A Metamodeling Approach for Bias Estimation of Biological Reference Points

Nick Grunloh

13 August 2024

Outline

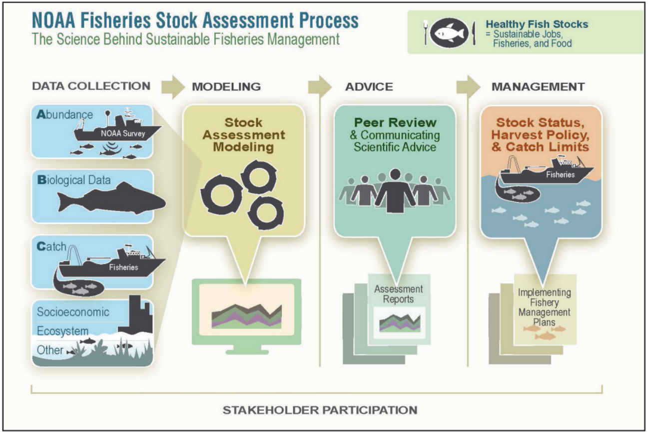
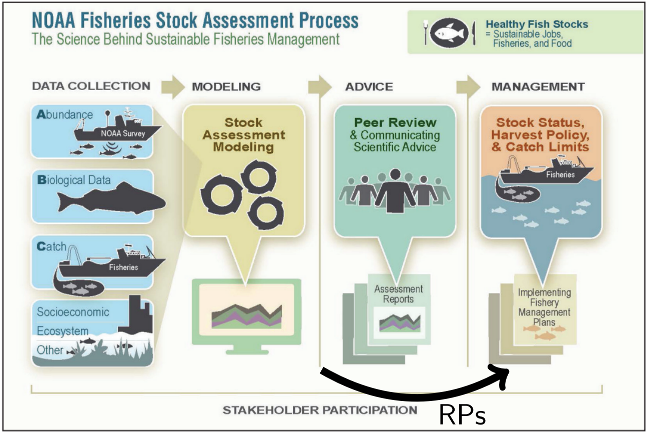


Figure 1: Overview of the stock assessment process from data collection through the provision of scientific advice to fishery managers. Stakeholders and other partners participate in each step of the assessment process. This report captures NOAA Fisheries products associated with the 'Advice' phase of the process. *

*NOAA Fisheries Annual Stock Assessment Report 2020



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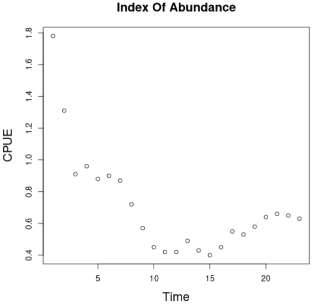
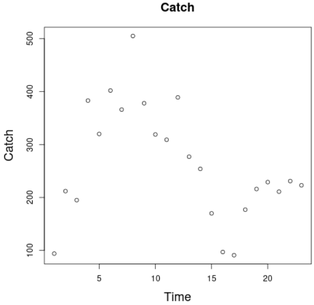
Surplus Production Model General Structure



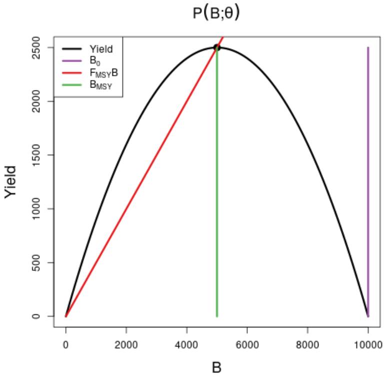


$$I_t = qB_te^{\epsilon} \quad \epsilon \sim N(0, \sigma^2)$$

$$\frac{dB}{dt} = P(B(t); \boldsymbol{\theta}) - Z(t)B(t)$$

Reference Points:

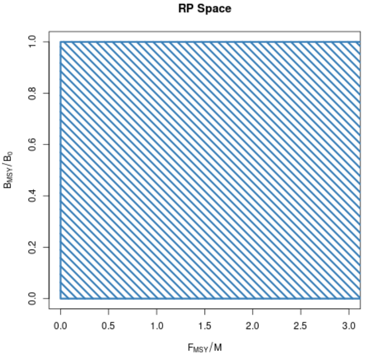
- Maximum Sustainable Yield (MSY)
- F_{MSY}[a]: Fishing rate to achieve MSY
- $\frac{B_{MSY}}{B_0}$: Biomass Depletion when at MSY
- Driven by the shape of P as determined by θ.



[a] or $\frac{F_{MSY}}{M}$

Conceptually:

$$\frac{F_{MSY}}{M} \in \mathbb{R}^+ \quad \frac{B_{MSY}}{B_0} \in (0,1)$$



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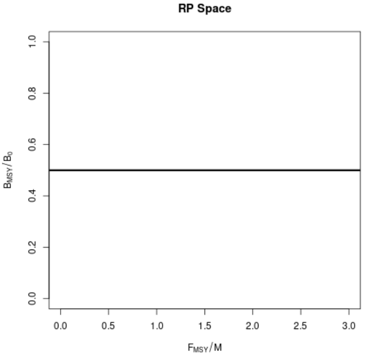
$$\frac{F_{MSY}}{M} \in \mathbb{R}^+ \quad \frac{B_{MSY}}{B_0} \in (0,1)$$

- Schaefer Model:
  $F_{MSY} \in \mathbb{R}^+ \quad \frac{B_{MSY}}{\bar{B}(0)} = \frac{1}{2}$



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- BH Model:
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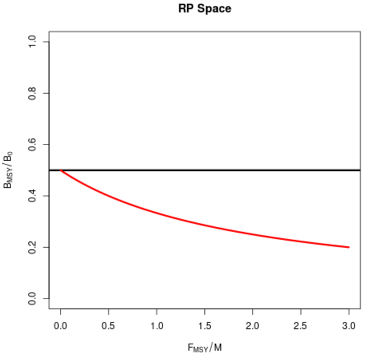

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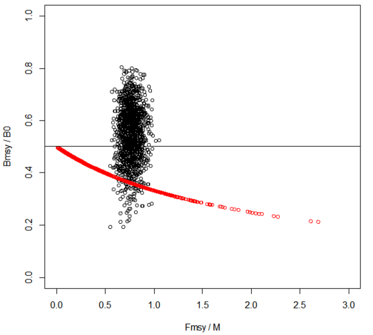
  $\frac{F_{MSY}}{M} \in \mathbb{R}^+ \quad \frac{B_{MSY}}{\bar{B}(0)} = \frac{1}{F_{MSY}/M+2}$
- Similar Constraints for other Two-Parameter Models:
  Fox, Ricker, etc...
- Three-Parameter Models Allow Independent RP Estimation



[a]

[a] Mangel et al. 2013, CJFAS

Outline

- P_ℓ is logistic production
- Logistic map in discrete time
- Implicit Natural Mortality
- Explicit Fishing Mortality

$$I_t = qB_t e^{\epsilon} \quad \epsilon \sim N(0, \sigma^2)$$

$$\frac{dB}{dt} = P_\ell(B(t);\boldsymbol{\theta}) - F(t)B(t)$$

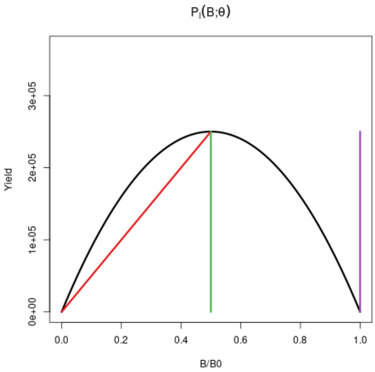
$$P_\ell(B;[r,K]) = rB\left(1-\left(\frac{B}{K}\right)\right)$$

Reference Points:

$$F^* = \frac{r}{2}$$

$$B^* = \frac{K}{2} \qquad B_0 = K$$

$$\frac{B^*}{B_0} = \frac{1}{2}$$



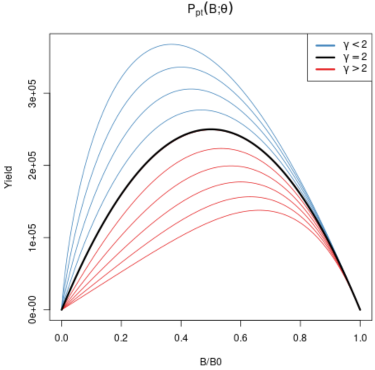
$$P_{pt}(B;[r,K,\gamma]) = \frac{rB}{\gamma-1}\left(1-\left(\frac{B}{K}\right)^{(\gamma-1)}\right)$$

Reference Points:

$$F^* = \frac{r}{\gamma}$$

$$B^* = K\left(\frac{1}{\gamma}\right)^{\frac{1}{\gamma-1}} \quad B_0 = K$$

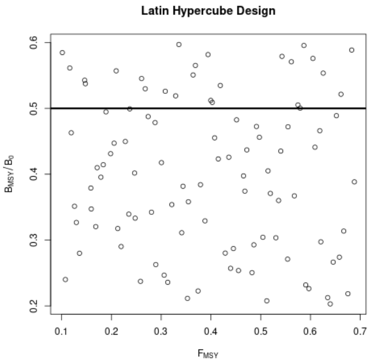
$$\frac{B^*}{B_0} = \left(\frac{1}{\gamma}\right)^{\frac{1}{\gamma-1}}$$



$$F^* = \frac{r}{\gamma} \qquad \frac{B^*}{\bar{B}(0)} = \left(\frac{1}{\gamma}\right)^{\frac{1}{\gamma-1}}$$

Closed-Form Inversion

$$r = \gamma F^* \quad \gamma = \frac{W\left(\frac{B^*}{\bar{B}(0)} \log\left(\frac{B^*}{\bar{B}(0)}\right)\right)}{\log\left(\frac{B^*}{\bar{B}(0)}\right)}$$



* Lambert W function inverts xe^x $s.t.$ $W(xe^x) = x$

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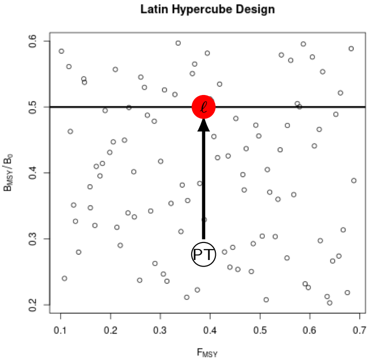
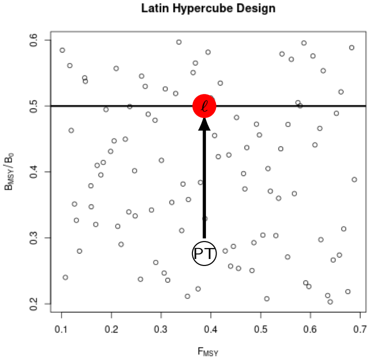
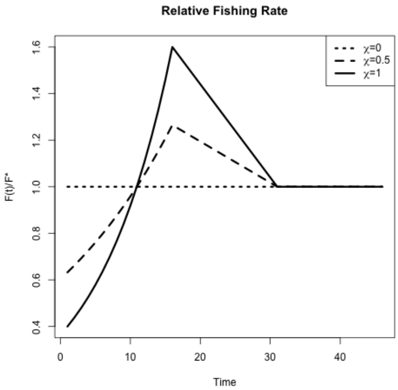


* Lambert W function inverts xe^x $s.t.$ $W(xe^x) = x$

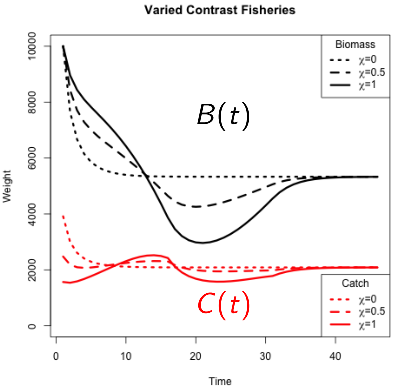
$$\underbrace{\left(F_{MSY}, \frac{B_{MSY}}{\bar{B}(0)}\right)}_{\text{PT Truth}} \overset{GP}{\mapsto} \underbrace{\left(\hat{F}_{MSY}, \frac{1}{2}\right)}_{\text{Shaefer Estimate}}$$

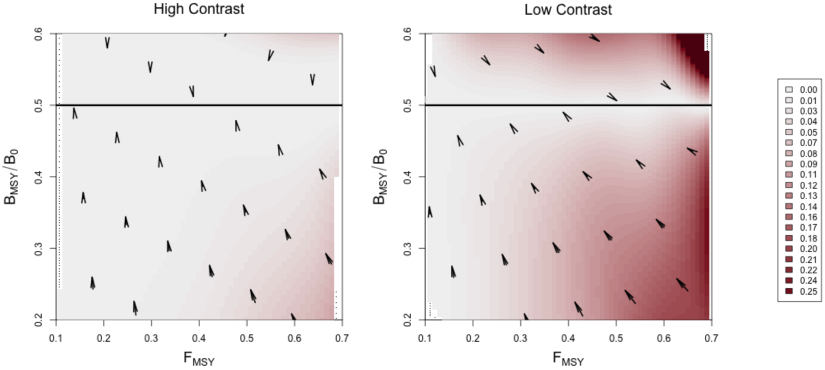


$$\frac{dB}{dt} = P(B(t);\theta) - F(t)B(t)$$
$$= P(B(t);\theta) - F^*_\theta \underbrace{\frac{F(t)}{F^*_\theta}}_{\text{Relative Fishing}} B(t)$$



$$\frac{dB}{dt} = P(B(t);\theta) - F(t)B(t)$$
$$= P(B(t);\theta) - \underbrace{F^*_\theta \frac{F(t)}{F^*_\theta} B(t)}_{C(t)}$$




High Contrast
Low Contrast
B_{MSY}/B_0
F_{MSY}
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.00
0.01
0.03
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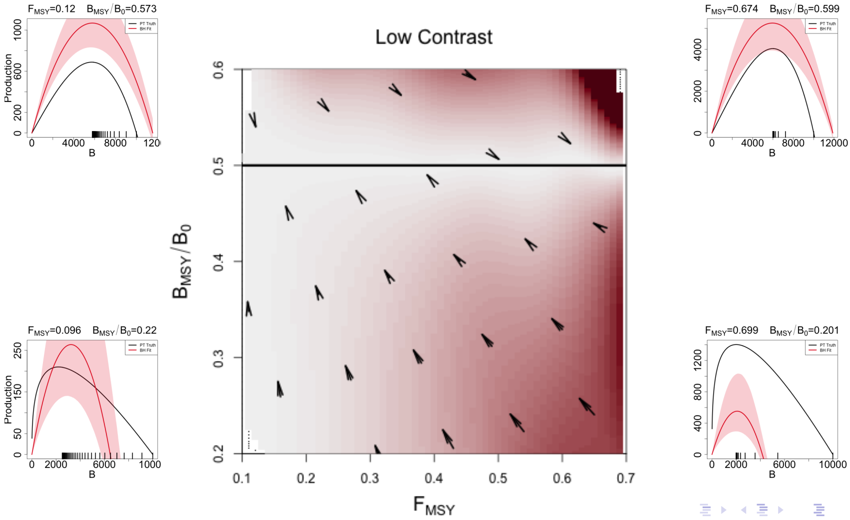
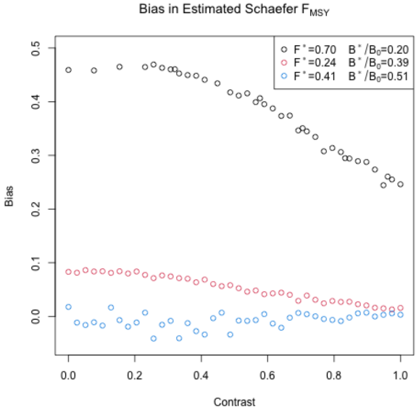
0.25

Mechanism for Bias in F_{MSY} via Contrast



Mechanism for Bias in F_{MSY} via Contrast

- Only observe upper half
- learn about slope at origin from upper biomass range
- as contrast increases biases perspective deminishes



Summary

- PT three-parameter generalization allows fully analytical RP designs.
- Novel simulation framework explicitly controlling for RP misspecification.
- The useful notion of contrast developed here together with the simplified geometry of the Schaefer model exposes a mechanism for RP bias
- What to do when the simulation design is not analytical?

Outline

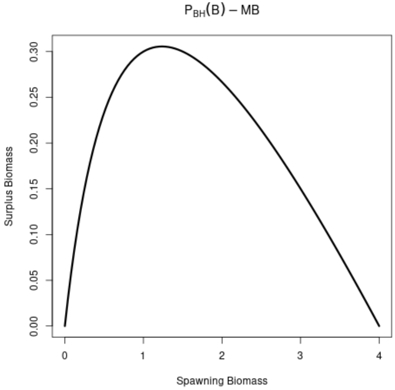
$$I_t = qB_te^{\epsilon} \quad \epsilon \sim N(0, \sigma^2)$$
$$\frac{dB}{dt} = P_{BH}(B; [\alpha, \beta]) - (M+F)B$$

$$P_{BH}(B; [\alpha, \beta]) = \frac{\alpha B}{1 + \beta B}$$

$$I_t = qB_t e^{\epsilon} \quad \epsilon \sim N(0, \sigma^2)$$

$$\frac{dB}{dt} = \underbrace{P_{BH}(B; [\alpha, \beta]) - MB}_{\text{Surplus Production}} - FB$$

$$P_{BH}(B; [\alpha, \beta]) = \frac{\alpha B}{1 + \beta B}$$



$$P_s(B;[\alpha,\beta,\gamma]) = \alpha B(1-\beta\gamma B)^{\frac{1}{\gamma}}$$

Logistic

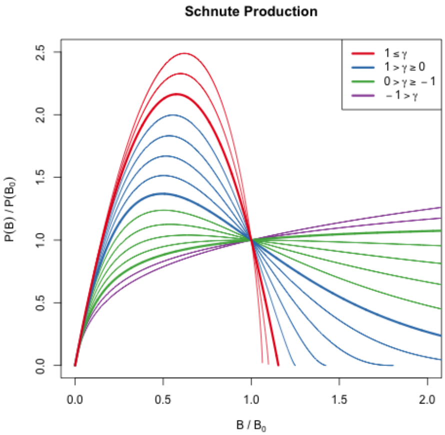
$\gamma = 1$

Ricker

$\gamma \to 0$

Beverton-Holt

$\gamma = -1$



$$\text{RPs} \mapsto \theta$$

Incomplete Inversion

$$\theta \mapsto \text{RPs}$$

$$\alpha = (M + F^*)\left(1 + \frac{\gamma F^*}{M + F^*}\right)^{1/\gamma}$$

$$\beta = \frac{1}{\gamma B_0}\left(1 - \left(\frac{M}{\alpha}\right)^{\gamma}\right)$$

$$\frac{B^*}{B_0} = \frac{1 - \left(\frac{M+F^*}{\alpha}\right)^{\gamma}}{1 - \left(\frac{M}{\alpha}\right)^{\gamma}}.$$

Schnute & Richards (1998). CJFAS.

RPs $\mapsto \theta$

Incomplete Inversion

$\theta \mapsto$ RPs

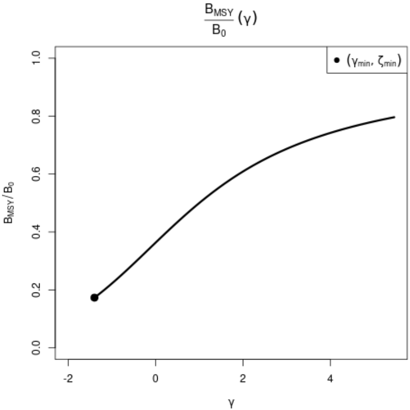
$$\alpha(\gamma)$$

$$\beta(\alpha(\gamma),\gamma)$$

$$\frac{B^*}{B_0}(\alpha(\gamma),\gamma)$$

Schnute & Richards (1998). CJFAS.

$$\frac{B^*}{B_0}(\gamma) = \frac{1-\left(\frac{M+F^*}{\alpha(\gamma)}\right)^{\gamma}}{1-\left(\frac{M}{\alpha(\gamma)}\right)^{\gamma}}$$



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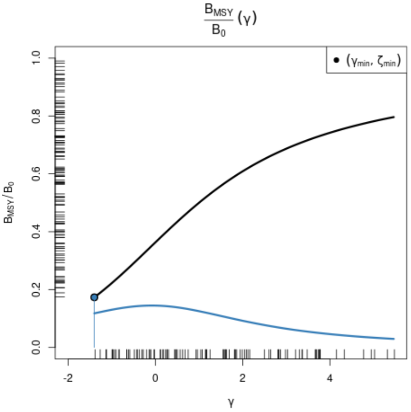
$$\gamma' \sim \zeta_{min}\delta(\gamma_{min}) + (1-\zeta_{min})t(\mu,\sigma,\nu)\mathbf{1}_{\gamma>\gamma_{min}}$$



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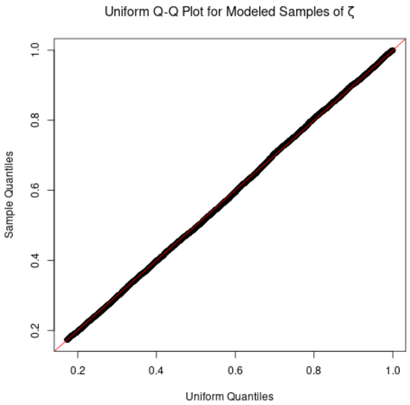


Schnute LHS Design

Logistic

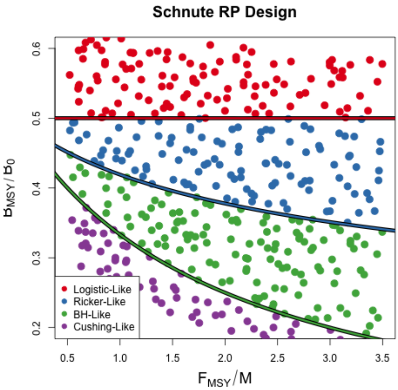
$\gamma = 1$

Ricker

$\gamma \to 0$

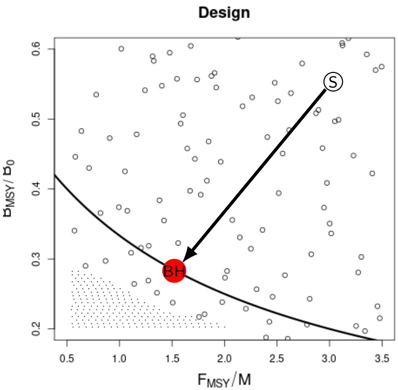
Beverton-Holt

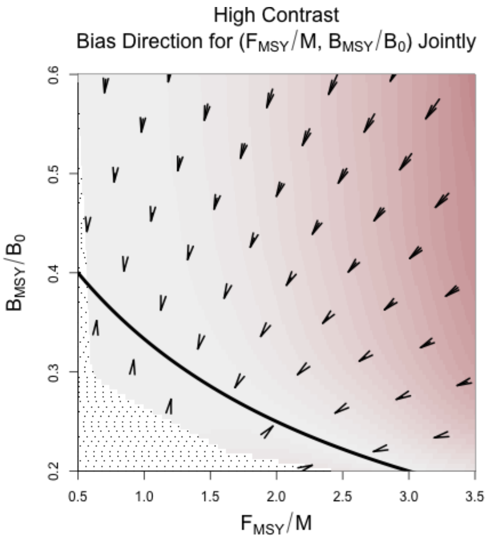
$\gamma = -1$



Schnute LHS Design

$$\underbrace{\left(\frac{F_{MSY}}{M}, \frac{B_{MSY}}{\bar{B}(0)}\right)}_{\text{Schnute Truth}} \overset{GP}{\mapsto} \underbrace{\left(\frac{\hat{F}_{MSY}}{M}, \frac{1}{\hat{F}_{MSY}/M+2}\right)}_{\text{BH Estimate}}$$




High Contrast
Bias Direction for $(F_{MSY}/M, B_{MSY}/B_0)$ Jointly
B_{MSY}/B_0
0.2
0.3
0.4
0.5
0.6
0.5
1.0
1.5
2.0
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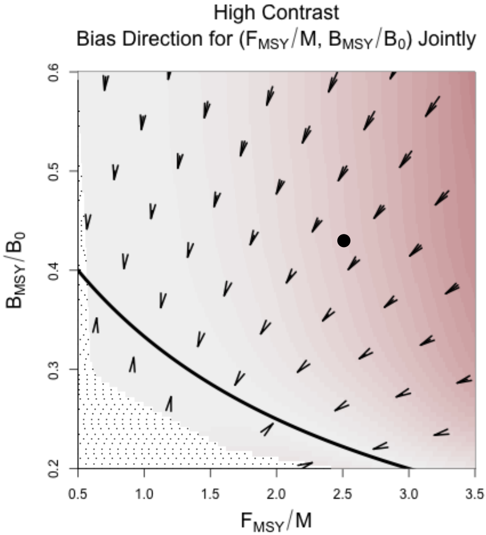
3.5
F_{MSY}/M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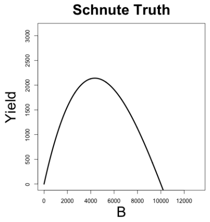
Schnute Truth
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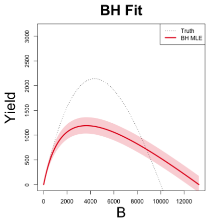

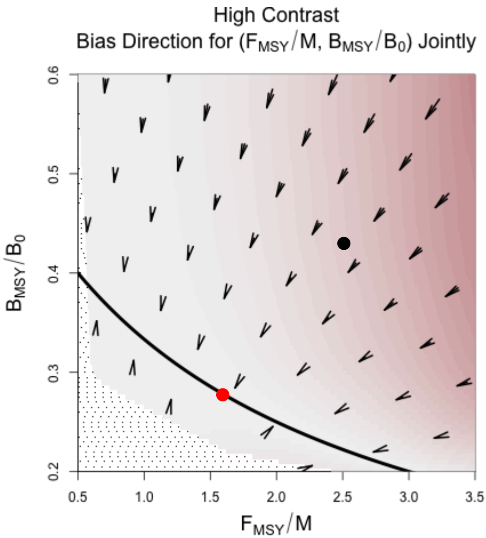

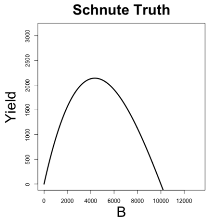

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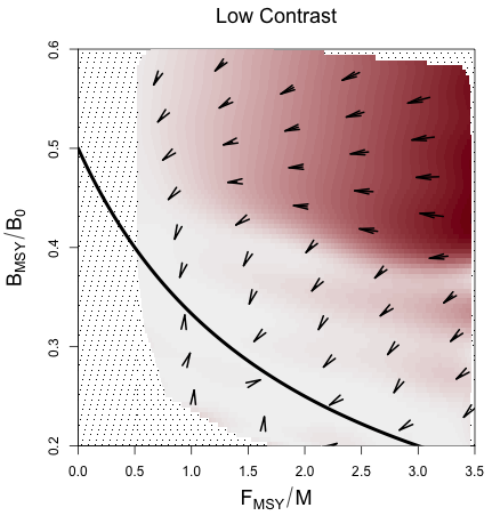
Low Contrast
0.2
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B_{MSY}/B_0
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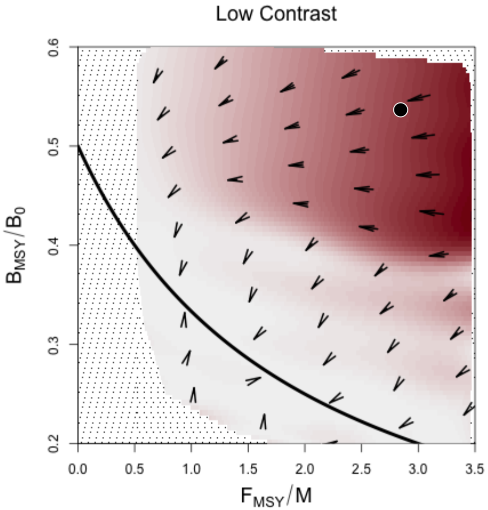
3.5
F_{MSY}/M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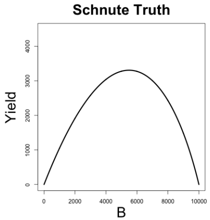
Schnute Truth
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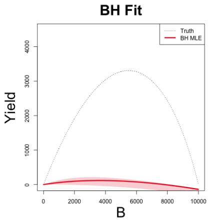
BH Fit
Truth
BH MLE
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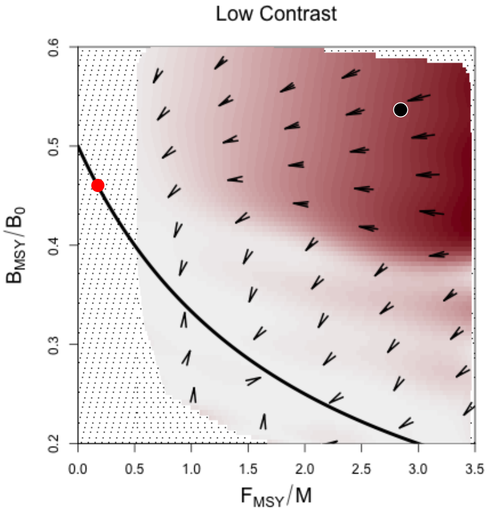
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F_{MSY}/M
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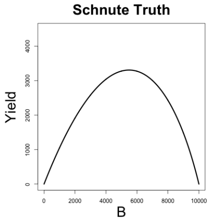
Schnute Truth
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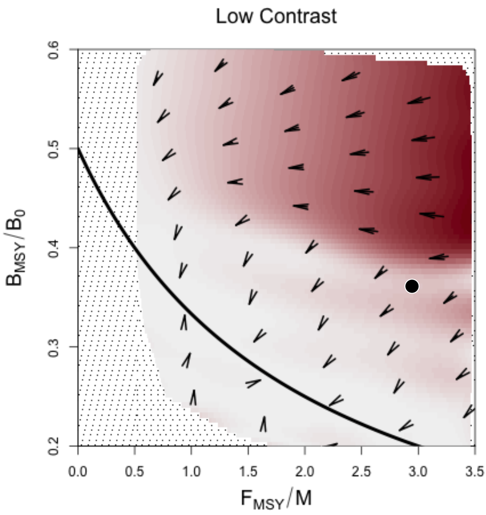
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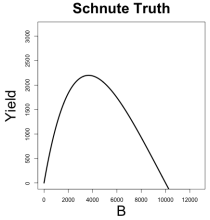
Schnute Truth
Yield
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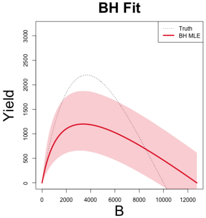
BH Fit
Truth
BH MLE
Yield
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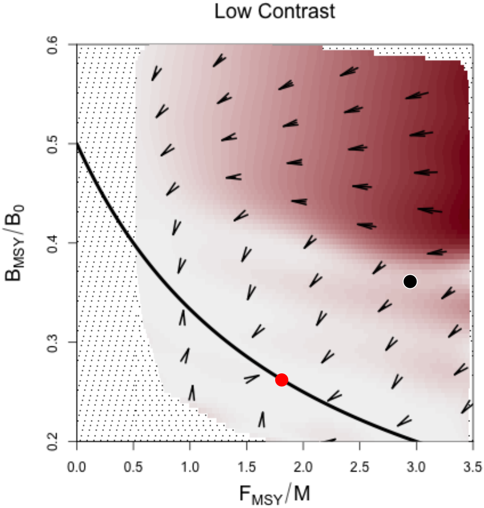
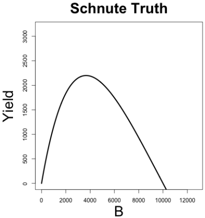
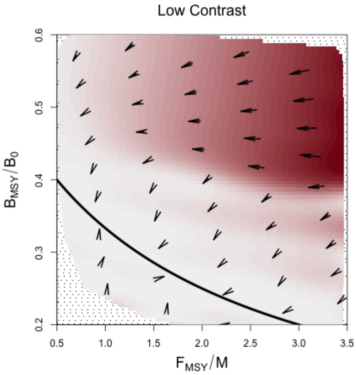
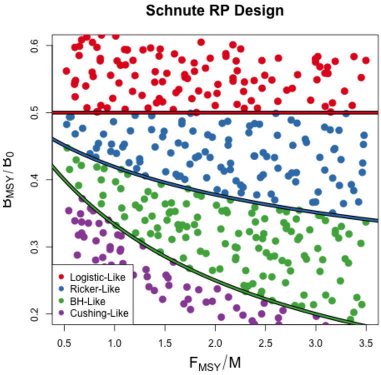

Low Contrast
B_{MSY}/B_0
F_{MSY}/M
0.2
0.3
0.4
0.5
0.6
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5


Schnute Truth
Yield
B
0
500
1000
1500
2000
2500
3000
0
2000
4000
6000
8000
10000
12000


Low Contrast
B_{MSY}/B_0
F_{MSY}/M
0.2
0.3
0.4
0.5
0.6
0.5
1.0
1.5
2.0
2.5
3.0
3.5


Schnute RP Design
B_{MSY}/B_0
F_{MSY}/M
Logistic-Like
Ricker-Like
BH-Like
Cushing-Like
0.2
0.3
0.4
0.5
0.6
0.5
1.0
1.5
2.0
2.5
3.0
3.5

Summary

- Schnute three-parameter generalizing model is very attractive since it interpolates the most common models of productivity.
  - Logistic, Ricker, Beverton-Holt
- A stable method of generating simulation designs desite non-analytical and numerically trechreous RPs$\leftrightarrow$ θ.
- GP metamodel demonstrates that misspecified BH models enjoy some sense of optimality in RP estimation.
  - Nearly shortest distance RP mapping as mediated by contrast.
  - but misspecified BH models induce a risk structure in RPs.
- Can more complex biological dynamics help RP estimation?

Outline

General Modeling Structure

$$I_t = qB_t e^{\epsilon} \quad \epsilon \sim N(0, \sigma^2)$$

$$\frac{dB}{dt} = \overbrace{w(a_s)R(B;\theta)}^{\text{Recruitment Biomass}} + \overbrace{\kappa\left[w_\infty N - B\right]}^{\text{Net Growth}} - \overbrace{(M+F)B}^{\text{Mortality}}$$

$$\frac{dN}{dt} = R(B;\theta) - (M+F)N$$

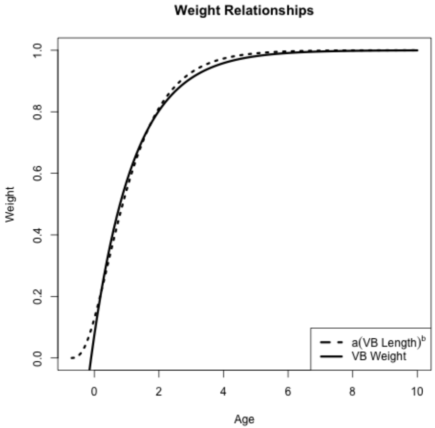
Individual Growth

$$w(a) = w_\infty(1 - e^{-\kappa(a-a_0)})$$

a_s : Lagged Maturity & Knife-Edge Selectivity

κ : Individual Growth

- Instant Growth: (Production Model)
  $a_s \to 0 \quad \kappa \to \infty$



Individual Growth

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a_s : Lagged Maturity & Knife-Edge Selectivity

κ : Individual Growth

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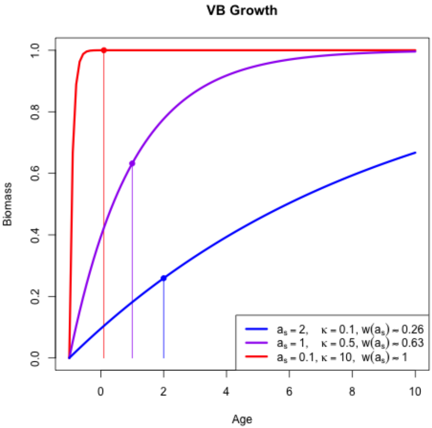


Schnute Recruitment

$$R(B;\alpha,\beta,\gamma) = \alpha B_{t-a_s}(1-\beta\gamma B_{t-a_s})^{\frac{1}{\gamma}}$$

Logistic

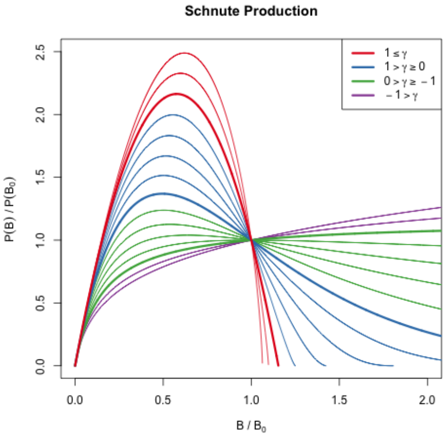
$\gamma = 1$

Ricker

$\gamma \to 0$

Beverton-Holt

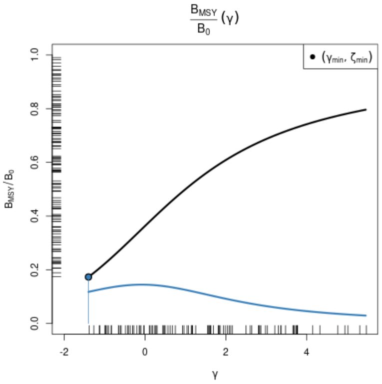
$\gamma = -1$

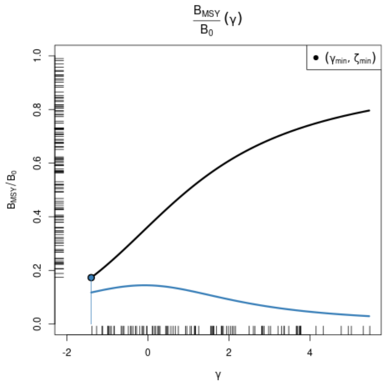


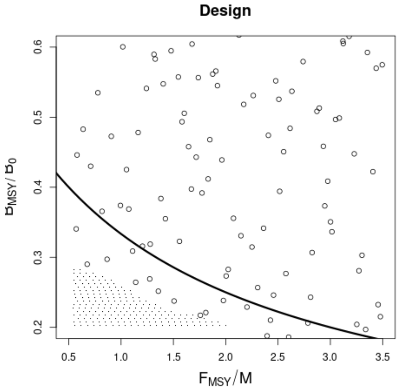
$$\alpha(\gamma):\alpha=\left[\left(\frac{Z^*(Z^*+\kappa)}{w(a_s)(Z^*+\frac{\kappa w_\infty}{w(a_s)})}\right)^{\gamma}+\left(\frac{\gamma F^*}{w(a_s)}\right)\left(\frac{Z^*(Z^*+\kappa)}{w(a_s)(Z^*+\frac{\kappa w_\infty}{w(a_s)})}\right)^{\gamma-1}\left(1+\frac{\left(\frac{\kappa w_\infty}{w(a_s)}\right)\left(\kappa-\frac{\kappa w_\infty}{w(a_s)}\right)}{(Z^*+\frac{\kappa w_\infty}{w(a_s)})^2}\right)\right]^{\frac{1}{\gamma}}$$

$$\beta(\alpha(\gamma),\gamma):\quad \beta=\frac{1}{\gamma B_0}\left(1-\left(\frac{M(M+\kappa)}{\alpha w(a_s)(M+\frac{\kappa w_\infty}{w(a_s)})}\right)^{\gamma}\right)$$

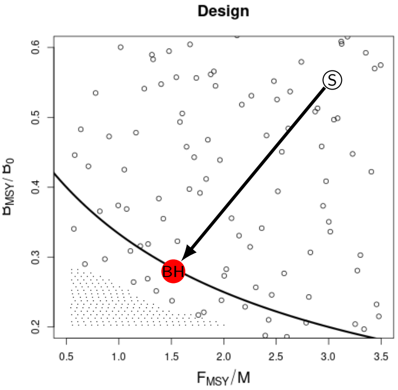
$$\frac{B^*}{B_0}(\alpha(\gamma),\gamma):\quad \frac{B^*}{B_0}=\frac{1-\left(\frac{(F^*+M)(F^*+M+\kappa)}{\alpha w(a_s)(F^*+M+\frac{\kappa w_\infty}{w(a_s)})}\right)^{\gamma}}{1-\left(\frac{M(M+\kappa)}{\alpha w(a_s)(M+\frac{\kappa w_\infty}{w(a_s)})}\right)^{\gamma}}$$


$\frac{B_{MSY}}{B_0}(\gamma)$
$(\gamma_{min}, \zeta_{min})$
B_{MSY}/B_0
0.0
0.2
0.4
0.6
0.8
1.0
-2
0
2
4
γ

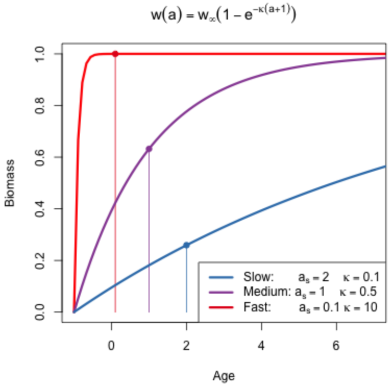

$\frac{B_{MSY}}{B_0}(\gamma)$
$(\gamma_{min}, \zeta_{min})$
B_{MSY}/B_0
γ

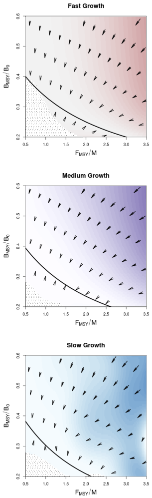

Design
B_{MSY}/B_0
F_{MSY}/M

$$\underbrace{\left(\frac{F^*}{M}, \frac{B^*}{\bar{B}(0)}\right)}_{\text{Schnute Truth}} \overset{\text{GP}}{\mapsto} \underbrace{\left(\frac{\hat{F}^*}{M}, \frac{B^*}{B_0}(-1; \hat{F}^*)\right)}_{\text{BH Estimate}}$$

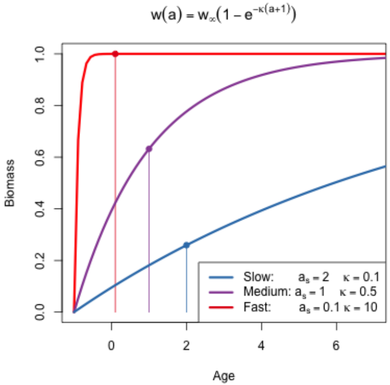


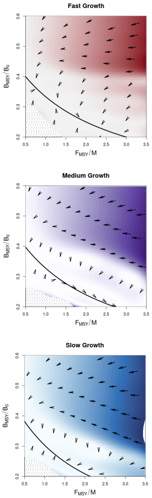
High Contrast



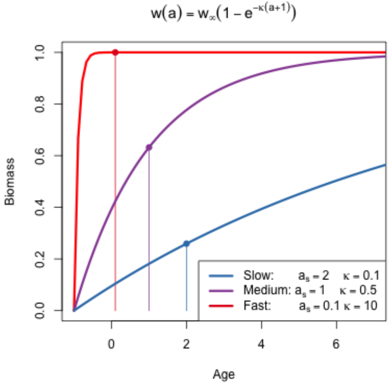


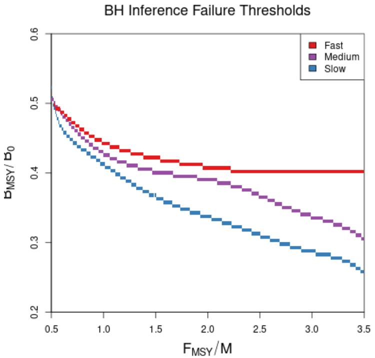
Low Contrast





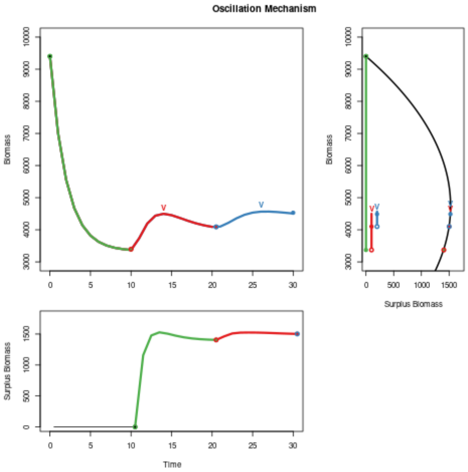
Low Contrast





Oscillation

- large a_s
- Fishing shocks within a_s
- Repeated shocks can lead to chaos.



Conclusions

- Similar RP mapping under BH-DDM as the BH-SPM.
- As growth dynamics are emphasized, the BH model becomes more brittle.
- Emphasizes the need to use more flexible SRR models.

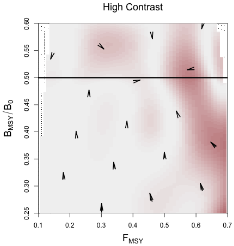
Future Work:

- Recruitment Deviations
- Further metamodeling techniques can expidite the simulation into more challenging simulation applications.
  - Targeted aquisition functions
  - Non-stationarity metamodels

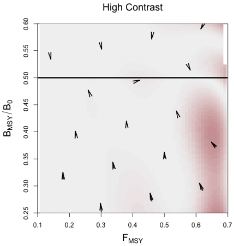
Many Thanks:

- UCSC Advisors
- Collaborators at NOAA
- NMFS Sea Grant

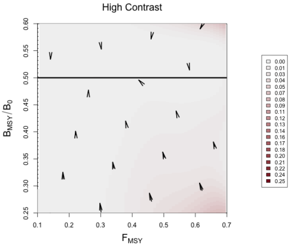
High Contrast PT $\sigma = 0.12$ Data



1x Samples



2x Samples



4x Samples

Metamodel Details

$$\mathbf{y} = \widehat{log(F_{MSY})} \quad - or - \quad \mathbf{y} = \widehat{log(B_0)}$$

$$\boldsymbol{X} = \left(\frac{F_{MSY}}{M}, \frac{B_{MSY}}{\bar{B}(0)} \right)$$

$$\mathbf{y} = \beta_0 + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{v} + \boldsymbol{\epsilon}$$

$$\boldsymbol{v} \sim N_n(\mathbf{0}, \tau^2 \boldsymbol{R}_\ell)$$

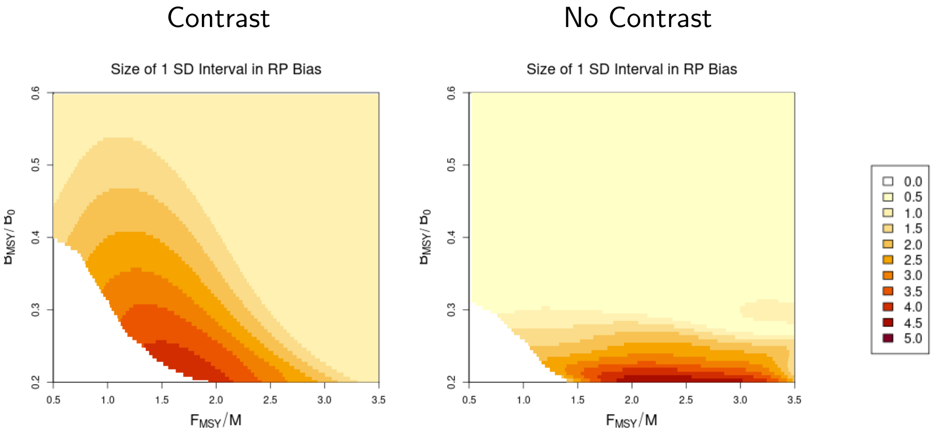
$$\boldsymbol{\epsilon} \sim N_n(\mathbf{0}, \omega' \boldsymbol{I})$$

$$R(\boldsymbol{x}, \boldsymbol{x'}) = \exp\left(\sum_{j=1}^{2} \frac{-(x_j - x_j')^2}{2\ell_j^2} \right)$$

Prediction

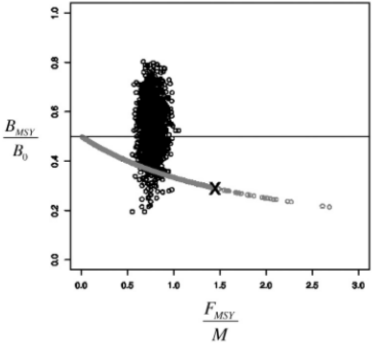
$$\hat{y}(\mathbf{x}^\star) = \beta_0 + \mathbf{x}^\star\boldsymbol{\beta} + \mathbf{r}(\mathbf{x}^\star)'\boldsymbol{R}_\ell^{-1}\Big(\mathbf{y} - \big(\beta_0 + \boldsymbol{X}\beta\big)\Big)$$

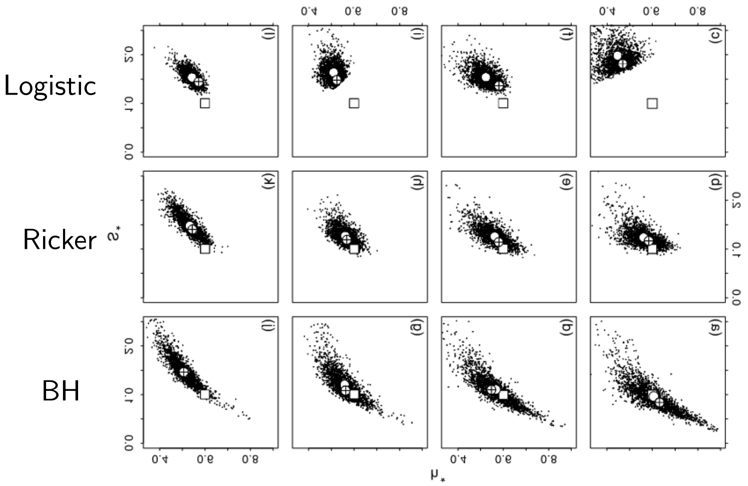
$$\hat{\sigma}^2(\mathbf{x}^\star) = \mathbf{R}(\mathbf{x}^\star, \mathbf{x}^\star) - \mathbf{r}(\mathbf{x}^\star)'\boldsymbol{R}_\ell^{-1}\mathbf{r}(\mathbf{x}^\star)$$


Contrast
No Contrast
Size of 1 SD Interval in RP Bias
Size of 1 SD Interval in RP Bias
BMSY/B0
FMSY/M
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.2
0.3
0.4
0.5
0.6
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0

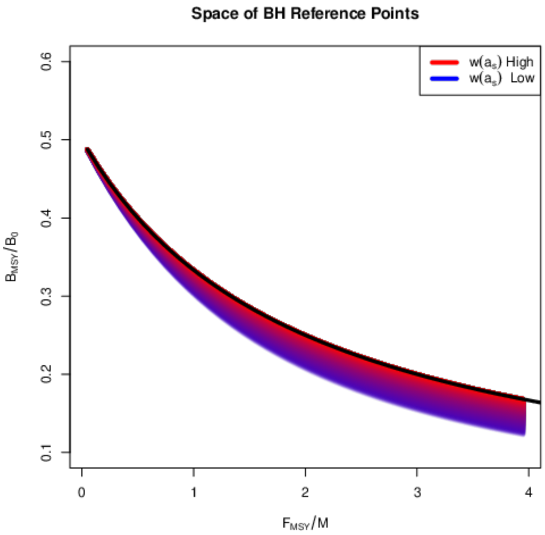
Mangel et al.

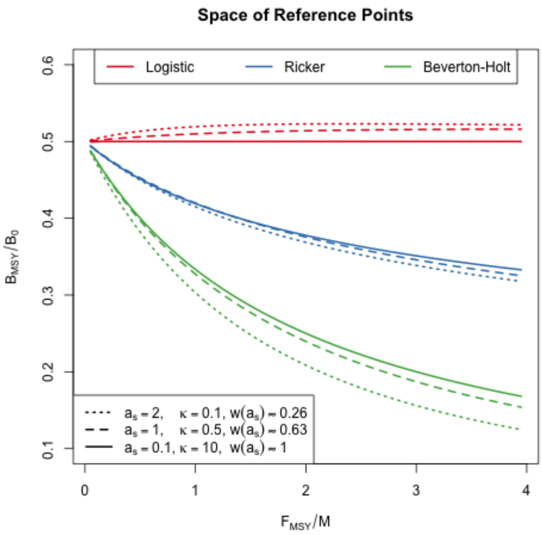
Fig. 4. DeYoreo et al. (2012) used both a BH-SRR and three-parameter SRR, similar to the S-SRR in a stock assessment of cowcod (*Sebastes levis*). We show samples from posterior distributions arising from different values of steepness. Unlike most stock assessments, we plot B_{MSY}/B_0 versus F_{MSY}/M. The grey circles show the results for the BH-SRR. This curve is another way of representing the constraint placed on a stock assessment by using a BH-SRR and specifying steepness — results must lie along this curve. The black circles represent the outcome of the three-parameter SRR. The black X represents the result when steepness is asserted to be 0.6.

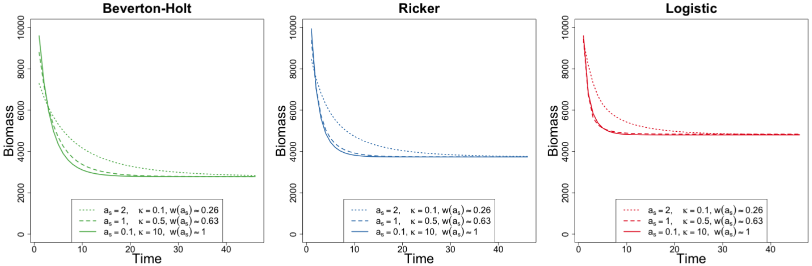




Schnute, J. T., & Kronlund, A. R. (2002). Estimating salmon stock recruitment relationships from catch and escapement data. Canadian Journal of Fisheries and Aquatic Sciences, 59(3), 433–449.


Space of BH Reference Points
w(a_s) High
w(a_s) Low
0.1
0.2
0.3
0.4
0.5
0.6
B_MSY/B_0
0
1
2
3
4
F_MSY/M


Space of Reference Points
Logistic
Ricker
Beverton-Holt
a_s = 2, κ = 0.1, w(a_s) ≈ 0.26
a_s = 1, κ = 0.5, w(a_s) ≈ 0.63
a_s = 0.1, κ = 10, w(a_s) ≈ 1
B_MSY/B_0
F_MSY/M
0.1
0.2
0.3
0.4
0.5
0.6
0
1
2
3
4


Beverton-Holt
Ricker
Logistic
Biomass
Time
0 2000 4000 6000 8000 10000
0 10 20 30 40
a_s = 2, κ = 0.1, w(a_s) ≈ 0.26
a_s = 1, κ = 0.5, w(a_s) ≈ 0.63
a_s = 0.1, κ = 10, w(a_s) ≈ 1