

# Forecasting distribution shifts using oceanographic indices: the spatially varying effect of cold-pool extent in the Eastern Bering Sea



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# Spatially-varying effects

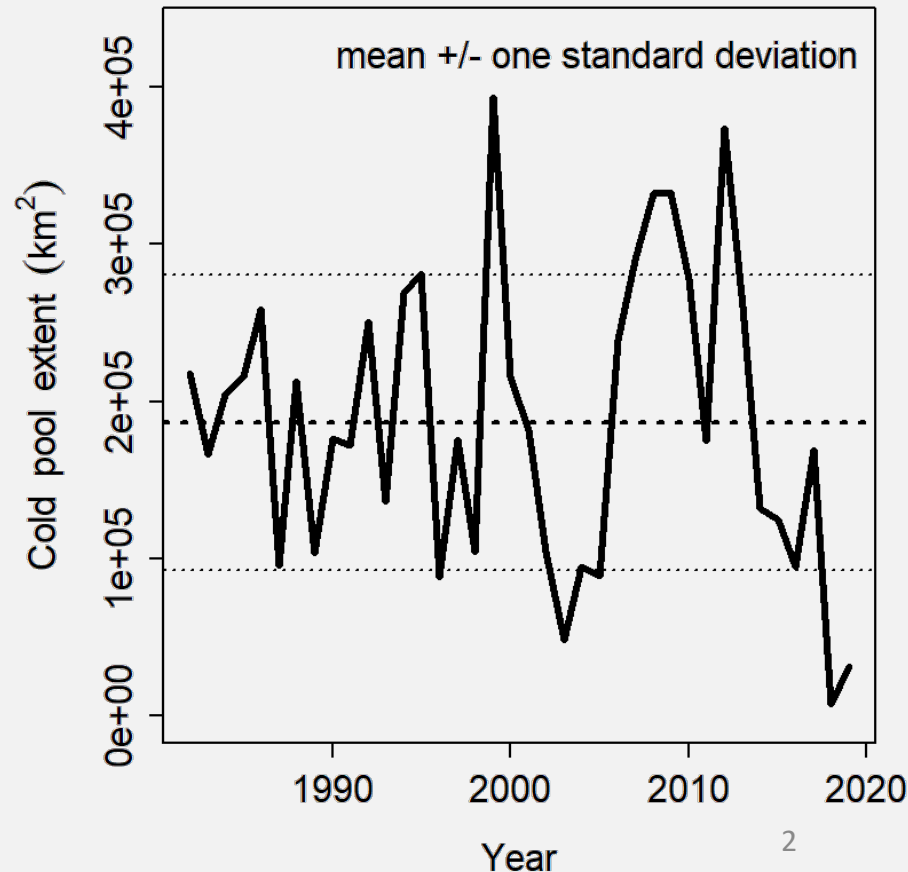
## Question

*How to identify the impact of oceanographic indices (e.g., PDO) on fish distribution*

## Approach

Develop model with “spatially varying coefficients”

- Represents localized impact of regional oceanographic index on local density
- Estimates “map” of response to regional conditions



# Spatially-varying effects

## Three interpretations of a spatially-varying coefficient model:

1. Varying slope model
2. Regression of spatio-temporal variation  $\varepsilon(s, t)$  on covariate  $X(s, t)$  for each location  $s$
3. Map of “teleconnections” for nonlocal environmental conditions on local density

# Spatially-varying effects

## What is a spatially-varying coefficient model:

- Conventional linear model

$$Y(s) = \beta + \gamma X(s) + \varepsilon(s)$$

- Model with spatially varying slope  $\gamma(s)$  for covariate  $X(s)$  when predicting variable  $Y(s)$

$$Y(s) = \beta + \gamma(s)X(s) + \varepsilon(s)$$

- Extension to spatio-temporal models

$$Y(s, t) = \beta(t) + \gamma(s)X(s, t) + \varepsilon(s, t)$$

- ... which can be used for effect of regional conditions

$$Y(s, t) = \beta(t) + \gamma(s)X(t) + \varepsilon(s, t)$$

## Where

- $Y(s)$  is response and  $X(s)$  predictor at location  $s$
- $\beta$  is intercept and  $\gamma(s)$  a slope term
- $\varepsilon(s)$  is residual error

# Spatially-varying effects

## Case study methods:

- Fit to multispecies survey
  - 17 groundfish and crabs
  - Eastern Bering Sea
- Compare four models
  1. No covariates (“None”)
  2. Local temperature effect (“Temp”)
  3. Spatially-varying cold pool effect (“Cold pool”)
  4. Both temperature and cold pool (“Both”)

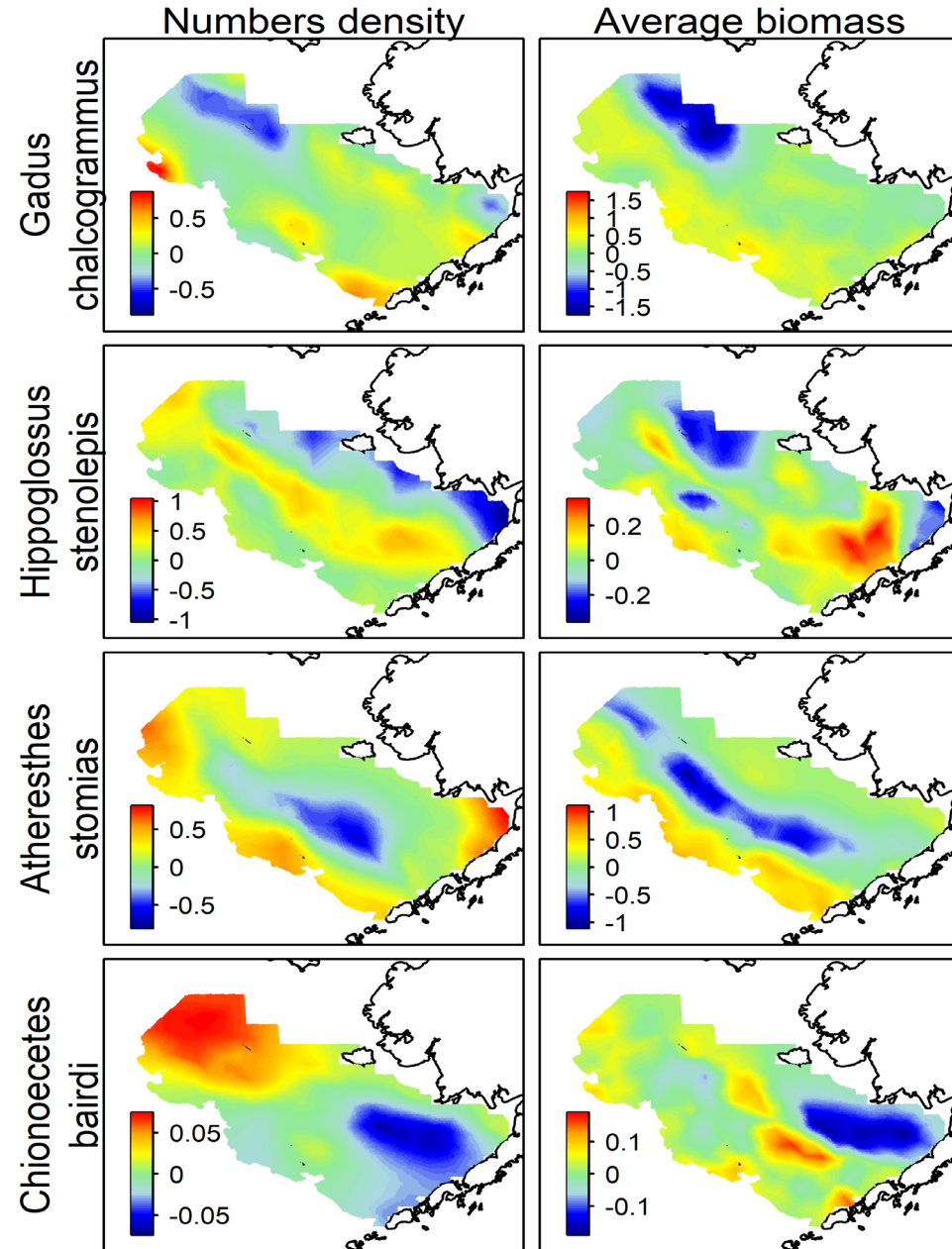
AIC for model fits (best fit in **Red**)

	None	Temp	Cold Pool	Both
Gadus chalcogrammus	239.4	68.2	138.5	<b>0.0</b>
Gadus microcephalus	528.6	134.4	363.8	<b>0.0</b>
Hippoglossoides elassodon	175.5	6.2	142.6	<b>0.0</b>
Chionoectes opilio	38.4	<b>0.0</b>	37.8	0.5
Hippoglossus stenolepis	260.9	87.5	178.4	<b>0.0</b>
Limanda aspera	79.8	6.4	67.4	<b>0.0</b>
Pleuronectes quadrituberculatus	70.3	37.4	20.7	<b>0.0</b>
Chionoectes bairdi	0.8	6.5	<b>0.0</b>	5.8
Podothecus accipenserinus	212.3	7.4	157.5	<b>0.0</b>
Atheresthes stomias	475.4	34.6	365.8	<b>0.0</b>
Hyas coarctatus	31.5	11.0	17.3	<b>0.0</b>
Myoxocephalus polyacanthocephalus	85.5	19.5	47.3	<b>0.0</b>
Lycodes palearis	98.4	8.5	62.4	<b>0.0</b>
Myoxocephalus jaok	104.5	26.4	70.1	<b>0.0</b>
Hyas lyratus	<b>0.0</b>	4.3	2.2	6.7
Paralithodes camtschaticus	32.4	9.1	23.1	<b>0.0</b>
Lycodes brevipes	8.1	<b>0.0</b>	11.2	2.8

# Spatially-varying effects

## Case study results:

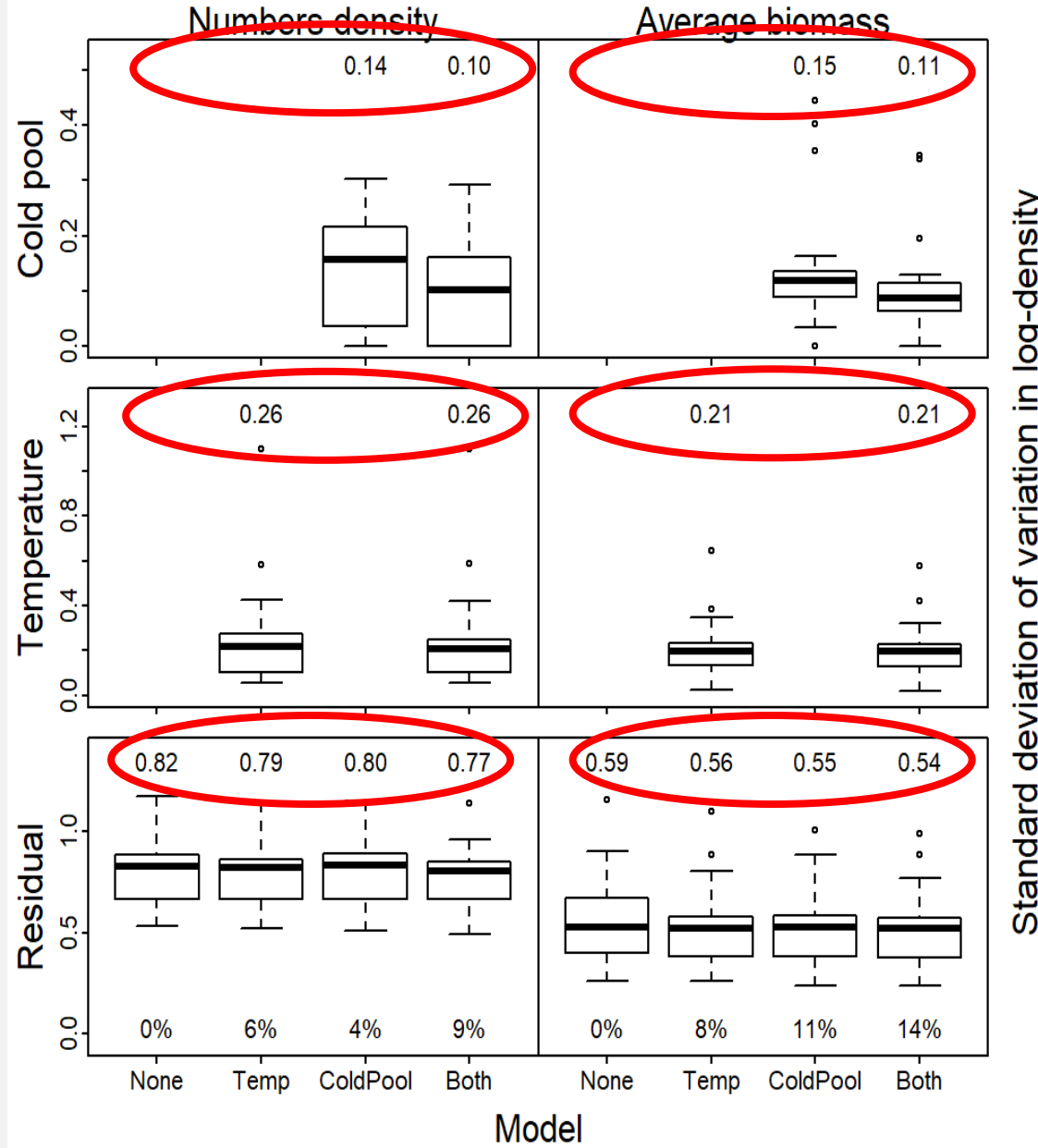
- Spatially varying effect of cold pool is different for each species
  - Distribution is not a simple function of temperature
- Most species show at least some variance associated with cold pool



Standard deviation of log-density variation for a given process

## Case study results:

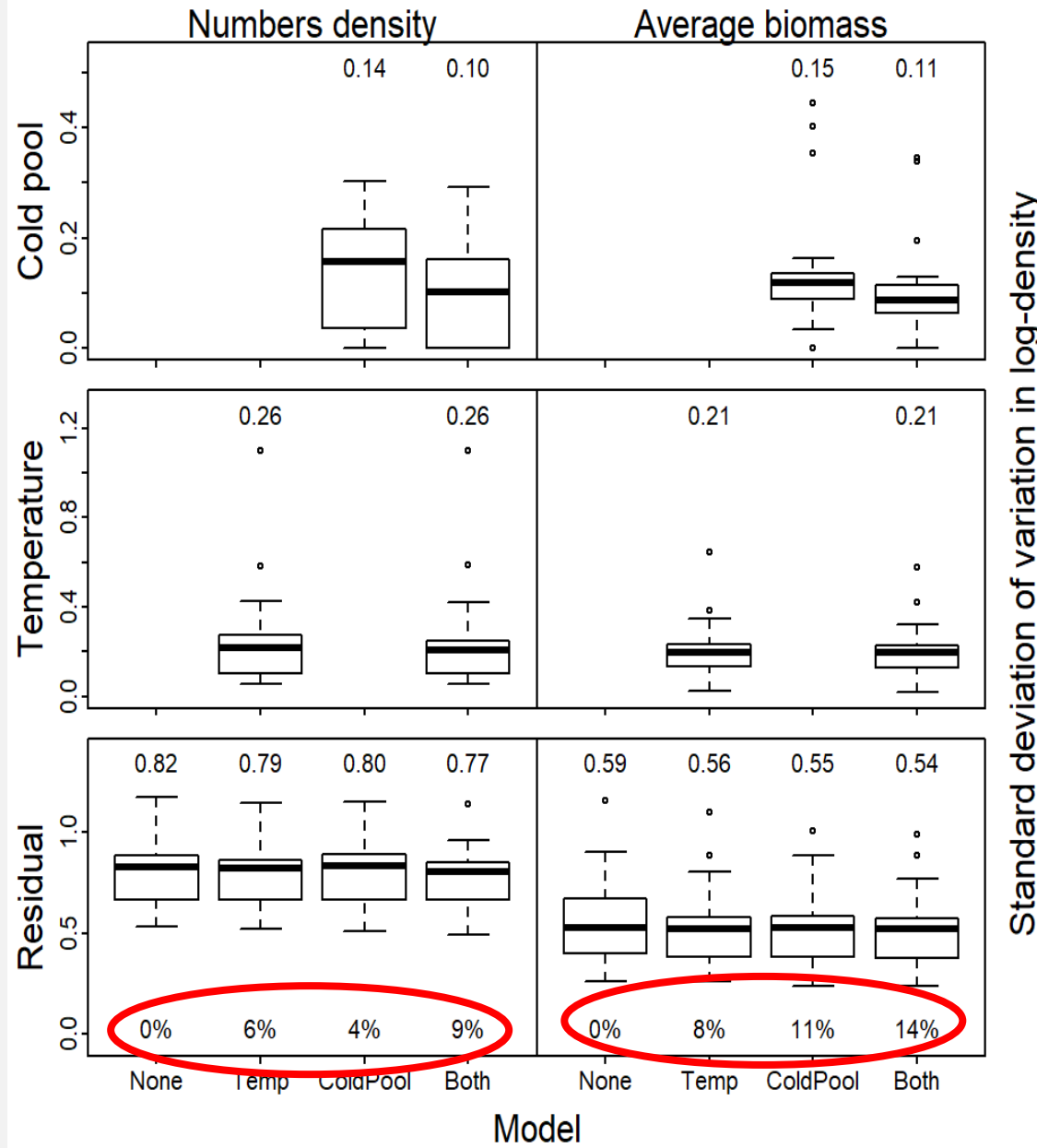
- Temperature reduces spatio-temporal variance
  - 6-8% reduction on average
- Both temperature and cold-pool have larger reduction
  - 9-14% reduction on average



## Residual variance explained

### Case study results:

- Temperature reduces spatio-temporal variance
  - 6-8% reduction on average
- Both temperature and cold-pool have larger reduction
  - 9-14% reduction on average





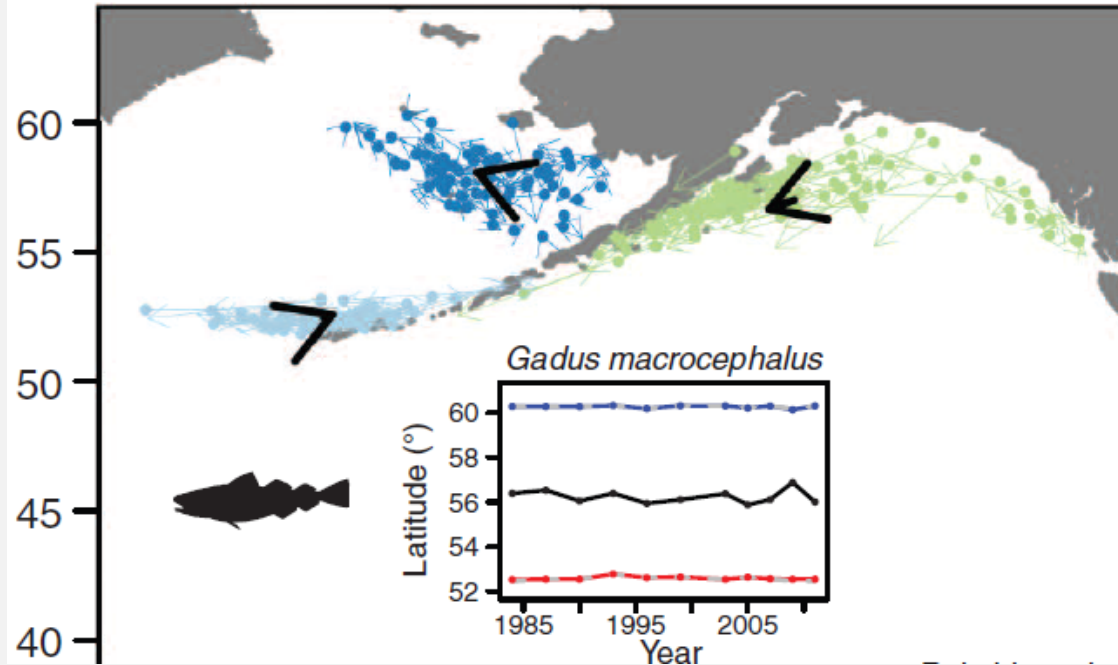
# Spatially-varying effects

Does spatially varying effect of cold pool improve forecasting?

## Skill-test experiment

1. Run with data through year T
2. Forecast center-of-gravity in year T+1, T+2, ...
3. Compare with later measurements

Published hindcast of distribution shifts for Alaska fishes



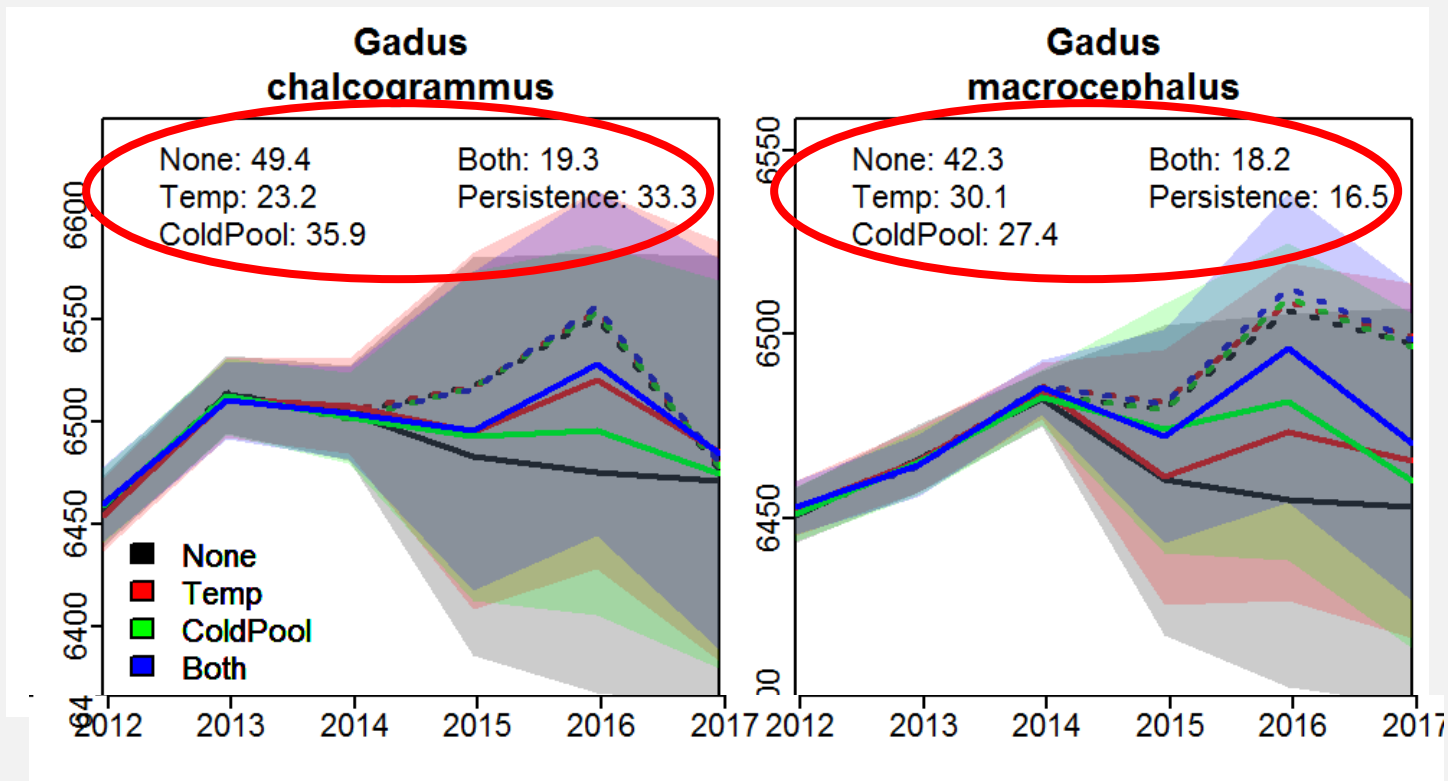
Pinsky et al. 2013 *Science* "Marine taxa track local climate velocity"

# Spatially-varying effects

- Temperature and cold-pool improve forecasts of distribution fitting through 2015 and forecasting 2016/2018

- Temperature helps with *G. chalcogrammus*
- Cold pool helps with *G. macrocephalus*

**Error in 3-year forecast**

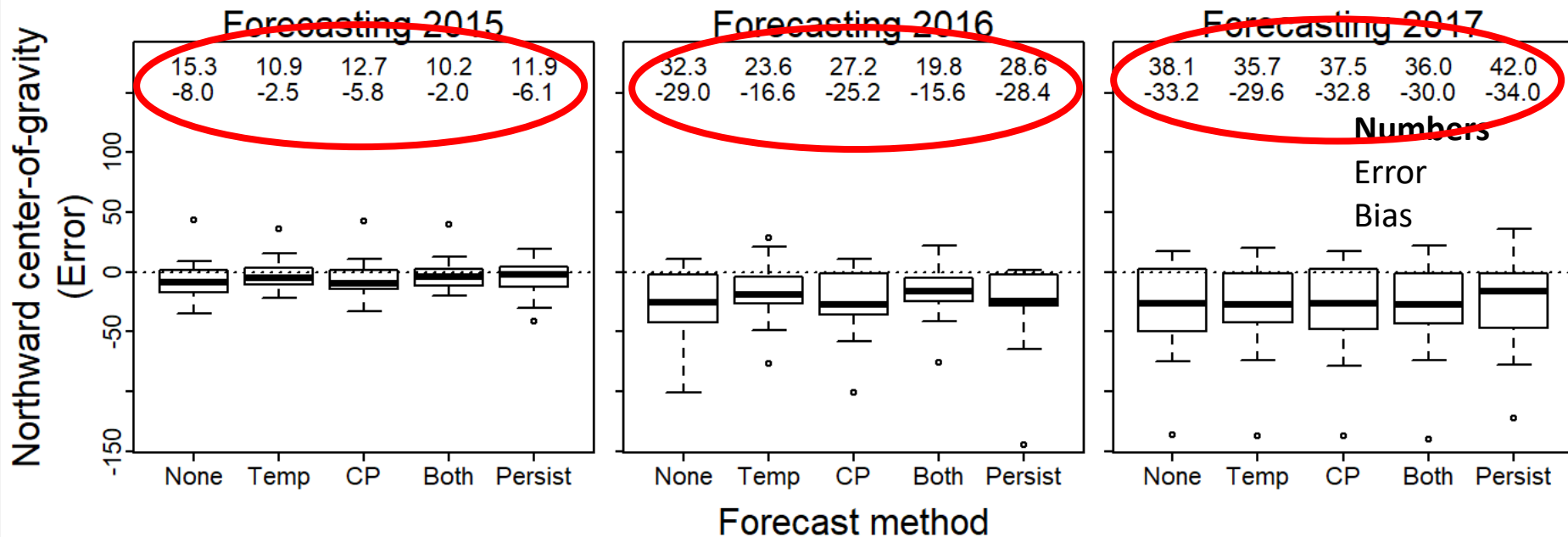


# Spatially-varying effects

## Case study results:

- Including both temperature and cold-pool reduce errors in northward center-of-gravity relative to a persistence forecast

Error in 3-year forecast,  
Averaged across all species



# Spatially-varying effects

## Other potential uses

1. Spatially varying effect of calendar date
  - Useful to inter-calibrate samples collected in different months
2. Identify locations with largest changes over time
  - Estimate spatially-varying coefficient associated with year
3. Include regional effects during index standardization
  - Easy method to include non-local environmental conditions in models being used in stock assessment

# Combining multiple surveys



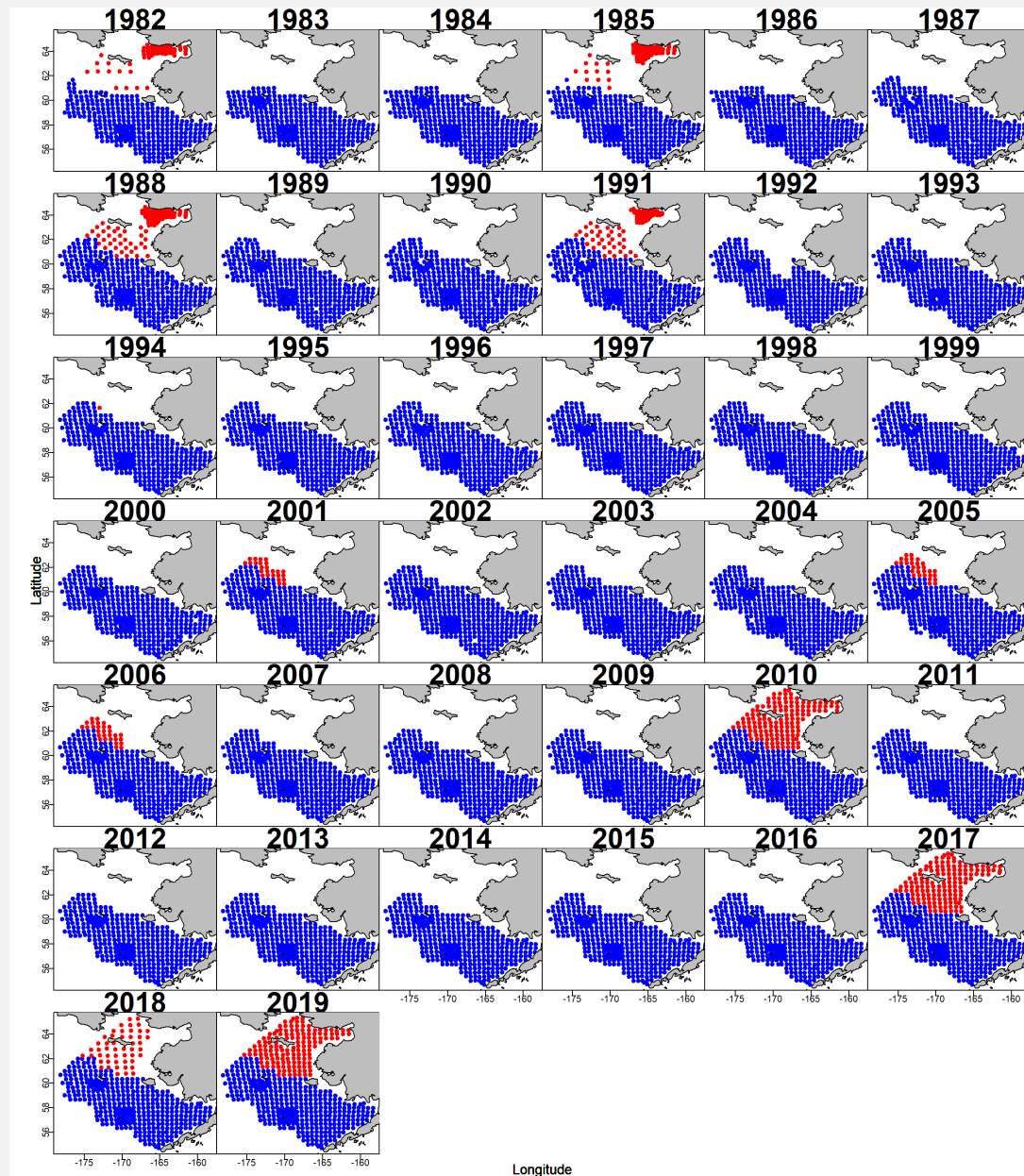
**Photo:** Chris Miller, [csmphotos.com](http://csmphotos.com)

Cecilia O'Leary, Jim Ianelli, Jim Thorson, Stan Kotwicki

# Combining multiple surveys

## Background

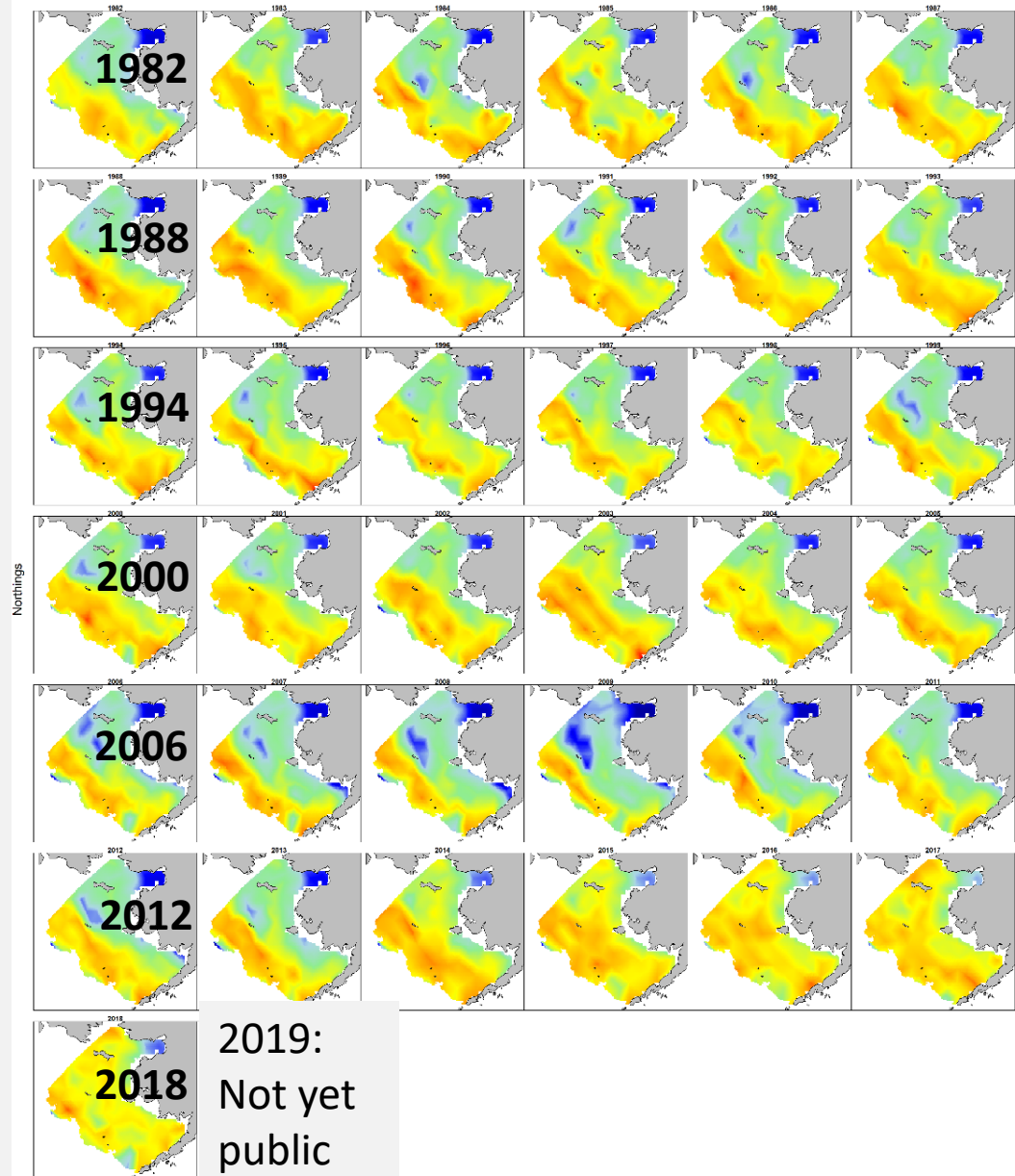
- **Eastern Bering Sea** surveyed 1982-2019
- **Northern Bering Sea** surveyed sporadically, and 2010, 2017-2019



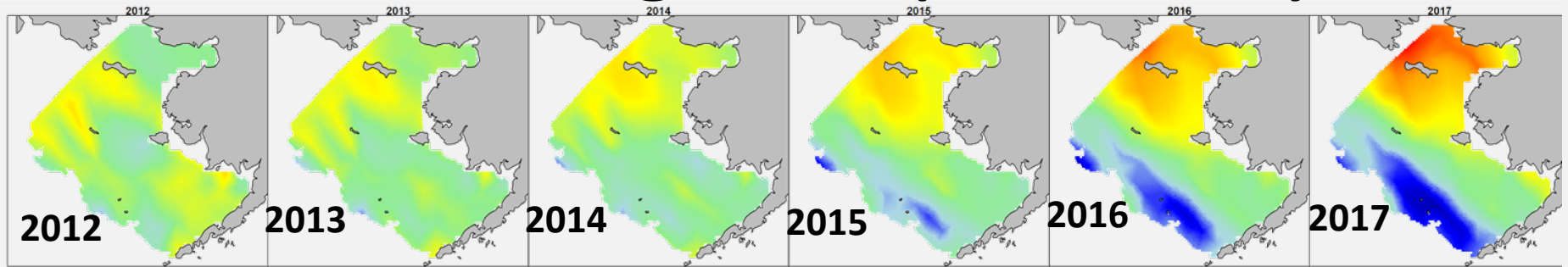
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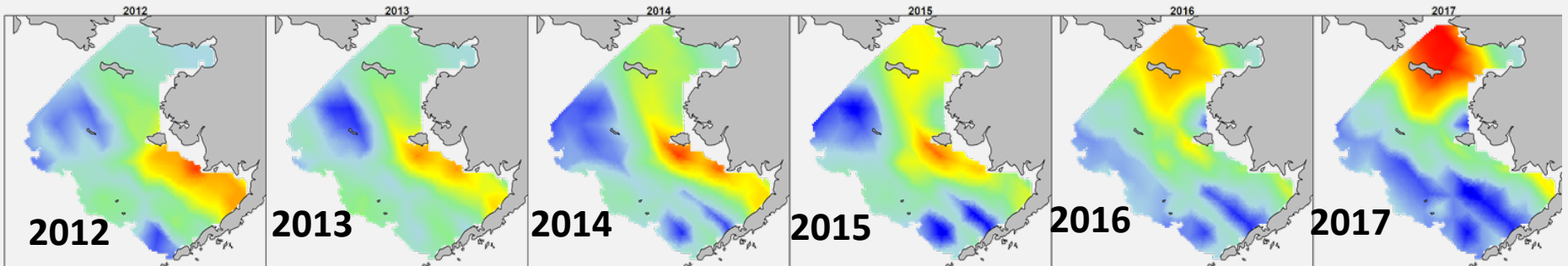
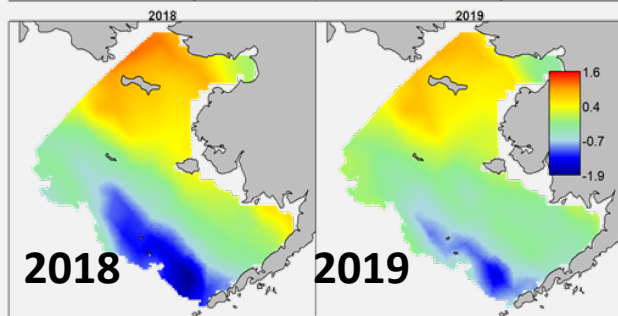
- Spatio-temporal model (VAST) used to combine eastern and northern Bering Sea for pollock assessment in 2018
- How to improve estimates in northern Bering Sea in unsampled years?



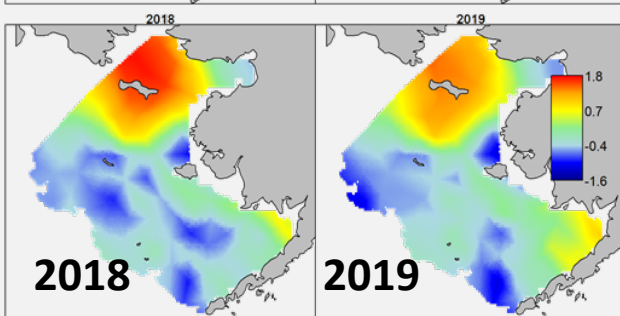
# Combining multiple surveys



**Effect of cold-pool extent on density for pollock**



**Effect of cold-pool extent on density for pollock**





# Spatially-varying effects

## Acknowledgements

- Lorenzo Ciannelli
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