GOA Pollock Updates

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Road map for today

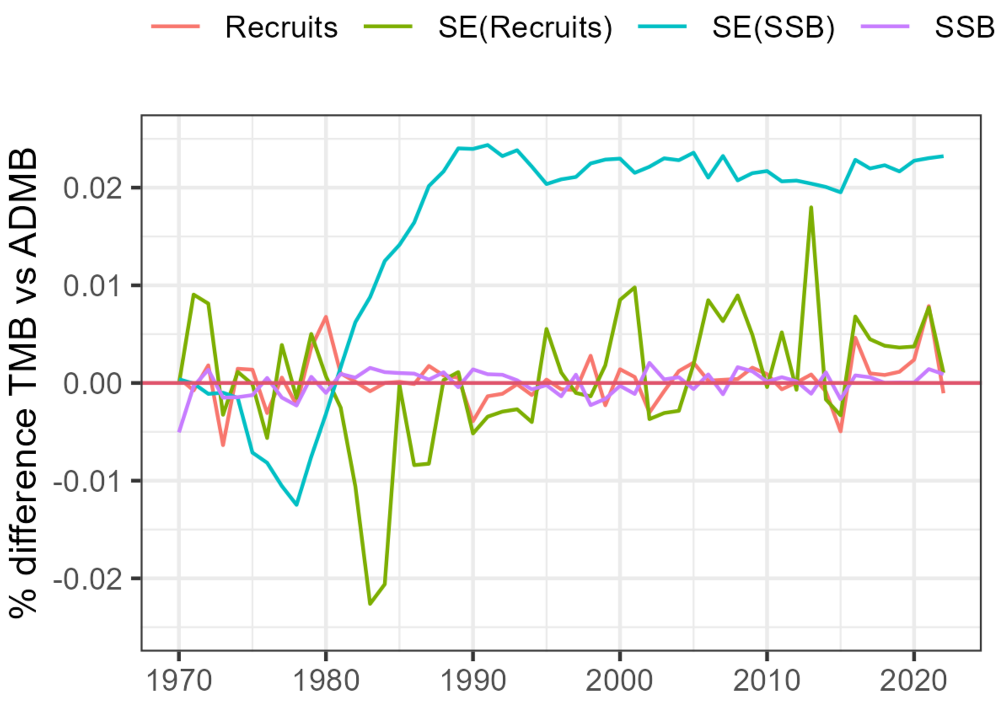
- Bridging to TMB
  - TMB overview
  - Results of bridging
- Issues w/ fish selex and more flexible options
- Review parametric, NP, SM selectivity models
  - par devs, 2D AR(1), 3D AR(1)

Bridging to TMB from ADMB

- ADMB is sunsetting in 2024 and **TMB is the successor**
  - Similar functionality: template, autodiff, delta method, MCMC
  - Main advantage: Laplace approximation of the marginal likelihood
  - Process errors are estimable within assessments: σ_R, time-varying devs, state-space transitions, etc.
- ADMB uses "penalized max likelihood" where process error fixed and random effects are estimated as parameters (e.g. recruitment deviations)

Kristensen et al. (2016), Monnahan and Kristensen (2018)

Bridging to TMB from ADMB



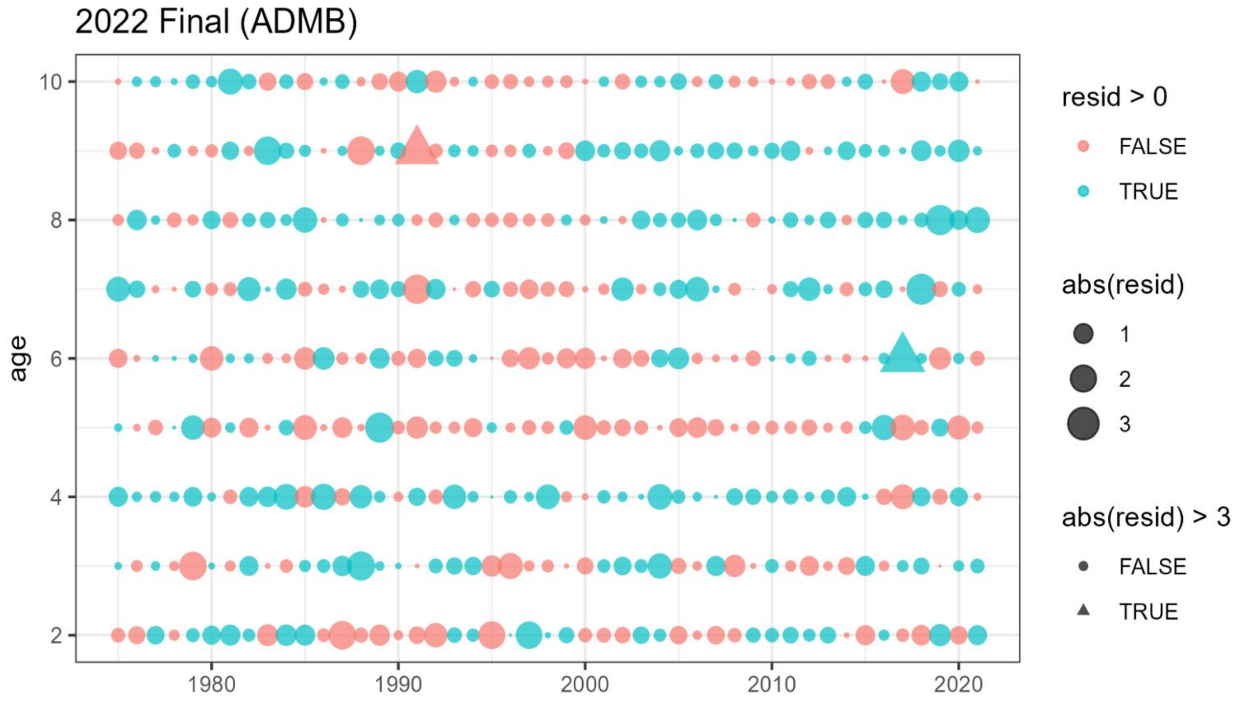
- We ported 19.1a
- Missing some auxiliary features
- Estimates and uncertainty are almost identical (<0.03%)

Bridging to TMB from ADMB

- We propose this change in software as **model 23.0 and recommend it** for adoption this year
- This will allow for more sophisticated statistical modeling for this stock in the future
  - Selectivity, maturity, weight at age, state-space transitions
- Good night ADMB, you had a good run…

Improving fisheries selectivity

- Persistent patterns in age residuals point of concern
- In 2022 some ad hoc approaches were explored
- Need more flexible and statistically justifiable approaches



Review of options for flexible selectivity

- Other regions use random effects
  - WHAM: 2D AR(1)
  - SAM: multivariate normal random effects
  - SS3: semi-parametric 2D AR(1) [penalized ML]
- There are parametric, non-parametric and semi-parametric approaches
- What are these, how do they work?

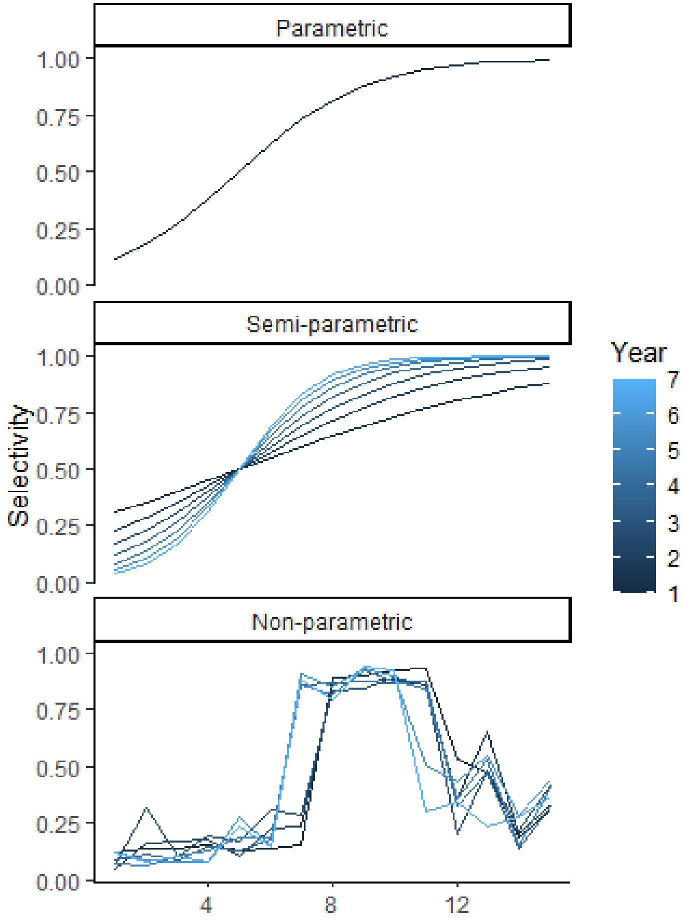
Stock and Miller 2021, Nielsen and Berg 2014, Method and Wetzel 2013

Review of random effect structures

- 1D:
  - RW or AR(1) vector of random effects (1 x years)
- 2D AR(1)
  - Matrix of random effects (ages x years)
  - Assumes MVN(0,Σ)
- 3D AR(1) (Cheng et al. 2023)
  - Same as 2D but parses covariance into age, year and **cohorts**
  - Two versions to consider: marginal and conditional variance

Options for flexible selectivity

- Parametric
  - Age/length based function that has a predefined shape (asymptotic or dome)
  - $Sel_{age,y} = f(\theta, \text{age/length})$
- Semi-parametric
  - Parametric base with non-parametric scaling
  - $Sel_{age,y} = f(\theta, \text{age/length}) * \exp(dev_{age,y})$
- Non-parametric
  - Estimate parameters for each age x year
  - $Sel_{age,y} = f(\theta, dev_{age,y})$



Candidate models explored

Model	Name	Type	Fixed (k) and random (p) effects associated with fisheries selectivity
0	Constant	Parametric double logistic	Initial and final inflection ages and slopes (k=4), no random effects (p=0). Used as a baseline (no variation).
1	ParDevs	Parametric double logistic with random walk on initial slope and inflection point	Initial and final inflection ages and slopes, plus one process error (k=5), two annual vectors of RE (p=116). Same as 19.1a, but the process error is estimated
7	2D-AR1	Nonparametric with random effects by age and year	Mean selectivity-at-age, process error, two correlations (k=13), and random effects matrix (p=580)
8	3D-AR1cond	Nonparametric with random effects by age and year, using partial correlations for age, year, and cohort. Conditional variation formulation	Mean selectivity-at-age, process error, three partial correlations (k=14), and random effects matrix (p=580)
9	3D-AR1mar	Same as 3D-AR1cond, but uses marginal variation formulation	Same as 3D-AR1cond

Selecting and validating models

We use three approaches to gauge model appropriateness:

1. Marginal AIC.
   a. Does not include penalties for random effects
   b. Delta AIC cutoff (~2) may not be correct (Maunder and Punt 2013; Punt 2023)
2. Residual patterns using OSA
   a. Better than Pearson (more tomorrow)
3. Projection behavior
   a. Does it make sense? Pretty ad hoc but a consideration

Improving selectivity projections

- Selectivity is extrapolated for assessment year
- 5-year average used for reference point calculations
- If there is a trend in selex, both will be biased, e.g.,
  - Trend toward younger fish
  - Targeting of a cohort
- **Want an approach that better accounts for trends**

Model	Total NLL	Fsh NLL	K	dAIC	2023 SSB	B0	B40	2023 OFL	2023 ABC
19.1 ADMB	--	--	--	--	204,554	469,000	188,000	173,470	148,937
0: Constant	573.3	228.6	182	112.3	219,996	468,000	187,000	196,809	168,216
1: ParDevs	514.5	125.5	185	0.8	226,254	487,000	195,000	193,353	166,533
7: 2D-AR1	509.4	113.6	195	10.6	226,073	480,000	192,000	194,805	167,410
8: 3D-AR1 cond	503.1	115.7	196	0	225,539	473,000	189,000	194,824	167,577

1: ParDevs

sigma	0.046 (0.03–0.06)

7: 2D-AR1

sigma	0.26 (0.17–0.38)
rho_a	0.87 (0.74–0.94)
rho_y	0.63 (0.34–0.81)

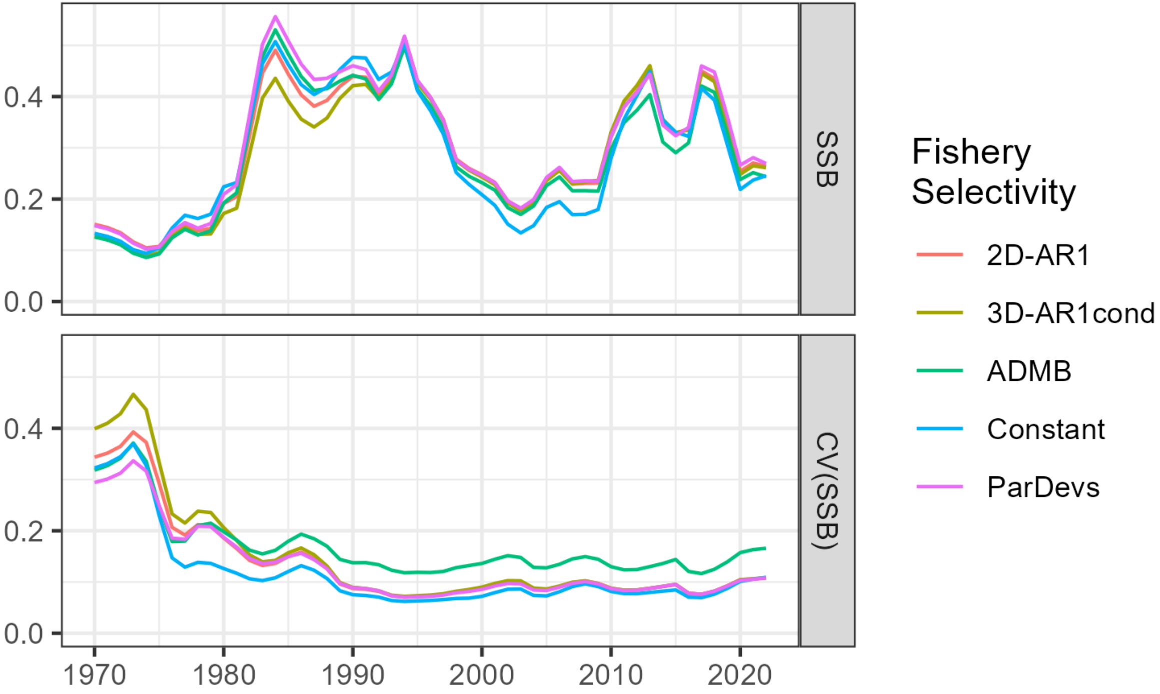
8: 3D-AR1 cond

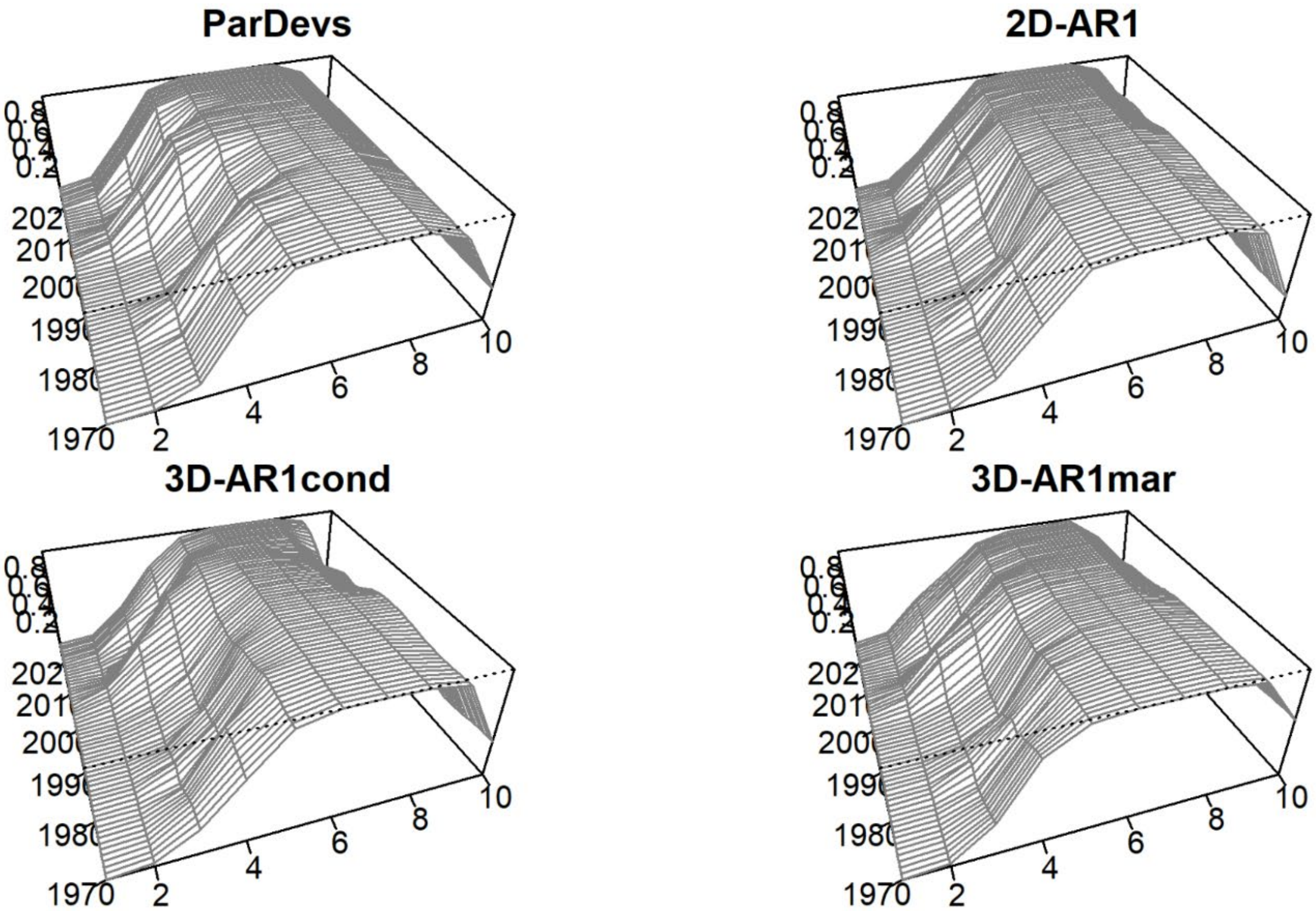
sigma	0.28 (0.20–0.39)
rho_a	0.72 (0.57–0.87)
rho_y	-0.08 (-0.60–0.45)
rho_c	0.40 (-0.25–1.05)

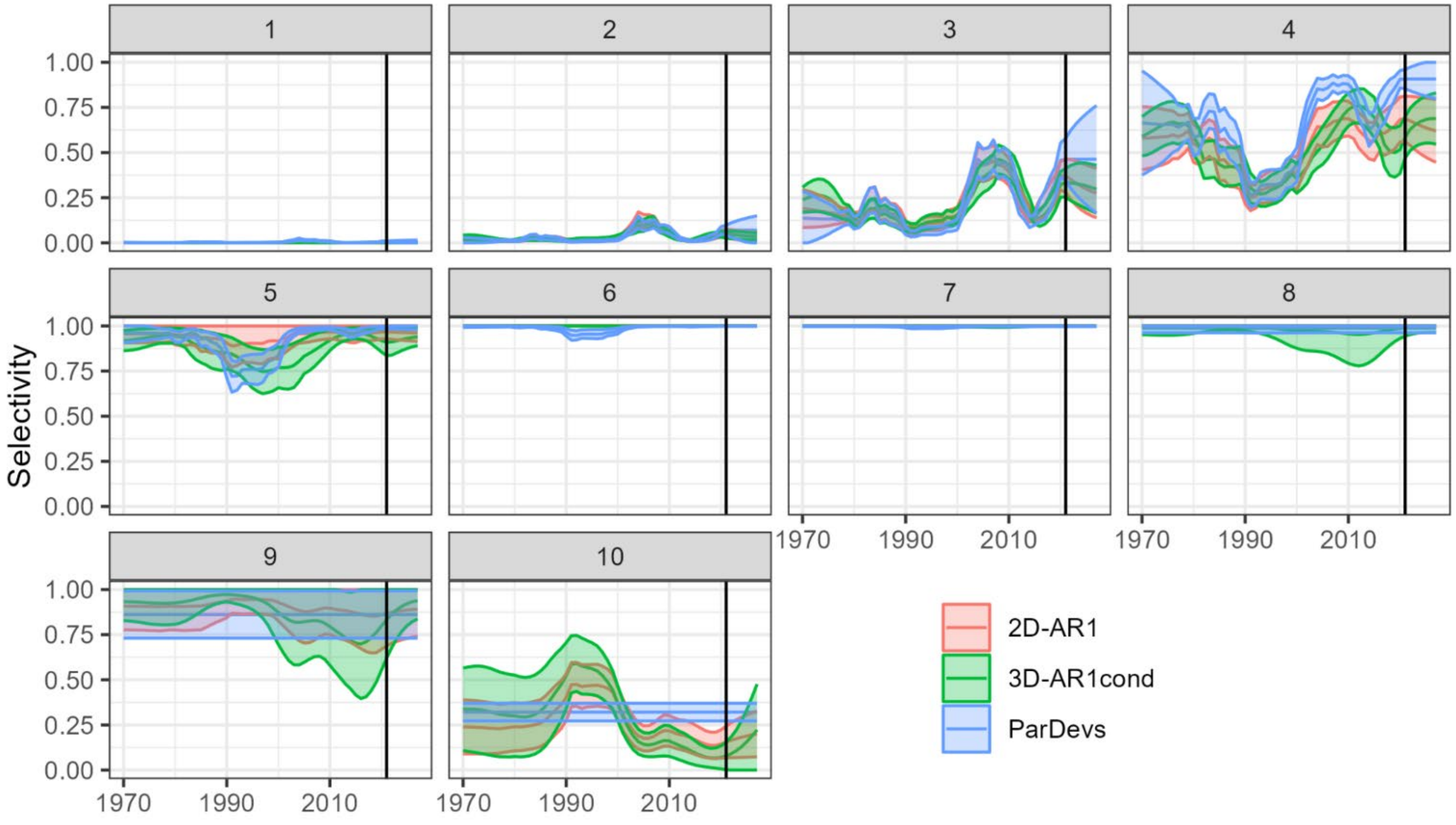
Caveat: Lingering mismatch w/ 19.1a so SSB, B0, B40 etc. will change when fixed

Similar SSB estimates among models

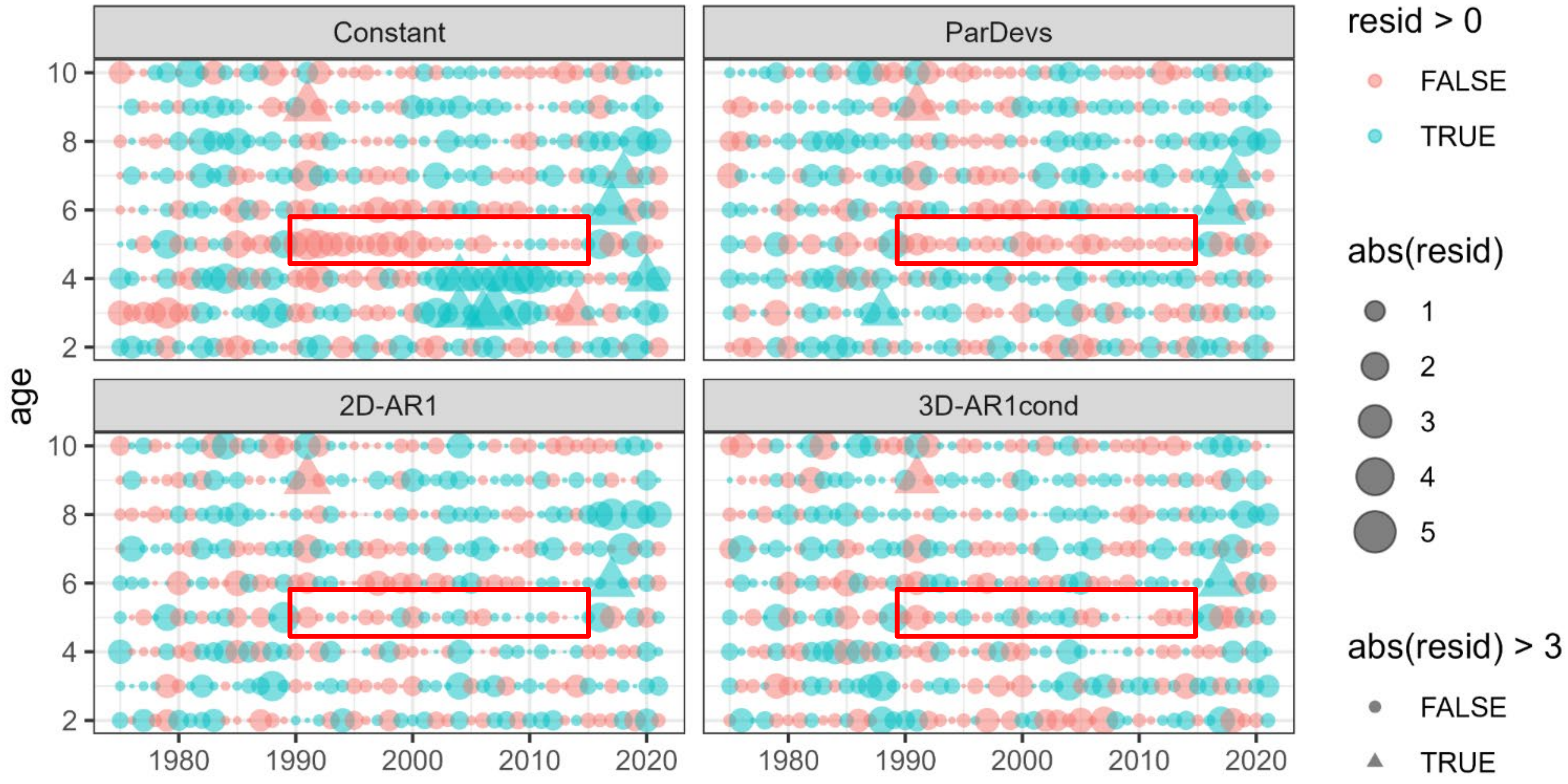
- Generally similar SSB estimates
- Uncertainty higher due to some temporary model mismatches (to be fixed)

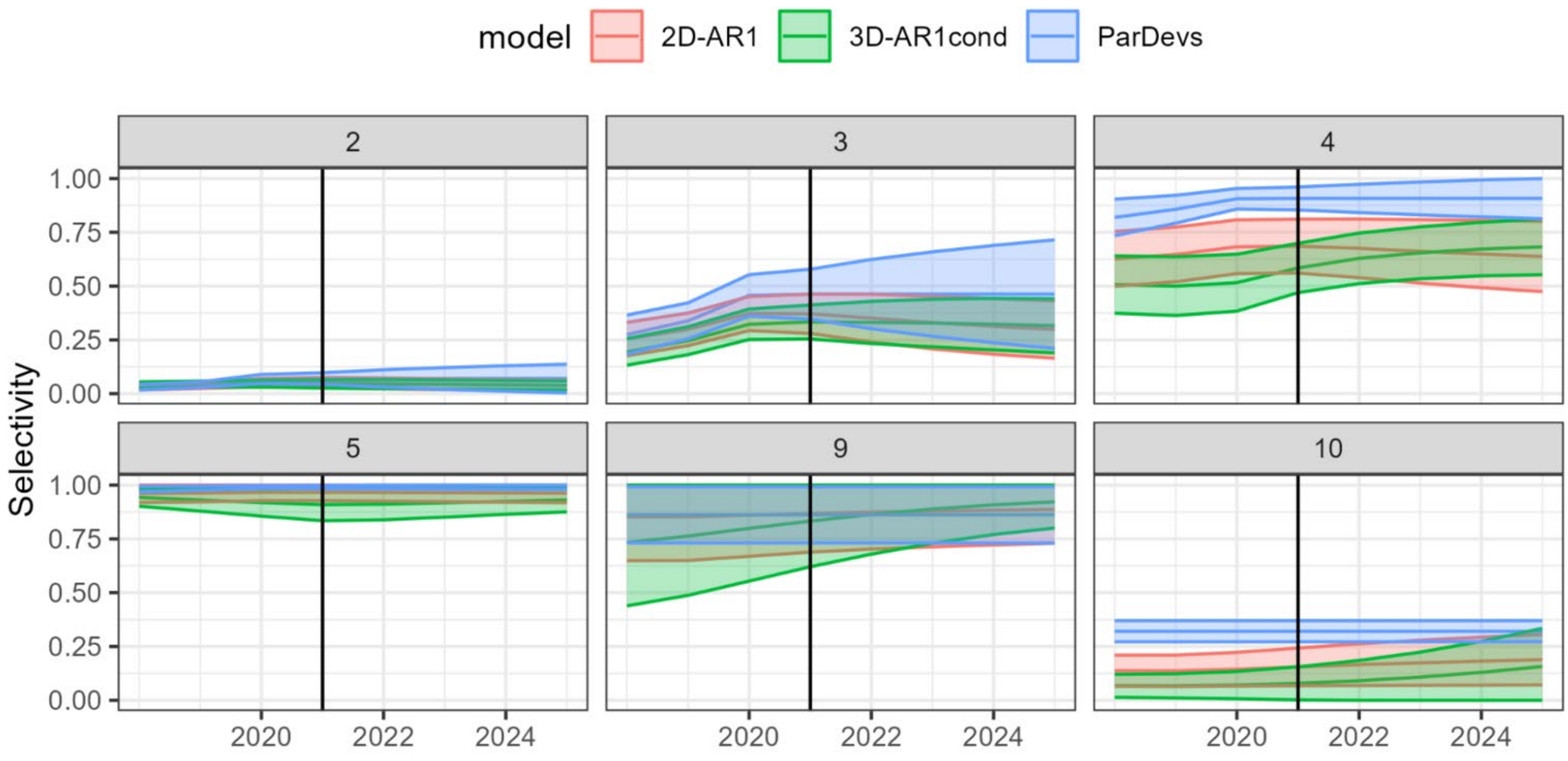



ParDevs
2D-AR1
3D-AR1cond
3D-AR1mar
0.8
0.6
0.4
0.2
1970
1980
1990
2000
2
4
6
8
10



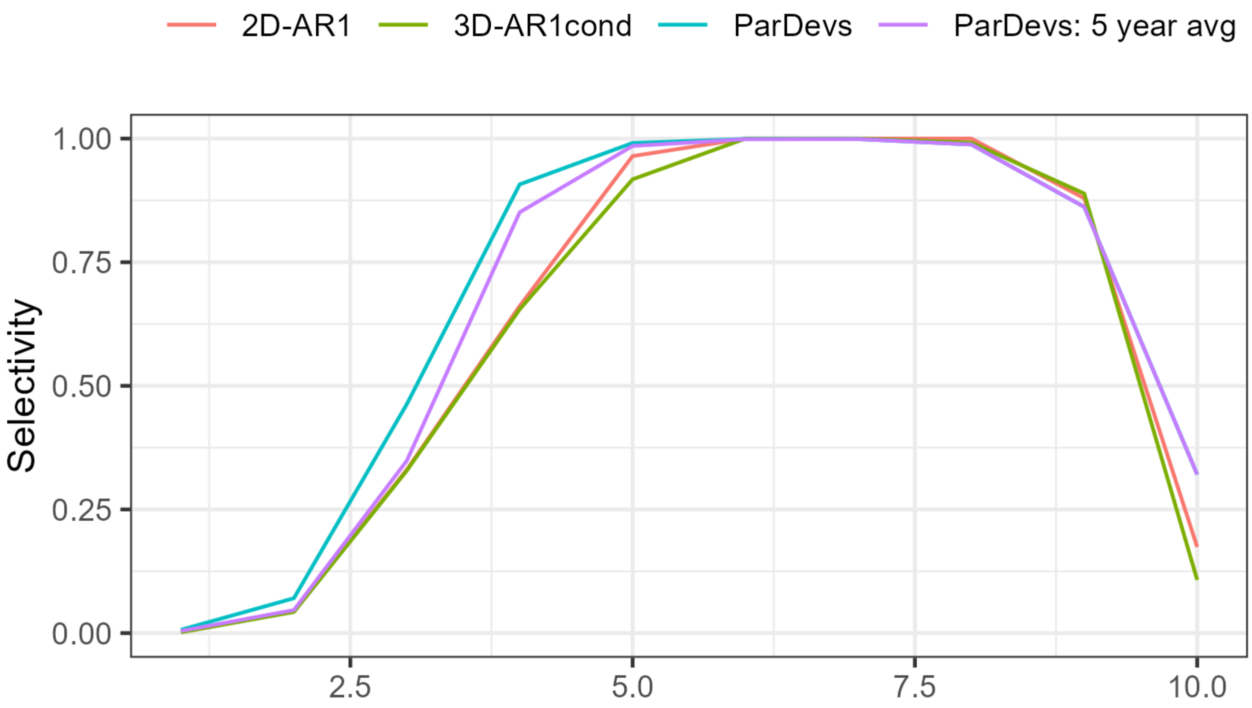
1
2
3
4
5
6
7
8
9
10
Selectivity
1.00
0.75
0.50
0.25
0.00
1970
1990
2010
2D-AR1
3D-AR1cond
ParDevs


Constant
ParDevs
2D-AR1
3D-AR1cond
age
10
8
6
4
2
1980
1990
2000
2010
2020
resid > 0
FALSE
TRUE
abs(resid)
1
2
3
4
5
abs(resid) > 3
FALSE
TRUE


model
2D-AR1
3D-AR1cond
ParDevs
2
3
4
5
9
10
Selectivity
1.00
0.75
0.50
0.25
0.00
2020
2022
2024

Improved projections?

Comparing 2022 estimates against 5-year average (2017-2021) from ParDevs (current approach)



Overview of statistical behavior

- Non-parametric approaches outperformed semi-parametric models (not shown), unclear why
- Could use retros to quantify predictive performance among selectivity curves
- 3D marginal approach has some advantages and would be good to get working
- Need to be careful to put flexibility in the right process (Szuwalski et al. 2017, Fisch et al. 2023)

Future extensions for selectivity

- Can likely fix several fixed effects and many random effects when selex = 1 for all years
- Unclear why semi-parametric models did not perform well, more research needed
- 3D has benefit of cohort effect, but was not significant here
  - But had better AIC and residuals
- 2D is a definite improvement in fits to data and also a very good option

Future extensions using non-parametric models

- Pollock have large variation in both WAA and maturity

year	1	2	3	4	5	6	7	8	9	10
2003	0.01	0.05	0.29	0.76	0.96	1.00	1.00	1.00	1.00	1.00
2004	0.01	0.09	0.50	0.91	0.99	1.00	1.00	1.00	1.00	1.00
2005	0.01	0.11	0.61	0.95	1.00	1.00	1.00	1.00	1.00	1.00
2006	0.01	0.04	0.22	0.66	0.93	0.99	1.00	1.00	1.00	1.00
2007	0.00	0.03	0.14	0.47	0.84	0.97	0.99	1.00	1.00	1.00
2008	0.01	0.09	0.53	0.93	0.99	1.00	1.00	1.00	1.00	1.00
2009	0.02	0.28	0.89	0.99	1.00	1.00	1.00	1.00	1.00	1.00
2010	0.01	0.04	0.21	0.65	0.93	0.99	1.00	1.00	1.00	1.00
2012	0.01	0.04	0.25	0.71	0.95	0.99	1.00	1.00	1.00	1.00
2013	0.00	0.03	0.13	0.45	0.82	0.96	0.99	1.00	1.00	1.00
2014	0.01	0.14	0.69	0.97	1.00	1.00	1.00	1.00	1.00	1.00
2015	0.00	0.02	0.11	0.40	0.78	0.95	0.99	1.00	1.00	1.00
2016	0.01	0.05	0.27	0.73	0.95	0.99	1.00	1.00	1.00	1.00
2017	0.01	0.14	0.71	0.97	1.00	1.00	1.00	1.00	1.00	1.00
2018	0.01	0.07	0.41	0.87	0.98	1.00	1.00	1.00	1.00	1.00
2019	0.01	0.07	0.39	0.86	0.98	1.00	1.00	1.00	1.00	1.00
2020	0.00	0.02	0.10	0.37	0.75	0.94	0.99	1.00	1.00	1.00
2022	0.01	0.09	0.54	0.93	0.99	1.00	1.00	1.00	1.00	1.00

0.01	0.09	0.21	0.28	0.44	0.91	1.22	1.28	1.72	1.58
0.01	0.08	0.25	0.49	0.50	0.75	1.34	1.34	1.45	1.31
0.01	0.08	0.31	0.55	0.77	0.73	0.80	1.17	1.20	1.84
0.01	0.07	0.26	0.43	0.83	1.12	1.16	1.33	1.49	1.88
0.01	0.06	0.22	0.45	0.84	1.25	1.38	1.44	1.79	1.90
0.01	0.10	0.27	0.48	0.80	1.37	1.89	1.87	1.88	2.01
0.01	0.08	0.26	0.52	0.73	1.07	1.66	2.01	2.10	2.07
0.01	0.08	0.24	0.67	1.09	1.29	1.83	2.09	2.29	2.23
0.01	0.08	0.26	0.66	1.01	1.31	1.66	1.82	2.11	2.08
0.01	0.08	0.27	0.65	0.93	1.34	1.48	1.55	1.93	1.94
0.01	0.13	0.35	0.63	1.16	1.37	1.60	1.77	1.85	2.26
0.01	0.06	0.30	0.59	0.71	1.29	1.34	1.53	1.57	1.67
0.01	0.09	0.20	0.54	0.88	1.06	1.43	1.50	1.59	1.65
0.01	0.13	0.30	0.39	0.56	0.75	0.86	1.12	1.12	1.18
0.01	0.13	0.35	0.45	0.50	0.58	0.91	0.95	1.38	1.34
0.01	0.09	0.18	0.52	0.54	0.61	0.68	0.89	1.38	1.34
0.01	0.06	0.22	0.49	0.64	0.70	0.74	0.79	0.88	1.04
0.01	0.07	0.17	0.31	0.48	0.71	0.81	0.81	0.80	0.85
0.01	0.19	0.32	0.49	0.68	0.86	0.88	1.02	1.05	1.06
0.01	0.05	0.37	0.55	0.61	0.87	0.84	1.18	1.05	1.13

Recommendations for 2023

- Overall do not expect substantial differences in management
- **Recommend model 23.0 (TMB port)**
- 3D is probably the best overall model, with 2D AR(1) second. ParDevs approach had worse residuals.
- Estimation is much slower (~30 mins) compared to penalized ML model (~2 mins), but doable

Acknowledgements

- Thanks to Matt Cheng and Jim Thorson for discussion on 3D AR(1) implementation
- Questions?

- See TMB port at https://github.com/afsc-assessments/GOApollock/tree/tmb_port

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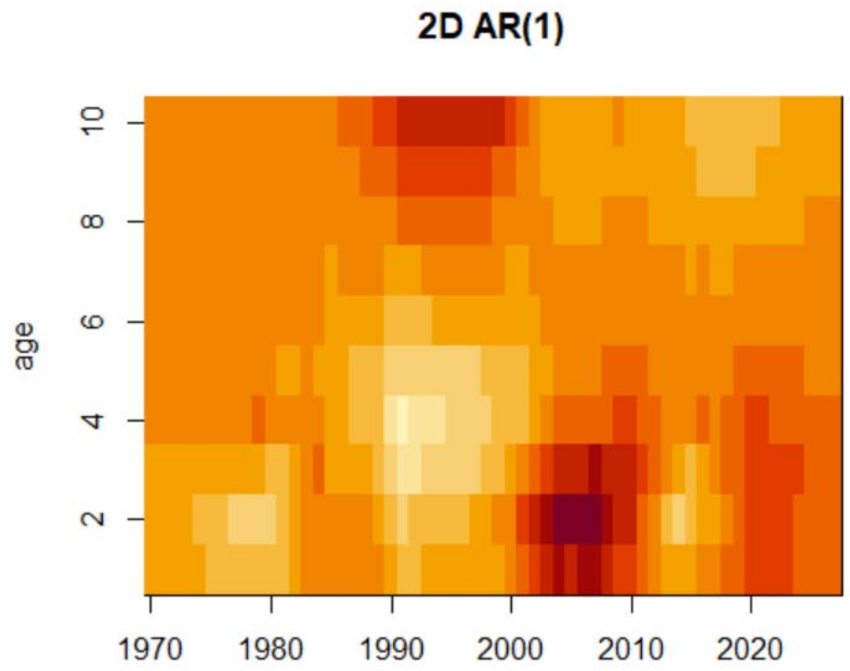
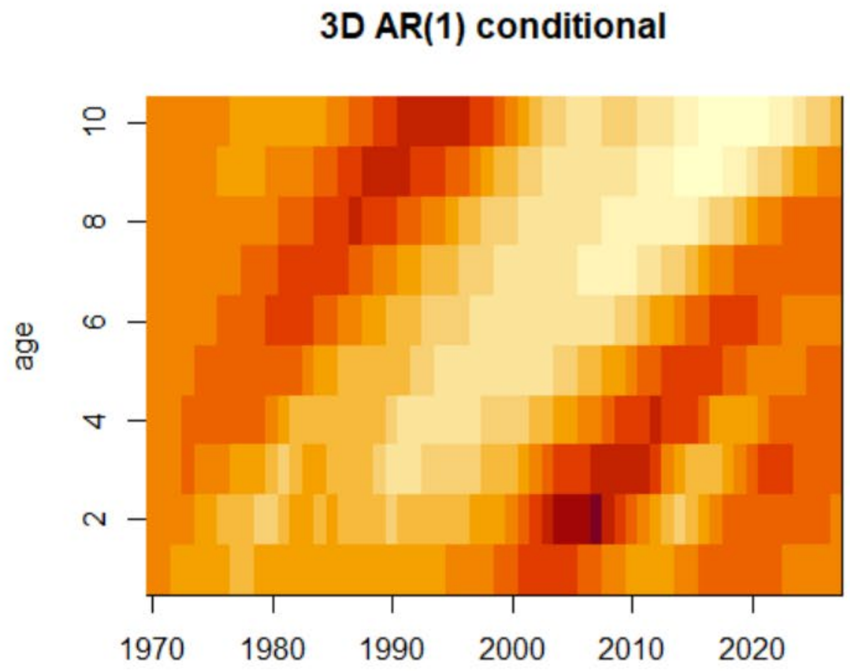
Further details of covariance matrices





Candidate models explored

Model	Name	Equation
0	Constant	$sel_{age} = \frac{1}{\left(1 + e^{-slp_1 * (\text{age} - inf_1)}\right)} \left(1 - \frac{1}{\left(1 + e^{-slp_2 * (\text{age} - inf_2)}\right)}\right)$
1	ParDevs	$sel_{age} = \frac{1}{\left(1 + e^{-\mathbf{slp_{1,y}} * (\text{age} - \mathbf{inf_{1,y}})}\right)} \left(1 - \frac{1}{\left(1 + e^{-slp_2 * (\text{age} - inf_2)}\right)}\right)$ $inf_{1,y} \sim \mathrm{N}\left(inf_{1,y-1}, 4 * \sigma\right)$ $slp_{1,y} \sim \mathrm{N}\left(slp_{1,y-1}, \sigma\right)$
7	2D-AR1	$sel_{age} = \frac{1}{\left(1 + e^{-\theta_{age} - dev_{age,y}}\right)}$ $dev_{age,y} \sim \mathrm{MVN}\left(0, \Sigma_{age,y}\right)$
8	3D-AR1cond	$dev_{age,y} \sim \mathrm{MVN}\left(0, \Sigma1_{age,c,y}\right)$
9	3D-AR1mar	$dev_{age,y} \sim \mathrm{MVN}\left(0, \Sigma2_{age,c,y}\right)$