Spatial assessment model for snow crab

Maxime Olmos

CPT, May 16 2022

Aquatic and Fishery Sciences
University of Washington

National Oceanic and Atmospheric Administration
U.S. Department of Commerce
NOAA

~~***Spatial assessment model for snow crab***~~

SPATIOTEMPORAL CONSIDERATIONS TO BETTER UNDERSTAND, PREDICT AND MANAGE NATURAL RESSOURCES

Eastern Bering Sea snow crab as a case study

Maxime Olmos

CPT, May 16 2022

Acknowledge

- **Cody Szuwalski**
- **Andre Punt**
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AQUATIC AND FISHERY SCIENCES
UNIVERSITY of WASHINGTON

|OUTLINE OF THIS TALK| A Summary of 2 postdoc projects on snow crab

1. IPM

2. MSE

|OUTLINE OF THIS TALK| A Summary of 2 postdoc projects on snow crab

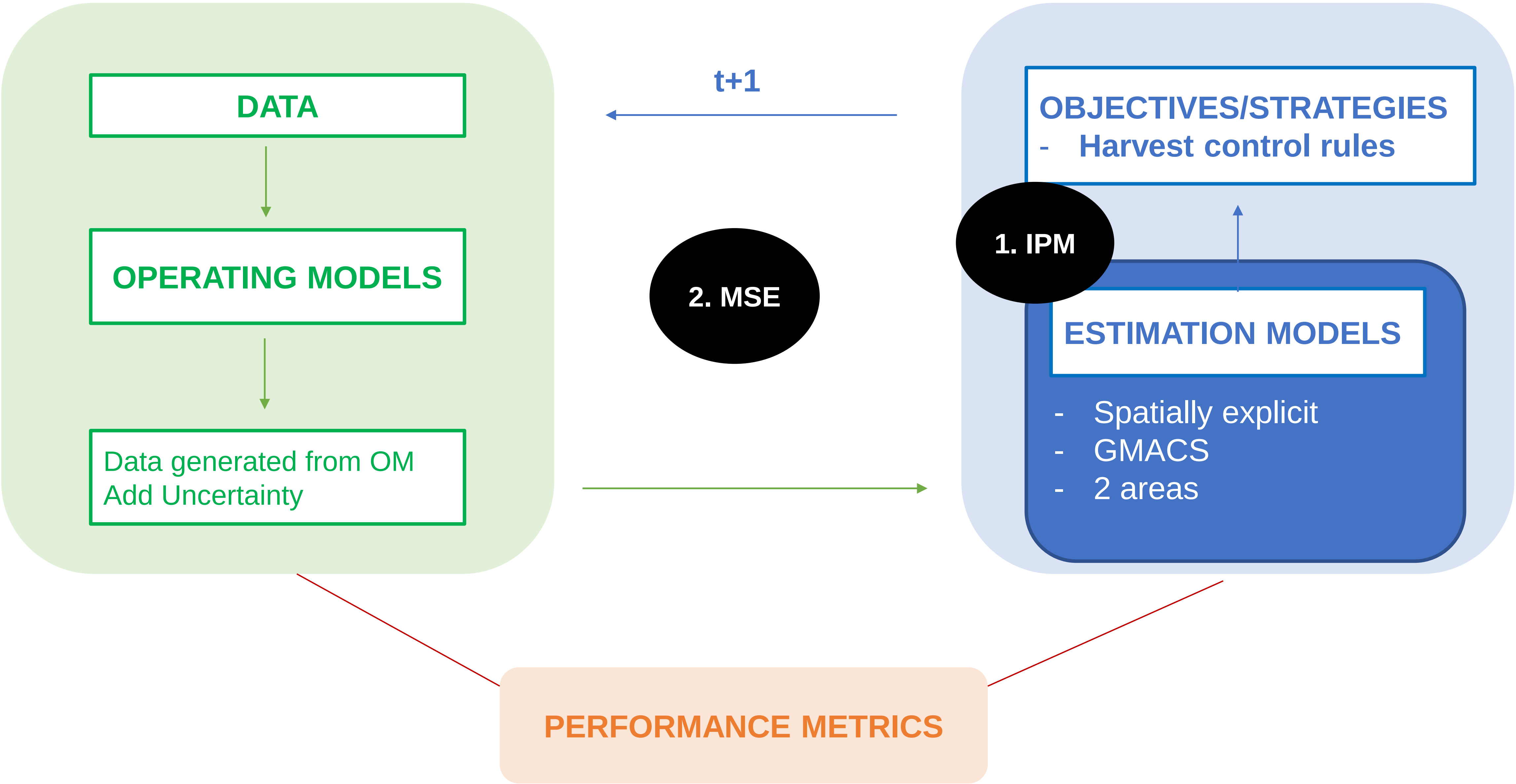
2. MSE

1. IPM

ESTIMATION MODELS

- Spatially explicit

|OUTLINE OF THIS TALK| A Summary of 2 postdoc projects on snow crab



|OUTLINE OF THIS TALK| A Summary of 2 postdoc projects on snow crab

1. IPM

ESTIMATION MODELS

- Spatially explicit

|CONTEXT| Motivations : accounting for spatial heterogeneity

- **Addressing spatial heterogeneity in population dynamics → critical to better manage natural resources**

- **Accounting for spatial processes in population dynamic is complex**

- **Management of natural resources → simplify assumptions about population spatial structure**

Contents lists available at ScienceDirect

Fisheries Research

journal homepage: www.elsevier.com/locate/fishres

Essential features of the next-generation integrated fisheries stock assessment package: A perspective

André E. Punt[a,b,*], Alistair Dunn[c], Bjarki Þór Elvarsson[d], John Hampton[e], Simon D. Hoyle[f], Mark N. Maunder[g,h], Richard D. Methot[i], Anders Nielsen[j]

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Spatial stock assessment methods: A viewpoint on current issues and assumptions

André E. Punt[a,b,*]

|CONTEXT| Solution : State-space spatiotemporal IPM

- **Spatiotemporal IPMs can be implemented at a finer spatial scale**
  - Allow population processes to vary continuously across space by utilizing spatial correlation to account for a continuous approximation of spatial dynamics
  - Can directly fit to fishery and survey data at the scale they are collected
  - Attribute variation in survey data among sampling location to both sampling error and spatial process heterogeneity

326
NRC Research Press
ARTICLE
Estimating spatio-temporal dynamics of size-structured populations
Kasper Kristensen, Uffe Høgsbro Thygesen, Ken Haste Andersen, and Jan E. Beyer

1808
NRC Research Press
ARTICLE
A spatiotemporal model for snow crab (*Chionoecetes opilio*) stock size in the southern Gulf of St. Lawrence[1]
Noel G. Cadigan, Elmer Wade, and Anders Nielsen

Ecology, 98(5), 2017, pp. 1277–1289
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Estimating partial regulation in spatiotemporal models of community dynamics
James T. Thorson,[1,4] Stephan B. Munch,[2] and Douglas P. Swain[3]

Explicit incorporation of spatial variability in a biomass dynamics assessment model
Raphaël R McDonald, David M Keith, Jessica A Sameoto, Jeffrey A Hutchings, Joanna M Flemming
ICES Jo

1897
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ARTICLE
Spatial delay-difference models for estimating spatiotemporal variation in juvenile production and population abundance
James T. Thorson,

Journal of Applied Ecology
British Ecological Society
Journal of Applied Ecology 2017, 54, 577–587 doi: 10.1111/1365-2664.12664
Using spatio-temporal models of population growth and movement to monitor overlap between human impacts and fish populations
James T. Thorson*, Jason Jannot and Kayleigh Somers

|CONTEXT| Solution : State-space spatiotemporal IPM

- **Spatiotemporal IPMs can be implemented at a finer spatial scale**
  - Allow population processes to vary continuously across space by utilizing spatial correlation to account for a continuous approximation of spatial dynamics
  - Can directly fit to fishery and survey data at the scale they are collected
  - Attribute variation in survey data among sampling location to both sampling error and spatial process heterogeneity

- **But still some key demographic processes to refine**
  - Movement
    - Explicitly

    → How to account for movement when the spatial distribution of the stock may change between the survey and the fishery

    - Implicitly

|CONTEXT| Case study : Snow Crab EBS

- **Spatial considerations are important for snow crabs in the EBS**
  - Biomass strongly declined recently (Zacher et al., 2021)
    → A need to better understand the spatiotemporal dynamic
  - Spatially concentrated fishery
  - Ontogenetic migration
  - Stock’s association with the cold pool
  - The potential for marine heat waves to influence dynamics

|CONTEXT| Purpose of the study

- **Refine the representation of spatial processes in IPMs (migration)**

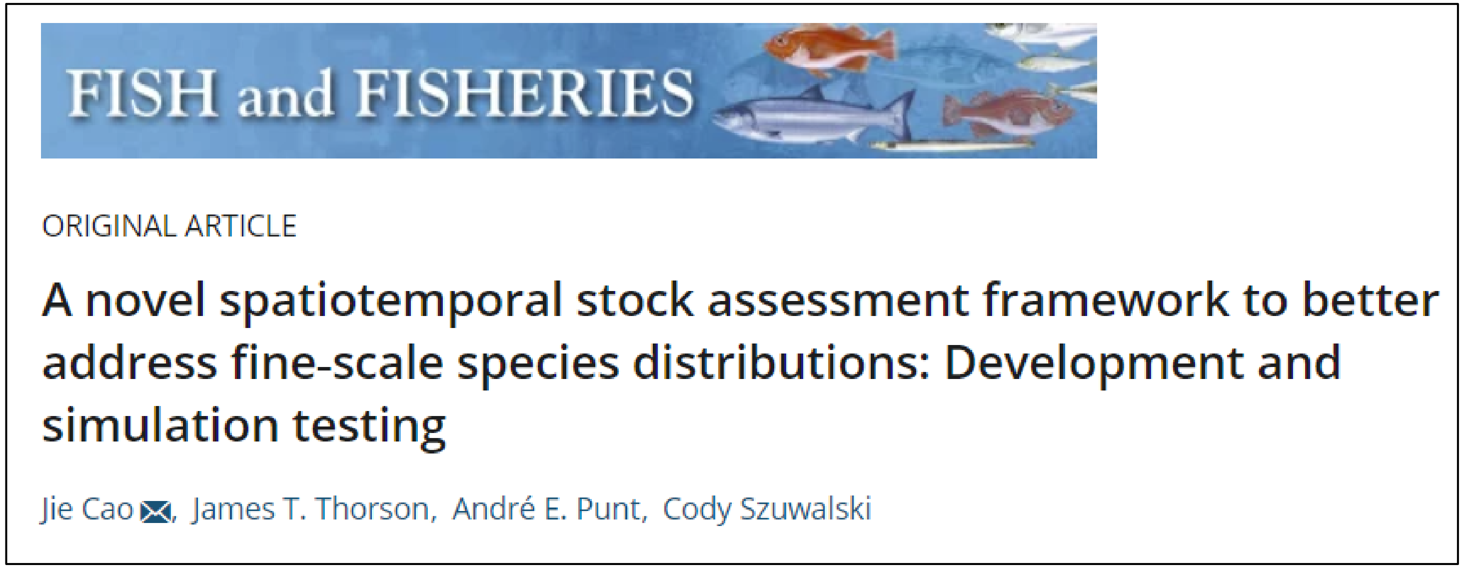
- **Use this spatially explicit framework to explore important questions**

  - To facilitate understanding of the drivers of the spatiotemporal population dynamics
    - Q1 : The effect of the cold pool on spatio-temporal variation in juvenile distribution ?

  - To Improve management advice
    - Q2 : Distribution of fishing mortality in space ?

|CONTEXT| Purpose of the study

- **The basic framework of our model is conceptually similar to Cao et al. (2020)**



FISH and FISHERIES

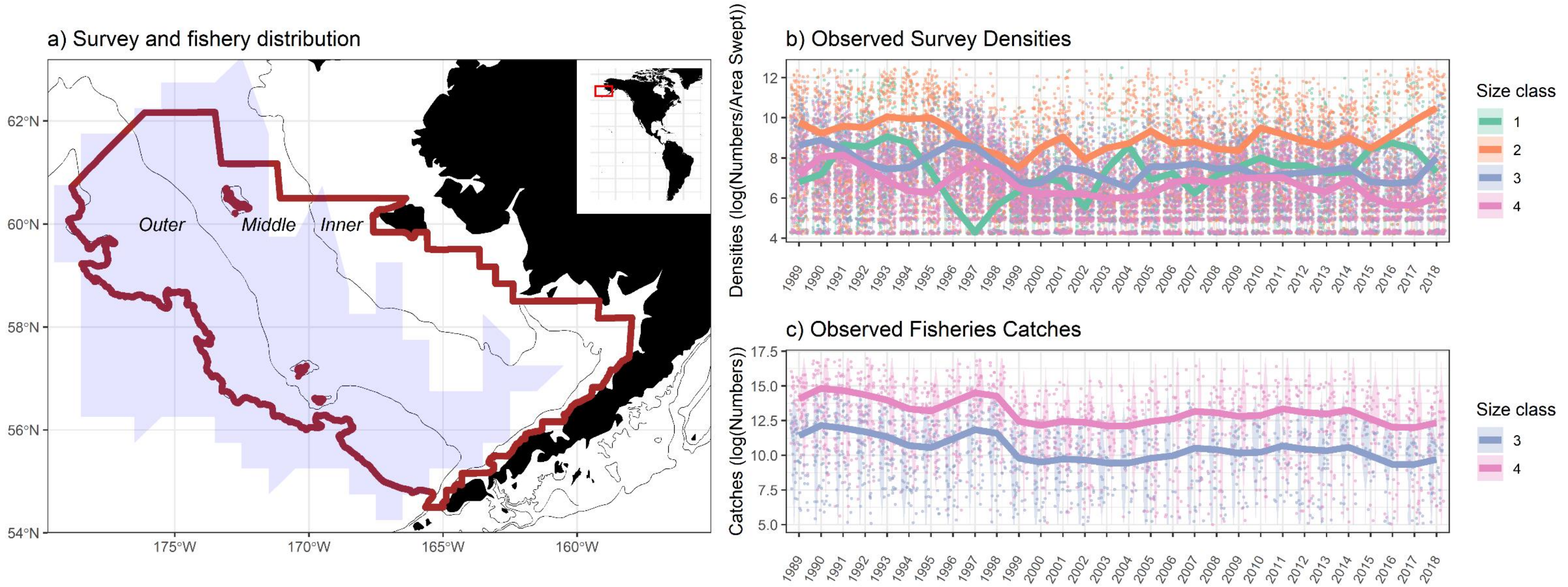
ORIGINAL ARTICLE

A novel spatiotemporal stock assessment framework to better address fine-scale species distributions: Development and simulation testing

Jie Cao, James T. Thorson, André E. Punt, Cody Szuwalski

|CONTEXT| Purpose of the study

- **The basic framework of our model is conceptually similar to Cao et al. (2020)**
- **With several improvements**
  - Fit to real data
  - The representation of several biological and sampling processes is improved (e.g. selectivity and maturity) and we account implicitly for seasonal movement.



|METHODS|

|METHODS| A Spatiotemporal size-structured population model

- **Size structure spatiotemporal population model**
    - Combines theory and methods from population dynamics and geostatistics
    - Assumes population density varies continuously across space
    - Tracks variation in population density for multiple life stages and their expected dynamics across space and time

|METHODS| A Spatiotemporal size-structured population model

1. **POPULATION DYNAMIC**

2. **DATA AND LIKELIHOOD**
   - Movement : accounts implicitly for seasonality

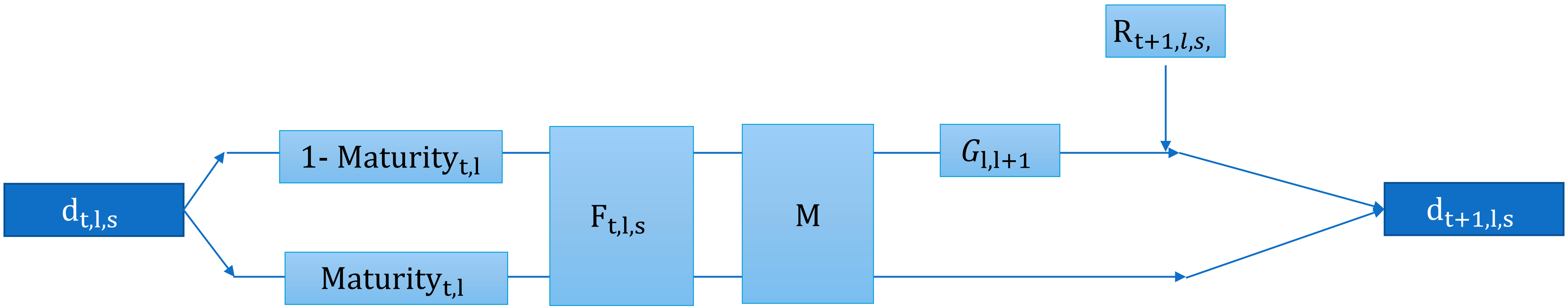
3. **PARAMETERS**
   - Pre-specified
   - Estimated
     - Fixed effects
     - Random effects

|METHODS| 1. Population Dynamic

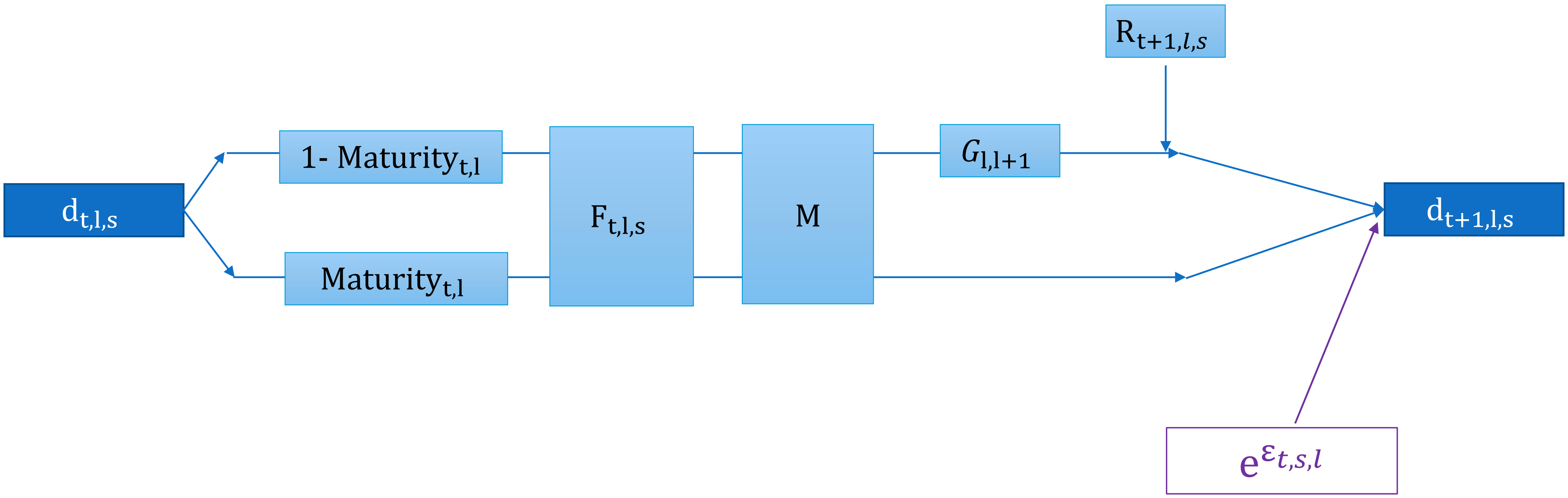
- **Densities** (d) **at size for a given size class** l**, location** s **and time** $t+1$ **is expressed as**

$$\mathrm{d}_{t+1,l,s} = g\left(\mathrm{d}_{t,s,l}\right) \times \mathrm{e}^{\varepsilon_{t,s,l}}$$

|METHODS| 1. Population Dynamic $g(\mathbf{d}_{t,s,l})$



|METHODS| 1. Population Dynamic $g(\mathbf{d}_{t,s,l})\, e^{\varepsilon_{t,s,l}}$



- $\varepsilon_{t,s,l}$ **accounts for unmodelled spatial and temporal process and follows a multivariate normal distribution**

$$vec[\boldsymbol{E}_t] \sim MVNormal(\boldsymbol{R}_{spatial} \otimes \boldsymbol{\Theta}_L)$$

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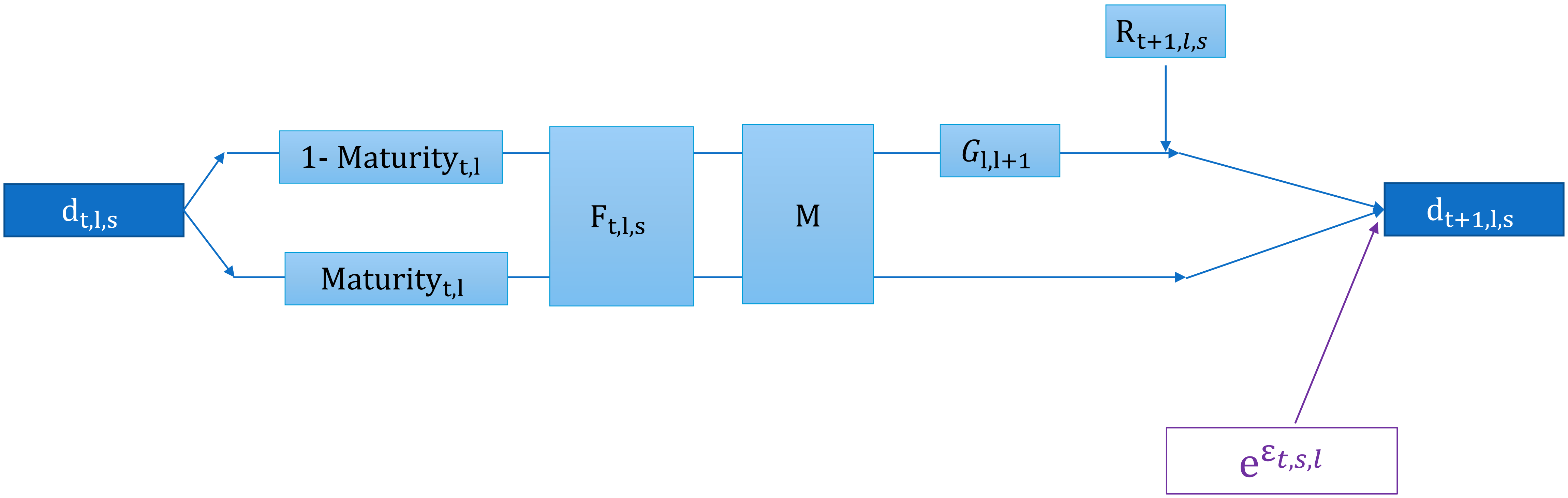


- $\varepsilon_{t,s,l}$ **accounts for unmodelled spatial and temporal process and follows a multivariate normal distribution**

$$vec[\boldsymbol{E}_t] \sim MVNormal(\boldsymbol{R}_{spatial} \otimes \boldsymbol{\Theta}_L)$$

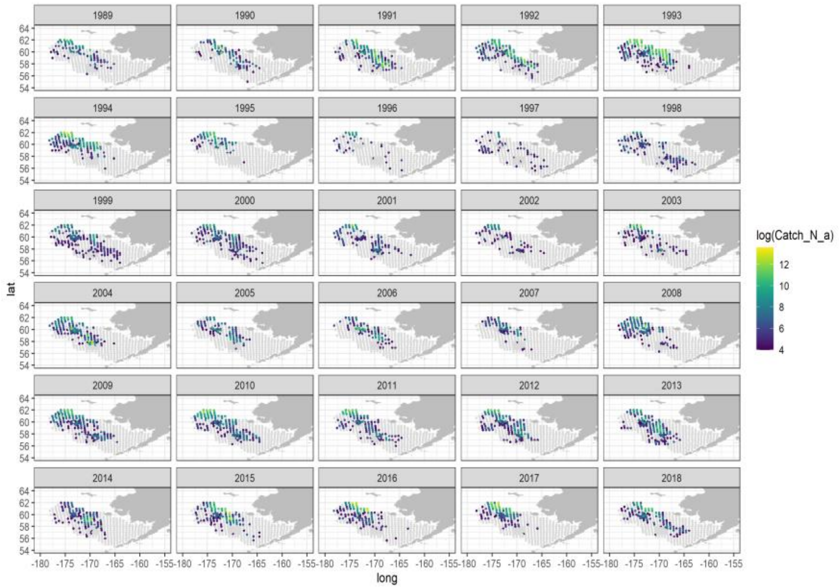
Spatial covariance matrix : between 2 locations follows a Matern function

Covariance among size classes l

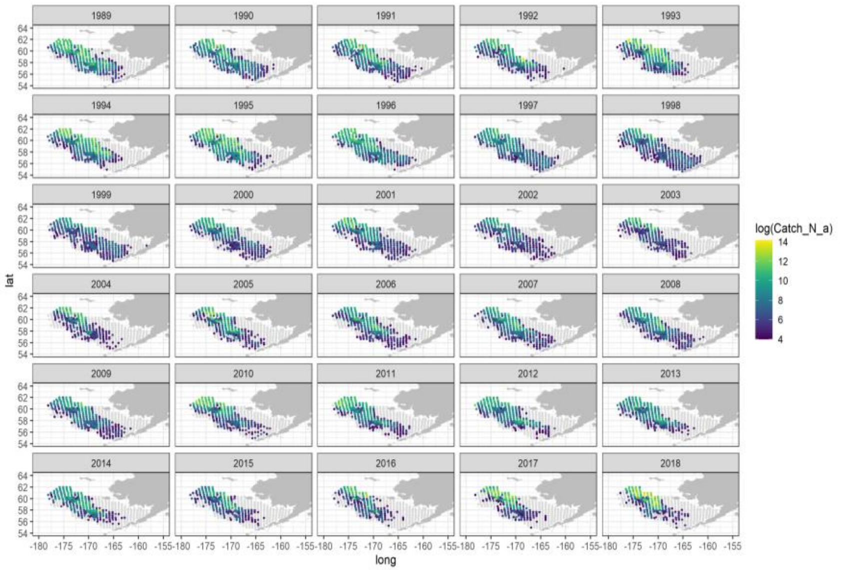
|METHODS| 2. Data – Survey Data

|METHODS| 2. Data – Survey Data : Densities (Ab/km2) – 1989 -2018

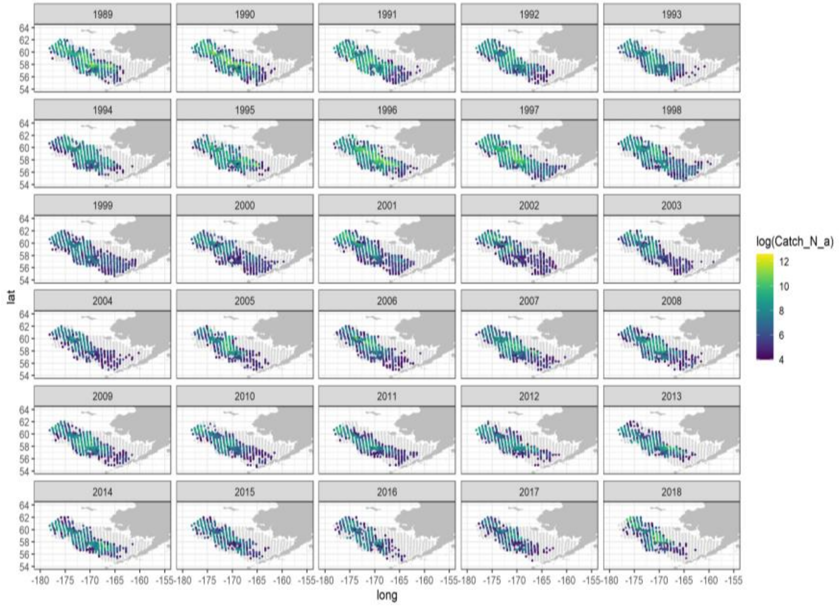
0-40mm



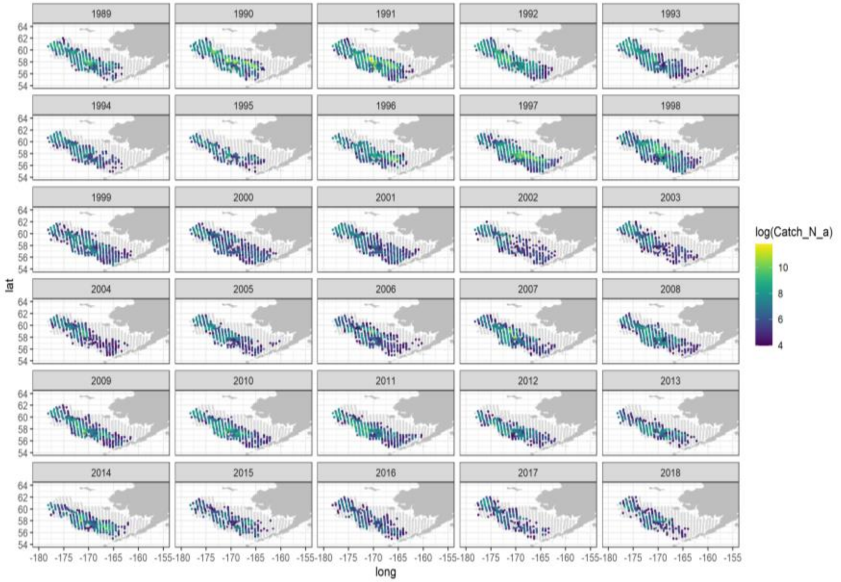
78-101mm



40-78mm



>101mm



|METHODS| 2. Data – Survey Data : Densities (Ab/km2) – 1989 -2018

- **Likelihood function**
  - Poisson link delta model (Thorson, 2017) to fit $d_{t,l,s}$ to samples of observed abundance density
  - Probability density function
    - Encounter probability
    - Positive catch rates

|METHODS| 2. Data – Fisheries data

|METHODS| 2. Data – Fisheries data

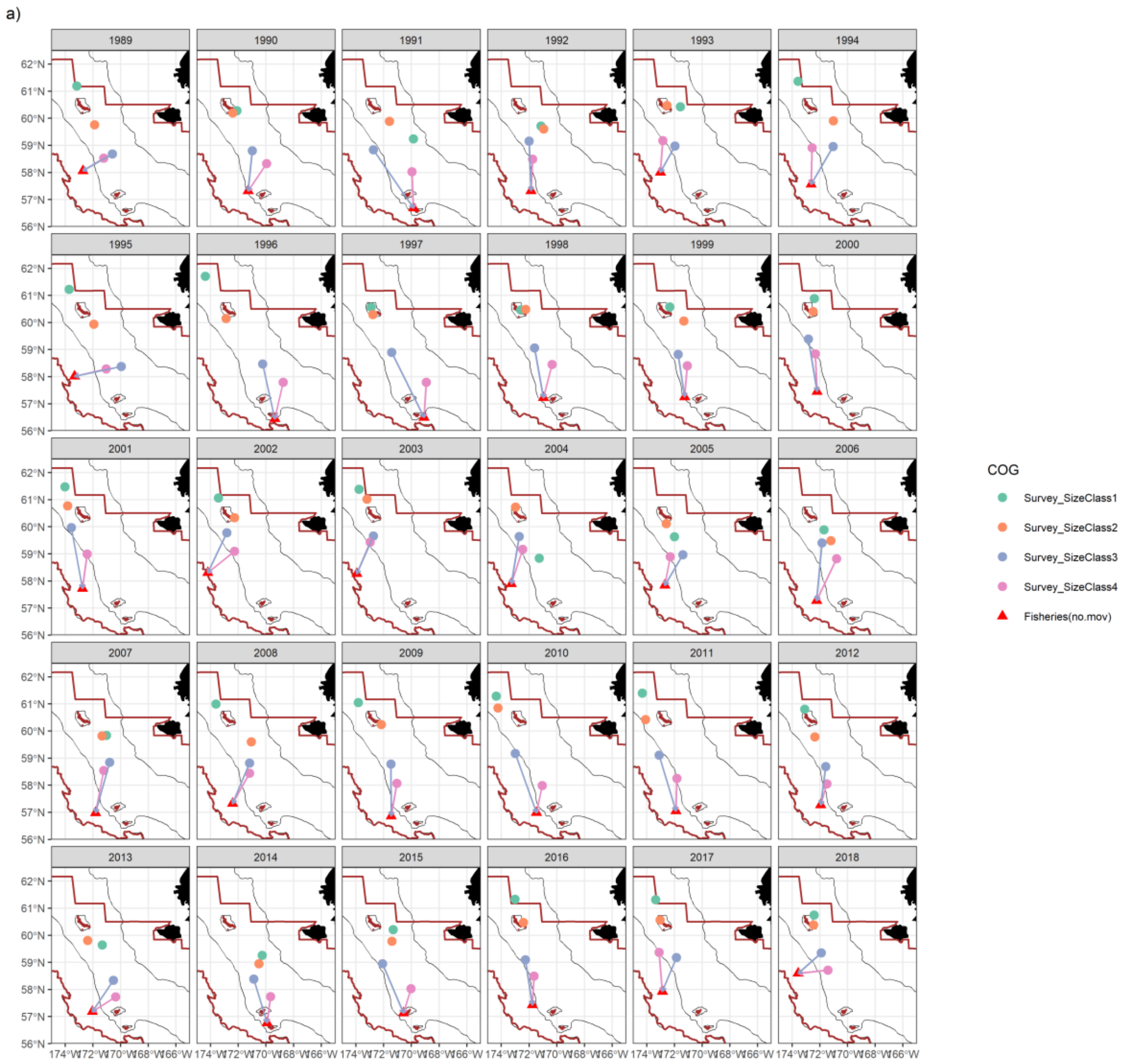
- **Temporal mismatch between Survey (summer) and Fisheries (winter)**
  - Because of ontogenetic migrations → Spatial mismatch

→ **Accounting implicitly for seasonality in the model**

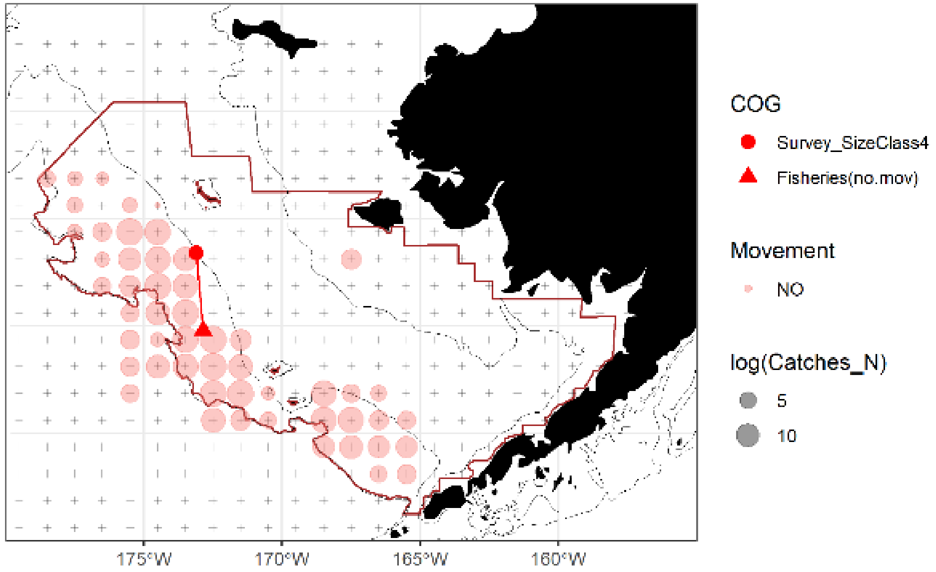
- **Strategy : Account for movement between survey and fisheries**
  - Determine the spatial distribution of Fisheries in Summer

|METHODS| 2. Data – Fisheries data

- **Accounting implicitly for movement : Difference of COG between Fisheries and Survey**



|METHODS| 2. Data – Fisheries data – Example Year = 2017



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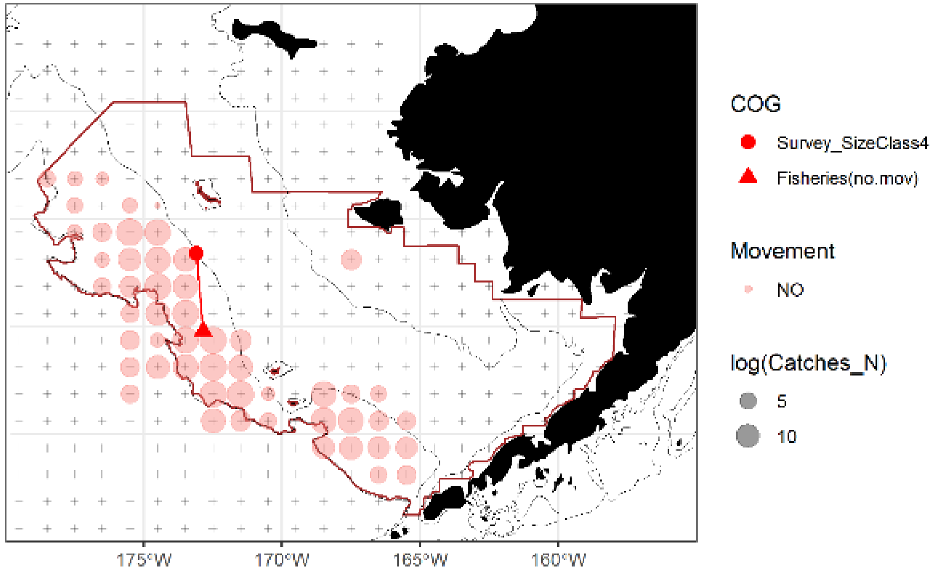

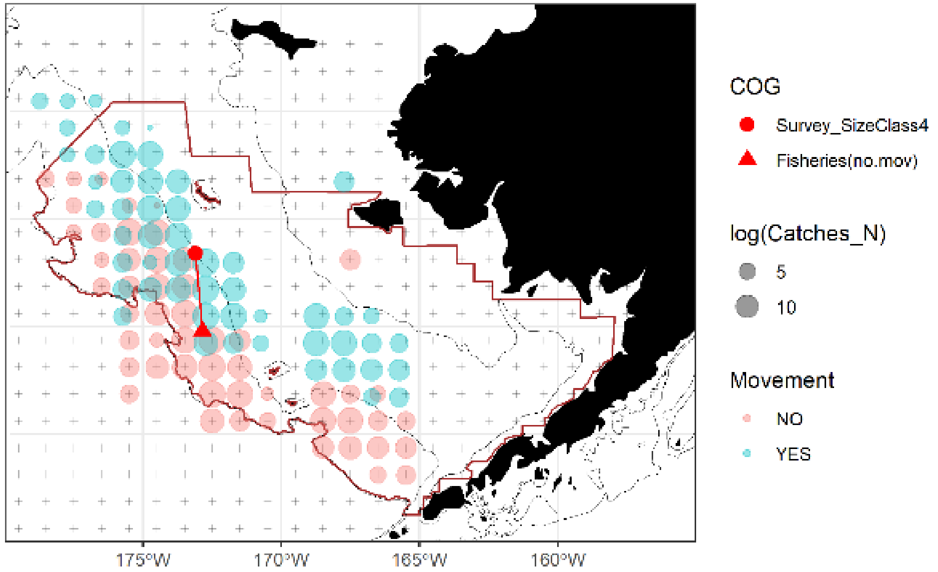

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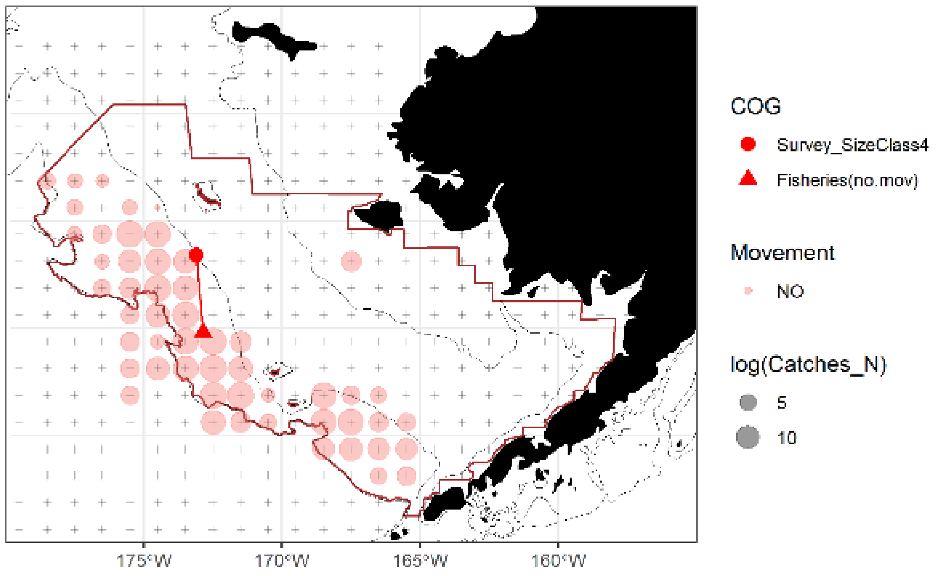

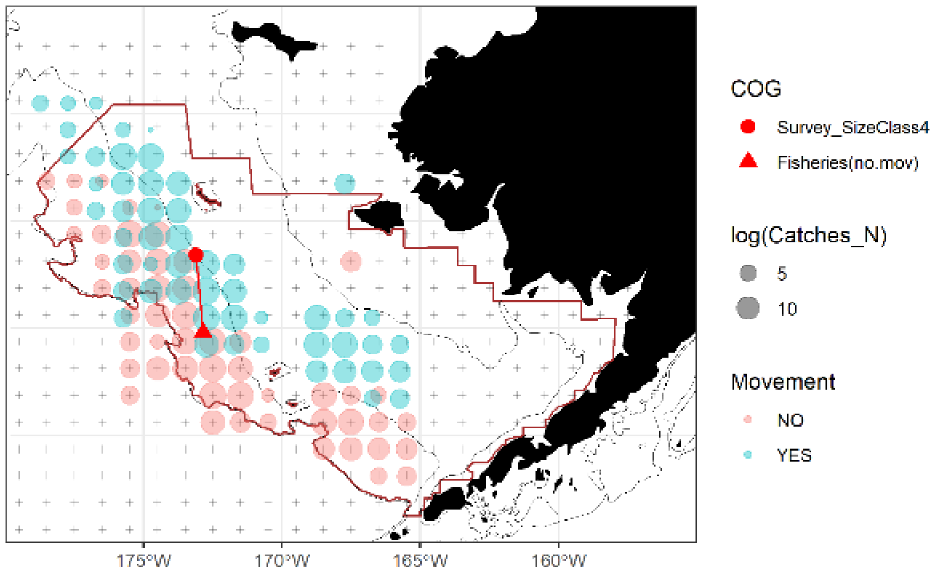

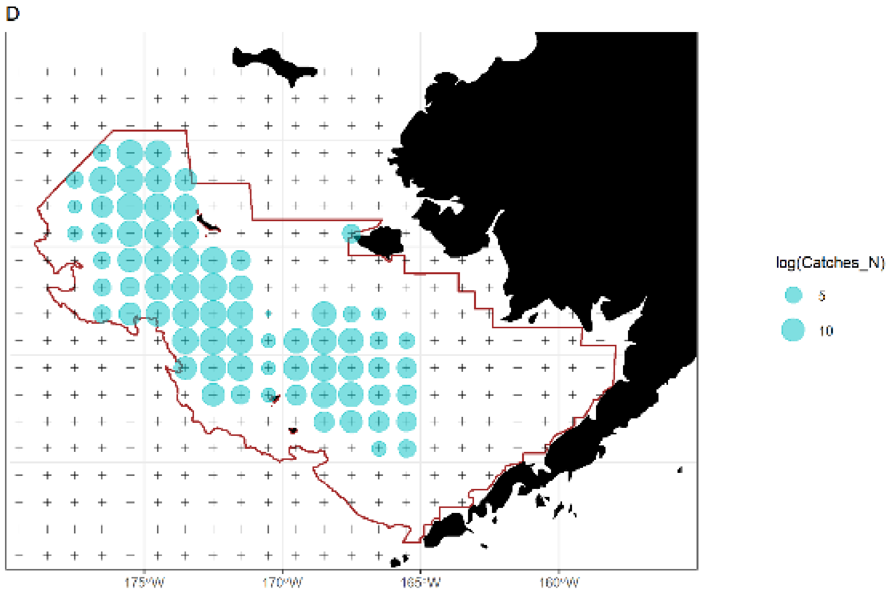

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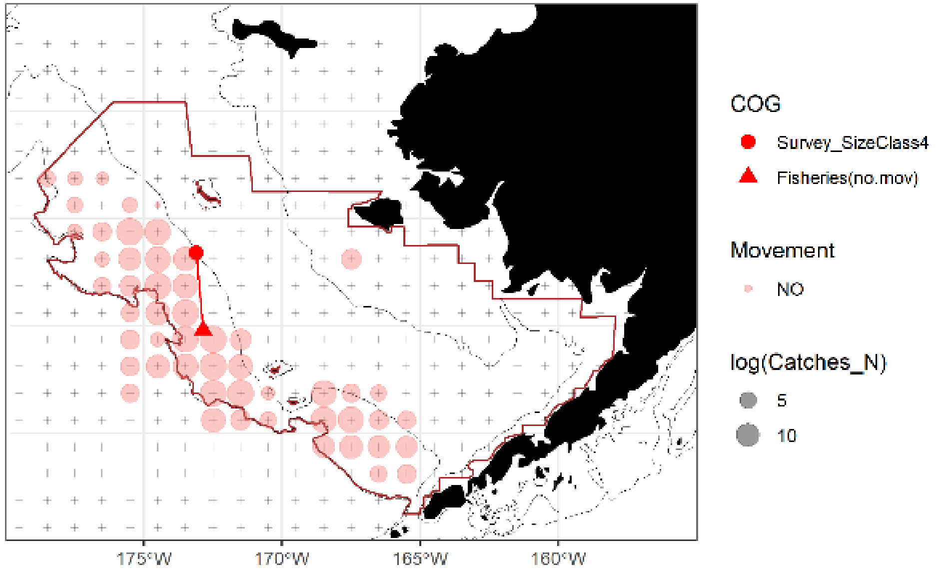

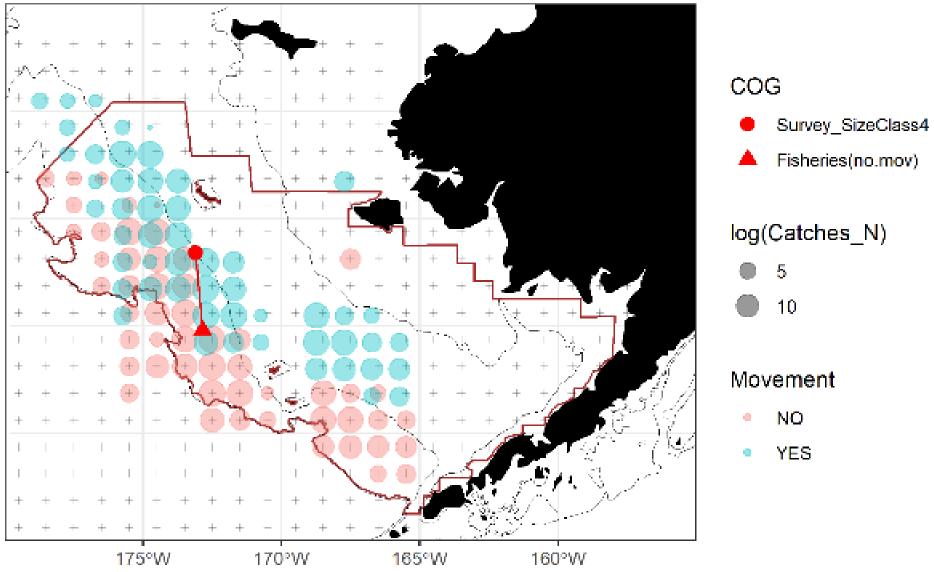

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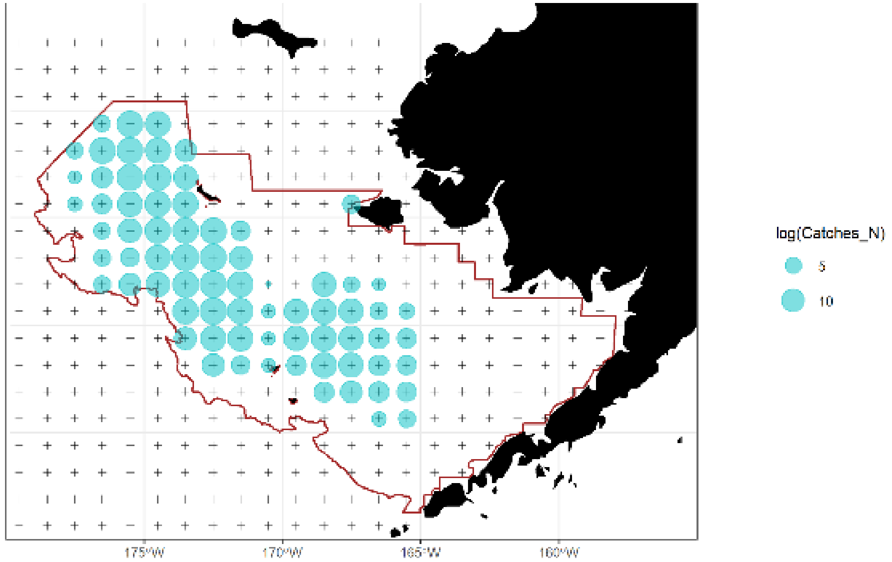

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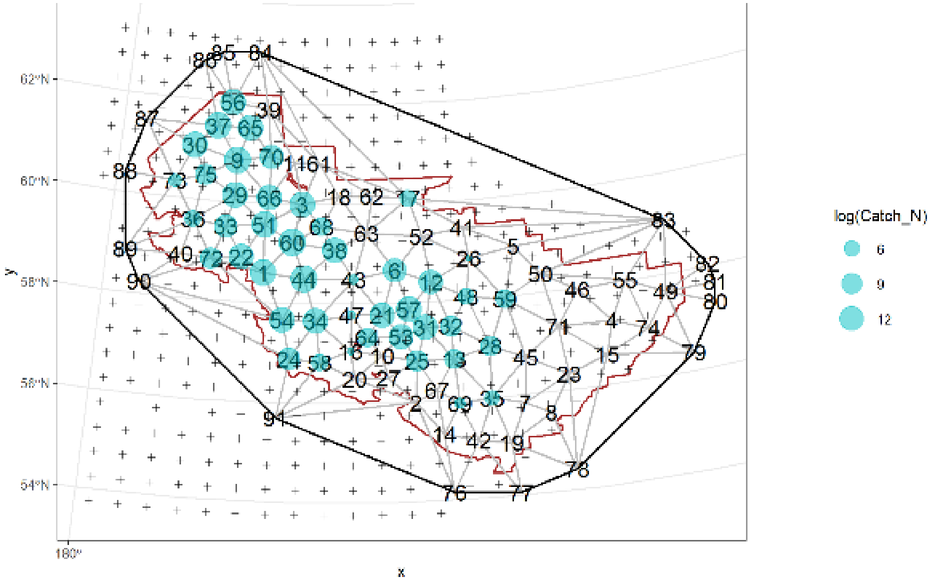
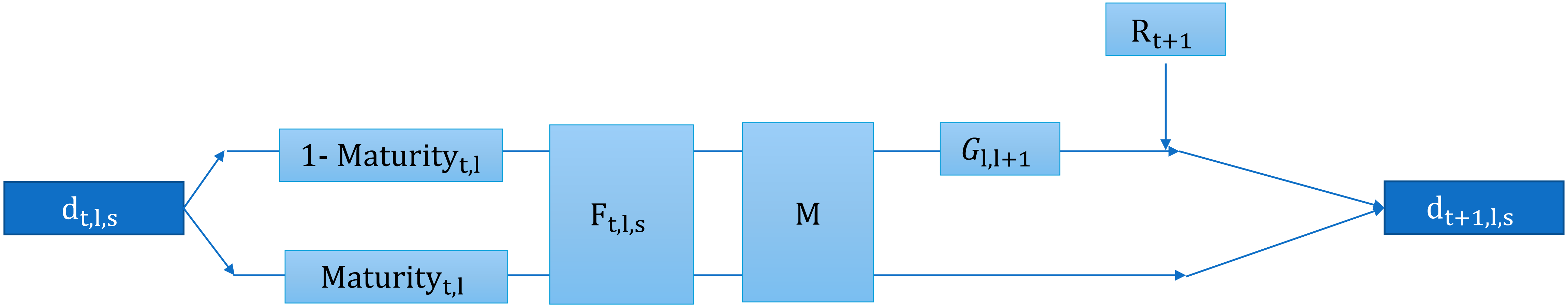
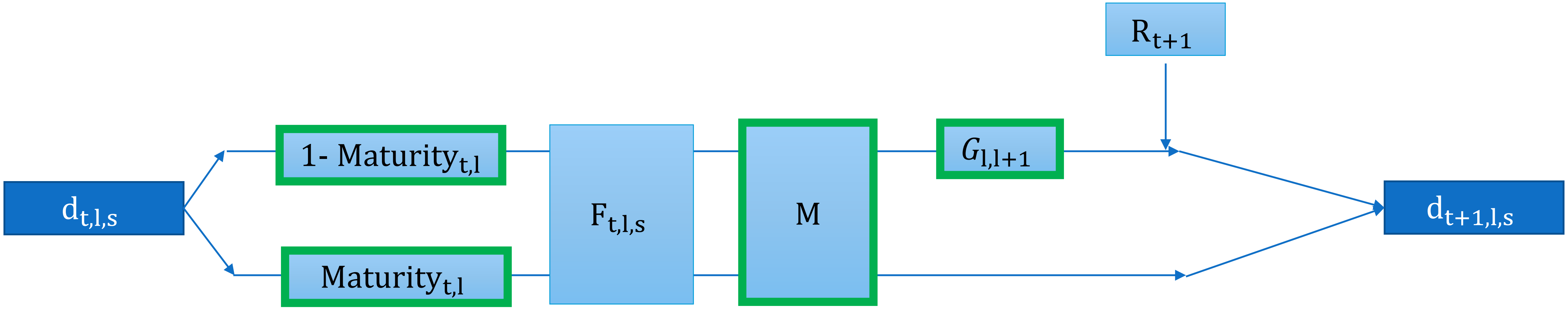


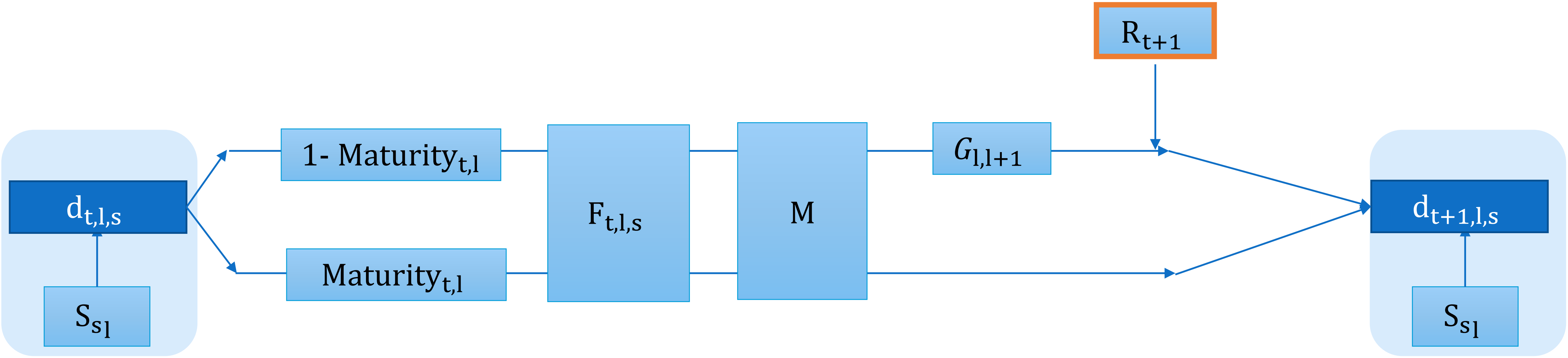
|METHODS| 3. Parameters



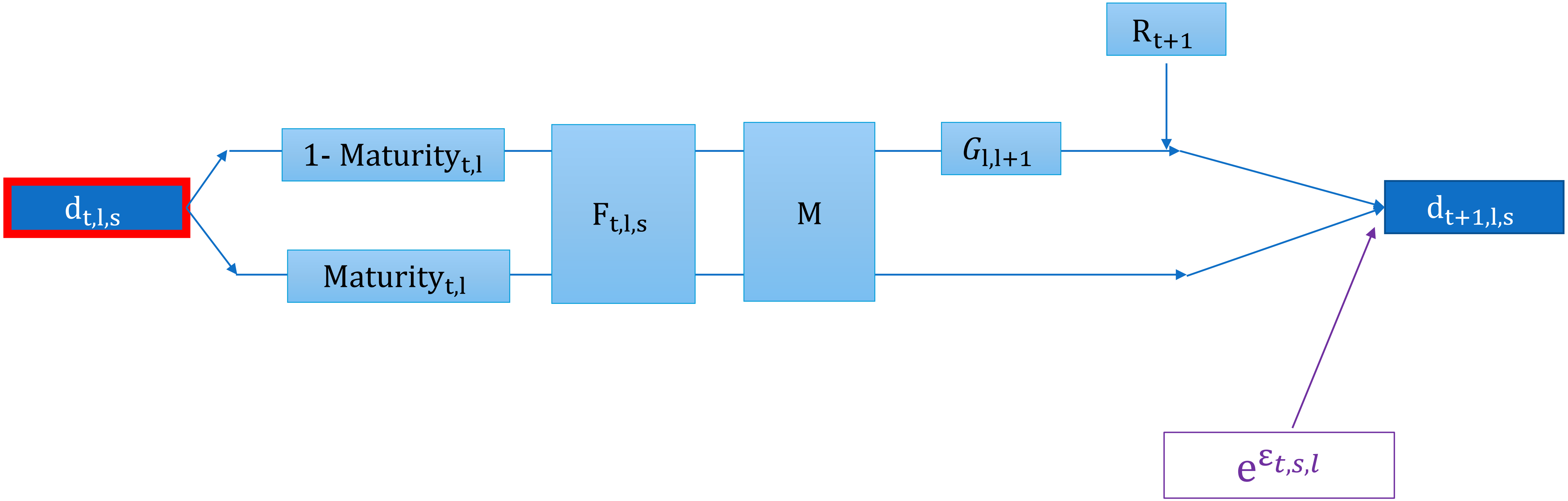
|METHODS| 3. Parameters – Pre-specified



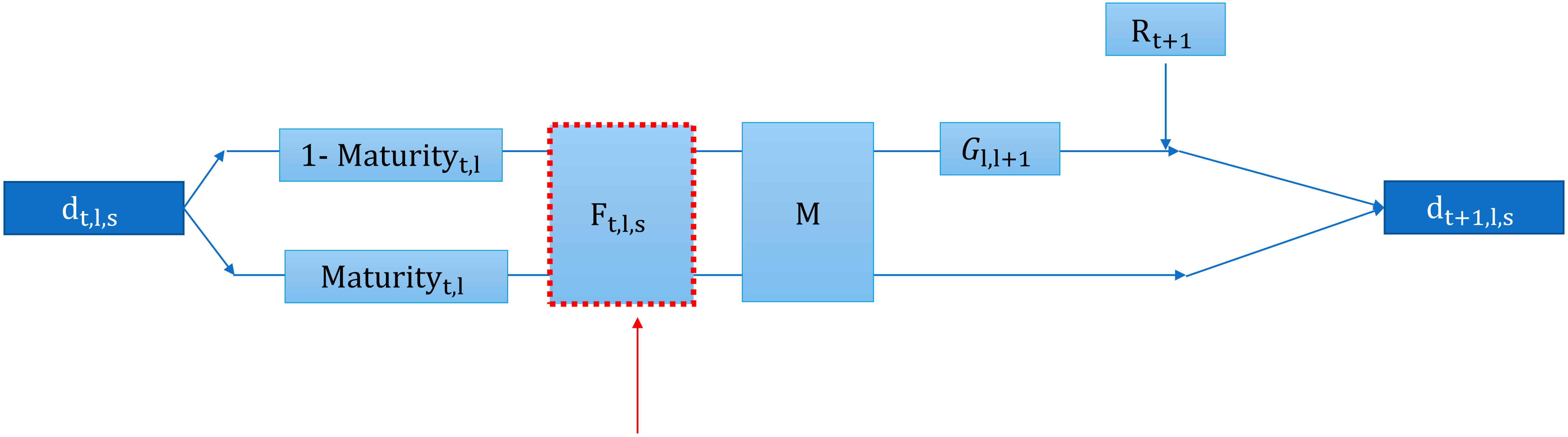
|METHODS| 3. Parameters – Fixed Effects



|METHODS| 3. Parameters – Random effects (State space parametrization)



|METHODS| 3. Parameters – Random effects – Fishing Mortality



$$\log\left(f_{t,s,l}\right) \mid \log\left(f_{t-1,s,l}\right) \sim N(\log, \left(f_{t-1,s,l}\right)\sigma^2_{f_l})$$

|METHOD| Derived quantities : Some explorations using this framework

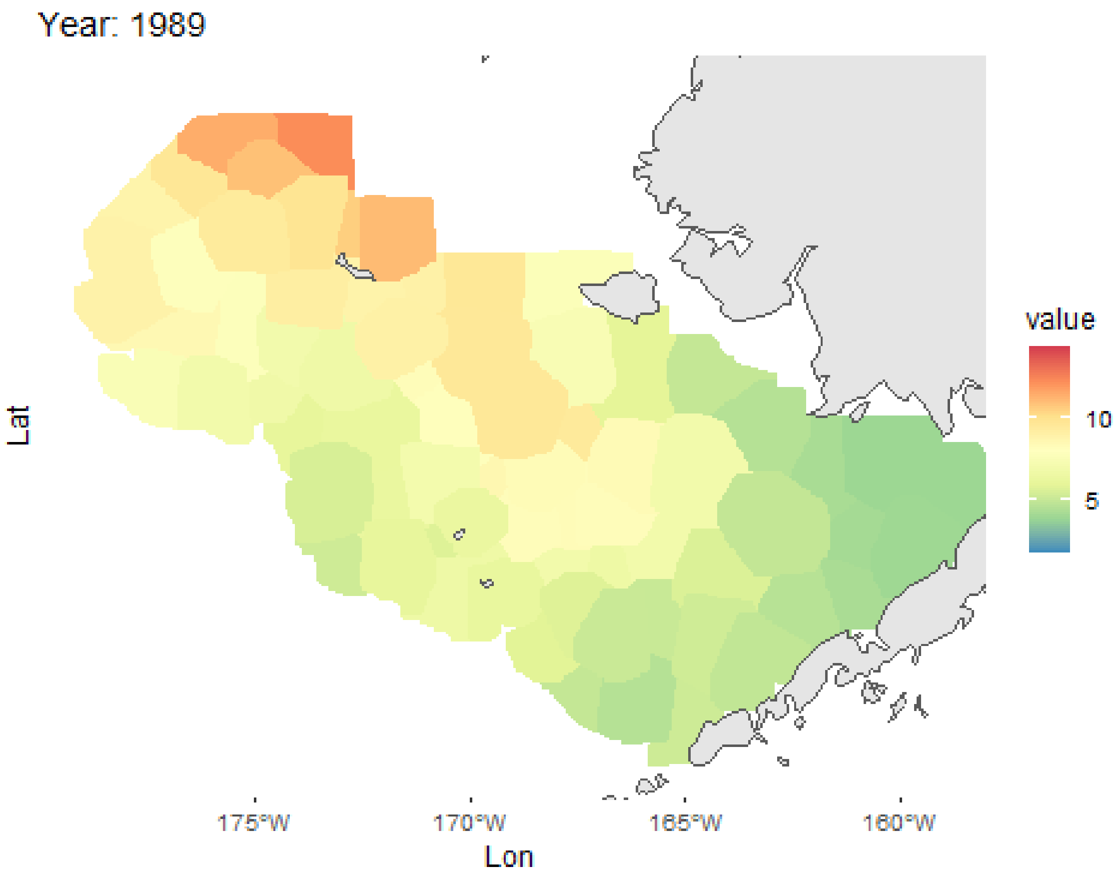
- **Q1 : The effect of the cold pool on spatio-temporal variation in juvenile distribution ?**
    - **Potential** underlying mechanisms : cold pool acts as a thermal barrier to Pacific cod and imposes a spatial mismatch between Pacific cod and juvenile crab distributions.
    - Expectation
        - ✓ During cold years the distribution of juvenile crab is spread across the Eastern Bering sea shelf
        - ✓ Whereas during warm years we expect that the distribution of juvenile crab to contract as a result of a smaller cold pool providing a smaller thermal refuge from cod predation.

- **Q2 : Distributed of fishing mortality in space**
    - By calculating exploitation rate

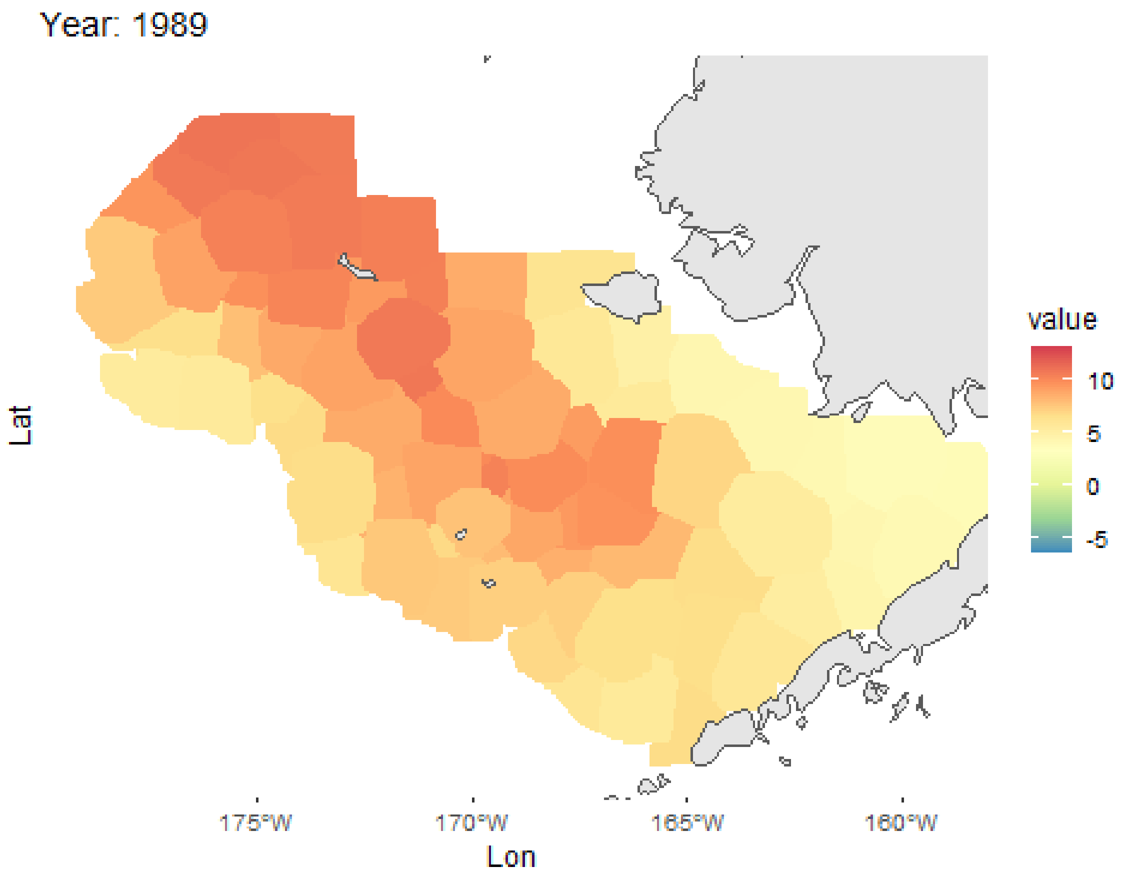
|RESULTS|

|RESULTS| Spatiotemporal changes in abundances (log scale)

Size class 1 : 0-40mm

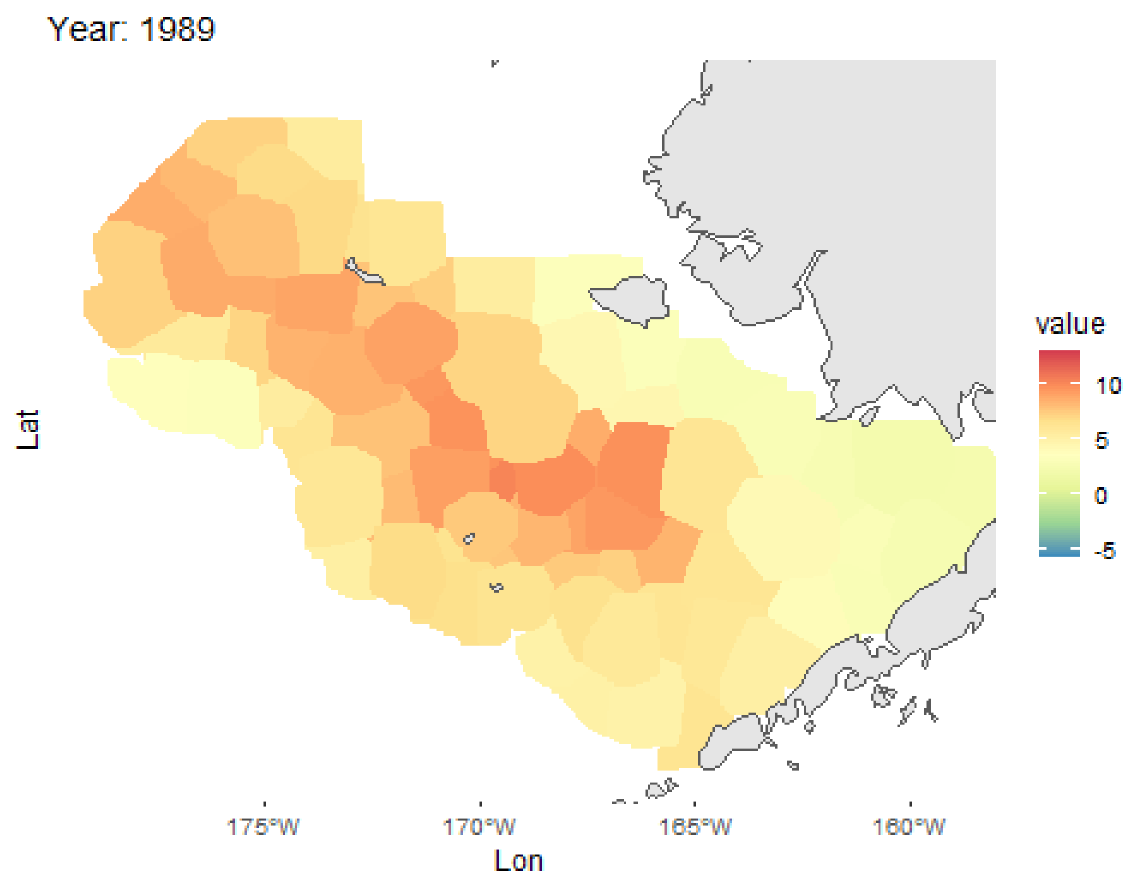


Size class 2 : 40-78mm

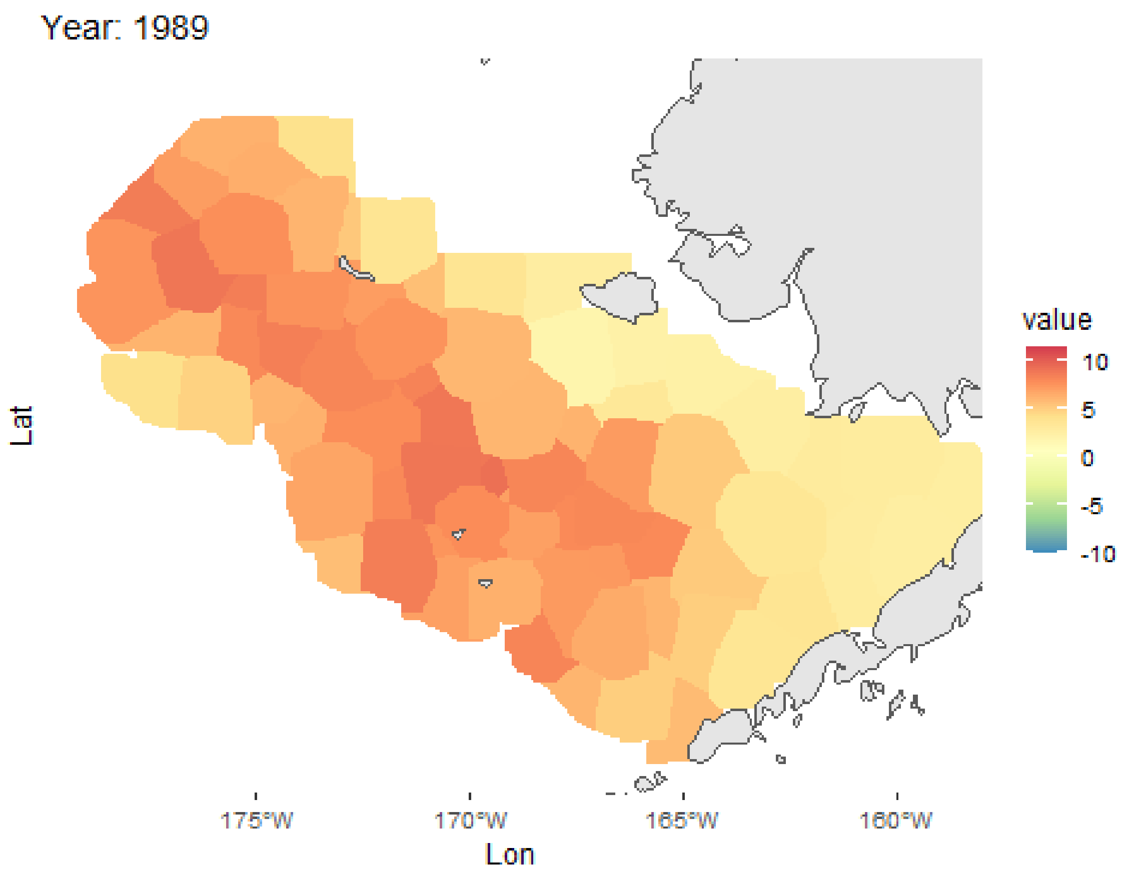


|RESULTS| Spatiotemporal changes in abundances (log scale)

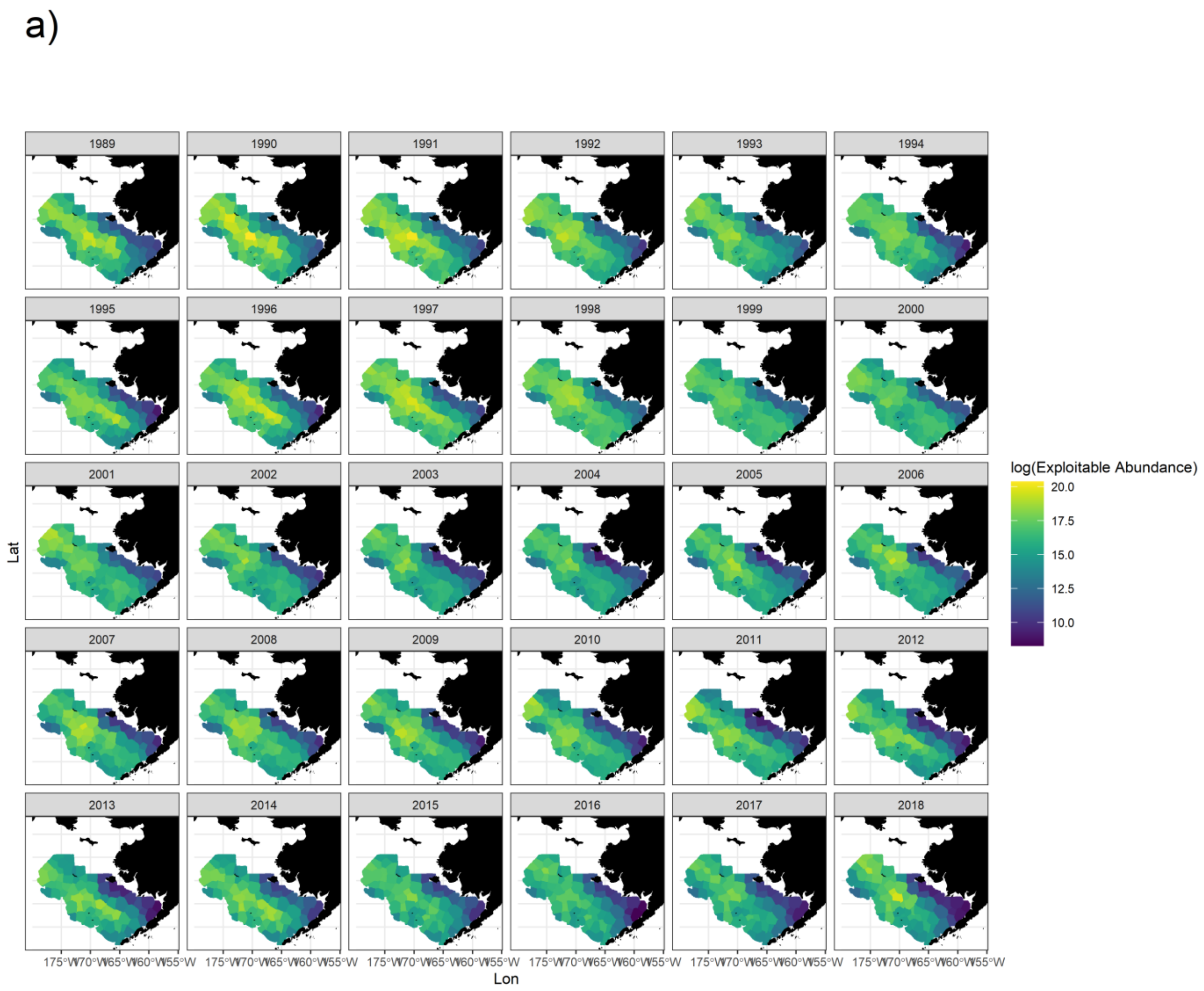
Size class 3: 78-101mm

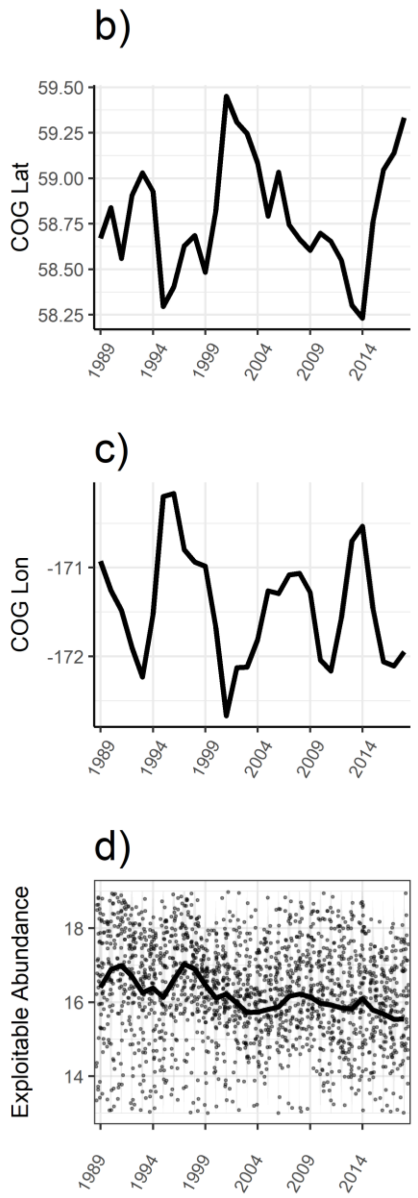


Size class 4 : >101mm



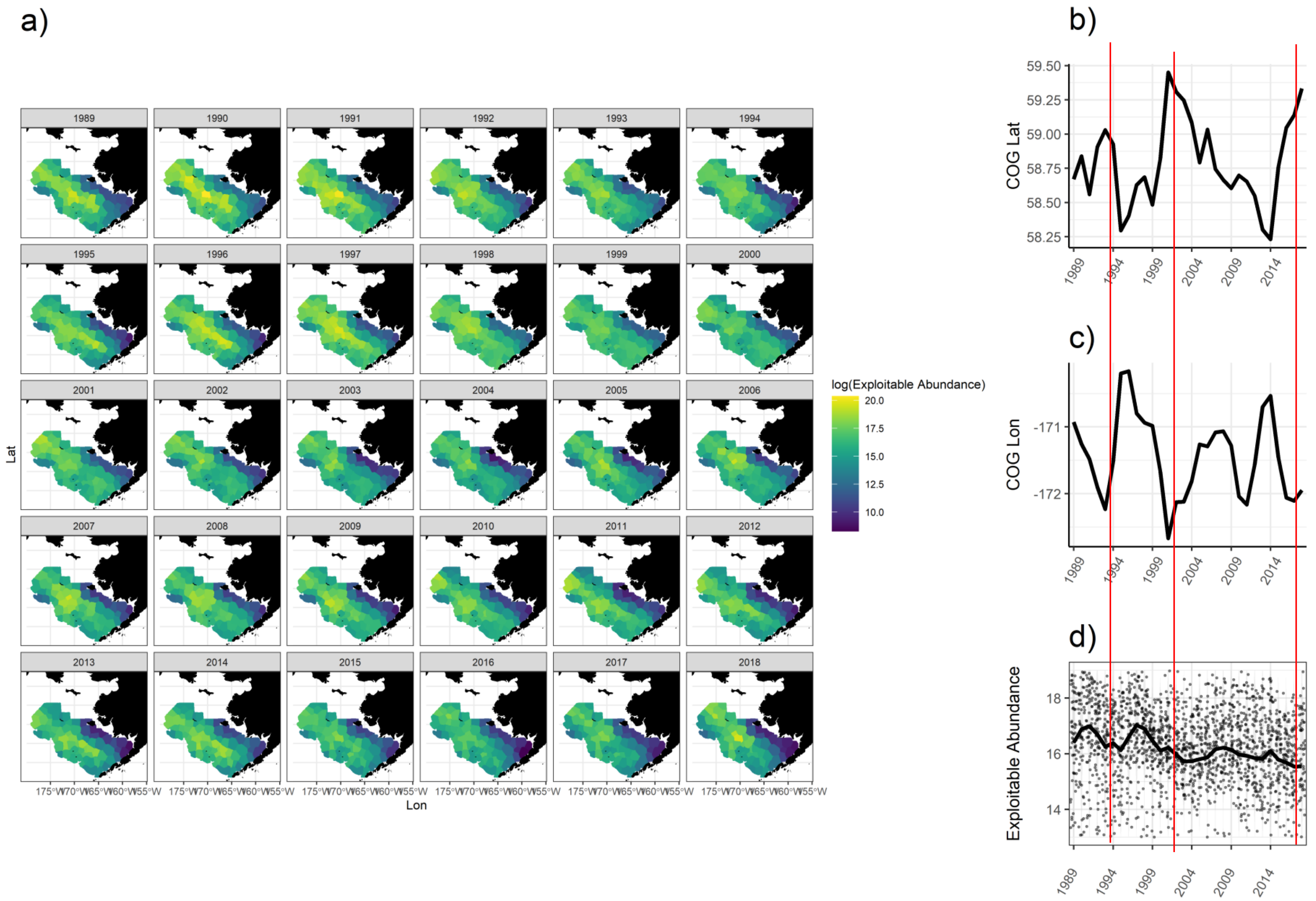
|RESULTS| Spatiotemporal changes in exploitable abundance





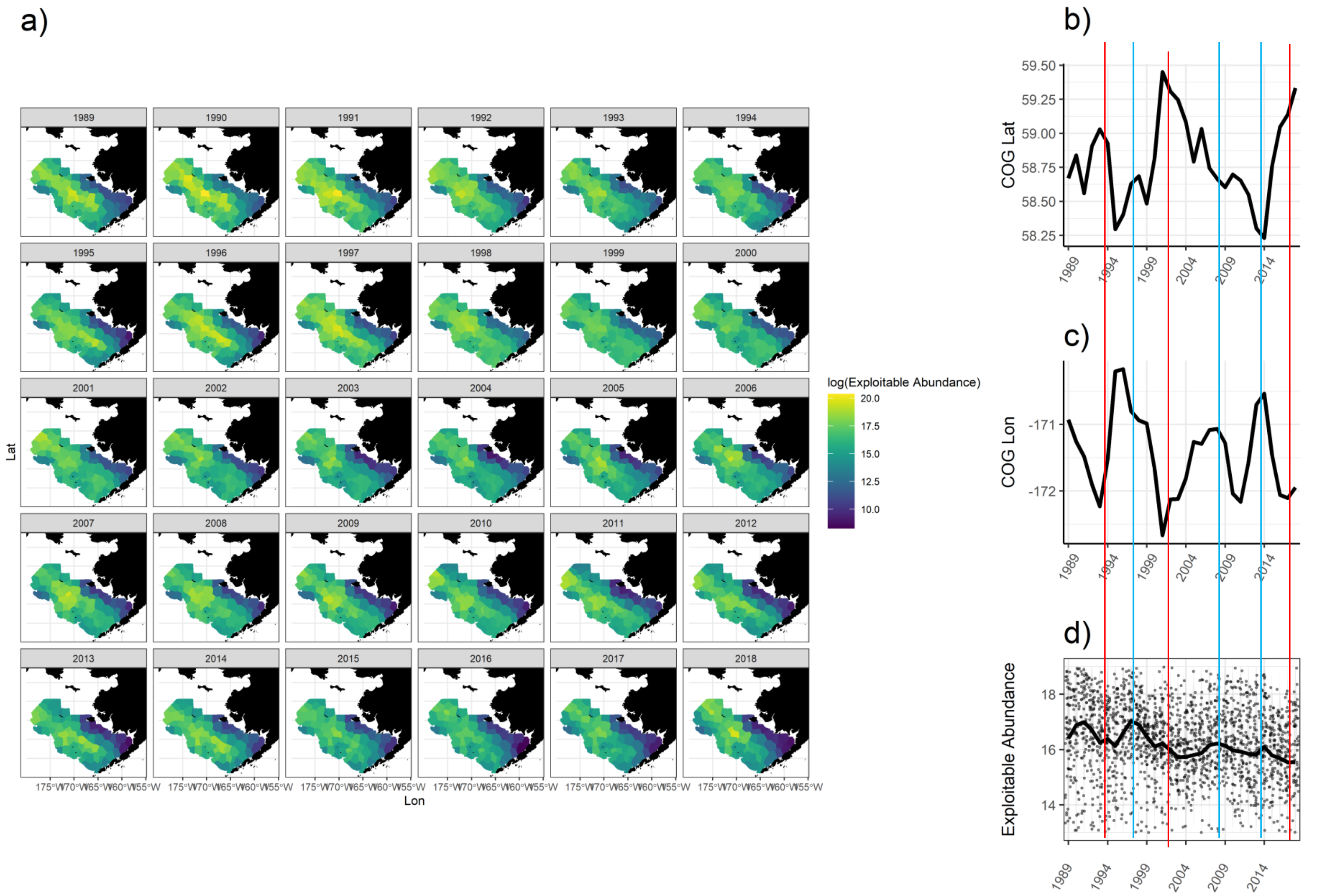
- Decline in exploitable abundance

|RESULTS| Spatiotemporal changes in exploitable abundance



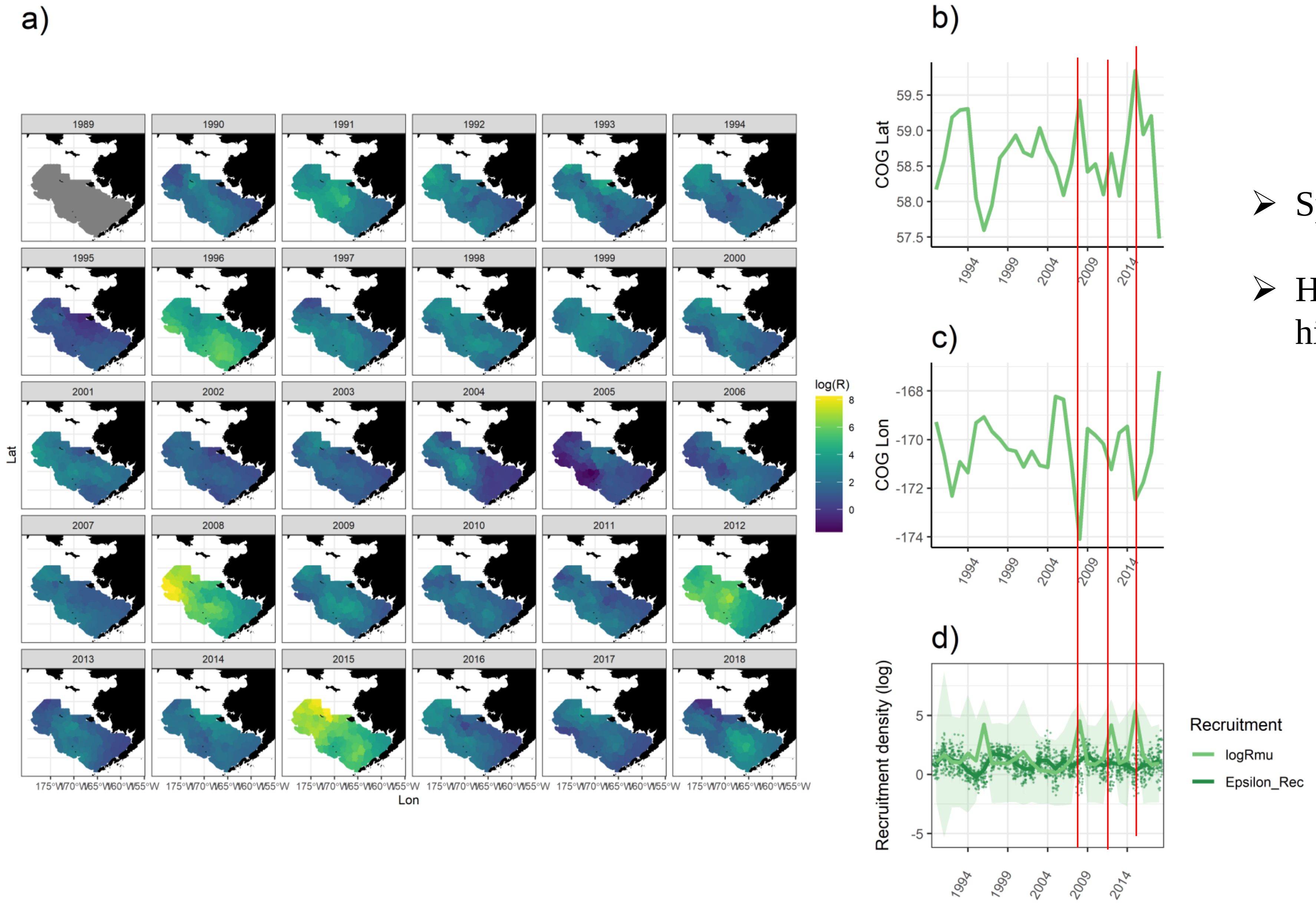
- ➢ Decline in exploitable abundance
- ➢ Years with marked declines, COG in high latitude

|RESULTS| Spatiotemporal changes in exploitable abundance



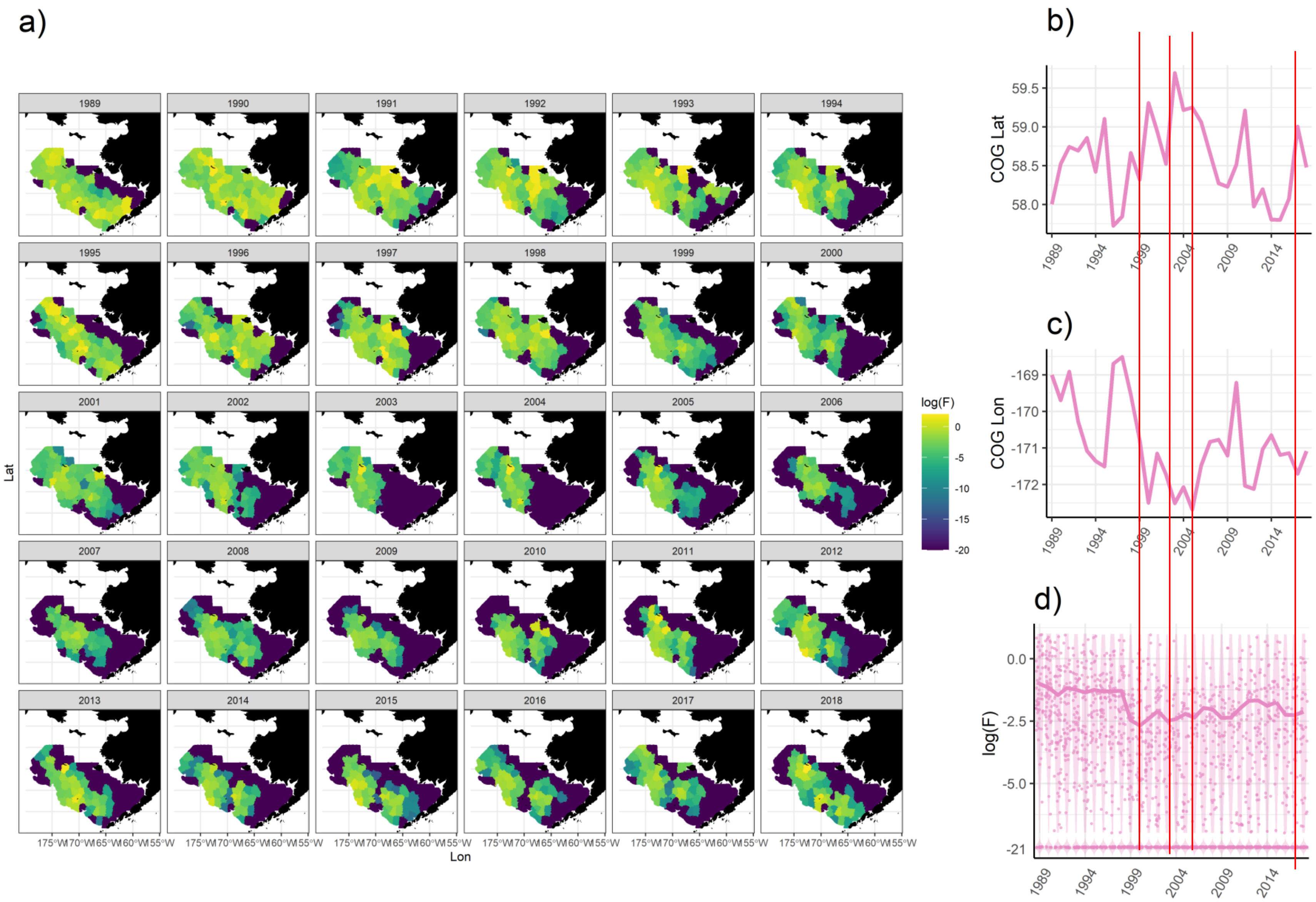
- Decline in exploitable abundance
- Years with marked declines, COG in high latitude
- Peak of abundances, COG in low latitude

|RESULTS| Spatiotemporal changes in recruitment



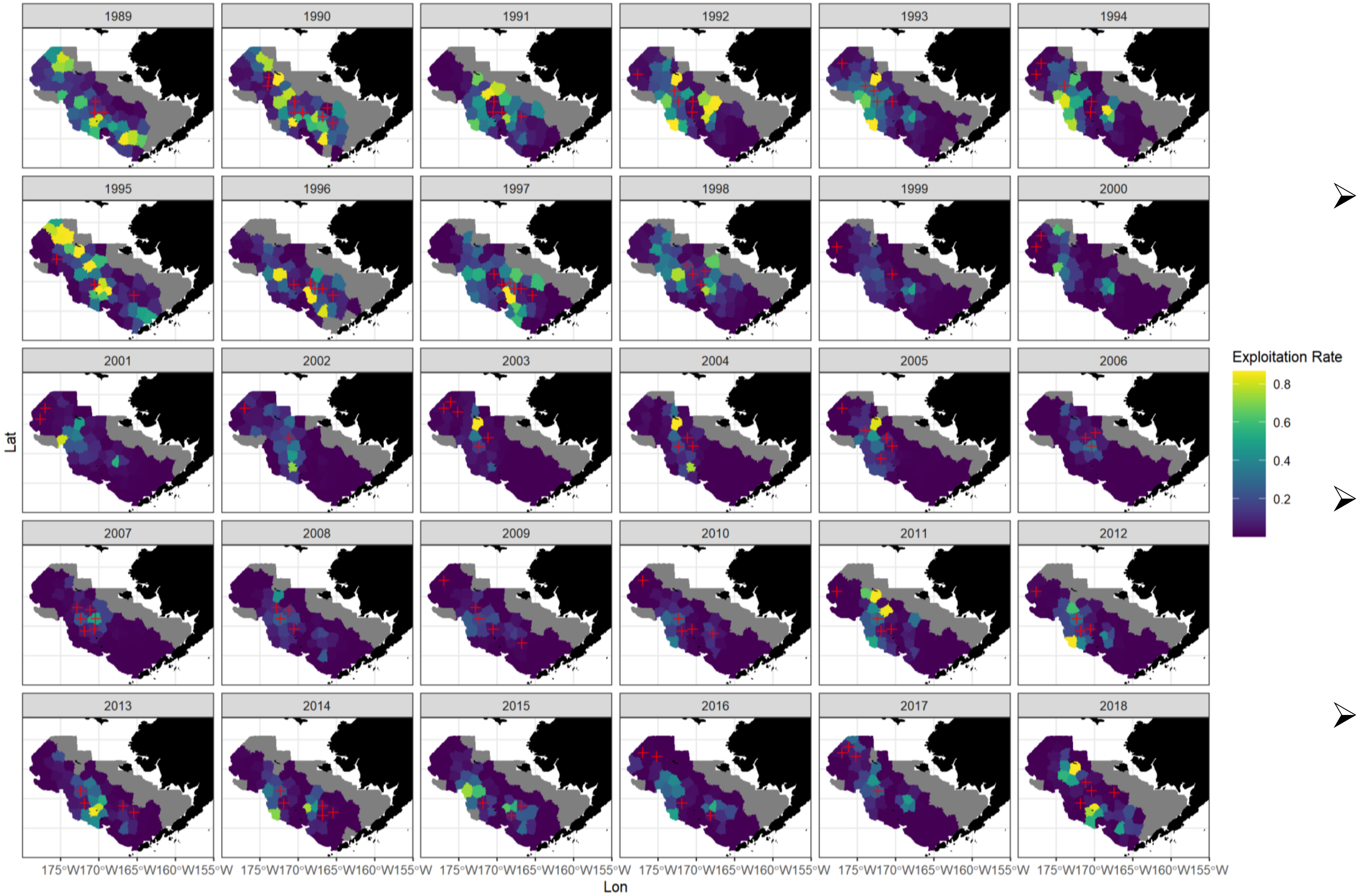
- ➢ Sporadic pattern
- ➢ High values associated with high latitude

|RESULTS| Spatiotemporal changes in fishing mortality



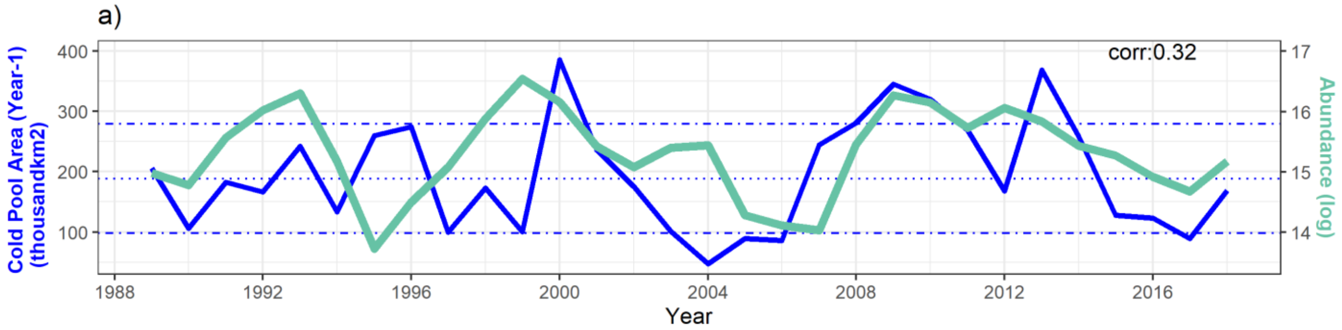
- High fishing mortality : 1989-1990
- Years of low fishing mortality (1999-2010)
  - more constrained spatial distribution of fishing mortality
  - COG in high latitude and western longitutde

|RESULTS| Spatiotemporal changes in exploitation rates



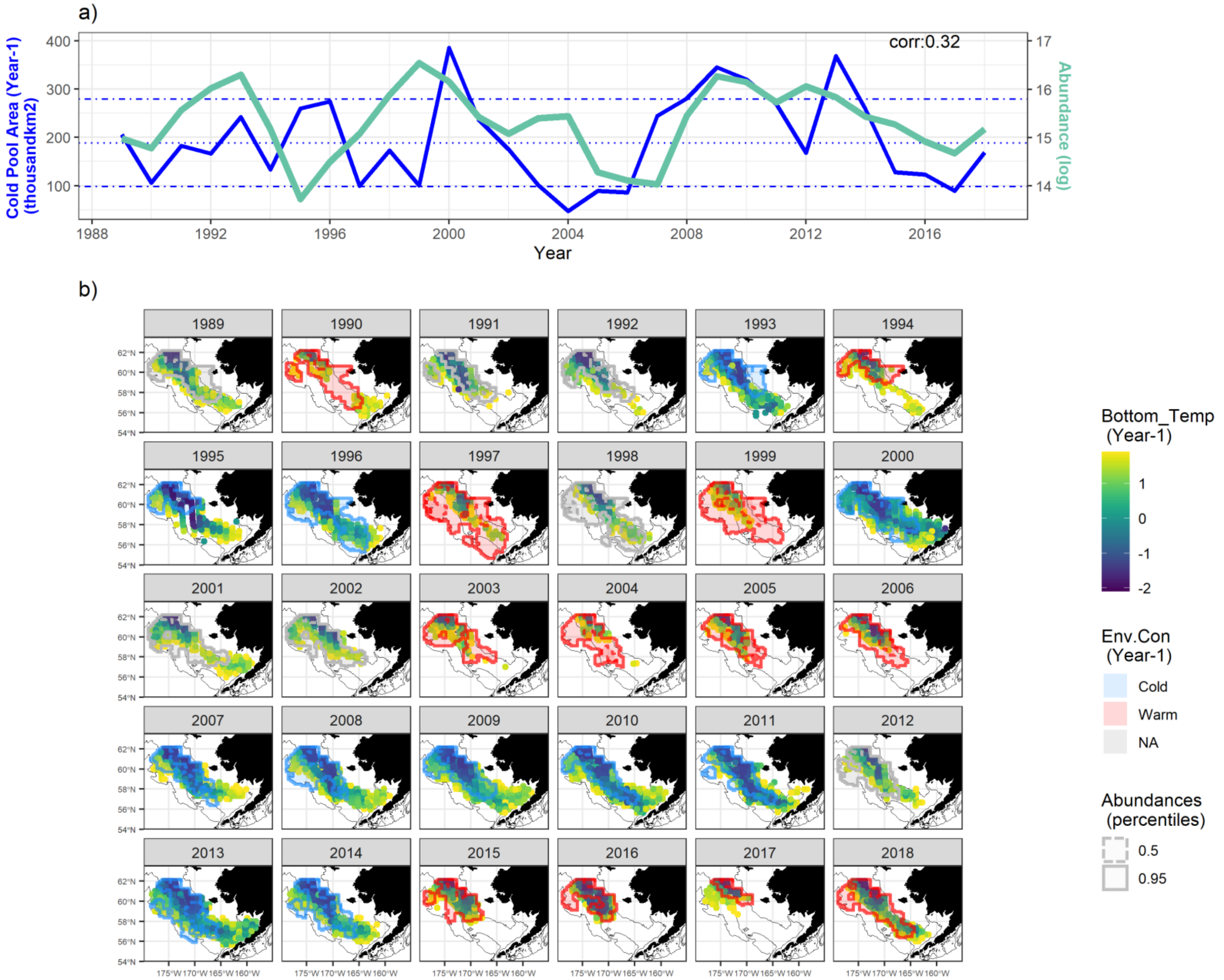
- 1989 to 1998, the western part of the EBS was strongly exploited
  - some areas the catches represent 80% of the abundance
- After 1999, when the stock was declared overfished, exploitation was strongly reduced
- Some areas have high abundance but very low harvest

|RESULTS| Link between spatiotemporal dynamic and cold pool extend ?



- ➢ correlation between the time-series of abundance for size-class 1 and the cold pool extend is positive

|RESULTS| Link between spatiotemporal dynamic and cold pool extend ?



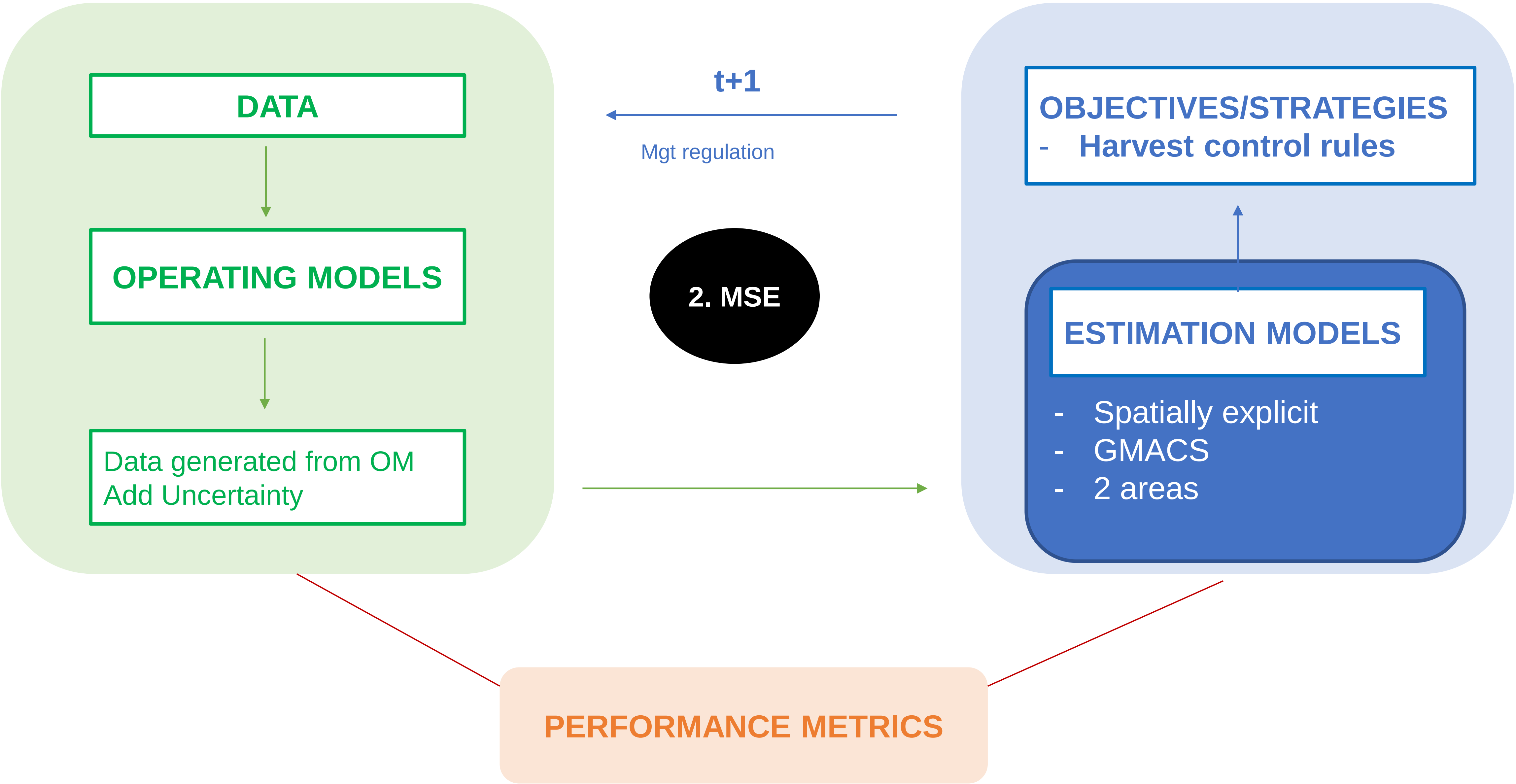
- correlation between the time-series of abundance for size-class 1 and the cold pool extend is positive
- spatiotemporal dynamics of the abundance of juveniles seems to be driven by the cold pool
  - cold years : the spatial distribution of the CP and abundance match and could extend over the entire EBS
  - warm years : the spatial distribution of abundance was more restricted, as was that of the cold pool

|DISCUSSION| Take home messages

- **We developed a size structure spatiotemporal model**
  - accounting implicitly for seasonal movement between survey and fishery
  - to estimate fine scale spatial dynamic and fishing impacts.
- **We applied the model to snow crabs in the Eastern Bering Sea,**
  - Provided for the first time, spatiotemporal variations in key quantities

- **The model showed a declines a in exploitable biomass and in fishing mortality, with the latest not evenly distributed.**
- **Results also show a sporadic recruitment, spatially concentrated in the northeast part of the EBS.**
- **Our result highlight that spatial distribution of juveniles are related to the cold pool**

|OUTLINE OF THIS TALK| A Summary of 2 postdoc projects on snow crab



PURPOSE OF THE MSE PROJECT

WHAT | Understand how fisheries respond and will respond to climate change

- Investigate the ability of management strategies to achieve fisheries management objectives considering current and future impacts of climate change
- Within a spatially explicit framework to
  - Better represent the mechanisms driving the system
  - Test for spatial management strategies

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CASE STUDY | Snow Crab

→ **Test different management strategies under climate change scenarios**

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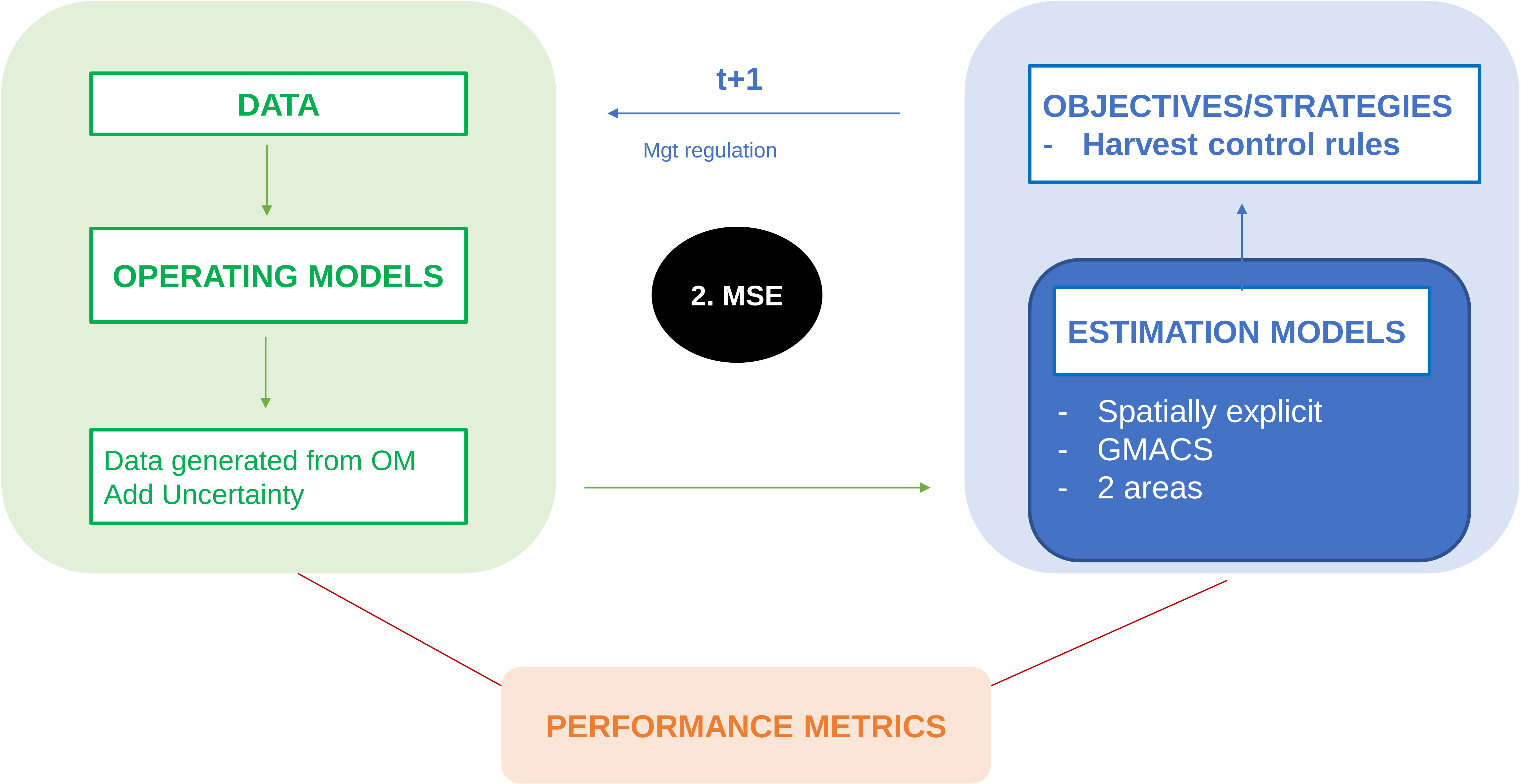
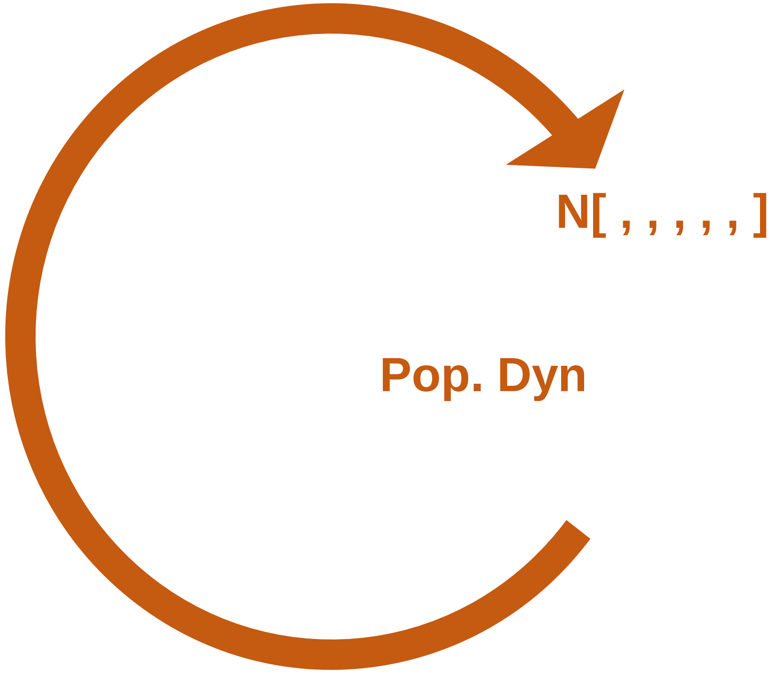
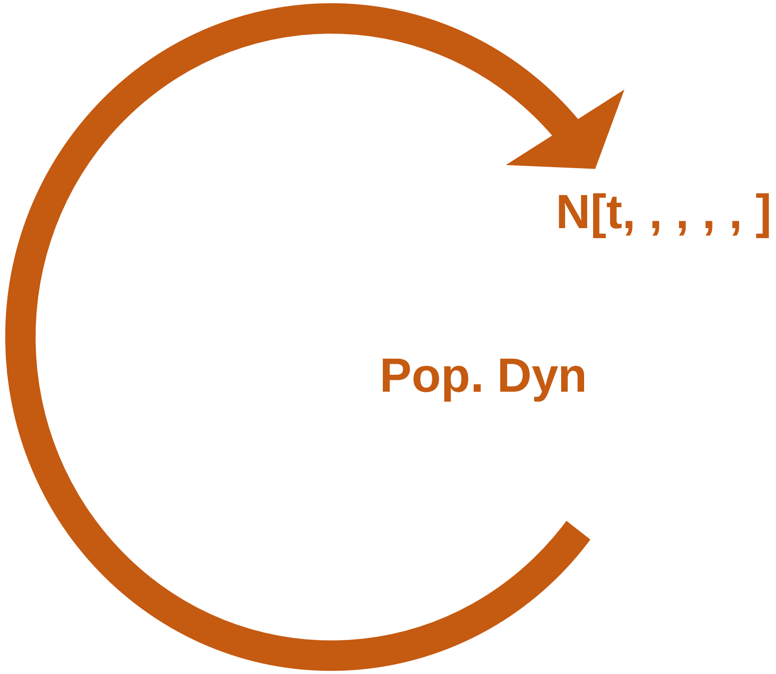


OPERATING MODELS

The population dynamic



The population dynamic

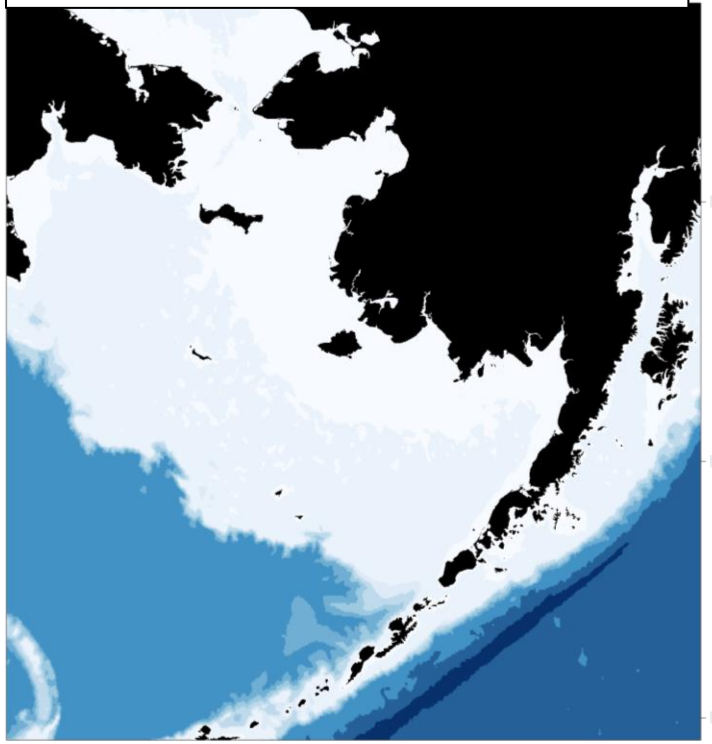


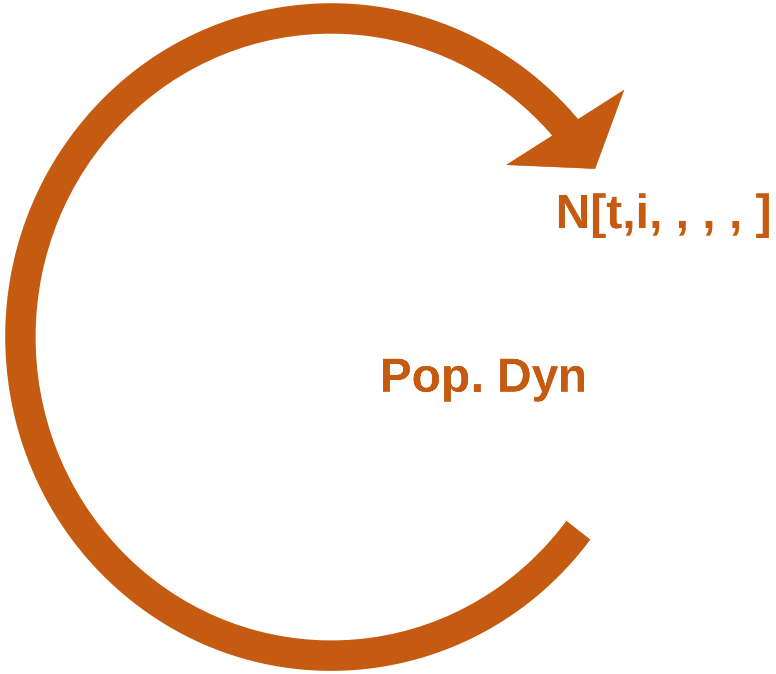
Time [t]

Year: Last year
Assessment
Season

The population dynamic

Space : [i]





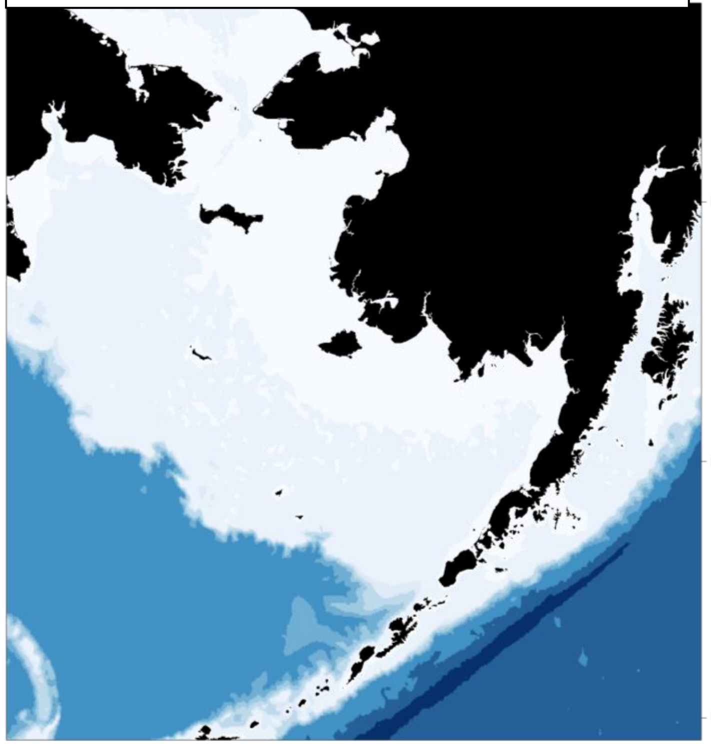
Time [t]

Year: Last year
Assessment
Season

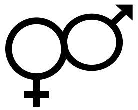
OPERATING MODELS

The population dynamic

Space : [i]

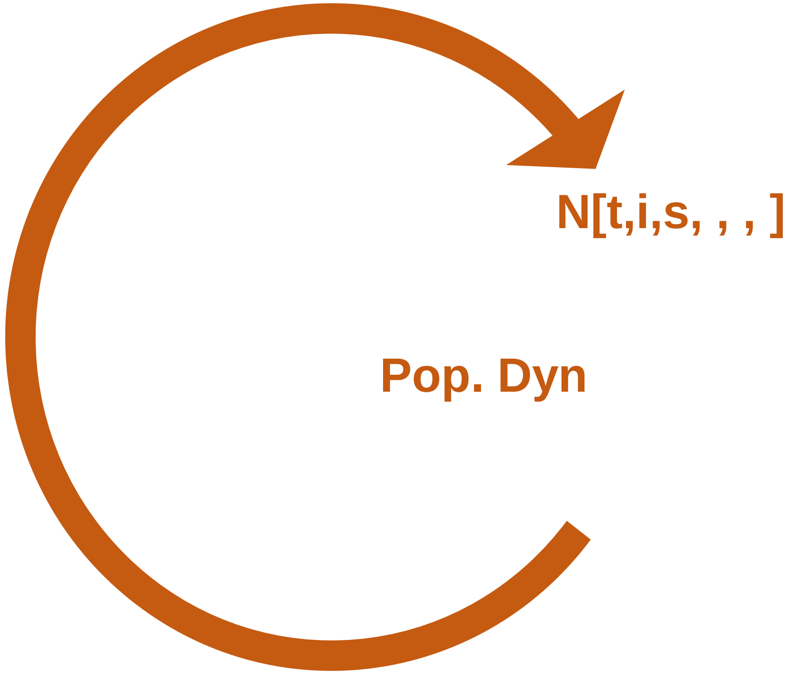


Sex [s]



Time [t]

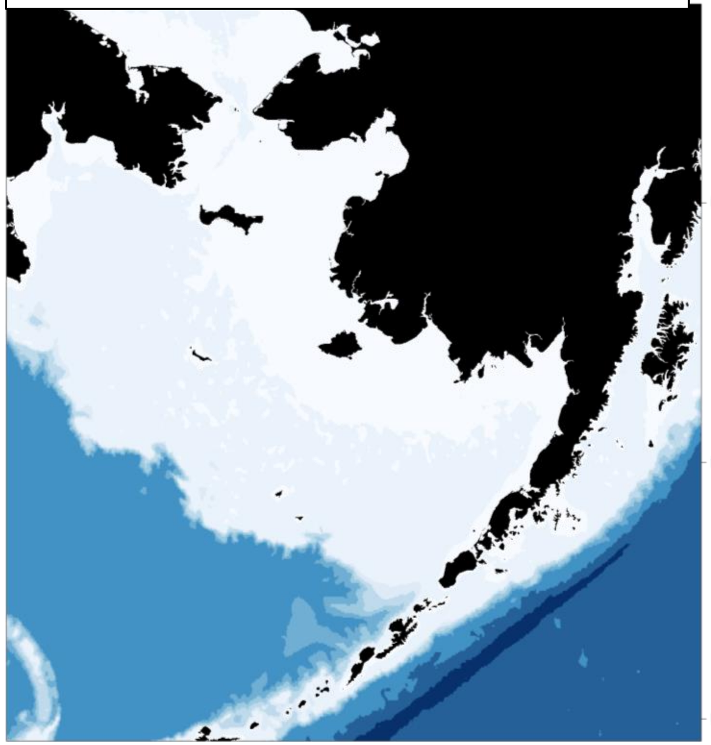
Year: Last year
Assessment
Season



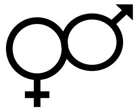
OPERATING MODELS

The population dynamic

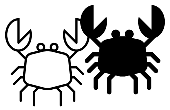
Space : [i]

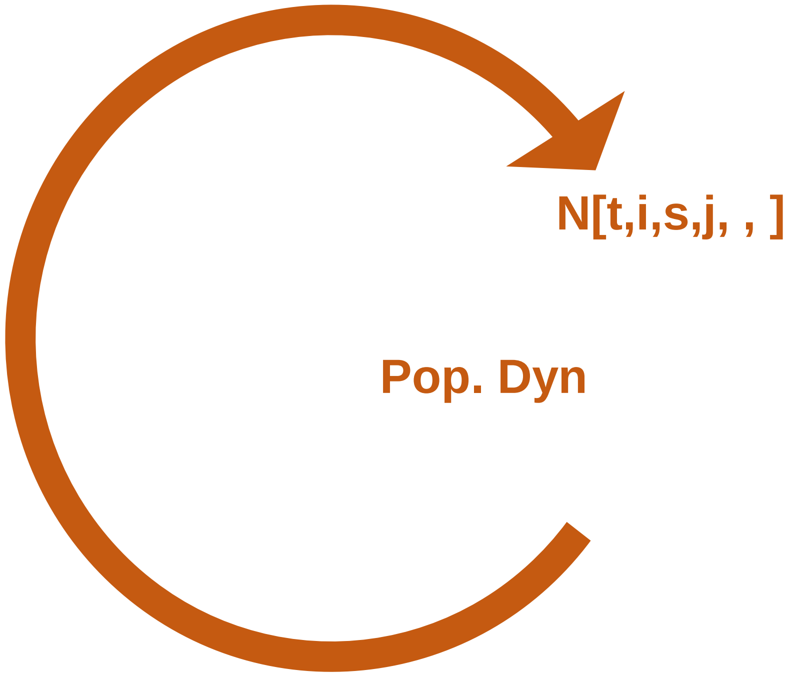


Sex [s]



Shell Cond [j]





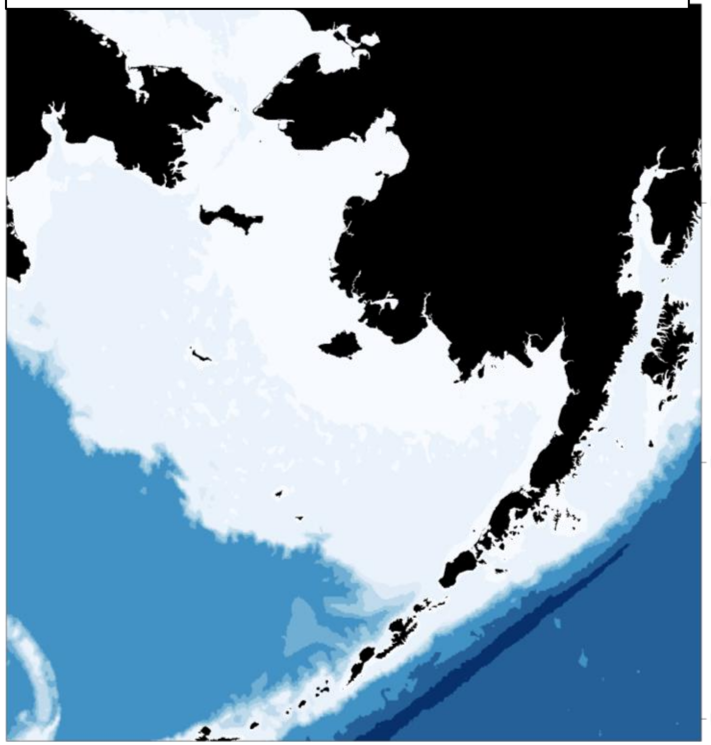
Time [t]

Year: Last year Assessment Season

OPERATING MODELS

The population dynamic

Space : [i]



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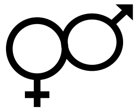
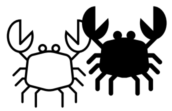
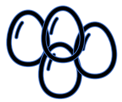


Shell Cond [j]

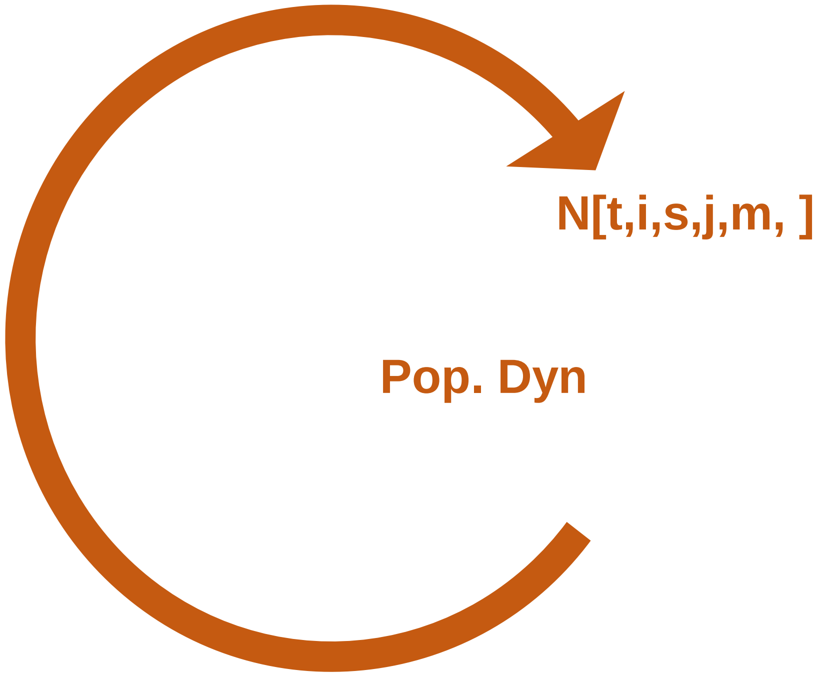


Maturity [m]



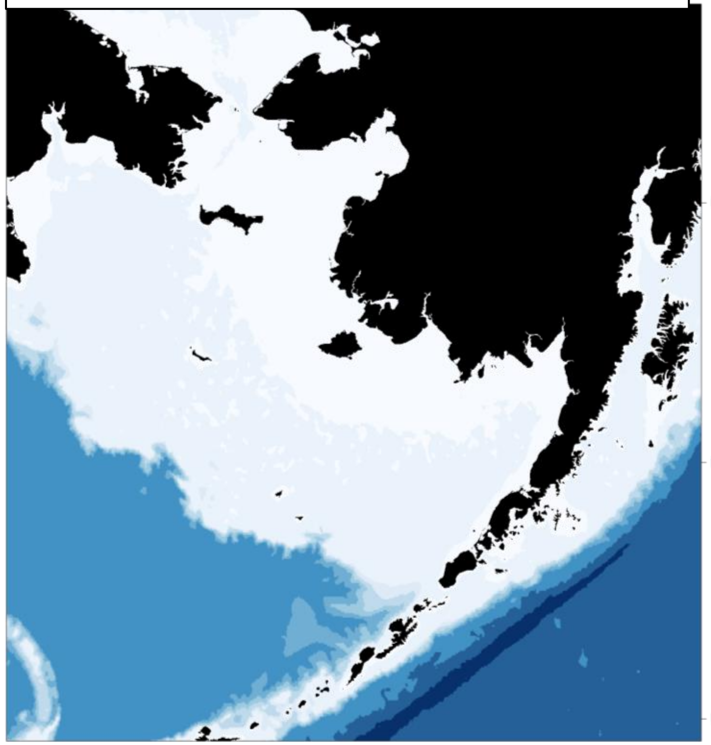
Time [t]

Year: Last year
Assessment
Season

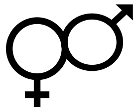


The population dynamic

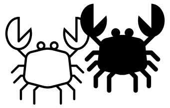
Space : [i]



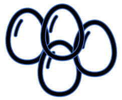
Sex [s]



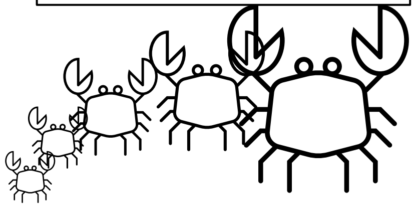
Shell Cond [j]



Maturity [m]

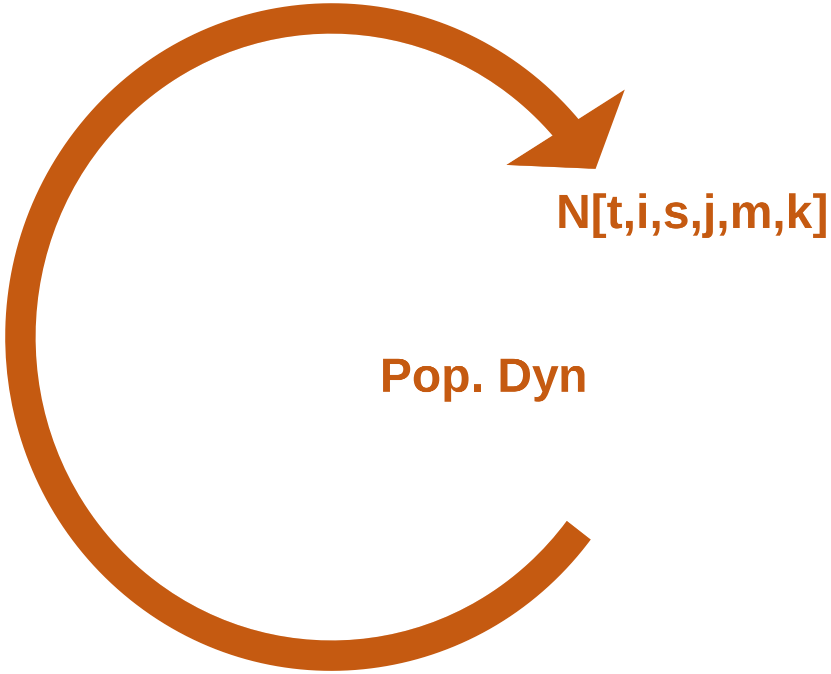


Size [k]



Time [t]

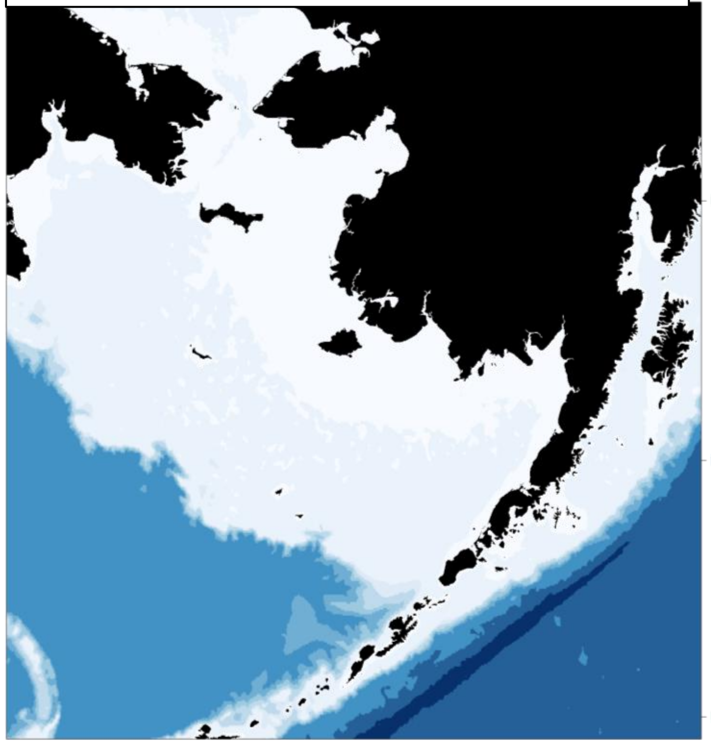
Year: Last year Assessment Season



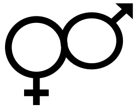
OPERATING MODELS

The population dynamic & Life History Processes (LHP)

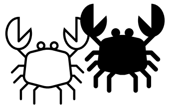
Space : [i]



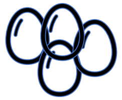
Sex [s]



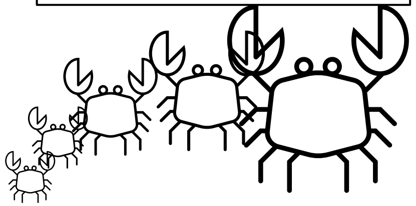
Shell Cond [j]



Maturity [m]

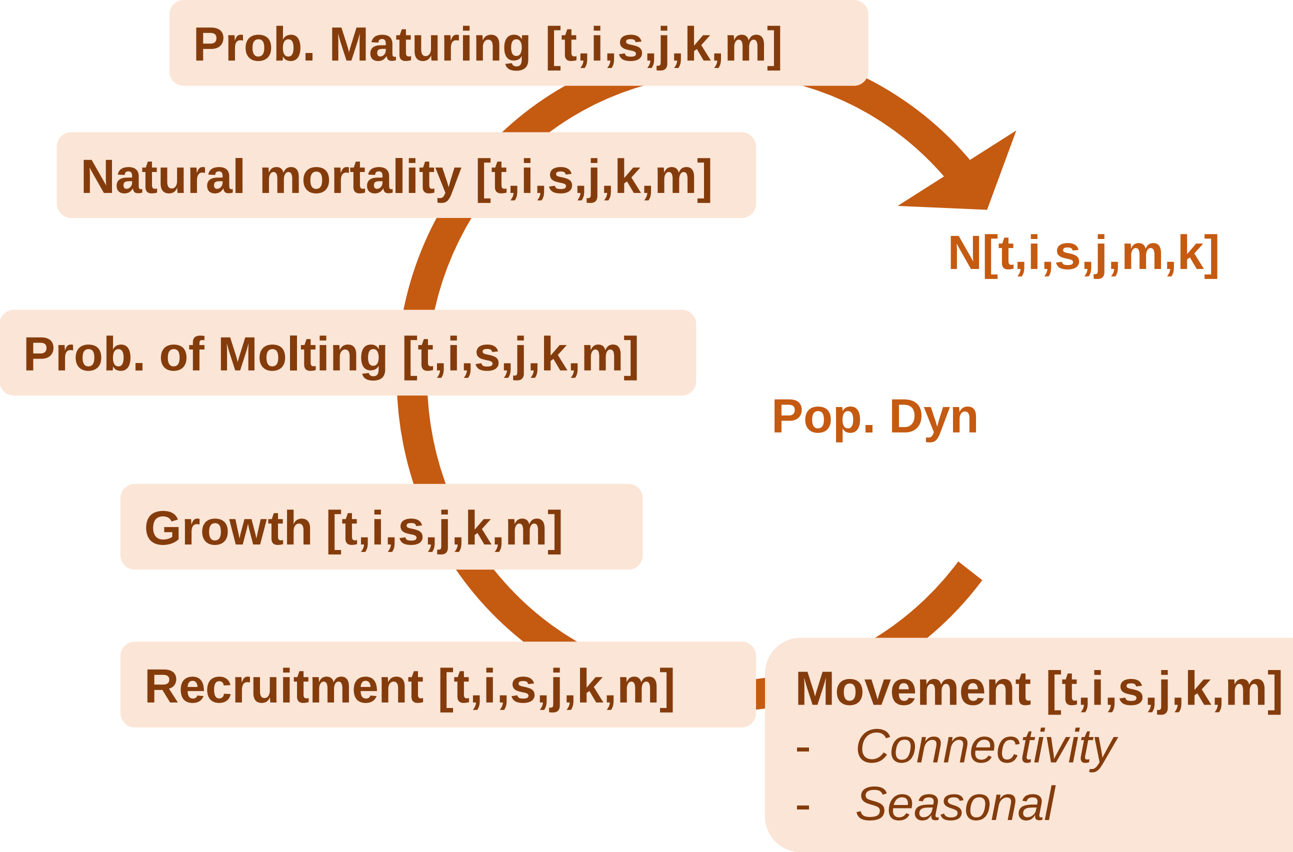


Size [k]



Time [t]

Year: Last year Assessment Season



Generating life history processes

1. **Different scenarios**

   i. Scenario 1 : Unconstrained → Random field

   ii. Scenario 2 : Predefined scenario – ex: latitudinal increase

   iii. Scenario 3 : Spatiotemporal variations : AR1

   iv. Scenario 4 : Spatiotemporal variation + Environmental variations

      a. Scenario 4.a : No preferential habitat

      b. Scenario 4.b : Preferential habitat

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SCENARIO 4 → Life history process driven by Env. Variations + Pref. Hab

SPATIOTEMPORAL VARIATIONS IN LHP = ENVIRONMENTAL SPATIOTEMPORAL VARIATION + RESIDUAL SPATIOTEMPORAL VARIATION

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$$\mathbf{LHP}_{\mathbf{t},\boldsymbol{i}} = \boldsymbol{f}(\boldsymbol{p}_{t,i}^{1}, .. \boldsymbol{p}_{t,i}^{n})$$

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$$p_{t,i}^{k} = \mu_{p^k} + \boldsymbol{\alpha} \times \boldsymbol{\omega}_{t,i} + \boldsymbol{\beta} \times \epsilon_{t,i}$$

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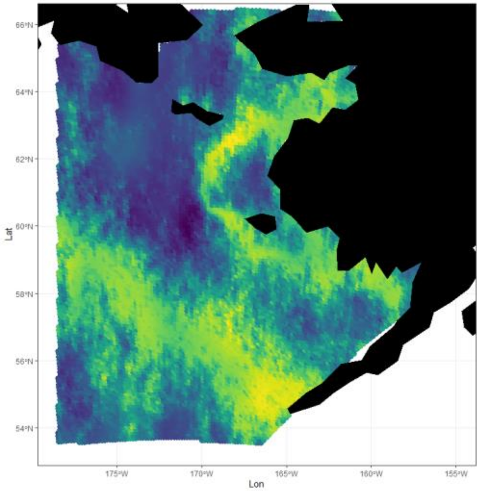
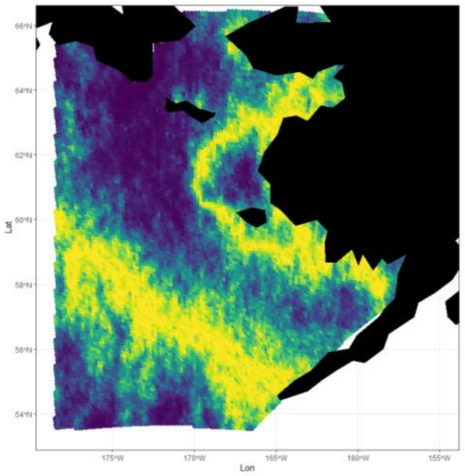
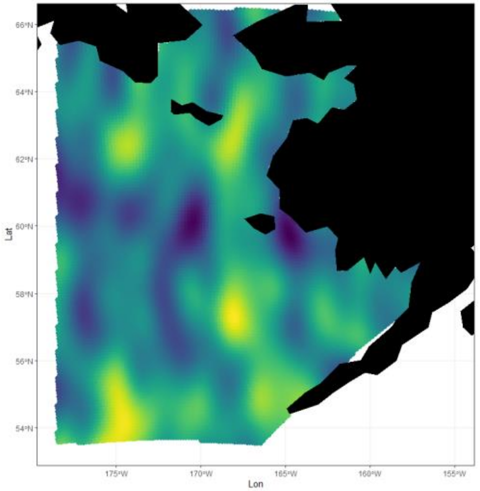


$=$ μ_{p^k} $+$



$\alpha = 0.1\mu_{p^k}$

$+$



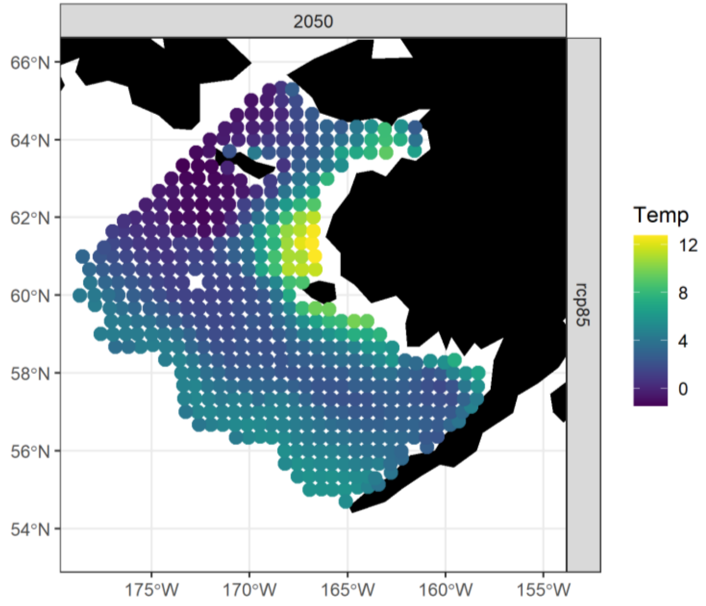
$\beta = 0.05\mu_{p^k}$

ENVIRONMENTAL SPATIOTEMPORAL VARIATION

$\omega_{t,i}$

ENVIRONMENTAL SPATIOTEMPORAL VARIATION

$\omega_{t,i}$

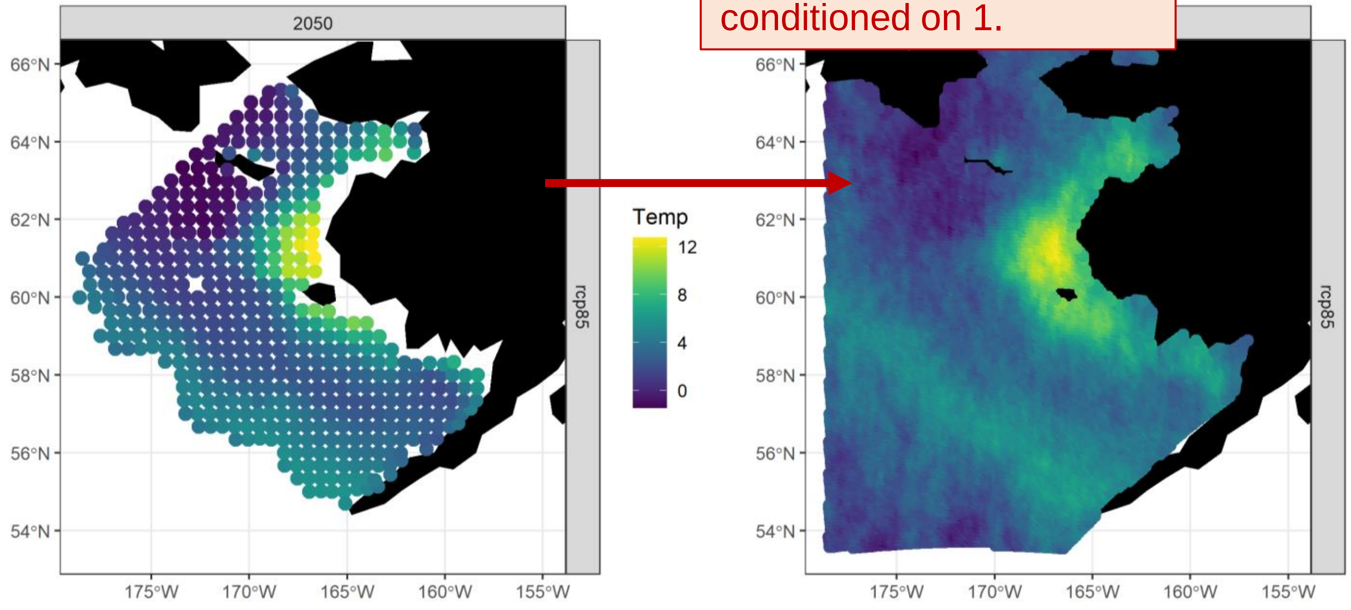


1. Year = 2030
 rcp45 –GFDL CMIP5

ENVIRONMENTAL SPATIOTEMPORAL VARIATION

$\omega_{t,i}$

2. Predict a RF conditioned on 1.



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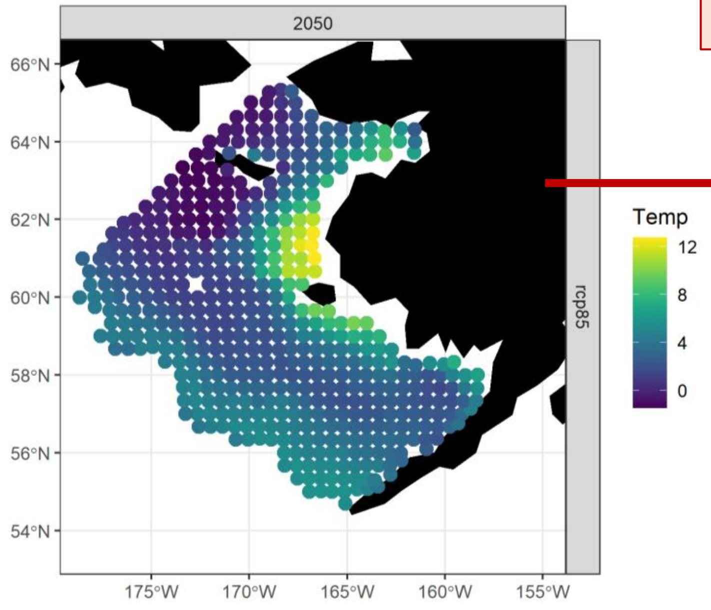

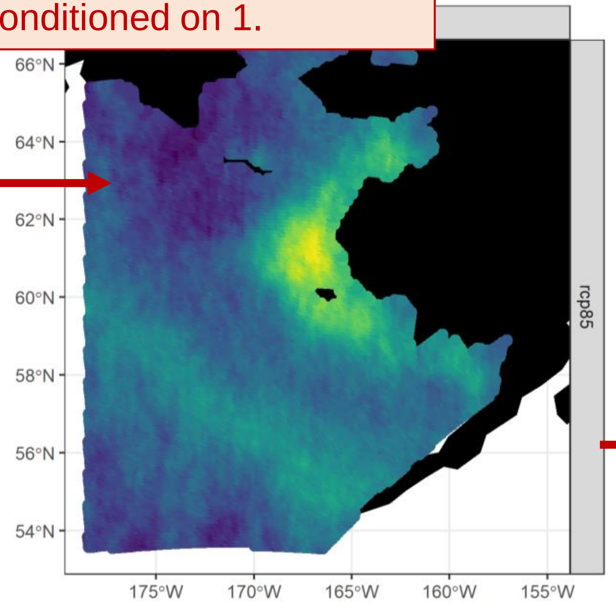

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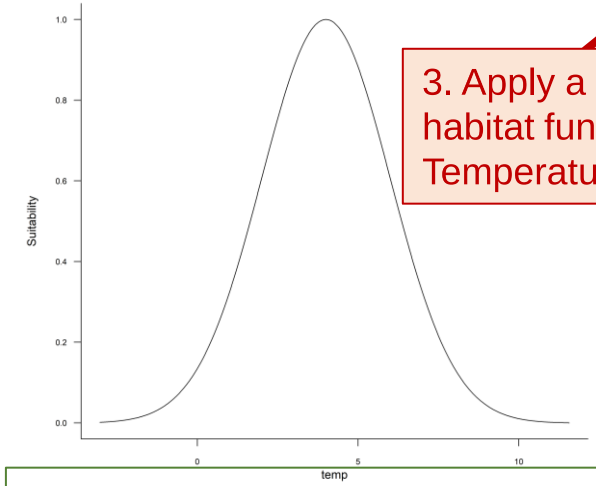
rcp45 –GFDL CMIP5



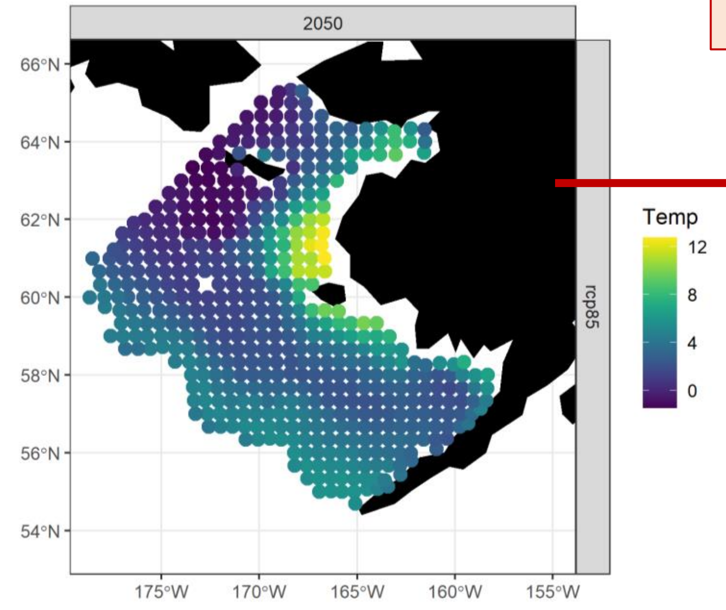
3. Apply a preferential habitat function based on Temperature

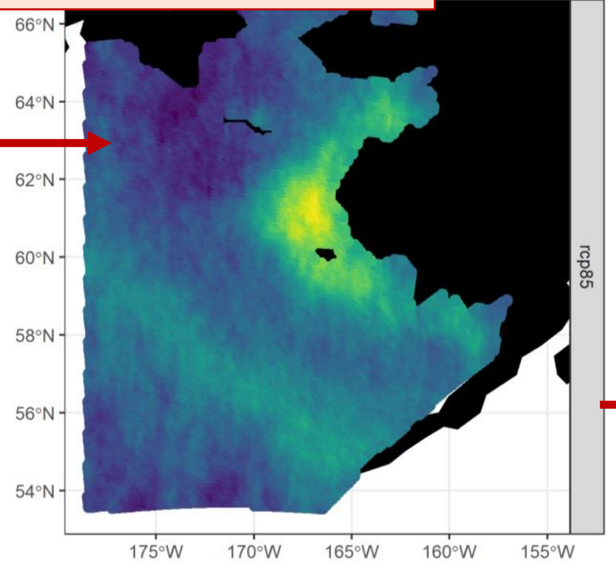
Preferential habitat function

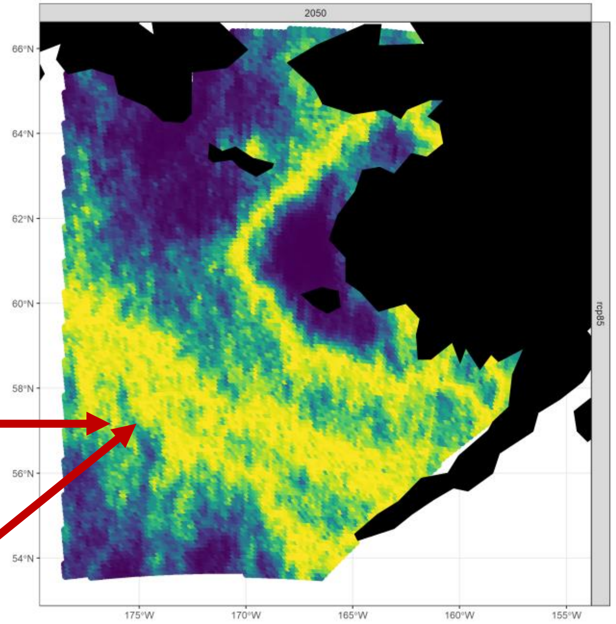
ENVIRONMENTAL SPATIOTEMPORAL VARIATION

$\omega_{t,i}$

2. Predict a RF conditioned on 1.







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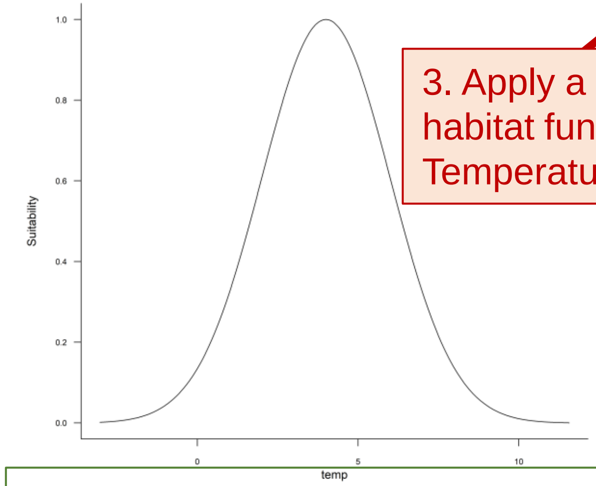
rcp45 –GFDL CMIP5



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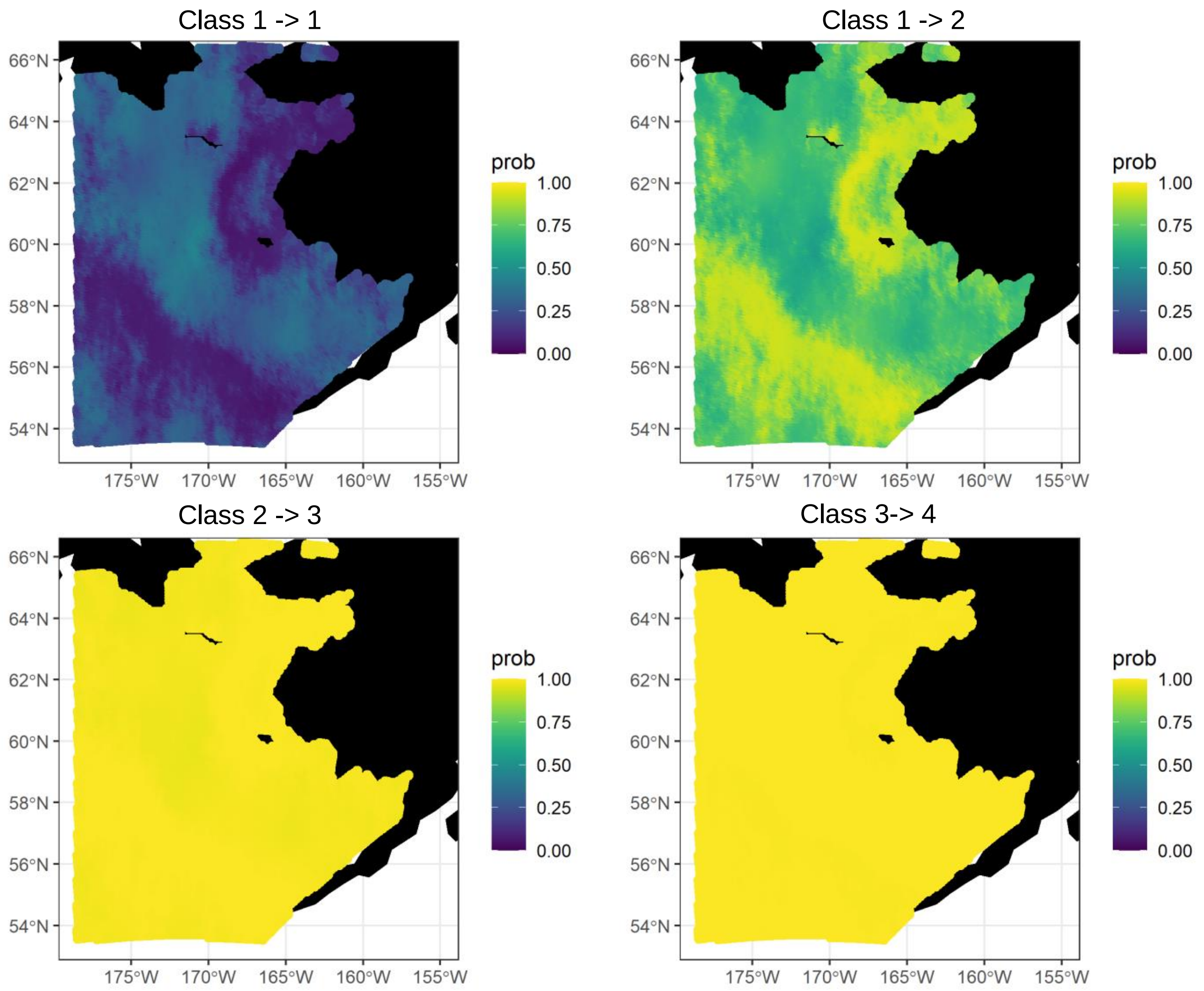
||

GROWTH

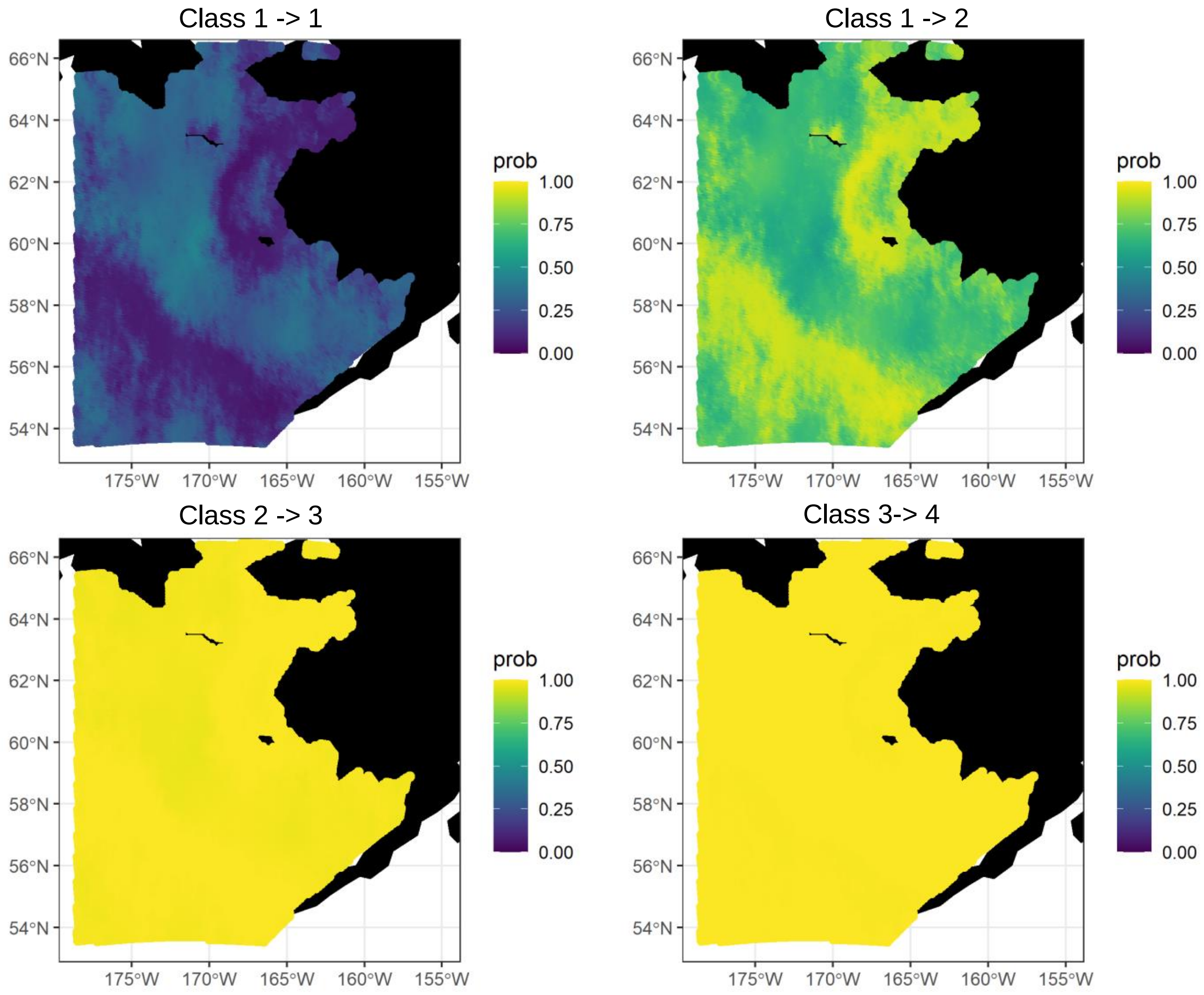
|SIMULATION GROWTH| Year= 2030 | Clim. Sc = rcp85 | sex = Male



HYPOTHESIS

- Preferential habitat function
- Additive effect

|SIMULATION GROWTH| Year= 2030 | Clim. Sc = rcp85 | sex = Male



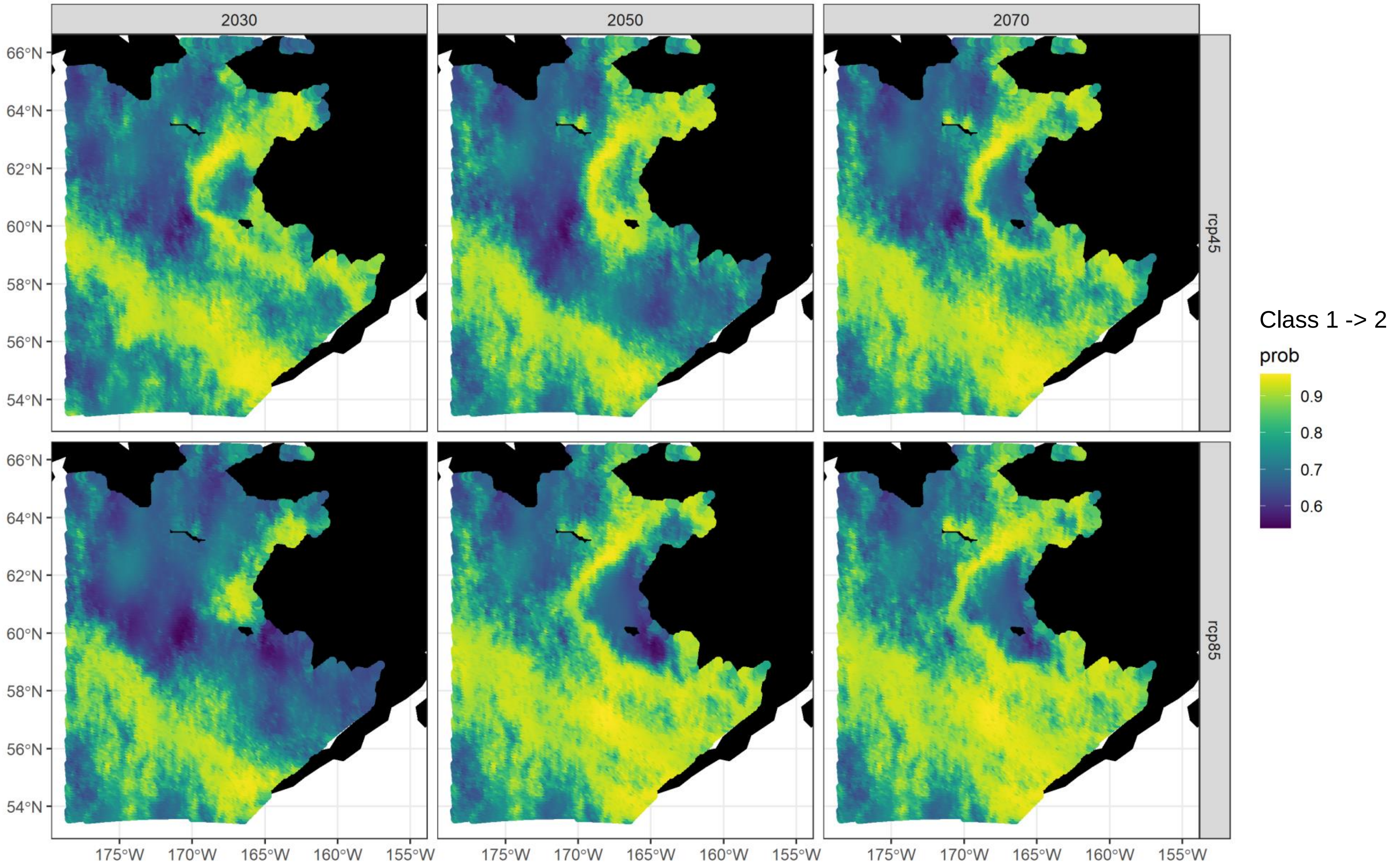
HYPOTHESIS

- Preferential habitat function
- Additive effect

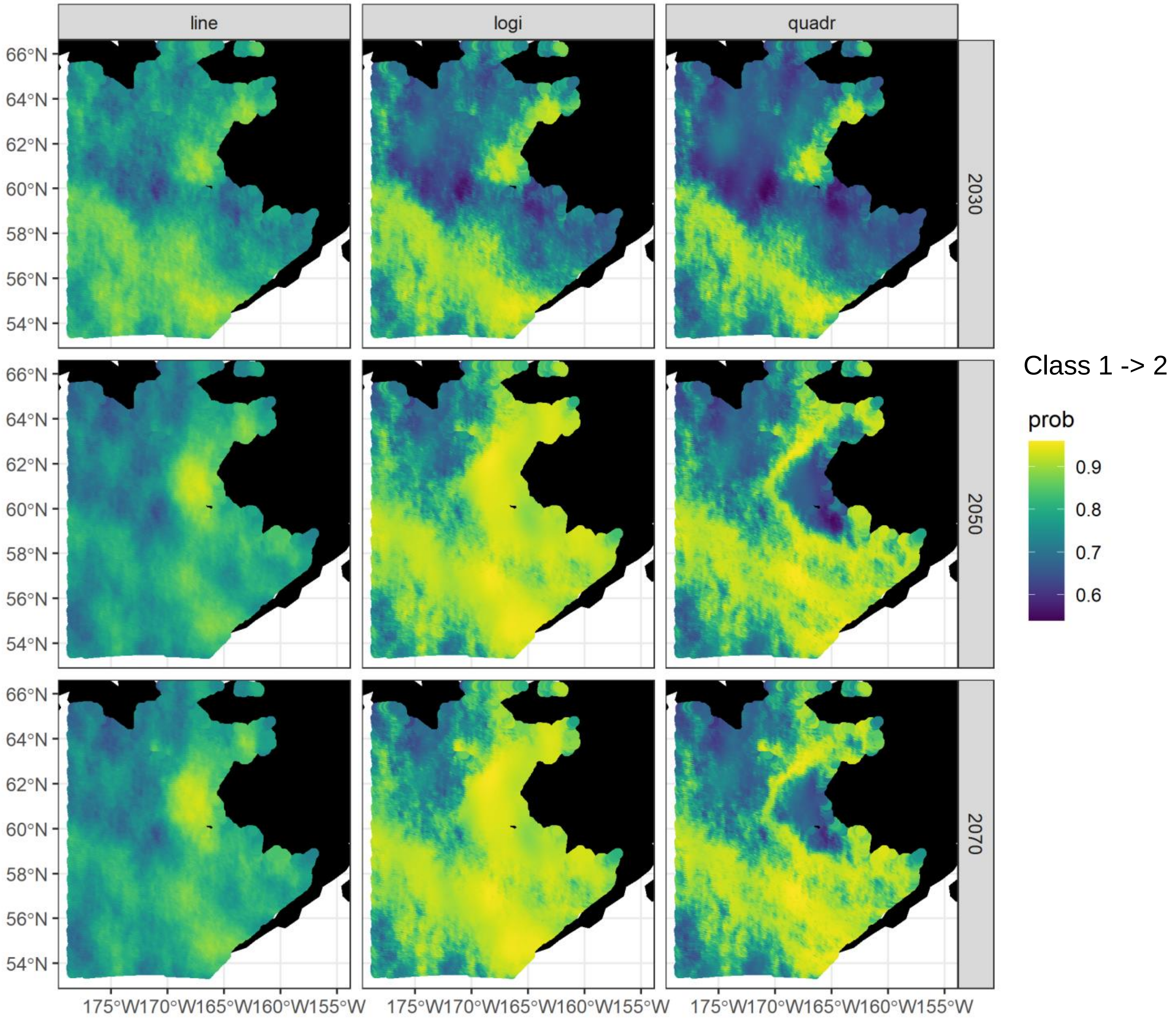
COULD GENERATE SOME UNCERTAINTIES

- Preferential habitat
  - Linear
  - Quadratic
  - Logistic
- Effect
  - Multiplicative

|SIMULATION GROWTH| Climate scenarios vs Years | HP function = quadrat.



|SIMULATION GROWTH| Years vs Preferential habitat function



DISCUSSION : SOME FEEDBACK

- **How much can vary the parameters with the potential climate scenarios ?**

$$p^k_{t,i} = \mu_{p^k} + \boldsymbol{\omega_{t,i}} + \epsilon_{t,i}$$

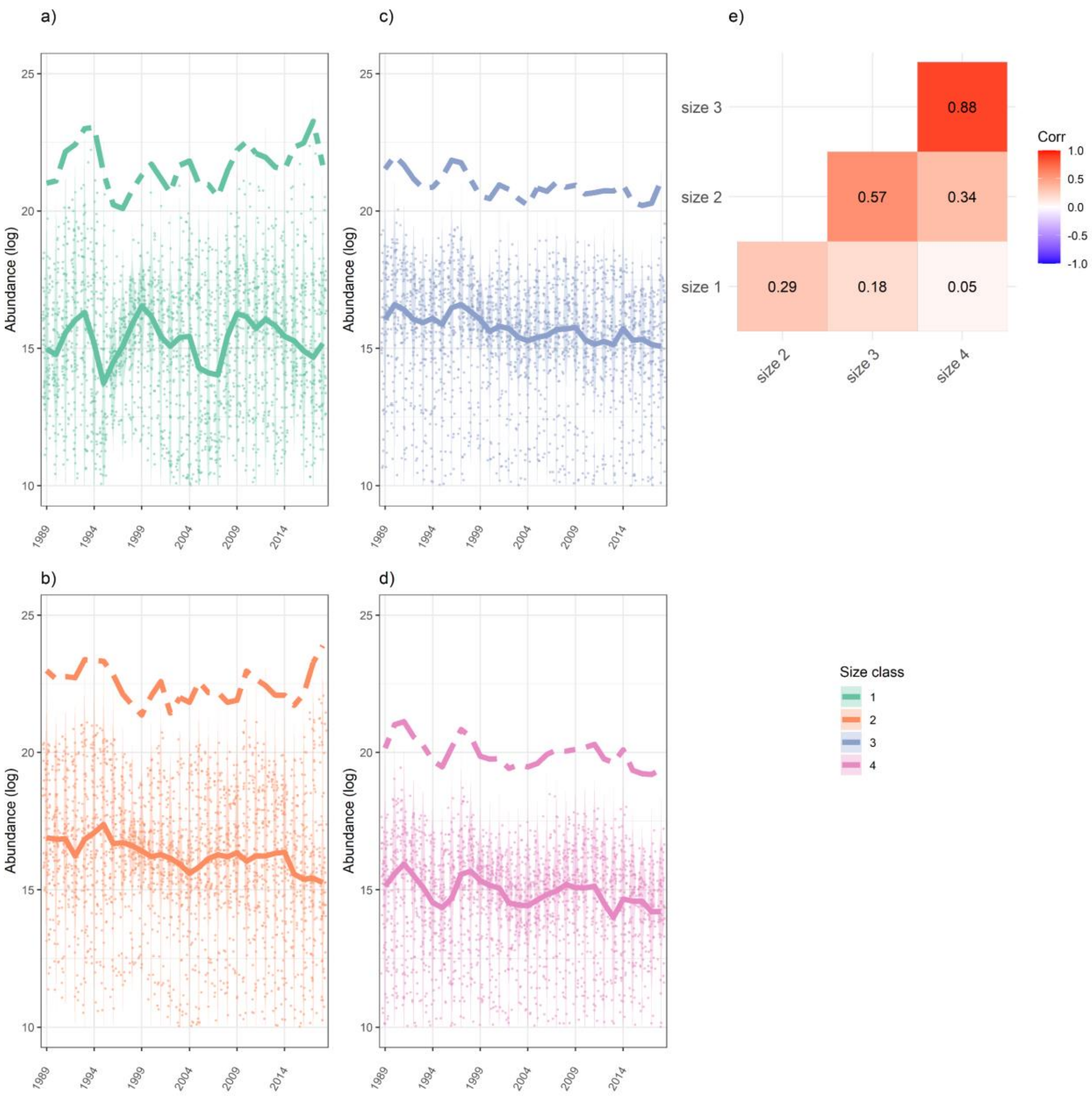
THANK YOU VERY MUCH

- **Cody Szuwalski**
- **Andre Punt**
- **Jie Cao**
- **Jim Thorson**
- **Cole Monnahan**
- **Kirstin Holsman**
- **William T. Stockhausen**
- **Anne Hollowed**
- **Alan Haynie**
- **ACLIM2 Collaborators**

Aquatic and Fishery Sciences
University of Washington

molmos@uw.edu

|RESULTS| Spatiotemporal changes in abundances



- Decline in average abundance
- Strong spatial variability in abundances
- Strong spatiotemporal correlations between large size classes