Pantropical climate interactions

The extended Recharge Oscillator (XRO) for ENSO and other climate modes

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Guest Lecture for OCN/ATMO666
April 22, 2025

Recent reviews on the topic

Science

REVIEW

Pantropical climate interactions

WENJU CAI, LIXIN WU, MATTHIEU LENGAIGNE, TIM LI, SHAYNE MCGREGOR, JONG-SEONG KUG, JIN-YI YU, MALTE F. STUECKER, AGUS SANTOSO, [...], AND PING CHANG +24 authors Authors Info & Affiliations

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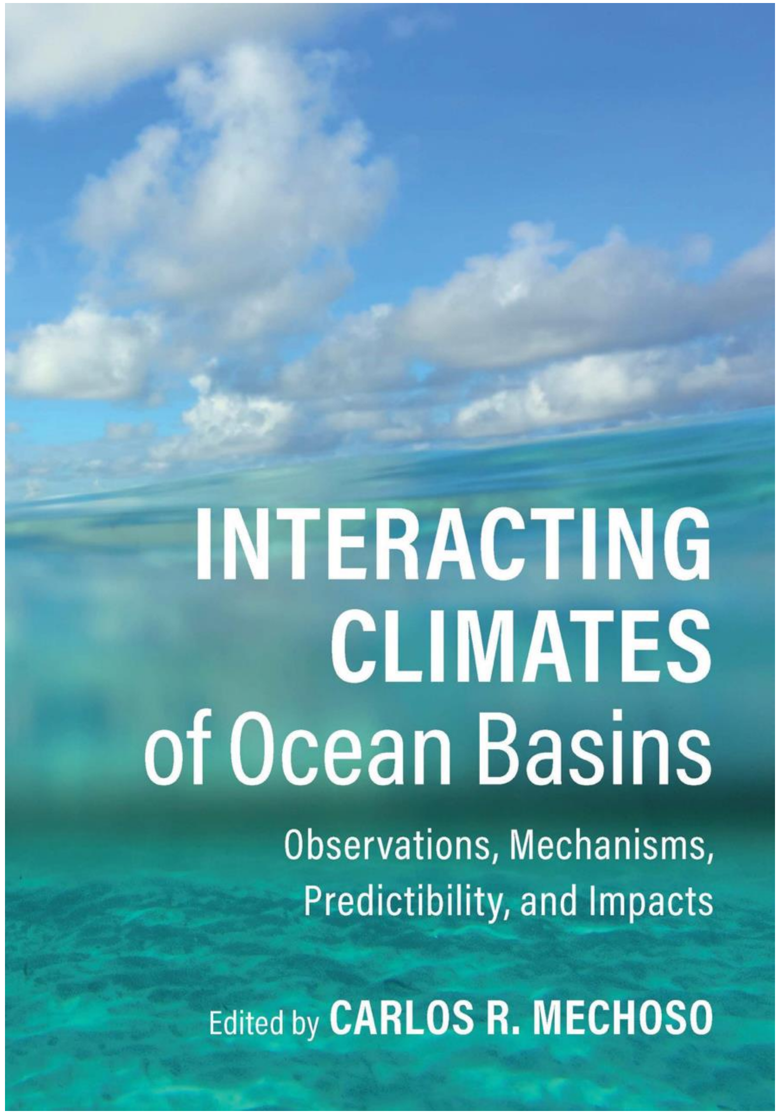
https://doi.org/10.1007/s00382-019-04930-x

Three-ocean interactions and climate variability: a review and perspective

Chunzai Wang[1]

Received: 23 April 2019 / Accepted: 5 August 2019 / Published online: 12 August 2019



Mechoso 2020

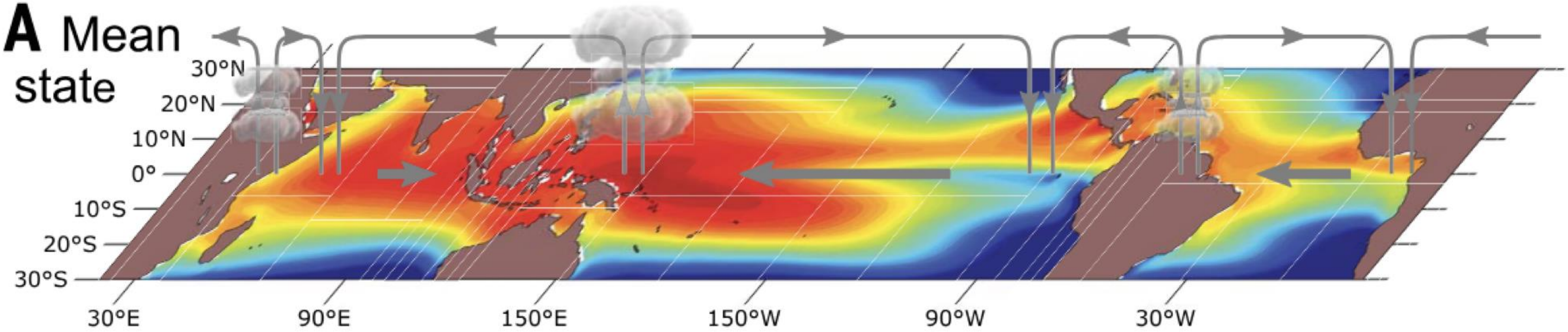
Outline

1. Overview of pantropical climate interactions
    - *Mean state and variability*
    - *Methodologies*

2. Conceptual understanding of pantropical climate variability and predictability
    - *ENSO Recharge Oscillator (RO) theory and predictability*
    - *Hasselmann theory and predictability of other climate modes*
    - *Extended nonlinear RO (XRO) model for interconnected global climate*

3. Hands-on Application of the XRO Model

Pantropical Oceans: Mean state

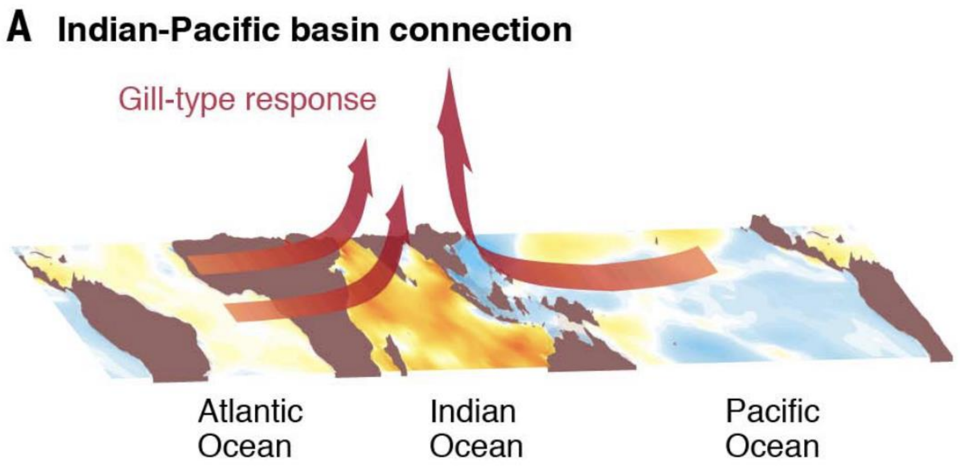


Cai et al. 2019

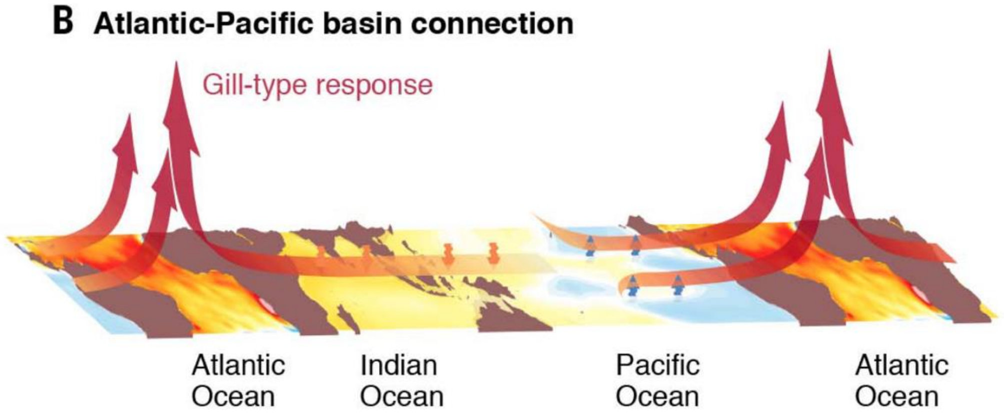
The tropical oceans — the Pacific, Atlantic, and Indian — are not separate but dynamically connected through atmospheric bridges and oceanic pathways:

1) Walker circulation (mainly driven by SST zonal gradient)
2) Mid-latitude teleconnection
3) Indonesian Throughflow

Interbasin interaction (decadal to long-term changes)



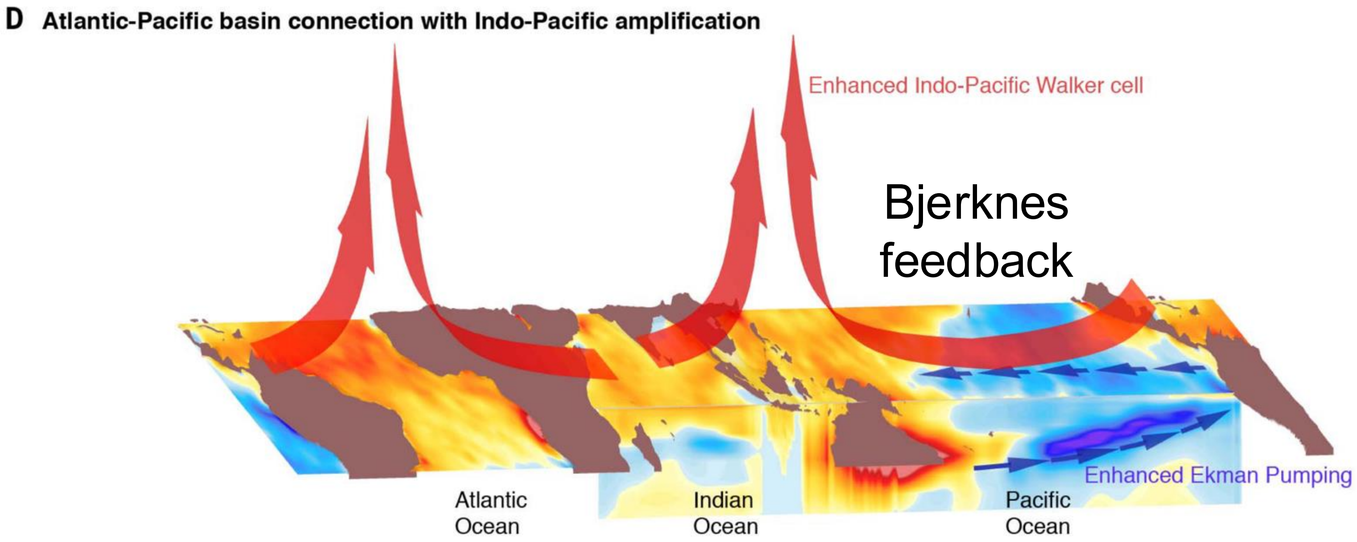
- Deep convection generated via **Indian Ocean warming creates a Gill-type response** that increases surface easterly winds and cold SSTs in the western Pacific.



- Deep convection generated via **Atlantic Ocean warming creates a Gill-type response**, generating anomalous easterlies over the Indian Ocean and western Pacific. These anomalous winds lead to SST warming over the Indian Ocean and SST cooling over the western and central Pacific.

Cai et al. 2019

Interbasin interaction (decadal to long-term changes)



- The atmospheric circulation and surface temperature changes generated owing to Atlantic warming in are **amplified by the Pacific Bjerknes feedback and IOD-Pacific interactions**.

Cai et al. 2019

Interbasin interactions are important for mean-state changes (See recent review in Watanabe et al. 2024)

2024

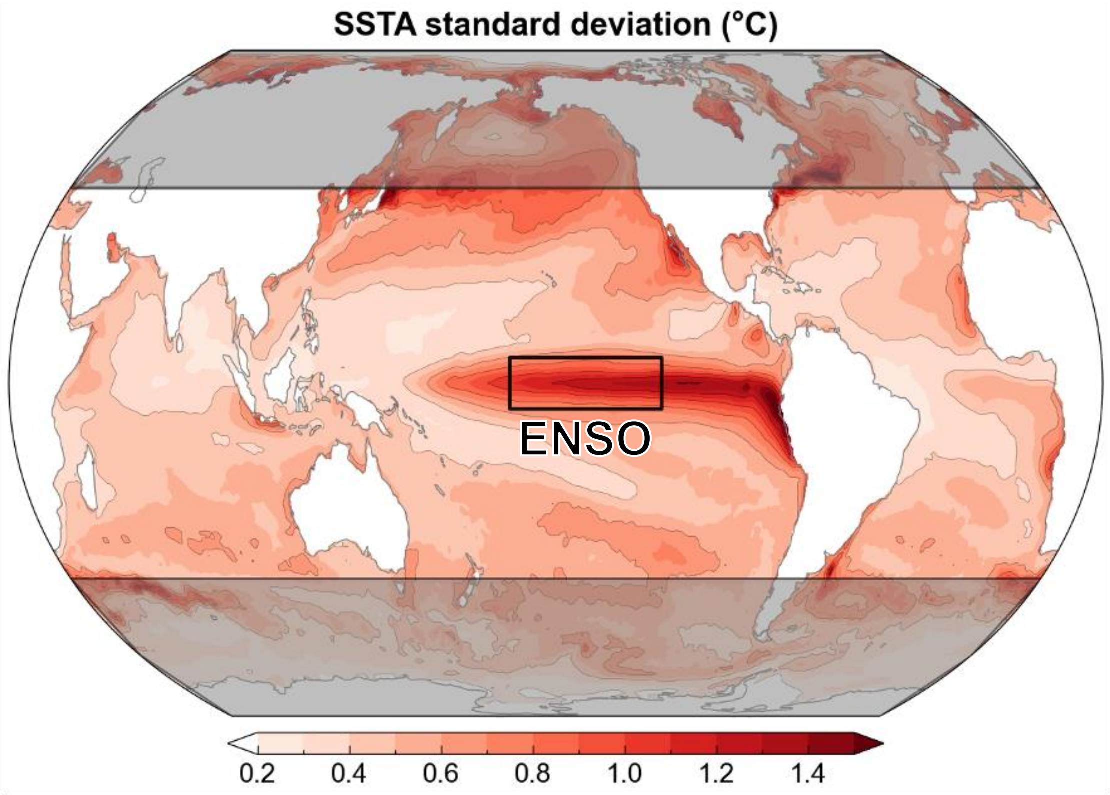
nature

Perspective

Possible shift in controls of the tropical Pacific surface warming pattern

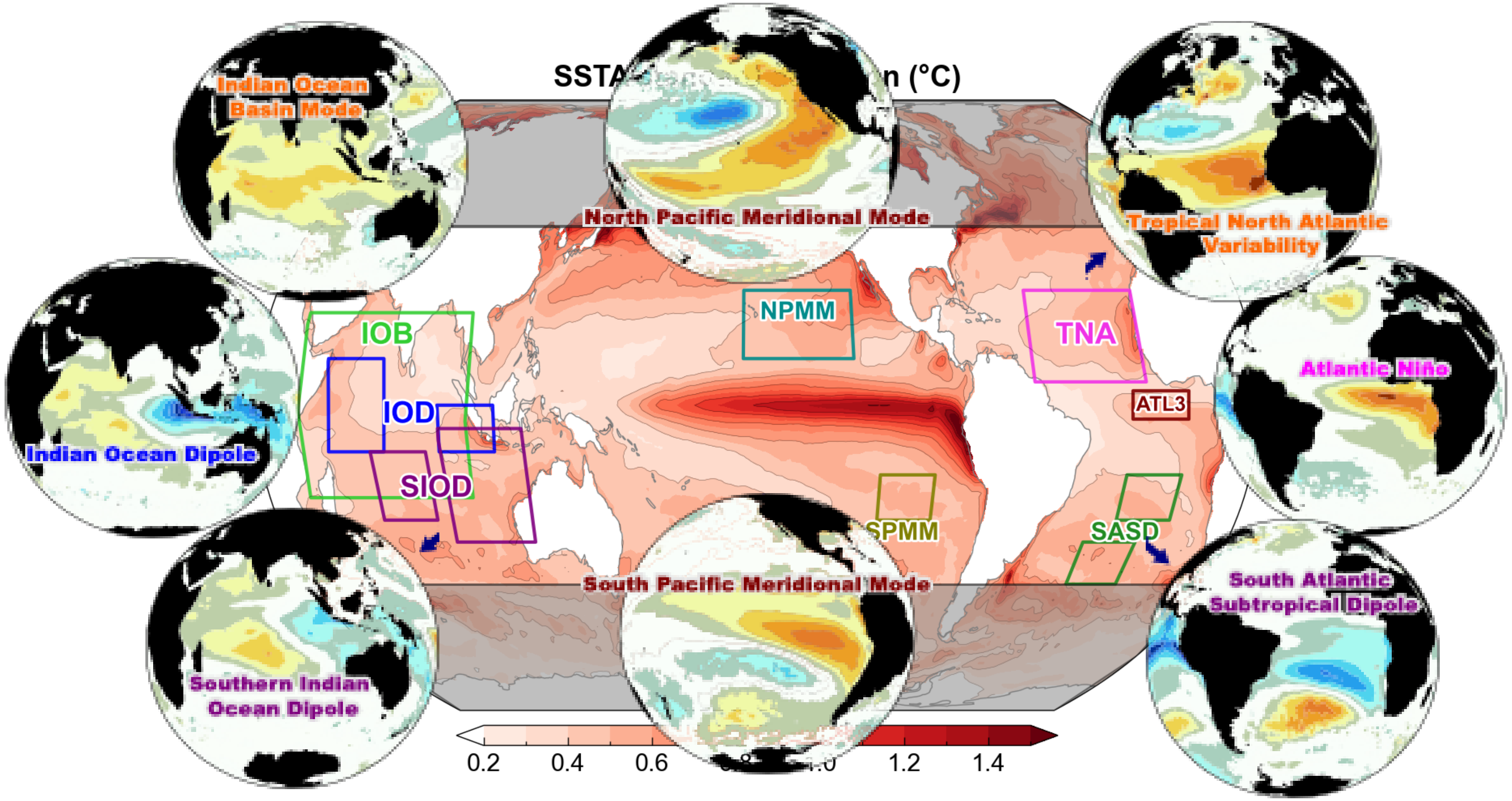
Masahiro Watanabe[1✉], Sarah M. Kang[2✉], Matthew Collins[3], Yen-Ting Hwang[4], Shayne McGregor[5] & Malte F. Stuecker[6]

We will focus on SST variability



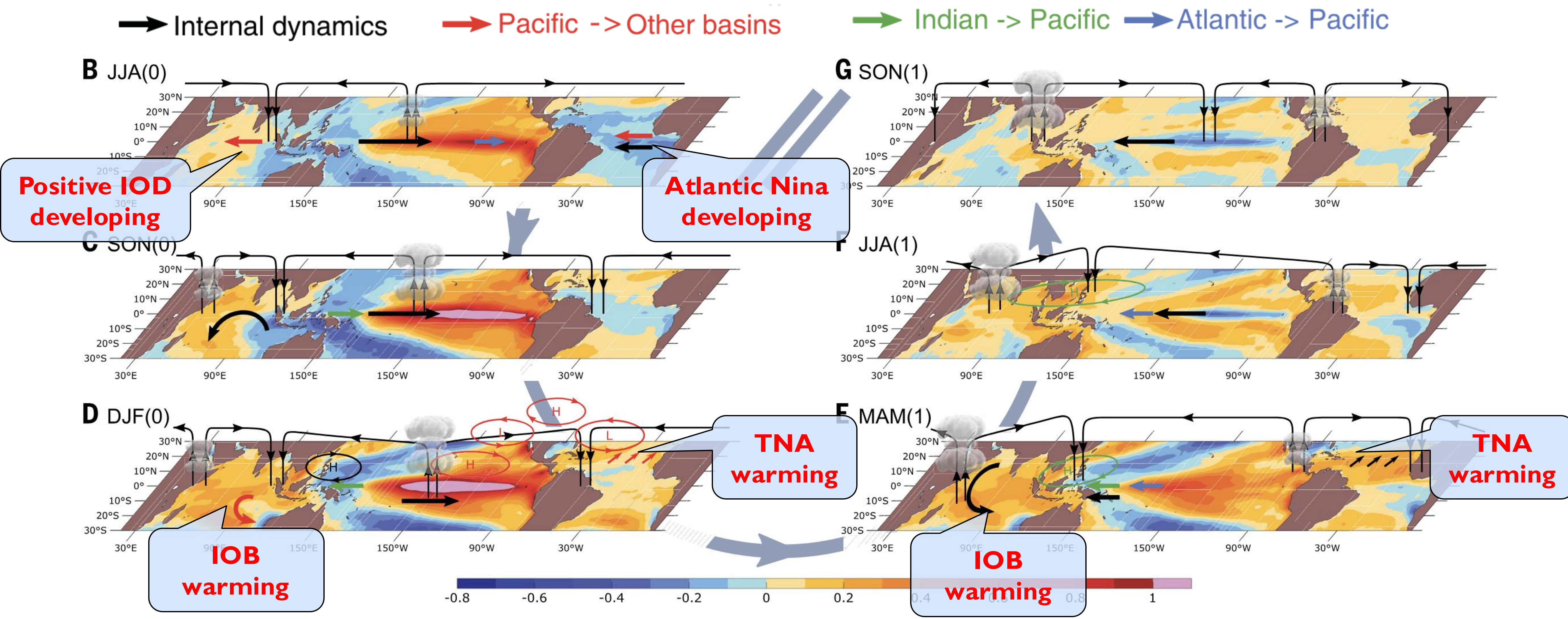
El Niño-Southern Oscillation (ENSO) is most prominent interannual signal in the global climate system. **ENSO provides most of the global seasonal climate forecast skill.**

Pantropical SST Variability: Other climate modes



Other climate modes/patterns of variability outside the tropical Pacific interact with ENSO, could provide additional sources of predictability that influences regional and even global climate

Evolution of tropical interbasin interactions during a typical El Niño event.



Seasonally stratified SST anomaly lead or lag regression with normalized December-January-February (DJF) Niño3.4

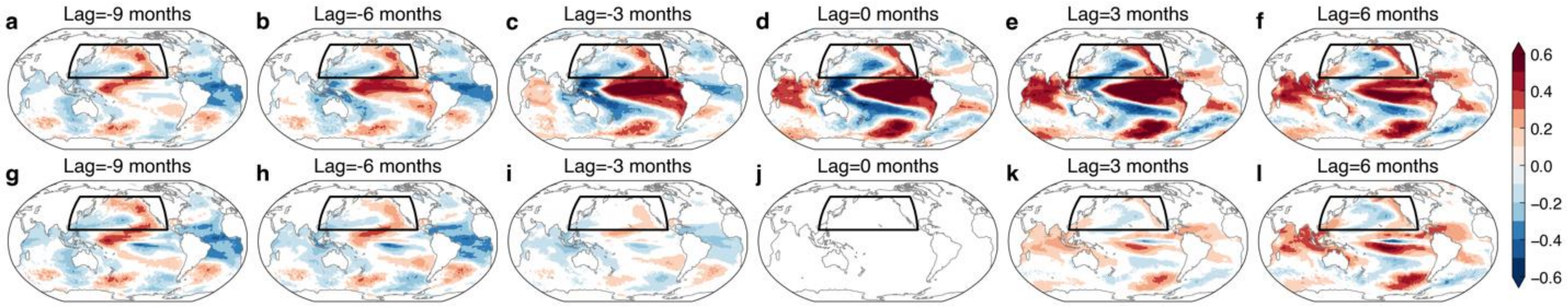
Cai et al. 2019

Methodologies (1)

1) Lead-lag regression/correlation analysis

A significant challenge is to completely remove the ENSO signal itself in this type of analysis due to ENSO's strong seasonal variance modulation, its amplitude nonlinearity, and its spatial pattern diversity (*An and Jin 2004*; *Stuecker 2018*; *Zhao et al. 2021*; *Richter et al. 2022*)

Lead-lag correlation of SSTA onto Niño3.4 index



Bottom: "removing" ENSO via simultaneous linear regression of the Niño3.4 index

The ENSO signal is not completely removed

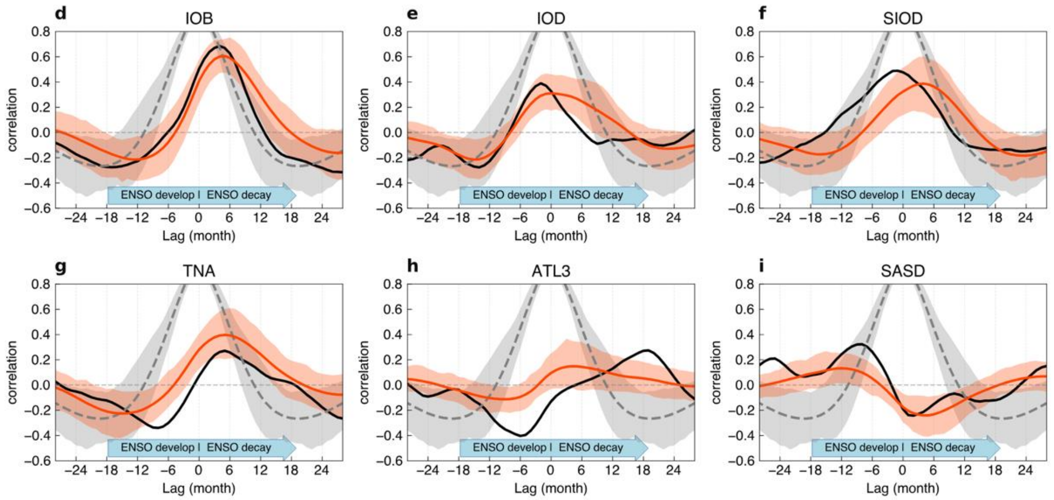
Zhao et al. 2024

Methodologies (2)

2) Coupled GCM experiments

- Partially coupled experiments *(e.g., Yu et al. 2002; Wu and Kirtman 2004; Kug et al. 2006; Ding et al. 2012; Santoso et al. 2012; Yang et al. 2015; Terray et al. 2016; Crétat et al. 2017)*
- Pacemaker experiments *(Stuecker 2018; Amaya et al. 2019)*
- Controlled fluxes experiments *(Chakravorty et al. 2020, 2021)*
- Mechanically decoupled experiments *(e.g., Larson et al. 2018; Zhang et al. 2021)*
- Partially coupled forecast experiments *(Luo et al. 2010, 2017)*,
- Partial initialization forecast experiments *(Frauen and Dommenget 2012; Kido et al. 2023)*,
- Relaxing towards observation forecast experiments *(Keenlyside et al. 2013; Exarchou et al. 2021)*

Biases in climate mean state and ENSO dynamics, thus hindering skill in predicting ENSO and complicating quantification of the other ocean basins' effect on ENSO predictability



Zhao et al. 2024

Methodologies (3)

3) Linear inverse models

$$\frac{dx}{dt} = \mathbf{L}\mathbf{x} + \xi,$$

Linear operator $\mathbf{L} = \tau_0^{-1}\ln\{\mathbf{C}(\tau_0)\mathbf{C}(0)^{-1}\},$

Noise forcing statistics $\mathbf{L}\mathbf{C}(0) + \mathbf{C}(0)\mathbf{L}^T + \mathbf{Q} = 0,$

x(t) is the state vector (PCs of SST/SSH anomalies) at time t, ξ is white noise forcing.

$\mathbf{C}(0) = \langle \mathbf{x}(t)\mathbf{x}^T(t)\rangle$ and $\mathbf{C}(\tau_0) = \langle \mathbf{x}(t+\tau_0)\mathbf{x}^T(t)\rangle$

(Penland & Sardeshmukh 1995;
Newman et al. 2011; Kido et al. 2023)

- Current linear inverse models are by construction not able to fully capture **ENSO's nonlinear dynamics and seasonality**
- State vectors (using EOFs and PCs) sometimes are not physical

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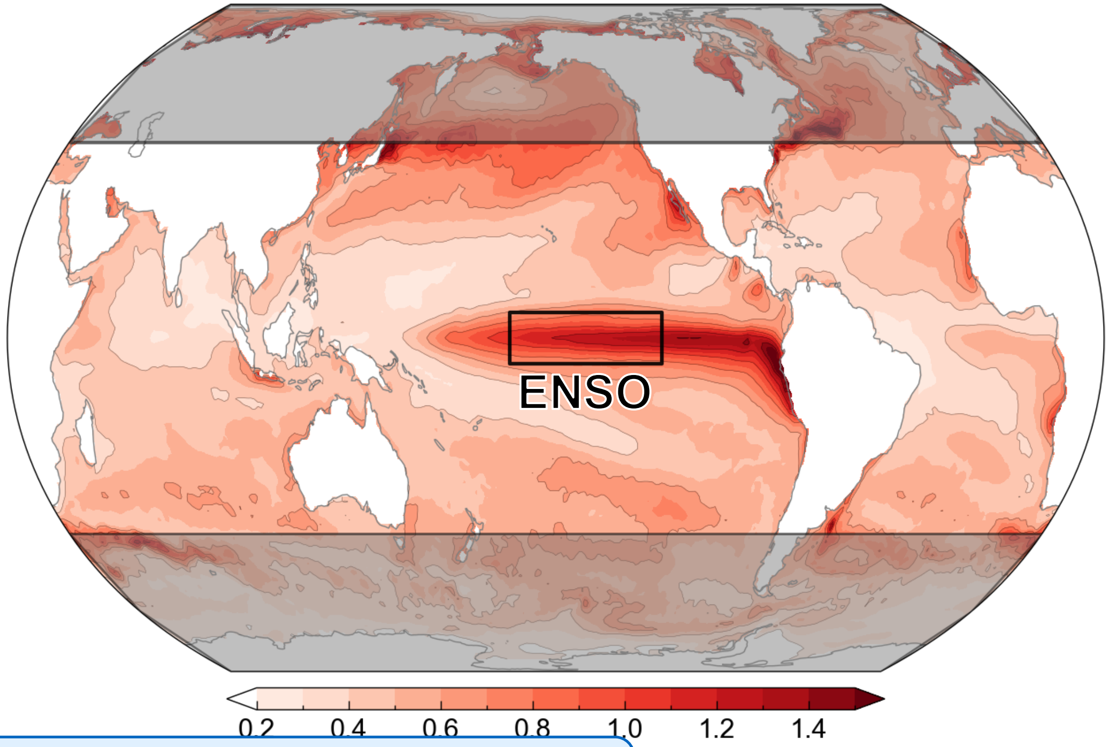
3. Hands-on Application of the XRO Model

ENSO Recharge Oscillator theory

SSTA standard deviation (°C)



Recharge Oscillator (RO) —— 2 degrees of freedom

$$\frac{d}{dt}\begin{pmatrix} T_{\mathrm{ENSO}} \\ h \end{pmatrix} = \begin{pmatrix} R_T & F_1 \\ F_2 & -\epsilon \end{pmatrix}\begin{pmatrix} T_{\mathrm{ENSO}} \\ h \end{pmatrix} + N_{\mathrm{ENSO}} + \xi$$

RO model can explain the basic features of ENSO:
its amplitude, periodicity, phase-locking, and asymmetry

(Jin 1997; Jin et al. 2020)

Reviews of Geophysics

Review Article | Open Access

The El Niño Southern Oscillation (ENSO) Recharge Oscillator Conceptual Model: Achievements and Future Prospects

J. Vialard, F.-F. Jin, M. J. McPhaden, A. Fedorov, W. Cai, S.-I. An, D. Dommenget, X. Fang, M. F. Stuecker, C. Wang, A. Wittenberg, S. Zhao, F. Liu, S.-K. Kim, Y. Planton, T. Geng, M. Lengaigne, A. Capotondi, N. Chen, L. Geng, S. Hu, T. Izumo, J.-S. Kug, J.-J. Luo, S. McGregor, B. Pagli, P. Priya, S. Stevenson, S. Thual
... See fewer authors ^

First published: 20 March 2025 | https://doi.org/10.1029/2024RG000843

ENSO Recharge Oscillator (RO) theory and predictability

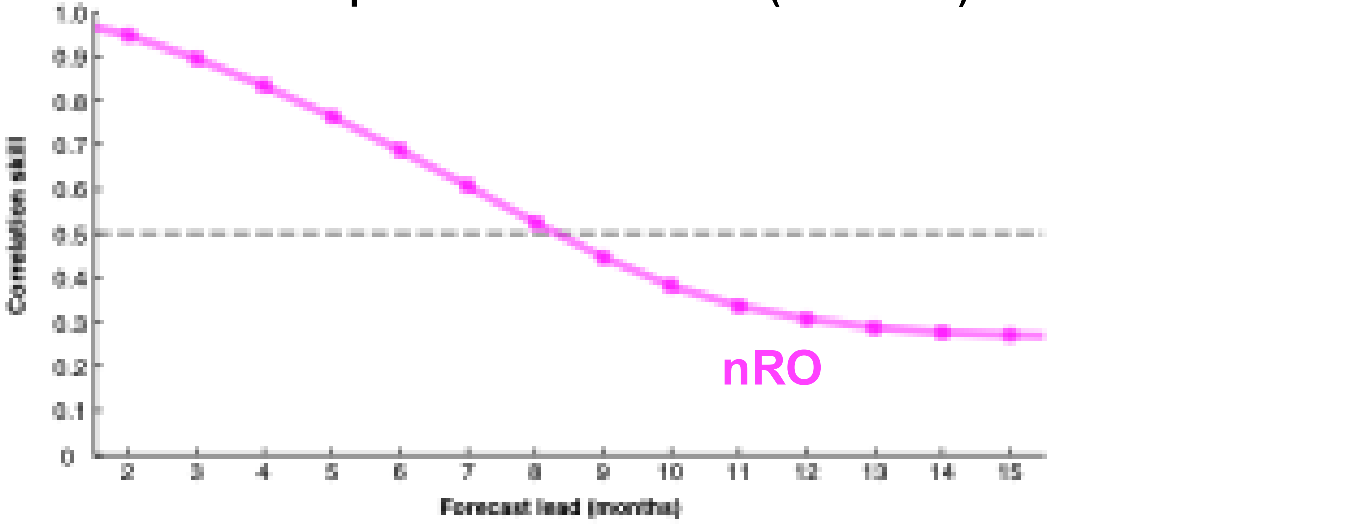
Recharge Oscillator (RO)
— 2 degrees of freedom

(Jin 1997; Jin et al. 2020)

$$\frac{d}{dt}\begin{pmatrix} T_{\mathrm{ENSO}} \\ h \end{pmatrix} = \begin{pmatrix} R_T & F_1 \\ F_2 & R_h \end{pmatrix}\begin{pmatrix} T_{\mathrm{ENSO}} \\ h \end{pmatrix} + \boldsymbol{N}_{\mathrm{ENSO}}$$

RO model can explain the basic features of ENSO: amplitude, periodicity, phase-locking, and asymmetry

Out-of-sample ENSO forecast skill (2002-2022)



(Zhao et al. 2024)

What is the predictive skill of RO?

- **ENSO is predictable 8 months in advance due to dynamical predictability from recharge/discharge of equatorial heat content.**

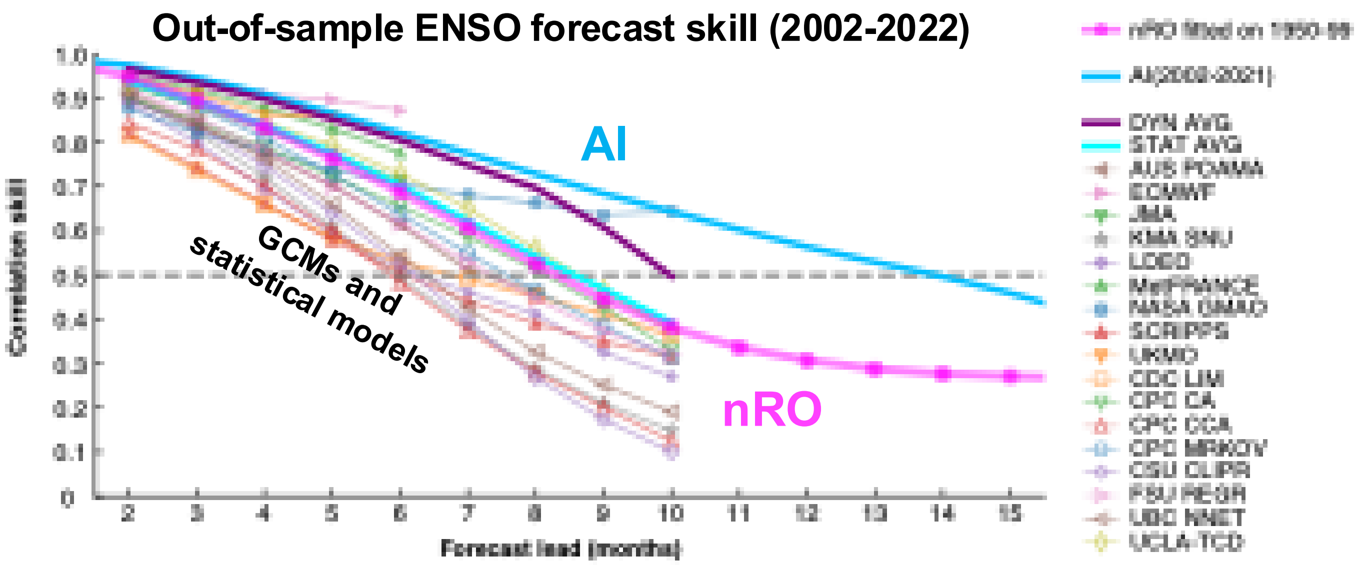
ENSO Recharge Oscillator (RO) theory and predictability

Recharge Oscillator (RO)
— 2 degrees of freedom

(Jin 1997; Jin et al. 2020)

$$\frac{d}{dt}\begin{pmatrix} T_{\text{ENSO}} \\ h \end{pmatrix} = \begin{pmatrix} R_T & F_1 \\ F_2 & R_h \end{pmatrix}\begin{pmatrix} T_{\text{ENSO}} \\ h \end{pmatrix} + \boldsymbol{N}_{\text{ENSO}}$$

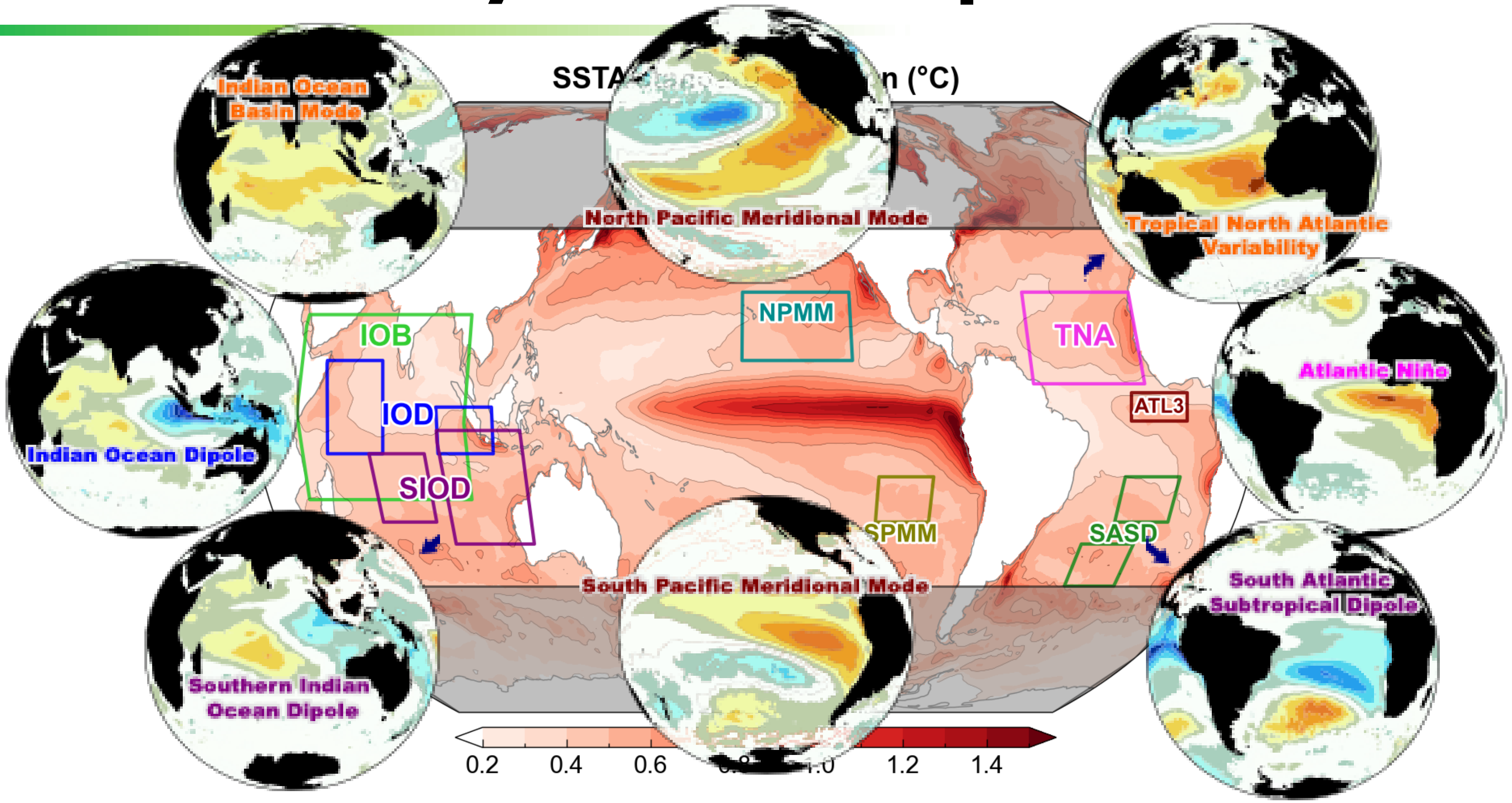
RO model can explain the basic features of ENSO: amplitude, periodicity, phase-locking, and asymmetry



(Zhao et al. 2024)

- **The RO show comparable skill to operational forecast systems (GCMs and statistical models)**
- **Suggesting RO is good starting point to explore further the sources of ENSO predictability.**

SST Variability outside equatorial Pacific



Hasselmann stochastic model: SST mostly follows

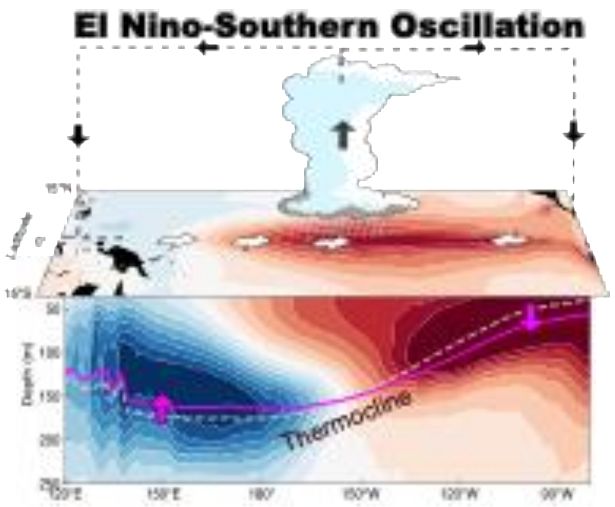
$$\frac{dT_j}{dt} = -\lambda_j T_j + \cdots$$

j = 1, 2…… n

(Hasselmann 1976)

Seasonally modulated λ_j measure the “SST memory” of each climate mode

Stochastic-dynamical model for other climate modes (IOD as an example)



$$\frac{dT_j}{dt} = -\lambda_j T_j + \beta_j T_{\mathrm{ENSO}} + \xi_j$$

Seasonally modulated damping + **Seasonally modulated ENSO forcing**

Our null hypothesis model for the IOD — it arises from the net effect of coupled air-sea feedbacks within the Indian Ocean, combined with **remote forcing from ENSO**

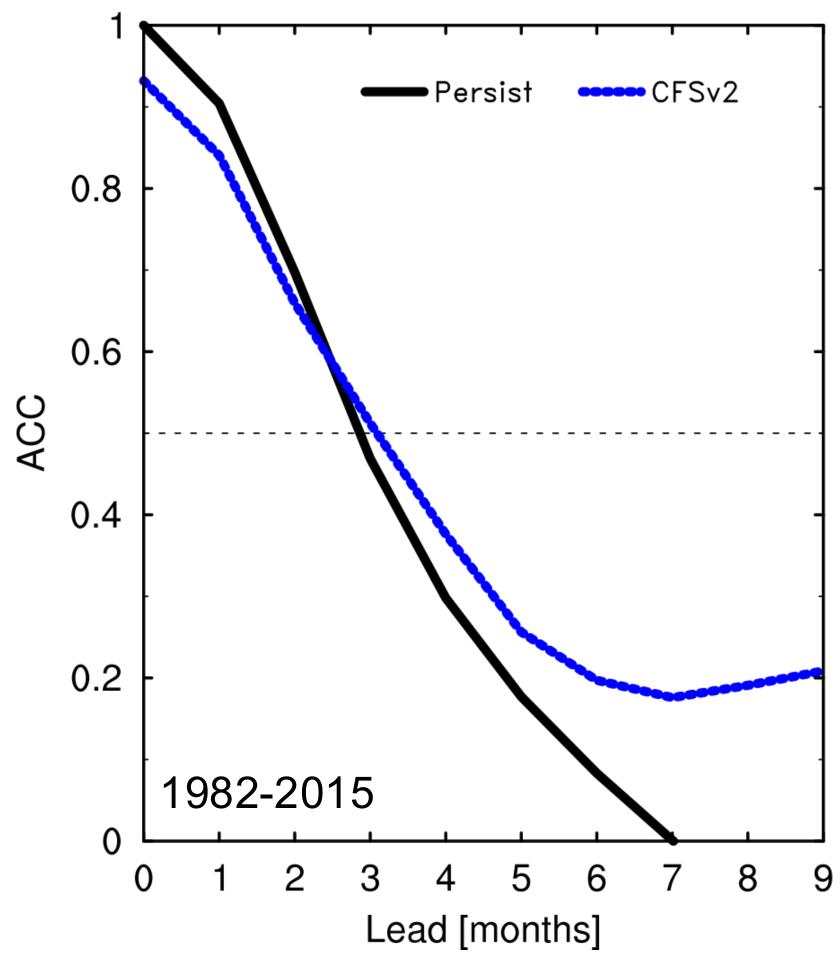
(Stuecker et al., 2017; Zhao et al., 2019)

Key feedback mechanisms include:

- **Positive Bjerknes feedback**, which amplifies IOD variability (Annamalai et al., 2003; Saji et al., 2006; Hong et al., 2008; Zhang et al., 2015).
- **Negative SST–cloud–radiation feedback**, which acts to dampen IOD variability (Li et al., 2003; Cai and Qiu, 2013; Ng et al., 2014).

Indian Ocean Dipole (IOD) predictability

Anomaly correlation coefficient (ACC) skill of DMI prediction



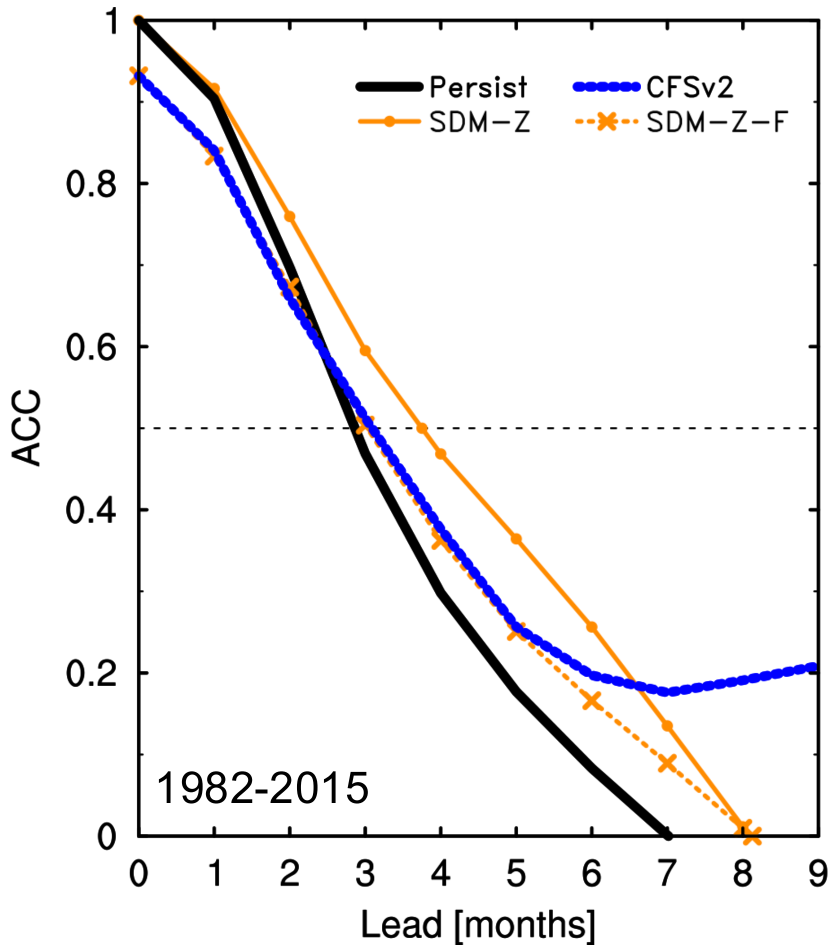
(Zhao et al. 2019)

- Operational dynamical forecasts only slightly better than persistence forecast (note the different initial conditions)

Indian Ocean Dipole (IOD) predictability

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}}$$

Anomaly correlation coefficient (ACC) skill of DMI prediction



(Zhao et al. 2019)

- Operational dynamical forecasts only slightly better than persistence forecast (note the different initial conditions)
- **SDM-Z**: Stochastic-Dynamical model with **zero (Z) ENSO** information with observed and CFSv2 initial conditions

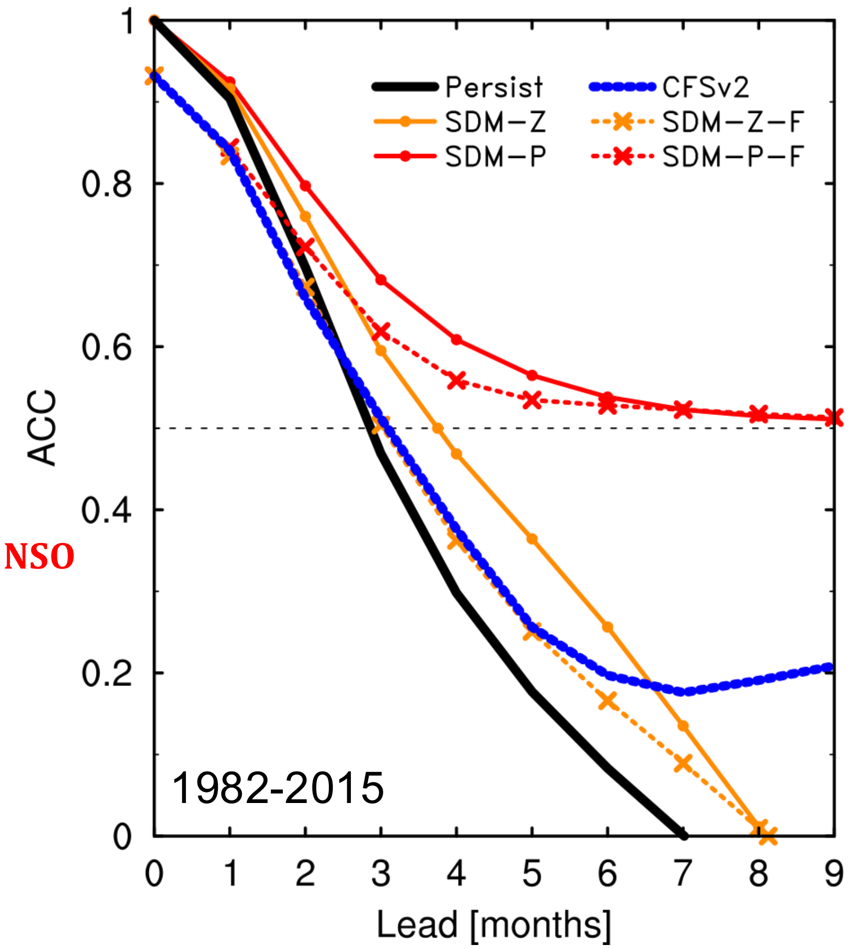
Indian Ocean Dipole (IOD) predictability

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}}$$

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}} + \beta(t)T_{\mathrm{ENSO}}$$

T_{ENSO} is observed ENSO

Anomaly correlation coefficient (ACC) skill of DMI prediction



(Zhao et al. 2019)

- Operational dynamical forecasts only slightly better than persistence forecast (note the different initial conditions)
- **SDM-Z**: Stochastic-Dynamical model with **zero (Z) ENSO** information with observed and CFSv2 initial conditions
- **SDM-P**: Stochastic-Dynamical model with **observed (P) ENSO** information with observed and CFSv2 initial conditions

Indian Ocean Dipole (IOD) predictability

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}}$$

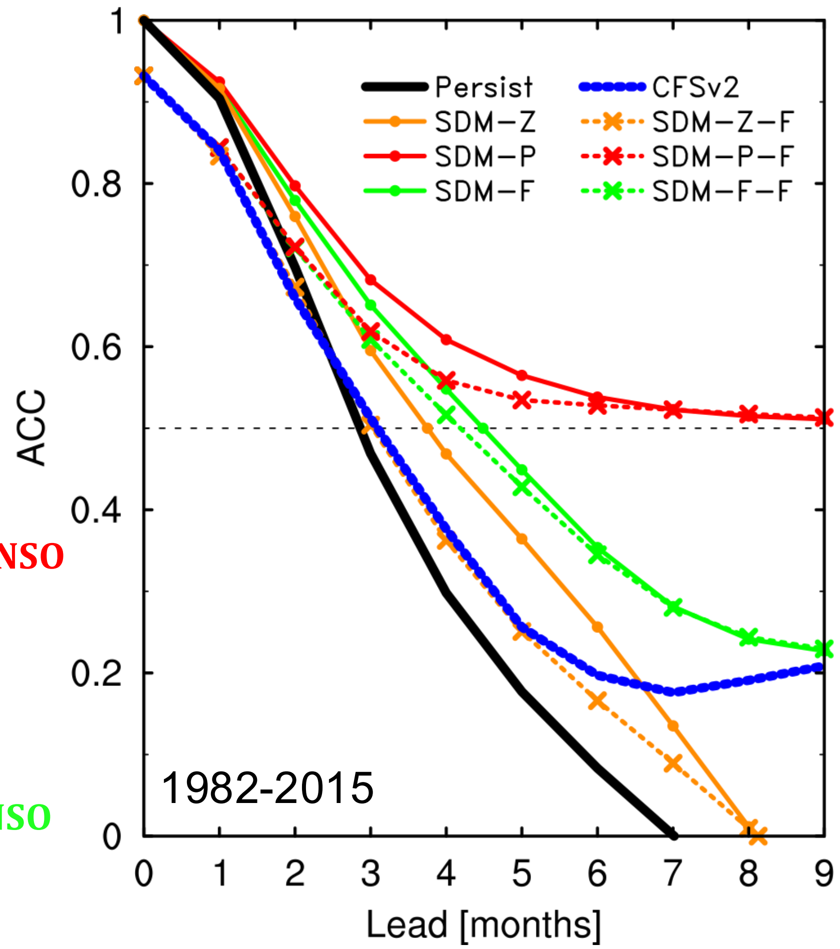
$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}} + \beta(t)T_{\mathrm{ENSO}}$$

T_{ENSO} is observed ENSO

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}} + \beta(t)T_{\mathrm{ENSO}}$$

T_{ENSO} is forecasted ENSO

Anomaly correlation coefficient (ACC) skill of DMI prediction



(Zhao et al. 2019)

- Operational dynamical forecasts only slightly better than persistence forecast (note the different initial conditions)
- **SDM-Z**: Stochastic-Dynamical model with **zero (Z) ENSO** information with observed and CFSv2 initial conditions
- **SDM-P**: Stochastic-Dynamical model with **observed (P) ENSO** information with observed and CFSv2 initial conditions
- **SDM-F**: Stochastic-Dynamical model with **CFSv2 forecasted (F) ENSO** information with observed and CFSv2 initial conditions

Indian Ocean Dipole (IOD) predictability

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}}$$

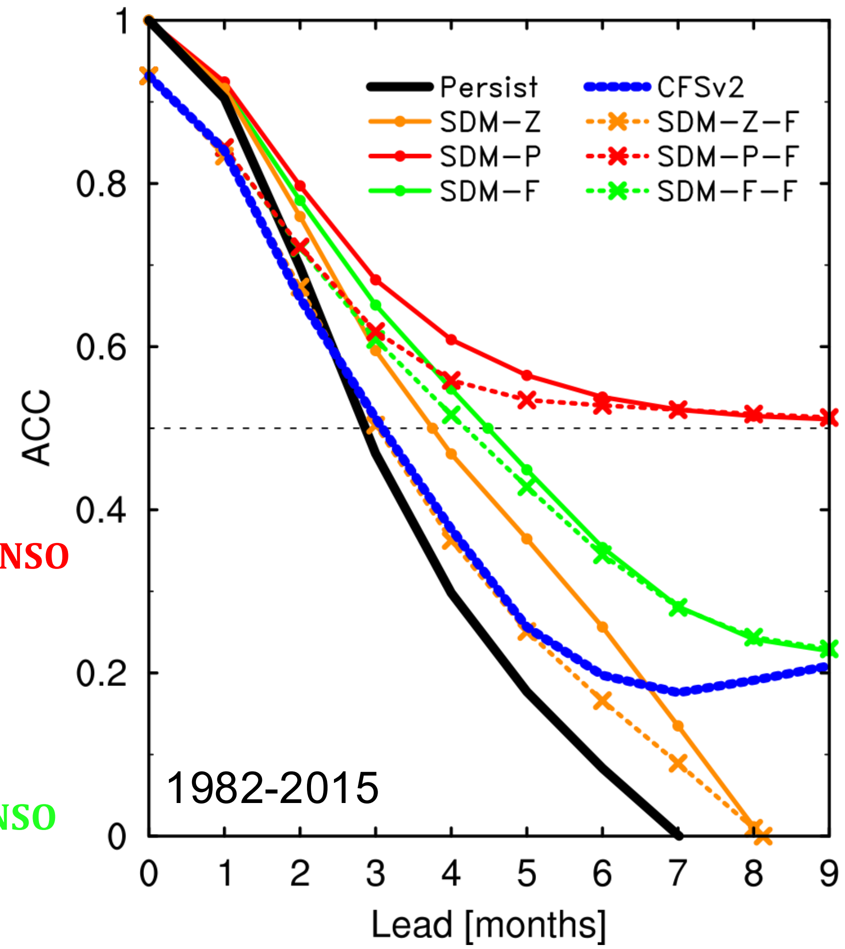
$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}} + \beta(t)T_{\mathrm{ENSO}}$$

T_{ENSO} is observed ENSO

$$\frac{dT_{\mathrm{IOD}}}{dt} = -\lambda(t)T_{\mathrm{IOD}} + \beta(t)T_{\mathrm{ENSO}}$$

T_{ENSO} is forecasted ENSO

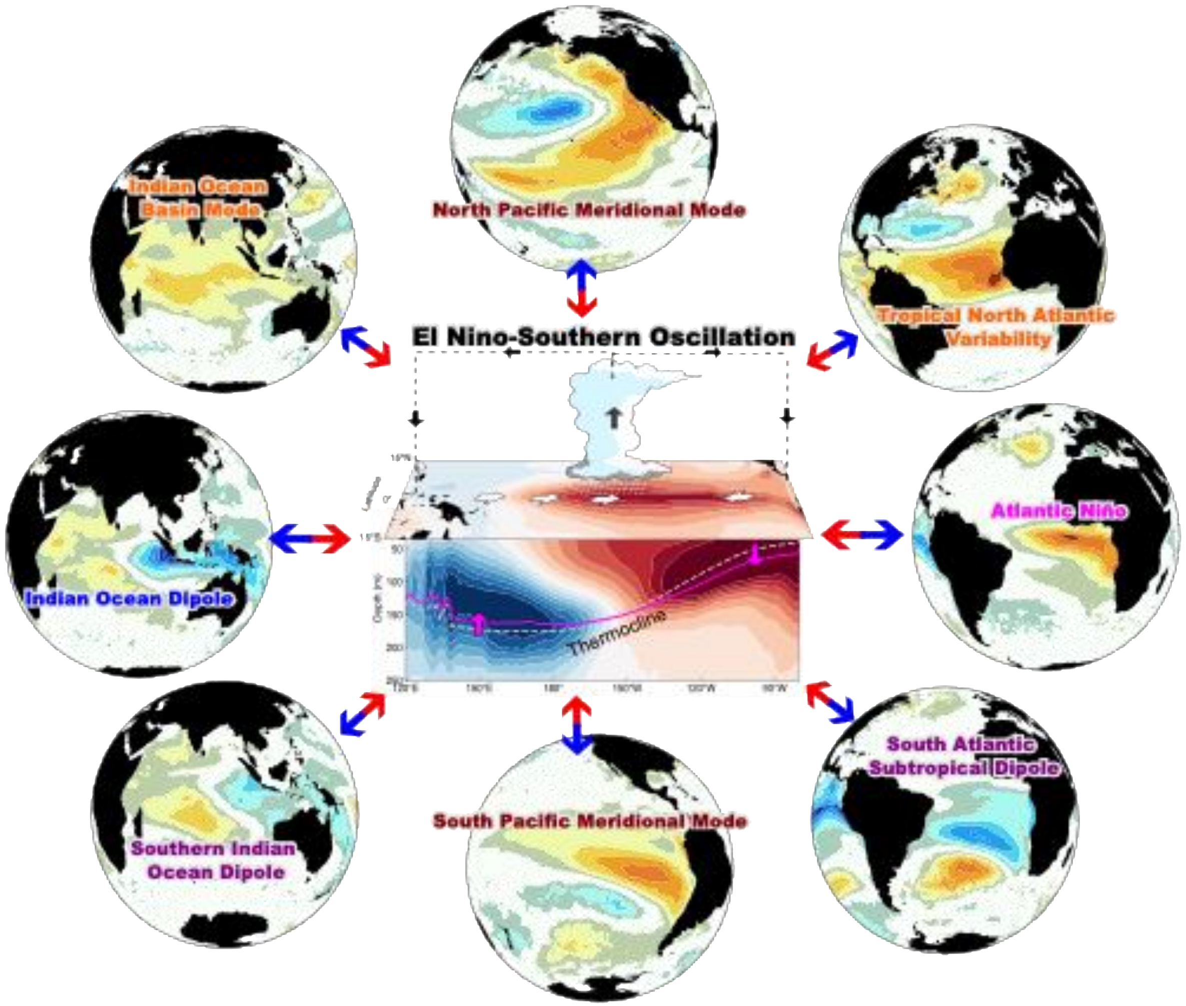
Anomaly correlation coefficient (ACC) skill of DMI prediction



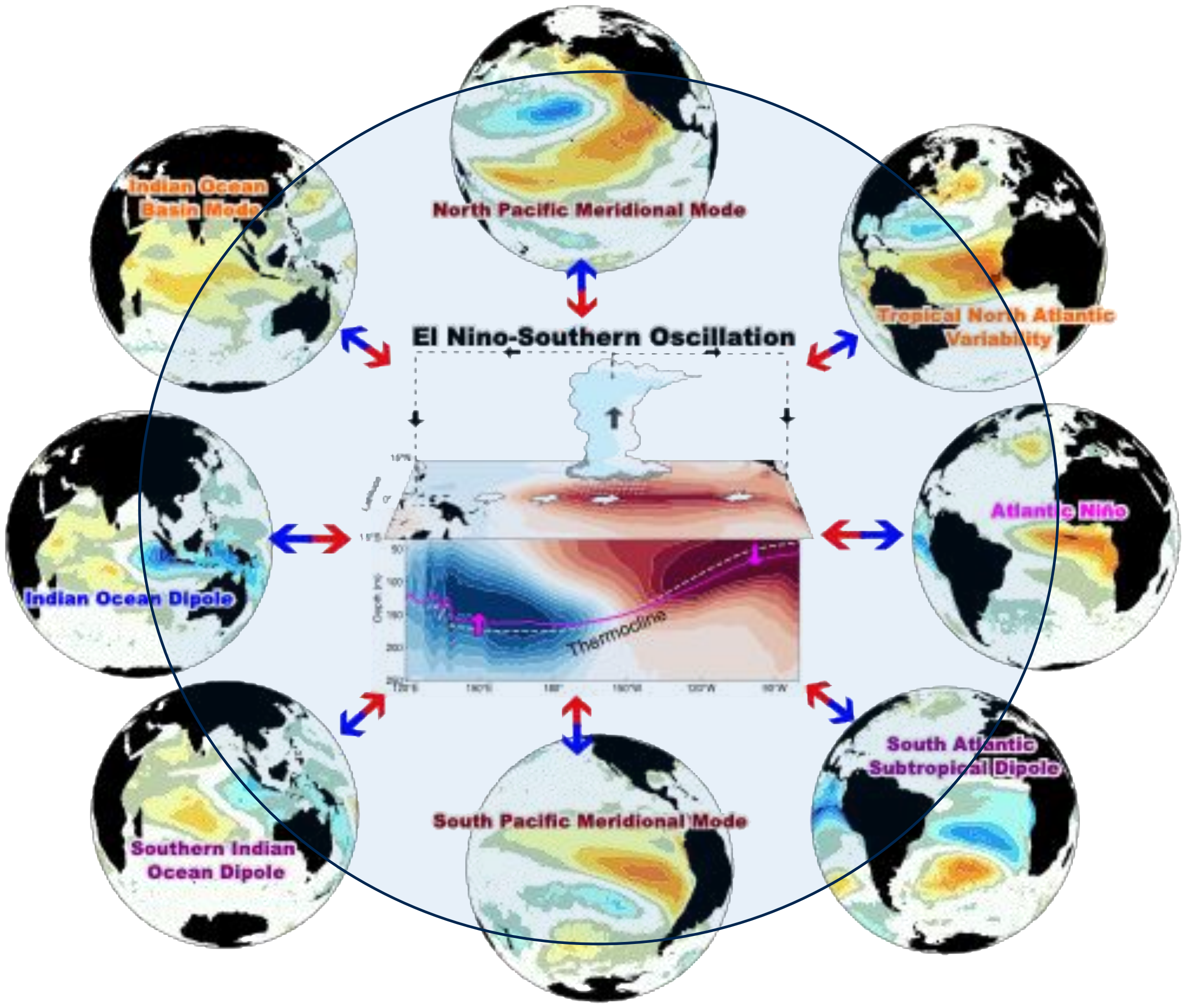
- Long-lead predictability of the Indian Ocean Dipole is entirely due to ENSO (Zhao et al. 2019; 2020)

Good news:

- If we can improve seasonal ENSO forecasts, we will automatically also increase IOD forecast skill!



a) Two way interactions between ENSO and other climate modes



a) Two way interactions between ENSO and other climate modes

b) Interactions among other climate modes

A new framework is needed to **quantify and understand** the complexity of these coupled interactions

Extended nonlinear RO (XRO) model for interconnected global climate

2024

Article

nature

Explainable El Niño predictability from climate mode interactions

Sen Zhao[1], Fei-Fei Jin[1,2] ✉, Malte F. Stuecker[2,3], Philip R. Thompson[3], Jong-Seong Kug[4], Michael J. McPhaden[5], Mark A. Cane[6], Andrew T. Wittenberg[7] & Wenju Cai[8,9,10,11]

https://doi.org/10.1038/s41586-024-07534-6

XRO model formulation

Original RO model for ENSO

$$\frac{d}{dt}\boldsymbol{X}_{\text{ENSO}} = \boldsymbol{L}_{\text{ENSO}}\boldsymbol{X}_{\text{ENSO}} + \boldsymbol{N}_{\text{ENSO}} + \boldsymbol{\xi}_{\text{ENSO}}$$

$$\boldsymbol{X}_{\text{ENSO}} = (T_{ENSO}, h) \quad \boldsymbol{L}_{\text{ENSO}} = \begin{pmatrix} R_T & F_1 \\ F_2 & R_h \end{pmatrix}$$

Hasselmann model with ENSO forcing

$$\frac{d\boldsymbol{T}_j}{dt} = -\boldsymbol{\lambda}_j \boldsymbol{T}_j + \boldsymbol{\beta}_j \boldsymbol{T}_{\text{ENSO}} + \boldsymbol{\xi}_j$$

One way interaction (ENSO force other modes)

Two way interactions

Other climate modes feedback to ENSO

$$\frac{d}{dt}\boldsymbol{X}_{\text{ENSO}} = \boldsymbol{L}_{\text{ENSO}}\boldsymbol{X}_{\text{ENSO}} + \boldsymbol{N}_{\text{ENSO}} + \sum_j \boldsymbol{\alpha}_j \boldsymbol{T}_j + \boldsymbol{\xi}_{\text{ENSO}}$$

$$\frac{d\boldsymbol{T}_j}{dt} = -\boldsymbol{\lambda}_j \boldsymbol{T}_j + \boldsymbol{\beta}_j \boldsymbol{X}_{\text{ENSO}} + \sum_{k}^{k \neq j} \boldsymbol{\alpha}_k \boldsymbol{T}_k + \boldsymbol{\xi}_j$$

ENSO forces other modes

Interactions among other modes

Extended nonlinear Recharge Oscillator (XRO) model

ENSO core RO dynamics

Other climate modes feedback to ENSO

Quadratic nonlinearity for ENSO and IOD

$$\frac{d}{dt}\begin{pmatrix} \boldsymbol{X}_{\mathrm{ENSO}} \\ \boldsymbol{X}_{\boldsymbol{M}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{L}_{\mathrm{ENSO}} & \boldsymbol{C}_1 \\ \boldsymbol{C}_2 & \boldsymbol{L}_{\boldsymbol{M}} \end{pmatrix} \begin{pmatrix} \boldsymbol{X}_{\mathrm{ENSO}} \\ \boldsymbol{X}_{\boldsymbol{M}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{N}_{\mathrm{ENSO}} \\ \boldsymbol{N}_{\boldsymbol{M}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\xi}_{\mathrm{ENSO}} \\ \boldsymbol{\xi}_{M} \end{pmatrix}$$

ENSO teleconnection to affect other modes

Internal dynamics for other modes

Stochastic forcing mimicking westerly wind bursts, MJO & weather systems

— 10 degrees of freedom

$\boldsymbol{X}_{\mathrm{ENSO}}$: (Nino3.4 SSTA, WWV), $\boldsymbol{X}_{\boldsymbol{M}}$: other eight climate modes (SSTA indices for NPMM, SPMM, IOB, IOD, SIOD, TNA, ATL3, SASD).

Zhao et al. 2024

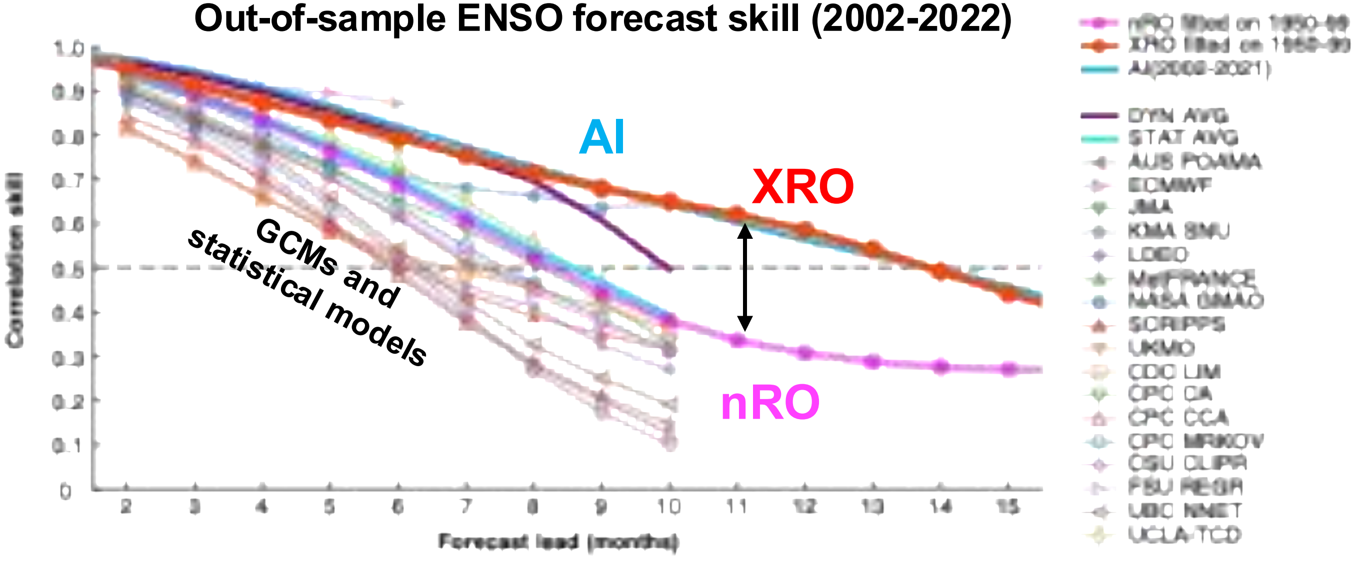
Improved ENSO predictive skill in XRO

XRO – 10 degrees of freedom **(Zhao et al. 2024)**

$$\frac{d}{dt}\begin{pmatrix} X_{\text{ENSO}} \\ X_M \end{pmatrix} = \begin{pmatrix} L_{\text{ENSO}} & C_1 \\ C_2 & L_M \end{pmatrix}\begin{pmatrix} X_{\text{ENSO}} \\ X_M \end{pmatrix} + \begin{pmatrix} N_{\text{ENSO}} \\ N_M \end{pmatrix} + \sigma_\xi \xi$$

XRO realistically simulates ENSO features and its relationship with other climate modes

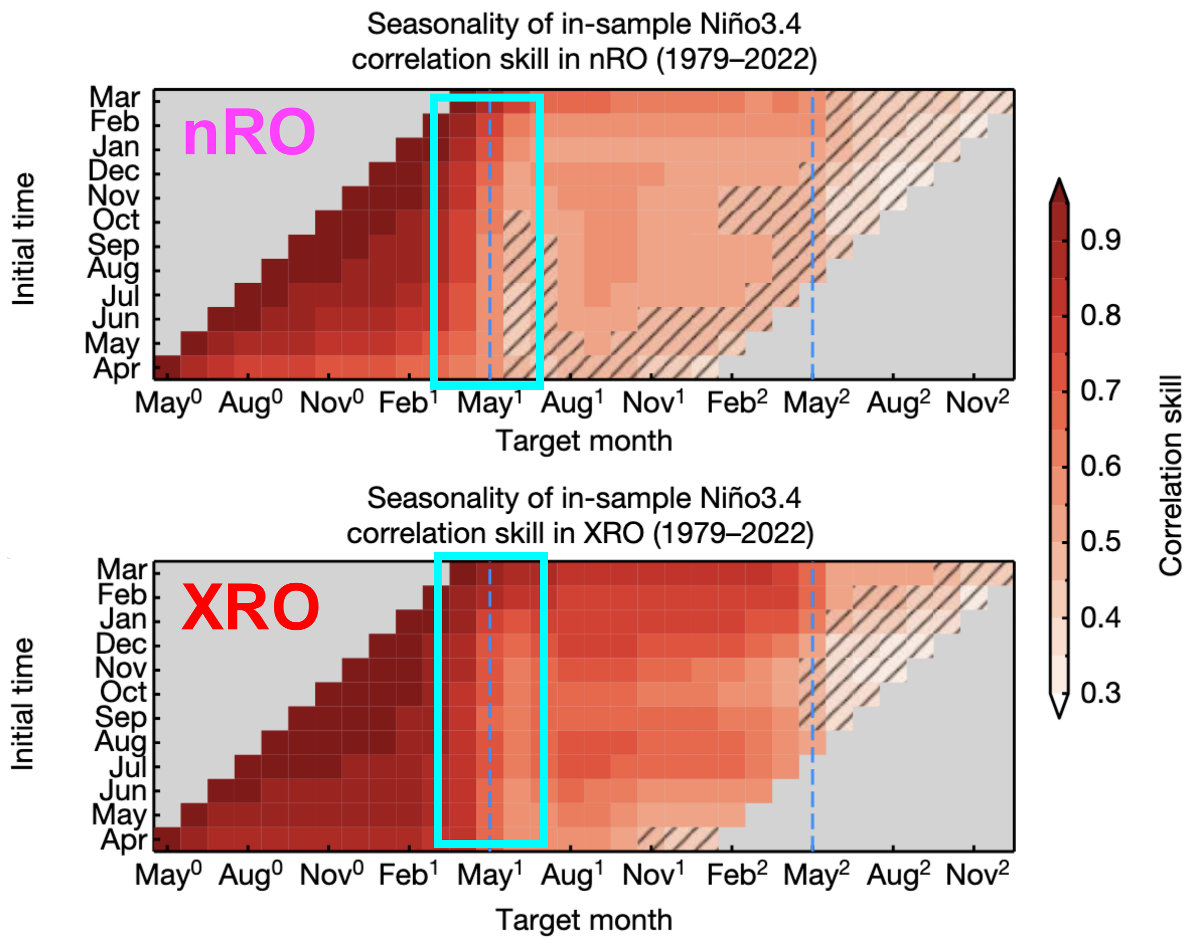
Out-of-sample ENSO forecast skill (2002-2022)



(Zhao et al. 2024)

- **The XRO shows comparable skill to the most skillful AI model** *(Ham et al. 2019; Zhou and Zhang 2023)*
- **XRO has number of parameters O(100) compared to O(100,000) for AI models**

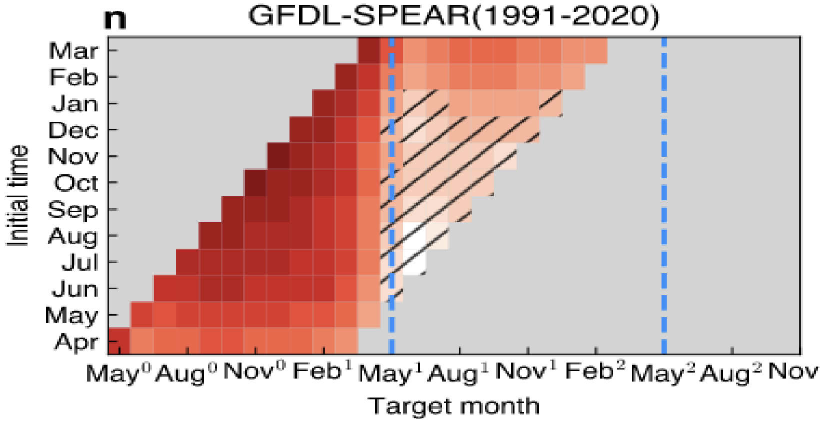
Where does the improvement lie?



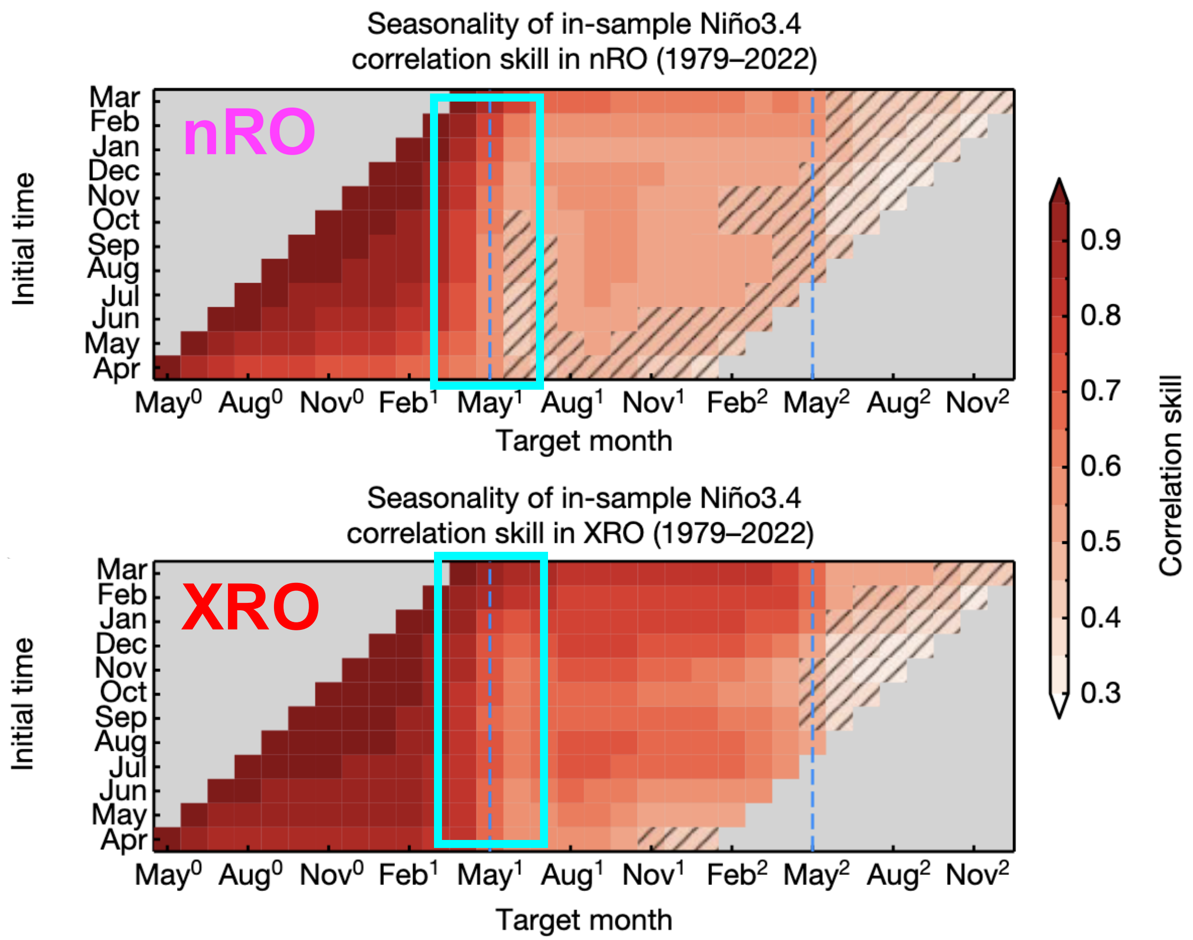
(Zhao et al. 2024)

What is the spring predictability barrier (SPB)?

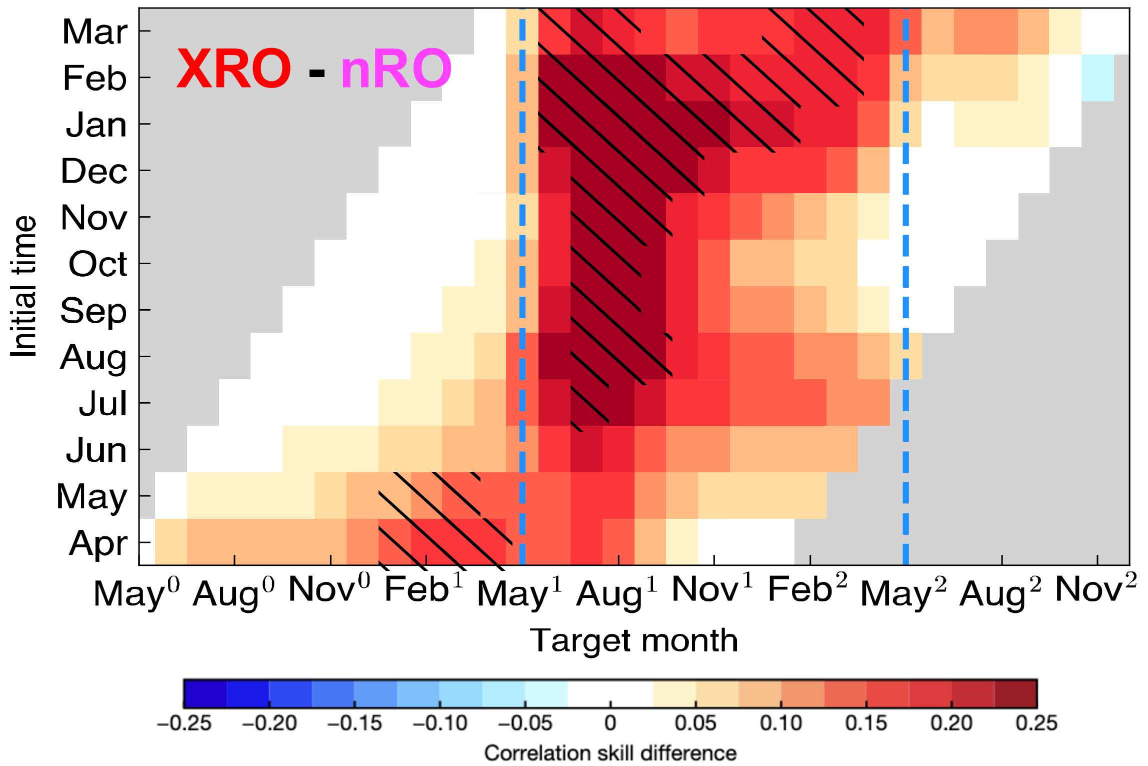
- SPB refers the sharp drop in the accuracy of ENSO forecasts when predictions are made **across the boreal spring (March–May).**



Where does the improvement lie?



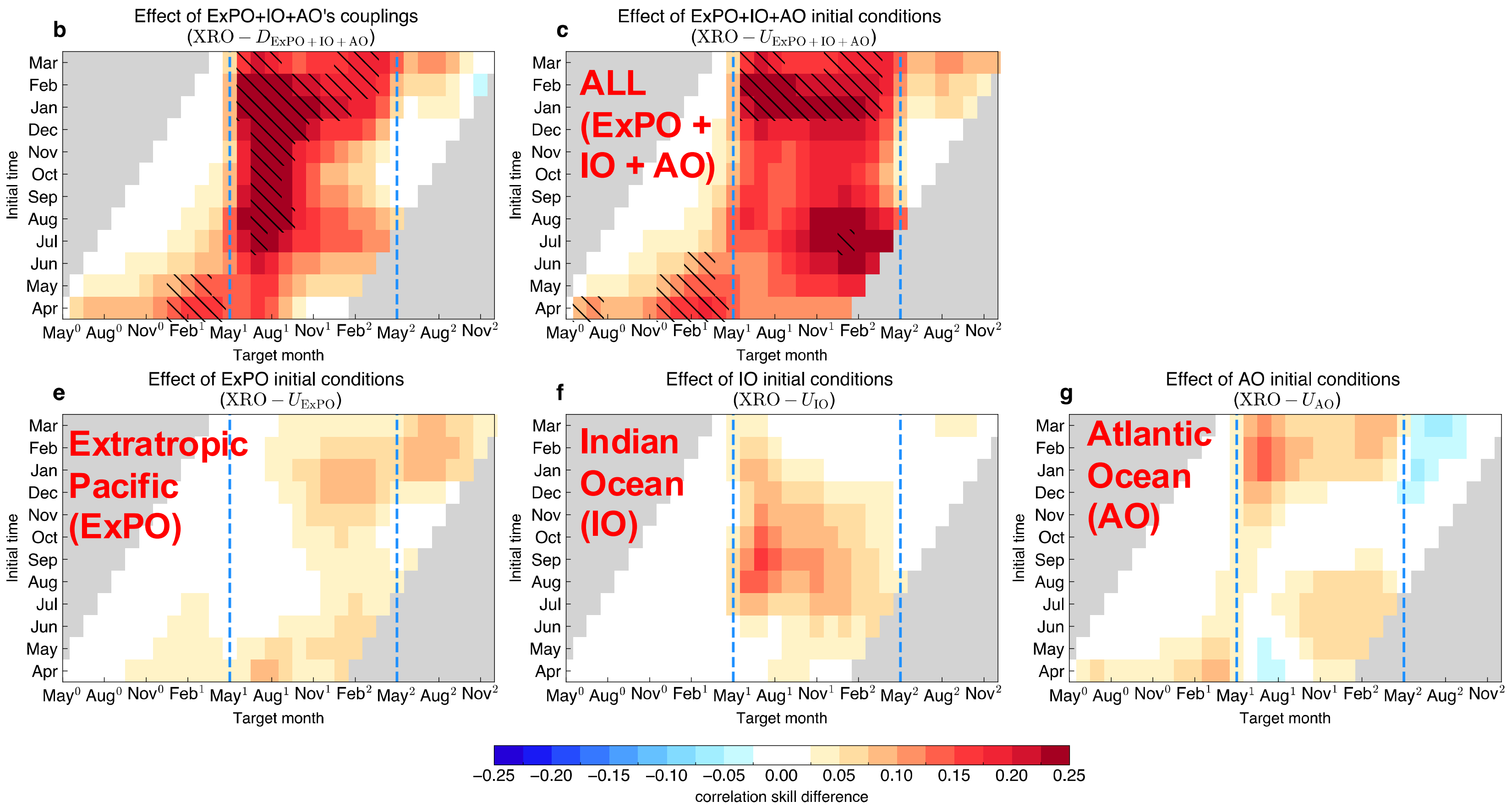
(Zhao et al. 2024)



- **Climate mode interactions reduce the spring predictability barrier (SPB)**

Improved predictive skill is dynamically explainable

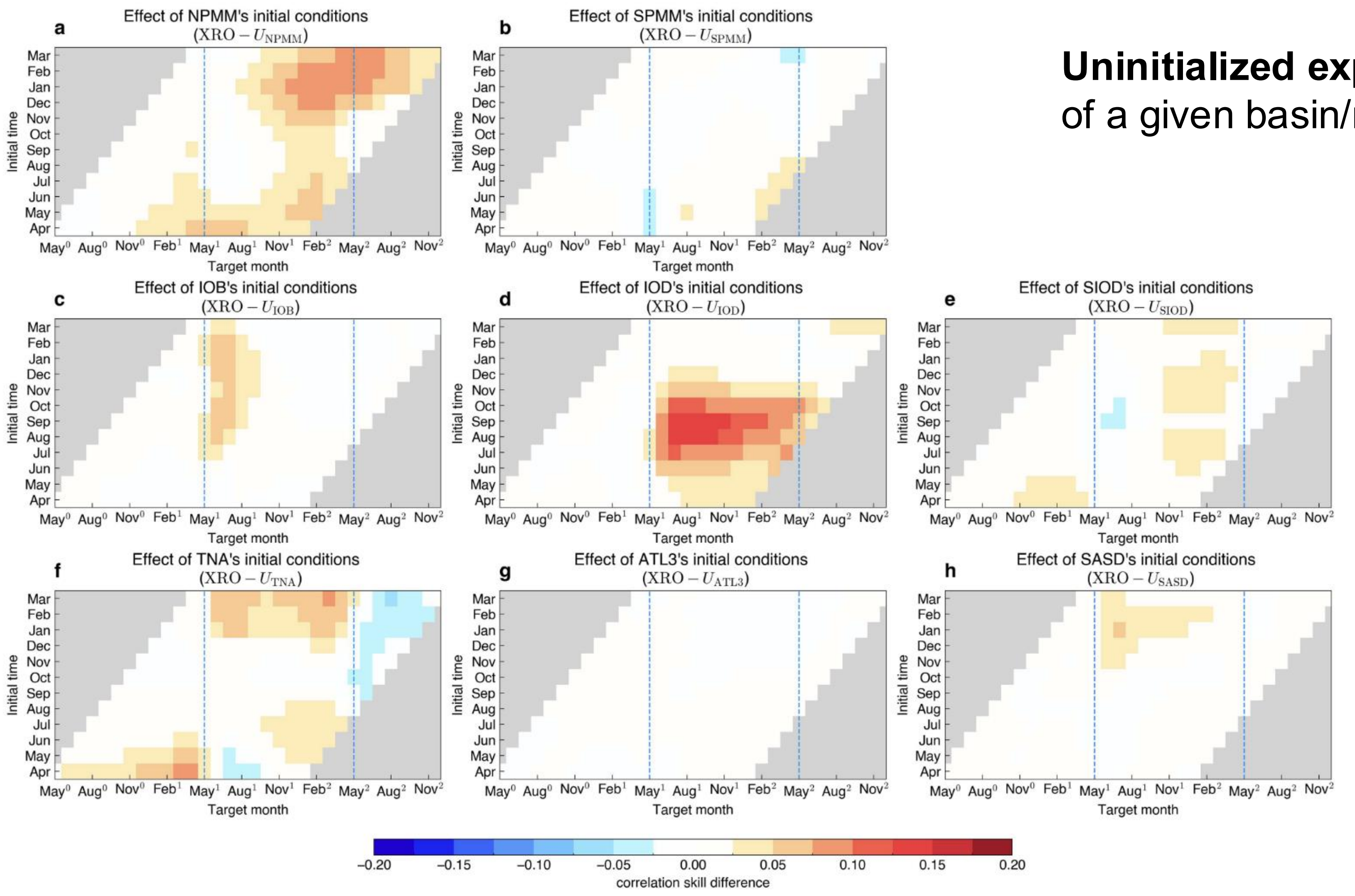
XRO Uninitialized experiment *U_j* : initial conditions of a given basin/mode *j* are set to zero
This allows us to **quantify** the contributions of these climate modes/basins



- Improved skills from three basins **highly depend on season and lead-time**

(Zhao et al. 2024)

Improved predictive skill is traceable

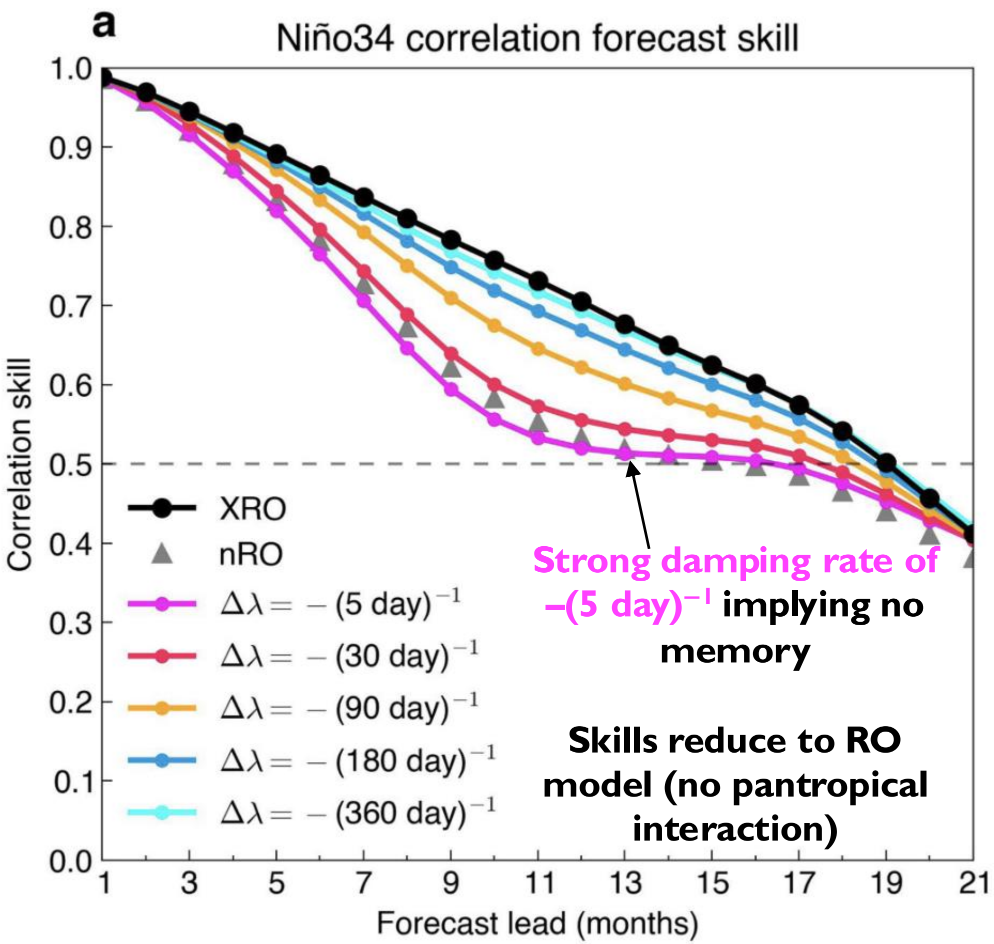


Uninitialized experiment U_j : initial conditions of a given basin/mode *j* are set to zero

- Improved ENSO predictive skill is traceable to the initial conditions of other climate modes **via their memory and interactions with ENSO**

Utilizing "SST memory" outside equatorial Pacific

Influence of the memory effect outside the equatorial Pacific on ENSO forecast skill.

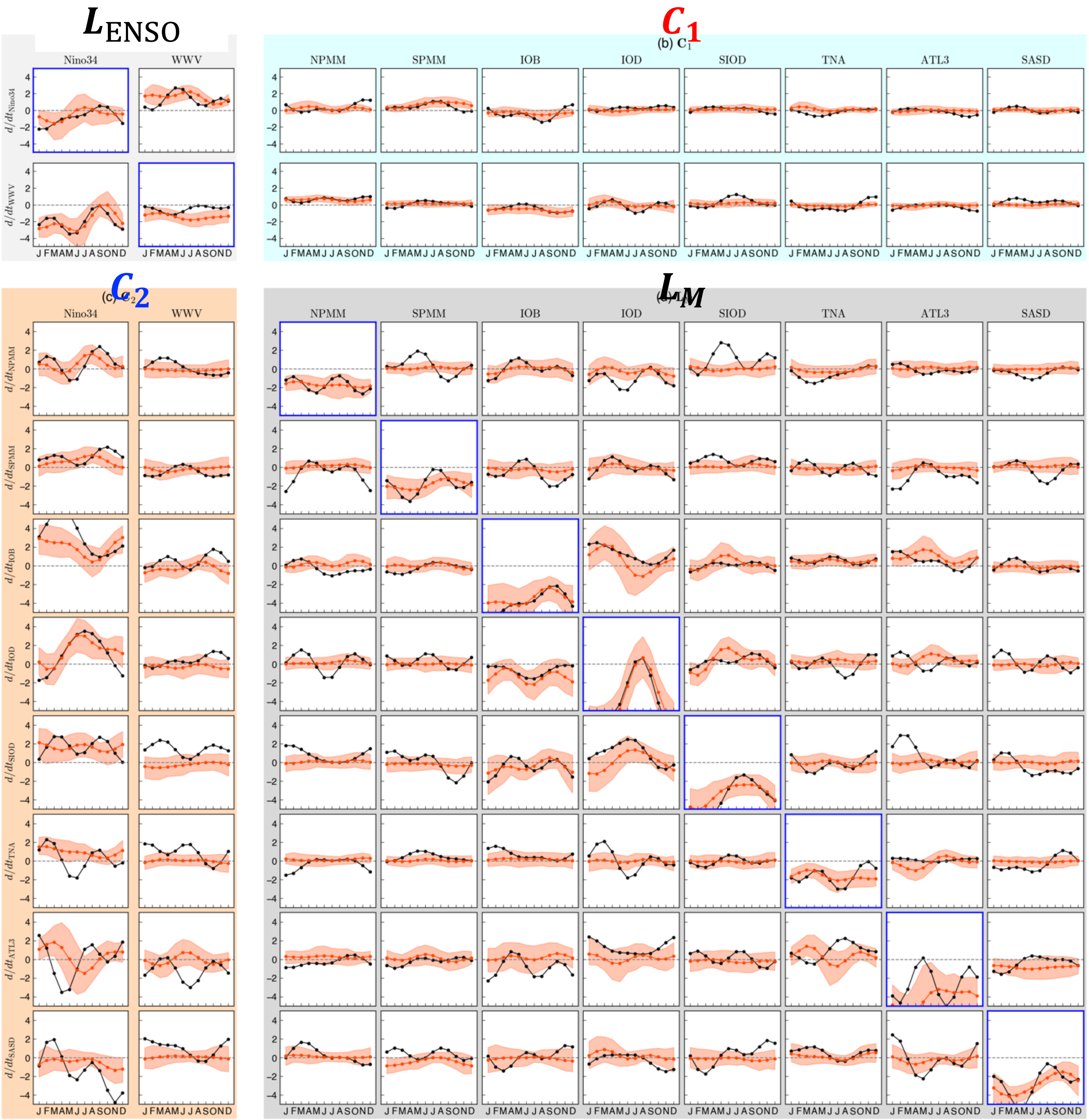


$$\frac{d}{dt}\begin{pmatrix} X_{\mathrm{ENSO}} \\ X_M \end{pmatrix} = \begin{pmatrix} L_{\mathrm{ENSO}} & C_1 \\ C_2 & L_M \end{pmatrix}\begin{pmatrix} X_{\mathrm{ENSO}} \\ X_M \end{pmatrix} + \begin{pmatrix} N_{\mathrm{ENSO}} \\ N_M \end{pmatrix} + \sigma_\xi \xi$$

"Losing memory" sensitivity experiments

- Add different damping rates to the non-ENSO modes

The initial condition memory effect of the climate modes outside equatorial Pacific extends the skill of ENSO forecasts.



Understanding climate model biases

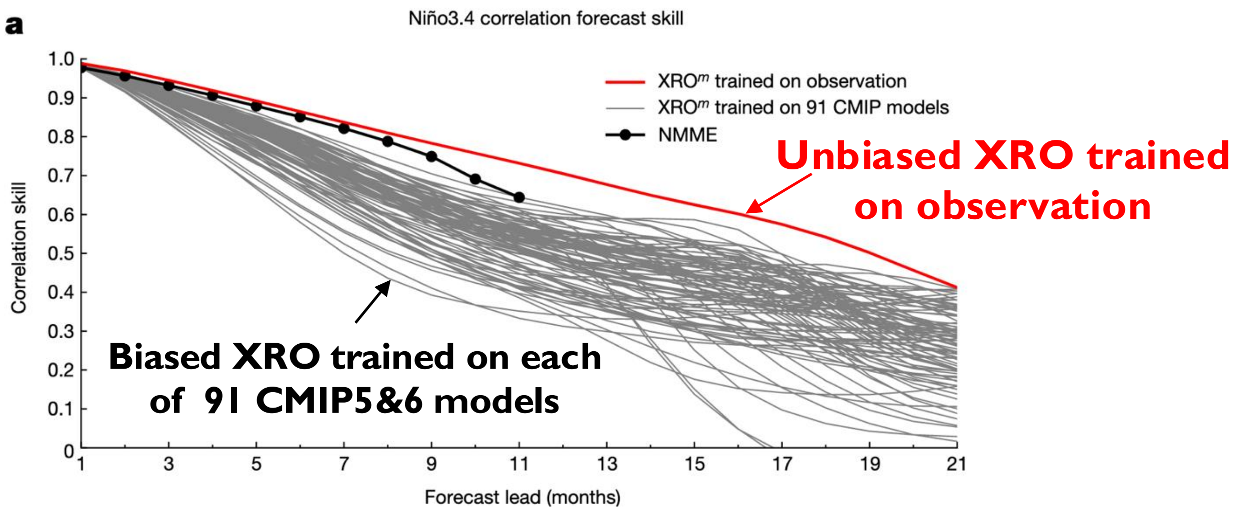
Train XRO on GCM outputs

$$\begin{pmatrix} L_{\text{ENSO}} & C_1 \\ C_2 & L_M \end{pmatrix}$$

Red: the ensemble mean with 10%–90% spread band of the 91 CMIP5/6 historical simulations.

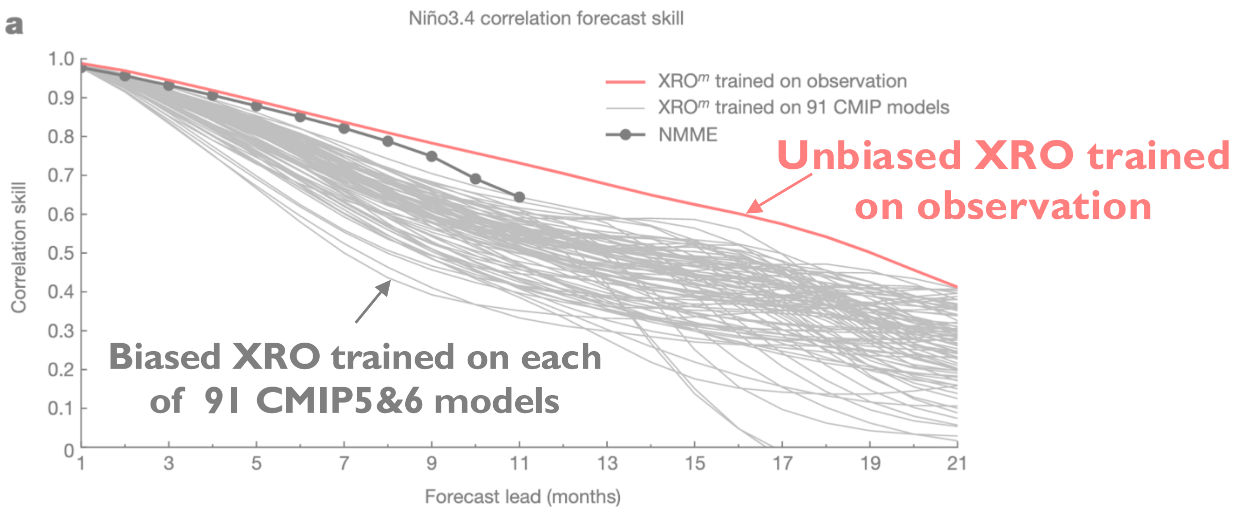
The climate models underestimate the strength of most of the mode interactions and miss the seasonality.

Understanding climate model biases

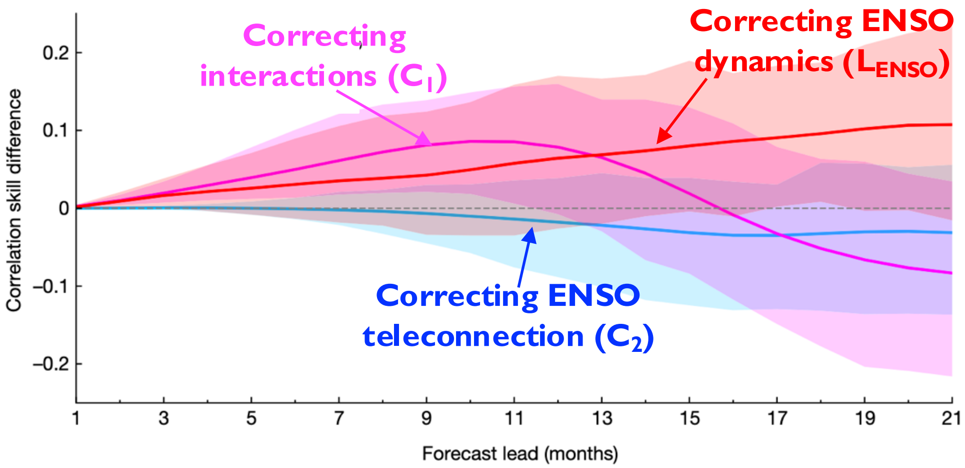


(Zhao et al. 2024)

Understanding climate model biases



Effects of correcting the dynamical operators in GCMs



(Zhao et al. 2024)

XRO dynamical operators

$$\begin{pmatrix} L_{\text{ENSO}} & C_1 \\ C_2 & L_M \end{pmatrix}$$

- ENSO predictability in GCMs is mainly hindered by **biases in ENSO dynamics**, and its **interactions with other climate modes**

Implications

To improve ENSO predictions, climate models must correctly capture the **recharge oscillator dynamics of ENSO** and *three compounding aspects of other climate modes*:

1) the initial conditions of each mode

2) the seasonally modulated damping rate (that is, the memory) of each mode

3) the seasonally modulated teleconnection to ENSO from each mode.

(Zhao et al. 2024)

Implications

To improve ENSO predictions, climate models must correctly capture the **recharge oscillator dynamics of ENSO** and *three compounding aspects of other climate modes*:

1) the initial conditions of each mode

   Need an integrated pantropical ocean observing system (Foltz et al. 2025)

2) the seasonally modulated damping rate (that is, the memory) of each mode

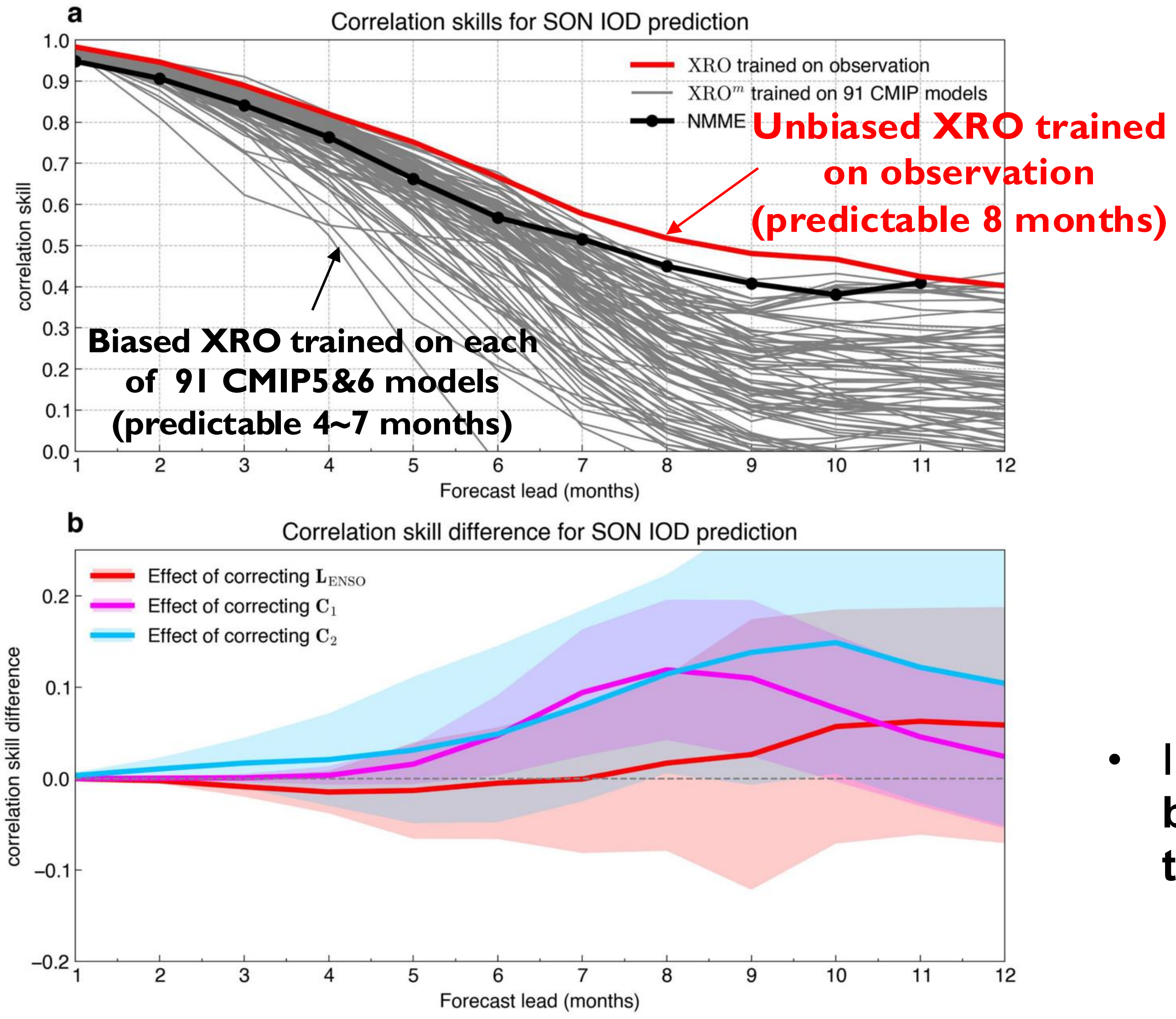
3) the seasonally modulated teleconnection to ENSO from each mode.

   Need to reduce the climate model biases in Indian and Atlantic Oceans

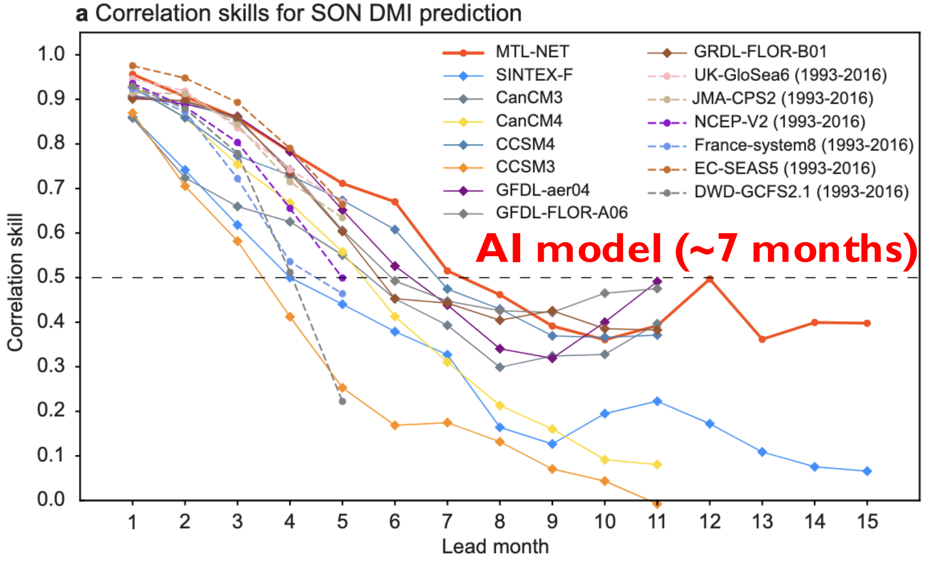
- Further tracing biases from the SSTA budget at the process level using the XRO framework can be used to inform climate model development

(Zhao et al. 2024)

Improved IOD predictability in XRO



(Zhao et al. 2024)



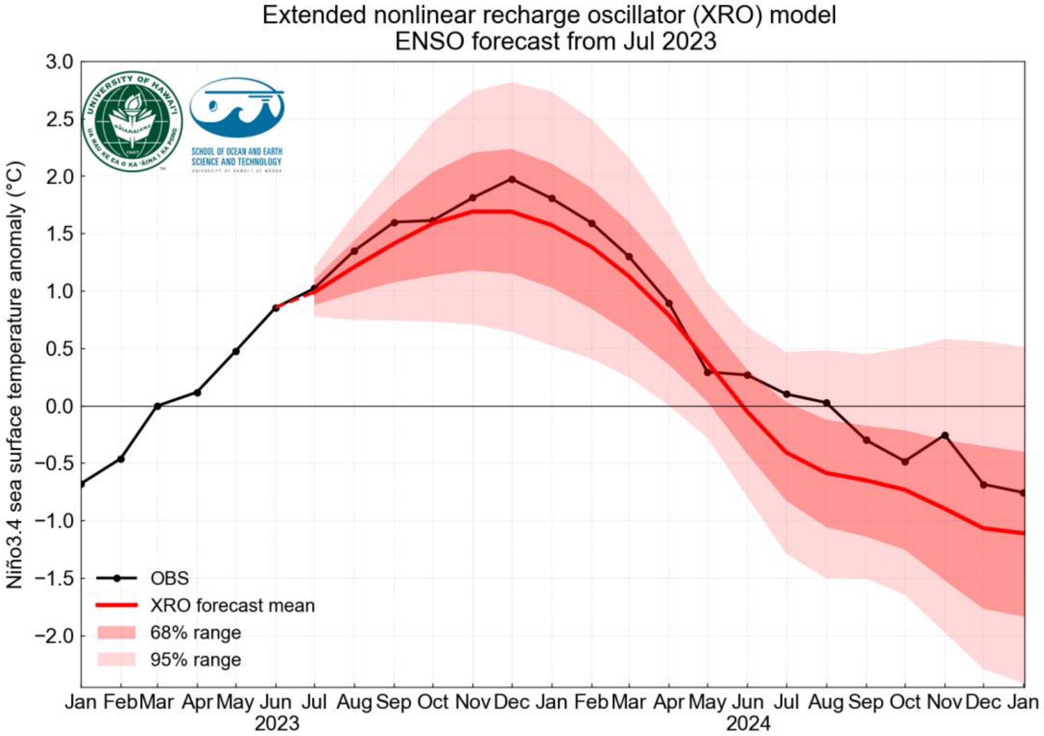
(Ling et al. 2022)

- IOD predictability in GCMs is mainly hindered by **biases in IOD internal dynamics**, and **ENSO's teleconnection impacts**

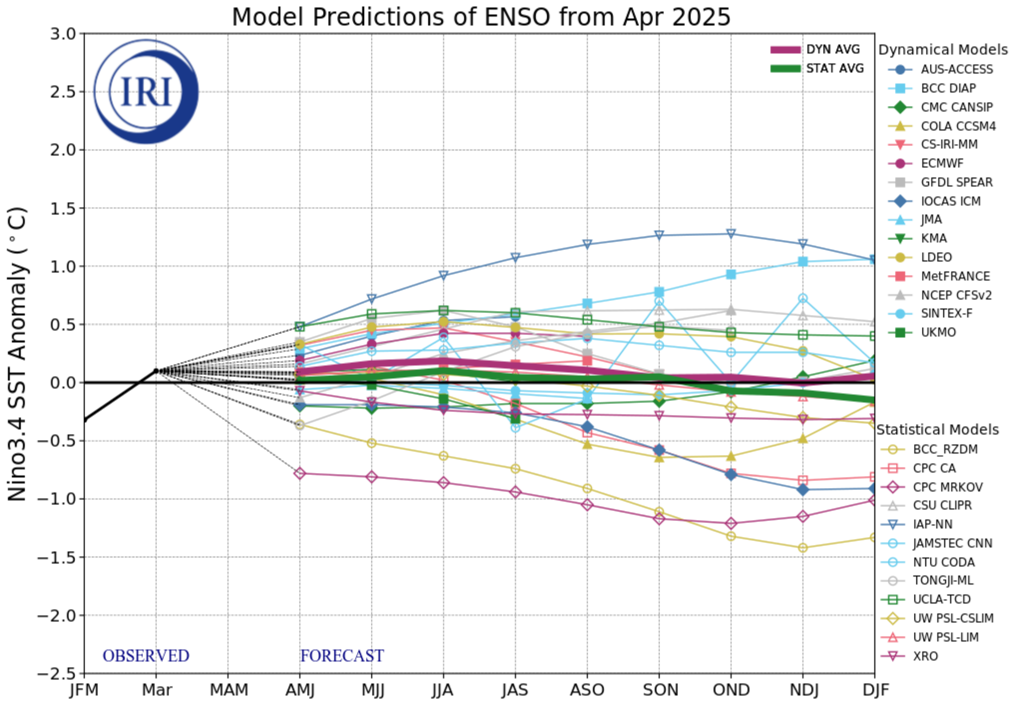
XRO operational ENSO forecasts

https://github.com/senclimate/XRO

Code is publicly available to community with cookbooks



XRO adopted at IRI ENSO forecasts



Forecasts at https://senzhao.netlify.app/climate/xro/

Outline

1. Overview of pantropical climate interactions
   - *Mean state and variability*
   - *Methodologies*

2. Conceptual understanding of pantropical climate variability and predictability
   - *ENSO Recharge Oscillator (RO) theory and predictability*
   - *Hasselmann theory and predictability of other climate modes*
   - *Extended nonlinear RO (XRO) model for interconnected global climate*

3. Hands-on Application of the XRO Model

Practical with XRO framework

1. **XRO Cookbook.** This cookbook demonstrate how to fit, simulate and reforecast ENSO and other climate modes in the XRO framework.
   - https://github.com/senclimate/XRO
   - Jupiter Notebook at XRO_Cookbook.ipynb

2. **Recharge Oscillator (RO) Practical** for the ENSO Winter School 2025. The practical covers theoretical and computational aspects of the RO framework, its applications in ENSO simulations, and forecasting.
   - https://github.com/senclimate/RO_practical
   - Jupiter Notebook at RO_practical_with_XRO_framework.ipynb

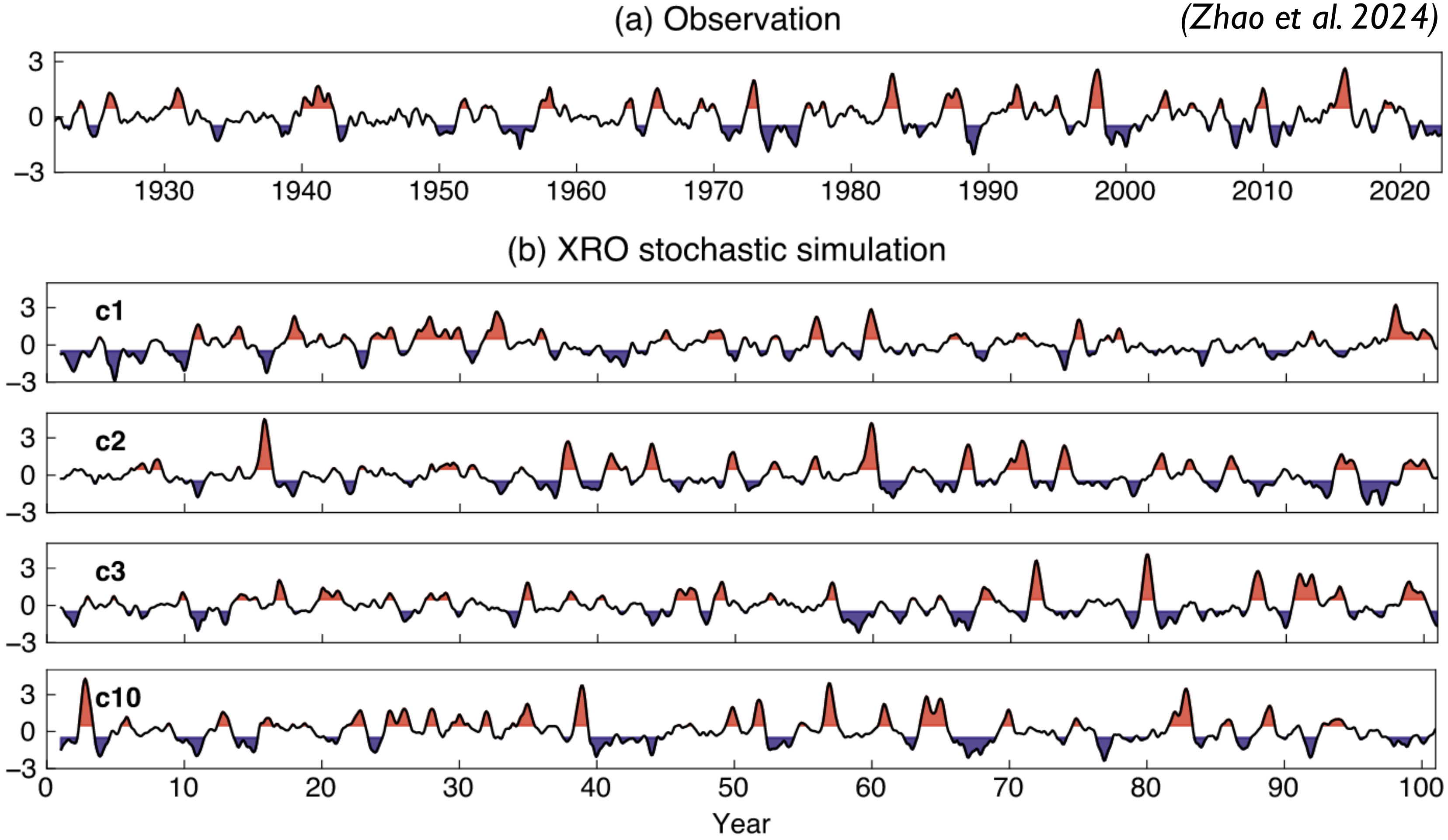
Supp. Slides

$$\frac{d}{dt}\begin{pmatrix} \boldsymbol{X}_{\mathrm{ENSO}} \\ \boldsymbol{X}_{\boldsymbol{M}} \end{pmatrix} = \begin{pmatrix} \boldsymbol{L}_{\mathrm{ENSO}} & \boldsymbol{C}_{1} \\ \boldsymbol{C}_{2} & \boldsymbol{L}_{M} \end{pmatrix}\begin{pmatrix} \boldsymbol{X}_{\mathrm{ENSO}} \\ \boldsymbol{X}_{\boldsymbol{M}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{N}_{\mathrm{ENSO}} \\ \boldsymbol{N}_{\boldsymbol{M}} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\xi}_{\mathrm{ENSO}} \\ \boldsymbol{\xi}_{M} \end{pmatrix}$$

- XRO parameters estimated using multiple regressions on observation (ORAS5 reanalysis, 1979-2022)

- **XRO stochastic simulations**
  - 43,000 yrs into 1,000 nonoverlapping parts.

(Zhao et al. 2024)

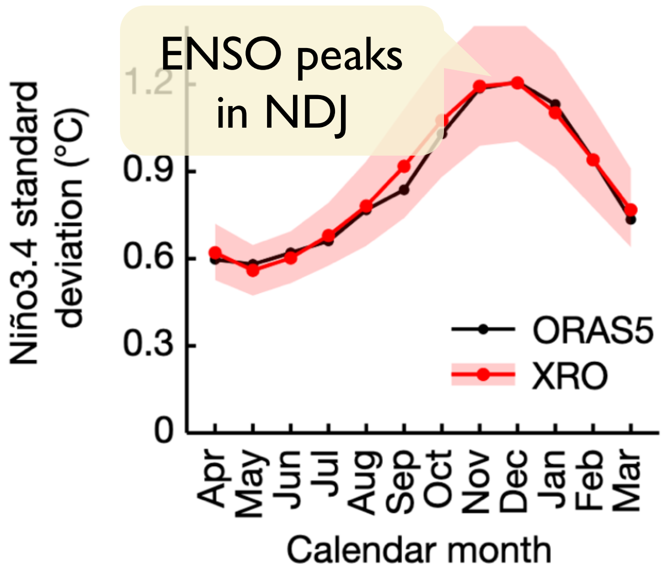


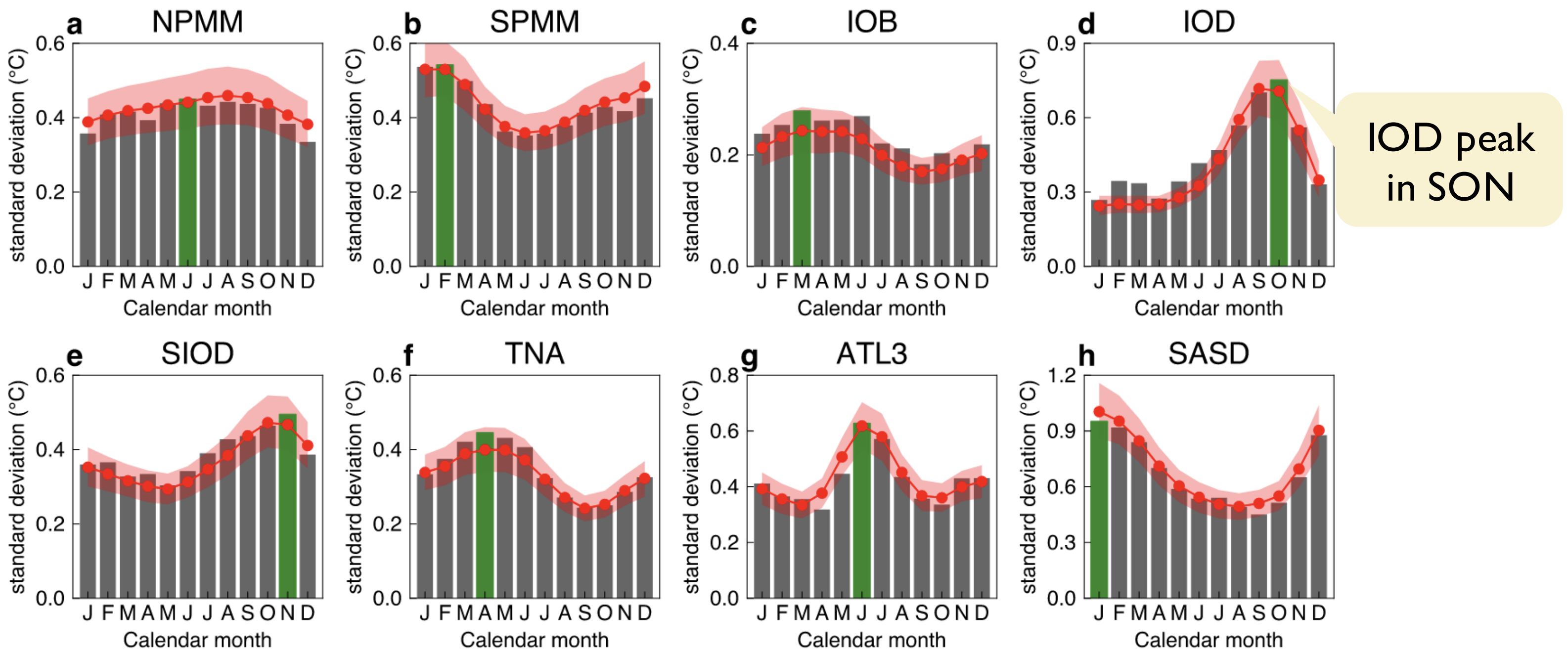
XRO stochastic simulation reproduces the irregular interannual oscillations between El Niño and La Niña.

Seasonality in the XRO

$$\mathbf{L} = \begin{pmatrix} \mathbf{L}_{ENSO} & \mathbf{C}_1 \\ \mathbf{C}_2 & \mathbf{L}_M \end{pmatrix}, \qquad \mathbf{L} = \mathbf{L}_0 + \sum_{j=1}^{2} \left(\mathbf{L}_j^c \cos j\omega t + \mathbf{L}_j^s \sin j\omega t \right),$$

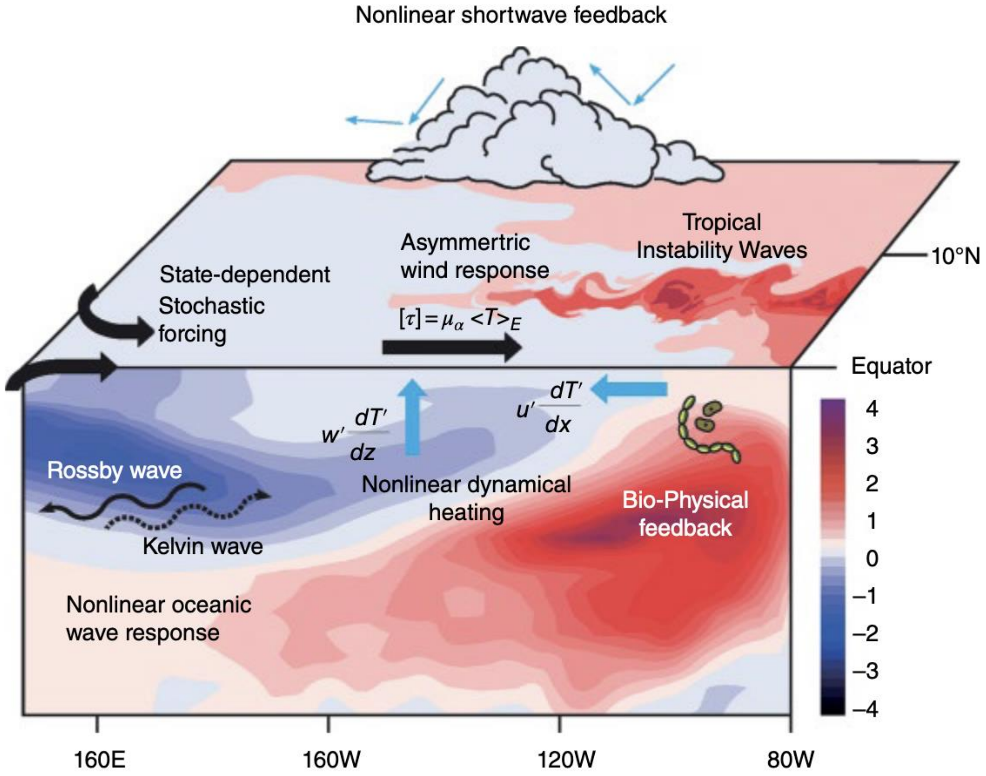
where ω = 2π /(12 months), and the subscripts 0, 1 and 2 indicate the mean, annual cycle and the semi-annual components, respectively.





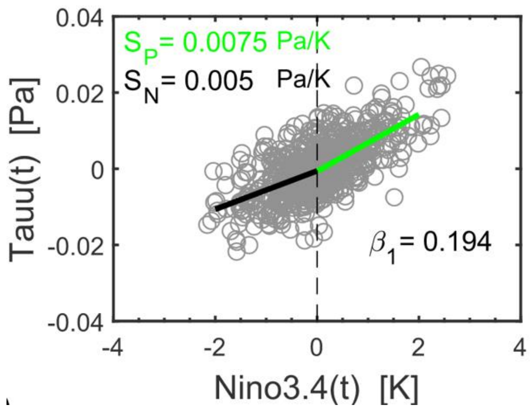
The XRO effectively capture the observed seasonal synchronization of ENSO and other climate modes

Nonlinearity in the XRO



An et al. (2020)

Asymmetric wind response

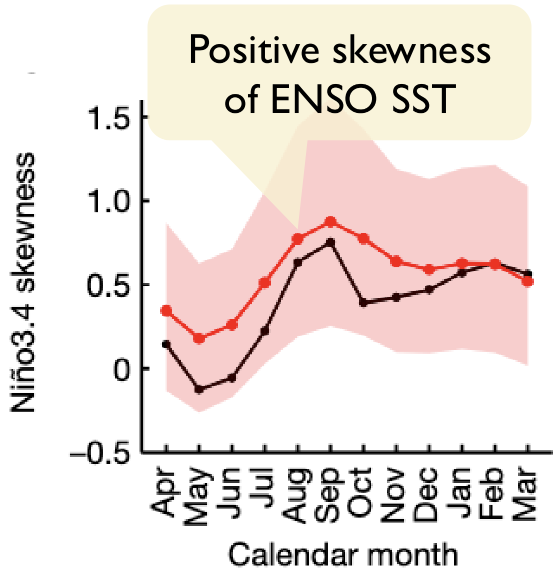


Geng et al. (2019)

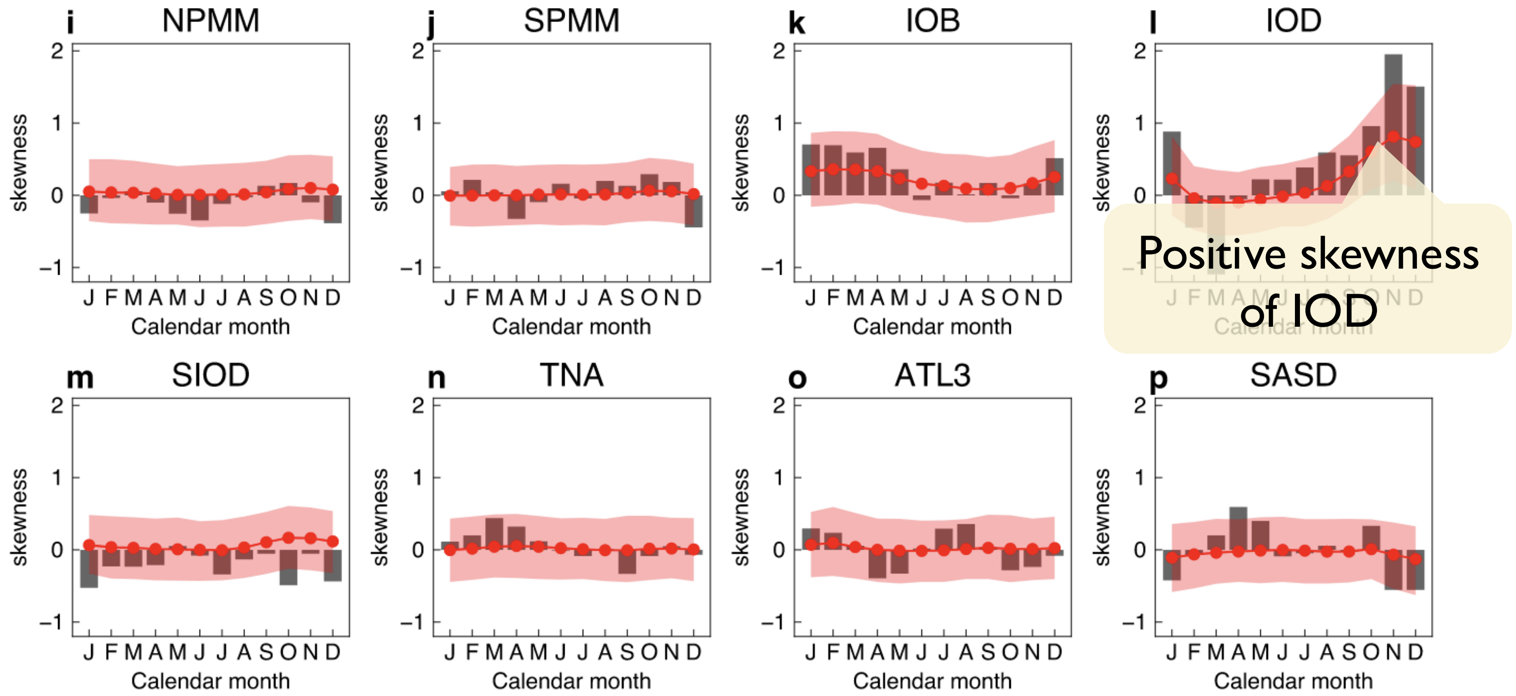
Quadratic nonlinearity for ENSO and IOD

$$\mathbf{N}_{\mathrm{ENSO}} = [b_1 T_{\mathrm{ENSO}}^2 + b_2 T_{\mathrm{ENSO}} h, 0]$$

$$\mathbf{N}_M = [0,0,0, b_3 T_{\mathrm{IOD}}^2, 0,0,0,0].$$



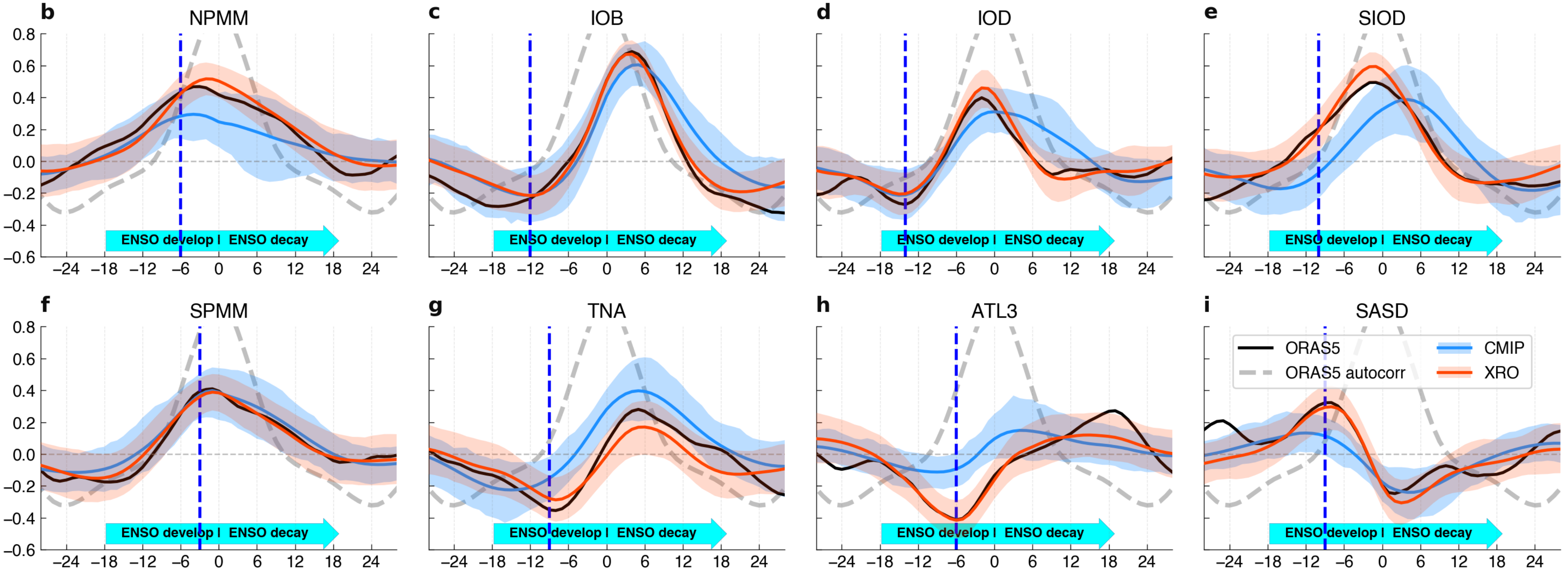
XRO realistically simulates ENSO amplitude asymmetry



(Zhao et al. 2024)

ENSO's lead-lag relationship with other climate modes

Cross-correlation of Niño3.4 SSTA with various indices in ORAS5, CMIP5/6 simulations, and XRO stochastic simulations

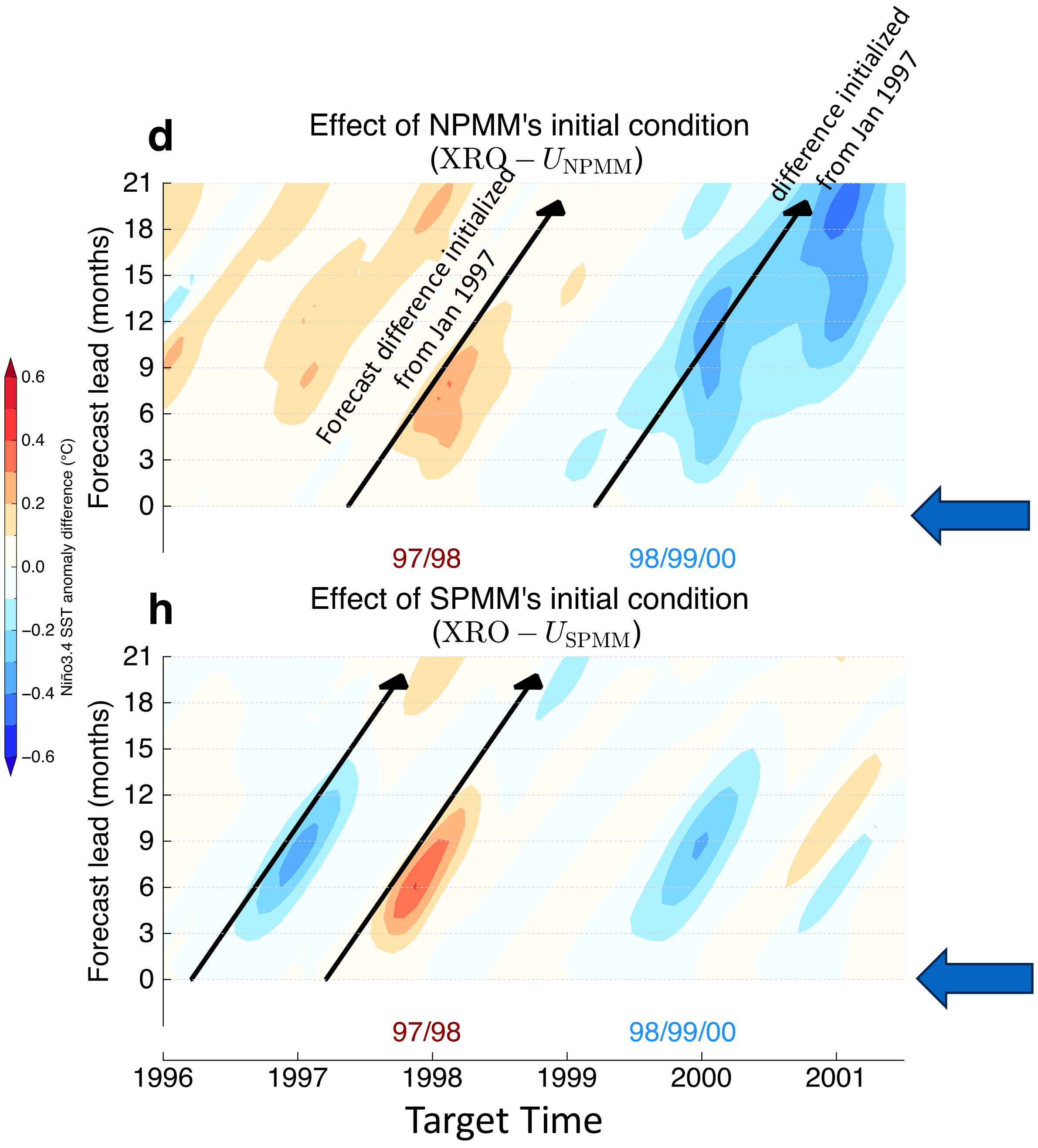


- **XRO realistically simulates ENSO's relationship with other climate modes**
- Simulating these observed relationships is <u>a major challenge for CMIP climate models</u>

(Zhao et al. 2024)

Quantifying **Extratropical Pacific** contributions to amplitude of individual ENSO events

- XRO : control reforecast experiment
- U_{NPMM} (turning off NPMM's initialization)
- U_{SPMM} (turning off SPMM's initialization)



Shadings: Nino3.4 index difference; *Contours*: WWV anomaly difference;

NPMM initialization

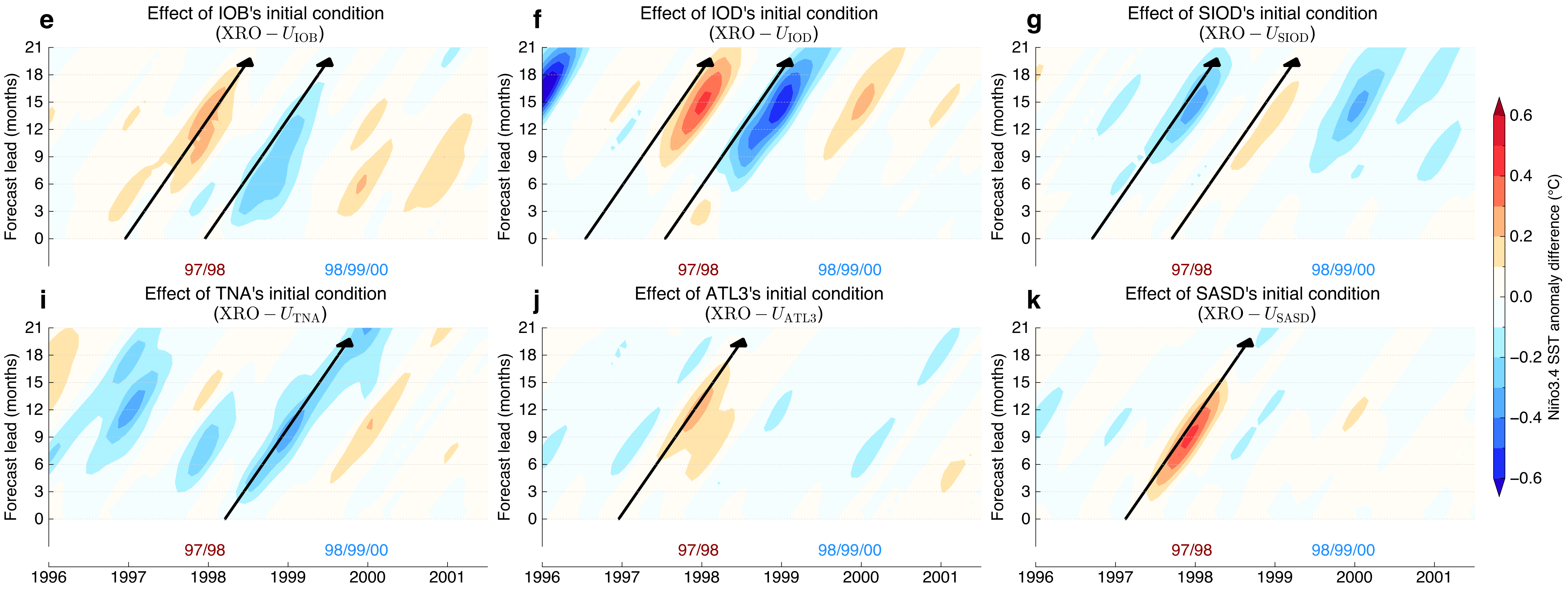
SPMM initialization

NPMM & SPMM can enhance ENSO SST 6-9 months later (NPMM contribution is larger!)

- NPMM warming recharges WWV (subsurface pathway)
- SPMM directly affects SSTs on the equator (surface pathway)

Quantifying Indian & Atlantic Ocean modes' contributions to ENSO amplitude

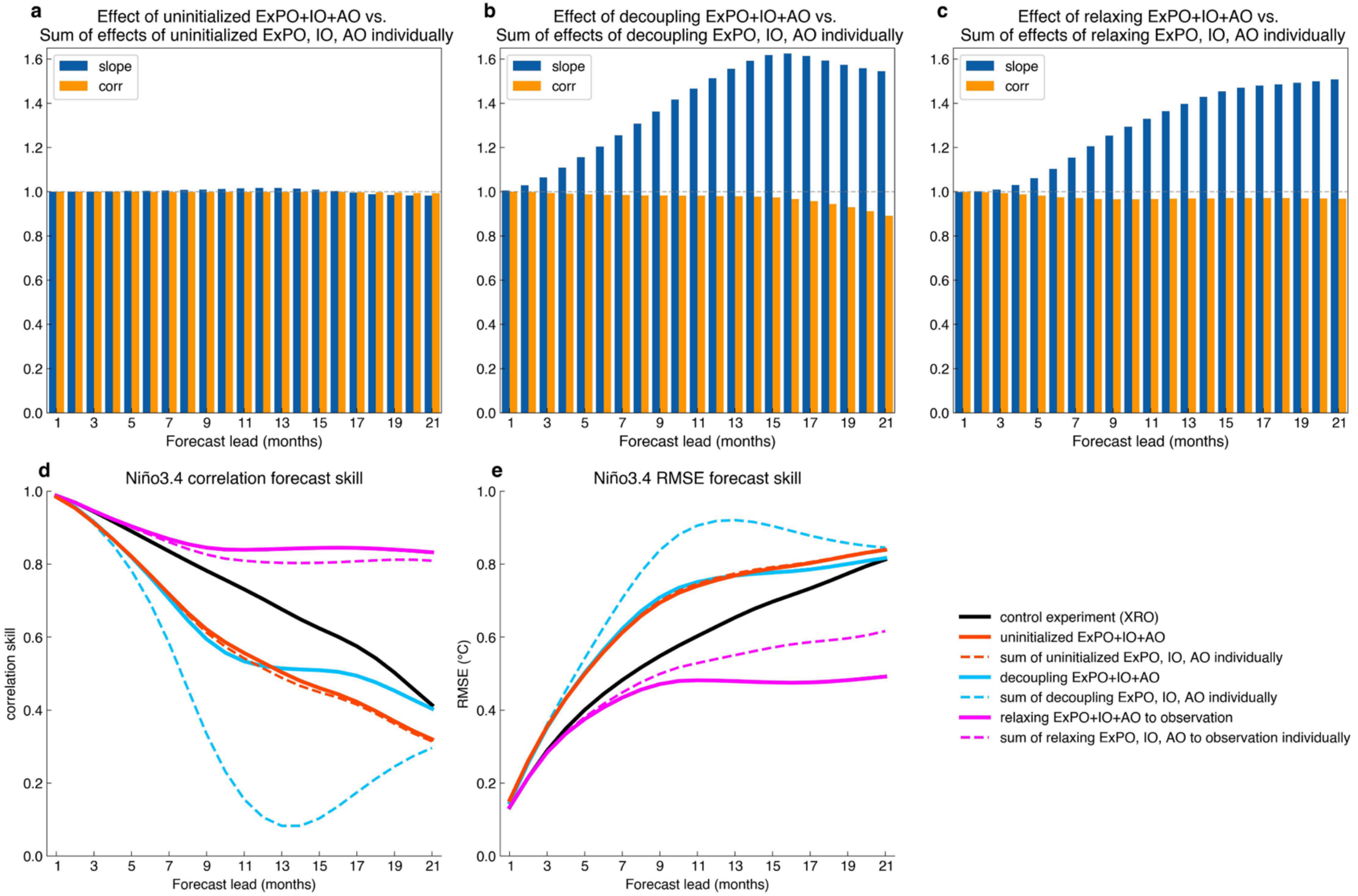
- U_j (turning off mode j's initialization)



Shadings: Nino3.4 index difference; *Contours*: WWV anomaly difference;

- IOD can affect ENSO 12-16 months later (largest effect for July-Nov init)
- TNA warming affects ENSO SST decrease 6-12 months later (largest effect for Dec-April init)

Quantitative reforecasting experiments: comparisons

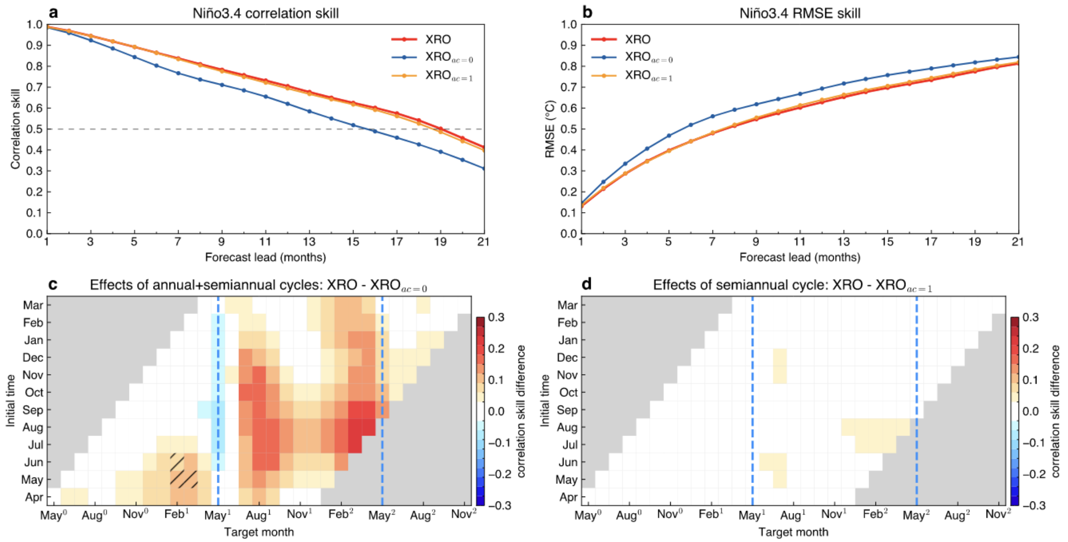


Only the "**uninitialized experiment framework**" (initial conditions of a given mode are set to zero) is suitable to diagnose the contributions of the other modes to ENSO predictability without overestimating the impact!

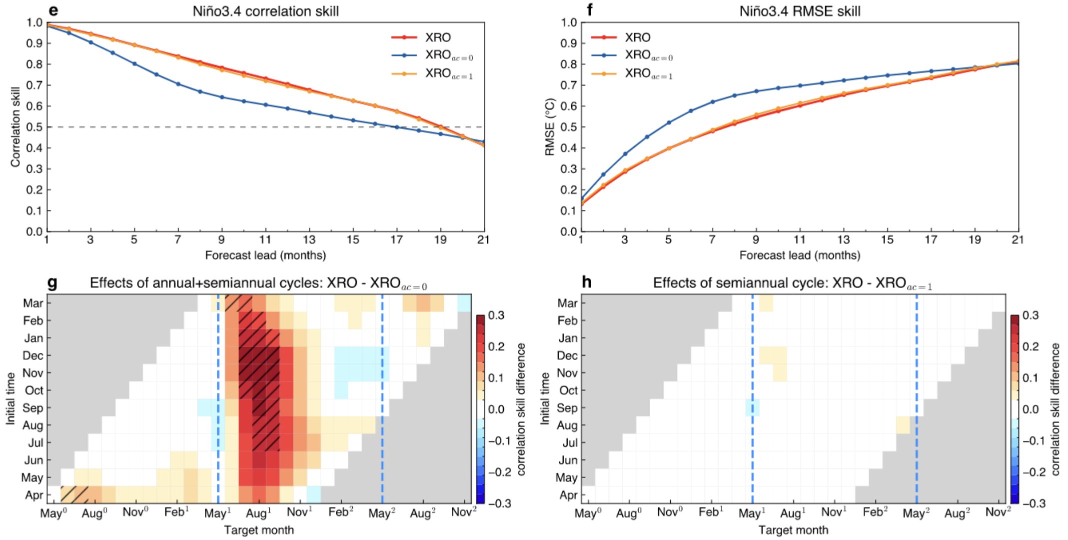
- The following frameworks overestimate impact of other modes on ENSO predictability:
  - **Decoupled experiments**: suppressing a specific mode by increasing their damping rate significantly
  - **Relaxation towards observations experiments**: relaxing a given mode towards the observed anomalies (timescale = 5 days)

Seasonality and Nonlinearity

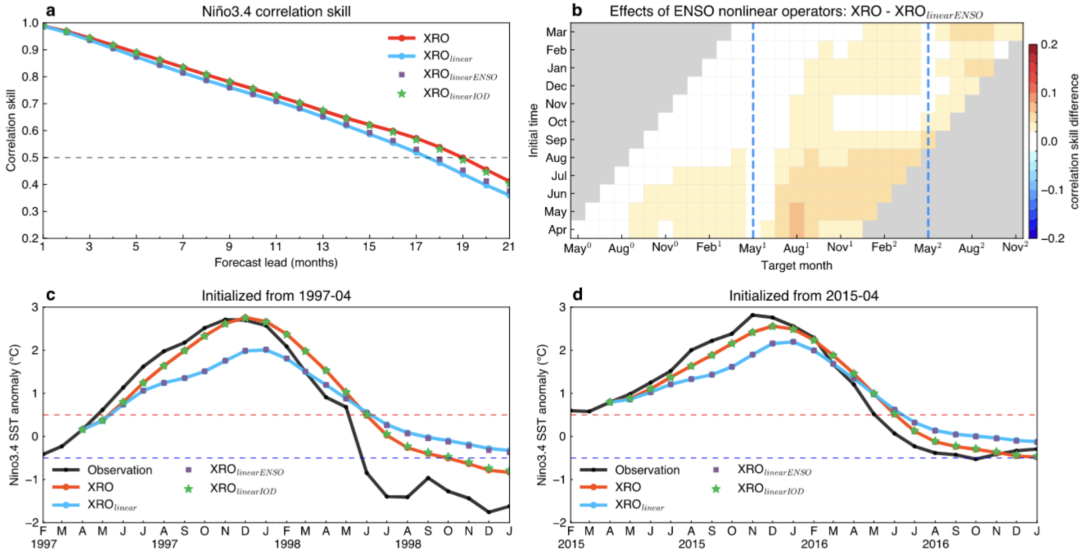
Effects of operator annual and semiannual cycles on ENSO's forecast skills (Parameters refitted separately)



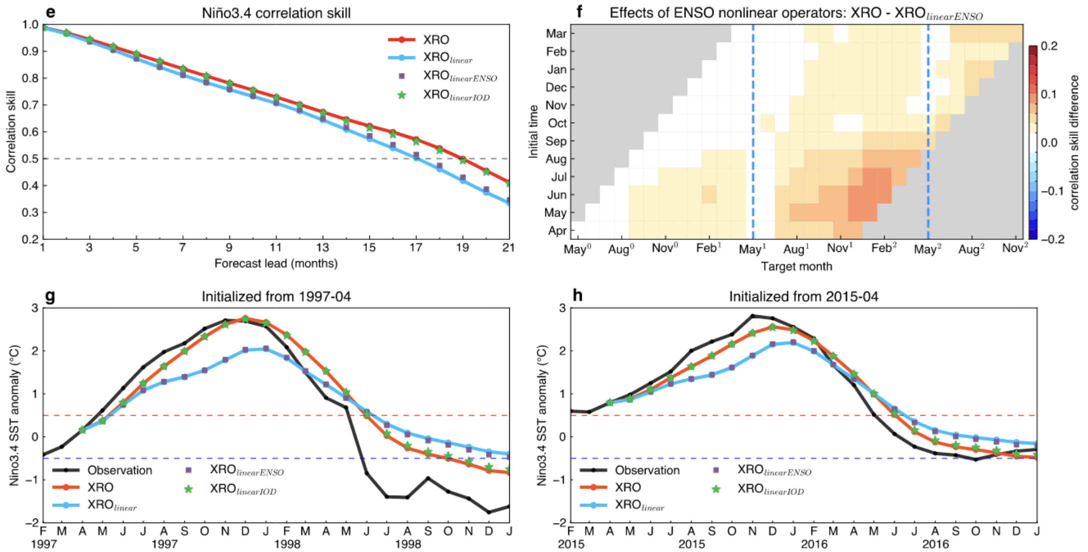
Effects of operator annual and semiannual cycles on ENSO's forecast skills (Parameters taken from XRO control)



Effects of nonlinear operators on ENSO's forecast skills (Parameters refitted separately)



Effects of nonlinear operators on ENSO's forecast skills (Parameters taken from XRO control)



100-member stochastic forecasts of ENSO by the XRO