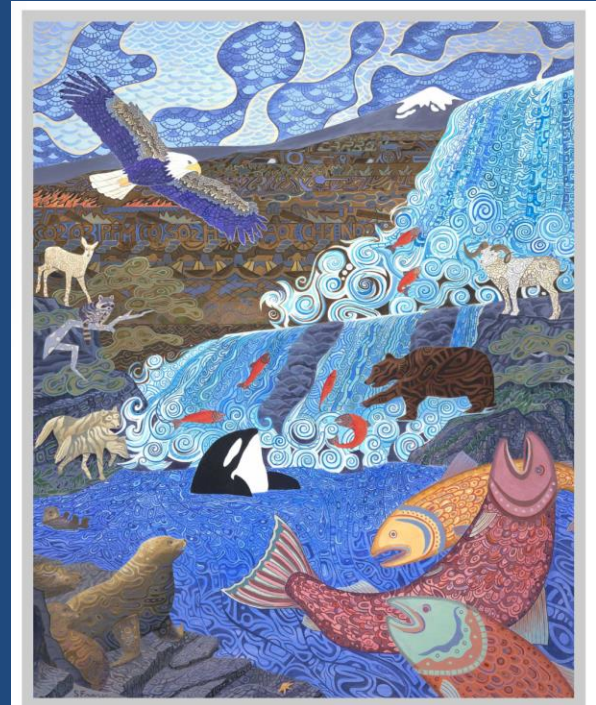


Recent advances toward detecting ecological thresholds and ecosystem shifts to inform fisheries management

Mary Hunsicker, Raine Detmer,
Bridget Ferriss, Jameal Samhour, and Eric Ward

PICES Annual Science Meeting
October 28, 2024

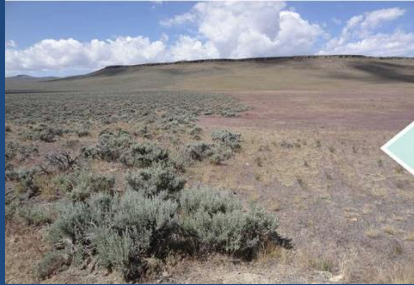


SPENCER FRAZER

STREAM OF CONSCIOUSNESS
(2020, OIL ON CANVAS)

5th National Climate Assessment
<https://nca2023.globalchange.gov/art-climate/>

Climate impacts on ecosystems and people



Sagebrush shrublands are becoming non-native grasslands as a result of wildfire, invasive species, land use, and climate change.

Arctic marine ecosystems are being altered by ocean acidification and harmful algal blooms.



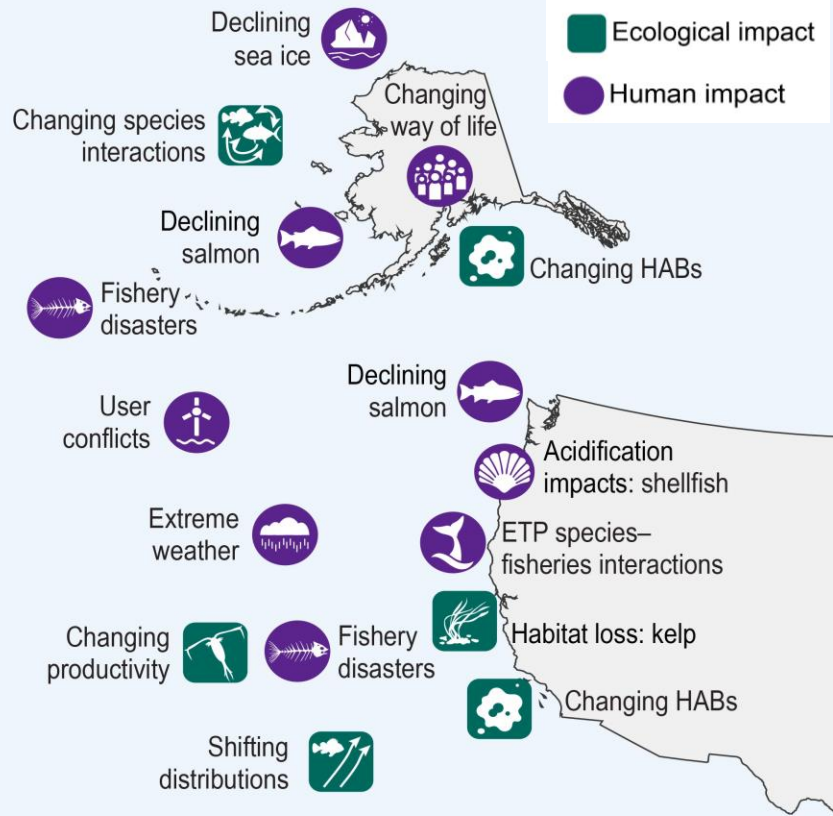
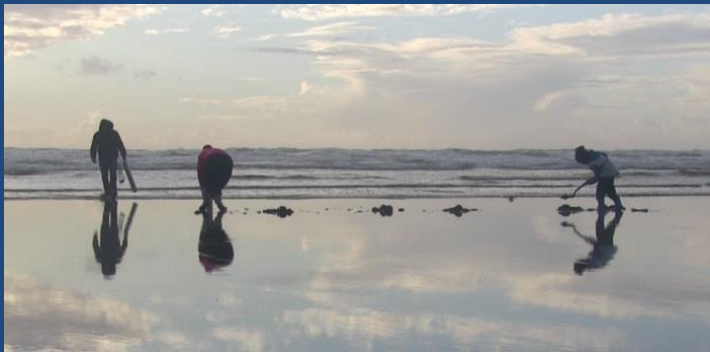
Dry forests and woodlands experiencing drought and wildfire are becoming grasslands and shrublands.



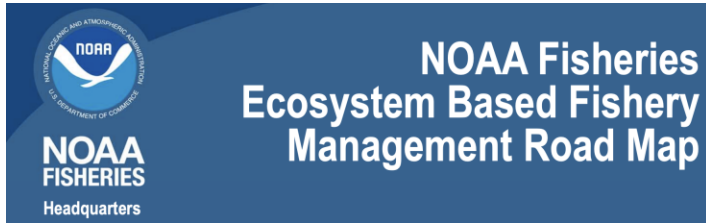
Coral reefs are being lost due to warming and ocean acidification.



Climate impacts on NE Pacific

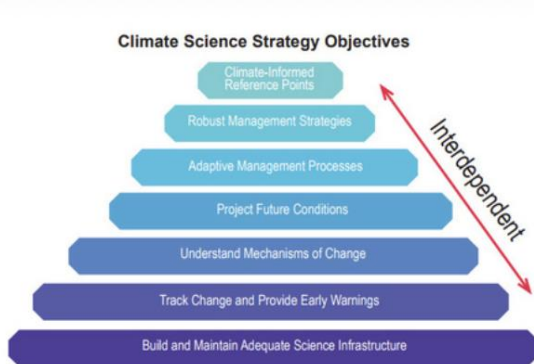


How to advance ecosystem-based fisheries management under a changing climate?



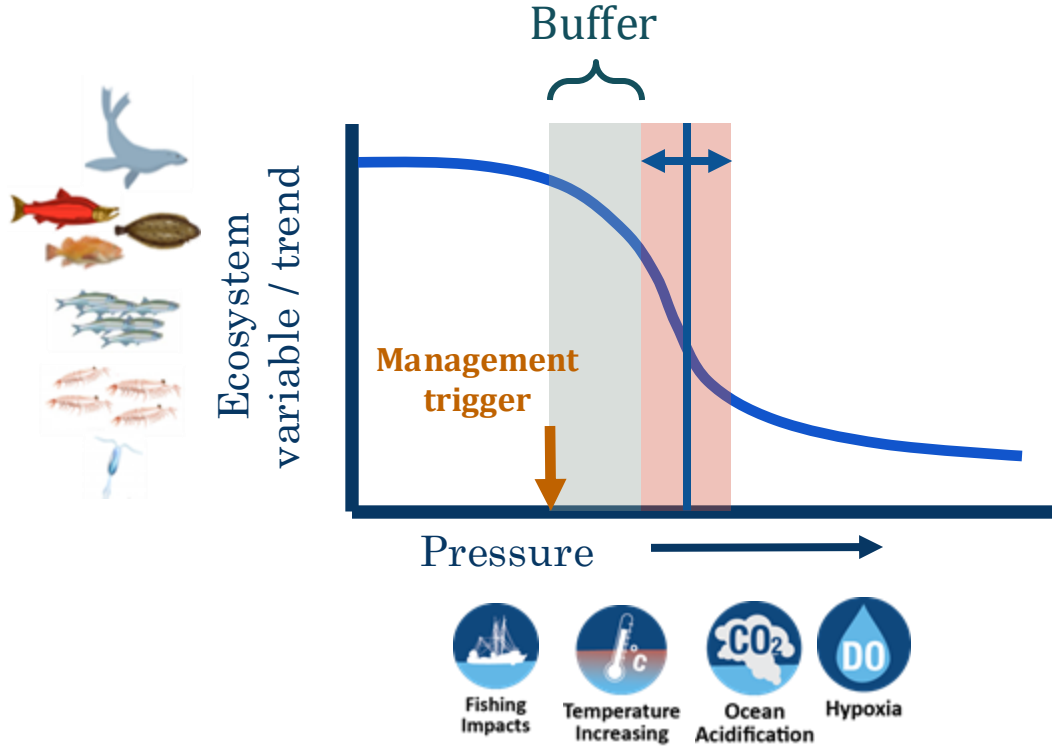
deReynier, Harvey, Link, Morrison et al. 2024

- Develop/monitor ecosystem reference points
- Identify nonlinear and nonstationary pressures and ecological surprises
- Provide early warning
- Minimize risk to resources, communities

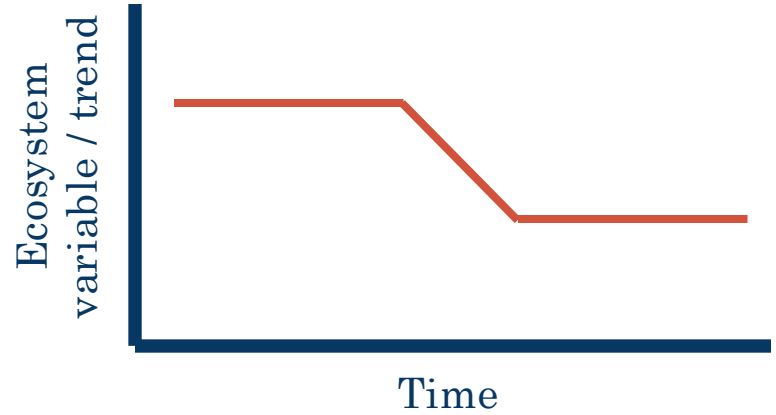
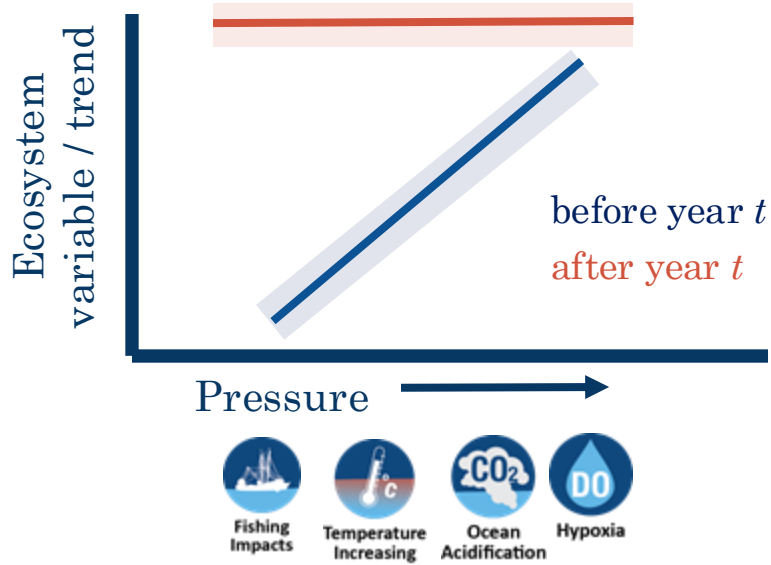


Link, Griffis, Busch et al. 2015

Ecosystem thresholds



Nonstationary change



Management pathways for ecosystem and climate information

2023-2024 CALIFORNIA CURRENT ECOSYSTEM STATUS REPORT

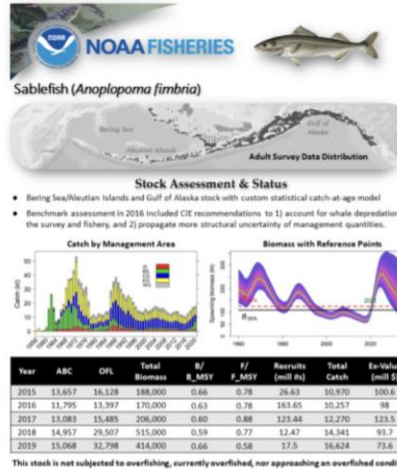
A report of the NOAA California Current Integrated Ecosystem Assessment Team (CCIEA) to the Pacific Fishery Management Council

Andrew Leising, Mary Hunsicker, Nick Tolimieri, Greg Williams, Abigail Harley

Ecosystem Status Report 2023 GULF OF ALASKA



Ecosystem and Socioeconomic Profile



Risk Tables

	Assessment-related considerations	Pop dynamics considerations	Ecosystem considerations	Fishery considerations
Level 1: Normal				
Level 2: Increased concern				
Level 3: Extreme concern				

A risk table to address concerns external to stock assessments when developing fisheries harvest recommendations

Martin W. Dorn and Stephani G. Zador

Outline

Ecosystem thresholds

- Simulation-based evaluation of a threshold detection tool

Nonstationary change

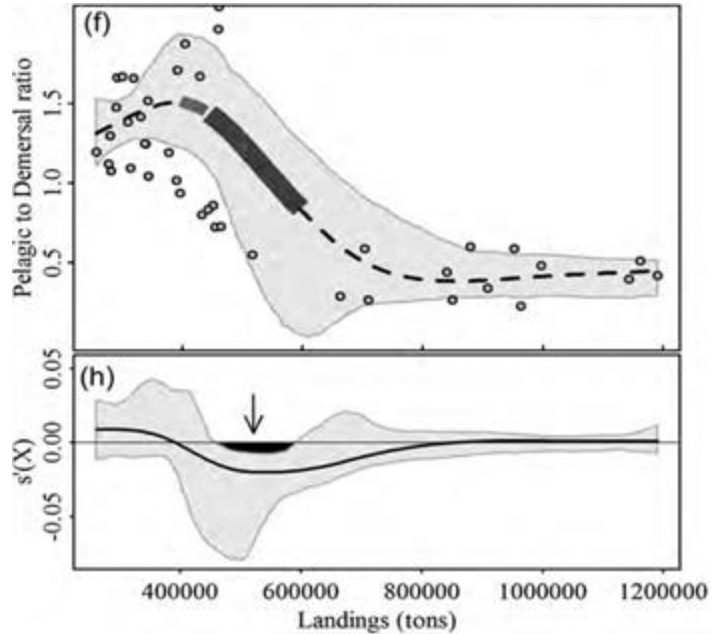
- Tracking ecosystem-level trends and shifts



SCARLETT W.
YOUTH ENTRY, GRADE 12

POLYCHROMATIC CAST
(2023, WATERCOLOR)

Evidence of ecological thresholds



Large et al. 2013 ICES JMS



Identifying social thresholds and measuring social achievement in social-ecological systems: A cross-regional comparison of fisheries in the United States

Perng et al. 2023

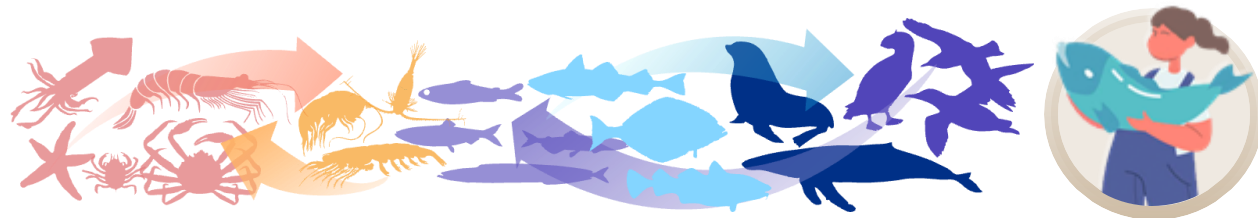
E.g. Samhuri et al. 2015, Tam et al. 2017, Boldt et al. 2021, Hunsicker et al. 2022 PICES WG36 Report

How to increase uptake of thresholds in management?

Sensitivity analyses of threshold models to time series length, missing environmental info, observation error, etc. -> improve confidence

Simulation studies to demonstrate how incorporating thresholds in management applications could improve knowledge of risk and uncertainty

Identifying underlying mechanisms through which thresholds may or may not arise can help inform management policies



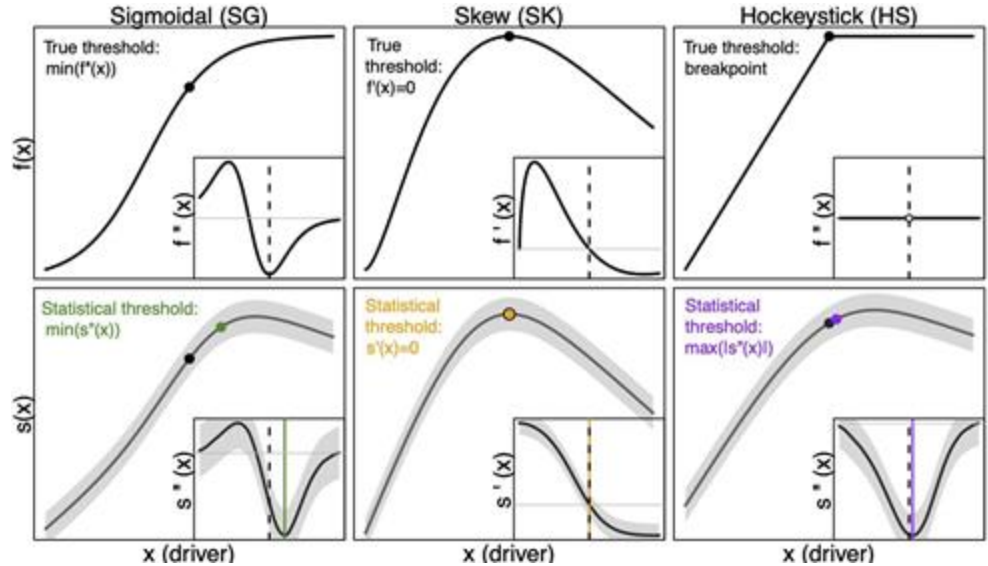


Are threshold detection tools robust or not?

Raine Detmer, UCSB
NSF INTERN program

Generalized Additive Models (GAM)

- Simulations to explore how method performs under various scenarios
- Several functional forms that differ in the definition of threshold locations
- Definition of ‘threshold’ that managers want to avoid may depend on the shape of relationship



Where slope of $s(x)$ is decreasing most rapidly

Local optimum of $s(x)$

Where slope of $s(x)$ is changing most rapidly

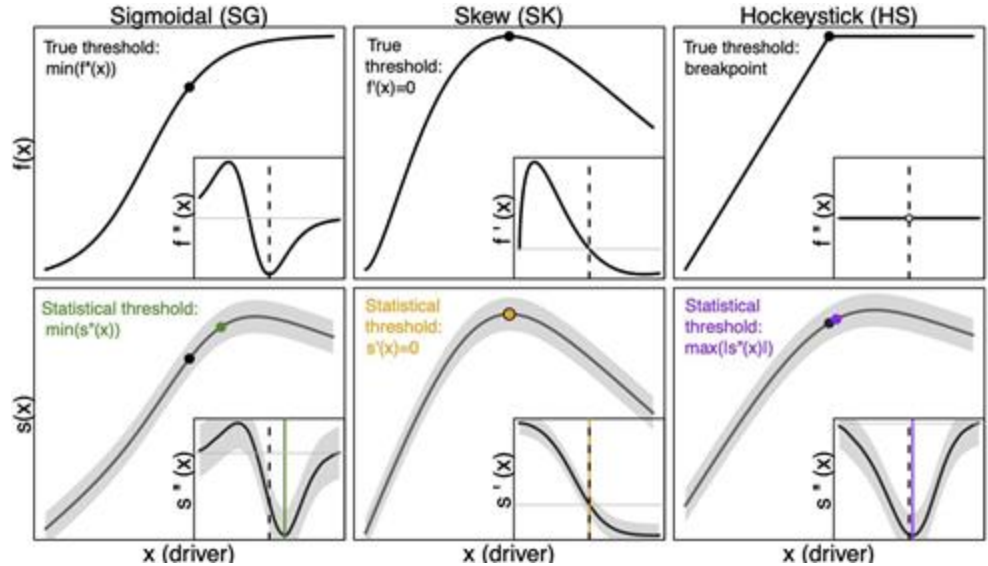


Are threshold detection tools robust or not?

Raine Detmer, UCSB
NSF INTERN program

Scenarios

- (1) Number of data points (time series length)
- (2) Observation error of response
- (3) Effect of a missing covariate

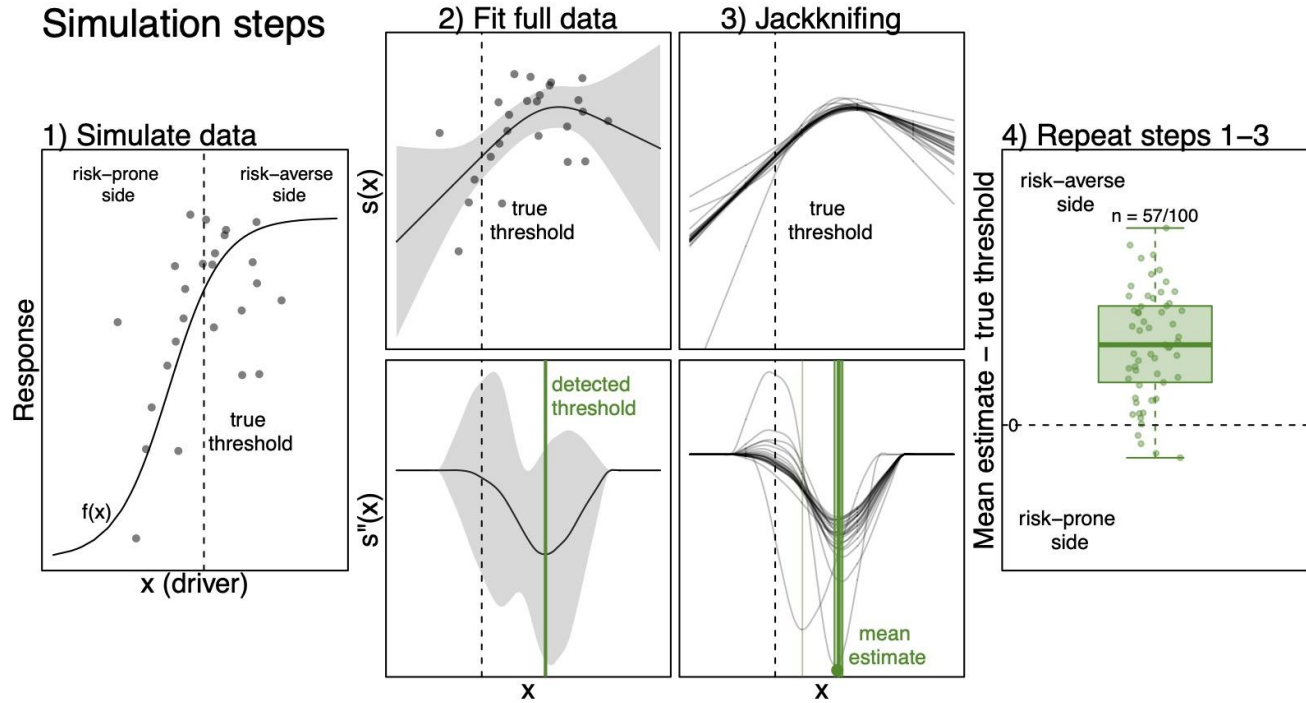


Where slope of $s(x)$ is decreasing most rapidly

Local optimum of $s(x)$

Where slope of $s(x)$ is changing most rapidly

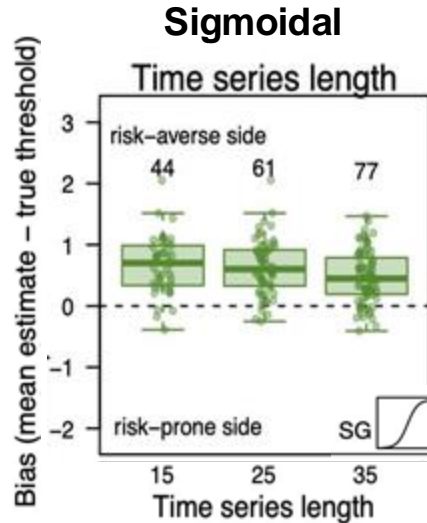
For each simulation scenario:



Jackknife resampling to evaluate robustness of each detected threshold existence and location

True and false positive rates were also calculated

GAMs generally performed best when time series were long

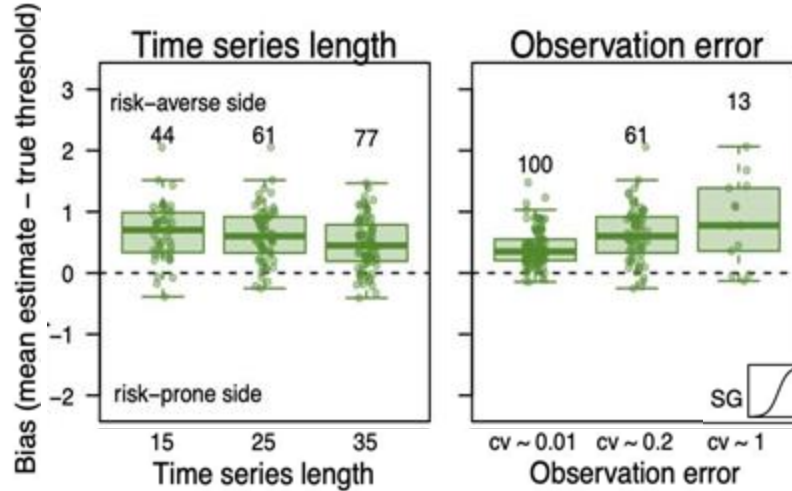


← Estimated threshold preceded abrupt change to undesired levels of the response

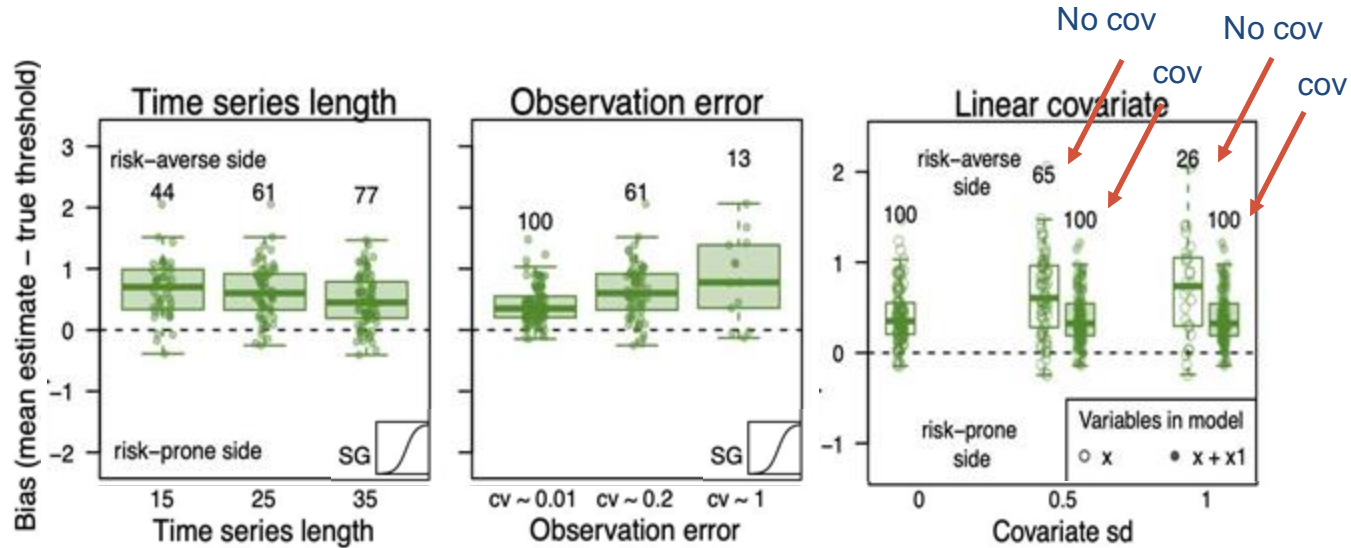
← Estimated threshold was on the “risk-prone” side with undesired response values

Sample sizes represent the number of simulations that detected a threshold, out of a total of 100 replicates

GAMs generally performed best when observation error was low

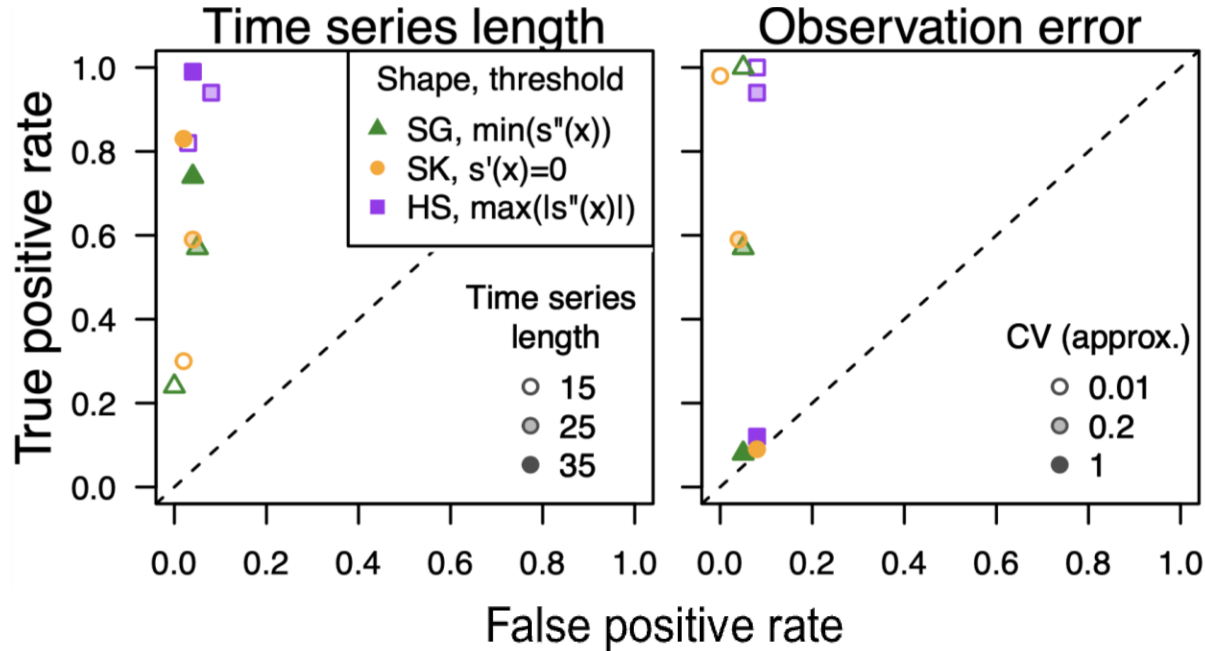


GAMs generally performed best when covariates were accounted for



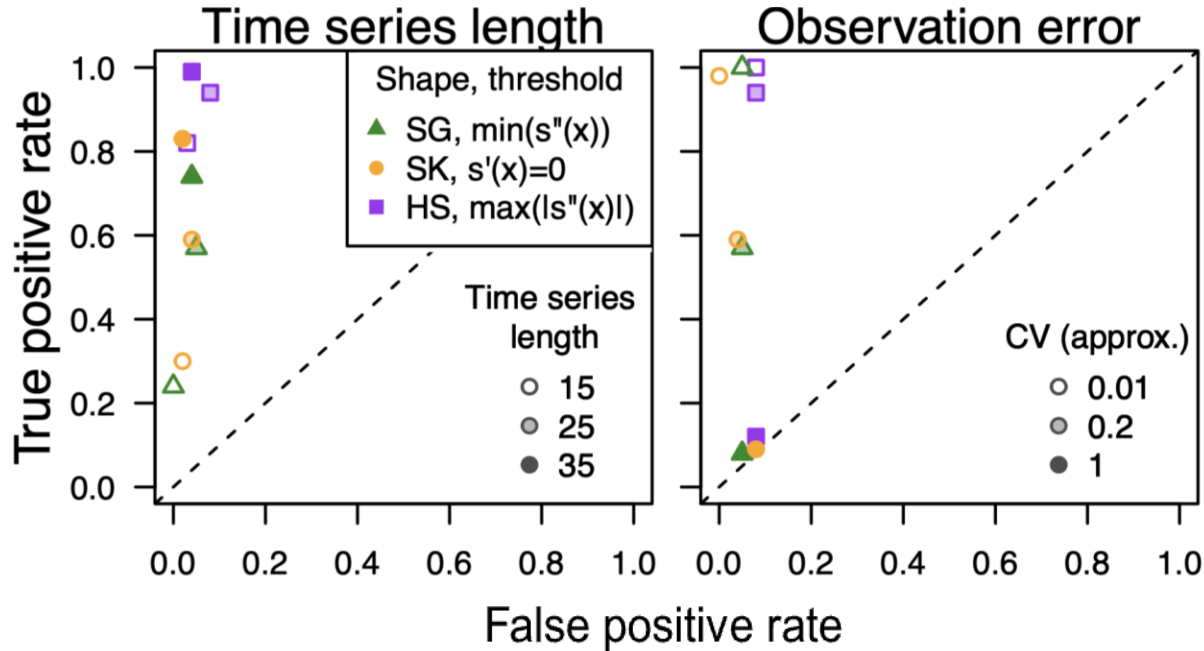
- Effects of factors held up across the functional forms
- Bias toward risk adverse side indicates low risk of mistakenly concluding a threshold lies far on the undesirable side of its true value

True positive rates were highest for long time series and low observation error



TPRs = fraction of simulation replicates that detected a threshold when one existed

False positive rates were generally low across parameter combinations



FPRs = fraction of simulation replicates that detected a threshold when true relationship was linear

Are threshold detection tools robust or not?

- GAMs generally performed best with long time series, low observation error, and covariates accounted for
- Direction of bias was generally towards risk-averse side of threshold -> low risk of mistakenly concluding a threshold lies far on the undesirable side of its true value
- Detectability depended on shape of relationship and definition of the threshold location
- Other factors to consider: temporal and/or spatial autocorrelation, nonstationarity, more complex driver-response-covariate relationships

Outline

Ecosystem thresholds

- Simulation-based evaluation of a threshold detection tool (GAM)

Nonstationary change

- Tracking ecosystem-level trends and shifts



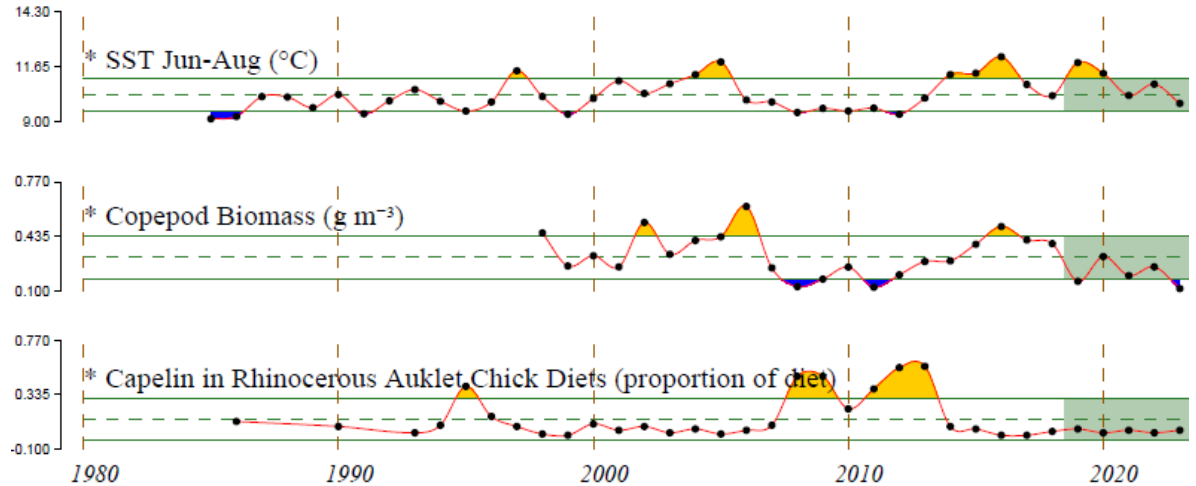
ANANYA A.
YOUTH ENTRY, GRADE 9

A DESPERATE OCEAN
(2023, ACRYLIC)



Bridget Ferriss
NOAA AFSC

Developing ecosystem state indicators: Gulf of Alaska

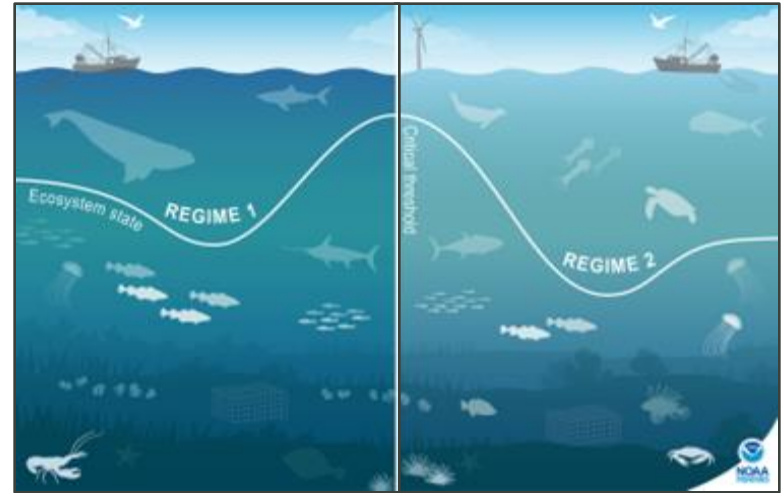
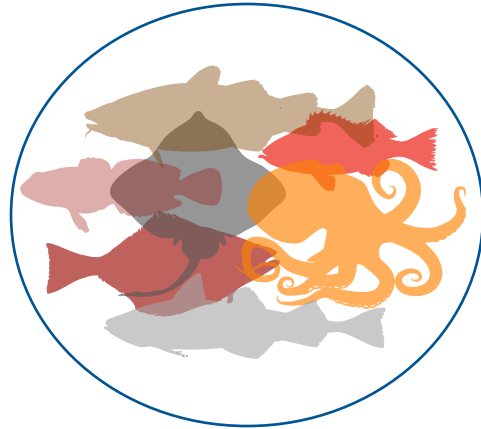


Annual synthesis of marine ecosystem conditions to inform fisheries management



Bridget Ferriss
NOAA AFSC

Developing ecosystem state indicators: Gulf of Alaska



May provide early detection of ecosystem-level changes

Ecosystem state indicators for NE Pacific ecosystems

- Identify shared trends among time series that are useful as indices
- Detect changes in mean ecosystem state
- Distinguish normal variability from changes signaling a major shift



Progress in Oceanography

Volume 186, July 2020, 102393



Evaluating ecosystem change as Gulf of Alaska temperature exceeds the limits of preindustrial variability Litzow et al. 2020

PLOS CLIMATE

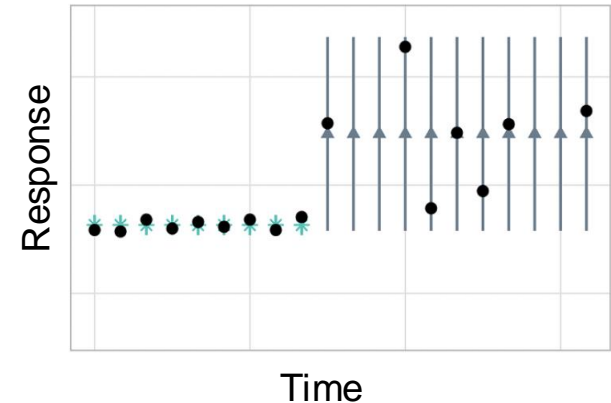
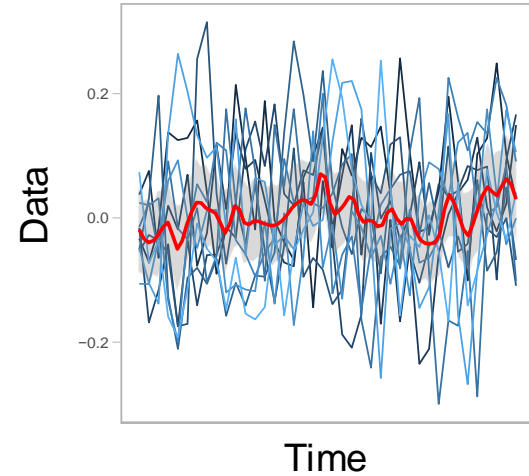
Tracking and forecasting community responses to climate perturbations in the California Current Ecosystem

Hunsicker et al. 2022

Methods

- Dynamic Factor Analysis (MARSS R package, Holmes et al. 2012)
 - Identify latent 'trends' that may be useful as environmental indices

- Hidden Markov Models (hmmTMB R package, Michelot and Glennie 2023)
 - Estimate underlying state at any point in time
 - Estimate means and variances in the response in each state
 - Estimate probability of state transitions



Seabird (13,10)

Reproductive success
Hatch date

Mid-trophic (8,8)

Forage fish abundance
Shrimp abundance
Jellyfish abundance
Juvenile salmon

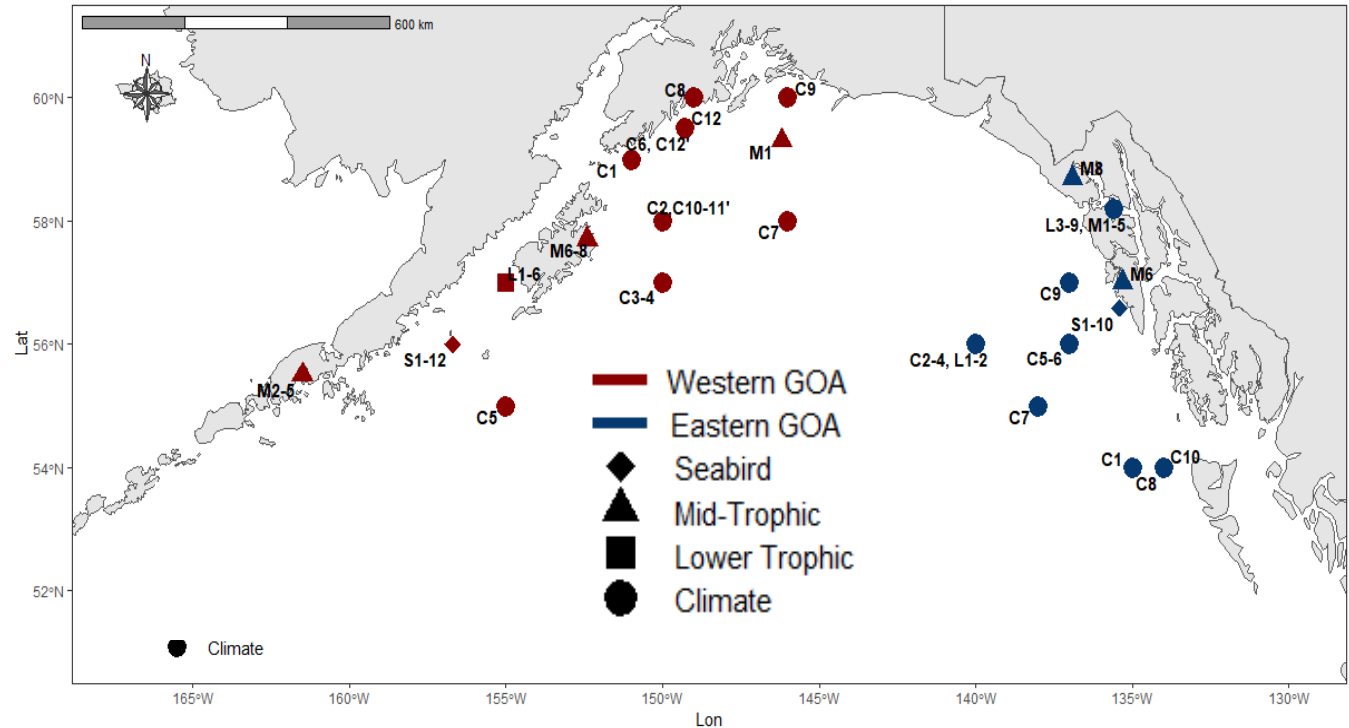
Lower trophic (10,9)

Chl-a
Zooplankton
Ichthyoplankton

Climate (12,10)

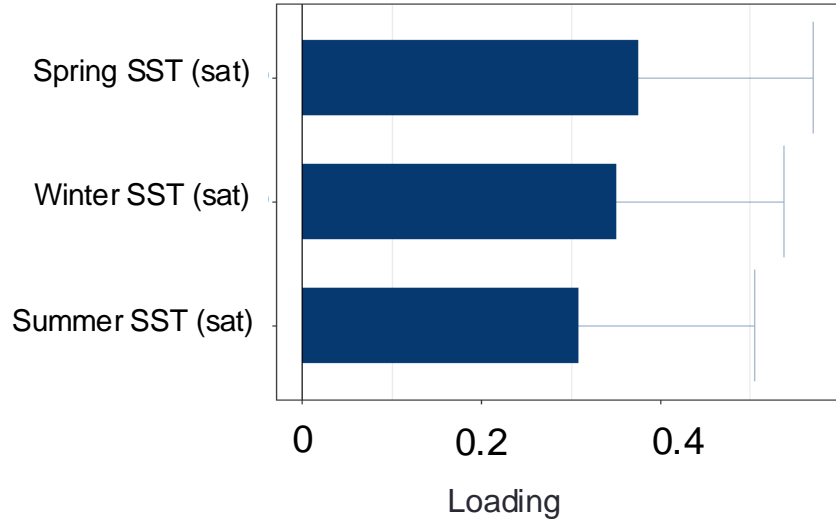
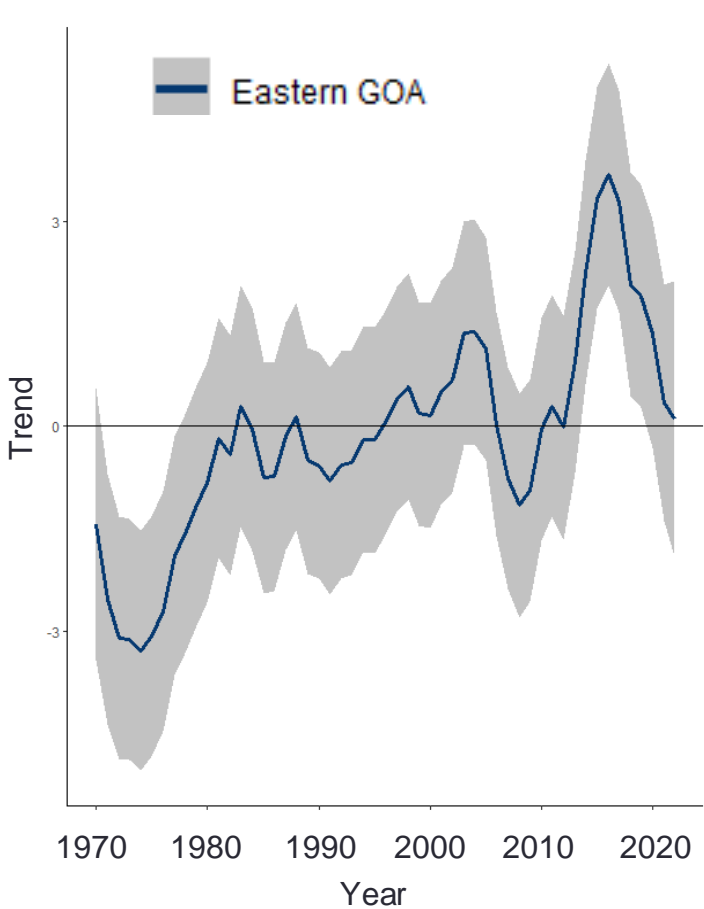
SST (seasonal)
Temperature at depth
Salinity
Wind direction
Upwelling

Gulf of Alaska time series

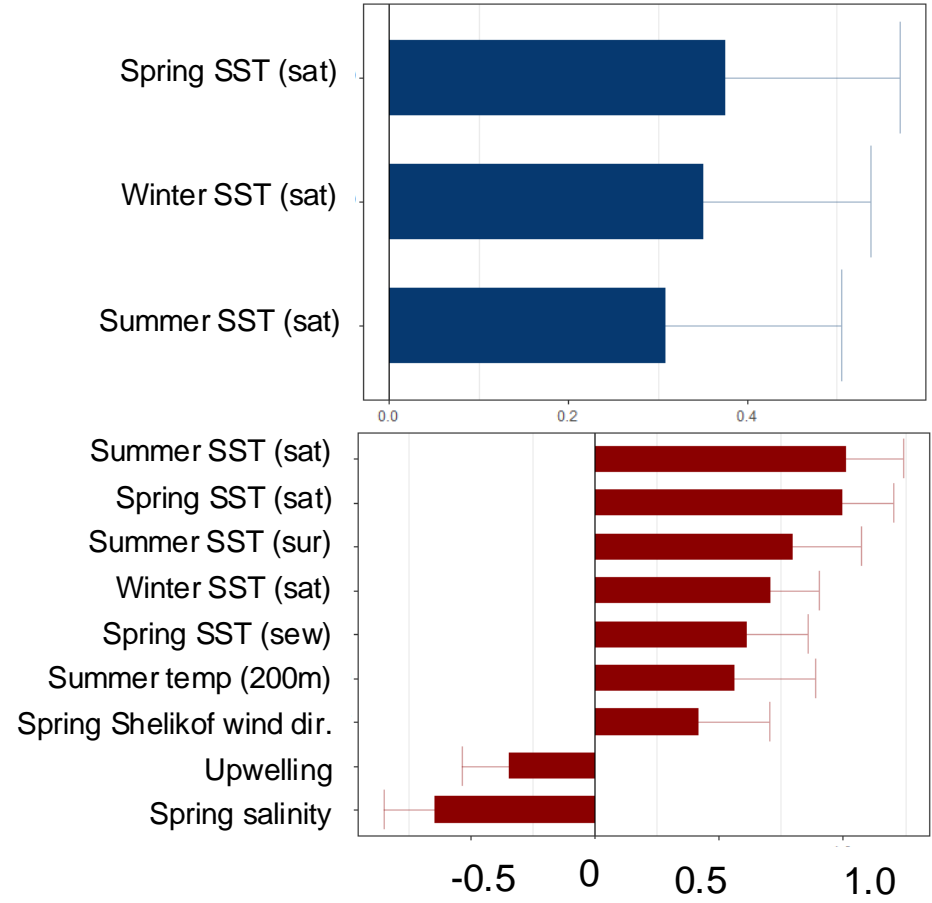
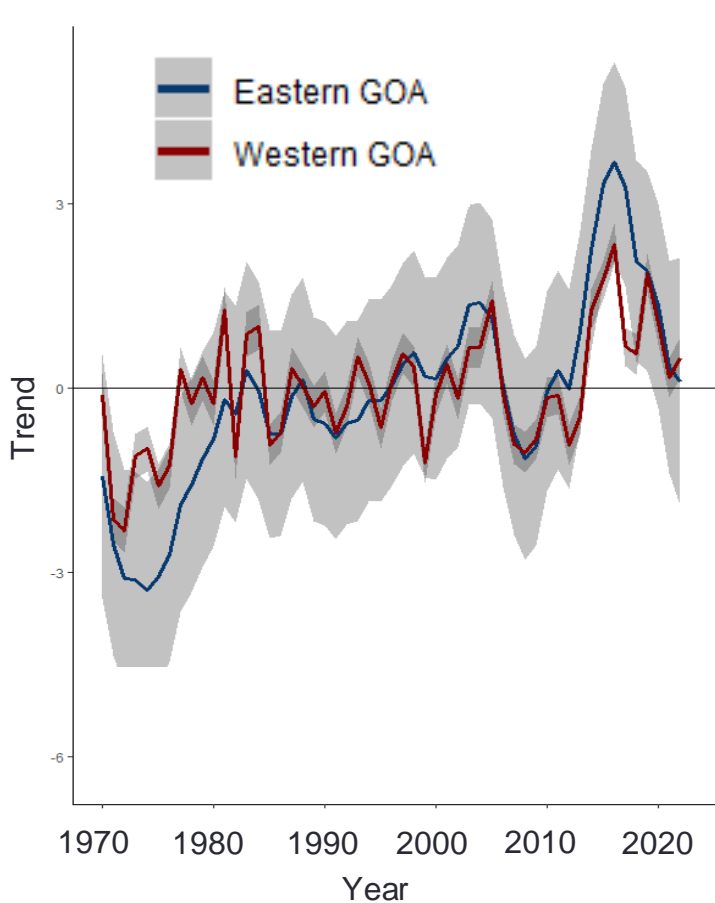


Time series ranged from 25 to 52 year in length, all ending in 2022

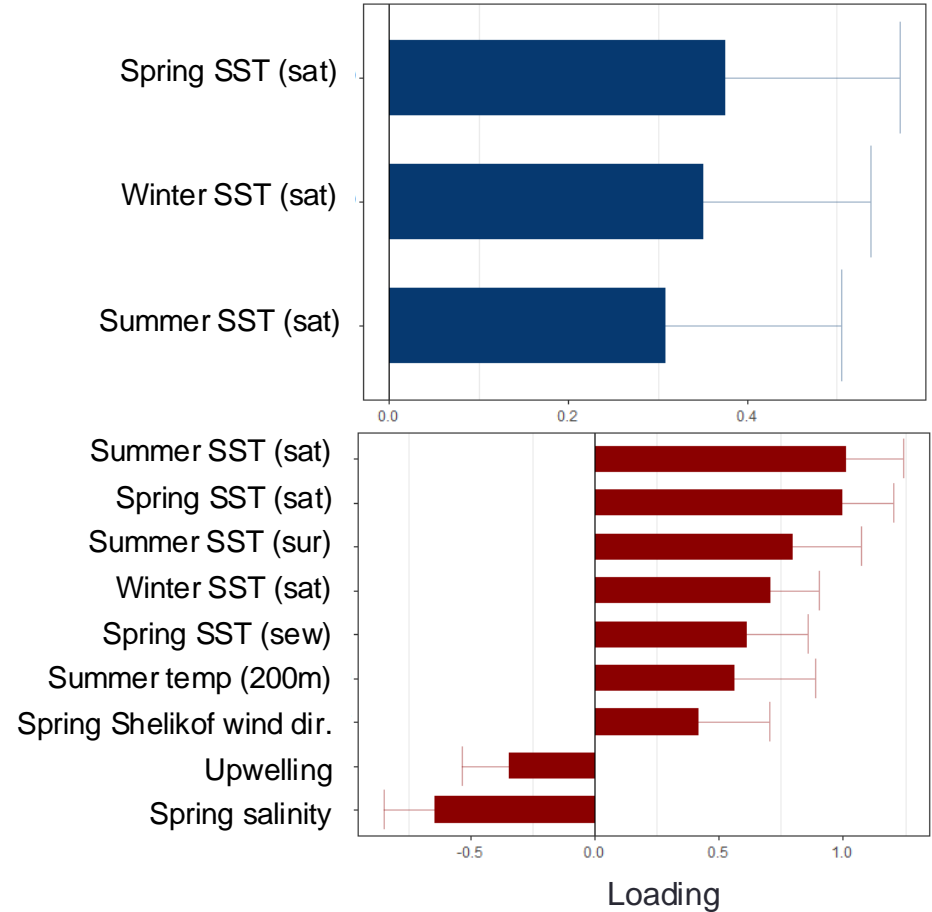
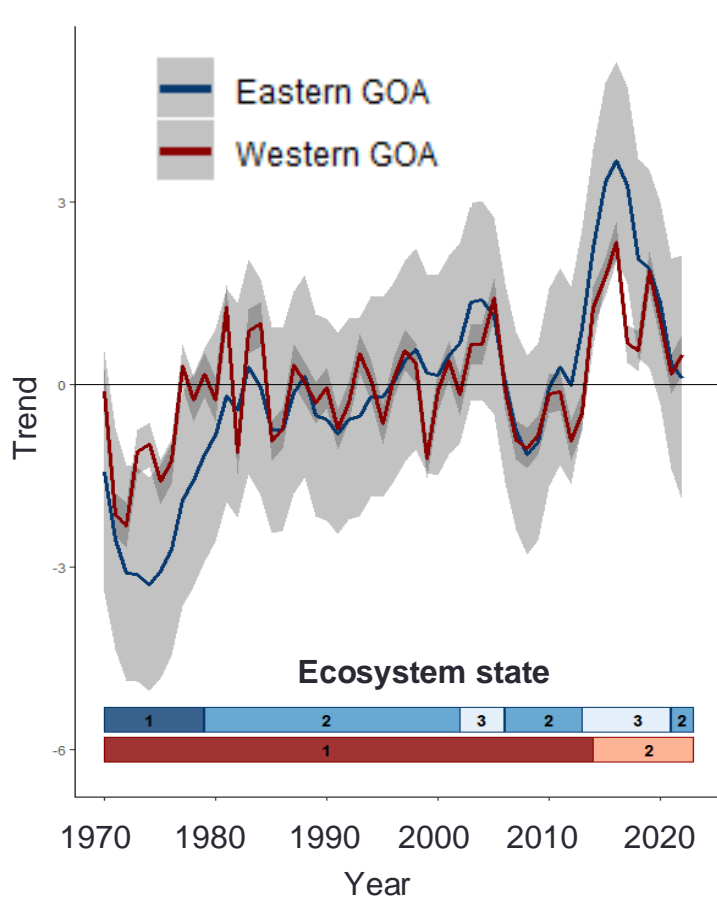
One common trend identified in EGOA climate variables



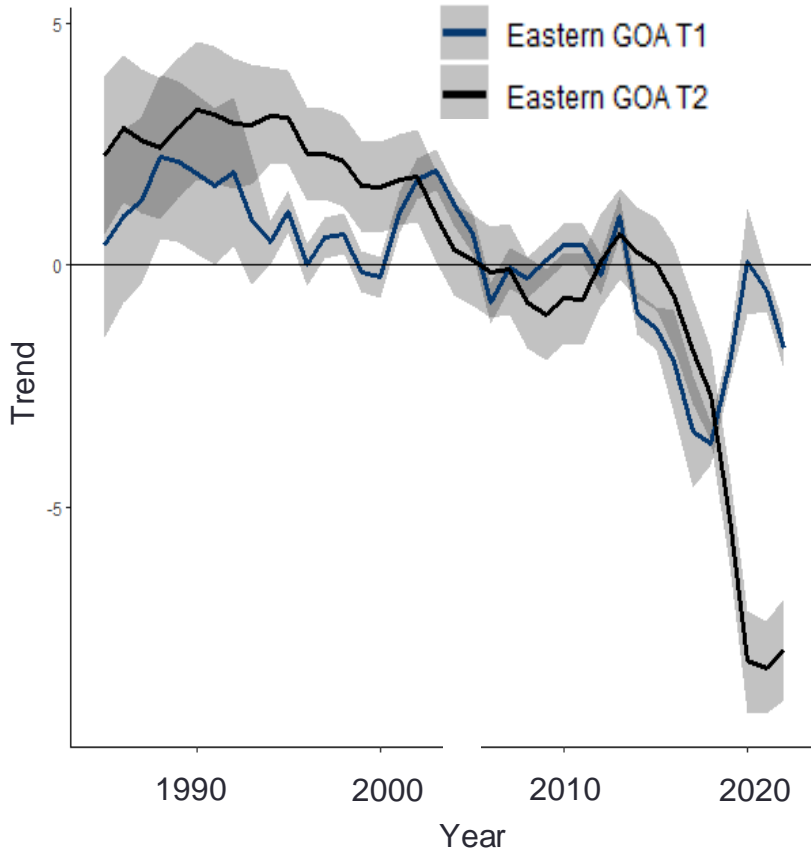
One common trend identified in WGOA climate variables



State transitions largely aligned with previous observations (1977,1988,2014)



Two common trends identified in EGOA biology variables



Eastern GOA T1

Humpback whale birth rate
Herring biomass (Craig)
Herring biomass (Sitka)
Juv chum salmon cpue
Chla biomass
Glaucous wing gull hatch
Thick billed murre hatch
Common murre hatch

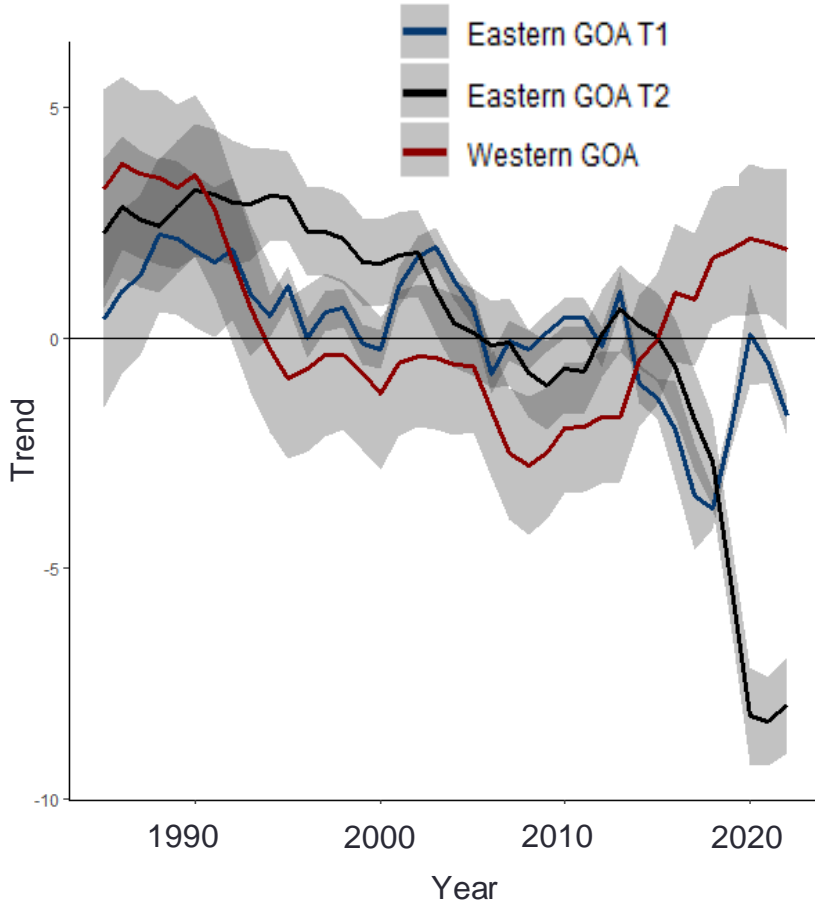


Eastern GOA T2

Chla biomass
Juv coho salmon cpue
Herring biomass (Craig)
Herring biomass (Sitka)



One common trend identified in WGOA biology variables



Eastern GOA T1

- Humpback whale birth rate
- Herring biomass (Craig)
- Herring biomass (Sitka)
- Juv chum salmon cpue
- Chla biomass
- Glaucous wing gull hatch
- Thick billed murre hatch
- Common murre hatch



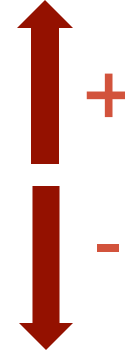
Eastern GOA T2

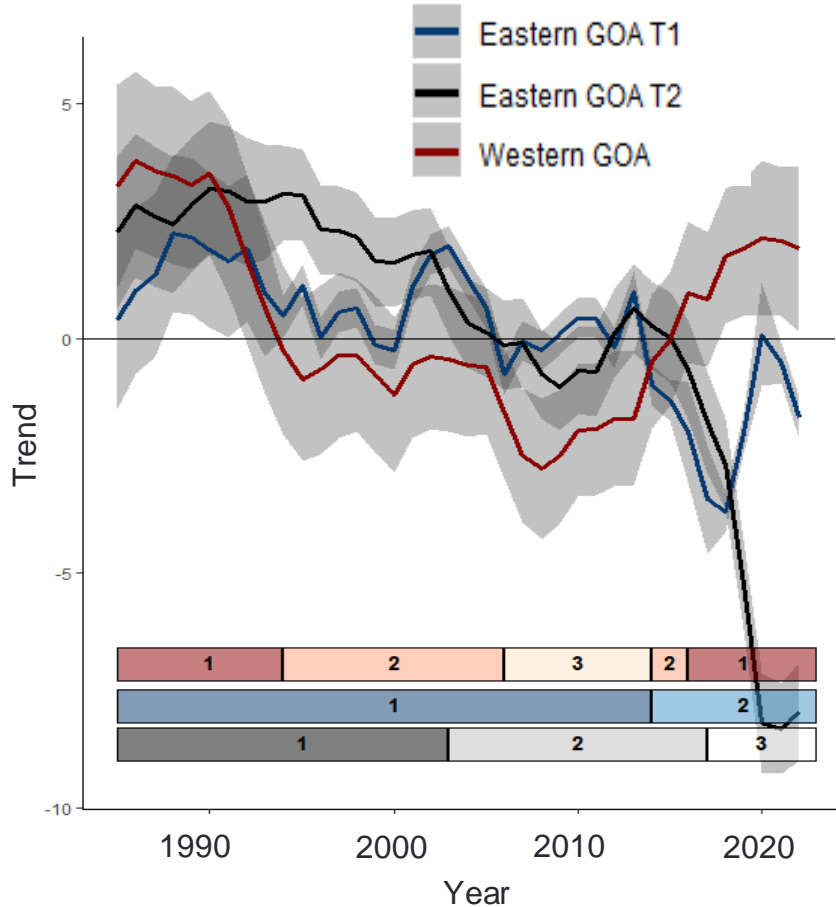
- Chla biomass
- Juv coho salmon cpue
- Herring biomass (Craig)
- Herring biomass (Sitka)



Western GOA

- Tufted puffin prod
- Chiniak pink shrimp
- Pavlof shrimp
- Pavlof capelin
- Chiniak jellyfish
- Chla biomass
- Prop. capelin in diet
- Tufted puffin hatch





Eastern GOA T1

- Humpback whale birth rate
- Herring biomass (Craig)
- Herring biomass (Sitka)
- Juv chum salmon cpue
- Chla biomass
- Glaucous wing gull hatch
- Thick billed murre hatch
- Common murre hatch



+

-

Western GOA

- Tufted puffin prod
- Chiniak pink shrimp
- Pavlof shrimp
- Pavlof capelin
- Chiniak jellyfish
- Chla biomass
- Prop. capelin in diet
- Tufted puffin hatch



+

-

Eastern GOA T2

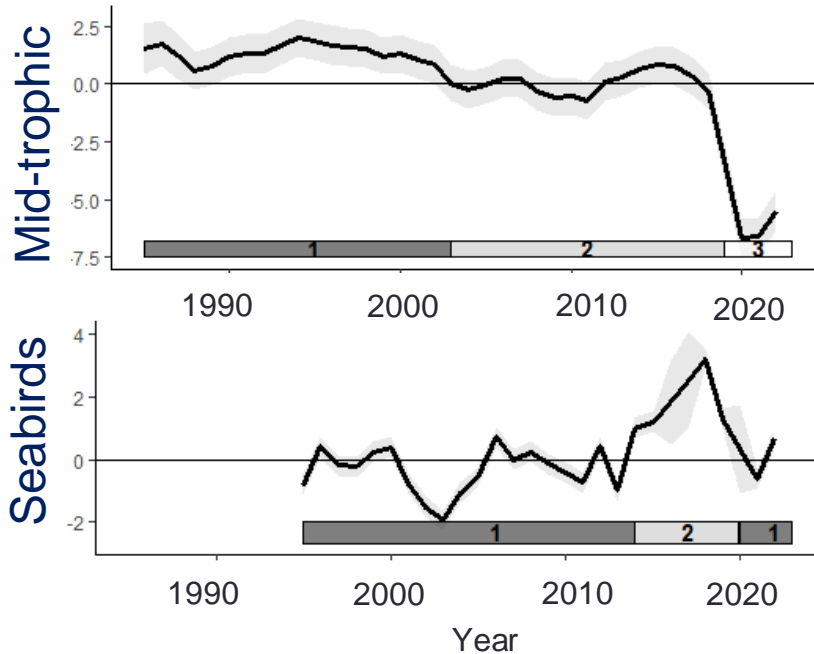
- Chla biomass
- Juv coho salmon cpue
- Herring biomass (Craig)
- Herring biomass (Sitka)



+

-

Common trends within trophic levels



Mid-trophic

- Juvenile coho salmon cpue
 - Juvenile pink salmon cpue
 - Juvenile chinook salmon cpue
 - Herring biomass (Craig)
 - Herring biomass (Sitka)
- ↑ +
- ↓ -

Seabirds

- Thick-billed murre hatch
 - Common murre hatch
 - Glaucous-winged gull hatch
- ↑ +

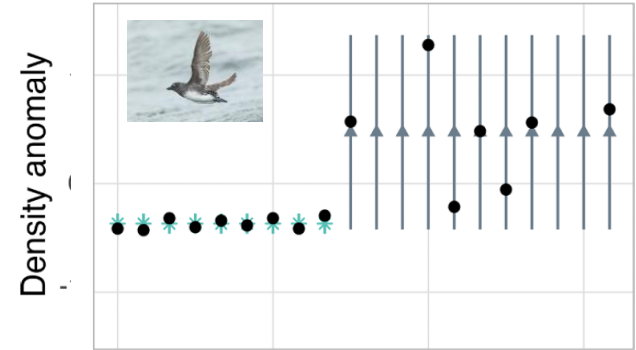
Useful for communication and identifying redundant indicators

Using Hidden Markov Models to develop ecosystem indicators from non-stationary time series

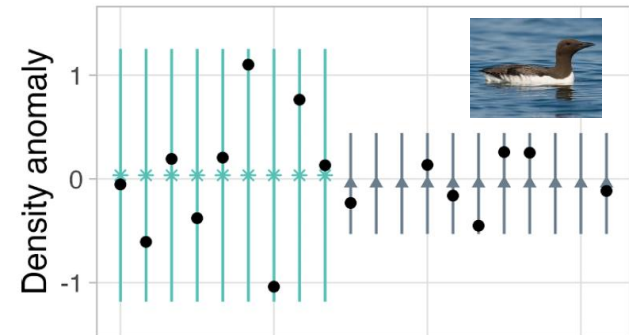
Zoe R. Rand^{a,*}, Eric J. Ward^b, Jeanette E. Zamon^c, Thomas P. Good^b, Chris J. Harvey^b

- Joint HMMs – multiple time series vs trend
- Estimate mean *and* variances in the response
- Identify timing of underlying shift
- Identify redundant indicators

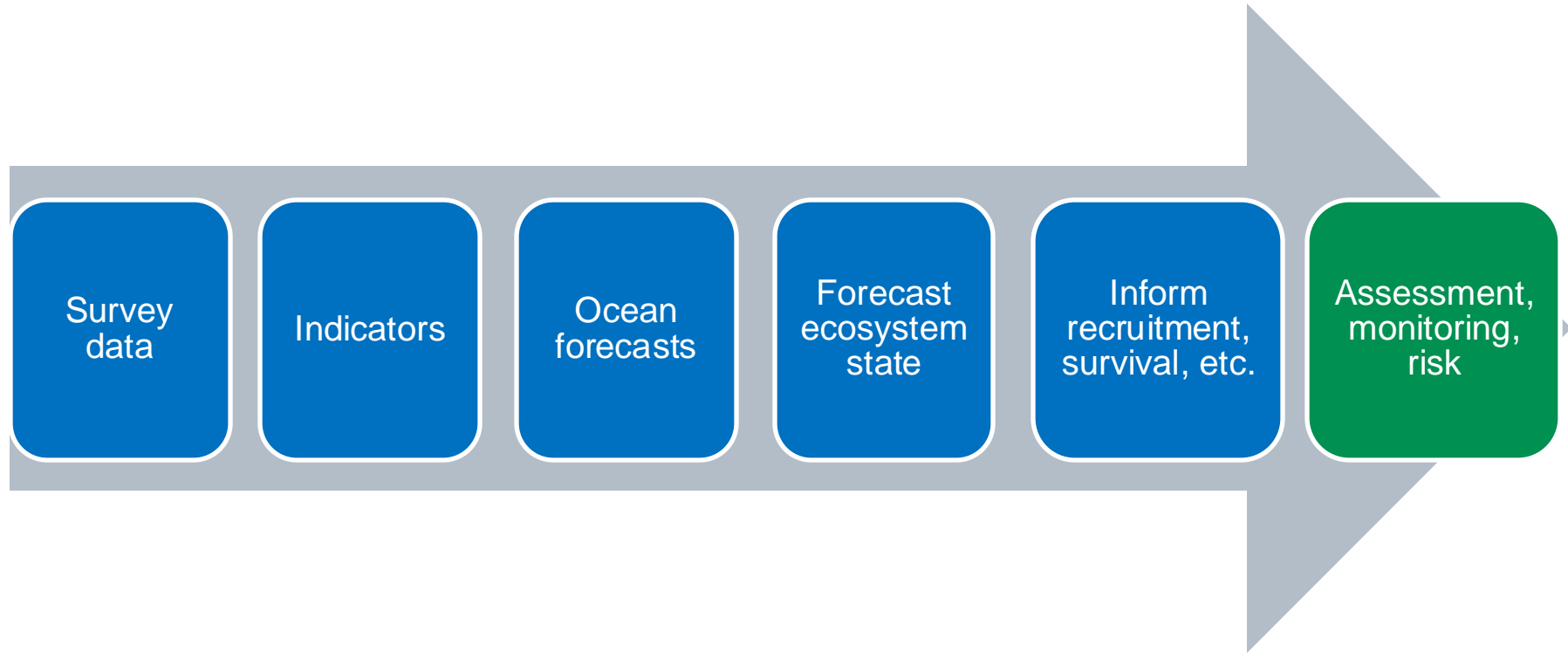
Cassin's auklet



Common Murre

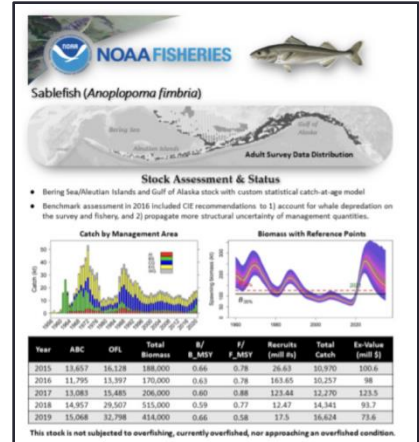


Forecast ecosystem state to help inform management decisions



How can we implement this information into management?

- Annual production of common trends and ecosystem state can streamline communication
- Operationalizing these tools in the management of GOA is achievable by building on existing frameworks
- These tools can provide ecosystem support to management decisions relative to groundfish productivity and resulting harvest specifications



Year	ABC	OYU	Total Biomass	B/F	F/F	Recruits (mill #)	Total Catch	Ex-Value
2015	15,657	15,120	188,000	0.68	0.78	26,632	20,970	100.6
2016	11,795	13,397	170,000	0.63	0.78	163,65	50,257	98
2017	13,083	15,485	206,000	0.60	0.88	123,44	12,270	123.5
2018	14,957	29,507	515,000	0.59	0.77	12,47	14,341	93.7
2019	13,068	33,798	414,000	0.66	0.58	17.5	16,628	73.6

Collaborators

Ecosystem thresholds

Kelly Andrews	Kristin Marshall
Michele Conrad	Stuart Munsch
Elliott Hazen	Kiva Oken
Kirstin Holsman	Will Satterthwaite
Julia Indivero	Kalei Shotwell
Scott Large	Andrew Thompson
Mike Malick	

Non-stationary change

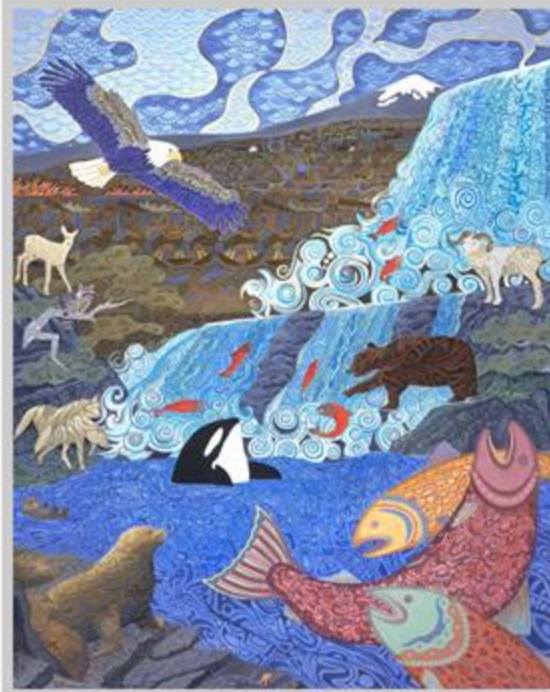
Mike Litzow	Kyle Herbert
Lauren Rogers	Russ Hopcroft
Matt Callahan	Emily Lemagie
Wei Cheng	Jens Nielsen
Seth Danielson	Kally Spalinger
Brie Drummond	William Stockhausen
Emily Fergusson	Wes Strasburg
Christine Gabriele	Shannon Whelan

Thank you!

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SPENCER FRAZER

STREAM OF CONSCIOUSNESS
(2020, OIL ON CANVAS)



5th National Climate Assessment
<https://nca2023.globalchange.gov/art-climate/>