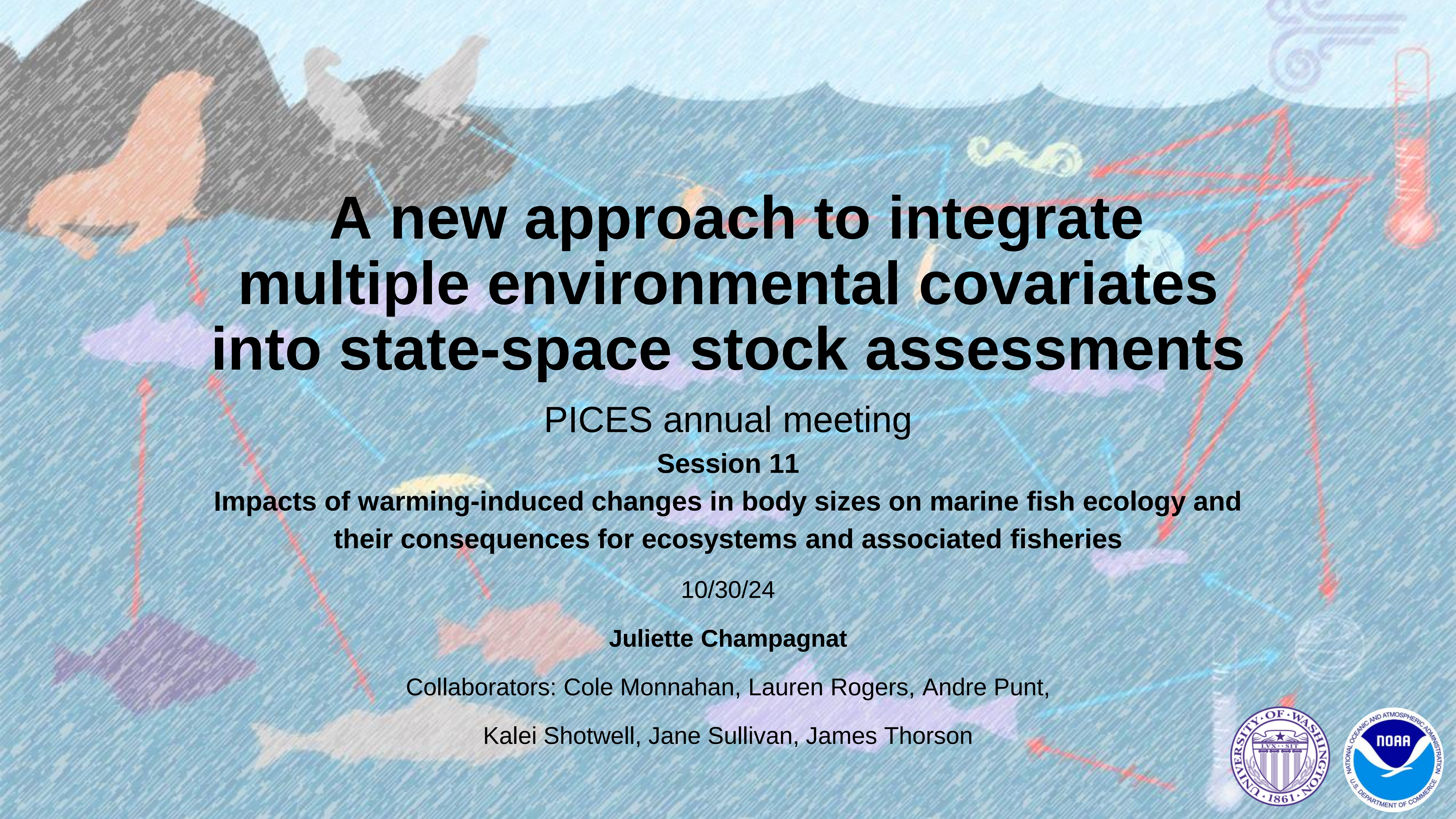


A new approach to integrate multiple environmental covariates into state-space stock assessments

PICES annual meeting

Session 11

Impacts of warming-induced changes in body sizes on marine fish ecology and their consequences for ecosystems and associated fisheries

10/30/24

Juliette Champagnat

Collaborators: Cole Monnahan, Lauren Rogers, Andre Punt,

Kalei Shotwell, Jane Sullivan, James Thorson

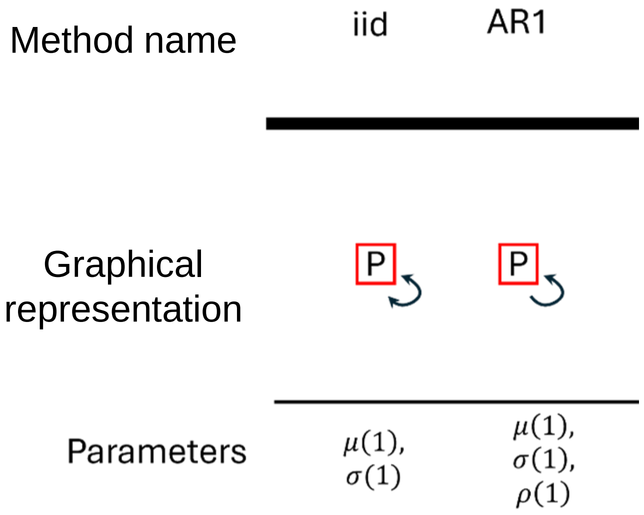
Challenges in stock assessment models

⇒ Accounting for productivity changes

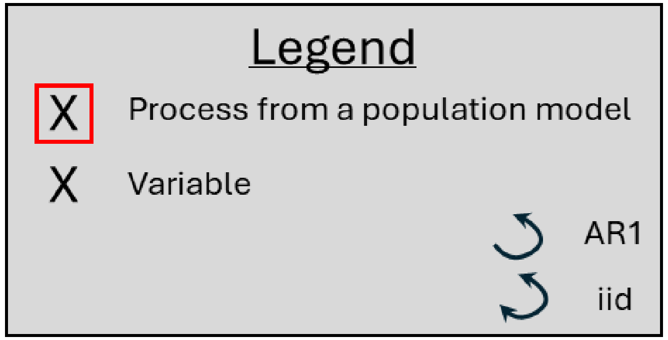
Challenges in stock assessment models

⇒ Accounting for productivity changes

Stochastic variation in biological parameter or population process



Method name	iid	AR1
Graphical representation	P	P
Parameters	$\mu(1)$, $\sigma(1)$	$\mu(1)$, $\sigma(1)$, $\rho(1)$



Legend

X Process from a population model

X Variable

AR1

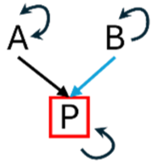
iid

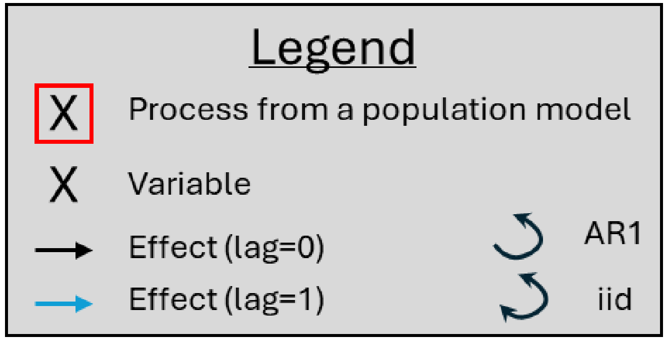
Challenges in stock assessment models

⇒ Accounting for productivity changes

Stochastic variation in biological parameter or population process

Explicit link between population process and environmental variables

Method name	iid	AR1	Smoothed Ecov regression
Graphical representation			
Parameters	$\mu(1)$, $\sigma(1)$	$\mu(1)$, $\sigma(1)$, $\rho(1)$	$\mu(3), \sigma(3)$, $\rho(2), \beta(2)$

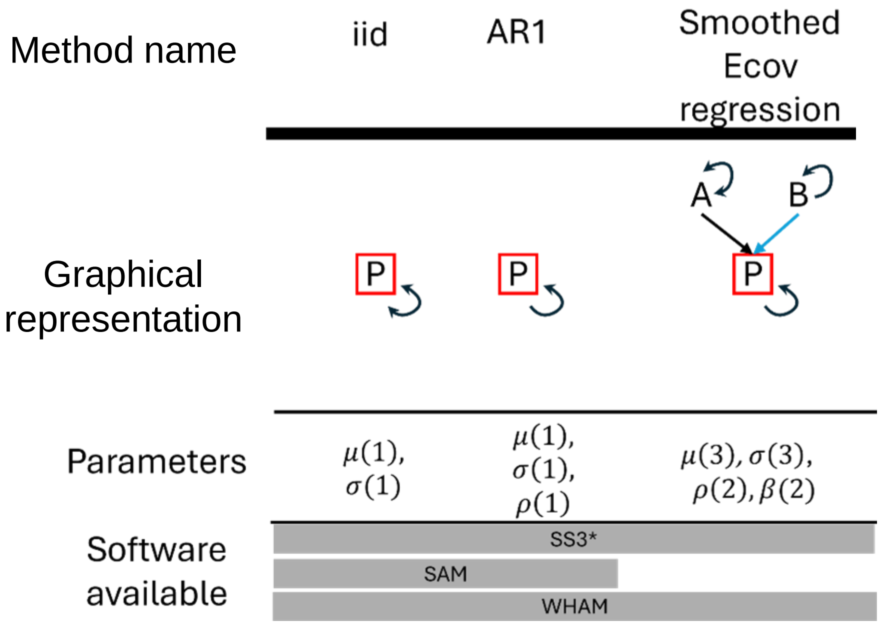


Challenges in stock assessment models

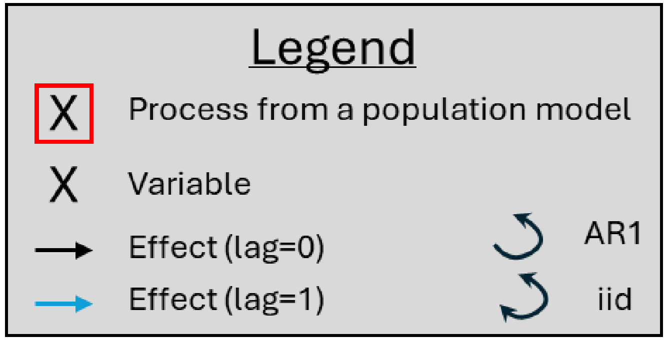
⇒ Accounting for productivity changes

Stochastic variation in biological parameter or population process

Explicit link between population process and environmental variables



Method name	iid	AR1	Smoothed Ecov regression
Graphical representation	P	P	A B P
Parameters	$\mu(1),$ $\sigma(1)$	$\mu(1),$ $\sigma(1),$ $\rho(1)$	$\mu(3), \sigma(3),$ $\rho(2), \beta(2)$
Software available	SS3* SAM WHAM	SS3* SAM WHAM	SS3* WHAM



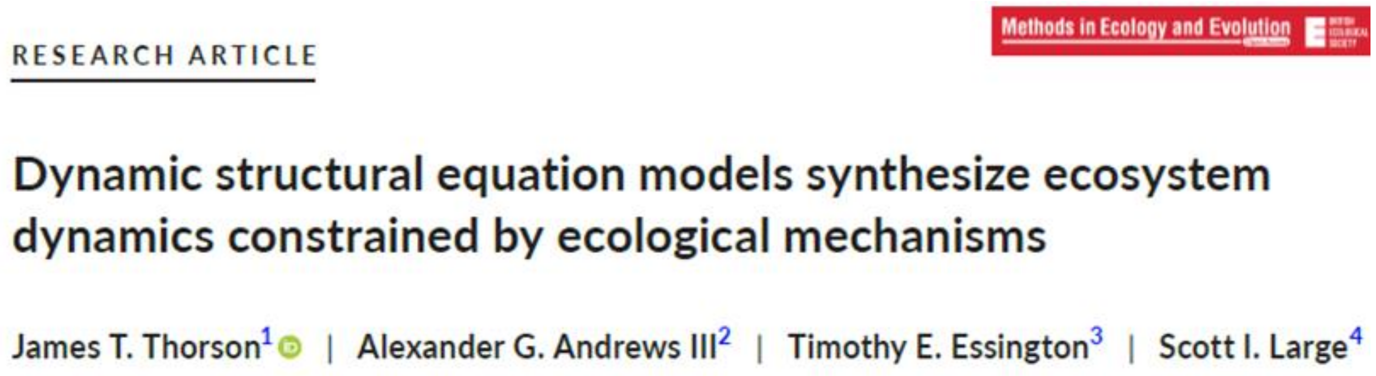
Legend

X	Process from a population model
X	Variable
→	Effect (lag=0)
→	Effect (lag=1)
⤸	AR1
⤸	iid

Methot & Wetzel (2013)
Nielsen & Berg (2014), Berg & Nielsen (2016)
Stock & Miller (2021)

New approach with DSEM

- Dynamic structural equation model = causal modelling



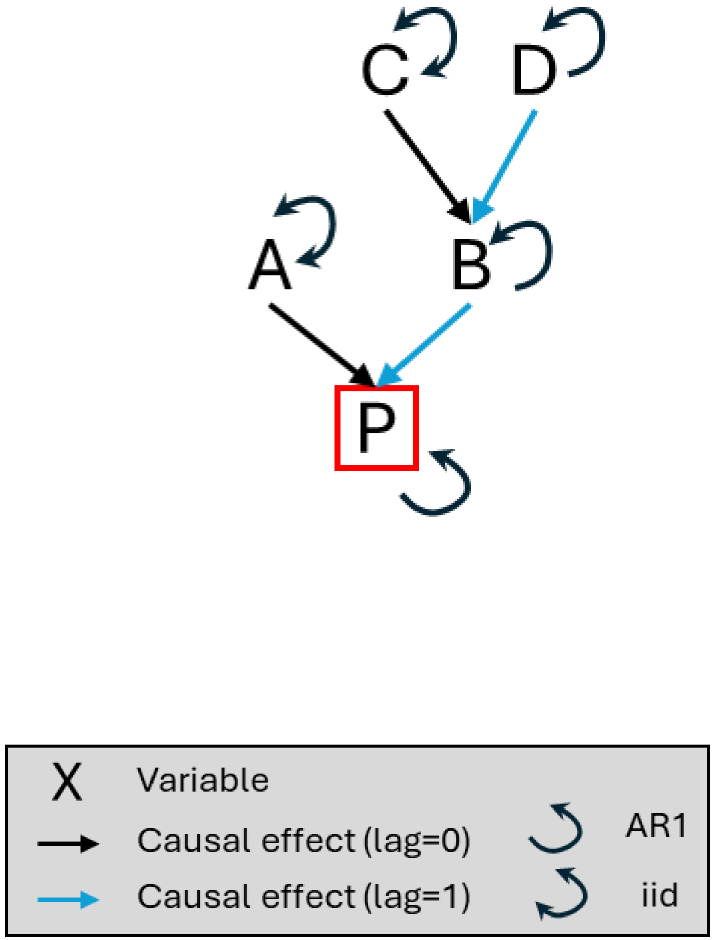
RESEARCH ARTICLE

Methods in Ecology and Evolution

Dynamic structural equation models synthesize ecosystem dynamics constrained by ecological mechanisms

James T. Thorson[1] | Alexander G. Andrews III[2] | Timothy E. Essington[3] | Scott I. Large[4]

- Allow estimation of multiple interactions (simultaneous & lagged) between variables
- Using GMRF to represent the interactions & fitting as a GLMM
- Consider measurement errors in data + handle Nas + non-normal distributions of data
- Estimation in TMB framework (quick)

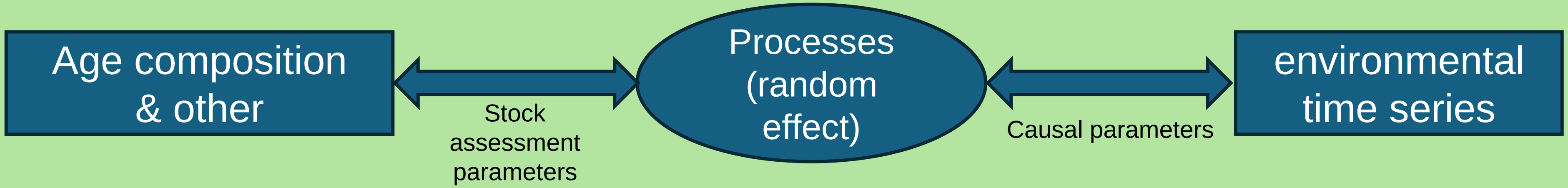


Couple stock assessment and DSEM

Stock assessment+DSEM

Inputs:
- fishery age composition + total catch, survey indices, W@A, mat@A, natural mortality …
- environmental time series (TS) + hypotheses on internal & external (causal) link **& link with population process(es)**

Model: population dynamic + dsem matrix calculus => minimize likelihood



Age composition & other

Stock assessment parameters

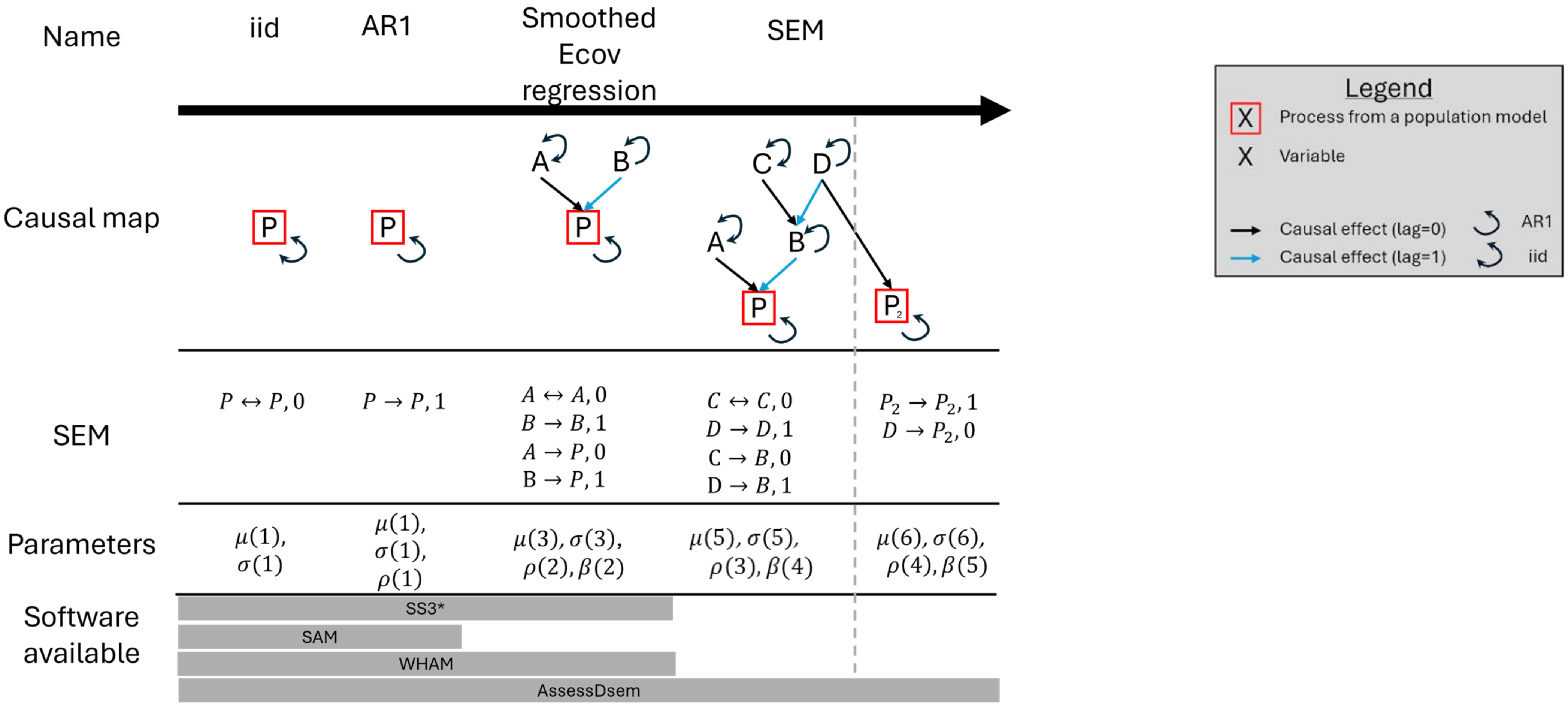
Processes (random effect)

Causal parameters

environmental time series

Outputs: population parameters, dsem parameters (causal links)
Recruitment, N@A, fishing mortality … => **stock status,**
environmental TS & process(es) forecast (driven by causal links)
=> derived quantities (population status)

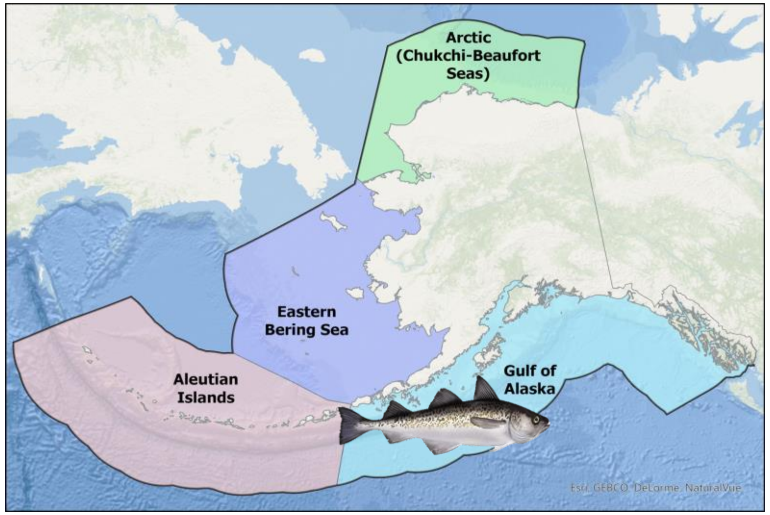
Benefit of coupling DSEM with stock assessment

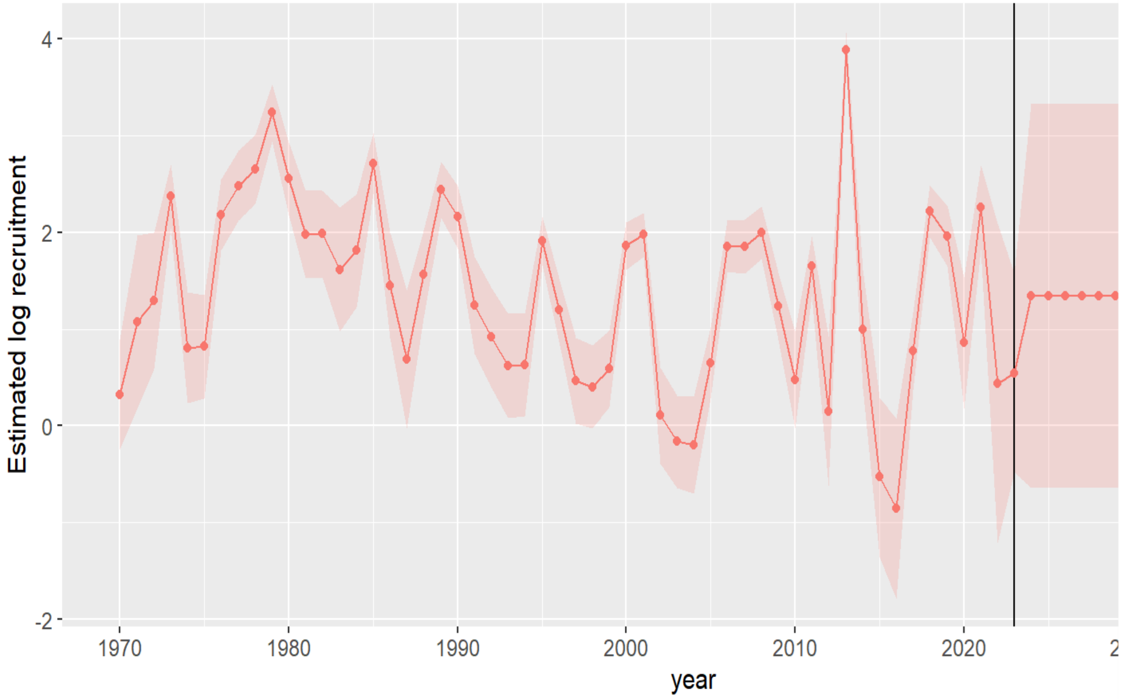


Name	iid	AR1	Smoothed Ecov regression	SEM	
SEM	$P \leftrightarrow P, 0$	$P \rightarrow P, 1$	$A \leftrightarrow A, 0$ $B \rightarrow B, 1$ $A \rightarrow P, 0$ $B \rightarrow P, 1$	$C \leftrightarrow C, 0$ $D \rightarrow D, 1$ $C \rightarrow B, 0$ $D \rightarrow B, 1$	$P_2 \rightarrow P_2, 1$ $D \rightarrow P_2, 0$
Parameters	$\mu(1)$, $\sigma(1)$	$\mu(1)$, $\sigma(1)$, $\rho(1)$	$\mu(3), \sigma(3), \rho(2), \beta(2)$	$\mu(5), \sigma(5), \rho(3), \beta(4)$	$\mu(6), \sigma(6), \rho(4), \beta(5)$

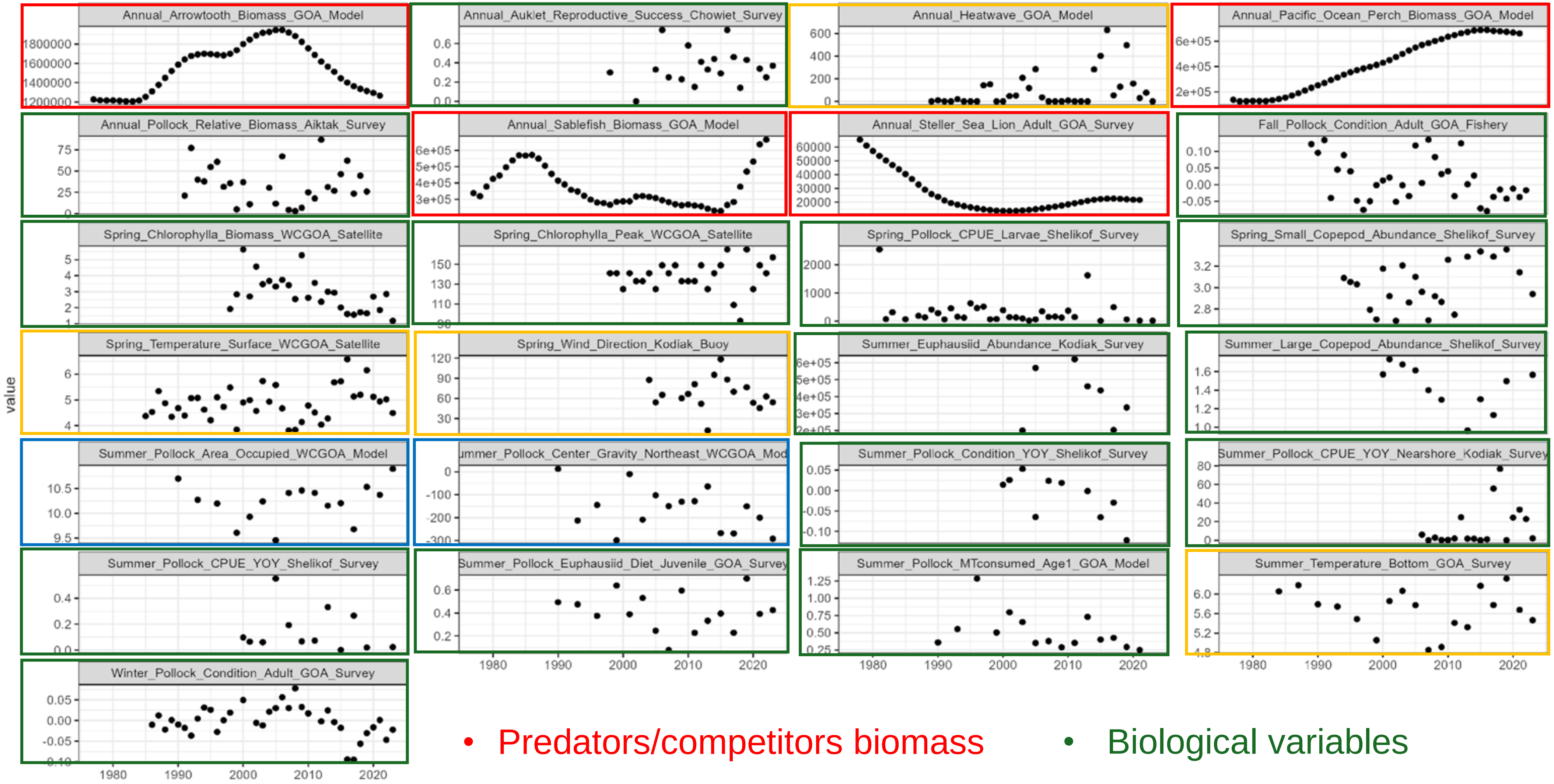
Case study

- Walleye pollock in the Gulf of Alaska
- Custom stock-assessment model in TMB
- Focus on **recruitment**
  - Abundance of age 1 fish
  - No stock-recruitment curve (mean hypothesis for forecast)
  - Lot of variability
- Ecosystem and Socioeconomic Profile (ESP) available
  - Identify important ecological variables



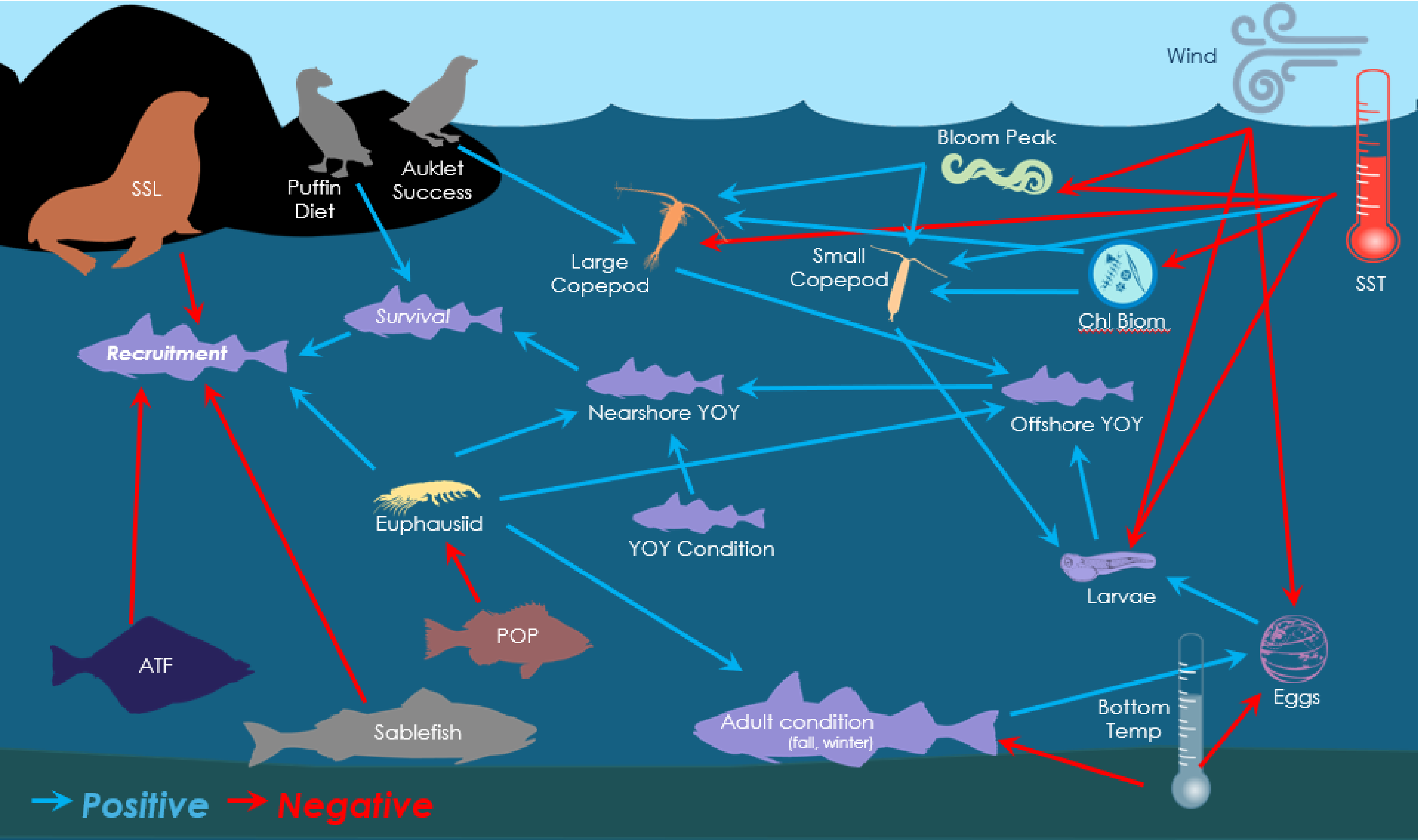


ESP dataset

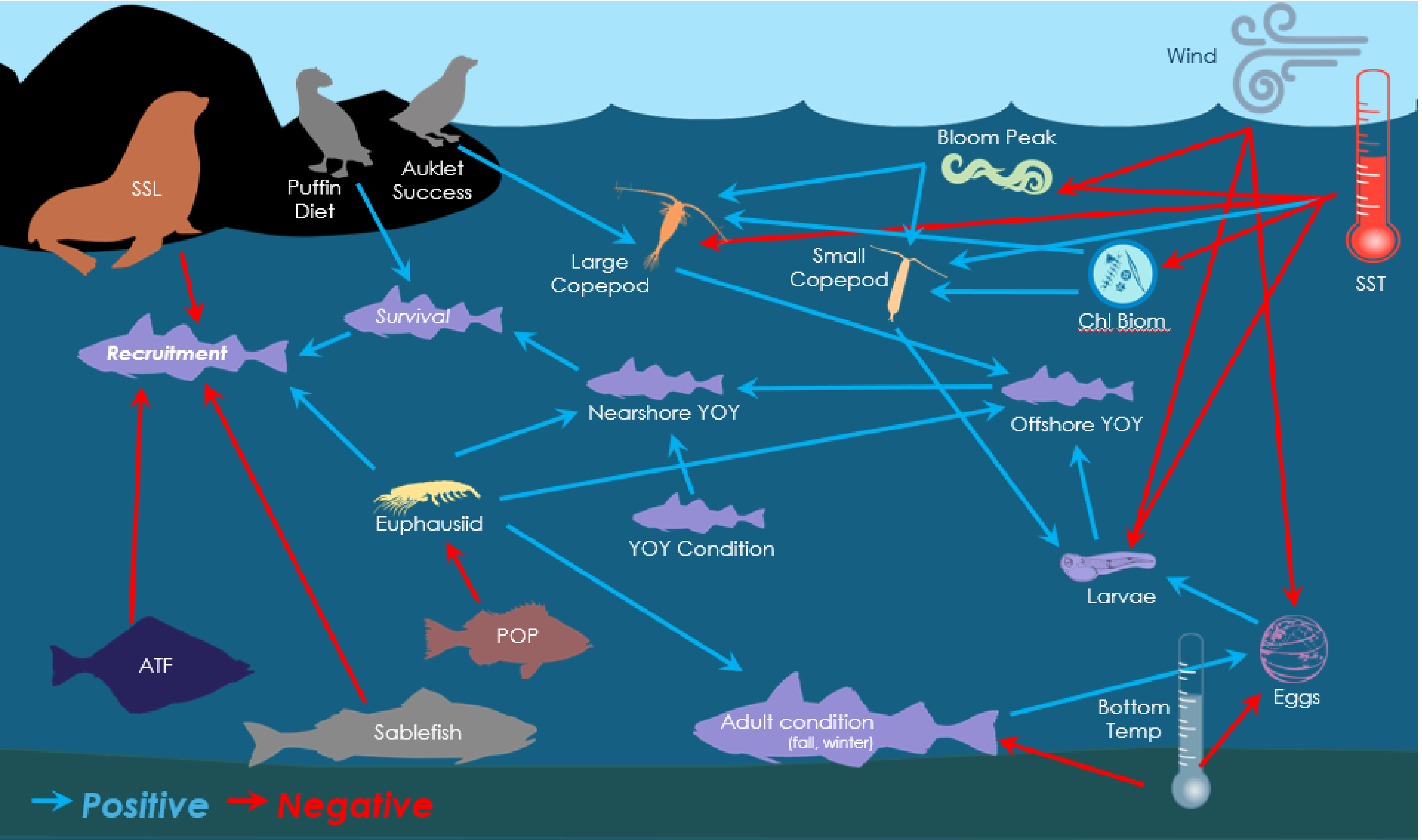


- Predators/competitors biomass
- Physical variables
- Biological variables
- Spatiotemporal indicators

Full causal map



Full causal map

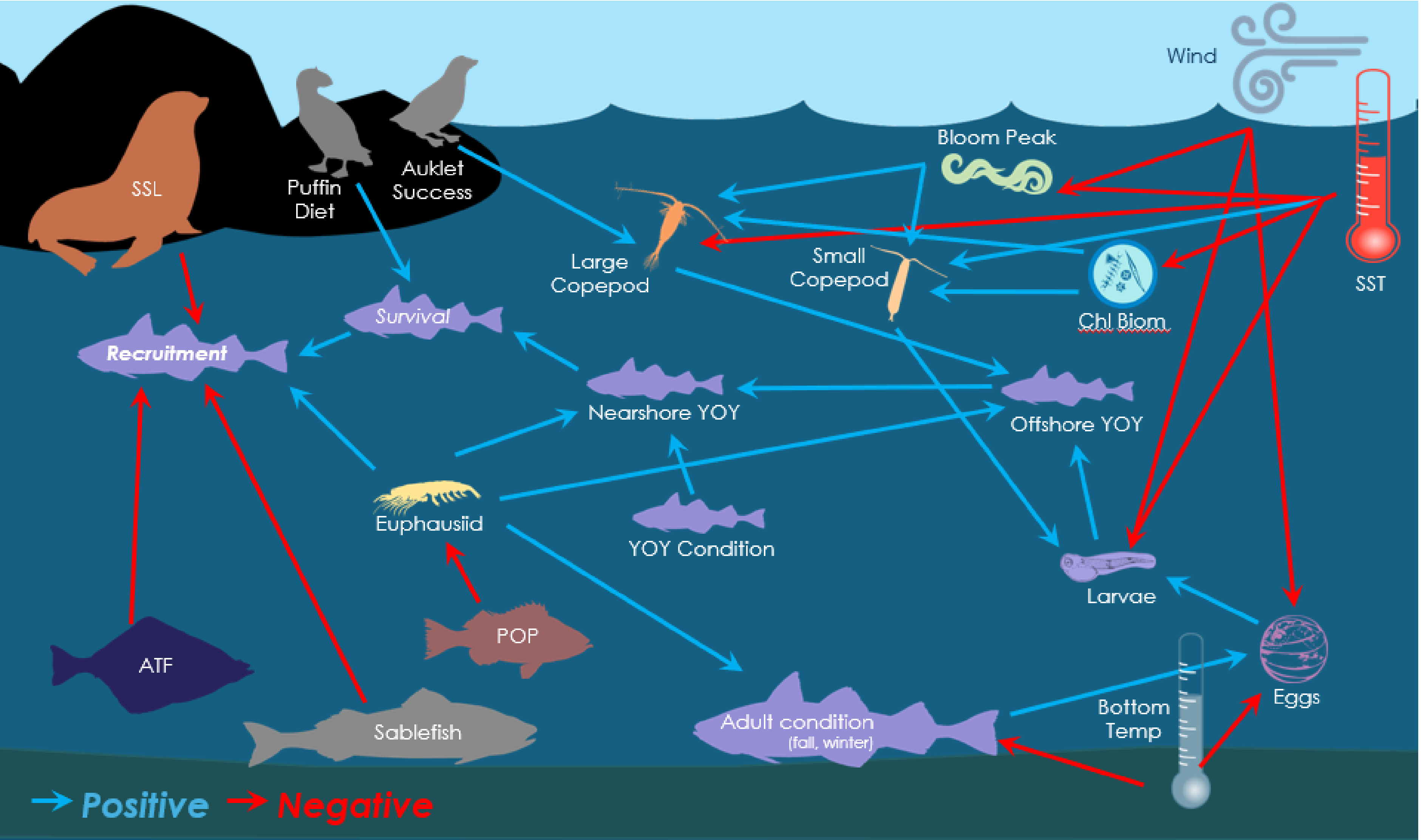


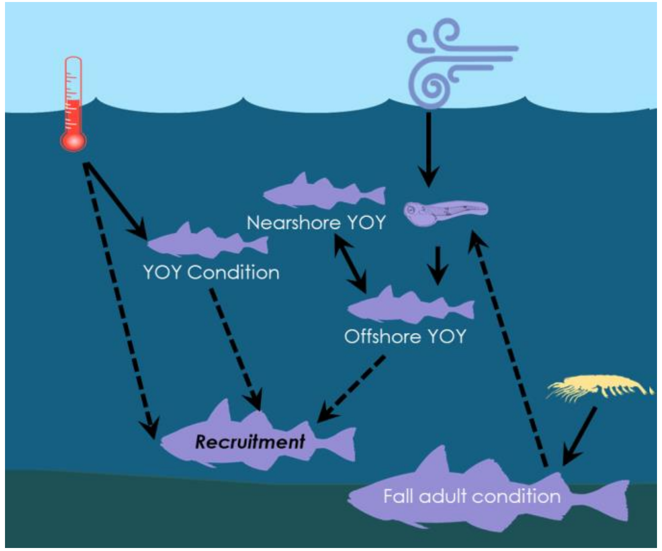
Cannot model all links
⇒ Need simplification

Candidate causal map

→ No lag

⇢ 1 year lag





Cannot model all links

⇒ Need simplification

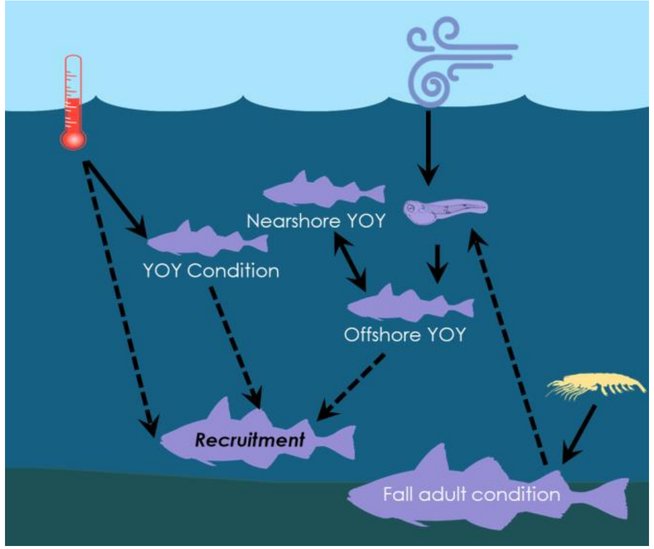
Estimation of causal links

→ No lag

⇢ 1 year lag

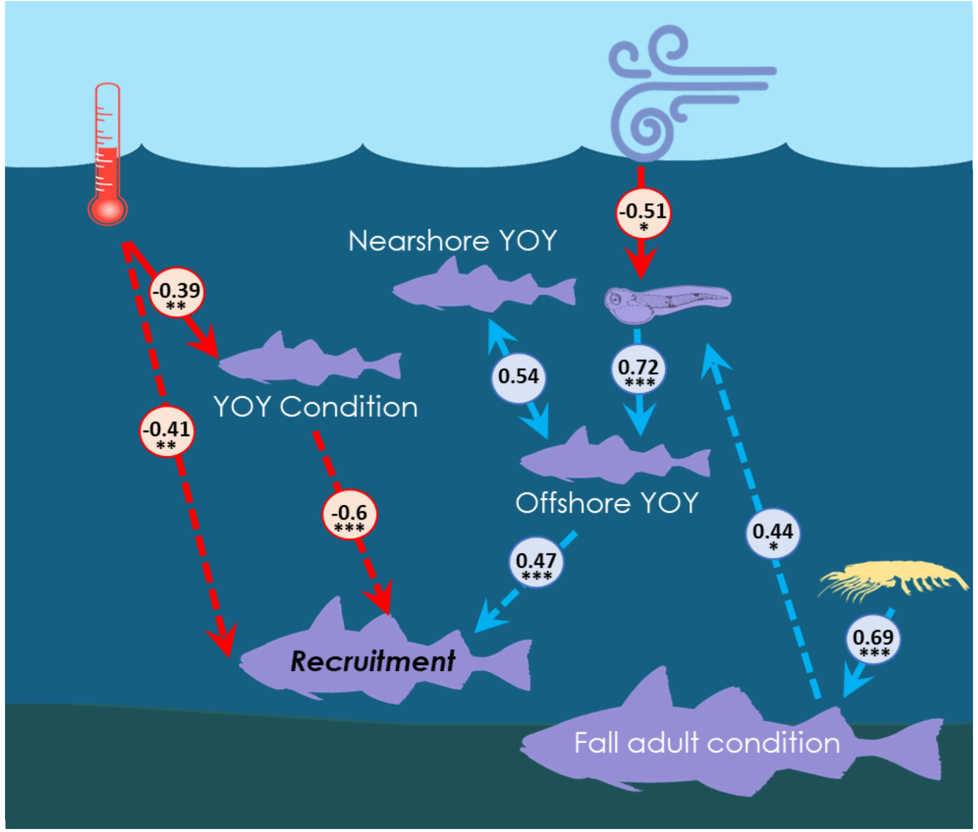
<u>Input</u>

<u>Hypothesis of causal map</u>



+ stock assessment data & hypotheses

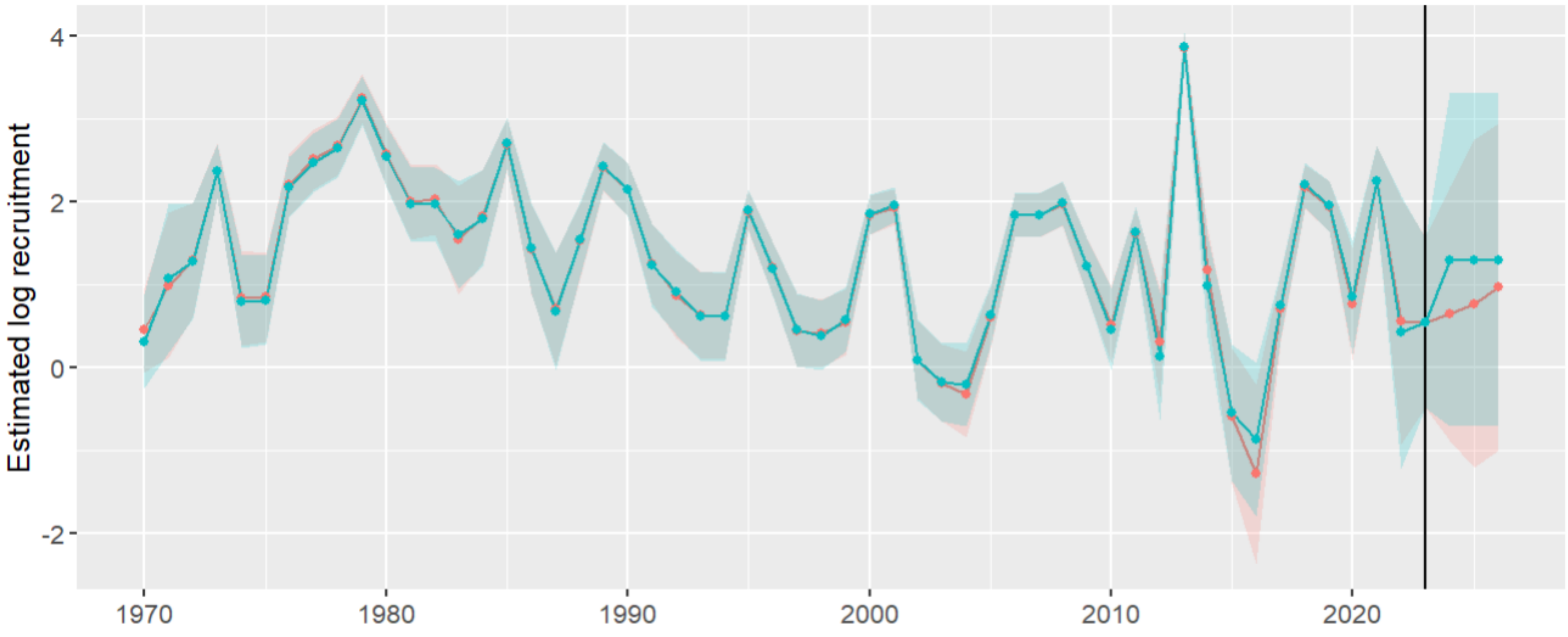
<u>Output: Value of the link</u>



<u>Significance of the link</u>

* (pvalue <0.05),** (pvalue <0.03), ***(pvalue <0.01)

Recruitment estimation and forecast

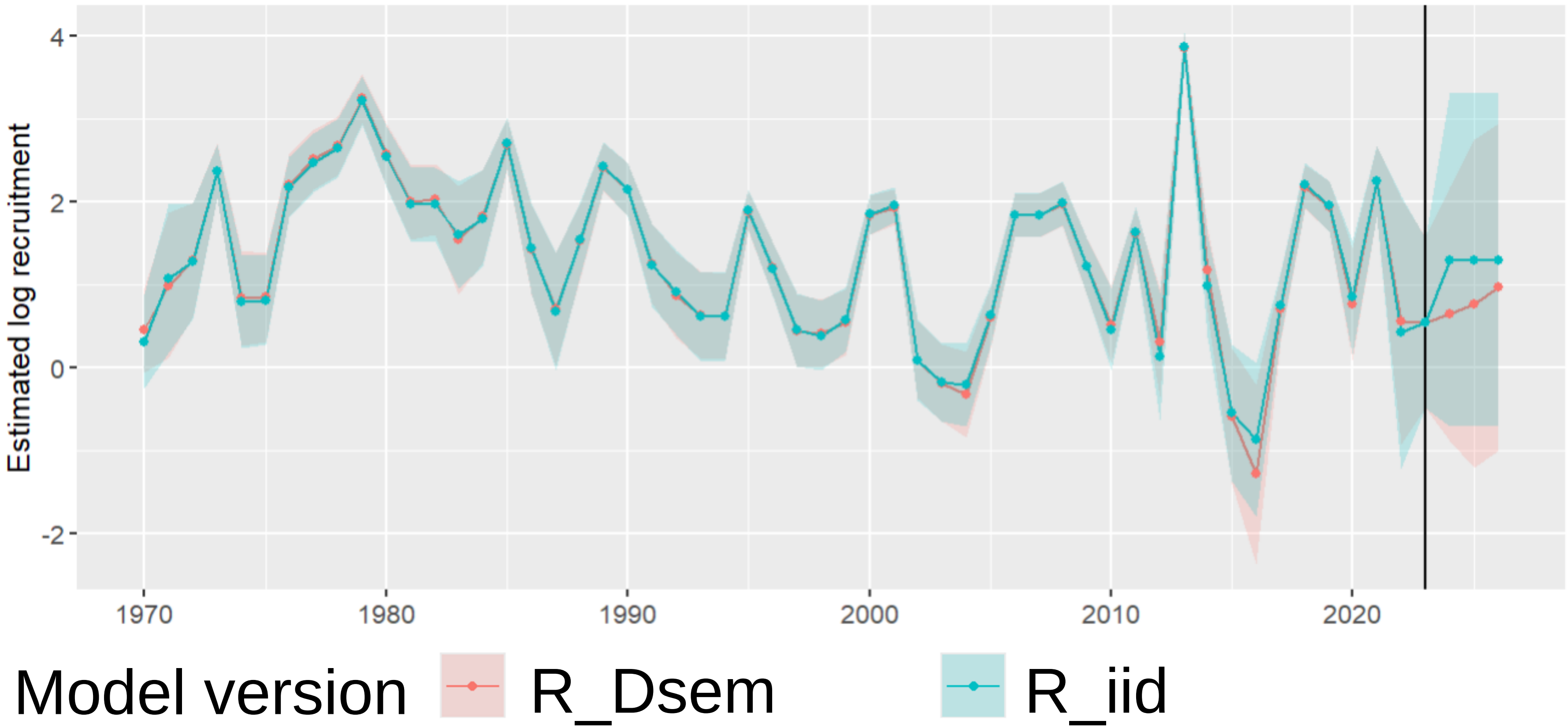


R is informed by the causal map

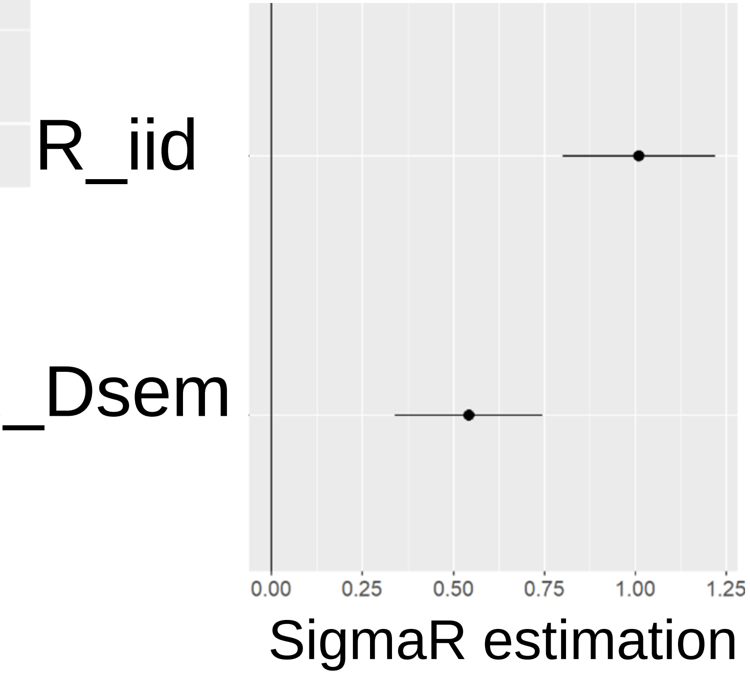
R is not informed by the causal map -> equivalent to usual assessment model

- Slight change of R estimation in the past
- Reduced R forecast

Recruitment estimation and forecast

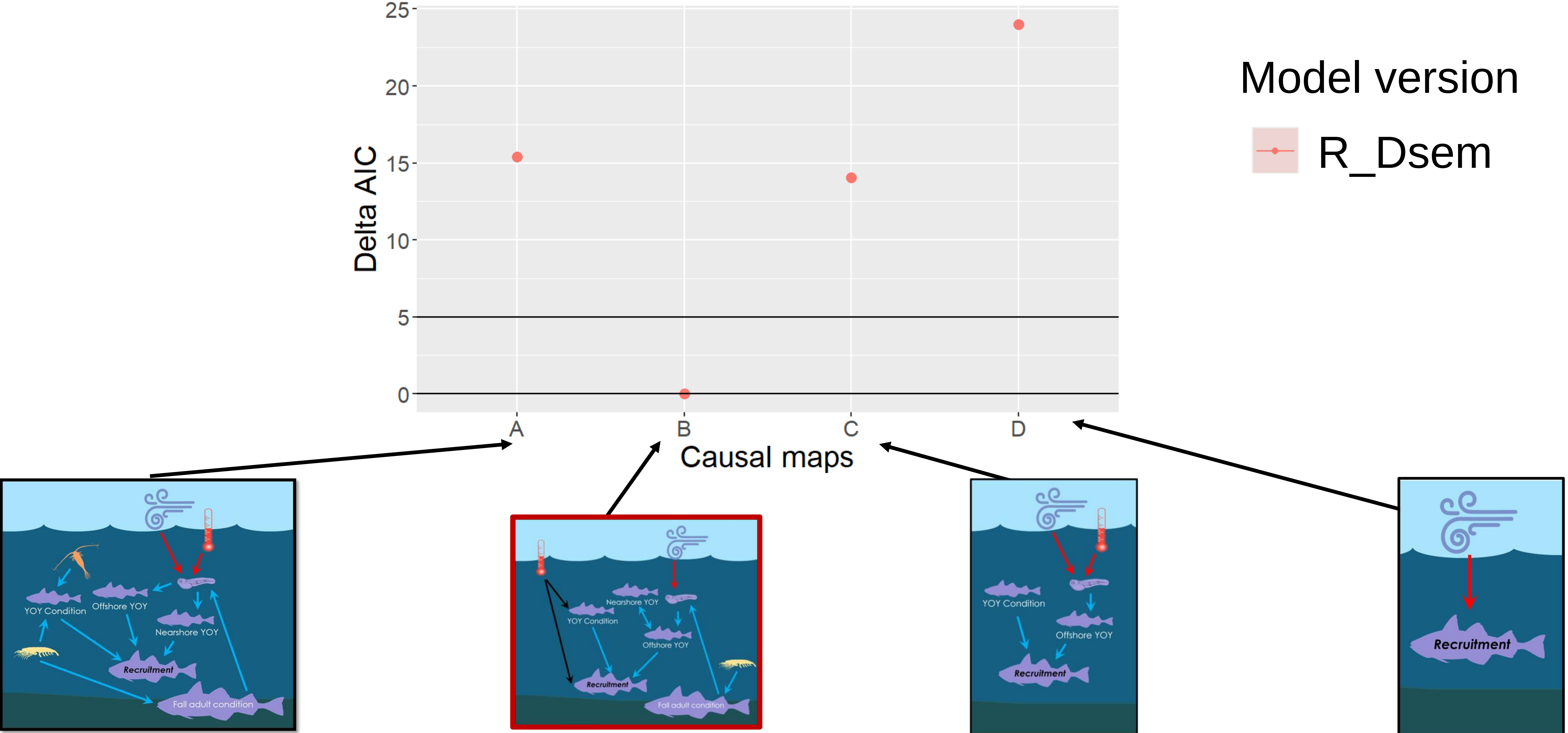


Variance reduction = -0.70



- Slight change of R estimation in the past
- Reduced R forecast
- Decreased SigmaR: explain a part of R variability
- $\Delta AIC = 17$

Comparison with other causal maps



Model validation

Is the model wrong?

- Are parameters and derived quantities biased?

⇒ Self test ✓

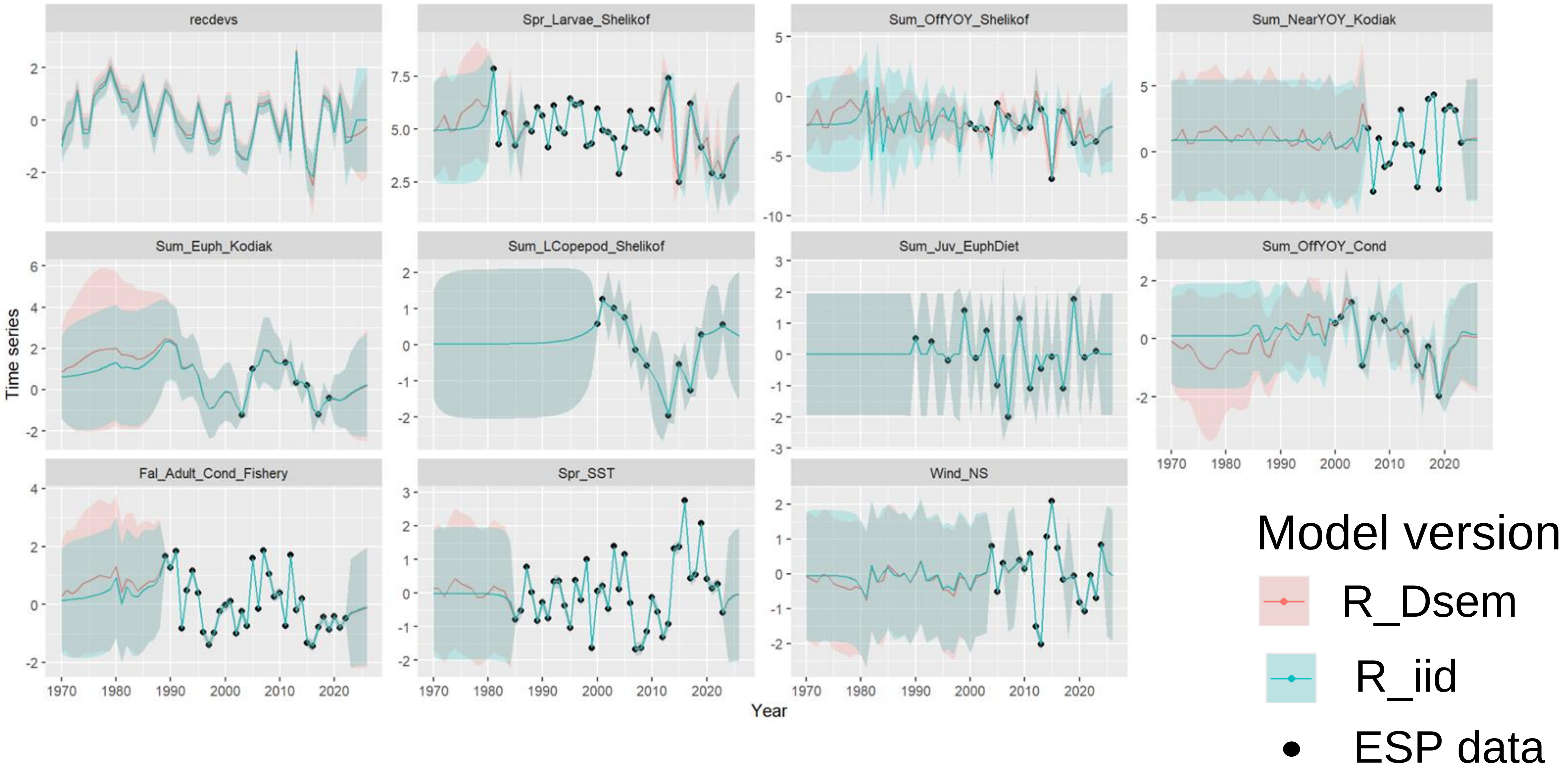
Is the model useful?

- Is the causal map improving the recruitment predictions?

= Predictive performance

⇒ 1 year ahead predictions ✓

Estimation of ESP time series



Conclusions

- It works !
  - Significant causal link
  - Reduced recruitment variance
  - Good self-test behavior (no bias)
  - Good predictive performance (AIC, 1y ahead prediction)
  - Quick to run (~2min)

⇒ flexible framework resolving the regression paradigm

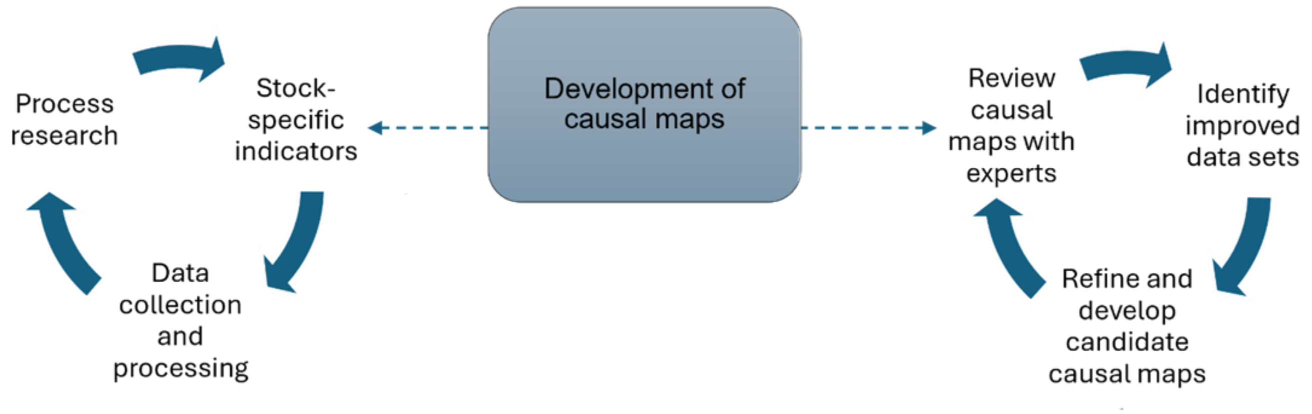
⇒ path forward for next-generation climate-linked assessment models

⇒ direct use of ESP data

Next steps

- Build workflow & good practices regarding causal map development

How to develop a causal map?



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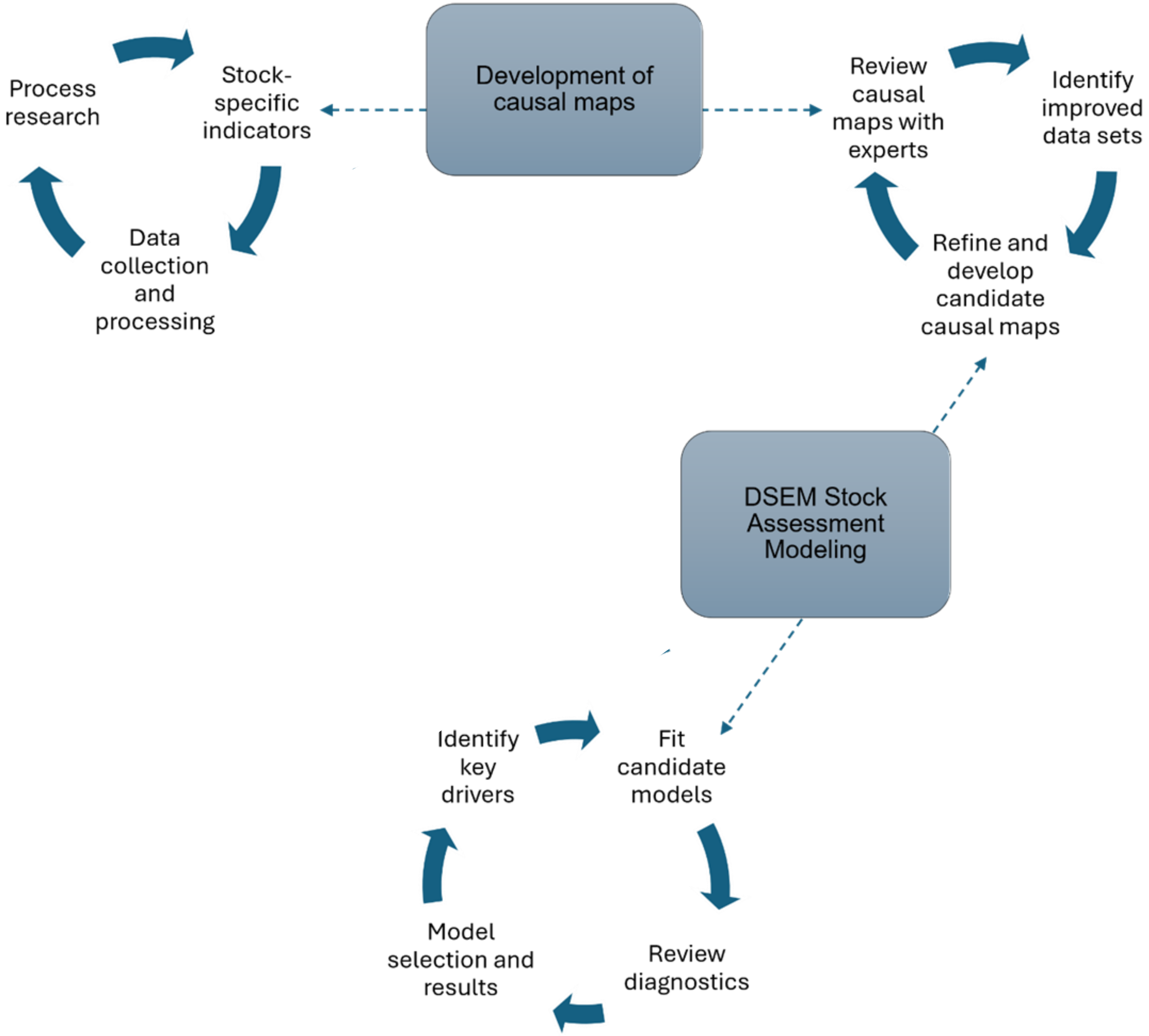
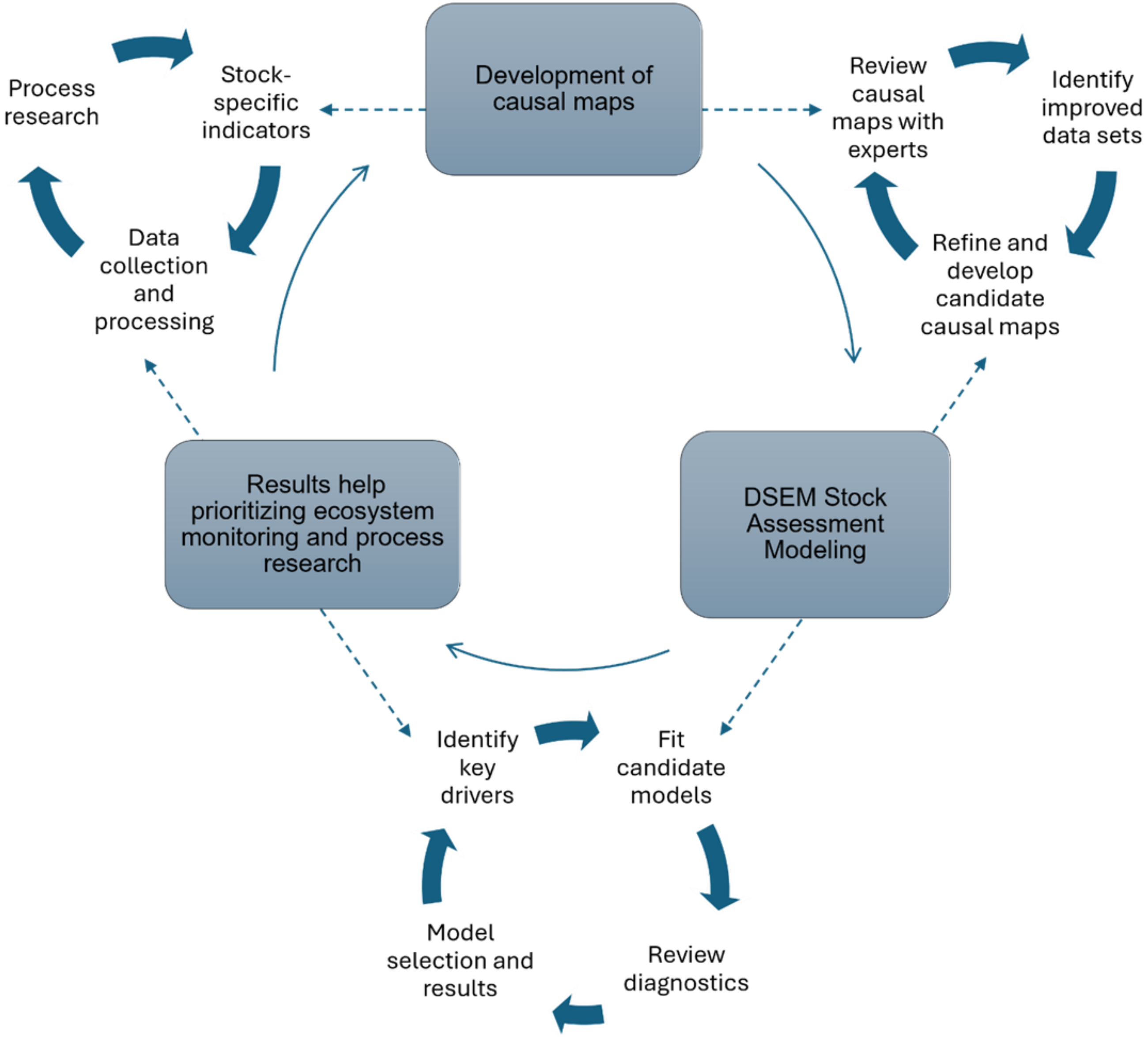


How to develop a causal map?



Development of causal maps

Process research

Stock-specific indicators

Data collection and processing

Review causal maps with experts

Identify improved data sets

Refine and develop candidate causal maps

DSEM Stock Assessment Modeling

Fit candidate models

Review diagnostics

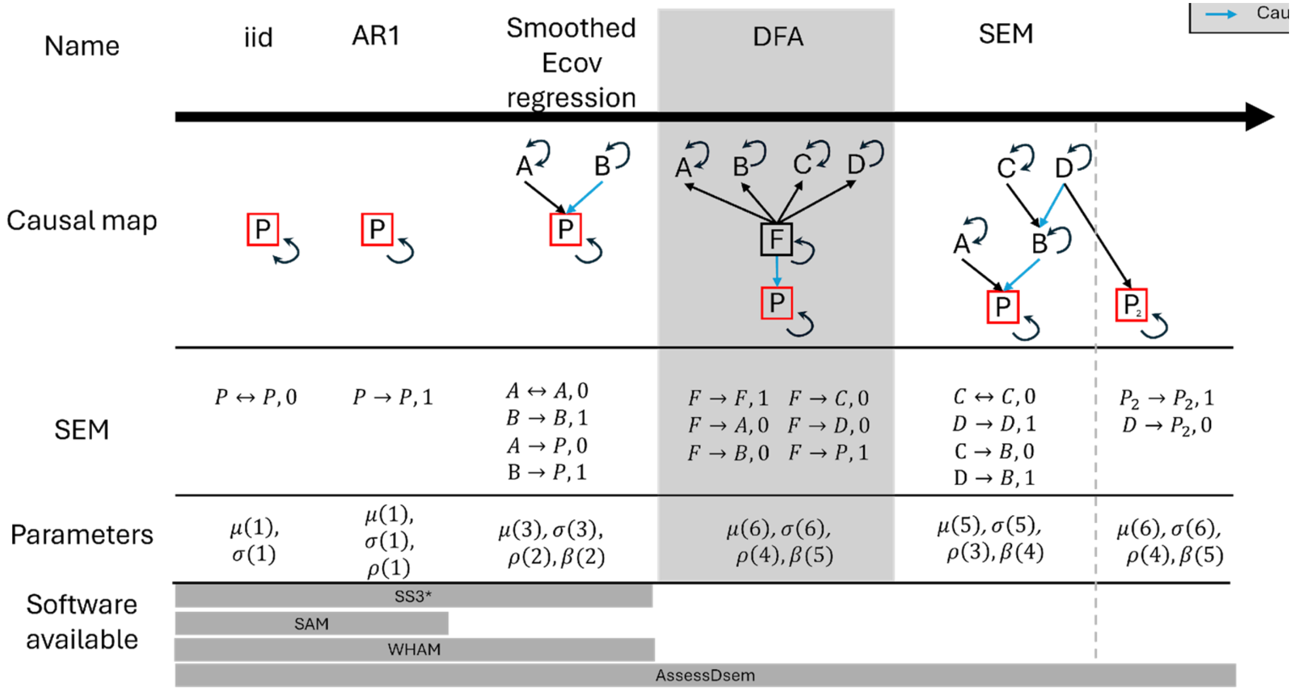
Model selection and results

Identify key drivers

Results help prioritizing ecosystem monitoring and process research

Next steps

- Build workflow & good practices regarding causal map development
- Test the DFA functionality for coupled assessment-DSEM model



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Next steps

- Build workflow & good practices regarding causal map development
- Test the DFA functionality for coupled assessment-DSEM model
- Test sensitivity to causal map misspecification (& cumul with other model misspecifications)
- Extend to multiple processes within the same model (e.g., recruitment & growth or natural mortalities …)
- Integration into a stock-assessment platform for broader dissemination

Thanks for your attention !

More information ?

⇒ reach out jchampag@uw.edu / juliette.champagnat@noaa.gov

Acknowledgements

- Co-authors: Cole Monnahan, Lauren Rogers, Andre Punt, Kalei Shotwell, Jane Sullivan, James Thorson
- ESP contributors
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