Conditioning IOTC Albacore OMs using the ABC approach

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Outline

- Presentation of paper *IOTC–2023–WPM14–13*
- Conditioning of ALB OMs using ABC MCMC approach:

  1. Model structure(s) & time-line
  2. Input data
  3. Stock status prior scenarios
  4. Axes of uncertainty
  5. Results
  6. Next steps

OM model structure: population dynamics

- Timeline: 2000 to 2020 (covers all existing cohorts)
- Age, sex and quarterly structured population model
- Beverton-Holt with exploited equilibirum initialisation
- Designed to mimic current assessment model structure
- Reproduces all key stock status variables:
  1. MSY variables: B_{msy}, H_{msy}, & C_{msy}
  2. Relative biomass (*eg.* relative to B_0)

OM model structure: fishery dynamics

- Merge "common" seasonal LL fleets 1–4
- Retain single PS and "Other" fleet: 6 in total
- Size data from LL and PS data (aggregated across time)
- LL CPUE from a given fleet (not jointly at this time)
- Seasonal *vs.* annual catchability explored

Stock status prior information

- Key feature of ABC approach
- Impose status priors (*eg*. from assessment) on OM
- Explore 4 types:

  1. Relative SSB: prior mean/SD for any range of years
  2. B_{msy} ratio: prior mean/SD for any range of years
  3. H_{msy} ratio: prior mean/SD for any range of years
  4. Overfishing probability: penalise *only if* $H > H_{\mathrm{msy}}$

- Integrate status information with LF & CPUE data
- Here where it diverges from assessment-to-OM approach

Suite of stock status priors

- Relative SSB: year 2000 mean (CI) of 0.5 (0.3–0.7)
- B_{msy} ratio: 2019, 2020 mean 2.25, 2 with SD 0.35
- H_{msy} ratio: 2000, 2020 mean of 0.6 with SD 0.2
- Overfishing penalty: $\mathbb{P}\left(H/H_{\mathrm{msy}} > 2\right) \leq 0.05$
- (to remove small numbers of runs with very high H)

Covering previous axes of uncertainty

1. Steepness & M: covariance joint prior (not discrete grid)
2. σ_r^2: (i) fixed at 0.3; (ii) estimated with prior CI 0.2–0.5
3. LF: weight/influence (aggregating and ABC discrepancy)
4. LL catchability: alternative 1% annual increasing trend
5. CPUE series: seasonal q using fleet 1 and 3 *separately*

Constructing $\pi(h, M)$ prior

- Define marginal priors for both parameters
- h mean 0.8, CI 0.7–0.9; M mean 0.3, CI 0.27–0.33
- Process:
  1. Calculate $\tilde{\Delta} = B_{\mathrm{msy}}/B_0$ for mean h & M
  2. Simulate h and M from marginal priors
  3. Define a tolerance interval ε
  4. Accept values of $\{h, M\}$ within ε of $\tilde{\Delta}$
  5. Calculate correlation in retained samples of $\{h, M\}$
- For $\varepsilon = 0.05$ correlation coefficient is -0.58

OM conditioning scenarios

- Explored seven individual scenarios for conditioning:

  1. **R1**: CPUE fleet 1, SSB but *not* H_{msy} priors
  2. **R1a**: CPUE fleet 3, SSB *and* H_{msy} priors
  3. **R1b**: same as **R1** with additional overfishing penalty
  4. **R2**: same as **R1** but σ_r^2 estimated
  5. **R2a**: same as **R1a** but σ_r^2 estimated
  6. **R3**: same as **R1** with 1% *p.a.* $\uparrow q$ trend
  7. **R3a**: same as **R1a** with 1% *p.a.* $\uparrow q$ trend

Approximate Bayesian Computation (ABC)

- Relaxes idea of strict likelihood: $\ell(D \mid \boldsymbol{\theta})$
- Focus is on derived quantities: $X = f(\boldsymbol{\theta})$
- Instead define a discrepancy function: $\pi(D, X)$
- Prior $\pi(\boldsymbol{\theta})$ has a wider role in ABC format
- Now includes stock status prior information
- Approximate posterior defined as follows:

$$\tilde{\pi}(\boldsymbol{\theta} \mid D) \propto \pi(D, X)\pi(\boldsymbol{\theta})$$

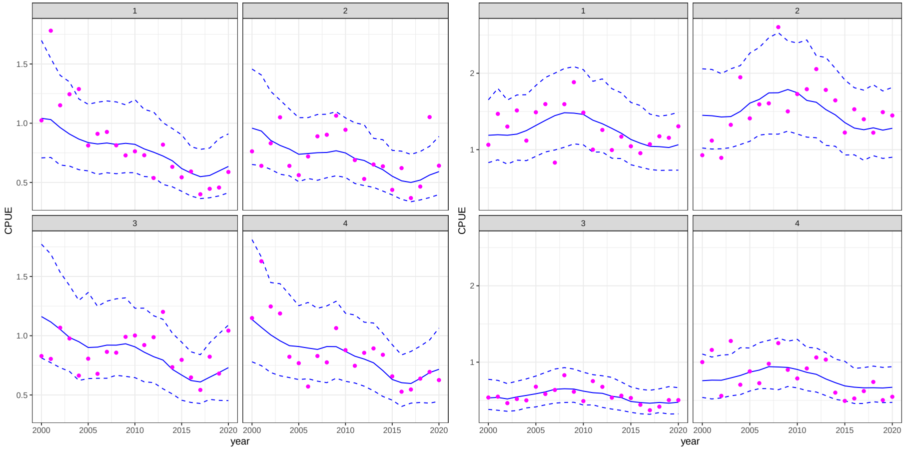
- Custom MCMC algorithm to sample from $\tilde{\pi}(\boldsymbol{\theta} \mid D)$

Discrepancy function & priors

- Deconstructing the discrepancy function, $\pi(D, X)$
- Data elements:
  1. CPUE: single fleet quarterly biomass index
  2. LF: time-averaged Kullback-Leibler divergence
- Parameter and process variable prior, $\pi(\boldsymbol{\theta})$:
  1. Direct parameter prior quasi-uninformative
  2. Implied prior on $\boldsymbol{\theta}$ via stock status priors
  3. Informative prior on σ_r^2 (inverse-gamma)

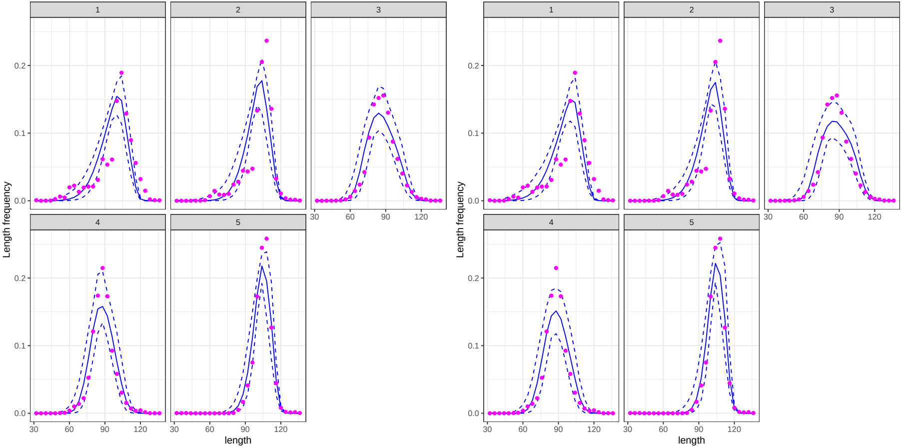
Fits to data: CPUE indices

- Fleet 1 (**R1**, left) & fleet 3 (**R1a**, right):



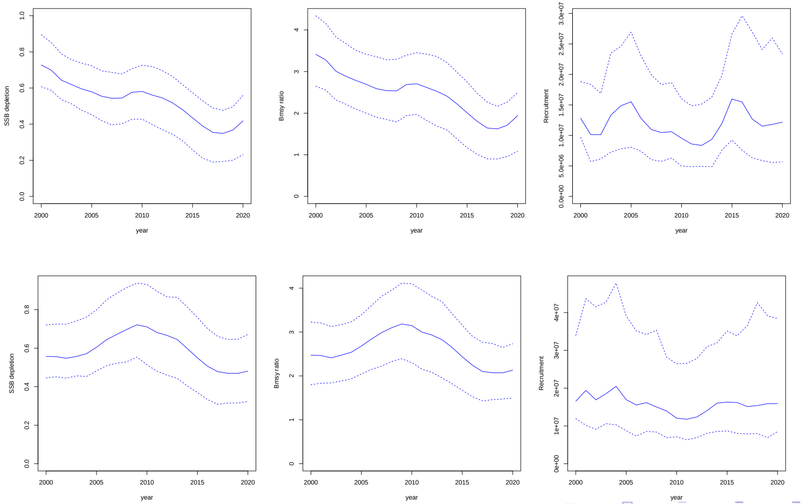
Fits to data: Length frequency data

- Scenario **R1** (left) & **R1a** (right):



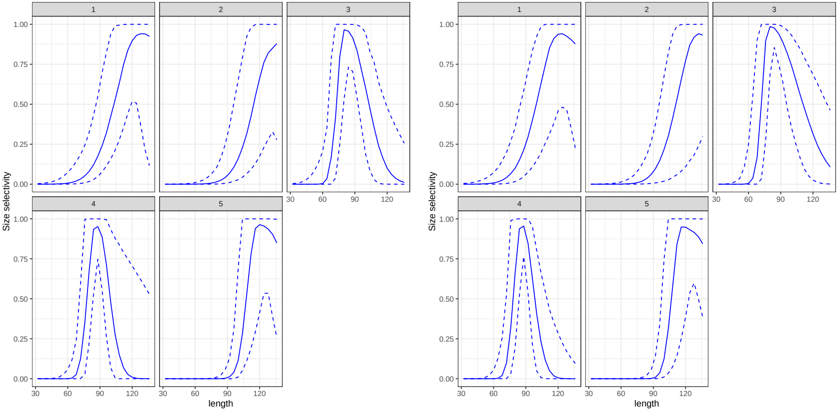
Population dynamics

- Scenario **R1** (top) & **R1a** (bottom):
- SSB depletion (l), B_{msy} ratio (m), recruitment (r)



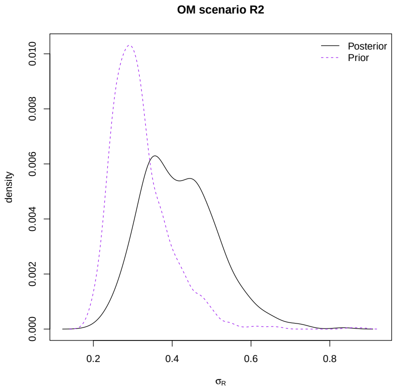
Selectivity (size-based)

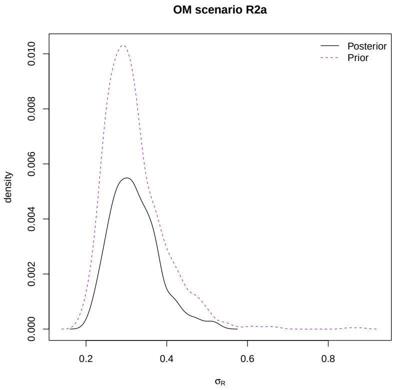
- Scenario **R1** (top) & **R1a** (bottom):



Estimates of σ_r^2

- Scenario **R2** (top) & **R2a** (bottom):





OM conditioning summary

- General summary across all OM scenarios:

OM scenario	Δ_{2000}	Δ_{2020}	$\tilde{\Delta}_{2020}$	$\mathcal{H}_{2020}$
Prior	0.5 (0.3–0.7)	n/a	2 (1.3–2.7)	0.6 (0.2–1)
R1	0.76 (0.61–0.97)	0.41 (0.22-0.56)	1.9 (1.02–2.58)	1.13 (0.5-3.78)
R1a	0.56 (0.4–0.72)	0.48 (0.3–0.69)	2.01 (1.42–2.61)	0.68 (0.33–1.38)
R1b	0.74 (0.61–0.9)	0.42 (0.24–0.54)	1.98 (1.16–2.49)	0.98 (0.46–2.4)
R2	0.71 (0.57–0.84)	0.41 (0.21–0.55)	1.91 (0.99–2.53)	1.22 (0.45–3.57)
R2a	0.56 (0.41–0.72)	0.47 (0.28–0.71)	2.03 (1.3–2.54)	0.65 (0.34–1.4)
R3	0.78 (0.6–0.91)	0.38 (0.15–0.52)	1.77 (0.7–2.44)	1.4 (0.58–5.06)
R3a	0.63 (0.48–0.77)	0.42 (0.25–0.59)	1.94 (1.23–2.5)	0.71 (0.35–1.45)

OM conditioning summary

- **R1**: CPUE inform scale, high upper CI $\mathcal{H}_y$ by 2020
- **R1a**: CPUE uninformative on scale requires $H_{\rm msy}$ priors
- **R1b**: *very* similar to **R1**, removes v. high late $\mathcal{H}_y$
- **R2**: pushes for higher σ_r^2 median 0.41 *vs.* 0.3
- **R2a**: very consistent with 0.3 - just increases certainty
- **R3**: similar to **R1** but more pessimistic recently
- **R3a**: similar to **R1a** but more pessimistic recently

Overall summary

- Successful application of ABC OM approach to IO ALB
- Focussed on 2000–2020 time-period (all living cohorts)
- Able to fit to all key data sources
- Mimics assessment model structure & status if required
- Able to cover previous uncertainty grid probabilistically
- Coherent range of plausible OMs
- Able to generate key MP data inputs

Future work

- Exploring translating results to previous OM
- Checking short-term projections
- Implementing Bayesian cross-validation methods
- Possible spatial extensions (conflicting CPUE trends)