# Best Practices for Modeling Time-Varying Selectivity

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# Parts to this talk

1. Motivation
2. Virtual & Synthetic methods
3. Selectivity Models
4. Simulation Experiment
   - Model overview
   - Simulation results
5. What I've learned so far

# Outline

# Motivation

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

# Outline

# VPA vs. SCA

- Virtual Population Analysis
  - Catch reported without error
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  - Incomplete cohorts
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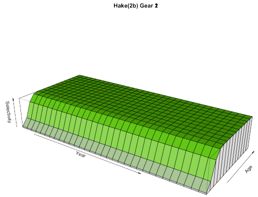
- Statistic Catch Age
  - Confounding between error & structural assumptions
  - Seprability (year & age effect)
  - Large number of latent variables

# Outline

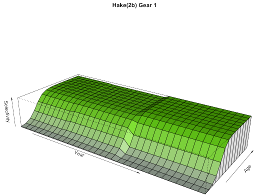
# Selectivity Models

**Fixed**



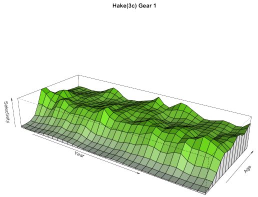

Asymptotic or dome?

**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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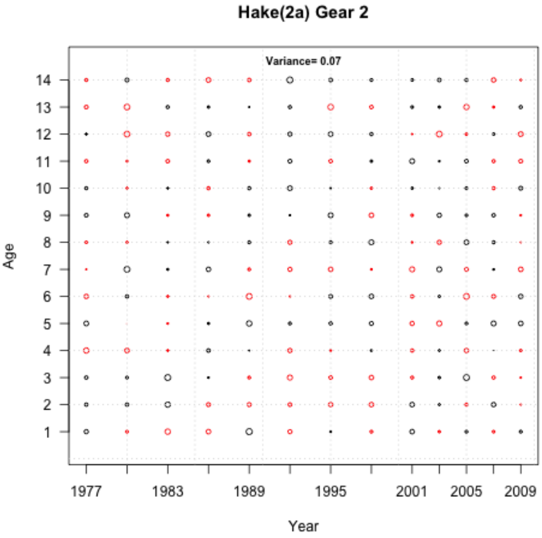
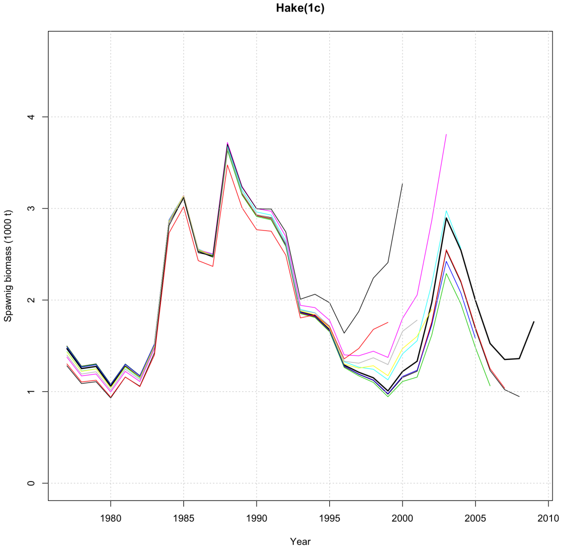
*Residual patterns*



# 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

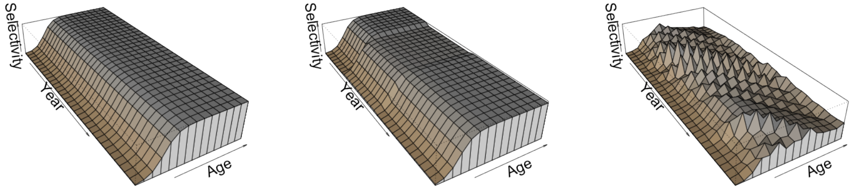
- Age-structured, assume $M$ is known.
- Conditioned on historical catch & parameters fixed at MLE values.
- Parameters: $B_o$, $h$, initial states, rec-devs, selectivities, F's, q, total variance.
- Concentrated likelihood for age-comps & estimate variance for survey & recruitment deviates.

Data:

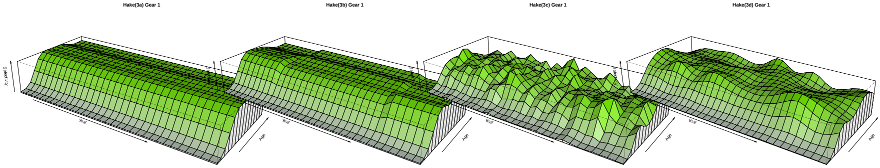
- Historical removals.
- Annual abundance index based on stationary $q$.
- Survey age composition (logistic–time invariant).
- Fishery age composition (selectivity: fixed, blocks, or continous).
- Index observation error: $\sigma = 0.30$
- Age-composition error (multivariate logistic): $\sigma = 0.30$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

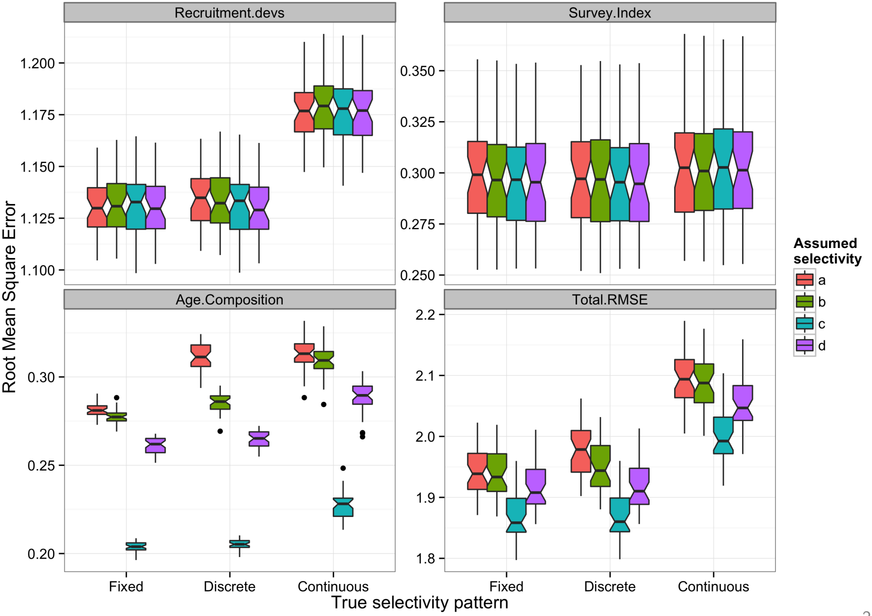
For each true state (fixed, discrete, continuous), fit 4 alternative assessment models to the data and calculate Deviance Information Criterion (DIC).

# 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

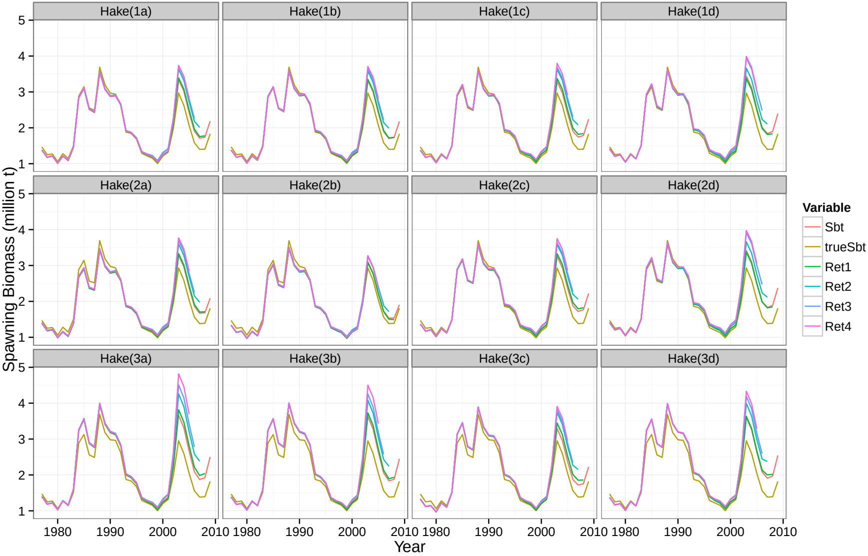


# Root Mean Square Error

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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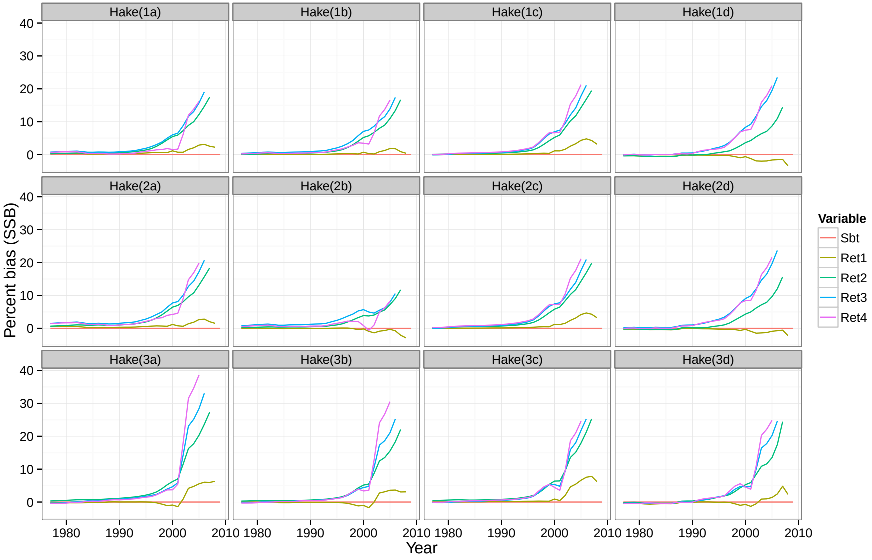
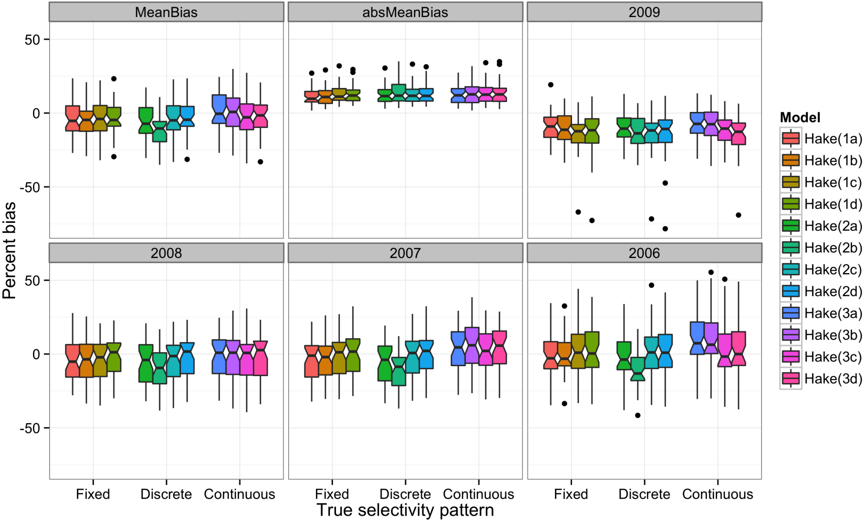


# Retrospective performance

## Monte Carlo trials



# Retrospective bias statistic $\Omega$

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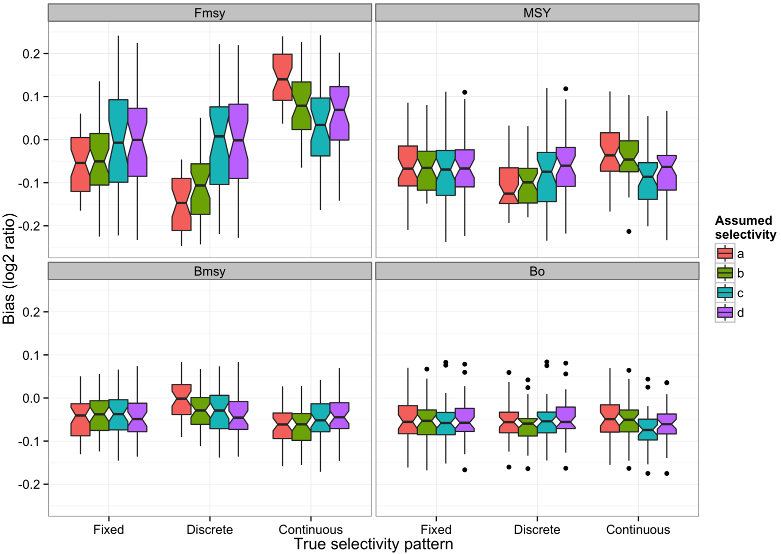
$$\Omega = \sqrt{\text{bias}^2 + |\text{bias}|^2}$$

# Retrospective bias statistic $\Omega$

$\Omega = 0$ 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

$F_{\mathrm{MSY}}$ 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 |
| $\Omega$ | b,a,d,c | d,a,c,b | a,c,b,d | a,**d**,c,b |
| $F_{\mathrm{MSY}}$ | d,c,b,a | c,d,b,a | c,b,d,a | c,**d**,b,a |

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# What I learned from this exercise

- Preferable to adopt a penalized random walk versus time blocks.
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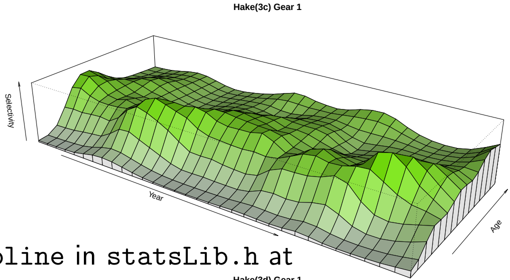
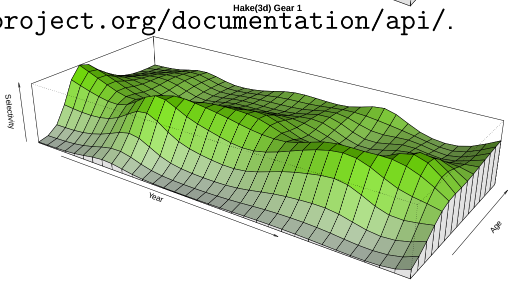
- Ensure parameterization is continuous and differentiable.
  - Avoid `max` function (not continous).

# 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.