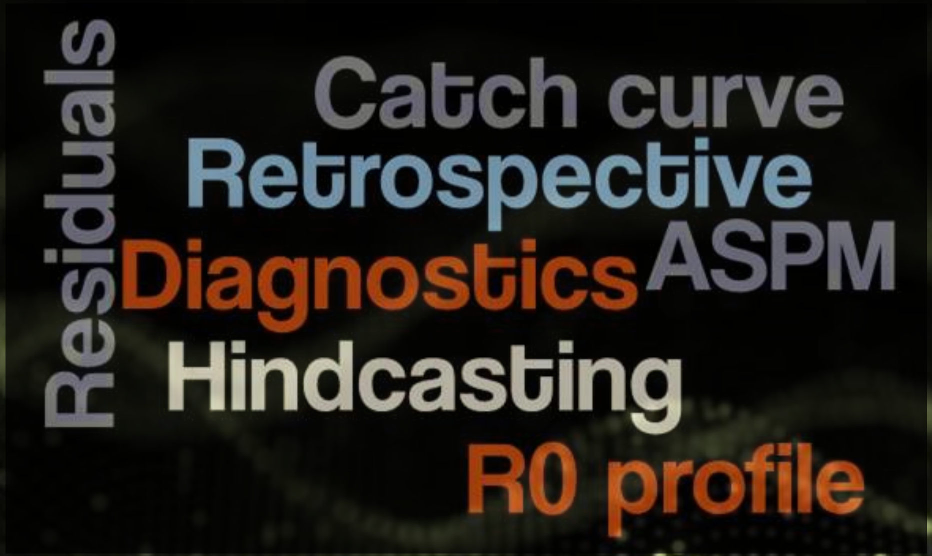

Ro likelihood component profile as a diagnostic tool: thumbs up or thumbs down

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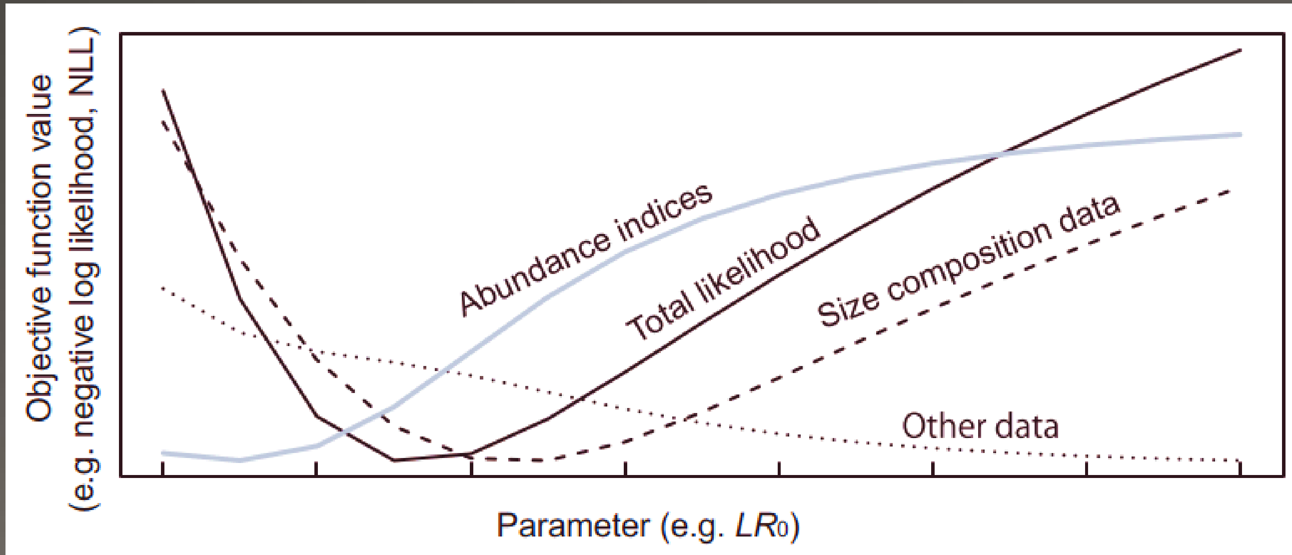
Likelihood component profile

- MLE: likelihood profile; Bayesian: posterior profile
- Constructed by refitting the assessment model to all data many times, each time with a different fixed value of the chosen parameter.
- The likelihood is evaluated for each data component
- Profiling over the parameter/derived quantity provides a tool to assess the contribution of each data component on the estimates of parameter/derived quantity given the model structure.



1. **Gradient**
2. **Location of minimal**

Likelihood component profile

- Lee et al. (2011) used it to detect what data component provide information on the estimate of natural mortality rate.
- Informative length or age composition data is needed to reliably estimate M.

Likelihood component		Total	Indices (survey)	Length comps	Age comps	Size-at-age	Mean body-weight
Arrowtooth	Female	+	+	+	–		
	Male	+	–	+	–		
Black RF_N	Young	+	–	+	+	–	
	Old	+	–	+	+	–	
Black RF_S	Young	+	+	+	–	–	+
	Old	+	–	+	–	–	–
Blue RF	Female	+	+	+	+		
	Male	+	+	+	+		
Canary	Young	–	+	–	–		
	Old	+	–	+	+		
Chilipepper		+	–	+			
Darkblotched		+	+	–	+		
English sole		–	–	–	–		–
Hake	Young	+	–	–	+		
	Old	+	–	–	+		
Sable		+	+	–	+	–	–
Shortbelly		+	+	–	+		
Yelloweye		+	+	–	+	–	

+, informative about natural mortality; –, uninformative about natural mortality.

Location of minimal

Likelihood component profile

- Lee et al. (2012) used it to detect what data component provide information on the estimate of steepness.
- Informative abundance-index data is needed to reliably estimate h.
- Good contrast in spawning biomass is important.

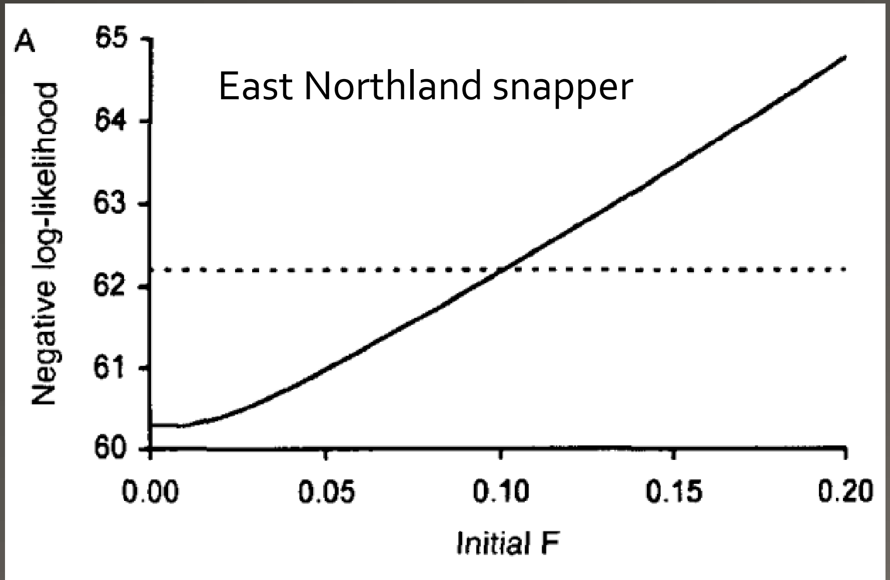
Likelihood component	Arrowtooth	Black RF_N	Black RF_S	Blue RF	Canary	Chilipepper	Darkblotched	English sole	Hake	Sable	Shortbelly	Yelloweye
Total	–	–	–	–	–	–	+	–	–	+	–	+
Indices (survey)	–	–	–	–	–	–	+	–	–	–	–	+
Discard							–	–		–		
Length comps	–	–	–	–	–	–	–	–	–	–	–	+
Age comps	–	–	–	–	–	–	+	–	–	+	–	–
Size-at-age		–	–							–		–
Mean body-weight			–					–		–		

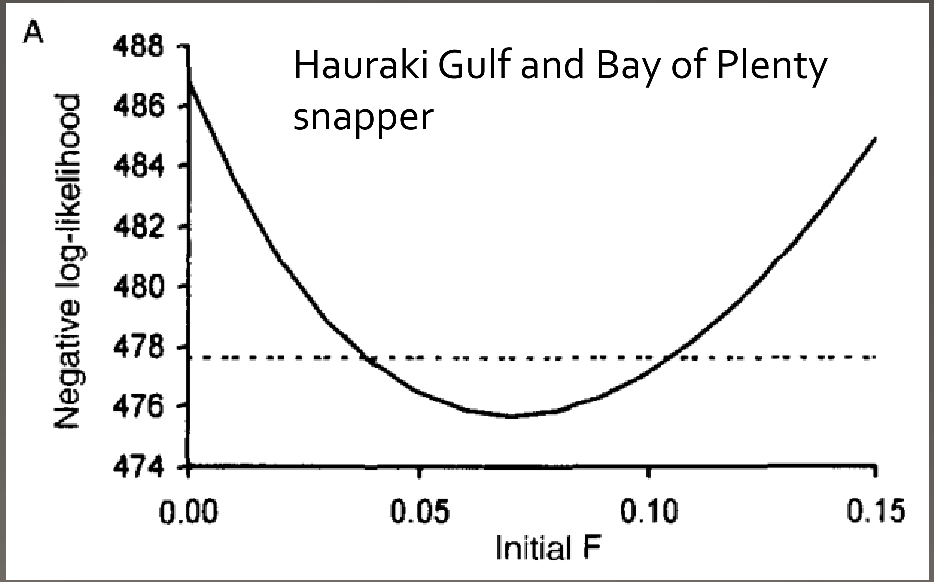
+, informative about steepness; –, uninformative about steepness.

Location of minimal

History of the profile over population scaling parameter

- Maunder and Starr (2001) profiled over initial fishing mortality to understand how informative of data about the initial fishing mortality rate.

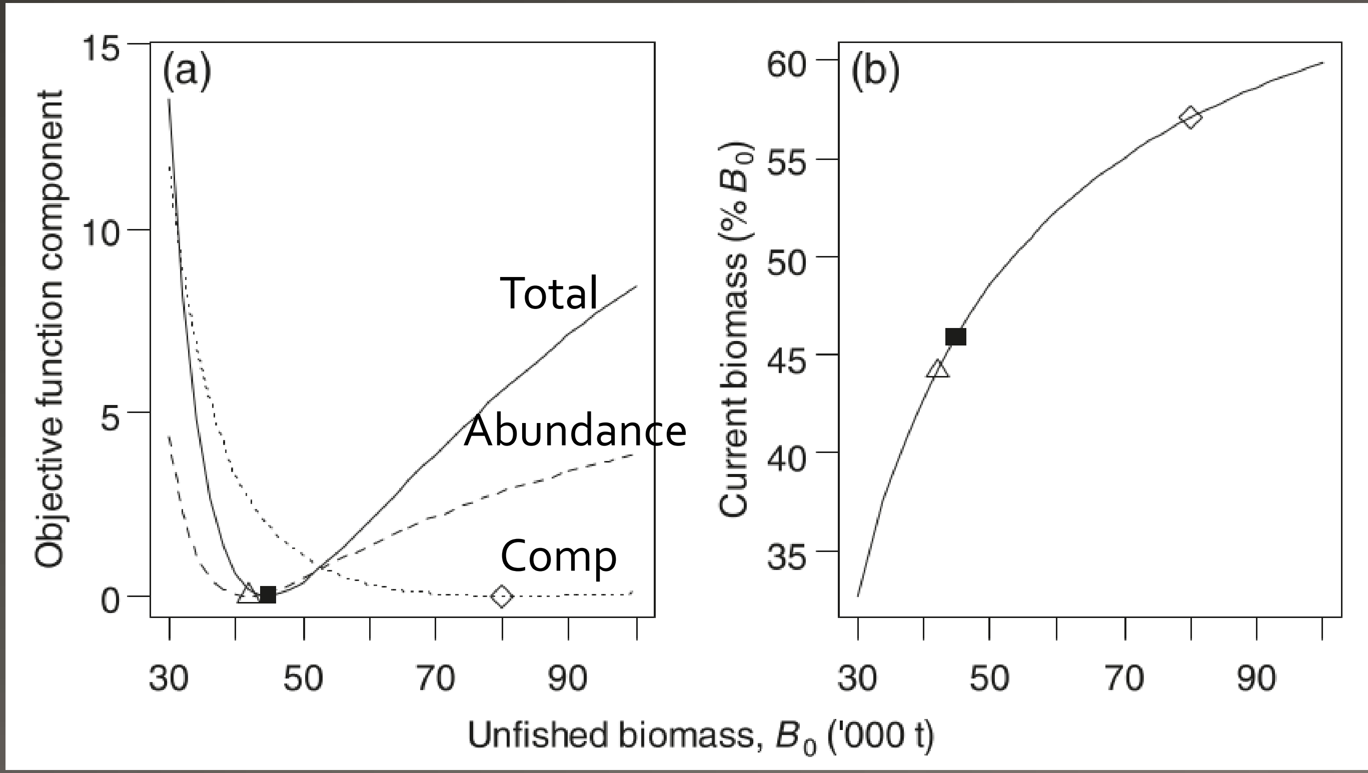




Location of minimal

History of the Ro profile

- Our first exposure is that Methot used it to explain his assessments (balance different data sets).
- Francis C. (2011) used it to demonstrate information from survey vs compositions in his data weighting paper.



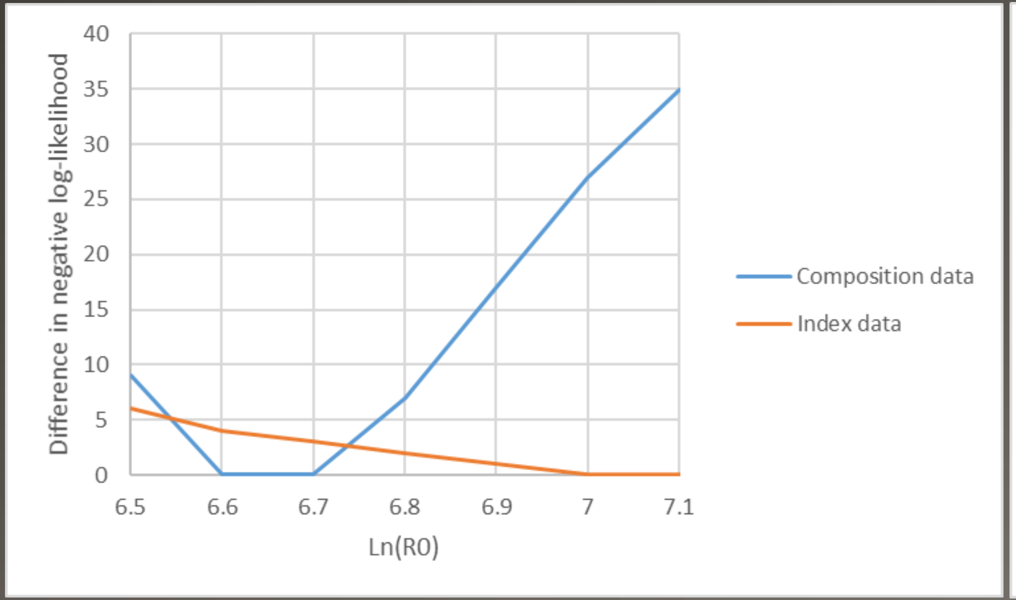
Location of minimal:
The data have been weighted so that the model estimate of Bo is quite close to the best estimate from the abundance data (have primacy to the abundance data).

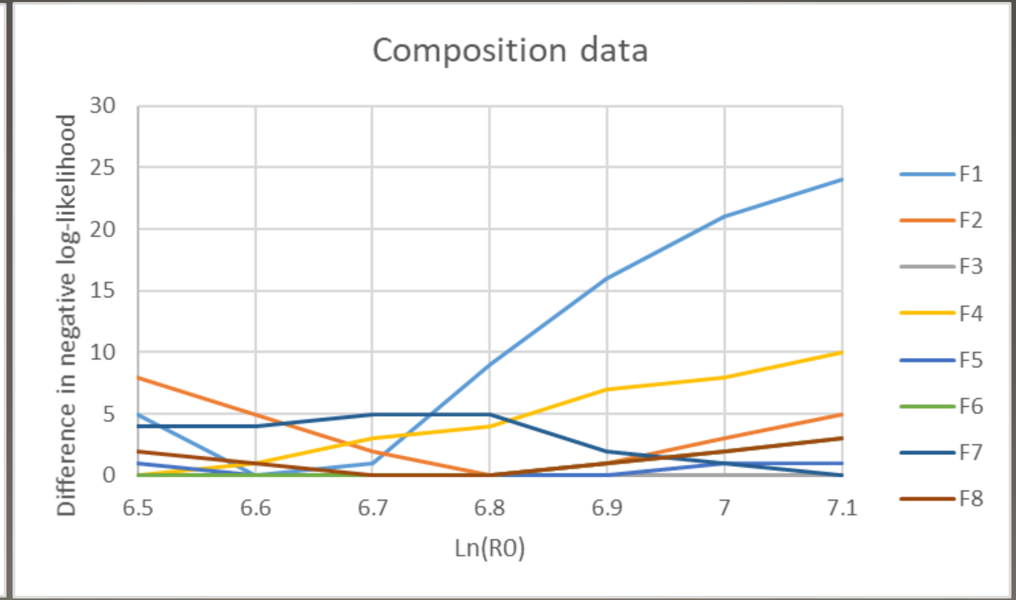
Fig. 1. Results from a profile on unfished biomass, Bo, in the New Zealand hake assessment of Horn and Francis (2010)

History of the Ro profile

- Lee et al. (2014) used it to structure an internally consistent model that prioritizes key data.
- Data components with steep gradients (F1 and F4) provide more information on scale than other data components with flat gradient.

Model 1 (initial model)

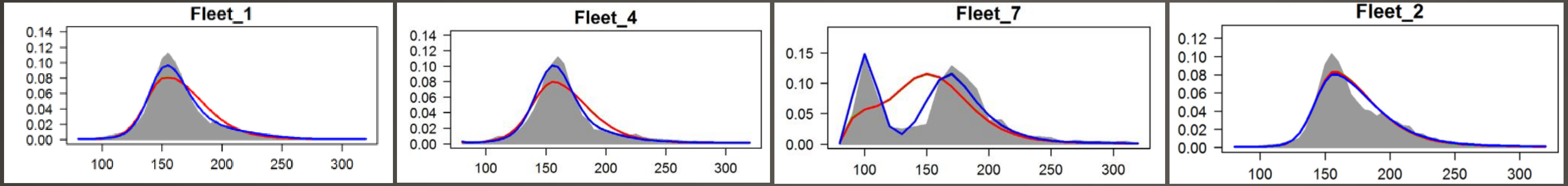




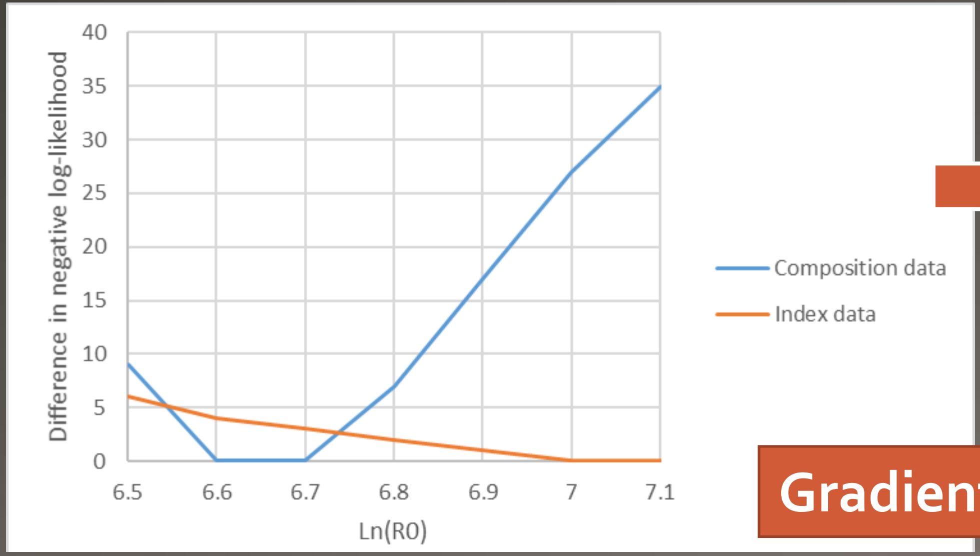
2013 Pacific blue marlin assessment

History of the Ro profile

- Lee et al. (2014): Cubic spline (F1 and F4), time-varying (F7), de-emphasize F2

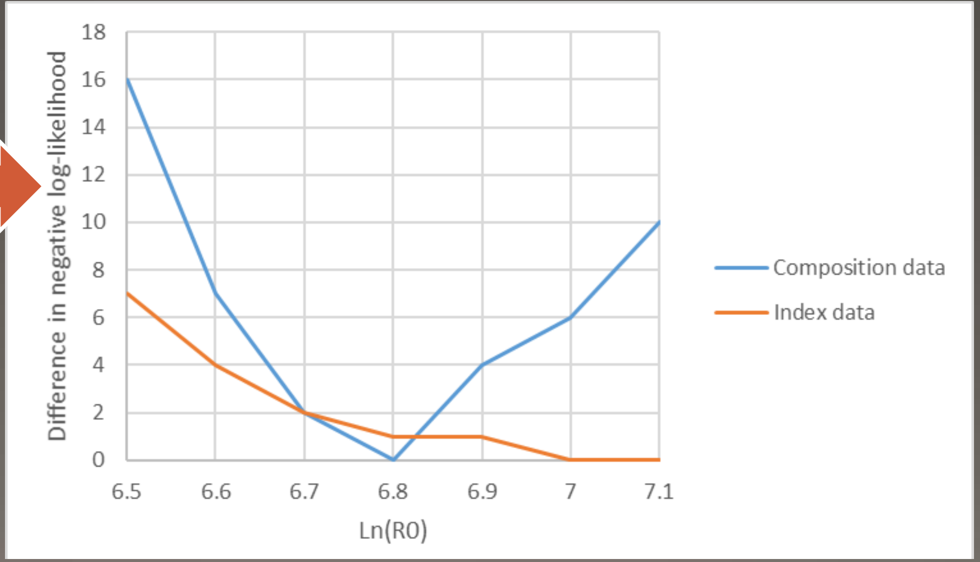


Model 1 (initial model)



Gradient

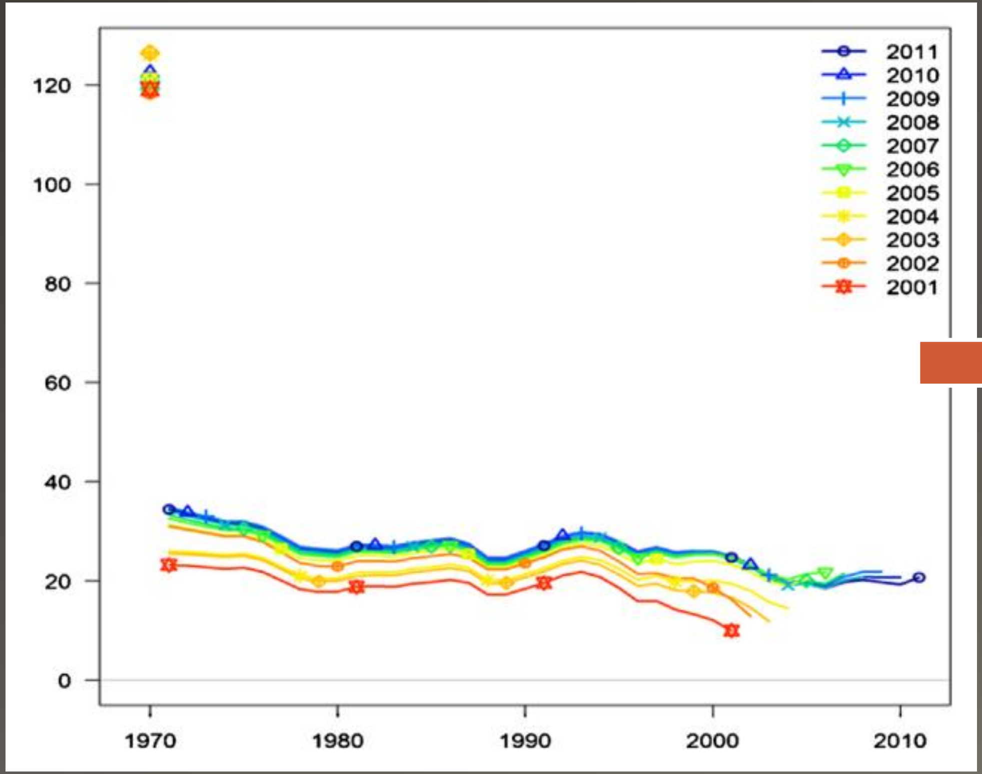
Model 4 (additional process + data weighting)



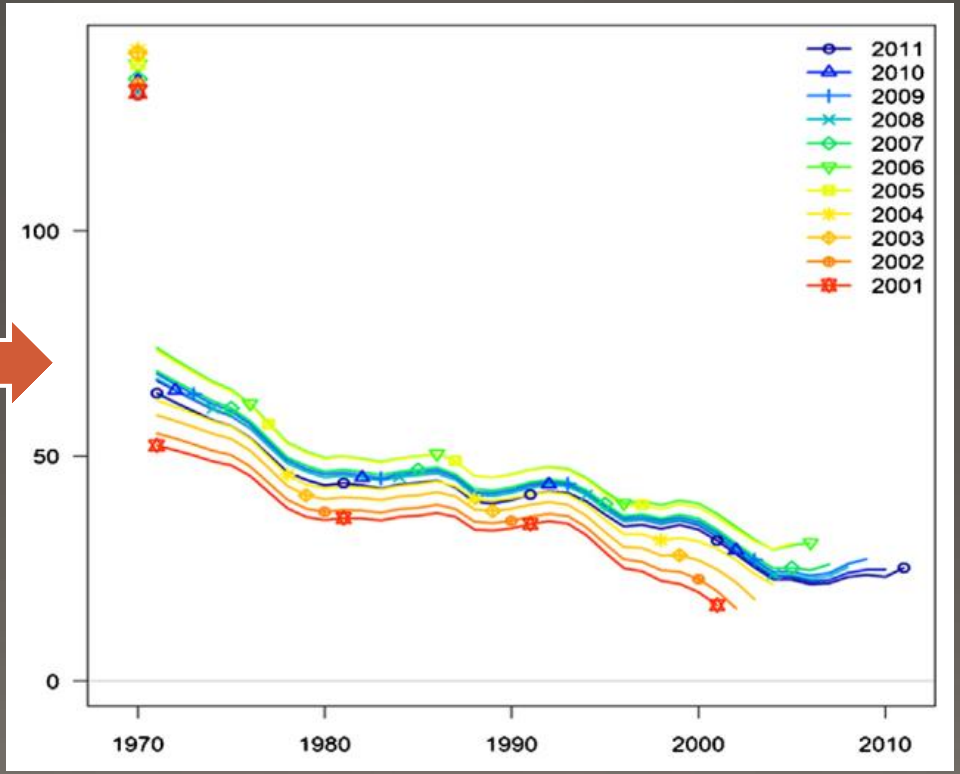
History of the Ro profile

- Lee et al. (2014): The information on scale can be used with the other diagnostic methods (e.g. retrospective analysis).

Model 1 (initial model)

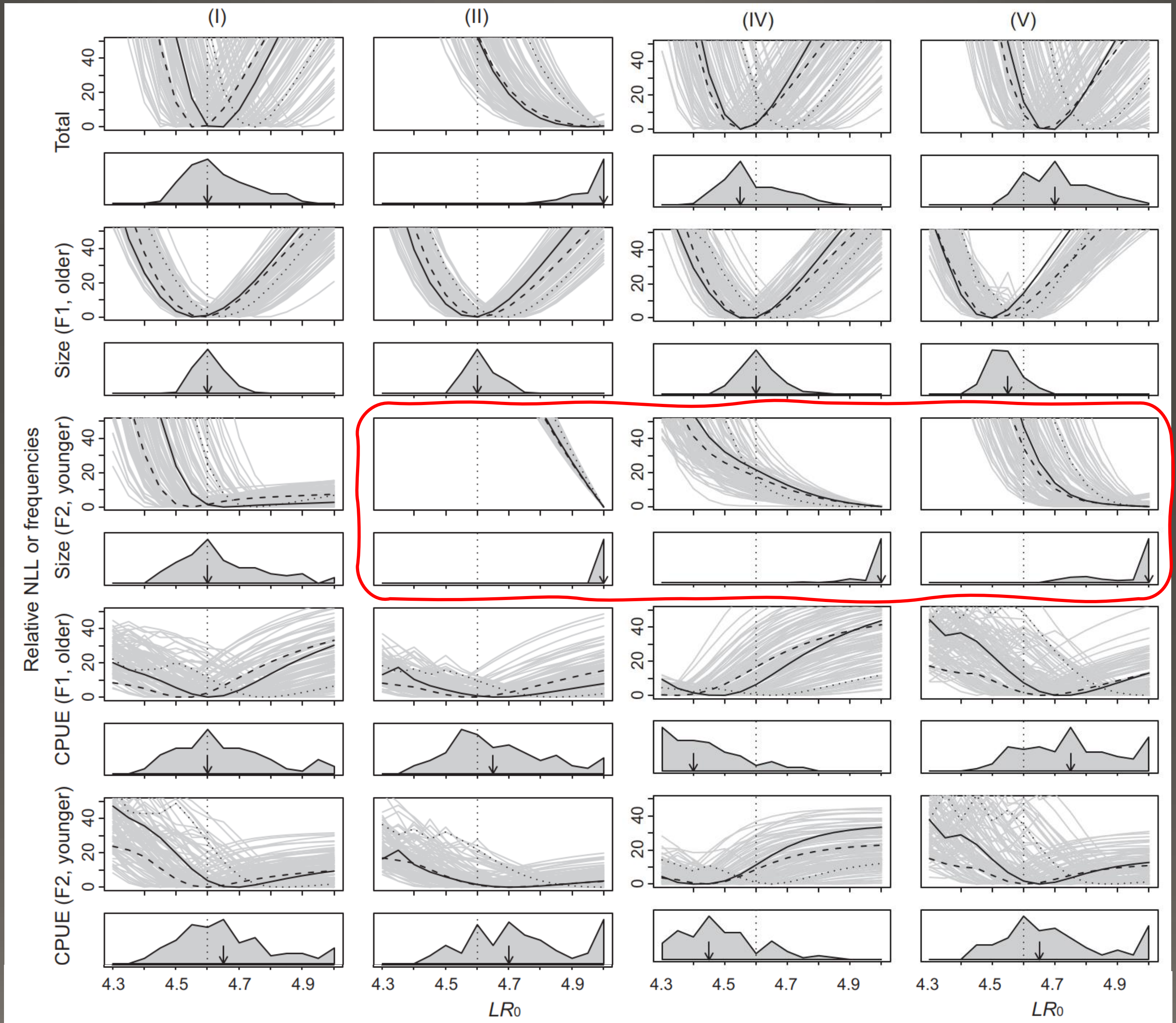


Model 4 (additional process + data weighting)



History of the Ro profile

(II) Scenarios with wrong fixed selectivity
(IV) (V) Scenarios with violation of constant selectivity



- Ichinokawa et al. (2014) used simulation to illustrate how the Ro profile identifies conflict among the data sources when selectivity is mis-specified.

Location of minimum

Pacific bluefin tuna assessment

History of the Ro profile

- Ichinokawa et al. (2014) used simulation to illustrate how the Ro profile identifies conflict among the data sources when selectivity is mis-specified.
- Under selectivity mis-specification, all data components were affected.
- The study shows the potential for the Ro profile to detect data conflicts caused by model mis-specification.

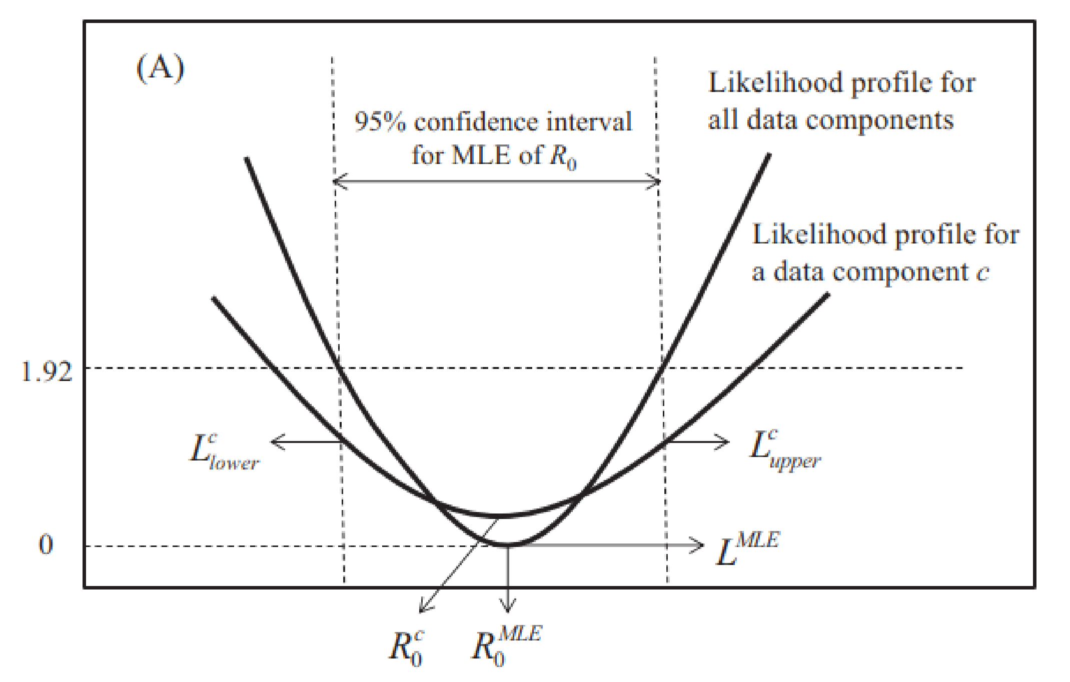
History for Ro profile

- Wang et al. (2014) used simulation to explore how the Ro profile identifies conflict in data when selectivity is either correctly or incorrectly specified.
- Quantified **gradient** using confidence intervals based on the likelihood ratio statistic concept.

if R_0^c is located within the 95% confidence interval for R_0^{MLE}

$$\varphi = \begin{cases} \max[(L^c_{\mathrm{lower}} - L^{\mathrm{MLE}}),\ (L^c_{\mathrm{upper}} - L^{\mathrm{MLE}})], & \\ \left| L^c_{\mathrm{lower}} - L^c_{\mathrm{upper}} \right|, & \text{otherwise} \end{cases}$$

phi



Gradient

A low value for φ for a data or penalty component indicates that it has a relatively small contribution to the estimation of Ro.

History of the Ro profile

- Wang et al. (2014): The Ro profile diagnostic was not able to correctly identify selectivity pattern misspecification.

φ

φ

Case A (misspecification of the selectivity curve).

Simulation	Catch	Survey	Lfreq_PS	Lfreq_LL	R_pen
True					
1	0.11	0.73	2.34	3.75	6.94
2	0.12	0.17	2.56	3.39	6.05
3	0.11	1.09	0.77	4.93	7.20
4	0.09	0.21	1.06	1.56	3.36
5	0.11	0.44	1.28	2.48	4.41
6	0.09	1.06	1.79	4.28	5.20
7	0.11	0.24	2.13	3.08	5.66
8	0.09	0.34	3.30	2.94	6.77
9	0.10	0.95	3.27	3.73	6.23
10	0.08	0.95	2.66	4.51	6.40
Mean	0.10	0.62	2.12	3.46	5.82
Misspecified					
1	0.61	2.82	2.88	5.97	1.38
2	0.76	1.23	2.58	5.20	1.47
3	0.41	4.19	2.99	6.73	1.65
4	0.44	1.79	4.99	10.38	2.66
5	0.70	1.16	5.11	9.99	2.85
6	0.59	0.88	3.86	4.75	1.41
7	0.65	0.62	6.31	7.58	1.43
8	0.35	3.74	3.53	8.45	1.51
9	0.65	0.60	4.99	7.41	2.26
10	0.77	0.63	5.35	6.39	1.51
Mean	0.59	1.77	4.26	7.29	1.81

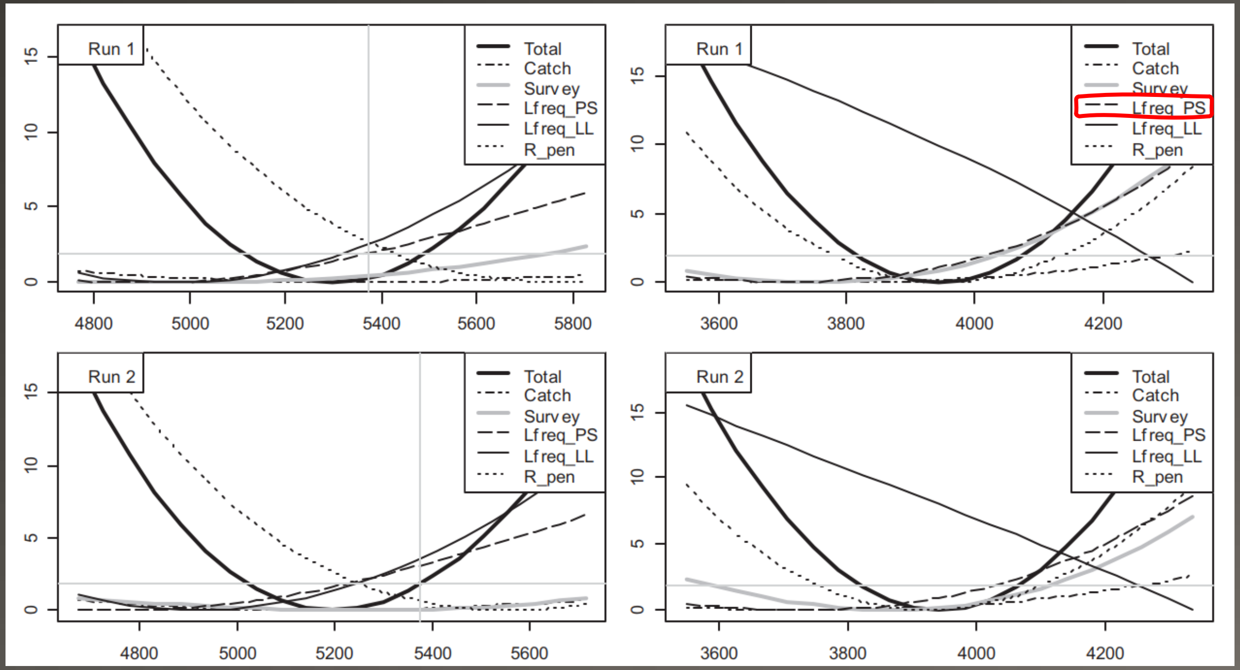
Case B (misspecification of time-varied selectivity).

Simulation	Catch	Survey	Lfreq_PS	Lfreq_LL	R_pen
True					
1	0.12	0.33	2.42	3.27	6.18
2	0.13	0.30	1.97	3.16	5.47
3	0.10	0.25	1.86	5.38	7.67
4	0.12	0.35	2.47	1.50	4.87
5	0.09	1.27	1.08	4.49	4.44
6	0.14	0.90	2.63	3.25	5.12
7	0.12	0.61	2.98	4.22	7.91
8	0.11	0.17	2.51	3.60	6.18
9	0.11	0.28	2.70	2.58	5.23
10	0.10	0.14	1.80	6.06	8.08
Mean	0.11	0.46	2.24	3.75	6.12
Misspecified					
1	0.20	1.08	3.15	5.04	7.11
2	0.20	1.32	3.22	4.88	6.71
3	0.17	1.32	2.86	6.86	8.43
4	0.18	1.42	3.69	3.73	6.01
5	0.15	2.27	2.34	5.60	5.70
6	0.26	2.84	4.13	5.47	6.70
7	0.20	1.45	4.01	6.06	8.59
8	0.19	2.05	3.78	5.27	7.02
9	0.22	2.05	3.51	4.71	6.17
10	0.18	1.33	2.84	7.44	8.95
Mean	0.19	1.71	3.35	5.51	7.14

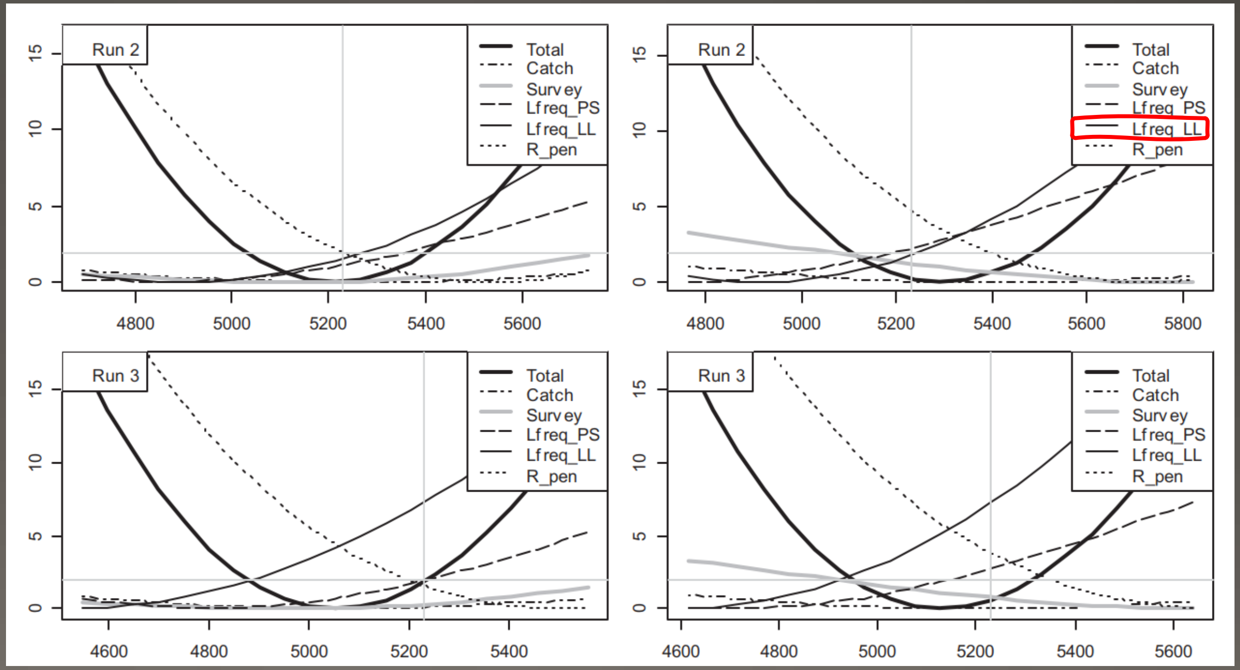
History of the Ro profile

- Wang et al. (2014): The index of abundance provided almost no information on population scale due to a lack of contrast in the index.
- Population scale was defined almost completely by the length comps.

True | Misspecified selex curve



True | Misspecified time-varying selex



2012 Eastern Pacific Ocean bigeye tuna assessment

History of the Ro profile

- Wang et al. (2014) used it to explore the contribution of data components when selectivity is either correctly or incorrectly specified.
- Prioritization of an abundance index (Francis, 2011) using the Ro profiling method appears to be appropriate for estimating the population scale when a strong production relationship is apparent in the data and they suggest using the age-structured production model (ASPM) diagnostics.

History of the Ro profile

- Carvalho et al. (2017) used it to detect model misspecification with other diagnostic tests (residual analysis, retrospective analysis, catch-curve analysis, ASPM).
- Extended the use of the φ statistic to identify data sets that are influential in the simulation (**gradient**).

Table 4
Mean and standard deviation (over simulations) of the R_0 component likelihood profile statistic ϕ based on various data components for each of the four EMs. The grey shaded area represents the value for all fleets combined.

Data component (Fleet)	CSM Mean (± SD)	EM_1 Mean (± SD)	EM_2 Mean (± SD)	EM_3 Mean (± SD)
Index	0.75 (0.19)	0.70 (0.15)	0.73 (0.17)	0.72(0.18)
CPUE 1 (1)	0.65 (0.14)	0.63 (0.11)	0.61 (0.12)	0.60 (0.14)
CPUE 2 (1)	0.61 (0.13)	0.58 (0.10)	0.60 (0.13)	0.63 (0.15)
CPUE 3 (1)	0.49 (0.09)	0.49 (0.11)	0.52 (0.15)	0.48 (0.13)
CPUE 4 (2)	1.39 (0.27)	1.09 (0.31)	1.10 (0.32)	1.13 (0.35)
CPUE 5 (3)	0.67 (0.13)	0.67 (0.15)	0.66 (0.14)	0.69 (0.17)
Size-composition data	0.70 (0.16)	0.67 (0.14)	0.68 (0.16)	0.67 (0.17)
Size-composition (1)	1.09 (0.22)	0.95 (0.21)	1.03 (0.23)	0.94 (0.25)
Size-composition (2)	0.58 (0.13)	0.66 (0.15)	0.55 (0.19)	0.61 (0.14)
Size-composition (3)	0.46 (0.09)	0.49 (0.11)	0.43 (0.13)	0.48 (0.12)
Rec penalty	1.44 (0.29)	1.49 (0.31)	1.47 (0.37)	1.48 (0.34)

EM1: Misspecified selex curves
EM2: Misspecified h
EM3: Misspecified M

If Ro can correctly identify a misspecified model, φ would increase in EMs.

History of the Ro profile

- Carvalho et al. (2017) extend the use of the φ statistic.
- The Ro profile had low rates of detection of misspecified models.
- No individual diagnostic can detect all forms of misspecification.

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

Increase comps weights

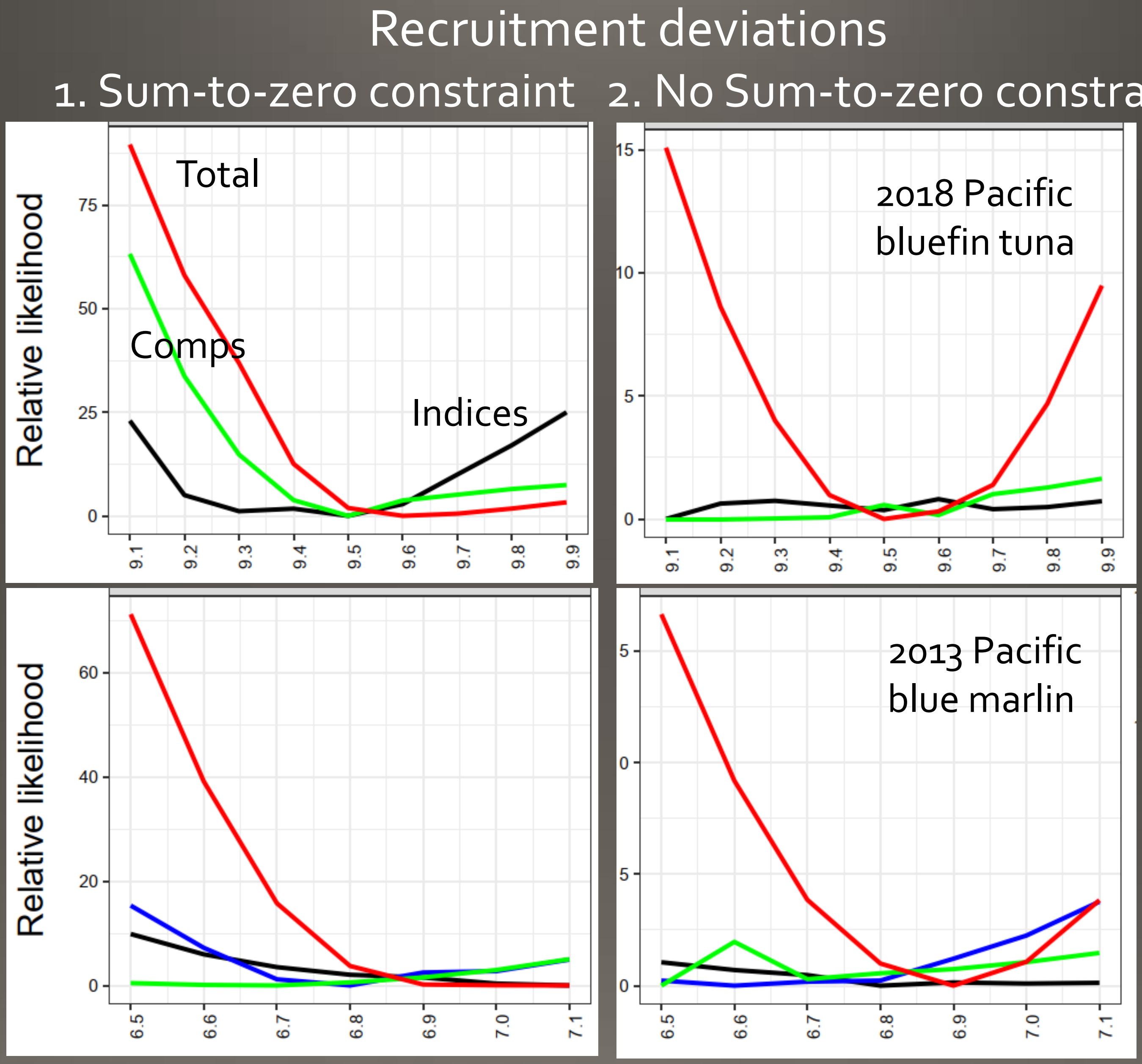
Diagnostic	CSM(%)	EM_1(%) selex	EM_2(%) h	EM_3(%) M	EM_4(%)
SDNR	5	79	24	24	6
Runs test	6	51	9	9	9
ASPM	4	9	86	87	4
Retrospective analysis	0	11	15	12	0
R_0 Likelihood component profile	4	5	4	5	–
CCA	91	92	–	–	–

Cons of the Ro profile

- Prioritization of data remains a situation specific task, which often requires subjective judgment.
- Prioritization of a single data source using the Ro profile may be more questionable when the survey is not informative or where a production relationship is not apparent.
- May have low power to detect the misspecified models.
- The recruitment penalty is often the largest component of the Ro profile.
- Things we really don’t understand in Ro profle.

We don’t fully understand

- The rec dev options alter the Ro profile.
- Care needs to be taken when interpreting the Ro profile.



Pros of Ro profile

- Reveals conflicts between components in the location of estimated population scale.
- Explains contribution of different data components in the model.

a) Identifies the misfit to composition data with large profile gradients that degrade the production relationship.

b) Reducing misfit to the composition data may not improve fit to the prioritized data but allowed those data to contribute proportionately more information to the models estimate of scale.

c) Evaluating the profile by the magnitude of the gradients of low priority data relative to high priority data is a good place to start the model structuring process.

- Finding non-converged models (sardine assessment).

Ro profile and beyond

- Ro profile: not a diagnostic tool to obtain the scale correctly nor to identify the misspecification.
- We do not rely on Ro profile to give us the scale anymore (falls apart when there is no production relationship).
- Move on to the ASPM (global scale, the level of depletion at the start of model).
- And still use Ro profile to structure the model (good way to explain the assessment, like Rick and Chris did) and may indicate problems with the model.

Future research

- Improve the quantitative measure to describe data conflict in the Ro profile.
- Research to detect misspecification and data conflict using multiple diagnostics.
- Further evaluate the effect of the recruitment penalty and the sum-to-zero constraint.
- Use Likelihood component profile over other model parameters (e.g. M, growth, recent recruitment) or derived quantities (e.g. current depletion level).