Oregon State University
College of Earth, Ocean, and Atmospheric Sciences

Incorporating the impacts of climate variability on growth in fish population dynamics models

Giancarlo Helar Morón Correa

Ph.D. dissertation defense

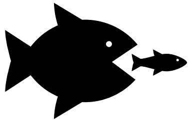
Ocean, Earth, and Atmospheric Sciences – Ocean Ecology and Biogeochemistry
College of Earth, Ocean, and Atmospheric Sciences
Oregon State University

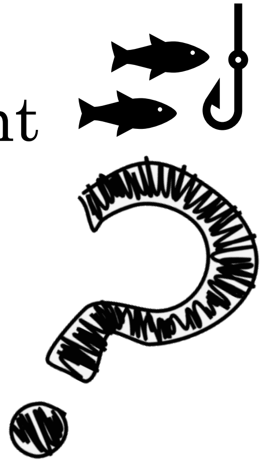
My Ph.D. journey

Pacific cod:
Ocean variability impacts on somatic growth

Fisheries management

Ocean conditions

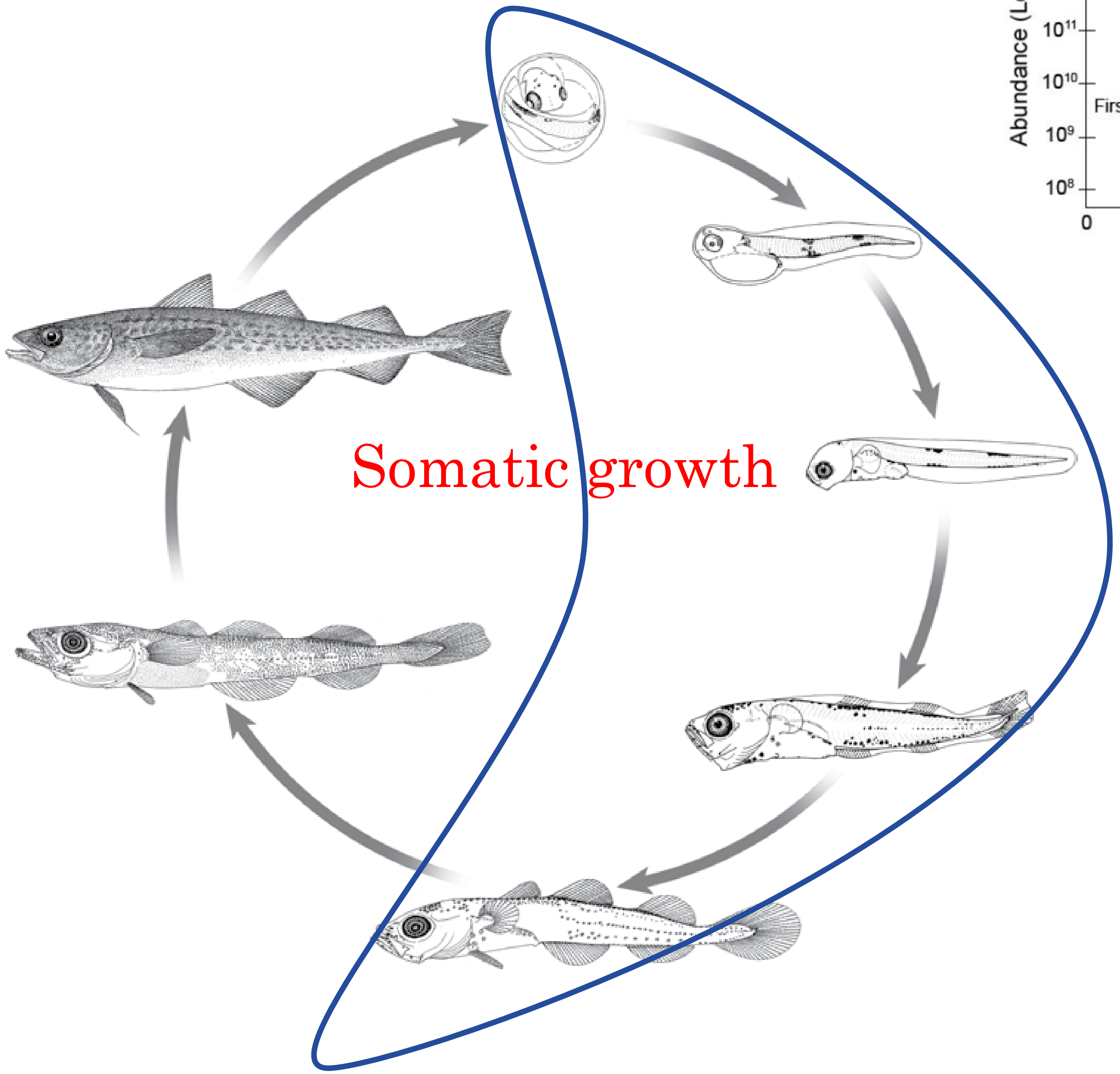


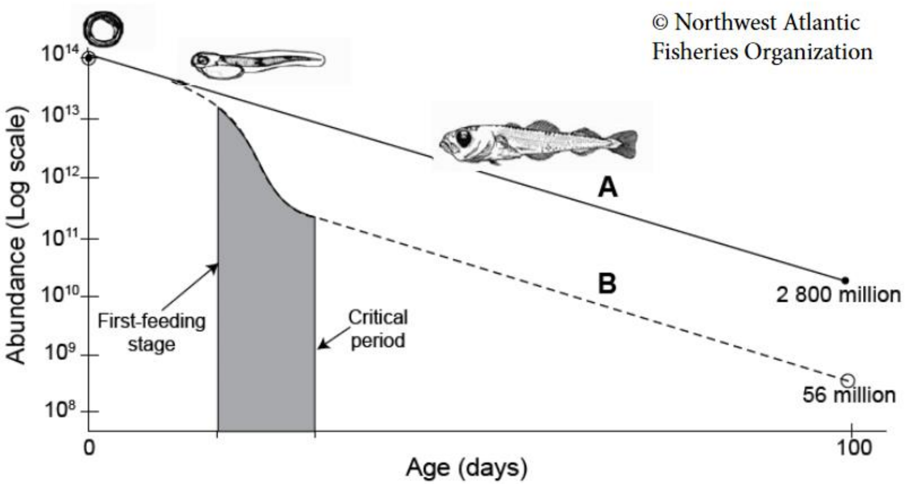


Peruvian anchovy:
- Population dynamics models
- Spatial dynamics
- Poor background in oceanography

Introduction

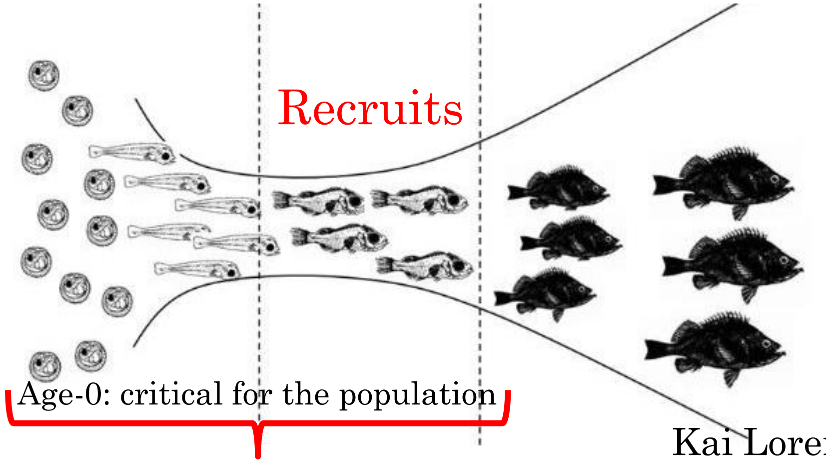
Fish life cycle





Houde (2008)

- Early life stages:
  - Egg and larval stages
  - Typically, the first year of life
  - High mortality
  - Modulates population abundance

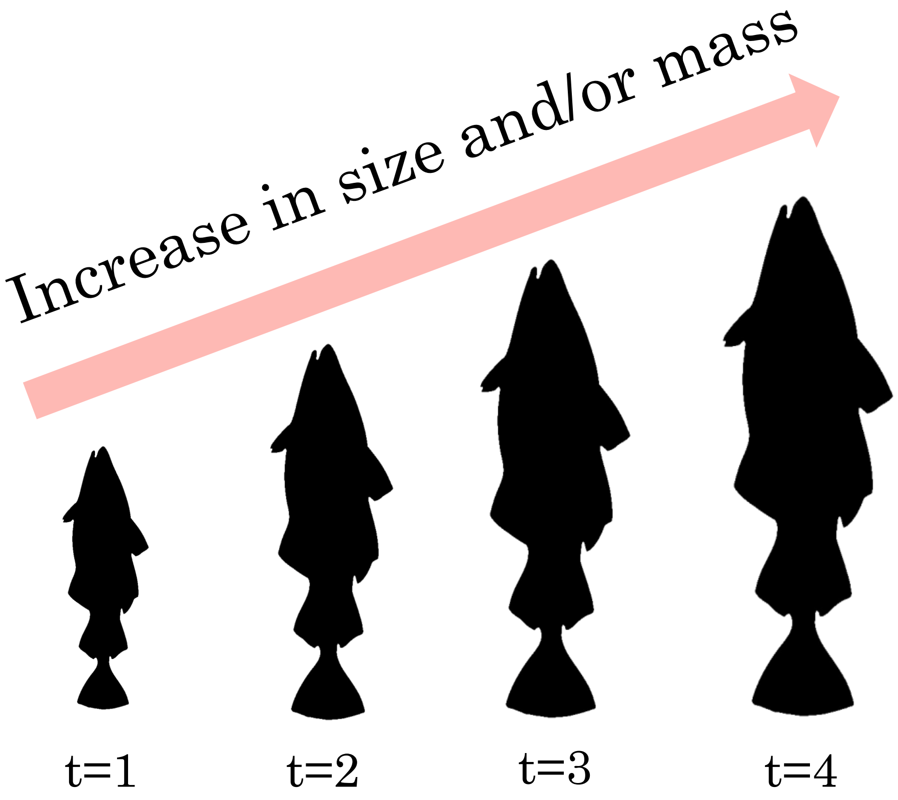


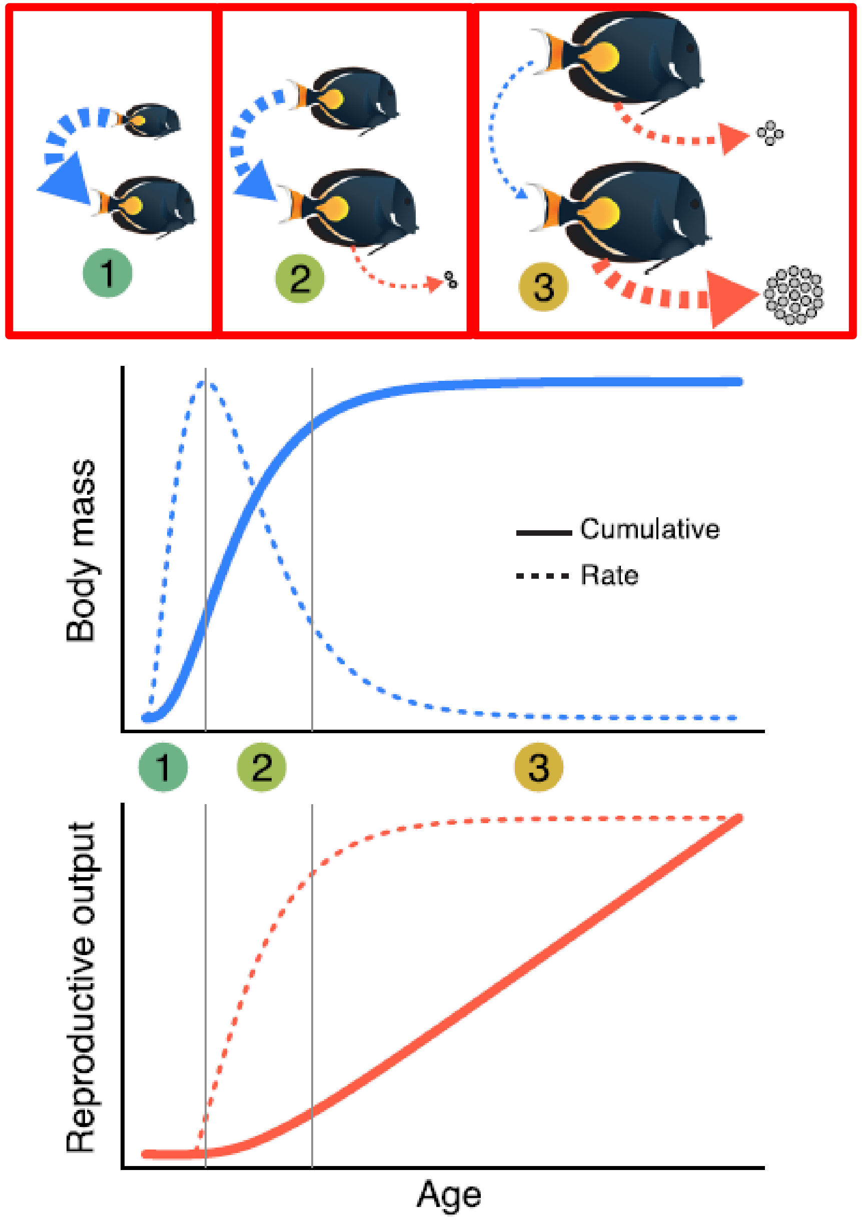
Kai Lorenzen, UF/IFAS

Somatic growth

A trade-off between somatic growth and reproductive strategies:

1. Faster growth/No reproduction
2. Growth slows down/Maturation
3. Growth stops/Fully mature

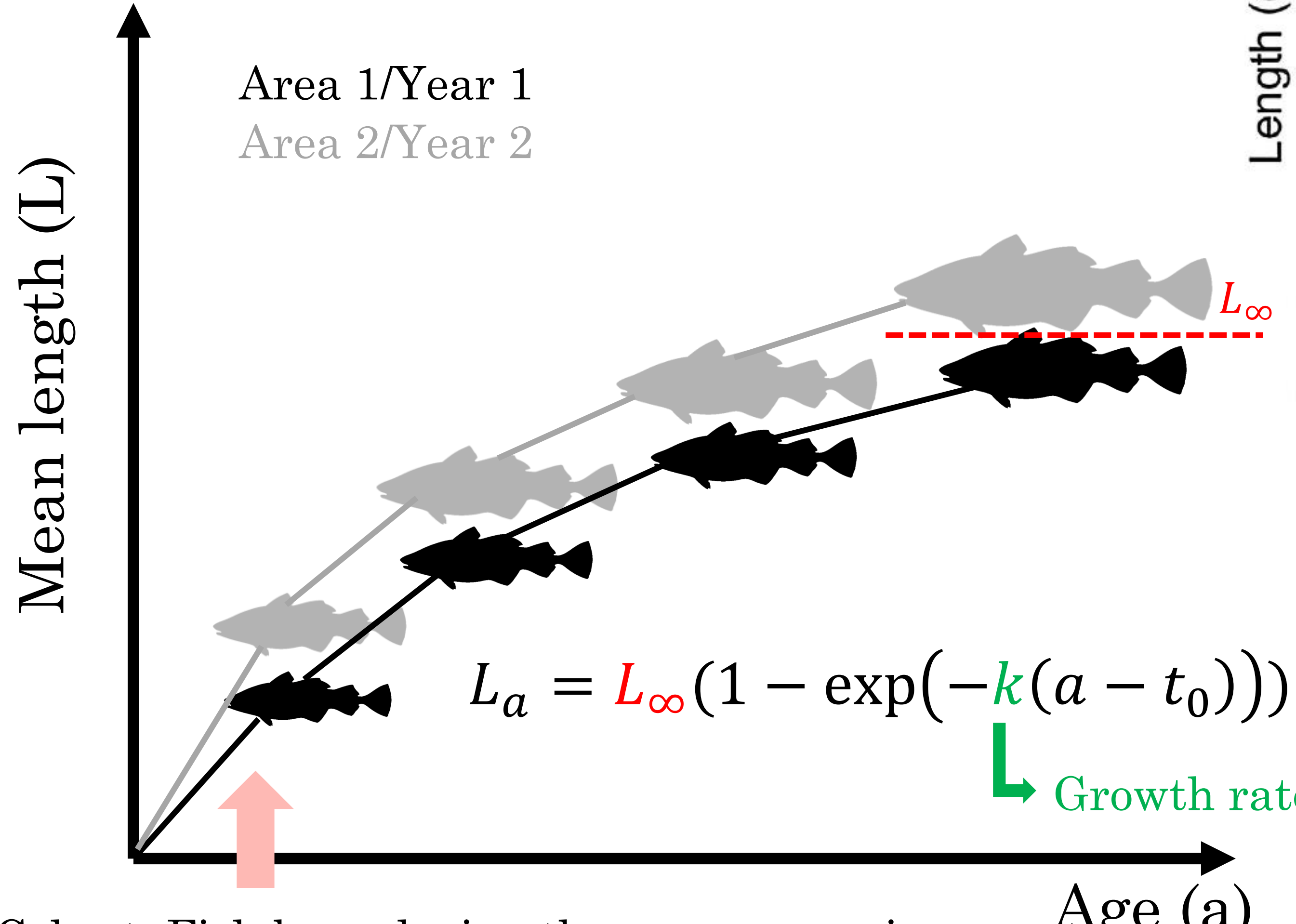




Morais and Bellwood (2020)

Length-at-age data

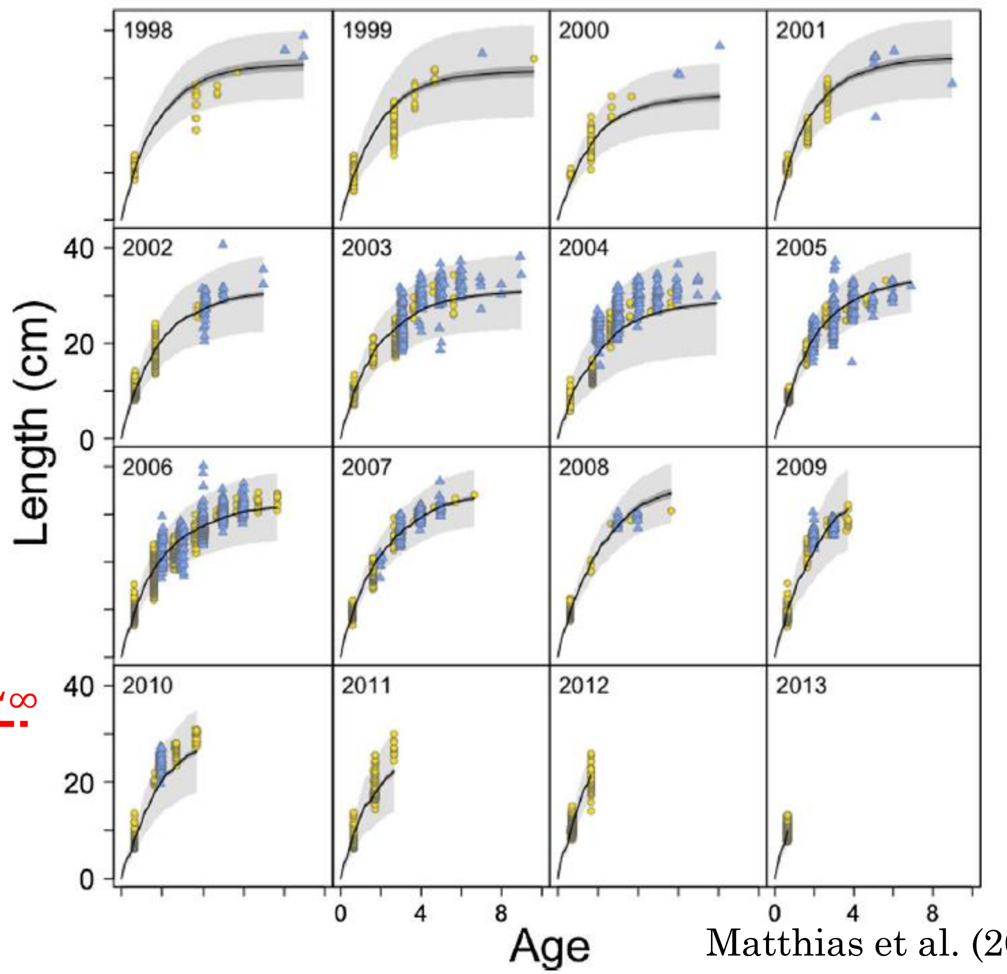
Length increase with fish age



$$L_a = L_\infty\left(1 - \exp\left(-k(a - t_0)\right)\right)$$

Growth rate

Cohort: Fish born during the same spawning event

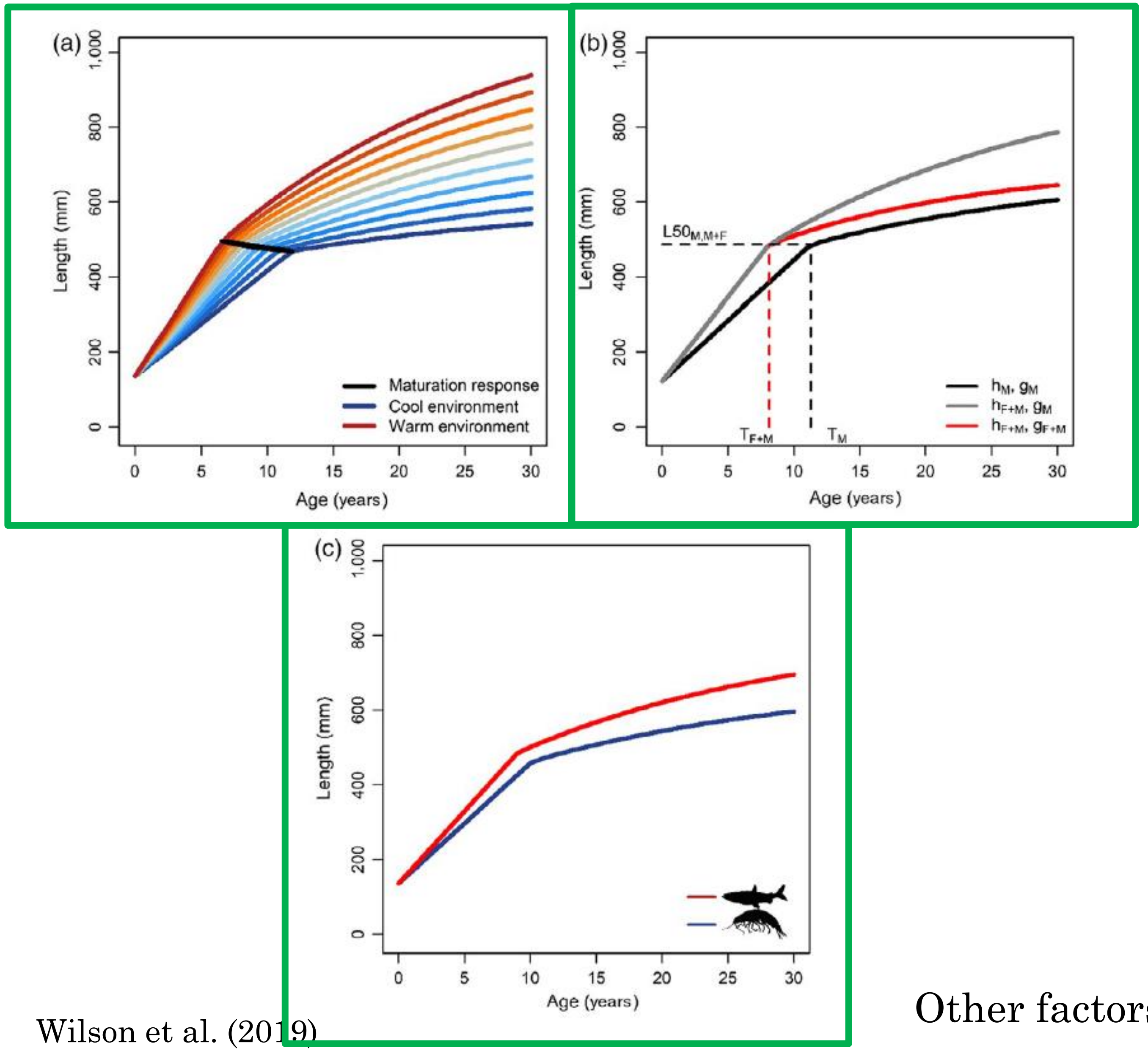


Matthias et al. (2018)

Not a single length per age

Growth may vary in time or space

Somatic growth variability



(a) Temperature:

- Warm environment: faster growth rates
- Cool environment: slower growth rates

(b) Fishery:

- No exploited: slower growth rates
- Exploited: faster growth rates

(c) Prey type:

- Low quality: slower growth rates
- High quality: faster growth rates

Wilson et al. (2019)

Other factors: genetics, density-dependence, or all of them!

Population biomass

Two ways to increase the population biomass:
1. Recruitment
2. Somatic growth

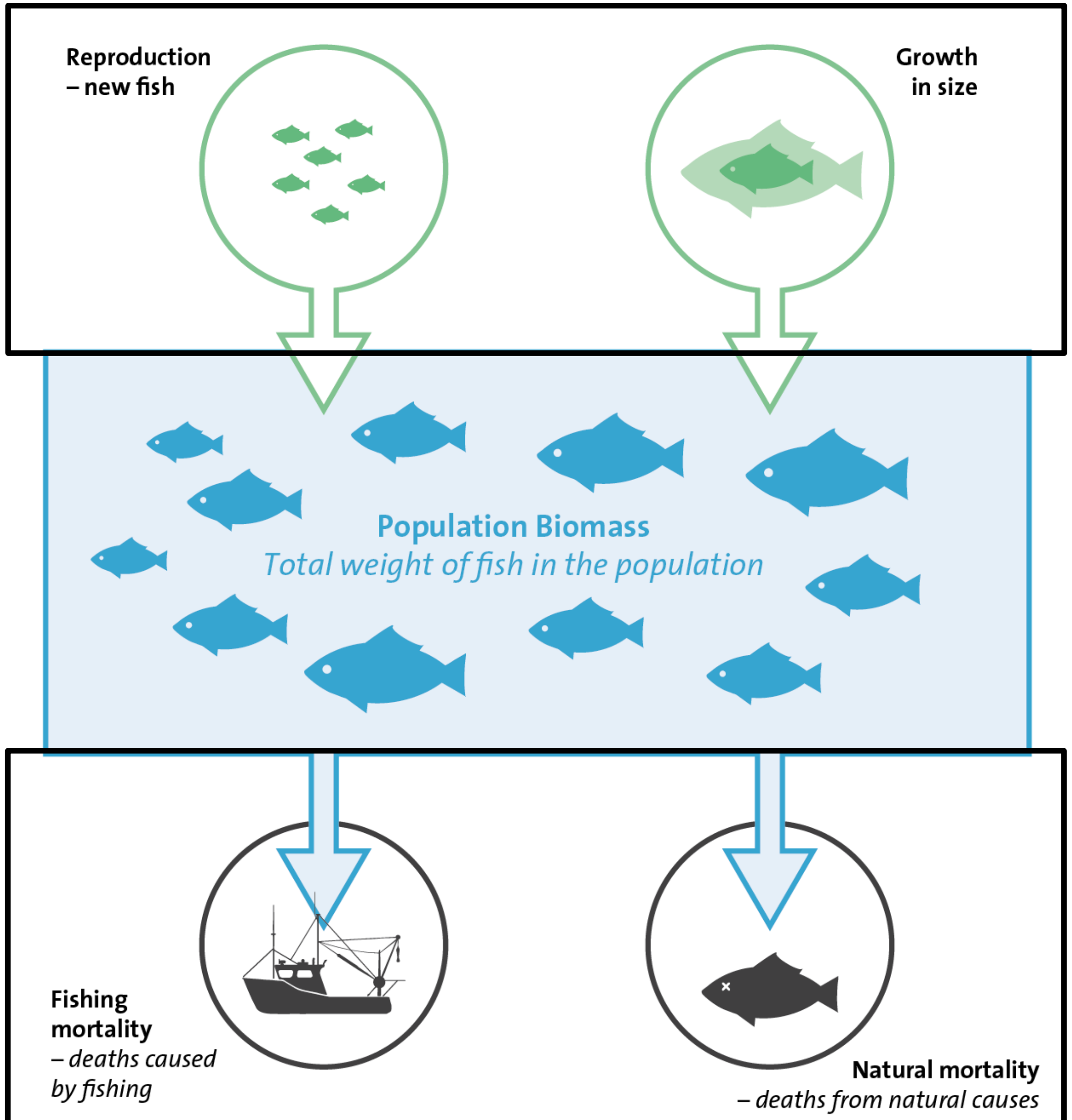
Somatic growth:
- Important driver of biomass variability (Stawitz et al. 2019)

Two ways to decrease the population biomass:
1. Fishing mortality
2. Natural mortality

Study the impacts of growth variability on fish populations?

Population dynamics models

Assuming a close fish population*:



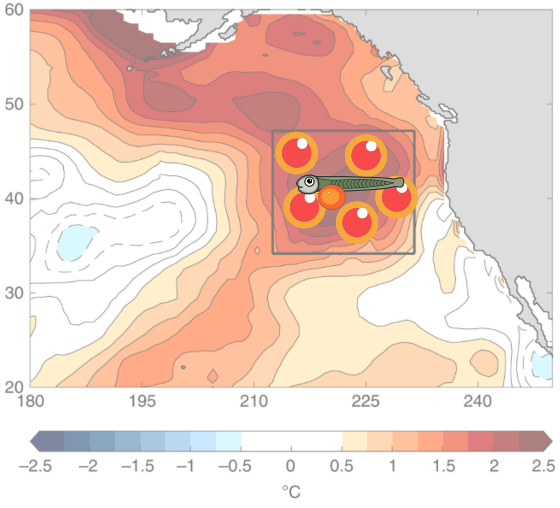
Baltic Sea Centre

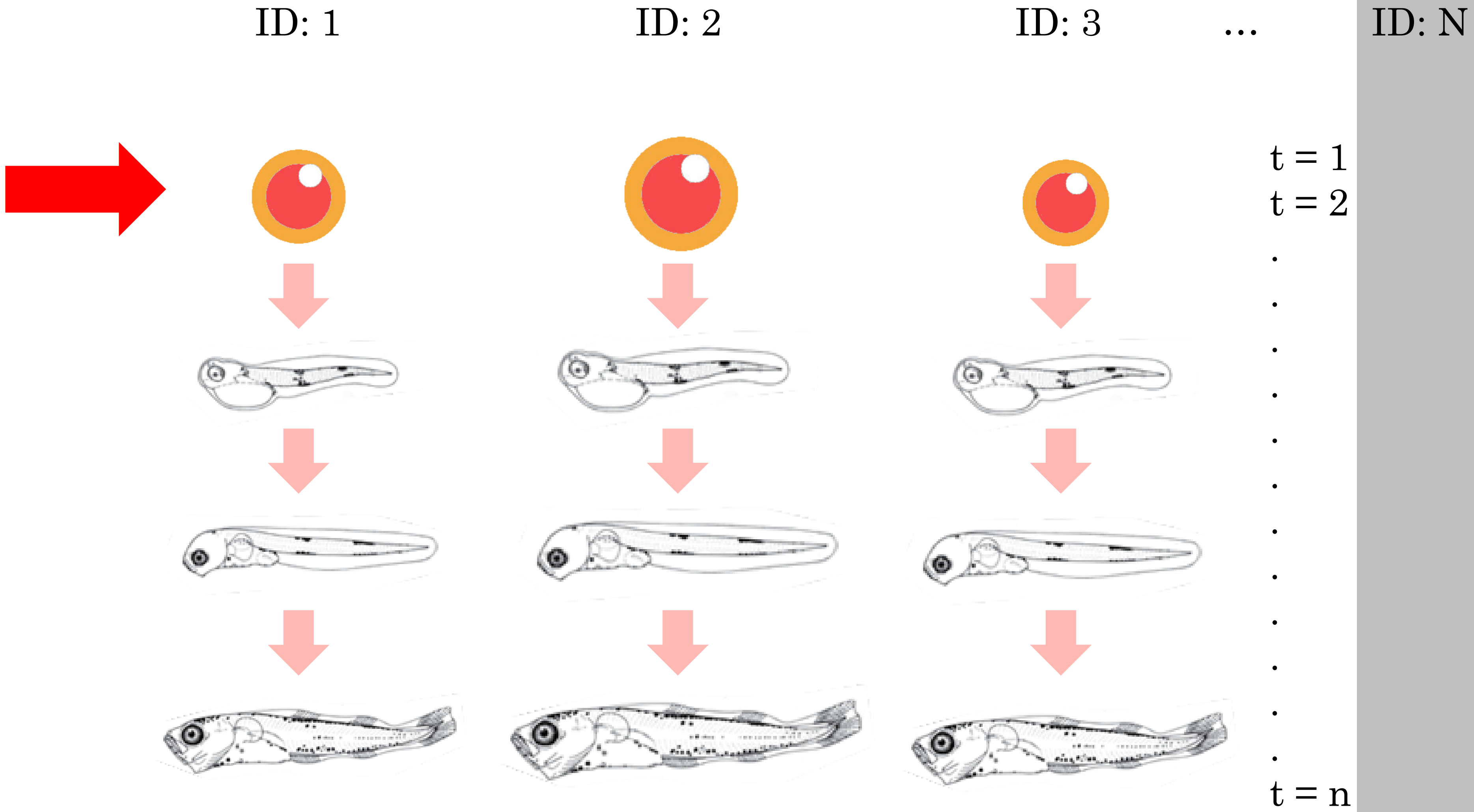
*Close population: No immigration or emigration

Individual-based models (IBM)

In a few cases used to study the dynamics of the entire population (e.g., Beaudouin et al. 2015)

Input: oceanographic data

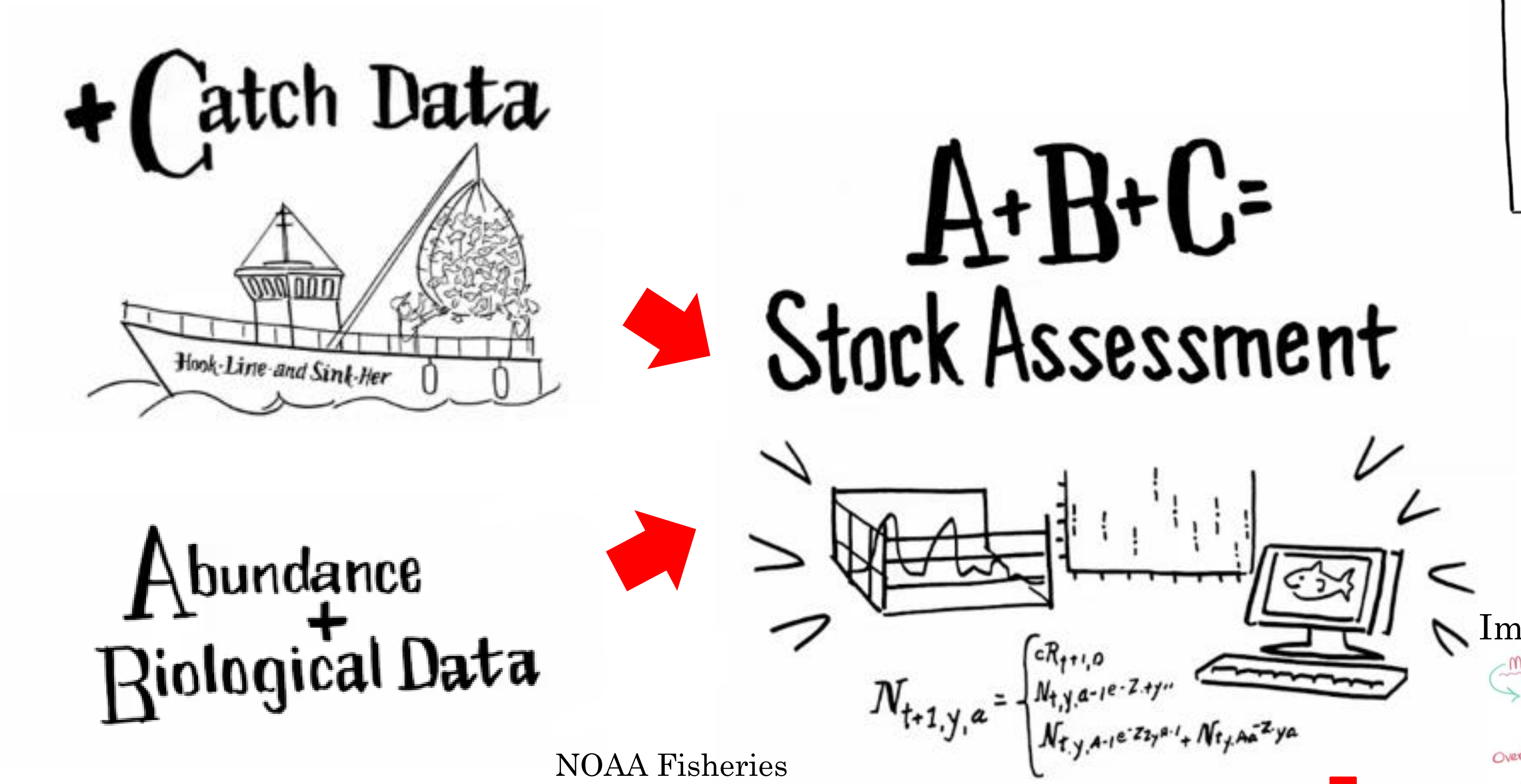




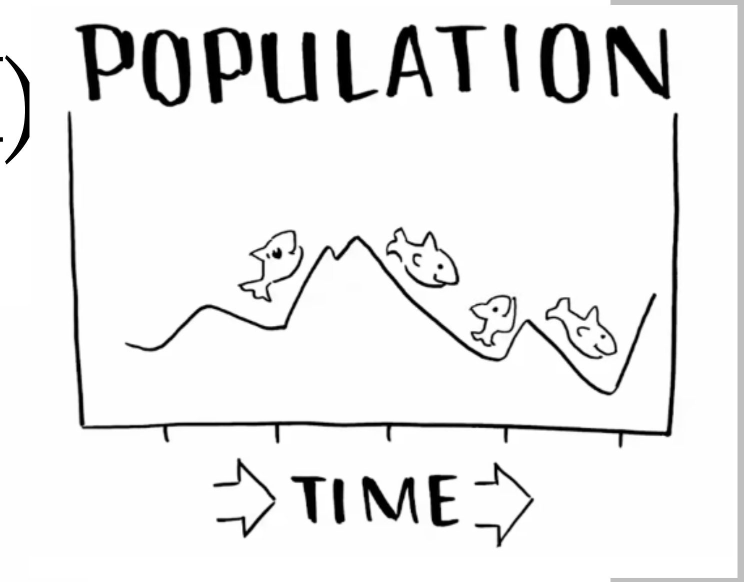
- Development
- Growth
- Survival
- Prey capture
- Predation
- Movement

Main goal: study **the early life stages** of fishes and their interaction with the environment

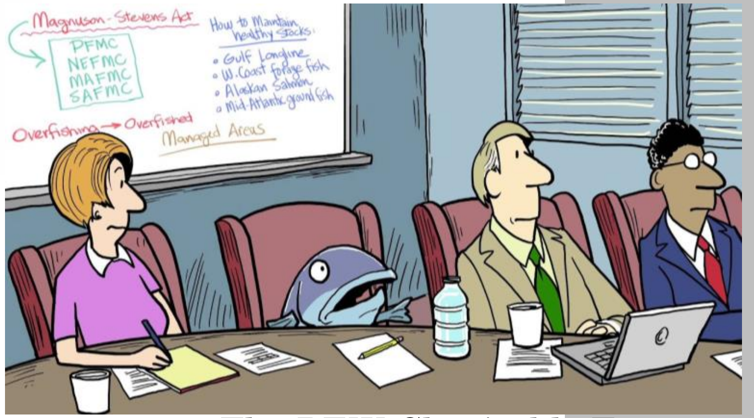
Stock* assessment models (SAM)



NOAA Fisheries



Important for fisheries management:



The PEW Charitable Trusts

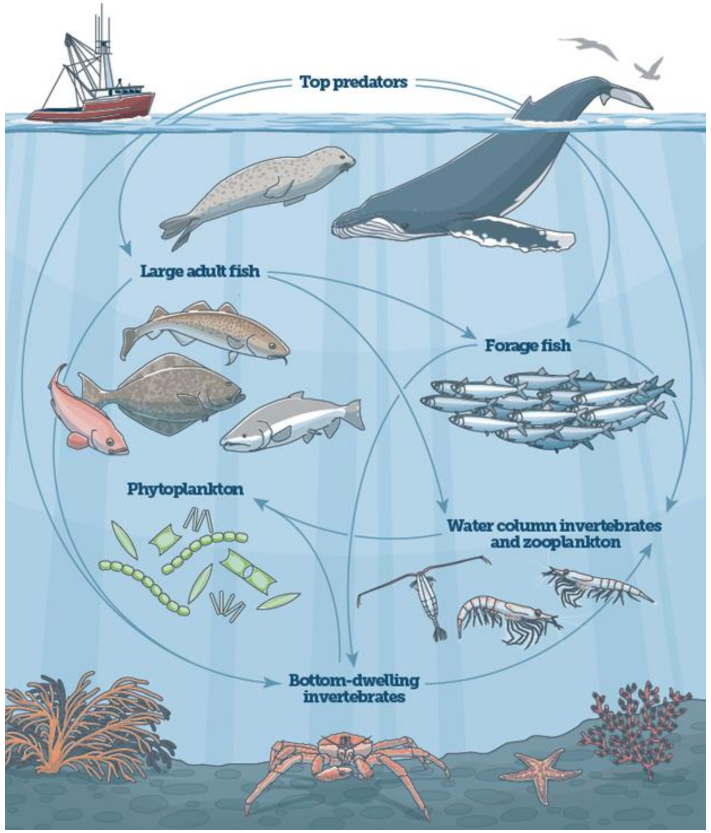
Main goal: study the response of **the entire fish population** to harvest strategies

*Fish stock: Isolated fish subpopulation

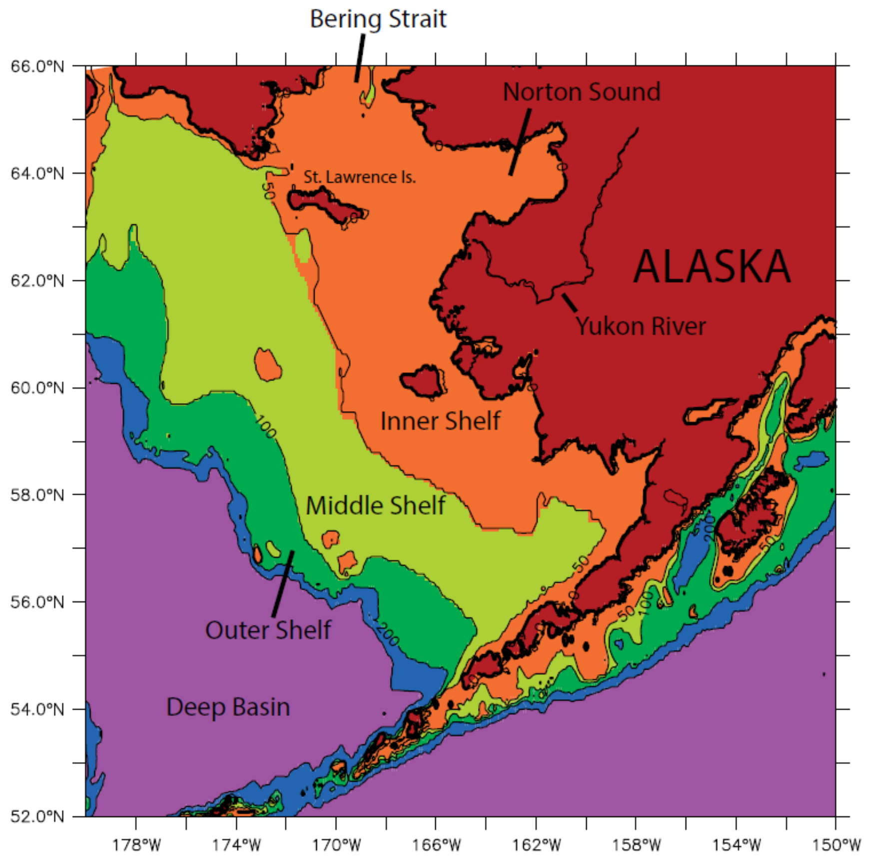
Eastern Bering Sea and Pacific cod

- Highly productive ecosystem
- Supports the most important U.S. fisheries
  - Second most important: Pacific cod
  - Support large fishing communities

Sea2Table



The Pew Charitable Trusts



Hermann et al. (2019)

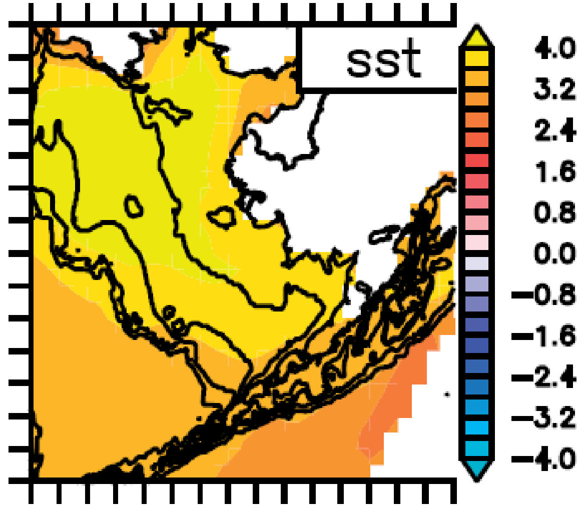
Modeling the multiple action pathways of projected climate change on the Pacific cod (*Gadus macrocephalus*) early life stages

Giancarlo M. Correa, Thomas P. Hurst, William T. Stockhausen, Lorenzo Ciannelli, Trond Kristiansen, Darren J. Pilcher

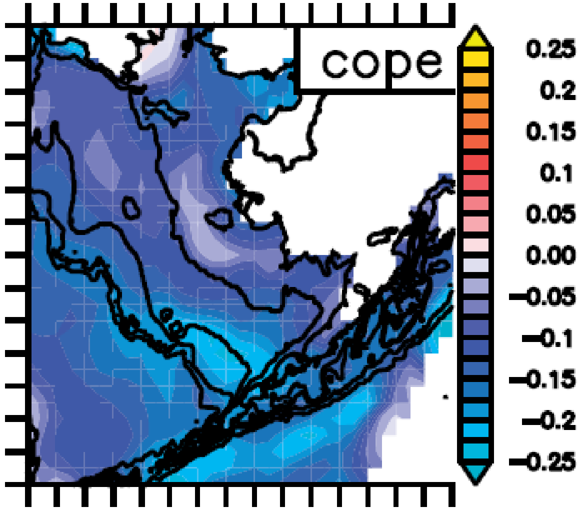
In preparation

Eastern Bering Sea: future changes

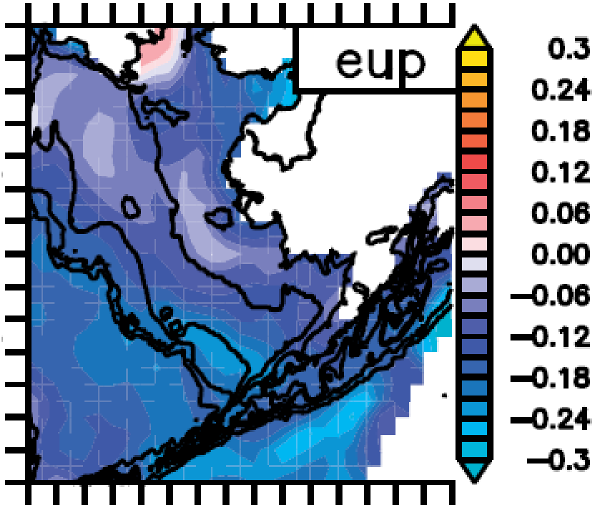
Surface temperature



Small-bodied copepods

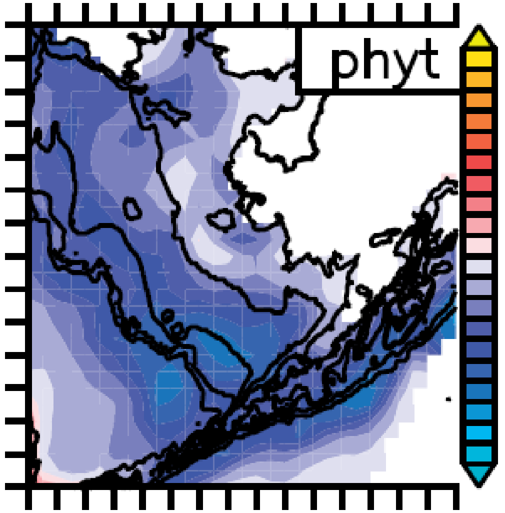


Euphausiids

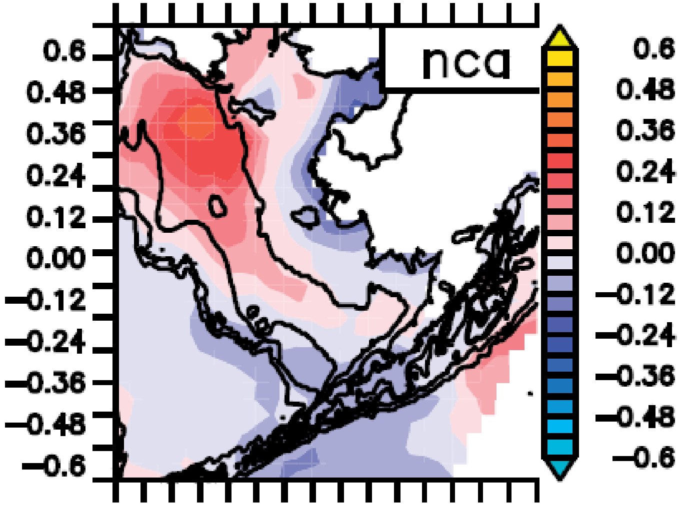


Decadal average change between 2010-2019 and 2090-2099 (RCP8.5)

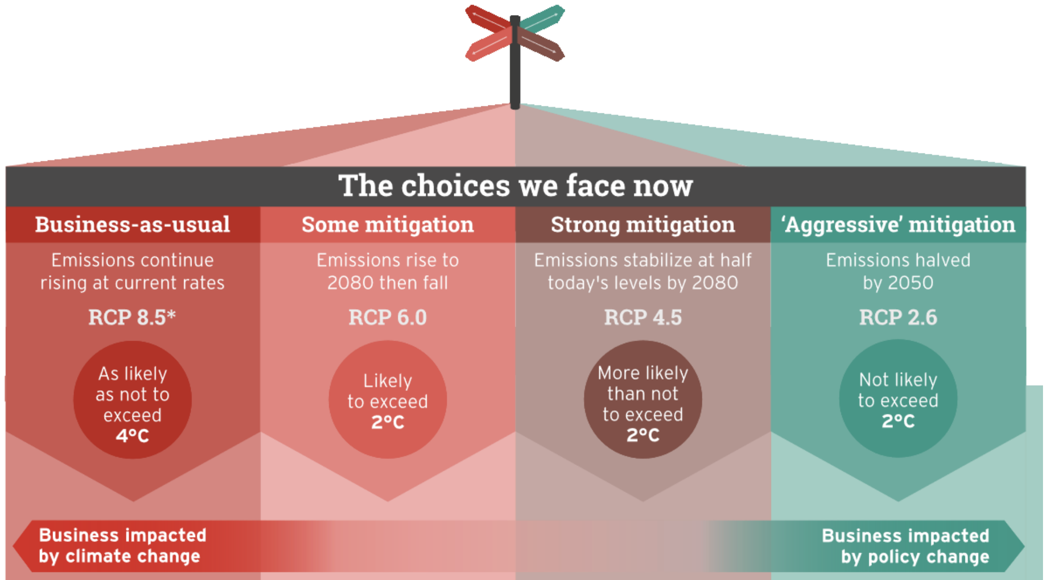
Phytoplankton



Large-bodied copepods



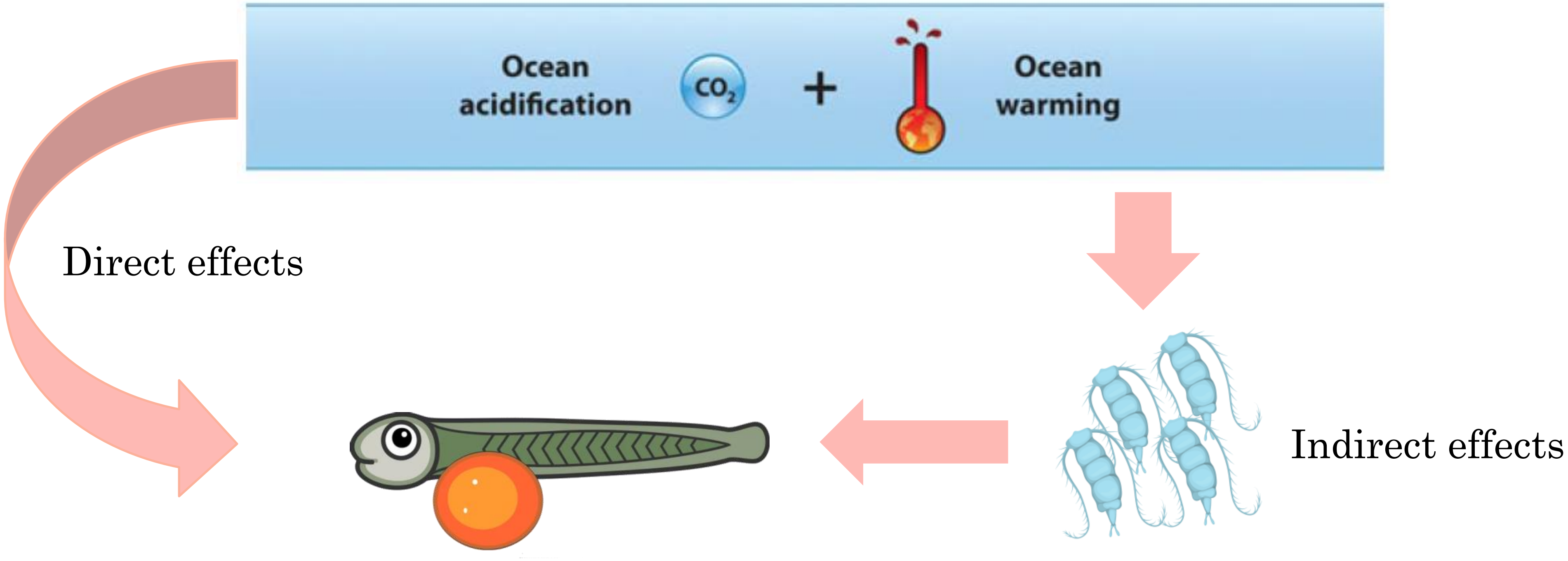
… and other environmental variables



Hermann et al. (2019)

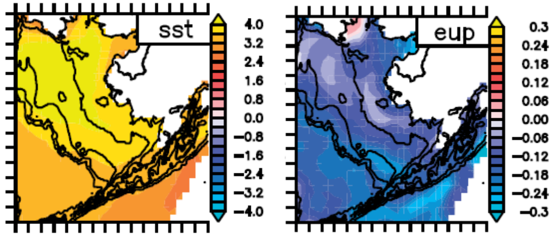
Objective

Investigate the direct and indirect impacts of future ocean conditions on the early life stages of the Pacific cod

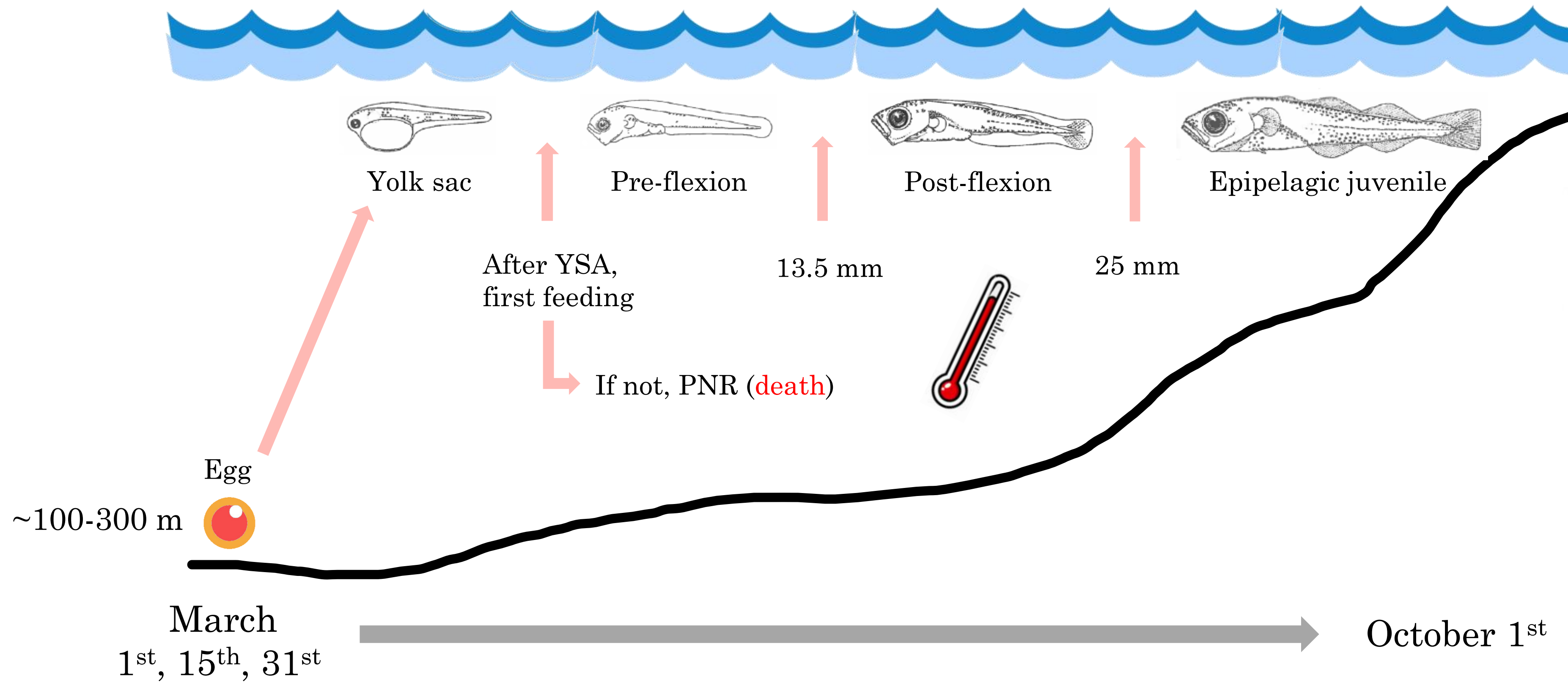


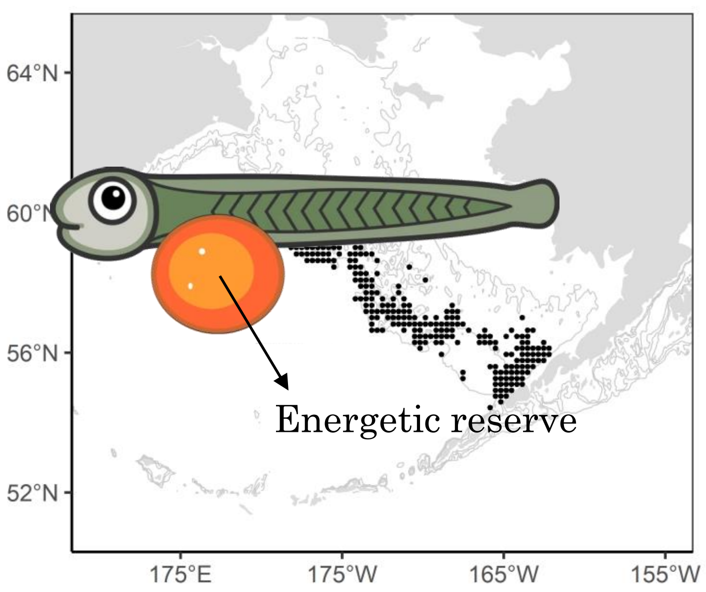
Individual-based model (IBM)

3D input: Bering10K
(2010-2100)



- Input: RCP4.5 and RCP8.5 emission scenarios
- Eggs released from spawning (initial) locations
- Fish features (e.g., weight, length) updated every hour





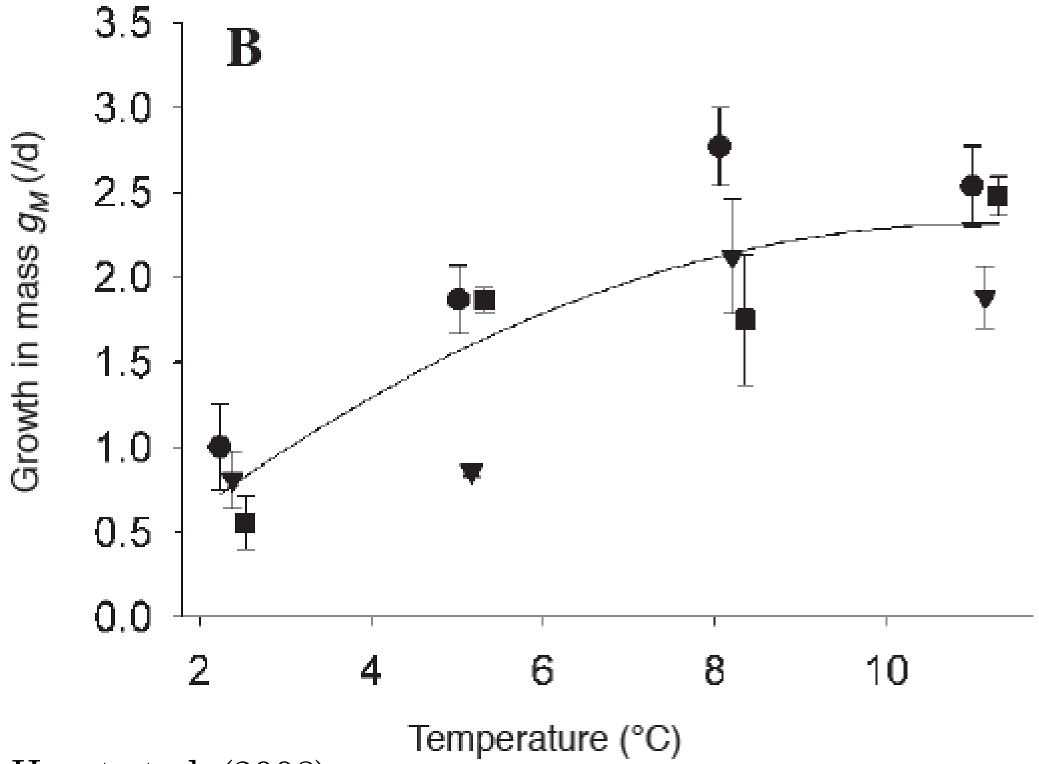
Neidetcher et al. (2014)

Individual-based model

Growth:

- Temperature and food-dependent (except when the yolk sac was still present)

Growth rate ~ f(T, food in stomach)

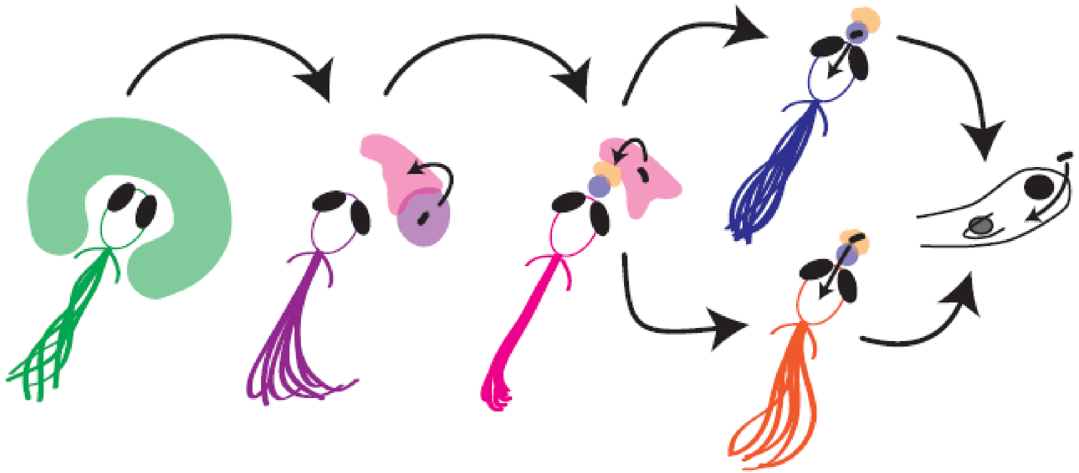


Hurst et al. (2008)

Foraging component:

- Perception
- Approach
- Attack
- Ingestion

Fiksen and MacKenzie (2002)



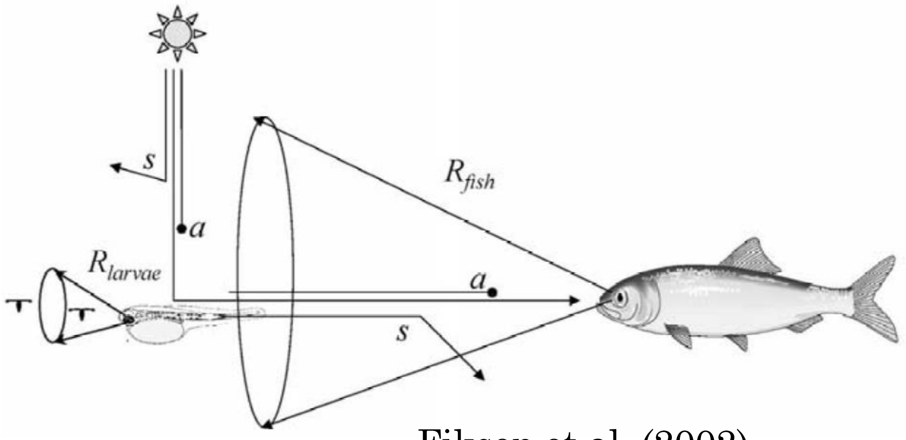
Mearns et al. (2020)

Food in stomach ~ f(prey density, prey length, larval size, light)

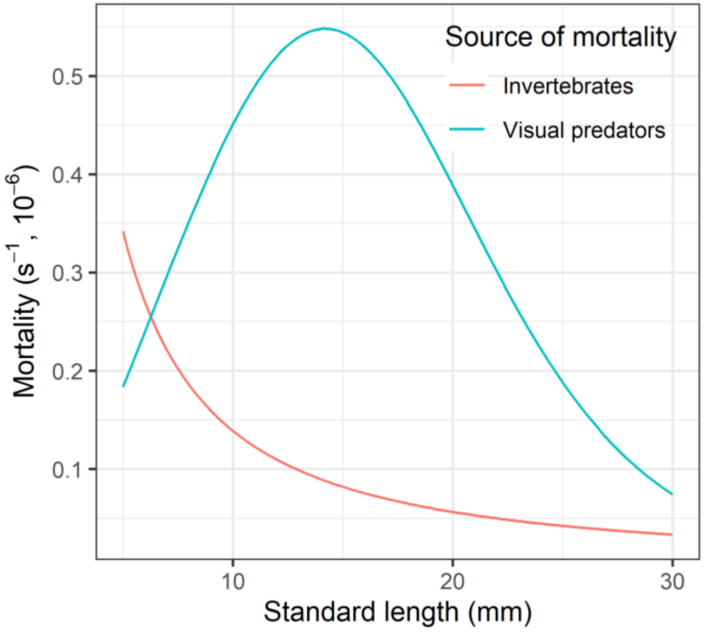
Individual-based model

Survival probability:

- ❑ Mortality by visual predators
  - f(larval size, light)
  - Predator density assumed constant
- ❑ Mortality by invertebrates
  - f(larval size)
- ❑ Mortality by periods of starvation
  - Constant added for time step *t* when the stomach was empty



Fiksen et al. (2002)



Individual-based model

Indices of recruitment:

- Estimated from hatch success (HS):

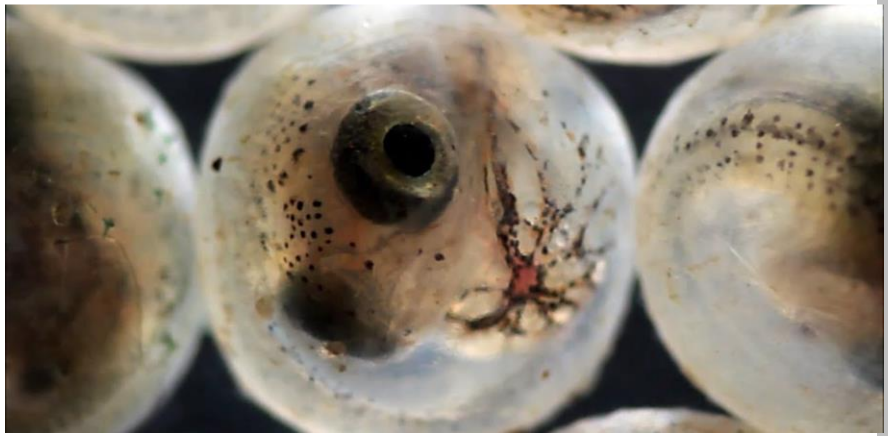
$$\sum_k HS_k \qquad k = \text{fish}$$

- Estimated from survival probability (P_s):

$$\sum_k {P_s}_k$$

- Estimated from HS and P_s:

$$\sum_k HS_k {P_s}_k$$



HS ~ f(Temperature)

Laurel and Rogers et al. (2020)

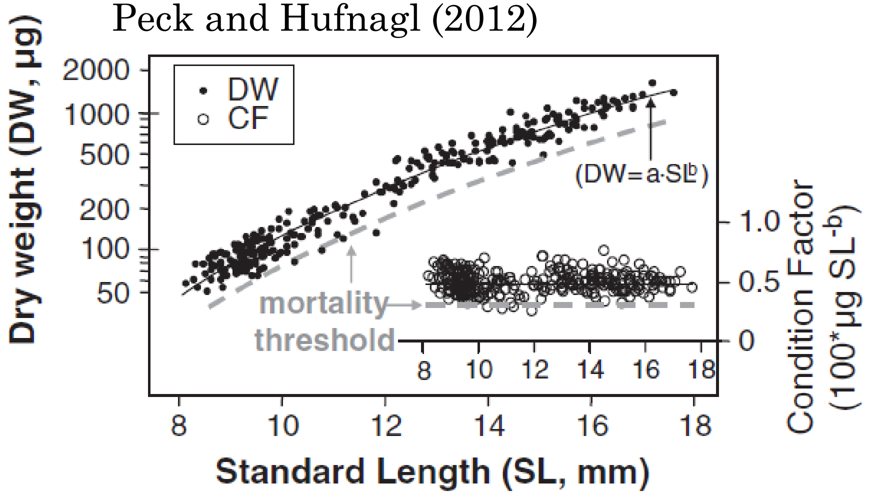
Individual-based model

Yonathon Zohar

Dead fish:

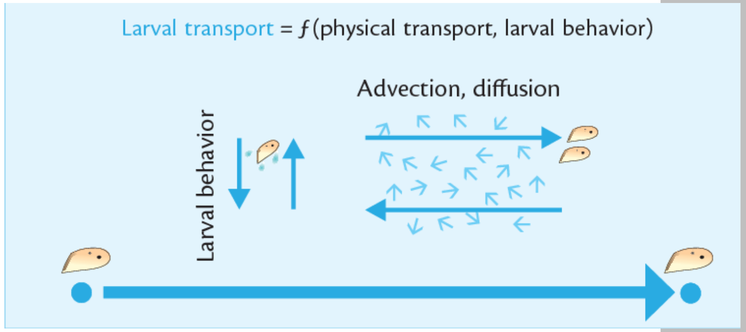
1. Reached the point-of-no-return (PNR)
    - Critical to pass from the YSL to FDL

Peck and Hufnagl (2012)



2. Starvation
    - Poor body condition

Pineda et al. (2007)

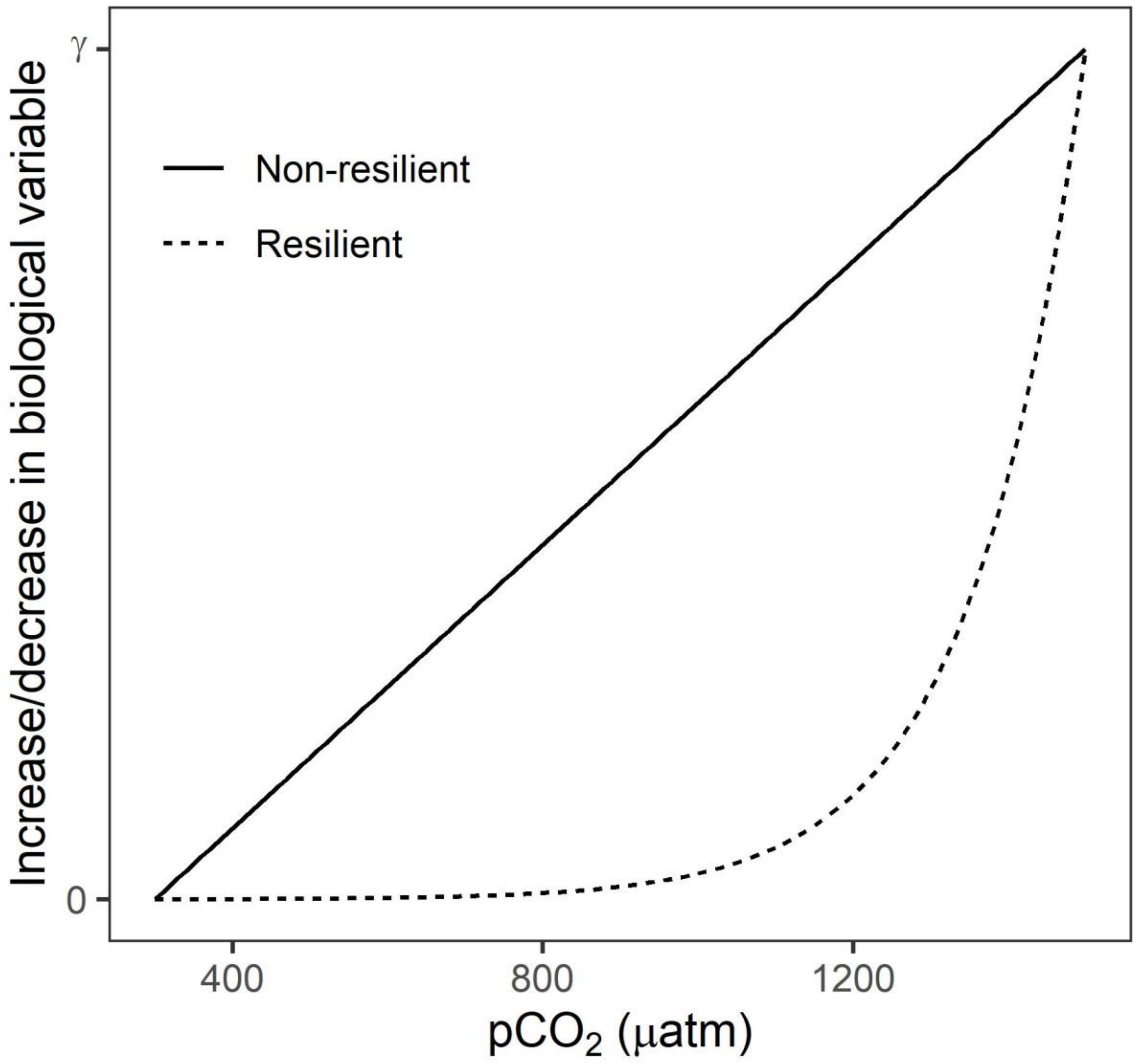


3. Advected out of the EBS

Impacts of ocean acidification

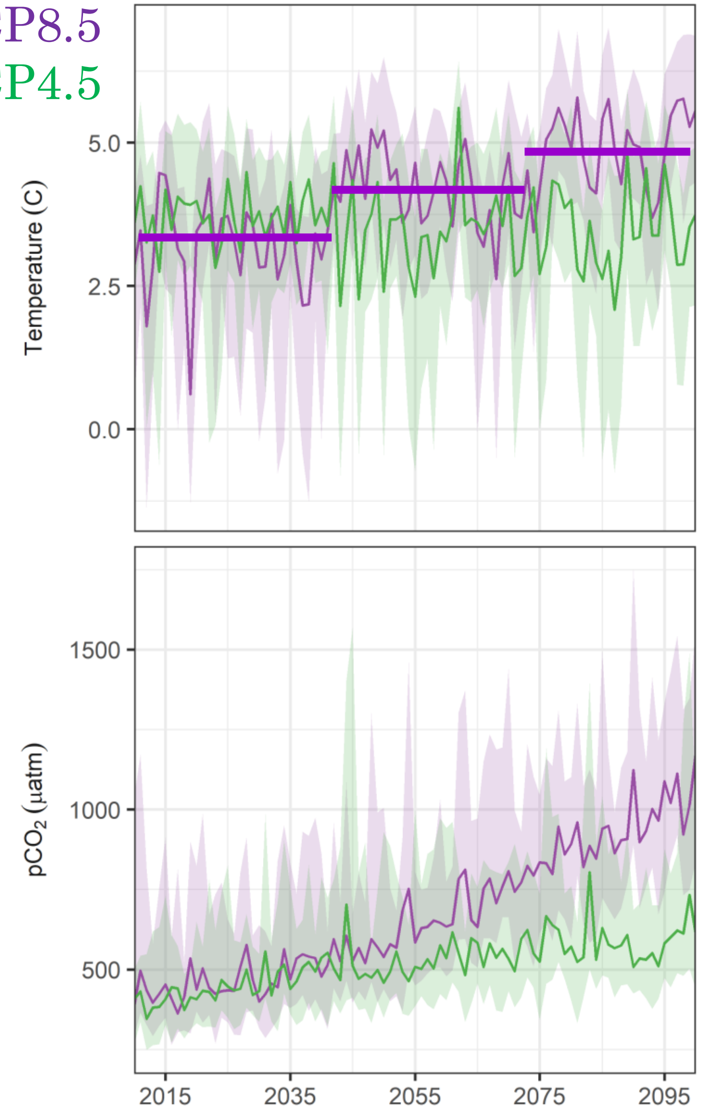
From laboratory studies in Pacific cod and other gadids in similar ecosystems:

1. Growth (*direct*)
2. Metabolism (*direct*)
3. Probability of prey-capture success (*direct*)
4. Prey abundance (*indirect*)
5. Prey weight (*indirect*)



Results: cod habitat

RCP8.5
RCP4.5

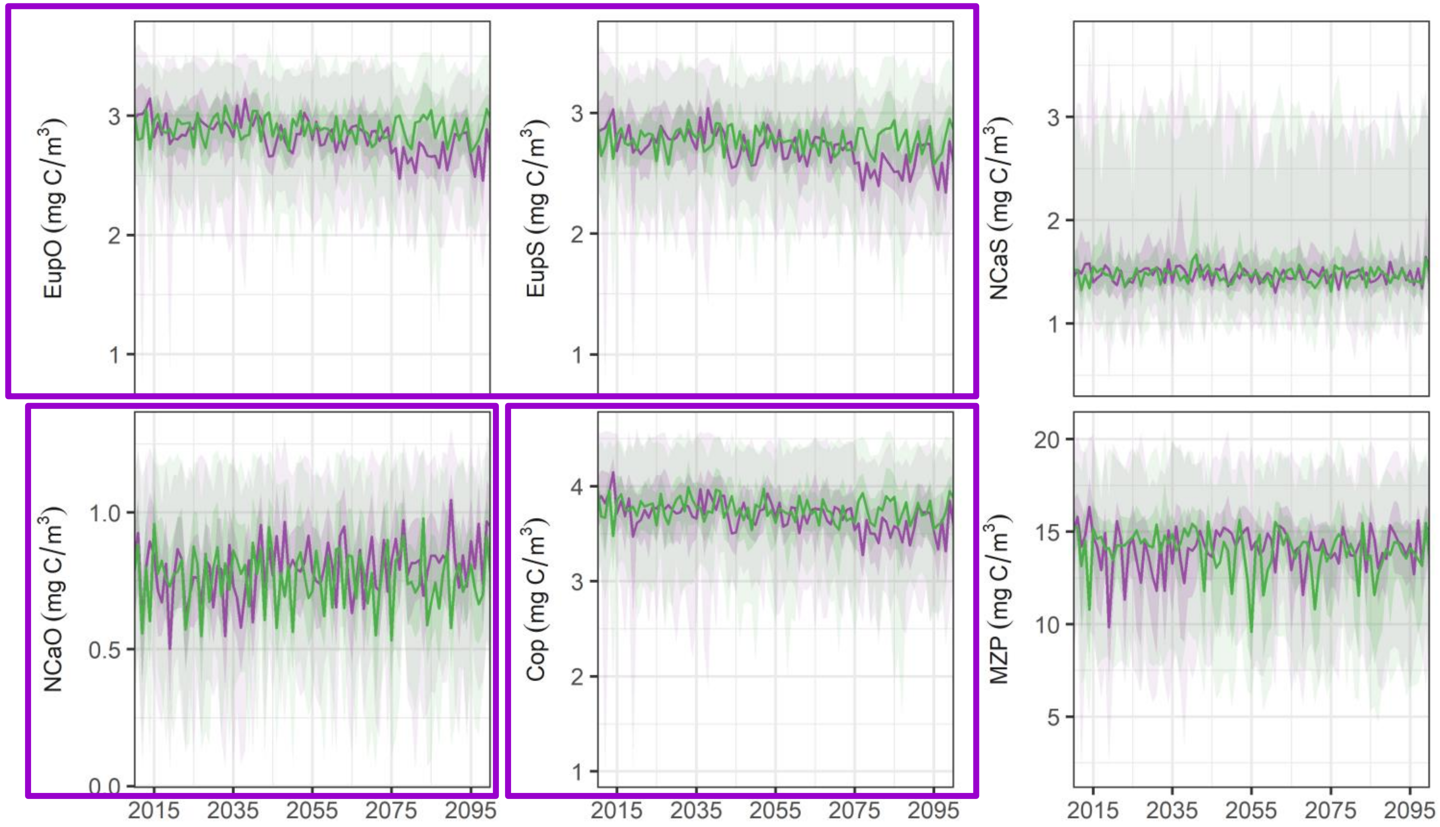


Temperature increase:

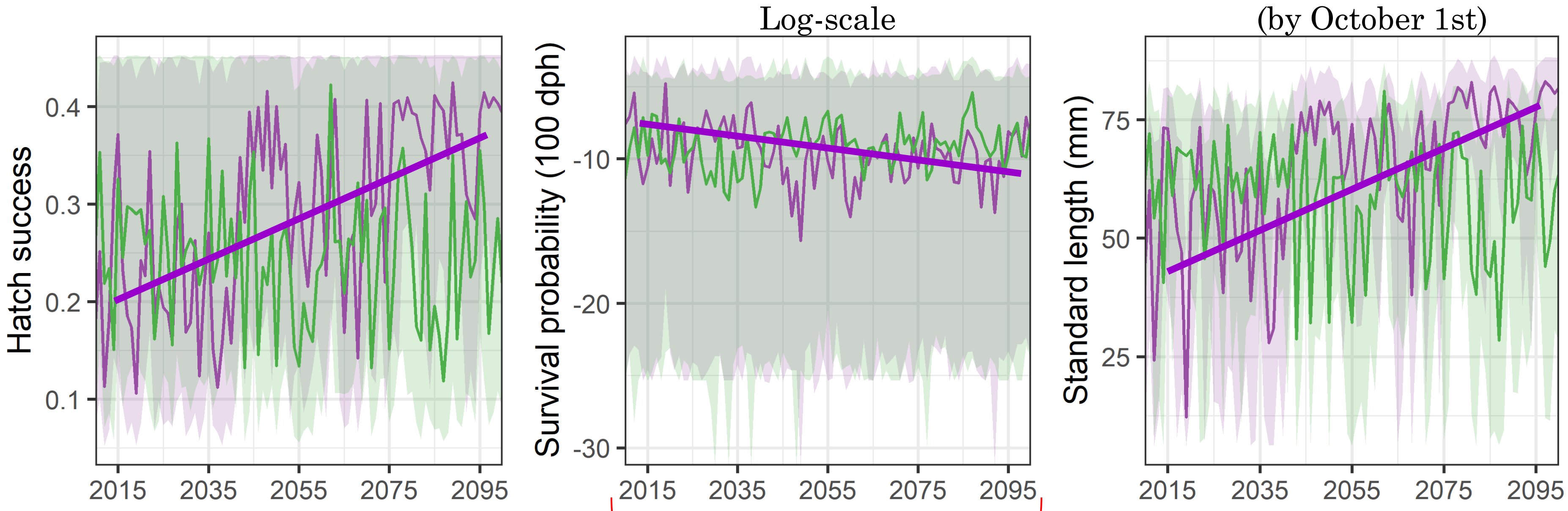
- Regime 1: 2010-2040
- Regime 2: 2041-2075
- Regime 3: 2076-2100

Average environmental conditions throughout the fish's lifespan

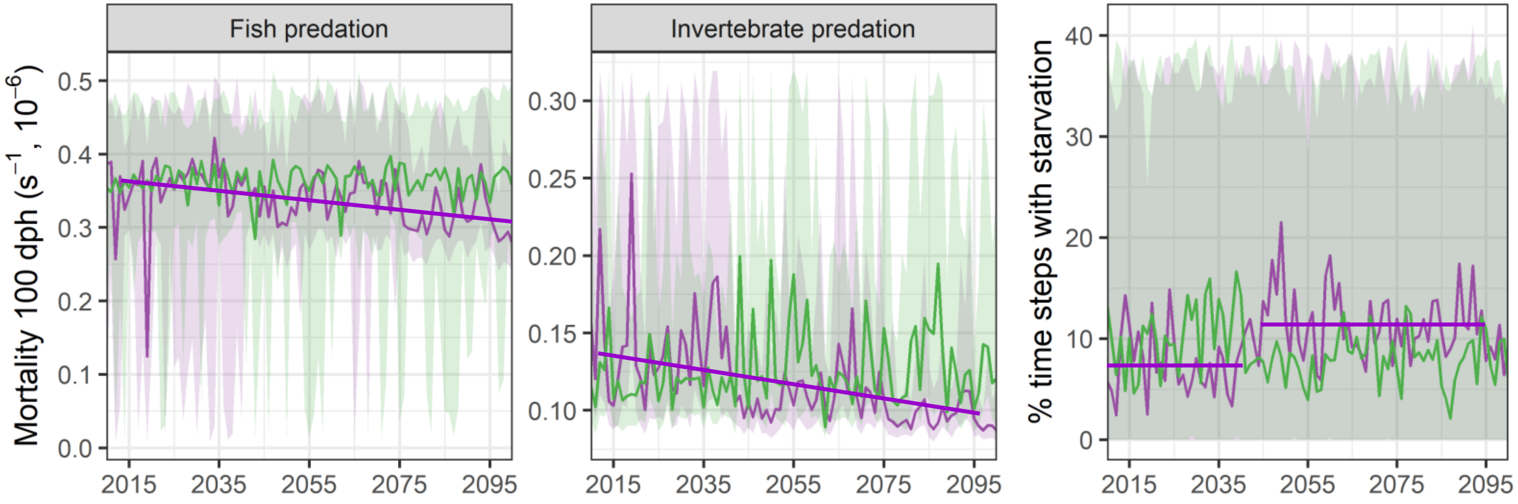
Prey density:



Results: cod ecology



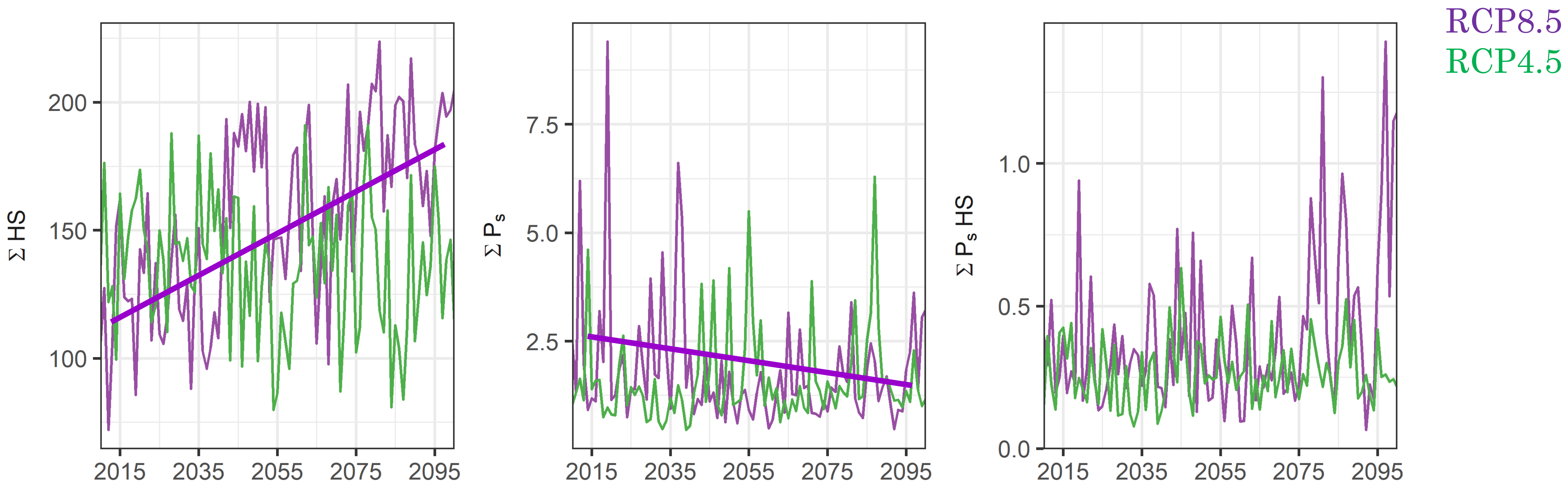
RCP8.5
RCP4.5



- Warmer years produced larger fish sizes

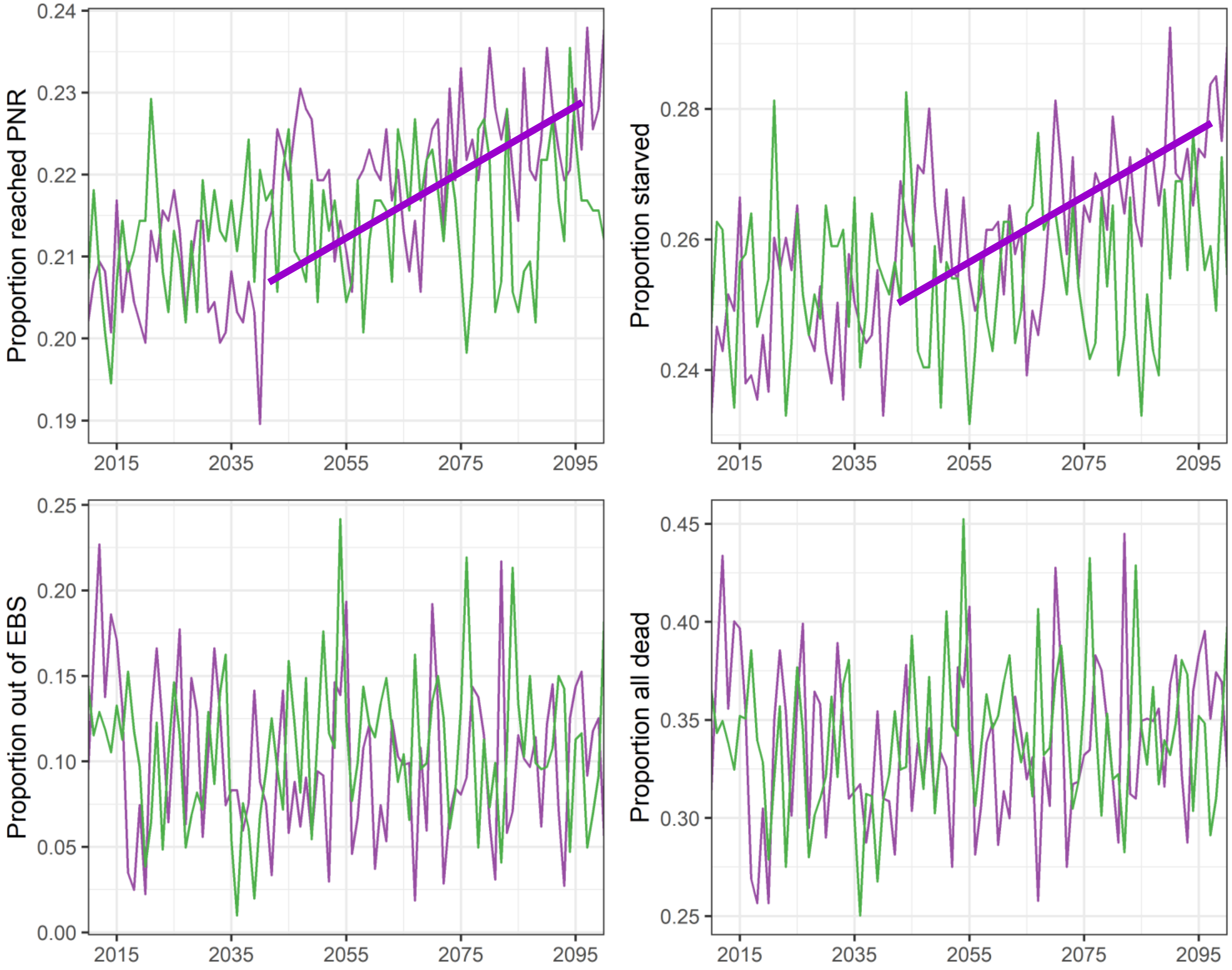
- Faster growth led to a decrease in mortality by predation

Results: recruitment



- HS (hatch success) negatively correlated with recruitment estimates from SAM (2010-2021)
- P_s agreed with periods of low and high recruitment during 2010-2021
- Potential decrease in recruitment in future years as found for walleye pollock (Mueter et al., 2011)

Results: dead cod



- Proportion that reached PNR and starved closely related

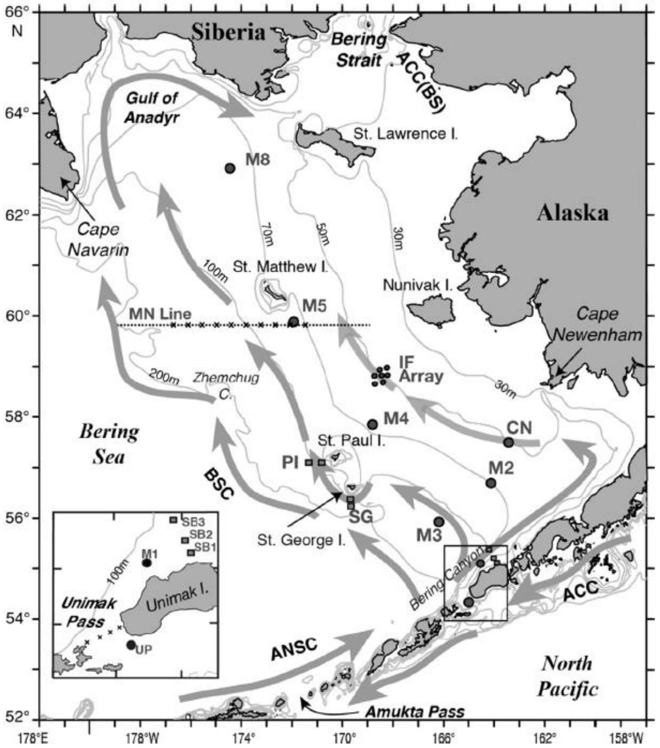
- Proportion that starved well correlated (negatively) with recruitment estimates:
  - Warmer years → higher deaths by starvation

- Death by advection was constant over time

RCP8.5
RCP4.5

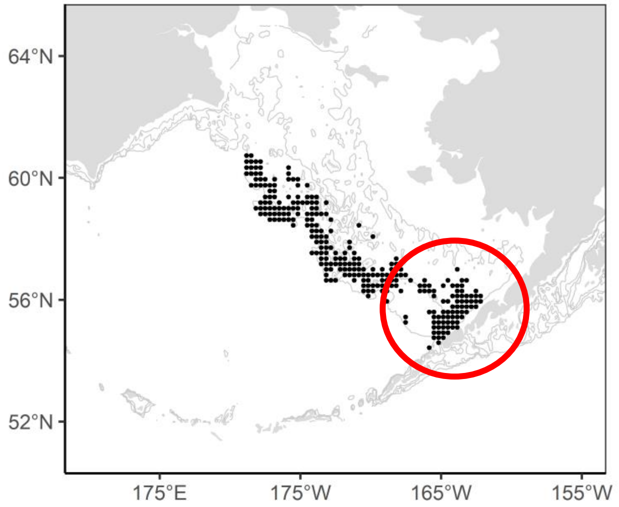
Results: cod spatial distribution

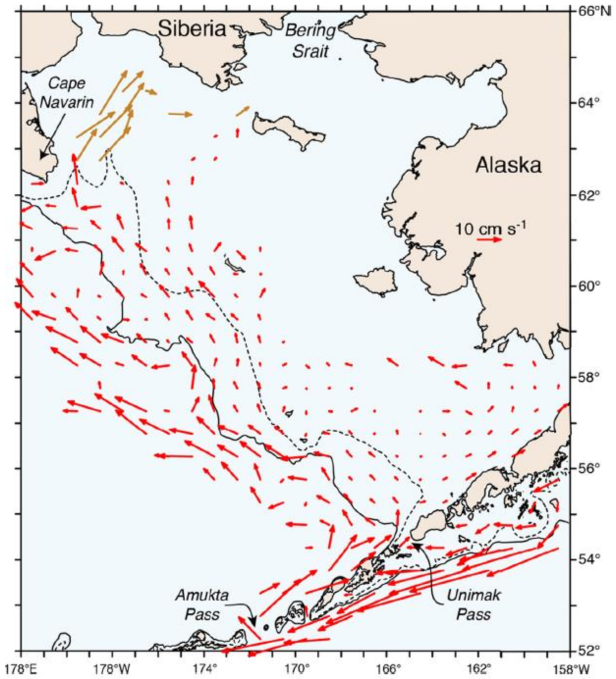
- Retention area in the southeastern Bering Sea
- Bering Slope Current important for advection of fish northward



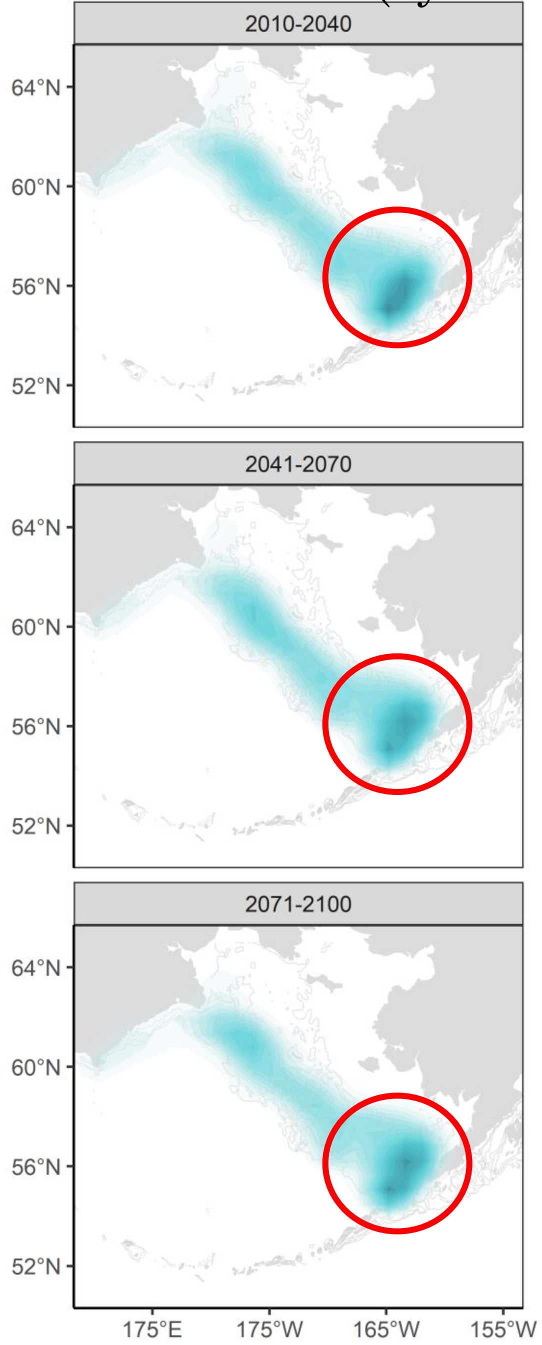
Stabeno et al. (2019)

Initial locations (March)

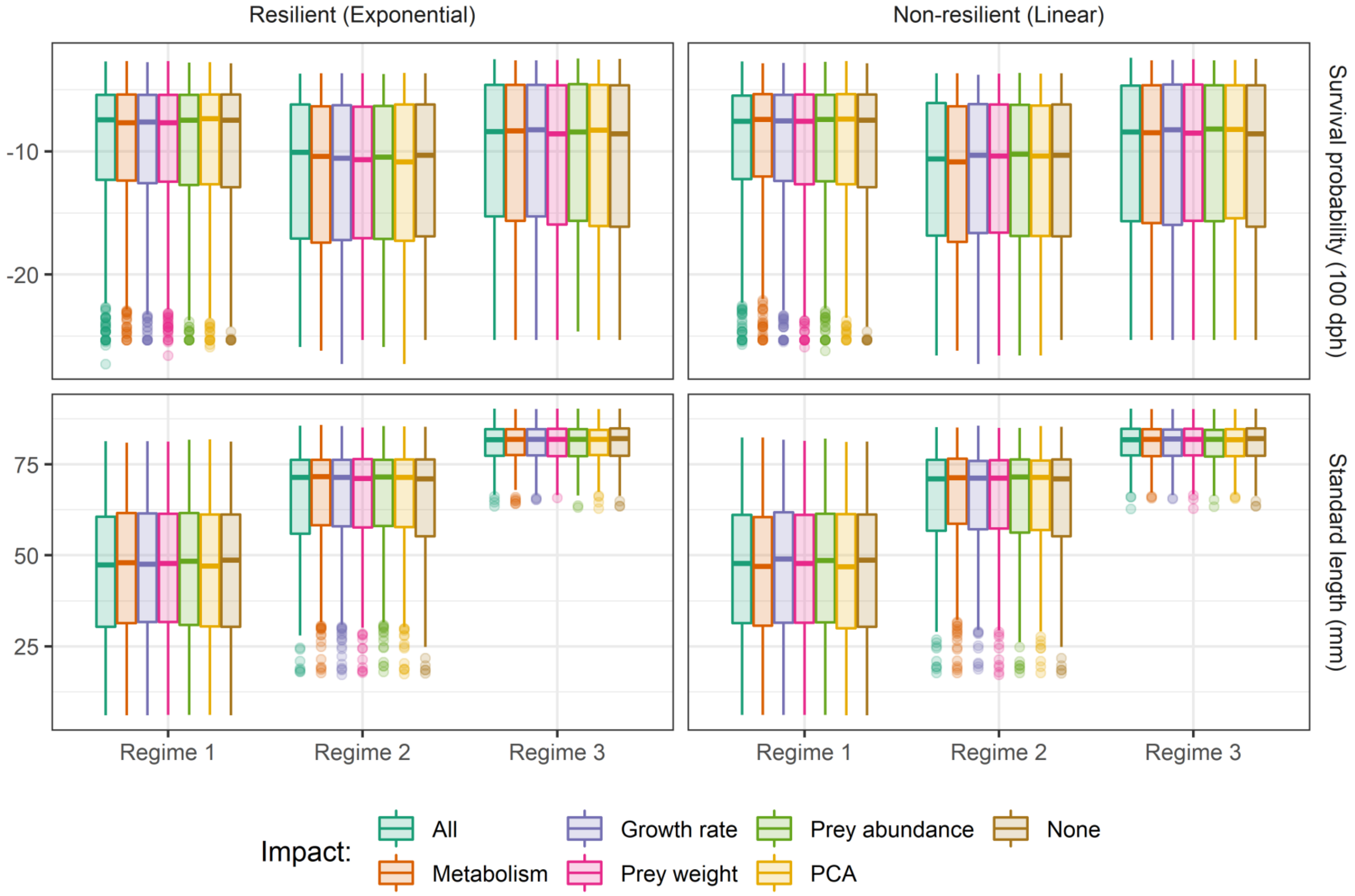




Final locations (by Oct 1st)



Results: ocean acidification impacts



No impacts of pCO_2 on our results

Need for more studies

Conclusions

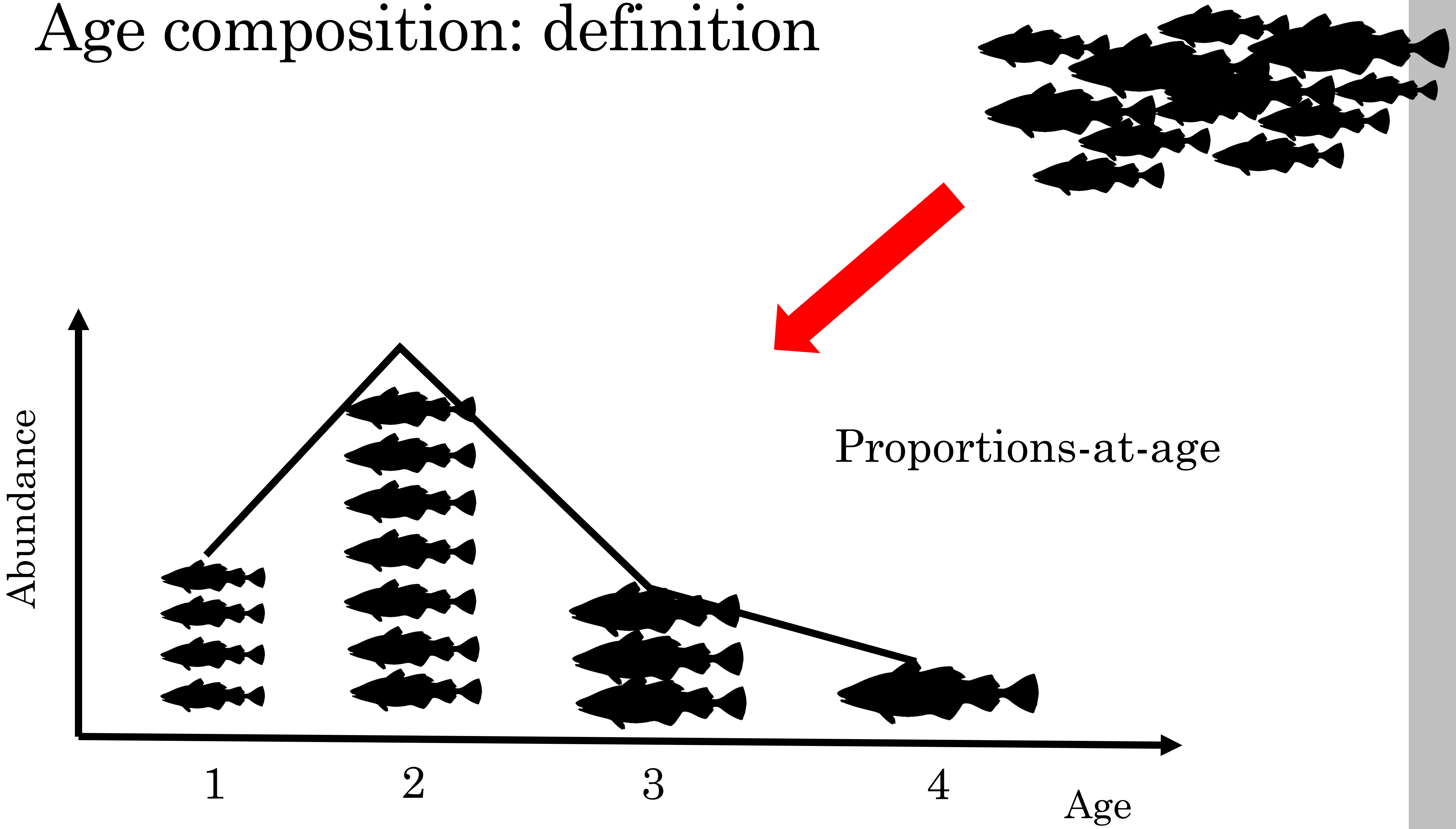
- Model outputs agreed with the current knowledge of the ecology of Pacific cod early life stages
- Impacts only observed for the RCP8.5 emission scenario
- Increase in hatch success and larval size in the future
- Decrease in survival probability and recruitment in the future
- Starvation as the most important driver of survival probability and recruitment
- Early life stages not impacted by ocean acidification under our assumptions

Improved estimation of age composition by accounting for spatiotemporal variability in somatic growth

Giancarlo M. Correa, Lorenzo Ciannelli, Lewis A.K. Barnett, Stan Kotwicki, Claudio Fuentes

Canadian Journal of Fisheries and Aquatic Sciences (2020)

Age composition: definition



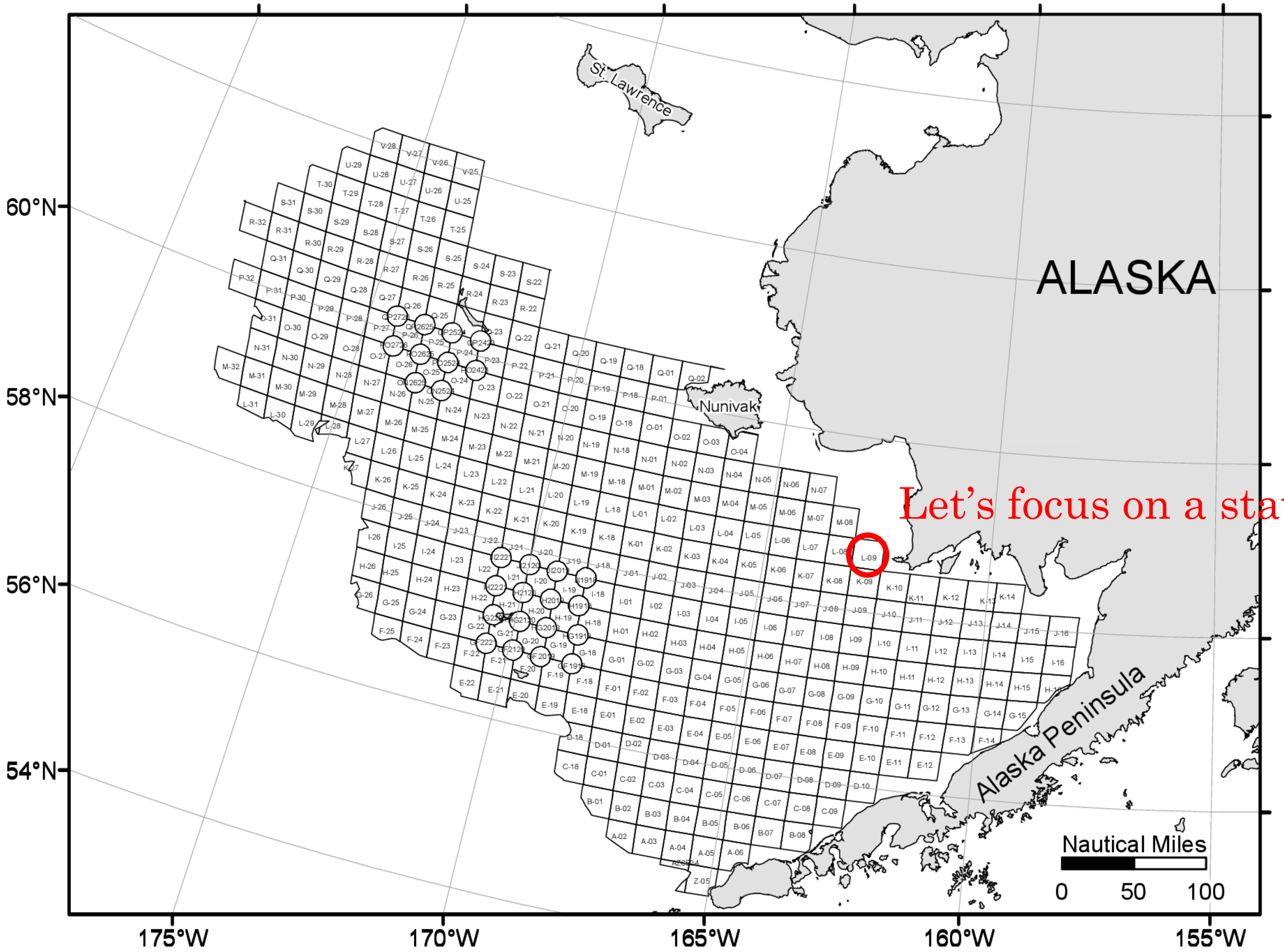
Age composition: estimation

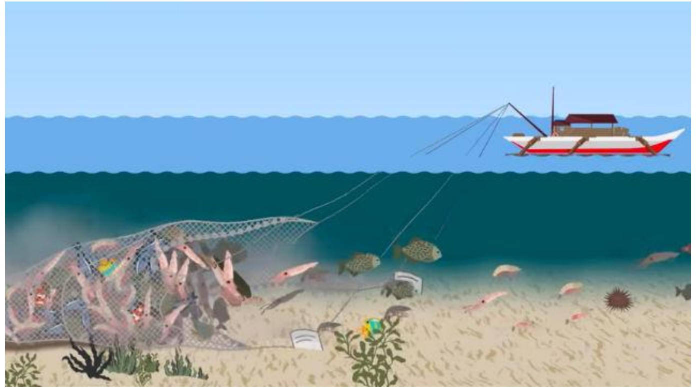
Estimated from fishery-dependent or independent sources.

NOAA - Fisheries

Bottom-trawl survey in the eastern Bering Sea (once a year)

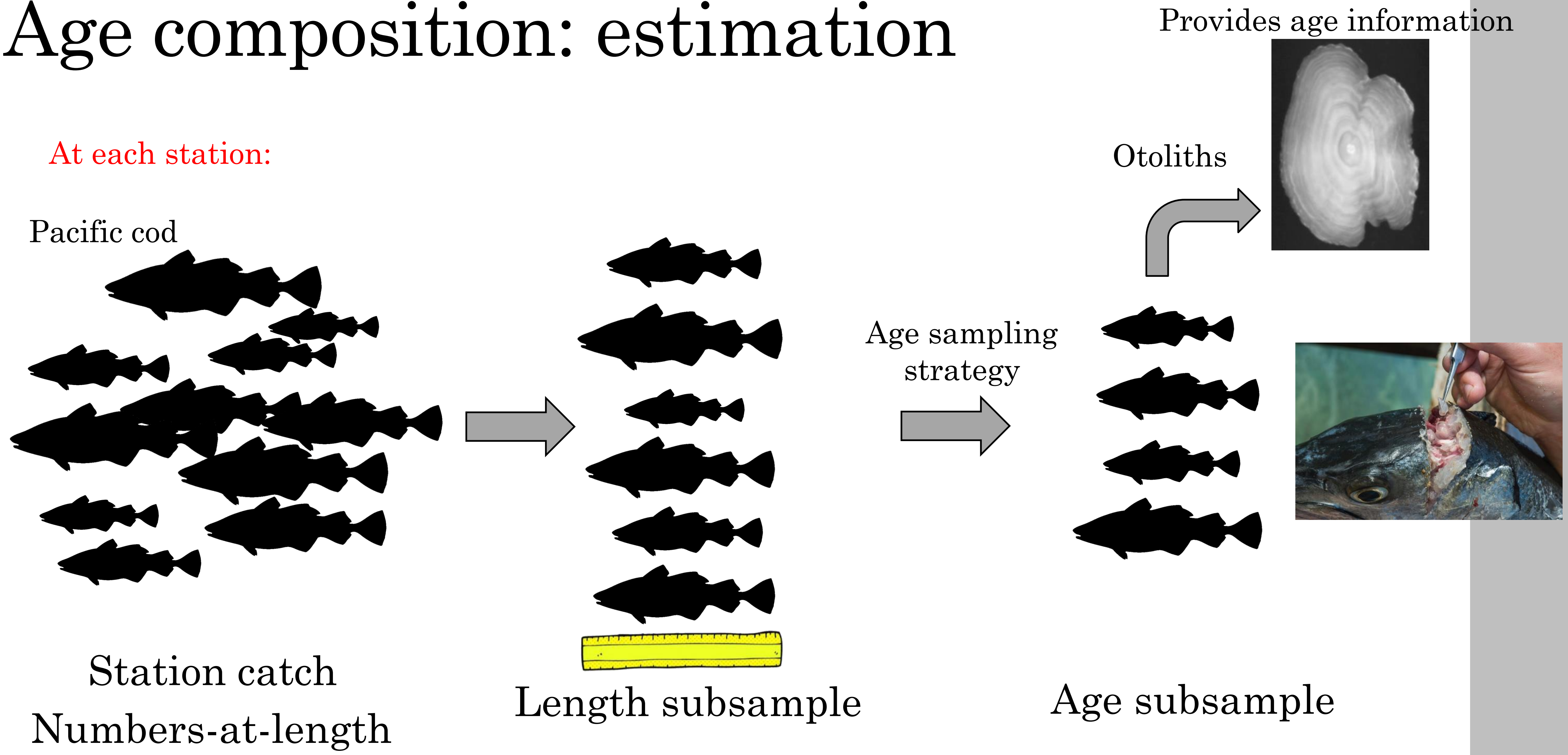
- 376 sampling stations
- Bottom-trawl net
- Study groundfishes





Age composition: estimation

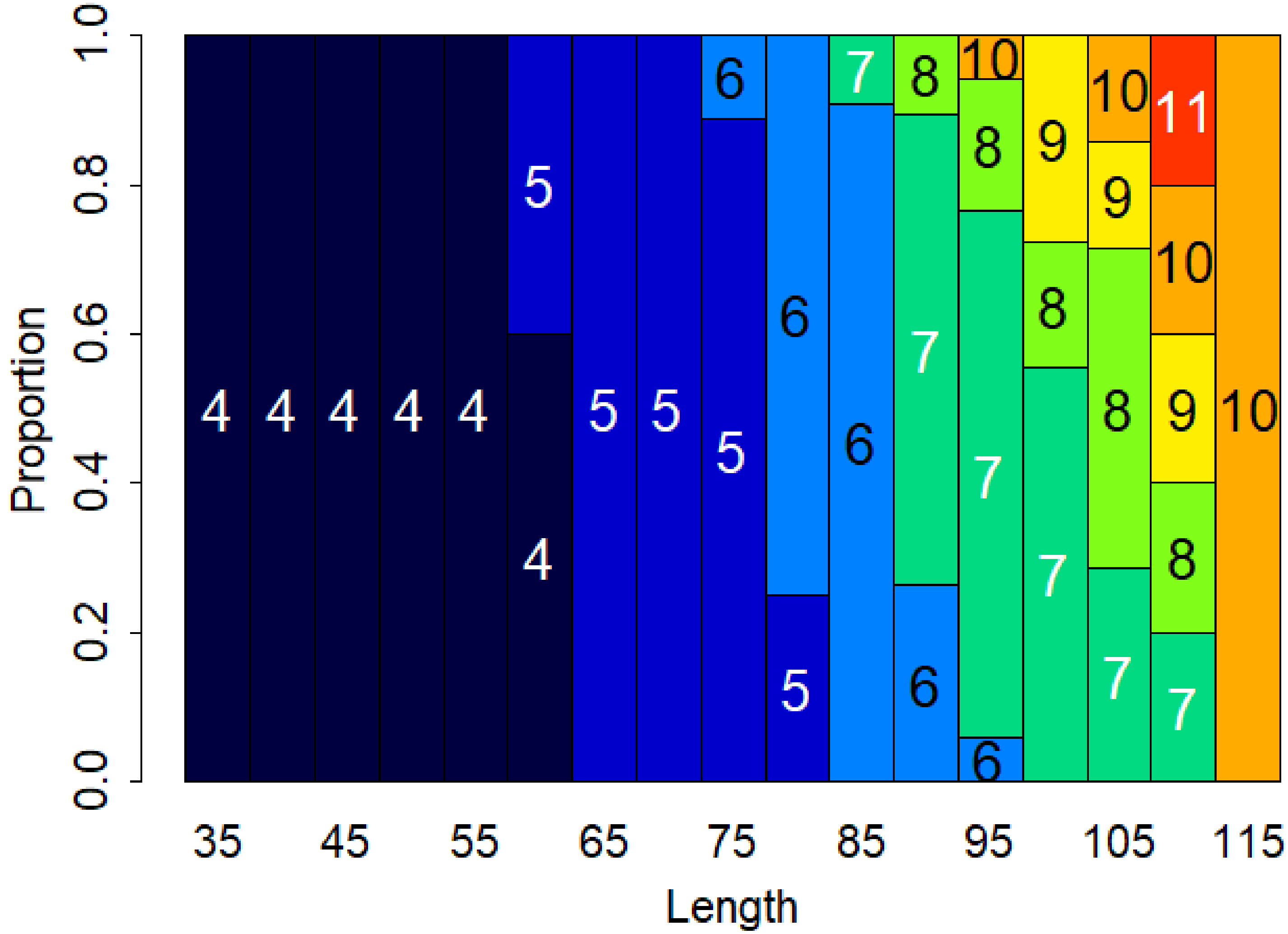
At each station:



This process is repeated for all stations!

Age-length keys (ALK)

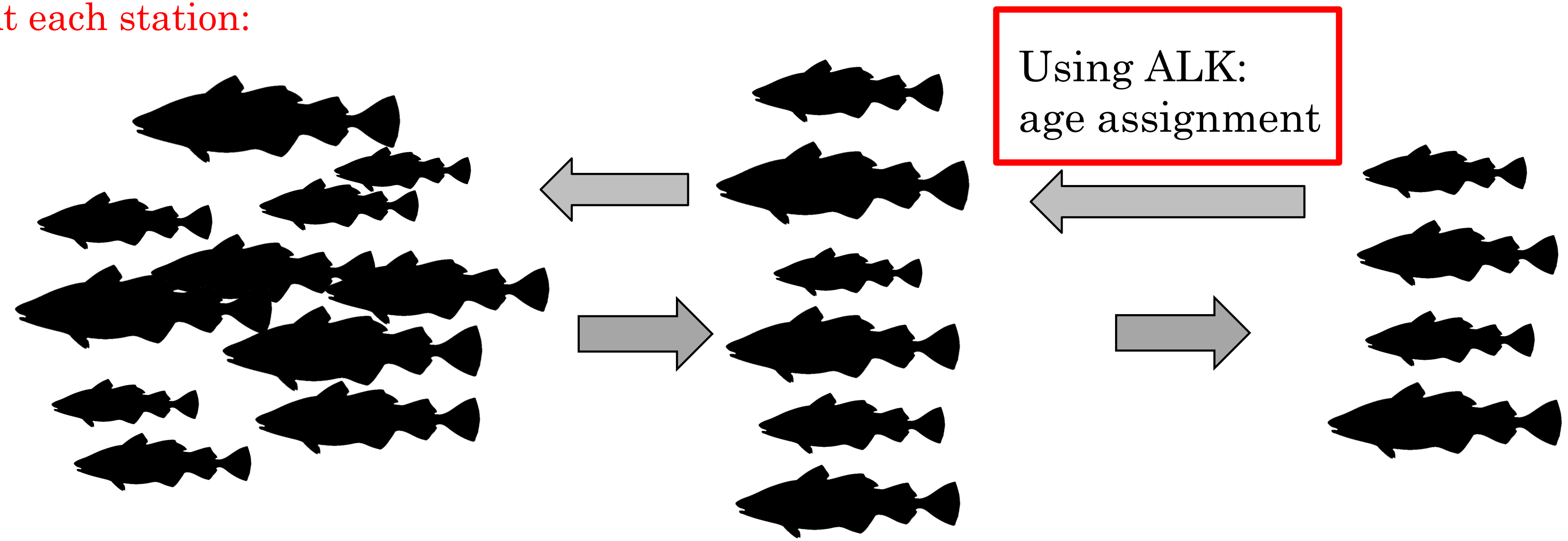
Construction from length and age information in the age subsample from all stations



Age composition: estimation

Using information from all stations, estimate age composition for the entire area.

At each station:



Haul catch

Numbers-at-length

Numbers-at-age

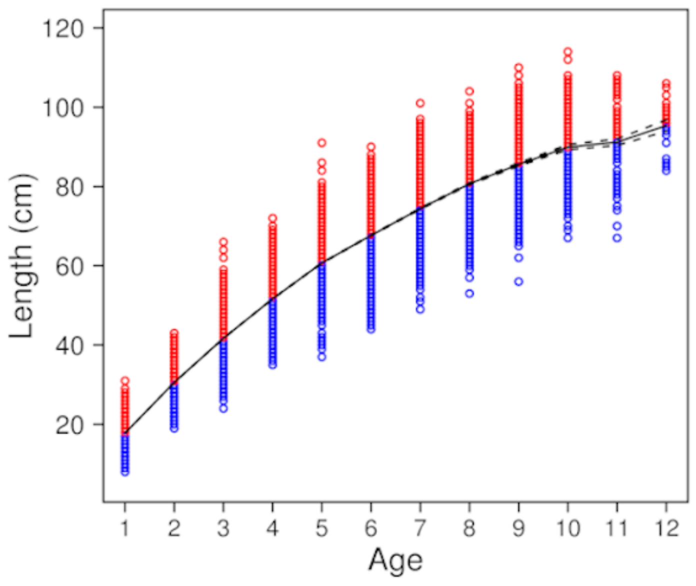
Length subsample

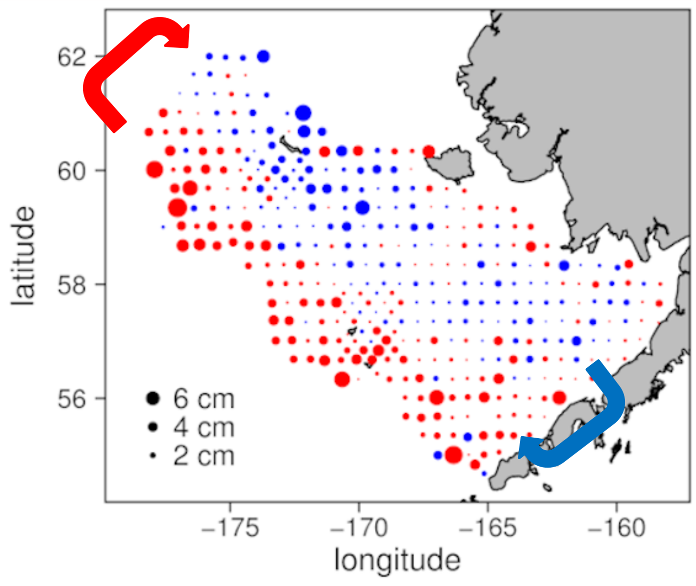
Age subsample

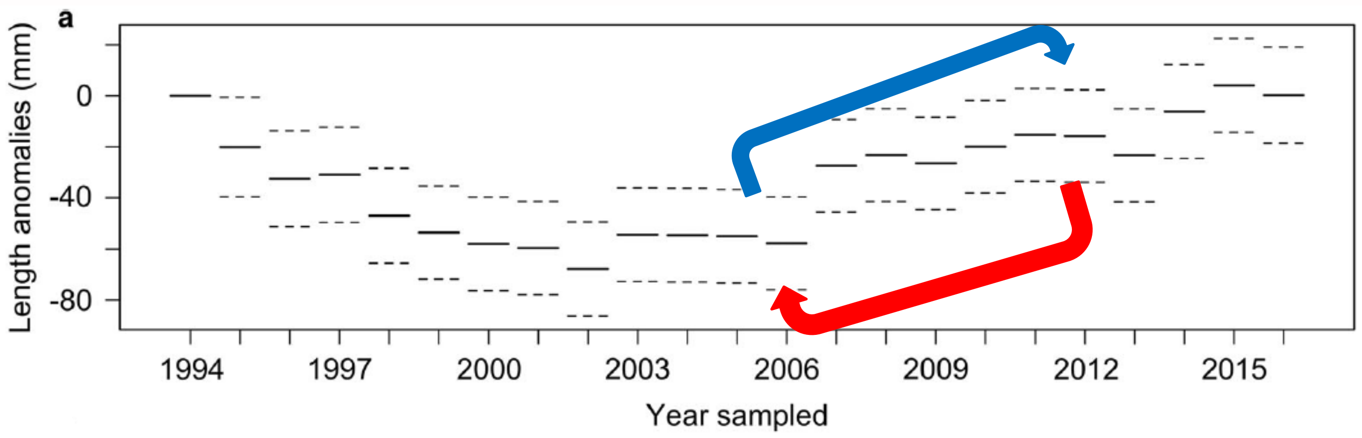
Age-length key (ALK)

Ciannelli et al. (2020)

- Simple construction
- Used worldwide
- Needs a large amount of data
- Normally pools data from the entire study area
- In some cases, pools data from different years/surveys







Alternative approaches to ALK?

- Puerta et al. (2018): used a generalized additive model (GAM):

At a given year (using information in the age subsample):

$$g[\mathbb{E}(a_j)] = \alpha + s_1(l_j) + s_2(lon_j, lat_j) + \varepsilon_j$$

g is the log-link function
a_j is the age of the sampled fish j in the age subsample
l_j is the length of the sampled fish j in the age subsample
lon_j, lat_j is the spatial location where the j fish was sampled
ε_j is the error term

Predict age in the length subsample:

	location		size	age
j	**lon**	**lat**	**l**	**a**
1	-170	58	35	2
2	-175	55	49	3
…	…	…	…	…
N	-173	60	68	7

Alternative approaches to ALK?

- Berg et al. (2012): used continuation ratio logits (CRL) and GAM for estimation:

At a given year (using information in the age subsample):

$$g[\mathbb{E}(\pi_{a,j})] = \alpha_a + \beta_a l_j + s_a\left(lon_j, lat_j\right) + \varepsilon_{a,j}$$

g is the logit-link function

$\pi_{a,j}$ is the conditional probability of a fish of being age a given that it is at least that age:

$$\pi_a = P(Y = a | Y \geq a) = \frac{p_a}{p_a + \cdots + p_{A^*}}$$

Then, the unconditional probabilities at age are estimated:

$$\tilde{p}_J = \hat{\pi}_J \qquad \tilde{p}_a = \hat{\pi}_a \prod_{j=J}^{a-1}(1 - \hat{\pi}_j)\,, \quad a > J$$

A^* is the maximum estimable age

J is the minimum estimable age

Predict prop-at-age in the length subsample:

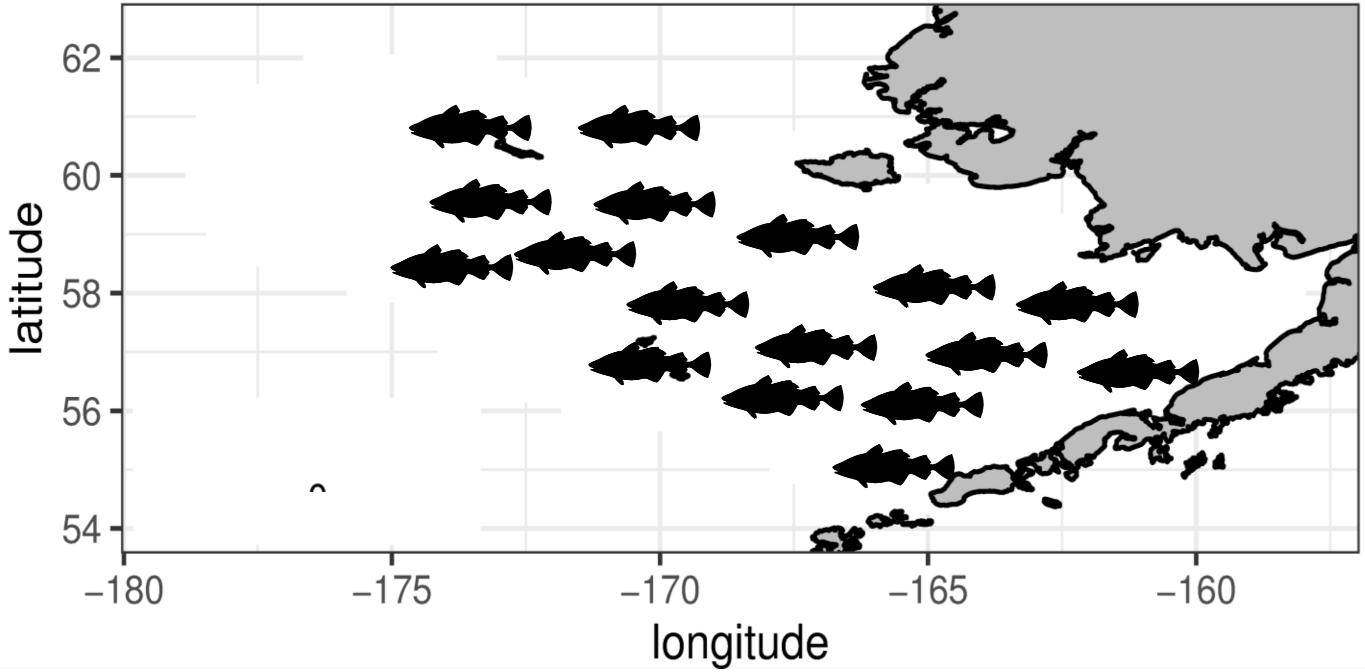
	location		size	Prop-at-age			
j	**lon**	**lat**	**l**	**1**	**2**	**…**	**8**
1	-170	58	35	0.2	0.1	…	0
2	-175	55	49	0.1	0.2	…	0.1
…	…	…	…	…	…	…	…
N	-173	60	68	0.3	0.1	…	0

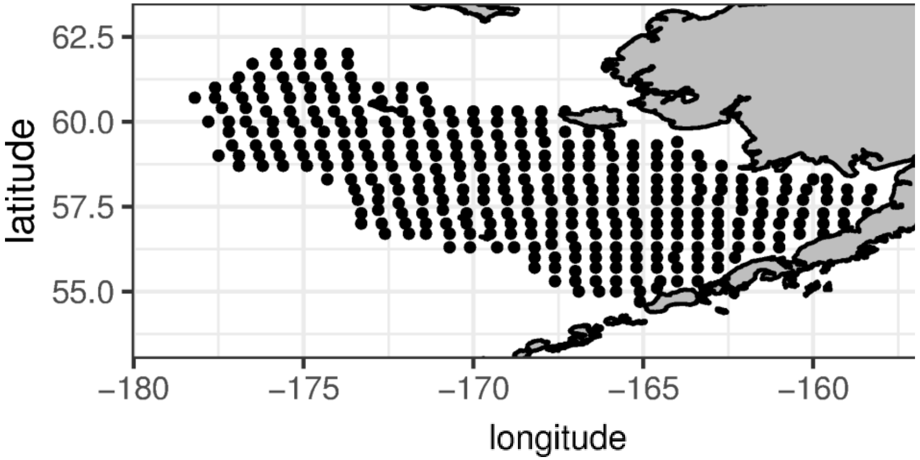
Objective

Evaluate the performance of classic age-length keys (design-based) and two alternative approaches (model-based) to estimate age compositions of a fish population with spatial and temporal variability in somatic growth

Simulation experiment

- Population dynamics of a Pacific cod-like species (1994-2016)
- A survey per year
  - Station catch
  - Length subsample
  - Age subsample
  - Age composition estimates per survey





Spatial and temporal variability in somatic growth

Two somatic growth scenarios:

- No spatial / No temporal (No S / No T)
- Spatial / Temporal (S / T)

$$L_a = L_\infty(1 - e^{-k^*(a-t_0)})$$

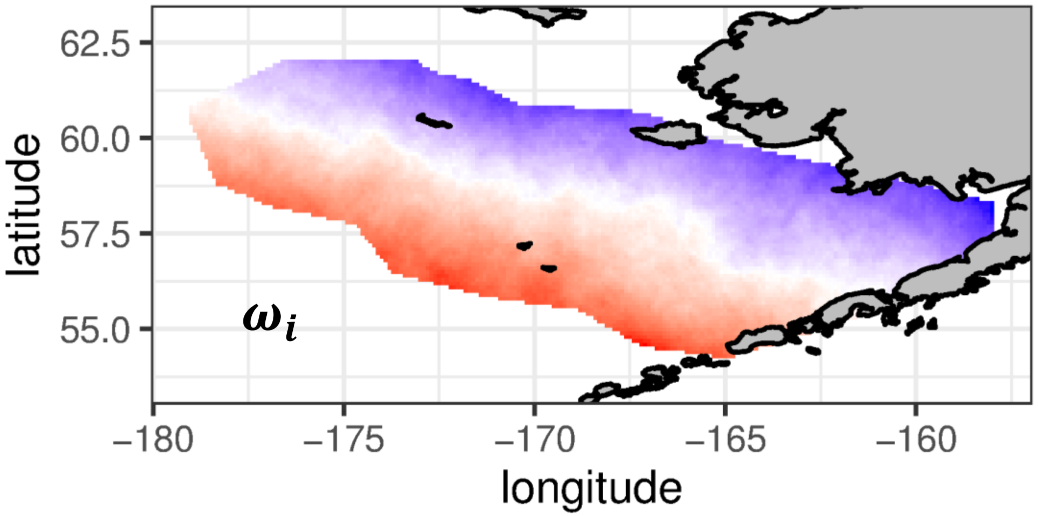
No S / No T:

$$k^* = k$$

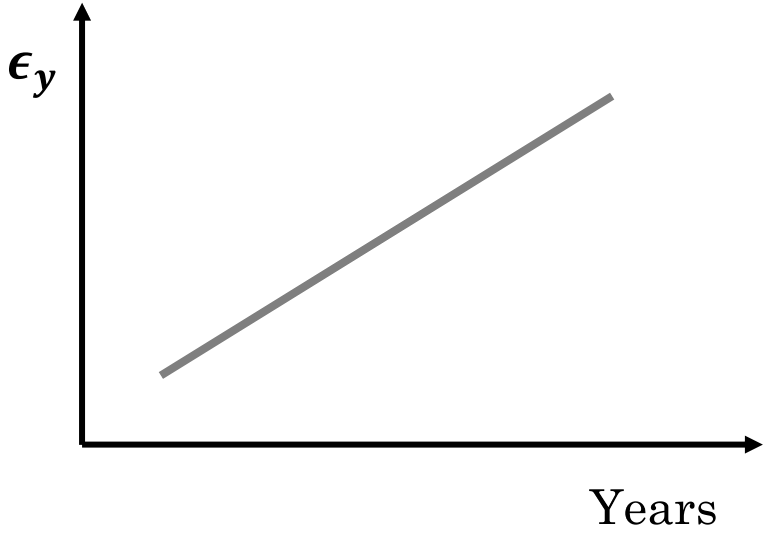
S / T:

$$k^* = k + \boxed{\omega_i} + \boxed{\epsilon_y}$$

Spatial variability:



Temporal variability:



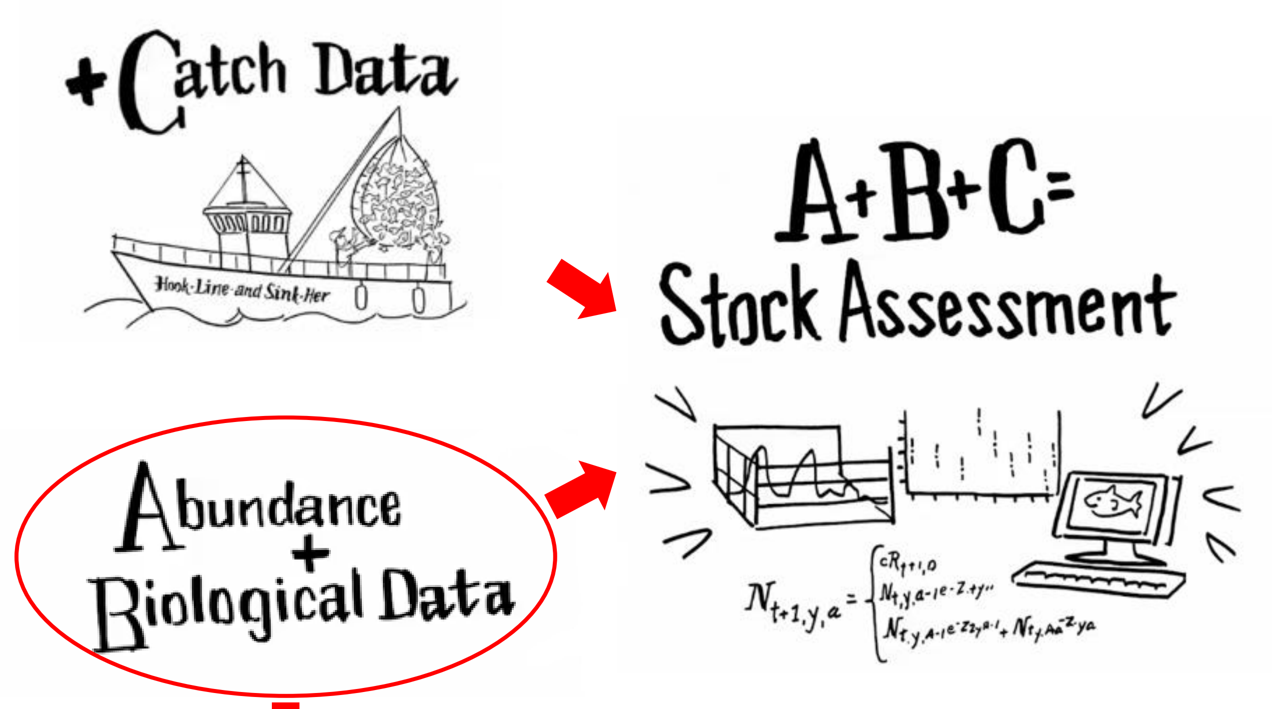
Performance of four methods

Using the information in the age subsample from the simulated survey:

1. **Pooled age-length key (pooled ALK):** information pooled over space and years → unique ALK.
2. **Annual age-length key (annual ALK):** information pooled over space → unique ALK per year
3. **Generalized Additive Models (GAM):** Puerta's approach. Age is the response variable.
4. **Continuation Ratio Logits (CRL):** Berg's approach. Proportion-at-age is the response variable.

Comparing age composition estimates using these methods with the true age composition in the population

Age compositions in stock assessment models



Age composition is an informative input to stock assessment models:

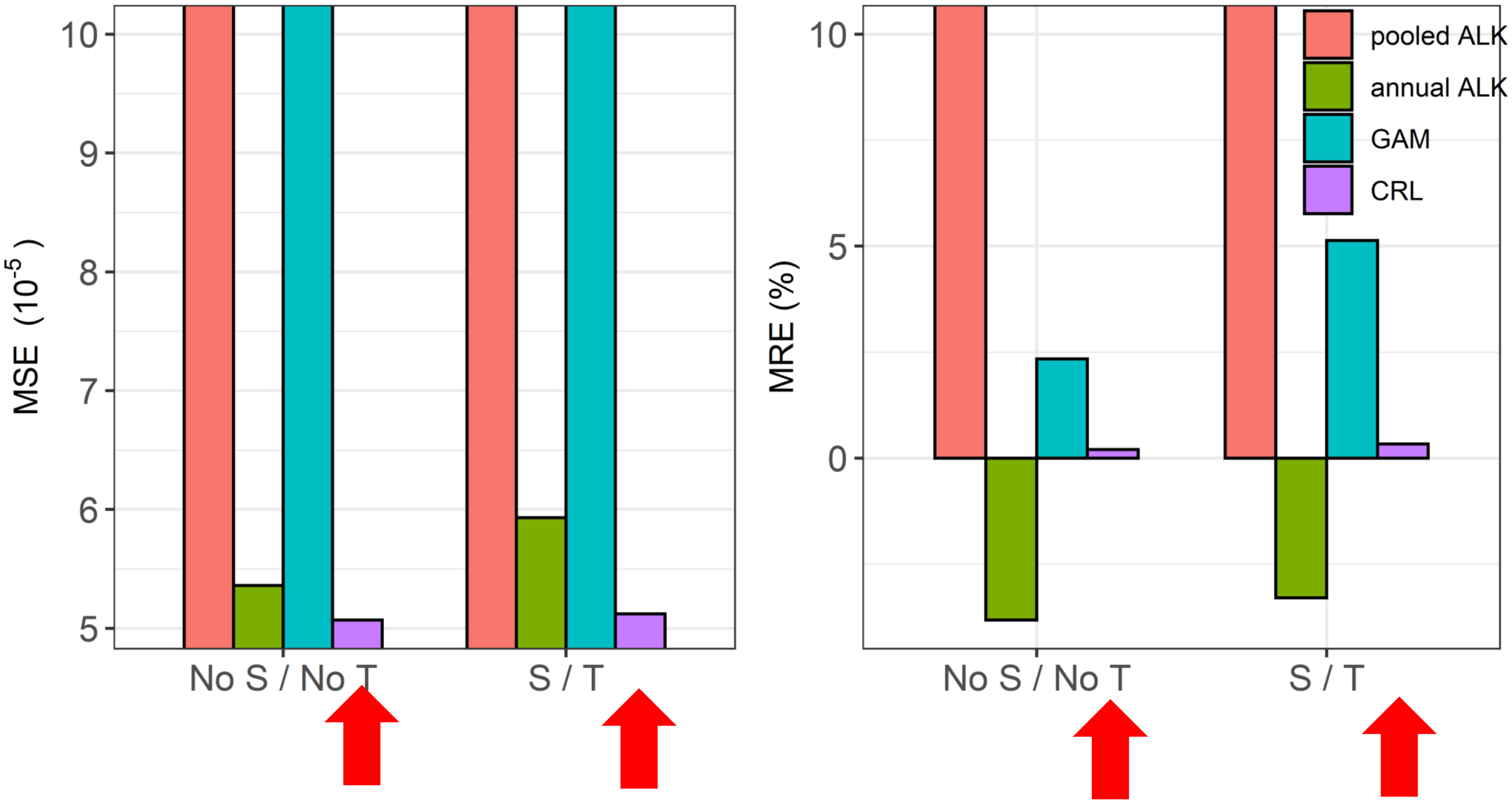
- Recruitment
- Mortality
- Somatic growth

Using survey data of Pacific cod in the eastern Bering Sea (1994 - 2016):

1. Estimate age compositions using the four evaluated approaches
2. Include these age compositions in the Pacific cod stock assessment model separately
3. Compare data consistency among stock assessment models

Results: simulation experiment

MSE: Measure of error
MRE: Measure of bias

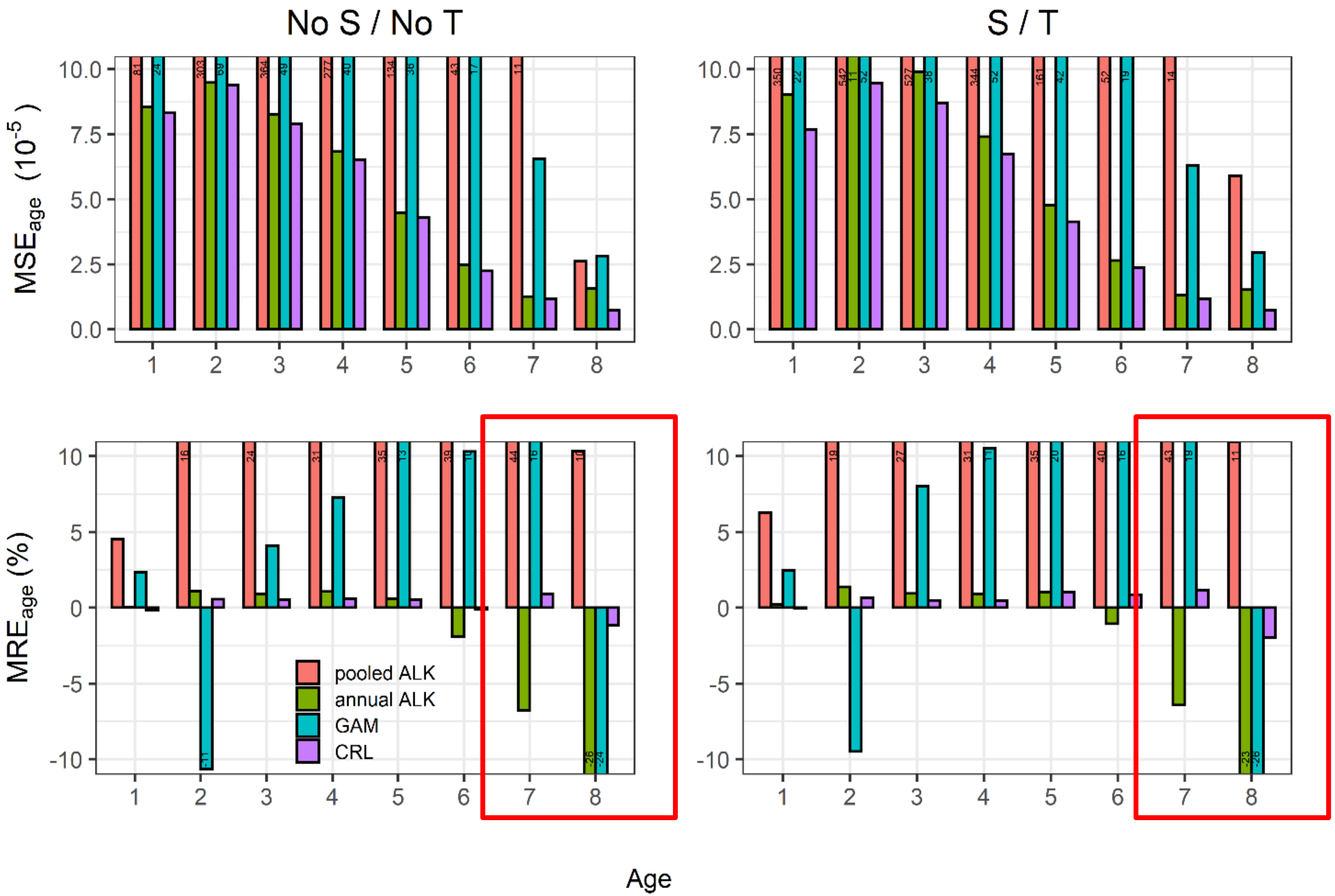


Best performance: CRL

Results: simulation experiment

MSE: Measure of error
MRE: Measure of bias

Indicators per age:



Large negative bias for older ages (too many data gaps!)

Best performance: CRL

Results: performance in stock assessment model

Age compositions in stock assessment models:

Component	SS pooled ALK	SS annual ALK	SS GAM	SS CRL
Total	92.53	75.18	88.96	$\boxed{72.93}$
Catch	5.9e–13	0.0105e–13	0.06e–13	0.35e–13
Equilibrium catch	11.4e–05	6.3e–05	9.6e–05	6.8e–05
Survey	–29.7	–40.7	–40.05	–40.15
Length composition	74.27	72.1	72.66	71.77
Age composition	76.32	61.83	71.26	59.43
Recruitment	–29.23	–19.03	–16.08	–19.09

Best data consistency using CRL method

Conclusions

- CRL approach was the most robust method to estimate age compositions

- Pooled ALK was the worst method

- Annual ALK was affected by data gaps in older ages

- Evidence that the CRL approach might improve data consistency and fit in stock assessment models

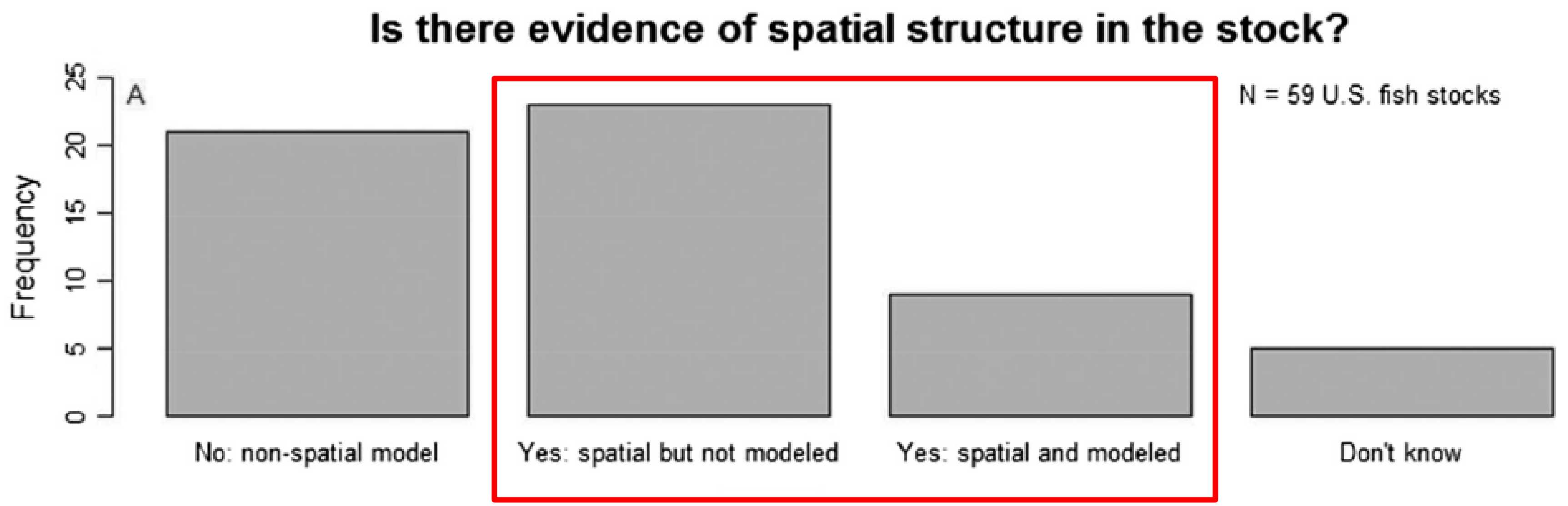
https://github.com/gmoroncorrea/STageCompsEstimation

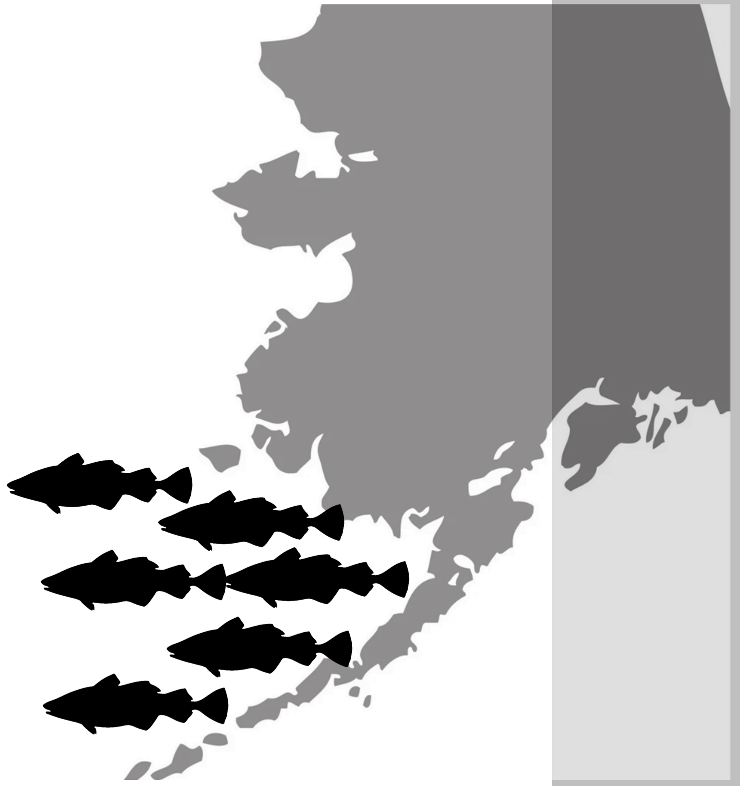
Spatial and temporal variability in somatic growth in fisheries stock assessment models: evaluating the consequences of misspecification

Giancarlo M. Correa, Carey McGilliard, Lorenzo Ciannelli, Claudio Fuentes

ICES Journal of Marine Sciences (2021)

Spatial structure in stock assessment models





Also, plenty of evidence of temporal variability in growth

Berger et al. (2017)

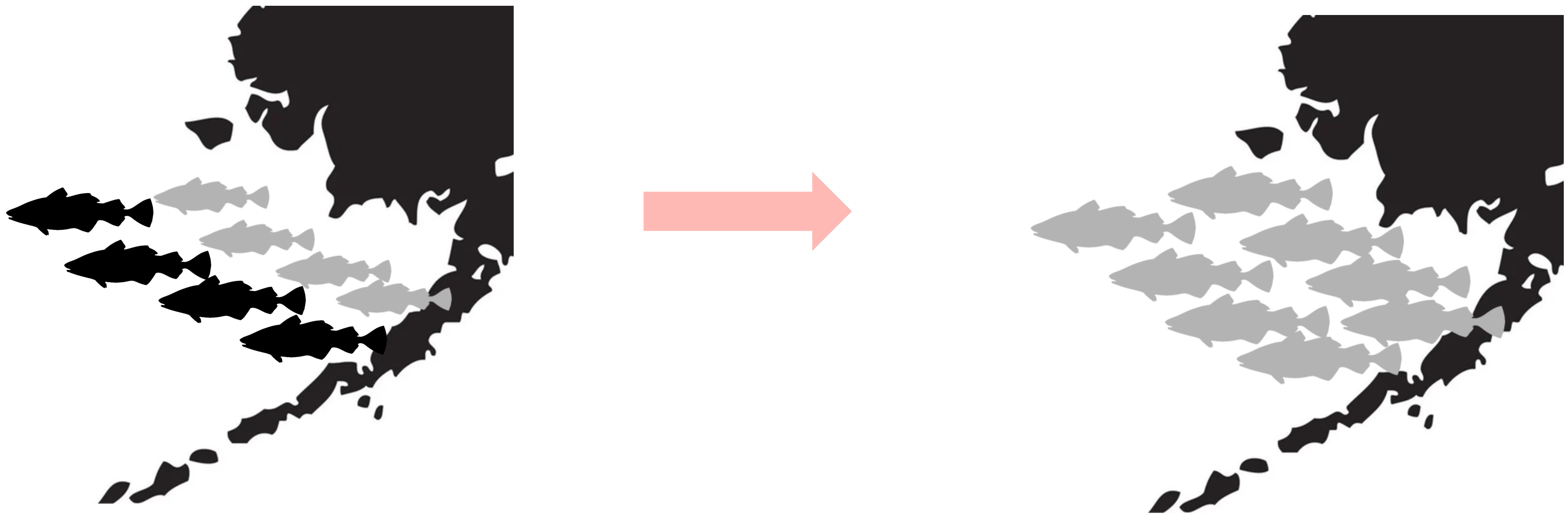
Objective

Evaluate the consequences of misspecification in somatic growth in stock assessment models

- Spatial and temporal variability
- Three life-histories: sardine – cod – rockfish

In the population

What we assume in the stock assessment model



Simulation experiments in stock assessment models

Scenario 1:

OM_1	EM_1	Compare EM estimates vs true (OM)
OM_2	EM_2	
⋮	⋮	
OM_n	EM_n	

Scenario 2:

OM_1	EM_1	Compare EM estimates vs true (OM)
OM_2	EM_2	
⋮	⋮	
OM_n	EM_n	

⋮

Scenario k:

Operating model (OM):
Simulate the true dynamics of a population

Estimation model (EM):
Assumption about the population dynamics

Data

- Simulation-estimation process
- Different 'realities' can be simulated
- Used for different purposes:
  - Movement
  - Recruitment
  - Natural mortality
  - Data quantity and quality
  - Somatic growth

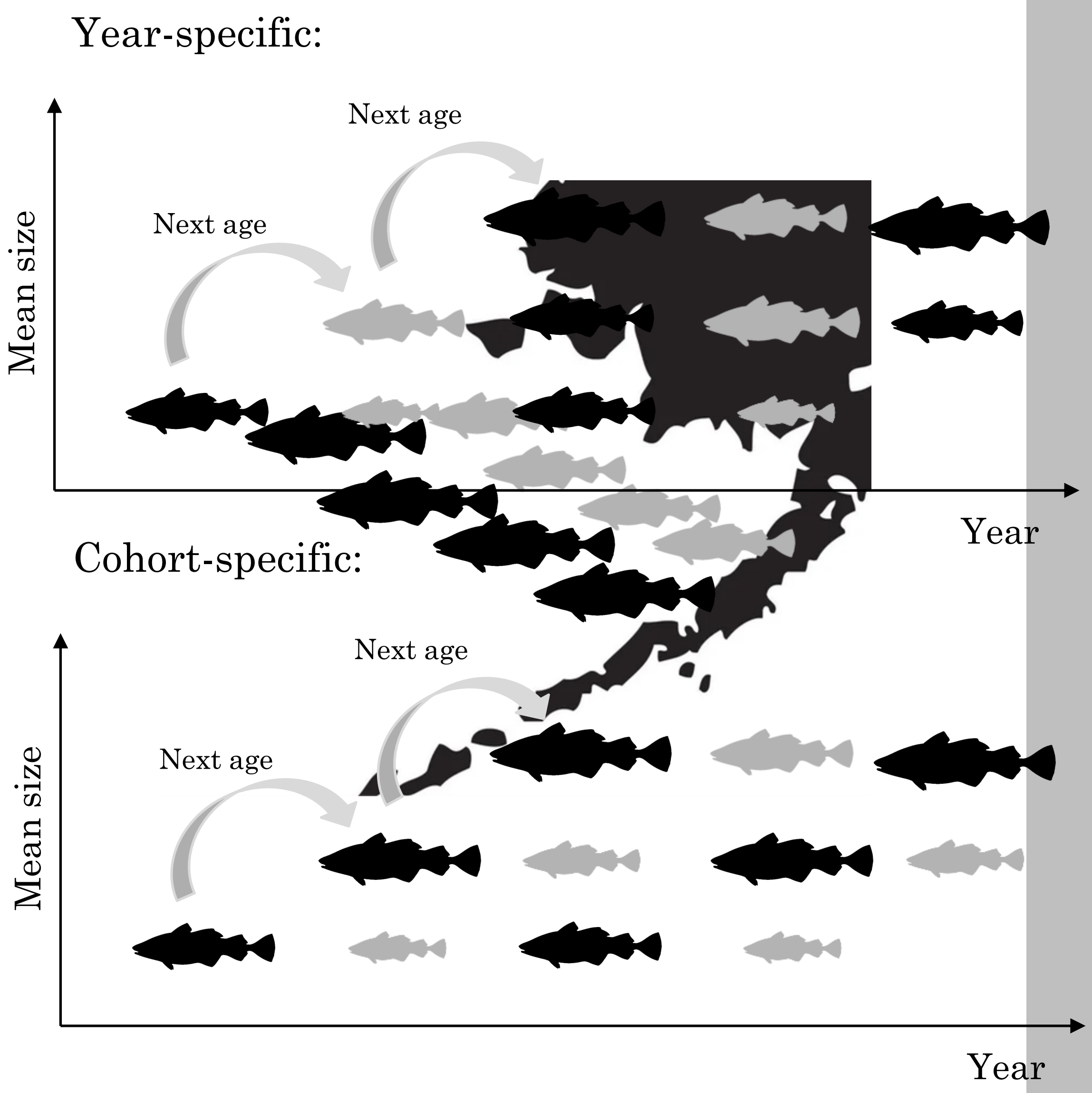
Somatic growth variability simulation

Operating model (OM, *in the population*)

Changes in mean size-at-age
- By varying in k or L_∞

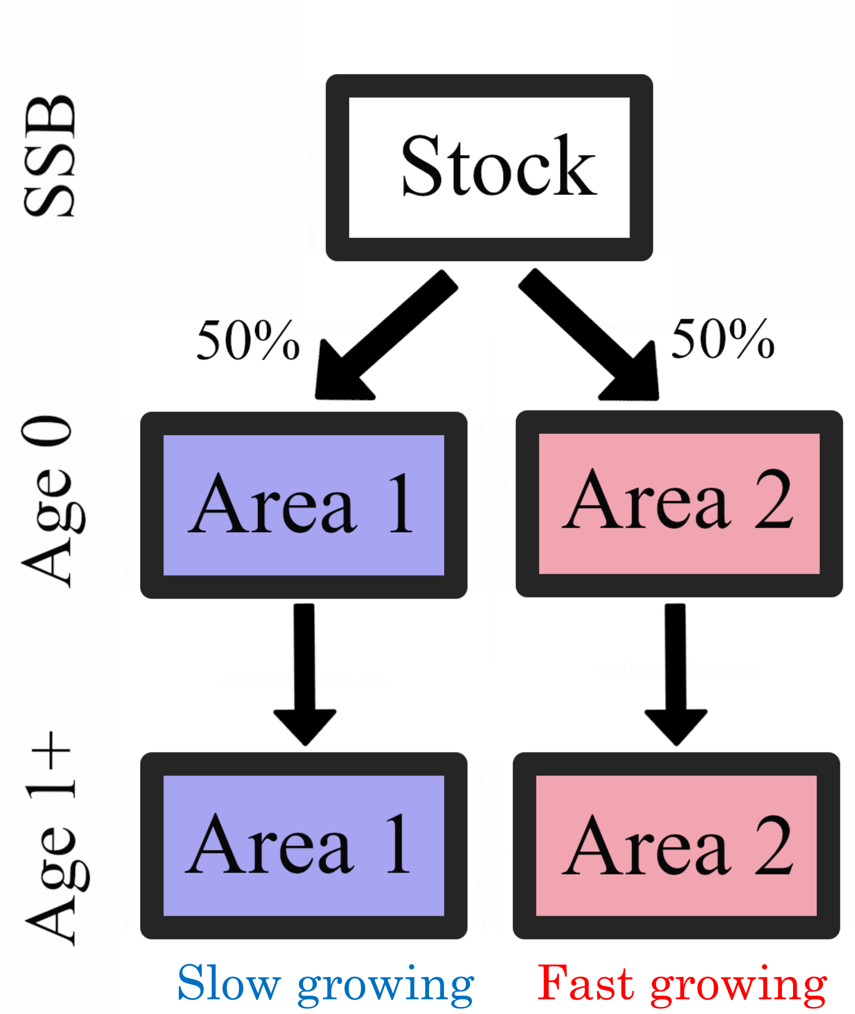
Temporal variability:
- Year-specific
- Cohort-specific

Spatial variability: Variation between two areas



Somatic growth variability simulation

Operating model (OM, *in the population*)

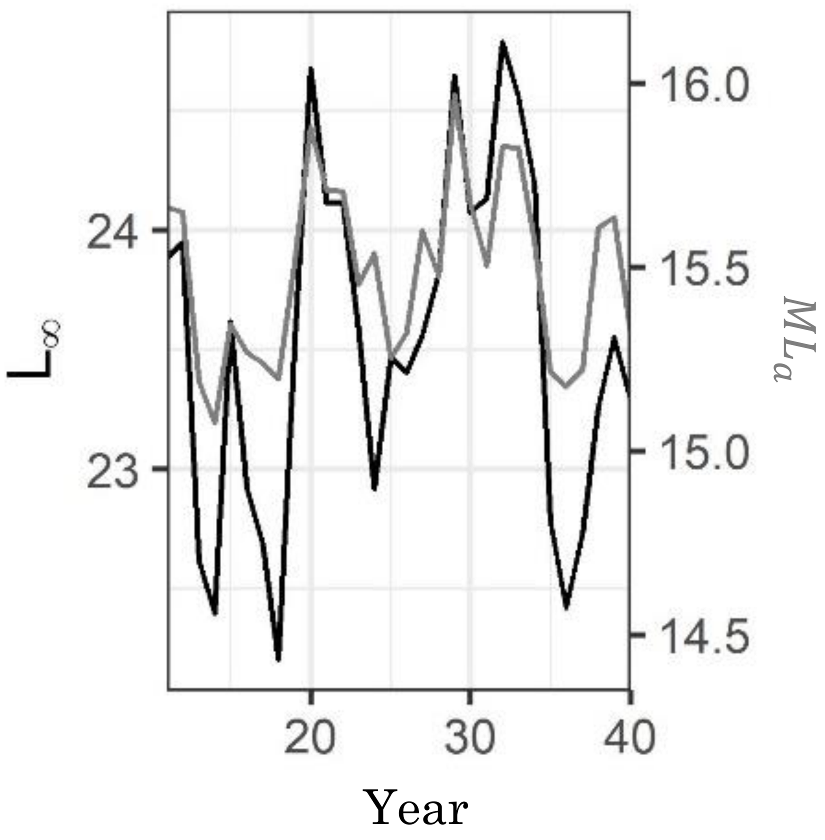


Somatic growth variability estimation

Estimation model (EM, *what we assume in the SAM*)

When OM simulates **temporal** variability, EM:

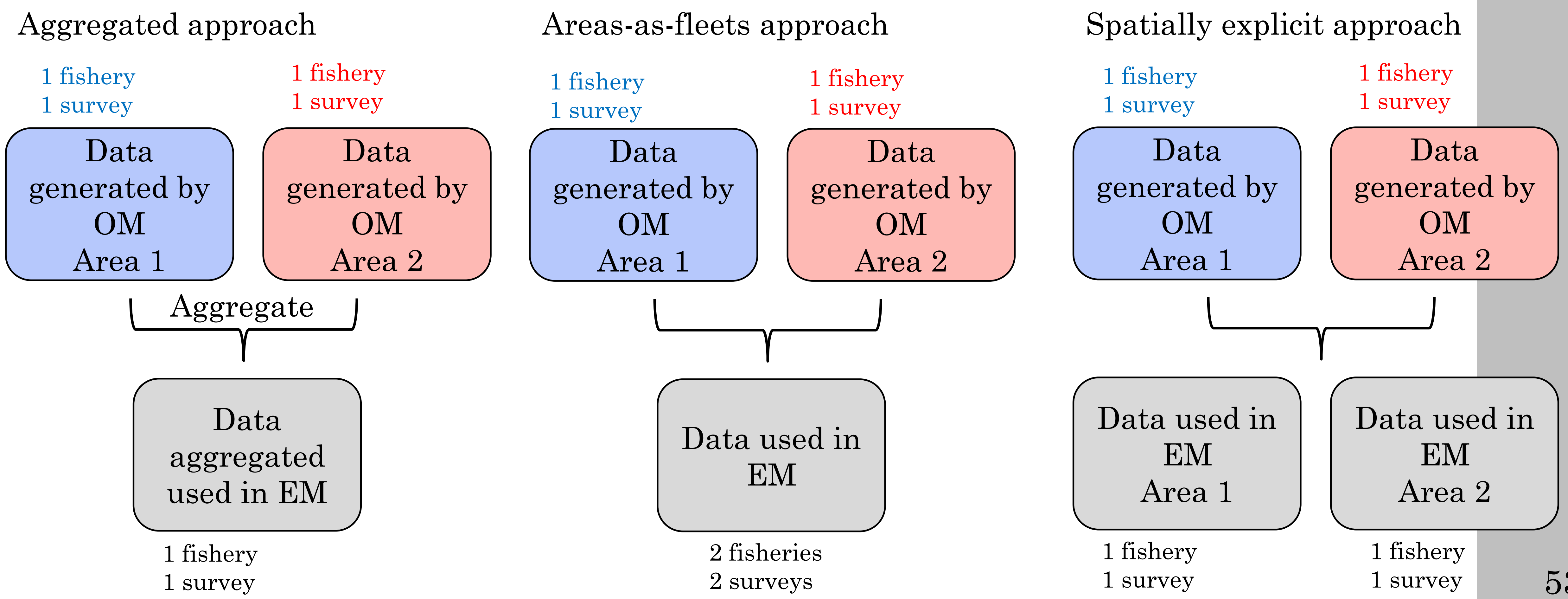
- Constant: Assumes k or L_∞ constant over time
- Env index: Includes an 'observed' environmental index (env_{obs})
- Deviates: Estimates deviates for k or L_∞ per year or cohort



Somatic growth variability estimation

Estimation model (EM, *what we assume in the SAM*)

When OM simulates **spatial** variability, EM:



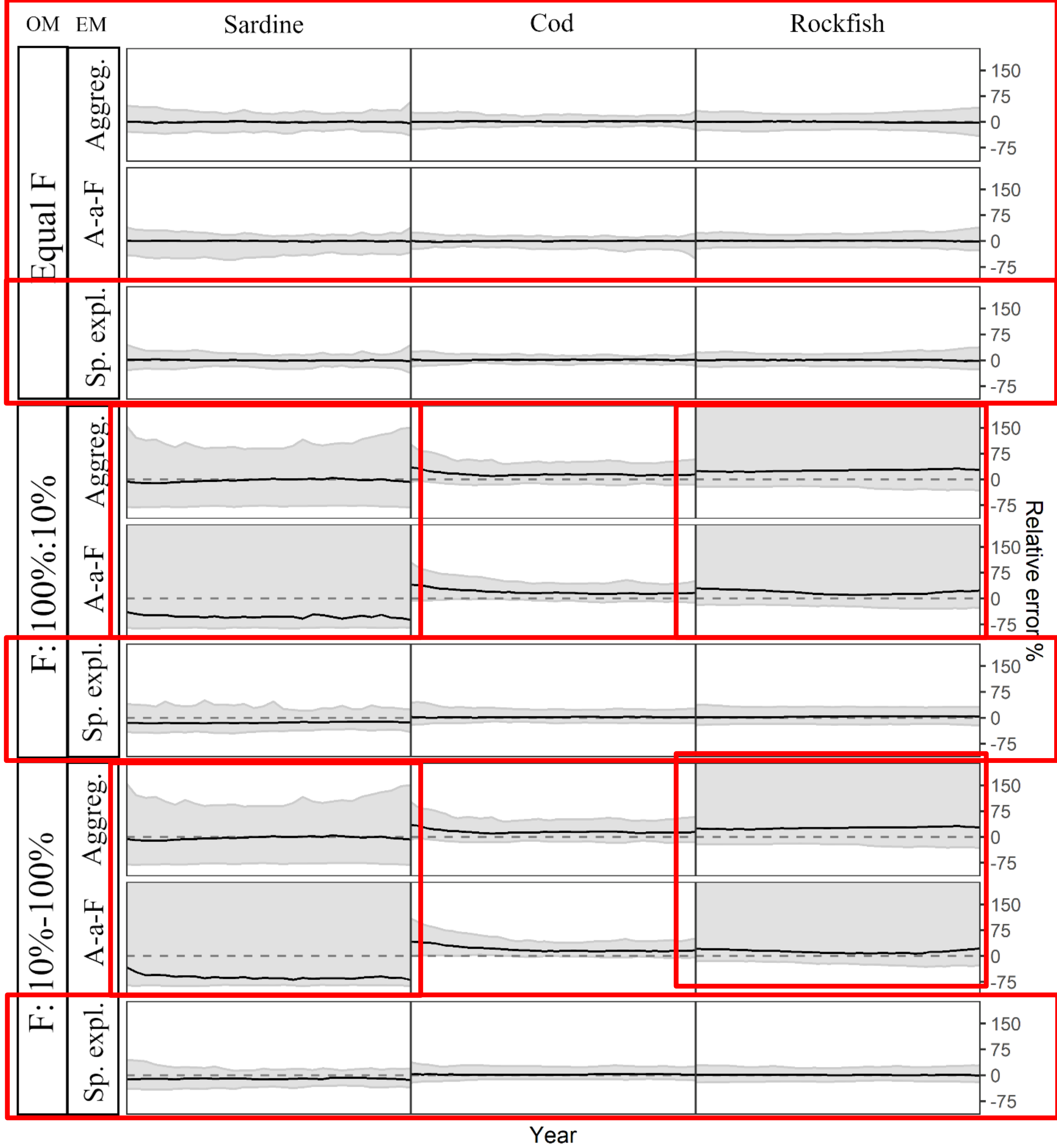
Results: Spatial variability

- 100 replicates per scenario
- Relative error (a measure of bias) of spawning biomass over time

OM:

- **No** spatial variability in somatic growth included.

- Good performance when F equally distributed between areas
- Spatially-explicit models always had a good performance
- Bad performance of models that ignored spatial structure.

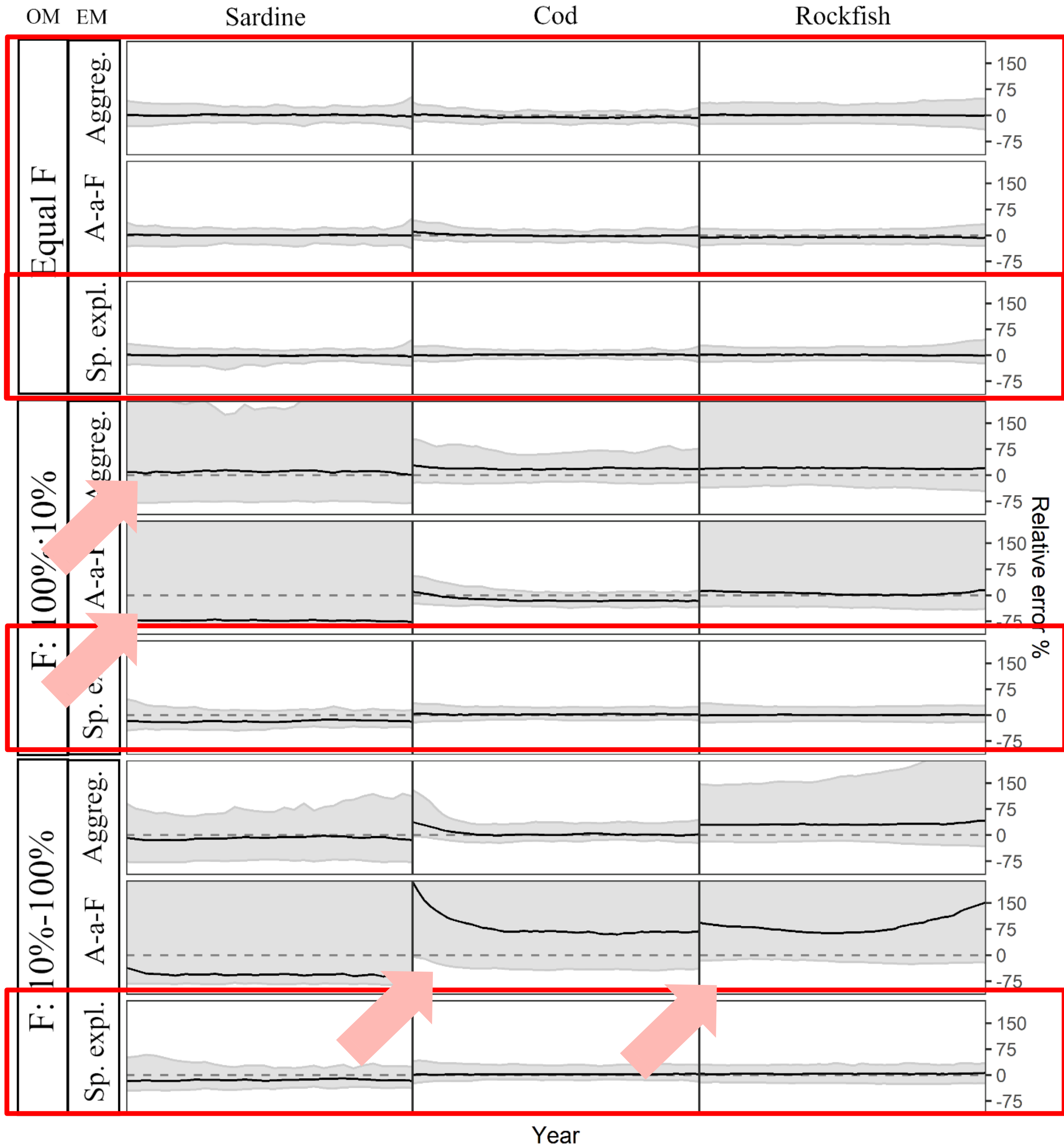


Results: Spatial variability

OM:

- Spatial variability in somatic growth included.

- Spatially-explicit models also had the best performance
- Growth variability by itself did not produce large impacts
- Main result: growth spatial variability worsened approaches that ignored spatial structure

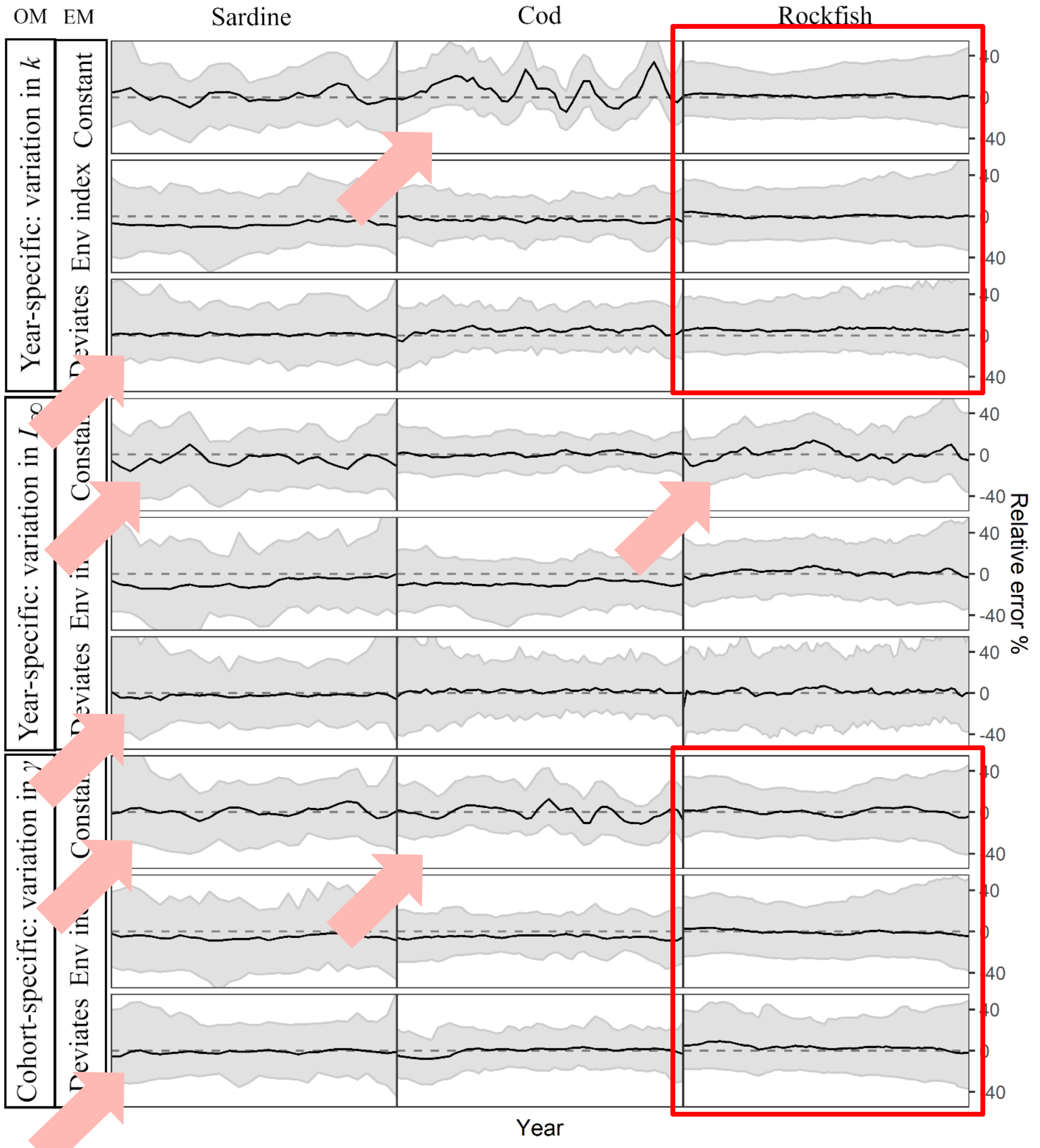


Results: Temporal variability

OM:

- Temporal variability in size-at-age.

- Ignoring temporal variability in growth led to years with under or overestimation.
- Some species were not affected by varying growth parameters.
- Estimating deviates showed the best performance.



Conclusions

- Spatial variability in somatic growth:
  - Approaches that ignored spatial structure → bad performance.
  - Spatially-explicit approach → best performance.
  - Only variability in growth may not produce bias in SSB.
  - Important to consider in SAM when variability in F also present.
- Temporal variability in somatic growth:
  - Ignoring either year or cohort-specific variability might produce bias in SSB estimates.
  - Including an environmental index or estimating deviates produced unbiased SSB estimates.

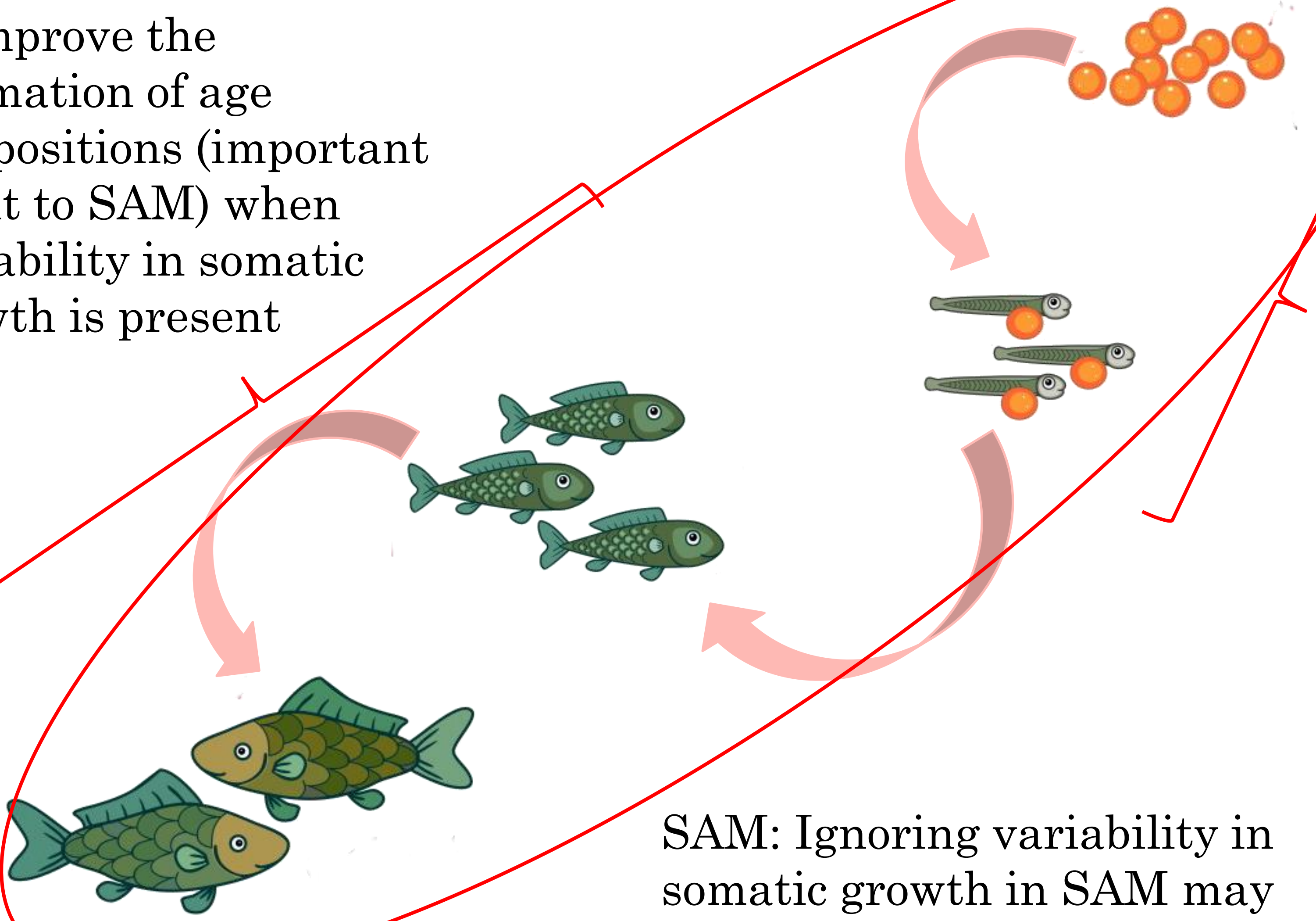
https://github.com/gmoroncorrea/spatiotemporal_growth

Conclusions

General conclusions

Somatic growth variability is present throughout the fish's lifespan.

Statistical models: useful to improve the estimation of age compositions (important input to SAM) when variability in somatic growth is present



IBM: Future ocean conditions might increase growth rates but decrease recruitment of the Pacific cod in the EBS

Multiple approaches to study somatic growth in fish populations

SAM: Ignoring variability in somatic growth in SAM may lead to large bias in outputs

Acknowledgements

Fisheries Oceanography Lab:
Jenn, Lorenzo, Rebecca, Laura, Derek, Caren, Kaia, and all!

Former mentors:
All my peers at IMARPE

My family:
Paola, Rosa, Andreana, Lesly, Helar, Maja, Leo, Ander, and my new family!

Academic support:
Lorenzo Ciannelli
Grant Thompson
Stan Kotwicki
Lewis A.K. Barnett
Carey McGilliard
Claudio Fuentes
Trond Kristiansen
Thomas Hurst
William Stockhausen
Darren Pilcher
and professors in CEOAS

My friends
Jenn, Nilza, Estefania, Kirsten, Keiko, Ben, Aidan, and all!

Funding support:

Oregon State University
College of Earth, Ocean, and Atmospheric Sciences

NOAA FISHERIES

Thank you!
Questions?

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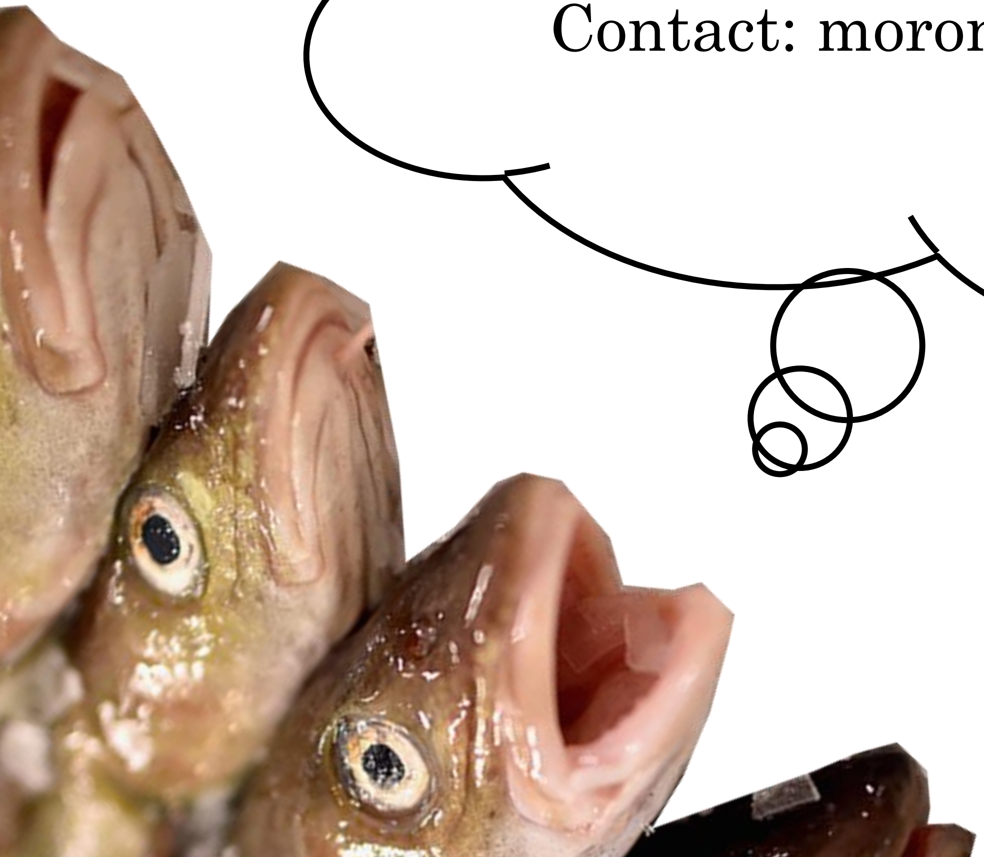
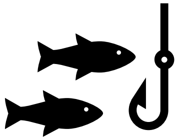


My Ph.D. journey:

Fisheries management



Ocean conditions