Международная конференция "Физика атмосферы
и климата", посвященная 70-летию Института
физики атмосферы им. А.М. Обухова РАН

ИДЕНТИФИКАЦИЯ И АНАЛИЗ ГЛАВНЫХ МОД КЛИМАТИЧЕСКОЙ ИЗМЕНЧИВОСТИ ПО АНСАМБЛЯМ РЕАЛИЗАЦИЙ МОДЕЛЕЙ ЗЕМНОЙ СИСТЕМЫ

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IDENTIFICATION AND ANALYSIS OF THE LEADING MODES OF CLIMATE VARIABILITY FROM EARTH SYSTEM MODEL ENSEMBLES

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Introduction

- State-of-the-art Earth system models (ESMs) exhibit inherent structural differences (e.g. associated with different spatial resolution and corresponding sub-grid parameterizations) that constitute a significant source of uncertainty in obtained climate projections

- It is important to identify which aspects of the forced response and internal variability are robust across multiple climate models and how this is related to observations

- Many state-of-the-art methods were collected and tested within ForceSMIP -- a recent effort to evaluate forced response estimation methods using large ensembles and apply them to single observation

Journal of Climate, 2026

Forced Component Estimation Statistical Method Intercomparison Project (ForceSMIP)

Robert C. J. Wills[a] , Clara Deser[b] , Karen A. McKinnon[c] , Adam Phillips[b] , Stephen Po-Chedley[d] , Sebastian Sippel[e] , Anna L. Merrifield[a] , Constantin Bône[f] , Céline Bonfils[d] , Gustau Camps-Valls[g] , Stephen Cropper[c] , Charlotte Connolly[h] , Shiheng Duan[d] , Homer Durand[g] , Alexander Feigin[i] , M. A. Fernandez[h] , Guillaume Gastineau[f] , Andrei Gavrilov[i,g] , Emily Gordon[j] , Moritz Günther[k] , Maren Höver[l,a] , Sergey Kravtsov[m] , Yan-Ning Kuo[n] , Justin Lien[o] , Gavin D. Madakumbura[c] , Nathan Mankovich[g] , Matthew Newman[p] , Jamin Rader[h] , Jia-Rui Shi[q] , Sang-Ik Shin[p,r] , Gherardo Varando[s]

#	Name	Institution(s)	Type of Method	Pattern Information	Multi-Field	N Parameters
1	RegGMST	NCAR	Regression	No	Yes	0
2	4th-Order-Polynomial	N/A	Reference	No	No	0
3	10yr-Lowpass	N/A	Reference	No	No	0
4	LFCA	ETHZ	LFCA	No	No	2
5	LFCA-2	ETHZ	LFCA	No	No	2
6	MF-LFCA	ETHZ	LFCA	No	Yes	2
7	MF-LFCA-2	ETHZ	LFCA	No	Yes	2
8	LIMnMCA	Cornell, Tohoku	LIM	No	Yes	2
9	ICA-lowpass	MPI-M	Other	No	No	3
10	LIMopt	ETHZ	LIM	No	No	3
11	LIMopt-filter	ETHZ	LIM	No	No	4
12	Colored-LIMnMCA	Cornell, Tohoku	LIM	No	Yes	5
13	DMDc	Valencia	LIM	No	No	75
14	GPCA	Valencia	Causal Inference	No	No	88
15	GPCA-DA	Valencia	Causal Inference	No	Yes	89
16	RegGMST-LENSem	NCAR	Regression	No	Yes	876
17	MLR-Forcing	LLNL	Regression	No	Yes	1.1e4
18	SNMP-OF	ETHZ	Fingerprinting	Yes	Yes	1.0e4
19	AllFinger	LLNL, WHOI, UCLA	Fingerprinting	Yes	No	1.0e4
20	MonthFinger	LLNL, WHO, UCLA	Fingerprinting	Yes	No	1.2e5
21	3DUNet-Fingerprinters	UCLA, LLNL, WHOI	NN	Yes	No	5.4e5
22	EOF-SLR	IAP, Milwaukee	Fingerprinting	Yes	No	O(1e6)
23	LDM-SLR	IAP, Milwaukee	Fingerprinting	Yes	No	O(1e6)
24	Anchor-OPLS	Valencia	Regression	Yes	No	2.1e6
25	UNet3D-LOCEAN	LOCEAN	NN	Yes	Yes	2.7e6
26	TrainingEM	N/A	Reference	Yes	Yes	9.1e6
27	RandomForest	UCLA	Random Forest	Yes	No	1.0e7
28	EncoderDecoder	CSU	NN	Yes	No	2.3e7
29	EnsFMP	ETHZ	Fingerprinting	Yes	Yes	4.5e7
30	ANN-Fingerprinters	LLNL	NN	Yes	No	1e16

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We represent the **multi-model Linear Dynamical Mode (LDM)** decomposition aimed at estimation of forced response and internal climate variability from multi-model ensembles

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Multi-model ensemble LDM decomposition

$\left\{\left(\mathbf{x}_1^{(m,k)},\ldots,\mathbf{x}_N^{(m,k)}\right)\right\}_{m=1,\ldots,M}^{k=1,\ldots,K}$ – consider multi-model ensemble of realizations

produced by *K* Earth system models, including *M* realizations of each model

$$\boxed{\mathbf{x}_n^{(m,k)} = \mathbf{A}\cdot\mathbf{p}_n^{(m,k)} + \mathbf{B}\cdot\mathbf{f}_n^{(k)} + \mathbf{c} + \sigma\boldsymbol{\xi}_n^{(m,k)}}$$

Modes of the internal variability

The internal component time series $\mathbf{p}_1^{(m,k)},\ldots,\mathbf{p}_N^{(m,k)}$ are the *M*-member ensembles for each of *K* model

Modes of the forced response

The forced components are represented by the same single time series $\mathbf{f}_1^{(k)},\ldots,\mathbf{f}_N^{(k)}$ in all *M* realizations within particular model

Determination of the number of distinct LDM modes and corresponding time scales and evaluation of the spatial patterns $\mathbf{A}$, $\mathbf{B}$ are performed objectively within the Bayesian framework, which provides the decomposition of optimal complexity

Employed models and datasets

Sea surface temperature (SST) and ocean heat content (OHC) data from historical climate simulations, produced by five models from **CMIP6**: **CESM2**, **HadGEM3-GC31-L**, **CanESM5**, **MPI-ESM1-2-LR**, **INMCM5** and **INMCM6P** model with improved parametrization of clouds, large-scale condensation, and aerosols

The OHC data are obtained by integration of potential temperature over a vertical coordinate in 0–300 m layer: $\boldsymbol{OHC} = \boldsymbol{\rho} \mathrm{C}_{\boldsymbol{p}} \int_{\mathbf{0}}^{\mathbf{300}} \boldsymbol{\theta}(\boldsymbol{z}) \boldsymbol{dz}$, where seawater density $\boldsymbol{\rho}$ **=1026 kg/m^3** and the specific heat capacity of seawater $\mathrm{C}_{\mathbf{p}}$**=3990$ J/(kg K)** are constants

***K* = 6** models

***M* = 10** realizations from each model

N = 260 - the size of each realization along the time axis (3 month step, January 1950 - December 2014)

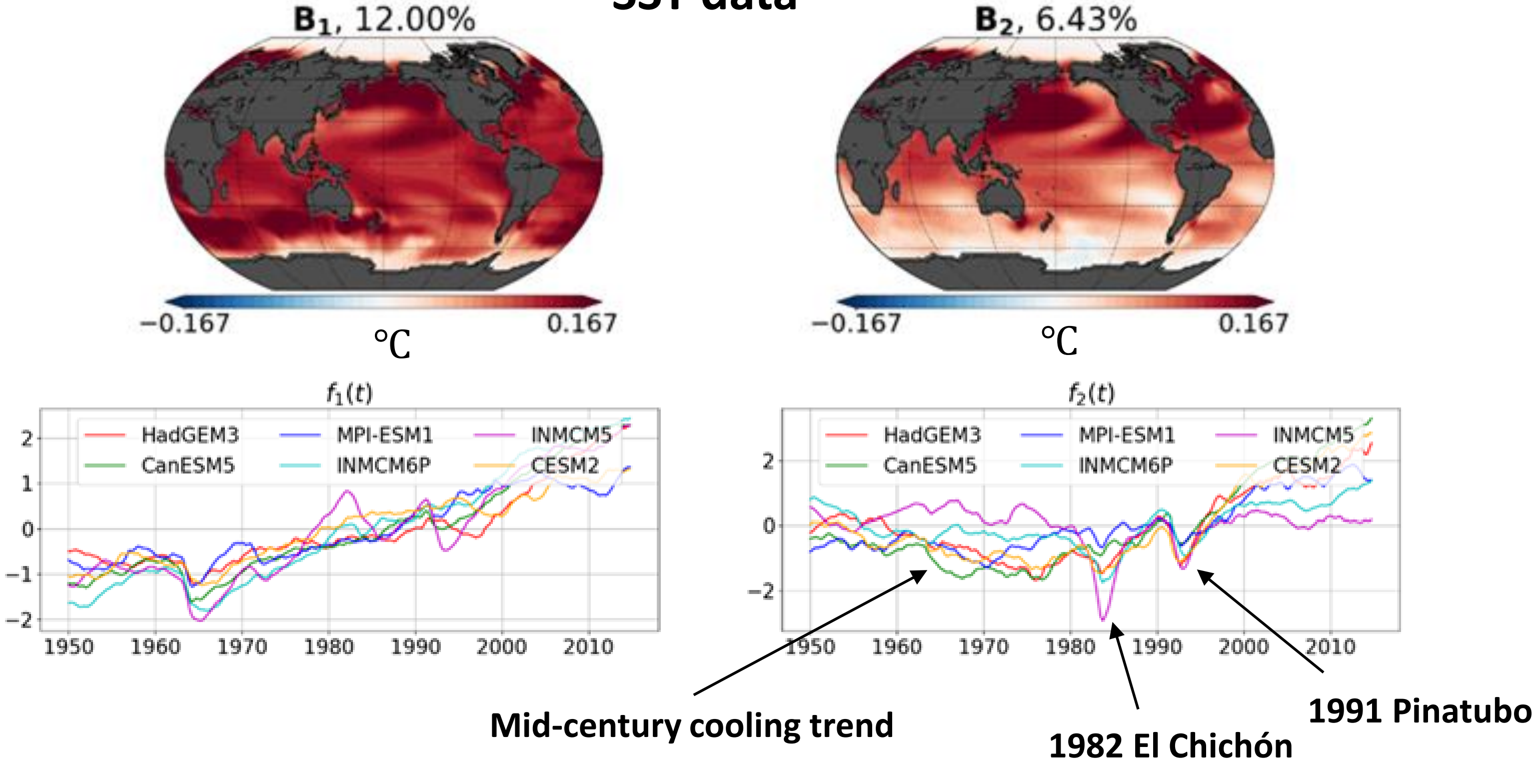
$$\left\{\left(\mathbf{x}_1^{(m,k)}, \ldots, \mathbf{x}_\mathrm{N}^{(m,k)}\right)\right\}_{m=1,\ldots,M}^{k=1,\ldots,K}$$

$$\mathbf{x}_\mathrm{n}^{(m,k)} = \mathbf{A} \cdot \mathbf{p}_\mathrm{n}^{(m,k)} + \mathbf{B} \cdot \mathbf{f}_\mathrm{n}^{(k)} + \mathbf{c} + \sigma \boldsymbol{\xi}_\mathrm{n}^{(m,k)}$$

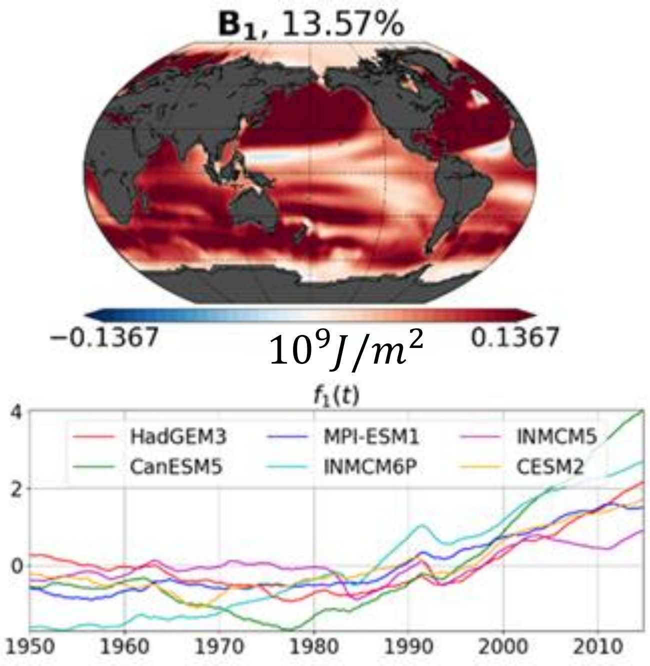
The multi-model LDM decomposition was performed distinctively for SST and OHC anomalies data

Leading modes of the forced response

SST data



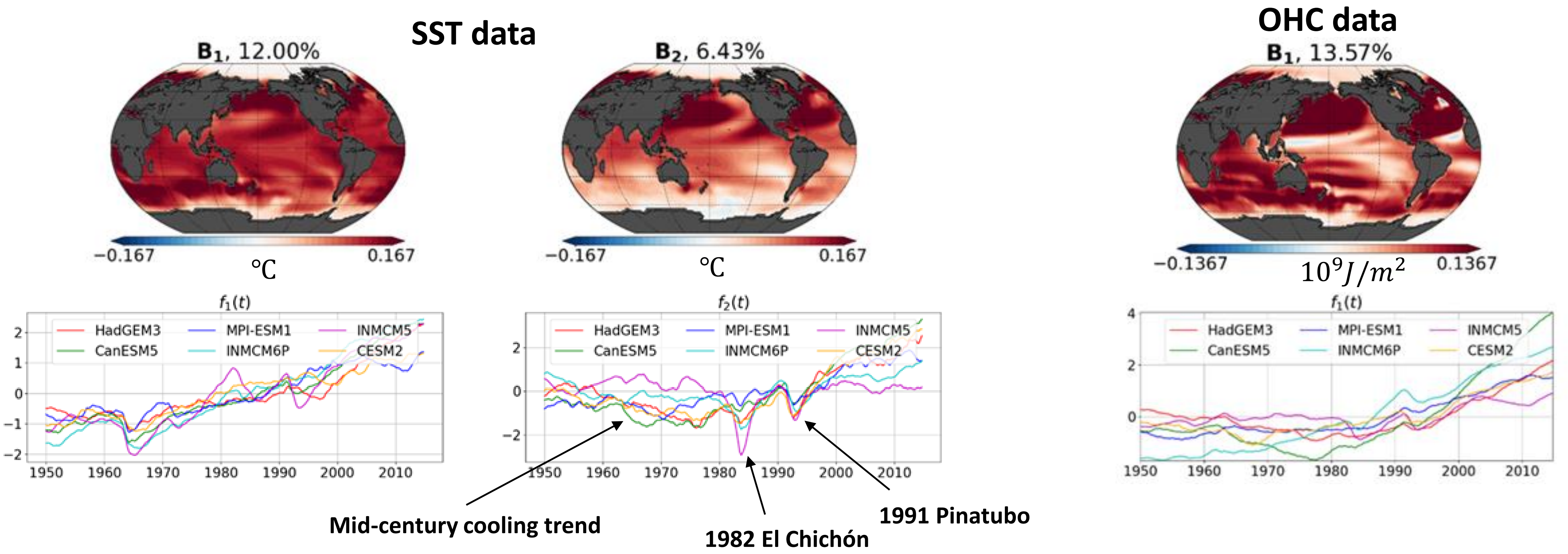
OHC data



- The first mode clearly reflects the familiar CMIP5/6 global warming SST trend which is relatively spatially uniform except for enhanced warming in the Northern Pacific and Atlantic and muted warming in the Southern Ocean

- The second mode can be primarily associated with aerosol forcing from both anthropogenic and natural (volcanic) aerosols

Leading modes of the forced response



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- The second mode can be primarily associated with aerosol forcing from both anthropogenic and natural (volcanic) aerosols

- The forced response in OHC data is dominated by single leading mode apparently reflecting the global warming trend

- In contrast to forced SST modes, we do not observe any clear manifestation of the aerosol forcing in OHC modes

Global warming SST/OHC rate in different ESMs

OHC (2014 - 1980) **SST (2014 - 1980)**

HadGEM3-GC31-L

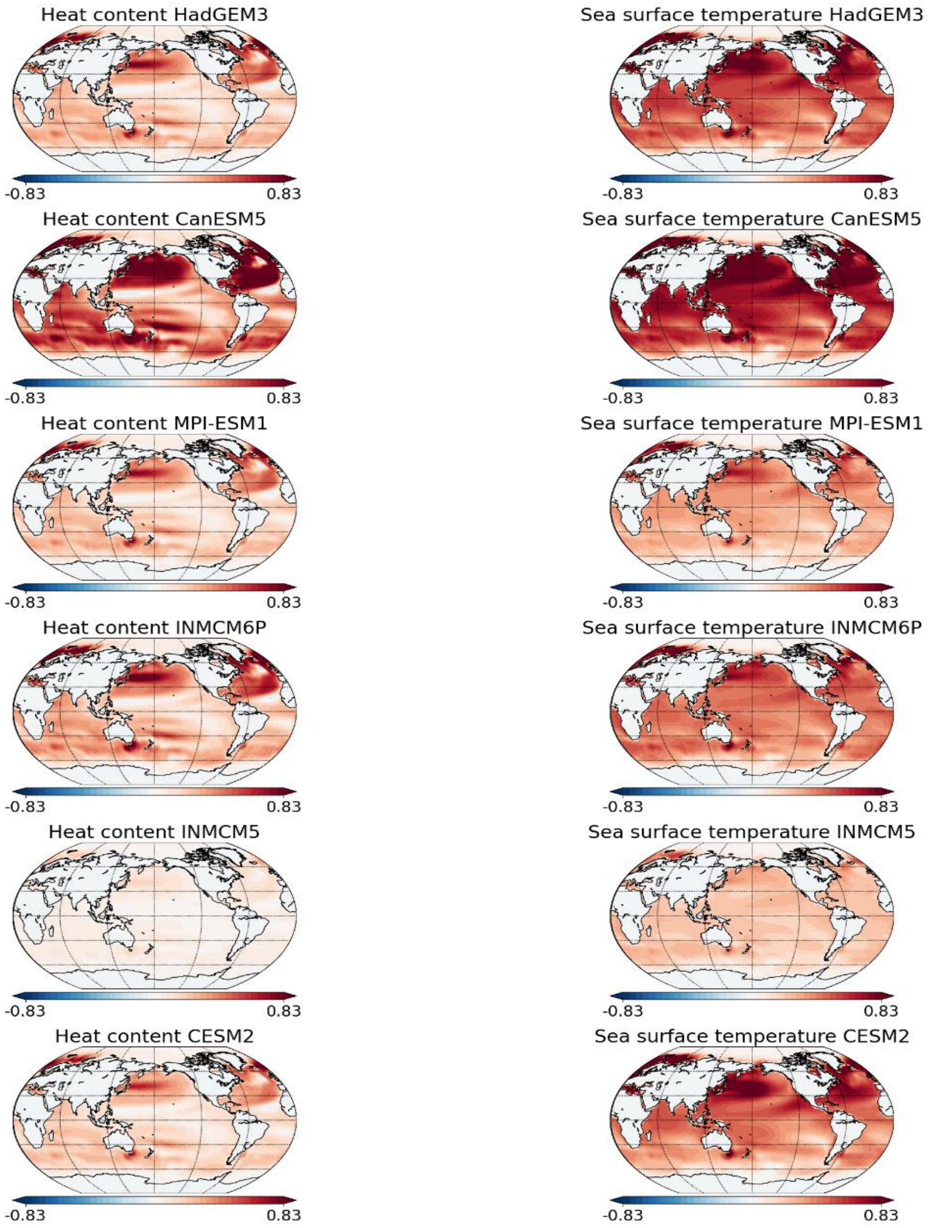
CanESM5

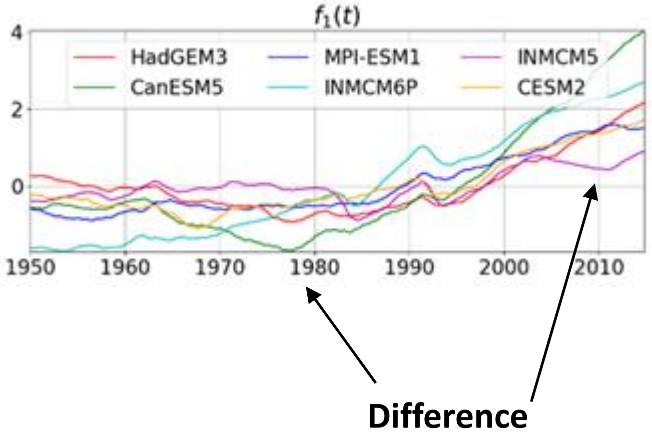
MPI-ESM1-2-LR

INMCM6P

INMCM5

CESM2





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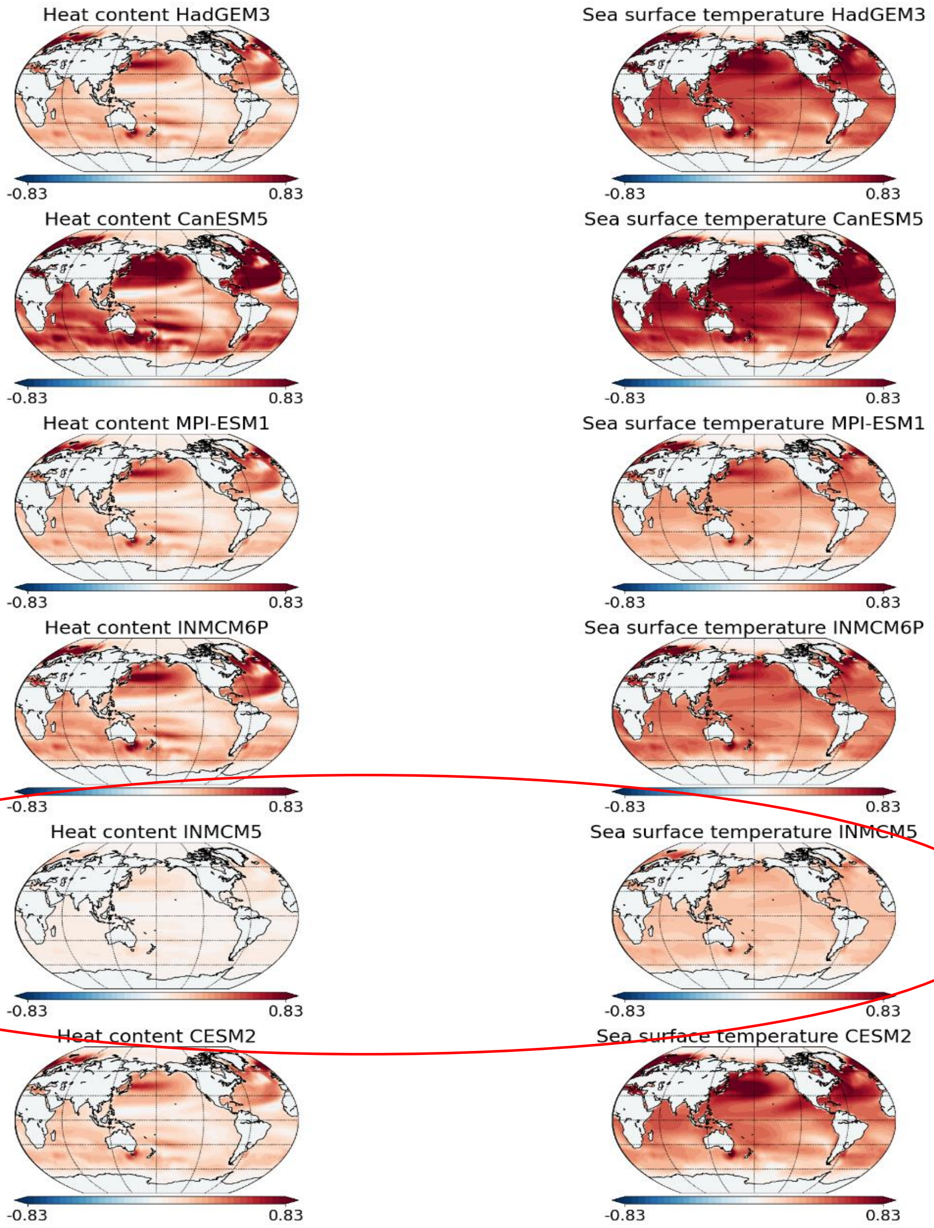
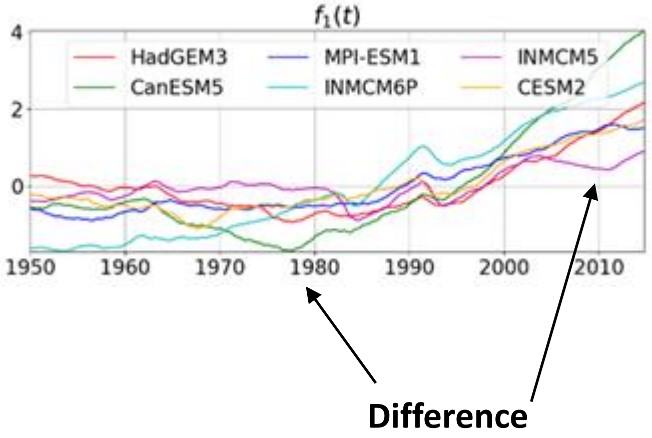
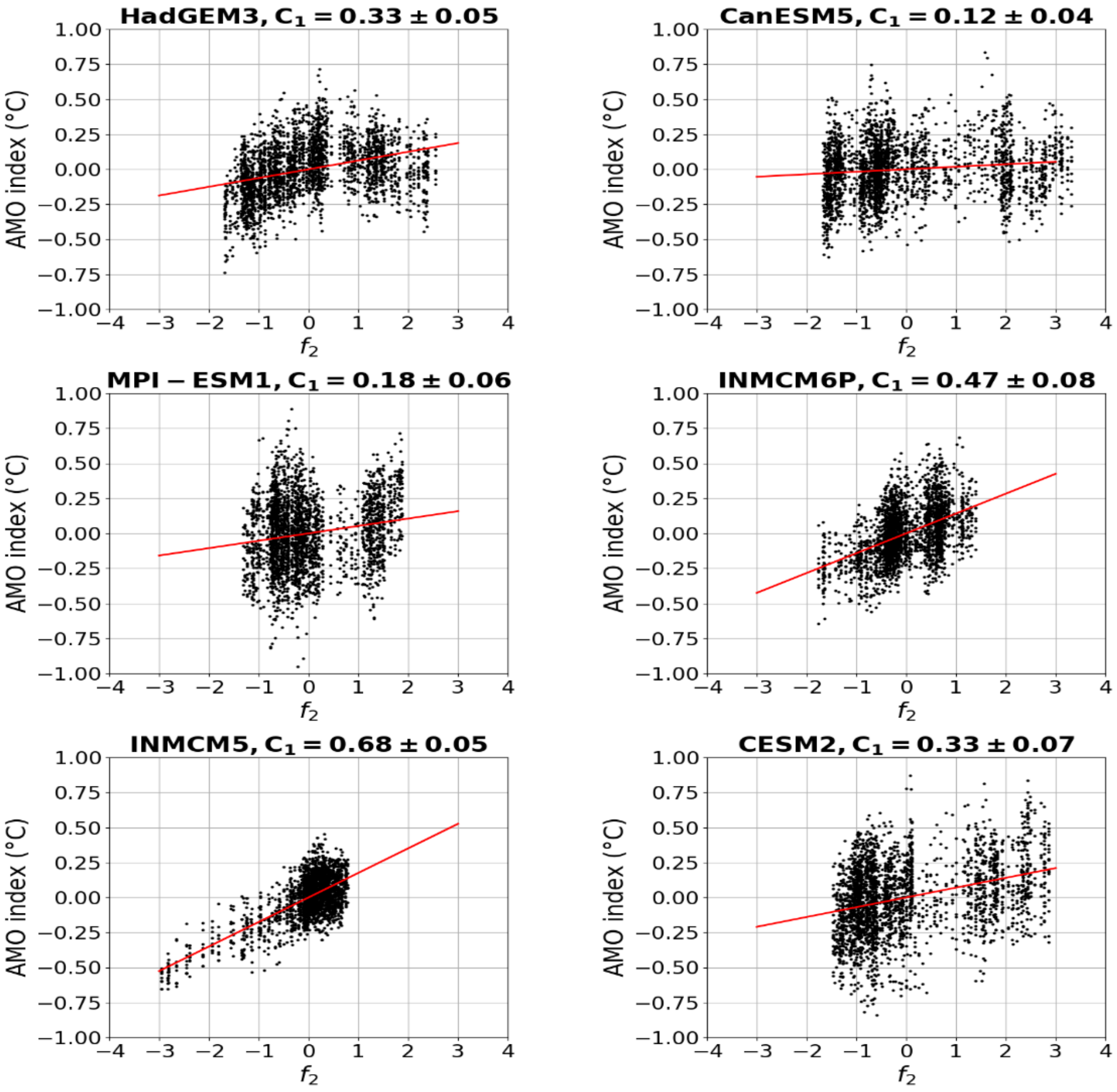
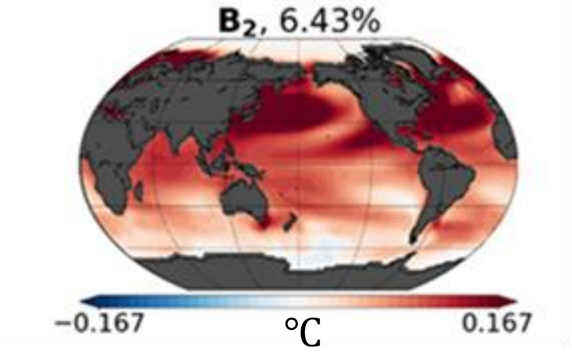


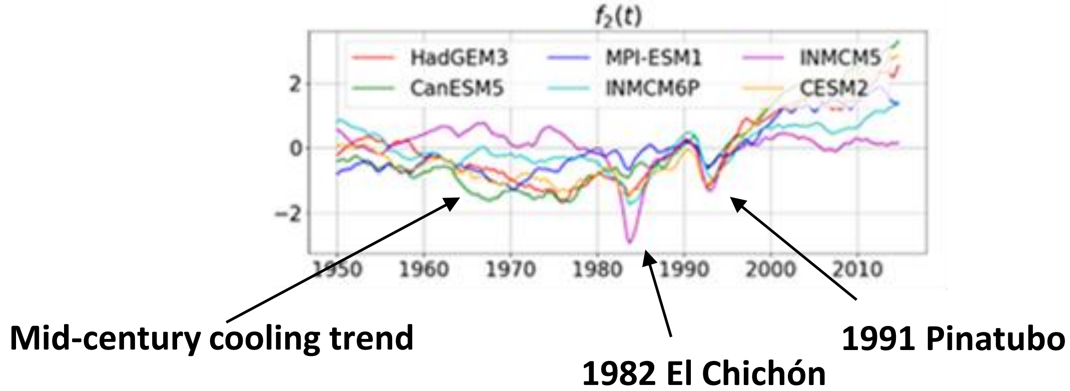


- The spread between estimated time series of the leading forced SST/OHC modes points to distinct sensitivity of the climate models to different forgings
- The INMCM5 model demonstrates the lowest rate of the global warming as compared to other models in both SST and OHC data
- This result is consistent with the fact that the INMCM5 model has the lowest equilibrium climate sensitivity (ECS) among CMIP6 models

Response of the North Atlantic SST variability to aerosol forcing in different ESMs



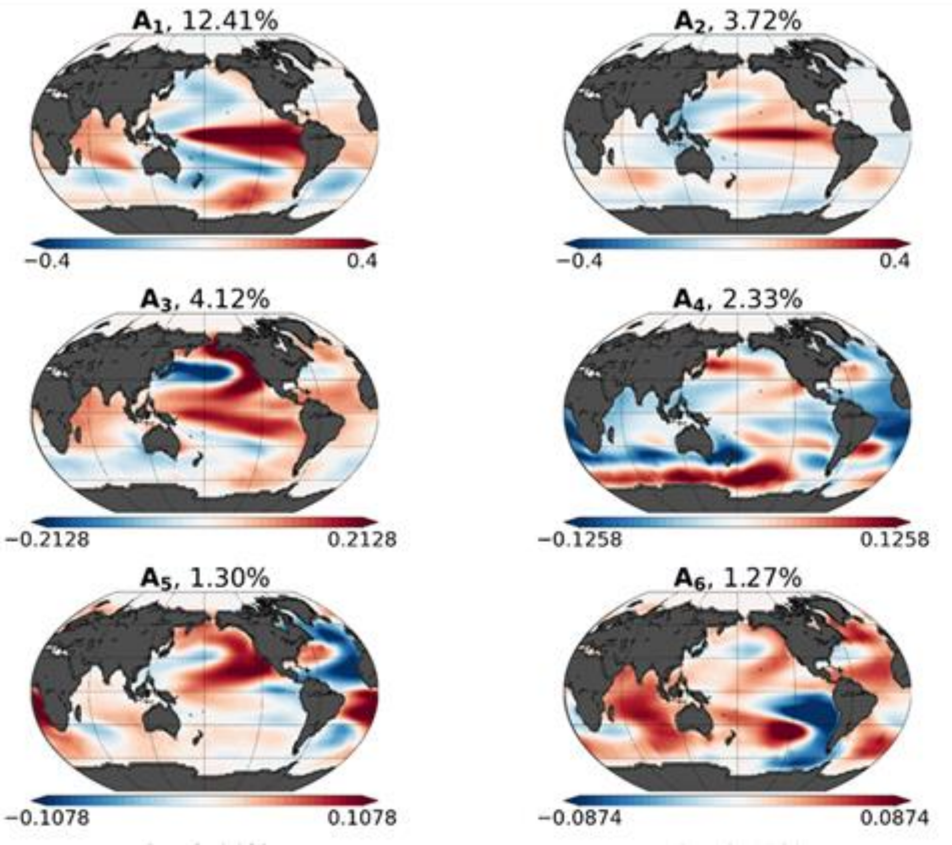




- The second forced SST mode demonstrates the significant contribution to the North Atlantic SST variability which is typically attributed to internal climate dynamics associated with Atlantic Multidecadal Oscillation (AMO)
- We found that the AMO indices, derived from INMCM5 and INMCM6P SST simulations demonstrate strong correlations with corresponding time series of the second forced mode

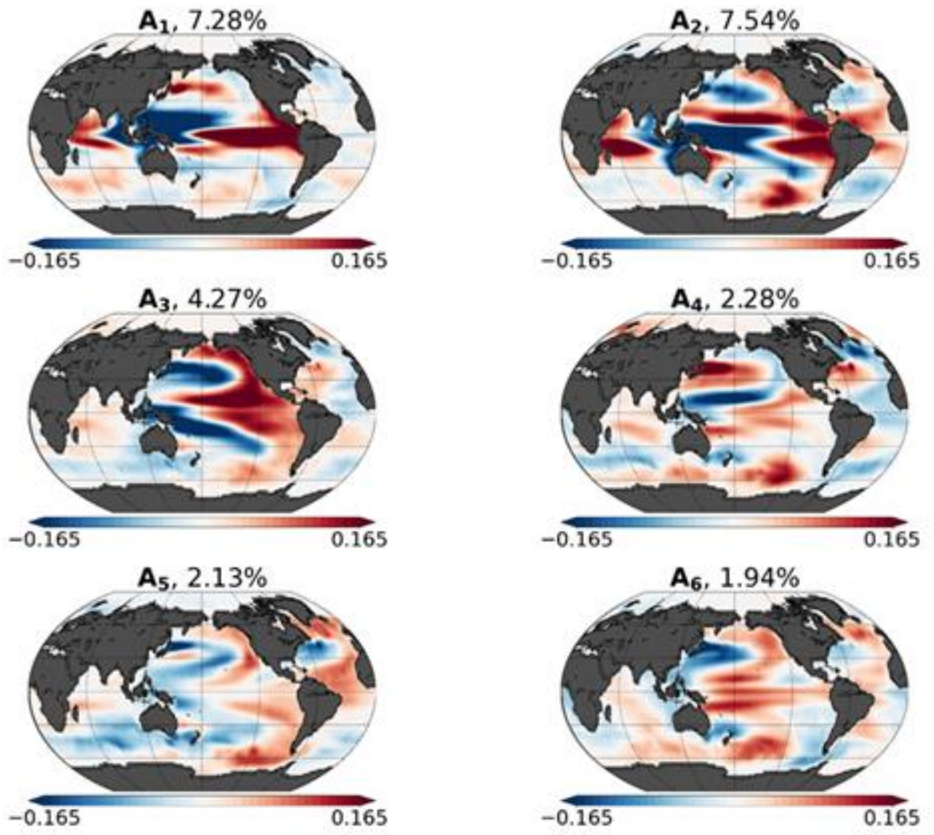
Leading modes of internal variability

SST data



℃

OHC data



$10^9 J/m^2$

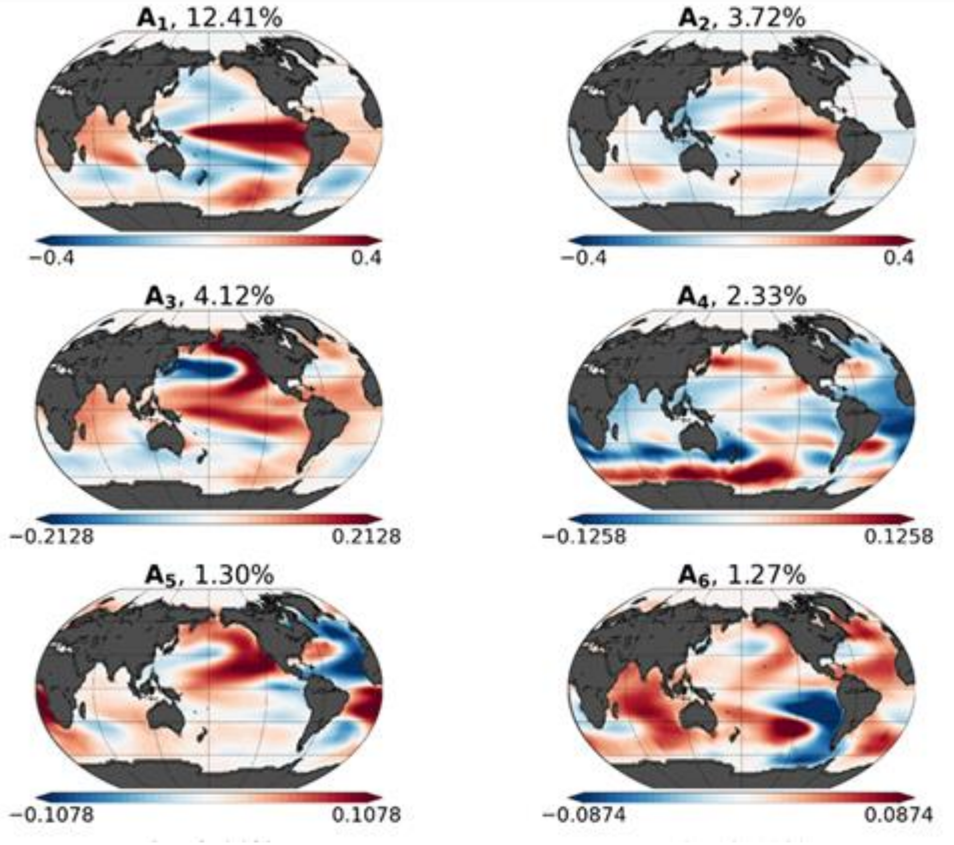
ENSO

Pacific decadal variability

Both the SST and the OHC internal modes are mainly dominated by ENSO-like and Pacific decadal variability

Leading modes of internal variability

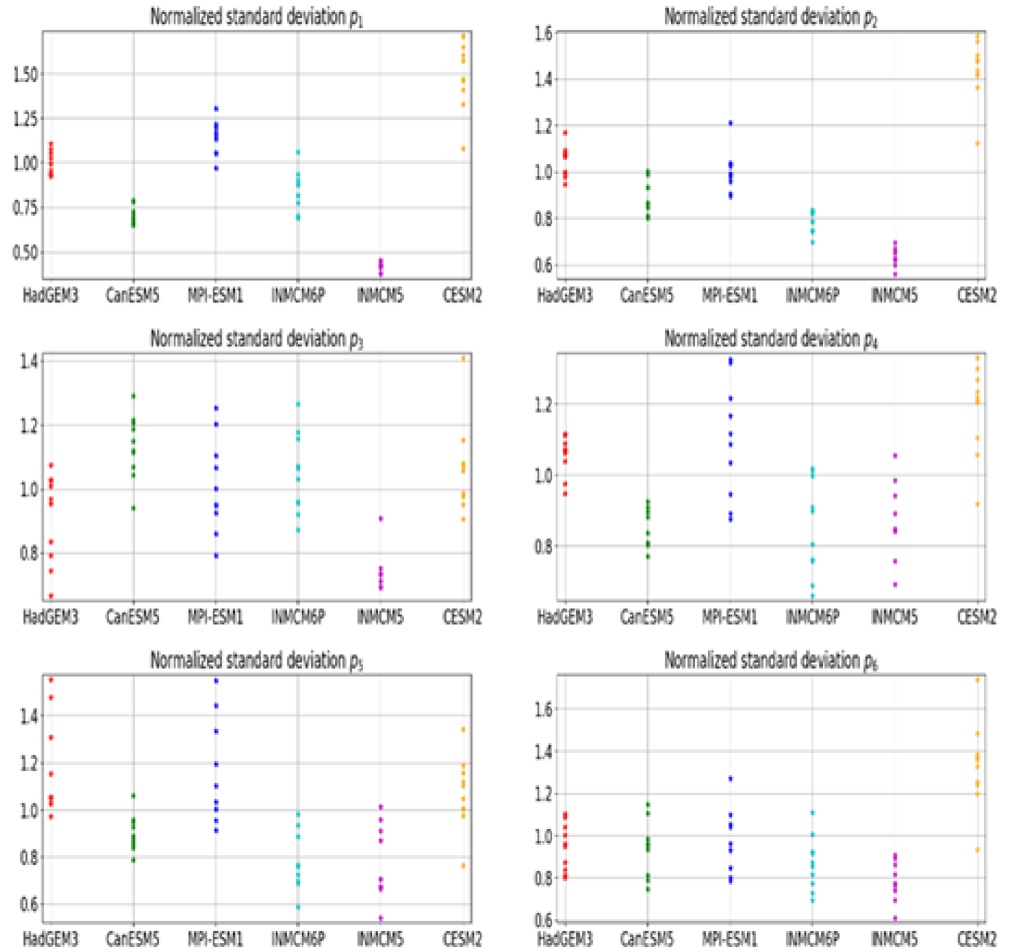
SST data



°C

ENSO

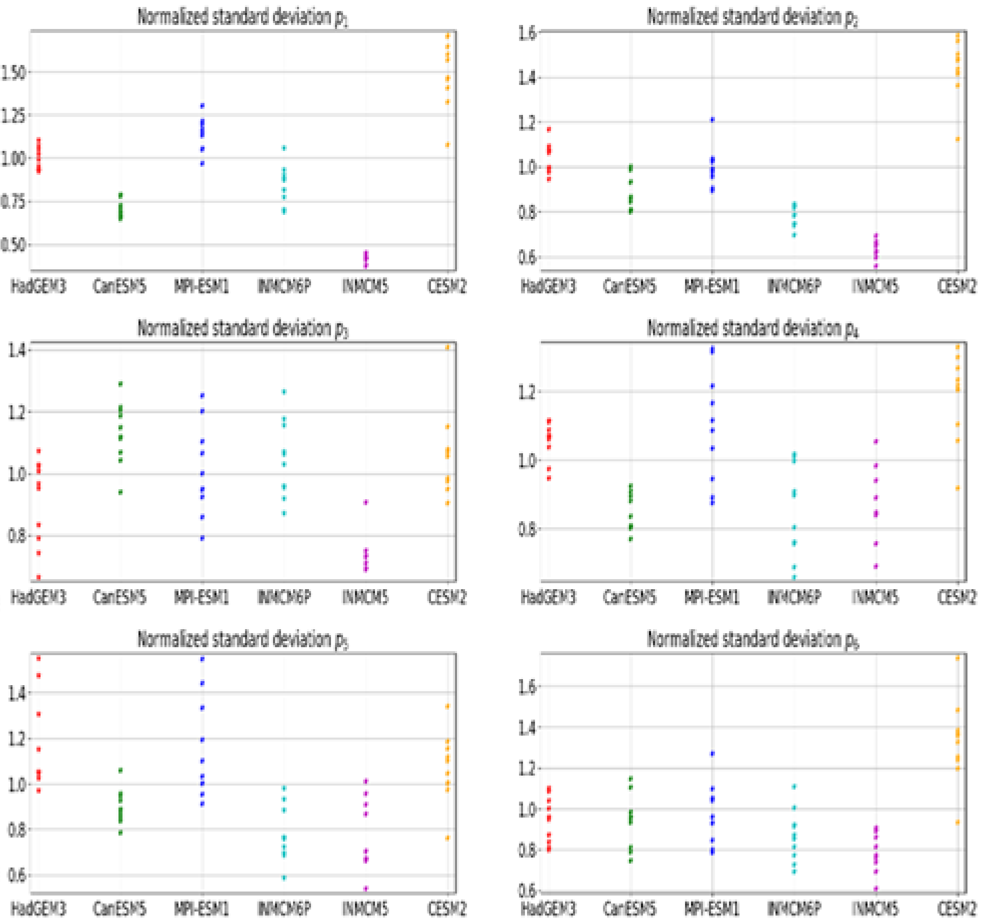
Pacific decadal variability



SST internal modes amplitudes

INMCM5 model demonstrates the lowest amplitude of the internal interannual-to-decadal variability associated with the leading SST/OHC modes

Leading modes of internal variability

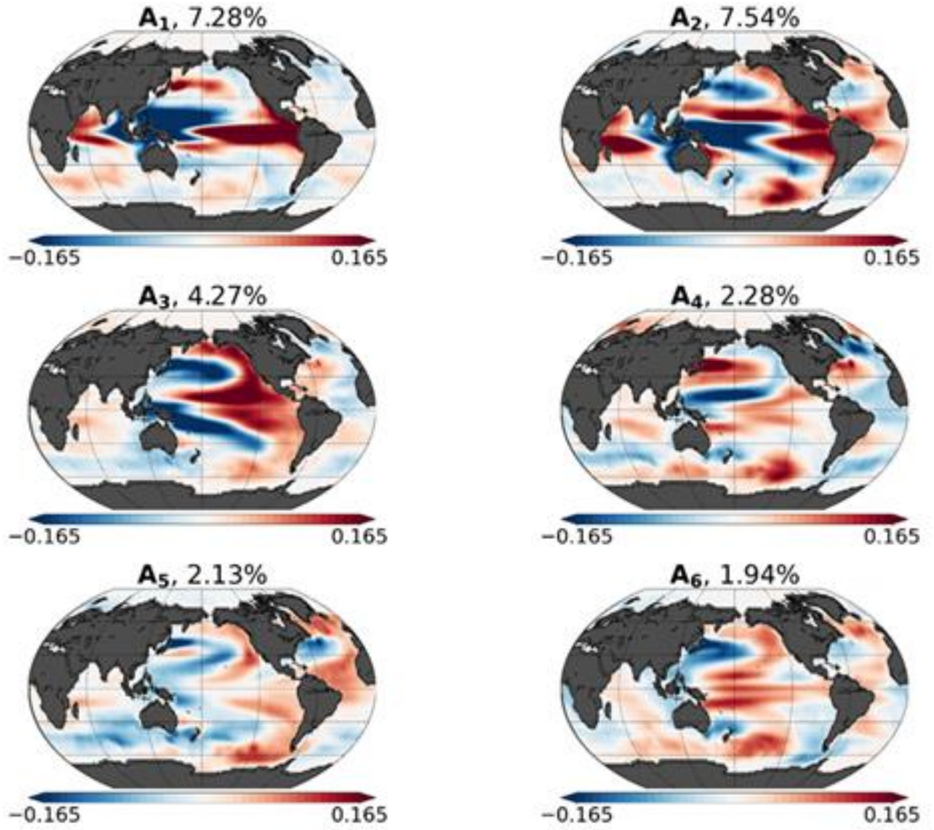


OHC internal modes amplitudes

ENSO

Pacific decadal variability

OHC data

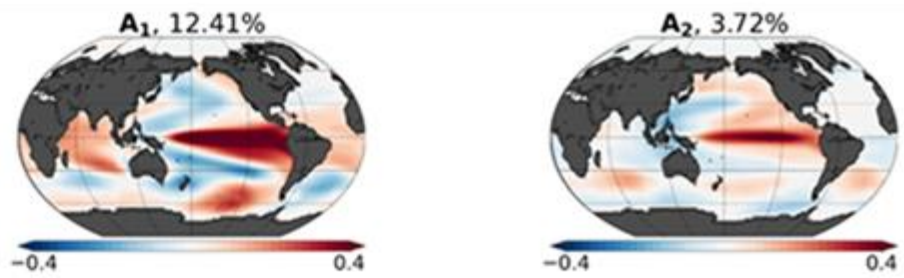


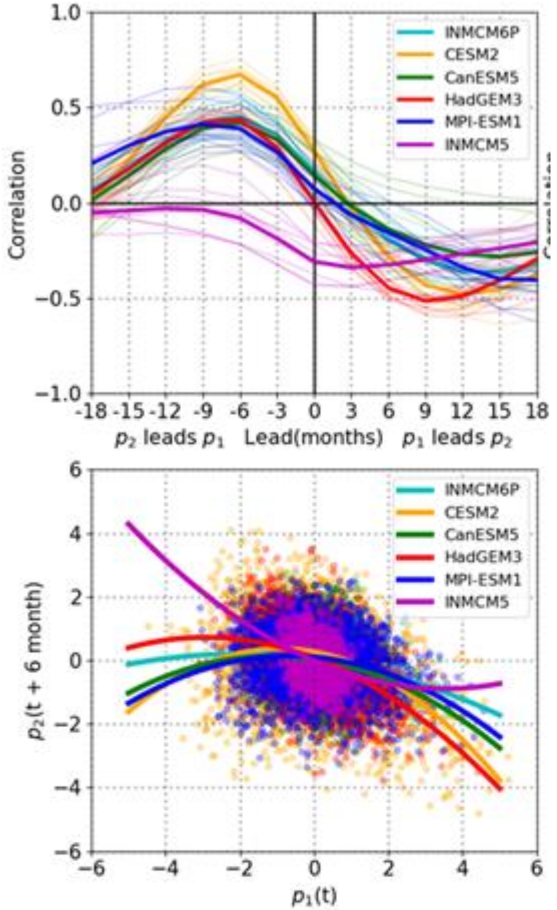
$10^9 J/m^2$

INMCM5 model demonstrates the lowest amplitude of the internal interannual-to-decadal variability associated with the leading SST/OHC modes

ENSO dynamics in different ESMs

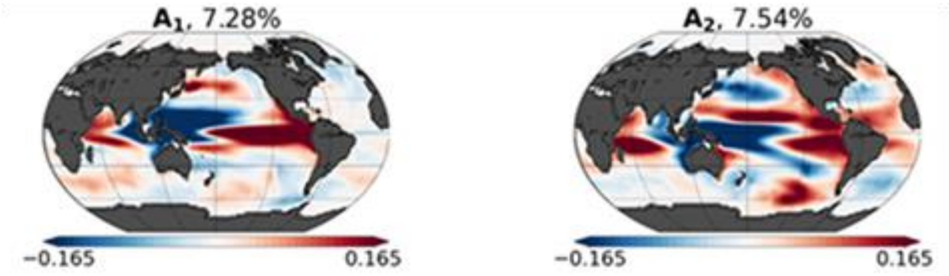
SST data

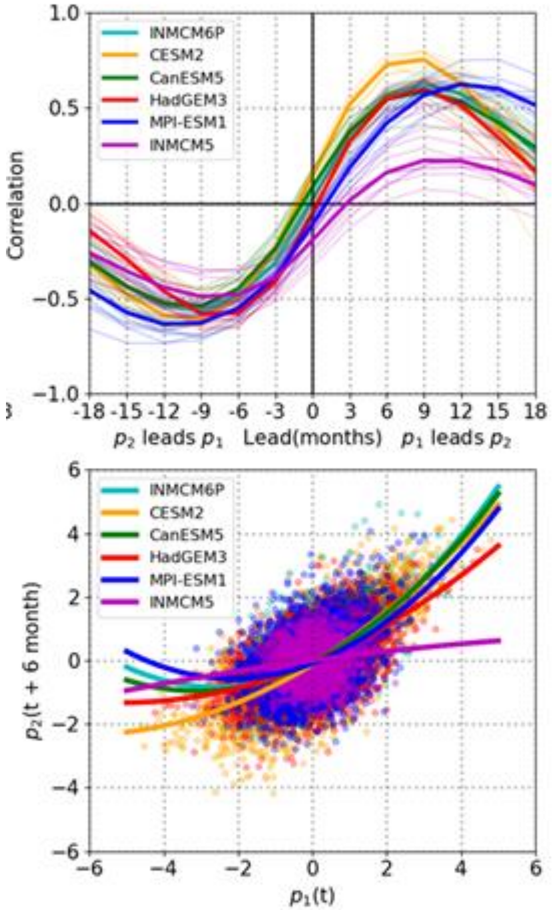




- Both SST and OHC modes demonstrate clear out-of-phase relations which are persistent across all members from ensemble of realizations within particular model
- Pronounced asymmetry of the two-dimensional probability density functions in the phase spaces of both SST and OHC modes is accompanied by statistically significant nonlinear dependencies
- INMCM5 model most poorly reproduces the essential features of observed ENSO associated with diversity and nonlinearity

OHC data





Concluding remarks

- The represented LDM method demonstrated its ability to decompose the output data of multi-model climate simulations into robust subset of forced and internal variability modes that are persistent across all models from ensemble

- Such an approach provides a natural way to objectively compare the key aspects of climate dynamics in the state-of-the-art ESMs, like CMIP5/CMIP6 models

Work in progress

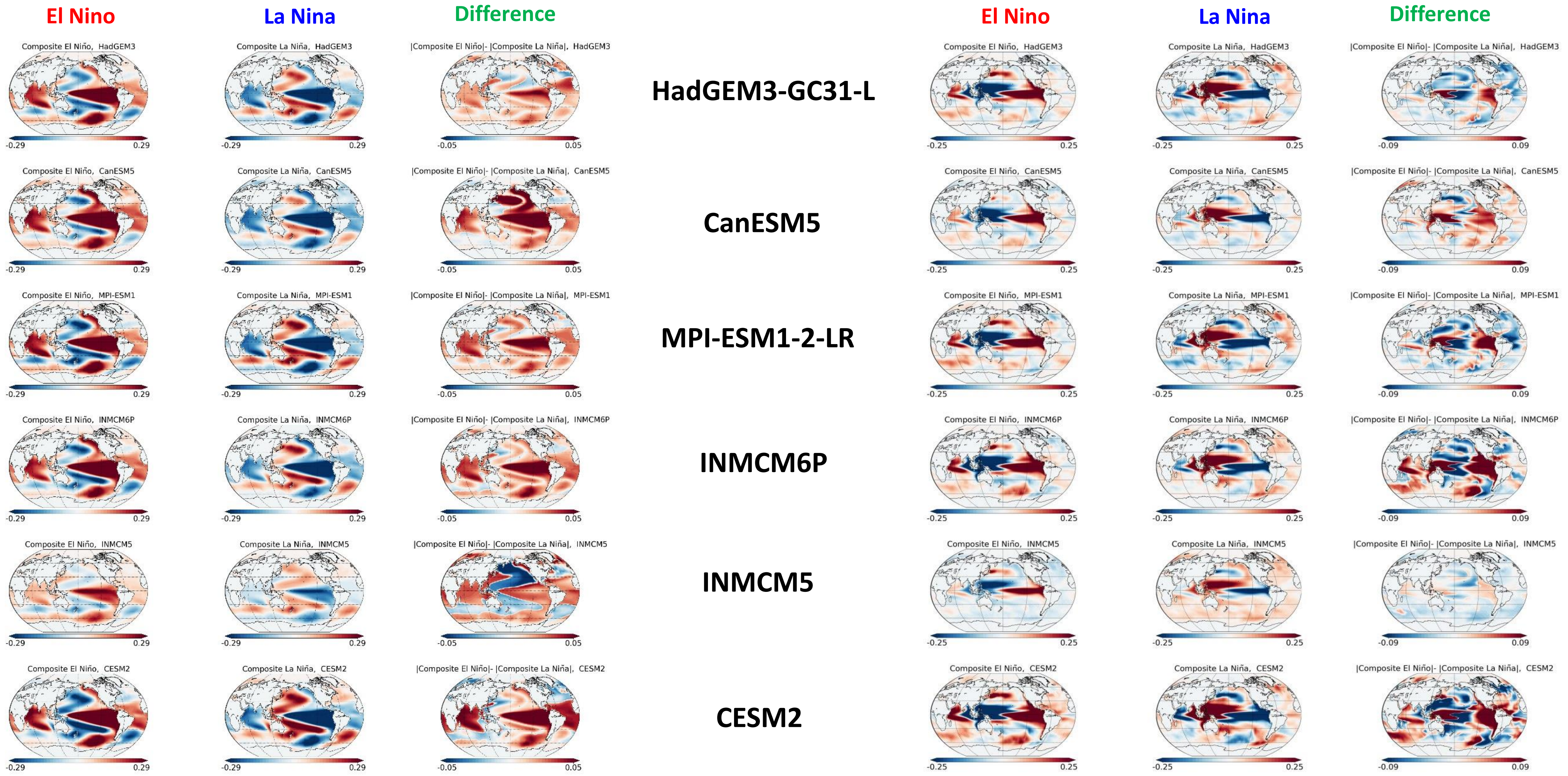
- **It is possible to include the single observed climate realization into analyzed ensemble and distinguish ESMs which dynamics best corresponds to the real climate**

- Another very promising direction is to apply LDM decomposition for phase space reconstruction aimed at getting **data-driven prognostic models**. Such a low-dimensional data-driven analogues can be utilized **for long term forecast of full climate system dynamics**, providing the **effective and computationally lightweight** tool for revealing its **dynamical response and sensitivity**

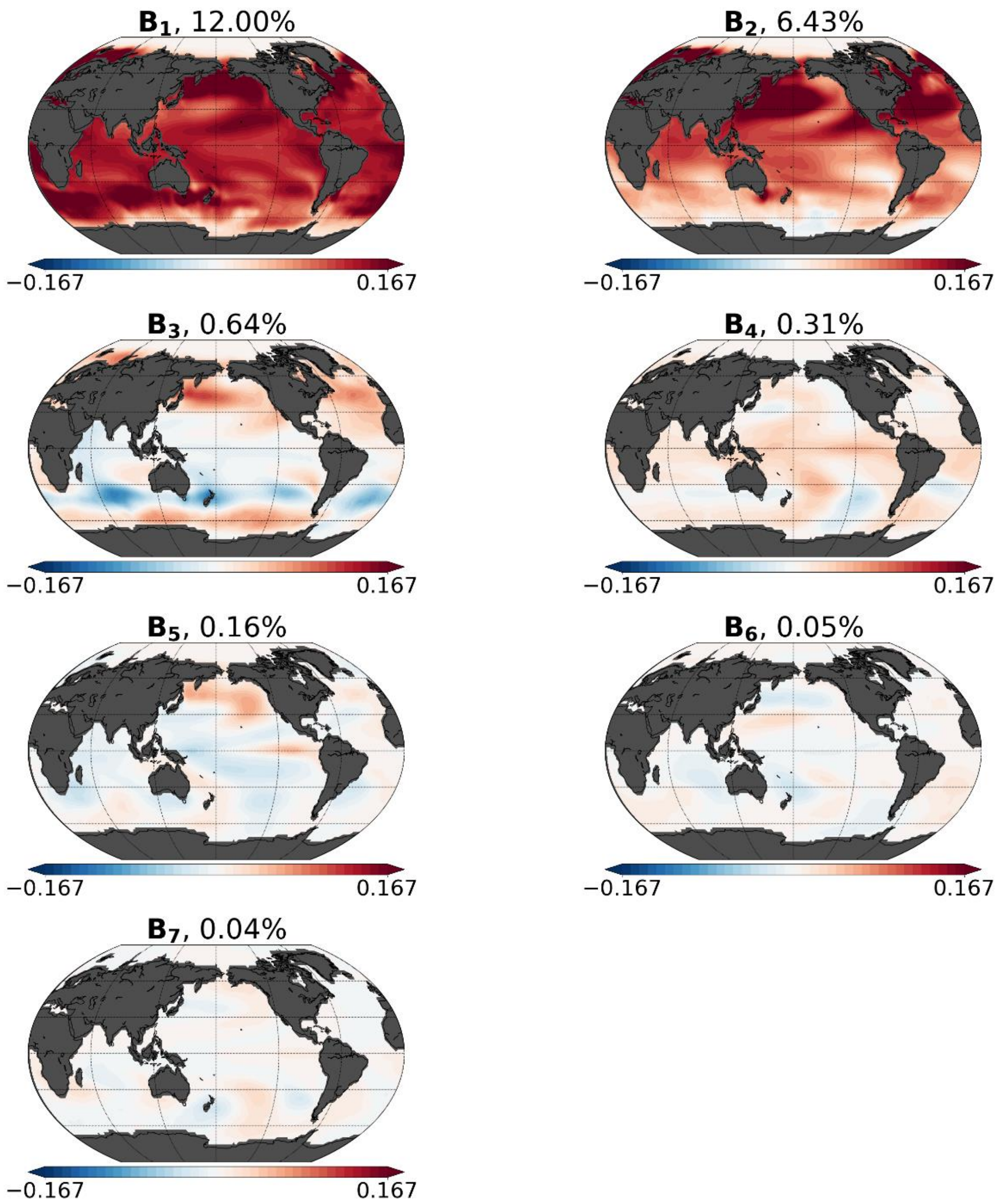
This research was supported by the state assignment of the Institute of Applied Physics of the Russian Academy of Sciences (Project No. FFUF-2025-0009)

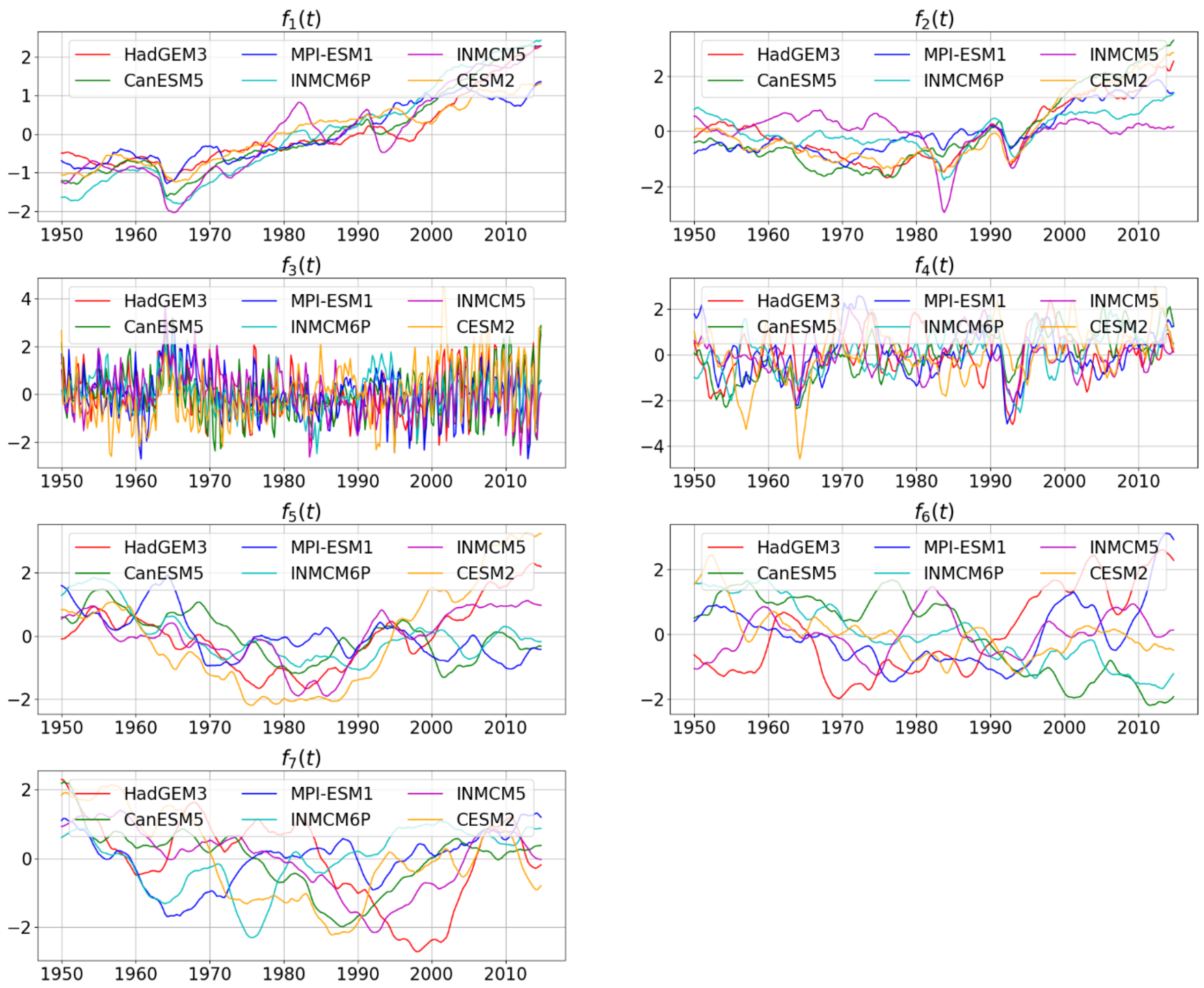
Extreme ENSO events composites

SST data **OHC data**

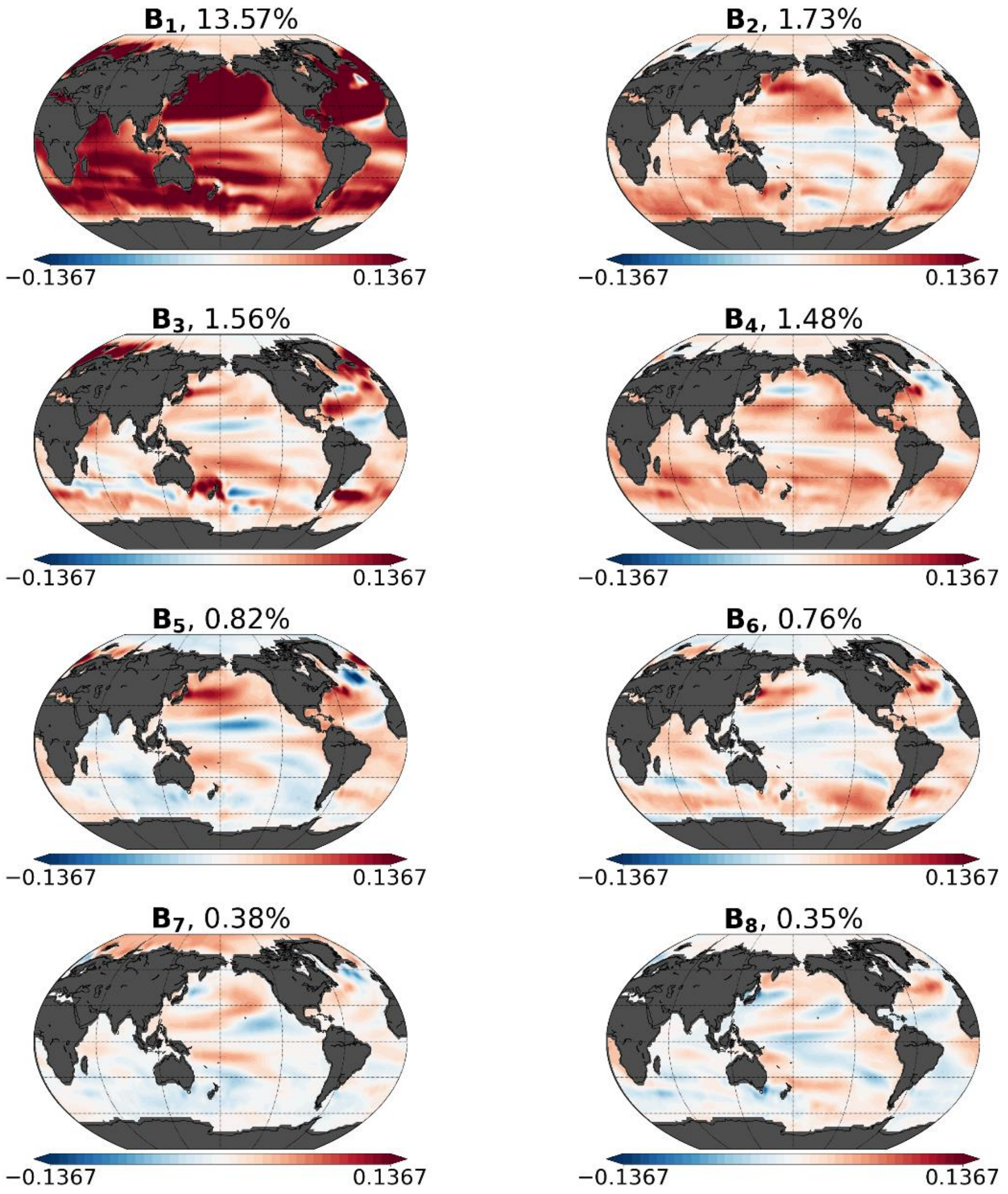


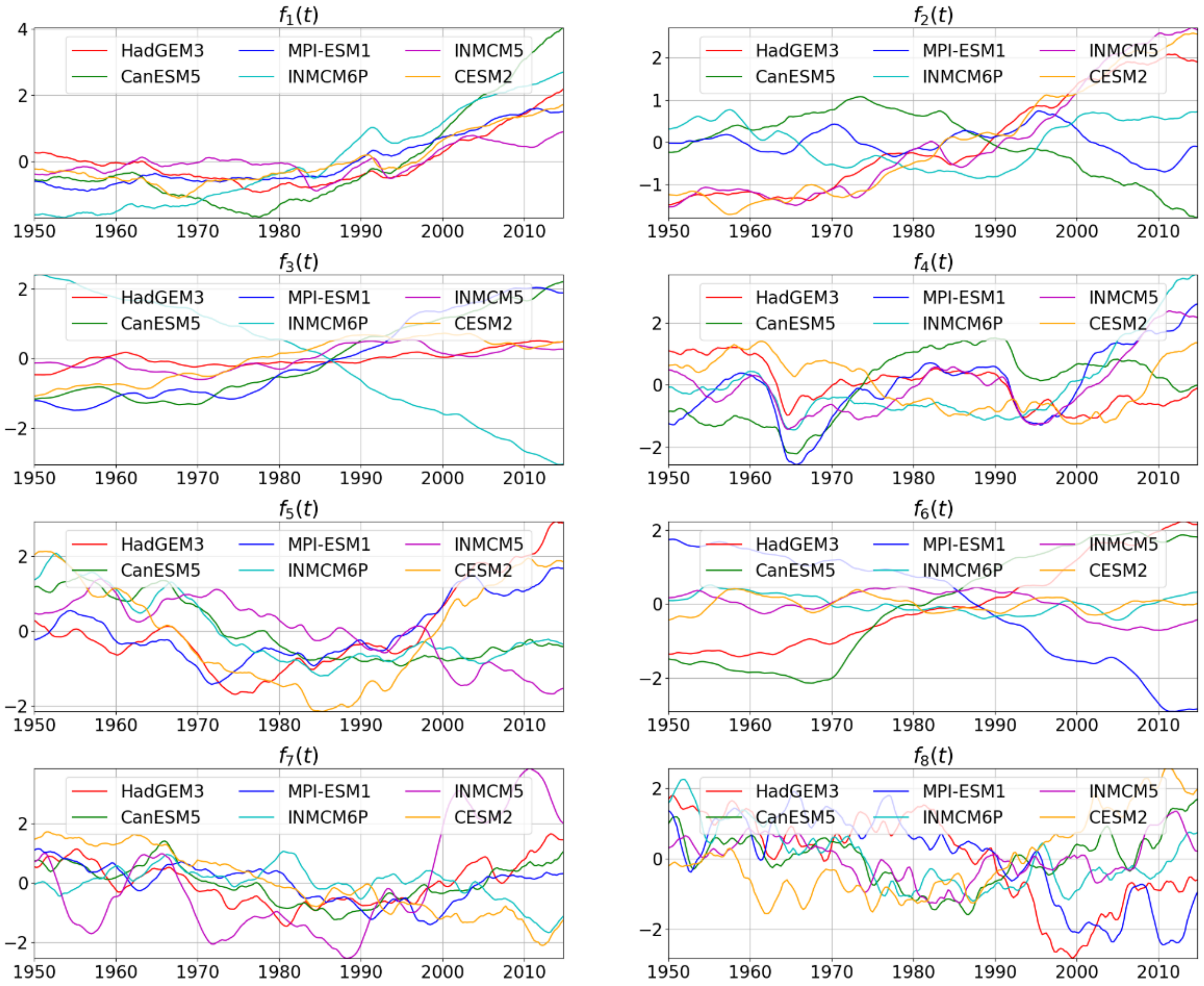
Forced SST modes



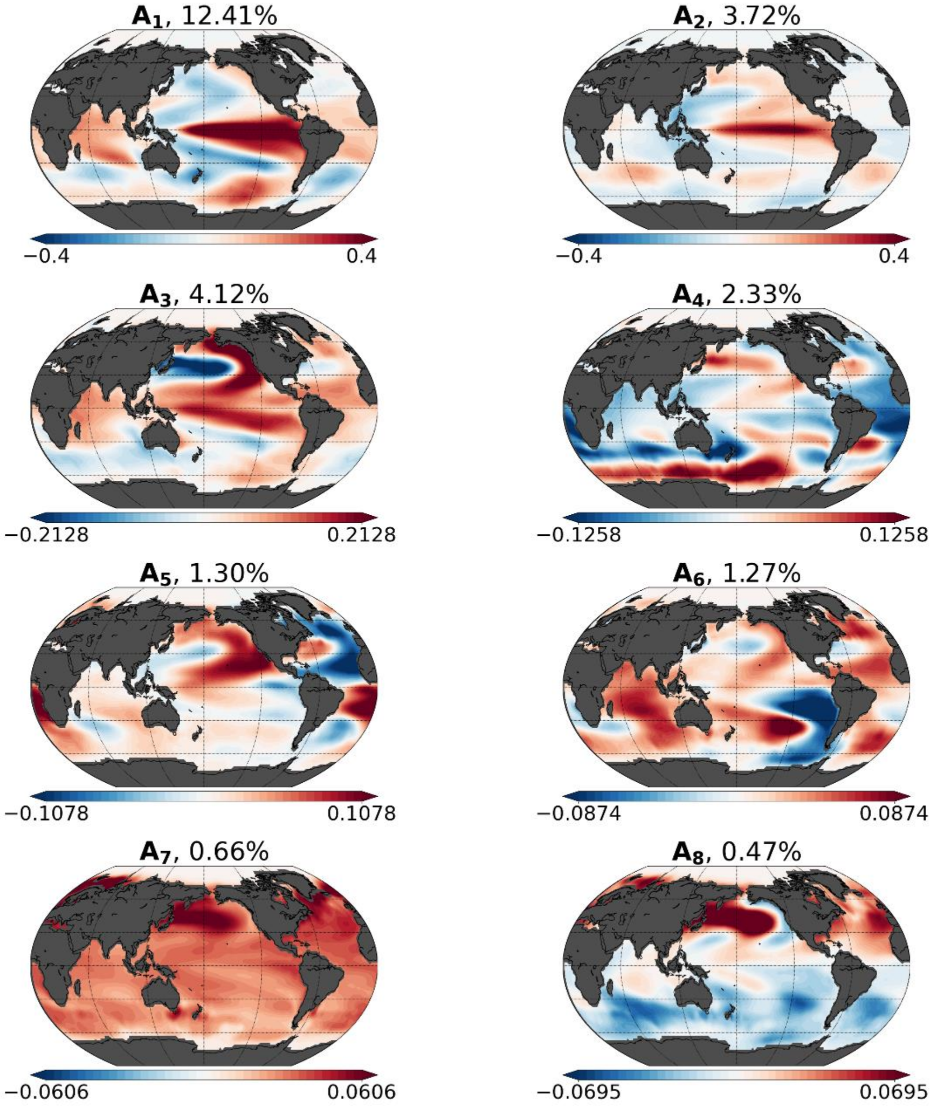


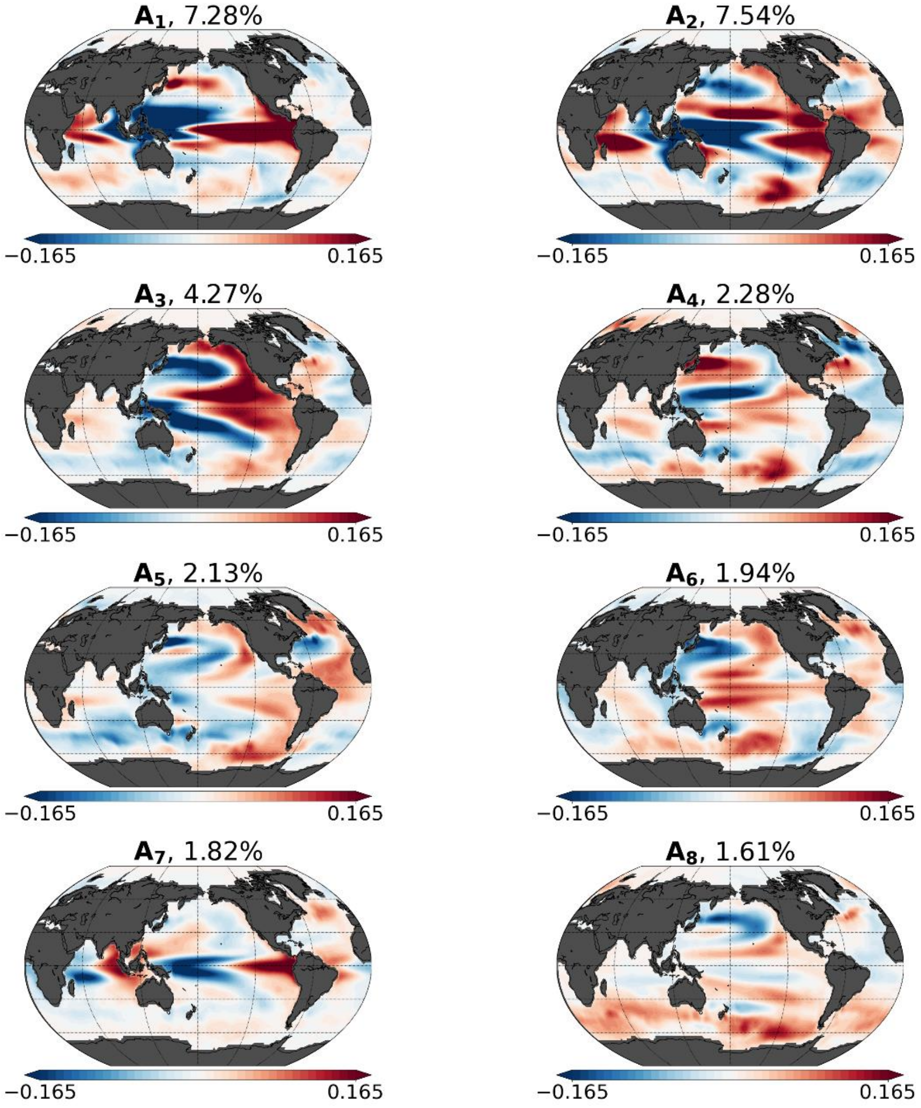
Forced OHC modes



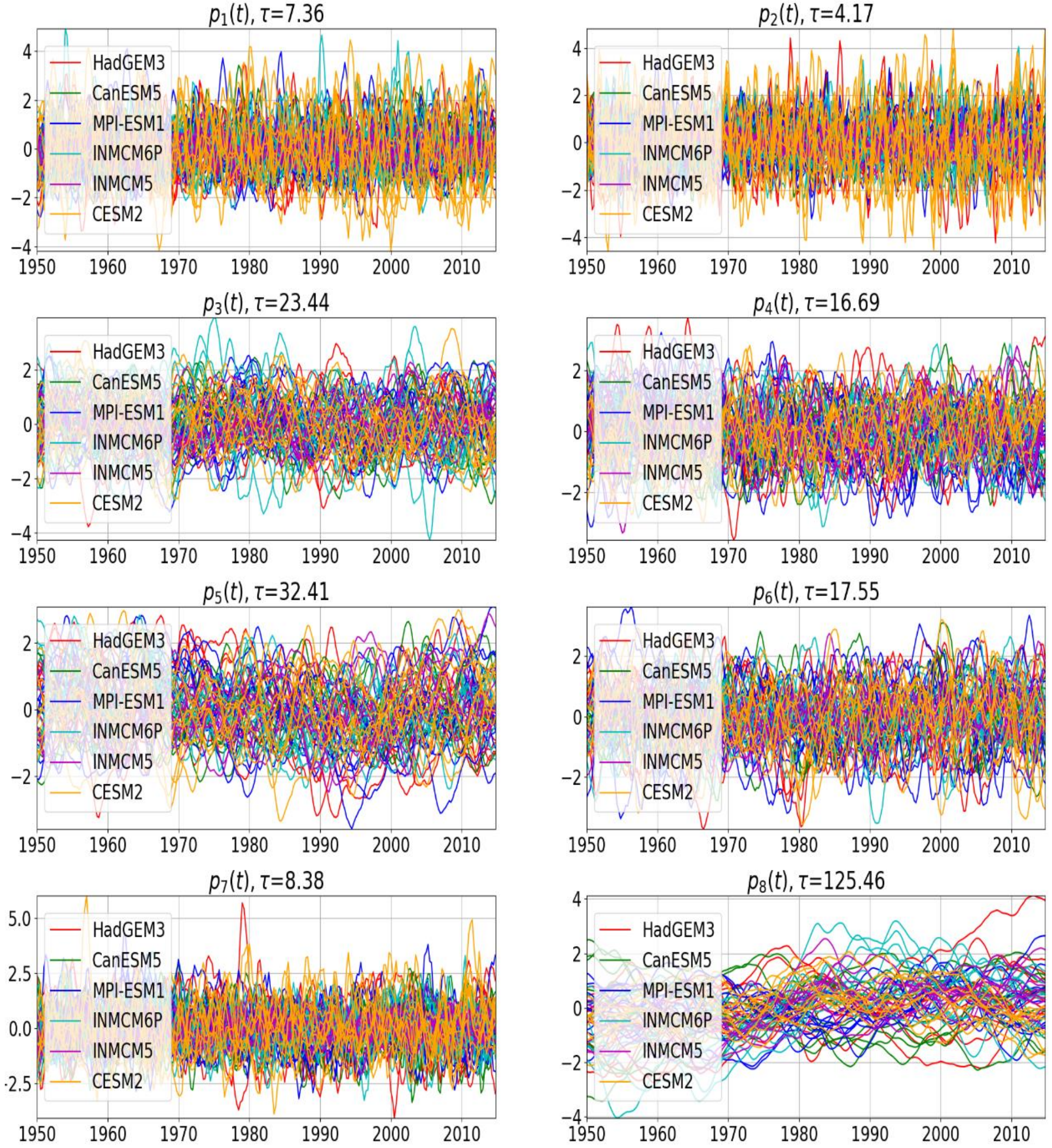


Leading modes of internal SST/OHC variability

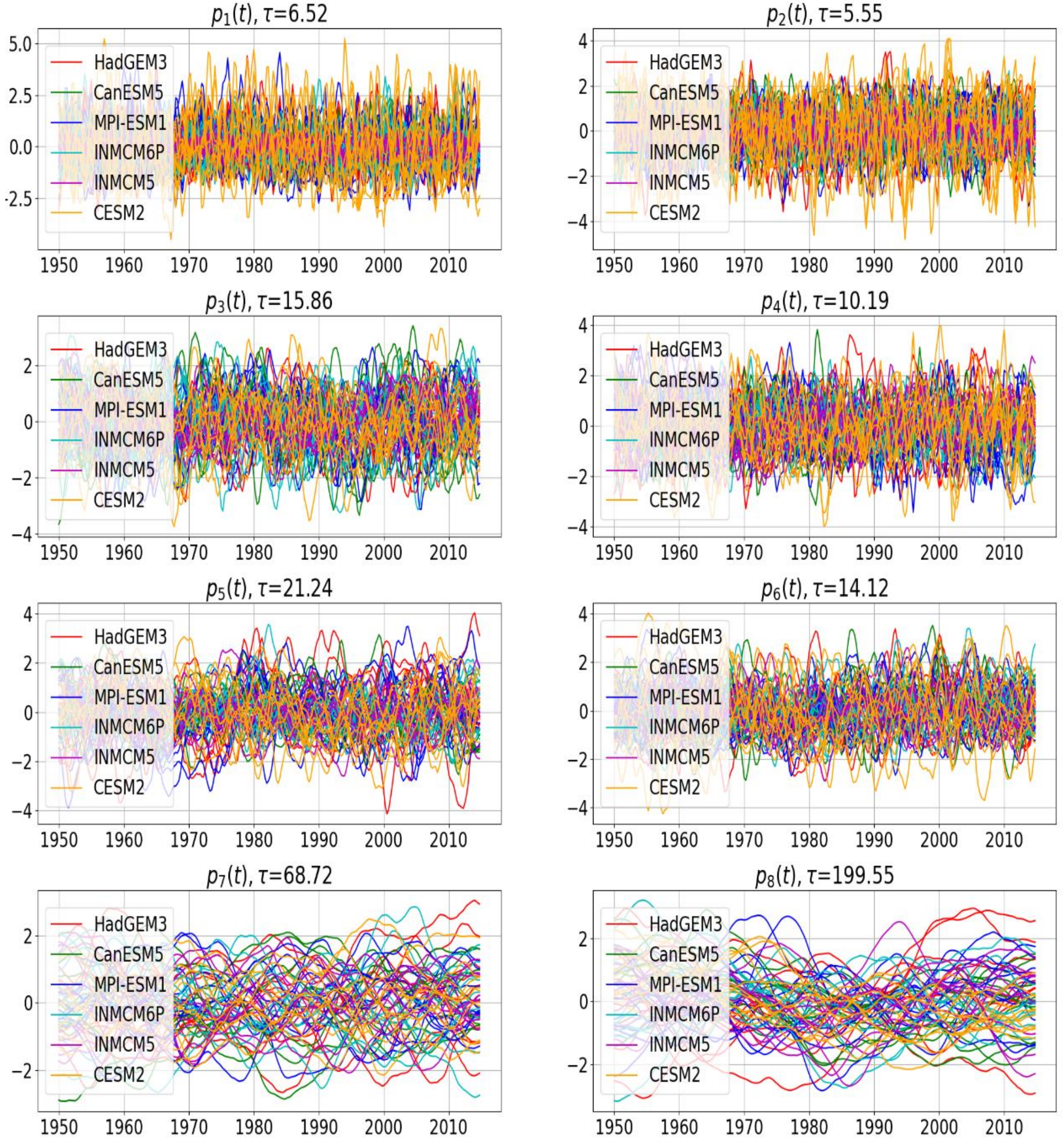


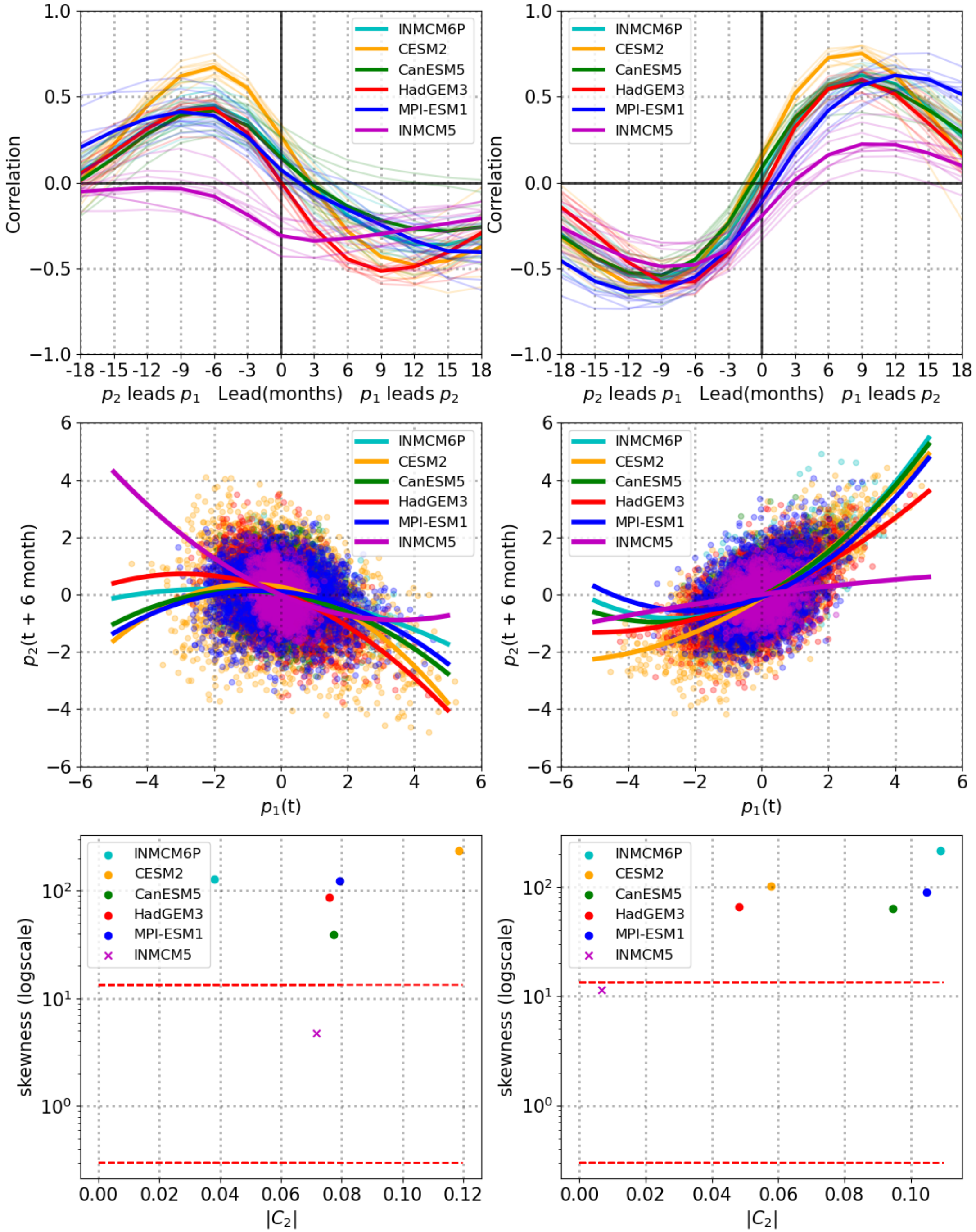


SST data



OHC data





Correlation
p_2 leads p_1 Lead(months) p_1 leads p_2
INMCM6P
CESM2
CanESM5
HadGEM3
MPI-ESM1
INMCM5
p_2(t + 6 month)
p_1(t)
skewness (logscale)
$|C_2|$