

# RADIOMETRIC OBSERVATIONS TO INVESTIGATE THE PHYTOPLANKTON BIOMASS : FROM SEASONAL TO DECADAL VARIABILITY IN THE GLOBAL OCEAN

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ELODIE MARTINEZ

LABORATOIRE D'OCÉANOGRAPHIE PHYSIQUE ET SPATIALE  
(BREST)



# OUTLINE

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## INTRODUCTION

Le phytoplancton, importance biogéochimique  
Pertinence de la télédétection de la couleur de l'océan

## 1. PRÉMICES DE LA RADIOMÉTRIE SPATIALE

1979-1985: apports de la mission Nimbus7 et du  
capteur CZCS (les prémices d'une vision  
globale et de la variabilité saisonnière)

## 2. CAPTEURS MODERNES

1997-....: apports des capteurs radiométriques modernes  
et des produits combinés: du saisonnier à  
l'interannuel

## 3. RECONSTRUCTION DÉCENNALES

Les produits reconstruits pour tenter d'appréhender la  
variabilité décennale

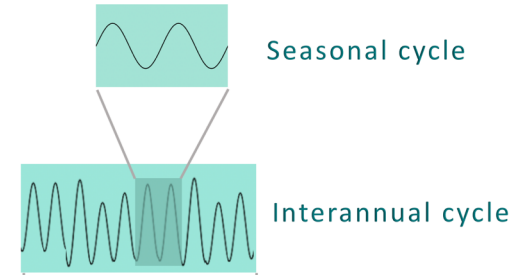
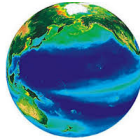
## 4. APPROCHES COMPLÉMENTAIRES

Combinaison des observations et intelligence artificielle:  
vers de nouvelles perspectives!?



### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

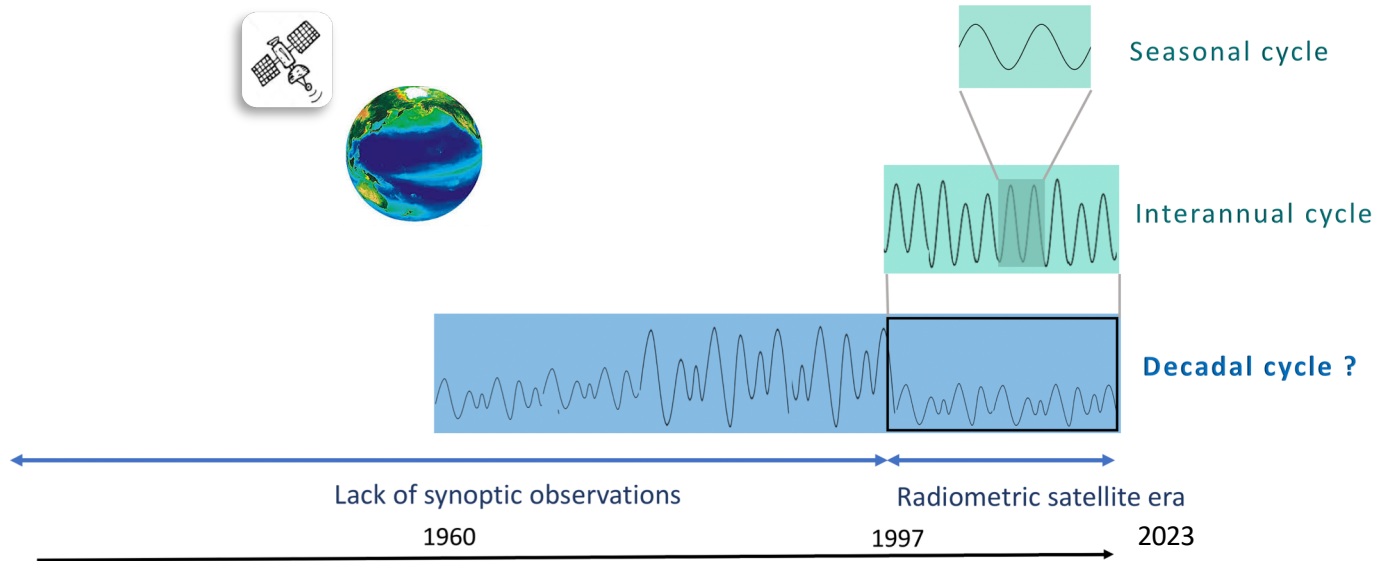
Why do we care about decadal cycles?



Radiometric satellite era  
1997 → 2023

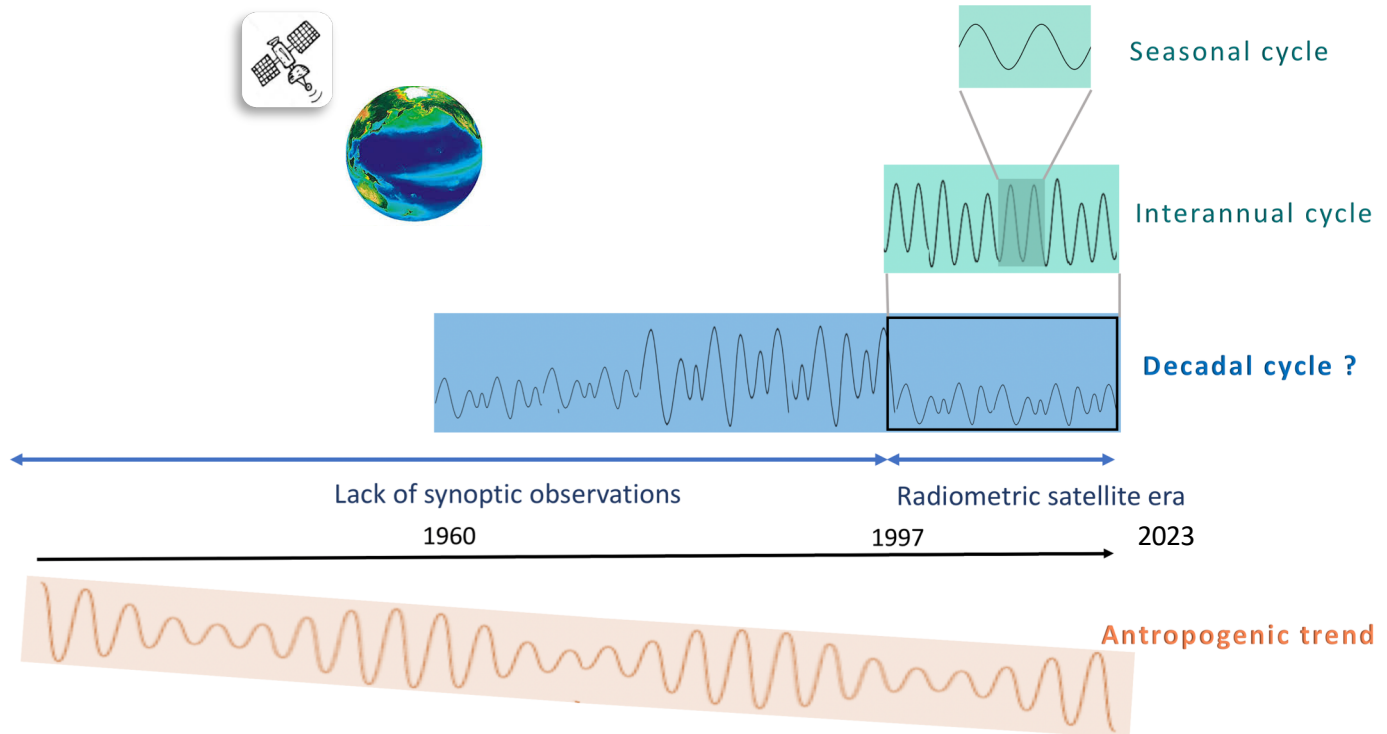
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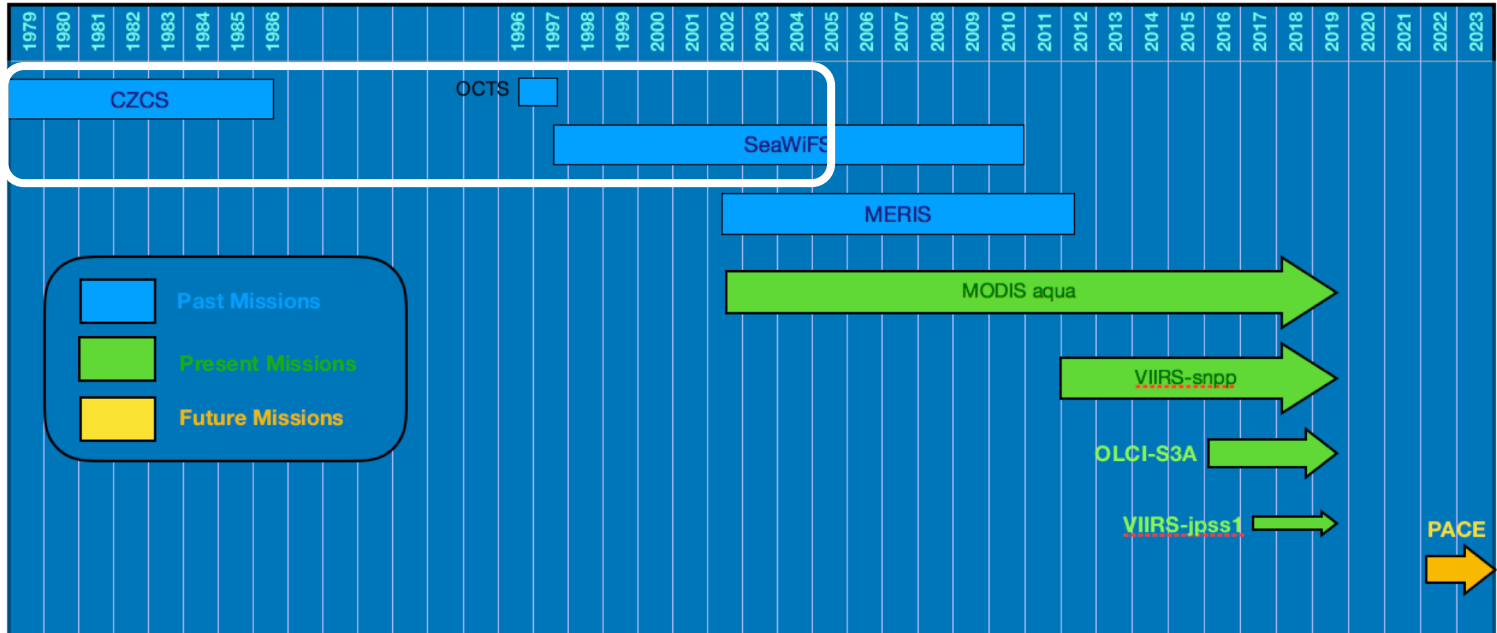
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Why do we care about decadal cycles?



### 3. DECADEAL VARIABILITY OF PHYTOPLANKTON

CZCS vs. modern satellite mission



# 3. DECADAL VARIABILITY OF PHYTOPLANKTON

## CZCS vs. modern satellite mission

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### Decadal changes in global ocean chlorophyll

Watson W. Gregg, Margarita E. Conkright

First published: 07 August 2002 | <https://doi.org/10.1029/2002GL014689> | Citations: 105

→ Level-2 blended with in situ data to reduce residual errors

CZCS (1979-1986) vs. SeaWiFS (1997-2000)



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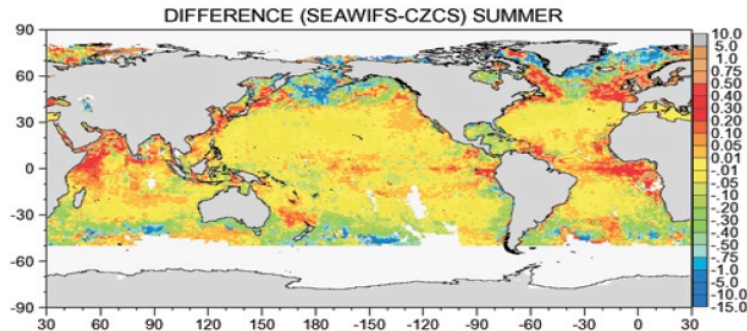
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→ Level-2 blended with in situ data to reduce residual errors

CZCS (1979–1986) vs. SeaWiFS (1997–2000)



→ Global spatial distributions and seasonal variability of ocean Chl were similar

but global means decreased over the two observational segments (≈6%)

# 3. DECADAL VARIABILITY OF PHYTOPLANKTON

## CZCS vs. modern satellite mission

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**Bridging ocean color observations of the 1980s and 2000s in search of long-term trends**

David Antoine , André Morel, Howard R. Gordon, Viva F. Banzon, Robert H. Evans

First published: 22 June 2005 | <https://doi.org/10.1029/2004JC002620> | Citations: 113

CZCS (1979-1986) vs. SeaWiFS (1998–2002)

→ A comprehensive revision of the Level 1 data-processing algorithms

(identical atmospheric correction and a single bio-optical algorithm, adjusted calibration)

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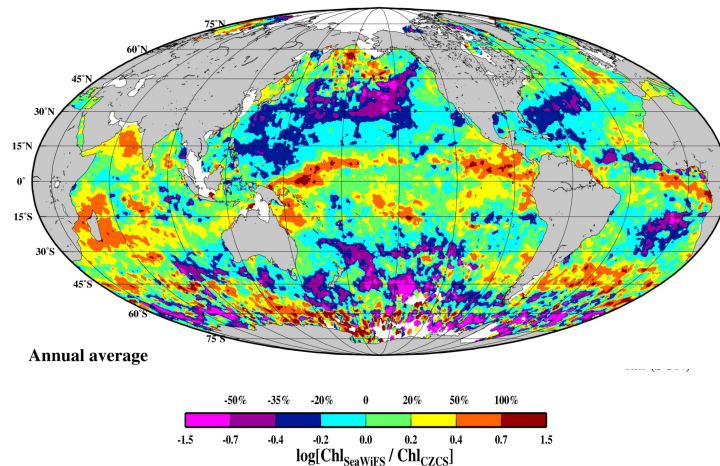
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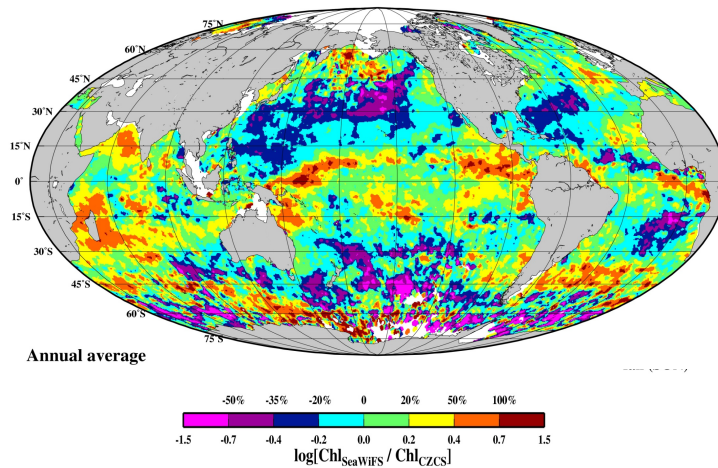
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Global mean increased over the two observational segments ( $\approx 22\%$ )

CZCS (1979-1986) vs. SeaWiFS (1998-2002)

→ A comprehensive revision of the Level 1 data-processing algorithms

(identical atmospheric correction and a single bio-optical algorithm, adjusted calibration)

→ Intertropics large increases  
(seasonal cycles also changed)

→ High latitude increase  
(no change in seasonal cycles)

→ Oligotrophic gyres decrease

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

CZCS vs. modern satellite mission

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Gregg & Conkright (2002)  $\searrow$  6%

Antoine et al. (2005)  $\nearrow$  22%

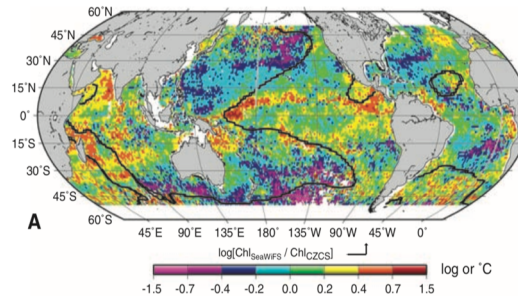
Importance of « climate quality » time-series and multi-sensor reprocessing

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

#### CZCS vs. modern satellite mission

1979-1983 vs. 1998-2002  
(CZCS) (SeaWiFS)

Martinez et al., (2009)

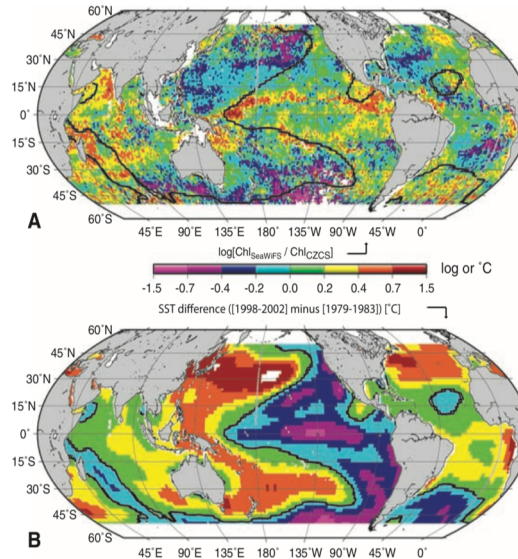


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Decadal cycles imprint on SST:

Atlantic: AMO

(Atlantic Multi-decadal Oscillation)

Pacific: IPO

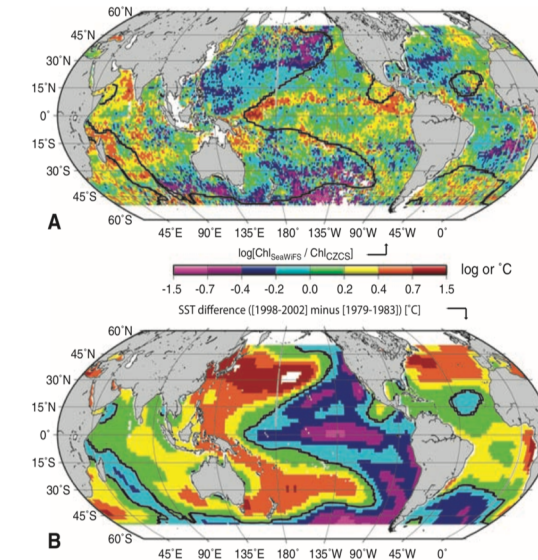
(Interdecadal Pacific Oscillation)

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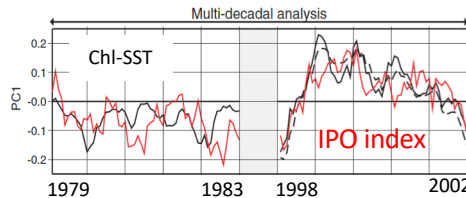
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→ Decadal cycles imprint on Chl

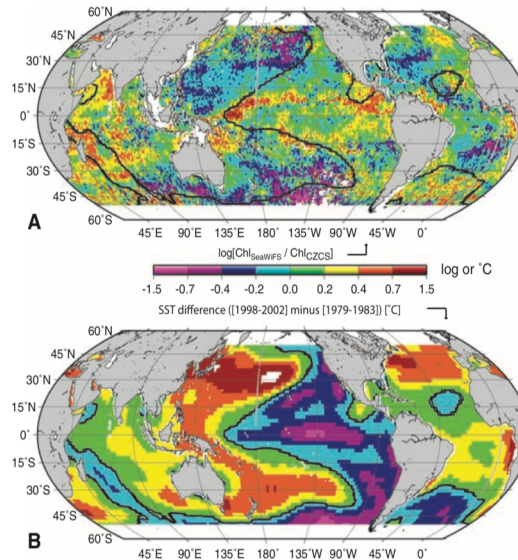


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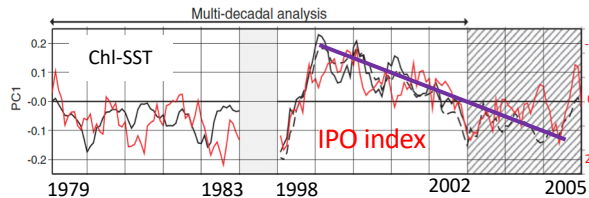
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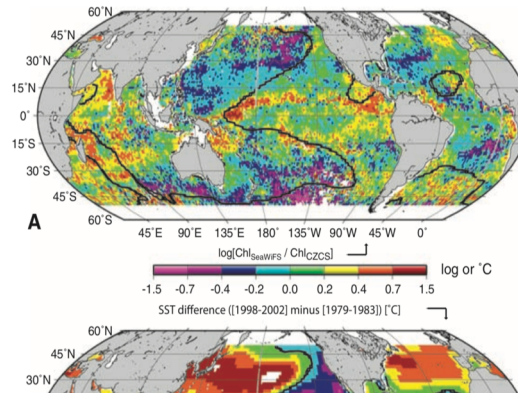
(Behrenfeld et al. Nature 2006)

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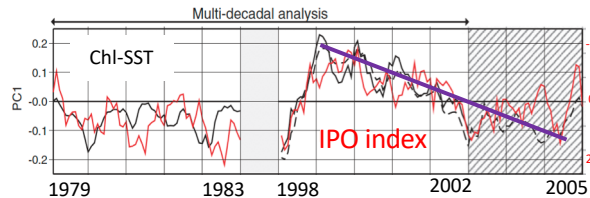
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Importance of decadal cycles in trend interpretation



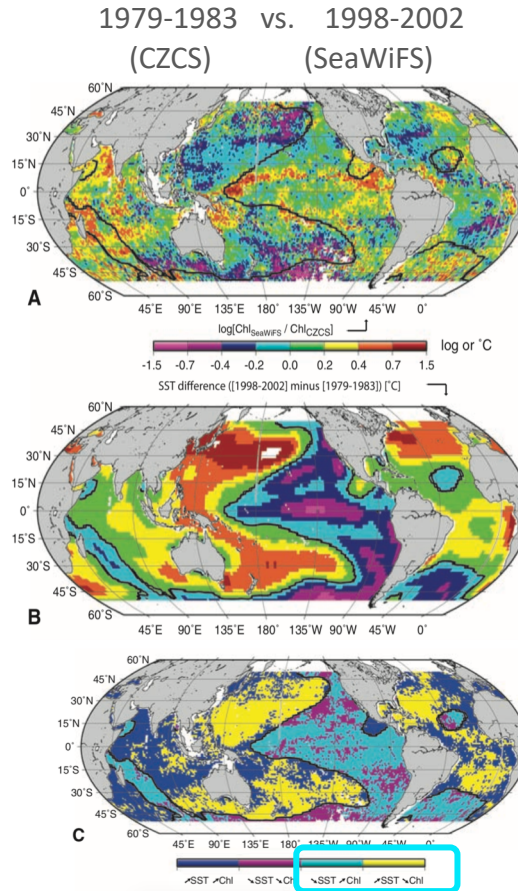
→ Decadal cycles imprint on Chl

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Martinez et al., (2009)



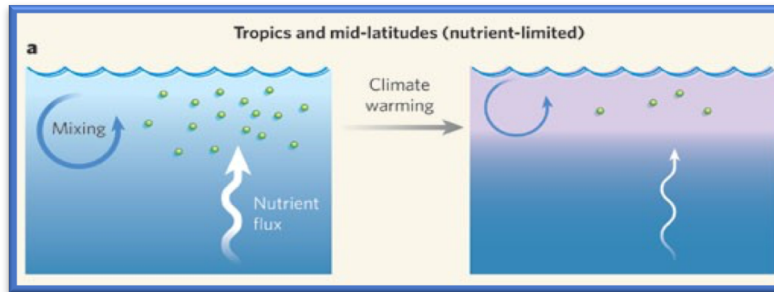
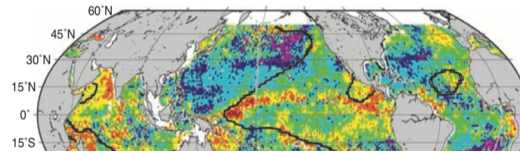
→ SST-Chl inverse relationship

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## CZCS vs. modern satellite mission

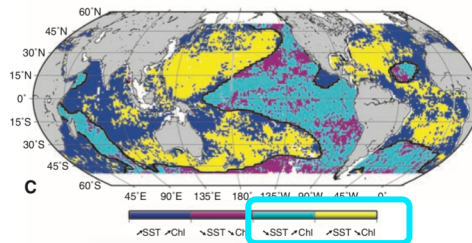
1979-1983 vs. 1998-2002  
(CZCS) (SeaWiFS)

Martinez et al., (2009)



↗ SST    ↘ MLD (↘ nutrient)    ↘ Chl

• → SST-Chl inverse relationship



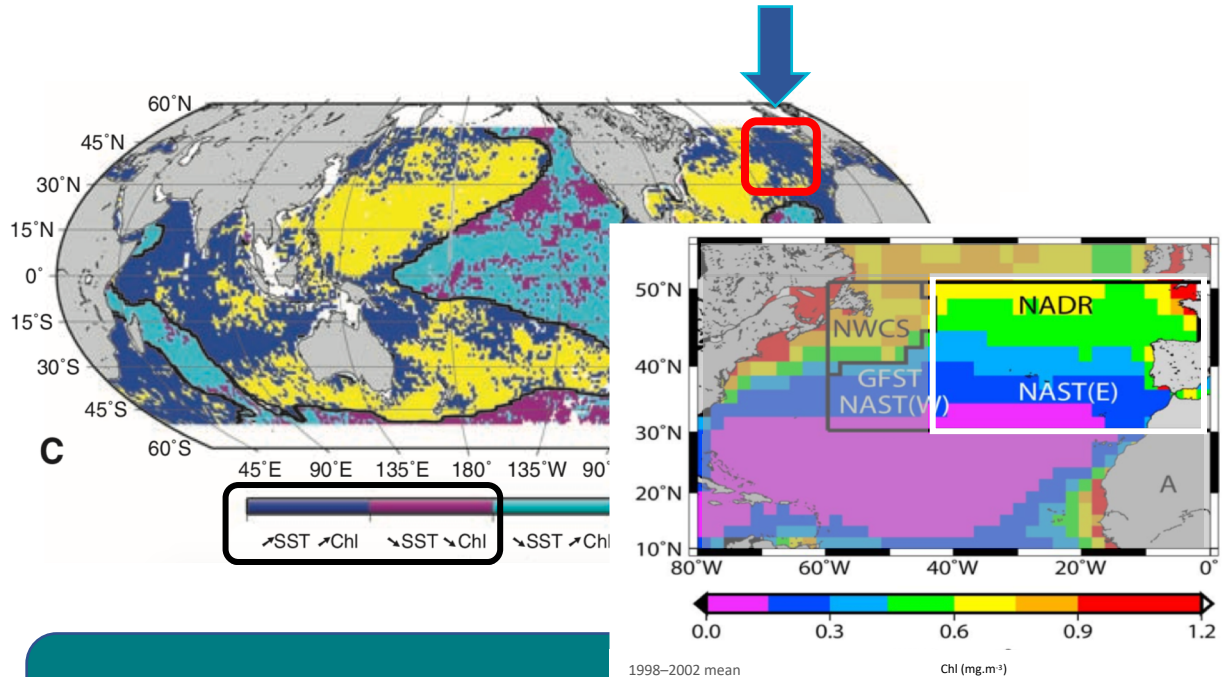
→ SST-Chl inverse relationship

Figure 1 is a global map showing Sea Surface Temperature (SST) and Chlorophyll *a* (Chl *a*) anomalies. The map uses a color scale to represent these anomalies, with a color bar at the bottom. The color bar is divided into two sections: the left section represents SST anomalies (blue to red) and the right section represents Chl *a* anomalies (green to yellow). The map is labeled with latitude and longitude coordinates. The color bar is labeled with the following text: [1979-1983] to [1998-2002]. The color bar is also labeled with the following text: SST, Chl, SST, Chl, SST, Chl, SST, Chl.

→ What about the postulate? Other processes involved?

### 3. DECADEAL VARIABILITY OF PHYTOPLANKTON

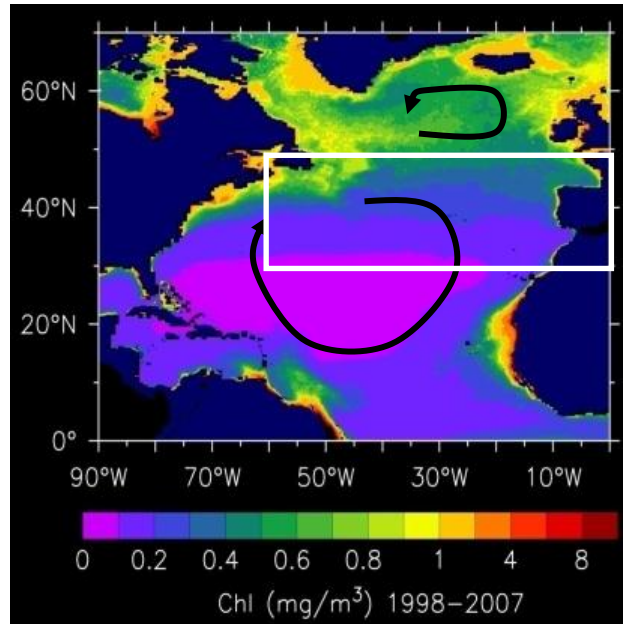
CZCS vs. modern satellite mission



→What about the postulate? Other processes involved?

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

CZCS vs. modern satellite mission



Subpolar gyre  
Light limited

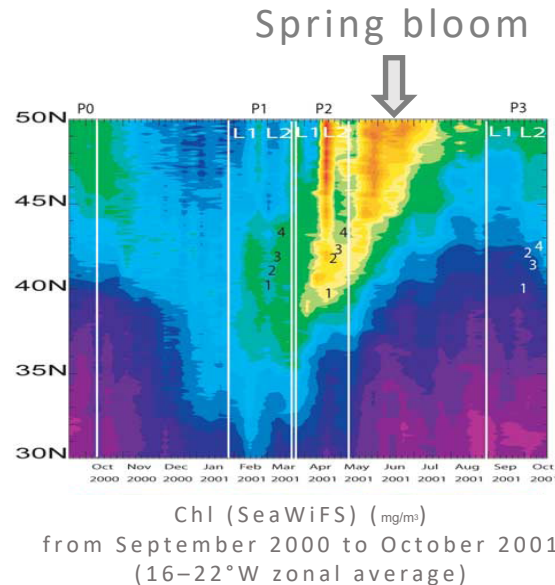
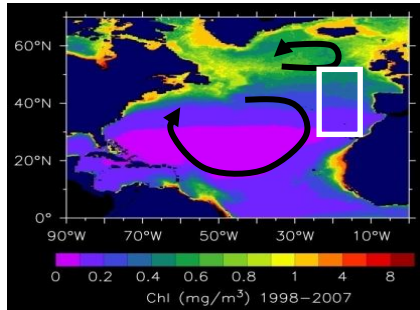
Subtropical gyre  
Nutrient limited



### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

modern satellite mission

Aside 3:



A four-dimensional mesoscale map of the spring bloom in the northeast Atlantic (POMME experiment): Results of a prognostic model

M. Lévy, M. Gavart, L. Mémerly, G. Caniaux, A. Paci

First published: 15 June 2005 | <https://doi.org/10.1029/2004JC002588> | Citations: 40

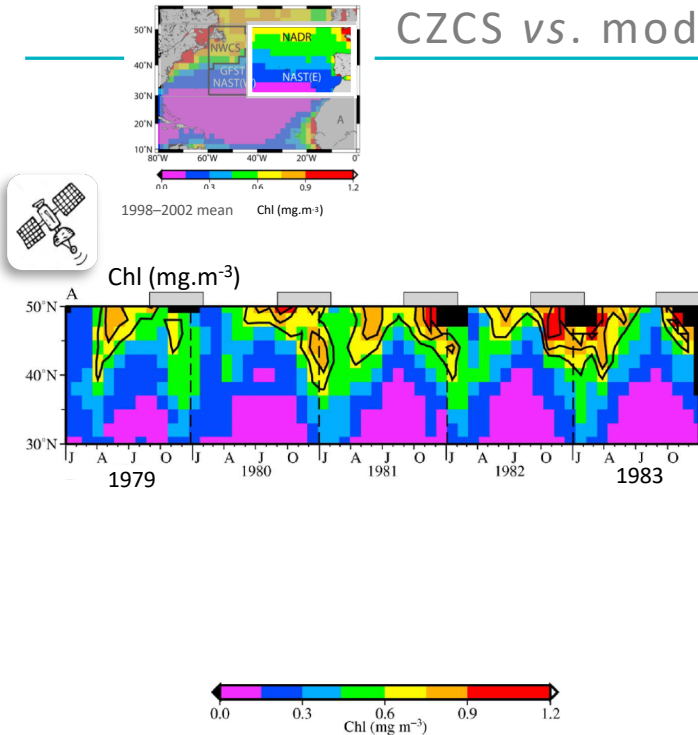
Sverdrup (1953); Yoder et al. (1993); Ducklow and Harris (1993); Sathyendranath et al. (1995); Kennelly et al. (2000); Williams et al. (2000); Dutkiewicz et al. (2001); Siegel et al. (2002); Follows and Dutkiewicz (2002); Williams and Follows (2003); Lévy et al. (2005); Platt et al. (2005); Ueyama and Monger (2005); Behrenfeld (2010).....



### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

CZCS vs. modern satellite mission

Martinez et al. (2011)

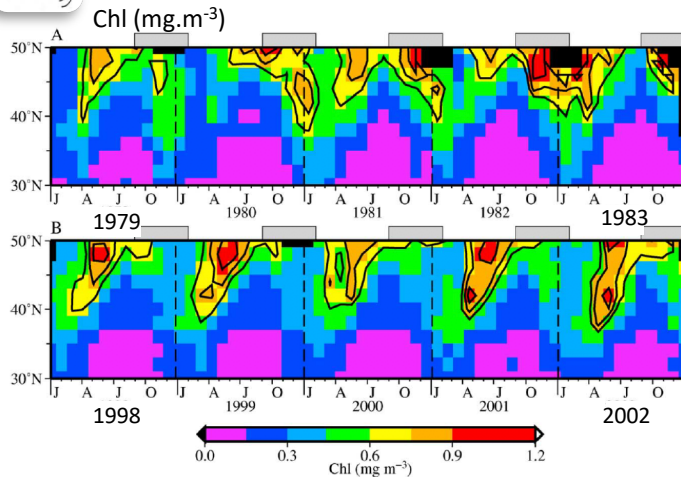
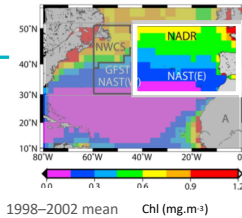


|             | SST | Winter MLD | Spring Chl | Fall Chl |
|-------------|-----|------------|------------|----------|
| 1980 → 2000 | ↗   |            | ↗          | ↘        |

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CZCS vs. modern satellite mission

Martinez et al. (2011)

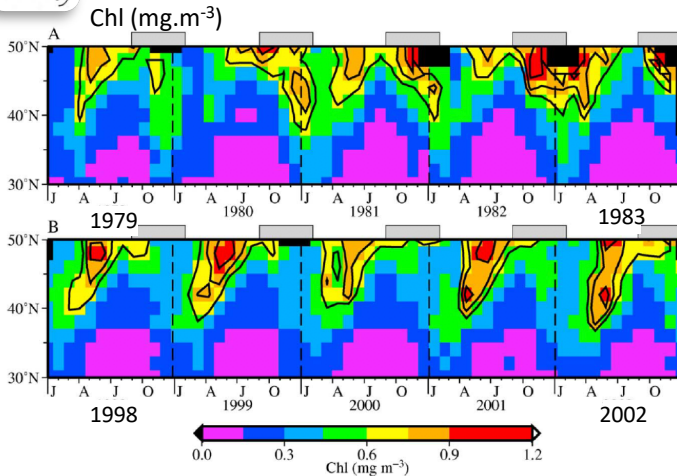
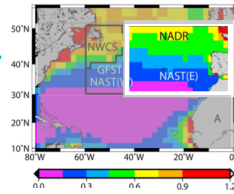


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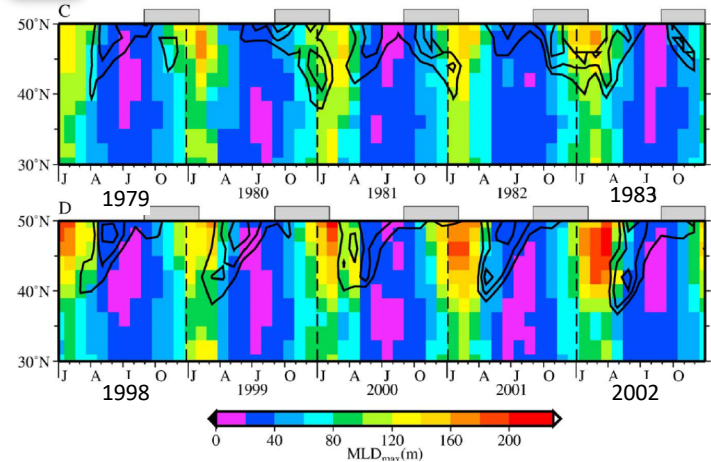
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Martinez et al. (2011)



MLD (m)

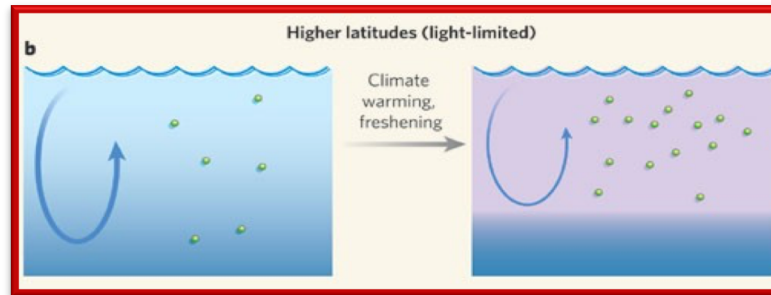


|             | SST | Winter MLD  | Spring Chl | Fall Chl |
|-------------|-----|-------------|------------|----------|
| 1980 → 2000 | ↗   | ↗ (↗ winds) | ↗          | ↘        |

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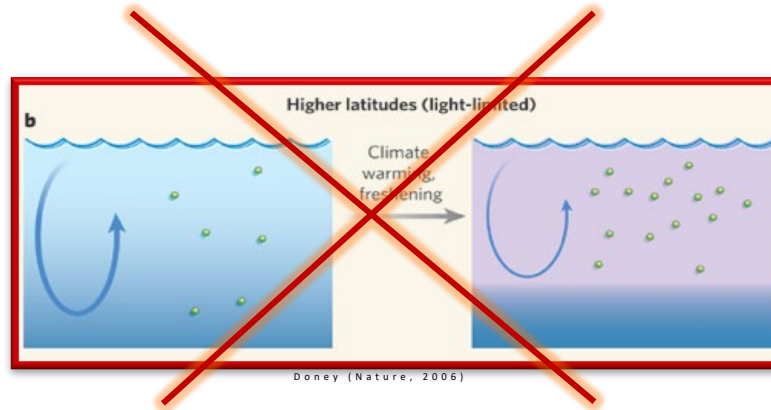
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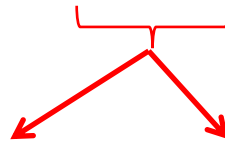
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CZCS vs. modern satellite mission



↗ SST    ↘ MLD    ↗ Chl



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CZCS vs. modern satellite mission

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Difficult to clearly interpret the impact of oceanic changes on Chl because:

1- it lies in the transition zone between the subtropical (limited nutrient) and subpolar gyre (light limited)

2- Do these changes reflect interannual variability or longer-term changes?

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Difficult to clearly interpret the impact of oceanic changes on Chl because:

1- it lies in the transition zone between the subtropical (limited nutrient) and subpolar gyre (light limited)

2- Do these changes reflect interannual variability or longer-term changes?

→ These changes were confirmed at decadal scales thanks to the combination of satellite Chl & an extensive in situ dataset (the CPR)

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

From silk to satellite, the Continuous Plankton Recorder (CPR, since 1960)

---

- On board of opportunity boats
- Deployed at the surface layer
- Silk filter mesh:  $270\mu\text{m}$
- Filter replacement rate = 10 cm/ 10 nautical mile
- "store" between 2 silk strips in a chamber containing formaldehyde
- Relative concentration in phytoplankton :Color index--> defined from color map
- Analysis of some phytoplankton, and zooplankton species





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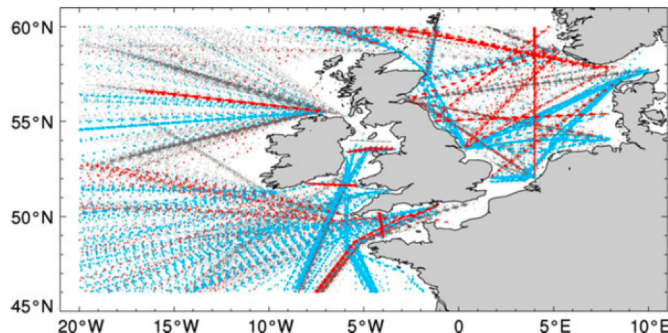


Fig. 1 Location of Continuous Plankton Recorder samples ( $n = 111\,803$ ) in the Northeast Atlantic Ocean and North Sea for 1948–2007. Red points represent the CPR samples during the CZCS period (1978–1981,  $n = 6121$ ), whereas blue data points represent CPR samples during the SeaWiFS era (1998 – 2007,  $n = 23\,174$ ).

Raitsos et al. (2014)

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

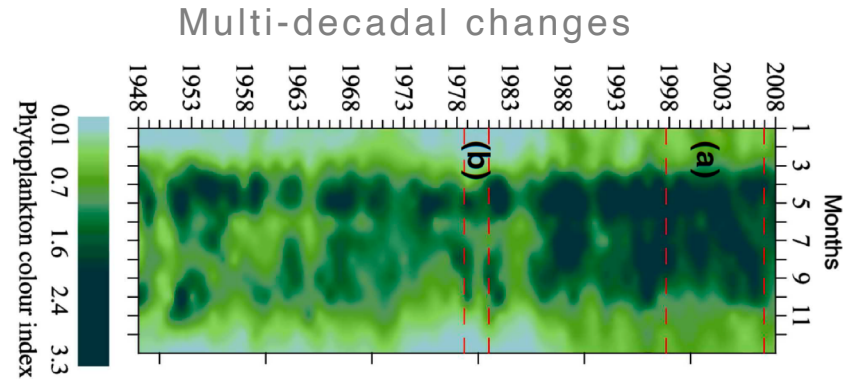
From silk to satellite, the Continuous Plankton Recorder (CPR, since 1960)



Global Change Biology (2014), doi: 10.1111/gcb.12457

#### From silk to satellite: half a century of ocean colour anomalies in the Northeast Atlantic

DIONYSIOS E. RAITOSOS\*, YASWANT PRADHAN†, SAMANTHA J. LAVENDER‡§, IBRAHIM HOTEIT¶, ABIGAIL MCQUATTERS-GOLLOP||, PHILLIP C. REID§\*\*, and ANTHONY J. RICHARDSON††‡‡



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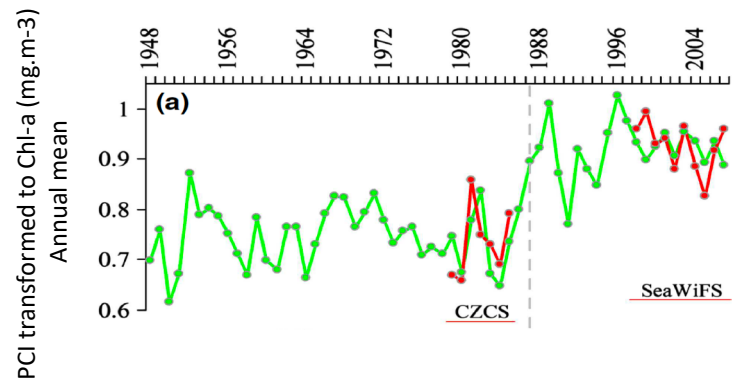
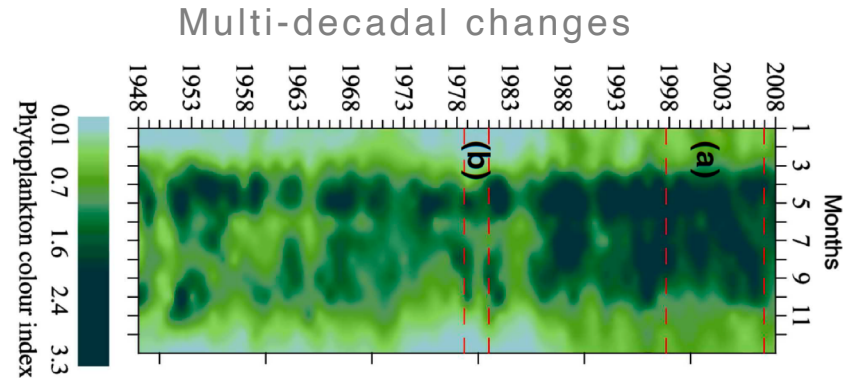
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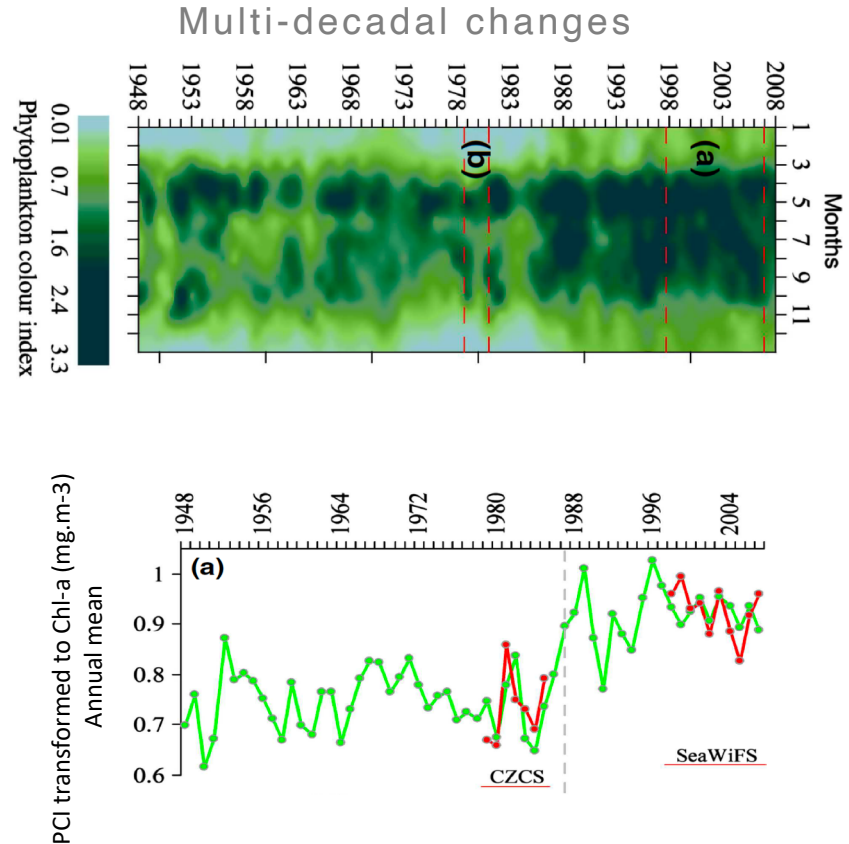
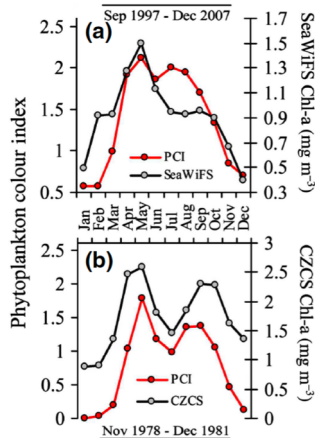
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# 3. DECADAL VARIABILITY OF PHYTOPLANKTON

What about secular trend?

nature

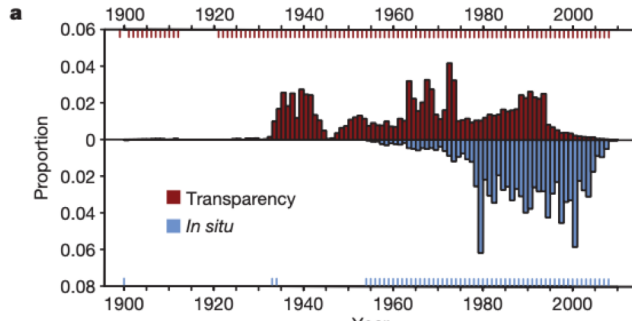
Article | Published: 29 July 2010

## Global phytoplankton decline over the past century

Daniel G. Boyce [✉](#), Marlon R. Lewis & Boris Worm

*Nature* **466**, 591–596(2010) | [Cite this article](#)

2279 Accesses | 576 Citations | 340 Altmetric | [Metrics](#)



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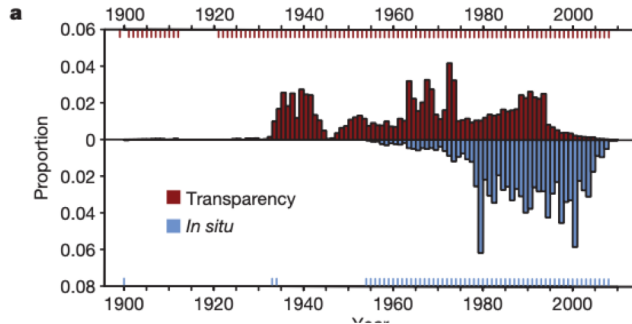
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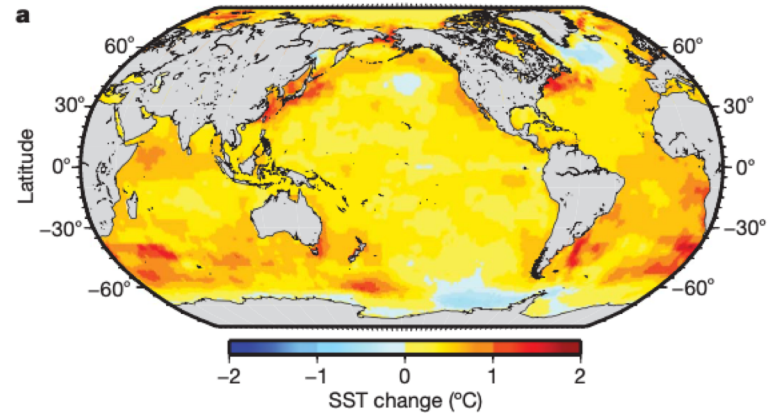
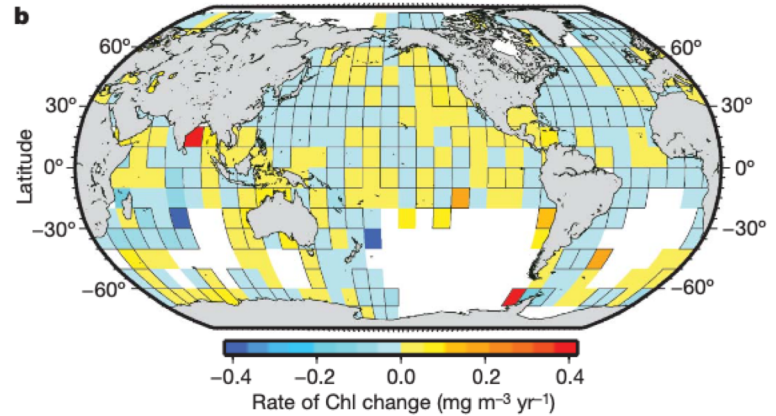
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⇒ Chl 1% /year



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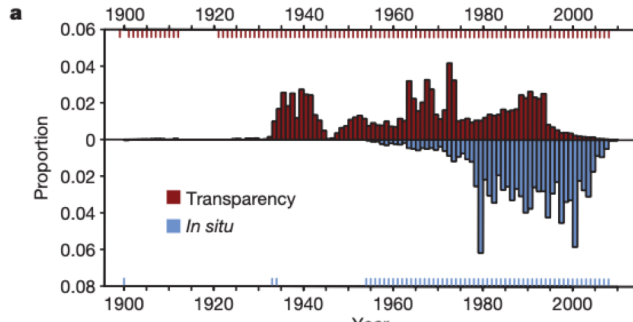
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## Global phytoplankton decline over the past century

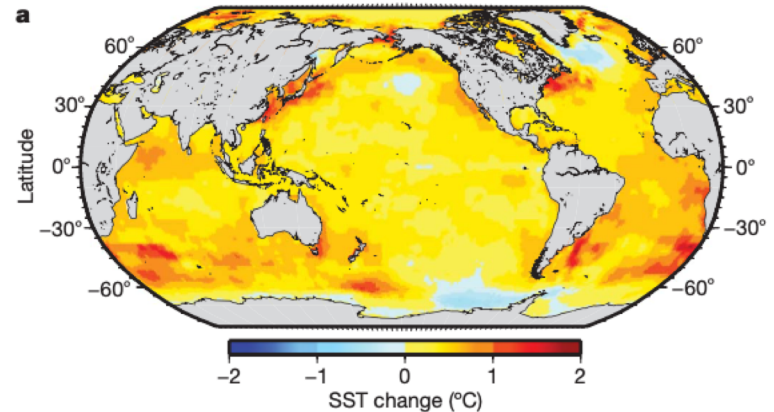
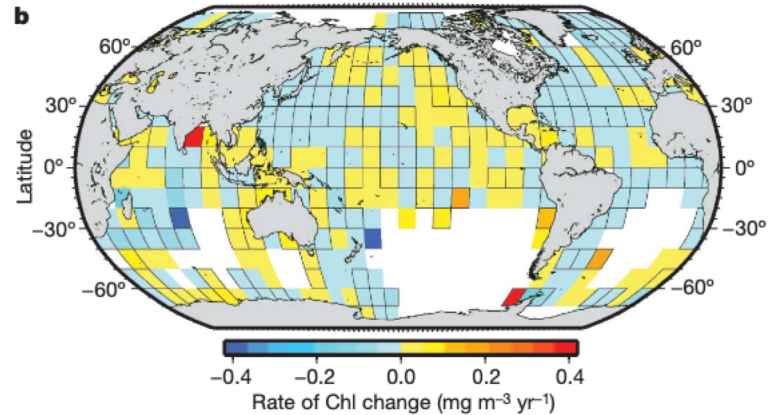
Daniel G. Boyce , Marlon R. Lewis & Boris Worm

*Nature* **466**, 591–596(2010) | [Cite this article](#)

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⇒ Chl 1% /year  
= 30% over the last century



# 3. DECADAL VARIABILITY OF PHYTOPLANKTON

What about secular trend?

nature

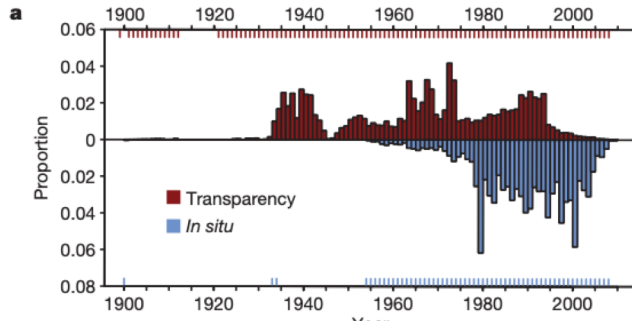
Article | Published: 29 July 2010

## Global phytoplankton decline over the past century

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However....

There is an over-estimation of Chl from transparency vs. in situ measurements

-> methodology can biased trend !



### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

Problematic about the low-frequency uncertainties

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#### **Large uncertainties remain, in particular**

- Inability to resolve decadal variability of phytoplankton biomass

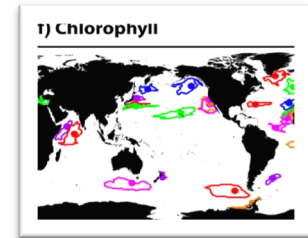
#### **Critically limit our ability to**

- Quantify contribution of biological carbon pump to carbon sequestration
- Predict response of marine ecosystems and subsequent carbon cycling to environmental and climate changes

### 3. DECADAL VARIABILITY OF PHYTOPLANKTON

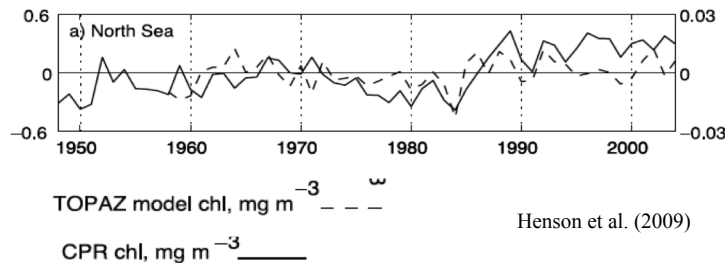
How can we study the low frequency cycles & trends?

- Radiometric observations → limited in time
- In situ observations → data too sparse (and limited in time)



Henson et al. (2016)

- Physical-biogeochemical numerical modelling  
→ uncertainties in processes & model parametrization of biogeochemical parameters



Henson et al. (2009)

Difficulties to solve regime shift

# OUTLINE

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## INTRODUCTION

Le phytoplancton, importance biogéochimique  
Pertinence de la télédétection de la couleur de l'océan

## 1. PRÉMICES DE LA RADIOMÉTRIE SPATIALE

1979-1985: apports de la mission Nimbus7 et du  
capteur CZCS (les prémices d'une vision  
globale et de la variabilité saisonnière)

## 2. CAPTEURS MODERNES

1997-....: apports des capteurs radiométriques modernes  
et des produits combinés: du saisonnier à  
l'interannuel

## 3. RECONSTRUCTION DÉCENNALES

Les produits reconstruits pour tenter d'appréhender la  
variabilité décennale

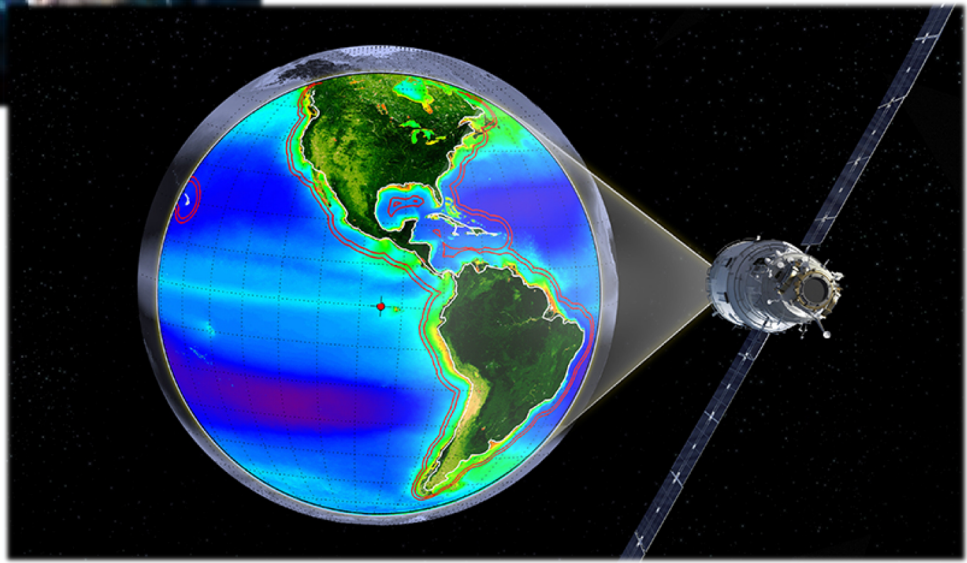
## 4. APPROCHES COMPLÉMENTAIRES

Combinaison des observations et intelligence artificielle:  
vers de nouvelles perspectives!?

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

Artificial Intelligence & Deep learning

---



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### Artificial Intelligence & Deep learning

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#### Some definitions:

**Artificial intelligence** is the capacity of an algorithm to assimilate information to perform tasks that are characteristic of human intelligence, such as recognizing objects and sounds, contextualizing language, learning from the environment, and problem solving.

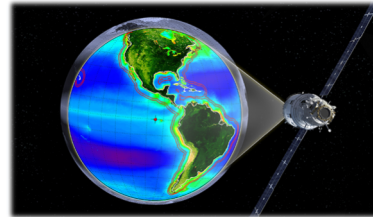
**Machine learning** is a field of statistical research for training computational algorithms that split, sort and transform a set of data to maximize the ability to classify, predict, cluster or discover patterns in a target dataset.

**Deep learning** refers to machine learning algorithms that construct hierarchical architectures of increasing sophistication. Artificial neural networks with many layers are examples of deep learning algorithms.

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### Artificial Intelligence & Deep learning

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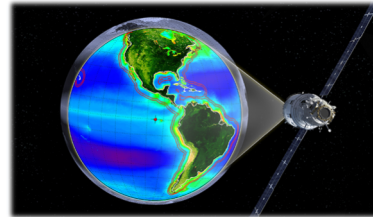


- a. Reconstruct & understand long-term satellite derived Chl
- b. Improve our understanding of physical-biological interactions (in situ)

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### Artificial Intelligence & Deep learning

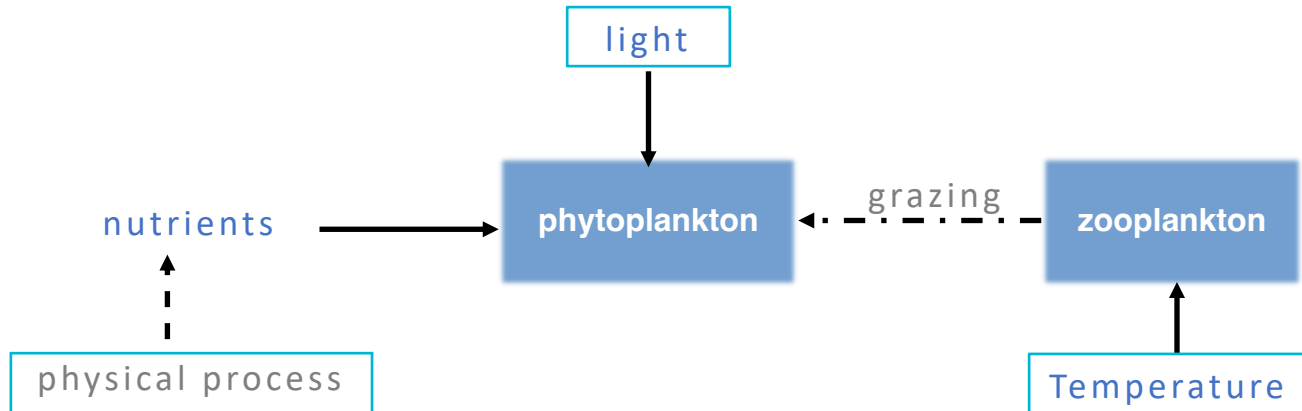
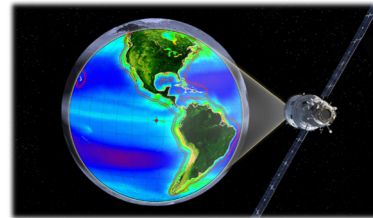
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a- Reconstruct & understand long-term satellite derived Chl

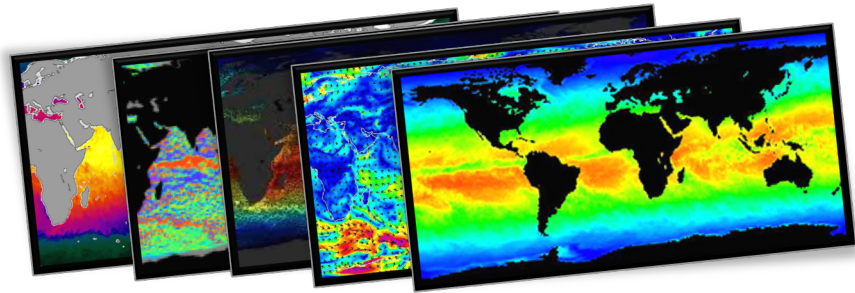




## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### a- Reconstruct & understand long-term satellite derived Chl

Predictors: SST, SLA, surface currents, PAR, winds



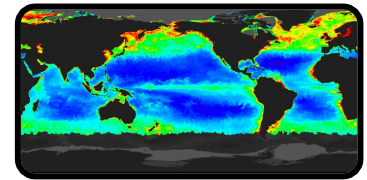
1900's

1998

2020



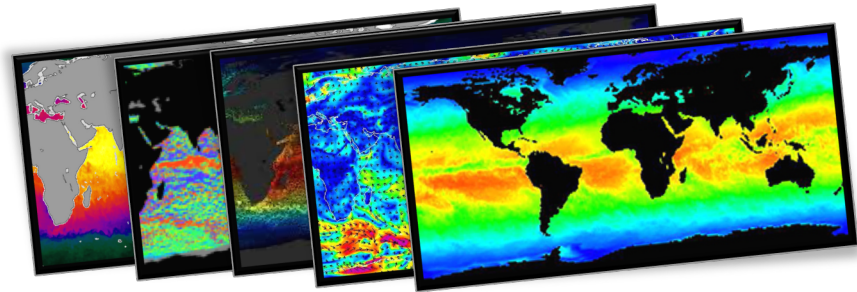
Chl



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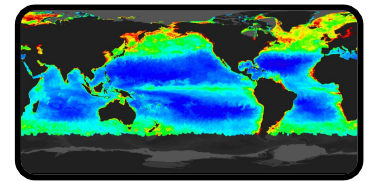
1998

2020

1 TRAIN

Numerical Schemes

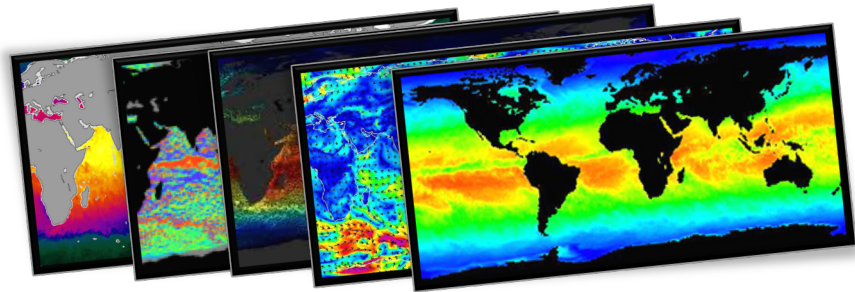
Chl



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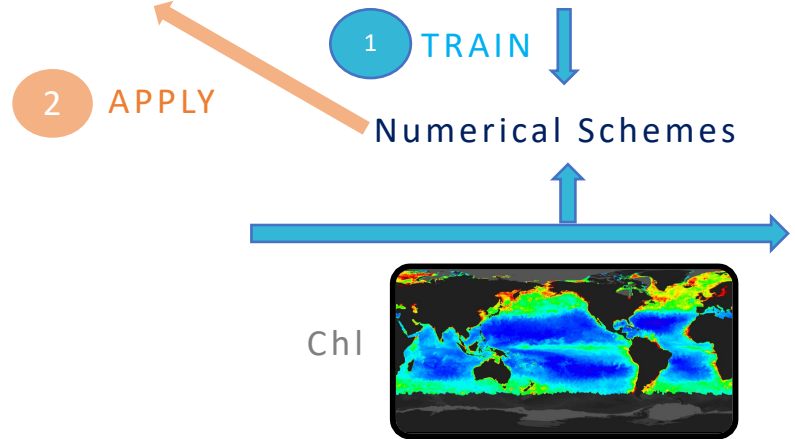
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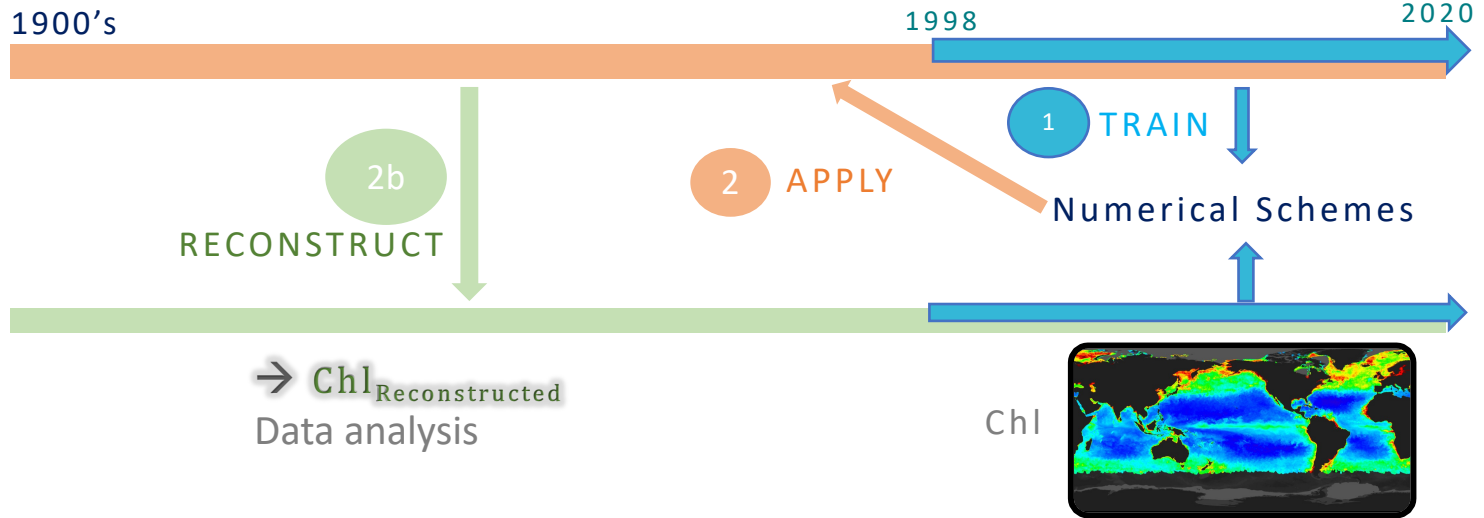
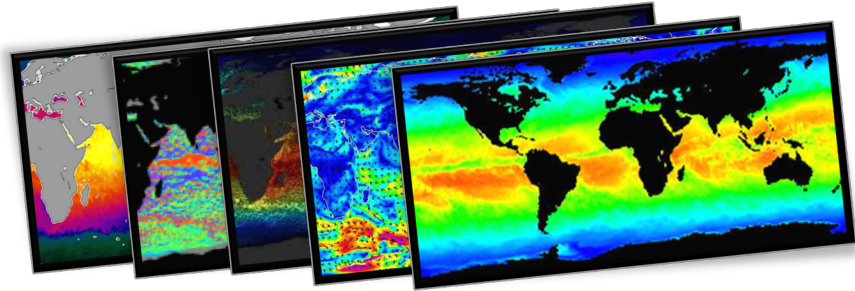
2020



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### a- Reconstruct & understand long-term satellite derived Chl

Predictors: SST, SLA, surface currents, PAR, winds



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

---

i) Proof of concept on the physical-BGC model NEMO-PISCES

| Physical predictors      | Chl                       | Method                                         |
|--------------------------|---------------------------|------------------------------------------------|
| <b>NEMO-PISCES</b> model | NEMO- <b>PISCES</b> model | SVR <small>(Support Vector Regression)</small> |

(physical & BGC data  
over 1979-2010  
monthly, 2°x2°)

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

i) Proof of concept on the physical-BGC model NEMO-PISCES

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(physical & BGC data  
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monthly, 2°x2°)

Training: 1998-2010, randomly selected on 7,2% of the full dataset

Reconstruction: 1979-2010 → we have both Chl PISCES & Chl<sub>reconstructed</sub>

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

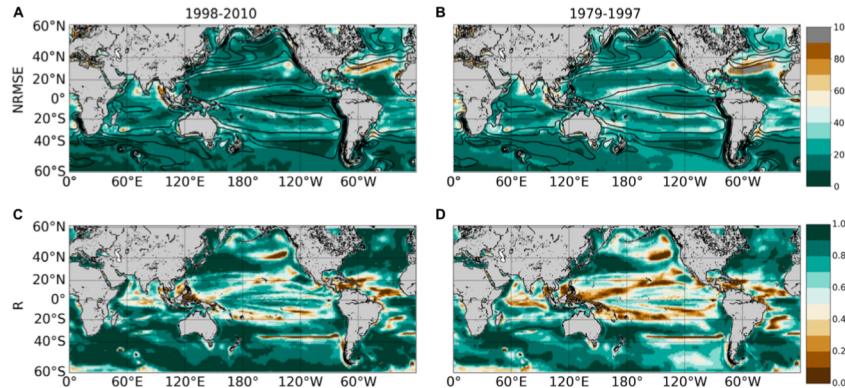
### i) Proof of concept on the physical-BGC model NEMO-PISCES

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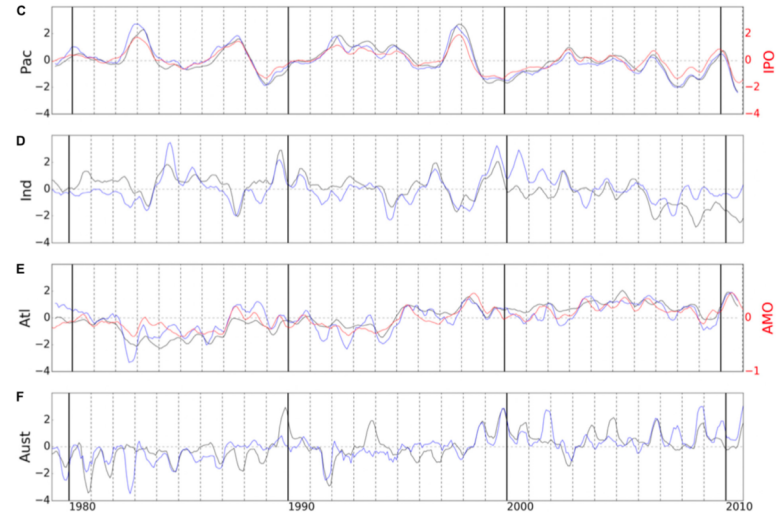
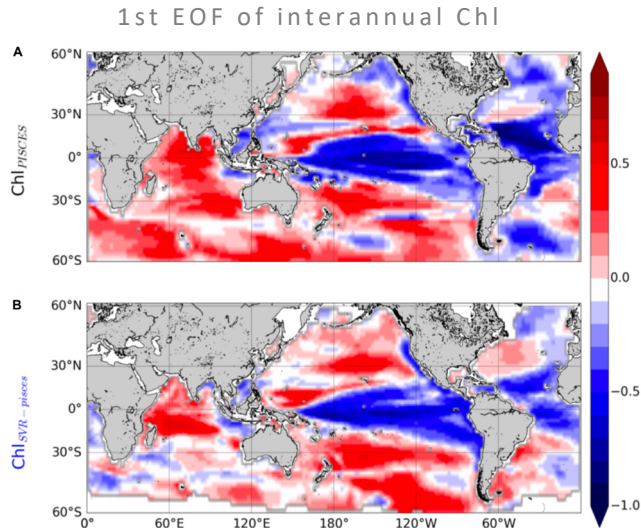
**FIGURE 5 | (A,B)** NRMSE (n%) and **(C,D)** correlation between Chl<sub>PISCES</sub> vs. Chl<sub>Sat</sub>-PISCES after applying a 5 month-running mean on both time-series. These 2 diagnostics are calculated over 1998-2010 (left column) and 1979-1997 (right column). Contours on the upper panels show their respective 1998-2010 Chl time average (every 0.1 mg.m<sup>-3</sup>).

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

i) Proof of concept on the physical-BGC model NEMO-PISCES

| Physical predictors | Chl               | Method                          |
|---------------------|-------------------|---------------------------------|
| NEMO-PISCES model   | NEMO-PISCES model | SVR (Support Vector Regression) |



**FIGURE 6** | First mode of basin-scale EOFs of interannual **(A)**  $Chl_{PISCES}$  and **(B)**  $Chl_{SVR} - PISCES$ , and their corresponding PCs over 1979–2010 in the **(C)** Pacific, **(D)** Indian, **(E)** Atlantic, and **(F)** Austral Oceans (black and blue lines, respectively). Climate indices are reported in red (right y-axis).

Martinez et al. (2020)



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

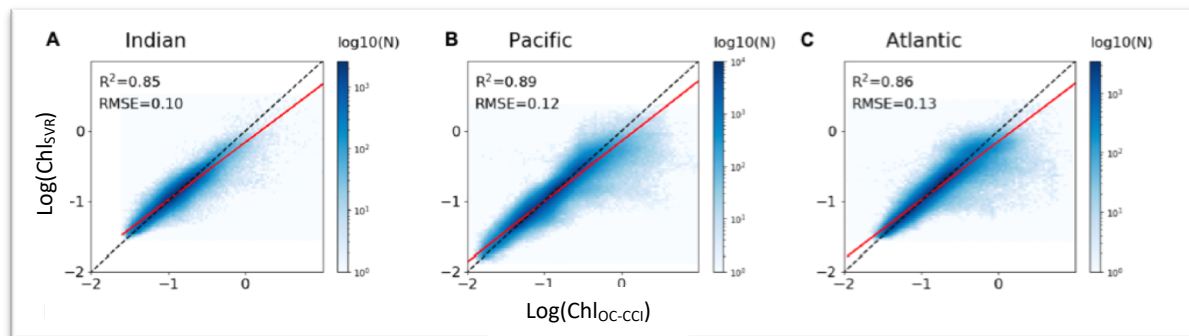
ii) Application to satellite obs

| Physical predictors | Chl               | Method |
|---------------------|-------------------|--------|
| NEMO-PISCES model   | NEMO-PISCES model | SVR    |
| NEMO-PISCES model   | <b>Satellite</b>  | SVR    |

Training: 1998-2010, randomly selected on 7,2% of the full dataset

Reconstruction: 1979-2010 →  $\text{Chl}_{\text{reconstructed}}$

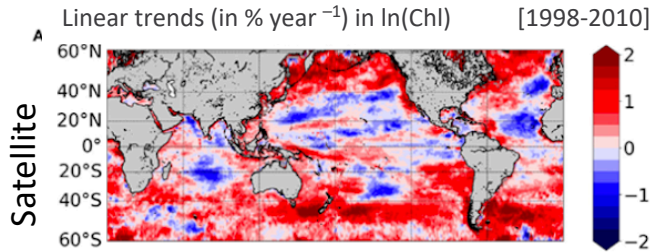
1998-2010



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

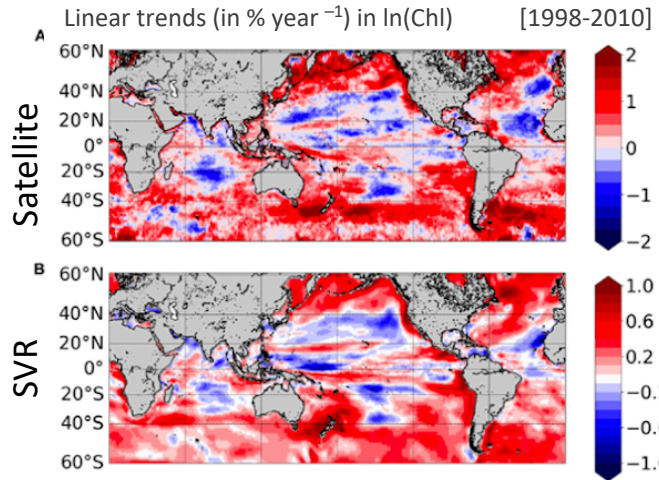
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## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

ii) Application to satellite obs



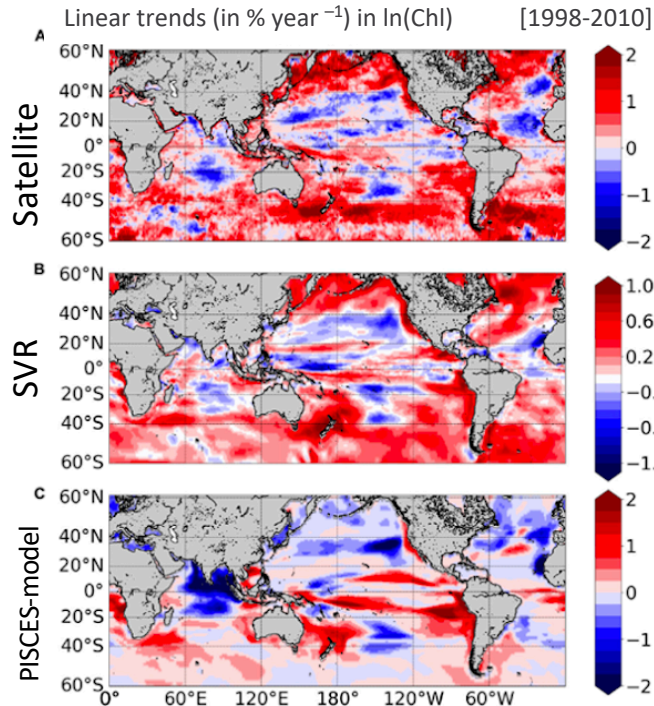
- Capture seasonal, interannual variability and trends
- **Regional bias,**
- **Amplitude underestimation**

Physical predictors from **NEMO model** vs. **Chl satellite**

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

ii) Application to satellite obs



- Capture seasonal, interannual variability and trends
- **Regional bias,**
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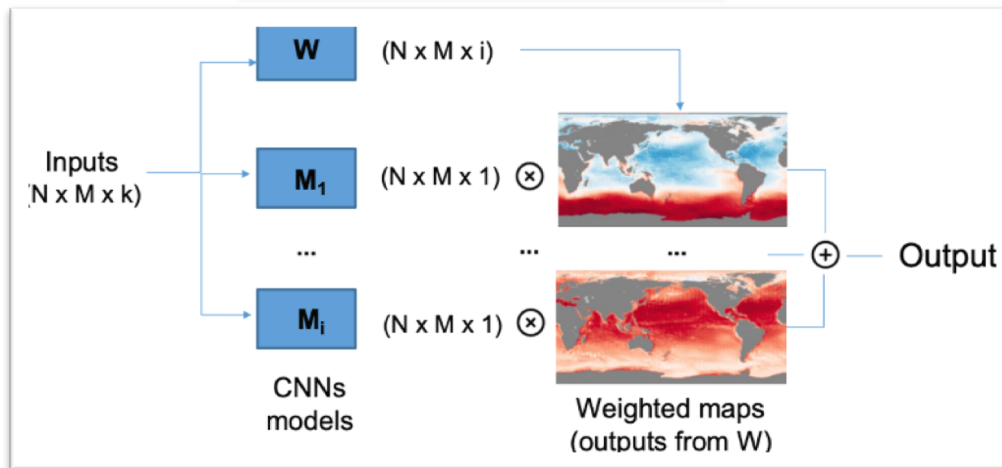
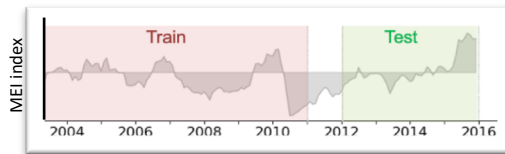
Physical predictors from **NEMO model** vs. **Chl satellite**

Same physics from the NEMO numerical model

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### a- Reconstruct & understand long-term satellite derived Chl

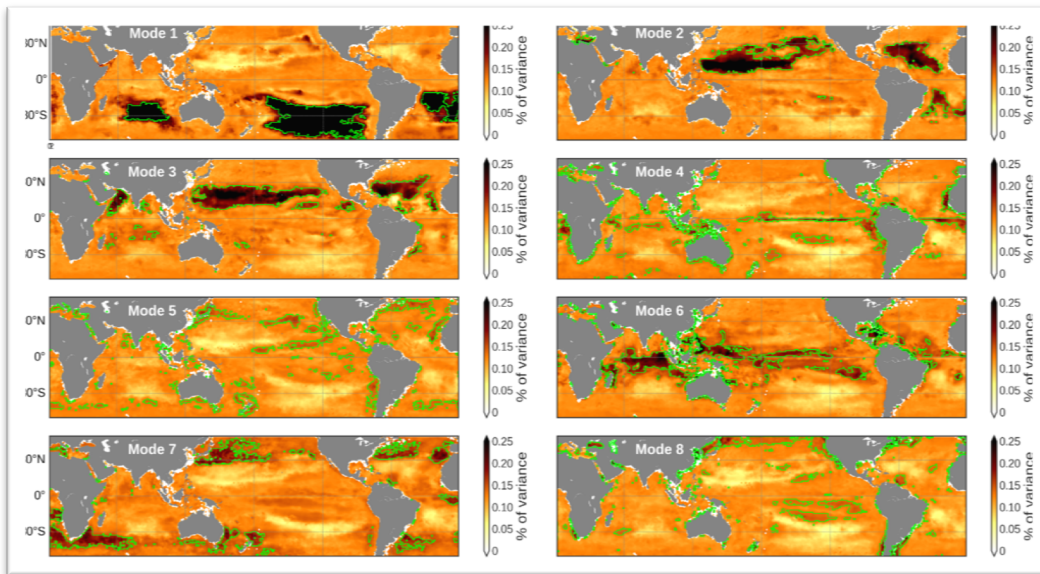
| Physical predictors | Chl               | Method                                        |
|---------------------|-------------------|-----------------------------------------------|
| NEMO-PISCES model   | NEMO-PISCES model | SVR (Support Vector Regression)               |
| NEMO-PISCES model   | Satellite         | SVR                                           |
| Satellite           | Satellite         | SVR & Multi-Layer Perceptron                  |
| Satellite           | Satellite         | Convolutional Neural Network & Multi-mode CNN |



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

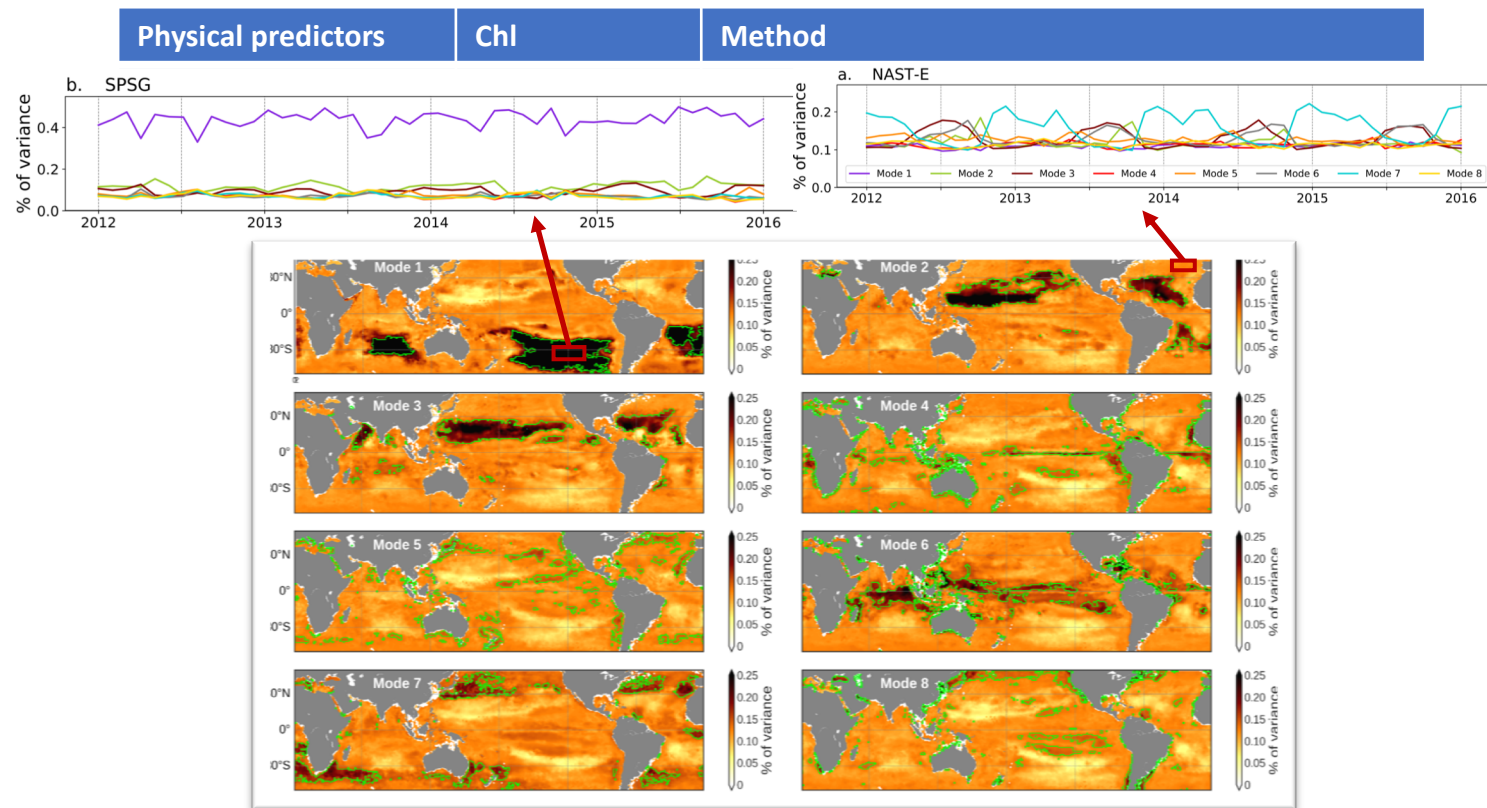
| Physical predictors | Chl       | Method                                        |
|---------------------|-----------|-----------------------------------------------|
| Satellite           | Satellite | Convolutional Neural Network & Multi-mode CNN |



Percentage of variance explained by each 8 modes of CNN<sub>MM8</sub>. Isolines of percentile-90 of the values are superposed in green.

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

a- Reconstruct & understand long-term satellite derived Chl

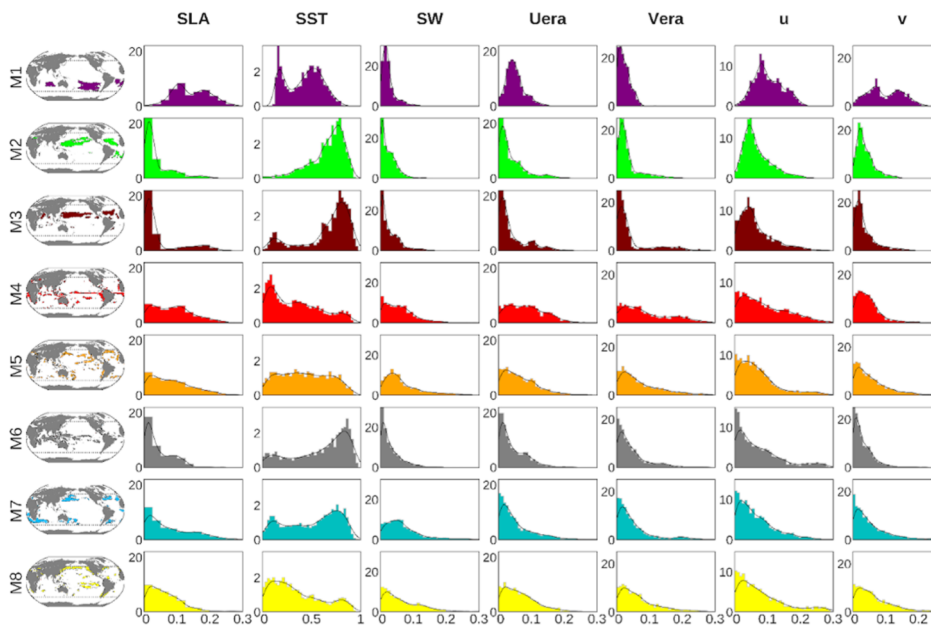


Percentage of variance explained by each 8 modes of  $CNN_{MM8}$ . Isolines of percentile-90 of the values are superposed in green.

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### a- Reconstruct & understand long-term satellite derived Chl

Not only a black box from which we can't obtain any informations



Normalized distribution (y-axis) of the relative importance of each predictors computed over the percentile-90 area for each mode (x-axis)



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### a- Reconstruct & understand long-term satellite derived Chl

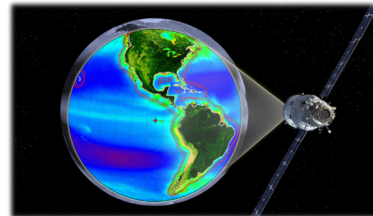
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- It is a hard task to characterize decadal variability of phytoplankton biomass due to the unavailability of long enough time series
- It is a critical issue to extend the time series of observations!
- It is a real challenge today, whatever the data are, to make consistent dataset from different means of observation
- There are large number of uncertainties regarding physical and biological forcing that influence the long-term variability of phytoplankton biomass

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

### Artificial Intelligence & Deep learning

---



- a. Reconstruct & understand long-term satellite derived Chl
- b. Improve our understanding of physical-biological interactions (in situ)

## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

b- Improve our understanding of physical-biological interactions (in situ)

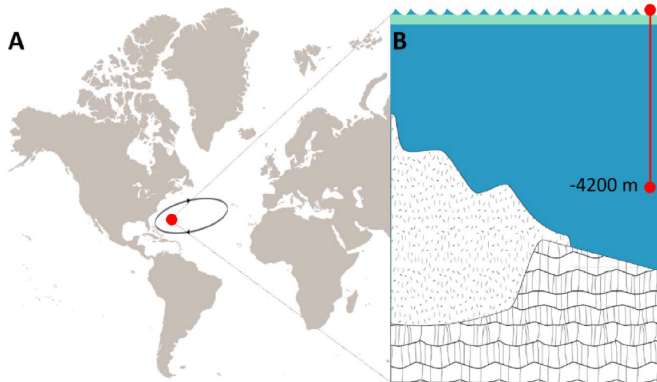
EXAMPLE

1

**SCIENTIFIC  
REPORTS**  
nature research

**Machine learning identifies a strong association between warming and reduced primary productivity in an oligotrophic ocean gyre** 2020

Domenico D'Alelio<sup>1,5\*</sup>, Salvatore Rampone<sup>2,5</sup>, Luigi Maria Cusano<sup>2</sup>, Valerio Morfino<sup>2</sup>, Luca Russo<sup>3</sup>, Nadia Sanseverino<sup>3</sup>, James E. Cloern<sup>4</sup> & Michael W. Lomas<sup>4\*</sup>



Station du climat BATS (Bermude)

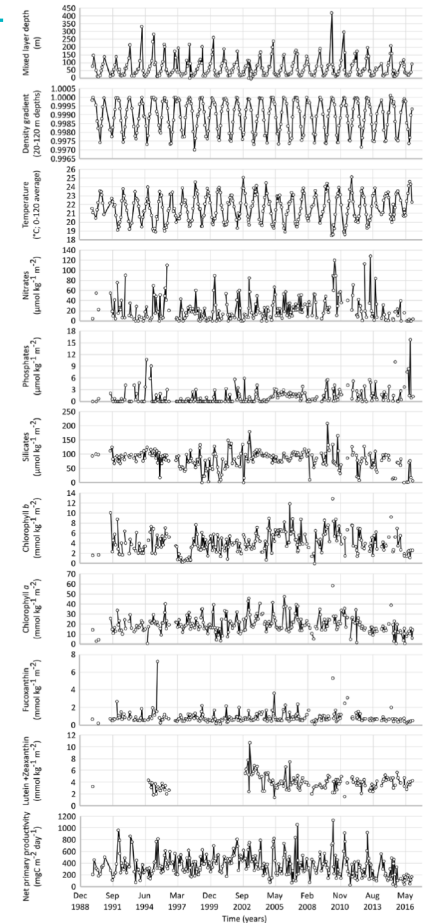
# 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

b- Improve our understanding of physical-biological interactions (in situ)

## EXAMPLE

1

Séries temporelles des variables  
environnementales et biologiques à  
BATS



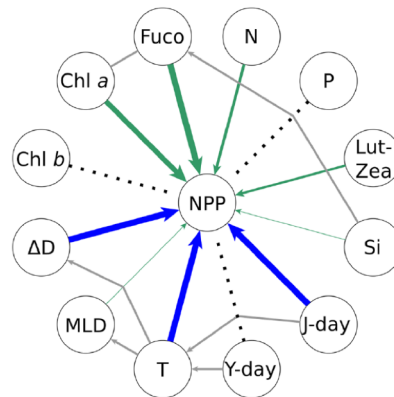
# 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

b- Improve our understanding of physical-biological interactions (in situ)

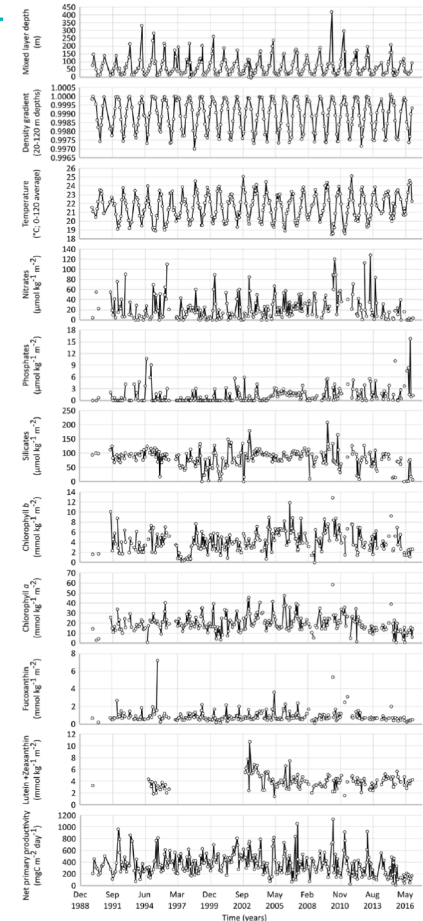
## EXAMPLE

1

Séries temporelles des variables  
environnementales et biologiques à  
BATS



— Positive impact    - - - No impact  
— Negative impact    — Hypothetical link

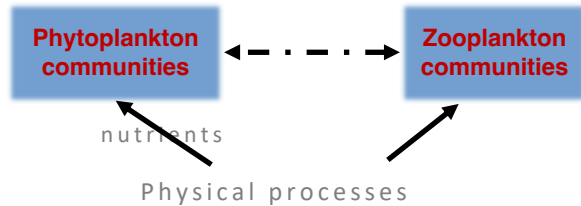


## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

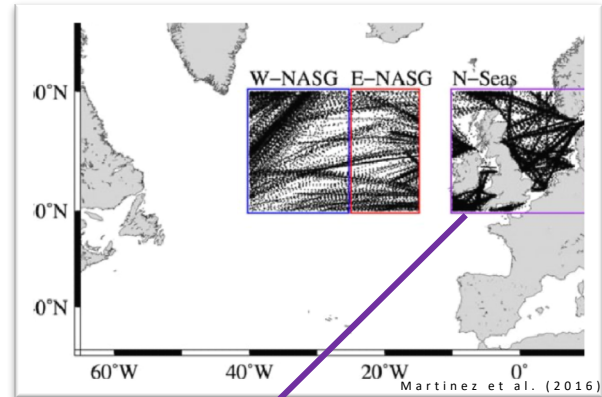
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EXAMPLE

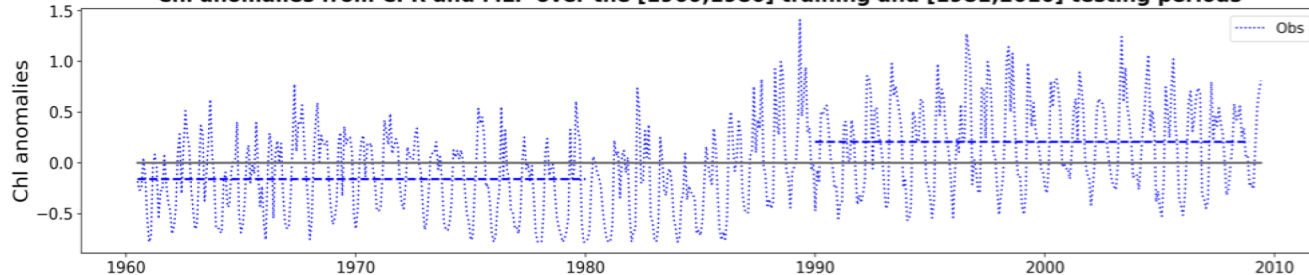
2



In situ obs.  
Continuous Plankton Recorder (CPR)



Chl anomalies from CPR and MLP over the [1960;1980] training and [1981;2010] testing periods

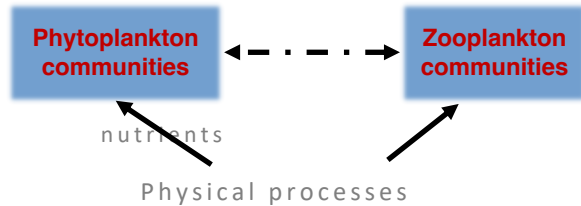


## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

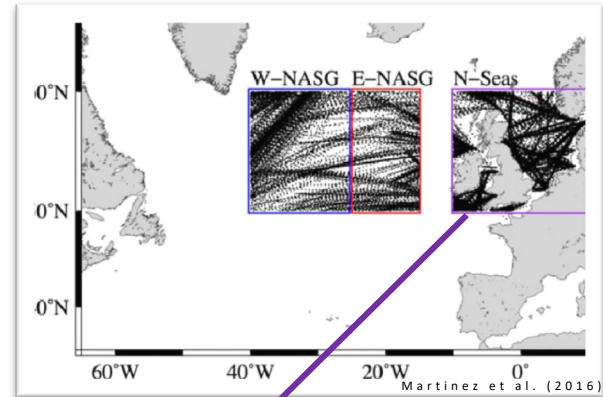
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EXAMPLE

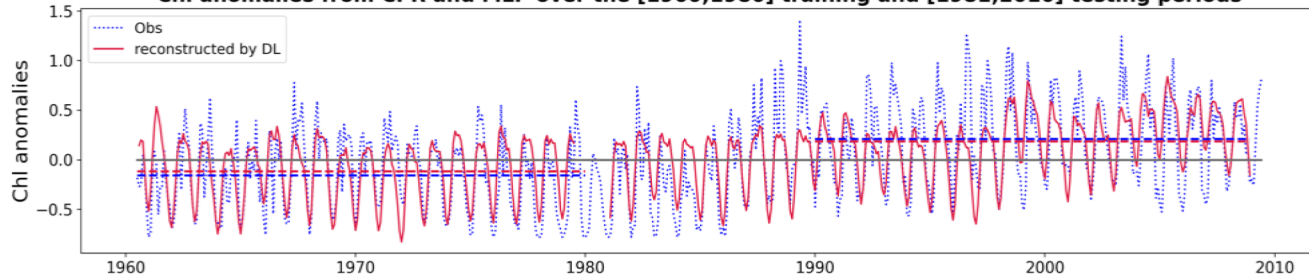
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In situ obs.  
Continuous Plankton Recorder (CPR)



Chl anomalies from CPR and MLP over the [1960;1980] training and [1981;2010] testing periods



## 4. COMPLEMENTARY/ALTERNATIVE APPROACHES

Always going further....

---

### Improve the deep learning architectures through 4 emulators:

- Data-driven: (1)  $Y = f(X) \rightarrow$  **not being constrained by a priori knowledge**

$Y = \text{Chl}$ ,  $X = \text{predictors}$

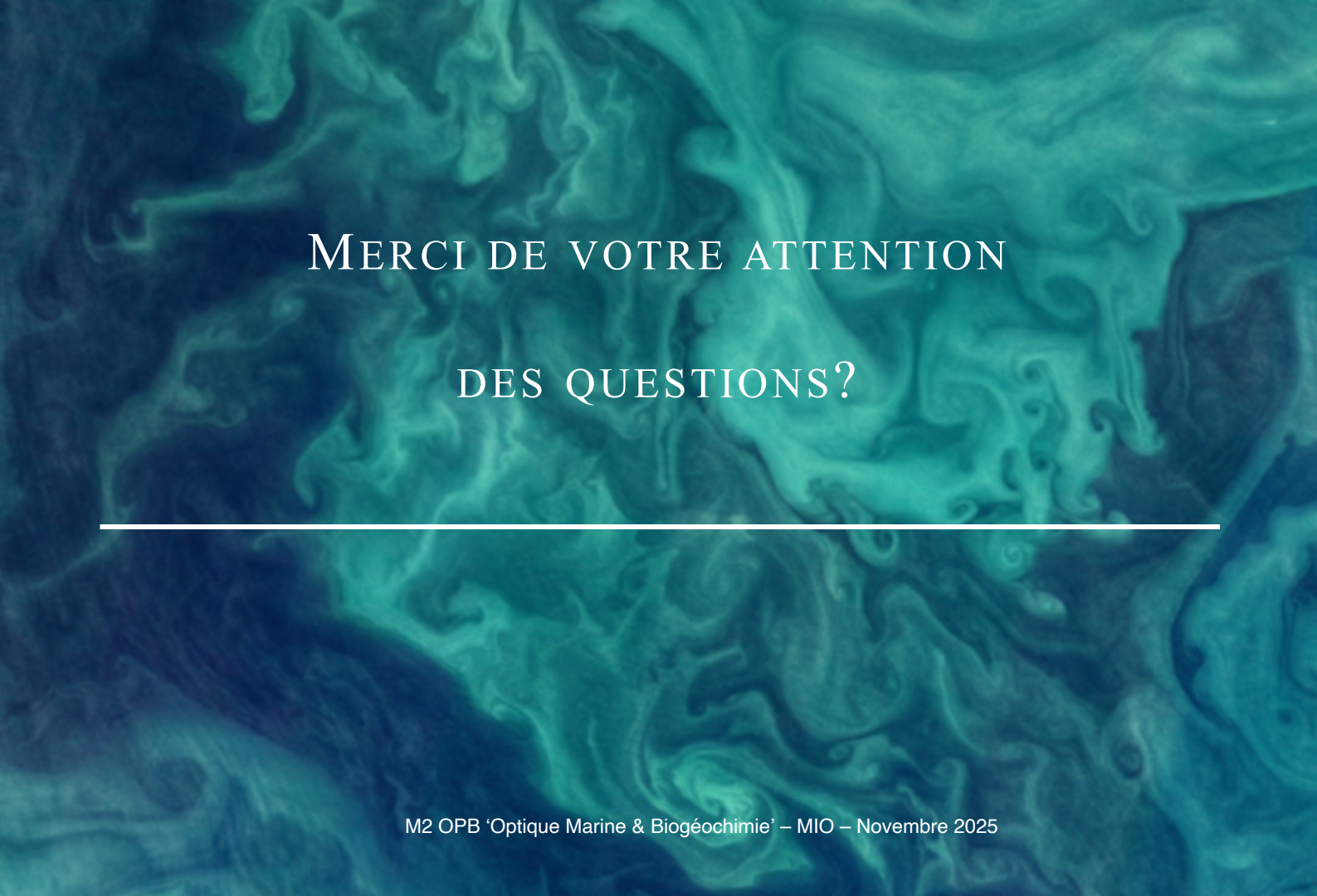
- Ordinary and Partial Differential Equations:

(2)  $\partial_t Y = f(\partial_t X) \rightarrow$  **role of the physical preconditioning**

(3)  $\partial_t Y = f(\partial_t X, \partial_t Y) \rightarrow$  **take into account biological processes**

(4)  $\partial_t Y = f(\partial_t \tilde{X}, \partial_t Y) \rightarrow$  **include explicit representation of hidden processes**





MERCI DE VOTRE ATTENTION  
DES QUESTIONS?

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