## Pacific CO<sub>2</sub> fluxes pattern analysis through SST clustering

## Pradeebane VAITTINADA AYAR Jerry TJIPUTRA



EGU General Assembly 2021 - April 27th 2021

## Outline









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## Outline









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**CONSTRAINT** the GCM uncertainties to obtain a better estimate of future climate change projections :



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CONTEXT

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One way to study spatial pattern thanks to **STATISTICAL CLUSTERING**.



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One way to study spatial pattern thanks to **STATISTICAL CLUSTERING**.

Aim : analyse carbon uptake pattern thanks SST clustering.



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CONTEXT	DATA AND METHOD	Results
Data		

Monthly **OBSERVATIONS** over pacific basin



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Data		

Monthly **OBSERVATIONS** over pacific basin

SST : JRA-55 reanalysis data 1958-2019 [KOBAYASHI *et al., 2015;* HARADA *et al., 2016*].



$( \cdot () \land () \vdash Y \downarrow$	$\frown$		 
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**fgCO**<sub>2</sub>, *P*<sub>CO<sub>2</sub></sub> : air-sea CO2 flux gridded product from 1982-2015 [LANDSCHÜTZER *et al., 2016*].



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Clustering (regrouping) applied to SST-based NINO3, NINO4 and PDO.



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## Gaussian mixture model

Approximate the distribution of a datafield x as a weighted sum of K (the number of cluster or groups) Gaussian distribution  $f_k$  [PEARSON, 1894; MCLACHLAN & PEEL, 2000] :

$$f(\mathbf{x}) = \sum_{k=1}^{K} \pi_k f_k(\mathbf{x}; \alpha_k)$$

where  $\pi_k$  is the mixture ratio.



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Each monthly field is assigned to one cluster  $C_k$  (represented by  $f_k$ ) by applying the principle of *posterior* maximum :

$$C_k = \{ \boldsymbol{x}; \pi_k f_k(\boldsymbol{x}, \boldsymbol{\alpha}_k) \geq \pi_j f_j(\boldsymbol{x}, \boldsymbol{\alpha}_j), \forall j = 1, \dots, K \}.$$

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**The BIC** to be minimised to determine K:  $BIC = -2 \log(L) + p \log(n)$ , with *p* the number of free parameters, *n* the sample's size, *L* the likelihood.

CONTEXT

DATA AND METHOD

RESULTS

Expectation-Maximization (EM) algorithm [DEMPSTER et al., 1977]

Successive iterations (i) of the E and M steps :

**EXPECTATION** (E) step : for each  $C_k$   $k \in [1, \dots, K]$ , and month  $j \in [1, \dots, n]$  :

$$\tau_k^i(x_j) = \frac{\pi_k^i f_k(x_j \mid \alpha_j^i)}{\sum\limits_{k=1}^K \pi_k^i f_k(x_j \mid \alpha_j^i)};$$

where  $\tau_k^i(x_j)$  is the posterior probability that  $x_j$  belongs to  $C_k$  at iteration *i*.



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where  $\tau_k^i(x_j)$  is the posterior probability that  $x_j$  belongs to  $C_k$  at iteration *i*.

**MAXIMIZATION** (M) step : for each  $C_k$   $k \in [1, \dots, K]$  :

$$\pi_k^{i+1} = \frac{1}{n} \sum_{j=1}^n \tau_k^i(x_j);$$

which is the Maximum likelihood of the ratios.



## Outline









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#### CONTEXT

#### DATA AND METHOD

RESULTS

## Clustering results



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#### DATA AND METHOD

RESULTS

## Observed patterns (1985-2014)





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#### DATA AND METHOD

#### RESULTS

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## Observed patterns (1985-2014)



Carbone Uptake Flux fgCO<sub>2</sub> Anomalies [TgC.yr<sup>-1</sup>]



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## CMIP6 patterns (1985-2014)



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RESULTS

## Results for CMIP6 : NINO34 vs. fgCO2 anomalies



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## CMIP6 NINO34 vs. fgCO2 anomalies

	Correlation fgCO <sub>2</sub> vs. NINO3.4		
	1985-2014	2071-2100	
OBS	.76	-	
ACCESS-ESM1-5	.63	5	
CanESM5-CanOE	.42	43	
CanESM5	.40	35	
CESM2	.69	.14	
CESM2-WACCM	.60	.27	
CNRM-ESM2-1	.23	.48	
GFDL-CM4	.16	54	
GFDL-ESM4	.40	24	
IPSL-CM6A-LR	.79	.35	
MIROC-ES2L	.83	34	
MPI-ESM1-2-HR	62	62	
MPI-ESM1-2-LR	54	83	
MRI-ESM2-0	.58	74	
NorESM2-LM	.32	27	
NorESM2-MM	.74	15	
UKESM1-0-LL	.52	.48	

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## CMIP6 NINO34 vs. fgCO2 anomalies

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## CMIP6 $fgCO_2$ anomalies vs. NINO3.4/ $P_{CO_2}^{nt}$ anomalies

**NON-THERMAL**  $P_{CO_2}^{nt} = P_{CO_2} \exp (\gamma_T (< SST > -SST)),$  $\gamma_T : CO_2$  temperature sensitivity (4.23%·°C<sup>-1</sup>), < SST > : long-term mean SST [LANDSCHÜTZER *et al., 2018*].



## CMIP6 $fgCO_2$ anomalies vs. NINO3.4/ $P_{CO_2}^{nt}$ anomalies

	Correlation fgCO <sub>2</sub> vs.				
	NIN	03.4	Non-thermal P		
	1985-2014	2071-2100	1985-2014	2071-2100	
OBS	.76		85		
ACCESS-ESM1-5	.63	5	38	.37	
CanESM5-CanOE	.42	43	33	.18	
CanESM5	.40	35	34	.14	
CESM2	.69	.14	3	28	
CESM2-WACCM	.60	.27	28	29	
CNRM-ESM2-1	.23	.48	01	60	
GFDL-CM4	.16	54	02	.38	
GFDL-ESM4	.40	24	16	04	
IPSL-CM6A-LR	.79	.35	24	28	
MIROC-ES2L	.83	34	36	.31	
MPI-ESM1-2-HR	62	62	.20	.17	
MPI-ESM1-2-LR	54	83	.09	.31	
MRI-ESM2-0	.58	74	54	.31	
NorESM2-LM	.32	27	09	.02	
NorESM2-MM	.74	15	27	.05	
UKESM1-0-LL	.52	.48	32	29	

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# Thank you for your attention !!

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