

Integrated analysis: the worst thing that happened to fisheries stock assessment

Mark Maunder

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

Kevin Piner

National Marine Fisheries Service (NMFS)
South West Fisheries Science Center (SWFSC)



CAPAM



Outline

- What is integrated analysis?
- Data conflict and model misspecification
- The problem with catch composition data
- What we know about population processes
- What processes change over time
- Diagnostics
- Conclusions

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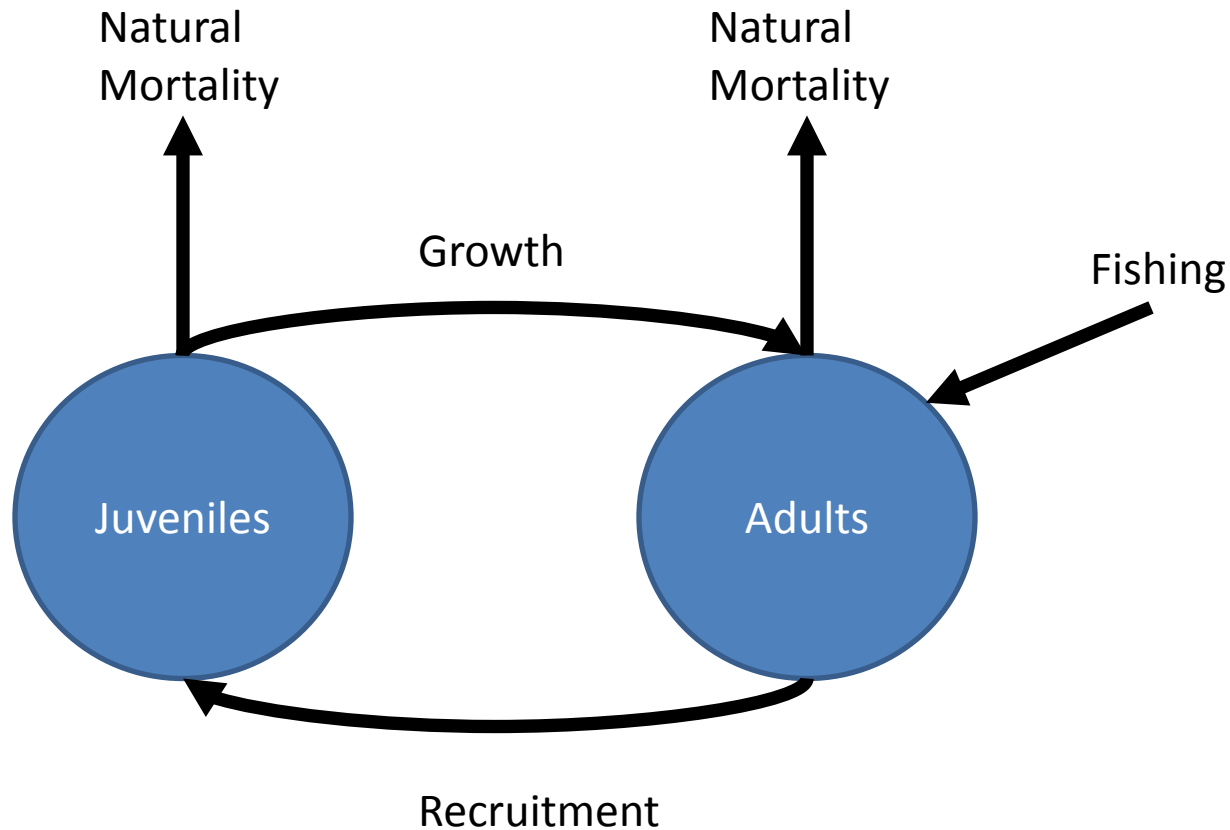
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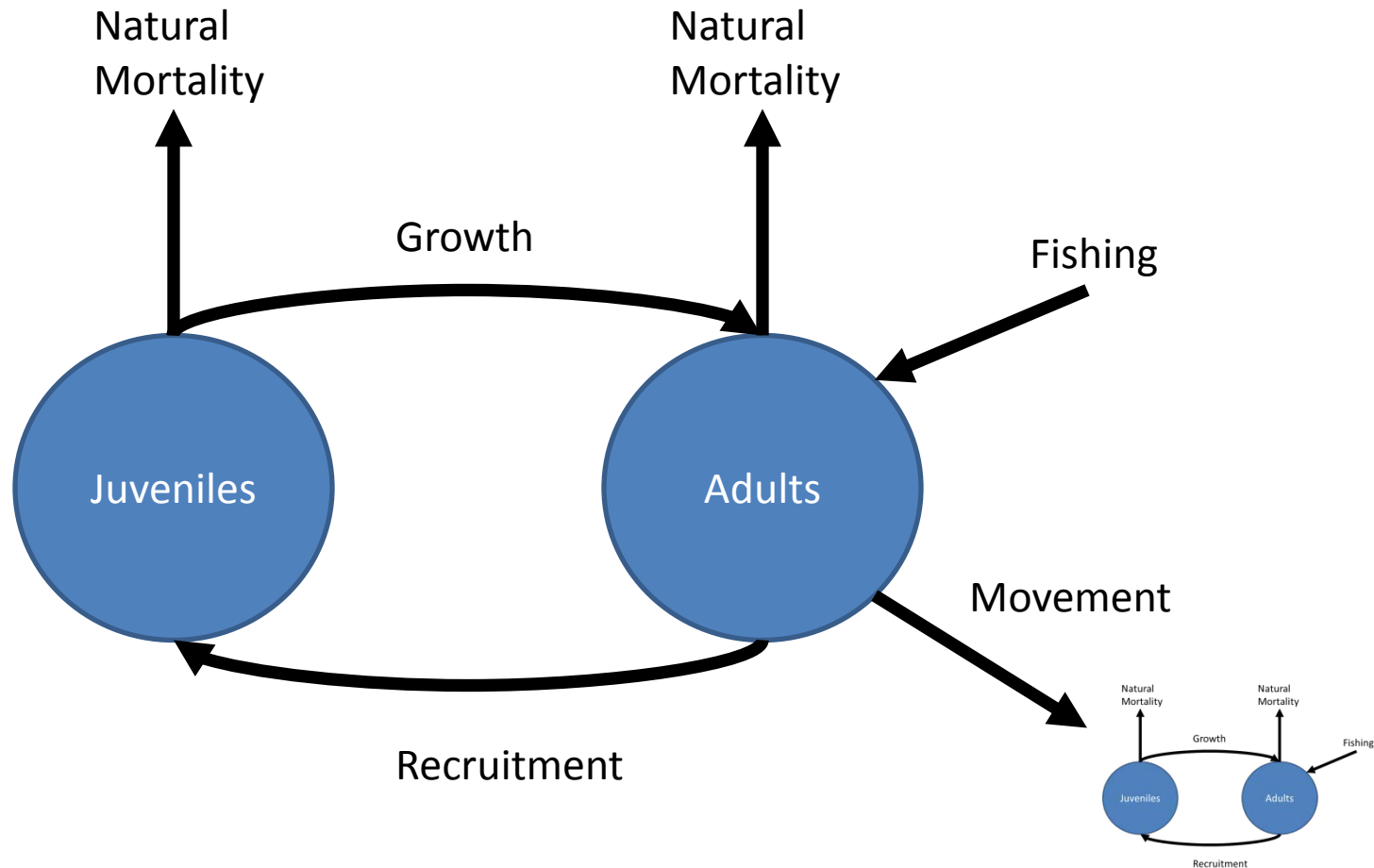
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What is integrated analysis?

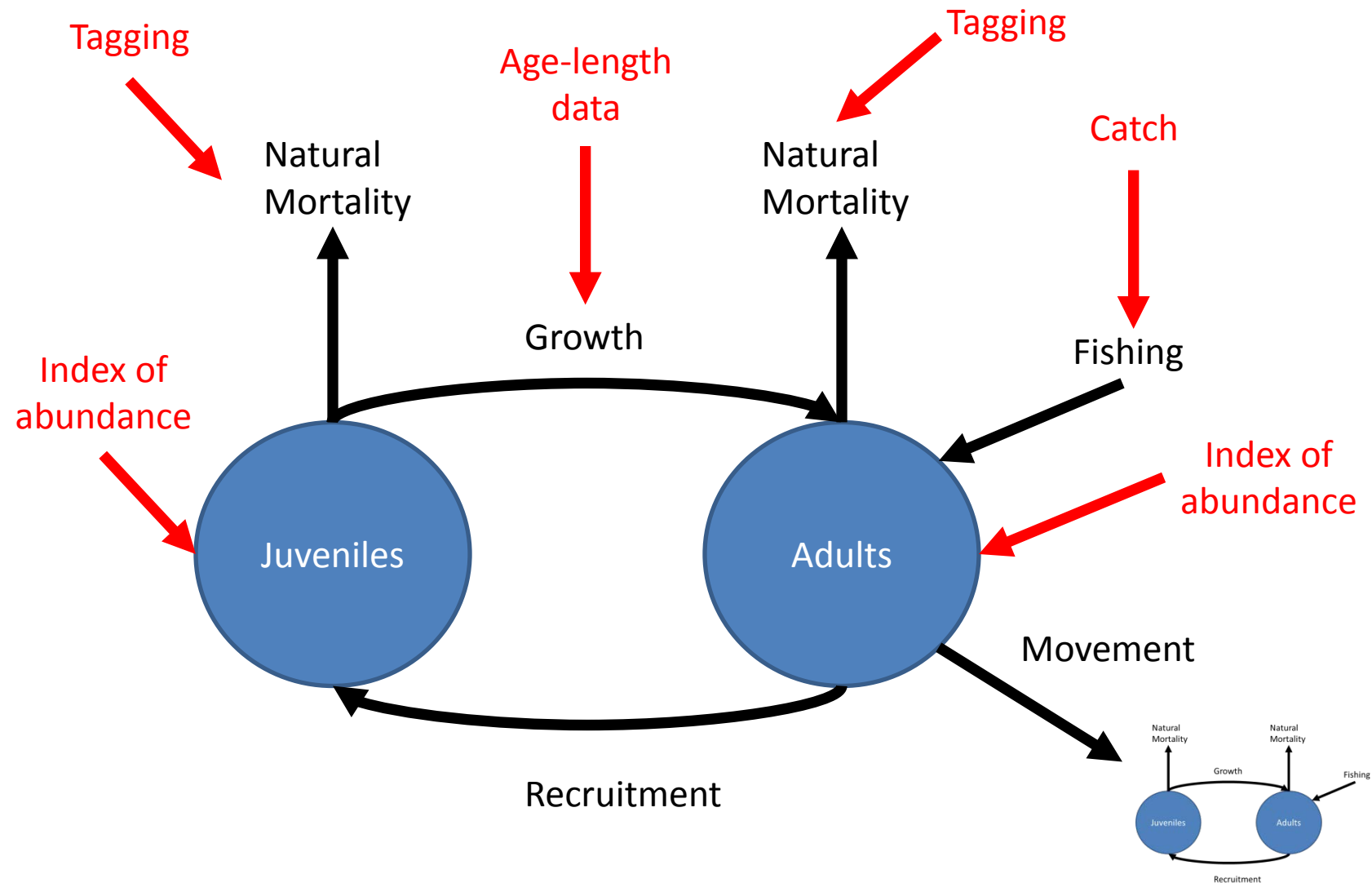
What is integrated analysis?



What is integrated analysis?



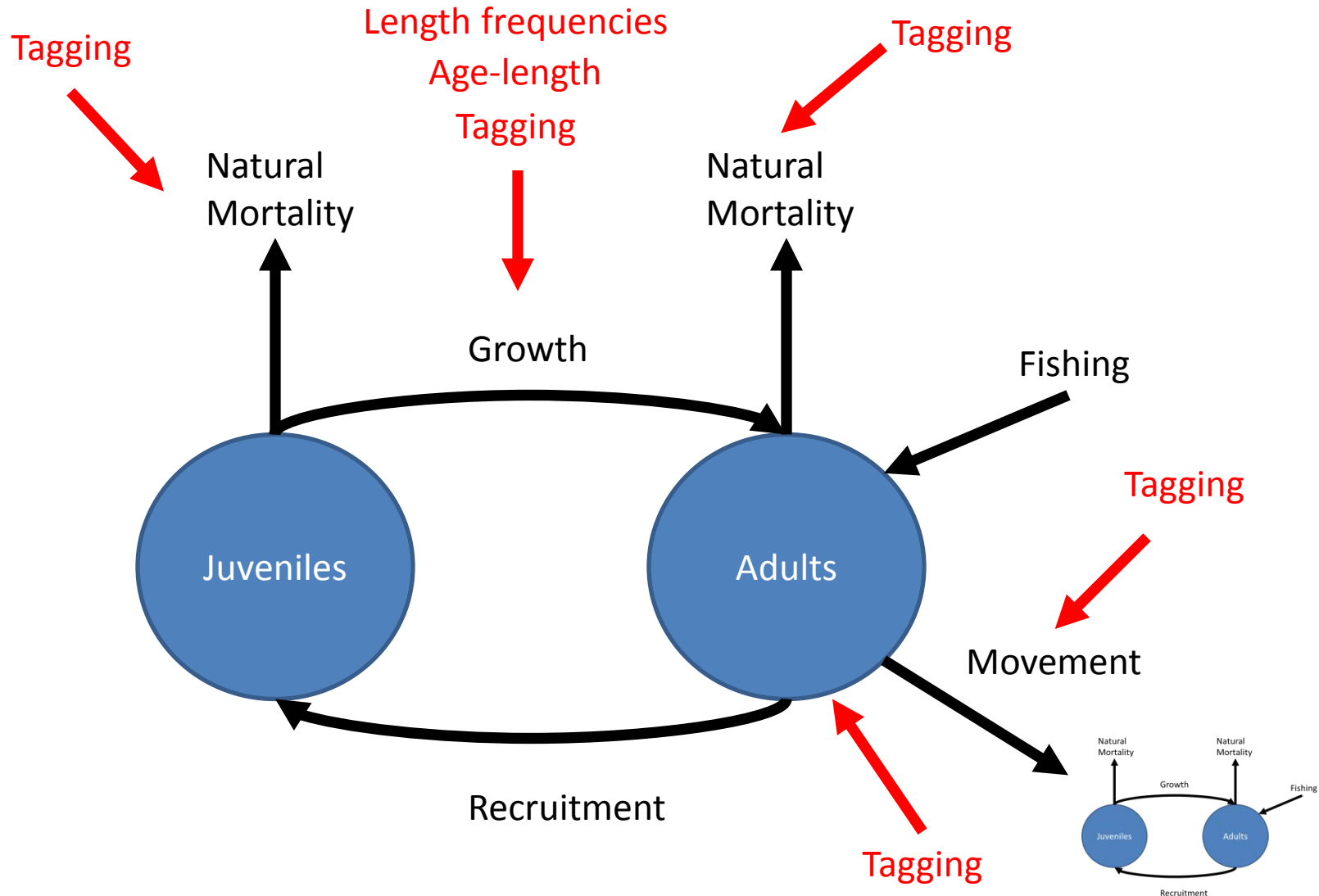
What is integrated analysis?



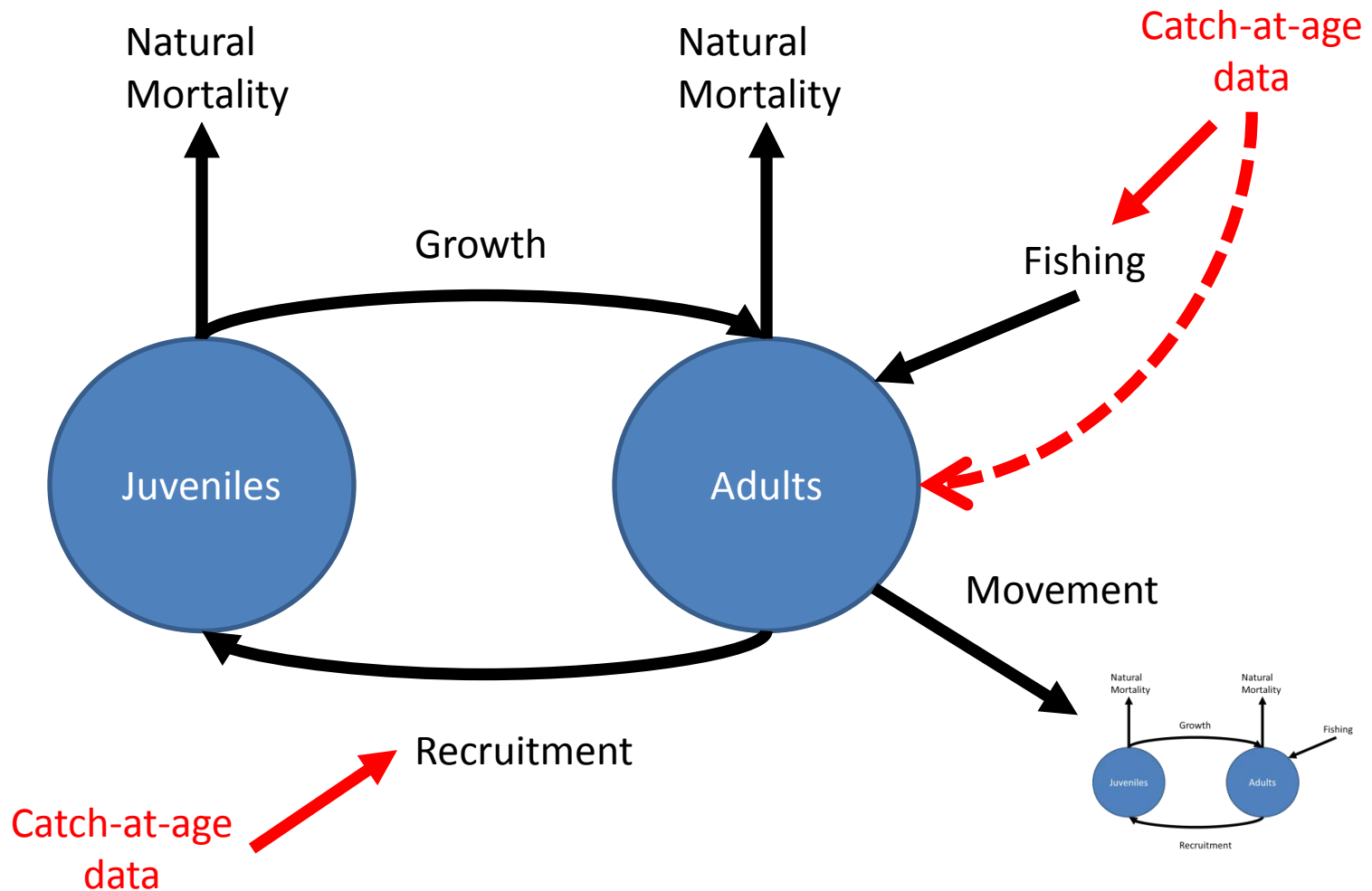
Why not analyze each data set separately?

- Information may be lost when data are summarized.
- Difficulty in fully accounting for uncertainty.
- The different analyses may be logically inconsistent.
- Reduced diagnostic ability.

What is integrated analysis?



What is integrated analysis?



Why is integrated analysis the **worst** thing that happened to fisheries stock assessment?

- We have adopted the mindset in which sophisticated statistical models that integrate diverse types of data and information (e.g. Bayesian priors) can overcome lack of data and biological information
- We do not collect the right data or do the right research
- We rely too much on catch-at-length data
- We use the separability assumption and McAllister and Ianelli's (1997) iterative reweighting of catch composition data

Why is integrated analysis the **best** thing that happened to fisheries stock assessment?

- Makes assumptions consistent and explicit
- Facilitates testing of different assumptions
- Allows us to identify data conflict and investigate model misspecification

Data conflict and model misspecification

Data Conflict

- Multiple data types provide information on the same processes
- Sometimes the different data types support substantially different values of the same parameter: data conflict
- Which data set should we believe?

The law of conflicting data

Axiom

Data is true

Implication

Conflicting data implies model misspecification

Caveat

Data conflict needs to be interpreted in the context of random sampling error

Significance

Down weighting or dropping conflicting data is not necessarily appropriate because it may not resolve the model misspecification

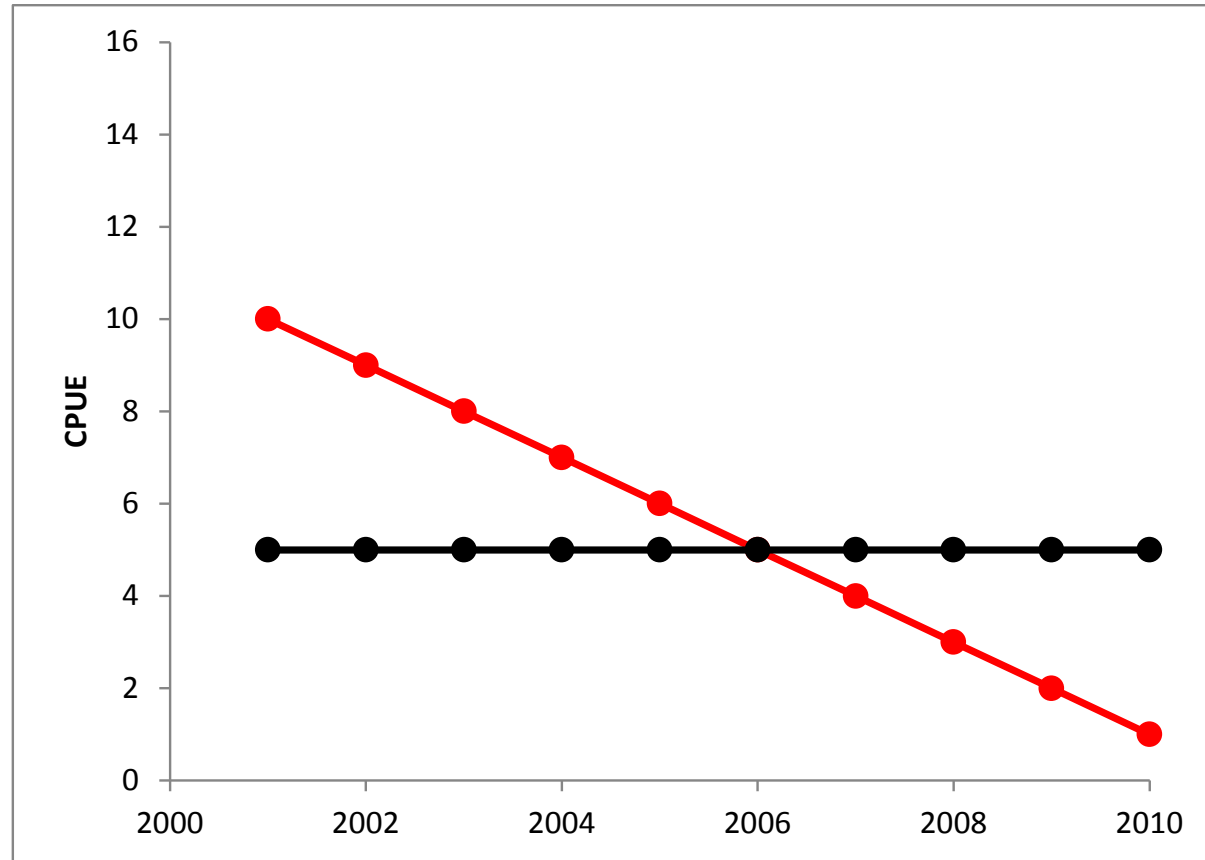
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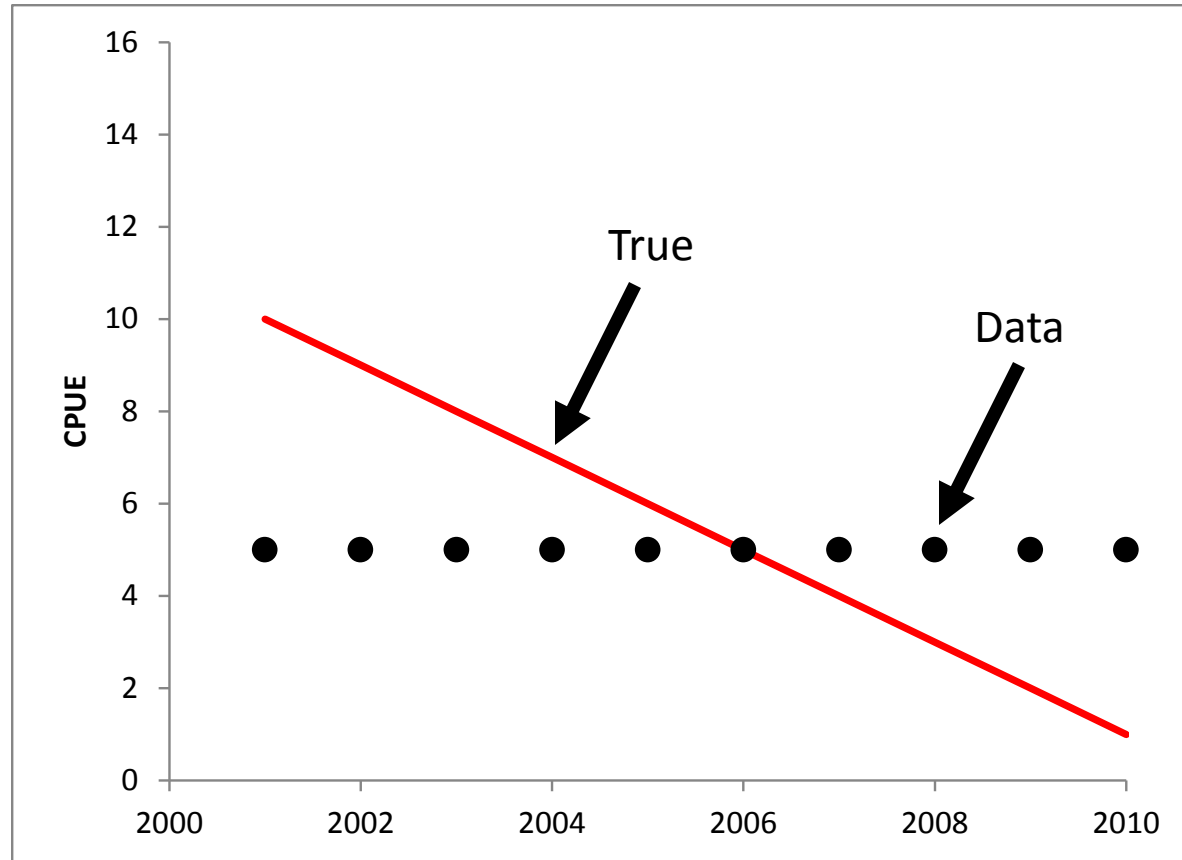
Reasons for data conflict

- Random sampling error
- Observation model misspecification
- System dynamics model misspecification
 - Parameters fixed at wrong values
 - Wrong model structure
 - Unmodeled temporal variation in parameter values

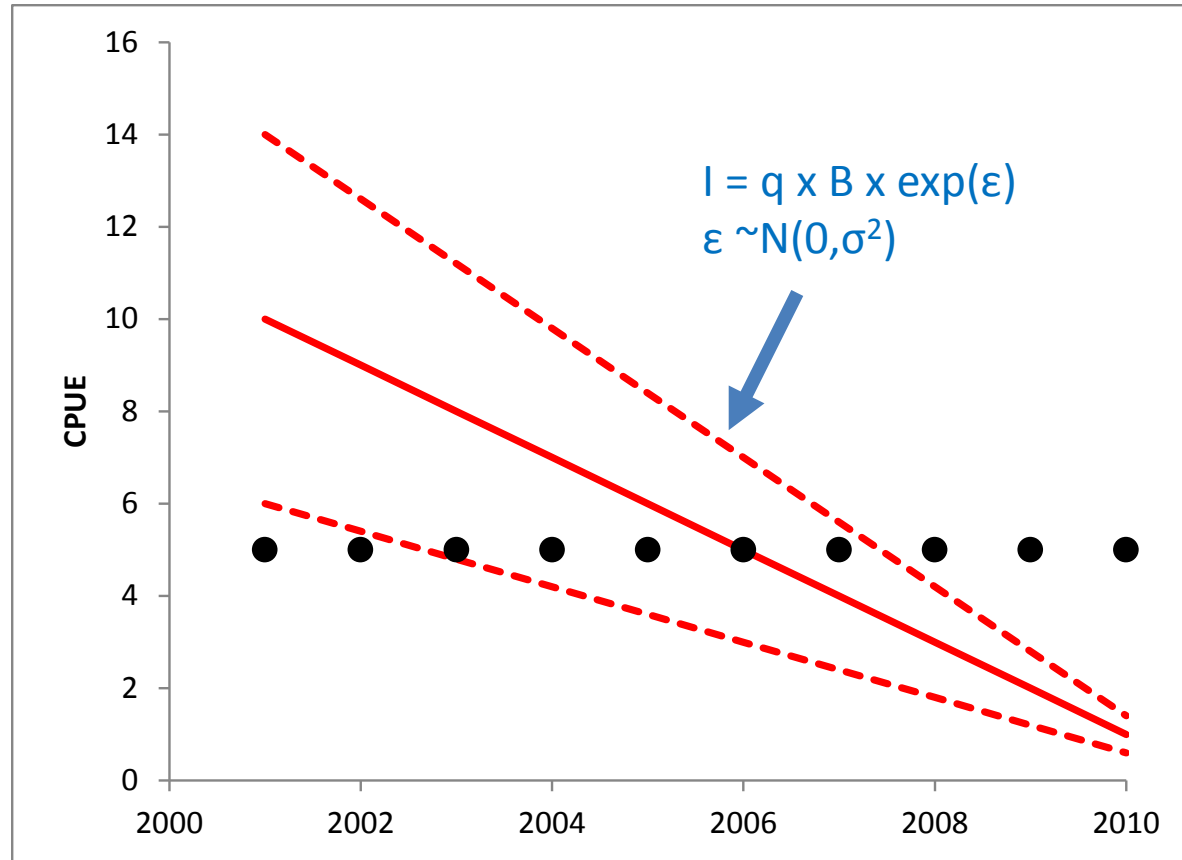
Data conflict: indices of abundance



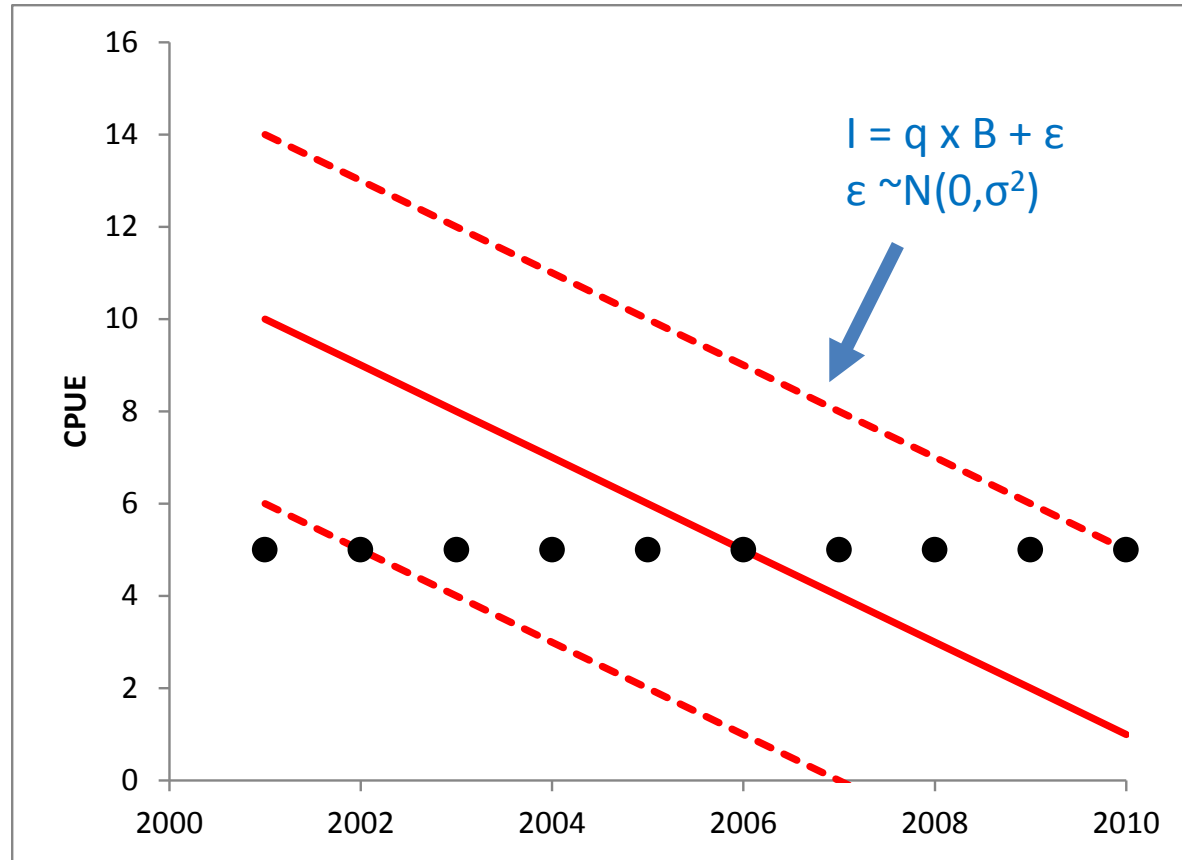
Data conflict: sampling error



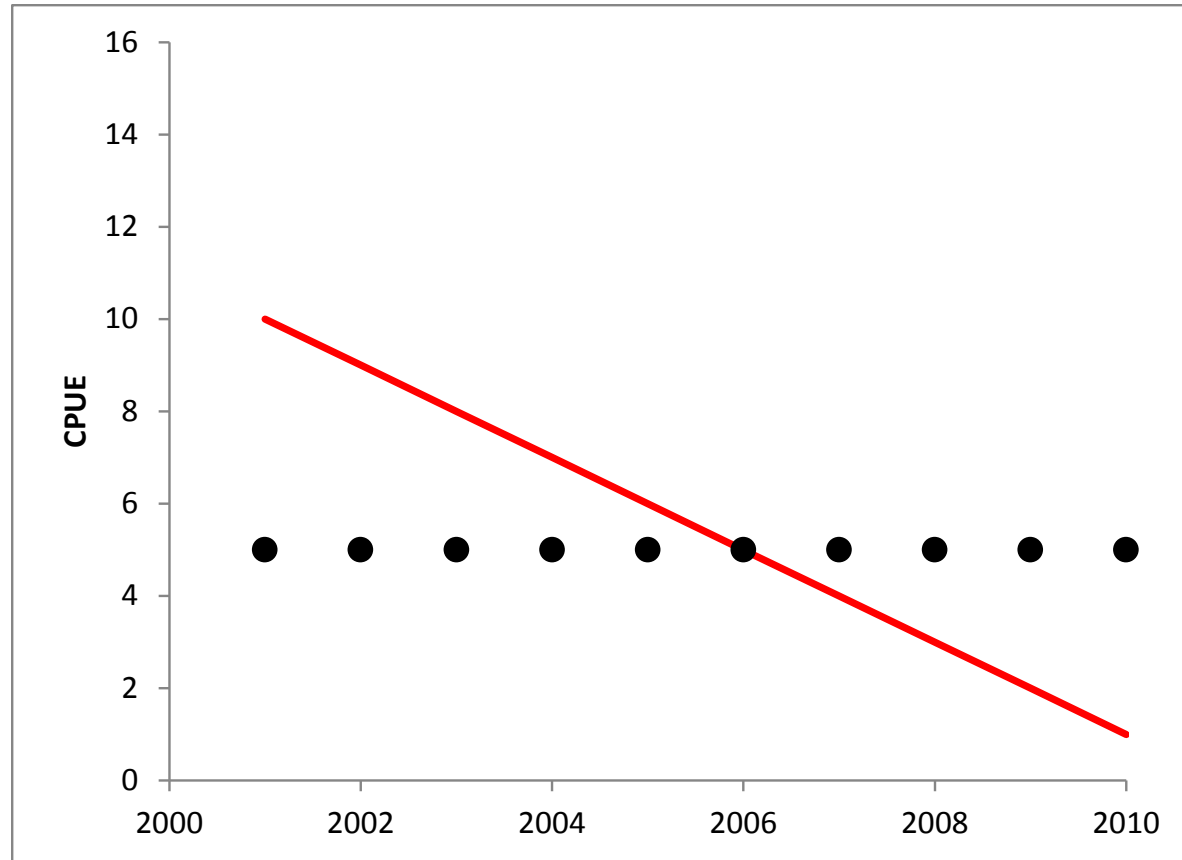
Data conflict: sampling error



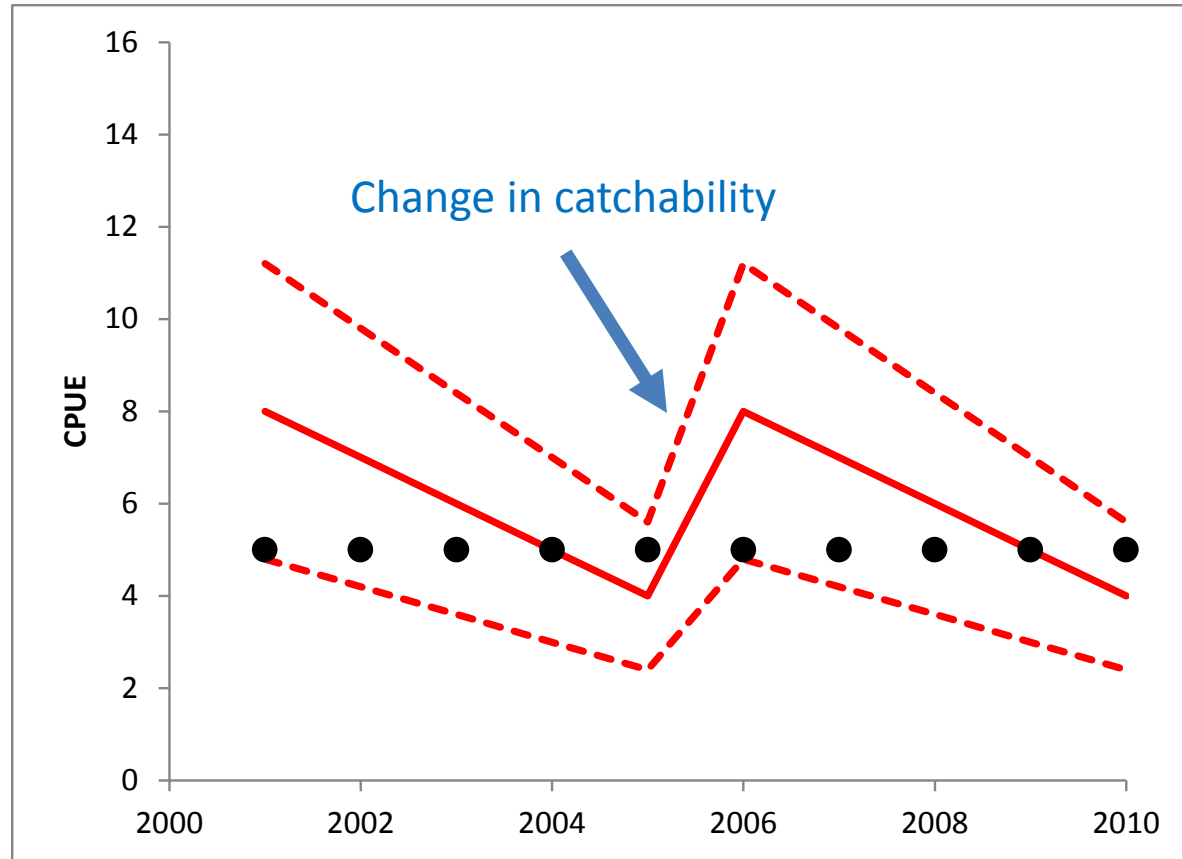
Data conflict: sampling error



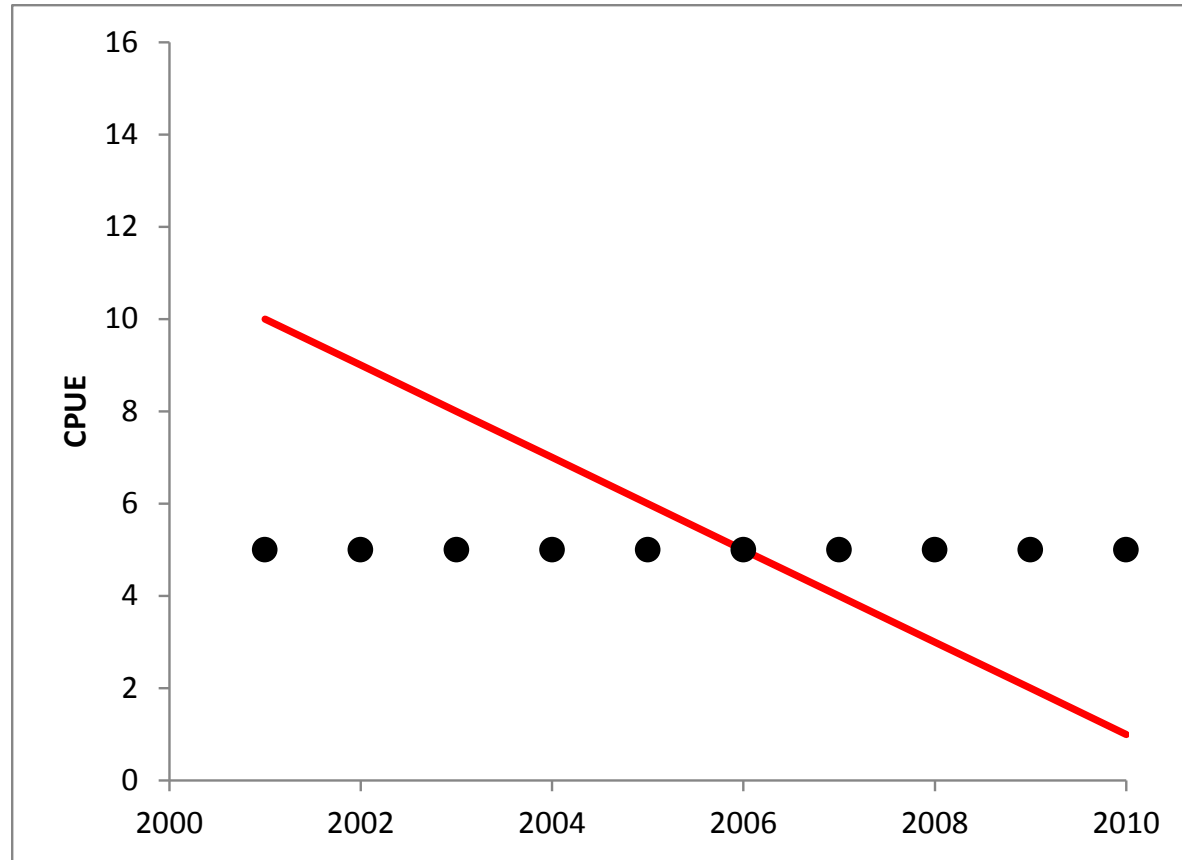
Data conflict: Observation model misspecification



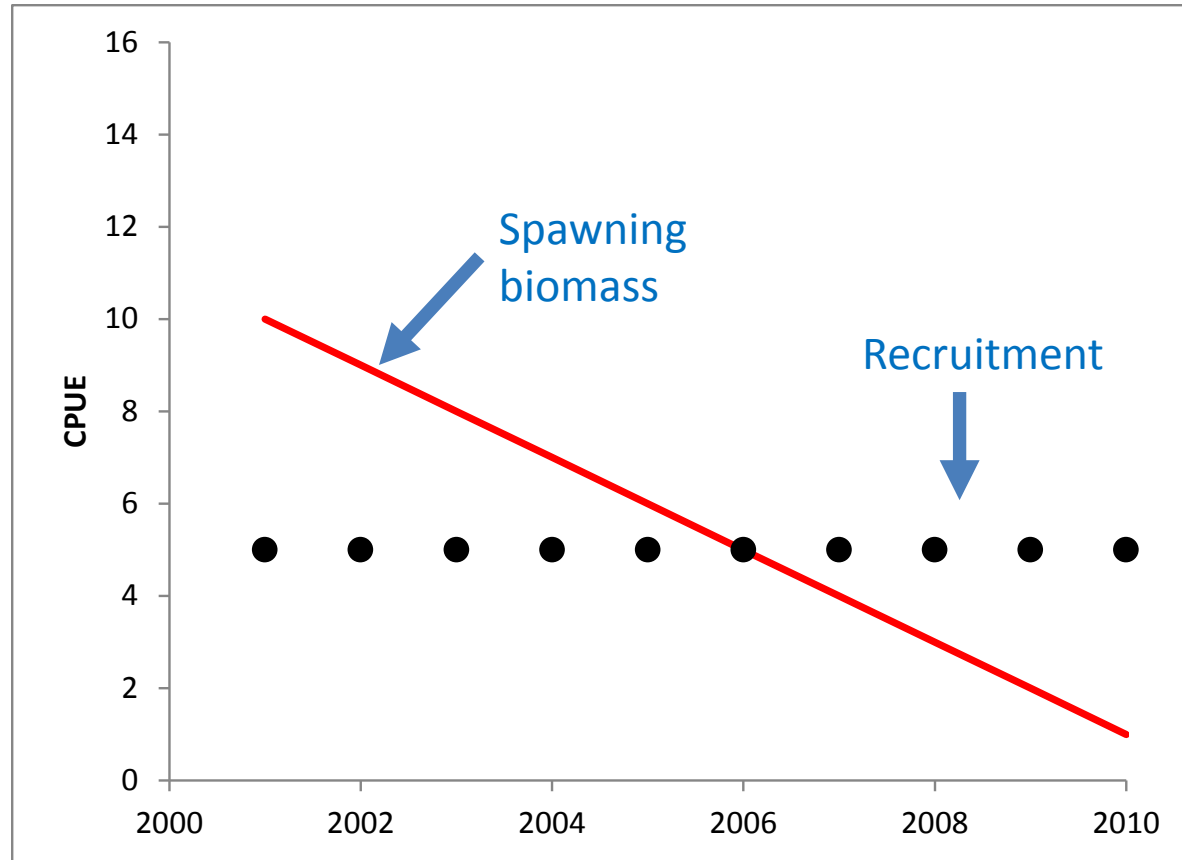
Data conflict: Observation model misspecification



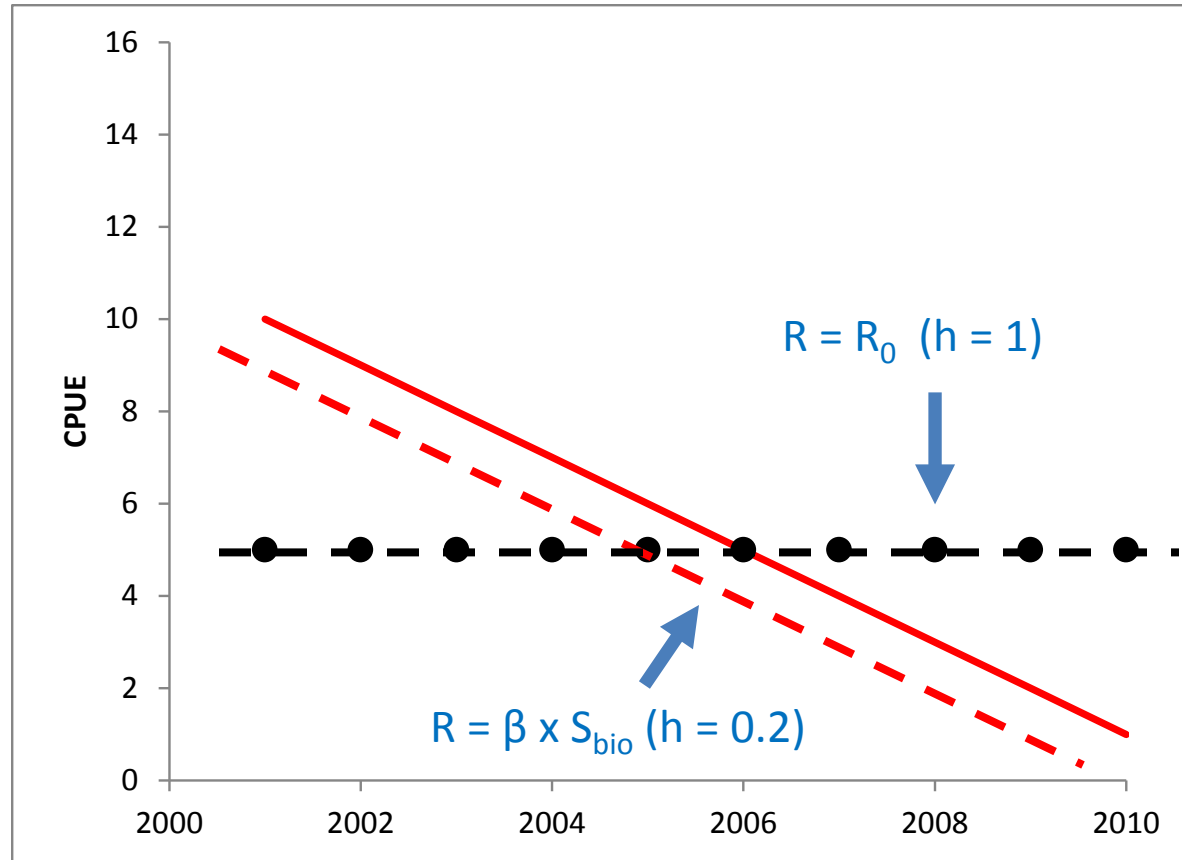
Data conflict: Process model misspecification



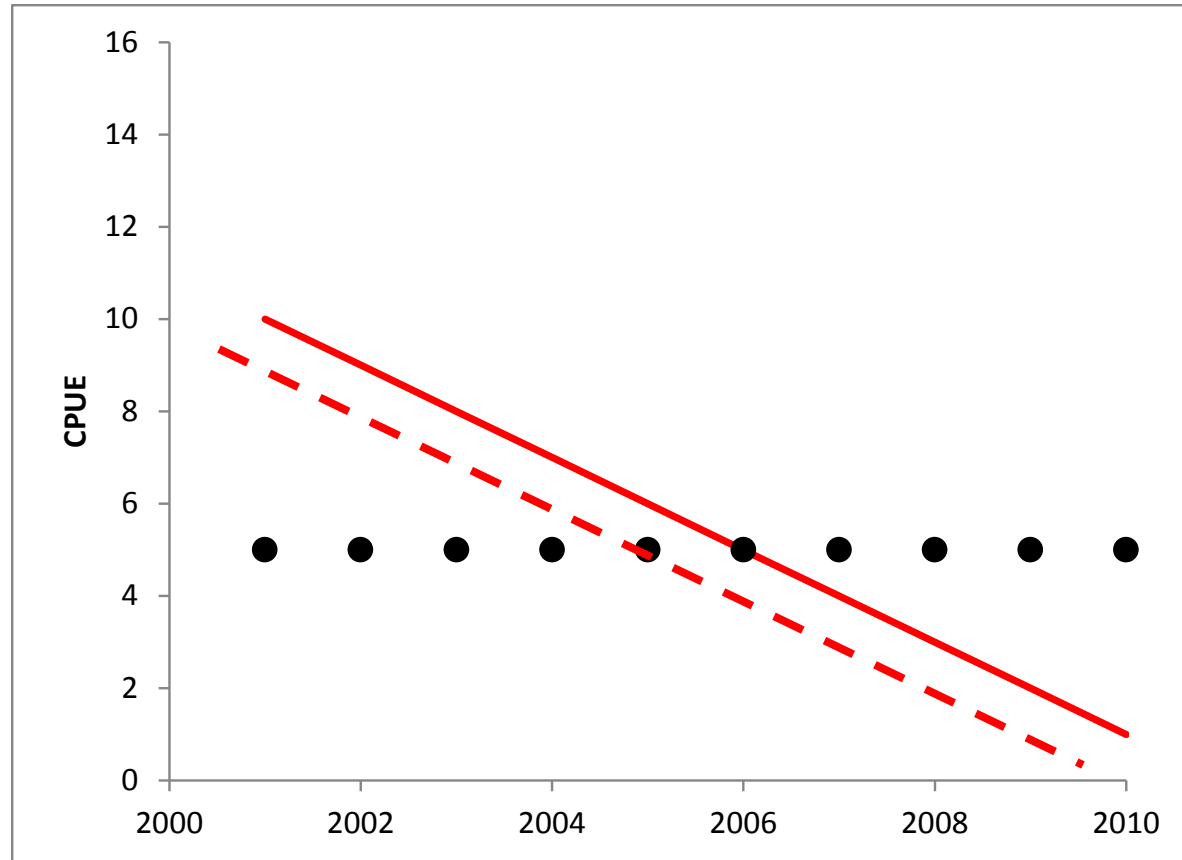
Data conflict: Process model misspecification



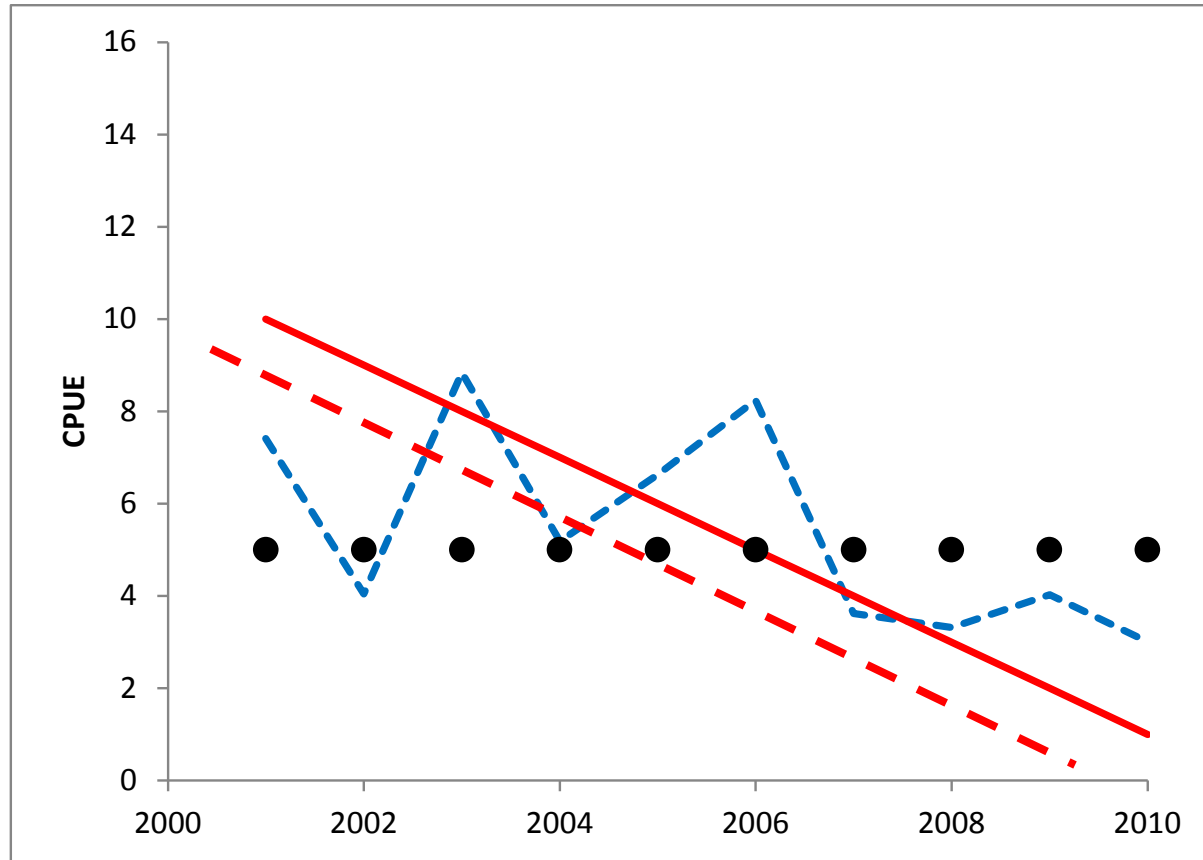
Data conflict: Process model misspecification (bias)



Data conflict: Process model misspecification (systematic temporal variation in environment-recruitment)



Data conflict: Process model misspecification (systematic temporal variation in environment-recruitment)



Reasons for data conflict

- Random sampling error
 - Not conflict
- Observation model misspecification
 - Dropping data appropriate
- System dynamics model misspecification
 - Dropping data probably not appropriate

The problem with composition data

- Composition data provides information on abundance trends and absolute abundance
- Information in composition data is highly sensitive to model misspecification
- Temporal variation in population and fishery processes influence composition data
- Information in composition data often conflicts with information from abundance index data
- Most integrated stock assessments are substantially biased because composition data has too much influence on absolute abundance and the model is misspecified

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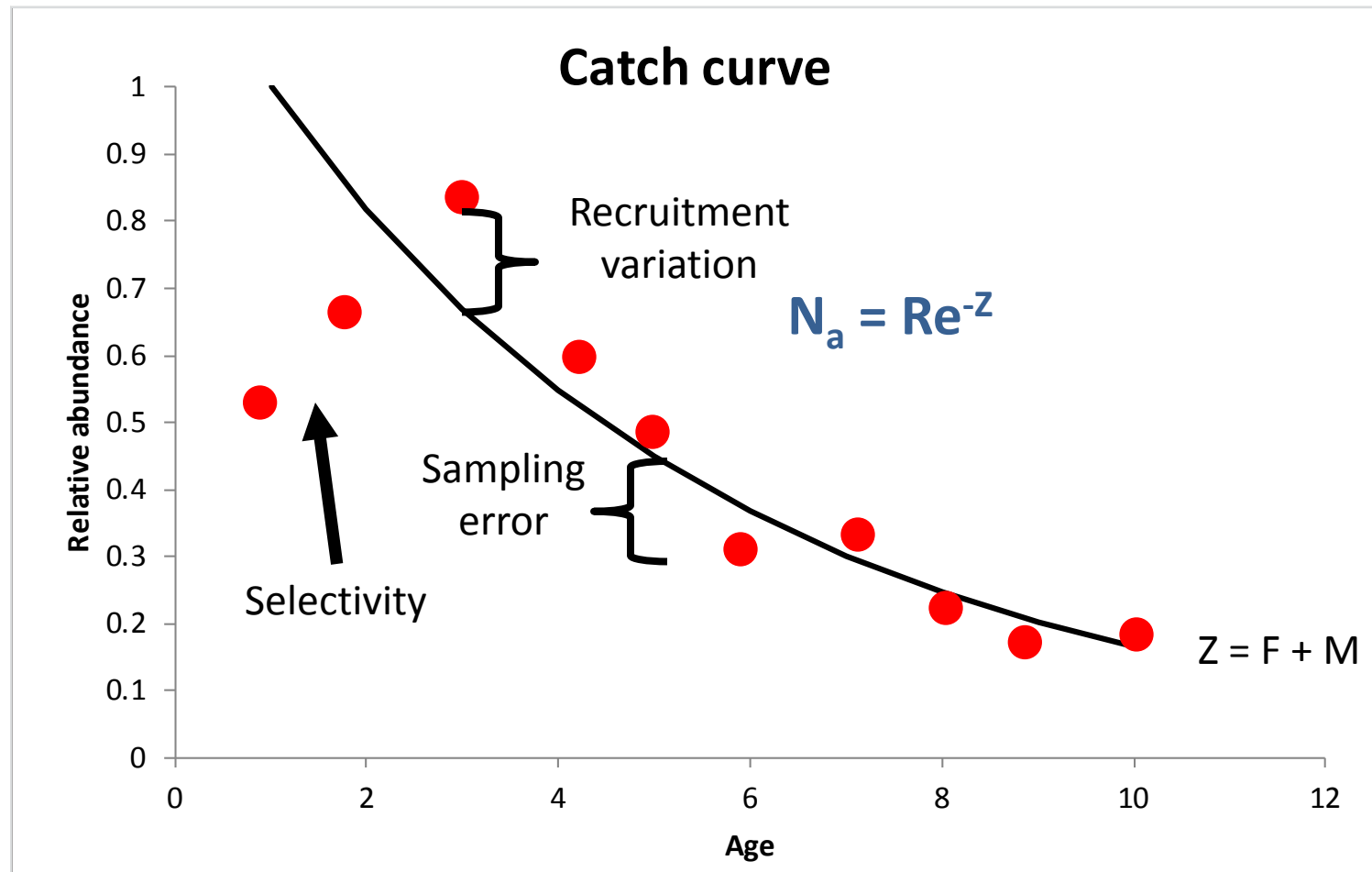
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Age composition data: abundance information

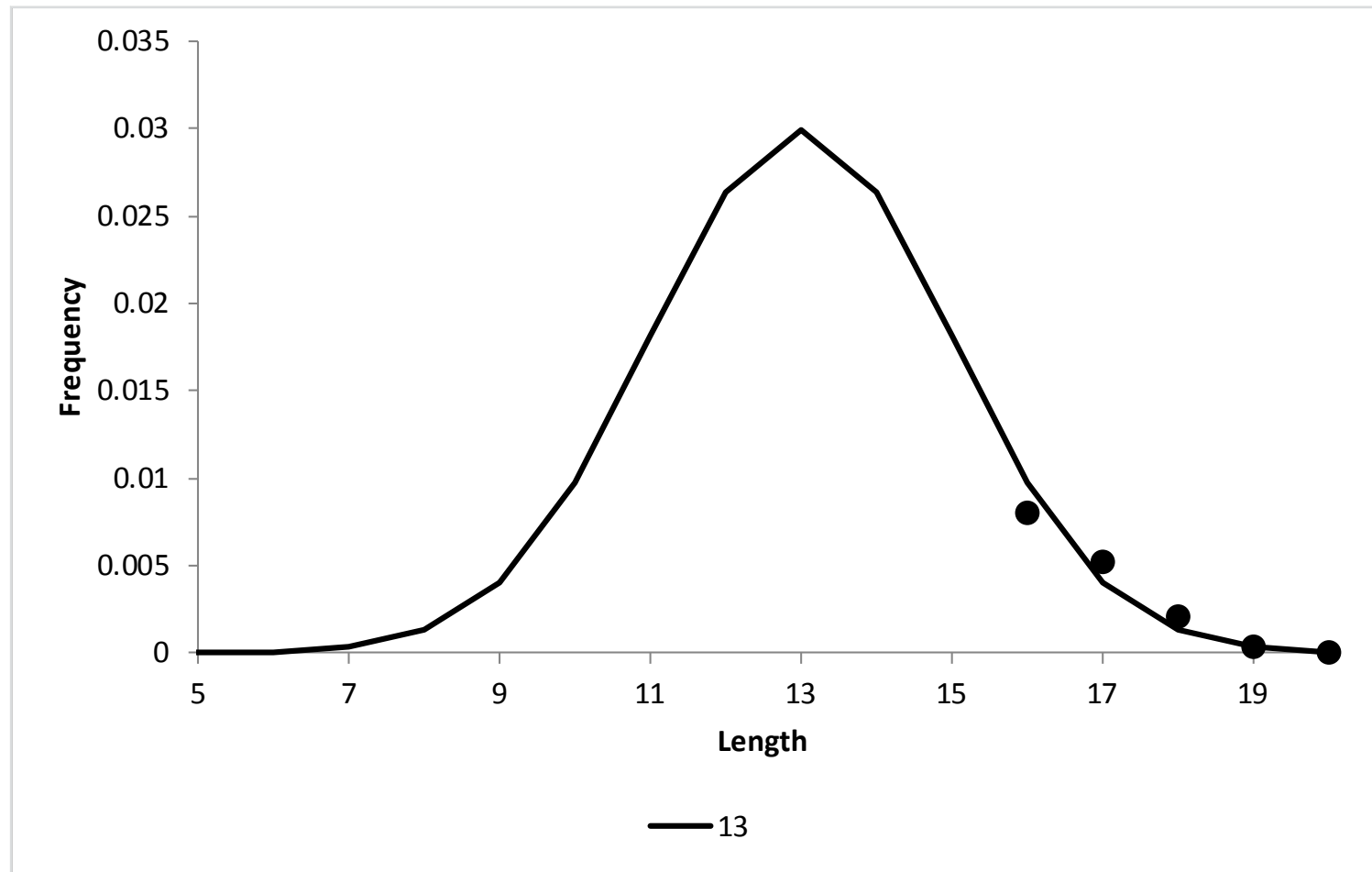
$$B \approx C/F$$

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

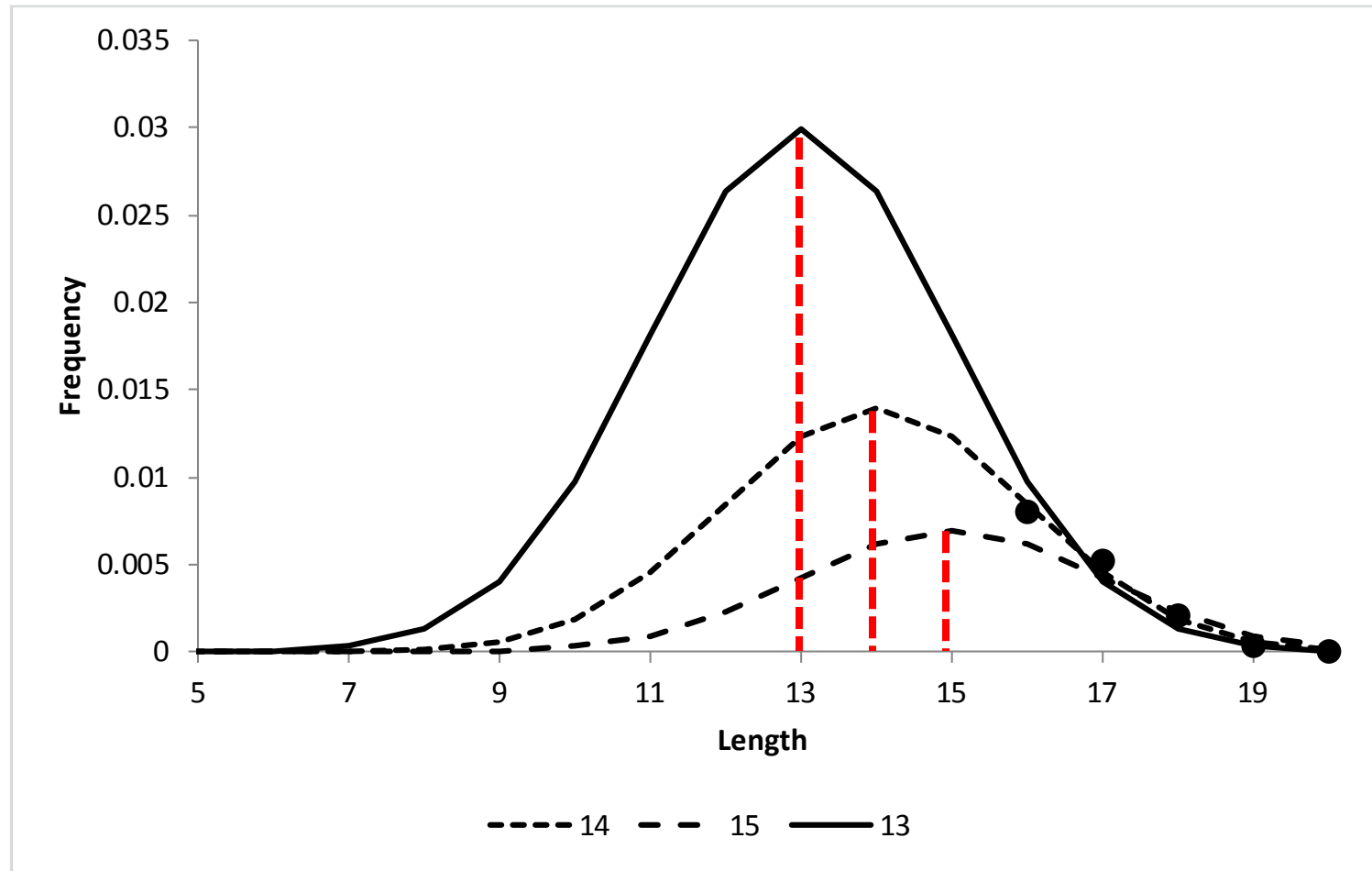
Catch curve



Length composition: asymptotic length



Length composition: asymptotic length



Requirements for Interpreting composition data

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

What we know about population processes

Selectivity

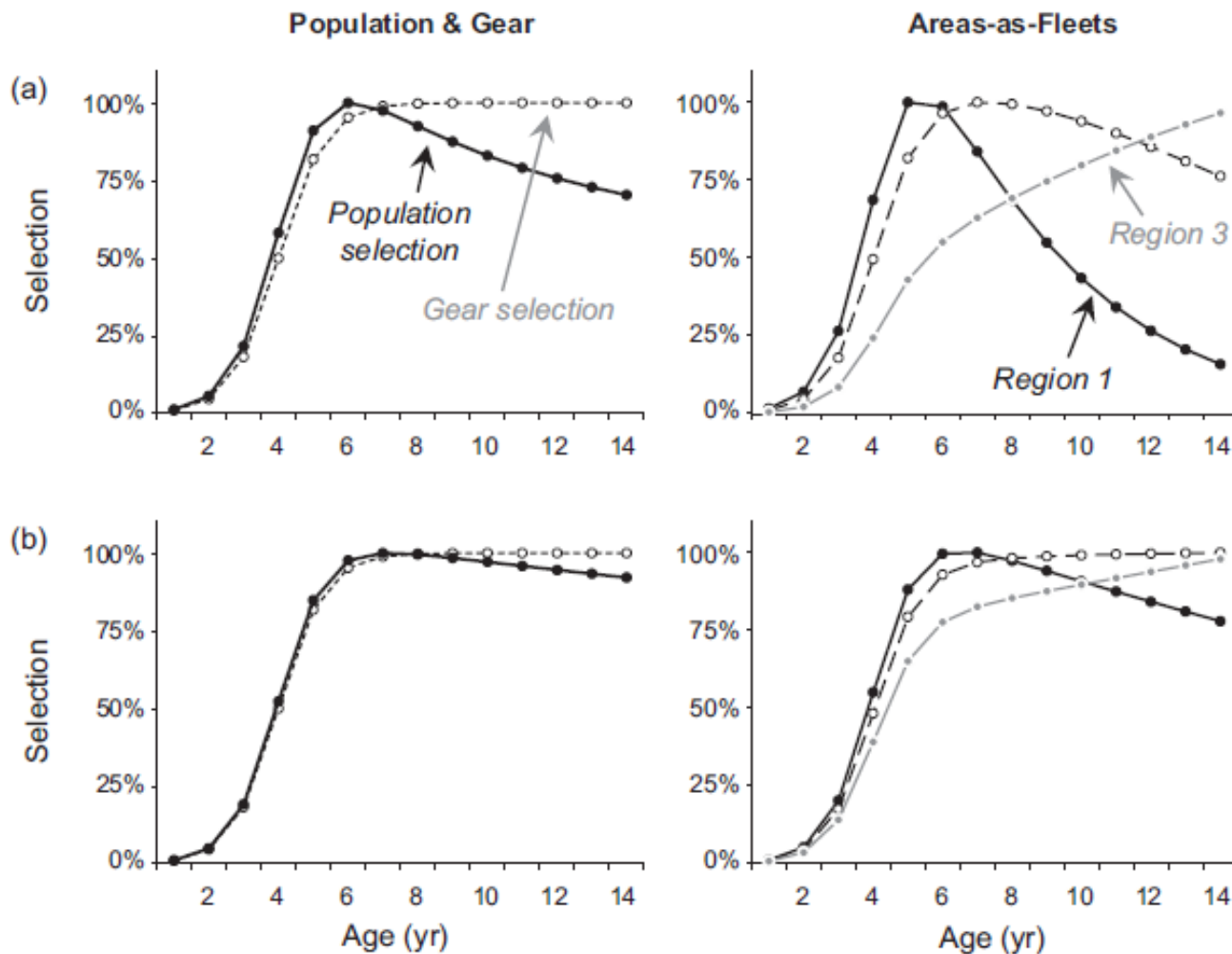
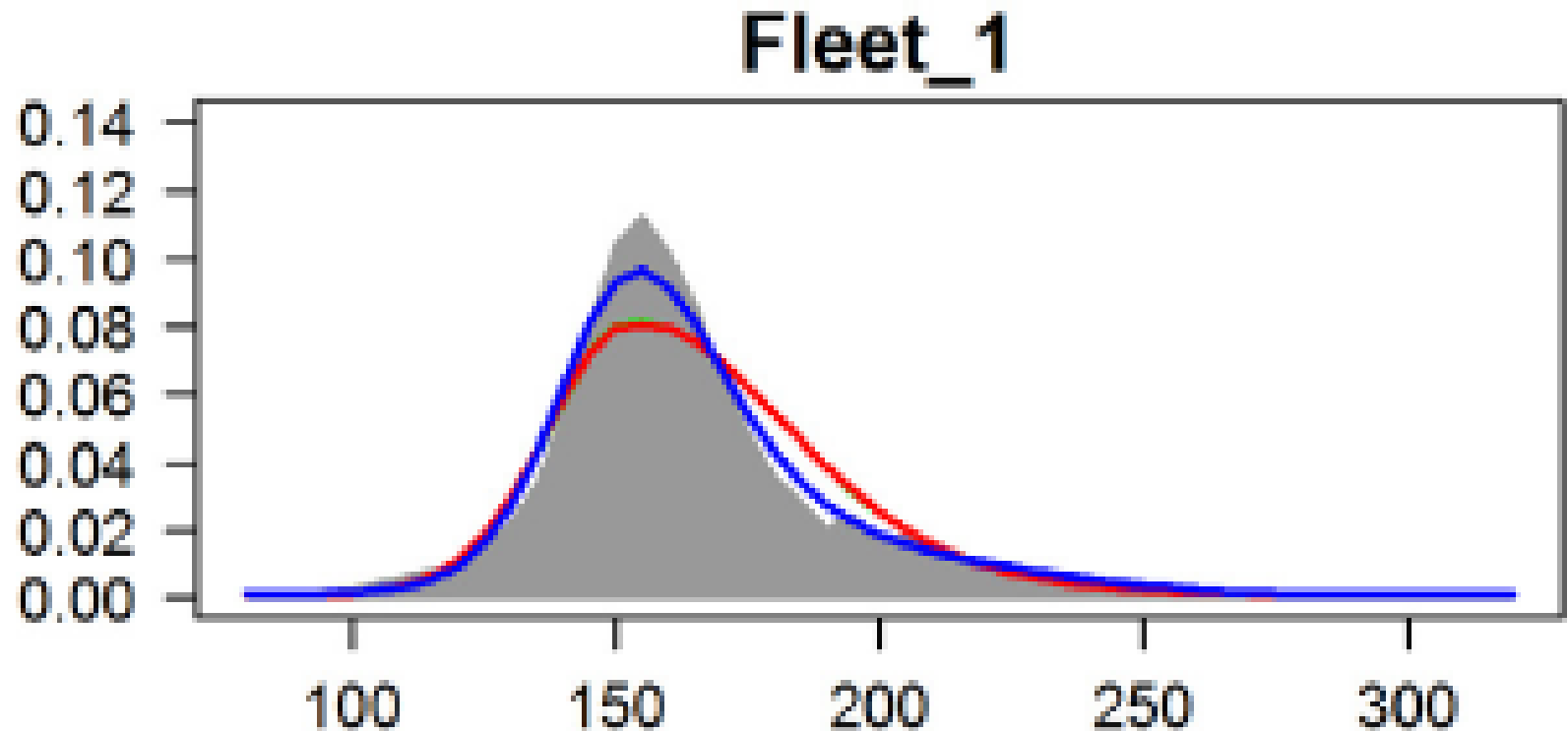
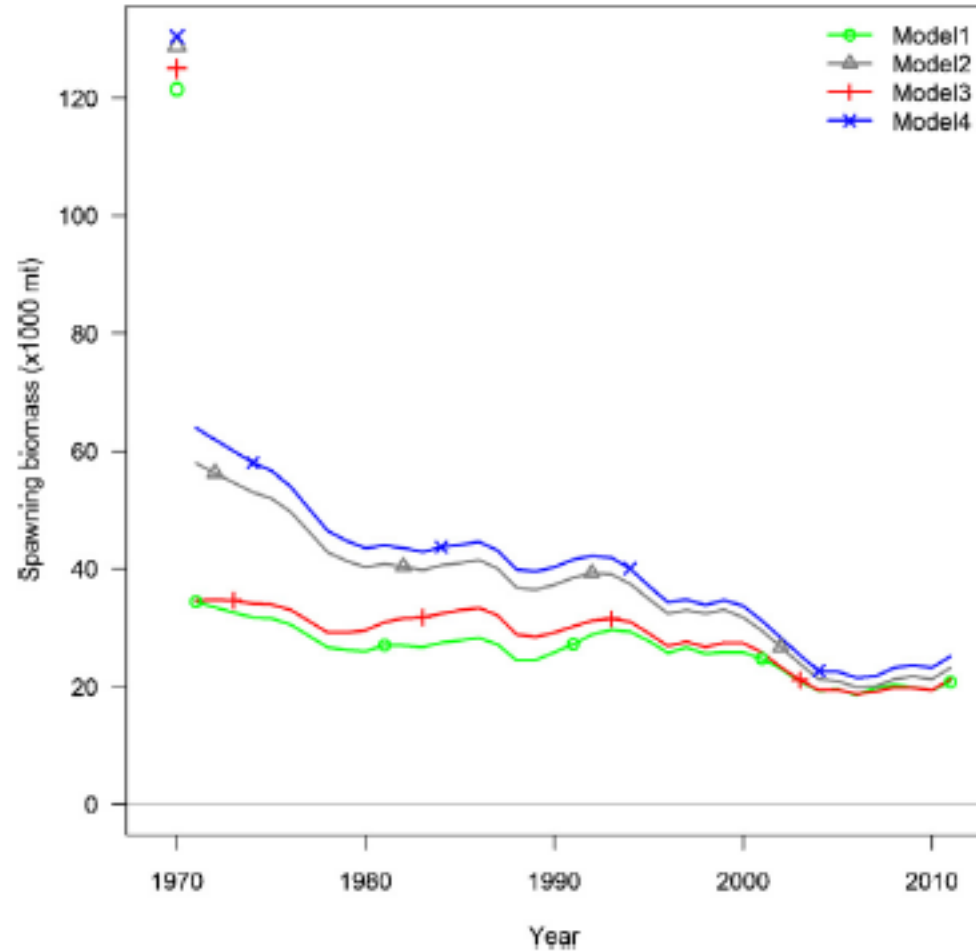


Fig. 1. Gear-selection and population-selection curves (on the left), and areas-as-fleets selection curves (on the right) for scenarios 1a (upper panels) and 1b (lower panels). The fishing mortality rates for regions 1, 2, and 3 are 0.4, 0.2, and 0.1 y^{-1} respectively in scenario 1a, and 0.08, 0.04, and 0.02 in scenario 1b. Regional recruitment is uniform and there is no movement of the fish.

Blue marlin in the Pacific Ocean



Blue marlin in the Pacific Ocean



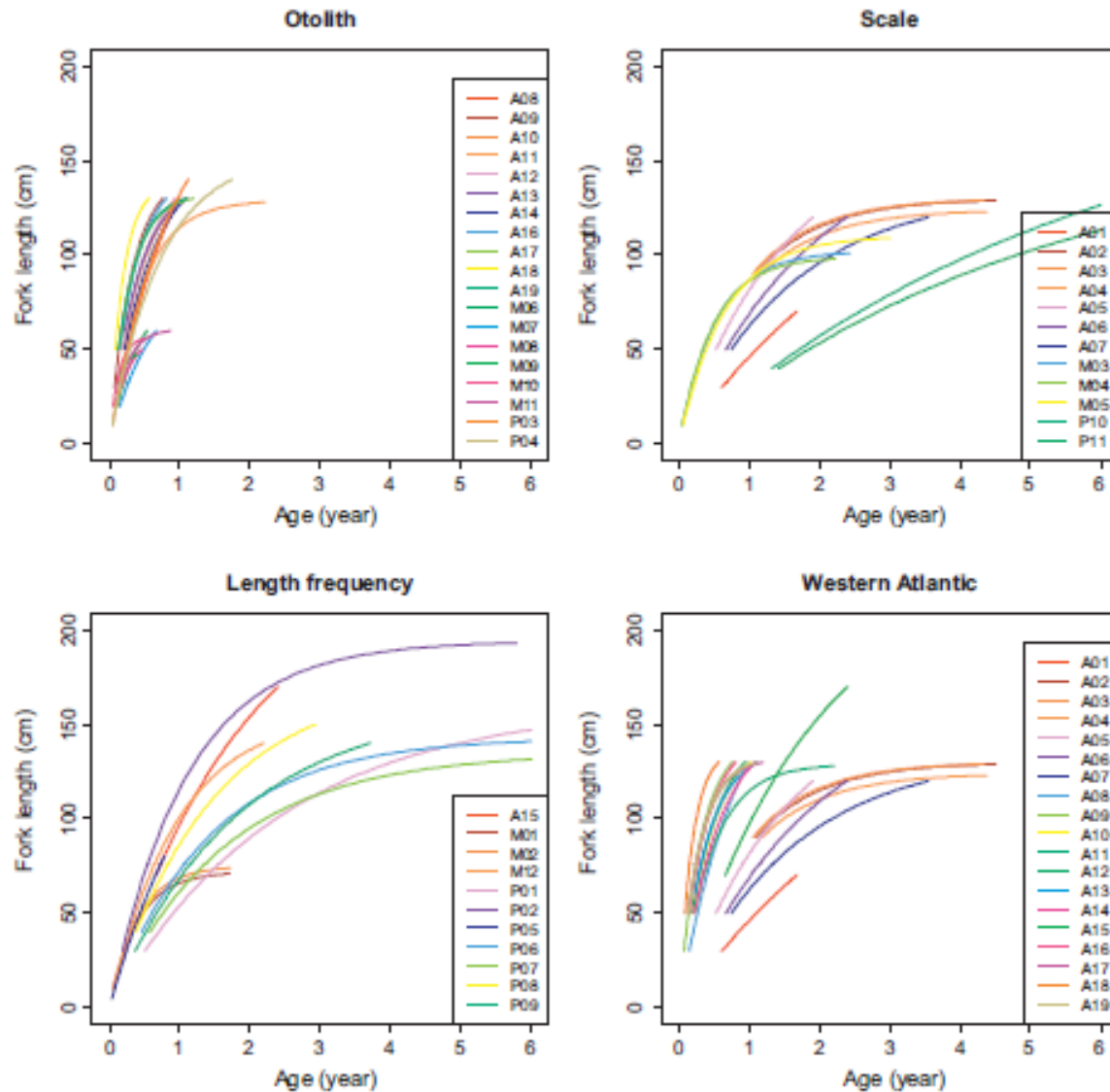
Lee, H. H., Piner, K. R., Methot Jr, R. D., & Maunder, M. N. (2014). Use of likelihood profiling over a global scaling parameter to structure the population dynamics model: an example using blue marlin in the Pacific Ocean. *Fisheries Research*, 158, 138-146

Guidelines

- Guideline 1: Do not naively down-weight or drop data
- Guideline 2: Do not over-weight composition data
- Guideline 3: Use flexible fishery selectivity curves

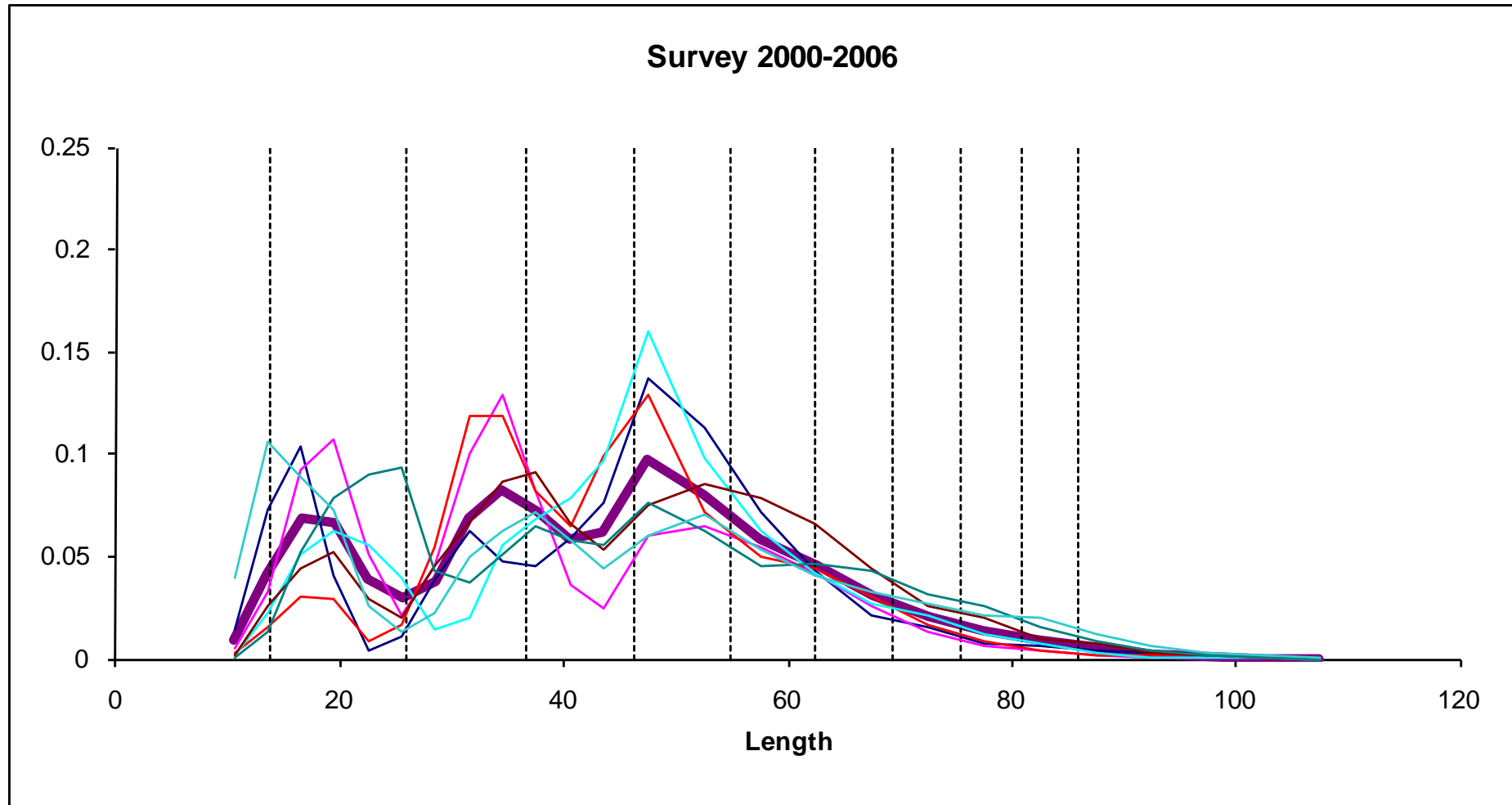
Growth

Uncertainty in growth estimates: Mahi mahi



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: Pacific cod



Pacific bluefin growth

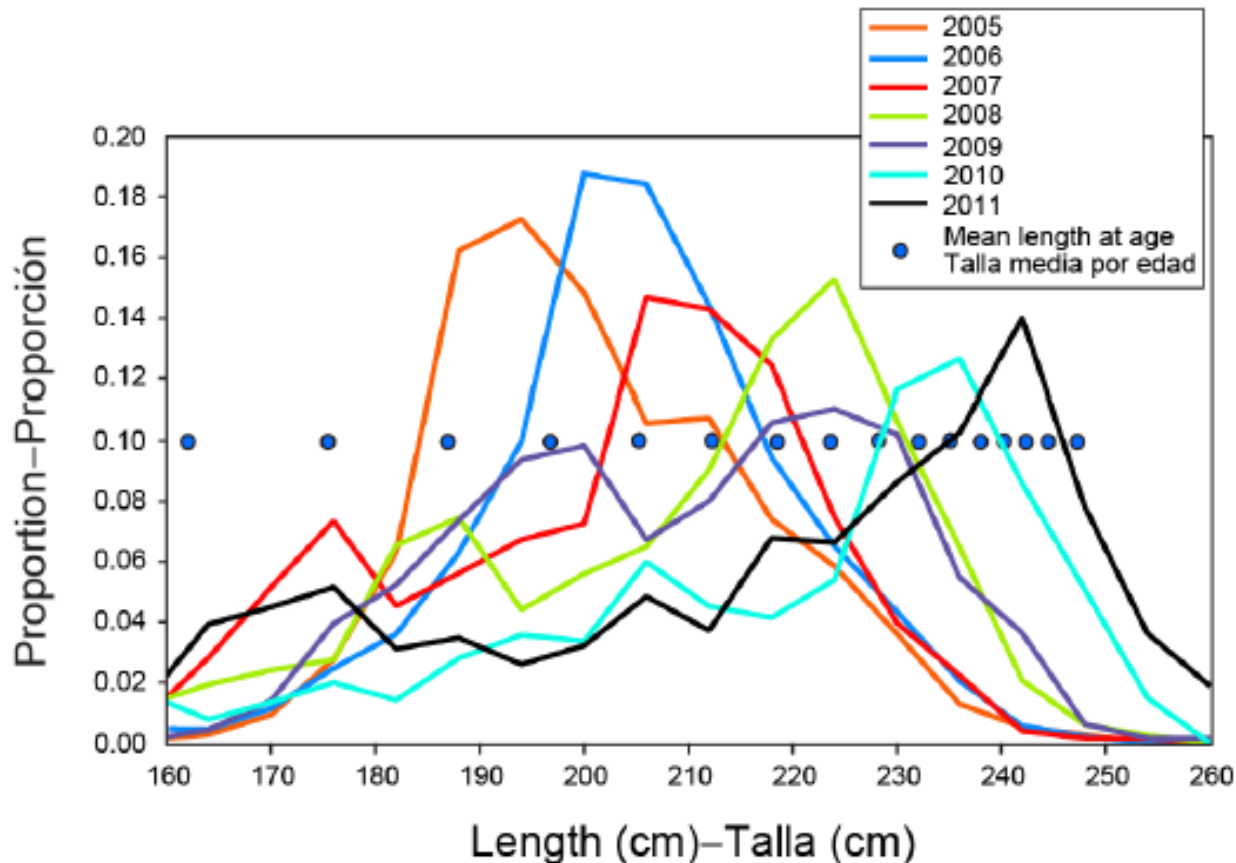
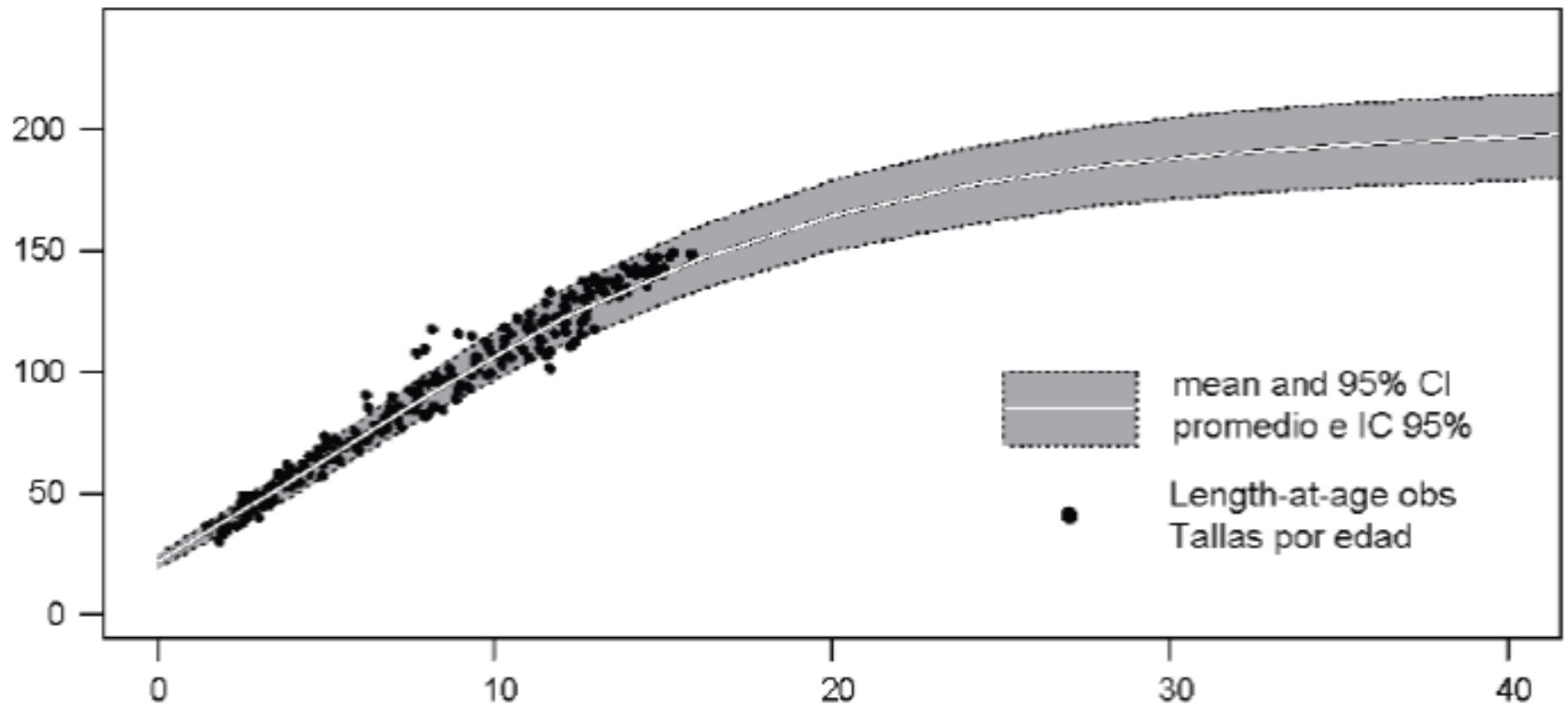


FIGURE 8. Comparison of mean length-at-age (dots) used in the ISC assessment model and the Japanese length-composition data.

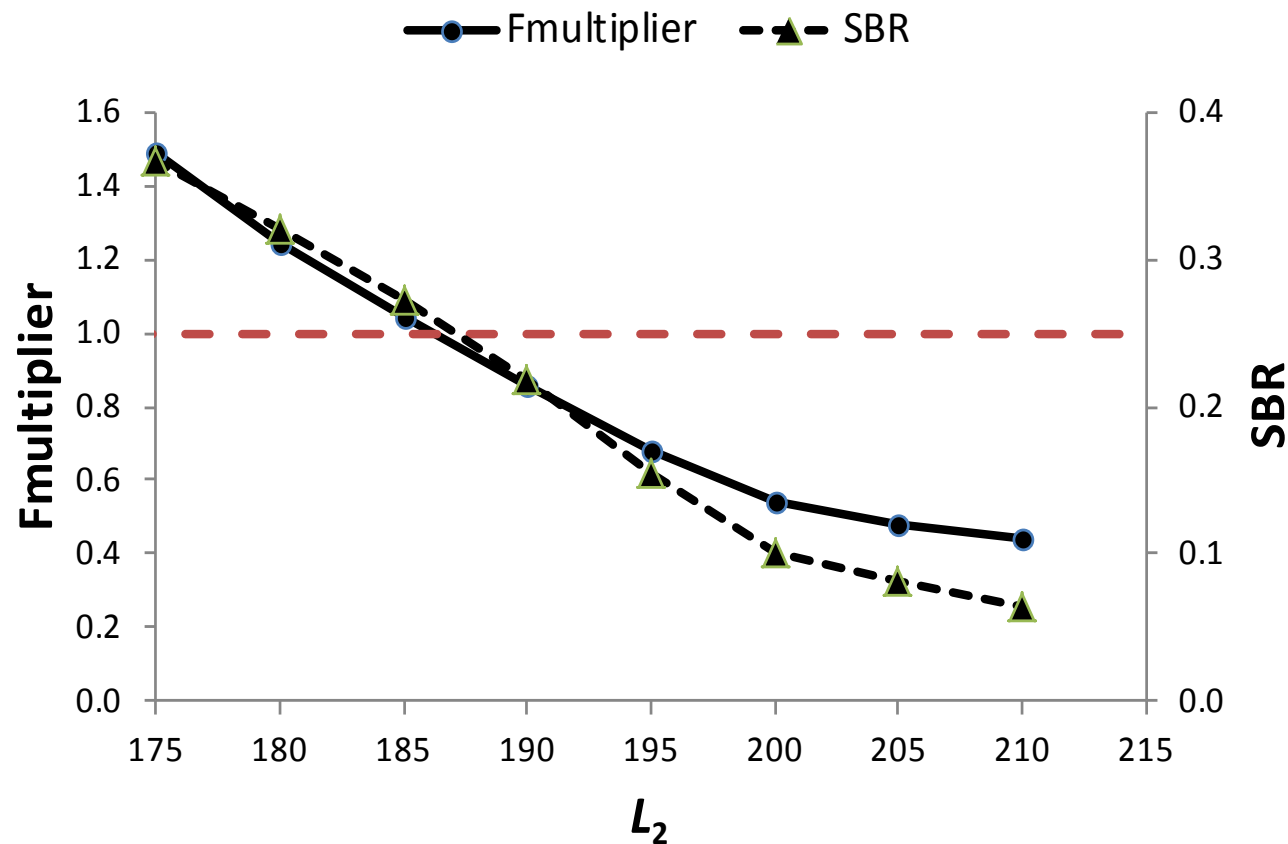
FIGURA 8. Comparación de la talla media por edad (puntos) usada en el modelo de evaluación del ISC y los datos japoneses de composición por talla.

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)



Natural mortality

Estimator:	Bayliff's	Hoening's	Sekharan's	Tanaka's	Kenchington's	Alverson & Carney's	Zhang & Megrey's	Rikhter & Efanov's First	Rikhter & Efanov's Second	Roff's First	Chen & Watanabe's	Charnov & Berigan's	Jensen's First	Alagamja's	Ralston's	Pauly's	Djabali's	Jensen's Third	Griffiths & Harrod's	Frisk's	Gislason's First and Second	Cubillos'	Jensen's Second	Peterson & Wroblewski's	Lorenzen's	Ursin's	Jennings & Dulvy's	Roff's Second	Groeneveld's
Dependent on regression																													
Estimates Z over years																													
Dependent on single maximal age																													
Affected by senescence																													
Requires validated ageing protocol																													
Ignores sample size																													
Requires extreme assumptions																													
Requires estimate of effective n																													
Requires data from unexploited era																													
Dependent on estimate of K																													
Requires other growth parameters																													
Requires validated age at maturity																													
Requires length at maturity																													
Requires temperature value																													

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).

What processes change over time

- Recruitment
 - Most variable process
 - Relative strength of a cohort generally persists for several years and is observed in multiple years of composition data
 - Usually estimated reasonably well in integrated assessment models with composition data
- Natural mortality
 - More variable for younger fish and species with small body size
 - Low variability for species that are captured at a relatively large size
 - Information from composition data indirect
- Growth
 - Low to moderate variability
 - Density dependent and environmentally driven
 - Spatial variation
 - Most variable for young fish
 - Direct information from age-length
- Fishing mortality
 - Moderate variability
 - Estimated from catch data
- Selectivity
 - Low to moderate variability
 - Directly links dynamics to composition data
 - Cohort targeting
 - Information from both age and length compositions

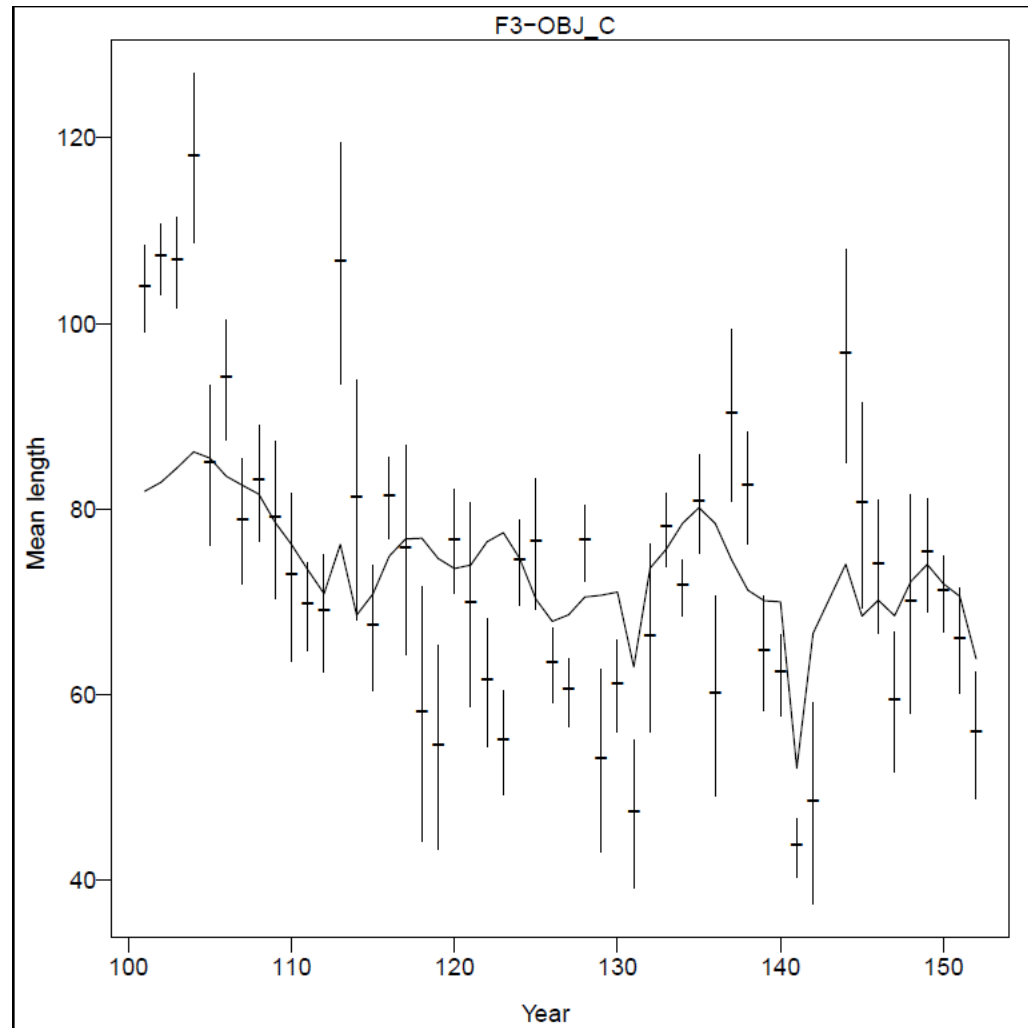
Guidelines

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- Guideline 4: Model time varying fishery selectivity

Bigeye tuna application

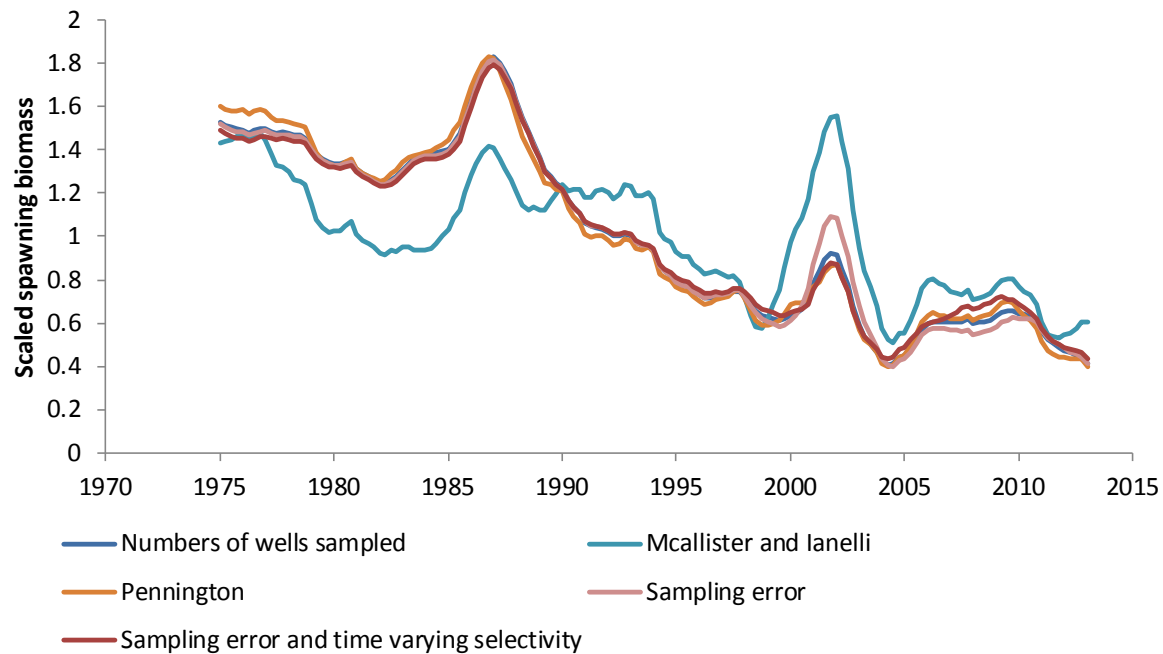
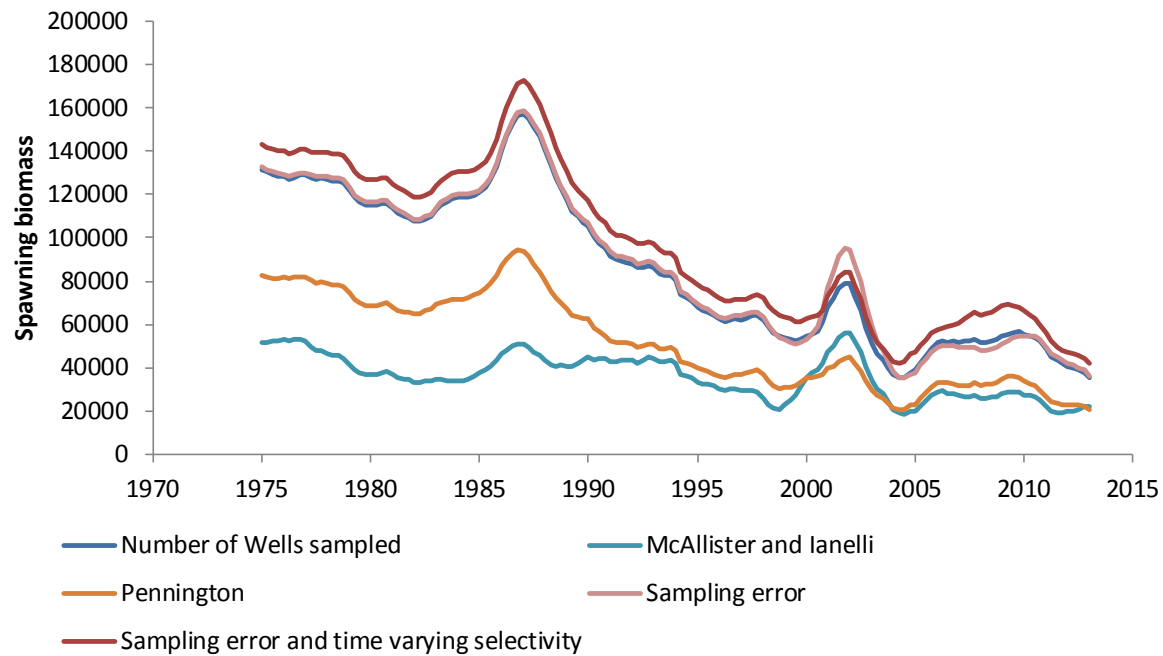
- Longline and purse seine fisheries
- Sampling error and time varying selectivity applied to purse seine fisheries

Estimated mean size (line) compared to the observed mean size using McAllister and Ianelli



Sample size

Fishery	Number of wells sampled	Sampling error	McAllister and Ianelli	Pennington	Pennington with temporal variation in selectivity
F1-OBJ_early	3.8		20.2	3.0	
F2-OBJ_S	19.3	66.4	89.0	9.6	45.1
F3-OBJ_C	15.6	42.2	67.5	4.7	36.3
F4-OBJ_I	2.8	9.4	6.6	1.3	
F5-OBJ_N	13.2	56.0	79.3	7.9	30.6



Guidelines

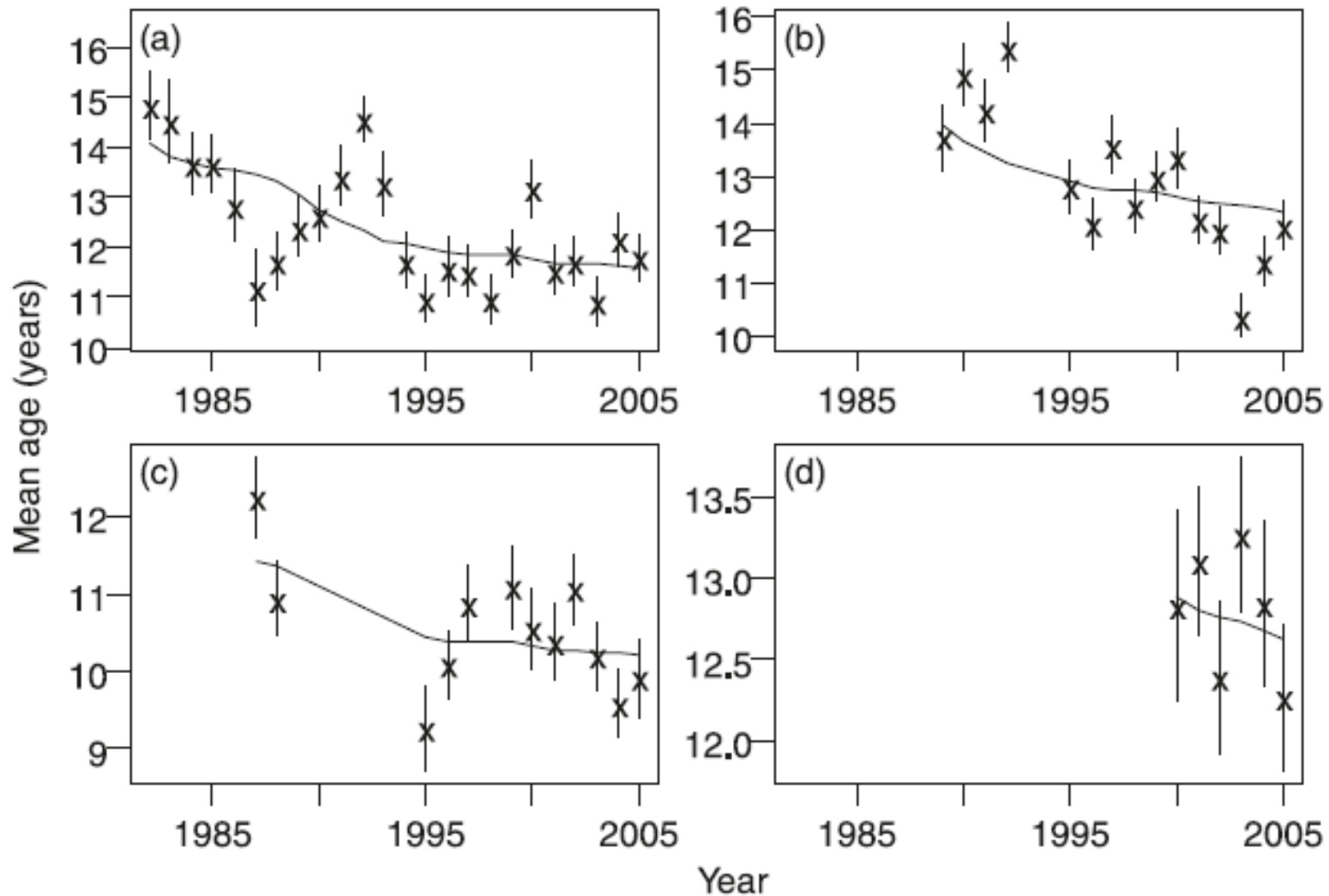
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- Guideline 2: Do not over-weight composition data
- Guideline 3: Use flexible fishery selectivity curves
- Guideline 4: Model time varying fishery selectivity
- Guideline 5: Estimate composition sampling error from sample design

Computation

- Methods
 - Nielsen, A., & Berg, C. W. (2014). Estimation of time-varying selectivity in stock assessments using state-space models. *Fisheries Research*, 158, 96-101.
 - Thompson, G. G., and Lauth, R. R. 2012. Assessment of the Pacific cod stock in the Eastern Bering Sea and Aleutian Islands Area. In: Plan Team for Groundfish Fisheries of the Bering Sea/Aleutian Islands (Compiler), *Stock Assessment and Fishery Evaluation Report for the Groundfish Resources of the Bering Sea/Aleutian Islands regions*. North Pacific Fishery Management Council, Anchorage, AK, pp. 245–544.
 - Thorson, J. T., Hicks, A. C., & Methot, R. D. (2014). Random effect estimation of time-varying factors in Stock Synthesis. *ICES Journal of Marine Science*

Diagnostics

Francis' mean age/length diagnostic

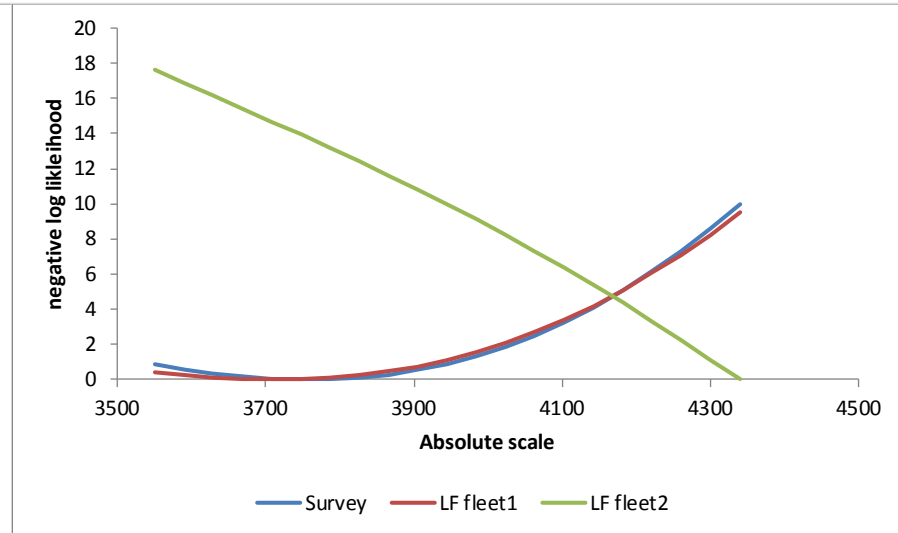
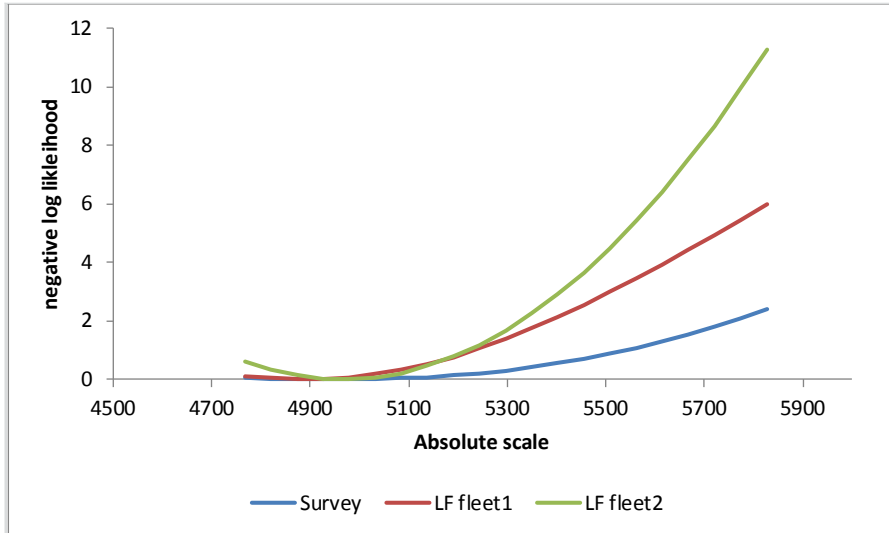


Comparing composition data with abundance index data – R0 profile: selectivity

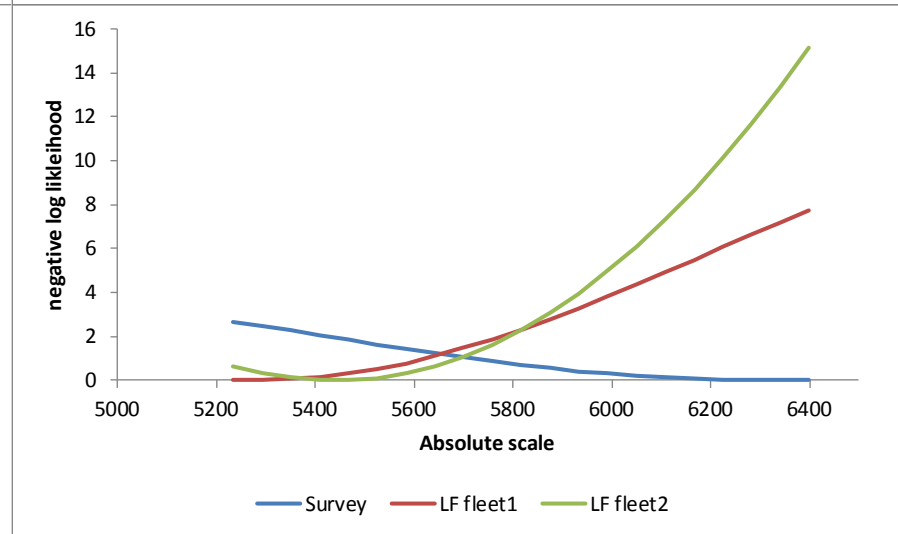
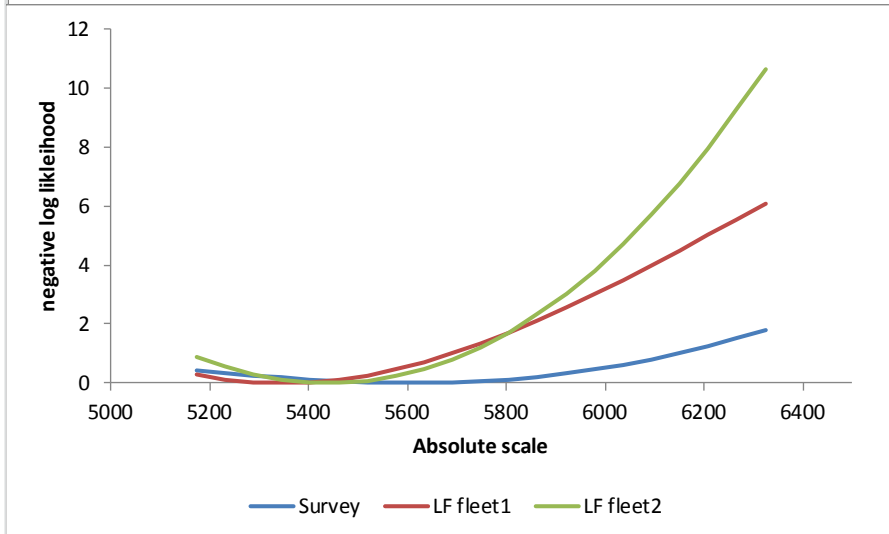
Correctly specified

Misspecified selectivity

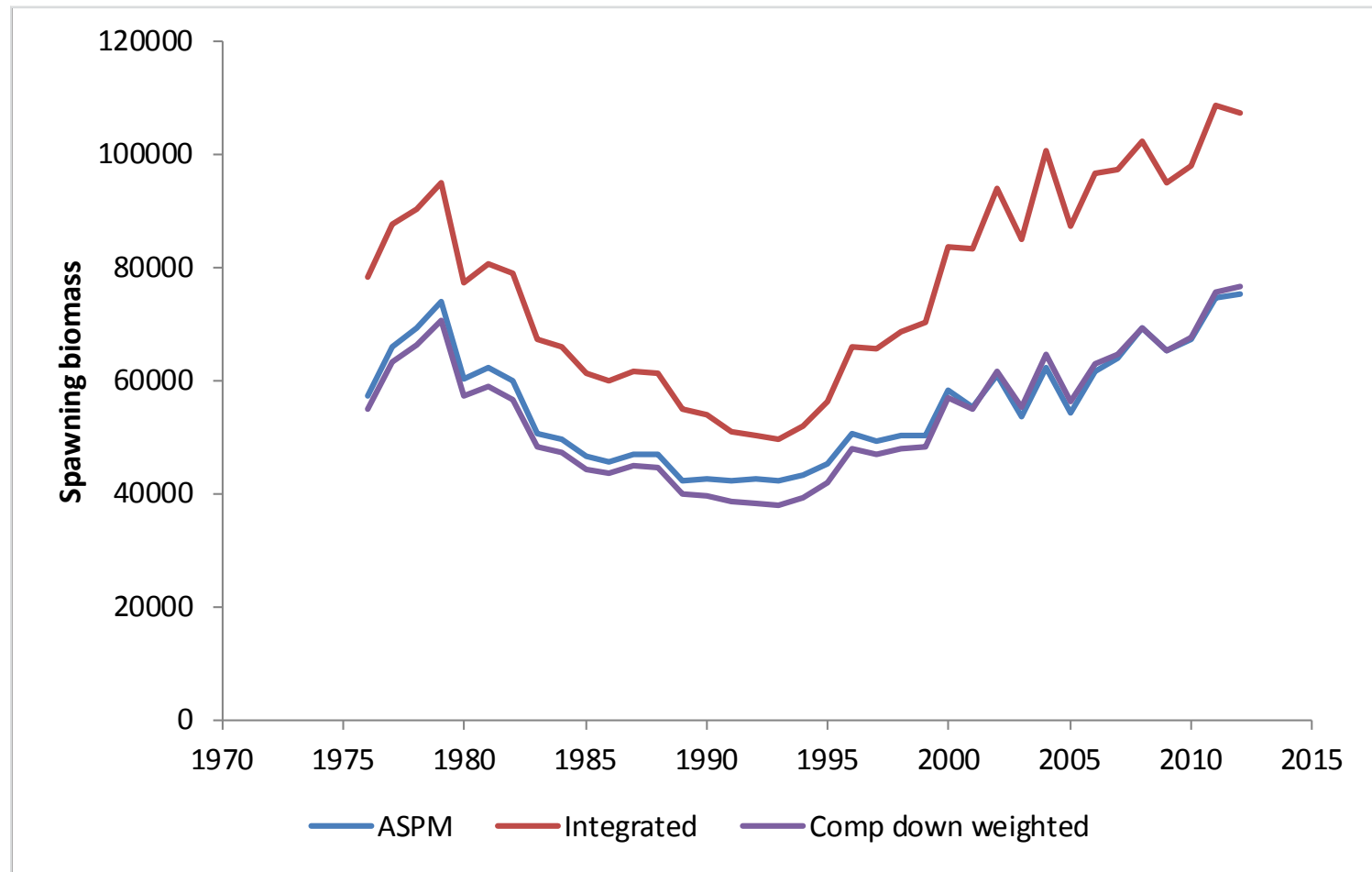
Shape



Temporal variation

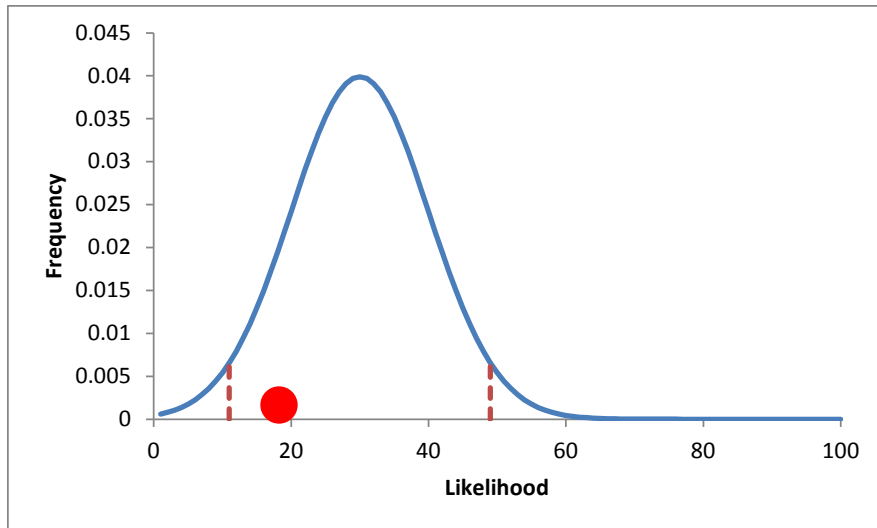


Age-structured Production Model Diagnostic

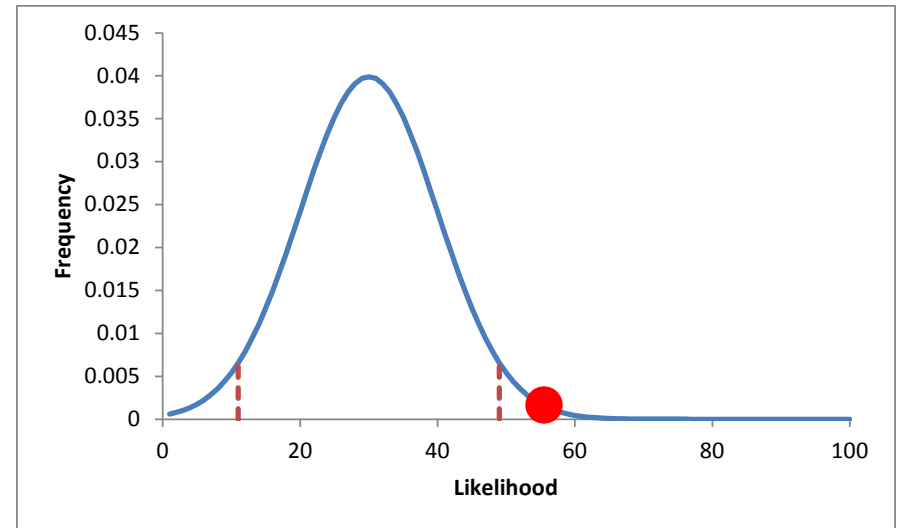


Likelihood distribution

Data 1



Data 2



Retrospective analysis

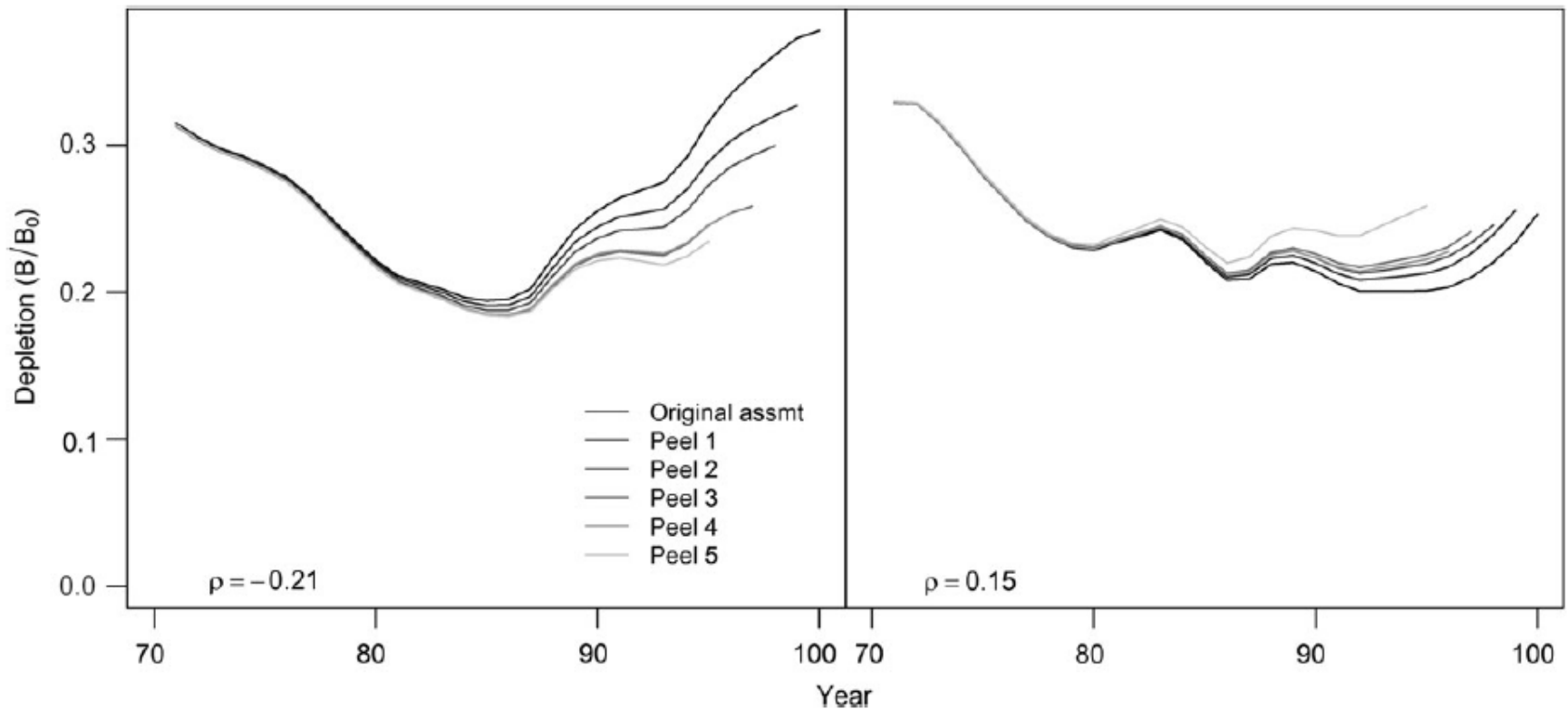


Figure 5. Sample results showing retrospective patterns for cod for fishing mortality “fish down and recovery”. Growth is time varying in the OM, with results for scenario 2 (a; recent, negative, gradual change) and scenario 3 (b; old, positive, gradual change).

Guidelines

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- Guideline 3: Use flexible fishery selectivity curves
- Guideline 4: Model time varying fishery selectivity
- Guideline 5: Estimate composition sampling error from sample design
- Guideline 6: Apply diagnostics to identify model misspecification

Optimal

- Survey index of absolute abundance (or F) (by age).
 - Can we estimate q inside stock assessment or
 - Contrast in index of abundance caused by catch
 - Survey age-composition data
 - Estimate q from non-stock assessment source
- Catch-at-age data for major fisheries
 - growth, selectivity, and recruitment from catch-at-age
- Problem is M and Stock-Recruitment
 - S-R steepness = 1 for many species within range of where you would like the stock to be
 - Is M estimable or do we need tagging data?

- Conclusions
 - Conflicting data indicates model misspecification
 - Down weighting or dropping conflicting data is not necessarily appropriate because it may not resolve the model misspecification.
- Modeling Recommendations
 - Estimate the sampling variance outside the model
 - Model time varying selectivity for all fisheries
 - Use flexible selectivity curves
 - Consider modelling temporal variability in growth if have catch-at-age data
 - Conduct diagnostic tests and model structure and parameter sensitivity analysis to identify possible model misspecification
- Data recommendations
 - Design surveys to have constant asymptotic selectivity
 - Collect age data
 - Estimate M
 - Estimate q

CAPAM research

- Selectivity workshop 2013
- Growth workshop 2014
- Data conflict and weighting, likelihood functions, and process error 2015

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- Numerous researchers for stimulating conversations and ideas
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 - Chris Francis
 - Andre Punt
 - Cleridy Lennert
 - Alexandre Aires-Da-Silva
 - Jim Thorson for inviting me to give the presentation