fixed @ M(0)	0.09	0.11	0.11	0.08	0.14

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

	Constant	Linear ⇓	Linear ⇑	Step ⇓	Step ⇑
Fixed @ M(0)	0.09	0.11	0.11	0.08	0.14
Fixed high	1.23	1.13	1.32	1.40	0.81

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

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Fixed @ M(0)	0.09	0.11	0.11	0.08	0.14
Fixed high	1.23	1.13	1.32	1.40	0.81
Fixed low	0.30	0.32	0.28	0.28	0.36

Minmax solution without estimating time-varying M

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Fixed high	1.23	1.13	1.32	1.40	0.81
Fixed low	0.30	0.32	0.28	0.28	0.36
Estimated	0.12	0.10	0.13	0.16	0.23

Minmax solution without estimating time-varying M

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Fixed @ M(0)	0.09	0.11	0.11	0.08	0.14
Fixed high	1.23	1.13	1.32	1.40	0.81
Fixed low	0.30	0.32	0.28	0.28	0.36
Estimated	0.12	0.10	0.13	0.16	0.23

MARE for fishing mortality in the terminal year

Minmax solution without estimating time-varying M

MARE for Spawning Stock Biomass in the terminal year

	Constant	Linear $\Downarrow$	Linear $\Uparrow$	Step $\Downarrow$	Step $\Uparrow$
Fixed @ M(0)	0.09	0.11	0.11	0.08	0.14
Fixed high	1.23	1.13	1.32	1.40	0.81
Fixed low	0.30	0.32	0.28	0.28	0.36
Estimated	0.12	0.10	0.13	0.16	0.23

MARE for fishing mortality in the terminal year

	Constant	Linear $\Downarrow$	Linear $\Uparrow$	Step $\Downarrow$	Step $\Uparrow$
Fixed @ M(0)	0.09	0.12	0.12	0.09	0.15
Fixed high	0.55	0.52	0.58	0.58	0.46
Fixed low	0.44	0.51	0.36	0.41	0.55
Estimated	0.12	0.11	0.13	0.14	0.28

Future work

- Age-specific natural mortality using a Lorenzen curve;
- Add sardine-like life history;
- How many parameters to estimate as the base case; and
- Meaningful metrics.

Future work

- Age-specific natural mortality using a Lorenzen curve;
- Add sardine-like life history;
- How many parameters to estimate as the base case; and
- Meaningful metrics.

Thank you

Examining common assumptions about recruitment using the RAM Legacy Stock Assessment Database

Cody Szuwalski, Katyana Vert-pre, Andre Punt, Trevor Branch and Ray Hilborn

Sea Grant Washington

SAFS School of Aquatic and Fishery Sciences

Abstract.—We analyzed 364 spawner-recruitment time series to determine whether recruitment is related to spawner abundance. We pose three questions: 1) Does the highest recruitment occur when spawner abundance is high? 2) Does the lowest recruitment occur when spawner abundance is low? and 3) Is the mean recruitment higher if spawner abundance is above rather than below the median? We found that when there is a sufficient range in spawner abundance the answer to all three questions is almost always "yes." Thus, spawner abundance cannot be ignored in the management of fish populations. Recruitment overfishing appears to be a common problem.

Is fish recruitment related to spawner abundance?

YES

Ransom A. Myers
Nicholas J. Barrowman
Science Branch, Northwest Atlantic Fisheries Centre
Department of Fisheries and Oceans
Box 5667, St John's, Newfoundland, Canada A1C 5X1

Towards a new recruitment paradigm for fish stocks

NO

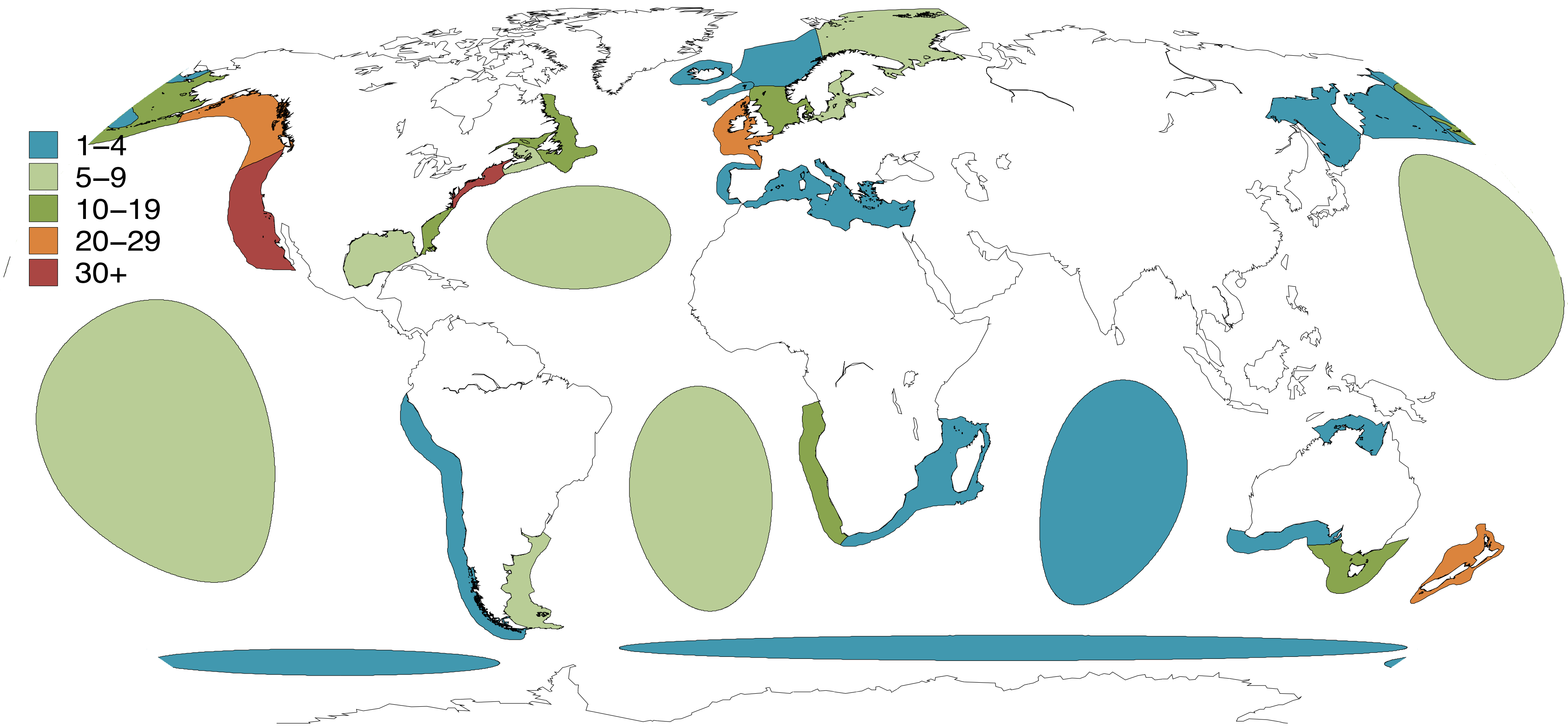
D.J. Gilbert

Abstract: The stock recruitment paradigm involves the hypothesis that recruitment (R) to a fish stock is positively related to the spawning stock biomass (SSB) of the stock, at low SSB. I propose a "recruitment states" hypothesis wherein R is independent of SSB but has different mean values during successive periods. Meta-analysis was used to test the null hypothesis that recruitment is a series of random, independent events, against these two alternative hypotheses, for 153 marine spawning bony fish stocks and 31 salmonid stocks. A test statistic for the stock recruitment paradigm, based on estimating derivatives from the first differences of the time series, was not significant for the marine stocks. The null hypothesis was rejected for the salmonid stocks. Recruitment states models significantly fitted time series for the marine stocks. Ricker models also significantly fitted these data, conflicting with the derivatives test result. However, because SSB is dependent on R, lagged by the age at maturity, a period in a low recruitment state would tend to lead to a period of low SSB. Therefore, the significance of the fit to the Ricker model may have been spurious. The recruitment states model best explained the meta-dataset for the marine stocks.

- Is recruitment related to spawning biomass?
- Do recruitment dynamics change over time?
- Are changes in recruitment dynamics synchronous within an LME?

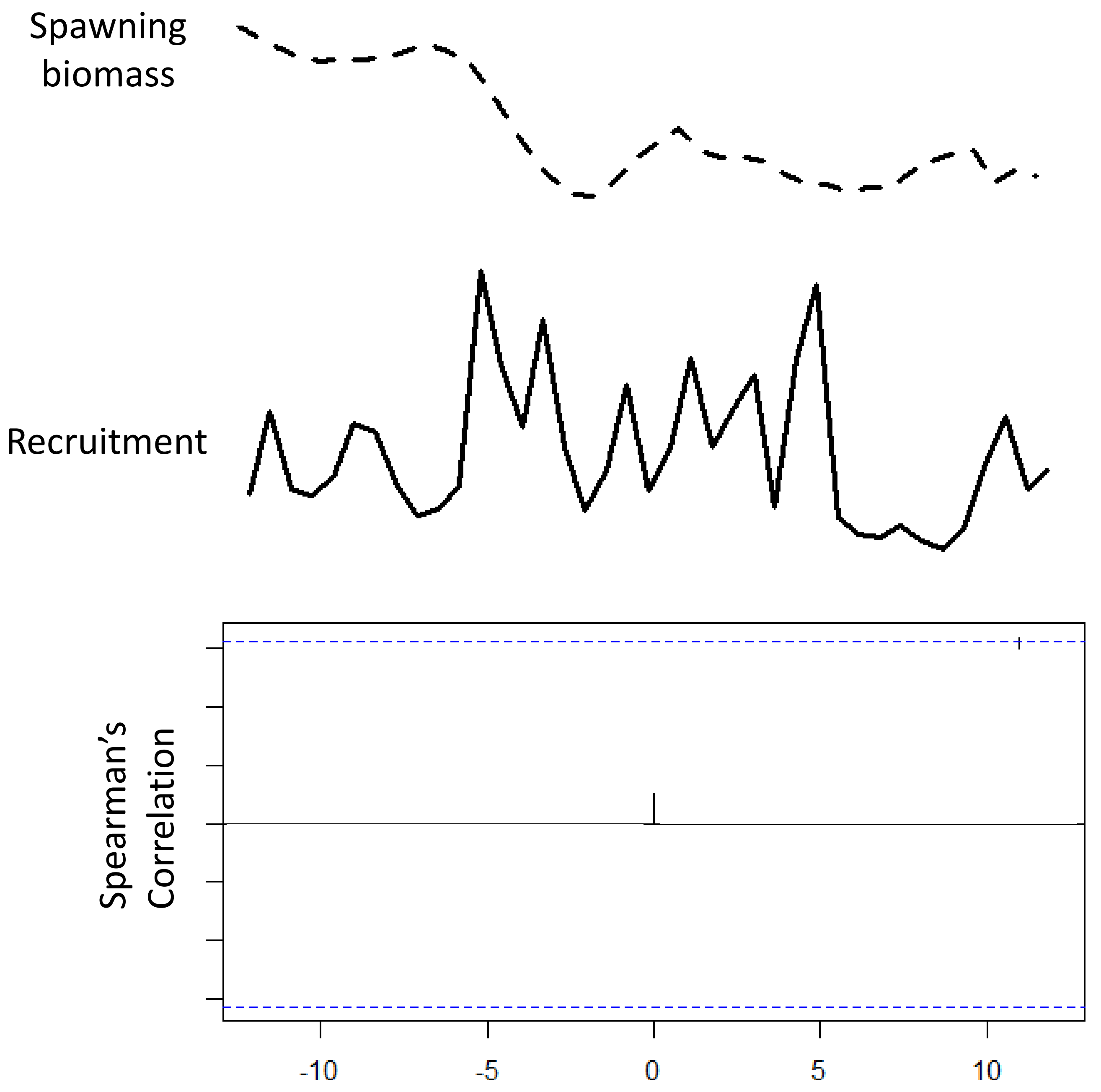
RAM legacy stock assessment database:

- \>= 20 estimates of recruitment and SSB
- No estimates directly from a s/r curve (the tails of the time series were often removed)
- 224 stocks

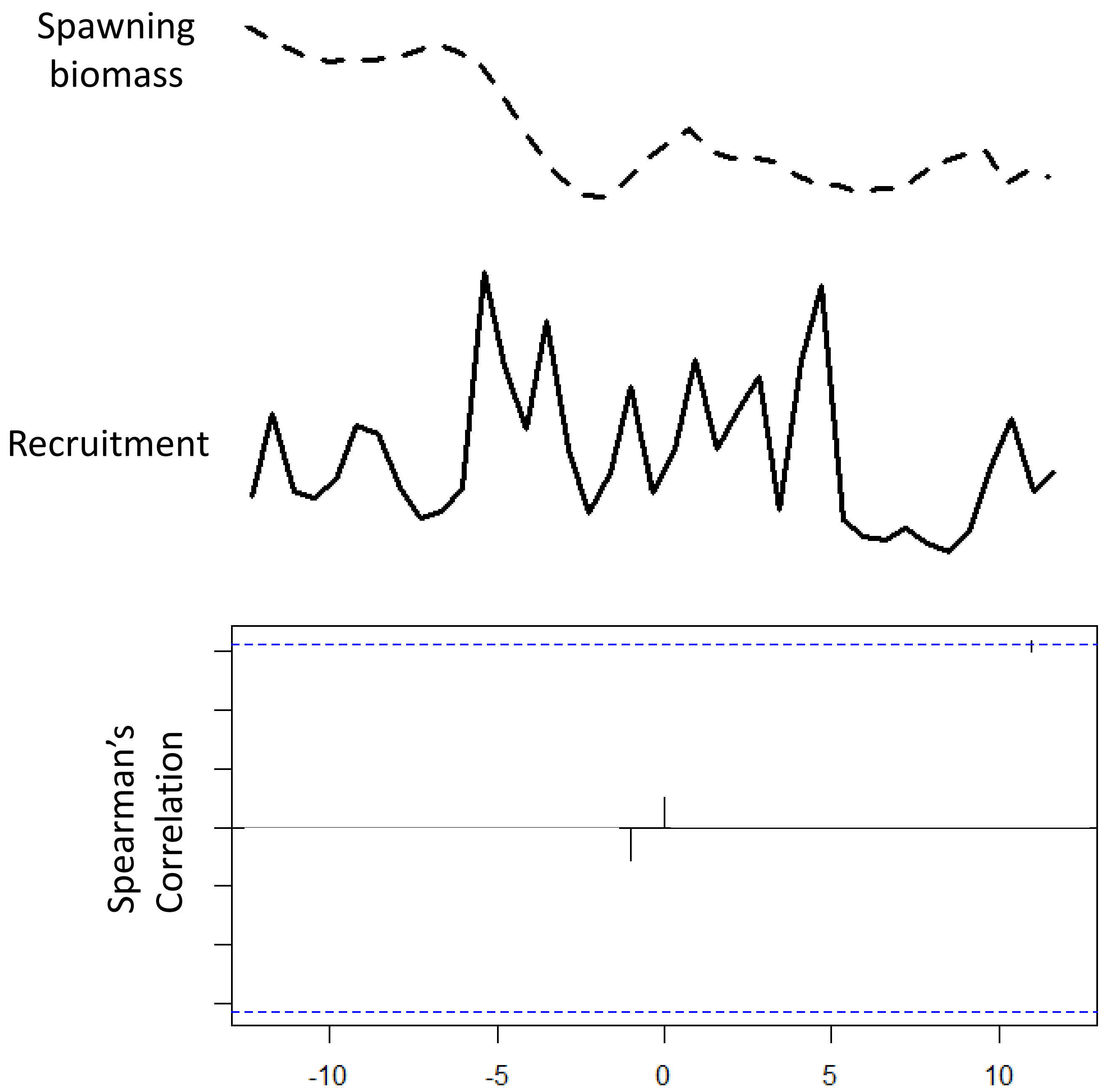


Although not ‘data’, these estimates are:

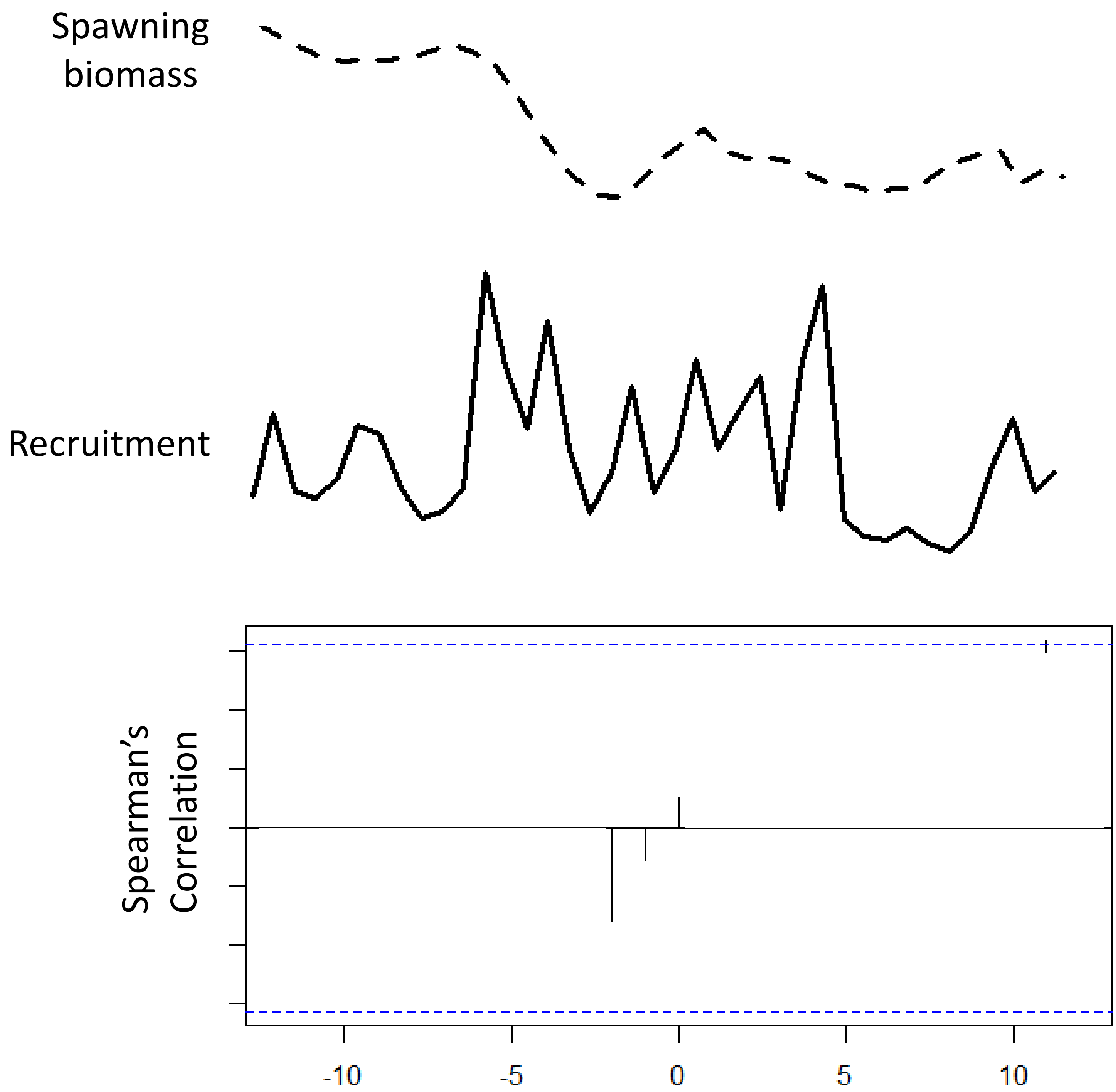
1) used to provide management advice
2) incorporate many data sources and represent the best available science



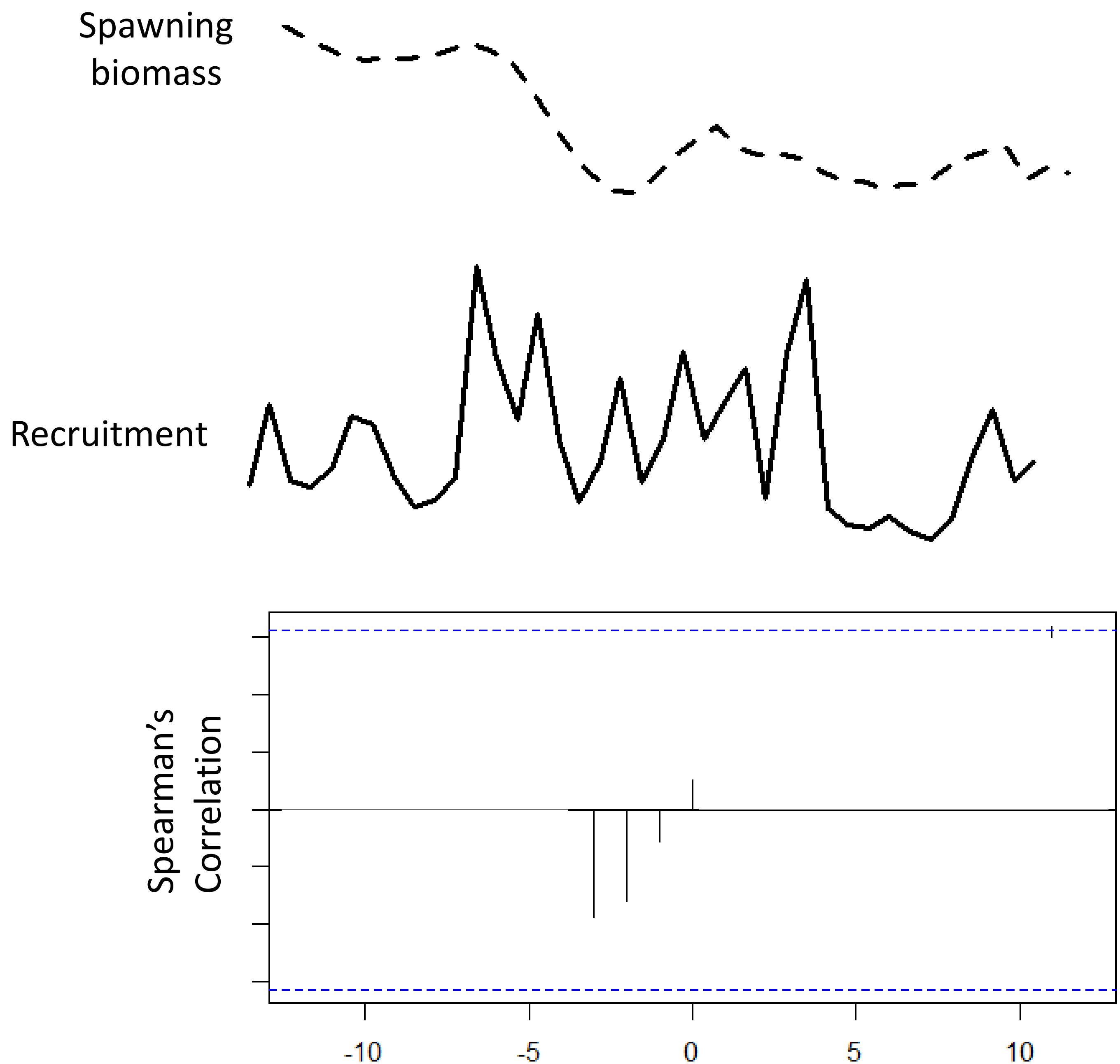
Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10

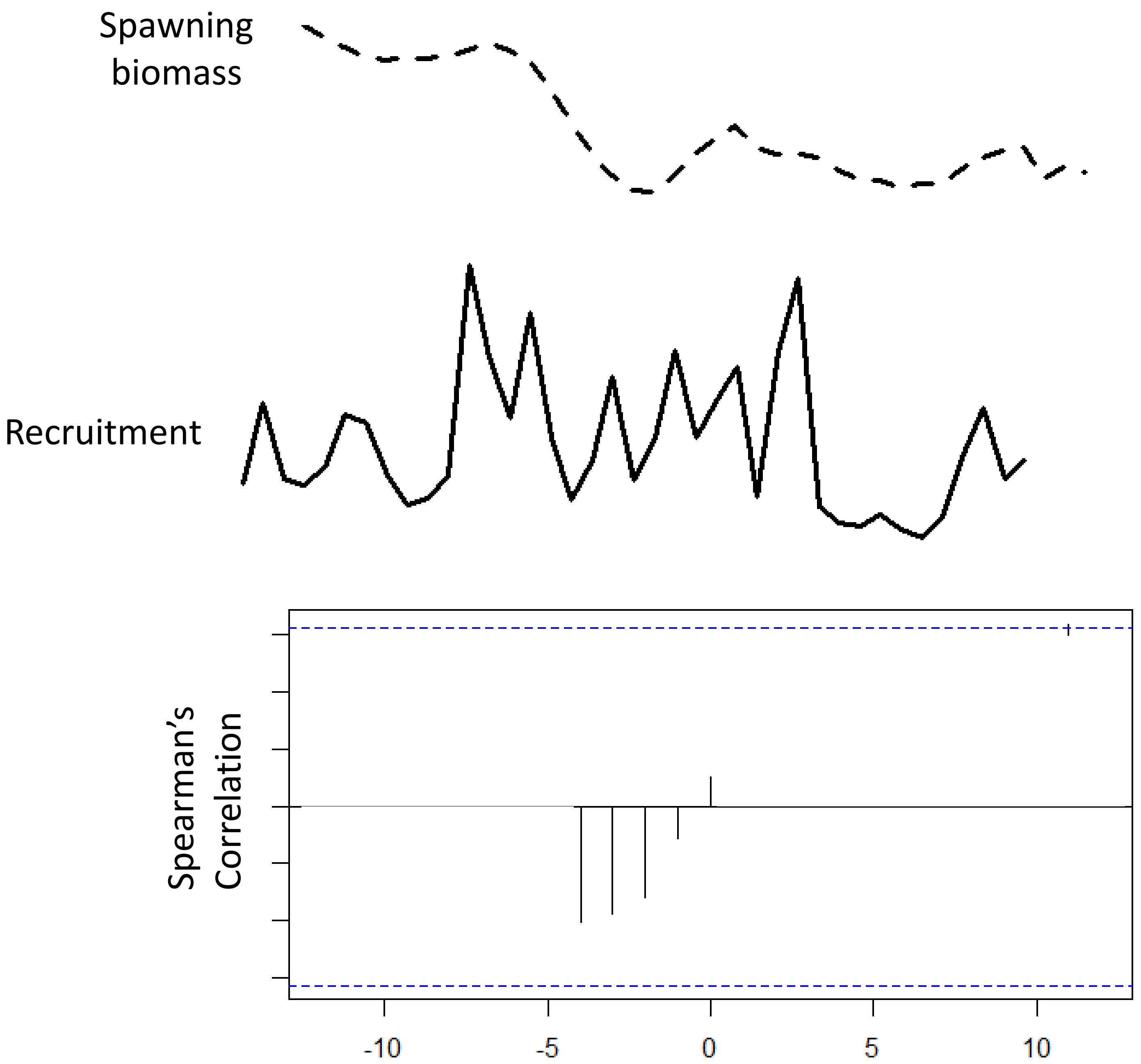


Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10

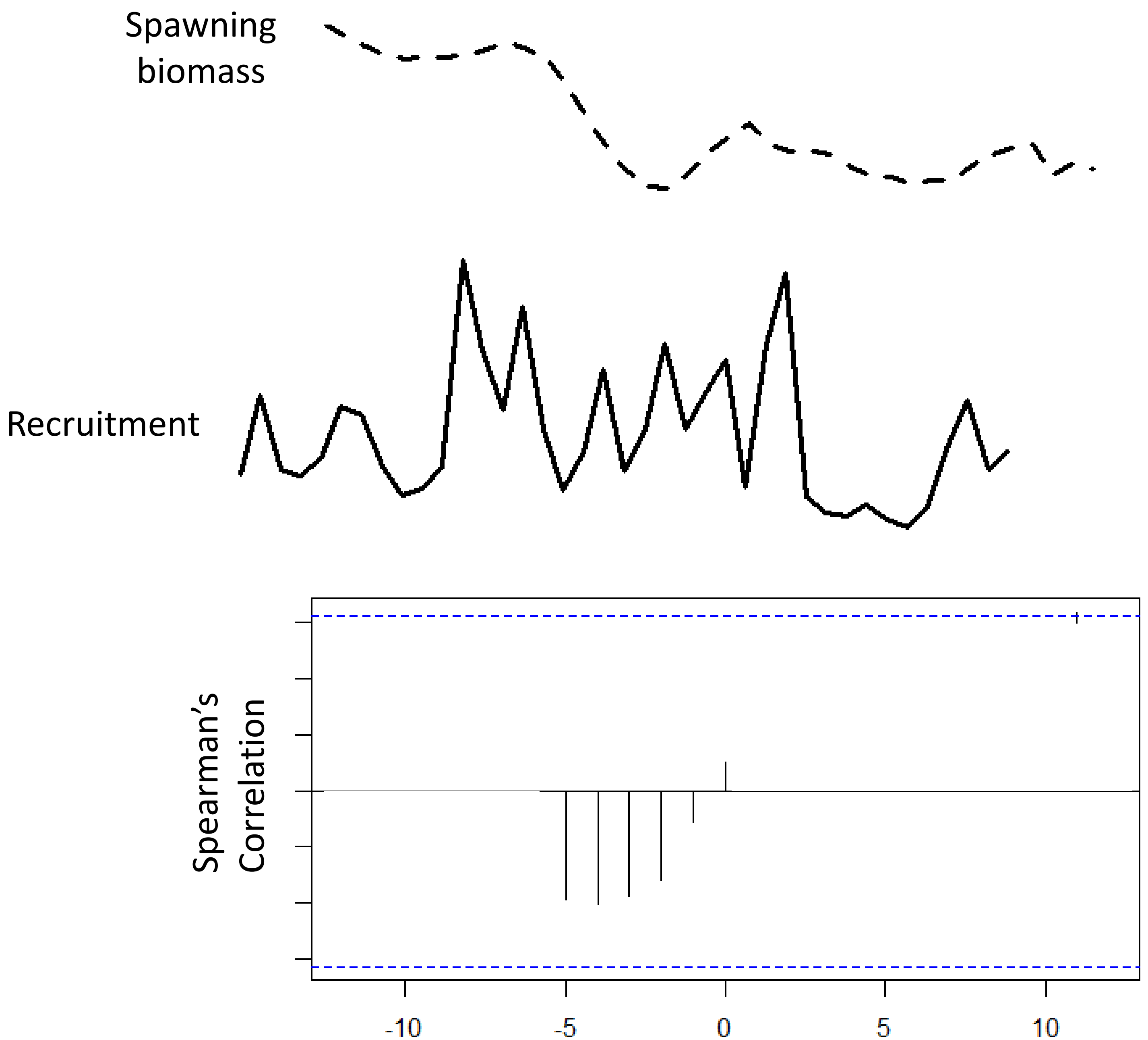


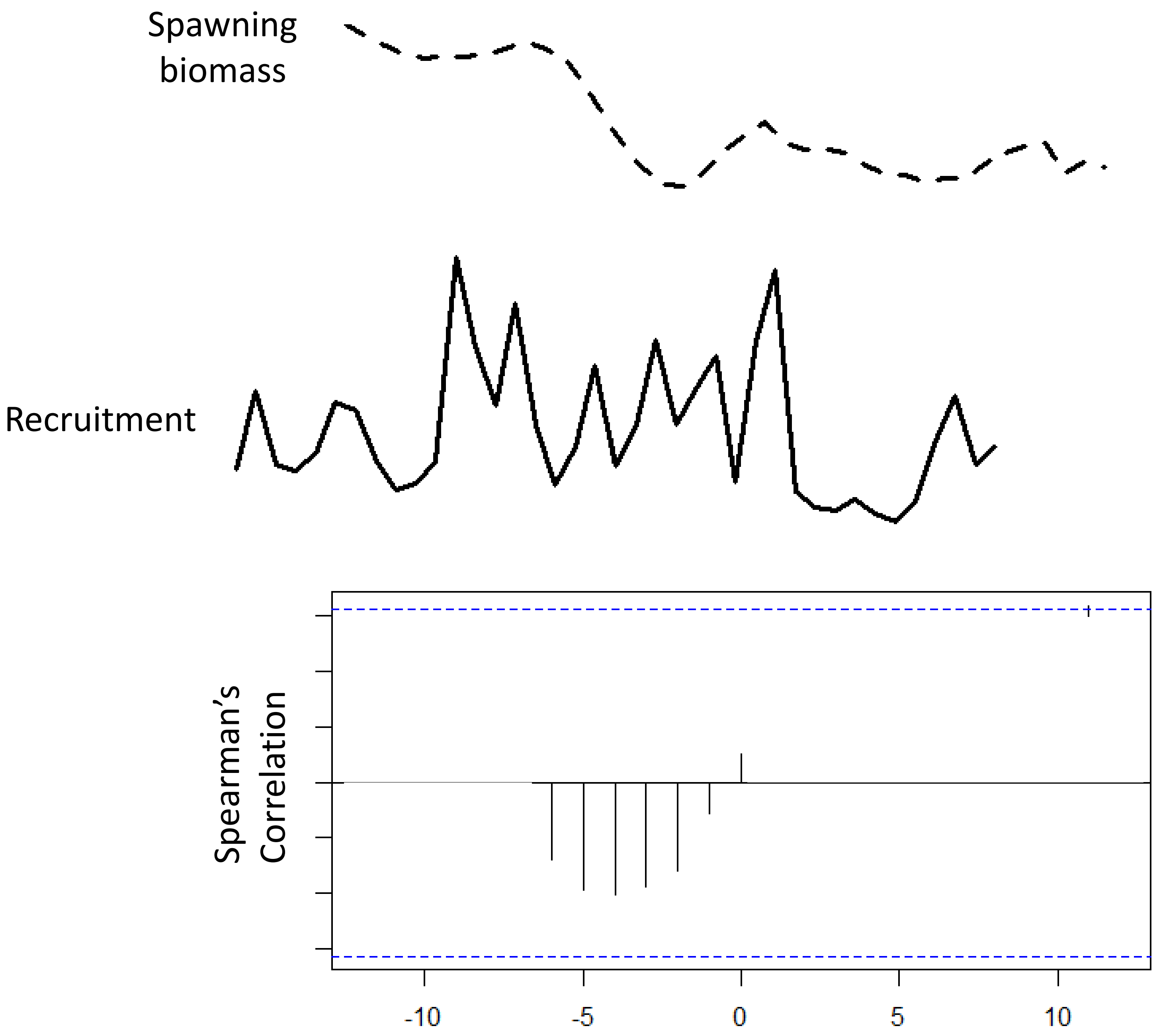
Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10


Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10

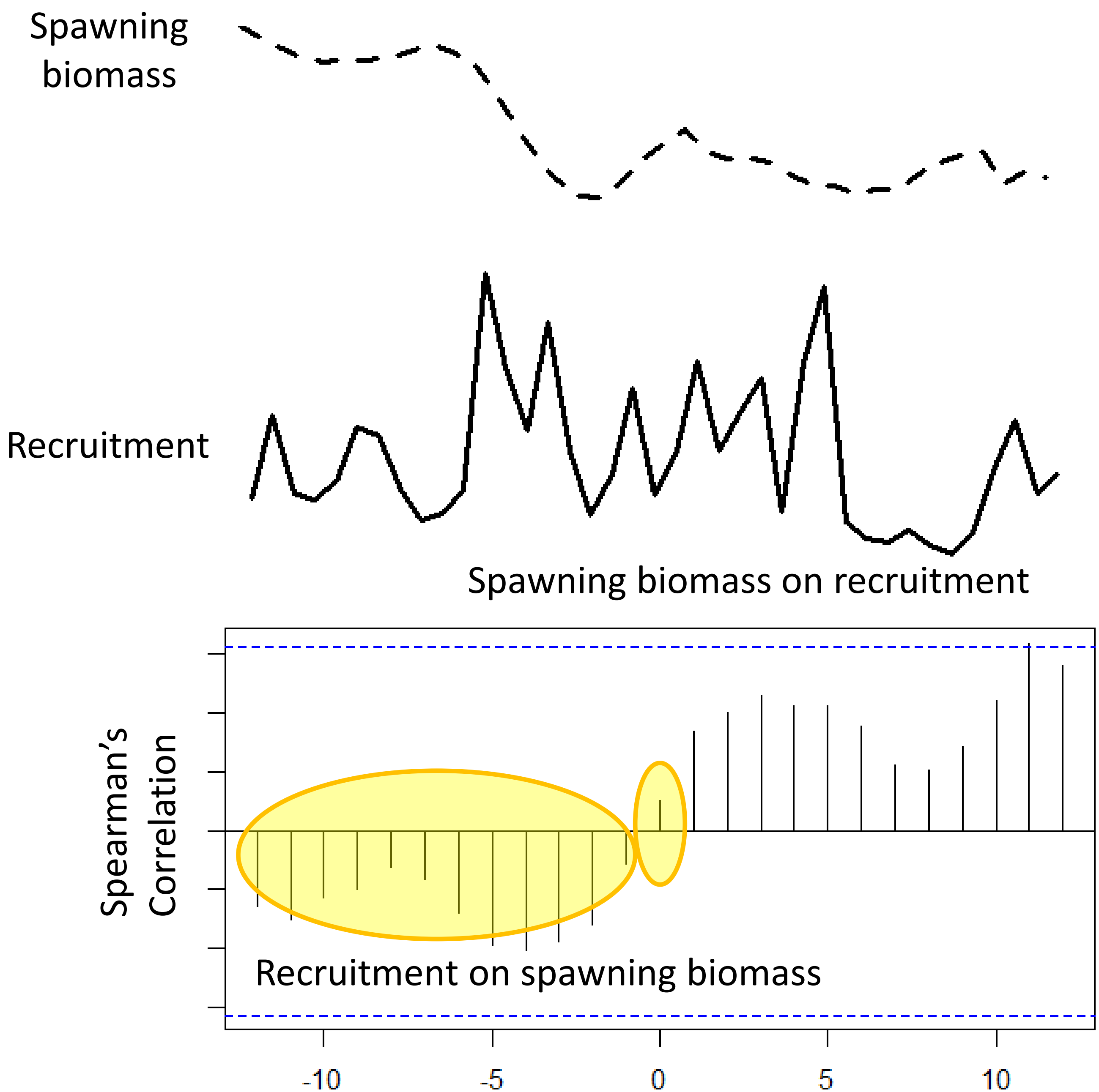


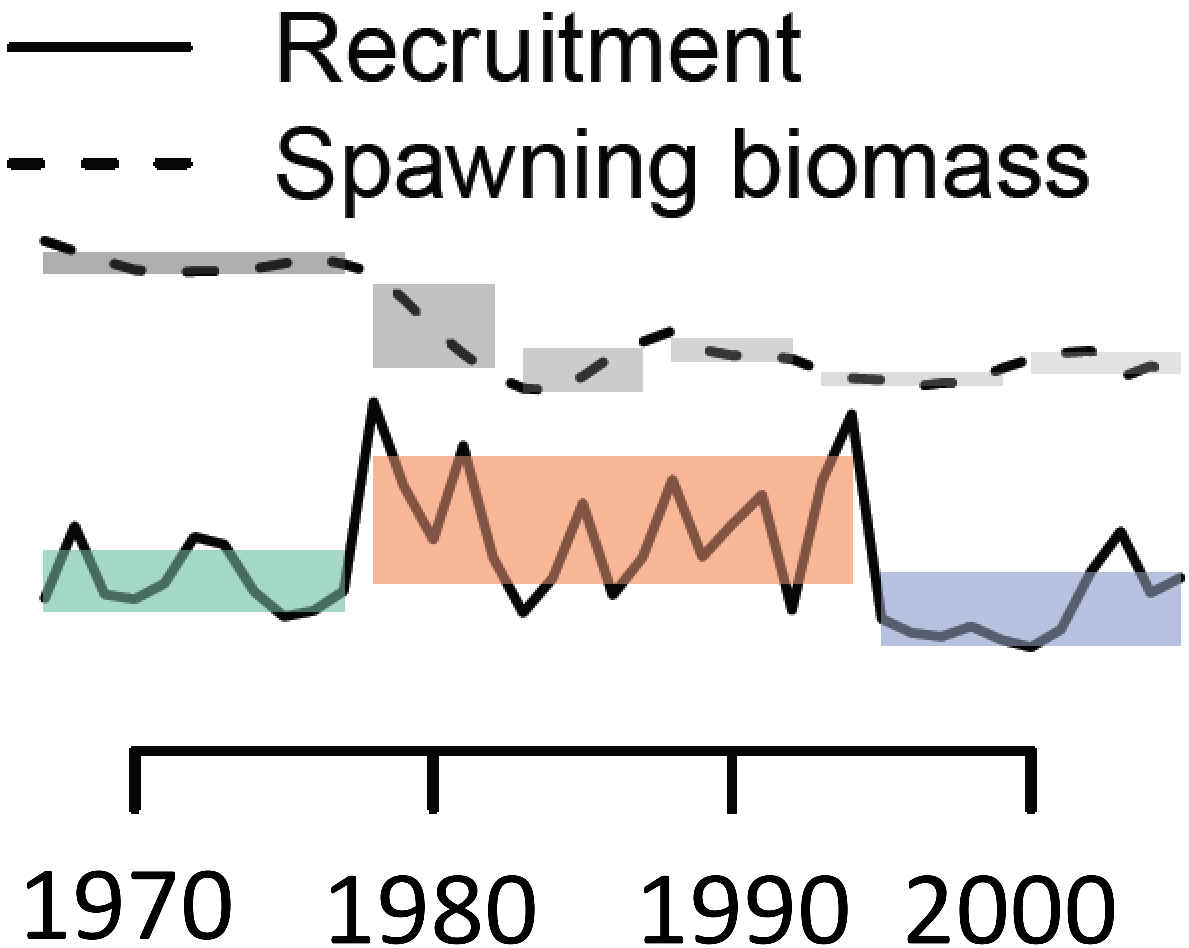
Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10


Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10

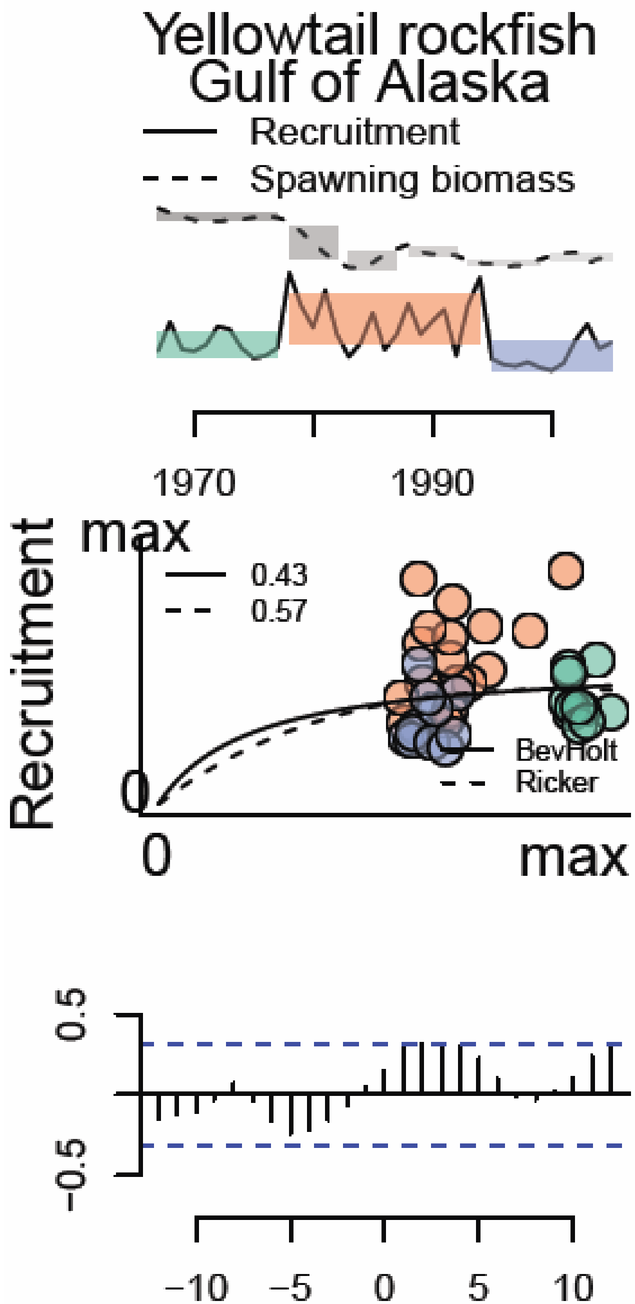


Spawning biomass
Recruitment
Spearman's Correlation
-10
-5
0
5
10

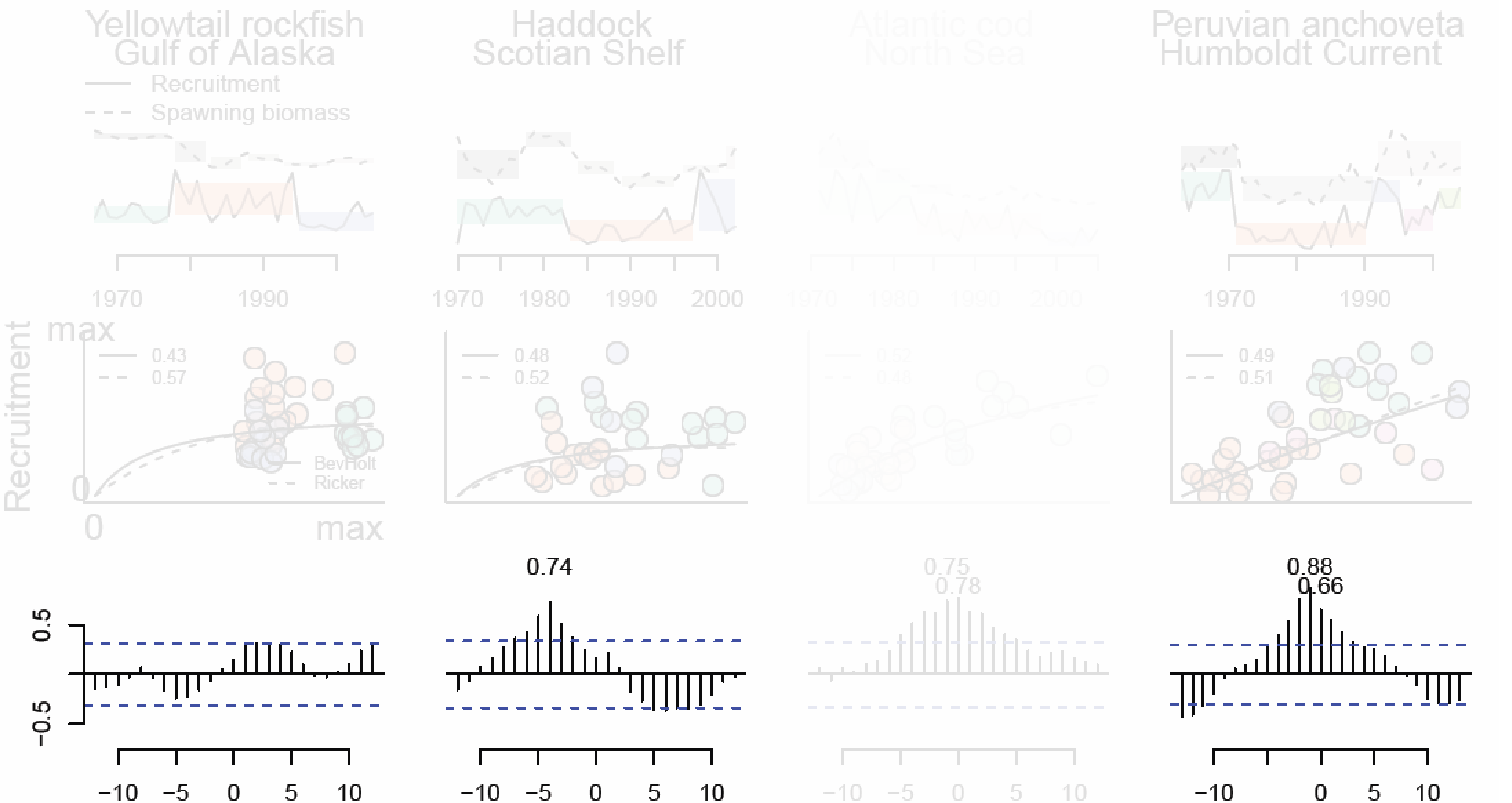

Spawning biomass
Recruitment
Spawning biomass on recruitment
Spearman's Correlation
Recruitment on spawning biomass
-10
-5
0
5
10



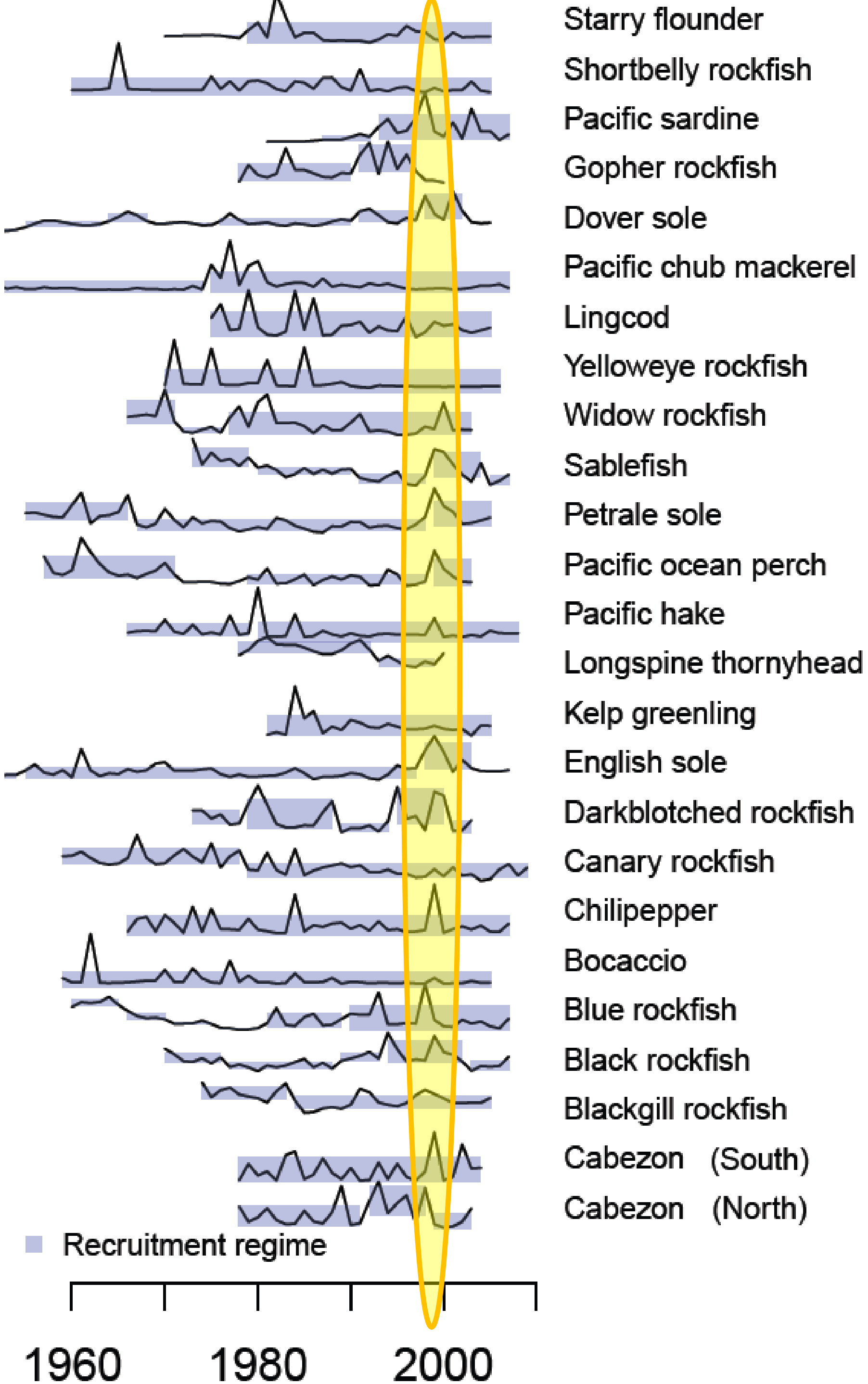
‘Sequential t-test for regime shifts’; Rodionov, 2004.

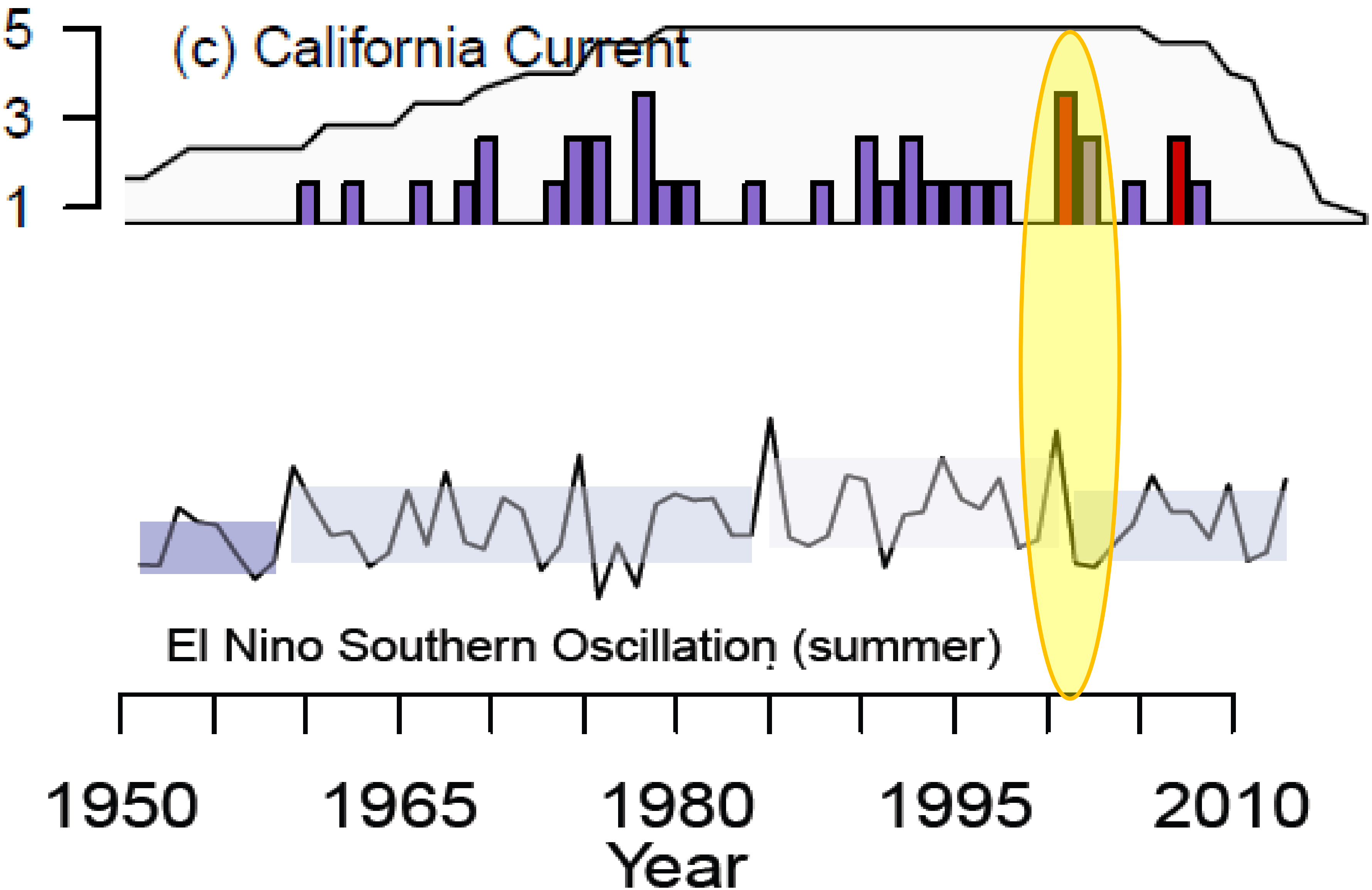


Yellowtail rockfish
Gulf of Alaska
Recruitment
Spawning biomass
1970
1990
Recruitment
max
0
0.43
0.57
BevHolt
Ricker
0
max
0.5
−0.5
−10
−5
0
5
10

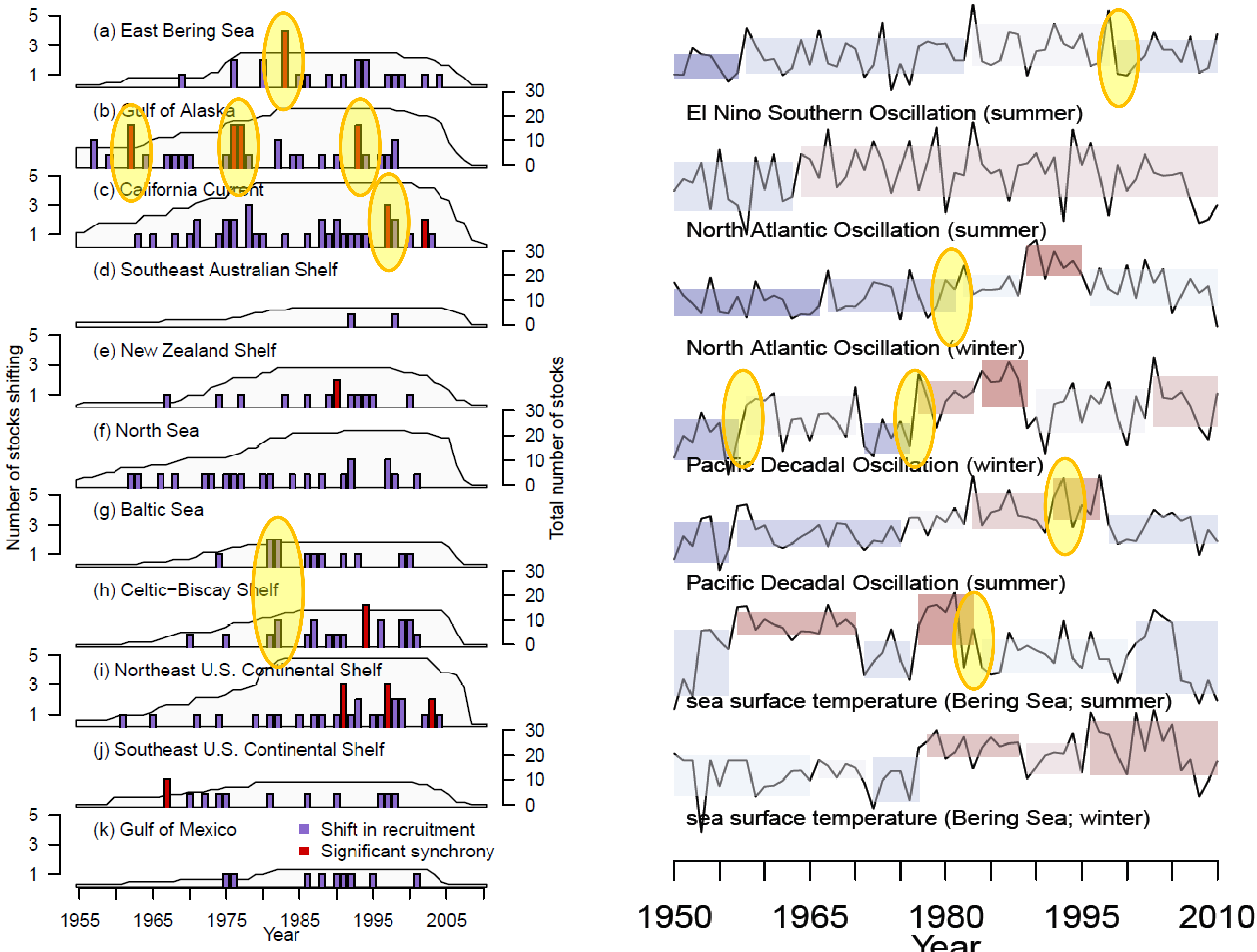


77% of stocks with recruitment not related to spawning biomass show changes in average recruitment over time


Starry flounder
Shortbelly rockfish
Pacific sardine
Gopher rockfish
Dover sole
Pacific chub mackerel
Lingcod
Yelloweye rockfish
Widow rockfish
Sablefish
Petrale sole
Pacific ocean perch
Pacific hake
Longspine thornyhead
Kelp greenling
English sole
Darkblotched rockfish
Canary rockfish
Chilipepper
Bocaccio
Blue rockfish
Black rockfish
Blackgill rockfish
Cabezon (South)
Cabezon (North)
Recruitment regime
1960
1980
2000



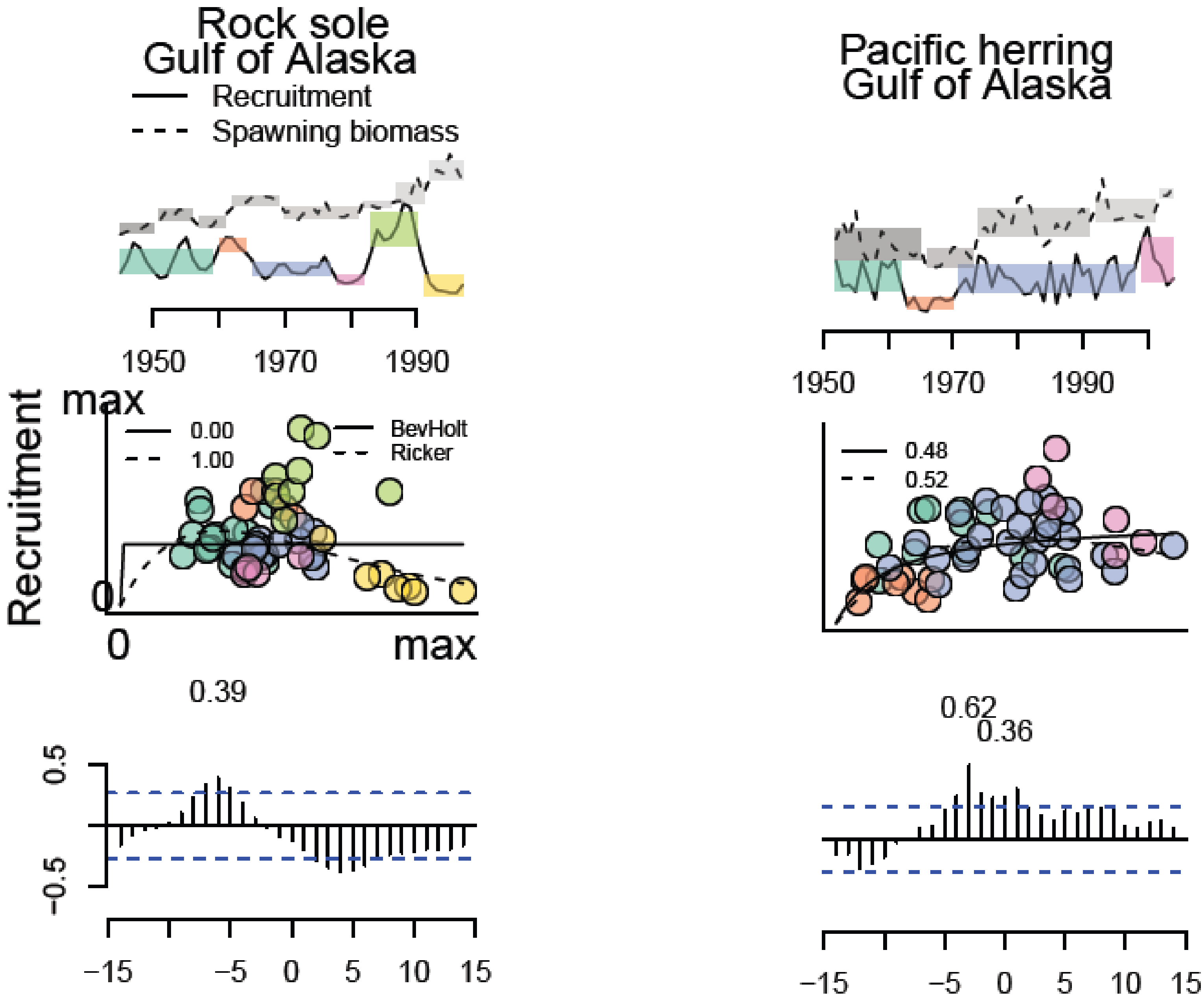
5
3
1
(c) California Current
El Nino Southern Oscillation (summer)
1950
1965
1980
1995
2010
Year



(a) East Bering Sea
(b) Gulf of Alaska
(c) California Current
(d) Southeast Australian Shelf
(e) New Zealand Shelf
(f) North Sea
(g) Baltic Sea
(h) Celtic−Biscay Shelf
(i) Northeast U.S. Continental Shelf
(j) Southeast U.S. Continental Shelf
(k) Gulf of Mexico
Shift in recruitment
Significant synchrony
Number of stocks shifting
Total number of stocks
Year
1955 1965 1975 1985 1995 2005
El Nino Southern Oscillation (summer)
North Atlantic Oscillation (summer)
North Atlantic Oscillation (winter)
Pacific Decadal Oscillation (winter)
Pacific Decadal Oscillation (summer)
sea surface temperature (Bering Sea; summer)
sea surface temperature (Bering Sea; winter)
1950 1965 1980 1995 2010
Year

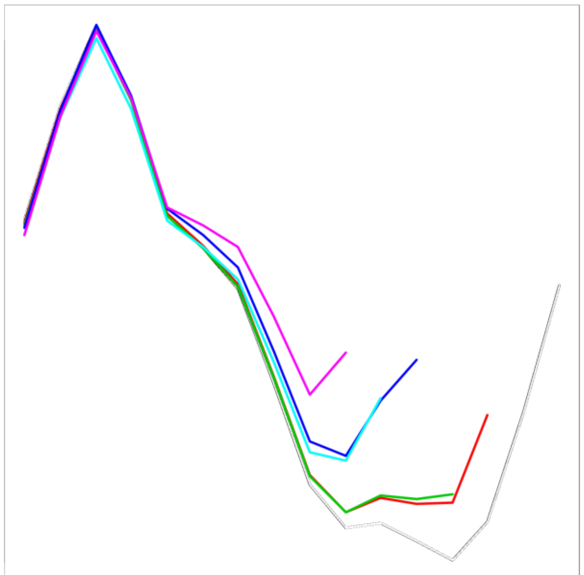
- Recruitment for 62% of stocks doesn’t increase as spawning biomass does.
- Only 14% of stocks appear to have a strong stock recruit relationship.
- Recruitment dynamics change for 77% of environmentally driven stocks.
- These changes often occur synchronously within LMEs.

Be careful with inference from stock recruit models when recruitment is 'regime-like'?



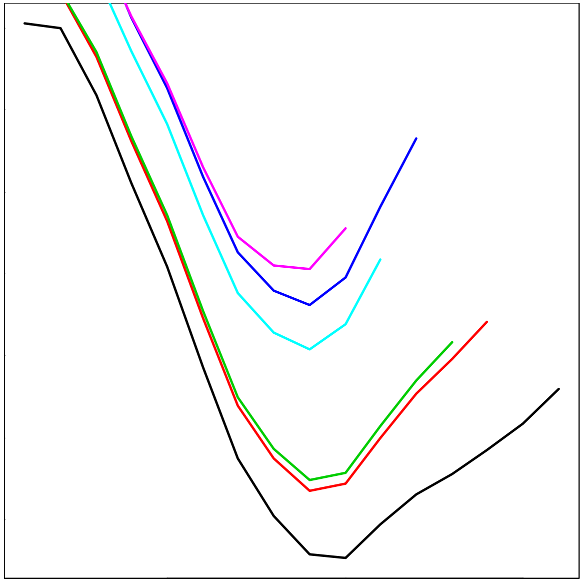

Thanks for your
attention!

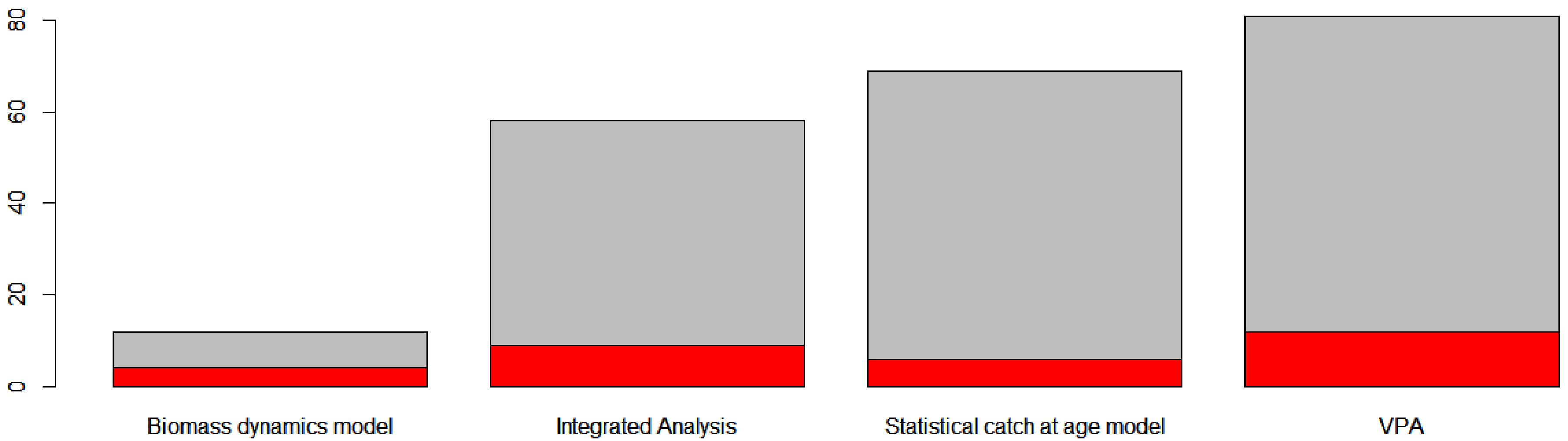
Retrospective bias + time-varying selectivity
=
good estimates of management quantities??



Flatfish-like
time-varying selectivity

Cod-like
time-varying growth

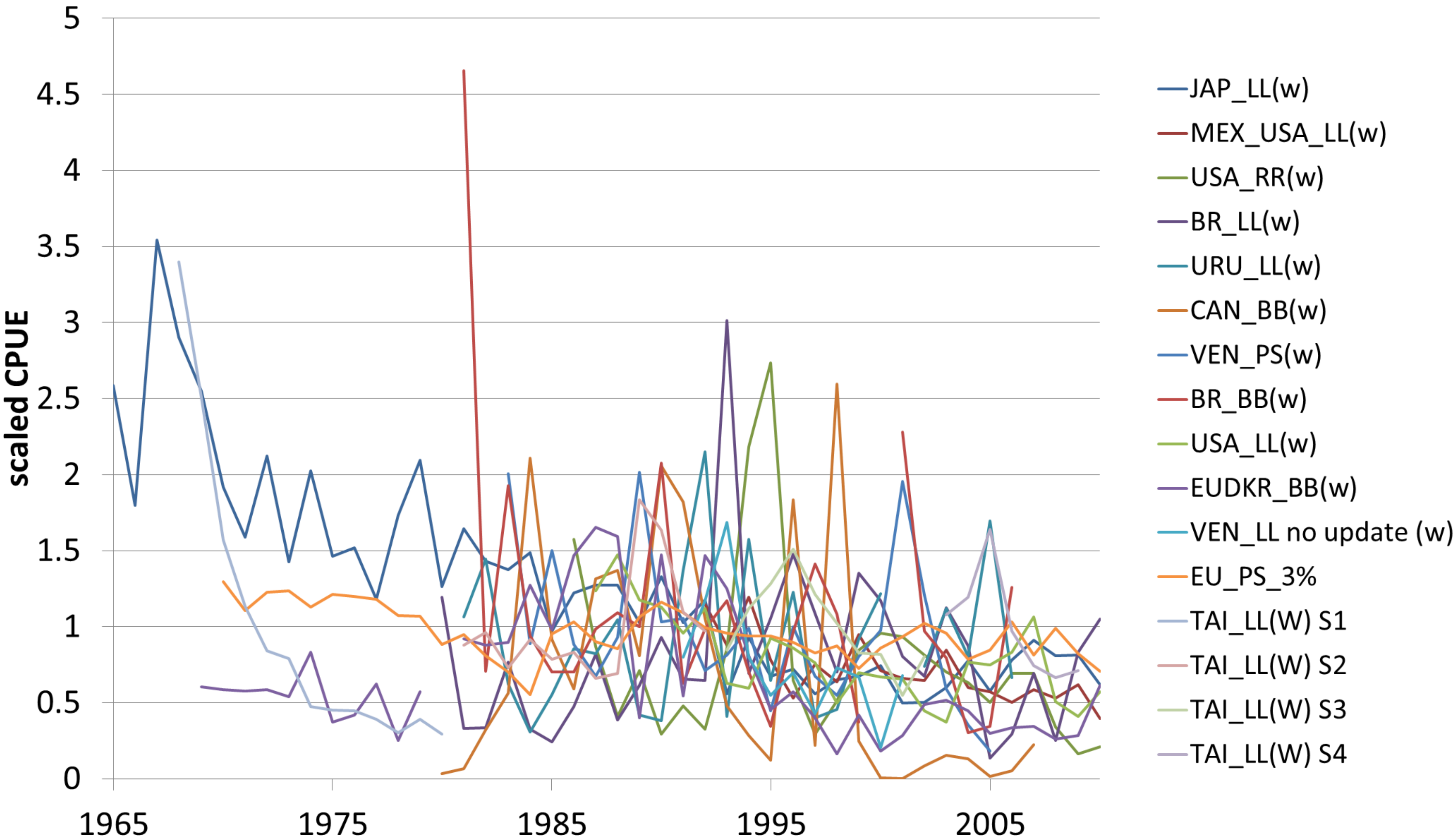



0
20
40
60
80
Biomass dynamics model
Integrated Analysis
Statistical catch at age model
VPA

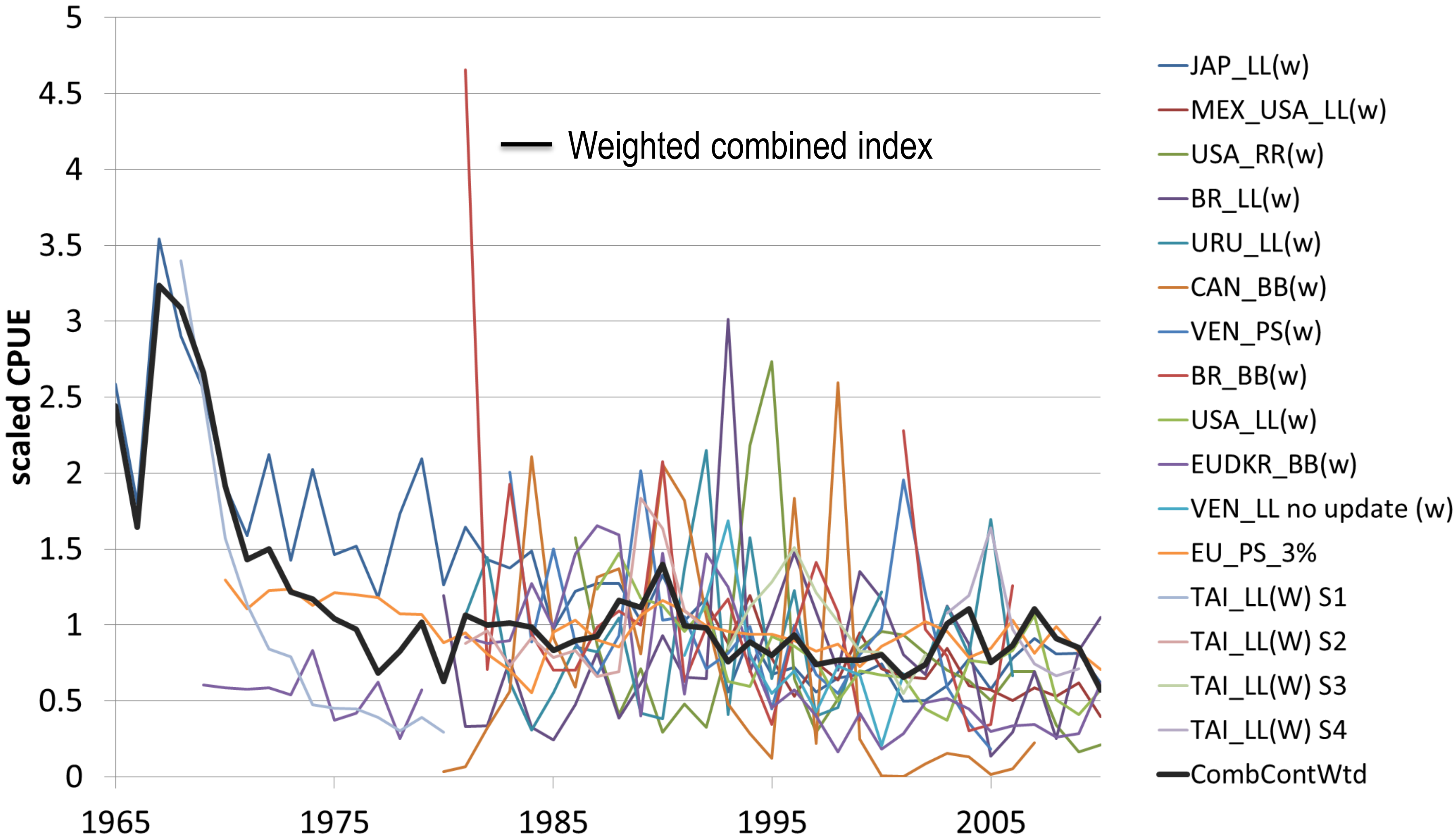
A method to identify CPUE values that exceed biological plausibility: with application to Atlantic Yellowfin tuna

John Walter
Shannon Cass-Calay
NOAA-Fisheries SEFSC

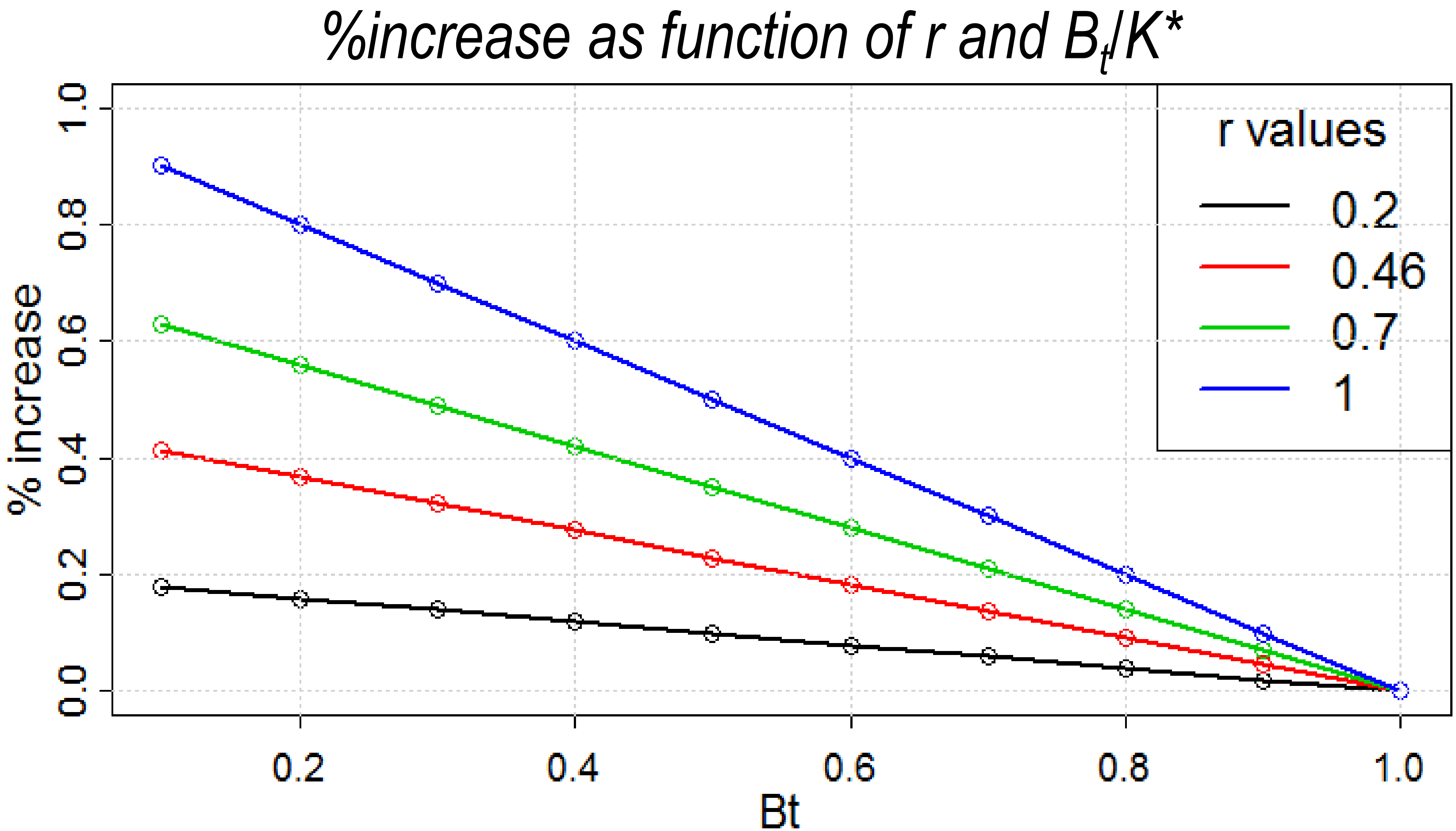
2011 ICCAT Yellowfin tuna assessment surplus production model indices -16



In practice some combined index weighted often produced



Does an index make biological sense or "Is it consistent with production model dynamics?"



* In context of Schaeffer SPM

Method definition:

*1. Upper bound (**UB_{t+1}**)* for the following year can be estimated by assuming that no fishing occurs as follows:

$$UB_{t+1} = B_t + r * (B_t) * (1 - B_t/K)$$

Where B_t and B_{t+1} are biomass at time t and one year later, K is the carrying capacity, and r is the intrinsic rate of population increase.

Method definition, continued

2. *Lower bound (**LB_{t+1}**)* for the subsequent year index value. Where population grows for entire year and then is reduced by exploitation at end:

$$\boldsymbol{LB_{t+1} = [B_t + r * (B_t) * (1 - B_t/K)] * (1 - maxU)}$$

using assumed maximum rate of annual exploitation, ***maxU***.

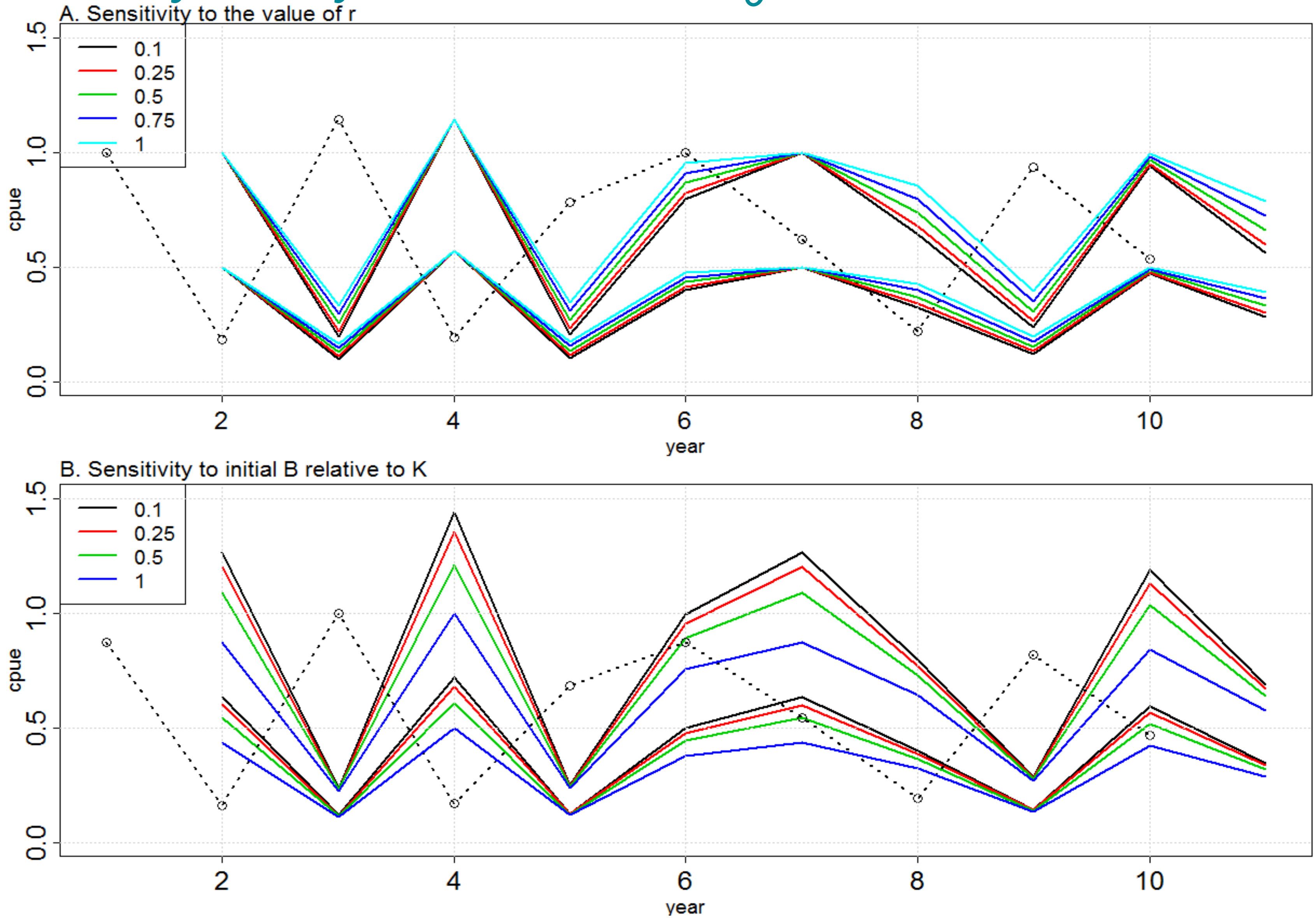
Key assumptions

1. r known
   - but method relatively insensitive
2. B1/K, or Bt/K for indices that start later than B1

3. Maximum rate of single year depletion
   - maximized if all fishing is at the end of the year

4. Production model dynamics

Sensitivity analyses to r and B_o/K



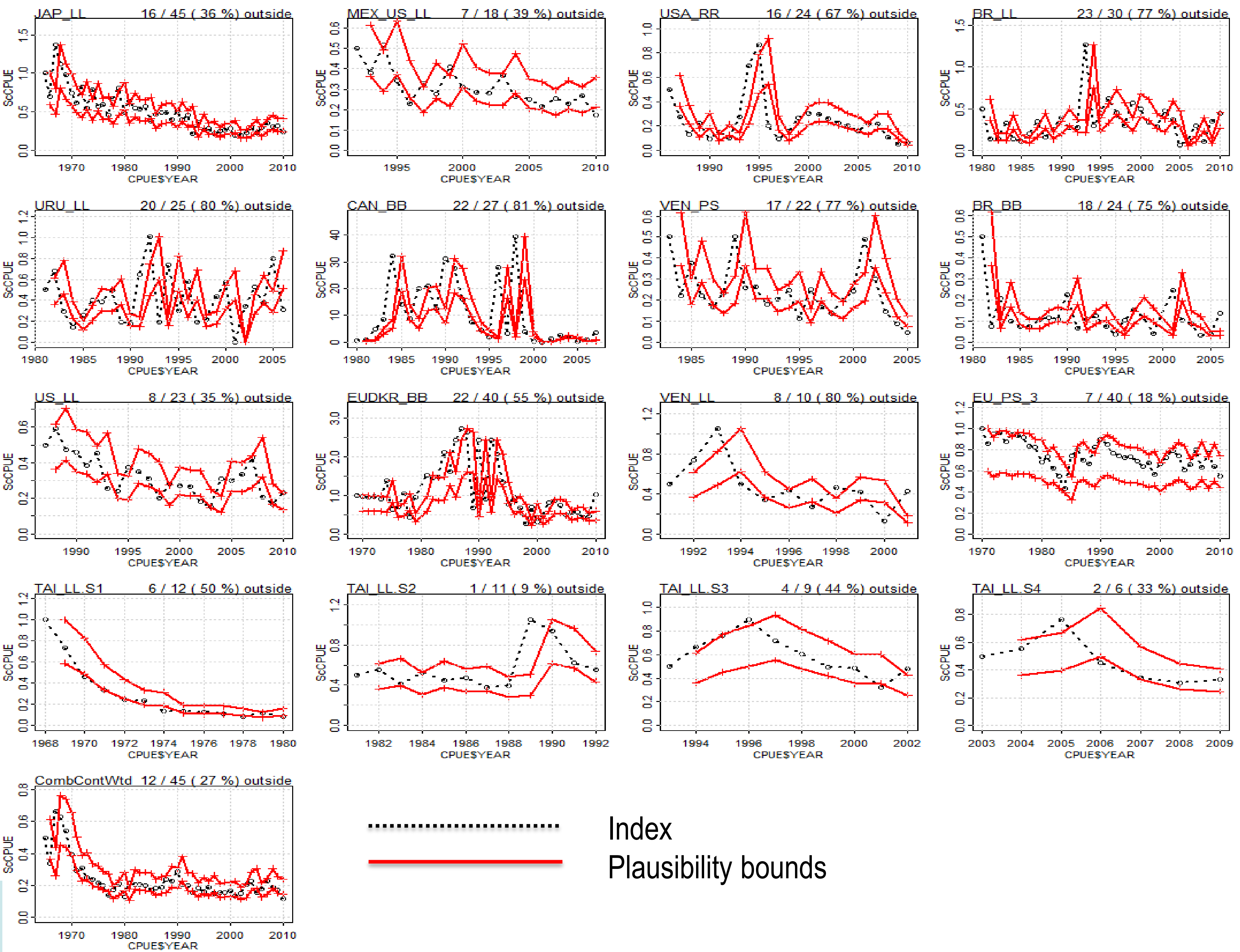
Application to 2011 YFT production model indices

- All indices were weight-based indices and assumed to represent the entire population biomass within the surplus production models

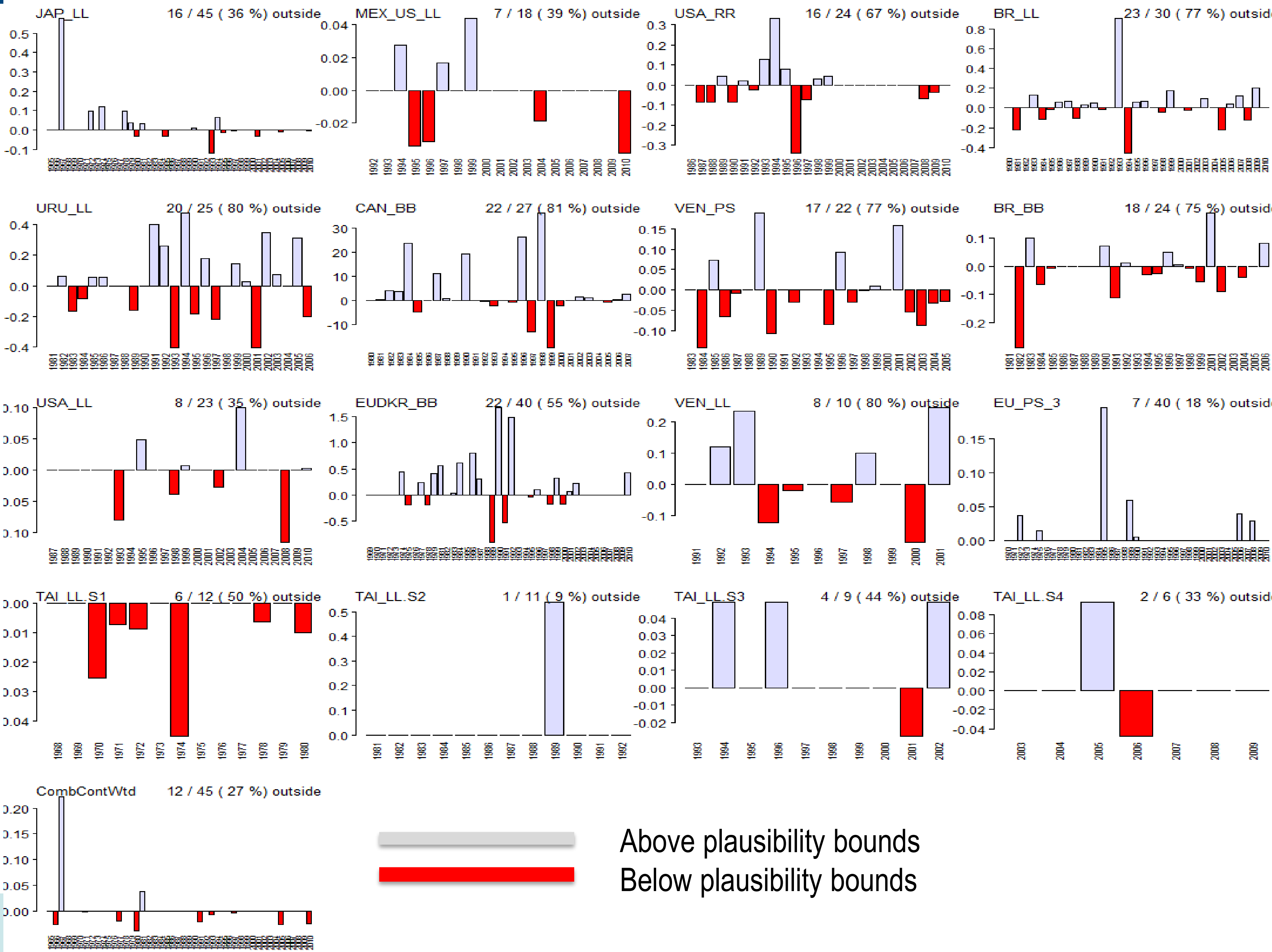
Assumptions

- ASPIC models assumed that B_1=K, also use a value of 1 for B_1 for the indices that start within the first 6 years of t=1.
- For all other indices we assume that B_1=0.5
- r=0.46 from ASPIC (Anon 2008) assessment estimate
- Maximum observed single year exploitation rate of 0.41 (Anon 2008).

Sensitivity to initial value of B_1 are presented.



JAP_LL 16 / 45 (36 %) outside
MEX_US_LL 7 / 18 (39 %) outside
USA_RR 16 / 24 (67 %) outside
BR_LL 23 / 30 (77 %) outside
URU_LL 20 / 25 (80 %) outside
CAN_BB 22 / 27 (81 %) outside
VEN_PS 17 / 22 (77 %) outside
BR_BB 18 / 24 (75 %) outside
US_LL 8 / 23 (35 %) outside
EUDKR_BB 22 / 40 (55 %) outside
VEN_LL 8 / 10 (80 %) outside
EU_PS_3 7 / 40 (18 %) outside
TAI_LL.S1 6 / 12 (50 %) outside
TAI_LL.S2 1 / 11 (9 %) outside
TAI_LL.S3 4 / 9 (44 %) outside
TAI_LL.S4 2 / 6 (33 %) outside
CombContWtd 12 / 45 (27 %) outside
ScCPUE
CPUE$YEAR
Index
Plausibility bounds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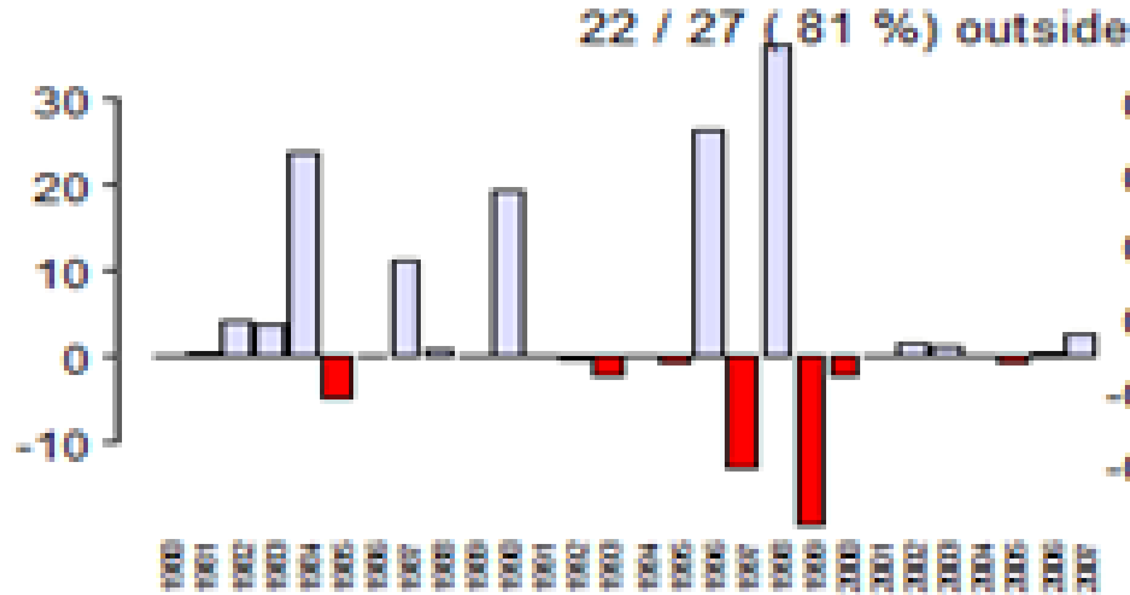
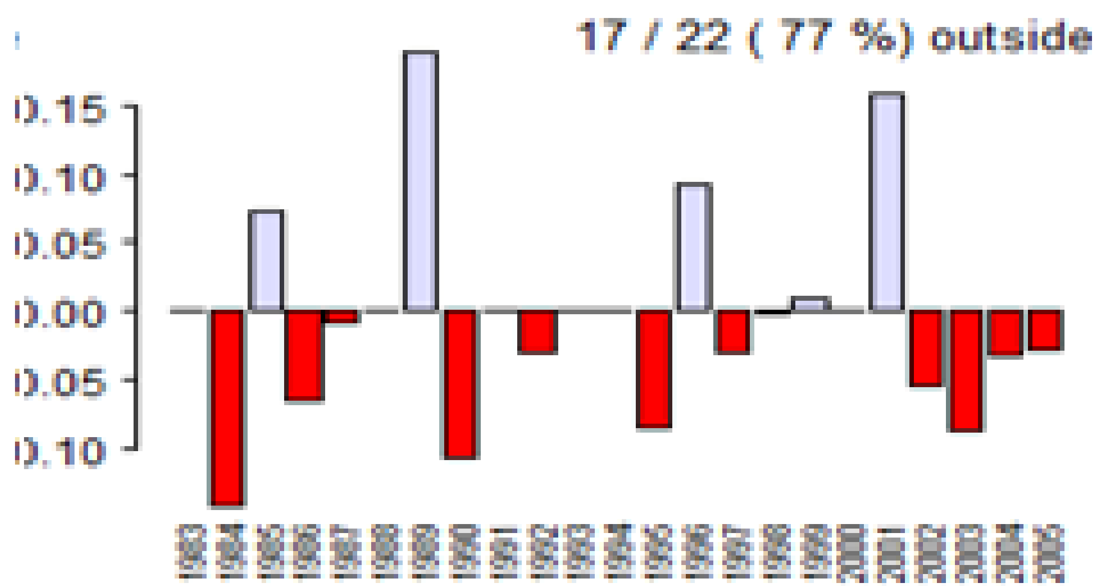
USA_LL 8 / 23 (35 %) outside
EUDKR_BB 22 / 40 (55 %) outside
VEN_LL 8 / 10 (80 %) outside
EU_PS_3 7 / 40 (18 %) outside
TAI_LL.S1 6 / 12 (50 %) outside
TAI_LL.S2 1 / 11 (9 %) outside
TAI_LL.S3 4 / 9 (44 %) outside
TAI_LL.S4 2 / 6 (33 %) outside
CombContWtd 12 / 45 (27 %) outside
Above plausibility bounds
Below plausibility bounds

Performance criteria

1. Magnitude of divergence
2. Percent of index values outside of range
3. Time trends





ICCAT Working group on stock assessments index evaluation table

Table 2. Elements to evaluate the sufficiency of CPUE series.

ELEMENT	*DESCRIPTION*	*SUFFICIENCY SCORE (1 is poor, 5 is best)*				
		1	*2*	*3*	*4*	*5*
1	Diagnostics	No diagnostics or assumptions clearly violated				Full diagnostics and assumptions fully met.
2	Appropriateness of data exclusions and classifications (e.g., to identify targeted trips).	Not appropriate				Fully appropriate
3	Geographical coverage	Small localized fishery/survey				Represents geographic range of population
4	Catch fraction	Small				Large
5	Length of time series relative to the history of exploitation.	Short				Long
6	Are other indices available for the same time period?	Many				It is the only available index
7	Does the index standardization account for known factors that influence catchability/selectivity?	No				Fully
8	Are there conflicts between the catch history and the CPUE response?	Yes				No
9	Is the interannual variability outside biologically plausible bounds (e.g., SCRS/2012/039)	Frequently				Seldom
10	Are biologically implausible interannual deviations severe? (e.g., SCRS/2012/039)	Very severe				Minimal
11	Assessment of data quality and adequacy of data for standardization purposes (e.g., sampling design, sample size, factors considered)	Low				High
12	Is this CPUE time series continuous?	Very discontinuous				Completely

http://www.iccat.int/Documents/Meetings/Docs/2012_METHODS_REP_ENG.pdf

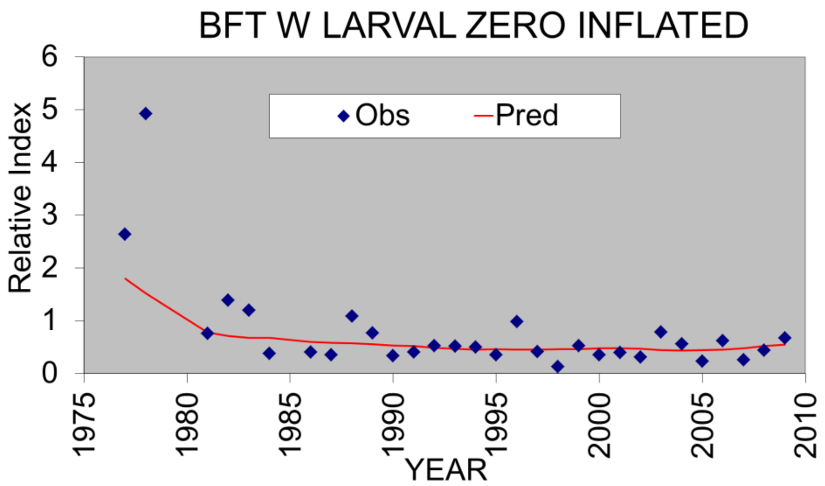
Caveats

Caveat 1: Biological plausibility- defined according to the biology that <u>we</u> give the model

Caveat 2: index can be highly noisy but still have a useful trend.

Caveat 3: age(s) specific indices… can between vary up to level of *sigma r* .

Caveat 4: models can handle process error.



Recap

1. Method requires: (1) an estimate of *r*, to which the method is not particularly sensitive, (2) an estimate of the stock status at the beginning of index time series and (3) some estimate of the maxU
2. Plausibility bounds useful for identifying unaccounted for process error i.e., interannual variability <u>inconsistent with model dynamics and assumptions</u>
3. Useful for determining suitability of an index but not sole criterion for exclusion/inclusion
4. In practice it can identify <u>process</u> error issues not considered by index authors or included in model

Acknowledgements

WCSAM steering committee

NOAA fisheries for funding travel

Authors of 16 ICCAT Yellowfin Tuna CPUE indices for being willing test subjects

ICCAT CICTA CICAA

INTERNATIONAL COMMISSION FOR THE CONSERVATION OF ATLANTIC TUNAS

COMMISSION INTERNATIONALE POUR LA CONSERVATION DES THONIDES DE L'ATLANTIQUE

COMISIÓN INTERNACIONAL PARA LA CONSERVACIÓN DEL ATÚN ATLÁNTICO

Code available from the author john.f.walter@noaa.gov

A stock synthesis model for Western Bluefin tuna:

Key challenges for moving from VPA to SCAA

Shannon L. Cass-Calay
John Walter
NOAA-Fisheries SEFSC

ICCAT CICTA CICAA
INTERNATIONAL COMMISSION FOR THE CONSERVATION OF ATLANTIC TUNAS
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ICCAT GBYP
Science for Sustainability

Objectives:

Virtual Population Analysis (VPA)

- PRO: modest data requirements
- CON: requires strong assumptions (i.e. catch-at-age known)

Statistical Catch at Age (SCA)

Relaxes assumption that CAA is known exactly

Can use length composition directly

Integrated model *may* better handle process errors

May better estimate growth and productivity

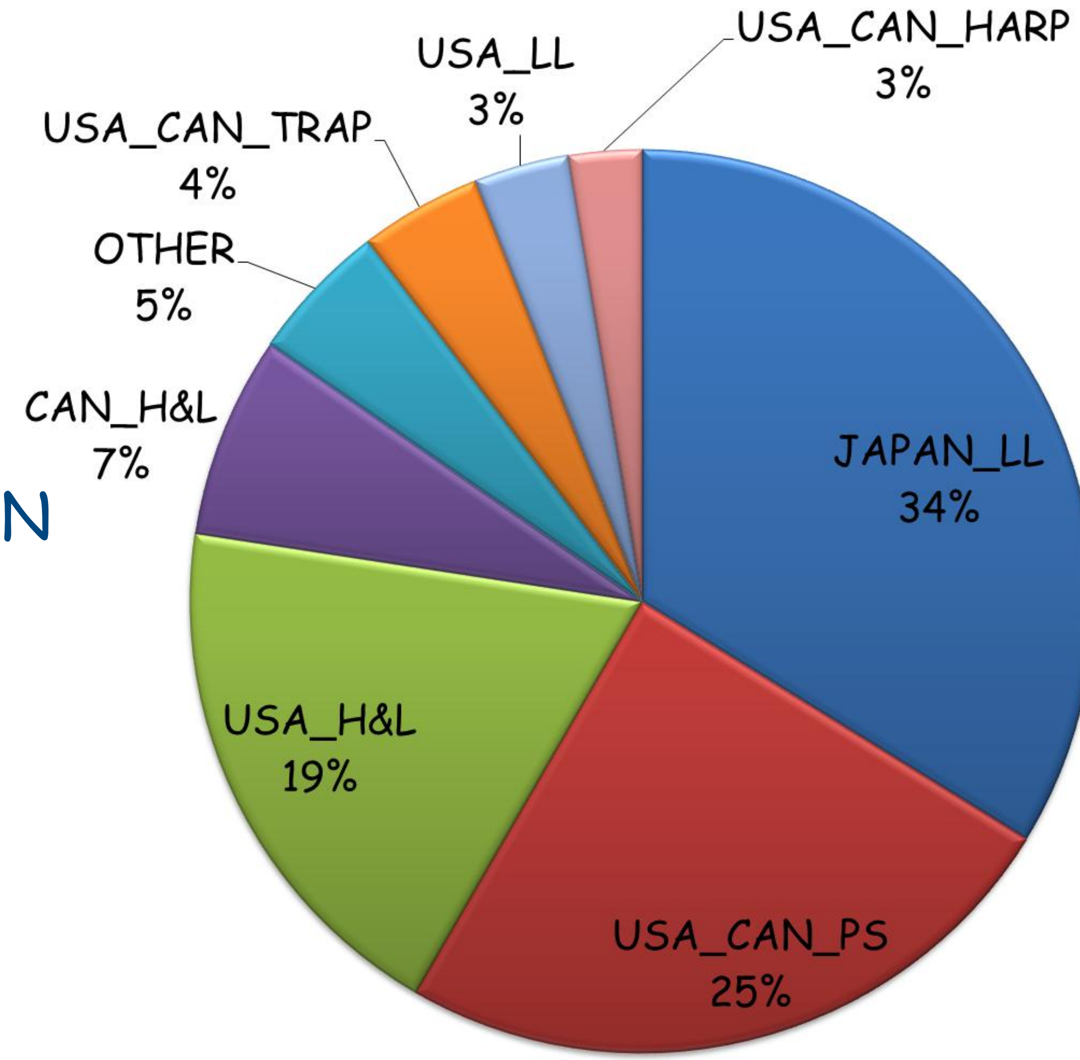
SS model Data Inputs (similar to VPA and MAST):

- Years: 1950-2011
- Ages: 0-25+
- One Gender (M+F)
- One Area (Western Atlantic)
- 8 Fleets
- 10 CPUE Indices of Abundance, 1 larval survey (SSB proxy)
- Catch at age from cohort sliced catch at size***
- Age-Based Selectivities modeled with double normal or logistic patterns
- Biological Parameters fixed:
  - M = 0.14 Linf = 315 cm, K = 0.089
  - Knife-Edged Maturity at 9+
  - Fecundity Proxy = WAA

Fleet Structure:

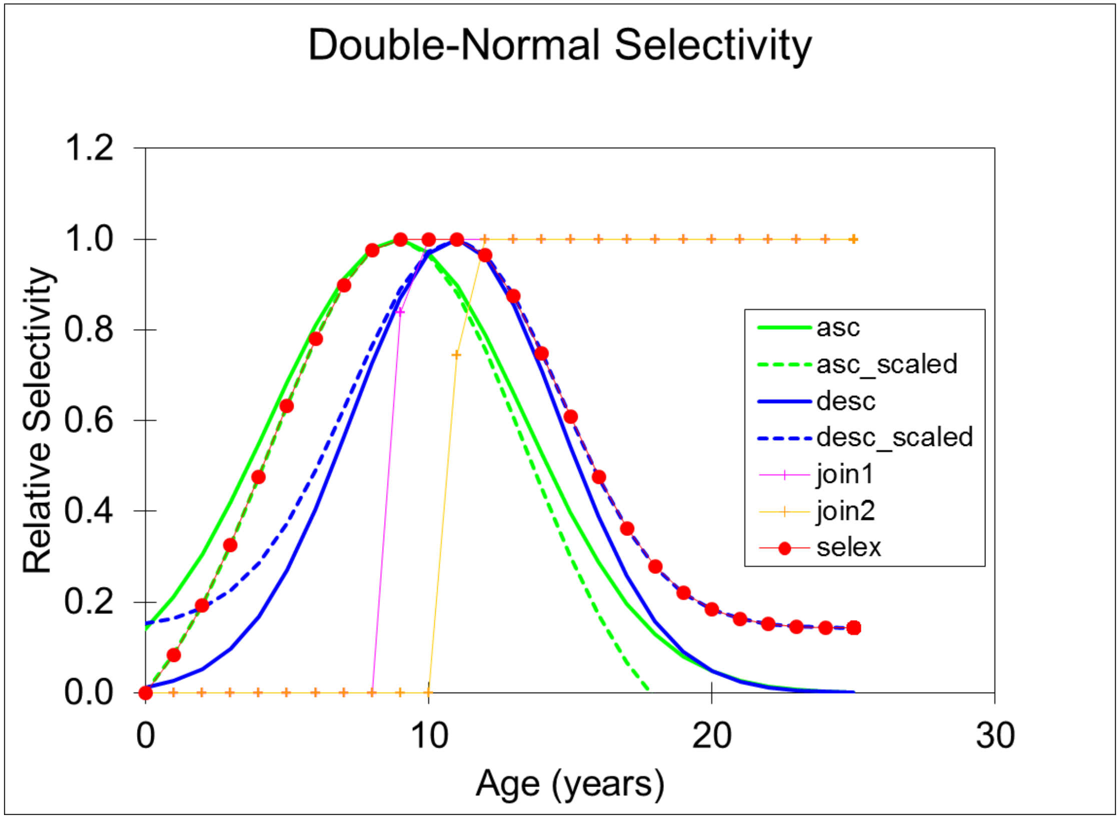
- 8 Fleets:
  - JAPAN _LL
  - USA_CAN_PS
  - USA_CAN_TRAP
  - USA_CAN_HARPOON
  - USA_ HOOK&LINE
  - USA_LL
  - CAN_ HOOK&LINE
  - OTHER

%Total Landings by Flag and Gear



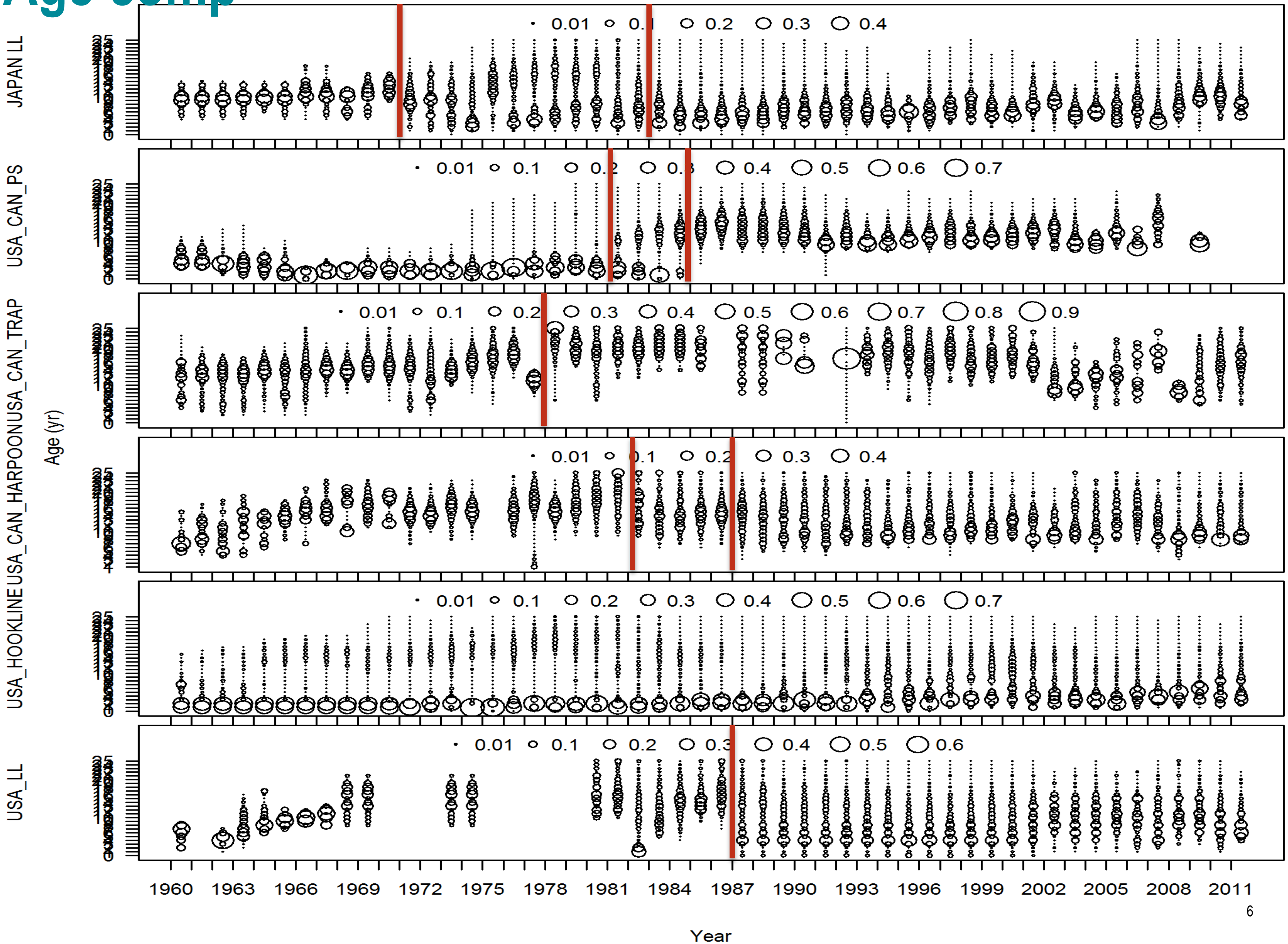
Modeling Selectivity:

- Used age-based functional shapes available in SS3
- Double Normal: All fleets and indices except:
  - Logistic: USA LL, US_RR>195cm, JAPAN_LL_GOM
  - SSB Index: SEAMAP Larval Survey



Age comp

VPA Catch at age sliced from catch at length, for each fleet.



Age comp

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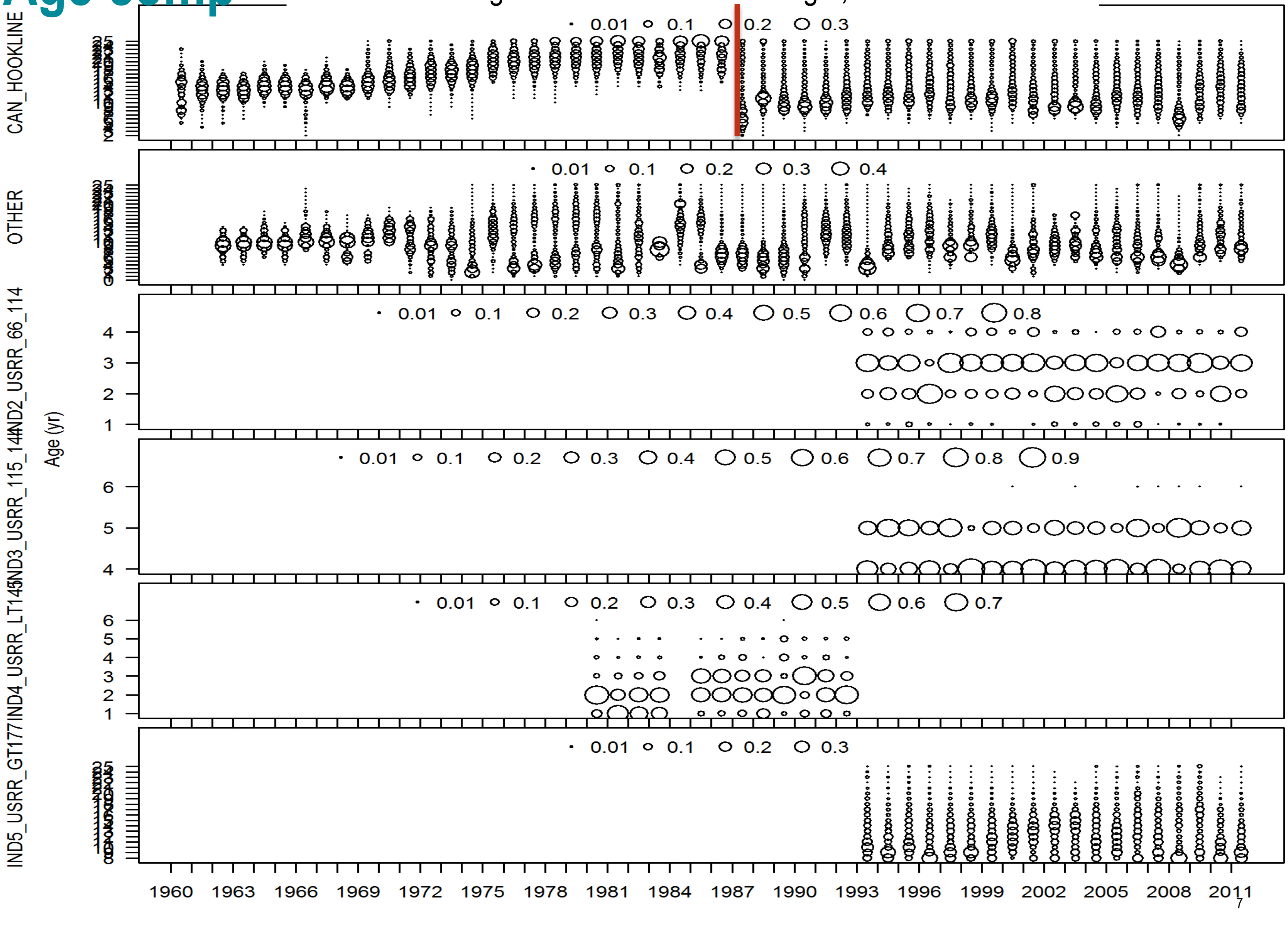


Stock Synthesis Modeling (nested structure)

1. Age-structured Prod. model (est steepness and R0)

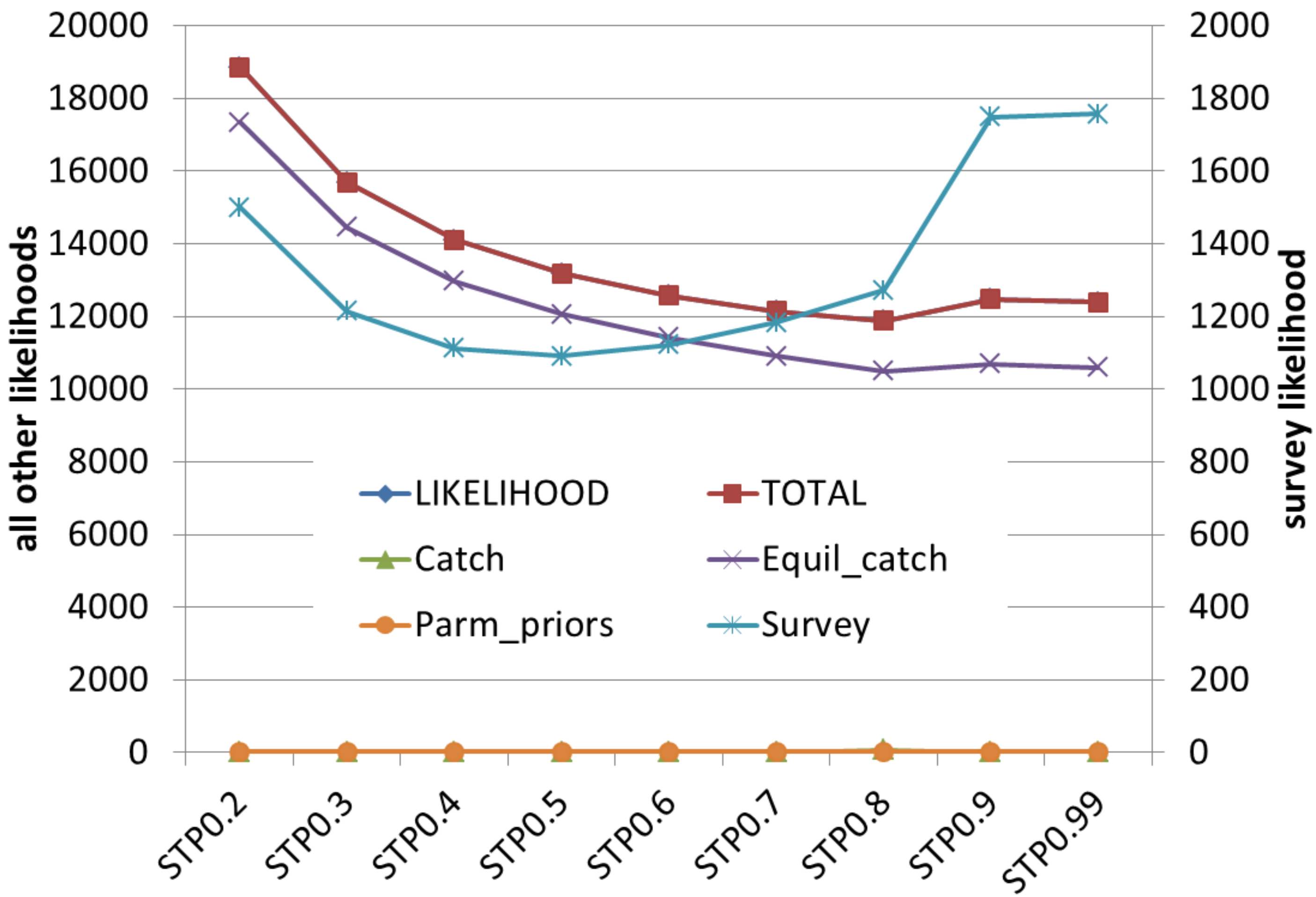
2. Age comp

3. Age comp and estimate recruitment deviations

4. *Length observations- TBD*

Estimability of productivity in production model

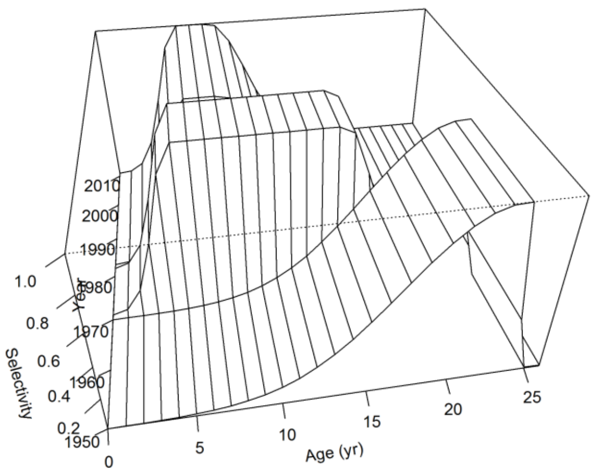
Piner plots



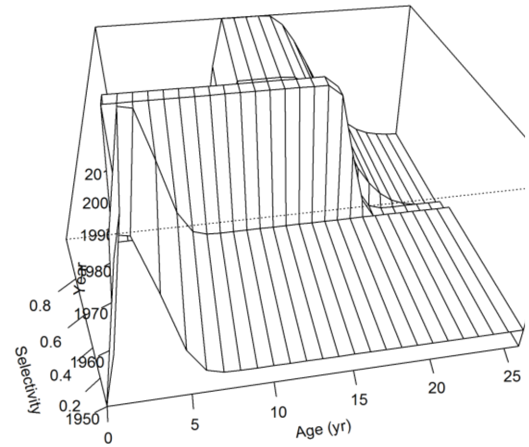
For full age comp and rec dev model steepness bounded at 0.99

Selectivities

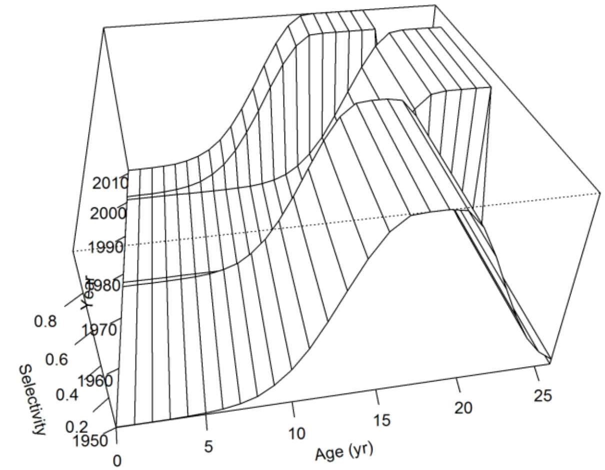
Time-varying selectivity for JAPAN LL



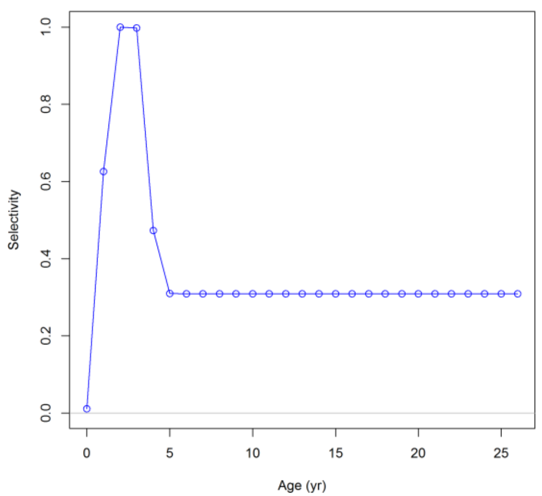
Time-varying selectivity for USA_CAN_PS



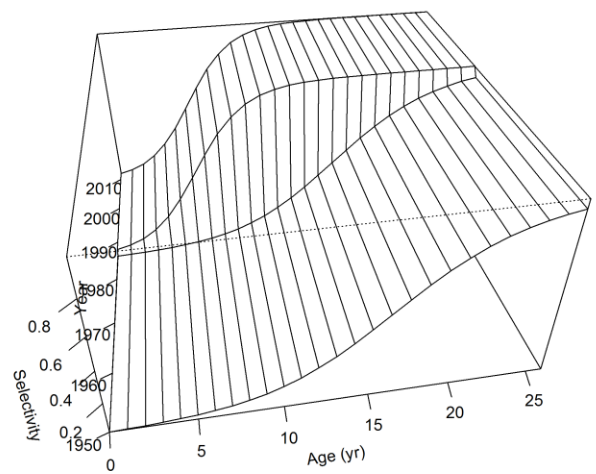
Time-varying selectivity for USA_CAN_TRAP



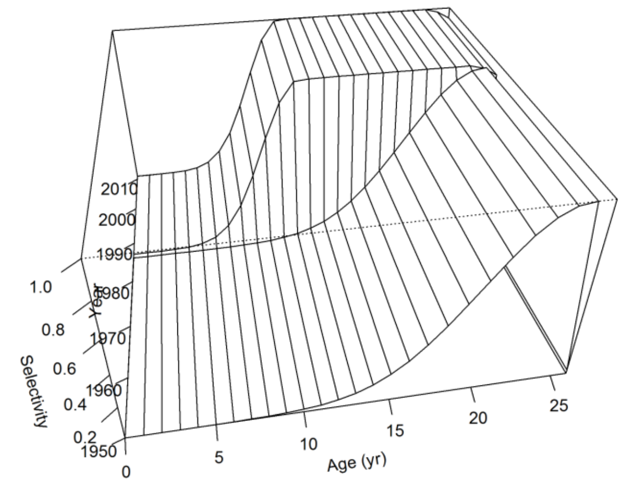
Ending year selectivity for USA_HOOKLINE



Time-varying selectivity for USA_LL



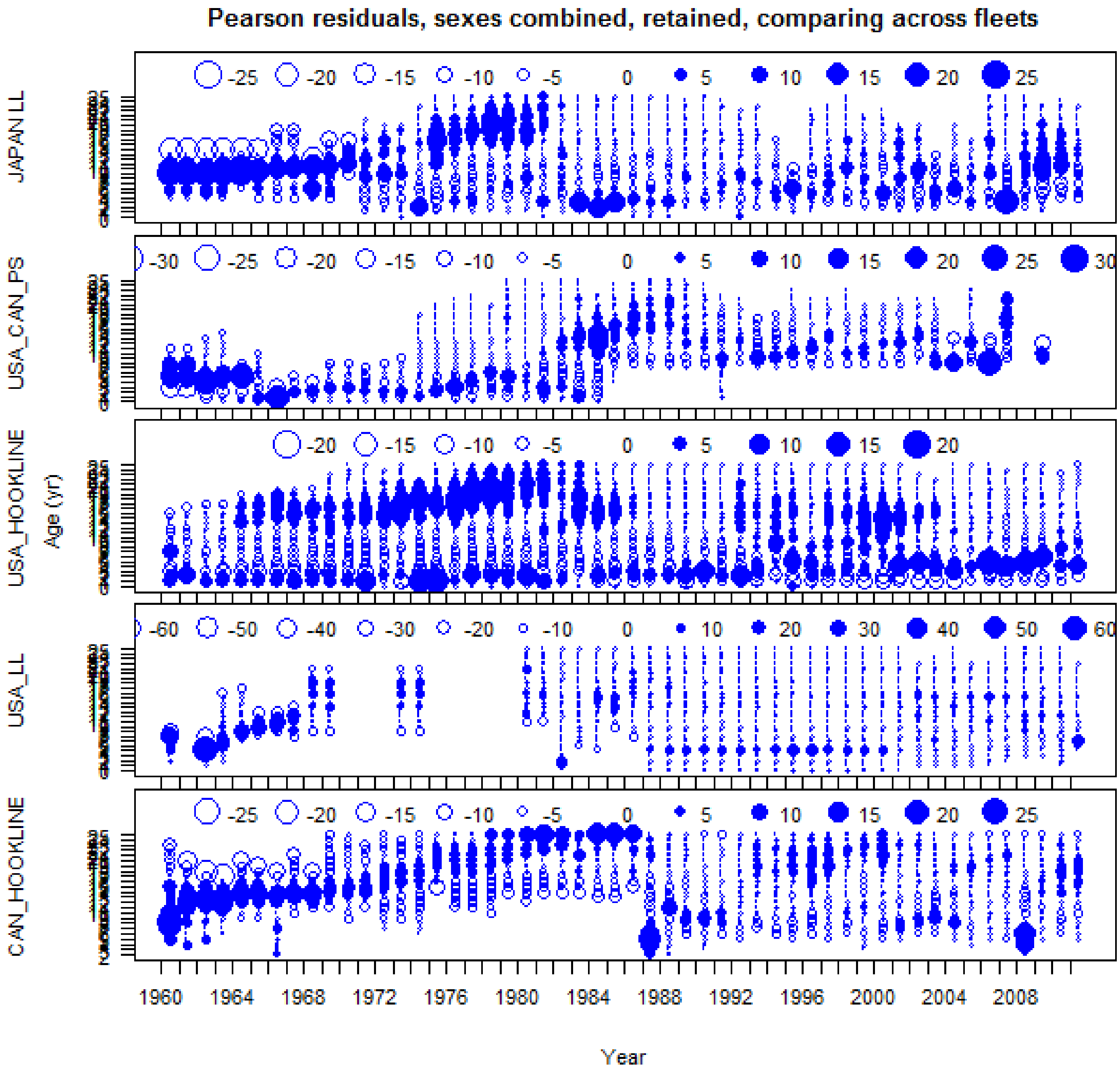
Time-varying selectivity for CAN_HOOKLINE



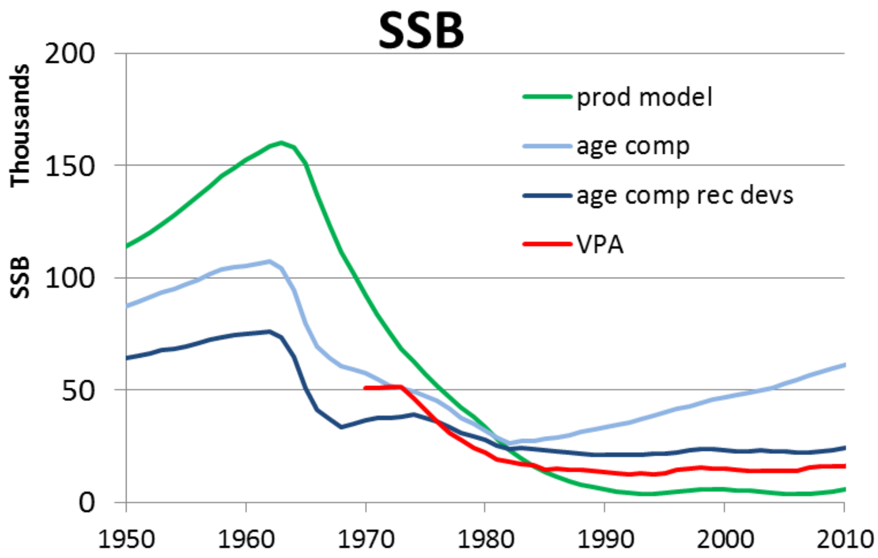
11 bounded selex parms

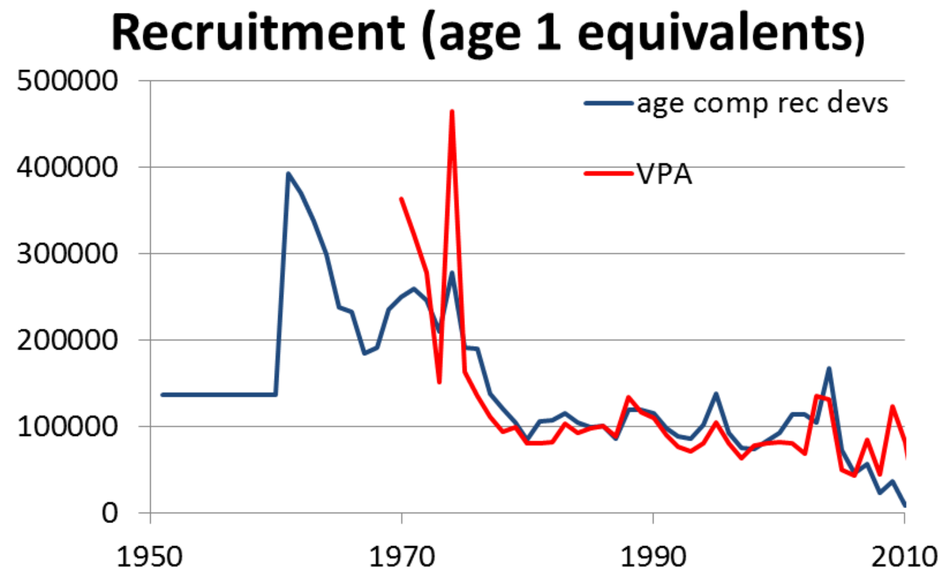
Age comp fits

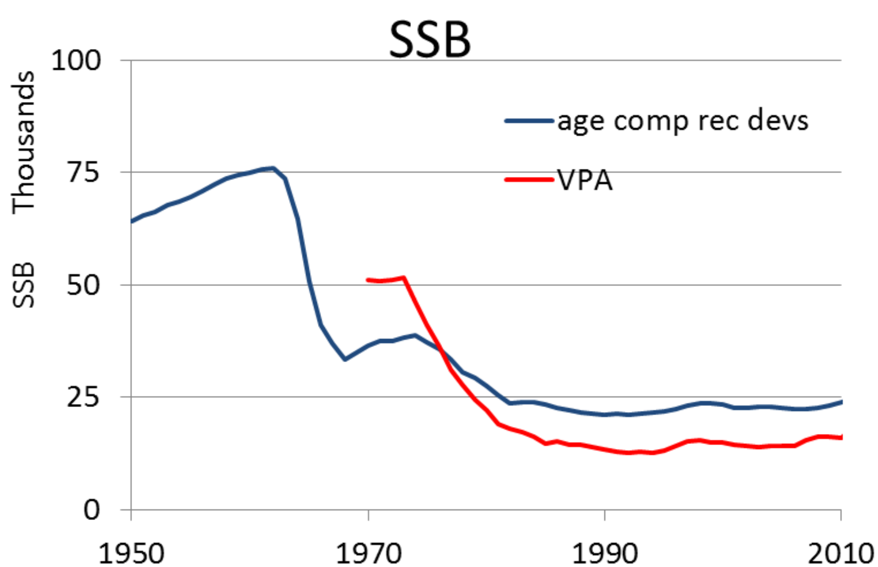
Substantial residual patterns, particularly in 1965-1980

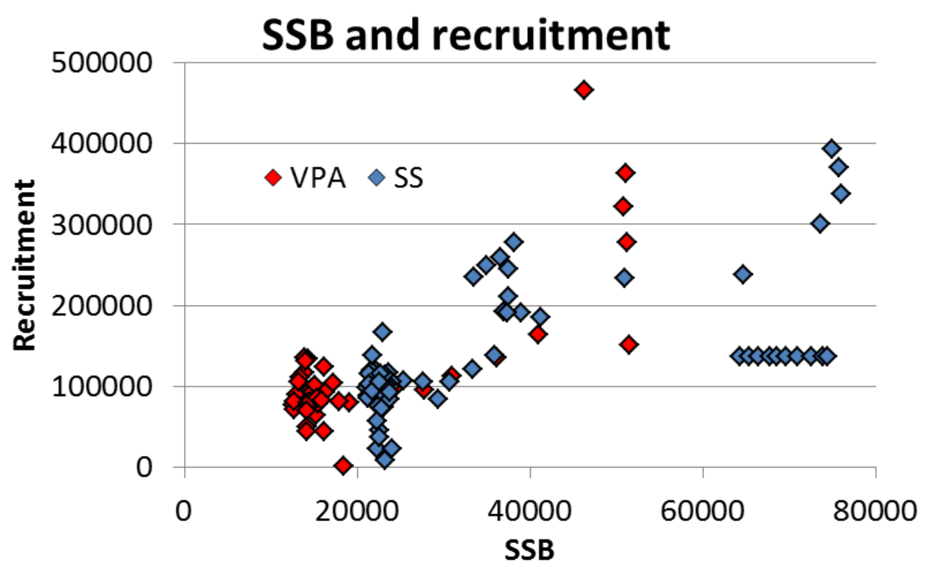


Preliminary results









Preliminary conclusions/concerns

- Preliminary results similar to VPA but model performance is poor due to bounding

- Preliminary model- Fleet structure, time blocks and selex decisions need to be reevaluated in consultation with national scientists

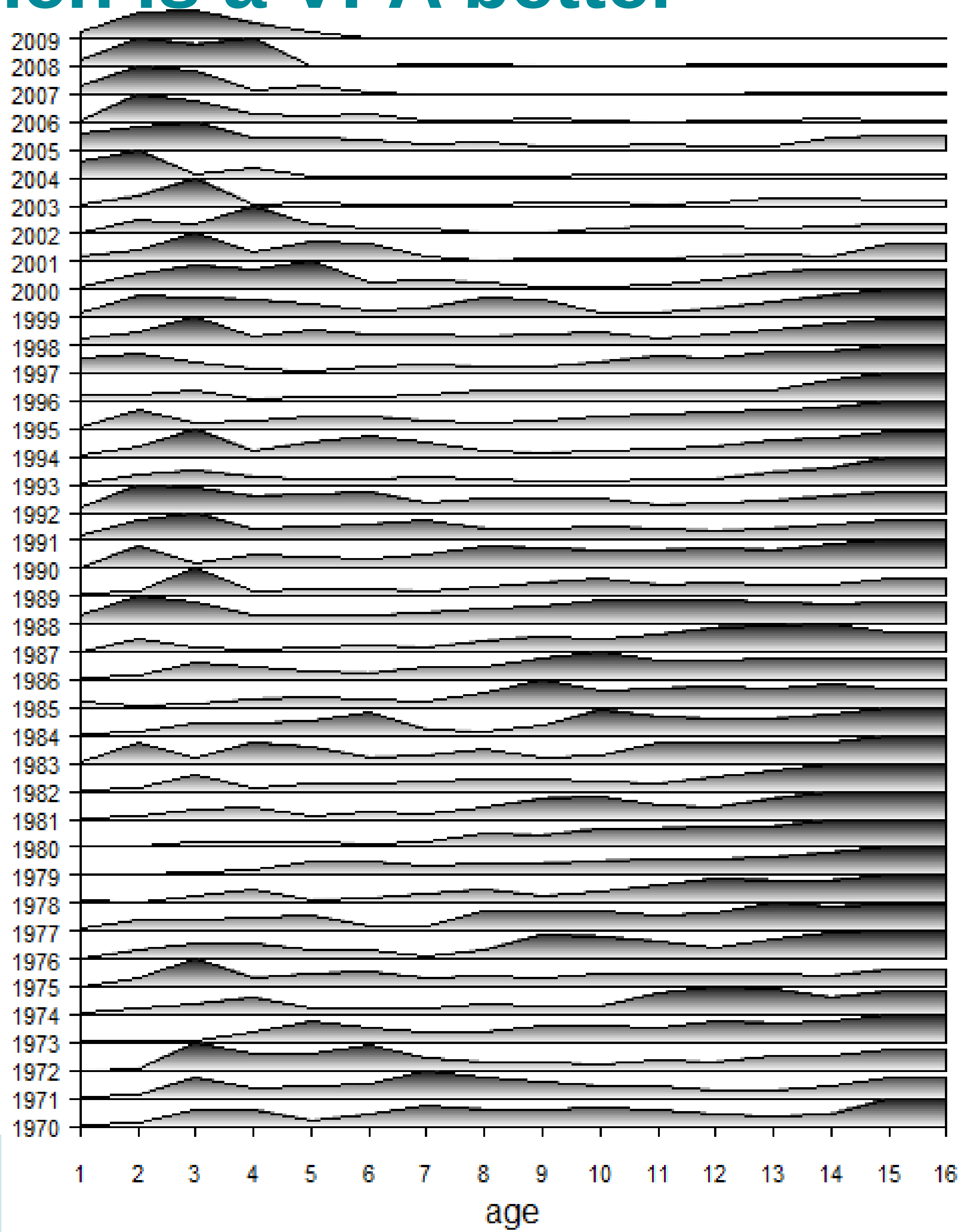
- Vagaries of construction of catch at age further complicate estimation of selectivities →Goal is to move to using observed lengths

- Time varying selectivities pose a substantial difficulty

Grand question: when is a VPA better than SCAA

Vastly time varying selectivities….

Testable HO:
VPA> SCA when sigma on CAA < sigma on annual change in selectivity



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  - BFT working group
- NOAA Contributors:
  - Clay Porch
  - Craig Brown
  - Michael Schirripa
  - Nancie Cummings
  - Jakob Tetzlaff
- WC-SAM Organizers

Time series assessment of catch-at-age data: North Sea cod, haddock, plaice and Georges Bank yellow flounder

Gudmundur Gudmundsson and
Thorvaldur Gunnlaugsson thg@hafro.is

Marine Research Institute, Iceland

Full model is elaborate and may include surveys.

Common simplifications can be tested by statistical methods.

TS assessment of CA data

State-space approach

First implemented as extended Kalman Filter

Used for many years in Icelandic groundfish assessments, for model comparison (good performance, in retrospect)

Experimental use with length-based assessments

Recently emulated in ADMB-RE with time-varying selectivity, stock and recruitment as random effects

TS assessment of CA data

Full description of model has been published:

Selection and estimation of sequential catch-at-age models

Gudmundur Gudmundsson and Thorvaldur Gunnlaugsson
Can. J. Fish. Aquat. Sci. 69:1760–1772 (2012)

Conventional notation is used where:
c, n, f, z represent logs of
Catch, Stock, Fishing and total mortality.

TS assessment of CA data

In Kalman Filter all assignments have variance

$$n_{a+1,\ t+1} = n_{a,\ t} - F_{a,t} - M + \varepsilon_{a,\ t}$$

where the error variance (noise) may be estimated zero.

Emulation in ADMB-RE, no assignments but:

```
objective_function_value g
random_effects_matrix n(a,t)
```

assuming no covariance:

```
SEPARABLE_FUNCTION stock( ... )
  g += -log(sigma_n)
  -0.5*norm2((n(a,t)-F(a,t)-M-n(a+1,t+1))/sigma_n)
```

TS assessment of CA data

Fishing effort is modeled as the sum of the product of state variables $\psi_{j,t}$ (with random walk and/or transitory changes) and prefixed selection patterns by age:

$$f_{a,\,t} = \sum_j \psi_{j,\,t} \Gamma_{j,a} + \delta_{a,\,t}$$

where the prefixed selection patterns by age are:

$\Gamma \equiv$ [constant, parabola, extreme young and/or old]

TS assessment of CA data

The observation error in the catch:

- variance allowed to be parabolic with age

- tested for correlation in residuals

The stock-survey relationship is tested for non-linearity

TS assessment of CA data

Tests on the need to include all variances have been published in open access:

Some catch-at-age analysis methods and models compared on simulated data

Thorvaldur Gunnlaugsson
Open J. Mar. Sci. 2:16–24 (2012)

Also compares Penalized Likelihood to State Space.

TS assessment of CA data

No gain in estimating noise in $F_{a,t}$ ($\sigma_F = 0$)

$\longrightarrow$ May drop random_effects_matrix f(a,t).

Natural mortality (M) can not be estimated
unless effort is highly variable.

For these four stocks, no evidence against the predetermined values for M was found in tests, so those values were used.

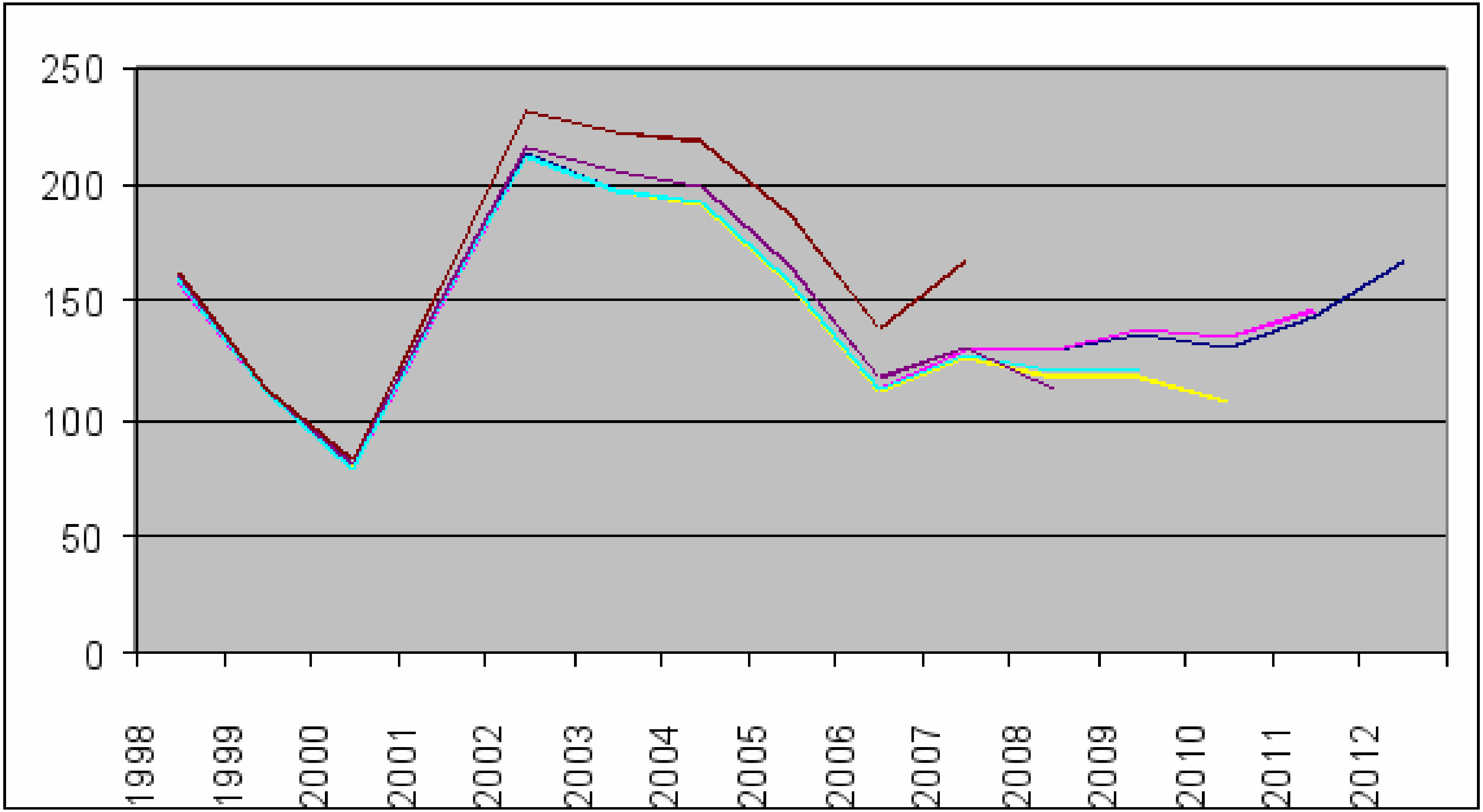
TS assessment of CA data

The results of applying this model to the
NS cod+haddock+saithe and GB yellow flounder are available online:

http://www.hafro.is/~thg/sisam/

with some ADMB-RE code.

TS assessment of CA data

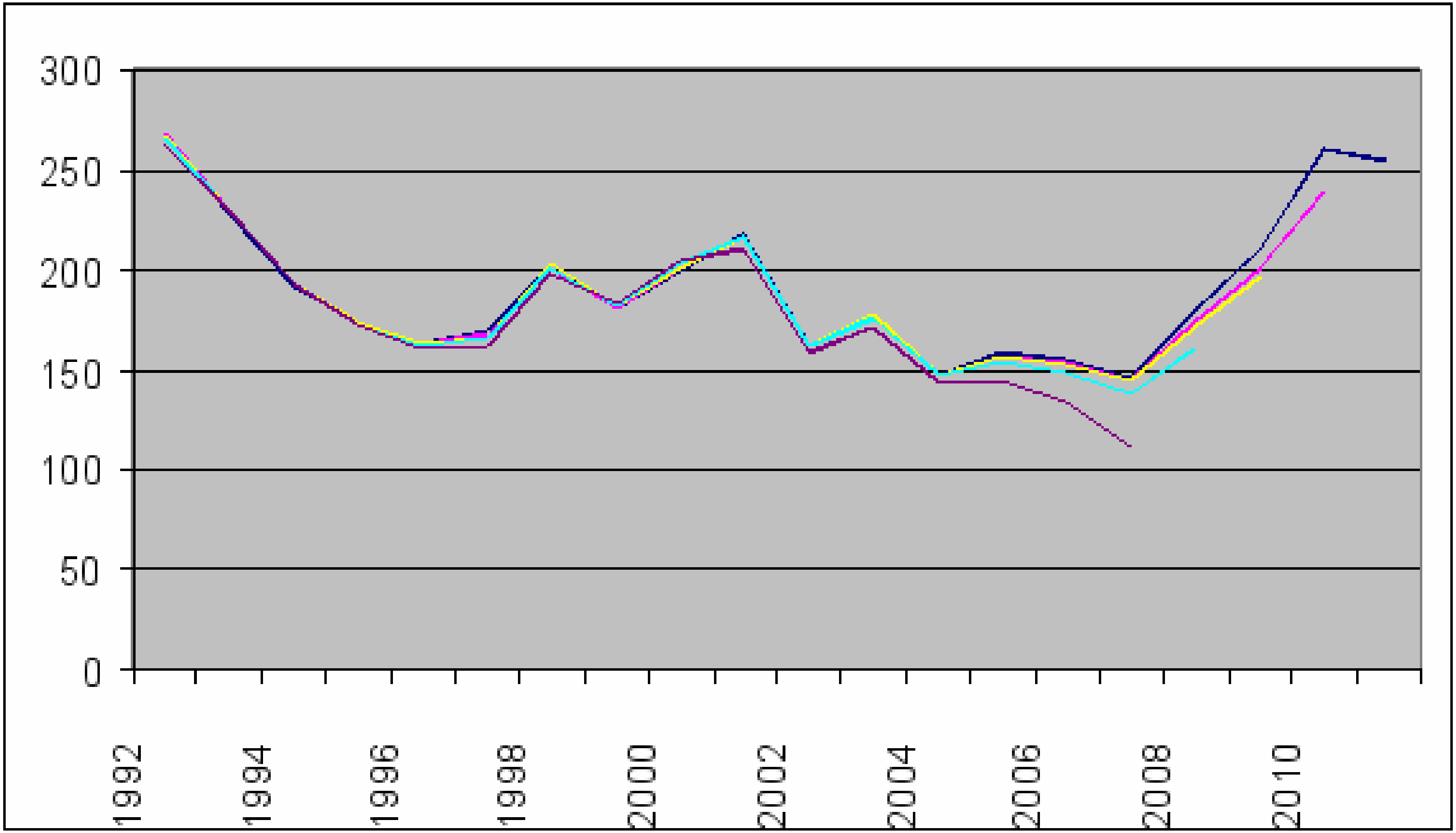


NS cod SSB from retrospective analysis

TS assessment of CA data

NS haddock SSB from different models

TS assessment of CA data



NS plaice SSB retrospective analysis