Spatiotemporal complexity and time-dependent networks in mid- to late Holocene simulations

Annalisa Bracco, **Fabrizio Falasca,** Julien Crétat,
and Pascale Braconnot

LSCE

Georgia Institute of Technology

Motivations

Main goal

Build a general data-mining framework to investigate climate variability in space and time.

Challenges

- Complex, chaotic dynamics
- Global scale regime shifts (i.e., Snowball Earth glaciations)
- Highly non-trivial (local) behaviors: i.e. order to chaos transitions
- Local regime shifts can “cascade” into the global system

Motivations

Main goal

Build a general data-mining framework to investigate climate variability in space and time.

Important point

The dynamics of the climate system are dominated by recurrent spatiotemporal patterns (e.g., ENSO, Atlantic Nino, Indian Ocean Dipole, monsoon system etc.) ⟶ dimensional reduction in space

Outline

Part 1

Proposed Framework

Outline

Part 1

Proposed Framework

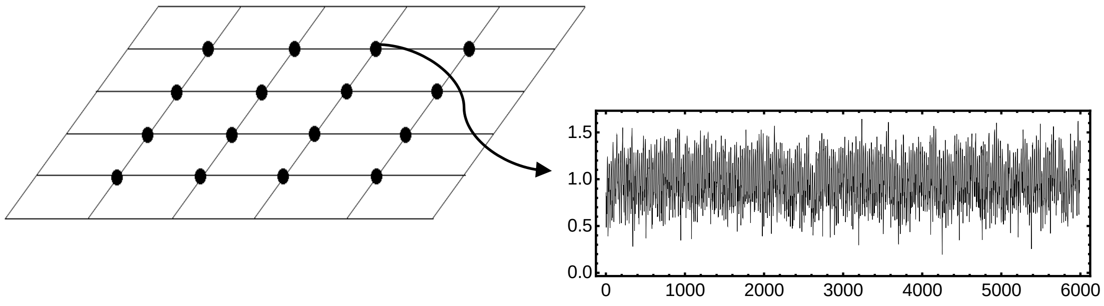
Part 2

Exploring mean state – variability interactions in the Indo-Pacific basin in paleoclimate simulations covering the mid- to late-Holocene

Part 1

Proposed Framework

Input: spatiotemporal climate field **X**(t)



Steps:

(1) From climate field **X**(t) to entropy field **S**(t)

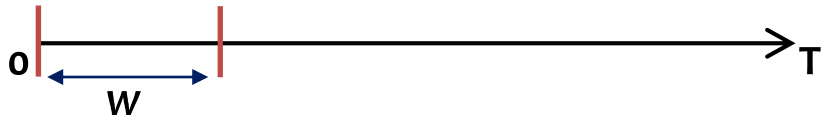
(2) Dimensionality reduction of **S**(t)

(3) Network inference between domains

Proposed Framework

Step (1) From climate field **X**(t) to entropy field **S**(t)

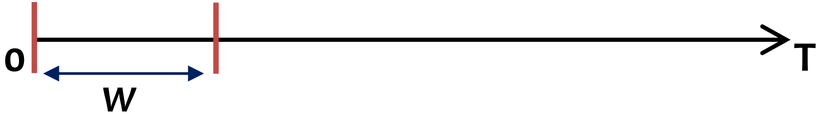
a) For each grid cell i we have a time series $x_i(t)$ with T data points
b) For each $x_i(t)$ consider a time window of ***W*** time steps: $y_i(t)$



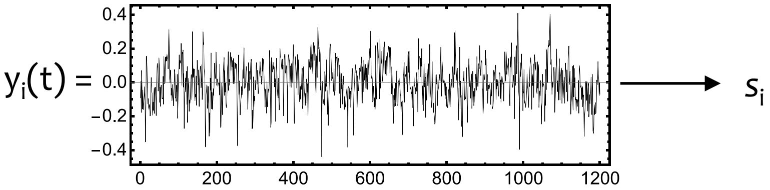
Proposed Framework

Step (1) From climate field **X**(t) to entropy field **S**(t)

a) For each grid cell i we have a time series $x_i(t)$ with T data points
b) For each $x_i(t)$ consider a time window of ***W*** time steps: $y_i(t)$



c) For each $y_i(t)$ compute its information entropy s_i (complexity quantifier)



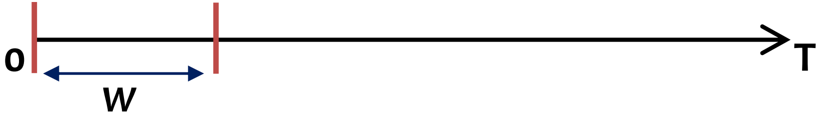
Complexity *s* (from Corso et al. (2018))

(a) From $x_i(t)$ compute its Recurrence Plot (RP)
(b) Sample a large number of microstates in the RP
(c) Complexity == Shannon entropy of microstates in the RP: $S(N^*) = -\sum_{i=1}^{N^*} P_i \log(P_i)$

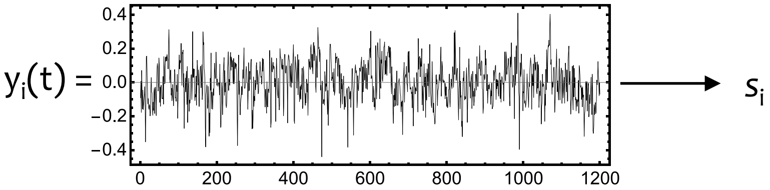
Proposed Framework

Step (1) From climate field **X**(t) to entropy field **S**(t)

a) For each grid cell i we have a time series $x_i(t)$ with T data points
b) For each $x_i(t)$ consider a time window of ***W*** time steps: $y_i(t)$



c) For each $y_i(t)$ compute its information entropy s_i (complexity quantifier)



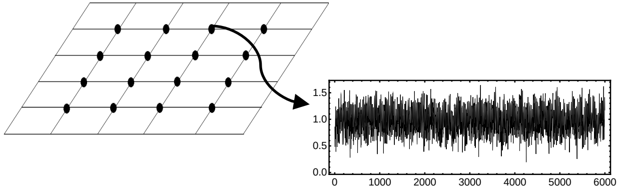
d) Repeat every Δ***W*** time steps

Proposed Framework

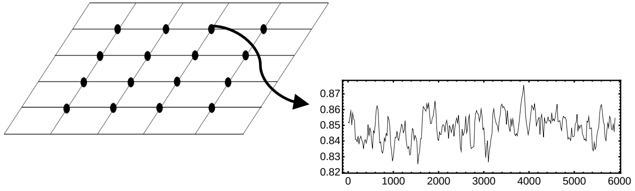
Step (1) From climate field **X**(t) to entropy field **S**(t)

Output:

From **X**(t)



to **S**(t)

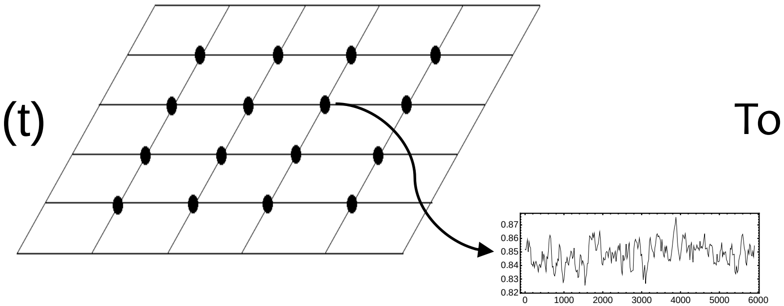


Proposed Framework

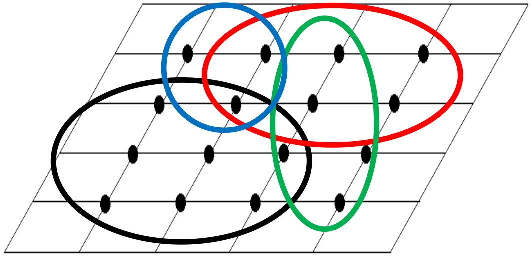
Step (2) Dimensionality reduction of **S**(t)

Identification of spatiotemporal patterns (*domains*) of the **S**(t) field

From **S**(t)



To



a) Spatially contiguous regions
b) Potentially overlapping
c) Homogeneous to the underlying variable

Methodology: **δ-MAPS** (Fountalis et al. 2018)
From spatiotemporal data to a weighted and lagged network between functional domains

Proposed Framework

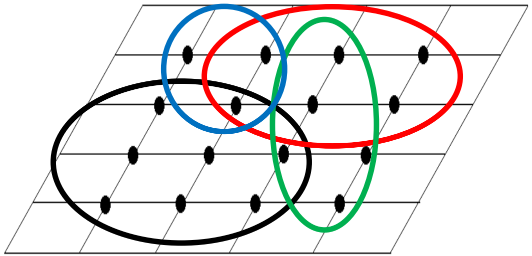
Step (3) Network inference between domains

Domains are connected through atmospheric and oceanic linkages

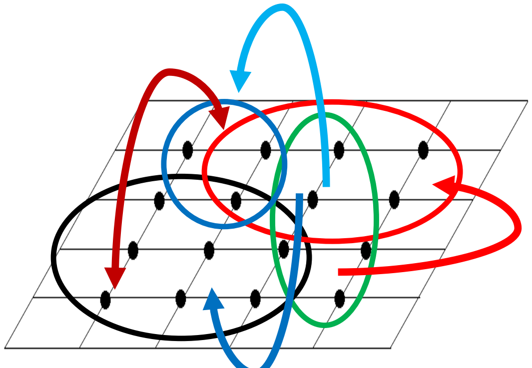
a) Consider a time window of ***Y*** time steps in the original climate field **X**(t)
b) Domain *A* signal : $X_A(t) = \sum_i^{|A|} x_i(t) \cos \phi_i$
c) For each pair of domains *A* and *B* :
- Compute the correlation $r_{A,B}(\tau)$ with $\tau \in [-\tau_{max}, \tau_{max}]$ and test significance
- If significant for a range of lags $R_{A,B}(\tau)$:
    - link weight → covariance at τ^*
    - link directionality based on $R_{A,B}(\tau)$

d) Do so every Δ***Y*** time steps

From



To



(t)

Summary

Input:

spatiotemporal climate field **X**(t)

Output:

weighted, direct and time dependent network between regions that are homogeneous in their time evolution

Benefits

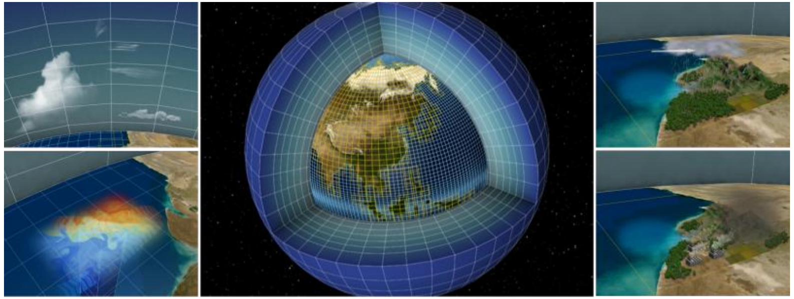
a) Domain D entropy signal $S_D(t) = \frac{1}{|D|}\sum_i^{|D|} s_i(t)$ informs about regime shifts of domain D

b) Time dependent network allows for the investigation of connectivity between the spatiotemporal patterns of the system

c) Arbitrarily long and complex climate simulations are compressed in few spatiotemporal patterns and their interactions

Part 2 # Mean state – variability interactions

IPSL Earth System model, mid- to late Holocene simulation covering the past 6000 years



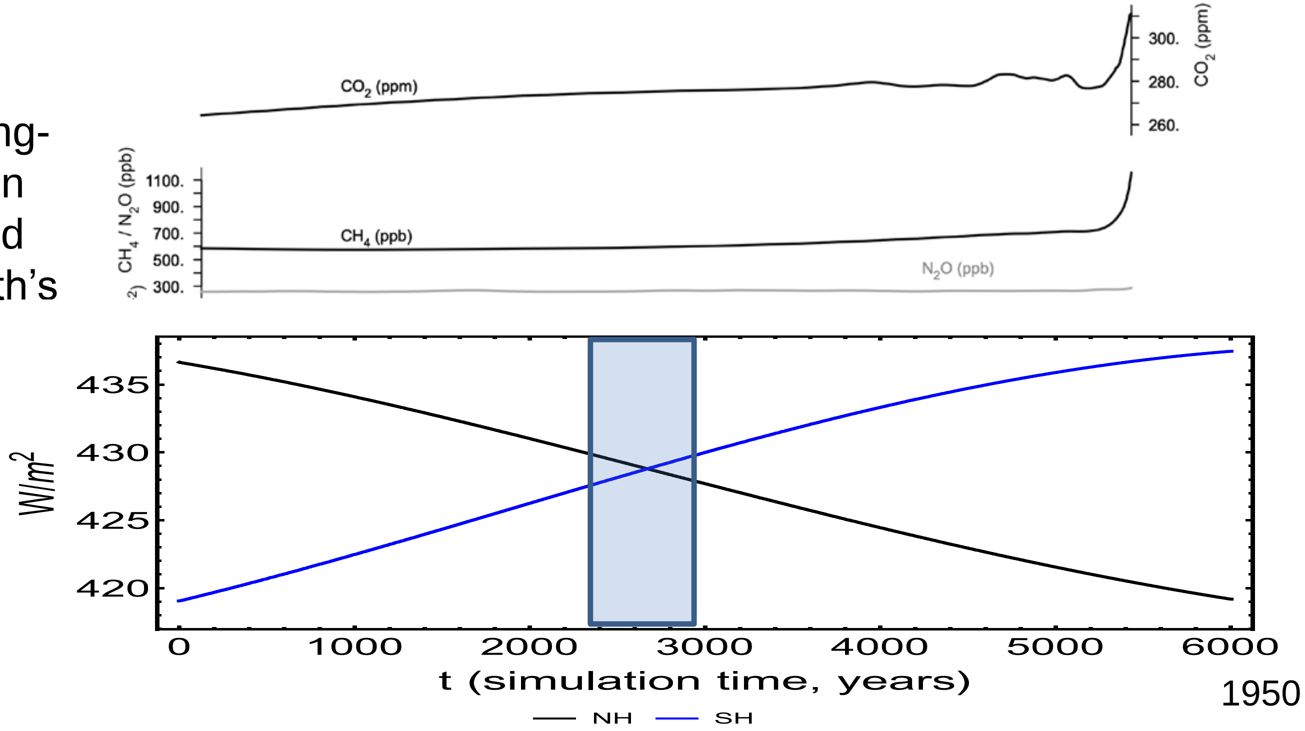
a) Atmosphere (LMDZ)-2°ocean (NEMO)-sea-ice (LIM) et land surface (ORCHIDEE)
b) Coupling with biogeochemical cycles : ocean and land carbone cycle , (dynamical vegetation)

- Two 6000 years long simulations (6000 years BP, i.e. to 1950)
    - Vlr01 spatial resolution (3.75° × 1.89°)
    - **Sr02 spatial resolution (2.5° × 1.27°)**

Braconnot et al. (2019)
Climate of the Past

Mean state – variability interactions

Model climate responds to long-term changes in trace gases and insolation (Earth's orbit)



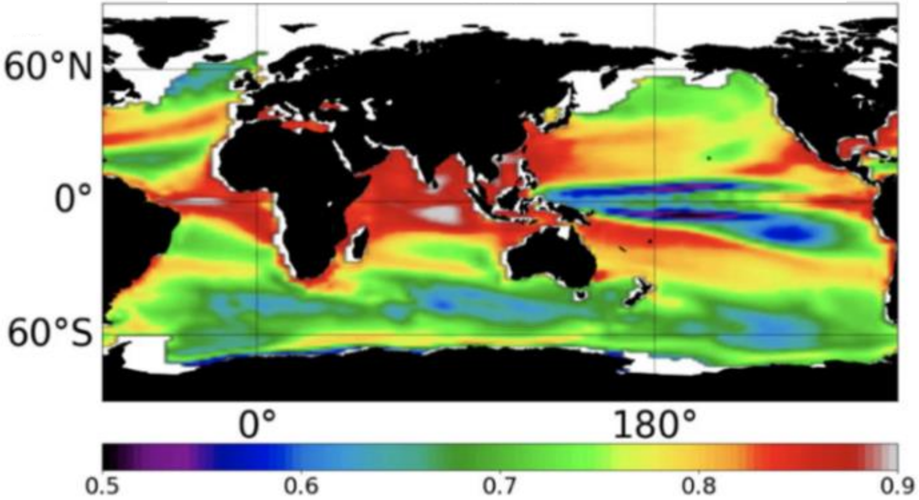
Incoming solar radiation at the top of the atmosphere in summer

Focus on Sea Surface Temperature (SST) monthly anomalies.
6000 x 12 = 72000 months at each grid points

Domains in the complexity field

Entropy computed for ***W*** = 100 years every Δ***W*** = 20 years

Mean state of the complexity field



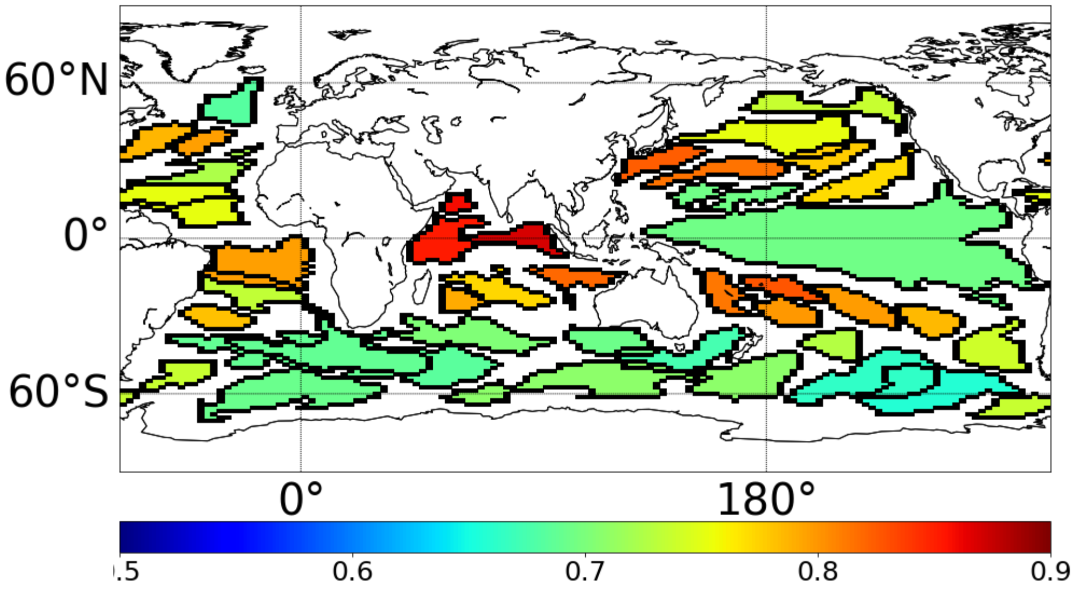
From Falasca et al., 2020, Eur. Phys. J. Plus. https://doi.org/10.1140/epjp/s13360-020-00403-x

Domains in the complexity field

Network domains based on the mean entropy field

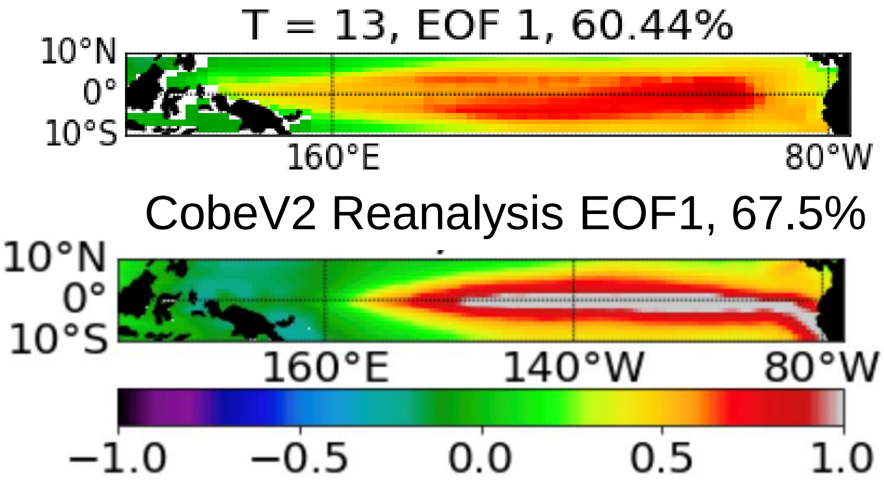
Color: average complexity of each domain

Complexity signal of domain A: $S_A(t) = \left(\frac{1}{|A|}\right) \sum_i^{|A|} s_i(t)$



Mean state – variability interaction

Contemporary modes of variability in the two basins

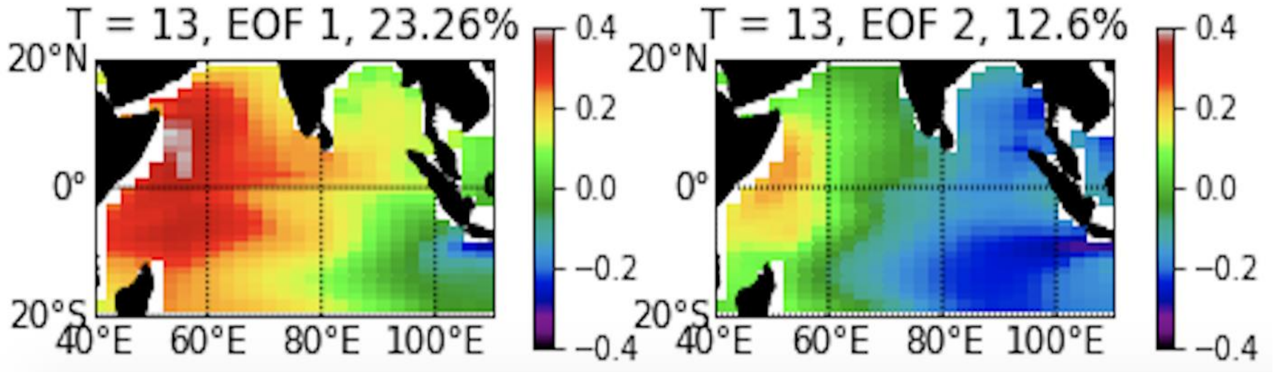


Main mode in the Tropical Pacific: ENSO

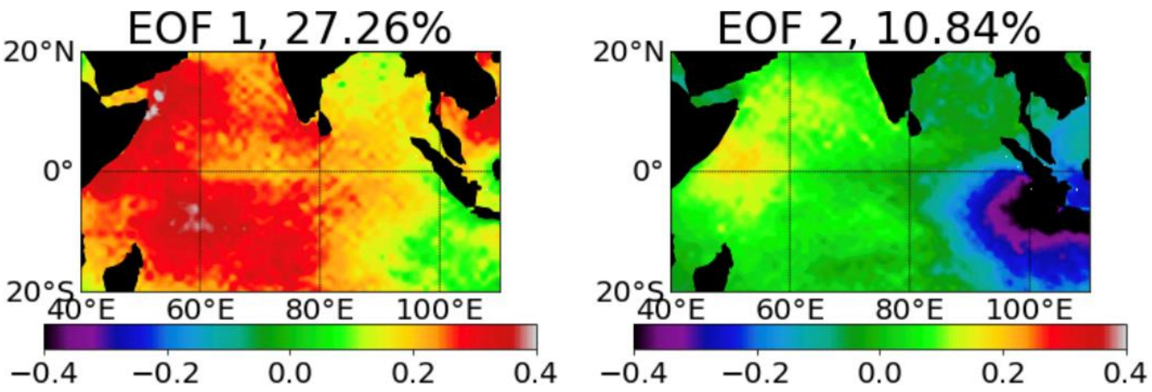
Last 100 years in the model (1851-1950) and 1980-2019 period in CobeV2

Mean state – variability interaction

Shift in variability in the Pacific-Indian Ocean system



Last 100 years in the model and 1980-2019 period in CobeV2



Modes in the Indian Ocean

1. **Indian Ocean Basin Mode (IOB)**
2. **Indian Ocean Dipole (IOD)**

Mean state – variability interaction

Pacific - Indian Oceans coupled dynamics

- **Recently published relevant literature**

SCIENCE ADVANCES | RESEARCH ARTICLE

CLIMATOLOGY

Emergence of an equatorial mode of climate variability in the Indian Ocean

Pedro N. DiNezio[1]*, Martin Puy[1], Kaustubh Thirumalai[2], Fei-Fei Jin[3], Jessica E. Tierney[2]

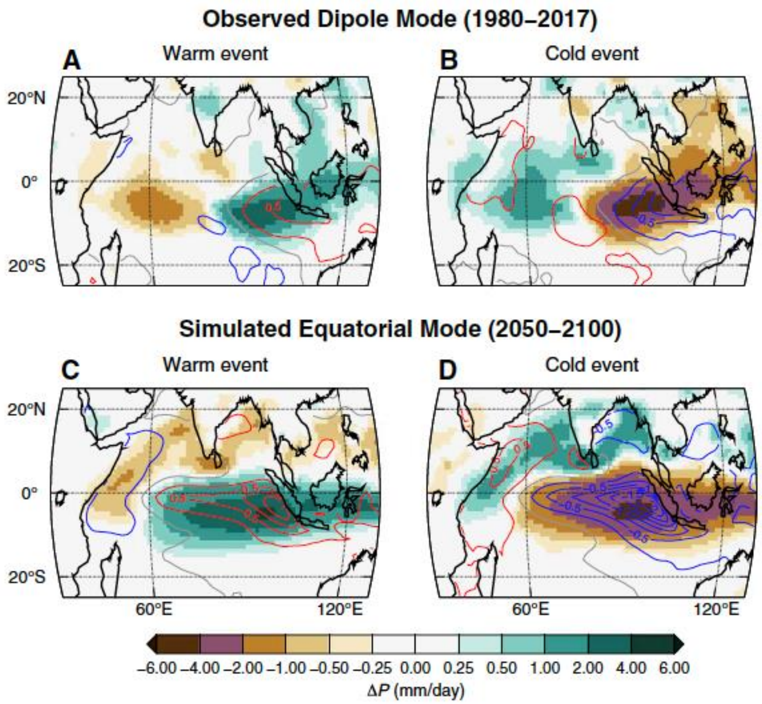
Presently, the Indian Ocean (IO) resides in a climate state that prevents strong year-to-year climate variations. This may change under greenhouse warming, but the mechanisms remain uncertain, thus limiting our ability to predict future changes in climate extremes. Using climate model simulations, we uncover the emergence of a mode of climate variability capable of generating unprecedented sea surface temperature and rainfall fluctuations across the IO. This mode, which is inhibited under present-day conditions, becomes active in climate states with a shallow thermocline and vigorous upwelling, consistent with the predictions of continued greenhouse warming. These predictions are supported by modeling and proxy evidence of an active mode during glacial intervals that favored such a state. Because of its impact on hydrological variability, the emergence of such a mode would become a first-order source of climate-related risks for the densely populated IO rim.

DiNezio *et al.*, *Sci. Adv.* 2020; **6** : eaay7684 6 May 2020

Mean state – variability interaction

Pacific - Indian Oceans coupled dynamics

- **Recently published relevant literature**



DiNezio *et al.*, *Sci. Adv.* 2020; **6** : eaay7684 6 May 2020

Mean state – variability interaction

Pacific - Indian Oceans coupled dynamics

- **Recently published literature relative to the LGM**

Paleoceanography and Paleoclimatology

An El Niño Mode in the Glacial Indian Ocean?

Kaustubh Thirumalai[1,2,3], Pedro N. DiNezio[2], Jessica E. Tierney[3], Martin Puy[2], and Mahyar Mohtadi[4]

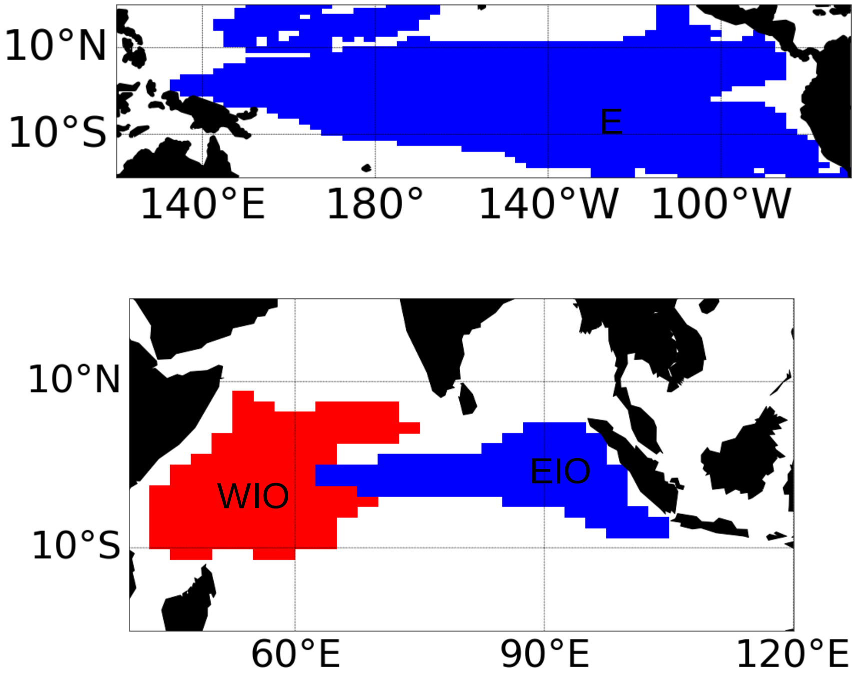
Key Points:

- Individual foraminiferal $\delta^{18}O$ reveal intensified climate variability in the Indian Ocean during the Last Glacial Maximum (LGM)
- Climate simulations indicate enhanced seasonal and interannual variability consistent with mean-state changes tied to shelf exposure
- We propose that an equatorial mode of variability was active in the LGM Indian Ocean, with dynamics mirroring modern El Niño in the Pacific

Thirumalai, K., DiNezio, P. N., Tierney, J. E., Puy, M., & Mohtadi, M. (2019). An El Niño mode in the glacial Indian Ocean? *Paleoceanography and Paleoclimatology*, *34*, 1316–1327. https://doi.org/10.1029/2019PA003669

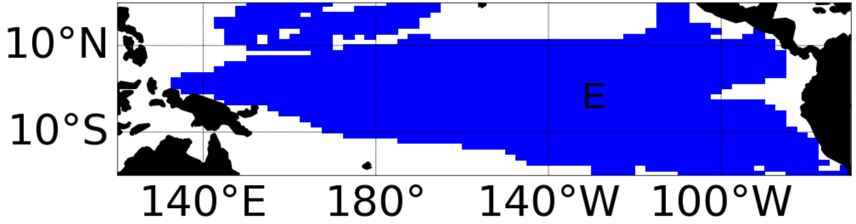
Mean state – variability interaction

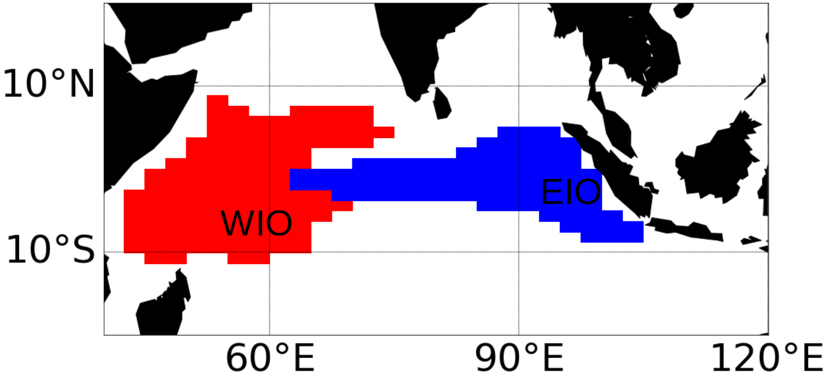
Shift in variability in the Pacific-Indian Ocean system in the network



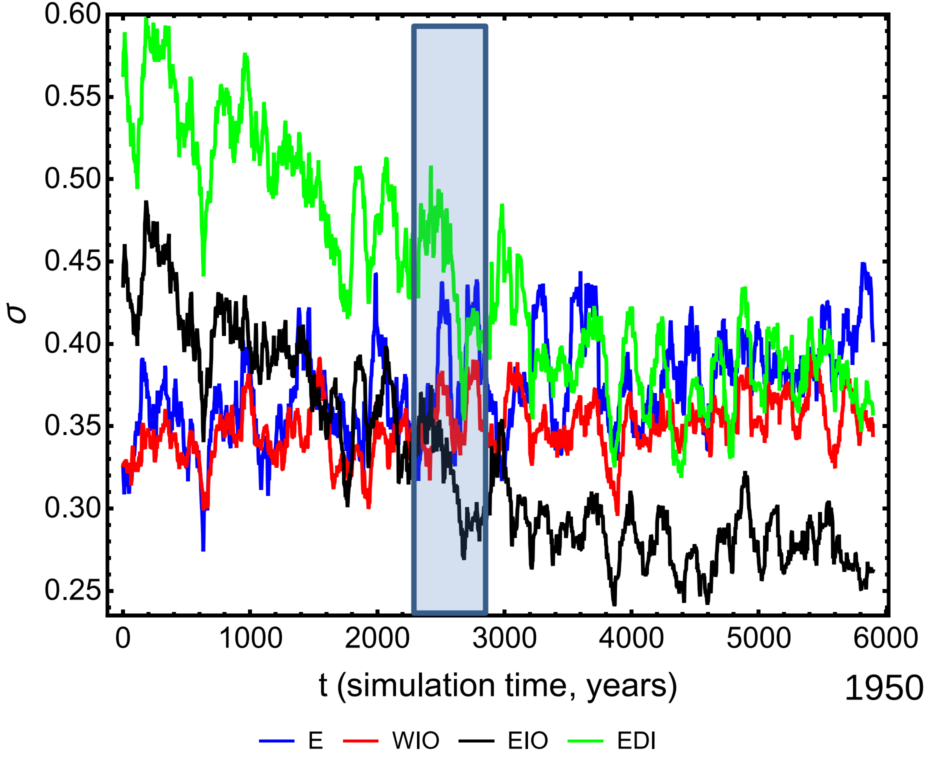
Mean state – variability interaction

Shift in <u>variability</u> in the Pacific-Indian Ocean system in the network





Evolution of standard deviation

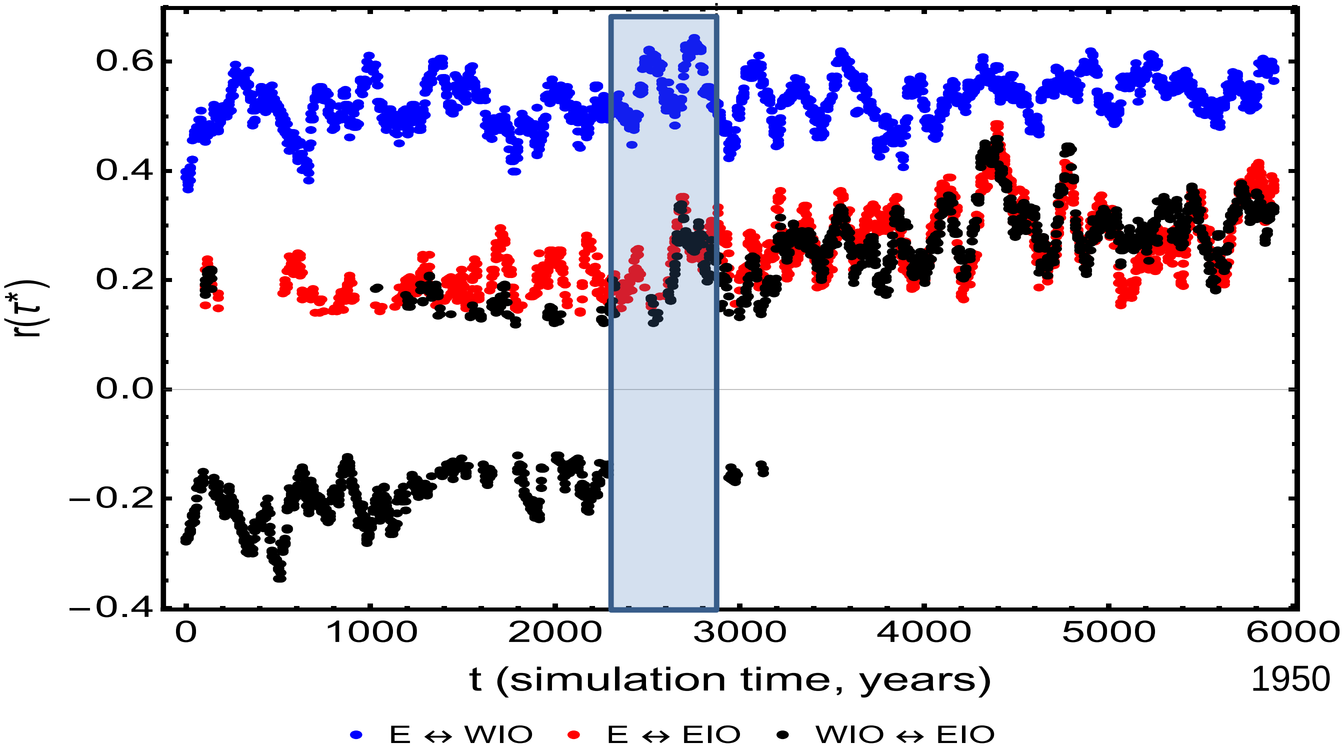


EDI=Equatorial Dipole Index (WIO-EIO)

Mean state – variability interaction

Shift in variability in the Pacific-Indian Ocean system in the network

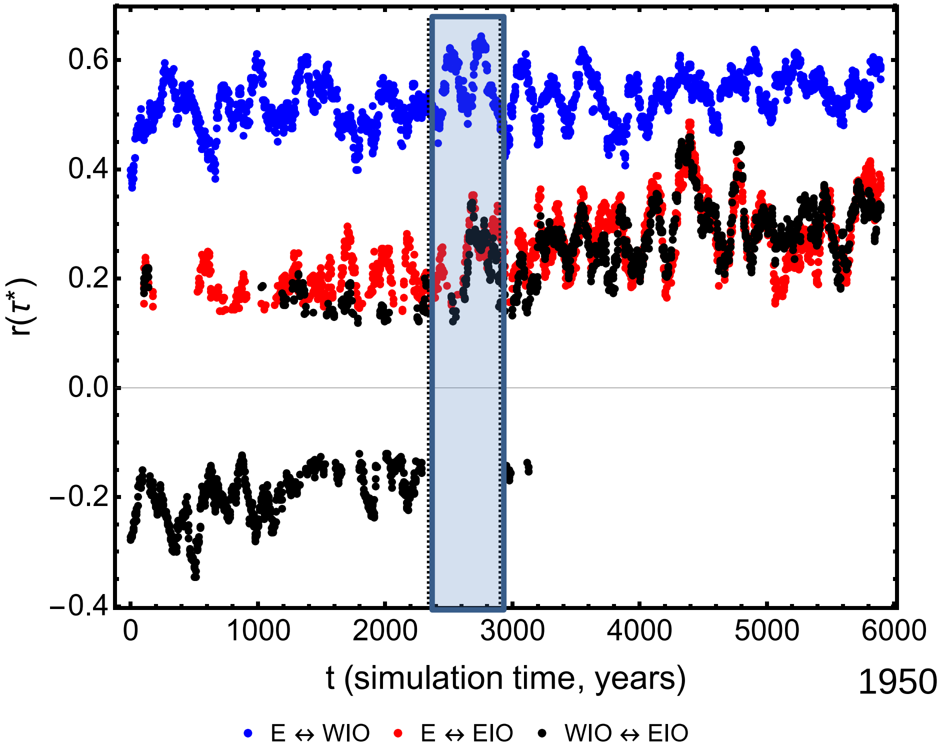
Evolution of max significance correlation $r(\tau^*)$

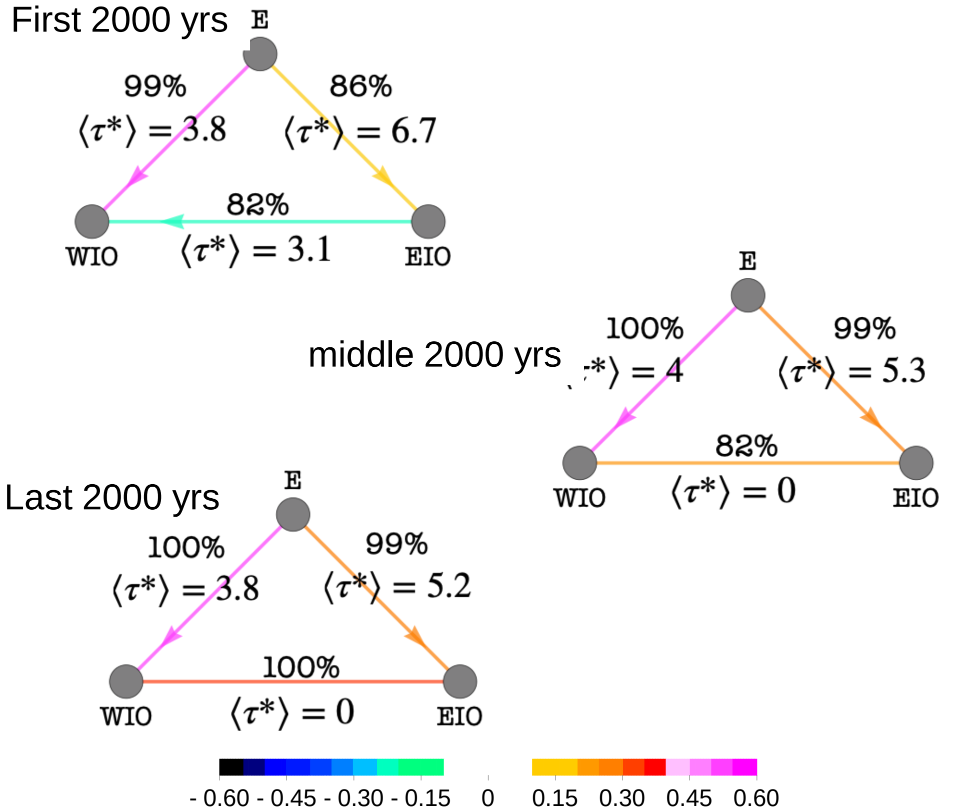


Mean state – variability interaction

Shift in variability in the Pacific-Indian Ocean system in the network

Evolution of max significance correlation r(τ^*)

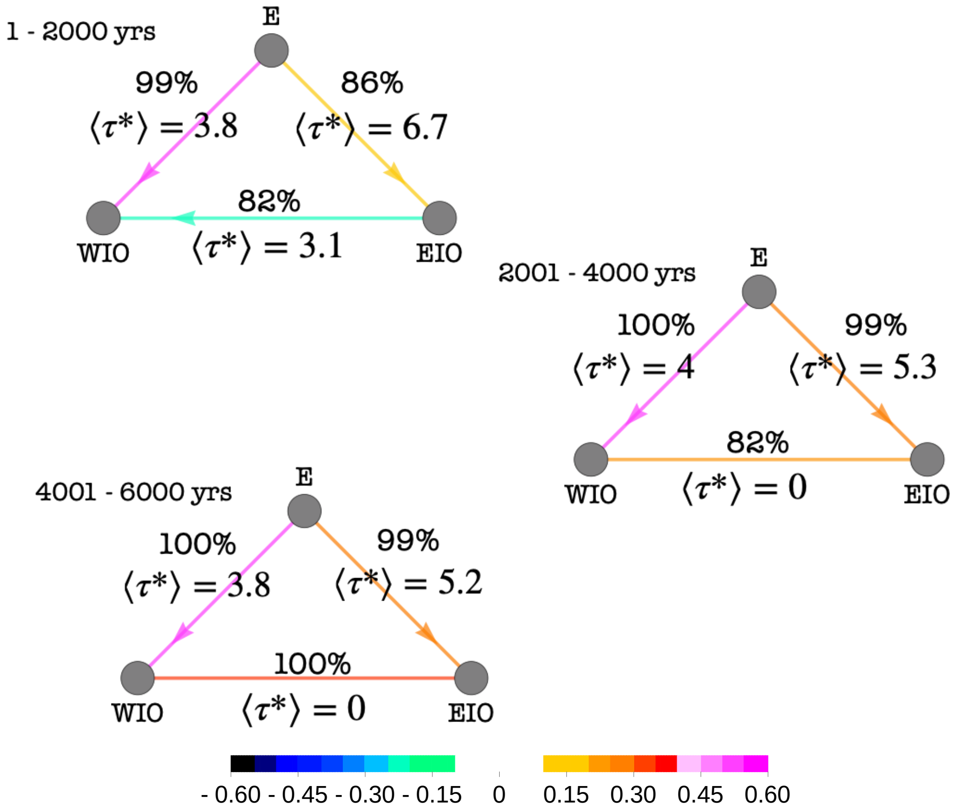




Mean state – variability interaction

Shift in <u>variability</u> in the Pacific-Indian Ocean system in the network

Shift from **EIO**+IOB to **IOB**+IOD as main modes of variability in the Indian Ocean in the last 6000 years



Main observation

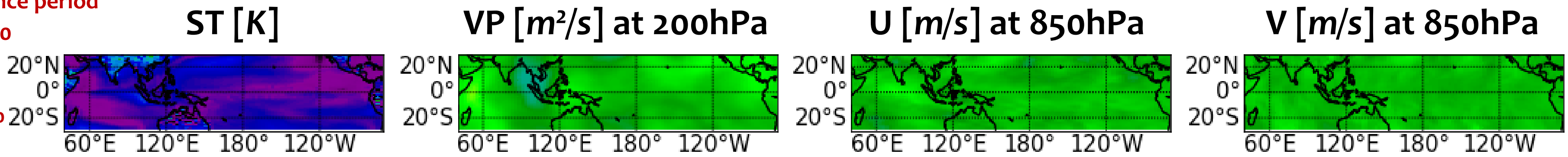
Non-abrupt shift forced by the external forcing

Mean state – variability interaction

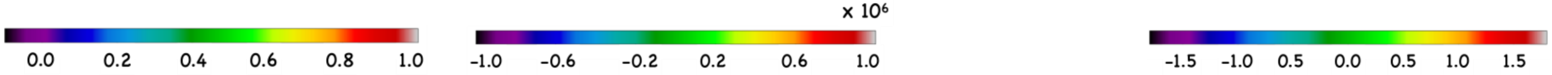
Reference period

yrs 1-500

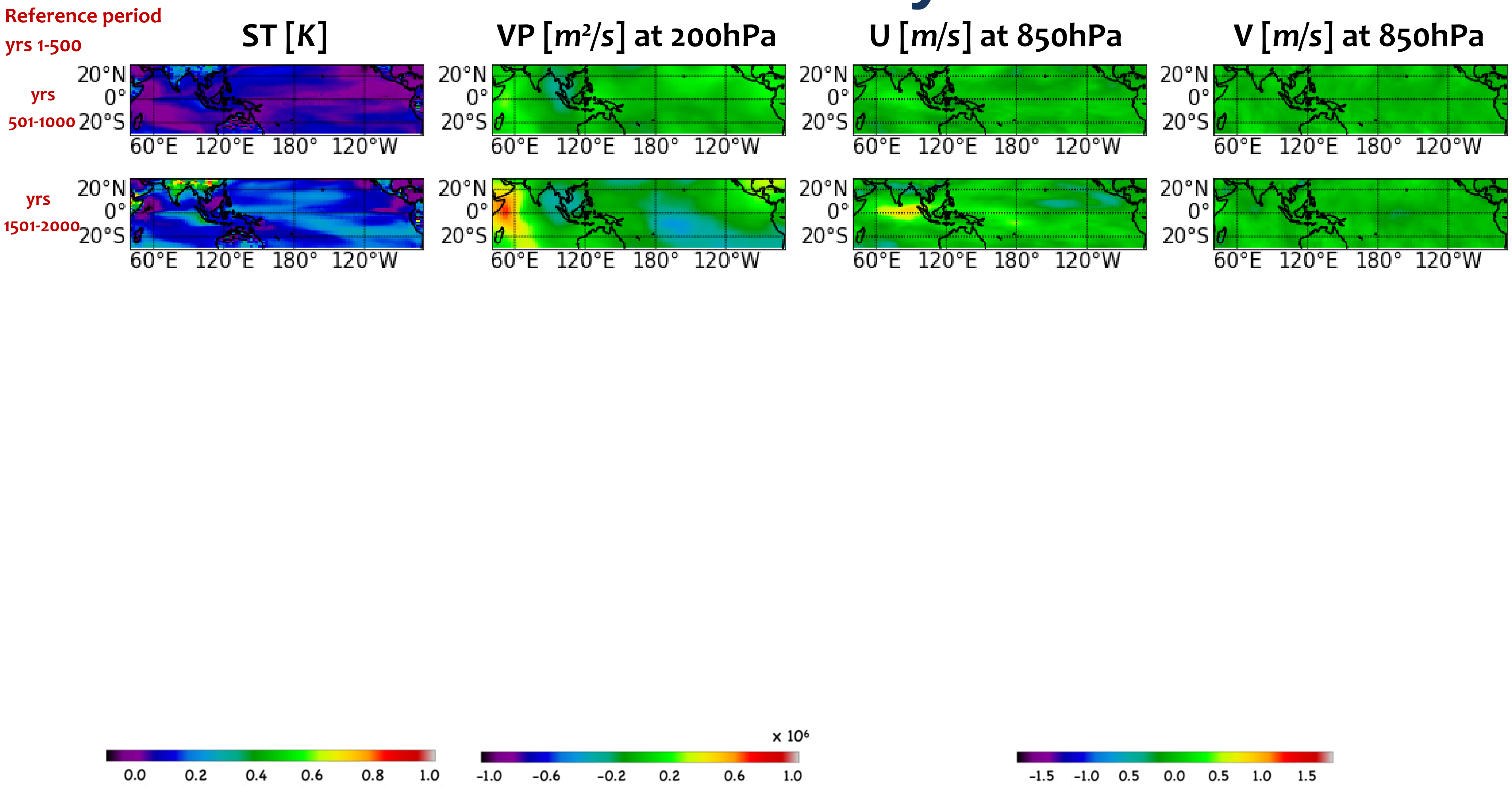
yrs 501-1000



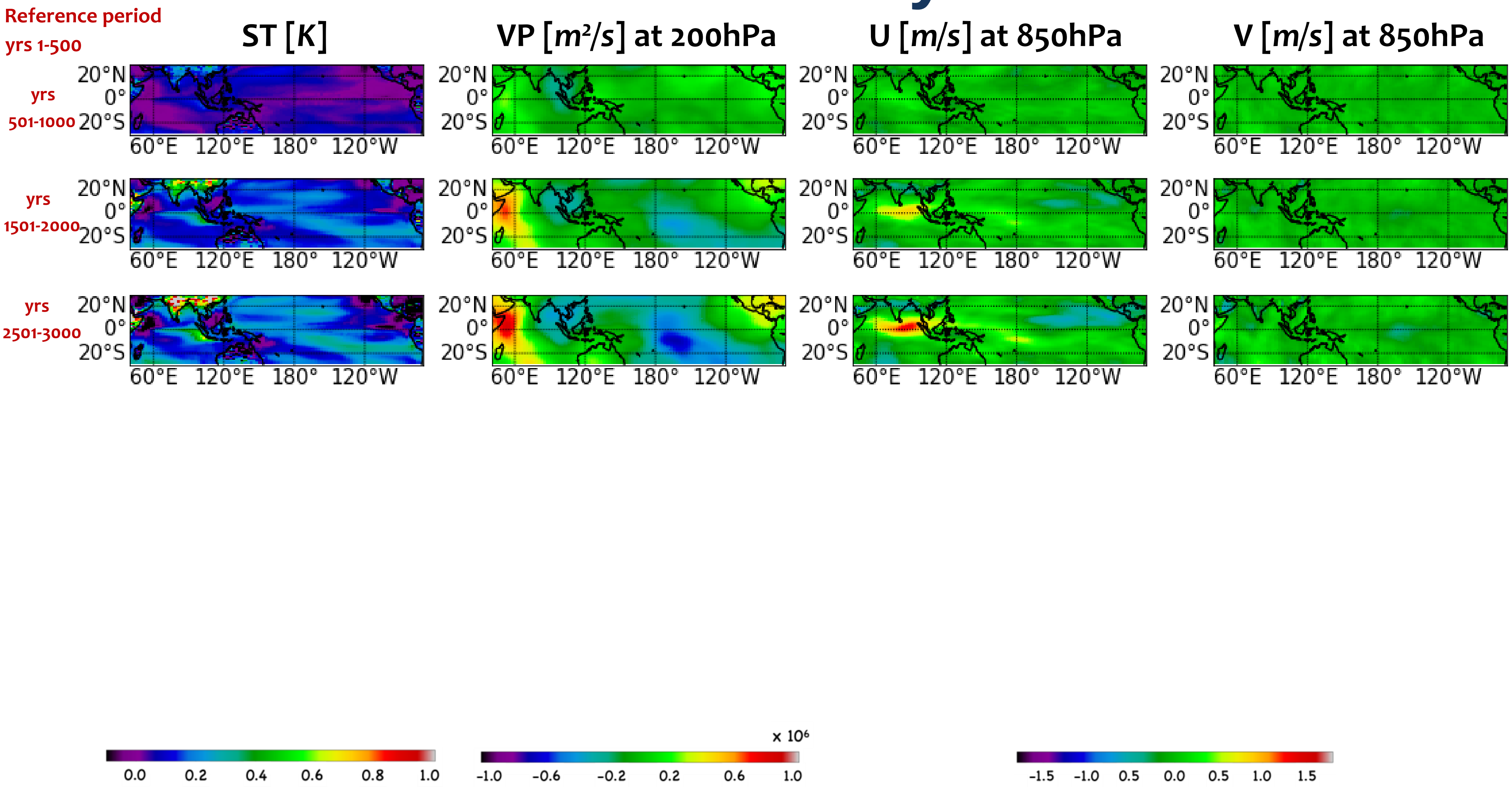
time



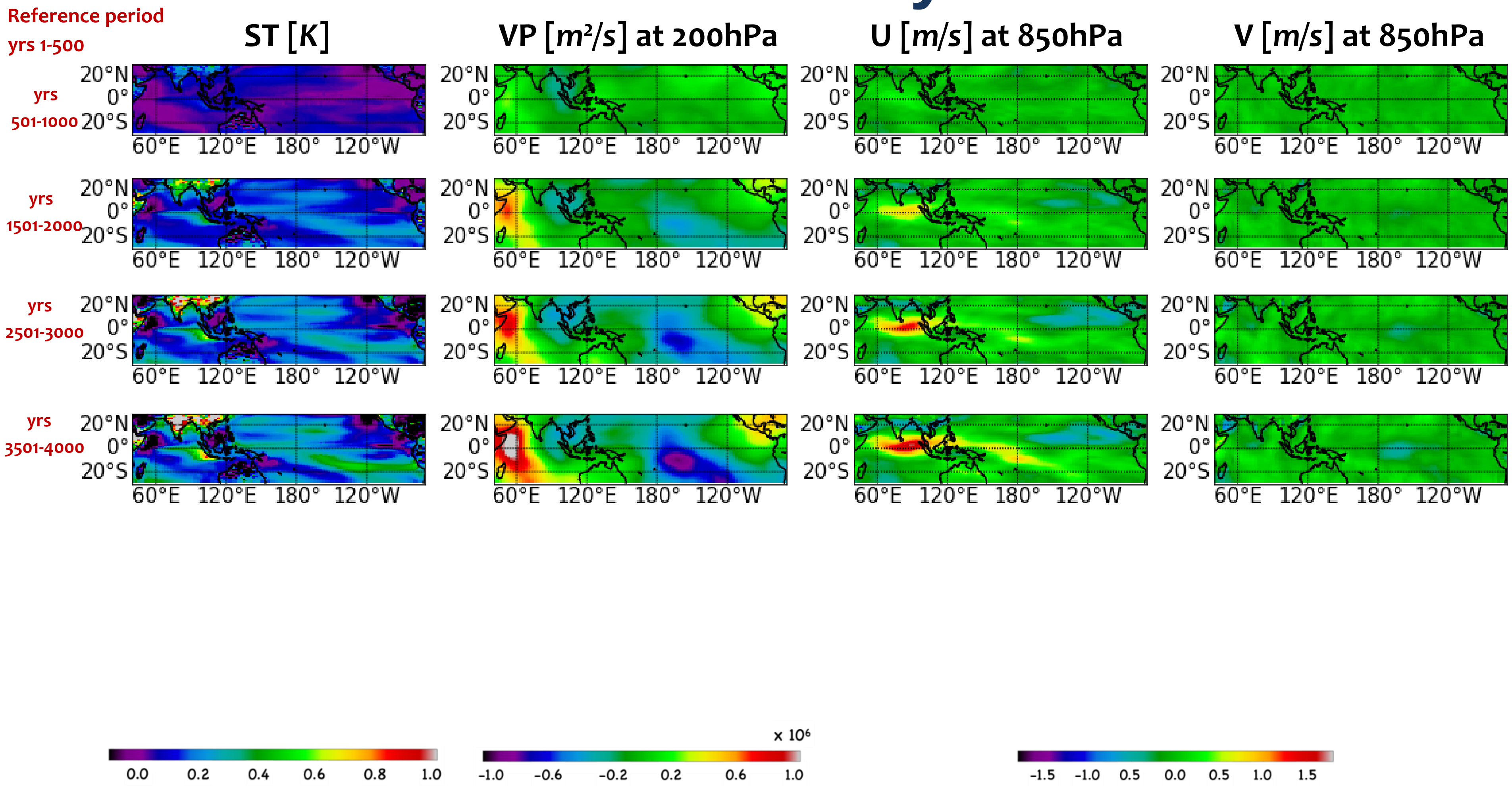
Mean state – variability interaction



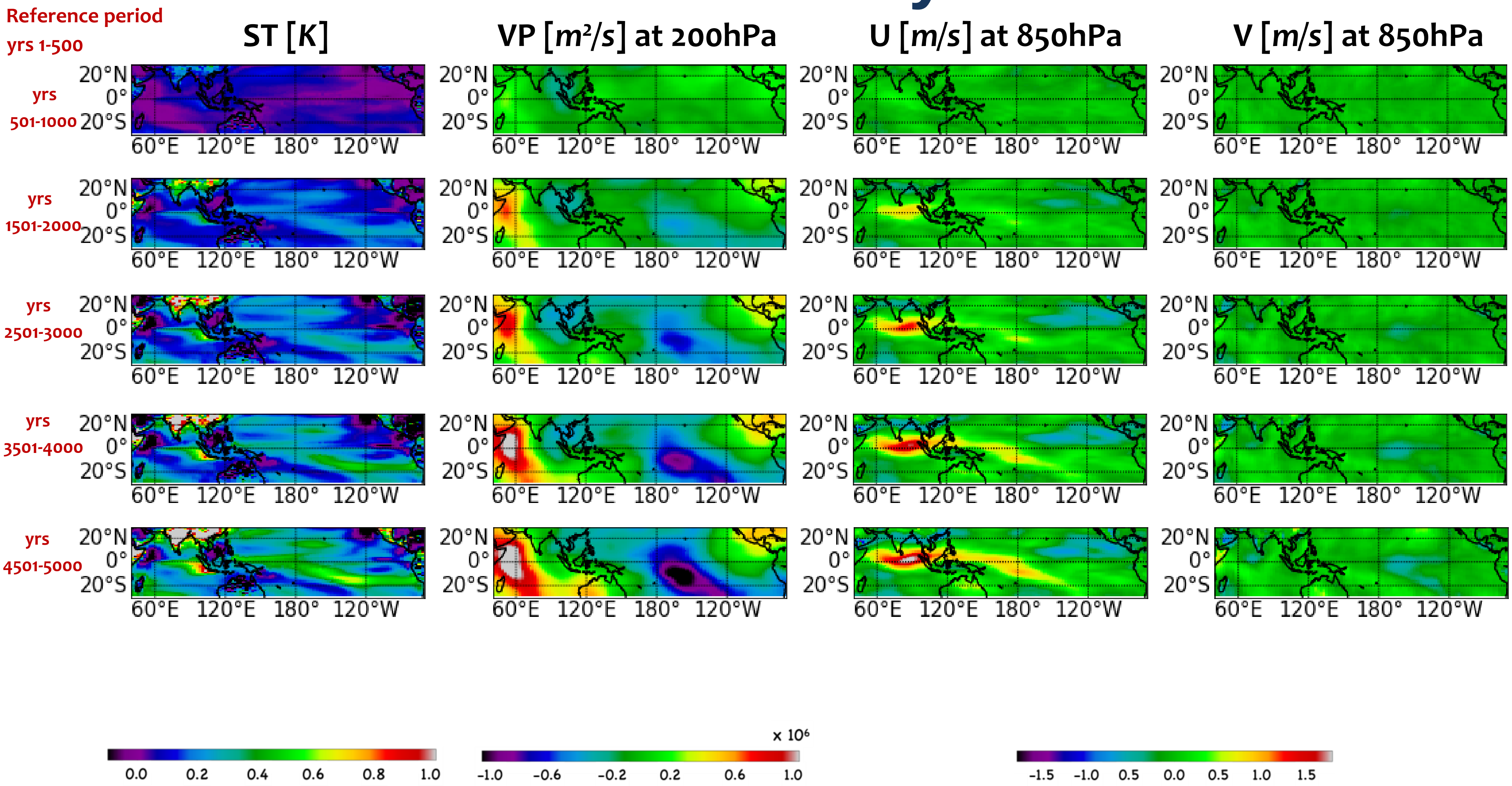
Mean state – variability interaction



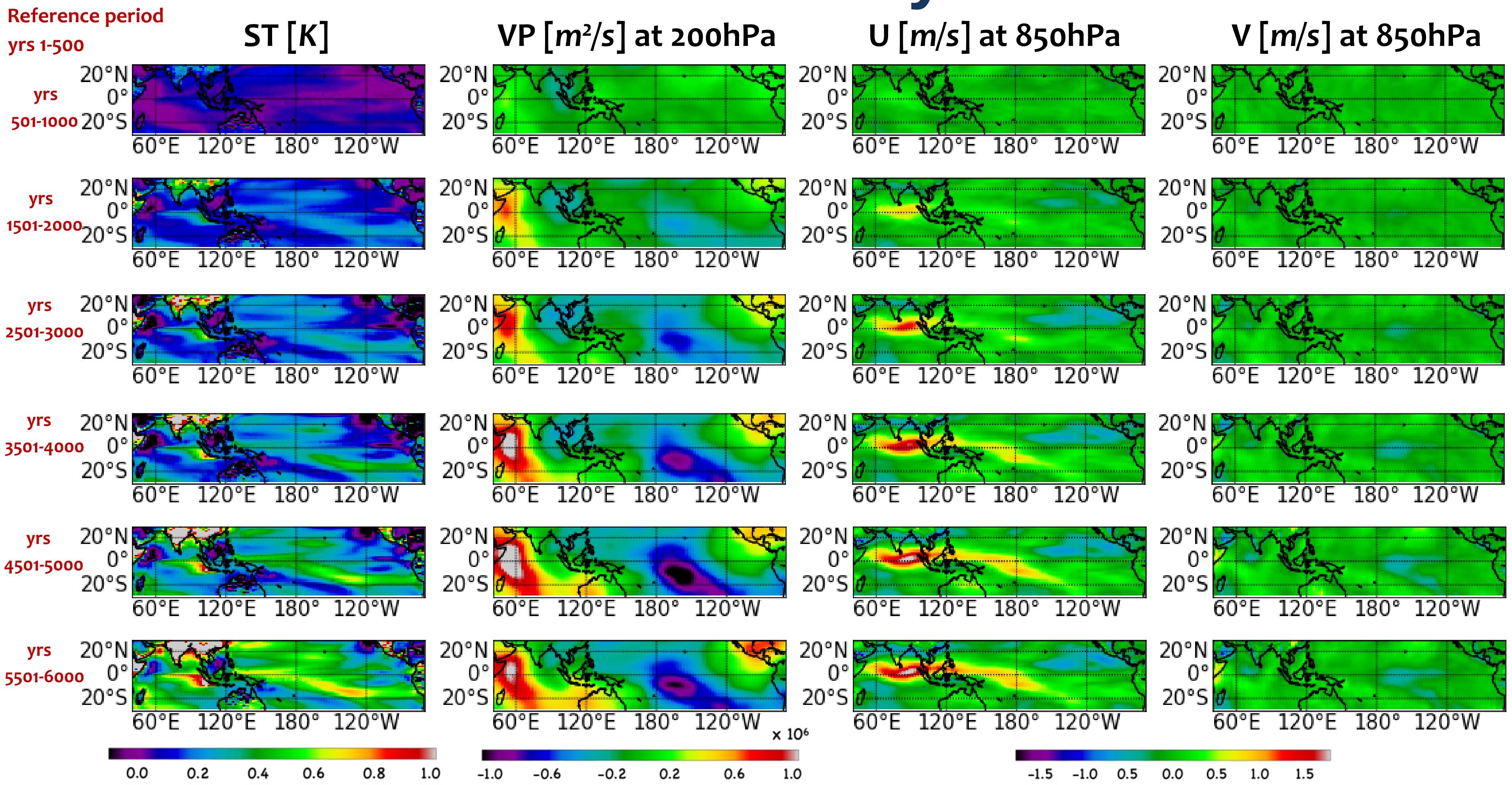
Mean state – variability interaction



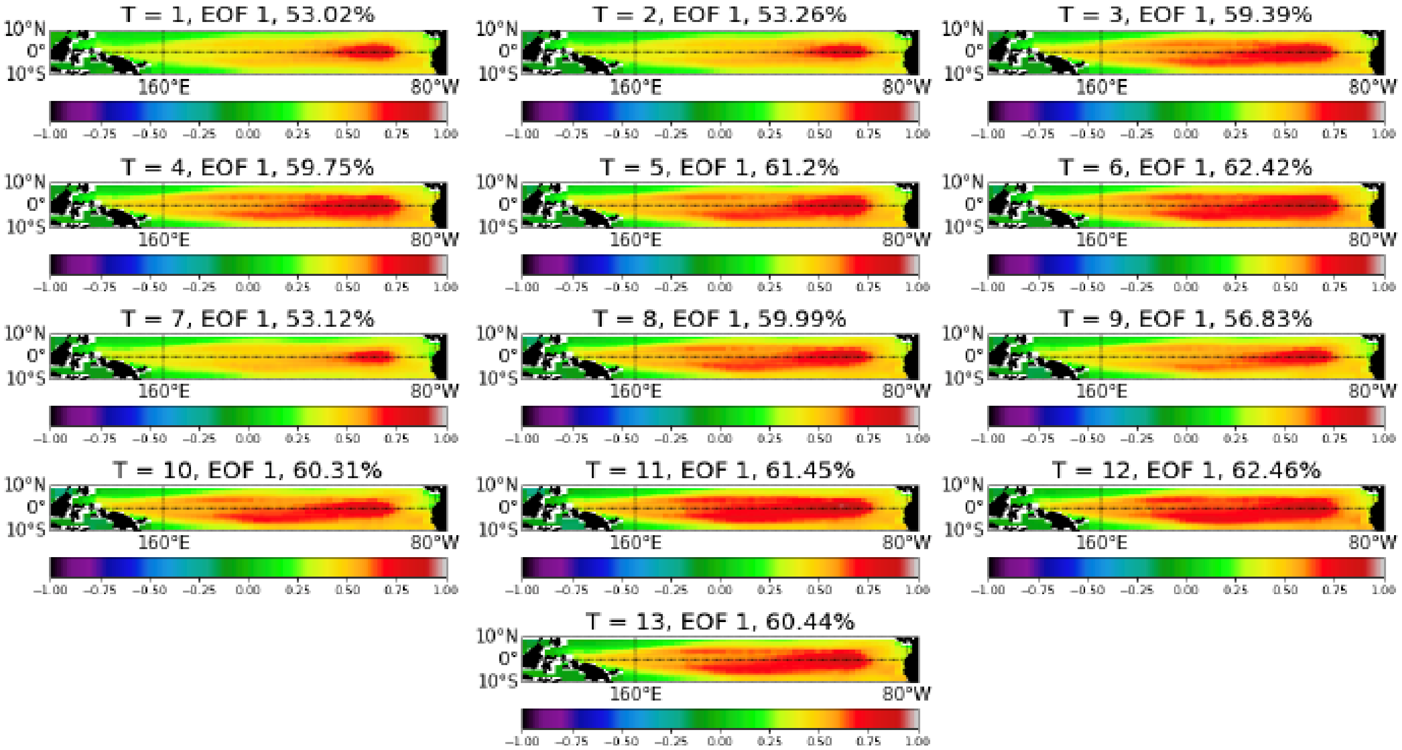
Mean state – variability interaction

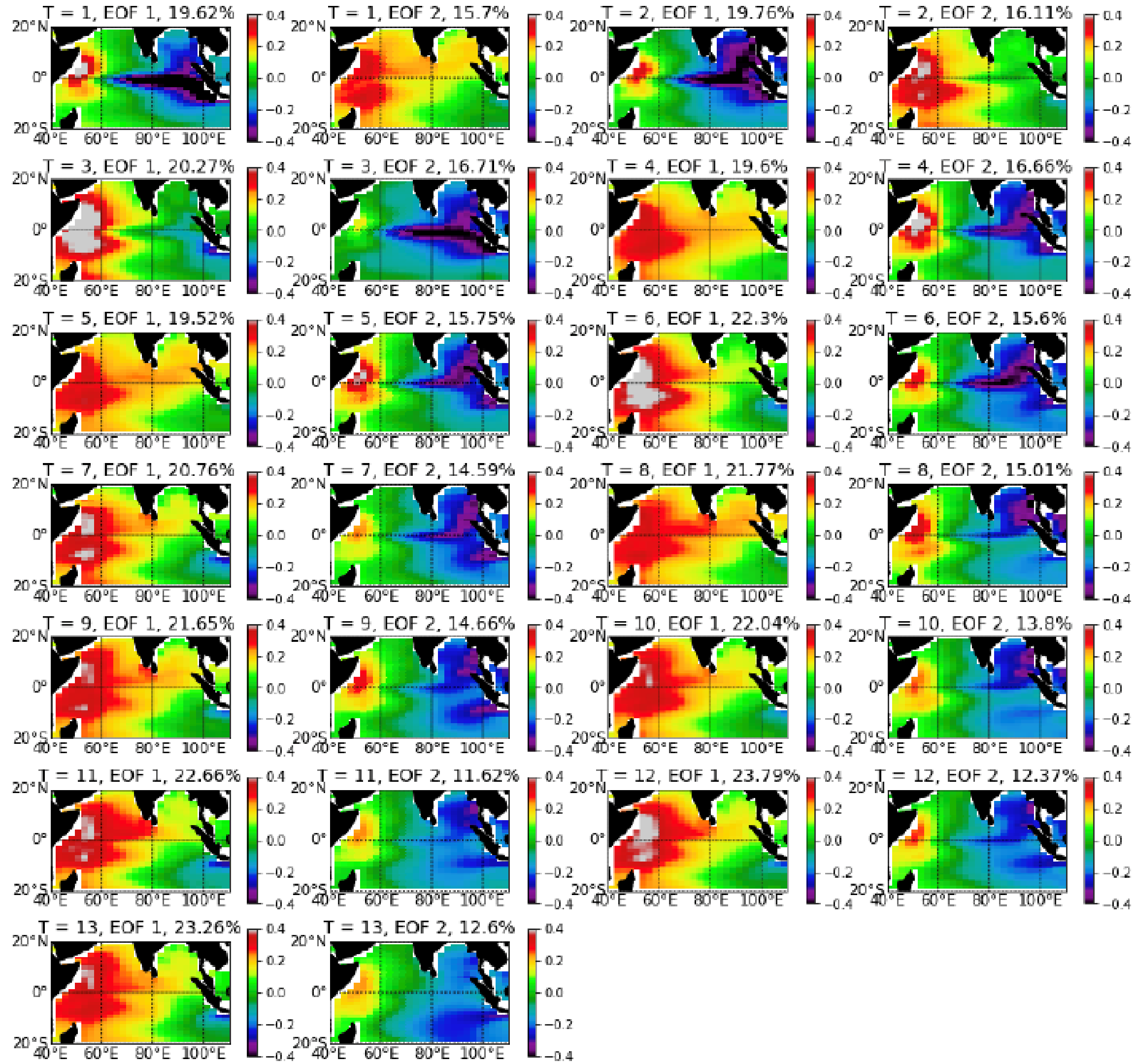


Mean state – variability interaction



Strengthening of ENSO through the Holocene





Changes in the IO seen by EOF1 and 2 (EIO → IOB+IOD)

Summary

Climate- like problem: "…determining a system evolution relative to internal and external forcing…" (Webster, 2020)

a) Changes in the mean state have had profound effects on climate variability of the Indian Ocean (and Pacific)

b) The shift from EIO to IOB as main mode in the Indian Ocean occurred slowly and was driven by changes in the mean state (increase in ENSO strength; weakening of the easterlies over the IO especially at the equator; decrease in SST gradient across the basin)

Thanks!!

References:

(a) Falasca, F., Crétat, J., Braconnot, and A. Bracco. Spatiotemporal complexity and time-dependent networks in sea surface temperature from mid- to late Holocene. Eur. Phys. J. Plus 135:392 (2020). https://doi.org/10.1140/epjp/s13360-020-00403-x

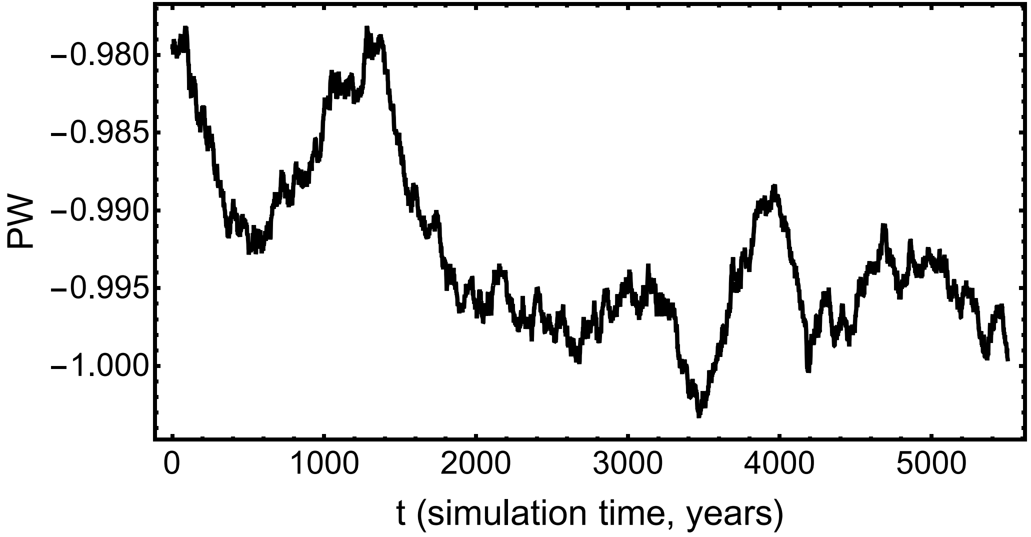
(Go here for the **free version** https://www.researchgate.net/publication/341107349_Spatiotemporal_complexity_and_time-dependent_networks_in_sea_surface_temperature_from_mid-_to_late_Holocene)

(b) Falasca, F., Crétat, J., A. Bracco, Braconnot P., and Marti, O. Mean state drives regime shifts in the Indo-Pacific from mid- to late Holocene. In preparation

Mean state – variability interaction

What about changes in the oceanic bridge?

A look at the Heat Transport in the ITF



- Significant change
- Extremely small magnitude (~0.02 PW)

Largest change in mean state related to the atmospheric bridge.
At least in the model…