Best Practices for Modeling Time-Varying Selectivity

Steven Martell & Ian Stewart

International Pacific Halibut Commission

stevem@iphc.int

March 13, 2013

Outline

Motivation

There are many **SUBJECTIVE** elements in stock assessment.

Outline

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
- Statistic Catch Age

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
  - Incomplete cohorts

- Statistic Catch Age

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
  - Incomplete cohorts
  - Error propagation
- Statistic Catch Age

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
  - Incomplete cohorts
  - Error propagation
- Statistic Catch Age
  - Confounding between error & structural assumptions

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
  - Incomplete cohorts
  - Error propagation

- Statistic Catch Age
  - Confounding between error & structural assumptions
  - Seprability (year & age effect)

VPA vs. SCA

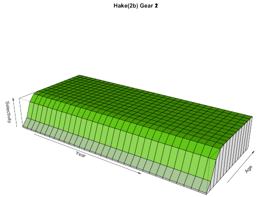
- Virtual Population Analysis
  - Catch reported without error
  - Incomplete cohorts
  - Error propagation

- Statistic Catch Age
  - Confounding between error & structural assumptions
  - Seprability (year & age effect)
  - Large number of latent variables

Outline

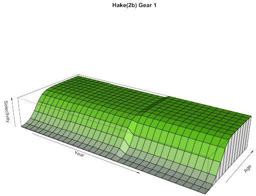
Selectivity Models

Fixed



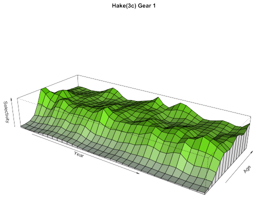
Asymptotic or dome?

Discrete



Choice of time blocks?

Continuous



Variance on penalty?

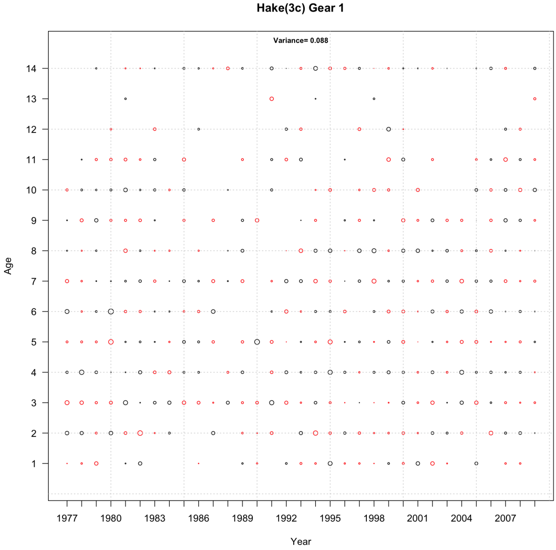
How do we go about choosing the appropriate model?

How do we go about choosing the appropriate model?

Fishing epochs

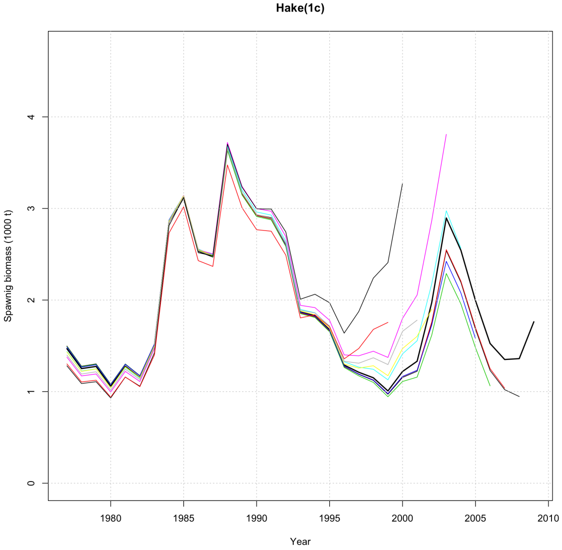

How do we go about choosing the appropriate model?

Residual patterns



How do we go about choosing the appropriate model?

Retrospective performance



How do we go about choosing the appropriate model?

Center for Independent Experts!

Outline

Simulation experiment

True states	Assumed selectivity states		
	Fixed (a) N=89	Discrete (b) N=93	Continuous (c) N=318
Fixed (1)	1a	1b	1c
Discrete (2)	2a	2b	2c
Continuous (3)	3a	3b	3c

Model structure

Simulation: based on 2010 Pacific hake assessment

- Age-structured, assume M is known.
- Conditioned on historical catch & parameters fixed at MLE values.
- Parameters: B_o, h, initial states, rec-devs, selectivities, F's, q, total variance.
- Concentrated likelihood for age-comps & estimate total variance.

Data:

- Historical removals.
- Annual abundance index based on stationary q.
- Survey age composition (logistic–time invariant).
- Fishery age composition (selectivity: fixed, blocks, or continous).
- Index observation error: $\sigma = 0.40$
- Age-composition error (multivariate logistic): $\sigma = 0.40$
- Process error: $\tau = 1.12$

Questions

1. Can DIC be used reliably to choose the correct selectivity model?
2. Impact of selectivity mis-specification on reference points?
3. Retrospective performance of selectivity mis-specification?

Algorithm

For each model scenario:

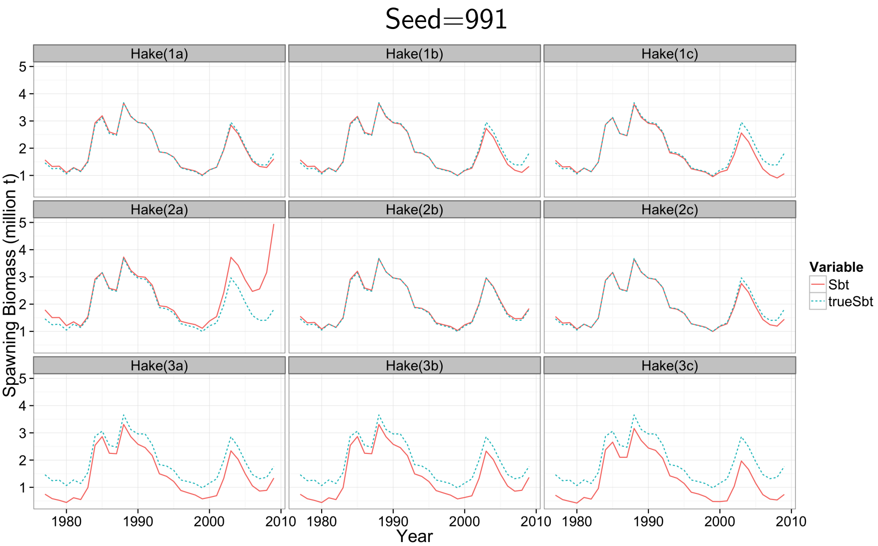
1. Estimate model parameters for 2010 hake assesment.
2. Simulate relative abundance and age-comps based on MLE values.
3. Estimate joint posterior for simulated observations.
4. Calculate DIC from 1000 posterior samples.
5. Compute bias in estimated reference points.
6. Compute 4-year mean retrospective bias.
7. Repeat steps 2:5 at least 100 times for each scenario (9).

Model Selection

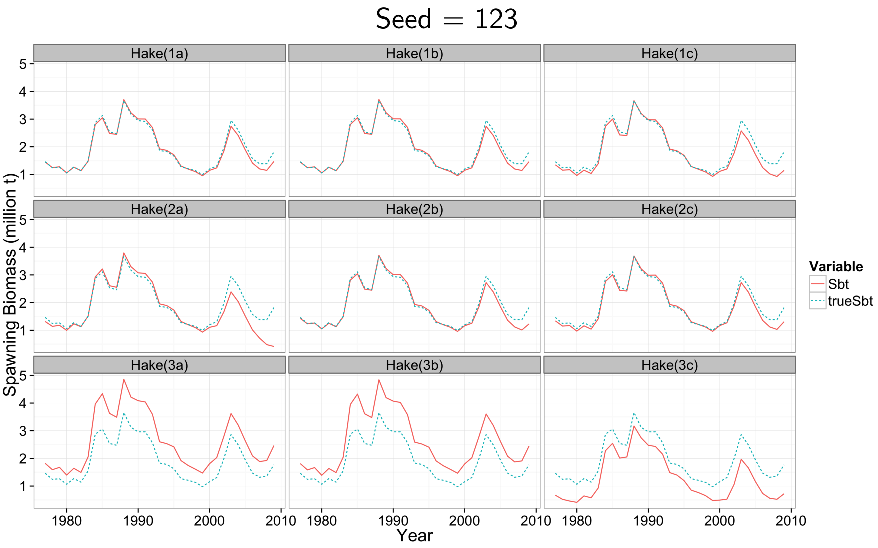
Can DIC be used reliably to choose the correct selectivity model?

DIC based on 1000 samples from the joint posterior.
Monte carlo runs based on 24 simulated data sets per treatment.

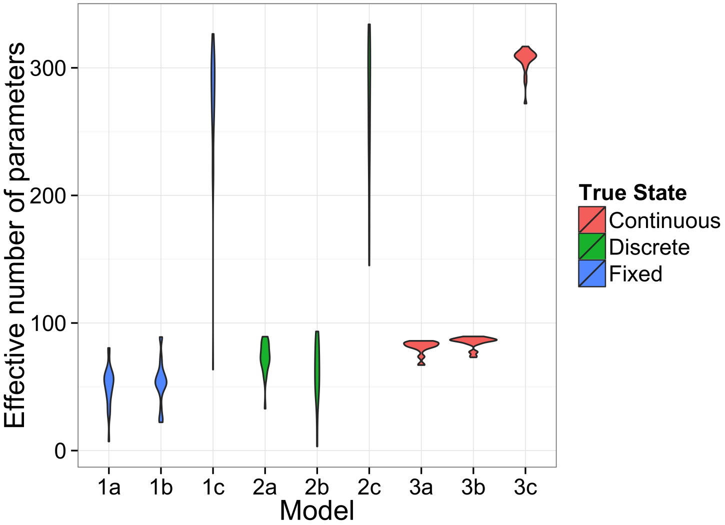
Spawning biomass



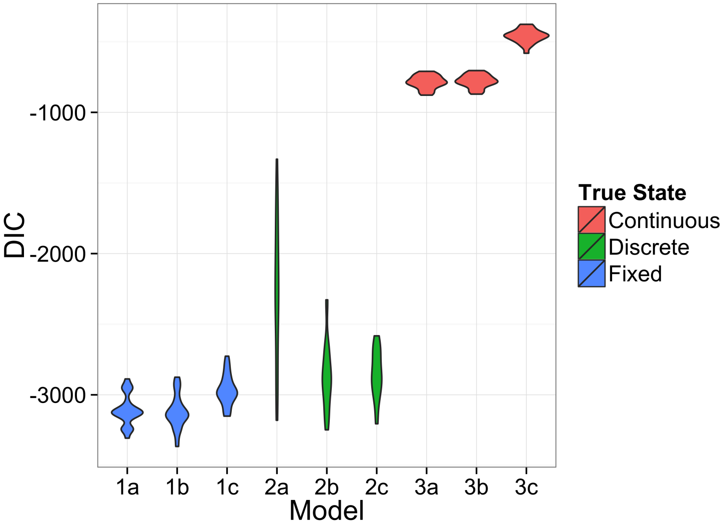
Spawning biomass



Effective number of parameters



Model selection vis-à-vis DIC



Impacts on reference points

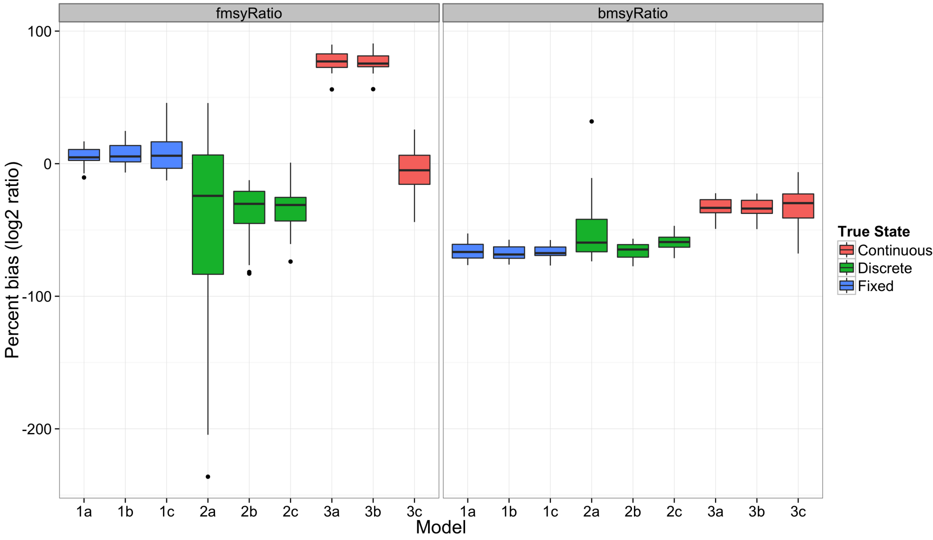
Impact of selectivity mis-specification on reference points?

MSY-based reference points based on MLE estimates.

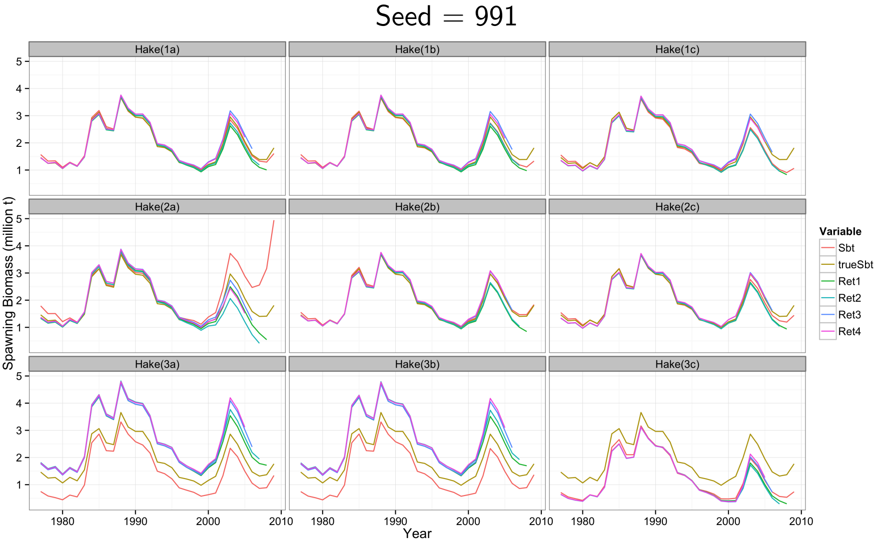
Monte carlo runs based on 24 simulated data sets per treatment.

Compute $\log_2\left(\frac{F_{est}}{F_{true}}\right)$

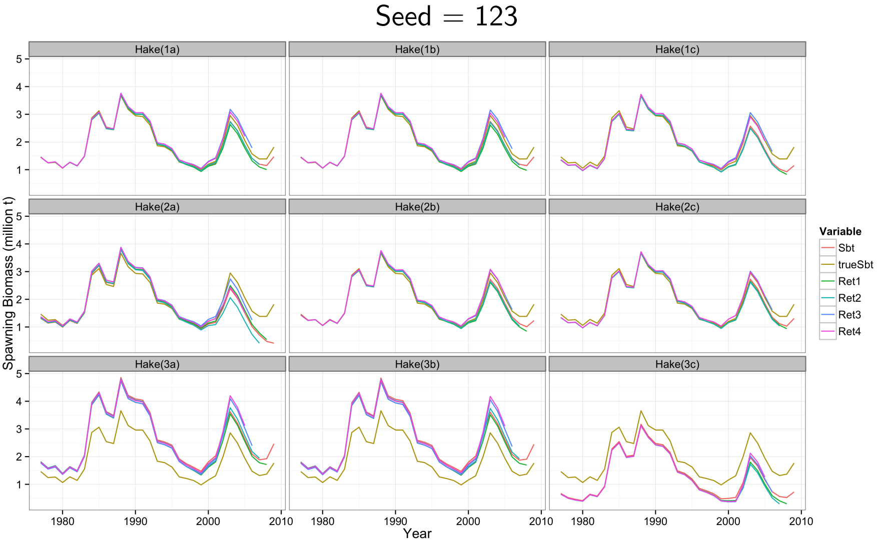
Impacts on reference points



Retrospective bias



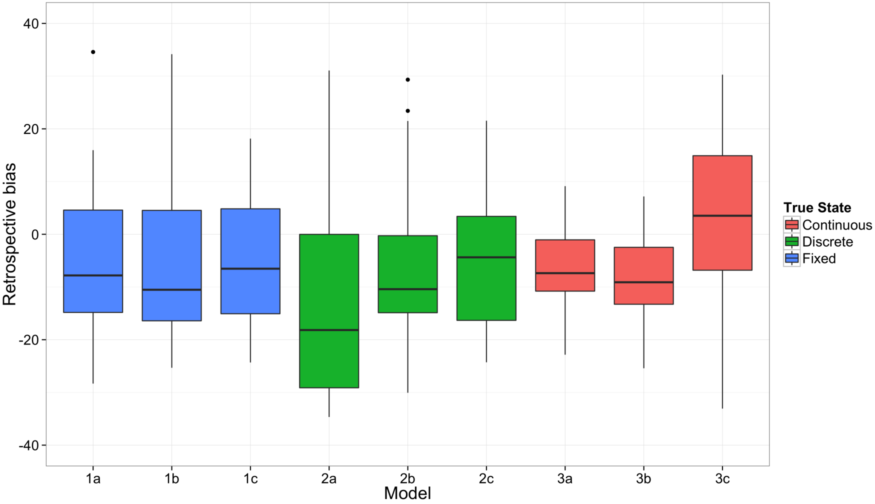
Retrospective bias



Retrospective bias

$$\text{bias} = \frac{1}{4} \sum_{t=2005}^{2009} 100 \frac{B_t^y - B_t^{2010}}{B_t^{2010}}$$

Retrospective bias



Outline

What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.

What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.

What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.
- Rather than add small constant, pool weak cohorts into adjacent year classes.

What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.
- Rather than add small constant, pool weak cohorts into adjacent year classes.
- Tagging data could help resolve confounding in integrated models.

What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.
- Rather than add small constant, pool weak cohorts into adjacent year classes.
- Tagging data could help resolve confounding in integrated models.
- Conduct simulation testing to verify that model selection criteria works.

What I learned from this exercise

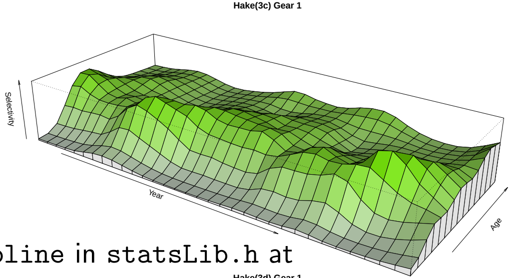
- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.
- Rather than add small constant, pool weak cohorts into adjacent year classes.
- Tagging data could help resolve confounding in integrated models.
- Conduct simulation testing to verify that model selection criteria works.
- And there is one more thing....

What I learned from this exercise

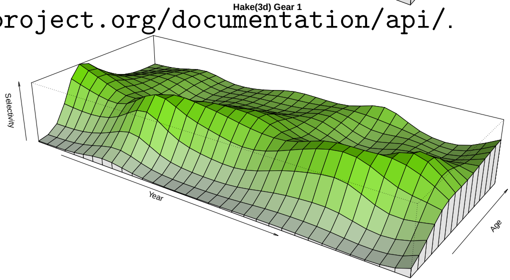
- Preferable to adopt a penalized random walk versus time blocks.
  - Less retrospective bias & less bias in F_{MSY}.
- Random walk models: loss of scale information, informative prior for survey q.
- Rather than add small constant, pool weak cohorts into adjacent year classes.
- Tagging data could help resolve confounding in integrated models.
- Conduct simulation testing to verify that model selection criteria works.
- And there is one more thing....
  - Can also use 2 dimensional splines for selectivity.

2d cubic splines

Top = 231 and bottom = 60 selectivity parameters.



See `bicubic_spline` in `statsLib.h` at
`http://admb-project.org/documentation/api/`.



The End

Acknowledgements:

IPHC, ADMB Foundation, CAPAM workshop organizers.

Jim Ianelli and Dave Fournier for the `vcubicspline_function_array` class.