Linking global to regional ocean forecsts: a hybrid dynamical-statistical approach

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What is unique about the Bering Sea?

Physical

- Seasonal ice with advection to the south
- Tidal mixing sets up distinct biophysical regimes Biological
- Ice plankton may be a major food source to higher trophic levels
- Benthic food chain is a major player

One prevailing paradigm: cold years are good for walleye pollock

Duffy-Anderson et al., 2014

Climate models

provide BCs/ICs to *regional coupled models*

GOAL: *mutidecadal* **projections of physics and biology in the Bering Sea**

Bering10K model

- Regional Ocean Modeling System (ROMS)
- Descendent of NEP5 (Danielson et al. 2012)
- 10 layers, 10-km grid
- Includes ice and tides
- CCSM bulk flux
- Details in Hermann et al. (DSR2, 2013, 2016)

Bering10K validation: the "Cold Pool"

DATA MODEL

Bottom Temp in deg C, summer 2009

Sources of uncertainty in climate predictions (Hawkins and Sutton, 2009)

Downscaling Methods

- Choose a subset of IPCC models for atmospheric forcing and oceanic boundary conditions (physical/biological) for our regional model (Bering10K)
- Model choice based on
	- Local validation (replicate present ice cover the Bering Sea)
	- Availability of needed forcing variables
	- Availability of multiple emission scenarios
	- NPZ and OA variable output (not available for all models)
- Ocean Acidification dynamics (e.g. pH, aragonite saturation) are now being added to Bering10K (D. Pilcher)

Scenario/Structural uncertainty in this study

- A1B
	- CGCM3.1-t47
	- ECHOG
	- MIROC
- rcp4.5
	- GFDL
		- CESM
		- MIROC
- rcp8.5
	- GFDL
	- GFDL w/bio
	- CESM
	- CESM w/bio
	- MIROC

- A1B runs used for 2000-2040
- rcp4.5/rcp8.5 runs used for 2010-2100

CMIP5 projected air temperature in the EBS (rcp8.5)

(from NOAA climate change web portal)

Knutti et al. dendogram of CMIP3/CMIP5 control states (based on SST and precip fields)

Our chosen global models replicate ice climatology for the Eastern Bering Sea (M. Wang)

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Change by 2050s (rcp8.5)

Change by 2090s (rcp8.5)

Can we expand this mini-ensemble?

- Dynamical downscaling is computationally expensive
- Statistics of mini-ensemble can be used to infer what would be obtained from a larger ensemble
- *Hybrid dynamical-statistical method* uses EOFs of all biophysical variables; multivariate correlation at the pattern level
	- How does the regional bell "ring" when struck in various ways

Multivariate Analysis: "Factor analysis of spatial EOFs"

- Calculate "traditional" spatial EOFs of each variable. This yields:
	- 1) A Spatial pattern (the "EOF" in the original units of that variable)
	- 2) A time series modulating the spatial pattern (the "PC", which has unit variance)
- Perform EOF analysis on that reduced set of time series to seek multivariate "factors" (i.e. *temporally correlated univariate spatial patterns*)
- *Project* atmospheric forcing from more CMIP5 members onto the multivariate patterns obtained from the mini- ensemble
- Get a much bigger ensemble of regional estimates!

The mathematical procedure

- 1. Decompose each variable into univariate EOF
- 2. Perform PC analysis on the multivariate collection of time series
- 3. This now forms a new basis set explaining the original data
- 4. Calculate the spatial patterns corresponding to that basis set
- 5. Project any new forcing data onto that basis set to get the corresponding time function

$$
V_{ilt} = \sum_{j} X_{jil} T_{jit}
$$

$$
T_{jit} = \sum_{k} M_{kji} \Gamma_{kt}
$$

$$
V_{ilt} = \sum_{k} C_{kil} \Gamma_{kt}
$$

$$
C_{kil} = \sum_{t} \Gamma_{kt} V_{ilt}
$$

$$
\Gamma^*_{ikt} = [\sum_l (V_{ilt} \ C_{kil})] / [\sum_l (C_{kil} \ C_{kil})]
$$

- Next step is to perform PC analysis on this set of univariate time series *Tjit*
- this yields a time series modulating all variables, with associated spatial patterns (multivariate modes) emphasizing covariance among variables

Time series of factor 1

CESM-rcp8.5 multivariate **PC_S**

$$
T_{jit} = \sum_{k} M_{x_i} \Gamma_{kt}
$$

Time series of factor 2

variable loadings suggest separate "heat" and "wind"

Large % Variance of training data explained using **ONLY** *TAIR PAIR UWIND VWIND* as "predictors"

CMIP5 projected air temperature in the EBS (rcp8.5)

(from NOAA climate change web portal)

Project CMIP5 output onto multivaraite modes to estimate change in sea bottom temperature (rcp8.5)

Individual realizations: change by 2090s

Average change by 2090s

Project CMIP5 output onto multivariate modes to estimate change in large crustacean zooplankton (rcp8.5)

Individual realizations: change by 2090s

Average change by 2090s

mean change rcp 4.5

mean change rcp 8.5

Conclusions

- 12 downscaling runs of global projections have been completed
- Bottom temperatures up to 5 degrees C warmer by 2100, highly dependent on emissions
- Multivariate method suggests independent "heat" and "wind" modes in several models
- "heat" mode is associated with biological change (e.g. enhanced microzooplankton, reduced euphausiids)
- Projection of "large ensemble" of forcings onto these modes yields a much bigger regional ensemble
- This method could (potentially) be used for other regions and time scales!