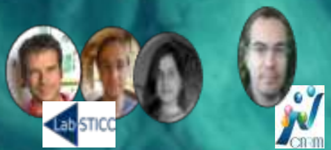
DEEP LEARNING APPROACHES TO ELUCIDATE PHYTOPLANKTONIC CLIMATE INDUCED VARIABILITY

(ANR PRC DREAM, 2023-27)

IA



R. Fablet, L. Dumetz
M. Lakra

O. Pannekoucke

Biogeochemistry

Thomas Gorgues *Elodie Martinez*

Keerthi Madhavan *Etienne Pauthenet*

Ecology

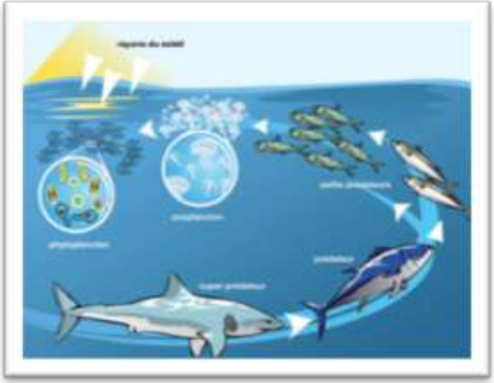
M. Sourisseau *D. Raitsos* *M. Messié*

M. Roux

Physics- Climate projections

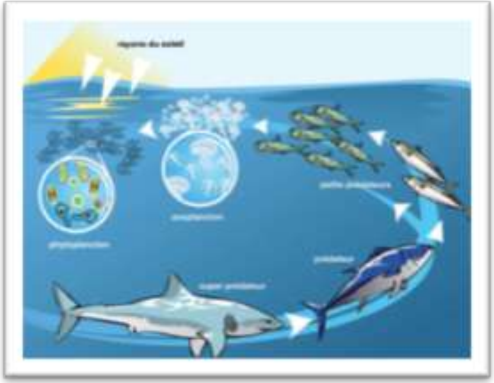
S. Kwatra

M. Lengaigne



Support the oceanic foodweb

- Impact on the upper trophic levels



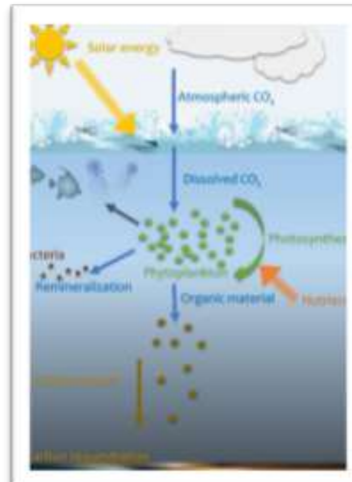
Support the oceanic foodweb

- Impact on the upper trophic levels

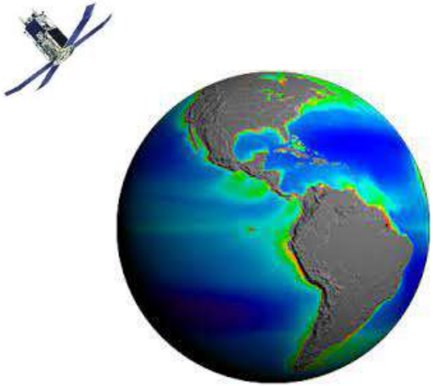
Key role in the global carbon cycle

- Sequestration of 2/3 of antropogenic Carbon (biological carbon pump; Takahashi et al., 2009)

- Production ½ of O2 on earth

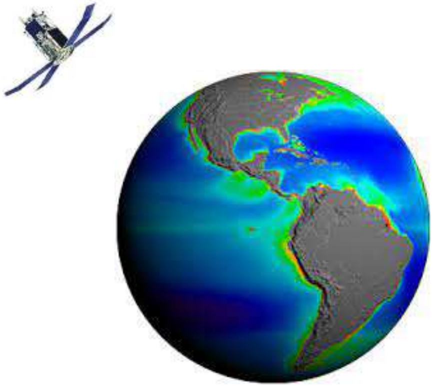


Satellite observations



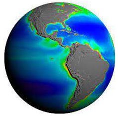
In situ observations

Satellite observations



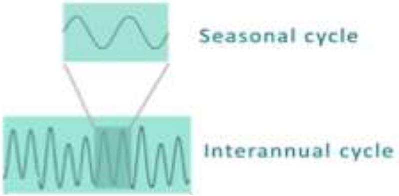
In situ observations

Numerical modelling



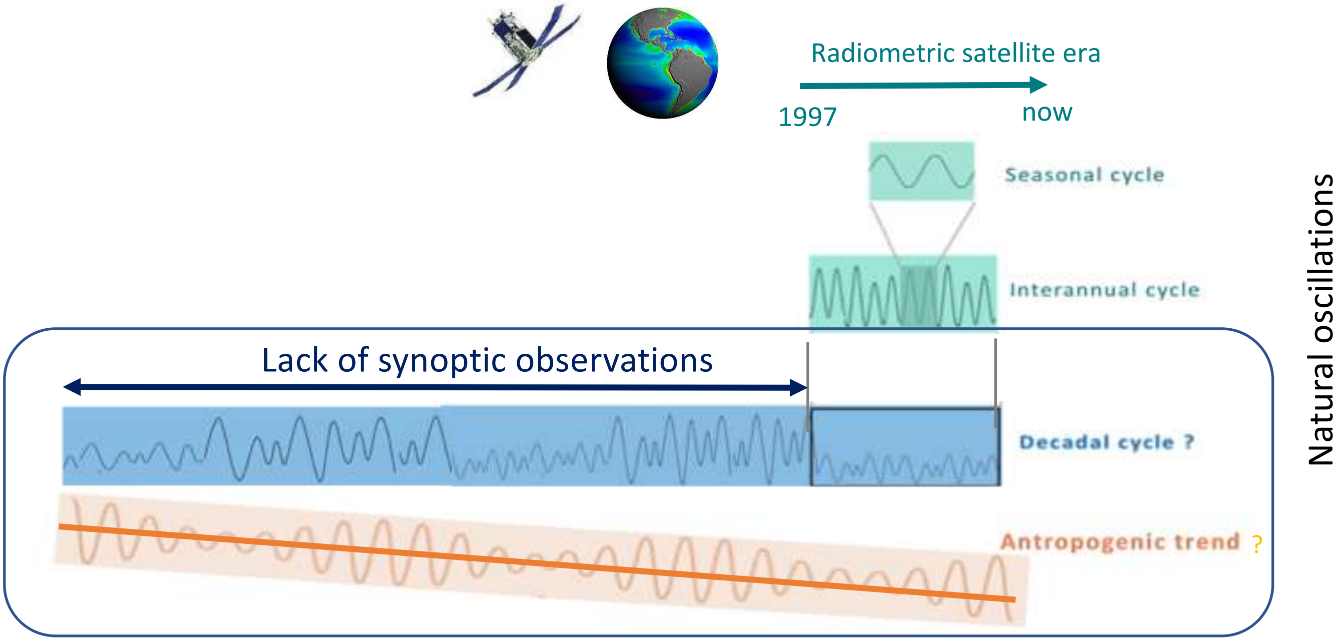
Radiometric satellite era

1997 now



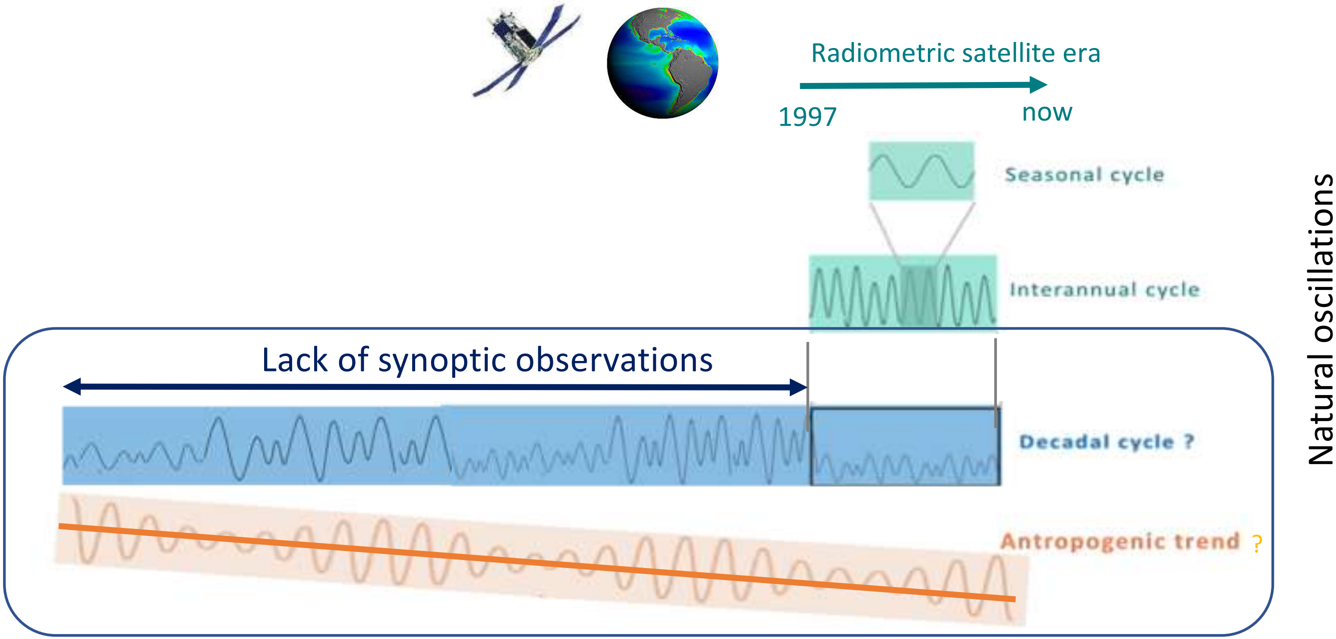
Natural oscillations

?



scientific lock 1:

- Too short satellite obs. time-series



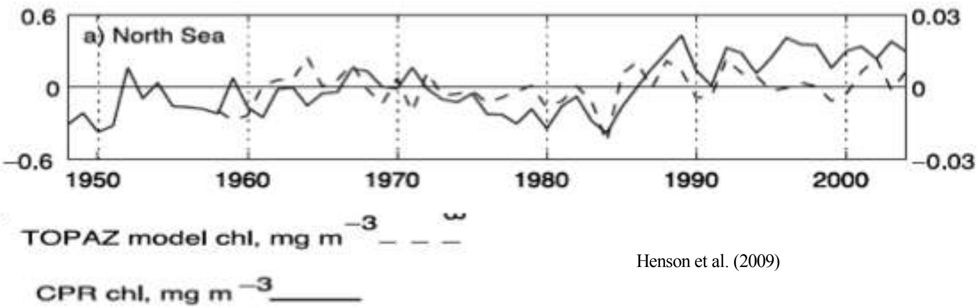
scientific lock 1:

- Too short satellite obs. time-series

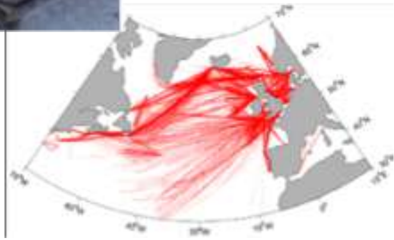
Aim 1:

- Identify the natural oscillations vs. anthropic trend
- Understand the underlying BGC-physical processes

Proof of concept with machine learning Martinez et al., 2020a; 2022; Roussillon et al. (2023)



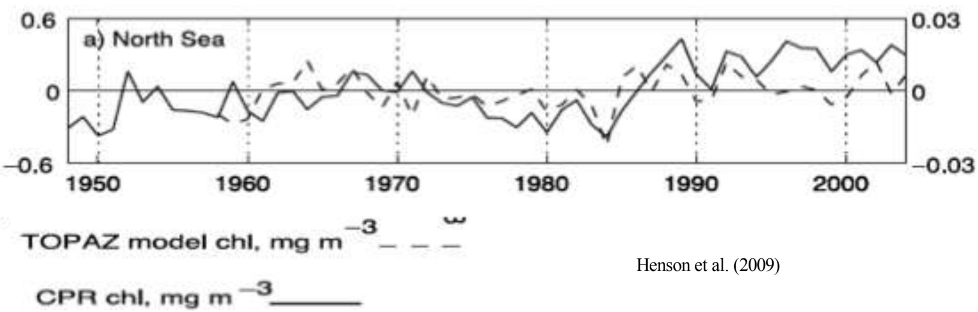
Henson et al. (2009)



Continuous Plankton Recorder (CPR) since 1960

scientific lock 2:

- Difficulty in parameterizing biology in BGC models (i.e., multi-decadal and regime shifts)



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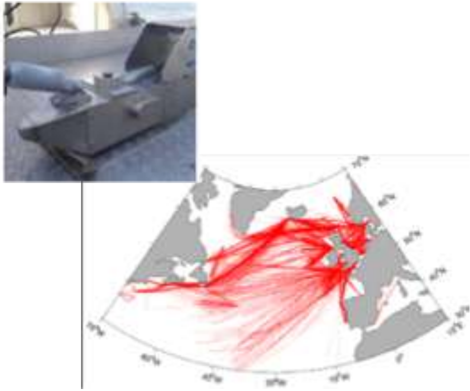


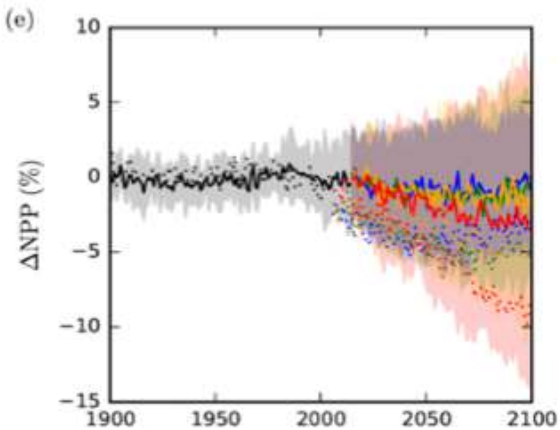
Continuous Plankton Recorder (CPR) since 1960

scientific lock 2:

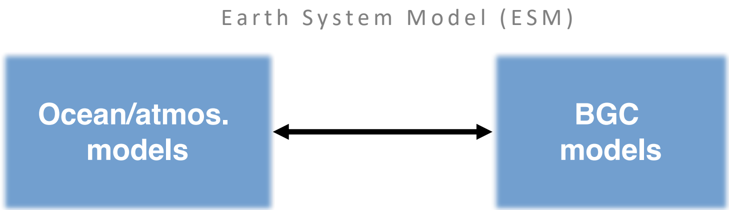
- Difficulty in parameterizing biology in BGC models (i.e., multi-decadal and regime shifts)

Aim 2:

- Better understand biotic and abiotic interactions on the phyto- & zoo plankton biomass and communities

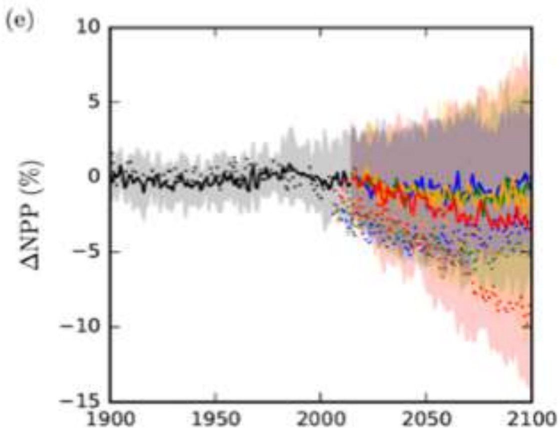


Global mean projections of depth-integrated net primary production (%)
(from Kwiatkowski et al., 2020)



scientific lock 3:

- Wide cone of uncertainty on climate projections



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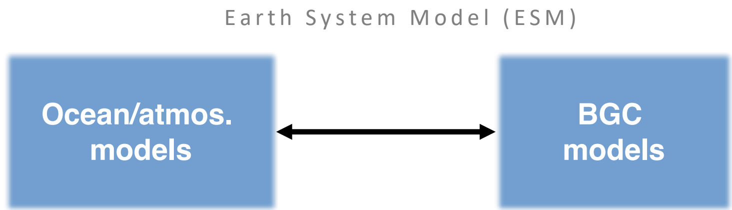


scientific lock 3:

- Wide cone of uncertainty on climate projections

Aim 3:

- Quantification of ESM’s uncertainty related to physical forcing & to biogeochemical model formulation
- Identification of physical processes

Aim:

- assess multi-decadal variability & trends of phytoplankton biomass
- Understand the underlying physical and BGC processes

WP1 Improve the deep learning architectures through various emulators

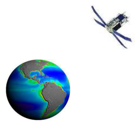
- Data-driven: Y= f(X)
- Ordinary and Partial Differential Equations: $\partial_t Y = f(\partial_t X)$, $\partial_t Y = f(\partial_t X, \partial_t Y)$....

Deep leaRning approaches to Elucidate phytoplAnktonic cliMate induced variability (ANR PRC DREAM, 2023-27)

Aim:

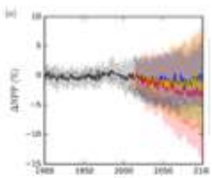
- assess multi-decadal variability & trends of phytoplankton biomass
- Understand the underlying physical and BGC processes

WP2a: reconstruct past multi-decadal reconstruction at global scale



1978 1985 1997 now

WP3: quantify physical & bgc uncertainties in climate models



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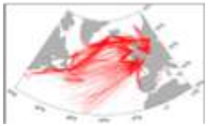
WP2b: better understand the link between phyto and zooplankton biomass and communities



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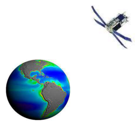

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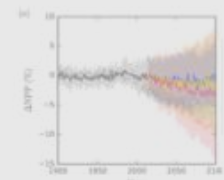

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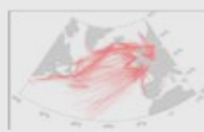
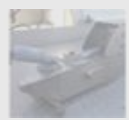
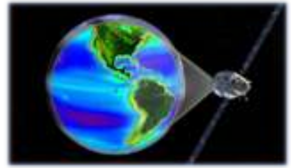
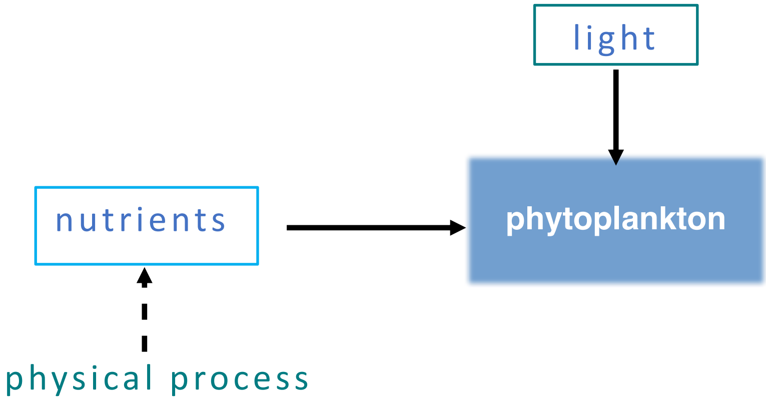




WP1 & 2.a: Reconstruct long time-series of Chl at global scale from DL

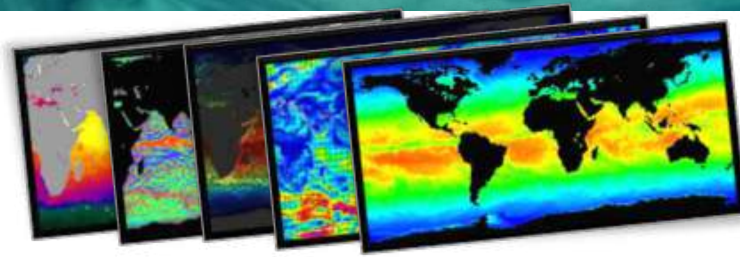




Hypothesis: physically driven at global scale

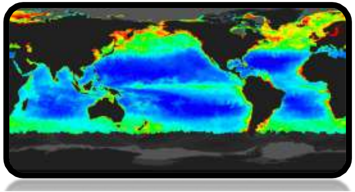
WP1 & 2.a: Reconstruct long time-series of Chl at global scale from DL

Physical predictors:
Sea surface temperature
Sea level anomaly
Surface currents
Light
….



2003

2022



Target:
Satellite Chl

WP1 & 2.a: Reconstruct long time-series of Chl at global scale from DL

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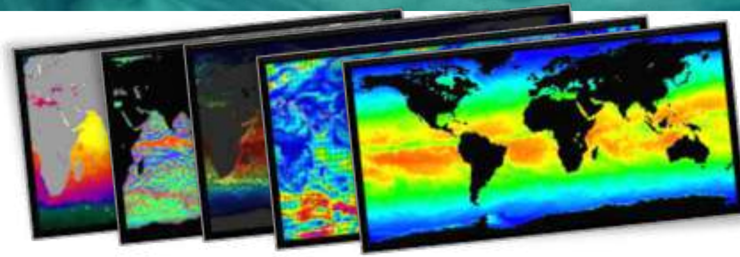

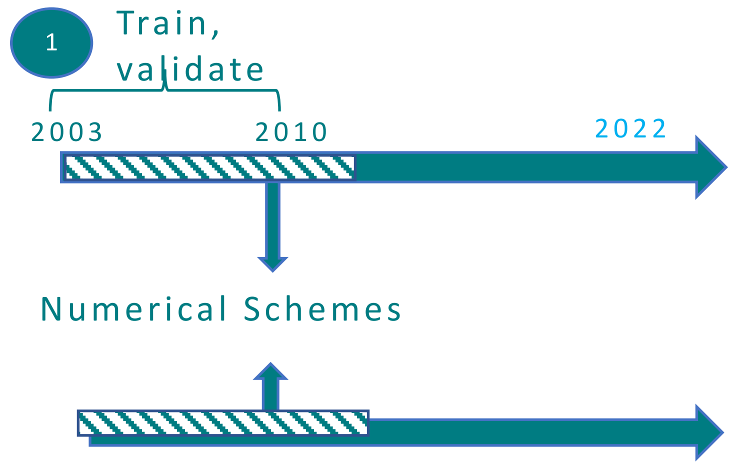

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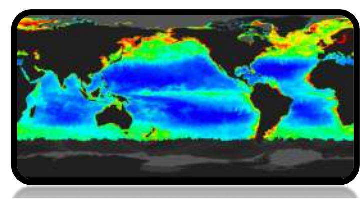

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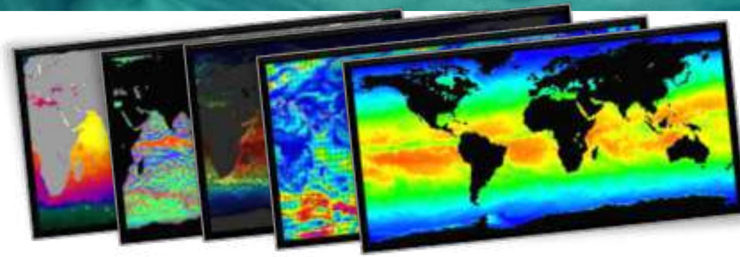

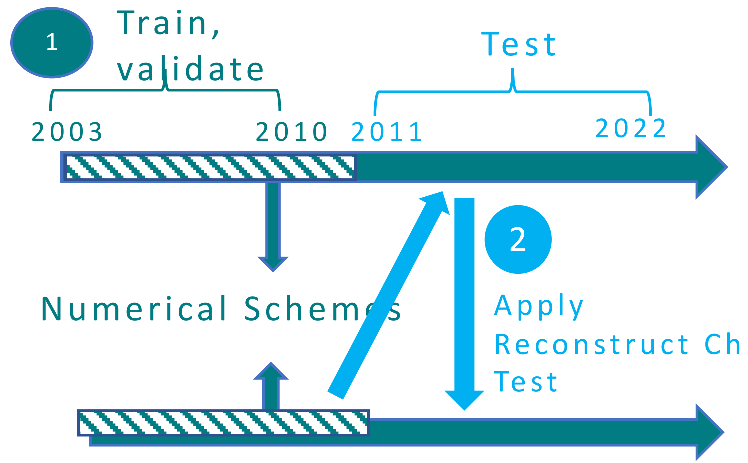

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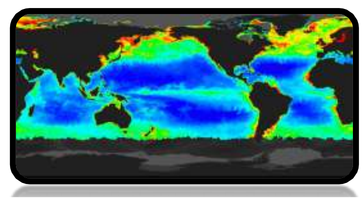

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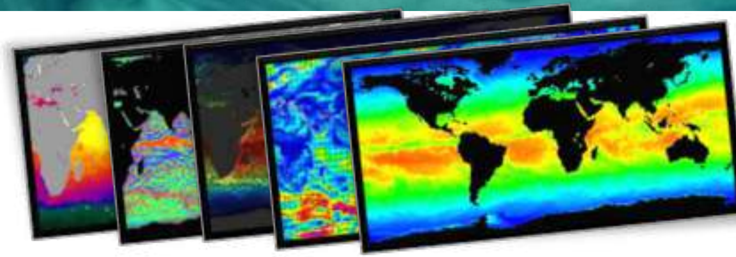
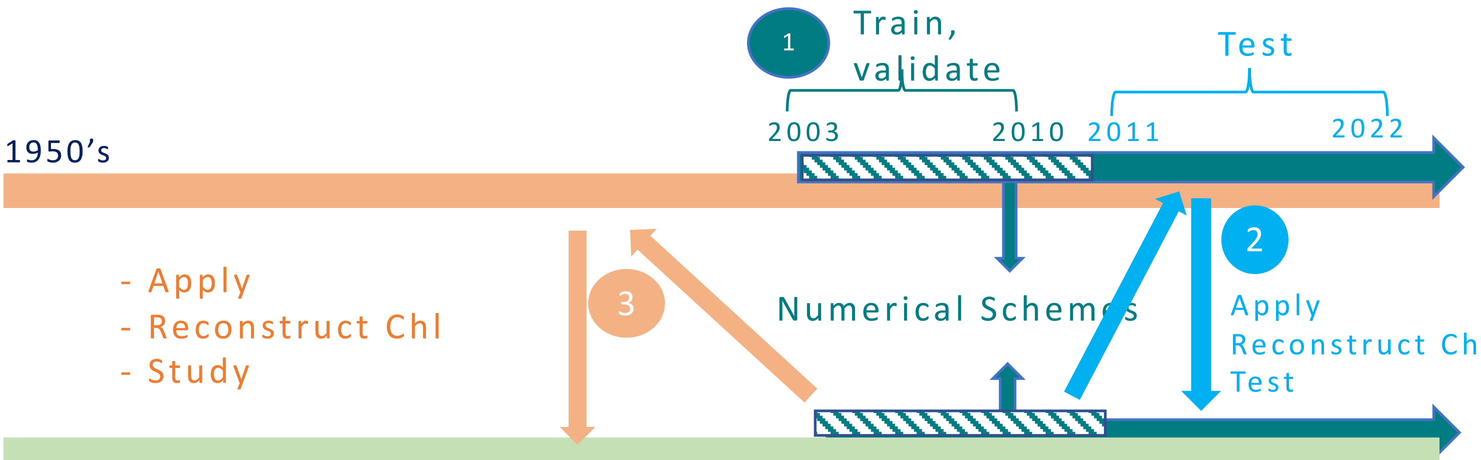
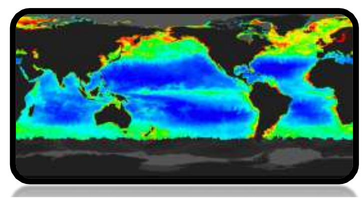


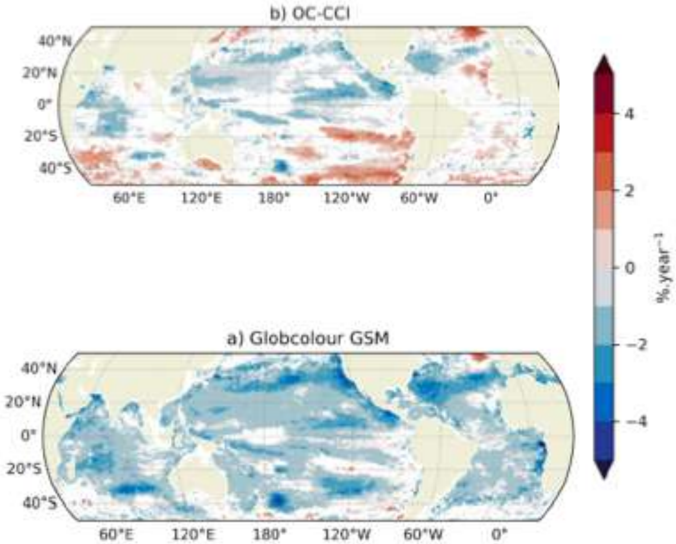


→ $Chl_{Reconstructed}$
Data analysis

Target:
Satellite Chl

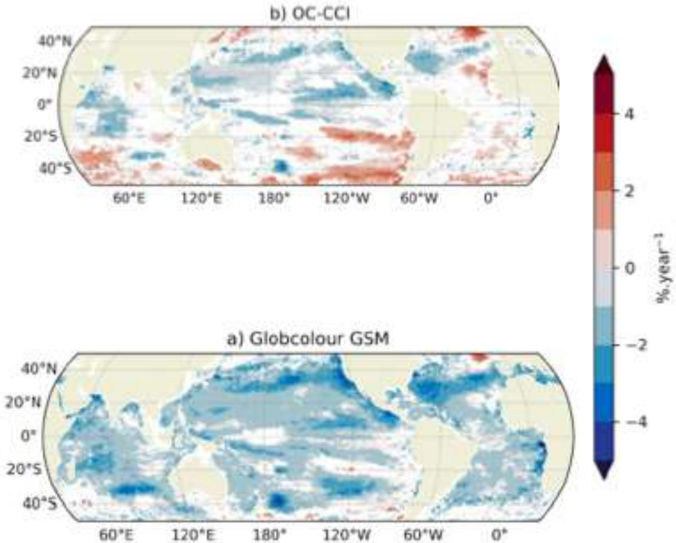


Satellite Chl trends over 2002-2020



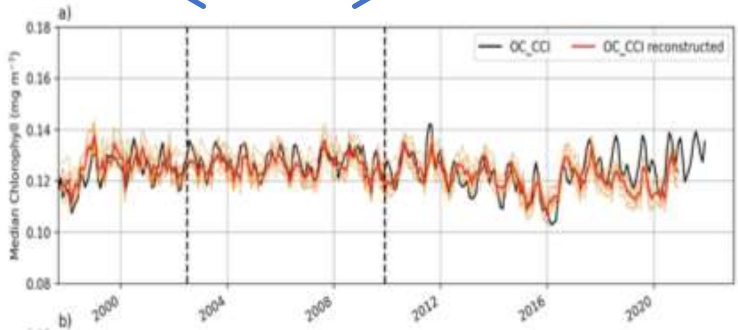
Pauthenet et al., GRL 2024

Satellite Chl trends over 2002-2020



CNN

Train/valid



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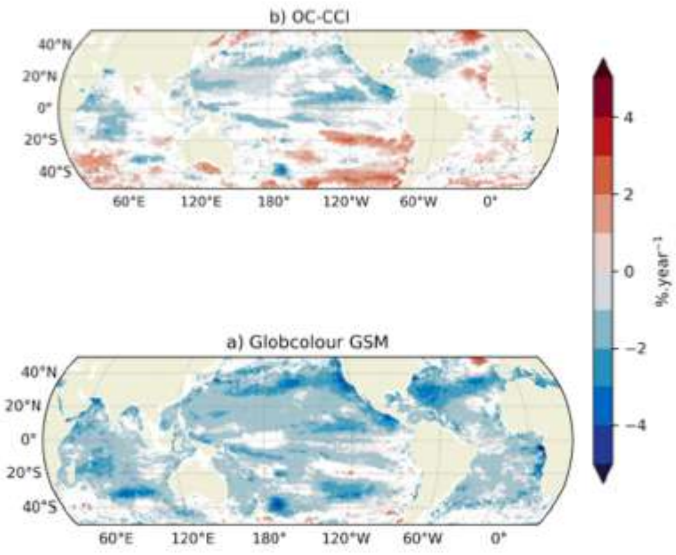

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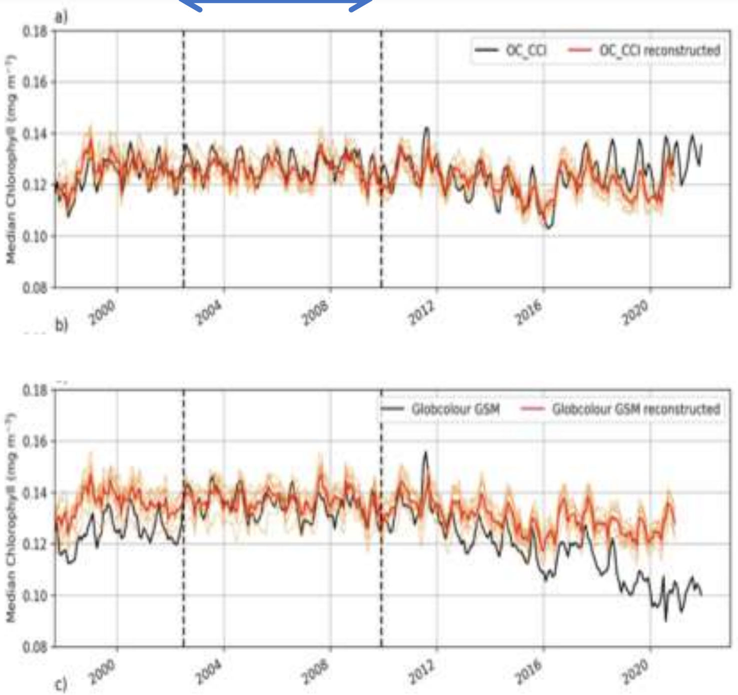


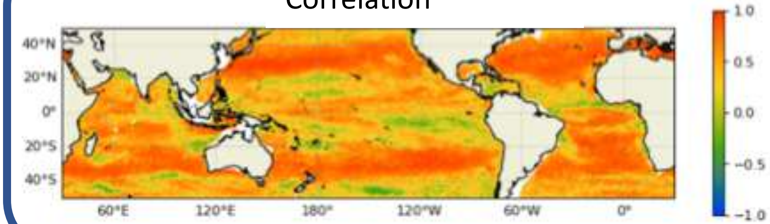
Still a biais: Underestimation Chl in reconstructed trend

Pauthenet et al., GRL 2024

Satellite vs. reconstructed Chl over the test period [2012-2017]

CNN

Correlation



- Data driven (static) **:** **Y= f(X)** (CNN, ConvLSTM, FourCastNet, Unet)

Satellite vs. reconstructed Chl over the test period [2012-2017]

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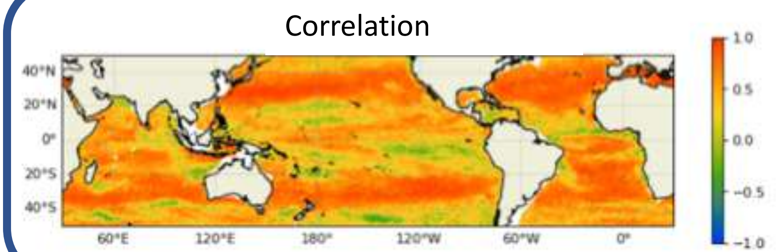

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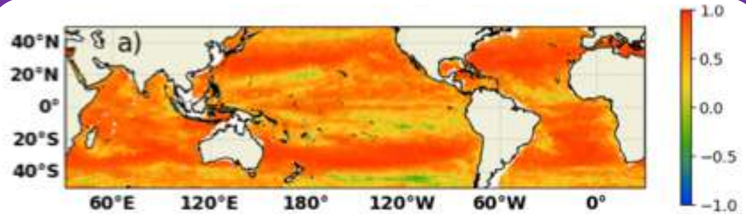
U-Net



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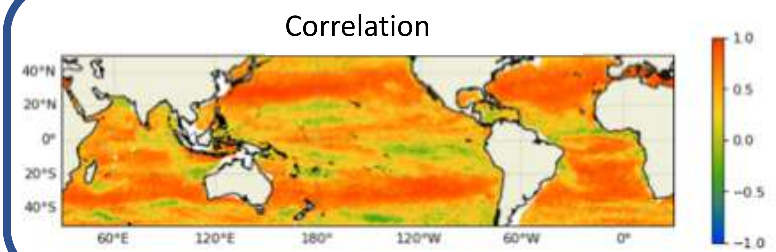
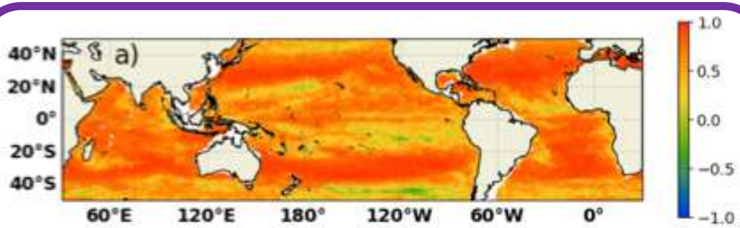


- Data driven (static) : **Y= f(X)** (CNN, ConvLSTM, FourCastNet, Unet)
- Sequence to sequence (forecasting): $\partial_t Y = f(\partial_t X),\ \partial_t Y = f(\partial_t X, \partial_t Y)$.... (1 to 6 months)

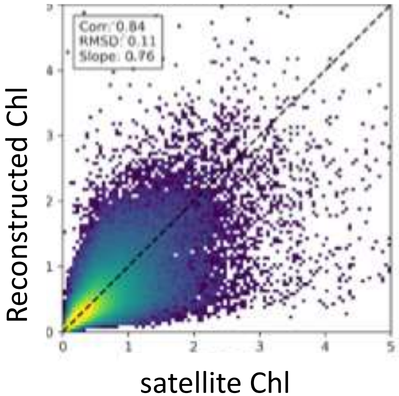
Lakra et al., IEESS to be submitted

U-Net



Satellite vs. reconstructed Chl (U-Net) over the test period [2012-2017]

Several predictors +SST (proxy MLD)



- Reconstruction OK

Mahadevan et al., GRL in prep

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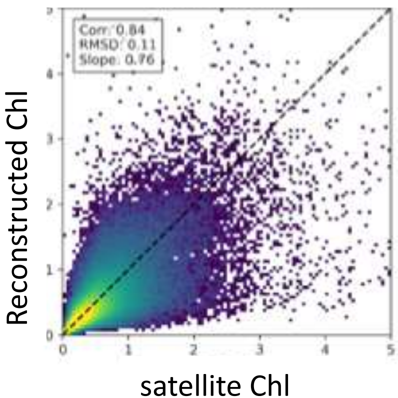
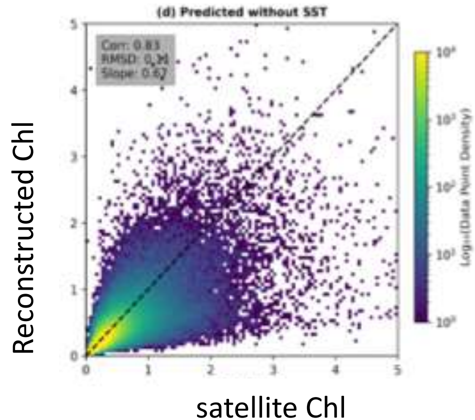


Several predictors + heat flux &wind (MLD forcing)



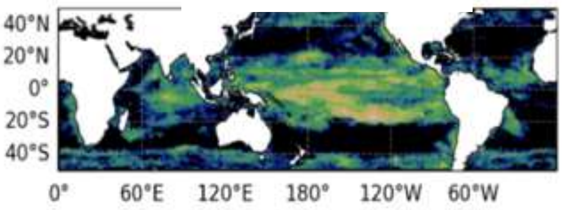
- Reconstruction OK
- Use forcing rather than proxy OK → better understanding of process

Mahadevan et al., GRL in prep

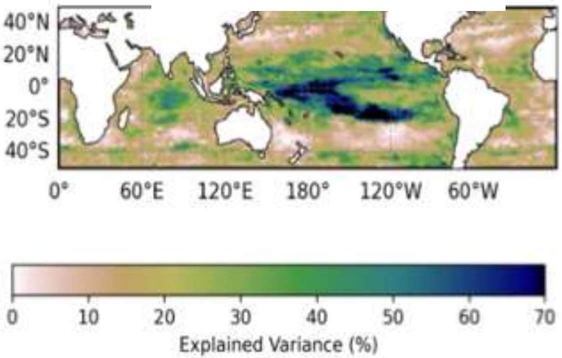
Test period [2012-2017]:

Satellite Chl

Seasonal signal



Interannual signal



Mahadevan et al., GRL in prep

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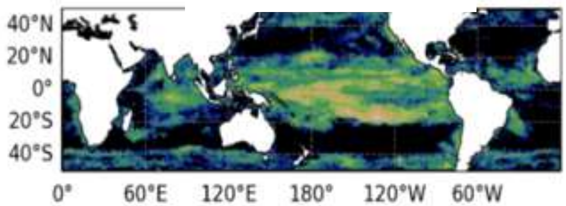

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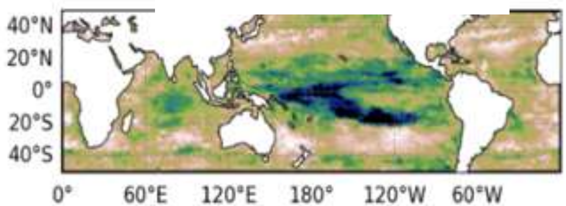
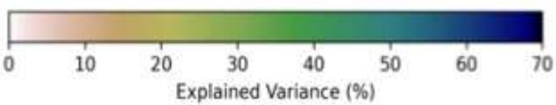
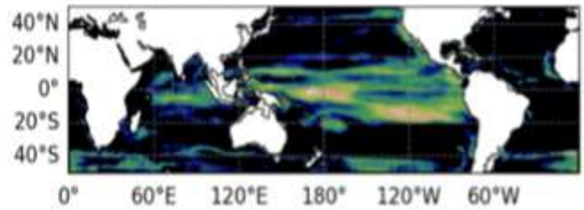


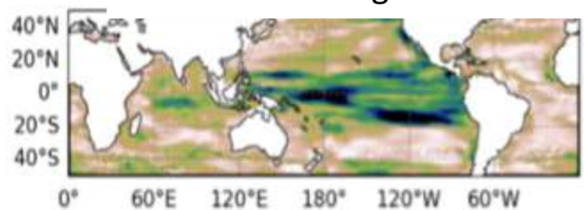


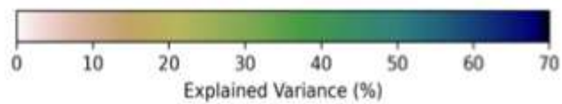
Unet reconstructed Chl

Seasonal signal



Interannual signal



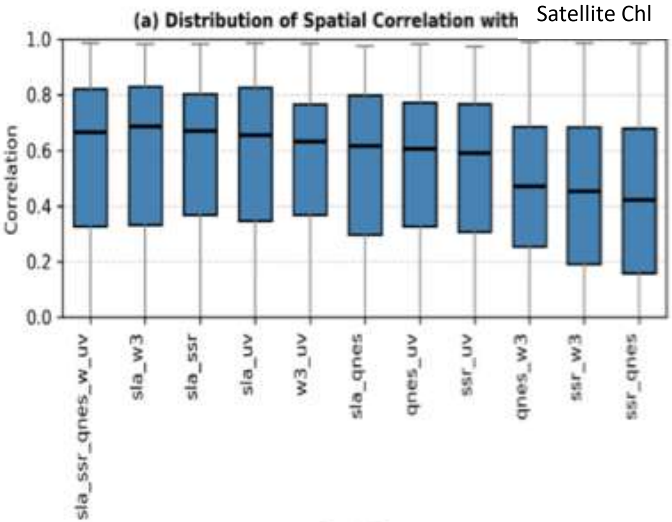


Mahadevan et al., GRL in prep

Test period [2012-2017]:

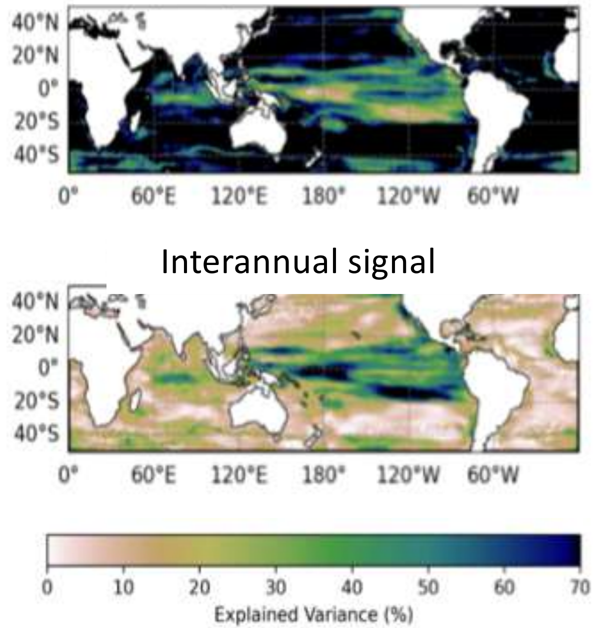
Unet reconstructed Chl

- Investigate physical process



Seasonal signal

Interannual signal



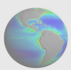
Mahadevan et al., GRL in prep

Deep leaRning approaches to Elucidate phytoplAnktonic cliMate induced variability (ANR PRC DREAM, 2023-27)

Aim:

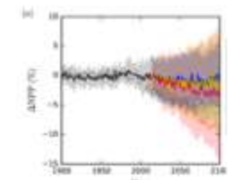
- assess multi-decadal variability & trends of phytoplankton biomass
- Understand the underlying physical and BGC processes

WP2a: reconstruct past multi-decadal reconstruction at global scale



1978 1985 1997 now

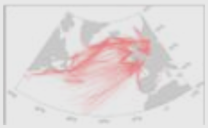
WP3: quantify physical & bgc uncertainties in climate models



WP1 Improve the deep learning architectures through various emulators

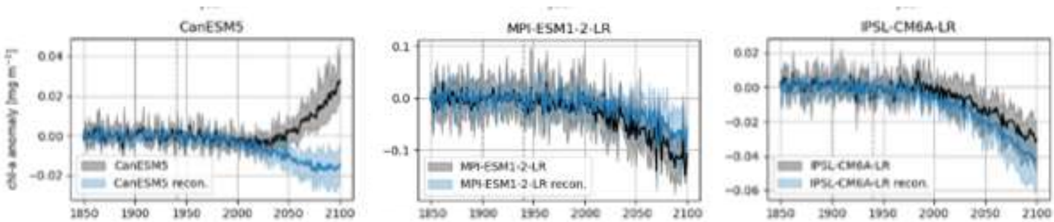
- Data-driven: Y= f(X)
- Ordinary and Partial Differential Equations: $\partial_t Y = f(\partial_t X)$, $\partial_t Y = f(\partial_t X, \partial_t Y)$....

WP2b: better understand the link between phyto and zooplankton biomass and communities



1 Succeed to reconstruct trends in time & space

15 Earth System Models (ESM)



Martinez et al., in prep

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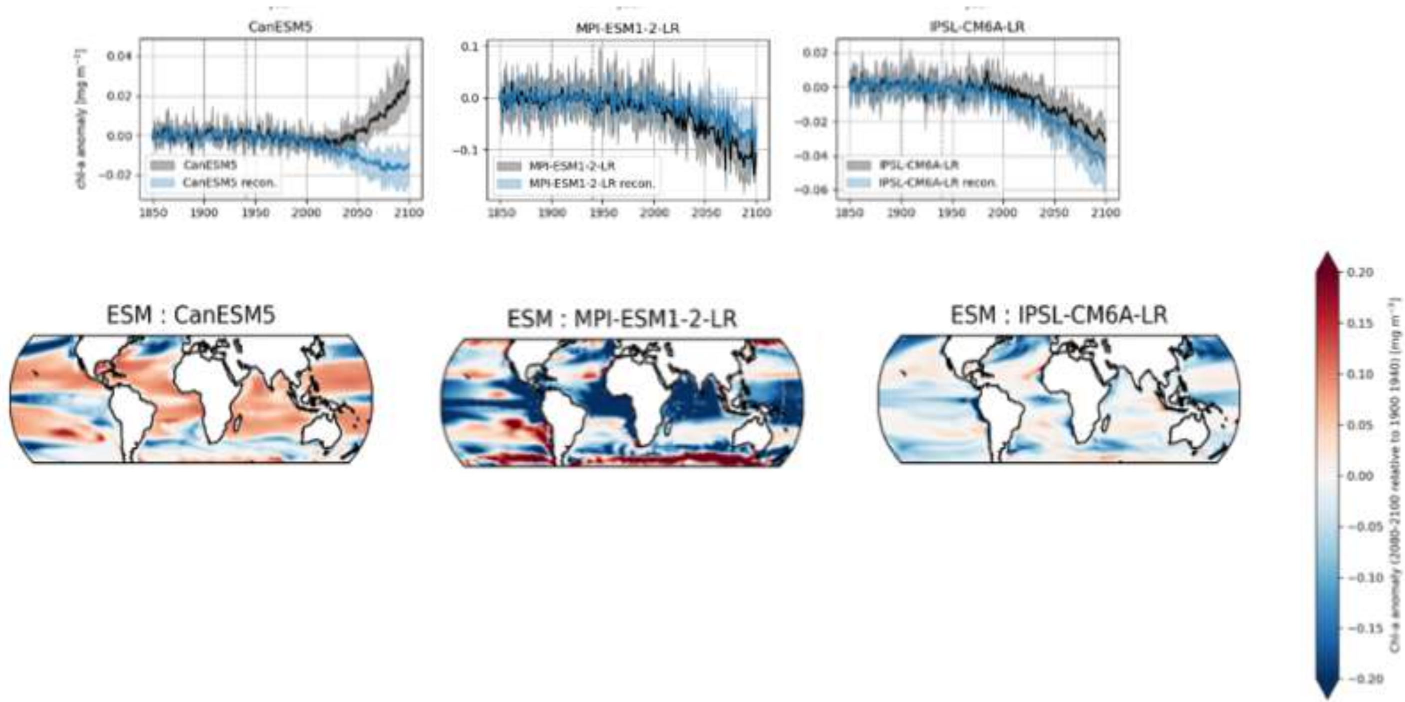
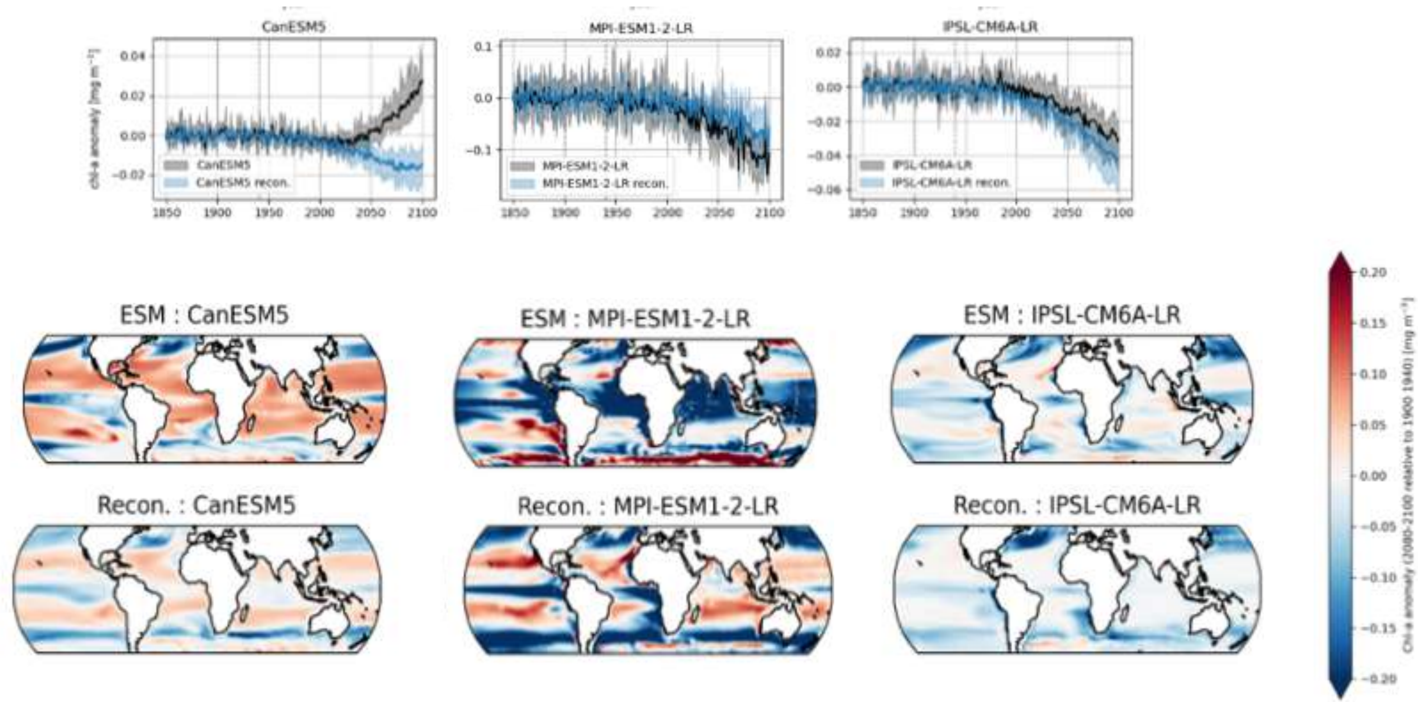


Martinez et al., in prep

WP3: from DL

1 Succeed to reconstruct trends in time & space

15 Earth System Models (ESM)



2. Allowed us to deconvoluate the physical from BGC signal

Martinez et al., in prep

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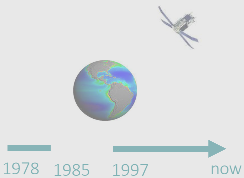
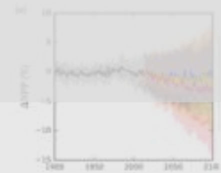


WP3: quantify physical & bgc uncertainties in climate models



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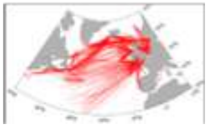
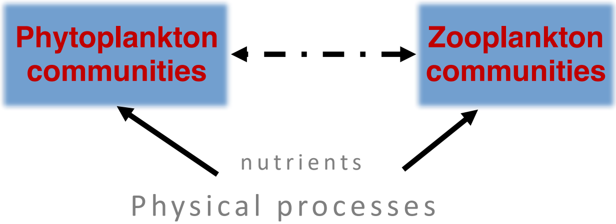
WP2b: better understand the link between phyto and zooplankton biomass and communities

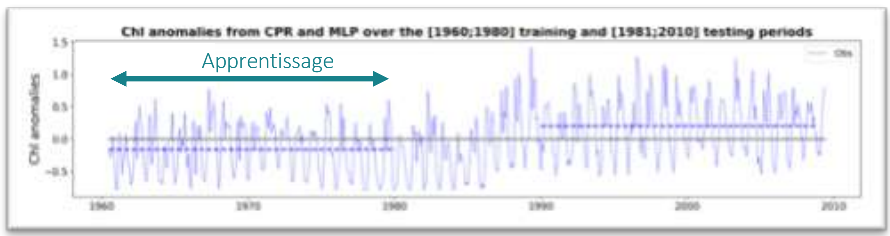


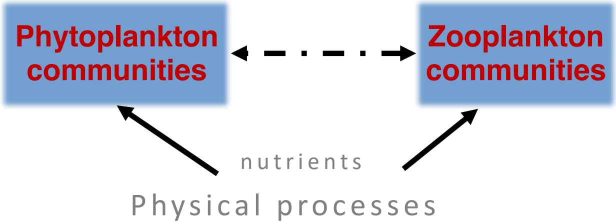


In situ obs. in contrasted BGC environment:

- Oligotrophic area (Hawaii)
- Coastal upwelling (California)
- High latitudes (North Atlantic)

In situ obs.(Mer du Nord)
Continuous Plankton Recorder (CPR)





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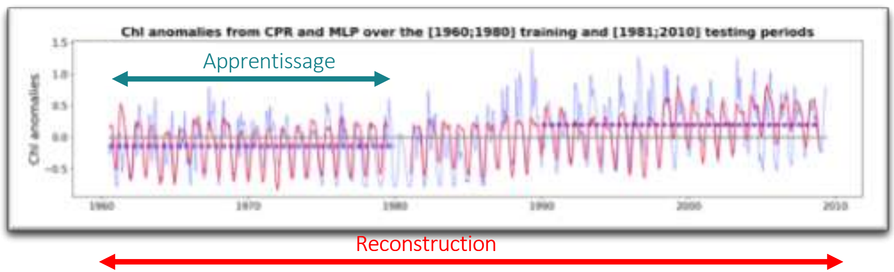
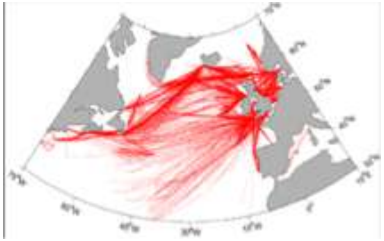
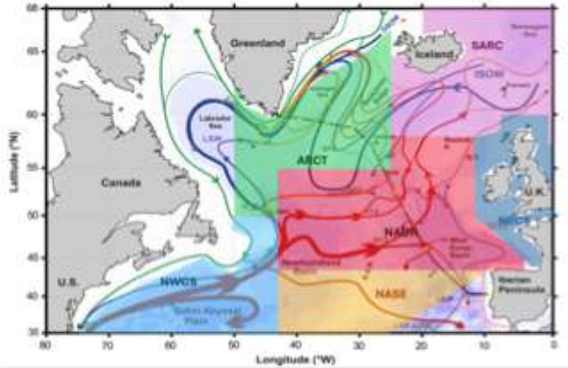


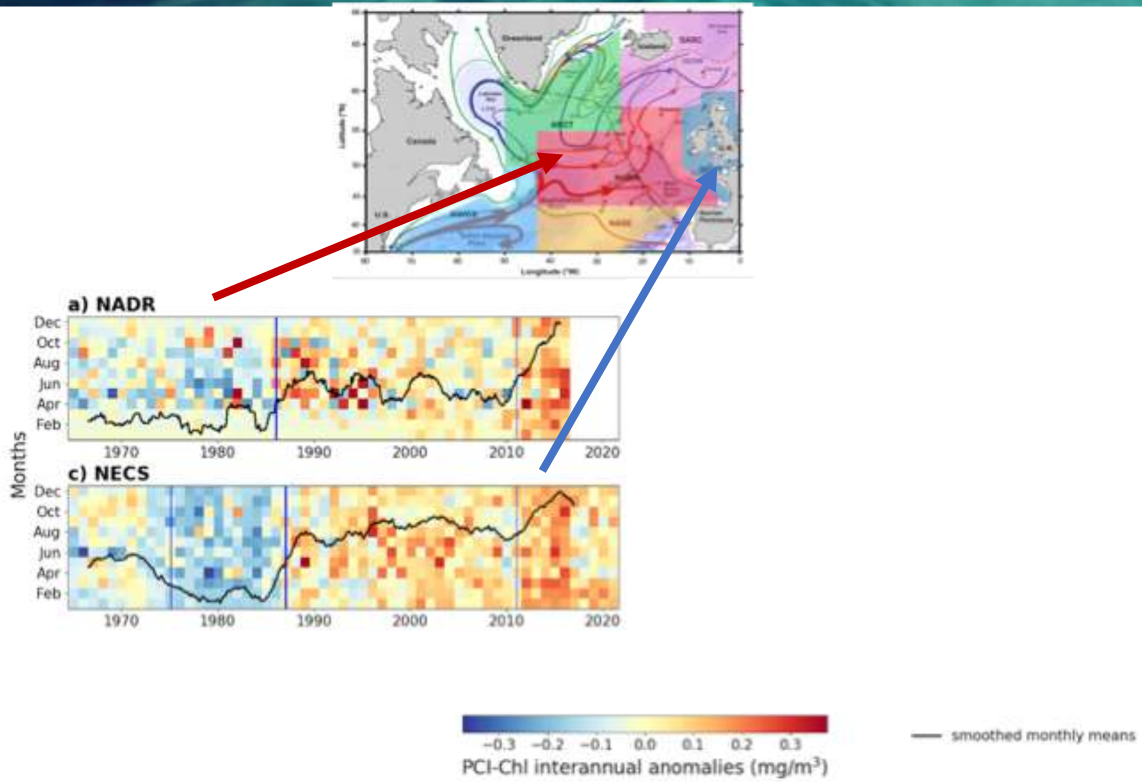
WP2.b: **Elucidating abiotic and phyto-zooplankton relationships from *in situ obs***



Continuous Plankton Recorder (CPR) dataset (1960-now)



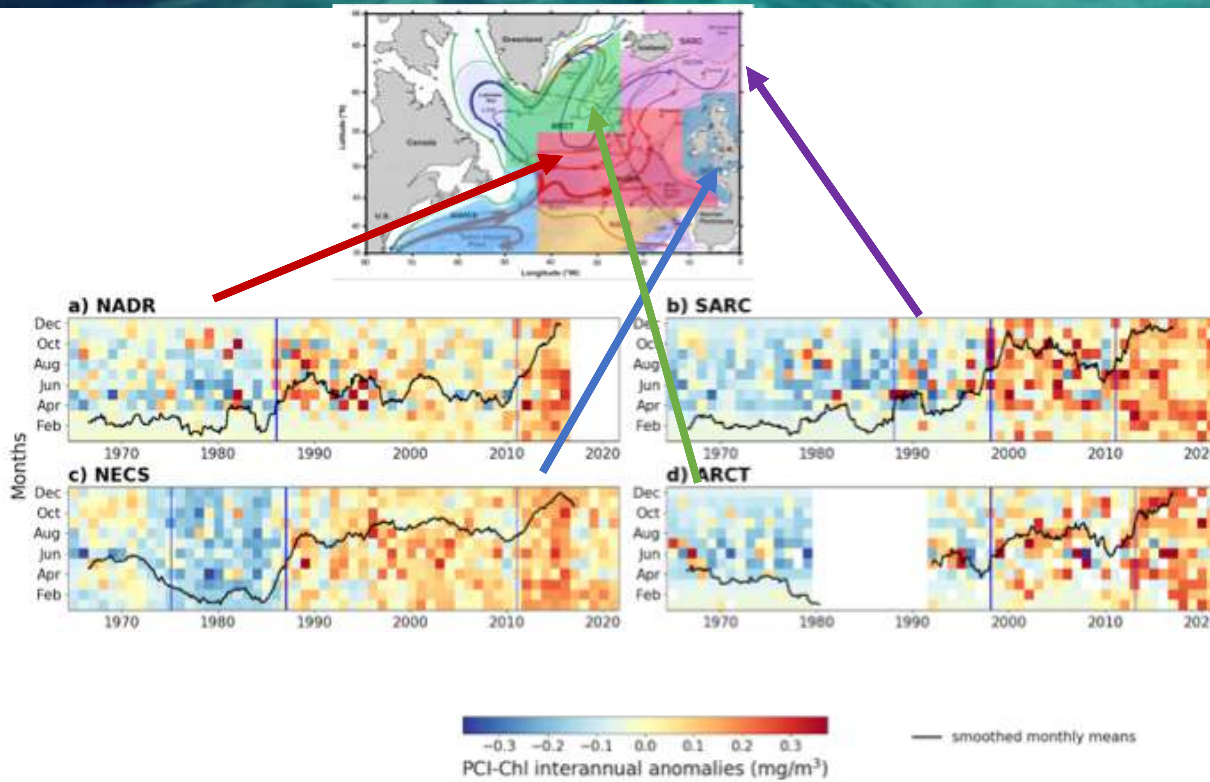
WP2.b: **Elucidating abiotic and phyto-zooplankton relationships from *in situ obs***



+ changes in phyto & zooplankton communities
+ physical process & climate modes at stake

Roux et al., Global Change Biology in prep

WP2.b: Elucidating abiotic and phyto-zooplankton relationships from *in situ obs*



+ changes in phyto & zooplankton communities

+ physical process & climate modes at stake

Roux et al., Global Change Biology in prep

Il reste 1,5 ans (2?). Que reste t'il à faire ?

WP2a: reconstruct past multi-decadal reconstruction at global scale

- Reconstruct decadal scale
- Investigate process (integrated gradient)

WP3: quantify physical & bgc uncertainties in climate models

- Investigate process

WP1 Improve the deep learning architectures through various emulators

- Diffusion model (analogue)

WP2b: better understand the link between phyto and zooplankton biomass and communities

- IA in the different area of the North Atlantic
- In the californian upwelling
- Oligotrophic area (Hawaii)

Thanks for your attention

Any questions?

Ingénieur d’étude 24 mois (au LOPS, brest), possible ouverture de poste

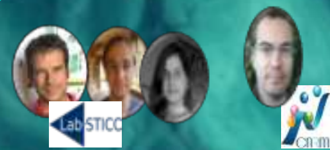
en intelligence artificielle/machine learning appliqué à l’océanographie

Site de l’IRD (elodie.martinez@irdf.fr)

THANKS FOR YOUR ATTENTION

ANY QUESTIONS?

IA



R. Fablet, L. Dumetz
M. Lakra

O. Pannekoucke

Biogeochemistry

Thomas Gorgues

Elodie Martinez

Keerthi Madhavan

Etienne Pauthenet

Ecology

M. Sourisseau

D. Raitsos

M. Messié

M. Roux

Physics- Climate projections

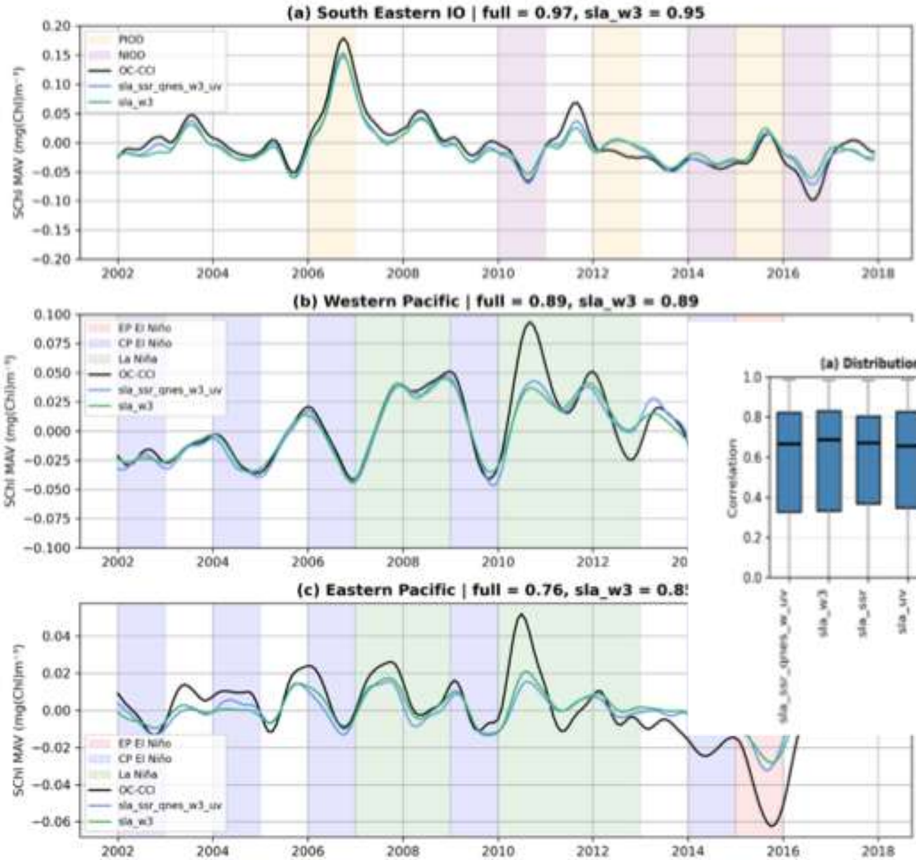
S. Kwatra

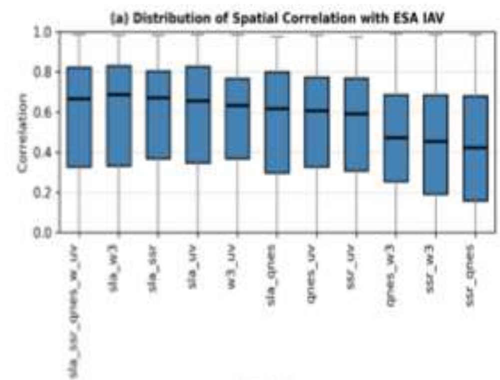
M. Lengaigne

anr agence nationale de la recherche

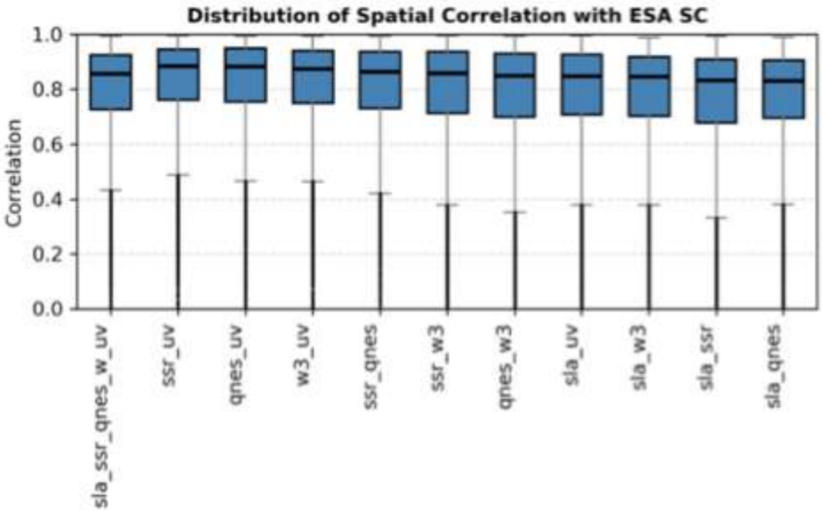
U-Net

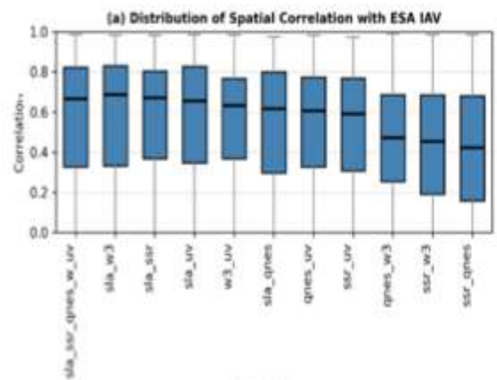
Satellite vs. reconstructed Chl over the test period [2012-2017]



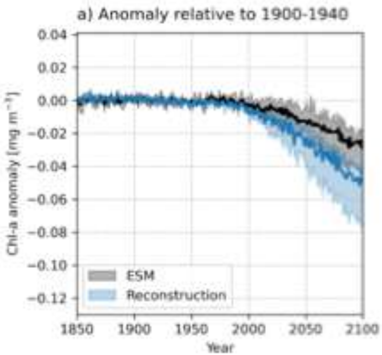


Ma





Mahadevan et al., GRL in prep



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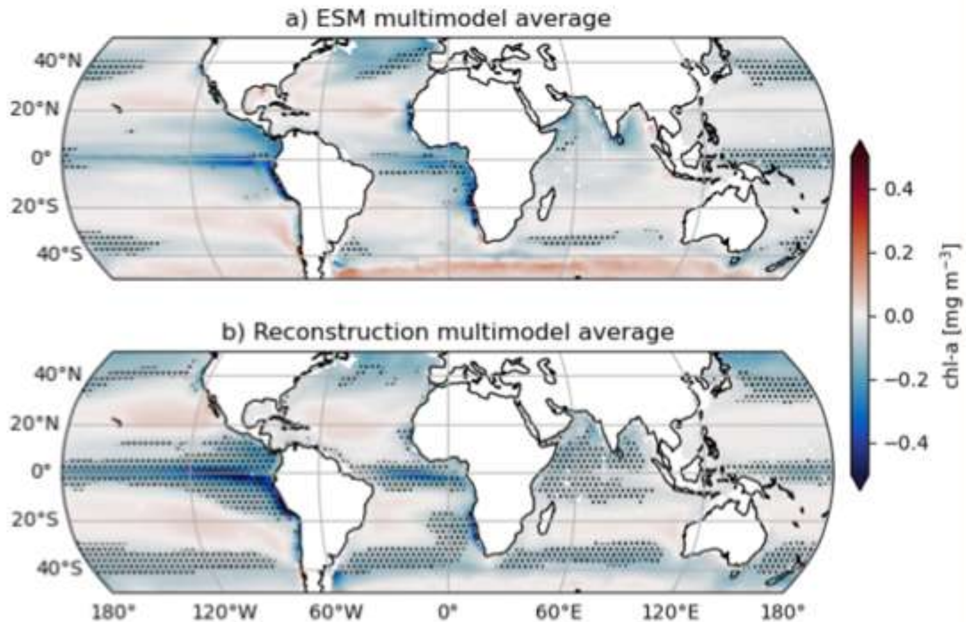
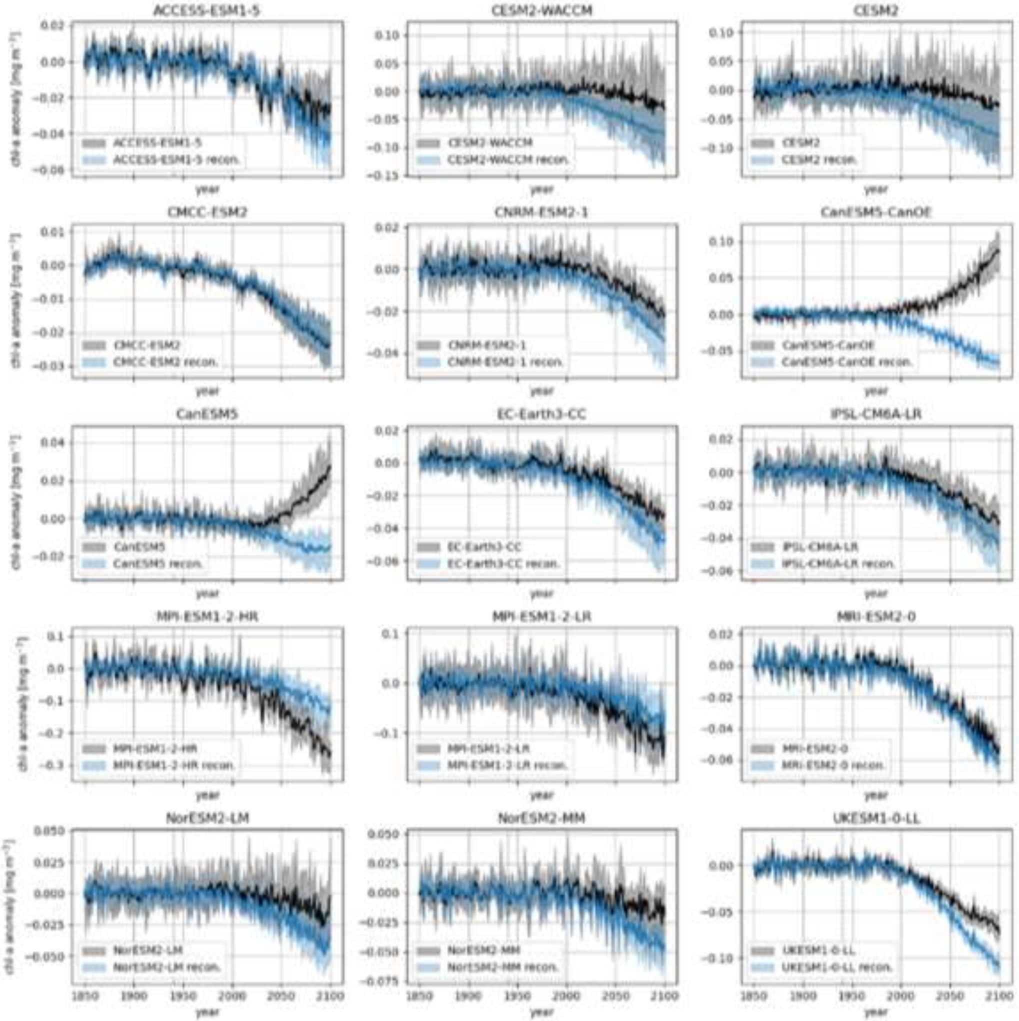


Martinez et al., Science in prep


ACCESS-ESM1-5
CESM2-WACCM
CESM2
CMCC-ESM2
CNRM-ESM2-1
CanESM5-CanOE
CanESM5
EC-Earth3-CC
IPSL-CM6A-LR
MPI-ESM1-2-HR
MPI-ESM1-2-LR
MRI-ESM2-0
NorESM2-LM
NorESM2-MM
UKESM1-0-LL
chl-a anomaly [mg m⁻³]
year
1850
1900
1950
2000
2050
2100