Expanding the biophysical ensemble: hybrid dynamical-statistical downscaling methods based on spatial/temporal scale

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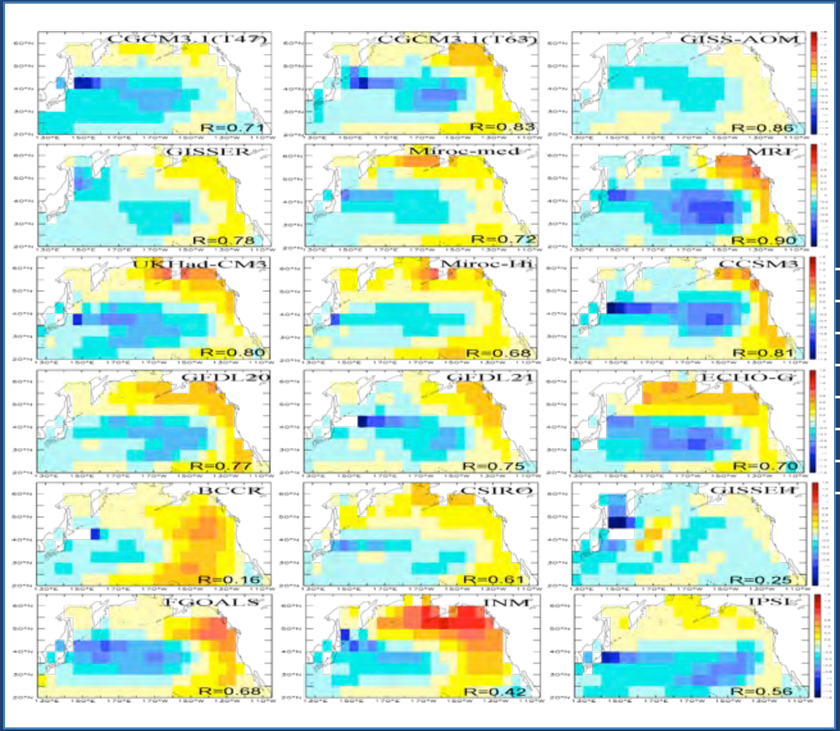
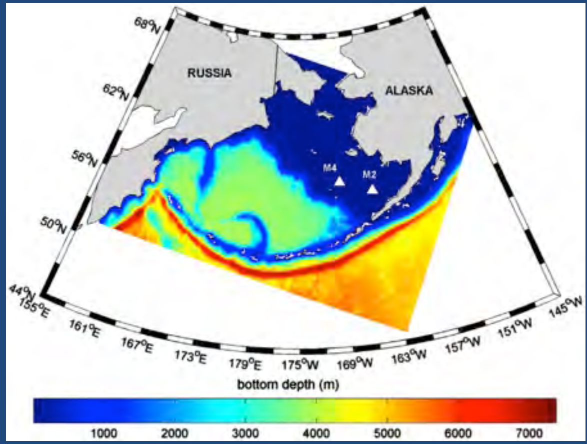
Climate models provide BCs/ICs to *regional coupled models*

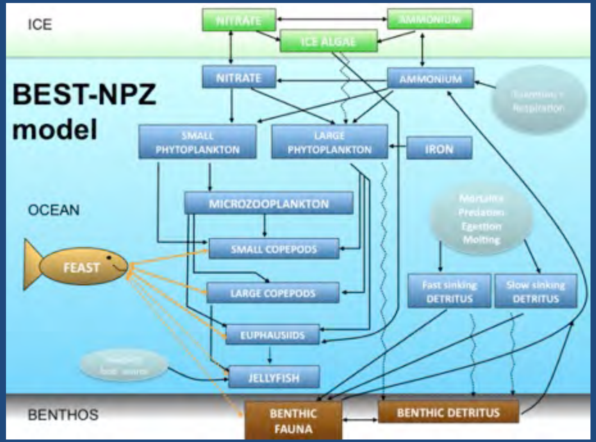


ensemble of runs

Bering10K



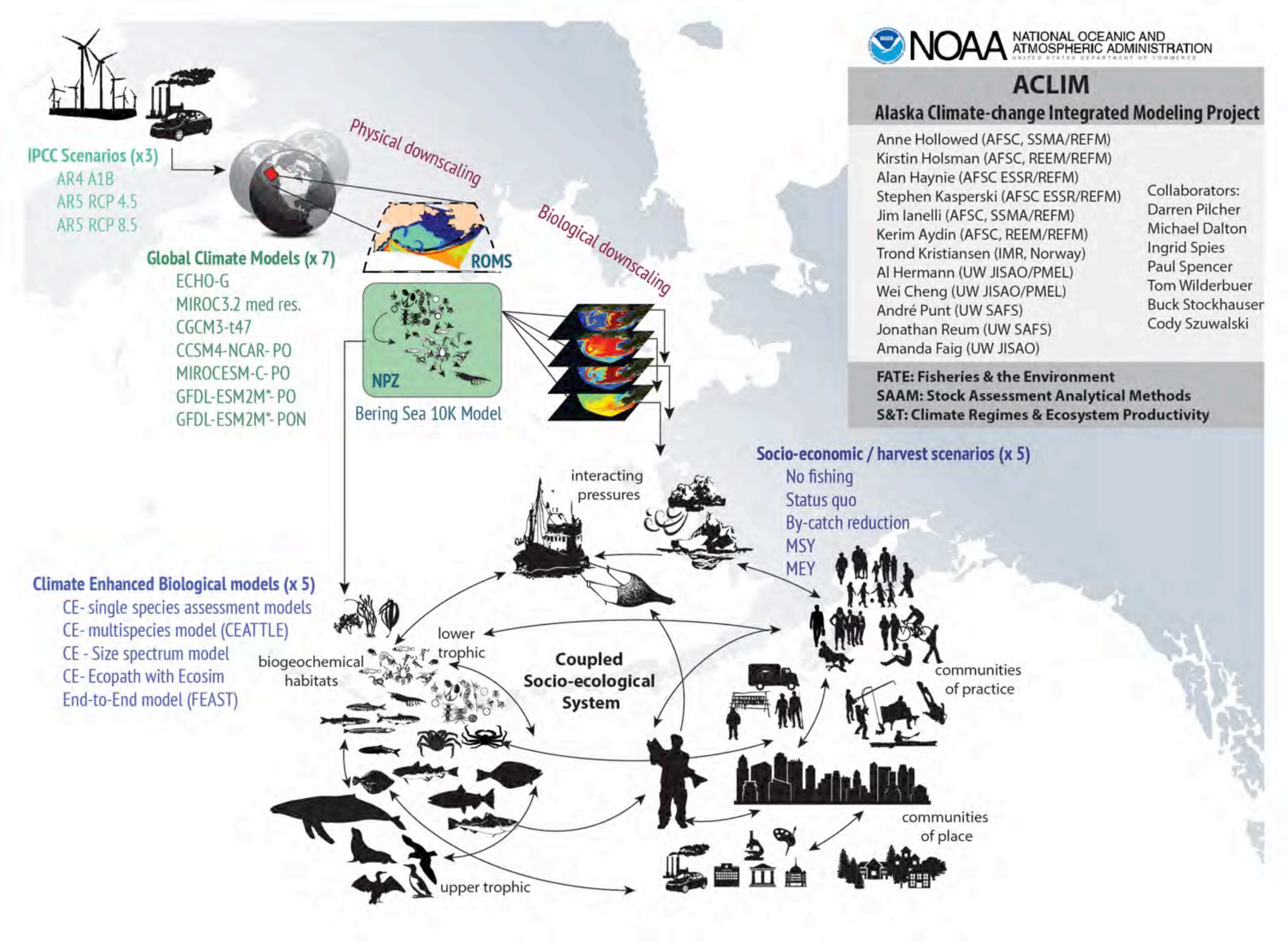
NPZ

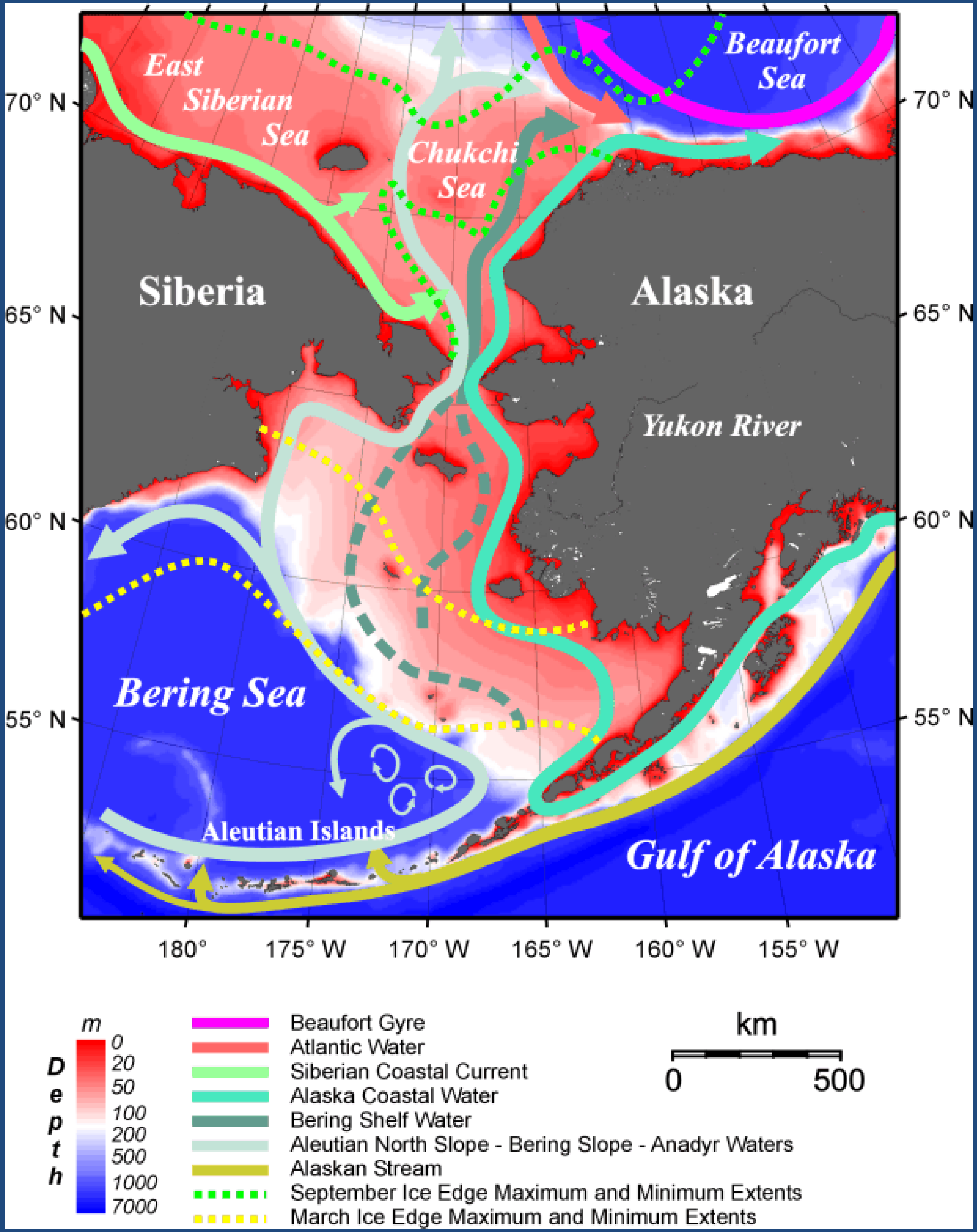


ensemble of projected futures

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

The ACLIM project

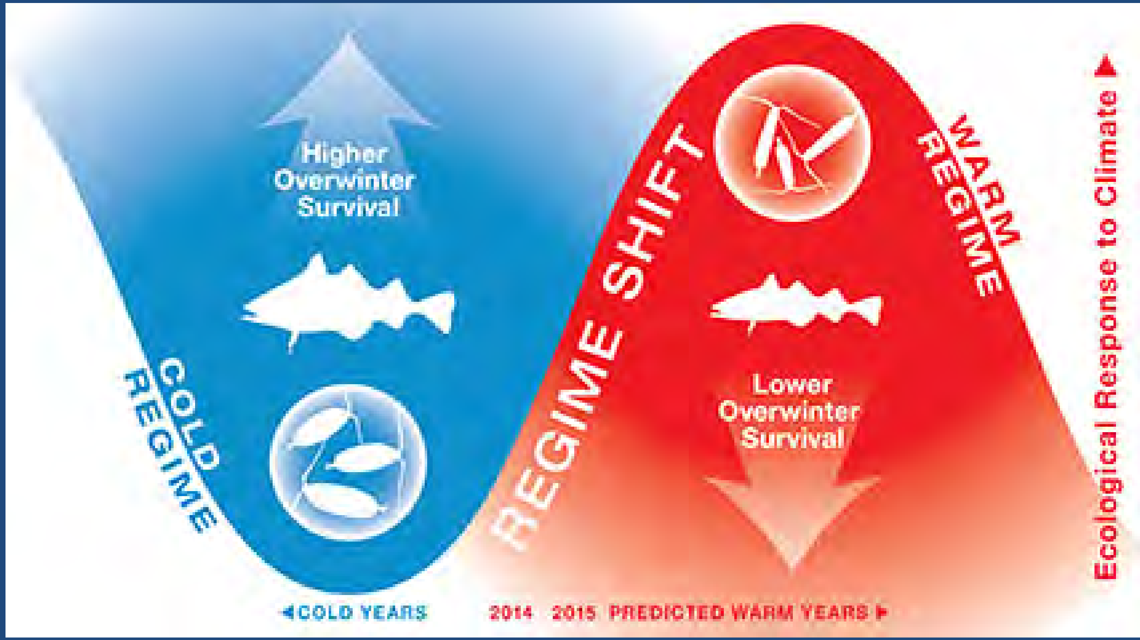




What is unique about the Bering Sea?

- 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

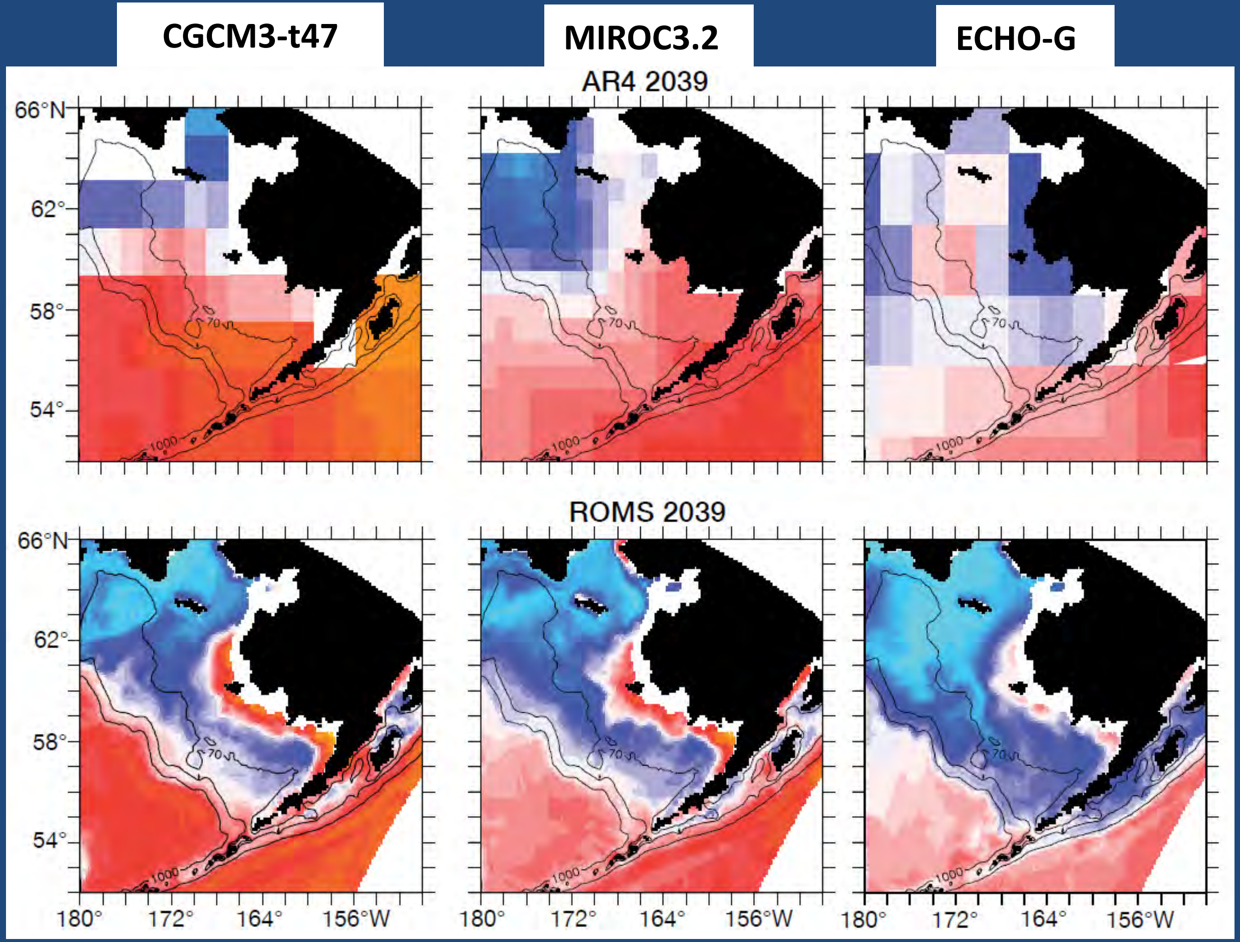


Duffy-Anderson et al., 2014

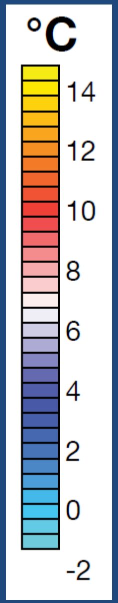
Dynamical downscaling achieves finer spatial resolution

Global models
(AR4)

Regional model
(Bering10K)



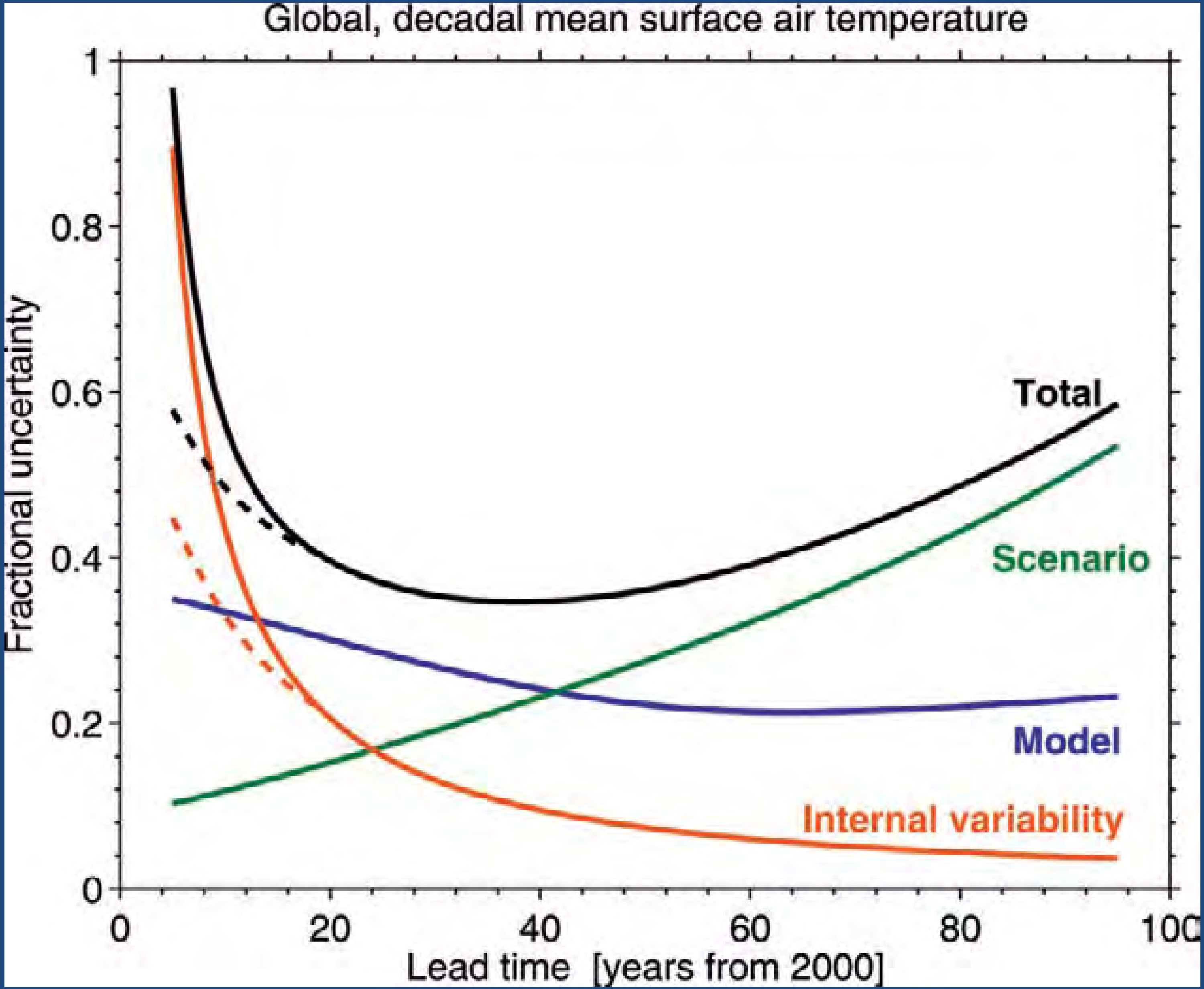
Ocean Temp
July 15 2039
(20m depth)



IPCC global atmosphere provides *surface forcing*

IPCC global ocean provides *boundary conditions*

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



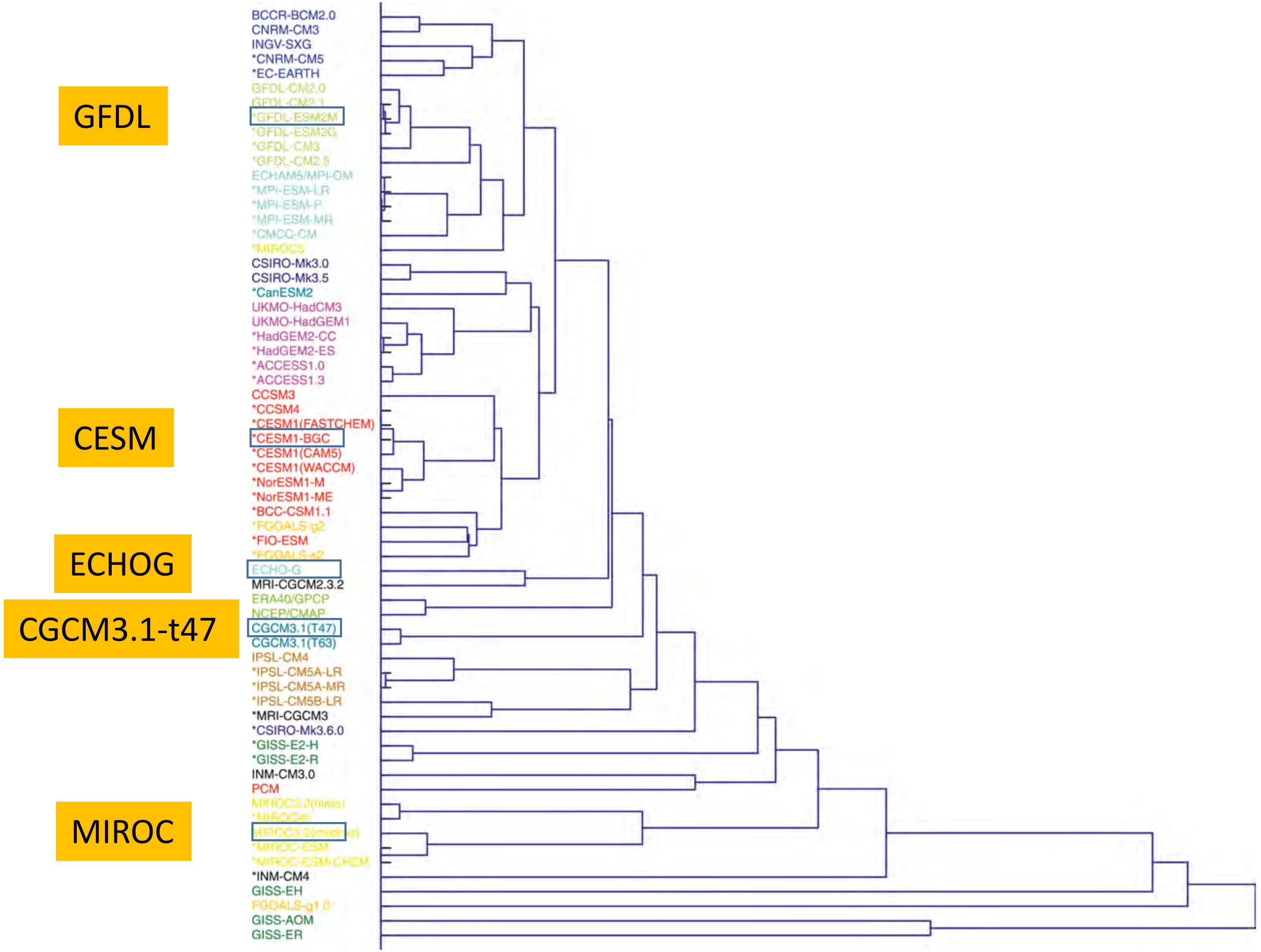
- Scenario (emissions)
- Structural (model)
- Internal (intrinsic)

Scenario/Structural uncertainty in this study

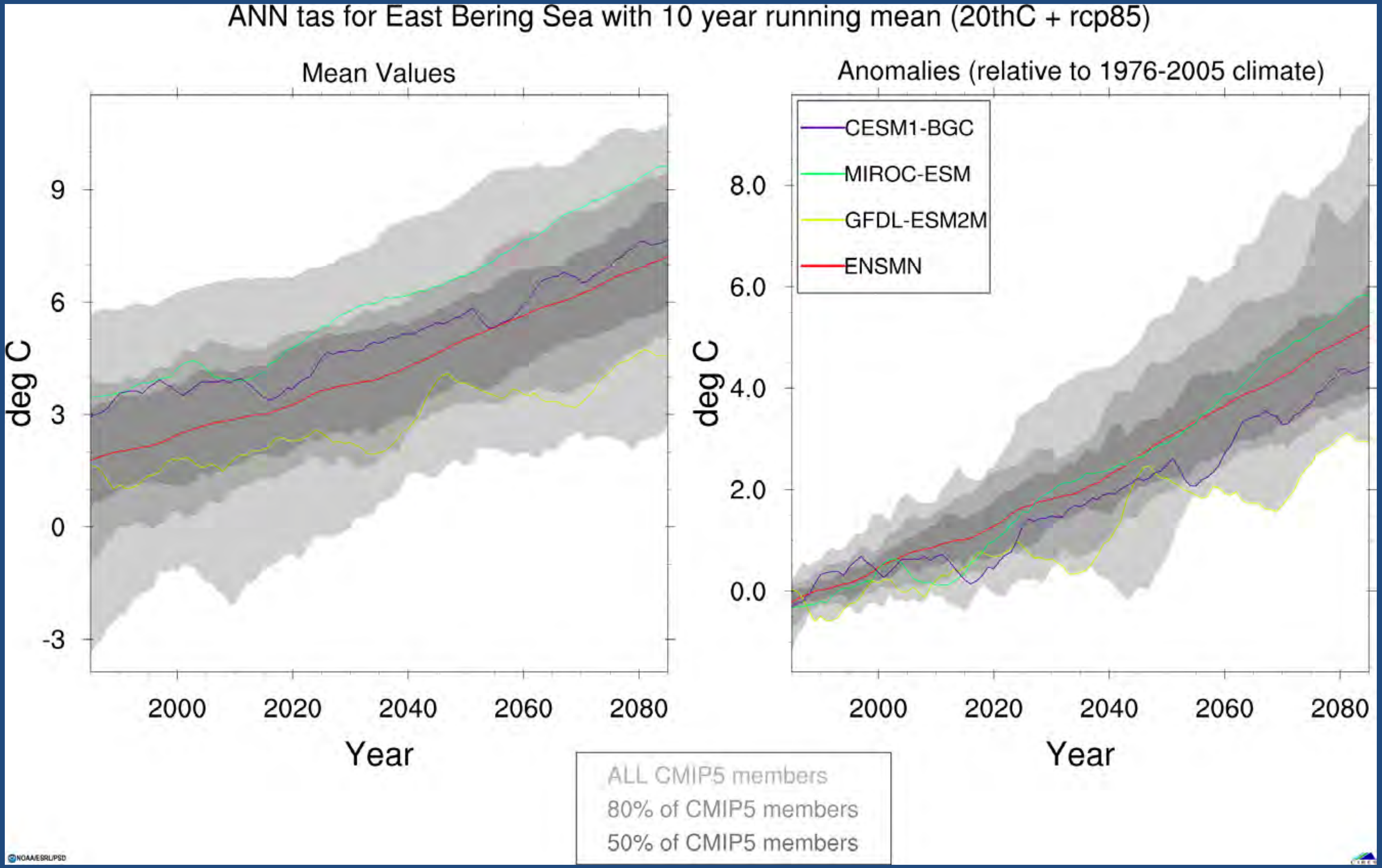
- rcp4.5
  - GFDL
  - CESM
  - MIROC
- rcp8.5
  - GFDL
  - GFDL w/bio
  - CESM
  - CESM w/bio
  - MIROC

rcp4.5/rcp8.5 runs used for 2010-2100

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



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



(from NOAA climate change web portal)

Can we expand our 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 methods* use EOFs of all biophysical variables (including the forcing of the regional model); multivariate correlation at the pattern level

A Simple Example

- Hit a bell one way and get a sound
- Hit it a different way and get a different sound
- This establishes forcing -> response which persists longer than the forcing
- Can use these observations OR could use a complex model which replicates reality for observed forcing
- In the bell example, these stats would include damping (e.g. loss of autocovariance at greater time lags)

Multivariate EOF Analysis (MEOF): “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*) relating the forcing to the response
- *Project* atmospheric forcing from more CMIP5 members onto the multivariate patterns obtained from the mini-ensemble
- Result is 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

$$V_{ilt} = \sum_j X_{jil} T_{jit}$$

$$T_{jit} = \sum_k M_{kji} \Gamma_{kt}$$

$$V_{ilt} = \sum_j X_{jil} \sum_k M_{kji} \Gamma_{kt} = \sum_k \Gamma_{kt} \sum_j M_{kji} X_{jil} = \sum_k C_{kil} \Gamma_{kt}$$

$$C_{kil} = \sum_t \Gamma_{kt} V_{ilt}$$

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

Could we use Linear Inverse Model (LIM) methods?

- LIM reduces nonlinear system (real or modeled) to a linear one forced by random elements
- $X_{t+1} = B\ X_t + S\ F_{t+1/2}$
- X = regional state, F = global forcing
- B is derived from observed correlations at some time lag
- Typically used to forecast the system given *observed* X and F
- Maps forcing and present state onto a future response

Compare LIM with MEOF

- Both LIM and MEOF are based on correlation matrices
- Both LIM and MEOF use dimensionally reduced time series
- MEOF looks at forcing and response together in coupled multivariate modes (but could also do this with LIM)
- Unlike LIM, MEOF only considers zero-lag correlations:
- $X_t = f(F_t)$

A middle path: Extended EOFs

- Look at forcing and response together, *including time lagged time series*

  (This may be especially important for seasonal signals, e.g. wind->N->P->Z)
- Derive multivariate modes which include all of these time series
- Use those modes to infer a response given past state, past forcing and present forcing, i.e.

  $X_t = f(X_{t-1}, F_t, F_{t-1})$ (note this entails stepping the solution forward in time)
- OR even simpler, just assume that the persistence of X can be captured by the past forcing

  $X_t = f(F_t, F_{t-1})$
- note this could capture a propagating signal generated by F_{t-1}

Extended Multivariate EOF Analysis (MEEOF): "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 **plus the time lagged series of the atmospheric forcing** to seek multivariate "factors" (i.e. *temporally correlated univariate spatial patterns*) relating the forcing to the response
- *Project* atmospheric forcing from more CMIP5 members onto the multivariate patterns obtained from the mini-ensemble
- Result is a much bigger ensemble of regional estimates

Application of the MEOF method to the Bering Sea

- 1) Derive **multivariate modes** from downscaled CMIP5 results, based on a limited (8-member) ensemble
- 2) Estimate the regional response to an expanded set of CMIP5 models under emission scenarios RCP4.5 and RCP8.5 by projecting available global atmospheric “forcing” variables onto those multivariate modes

  air temperature , air pressure, zonal winds, meridional winds

- **3)** Take a weighted average of the statistically and dynamically downscaled results. This is our estimate of future regional conditions

For details see this paper in ICES JMS

ICES Journal of Marine Science

ICES CIEM

ICES Journal of Marine Science (2019), 76(5), 1280–1304. doi:10.1093/icesjms/fsz043

Contribution to the Symposium: '*The Effects of Climate Change on the World's Oceans*'

Original Article

Projected biophysical conditions of the Bering Sea to 2100 under multiple emission scenarios

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A regional biophysical model is used to relate projected large-scale changes in atmospheric and oceanic conditions from CMIP5 to the finer-scale changes in the physical and biological structure of the Bering Sea, from the present through the end of the twenty-first century. A multivariate statistical method is used to analyse the results of a small (eight-member) dynamically downscaled ensemble to characterize and quantify dominant modes of variability and covariability among a broad set of biophysical features. This characterization provides a statistical method to rapidly estimate the likely response of the regional system to a much larger (63-member) ensemble of possible future forcing conditions. Under a high-emission [Representative Concentration Pathway 8.5 (RCP8.5)] scenario, results indicate that decadally averaged Bering Sea shelf bottom temperatures may warm by as much as 5°C by 2100, with associated loss of large crustacean zooplankton on the southern shelf. Under a lower emission scenario (RCP4.5), these effects are predicted to be approximately half their calculated change under the high emission scenario.

Keywords: Bering Sea, biophysical modelling, climate change, regional modelling

Introduction

Widespread change is anticipated for the Bering Sea (AK) under climate change, including substantial oceanographic warming that scales with future carbon mitigation scenarios (IPCC, 2013, 2014). Climate-driven changes to oceanographic conditions have the potential to propagate through the food web and impact fish and fisheries in the region (Holsman *et al.*, 2018). The Bering Sea is a highly productive system that supports a wide diversity of species, some critically endangered, as well as multiple small coastal fishing communities that depend on subsistence harvest (Haynie and Huntington, 2016) and large-scale commercial fisheries that annually represent more than 40% of the U.S. commercial catch (Fissel *et al.*, 2017). In this article, we report estimates of anticipated change to the physical and lower trophic level dynamics of the Bering Sea, derived both through application of dynamical model downscaling and through statistical projections based on those results.

Overview of the Bering Sea ecosystem

Prominent physical features of the Bering Sea include seasonal ice cover, strong advection of ice, and tidally generated biophysical domains. Ice formed each winter in the northern Bering Sea is advected to the southeast, where it gradually melts as it encounters warmer water and air temperatures. This southward advection contributes to the latitudinal salinity gradient of the Bering Sea and its interannual variability. A cross-shelf gradient in the

Variables analyzed

(some log transformed)

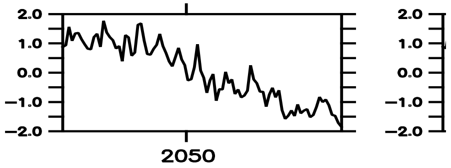
Sea bottom temperature

Large crustacean zooplankton

"Forcing" variables

Surface Temperature	SST	°C
Bottom Temperature	SBT	°C
Surface Salinity	SSS	psu
Ice cover	ICECOVER	fractional area
Mixed Layer Depth	MLD	m (positive up coordinates; hence negative change denotes deepening MLD)
Vertical Mixing (depth ave)	AKTS	$m^2\ s^{-1}$
Nitrate + Ammonium (depth ave)	NUT	$mgN\ m^{-3}$
Ice Phytoplankton	ICEPHYT	$mgC\ m^{-3}$
Small plus Large Phytoplankton (depth ave)	PHYT	$mgC\ m^{-3}$
Microzooplankton (depth ave)	MZOO	$mgC\ m^{-3}$
Small Copepods (depth ave)	COPE	$mgC\ m^{-3}$
Neocalanus (depth ave)	NCA	$mgC\ m^{-3}$
Euphausiids (depth ave)	EUP	$mgC\ m^{-3}$
Benthic detritus	DETBENTHIC	$mgC\ m^{-2}$
Benthic infauna	BENTHIC	$mgC\ m^{-2}$
Sea Surface Height	SSH	m
Sea Surface cross-shelf velocity	UTOP	$m\ s^{-1}$
Sea Surface alongshelf velocity	VTOP	$m\ s^{-1}$
Air Temperature	TAIR	°C
Air Pressure	PAIR	mbar
Specific Humidity	QAIR	$kg\ kg^{-1}$
Zonal wind	UWIND	$m\ s^{-1}$
Meridional wind	VWIND	$m\ s^{-1}$
Downward longwave radiation	LWRAD_DOWN	$W\ m^{-2}$
Downward shortwave radiation	SWRAD	$W\ m^{-2}$

CESM-rcp8.5 univariate PCs



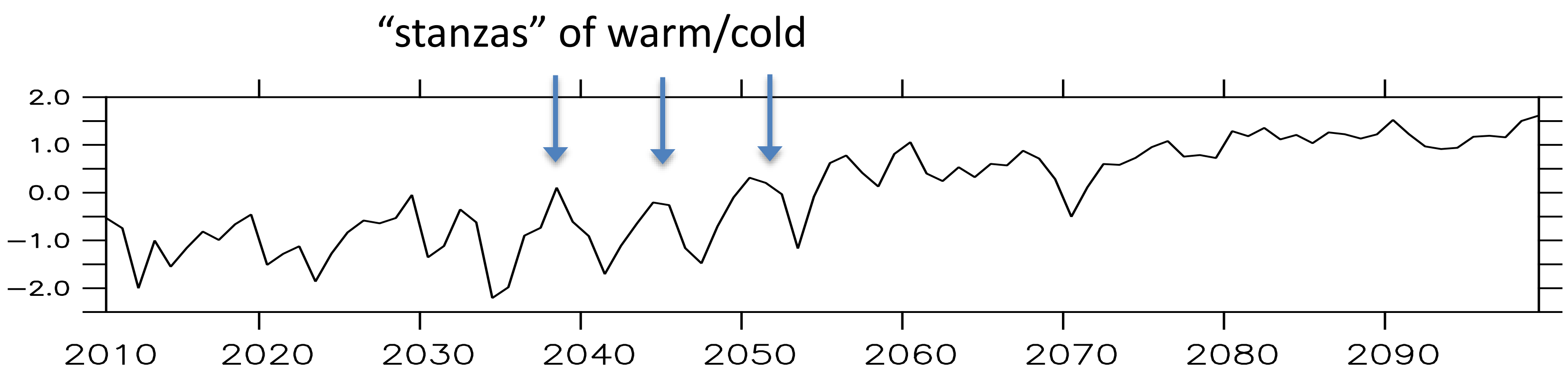
SST	SBT	SSS	PHYT	NUTS
MZOO	COPE	NCA	EUP	AKTS
BENTHIC	DETBENTHIC	ICECOVER	MLD	ICEPHYT

$$V_{ilt} = \sum_j X_{jil} T_{jit}$$

- 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

CESM-rcp8.5 multivariate PCs

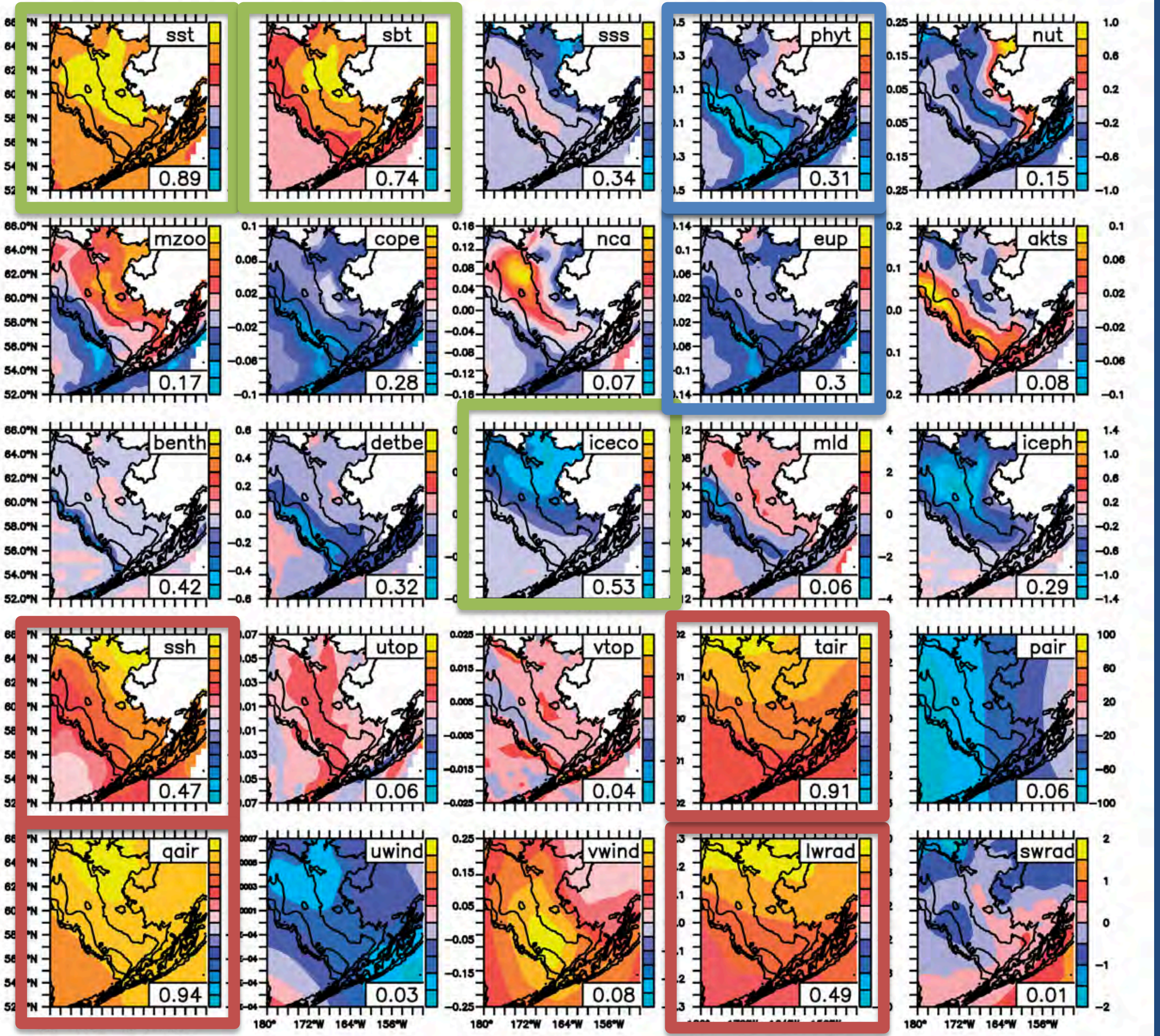
$$T_{jit} = \sum_k M_{kji} \Gamma_{kt}$$



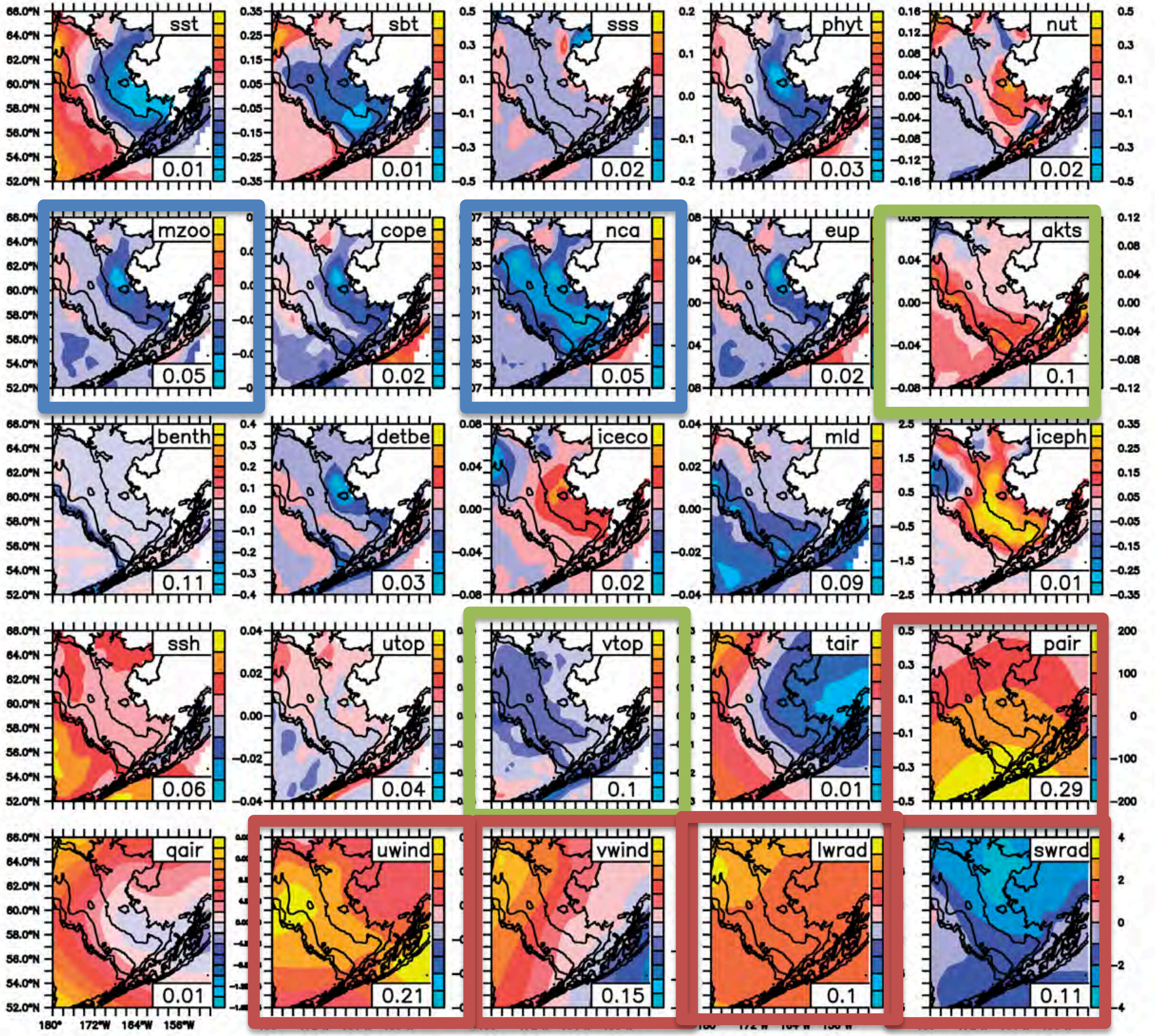
Time series of factor 1

Time series of factor 2

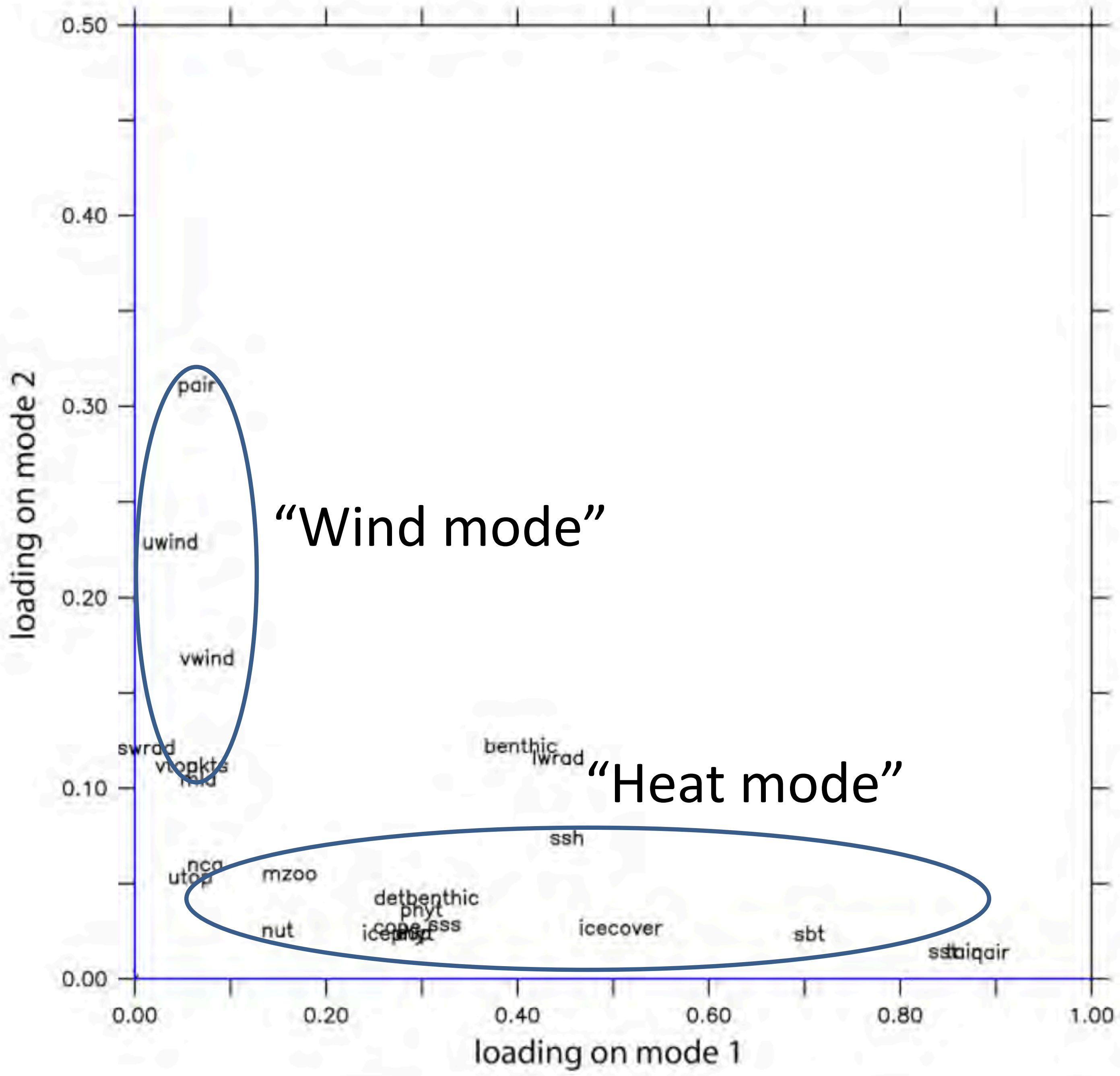
Multivariate mode 1
“heat mode”



Multivariate mode 2
“wind mode”



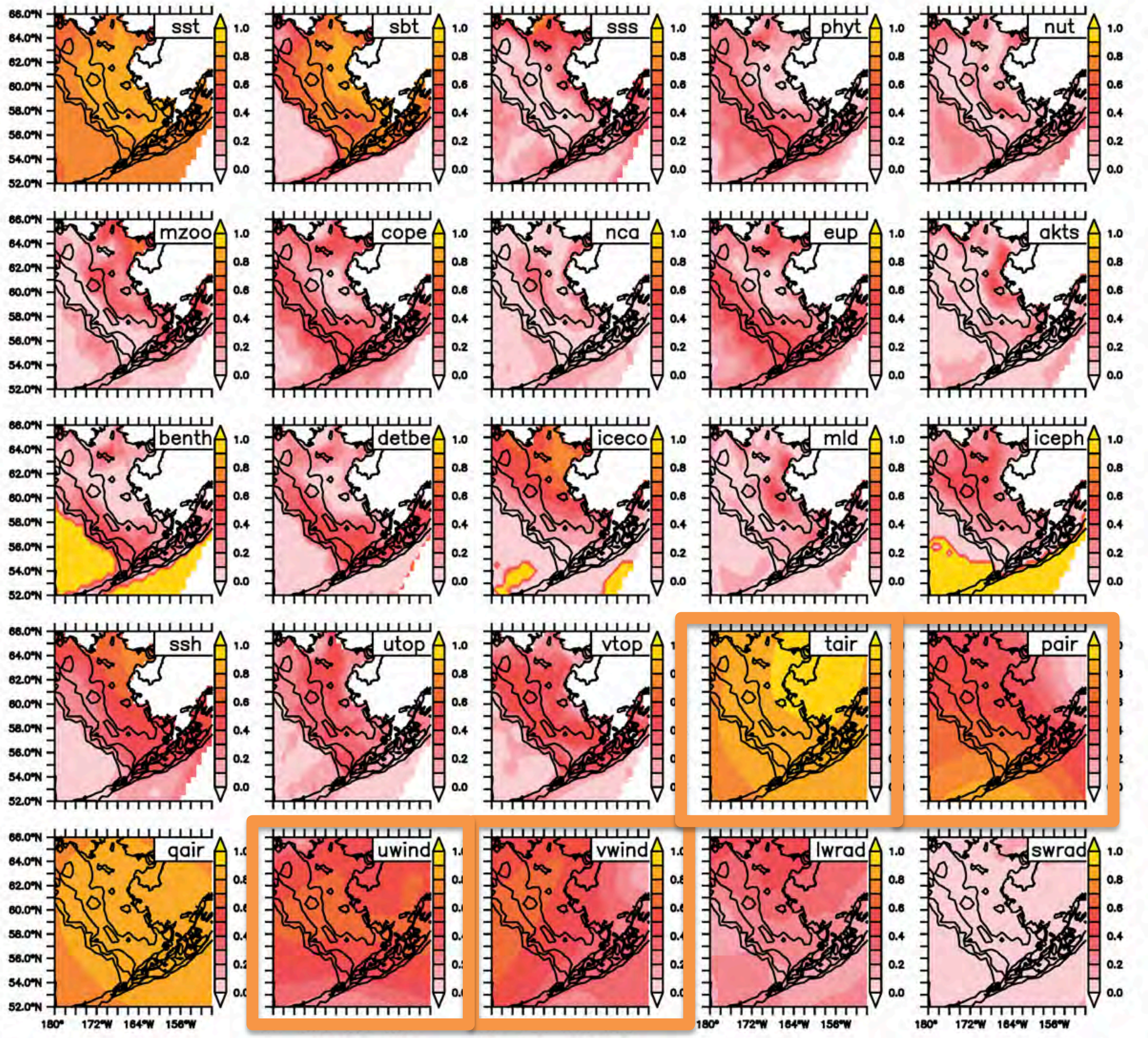
Variable loadings



Large fractional variance of training data is explained using ONLY these as predictors:

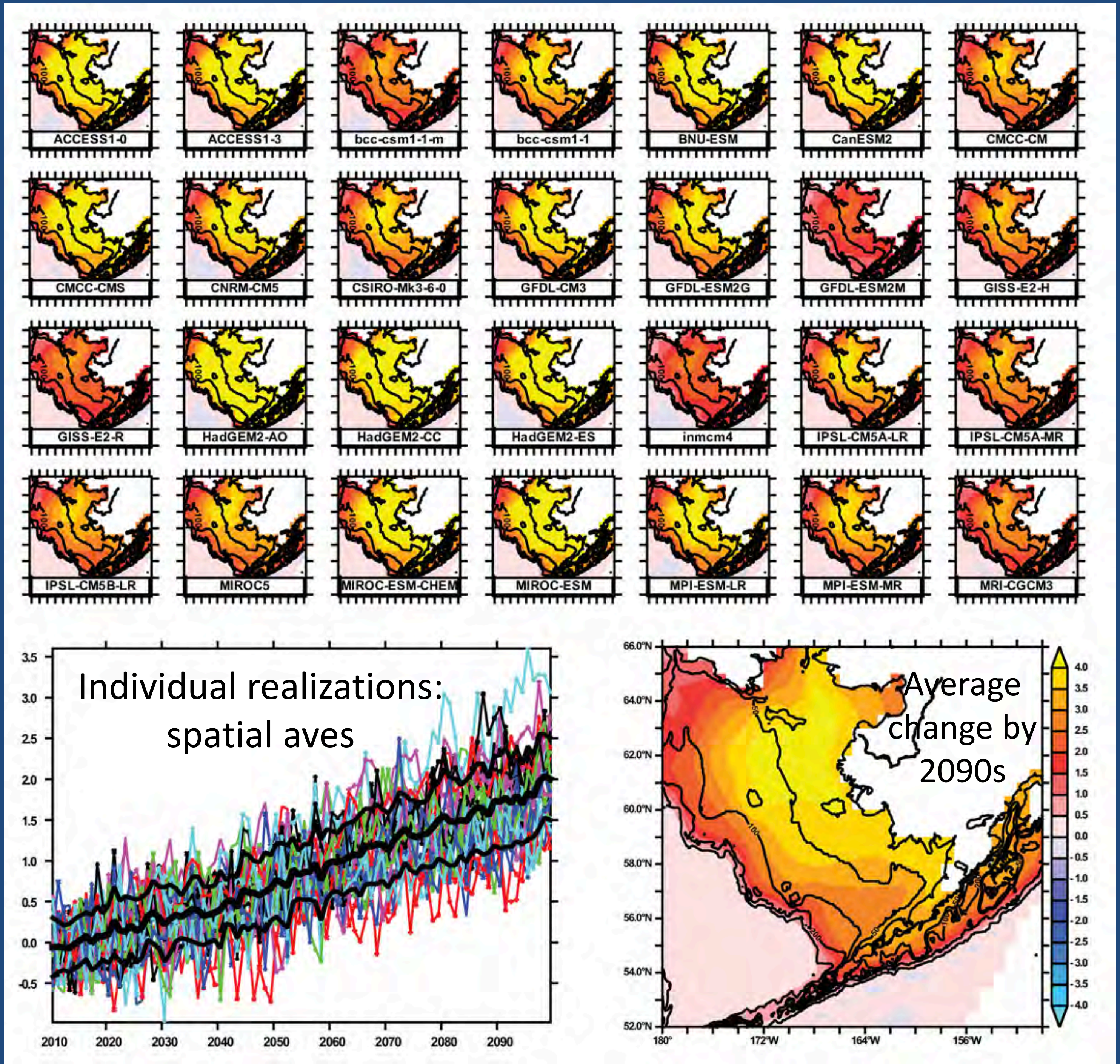
TAIR
PAIR
UWIND
VWIND

Orange = 1.0
Red = 0.5
White = 0.0



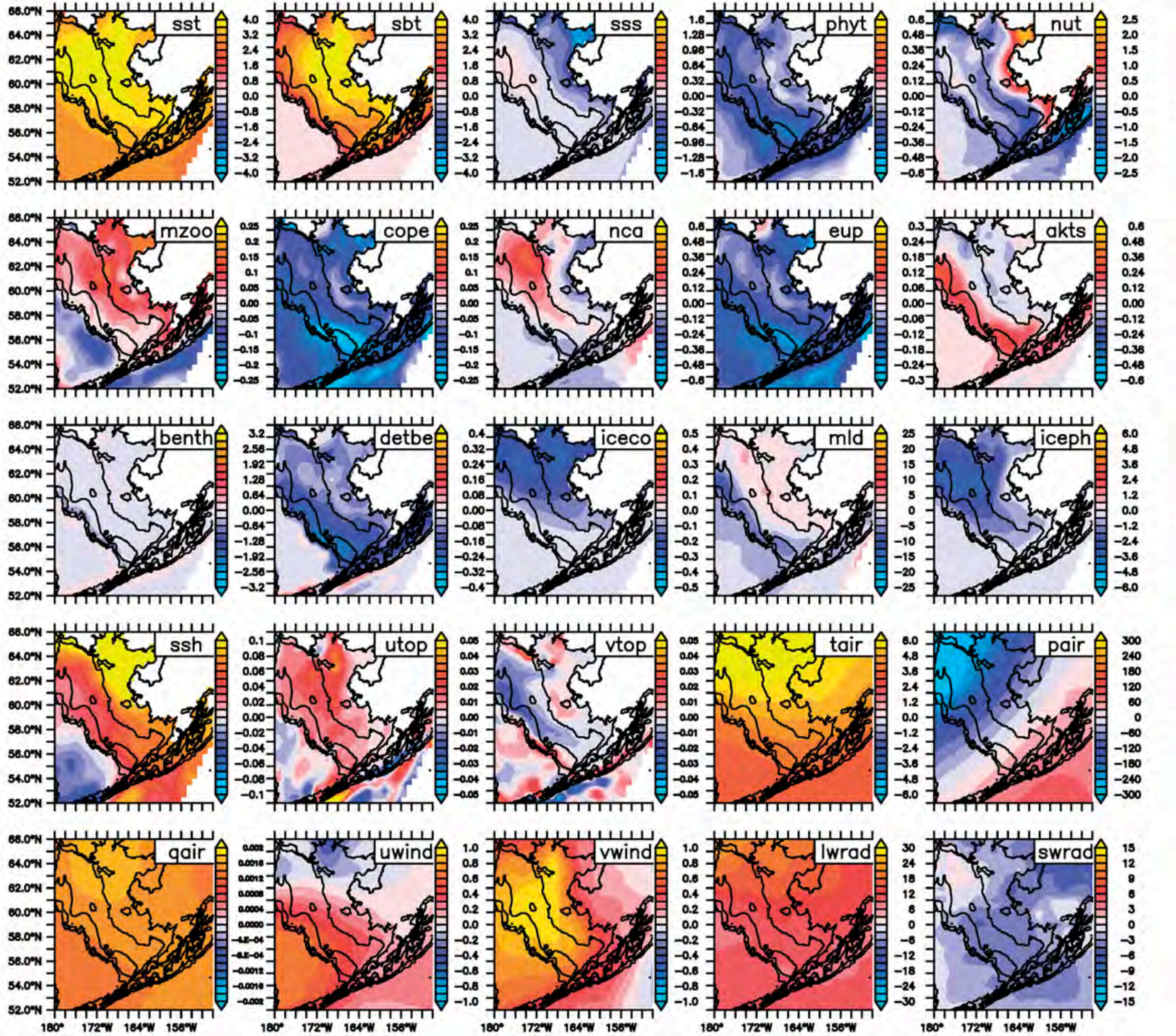
Individual realizations: change by 2090s

Project future ***TAIR, PAIR, UWIND, VWIND*** from *other* CMIP5 models onto these modes: e.g. expand the rcp8.5 ensemble to **28** members



Final result: hybrid method yields regional estimates of change to 2100 using all available CMIP5 projections

Shown here: estimated change between 2010s and 2090s under rcp8.5



Conclusion

- Multivariate EOF method (MEOF) yields sensible results which expand a small dynamical ensemble to include most of CMIP5
- Extended EOF approach (MEEOF) *might* result in better fit via persistence/propagation generated by previous forcing
- LIM methods might be even better! Need to compare with MEOF and MEEOF.