2019 PICES Annual Meeting

An evaluation of the short-term prediction skill of FIO-ESM in the North Pacific

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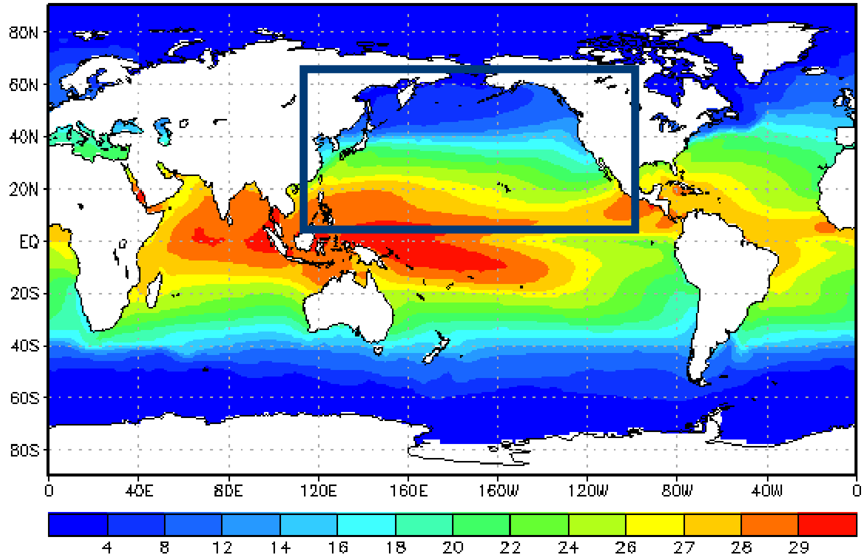
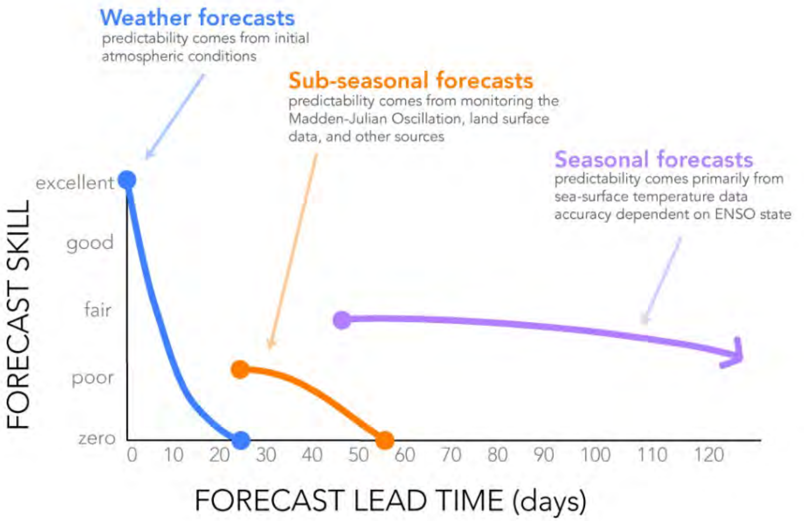
Content

1. Background

Sea Surface Temperature





- North Pacific SST can strongly influence ENSO, and modulate the weather and climate over the North America, Canada and East Asia on the different time scale.
- Accurate predictions of SST, as well as precipitation, are crucial for social management and disaster prevention.

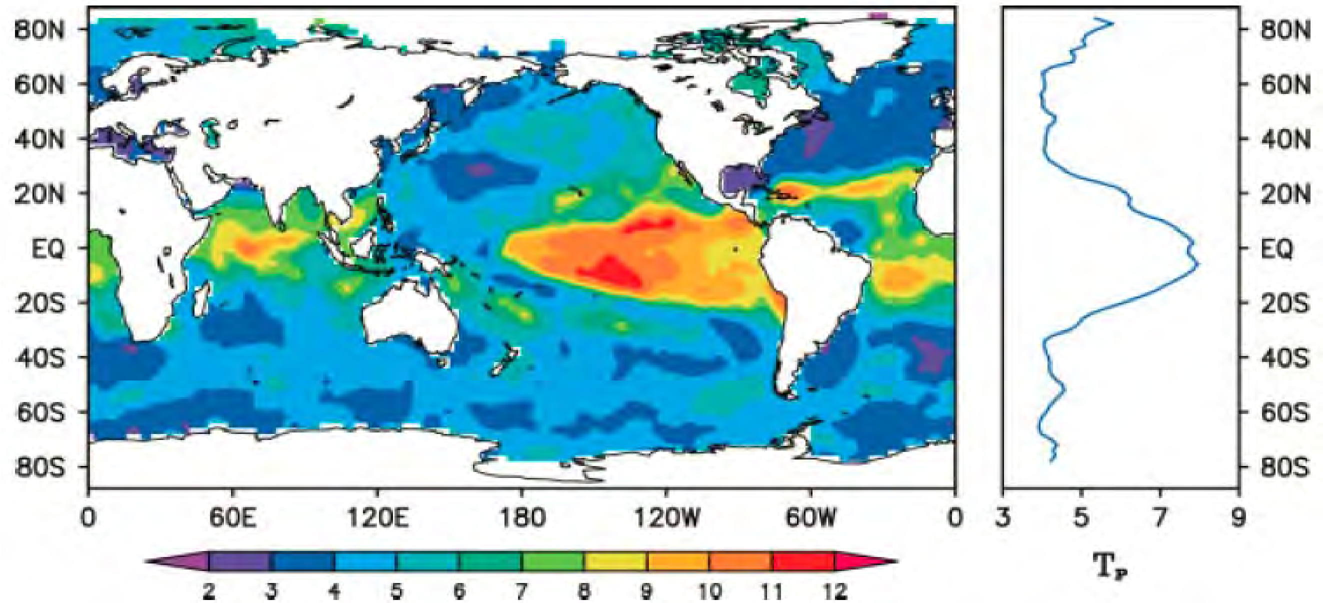
1. Background

North Pacific seasonal forecast

Model	Time	Method	Prediction ability	References
canonical correlation analysis (CCA) model	1982-2000	Linear statistical method	Not include the effects of Pacific SST on climate system, The ability to predict extreme event is low	Landman&Mason (2001)
linear inverse model (LIM)	1951-2000	Linear statistical method		Alexander et al. (2008)
"two tier" model	1998-2002	Two tier method	Not include air-sea interaction processes	Auad et al. (2004)
CCCma-CHFP2	1979-2008	Air-land-sea coupled	more comprehensive physical processes, reasonably reflect the sea-air boundary conditions	Lienert (2011)
NCEP-CFSv1	1981-2006	Air-land-sea coupled		Wen et al. (2012)
NCEP-CFSv2	1982-2010	Air-land-sea-ice coupled		Hu et al. (2014)

1. Background

SSTA Predictable period



(Li and Ding, 2013)

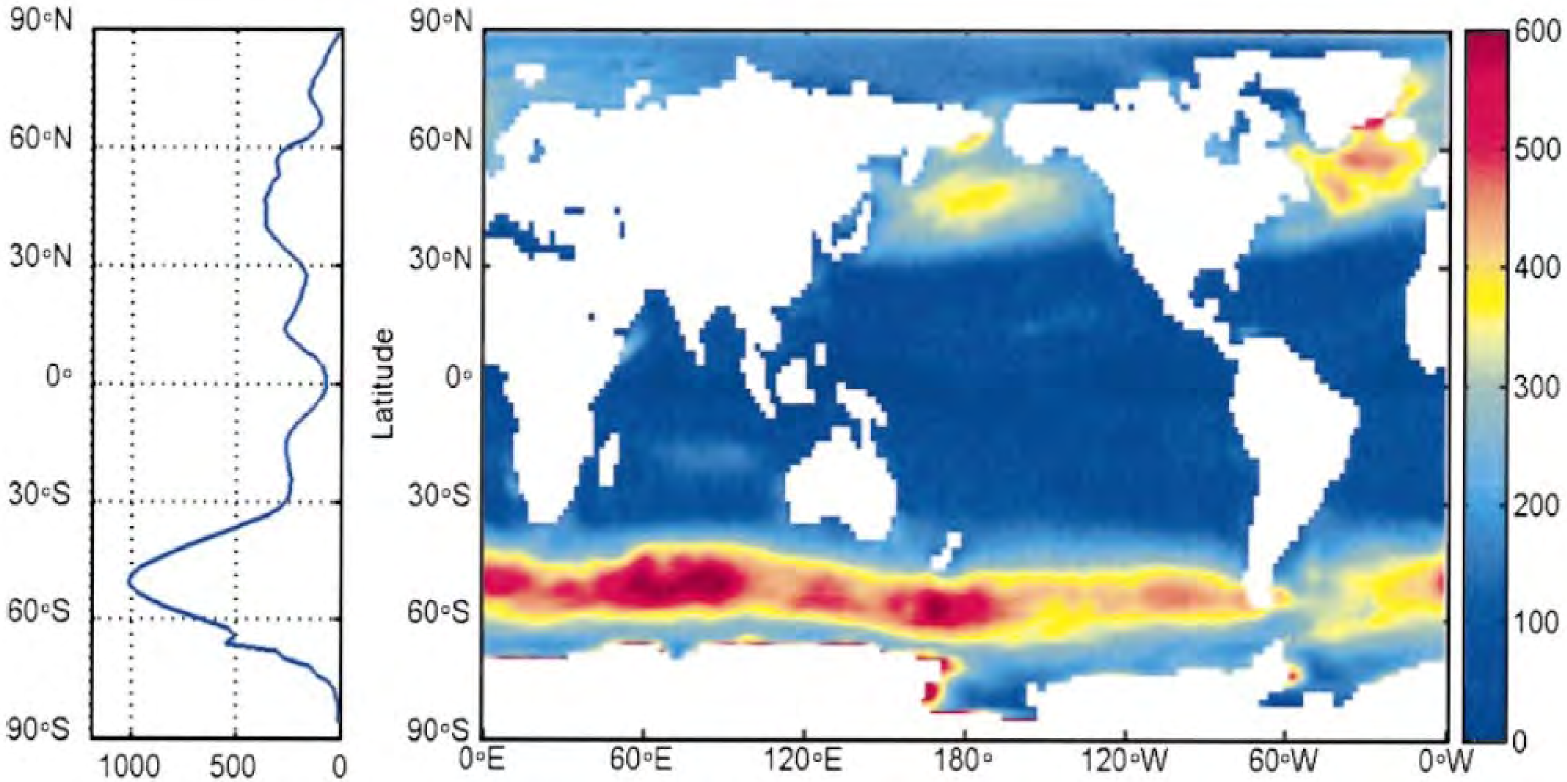
To make accurate prediction

- **High-quality of ocean observation data**
- **Initialize method improvement**
- **Improve physical processes in climate model**

1. Background

Ocean wave effect

Surface wave energy input



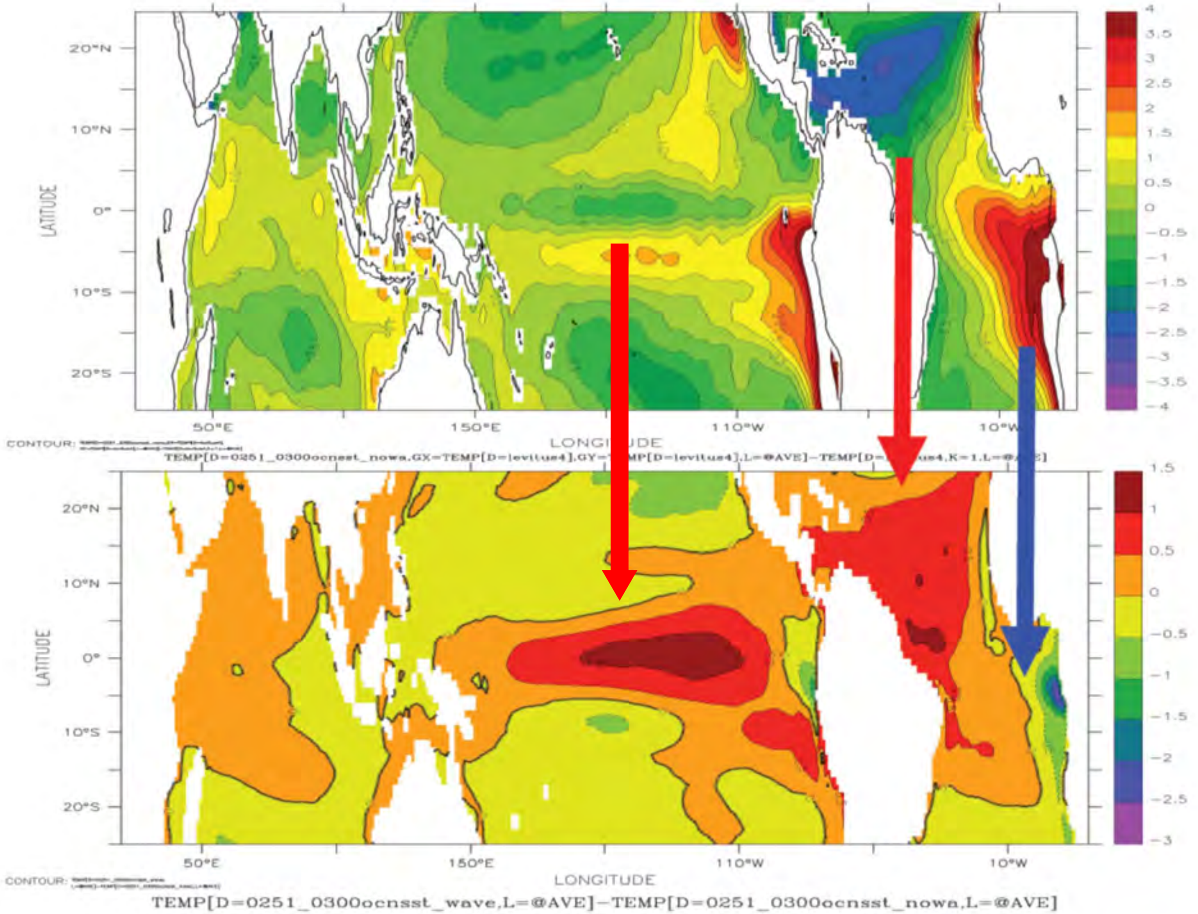
Ocean wave maintain the global mechanical energy balance, it play an important role in the climate system.

(Wang and Huang, 2004)

1. Background

Wave process

The “too cold tongue” SST biases in the eastern tropical Pacific and the reversed equatorial SST gradient in the Atlantic can be improved by including the wave-induced mixing.



50a averaged SST (251-300a).

Up: Exp1-Levitus, Down: Exp2-Exp1

Exp1: CCSM3 without Bv

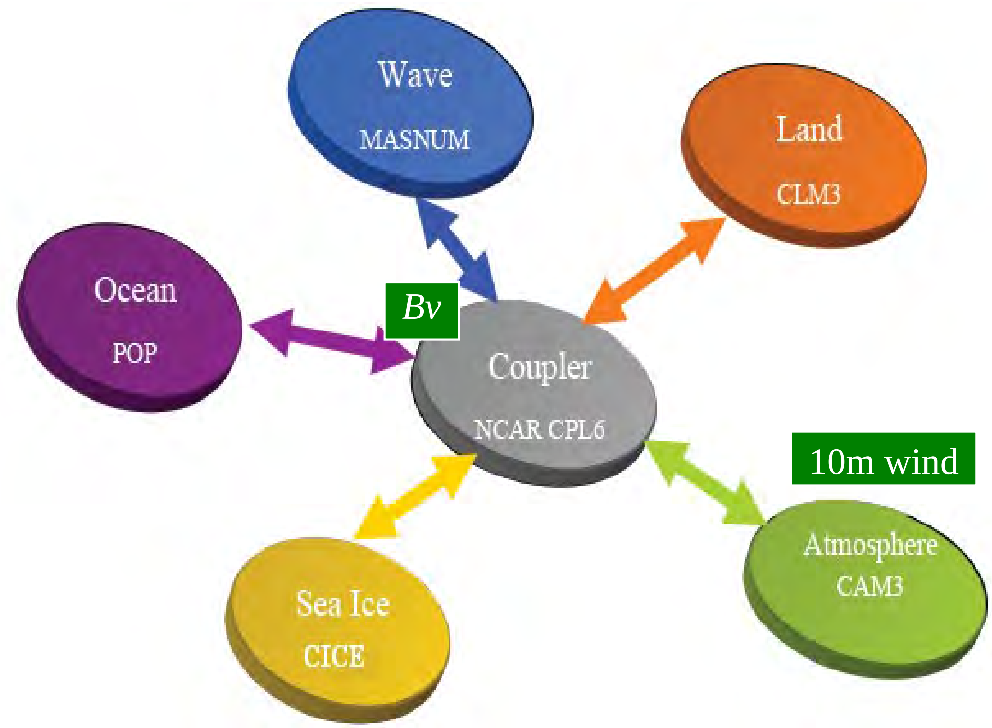
Exp2: with Bv

(Song et al., 2012, J. Geophys. Res.)

Content

2. Model and assimilation method

FIO-ESM



●ATM	: CAM3.5	T42, L26
●LAND	: CLM3	T42
●OCEAN	: POP2	1.1°×0.3~0.5°, L40
●ICE	: CICE4	1.1°×0.3~0.5°
●WAVE	: MASNUM	2°×2°

(Qiao et al., 2013, J. Geophys. Res.)

$$Bv = \alpha \iint_{\vec{k}} E(\vec{k}) \exp(2kz) d\vec{k} \frac{\partial}{\partial z} \left[\iint_{\vec{k}} \omega^2 E(\vec{k}) \exp(2kz) d\vec{k} \right]^{1/2}$$

(Qiao et al., 2004)

2. Model and assimilation method

Satellite Observations

Assimilation data

1 SLA (Sea Level Anomalies) daily data

- AVISO (Archivage, Validation et Interpretation des donnes des Satellite Oceanographiques)
- Horizontal resolution: 1/3° ×1/3°

2 SST daily data

- NOAA/National Climate Data Center
- Horizontal resolution: 1/4° × 1/4°

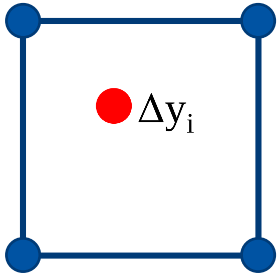
2. Model and assimilation method

assimilation method Ensemble Adjusted Kalman Filter (EAKF)

1. Use observation to calculate the model adjustment at observation points

$$\Delta y_i = \left[\left(\frac{\overline{y}^m}{1+r^2} + \frac{y^o}{1+r^{-2}} \right) + \left(\frac{y_i^m - \overline{y}^m}{\sqrt{1+r^2}} \right) \right] - y_i^m$$

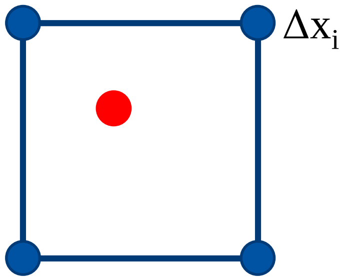
$$r = \frac{\sigma_y^m}{\sigma^o}$$



2. Calculate the corresponding adjustment of variables at each model grid point

$$x_i^a = x_i^m + \frac{c_{xy}^m}{\left(\sigma_y^m\right)^2} \cdot \Delta y_i$$

$$c_{xy}^m = \frac{1}{N} \sum_{i=1}^{N} \left(x_i^m - \overline{x}^m \right) \cdot \left(y_i^m - \overline{y}^m \right)$$



Experiment

Experiment	time	ensemble	Prediction start	Prediction period
assimilation	1993-2019	10	×	×
hindcase	1993-2019	10	Every month	6 month

OBS data:

SST： AVHRR

Temp： EN4

Precipitation： GPCP

$$\text{RMSE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(S_t - O_t\right)^2}$$

S: simulation

O: obs

$$ACC_{i,j} = \frac{\text{cov}(S_t, O_t)}{\sigma_S \sigma_O}$$

cov(St,Ot) :covariance of model prediction and obs anomaly

σ : standard deviation of SST anomaly

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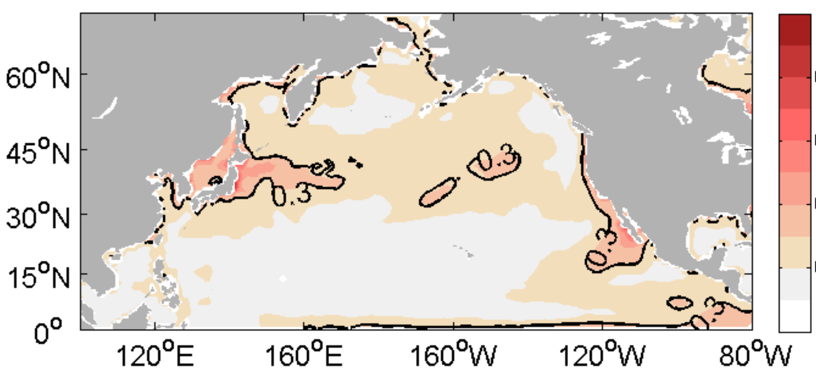
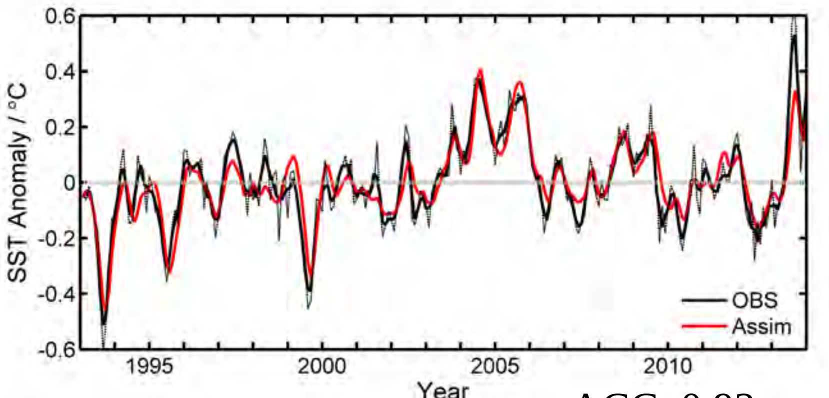
3. Results evaluation

Assimilation results

RMSE of SSTA

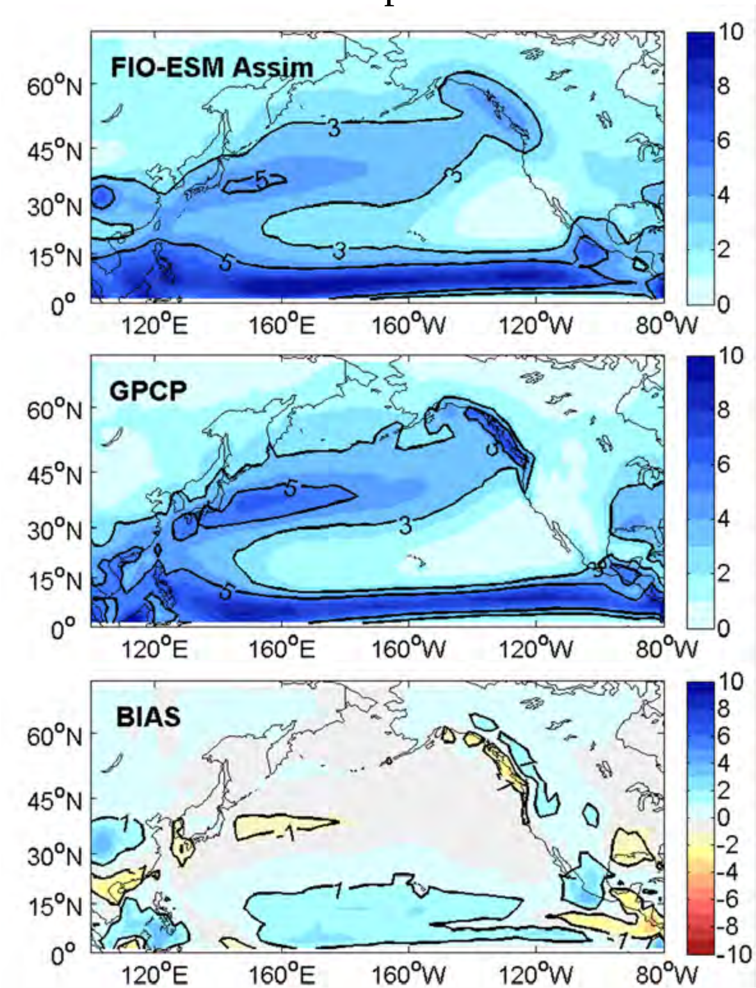


Time series of SSTA



ACC: 0.92
RMSE:0.058°C

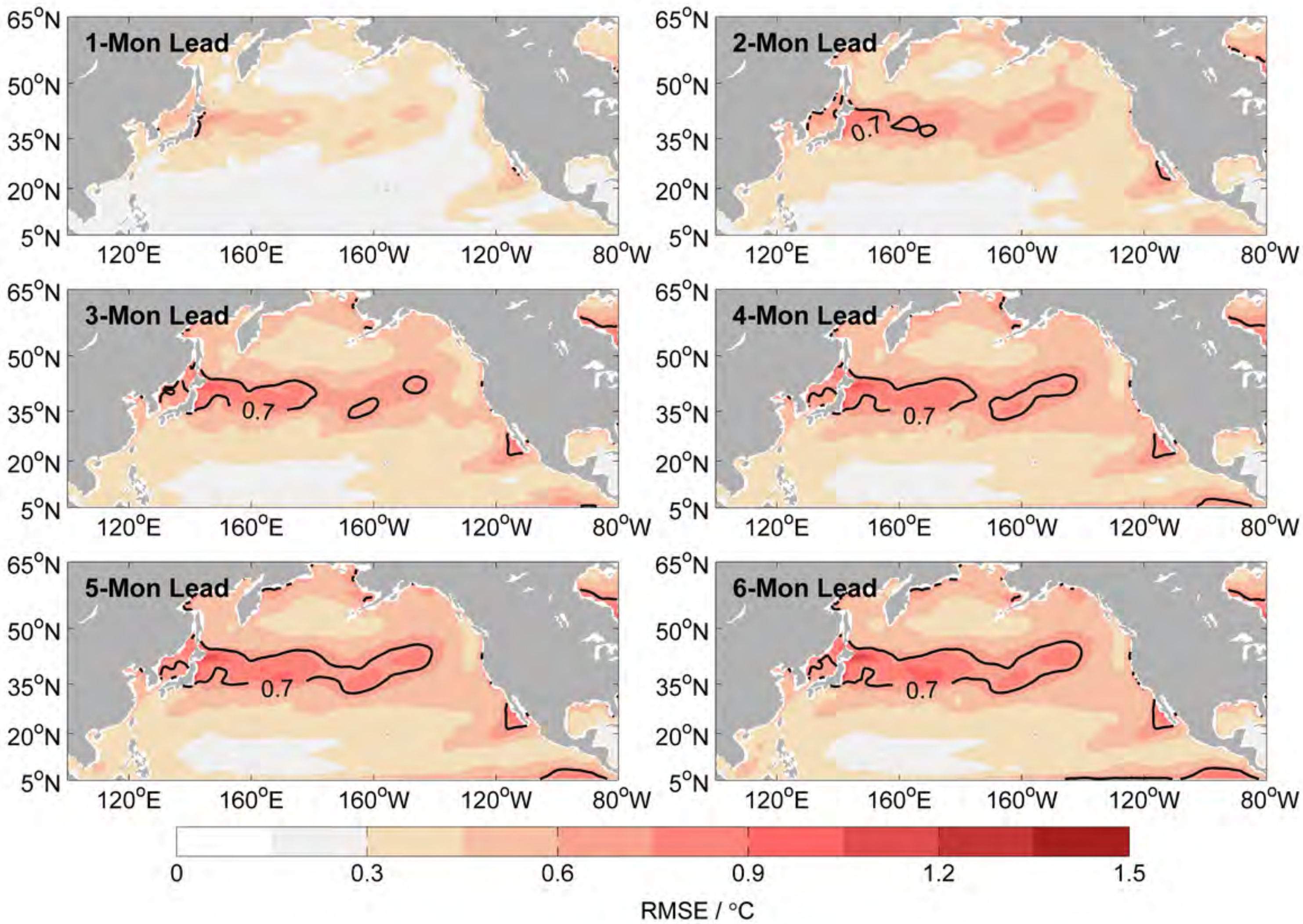
Precipitation



3. Results evaluation

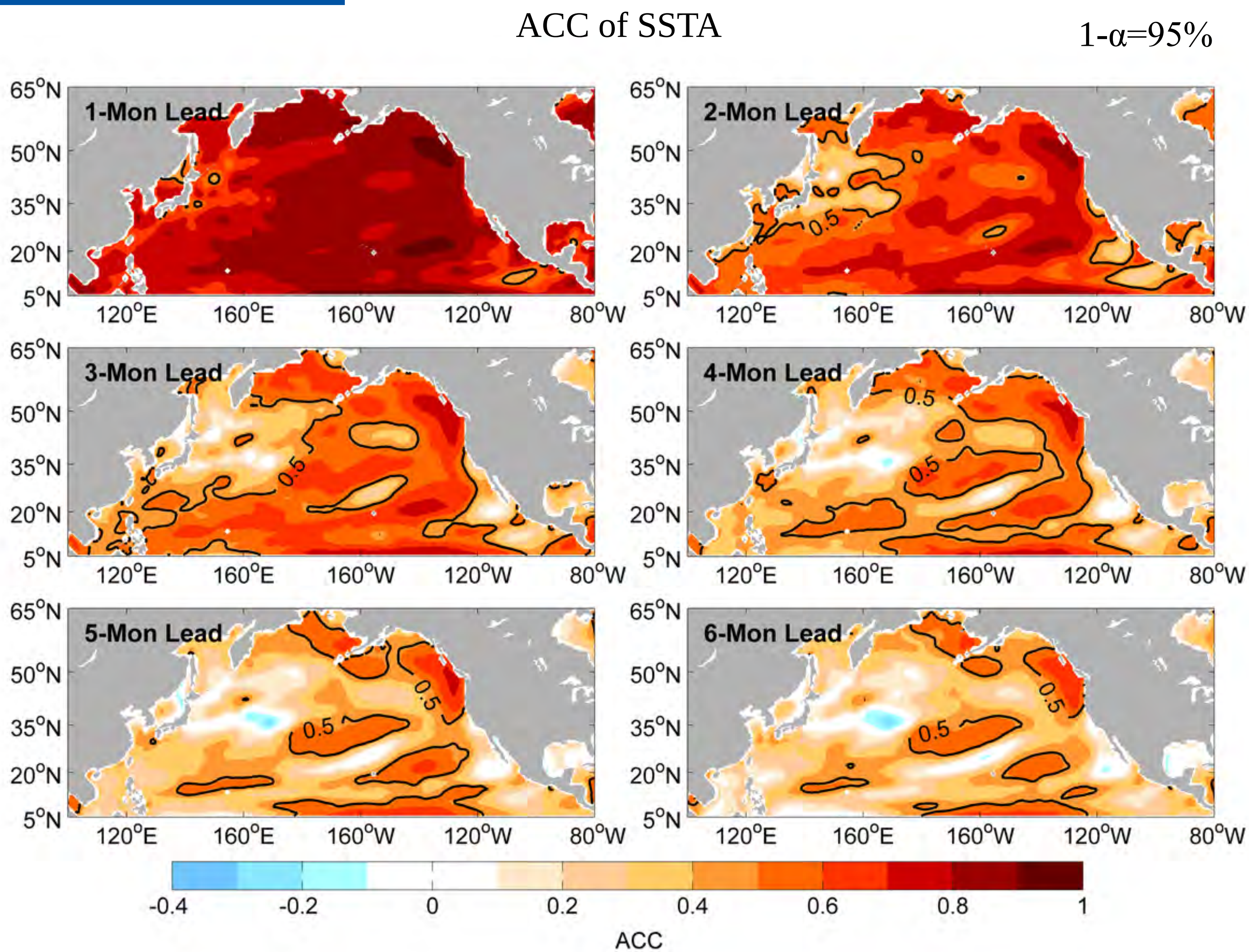
SST prediction skills

RMSE of SSTA



3. Results evaluation

SST prediction skills



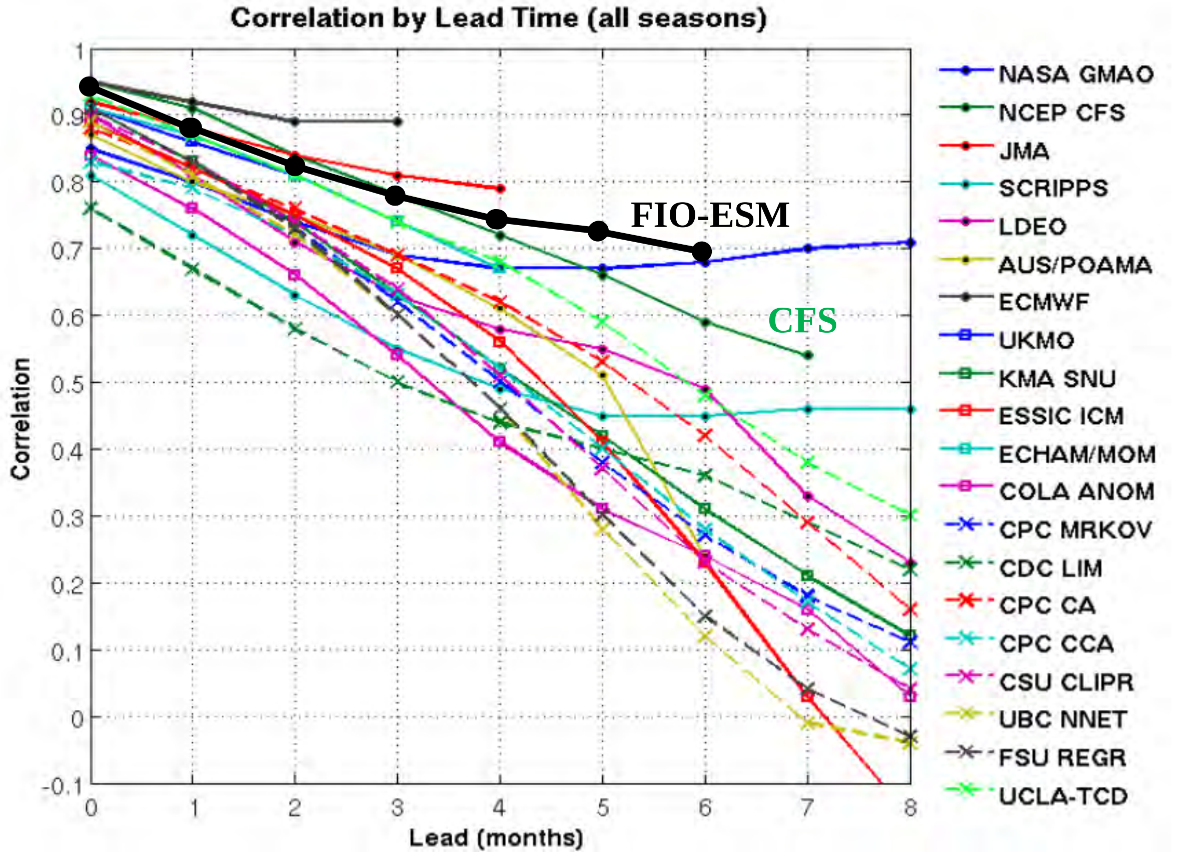
3. Results evaluation

SST prediction skills

CFSv2:

- Air-land-ice-ocean coupled
- Operational system of the North American
- With best performance in NMME（North American Multi-Model Ensemble）

Skills of different models in Nino3.4 prediction



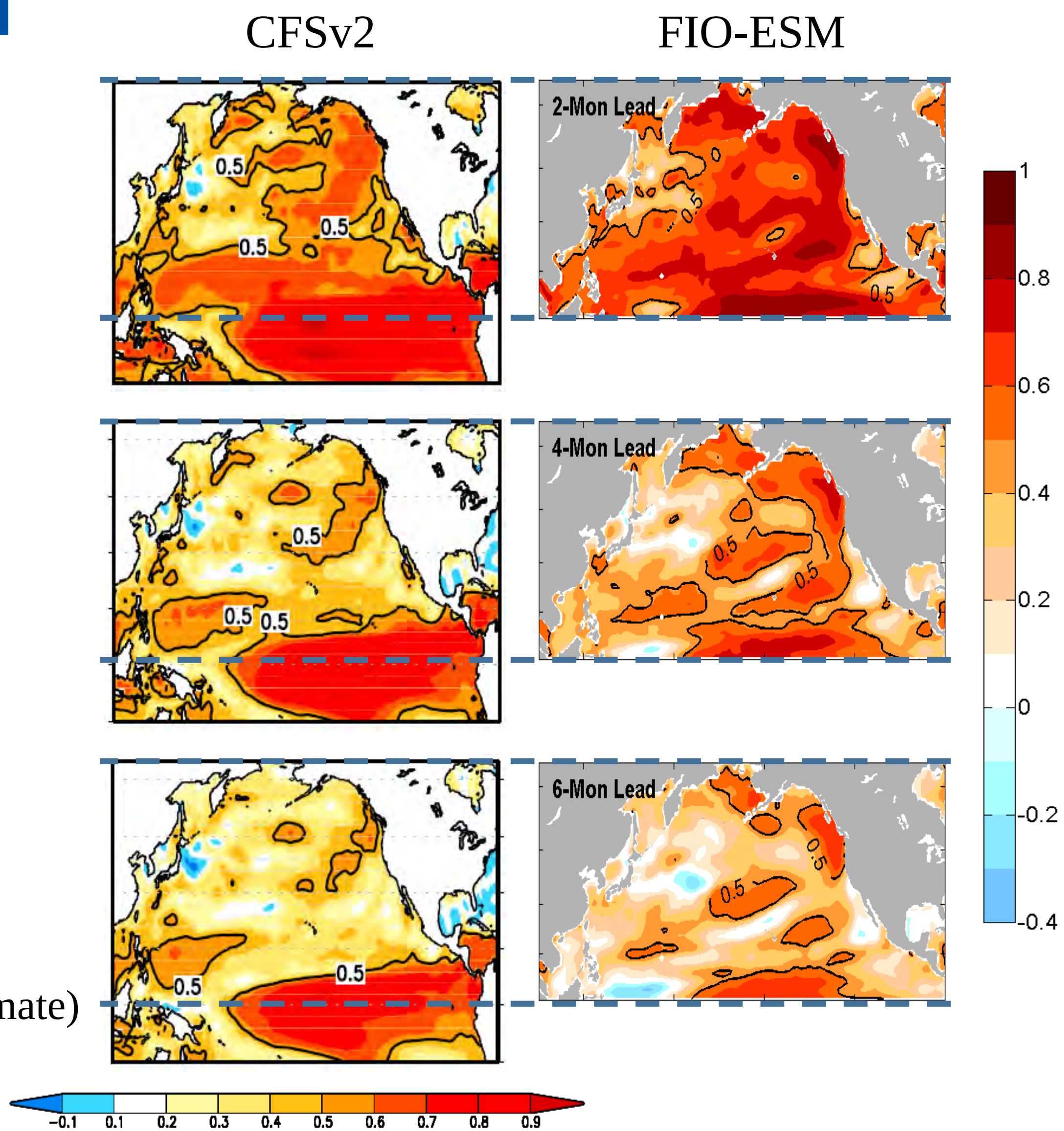
(Barnston et al., 2012)

3. Results evaluation

SST prediction skills

CFSv2:

- Air-land-ice-ocean coupled
- Operational system of the North American
- With best performance in NMME（North American Multi-Model Ensemble）



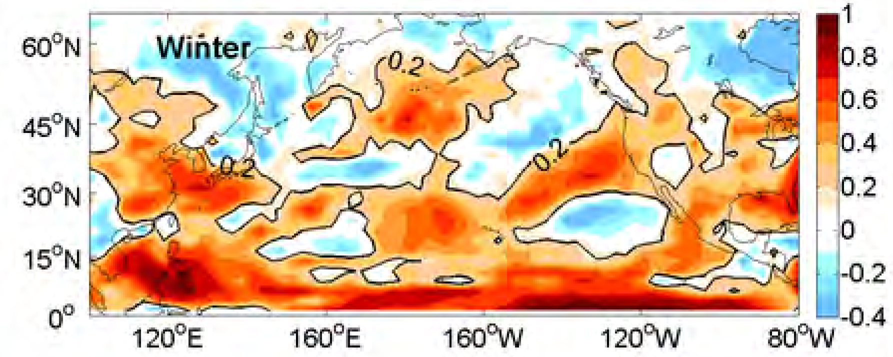
(Hu et al., 2014, J. Climate)

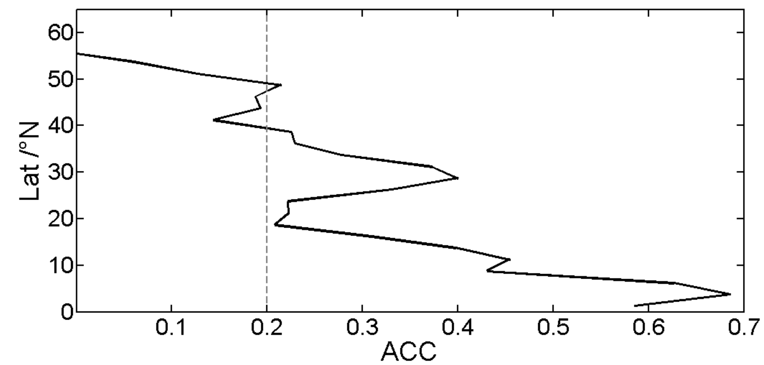
3. Results evaluation

precipitation prediction skills

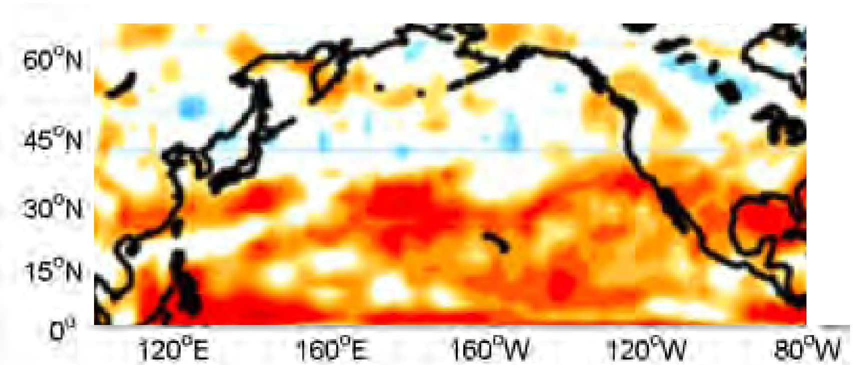
ACC of winter rainfall FIO-ESM(3-mon lead)

1-α=95%

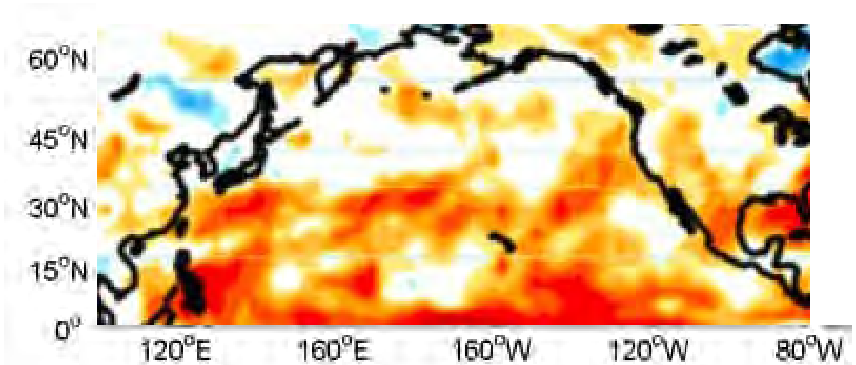


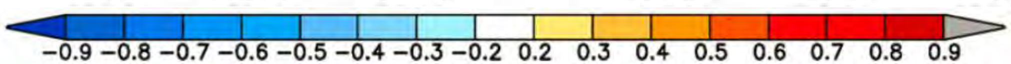


ECMWF Sys4



NCEP CFSv2





(Kim et al., 2012, CD)

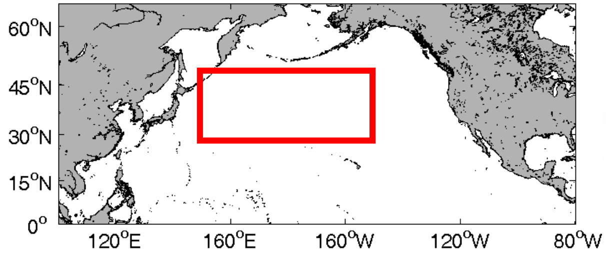
- Skillful precipitation predictions mostly reside in the tropical oceans.
- FIOESM shows high skills at mid-latitudes.

3. Results evaluation

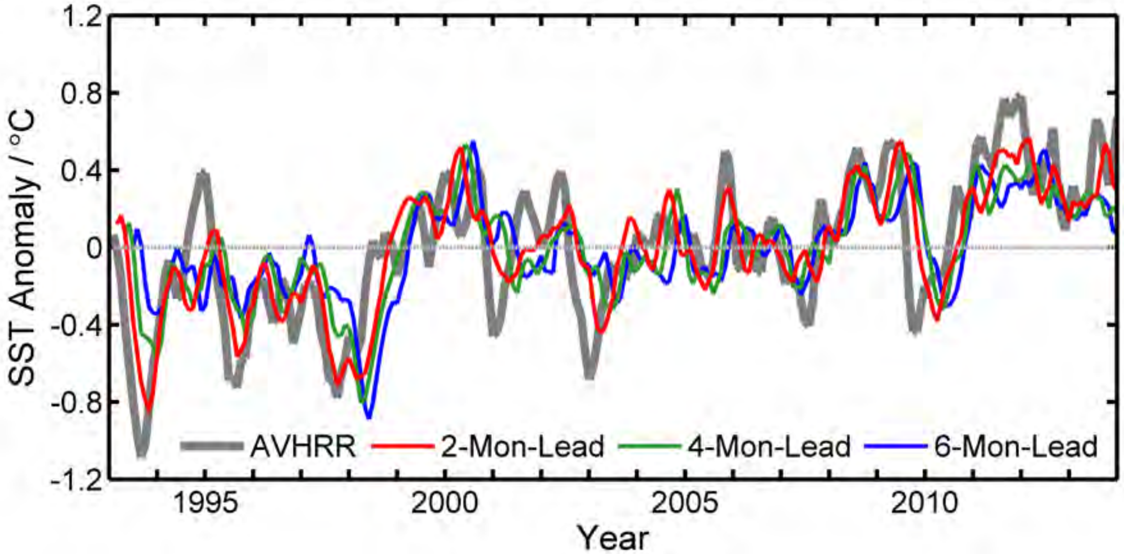
NPV index

North Pacific variability index：

area mean SSTA (30°–50°N, 150°E–150°W)



NPV index

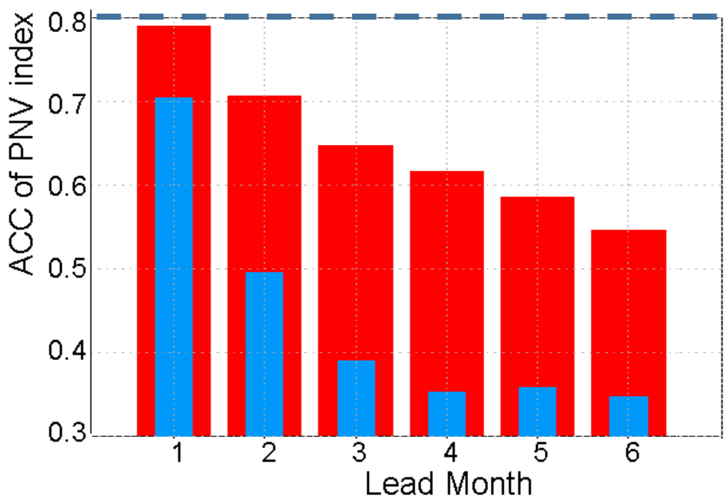


- The hindcasts results (color lines) can basically catch the observation variability (grey line).
- The development of cold and warm events in the North Pacific also can be reflected.
- It is notable that the NPV index exhibits different skills in different time periods, which shows interannual and seasonal dependence.

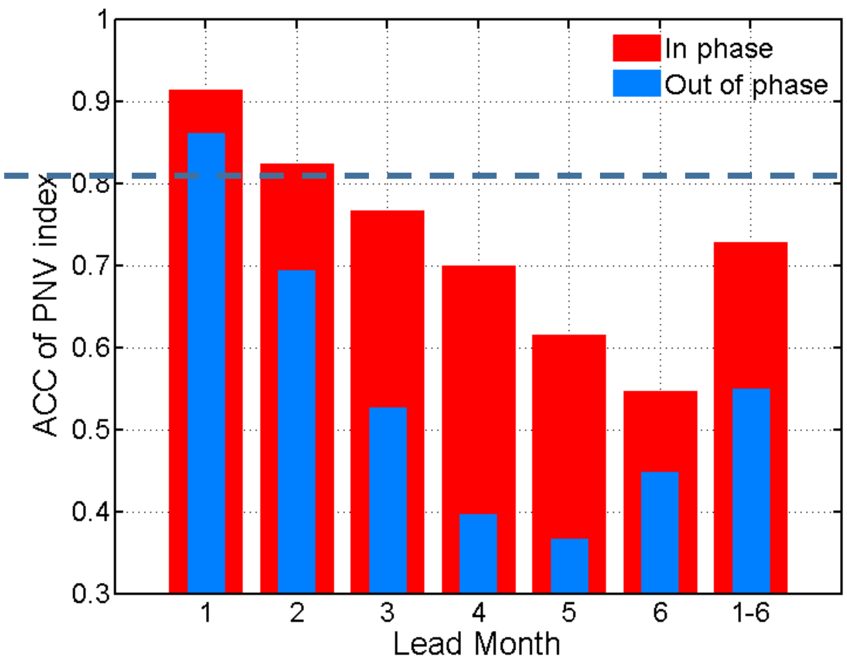
3. Results evaluation

NPV index ENSO and NPV are in phase and out of phase

CFSv2



FIO-ESM



Time	1-mon	2-mon	3-mon	4-mon	5-mon	6-mon
CFSv2	0.74	0.59	0.51	0.49	0.47	0.45
FIO-ESM	0.88	0.75	0.64	0.55	0.49	0.50

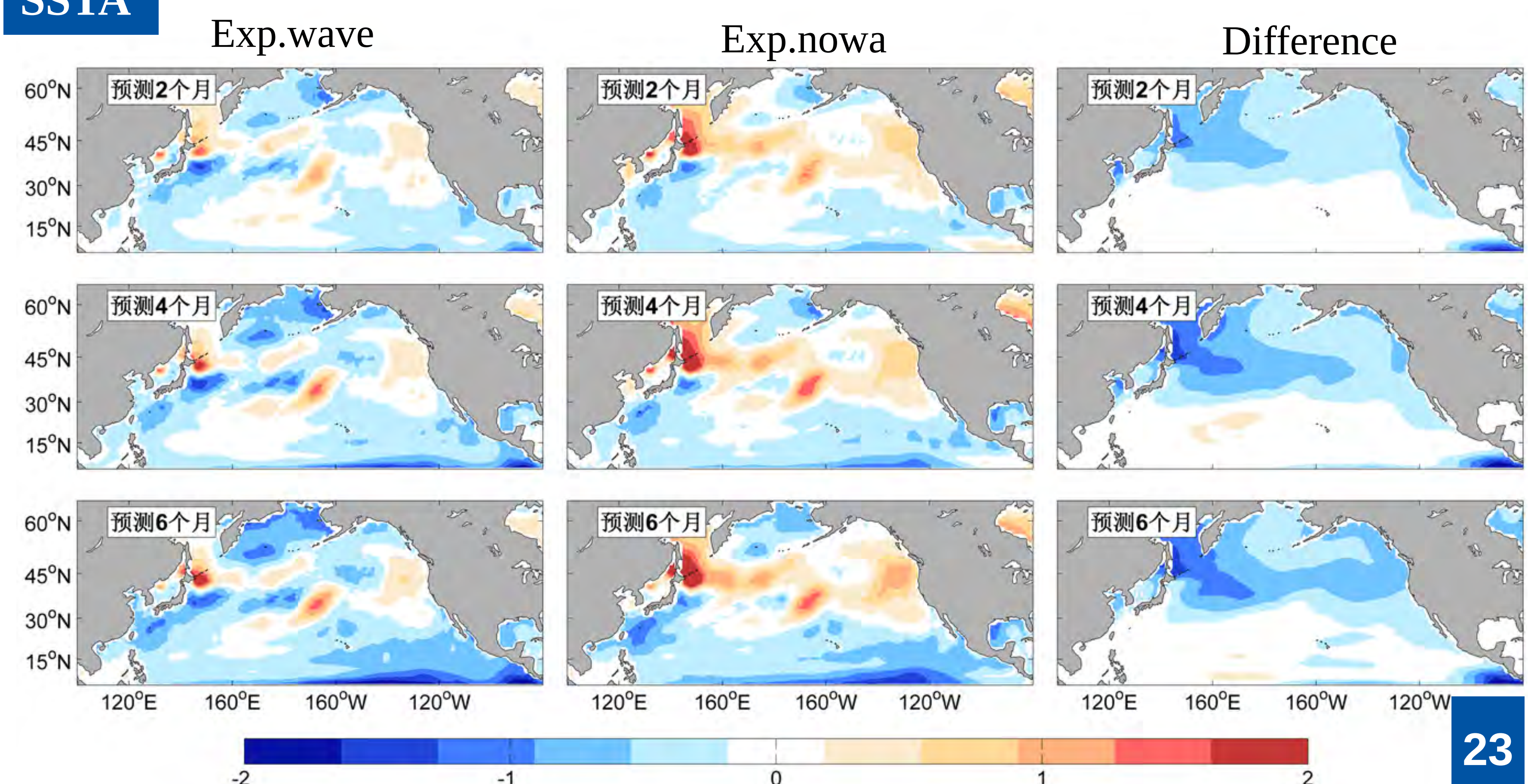
- In phase: skills increase 11.6%
- Out phase: skills increase 23.6%

Content

4. Ocean effect on SSTA prediction

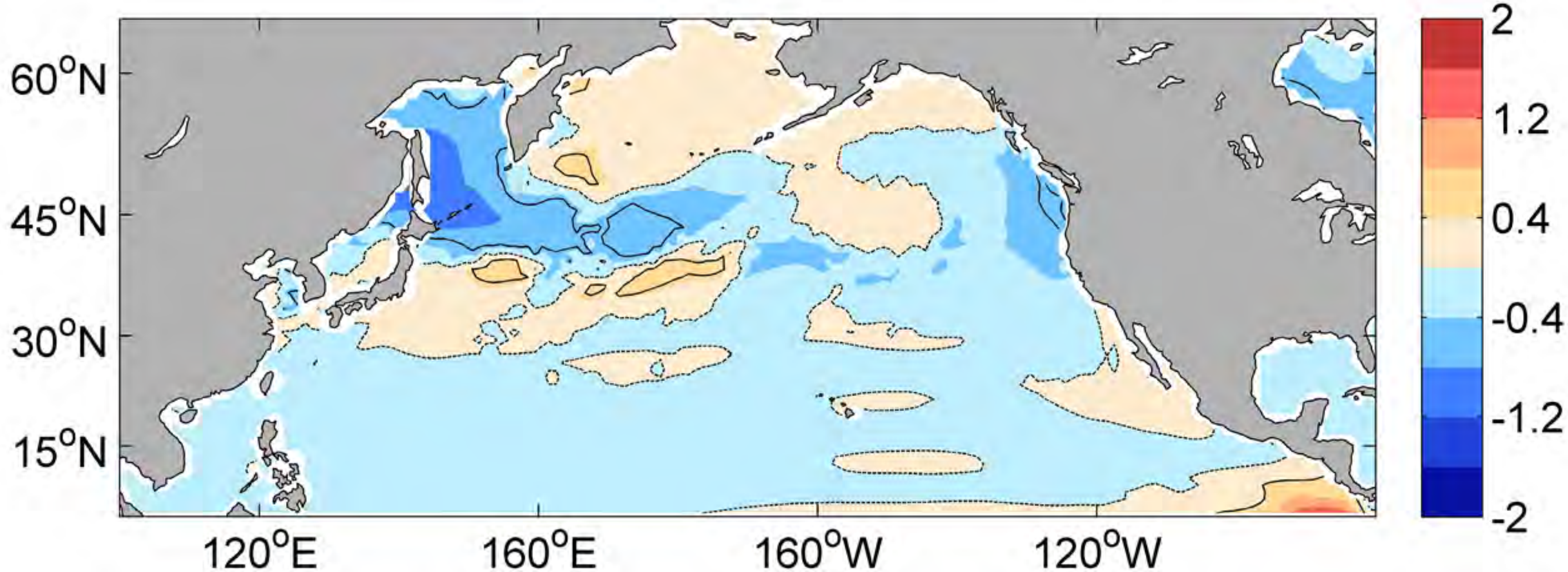
EXP	Time	Initial state	Wave model
Exp.wave	2016	EAKF assimilation	√
Exp.nowa	2016	EAKF assimilation	×

SSTA



4. Ocean effect on SSTA prediction

(Exp.wave – OBS) – (Exp.nowa - OBS)



- SST substantially decrease in mid-latitudes
- SST slightly increases in low latitudes

4. Ocean effect on SSTA prediction

Heat budget analysis

Mix layer temperature equation:

$$\frac{\partial T}{\partial t} = -u\frac{\partial T}{\partial x} - v\frac{\partial T}{\partial y} - w\frac{\partial T}{\partial z} + \frac{K_h}{\Delta z}\frac{\partial T}{\partial z}\bigg|_{z=\Delta z} + \frac{Q_T}{\rho_0 C_p \Delta z}$$

$$Tt = Q = Q_u + Q_v + Q_w + Q_{zz} + Q_q$$

(Huang et al., 2010, J. Climate)

Q_u: zonal advection

Q_v: meridional advection

Q_w: vertical convection

Q_{zz}: vertical diffusion

Q_q: net heat flux

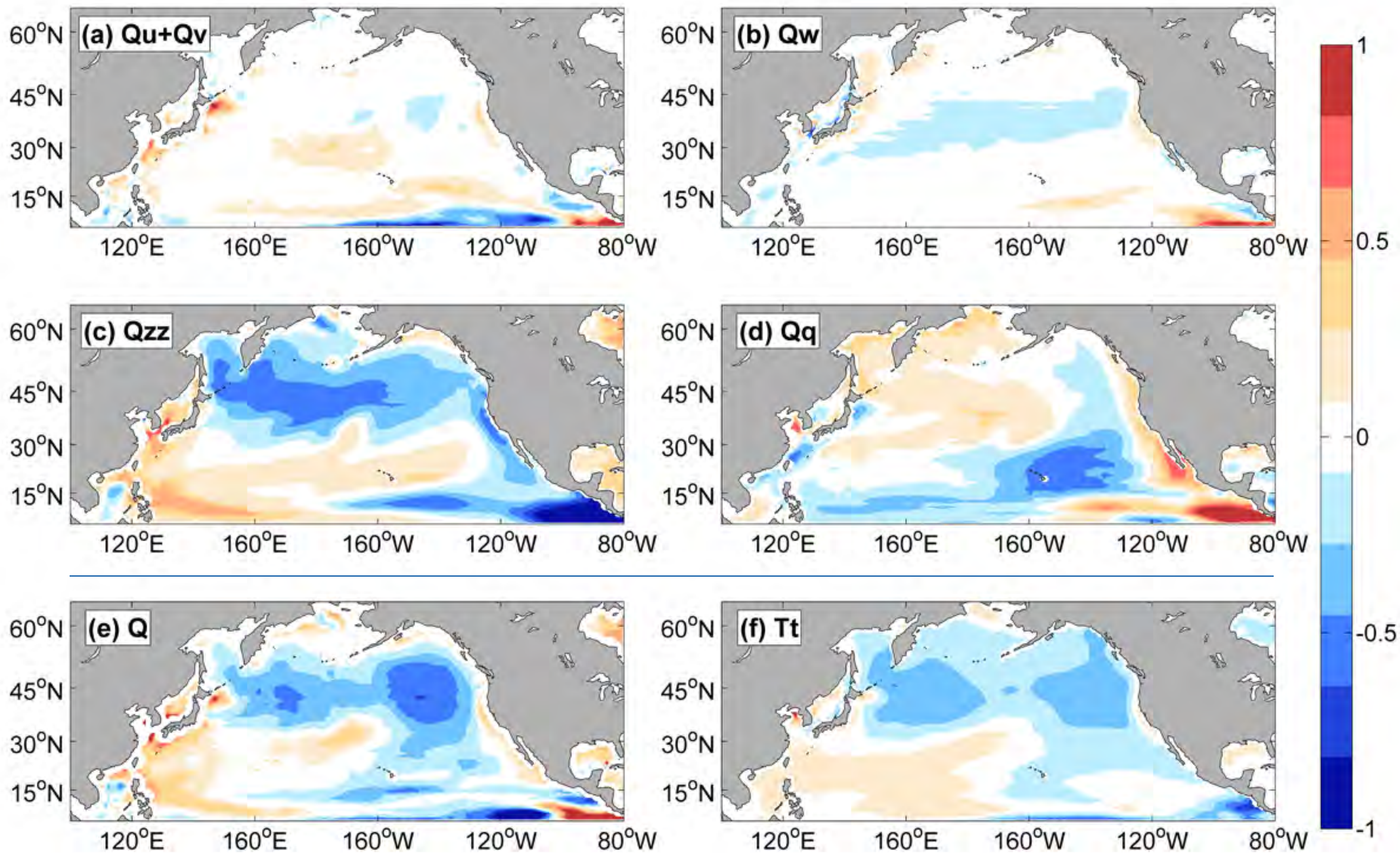
4. Ocean effect on SSTA prediction

Heat budget analysis

Qzz is the leading factor for ocean temperature difference

Qq has negative effect on upper ocean temperature

6-mon-lead



5. Conclusion

I. Short-term climate prediction system FIO-ESM exhibits high SST prediction skills over most of the North Pacific for two seasons in advance, and remains skillful at long lead times at mid-latitudes.

II. Reliable prediction of SST can transfer fairly well to the prediction of precipitation, contributing to high precipitation skills at mid-latitudes.

III. Surface wave can reduce warm bias of predicted SSTA, especially in mid latitudes of Northwest Pacific.

Thank you for your attention