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

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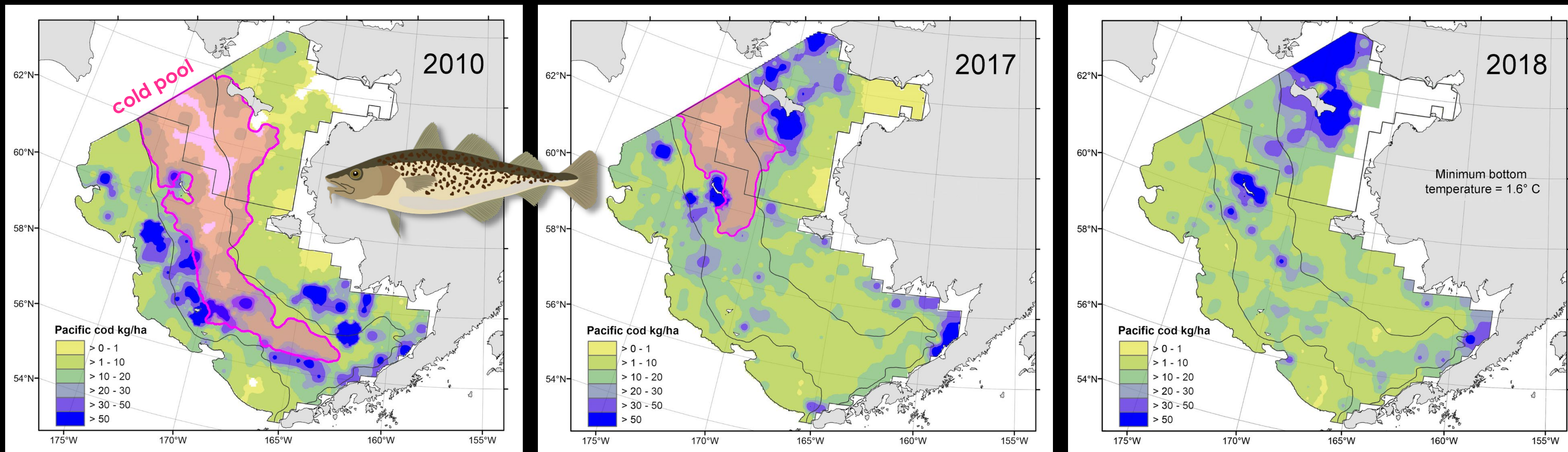
Chris Rooper

University of Washington
Tim Essington



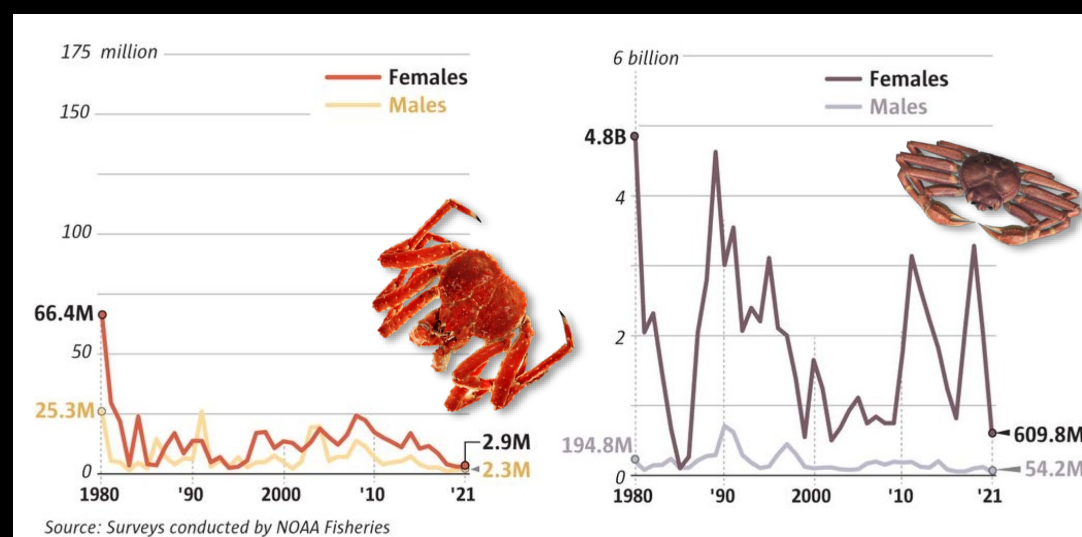
Growing need to anticipate effects of climate change

Northward Mvmt



Stevenson and Lauth 2019

Decreased Abundance



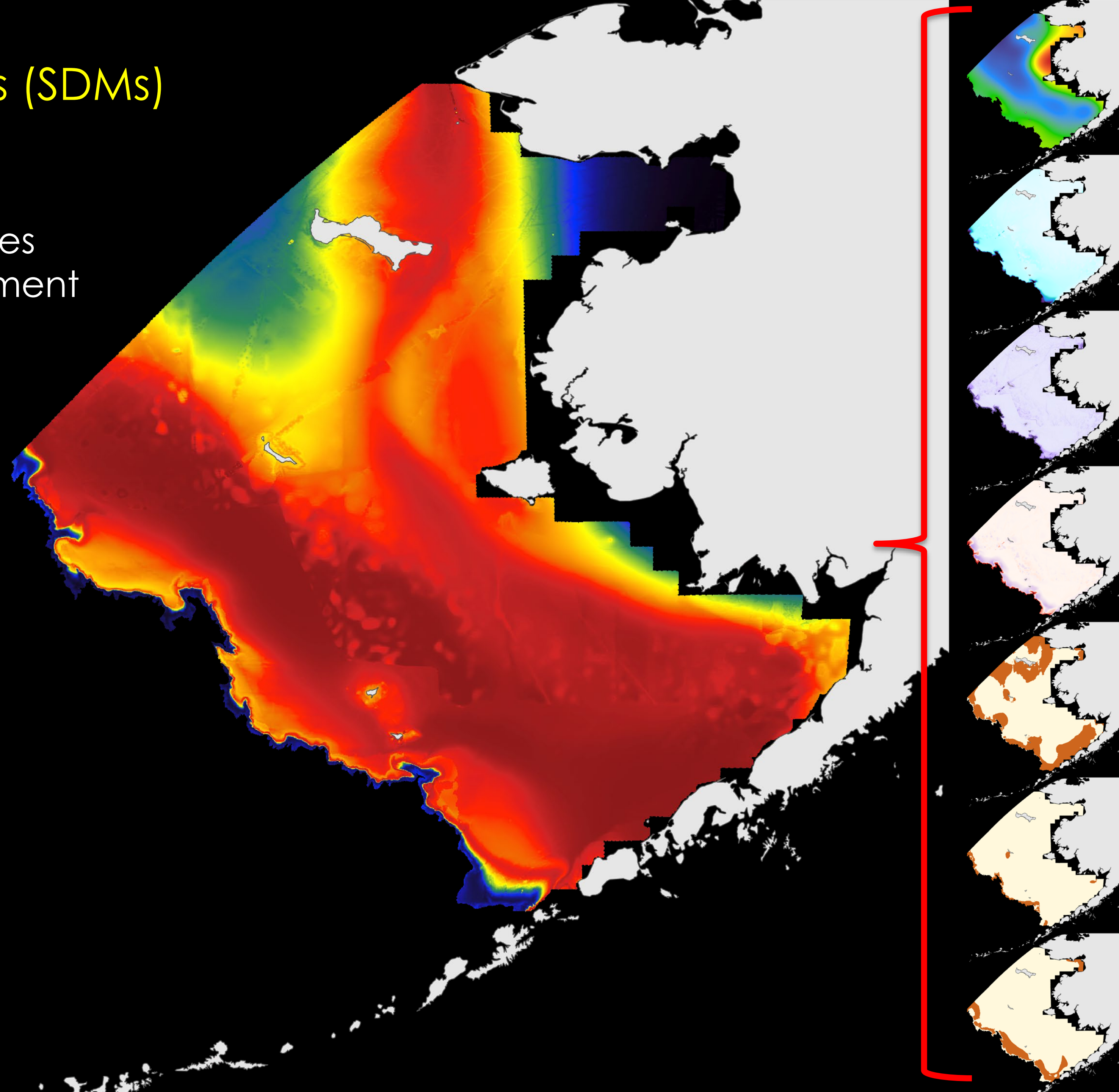
Species Distribution Models (SDMs)

Objective

- distributions and/or densities
  as function of the environment

Applications

- fisheries management
  - *e.g.,* stock assessment
  - *e.g.,* essential fish habitat



Species Distribution Models (SDMs)

"static"

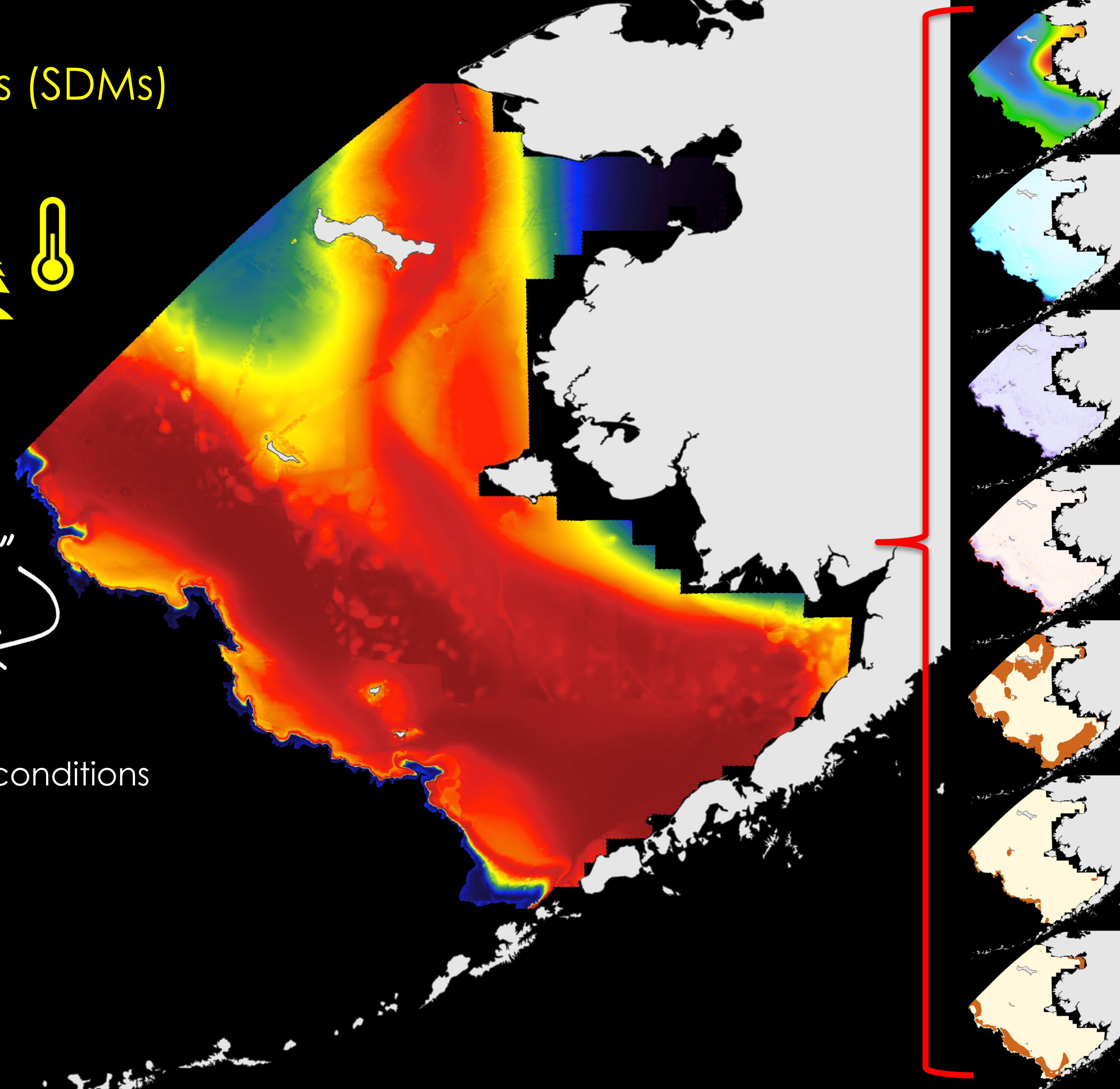
Conventional SDMs

- spatial variation
- long-term mean conditions

"dynamic"

Climate-informed SDMs

- spatial variation
- temporal variation
- year-specific environmental conditions



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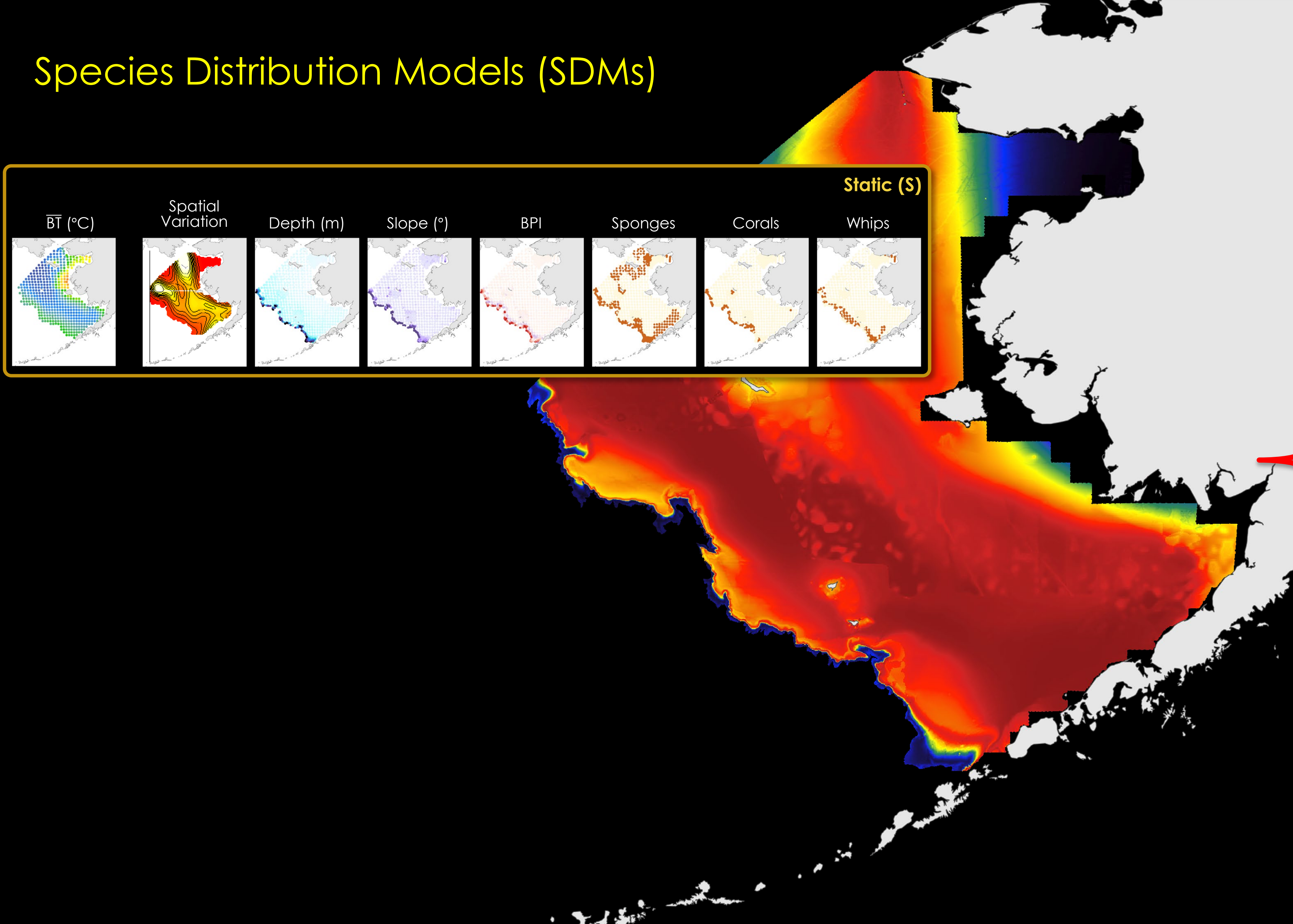

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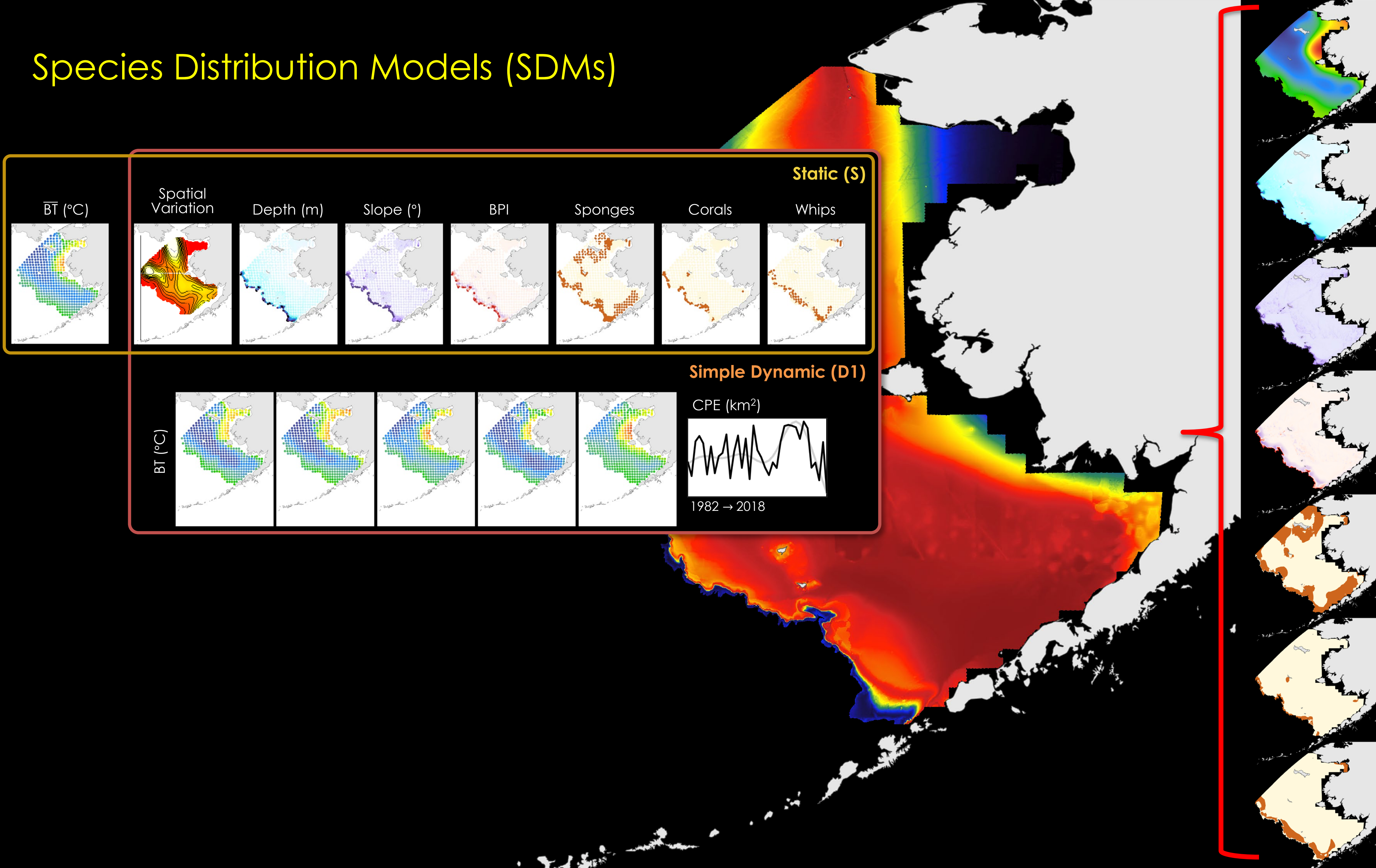

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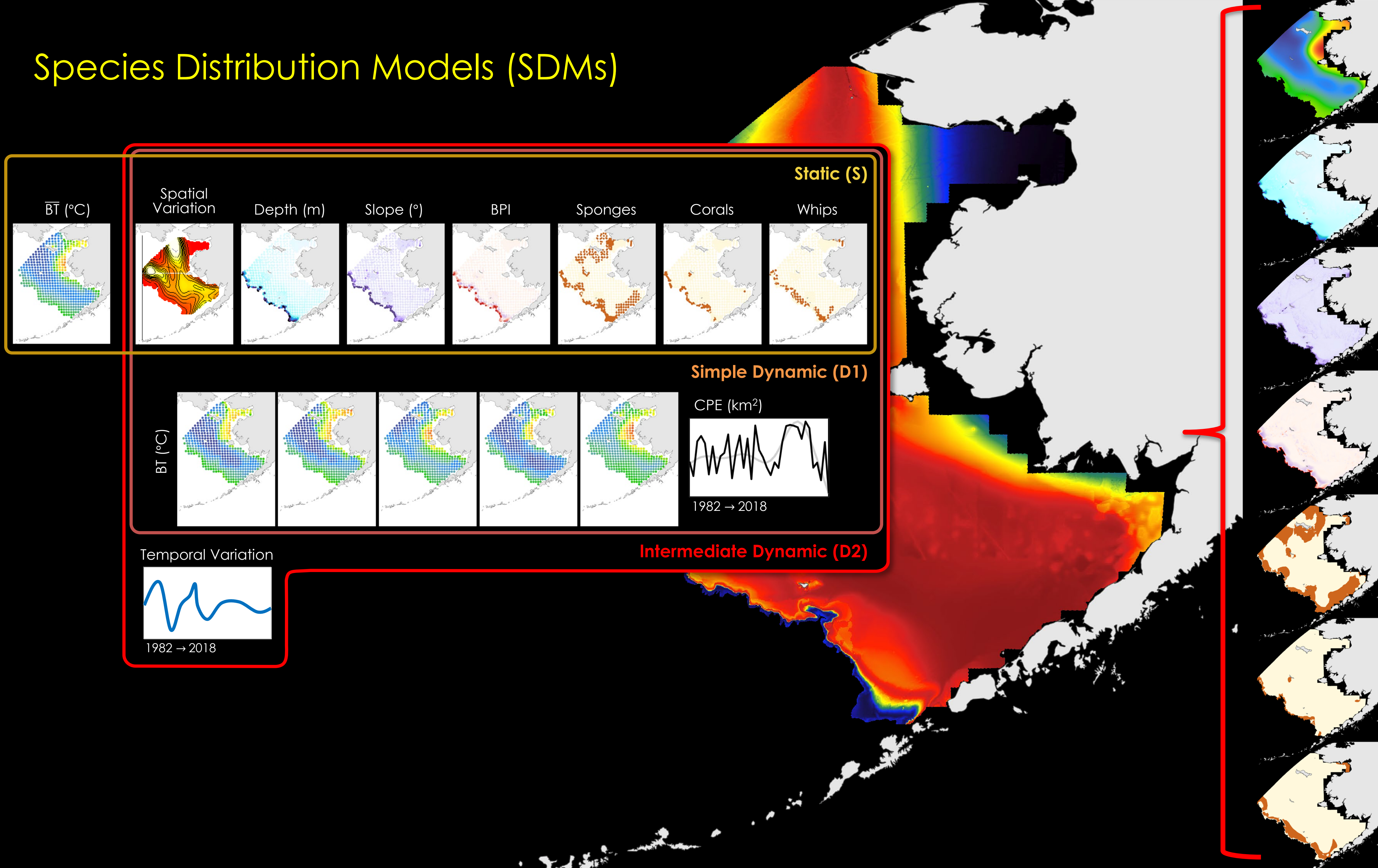

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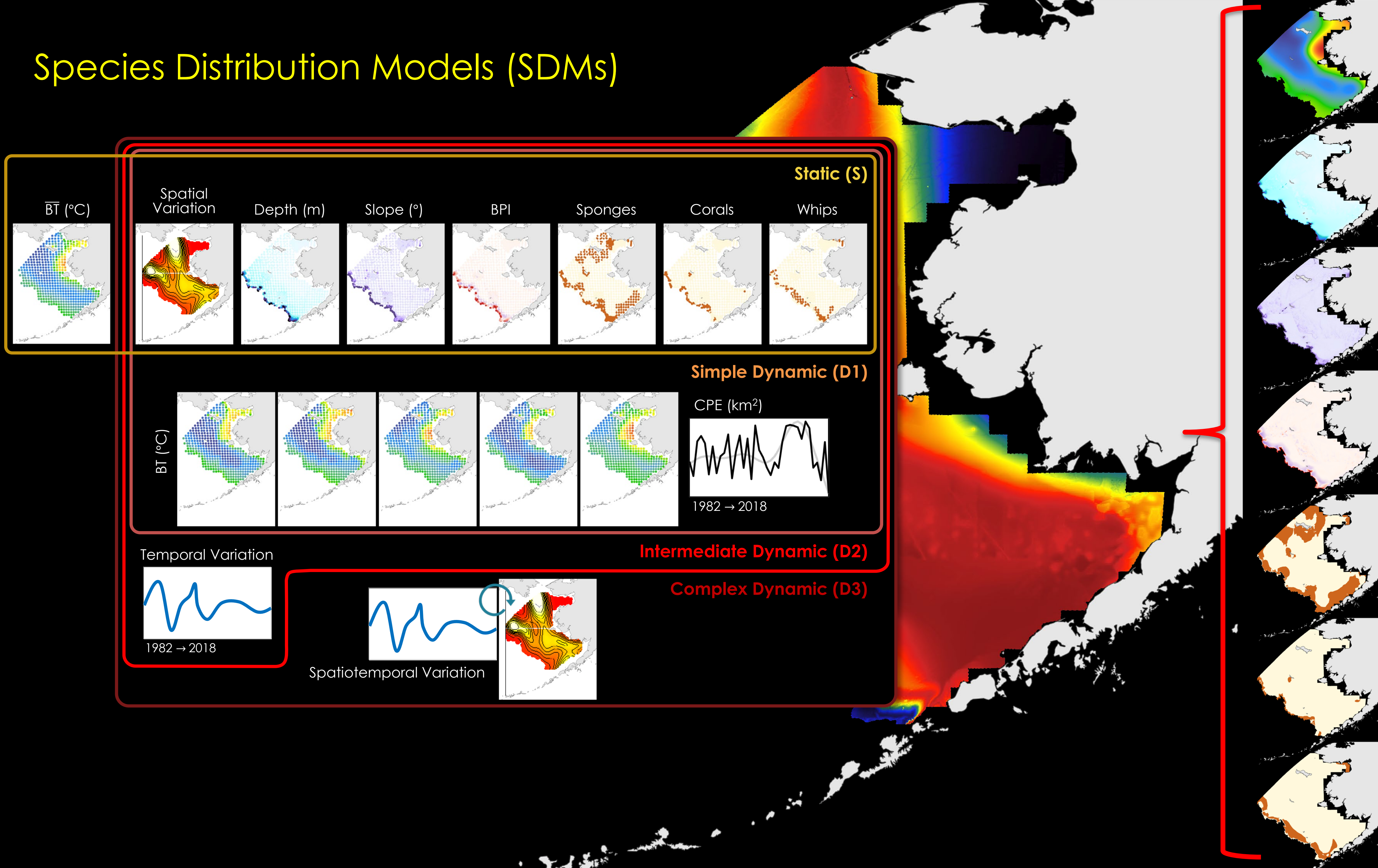
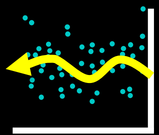
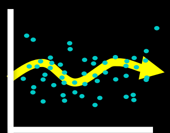


Research Questions

Do dynamic SDMs improve our ability to:



hindcast species-habitat associations?



forecast near-term responses to climate change?

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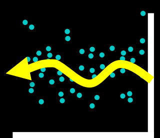
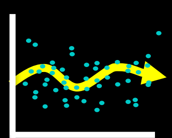


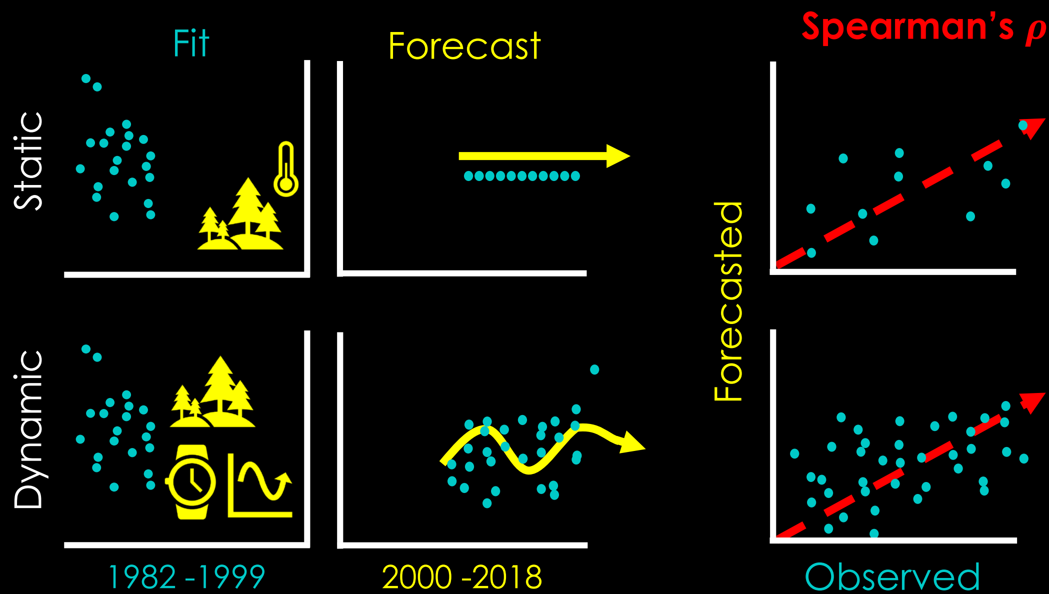
hindcast species-habitat associations?

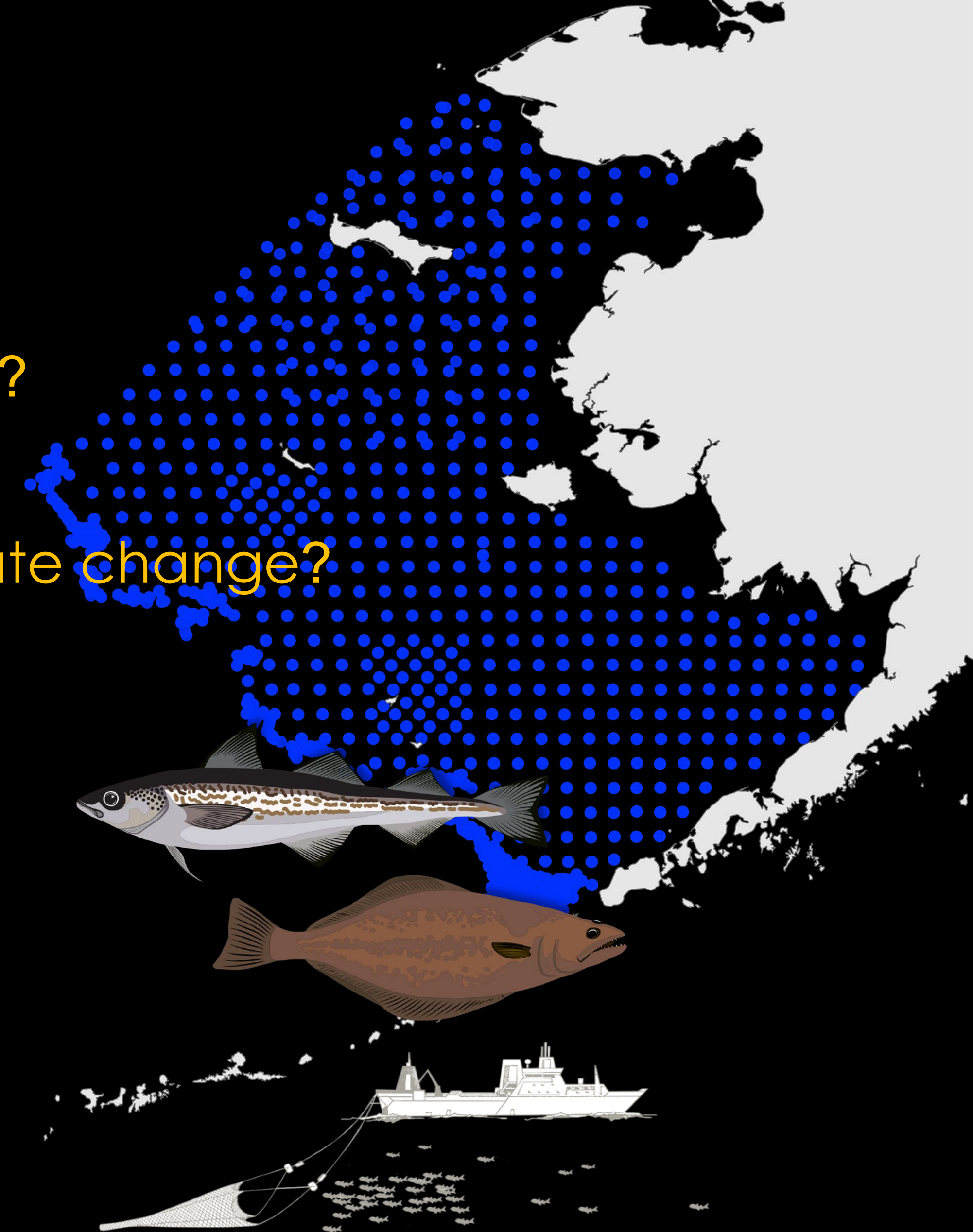
R^2, % Deviance Explained, UBRE/GCV



forecast near-term responses to climate change?

retrospective skill testing (*sensu* Thorson 2019)





Generalized Additive Models (GAMs), 1982 to 2018

Resource Assessment and Conservation Engineering Division

Alaska Fisheries Science Center, NOAA

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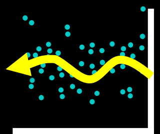

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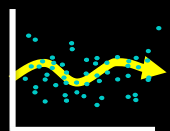

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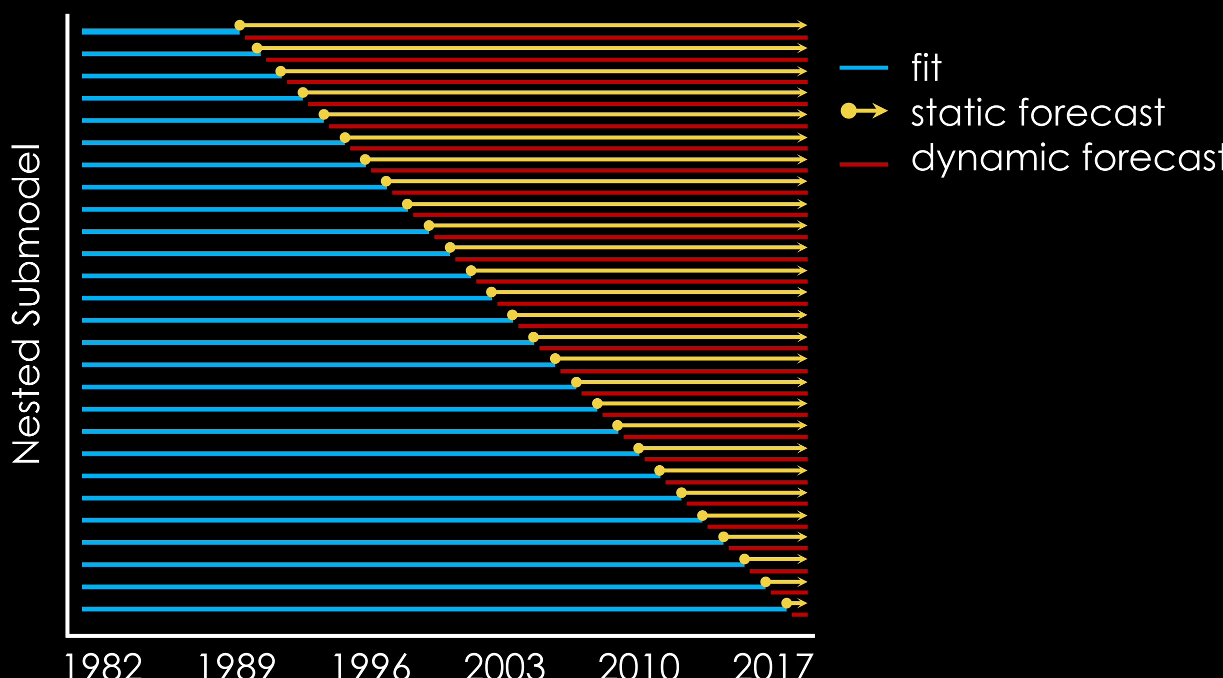

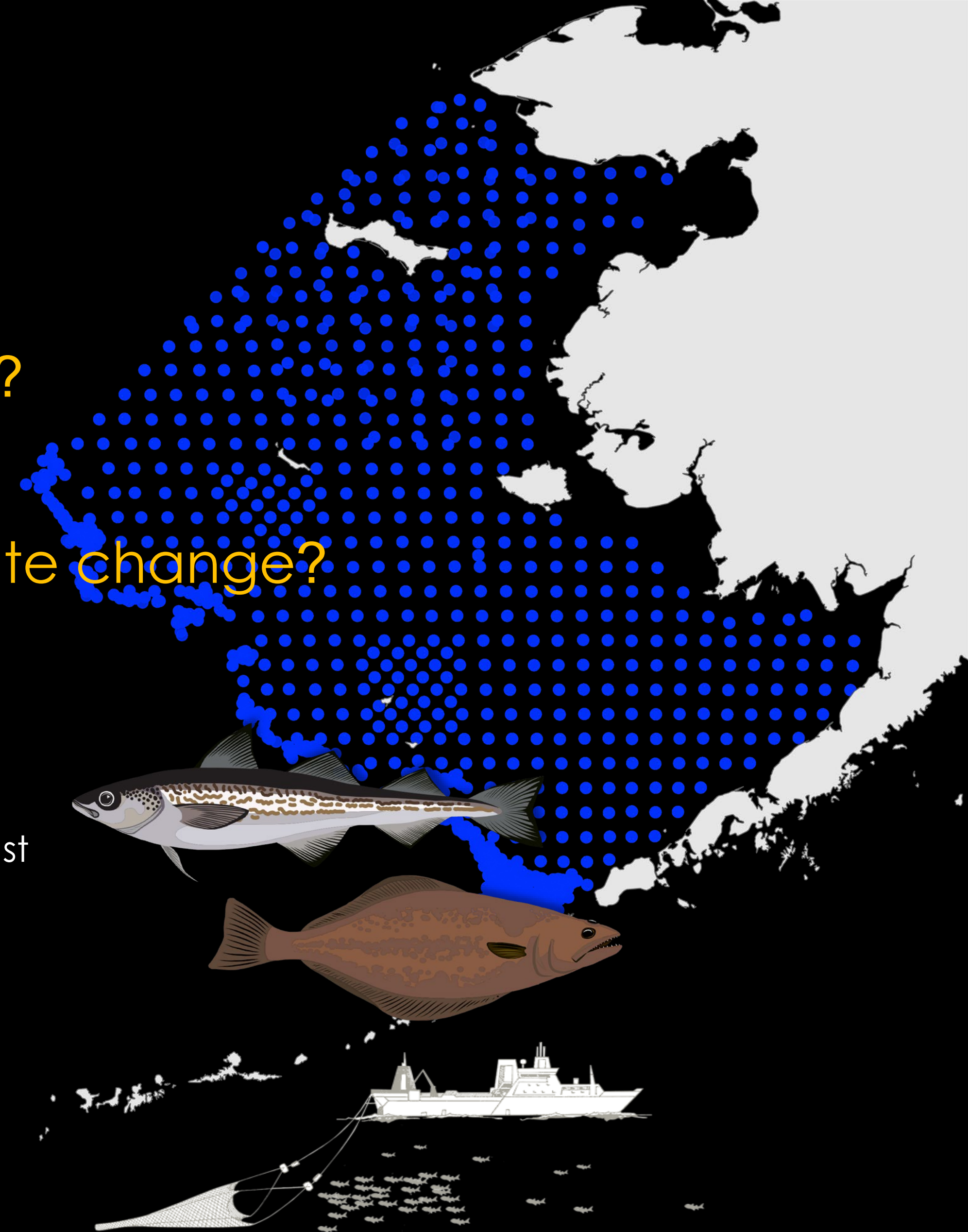

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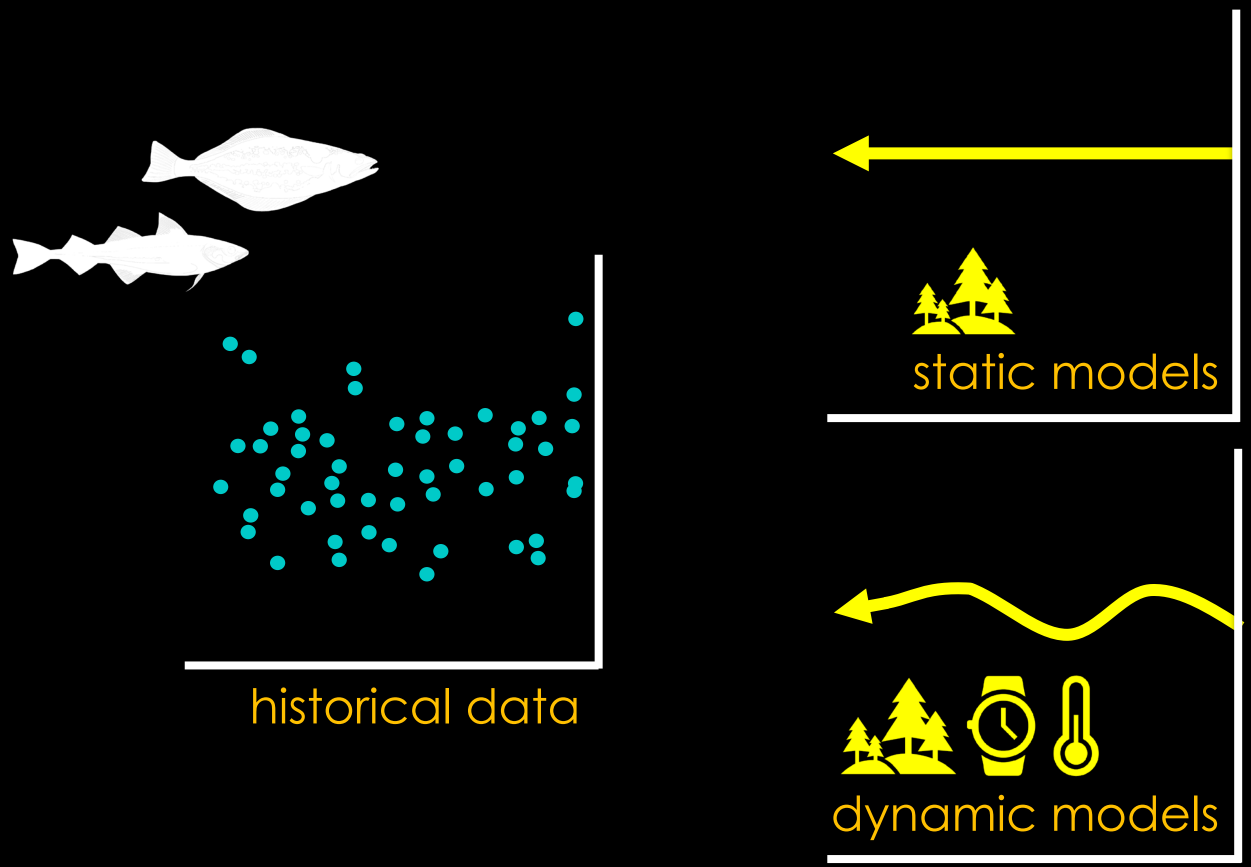
hindcasting species-habitat associations



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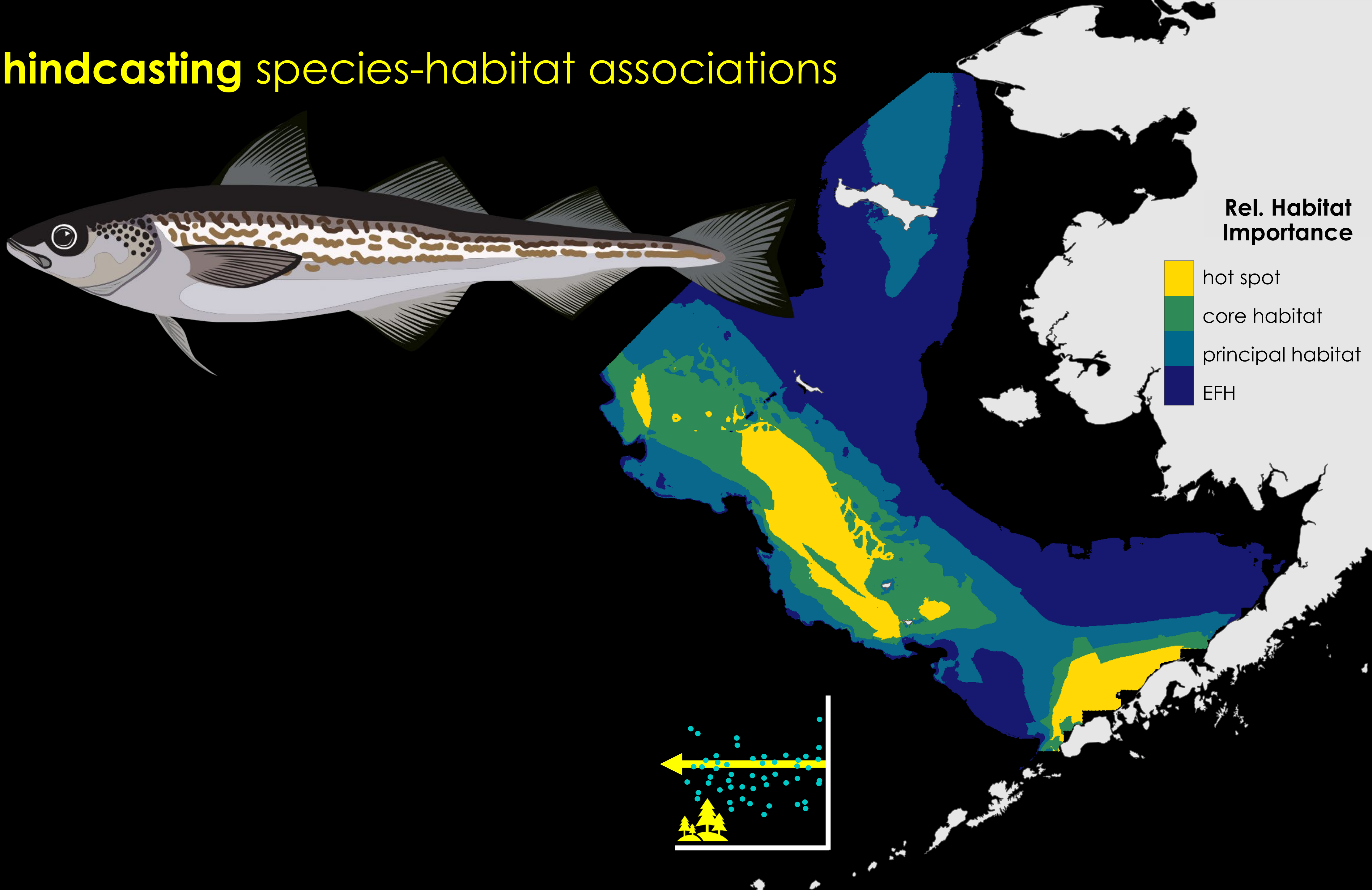

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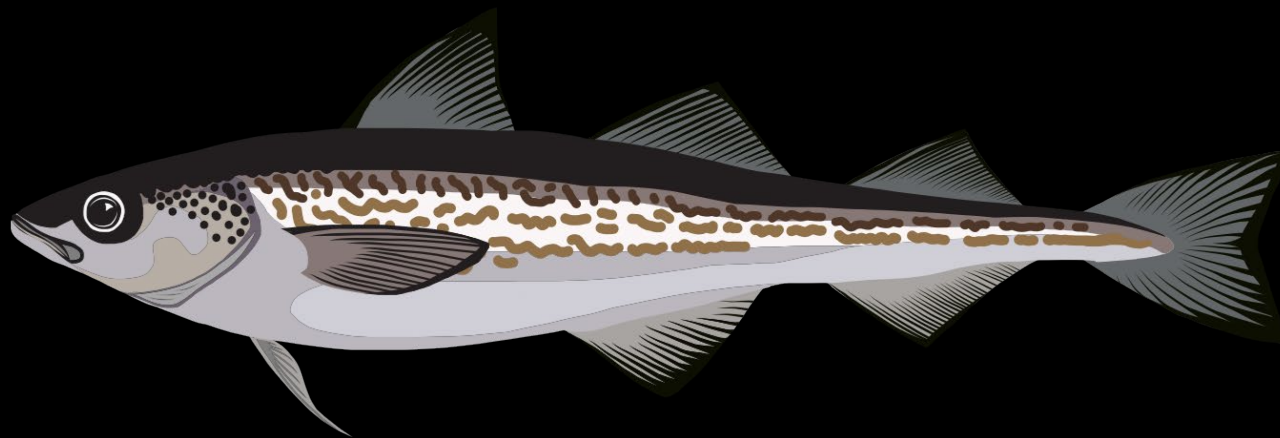
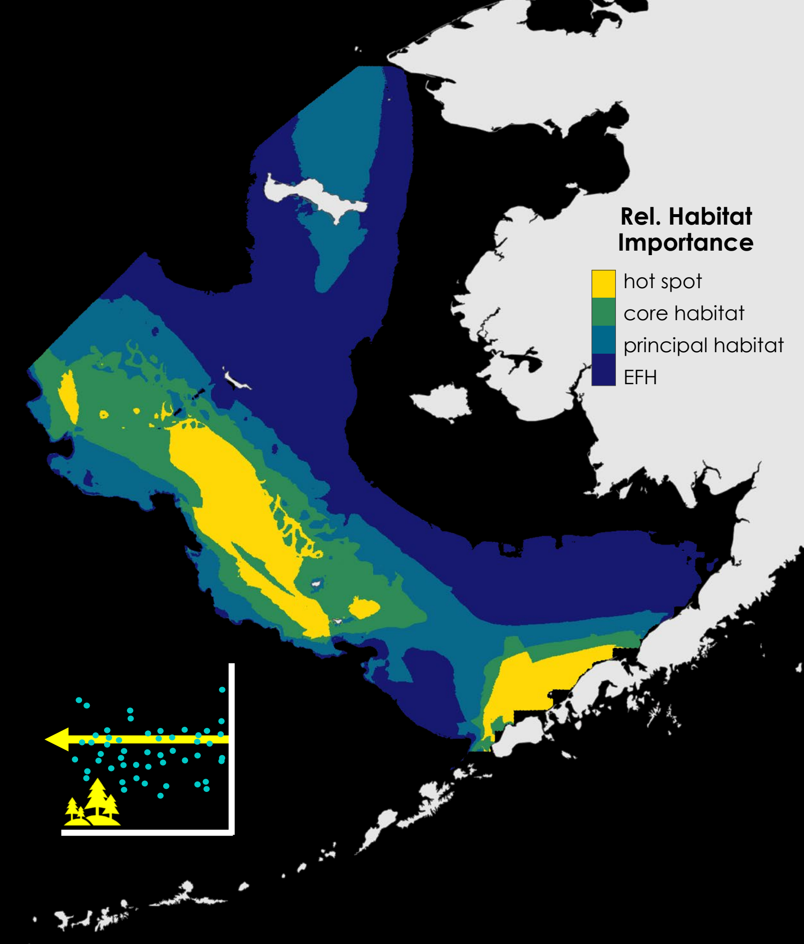
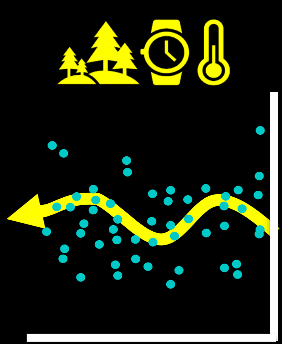
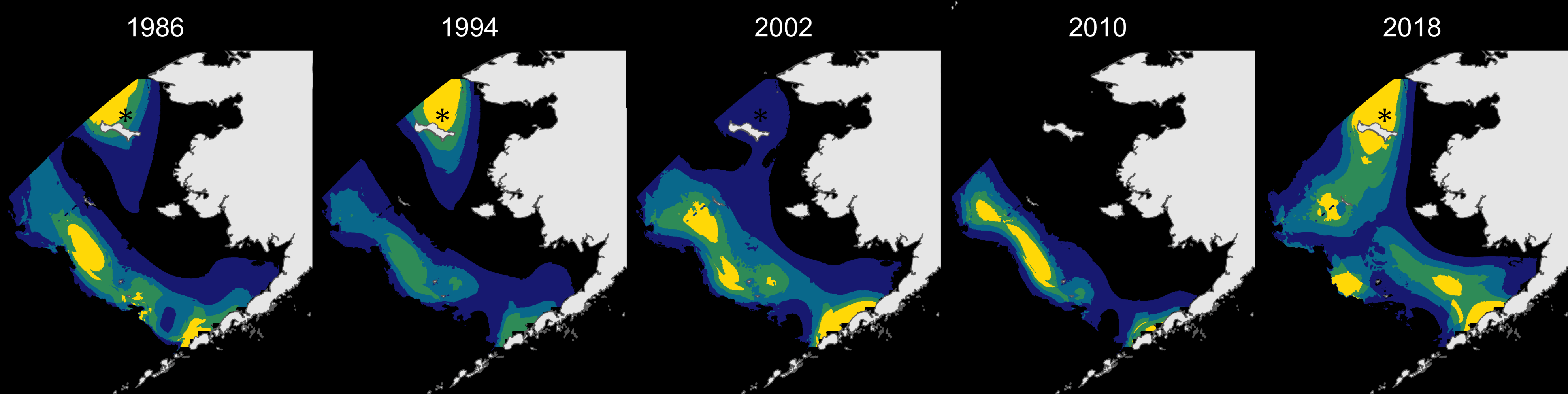




complex dynamic models = best-fit

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





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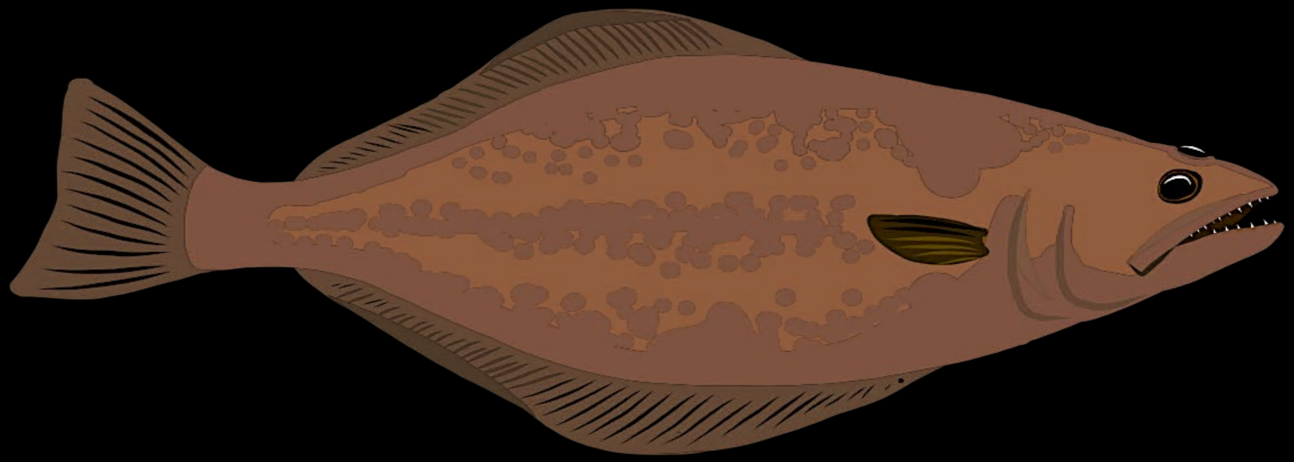

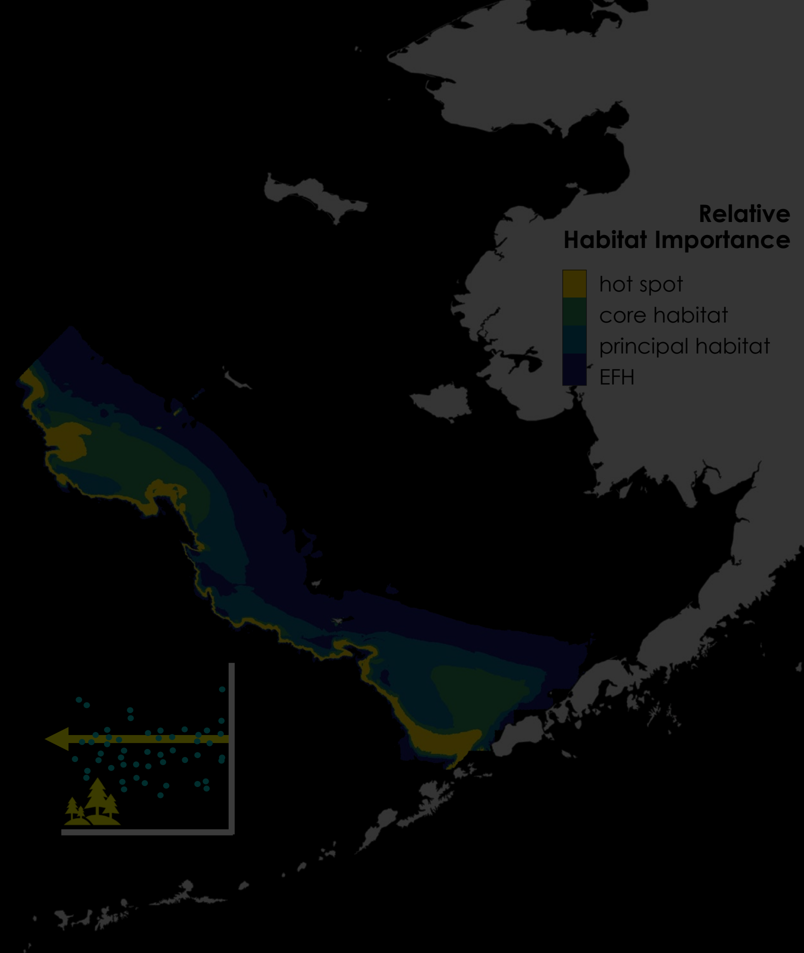

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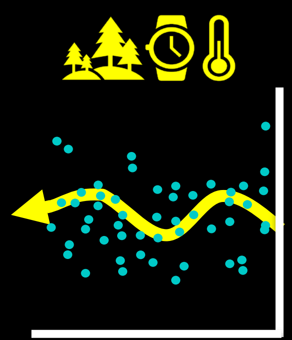
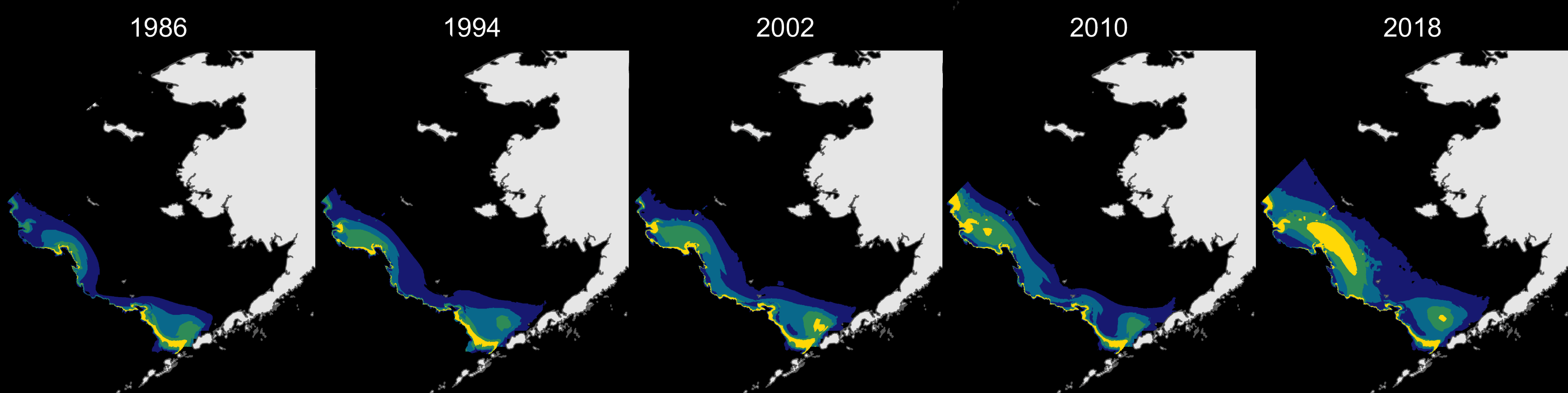
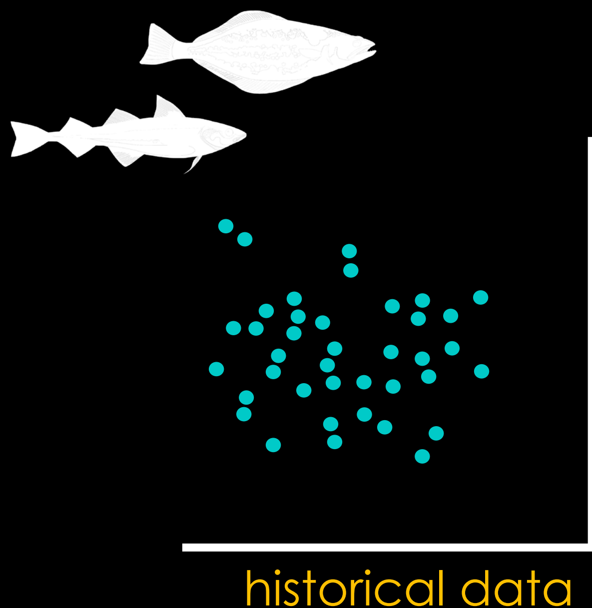
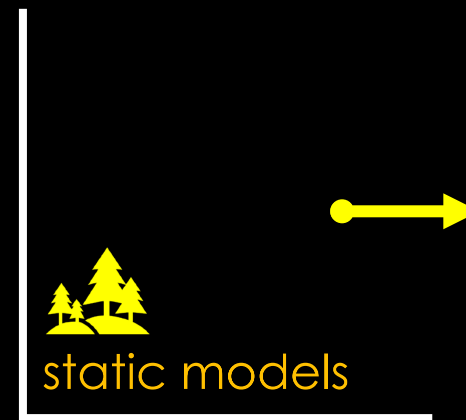
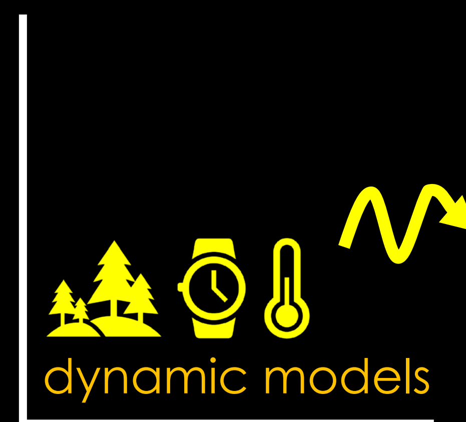




forecasting species responses to climate change







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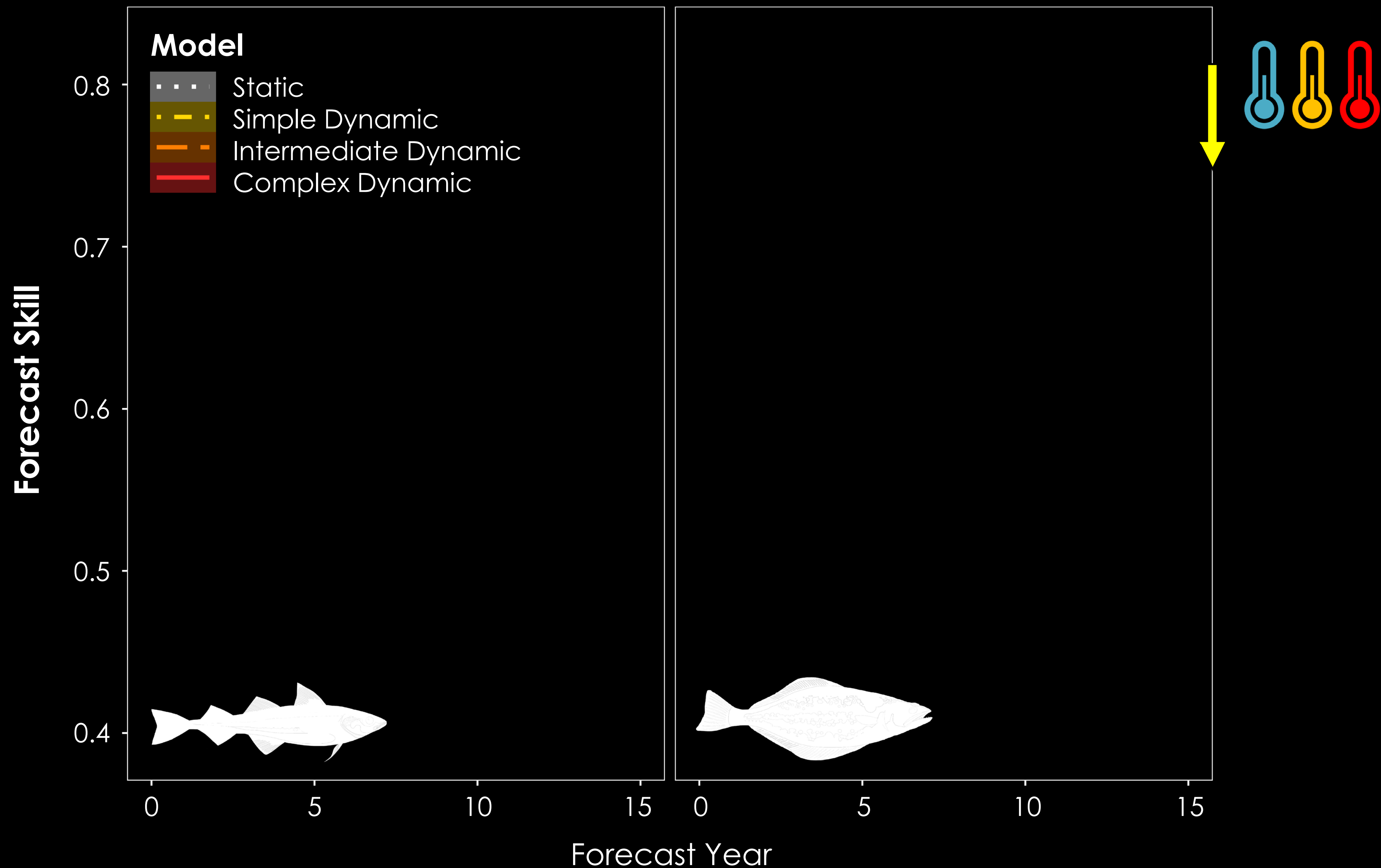

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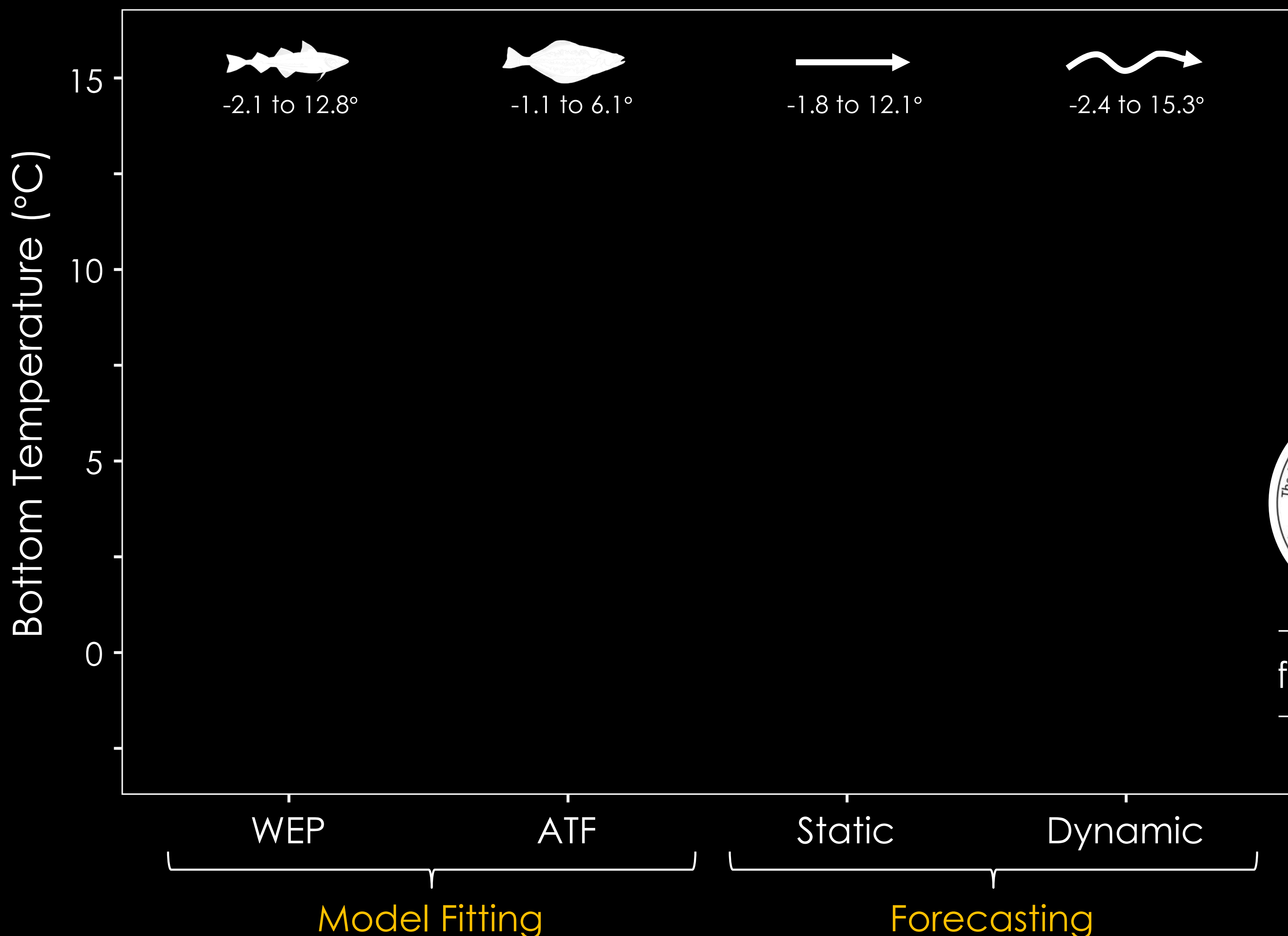
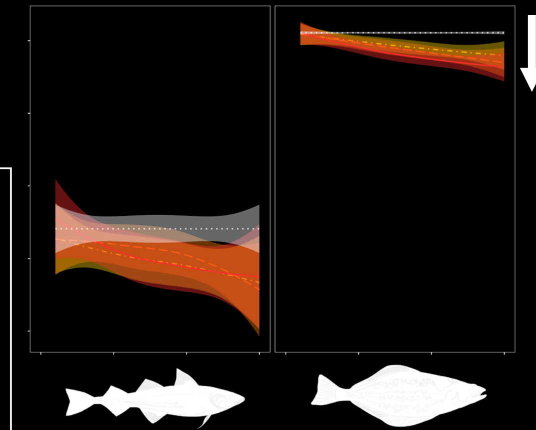




fit vs forecast

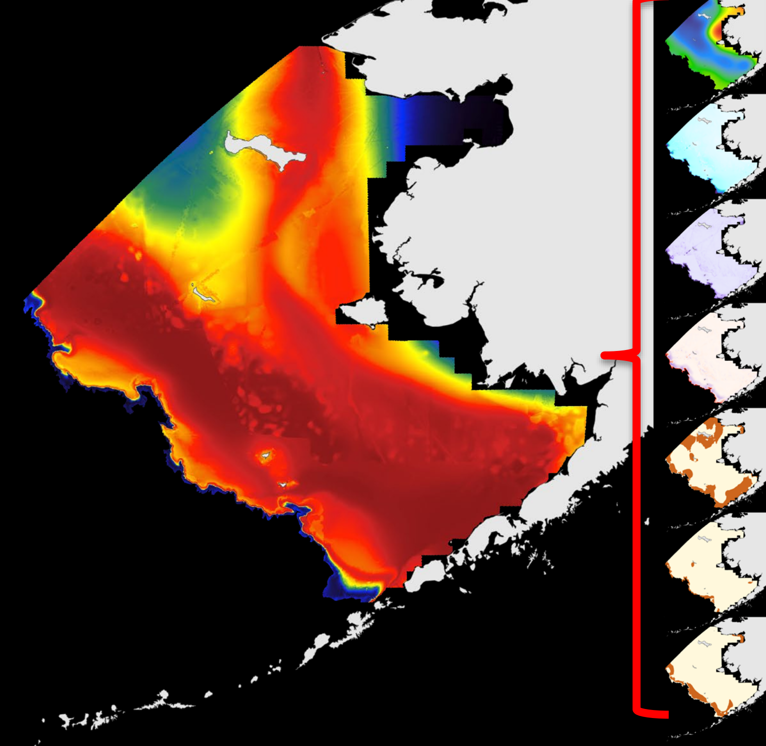
Research Questions

Do dynamic SDMs improve our ability to:

✓ **hindcast** species-habitat associations?

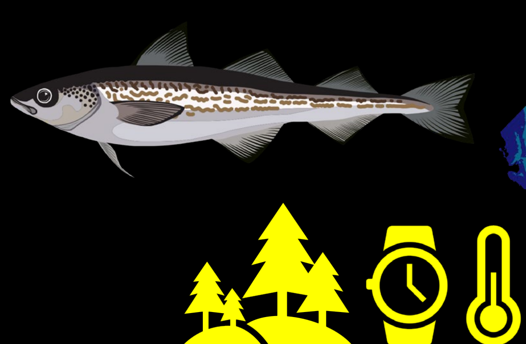
✗ **forecast** near-term responses to climate change?

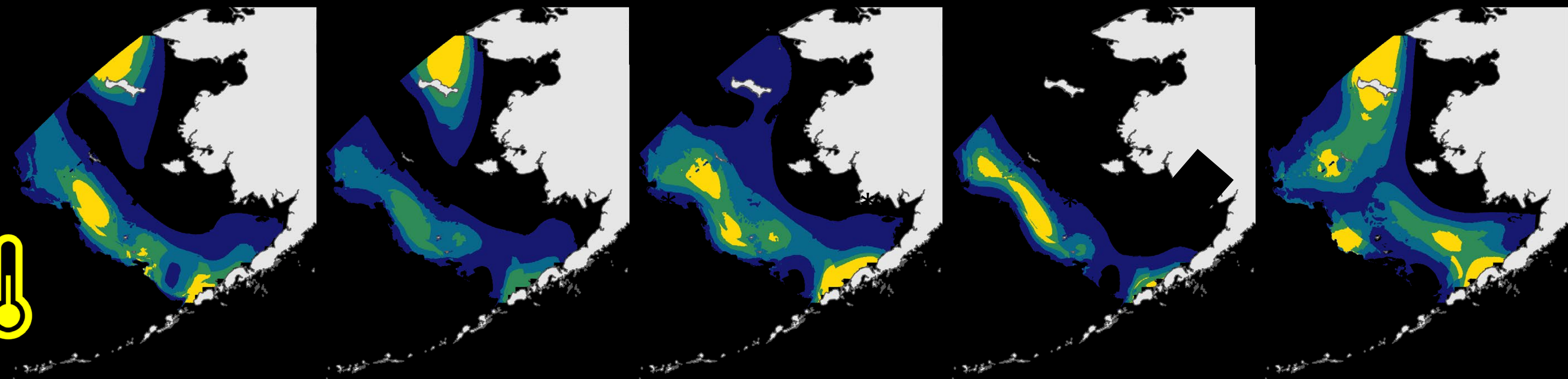
- static models
- persistence forecasts from dynamic models

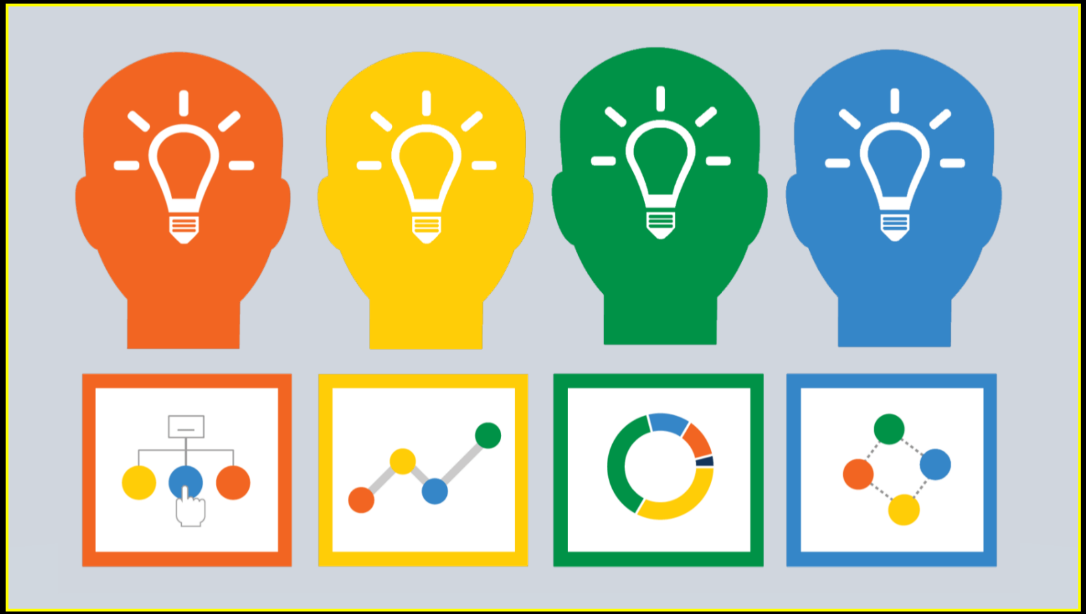


Recommendations for SDM users:

- use retrospective skill testing for forecast model selection
- use caution when forecasting based on temperature







Can we talk about forecasting?

- modeling frameworks
- environmental covariates
- model specifications
- metrics for forecast skill

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Funding

MSA Implementation (NOAA)

Data

ACLIM
AFSC
AKRO
HCD
RACE

Fish Art

Nick Ingram

Link to Barnes et al. 2022

INTEGRATED MARINE FISHERIES LAB

Department of Fisheries, Wildlife, and Conservation Sciences
Coastal Oregon Marine Experiment Station, Oregon State University
Marine Resources Program, Oregon Dept. of Fish and Wildlife

MS or PhD Opportunity

HATFIELD
MARINE SCIENCE CENTER
Newport, OR

Predators as samplers: using food habits data to inform climate- and community-driven shifts in marine species distributions

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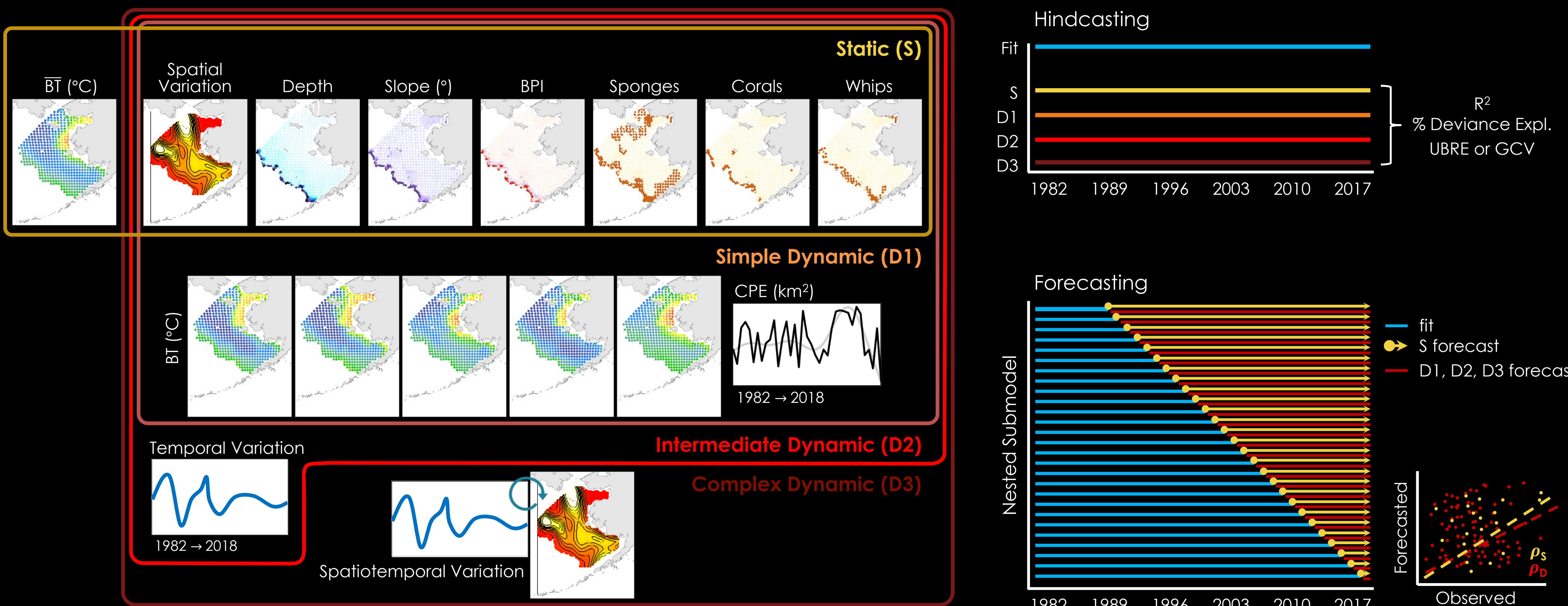
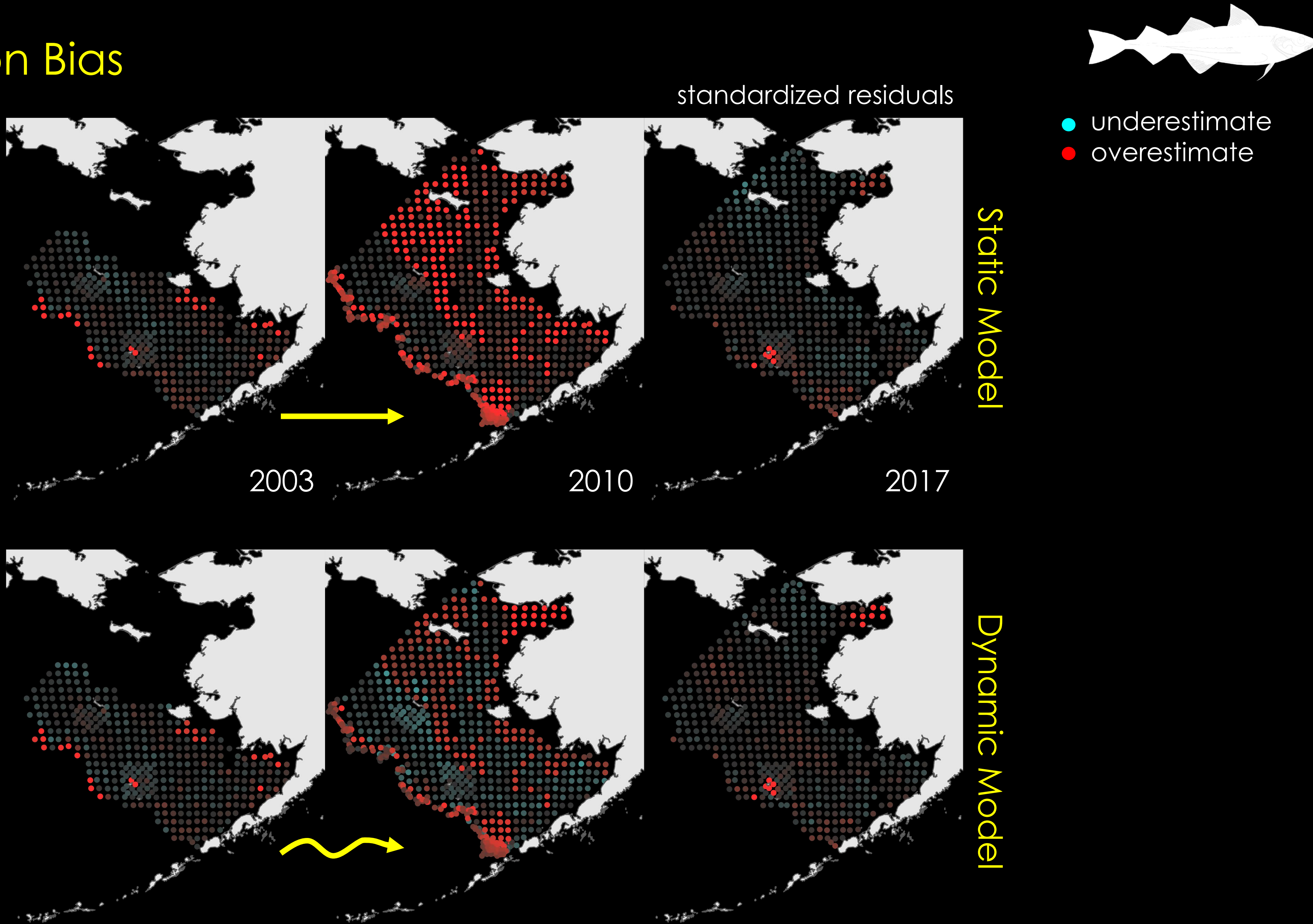


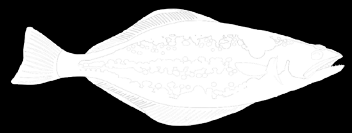
Barnes *et al.*, Accepted

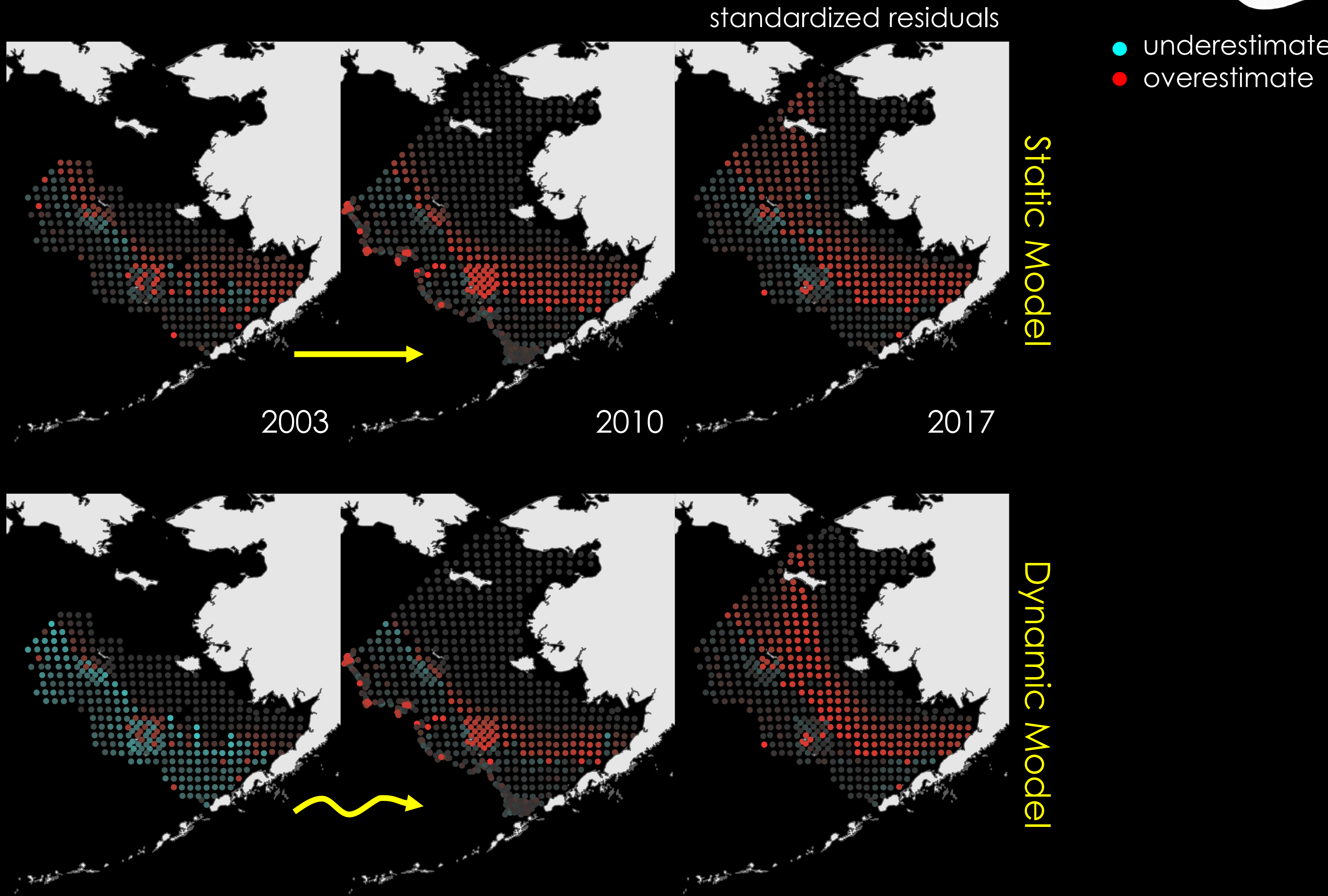
Estimation Bias



greater bias ~ lower ROMS skill

Estimation Bias





greater bias ~ lower ROMS skill

Hindcast Model Performance

a) Probability of Occurrence

	Arrowtooth Flounder				Walleye Pollock			
	S	D1	D2	D3	Static	D1	D2	D3
R^2	0.613	0.654	0.723	**0.736**	0.365	0.454	0.466	**0.492**
% Deviance Exp.	55.4	60.3	67.3	**69.3**	34.3	43.9	45.6	**48.6**
UBRE or GCV	-0.396	-0.459	-0.552	**-0.572**	-0.469	-0.542	-0.555	**-0.571**
Spearman's rho	0.751	0.750	0.797	**0.803**	0.472	0.492	0.507	**0.521**

b) Numerical Abundance

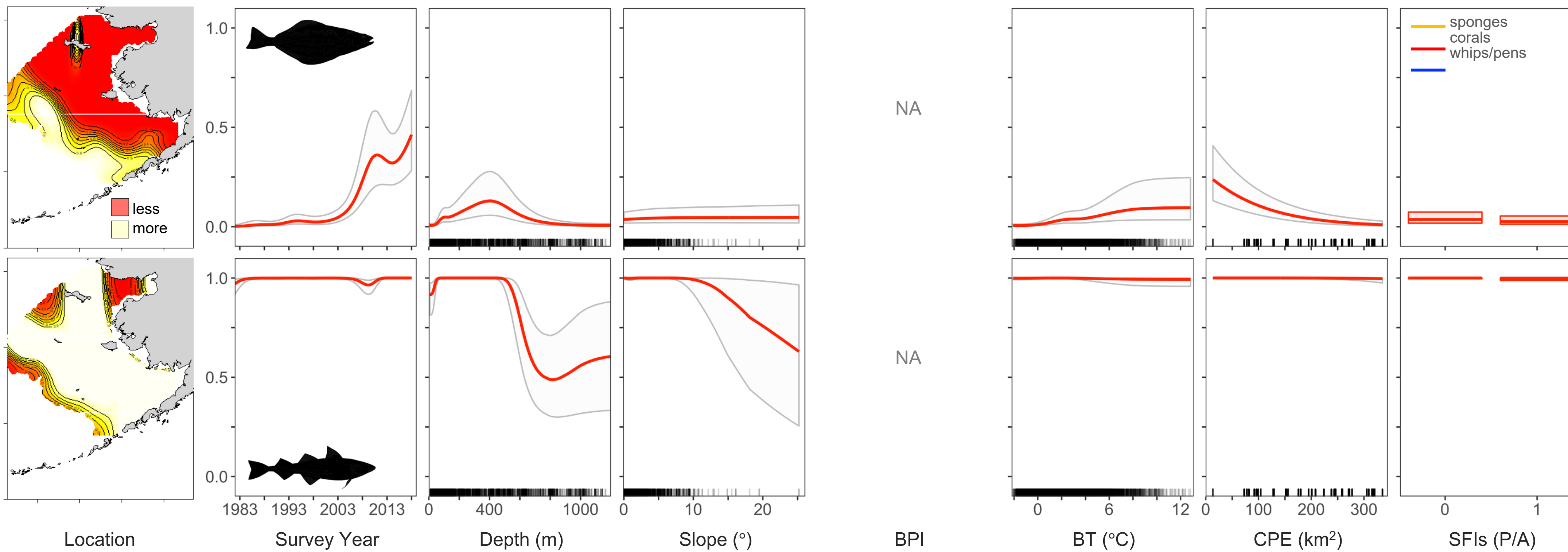
	Arrowtooth Flounder				Walleye Pollock			
	S	D1	D2	D3	Static	D1	D2	D3
R^2	0.154	0.169	0.196	**0.227**	0.098	0.108	0.127	**0.159**
% Deviance Exp.	34.1	36.5	41.5	**46.8**	25.4	29.0	31.6	**36.1**
UBRE or GCV	22.02	21.19	19.45	**17.63**	935.4	889.3	856.9	**800.3**
Spearman's rho	0.770	0.755	0.809	**0.820**	0.628	0.670	0.683	**0.696**

c) Biomass

	Arrowtooth Flounder				Walleye Pollock			
	S	D1	D2	D3	Static	D1	D2	D3
R^2	0.147	0.153	0.161	**0.191**	0.083	0.085	0.084	**0.104**
% Deviance Exp.	37.9	40.2	47.2	**51.7**	25.0	30.9	33.2	**36.8**
UBRE or GCV	0.933	0.907	0.804	**0.750**	2.10	1.94	1.88	**1.795**
Spearman's rho	0.773	0.757	0.817	**0.824**	0.589	0.629	0.648	**0.668**

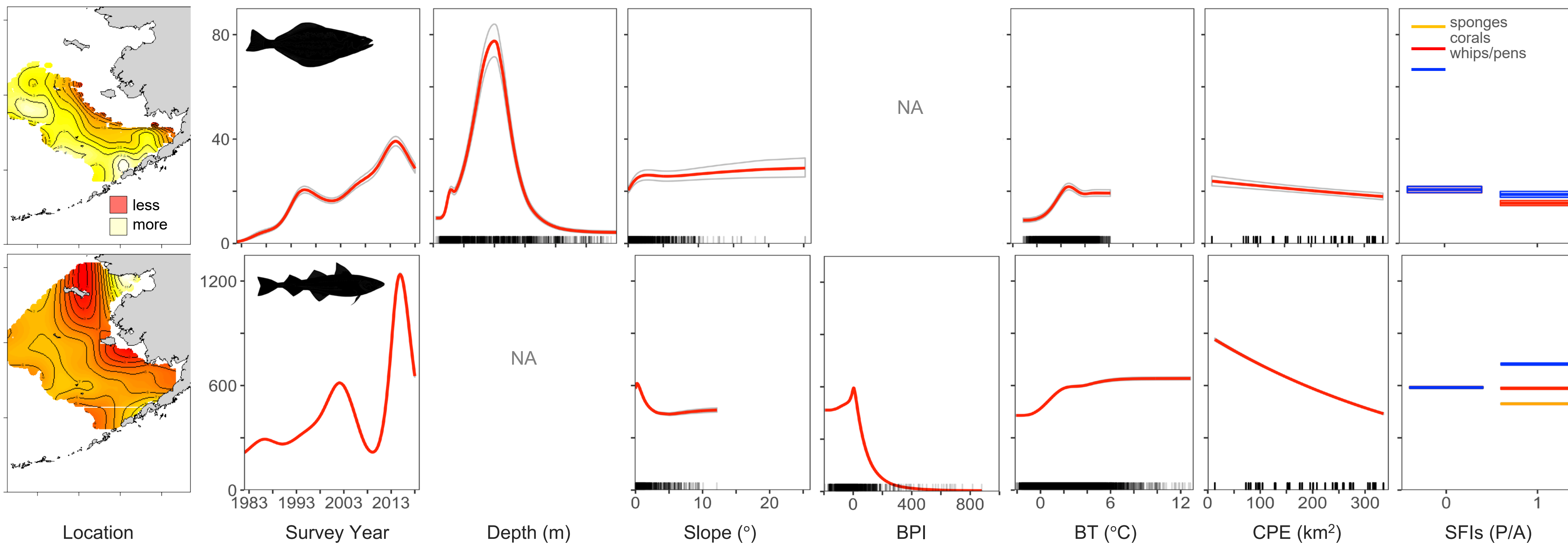
Partial Covariate Effects (Complex Dynamic Models)

Probability of Occurrence



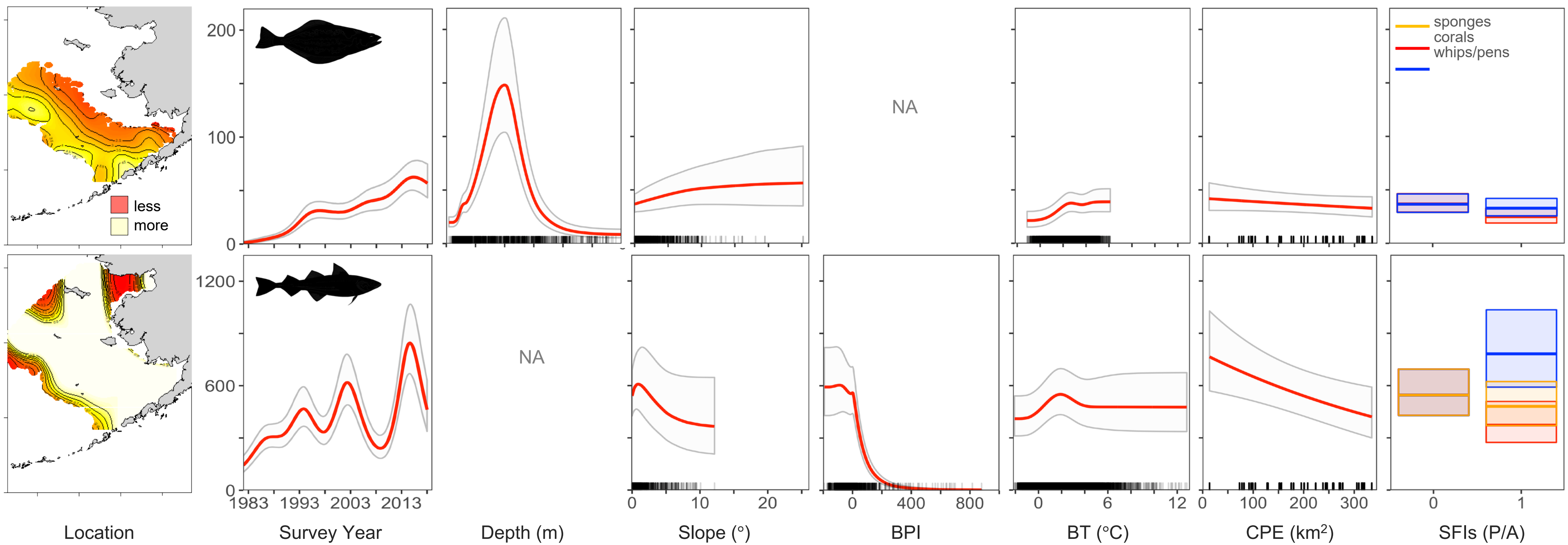
Partial Covariate Effects (Complex Dynamic Models)

Numerical Abundance

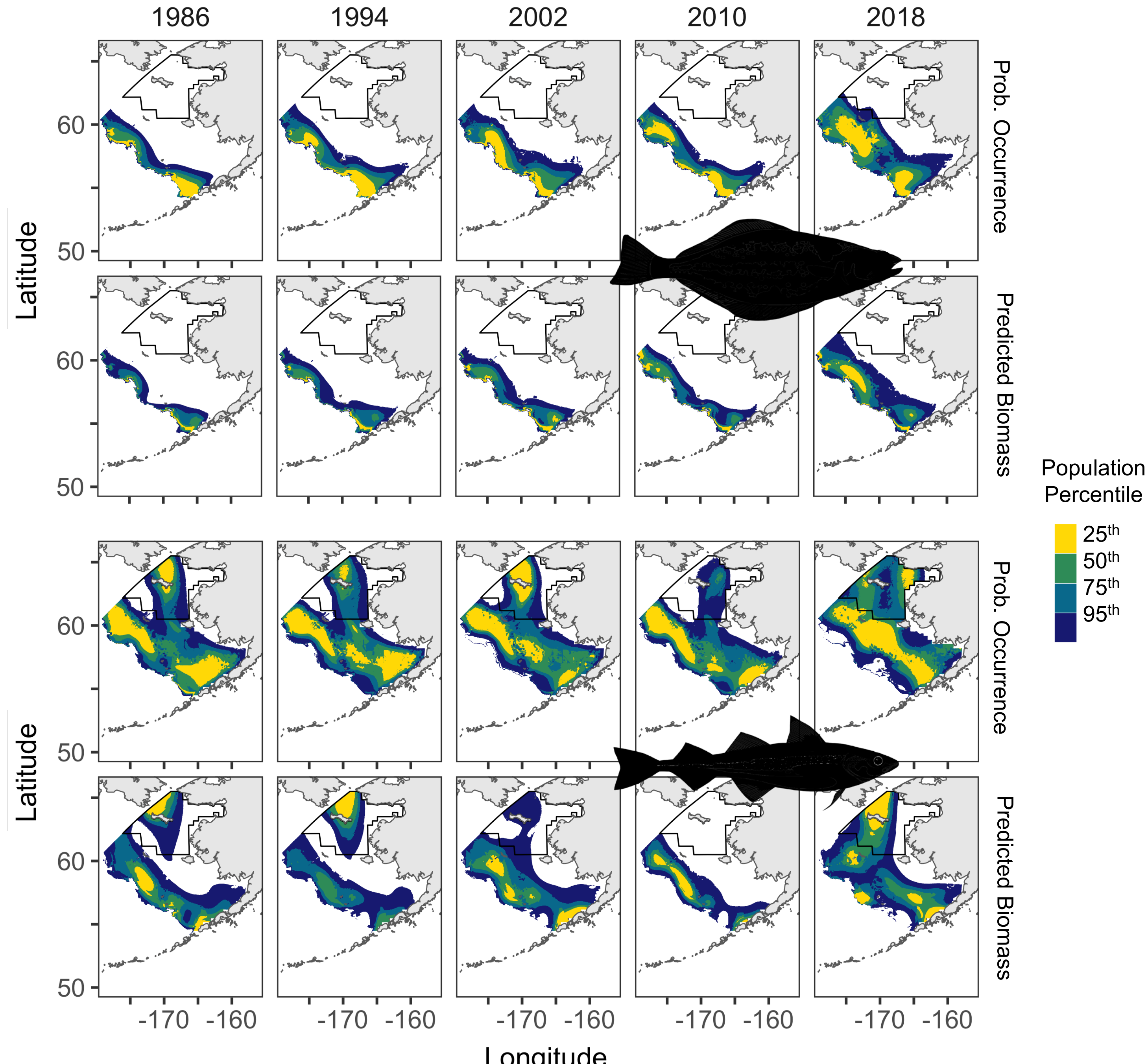


Partial Covariate Effects (Complex Dynamic Models)

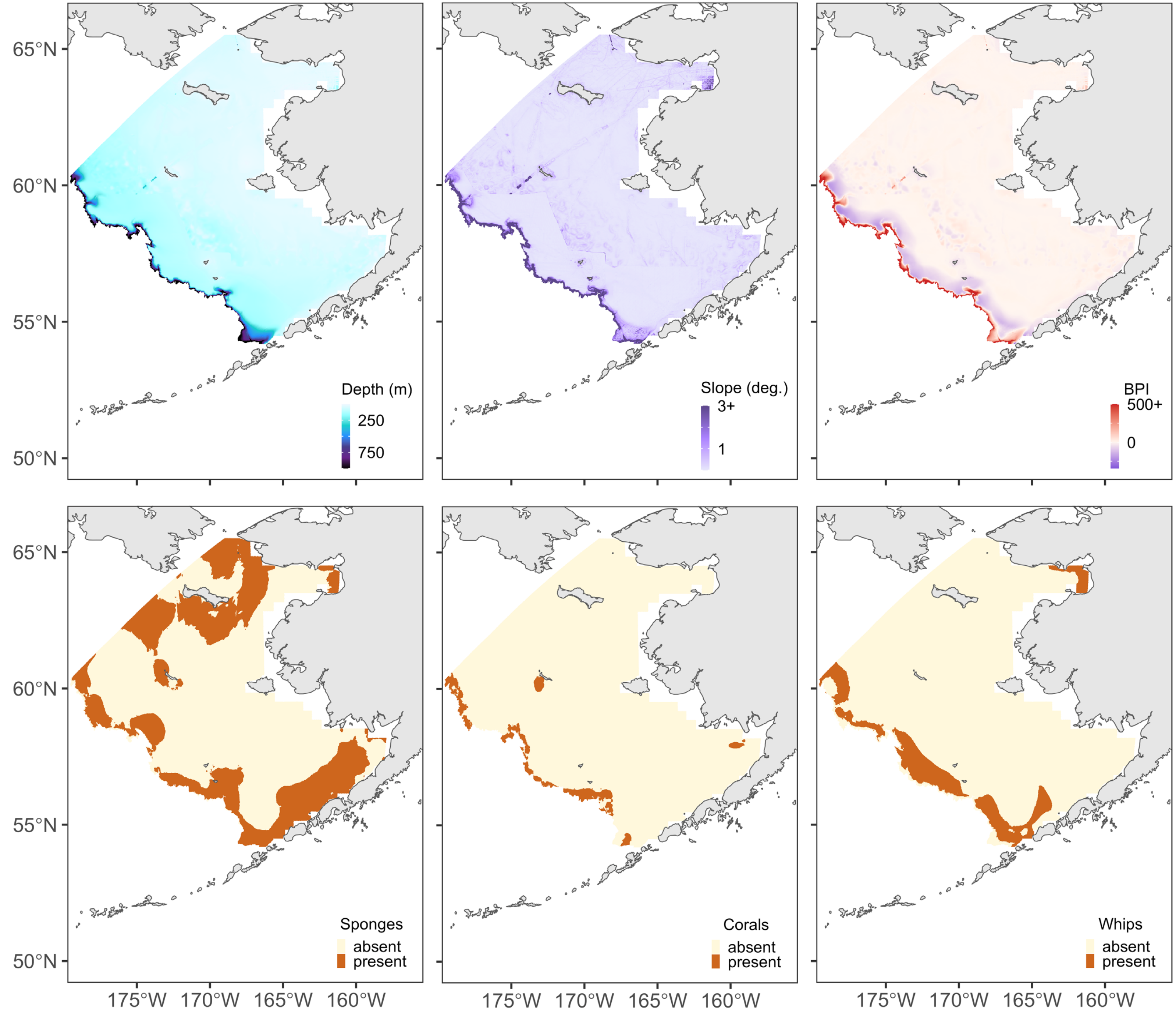
Biomass



Relative Habitat Importance



Model Covariates



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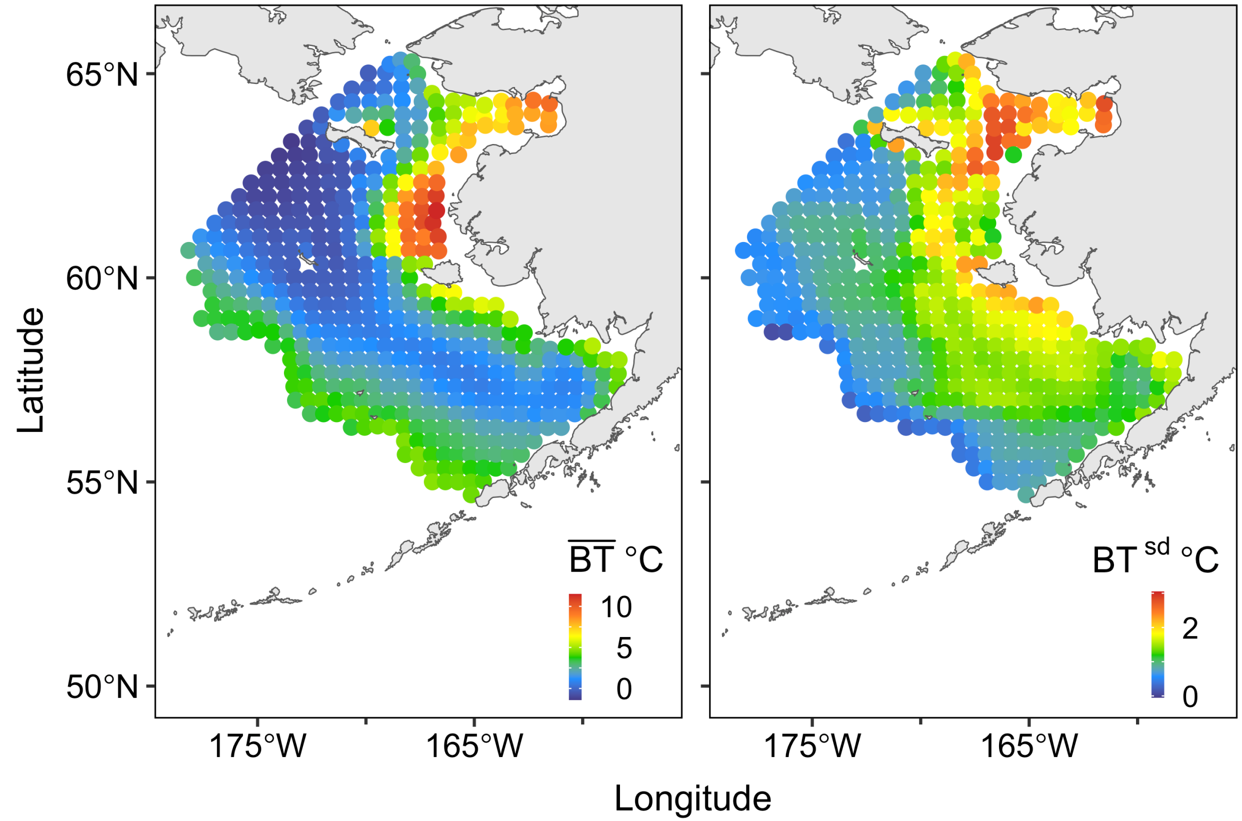
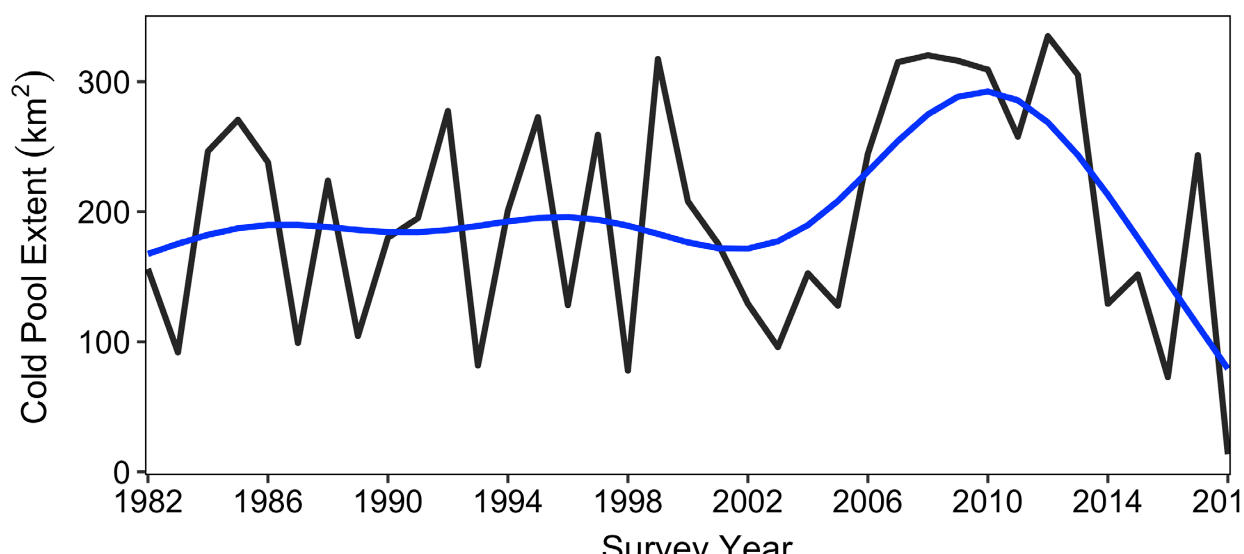
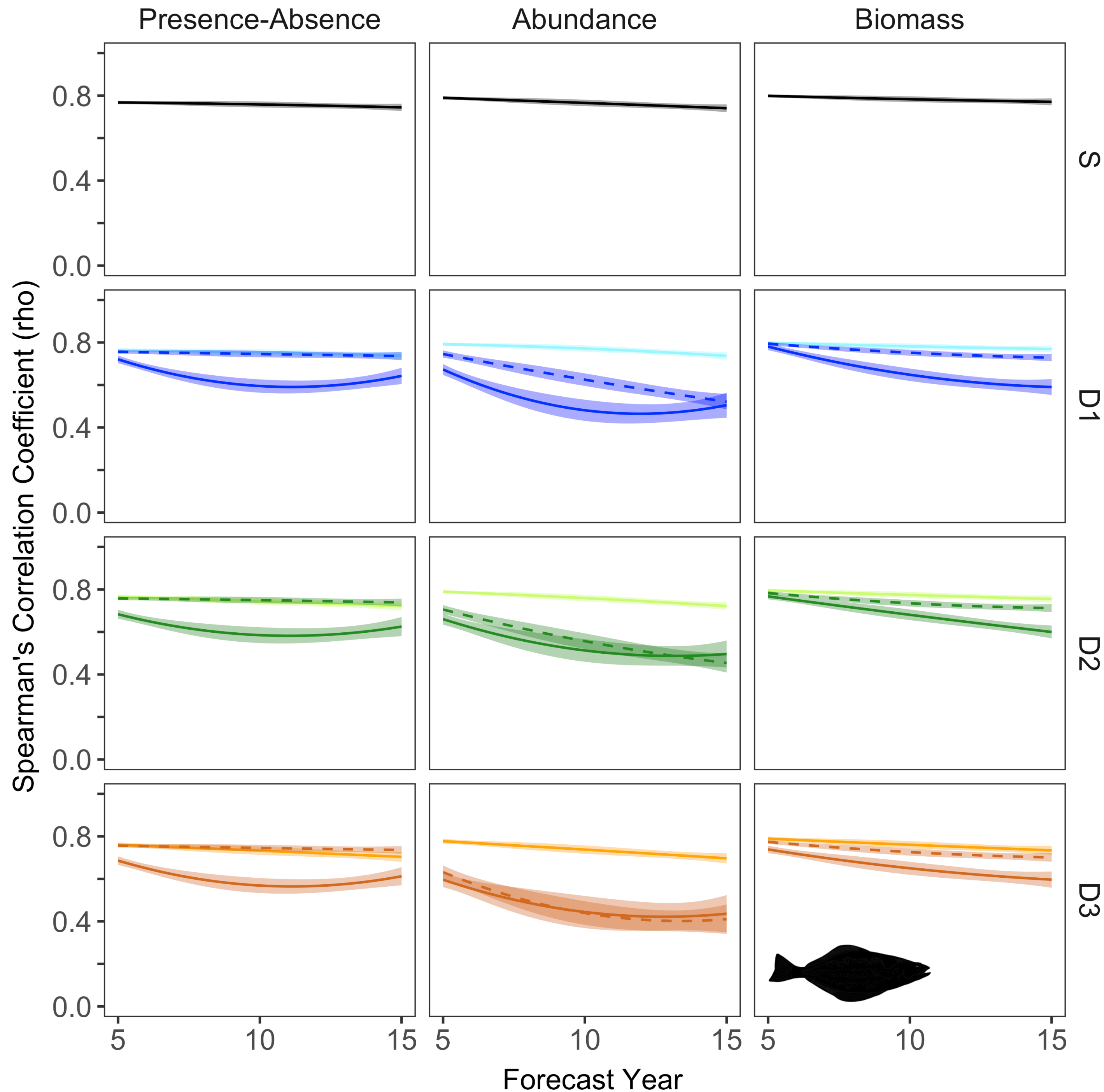




Exploratory Modeling

Temperature Effects



Exploratory Modeling

Temperature Effects