Information Entropy as Quantifier of Potential Predictability in the Tropical Indo-Pacific basin

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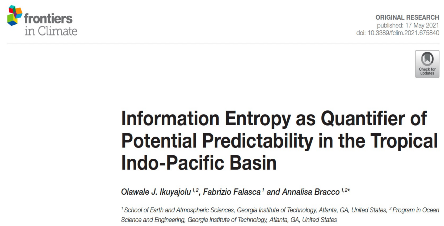
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ORIGINAL RESEARCH
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Information Entropy as Quantifier of Potential Predictability in the Tropical Indo-Pacific Basin

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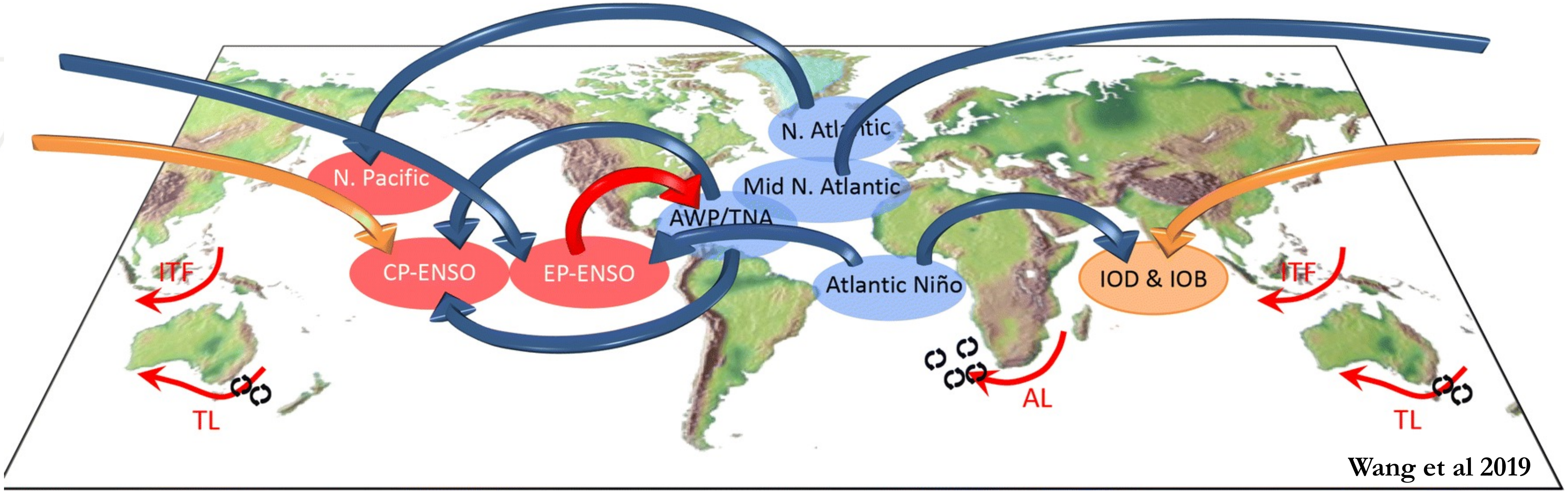
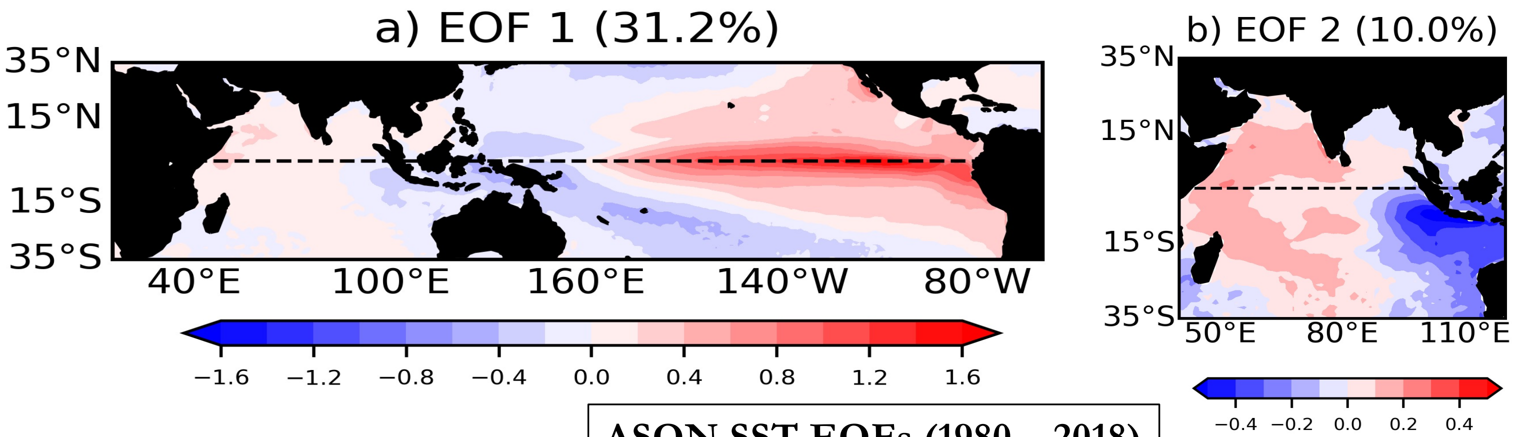
Tropical Indo-Pacific Basin





ASON SST EOFs (1980 – 2018)

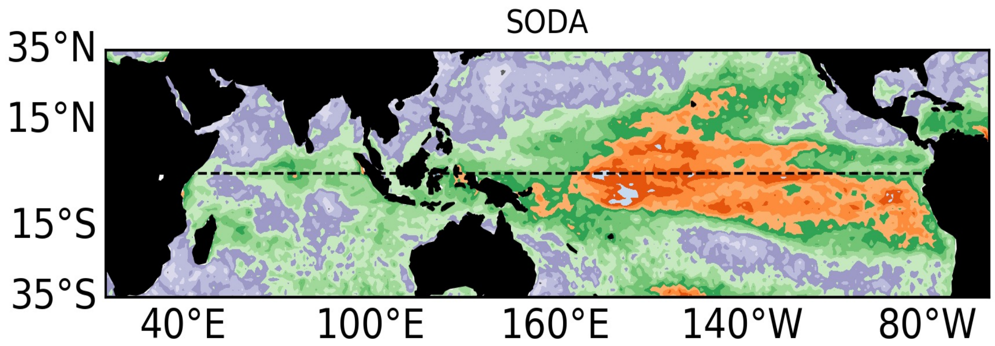
OBJECTIVE

We introduced a new method, building upon tools developed within the non-linear dynamical systems community, to quantify predictability in terms of information entropy.

The information entropy of a climate field quantifies the degree of complexity of a given region or grid point in terms of recurrence

It provides a quick framework to investigate potential predictability and verify how well climate models represent it.

ASON ENTROPY (1980 – 2018)



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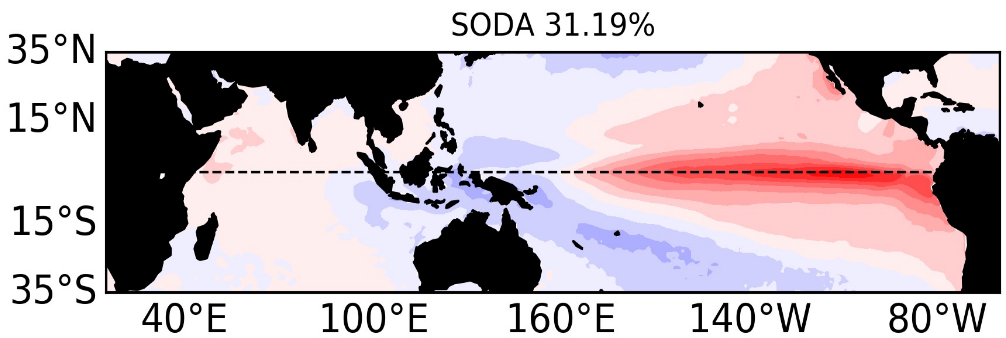


Presentation Progress

i. Recurrence Plot & Information Entropy

ii. Data

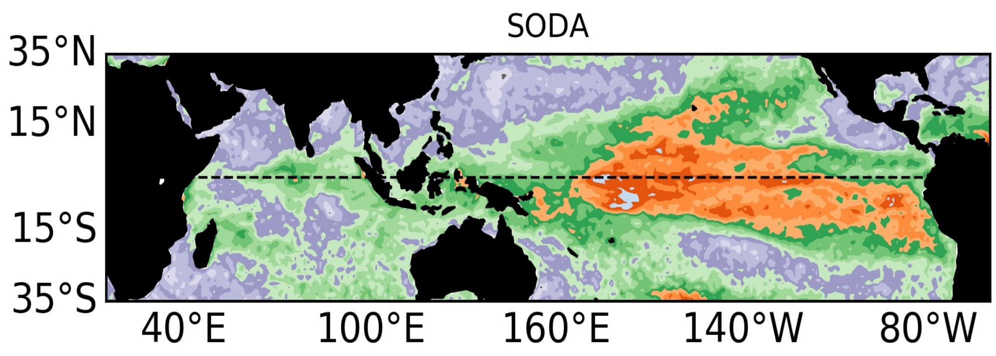
iii. Spring Predictability Barrier

iv. Entropy in Historical and RCP8.5

v. Entropy & Other Traditional Linear Methods: EOFs and Power Spectra

vi. Conclusion

ASON ENTROPY (1980 – 2018)



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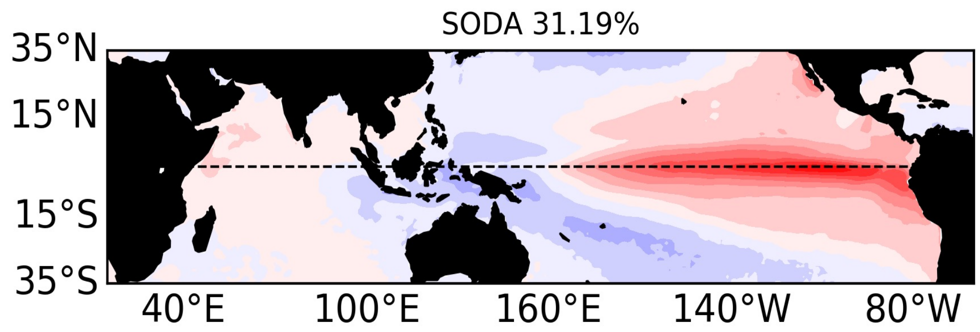
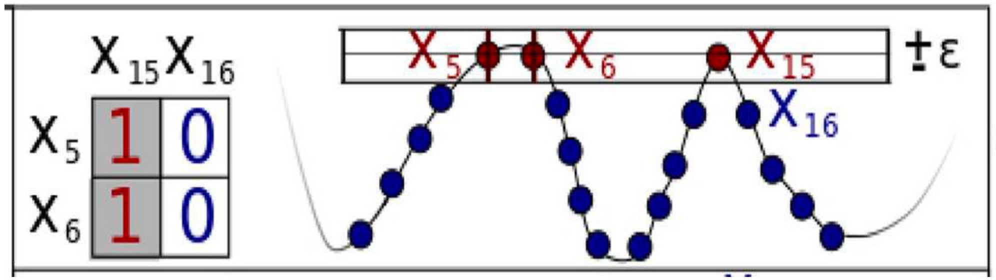


RECURRENCE PLOT

Given a trajectory $\boldsymbol{x}_i$ of a dynamical system in a d-dimensional state space at time i, a RP is an $N \times N$ matrix of 1 and 0 such that:

$$RP_{i,j}(\varepsilon) = \Theta\left(\varepsilon - \left\|x_i - x_j\right\|\right),\ x_i \in \mathbb{R}^d,\ i,j = 1,\ldots,N.$$



ε : Threshold distance and defines the neighborhood of a state $\boldsymbol{x}$,
Θ : Heaviside function
‖ ‖ : norm and N is the number of states considered

“1” if two states are recurrent, “0” if they are not recurrent

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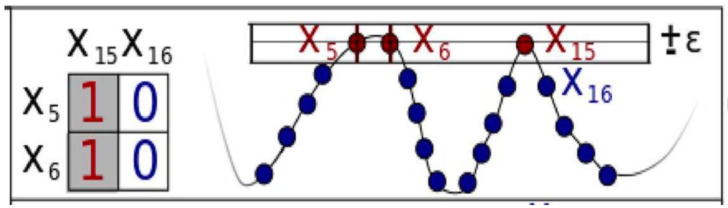


0	1	0	1	0	1
1	0	1	0	1	0
0	1	0	1	0	1
1	0	1	0	1	0
0	1	0	1	0	1
1	0	1	0	1	0

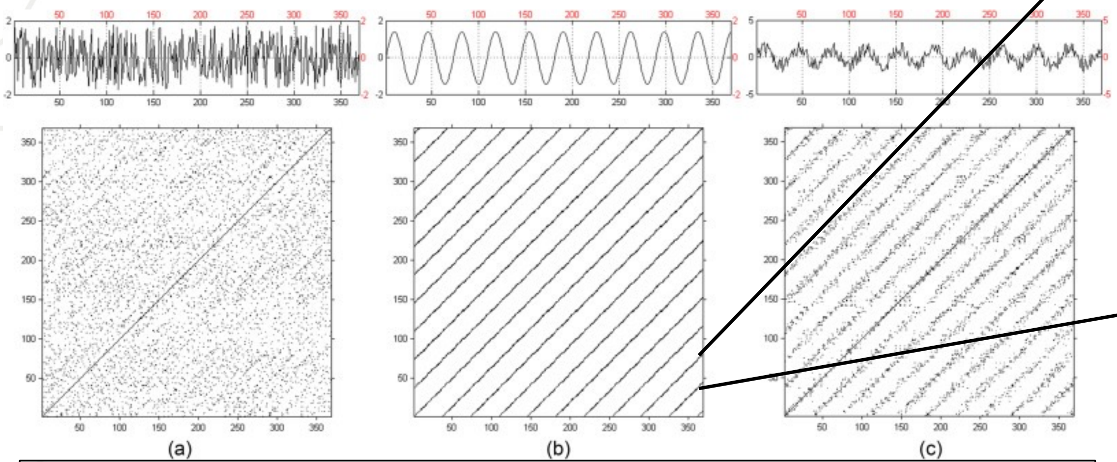
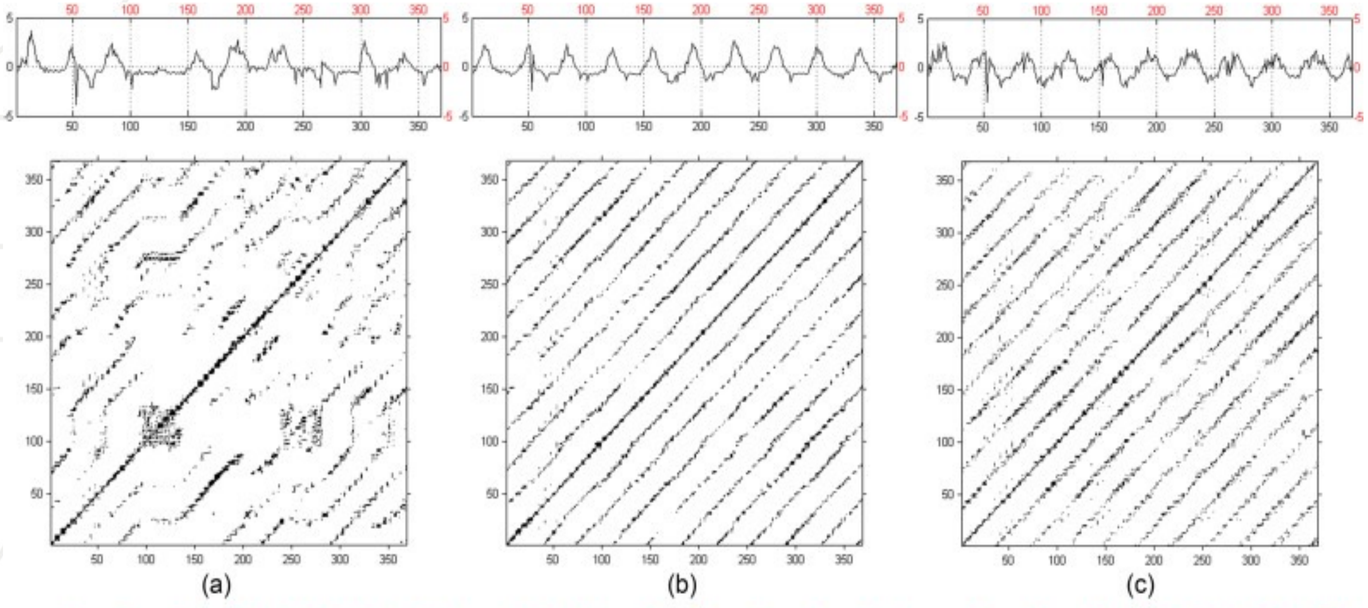


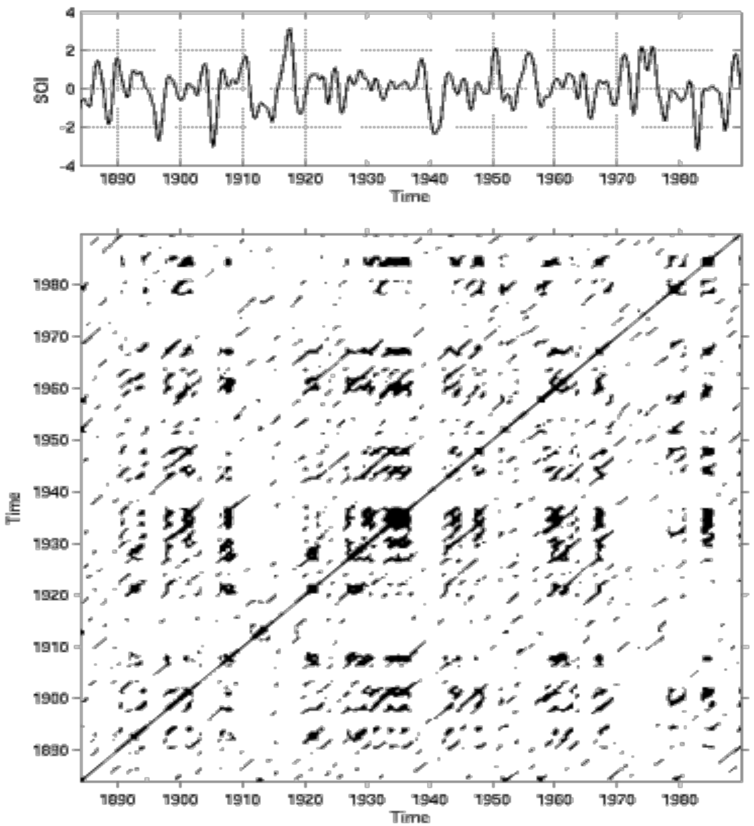
Fig: The RPs of synthetic time series. (a) stochastic series; (b) sine wave series; (c) noise-sinusoidal series. The series length is 387 data points and threshold 0.05 (Zhao et al., 2015)

RECURRENCE PLOT AND INFORMATION ENTROPY



The RPs of the NDVI series at typical meteorological stations. Threshold: 5% (fixed neighbors amount) (Zhao et al., 2015)

SOI



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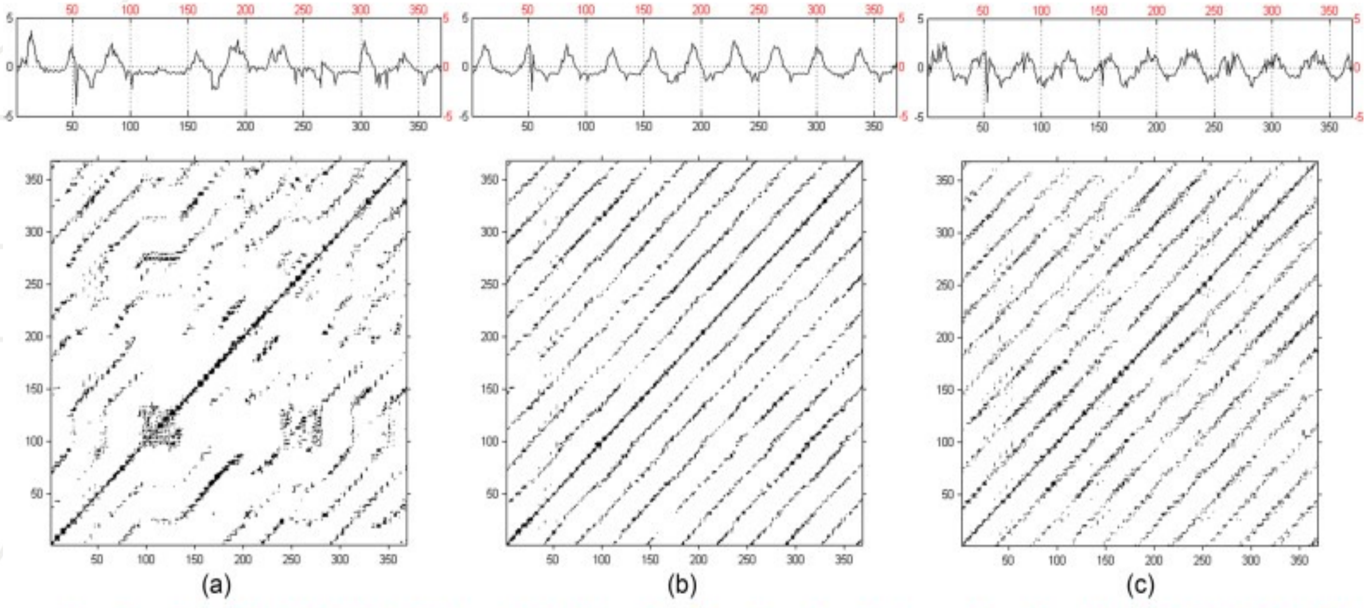

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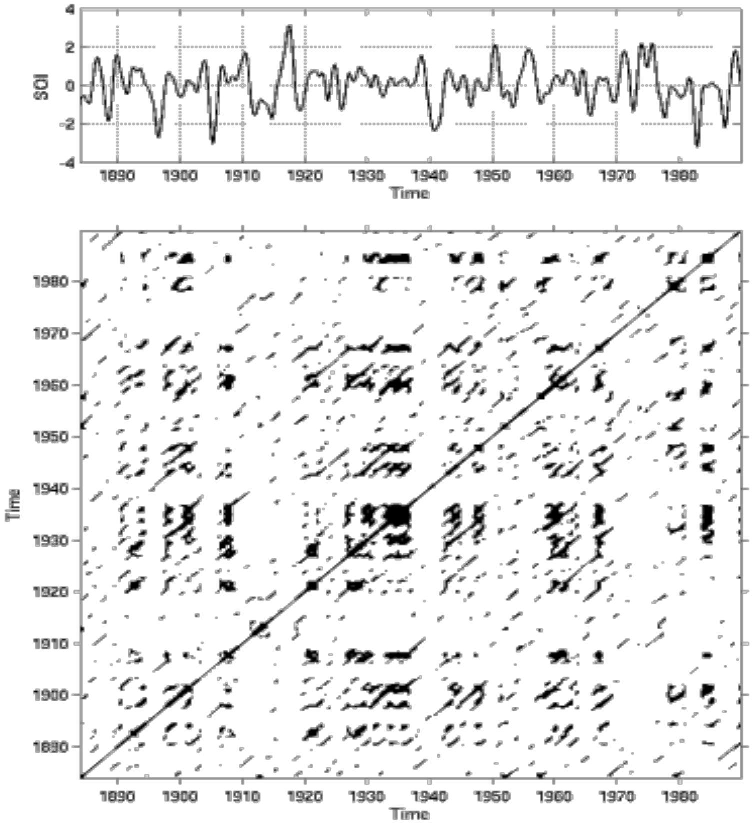
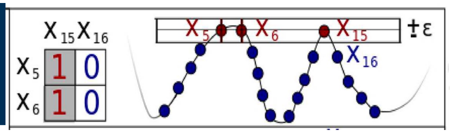


How do we evaluate of all these complex behaviors using a comprehensive quantifier:

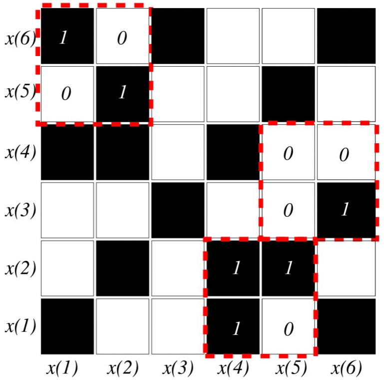
The Shannon entropy

RECURRENCE PLOT AND INFORMATION ENTROPY



Prado et al 2020

We use the concept of microstates for a RP. Small matrices of dimension **M × M** sampled from the RP
Total number of configurations of 1 and 0 in a microstate of size ***M*** is $\boldsymbol{M}^* = 2^{\mathrm{M \times M}}$



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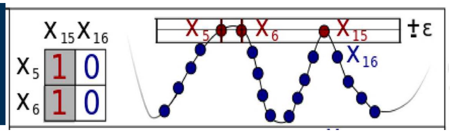

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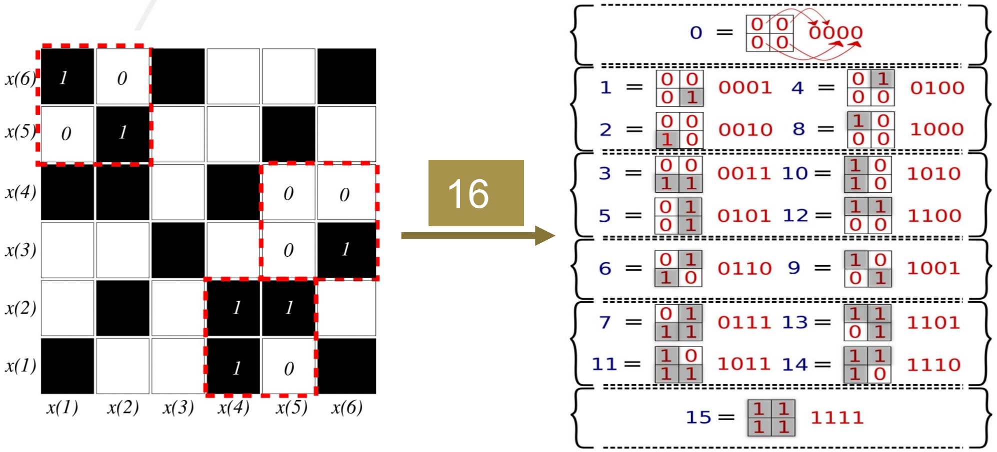

Prado et al 2020

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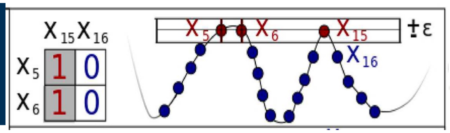

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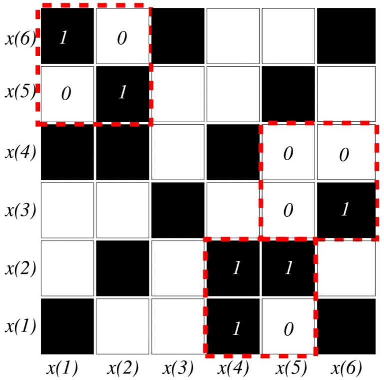

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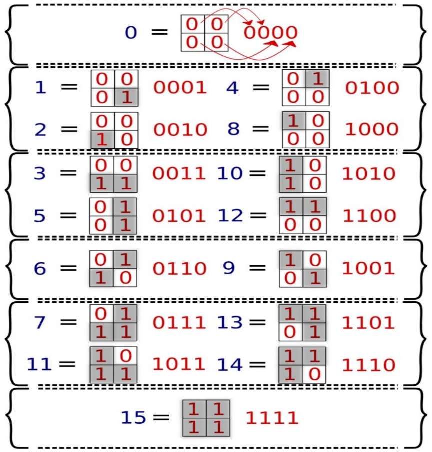

Prado et al 2020

Probability of occurrence

Information entropy

$$P_k = \frac{n_k}{M^*} \rightarrow S(M^*) = -\sum_{k=1}^{M^*} P_k \log P_k.$$

Low entropy/complexity = High Predictability
High entropy /complexity = Low Predictability

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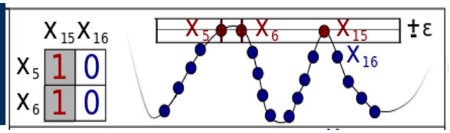
RECURRENCE PLOT AND INFORMATION ENTROPY



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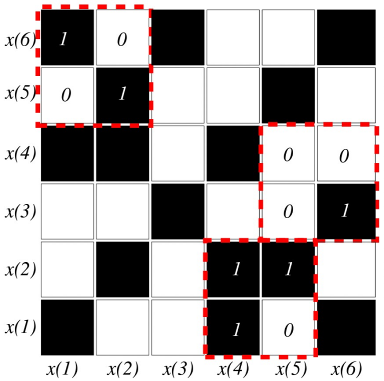

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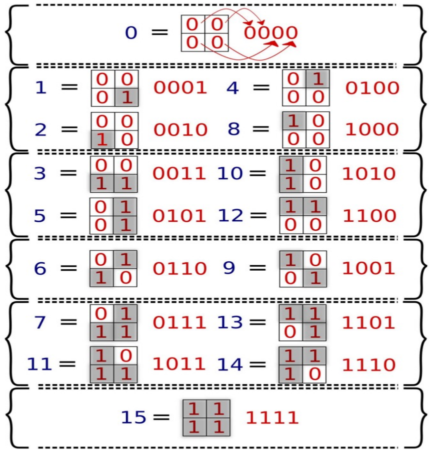

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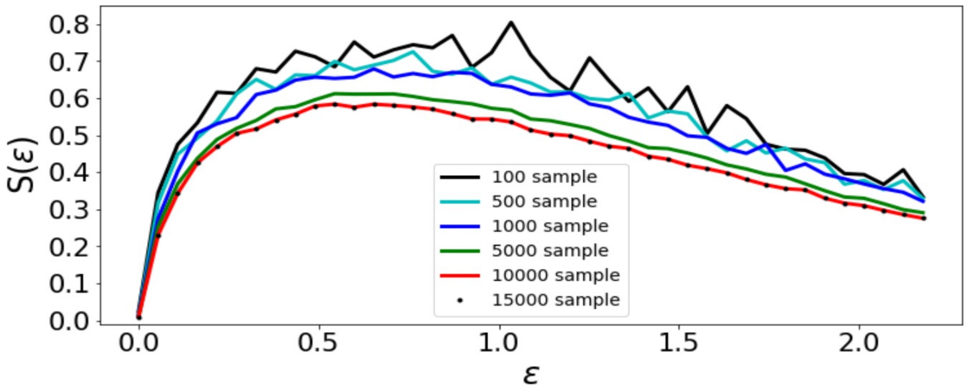

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DATA

Models acronym	Model	Institute, country	Ensemble members	
			Hist	RCP8.5
ACCESS1.0	Australian Community Climate and Earth-System Simulator, version 1.0	Commonwealth Scientific and Industrial Research Organisation (CSIRO)–Bureau of Meteorology	2	1
ACCESS1.3	Australian Community Climate and Earth-System Simulator, version 1.3	BOM, Australia	1	1
CanESM	Second Generation Canadian Earth System Model	Canadian Centre for Climate Modelling and Analysis (CCCma), Canada	3	1
CCSM4	Community Climate System Model, version 4	NCAR, United States	3	1
CMCC	Centro Euro-Mediterraneo per I Cambiamenti Climatici Climate Model	Centro Euro-Mediterraneo per I Cambiamenti Climatici (CMCC), Italy	1	1
CNRM	Centre National de Recherches Meteorologiques Coupled Global Climate Model, version 5	Centre National de Recherches Meteorologiques (CNRM)–Centre Europeen de Recherche et de	3	1
GFDL	Geophysical Fluid Dynamics Laboratory Climate Model, version 3	National Oceanic and Atmospheric Administration (NOAA)/Geophysical Fluid	3	1
GISSE2-H	Goddard Institute for Space Studies Model E2, coupled with the Hybrid Coordinate Ocean Model (HYCOM)	National Aeronautics and Space Administration (NASA) Goddard Institute for Space	3	1
GISSE2-R	Goddard Institute for Space Studies Model E2, coupled with the Russell ocean model	NASA GISS, United States	3	1
HadGEM2-ES	Hadley Centre Global Environment Model, version 2–Earth System	UKMO Hadley Centre, United Kingdom	3	1
INM-CM4	Institute of Numerical Mathematics Coupled Model, version 4.0	Institute of Numerical Mathematics (INM), Russia	1	1
IPSL-CM5A-LR	L'Institut Pierre-Simon Laplace Coupled Model, version 5A, coupled with Nucleus for European Modelling of the Ocean	L'Institut Pierre-Simon Laplace (IPSL), France	3	1
IPSL - CM5A-MR	L'Institut Pierre-Simon Laplace Coupled Model, version 5A, coupled with NEMO, mid resolution	IPSL, France	1	1
MPI-ESM-LR	Max Planck Institute Earth System Model, low resolution	Max Planck Institute for Meteorology (MPI-M), Germany	1	1
MRI-CGCM3	Meteorological Research Institute Coupled Atmosphere–Ocean General Circulation Model, version 3	Meteorological Research Institute (MRI), Japan	3	1

- 15 CMIP5 models
- Simple Ocean Data Assimilation (SODA) version 3.4.2
- ERA-Interim

We focus on Extended boreal fall season: **ASON**

1967 - 2005: Historical
2071 - 2100: RCP8.5
1980 - 2018: Reanalysis.

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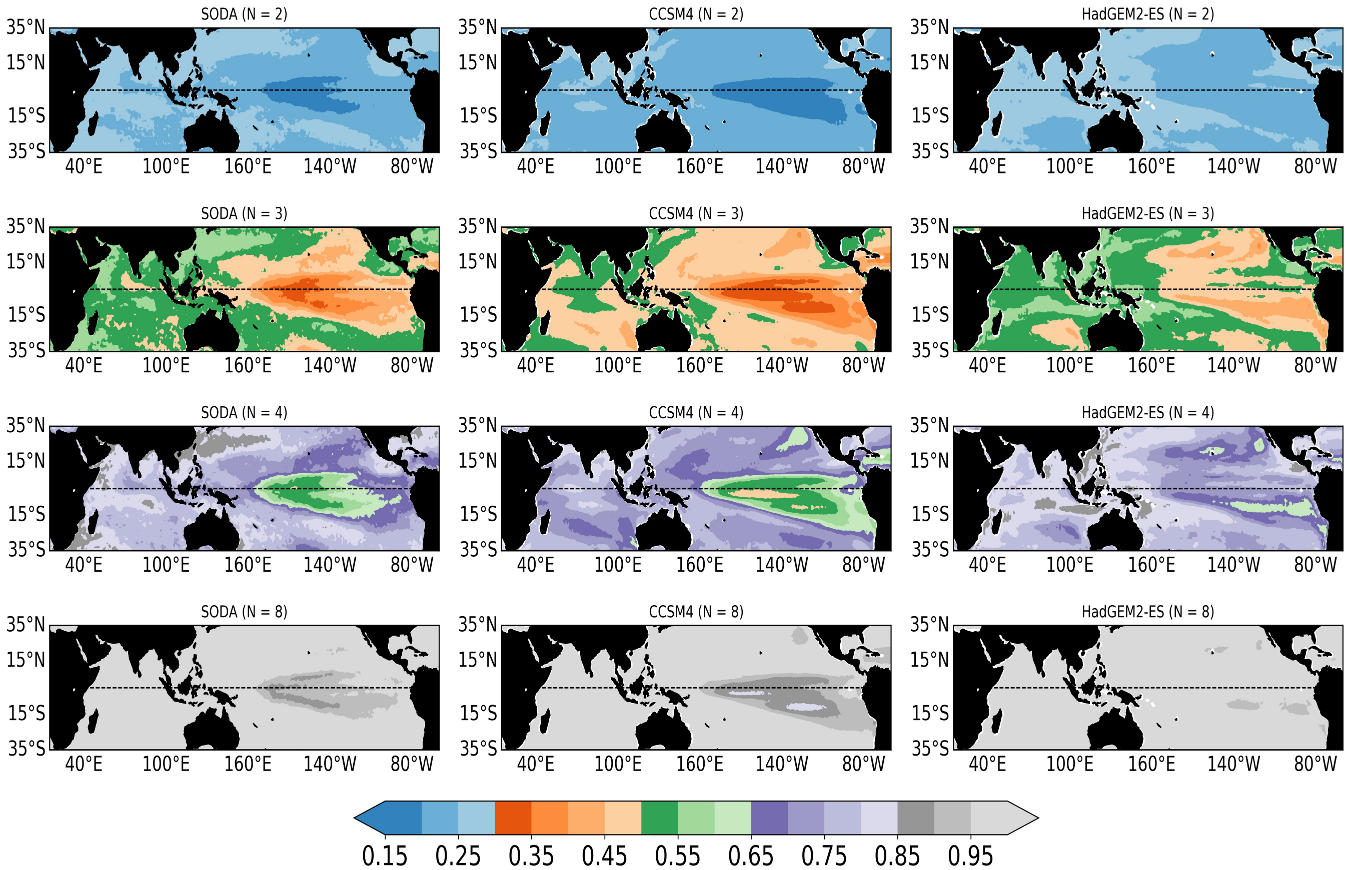
What are the Effects of Microstates on Entropy?

Low entropy/complexity = High Predictability
High entropy /complexity = Low Predictability



SST entropy fields with microstates, $N = 2$, 3, 4, and 8 for SODA reanalysis (left column), CCSM4 (middle column) and HadGEM2-ES (right column) CMIP5 historical runs. All months are considered.

- Highest predictability in the central TPO & the Upwelling region (South America – cold tongue and the Arabian Sea)
- CCSM4 overestimates predictability nearly everywhere
- HadGEM2-ES does not capture the ENSO predictability potential around the Equator and overestimates predictability in the upwelling systems in the Pacific and to the west of Australia.

Seasonal scope of our analysis: M = 3

N increase (recurrence in longer time) Entropy increases / predictability decreases

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SPRING PREDICTABILITY BARRIER

Low entropy/complexity = High Predictability
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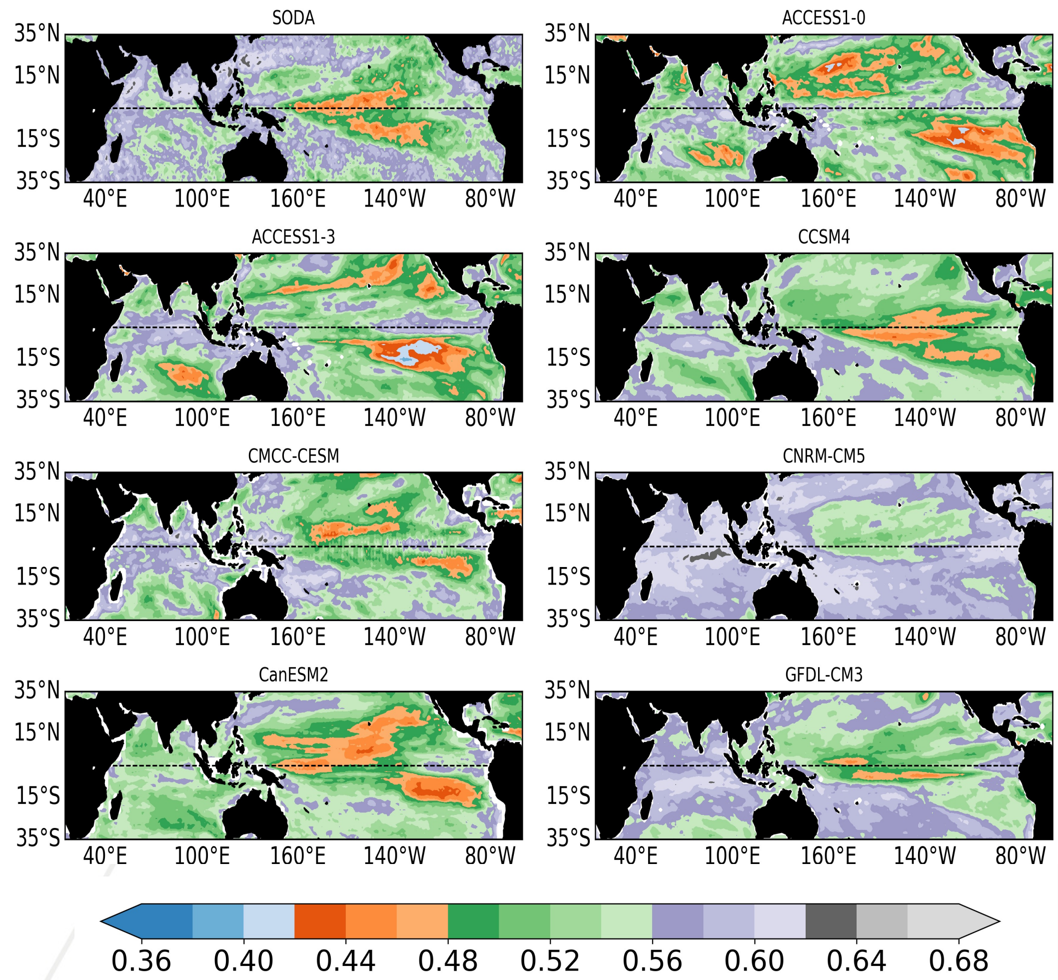

- ❖ As expected, low predictability in the Pacific in all models
- ❖ No ENSO predictability pattern
- ❖ Little agreement is found among models on the spring predictability of IO

SST entropy fields with microstates, $N = 3$ for MAM

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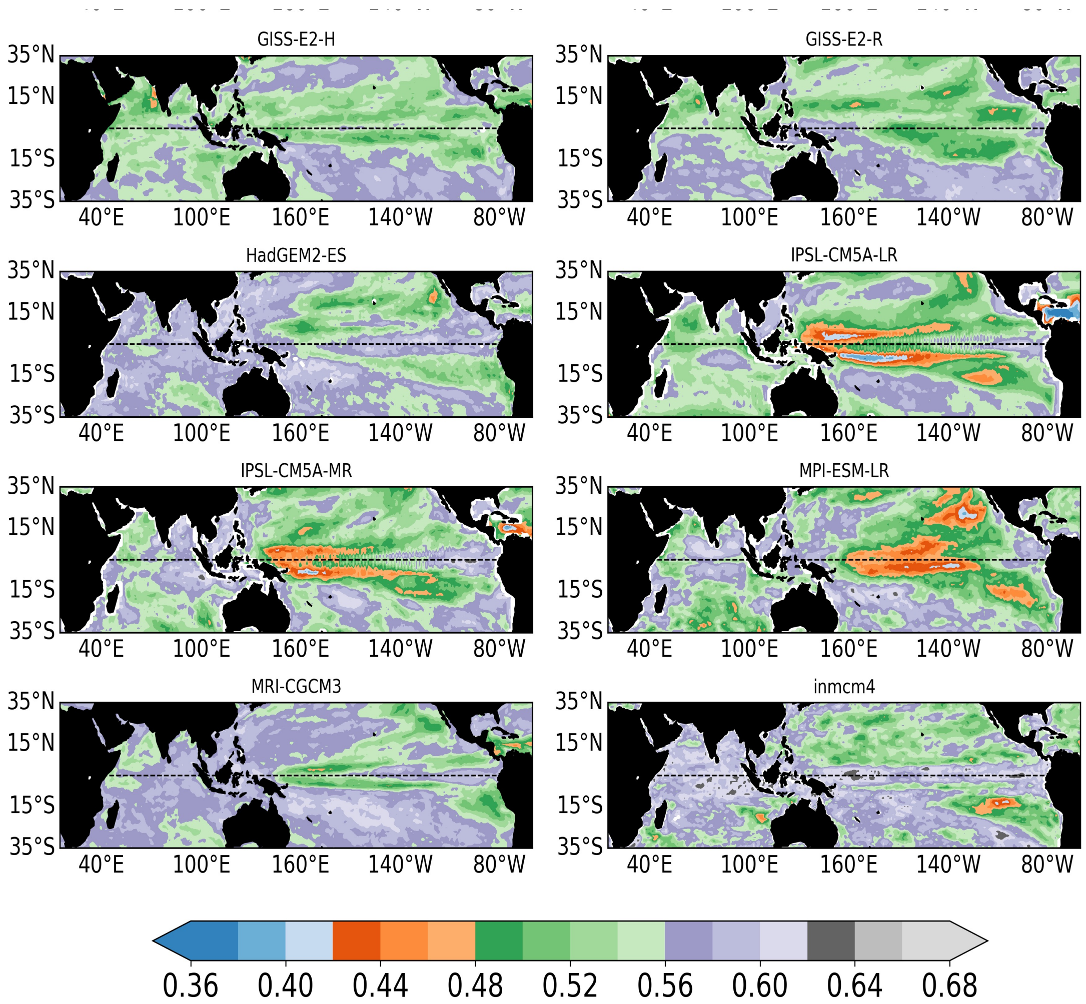

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ENTROPY FIELDS IN ASON: Historical

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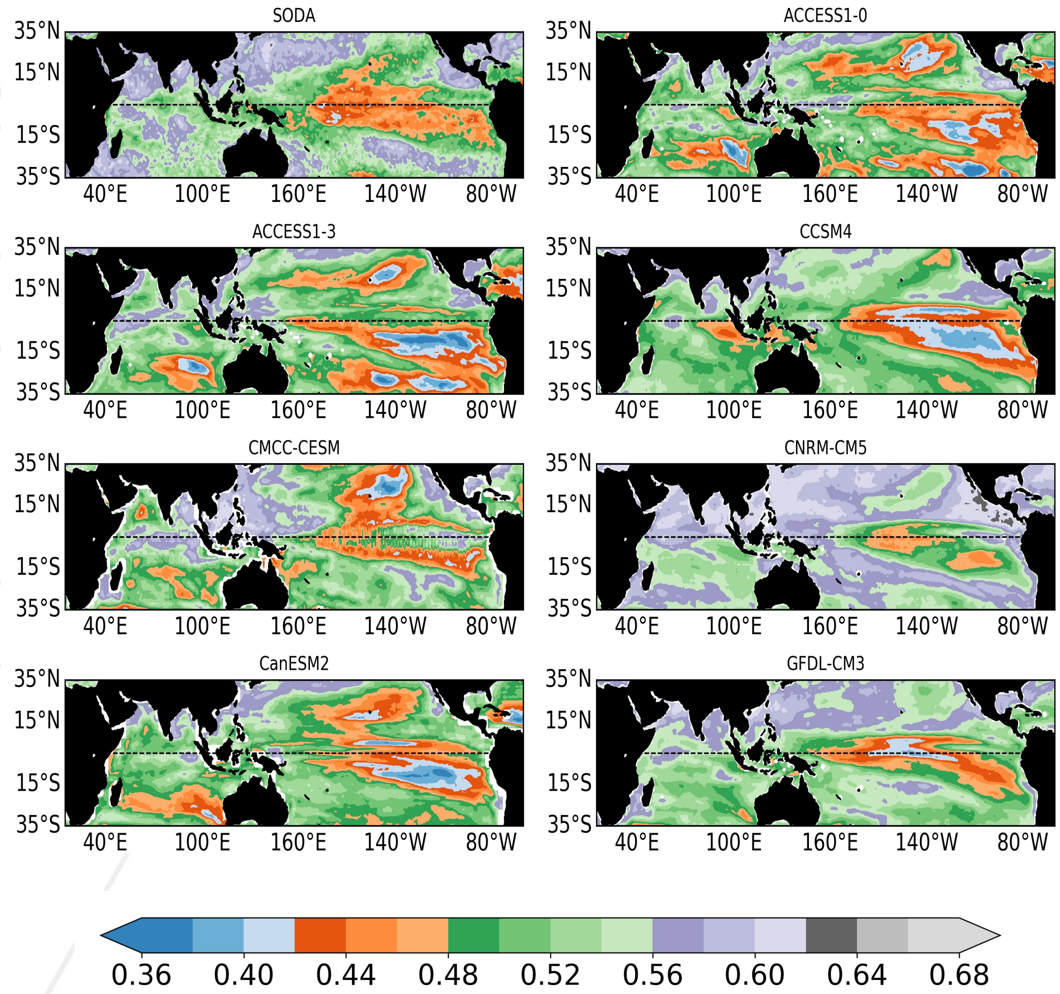

SST entropy fields with microstates, $N = 3$ for ASON

- ❖ Underestimate entropy in the ENSO region - CCSM4, CanESM2
- ❖ Overestimate the predictability in the IO, west of Sumatra - CCSM4
- ❖ West of Australia in CanESM2

- ❖ CNRM-CM5 reproduces best the entropy patterns in both basins.

- ❖ SODA : Predictability potential in the eastern, equatorial and part of the western IO.

- ❖ Arabian Sea larger complexity, likely due to the energetic mesoscale field characterizing this upwelling system in fall.

- ❖ Other models share the bias in the IO - ACCESS1.0 and 1.3, CMCC-CESM.

ENTROPY FIELDS IN ASON: Historical

Low entropy/complexity = High Predictability
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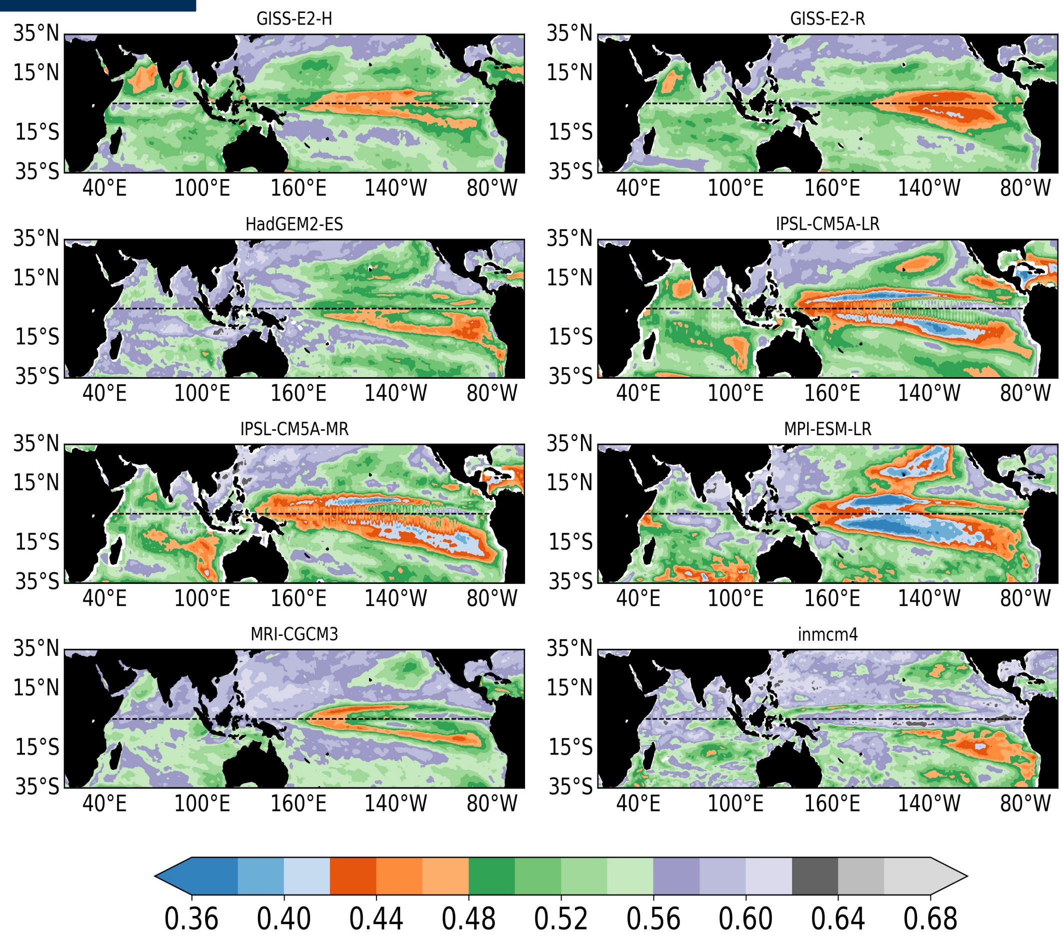
- ❖ Models that underestimate entropy in the ENSO region - MPI
- ❖ West of Australia MPI.

- ❖ IPSL models - ENSO pattern protruding too far west into the warm pool area.

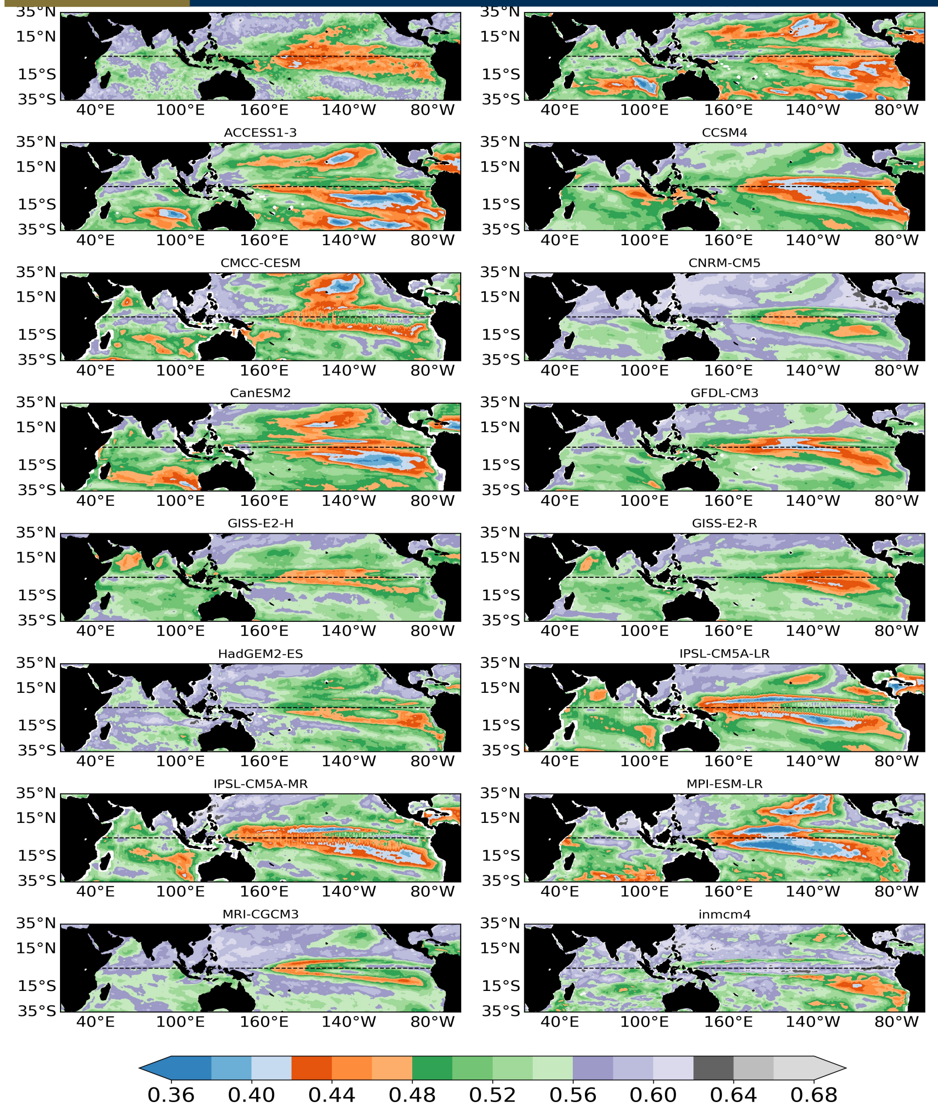
In the IO, many models underestimate the entropy in the 15S−35S band and overestimate it along the equatorial ocean.

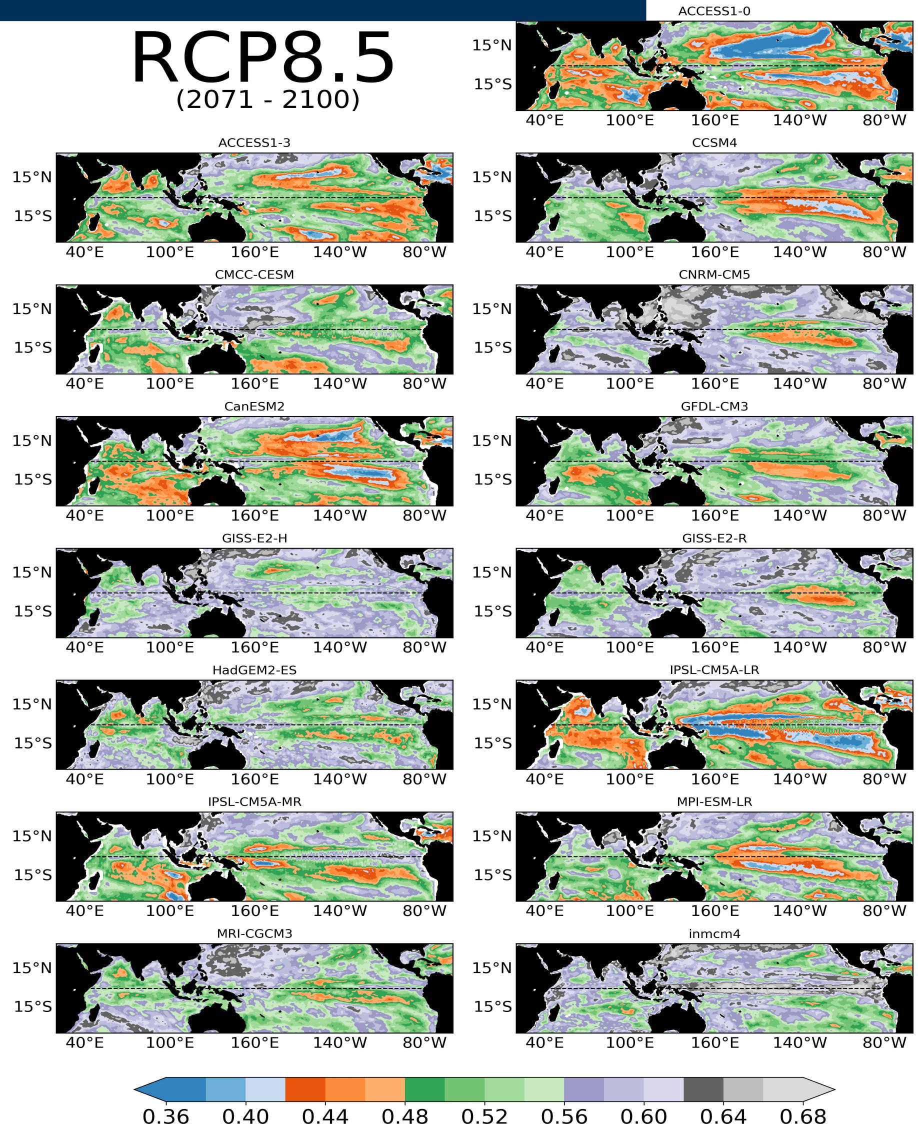
Missing the ENSO-IOD related predictability?



SST entropy fields with microstates, $N = 3$ for ASON

ENTROPY FIELDS IN ASON: Historical & RCP8.5





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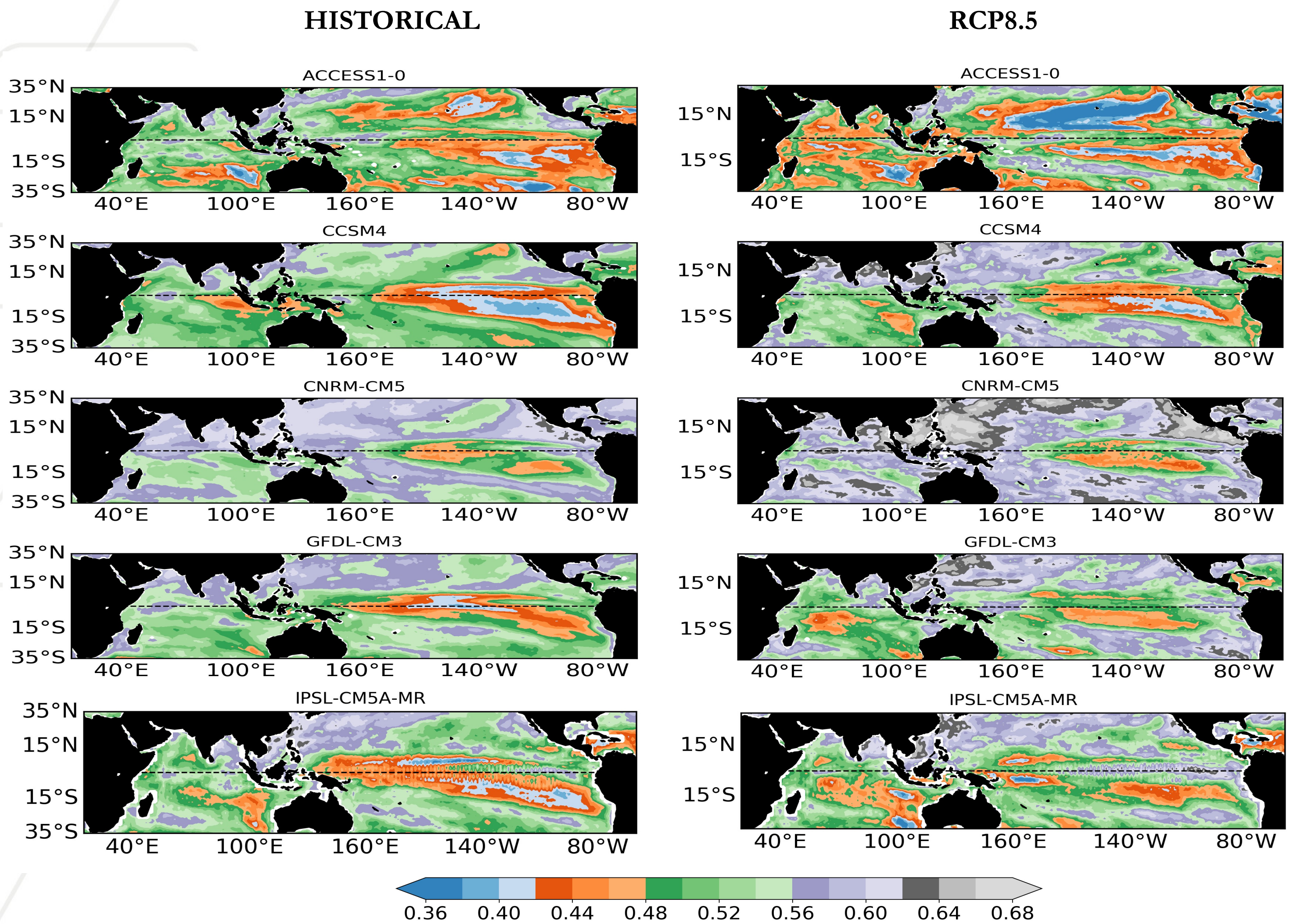
ENTROPY FIELDS IN ASON: Historical & RCP8.5



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ACCESS1.0, CanESM, IPSL-CM5A-LR

ACCESS1.3, CMCC-CESM, GFDL-CM3, GISS models, HadGEM2-ES, IPSL-CM5A-MR, MPI-ESM-LR and INMCM4.

IO

ACCESS and IPSL models, CanESM, MRI and in the GFDL model south of the Equator

Increases in the CNRM-CM5 run, which had the closest representation to the reanalysis in the historical period

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How does the entropy measure compare with more traditional linear methods of analysis?

EOFs and Power Spectra

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ENTROPY & EOFs

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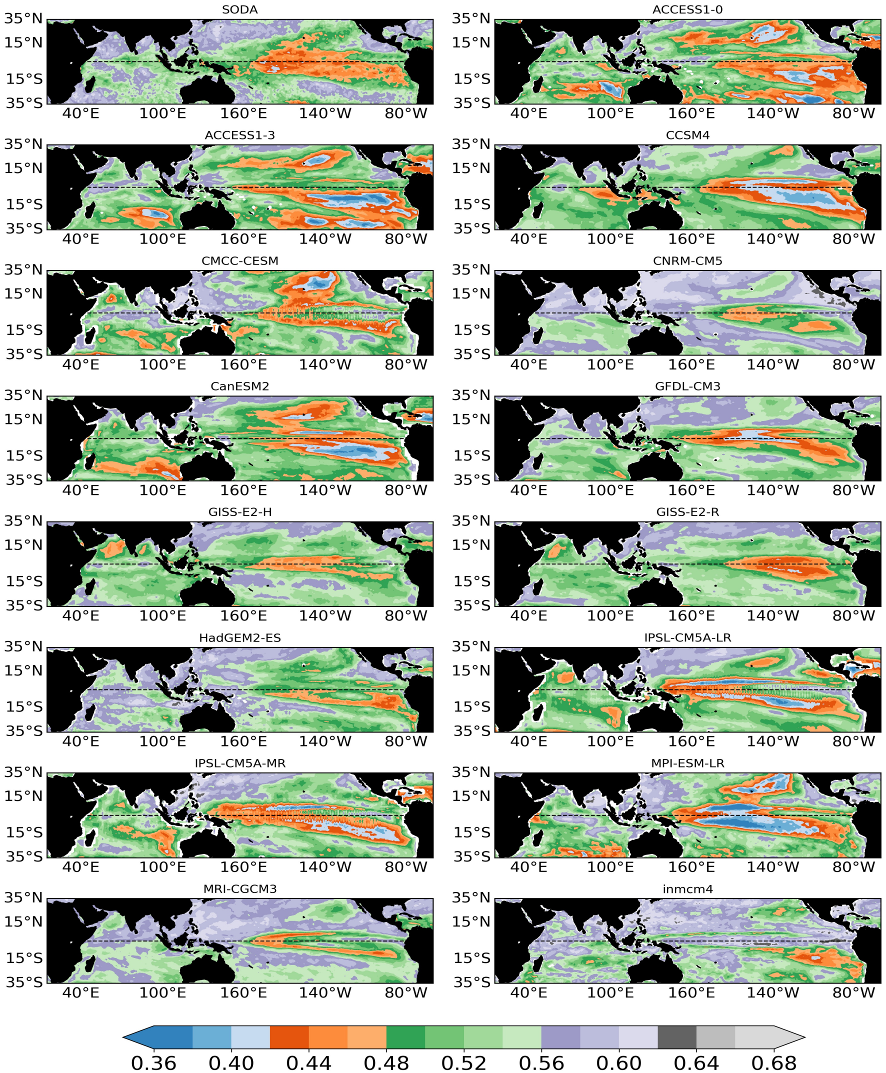

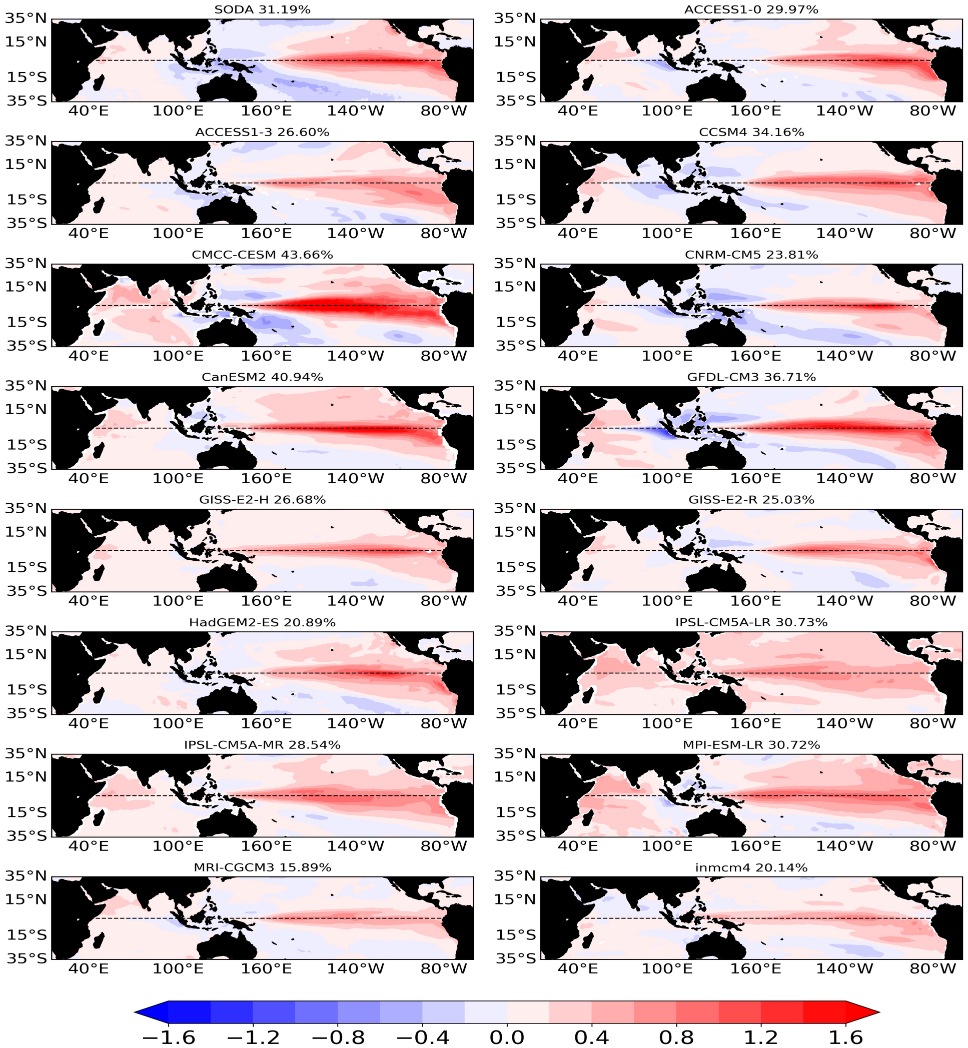

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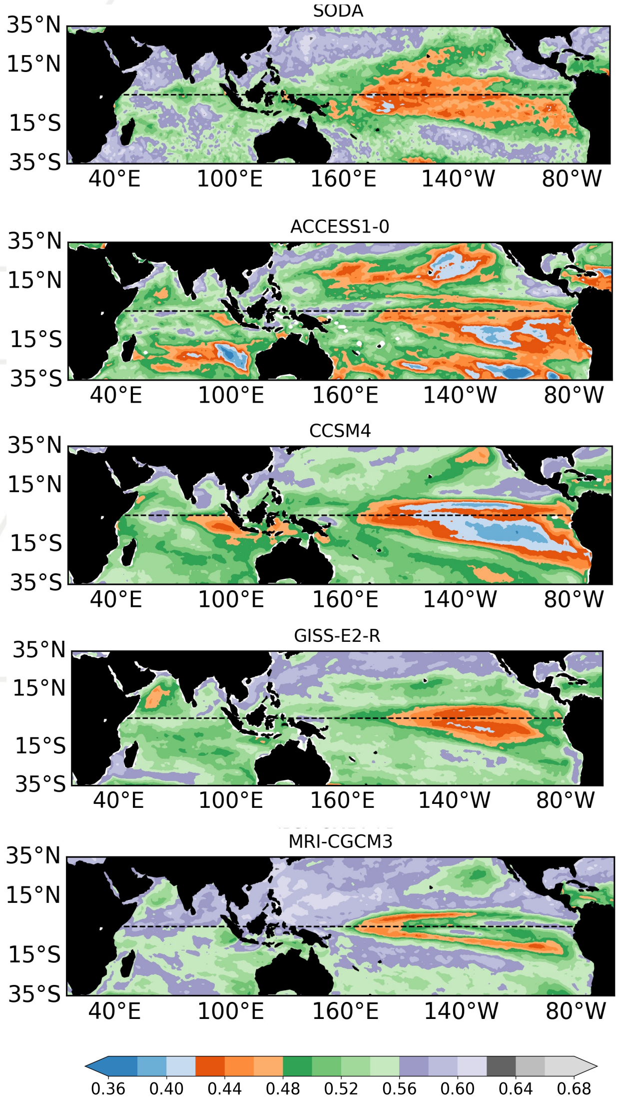
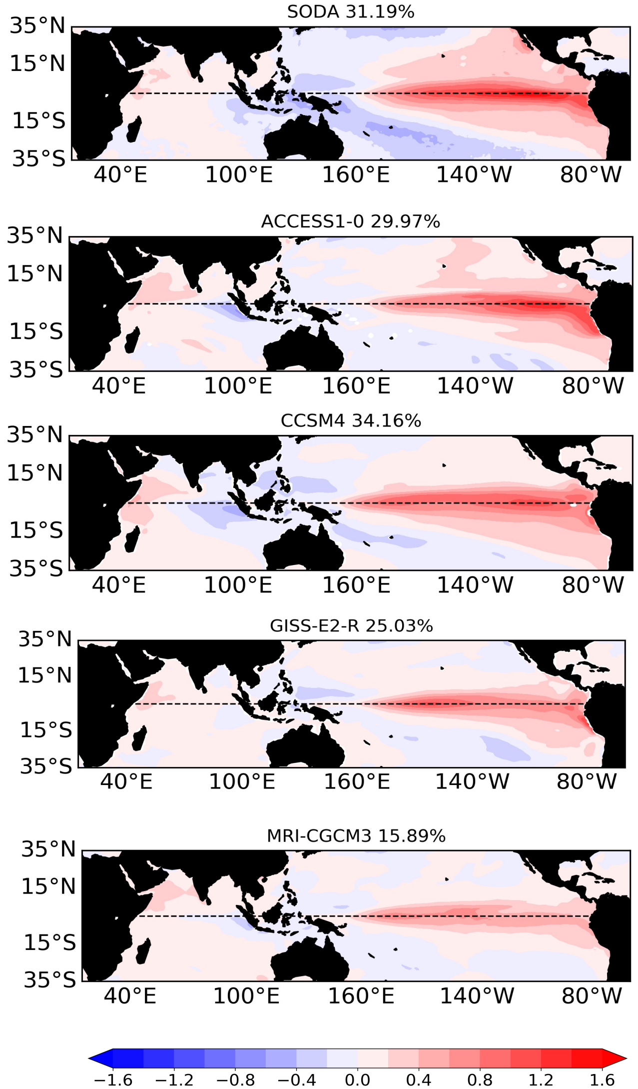




EOF patterns are generally more in agreement with reanalysis data than the entropy field.

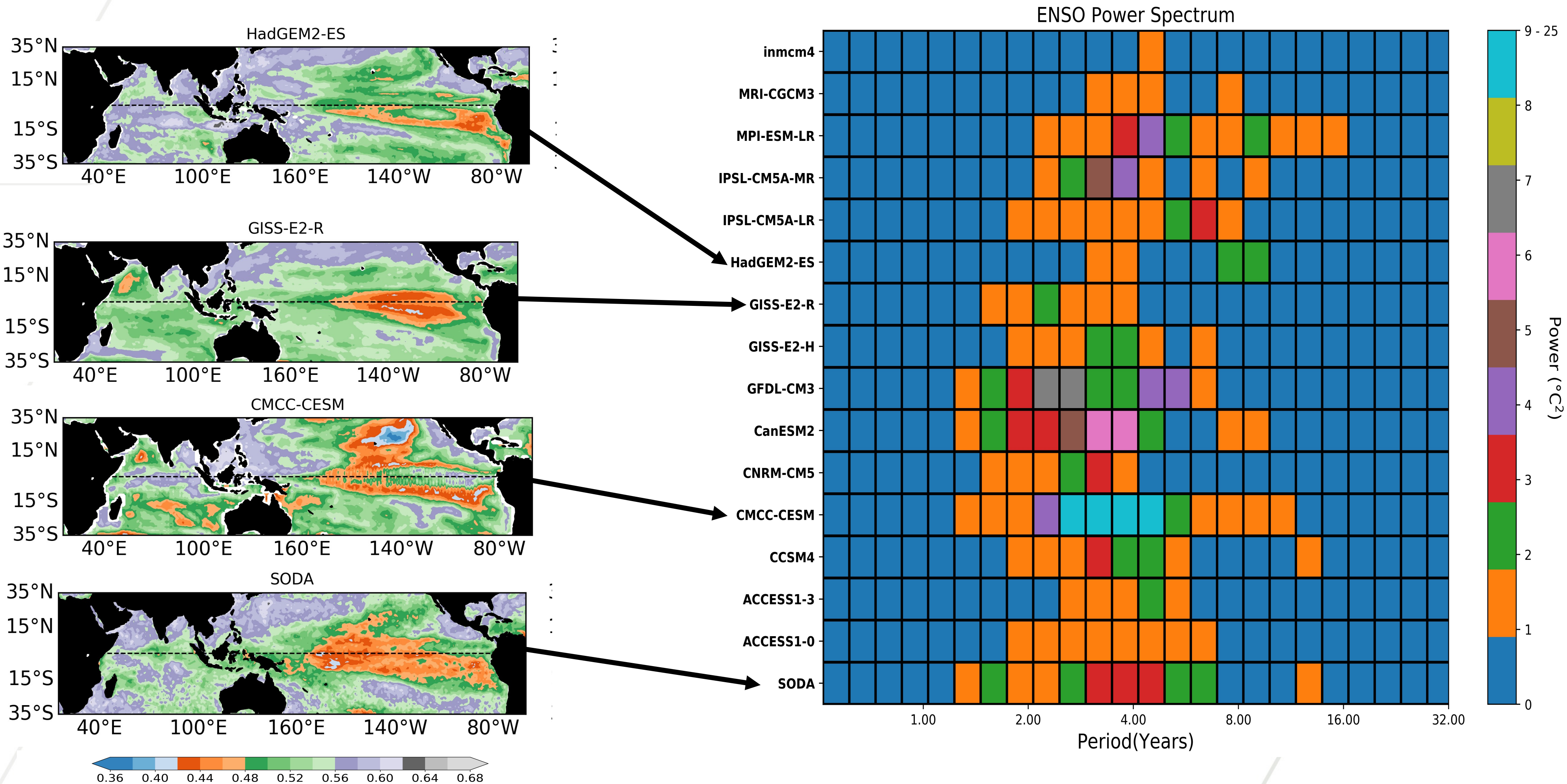
Too large complexity - structural problem common to several models

Equatorial dynamics both in the atmosphere and in the ocean

The EOF patterns, again, do not correspond to the entropy ones, especially south of 15S, where the SST predictability is often greatly overestimated by the models.

ENTROPY & POWER SPECTRA

The bias in the modeled spectra is reflected in that of the entropy field



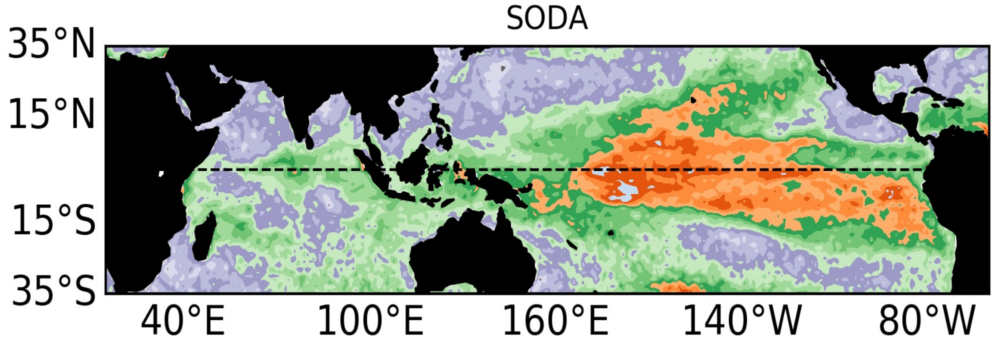
Many CMIP5 models Underestimate the complexity of the Indian Ocean SST variability, which is neither a mere response to ENSO or independent of it.

CONCLUSION

- Highlights the limitations that climate models still face in addressing predictability and its potential changes.
- In the historical period, very few models capture both pattern and intensity of the entropy signal of the reanalysis.
- No robust signal is found in the models, in both basins, as to how predictability will evolve in the future.
- Many models struggle at the equator, in both basins, and display unrealistic regular dynamics in the IO, especially south of the equator and/or in the Arabian Sea.
- Biased representation of coupled equatorial dynamics and of the atmospheric and subsurface oceanic bridge between the Pacific and Indian Oceans via the ITF contribute to the poor representation of the Indo-Pacific entropy in fall
- Our results exemplify how information entropy may contribute a new powerful tool to investigate the potential predictability of the climate system.
- Applying it across time scales and with high frequency (at least daily) data could be used to quantify how and where climate predictability emerges from the weather noise.

THANK YOU

ASON ENTROPY (1980 – 2018)



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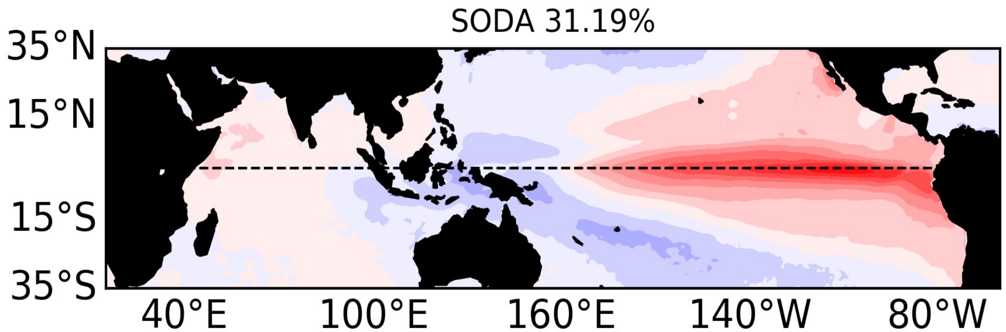

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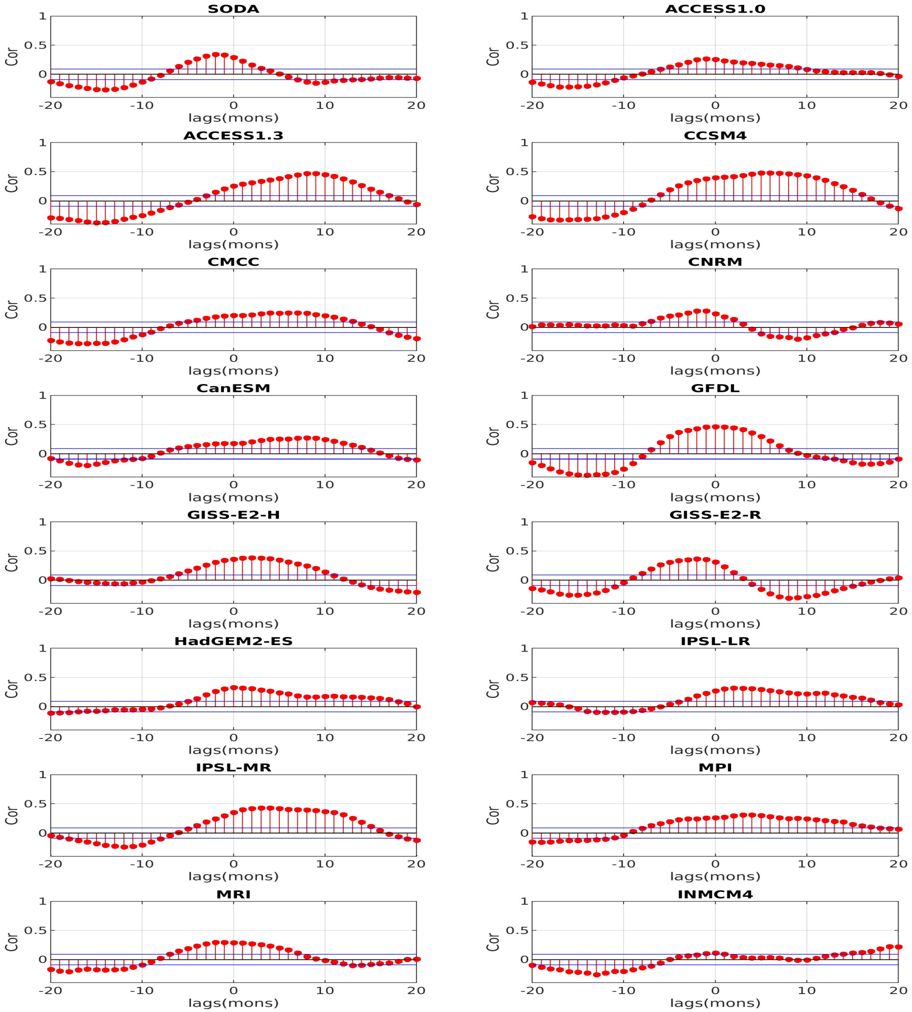
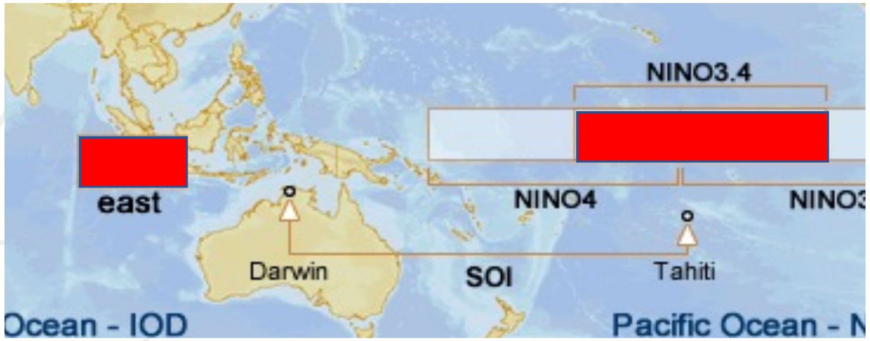
PREDICTABILITY POTENTIAL ACROSS THE BASINS



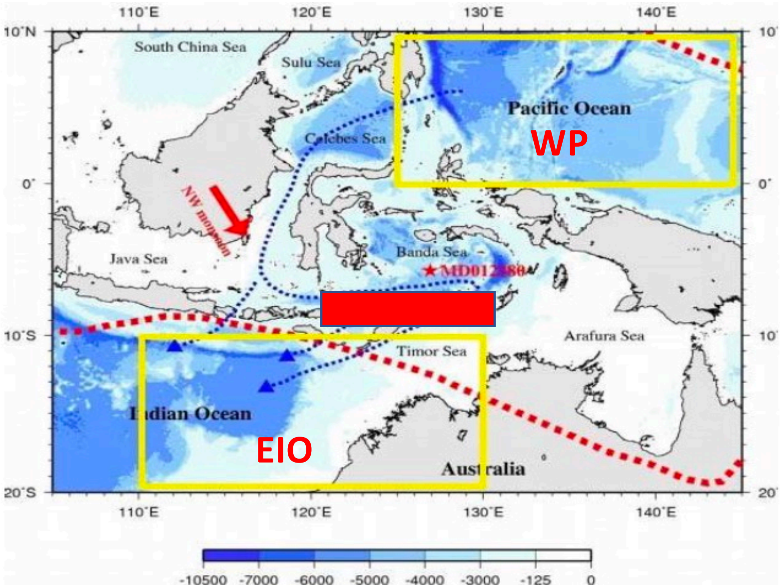
Nino 3.4 index autocorrelation with IOD in ASON

Atmospheric and oceanic connections induced by developing ENSO events affect the IO and vice versa.

Atmospheric Connection



Oceanic Connection



Z20 proxy

Bracco et al 2005

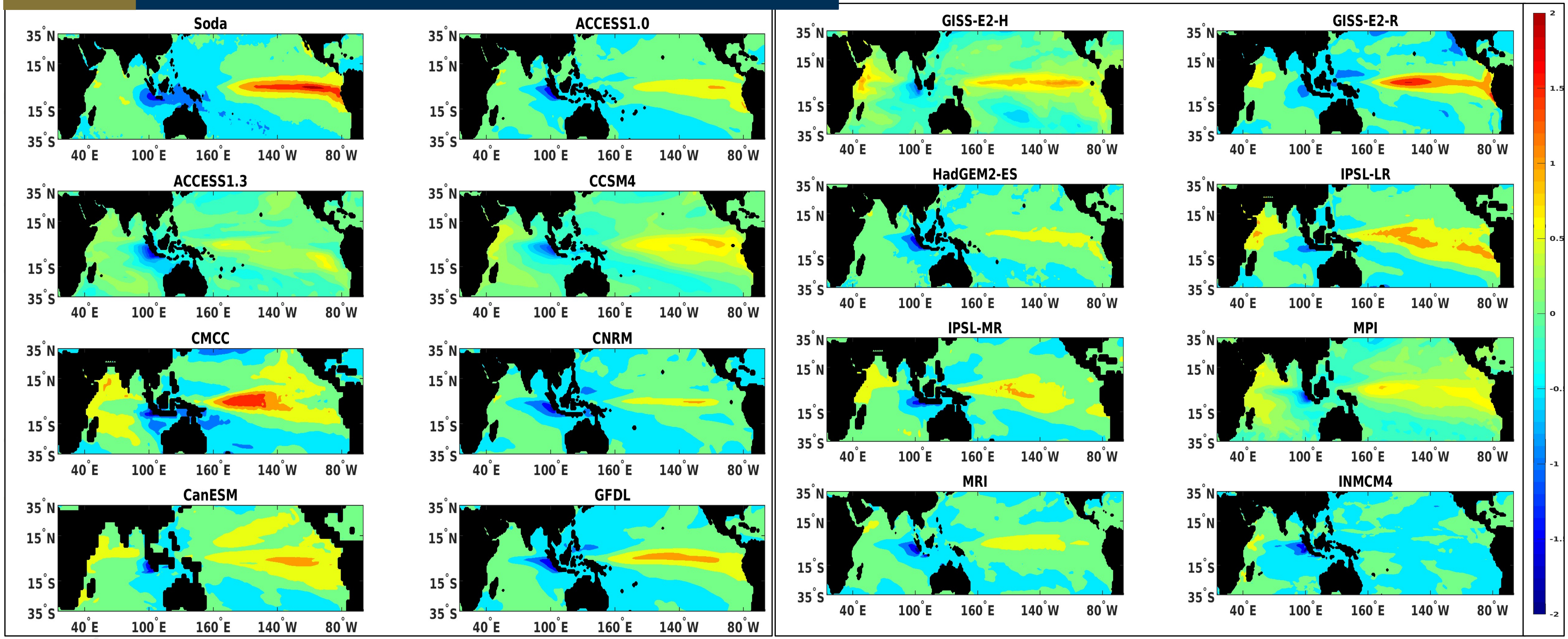
SLA Proxy = WP –EIO

Negative during El Nino

Positive during La Nina

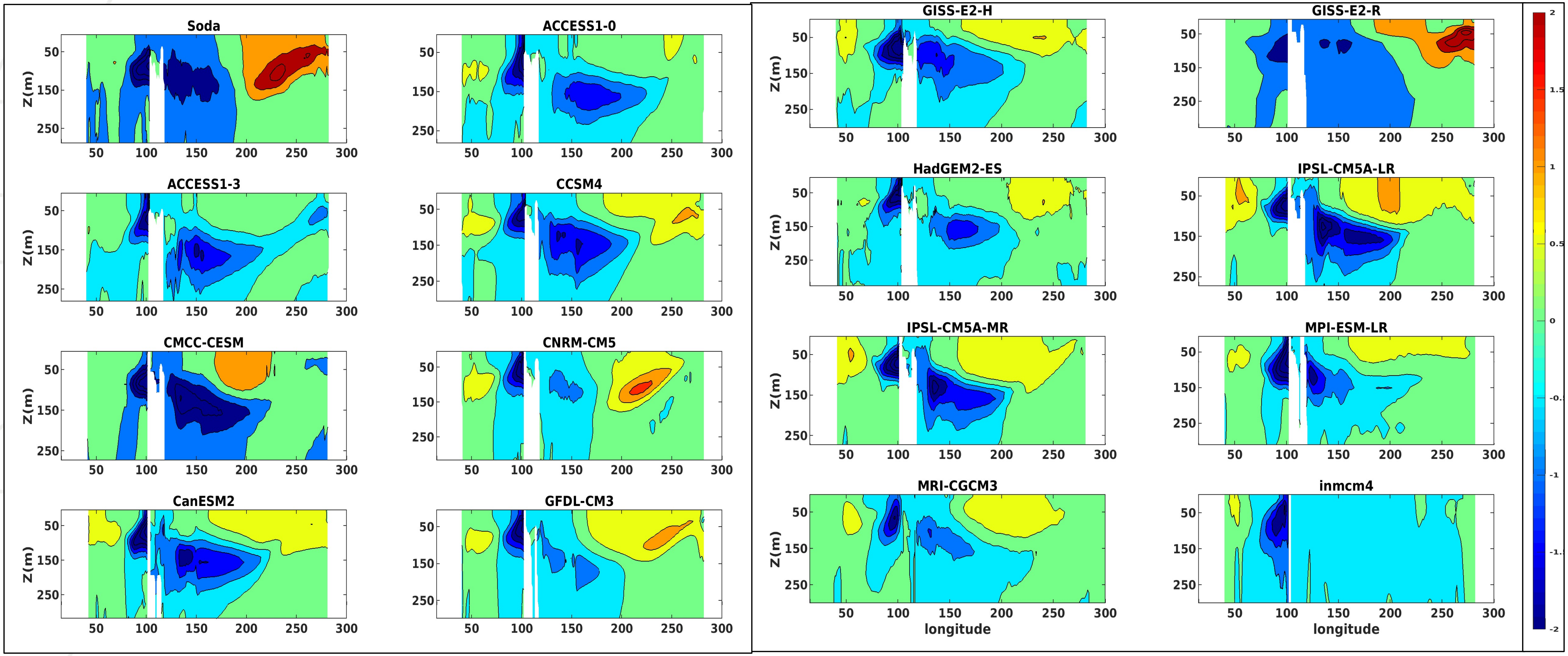
(Mayer et al 2011)

IOD & Surface Temperature



Regression maps of the tropical Indo-Pacific sea surface temperatures onto the IOD.

IOD & Subsurface Temperature



Regression maps of the tropical Indo-Pacific sea subsurface temperatures averaged between 5°N-5°S onto the IOD.