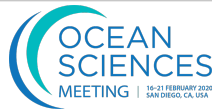




Oregon State University
College of Earth, Ocean,
and Atmospheric Sciences



NOAA
FISHERIES



Accounting for spatiotemporal variability in somatic growth in age composition estimation for stock assessment models

Giancarlo M. Correa¹, Lorenzo Ciannelli¹, Lewis Barnett², Stan Kotwicky²

¹College of Earth, Ocean, and Atmospheric Sciences. Oregon State University.

²NMFS, Alaska Fisheries Science Center, NOAA.

Stock assessment models

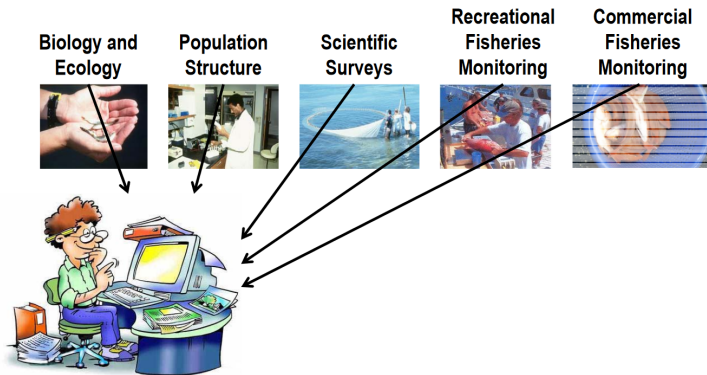


Figure: NOAA Fisheries

Stock assessment models

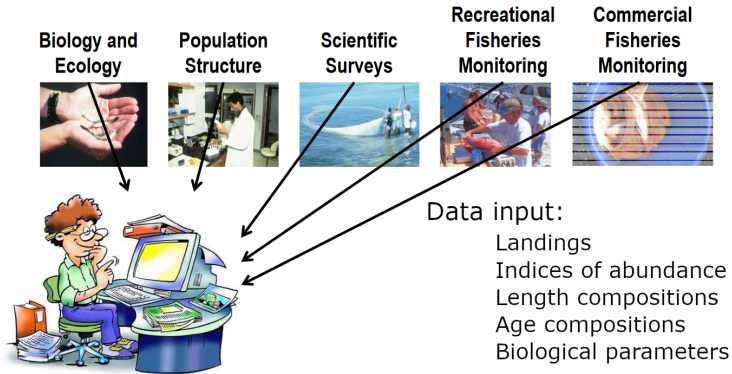


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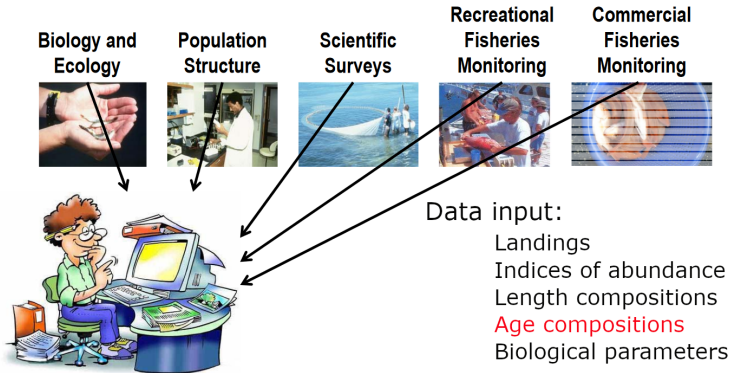
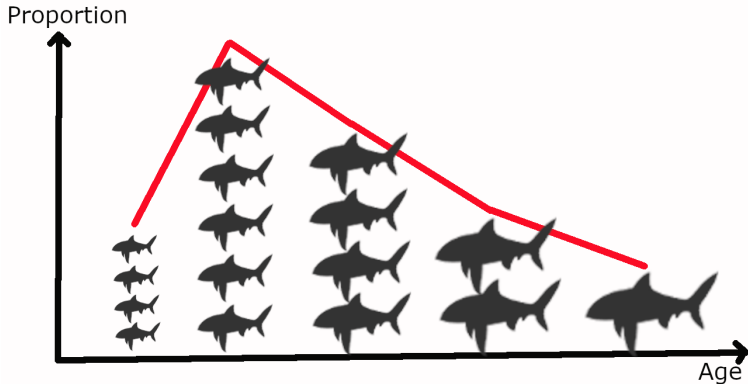


Figure: NOAA Fisheries

Age compositions: definition

Proportion of individuals in each age class:



Age compositions: what do they inform?

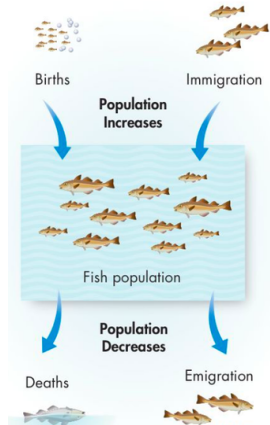
Provide information about Status of the stock:

- Recruitment
- Mortality
- Somatic growth
- Selectivity

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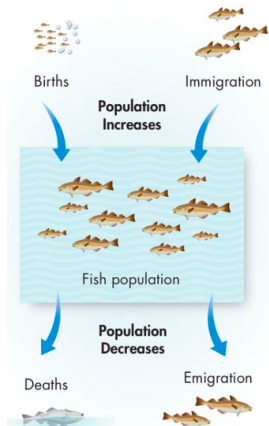
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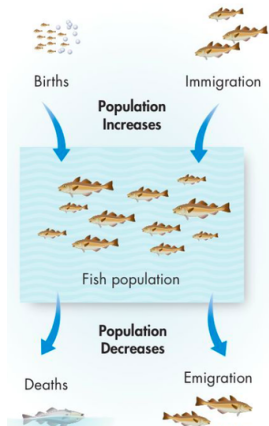
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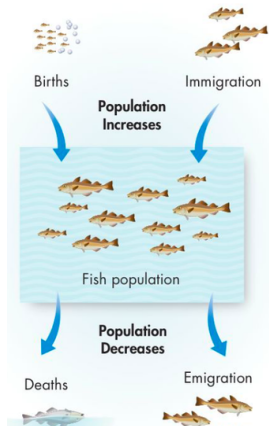
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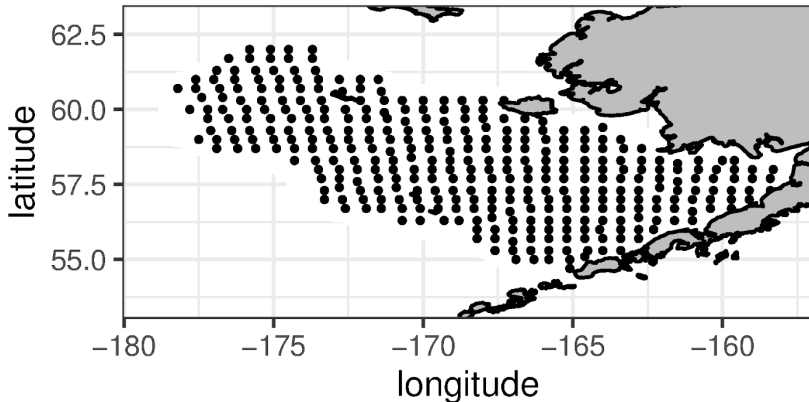
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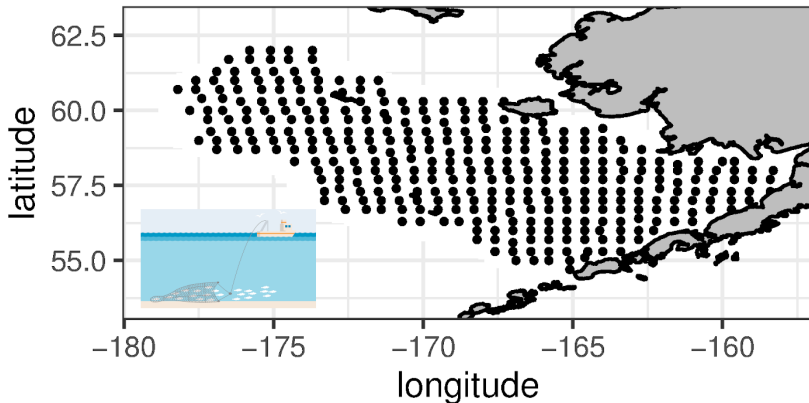
Age compositions: estimation

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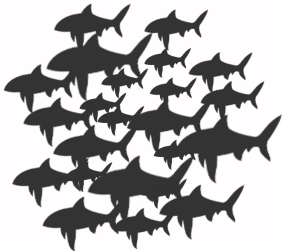
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At each station:

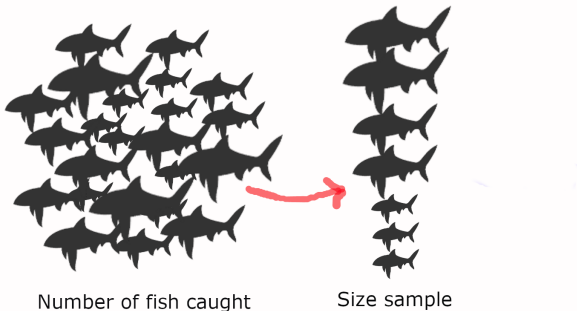


Number of fish caught

Age composition

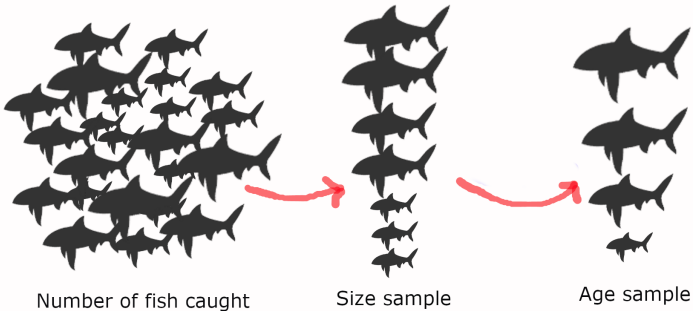
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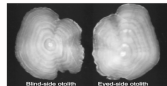
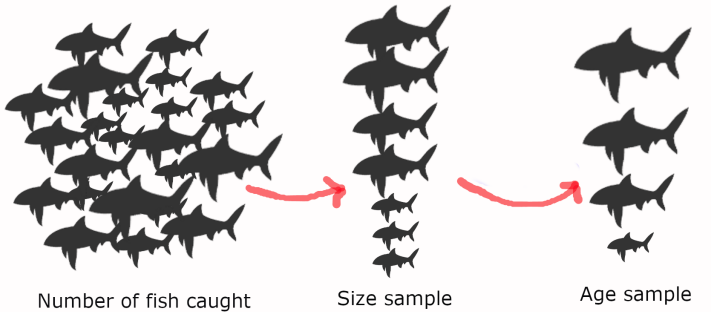
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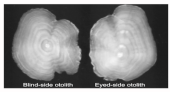
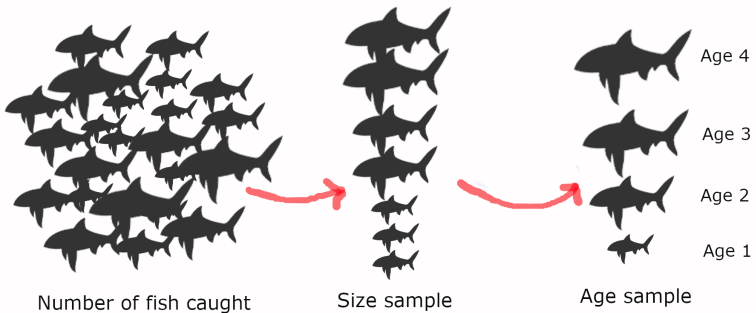
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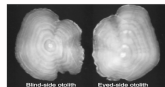
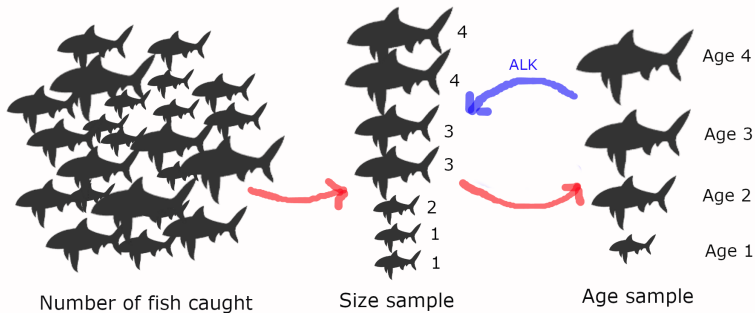
Age compositions: Age length key (ALK)

Using ALL age samples collected in a survey (or in many years):

Length (cm)	Age							
	1	2	3	4	5	6	7	8
10	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
11	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
13	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
14	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
15	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	0.99	0.01	0.00	0.00	0.00	0.00	0.00	0.00
17	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
19	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
21	0.99	0.01	0.00	0.00	0.00	0.00	0.00	0.00
22	0.98	0.02	0.00	0.00	0.00	0.00	0.00	0.00
23	0.97	0.03	0.00	0.00	0.00	0.00	0.00	0.00
24	0.95	0.05	0.00	0.00	0.00	0.00	0.00	0.00
25	0.91	0.09	0.00	0.00	0.00	0.00	0.00	0.00
26	0.88	0.12	0.00	0.00	0.00	0.00	0.00	0.00
27	0.81	0.19	0.00	0.00	0.00	0.00	0.00	0.00
28	0.73	0.27	0.00	0.00	0.00	0.00	0.00	0.00
29	0.58	0.42	0.00	0.00	0.00	0.00	0.00	0.00
30	0.40	0.60	0.01	0.00	0.00	0.00	0.00	0.00

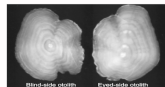
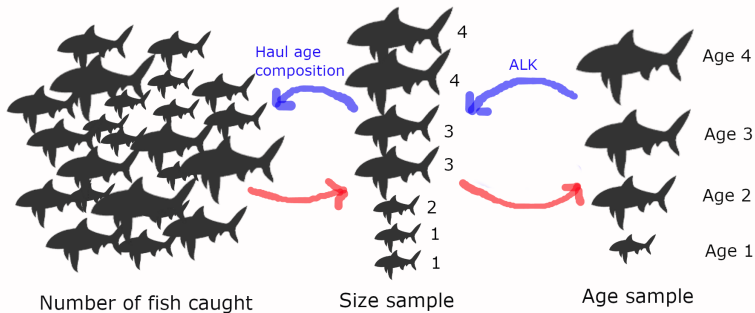
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- Age sampling process
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Objectives

- Evaluate the performance of classic ALKs and two statistical models to estimate age compositions of a fish population with a substantial spatiotemporal variability in somatic growth.
- Assess the effects of different age compositions estimated by ALKs or statistical models on stock assessment outputs uncertainties.

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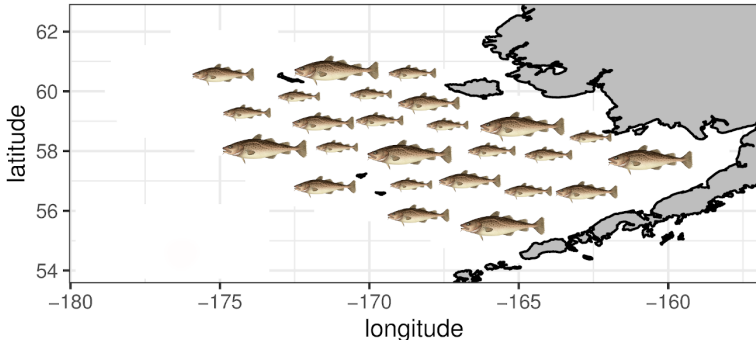
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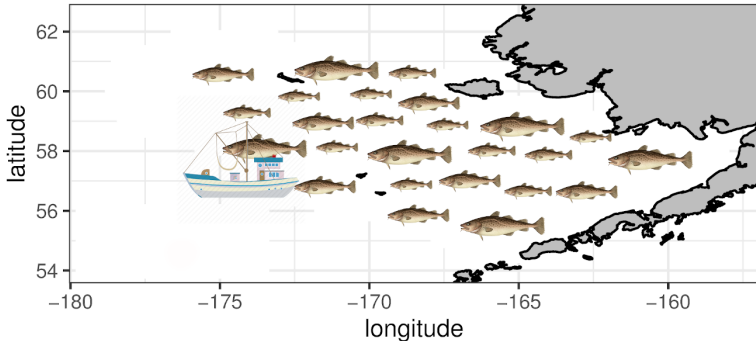
Methods

We simulate the dynamics of a fish population in time (40 years) and space. We use Pacific cod biological parameters in the eastern Bering Sea (EBS).



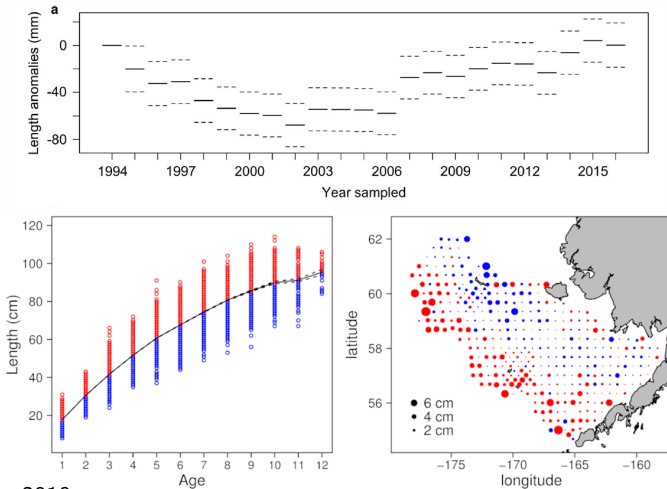
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Why Pacific cod in the EBS?



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Two somatic growth scenarios:

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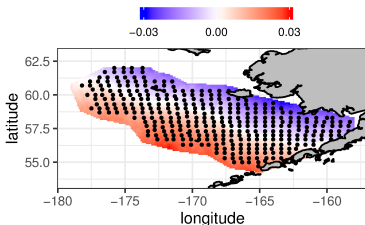
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Spatial field (ω_i):



Methods

Using simulated survey age sample data, we compared these methods:

- Design-based approaches:
 - Pooled ALK: combines information of many years. Helps to reduce data gaps.
 - Annual ALK: uses year-specific information.
- Model-based approaches (Puerta et al., 2018, Berg et al., 2012):
 - GAMs: $Age_{y,i} = \alpha_y + s_{1,y}(l_i) + s_{2,y}(lon_i, lat_i) + \epsilon_i$
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¹CRL: continuation ratio logits, GAM for estimation

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We ran 250 replicates and compared performance of these methods.

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We applied these four methods to real Pacific cod data in the EBS.

pooled ALK



year ALK



GAM



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Methods

We applied these four methods to real Pacific cod data in the EBS. Then, include these age compositions as input data. Evaluate effects on outputs uncertainties (standard deviations).

pooled ALK



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GAM

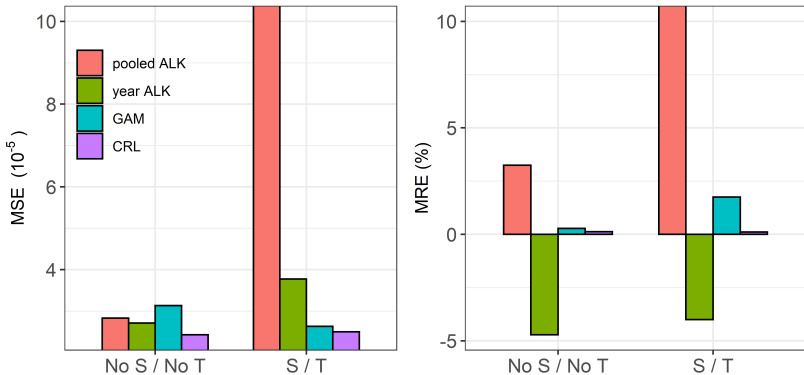


CRL



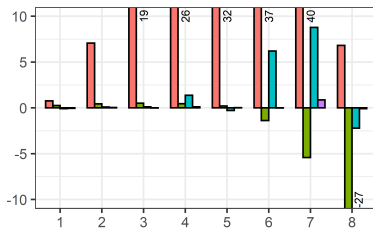
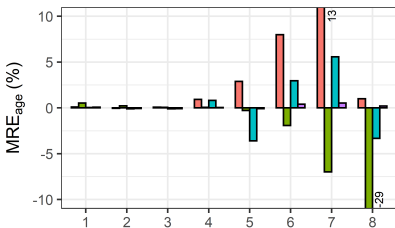
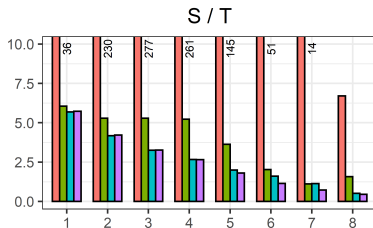
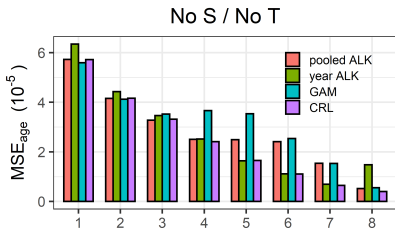
↓
Outputs uncertainties

Results: simulation experiment



MSE = measure of error. MRE = measure of bias.

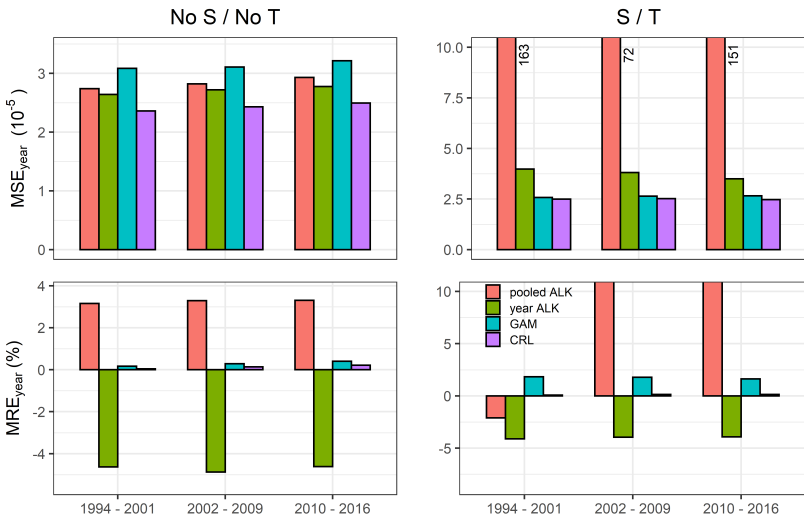
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Age

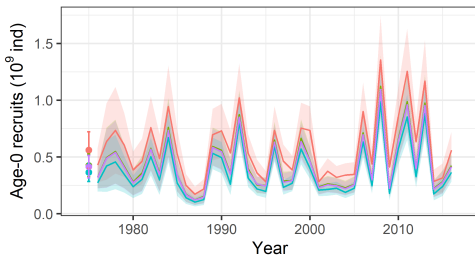
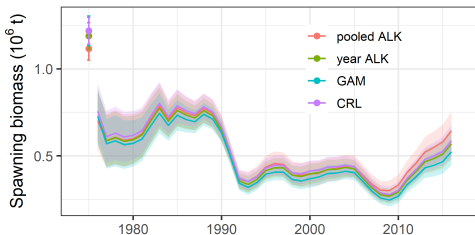
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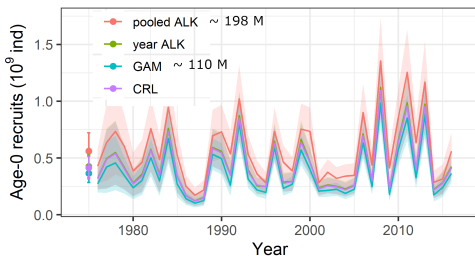
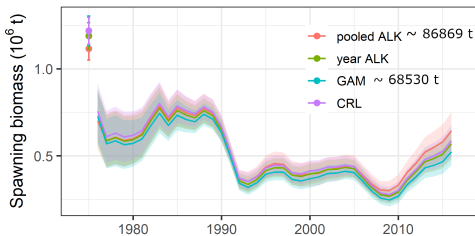
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Results: stock assessment



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Average of standard deviations of the entire time series.



Results: stock assessment

Parameters influenced by age composition data:

Model name	L_{∞}	$\ln(R_0)$
pooled ALK	113.2 (13.2)	13.2 (0.29)
year ALK	109.8 (13.8)	12.96 (0.24)
GAM	106 (12.7)	12.8 (0.22)
CRL	110 (13.6)	12.94 (0.24)

Table: Estimated parameters: Mean (Sd)

Conclusions

- Somatic growth spatiotemporal variability impacts ALKs.
- Performance of alternative approaches has not been evaluated yet.
- Using a simulation experiment, we showed that these alternative approaches are more robust to estimate age compositions.
- Lower uncertainties in stock assessment models.
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Picture from ellaquaint