SEDAR 87 : Gulf of America Brown, White, and Pink Shrimp Benchmark Assessments

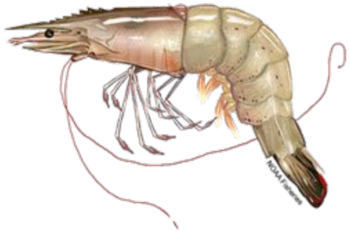
Gulf Fisheries Branch

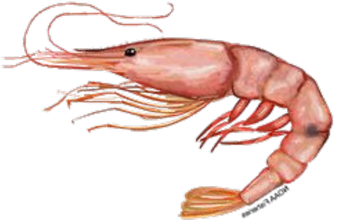
NOAA SEFSC

Tampa, FL June 23-27 2025

Presentation Outline

- Background
  - Review workshop TORs
  - Assessment History
  - Species Life History and Environment
- Data
  - Environmental Indices
  - Fishery Landings and Economic Considerations
  - Fishery Independent Surveys
- Brown Shrimp
  - VAST index methodology, results and discussion
  - JABBA methodology, results and discussion
  - EDM methodology, results and discussion
- White Shrimp
  - VAST index results and discussion
  - JABBA results and discussion
  - EDM results and discussion
- Pink Shrimp
  - VAST index results and discussion
  - JABBA results and discussion
  - EDM results and discussion
- Conclusions and Recommendations





Review Workshop Terms of Reference

1. Evaluate the degree to which the terms of reference from the Data and Assessment processes were addressed.

2. Evaluate the data used in the assessment, including discussion of the strengths and weaknesses of data sources and decisions. Consider the following:
   - Are data decisions made by the Data and Assessment processes justified?
   - Are data uncertainties acknowledged, reported, and within normal or expected levels?
   - Is the appropriate model(s) applied properly to the available data?
   - Are input data series sufficient to support the assessment approach?

3. Evaluate and discuss the strengths and weaknesses of the methods used to assess the stock, given the available data. Consider the following:
   - Are methods scientifically sound and robust?
   - Are priority modeling issues clearly stated and addressed?
   - Are the methods appropriate for the available data?
   - Are assessment models configured properly and used in a manner consistent with standard practices?

Review Workshop Terms of Reference

4. Consider how uncertainties in the assessment, and their potential consequences, are addressed.
   - Comment on the degree to which methods used to evaluate uncertainty reflect and capture the significant sources of uncertainty in the population, data sources, and assessment methods.
   - Comment on the likely relationship of this variability with possible ecosystem or climate factors and possible mechanisms for including this into management reference points.

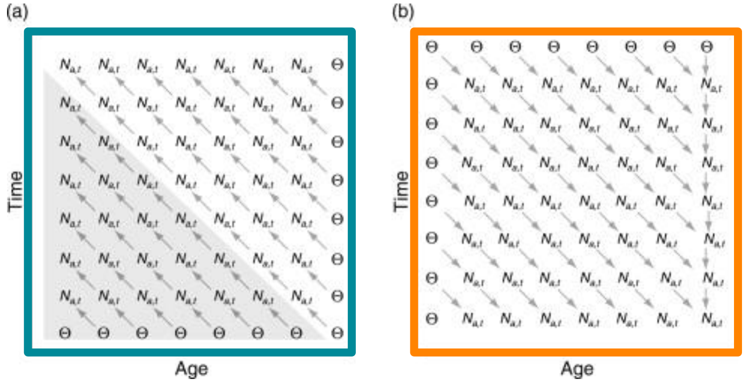
5. Provide, or comment on, recommendations to improve the assessment
   - Consider the research recommendations provided by the Data and Assessment processes in the context of overall improvement to the assessment, and make any additional research recommendations warranted.
   - If applicable, provide recommendations for improvement or for addressing any inadequacies identified in the data or assessment modeling. These recommendations should be described in sufficient detail for application, and should be practical for short-term implementation (e.g., achievable within ~6 months). Longer-term recommendations should instead be listed as research recommendations above.

6. Provide recommendations on possible ways to improve the Research Track Assessment process.

7. Prepare a Review Workshop Summary Report describing the Panel's evaluation of the Research Track stock assessment and addressing each Term of Reference.

Gulf Shrimp Assessments - A brief history

- Virtual Population Analysis (VPA)
  - Nichols 1984, 1986; Nance & Nichols 1988; Nance 1989
  - NMFS 2009 - Pink shrimp assessment internal review – *"the current VPA model cannot be considered to produce a reliable indicator of current shrimp abundance"*
- Stock Synthesis (SS)
  - Hart & Nance 2010, Hart 2012a,b,c, Hart 2016a,b,c, Hart 2018a,b,c
  - 2019 internal review – *"analytical staff have found several concerning issues that must be addressed before developing new shrimp assessment models"*



Martell 2008

- Both age structured models – neither adequate for modeling penaeid shrimp dynamics

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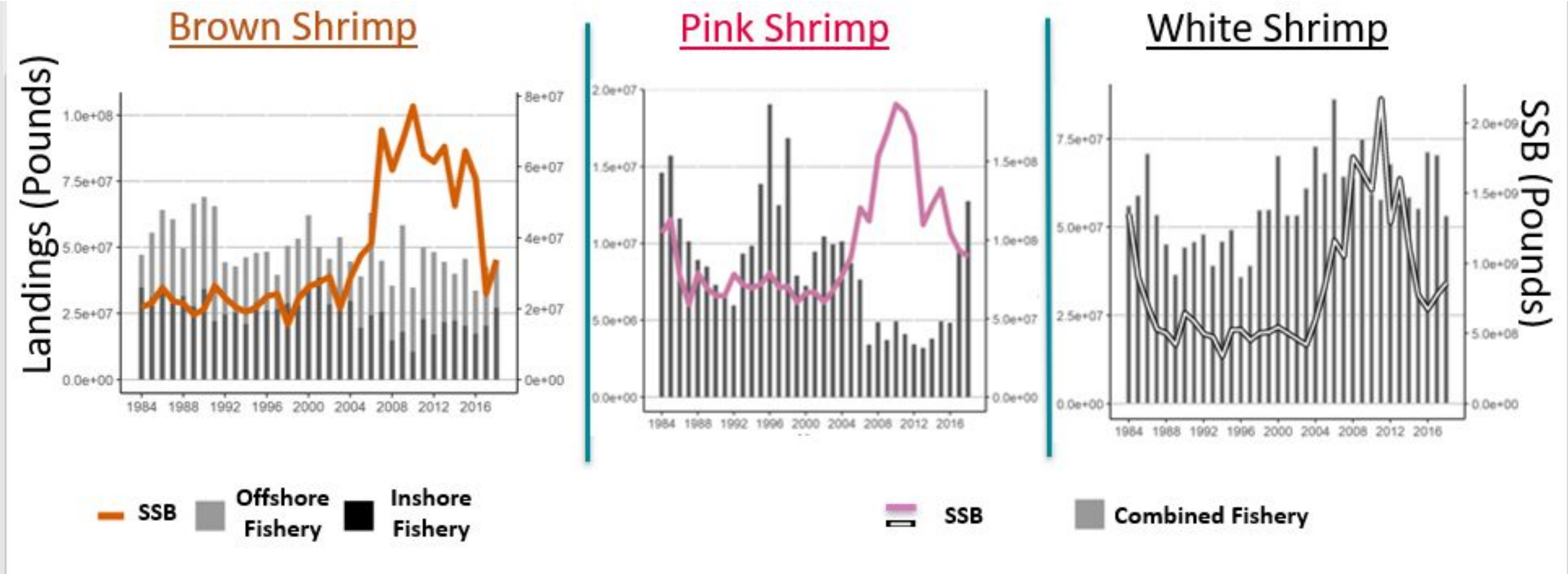
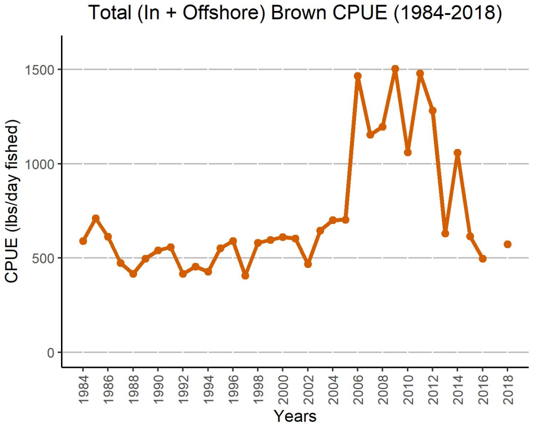
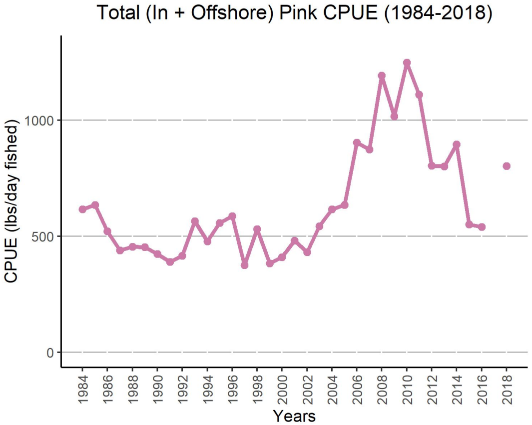
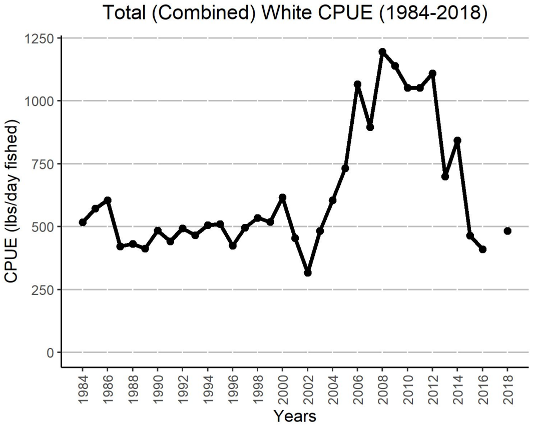
Age structured models

- Why age structured models are not adequate…
  - Short lived species (1-2 years?)
  - Age data lacking
  - Growth environmentally driven and time-varying (data lacking)
  - Recruitment success largely determined by environmental factors rather than a stock-recruit relationship – *“failure to incorporate environmental signals in SS when the recruitment dynamics are environmentally driven leads to bias in estimates of SSB, R, and F”* (Cao et al. 2016)
  - Lag time is too long to acquire and process the necessary fisheries data to populate an integrated age structured model like SS – Need for more timely and nimble management advice due to species life history


Brown Shrimp
Pink Shrimp
White Shrimp
Landings (Pounds)
SSB (Pounds)
SSB
Offshore Fishery
Inshore Fishery
Combined Fishery


Total (In + Offshore) Brown CPUE (1984-2018)
CPUE (lbs/day fished)
Years


Total (In + Offshore) Pink CPUE (1984-2018)
CPUE (lbs/day fished)
Years


Total (Combined) White CPUE (1984-2018)
CPUE (lbs/day fished)
Years

Relative abundance indices

- If fishery dependent CPUE data are to be useful they must be weighted by area (not by directed effort as has been done in the past) and the impact of any other variable that impacts catch rates (other than abundance) must be removed through standardization (e.g. time of day, depth, location)
- For shrimp, there is no information on time of day, gear efficiency, depth or precise location associated with the fishery dependent CPUE data

Specific issues with previous SS models

- Model instability
- Convergence issues
- Poor diagnostics
- Selectivity poorly estimated
- Conflicting indices
- Insufficient fishery independent data to support monthly models
- Biomass estimates driven by fishery dependent CPUE
- No clear relationship between catch and biomass

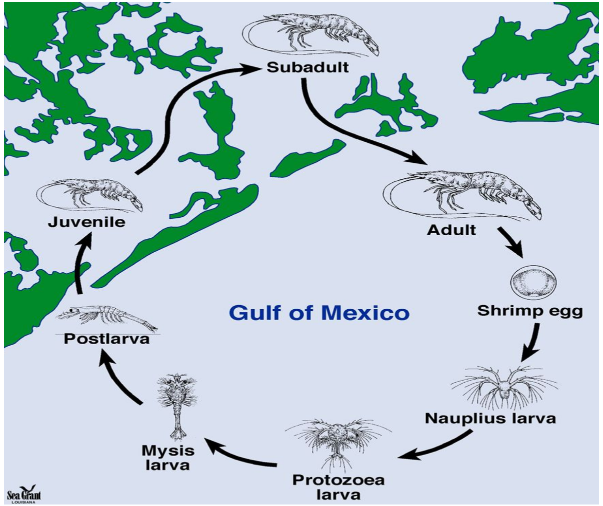
Formation of Shrimp Topical Working Groups

- Southeast Fisheries Science Center worked in conjunction with the Gulf Council and stakeholders to address these issues through a series of workshops in 2021
- Working Groups
  - Landings Data Estimation
  - Effort Estimation
  - Indices
  - Life History and Environment
  - Bycatch Estimation

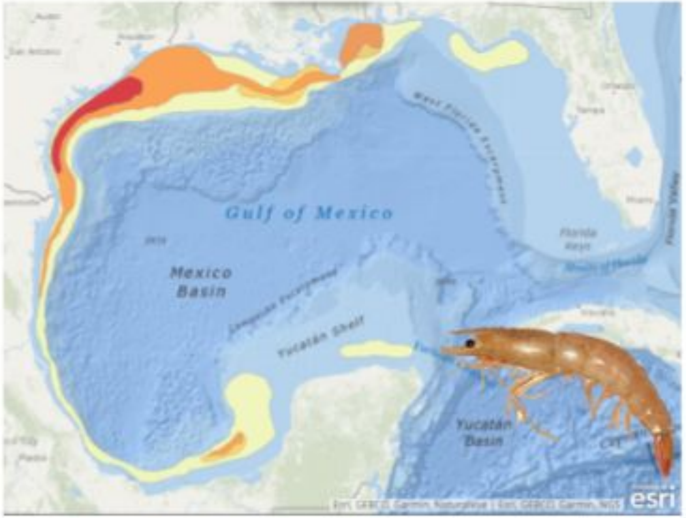
Benchmark Assessment

- Opportunity to explore and test alternative stock assessment models
  - **JABBA** : **J**ust **A**nother **B**ayesian **B**iomass **A**ssessment
  - **EDM**: **E**mpirical **D**ynamic **M**odeling
  - **VAST**: **V**ector **A**utoregressive **S**patio-**T**emporal Model *(Index Standardization)*
- Assessment models with simplified dynamics
- VAST and EDM allow us to explore environmental drivers of abundance and nonlinear dynamics

Life History and Environment



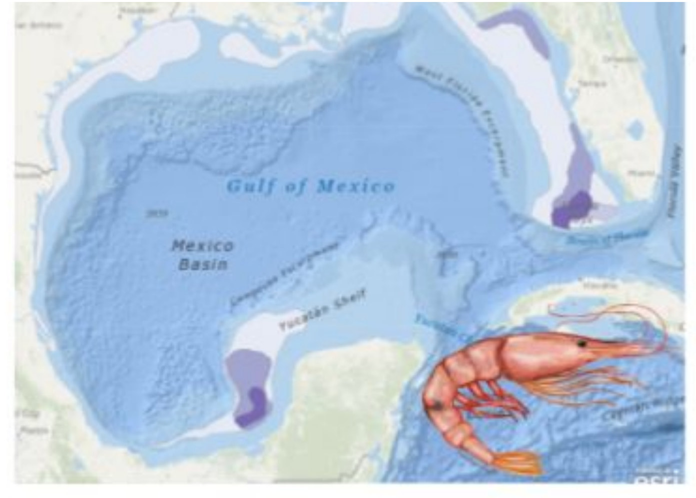
- Brown (*Farfantepenaeus aztecus*), white (*Litopenaeus setiferus)* and pink (*Farfantepenaeus duorarum*) shrimp follow a similar ontogeny
- Adults spawn offshore, and their planktonic larvae disperse into nearshore estuarine habitat. Nearshore marsh habitat serves as a nursery area for several months until the subadults migrate offshore
- Environmental drivers with greatest impact on brown, white, and pink shrimp productivity will be from the nearshore environmental conditions that impact the juvenile and subadult life stages.
- Life span 1-2 years



Shrimp Distribution Based on Landings

(SEDAR87 DW Report, Figure 3.2)

[Shrimp fishery story map]

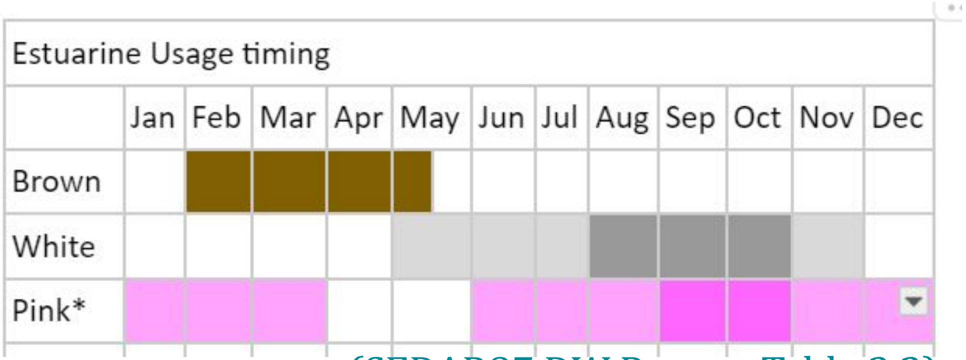


Life History and Environment

Brown Shrimp	White Shrimp	Pink Shrimp
Bury day, emerge night	In water column day & night	Bury day, emerge night
Higher salinity / offshore	Lower salinity / coastal	More tropical
Deeper, 27-73m (up to 183m)	Shallower (0-35m)	11-36m (up to 137m)
Muddy	Marsh	Sandy
Emigrate in late spring	Emigrate in fall	Emigrate in fall or overwinter in estuaries and migrate offshore in the spring

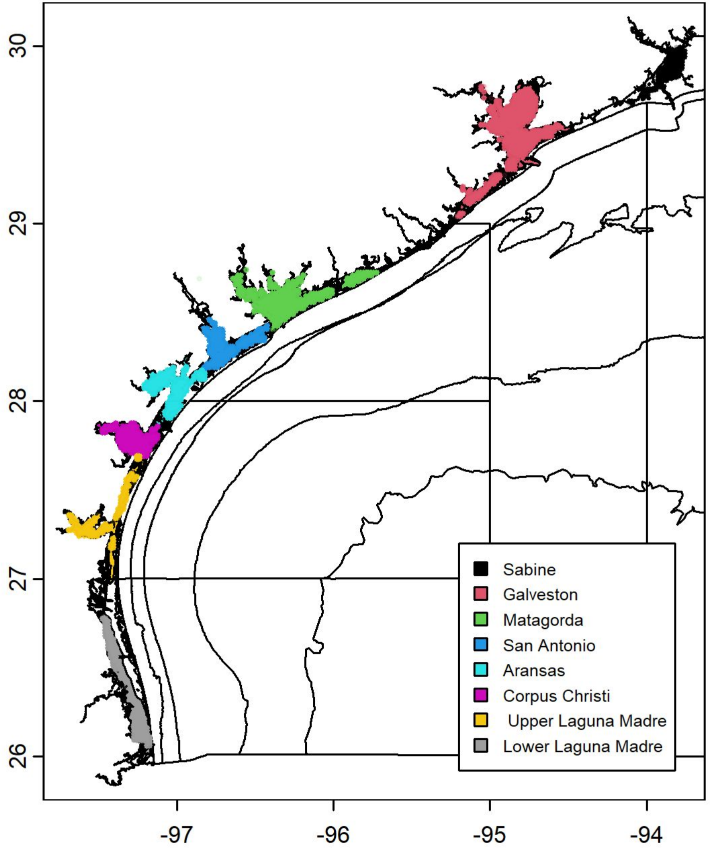
Life History and Environment

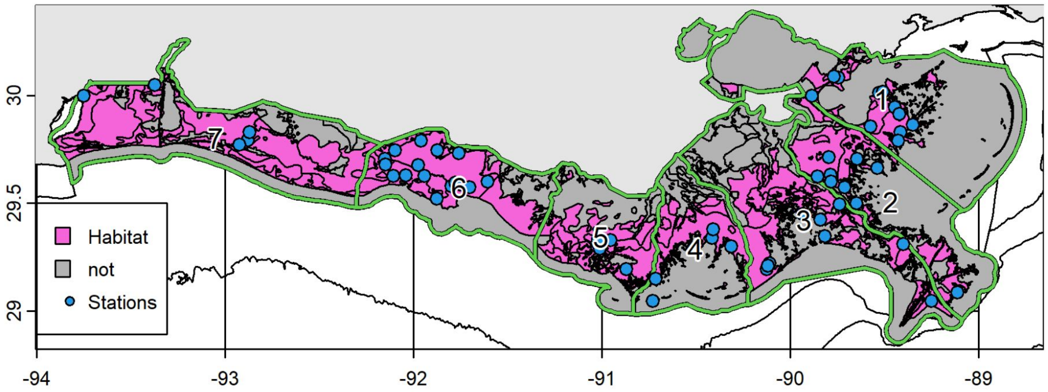
- Salinity : primary environmental driver of productivity for all three species; temperature : secondary.



(SEDAR87 DW Report, Table 3.2)

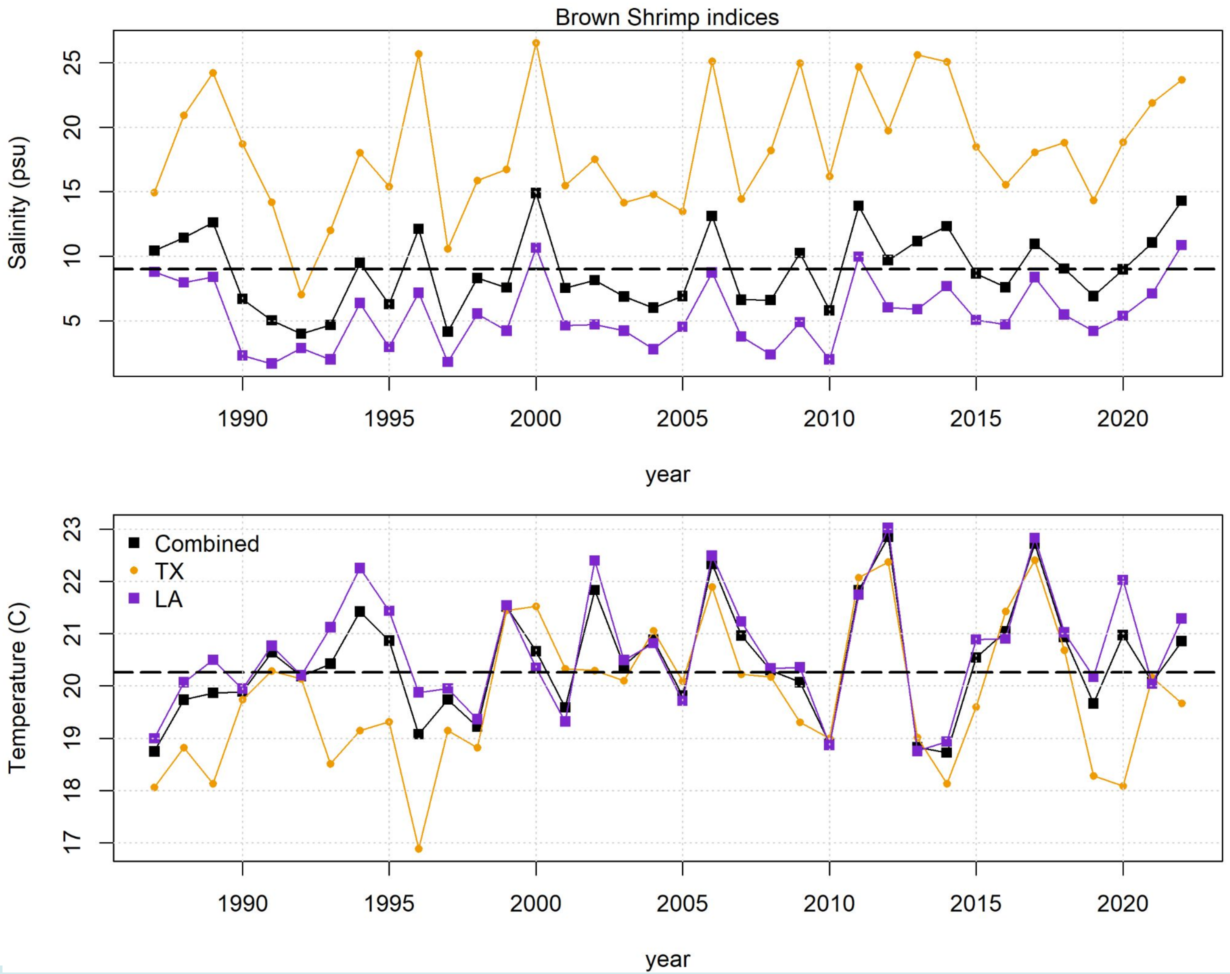
- We hypothesize that these drivers will have the greatest impact on shrimp while they inhabit their nearshore, estuarine nursery habitat, as this is where density dependence is expected to occur.



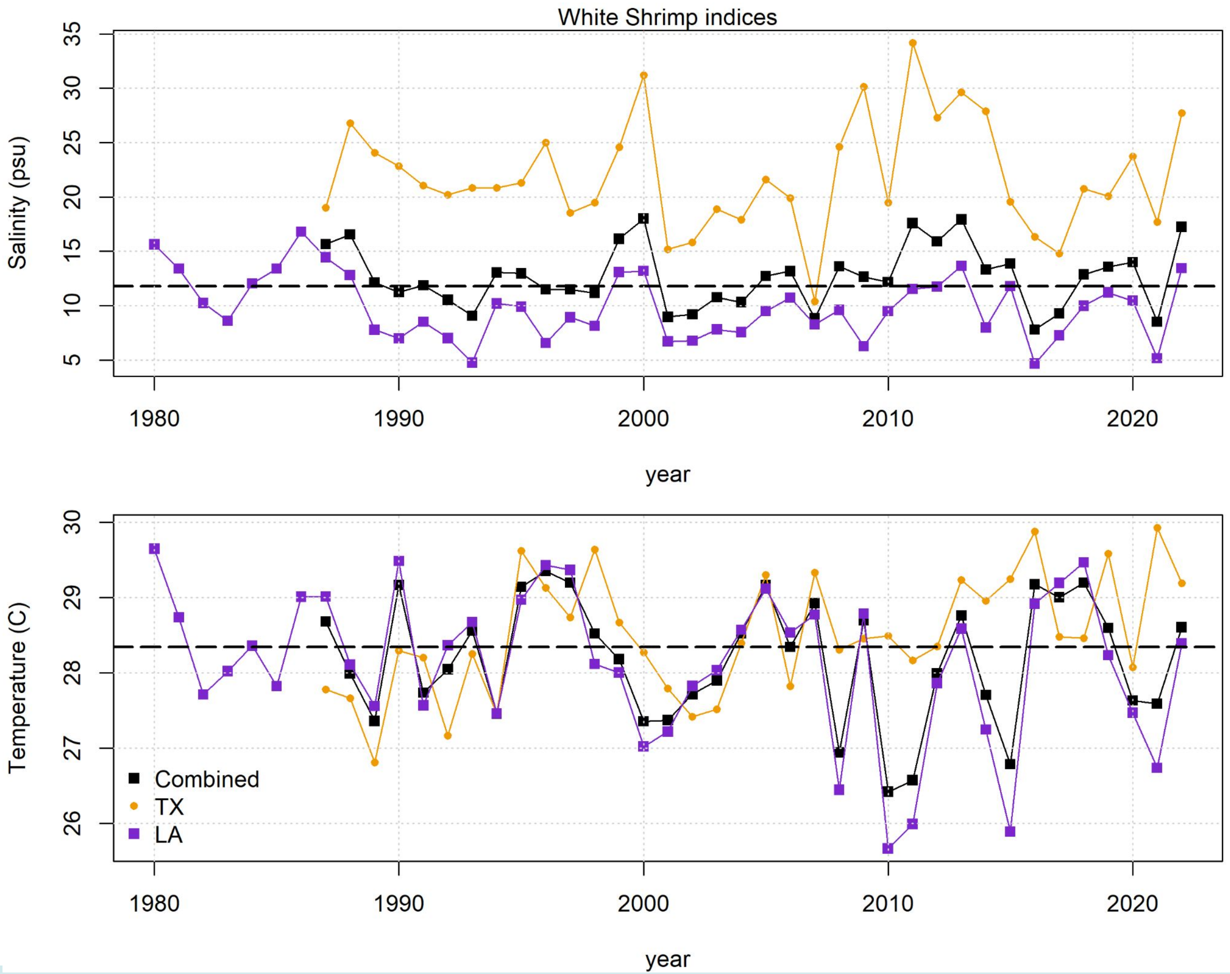


- Environmental indices developed from long-term monitoring data collected by LDWF (monthly, 16ft Trawl) and TPWD (monthly Bay Trawl).
- Survey data were weighted by area sampled
- Habitat classification used in LA were based on USGS surveys and LDWF data.

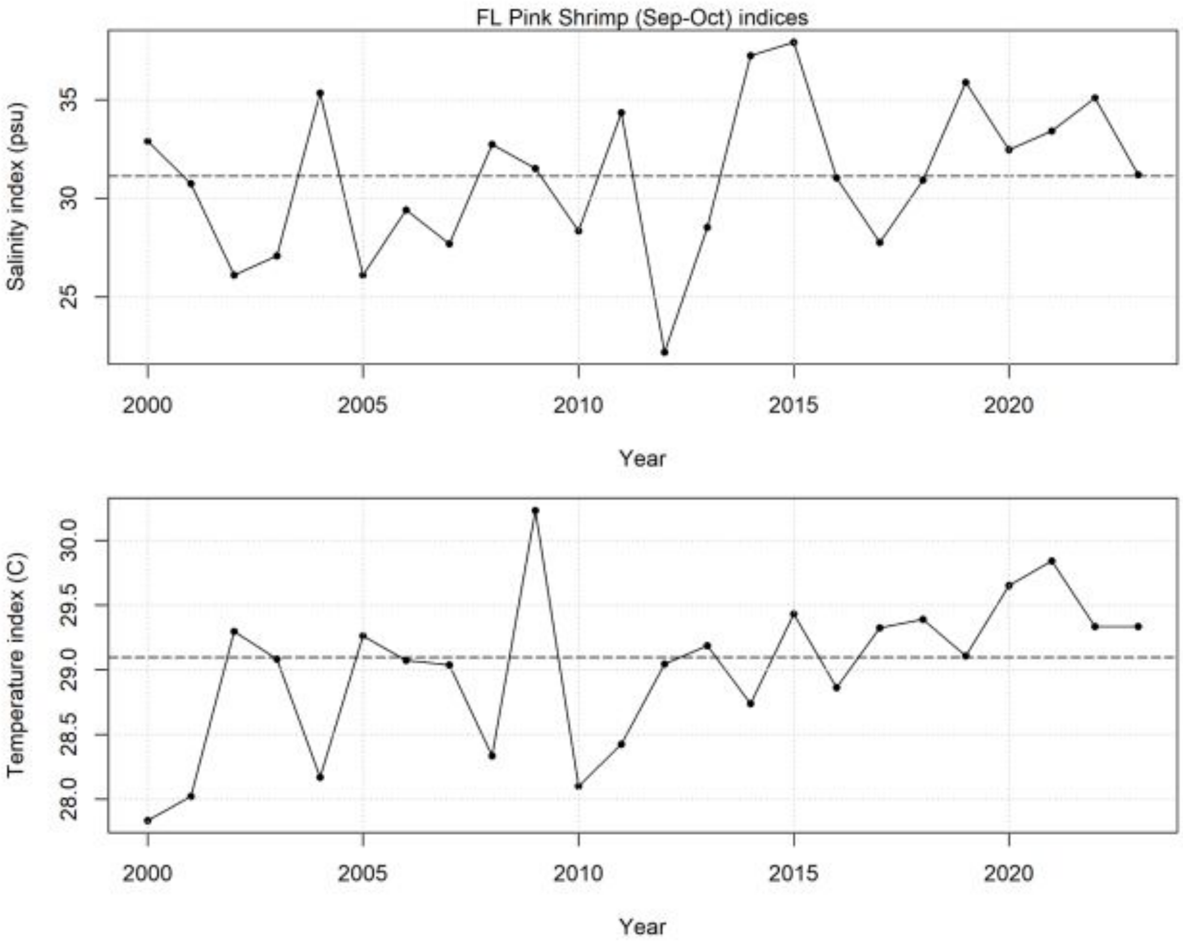
Turley et al 2023



- **Brown shrimp** environmental indices using TX and LA data from **February to May**.
- Combined indices (black) are weighted using calculated areas.
- The dashed lines are the overall median values of the combined indices.

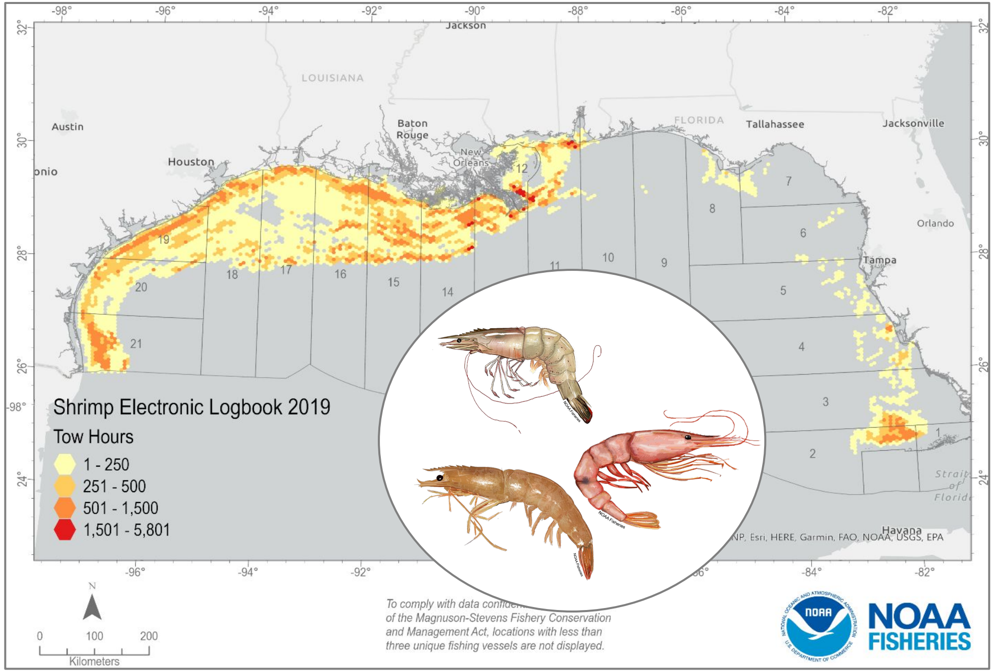


- **White shrimp** environmental indices using TX and LA data from **August to October**.
- Combined indices (black) are weighted using calculated areas.
- The dashed lines are the overall median values of the combined indices.

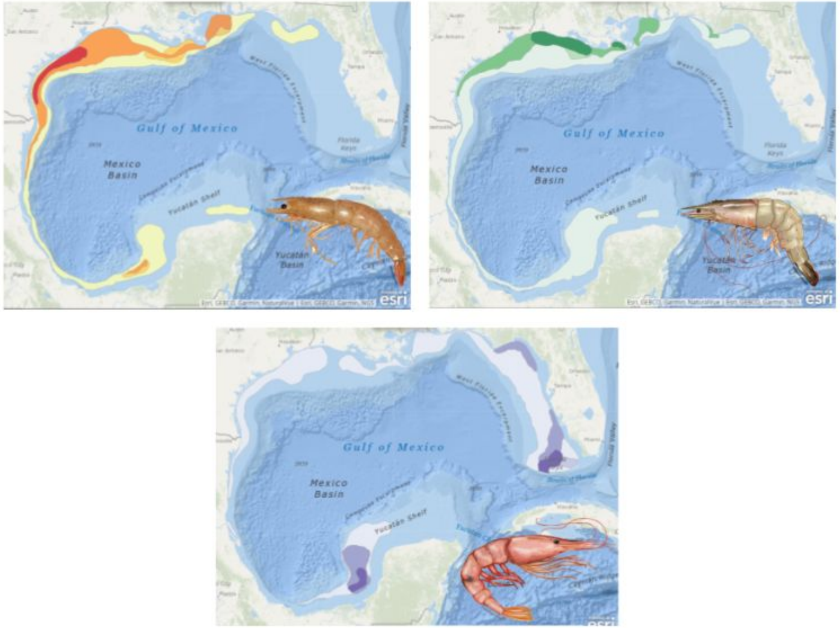


- **Pink shrimp** environmental indices using Everglades buoy data from **September to October**.
- The dashed lines are the overall median values for the time series.

The Fishery

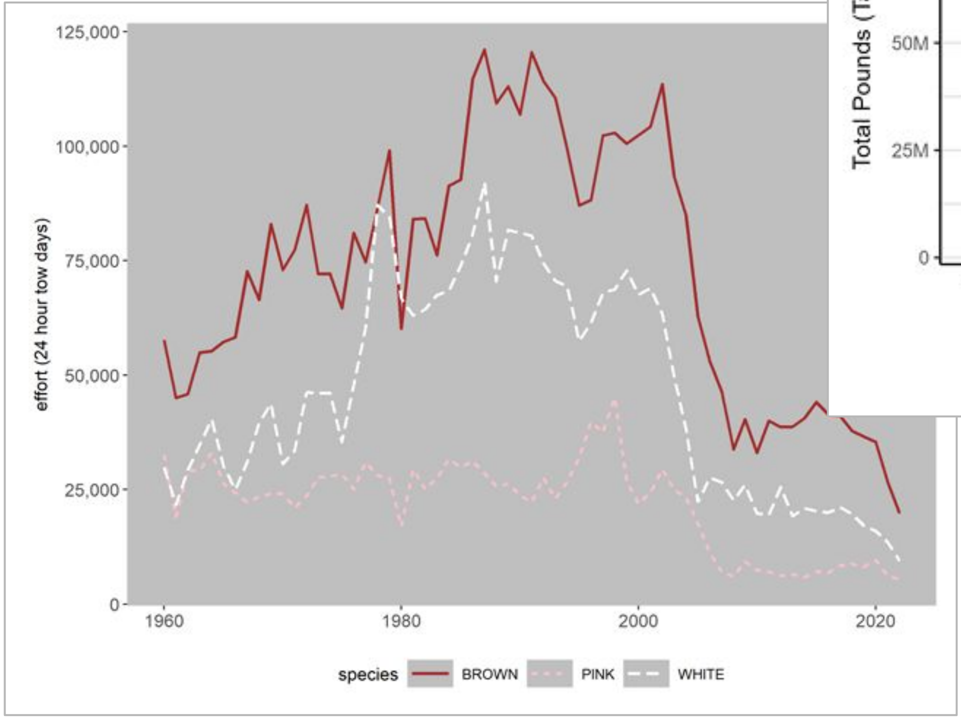


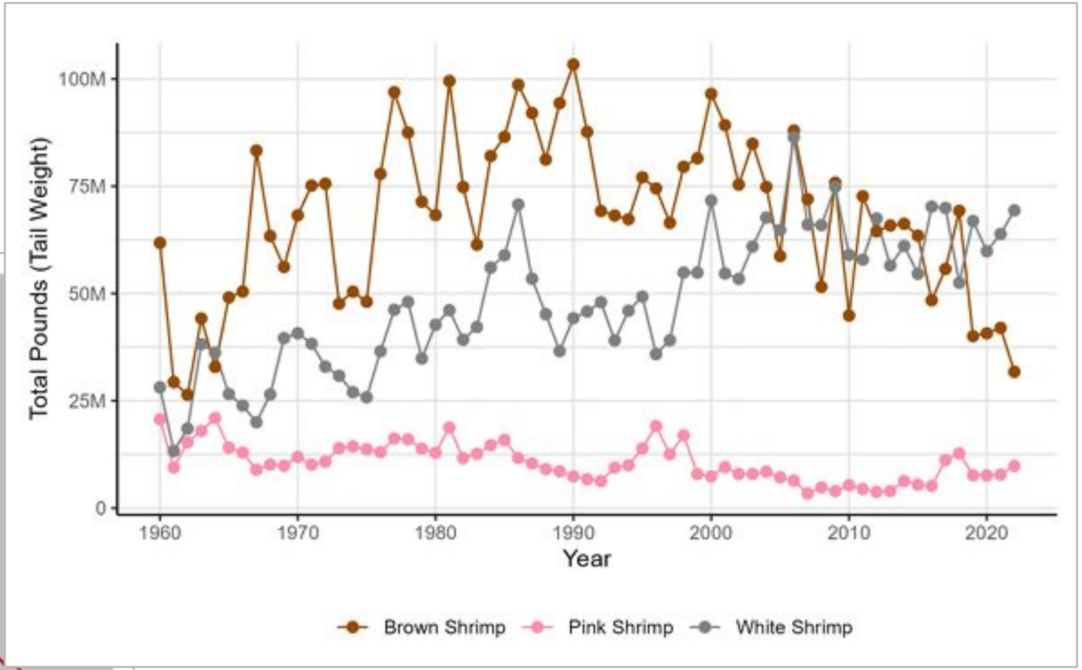
SEDAR87-DW-16



SEDAR87 DW Report, Figure 3.2

The Fishery





SEDAR87-DW-06

SEDAR87-DW-01

The Texas Closure

- Since 1960 Texas territorial sea closed for 45-60 days during peak migration of brown shrimp to the Gulf.
- 1981 closure extended to 200 miles to include the U.S. EEZ ~ May 15-July 15 of each year.
- Objective: increase value of harvest by protecting brown shrimp until they reach larger, more valuable size and reduce waste through discarding.

Global Penaeid Shrimp Market

- **Investment in overseas aquaculture**
  - Global market dominated by imports
  - Domestic ex-vessel prices plummet
  - Industry consolidation (e.g. trawling less, exiting the fishery)

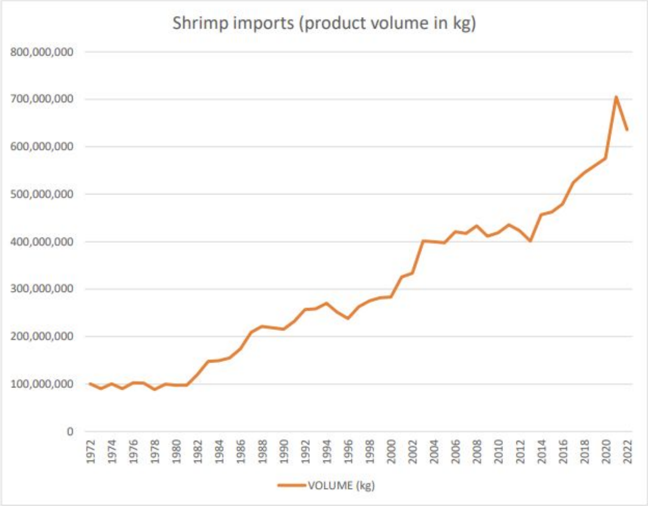
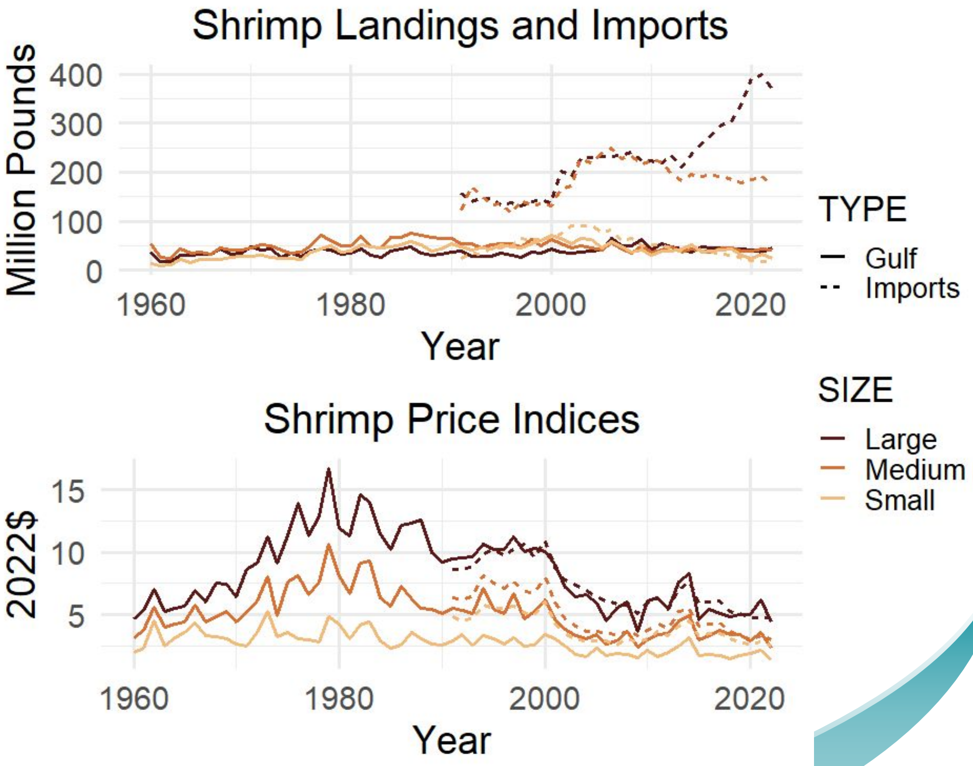


Figure 1: Imports of shrimp products 1972-2022. (Processed products removed) SEDAR87-DW-10



 U.S. Department of Commerce | National Oceanic and Atmospheric Administration | National Marine Fisheries Service

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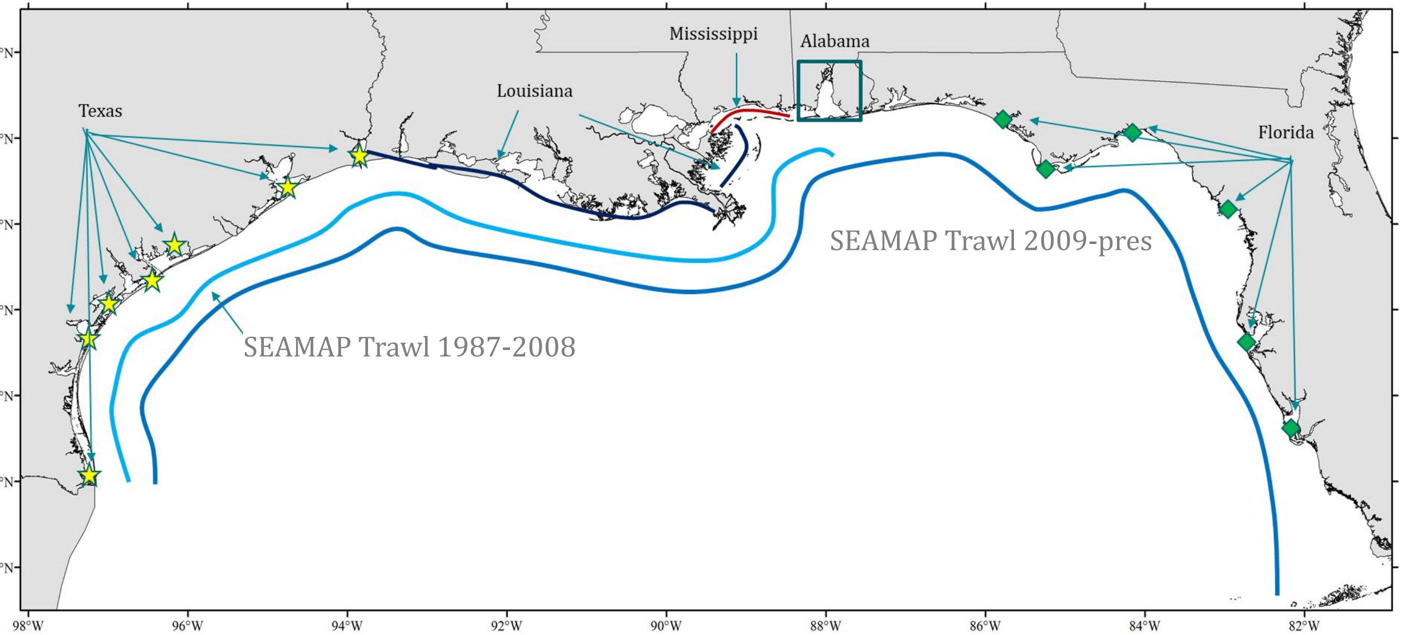
Fishery Independent Surveys



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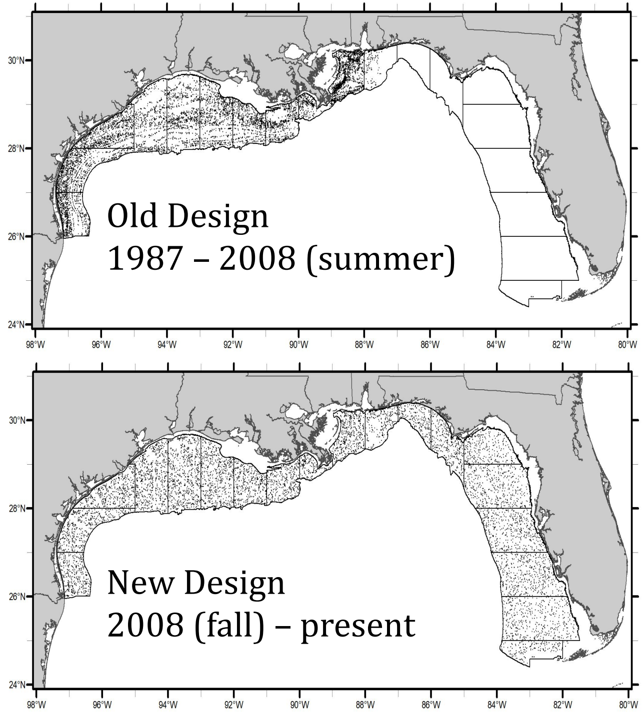
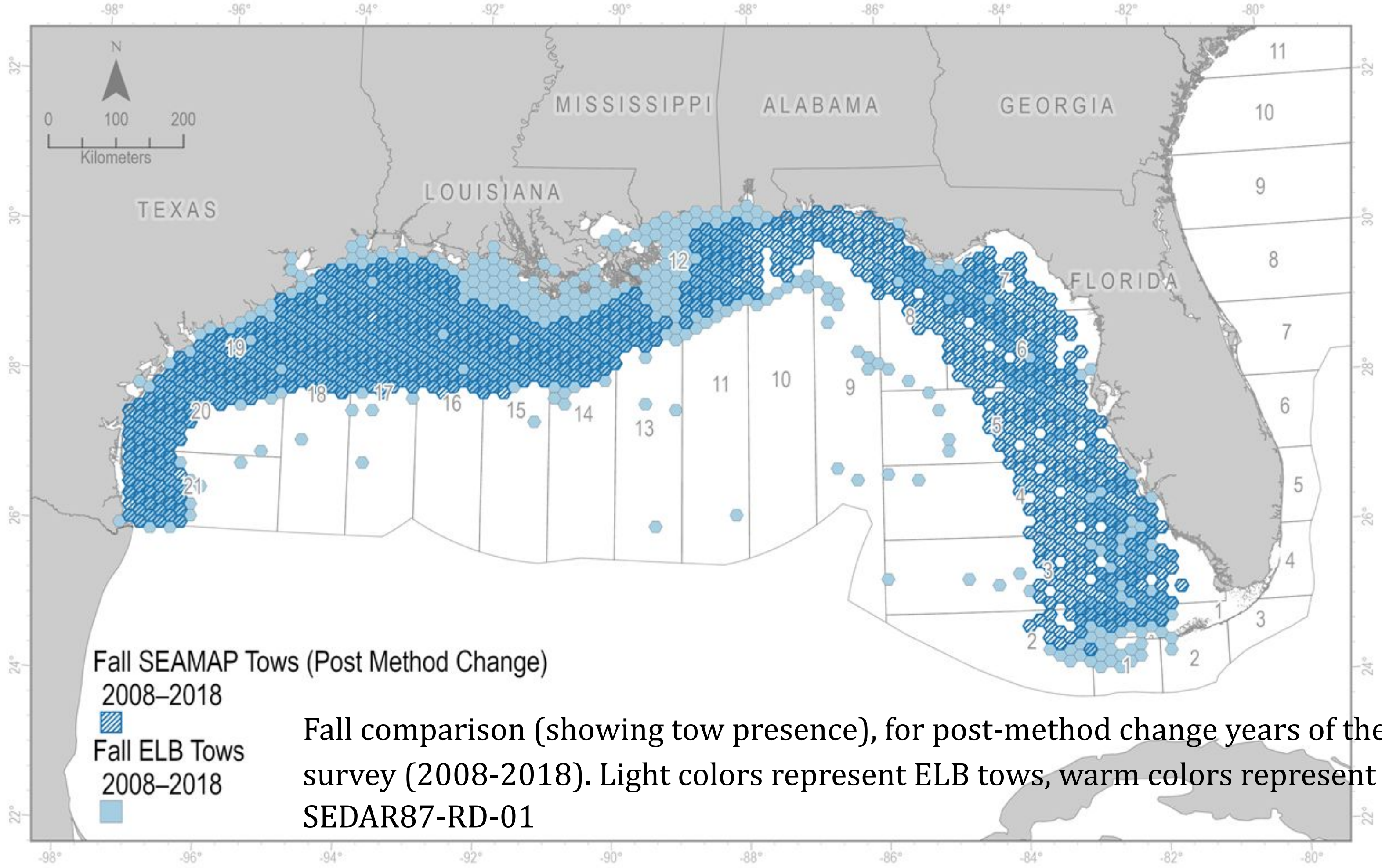
Fishery Independent Surveys: Suitable, Considered

- SEAMAP (state/federal) – **BSH / PSH**
  - 42 foot otter trawl
- Texas Parks and Wildlife (TPWD)
  - Gulf 20 foot otter trawl (1987) – **BSH**
  - Bay 20 foot otter trawl
- Louisiana Wildlife and Fisheries (LDWF) – **WSH**
  - 16 foot otter trawl (1980)
- Mississippi Department of Marine Resources and University of Southern Mississippi Gulf Coast Research Laboratory
  - 16 foot otter trawl (1984)
- Alabama Marine Resources Division
  - 16 foot otter trawl (2001)
- Florida Fish and Wildlife Conservation Commission's Fish and Wildlife Research Institute (FWC-FWRI)
  - 20 foot otter trawl (1998)
  - 70 foot seine (1998)

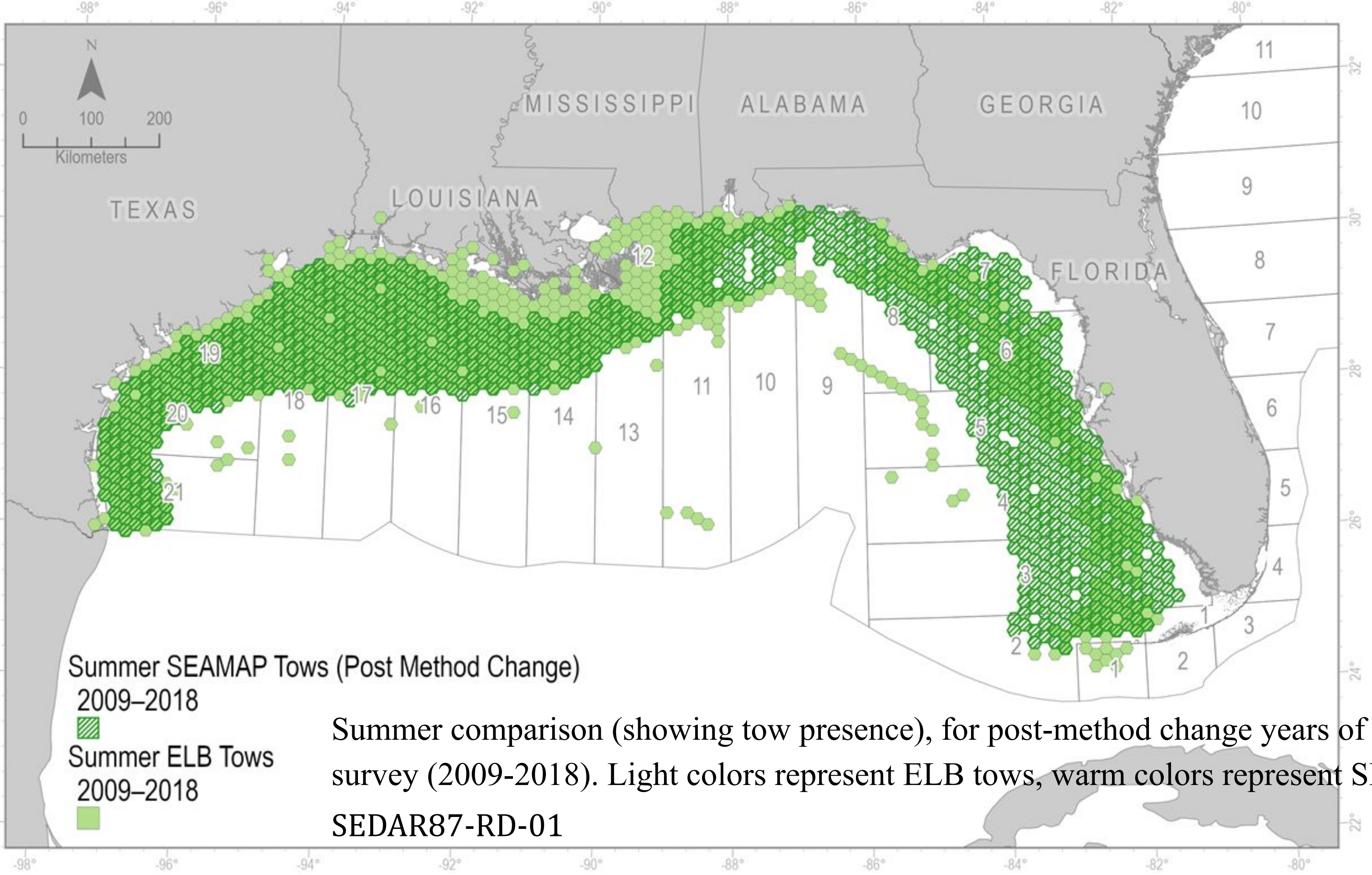
SEAMAP (BSH, WSH, PSH)

- SEAMAP is a trawl survey conducted in the Summer and Fall designed to collect, manage, and disseminate fishery-independent data in the southeastern U.S.
- 1987-2022 (No 2020 Summer due to covid)
- Design change in Summer 2008
- Recommended start years
  - 1987 for brown shrimp
  - 2010 (Summer only) for pink shrimp consistent funding for sampling expanded grids not until 2014 for Fall
  - Not recommended for white shrimp
    - Not capturing bulk of population





Fall comparison (showing tow presence), for post-method change years of the SEAMAP survey (2008-2018). Light colors represent ELB tows, warm colors represent SEAMAP tows SEDAR87-RD-01



Summer comparison (showing tow presence), for post-method change years of the SEAMAP survey (2009-2018). Light colors represent ELB tows, warm colors represent SEAMAP tows

SEDAR87-RD-01

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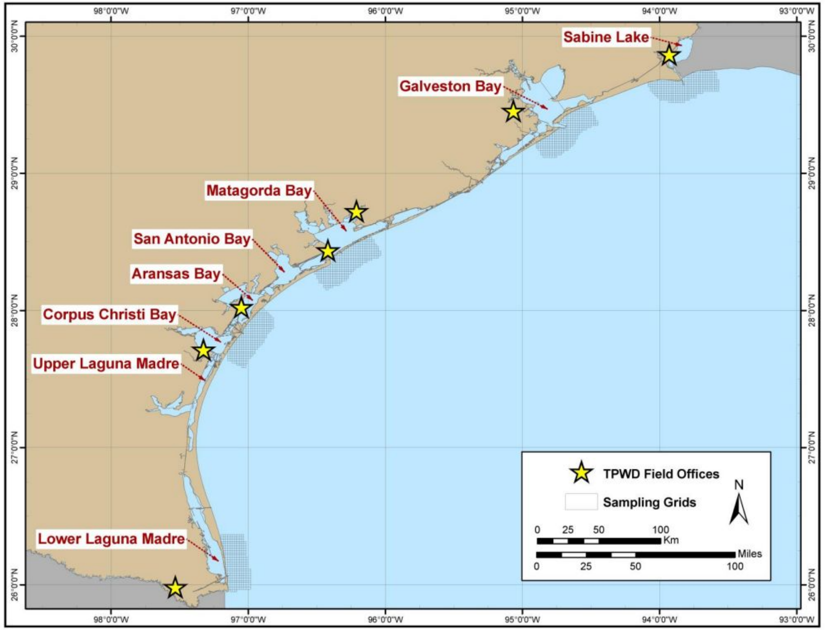
Texas Parks and Wildlife Department (TPWD)

- Gulf trawl survey data considered for brown shrimp abundance index development beginning in 1987
  - Some spatial overlap with SEAMAP
  - Daytime sampling
  - Monthly sampling
  - Most representative for the smallest size category of brown and white shrimp
- Bay trawl restricted to nursery grounds

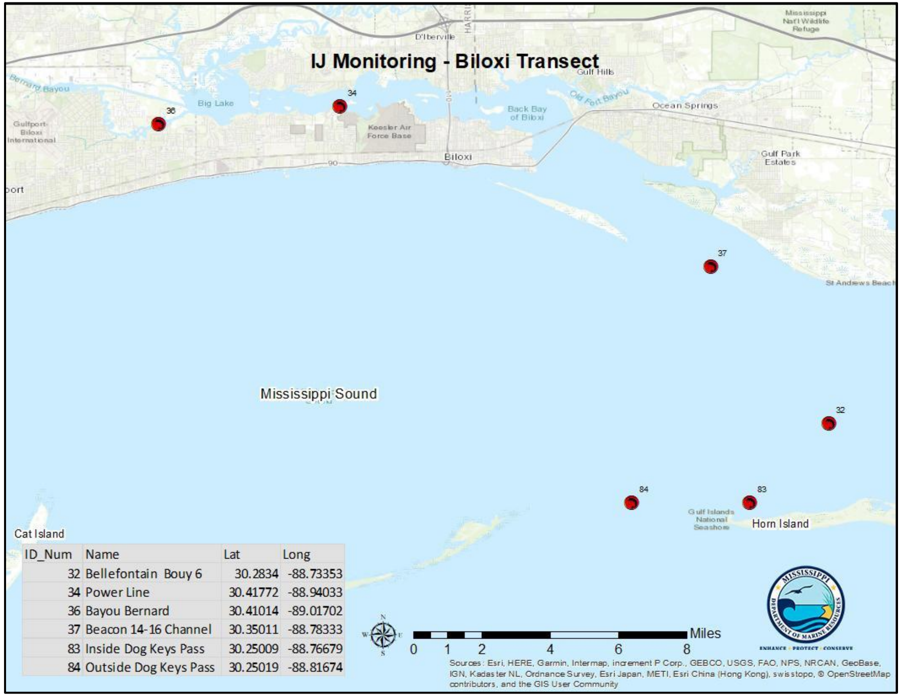


Louisiana Department of Wildlife and Fisheries (LDWF)

- Trawl survey began in 1965, but recommended for white shrimp index development beginning in 1980
  - Monthly sampling at fixed stations
  - Brown shrimp: March-June most representative for small and medium size categories
  - White shrimp: all months and size classes
- LDWF better represents white shrimp than SEAMAP
  - SEAMAP too deep to capture full range of sizes (e.g. missing depth strata that encompasses peak abundance)
  - LDWF samples full range of sizes

Mississippi Department of Marine Resources (MDMR)

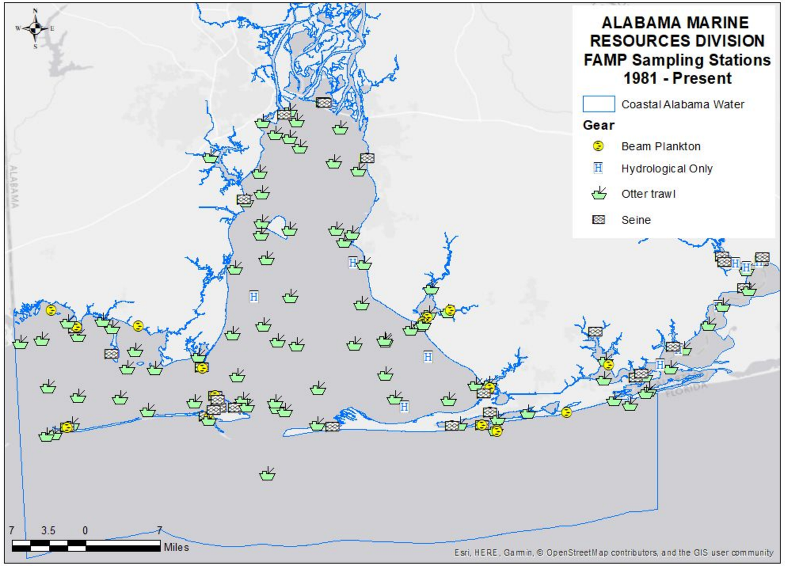
- Trawl survey began in 1973 with 4 fixed sites
  - Length data available 1984
  - Survey expanded in 2009
- High variability prior to 2000s
- Changes in gear, protocol, and sampling timing that is not well documented



ID_Num	Name	Lat	Long
32	Bellefontain Bouy 6	30.2834	-88.73353
34	Power Line	30.41772	-88.94033
36	Bayou Bernard	30.41014	-89.01702
37	Beacon 14-16 Channel	30.35011	-88.78333
83	Inside Dog Keys Pass	30.25009	-88.76679
84	Outside Dog Keys Pass	30.25019	-88.81674

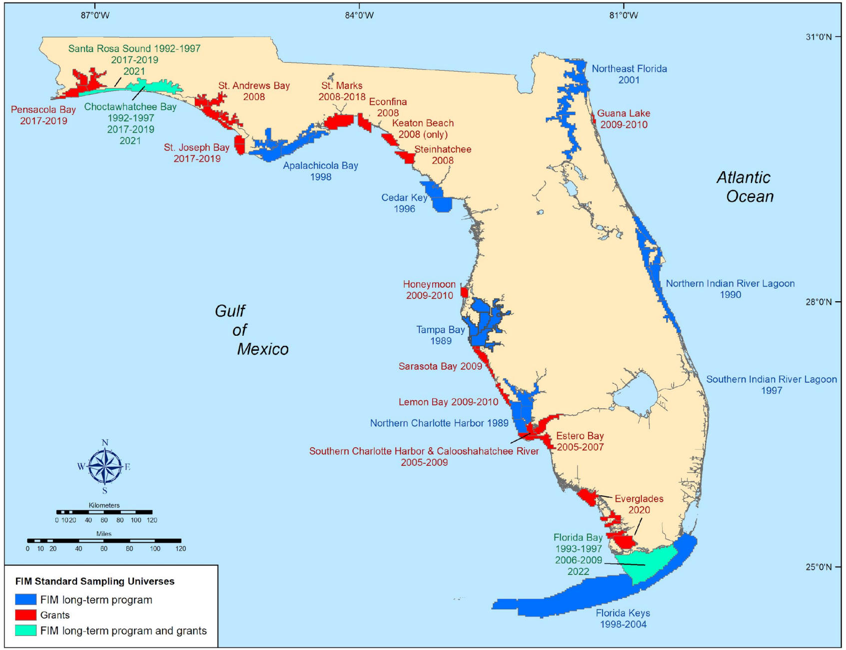
Alabama Marine Resources Division (AMRD)

- Trawl survey began in 1980 with monthly sampling at fixed sites
  - 1990 SEAMAP procedures implemented
  - 1998 program shifted to interagency program targeting water quality
  - Some length data available and monthly sampling resumed by 2001
- High variability prior to 2000s



Florida Fish and Wildlife Conservation Commission's Fish and Wildlife Research Institute (FWC-FWRI)

- Fisheries-independent monitoring (FIM) surveys since 1989 in estuaries of Florida's Gulf Coast
  - No consistent sampling south of Charlotte Harbor
  - No spatial overlap with SEAMAP
- Indices of abundance for pink shrimp were developed beginning 1998, most representative for smallest size class
- Evidence that primary Tortugas fishing grounds are supplied from southern estuaries in the Everglades (Costello & Allen 1966, Browder & Robblee 2009)



Summary

- **VAST**
  - Brown : SEAMAP & TPWD Gulf
  - White : LDWF
  - Pink : SEAMAP
- **EDM**
  - Brown : SEAMAP
  - White : LDWF
  - Pink : SEAMAP

BROWN SHRIMP

VAST index

VAST (Thorson and Barnett 2017)

- R package that uses a delta-generalized linear mixed model to approximate spatial and spatiotemporal variation
- Wide range of uses (species distribution models, estimating shifts in species distributions, etc.)
- Ability to combine multiple data streams and deal with spatially unbalanced data
- Here used to create single species indices of abundance as needed for the SEDAR 87 stock assessments

VAST

- VAST predicts density across space *s* and year *t* using two linear predictors.
- The first linear predictor *p1* represents encounter probability in a delta-model, or zero-inflation in a count-data model. The second linear predictor *p2* represents positive catch rates in a delta-model, or the count-data intensity function in a count-data model.
- Both are expressed as follows :

$$p_1(i) = \underbrace{\beta_1(t_i)}_{Temporal\ variation} + \underbrace{\omega_1^*(s_i)}_{Spatial\ variation} + \underbrace{\varepsilon_1^*(s_i, t_i)}_{Spatio-temporal\ variation} + \underbrace{\nu_1(t_i)}_{Habitat\ covariates} + \underbrace{\zeta_1(i)}_{Catchability\ covariate}$$

VAST

- Unmeasured processes are approximated through spatial and spatio-temporal random effects.
  - Two points in space are more strongly correlated if they are neighbours
- In addition, VAST allows users to specify either density or catchability covariates
  - VAST “controls for” catchability covariates when calculating an index (i.e., removes their estimated effect) while “conditioning on” density/habitat covariates when calculating an index (i.e., uses them to improve interpolated/extrapolated predictions of density)

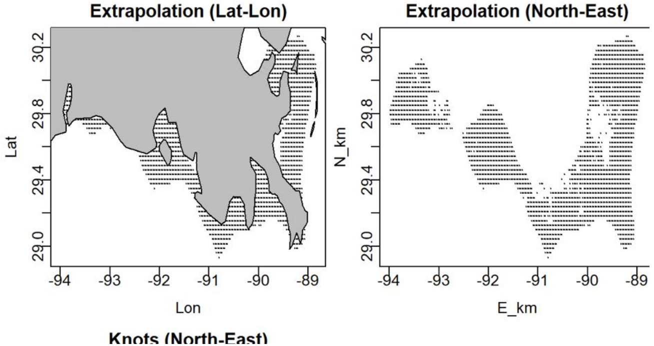
$$p_1(i) = \underbrace{\beta_1(t_i)}_{Temporal\ variation} + \underbrace{\omega_1^*(s_i)}_{Spatial\ variation} + \underbrace{\varepsilon_1^*(s_i, t_i)}_{Spatio-temporal\ variation} + \underbrace{\nu_1(t_i)}_{Habitat\ covariates} + \underbrace{\zeta_1(i)}_{Catchability\ covariate}$$

VAST - Temporal variation

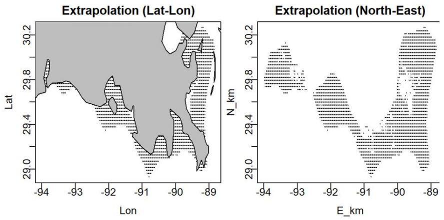
- Accounted for by fitting year as a fixed effect (separate intercept for each year)
  - Ensures that estimates of abundance are independent for each modeled year

VAST - Spatial variation

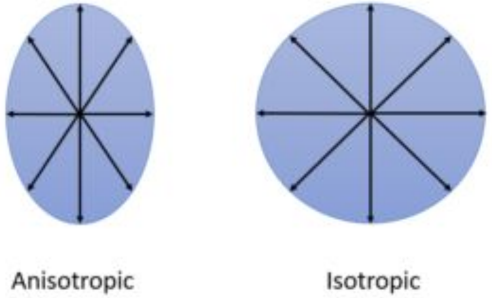
- Stable over time - average distribution
- Estimated as a random effect using Gaussian Markov Random Fields (GMRF)
  - Grid of values over region of interest (random field)
  - At each point in grid density depends on densities at neighboring point but not on densities at points that are further away (Markov property)
  - Density values across the entire grid follows a normal distribution (Gaussian)



VAST - Spatial variation

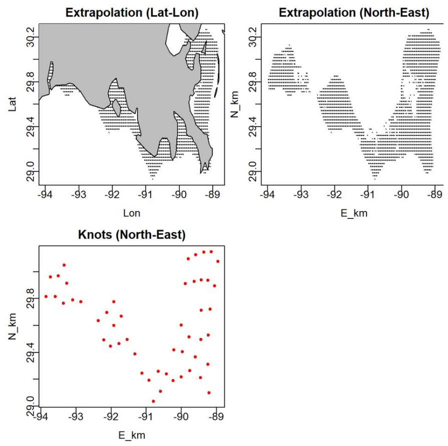


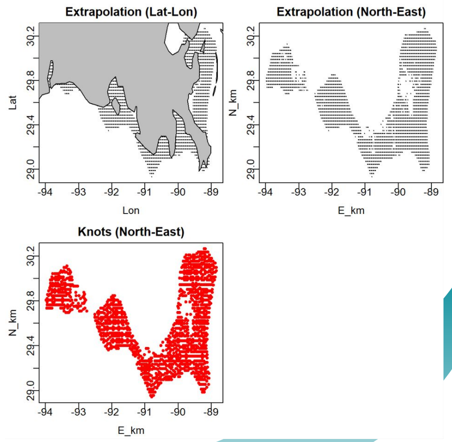
- Can specify a Matérn function for the correlation between neighboring points
  - Parameter governing the distance at which locations are essentially uncorrelated
  - Transformation matrix representing geometric anisotropy (spatial correlation structure depends on both the distance and the direction between points) or isotropy (same spatial correlation in all directions)
- Would expect geometric anisotropy to be generally important for shrimp along a continental shelf like the Gulf, where correlations decline faster moving onshore–offshore rather than moving alongshore



VAST - Spatial variation

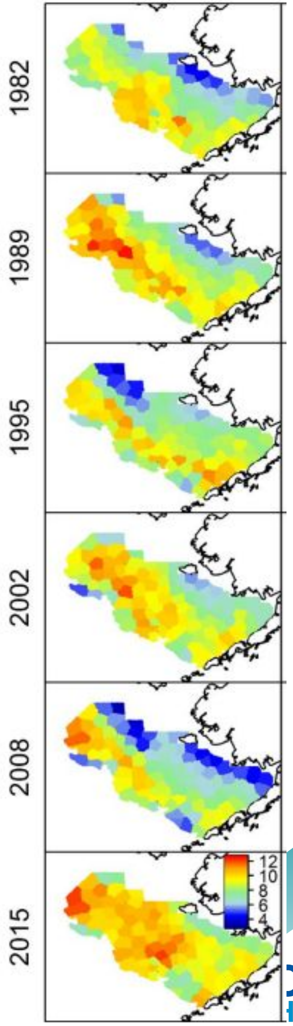
- To improve estimation efficiency, a mesh of discrete locations “knots” is created (k-means algorithm) to represent a reduced set of locations to approximate the sampling area.
- Knots are spatially allocated in proportion to the underlying sampling intensity.
- Encounter probability and positive catch over the entire extrapolation grid are estimated using bilinear interpolation between knot means.





VAST - Spatio-temporal variation

- Annual distributional shifts
- Modeled using separate GMRFs for each year



Thorson et al. 2017 - Pollock

VAST - Covariates

- Habitat covariates (e.g., depth, substrate, temperature and salinity) can be integrated to evaluate whether their inclusion helps explain the distribution of the species. Habitat covariates are used when predicting densities across space (not standardized out). *Value needed at every location across a modelled spatial and temporal domain.*
- Catchability covariates (e.g. time of day, vessel) are included to explain changes in catchability over space and time. The effect of catchability is removed from the index (standardized out). *Value only needed at sampling locations.*
- The spatiotemporal index standardization can provide a more precise abundance index than the design-based estimator or conventional models by explaining spatial variation in densities

VAST

$$p_1(i) = \underbrace{\beta_1(t_i)}_{Temporal\ variation} + \underbrace{\omega_1^*(s_i)}_{Spatial\ variation} + \underbrace{\varepsilon_1^*(s_i,t_i)}_{Spatio-temporal\ variation} + \underbrace{\nu_1(t_i)}_{Habitat\ covariates} + \underbrace{\zeta_1(i)}_{Catchability\ covariate}$$

- Link transformed predictors :

$$r_1(i) = logit^{-1}(p_1(i))$$
$$r_2(i) = a_i \times log^{-1}(p_2(i))$$

Area swept or effort offset

- Predicted density *d**

Effect of catchability covariates set to 0

$$d^*(s,t) = r_1^*(s,t) \times r_2^*(s,t)$$

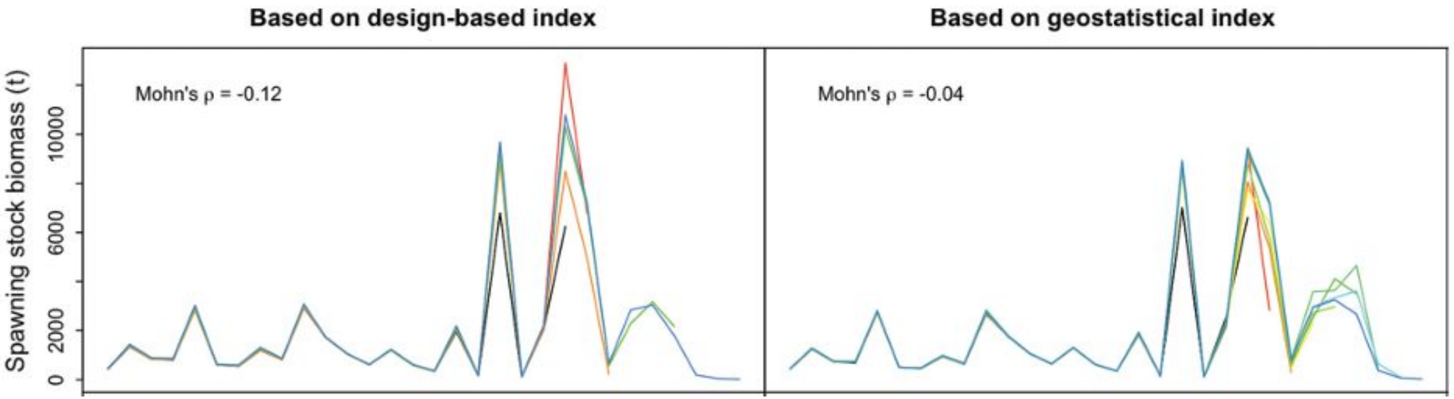
- Density is multiplied by area to calculate abundance in each extrapolation-grid cell. The index of abundance is then calculated by summing across extrapolation-grid cells.

knots

$$I(t) = \sum_{x=1}^{n_x} a(s)\ d^*(s,t)$$

Why VAST?

- Spatiotemporal models have been demonstrated to
  - produce more precise and accurate abundance indices than either design-based or conventional model-based approaches (Shelton et al. 2014; Thorson et al. 2015b), and
  - improve stock assessment results and performance (Cao 2017)



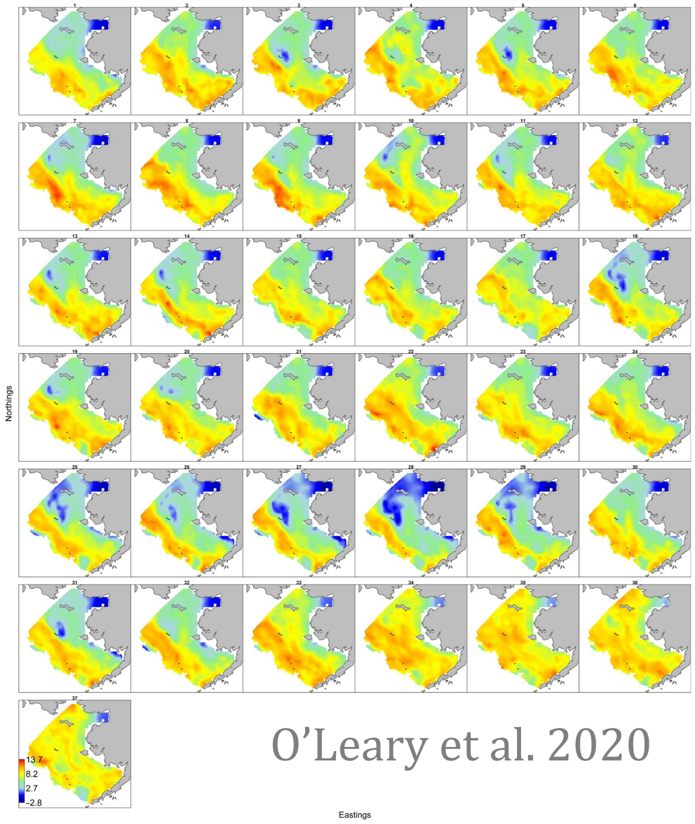
Cao et al. 2017

Why VAST?

- Incorporating habitat covariates can lead to more precise estimates of abundance when the underlying population distribution is largely dependent on habitat variables.
  - Better accounting for variability in sampling over space and time that otherwise would violate the assumptions of time-invariant catchability and selectivity in stock assessment models
  - Temporal variability of population abundance may be exaggerated by a design-based estimator when the randomized sampling locations happen to fall in good habitat for some years and vice versa (Shelton et al. 2014)

Why VAST?

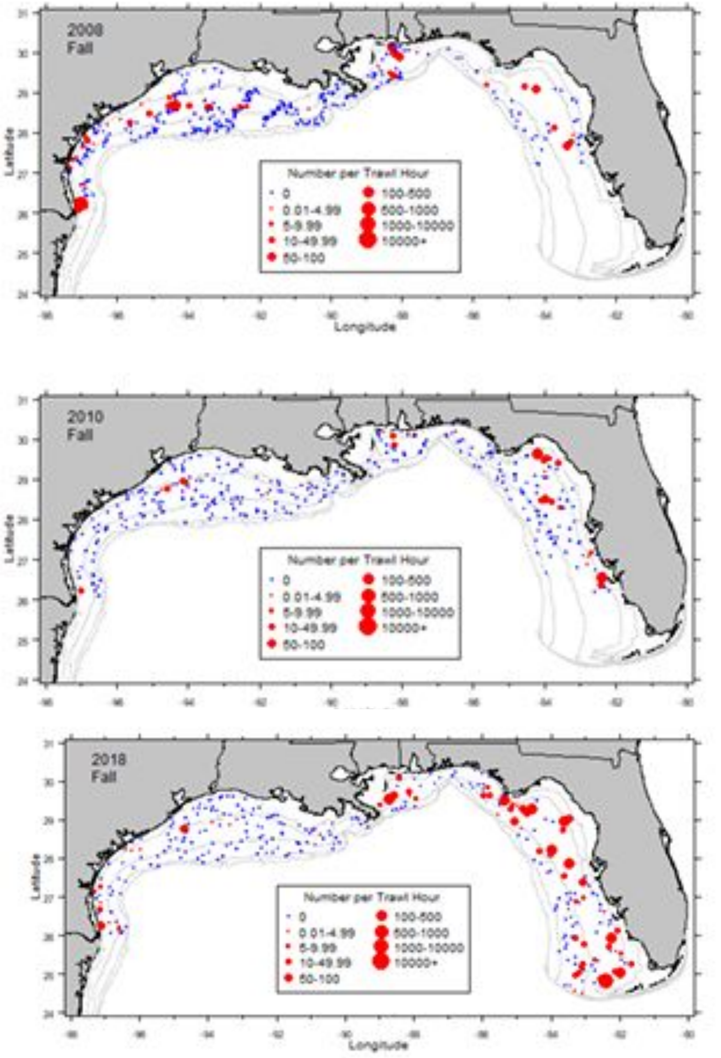
- Ability to combine data from multiple spatio-temporally overlapping surveys
- Improved communication and intuition by visualizing survey products on a map



O’Leary et al. 2020

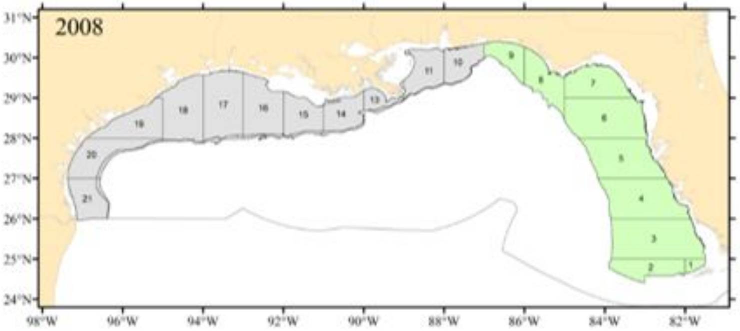
VAST - Motivation

- Develop an index of relative abundance that can control for survey design changes and correct for sampling gaps (e.g., Summer 2020) and delays (e.g., Summer 2022) by using information from a partially overlapping survey.
- Testing impact of Nursery Conditions on abundance (habitat covariates)



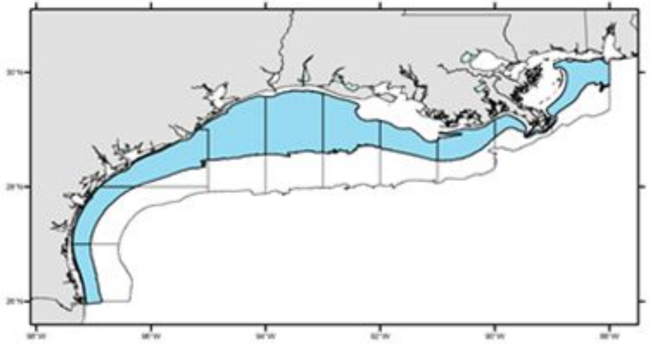
SEAMAP Design Change

- 1987-2022 (No 2020 Summer)
- 42 ft otter trawl
- Summer and Fall
- Survey design change between 2008 Fall and 2009 Summer surveys (SEDAR87-RD-01)
    - Extend to SSZ 1-9
    - Variable tow time (10-55 min) □ 30 min
    - Across depth strata □ random direction
    - TOD stratification dropped (no longer 1:1)
    - Changes in sampling effort allocation



5 – 20 Fathom Breakdown

Stat Zones	Old Design	Current Design
11	0.13	0.04
13-15	0.13	0.09
16-17	0.13	0.17
18-19	0.13	0.16
20-21	0.13	0.07

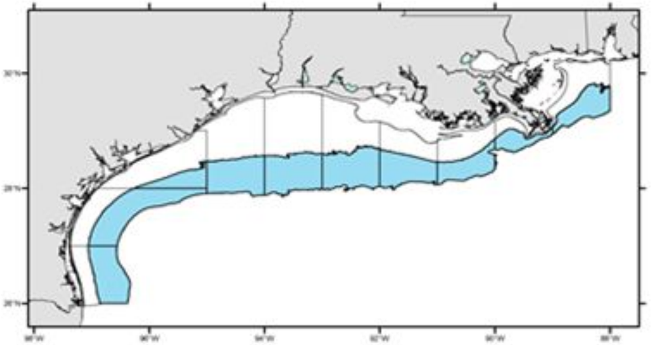


Overall Strata Proportions

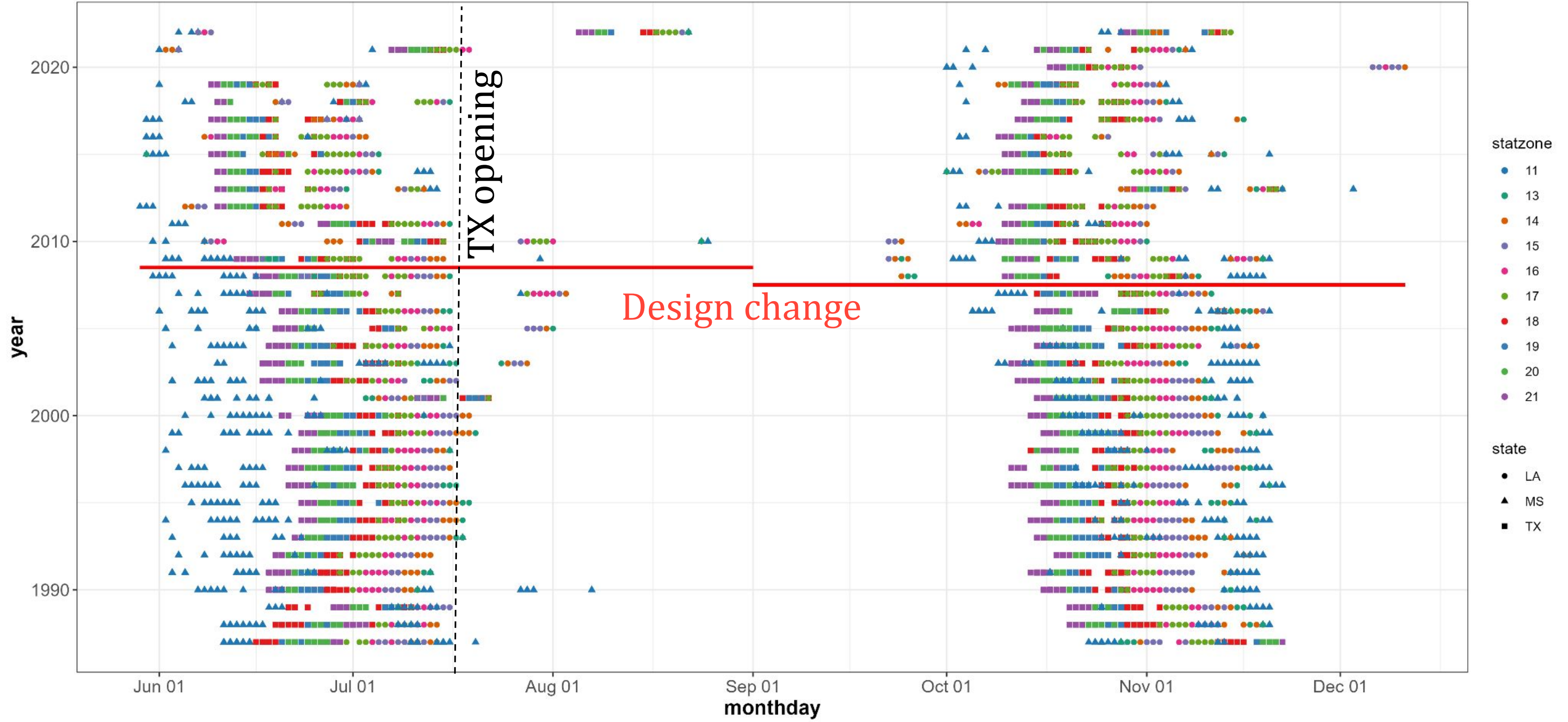
Stat Zones	Old Design	Current Design
11	0.2	0.08
13-15	0.2	0.19
16-17	0.2	0.29
18-19	0.2	0.24
20-21	0.2	0.19

20 – 60 Fathom Breakdown

Stat Zones	Old Design	Current Design
11	0.07	0.04
13-15	0.07	0.10
16-17	0.07	0.12
18-19	0.07	0.08
20-21	0.07	0.12



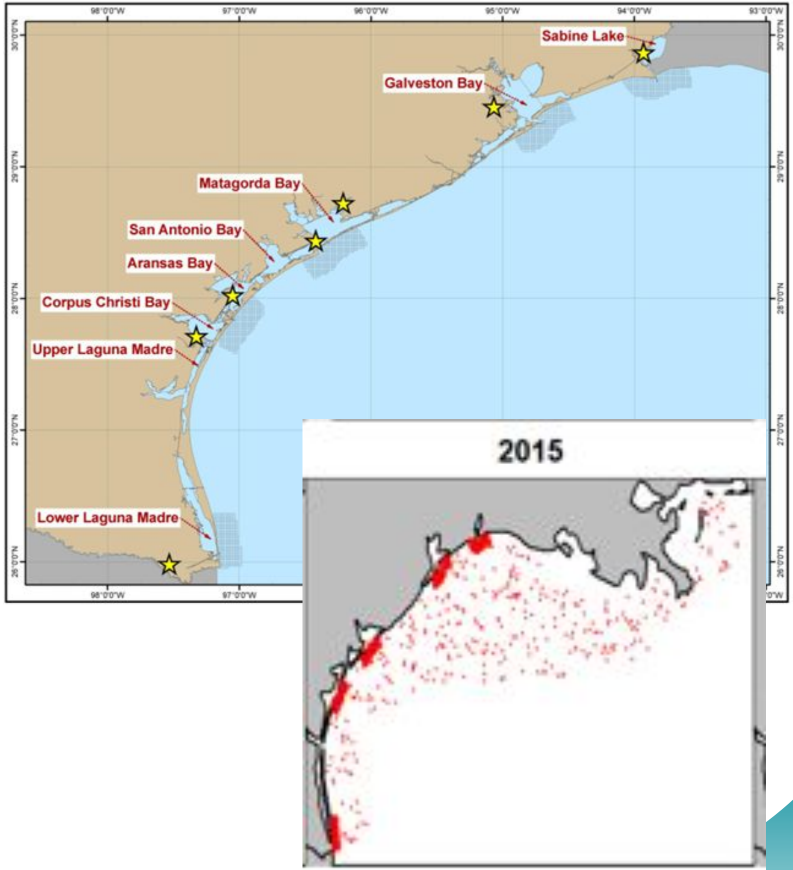
NOAA FISHERIES



TX opening
Design change
year
2020
2010
2000
1990
monthday
Jun 01
Jul 01
Aug 01
Sep 01
Oct 01
Nov 01
Dec 01
statzone
11
13
14
15
16
17
18
19
20
21
state
LA
MS
TX

TPWD Gulf Survey

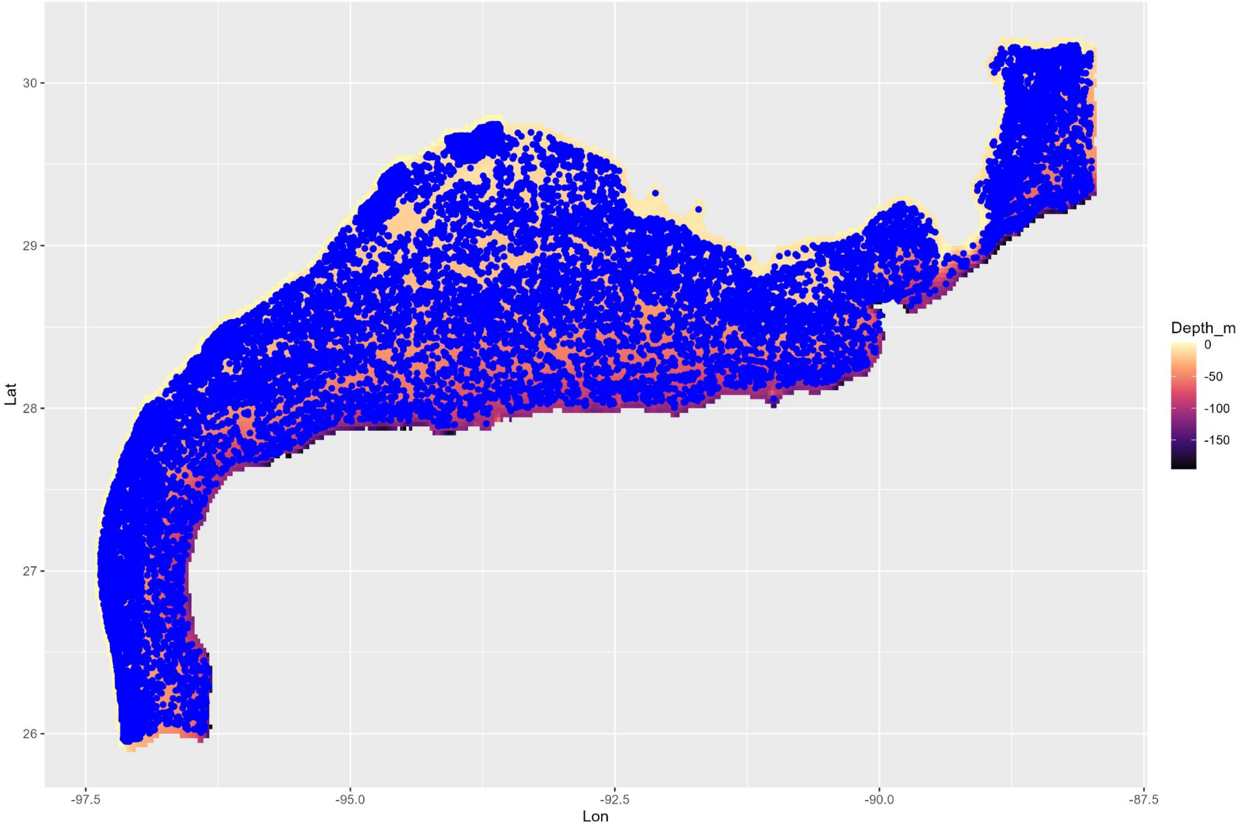
- TPWD (SEDAR87-RD-07)
  - 1987-2022 (No April/May in 2020)
  - 20 ft otter trawls, 1.5in mesh,
  - 16 samples / month / area (5 areas)
    - locations randomly selected from grids (1-minute latitude by 1-minute longitude) that contain water >1.8 m deep in at least ⅓ of the grid and are known to be free of obstructions
  - Monthly, daytime
  - Towed parallel to fathom curve
  - 10 min tow



VAST

	BSH
Survey(s)	SEAMAP (Summer and Fall) + TPWD (Jan-Dec)
Years	1987-2022
Area	SSZ 11-21
Catchability covariates	Survey, TOD, month
Density covariates	Median annual nursery temperature & salinity (+ 1 to 2 year lags)

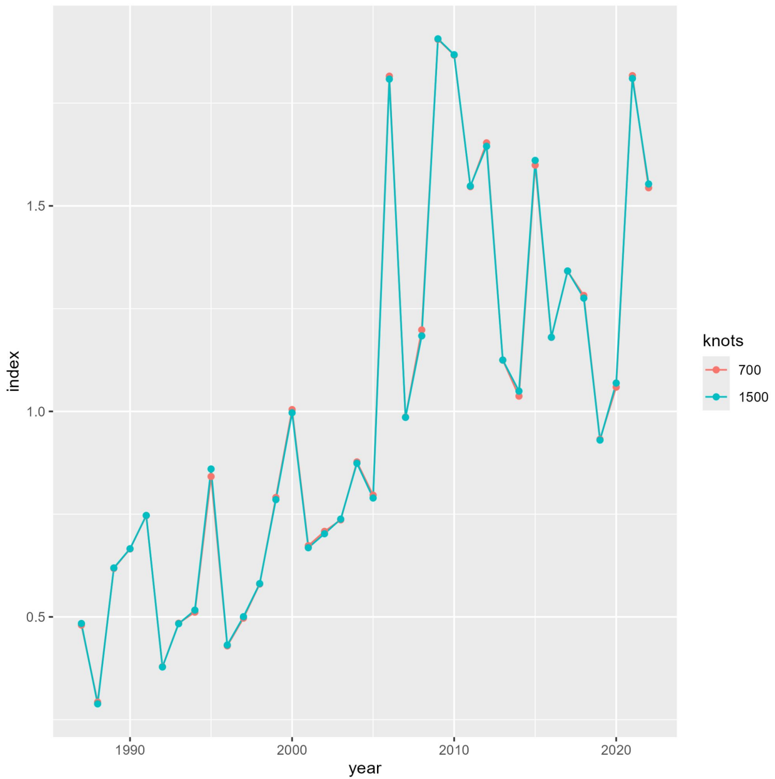
Data preprocessing - Prediction grids



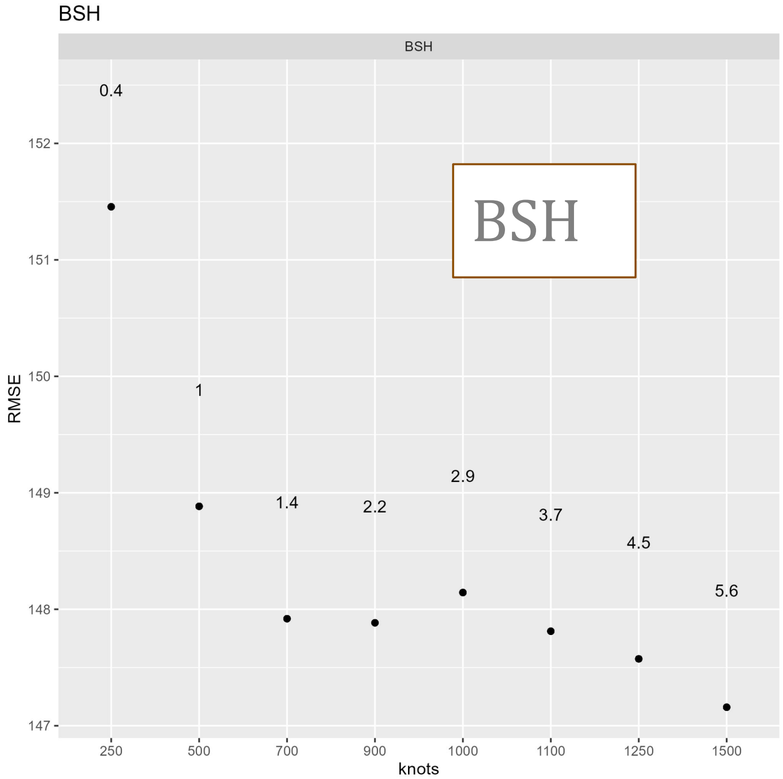
Workflow

- Using default model (delta-lognormal), search for optimal number of knots
  - fitting models with an increasing number of knots between 250 and 1500 and calculating RMSE to find asymptote
- Select model error distributions and link functions (convergence checks, AIC and Q-Q plots)
  - Temporal variation: year as fixed effect
  - Spatial and spatio-temporal random effects turned on
  - Bias correction on
  - Anisotropy
  - Optimal knot size
  - No covariates
- Test inclusion of spatial and spatiotemporal random effects and isotropy vs. anisotropy
- Test inclusion of covariates (AIC, pseudo-R^2)
  - Catchability covariates
  - Density covariates

Knots



index
1.5
1.0
0.5
1990
2000
2010
2020
year
knots
700
1500

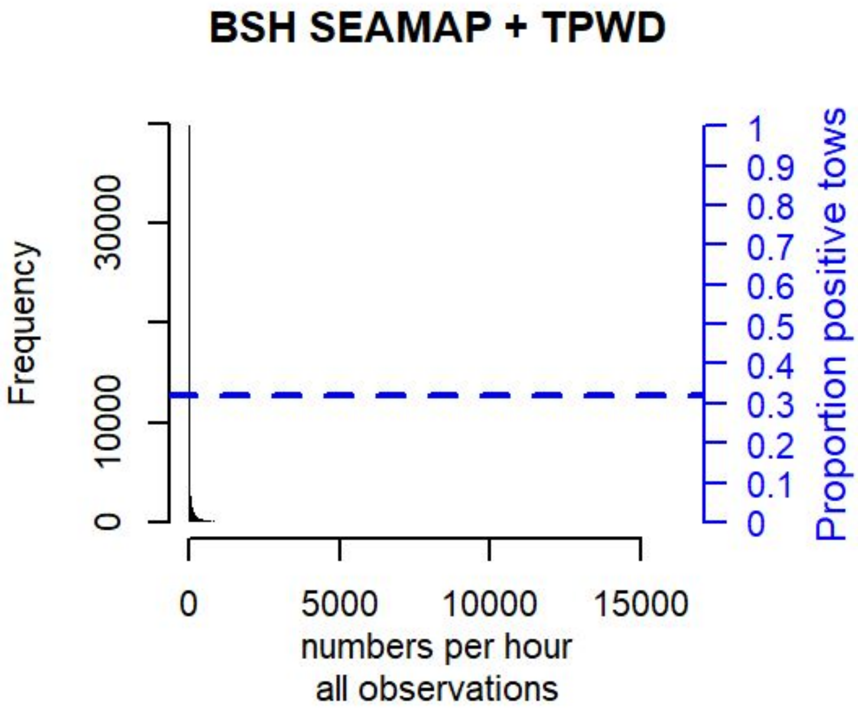


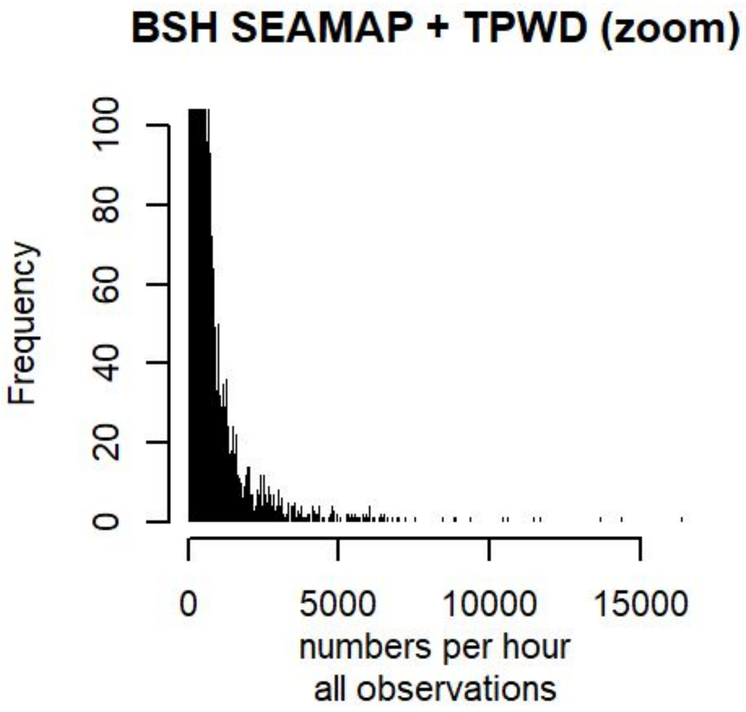
BSH
BSH
RMSE
152
151
150
149
148
147
0.4
1
1.4
2.2
2.9
3.7
4.5
5.6
BSH
250
500
700
900
1000
1100
1250
1500
knots

Distribution and Error

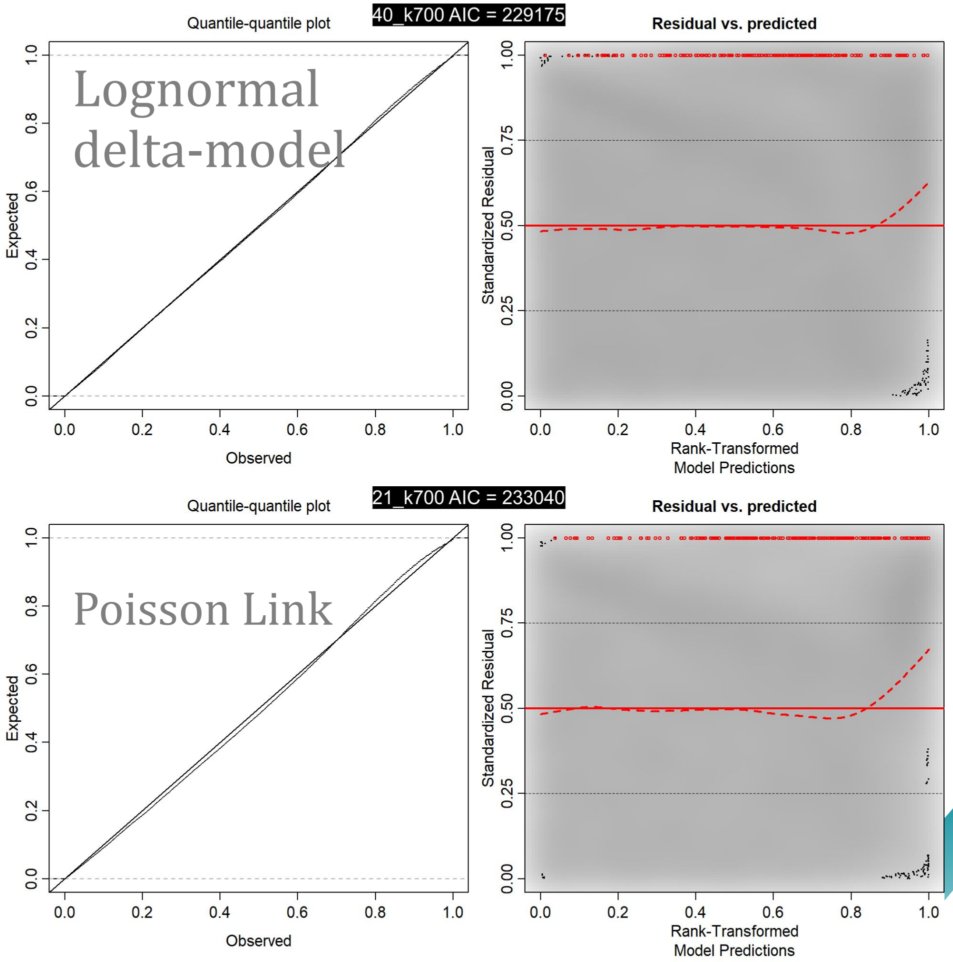
- **Poisson-link delta-model (2,1)** (log-linked linear predictor for encounter probability (i.e., Poisson), and a gamma error distribution for positive catch rates)
- **Zero-inflated negative binomial (5,0)** (1st linear predictor for logit-linked zero-inflation; 2nd linear predictor for log-linked conditional mean of NB), using two variance parameters for linear and quadratic components
- **Conventional lognormal delta-model (4,0)** using logit-link for encounter probability and log-link for positive catch rates

NOAA FISHERIES

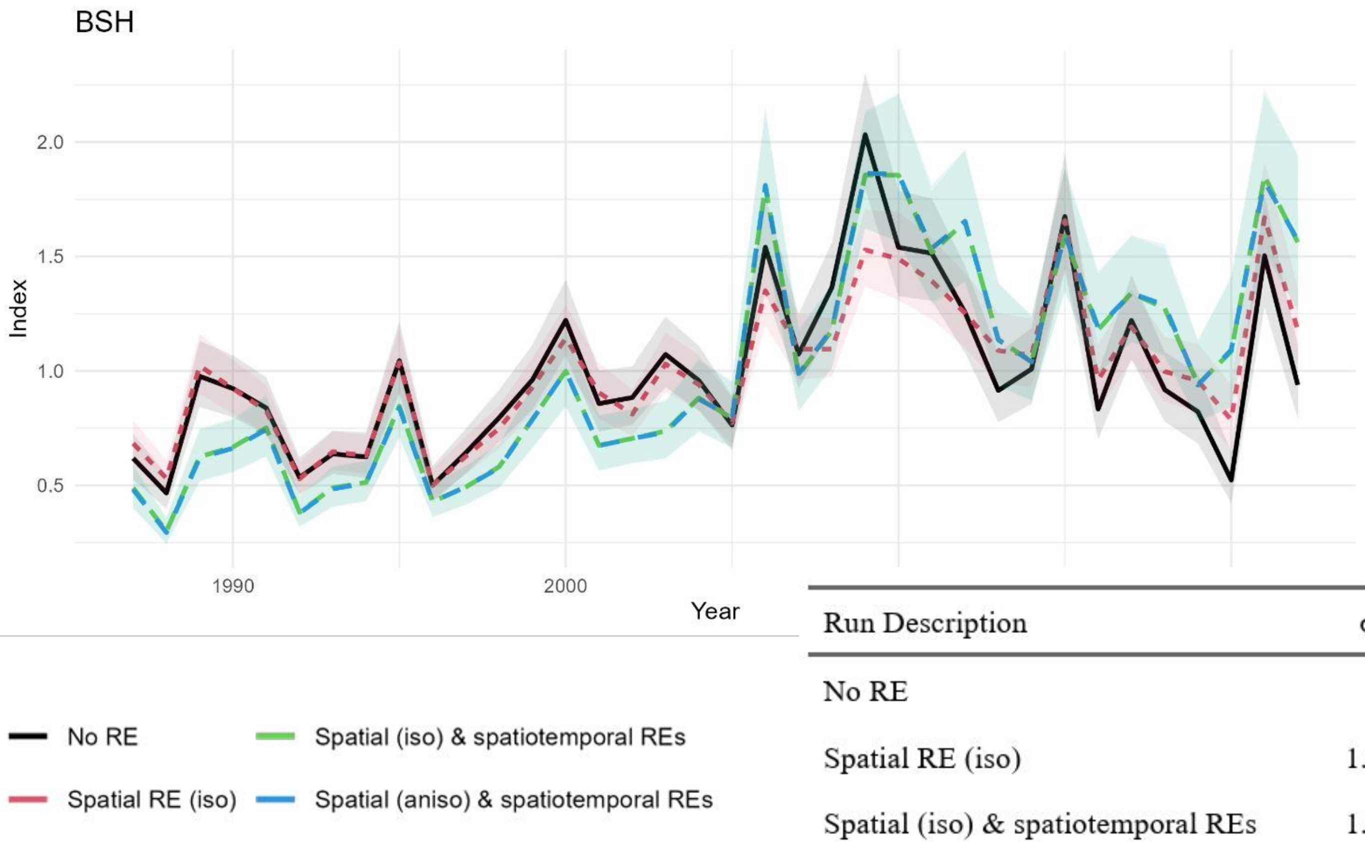

BSH SEAMAP + TPWD
Frequency
0
10000
30000
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Proportion positive tows
0
5000
10000
15000
numbers per hour
all observations


BSH SEAMAP + TPWD (zoom)
Frequency
0
20
40
60
80
100
0
5000
10000
15000
numbers per hour
all observations

Distribution and Error



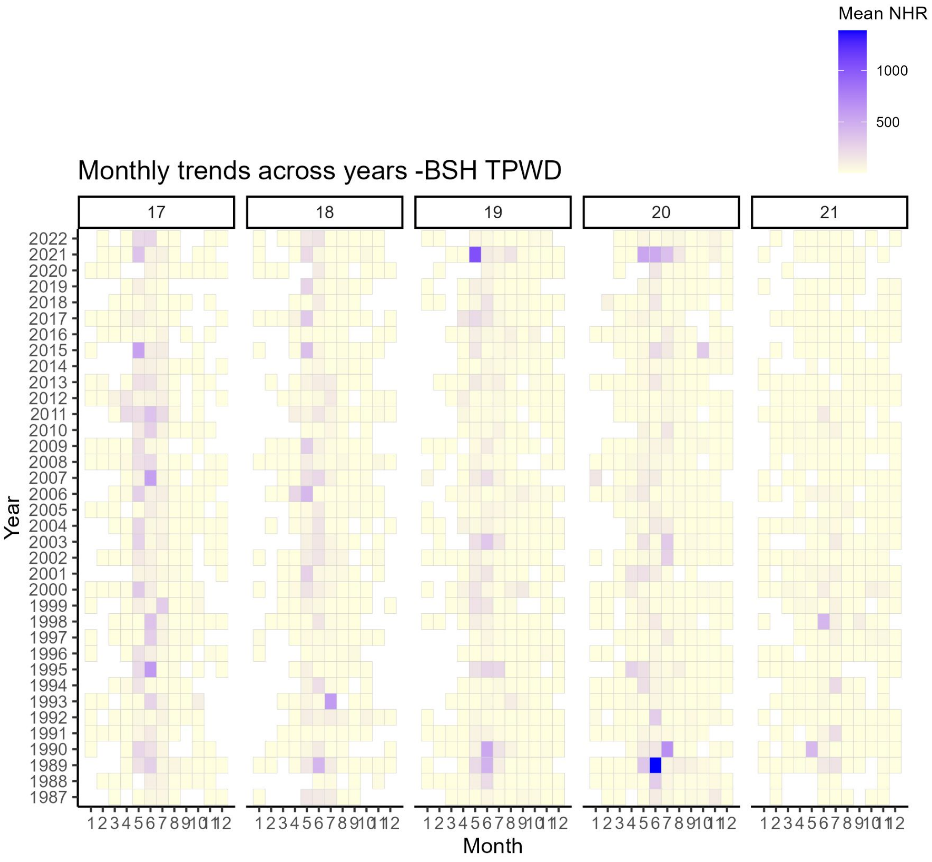
Spatial and Spatio-temporal Random Effects (RE)

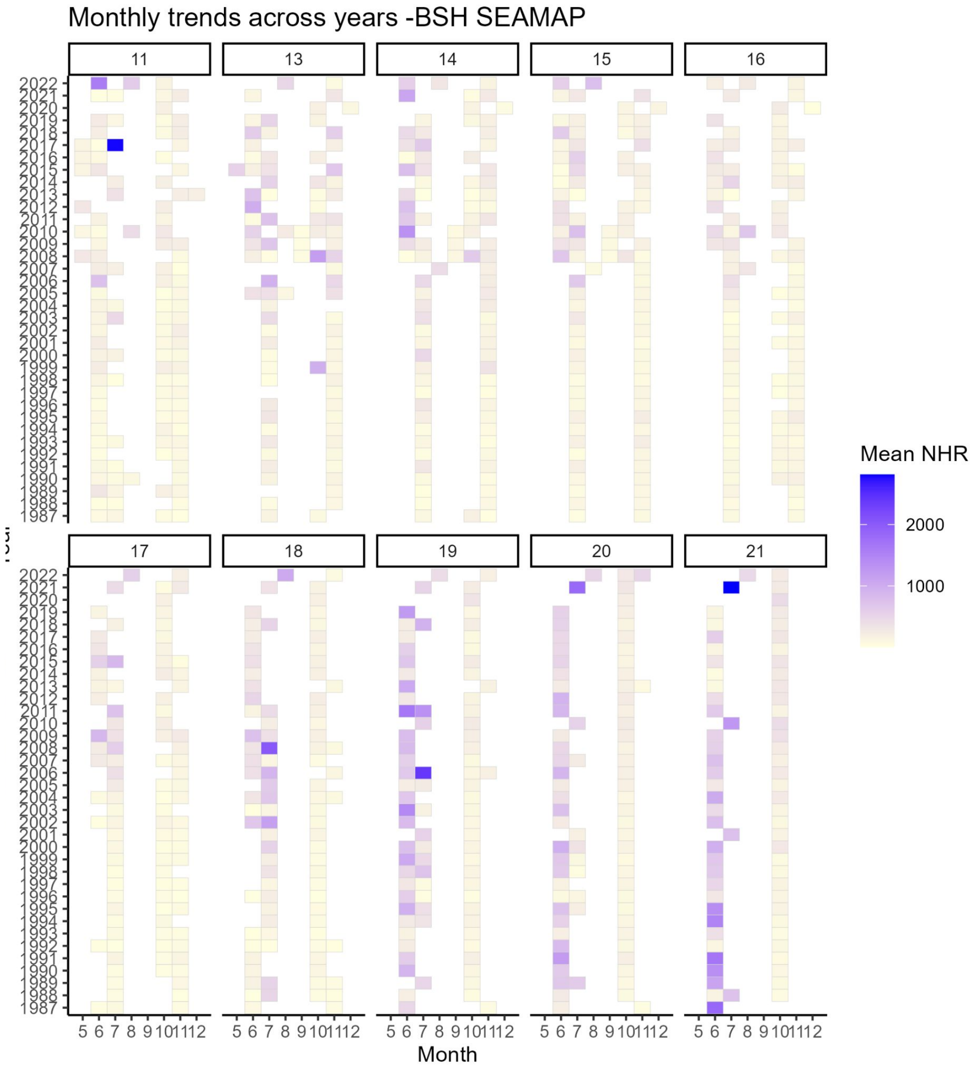


noRE: no spatial or spatiotemporal random effects
noEps: spatial but no spatiotemporal RE
Iso: isotropy
Aniso: anisotropy
Sigma: estimated variance of the RE
Omega: spatial RE
Epsilon: spatiotemporal RE

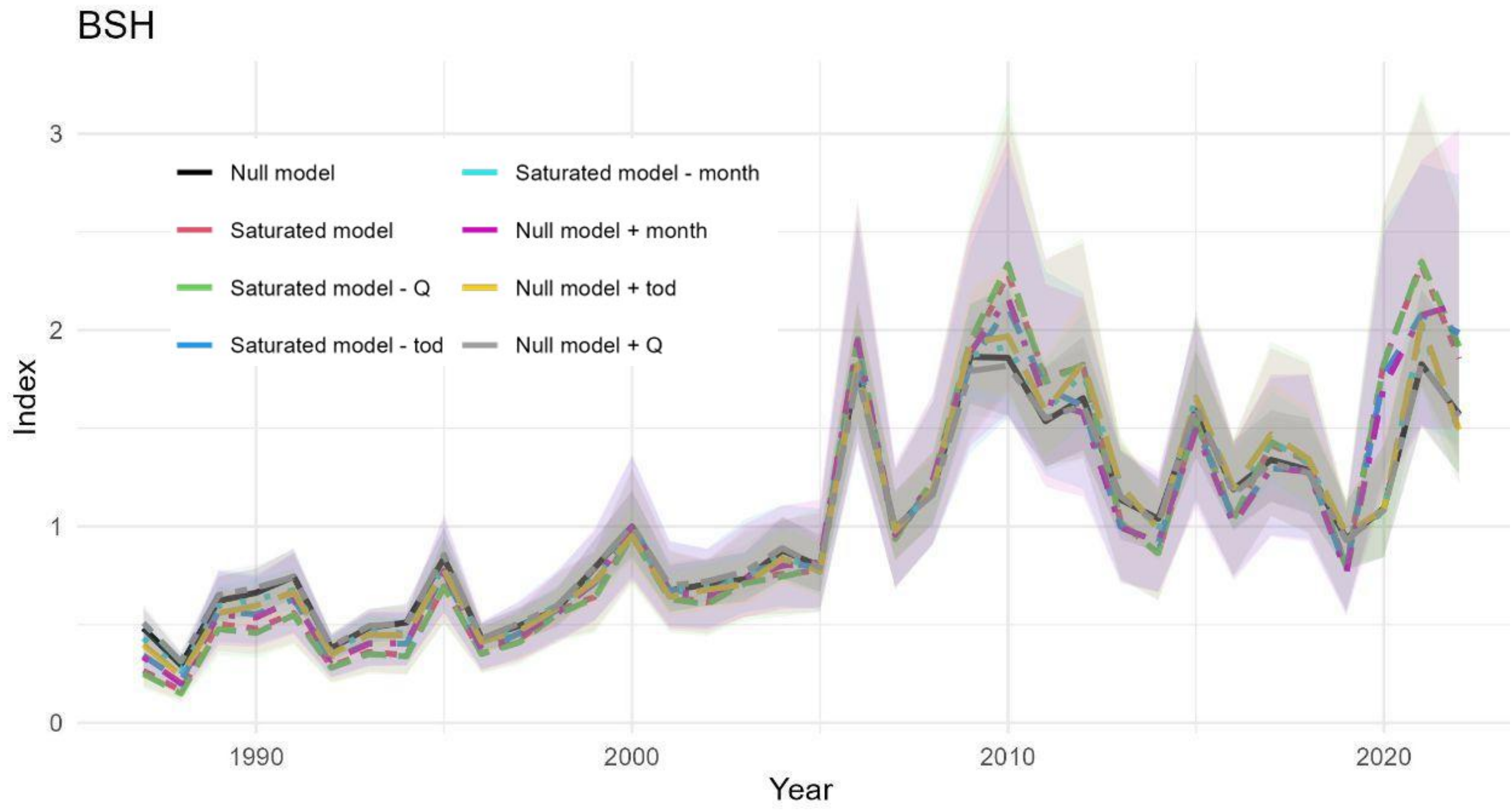
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
No RE					250,341	21,166
Spatial RE (iso)	1.96	0.81			230,465	1,290
Spatial (iso) & spatiotemporal REs	1.86	0.79	0.47	0.72	229,200	25
Spatial (aniso) & spatiotemporal REs	**1.94**	**0.82**	**0.48**	**0.73**	**229,175**	**0**

Monthly trends across years and areas



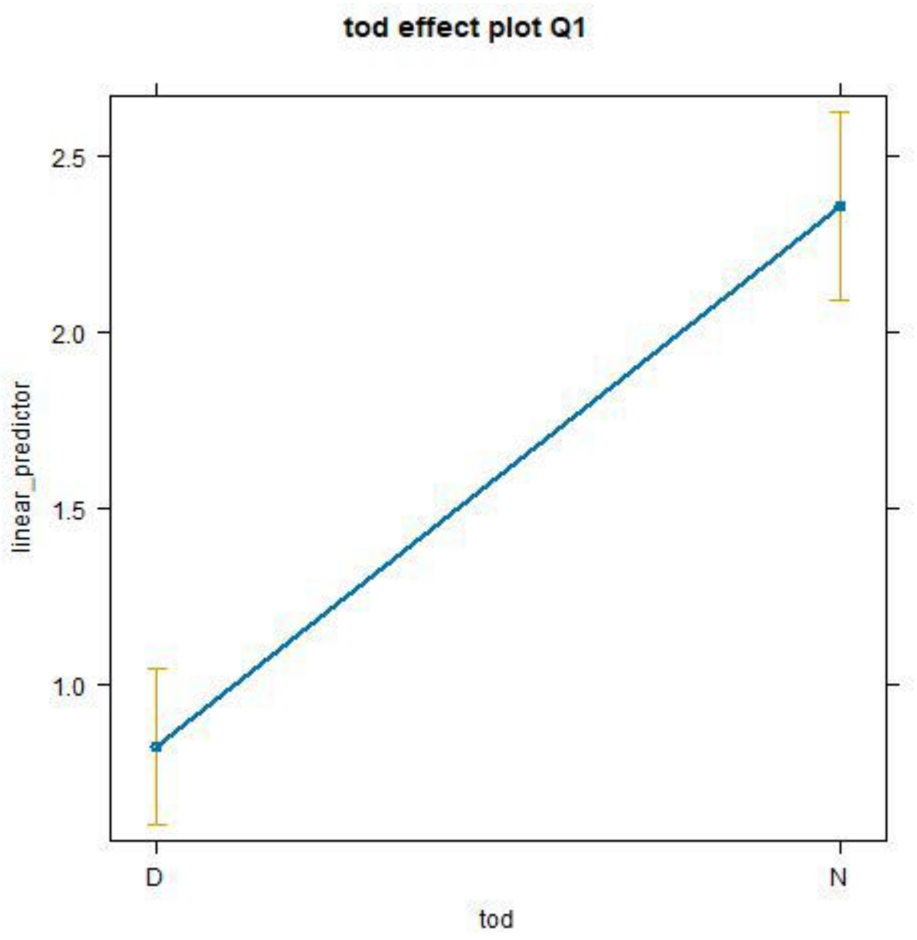


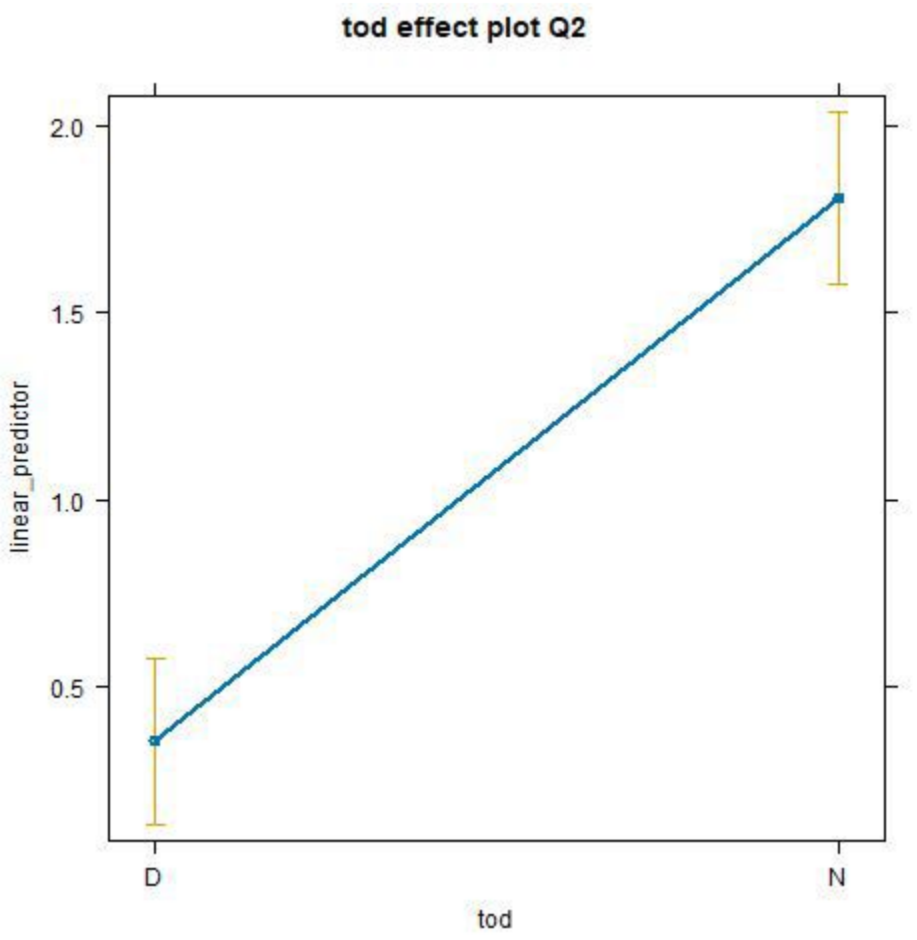
Catchability Covariates

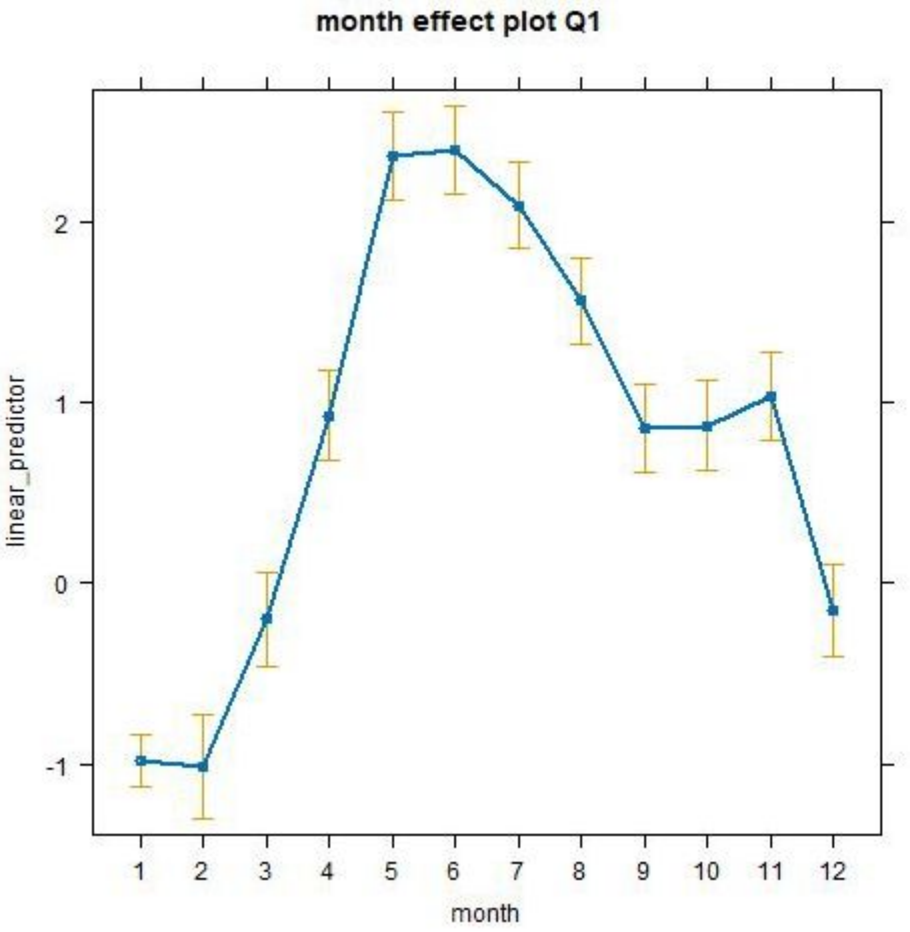


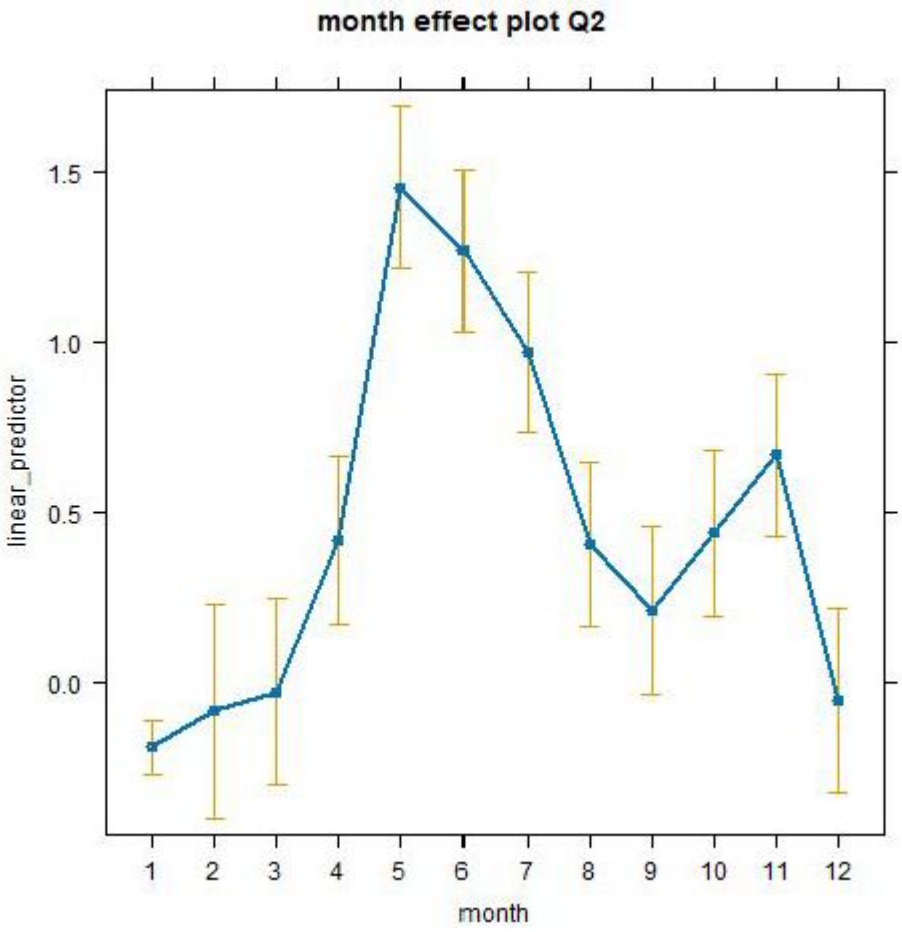
Catchability Covariates

Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
Null model	1.94	0.82	0.48	0.73	229,175	13,110
Saturated model	**1.87**	**0.88**	**0.69**	**0.71**	**216,065**	**0**
Saturated model - Q	2.07	0.89	0.69	0.71	216,474	409
Saturated model - tod	1.70	0.73	0.65	0.80	219,930	3,865
Saturated model - month	1.67	0.89	0.53	0.67	224,138	8,073
Null model + month	1.97	0.78	0.62	0.78	221,075	5,010
Null model + tod	2.01	0.91	0.54	0.67	224,859	8,794
Null model + Q	1.54	0.75	0.50	0.74	227,541	11,476


tod effect plot Q1
2.5
2.0
1.5
1.0
linear_predictor
D
N
tod


tod effect plot Q2
2.0
1.5
1.0
0.5
linear_predictor
D
N
tod


month effect plot Q1
linear_predictor
month
2
1
0
-1
1
2
3
4
5
6
7
8
9
10
11
12

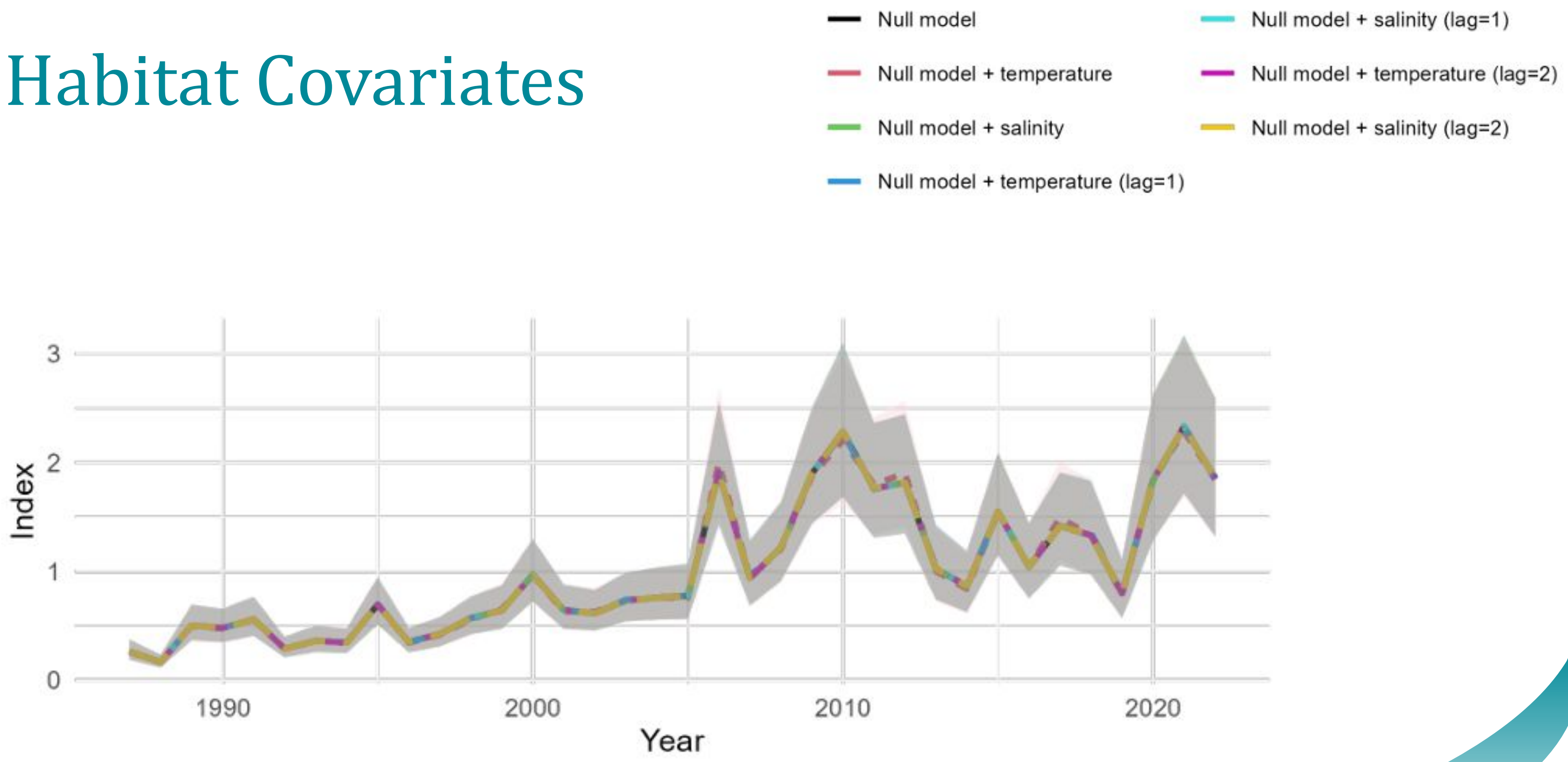

month effect plot Q2
linear_predictor
month
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7
8
9
10
11
12

Habitat Covariates

- Nursery temperature and salinity indices were included in the analysis as a spatially explicit annual zero-centered covariate to predict changes in density across space and time.
- Each of the covariates was standardized to have mean of zero and unit variance prior to inclusion in the model.
- We calculated the pseudo-R2 ("reduction in variance") to determine the proportion of variance from the null model (i.e., the model has no habitat variables) that was explained by including habitat variables (Cao et al. 2017)

$$\text{pseudo-}R^2 = 1 - \frac{\sigma^2_{\omega,m} + \sigma^2_{\varepsilon,m}}{\sigma^2_{\omega,\text{null}} + \sigma^2_{\varepsilon,\text{null}}}$$

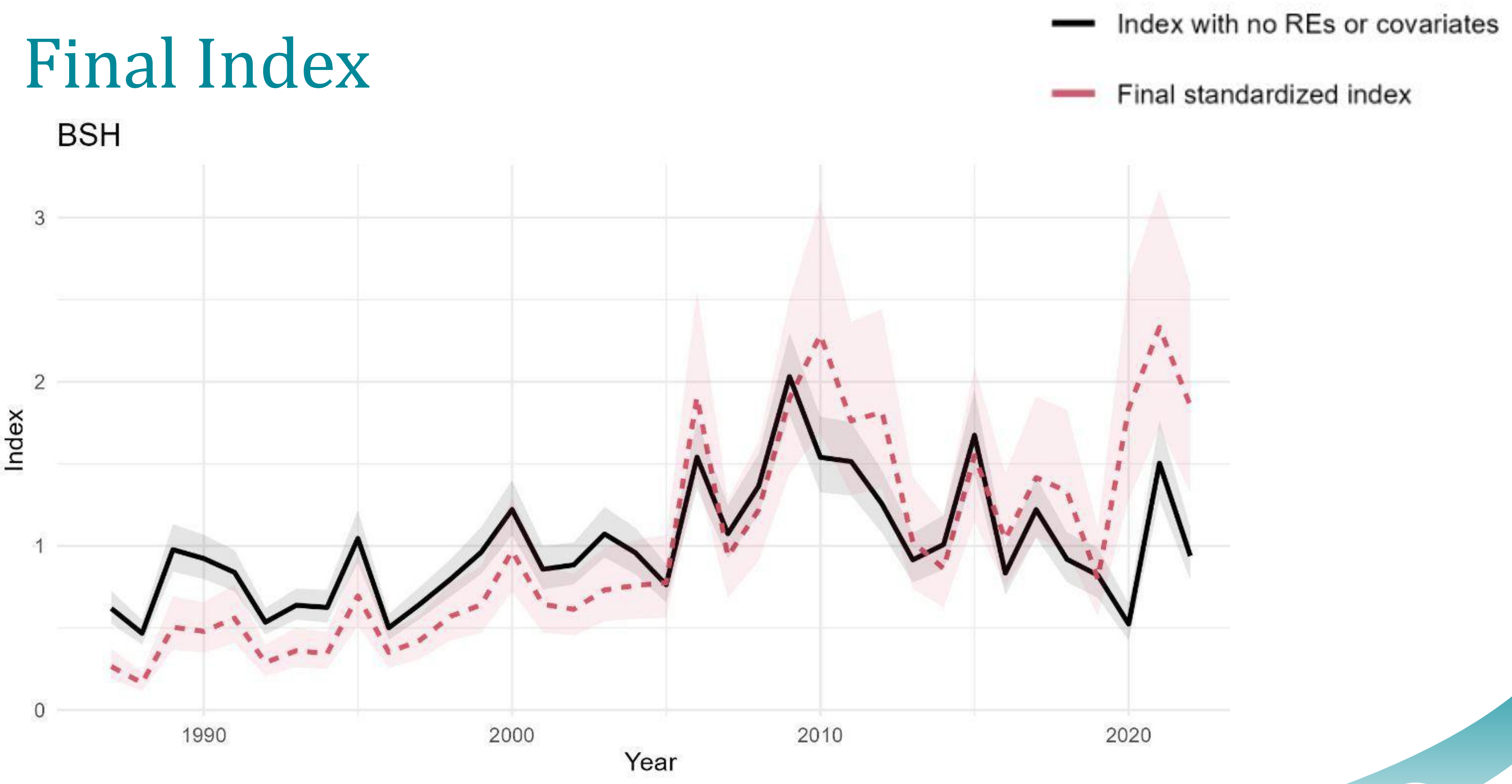
Habitat Covariates



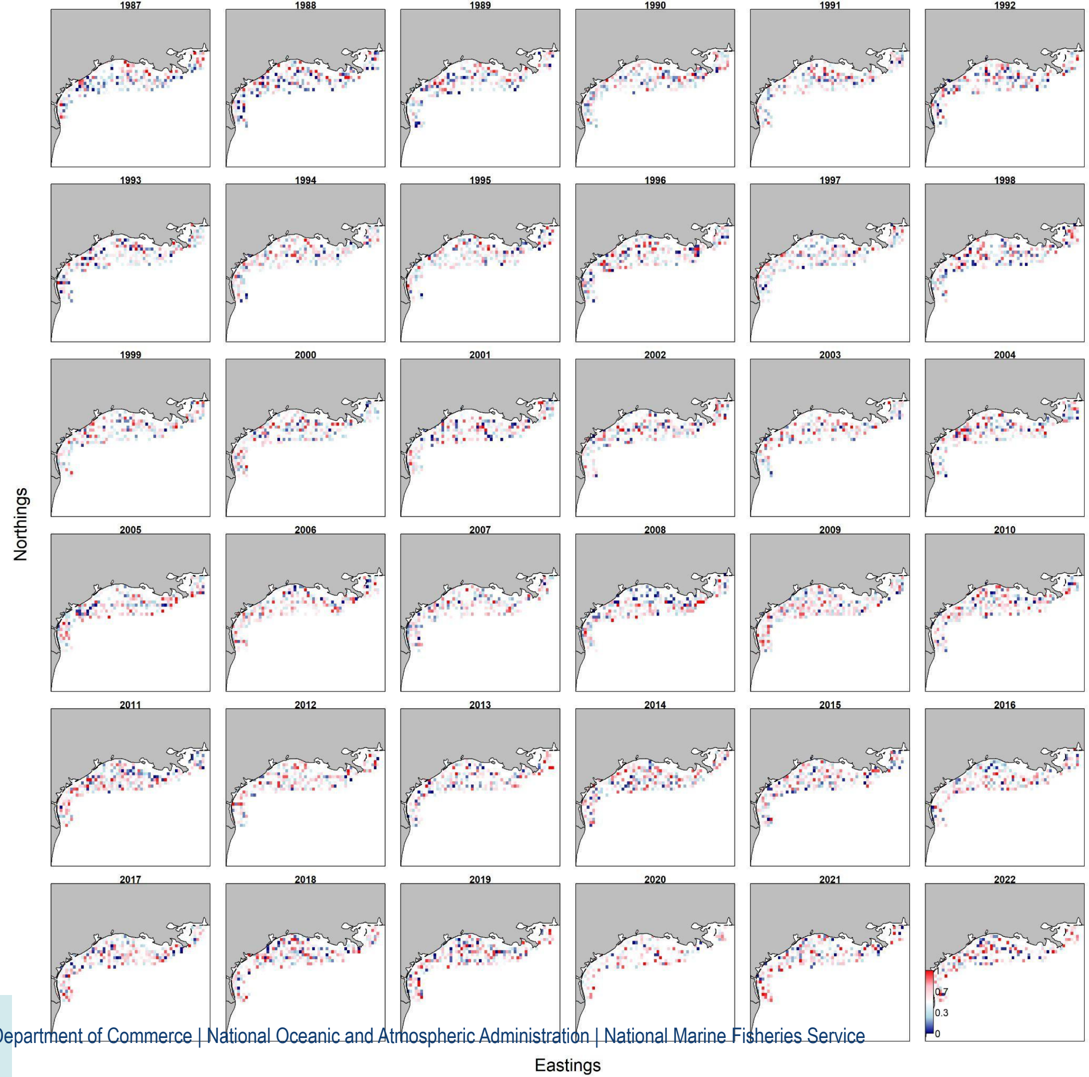
Habitat Covariates

Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	$pseudoR^2_1$	$pseudoR^2_2$	AIC	ΔAIC
Null model	1.87	0.88	0.69	0.71	0.000	0.000	216,065	13
Null model + temperature	**1.87**	**0.88**	**0.69**	**0.69**	**0.001**	**0.019**	**216,052**	**0**
Null model + salinity	1.87	0.88	0.69	0.71	0.000	0.002	216,067	15
Null model + temperature (lag=1)	1.87	0.88	0.69	0.70	0.000	0.006	216,064	12
Null model + salinity (lag=1)	1.87	0.88	0.69	0.71	0.000	0.000	216,067	15
Null model + temperature (lag=2)	1.87	0.88	0.69	0.71	0.000	0.002	216,067	15
Null model + salinity (lag=2)	1.87	0.88	0.69	0.71	0.000	0.000	216,067	15

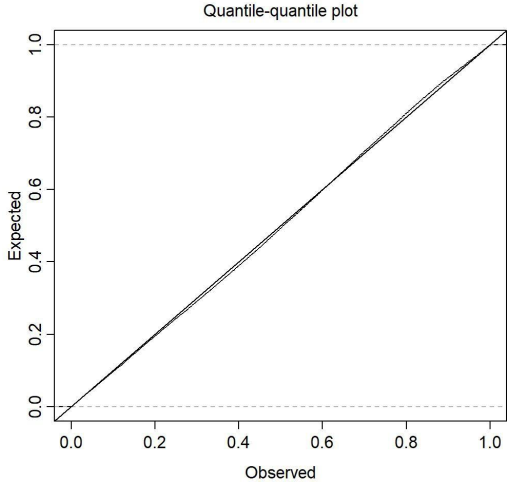
Final Index



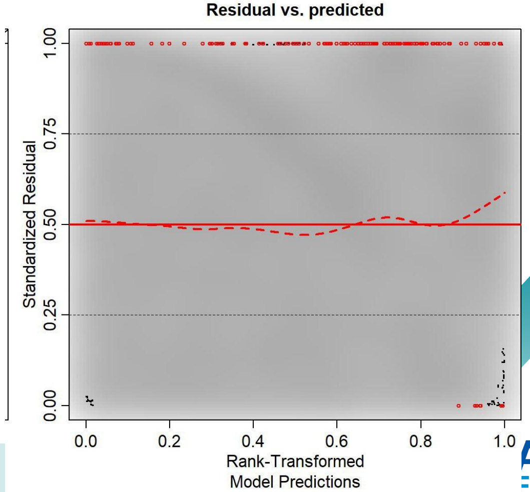
Index with no REs or covariates
Final standardized index
BSH
3
2
1
0
Index
1990
2000
2010
2020
Year



1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
0.7
0.3
0
Northings
Eastings



Quantile-quantile plot
Expected
Observed
0.0
0.2
0.4
0.6
0.8
1.0



Residual vs. predicted
Standardized Residual
Rank-Transformed
Model Predictions
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0

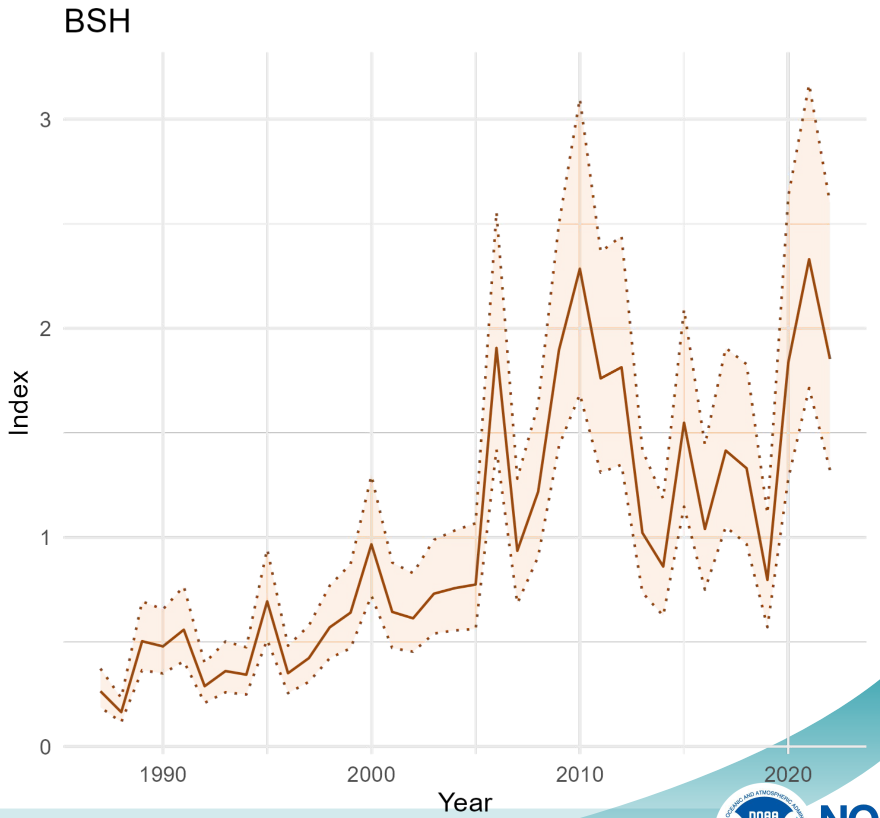
BROWN SHRIMP INDEX RECOMMENDATIONS

Brown Shrimp
SEAMAP (summer and fall) +
TPWD 1987-2022

Delta-lognormal
Numbers per tow with effort offset (fish time)
Spatial and spatiotemporal RE (anisotropy)
Catchability covariates :

- tod
- survey
- Month

We recommend the use of this index for input into JABBA based on the model configurations listed above.



JABBA

JABBA

- Bayesian state-space surplus production model (SPM)
  - **SPM** : pools the overall effects of recruitment, somatic growth, natural mortality and associated density-dependent processes into a single production function dealing with undifferentiated biomass.
  - **State-space** : allows for the estimation of observation and process error.
  - **Bayesian** : defines prior distributions for each parameter in the model to represent the initial beliefs about the parameters before observing any data.


ELSEVIER

Fisheries Research

Volume 204, August 2018, Pages 275-288

JABBA: Just Another Bayesian Biomass Assessment

Henning Winker [a b], Felipe Carvalho [c], Maia Kapur [c d]

JABBA

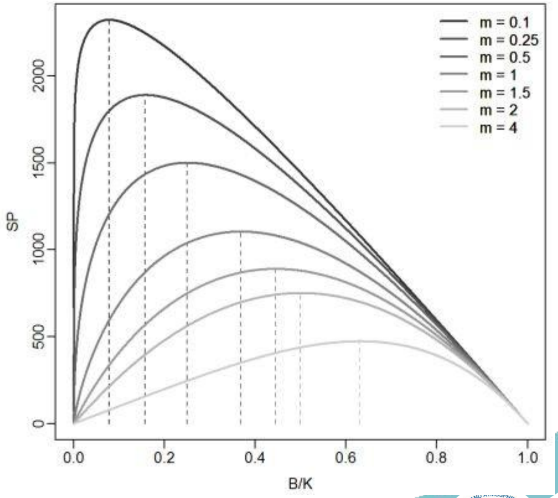
- Data inputs
  - **Index of abundance** (proportional to the exploitable part of the stock biomass)
  - Time series of **fishery removals**
- Need **contrast** in time series
  - Need high Fs to observe r at low biomass ; Need low Fs to detect K and any density dependent changes in recruitment, growth or mortality at high biomass
  - Lack of contrast can arise when stock dynamics are driven more by environmental factors than by the catches

Production Function

- **Pella–Tomlinson** (generalized production function with Schaefer and Fox as special cases)
  - **Schaffer** (assumes a symmetrical production curve ; does not consider that below a certain stock size recruitment gets impaired)
    - **m = 2**
    - MSY = K/2
  - **Fox** (asymmetrical production curve)
    - **m → 1**
    - MSY ~0.37K
  - 0<m<2 → attains MSY at biomass levels <K/2
  - m > 2 → attains MSY at biomass levels >K/2

r : intrinsic rate of population increase at time t,
K is the carrying capacity
B : stock biomass at time t
m : shape parameter that determines at which
B/K : ratio maximum surplus production is attained

$$SP_t = \frac{r}{m-1} B_t \left(1 - \left(\frac{B_t}{K}\right)^{m-1}\right)$$



Winker et al 2018

Parameters

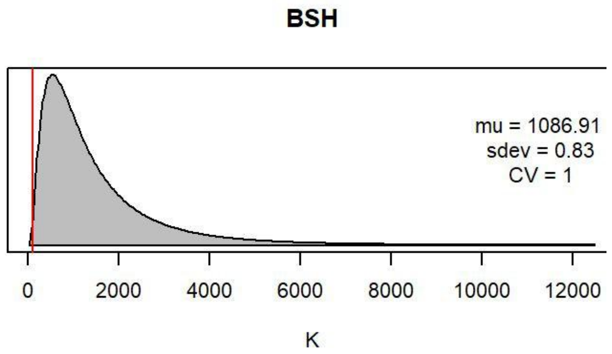
- **r** : intrinsic rate of population increase
- **K** : carrying capacity
- **m** : shape parameter that determines at which B/K ratio maximum surplus production is attained.
- **q** : catchability coefficient
- **psi** : initial biomass depletion at start of catch time series
- **process variance** ($\sigma 2$; fixed or estimated)
- **observation variance** ($\tau 2$; fixed or estimated) : input observation error + year to year variation in catchability

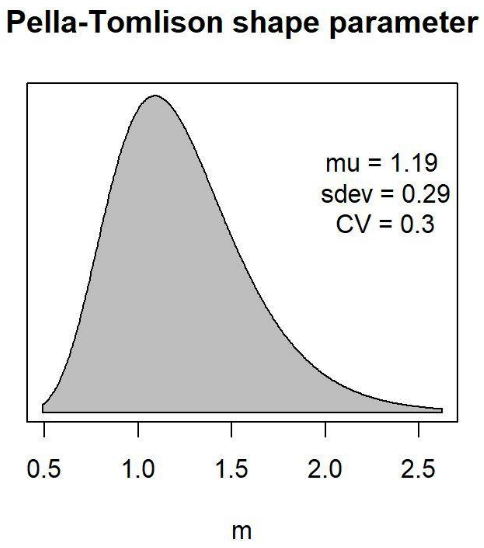
Prior assumptions

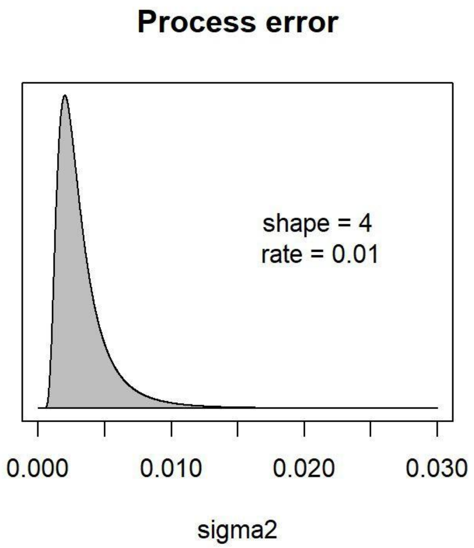
- **K** : max catch - 10x max catch
- **Production function:** Pella-Tomlinson (MSY at $B_{msy}/K = 0.4$; CV = 0.3)
- **Process error variance**: default ~ 1/gamma(4, 0.01)
- **Uncertainty grid :**

R prior *Medium and High resilience categories in FishBase - Froese et al. 2019*	**Medium** (0.2–0.8)	**High** (0.6–1.5)	**Very high** (1.2-3) *(BSH only)*
Initial biomass depletion	**Low** Lognormal (mu=.9, CV=.25)	**High** Lognormal (mu=.25, CV=.5)	
Additional observation error around index	**Yes** Default ~ 1/gamma(0.001, 0.001)	**No**	

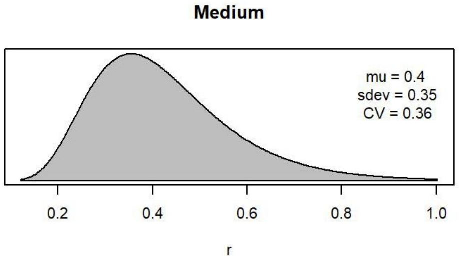
Priors (all runs)

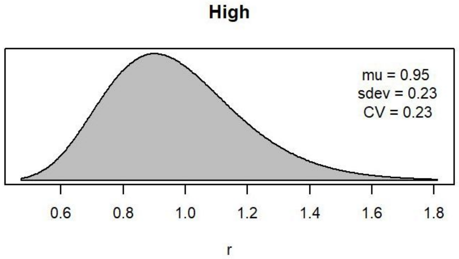


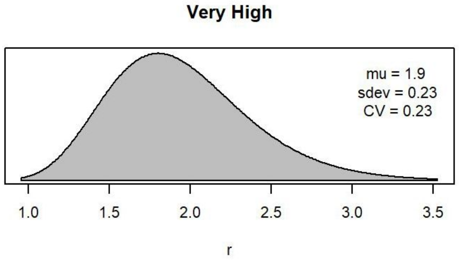


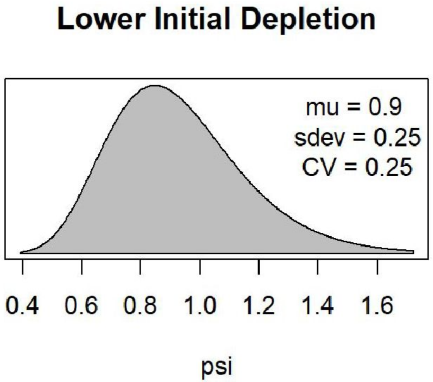


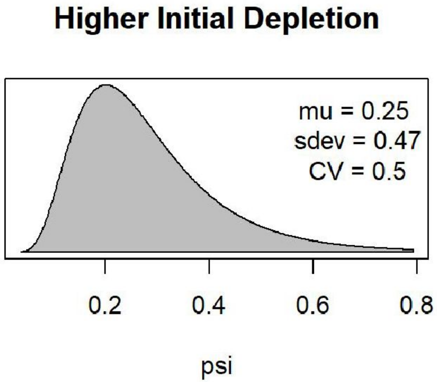
Priors (uncertainty grid)

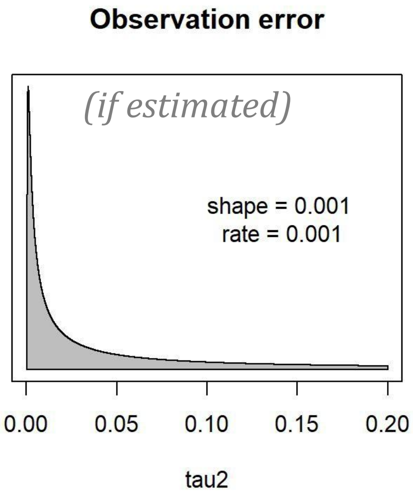












Uncertainty in landings

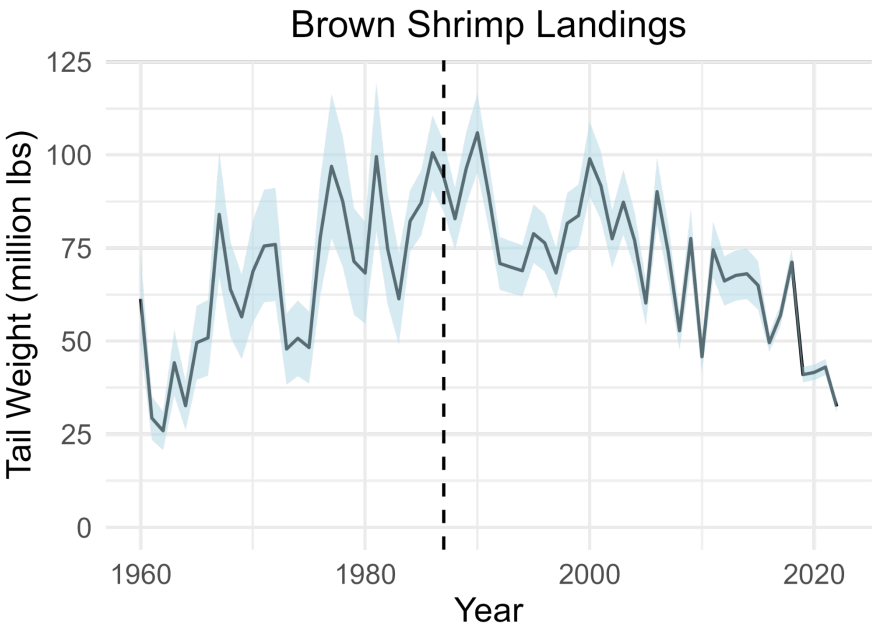
CVs : **1960-1983:** 0.2, **1984-2015:** 0.1, **2016-2022:** 0.05

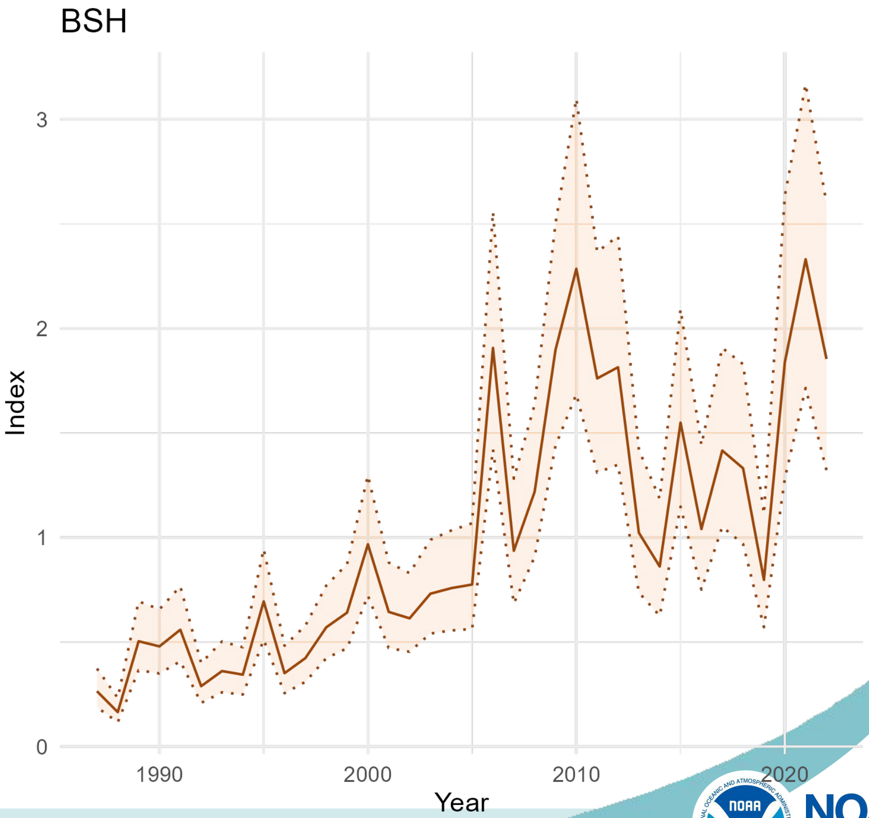
Table 11. Estimates of uncertainty (CV) by state and collection program.

Year	TX	LA	MS	AL	FL	Comments
1960-1983	0.2	0.2	0.2	0.2	0.2	Data collected and maintained by NMFS Headquarters
1984-1999	0.1	0.1	0.1	0.1	0.1	SEFSC responsible for collecting and maintaining GSS in 1984
2000-2001	0.1	0.05	0.1	0.1	0.1	LA starts state trip ticket in 1999; used starting in 2000
2002	0.1	0.05	0.1	0.05	0.1	AL starts state trip ticket; used starting in 2002
2003-2013	0.1	0.05	0.1	0.05	0.05	FL starts state trip ticket in 1984; used starting in 2003
2014-2015	0.05	0.05	0.1	0.05	0.05	TX starts state trip ticket in 2008; used starting in 2014
2016-2022	0.05	0.05	0.05	0.05	0.05	MS starts state trip ticket in 2012; used starting in 2016

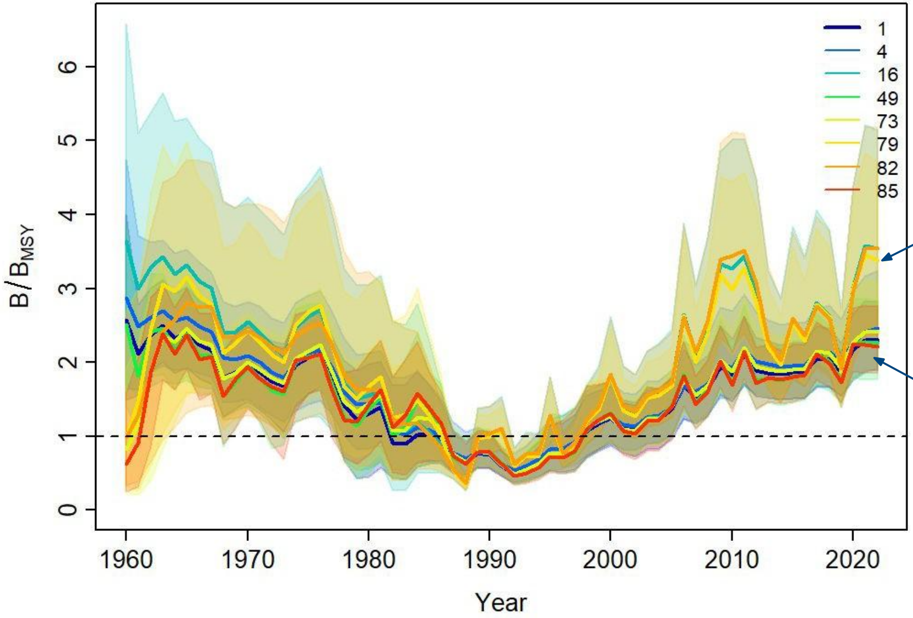
SEDAR87-DW-06

Data - Brown Shrimp





Brown Shrimp Results



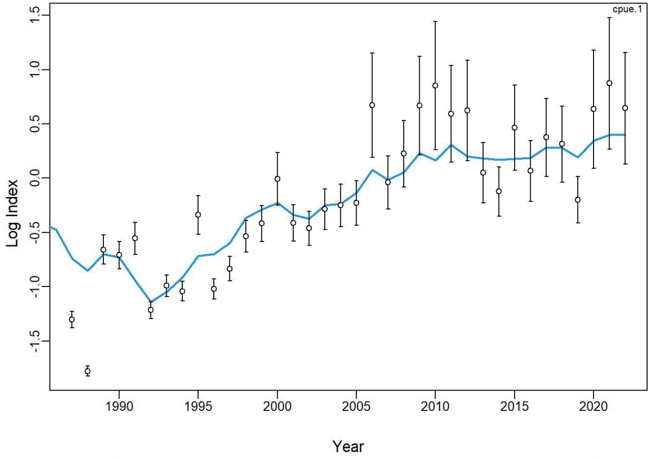
Run	Description
16	Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.
79	Sigma Estimation FALSE. R prior High range. Prior distribution for psi lnorm with mean 0.25.
82	Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.
1	Sigma Estimation TRUE. R prior High range. Prior distribution for psi lnorm with mean 0.9.
4	Sigma Estimation TRUE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.
49	Sigma Estimation TRUE. R prior Very High range. Prior distribution for psi lnorm with mean 0.9.
73	Sigma Estimation TRUE. R prior High range. Prior distribution for psi lnorm with mean 0.25.
85	Sigma Estimation TRUE. R prior Very High range. Prior distribution for psi lnorm with mean 0.25.

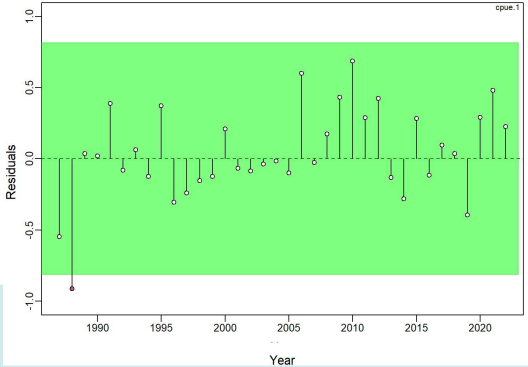
Brown Shrimp Model Diagnostics

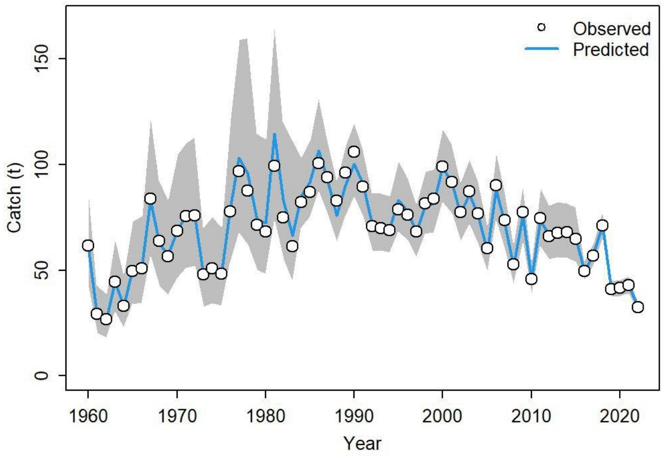
	Model Convergence			Model Fit		Model Consistency				Process Error	Prediction Skill	
run	CONV_gw	CONV_hw	CONV_hs	CPUE_rt_rand	CPUE_rt_outl	RETRO_B	RETRO_F	RETRO_B.Bmsy	RETRO_F.Fmsy	ProcB_CI	HX_MASE	DIC
BSH_1_P_rH_psil0.9_sigT_60	PASS	PASS	PASS	PASS	FAIL	0.02	-0.02	-0.02	0.02	PASS	0.85	-469.80
BSH_4_P_rM_psil0.9_sigT_60	FAIL	PASS	PASS	PASS	FAIL	0.21	-0.15	-0.04	0.03	PASS	1.00	-461.50
BSH_16_P_rM_psil0.9_sigF_60	PASS	PASS	PASS	PASS	FAIL	-0.29	0.45	0.03	0.00	FAIL	0.82	-525.60
BSH_49_P_rV_psil0.9_sigT_60	PASS	PASS	PASS	PASS	FAIL	0.03	-0.03	-0.05	0.05	PASS	0.91	-451.60
BSH_73_P_rH_psil0.2_sigT_60	PASS	PASS	PASS	PASS	FAIL	0.15	-0.12	-0.05	0.04	PASS	0.84	-461.30
BSH_79_P_rH_psil0.2_sigF_60	PASS	PASS	PASS	PASS	FAIL	-0.34	0.52	0.03	0.01	FAIL	0.73	-524.30
BSH_82_P_rM_psil0.2_sigF_60	FAIL	PASS	PASS	PASS	FAIL	-0.43	0.85	0.03	0.02	FAIL	0.82	-522.80
BSH_85_P_rV_psil0.2_sigT_60	PASS	PASS	PASS	PASS	FAIL	0.10	-0.08	-0.01	0.01	PASS	0.85	-466.90

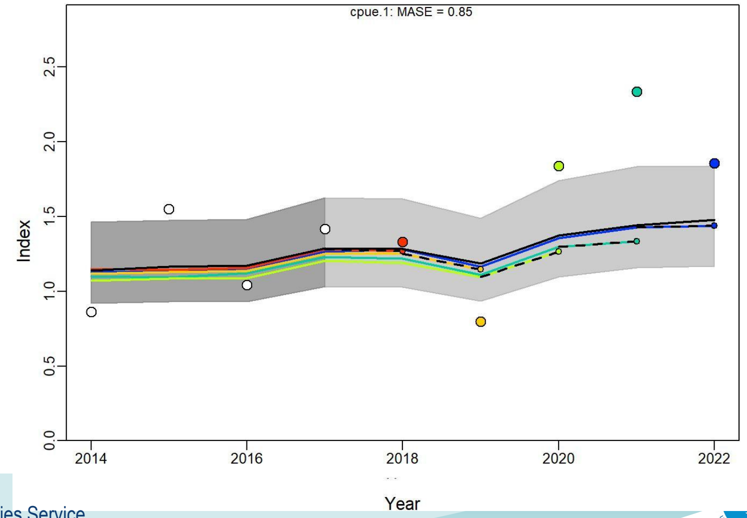
Brown Shrimp - Example Run

1 Sigma Estimation TRUE. R prior High range. Prior distribution for psi lnorm with mean 0.9.



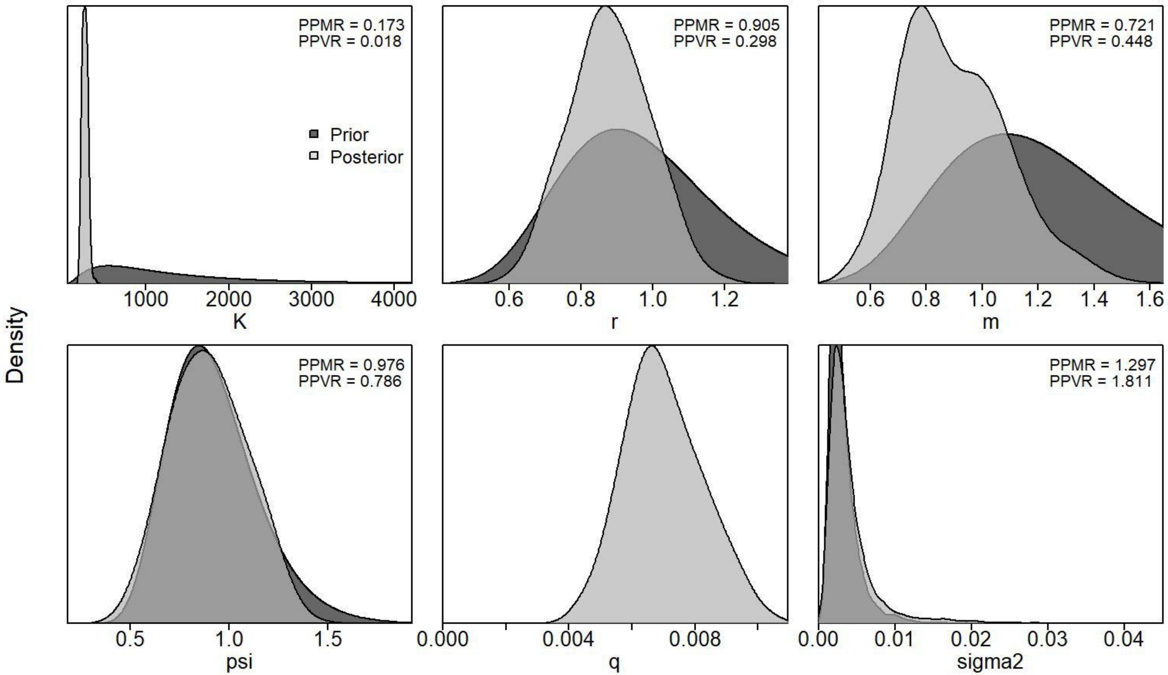


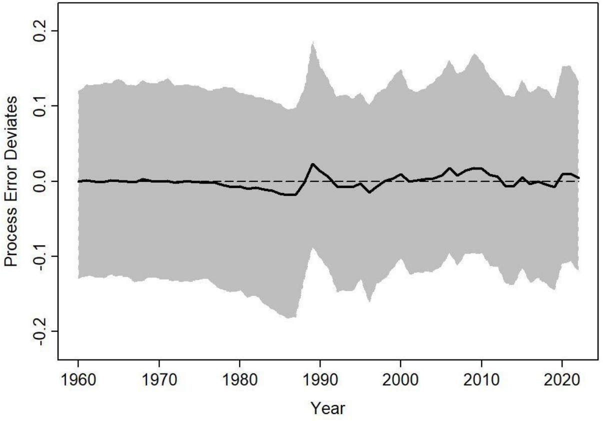




Priors, Posteriors and Process Error

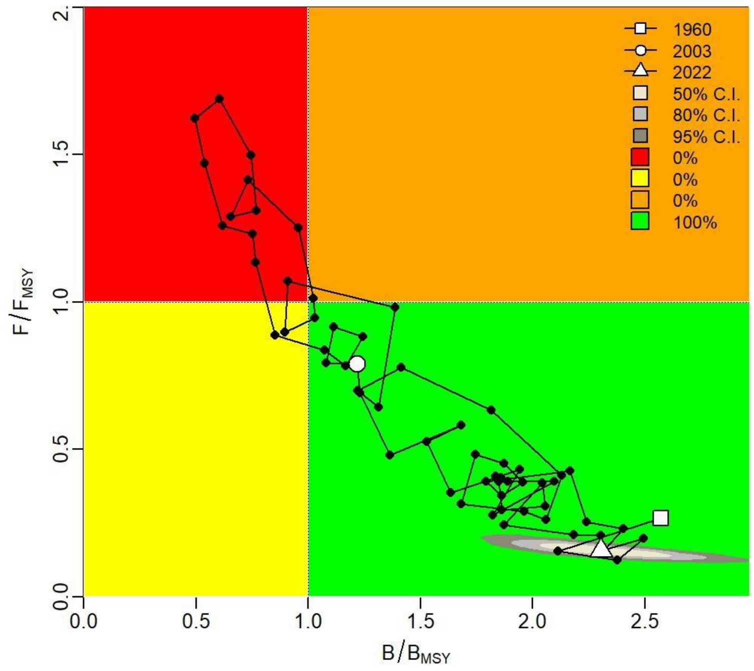
1 Sigma Estimation TRUE. R prior High range. Prior distribution for psi lnorm with mean 0.9.

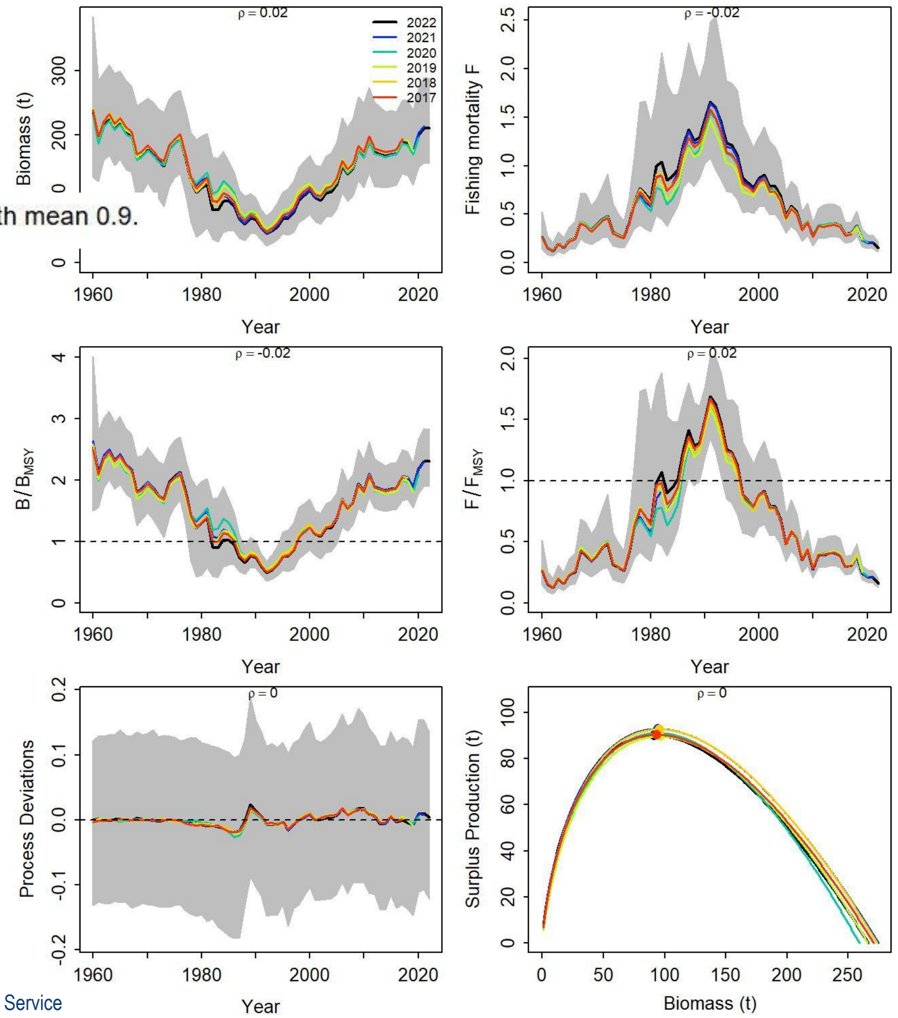




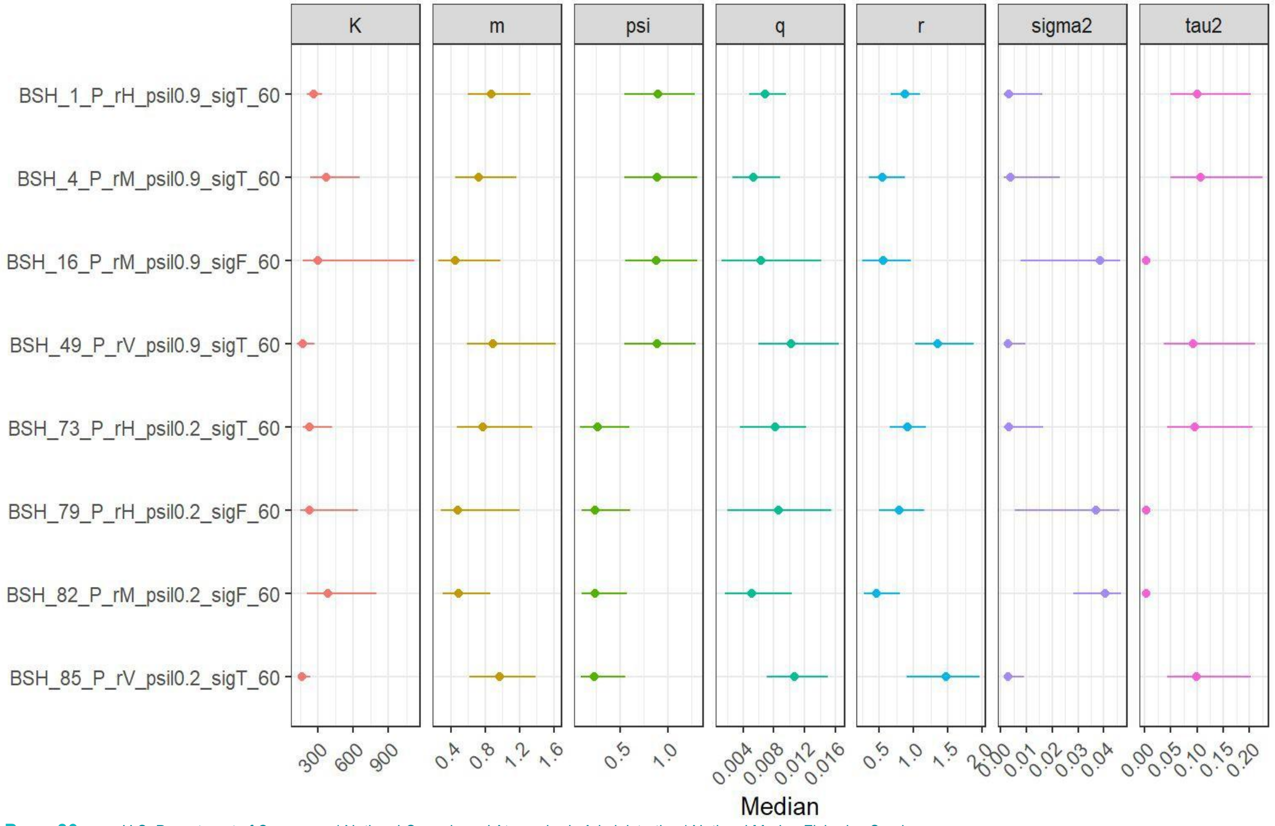
Retrospective Analysis & Kobe Plot

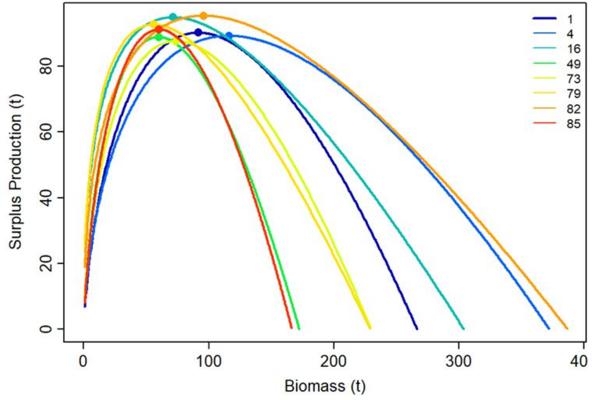
1 Sigma Estimation TRUE. R prior High range. Prior distribution for psi lnorm with mean 0.9.



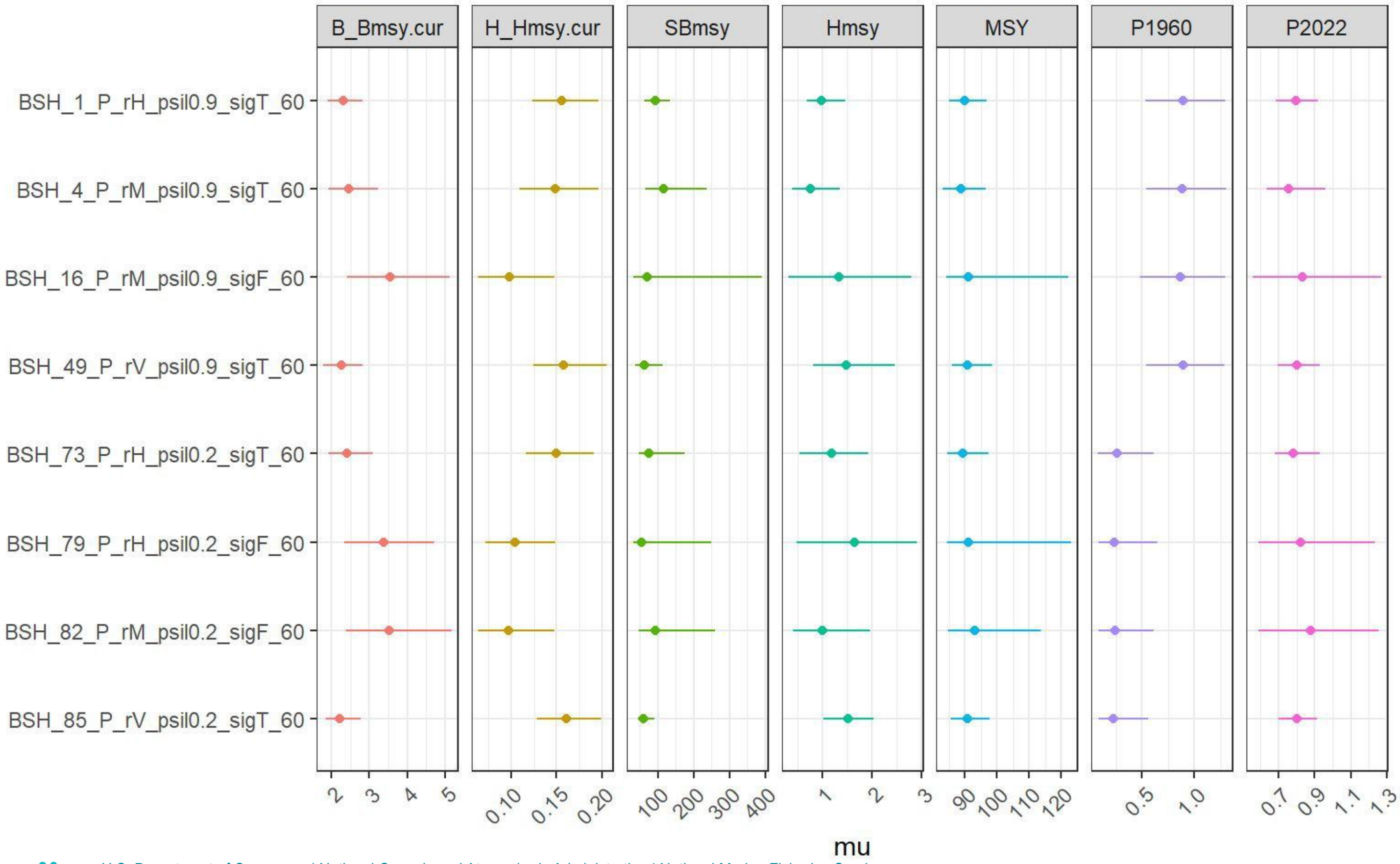


Brown Shrimp Parameter Estimates





Brown Shrimp Management Quantities

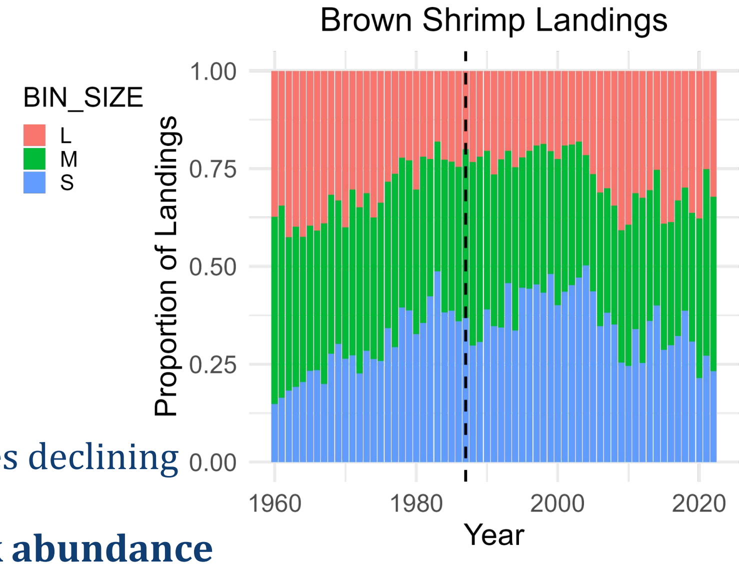


B_Bmsy.cur : Current stock status B2022/Bmsy
H_Hmsy.cur : Current stock status F2022/Fmsy
SBmsy : Bmsy (millions lbs tail weight)
Hmsy : Fmsy
MSY : MSY (millions lbs tail weight)
P1960 : Depletion in start year
P2022 : Depletion in terminal year

BROWN SHRIMP JABBA SUMMARY

Strengths

- Data-limited approach with state-space formulation
- Acceptable diagnostics



Weaknesses

- Lack of contrast
  - "One way trip" : index only available over period of catches declining
- Assumptions likely violated
  - SPMs assume that **catch** levels reflect **changes in stock abundance**
    - Recent pattern of exploitation driven by economic considerations rather than shrimp availability
  - SPMs assume that the **stock dynamics** are **adequately represented** by the underlying model equations
    - Environmental changes likely affect both K and r for shrimp
  - SPMs assume **constant catchability / selectivity** through time
    - There have been known changes in size composition and timing of catches through time

BROWN SHRIMP JABBA SUMMARY

- JABBA models were generally well behaved but the results are limited by the general constraints of surplus production models
- We explored EDM as an alternative modeling platform to better capture the dynamics of a stock whose patterns of abundance and exploitation are primarily driven by environmental and economic considerations

Empirical Dynamic Modeling (EDM)

Empirical Dynamic Modeling (EDM)

- Lagged abundance data have been used in fisheries for a long time within age-structured models

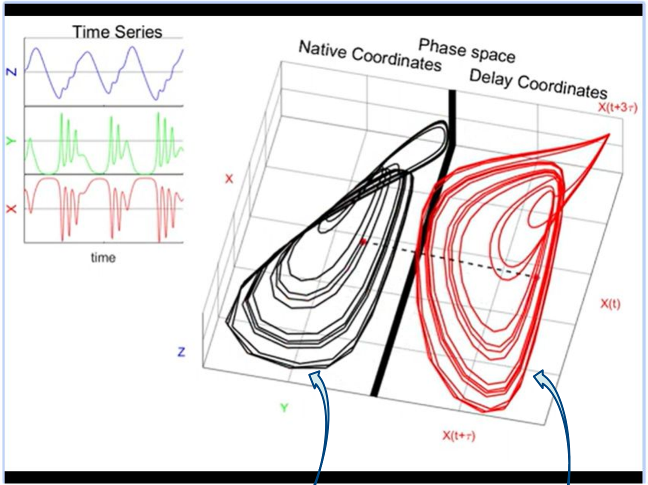
- Takens' Theorem on delay embedding makes this idea more general by incorporating additional lags under no model form:
    when there's a system with many variables but only a few are observed, time lags can be used to reconstruct the full system dynamics
    → don't need data on all variables to make accurate predictions
    → don't need to specify model form

- Examples of variables not observed directly: environment, predators, food items, economic influences

Empirical Dynamic Modeling (EDM)

- Relies on time series data to reveal dynamic relationships among variables
- Treats time series as an observation on a dynamic system
- Uses lags from of a single state variable to reconstruct a shadow version of the original attractor manifold (Takens Theorem)
- Allows us to recover states of the original by using lags of just a single time series

state variables



attractor manifold

reconstructed shadow

Empirical Dynamic Modeling (EDM)

Three-species model
with type-2 functional response
Z – predator
Y – grazer
X – producer

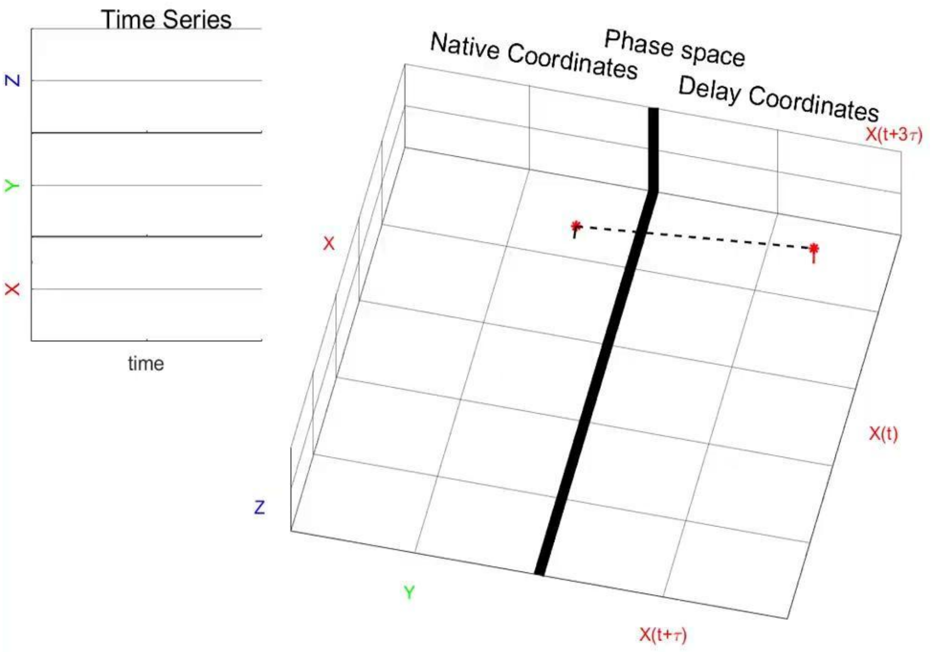
Trace nearby trajectories to
obtain discrete time model

$$x_{t+1} = F[x_t, y_t, z_t]$$

Analogous model in ‘delay coordinates’

$$x_{t+1} = \tilde{F}\,[x_t, \ldots, x_{t-E}]$$

Dynamics equivalent to full state space,
based only on observed time series



Gaussian Process EDM (GP-EDM)

- GP regression can be used to approximate the delay-embedding map $\boldsymbol{f}$

$$P(y_t \mid f, X_{t\text{-}m}, z, V_e) \sim Normal(f(X_{t\text{-}m}, z), V_e)$$

$$P(f \mid \phi, \tau) \sim GP(0, \Sigma)$$

where the probability of observing abundance $\boldsymbol{y}$ at time $\boldsymbol{t}$ is dependent on the function approximation $\boldsymbol{f}$, vector of abundance indices $\boldsymbol{X}$ with $\boldsymbol{m}$ lags ($\boldsymbol{X_{t\text{-}m} = \{x_{t\text{-}1}, \ldots, x_{t\text{-}m}\}}$), optional covariates $\boldsymbol{z}$, process noise $\boldsymbol{V_e}$. $\boldsymbol{f}$ is dependent on inverse length scales $\boldsymbol{\phi}$ and pointwise prior variance $\boldsymbol{\tau}$, and is assigned a GP prior with mean zero, covariance function $\boldsymbol{\Sigma}$.

- GP-EDM with m=1 can be thought of as a nonparametric production model (Thorson *et al.*, 2014)
  - Abundance next year is dependent on abundance this year

Incorporating Catch in GP-EDM

- Expand the delay embedding map to include removals (catch or landings)

$$P(y_t \,|\, f, (X_{t-m} - qC_{t-m}), z, V_e) \sim Normal(f((X_{t-m} - qC_{t-m}), z), V_e)$$

where the removals $\boldsymbol{C_{t-m} = \{c_{t-1},\ldots, c_{t-m}\}}$ corresponds to the same time step of the estimate of population abundance $\boldsymbol{X_{t-m}}$ scaled by catchability coefficient $\boldsymbol{q}$.

- Sufficiently low q will ignore landings altogether
  - Defeats the purpose if our goal is to project MSY
  - Filtered data where q > 0.001 CPUE/tailsmp (data generally show >0.01)

Fishery production model

$$B_{t+1} = B_t - C_t + P(B_t - C_t)$$

e.g., $P(x) = rx(1 - \frac{x}{k})$ for production function

B: biomass (lbs)
C: catch (lbs)
P: production (lbs)
I: abundance index (#/tow)
q: #/lbs/tow
u: exploitation rate (lbs/lbs)

$$I_t = qB_t$$

$$u_t = \frac{C_t}{B_t}$$

Re-write production model in terms of observables

$$qB_{t+1} = qB_t - qC_t + qP(B_t - C_t)$$

$$I_{t+1} = I_t - qC_t + qP[\frac{(I_t - qC_t)}{q}]$$

Now we have model linking index and catch
Note that $(I_t - qC_t)$ is proportional to surviving biomass $(B_t - C_t)$

Fishery EDM model

$$I_{t+1} = f(I_t - qC_t, I_{t-1} - qC_{t-1}, .., I_{t-E} - qC_{t-E})$$

EDM uses $I_t - qC_t$ as proxy for surviving biomass as per fishery production model, but does not assume a known production function, such that the function *f* of time lags allows for unobserved state variables and species interactions

Tsai, C.-H., Munch, S.B., Masi, M.D. & Stevens, M.H. (2024). Empirical dynamic modeling for sustainable benchmarks of short-lived species. ICES Journal of Marine Science.

GP-EDM Prior Specifications

- Specify priors such that the variance <2x observed and the most likely model is flat with one local maxima (Munch *et al.* 2017)

$$P[V_e, \tau, \phi]$$

process noise $\boldsymbol{V_e}$, pointwise prior variance $\boldsymbol{\tau}$, and inverse length scales $\boldsymbol{\phi}$

- Covariance function $\boldsymbol{\Sigma}$ for estimates of abundance $\boldsymbol{y}$

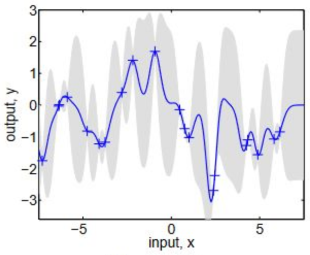
$$\Sigma(y_t, y_s) = \tau * exp[-\Sigma_{i=1}^{m+z}\phi_i(X_{it} - X_{is})^2]$$

at times $\boldsymbol{t}$ and $\boldsymbol{s}$ where $\boldsymbol{s}$ in $\boldsymbol{T}$ time series length for observations $\boldsymbol{X}$

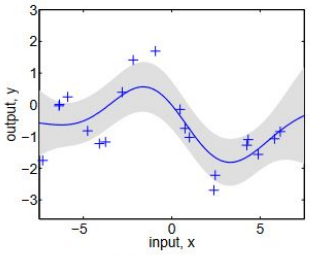
- Covariance function $\boldsymbol{\Sigma}$ with inverse length scales $\boldsymbol{\phi}$ control the degree of nonlinearity

$\boldsymbol{\phi}$=0 indicates a flat relationship, larger length scale $\boldsymbol{l}$ in figure to the right

$\boldsymbol{\Sigma}$ defines how tightly to fit the data



(b), $\ell = 0.3$



(c), $\ell = 3$

Rasmussen and Williams, 2008. Gaussian Processes for Machine Learning. MIT press, Cambridge, MA.

GP-EDM Prior Specifications

- Option for a linear prior that assumes a relationship between abundance in current and previous time step
  - Can aid in grounding the population to 0 at high harvest rates
  - Introduces more biological realism where we don't have data to inform the model

$$y_t = \beta_0 + \beta_1[x_{t-1} - q * c_{t-1}] + f(X_{t-m} - q * C_{t-m}, z)$$

- Essentially equivalent to a prior for a Ricker model when $y_t = log(x_{t+1}/x_t)$

EDM Application to Gulf Shrimp

- Long-standing fishery independent indices of abundance and commercial fishery landings
- Population dynamics are chaotic and/or not directly correlated to previous year's abundance
  - Environmental changes likely affect both carrying capacity and growth rate
  - Exploitation driven by economic considerations rather than shrimp availability
  - Fishery impacts on the annual population variation may be minimal
- Great candidate for Empirical Dynamic Modeling (EDM)

Formation of EDM Workgroup

- The workgroup was convened following a request to the SEFSC from the Gulf Council following their April 2022 Meeting.

  "… the Council thinks that the continued engagement of the aforementioned groups [SSC members, Council staff, and shrimp industry representatives] during the development of the shrimp EDMs is preferable, as there were numerous logistical and ground truthing questions regarding operations of the shrimp industry and data utilization that could assist in a more robust result that can be employed by management, versus waiting to the end to be engaged. Specifically, the various AP and SSC members can provide technical insight, historical institutional knowledge, management expertise, and on-the-water perspectives that will improve the quality and the buy-in of the resulting analytical tools."

- Met 3 times August-October 2022

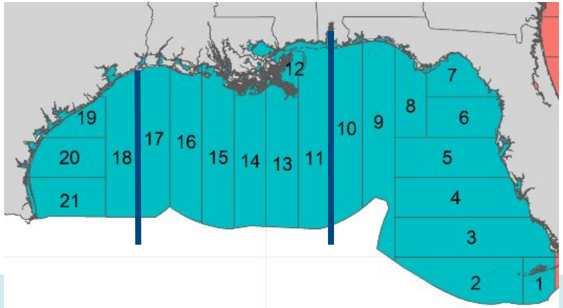
  ***Participants**: Jim Nance, Leann Bosarge, Steve Bosarge, Glen Delaney, Nathan Putman, Benny Gallaway, John Froeschke, Matt Freeman, Dave Chagaris, Corky Perret, Lew Bullock*

Gulf of Mexico Shrimp EDM

- Tsai *et al.*, 2023
  - Hierarchical EDM fitting separately to each shrimp grid (area)
- Tsai *et al.*, 2024
  - Collapsed spatially, added catch estimation
  - Proof of concept for MSY using EDM
- SEDAR87
  - Practical application
  - Adding complexity back in alongside catch
  - Testing environmental and economic covariates from DW working group recommendations

Stratification of Shrimp Data

- **Species:** brown (*Farfantepenaeus aztecus*), pink (*F. duorarum*), white (*Litopenaeus setiferus*)
- **Area:** Gulf fishing areas 1-10, 11-17, 18-21
- **Size Bins:** "Small", "Medium", "Large";
  >67, 67-31, <=30 shrimp tails per pound;
  <129mm, 129mm-166mm, >=167mm total length
- **Season:** Winter (JFMA), Summer (MJJA), Fall (SOND)
- **Year:** 19XX-2022



NOAA FISHERIES

Model Configuration

- Define the system being modeled
- Stratify data such that system variability can be captured
  - Modeled as “populations” within a hierarchical model
  - Modeled independently with no shared parameters
- $\boldsymbol{\rho}$ is the degree to which the dynamics are correlated and quantifies the similarity of population responses across predictor space (0:1)
  - Hierarchical models will share parameters (including models with ρ=0, or independent dynamics)
  - ρ = 1 means the dynamics of each population are identical

Model Configuration

- A number of decisions need to be made a priori based on what we know about the system and data
- Scaling [standardize to mean=0, sd=1]
  - Global - scaling the data across populations to have the same mean
  - Local - scaling the data within populations
  - Independent Models
- ytrans: transformation to apply to y before fitting
  - none: no transformation
  - log: $\log(y_t)$
  - gr1: $\log(y_t/y_{t-1})$
  - gr2: $\log(y_t/(y_{t-1} - qC_{t-1}))$
- Catchability, q
  - Shared among populations if specified
  - Distinct within populations if specified

Model Configuration

- Embedding dimension $\boldsymbol{E}$ approximates system dynamics using lags of the observed states to account for unobserved state variables
  - Limited by time series length $\boldsymbol{T}$, where $\boldsymbol{E} <= \text{sqrt}(\boldsymbol{T})$

- Covariates $\boldsymbol{z}$ have the potential to improve model fits and short-term predictive accuracy
  - Environmental: temperature, salinity
  - Economic: price index, imported shrimp biomass

- Factorial design was implemented to investigate the impact of each decision

Parameters

- $\boldsymbol{\phi}$ (1:E, covariates) - length scale parameters
- $\boldsymbol{V_e}$ - process variance
- $\boldsymbol{\tau}$ - pointwise prior variance in f
- $\boldsymbol{\rho}$ - dynamic correlation between populations (0:1, hierarchical dynamics)
- $\boldsymbol{q}$ - catchability coefficient(s)

Model Performance

- Ultimate purpose is to project abundance/landings and estimate MSY
- Predict method for the training data
  - "lto" - leave time out, leaves out all data points taken at the same time across all populations
  - **"sequential" - leave future out prediction, leaves out all future time points across all locations; more appropriate for measuring projection ability**
  - Compare out of sample R2 values to select best models (e.g. prediction accuracy)
- Covariates
  - Lags of covariates can be included to accurately forecast or predict near-term population abundance
  - **No covariates were included to avoid additional assumptions for projecting MSY, a natural biological state**

Model Performance

- In sample fit statistics
    - R2 - proportion of variance explained by model (independent or hierarchical)
    - R2pop - proportion of variance explained for each population within a hierarchical model
    - R2scaled - proportion of variance explained by a hierarchical model, centered and scaled by population means
    - rmse - root mean square error
    - df - degrees of freedom, trace of the smoother matrix
- Out of sample fit statistics
    - R2_out - out of sample R2
    - R2_outpop - out of sample R2pop
    - R2_outscaled - out of sample R2scaled
    - rmse_out - out of sample rmse

Model Selection Summary

- Selection decisions focusing on ‘no covariate’ models with ‘sequential’ cross-validation
  - Top 5 overall models considering R2out and R2outscaled
  - Models that perform well considering both of these metrics, pulling overlap from…
    - Top 30 from R2out
    - Top 30 from R2outscaled
  - Top 5 R2out aggregated Gulf-wide models
- Resulted in 54 top performing models going through MSY estimation for Brown Shrimp

Model Selection Summary

- Test robustness of top performing models' MSY estimates
  - Filter out unrealistic landings estimates (5 models left)
    - MSY >10x historical landings record
    - MSY at harvest rate U =1 (entire population)
  - Peel back 1:5 time steps and re-estimate MSY (2 models left)
    - If any iteration fails (MSY >10x OR U=1), drop from further consideration
    - Flag any retrospective bias and investigate/drop
- Select final model based on complexity, relative stability

Estimating MSY within EDM

- Maximum Sustainable Yield (MSY) within EDM is defined as the long-run average yield at optimal constant harvest rate
  - EDM captures naturally fluctuating sustainable state of the population
  - MSY is the average of these fluctuations and approximates a static benchmark for management

Fishery production model

$$B_{t+1} = B_t - C_t + P(B_t - C_t)$$

e.g., $P(x) = rx(1 - \frac{x}{k})$ for production function

B: biomass (lbs)
C: catch (lbs)
P: production (lbs)
I: abundance index (#/tow)
q: #/lbs/tow
u: exploitation rate (lbs/lbs)

$$I_t = qB_t$$

$$u_t = \frac{C_t}{B_t}$$

Re-write production model in terms of observables

$$qB_{t+1} = qB_t - qC_t + qP(B_t - C_t)$$

$$I_{t+1} = I_t - qC_t + qP[\frac{(I_t - qC_t)}{q}]$$

Now we have model linking index and catch
Note that $(I_t - qC_t)$ is proportional to surviving biomass $(B_t - C_t)$

Fishery EDM model

$$I_{t+1} = f(I_t - qC_t, I_{t-1} - qC_{t-1}, \ldots, I_{t-E} - qC_{t-E})$$

EDM uses $I_t - qC_t$ as proxy for surviving biomass as per fishery production model, but does not assume a known production function, such that the function *f* of time lags allows for unobserved state variables and species interactions

EDM-based MSY

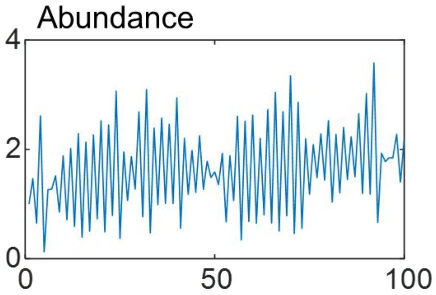
1. Let exploitation rate U_t a controlled variable ranged from zero to one
2. Initialize the history of index I_t and catch C_t and predict the next time step index I_{t+1} using the best-fitted parameters and function *f* iteratively
3. Find the long-run averaged index and catch at MSY given a particular range of exploitation rate

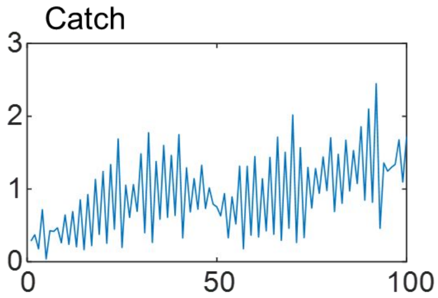
Tsai, C.-H., Munch, S.B., Masi, M.D. & Stevens, M.H. (2024). Empirical dynamic modeling for sustainable benchmarks of short-lived species. ICES Journal of Marine Science.

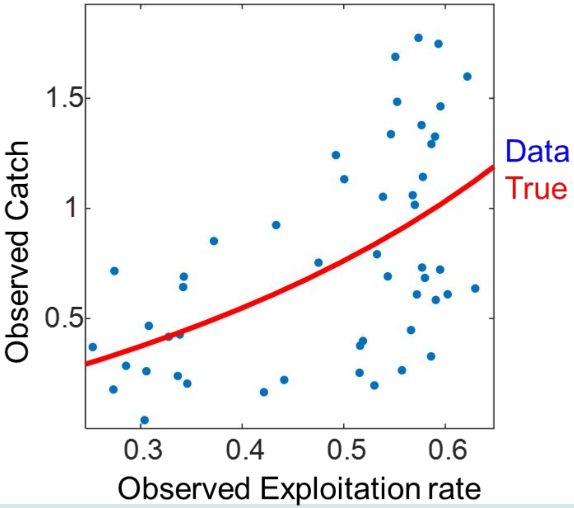
Maximum Sustainable Yield (MSY)

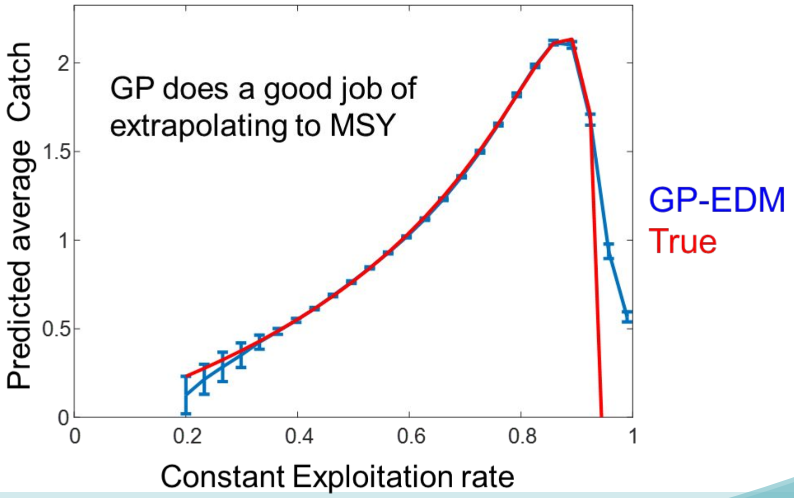
Proof of concept with simulated data

Use GP to estimate MSY









Definitions and Reference Points

- **Timestep: t** (year or year2 with seasonal steps)
- **Landings: Ct** (BSH/PSH: tailmp , WSH: tail10mp)
- **CPUE: Xt** (SEAMAP: shrimp/hr , LDWF: shrimp/10min)
- **Catchability: q** (SEAMAP: CPUE/tailmp , LDWF: CPUE/tail10mp)
- **Harvest rate: U** (Ut = Ct*q / CPUEt ⟶ unitless, 0:1)
- **Fishing mortality rate: F** (Ft = -ln(1-Ut))
- **MSY:** max(C=F*CPUE/q) over range of U 0:1
- **FMSY:** rate F where C=MSY
- **BMSY:** Biomass CPUE ; translated to units of C (where C=MSY) using CPUE/q

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Definitions and Reference Points

- Models were configured with ***t*** annual or ***p*** seasonal time steps in a year, but all reference points are presented annually
- **Landings: Ct**
  - Ct = p * Ct/p , where p=2 would require doubling the seasonal landings to obtain an annual estimate
- **Harvest rate: Ut**
  - Ut = 1 - (1-Ut/p)^p , where the seasonal harvest rate 0:1 is adjusted to the rate over an annual scale 0:1

Benefits of MSY Estimation with EDM

- No need to specify production function
- Acknowledges potential shifts in productivity through time
  - Populations that exhibit non-equilibrium dynamics and nonlinear state-dependent behavior (i.e. where interactions change over time and as a function of the system state)
- Long-run average is something we can project; doesn't matter where we start on the attractor, we get the right average

Building EDM

- Goal: Capture reality using the simplest model with the most accurate projection capability (e.g. out of sample prediction)
- Aggregate where appropriate while still capturing stock dynamics

Stratification of Brown Shrimp Data

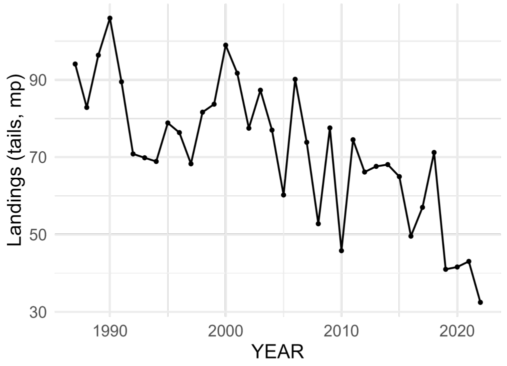
A. **Aggregated:** ANNUAL ; SIZE BINS AGG ; AREA AGG (11:21)
B. **Area:** ANNUAL ; SIZE BINS AGG ; AREA (11:17, 18:21)
C. **Size:** ANNUAL ; SIZE BINS (>67, 67-31, <=30) ; AREA AGG (11:21)
Csm. **Size2:** ANNUAL ; SIZE BINS (>31, <=30) ; AREA AGG (11:21)
D. **Size_Area:** ANNUAL ; SIZE BINS (>67, 67-31, <=30) ; AREA (11:17, 18:21)
Dsm. **Size2_Area:** ANNUAL ; SIZE BINS (>31, <=30) ; AREA (11:17, 18:21)
E. **Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS AGG ; AREA AGG (11:21)
F. **Area_Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS AGG ; AREA (11:17, 18:21)
G. **Size_Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS (>67, 67-31, <=30) ; AREA AGG (11:21)
Gsm. **Size2_Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS (>31, <=30) ; AREA AGG (11:21)
H. **Size_Area_Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS (>67, 67-31, <=30) ; AREA (11:17, 18:21)
Hsm. **Size2_Area_Season:** SEASONAL (SUMMER, FALL+WINTER) ; SIZE BINS (>31, <=30) ; AREA (11:17, 18:21)

Brown Shrimp EDM Construction

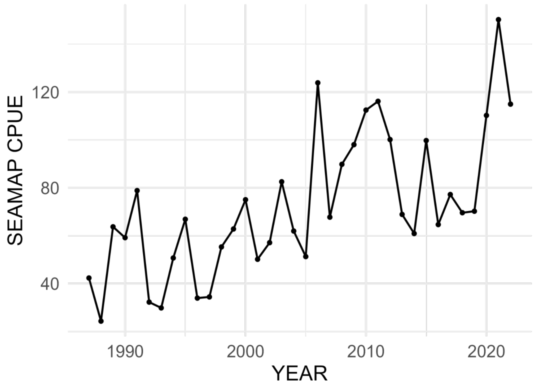
- Brown shrimp
  - SEAMAP, 1987-2022, Fall/Summer
    - Summer estimates what's recruited to the population, Fall is what's left after fishing
  - Embedding dimension E is m+1 (or m+z+1)
    - $E \leq \sqrt{T}$, where T=36, $E \leq 6$ (up to 5 lags, or 3 lags and 2 covariates, etc) for annual model
    - Previous publications use a lag of 4

Brown Shrimp

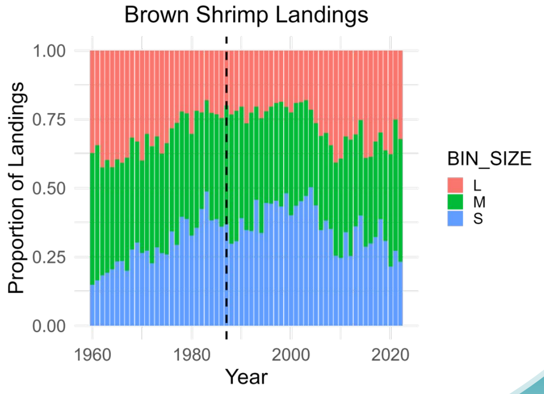
Landings



CPUE



- Model structure options
  - Annual (shown here)
  - Individual models
  - Hierarchical to share information and parameters

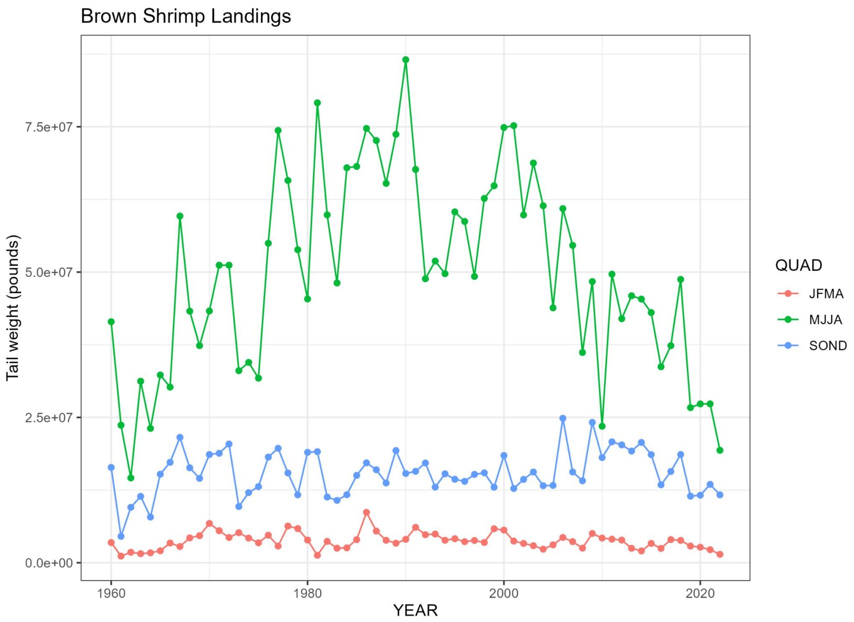


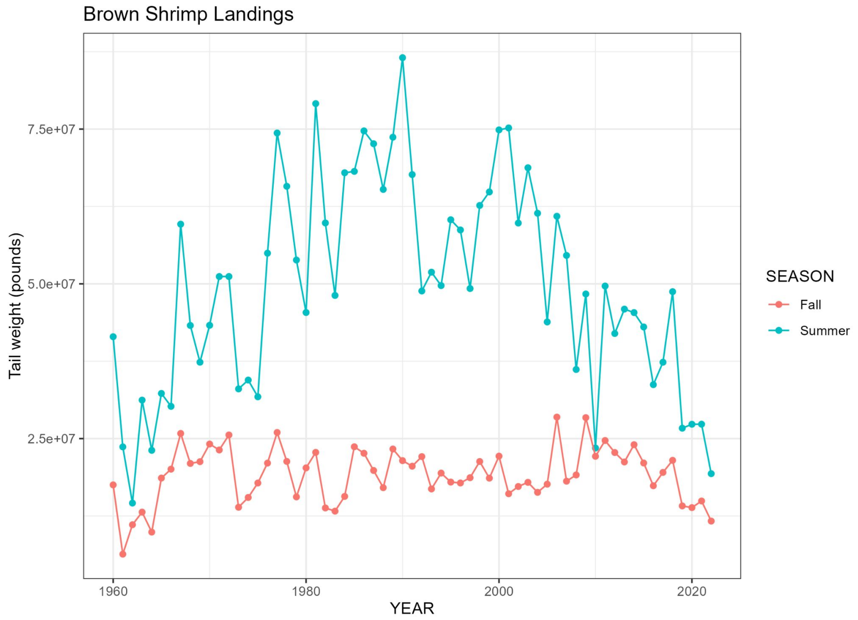
 U.S. Department of Commerce | National Oceanic and Atmospheric Administration | National Marine Fisheries Service

Accounting for All Landings

- SEAMAP survey operates in the Summer and Fall, but Winter landings need to be modeled as well
- Winter Brown Shrimp landings have remained low and stable through time
- Aggregated Winter (JFMA) landings with the previous year's Fall (SOND) landings

Aggregate Landings for 2 Season Model





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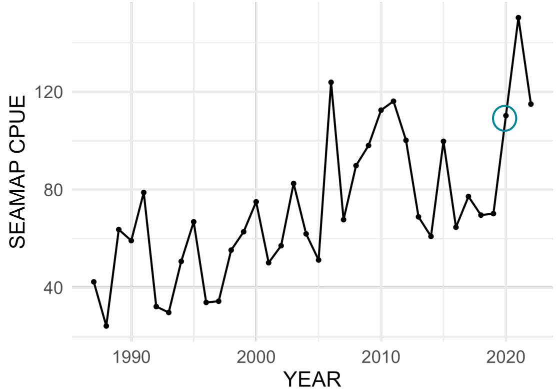
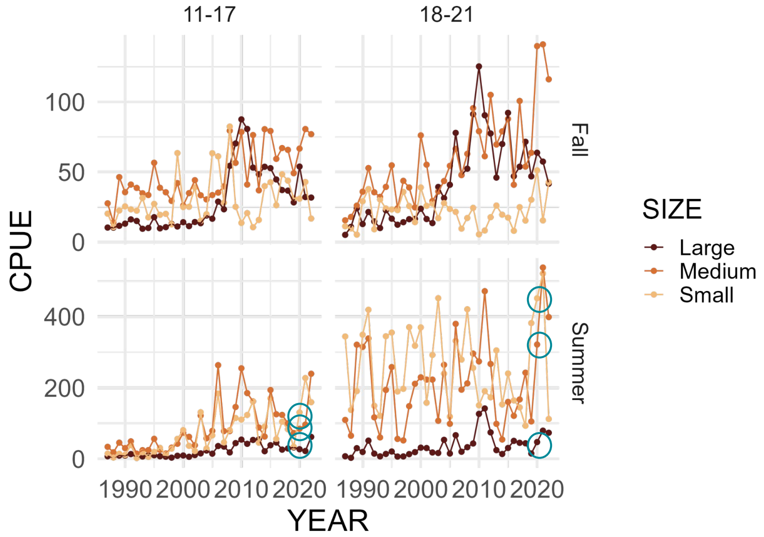
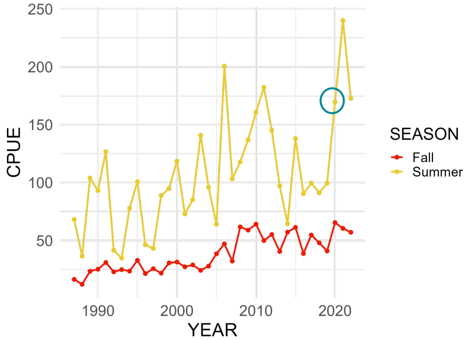
Missing raw survey data

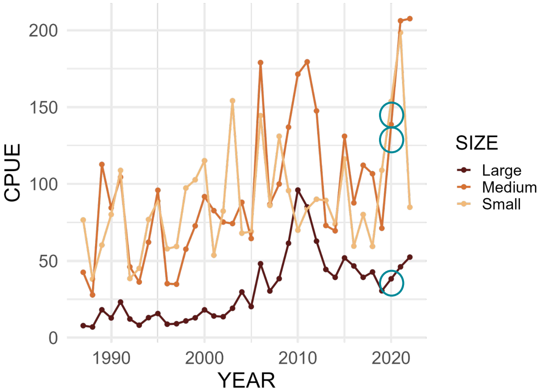
- SEAMAP survey did not operate in Summer 2020
- If data are missing, model can't estimate 2020:2020+m lags (e.g. model would essentially be truncated to 2019)
    - Some options with EDM variable time steps, but not worth doubling embedding dimension for one year
- Averaged index 2019-2021 to fill in Summer 2020 and used full data set for model selection

Averaged index for Summer 2020



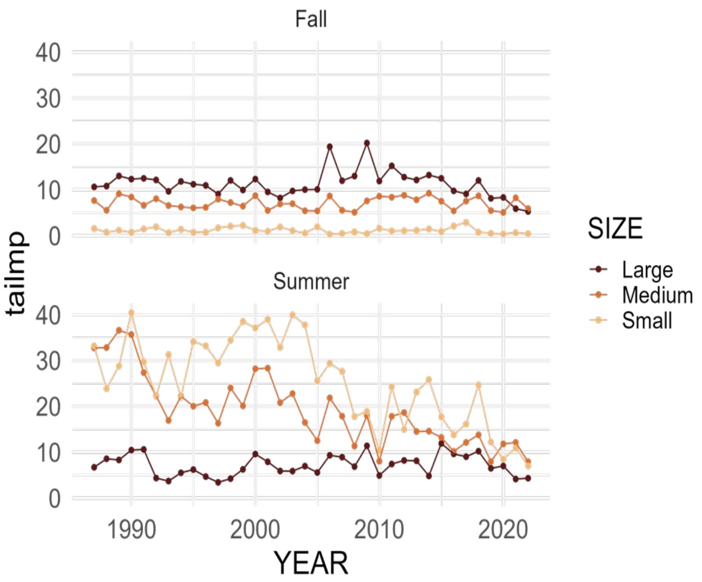




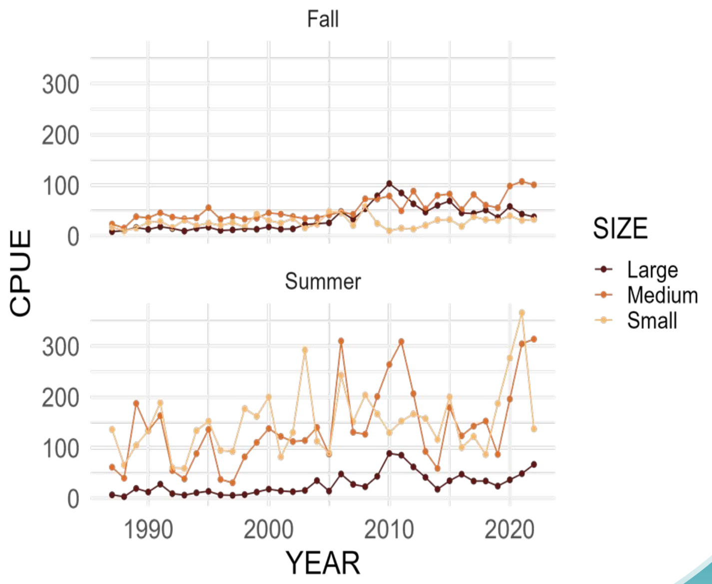


Landings and CPUE stratified by Season and Size Class

Landings



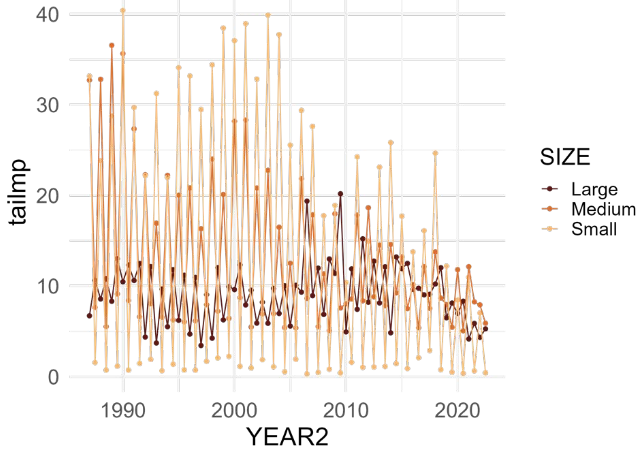
CPUE



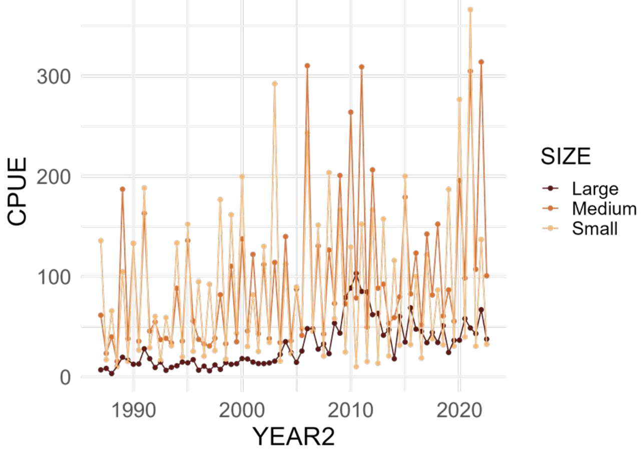
- Visualizes annual trends within season

Seasonally Oscillating Landings and CPUE stratified by Size Class

Landings

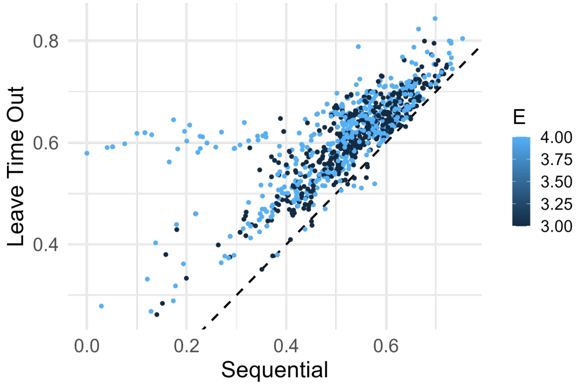


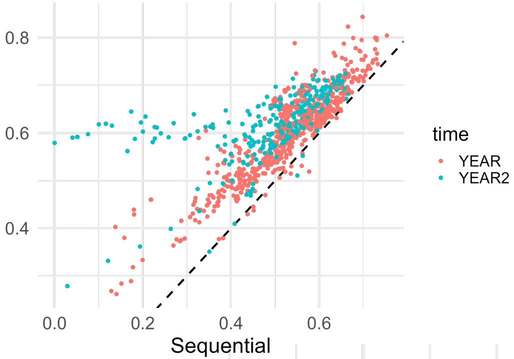
CPUE



- Visualizes the full variability in the system
- Real time fluctuations by size class

R2 Out of Sample Fit Statistics

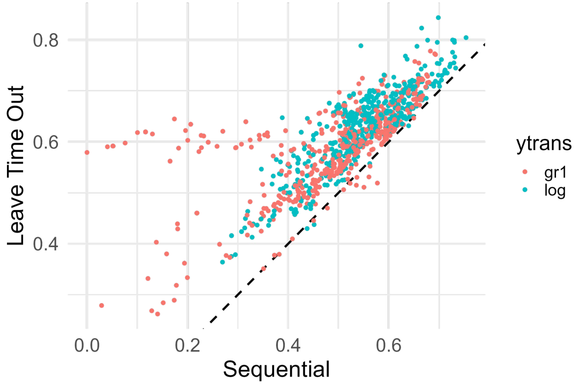


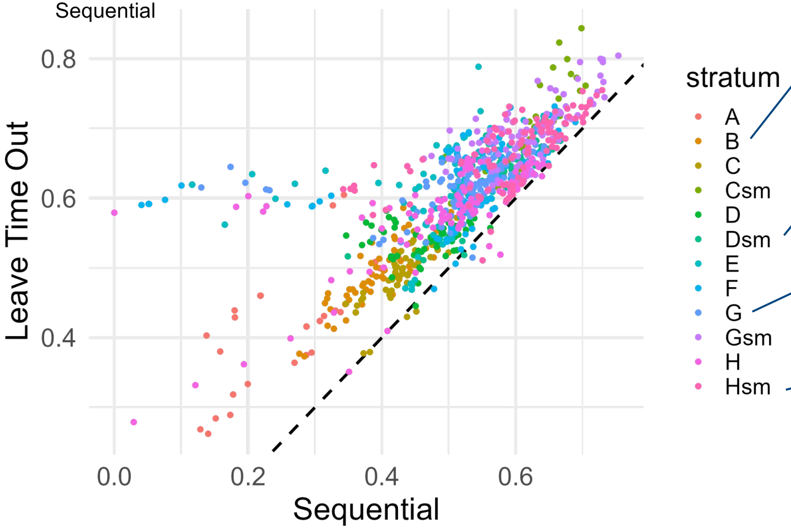


Model Training Dataset

Leave Time Out: Excludes random time points for all populations

Sequential: Peels back time (can indicate prediction accuracy better)





A. **Aggregated**
B. **Area**
C. **Size**
Csm. **Size2**
D. **Size_Area**
Dsm. **Size2_Area**
E. **Season**
F. **Area_Season**
G. **Size_Season**
Gsm. **Size2_Season**
H. **Size_Area_Season**
Hsm. **Size2_Area_Season**

Top Performing Model Runs

Run	Time	Stratum	Pop	E	rho	R2	R2_out	R2_outscaled	ProcessVar	PriorVar
BSH_G21023	Seasonal	Gsm	SIZE	5	0.67	0.825	0.628	0.511	0.072	0.637
BSH_G10435	Seasonal	Gsm	SIZE	4	0.51	0.918	0.714	0.503	0.189	1.457
BSH_G21031	Seasonal	Gsm	SIZE	5	0.49	0.917	0.706	0.497	0.189	1.478
BSH_G20047	Seasonal	G	SIZE	5	0.96	0.684	0.427	0.416	0.252	0.813
BSH_G10323	Seasonal	Gsm	SIZE	4	0.77	0.797	0.55	0.409	0.086	0.81
BSH_G10890	Annual	Gsm	SEAS_SIZE	4	0.94	0.913	0.808	0.389	0.382	0.698
BSH_G20023	Seasonal	G	SIZE	5	0.96	0.729	0.485	0.364	0.103	0.689
BSH_G10442	Annual	Gsm	SEAS_SIZE	4	0.93	0.903	0.8	0.359	0.412	0.696
BSH_G21040	Annual	Gsm	SEAS_SIZE	5	0.96	0.888	0.786	0.347	0.346	0.632
BSH_G10876	Annual	Gsm	SEAS_SIZE	3	0.95	0.858	0.783	0.342	0.456	0.654
BSH_G21016	Annual	Gsm	SEAS_SIZE	5	0.96	0.861	0.729	0.336	0.602	0.582
BSH_G10554	Annual	Gsm	SEAS_SIZE	4	0.96	0.896	0.791	0.332	0.352	0.624
BSH_G21008	Annual	Gsm	SEAS_SIZE	5	0.95	0.886	0.782	0.318	0.369	0.705
BSH_G10428	Annual	Gsm	SEAS_SIZE	3	0.95	0.831	0.768	0.302	0.493	0.679
BSH_G10106	Annual	Gsm	SEAS_SIZE	4	0.95	0.892	0.785	0.3	0.37	0.631
BSH_G21064	Annual	Gsm	SEAS_SIZE	5	0.87	1	0.771	0.29	0.019	1.335
BSH_G10540	Annual	Gsm	SEAS_SIZE	3	0.93	0.83	0.752	0.278	0.429	0.513
BSH_G21024	Annual	Gsm	SEAS_SIZE	5	0.95	0.874	0.74	0.27	0.378	0.611
BSH_G21032	Annual	Gsm	SEAS_SIZE	5	0.87	1	0.775	0.194	0.017	1.15
BSH_G10092	Annual	Gsm	SEAS_SIZE	3	0.77	0.863	0.732	0.123	0.387	0.701

Filtered by Strata G

20 out of top 54 models

Seasonal Models

- G. Size
- Gsm. Size

Annual Models

- G. Size_Season
- Gsm. Size_Season

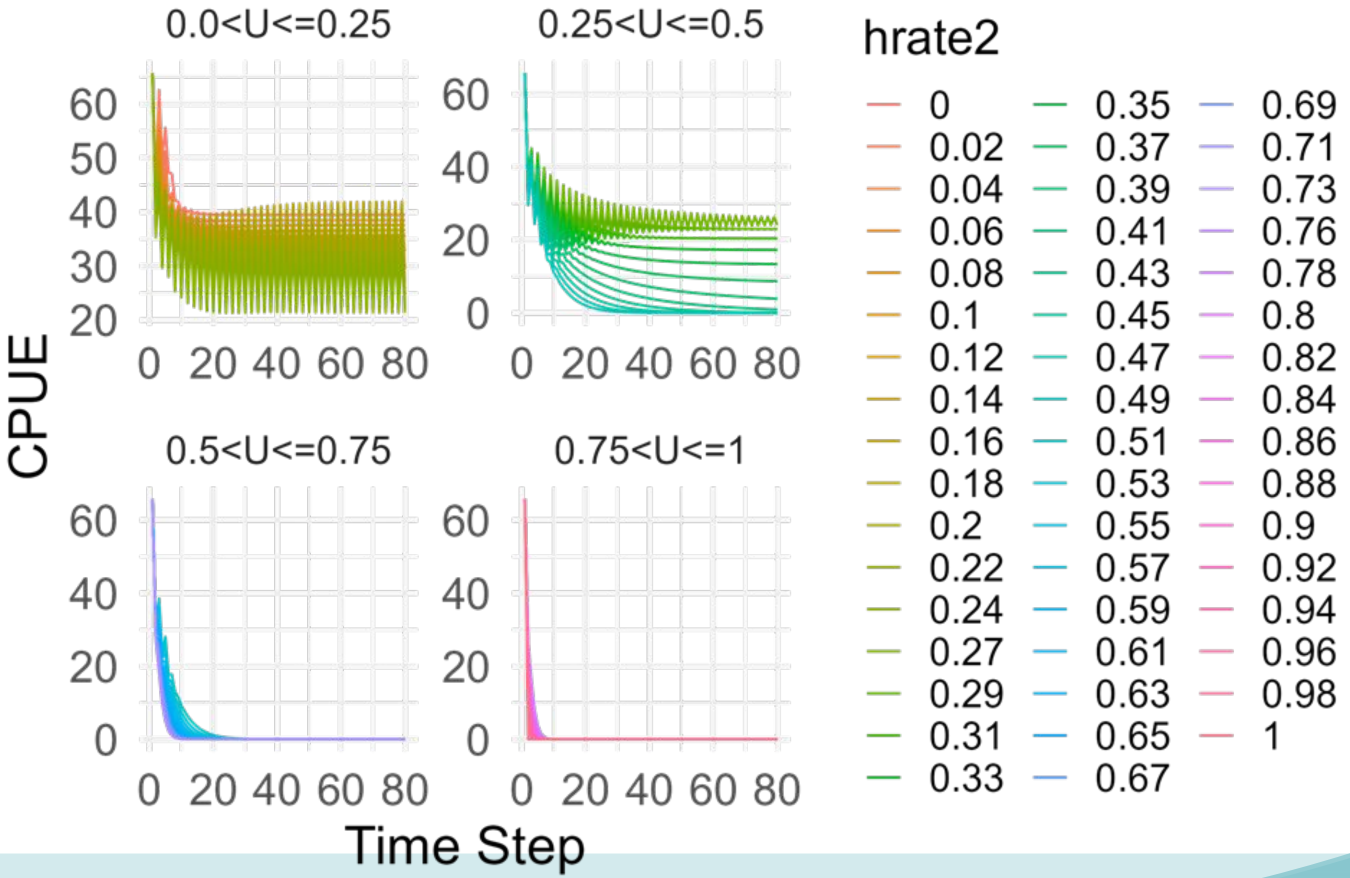
Top 2 Model Runs boxed (e.g. passed MSY checks)

BROWN SHRIMP EDM
Maximum Sustainable Yield

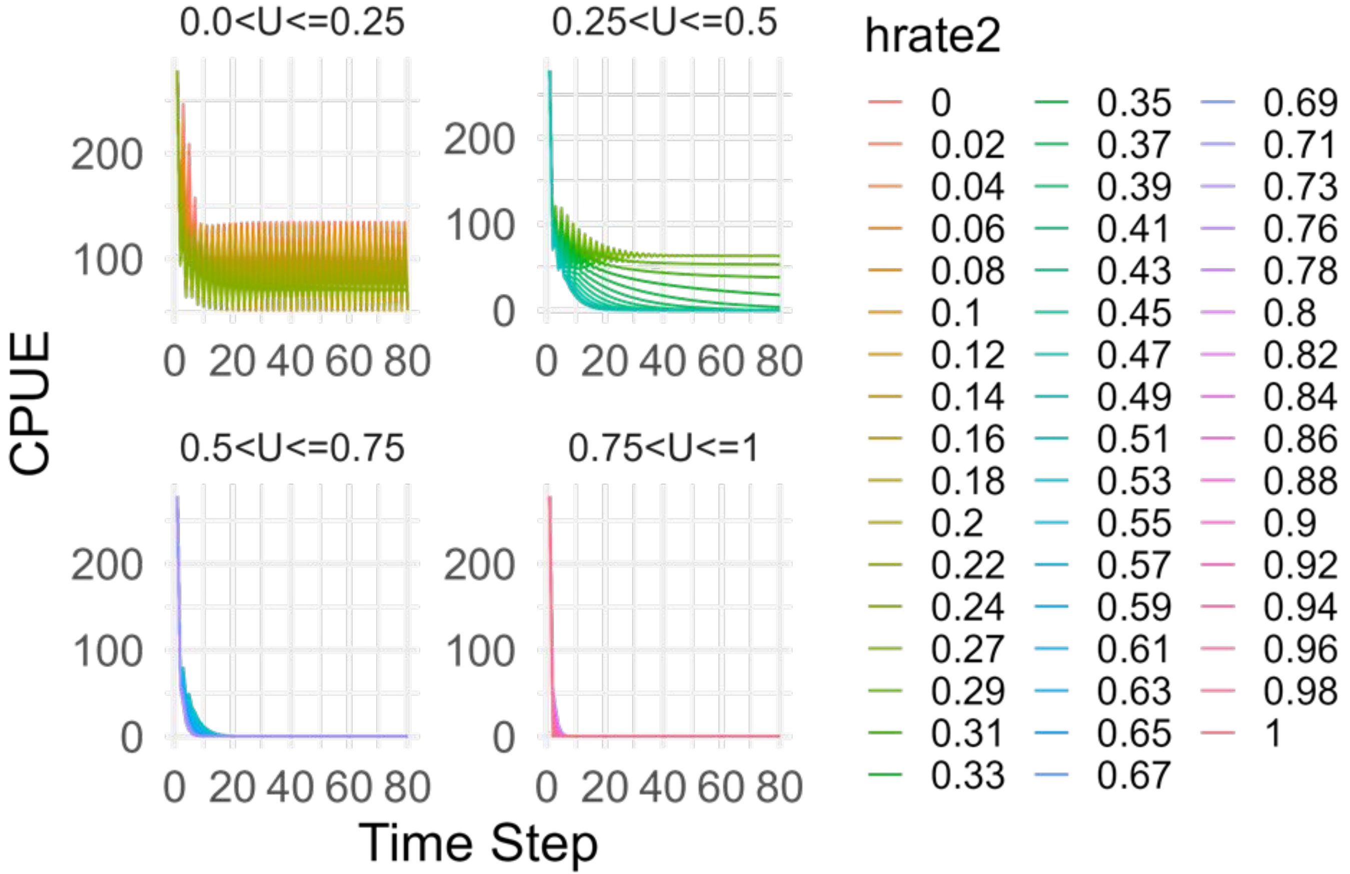
Top Performing Models for MSY

- **Size-structured** (Large, Medium, Small), shared catchability, **seasonal** time steps, E=5, *y* transformation **gr2** ($\log(y_t/(y_{t-1} - qC_{t-1}))$) [G20023]
- **Size-structured** (Large, Smedium), shared catchability, **seasonal** time steps, E=4, *y* transformation **gr2** ($\log(y_t/(y_{t-1} - qC_{t-1}))$) [G10323]
- Both models have seasonal time steps and could allow for more timely management advice (e.g. can predict Fall using Summer inputs)

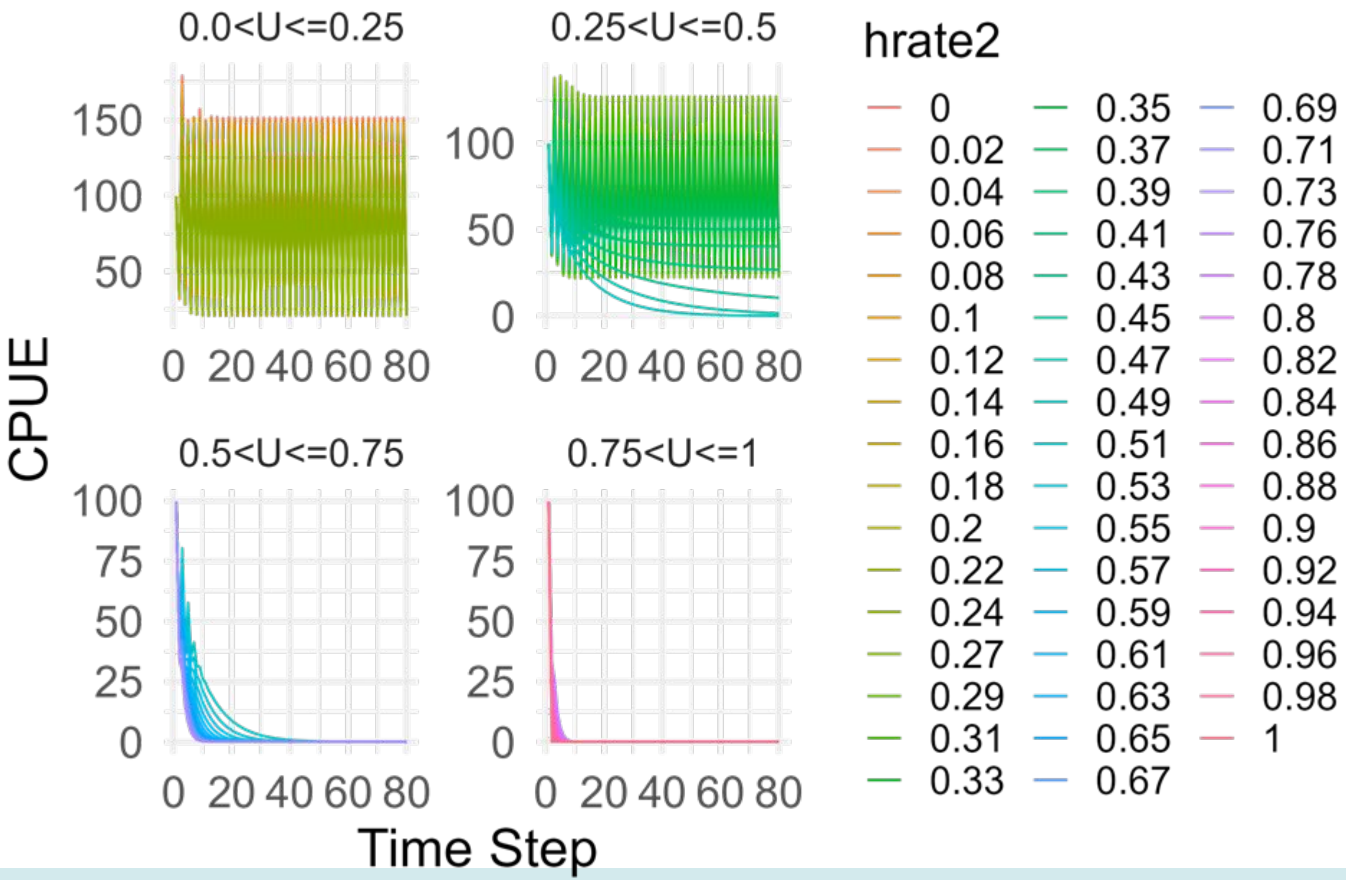
BSH_G20023 Large Projections



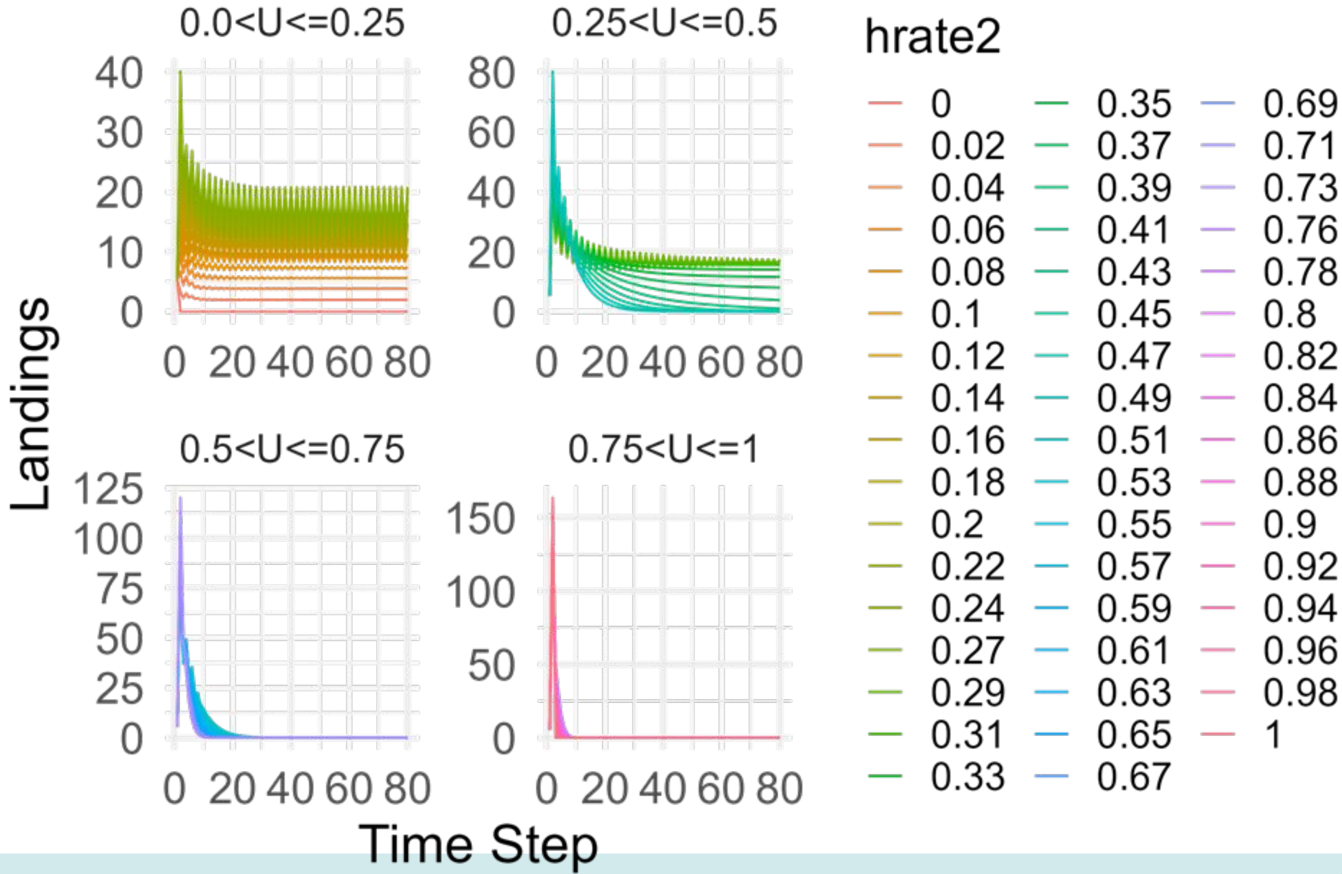
BSH_G20023 Medium Projections



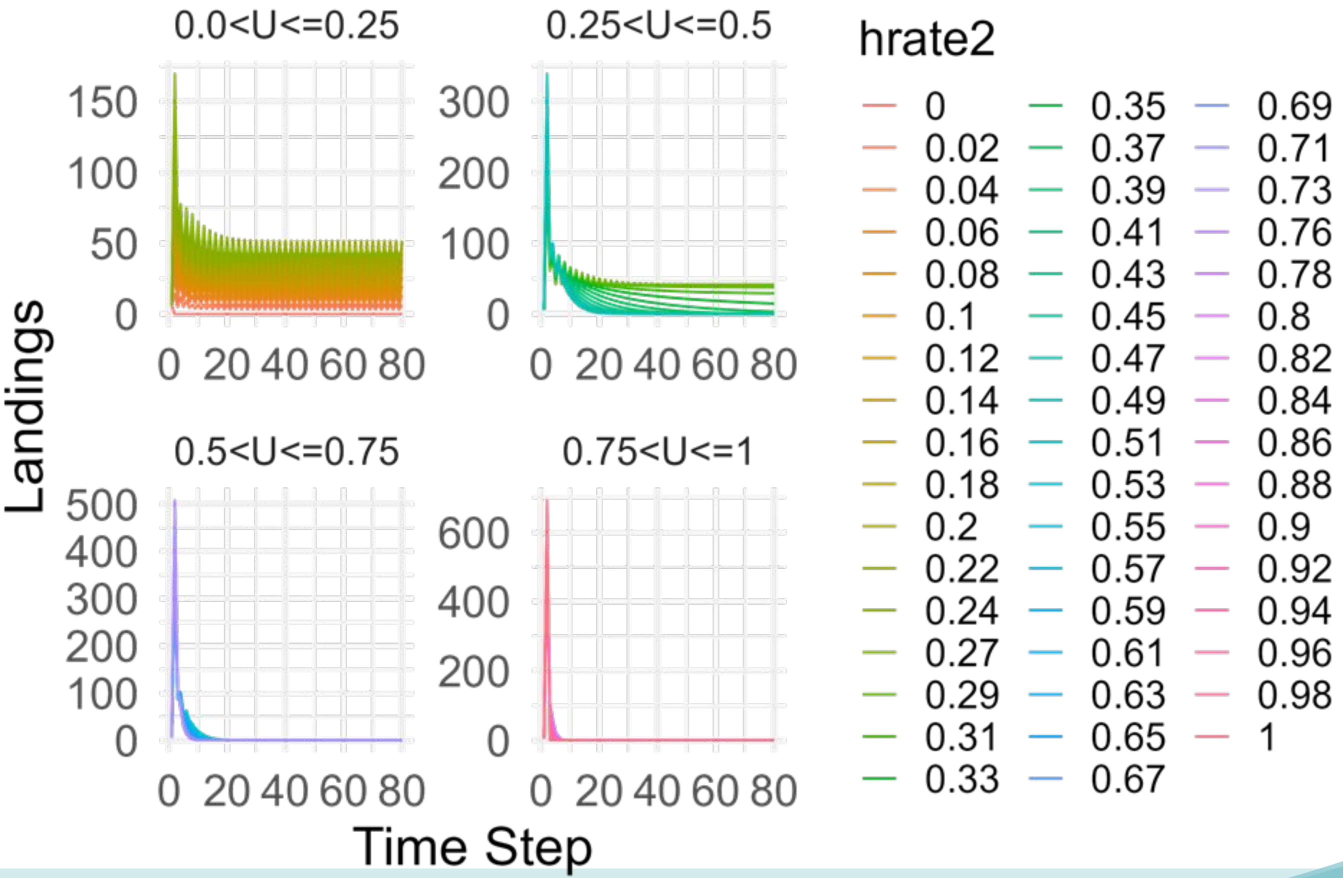
BSH_G20023 Small Projections



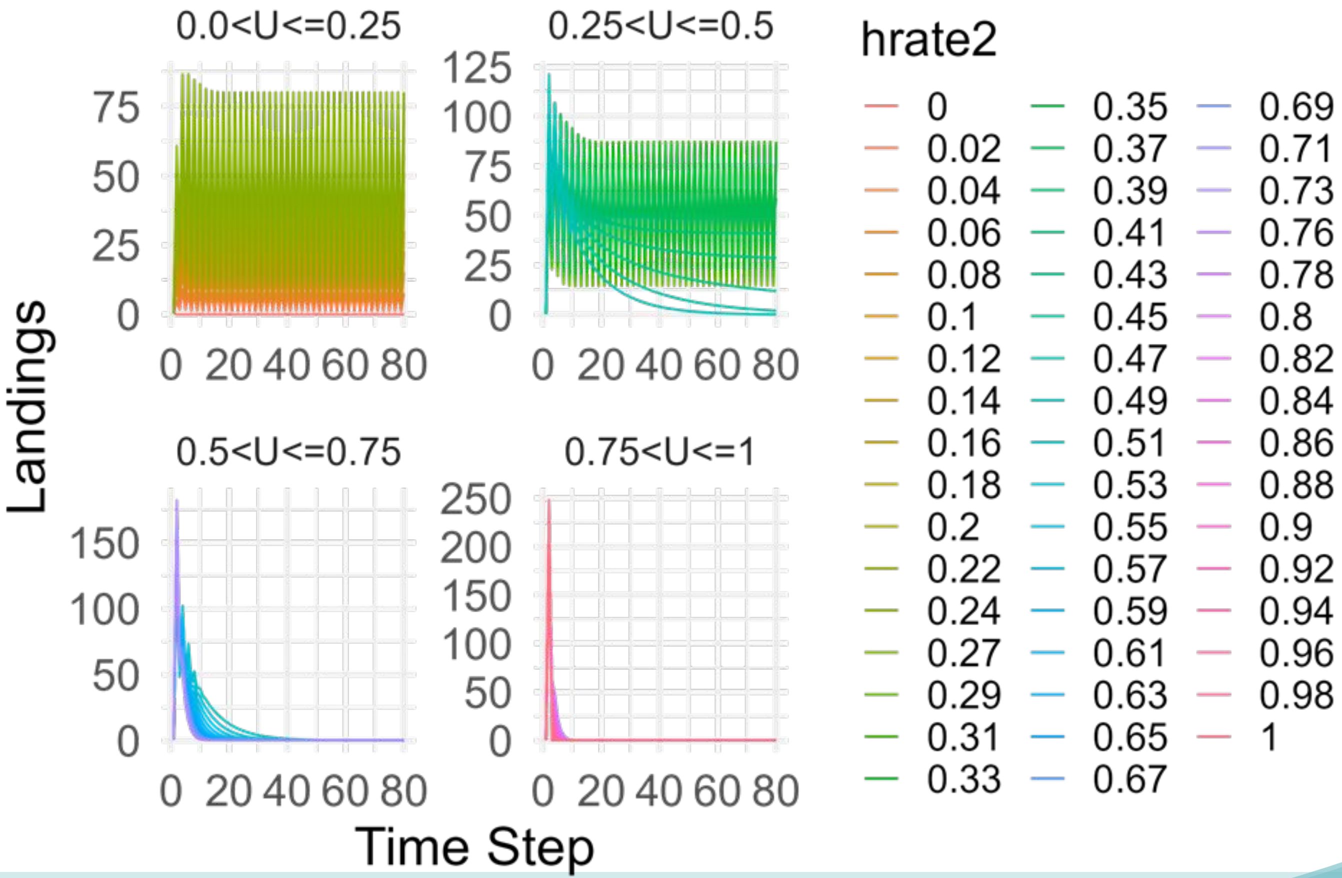
BSH_G20023 Large Projections

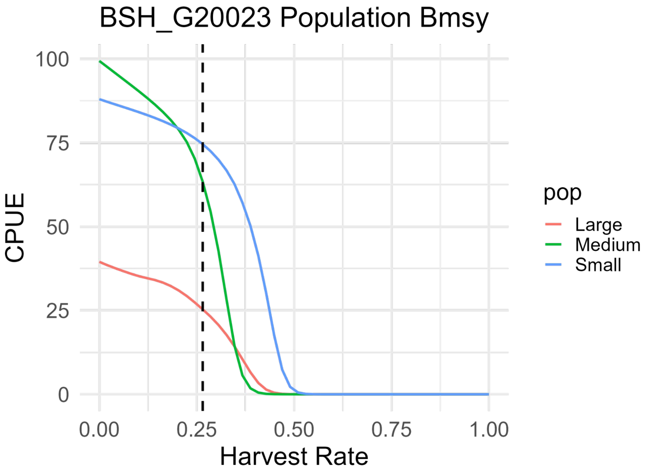


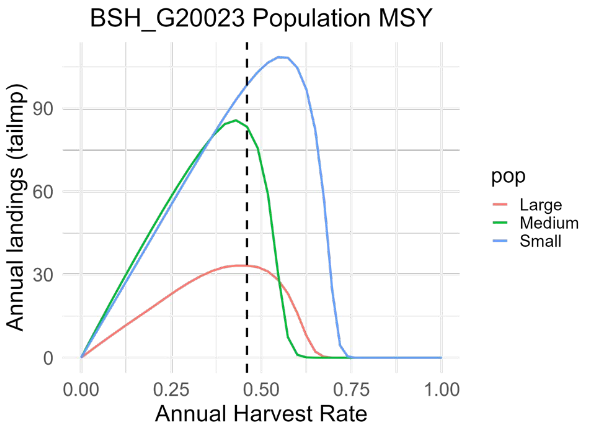
BSH_G20023 Medium Projections

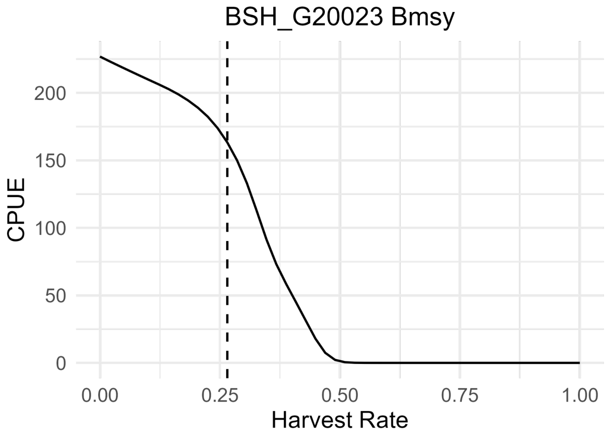


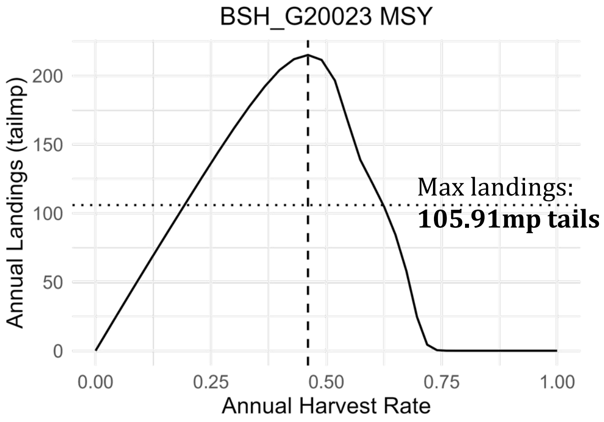
BSH_G20023 Small Projections







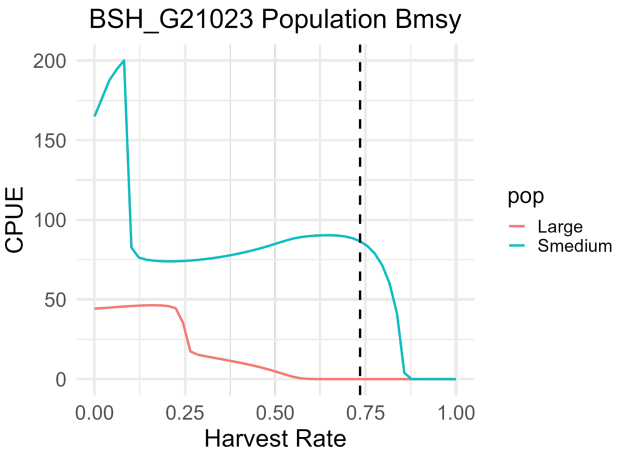


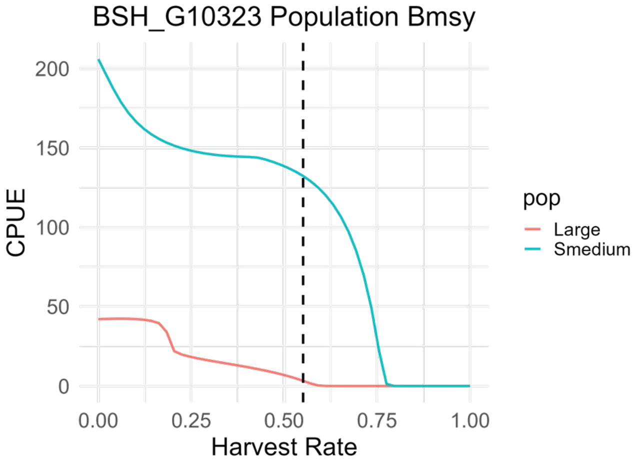


MSY is added across populations

Statistic	BSH_G20023
MSY_mptails	215.069
Fmsy	0.617
Umsy_annual	0.460
Umsy_seasonal	0.265
Bmsy_mp	405.394
df	28.529
R2	0.729
R2Scaled	0.700
R2_outsample	0.485
R2Scaled_outsample	0.364

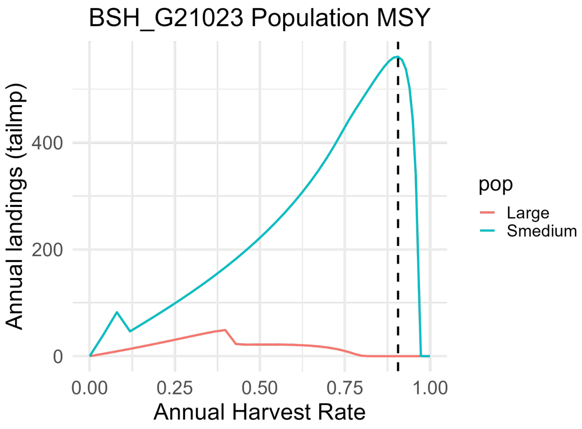
Max landings throughout time series were observed in 1990: **105.91mp tails**

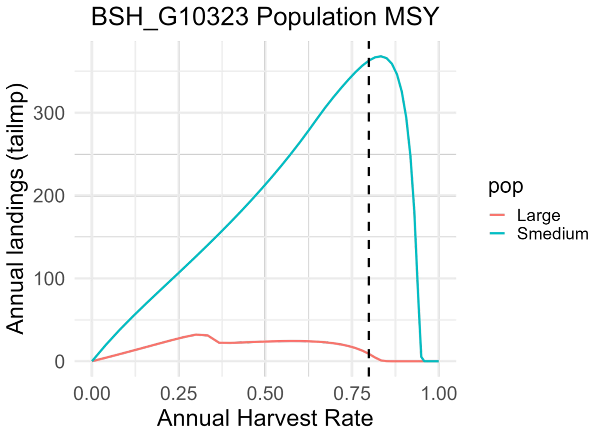




MSY is added across populations

MSY for Smedium is observed at a harvest rate where no Large shrimp are left





Max landings throughout time series were observed in 1990: **105.91mp tails**

Model Diagnostics: Peel back years

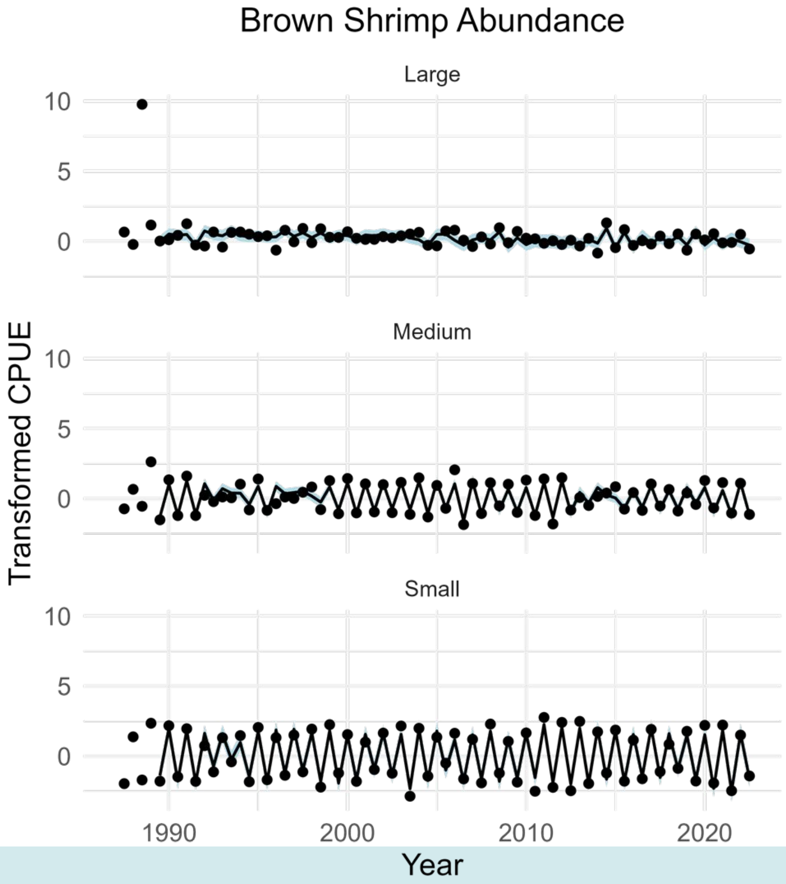
Run	MSY	BMSY_mp	MSY_factor
BSH_G20023_0	215.07	405.39	2.03
BSH_G20023_1	217.66	410.20	2.06
BSH_G20023_2	219.29	383.76	2.07
BSH_G20023_3	233.54	357.61	2.21
BSH_G20023_4	228.08	349.24	2.15
BSH_G20023_5	232.40	379.59	2.19

Top line is MSY estimate from terminal year 2022

_1 means 1yr peeled back (e.g. data through 2021) and so forth

Stable model with no apparent retrospective bias

Size-structured (Large, Medium, Small), shared catchability, seasonal time steps, E=5, ytransformation gr2 ($\log(y_t/(y_{t-1} - qC_{t-1}))$) [G20023]



Population	SIZE
Lags	5
R2	0.729
R2_out	0.485
R2_outscaled	0.365
R2pop_out_Large	0.345
R2pop_out_Medium	0.331
R2pop_out_Small	0.415
df	28.529
Catchability, q	0.402
Dynamic correlation, ρ	0.957
Pointwise Prior Variance	0.689
Process Variance	0.103

BROWN SHRIMP EDM SUMMARY

- Size structured model (Large, Medium, Small), shared catchability, seasonal time steps, E=5, y transformation gr2 ($\log(y_t/(y_{t-1} - qC_{t-1}))$) [G20023]
- Robust model that captures brown shrimp dynamics
- Provides stable estimates of maximum sustainable yield
  - MSY: 215.07 million pounds of tails
  - F_{MSY}: 0.617 B_{MSY}: 405.39 million pounds of tails
  - F_{2022}: 0.018 B_{2022}: 1,716.53 million pounds of tails
  - F_{2022}/F_{MSY}: 0.029 B_{2022}/B_{MSY}: 4.23

BROWN SHRIMP CONCLUSIONS

- EDM particularly suitable for populations that exhibit non-equilibrium dynamics and nonlinear state-dependent behavior
- JABBA relies on very rigid SPM assumptions about stock and fishery dynamics that likely do not hold true for shrimp.
- EDM models performed very well and had high levels of prediction accuracy, therefore we recommend that EDM be used for providing management advice.

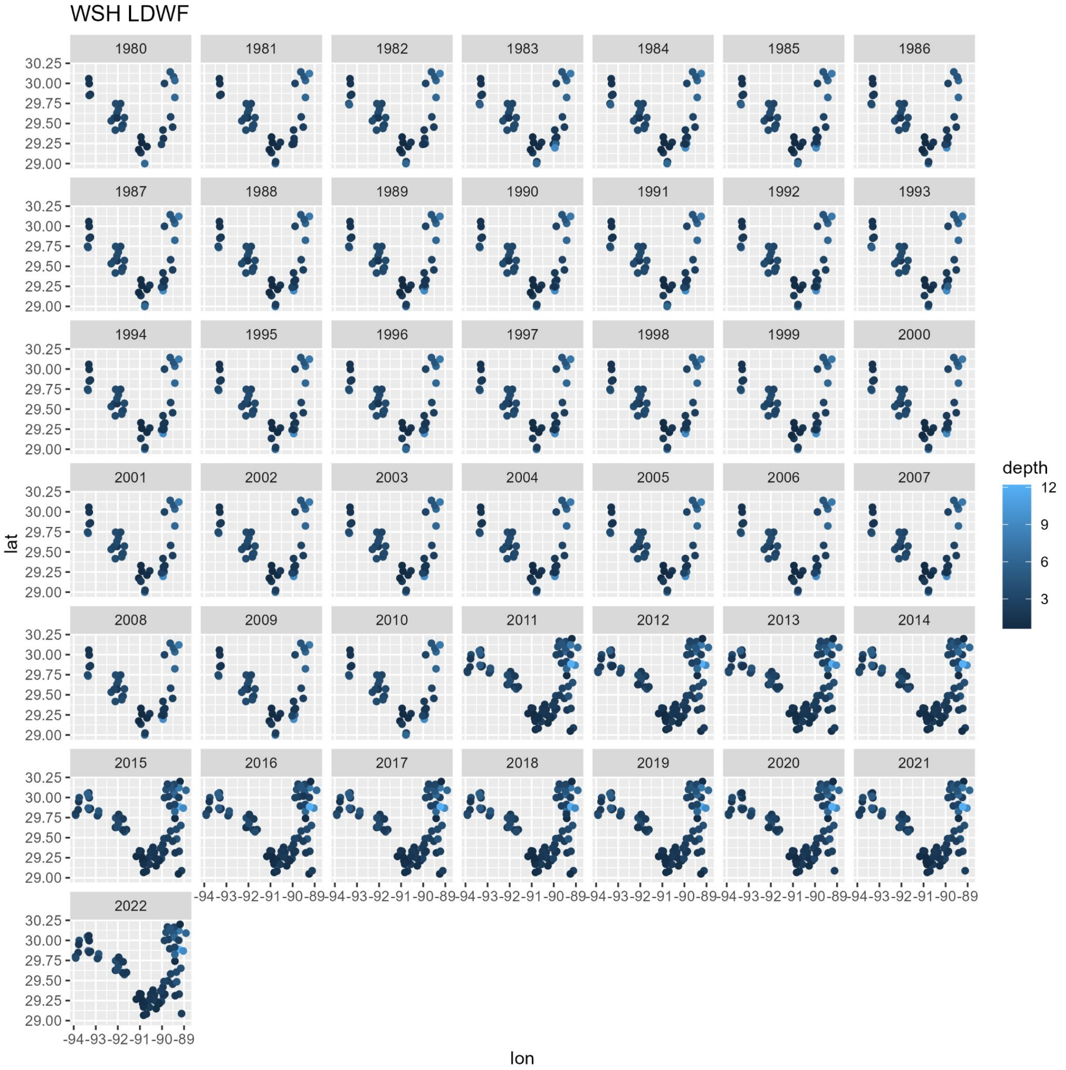
WHITE SHRIMP

NOAA FISHERIES

VAST index

VAST - Motivation

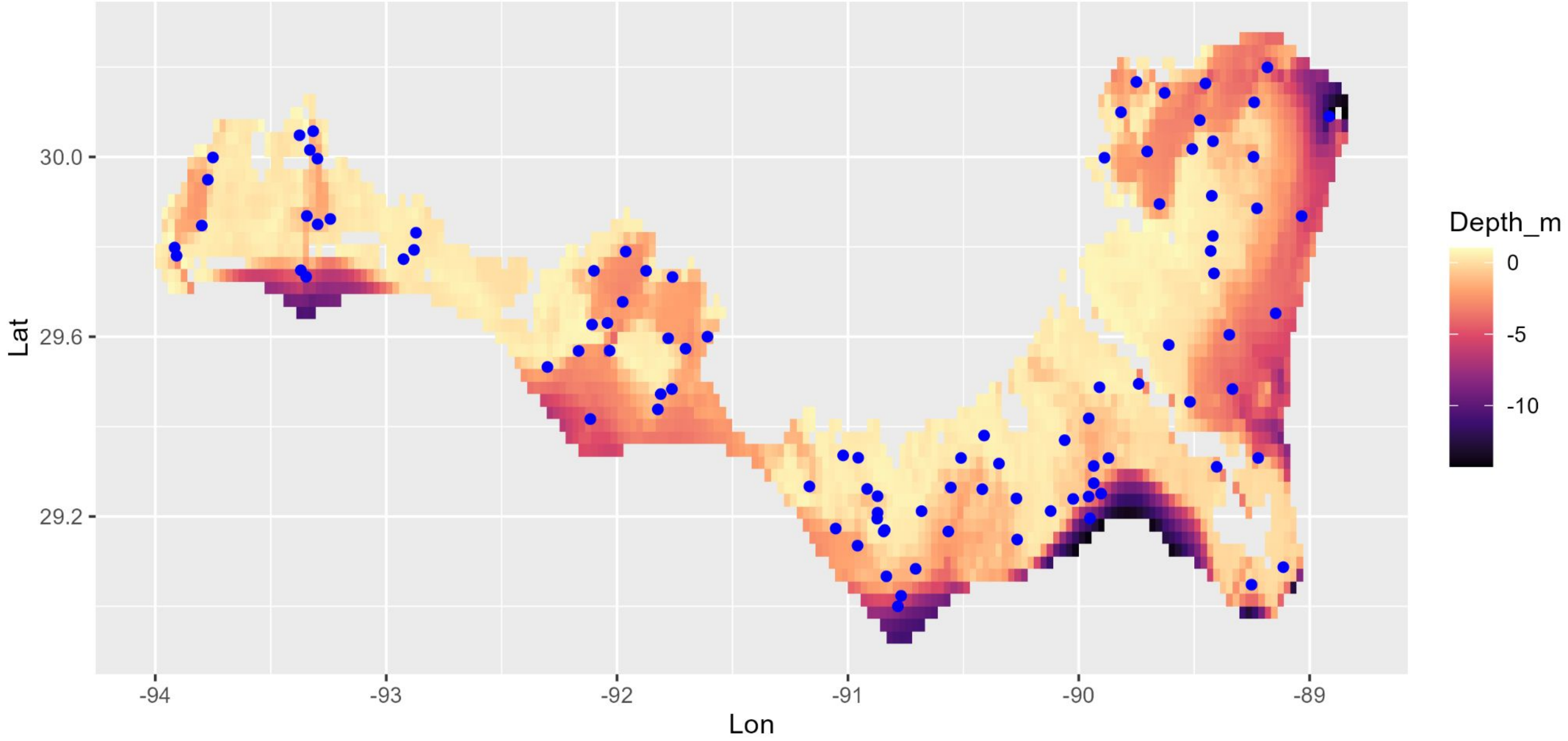
- Develop an index of relative abundance that can control for some of the survey's early changes in spatial footprint
- Testing impact of Nursery Conditions



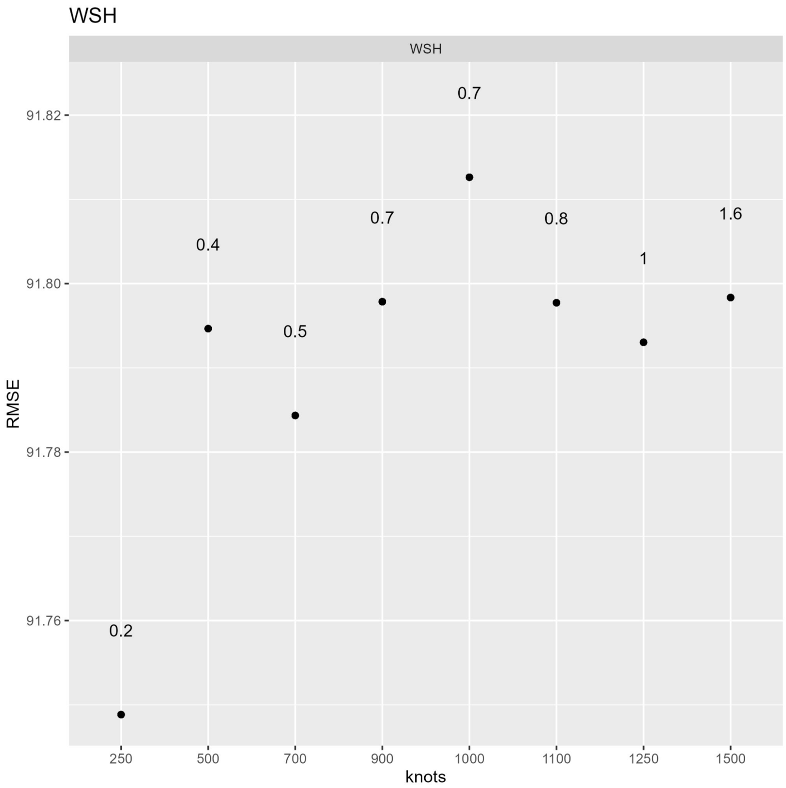
VAST

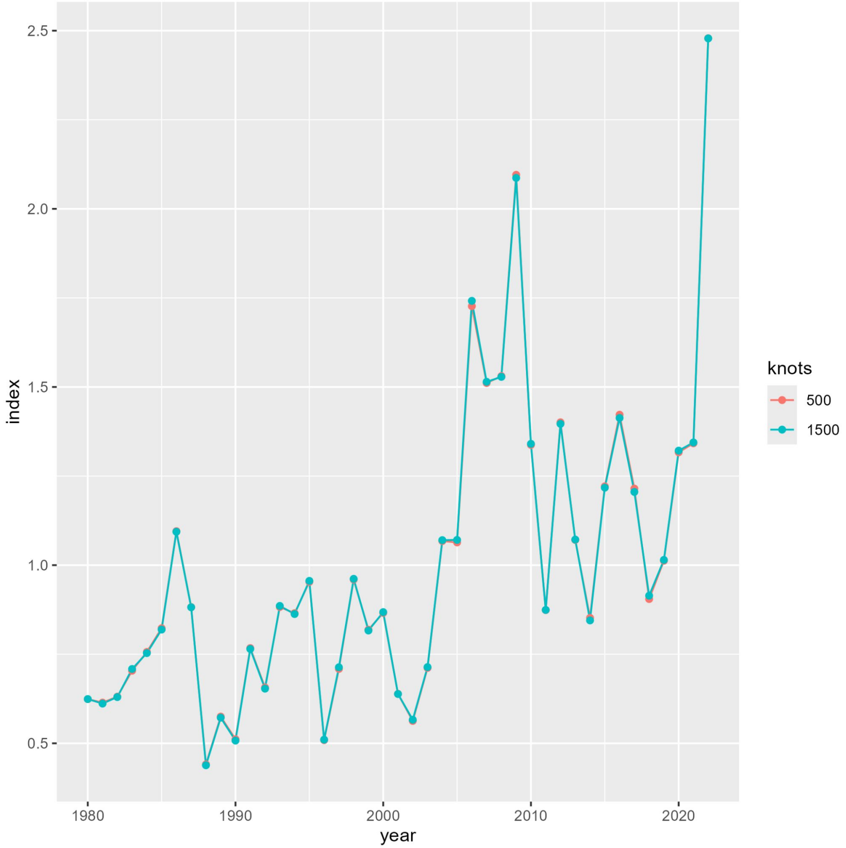
	WSH
Survey(s)	LDWF (Jan-Dec)
Years	1980-2022
Area	Coastal LA
Catchability covariates	Month
Density covariates	Median annual nursery temperature & salinity (+ 1 to 2 year lags)

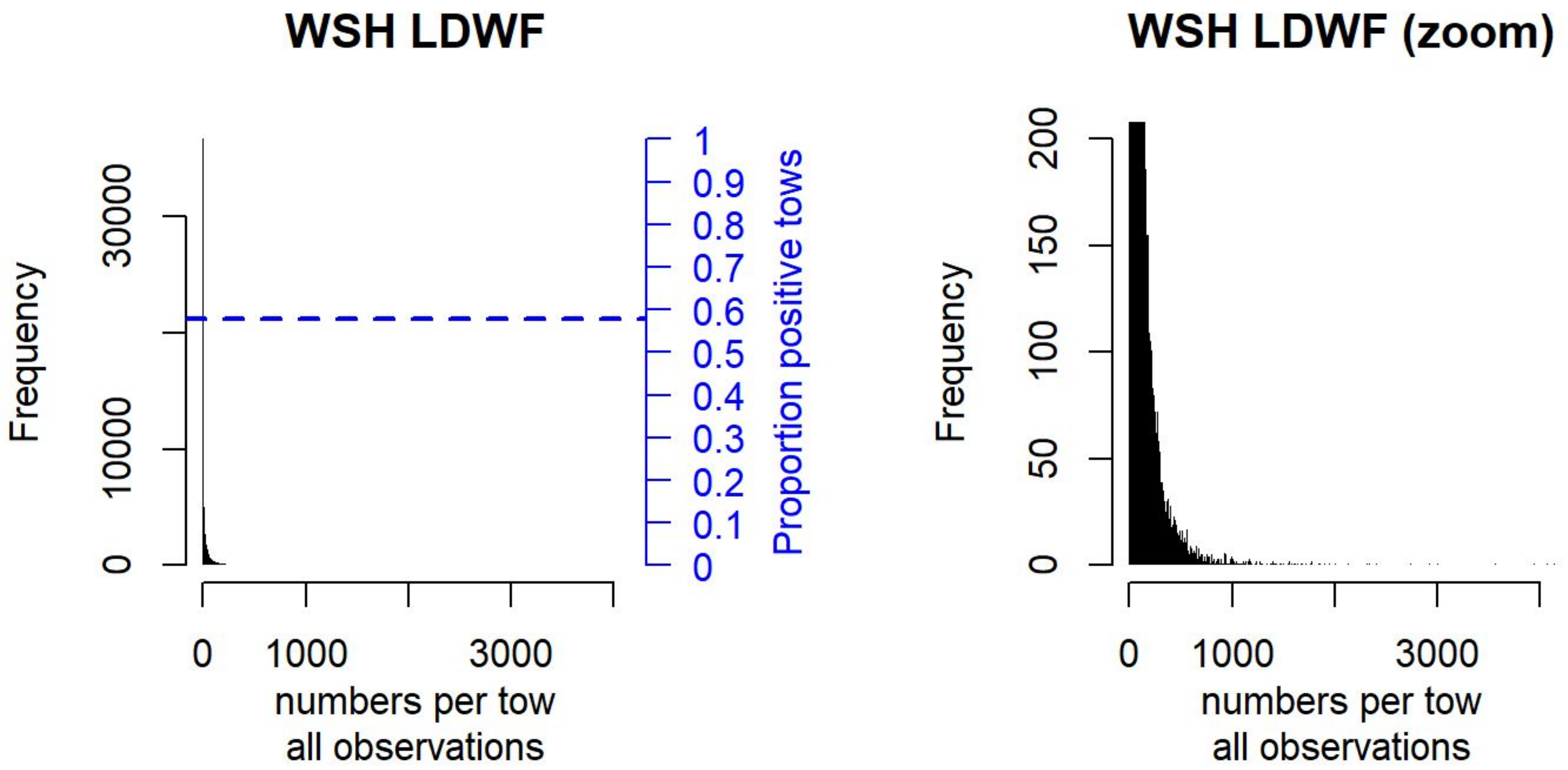
Data preprocessing - Prediction grids



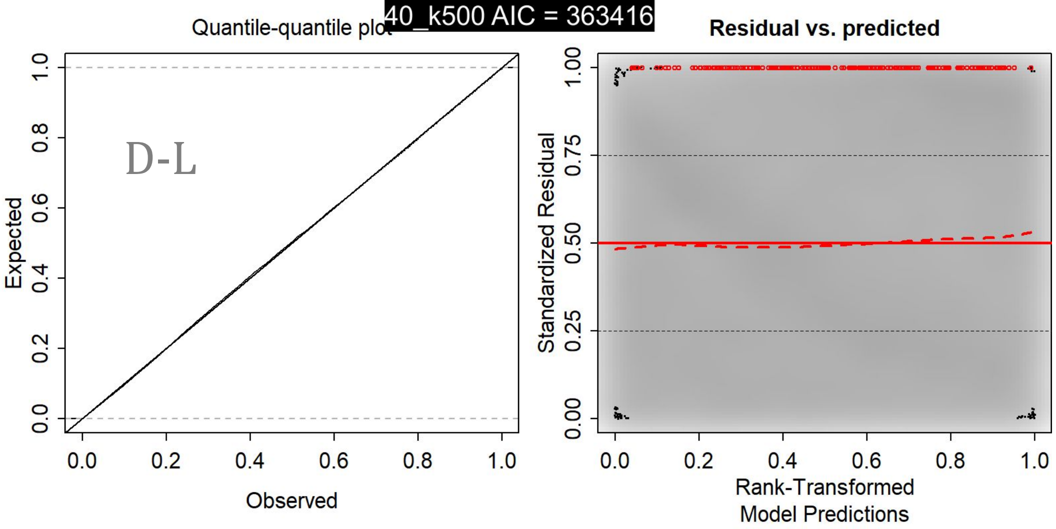
Knots

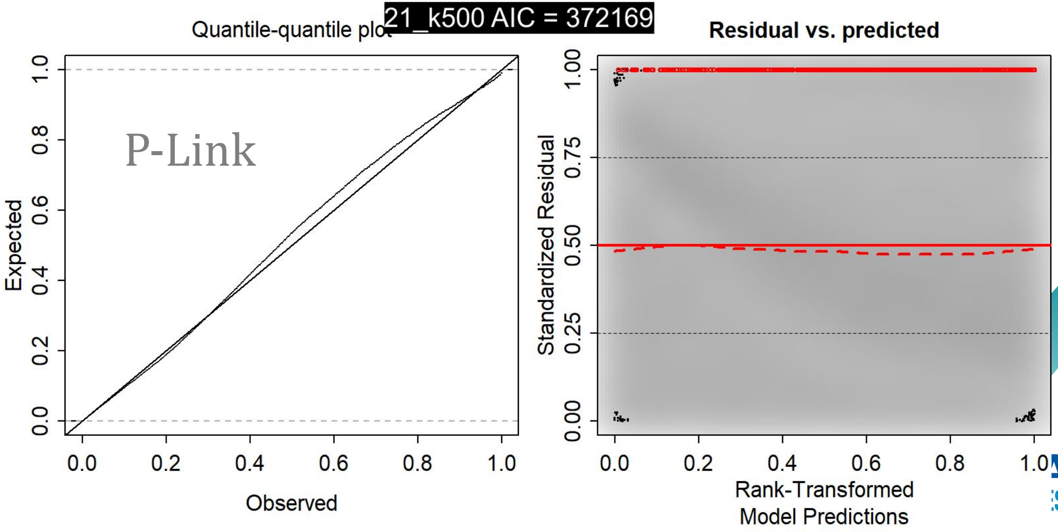

WSH
WSH
RMSE
91.82
91.80
91.78
91.76
0.2
0.4
0.5
0.7
0.7
0.8
1
1.6
250
500
700
900
1000
1100
1250
1500
knots


index
2.5
2.0
1.5
1.0
0.5
1980
1990
2000
2010
2020
year
knots
500
1500

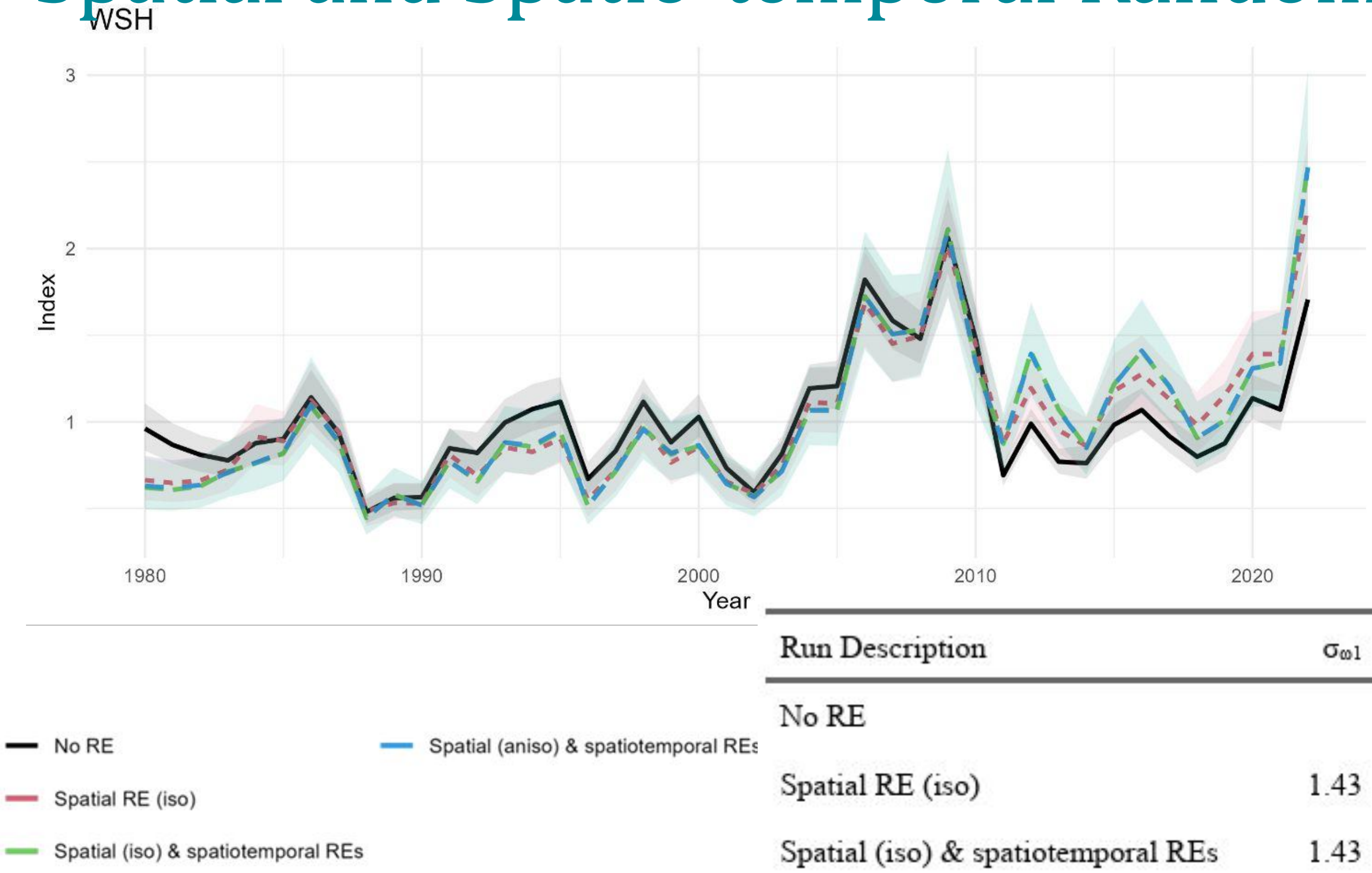

WSH LDWF
Frequency
0
10000
30000
0
1000
3000
numbers per tow
all observations
Proportion positive tows
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
WSH LDWF (zoom)
Frequency
0
50
100
150
200
0
1000
3000
numbers per tow
all observations

Distribution and Error





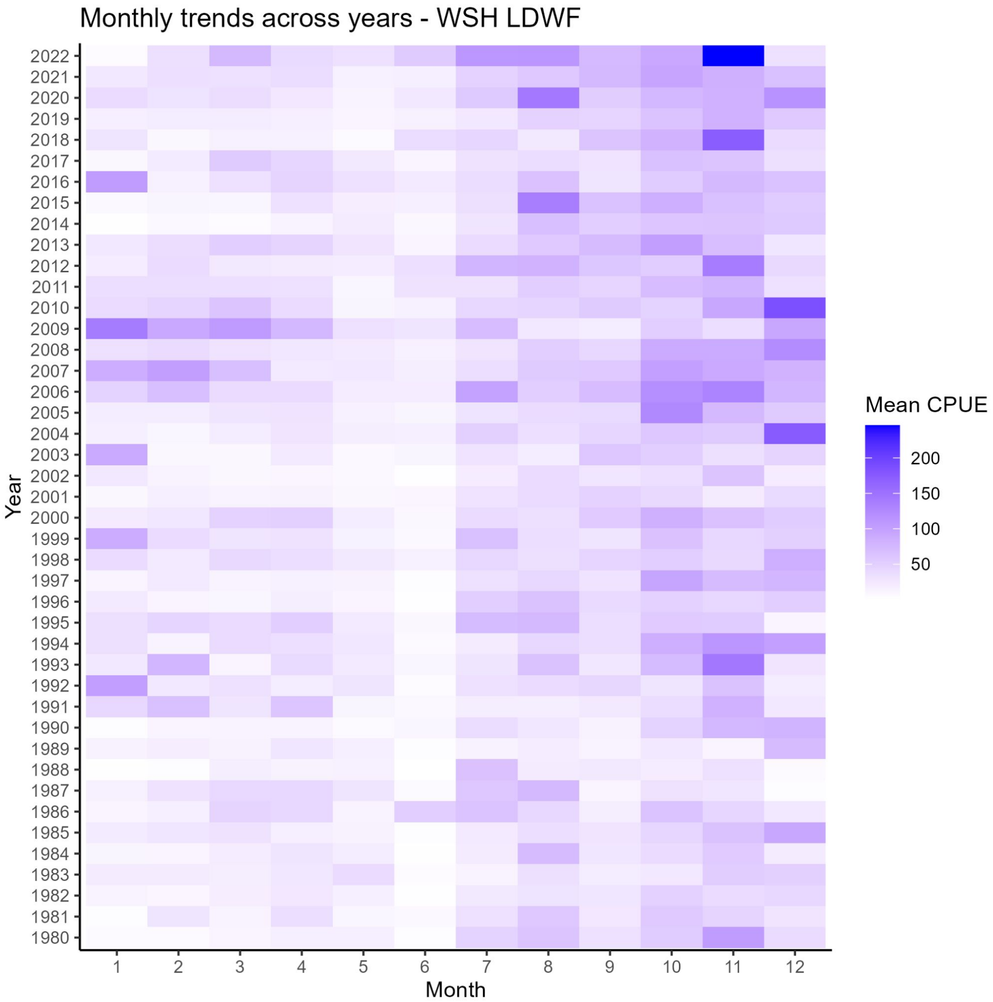
Spatial and Spatio-temporal Random Effects (RE)



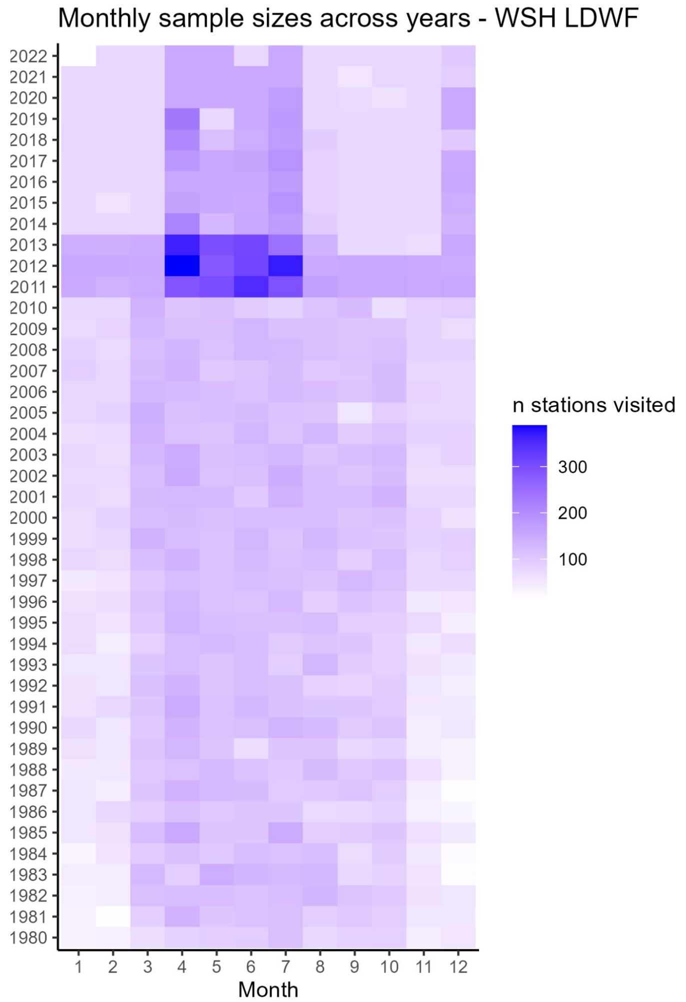
noRE: no spatial or spatiotemporal random effects
noEps: spatial but no spatiotemporal RE
Iso: isotropy
Aniso: anisotropy
Sigma: estimated variance of the RE
Omega: spatial RE
Epsilon: spatiotemporal RE

Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
No RE					381,862	18,446
Spatial RE (iso)	1.43	0.88			365,112	1,695
Spatial (iso) & spatiotemporal REs	1.43	0.97	0.52	0.33	363,423	6
Spatial (aniso) & spatiotemporal REs	**1.44**	**0.97**	**0.53**	**0.33**	**363,416**	**0**

WSH



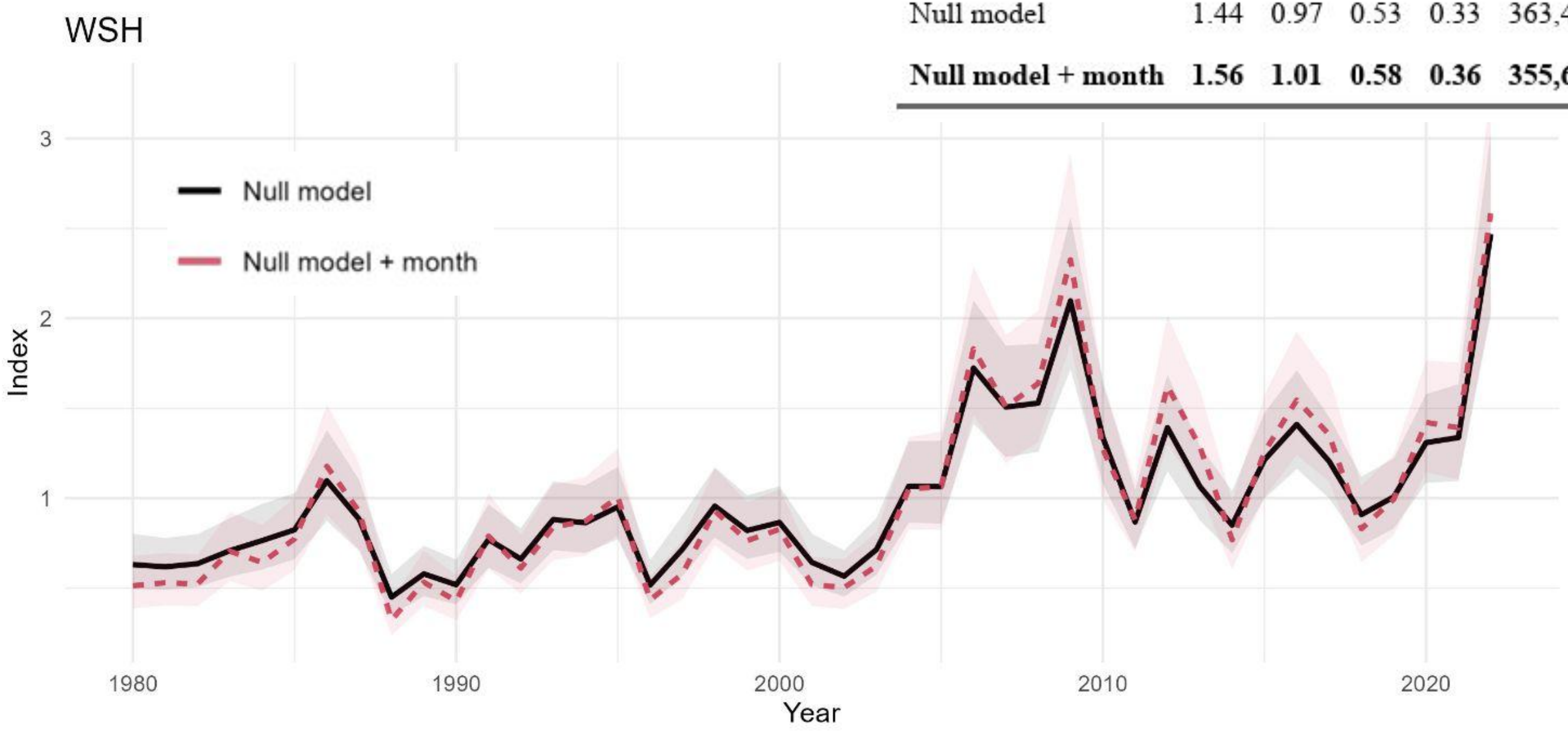
Monthly trends across years - WSH LDWF
Year
Month
Mean CPUE
200
150
100
50

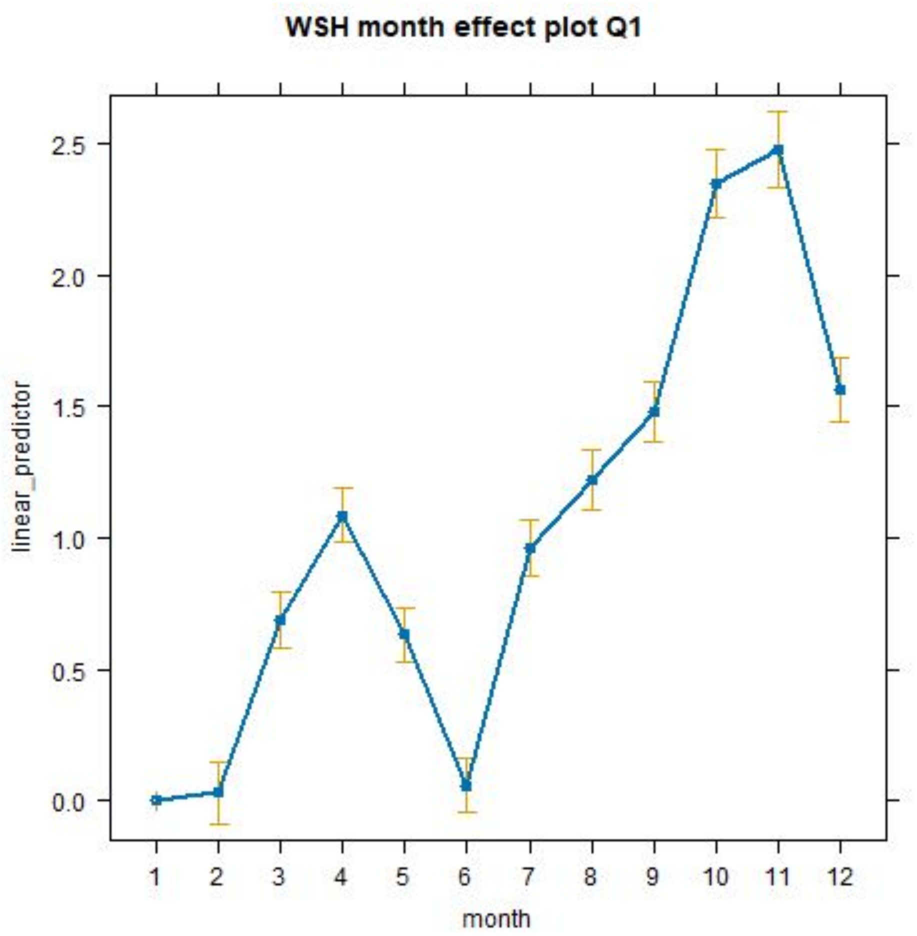


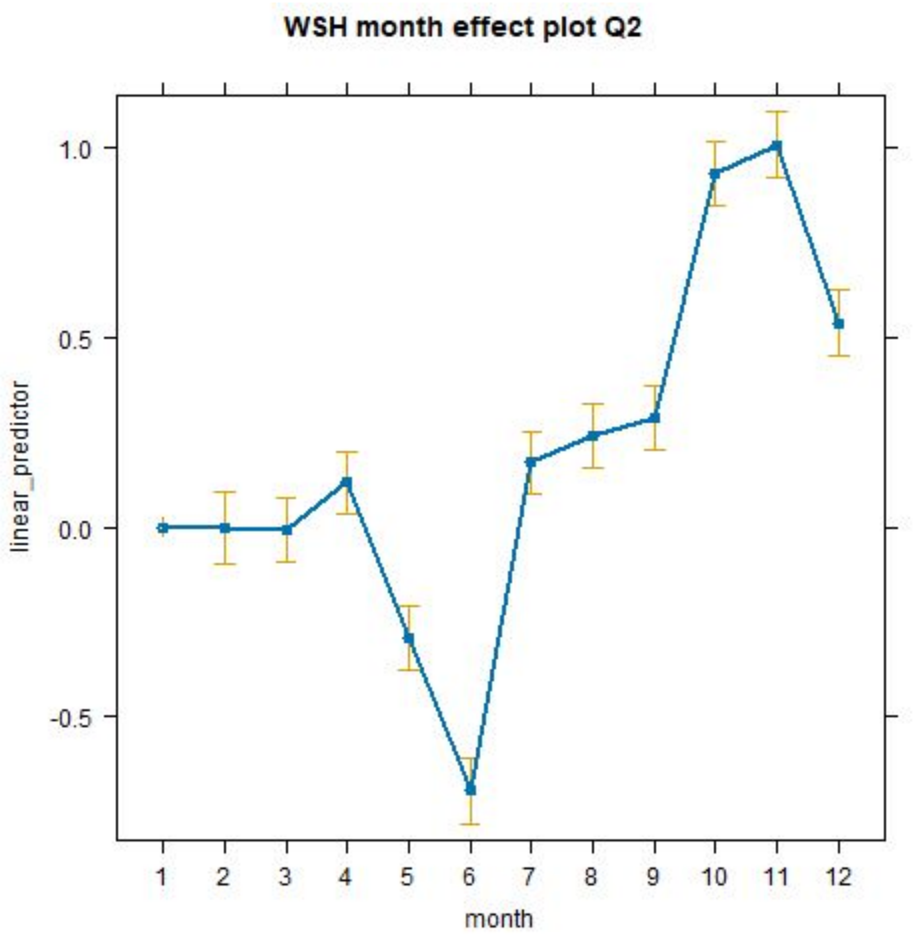
Monthly sample sizes across years - WSH LDWF
Month
n stations visited
300
200
100

Catchability Covariates

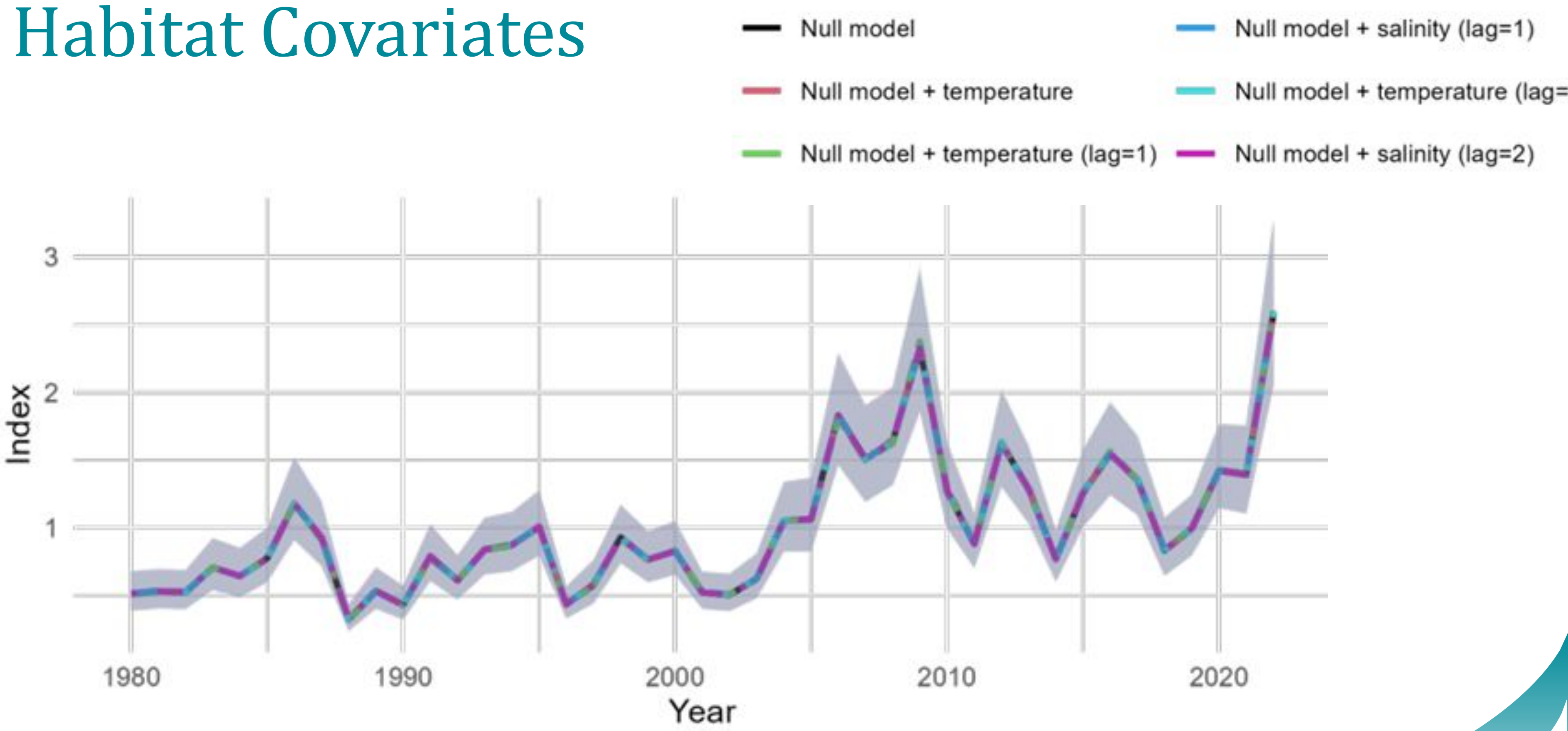
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
Null model	1.44	0.97	0.53	0.33	363,416	7,809
Null model + month	**1.56**	**1.01**	**0.58**	**0.36**	**355,607**	**0**




WSH month effect plot Q1
linear_predictor
0.0
0.5
1.0
1.5
2.0
2.5
1 2 3 4 5 6 7 8 9 10 11 12
month


WSH month effect plot Q2
linear_predictor
-0.5
0.0
0.5
1.0
1 2 3 4 5 6 7 8 9 10 11 12
month

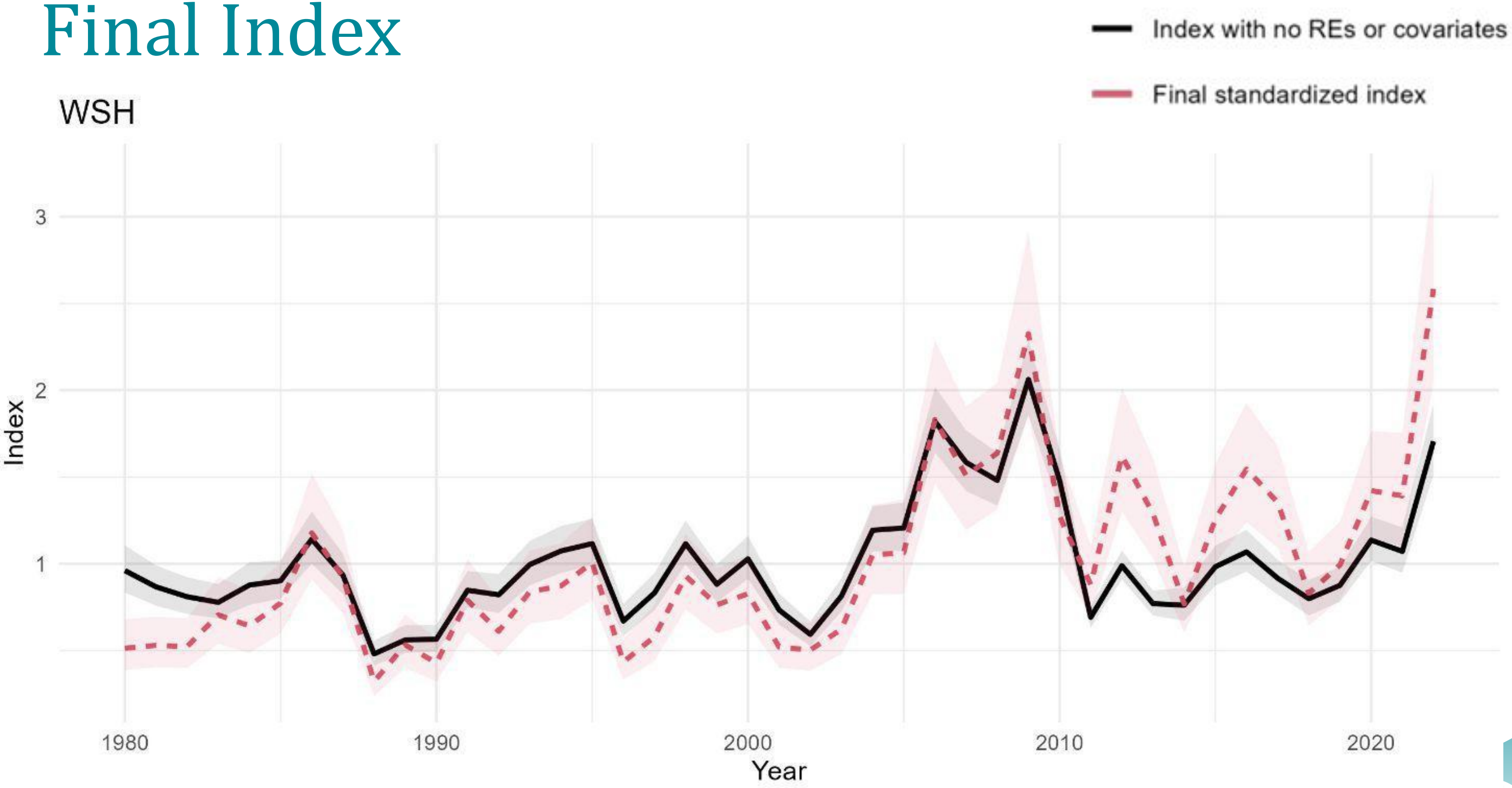
Habitat Covariates



Habitat Covariates

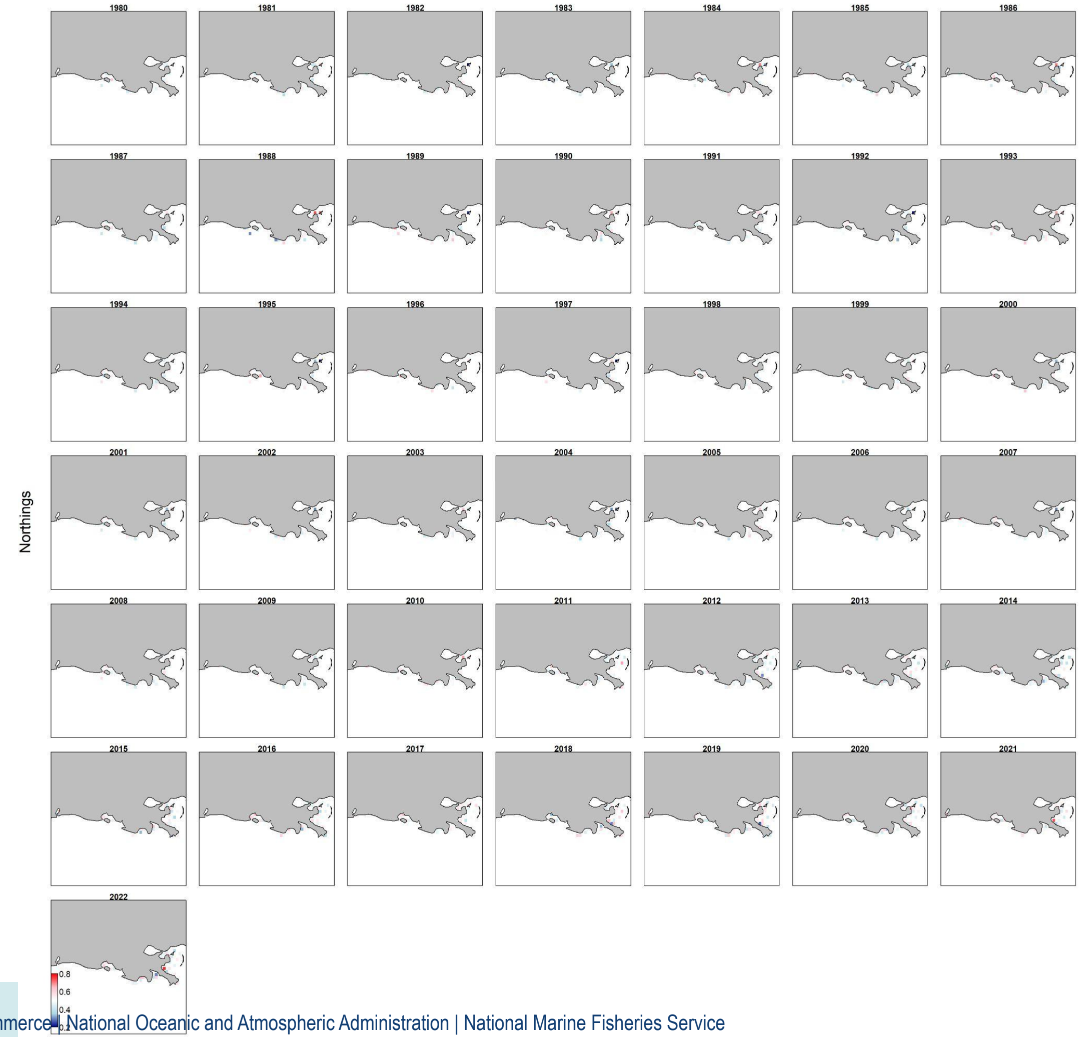
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	$pseudoR^2_1$	$pseudoR^2_2$	AIC	ΔAIC
Null model	1.56	1.01	0.58	0.36	0.000	0.000	355,607	21
Null model + temperature	1.56	1.00	0.58	0.35	0.003	0.008	355,603	17
Null model + temperature (lag=1)	**1.55**	**0.99**	**0.57**	**0.35**	**0.013**	**0.038**	**355,586**	**0**
Null model + salinity (lag=1)	1.56	1.01	0.57	0.35	0.002	0.006	355,596	10
Null model + temperature (lag=2)	1.56	1.01	0.57	0.36	0.008	0.003	355,605	18
Null model + salinity (lag=2)	1.57	1.01	0.57	0.36	-0.005	0.002	355,598	12

Final Index

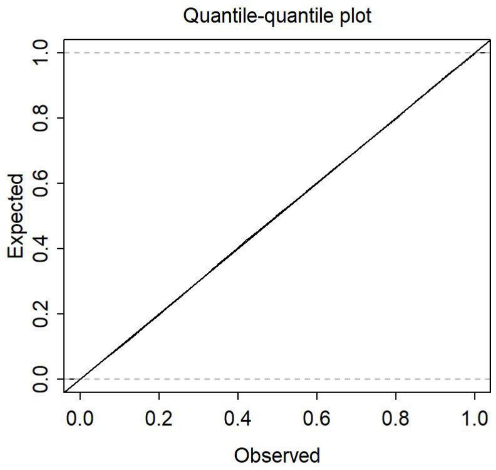


Index with no REs or covariates
Final standardized index
WSH
Index
3
2
1
1980
1990
2000
2010
2020
Year

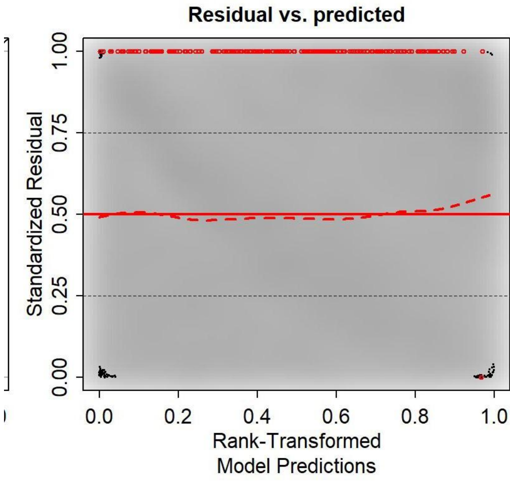
WSH



1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
0.8
0.6
0.4
Northings
Eastings



Quantile-quantile plot
Expected
Observed
0.0
0.2
0.4
0.6
0.8
1.0



Residual vs. predicted
Standardized Residual
Rank-Transformed Model Predictions
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0

WHITE SHRIMP INDEX RECOMMENDATIONS

White Shrimp

LDWF

1980-2022

Delta-lognormal

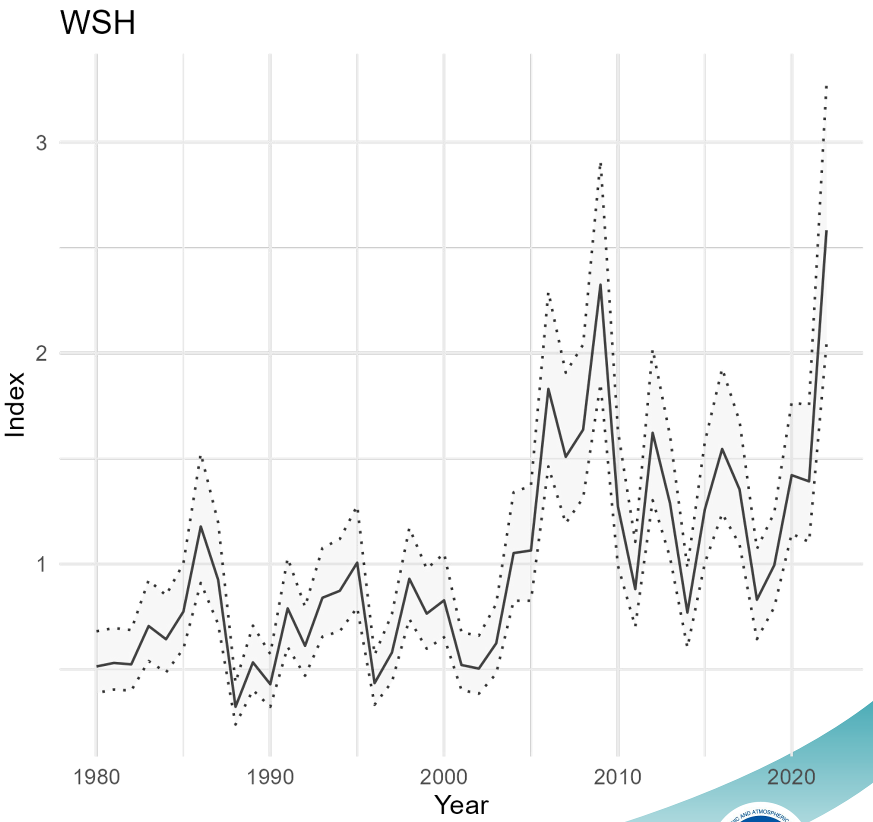
Numbers per tow

Spatial and spatiotemporal RE (anisotropy)

Catchability covariates :

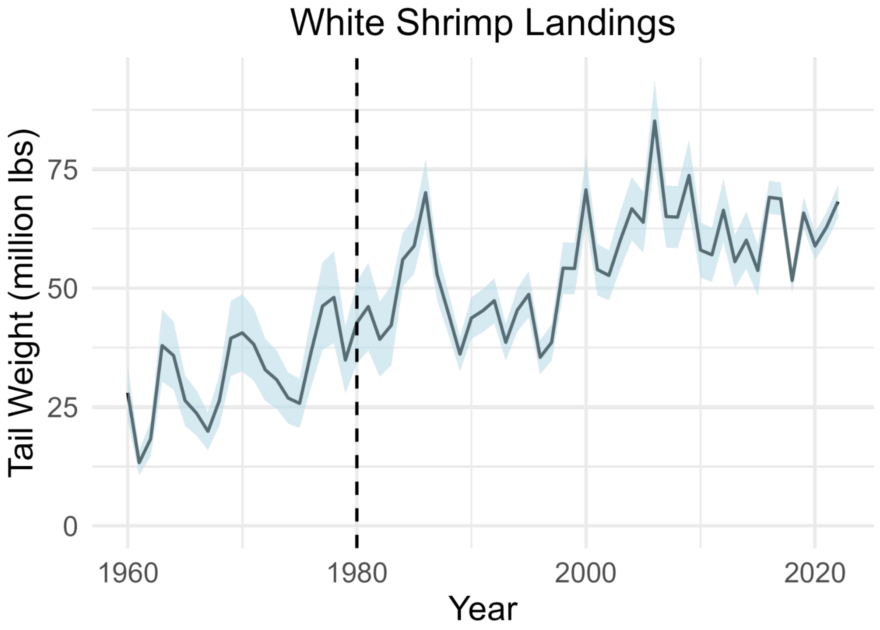
- Month

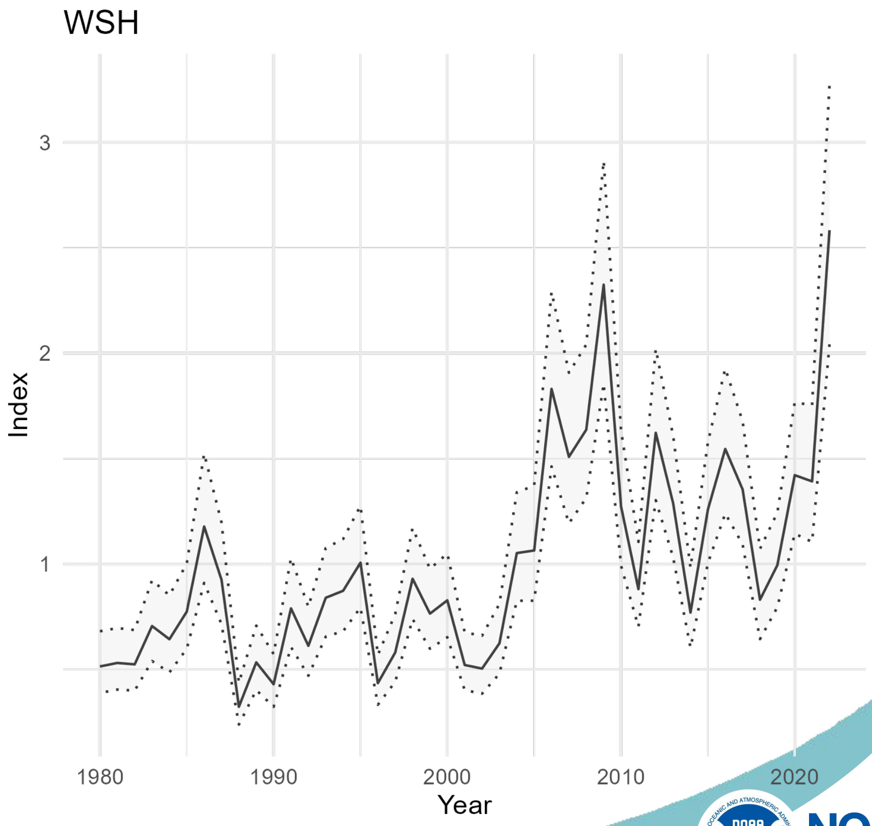
We recommend the use of this index for input into JABBA based on the model configurations listed above.



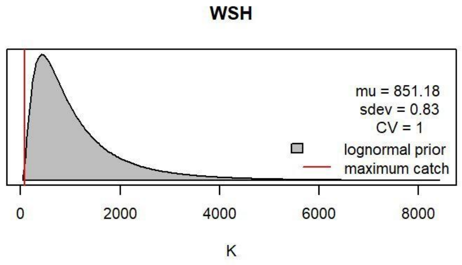
JABBA

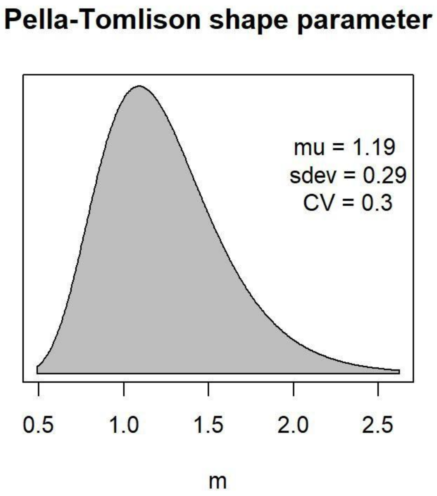
Data - White Shrimp

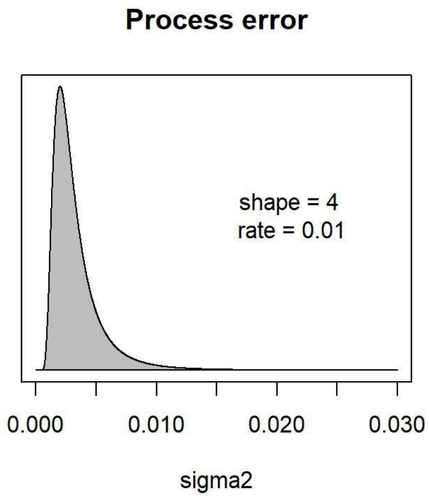




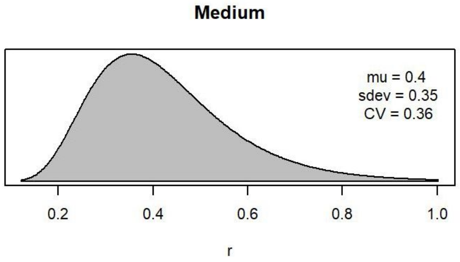
Priors (all runs)

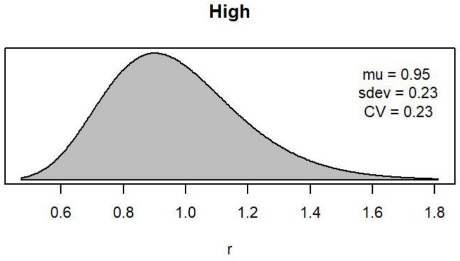


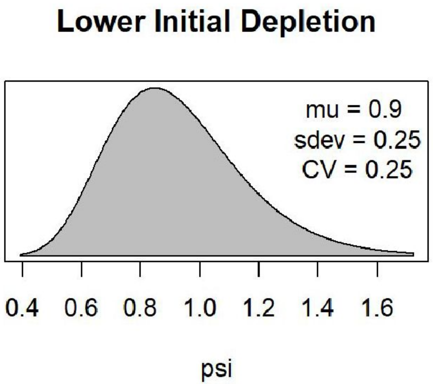


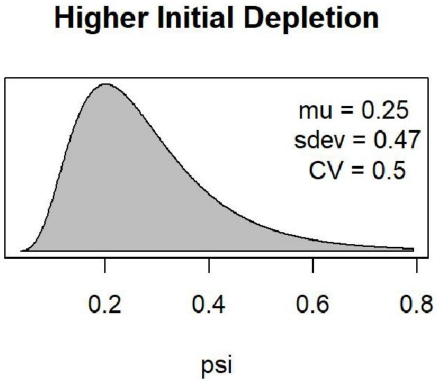


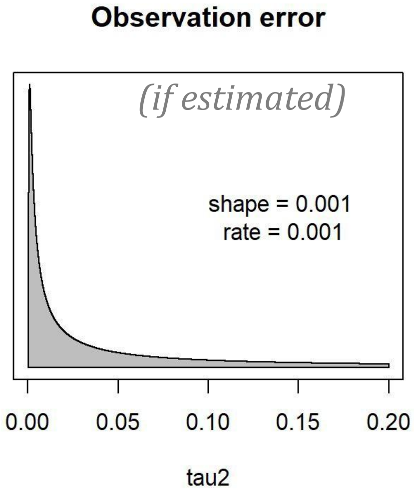
Priors (uncertainty grid)



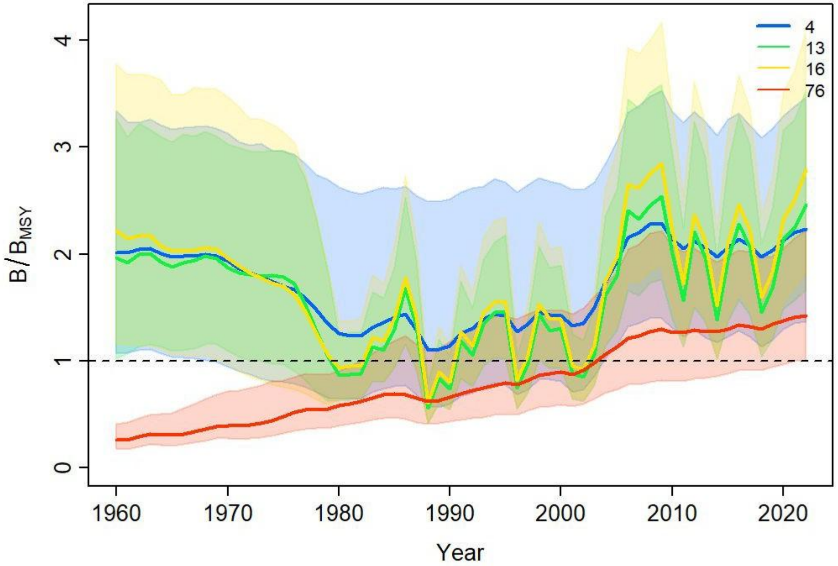








White Shrimp Results



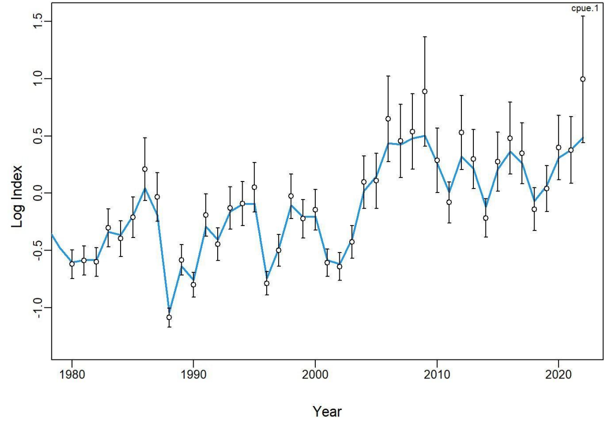
Run	Description
16	Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.
13	Sigma Estimation FALSE. R prior High range. Prior distribution for psi lnorm with mean 0.9.
4	Sigma Estimation TRUE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.
76	Sigma Estimation TRUE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.

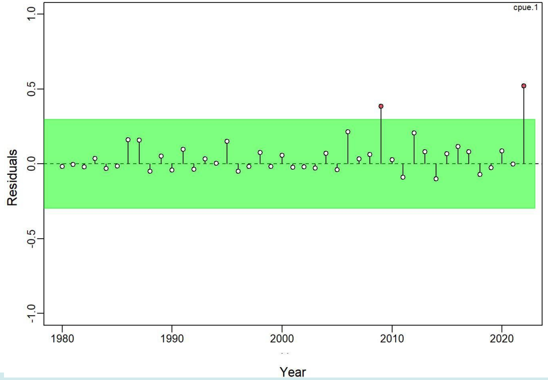
White Shrimp Model Diagnostics

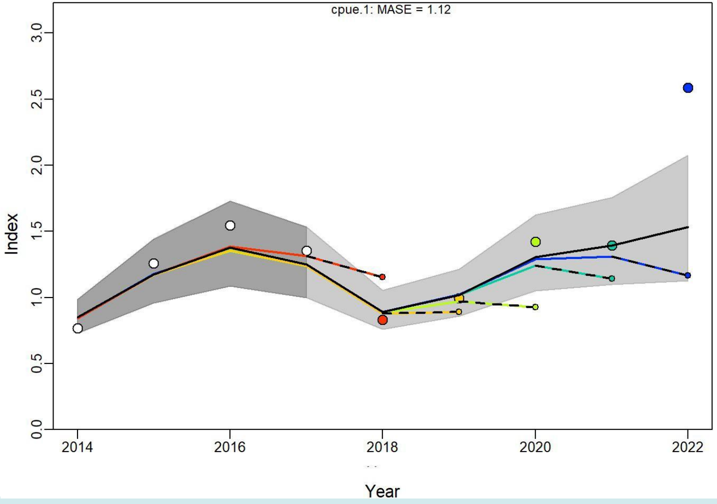
	Model Convergence			Model Fit		Model Consistency				Process Error	Prediction Skill	
run	CONV_gw	CONV_hw	CONV_hs	CPUE_rt_rand	CPUE_rt_outl	RETRO_B	RETRO_F	RETRO_B.Bmsy	RETRO_F.Fmsy	ProcB_CI	HX_MASE	DIC
WSH_4_P_rM_psil0.9_sigT_60	FAIL	PASS	PASS	PASS	PASS	-0.05	0.09	-0.02	-0.03	PASS	1.17	-369.70
WSH_13_P_rH_psil0.9_sigF_60	FAIL	PASS	PASS	PASS	FAIL	-0.05	0.08	0.01	0.04	FAIL	1.13	-514.90
WSH_16_P_rM_psil0.9_sigF_60	PASS	PASS	PASS	PASS	FAIL	-0.00	0.01	0.04	-0.02	FAIL	1.12	-518.50
WSH_76_P_rM_psil0.2_sigT_60	PASS	PASS	PASS	PASS	PASS	0.01	0.00	0.21	-0.16	PASS	1.10	-462.50

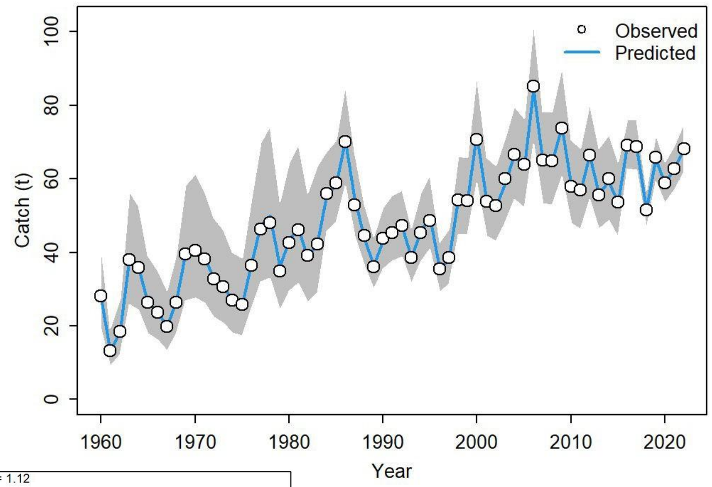
White Shrimp - Example run

16 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.



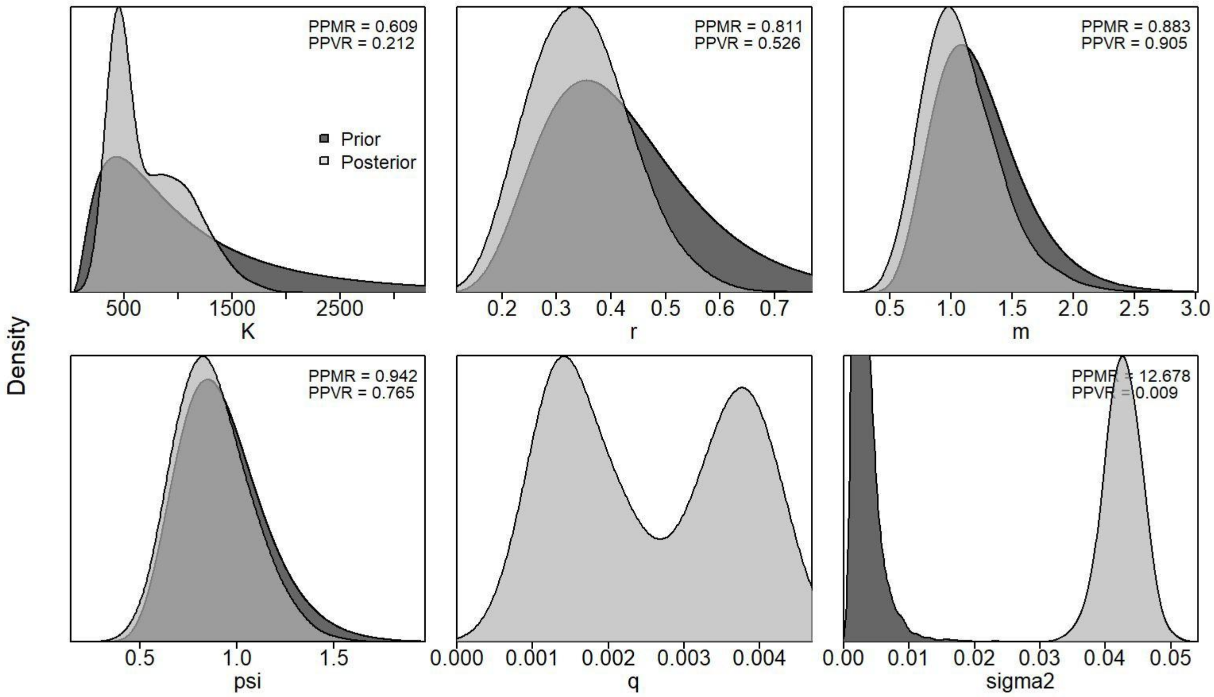


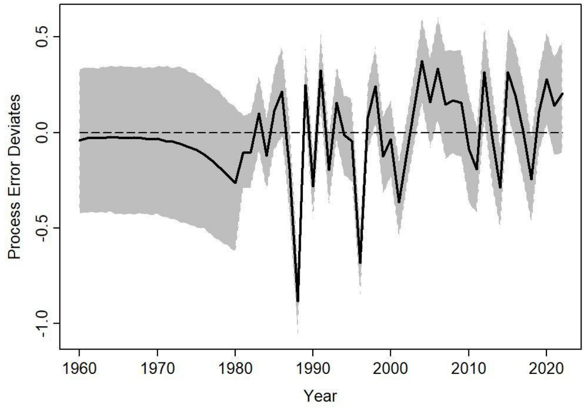




Priors, Posteriors and Process Error

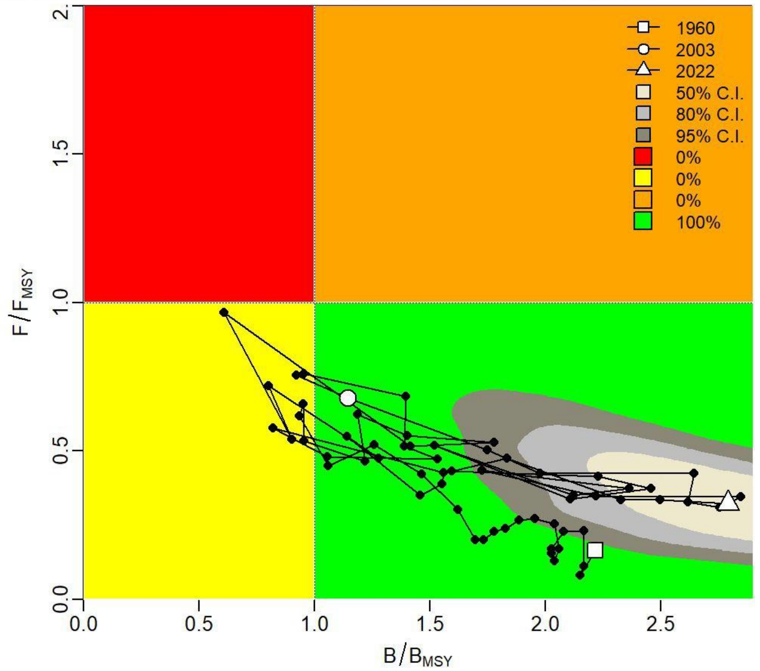
16 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.

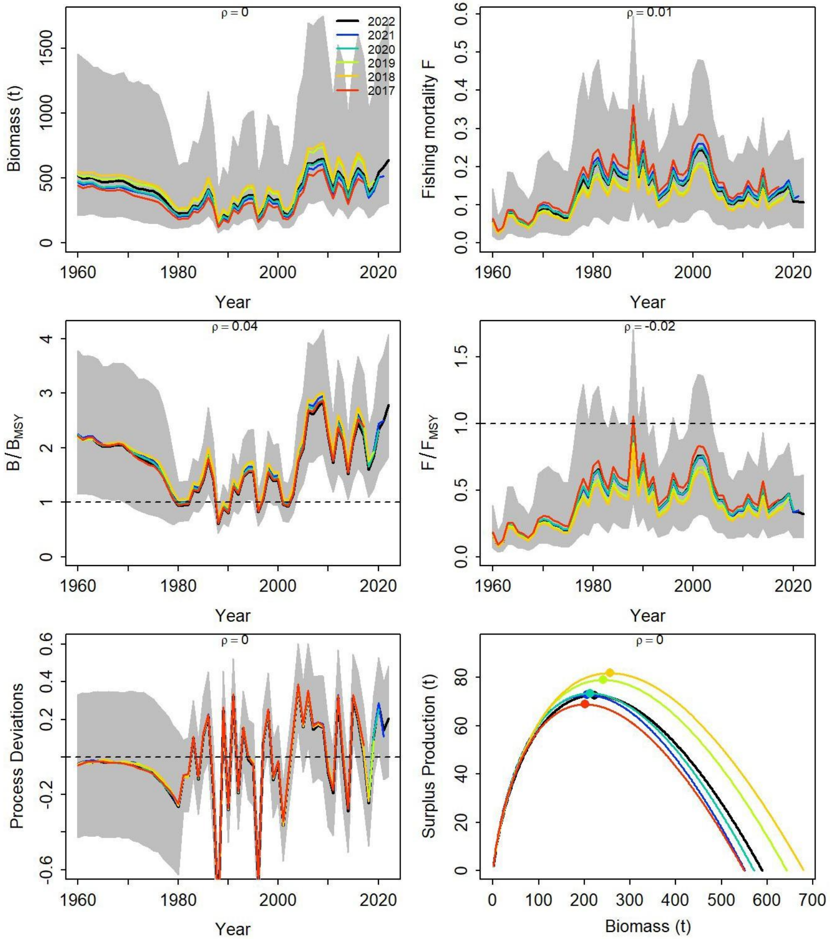




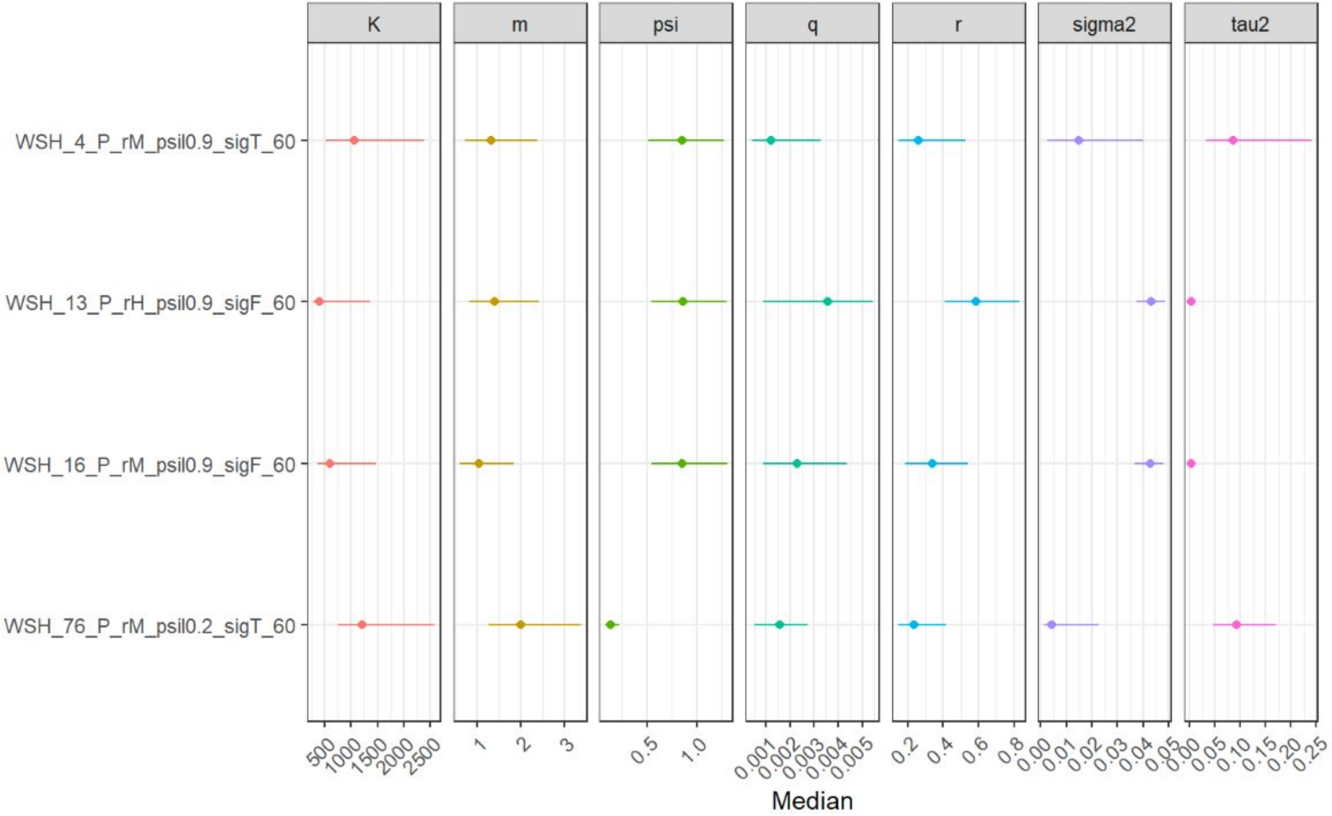
Retrospective Analysis & Kobe Plot

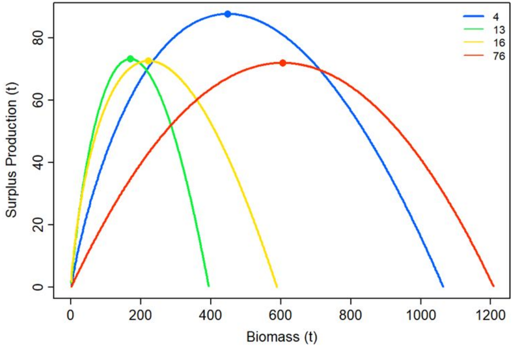
16 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9





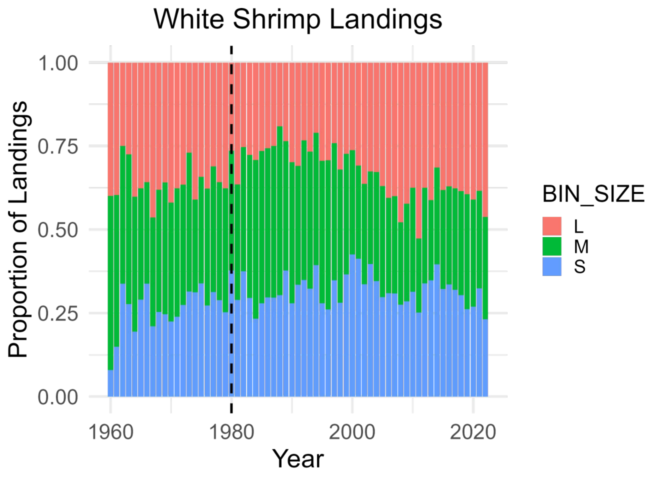
White Shrimp Parameter Estimates





WHITE SHRIMP JABBA SUMMARY

- Similar weaknesses as raised with Brown Shrimp (main assumptions likely violated)
- Non-informative catch rates (CPUE and catches follow same trends)
- Poor diagnostics
  - Sensitive to initial depletion prior
  - Low information (not much departure from priors)
  - Poor prediction skill for the index



Recommendation

- JABBA **not recommended** for White Shrimp

EDM

Stratification of White Shrimp Data

A. **Aggregated:** ANNUAL ; SIZE BINS AGG

C. **Size:** ANNUAL ; SIZE BINS (>67, 67-31, <=30)

Cml. **Size2:** ANNUAL ; SIZE BINS (>67, <=66)

E. **Season:** SEASONAL (WINTER, SUMMER, FALL) ; SIZE BINS AGG

G. **Size_Season:** SEASONAL (WINTER, SUMMER, FALL) ; SIZE BINS (>67, 67-31, <=30) –**omitted**

Gml. **Size2_Season:** SEASONAL (WINTER, SUMMER, FALL) ; SIZE BINS (>67, <=66) –**omitted**

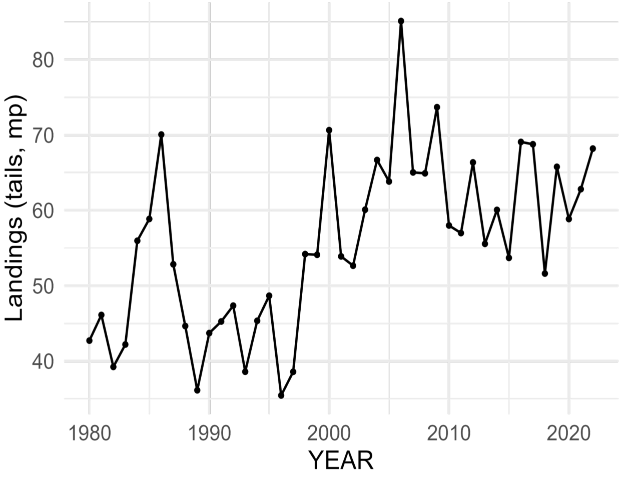
Note: Single area from LDWF so area-specific strata B, D, F, H not included. Aggregated medium/large shrimp for alternate size structure due to LDWF survey best representing shrimp in the smallest size class.

White Shrimp EDM Construction

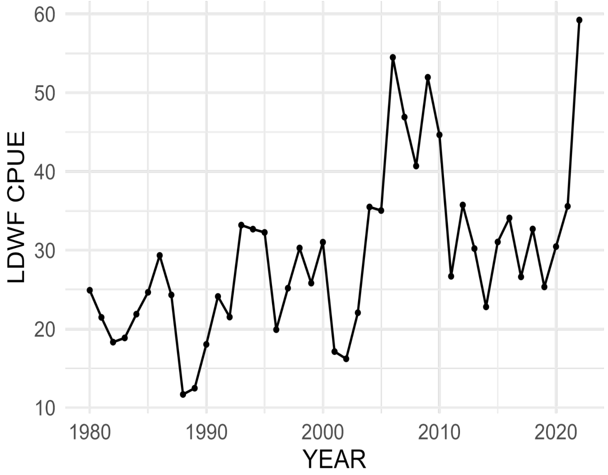
- White shrimp
  - LA Index, 1980-2022, Quadrimester
    - $E \leq \sqrt{T}$, annual model T=43, $E \leq 6$-7 (up to 5-6 lags)
    - T = 43yrs * 3 quadrimesters = 129, $E \leq 11$-12, not limited by embedding dimension

White Shrimp

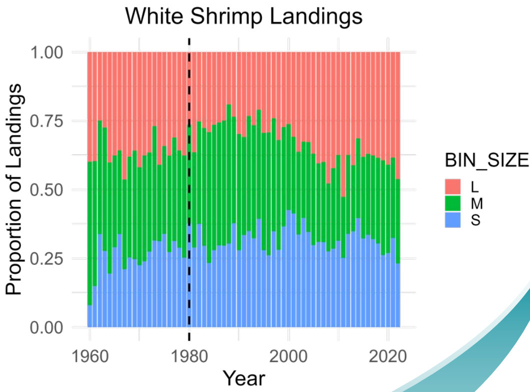
Landings



CPUE

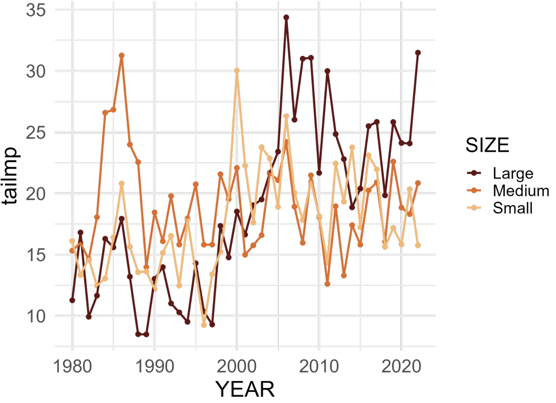


- Model structure options
  - Annual (shown here)
  - Individual models
  - Hierarchical to share information and parameters

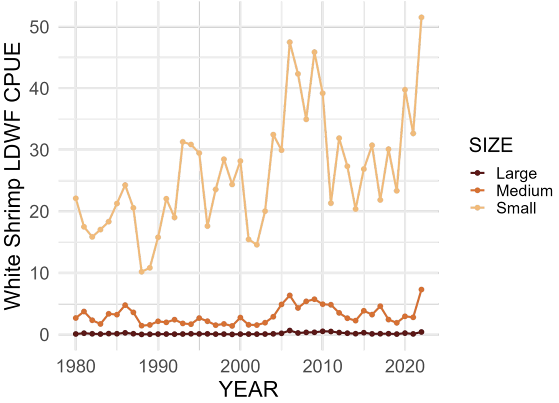


White Shrimp

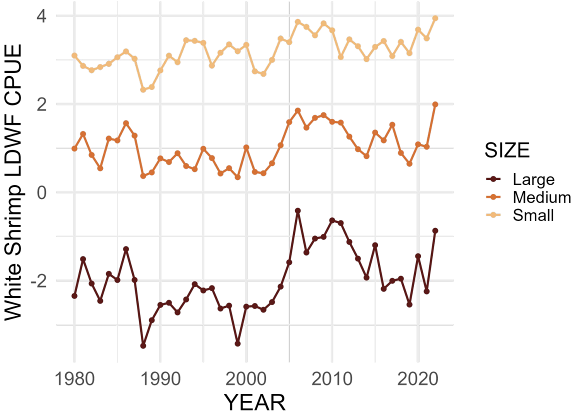
Landings



CPUE

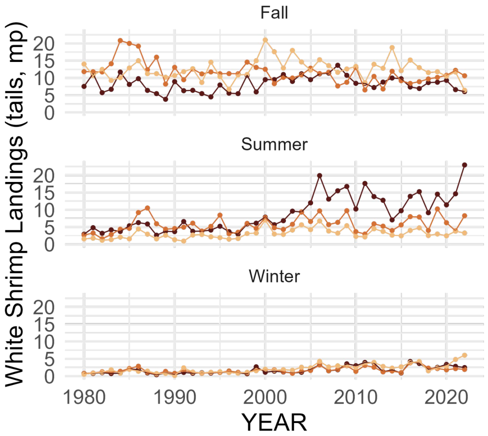


log transformed

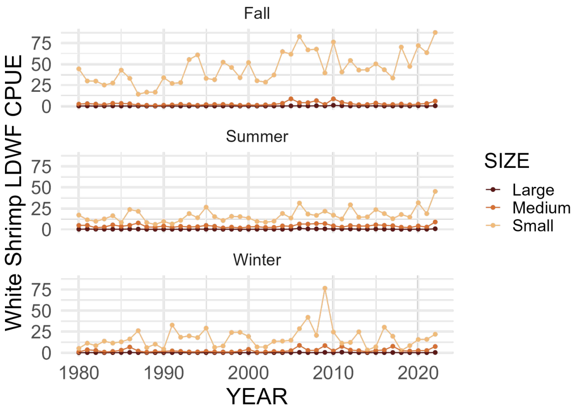


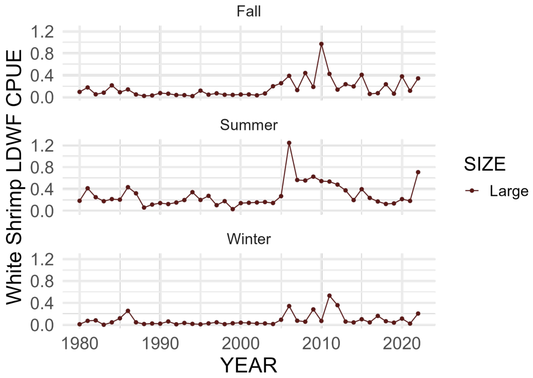
- Size class model (Pop=Size)
- Reduction in effort allows population estimates across all sizes to increase in mid-2000s
- Market demand for Large shrimp exceeds other size classes, observed in landings

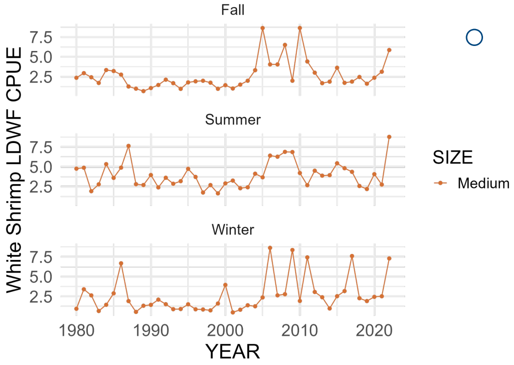
Landings



CPUE







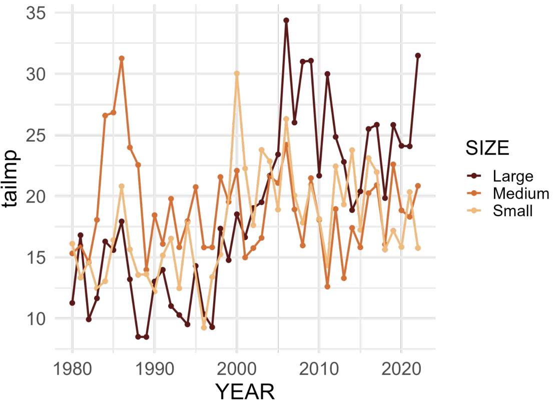
White Shrimp

- Seasonal-size class model (Pop=Size_Seas)
  - Very low or 0 abundance observed (e.g. 1983 Winter Large = 0)
  - **Did not pursue this stratification**
- “Large” landings primarily in the Summer
  - Changes in time/space

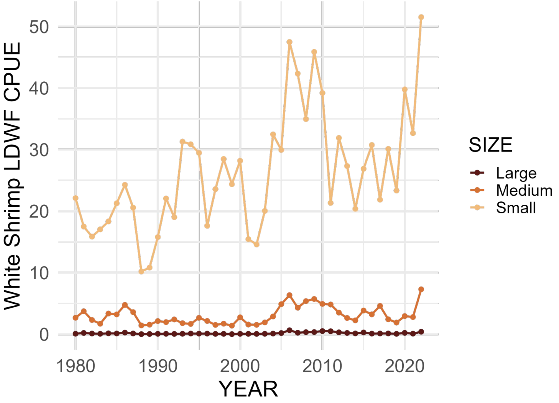
White Shrimp

- Transformed CPUE
  - log: $\log(y_t)$
  - gr1: $\log(y_t/y_{t-1})$
  - gr2: $\log(y_t/(y_{t-1} - qC_{t-1}))$

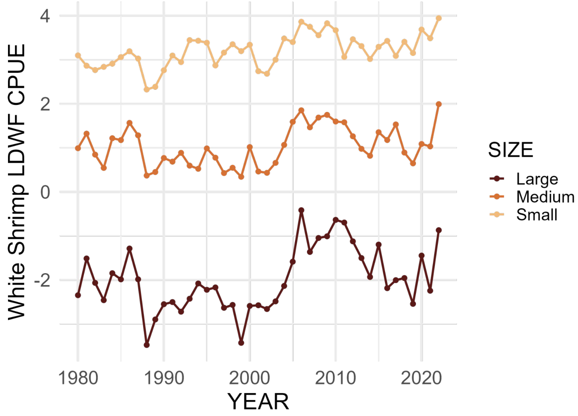
Landings

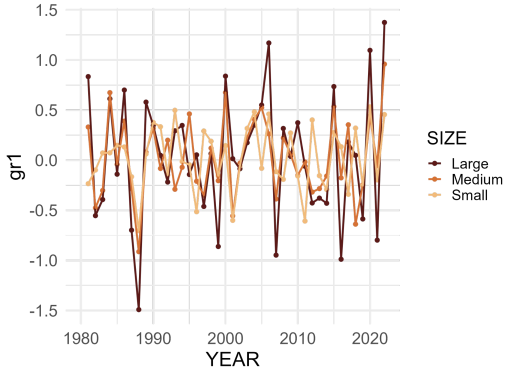


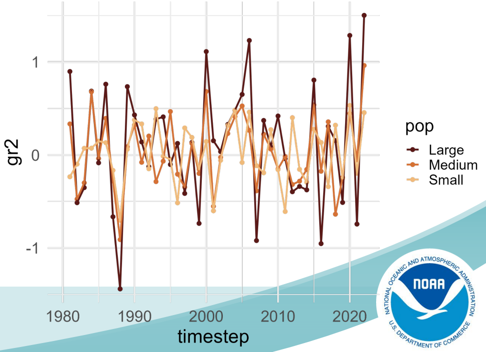
CPUE



log transformed



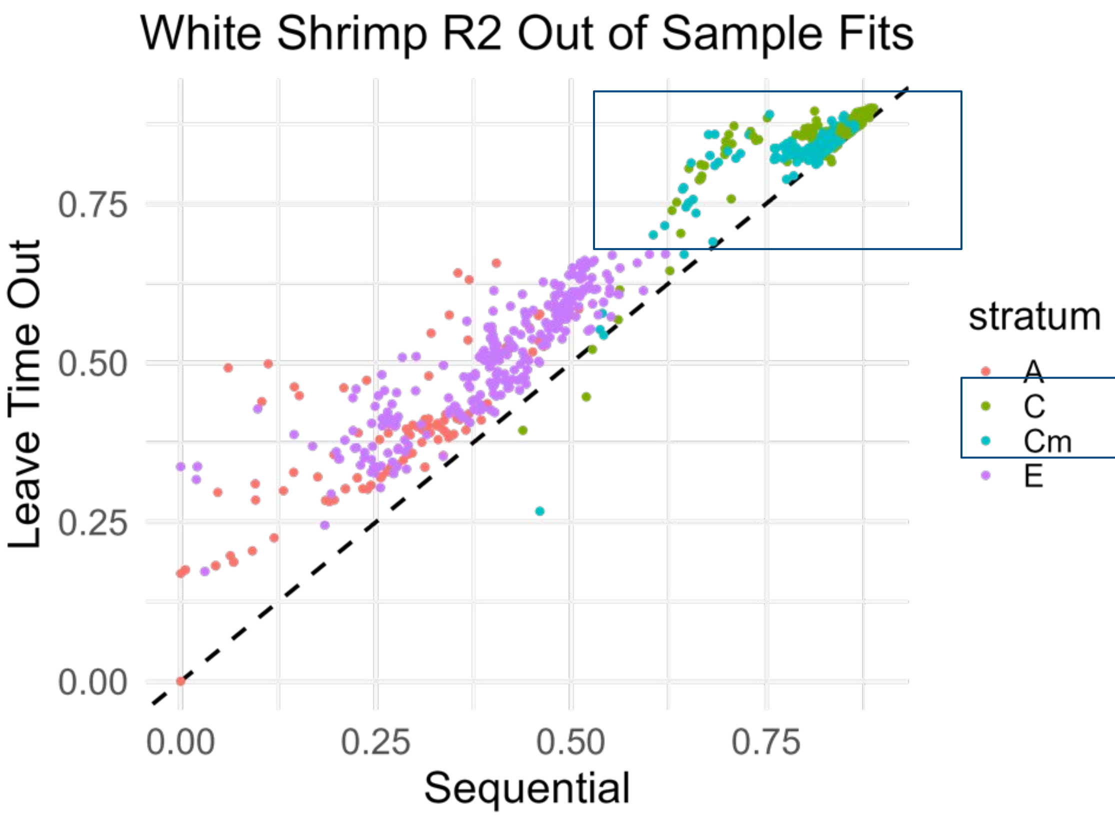




Constant catchability among populations in hierarchical model may pose a problem for ytrans = none, log

e.g. “Small” is most abundant, but not highest in landings

R2 Out of Sample Fit Statistics



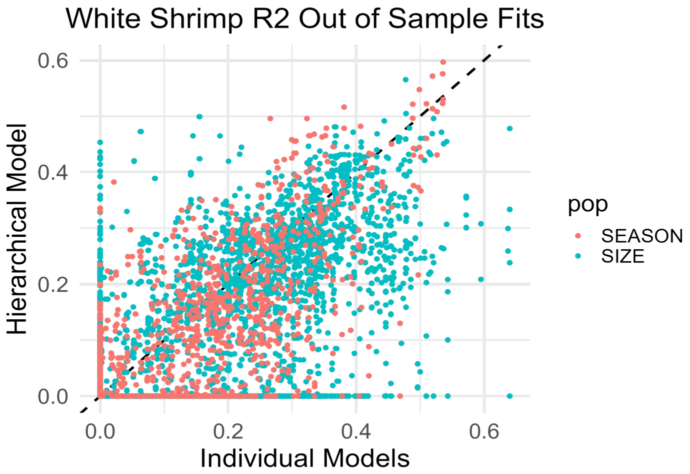
A. **Aggregated**
C. **Size**
Cml. **Size2**
E. **Season**

Model Training Dataset

Leave Time Out: Excludes random time points for all populations

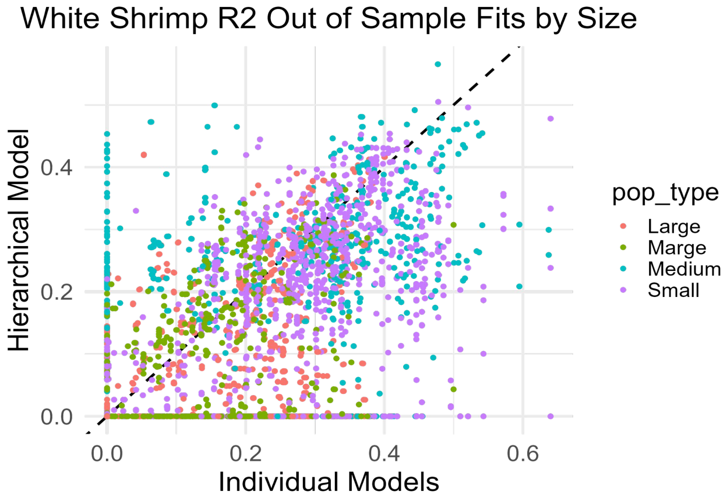
Sequential: Peels back time (can indicate prediction accuracy better)

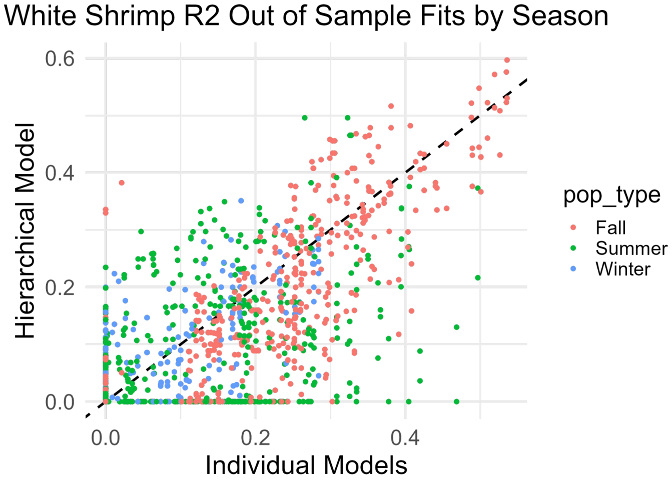
Hierarchical population fits compared to independent model fits, ALL MODELS



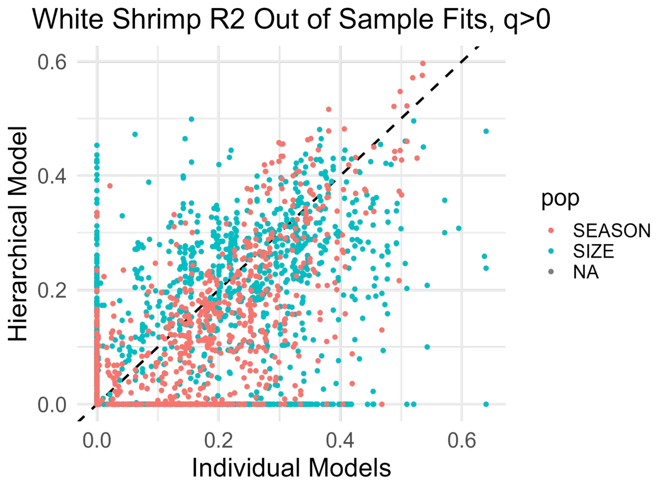
Size: better fits for Small/Med
Season: better fits for Fall

No strong evidence to move towards individual independent models



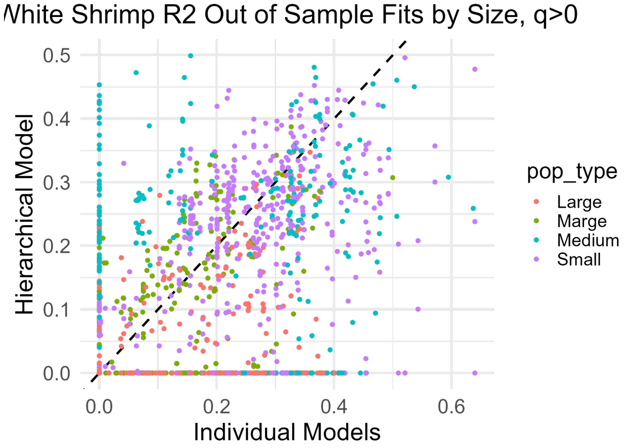


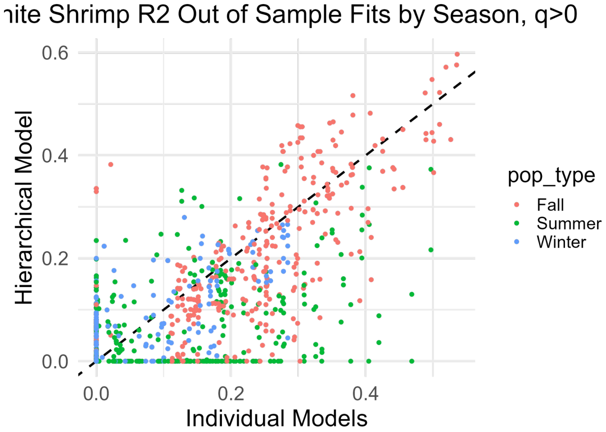
Hierarchical population fits compared to independent model fits, MODELS FILTERED q>0



Size: better fits for Small/Med
Season: better fits for Fall

No strong evidence to move towards individual independent models





Top Performing Model Runs

Run	Stratum	Pop	E	ytrans	Catchability	LinPrior	rho	R2	R2_out	R2_outscaled	ProcessVar	PriorVar
WSH_C3412	C	SIZE	5	none	Distinct	Yes	0.85	0.949	0.868	0.336	0.642	0.557
WSH_C20072	C	SIZE	6	none	Shared	Yes	0.59	0.944	0.87	0.327	0.714	0.455
WSH_C3368	C	SIZE	3	none	Distinct	Yes	0.74	0.907	0.869	0.301	0.863	0.252
WSH_C3896	C	SIZE	3	gr1	Distinct	Yes	0.6	0.884	0.87	0.298	0.971	0.074
WSH_C3940	C	SIZE	5	gr1	Distinct	Yes	0.76	0.917	0.867	0.298	0.806	0.27
WSH_C2840	C	SIZE	3	gr1	Shared	Yes	0.62	0.885	0.869	0.296	0.967	0.078
WSH_C20120	C	SIZE	6	gr1	Distinct	Yes	0.75	0.914	0.865	0.293	0.834	0.268
WSH_C2862	C	SIZE	4	gr1	Shared	Yes	0.62	0.886	0.867	0.292	0.965	0.089
WSH_C3126	C	SIZE	4	gr2	Shared	Yes	0.62	0.886	0.868	0.279	0.97	0.085
WSH_C3104	C	SIZE	3	gr2	Shared	Yes	0.63	0.885	0.868	0.278	0.969	0.083
WSH_C3148	C	SIZE	5	gr2	Shared	Yes	0.75	0.915	0.865	0.278	0.799	0.274
WSH_C20096	C	SIZE	6	gr2	Shared	Yes	0.74	0.913	0.863	0.273	0.83	0.27
WSH_C244	C	SIZE	5	none	Shared	None	0.95	0.882	0.854	0.245	0.717	1.039
WSH_C20008	C	SIZE	6	none	Shared	None	0.95	0.881	0.847	0.227	0.742	1.037
WSH_C3676	C	SIZE	5	log	Distinct	Yes	0.8	0.922	0.861	0.221	0.748	0.357
WSH_C728	C	SIZE	3	gr1	Shared	None	0.89	0.88	0.865	0.216	0.868	0.448
WSH_C20112	C	SIZE	6	log	Distinct	Yes	0.8	0.922	0.857	0.215	0.755	0.377
WSH_C20128	C	SIZE	6	gr2	Distinct	Yes	0.87	0.895	0.857	0.211	0.828	0.337
WSH_C1828	C	SIZE	5	gr1	Distinct	None	0.87	0.929	0.859	0.203	0.668	0.437
WSH_C1806	C	SIZE	4	gr1	Distinct	None	0.9	0.878	0.863	0.202	0.881	0.487
WSH_C1784	C	SIZE	3	gr1	Distinct	None	0.89	0.879	0.863	0.199	0.869	0.393
WSH_C750	C	SIZE	4	gr1	Shared	None	0.89	0.879	0.863	0.197	0.876	0.463
WSH_C20056	C	SIZE	6	gr1	Distinct	None	0.86	0.927	0.855	0.191	0.689	0.44
WSH_C772	C	SIZE	5	gr1	Shared	None	0.85	0.917	0.852	0.191	0.703	0.391
WSH_C20024	C	SIZE	6	gr1	Shared	None	0.84	0.914	0.848	0.178	0.731	0.386
WSH_C4182	C	SIZE	4	gr2	Distinct	Yes	0.86	0.887	0.856	0.174	0.821	0.416
WSH_C4160	C	SIZE	3	gr2	Distinct	Yes	0.87	0.882	0.857	0.17	0.829	0.502
WSH_C992	C	SIZE	3	gr2	Shared	None	0.89	0.879	0.861	0.057	0.828	0.466
WSH_C1014	C	SIZE	4	gr2	Shared	None	0.89	0.879	0.86	0.044	0.833	0.484
WSH_C1036	C	SIZE	5	gr2	Shared	None	0.89	0.897	0.849	0.008	0.742	0.401

Filtered by Strata C

30 out of top 59 models

Linear Prior, Distinct Catchability preferred

Top 2 Model Runs boxed (e.g. passed MSY checks)

U.S. Department of Commerce | National Oceanic and Atmospheric Administration | National Marine Fisheries Service

WHITE SHRIMP EDM
Maximum Sustainable Yield

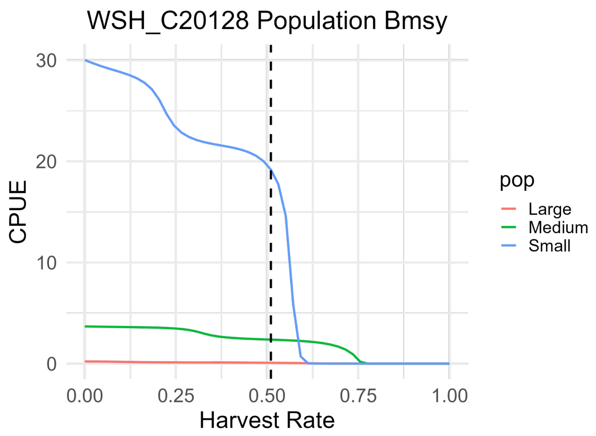
Top Performing Models

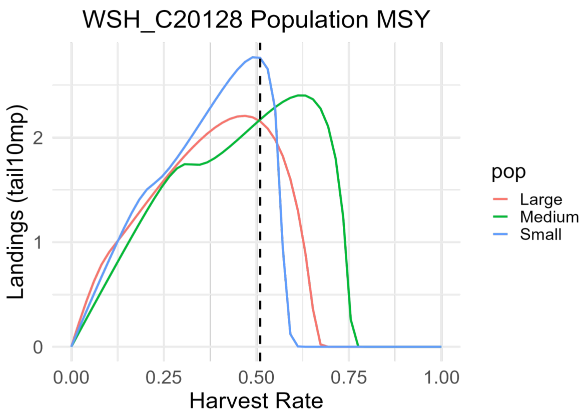
- **Size-structured** (Large, Medium, Small), separately estimated catchability, **annual** time steps, **E=6**, y transformation **gr2** ($\log(y_t/(y_{t-1} - qC_{t-1}))$), linear prior [C20128]
- **Size-structured** (Large, Medium, Small), separately estimated catchability, **annual** time steps, **E=4**, y transformation **gr2** ($\log(y_t/(y_{t-1} - qC_{t-1}))$), linear prior [C4182]
- Models have identical parameterizations, except for **complexity** in the embedding dimension

Linear Prior

- Assumes a relationship between biomass and harvest rate
- The model returns to the mean of the prior outside of the range of the data, which can be nonsensical for harvest rate simulations
- Can aid in grounding the population to 0 as the harvest rate, $\boldsymbol{U}$, approaches 1 (i.e. the entire population is harvested)
- Introduces more biological realism where we don’t have data to inform the model

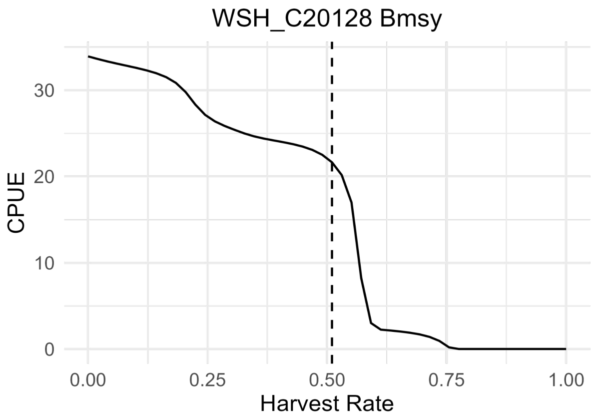
Size-structured (Large, Medium, Small), separately estimated catchability, annual time steps, E=6, y transformation gr2 (log(yt/(yt-1 - qCt-1)), linear prior [C20128]

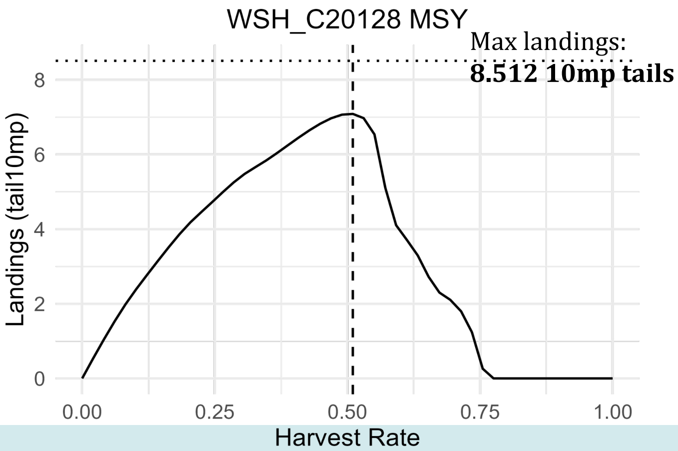




MSY is added across populations

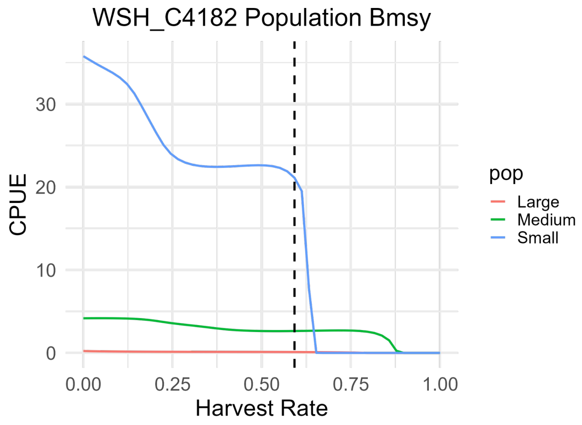
More complex (larger embedding dimension) compared to similarly performing model

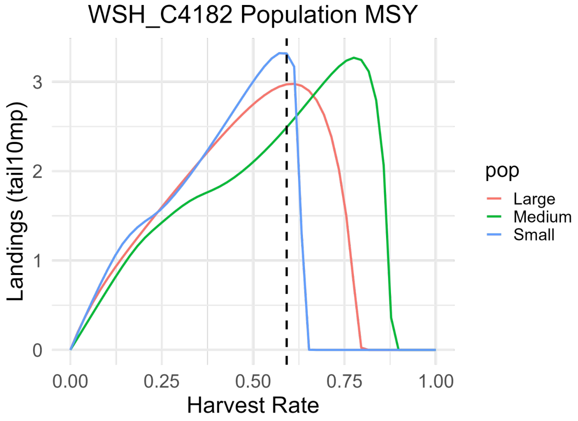




MSY estimate 70.9mp tails is less than the max landings observed in 2006, 85.12mp tails

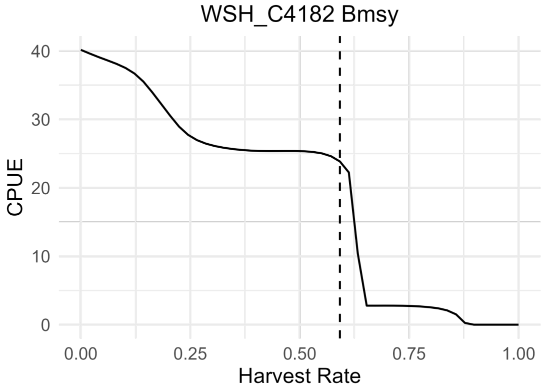
Size-structured (Large, Medium, Small), separately estimated catchability, annual time steps, E=4, y transformation gr2 (log(yt/(yt-1 - qCt-1)), linear prior [C4182]

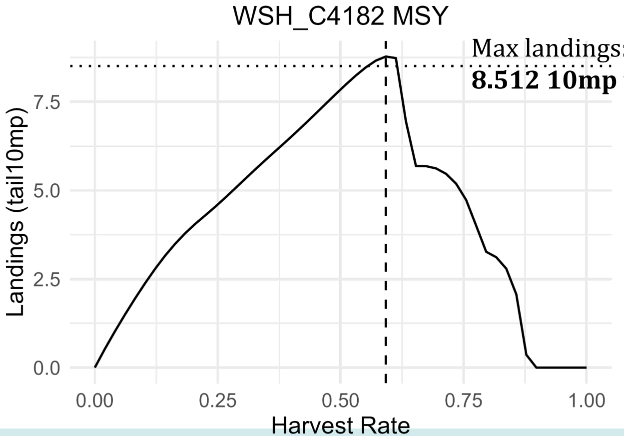




MSY is added across populations

Statistic	WSH_C4182
MSY_10mptails	8.780
Fmsy	0.896
Umsy_annual	0.592
Bmsy_10mp	14.835
df	9.579
R2	0.887
R2Scaled	0.312
R2_outsample	0.856
R2Scaled_outsample	0.174





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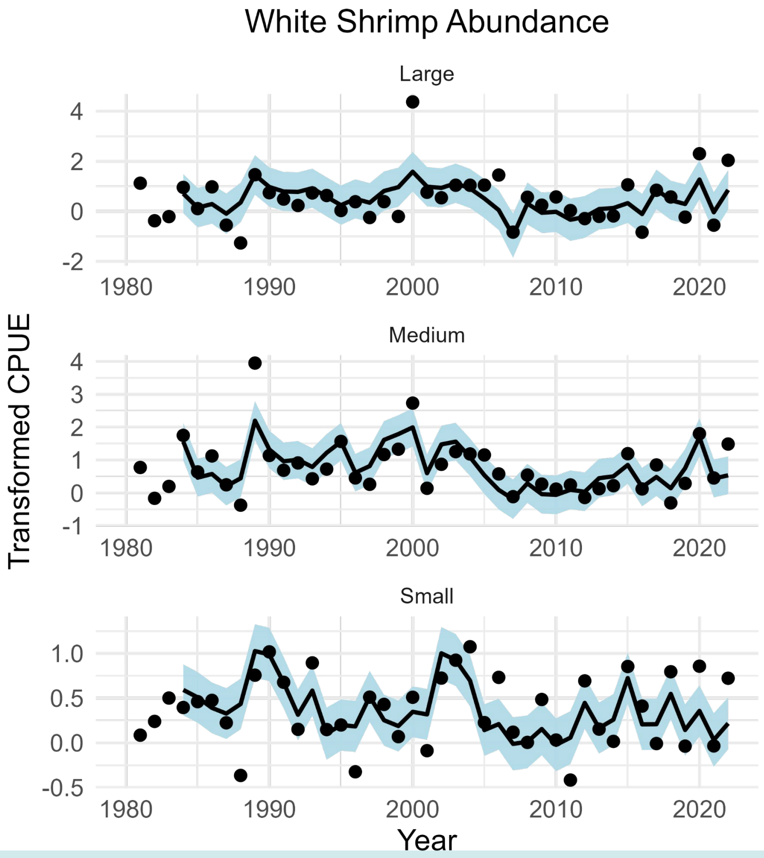
Size-structured (Large, Medium, Small), separately estimated catchability, annual time steps, E=4, y transformation gr2 ($\log(y_t/(y_{t-1} - qC_{t-1}))$), linear prior [C4182]



Parameter	WSH_C4182
CatchabilityLarge	0.021
CatchabilityMedium	0.627
CatchabilitySmall	3.767
DynamicCorrelation	0.864
LengthScale1	1.216
LengthScale2	0.039
LengthScale3	0.000
LengthScale4	0.000
PointwisePriorVariance	0.416
ProcessVariance	0.821

Model Diagnostics: Peel back years

Run	MSY	BMSY_mp	MSY_factor
WSH_C4182_0	8.78	14.84	1.03
WSH_C4182_1	9.05	11.37	1.06
WSH_C4182_2	8.91	14.55	1.05
WSH_C4182_3	8.62	11.12	1.01
WSH_C4182_4	8.66	11.16	1.02
WSH_C4182_5	8.85	11.11	1.04

Top line is MSY estimate from terminal year 2022

_1 means 1yr peeled back (e.g. data through 2021) and so forth

Stable model with no apparent retrospective bias

Max landings were observed in 2006:
85.12mp tails (**8.512 tail10mp**)

WHITE SHRIMP EDM SUMMARY

- Size-structured (Large, Medium, Small), separately estimated catchability, annual time steps, E=4, y transformation gr2 ($\log(y_t/(y_{t-1} - qC_{t-1}))$), linear prior [C4182]
  - Similar parameterization as next best model, but smaller embedding dimension and fewer degrees of freedom
- Robust model that captures white shrimp dynamics
- Provides stable estimates of maximum sustainable yield
  - MSY: 87.80 million pounds of tails
  - F_{MSY}: 0.896 — B_{MSY}: 148.35 million pounds of tails
  - F_{2022}: 0.132 — B_{2022}: 449.9 million pounds of tails
  - F_{2022}/F_{MSY}: 0.147 — B_{2022}/B_{MSY}: 2.48

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WHITE SHRIMP CONCLUSIONS

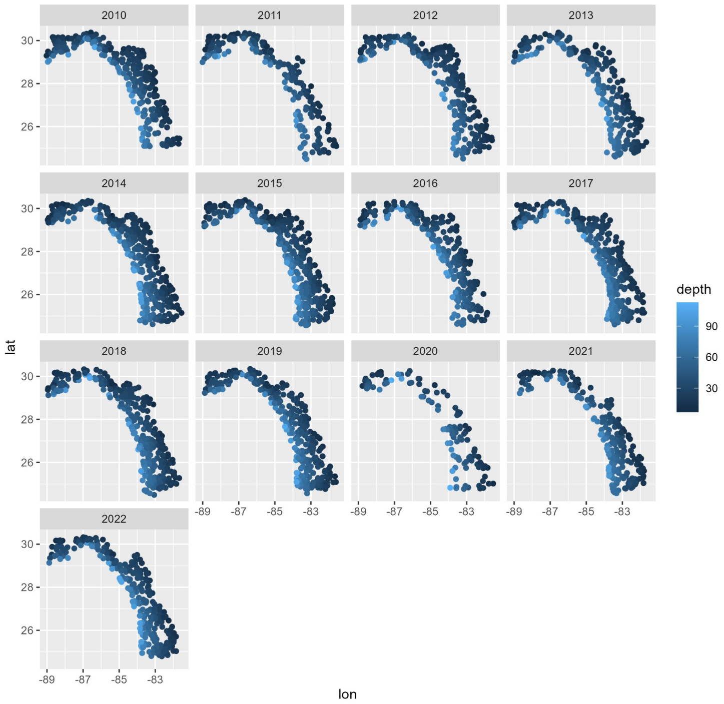
- EDM particularly suitable for populations that exhibit non-equilibrium dynamics and nonlinear state-dependent behavior
- JABBA models were generally poor and limited by the overarching constraints of surplus production models
- EDM had better performance metrics and diagnostics than JABBA, therefore we recommend that EDM be used for providing management advice.

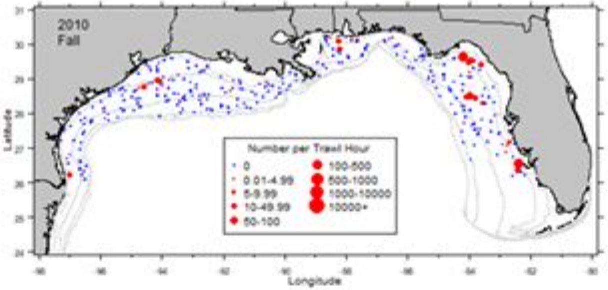
PINK SHRIMP

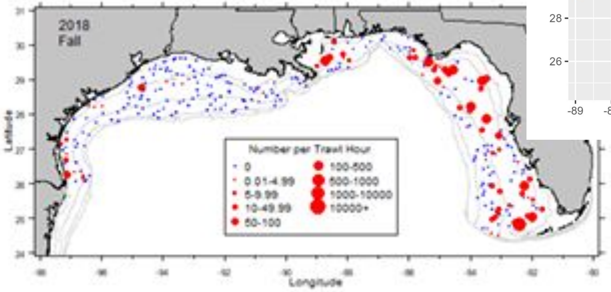
VAST index

VAST - Motivation

- Develop an index of relative abundance that can control for some of the survey's early changes in spatial footprint
- Testing impact of nursery conditions







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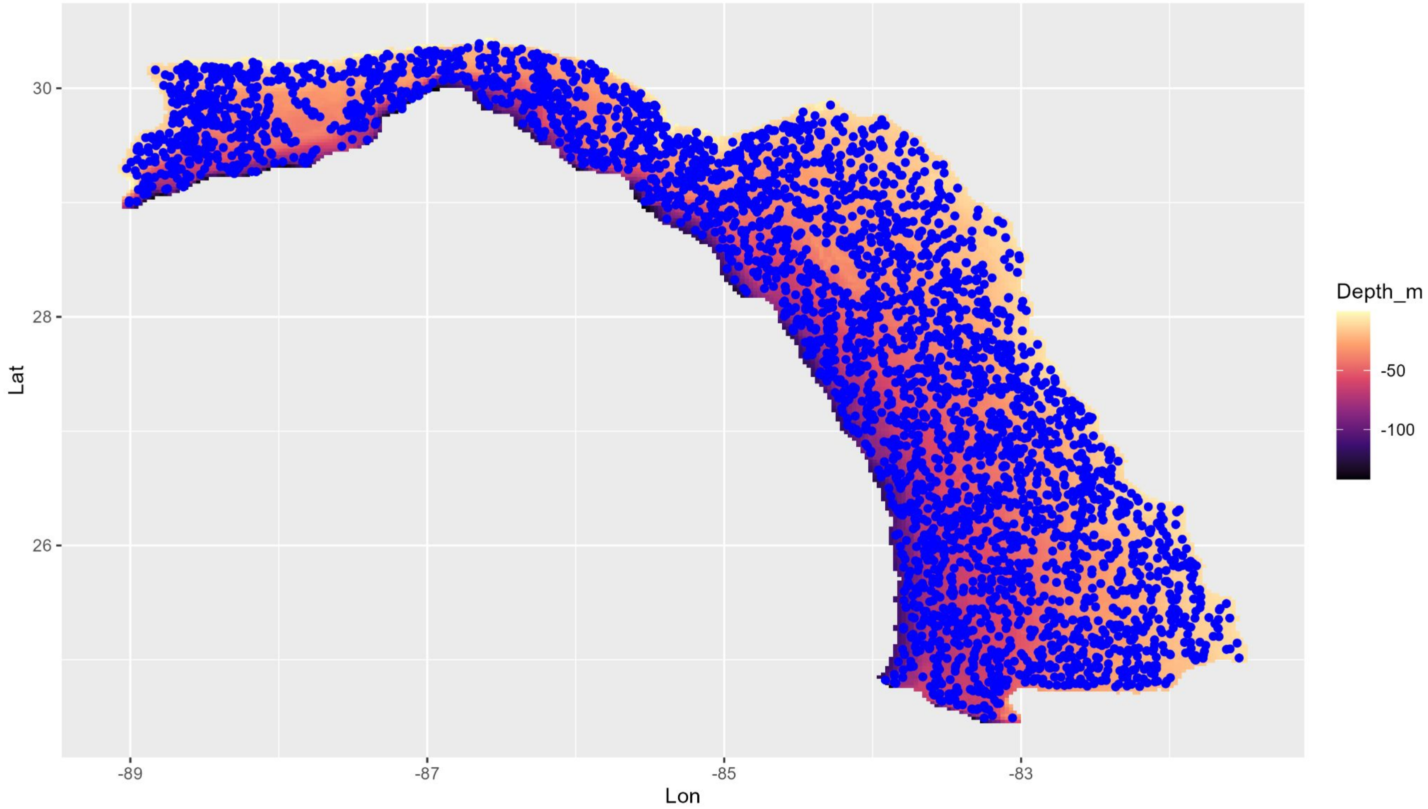
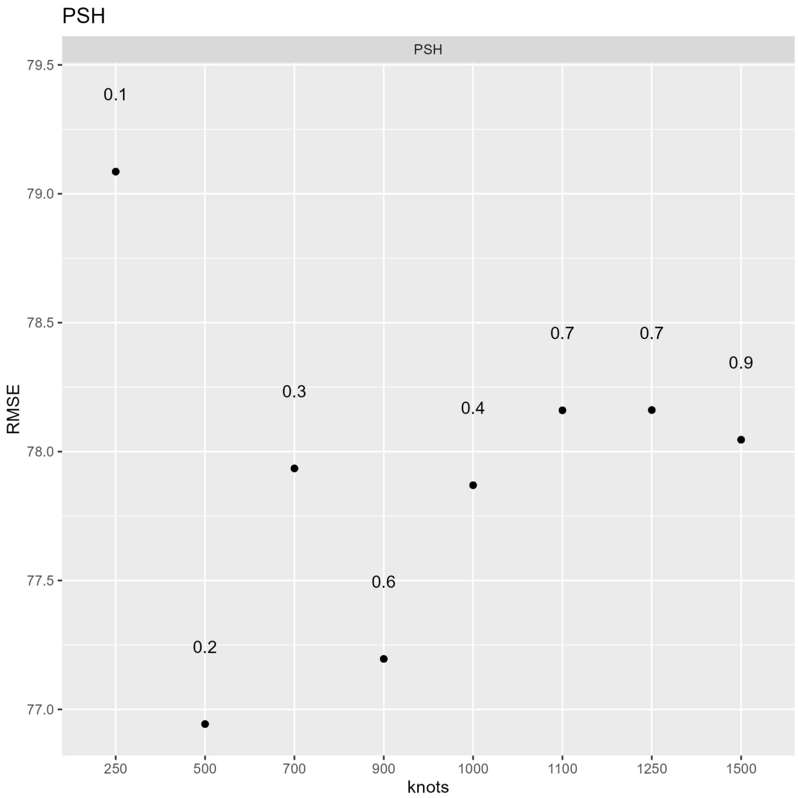
VAST data inputs

	PSH
Survey(s)	SEAMAP (Summer and Fall)
Years	2010-2022
Area	SSZ 2-10
Catchability covariates	TOD, month
Density covariates	Median annual nursery temperature & salinity (+ 1 to 2 year lags), depth (spline)

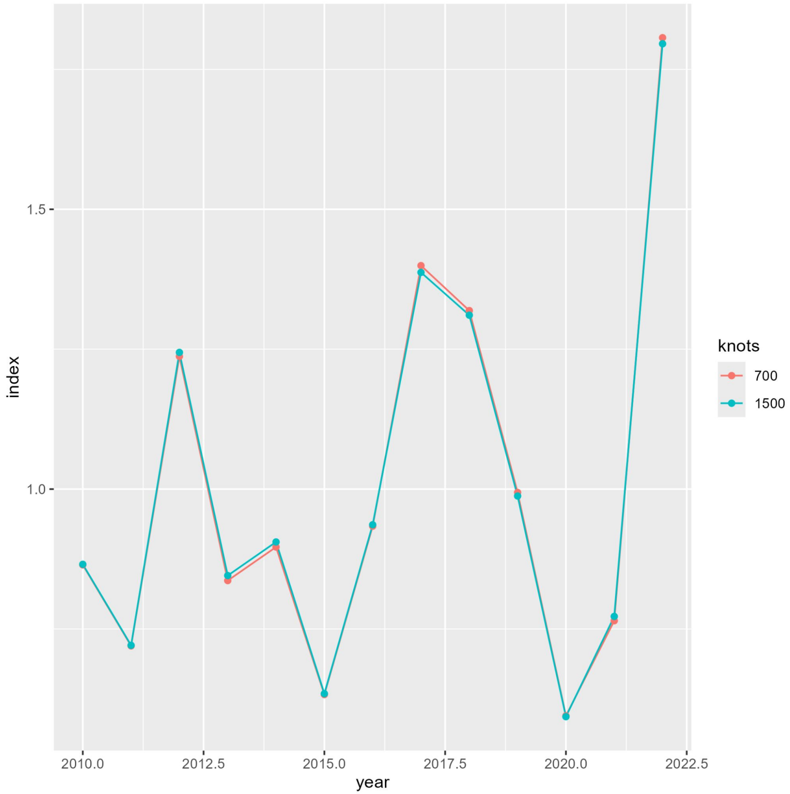
Data preprocessing - Prediction grids



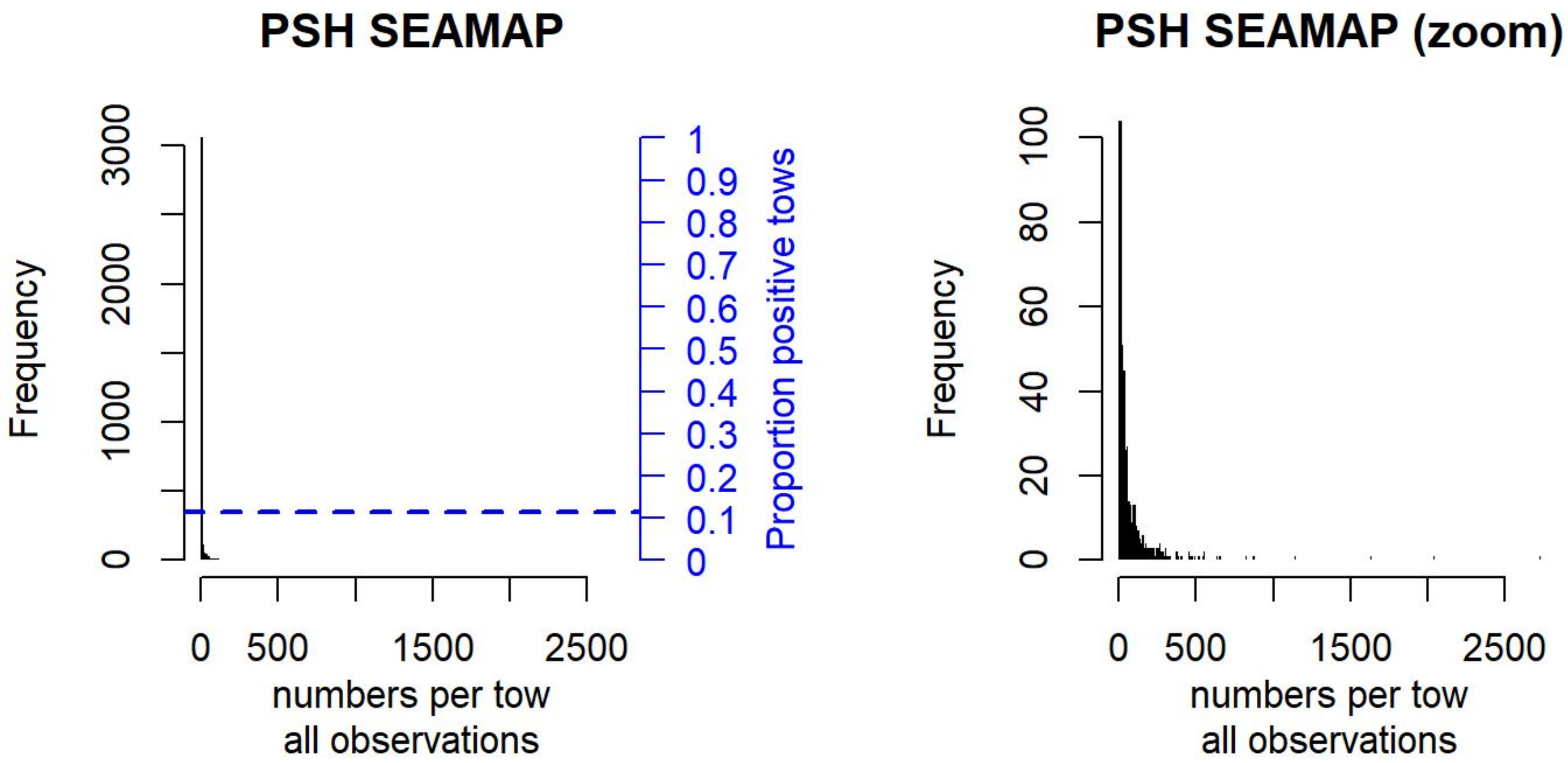
Knots



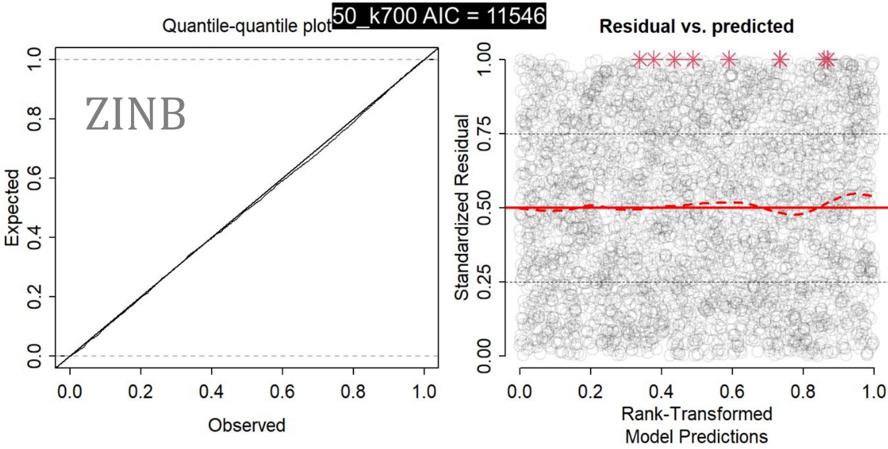
PSH
PSH
RMSE
knots
0.1
0.2
0.3
0.6
0.4
0.7
0.7
0.9
79.5
79.0
78.5
78.0
77.5
77.0
250
500
700
900
1000
1100
1250
1500

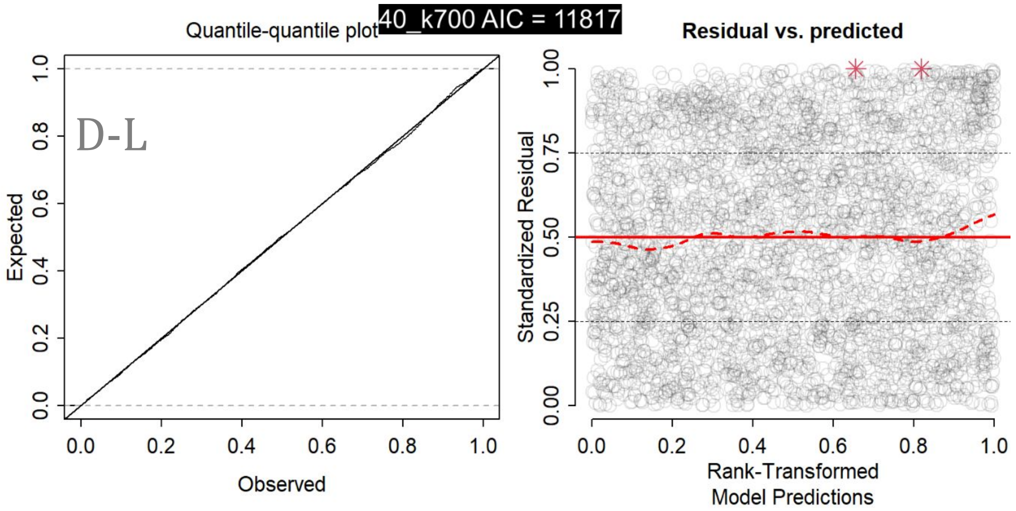


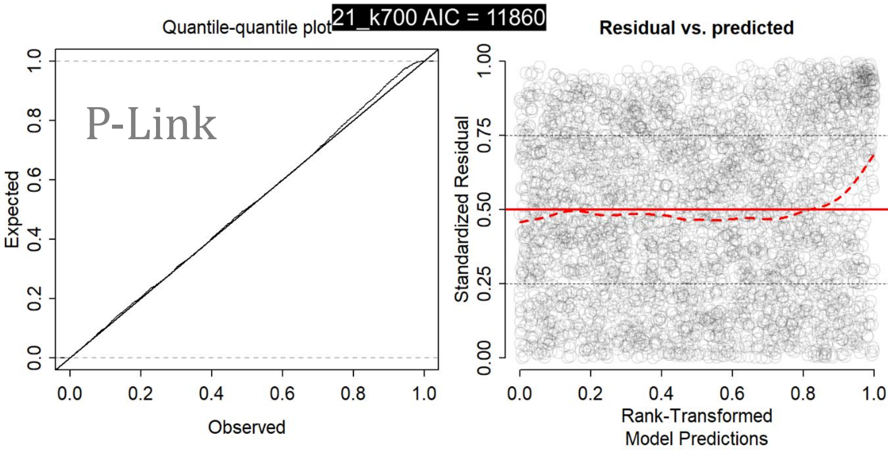
index
year
1.5
1.0
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
knots
700
1500


PSH SEAMAP
Frequency
0
1000
2000
3000
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Proportion positive tows
0
500
1500
2500
numbers per tow
all observations
PSH SEAMAP (zoom)
Frequency
0
20
40
60
80
100
0
500
1500
2500
numbers per tow
all observations

Distribution and Error







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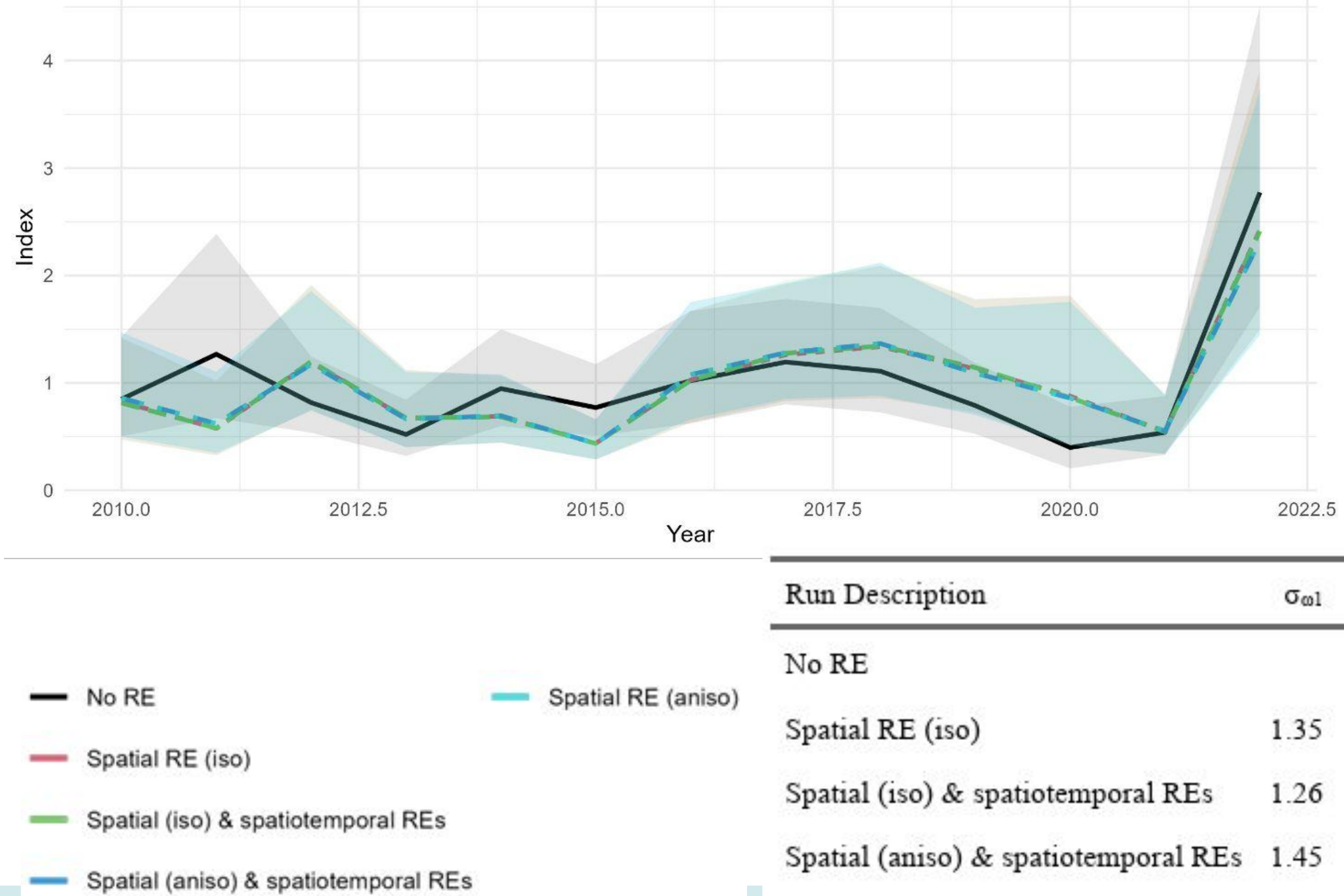
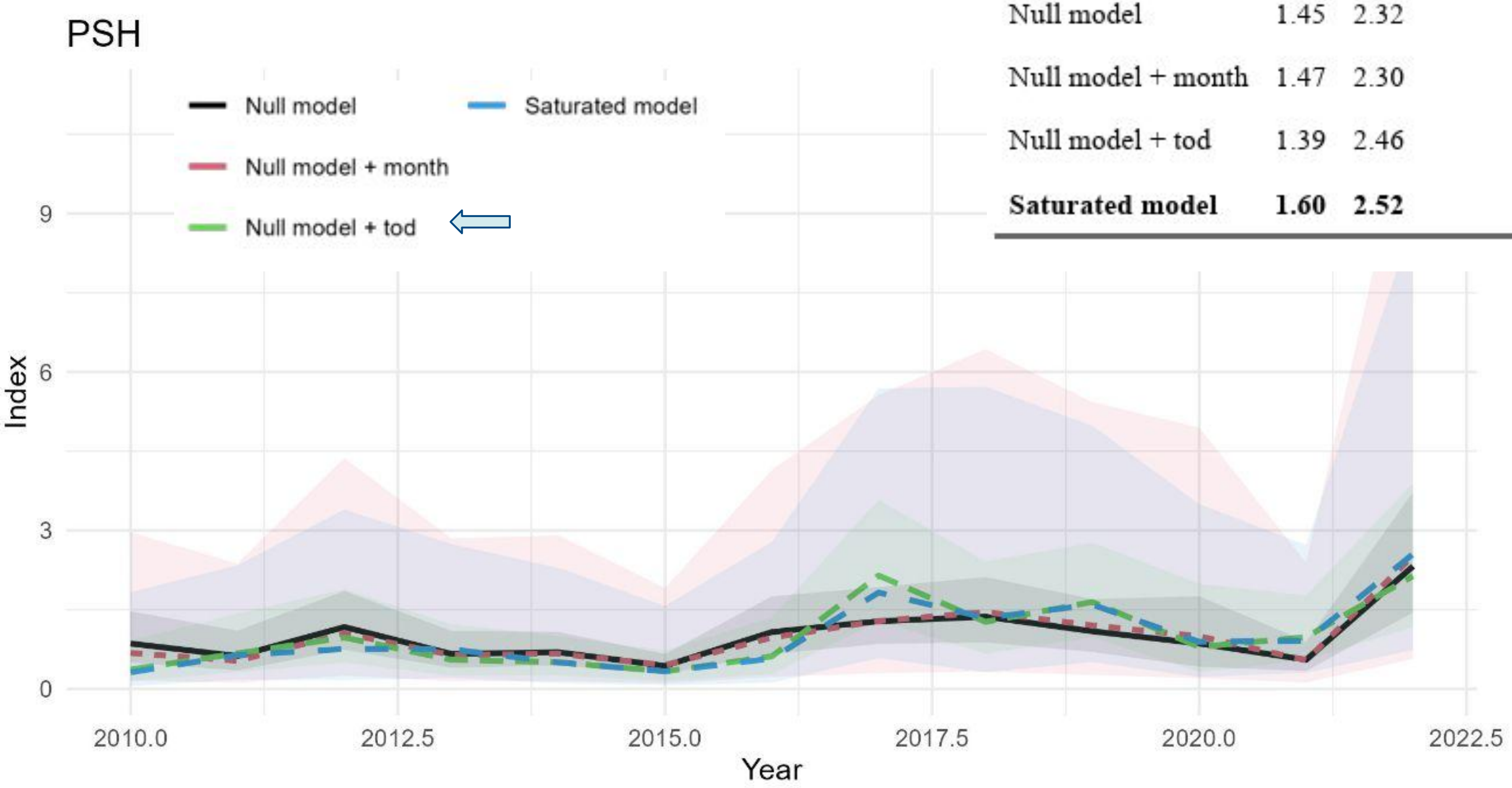
Spatial and Spatio-temporal Random Effects (RE)



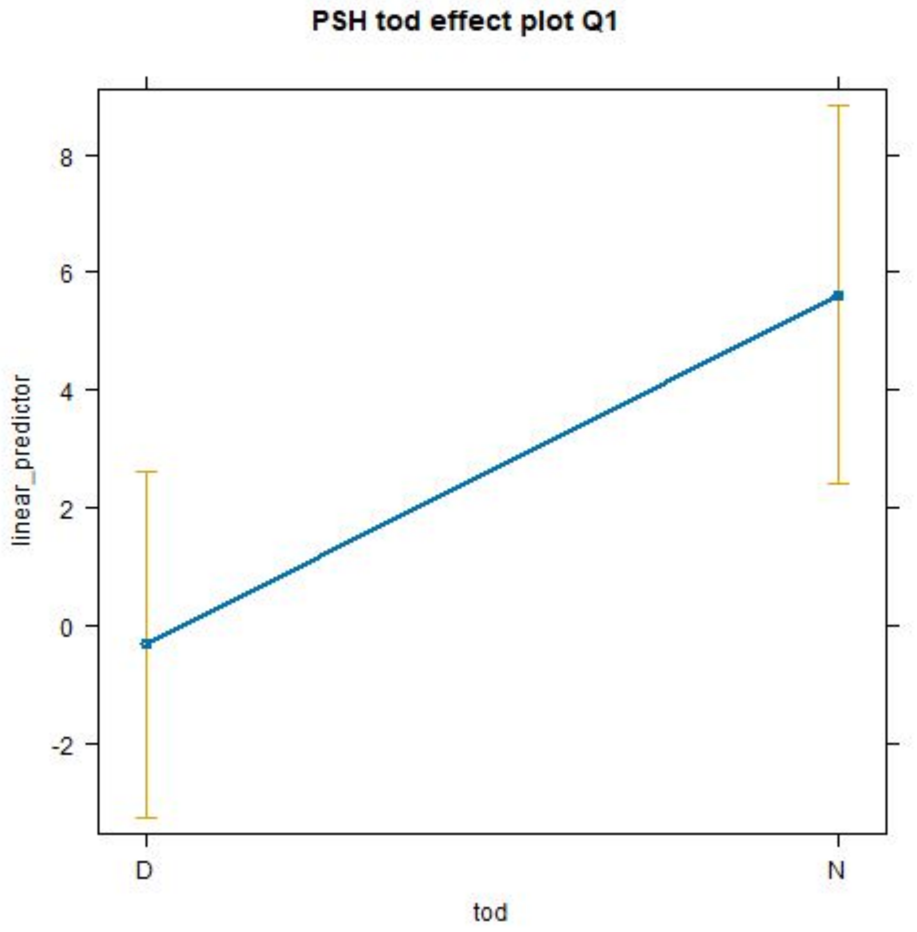
noRE: no spatial or spatiotemporal random effects
noEps: spatial but no spatiotemporal RE
Iso: isotropy
Aniso: anisotropy
Sigma: estimated variance of the RE
Omega: spatial RE
Epsilon: spatiotemporal RE

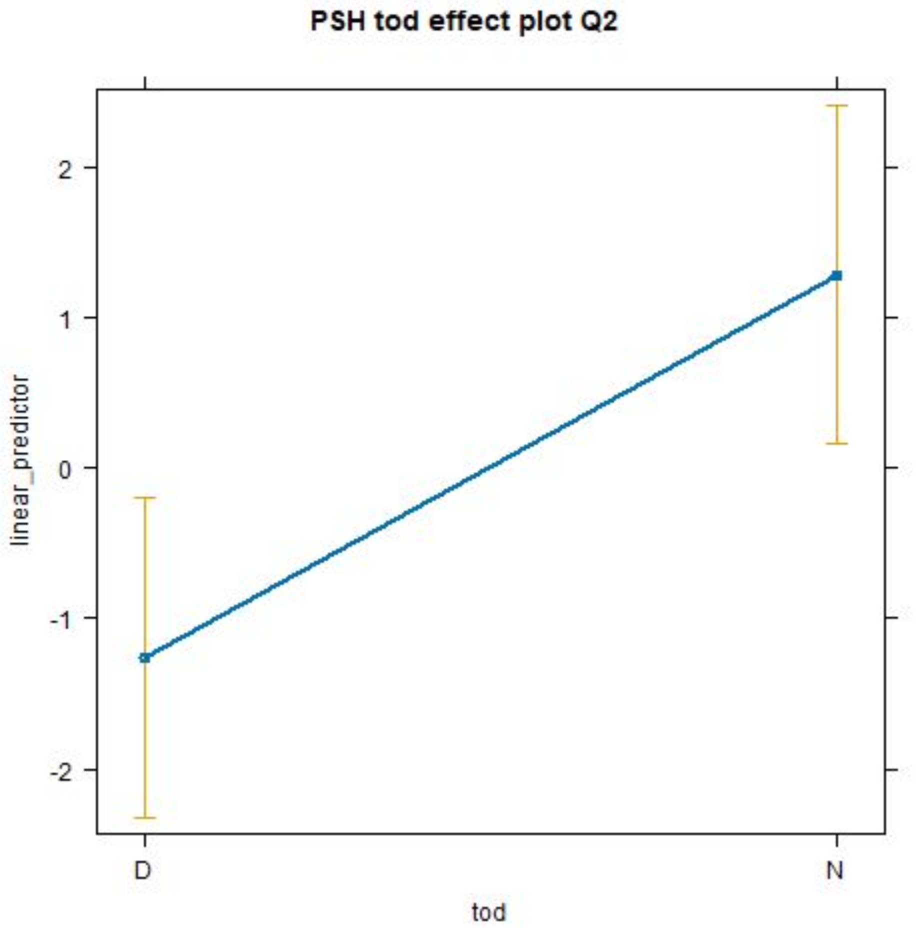
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
No RE					12,324	782
Spatial RE (iso)	1.35	2.35			11,549	7
Spatial (iso) & spatiotemporal REs	1.26	2.39	-0.19	0	11,553	11
Spatial (aniso) & spatiotemporal REs	1.45	2.32	0.00	0	11,546	4
Spatial RE (aniso)	**1.45**	**2.32**			**11,542**	**0**

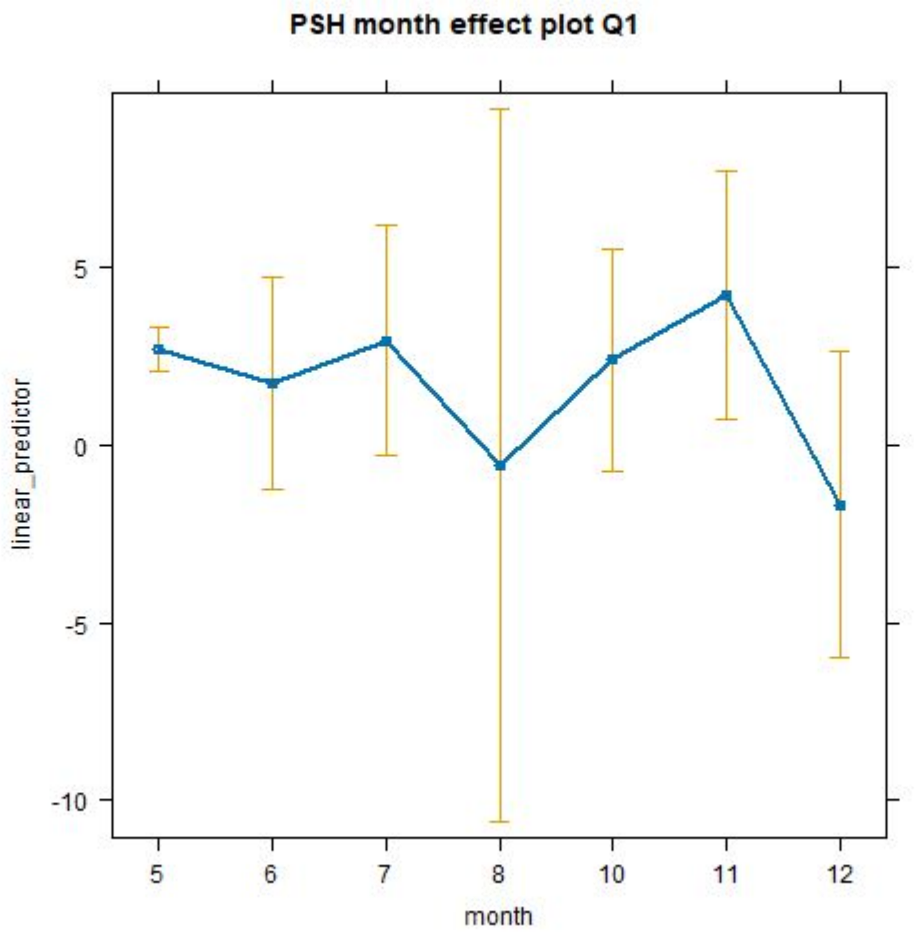
Catchability Covariates



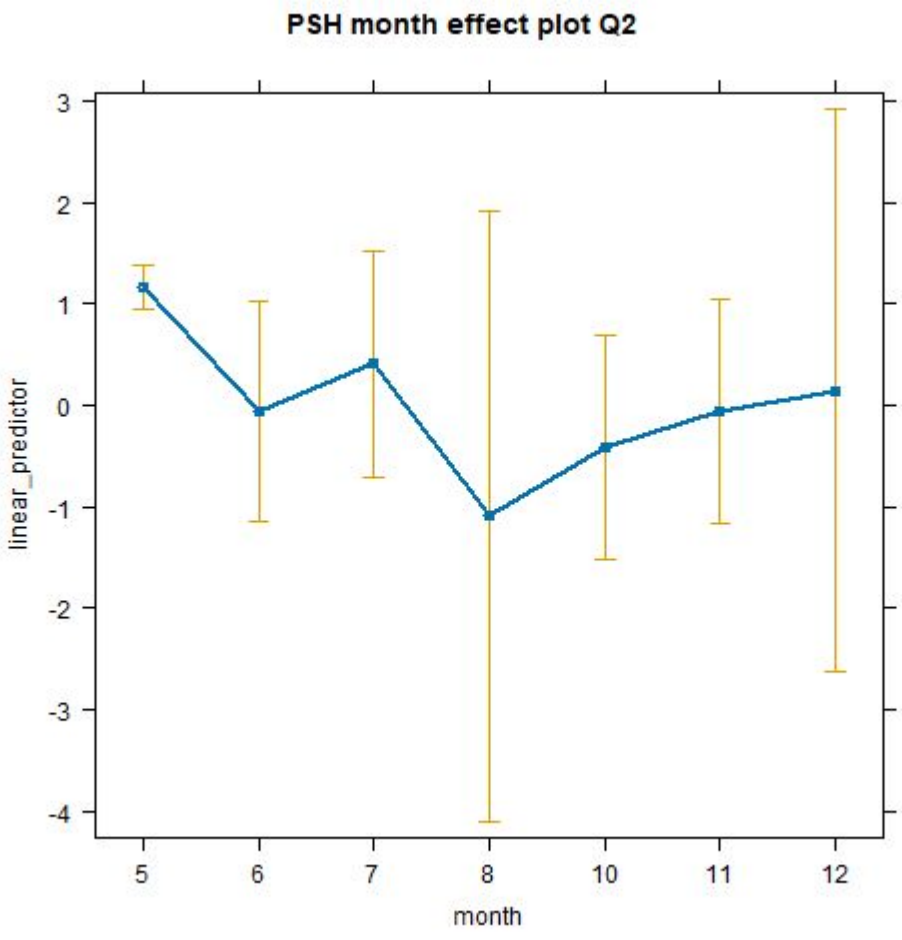
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	AIC	ΔAIC
Null model	1.45	2.32			11,542	1,319
Null model + month	1.47	2.30			11,533	1,311
Null model + tod	1.39	2.46			10,246	24
Saturated model	**1.60**	**2.52**			**10,223**	**0**


PSH tod effect plot Q1
8
6
4
2
0
-2
linear_predictor
D
N
tod


PSH tod effect plot Q2
2
1
0
-1
-2
linear_predictor
D
N
tod

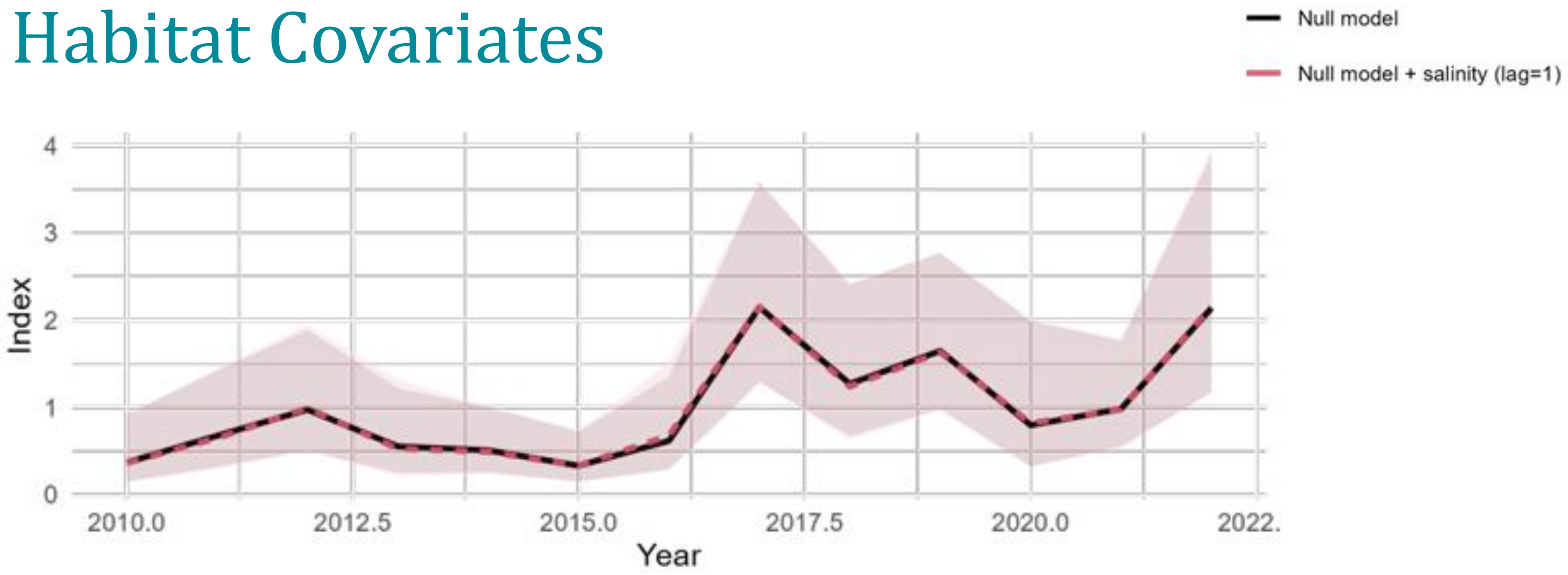


PSH month effect plot Q1
5
0
-5
-10
linear_predictor
5
6
7
8
10
11
12
month



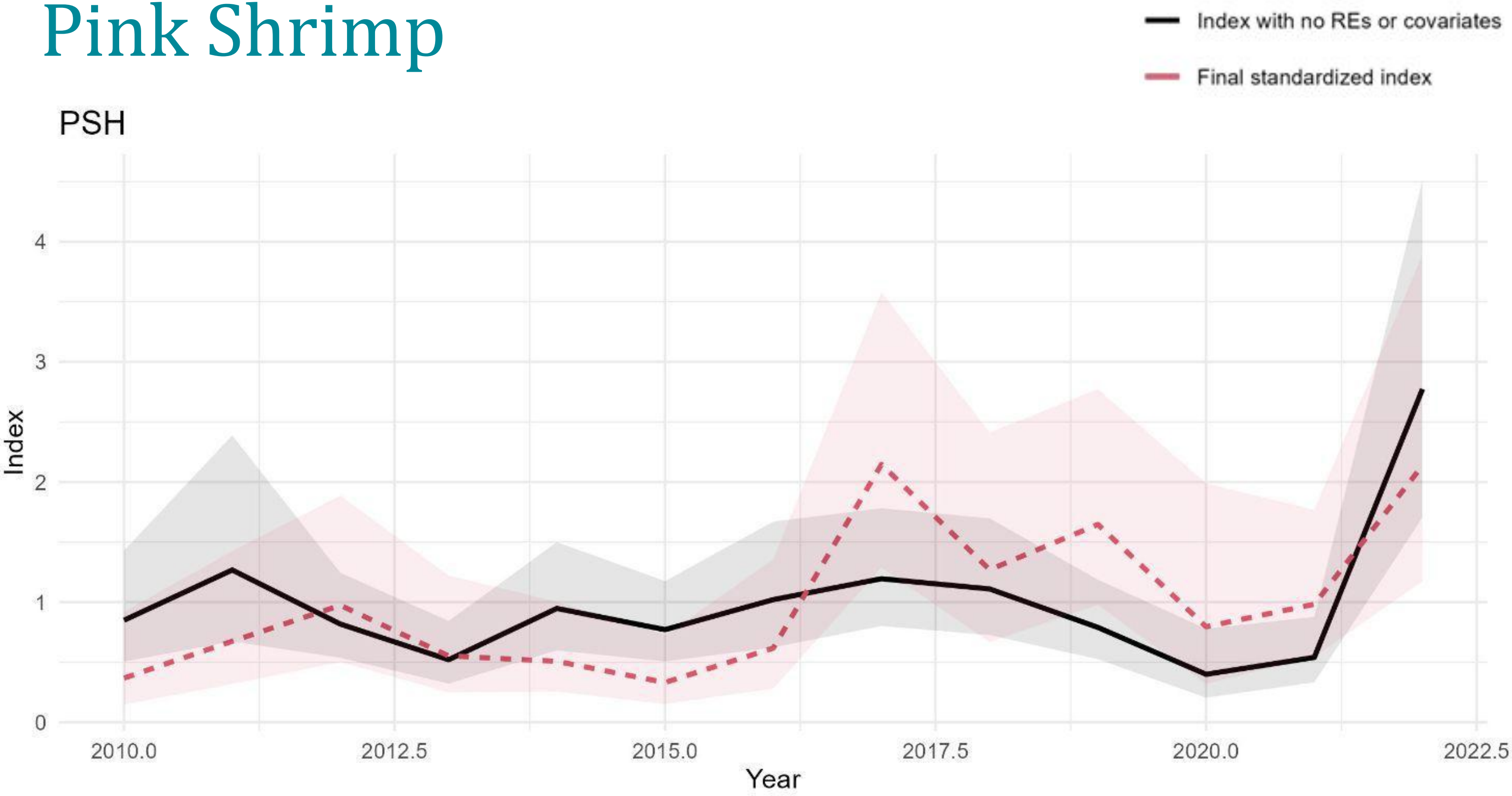
PSH month effect plot Q2
3
2
1
0
-1
-2
-3
-4
linear_predictor
5
6
7
8
10
11
12
month

Habitat Covariates

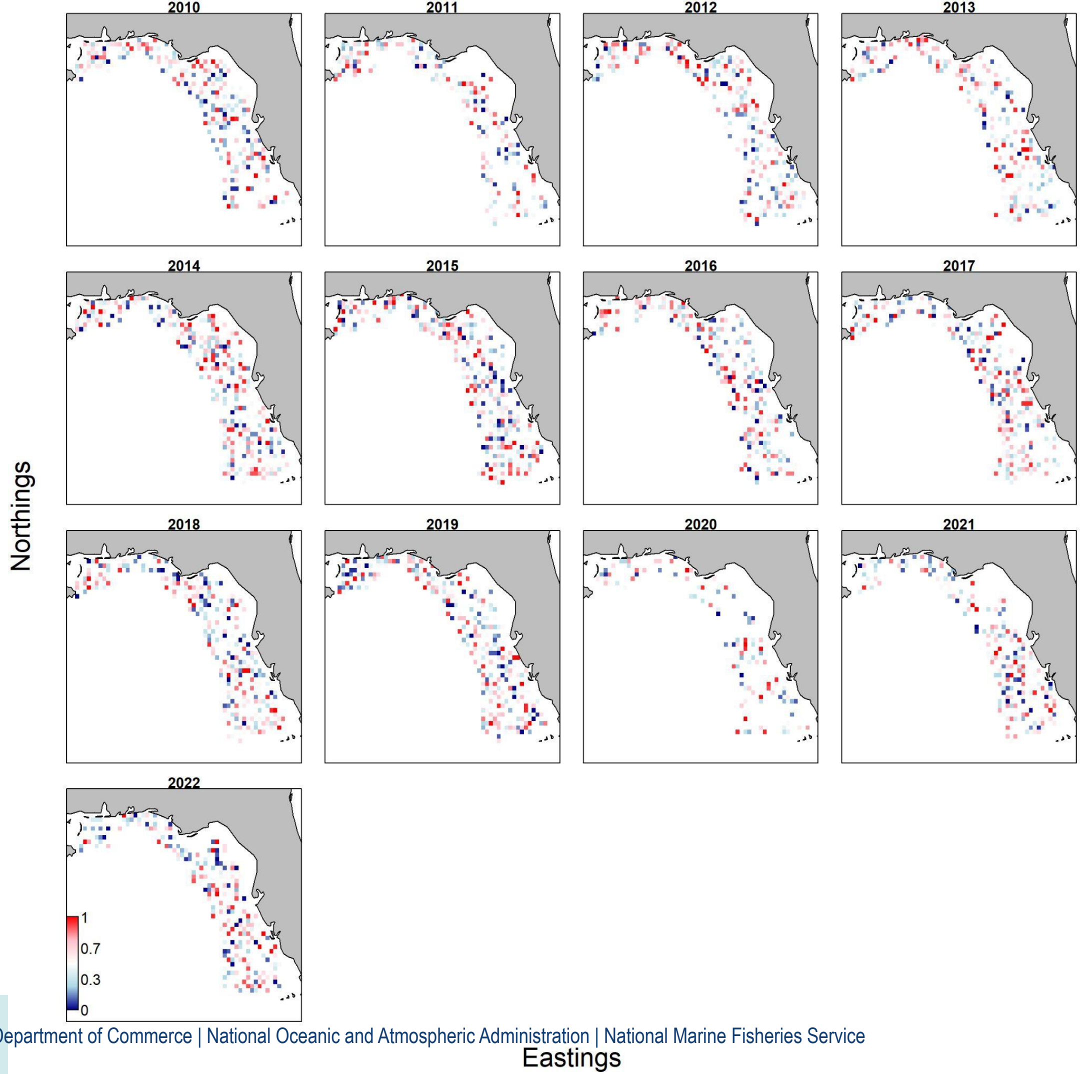


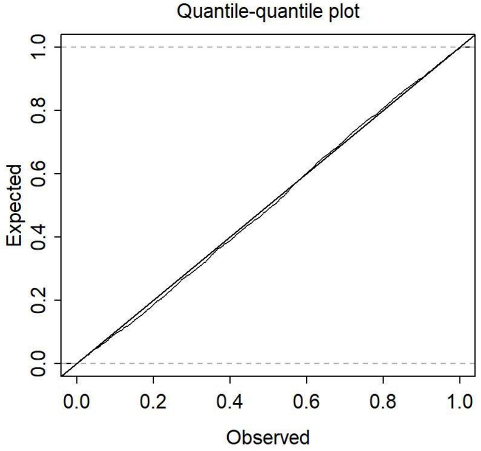
Run Description	$\sigma_{\omega 1}$	$\sigma_{\omega 2}$	$\sigma_{\varepsilon 1}$	$\sigma_{\varepsilon 2}$	$pseudoR^2_1$	$pseudoR^2_2$	AIC	ΔAIC
Null model	**1.39**	**2.46**			**0.000**	**0.000**	**10,246**	**0**
Null model + salinity (lag=1)	1.39	2.46			0.006	-0.005	10,249	3

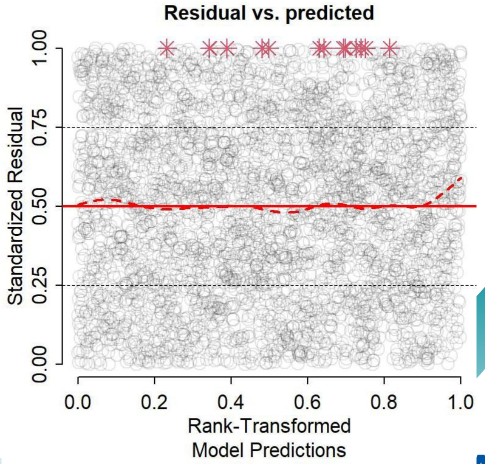
Pink Shrimp



Index with no REs or covariates
Final standardized index
PSH
Index
4
3
2
1
0
2010.0
2012.5
2015.0
2017.5
2020.0
2022.5
Year


2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
1
0.7
0.3
0
Northings
Eastings


Quantile-quantile plot
Expected
0.0
0.2
0.4
0.6
0.8
1.0
Observed


Residual vs. predicted
Standardized Residual
0.00
0.25
0.50
0.75
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Rank-Transformed
Model Predictions

PINK SHRIMP INDEX RECOMMENDATIONS

Pink Shrimp

SEAMAP (summer and fall)

2010-2022

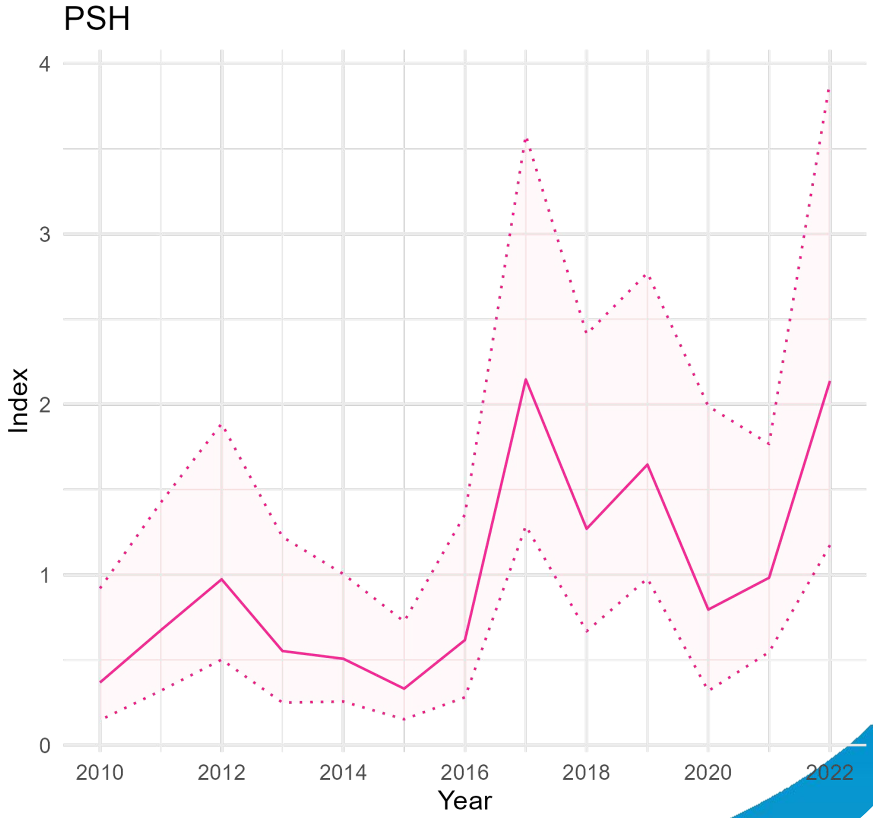
Zero-inflated negative binomial

Numbers per tow

Spatial RE (anisotropy) (no spatiotemporal RE)

Catchability covariates :

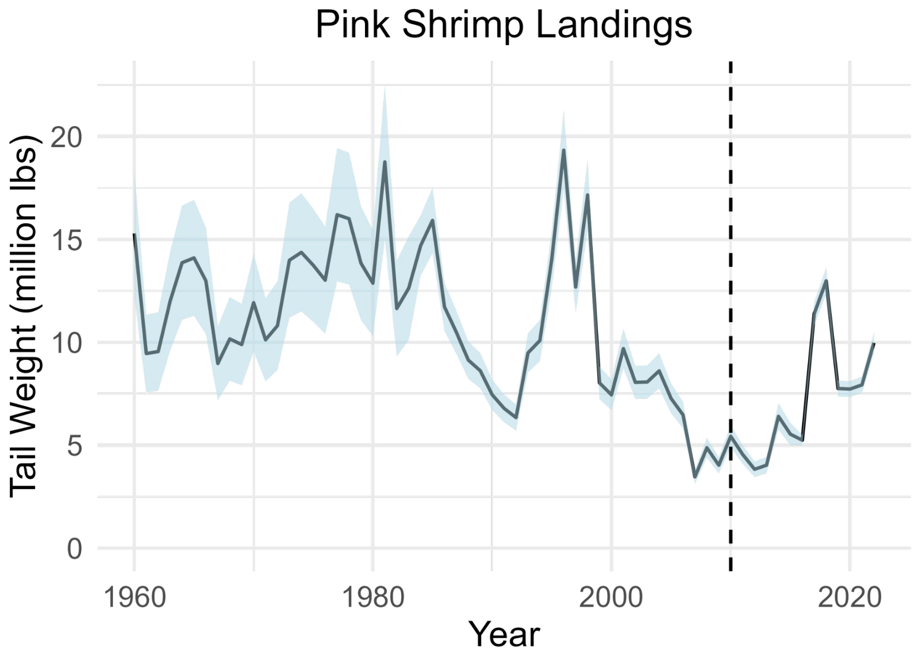
- Tod

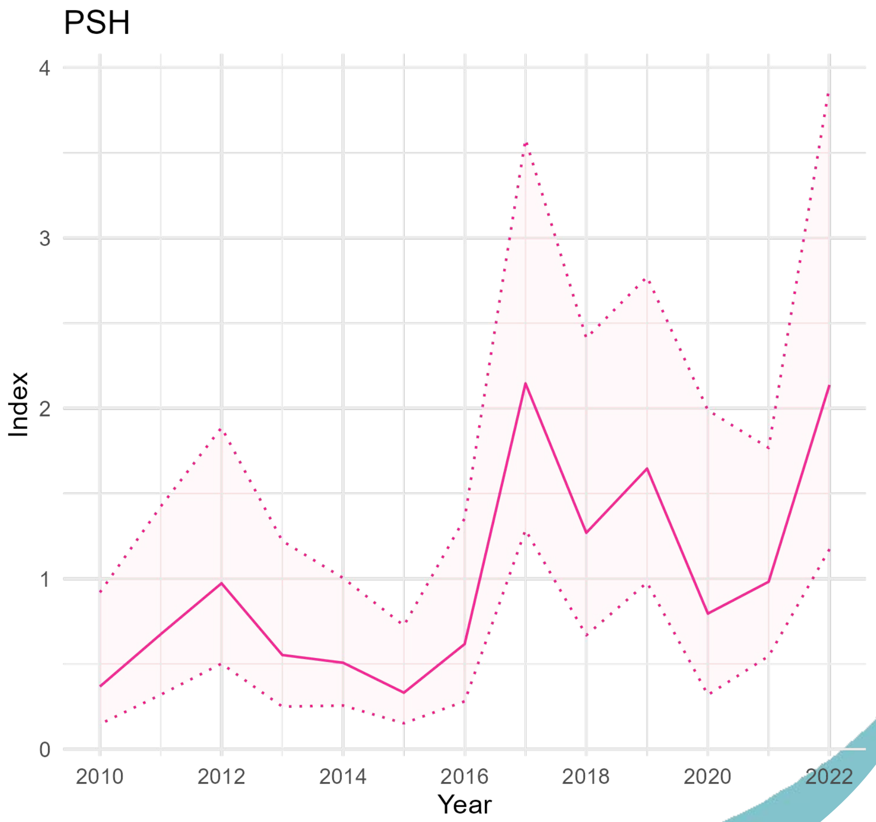


We recommend the use of this index for input into JABBA based on the model configurations listed above.

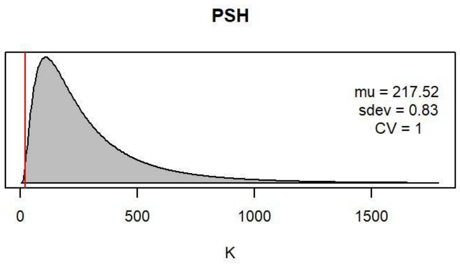
JABBA

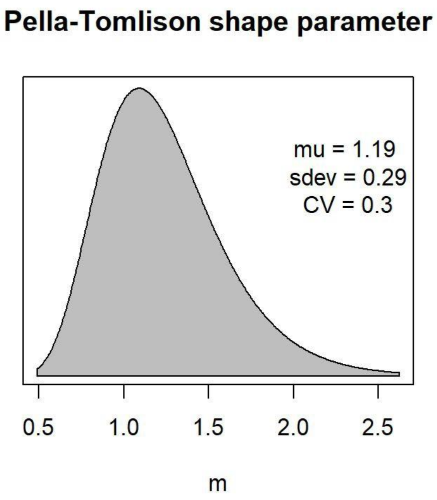
Data - Pink Shrimp

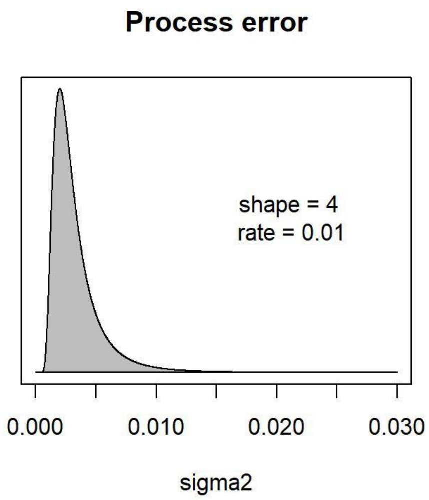




Priors (all runs)

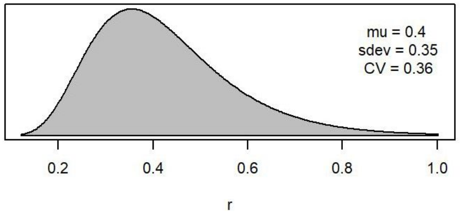




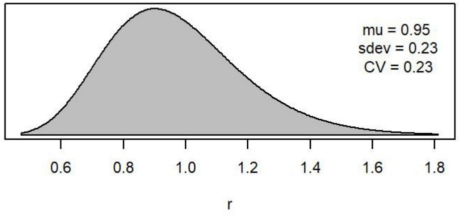


Priors (uncertainty grid)

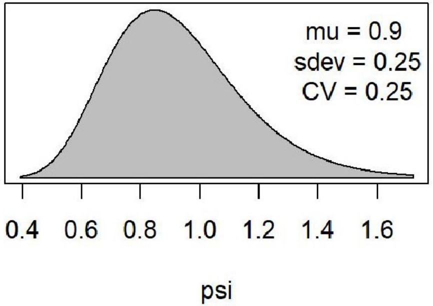
Medium



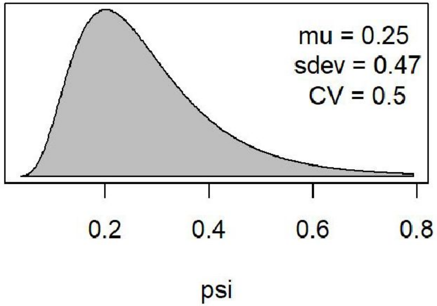
High



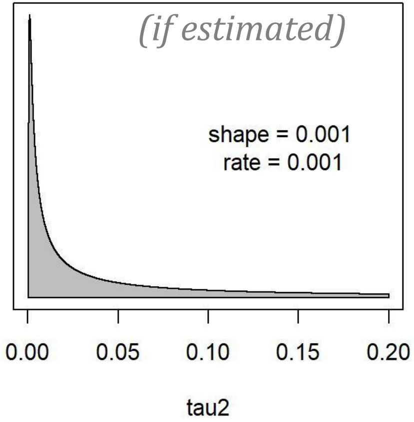
Lower Initial Depletion



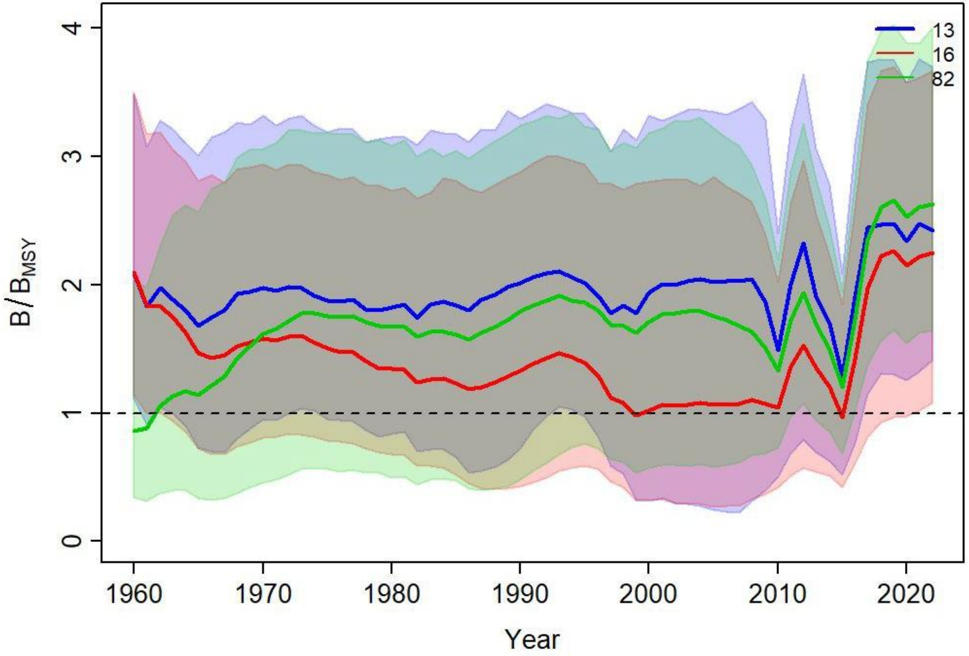
Higher Initial Depletion



Observation error



Pink Shrimp Results



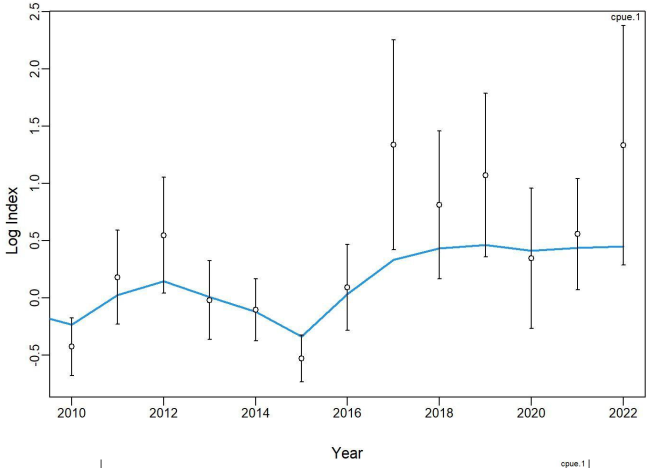
Run	Description
13	Sigma Estimation FALSE. R prior High range. Prior distribution for psi lnorm with mean 0.9.
16	Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.9.
82	Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.

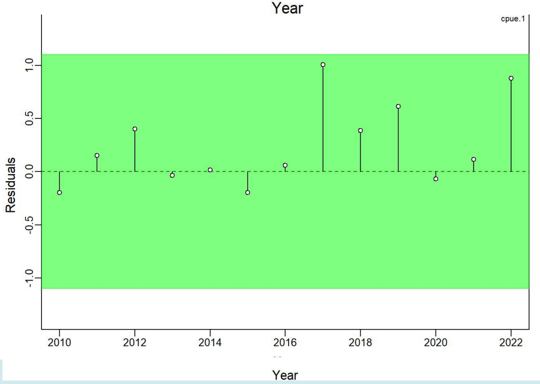
Pink Shrimp Model Diagnostics

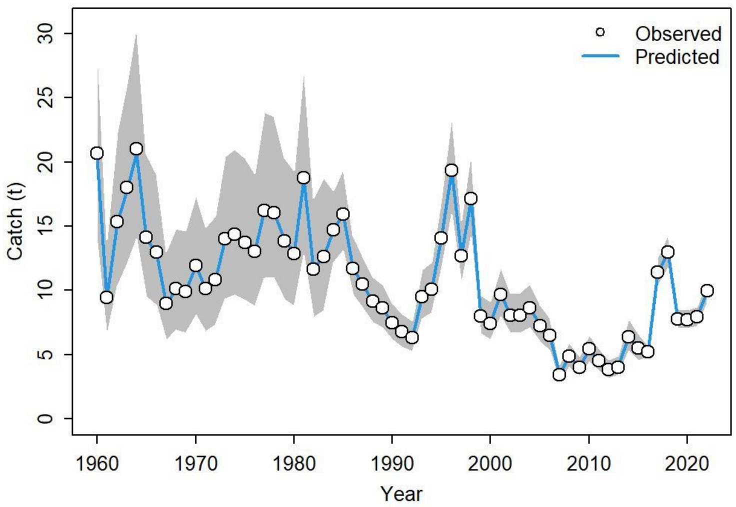
	Model Convergence			Model Fit		Model Consistency				Process Error	Prediction Skill	
run	CONV_gw	CONV_hw	CONV_hs	CPUE_rt_rand	CPUE_rt_outl	RETRO_B	RETRO_F	RETRO_B.Bmsy	RETRO_F.Fmsy	ProcB_CI	HX_MASE	DIC
PSH_13_P_rH_psil0.9_sigF_60	FAIL	PASS	PASS	FAIL	PASS	0.11	-0.06	0.02	-0.30	FAIL	1.76	-456.30
PSH_16_P_rM_psil0.9_sigF_60	PASS	PASS	PASS	PASS	PASS	0.29	-0.21	0.16	-0.41	FAIL	1.49	-466.80
PSH_82_P_rM_psil0.2_sigF_60	PASS	PASS	PASS	PASS	PASS	0.00	-0.00	0.01	-0.17	FAIL	1.49	-472.80

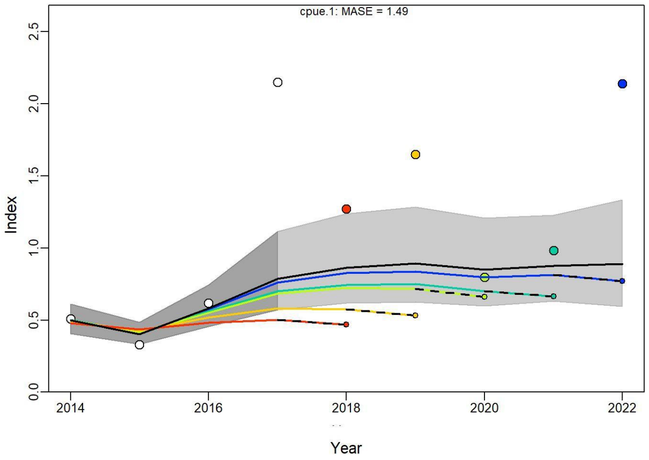
Pink Shrimp - Example run

82 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.



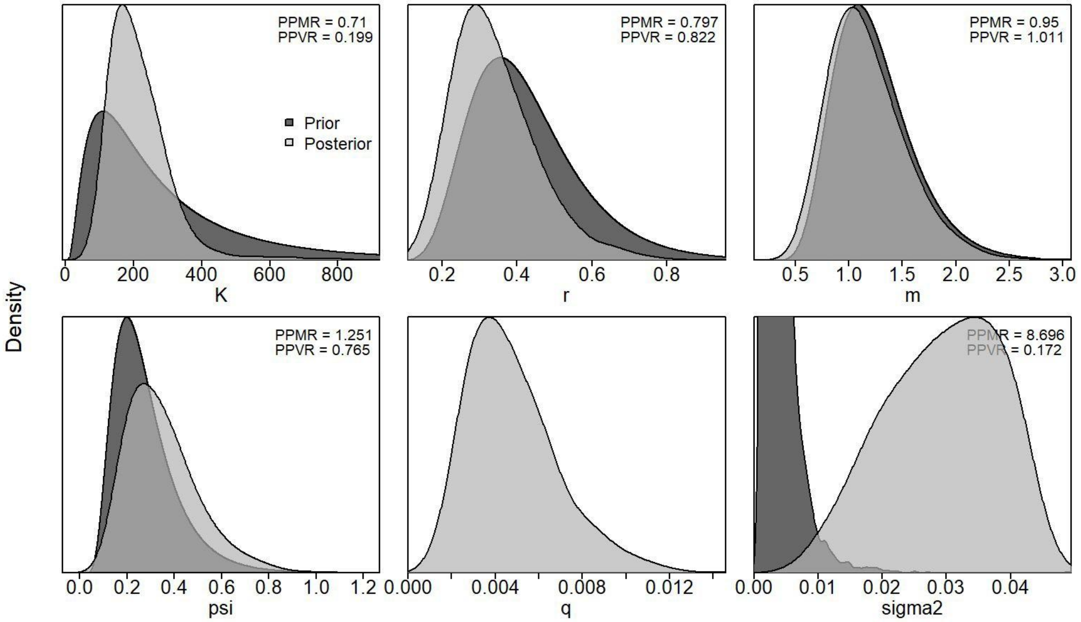


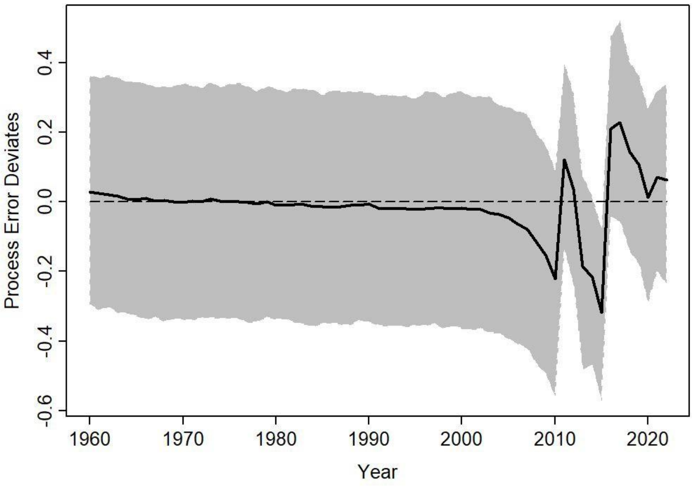




Priors, Posteriors and Process Error

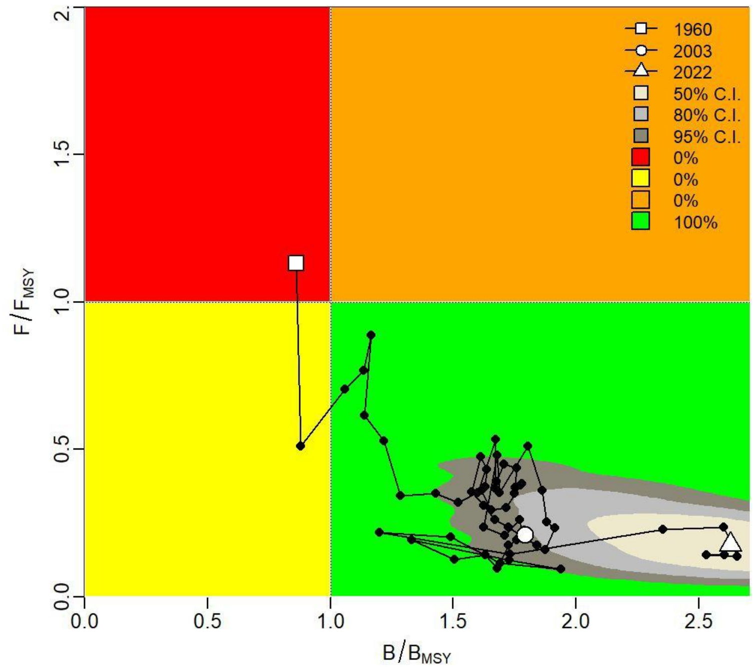
82 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.

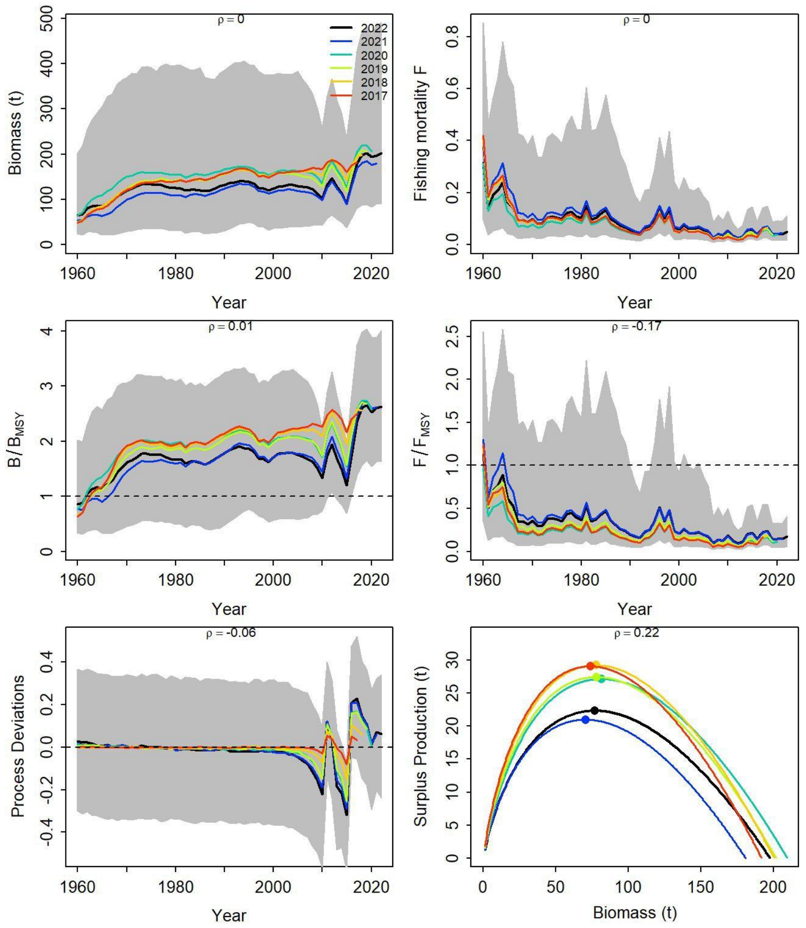




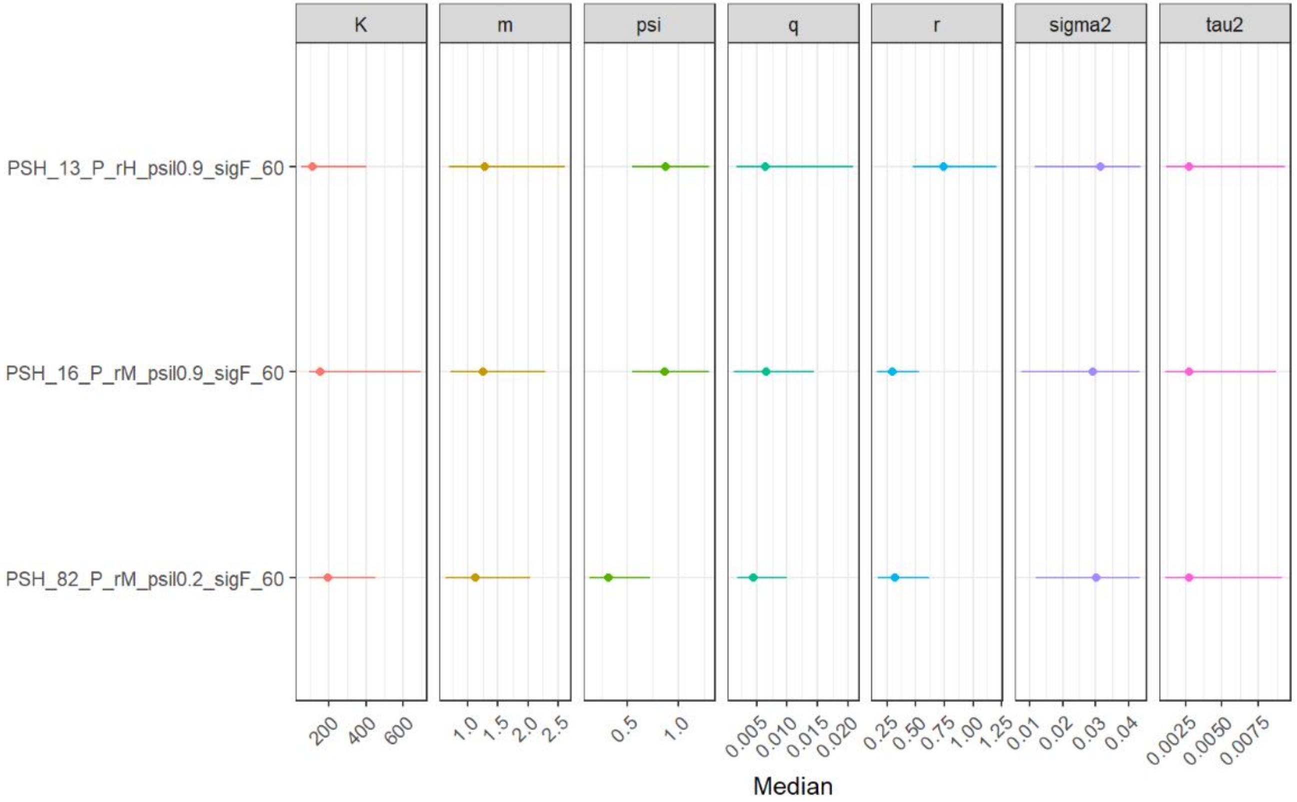
Retrospective Analysis & Kobe Plot

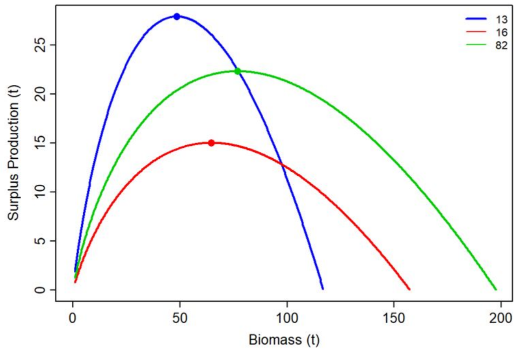
82 Sigma Estimation FALSE. R prior Medium range. Prior distribution for psi lnorm with mean 0.25.





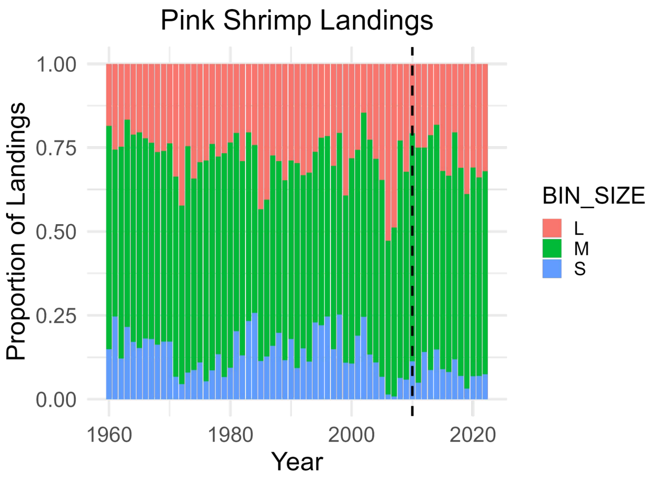
Pink Shrimp Parameter Estimates





PINK SHRIMP JABBA SUMMARY

- Similar weaknesses as raised with brown and white shrimp (some of the main assumptions likely violated)
- Non-informative catch rates (CPUE and catches both follow same trends)
- Short index time series
- Poor diagnostics
  - Poor prediction skill for the index
  - Low information (not much departure from priors)



Recommendation

- JABBA **not recommended** for pink shrimp

EDM

Stratification of Pink Shrimp Data

A. **Aggregated:** ANNUAL ; SIZE BINS AGG

C. **Size:** ANNUAL ; SIZE BINS (>67, 67-31, <=30)

Csm. **Size2:** ANNUAL ; SIZE BINS (>31, <=30)

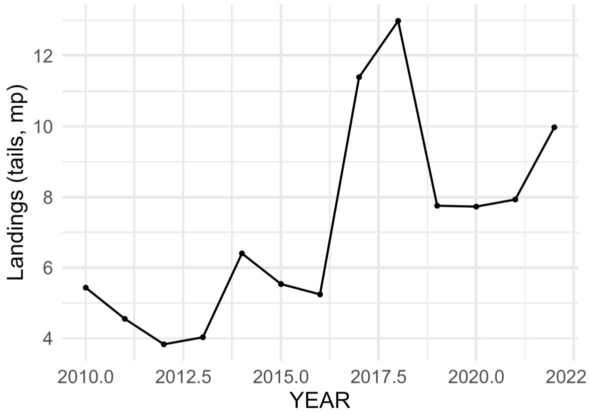
Note: Single area- and season- models for pink shrimp due to limited biological range and delayed SEAMAP survey expansion, respectively. Area- and season-specific strata B, D, E, F, G, H not included.

Pink Shrimp EDM

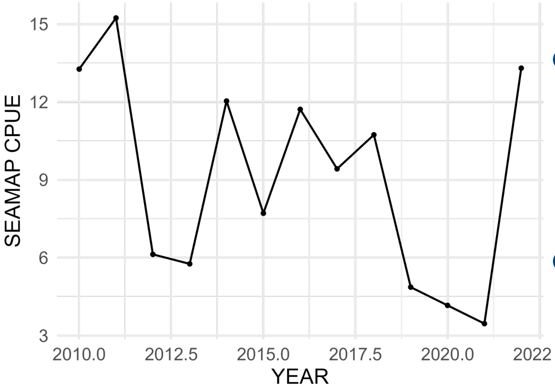
- Pink shrimp
  - SEAMAP, 2010-2022, Summer only
    - $E \leq \sqrt{T}$, where T=13, $E \leq$ 3-4 (up to 2-3 lags, or 1-2 lags and 1 covariate, etc)
    - Pushing limits for time series length
  - Could add SEAMAP Fall 2014-2022, but that would limit time series length further or unnecessarily increase embedding dimension to accommodate variable time steps

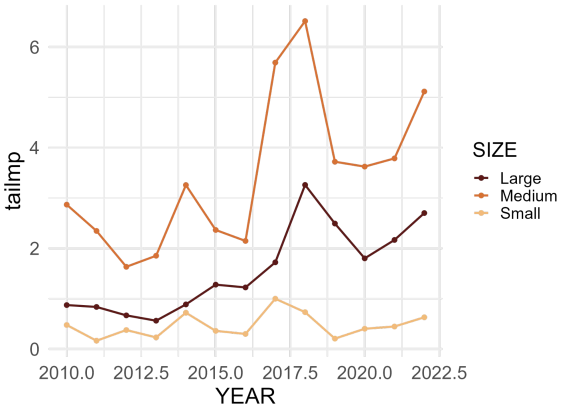
Pink Shrimp

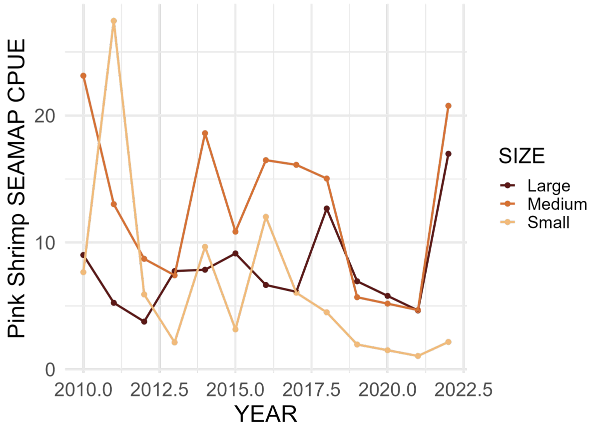
Landings



CPUE







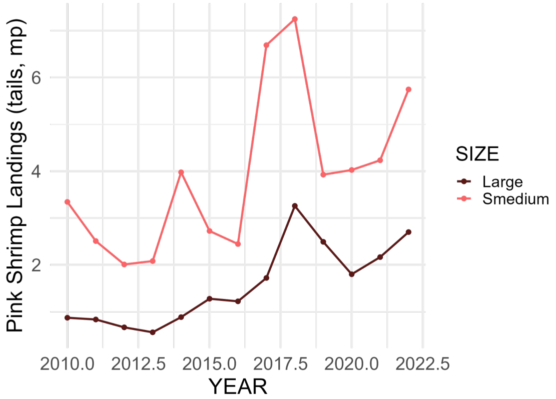
- Model structure options
  - Individual models
  - Hierarchical to share length scales
- Size model hypotheses (Pop=Size)
  -

Year	State	Total Landings (tails, mp)	Landings Missing Size (tails, mp)	Percent Missing Size
2010	FL	5.434	1.218	22.4%
2011	FL	4.552	1.207	26.5%
2012	FL	3.830	1.153	30.1%
2013	FL	4.030	1.386	34.4%
2014	FL	6.404	1.542	24.1%
2015	FL	5.537	1.535	27.7%
2016	FL	5.243	1.575	30.0%
2017	FL	11.394	2.984	26.2%
2018	FL	12.989	2.484	19.1%
2019	FL	7.755	1.337	17.2%
2020	FL	7.730	1.904	24.6%
2021	FL	7.931	1.532	19.3%
2022	FL	9.975	1.530	15.3%

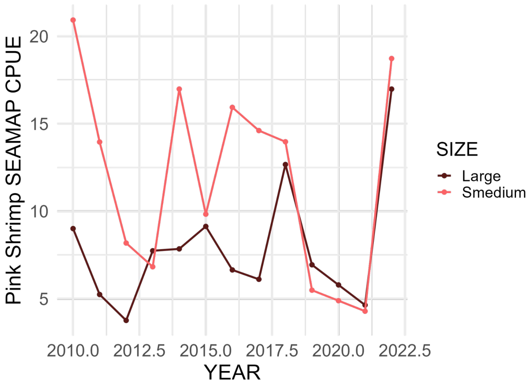
Pink Shrimp

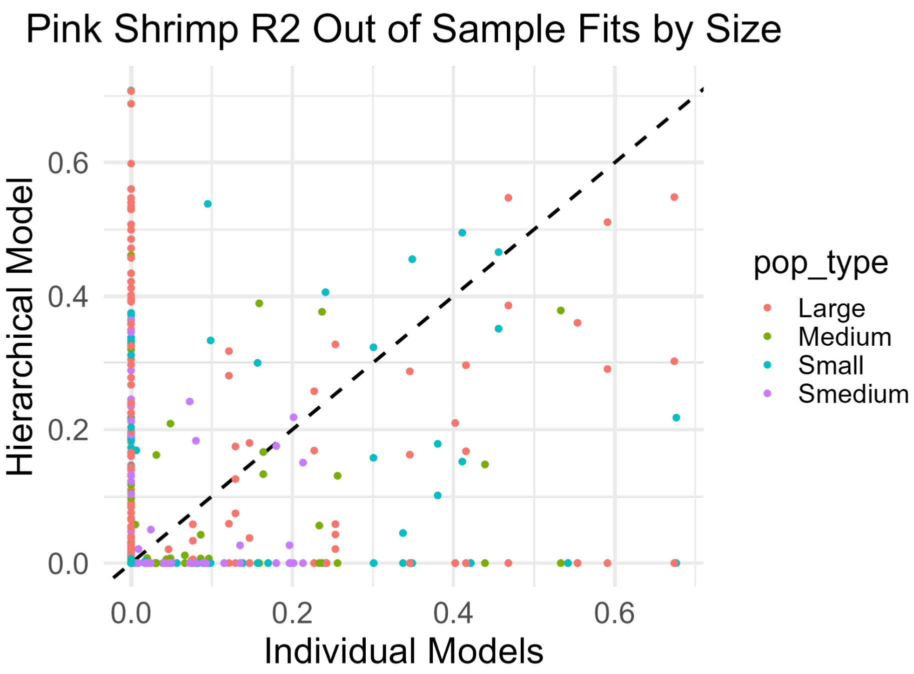
- Model structure options
  - Individual models
  - Hierarchical to share length scales
- Aggregated sizes

Landings



CPUE





Hierarchical population fits compared to independent model fits, ALL MODELS

No strong evidence to move towards individual independent models

Top Performing Model Runs

Run	Stratum	Pop	E	ytrans	Catchability	LinPrior	rho	R2	R2_out	R2_outscaled	ProcessVar	PriorVar
PSH_A20051	A	GULF	4	none	Distinct	Yes	0.5	0.641	0.128	0.128	0.583	1.595
PSH_C1035	C	SIZE	3	log	Distinct	None	0.67	0.485	0.327	0.016	0.766	0.45
PSH_C20039	C	SIZE	4	none	Distinct	None	0.76	0.682	0.297	0	0.544	0.615
PSH_C859	C	SIZE	3	none	Distinct	None	0.73	0.536	0.279	0	0.629	0.468
PSH_C10155	Csm	SIZE	3	none	Shared	None	0.37	0.561	0.235	0	0.774	0.399
PSH_C309	C	SIZE	2	log	Shared	None	0.62	0.282	0.221	0	0.957	0.298
PSH_C1013	C	SIZE	2	log	Distinct	None	0.62	0.282	0.221	0	0.957	0.298
PSH_C10133	Csm	SIZE	2	none	Shared	None	0.56	0.312	0.16	0	0.92	0.766
PSH_C21069	Csm	SIZE	4	none	Shared	Yes	0.49	0.855	0.154	0	0.277	1.416
PSH_C1519	C	SIZE	3	none	Shared	Yes	0.45	0.47	0.15	0	0.546	0.927
PSH_C89	C	SIZE	2	none	Shared	None	0.52	0.316	0.132	0	0.548	0.934
PSH_C793	C	SIZE	2	none	Distinct	None	0.52	0.316	0.132	0	0.548	0.934
PSH_C1695	C	SIZE	3	log	Shared	Yes	0.44	0.382	0.12	0	0.584	1.124
PSH_C21037	Csm	SIZE	4	none	Distinct	None	0.38	0.896	0.12	0	0.169	1.281
PSH_C1497	C	SIZE	2	none	Shared	Yes	0.51	0.312	0.115	0	0.596	0.949
PSH_C10815	Csm	SIZE	3	none	Distinct	None	0.36	0.902	0.114	0	0.135	1.331
PSH_C265	C	SIZE	2	log	Shared	None	0.49	0.265	0.114	0	0.654	1.206
PSH_C10969	Csm	SIZE	2	log	Distinct	None	0.5	0.248	0.097	0	0.645	1.336
PSH_C10265	Csm	SIZE	2	log	Shared	None	0.5	0.248	0.097	0	0.645	1.336
PSH_C10111	Csm	SIZE	3	none	Shared	None	0.37	0.899	0.094	0	0.141	1.318
PSH_C10793	Csm	SIZE	2	none	Distinct	None	0.51	0.305	0.093	0	0.491	1.213
PSH_C10089	Csm	SIZE	2	none	Shared	None	0.51	0.305	0.093	0	0.491	1.216
PSH_C12223	Csm	SIZE	3	none	Distinct	Yes	0.36	0.898	0.089	0	0.192	1.788
PSH_C20069	C	SIZE	4	none	Shared	Yes	0.47	0.416	0.084	0	0.63	0.89
PSH_C11695	Csm	SIZE	3	log	Shared	Yes	0.49	0.649	0.077	0	0.51	1.965
PSH_C11519	Csm	SIZE	3	none	Shared	Yes	0.37	0.894	0.077	0	0.196	1.764
PSH_C12399	Csm	SIZE	3	log	Distinct	Yes	0.49	0.645	0.074	0	0.512	1.906
PSH_C21045	Csm	SIZE	4	log	Distinct	None	0.42	0.713	0.066	0	0.397	1.619
PSH_C287	C	SIZE	3	log	Shared	None	0.3	0.596	0.062	0	0.42	0.983
PSH_C21109	Csm	SIZE	4	log	Distinct	Yes	0.49	0.643	0.052	0	0.578	1.935

Top 30 Models

None have any predictive capabilities

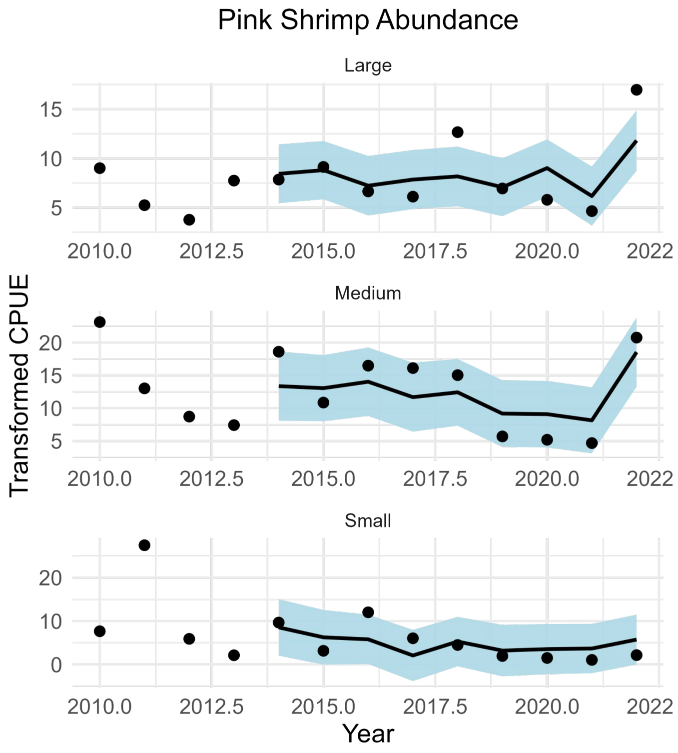
NOAA FISHERIES

PINK SHRIMP EDM
Maximum Sustainable Yield

Top Performing Models

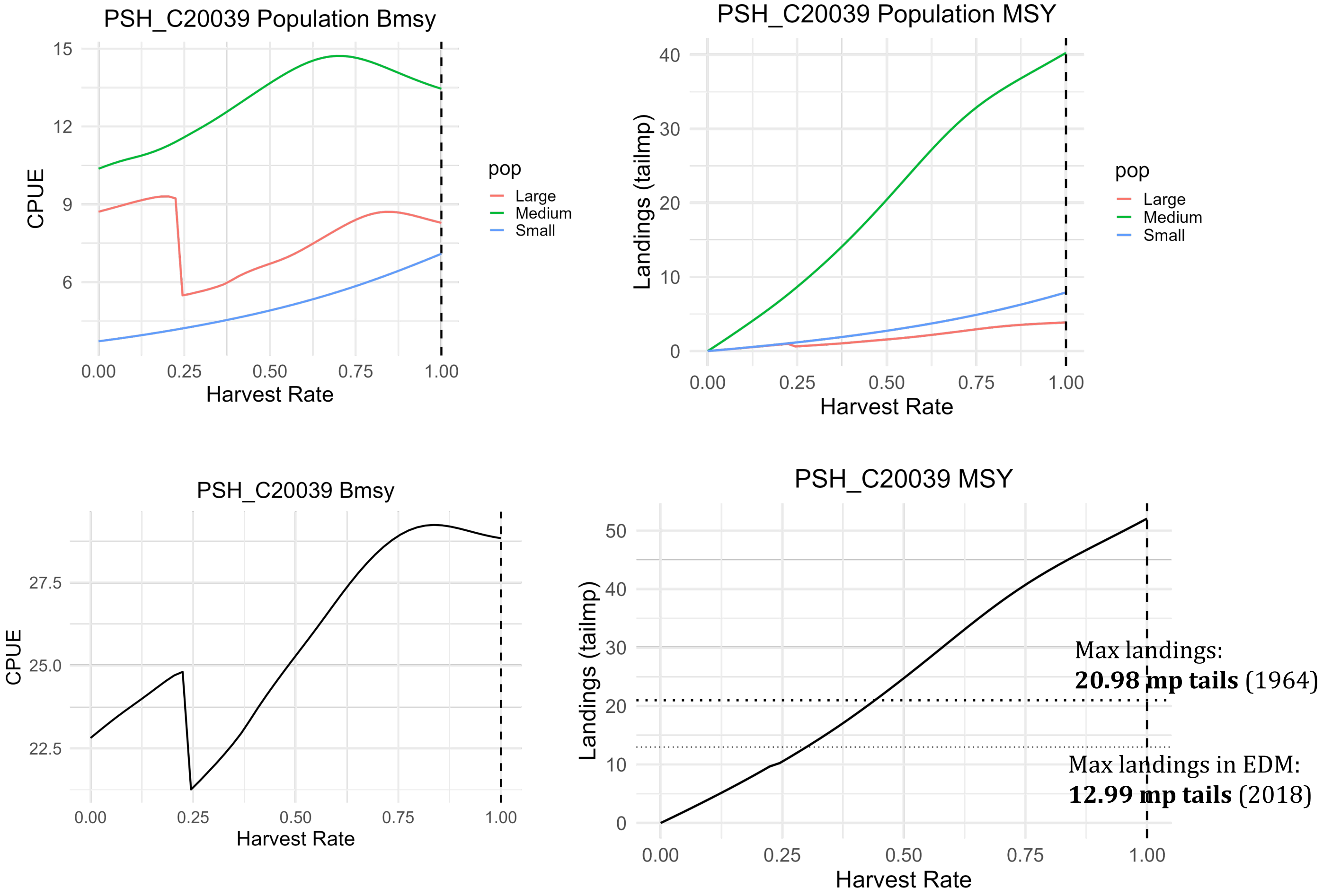
- No pink shrimp models passed the selection criteria
- Insufficient time series length to accurately projection pink shrimp population and landings

Size-structured (Large, Medium, Small), separately estimated catchability, annual time steps, E=4, no transformation on y [C20039]



Vars	Value
spp.run	PSH_C20039
stratum	C
E	4
Covariate	none
pop	SIZE
Shared_catchability	FALSE
scaling	local
ytrans	none
df	7.531
R2	0.682
R2out	0.297
R2out_scaled	0
Large	0
Medium	0.101
Small	0

MSY is added across populations



Vars	Value
spp.run	PSH_C20039
msy	52.056
fmsy	1
Bmsy	28.833
df_0	7.531
Bmsy_landunit	41.846
R2_0	0.682
R2scaled_0	0.54
R2_out_0	0.297
R2scaled_out_0	0
rho_0	0.756
bLarge_0	2.142
bMedium_0	0.334
bSmall_0	0.896

PINK SHRIMP EDM SUMMARY

- Short time series for abundance doesn’t capture system dynamics
  - $T=13$, $E \leq \sqrt{T}$ where $E \leq 3\text{-}4$, theoretically allowing 2-3 lags
  - More than 2-3 drivers impacting the population abundance
  - Oversimplification of a complex system
- Revisit when additional years of data are available

NOAA FISHERIES

PINK SHRIMP CONCLUSIONS

- Insufficient time series length to accurately project pink shrimp population and landings within EDM framework
- Neither EDM nor JABBA are recommended
- Data-limited management methods can be considered with potential to monitor abundance using VAST
    - VAST will help determine whether a general downward trend occurs that may be of concern to managers

Conclusions & Recommendations

Biomass Assessment Models

Gulf shrimp stock dynamics were generally not well captured by the biomass assessment models.

"A lack of such contrast can also arise when the stock dynamics are driven more by environmental factors than by the catches so that the stock can appear to respond to the fishery in unexpected ways (e.g. large changes to the stock despite no changes in catch or effort)."

"The index, however it is made, is assumed to reflect the biomass available to the method used to estimate it (fishery-dependent cpue or an independent survey) and this biomass is assumed to be affected by the catches removed by the fishery."

Haddon, M. (2020). Using R for Modelling and Quantitative Methods in Fisheries (1st ed.). Chapman and Hall/CRC. https://doi.org/10.1201/9781003032601

Benefits of EDM in Stock Assessment

- Short-lived species with chaotic dynamics are better modeled using EDM compared to traditional stock assessment models
    - Does not require life history data or any functional form
    - Captures large fluctuations in biomass and accurately projects into the future if state space is mapped with appropriate time series length
    - Does not require direct measurements of information driving fluctuations
- Improved model fits and predictive capability over traditional stock assessment models
- Accommodates benchmark estimation for management

SUMMARY OF RECOMMENDATIONS

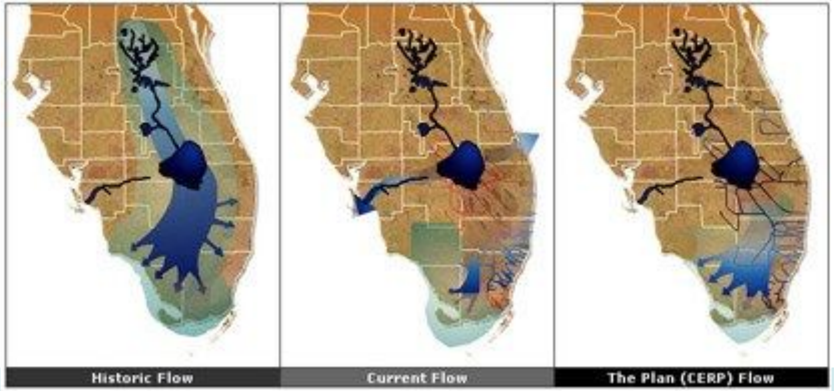
- Brown Shrimp - EDM summary
  - MSY: 215.07 million pounds of tails
  - F_{MSY}: 0.617, B_{MSY}: 405.39 million pounds of tails
  - F_{2022}/F_{MSY}: 0.029, B_{2022}/B_{MSY}: 4.23
- White Shrimp - EDM summary
  - MSY: 87.80 million pounds of tails
  - F_{MSY}: 0.896, B_{MSY}: 148.35 million pounds of tails
  - F_{2022}/F_{MSY}: 0.147, B_{2022}/B_{MSY}: 2.48
- Pink Shrimp
  - Data-limited management with VAST available for monitoring trends if requested
  - Attempt EDM at next update with additional years of data if possible

RESEARCH RECOMMENDATIONS

- EDM
  - Create a feedback loop between size classes to account for impact of removing larger shrimp on future production & impact of removing smaller shrimp on Large shrimp abundance (e.g. mixed-age EDM), and overall impacts on optimal harvest rates.
  - Additional research into covariates. To forecast MSY, the cyclical nature of environmental covariates would need to be captured and the relationship between economic covariates and projected harvest rates would need to be explicitly defined.
  - Investigate impact of using an average of 2019/21 for missing summer 2020 SEAMAP data and implications for future gaps in survey data.
  - Investigate implications of the LDWF survey capturing mostly Small shrimp & fishery capturing mostly Large shrimp for estimating catchability (White Shrimp)
  - Investigate catchability blocks for pre-defined eras of fleet behavior

RESEARCH RECOMMENDATIONS

- Environmental Linkages
  - Investigate the development and use of an index of suitable juvenile habitat availability to help predict shrimp population size (i.e., including not only salinity and temperature but other metrics like flooded marsh area and amount of marsh edge habitat available)
  - Investigate pink shrimp growth and carrying capacity as it relates to salinity, where freshwater diversions to agriculture in the 20th century led to salinity spikes in Florida Bay with recent efforts to restore Everglades historic freshwater flows

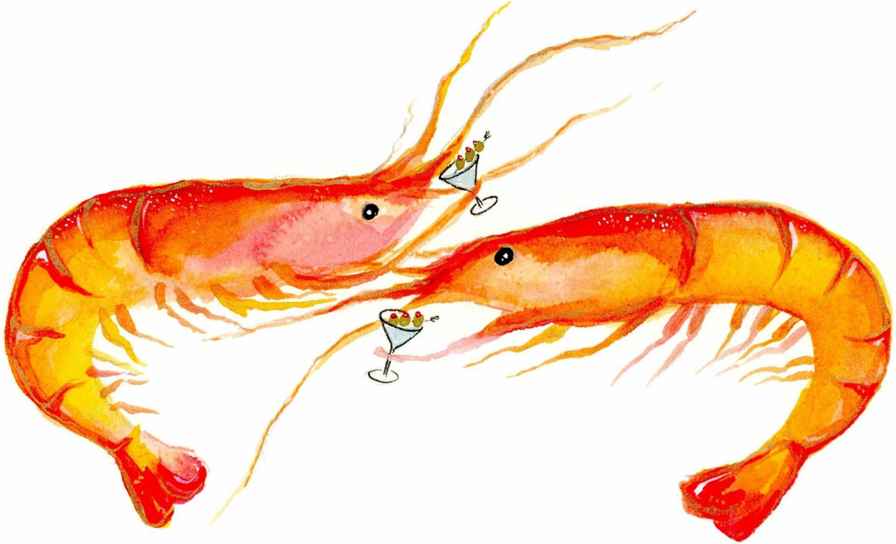


NOAA FISHERIES

NEXT STEPS

- *Review Workshop: Tampa, FL ....Week of June 23, 2025*
- First Draft Review Reports... (end of workshop)
- Review Workshop Panel Drafts due to Chair..18 July 2025
- Review Workshop Addenda/Revision Reports due ….....................18 July 2025
- Review Workshop Reports due to SEDAR Staff: ....1 August 2025
- Complete Assessment Report Submitted…….................................8 August 2025

Questions?



@CorrineCroneArt

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