Climate Predictions for Fisheries Applications

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WITH MANY THANKS TO CHARLIE STOCK, MIKE ALEXANDER, GAELLE HERVIEUX, MIKE JACOX, GABE VECCHI, LIWEI JIA, ALISTAIR HOBDAY, KATHY PEGION, JON-YEONG PARK AND MANY OTHERS

Outline

- The need for S2D climate predictions – a fisheries prospective
- Overview of seasonal SST forecast skill at a fishery relevant scale
- Forecast applications
- Future research needs

Impacts of climate variability on fisheries

Recruitment

Status quo	Status quo
Adj $B47\%$	Adjust fishing mortality at stc $>B_{msy}$
20-year $B_0\%$	Compute B_0 based on recent mean recruitment
wtd $B_0\%$	Compute B_0 weighted by rece recruitment to spawning[a]
Low cap	Low cap
High cap	No cap
Const F	Constant fishing mortality

[a]Computed as spawning biomass per recruit mul

Walleye pollock

Ianelli et al. 2011

Growth

larvae were fed on rotifers and *Artemia* until we
dry feed. During the larval period the temperat
gradually increased from 8 to 12 °C. The initi
weights of the experimental fish were 1, 4, 9, 37,

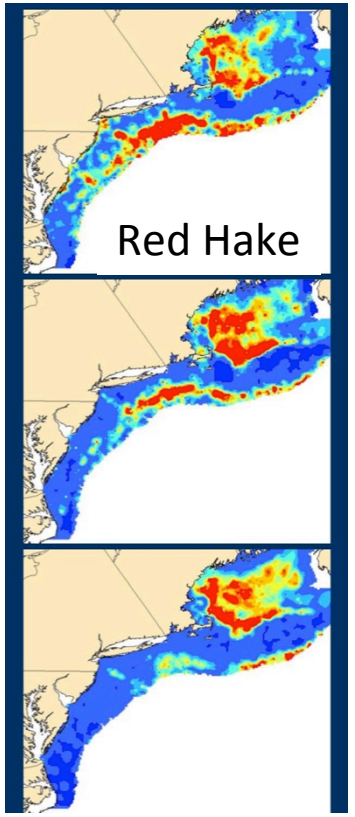
Table 1
The proximate composition of the dry feed according to the

Experiment	Feed type	Protein
A	Dan-Ex 0.5/1.0 mm	62
B	Dan-Ex 1.3 mm	62
C	FB 15/53 2 mm	53
D	FB 15/53 3 mm	53
E	FB 15/53 4 mm	53
F	FB 15/53 8 mm	53
G	FB 18/50 12 mm	53

Atlantic cod

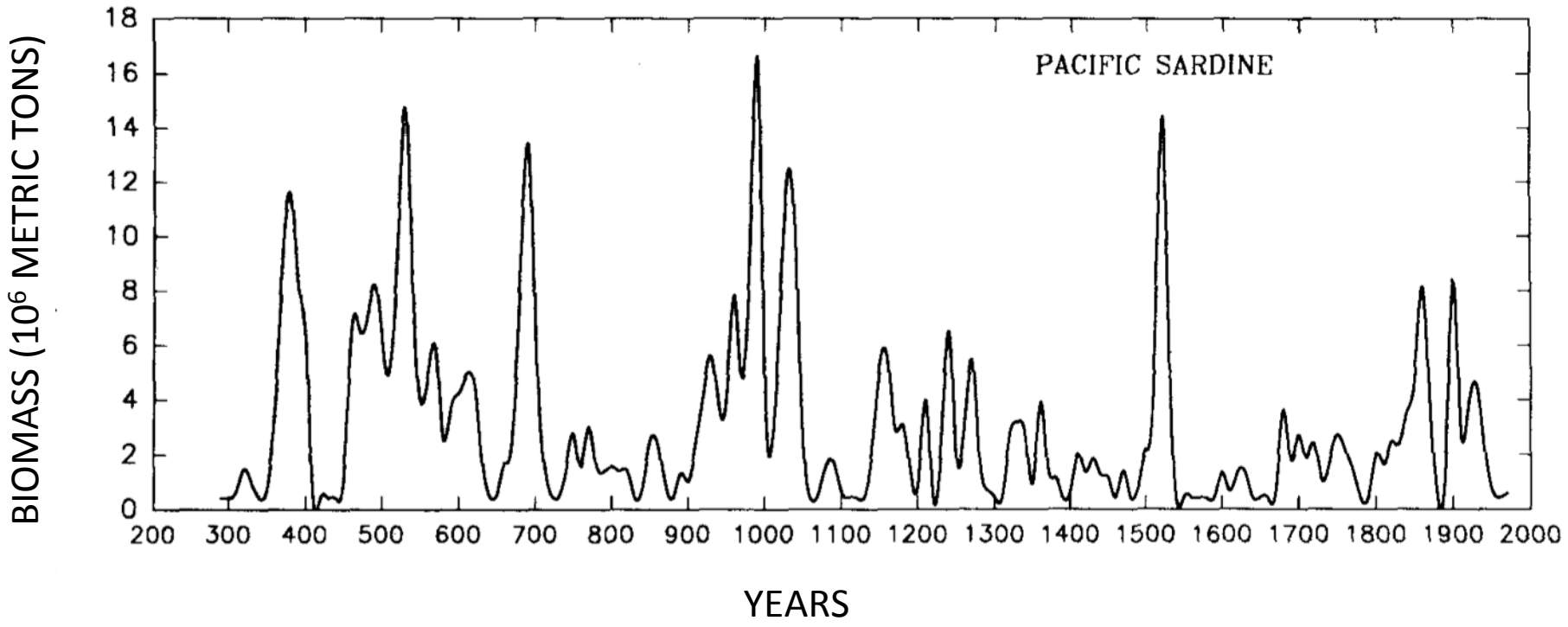
Bjornsson et al. 2007

Distribution



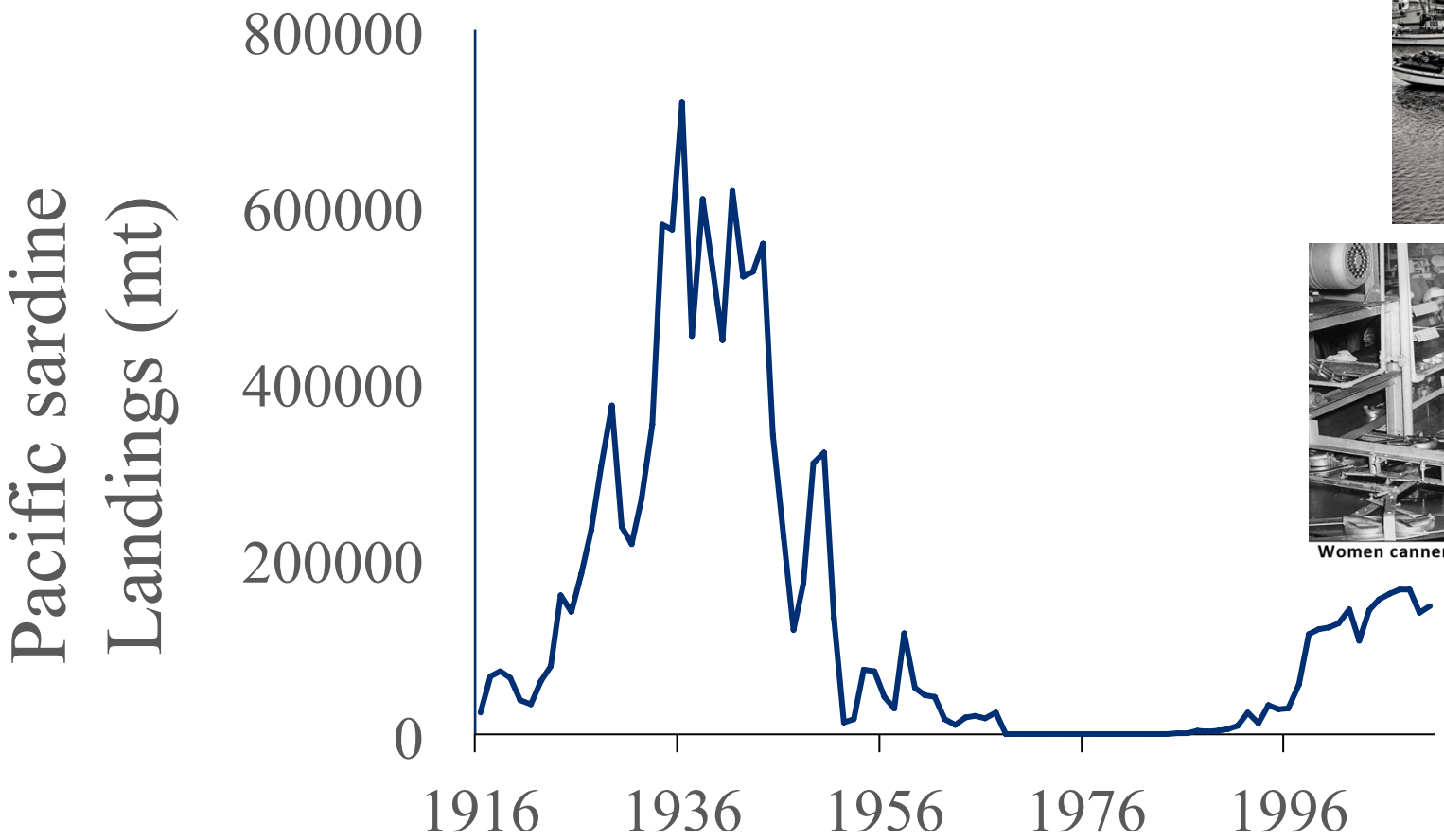
Nye et al. 2009

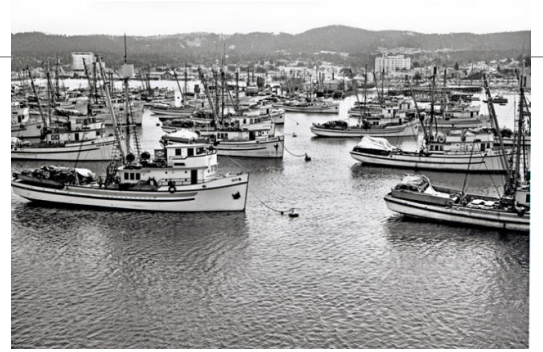
Impacts of climate variability on fisheries



Baumgartner et al. 1992

The demise of cannery row





Unloading sardines - 1920s

Women cannery workers on the line - 1949

End of an Era - Cannery Row.1950

Photos courtesy of the city of Monterey

In Maine, More Lobsters Than They Know What to Do With
Price down to a 40-year low

New York Times, June 2012

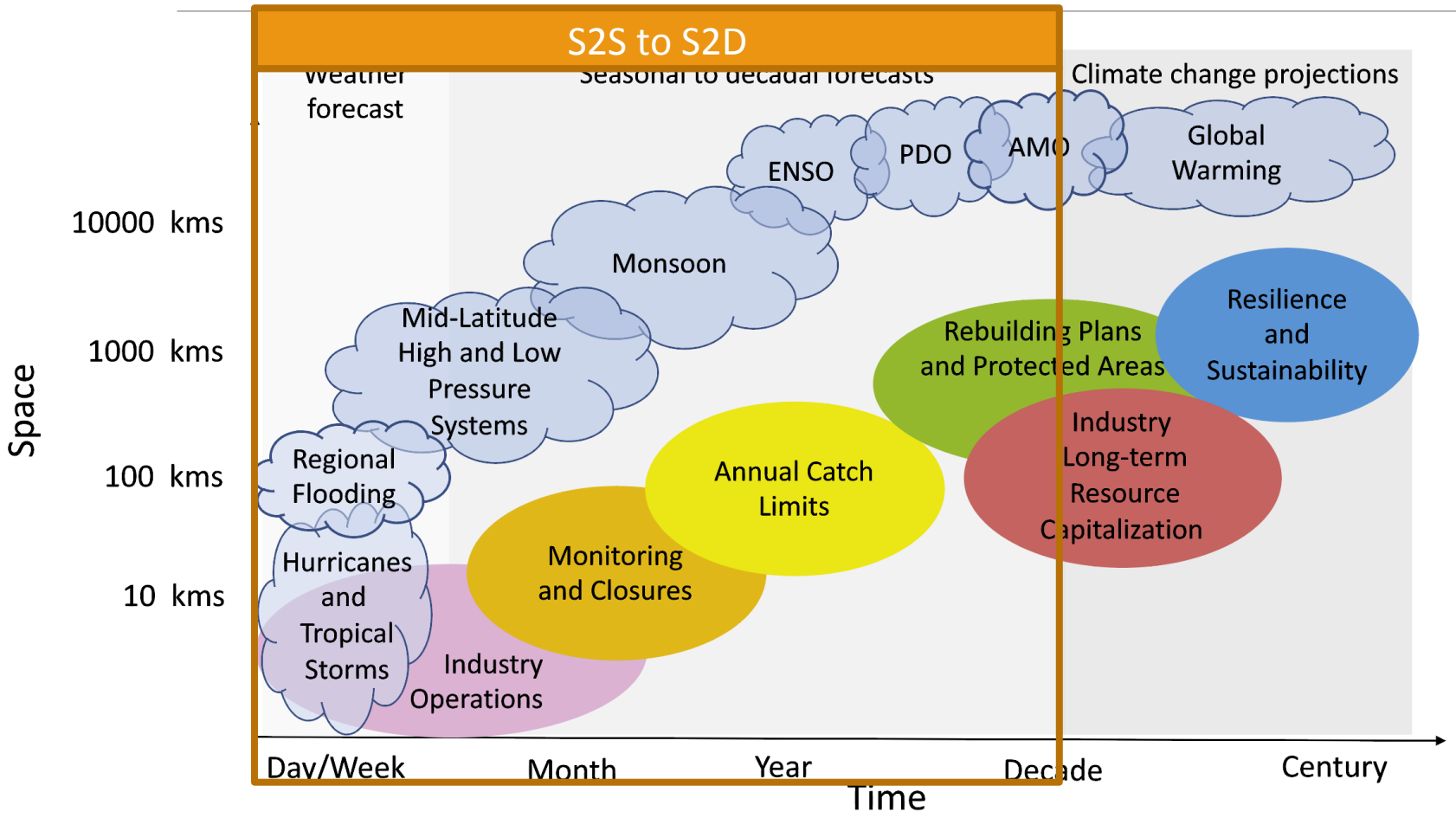
http://www.nytimes.com/2012/07/29/us/in-maine-fishermen-struggle-with-glut-of-lobsters.html?mcubz=3

West coast fisheries hit hard by poor ocean conditions

Oregon Public Broadcasting News , October 2016

http://www.opb.org/news/article/west-coast-fisheries-hit-hard-by-poor-ocean-conditions/

Fisheries decisions across time scales are impacted by climate effects



Aquaculture
- Extreme weather responses
- Stocking/harvest time

Fishing Industry
- Labor and gear needs
- Where/when/what to fish for

Coastal Management
- Beach closures (e.g. HAB's, jellies)

Fisheries Management
- Fisheries closures to reduce unwanted and incidental capture
- Provision of catch advice
- Rebuilding plans

Tommasi et al., 2017; Progress in Oceanography

But fisheries decisions rarely include climate or ecosystem effects

- After a review of 1200 stocks worldwide, only 2% include environmental drivers in tactical management decisions

Skern-Mauritzen et al., 2016; Fish and Fisheries

Challenges to integration of environmental effects into fisheries management

- No skillful forecasts of environmental conditions at the scale at which the fish operate and are managed
- Emergent effects of climate on marine ecosystems are complex
- Limited availability of time series for model development and validation

Tommasi et al., 2017; Progress in Oceanography

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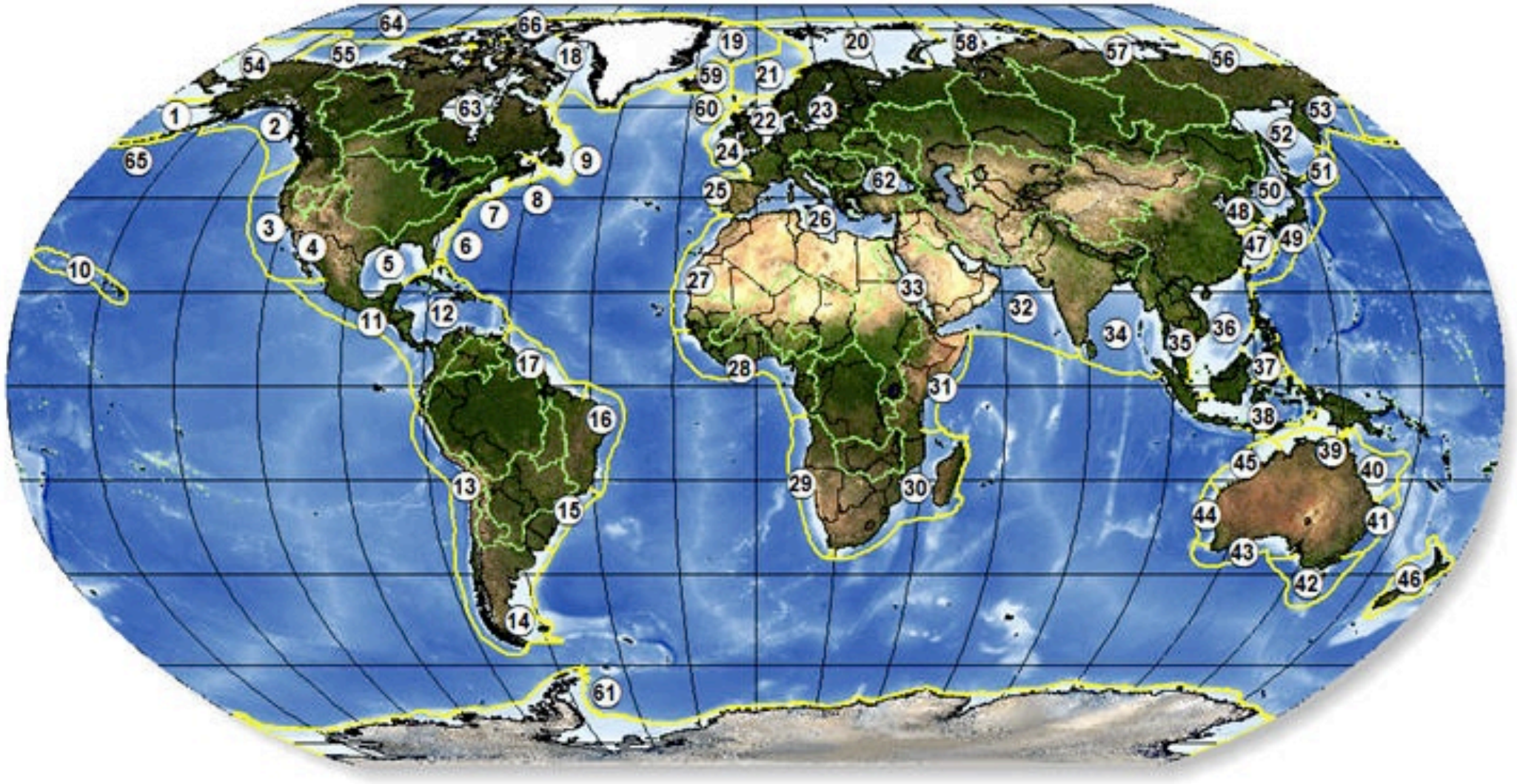
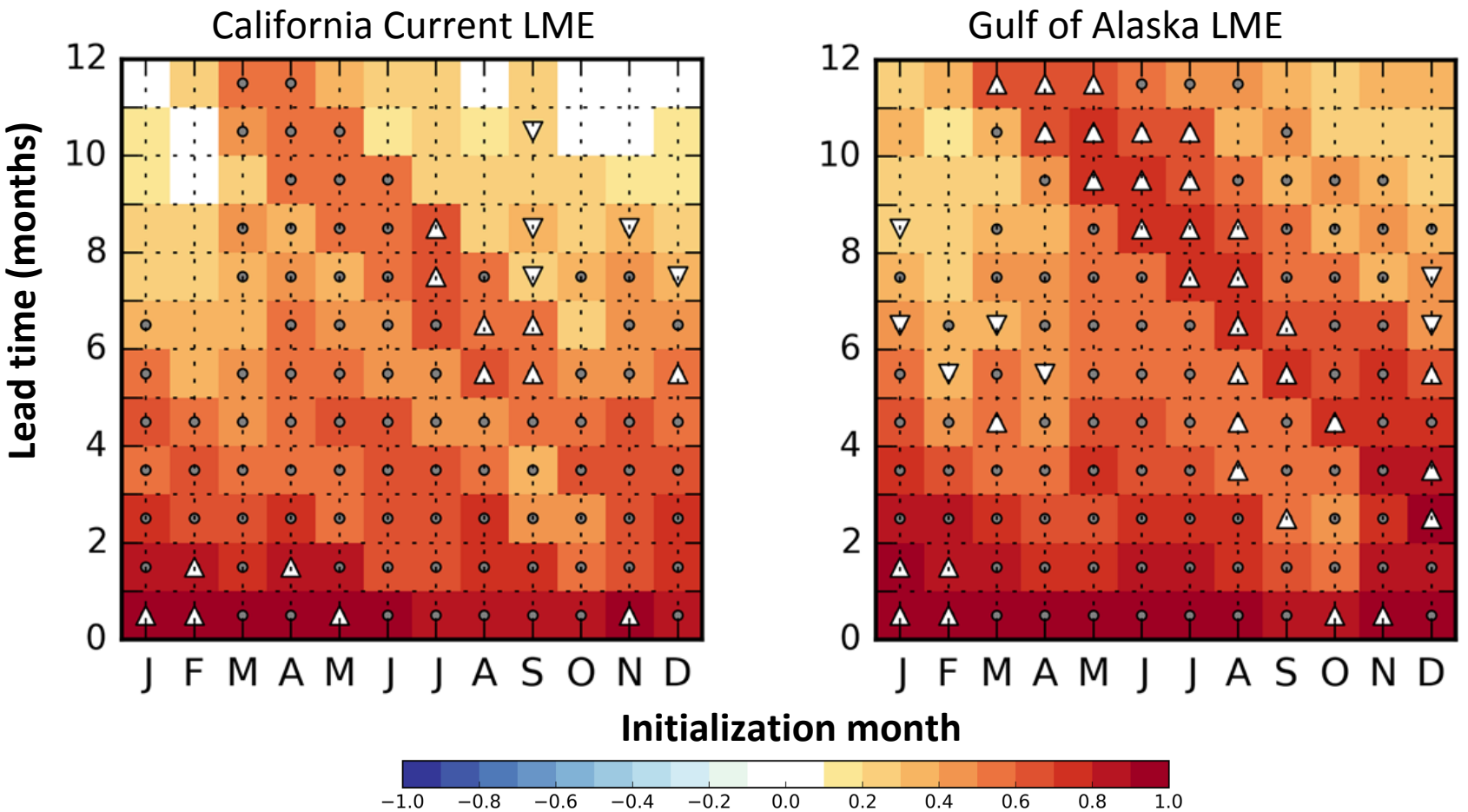
But things are changing…

Tommasi et al., 2017; Progress in Oceanography

Large Marine Ecosystems (LMEs) produce 80% of global annual fish catch



Skillful seasonal SST predictions at fishery relevant scales



Based on the Anomaly correlation coefficient (ACC) between the NMME Ensemble mean forecast SST anomalies and OISST observations from hindcasts during 1982- 2009

Anomaly correlation coefficients:
- above 0 at 5% level
- above persistence at 10% level with ACC > 0.5
- above persistence at 10% level with ACC < 0.5.

Stock et al., 2015; Progress in Oceanography; Hervieux et al., 2017; Jacox et al., 2017; Climate Dynamics

Mechanisms of Predictability for the California Current

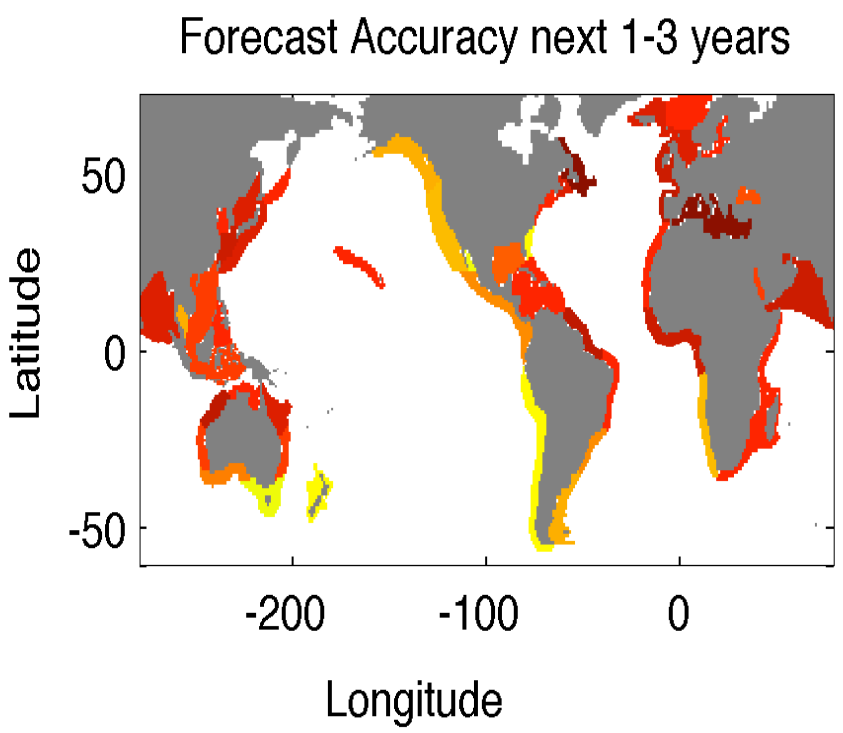
tribute disproportionately to seasonal forecast skill. Indeed, when hindcast skill above persistence is partitioned into the years following medium to strong ENSO events [i.e., when the 3-month running mean of Niño 3.4 SST anomalies, also termed the Oceanic Niño Index (ONI), exceeds a magnitude of 1] and the years associated with neutral or weakly

contributions of surface heat flux and comparable magnitude in the nearshor where wind-driven coastal upwellin control over ocean temperature varial ies confirm the importance of wind driving environmental change in the

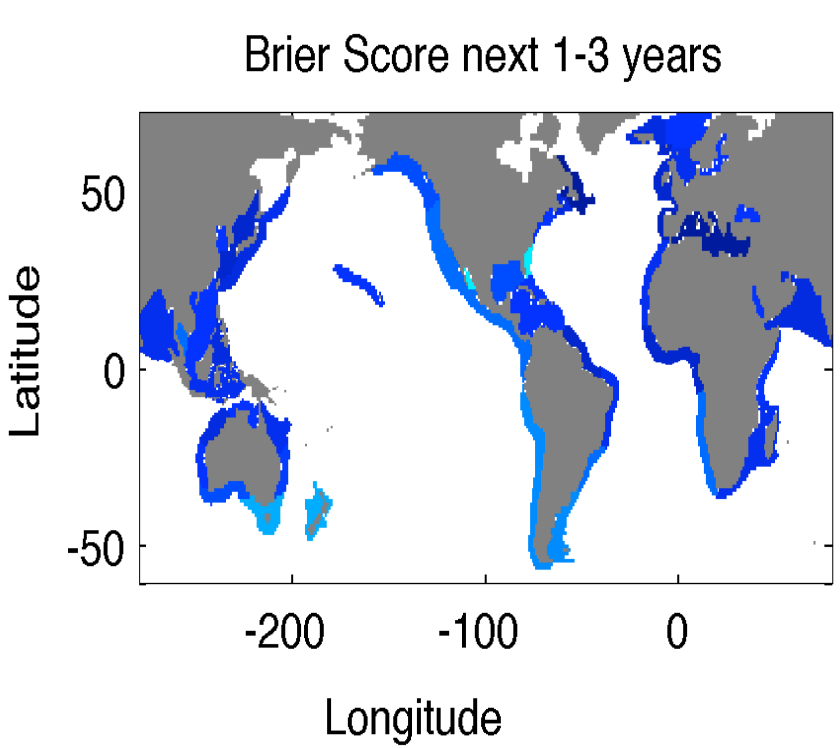
Forecast skill above persistence = ACC of the dynamical forecast minus the ACC of the persistence forecast
Persistence + ENSO = a statistical forecast based on California Current and Nino 3.4 SST anomalies in the month prior to initialization

Jacox et al., 2017; Climate Dynamics

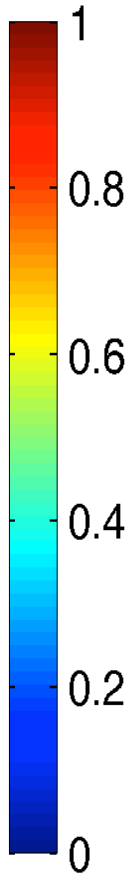
Predictions at multi-annual scales



Forecast Accuracy = proportion correct of a yes/no forecast of an event



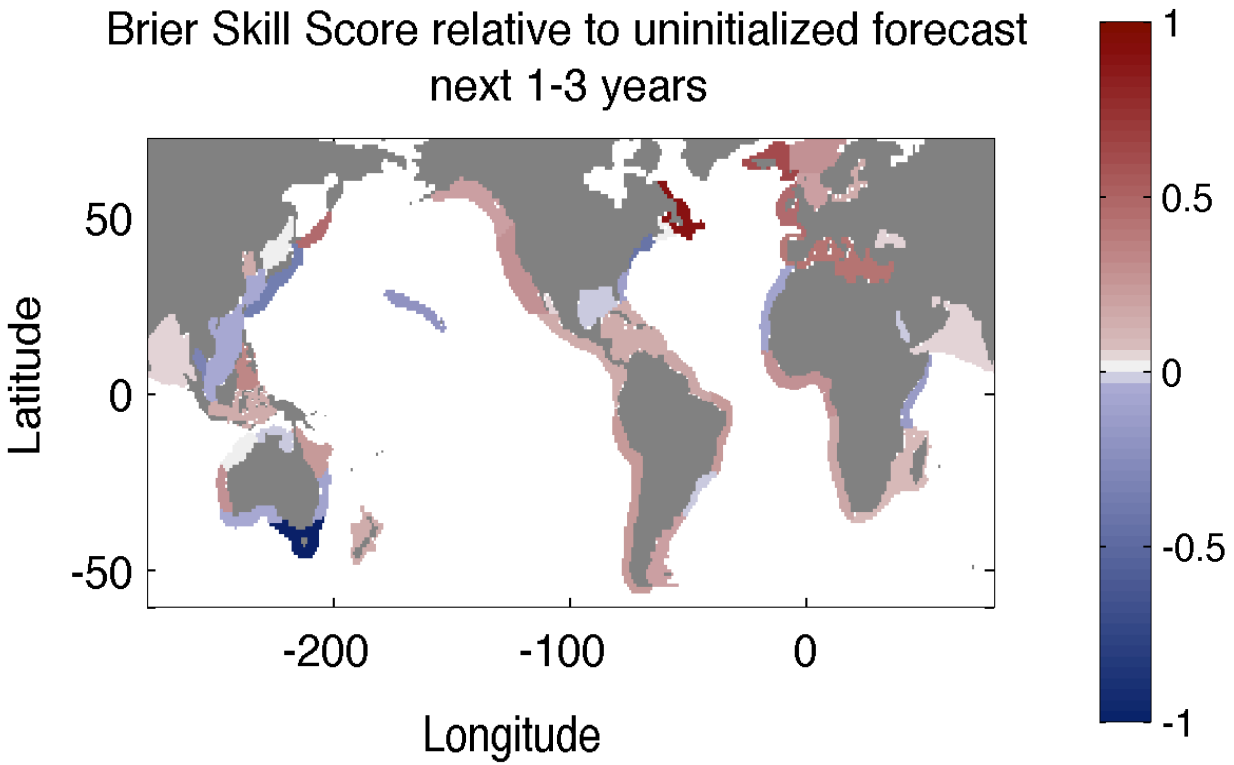
Brier Score = estimate of the mean square error of the probabilistic forecast



Skill for the probabilistic forecast of SST over the next 1-3 years being in the upper (warm) tercile based on reforecasts from 1965-2011

Tommasi et al., 2017; Frontiers in Marine Science

Skillful predictions at multi-annual scales



Except for North Atlantic LMEs, skill was due to the predictable signature of radiative forcing changes over the 50 year time period rather than prediction of evolving modes of climate variability

Brier Skill Score = Negative scores indicate no additional skill as compared to an uninitialized forecast

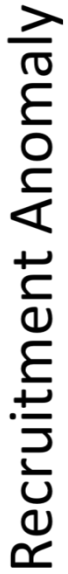
Tommasi et al., 2017; Frontiers in Marine Science

Skillful SST seasonal prediction at a fishery relevant scale

Can incorporation of seasonal climate forecasts make marine ecosystems decisions more effective?

Pacific sardine recruitment depends on SST

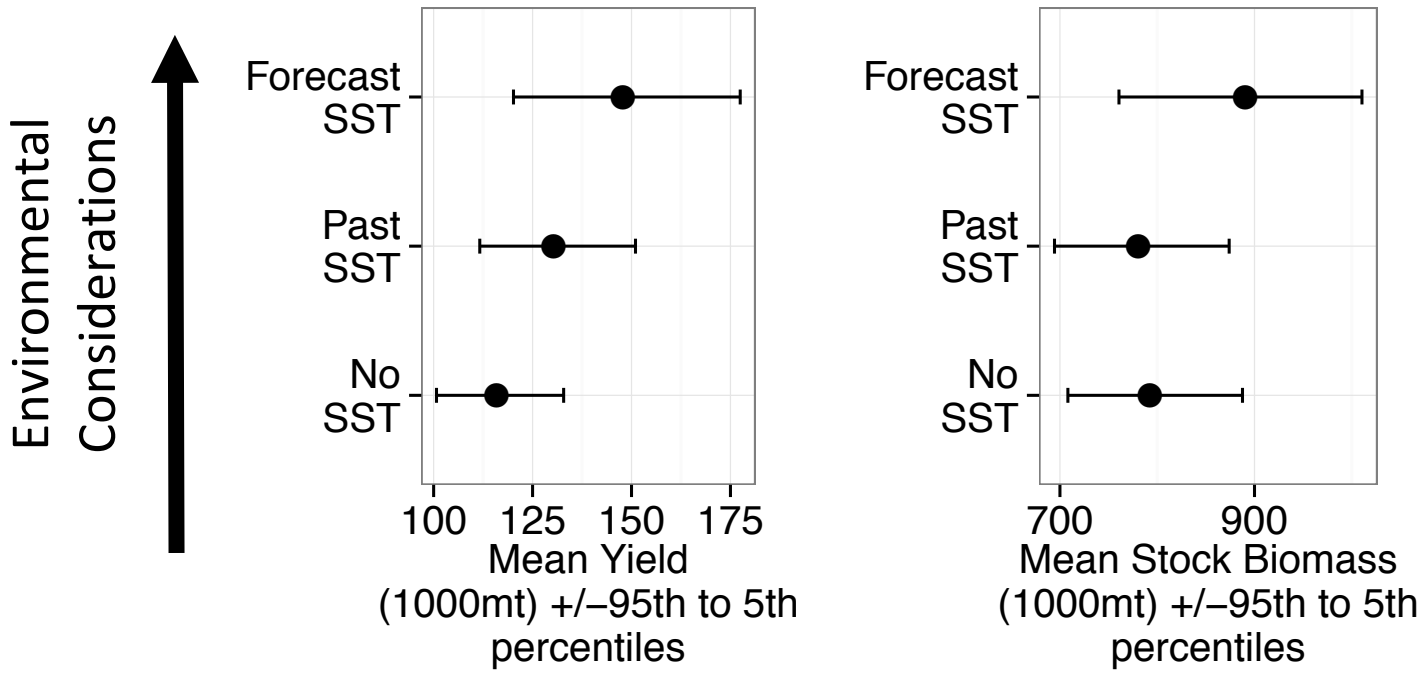
possible set of predictors. In addition, we perf
dation analysis by fitting the set of final mo
selected subset of the data (Picard and Cook 19
to 75% of the observations, and assessed the pr
the models by comparing the observed values
R estimates for the remaining subset. The cross
was repeated 1000 times, i.e., with a new set of
time, to assess the range of uncertainty assoc
dictions. All statistical analyses were con
R software (www.r-project.org).



SST

Lindegren and Checkley, 2013; Canadian Journal of Fisheries and Aquatic Sciences

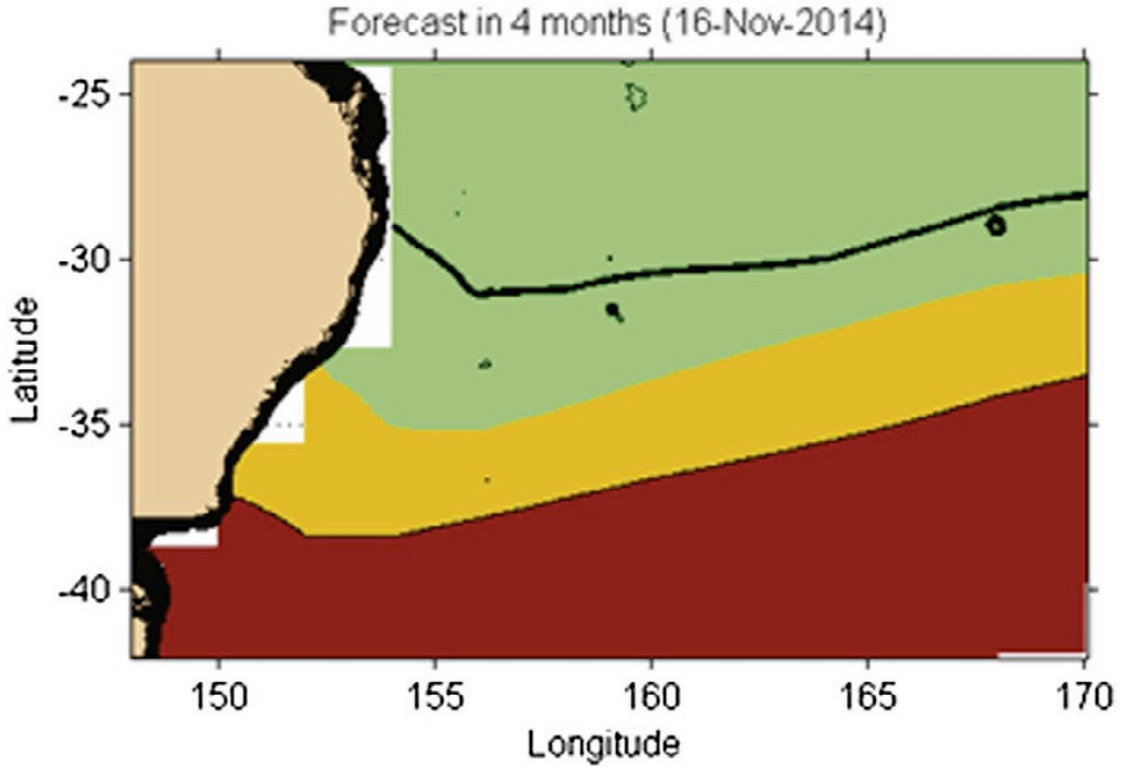
Seasonal forecasts to improve catch advice for California sardine



- Skillful SST forecast generated higher stock biomass and yield
- Lower risk of collapse if combined with existing harvest cutoff

Tommasi et al., 2017; Ecological Applications

Seasonal forecasts to reduce bycatch in the Australian east coast eastern tuna and billfish fishery



- Seasonal forecasts of probabilistic Southern Bluefin Tuna distribution zones.
- Skillful up to 5 months in advance
- Reduced the need for managers to set up large area closures while still meeting bycatch reduction management goals

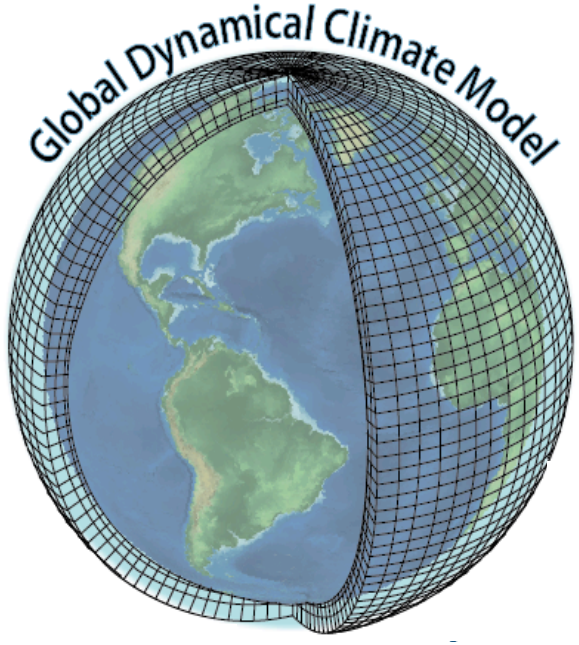
Hobday et al. 2011, Canadian Journal of Fisheries and Aquatic Sciences

Other current applications of seasonal forecasts in marine ecosystems decisions

- Coral reef management, *Spillman et al. 2011, Eakin et al. 2012*
- Prawn or salmon aquaculture farm management in Australia, *Spillman et al. 2014*, *Spillman et al. 2015*
- Economic efficiency of Great Australian Bight tuna fishery, *Eveson et al. 2015*
- Control of illegal tuna fisheries in Indonesia, *Gehlen et al. 2015*
- Sardine spatial distribution, *Kaplan et al. 2016, Siedlecki et al. 2016*
- Forecast of the start of the lobster fishing season in the Gulf of Maine, *Mills et al. 2017*

Future Research Needs

- Reduction in climate model bias through improvements in model formulation and initialization



Future Research

- Verify predictability of ecosystem relevant variables at decision relevant scales beyond SST

In hot water: Columbia's sockeye salmon face mass die-off

Warm water temperatures have made life 'grim' for sockeye salmon in the Pacific Northwest

River flow - Check out B4-04 to B4-07
Sea Ice – B5-07, B6-07, B6-08

Future Research

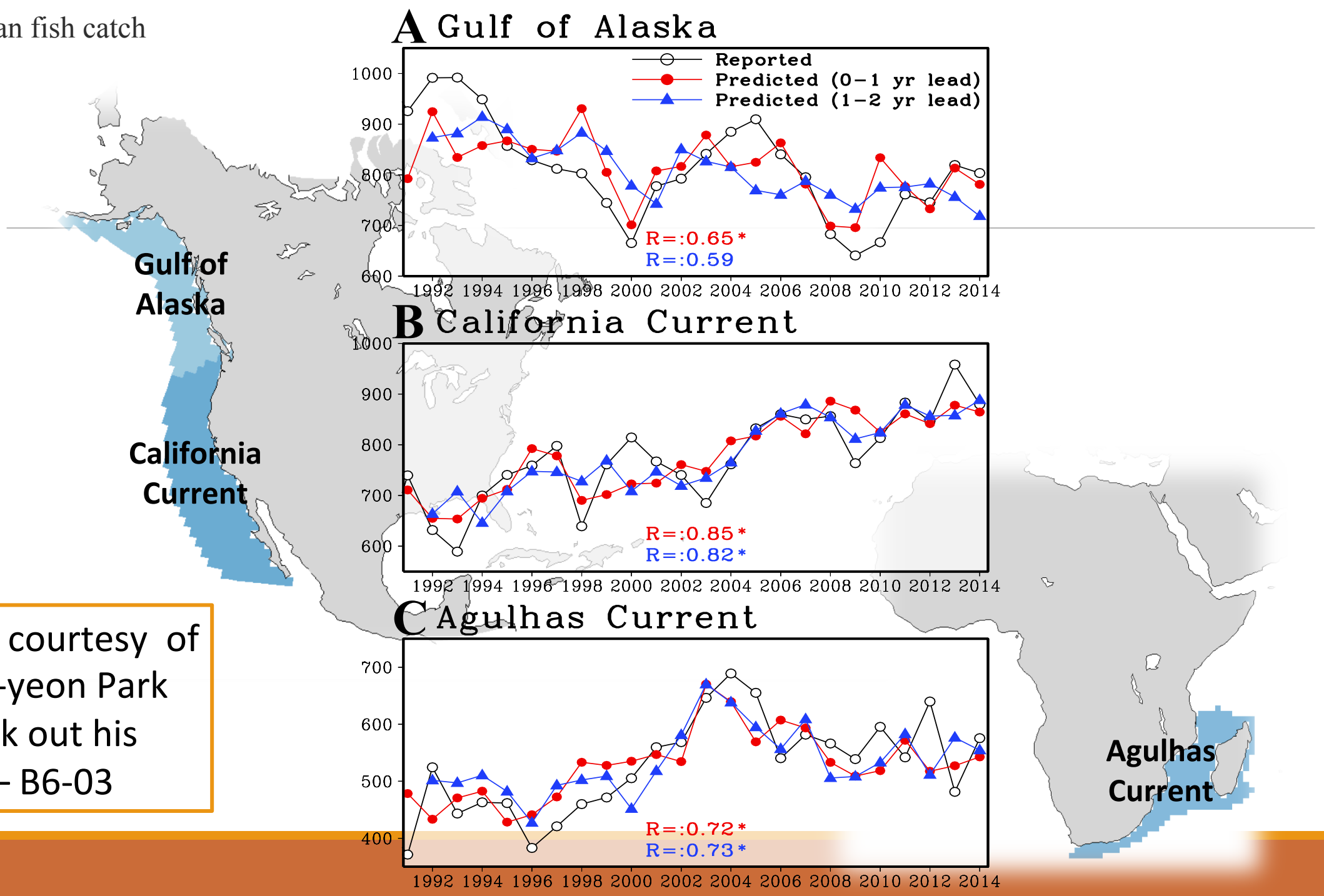
- Develop biogeochemical prediction capabilities

SEACHANGE Oyster dying as coast is hit hard

A Washington family opens a hatchery in Hawaii to escape lethal waters.

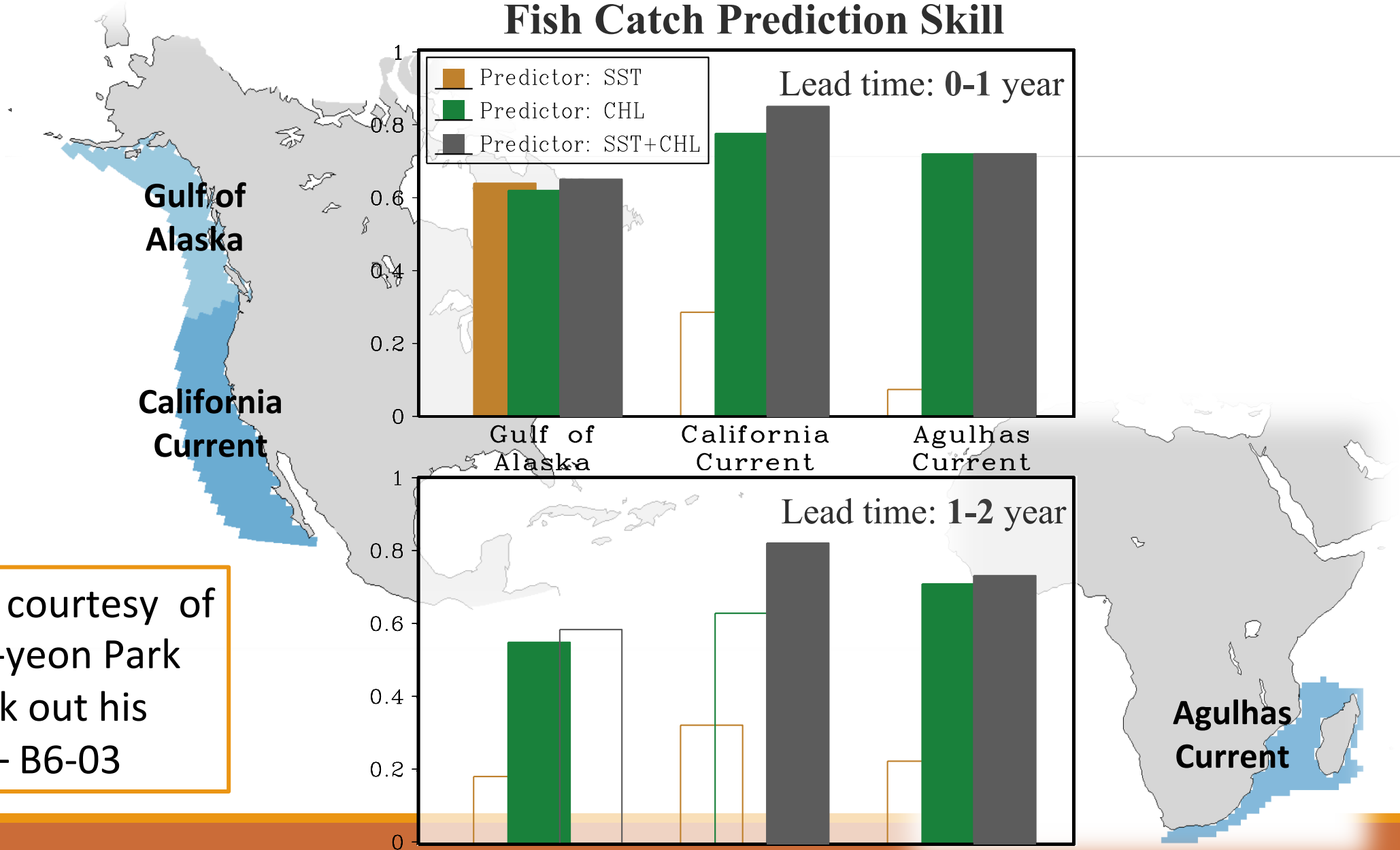
Check out B6-02 to B6-06 Talks

Annual mean fish catch



Slide courtesy of Jong-yeon Park
Check out his talk – B6-03

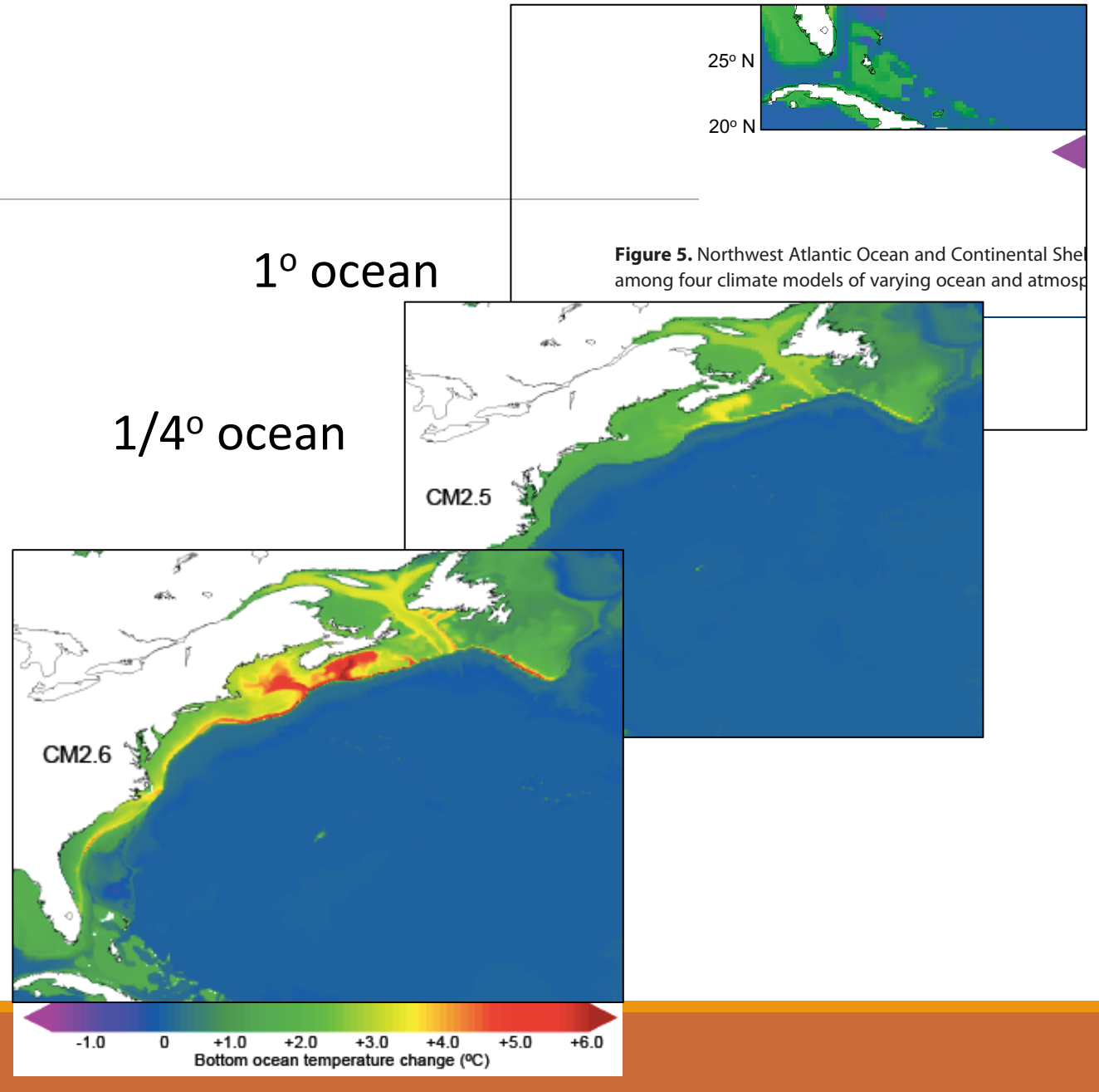
Correlation coefficients between reported and predicted annual fish catch



Slide courtesy of Jong-yeon Park
Check out his talk – B6-03

Future Research

- Unresolved local processes can limit predictability of ecosystem relevant variables



Saba et al. 2016, Journal of Geophysical Research

Future Research

- Improve climate predictability at LMR-relevant regional scales through higher resolution global prediction systems

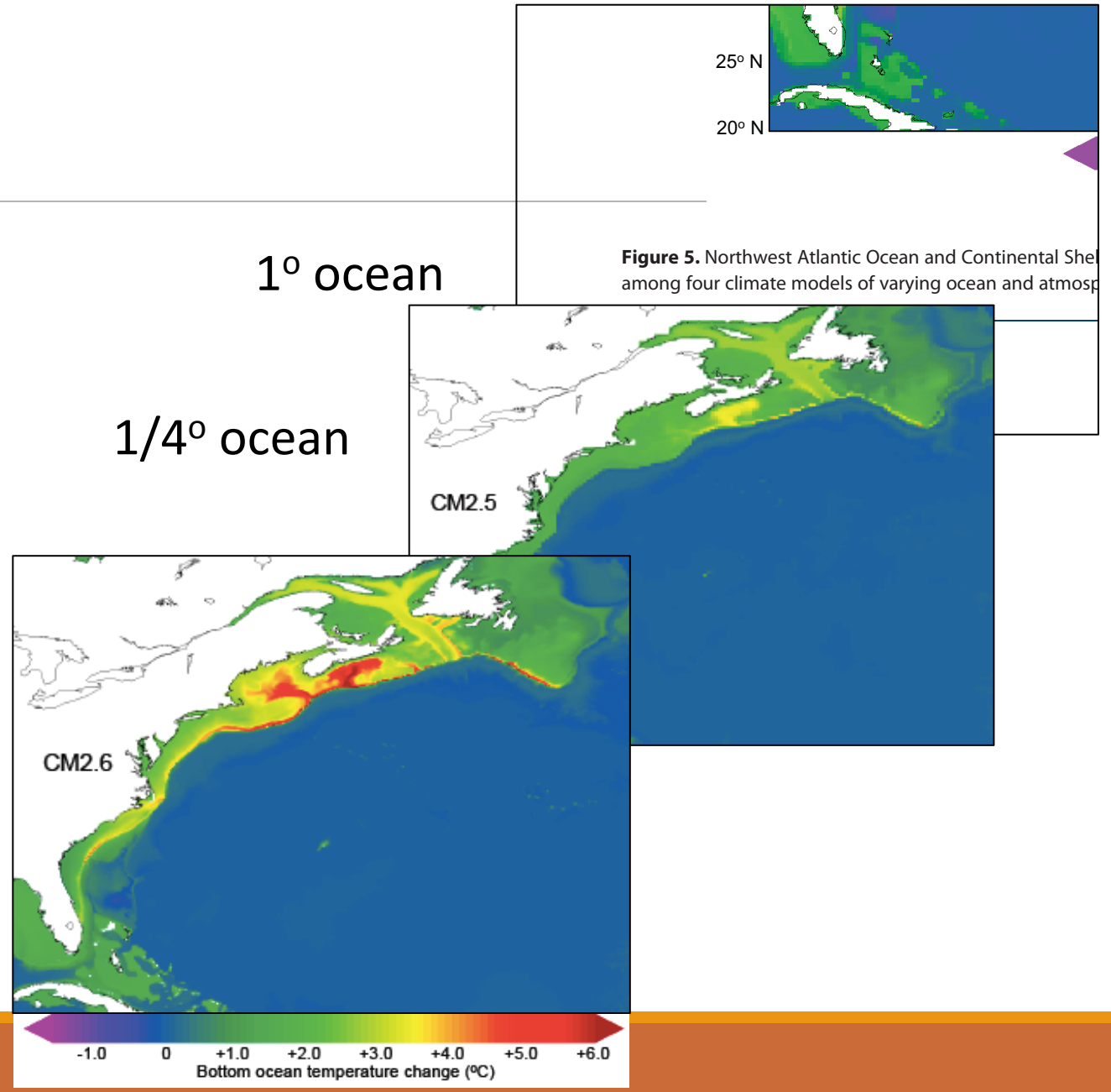
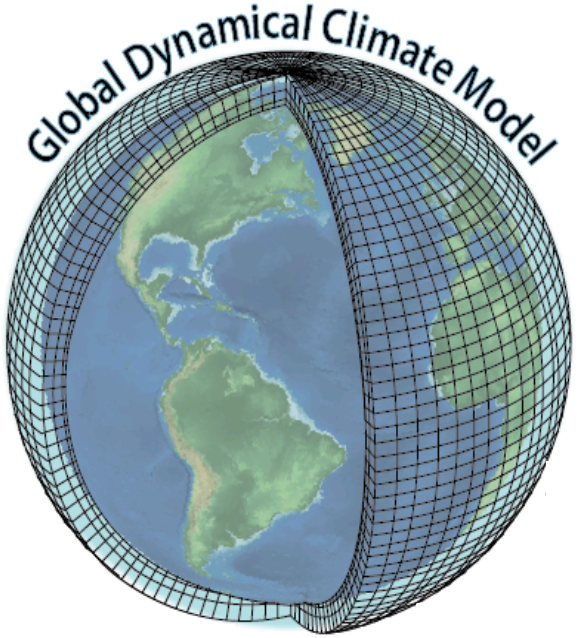


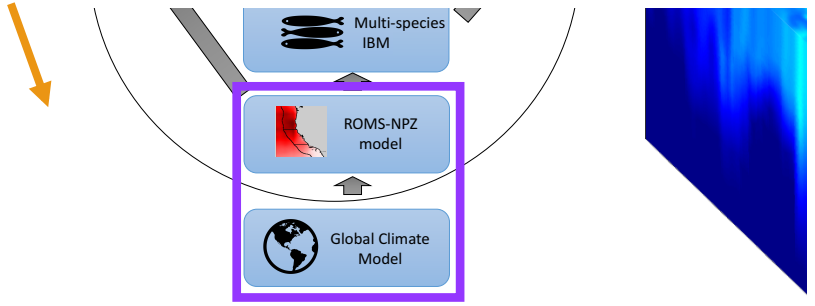
Figure 5. Northwest Atlantic Ocean and Continental Shel
among four climate models of varying ocean and atmosp

Saba et al. 2016, Journal of Geophysical Research

Future Research

- Improve climate predictability at fisheries relevant regional scales through the development of dynamical downscaling frameworks

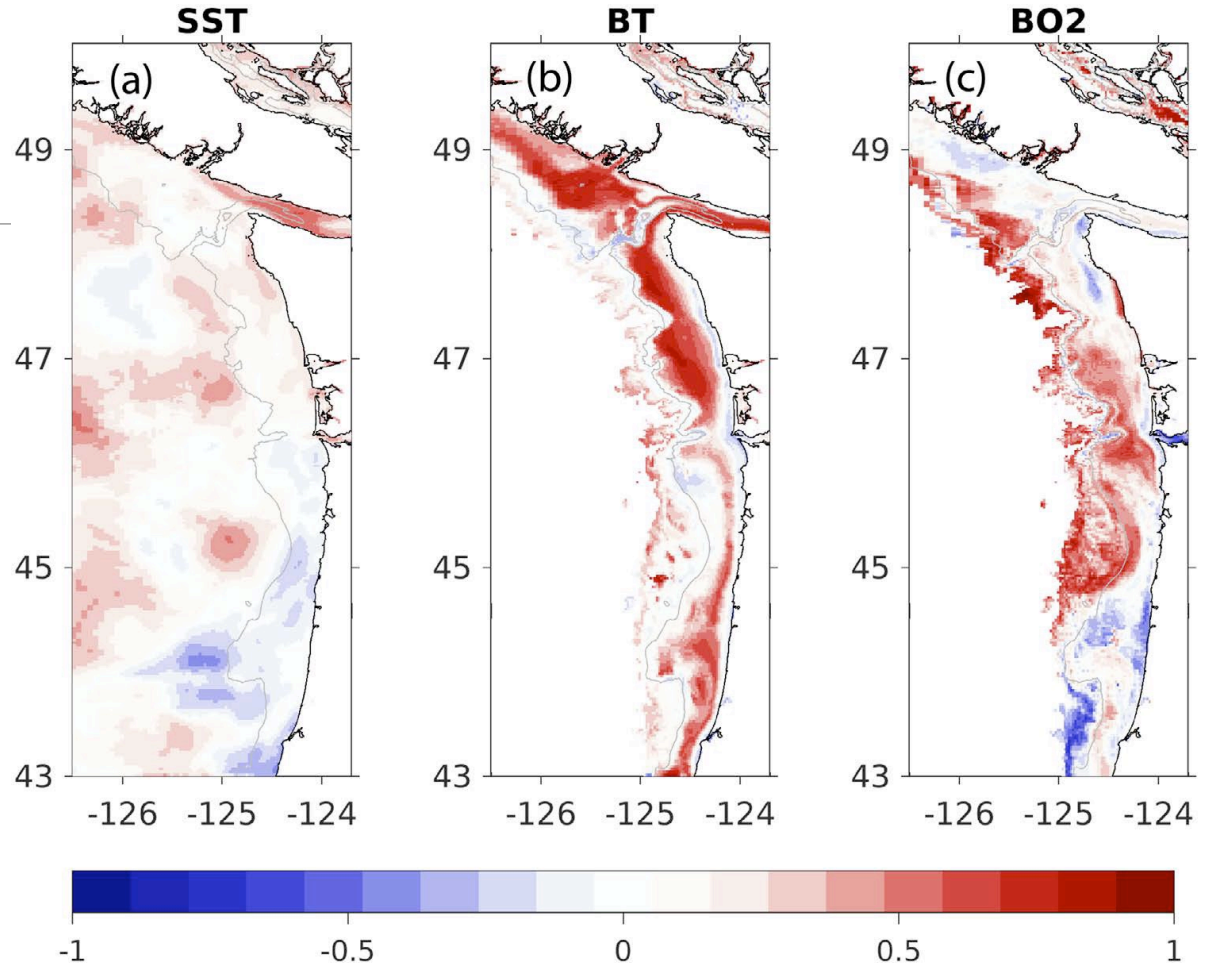




Regional Ocean Modeling System (ROMS)

Future Research

- Improve climate predictability at fisheries relevant regional scales through the development of dynamical downscaling frameworks



Anomaly correlation coefficient (ACC) between dynamically downscaled J-SCOPE forecasts (forced by CFS global prediction system) and reanalysis.

MAPP
Modeling, Analysis, Predictions, and Projections

Siedlecki et al., 2016; Scientific Reports

Future

- Take advantage of dynamical forecasts systems (e.g. NOAA-GFDL FLOR) to anticipate changes in hydrographic conditions in estuaries using empirical statistical downscaling (NOAA-GFDL FUDGE)

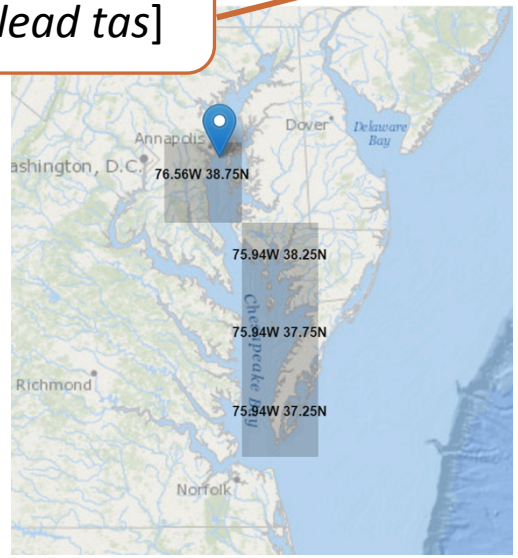
TPLM2 C-MAN daily *tas*

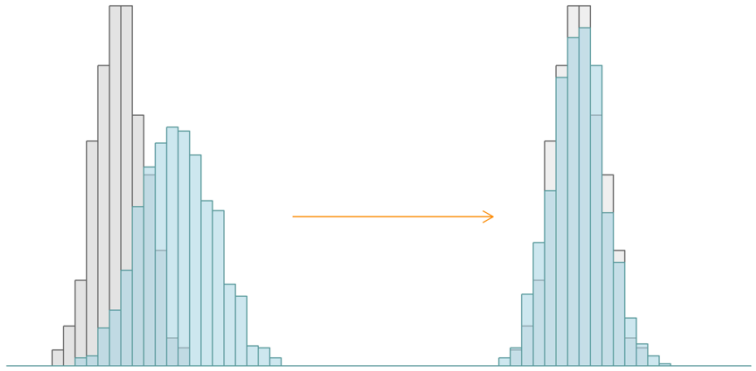
FLOR daily forecast [*1 month lead tas*]

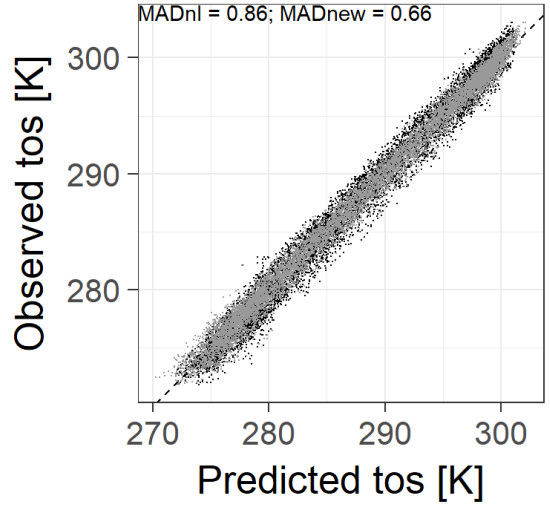
FUDGE ESD-QM

1 month lead ESD-FLOR daily *tas*

1 month lead ESD-FLOR weekly *tos*







Slide courtesy of Fernando Taboada

Taboada, Tommasi et al. in preparation

Thank you!

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