UNIVERSITY OF MIAMI
ROSENSTIEL SCHOOL of MARINE & ATMOSPHERIC SCIENCE

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Advancing Decadal Predictability in North Atlantic SST and US Rainfall

Wei Zhang; Ben Kirtman

University of Miami – Rosenstiel School of Marine and Atmospheric Science, Miami, FL

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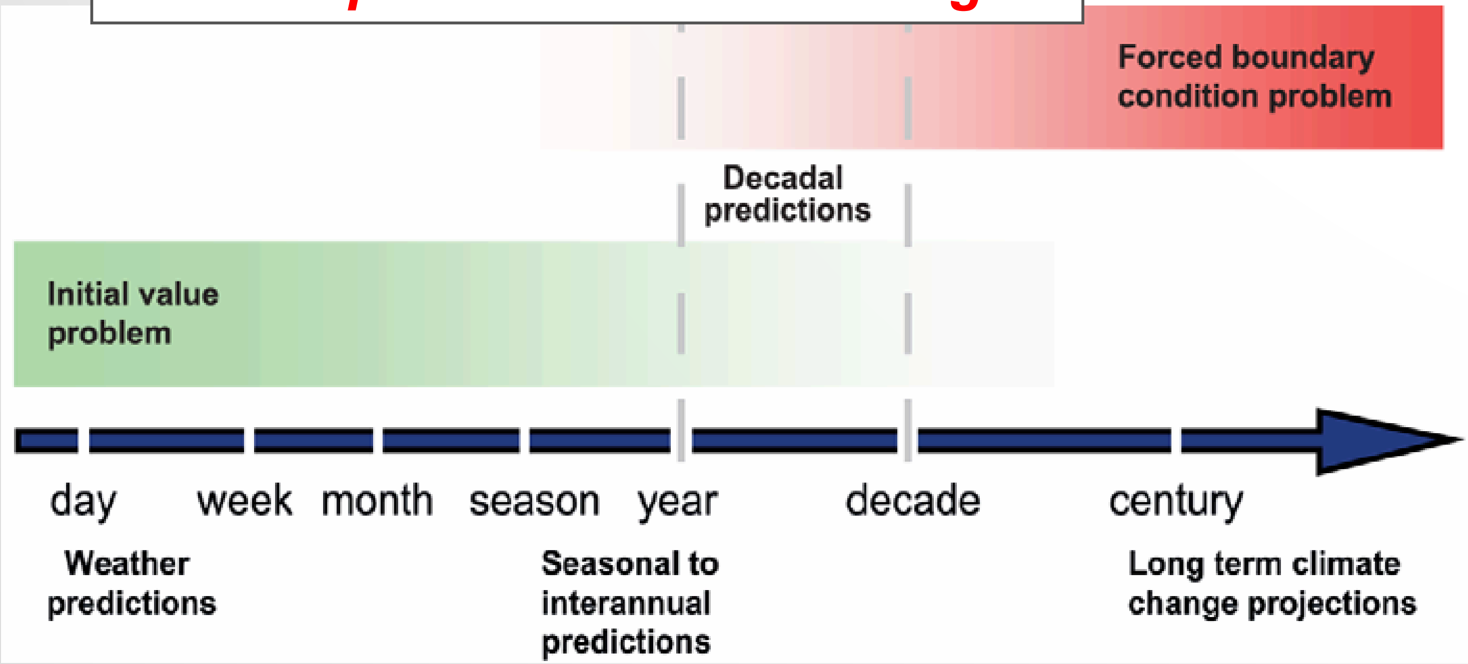
Web: *weizh.weebly.com;* Lab: *benkirtman.weebly.com;* Email: *wei.zhang@rsmas.miami.edu*

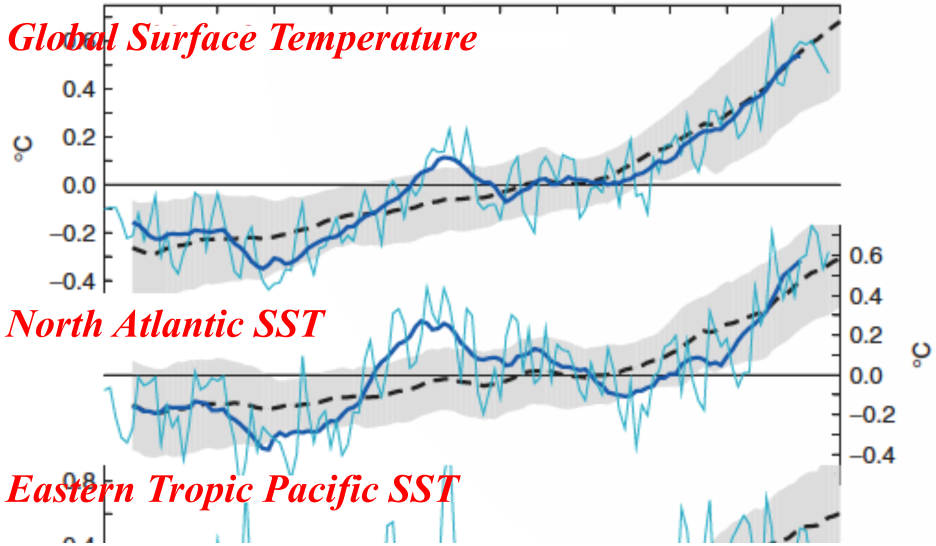
Motivations

- Increasing demand for decadal prediction system to support near-term decision-making in agriculture, energy and water management, etc.
- “Seamless” climate prediction systems, bridging gaps between weather and climate.

Decadal prediction is a challenge!



- **Challenges/Questions**
  - **Challenge I: Limits, sources and mechanisms of decadal predictability are not fully understood**



Decadal Climate Variability

Internal Dynamics

(e.g., AMO, PDO)

External Forcing

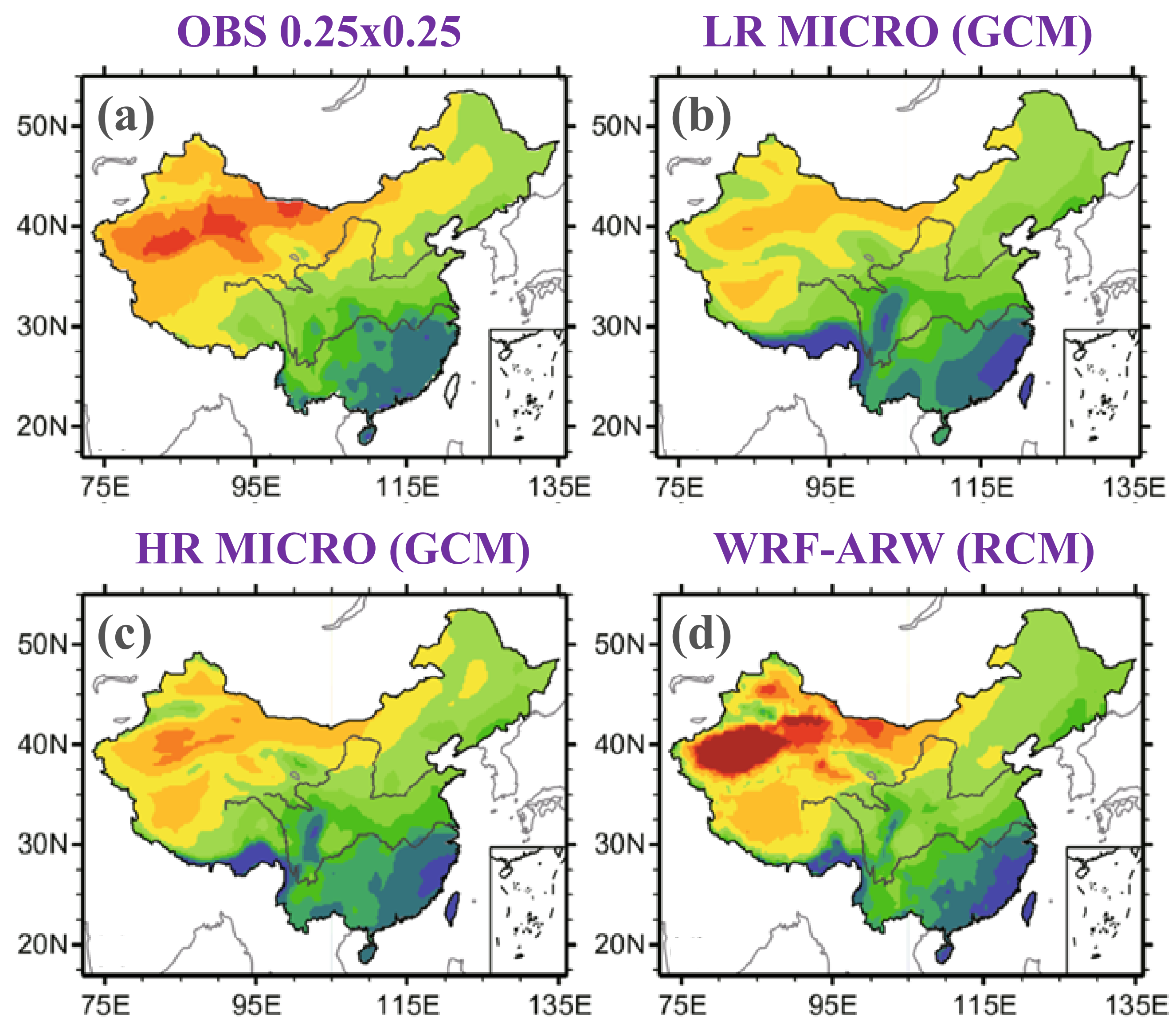
(e.g., Anthropogenic GHGs, aerosols, solar variations, volcanic forcing)

Coupled Ocean-atmosphere Variability

Noise due to Internal Dynamics

- **Challenges/Questions**

- **Challenge II: Impact of model resolution on decadal predictability in GCM & RCM**



Guo & Wang 2016

▪ GCM Experiments and RCM Simulations

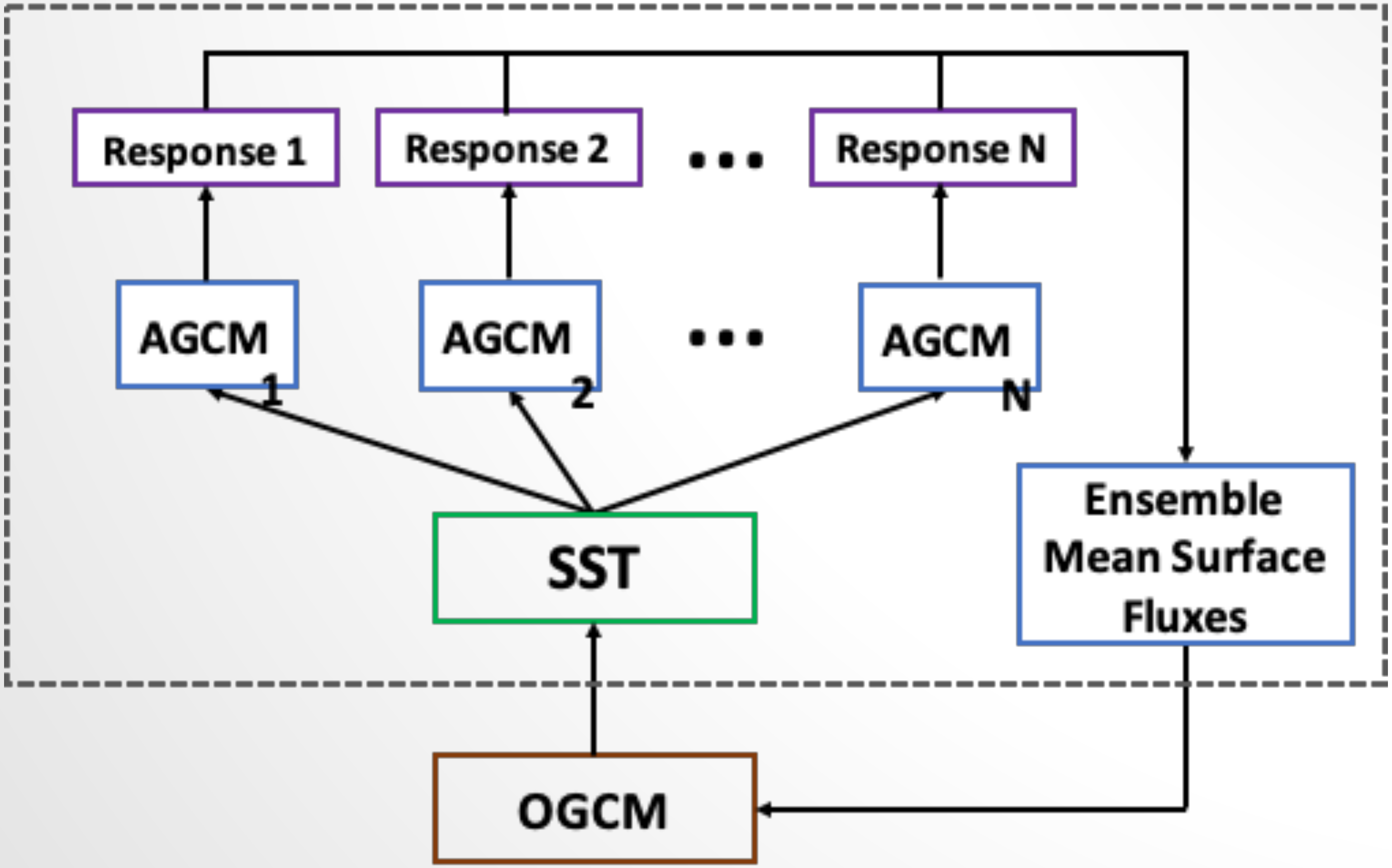
GCM: CCSM4	Ocean resolution	Atmosphere resolution	Ensemble size	Simulation length (year)
Standard control eddy parameterized (LR)	1.0° Lat × 1.0° Lon (Telescoping in the tropics)	~0.5°	1	255
IE eddy parameterized (LRIE)	1.0° Lat × 1.0° Lon (Telescoping in the tropics)	~0.5°	1 ocean, 10 atmospheres	225
Standard control eddy resolving (HR)	0.1° Lat × 0.1° Lon Globally	~0.5°	4	~70
IE eddy resolving (HRIE)	0.1° Lat × 0.1° Lon Globally	~0.5°	1 ocean, 10 atmospheres	163

Driver	RCM	Resolution	Simulation length
GFDL-ESM2M	**WRF**	**0.44°** **0.22°**	**Historical 1950-2005 (bias-corrected)**

IE: Interactive Ensemble

Kirtman et al., 2017; Zhang & Kirtman 2019 GRL Accepted

Interactive Ensemble (IE) Coupling Strategy



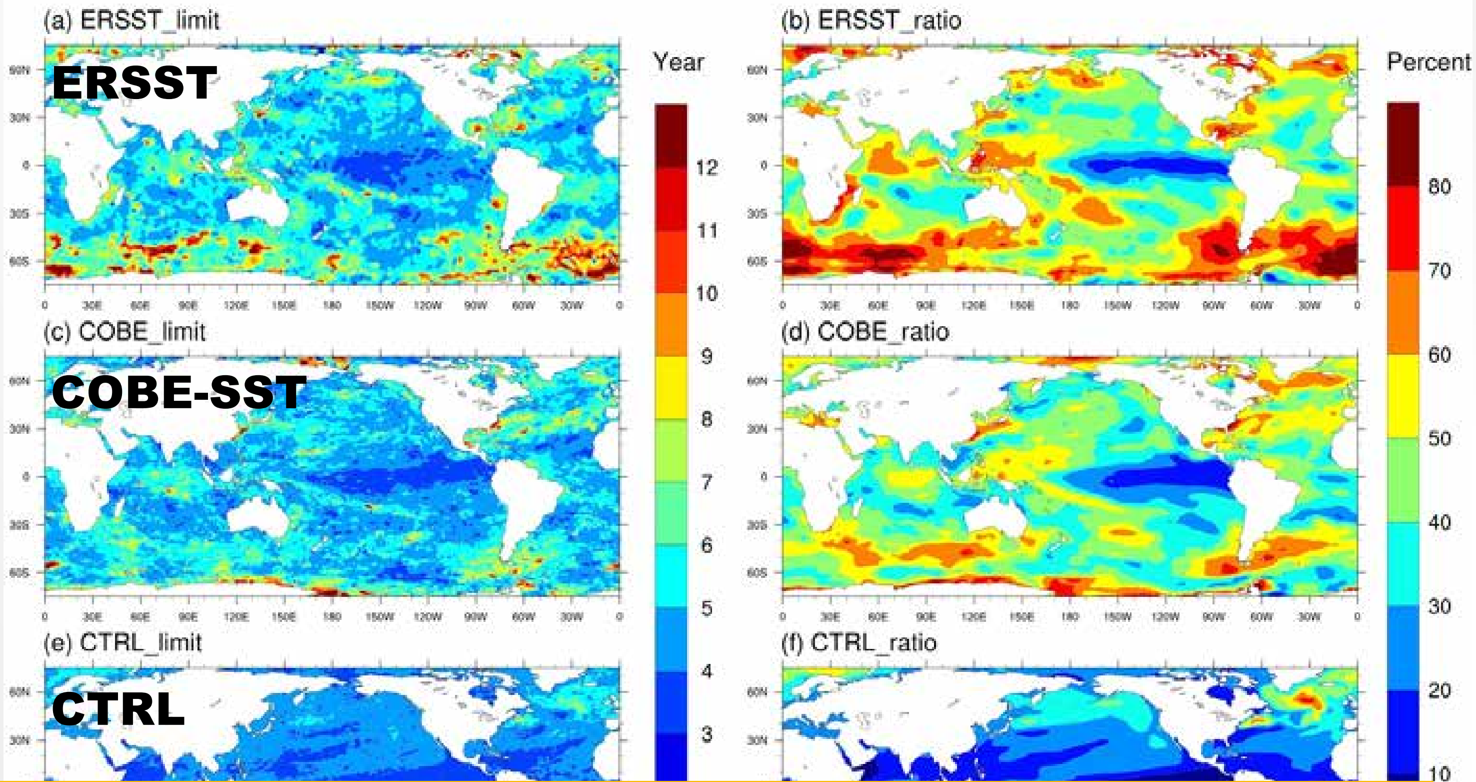
The basic intent of the IE is to reduce internal atmospheric noise, allowing an assessment of how noise impacts decadal predictability.

▪ Decadal SST Predictability (LR simulations)

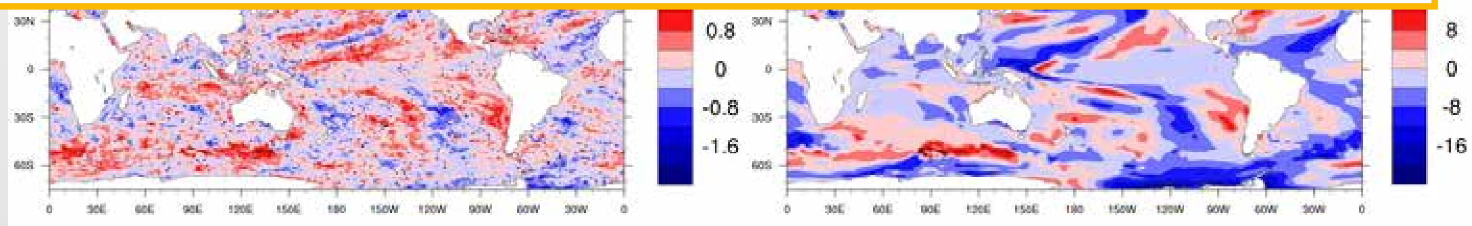
Limit of Predictability
Nonlinear Local Lyapunov Exponent method to find analog pairs based on error saturation theory *(Ding et al., 2016)*

Potential Predictability:
Ratio of 9-year low-pass filtered variance to the total variance *(Boer, 2000)*

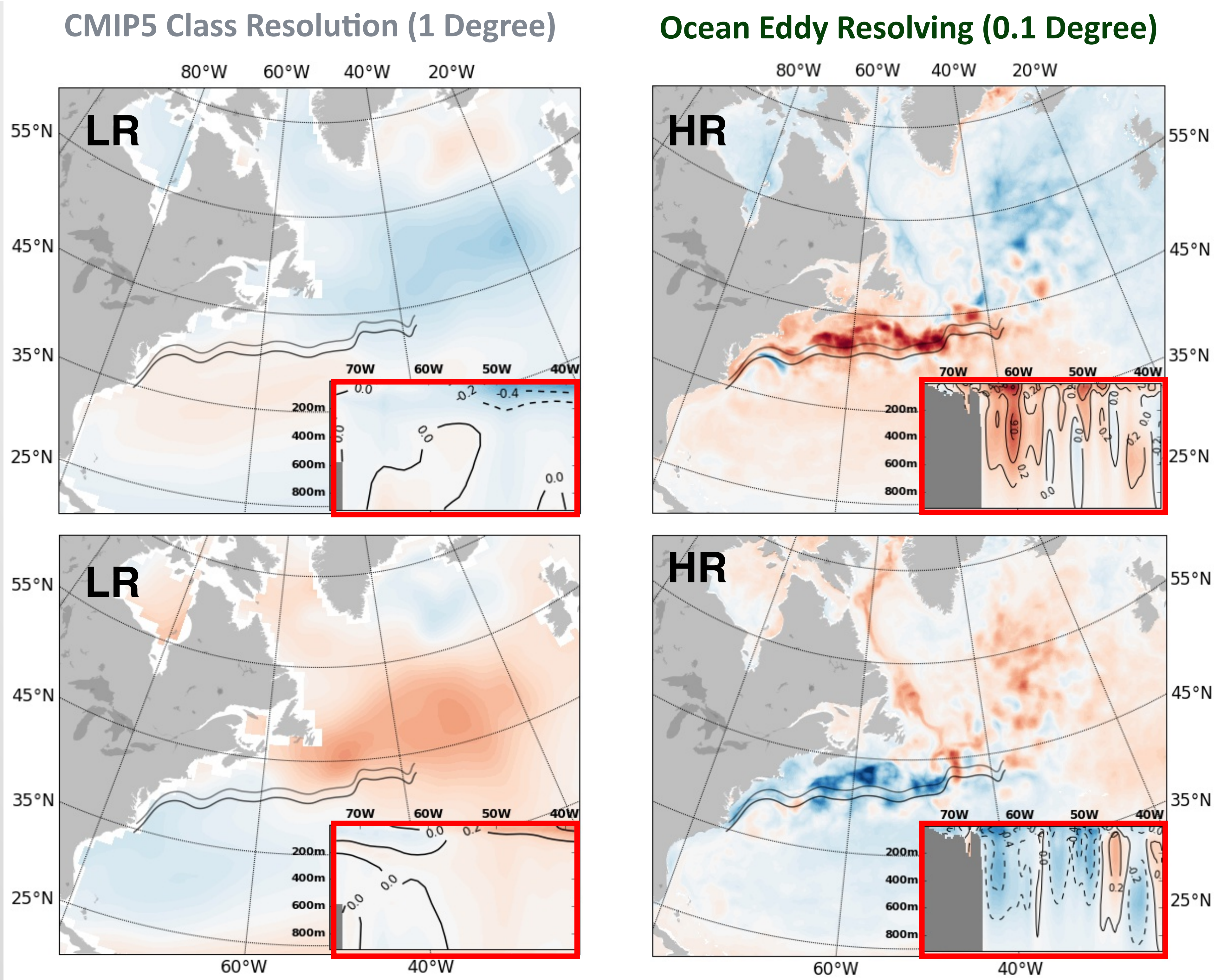
Decadal Predictability Limit | **Decadal Potential Predictability**



Models underestimate decadal SST predictability; reducing internal atmospheric noise may increase or decrease decadal SST predictability depending on background air-sea coupling and dynamics.

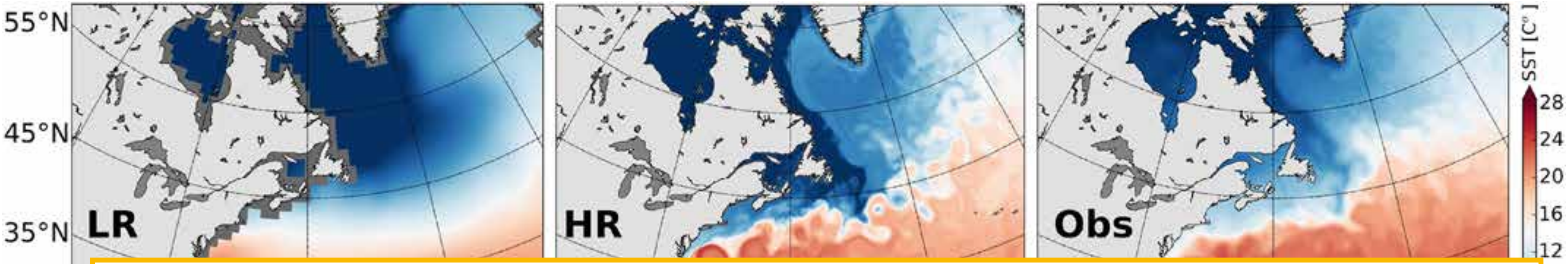


Zhang & Kirtman 2019 GRL (Research Highlight)



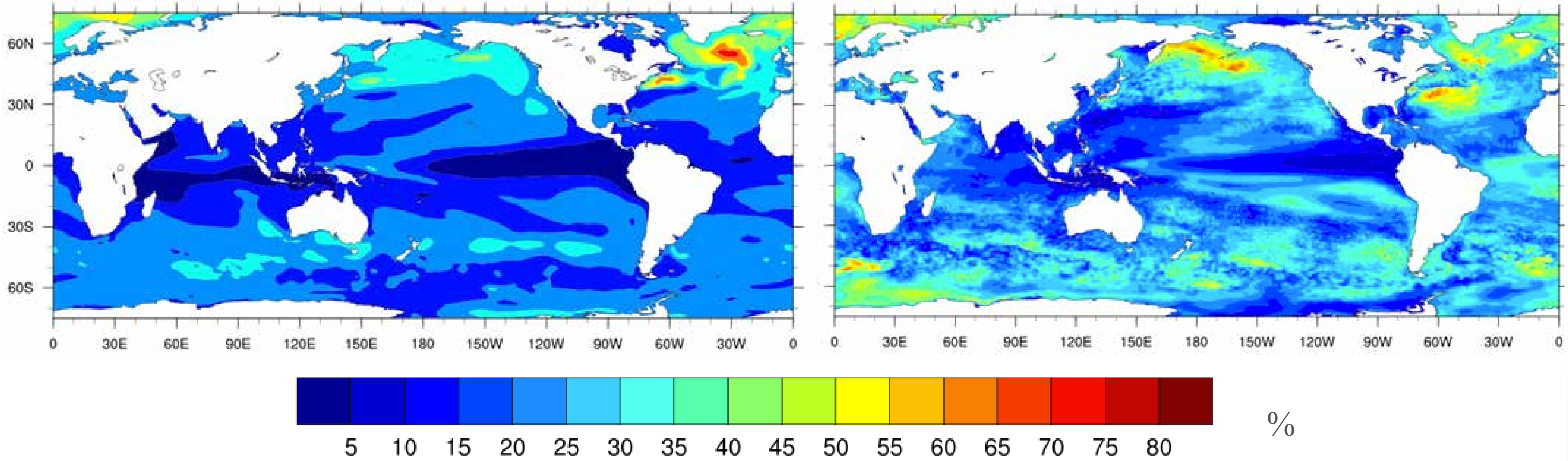
CMIP5 Class Resolution (1 Degree)
Ocean Eddy Resolving (0.1 Degree)
LR
HR
LR
HR
80°W
60°W
40°W
20°W
55°N
45°N
35°N
25°N
70W
60W
50W
40W
200m
400m
600m
800m

CCSM4-LR **CCSM4-HR** **OBS: MUR-SST**

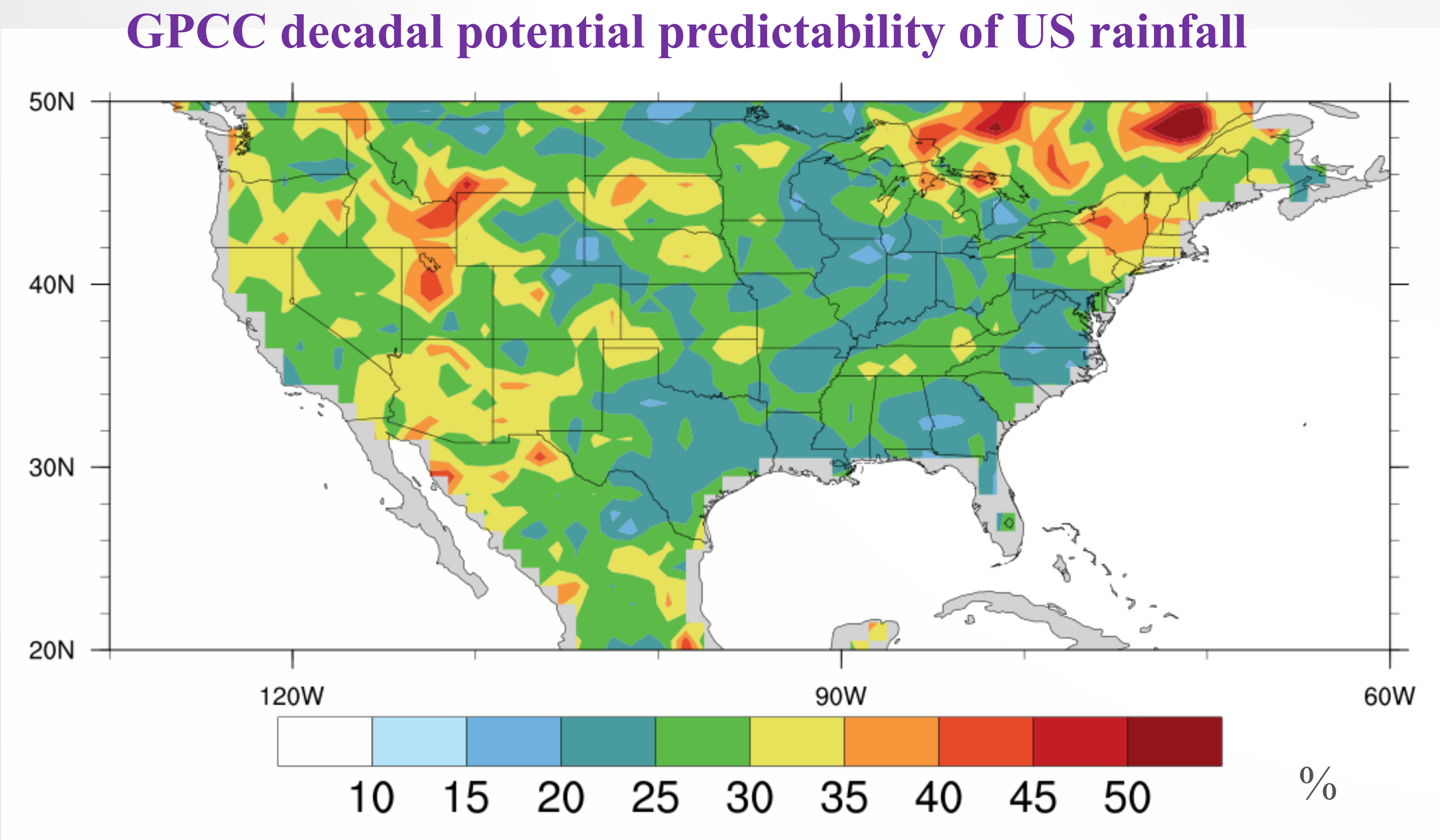


Eddy-resolving models can improve the representation of ocean fronts and eddies and associated air-sea interactions, contributing to more realistic simulations of decadal variability, and hence improve the estimates of decadal predictability.

LR CCSM4 Predictability **HR CCSM4 Predictability**

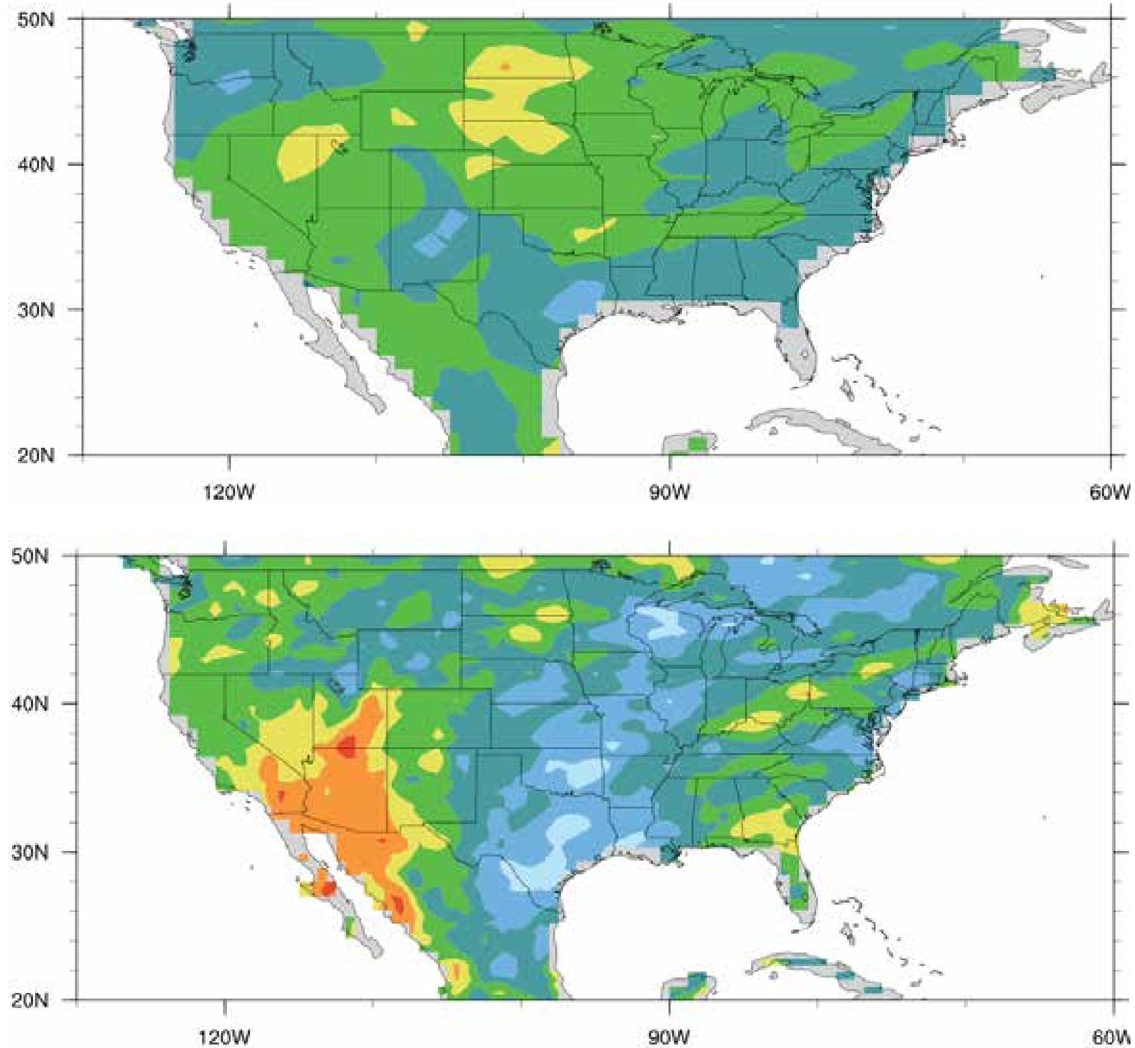


- **Decadal Predictability of US Rainfall**



LR CCSM4

HR CCSM4

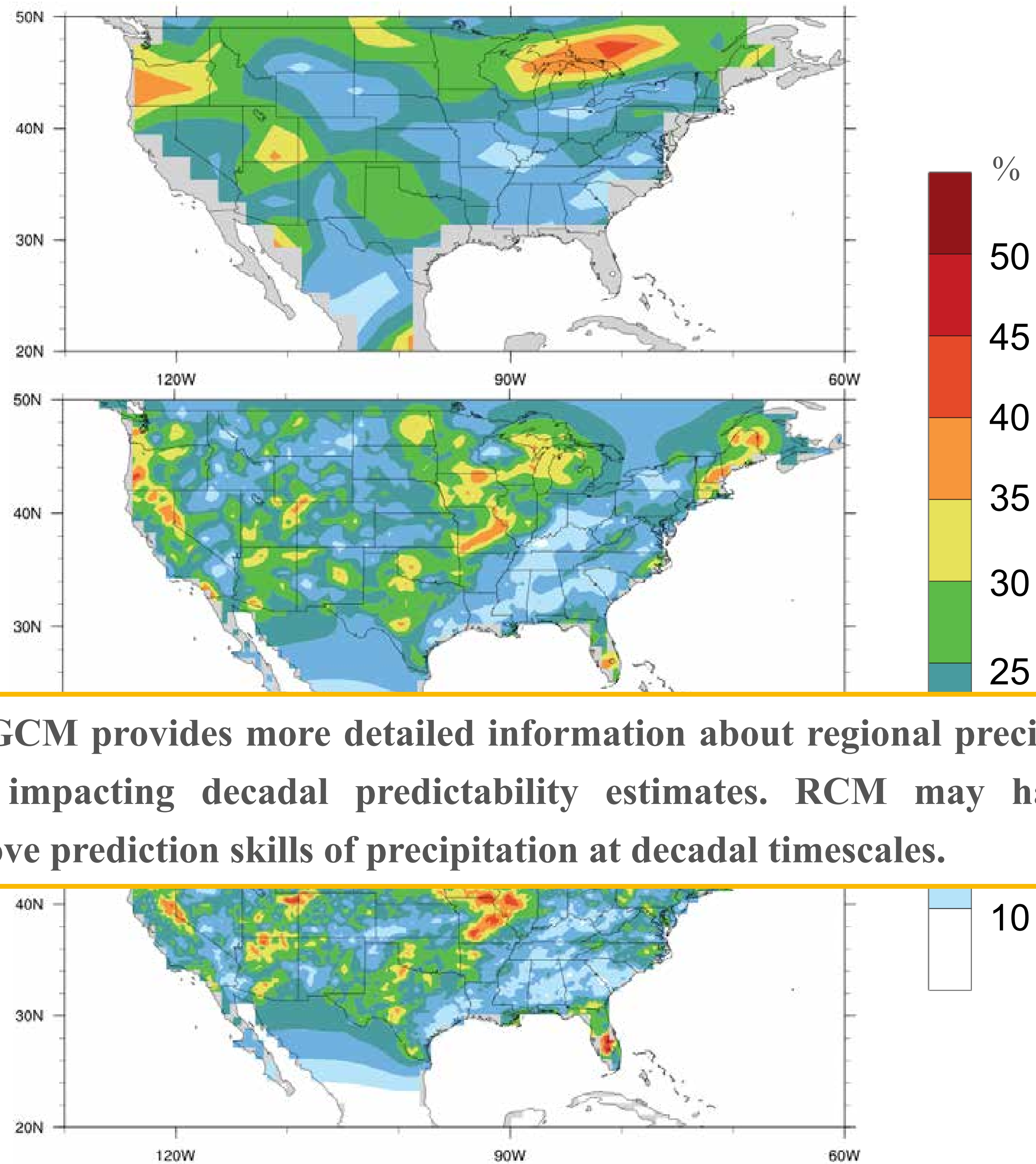


Eddy-resolving model significantly impact decadal predictability of US precipitation, suggesting the influence of resolved ocean features on precipitation over land in terms of air-sea interactions and teleconnections.

GFDL-ESM2M (~2°)

WRF 0.44°

WRF 0.22 °



RCM driven by GCM provides more detailed information about regional precipitation variability, thus impacting decadal predictability estimates. RCM may have the potential to improve prediction skills of precipitation at decadal timescales.

▪ Summary

- LR CCSM4 underestimates decadal SST predictability in most regions; HR CCSM4 with resolved ocean features improve the representation of decadal variability, leading to improved estimates of decadal predictability.

- Reducing internal atmospheric noise (CTRL vs IE) may increase or decrease decadal SST predictability depending on background air-sea coupling and dynamics.

- Resolved ocean features significantly impacts estimates of decadal precipitation predictability in the US. RCM provides the potential for improving decadal prediction skills of precipitation at regional scales.

▪ References

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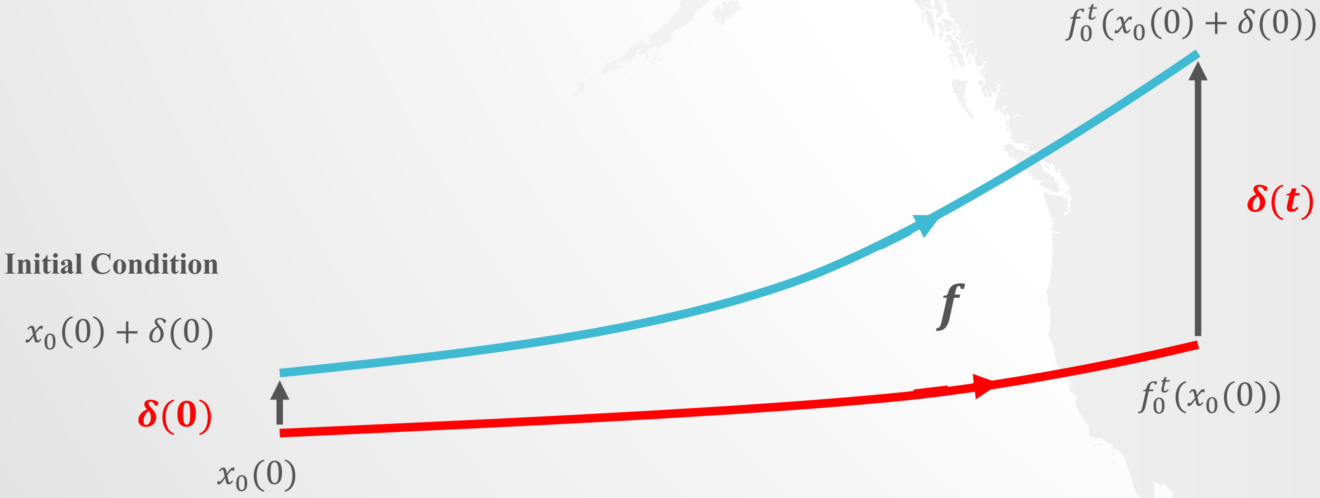
Thank You!

Supporting Materials

- # Methods of quantifying decadal predictability

Method I: Nonlinear Local Lyapunov Exponent (NLLE) *(Ding et al. 2016)*

Chaotic System: Error Saturation Theory based on butterfly effect *(Lorenz, 1963)*



We use NLLE to estimate the limit of predictability for a variable or a time series for any time-scale.

Methods of quantifying decadal predictability

Consider a n-D continuous-time chaotic system,

$$\frac{d\mathbf{X}(t)}{dt} = \underbrace{\mathbf{F}(\mathbf{X}(t))}_{\text{Dynamics, n-D vector field}}$$

Definition of error:

$$\delta(t) = \mathbf{X}(t) - \underbrace{\mathbf{X}_0(t)}_{\text{Reference/Fiducial Trajectory}}$$

Error evolution equation:

$$\frac{d}{dt}\delta = \underbrace{\mathbf{J}(\mathbf{x})\delta}_{\text{Tangent Linear Term}} + \mathbf{G}(\mathbf{x}, \delta)$$

High-order Nonlinear Term

Tangent Linear Term
J(x): Jacobian matrix

Tangent Linear Model

$$\Rightarrow \quad \delta_\mu(t) = \underbrace{\mu(\mathbf{X}_0, t)}_{\text{Linear Propagator}}\delta(0)$$

Or $\delta_\mu(t) = e^{\lambda t}\,\delta(0)$

Definition of Traditional Lyapunov Exponent

Define NLLE

$$\delta_\eta(t) = \underbrace{\eta(\mathbf{X}_0, \delta(0), t)}_{\text{Nonlinear Propagator}}\delta(0)$$

$$\lambda(\mathbf{X}_0, \delta(0), t) = \frac{1}{t}\ln\frac{\|\delta_\eta(t)\|}{\|\delta(0)\|}$$

Definition of NLLE

▪ Methods of quantifying decadal predictability

For NLLE, averaging over a lot of X_0

$$\bar{\lambda}\left(\boldsymbol{\delta}(0), t\right) = \left\langle \lambda(\mathbf{X}_0, \boldsymbol{\delta}(0), t) \right\rangle_N = \frac{1}{Nt}\sum_{i=1}^{N} \ln \frac{\| \delta_i(t) \|}{\| \delta_i(0) \|}$$

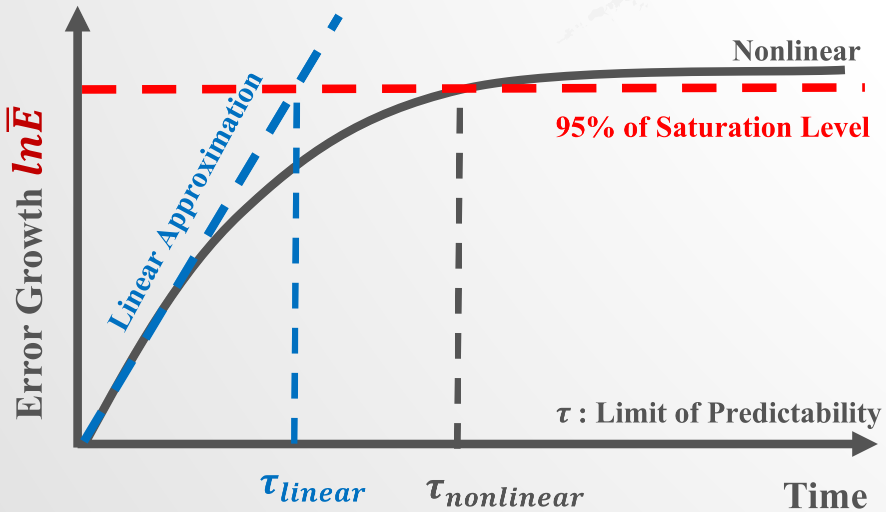
Mean relative growth of initial error

$$\bar{E}(\boldsymbol{\delta}(0), t) = \exp\left(\bar{\lambda}(\boldsymbol{\delta}(0), t)t\right)$$

$N \to \infty$

Constant

Saturation Level



(b) Mean Error Evolution Curve for a time series

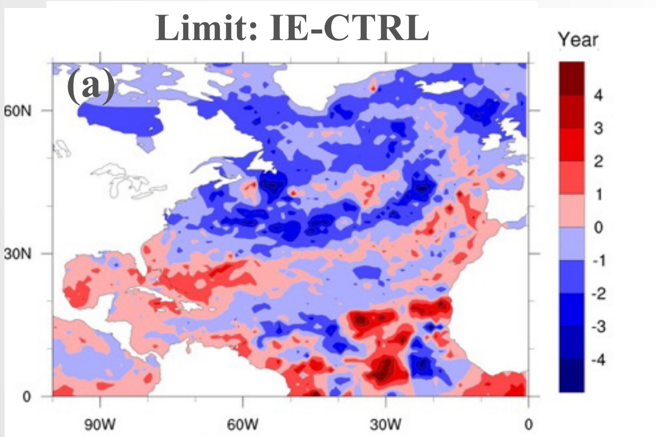
- # Methods of quantifying decadal predictability

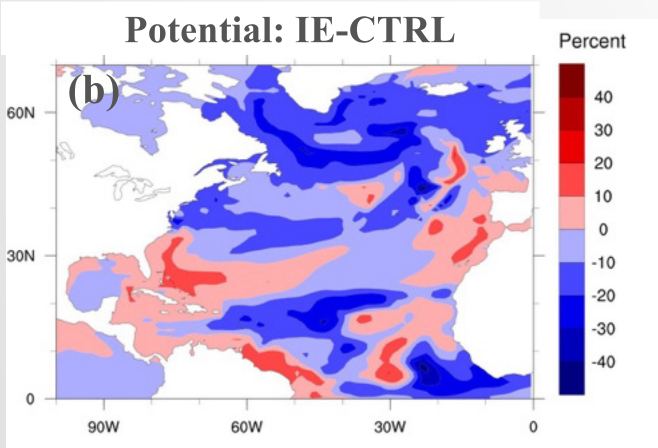
Method II: Decadal Potential Predictability (Boer, 2000)

$$\boldsymbol{Dedacal\ Timescale\ Ratio\ (DTR)} \ = \ \frac{\boldsymbol{Low.pass\ Filtered\ Variance}}{\boldsymbol{Total\ Variance}} \times \mathbf{100\%}$$

The *DTR* indicates the intensity of decadal variability, and is suggestive of the potential of decadal predictability.

Eddy-parameterized LR Simulations

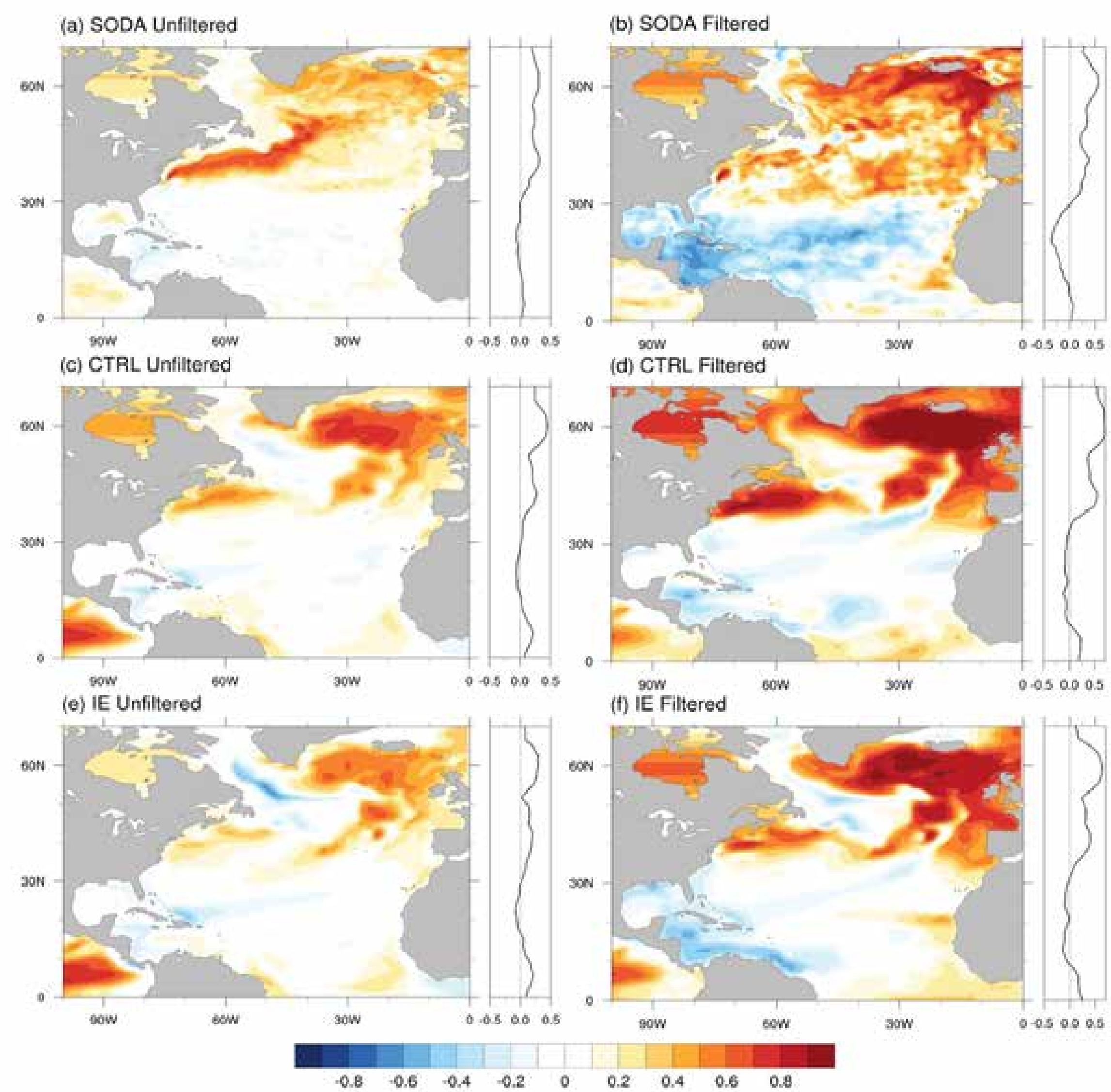




SODA

CTRL

IE

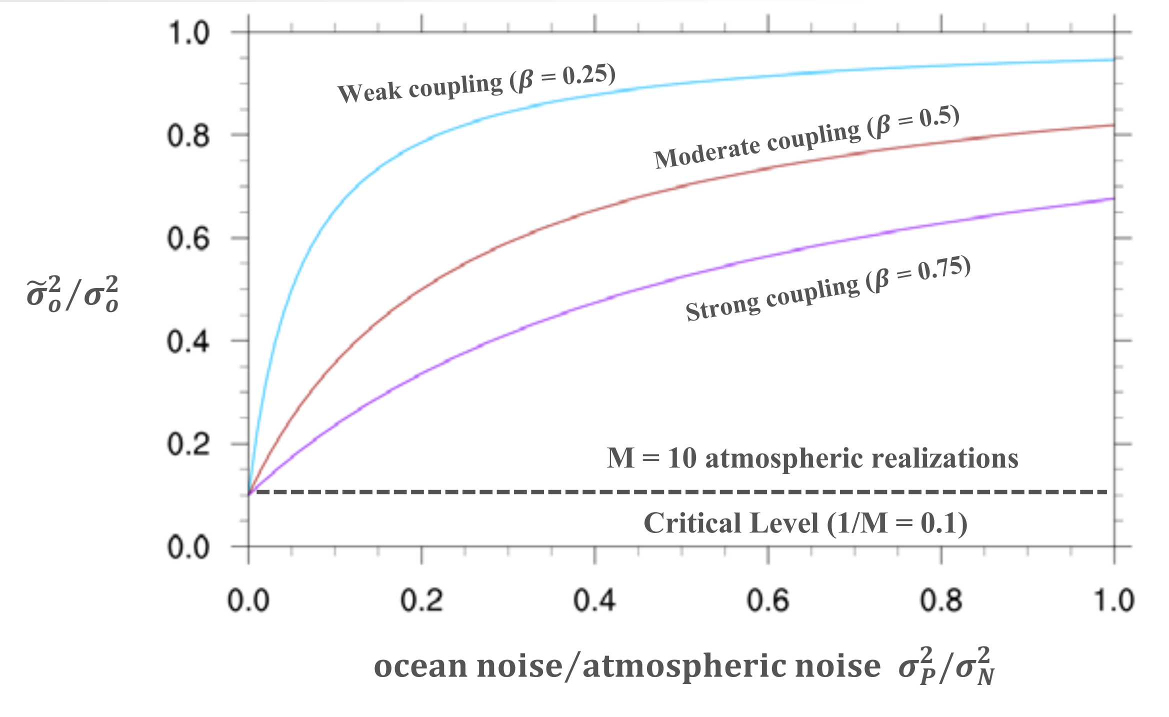


Reducing the noise decreases subsurface decadal predictability of ocean temperature especially in the subpolar regions.

LR CCSM4 simulations misrepresent the vertical connectivity between SST and subsurface ocean temperature, especially in the subtropics.

▪ Preliminary Results

- **Variance Test based on Hasselmann Hypothesis** *(Hasselmann, 1976)*



IE/CTRL Variance Ratio (e.g., SST)

$$\frac{\tilde{\sigma}_o^2}{\sigma_o^2} = \frac{\beta^2/M + \sigma_P^2/\sigma_N^2}{\beta^2 + \sigma_P^2/\sigma_N^2}$$

$\tilde{\sigma}_o^2/\sigma_o^2$ < 1/M (M=10)

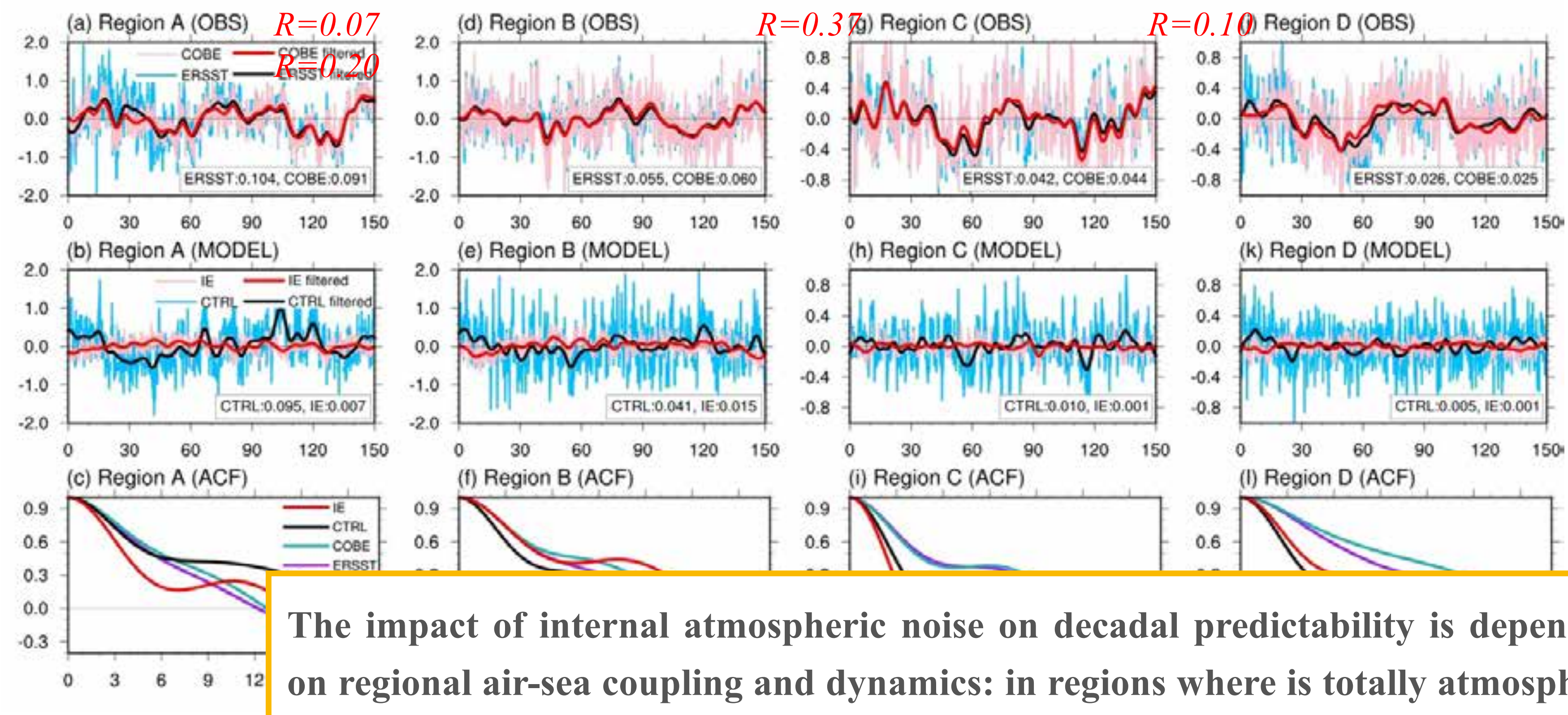
Null hypothesis works! Totally atmospheric noise forced

1/M < $\tilde{\sigma}_o^2/\sigma_o^2$ < 1.0

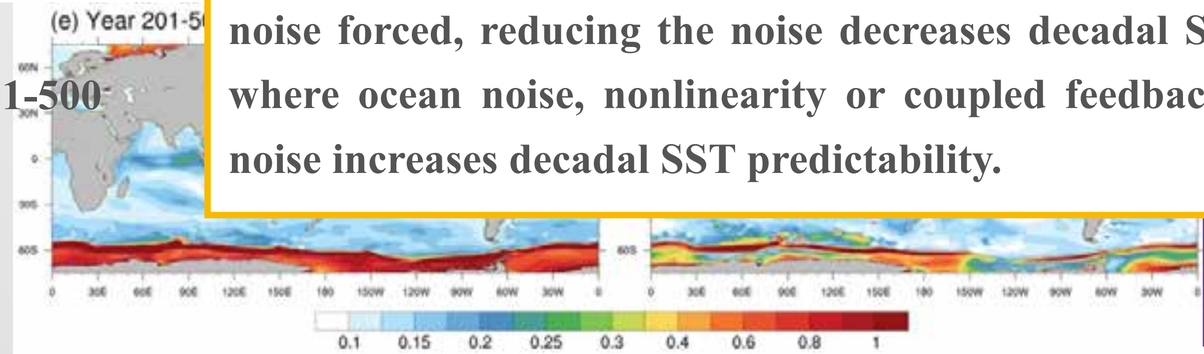
Either Atmospheric noise, Ocean noise or nonlinear dynamics comes into play

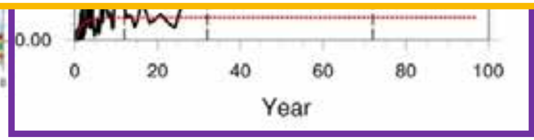
$\tilde{\sigma}_o^2/\sigma_o^2$ > 1.0

Null hypothesis fails! Unstable coupled feedbacks or nonlinear dynamics



Year 201-500





The impact of internal atmospheric noise on decadal predictability is dependent on regional air-sea coupling and dynamics: in regions where is totally atmospheric noise forced, reducing the noise decreases decadal SST predictability; in regions where ocean noise, nonlinearity or coupled feedbacks play a role, reducing the noise increases decadal SST predictability.

The End