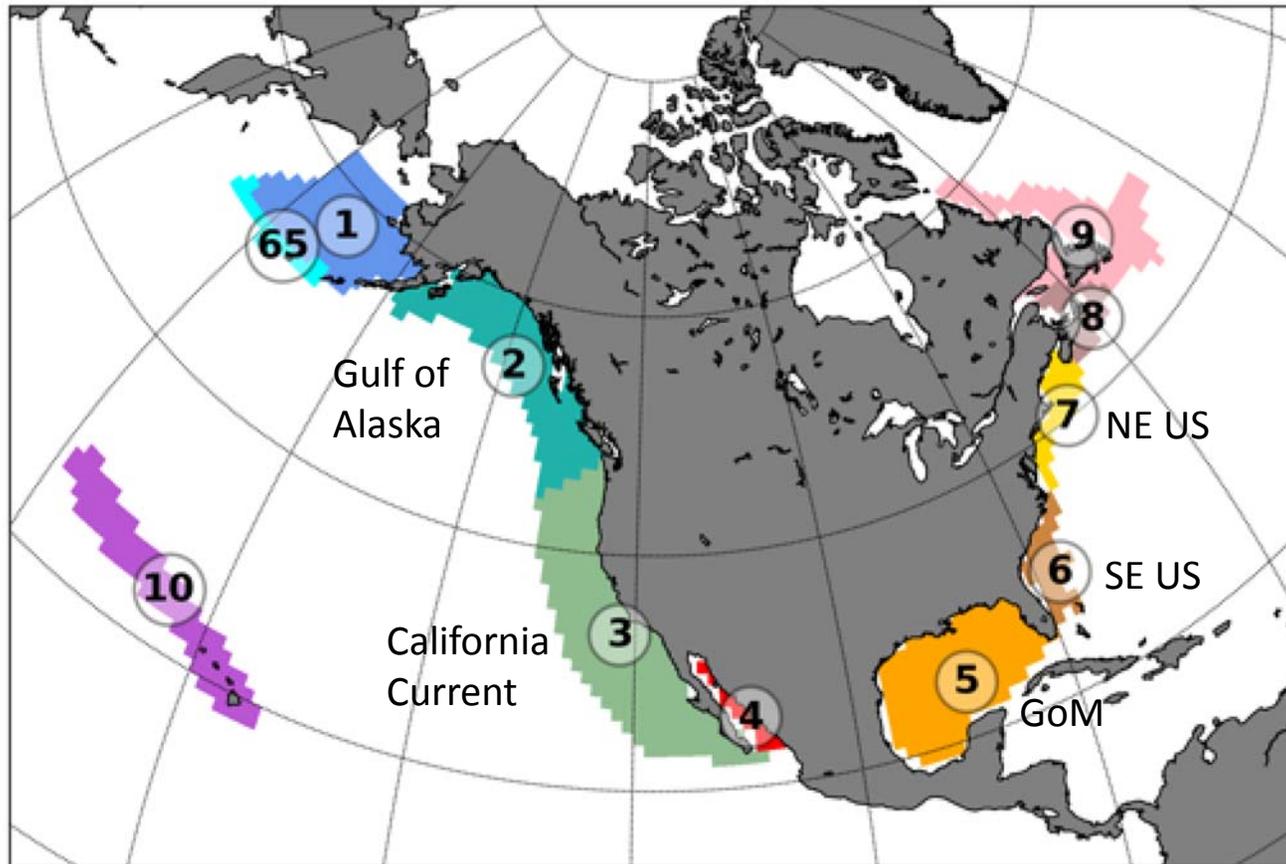


# The Skill of North American Multi-Model Ensemble (NMME) SST forecasts for US coastal ecosystems

Michael Alexander  
NOAA/Earth System Research Lab

Gaelle Hervieux, Michael Jacox, Charles Stock,  
Desiree Tommasi, Kathleen Pegion, Emily  
Becker, and Fred Castruccio

# Large Marine Ecosystems (LMEs)



LMEs - coherent ocean areas along continental margins (productive regions).

LMEs have been defined based on ecological criteria, bathymetry, hydrography, productivity and trophic relationships

LMEs 1: East Bering Sea (EBS), 2: Gulf of Alaska (GoA), 3: California Current (CC), 5: Gulf of Mexico (GoM), 6: Southeast U.S. Continental Shelf (SEUS), 7: Northeast U.S. Continental Shelf (NEUS), 8: Scotian Shelf (SS), 9: Newfoundland-Labrador Shelf (NL), 10: Insular Pacific Hawaiian (IPH), 65: Aleutian Islands

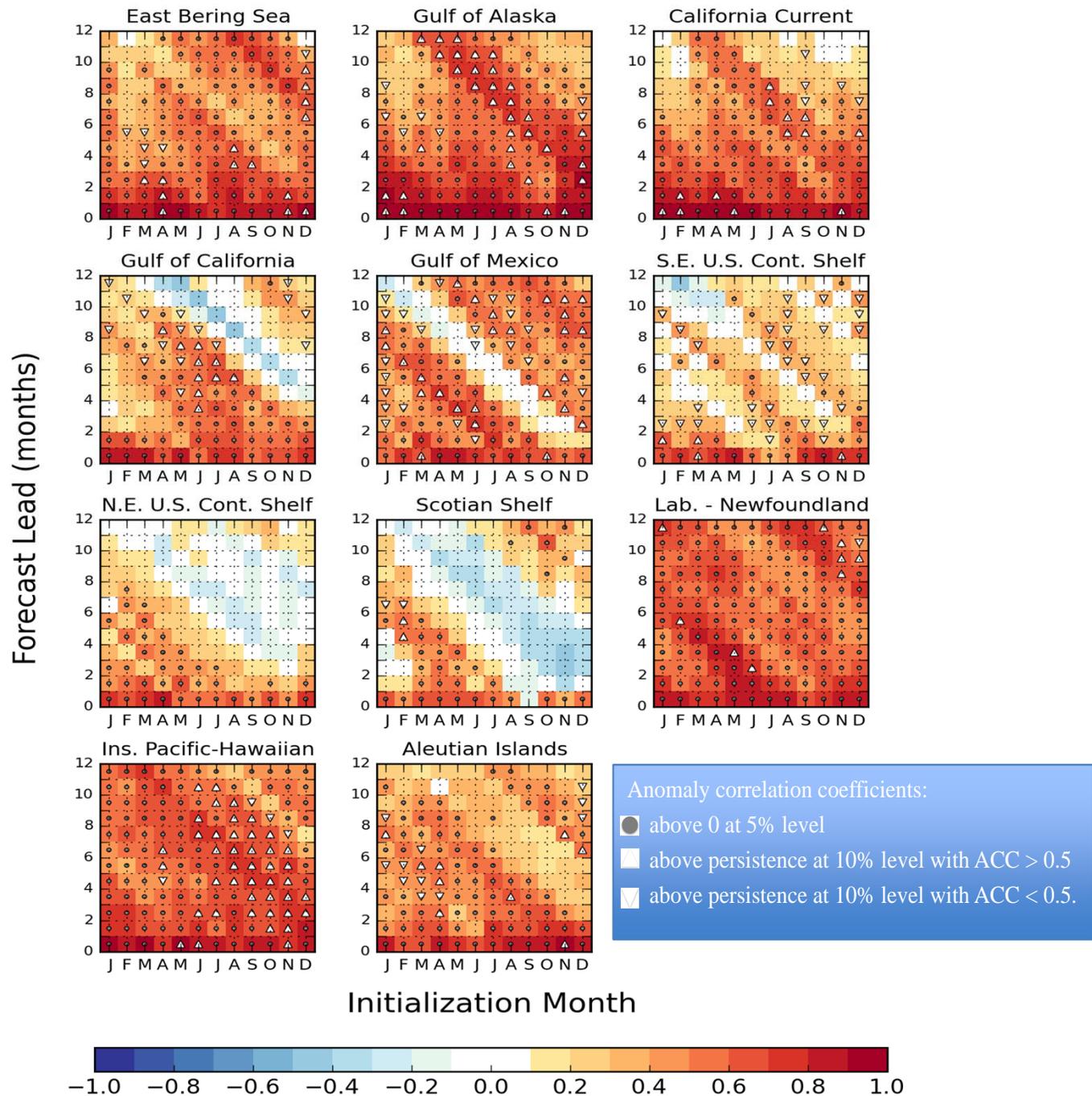
# Multi-Model Forecasts

- Many studies have found that forecasts from multiple models are better than those from any single model
- Here we examine the skill of SST hindcasts from the North American Multi-Model Ensemble (NMME), phase 1 (*Kirtman et al. 2014, BAMS*)
- Monthly Hindcasts during 1982-2002 from 14 models
  - All output on a 1° lat x 1° lon grid
- Skill estimated by:
  - First average ensembles from individual models
  - Average models to create a multi-model mean hindcast
  - Bias correct hindcasts by removing drift (initialization month, lead)
  - Skill of SST hindcasts evaluated relative to ¼° Reynolds OI SST data set
- What is the skill of SST forecasts in the US Large Marine Ecosystem regions around the US?

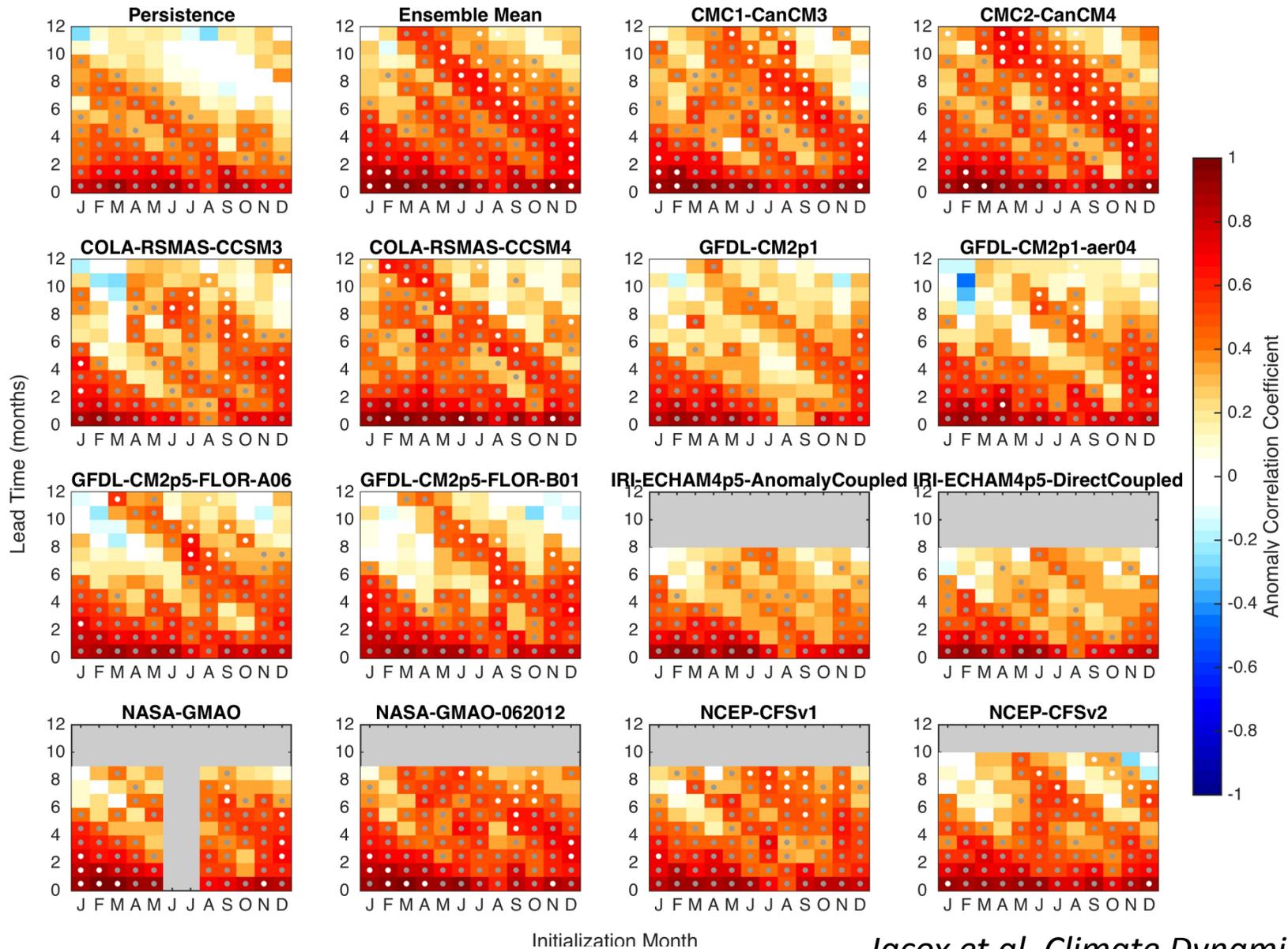
Anomaly  
Correlation  
Coefficients (ACC)  
for Ensemble  
mean  
SST NMME  
Forecasts for US  
LME regions

(all NMME  
models averaged  
together)

*Hervieux et al.  
Climate Dynamics*

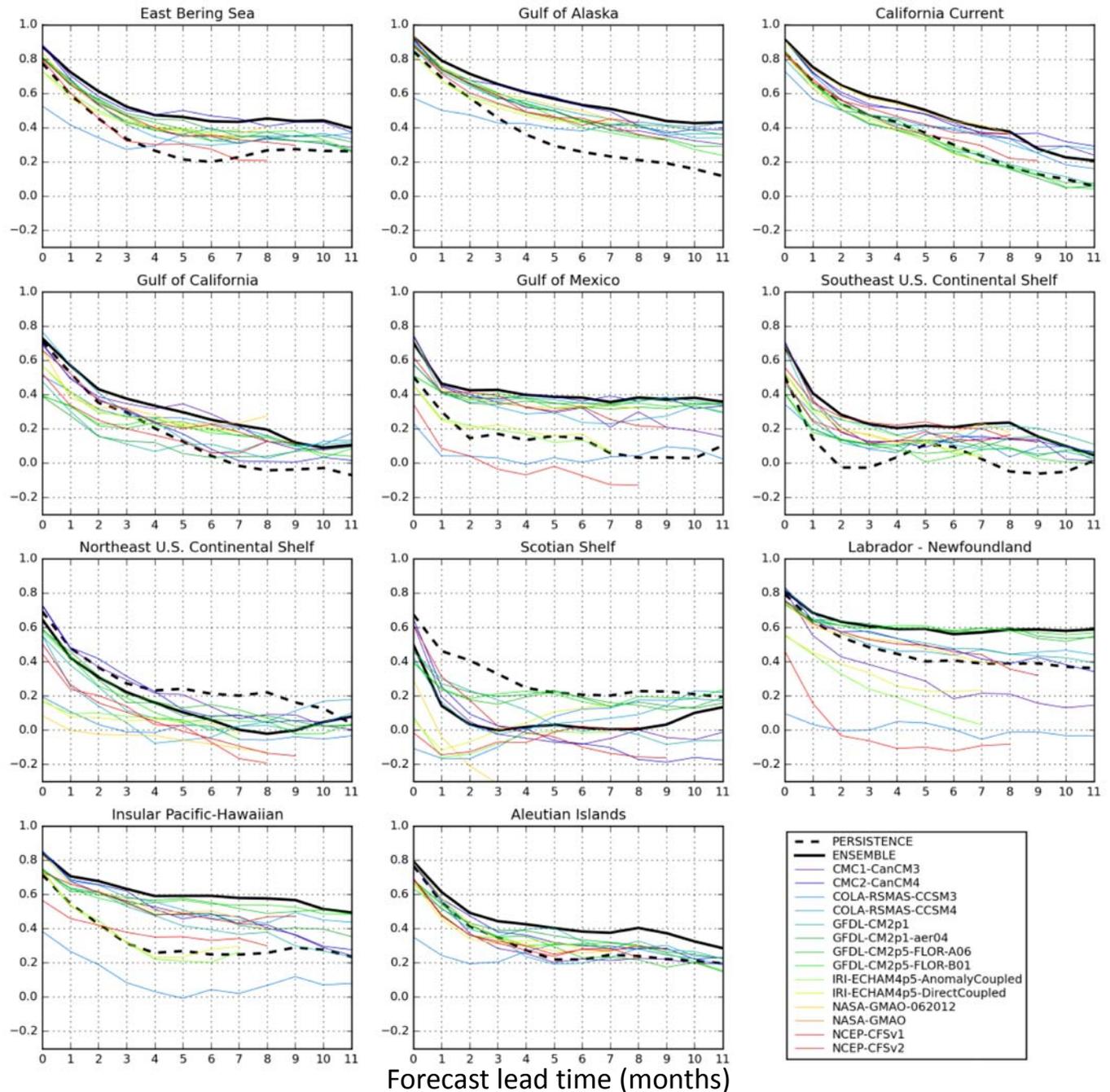


# Anomaly Correlation for CCS



## Anomaly Correlation Coefficient (ACC)

Average of ACCs over all initialized months as a function of forecast lead time for each model, persistence and the multi-model mean.

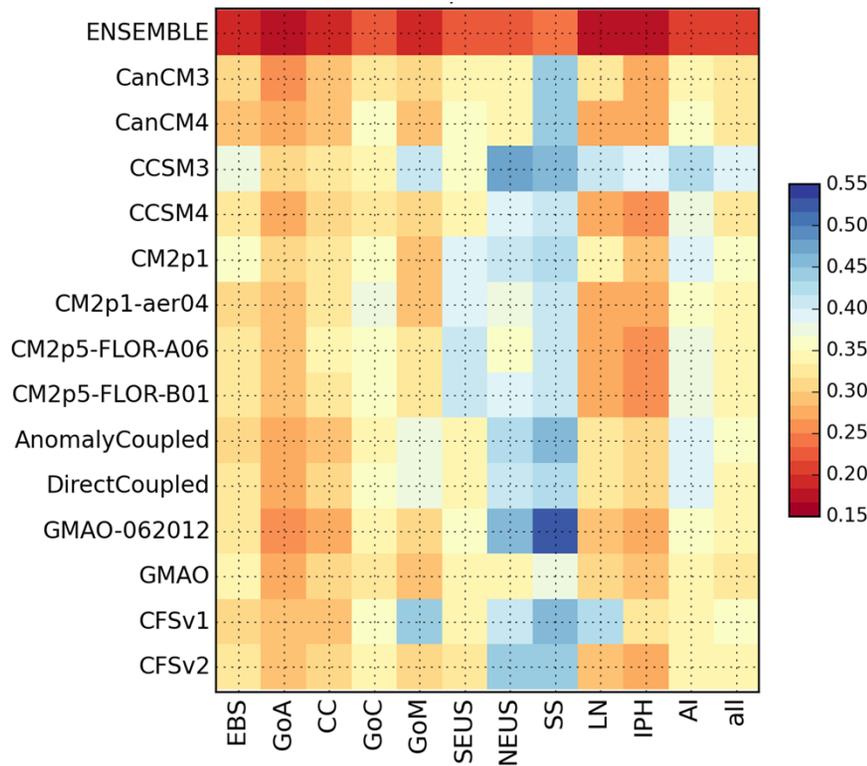




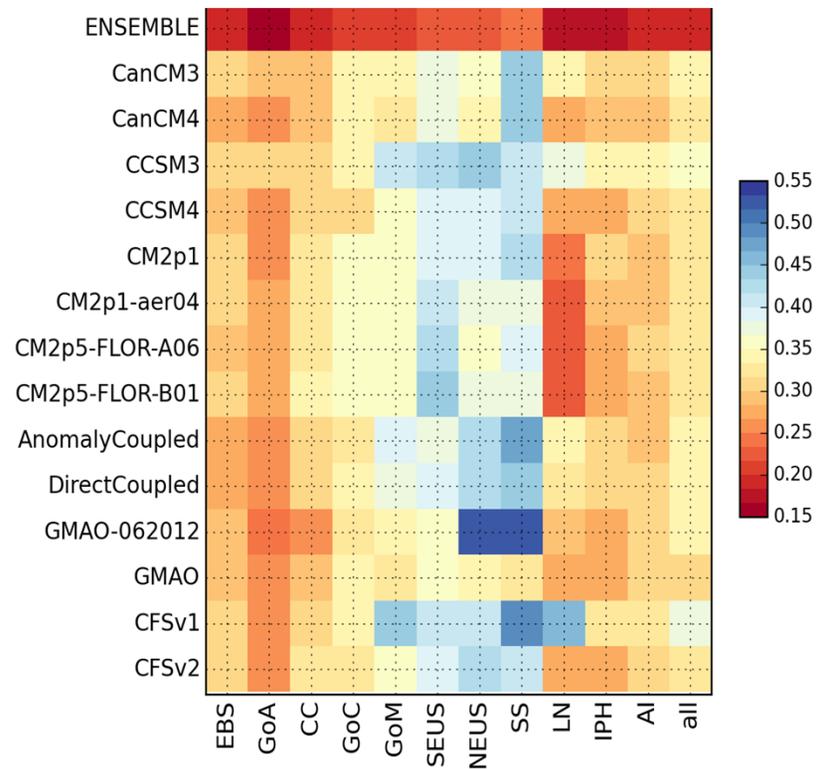
# Probability forecast assessment

Brier score how well do models forecast the probability of an SST anomaly being in the cold (lower), neutral or warm tercile  
Lower score is more skillful

BrS Cold Tercile



BrS Warm Tercile



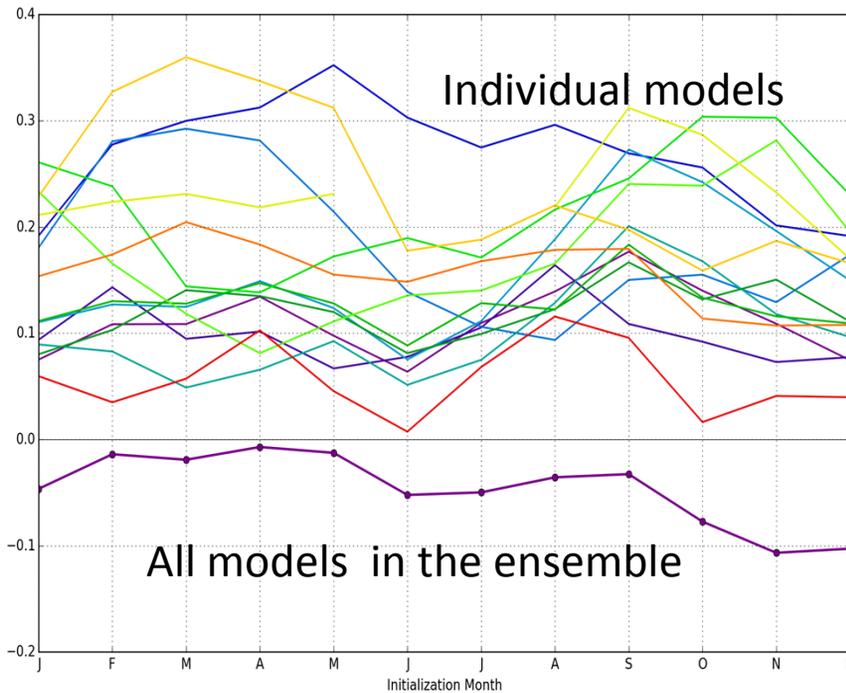
# Brier Score Decomposition

BrS = Reliability + Resolution + Uncertainty

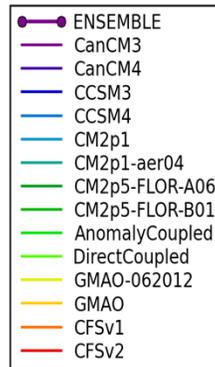
- **Reliability** - how well the a priori predicted probability forecast of an event coincides with the posteriori observed frequency of the event.
- **Resolution** - indicates how well forecasts distinguish situations with distinctly different frequencies of occurrence. In the worst case, when the climatic probability is always forecast, the resolution is zero. In the best case,
- **Uncertainty** - measures the variability of the observations, and is independent of the forecast. It indicates the degree to which situations are easy or difficult to predict.

# Model Spread vs skill

4 MONTH FORECAST  
RMSE – SPREAD (Ideally =0)

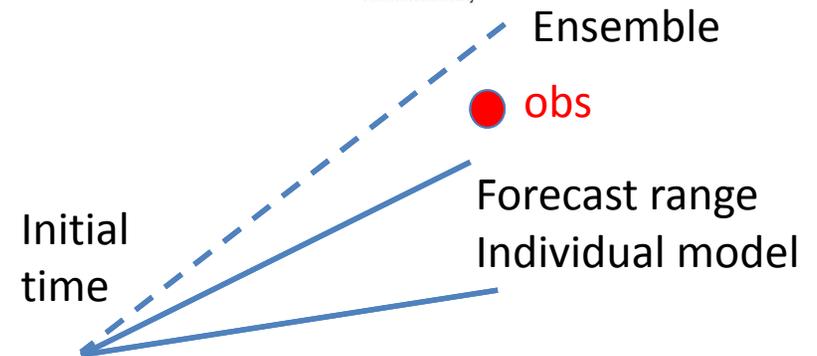
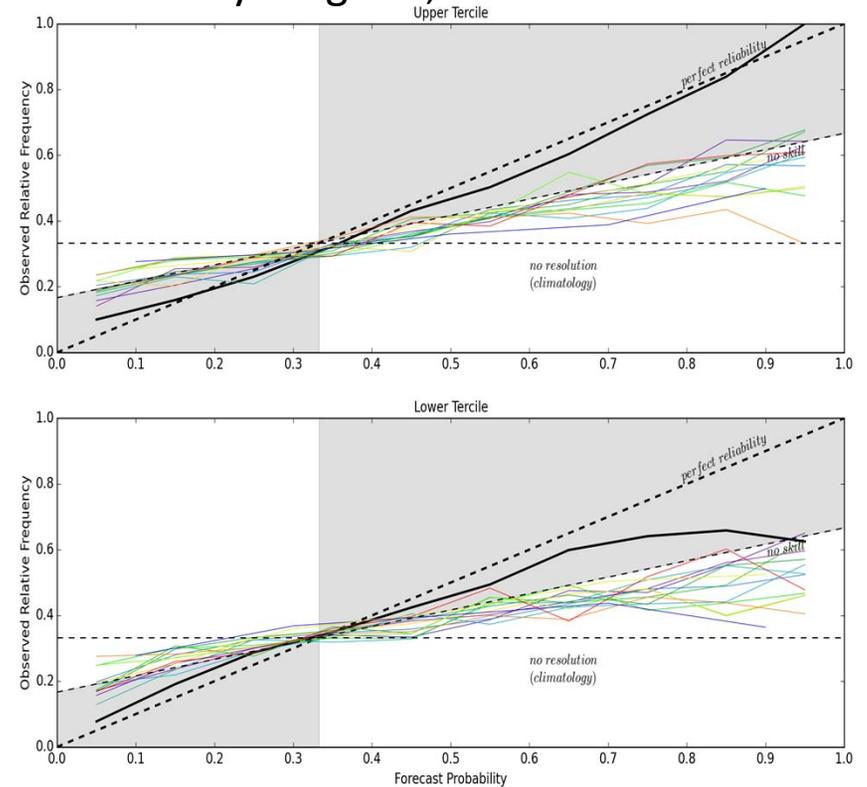


Individual Models  
Spread < RMSE;  
“underdispersive”  
“Overconfident”



Ensemble also improved the Resolution

Reliability Diagram; 4 month forecast

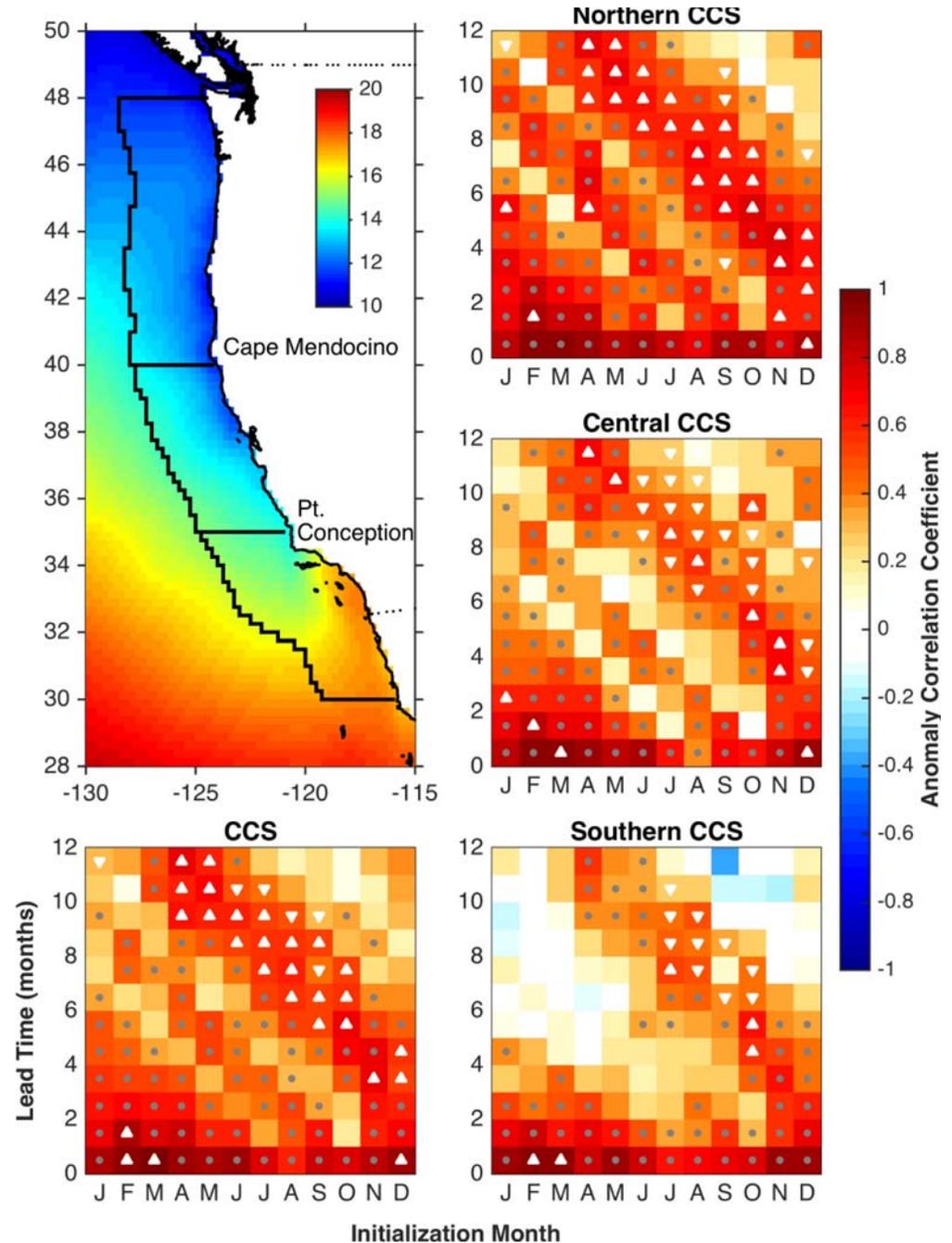


# Hindcast skill (ACC) for 3-sub regions in the California Current LME from CanCM4

Anomaly correlation coefficients:

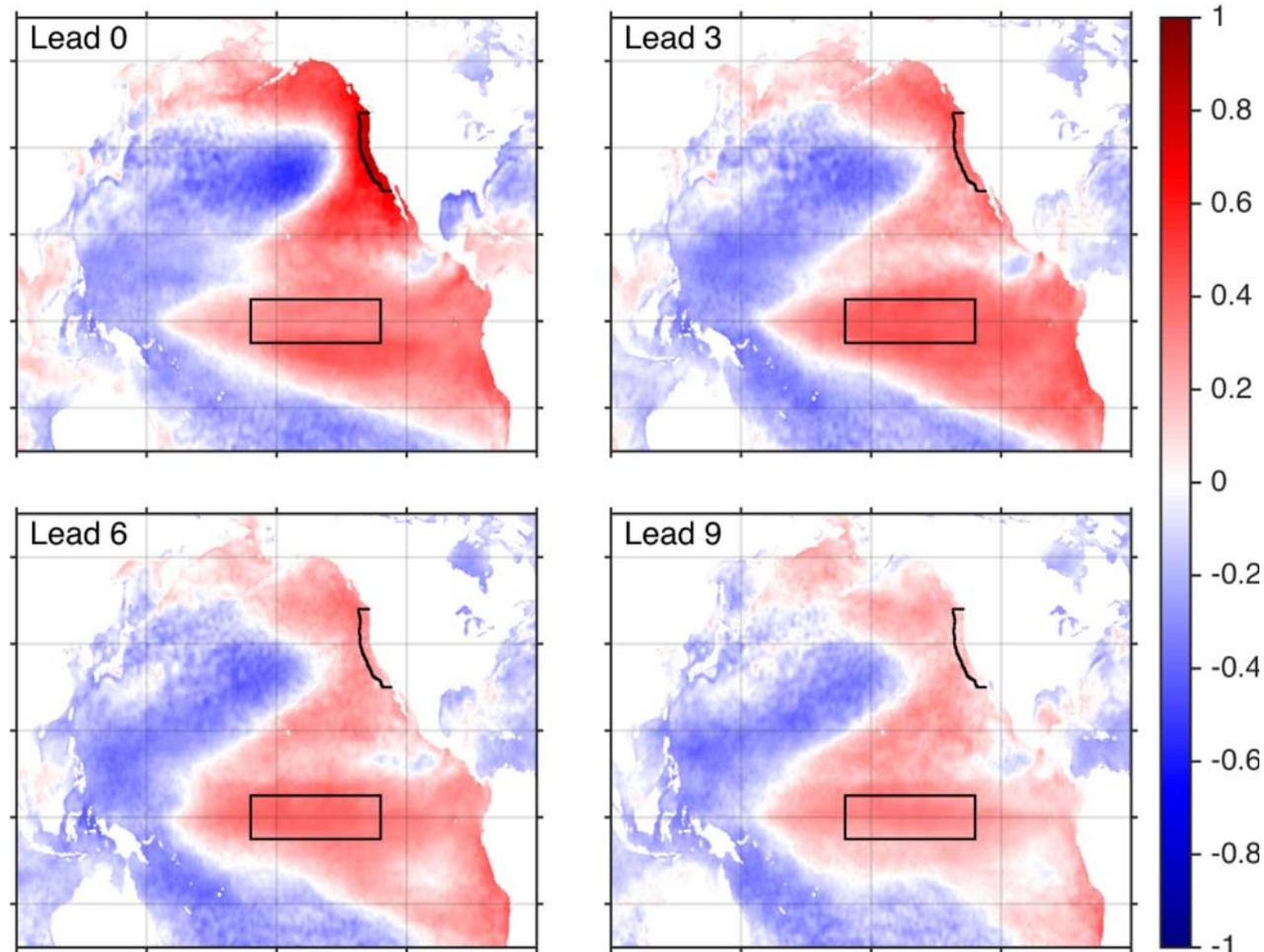
- above 0 at 5% level
- ▲ above persistence at 10% level with ACC > 0.5
- ▼ above persistence at 10% level with ACC < 0.5.

*Jacox et al., Climate Dynamics*



# Processes that influence predictability

## ENSO



Correlation of Pacific basin wide SST with CCS regionally averaged SST 0, 3, 6, and 9 months prior in CanCM4 model

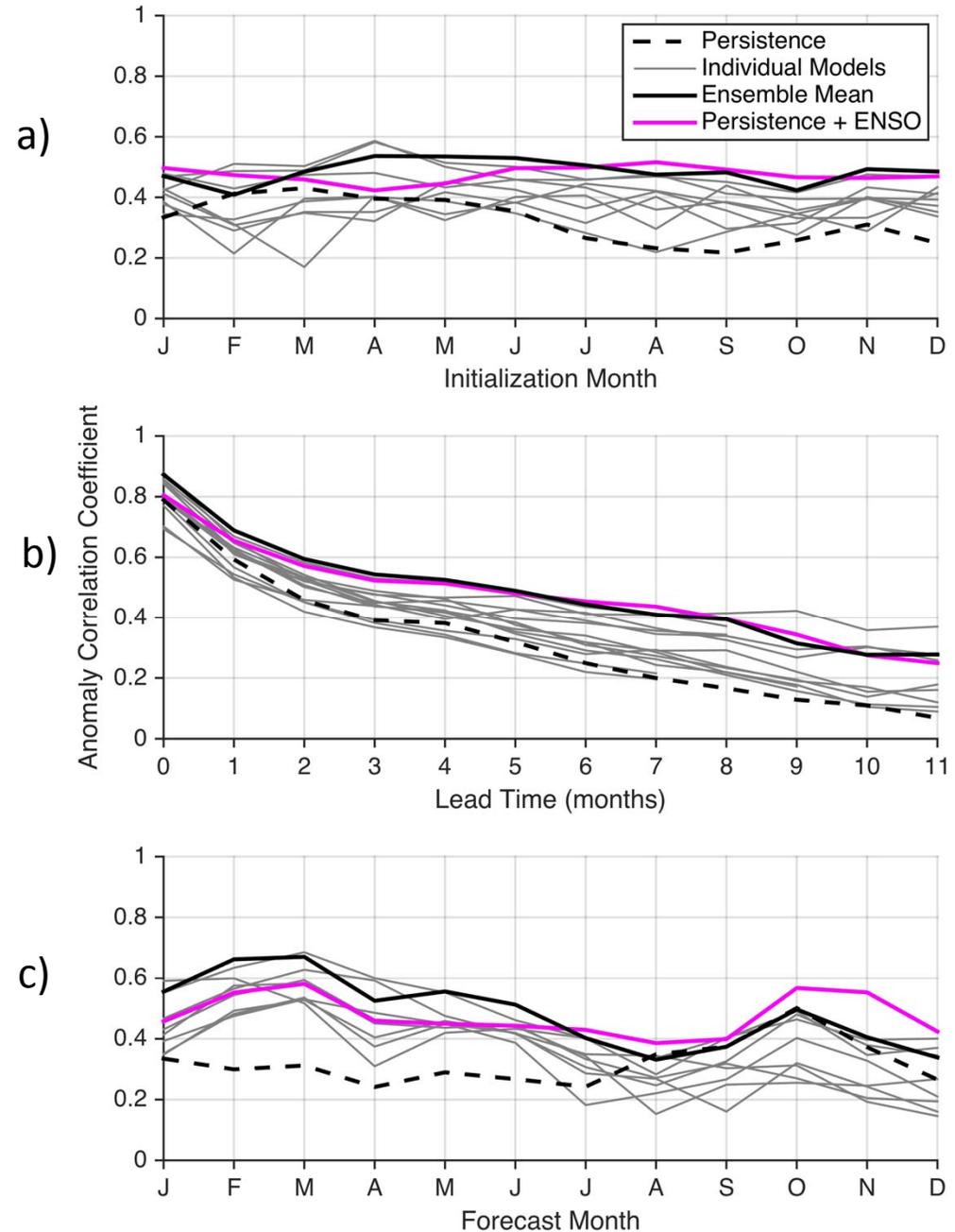
# Forecast Skill in the CC LME for:

a) initialization,

b) lead time

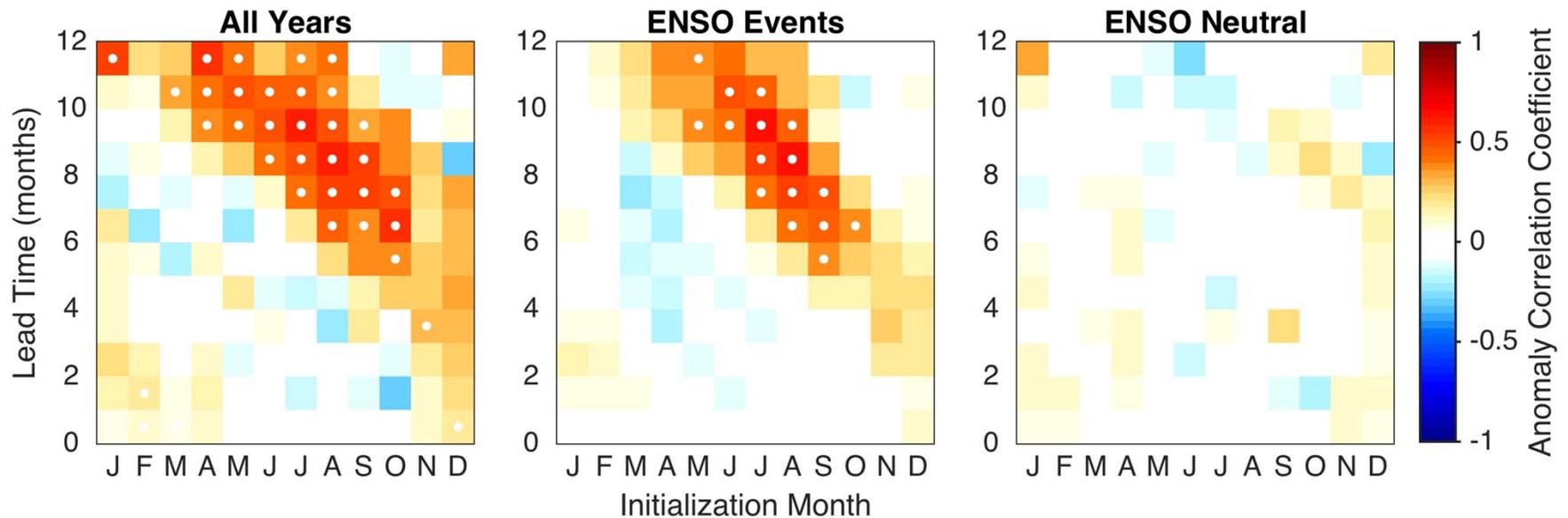
c) forecast month

Persistence + Nino3.4  
forecast from a simple  
multiple linear  
regression model



# Forecast skill above persistence

ACC of dynamical forecast minus ACC of persistence forecast

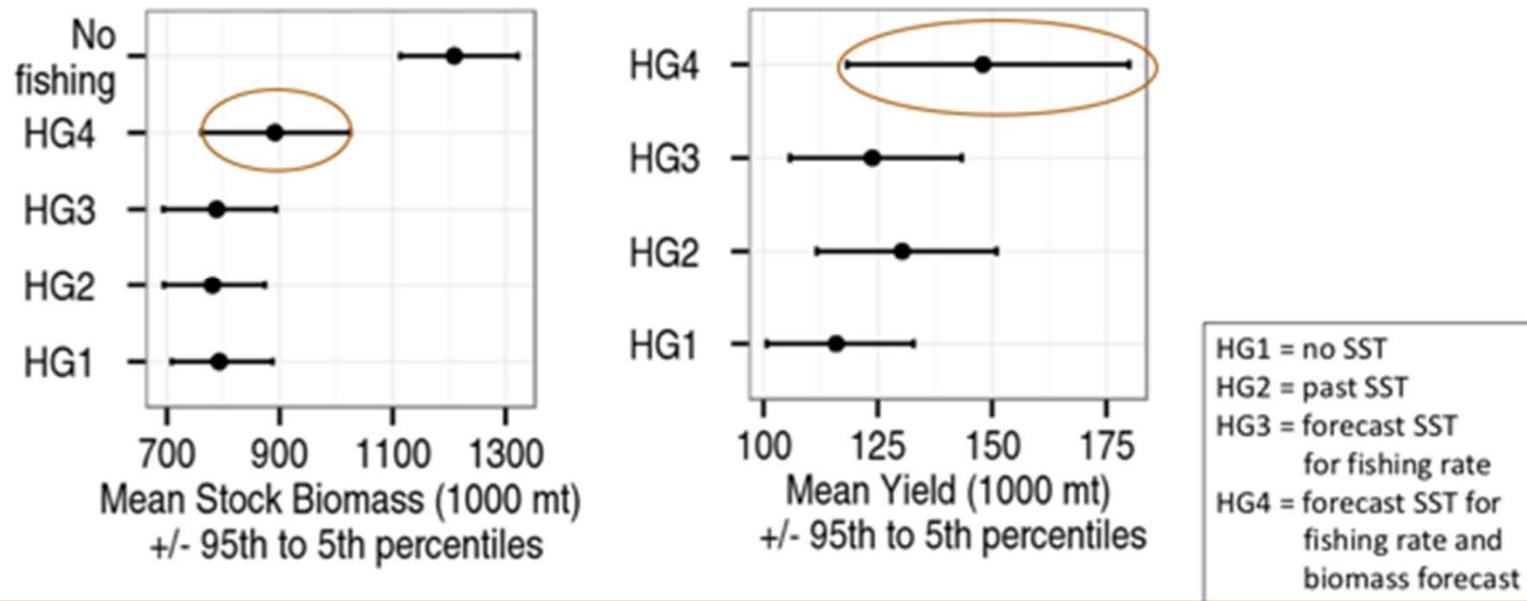


The contribution to skill in CanCM4 above persistence by years that follow a moderate to strong El Niño or La Niña (N=10) and by all other years (N=18) is shown in the *middle* and *right panels*, respectively.

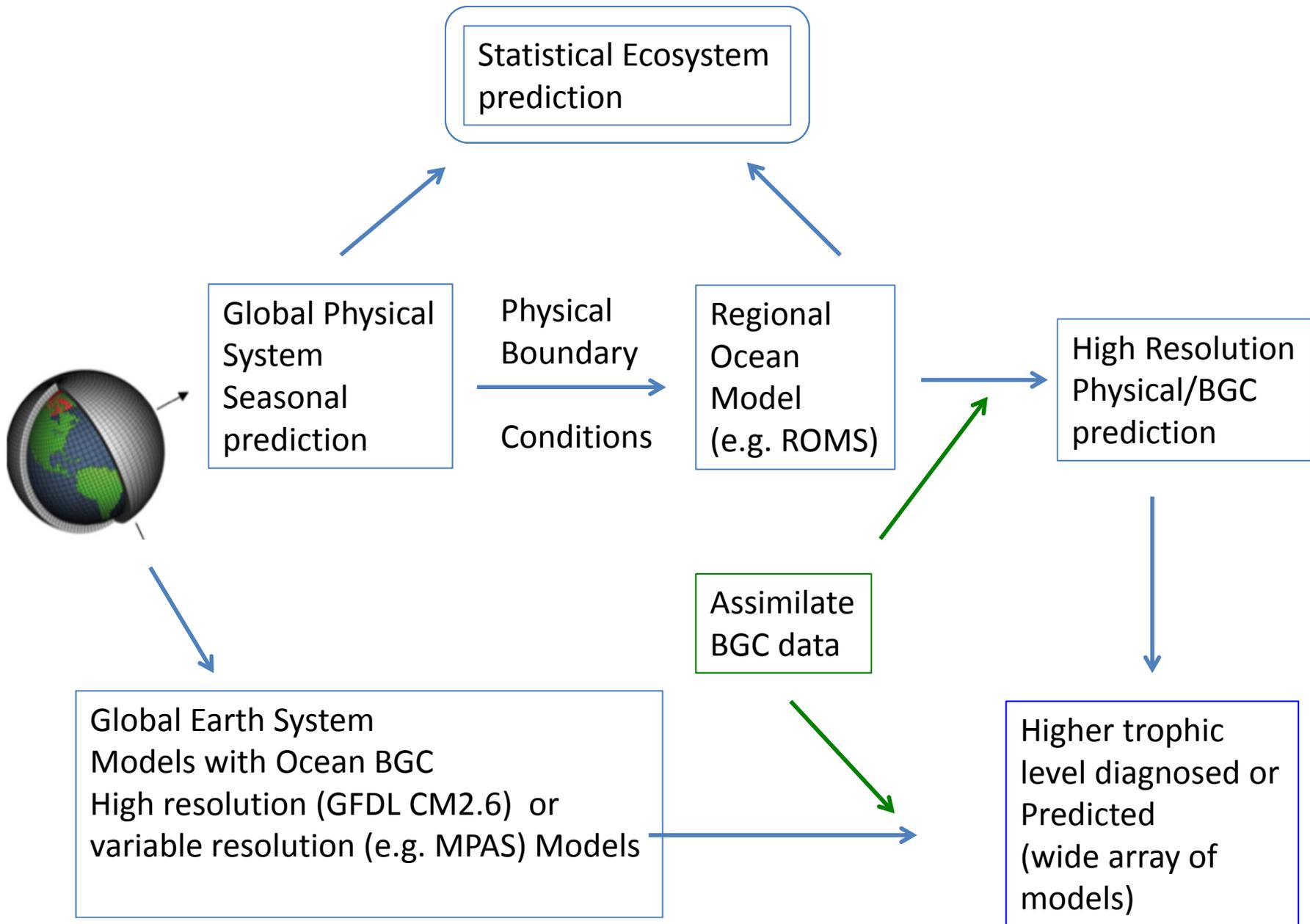
*White dots* indicated significant skill above persistence (95% confidence level).

# Application of SST forecasts to Pacific Sardines

- Sardine population simulated using an age-structured model
  - Recruitment dependent on parents biomass and SST
- Current harvest guideline (HG) dependent on previous year's SST and biomass in CC LME (HG2)
- Use late winter/early spring SST forecast from an NMME model
  - Use in Hg (controls fishing rate) to get predicted biomass (HG3)
- Use the predicted Biomass to inform the following years biomass (HG4)



# Ecosystem Prediction



# Summary

- As a first step explored seasonal SST forecast skill from climate models
- GCMs have skill in predicting SSTs but varies widely by region,
  - Gulf of Alaska & California Current reasonably good
- Skill in LME CC sub-regions
  - Decreases from north to south in the 3 California Current subregions
  - CC Skill mainly from persistence and ENSO
- Multi-model mean generally the best forecast though not necessarily for all regions at all time
  - Increase in skill of ensemble large for probability forecasts
- Steps that are needed to go from large-scale physical model forecasts to fine-scale ecosystem forecasts are discussed

# CPO Supported Publications

- Stock, C., K., Pegion, G. Vecchi, M. Alexander, D. Tommasi, et al., 2015: Seasonal Sea Surface Temperature Anomaly Prediction for Coastal Ecosystems. *Progress in Oceanography*, 137, 219-236.
- Hervieux, G., M. A. Alexander, C. A. Stock, M. G. Jacox, K. Pegion, E. Becker, F. Castruccio, and D. Tommasi. More reliable coastal SST forecasts from the North American Multimodel Ensemble. *Climate Dynamics*. Submitted.
- Jacox, M. G., M. A. Alexander, C. A. Stock, G. Hervieux, 2017. On the Skill of Seasonal Sea Surface Temperature Forecasts in the California Current System and its Connection to ENSO Variability, *Climate Dynamics*, accepted.
- Tommasi, D., Stock, C. A., Pegion, K., Vecchi, G. A., Methot, R. D., Alexander, M. A. and Checkley, D. M. (2017), Improved management of small pelagic fisheries through seasonal climate prediction. *Ecol Appl.* doi:10.1002/eap.1458

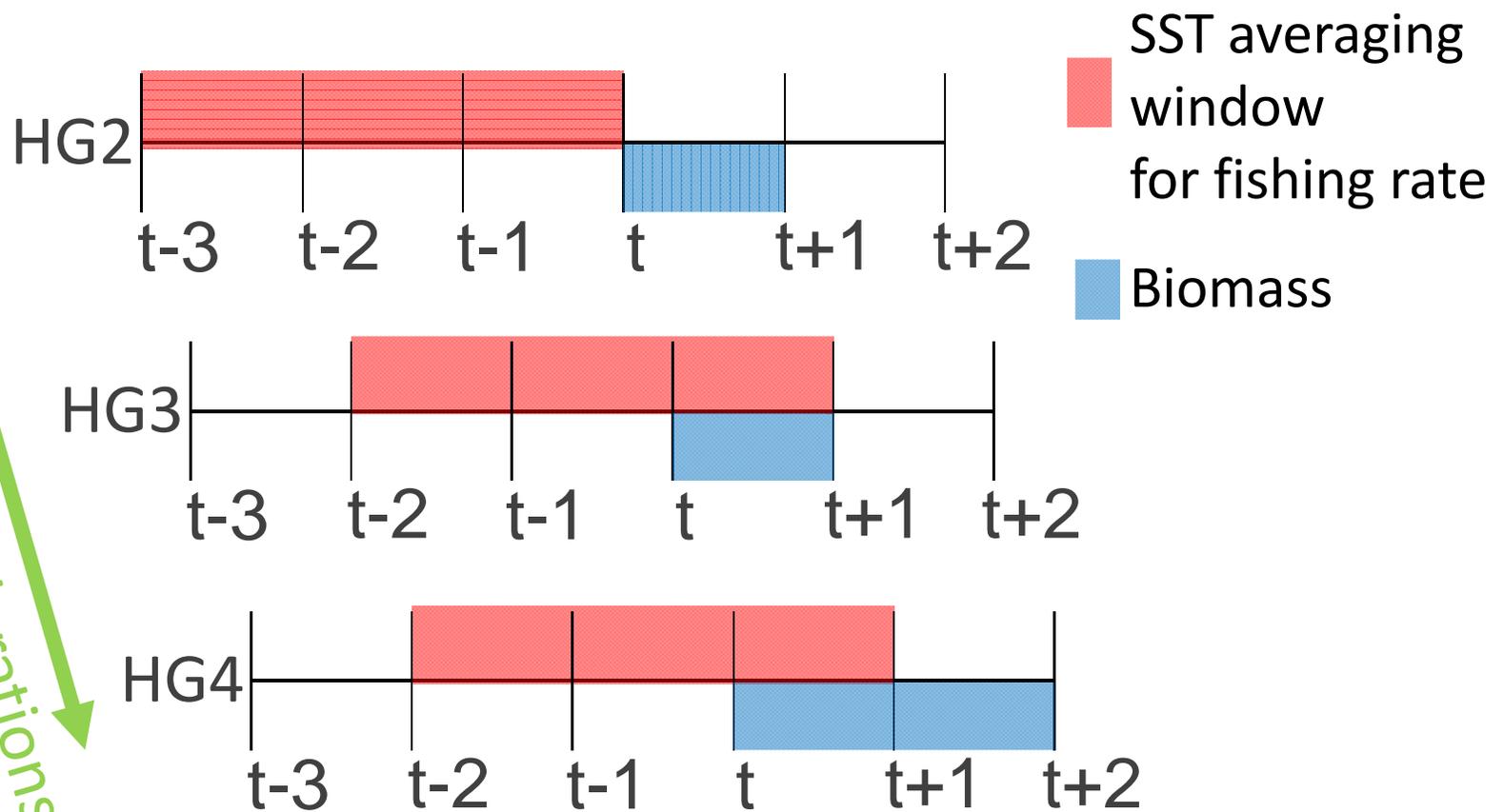
# Application of SST forecasts to Pacific Sardines

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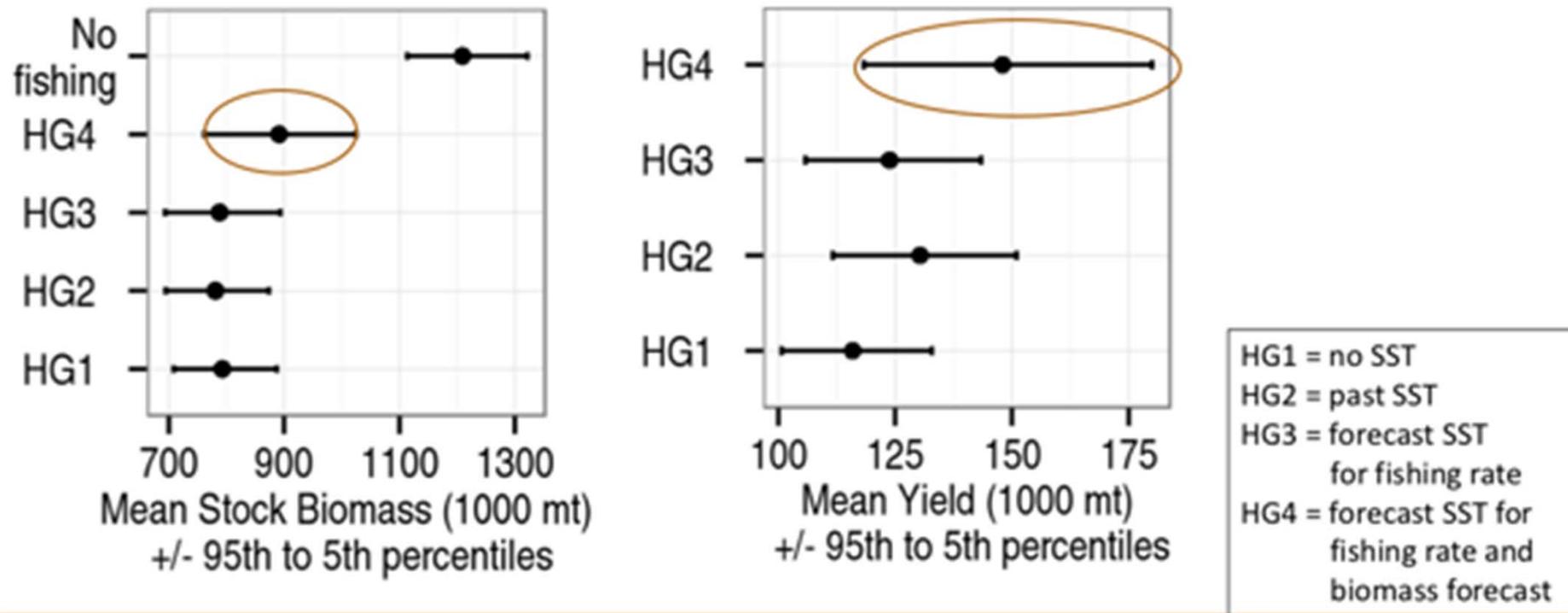
# To test forecast utility, compared effectiveness of four different sardine HGs

HG1 – constant fishing rate of 0.18

Environmental Considerations



# Application of SST forecasts to Pacific Sardines



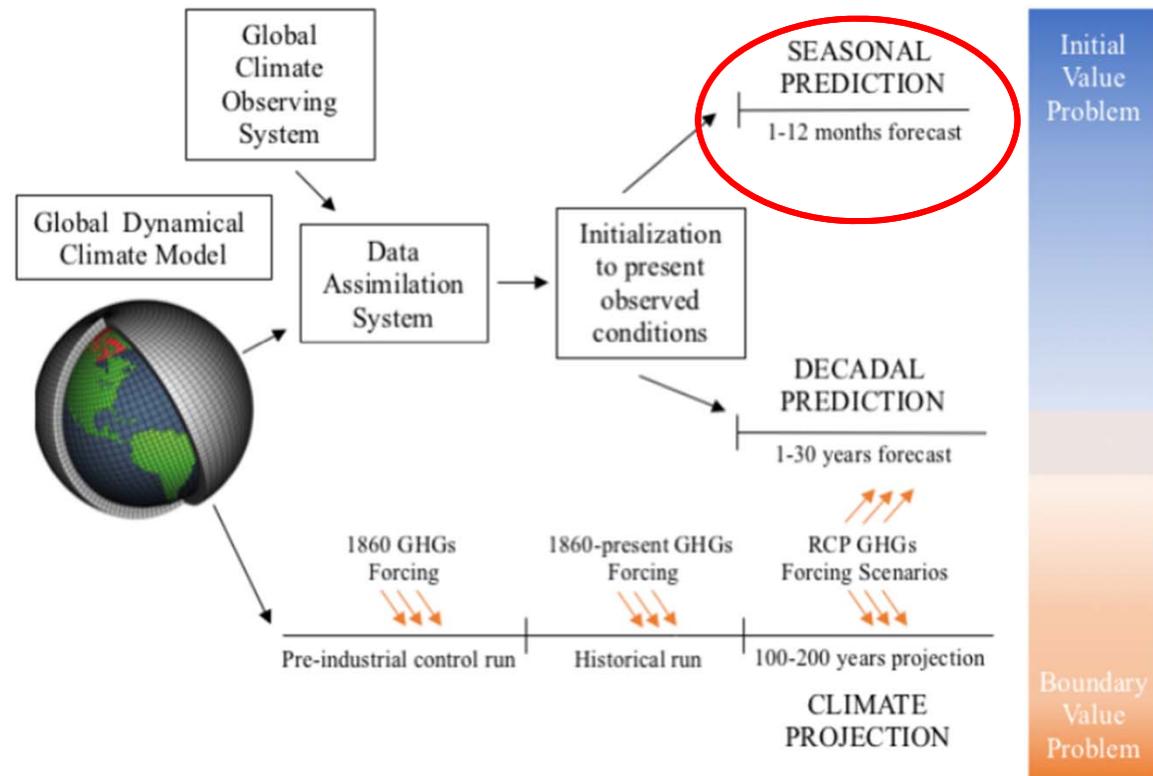
### 3. Providing uncertainty estimates on the forecasts

- Can draw on expertise from the weather forecast community on skill estimates for probability forecasts. Many methods to estimate probability skill
- Using large ensembles from multiple models
- Some data assimilation systems (e.g. ensemble Kalman filters)
- Some statistical prediction methods, e.g. Linear Inverse models (LIMs), provide error estimates and state based estimates of skill.

# Global Climate Models (GCMs)

- Developed to study climate variability and change
- GCM Forecast system developed – mainly to predict ENSO
- Now being used to make seasonal to decadal forecasts of global SSTs and other climate variables

Here we evaluate SST forecast skill of GCMS from the North American Multi-Model Ensemble (NMME) for Large Marine Ecosystems (LMEs) – here: CC, GoA

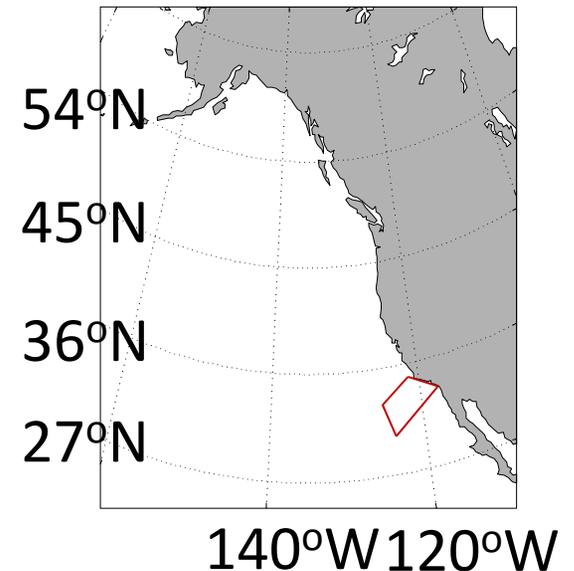


GCM – ocean, atmosphere, land, and sea ice

Figure courtesy of D. Tommasi

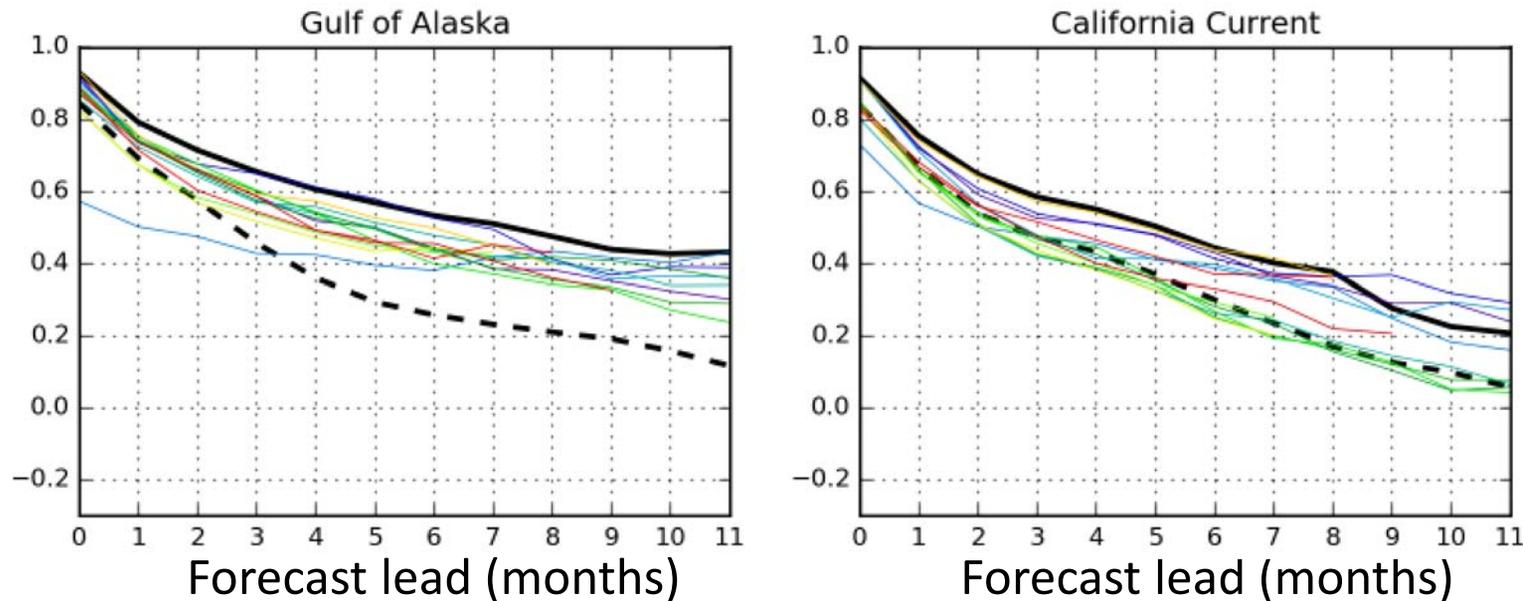
# Application of SST forecasts to Pacific Sardines

- Robust recruitment – spring SST relationship
- Climate variability drives fluctuations in abundance
- Current harvest guideline (HG) dependent on previous year's SST in southern California Current LME

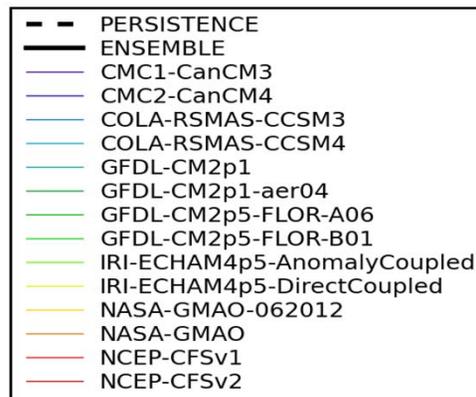


# SST Forecast Skill for the Gulf of Alaska and the California Current LMEs

## Anomaly Correlation Coefficient (ACC)



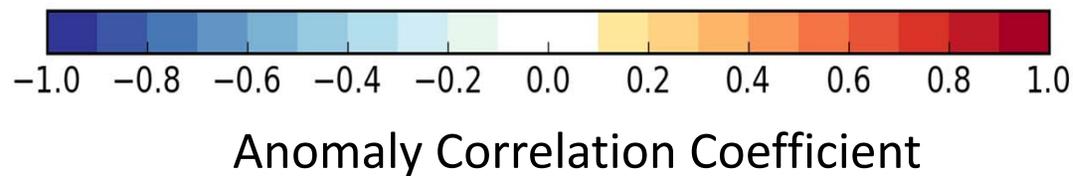
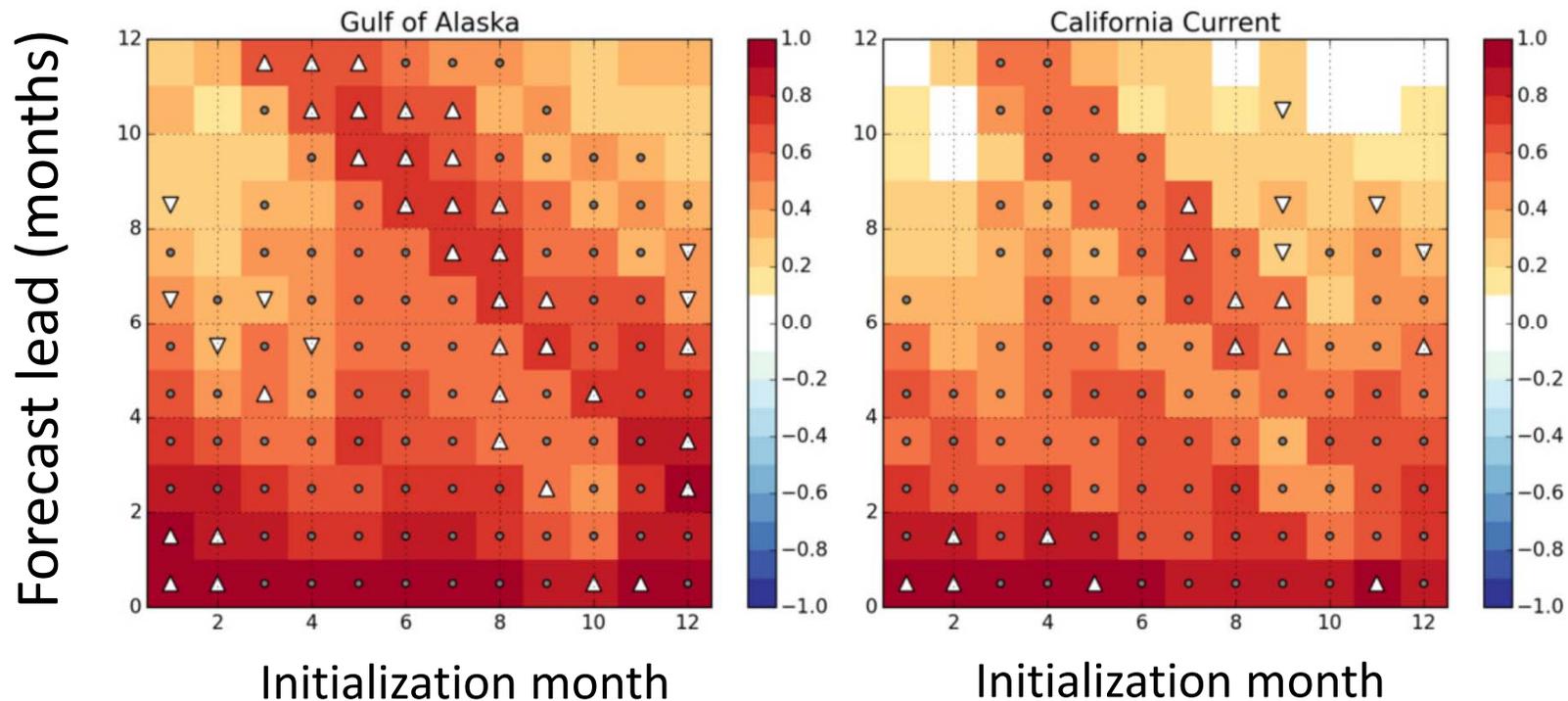
### Prediction system



Average of ACCs over all initialized months as a function of forecast lead time for each model, persistence and the multi-model mean.

# NMME Ensemble SST Forecast Skill

## Gulf of Alaska and the California Current LMEs



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.