Best Practices for Modeling Time-Varying Selectivity

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International Pacific Halibut Commission

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Parts to this talk

Outline

Motivation

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

Outline

VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error

- Statistic Catch Age

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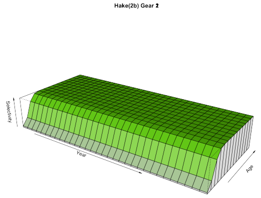
- Statistic Catch Age
  - Confounding between error & structural assumptions
  - Seprability (year & age effect)
  - Large number of latent variables

Outline

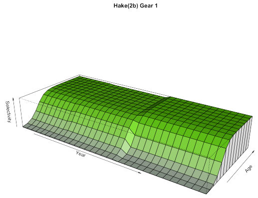
Selectivity Models

Fixed



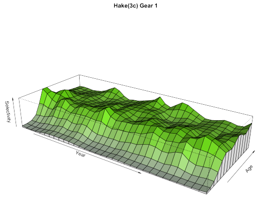
Asymptotic or dome?

Discrete



Choice of time blocks?

Continuous



Variance on penalty?

How do we go about choosing the appropriate model?

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Fishing epochs

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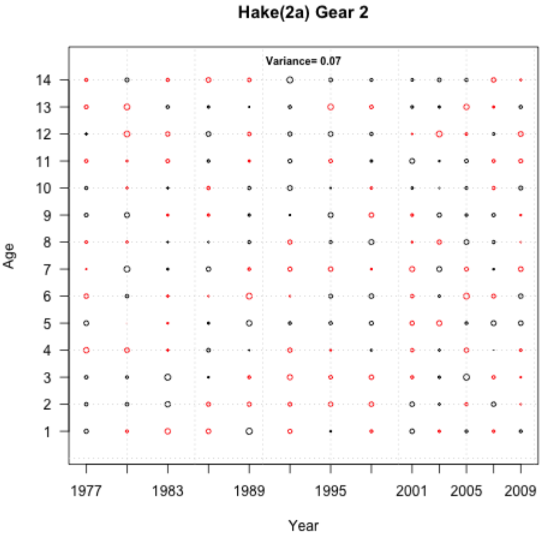
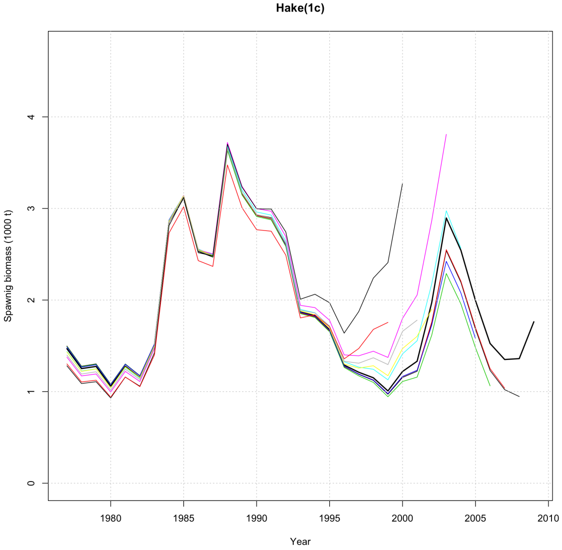
Residual patterns



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)	Disc. (b)	Cont. (c)	Bicub (d)
No. parameters	N=156	N=160	N=385	N=239
Estimated No.	N=89	N=93	N=318	N=172
Fixed (1)	1a	1b	1c	1d
Discrete (2)	2a	2b	2c	2d
Continuous (3)	3a	3b	3c	3d

Model structure

Simulation: based on 2010 Pacific hake assessment

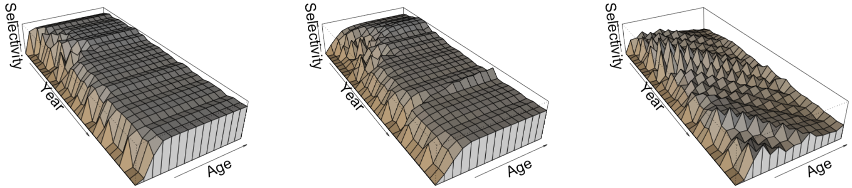
- Age-structured, assume M is known.
- Conditioned on historical catch & parameters fixed at MLE values.
- Parameters: B_o, h, initial states, rec-devs, selectivities, F's, q, total variance.
- Concentrated likelihood for age-comps & estimate variance for survey & recruitment deviates.

Data:

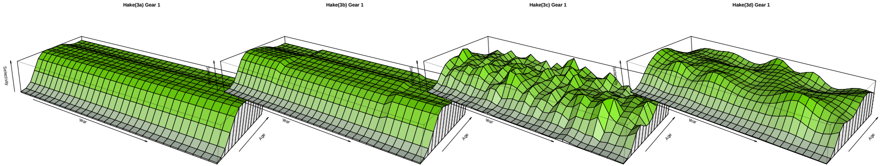
- Historical removals.
- Annual abundance index based on stationary q.
- Survey age composition (logistic–time invariant).
- Fishery age composition (selectivity: fixed, blocks, or continous).
- Index observation error: $\sigma = 0.30$
- Age-composition error (multivariate logistic): $\sigma = 0.30$
- Process error: $\tau = 1.12$

Selectivities

Simulated



Estimated (7 knot cubic spline)



Questions

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

Model selection based on DIC

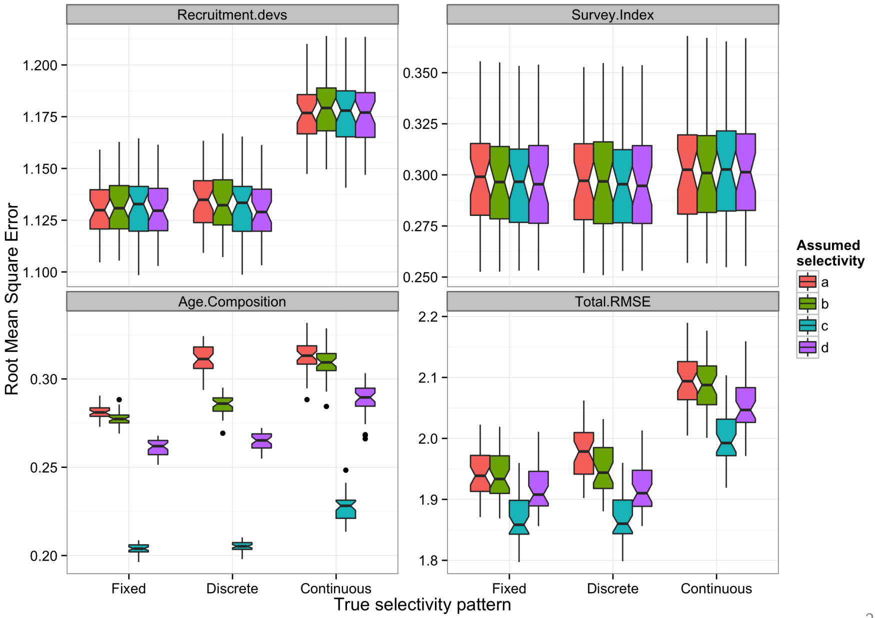
For each true state (fixed, discrete, continuous), fit 4 alternative assessment models to the data and calculate Deviance Information Criterion (DIC).

Model selection based on DIC

ΔDIC

True states	Assumed selectivity states			
	Fixed (a)	Disc. (b)	Cont. (c)	Bicub (d)
Fixed (1)	10.28	21.92	26.23	0.00
Discrete (2)	195.52	45.45	0.00	2.70
Continuous (3)	1.72	8.45	3.05	0.00

Root Mean Square Error

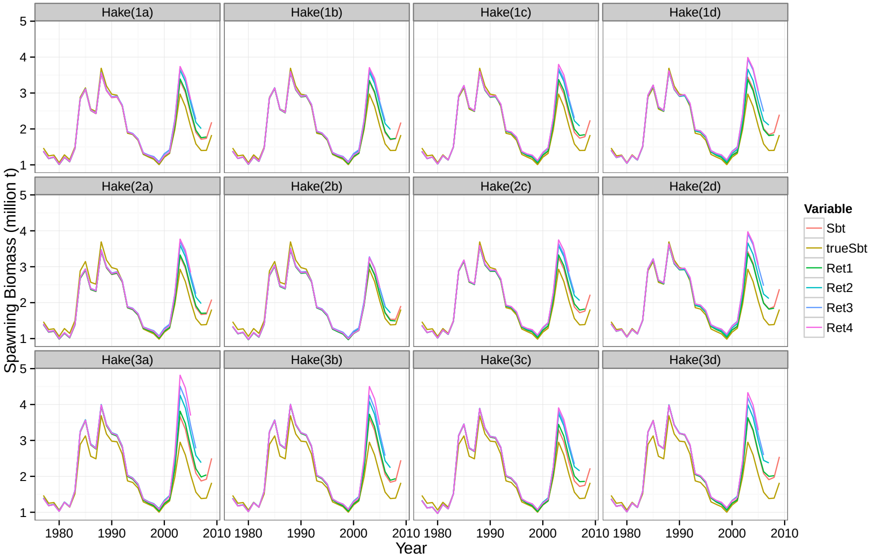


Root Mean Square Error

RMSE

True states	Assumed selectivity states			
	Fixed (a)	Disc. (b)	Cont. (c)	Bicub (d)
Fixed (1)	1.942	1.937	1.867	1.915
Discrete (2)	1.979	1.949	1.868	1.918
Continuous (3)	2.093	2.087	1.999	2.053

Retrospective performance



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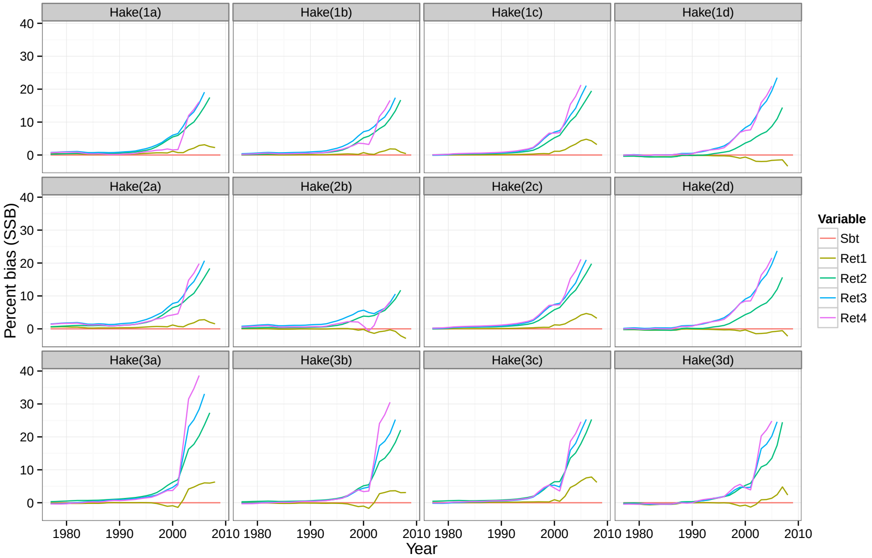
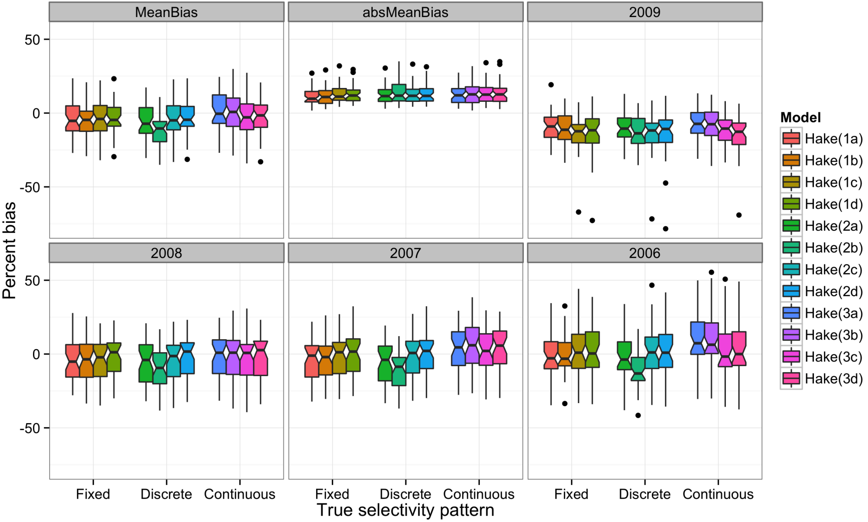


Retrospective performance

Monte Carlo trials



Retrospective bias statistic Ω

Distance between average and absolute average bias:

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

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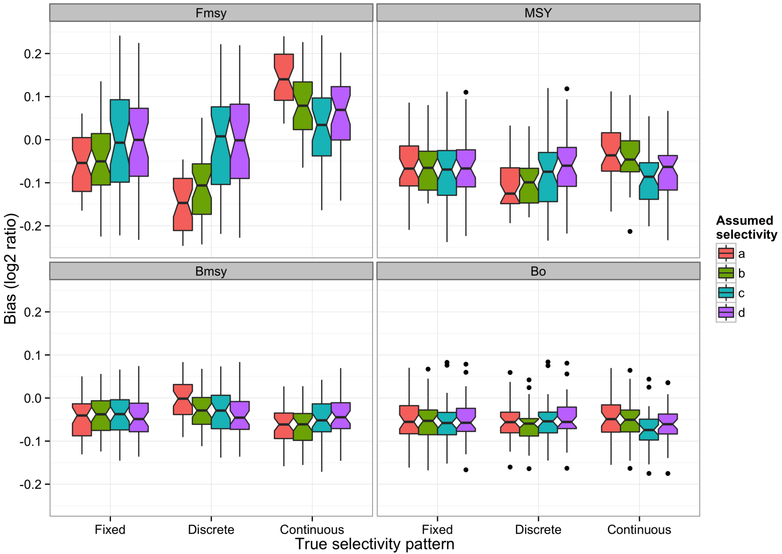
$$\Omega = \sqrt{\text{bias}^2 + |\text{bias}|^2}$$

Retrospective bias statistic Ω

$\Omega = 0$ implies no bias

True states	**Assumed selectivity states**			
	Fixed (a)	Disc. (b)	Cont. (c)	Bicub (d)
Fixed (1)	15.75	15.66	16.53	16.40
Discrete (2)	16.62	18.99	16.73	16.55
Continuous (3)	16.62	17.47	17.40	17.48

Bias in reference points



Bias in reference points

F_{MSY} bias

True states	**Assumed selectivity states**			
	Fixed (a)	Disc. (b)	Cont. (c)	Bicub (d)
Fixed (1)	-0.054	-0.050	-0.009	0.007
Discrete (2)	-0.155	-0.120	0.003	0.013
Continuous (3)	0.142	0.086	0.064	0.100

Rank scores

True states	Assumed selectivity states			
	Fixed (1)	Disc. (2)	Cont. (3)	Rank order
DIC	d,a,b,c	c,d,b,a	d,a,c,b	**d**,c,b,a
Ω	b,a,d,c	d,a,c,b	a,c,b,d	a,**d**,c,b
F_{MSY}	d,c,b,a	c,d,b,a	c,b,d,a	c,**d**,b,a

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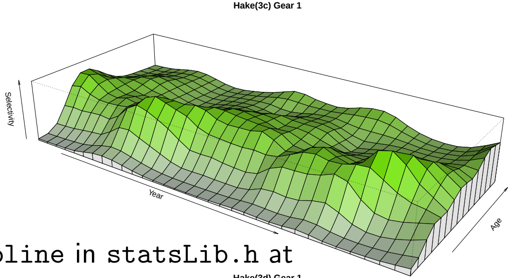
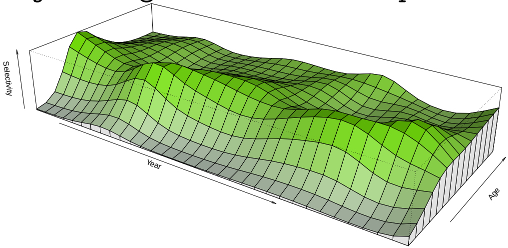
- Ensure parameterization is continuous and differentiable.
  - Avoid `max` function (not continous).

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

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