Reconstructing conservation unit-level spawner abundances from stream survey data using empirical dynamic modelling



Credit: Aimée van Drimmelen

Bruno S. Carturan (me!), Stephanie J. Peacock

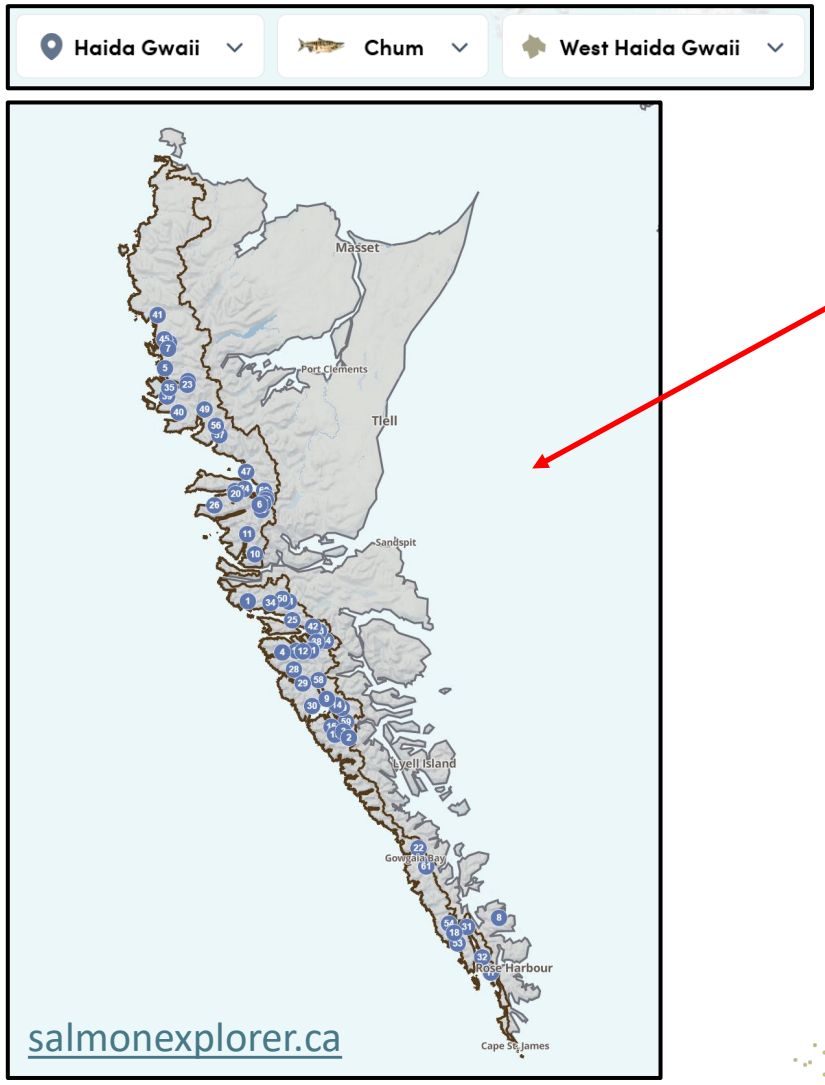
PACIFIC SALMON FOUNDATION

PICES 2026 Annual Meeting, Nanaimo, BC, 2026-10-28

S10. Using long-term ocean observations to understand ocean change and support resilient ecosystems and communities in the North Pacific

Objective: to fill data gaps in spawner survey data to reliably estimate **CU**-level abundance in a context of declining monitoring.

"Conservation Unit"





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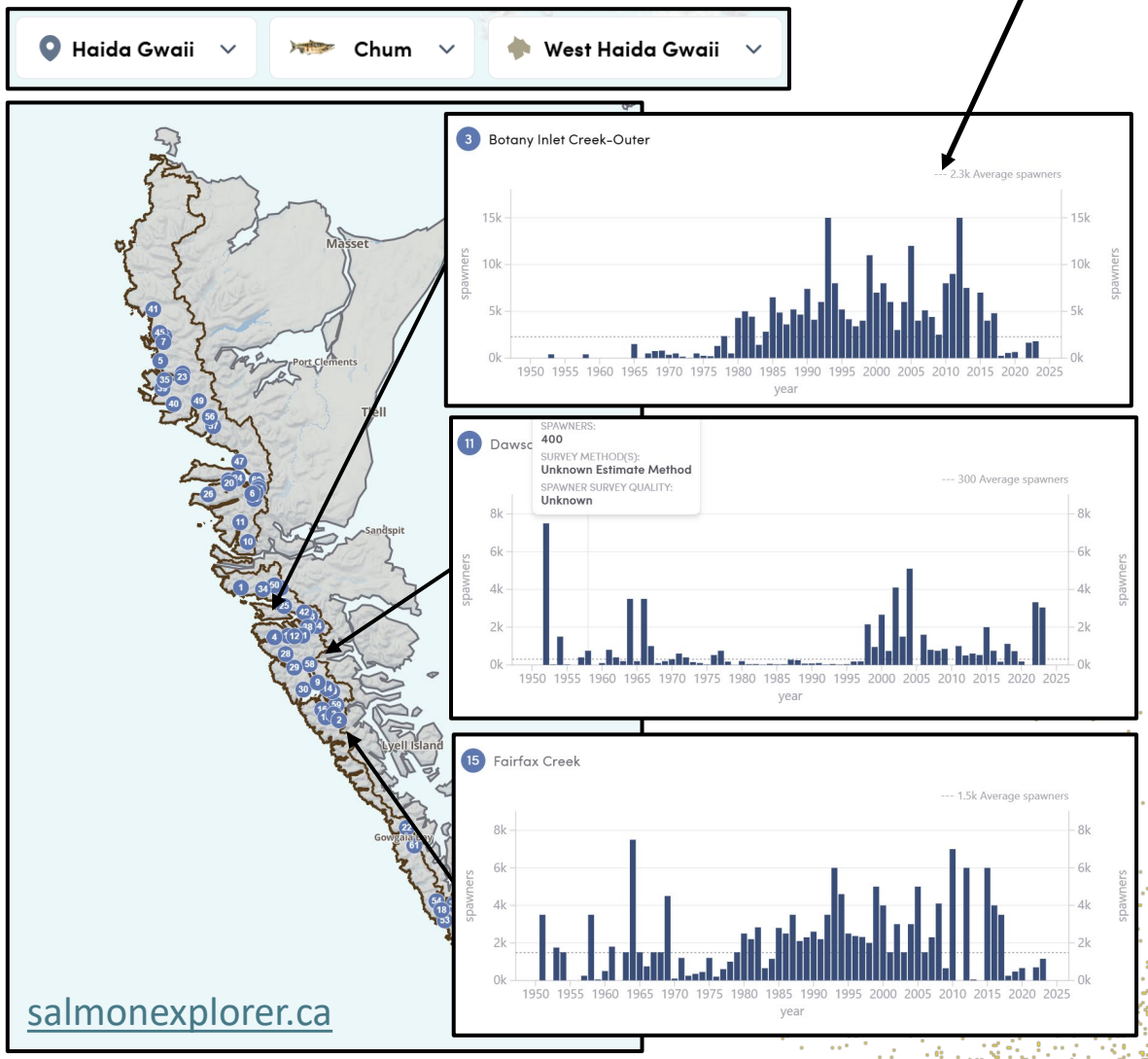

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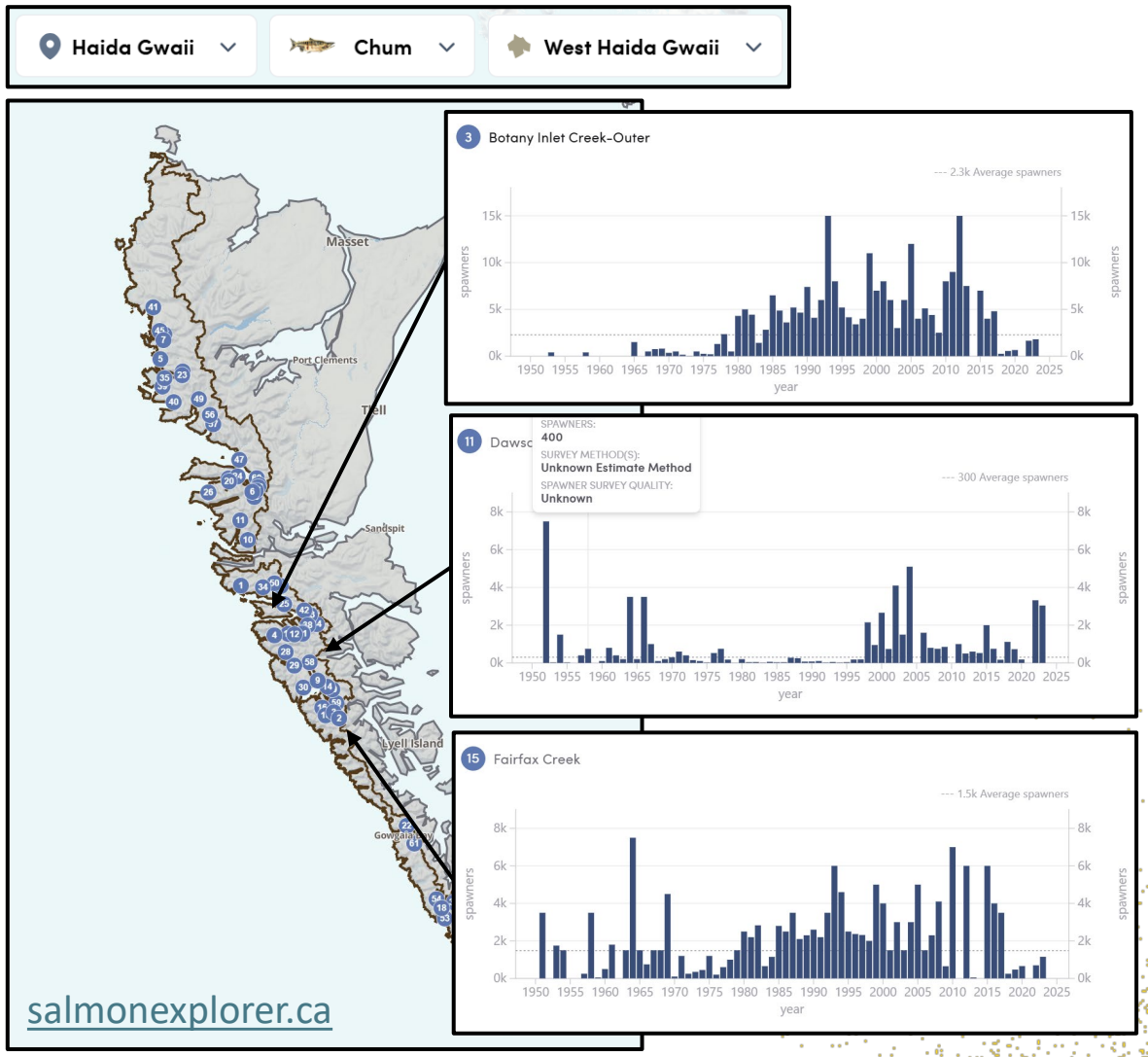
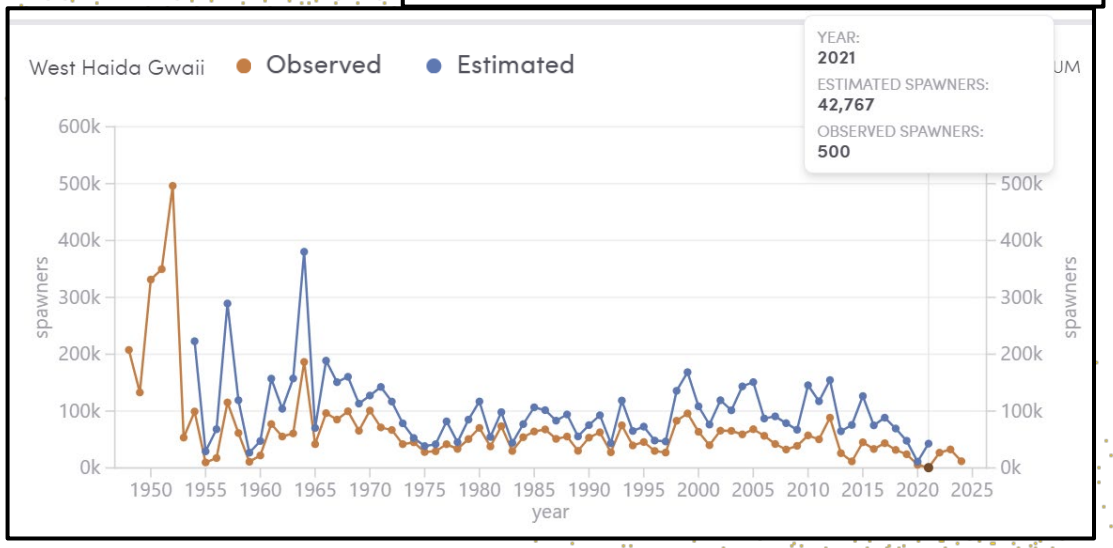
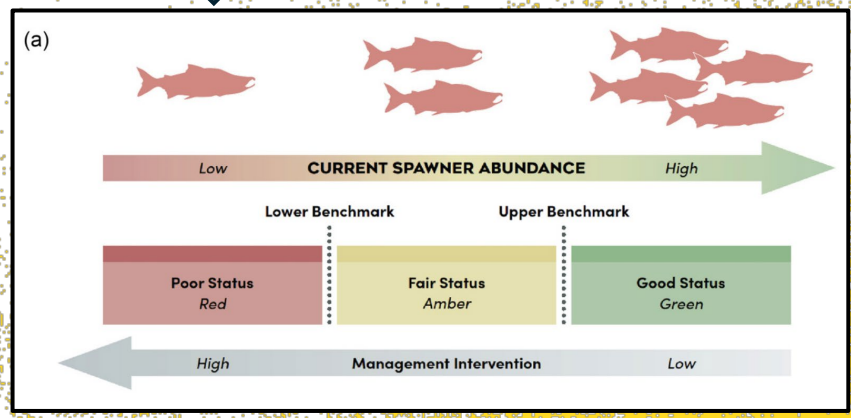


Expansion factor approach (English et al. 2018)

Estimated CU-level abundance





(Connors, Peacock et al. 2026)

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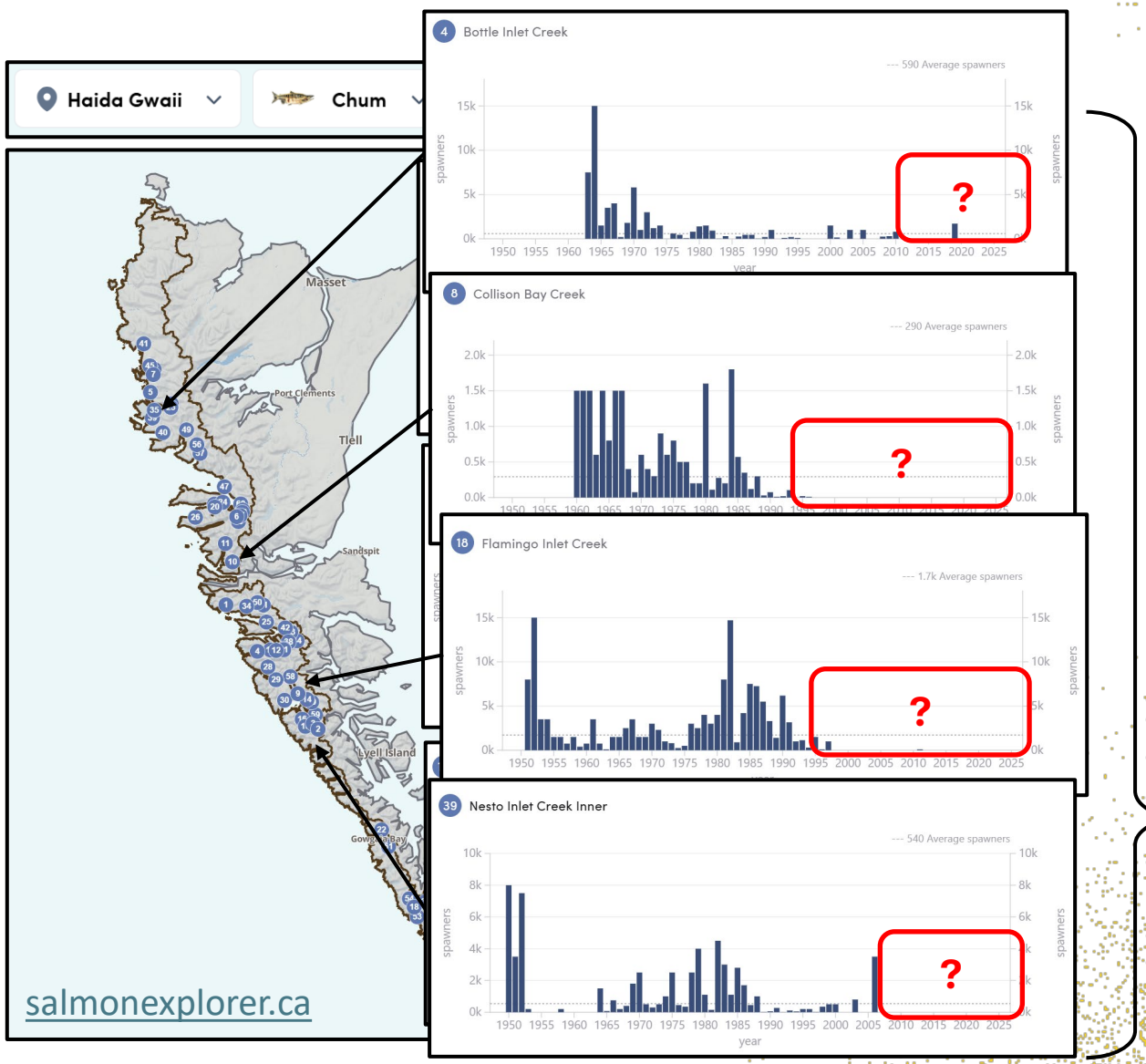

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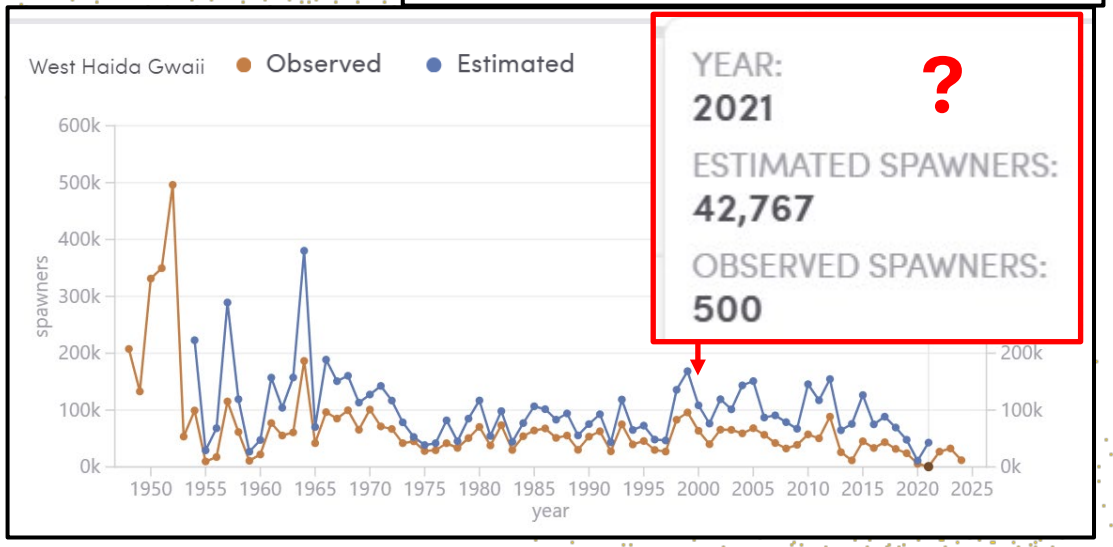

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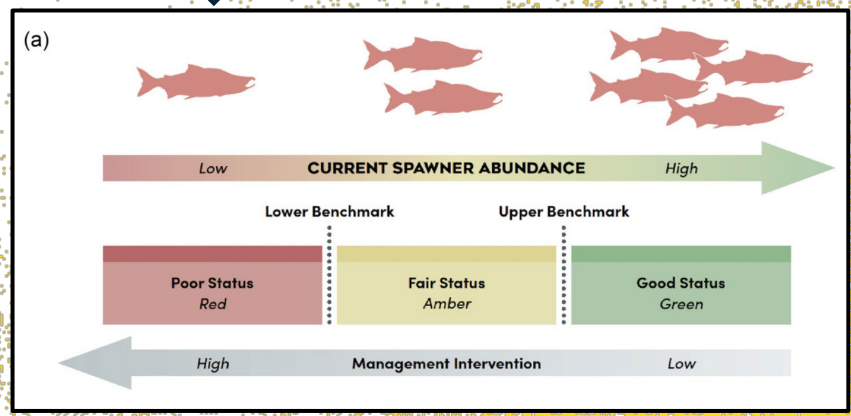

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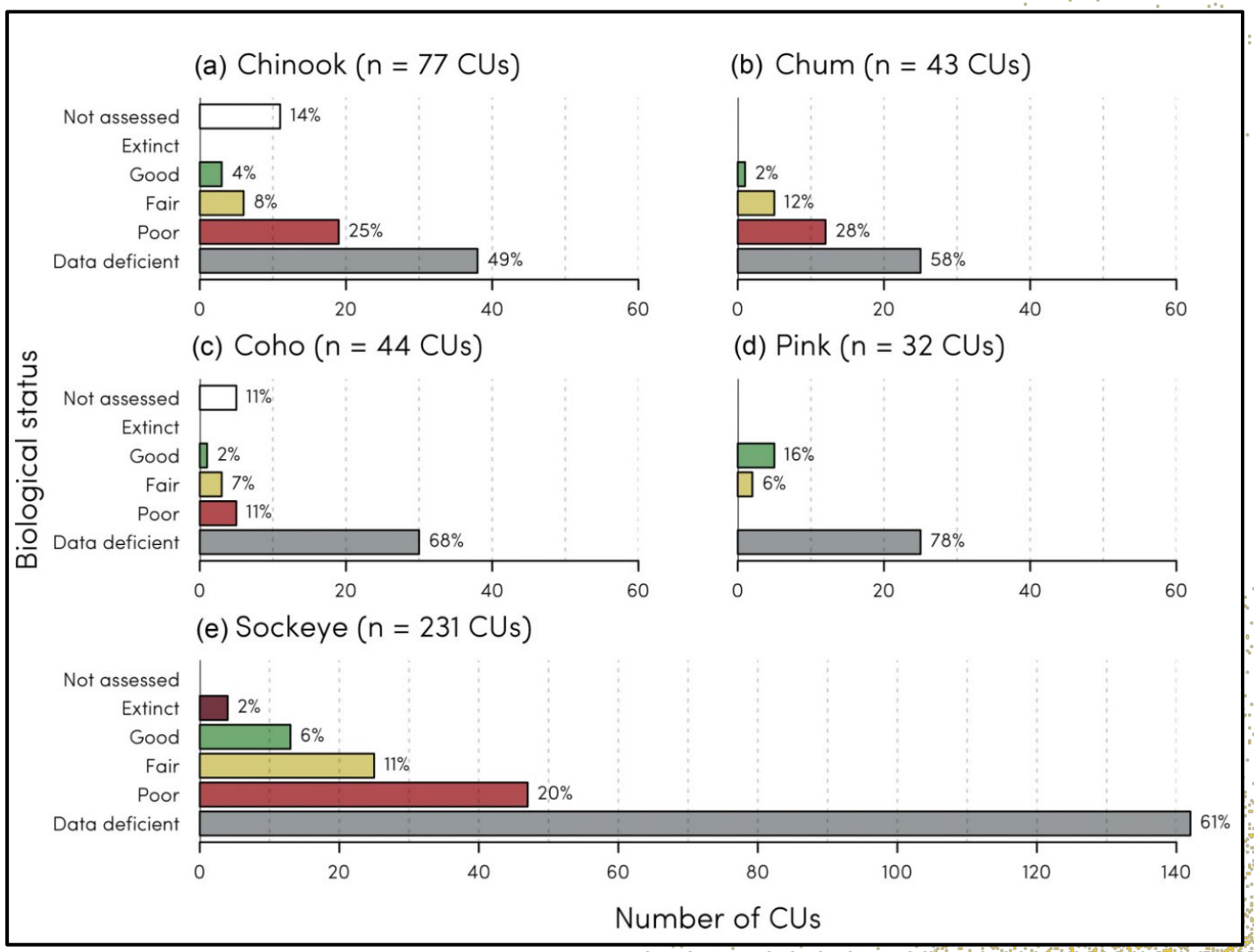
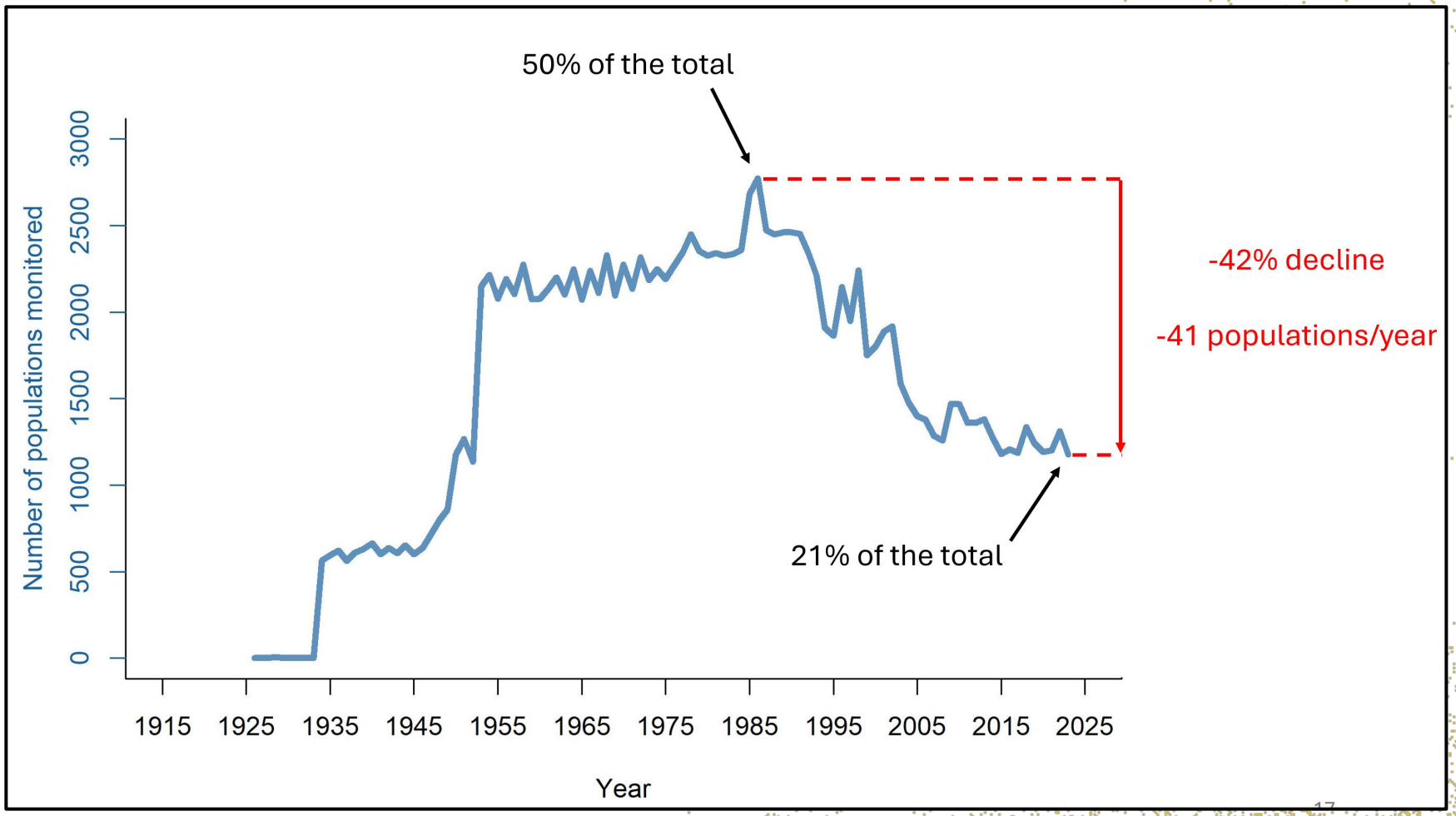


"Thirty CUs (7%) lacked a single spawner survey, while 188 CUs (44%) lacked estimates of spawner abundance at the CU-scale" (Connors, Peacock et al. 2026).

Objective: to fill data gaps in spawner survey data to reliably estimate CU-level abundance in a context of declining monitoring.



(Atkinson, Carturan et al. 2025)

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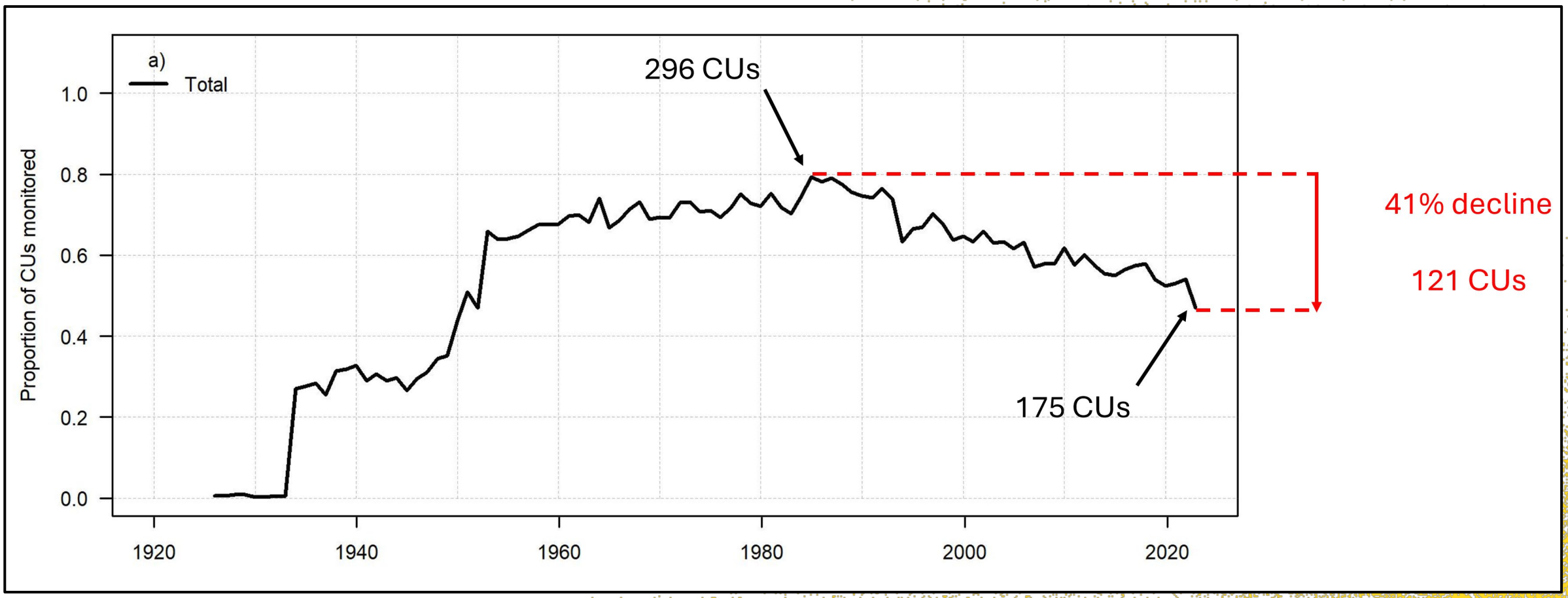

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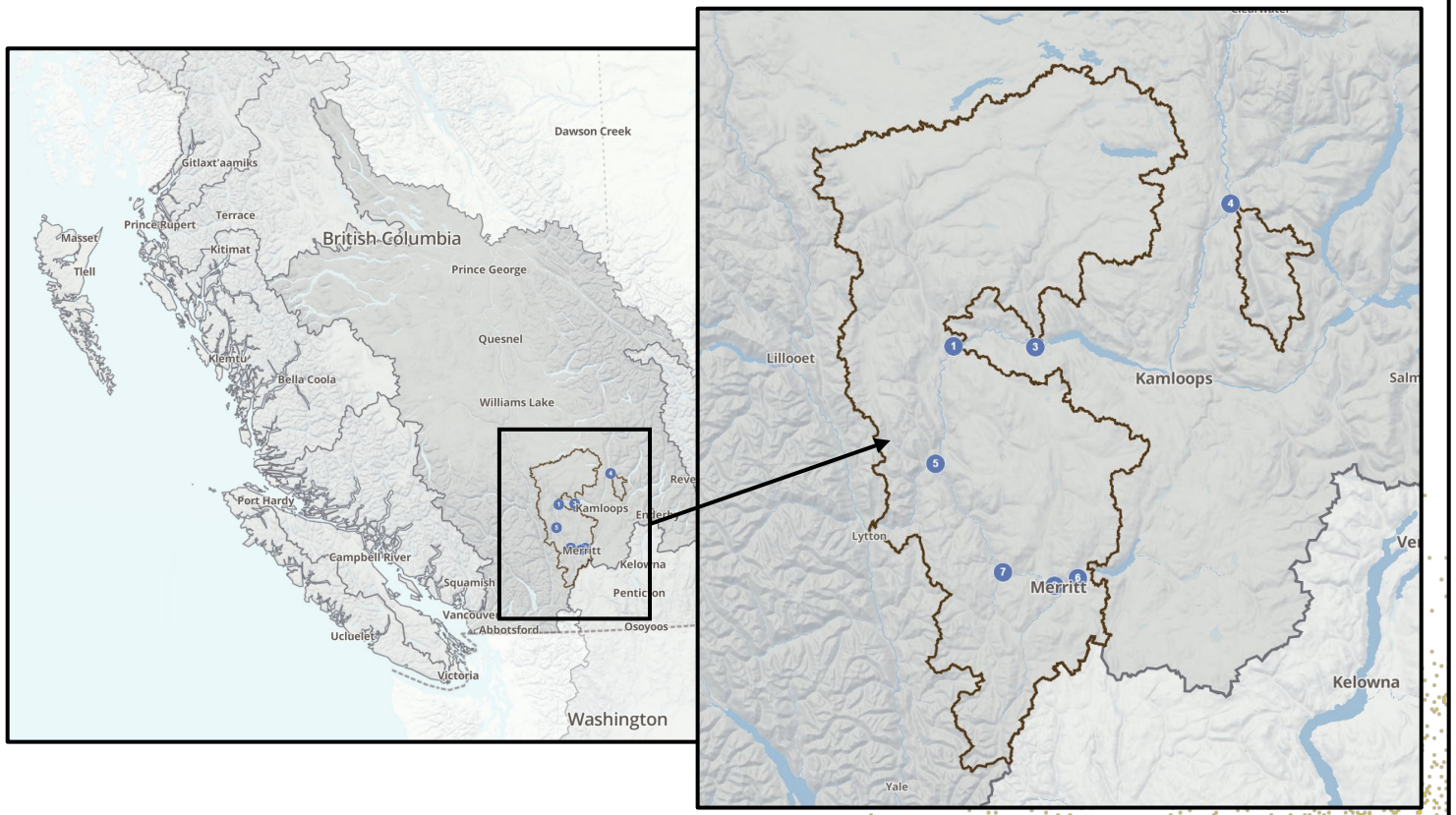
Objective: to fill data gaps in spawner survey data to reliably estimate CU-level abundance in a context of declining monitoring.

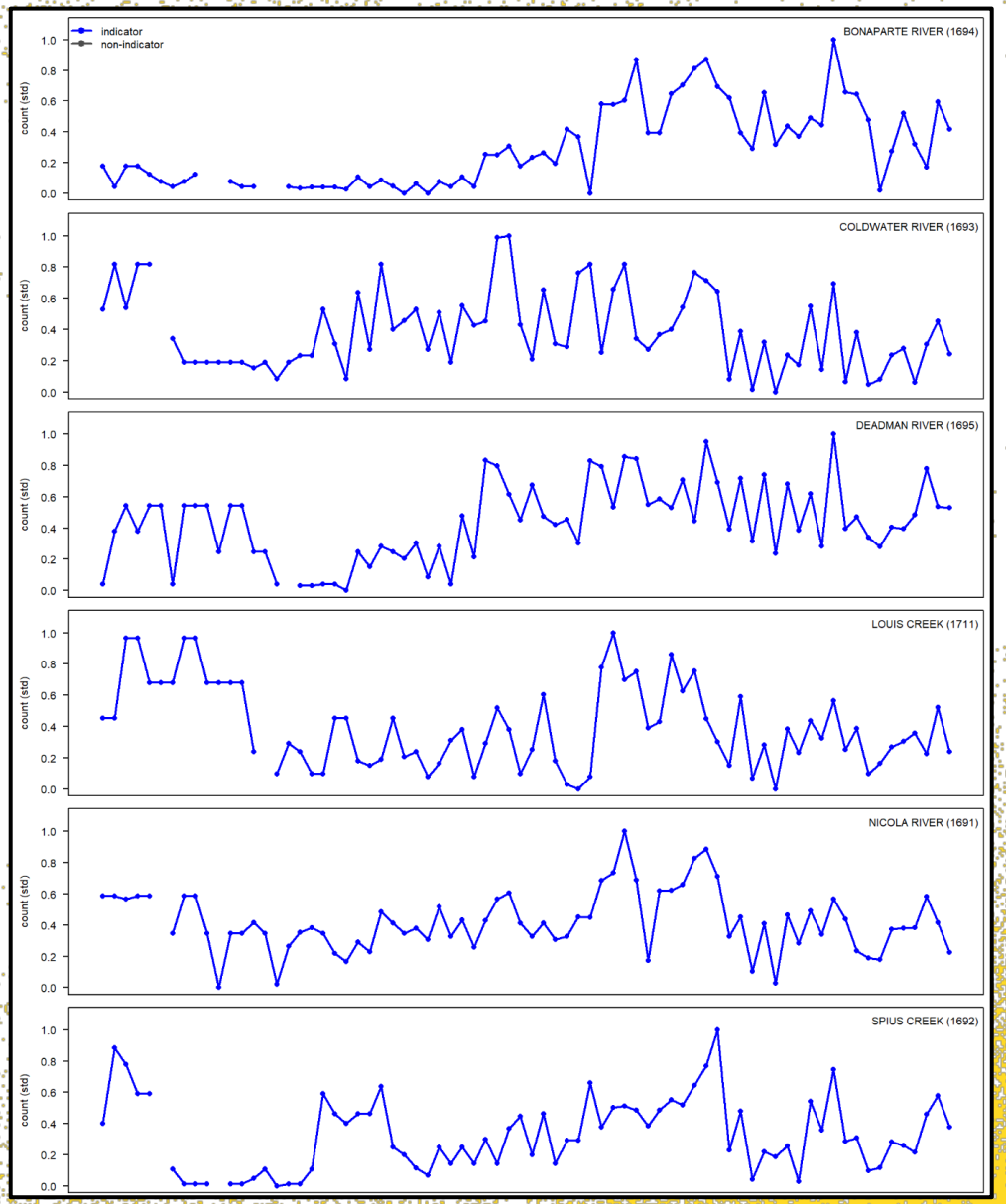
Spawner surveys remain essential.

But meanwhile, can we leverage the existing data to compensate for this decline in monitoring?

Methods: Data and case study







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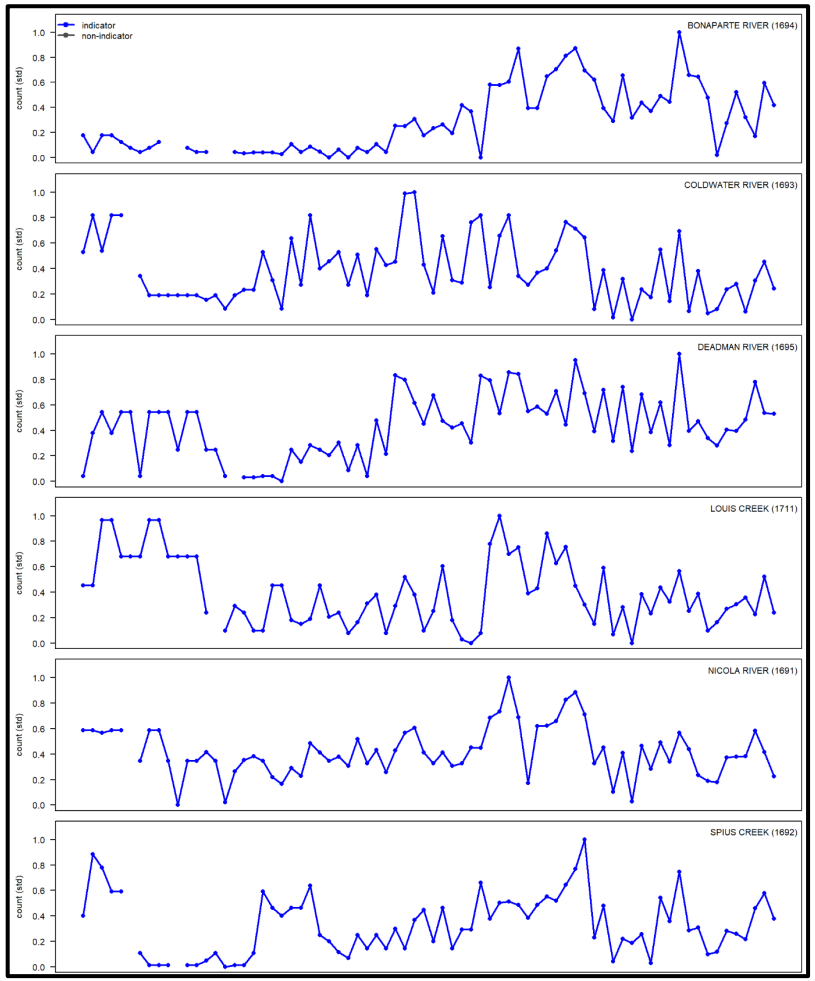
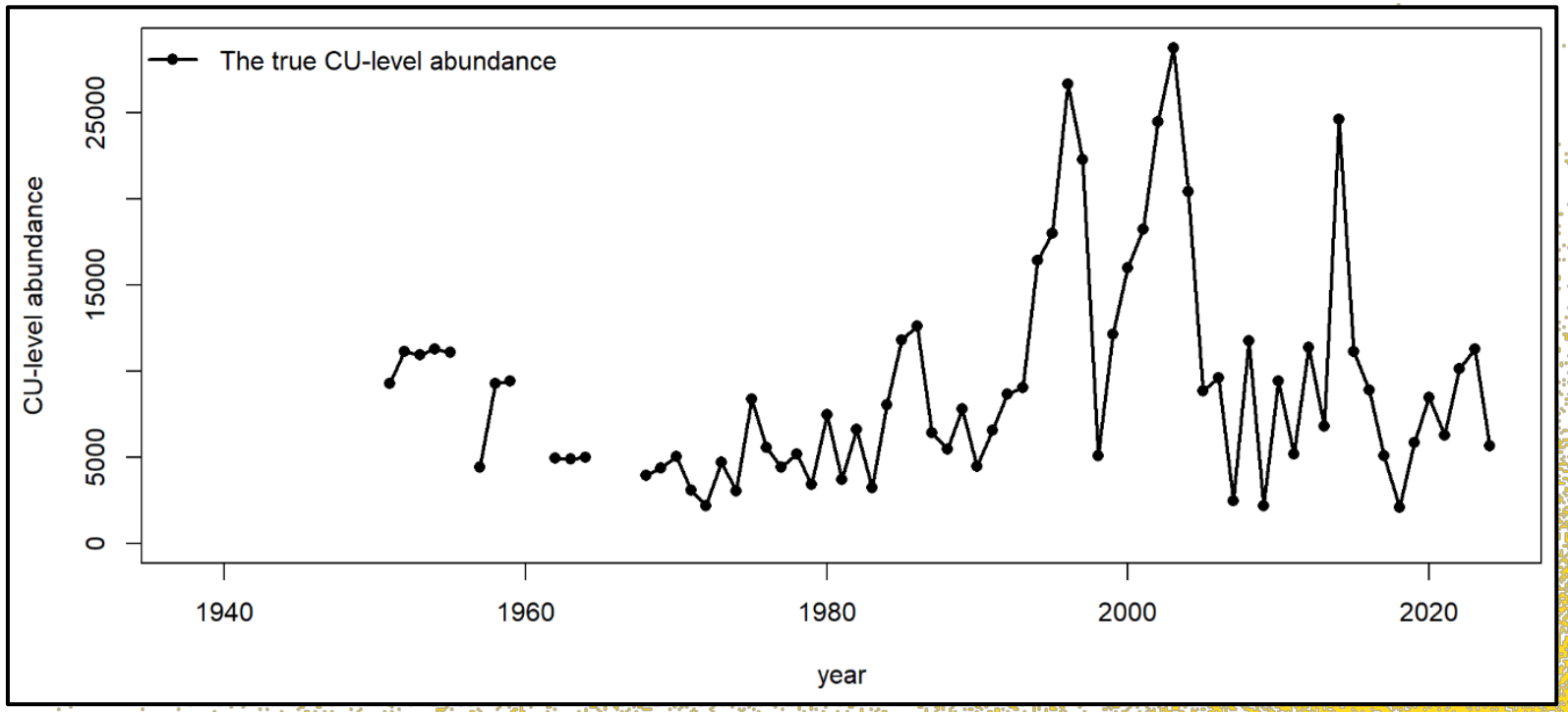


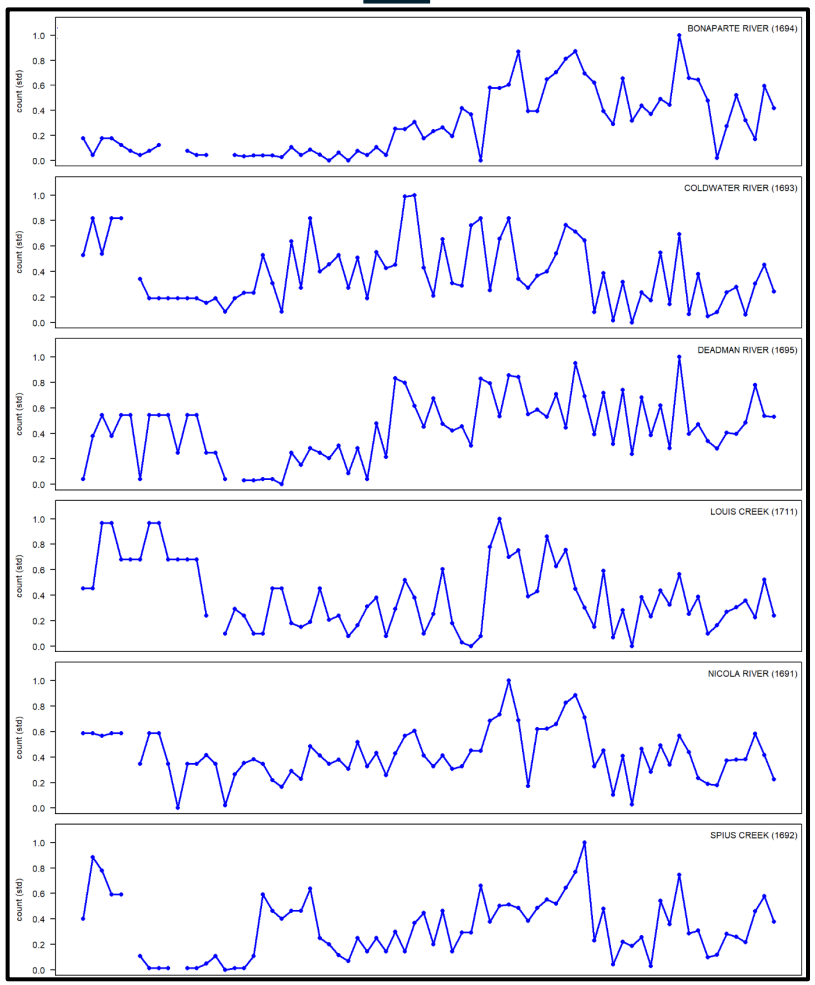
sum

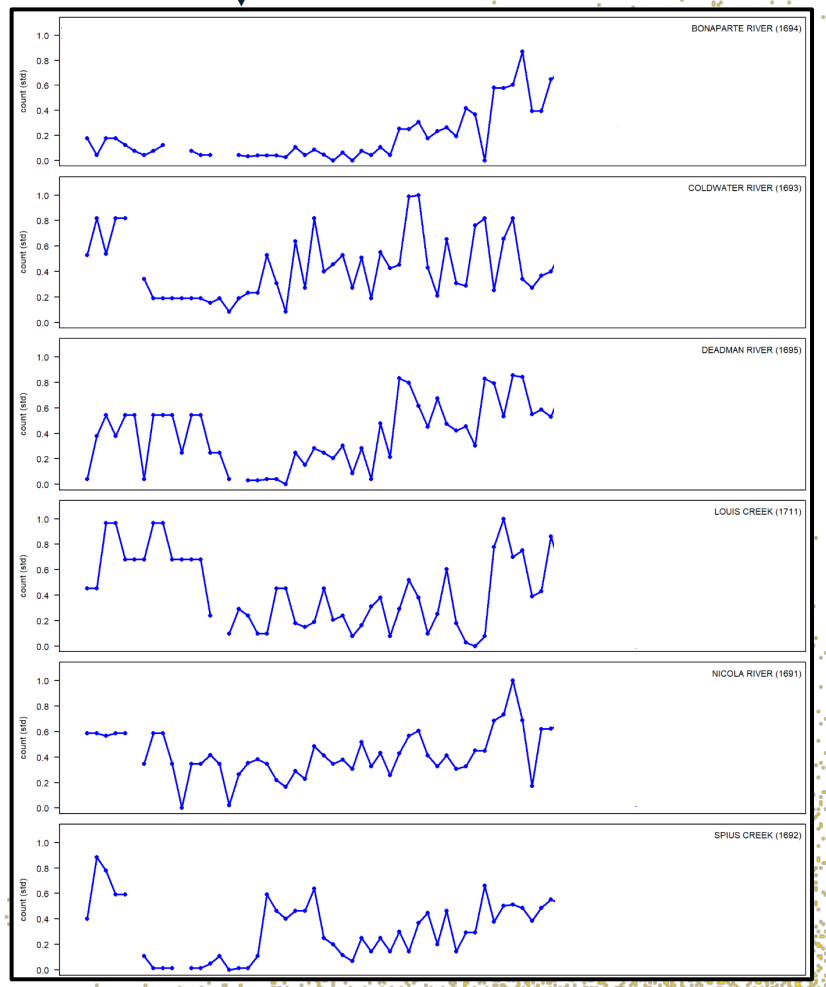


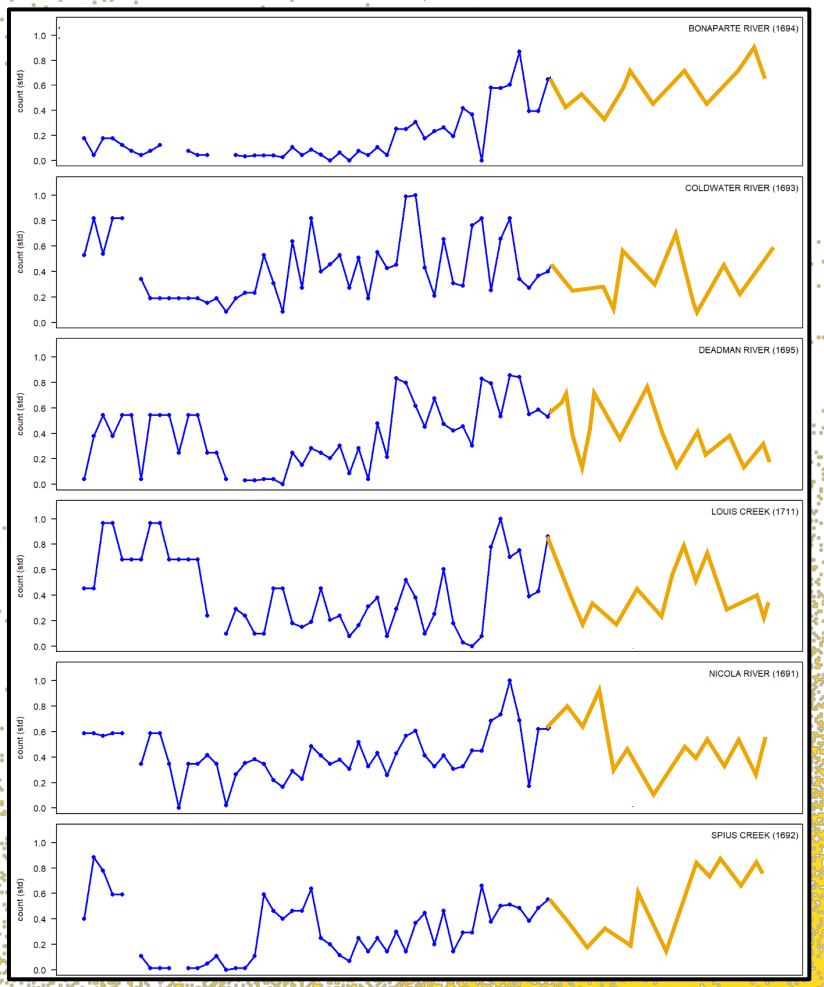
Methods: Data and case study

Remove data points after 2000

Predict missing values







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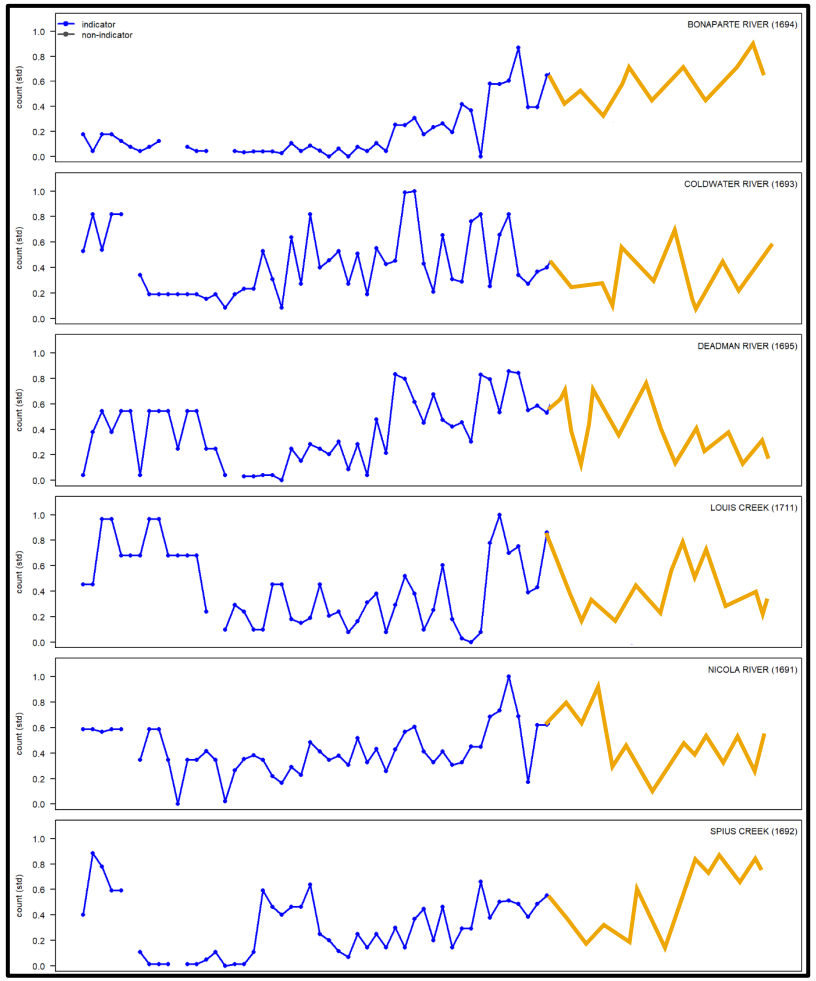

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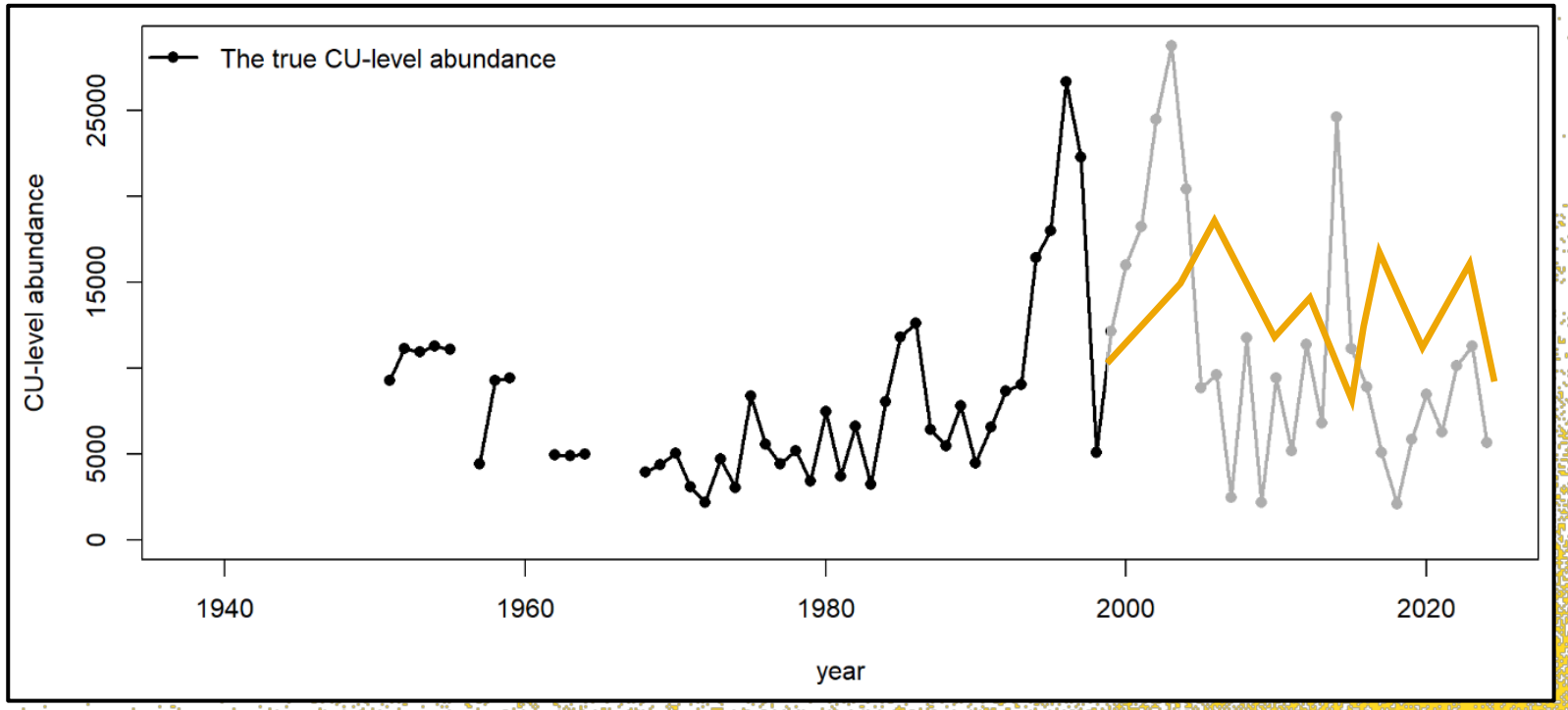

Methods: Data and case study



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NuSEDS-New Salmon Escapement Database System

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Additional Information

Contact Email:
Zhipeng.Wu@dfo-mpo.gc.ca

Keywords:

Pacific Ocean | British Columbia | Yukon Territory | Vancouver Island | Haida Gwaii | Pacific Salmon | Escapement | BC16 | Salmon Spawning Observations | Summary Estimate Narrative (SEN) | Salmon Spawner Abundance

Salmon escapement data constitute important corporate knowledge which must be adequately maintained and accessible. The Salmon Escapement Database (NuSEDS) is the DFO Pacific Region's central database that stores individual spawner survey data records, spawner abundance estimates and the linkages between the two. Annual abundance estimates are maintained by population, as defined by freshwater location and run timing. Each population is referenced to the location of the stream mouth. The watershed-coding system provides unique stream identification and incorporates the natural organization, direction, and hierarchical nature of stream channels and their tributaries.

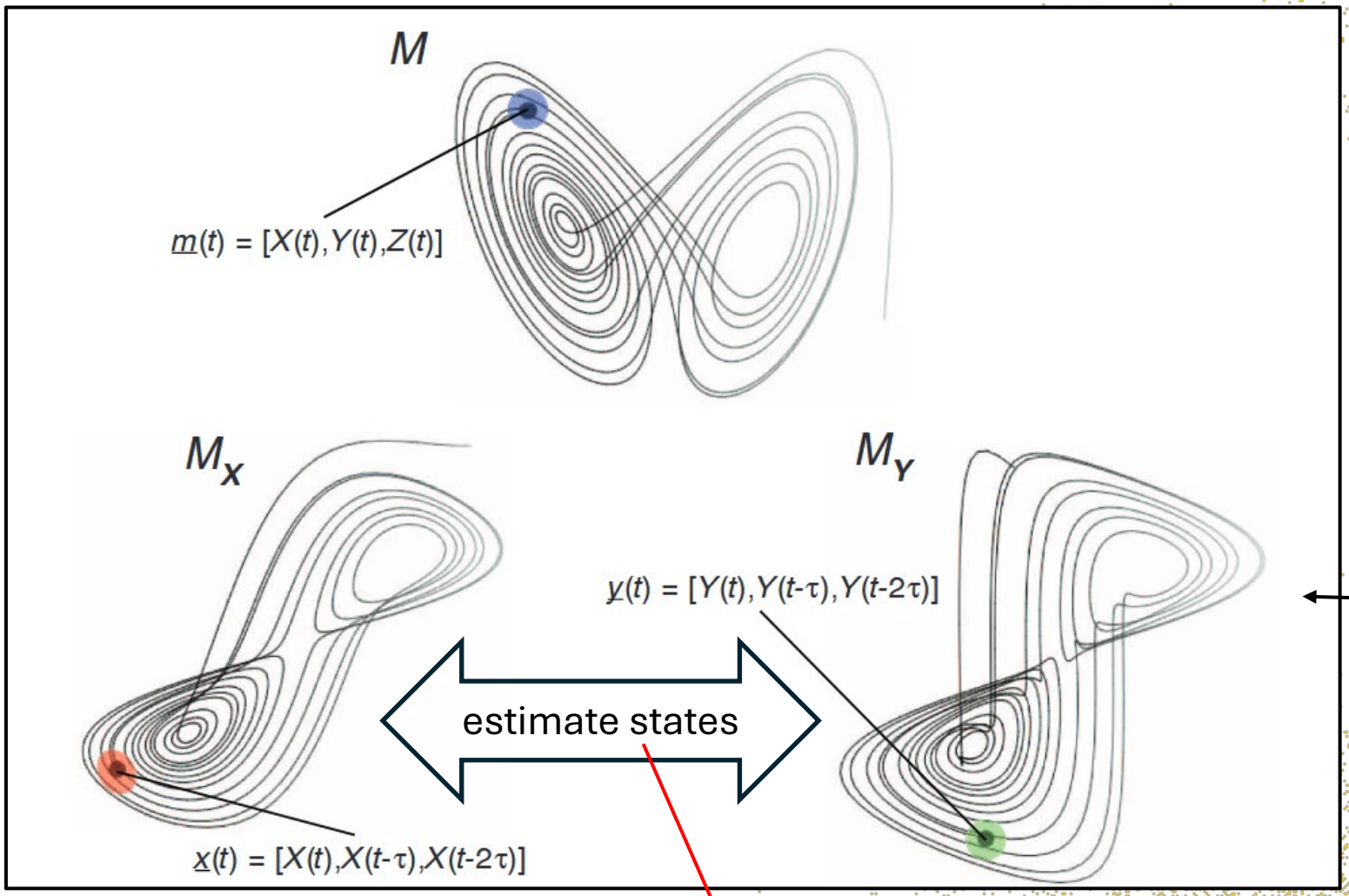
The NuSEDS database currently reports salmon spawning observations for 9100+ individual populations but escapement estimates (all levels of survey intensity) are available for 9800+ populations.

This database contains historic population data starting in the 1920's (older data for some rivers exists in other formats). Prior to 1995 a standardized form (BC-16) was used to summarize the estimate of the spawning population size, but the historical database lacked the capacity to describe the number of observations, individual counts or methods used to estimate the abundance of the population. In 1995, responsibility for salmon enumeration was moved to the DFO Science section. At that time, the database was re-written to include descriptive information for each abundance estimate, providing underlying data and the estimation method(s). Many of the historic estimates prior to 1995 are labeled Unspecified Returns because the database was limited to storing one estimate for any given stock. As time and resources permit these data are being replaced with more accurate categorization. With the introduction of the Wild Salmon Policy (2005),

Use of all the spawner survey data in the **Fraser region**, including **all five species of salmon** and **steelhead**

→ Leverage a LOT of data
→ Not just the time series in the same CU like for the expansion factor approach

Methods: based on Empirical Dynamic Modelling…



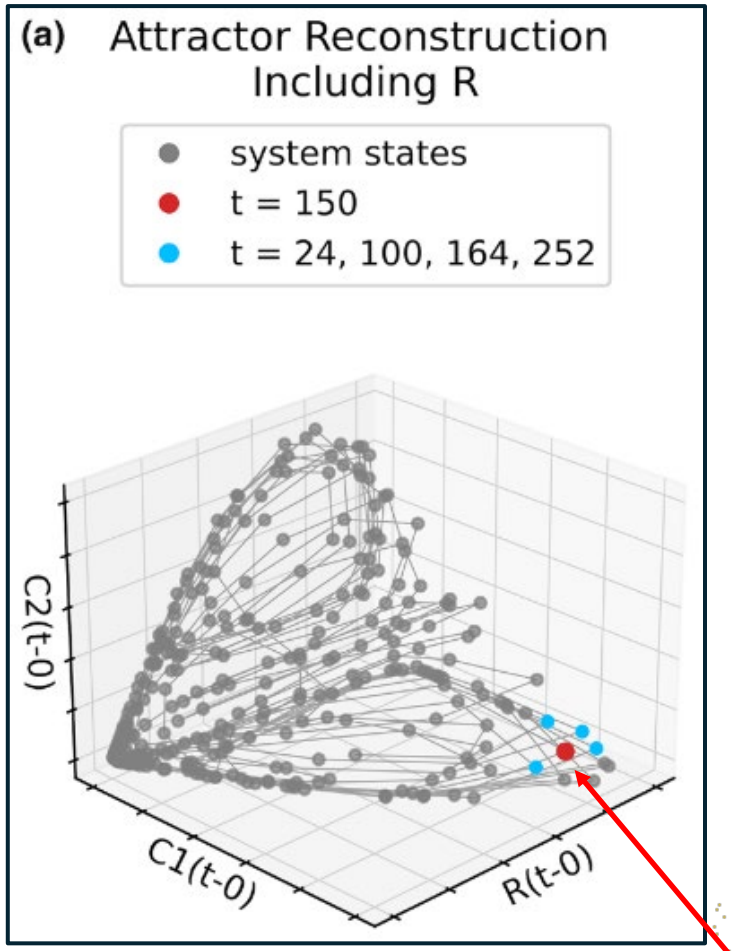
M = “manifold”
~
“system view”
~
“state space”

Two different “system views” or “state spaces” of embedding dimension E = 3

(Sugihara et al. 2012)

Cross Mapping (CM)

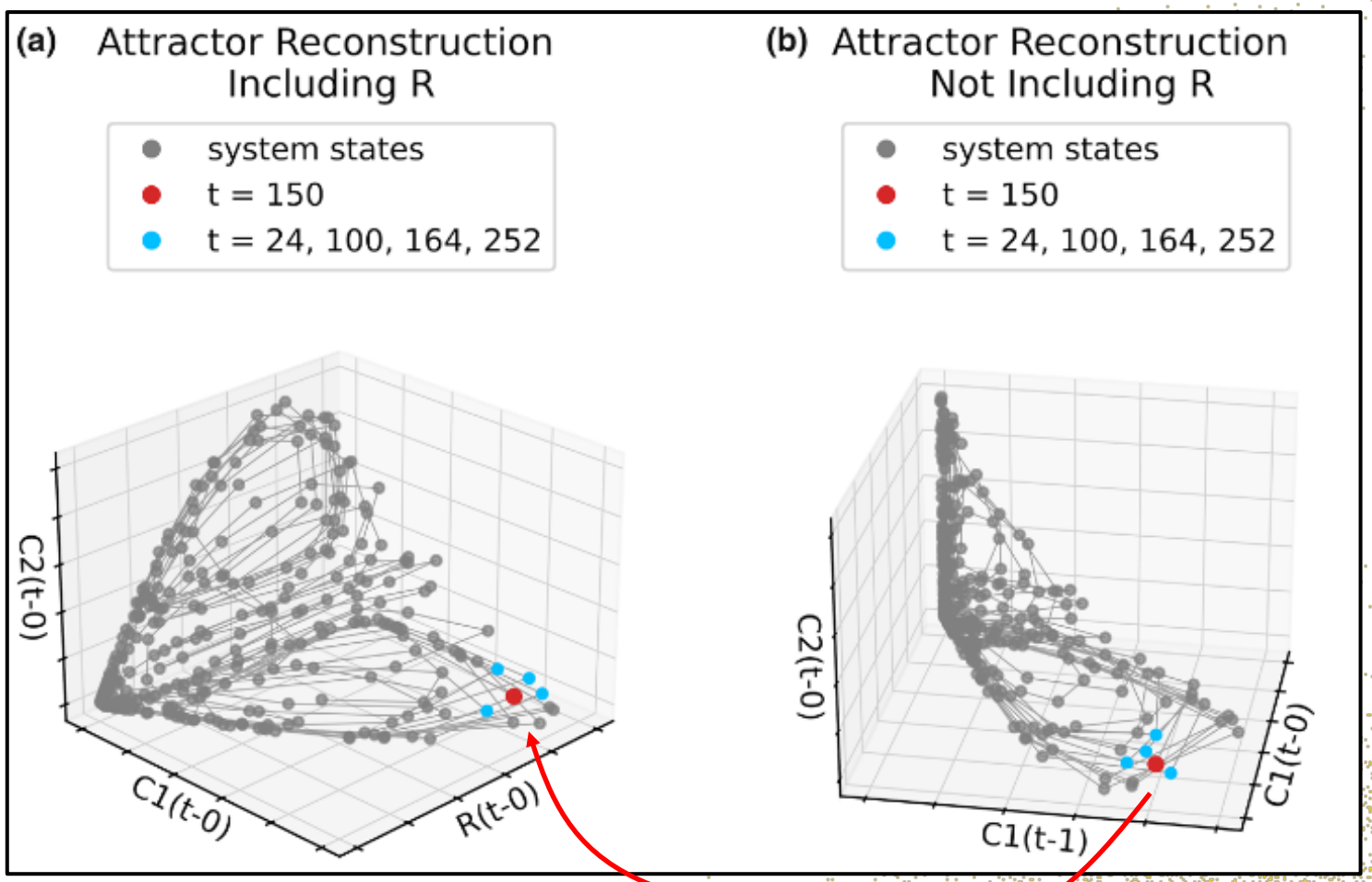
Methods: based on Empirical Dynamic Modelling…



(Carpenter et al. 2025)

R(t = 150) = ?

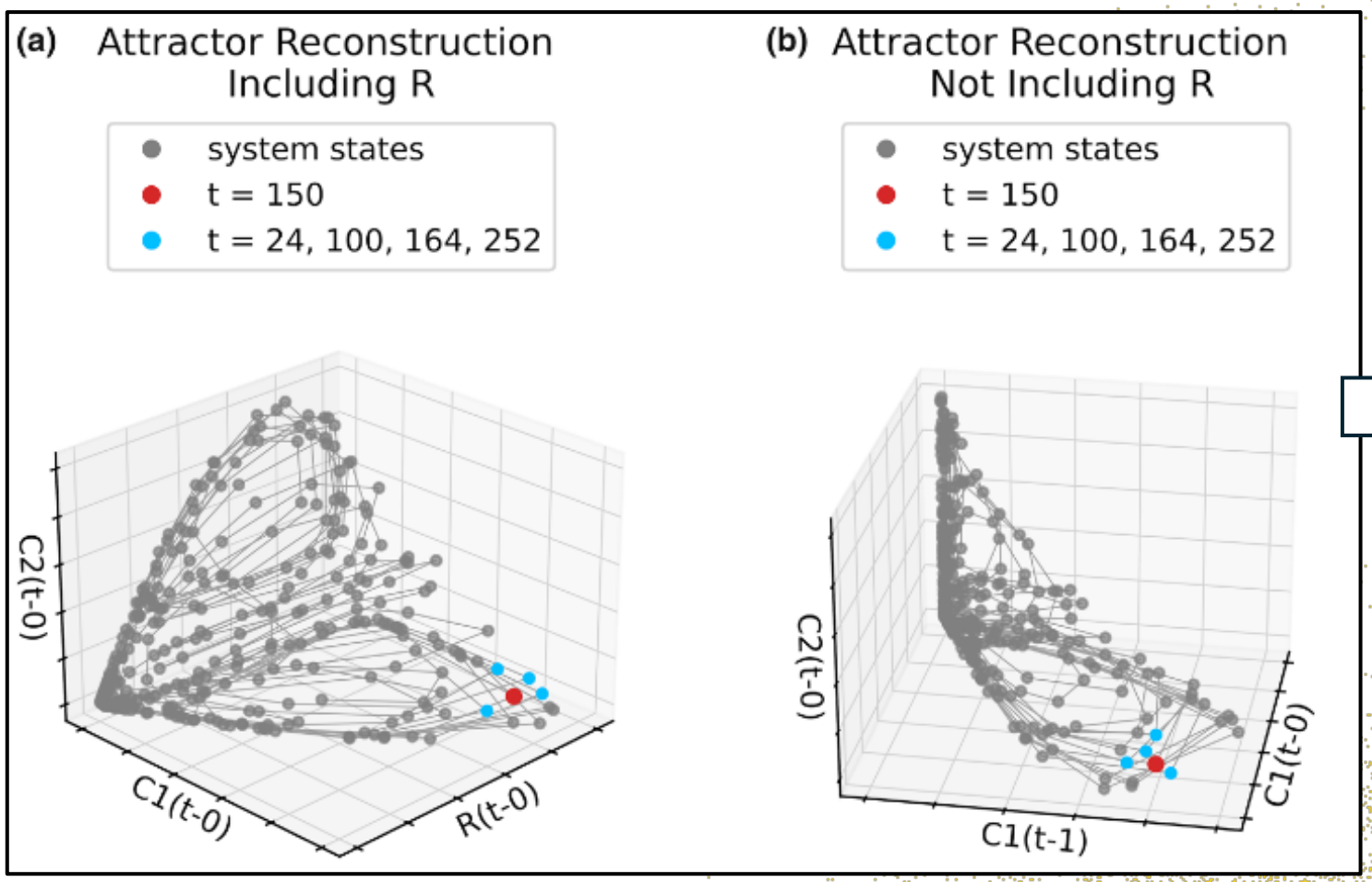
Methods: based on Empirical Dynamic Modelling…



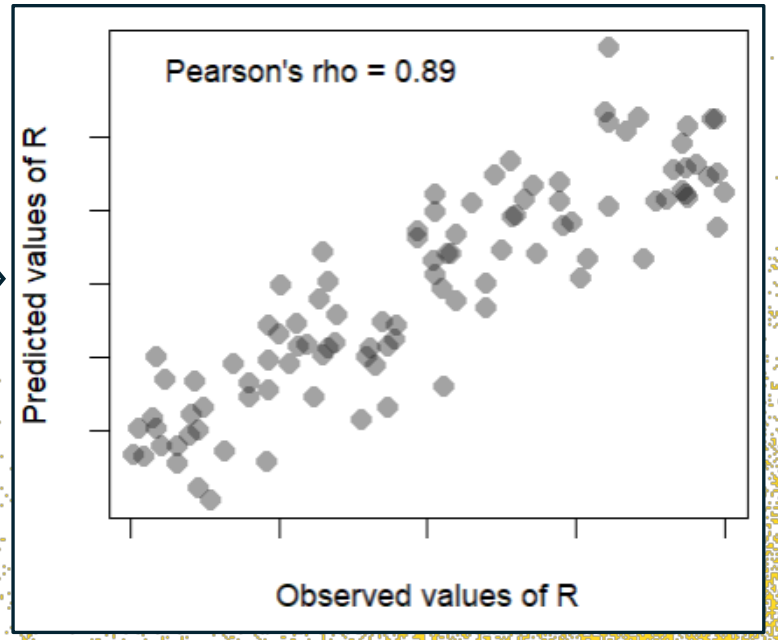
(Carpenter et al. 2025)

$R(t = 150) = \text{mean}_w\,(R(t = 24), R(t = 100), R(t = 164), R(t = 252))$

Methods: based on Empirical Dynamic Modelling…



Performance metric of a given view:



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Methods: … and based on Multi-View Cross-Mapping (MVCM)

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RESEARCH ARTICLE

BRITISH ECOLOGICAL SOCIETY | Methods in Ecology and Evolution

Repairing gaps in ecological time series

Delia Carpenter[1] | Ethan Deyle[2] | Joseph Park[1,3] | Erik Saberski[1] | George Sugihara[1]

rEDM & pyEDM packages

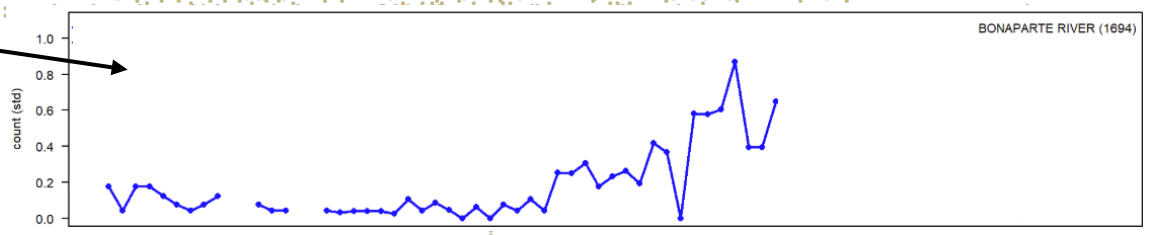
(Carpenter et al. 2025)

Methods: … and based on Multi-View Cross-Mapping (MVCM)

(Carpenter et al. 2025)

Steps: to fill the gaps in one time series (“target”)

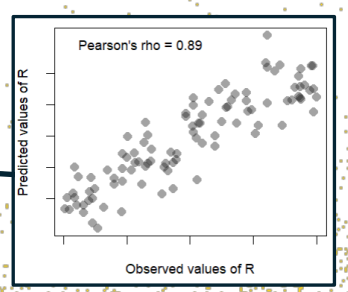
1. Find the best (n = 25) time series for predictions (“**partners**”) using **Simplex()** and for E = 1, 2, 3… 10 (retain the ones with the highest rho)



NuSEDS-New Salmon Escapement Database System

Cross mapping with Simplex

(univariate views)



Potential partners	rho
Stream 1	0.034
Stream 2	0.763
…	-0.624
Stream 198,362	0.002
Stream 198,363	0.952

Take the best 25

Methods: … and based on Multi-View Cross-Mapping (MVCM)

(Carpenter et al. 2025)

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1. Find the best (n = 25) time series for predictions ("**partners**") using **Simplex()** and for E = 1, 2, 3… 10 (retain the ones with the highest rho)

2. Lag the partners (tau = -1 and +1, number of lags = 3) at t-0, t-1, t-2, t+1, t+2 (in the **block**)

e.g. Stream 5(t-2), Stream 5(t-1), Stream 5(t-0), Stream 5(t+1), Stream 5(t+2)

→ 25 x 5 = 125 lags

Methods: … and based on Multi-View Cross-Mapping (MVCM)

(Carpenter et al. 2025)

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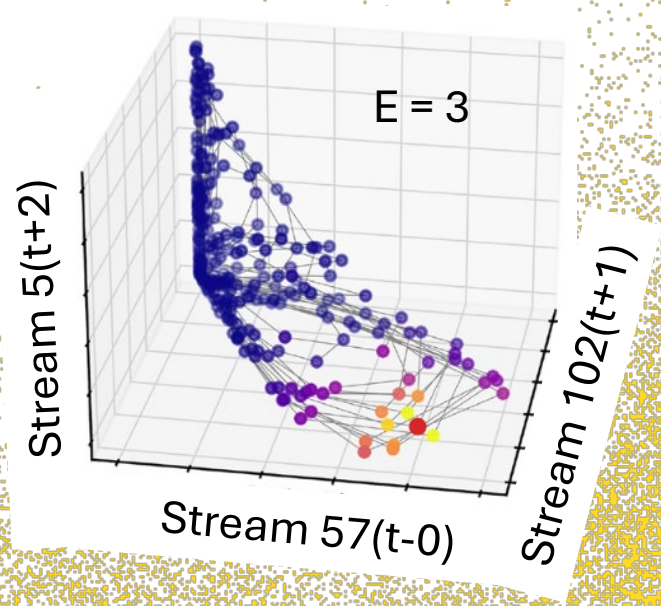
3. Create all possible views with **E = 2 and 3** dimensions

e.g.
- Stream 87(t+0) & Stream 87(t-1)
- Stream 5(t+0) & Stream 87(t-1)
- Stream 5(t-2) & Stream 102(t-1) & Stream 753(t+0)
- Stream 34(t+2) & Stream 57(t-0) & Stream 9(t+1)
- Stream 5(t+2) & Stream 57(t-0) & Stream 102(t+1)
- Etc.

→ 325,500 views



Methods: … and based on Multi-View Cross-Mapping (MVCM)

(Carpenter et al. 2025)

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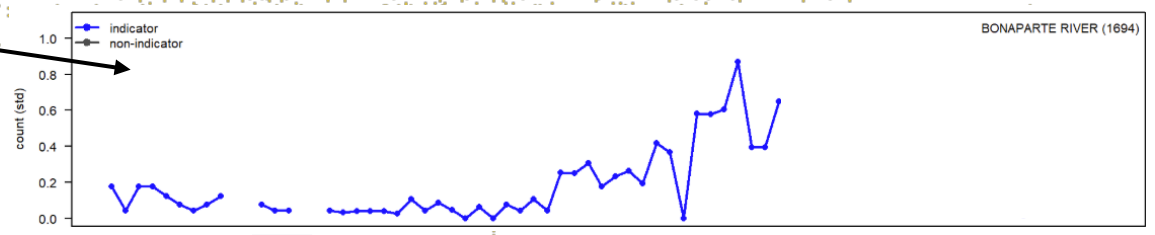
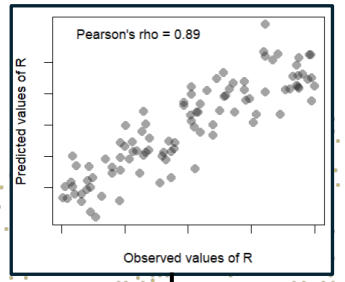
4. Assess the performance of each view with **rho** using **SMap()** (optimise theta)



Cross mapping with S-map

(multivariate views)



Views	rho
- Stream 87(t+0) & Stream 87(t-1)	0.034
- Stream 5(t+0) & Stream 87(t-1)	0.763
…	-0.624
- Stream 5(t-2) & Stream 102(t-1) & Stream 753(t+0)	0.002
- Stream 5(t+2) & Stream 57(t-0) & Stream 102(t+1)	0.952

Methods: … and based on Multi-View Cross-Mapping (MVCM)

(Carpenter et al. 2025)

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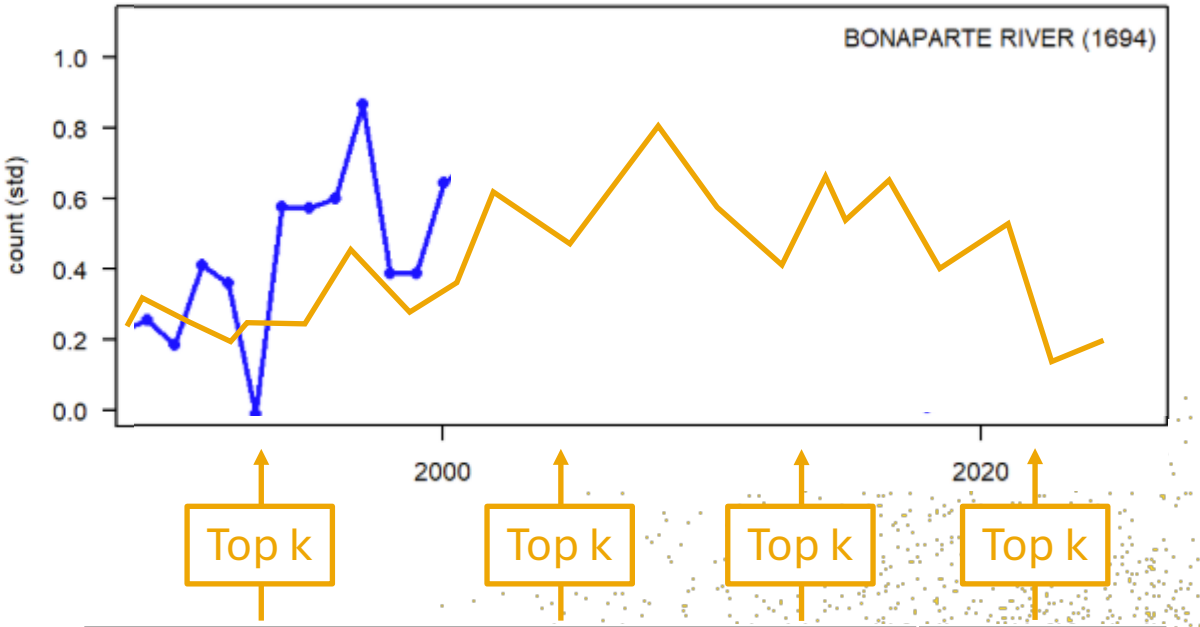
4. Assess the performance of each view with **rho** using **SMap()** (optimise theta)

5. For each year:
   a. select the views able to predict
   b. within those, select the top **k** views based on **rho** (e.g. k = 100)
   c. average the predictions of the top k views using **rho as a weight**



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Methods: … and based on Multi-View Cross-Mapping (MVCM)

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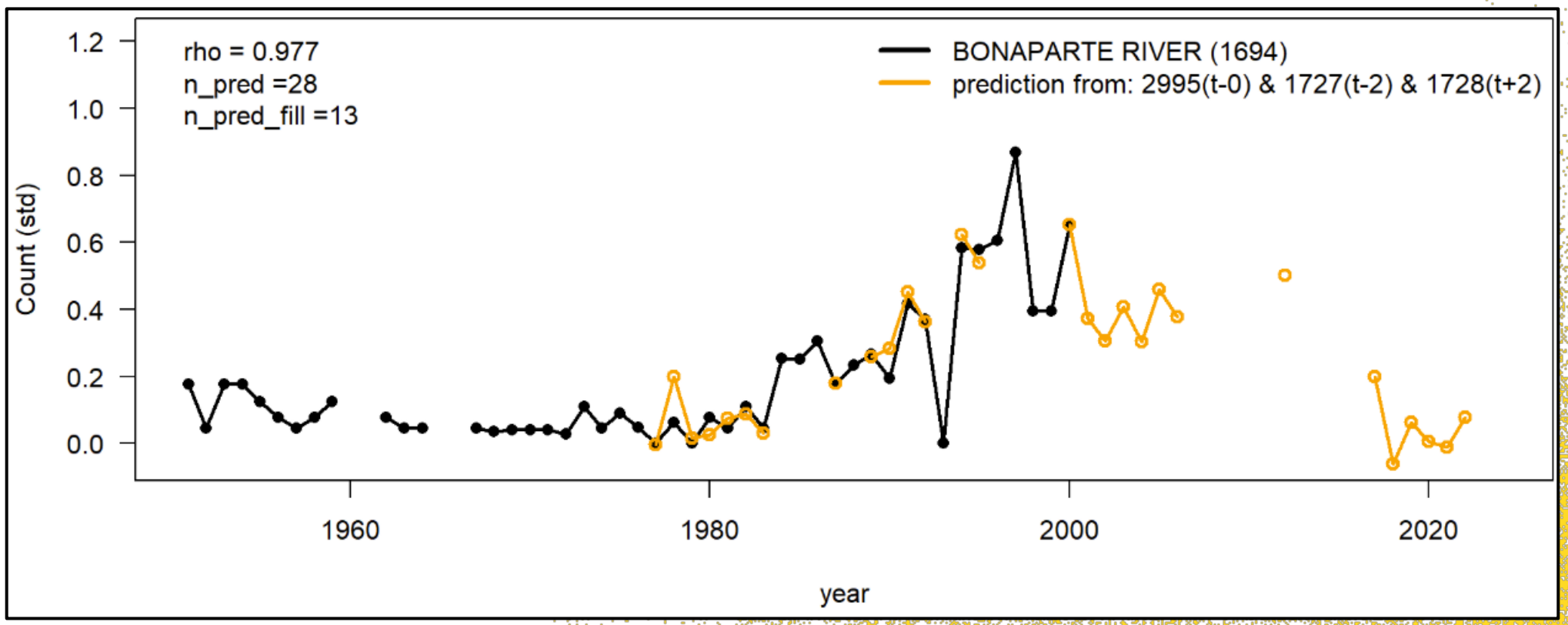

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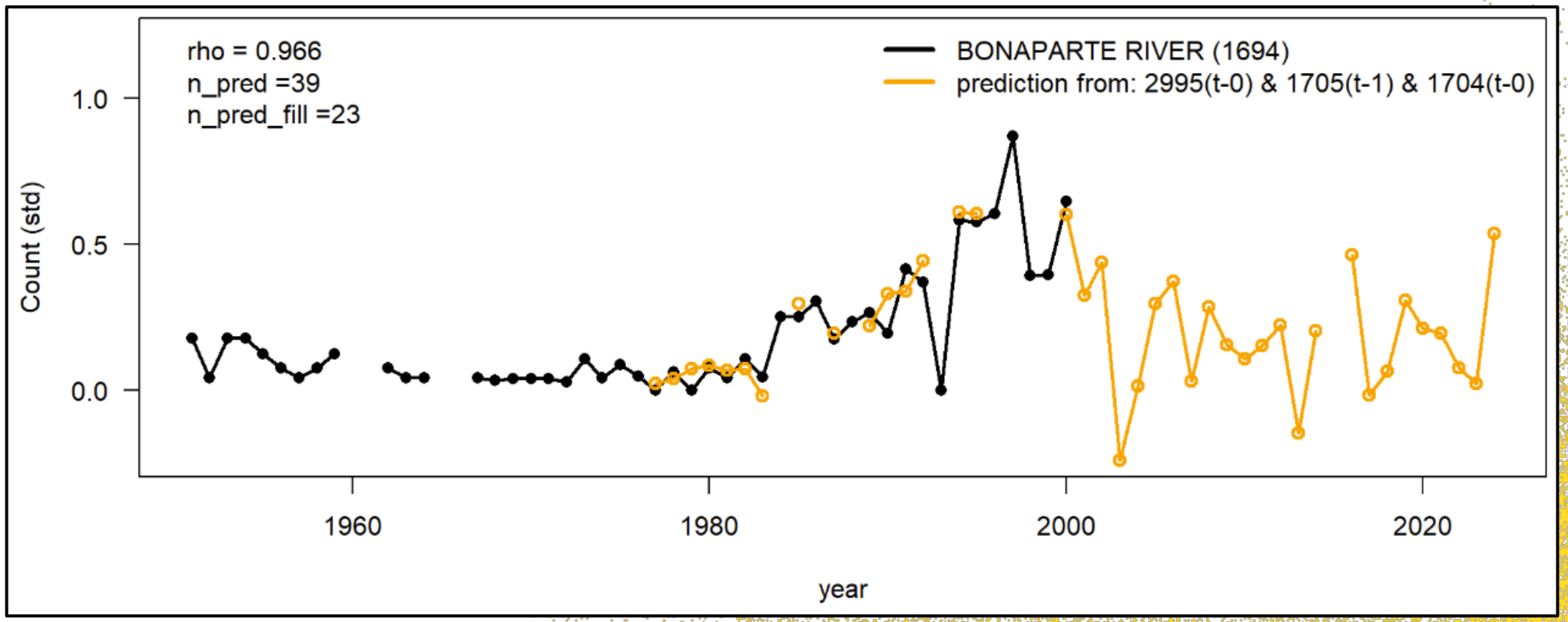
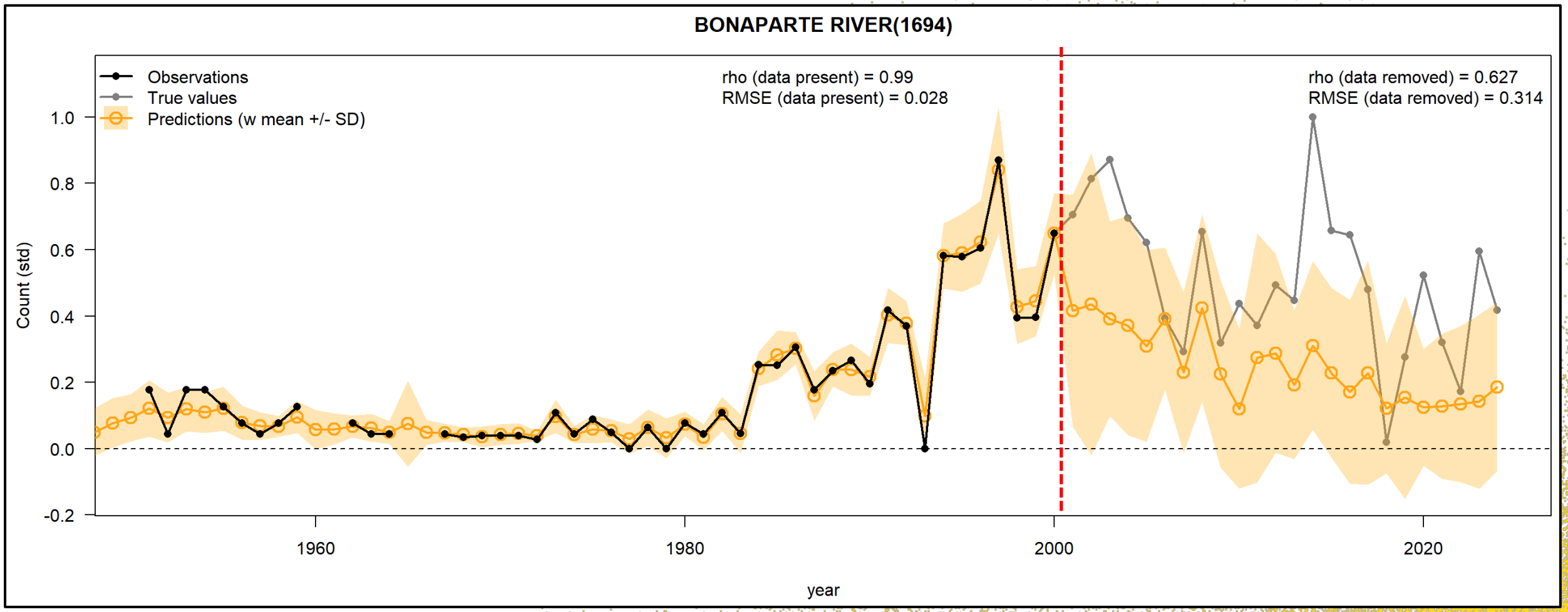
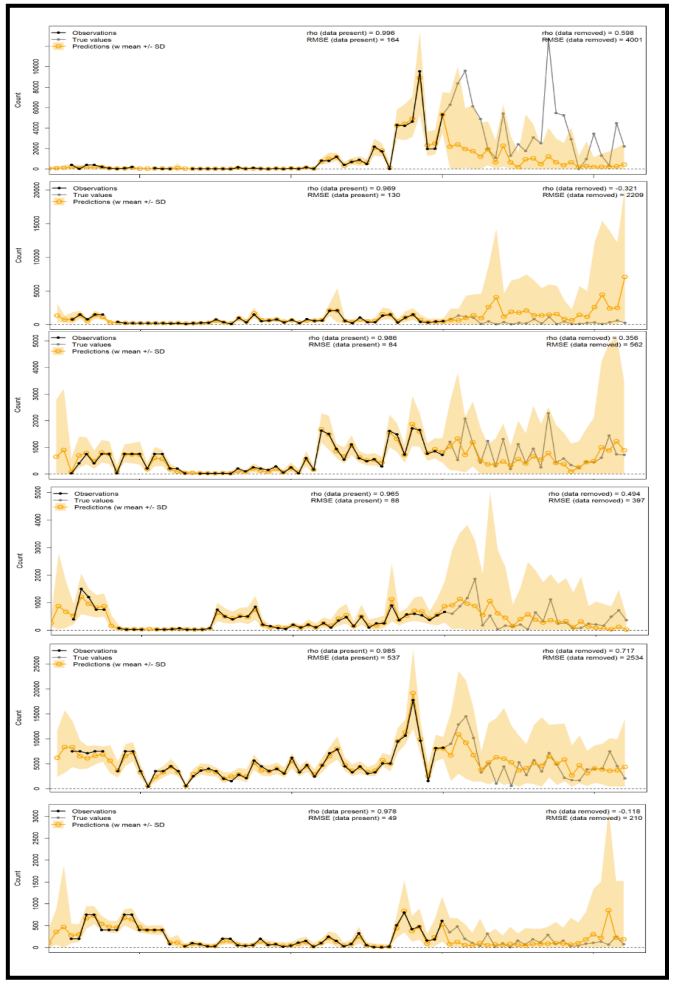


Results: Predicted weighted average spawner abundance for each year



Results: Predicted CU-level spawner abundance



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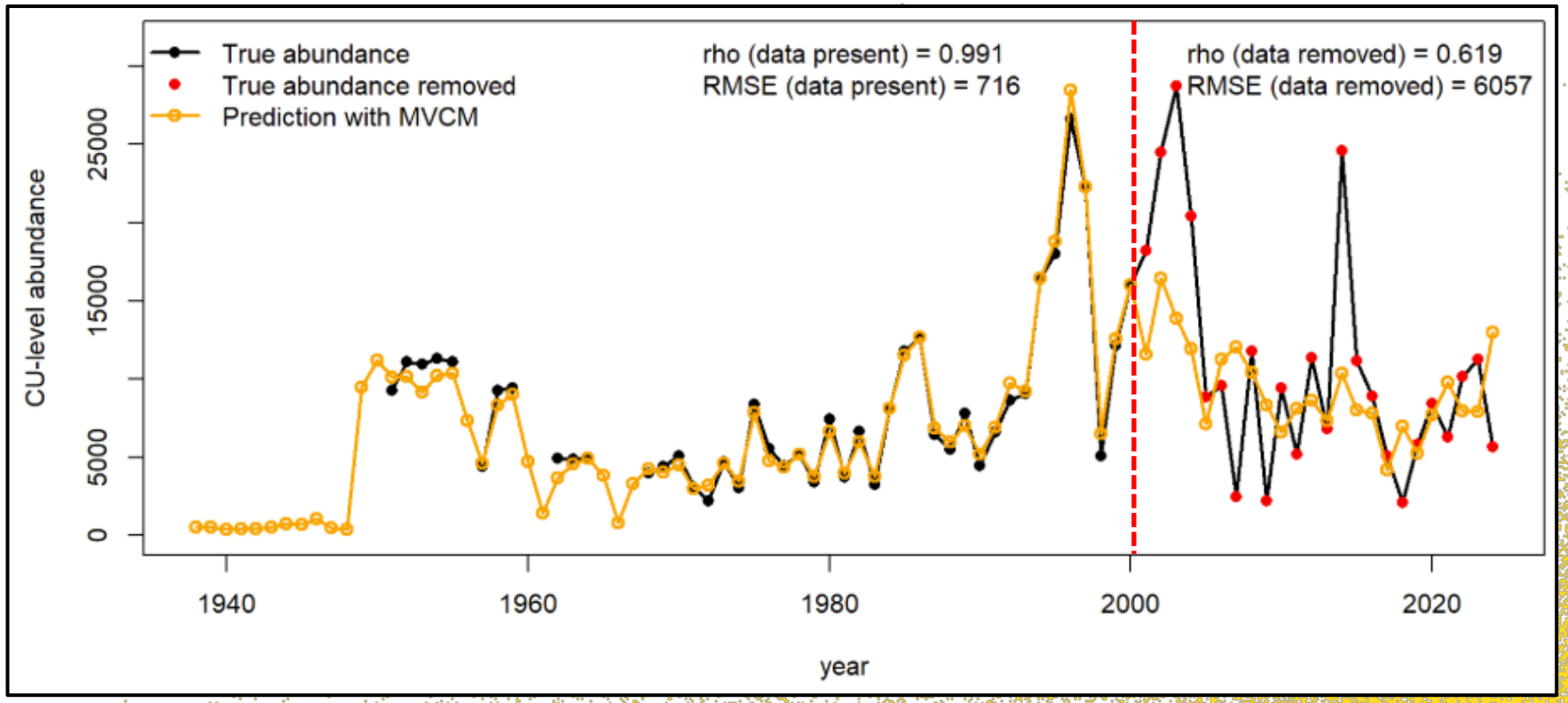
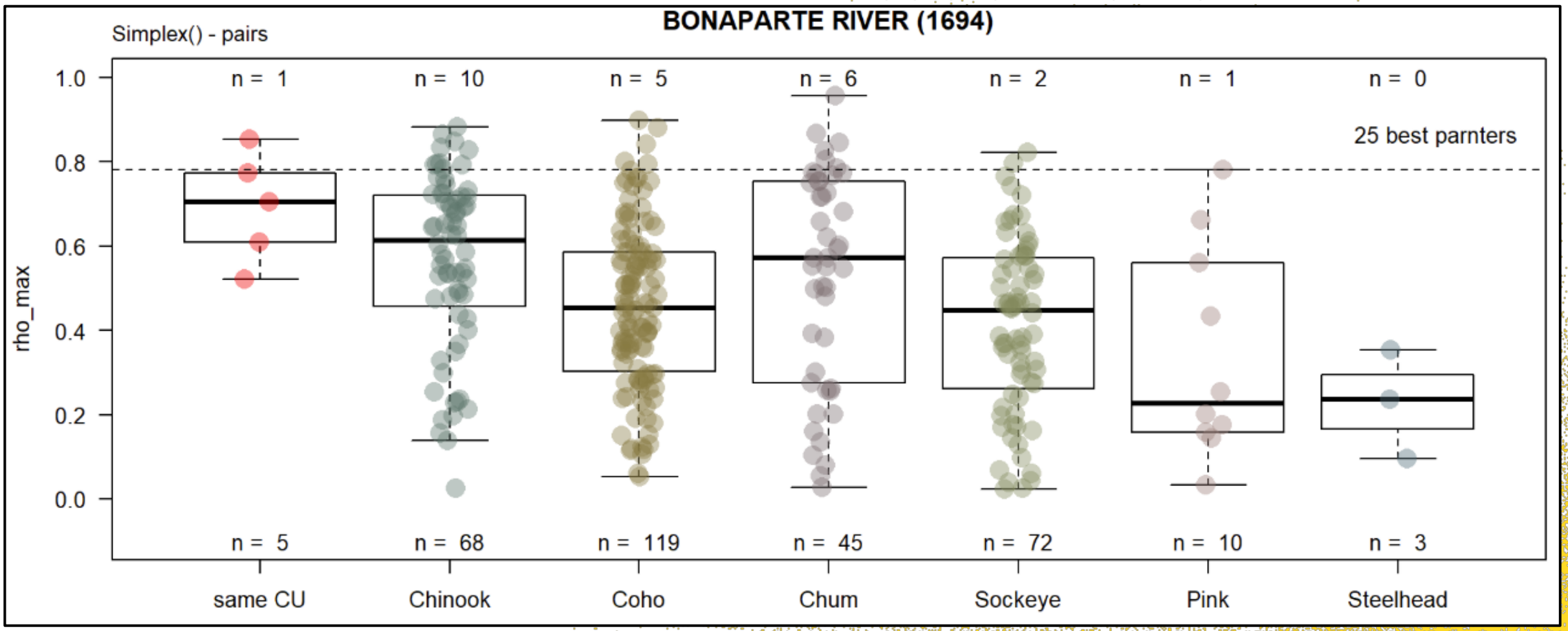


Results - Exploration analysis: does the concept of CU hold against the shared dynamics CUs and species?

Step 1: Find the best (n = 25) time series ...

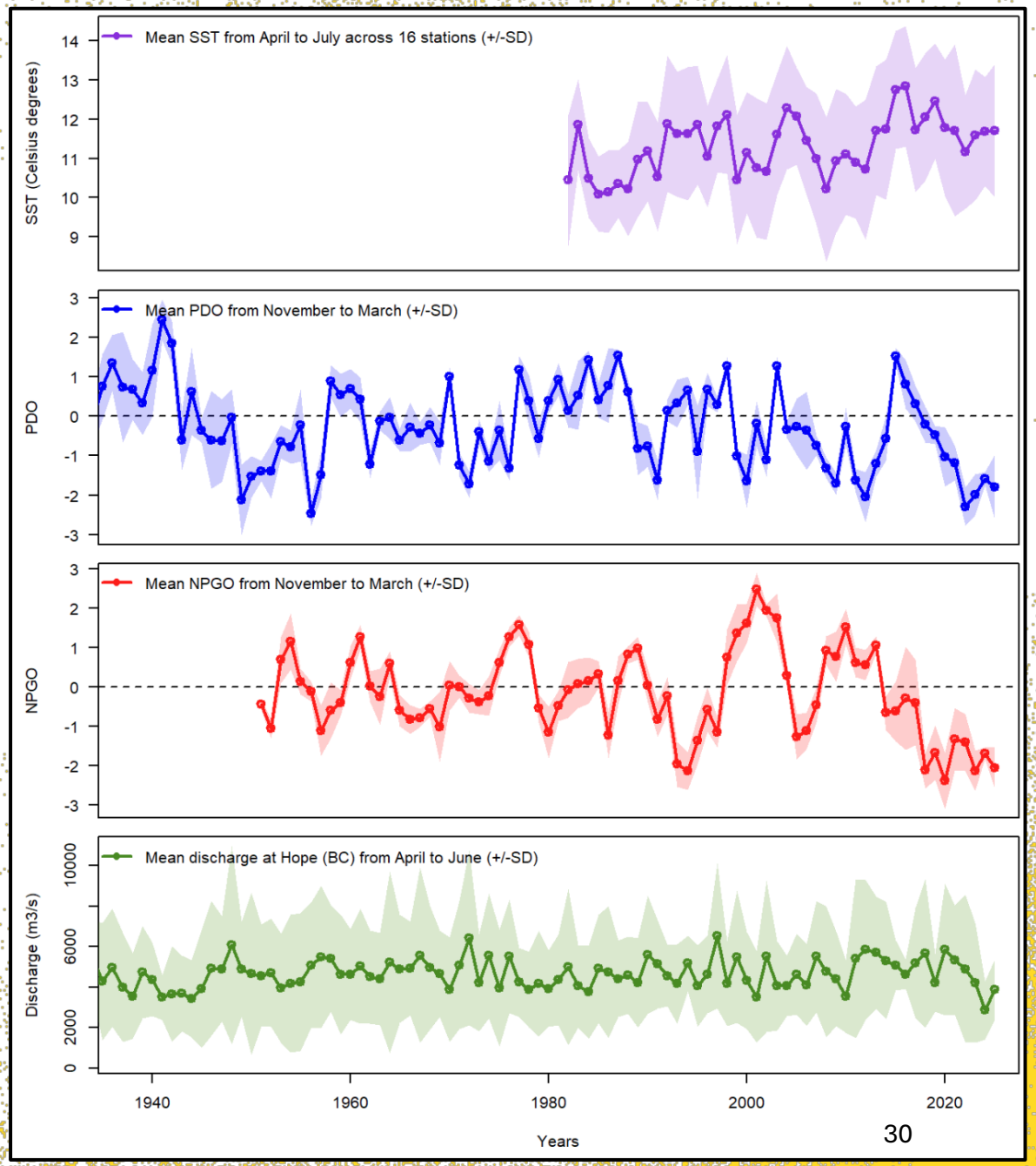


Conclusion:

- Approach very promising to fill data gaps in spawner surveys
- It can also provide insights on the shared dynamics across CUs and species
- Any suggestions?

Future steps:

- Include environmental factors
- Parameter optimization
- Test for regime change
- Any suggestions?



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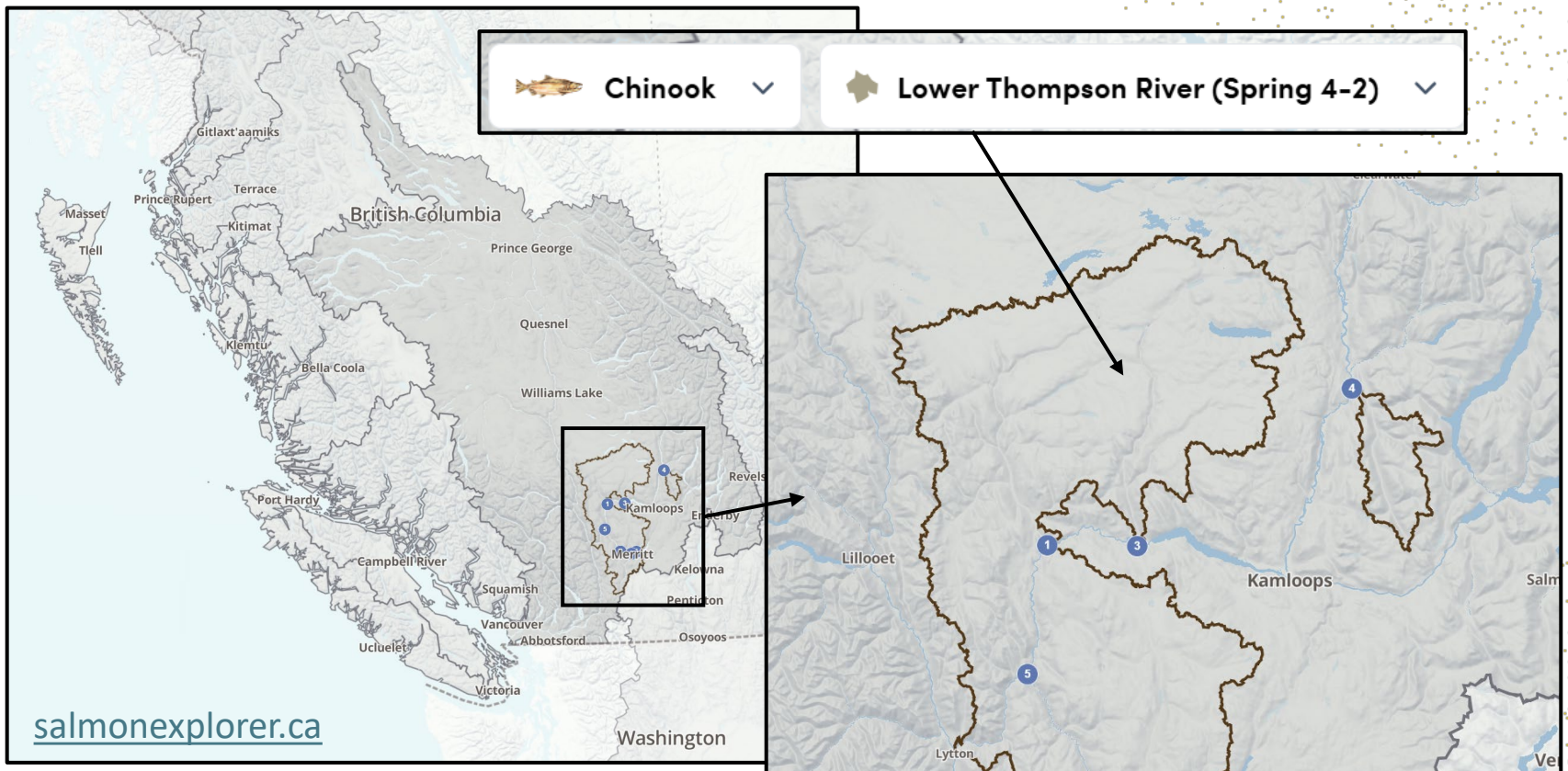
PACIFIC SALMON FOUNDATION

Objective: to fill data gaps in spawner survey data to reliably estimate CU-level abundance in a context of declining monitoring.



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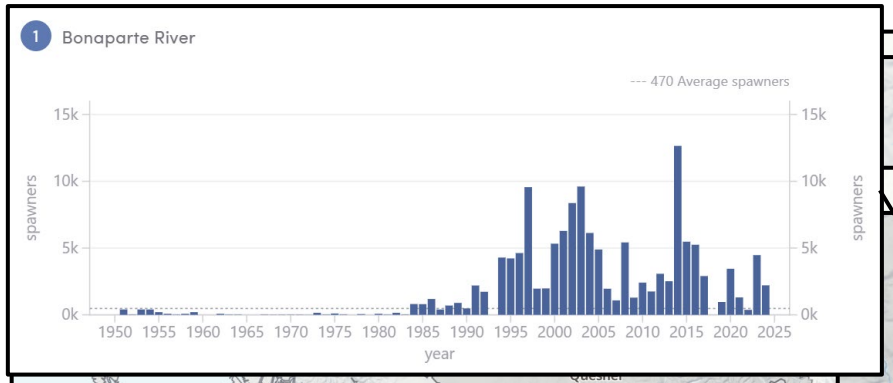



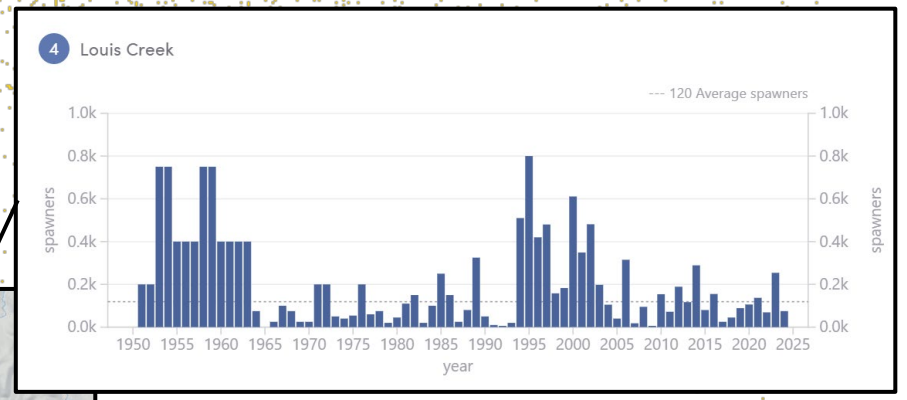

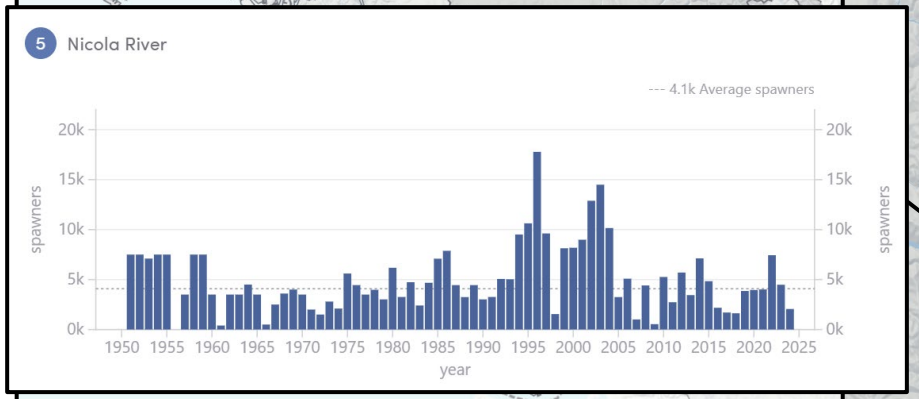

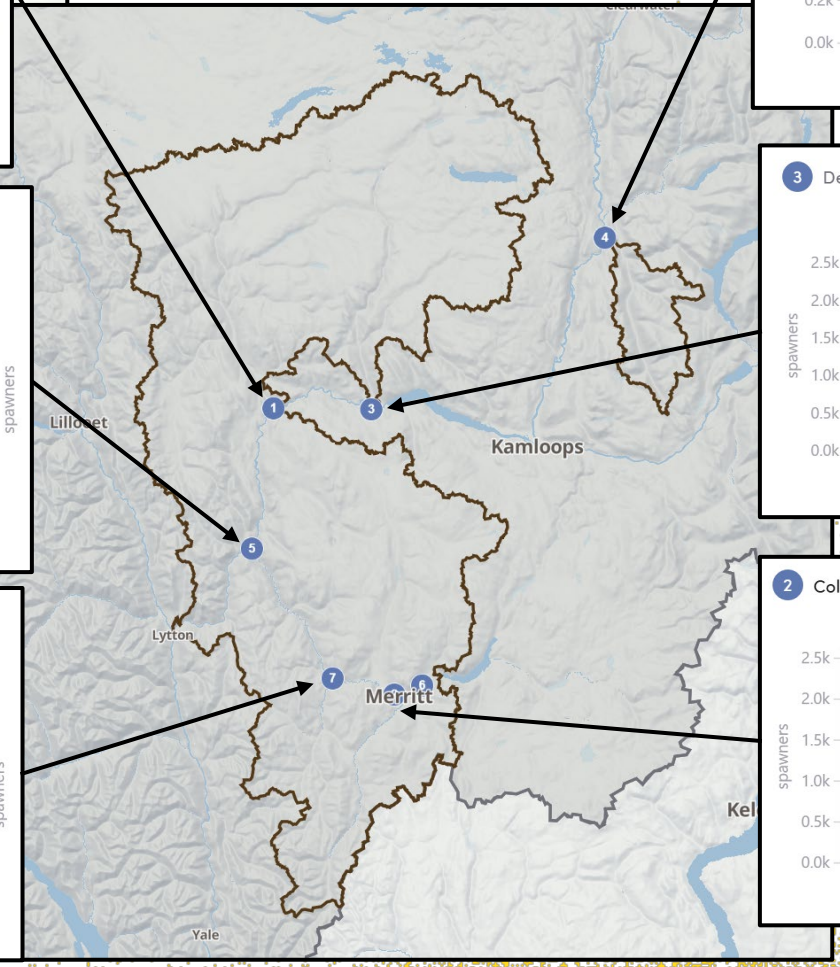

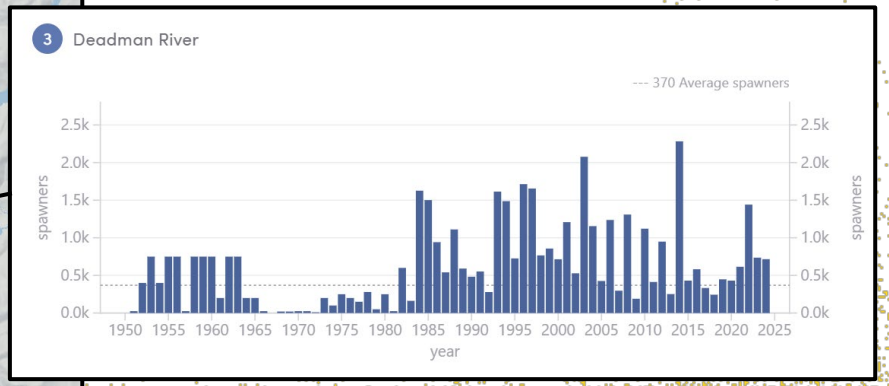

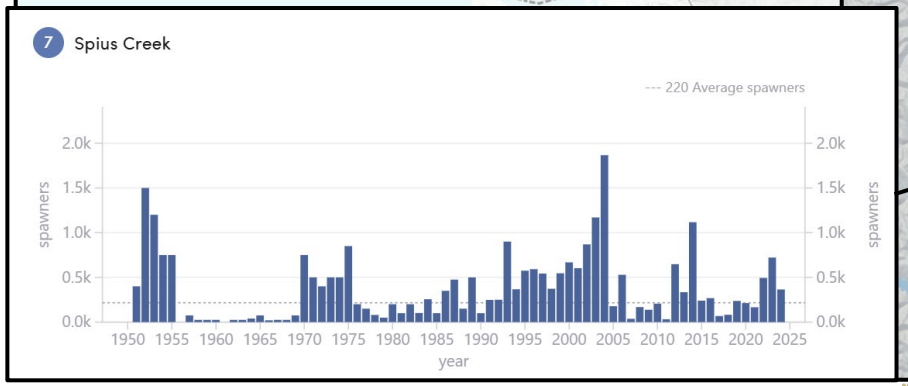

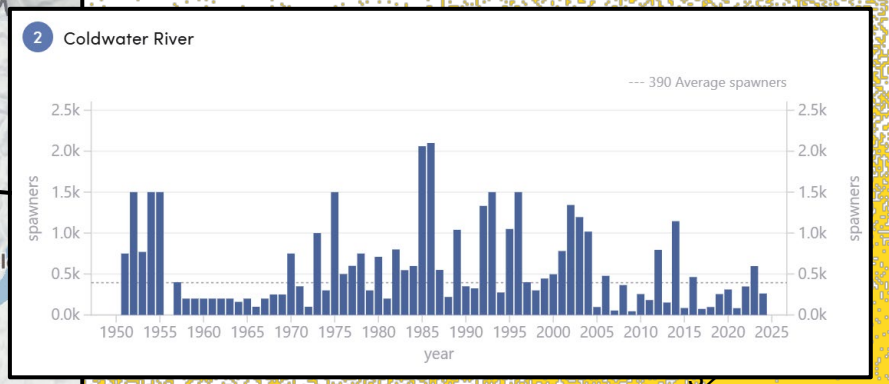

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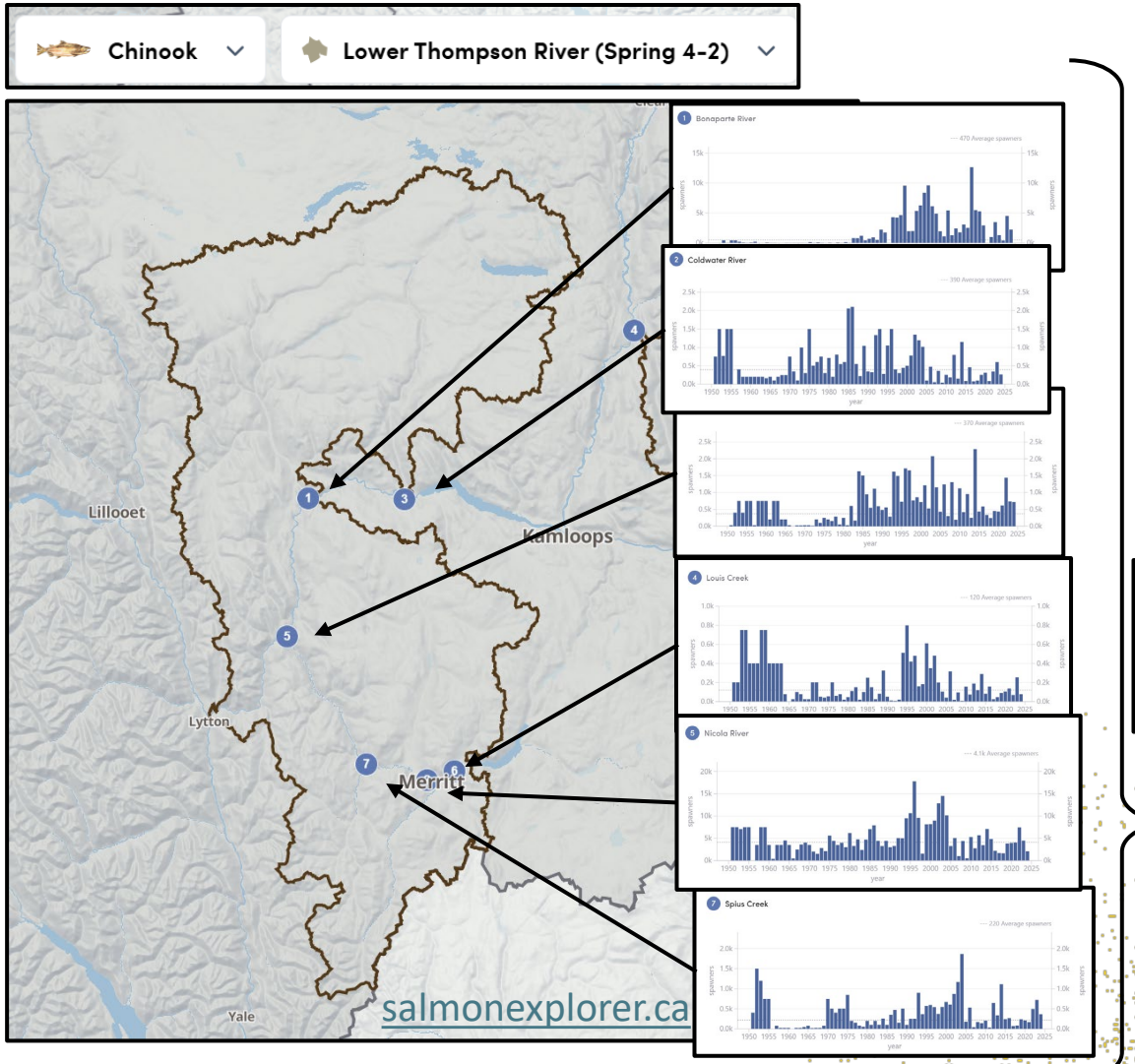
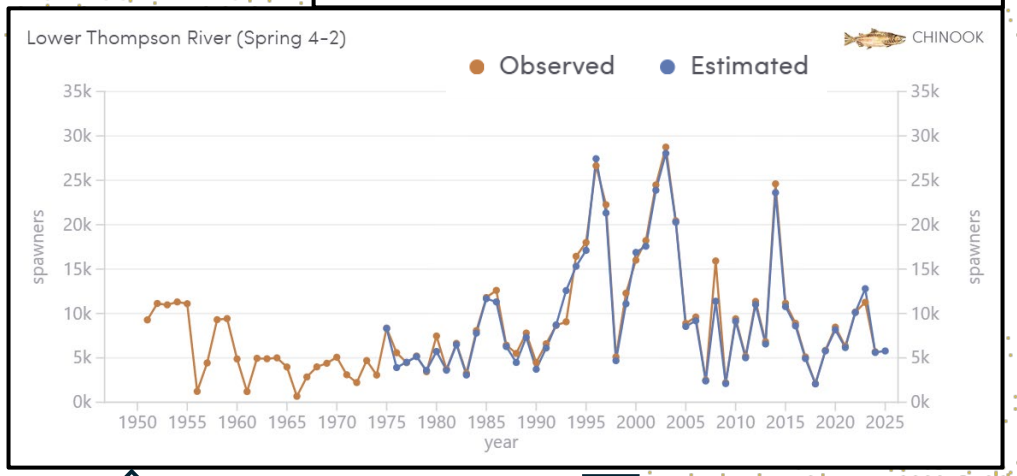
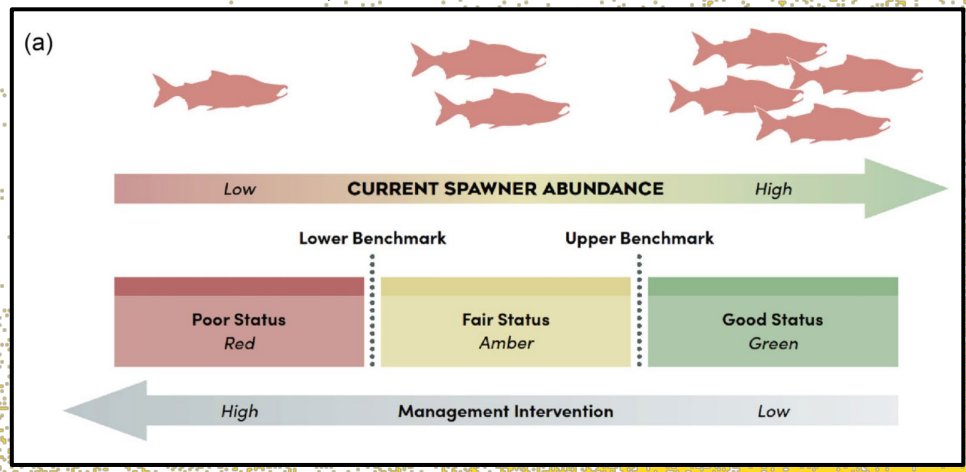


Expansion factor Method (English et al. 2018)

Estimated CU-level abundance



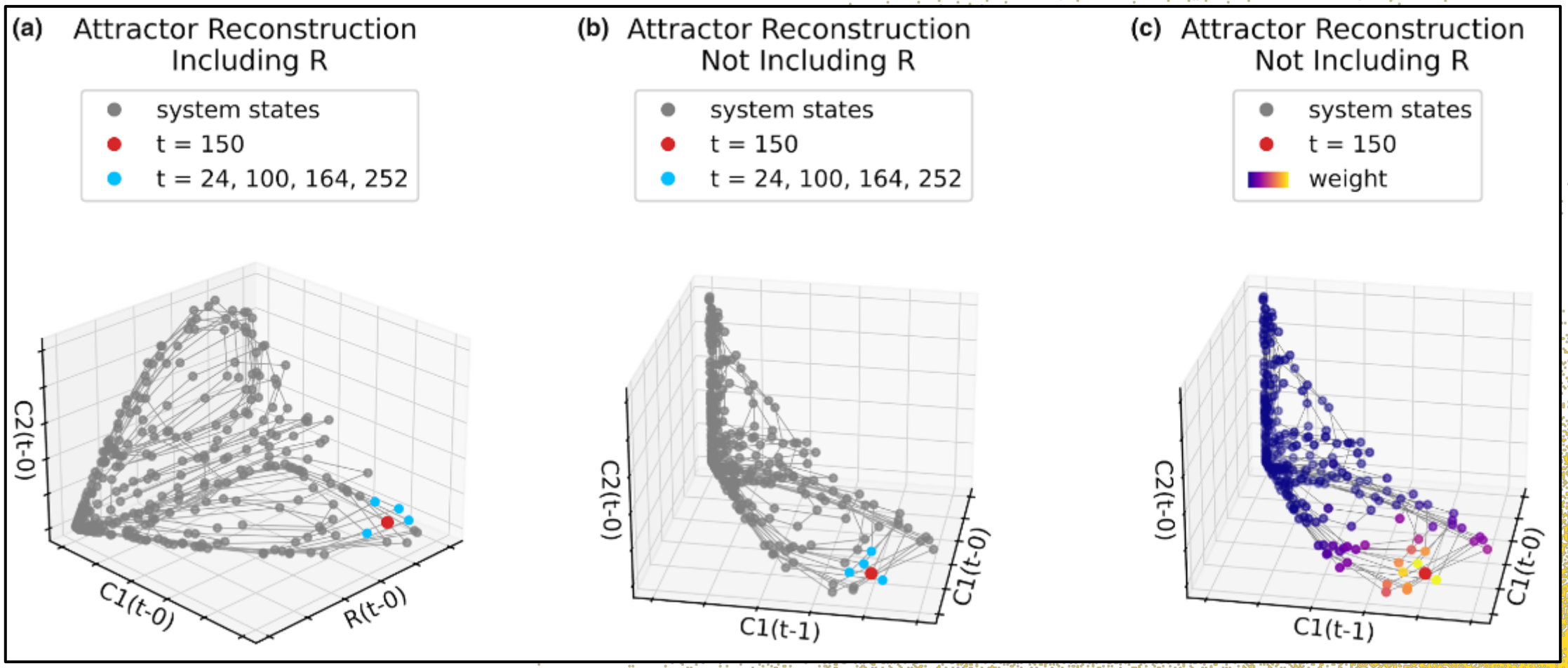


(Connors, Peacock et al. 2026)

Methods: based on Empirical Dynamic Modelling…

Simplex algorithm

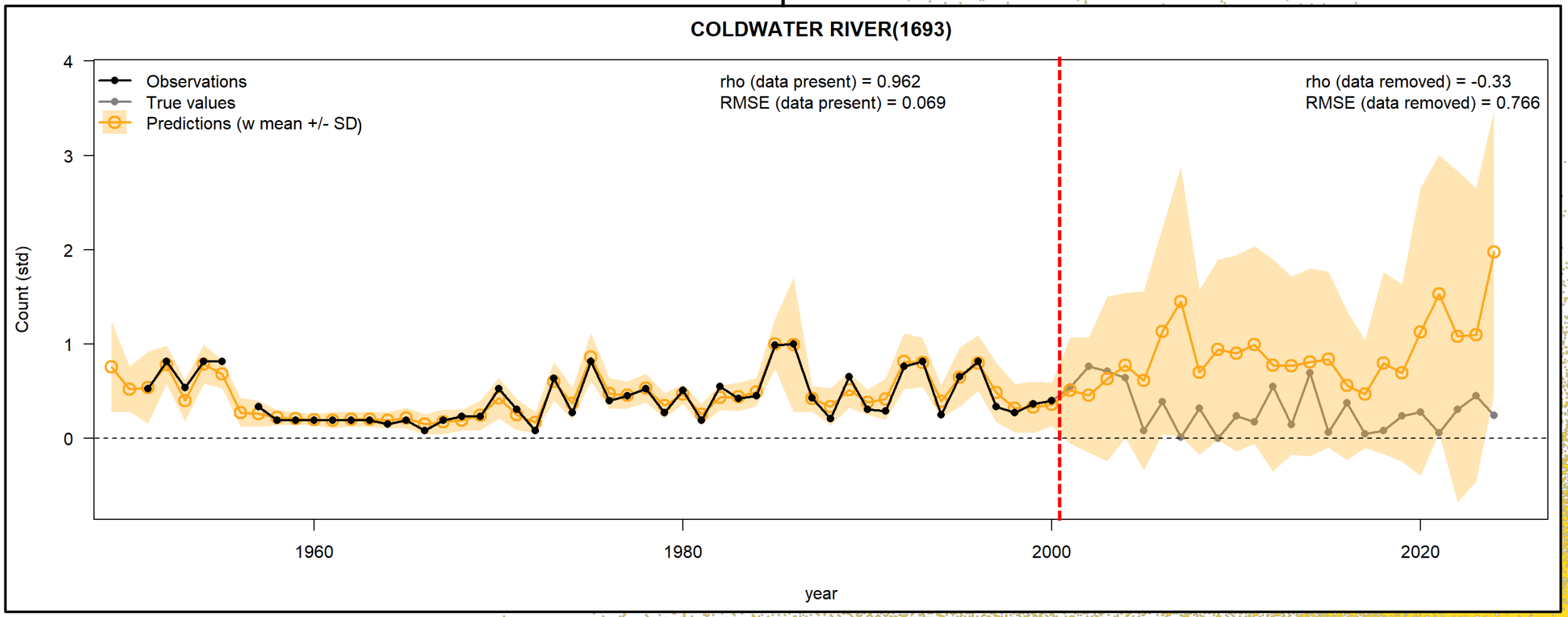
S-map algorithm



(Carpenter et al. 2025)

Results: Predicted weighted average spawner abundance for each year

Stream with one of worst rho



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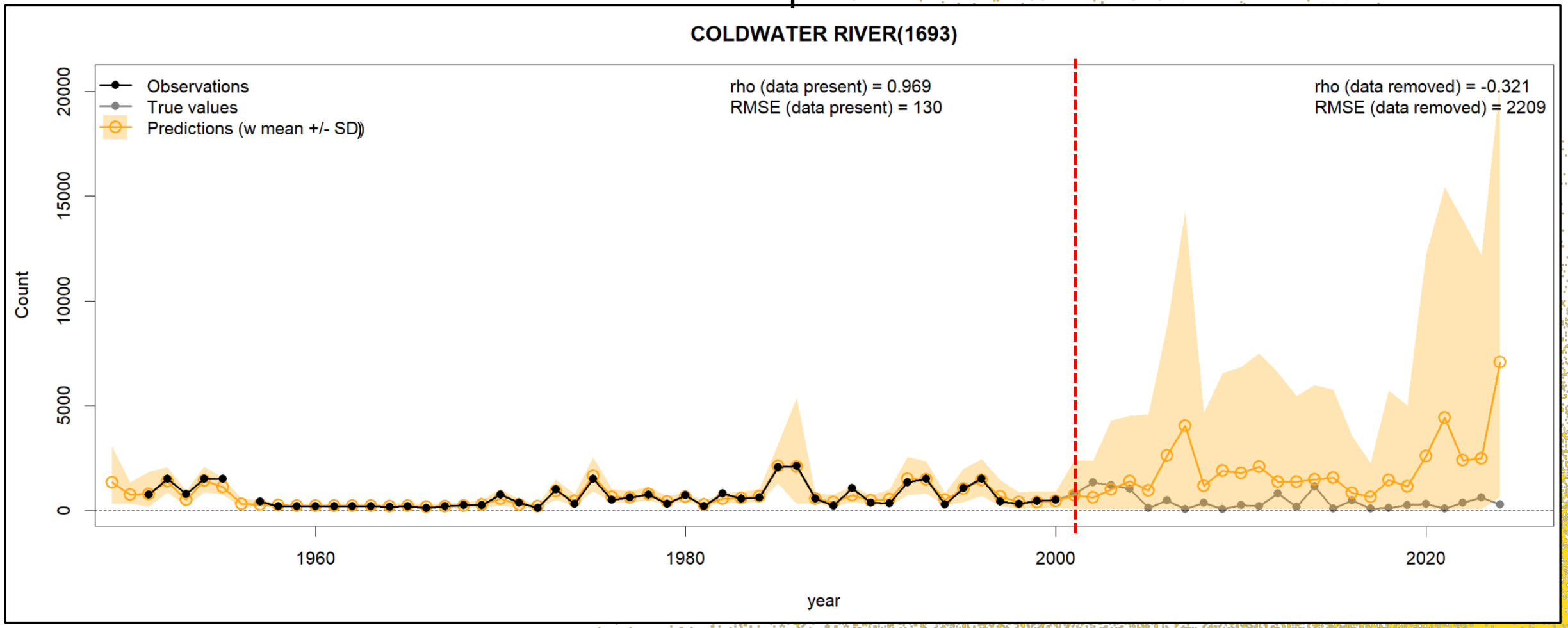

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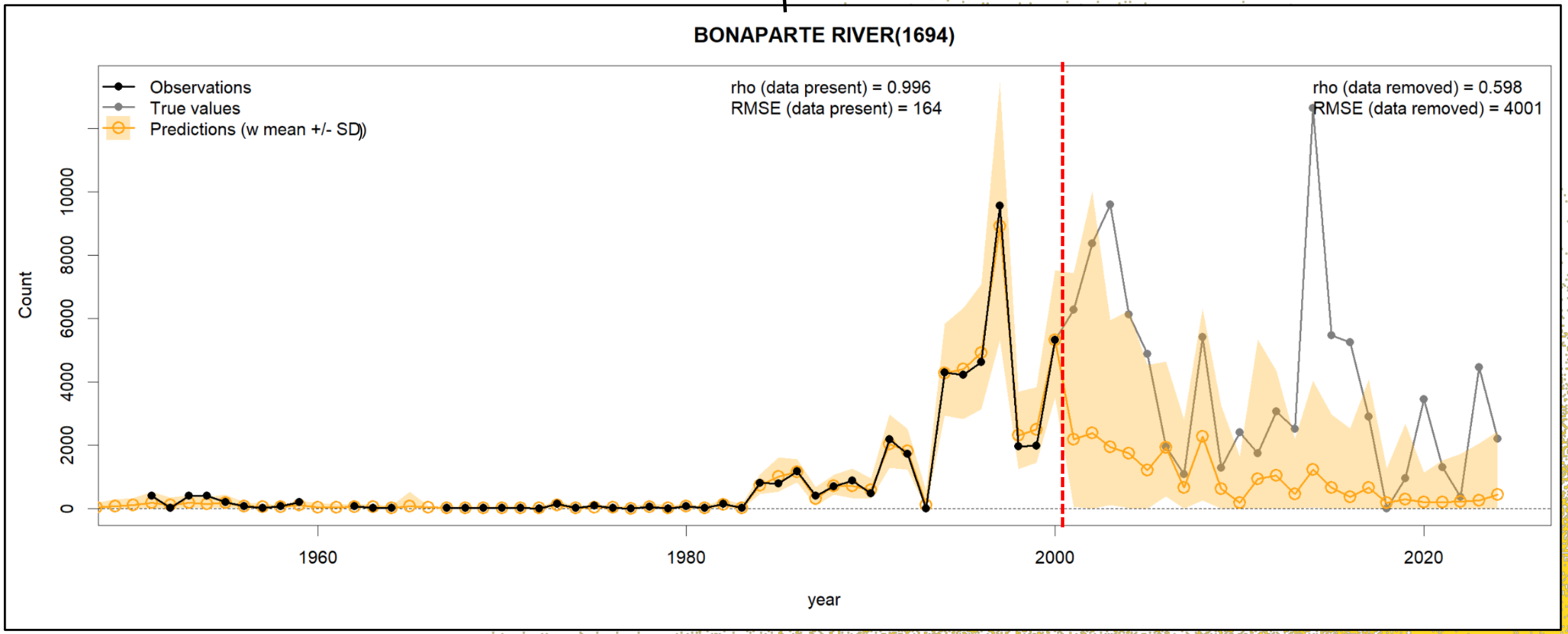
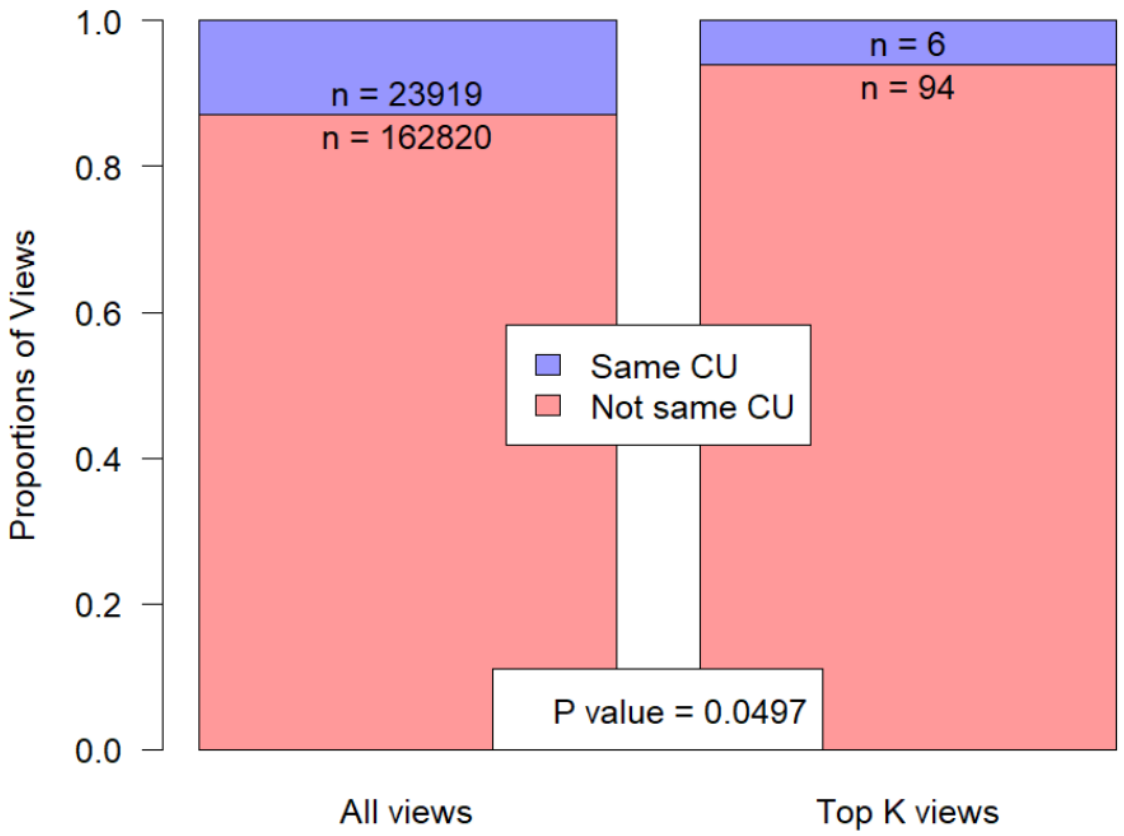
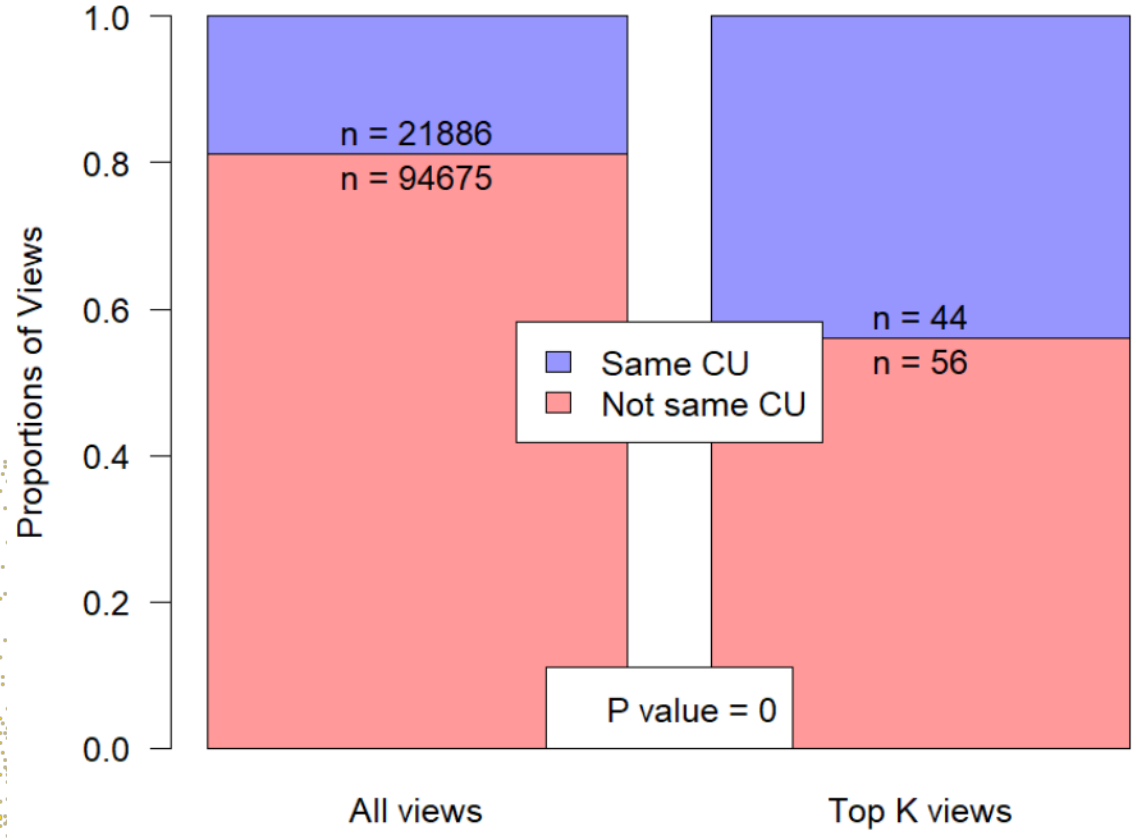


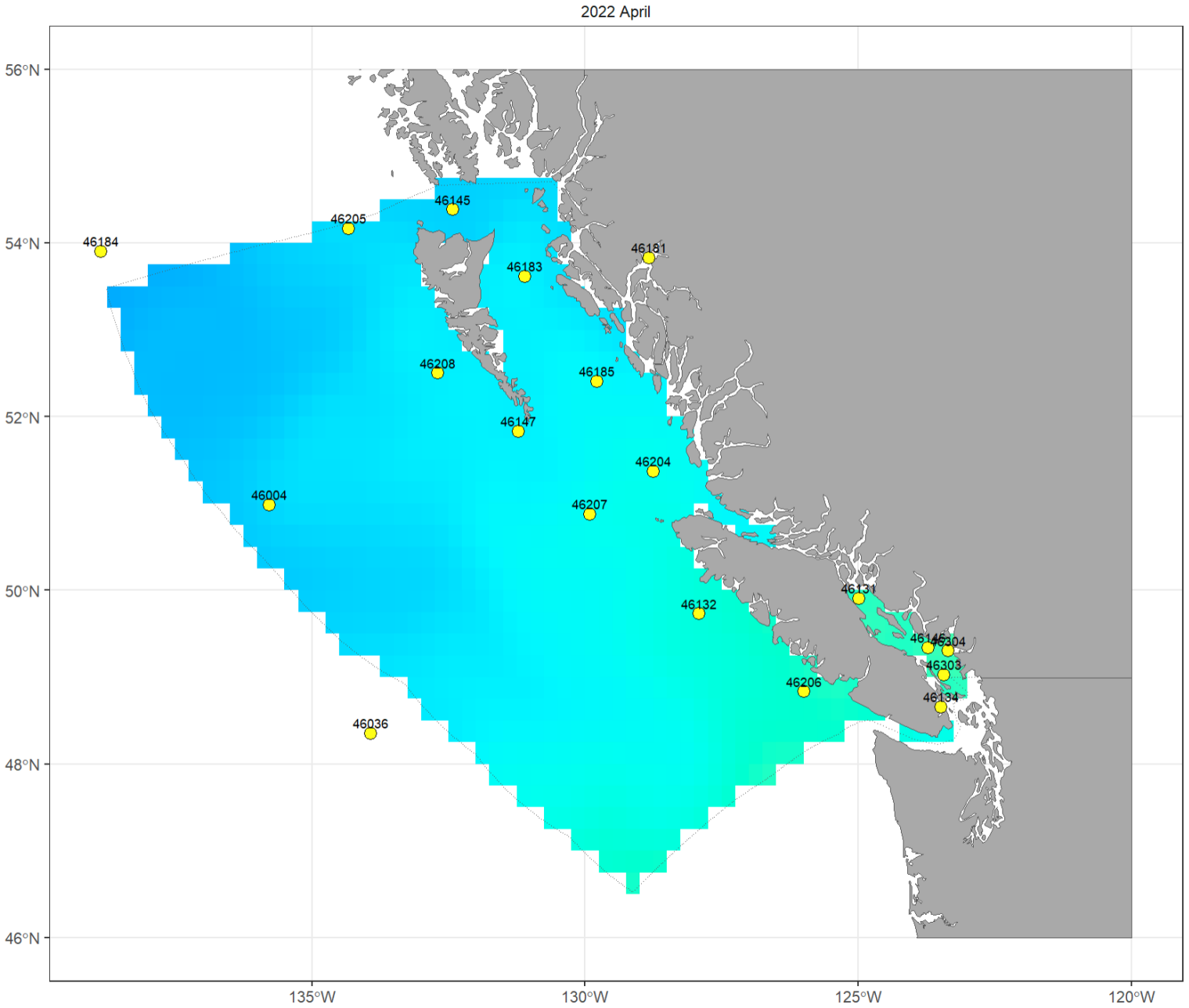
Results - Exploration analysis: does the concept of CU hold against the shared dynamics CUs and species?

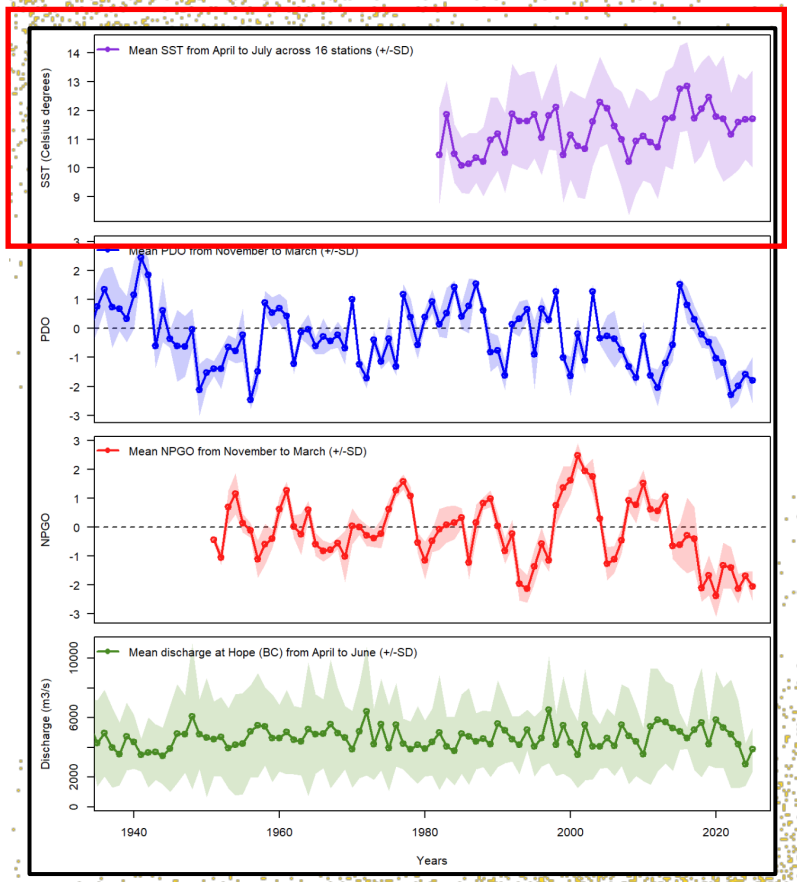
Bonaparte River



Spius creek




2022 April
56°N
54°N
52°N
50°N
48°N
46°N
135°W
130°W
125°W
120°W
46145
46205
46184
46183
46181
46208
46185
46147
46204
46004
46207
46131
46132
46145
46304
46303
46206
46134
46036
Temperature (°C)
20
15
10
5
0


Mean SST from April to July across 16 stations (+/-SD)
SST (Celsius degrees)
Mean PDO from November to March (+/-SD)
PDO
Mean NPGO from November to March (+/-SD)
NPGO
Mean discharge at Hope (BC) from April to June (+/-SD)
Discharge (m3/s)
1940
1960
1980
2000
2020
Years