

**NOAA  
FISHERIES**

# Gulf of Mexico Shrimp Empirical Dynamic Modeling Workgroup Summary

NOAA Fisheries  
Southeast Fisheries Science Center  
Gulf Branch - Sustainable Fisheries Division

March 7, 2023

# Workgroup Purpose

- This workgroup is convened following a request to the Southeast Fishery Science Center 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.”*

# Meeting Summary

- 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

# Workshop Briefing

- Provided an overview of EDM theory and examples in fisheries applications.
- Provided an overview of current Gulf of Mexico Shrimp EDM methods, results, and proposed next steps for Gulf of Mexico Shrimp EDM work.

# Workshop Meeting Objectives

- Brief workgroup members on Empirical Dynamic Models (EDM) and Gulf of Mexico Shrimp EDM results.
- Receive input from workgroup members and discuss future model development.
- Receive input from workgroup participants and discuss utility of Shrimp EDM to inform management.

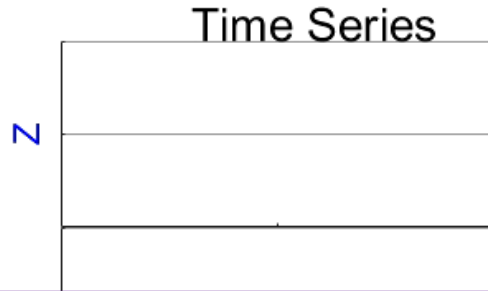
Environmental drivers and other species have their own dynamics – not really ‘noise’

Feedbacks between the focal stock and other parts of ecosystem may be important

But we don't have data for everything - Need a method that will allow us to implicitly account for these!

# Empirical Dynamic Modeling: an example

Three-species model  
with type-2 functional  
response



Z – pr  
Y – gr  
X – pr

**EDM:**

1. Don't need data on all variables to make accurate predictions
2. Don't need equations, if we have enough data

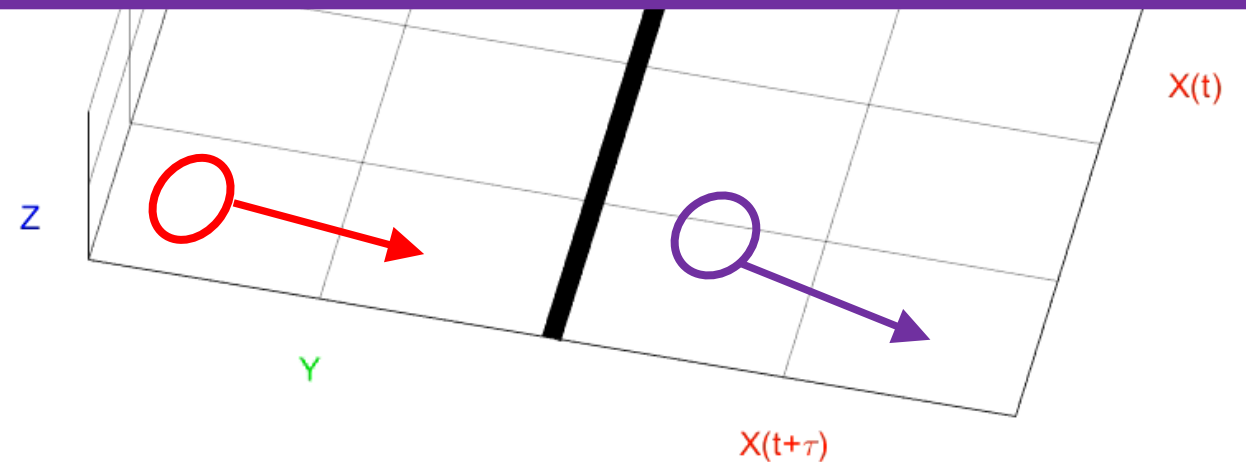
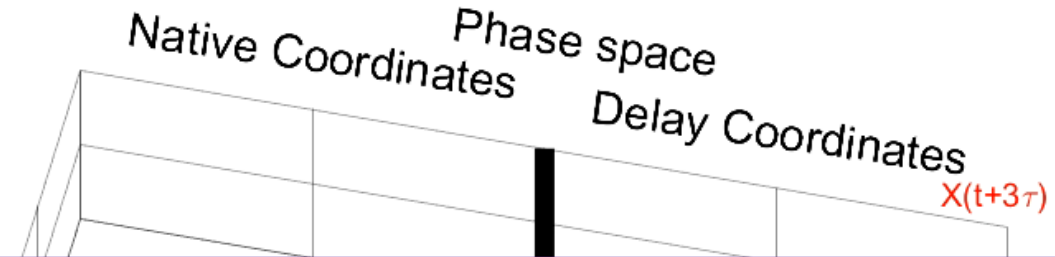
Trace nearby  
obtain discrete

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

Analogous model in 'delay  
coordinates'

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

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



# Takens *without* Topology

Observed variables

$$x_{t+1} = F(x_t, y_t)$$

Unobserved variables

$$y_{t+1} = G(x_t, y_t)$$

Given enough data  
we can approximate ***past*** value of  
y (aka solve for y in terms of x)  
Leading to a model in delay  
coordinates

$$x_{t+1} = E_{y|x_t, \dots, x_{t-E}} \{F(x_t, y)\} = \tilde{F} [x_t, x_{t-1}, \dots, x_{t-E}]$$

Takens guarantees that, in theory,  
this can be made ***exact***

In both the deterministic and stochastic case, we need to approximate  
 $\tilde{F}$  (the map from past states to future)  
-use Bayesian GP regression, with automatic relevance  
determination prior



# Why 'delay coordinates'? An example using the standard age-structured model

$$n_{a+1,t+1} = s_a n_{a,t}$$

$n_{a,t}$  numbers at age  $a$  in year  $t$

$s_a$  survival from age  $a$  to  $a+1$

$$B_t = \sum_{a=A_m}^{\infty} m_a n_{a,t}$$

$m_a$  mass at age  $a$   
(proportional to fecundity)

$$n_{0,t+1} = f(B_t)$$

$B_t$  spawning biomass

$f$  density dependent recruitment

So, we've used lags in fisheries for a long time, as approximations to an age-structured model. Takens just makes this idea more general.

$$s_a = \prod_{j=0}^{a-1} s_j$$

Can re-write age structured model several ways in terms of lags of a single 'observable'

1. Using a single age class, e.g. age 0, (Renewal Equation)

$$n_{0,t+1} = f\left(\sum_{a=A_m}^{\infty} m_a s_a n_{0,t-a}\right)$$

2. Production model

- a) survival is constant across ages
- b) growth is ~linear so that  $m_{a+1} = g m_a$

$$B_{t+1} = g s B_t + b m_{A_m} s_{A_m} f(B_{t-A_m})$$

# Finding reference points and control rules from EDM

1. MSY
2. Optimal control rules
  - numerically intensive,
  - statistically challenging
- 2a. Harvest control rules

# Steady state yield and MSY

## Standard approach

Fit assessment model

Fix harvest rate, run to equilibrium, find sustainable yield

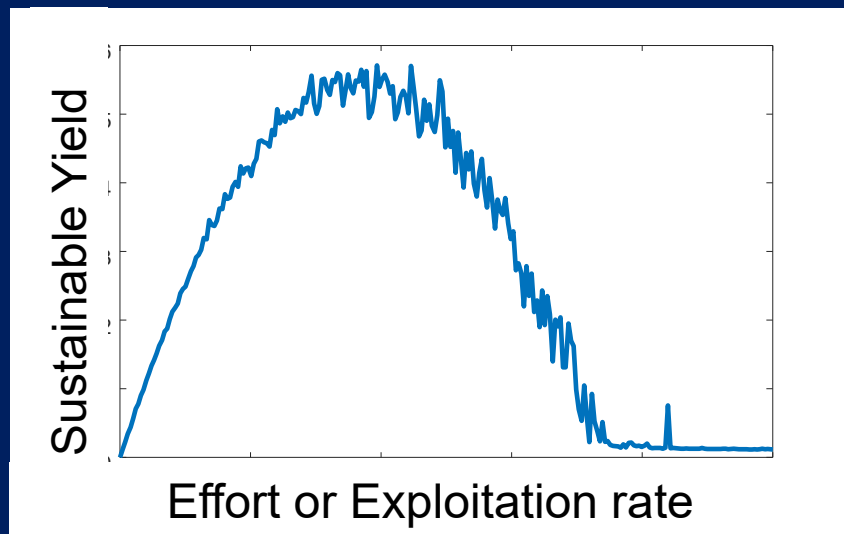
Vary harvest rate to find maximum sustainable yield

## EDM approach

Fit EDM model with abundance and landings  
(or landings and effort)

Fix harvest rate, run to equilibrium, find sustainable yield

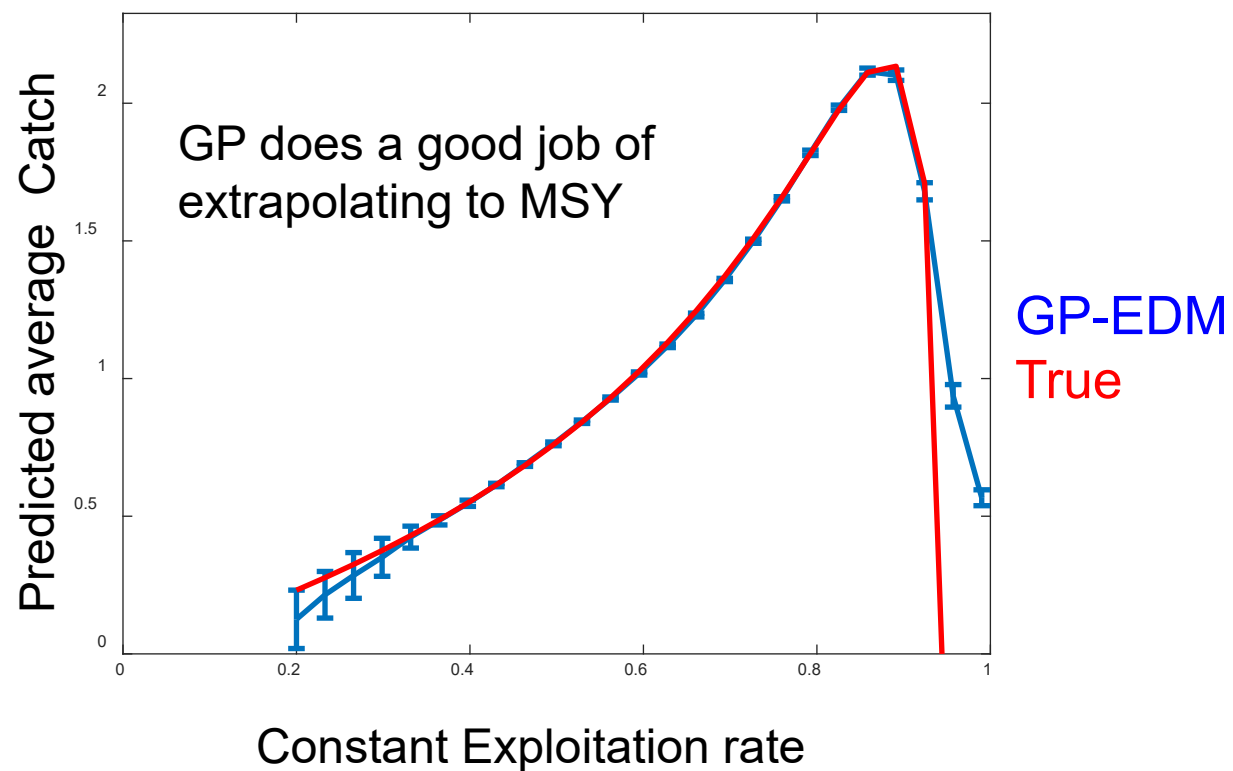
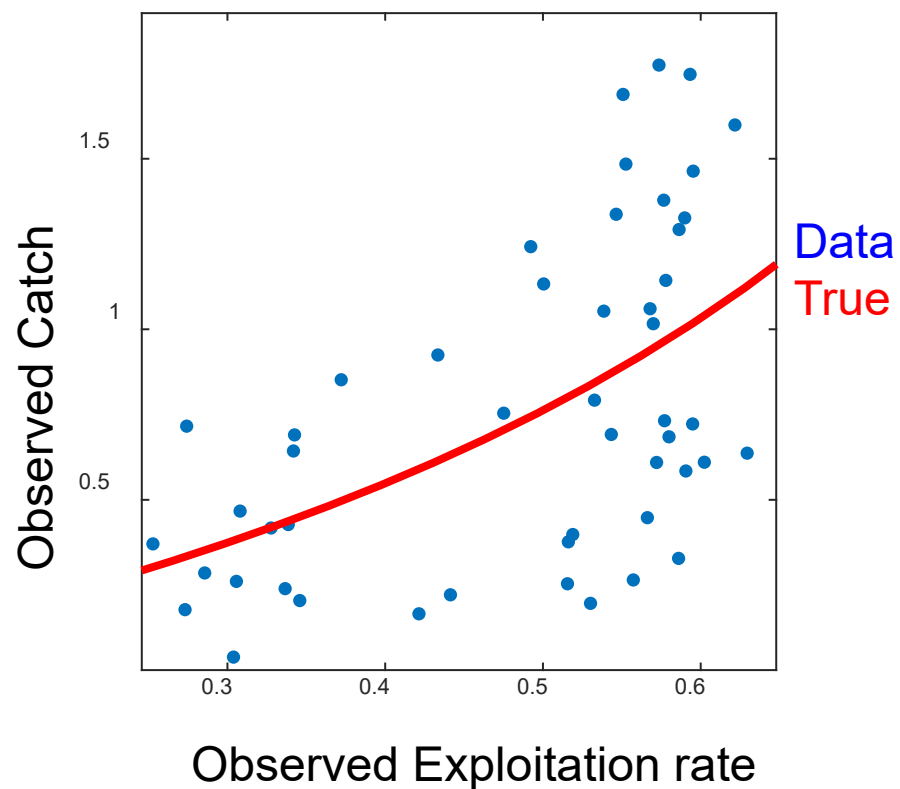
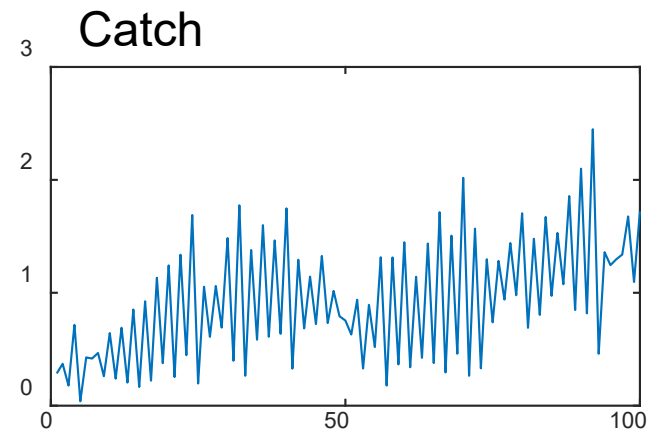
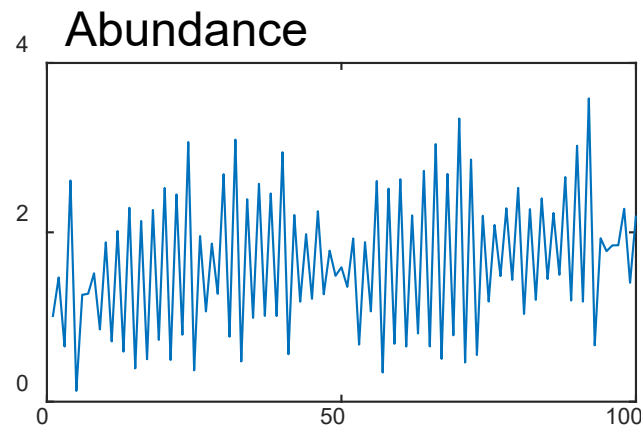
Vary harvest rate to find maximum sustainable yield



# Using GP-EDM to estimate MSY: an example

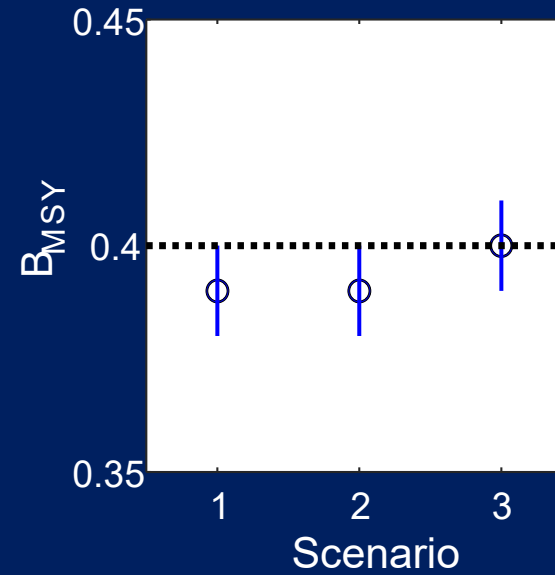
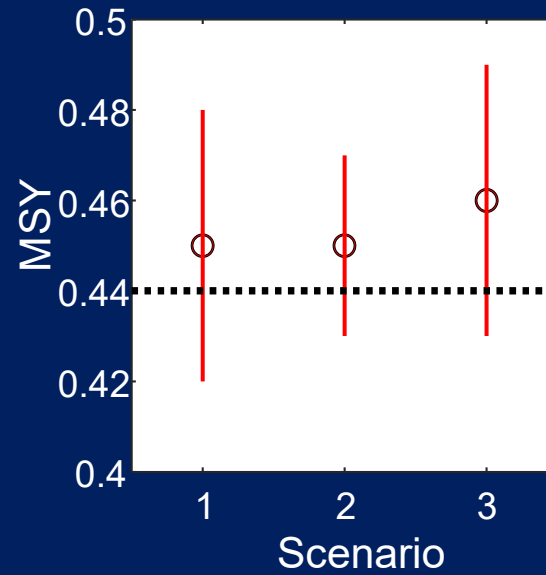
Simulate Ricker model  
with fishing

Use GP to estimate MSY

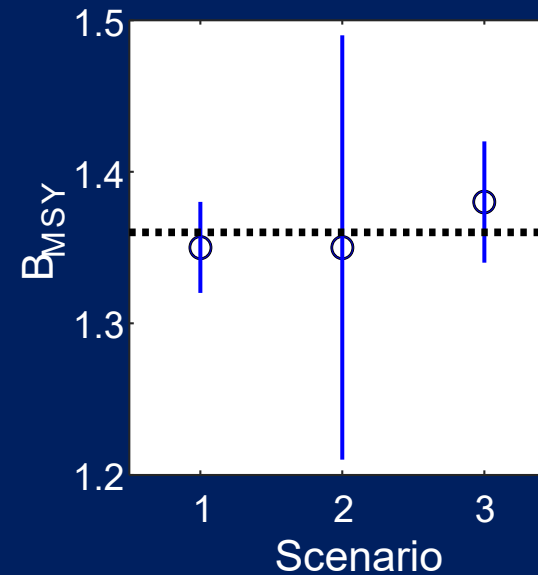
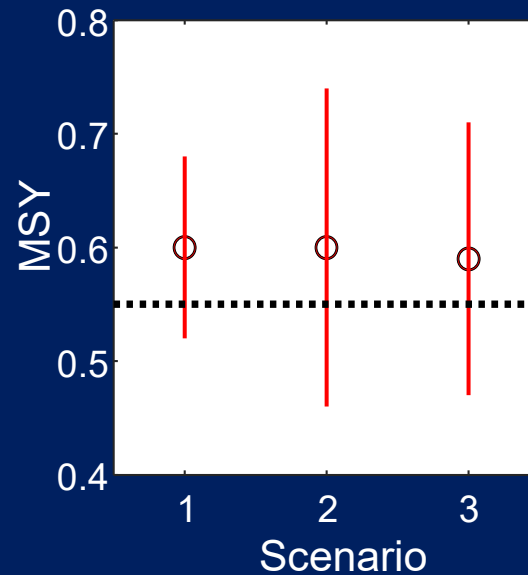


# Testing EDM-> MSY

Pella-  
Thomlinson



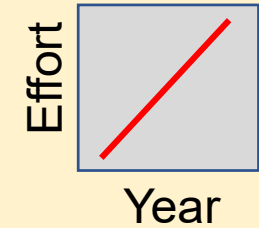
Two-species  
(predator  
harvested)



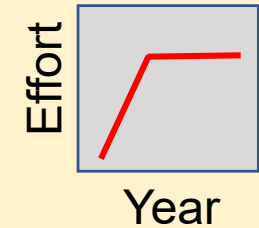
Cheng-han  
Tsai

Exploitation Scenarios:

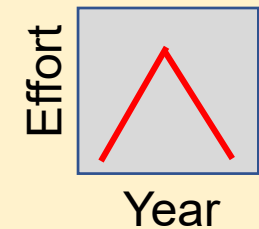
1. One way trip



2. Effort levels out



3. Effort rises and falls



# **Applications to brown and white shrimp**

# Background of EDM development for Gulf shrimp

- Previously we developed spatial hierarchical models using only SEAMAP and in situ environmental data (manuscript in publication)
- Previously we concluded using SEAMAP summer index as the first version model potentially used for index-based management
- To facilitate the interpretation and exploring harvest policies using simpler models, we investigate the aggregated gulf-mean SEAMAP and fishery catch data for EDM forecasts
- Additionally, environmental variables (temperature, oxygen, salinity) and Louisiana recruitment indices (statewide, westside, eastside) are investigated at the aggregated gulf-mean scale, together with catch data

# Current models

GP-EDM used to predict average annual CPUE in SEAMAP survey.

Models include lags of CPUE and catch

Prediction accuracy assessed with leave-one-out forecasts

Also tested temperature, salinity, and dissolved oxygen and Louisiana recruitment index as inputs

$x_t$   $\log(\text{SEAMAP CPUE})$

$y_t$   $\log(\text{catch})$

Delay embedding map

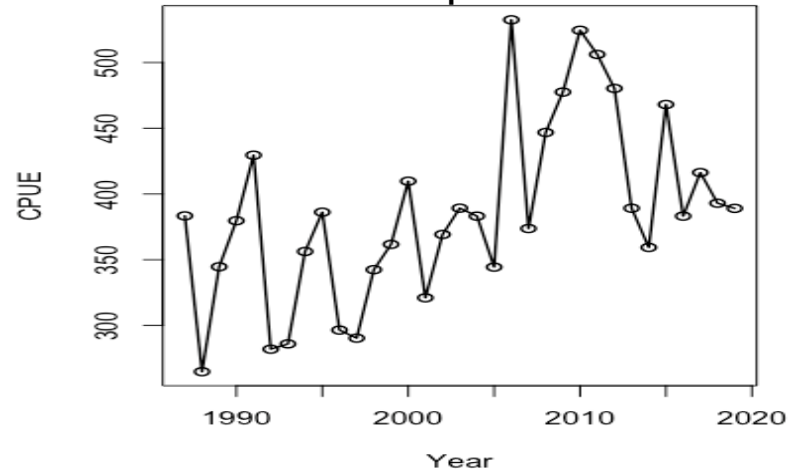
$$x_t = f(x_{t-1} - b y_{t-1}, \dots, x_{t-E} - b y_{t-E}) + \varepsilon_t$$

<sup>\*\*</sup>  $b$  – additional scaling factor to convert SEAMAP and Catch into same units



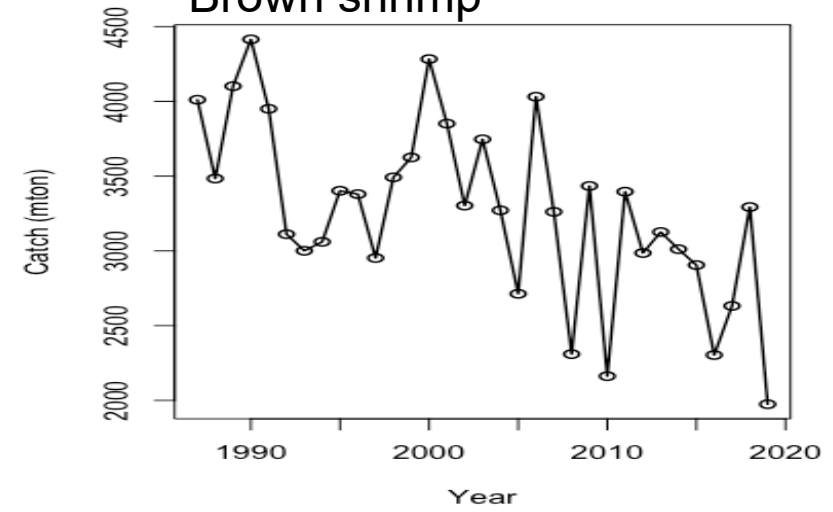
## SEAMAP data (annual average)

### Brown shrimp

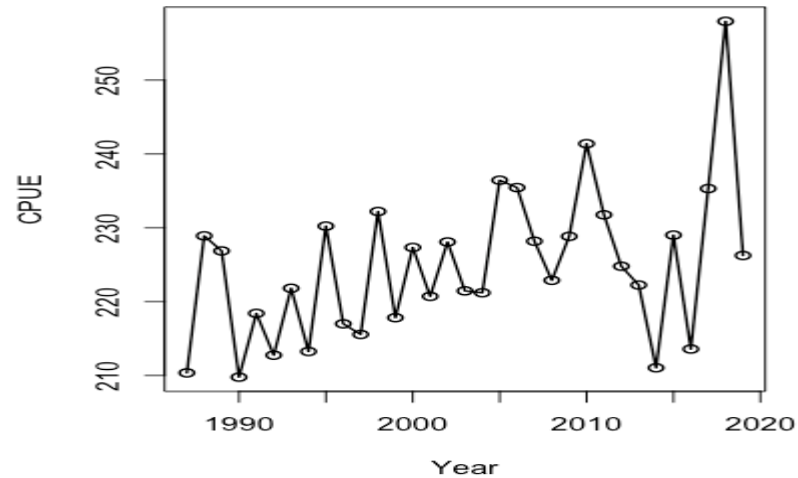


## Catch data (annual average)

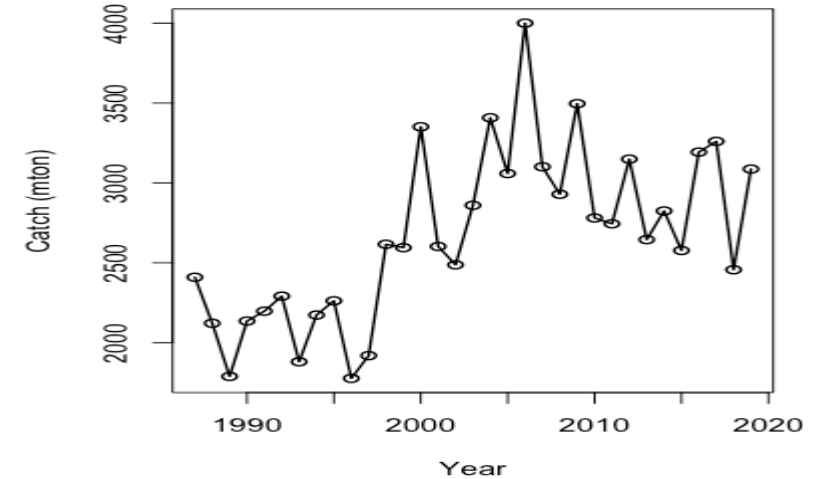
### Brown shrimp



### White shrimp

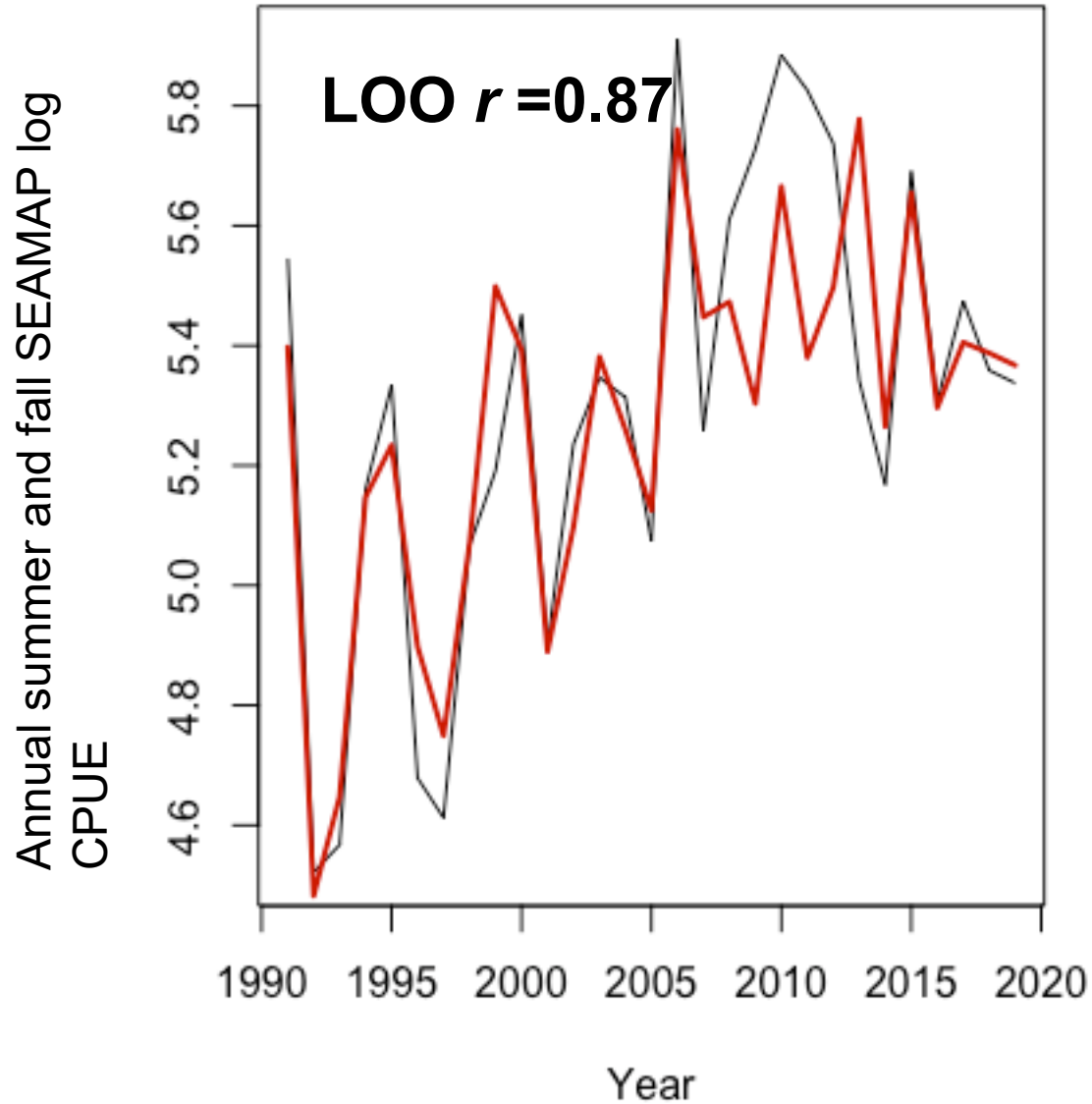


### White shrimp

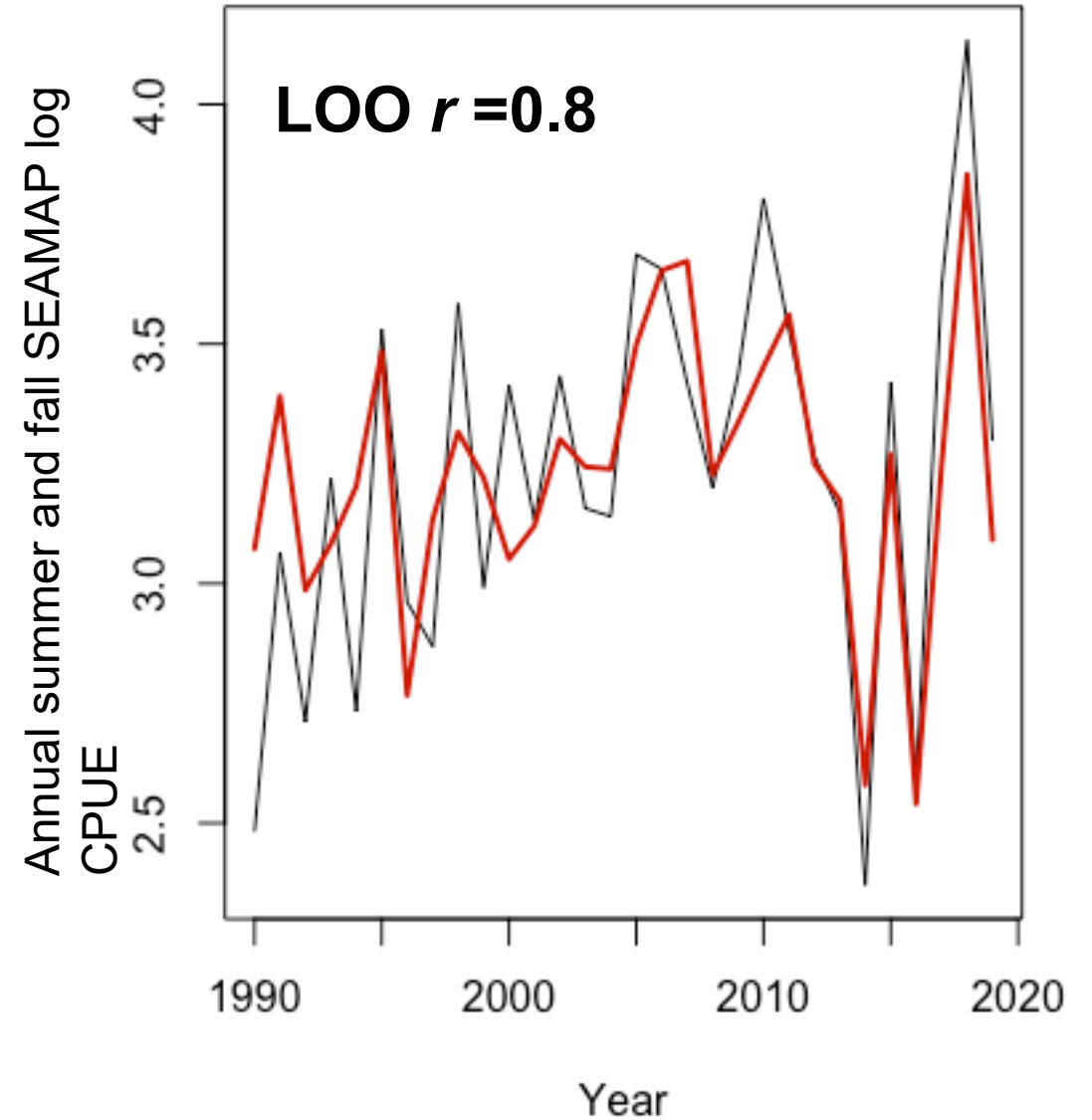


# EDM out-of-sample forecasting

Brown Shrimp SEAMAP+Catch



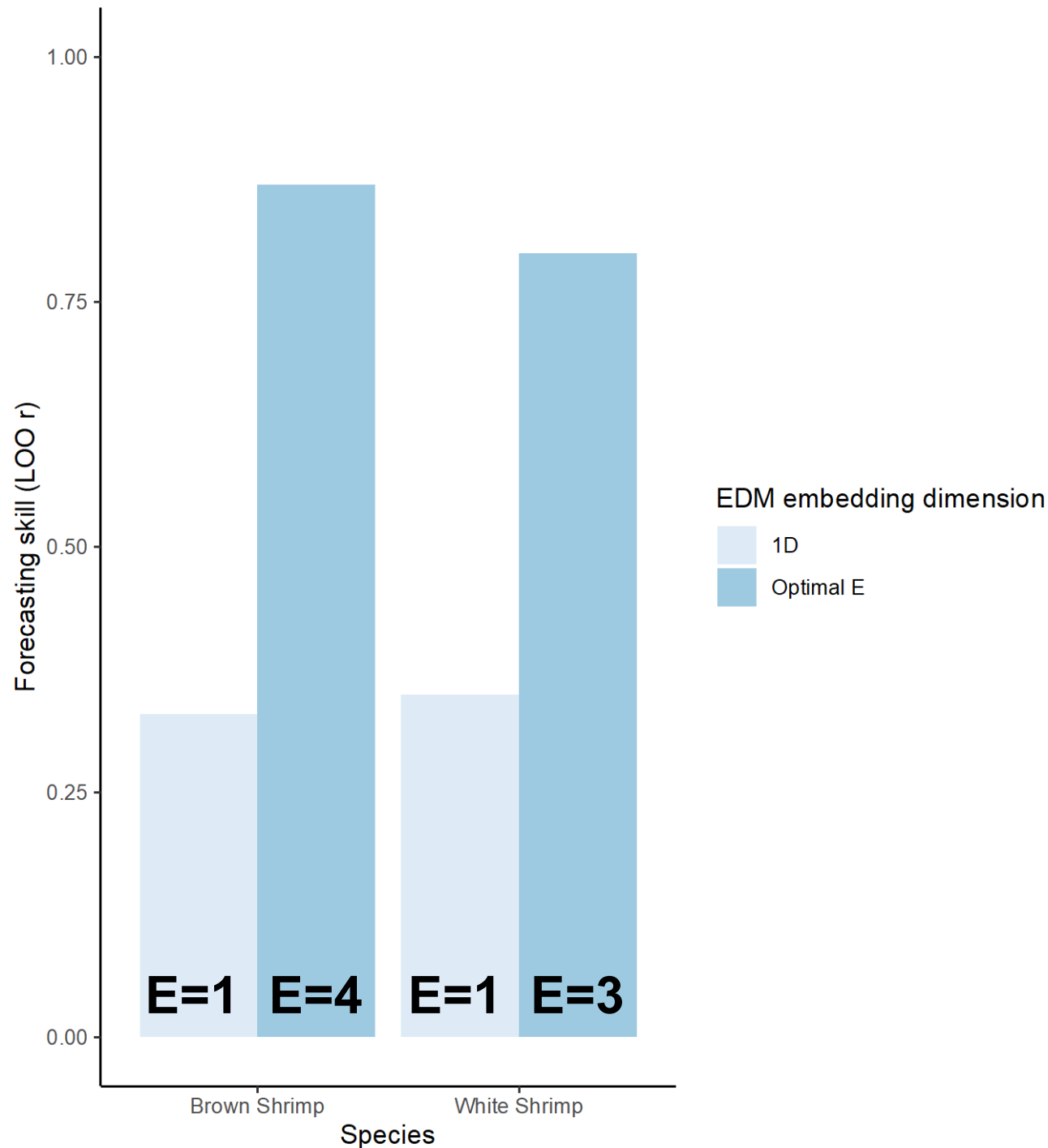
White Shrimp SEAMAP+Catch



# Comparison of EDM forecasting between optimal embedding dimension vs. 1-d model (i.e. a non-parametric production model)

1-d model  $r \sim 0.3$

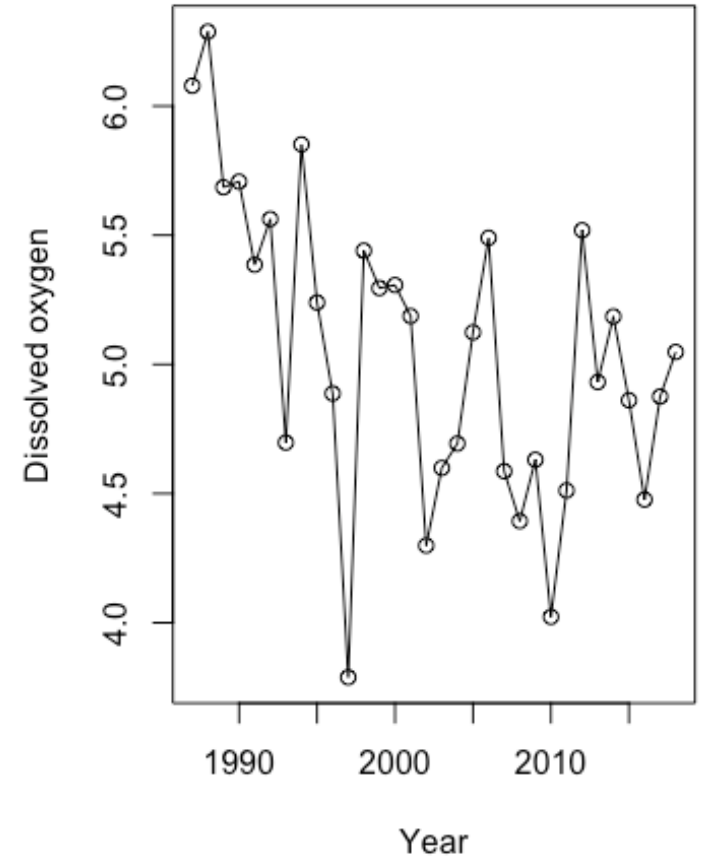
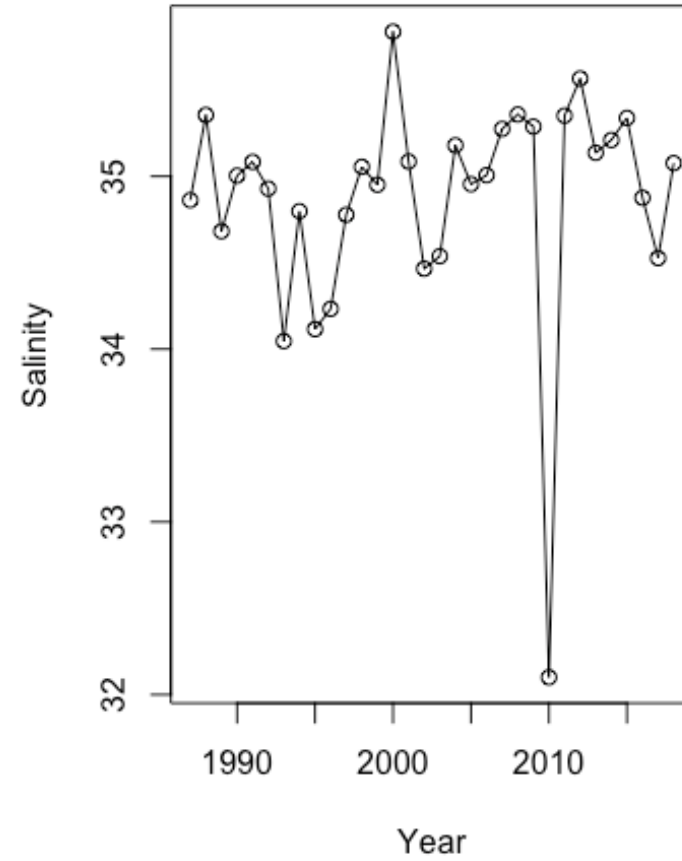
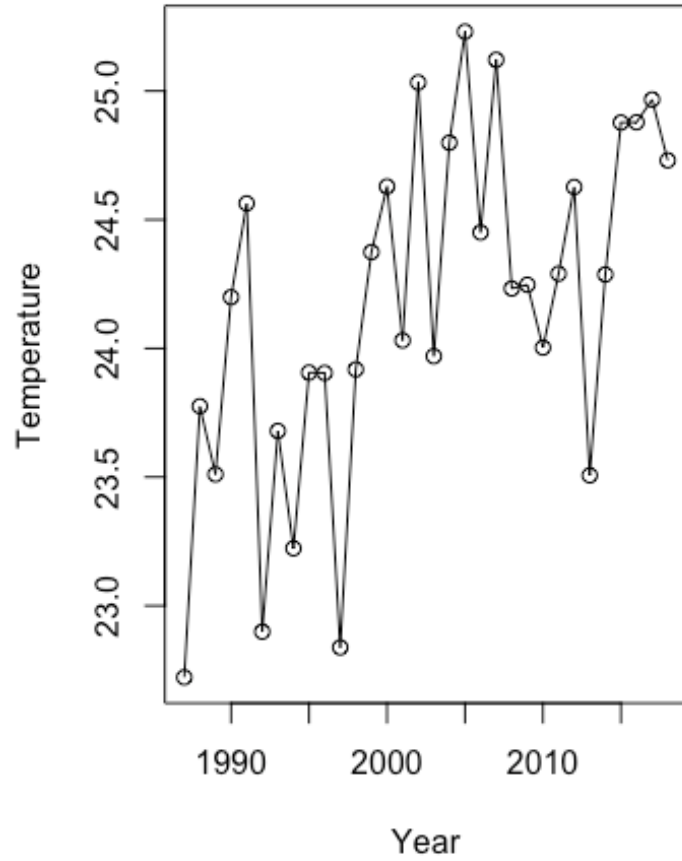
EDM produces 2-3x more accurate forecasts than just using current stock



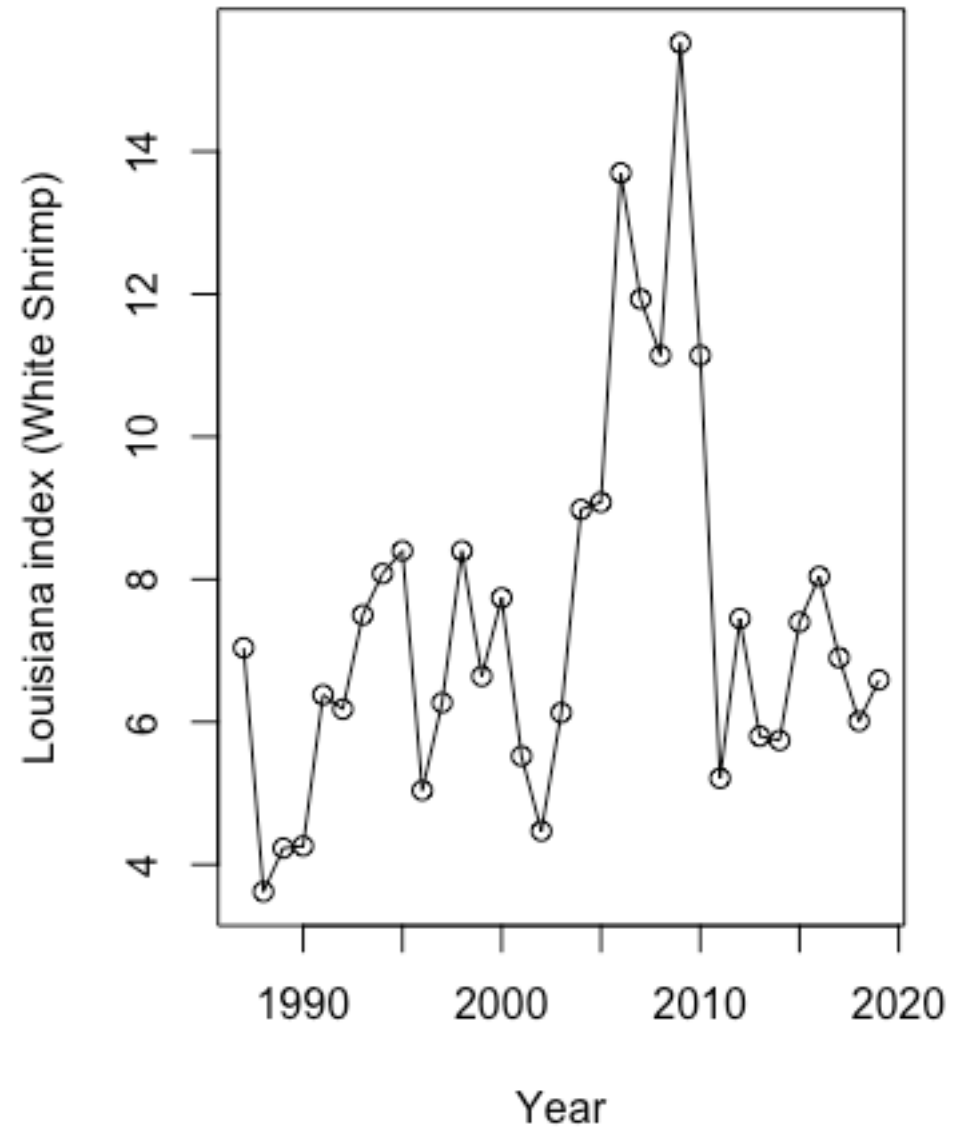
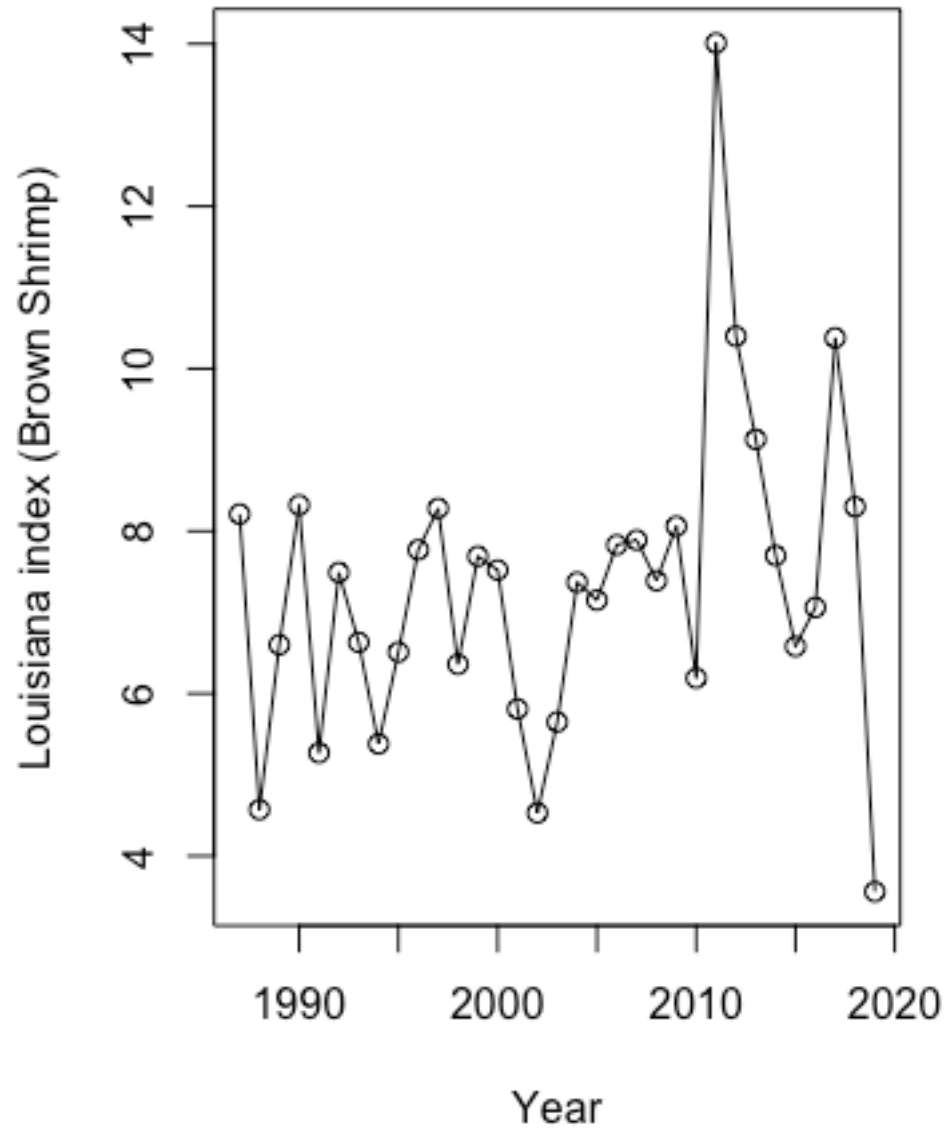
# Exploration of predictors other than SEAMAP and catch data

- Environmental variables (bottom temperature, oxygen, salinity)
- Louisiana recruitment indices.

# Gulf-mean environmental data



# Louisiana survey indices



# Comparison of Gulf-mean EDM forecasting skill w/wo environmental variables

Forecasting skill (LOO r)

1.00  
0.75  
0.50  
0.25  
0.00

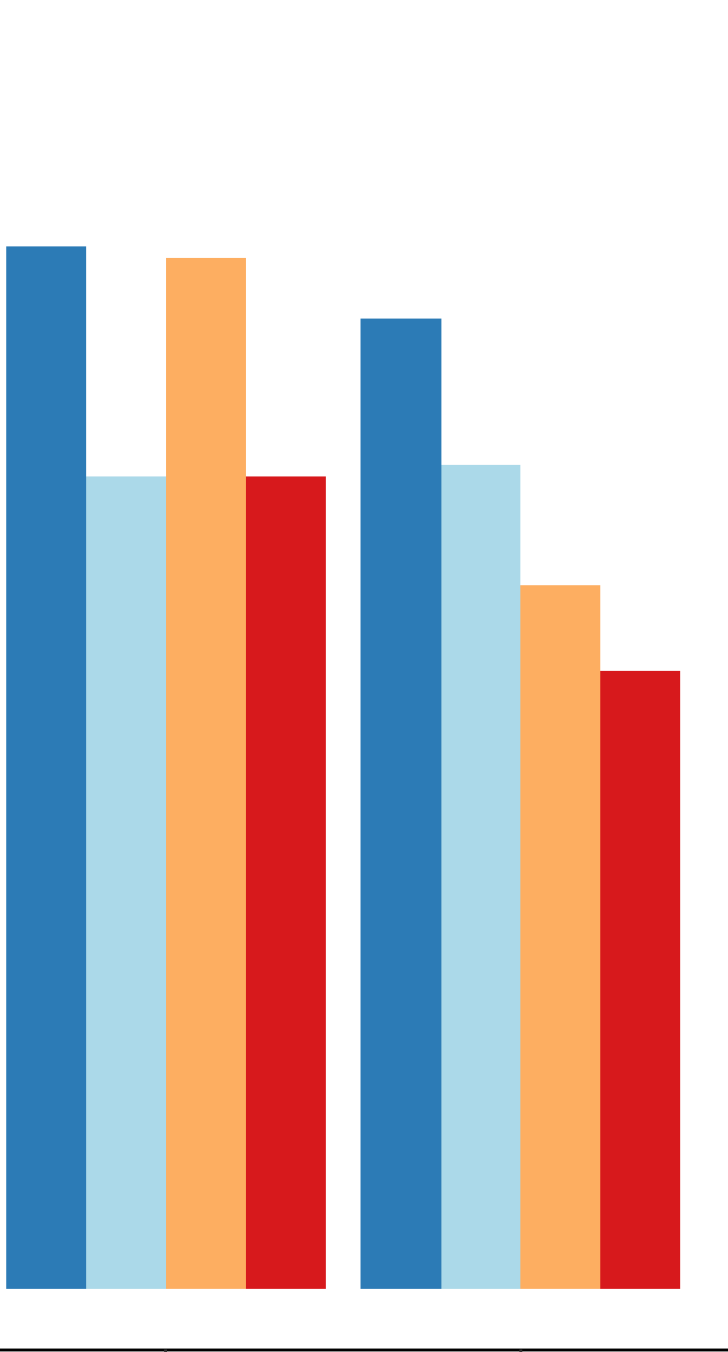
Brown Shrimp

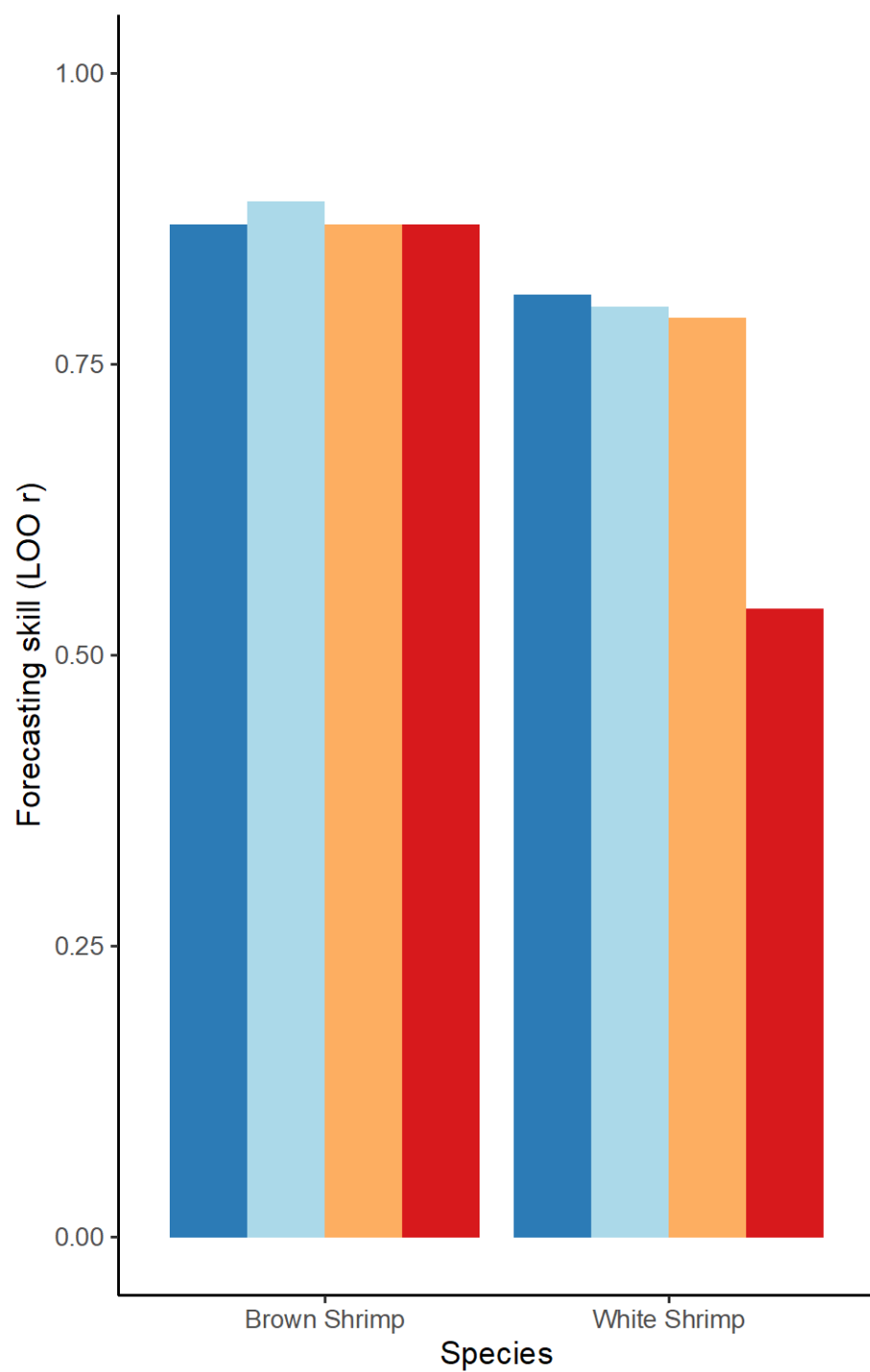
White Shrimp

Species

Input variable (gulf mean)

- SEAMAP(t)+CATCH(t)
- SEAMAP(t)+CATCH(t)+Oxygen(t)
- SEAMAP(t)+CATCH(t)+Salinity(t)
- SEAMAP(t)+CATCH(t)+Temp(t)





Comparison of Gulf-mean EDM forecasting skill at (t+1) w/wo Louisiana indices at (t+1, t, and t-1)

Input variable (gulf mean)

- SEAMAP(t)+CATCH(t)
- SEAMAP(t)+CATCH(t)+LSA(t-1)
- SEAMAP(t)+CATCH(t)+LSA(t)
- SEAMAP(t)+CATCH(t)+LSA(t+1)



# Comparing production model and EDM

(data, parameters, biomass)

Biomass dynamics

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

$$P(x) = rx(1 - \frac{x}{k}) \text{ production function}$$

$B$ : Biomass (lbs)

$C$ : Catch (lbs)

$P$ : production (lbs)

$I$ : abundance index (#/tow)

$q$ : #/lbs/tow

$$I_t = qB_t$$

$u$ : exploitation rate (lbs/lbs)

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

Regression to estimate parameters  $q, r, k$

AND biomass through time,  $B_1, B_2, \dots$

*ASSUMES ALL PARAMETERS ARE CONSTANT*

Model if fishing comes after reproduction

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

Re-write model just in terms of observables:  
(multiply by  $q$ )

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

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

Now we have model in terms of Index and Catch

Note that  $(I_t - qC_t)$  is proportional to  
surviving biomass  $(B_t - C_t)$

## EDM MODEL:

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

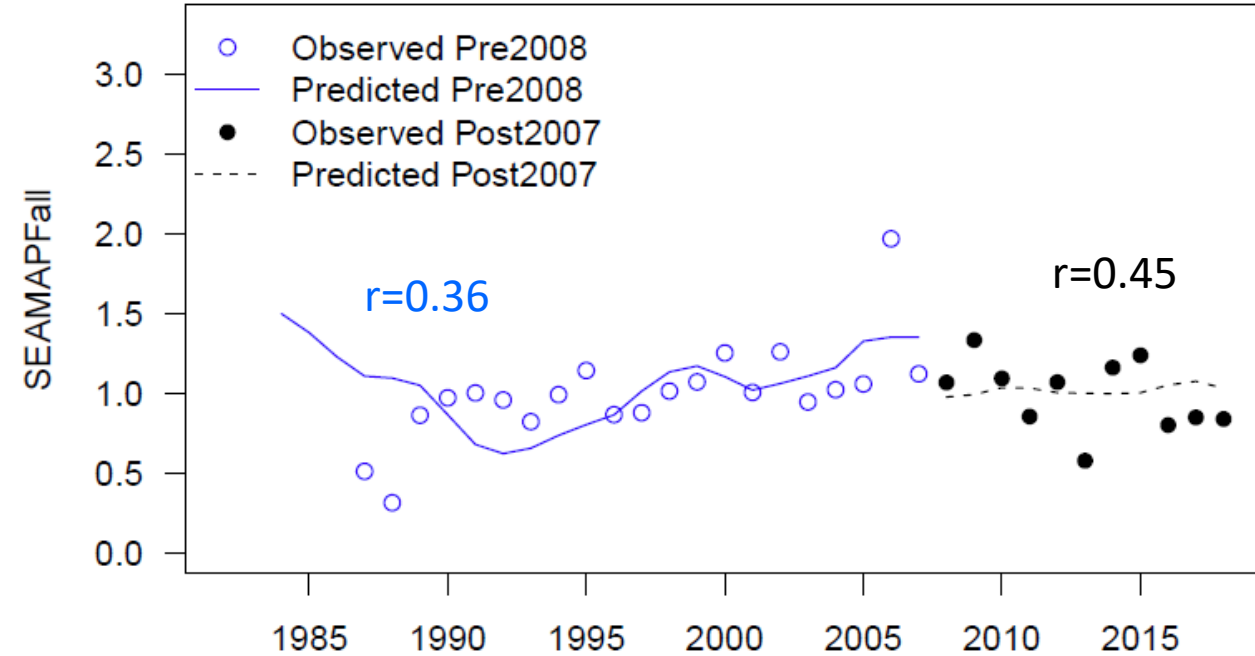
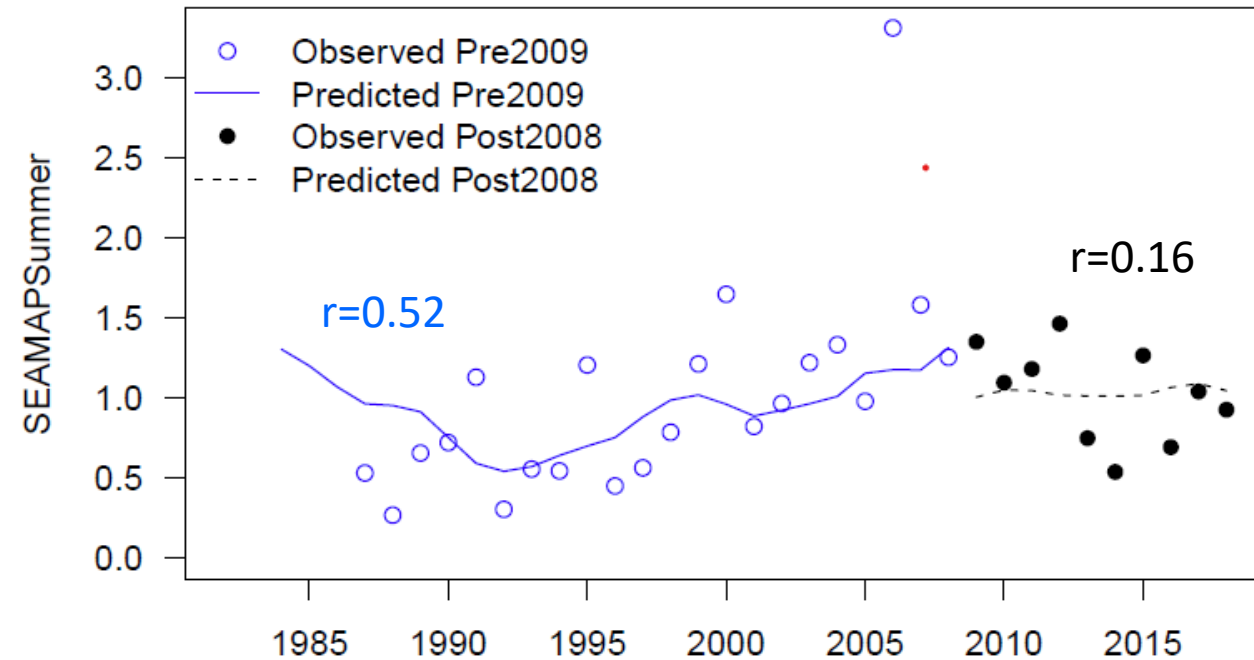
Uses  $I_t - qC_t$  as proxy for surviving biomass

Estimates  $q$

But does not assume a known production function

Lags allow for unobserved state variables

# Production model fit (courtesy of Lew Coggins)



Overall correlation with index  $\sim 0.4$  (in sample)

1-lag EDM model (production model analogue):  $r \sim 0.3$  (out of sample)

4-lag EDM model:  $r \sim 0.8$

# Predicting abundance

Models using SEAMAP and fishery catch data, in general, **outperform** the models including **environmental** variables (bottom temperature, oxygen, salinity)

Models using SEAMAP and fishery catch data, in general, **perform equally well** with the models including **Louisiana recruitment** indices.

This **DOES NOT** mean that these other variables are irrelevant! Just means that the information they provide is already contained in the lags of shrimp.

EDM predictions are 2-3x more accurate than production model- because of lags (1-d EDM is about same as production model).

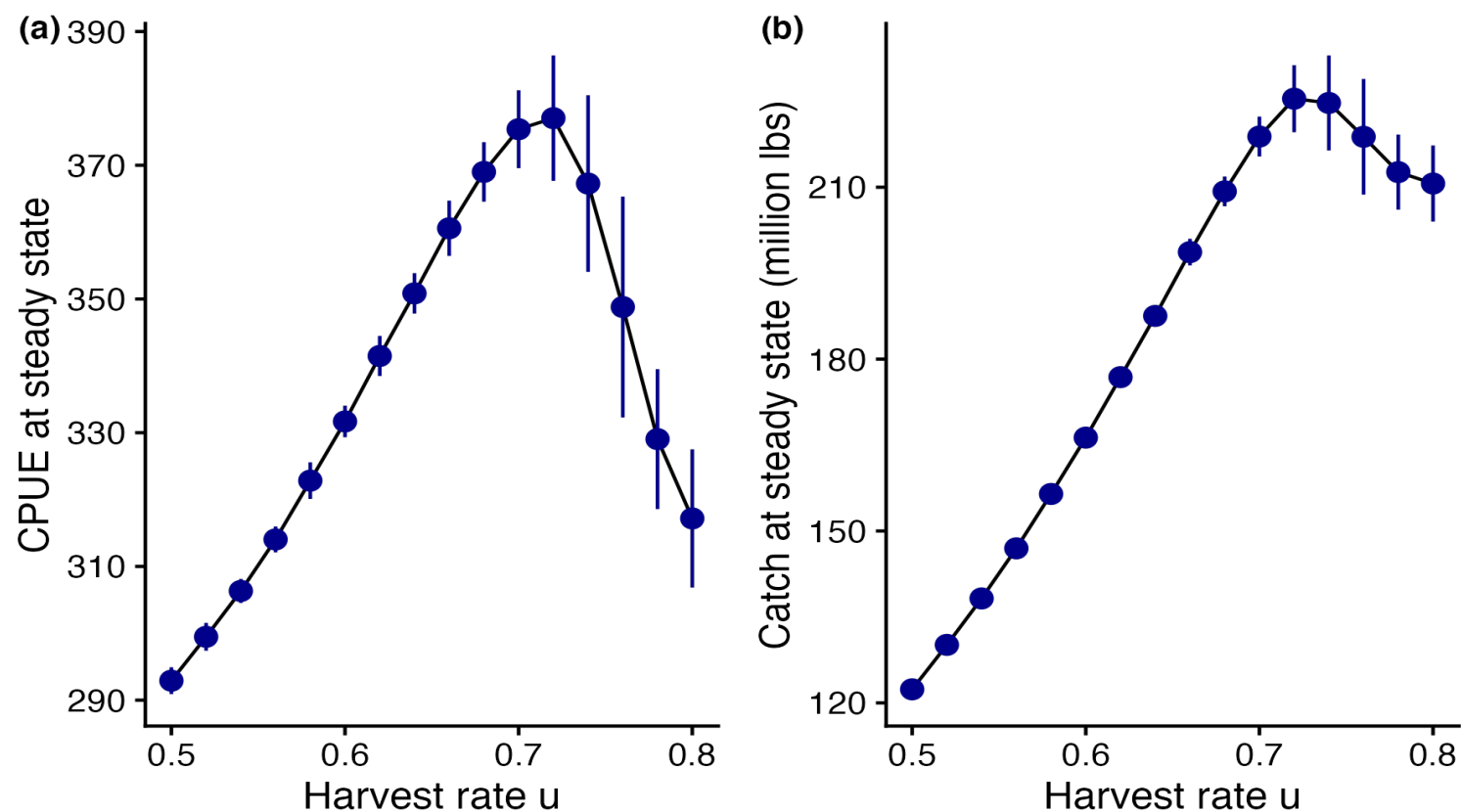
Can do same post-hoc calculations we'd do with a production model (e.g. stock status, etc)-- Use best-fitted EDM to produce benchmarks for constant catch/effort policy.

# Exploration of management policies for brown shrimp

Use posterior simulation to explore the performance of different constant catch levels:

1. We use the best-fitted EDM and the same initial condition of the first year of CPUE data to predict forward in time with varied constant catch level.
2. The year-ahead prediction was randomly generated from posterior probability density of best-fitted EDM and iterated for 30 years.
3. Overall  $N=500$  simulations were conducted for each run.

# EDM-MSY for brown shrimp



U: FRACTION of BIOMASS REMOVED (CATCH/BIOMASS)

EDM  
Umsy ~0.72  
MSY ~ 225 million lbs

Production model  
Umsy ~ 0.9  
MSY ~95 million lbs

# Summary

Using EDM:

Estimate model of changes in abundance index using catch, SEAMAP  
-Prediction accuracy is pretty good ( $r > 0.8$ )

EDM more closely describes what we see in the data, because of the **lags**  
(1-d model & production model are about the same)

Use fitted function to determine MSY / BMSY / UMSY

...Could also estimate current biomass (and stock status)

$$I_t = qB_t \rightarrow B_t = I_t/q$$

Can also evaluate other harvest control rules (e.g. hockey stick, etc)

# Summary Workshop Meeting Objectives

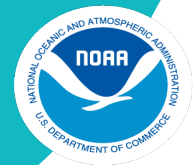
- Brief meeting participants on Shrimp Fishery Management Plan and stock assessment requirements.
- Brief meeting participants on Gulf of Mexico Shrimp SEDAR research track assessment planning.

# Shrimp SEDAR Research Track Assessment Planning

- Two meetings including SEFSC, SEDAR, SERO and SSC Chair
  - Identify Data Providers – *done*
  - Potential SEDAR Participants by Stage – *in progress*
    - Work with Council and SERO to appoint – *in progress*
  - Construct a conceptual model along with the data provision and review
  - Data Scoping, Beginning July 2023
  - Stage 2- Data Workshop, September 2023
    - Format and content of data workshops (multiple species considerations)



# Questions?



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