

Climate-informed models benefit hindcasting but present challenges when forecasting species-habitat associations

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Species Distribution Models (SDMs)

Objective

- distributions and densities as function of the environment

Applications

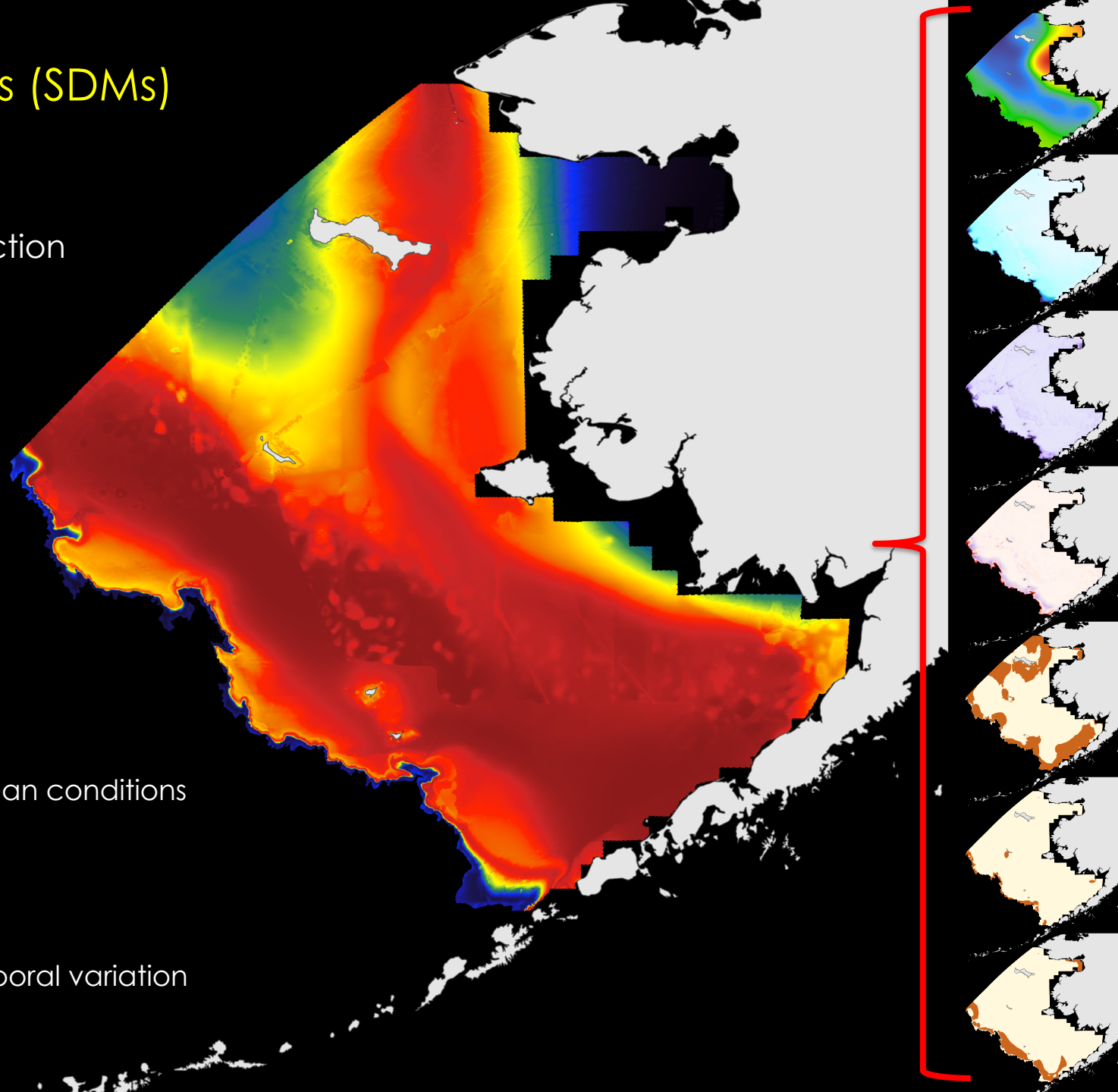
- species-habitat associations
- ecological inferences
 - e.g., predation, competition
- fisheries management
 - e.g., stock assessment, EFH

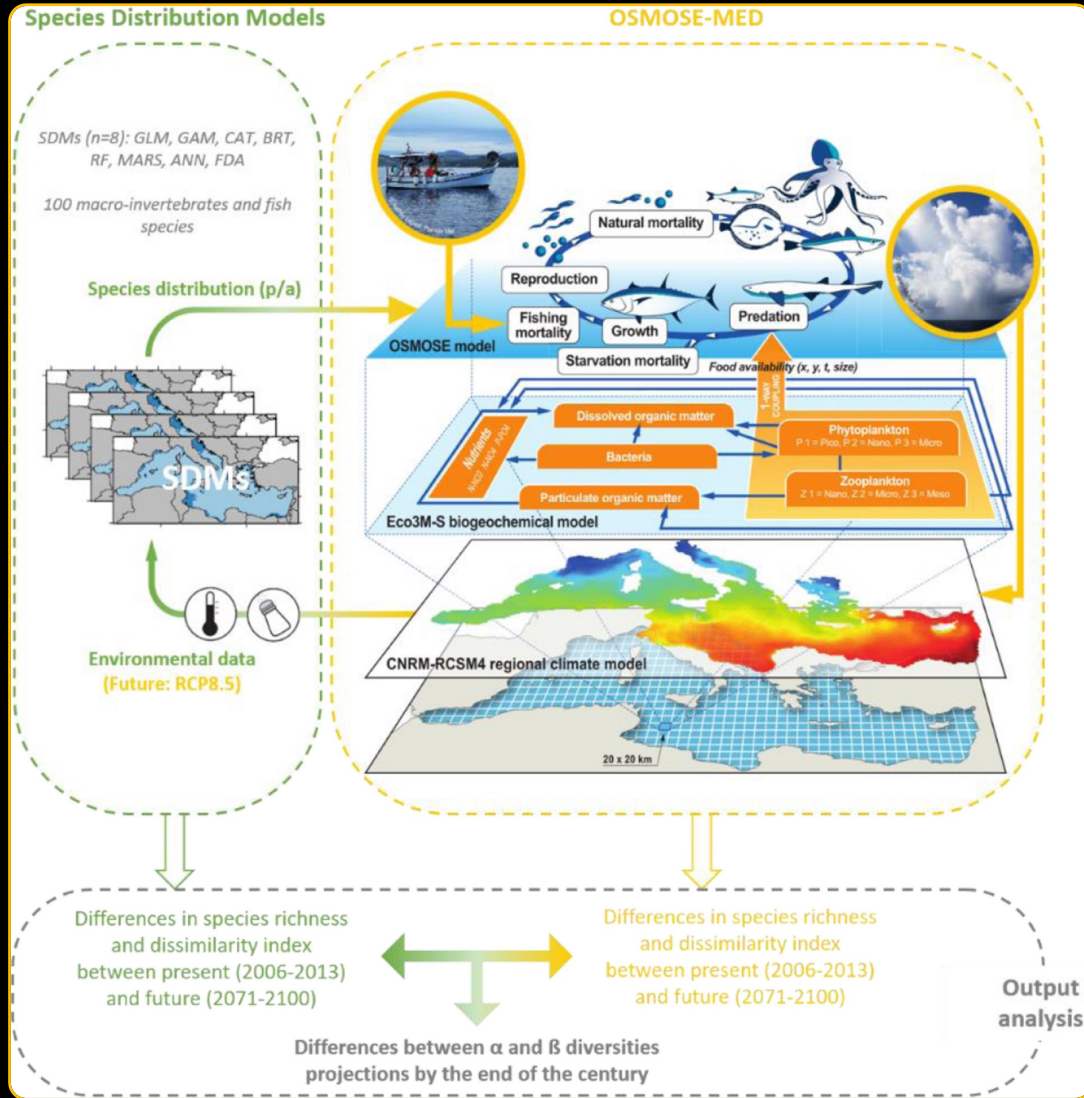
Conventional SDMs

- static approach
 - i.e., spatial variation, long-term mean conditions

Climate-informed SDMs

- dynamic approach
 - e.g., spatial, temporal, spatiotemporal variation
 - year-specific conditions





Moullec et al. 2022

stakeholder interest:
balance model complexity
and interpretability

Research Questions

static vs. dynamic

How does model complexity affect our ability to:

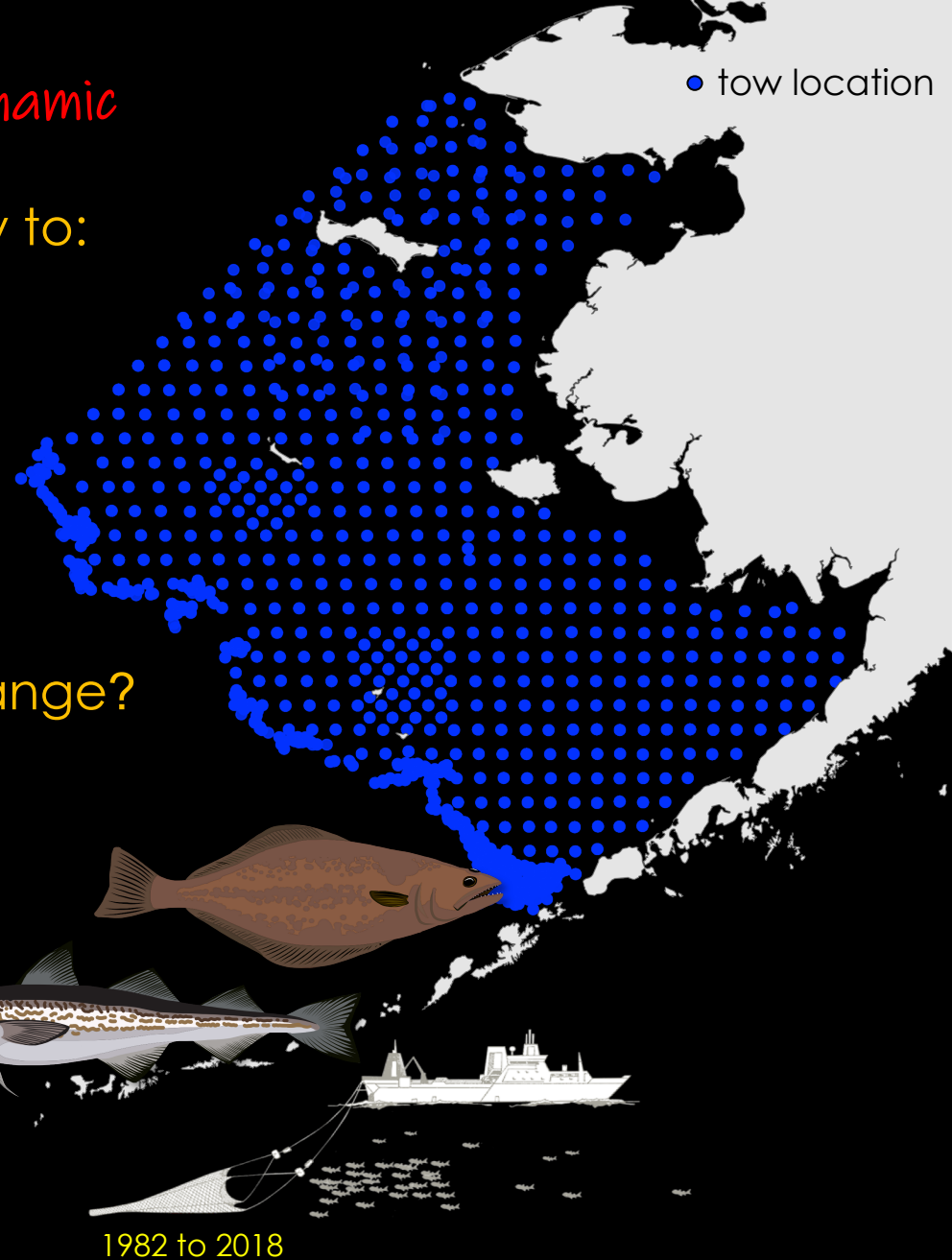
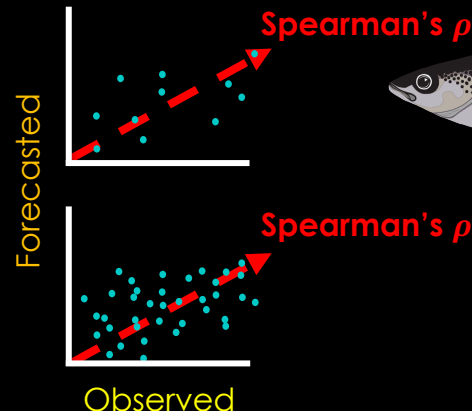
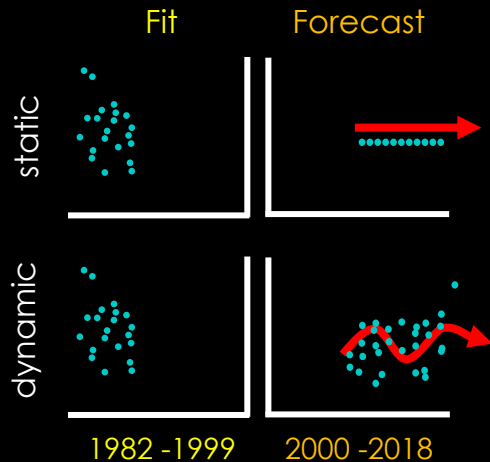
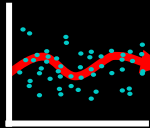
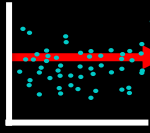
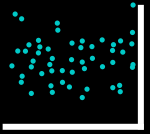
- bottom trawl survey data
- generalized additive models (GAMs)

hindcast species-habitat associations?

- R^2 , % Deviance Explained, UBRE/GCV

forecast species responses to climate change?

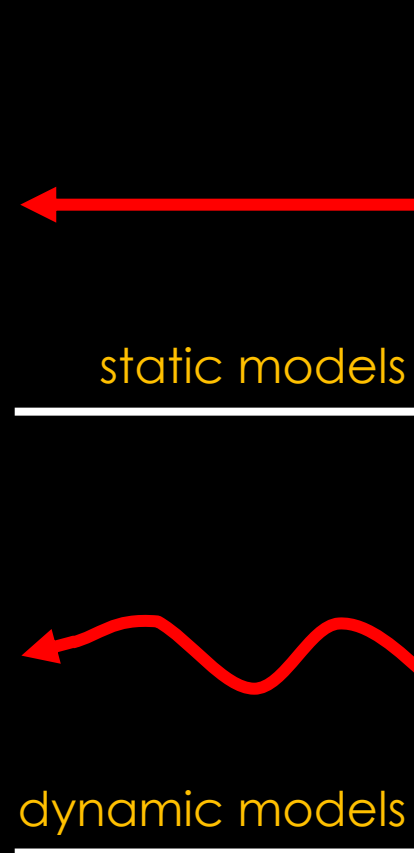
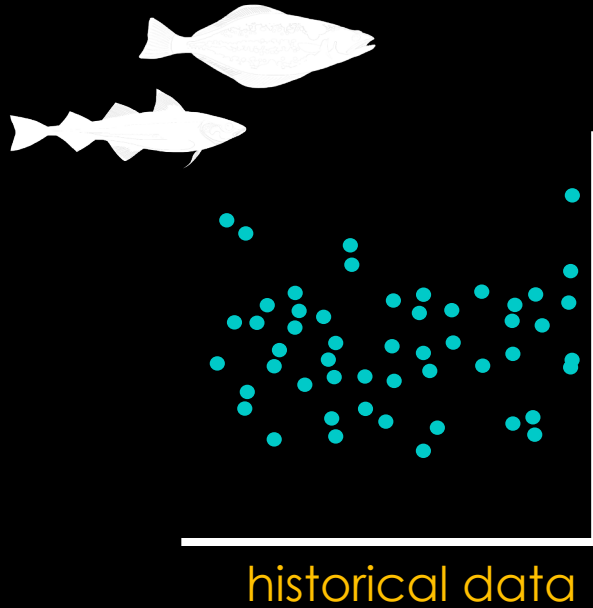
- retrospective skill testing (*sensu* Thorson 2019)



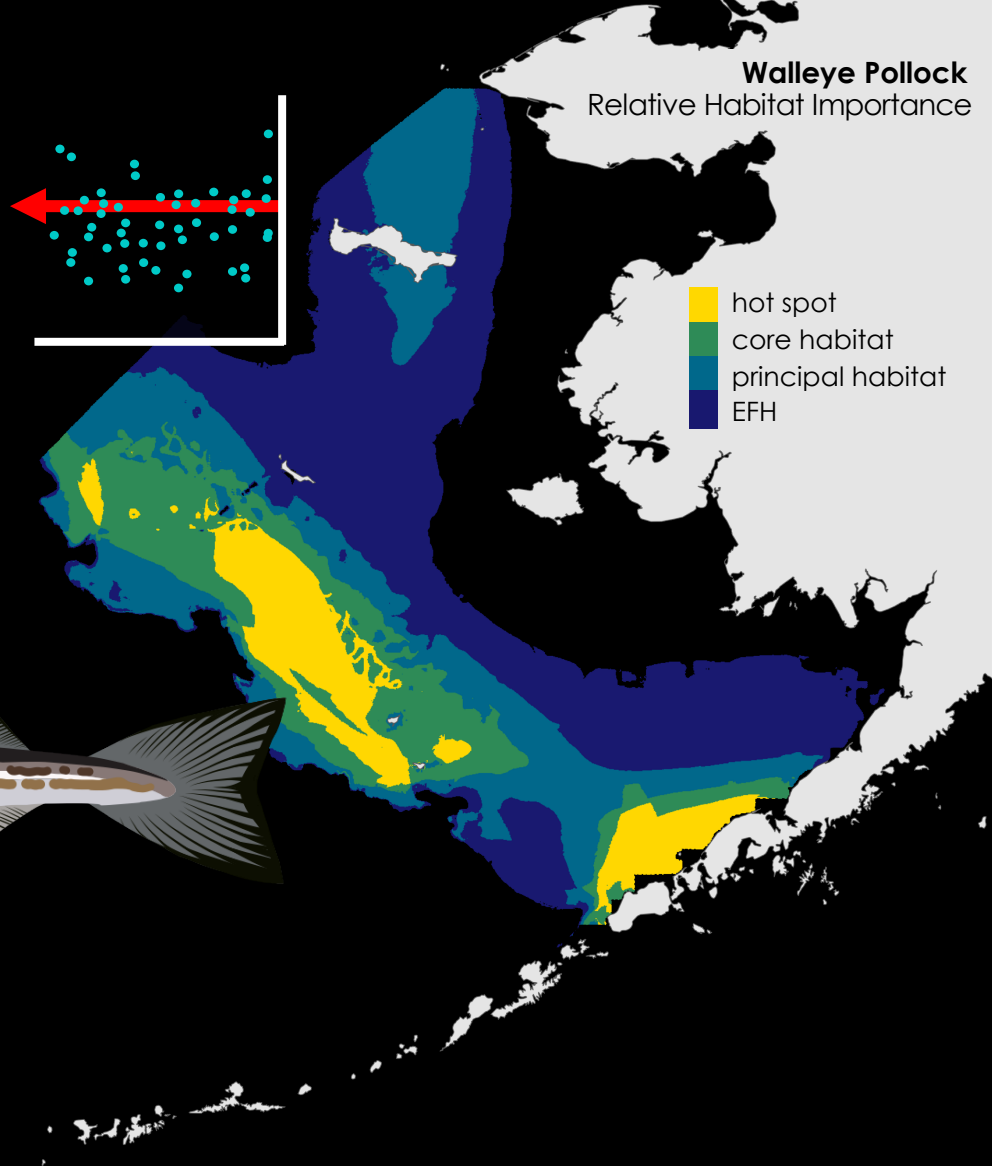
1982 to 2018

Resource Assessment and Conservation Engineering Division
Alaska Fisheries Science Center, NOAA

hindcasting species-habitat associations



hindcasting species-habitat associations



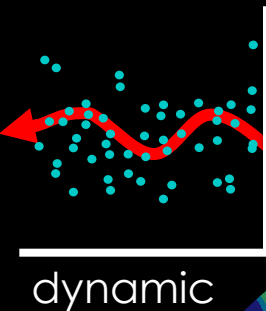
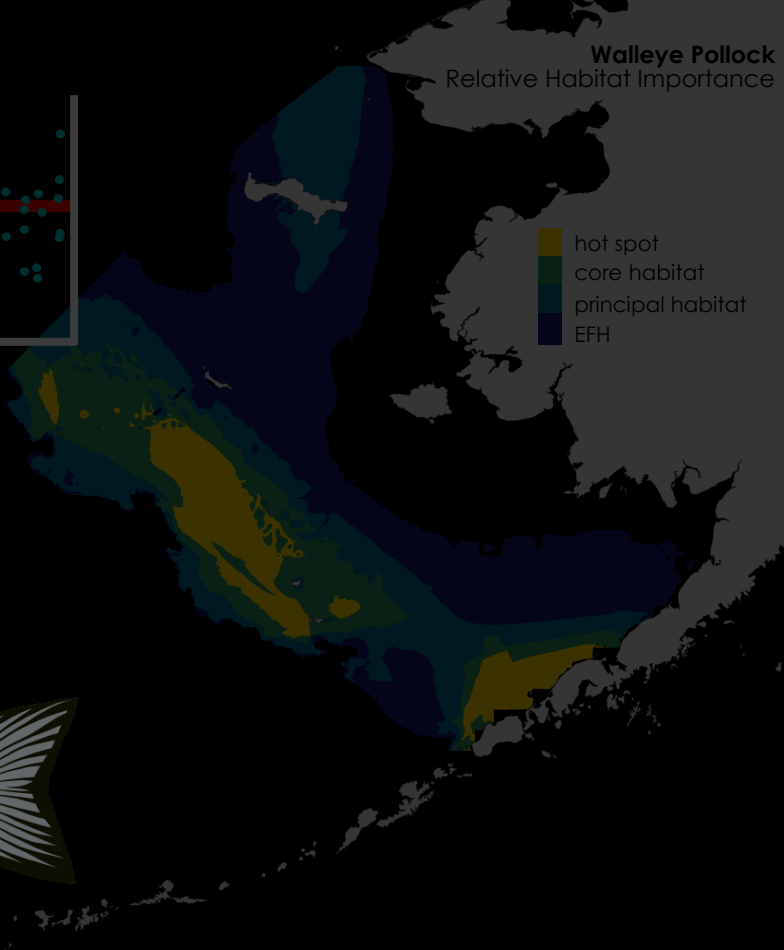
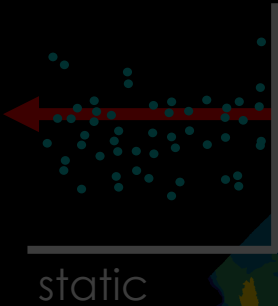
Essential Fish Habitat (EFH)

the physical, biological, and chemical characteristics necessary for a particular species to survive, grow, and reproduce.

hindcasting species-habitat associations

complex dynamic models = best-fit

↑ R^2 , ↑ % Deviance Explained, ↓ UBRE/GCV



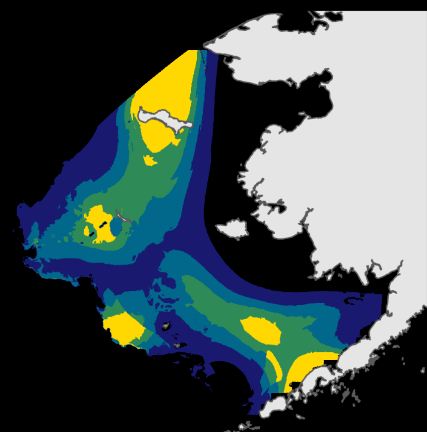
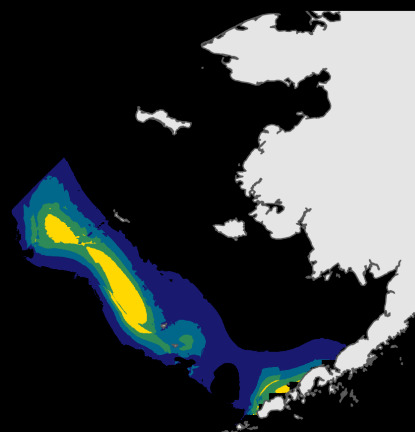
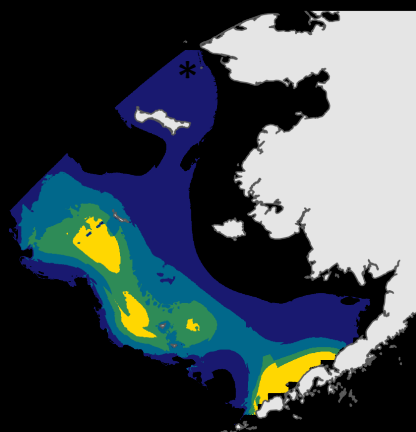
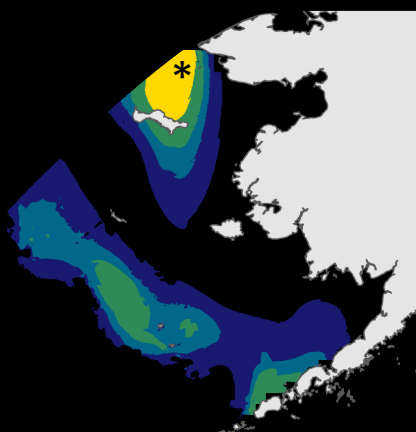
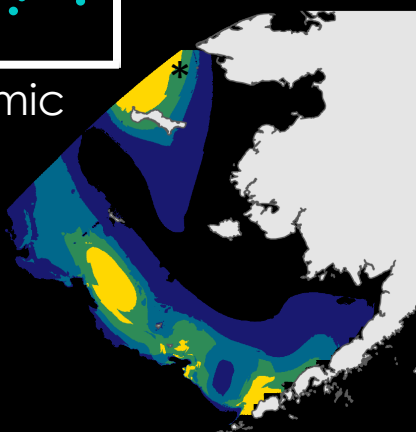
1986

1994

2002

2010

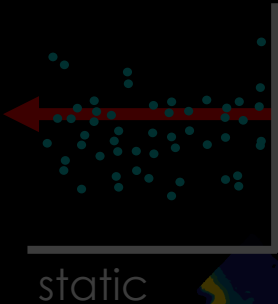
2018



hindcasting species-habitat associations

complex dynamic models = best-fit

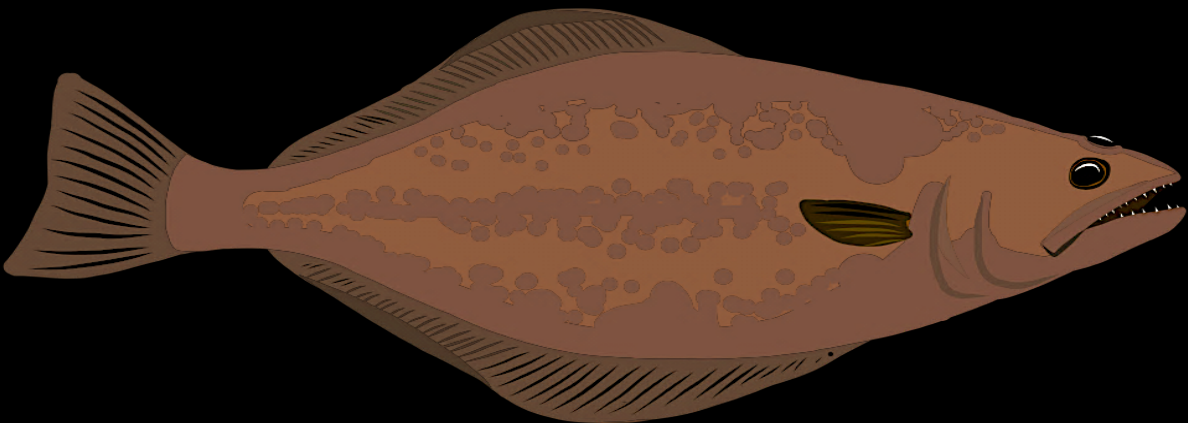
↑ R^2 , ↑ % Deviance Explained, ↓ UBRE/GCV



static

Arrowtooth Flounder
Relative Habitat Importance

hot spot
core habitat
principal habitat
EFH



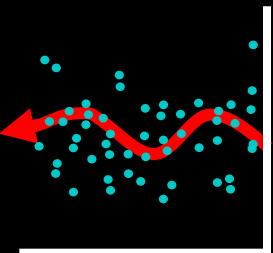
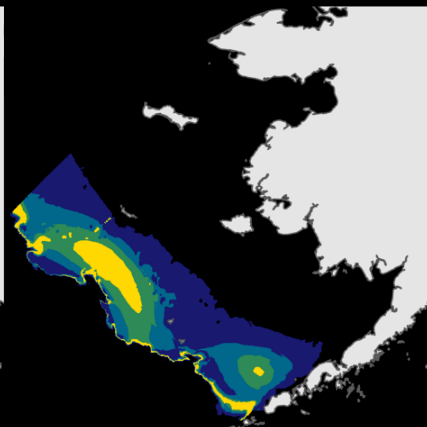
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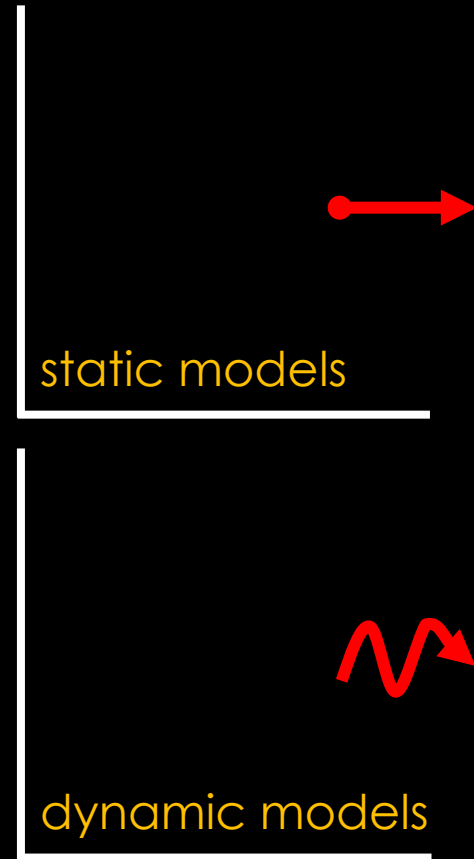
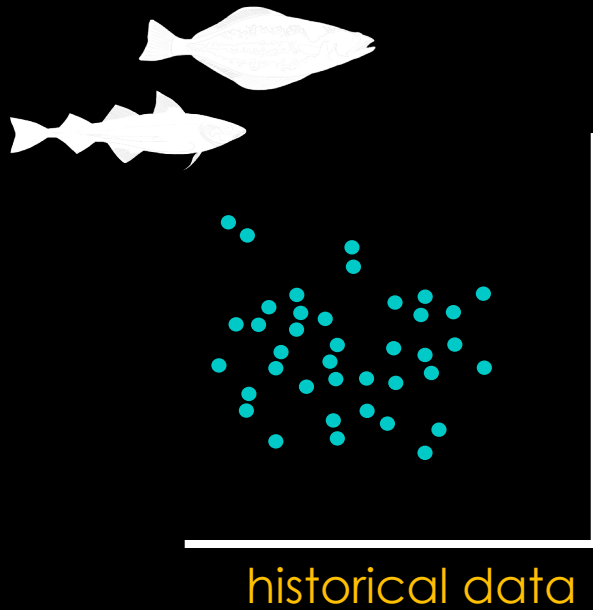
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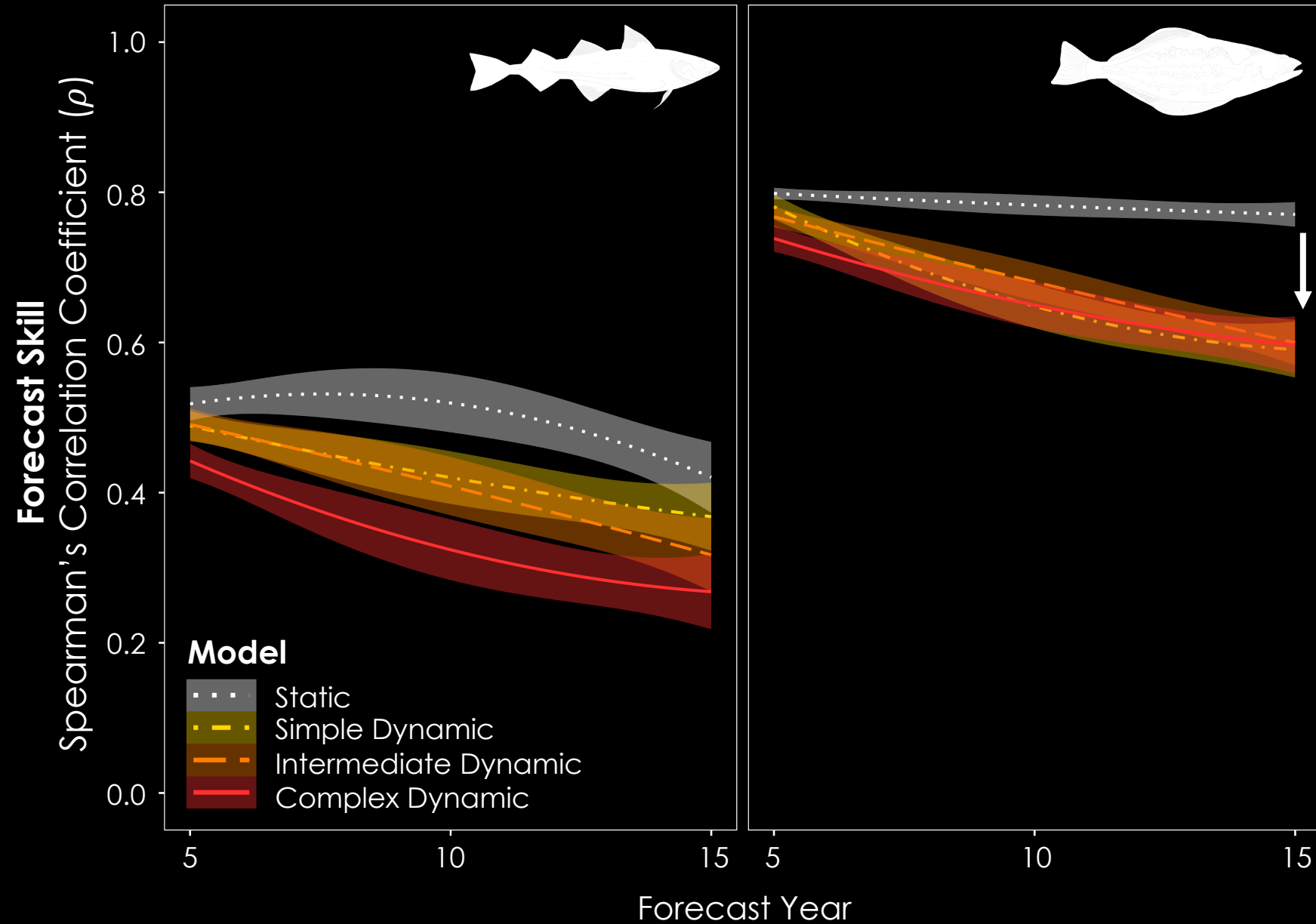


dynamic

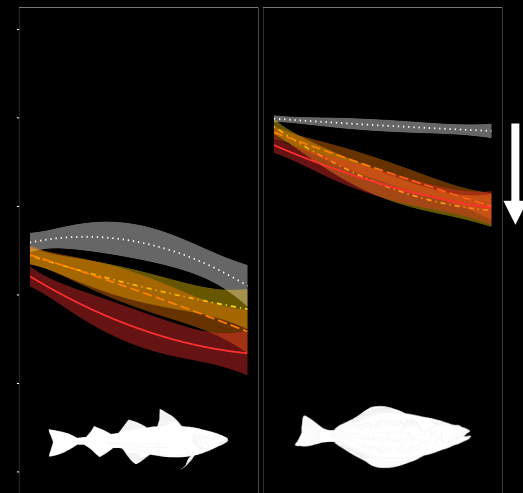
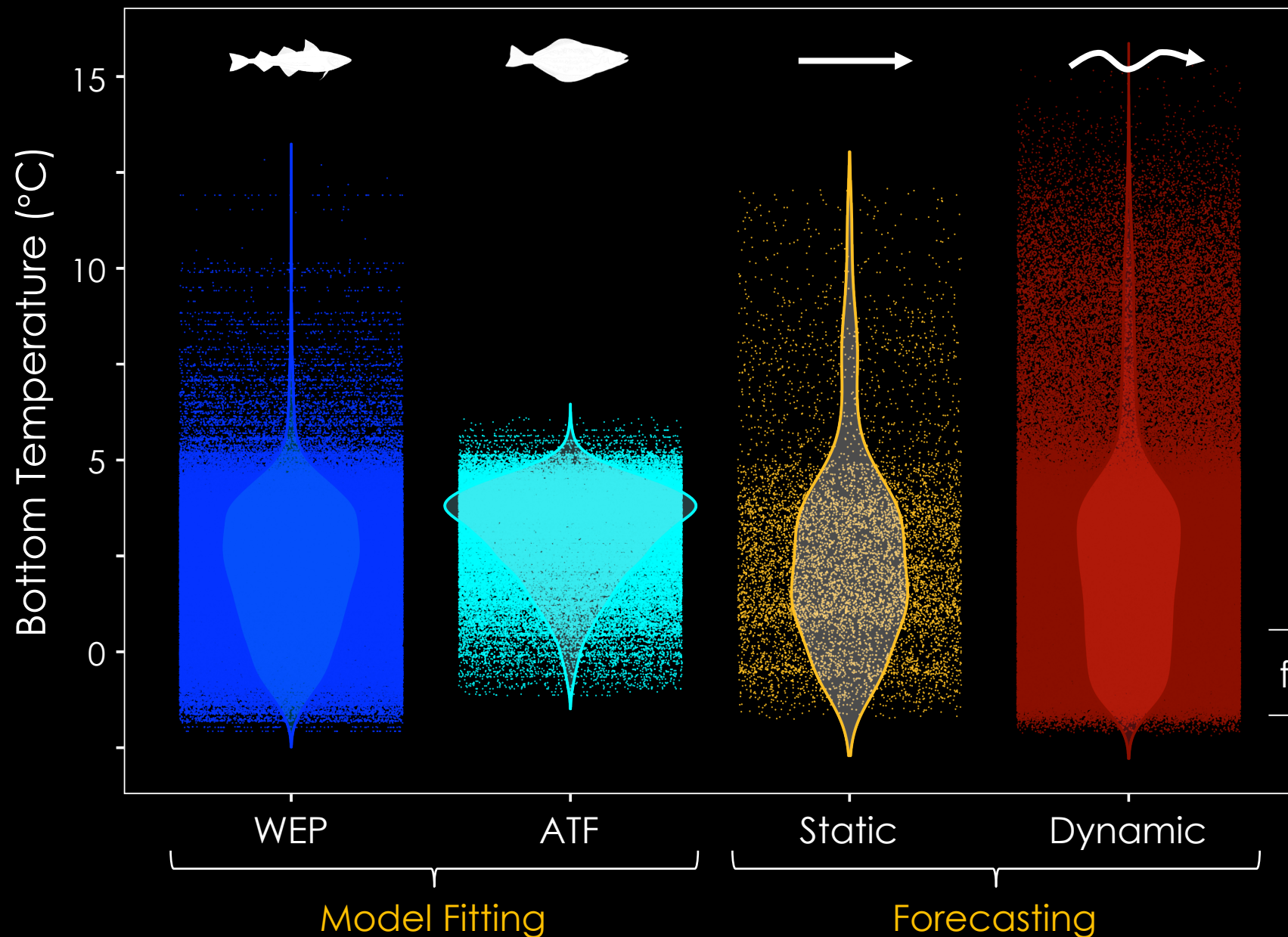
forecasting species responses to climate change



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Climate-informed models benefit hindcasting but present challenges when forecasting species-habitat associations

Take-home messages:

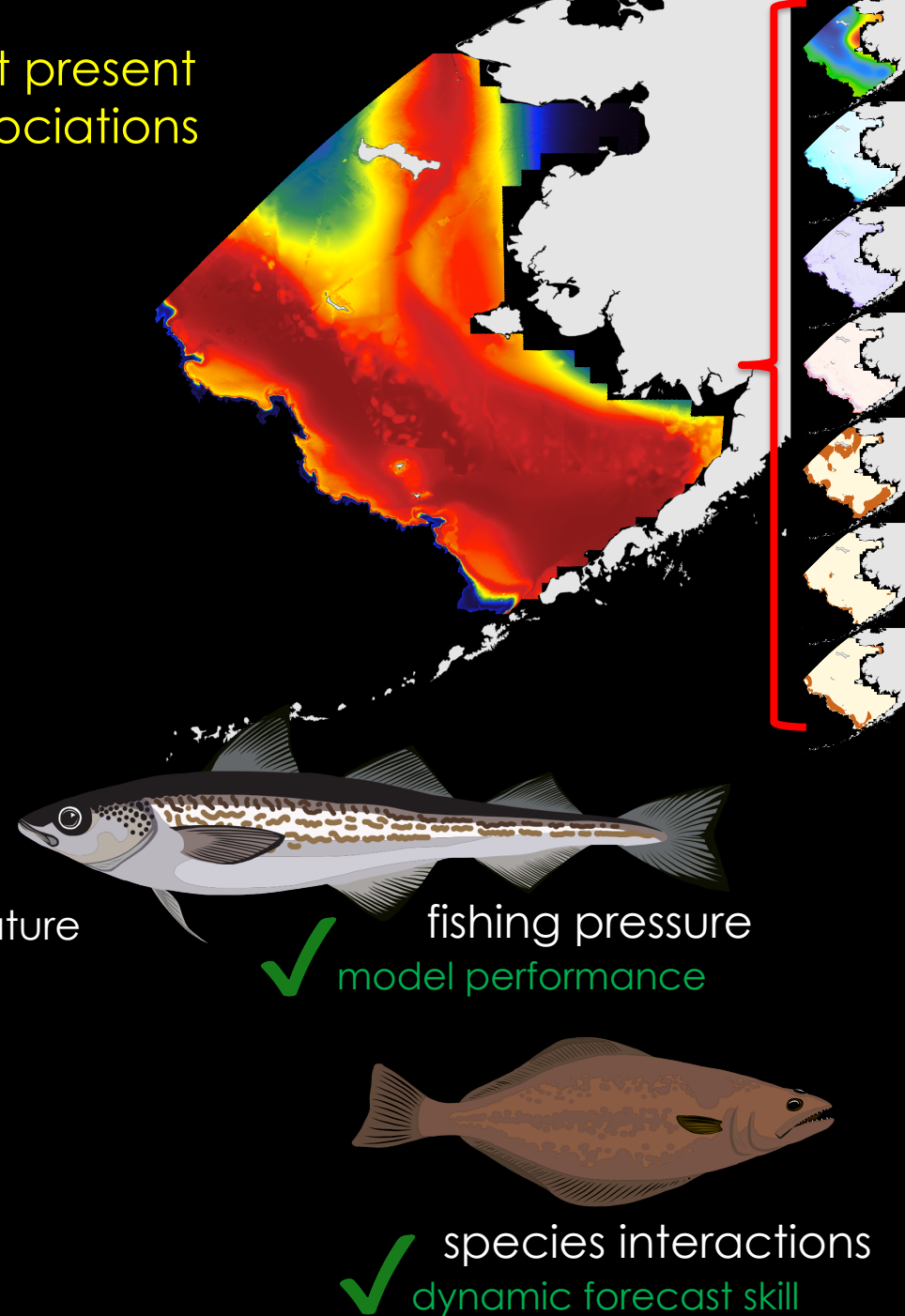
- dynamic SDMs best suited for hindcasting
 - no improvement or decrease in near-term forecast skill

Recommendations for SDM users:

- analyses based on prediction task
 - hindcasting
 - complex dynamic models
 - spatial, temporal, and spatiotemporal variation
 - static and dynamic covariates
 - forecasting
 - retrospective skill testing for model selection
- exercise caution when forecasting based on temperature

Where do we go from here?

- continue advancing development of dynamic SDMs
 - e.g., incrementally adding non-environmental variables
- develop absolute measures of forecast skill





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**NOAA
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Funding:

MSA Implementation (NOAA)



Data:

ACLIM

HCD, AKRO

RACE, AFSC

Fish Art:

Nick Ingram

