IBS Center
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Progress and Plans on Sub-seasonal to Multi-year Prediction Activities in PNU/ICCP

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IBS Center
for Climate Physics










Progress and Plans on Sub-seasonal to Multi-year Prediction Activities in PNU

June-Yi Lee

ICCP: Yong-Yub Kim, Axel Timmermann, Sun-Seon Lee, Eun-Young Kwon, Wonsun Park, Jun-Young Park, Abhinav R Subrahmanian **RCCS**: Arya V. S., Alexia Karwat, Lucie Mumo, Jung-Eun Yun

External Collaborators: Yoshimitsu Chikamoto, A. K. M. Nahid Hasan (Utah State Univ.), Ingo Bethke, Sara Filippa K. Fransner (Bjerknes Center for Climate Research), Pang-Chi Hsu, Young-Min Yang (NUIST), Dae-Hyun Kang (KIST)










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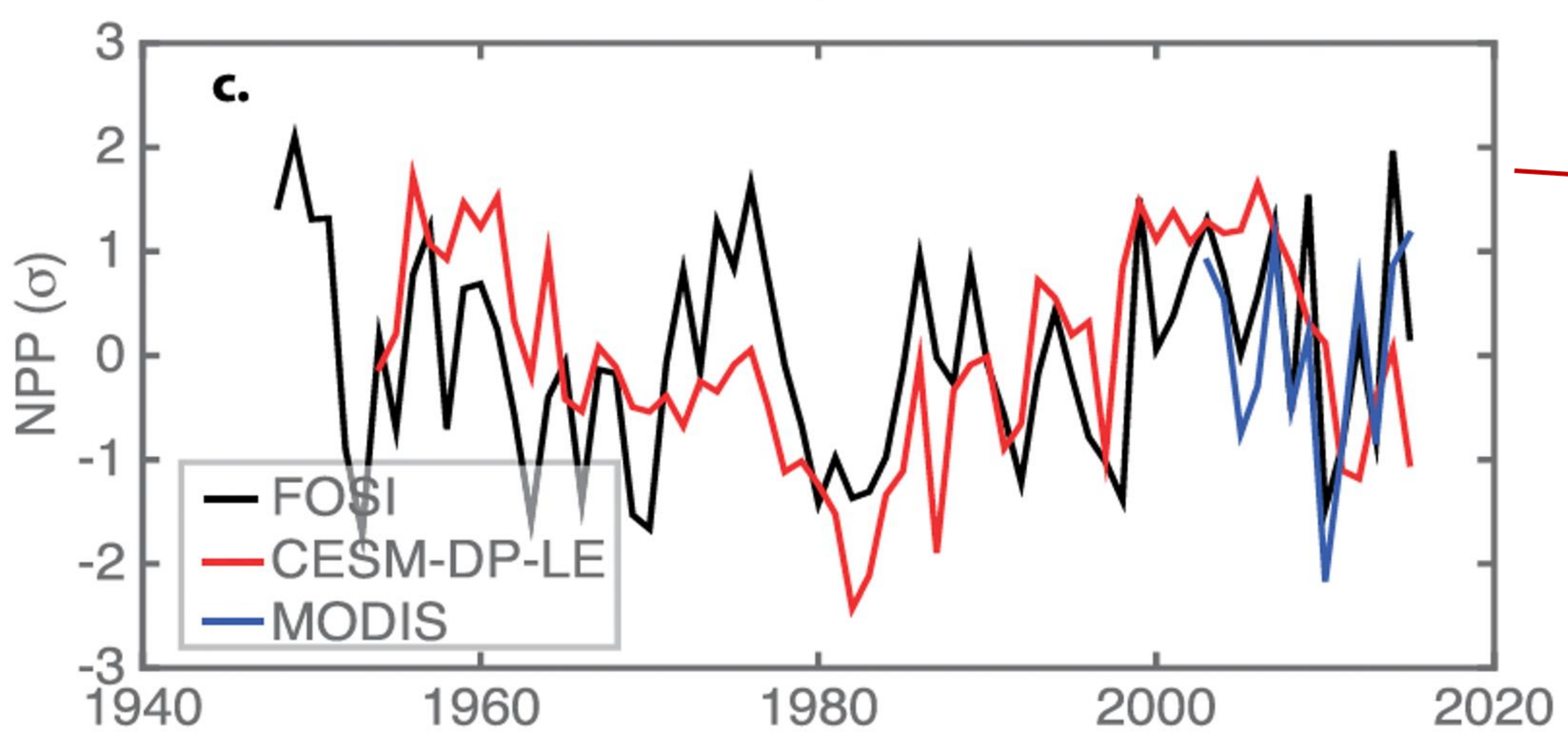
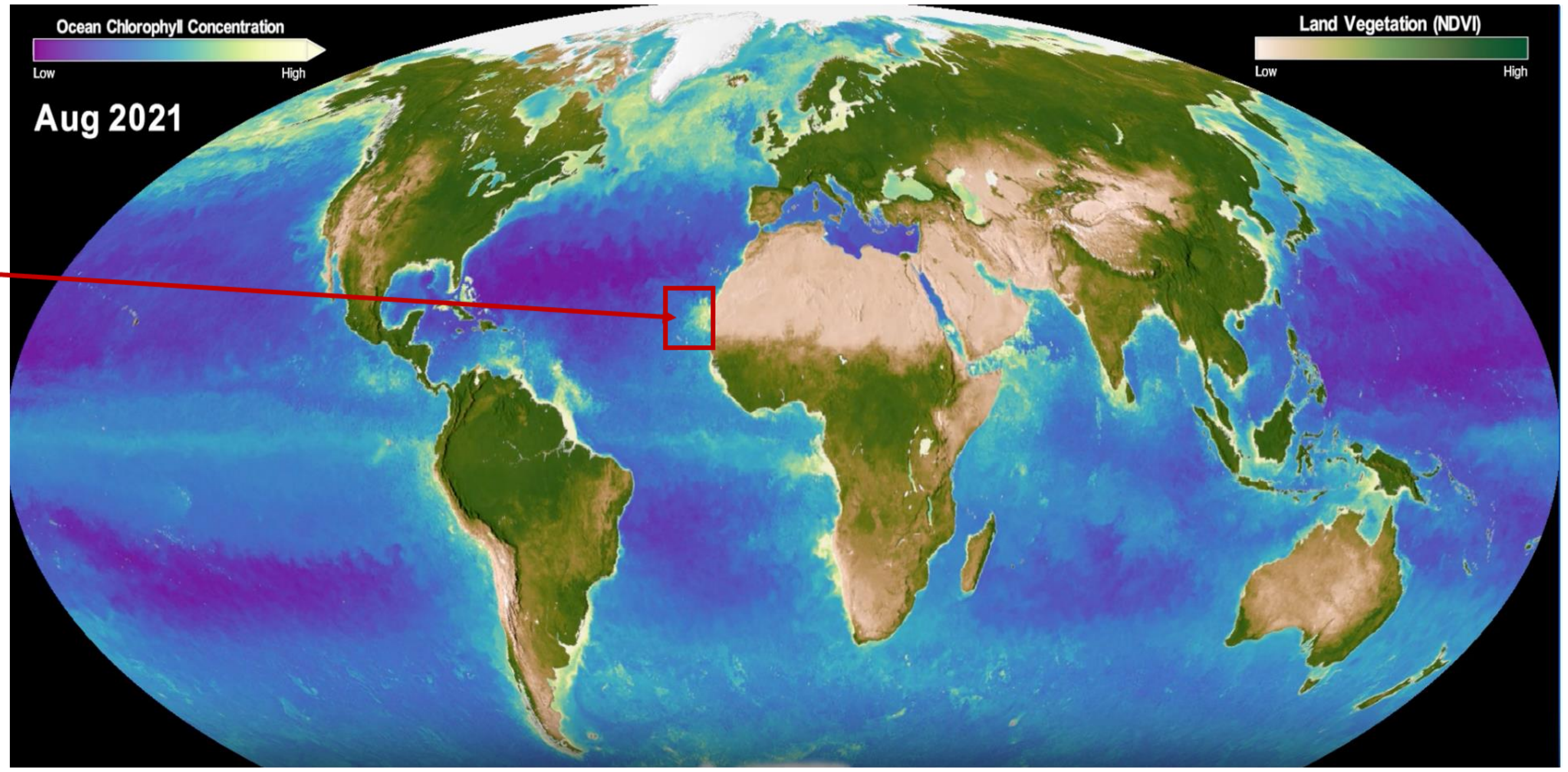
Main Research Questions

- How can we **enhance our predictive capability of Earth system components**, not only **physical** but also **ecological** variables, on timescales of **weeks to decades**, using improved comprehensive Earth System models and innovative technologies?

- What are **the essential physical and ecological sources for longer-term earth system predictability**?

Temporal evolution of standardized NPP anomalies
in the Canary Current region (Yeager et al. 2018)





Models and Tools for the Earth System Predictability Project

Predictability of
Sea Level and Ice Sheet

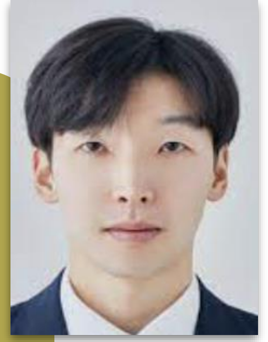
***Climate-Ice-Sheet Coupled Prediction System (CESM1.2.2+PSUISM)**

Subseasonal-to-Seasonal S2S Prediction Project

S2S Prediction Models

CESM2 Large Ensemble (LENS2)

Multi-year Prediction System based on CESM2



****AI Global Climate Prediction Model**

Predictability from Forcing

Predictability of
Extreme Events

Predictability from Forcing and
Internal Variability

Days → Weeks → Months → Seasons → Years → Decades → Centuries

* Development of a climate-ice-sheet coupled prediction system based on CESM1.2.2 and PSUISM is on progress for sea-level and ice-sheet predictability study

** Development of AI Global Climate Prediction Model is on progress collaborating with KIST, POSTECH, and Chonnam Univ.

ICCP

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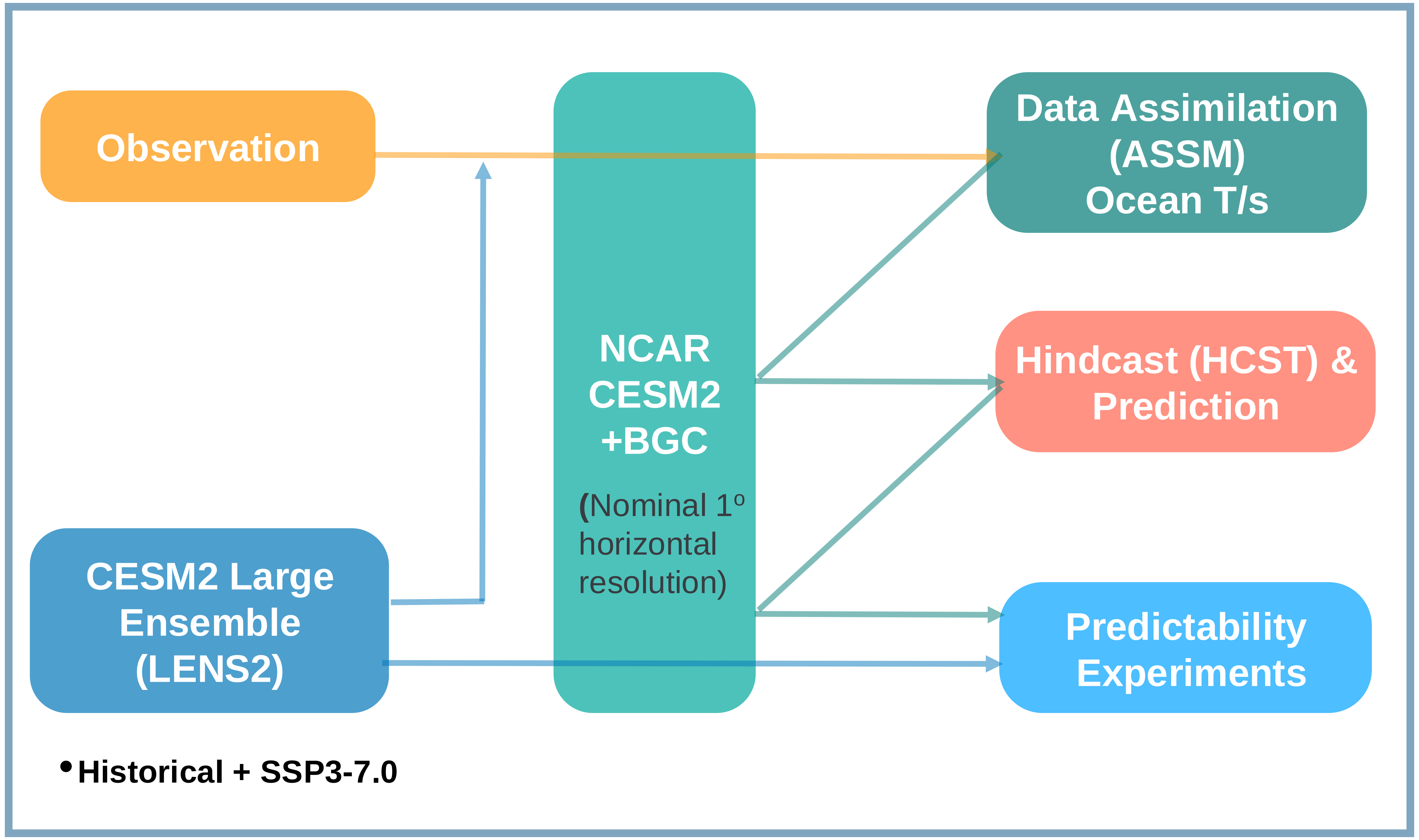
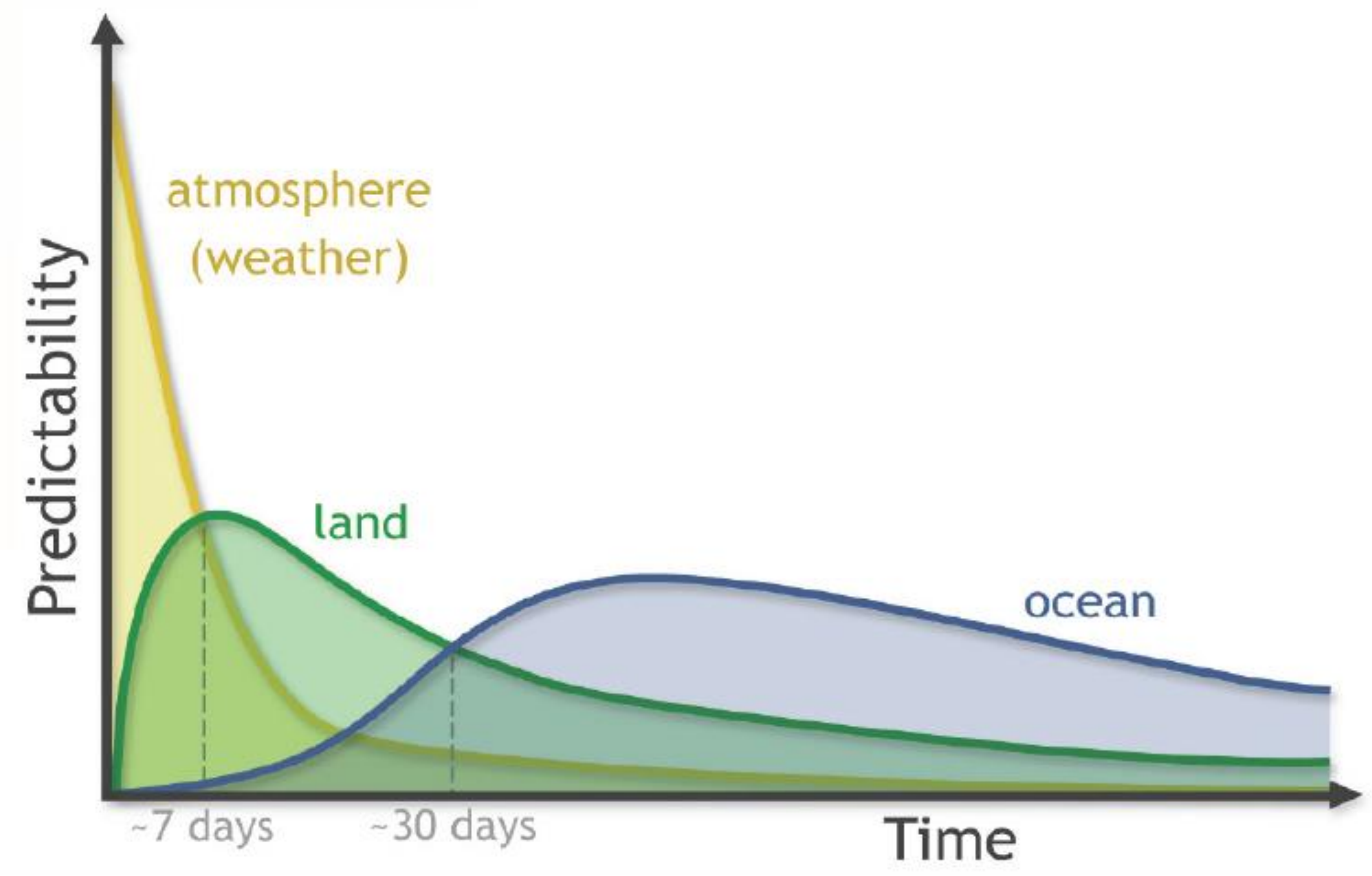
The Multi-year Prediction System in ICCP

To identify the physical and ecological sources for longer-term earth system predictability



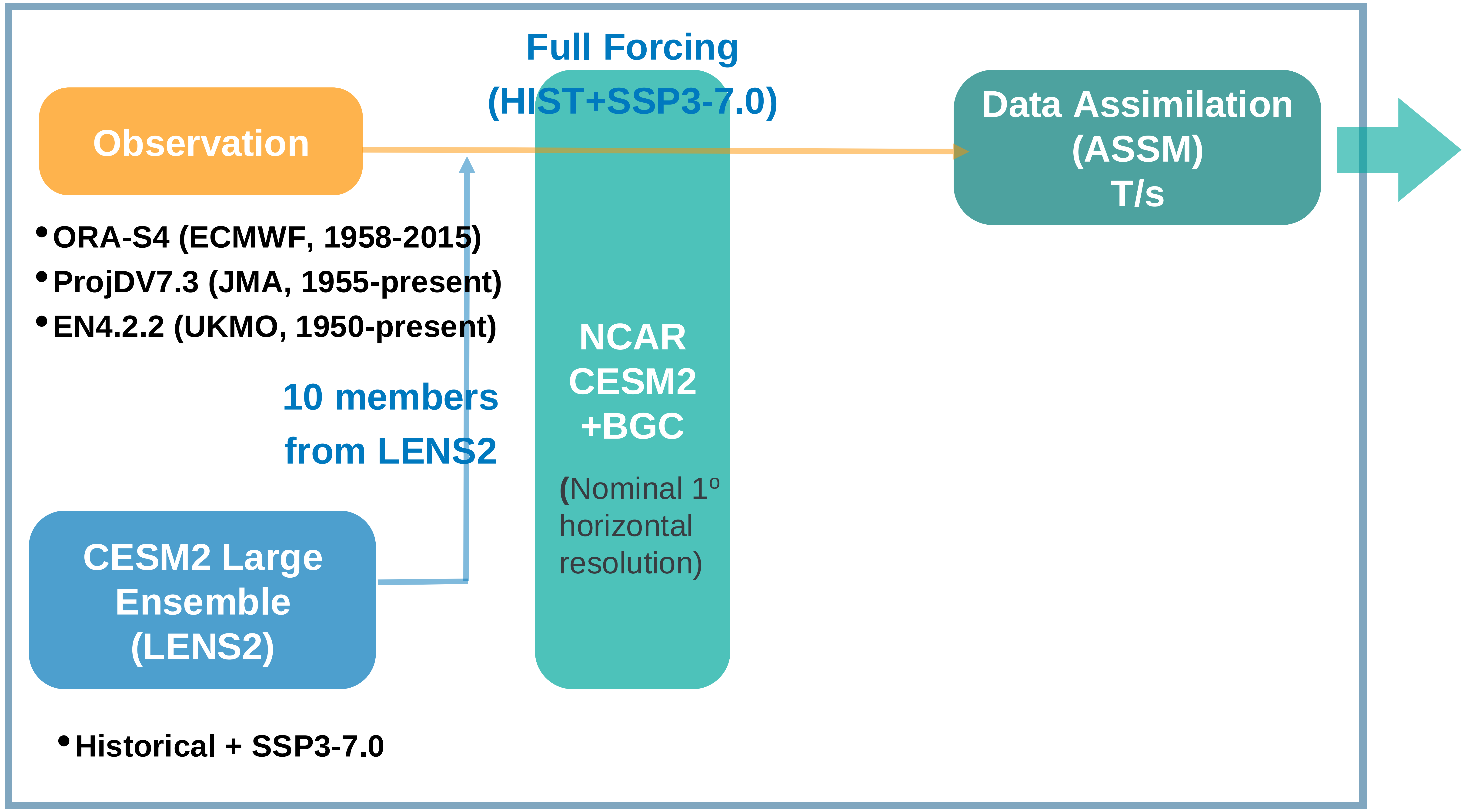
Target Variables

- Large-scale circulation & MOVs (ENSO, AMV, PDV, TBV, etc)
- Soil moisture
- Vegetation and NPP
- Wildfire
- Dust
- Carbon cycle
- Marine ecosystem
- Statistics of climate extremes



(Figure source: GMU)

3-D Ocean Anomaly Data Assimilation



Experiments

- Ocean anomaly data assimilation

(3-D T & S, 30 members, 1960-2021)

(Chikamoto et al., 2019)

Based on Three Ocean Analyses

- **ORA-S4** (Balmaseda et al., 2013)
- **ProjDV7.3** (Ishii et al., 2017))
- **EN4.2.2** (Gouretski and Cheng, 2020)

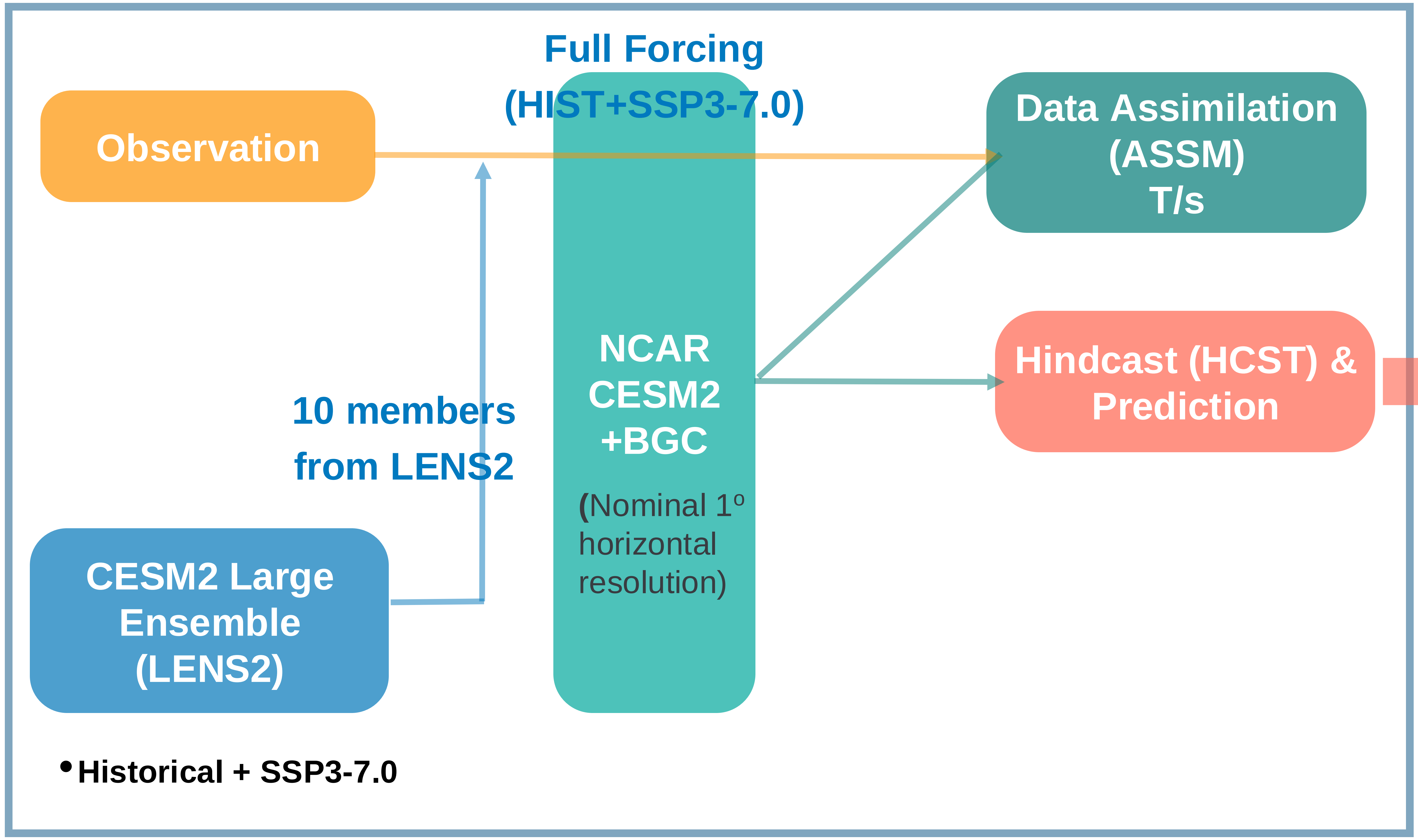
- Plan for the further experiment

- ○ **Partial ocean assimilation**
- ○ **Atmospheric nudging**
- ○ **Ocean & atmospheric nudging**

- **ASSM – LENS2**: The effect of anthropogenic and natural forcing can be removed and the effect of ocean assimilation on climate variability can be identified.

The Multi-year Predictability and Prediction



Experiments

- Hindcast with full forcing (Jan 1st IC for 5 years, 30 members, 1960-2021, May 1st IC, Aug 1st IC, Nov 1st IC, 10-year integration)

- Plan for the further experiment
  - ○ Hindcast with partial ocean assimilation
  - ○ Hindcast with full forcing but aerosol
  - ○ Hindcast with full forcing but volcano

- ASSM (-LENS2) vs HCST (-LENS2): Predictability from ocean internal variability
- HCST (-LENS2) vs OBS (-LENS2): Actual prediction skill from ocean initial condition & internal variability

Estimating Potential Predictability of SST

Anomaly Correlation Coefficient Year 1, 1960-2021

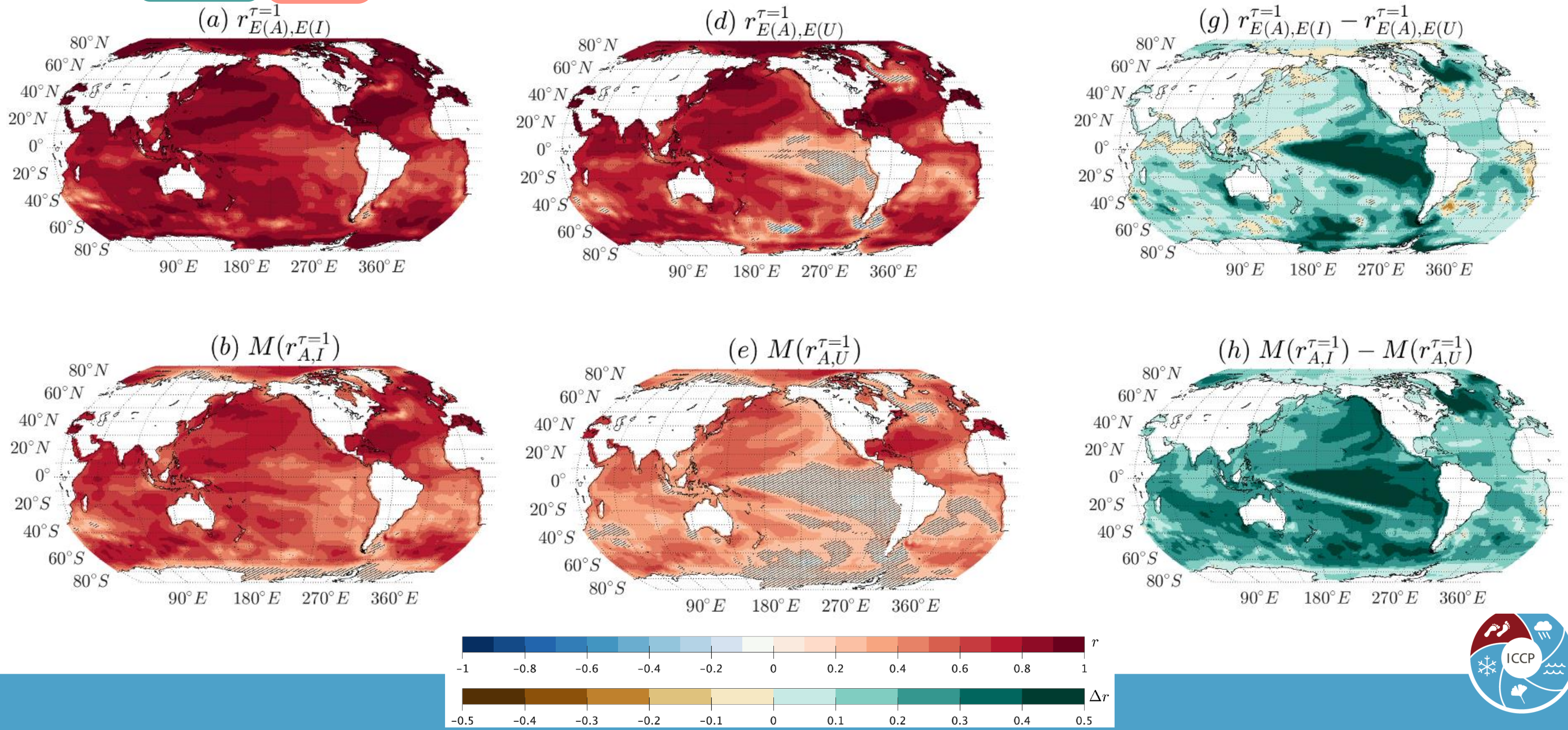
$TS, R^{ODA:HCST}, LY1$ — ASSM HCST

$TS, R^{ODA:LENS2}$ — ASSM LENS2

$TS, R^{ODA:HCST} - R^{ODA:LENS2}_{ext}, LY1$ — INI Effect

EnsM. Approach

AVG-IndM. Approach



Estimating Potential Predictability / Ocean

AVG-IndM. Approach
Year 1

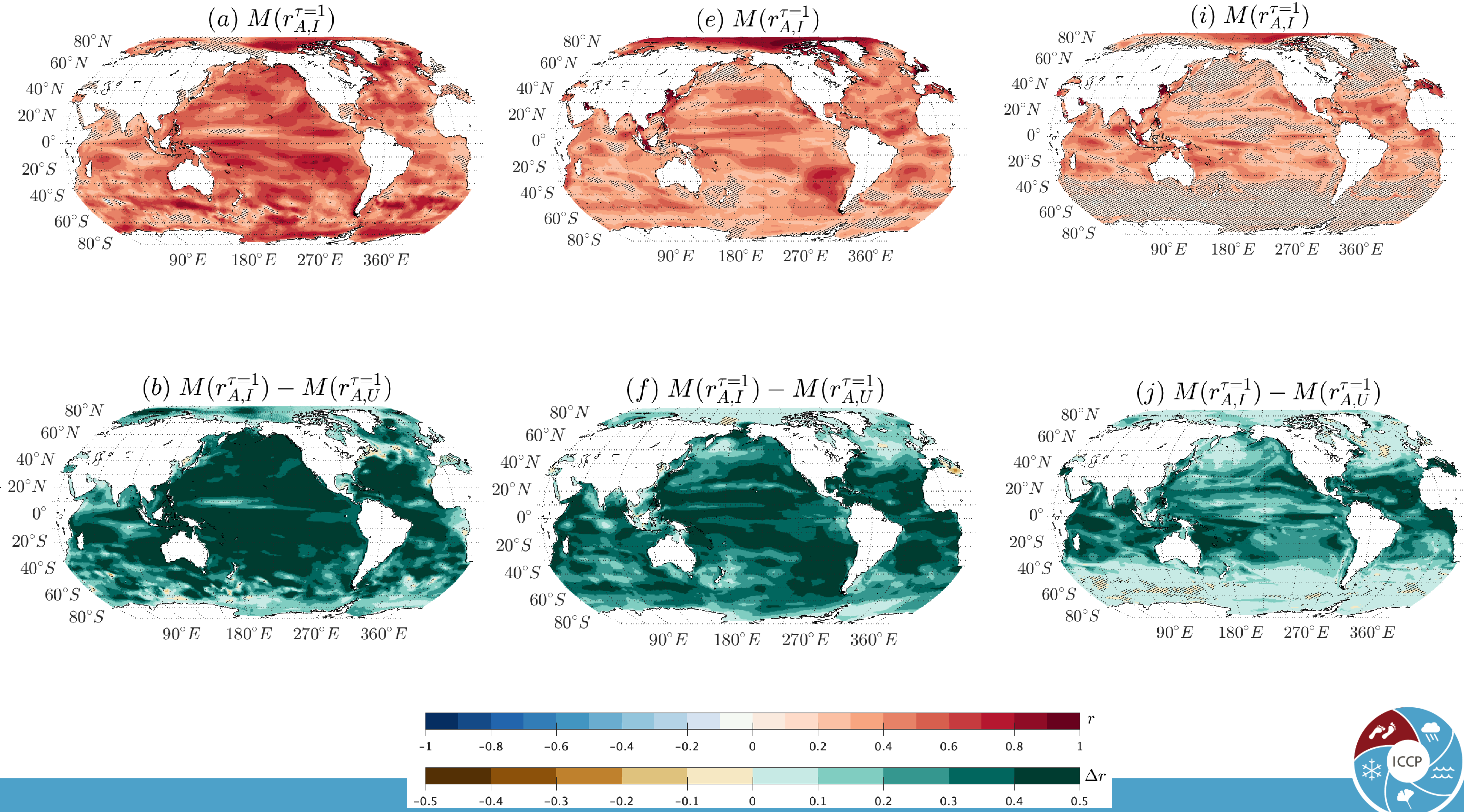
Sea Surface Height	Surface Nitrate	NPP (Sfc~100m)

$TS, R^{ODA:HCST}, LY1$

ASSM HCST

$TS, R^{ODA:HCST} - R_{ext}^{ODA:LENS2}, LY1$

INI Effect



Estimating Potential Predictability / Ocean

AVG-IndM. Approach
Year 2-5

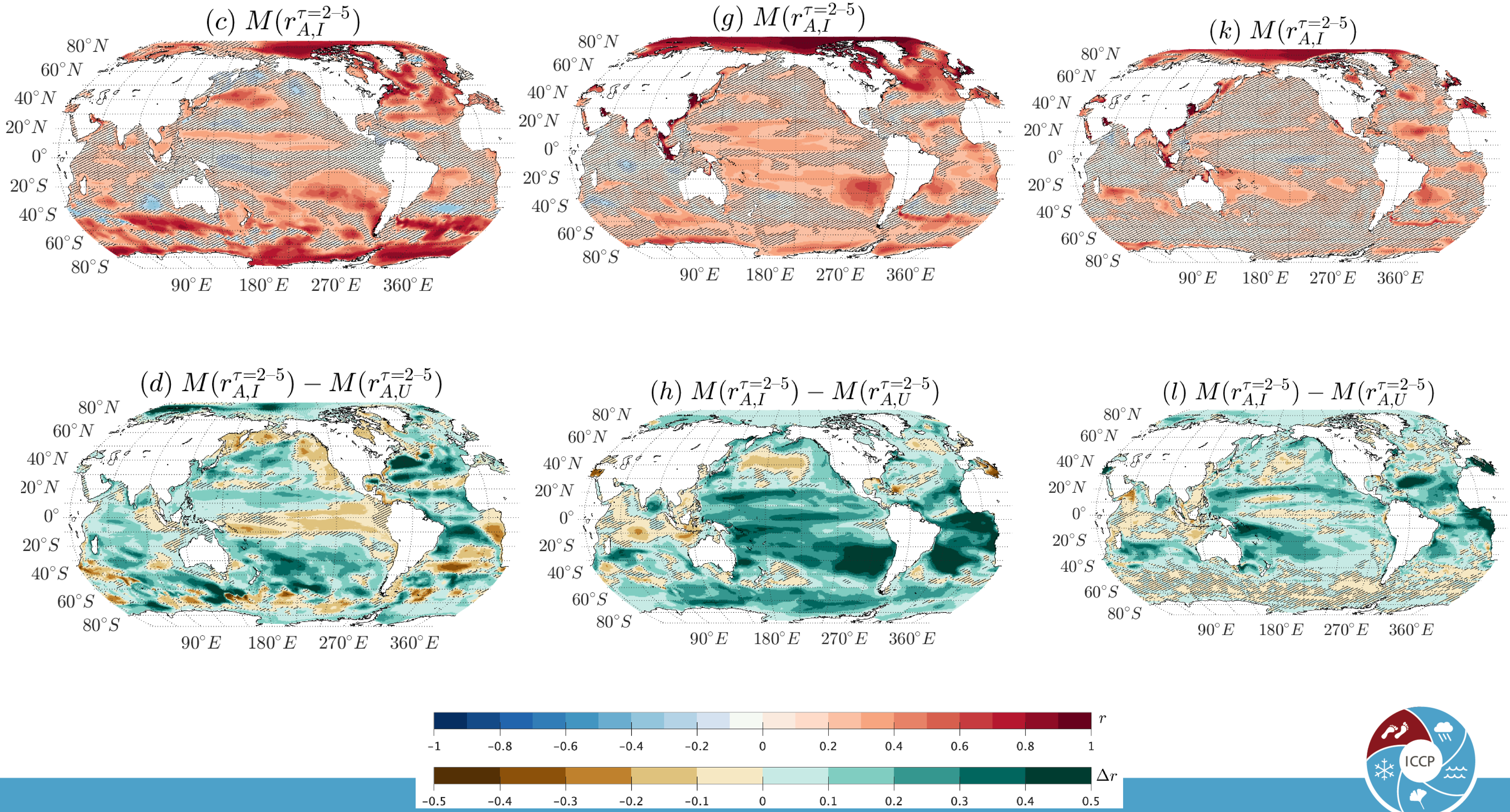
Sea Surface Height | **Surface Nitrate** | **NPP (Sfc~100m)**

$TS, R^{ODA:HCST}, LY2-5$

ASSM | HCST

$TS, R^{ODA:HCST} - R_{ext}^{ODA:LENS2}, LY2-5$

INI Effect



Estimating Potential Predictability / Atmosphere

AVG-IndM. Approach
Year 1

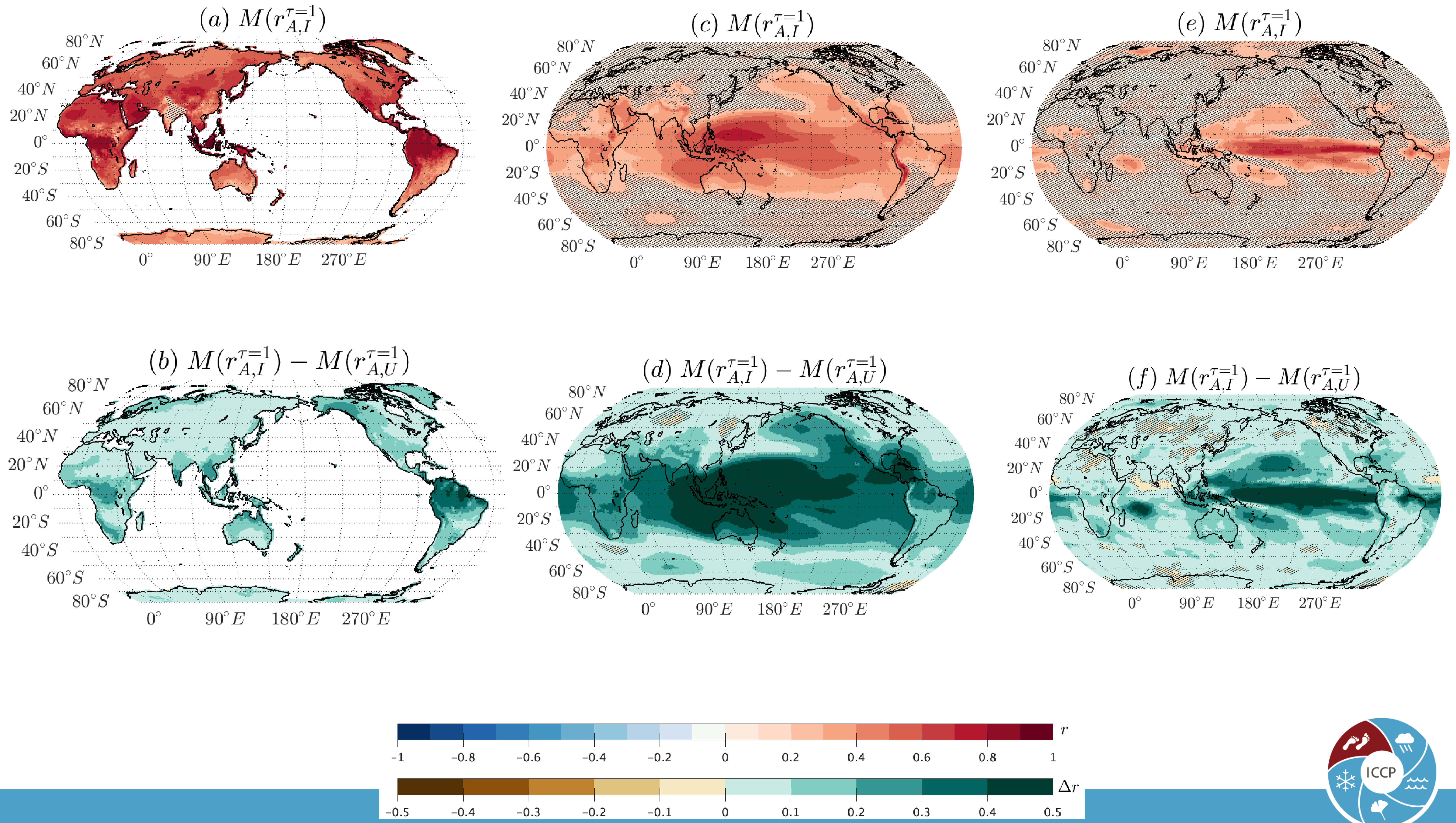
2-m Air Temperature | **Sea Level Pressure** | **Precipitation**

$TS, R^{ODA:HCST}, LY1$

ASSM | HCST

$TS, R^{ODA:HCST} - R^{ODA:LENS2}_{ext}, LY1$

INI Effect



Estimating Potential Predictability / Land

AVG-IndM. Approach
Year 1

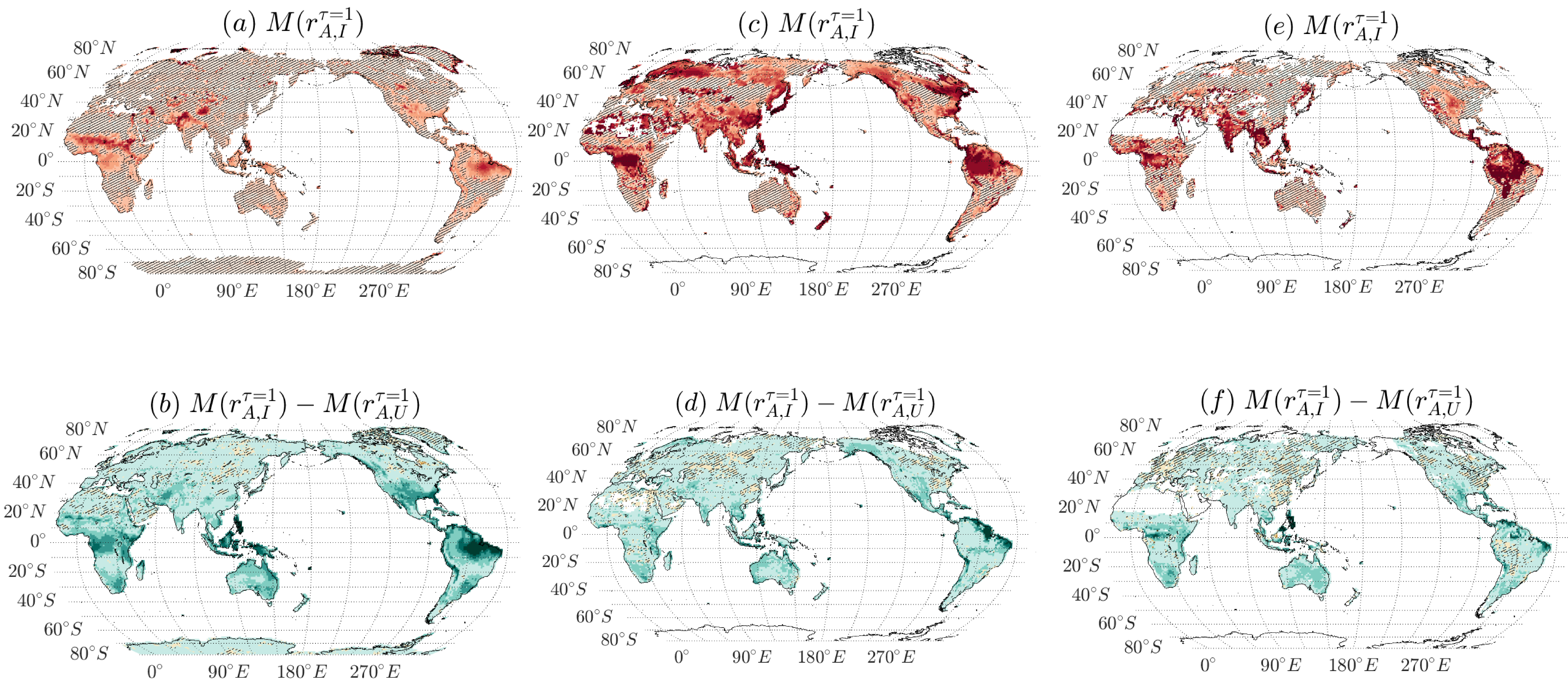
Total Water Storage | **GPP** | **Fire Count**

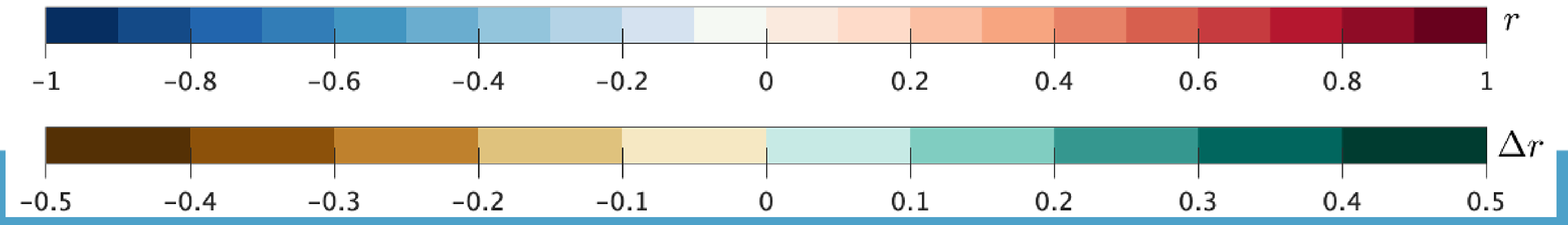
$TS, R^{ODA:HCST}, LY1$

ASSM HCST

$TS, R^{ODA:HCST} - R_{ext}^{ODA:LENS2}, LY1$

INI Effect





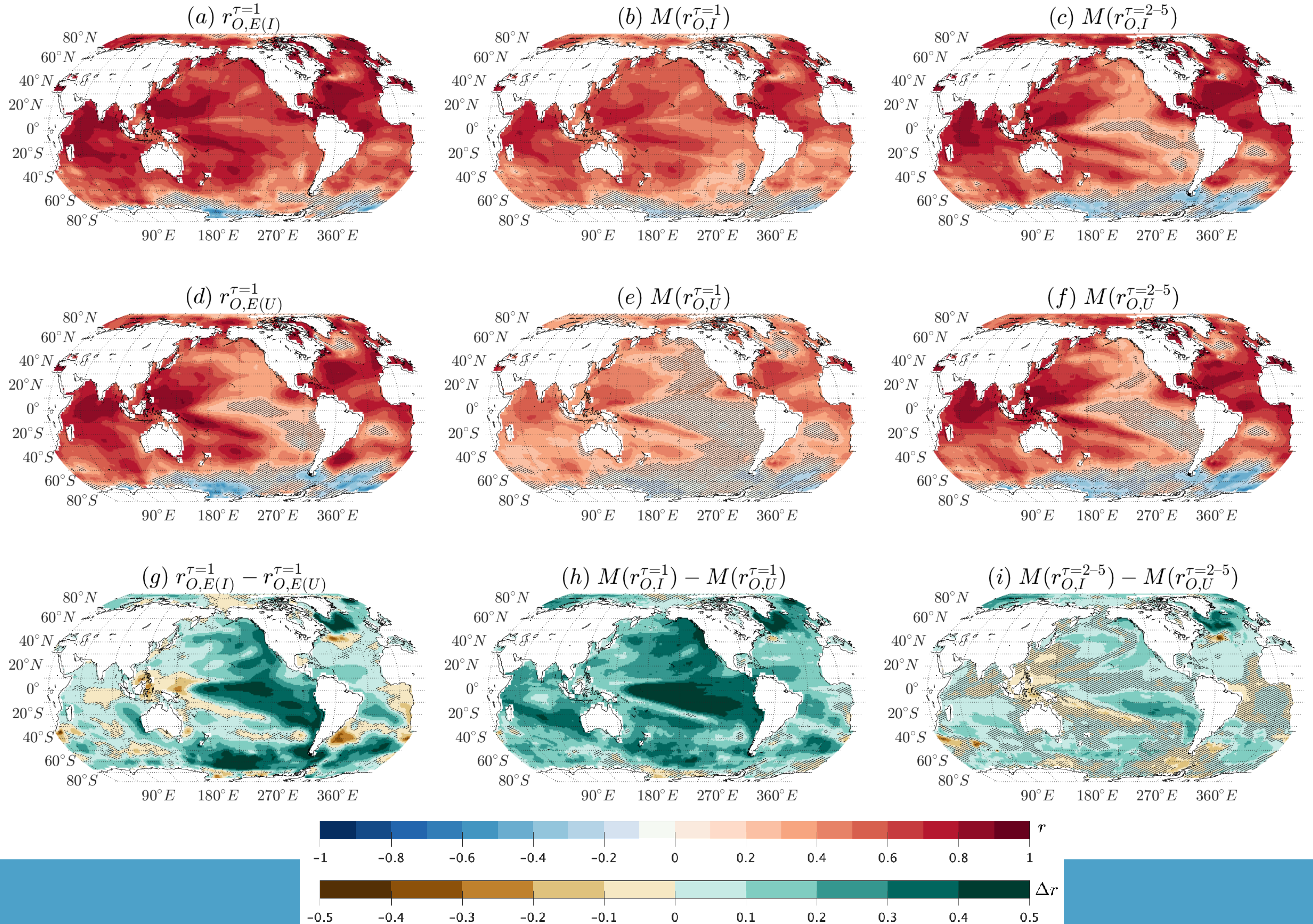
Estimating Prediction Skills/ SST

EnsM. Approach | **AVG-IndM. Approach** | **AVG-IndM. (Y2-5) Approach**

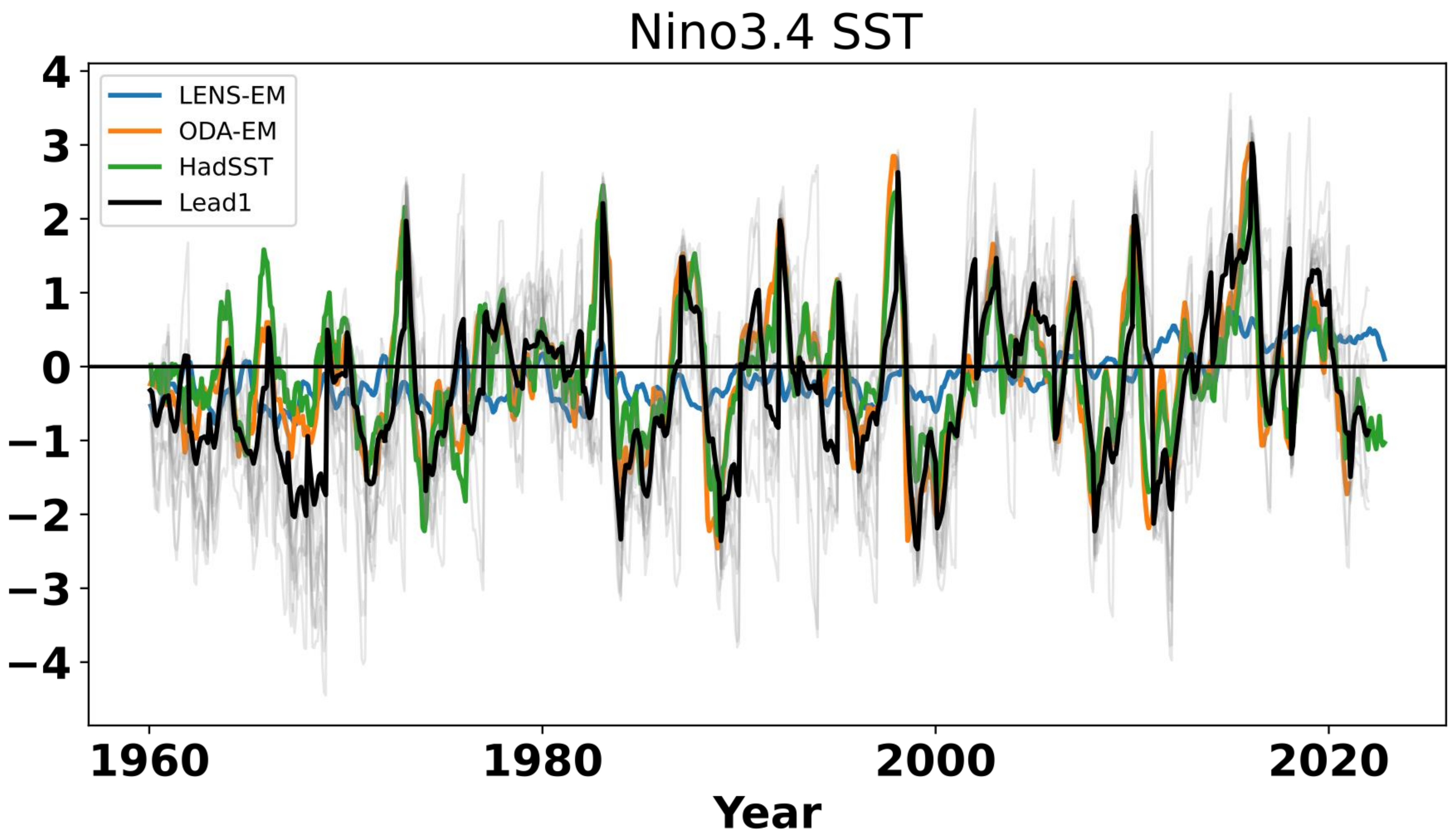
OBS HCST

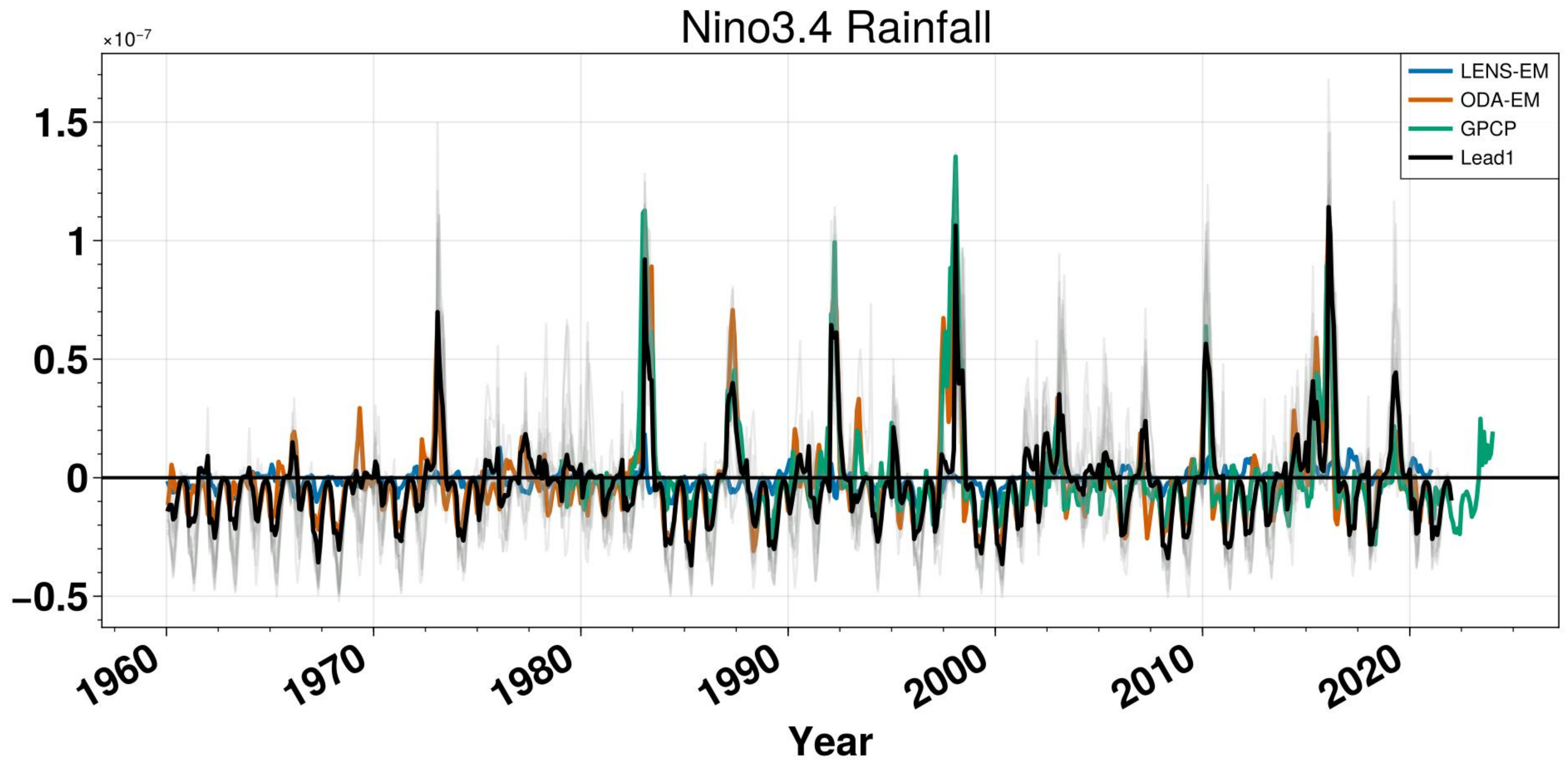
OBS LENS2

INI Effect



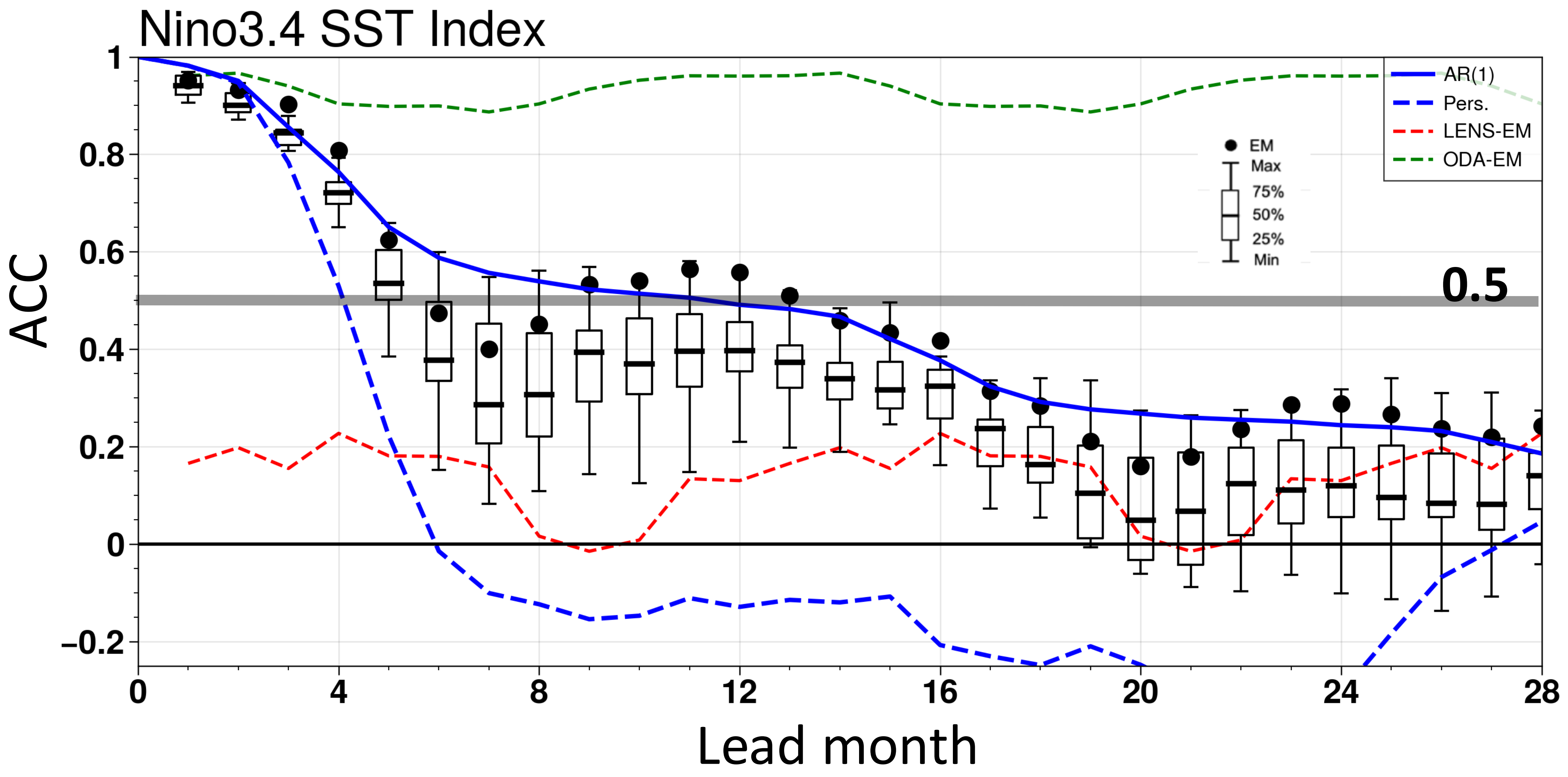
Prediction of Mode of Variability: ENSO



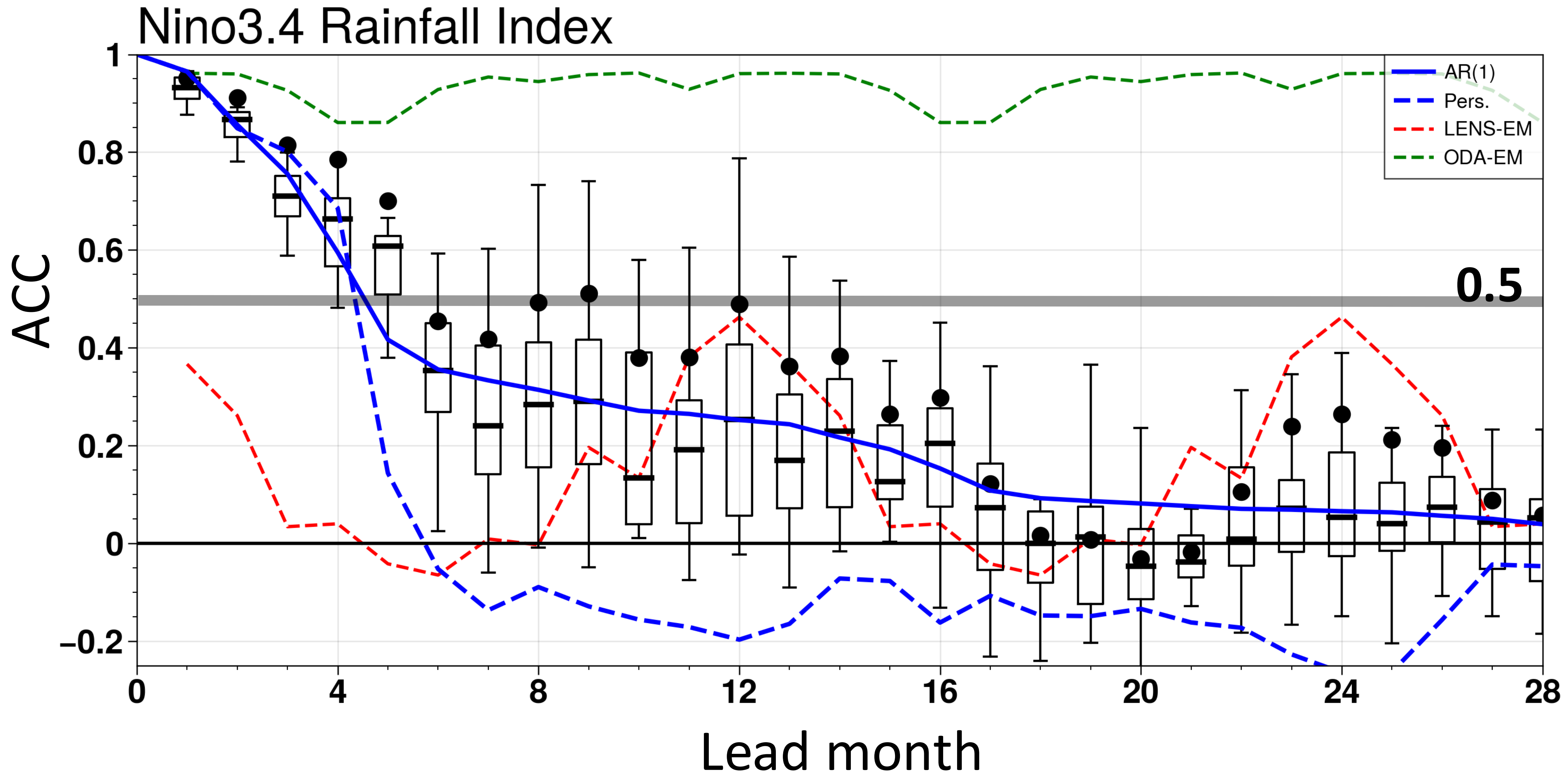


Prediction of Mode of Variability: ENSO

Nino3.4 SST Index



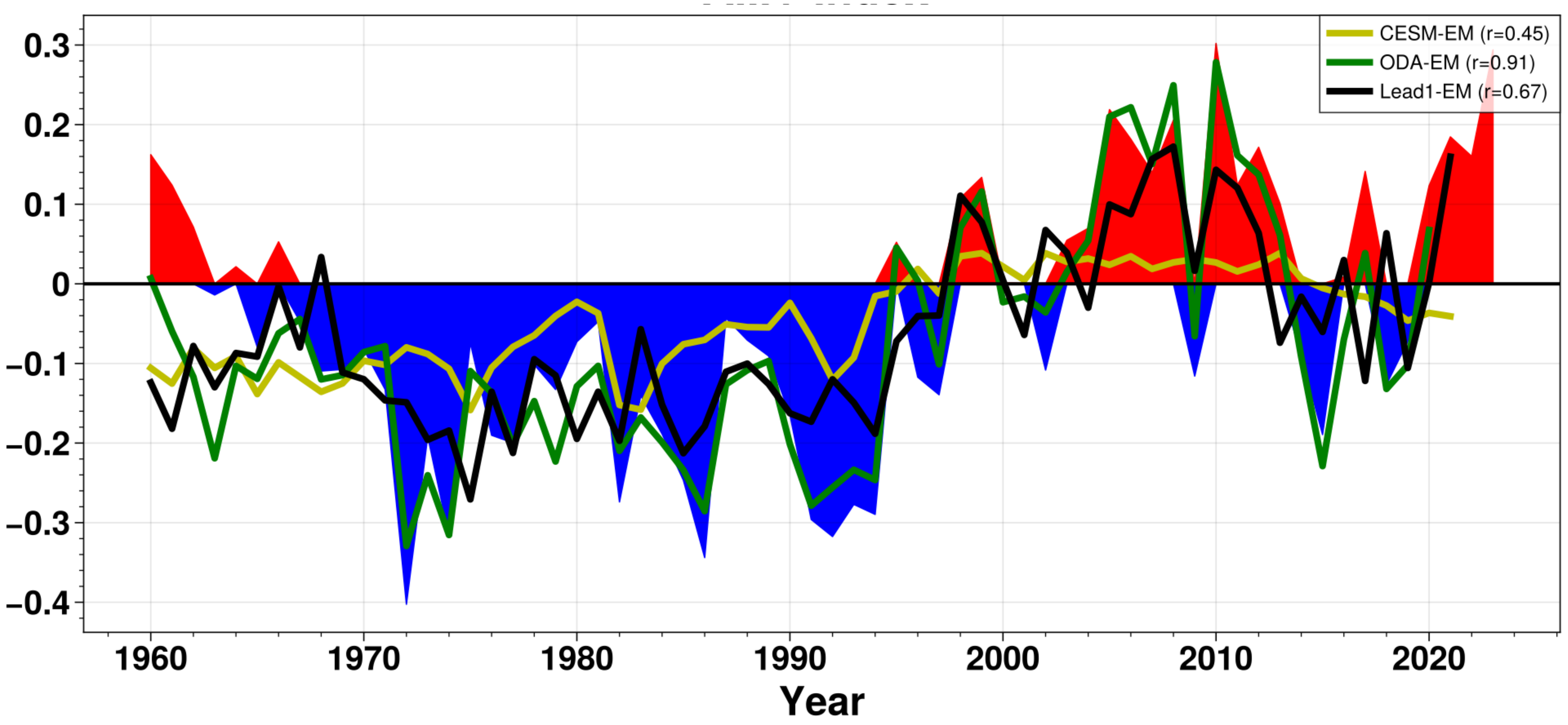
Nino3.4 Rainfall Index



- The ensemble mean of CESM2 hindcast has a useful skill of 0.5 for the monthly Nino 3.4 index up to the 14-month forecast lead.
- The CESM2 hindcast has a slightly higher skill for the annual mean Nino 3.4 SST index at 1-year and 2-year forecast lead.

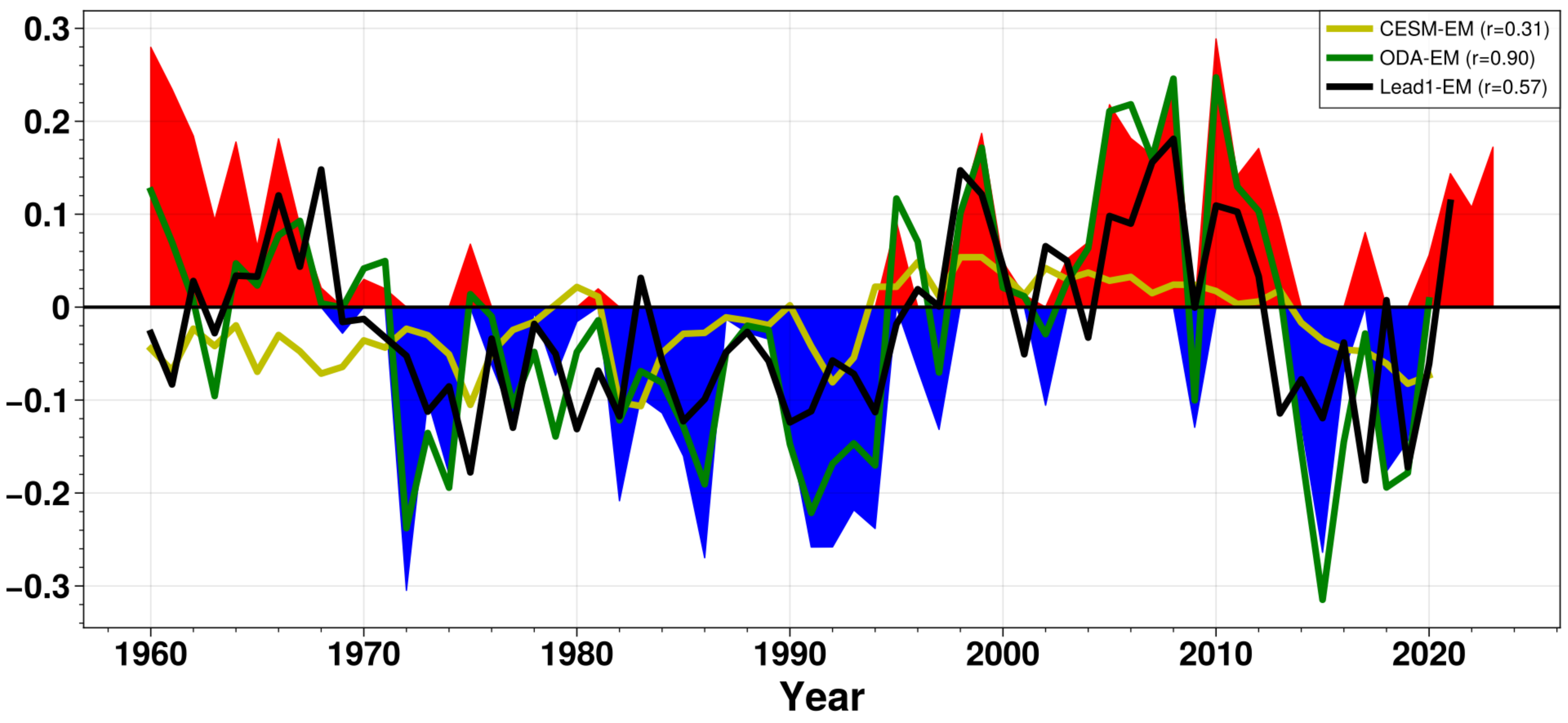
Prediction of Mode of Variability: AMV

AMV Index
Conventional Method
(Trenberth and Shea, 2006)



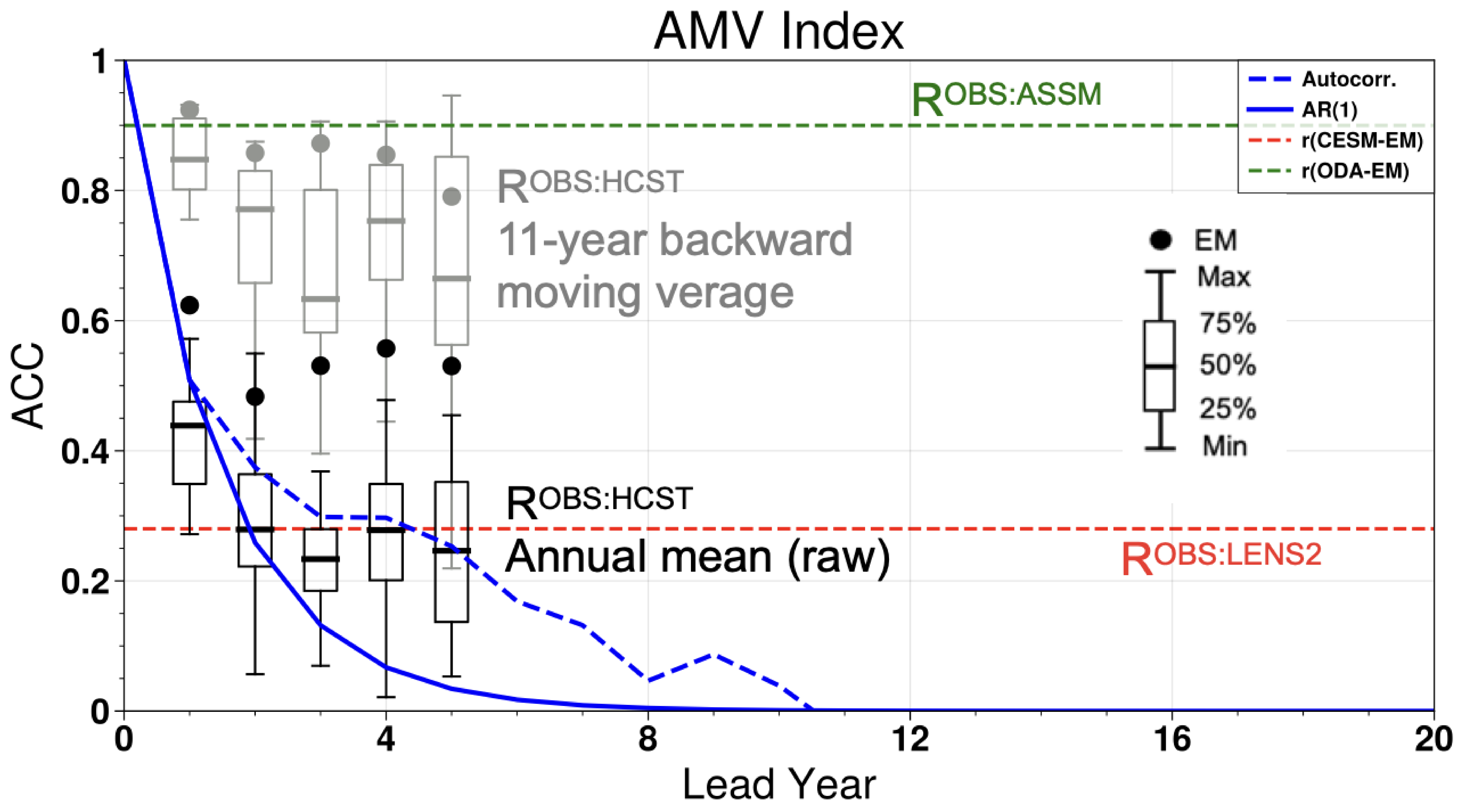
Definition: Subtract global mean SST (G) from the SSTA at each grid box and time step and then regress these data onto the NA-G index

iAMV Index
Global Residual Method
(Deser & Phillips, 2021)



Definition: subtract the pattern of SSTA associated with G from the SSTA at each grid box and time step, and then regress these data onto the NA-G index

Prediction of Mode of Variability: AMV



Global Residual Method (Deser & Phillips, 2021)

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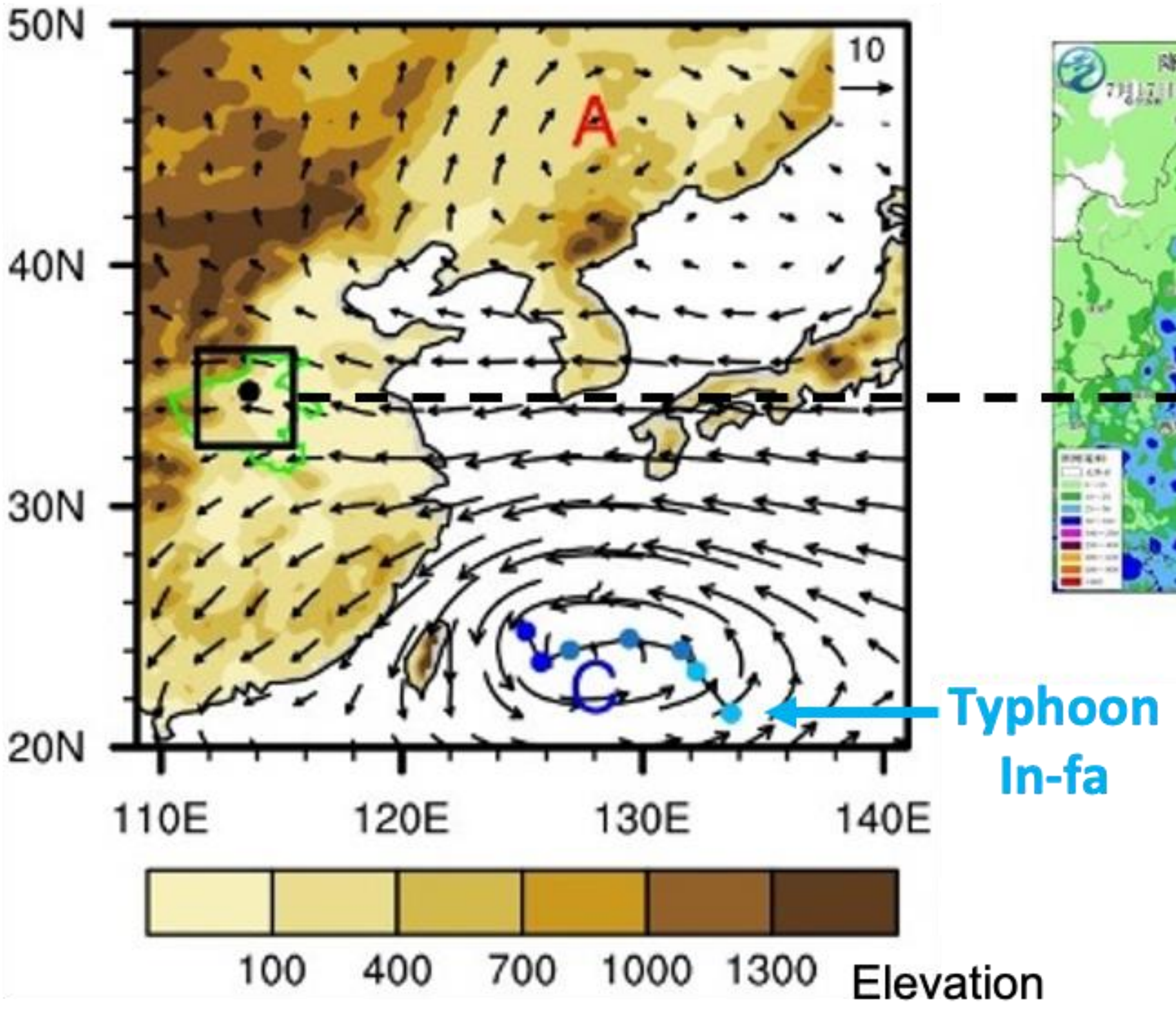
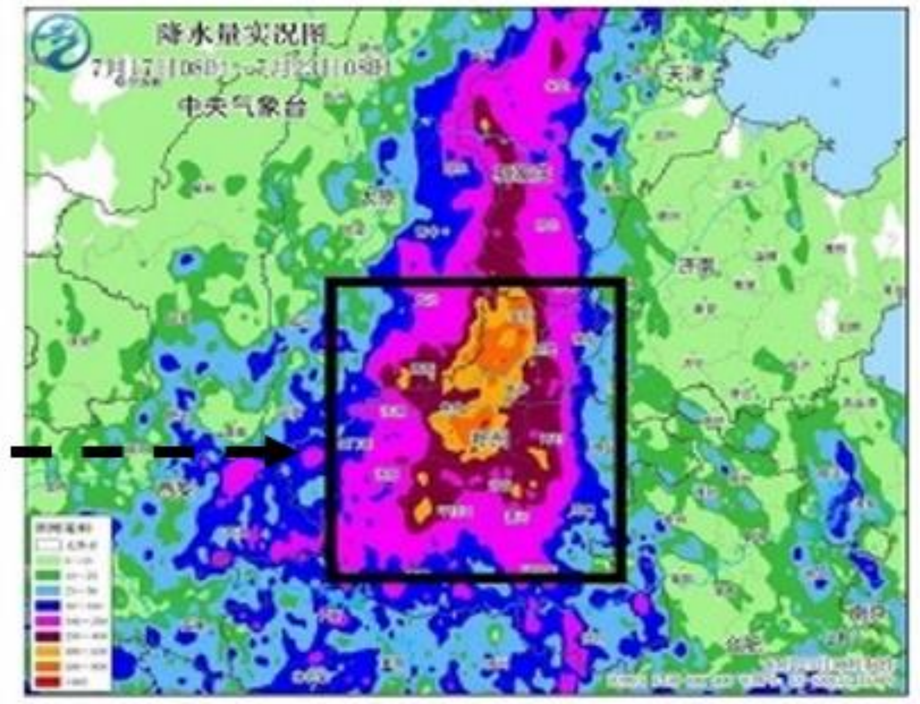
Subseasonal Prediction: The 21.7 Flooding Event

ERA5 850-hPa Wind (17-23, July)



CMA Rainfall



Weather and Climate Extremes 39 (2023) 100541

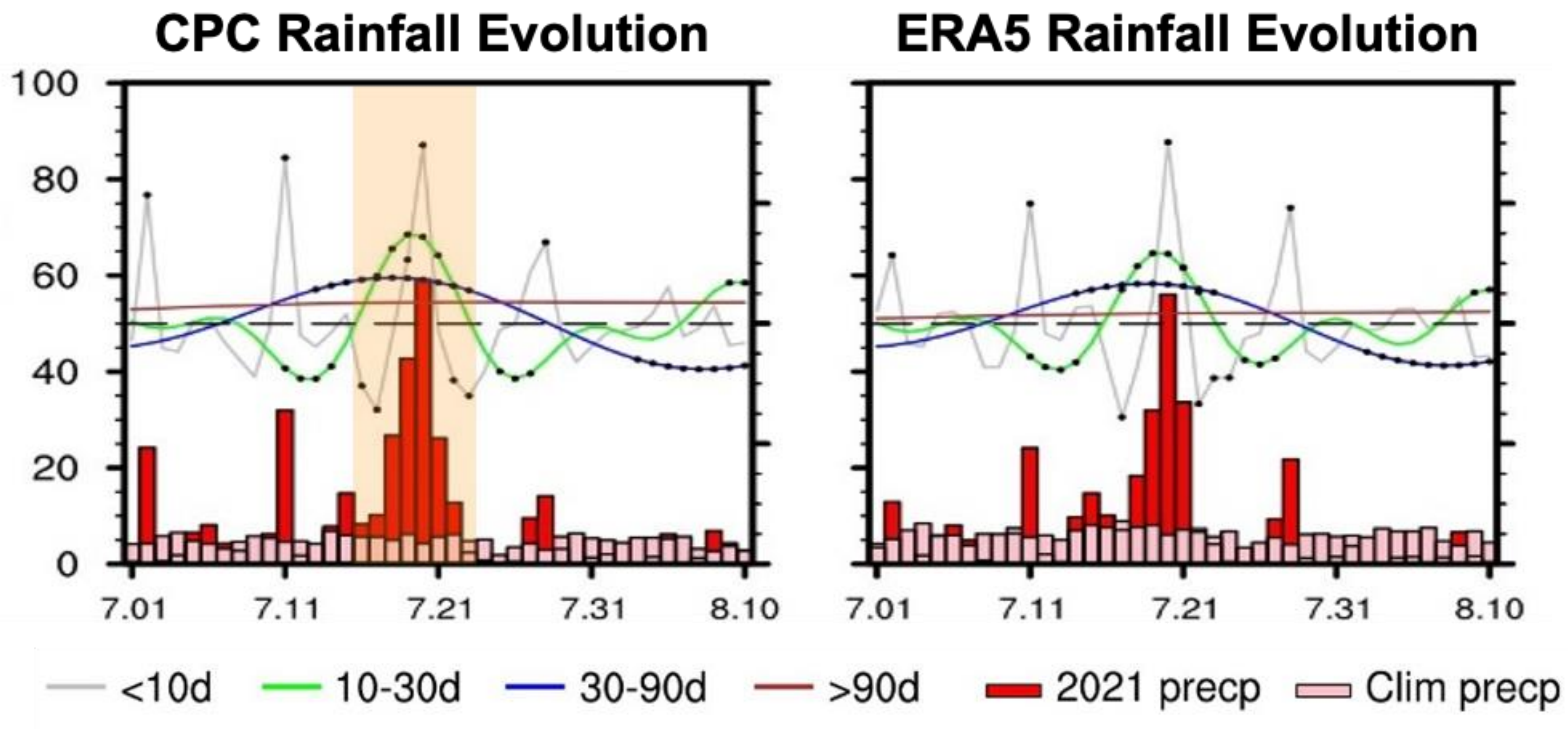
Contents lists available at ScienceDirect

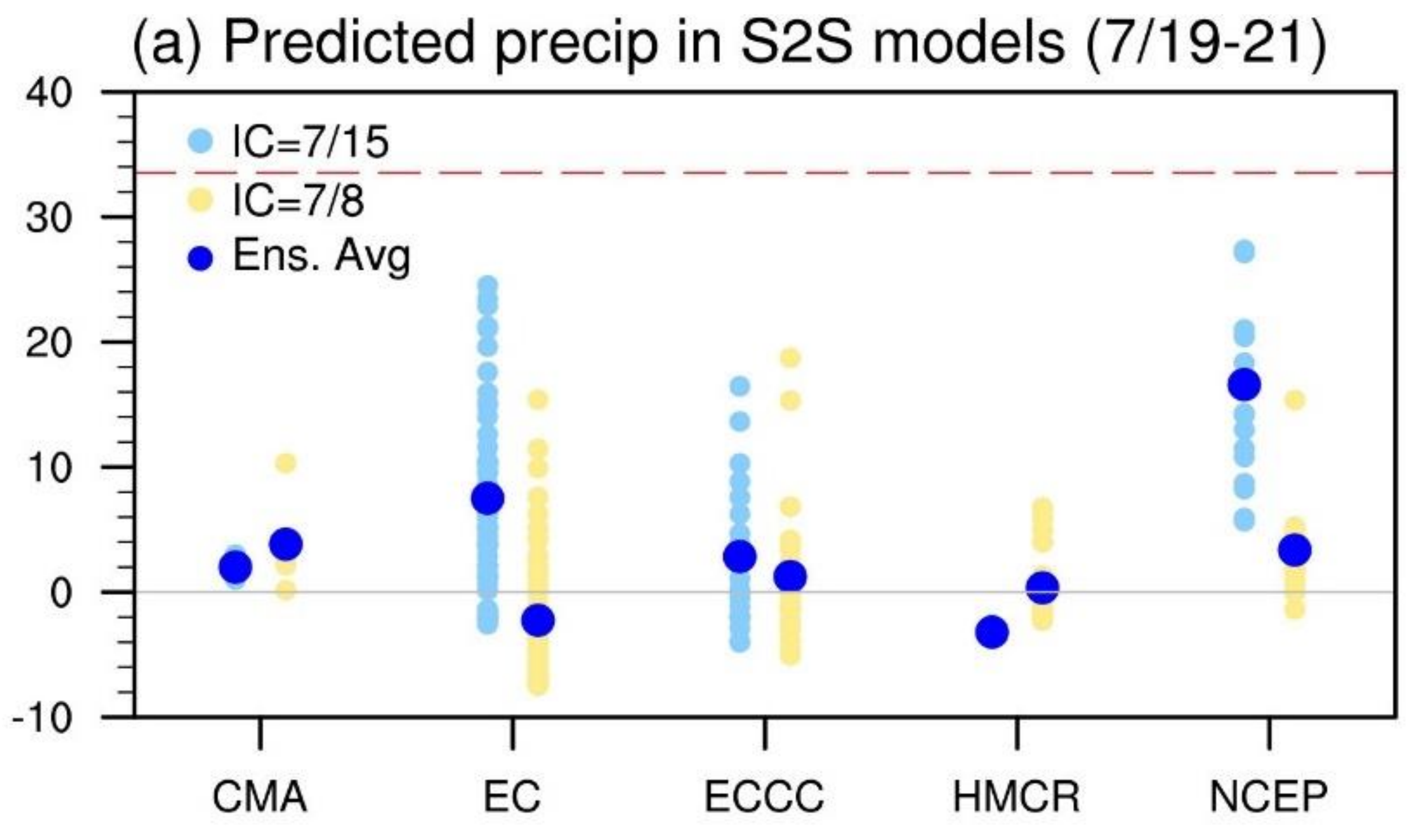
Weather and Climate Extremes

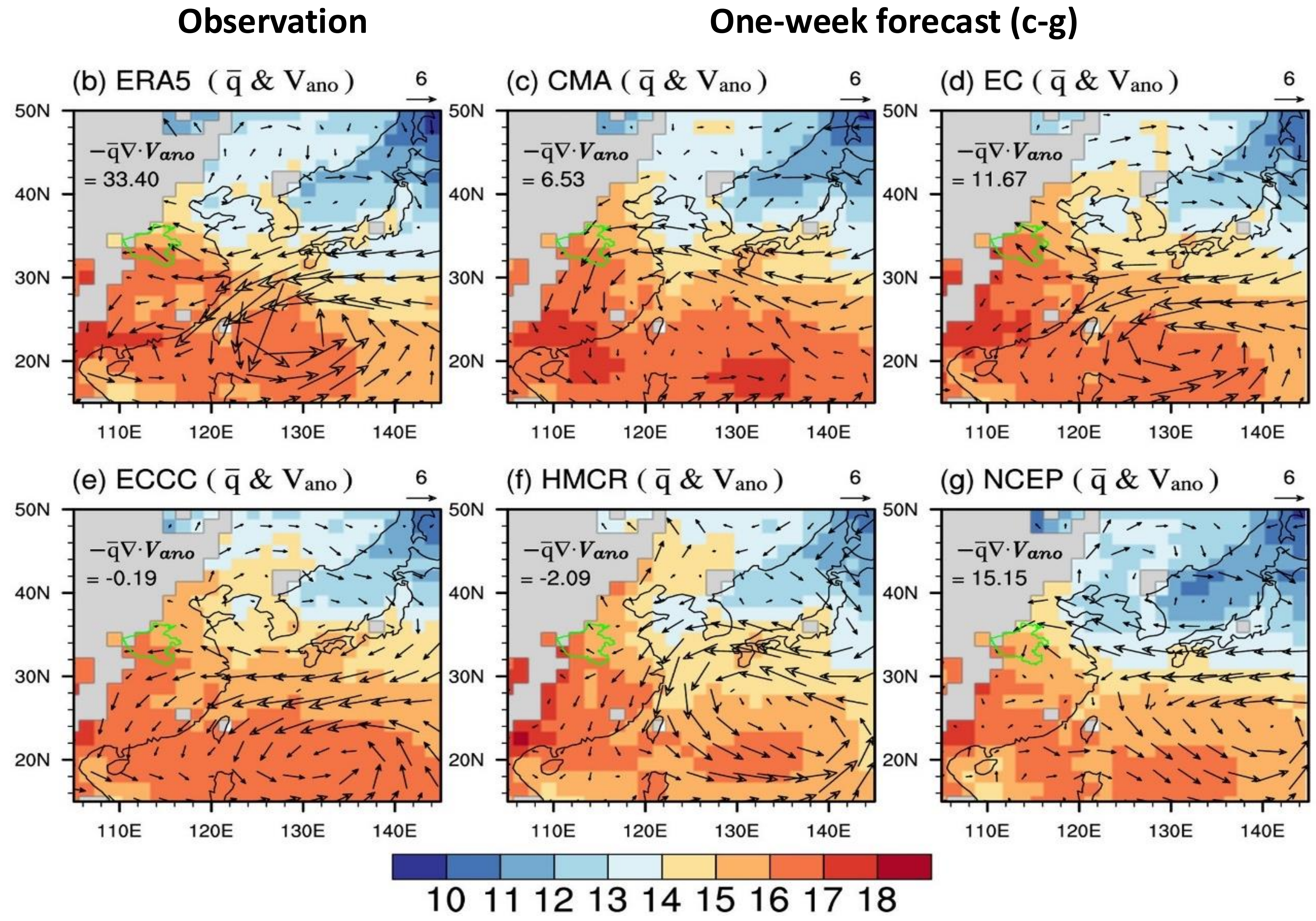
journal homepage: www.elsevier.com/locate/wace

Multiscale interactions driving the devastating floods in Henan Province, China during July 2021

Pang-Chi Hsu[a,b,**], Jinhui Xie[a], June-Yi Lee[c,d,*], Zhiwei Zhu[a], Yan Li[a], Bin Chen[b], Shengjun Zhang[b]

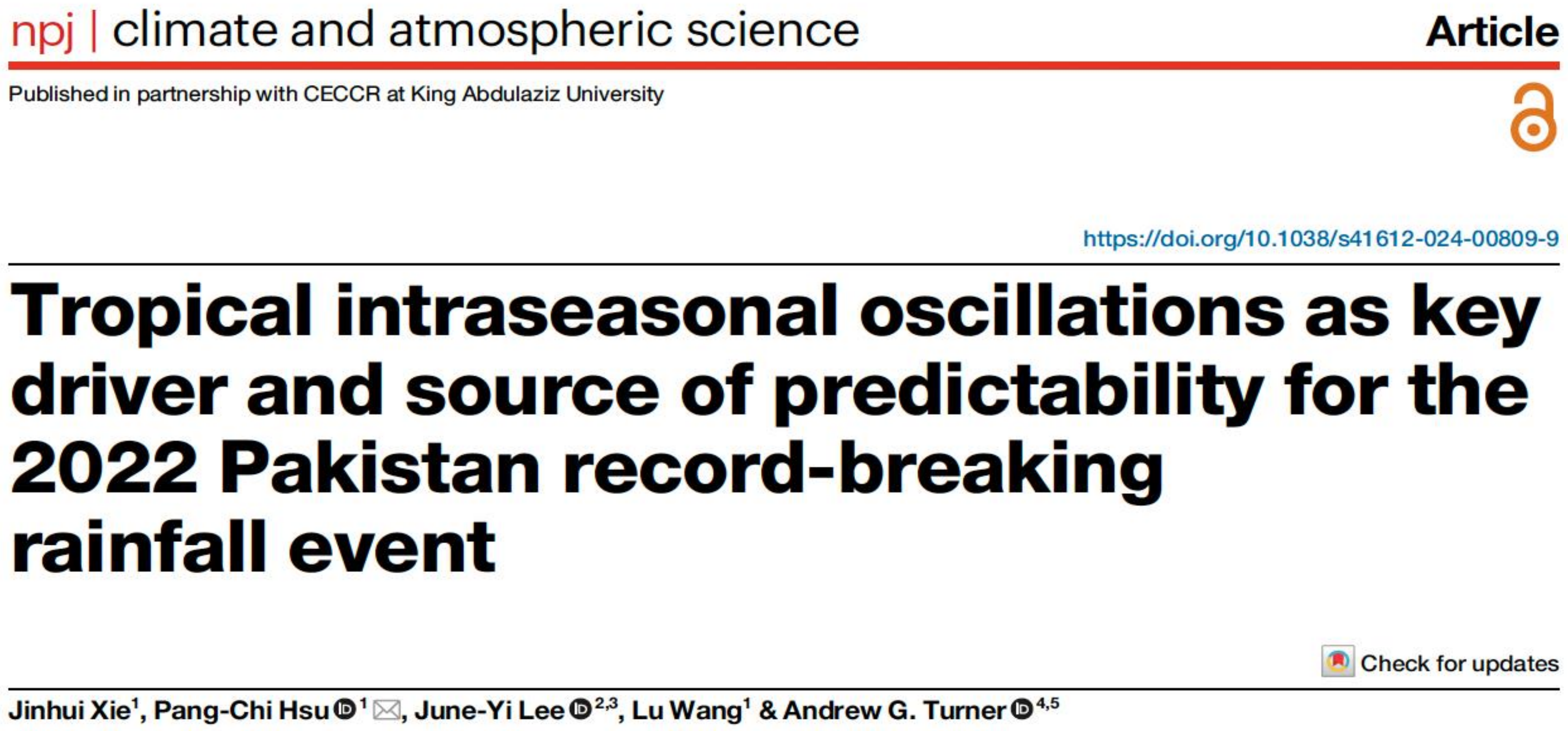






- **All five S2S models** tended to underestimate the amount of rainfall over Henan Province compared to the observations.
- The ensemble-mean predictions of **ECMWF and NCEP at a one-week lead time captured the enhanced precipitation in Henan Province**, although the amplitude was too weak due **to biases in the pattern and strength of subseasonal wind anomalies**.
- **The improvement of model fidelity in simulating/predicting subseasonal circulation anomalies** is crucial for **improving the extreme rainfall predictions.**

Subseasonal Prediction: The 2022 Pakistan Flood


npj | climate and atmospheric science — Article

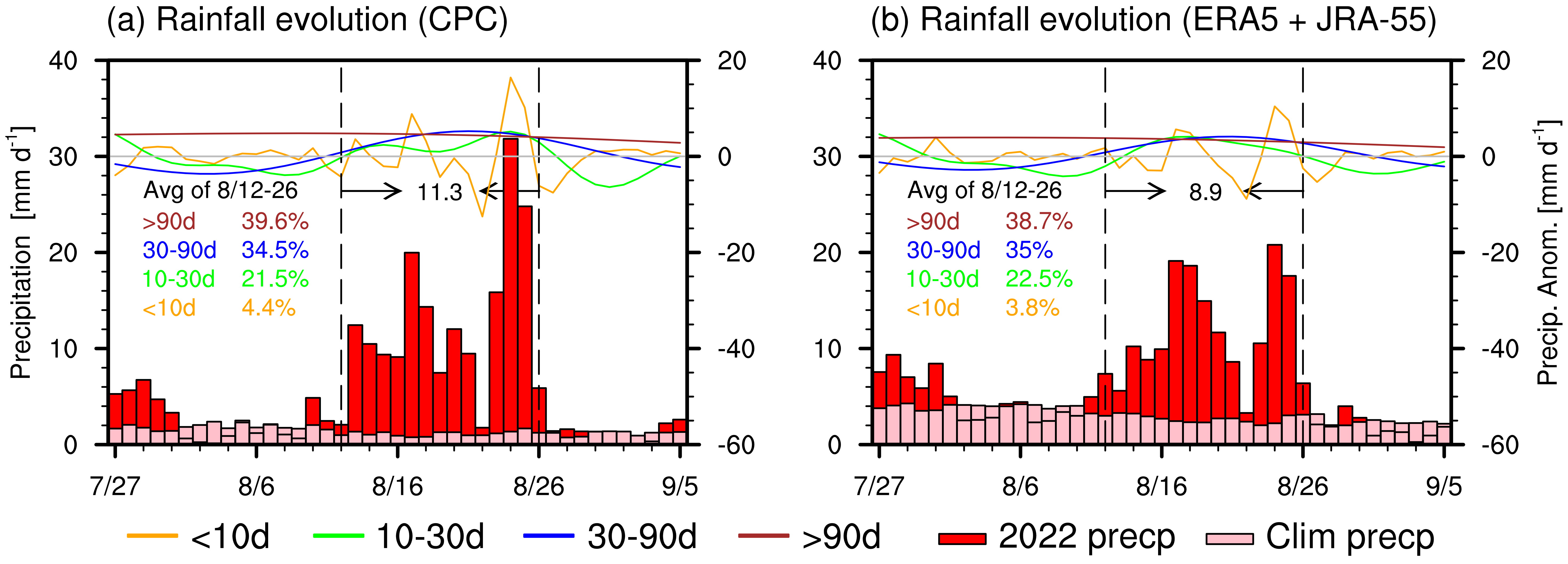
Published in partnership with CECCR at King Abdulaziz University

https://doi.org/10.1038/s41612-024-00809-9

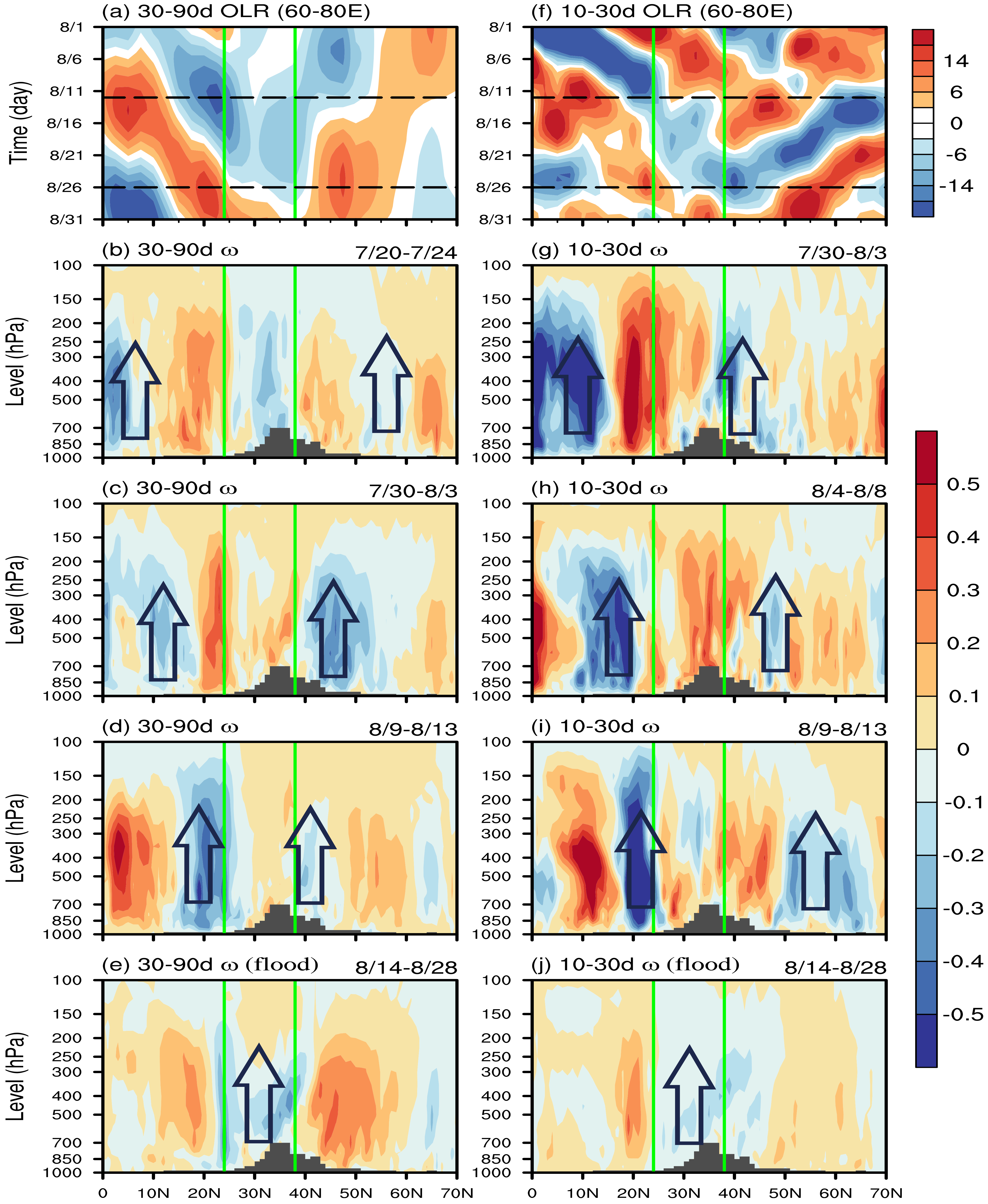
Tropical intraseasonal oscillations as key driver and source of predictability for the 2022 Pakistan record-breaking rainfall event

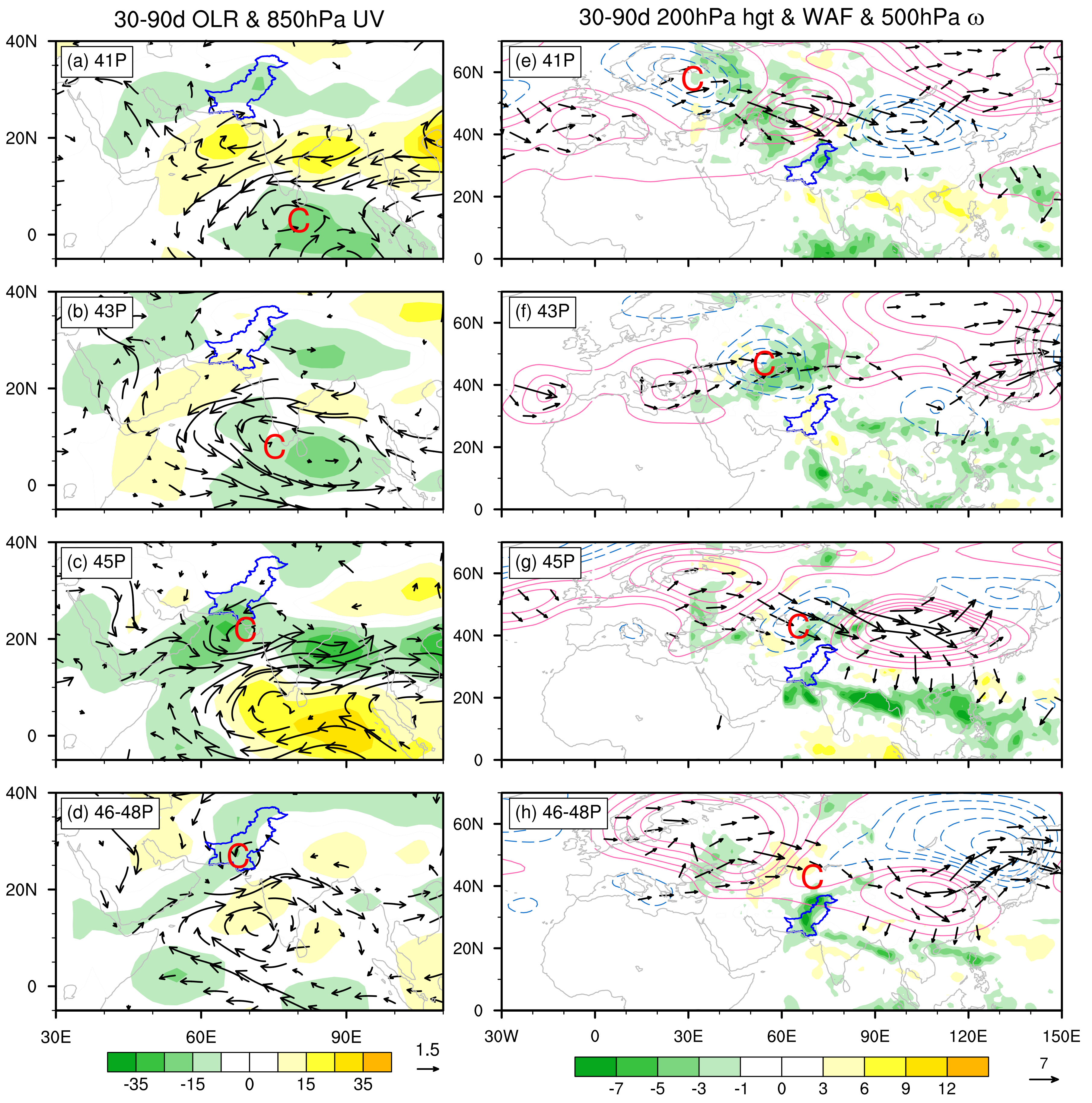
Check for updates

Jinhui Xie[1], Pang-Chi Hsu[1], June-Yi Lee[2,3], Lu Wang[1] & Andrew G. Turner[4,5]

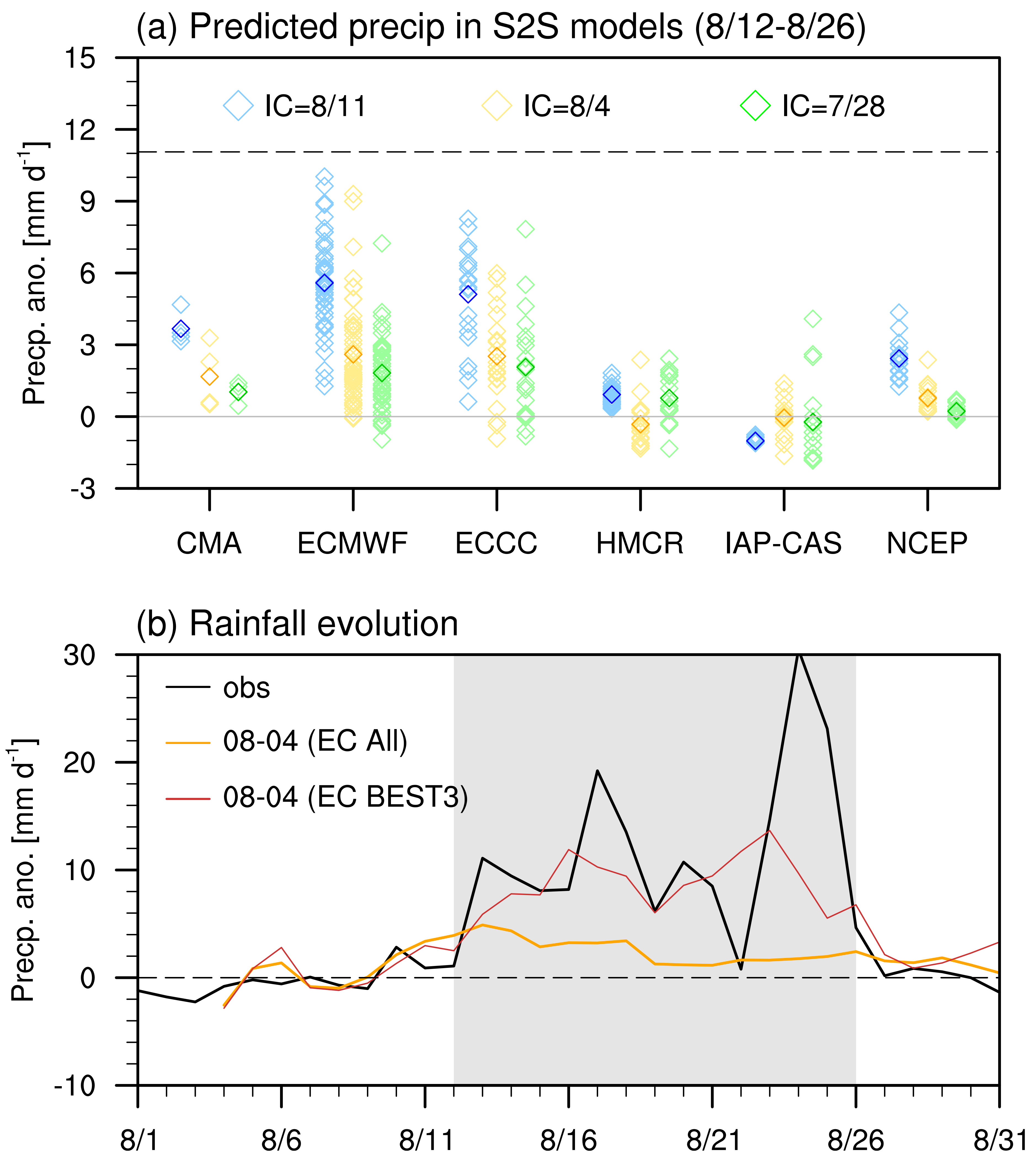


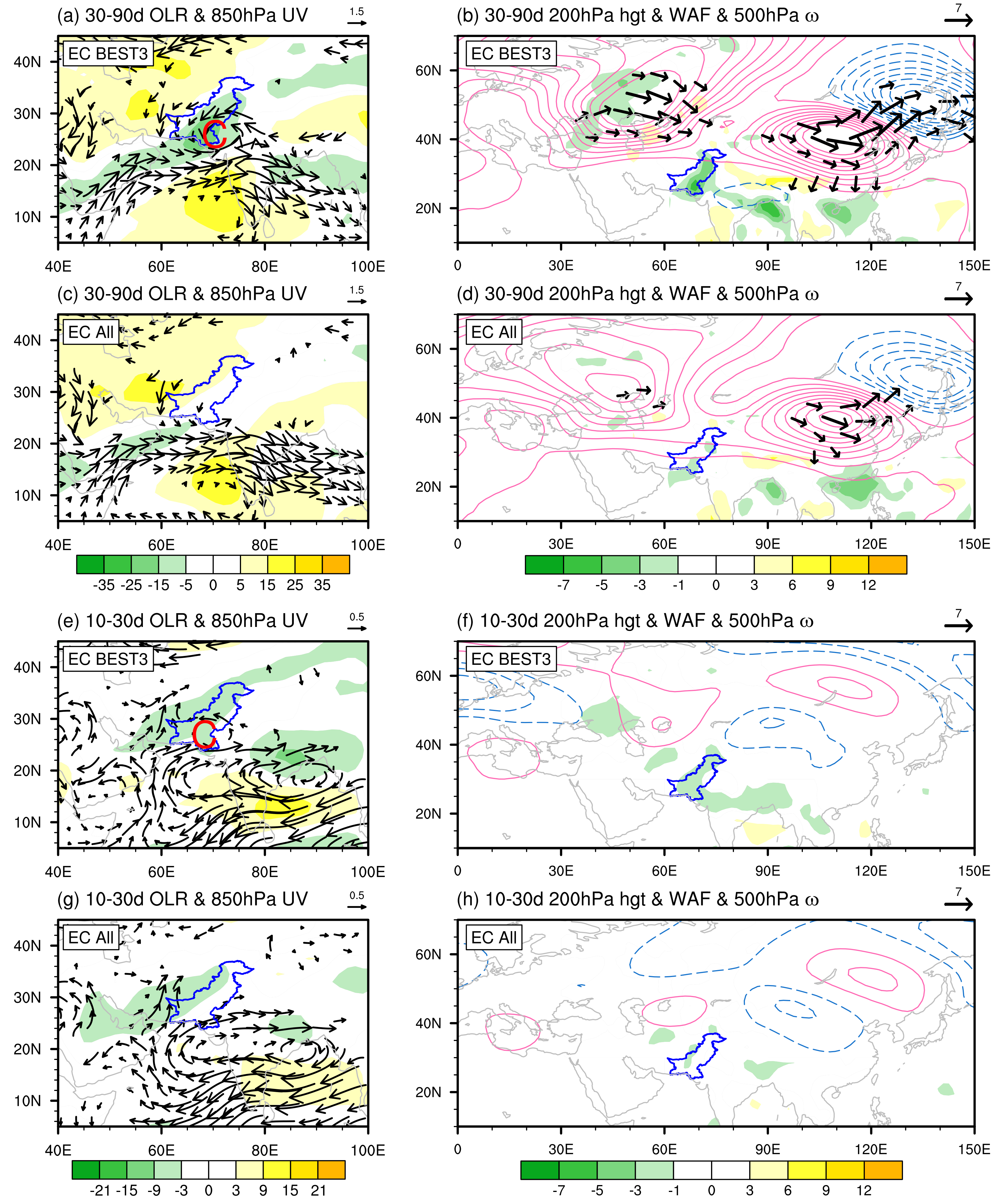
- **The intense rainfall in Pakistan was triggered and sustained by enhanced moisture convergence anomalies, primarily driven by interactions between intraseasonal circulation anomalies and the prevailing background moisture field.**





- **The intensified convergence and upward motion anomalies occurred as the northward-propagating tropical 30–90-day and 10–30-day intraseasonal convections converged with the southeastward-moving mid-latitude 30–90-day wave train over the Pakistan region.**





- **The validation of subseasonal prediction products highlights the critical role of tropical intraseasonal modes in causing the extreme rainfall event in Pakistan. The models, that accurately predicted the northward propagating intraseasonal convections at lead time of 8-22 days, they had better skills for predicting the extreme rainfall over Pakistan.**

Boreal Summer MJO Prediction using Machine Learning

npj | climate and atmospheric science

Article

Published in partnership with CECCR at King Abdulaziz University

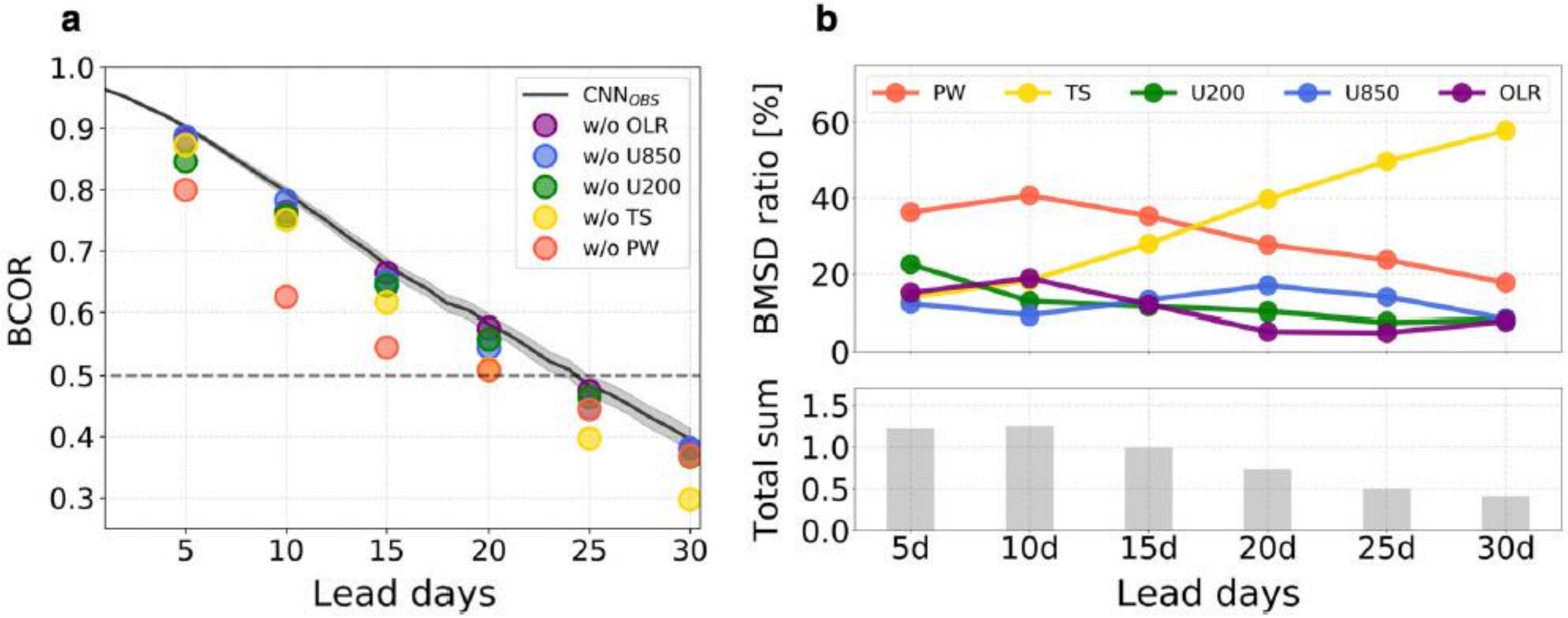
https://doi.org/10.1038/s41612-024-00799-8

Data-driven investigation on the boreal summer MJO predictability

Check for updates

Na-Yeon Shin [1,6], Daehyun Kang [2,6], Daehyun Kim [1], June-Yi Lee [3,4] & Jong-Seong Kug [1,5]

Performance of the CNN model for the summer MJO



- The **Machine-Learning-based** **summer MJO prediction model** has a correlation skill of **0.5** **at about 24-day forecast lead.**
- By utilizing eXplainable Artificial Intelligent (XAI), we discern **precipitable water** and **surface temperature** as the most influential **sources for the summer MJO predictability.**
- Machine-learning-based approaches are useful for identifying sources of climate predictability.

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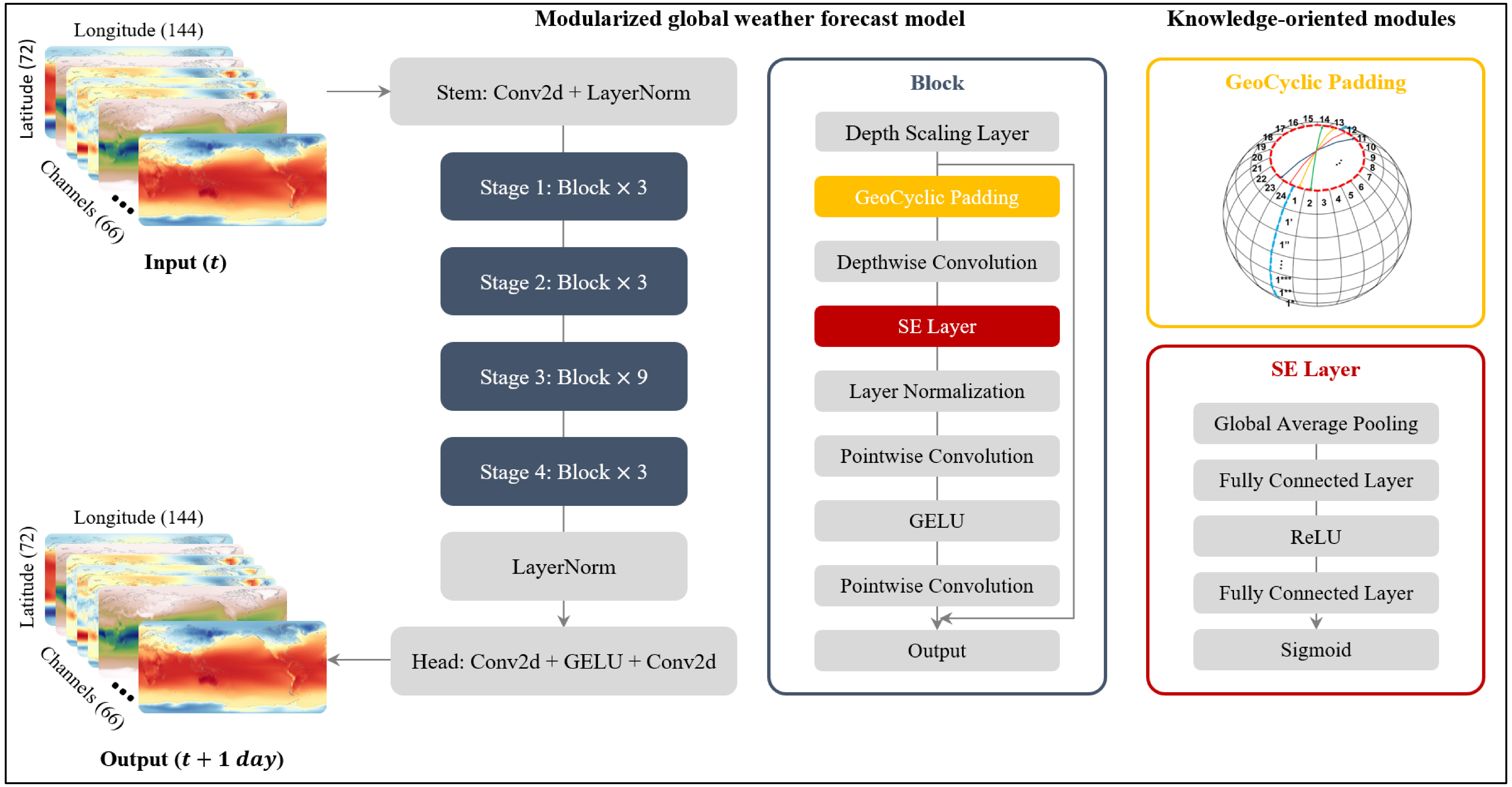
S2S Prediction using an AI Global Climate Model



KARINA (2024)
ConvNeXt backbone
+ SENet and Geocyclic Padding

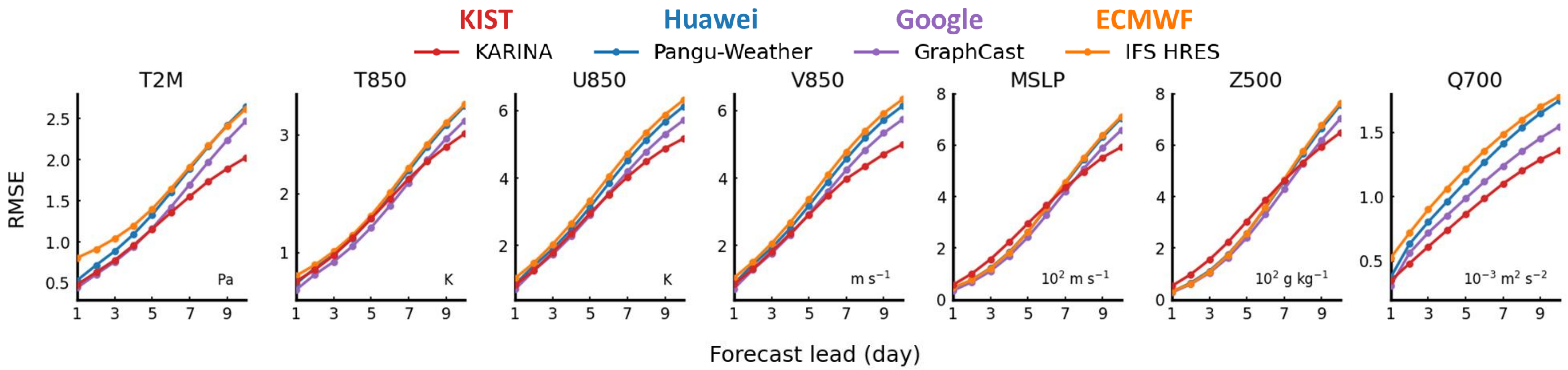
KARINAv1: Global 2.5-degree (image size: 144x72)
Prediction at daily interval (using daily-mean)
Training 1979-2015, Validation 2016-17, Test (skill intercomparison) 2018

Cheon et al. under review: KARINA: An efficient deep learning model for global weather forecast.
arxiv.org/2403.10555v1

ICCP

S2S Prediction using an AI Global Climate Model

Globally averaged latitude-weighted RMSE in 2018 (skill data source: weatherbench2)



- **KARINA has comparable skill for weather forecast with other AI global weather prediction models and has potential for subseasonal prediction**

Cheon et al. under review: KARINA: An efficient deep learning model for global weather forecast. arxiv.org/2403.10555v1

Global Basic Laboratory

The **G**lobal Basic Research Laboratory on the Near-term Earth System Changes and their **Impact**s on Economy and Planetary Health (**G-Impact**)

June-Yi Lee (PI)
PNU

Climate

Christian Franzke (Co-PI)
PNU

Economy

G-Impact

Health

Whan Hee Lee (Co-PI)
PNU

Ecosystem

Young-Min Yang (Co-PI)
JNU

SUSTAINABLE DEVELOPMENT GOALS

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4 양질의 교육

13 기후변화 대응

14 해양생태계

15 육상생태계

17 글로벌 파트너십

KUNMING MONTREAL GLOBAL BIODIVERSITY FRAMEWORK

Global Health Security Agenda

Thank You!