Age-structured production model and catch curve analysis diagnostics for integrated models

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Virtual workshop on Model Diagnostics in Integrated Stock Assessments

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Age-structure production model

- Proposed by Maunder and Piner (2015)
- Based on the idea of having a good approximation production function (recruitment, growth, natural morality) that can explain changes in the population given the catches

ICES Journal of Marine Science

ICES CIEM International Council for the Exploration of the Sea Conseil International pour l'Exploration de la Mer

ICES Journal of Marine Science (2015), 72(1), 7–18. doi:10.1093/icesjms/fsu015

Original Articles

Contemporary fisheries stock assessment: many issues still remain

Mark N. Maunder[1,2*] and Kevin R. Piner[3]

Age-structure production model

- Proposed by Maunder and Piner (2015)
- Based on the idea of having a good approximation production function (recruitment, growth, natural morality) that can explain changes in the population given the catches
- Importance of estimating the abundance?
  - Will be the basis of total allowable catches (TAC)
- Where does information about abundance comes from?
  - Indices of abundance + catches
  - Other information

Index of relative abundance

- It is assumed to be a function of abundance of the population:

$$I_t = f(B_t)$$

- The simplest assumption is

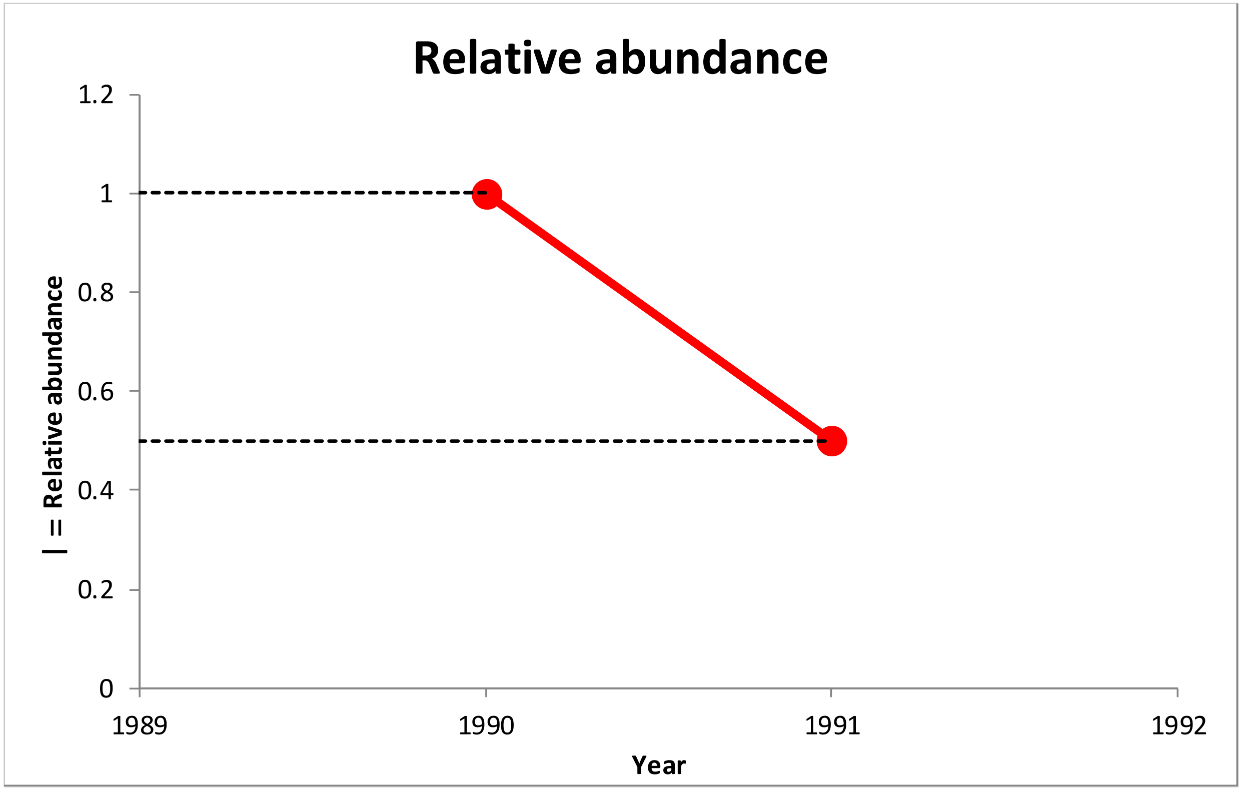
$$I_t = q.B_t$$

The index is directly proportional to the biomass

(q - catchability)

Depletion plot

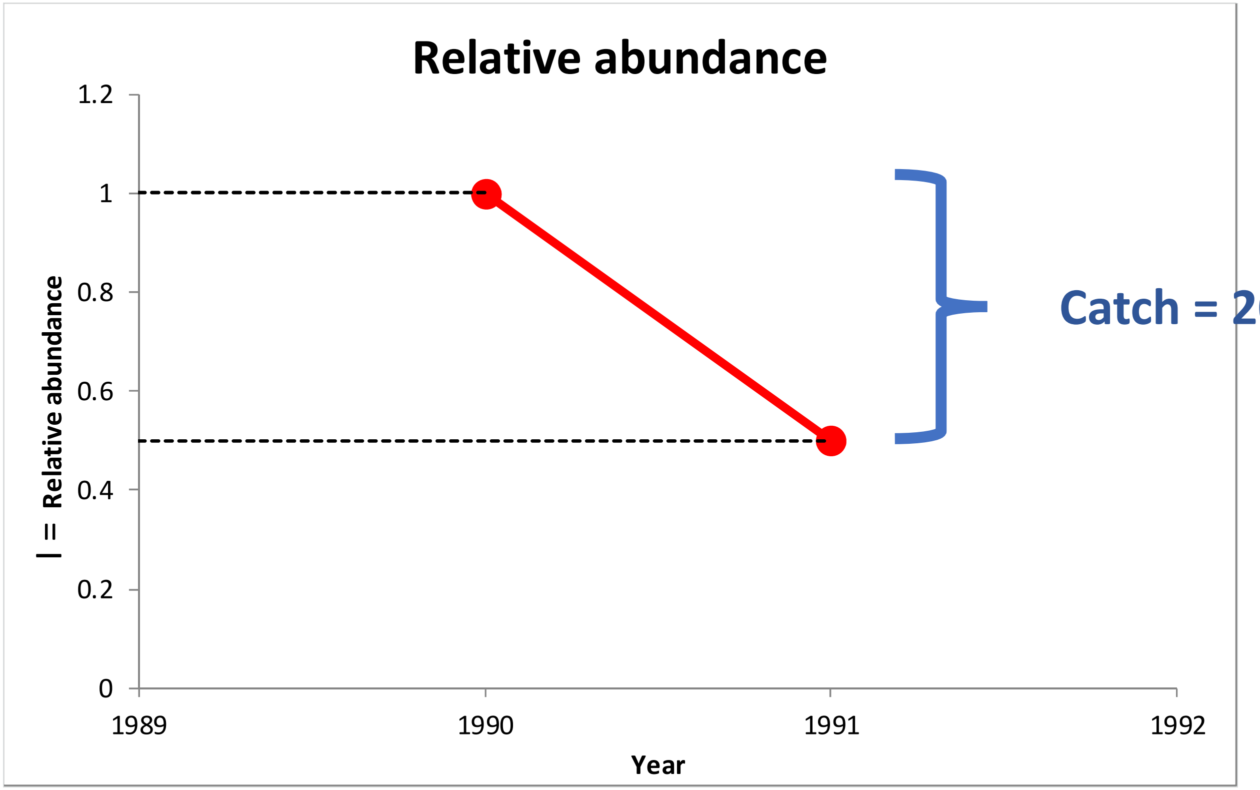
$I_t = q.B_t$



Maunder and Piner (2015)

Depletion plot

It = q.Bt



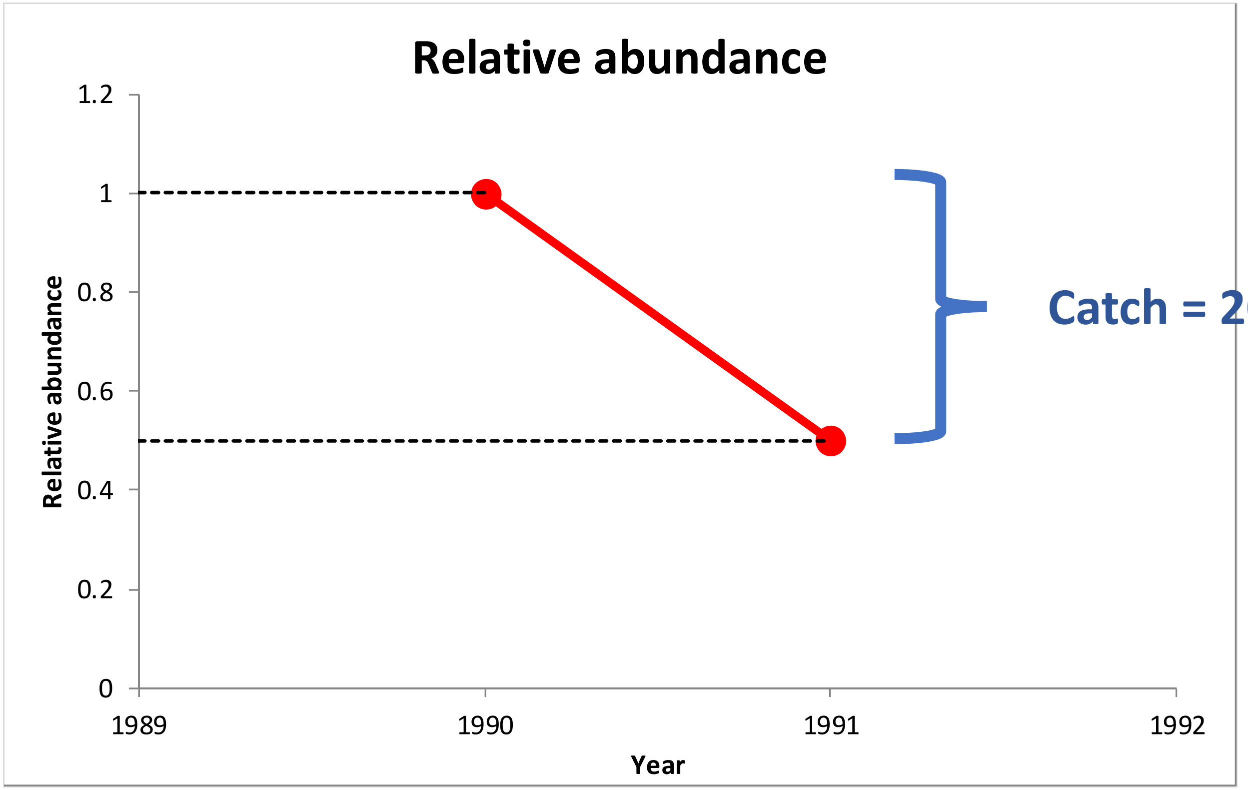
Catch = 200t

Maunder and Piner (2015)

Depletion plot

d = 0.5

d=I*1991* / I*1990* = 0.5 / 1 =0.5

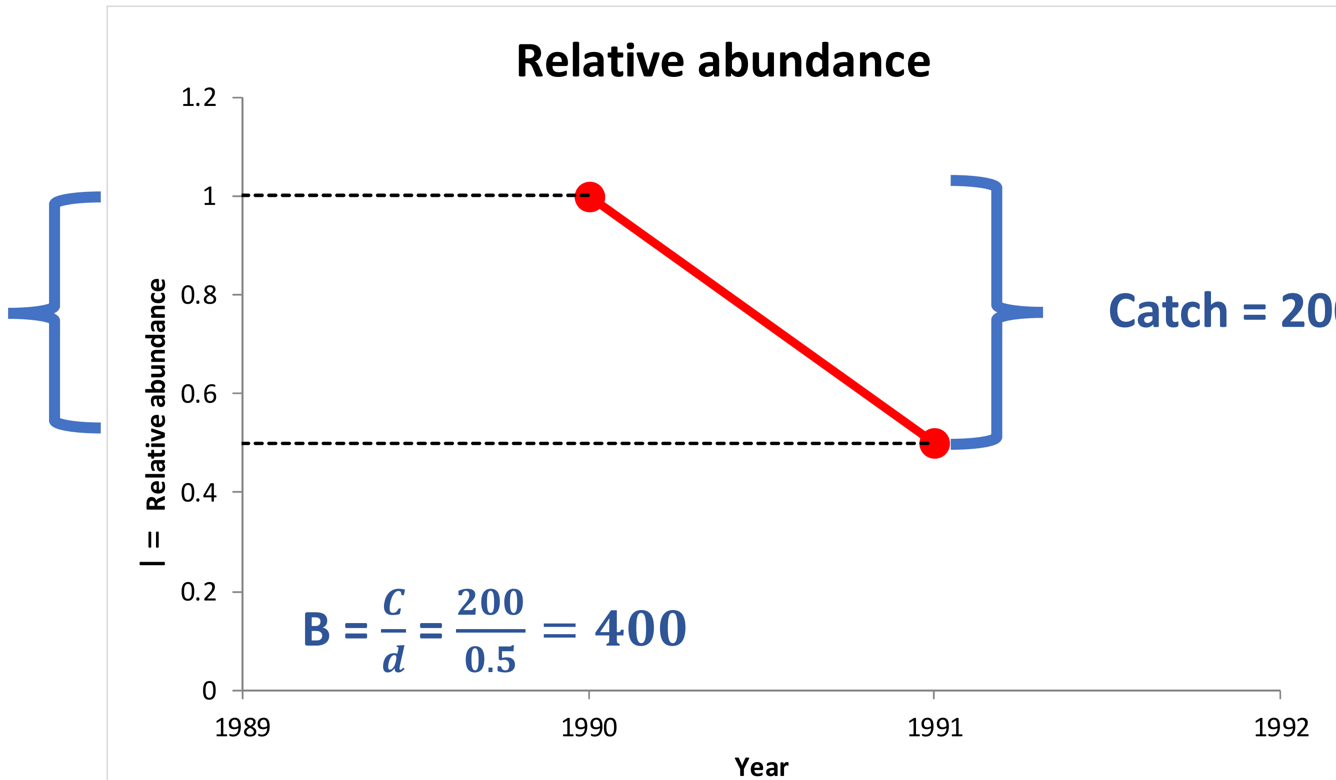


Catch = 200t

Maunder and Piner (2015)

Depletion plot

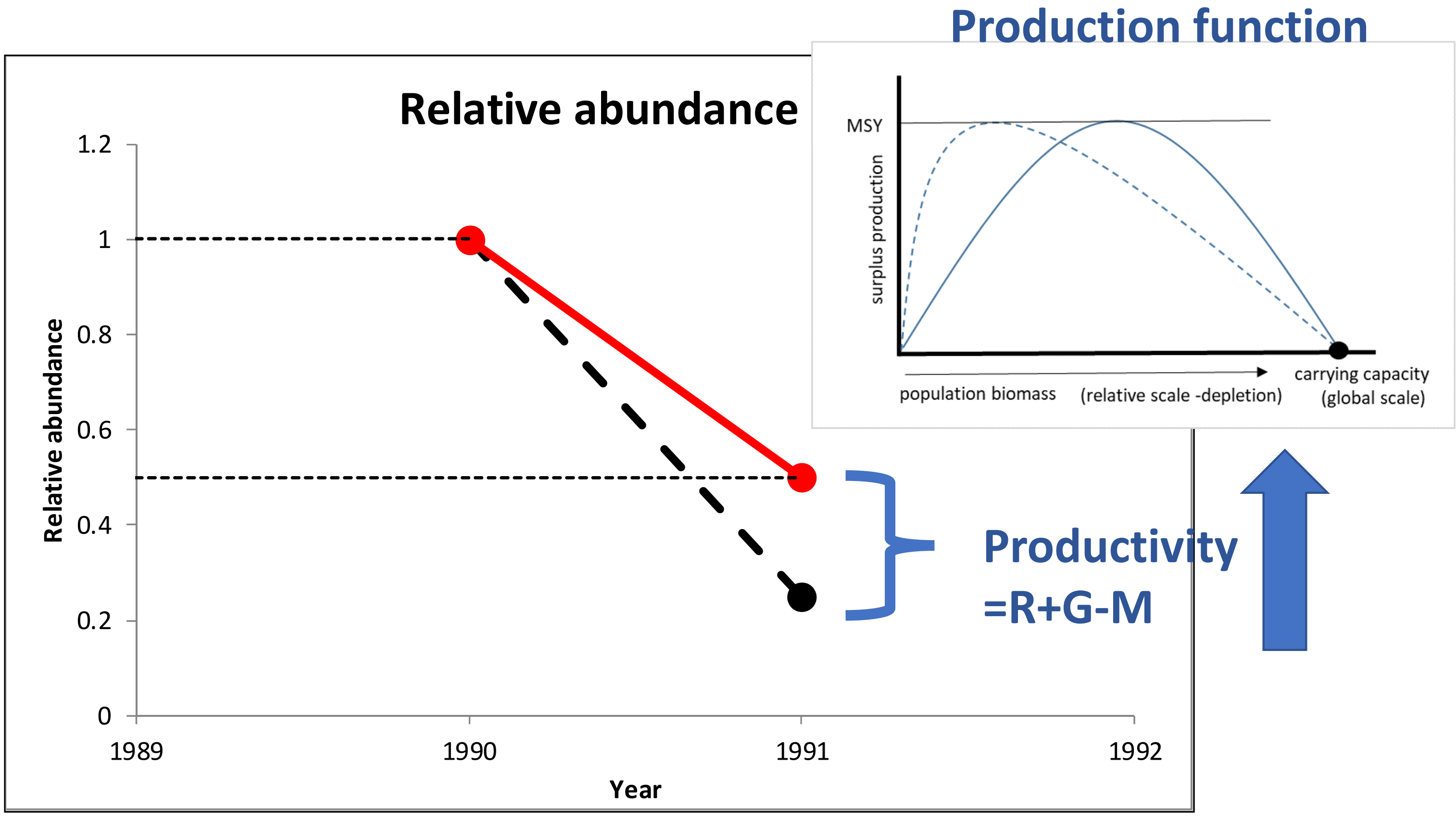
d = 0.5



Catch = 200t

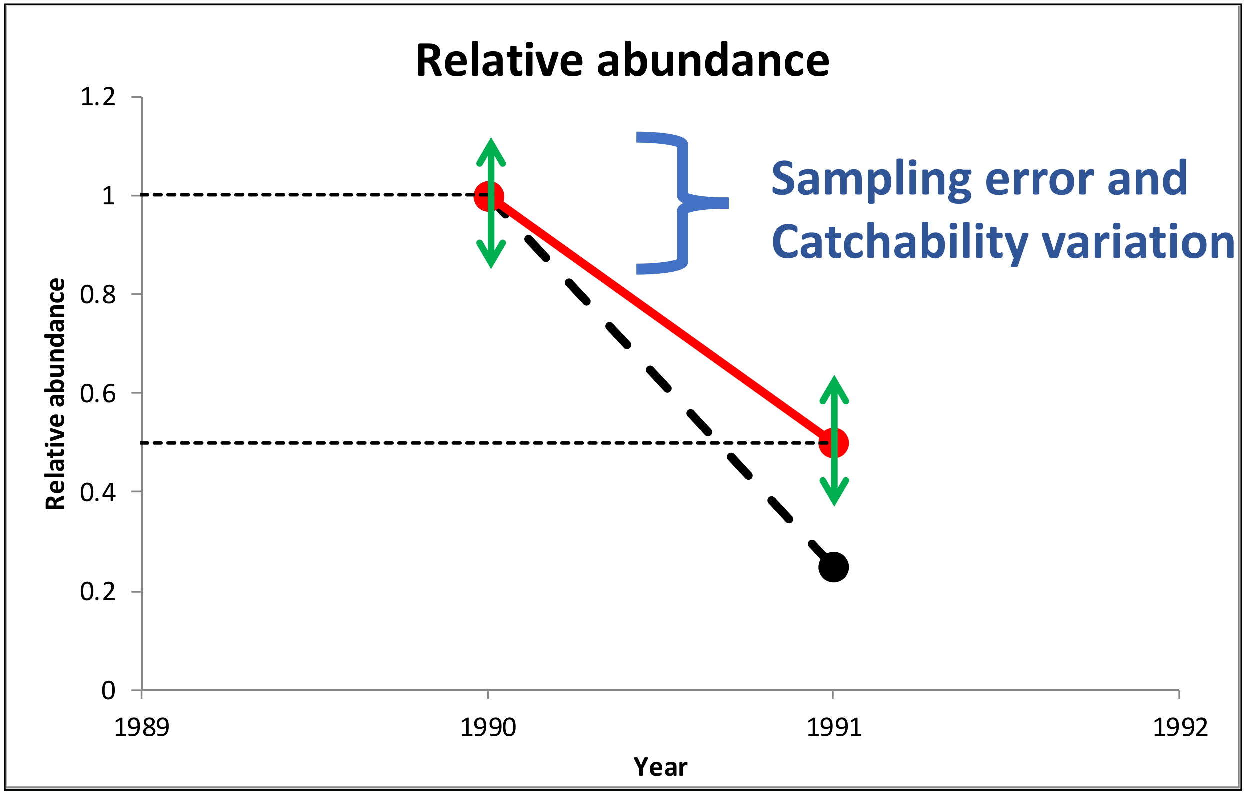
Maunder and Piner (2015)

Depletion plot



Maunder and Piner (2015)

Depletion plot



Maunder and Piner (2015)

Age-structure production model

- Production models have been used since the 1950's, making simplifying assumptions on selectivity and biology, but in right conditions can inform the effect of fisheries by explaining changes indices of abundance from variation in catches (Hilborn and Walters 1999).
- Starting from an integrated model, more realistic and tailored assumptions on selectivity, growth and natural mortality at age (and sex, etc) can be made to build a custom-made age-structure production model

How to compute the ASPM:

(i) run the integrated model;

(ii) fix selectivity parameters at the maximum likelihood estimate (MLE) from the integrated model,

(iii) turn off the estimation of all parameters except the scaling parameters, and set the recruitment deviates to zero (early recruitment and model period recruitments);

(iv) fit the model to the indices of abundance only;

(v) compare the estimated trajectory to the one obtained in the integrated model.

Also look at:

Fisheries Research 240 (2021) 105959

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

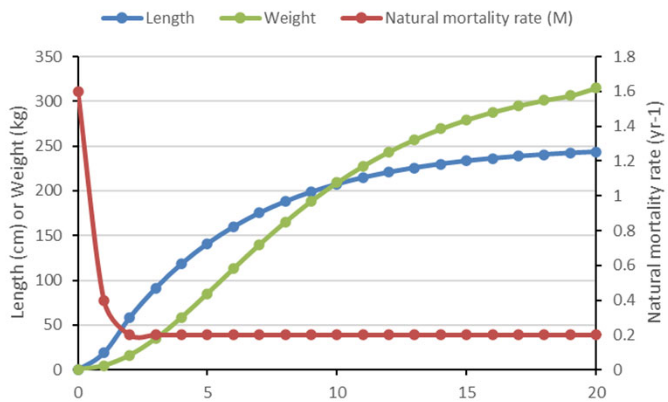
A cookbook for using model diagnostics in integrated stock assessments

Felipe Carvalho[a,*,1], Henning Winker[b,1], Dean Courtney[c], Maia Kapur[d], Laurence Kell[e], Massimiliano Cardinale[f], Michael Schirripa[g], Toshihide Kitakado[h], Dawit Yemane[i], Kevin R. Piner[j], Mark N. Maunder[k,l], Ian Taylor[m], Chantel R. Wetzel[m], Kathryn Doering[n], Kelli F. Johnson[m], Richard D. Methot[m]

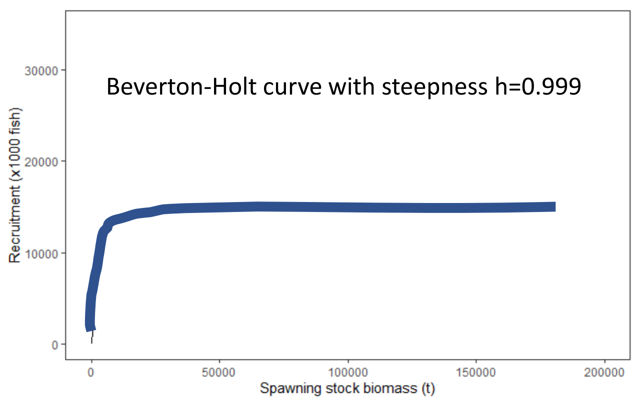
Application 1: Pacific Bluefin Tuna ISC/20/ANNEX/11

Production

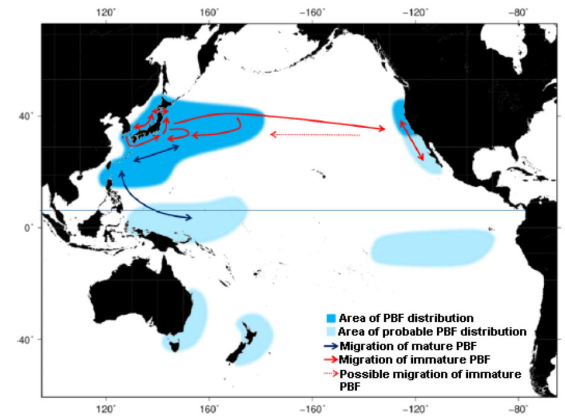
Growth and natural mortality



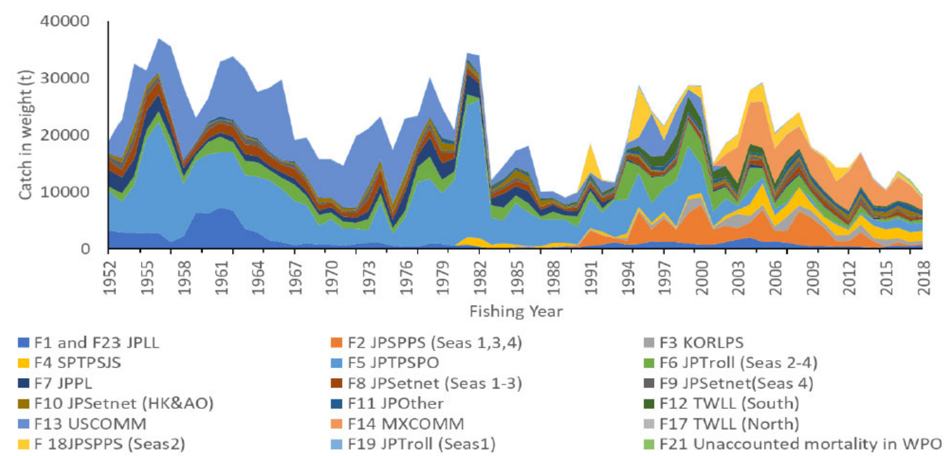
Recruitment



Catches

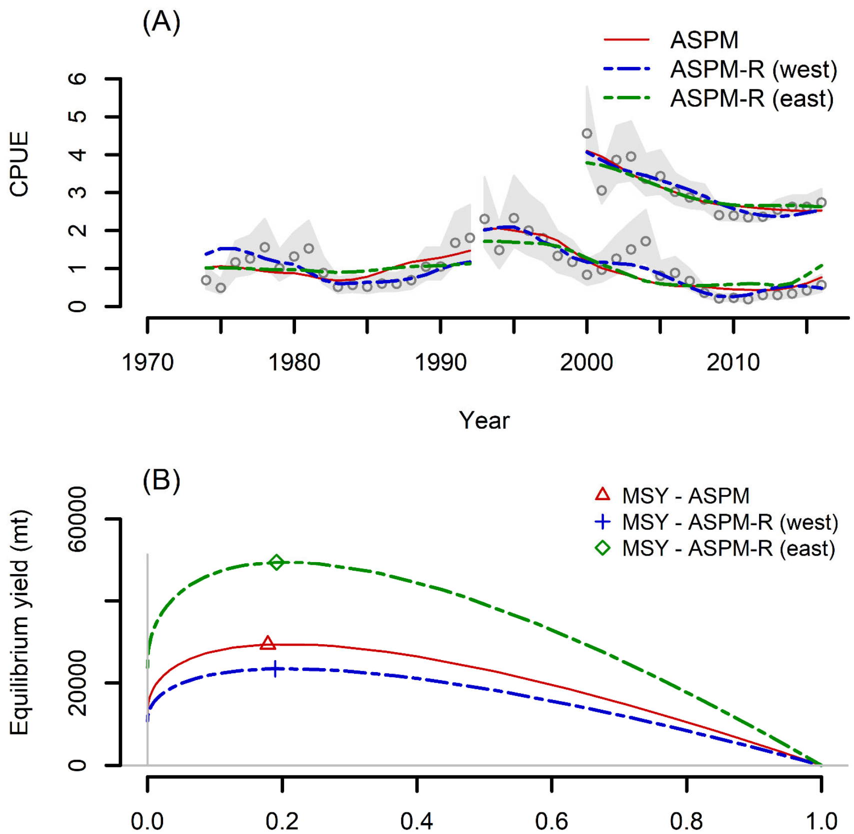


Catches by fishery



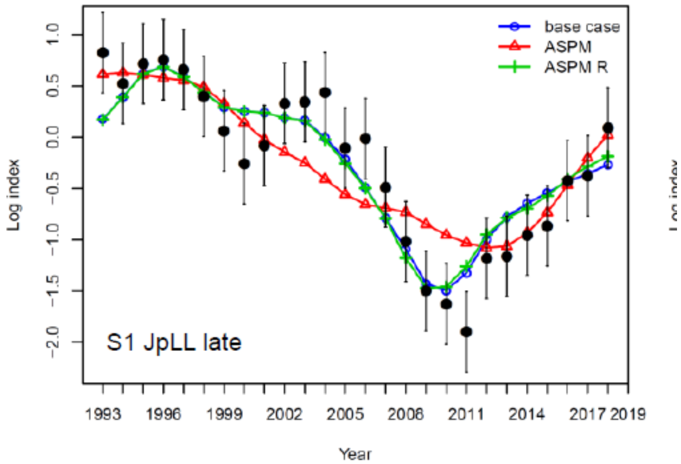
Application 1: Pacific Bluefin Tuna

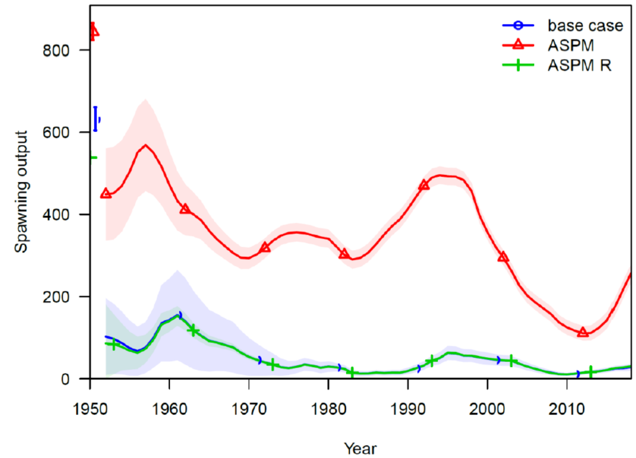
Lee et al (unpublished)



- expand on the simulation study of Carvalho et al. (2017) and use catch, adult population trends from indices of abundance, and the production function from Pacific bluefin tuna, *Thunnus orientalis* (PBF) to evaluate how representative recruitment indices are of the true recruitment variation.
- ASPM also estimated natural mortality , one of the components of productivity
- the alternative recruitment indices can be thought of as providing information on the process variability in the production function
- Use randomization to assess if consistency could appear by chance

Application 1: Pacific Bluefin Tuna





- ASPM fit the adult indices well
- ASPM–R allows for variation in recruitment to match the juvenile index and improved the model fits to all indices

ASPM:

- Process contributing to productivity and selectivity and the catch time series explain the effects of fishing that lead to changes in adult fish indices.
- The **production model effect alone can provide information of the population scale** (unfished stock size).

ASPM-R:

- Recruitment variation further explains the changes in the catches
- There is information in the indices about the variation
- Closer in scale to the integrated model

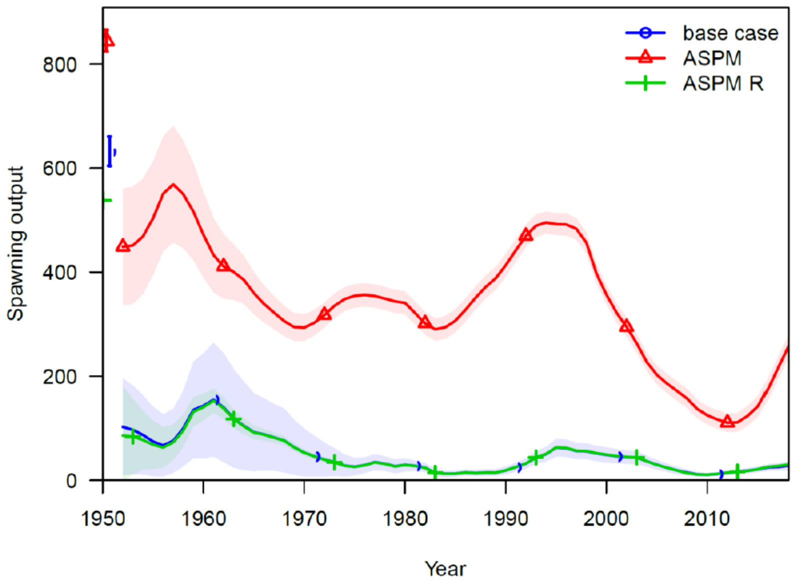
Both:

- The composition data does not determine the results

Application 1: Pacific Bluefin Tuna ISC/20/ANNEX/11

ASPM vs other diagnostics

PASPM



Retrospective analysis

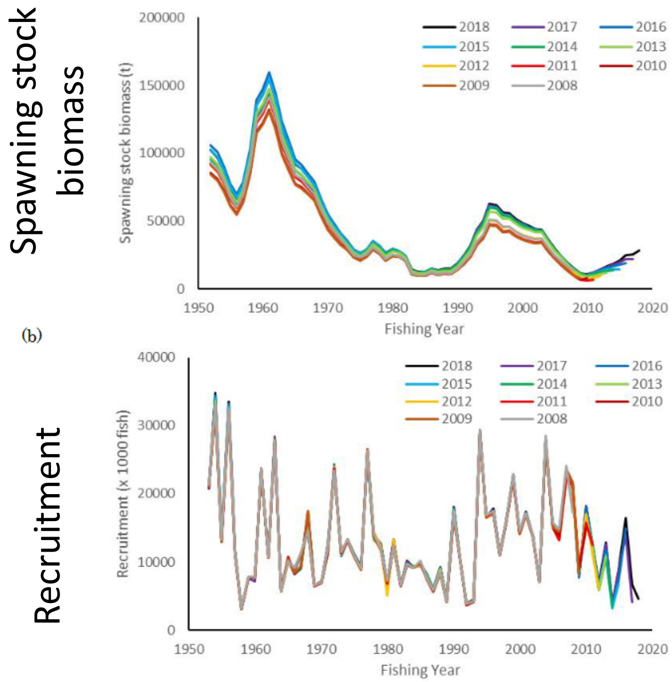
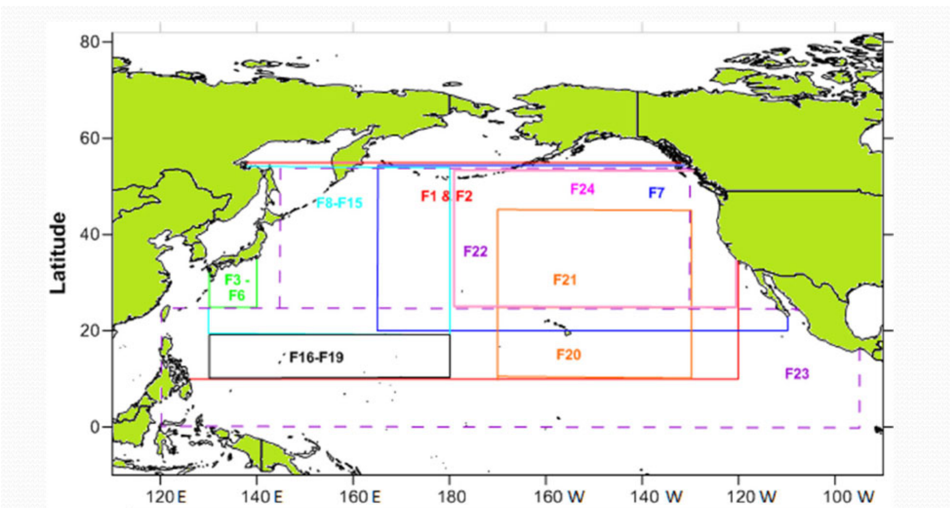


Figure 5-8. Nine-year retrospective analysis of the (a) spawning stock biomass and (b) Recruitment of Pacific bluefin tuna (*Thunnus orientalis*) from the base-case.

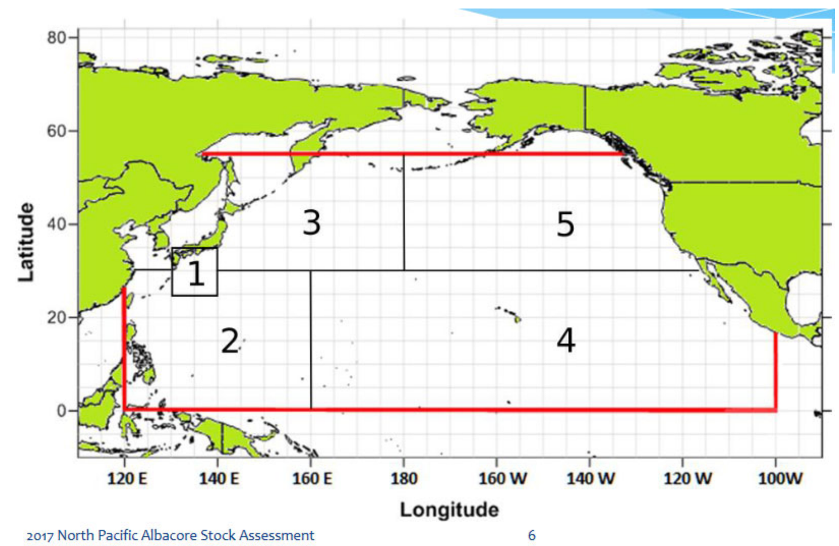
Application 2: North Pacific albacore tuna

2014 Assessment



- Fisheries based on distribution of fleets
- Model fit to 4 indices (JPN LL)

2017 Assessment



- Areas based on **conceptual model for the stock** and cluster analysis of size composition data
- Age selectivity used as proxy for movement (availability)
- Length selectivity used to model gear contact
- Model fit to 1 index (JPN area 2)

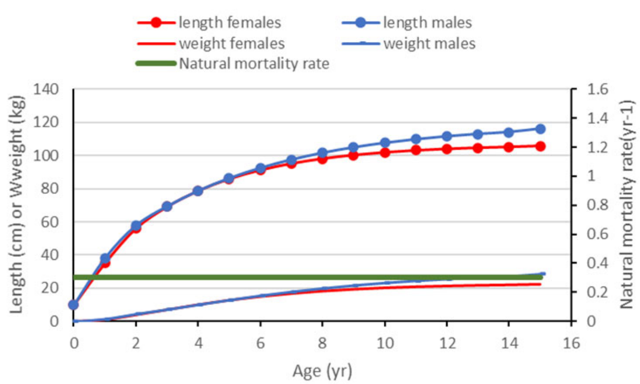
Application 2: North Pacific albacore tuna

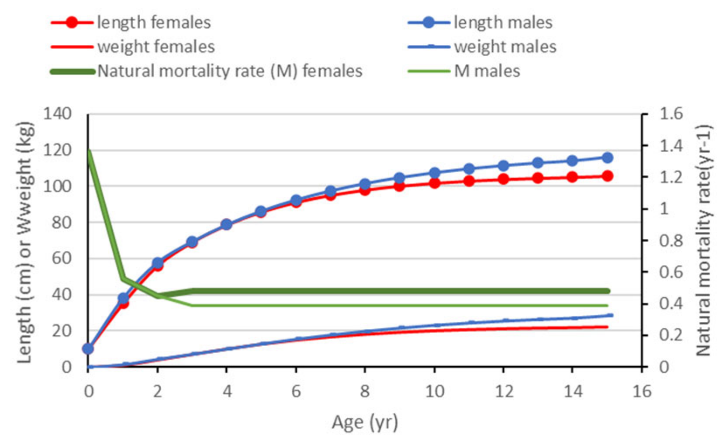
2014 Assessment

2017 Assessment

Production

Growth and natural mortality



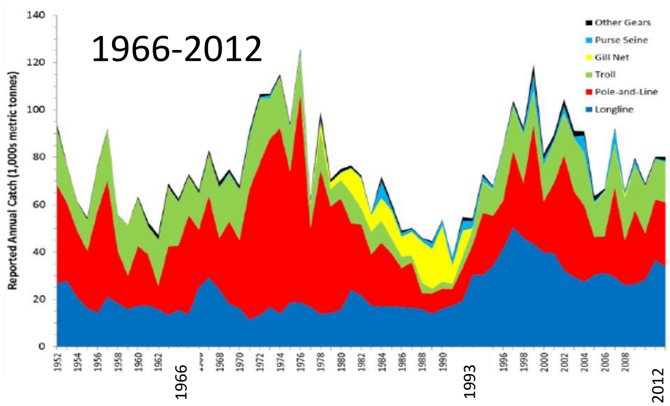


Recruitment

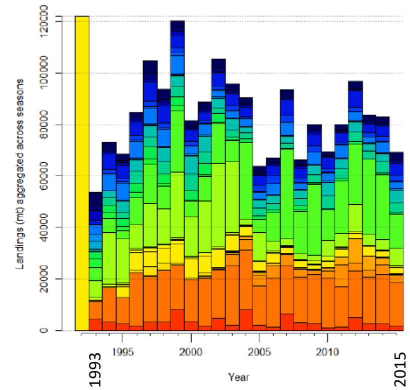
Beverton-Holt curve with steepness h=0.90

Beverton-Holt curve with steepness h=0.90

Catches

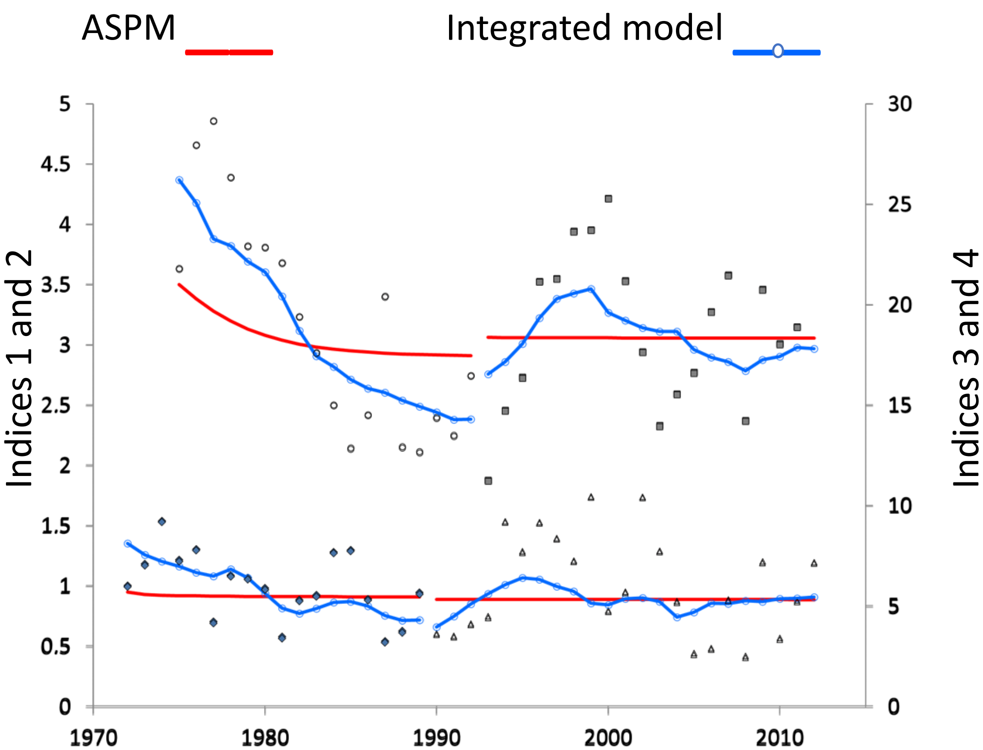


1993-2015

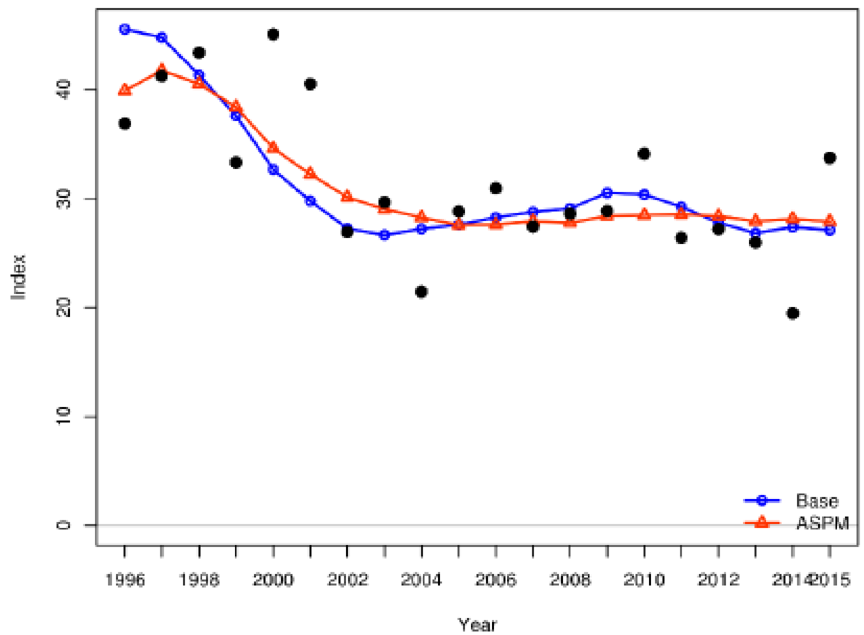


Application 2: North Pacific albacore tuna

2014 Assessment

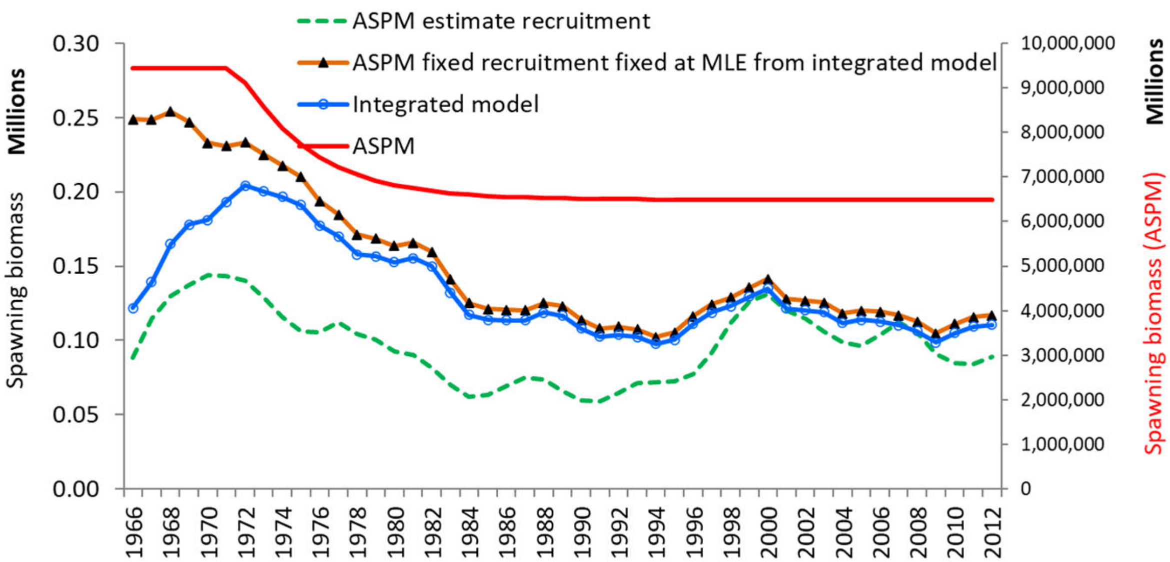


2017 Assessment



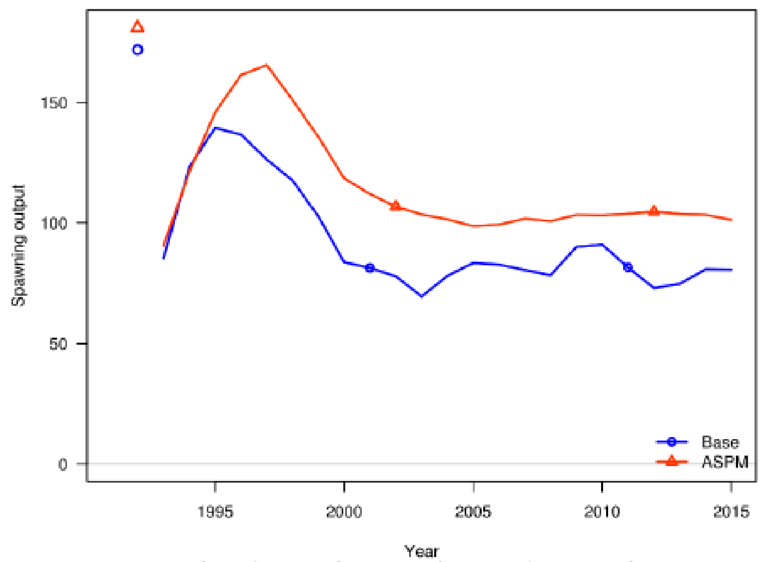
Application 2: North Pacific albacore tuna

2014 Assessment



- ASPM scale completely off
- ASPM- dev and ASPM-fix with similar scales to the integrated model, process error need to fit the data

2017 Assessment



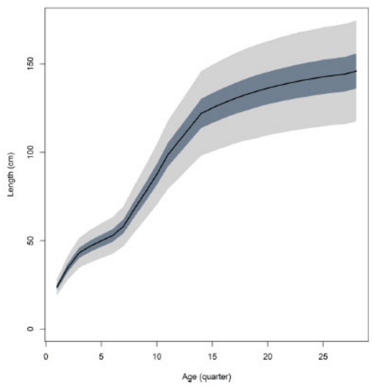
- ASPM had similar scale and populations trends to integrated model
- Fixed production processes catches able to explain the index
- No need for addition of process error (changes in productivity)

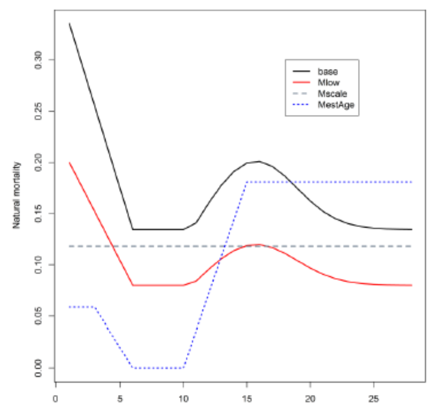
Application 4: Indian Ocean Yellowfin

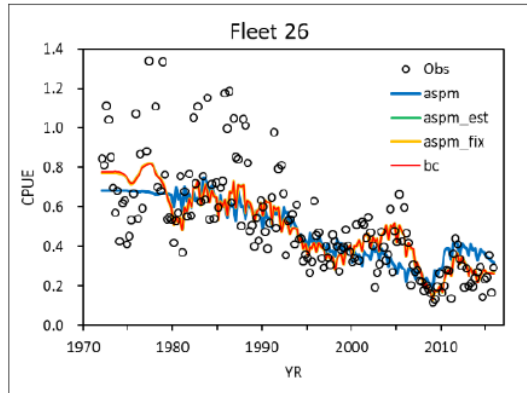
IOTC-2018-WPTT20-42-Rev 1

Production

Growth and natural mortality



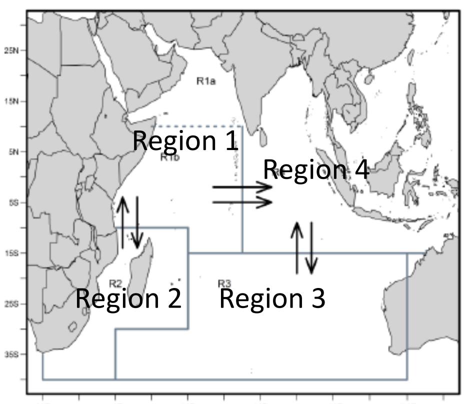


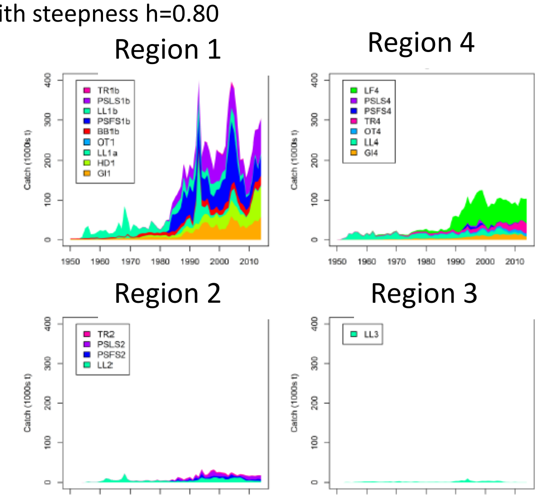


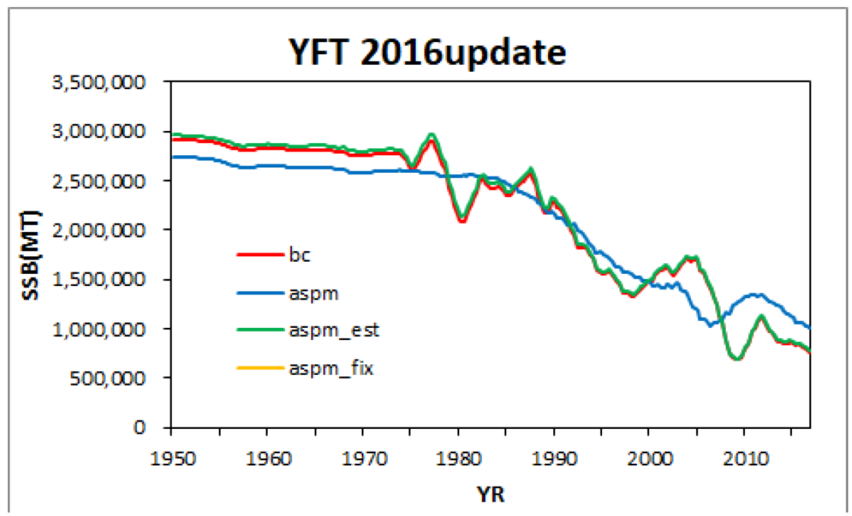
Recruitment

Beverton-Holt curve with steepness h=0.80

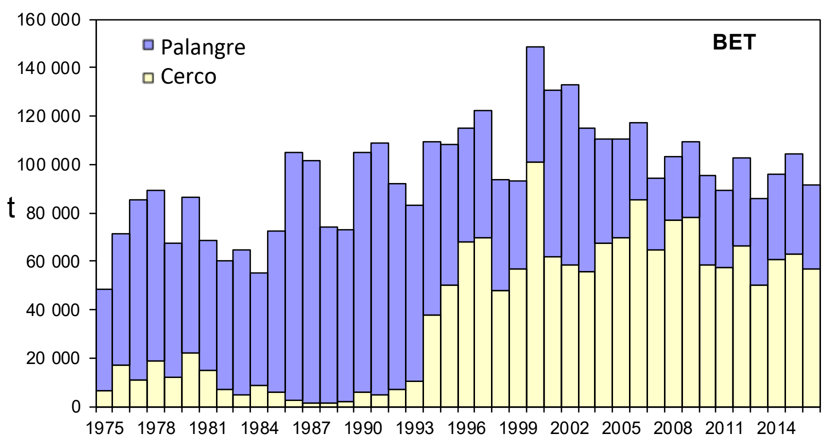
Catches

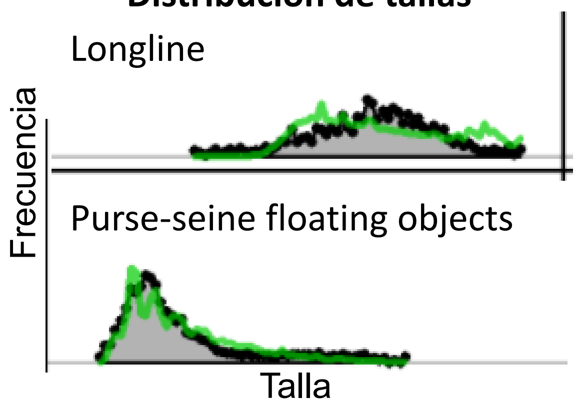


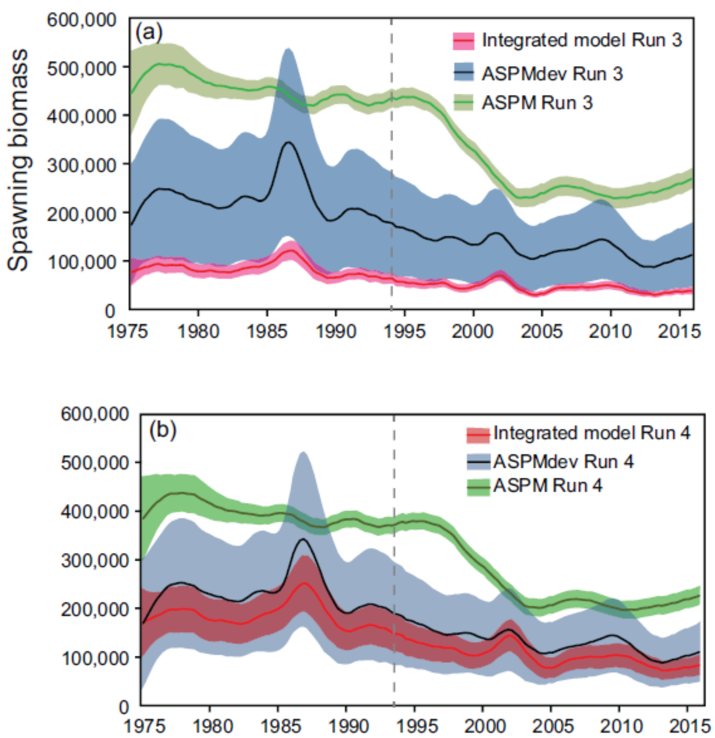




Application 5: Bigeye tuna in the Eastern Pacific Ocean







L2= 196 cm

L2= 183 cm

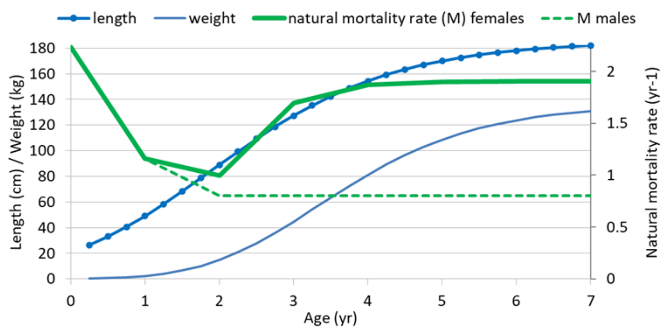
http://dx.doi.org/10.1016/j.fishres.2017.01.014

CIAT IATTC

Application 5: Yellowfin tuna in the Eastern Pacific Ocean

Production

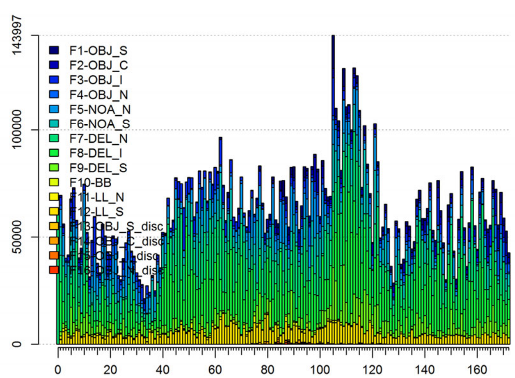
Growth and natural mortality



Recruitment

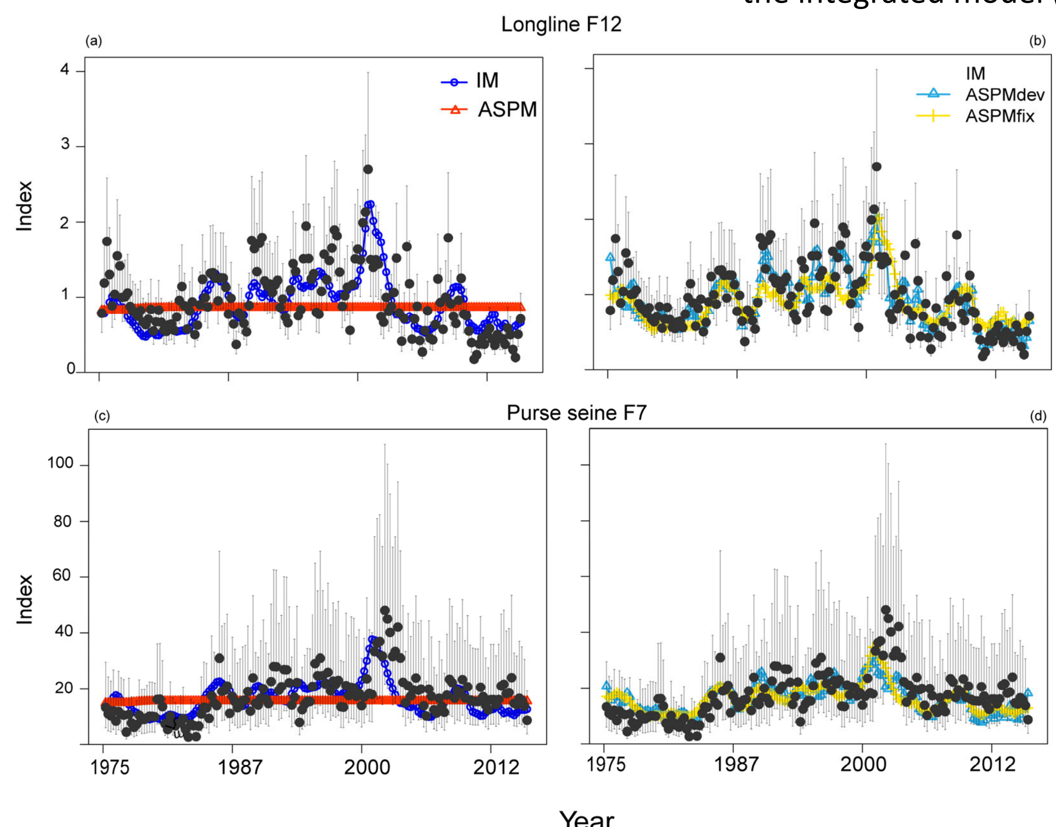
Beverton-Holt curve with steepness h=1

Catches



1975 quarter 2016

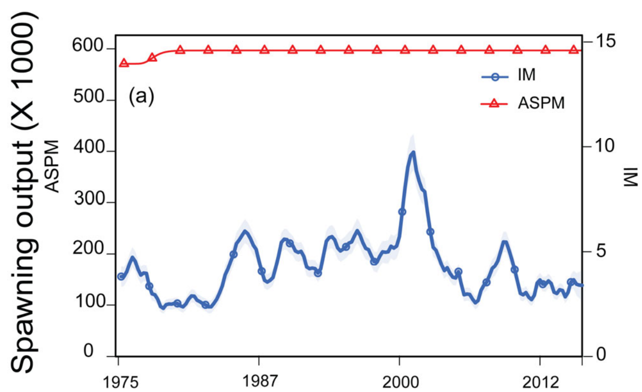
- ASPM:
  - does not fit the indices
- ASPMdev:
  - fit the indices as well as the integrated model (IM)



ICES Journal of Marine Science (2021), https://doi.org/10.1093/icesjms/fsab213

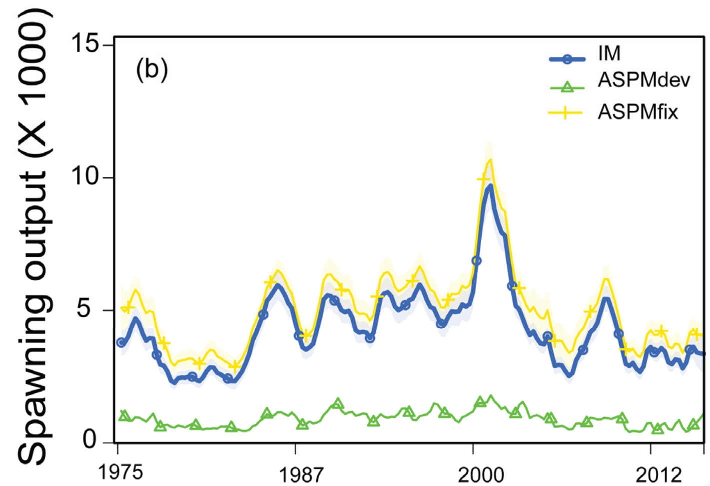
Application 5: Yellowfin tuna in the Eastern Pacific Ocean

- ASPM:
  - does not fit the indices
  - does not capture the relative trends
  - estimates a absolute abundance orders of magnitude larger tan the IM

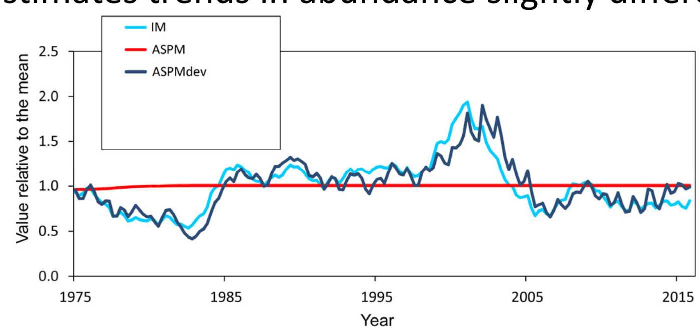


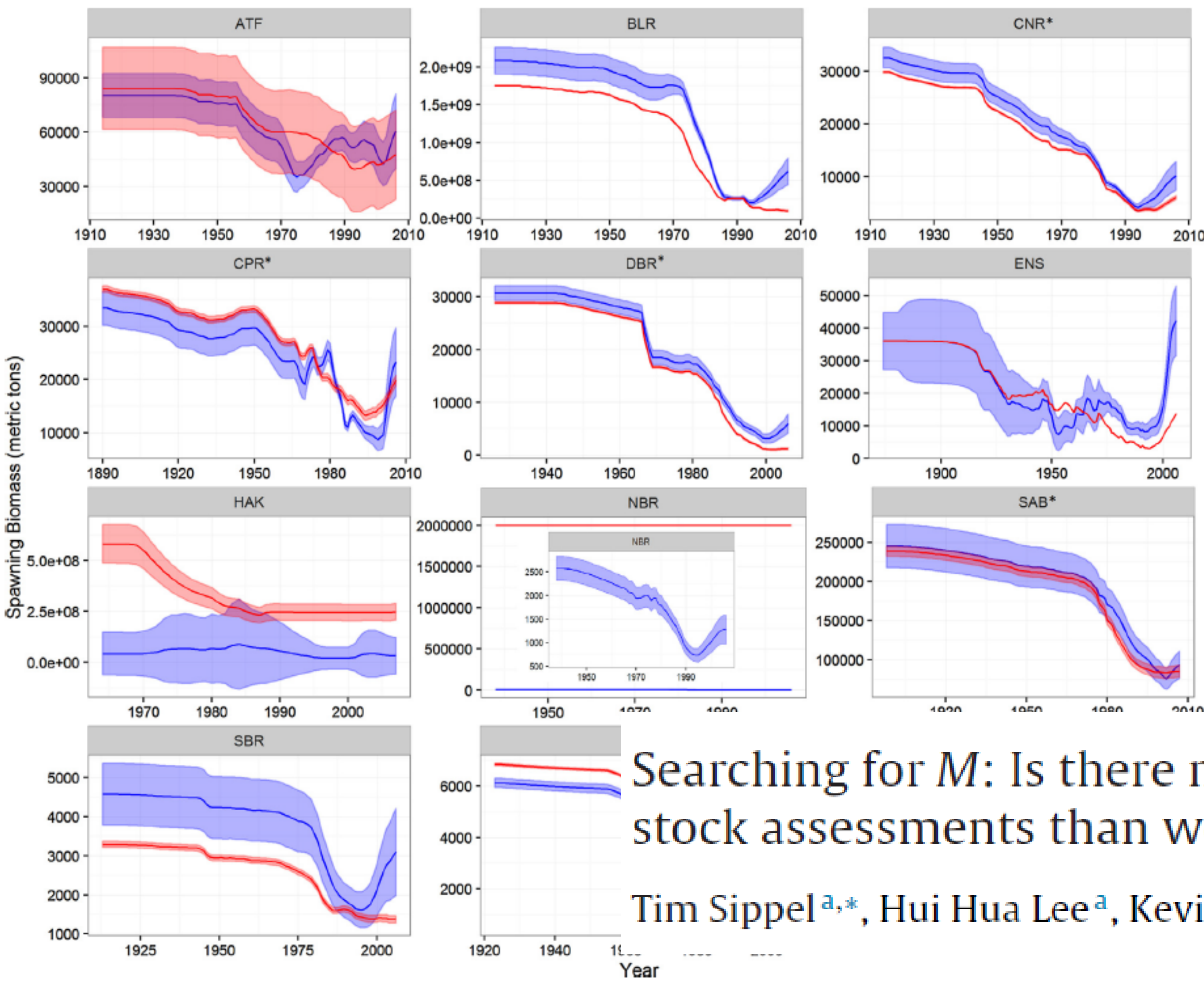
ICES Journal of Marine Science (2021), https://doi.org/10.1093/icesjms/fsab213

- ASPMdev:
  - fit the indices as well as the integrated model (IM)
  - estimates a smaller absolute abundance



- estimates trends in abundance slightly different the IM





Species	Abbr.	Ability to estimate M (Lee et al., 2011)	Correlation ΔSSB (final 20 yrs)	Average Normalized Absolute Difference (final 20 yrs)	Pr ov
Arrowtooth Flounder[a]	ATF	Weak/Weak (female/male)	0.52	0.15	1.(
Blue Rockfish[a]	BLR	Moderate/Strong (female/male)	0.13	0.25	0.3
Canary Rockfish[b]	CNR	Weak/Moderate (old/young)	0.94	0.17	0.3
Chillipepper Rockfish	CPR	Strong	0.72	0.16	0.2
Darkblotched Rockfish	DBR	Strong	0.95	0.21	0
English Sole	ENS	Weak	0.75	0.24	0
Hake[b]	HAK	Weak/Weak (old/young)	0.06	3.01	0
Northern Black Rockfish[b]	NBR	Weak/Moderate (old/young)	NaN	1565	0
Sablefish	SAB	Weak	0.71	0.08	1.0
Southern Black Rockfish[b]	SBR	Weak/Weak (old/young)	0.36	0.19	0.7
Yelloweye Rockfish	YER	Moderate	0.95	0.09	0.3

Searching for *M*: Is there more information about natural mort stock assessments than we realize?

Tim Sippel[a,*], Hui Hua Lee[a], Kevin Piner[b], Steven L.H. Teo[b]

Fig. 1. Comparisons of median trajectory of spawning biomass (SSB) estimated from the ASPM (blue line) and the final integrated assessment model (red line) for each stock, including 95% confidence intervals. SSB scale differences in NBR were too large to elucidate the contrasting trends from the ASPM (flat trend) and assessment (two-way trip

ASPM, what it can do:

- Understand if the changes in the index of abundance can be explained by the changes in the catches given the fixed selectivities, fixed biology and constant recruitment.
- Assess whether there is enough information in the IM to estimate the relative abundance and absolute scale of abundance.
- Assess whether there is model misspecification.
- Evaluate the information about absolute abundance in the relative index of abundance without the influence of composition data.
- Assess whether the population trend estimated by the integrated model is mainly fishery-driven (ASPM) or recruitment-driven (ASPM-Rdev)
- Assess whether additional information on recruitment is needed to estimate abundance

ASPM – simulation testing

Table 7
Percentage of models identified as misspecified by each diagnostic test under different scenarios.

	Self test	Misspecification in selectivity
Diagnostic	CSM(%)	EM_1(%)
SDNR	5	79
Runs test	6	51
ASPM	4	9
Retrospective analysis	0	11
R_o Likelihood component profile	4	5
CCA	91	92

Expected is 5% (Type I error - falsely rejecting a correctly specified model)

Power, expected is large (e.g. 80%, then Type II error = 20% falsely accepting a misspecified model)

Identification of misspecification defined as: SSBterm/SSBinit from an ASPM (or CCA) for an EM fell outside the (asymptotic) 95% CI of its corresponding fully-integrated model

http://dx.doi.org/10.1016/j.fishres.2016.09.018

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ELSEVIER

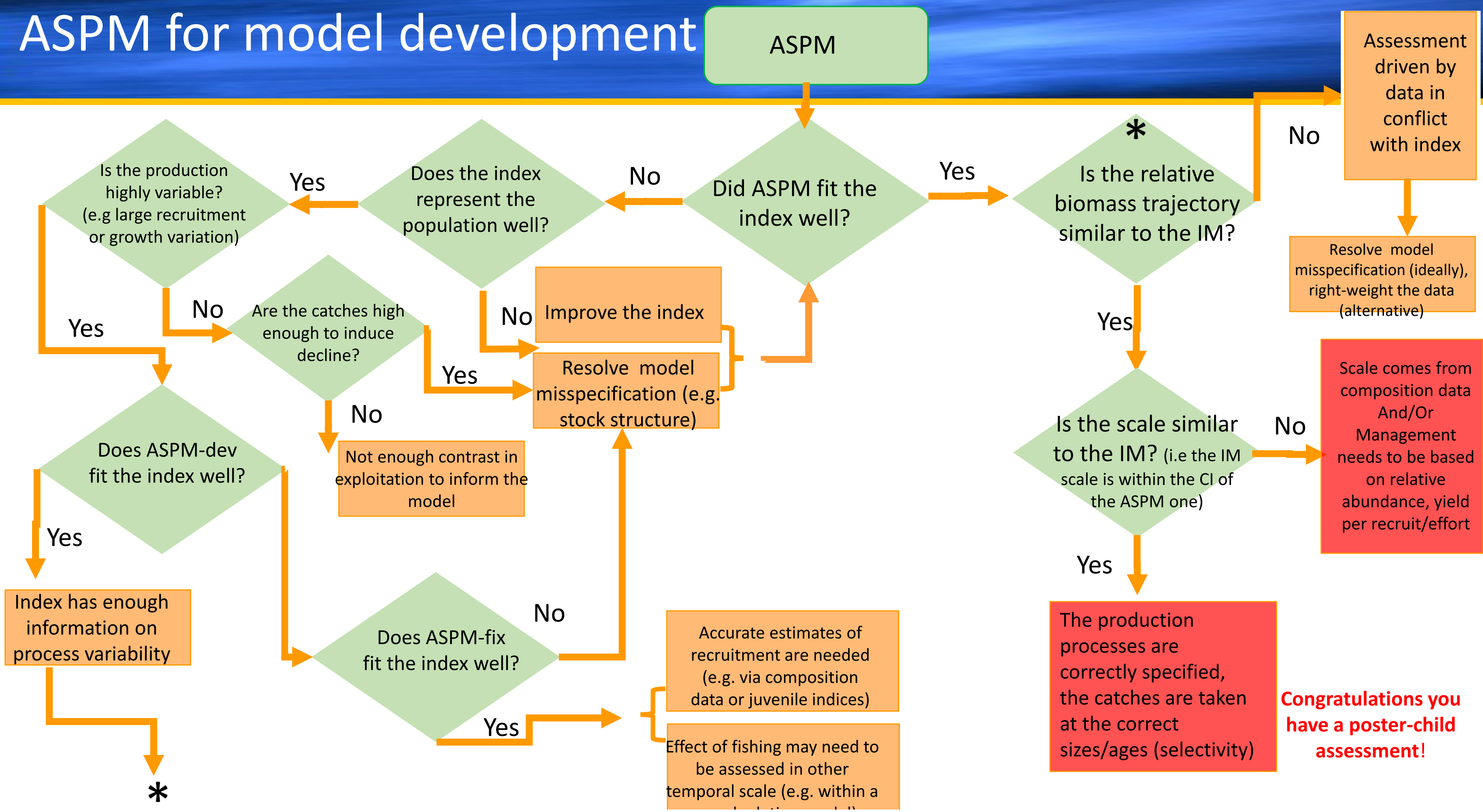
Full length article

Can diagnostic tests help identify model misspecification in integrated stock assessments?

CrossMark

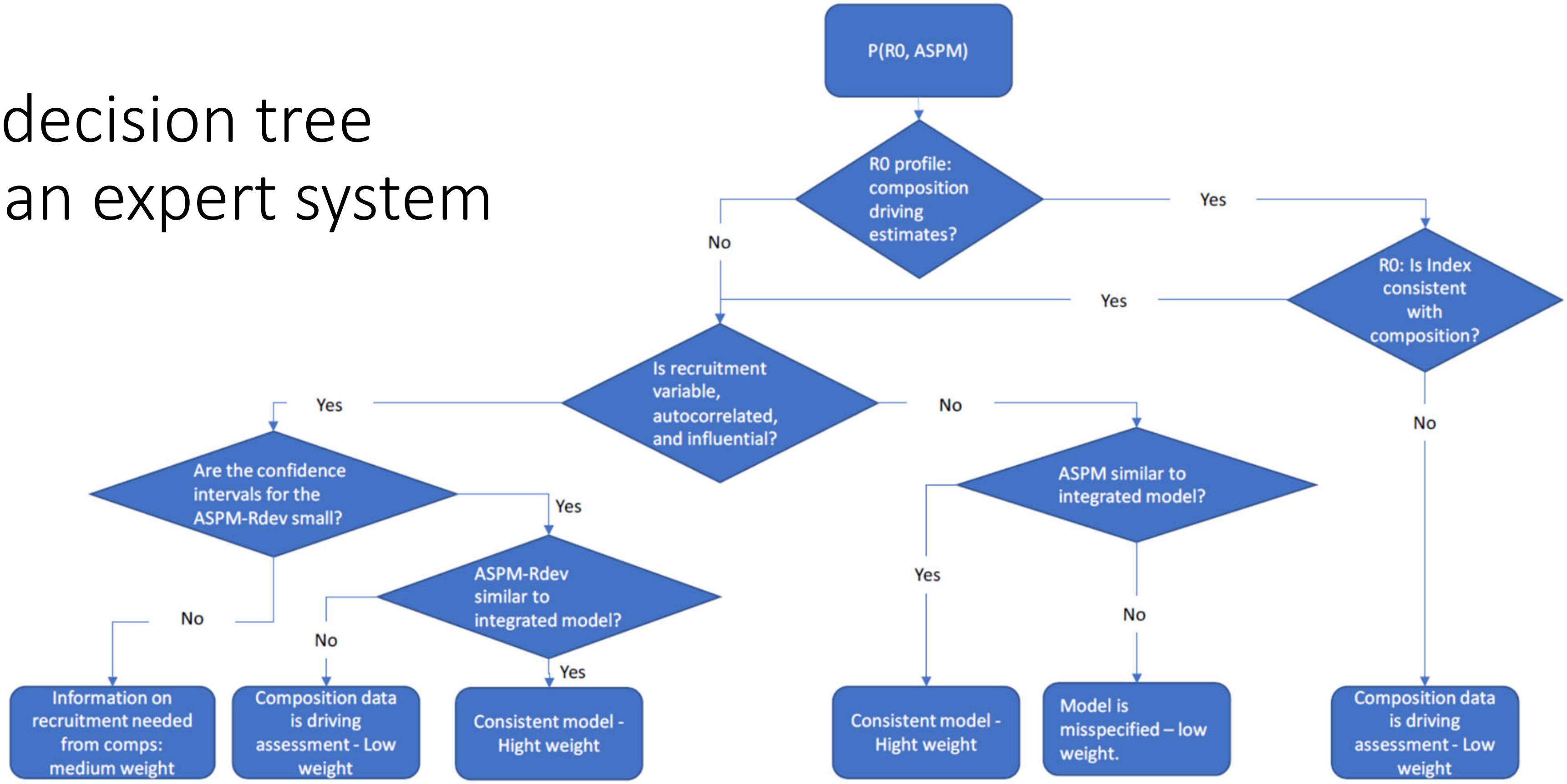
Felipe Carvalho[a,b,*], André E. Punt[c], Yi-Jay Chang[d], Mark N. Maunder[e,f], Kevin R. Piner[g]

ASPM for model development



ASPM for model weighting / hints on combining diagnostics

A decision tree
is an expert system



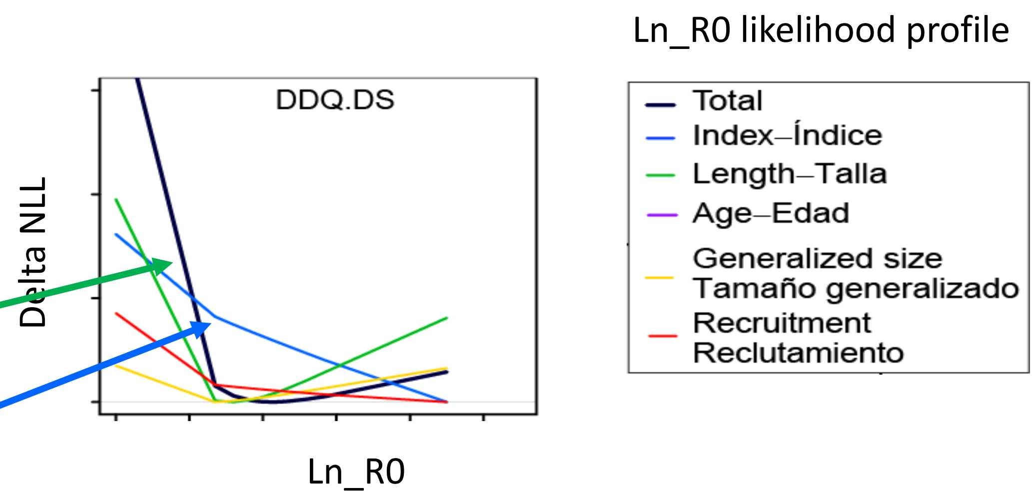
Maunder et al. 2020. Implementing reference point-based fishery harvest control rules within a probabilistic framework that considers multiple hypotheses. IATTC Document SAC-11 INF-F REV

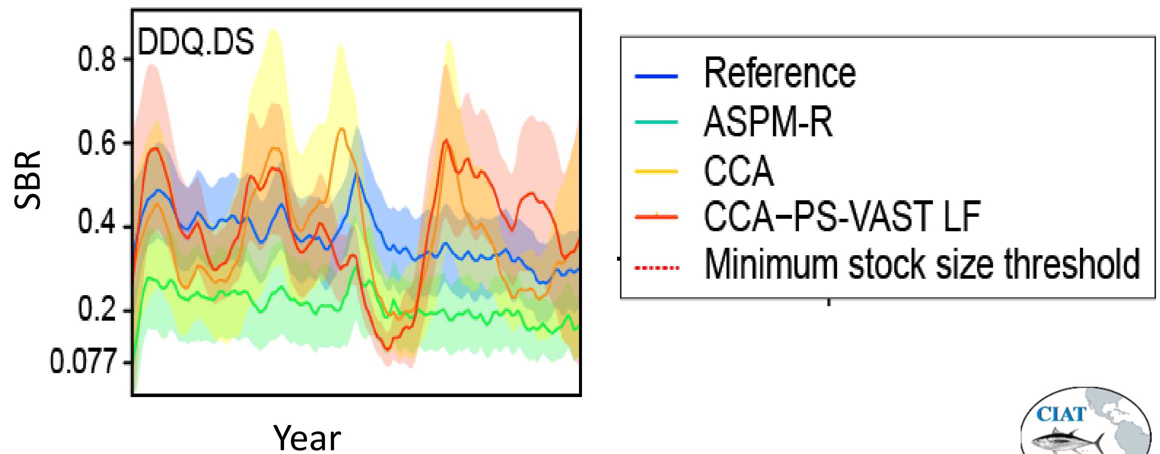
ASPM for model weighting W(ASPM, R0 profile, CCA)

Weight:

LOW

- R0 profile:
  - Length frequencies control estimates
  - The index is **NOT** consistent with the sizes
- ASPM-R, CCA:
  - Recruitment is variable
  - ASPM-R confidence intervals are not small
  - The information in the length frequencies is necessary to estimate recruitment

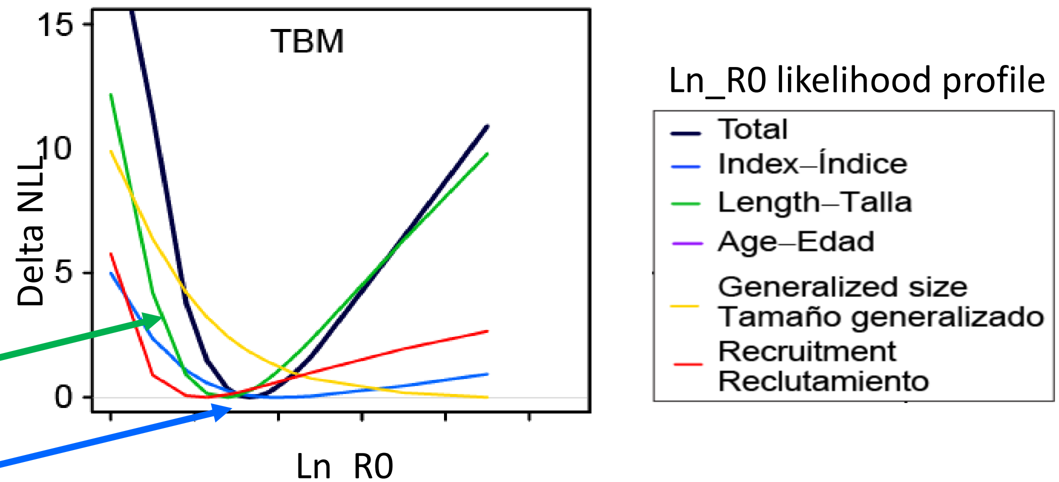




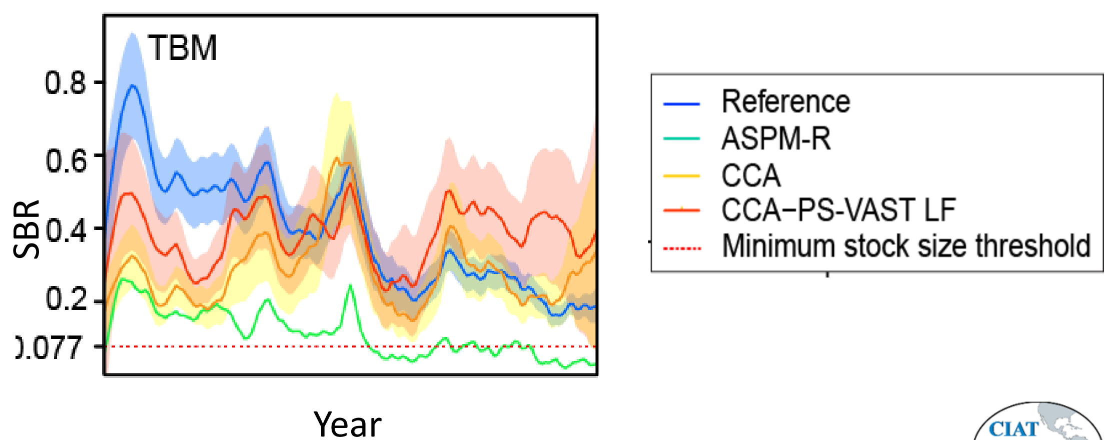
ASPM for model weighting W(ASPM, R0 profile, CCA)

Weight

MEDIUM



- Perfil de R0:
  - Length frequencies control estimates
  - The index **IS** consistent with the length
- ASPM-R, CCA:
  - Recruitment is variable
  - ASPM-R confidence intervals are not small (there was no Hessian matrix, variation is considered to be large)
  - The information in the length frequencies is necessary to estimate recruitment



Questions for further research

- What does in means if the uncertainty estimate for derived quantities (*e.g.* spawning stock biomass) in the ASPM is low (tight confidence intervals)?
- Does the confidence interval (CI) for derived quantities from the ASPM should contain the CI from the IM for the IM to be considered a good model (pass)?
- What metric could be used to quantify good diagnostic vs bad diagnostic?

Catch-curve analysis

- Proposed by Carvalho et al 2017
- Based on the idea of “catch curve”: exponential decline of numbers at age

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Full length article

Can diagnostic tests help identify model misspecification in integrated stock assessments?

CrossMark

Felipe Carvalho[a,b,*], André E. Punt[c], Yi-Jay Chang[d], Mark N. Maunder[e,f], Kevin R. Piner[g]

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Catch-curve analysis

- Proposed by Carvalho et al 2017
- Based on the idea of “catch curve”: exponential decline over numbers ay age
- Importance of estimating the abundance?
  - Will be the basis of total allowable catches (TAC)
- Where does information about abundance comes from?
  - Indices of abundance + catches (ASPM)
  - Age and length composition data + catches

Basic concepts

Fishing mortality ≈ Catches/Biomass

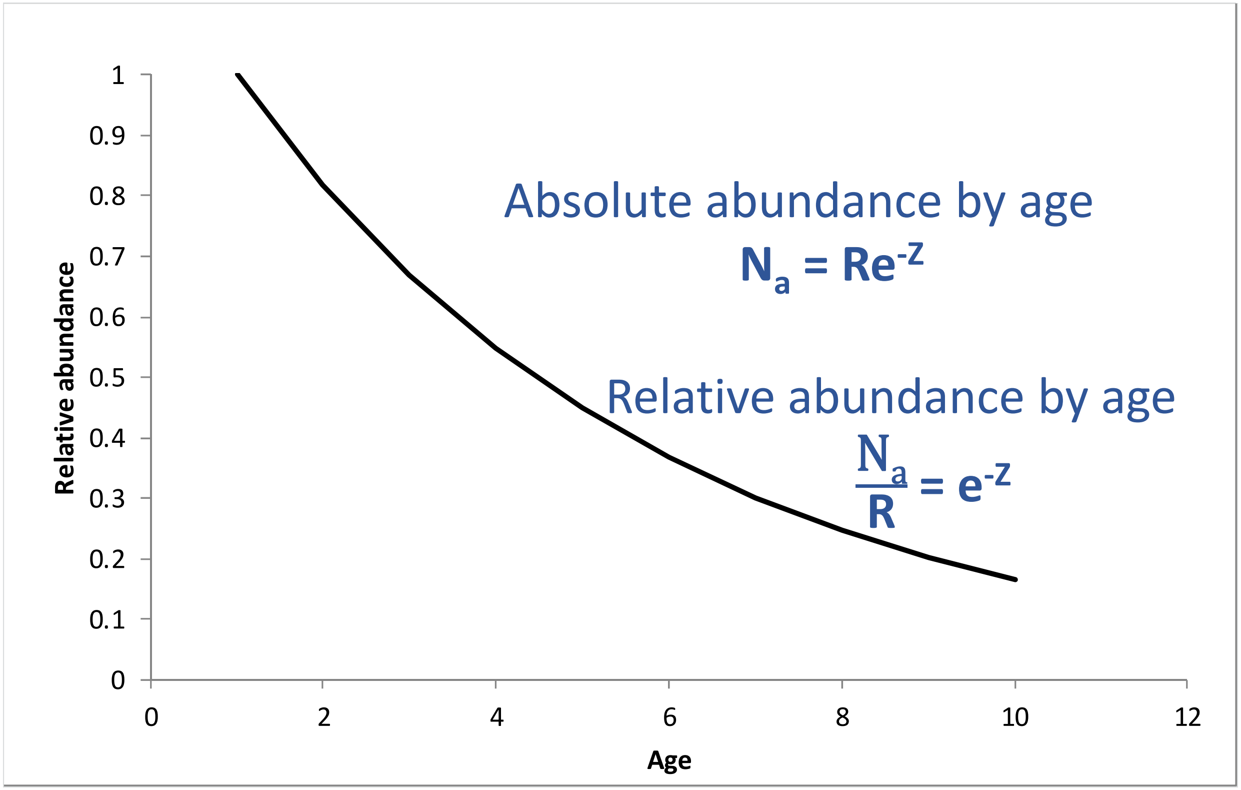
Thus

Biomass ≈ Catches/ Fishing mortality

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

Basic concepts

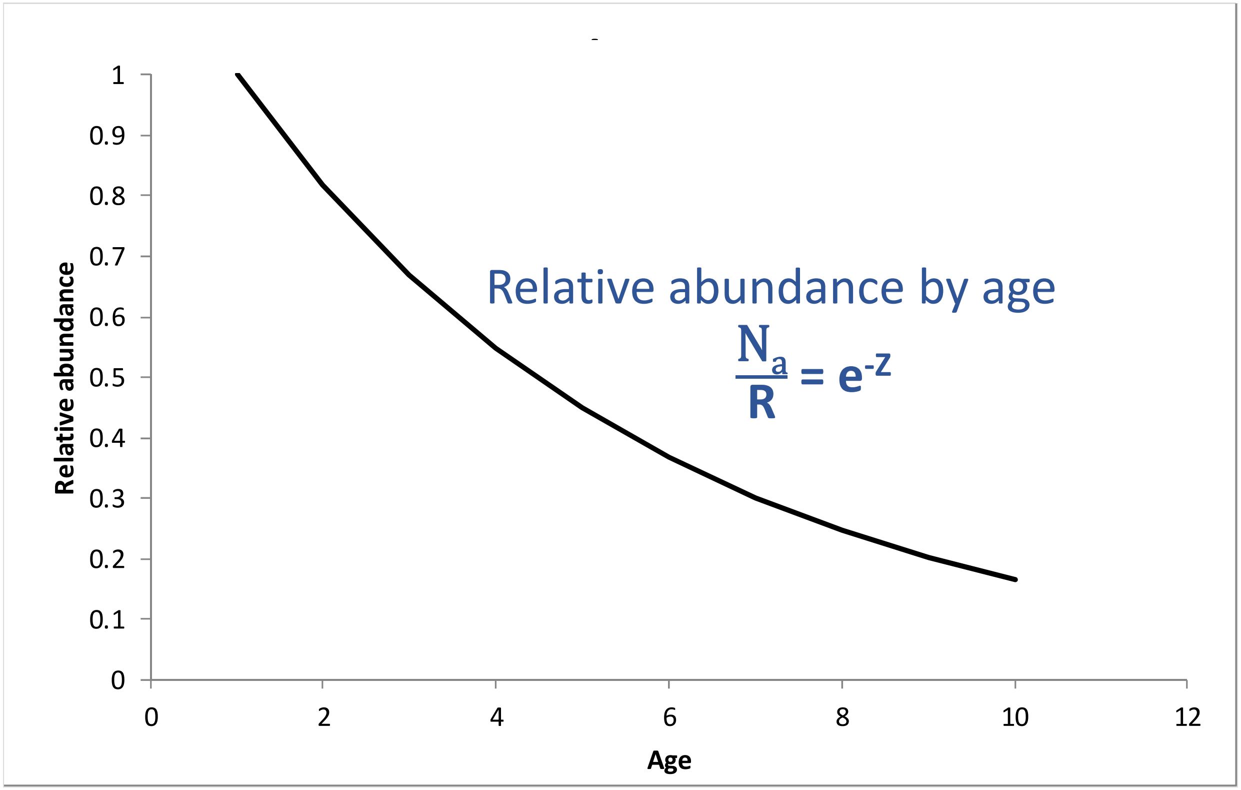
Relative abundance by age in the population



Maunder and Piner (2015)

Basic concepts

Relative abundance by age in the population



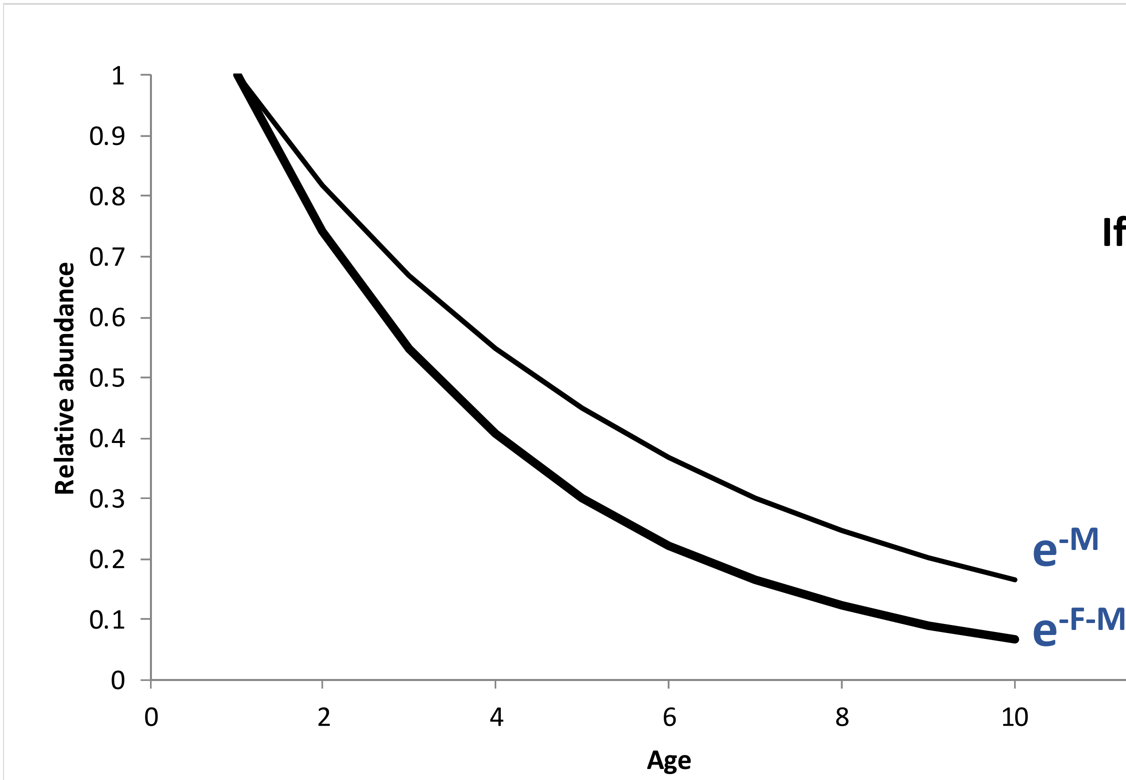
$$\log \frac{N_a}{R} = -Z$$

Slope of linear regression of numbers at age *vs* age = estimate of total mortality (Z)

Maunder and Piner (2015)

Basic concepts

Relative abundance by age in the population



If you know Z and M, you know F

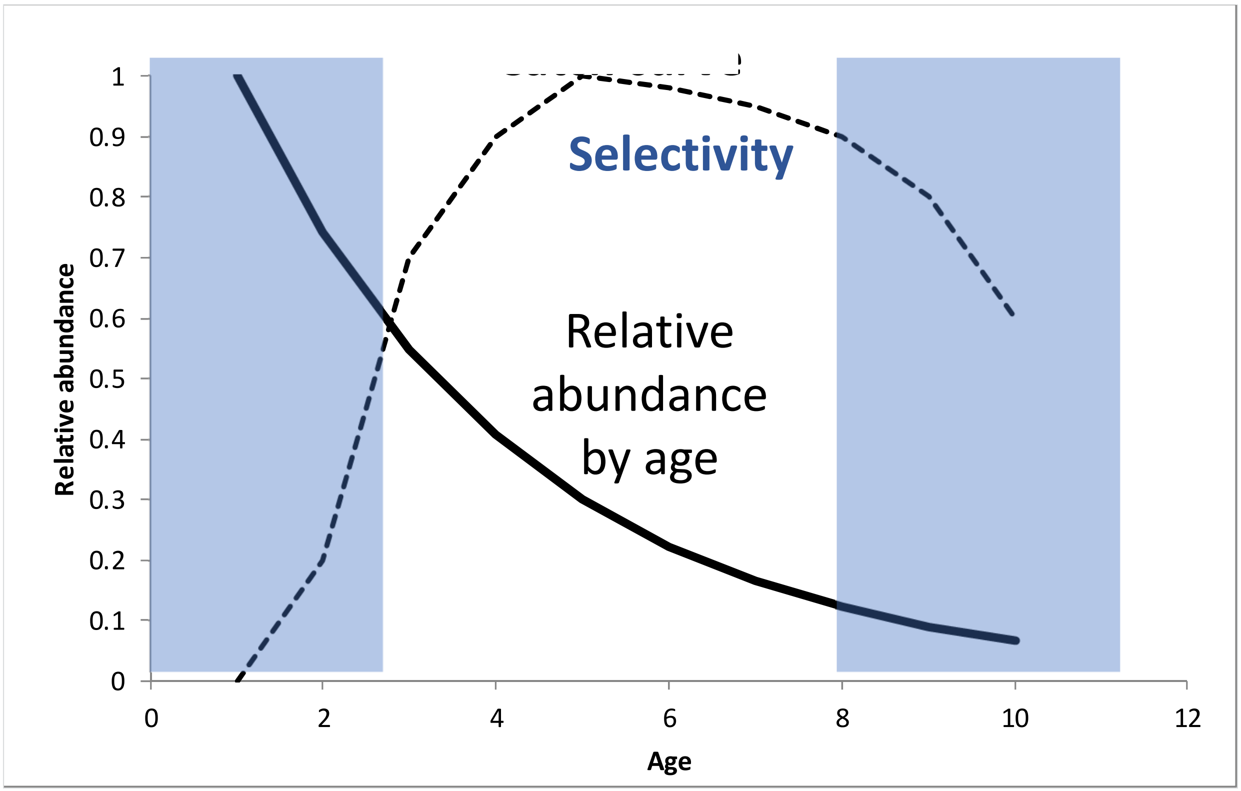
Z= M when no fishing

Z= F+ M when fishing

Maunder and Piner (2015)

Basic concepts

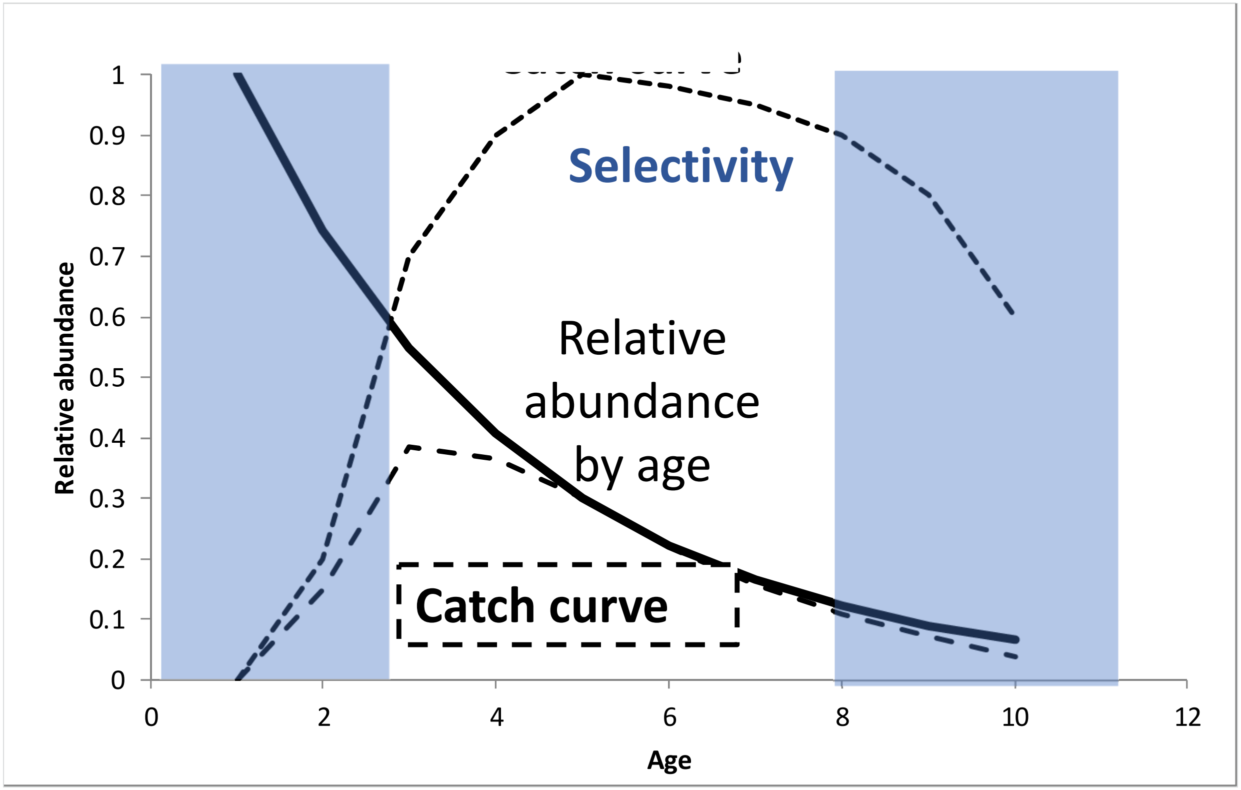
Proportion at age: effect of selectivity



Maunder and Piner (2015)

Basic concepts

Catch curve: effect of selectivity



Maunder and Piner (2015)

Catch curve: proportions at age in the catches

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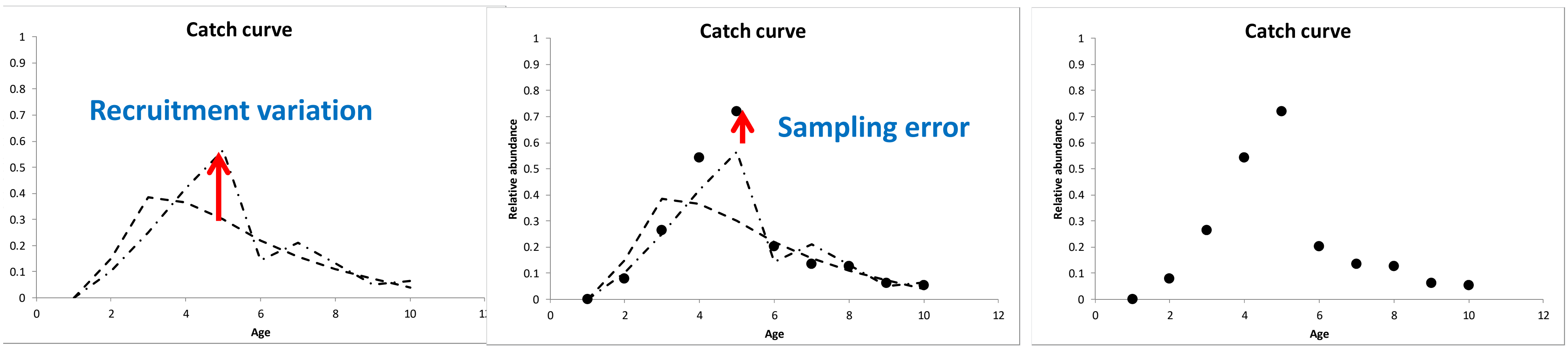
Basic concepts

Process error | Observation error | **what you see**

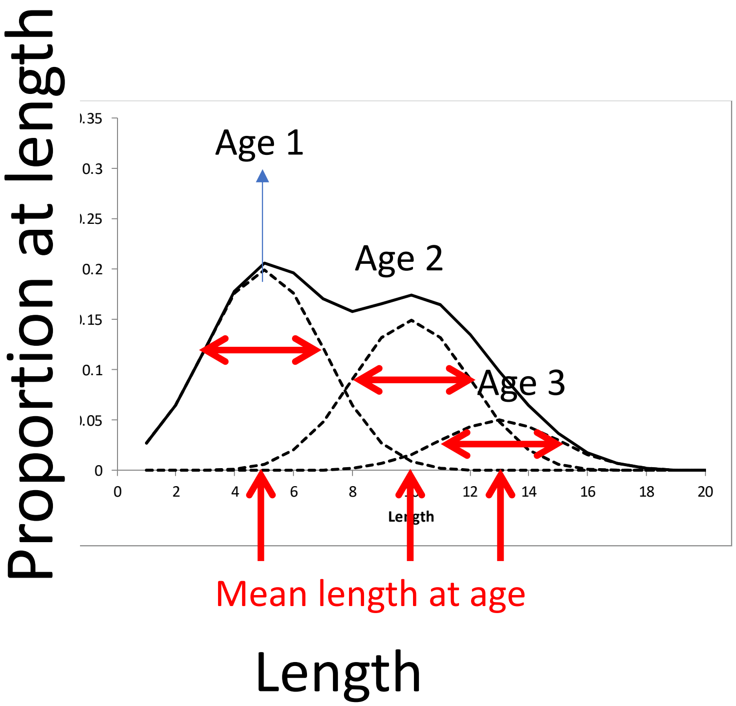
Proportion at age



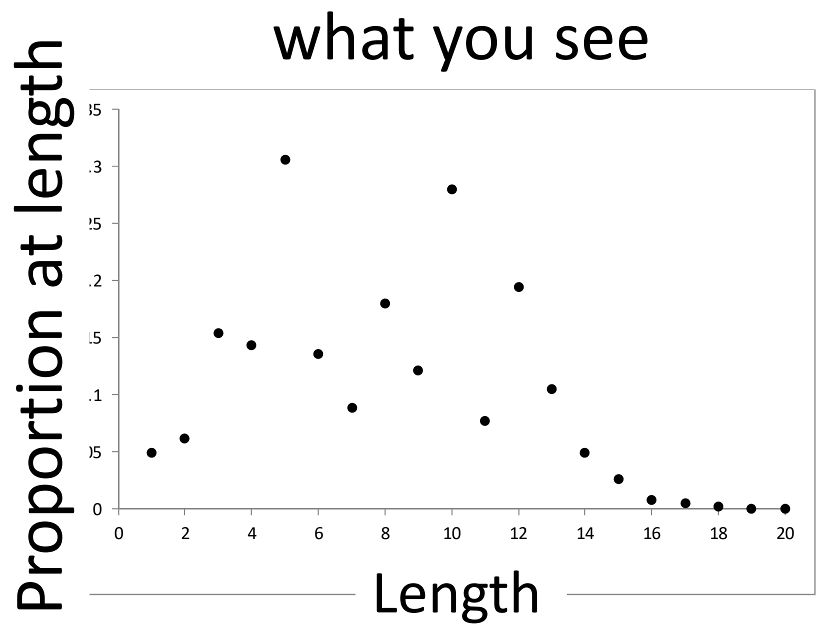
Age

Maunder and Piner (2015)

Basic concepts



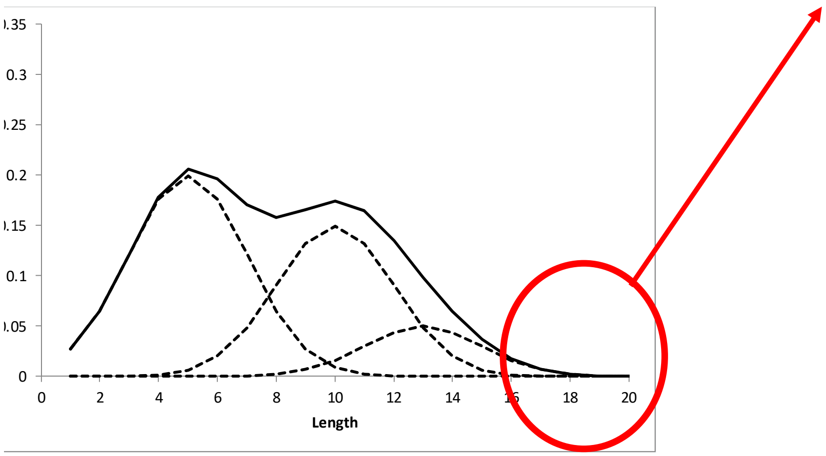
Process error +
Observation error



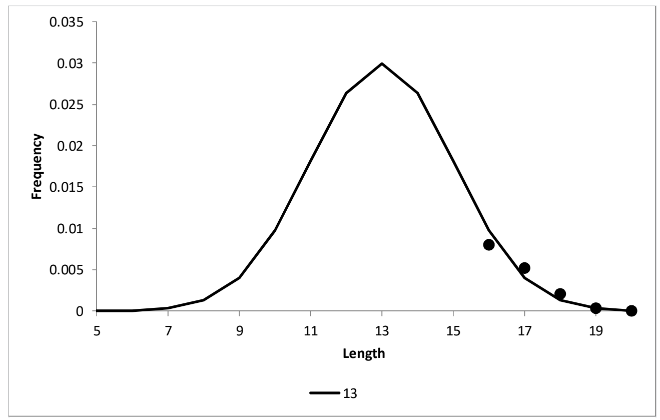
Maunder and Piner (2015)

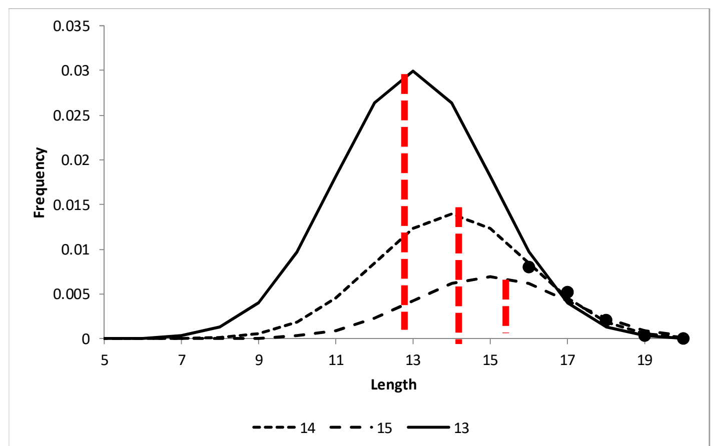
Basic concepts

Proportion at length



Length



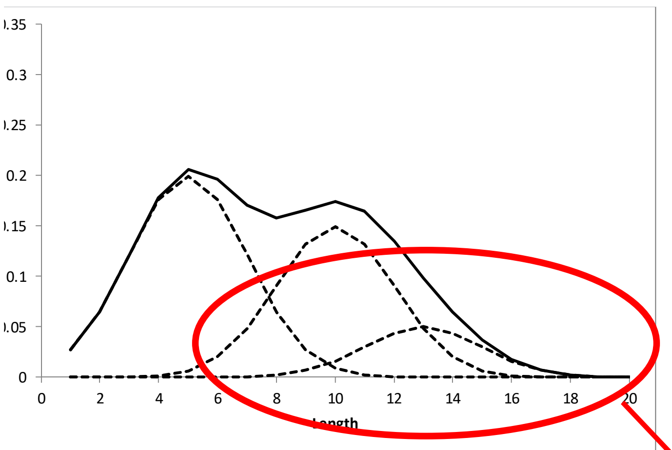


Asymptotic length: Influential on interpretation

Maunder and Piner (2015)

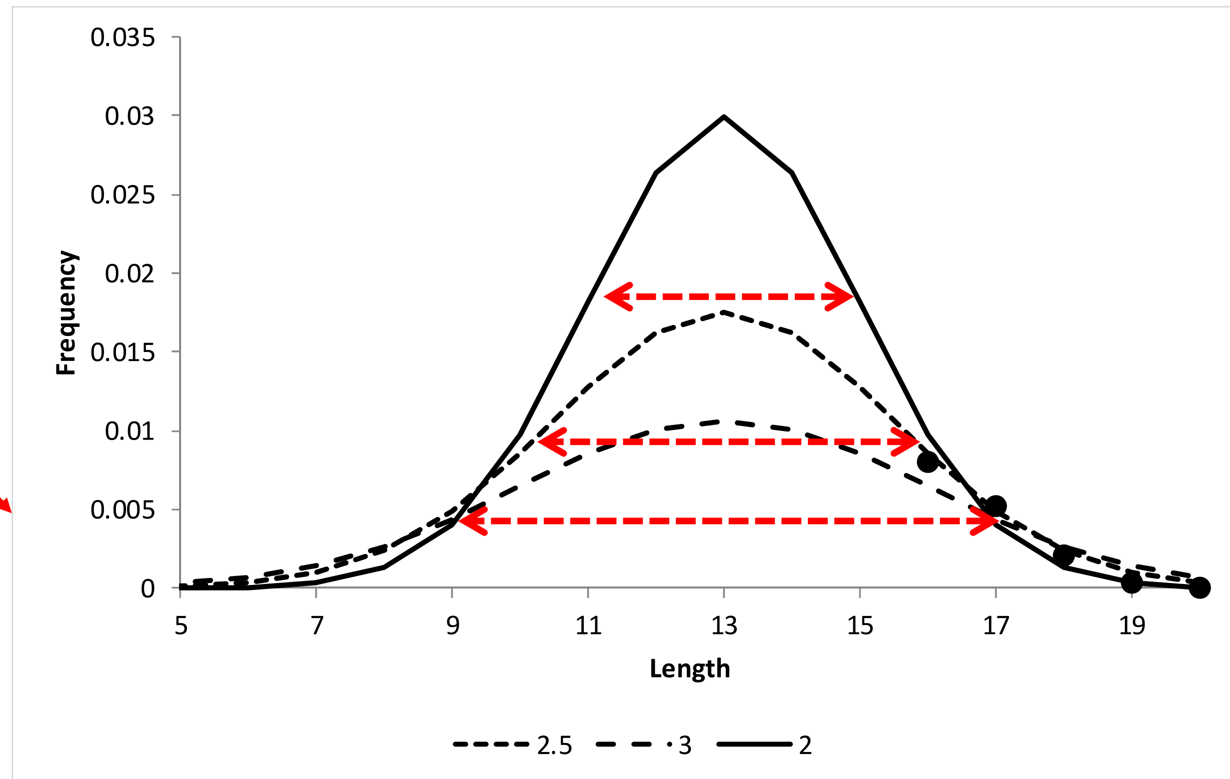
Basic concepts

Proportion at length



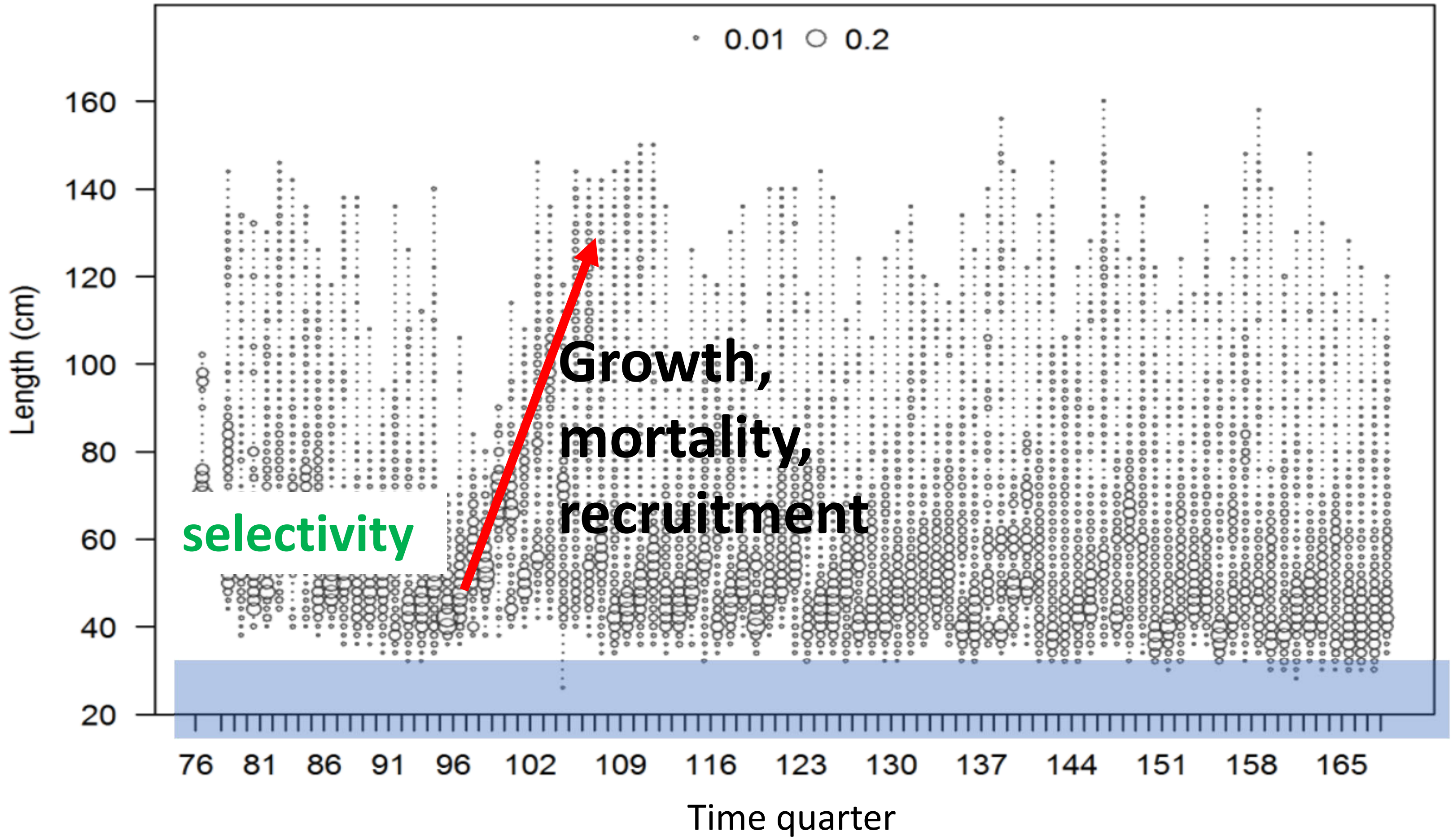
Length

Variation of length-at-age
Influential on interpretation



Maunder and Piner (2015)

Length composition data



Goals of the Catch Curve Analysis diagnostic

- Understand how influential the composition data on the estimate of total abundance and trends in abundance is.
- Assess if the composition data is in contradiction with the indices (both absolute and relative trends)
- Assess whether there is model misspecification
- Assess if the information from the composition data changes over time (could indicate temporal changes in selectivity or growth).

How it is done

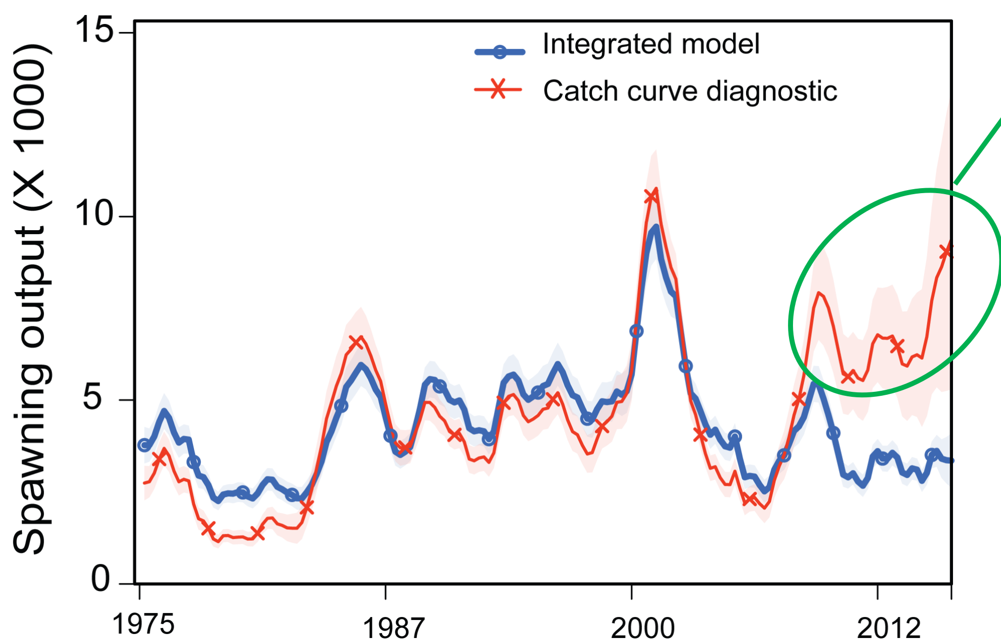
- Estimate selectivity and scale parameters only:
  - All observation model parameters related to the indices of abundance (*e.g*. CV and catchability) should NOT be estimated turned off (the phase should be set to a negative number)
  - but not selectivity parameters if the index has composition data and that is being used in the catch-curve analysis]
- Only fit to the composition data
  - All likelihood related to the indices of abundance should be turned off (lambda set to 0, but not the composition data related to the index)
  - Only fit to the composition data
- **Variations:** fits to subsets of composition data

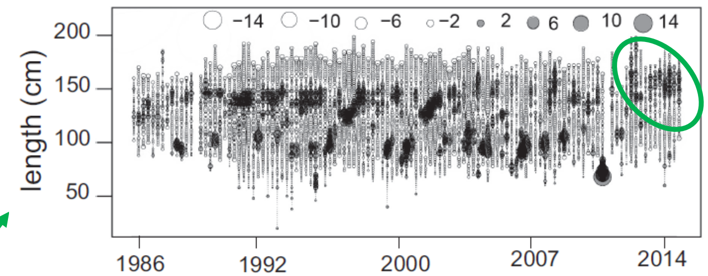
What we expect to see:

- If the composition data are driving the IM results the CCA and the IM should have similar results
- (if the model is correctly specified): Trends in abundance similar to the indices of abundance (and ASPM)

Example application 1: Yellowfin tuna in the Eastern Pacific Ocean

- CCA
  - estimaste about the same scale than the IM
  - captures the relative trends well except from 2010 on
  - indicates that there is model mispecification (changes in selectivity unaccounted for?)





ICES Journal of Marine Science

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International Council for the Exploration of the Sea
Conseil International pour l'Exploration de la Mer

ICES Journal of Marine Science (2021), https://doi.org/10.1093/icesjms/fsab213

Review Article

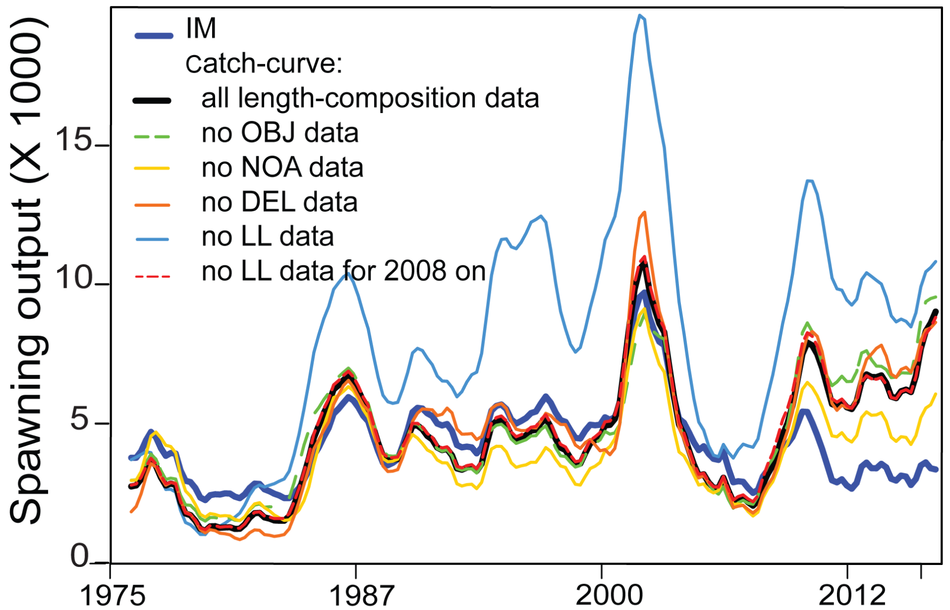
Auxiliary diagnostic analyses used to detect model misspecification and highlight potential solutions in stock assessments: application to yellowfin tuna in the eastern Pacific Ocean

Carolina V. Minte-Vera[1,*], Mark N. Maunder[1,2], and Alexandre M. Aires-da-Silva[1]

https://doi.org/10.1093/icesjms/fsab213

Example application 1: Yellowfin tuna in the Eastern Pacific Ocean

- Variations of the CCA
  - Remove one group of composition data and fit the IM to the rest
  - Longline size composition data is more influential than other data (asymptotic selectivity)



https://doi.org/10.1093/icesjms/fsab213

CCA – pros and cons

Pros:

- Easy to implement once the IM is set up
- Seem useful in the YFT example

Cons:

- In simulation studies, large type I error – falsely detected model misspecification in the correctly specified model"self-test" (Carvalho et al 2017) – maybe not enough information in the composition about trends in the simulated data even when no misspecification present?

Table 7
Percentage of models identified as misspecified by each diagnostic test under different scenarios.

	Self test	Misspecification in selectivity
Diagnostic	CSM(%)	EM_1(%)
SDNR	5	79
Runs test	6	51
ASPM	4	9
Retrospective analysis	0	11
R_o Likelihood component profile	4	5
CCA	91	92

Expected is 5% (Type I error - falsely rejecting a correctly specified model)

Power, expected is large (e.g. 80%, then Type II error = 20% falsely accepting a misspecified model)

Identification of misspecification defined as: SSBterm/SSBinit from an ASPM (or CCA) for an EM fell outside the (asymptotic) 95% CI of its corresponding fully-integrated model

New diagnostic: cohort-based depletion model

Proposed by Maunder (unpublished, and Clark 2022):

- Needs index of abundance by age (maybe from spatiotemporal models by age or size class)
- Needs catch-at-age in numbers (from sampling)
- Assumes a simple model:

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Why natural mortality is estimable, in theory if not in practice, in a data-rich stock assessment

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$$N_{t+1,a+1} = N_{t,a}e^{-M_a} - C_{t,a}$$

Where $N_{t,a}$ are the number of fish in time t at age a, $C_{t,a}$ is the catch in numbers in time t of age a, M_a is natural mortality at age a.

New diagnostic: cohort-based depletion model

Depletion estimator

The depletion estimator for $N_{t,a}$ using age-specific indices of abundance $I_{t,a}$ with catchability q_a is based on the following assumptions

$$N_{t,a} = qI_{t,a} \qquad \text{Eq. 2}$$

Such that the ratio N_{a+1}/N_a is,

$$\frac{I_{t+1,a+1}/q_{a+1}}{I_{t,a}/q_a} = \frac{N_{t,a}e^{-M_a} - C_{t,a}}{N_{t,a}} \qquad \text{Eq. 3}$$

Rearranging Eq. 3 gives the abundance of age *a* at time *t* from the indices and catch for a given M_a, q_a, and q_{a+1}.

$$\widetilde{N}_{t,a} = \frac{C_{t,a}}{e^{-M_a} - \frac{I_{t+1,a+1}/q_{a+1}}{I_{t,a}/q_a}} \qquad \text{Eq. 4}$$

New diagnostic: cohort-based depletion model

- Estimation can be done using observation error or process error assumptions
- To avoid negative values of numbers at age the calculations can be started at the last age
- Conditions for estimability can be explored
  - It can be shown that estimation of age-specific parameters for both catchability and natural mortality can be problematic.

Substituting $$\beta_a = \frac{q_{a+1}}{q_a} e^{-M} \quad \text{Eq. 15}$$

Leads to a multiple regression for each *a* with no intercept term ($\alpha = 0$).

$$I_{t,a} = \beta_a I_{t-1,a} + q_a C_{t,a} \quad \text{Eq. 16}$$

New diagnostic: cohort-based depletion model

Where

$$M_a = -ln\left(\beta_a \frac{q_a}{q_{a+1}}\right) \quad \text{Eq. 17}$$

And

$$M_a = \frac{(I_{t,a} - q_a C_{t,a})q_a}{I_{t-1,a} q_{a+1}} \quad \text{Eq. 18}$$

Therefore, both coefficients must be estimated precisely to estimate M_a precisely

New diagnostic: cohort-based depletion model

- if there is a proportional relationship between the index and catch, which may occur if there is no contrast in both or the stock is fished at constant exploitation rate,
- then M at age and catchability at age (selectivity) will be highly confounded.
- catch cannot change over time while the index remains constant unless some other process, such as M, changes over time.
- It is not the contrast in the index over the whole time period that is important, but the change in the index from one year to the next
- this change must be larger than the observation error in the index.
- This implies that in most cases (i.e. where the observation error for the index of abundance is moderate to high) exploitation rate must be high and must change over the history of the fishery to be able to estimate age specific natural mortality.
- If M is independent of age, then it is shared among the multiple linear regressions and contrast among ages in I_(t,a) q_(a+1)/q_a can be substituted for contrast over time

Relationship

	ASPM	CCA	Cohort-depletion
Data	index (aggregated) Catches (aggregated)	Composition data Catches (aggregated)	Index desegregated by age (need composition data) Catch by age (need composition data to “slice it”)
Model	Complex age-structured No stochasticity	Complex age-structured No stochasticity	Simple cohort-depletion
Diagnostic	Fit to indices SSB compared with SSB_integrated model	Fit to composition data SSB compared with SSB_integrated model	N at age compared with N at age integrated model

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Thank you