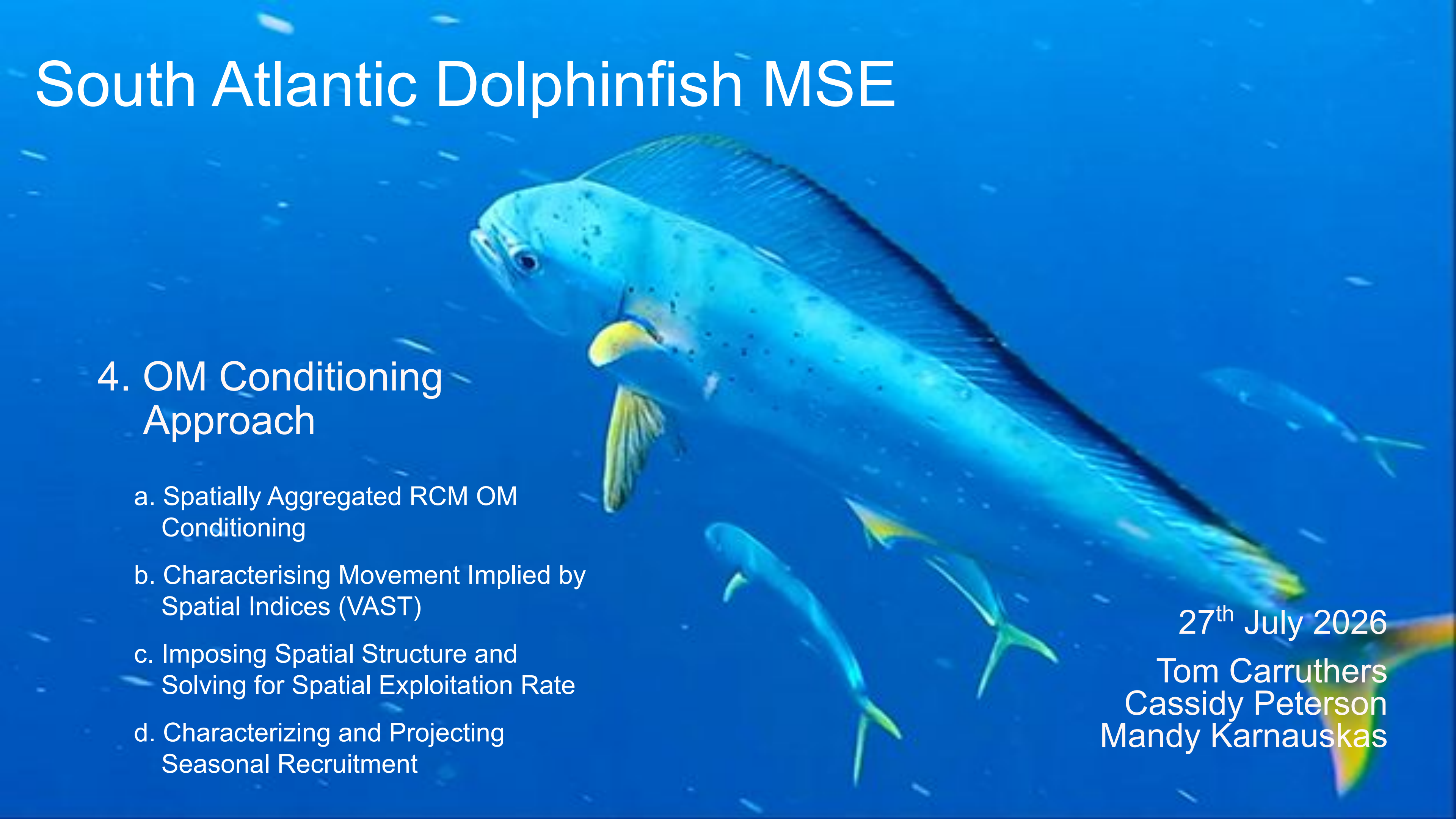


# South Atlantic Dolphinfish MSE

## 4. OM Conditioning Approach

a. Spatially Aggregated RCM OM Conditioning

b. Characterising Movement Implied by Spatial Indices (VAST)

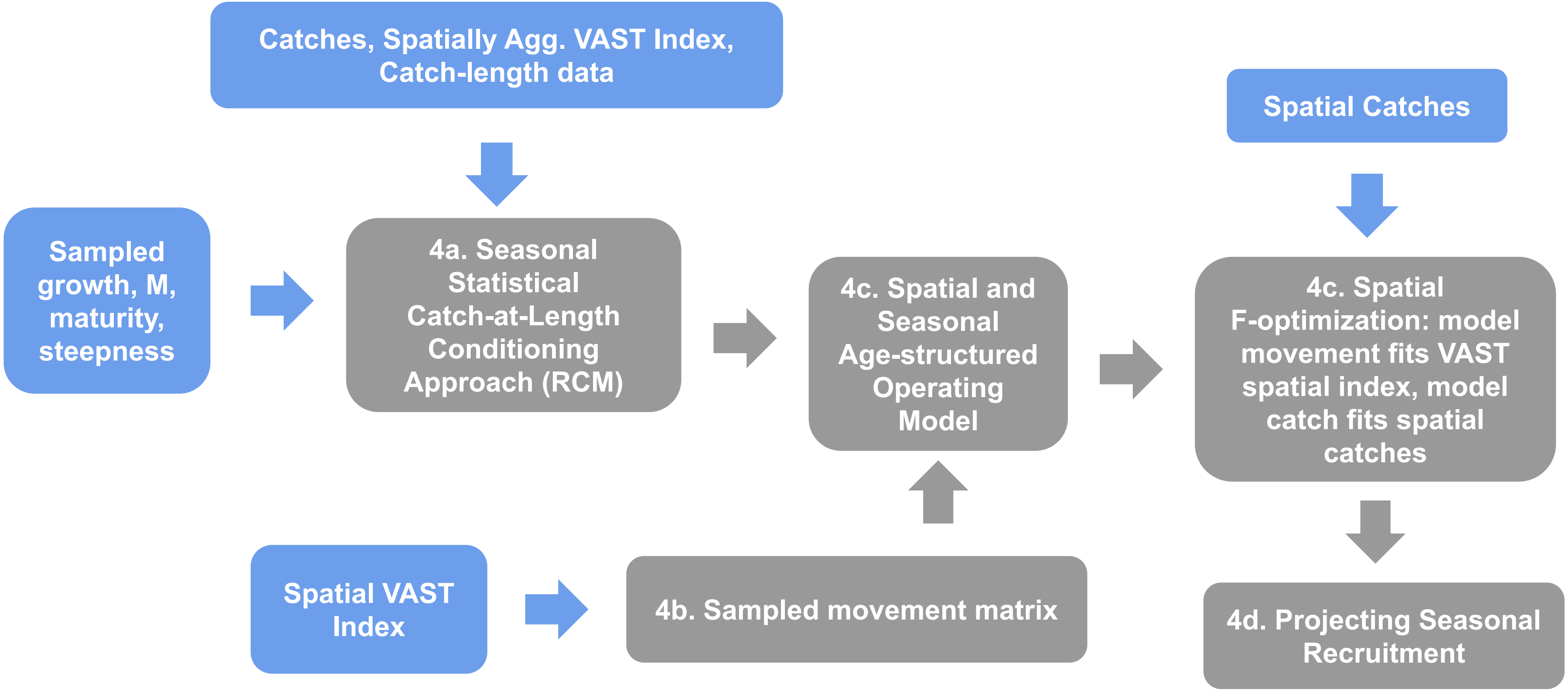
c. Imposing Spatial Structure and Solving for Spatial Exploitation Rate

d. Characterizing and Projecting Seasonal Recruitment

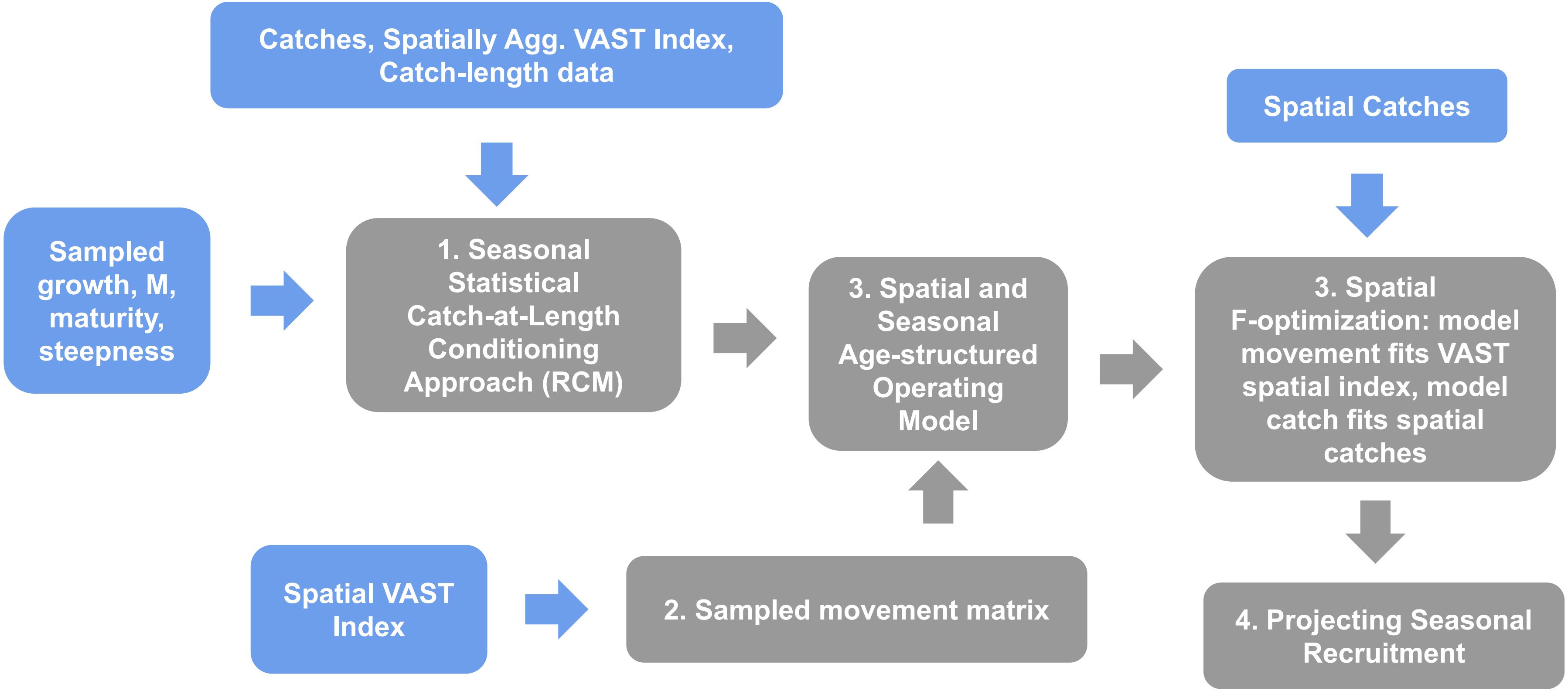
27th July 2026

Tom Carruthers
Cassidy Peterson
Mandy Karnauskas

# Approach to Specifying a Spatial-Seasonal Multi-fleet Operating Model for Dolphinfish



# Approach to Specifying a Spatial-Seasonal Multi-fleet Operating Model for Dolphinfish



# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Rapid Conditioning Model (RCM, SAMtool, Huynh et al. 2026) ([https://openmse.com/tutorial-rcm](https://openmse.com/tutorial-rcm))**

All operating models were conditioned in the R statistical environment (R Core Team 2024) using the Rapid Conditioning Model (RCM, Huynh et al. 2025) of the SAMtool package (Huynh et al. 2026),

The RCM is a statistical catch-at-age (or catch-at-length) model similar to stock assessment frameworks such as the Woods Hole Assessment Model (WHAM; Stock and Miller 2021) in that it is implemented in R using the Template Model Builder (TMB) library for non-linear estimation (Kristensen et al. 2016). A key feature of RCM is the ability to conduct replicate fits across sampled parameters and data sets including additional stochasticity in historical dynamics and assumptions.

The RCM has previously been applied as an operating model conditioning approach:

- B.C. Inside Yelloweye Rockfish (Haggarty et al. 2022) & Quillback Rockfish (DFO 2023),
- four species of B.C. invertebrates (Carruthers et al. 2025)
- Bay of Fundy Herring MSE (Carruthers et al., 2023a)
- MERA approach to data-moderate fisheries management (Carruthers et al., 2023b).
- The RCM has also been used to demonstrate OM conditioning in preliminary MSE analyses for a range of pelagic species such as South Atlantic Swordfish (Taylor et al. 2022), North Atlantic Blue Shark (Carruthers 2024) and Pacific Neon Flying Squid (Dai 2025).

# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

| Model attribute | Configuration |
|---|---|
| Stock-recruitment relationship | Beverton-Holt |
| Somatic growth | von Bertalanffy |
| Initial depletion | Equilibrium catch |
| Selectivity: USCom (Intl, Disc, Unrep) | Logistic length (‘flat-topped’) |
| Selectivity: RecN, RecS, HireN, HireS | Double normal length (‘dome-shaped’) |
| VAST survey selectivity | Mirrors USCom |
| Maximum seasonal exploitation rate (most selected age class) | 2.3 (harvest rate of 90%) |
| Standard deviation in log recruitment deviations (‘sigma-R’) | 2.0 (nearly freely estimated) |
| Maximum age classes (seasons) | 16 |
| Include age-zero calculation | Yes |
| Include ‘plus group’ calculation | No |

# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

Using RCM, a multi-fleet, spatially-aggregated, seasonal model was conditioned on annual catches, the total VAST abundance index (all areas summed) and the fleet length composition data to estimate:

- Unfished recruitment (stock-wide productivity, scale)
- Recruitments (per year and season),
- Apical fishing mortality rate at age
- Selectivity of UScom, RecN, RecS, HireN, HireS (Intl, Disc, Unrep mirror UScom)

| Recruitment Deviations | Details | N |
|---|---|---|
| Selectivity Parameters | 4 Rec fleets are 3 parameter dome (12) plus a 2 parameter logistic for USCom | 14 |
| Apical F | 148 season-years, 8 fleets (note some season-fleets have zero catches and F is not estimated) | 982 |
| Unfished recruitment | Recruitments 1990 - 2021.75 (first 16 and last 4 seasons are not estimated) | 128 |
| Catchability (VAST) | Scales VAST index to total biomass | 1 |
| Total | No. parameters | 1125 |

# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

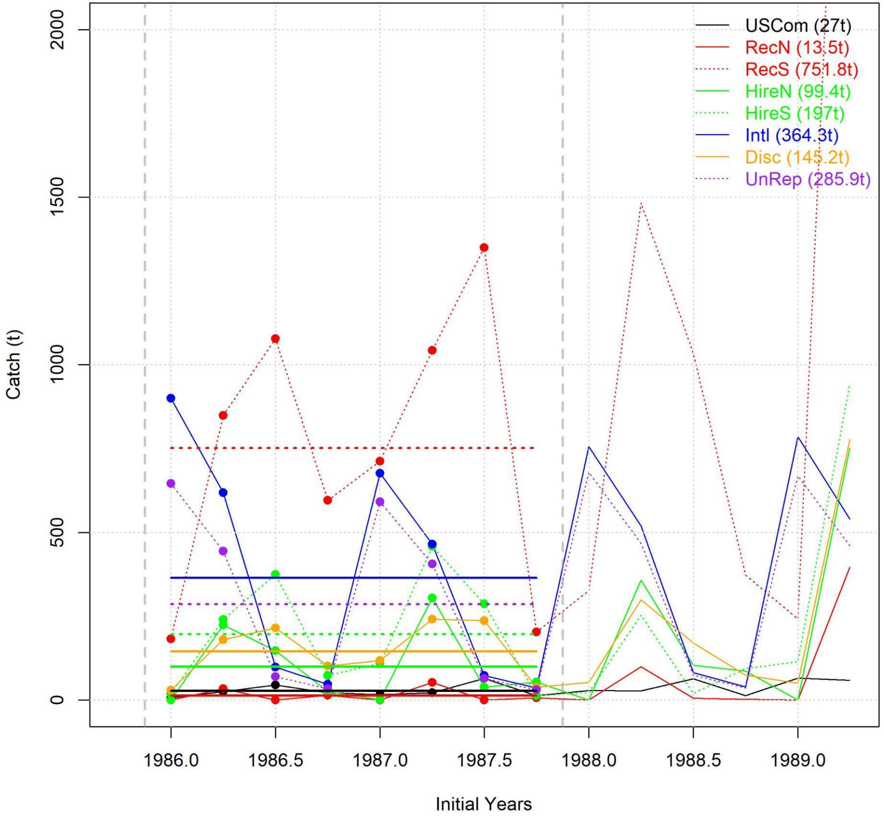
| Data Input | Likelihood function | Precision |
|---|---|---|
| VAST Index (biomass) | Lognormal | Annual CV (0.05 - 0.77) |
| Catch-length | Multinomial | Effective sample size of mean 30 across years |
| Catch | Lognormal | CV US Comm: 0.05 |
| - | - | CV Rec/Hire Comm: 0.1 |
| - | - | CV Int, Disc, Unrep: 0.15 |

RCM directly provides a seasonal, multi-fleet, spatially aggregated OpenMSE operating model.

# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Equilibrium Catches Prior to 1985**

In order to initialize models in an exploited state - there was exploitation prior to 1986 - the mean of the first 2 years was assumed to initialize the model (‘spool-up catches’)



# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

## RCM Fitting Reports

### 7.2.6 RCM Model Fitting Reports

The RCM model includes standardized reporting that describes inputs, model estimates, likelihood components and visualizes fit to data.

RCM model fitting reports are available for all reference case operating models. Note that reference operating model factors relating to future recruitment and movement are added post-hoc to the fitted spatial aggregated operating models of conditioning step 1. Hence there are eight conditioned operating models spanning two levels for natural mortality, steepness and historical catch levels. The RCM fitting reports for the eight conditioned OMs are available in the following table:

**Show** 10 **entries**

| | RCM Conditioning Report |
|---|---|
| | All |
| 1 | Fit_1.html |
| 2 | Fit_2.html |
| 3 | Fit_3.html |
| 4 | Fit_4.html |
| 5 | Fit_5.html |
| 6 | Fit_6.html |
| 7 | Fit_7.html |
| 8 | Fit_8.html |

Showing 1 to 8 of 8 entries

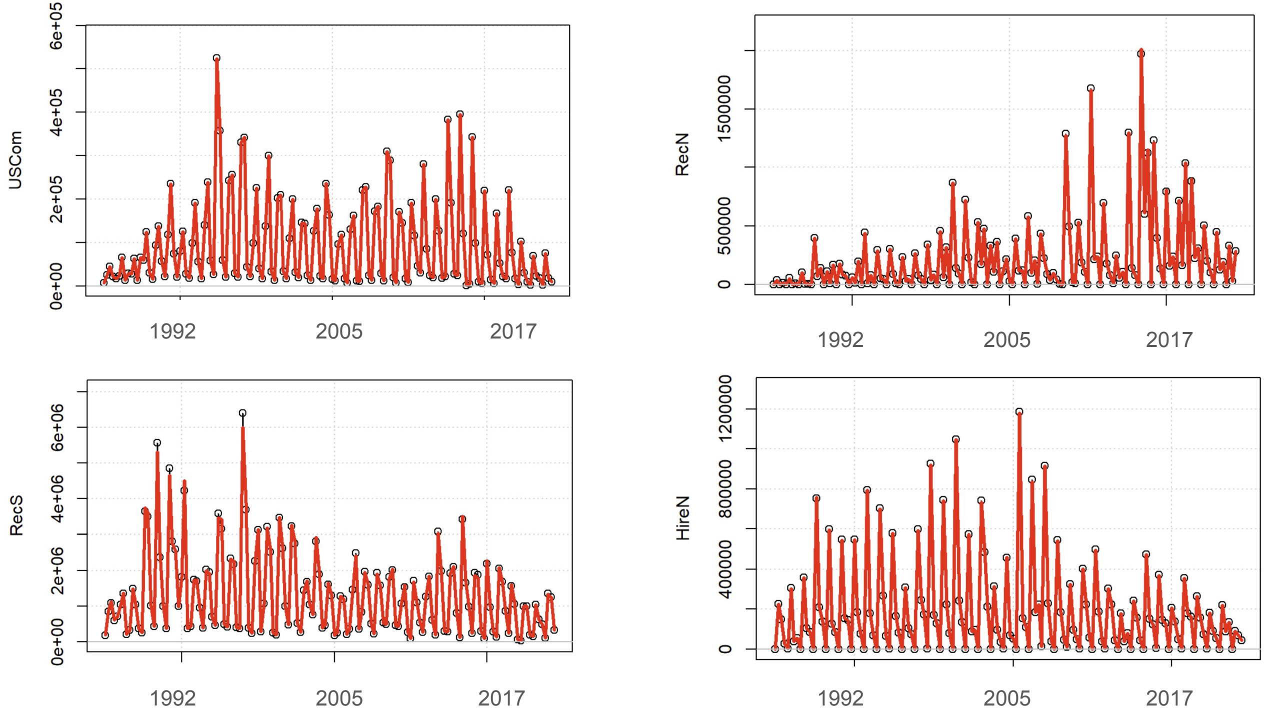
Previous 1 Next

# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

Total Catches

Generally very good fit



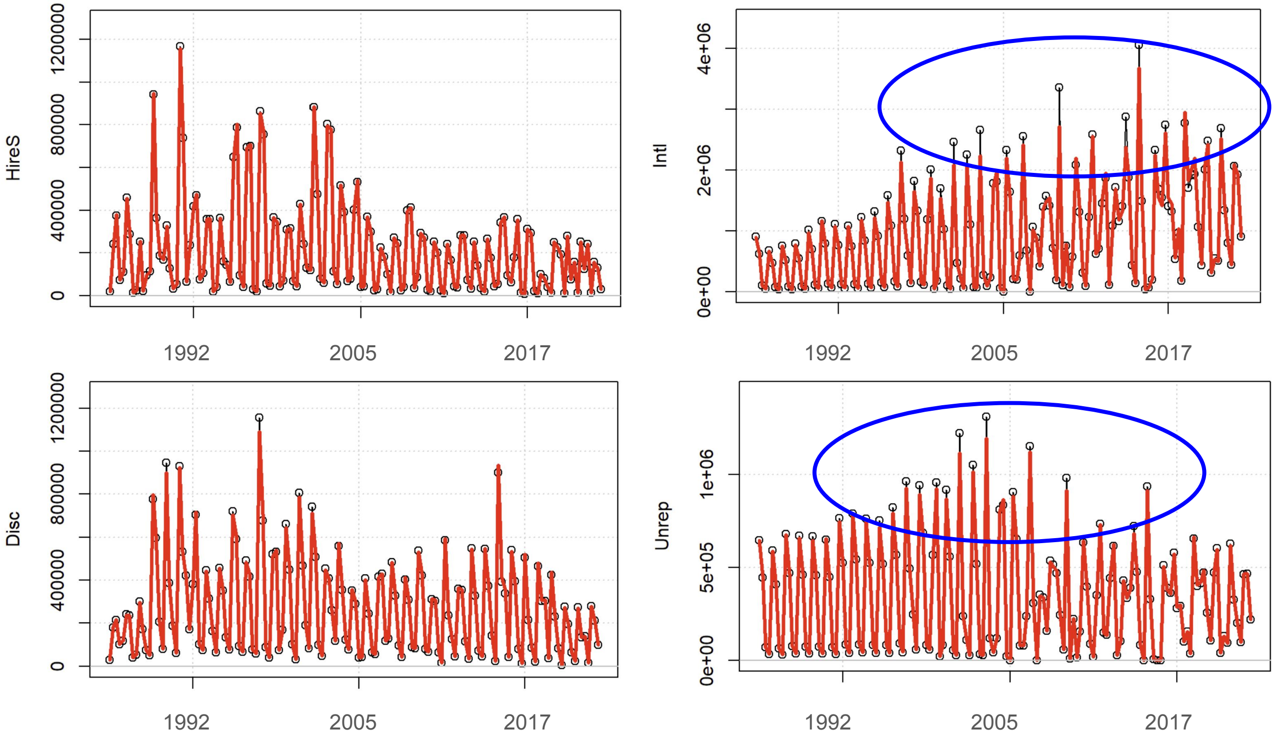
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**Total Catches**

Generally very good fit

Failure to fit extremely large catches in International (Intl) and Unreported (Unrep) fleets.

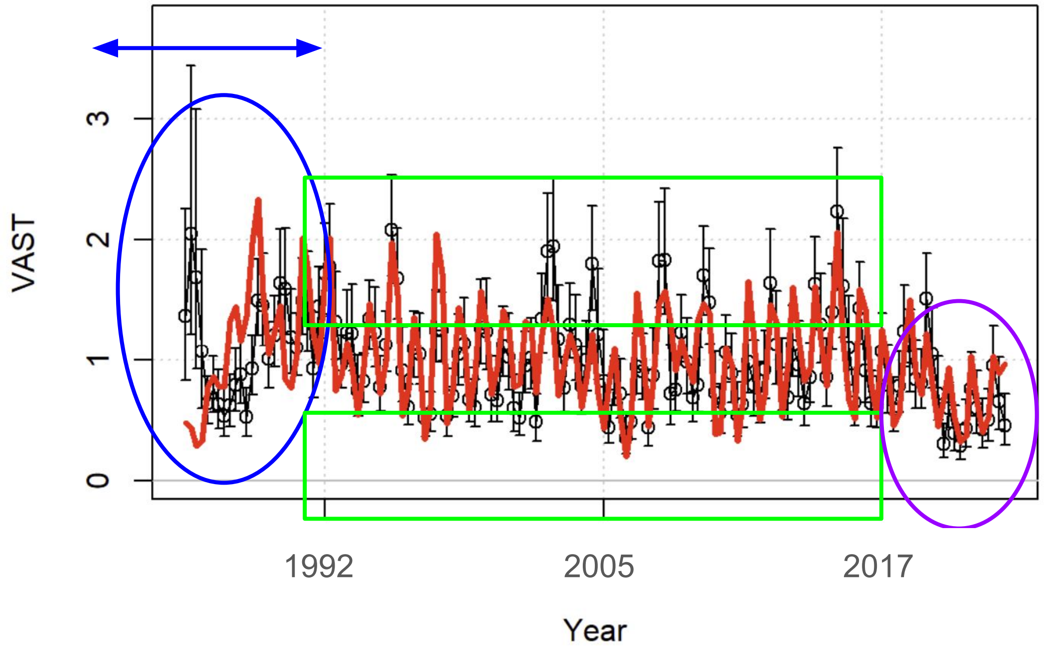


# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**VAST spatially-aggregated index**

Initialization period




Observed (black) and predicted (red) index from survey 1.

Early VAST time series suffers from sparse data points in certain strata. Rec devs fixed to 1 for 16 seasons, Model is 'dialed-in' after 1990.

RCM is generally more stable and fails to fit the full extent of biomass inferred by the VAST model.

Captures recent declines

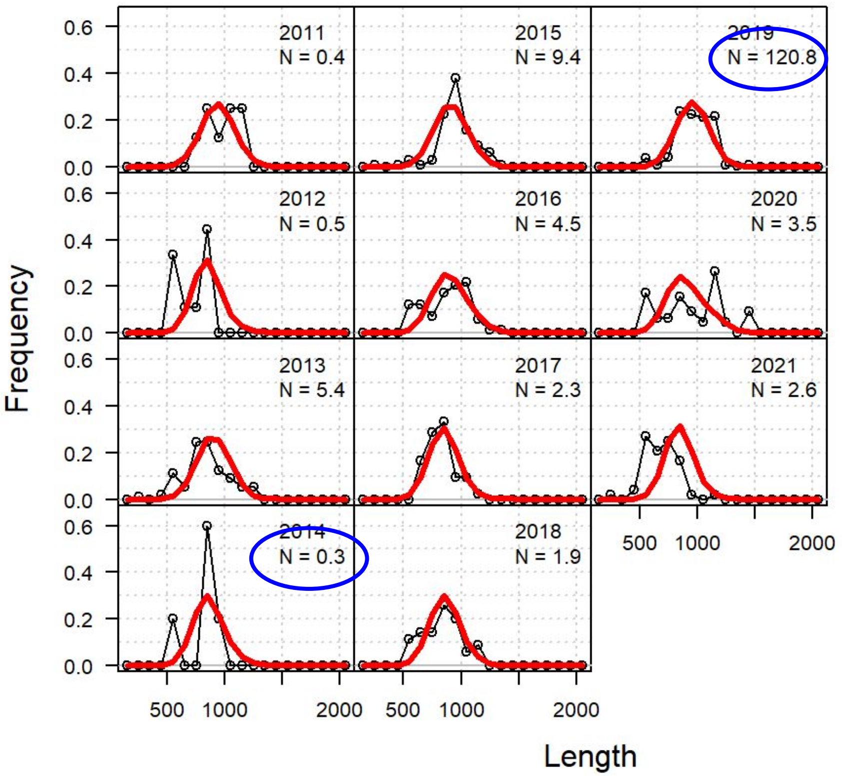
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29 (M 0.25, Steepness 0.7, Catches 100%)**

**Catch - length composition data**
**USCom**

Overall fit is reasonable but input data are relatively sparse (e.g. 2021.75)

Note the effective sample size



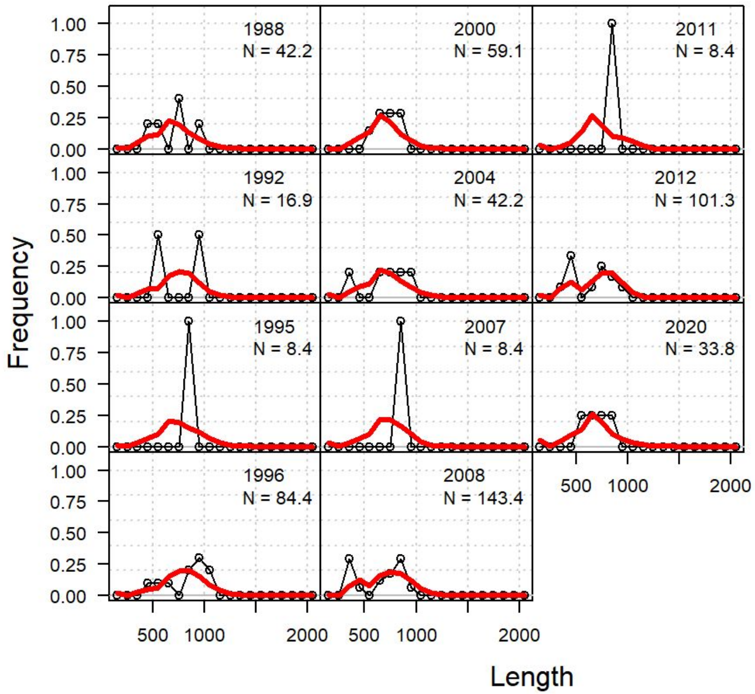
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**Catch - length composition data**

**RecN**

Overall fit is reasonable but input data are inconsistent and sparse.



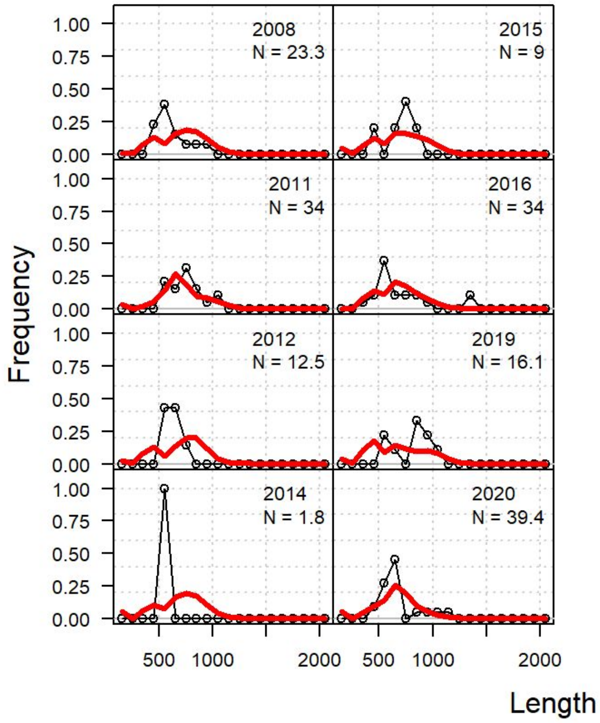
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**Catch - length composition data**

**RecS**

Overall fit is reasonable but input data are inconsistent and sparse.



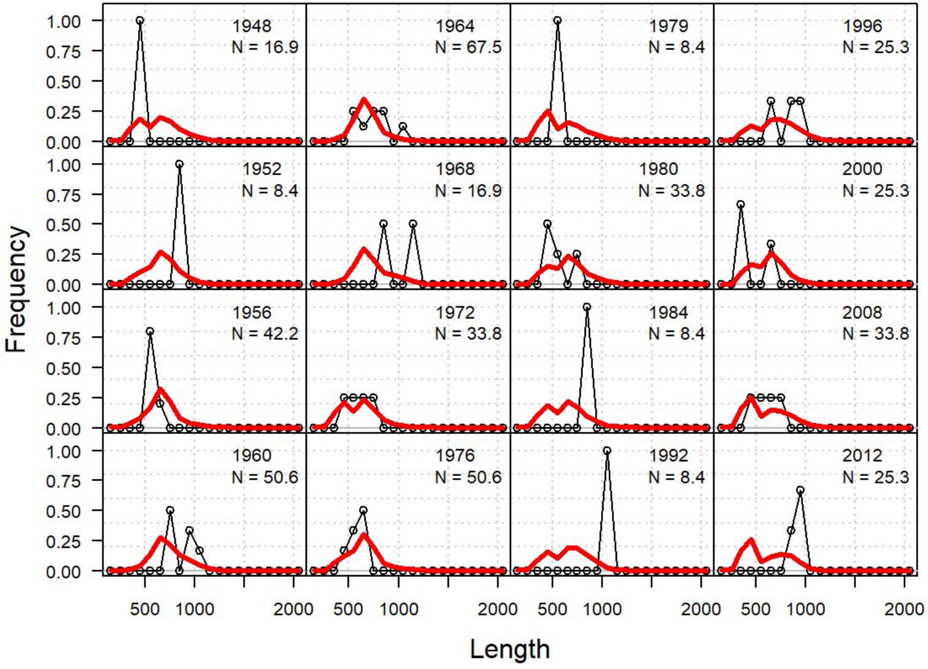
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**Catch - length composition data**

**HireN**

Overall fit is reasonable but input data are inconsistent and sparse.



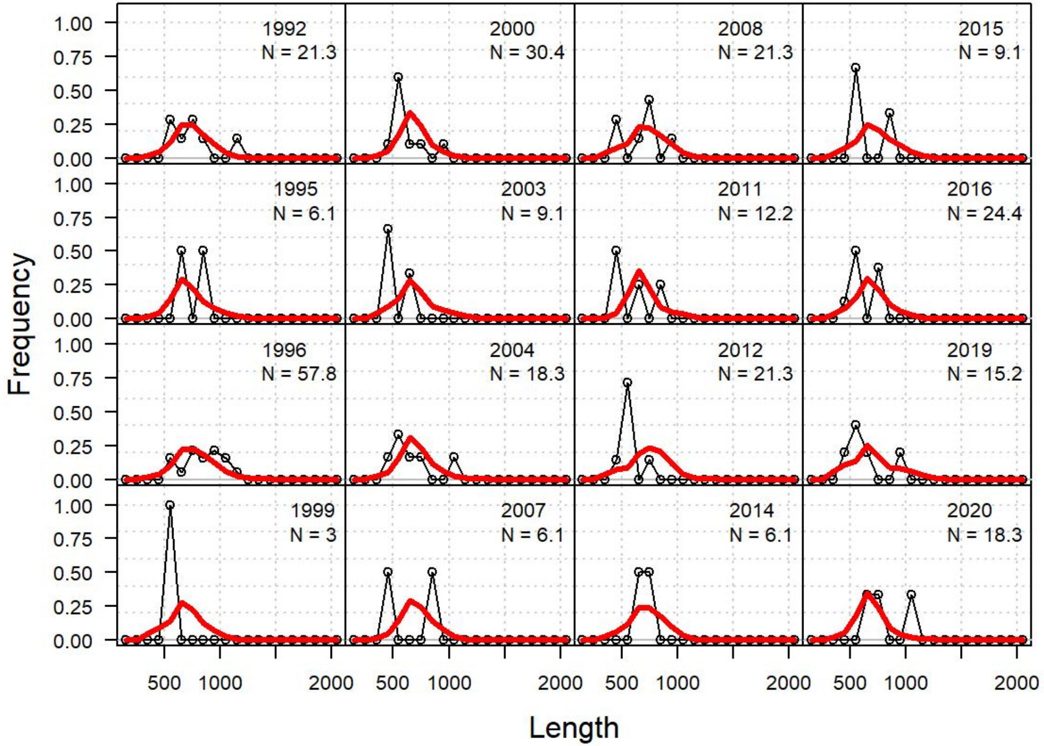
# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example fit for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

**Catch - length composition data**

**HireS**

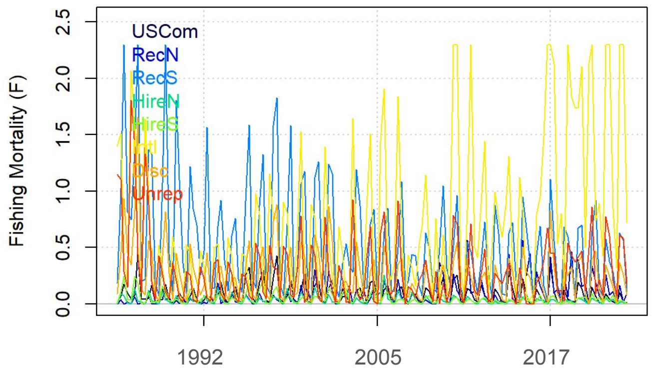
Overall fit is reasonable but input data are inconsistent and sparse.

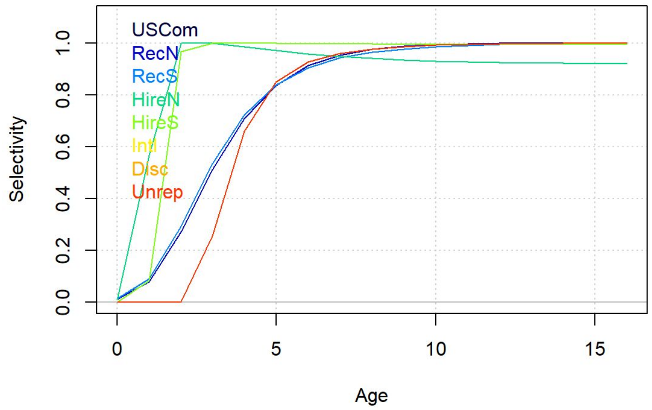


# 4a. Step 1: Spatially Aggregated RCM OM Conditioning

**Example estimates for OMs 5, 13, 21 & 29  (M 0.25, Steepness 0.7, Catches 100%)**

Overall fit is reasonable but input data are inconsistent and sparse.



# 4b. Step 2: Characterising Movement Implied by Spatial Indices (VAST)

**We have:**

A seasonal, spatial distribution predicted by VAST

**We don't know**

Exactly how individuals move among the various areas (that would require extensive tagging data)

The degree of viscosity (mixing among areas).

**We need:**

A seasonal movement matrix so that biomass can be moved among areas. Must capture the key aspects of the VAST index: seasonality, mean biomass varies among areas, degree of seasonality varies among areas.

A seasonal movement matrix for which we can impose varying degrees of stock viscosity while capturing the key aspects above.

# 4b. Step 2: Characterising Movement Implied by Spatial Indices (VAST)

### Gravity modelling approach (Carruthers et al. 2011; Taylor et al. 2011)

| | | $D_t$ Fraction in: | LOGIT Markov mov. Mat. $\Delta_{t+1}$ | | | | | Row sum |
|---|---|---|---|---|---|---|---|---|
| | CAR+FLK | 0.35 | $g_1 + v_1$ | $g_2$ | $g_3$ | $g_4$ | 0 | 1 |
| 2019 | NCA | 0.52 | $g_1$ | $g_2 + v_2$ | $g_3$ | $g_4$ | 0 | 1 |
| Winter | NCFL | 0.03 | $g_1$ | $g_2$ | $g_3 + v_3$ | $g_4$ | 0 | 1 |
| | NED | 0.09 | $g_1$ | $g_2$ | $g_3$ | $g_4 + v_4$ | 0 | 1 |
| | NNC+VBM | 0.01 | $g_1$ | $g_2$ | $g_3$ | $g_4$ | $v_5$ | 1 |
| | $D_{t+1}$ | Fraction out: | 0.24 | 0.35 | 0.22 | 0.09 | 0.10 | |
| | | | CAR+FLK | NCA | NCFL | NED | NNC+VBM | |
| | | | | | 2019 Spring | | | |

The predicted distribution $\hat{D}_t$ is given by: $$\hat{D}_t = D_{t-1}\Delta_t$$

The likelihood function for observed distribution (D): $$log(D_t) \sim N(log(\hat{D}_t), 0.025)$$

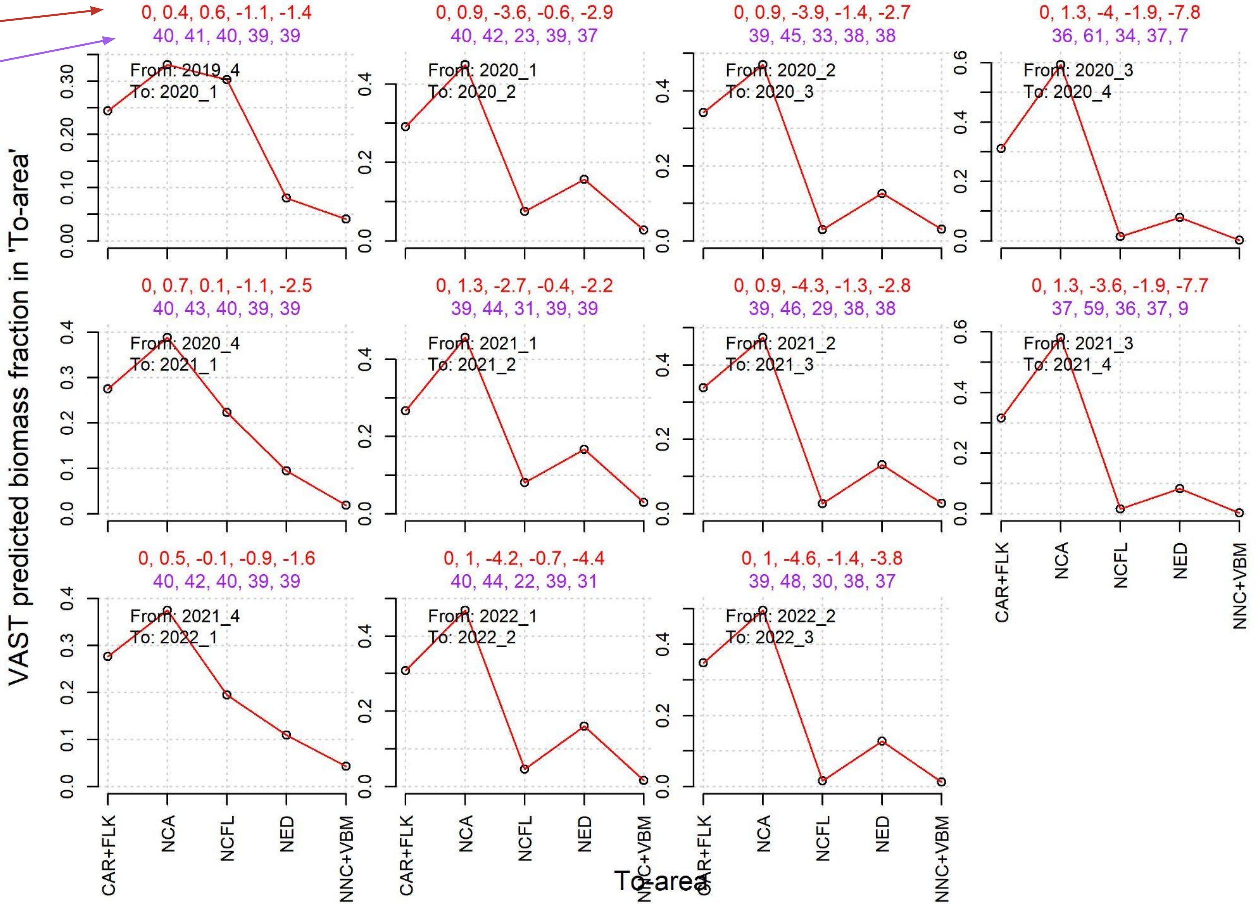
User specified prior on viscosity (V) (prob. Staying, pos. diagonal) $$log(\Delta_{t,from,to}) \sim N(log(V), 0.35), \quad \text{where } from = to$$

Uninformative priors on gravity and viscosity terms: $$g \sim N(0, 5)$$ $$v \sim N(0, 5)$$

# 4b. Step 2: Characterising Movement Implied by Spatial Indices (VAST)

Gravity terms (g)

Viscosity terms (v)




Observed VAST distribution

Fitted gravity model

This was given a user-specified prior viscosity (prob. staying)′V of 40%

# 4b. Step 2: Characterising Movement Implied by Spatial Indices (VAST)

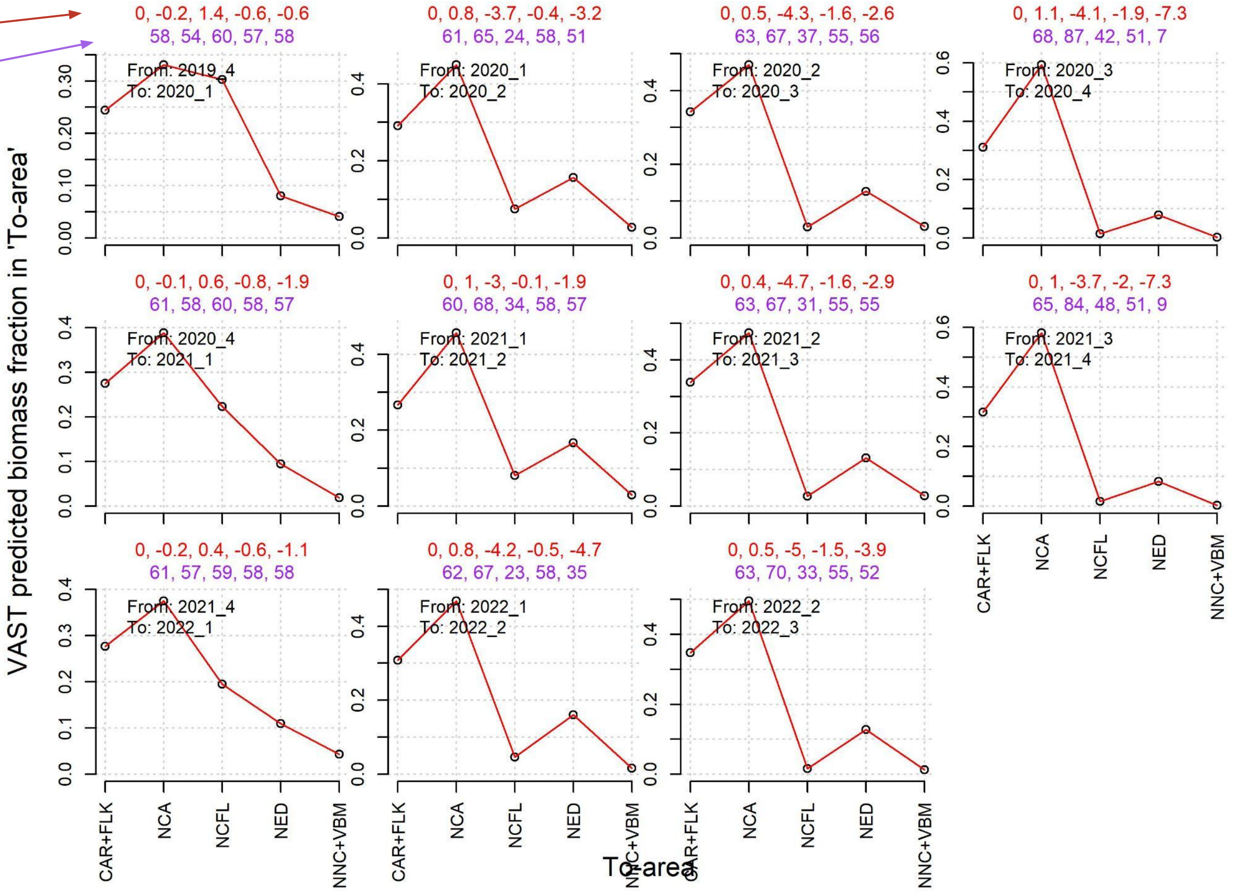
Gravity terms (g)

Viscosity terms (v)

Observed VAST distribution

Fitted gravity model

This was given a user-specified prior viscosity (prob. staying)′V of 60%

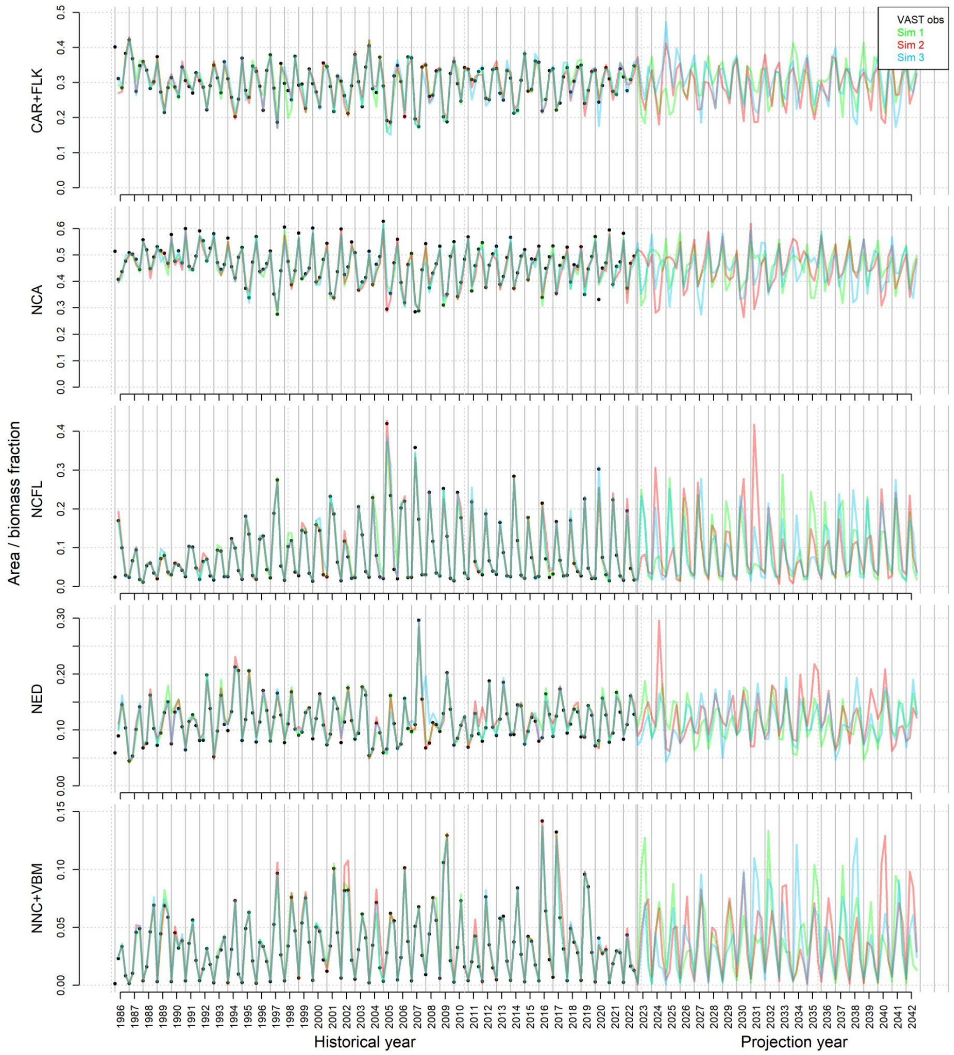


# 4b. Step 2: Characterising Movement…

Historical movements are drawn from a multivariate normal distribution (g and v terms) from the fit to the spatial VAST index (the inverse Hessian arising from the nlminb fit of the gravity model).

Projected movement is constructed by the same method but sampling historical years at random (blocks of 4 seasons together).

Shared history (with estimation error), differing simulated projections.



# 4c. Step 3. Impose Spatial Structure and Solve for Spatial Exploitation Rate

The spatially-aggregated RCM operating model was extended to a spatial model by superimposing the movement matrices calculated in step 2 above.

These movement matrices provide a distribution of stock biomass that closely matches the spatial VAST index. A key requirement of the operating models is that they also match the historical pattern of spatial exploitation rate.

To achieve this, we employed an iterative numerical approach known as as Walrasian Tatonnement which has been used to solve for very complex fishery exploitation dynamics across many hundreds of stocks (Carruthers et al. 2019) and for density dependence within stock assessments (Carruthers and Wang 2026, in review).

# 4c. Step 3. Impose Spatial Structure and Solve for Spatial Exploitation Rate

An initial distribution of historical exploitation rate (apical F, the exploitation rate of the most selected age class) by time step $t$, simulation $s$, fleet $f$ and area $r$, was proposed. This initial guess is calculated by dividing observed spatial catches $C_{obs}$ by the VAST spatial distribution $D$ multiplied by the spatially aggregated OM estimate of stock biomass $B_{agg}$:

$$F_{1,s,t,r,f} = C_{obs,t,r,f}/(B_{agg,s,t}D_{t,r})$$

For reasons of numerical stability a maximum value of 0.8 was assumed for the $F$ terms in this initial step.

The spatial operating model can now be initialized providing a prediction of spatial catches $C_{pred}$. Over 15 iterations, the spatial exploitation rates were updated such that the operating model prediction of spatial catches closely matched those observed. In each iteration $i$ the ratios of observed to predicted catches were calculated:

$$\delta_{i,s,t,r,f} = C_{obs,t,r,f}/C_{pred,i-1,s,t,r,f}$$

For the next iteration exploitation rate are updated according to this ratio and an adjustment factor. The adjustment factor is needed to slowly move the numerical approach to a stable equilibrium. Immediately updating the historical F distribution according to $_delta$ would lead to instability and 'flip-flopping' as previous values of F would impact those in subsequent time steps. Here an adjustment factor of 0.7 was assumed:

$$F_{i,t,s,t,r,f} = exp(0.7 \cdot log(\delta_{i,s,t,r,f})) \cdot F_{i-1,t,s,t,r,f}$$

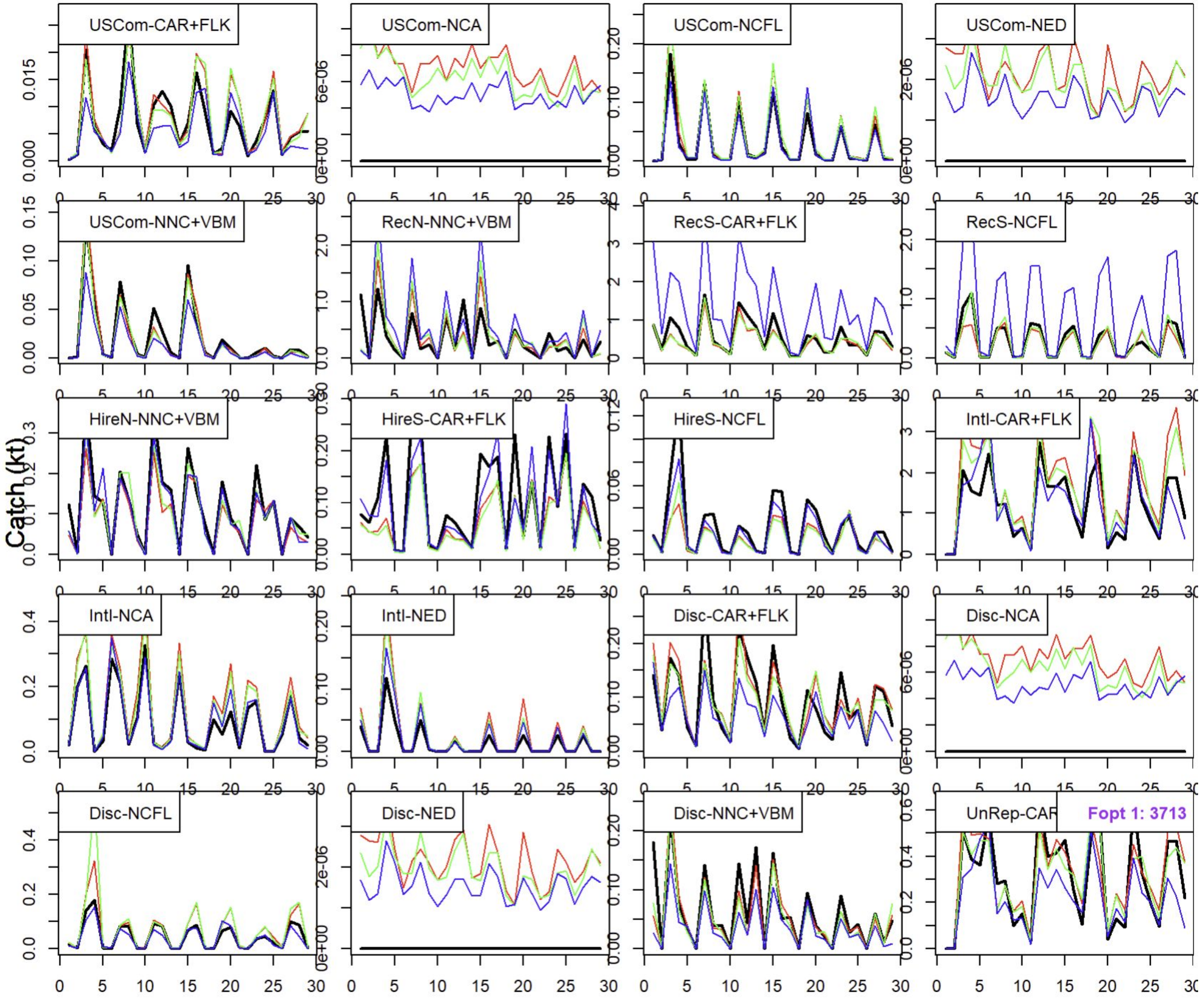
A maximum F in any time step of 2.3 (harvest rate of 90%) was imposed.

In this application running the algorithm for 15 iterations was to ensure convergence. For most operating models, catches were very close to those observed after just 8 iterations:

# 4c. Step 3. Impose Spatial Structure and Solve for Spatial Exploitation Rate

Iteration 1: Initial guess

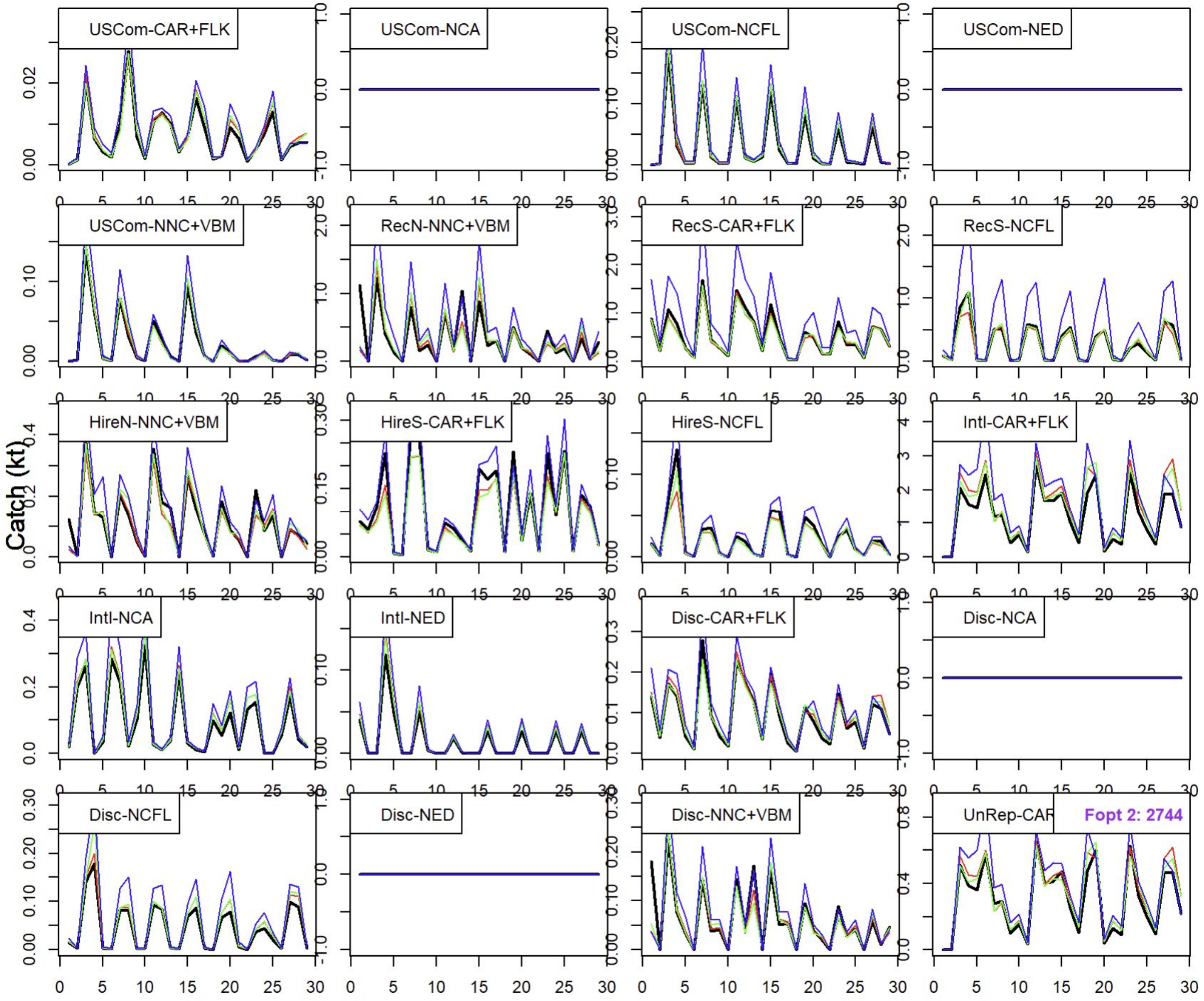
**Observed catches**
Sim. 1
Sim. 2
Sim. 3



# 4c. Step 3. Impose Spatial Structure and Solve for Spatial Exploitation Rate

Iteration 2: After 1st updated

**Observed catches**
Sim. 1
Sim. 2
Sim. 3



# 4c. Step 3. Impose Spatial Structure and Solve for Spatial Exploitation Rate

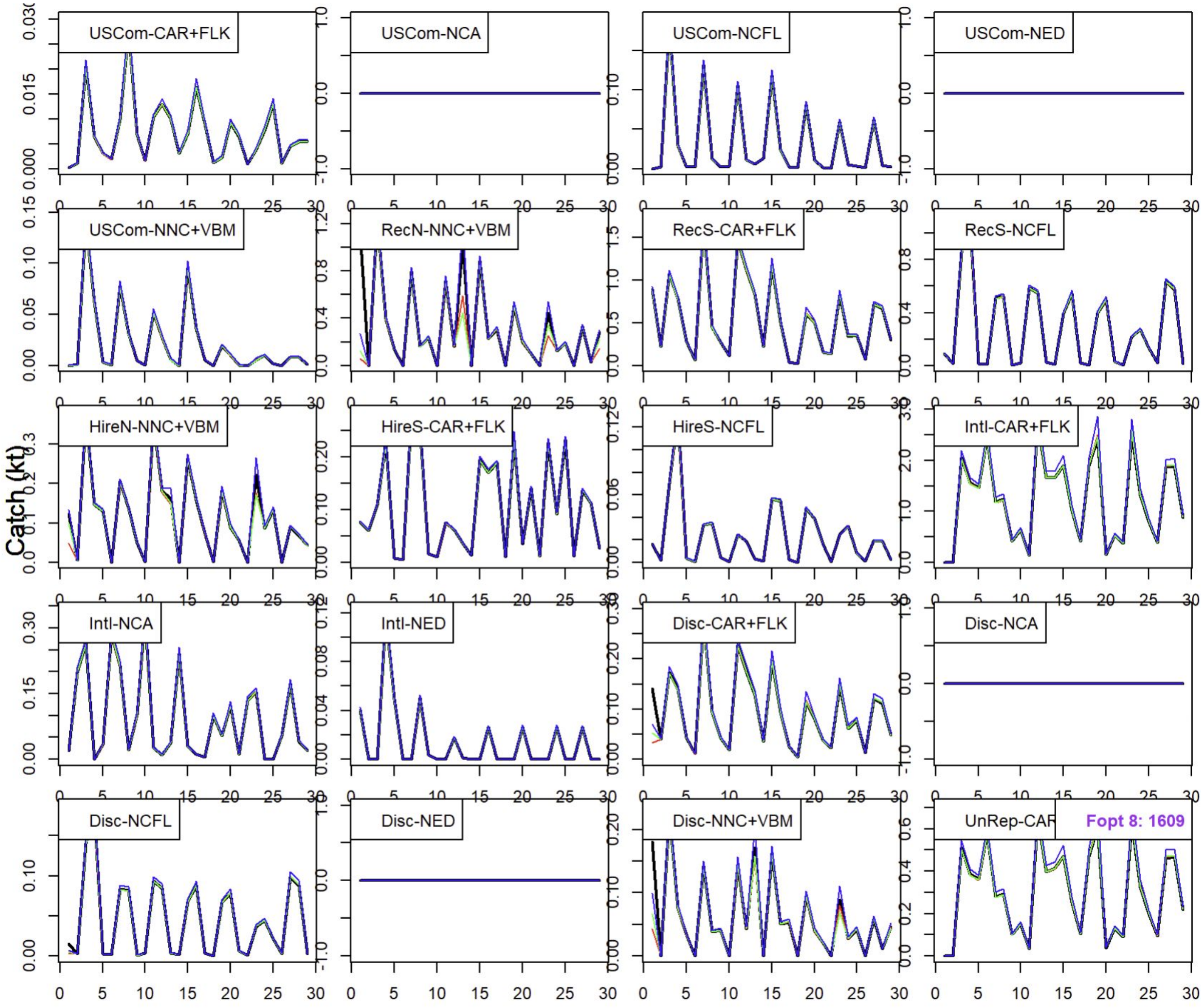
Iteration 8: After 7 updates

**Observed catches**

Sim. 1

Sim. 2

Sim. 3



# 4d. Step 4. Characterizing and Projecting Seasonal Recruitment

**Historical Recruitment**

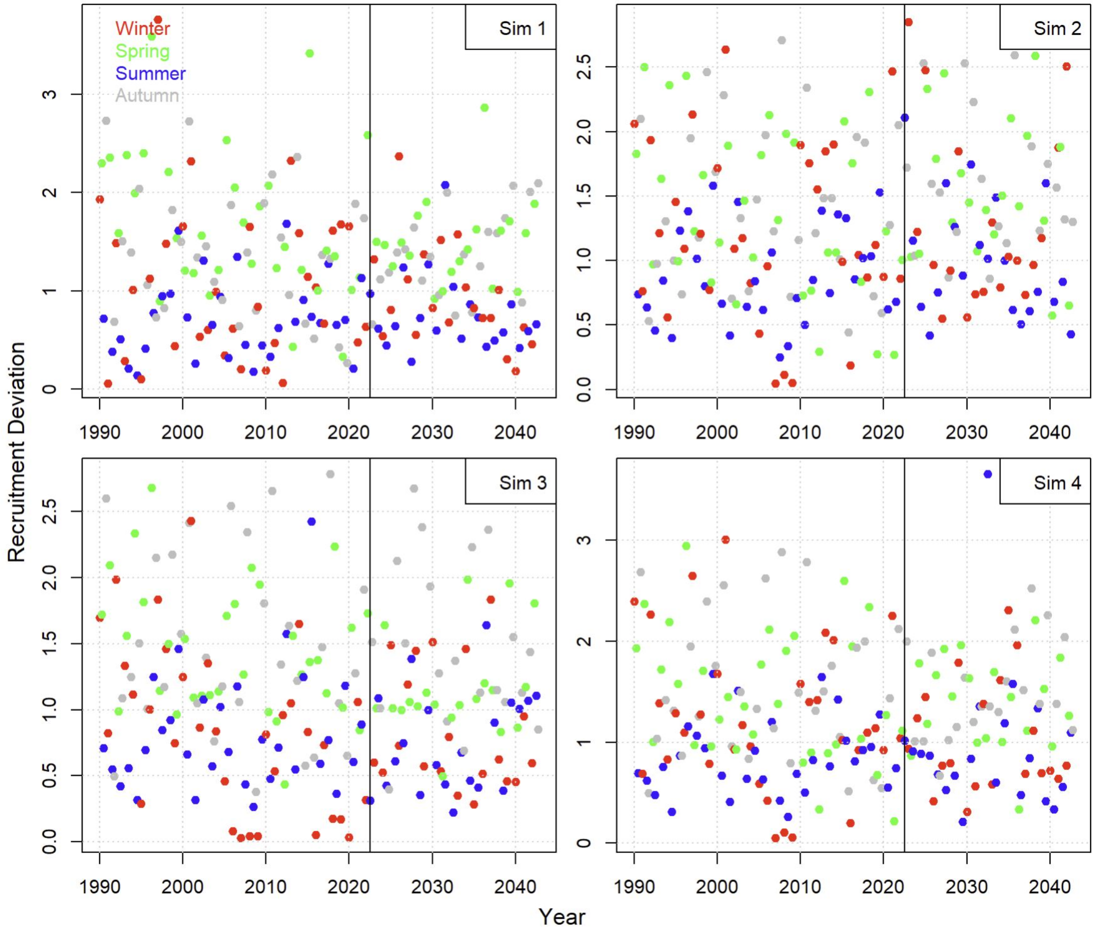
Recruitment deviations sampled from the var-covar of RCM model fit

**Future Recruitment**

By simulation-season: estimated the historical mean and standard deviation.

Generated projected seasonal recruitments according to those means and standard deviations.

Lag-1 autocorrelation was low in historical estimated recruitments (< 0.2) so was not imposed on projections.



# 4. Conclusions

**The sequential approach to conditioning operating models for Dolphinfish captures the important properties of dolphinfish dynamics:**

- Plausible scale and recruitment variability (Step 1: Estimate scale, seasonal reproduction and fishery selectivity in a spatially aggregated model)
- Captures uncertainty in stock and fishery dynamics (stochastic inputs for M, K and stochastic estimates of selectivity, Step 1: Estimate scale, seasonal reproduction and fishery selectivity in a spatially aggregated model)
- Absolute abundance differences among areas (Step 2: Characterize movement implied by spatial indices)
- Seasonality in abundance (Step 2: Characterize movement implied by spatial indices)
- Varying seasonality among areas (Step 2: Characterize movement implied by spatial indices)
- Matches spatial catches by fleet and season (Step 3: Imposing Spatial Structure and Solving for Spatial Exploitation Rate)
- Captures and projects seasonality in recruitment (Step 4: Characterize and Project Seasonal Recruitment)

# Applicable TORs

2. Evaluate the strengths and weaknesses of methods used to simulate the stock.

   a. Are methods to generate operating models scientifically sound?

   b. Did methods meet the needs of stakeholders and/or research questions (i.e., appropriate spatial resolution, time-step, ability to measure key performance statistics)?

   c. If data were unavailable to parameterize the model, were the assumptions used to overcome this limitation reasonable and/or multiple assumptions included as an axis of uncertainty?

   d. Was plausibility weighting of reference operating models appropriate and sufficiently justified?

   e. Does the robustness of the operating model grid allow the management procedure to fail?

4. Evaluate MSE projections.

   a. Did the operating models project data that would be available to the management procedure?

   b. Were projection assumptions reasonable and appropriate for the stock (e.g., decisions about future parameter estimates and uncertainty; resampling approaches to generate future data; future nonstationarity, productivity, etc.)?