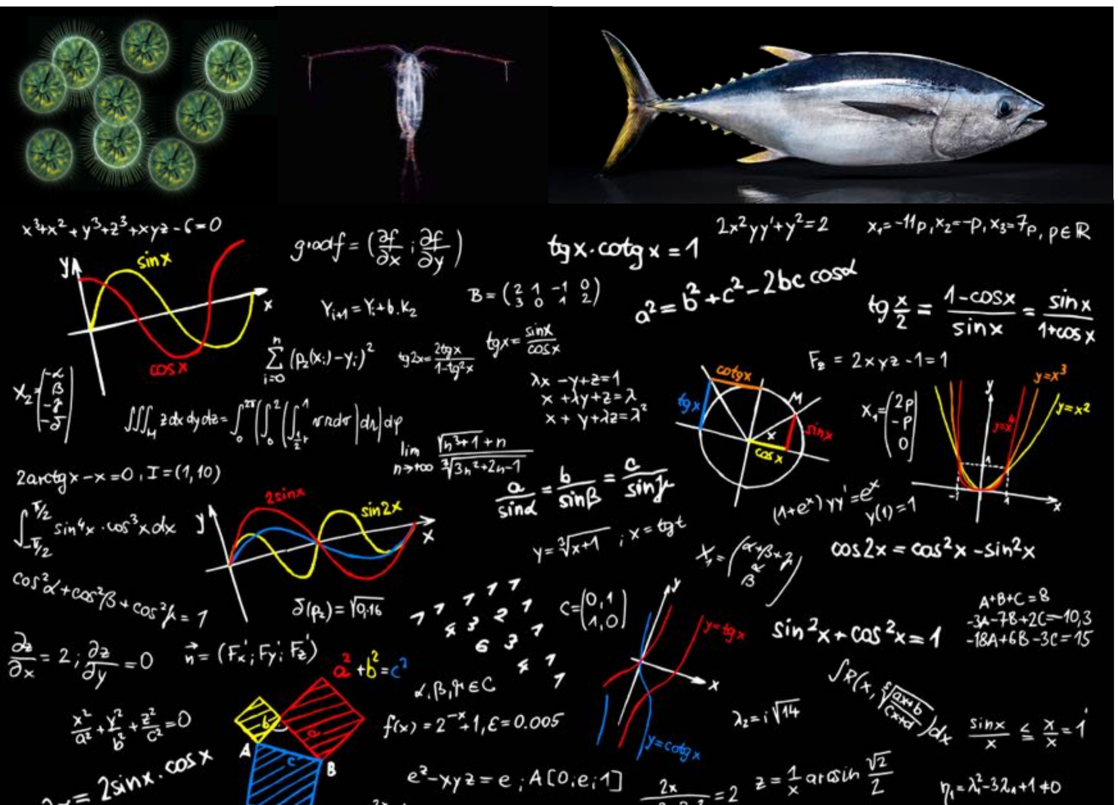
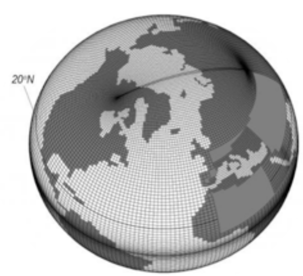
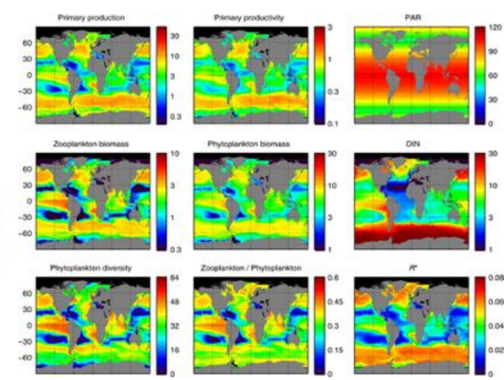
ML4Oceans summer school 2022
SCAI/SU - Paris

2^{nd} of September 2022
Dynamic modelling

Marine ecosystem modelling







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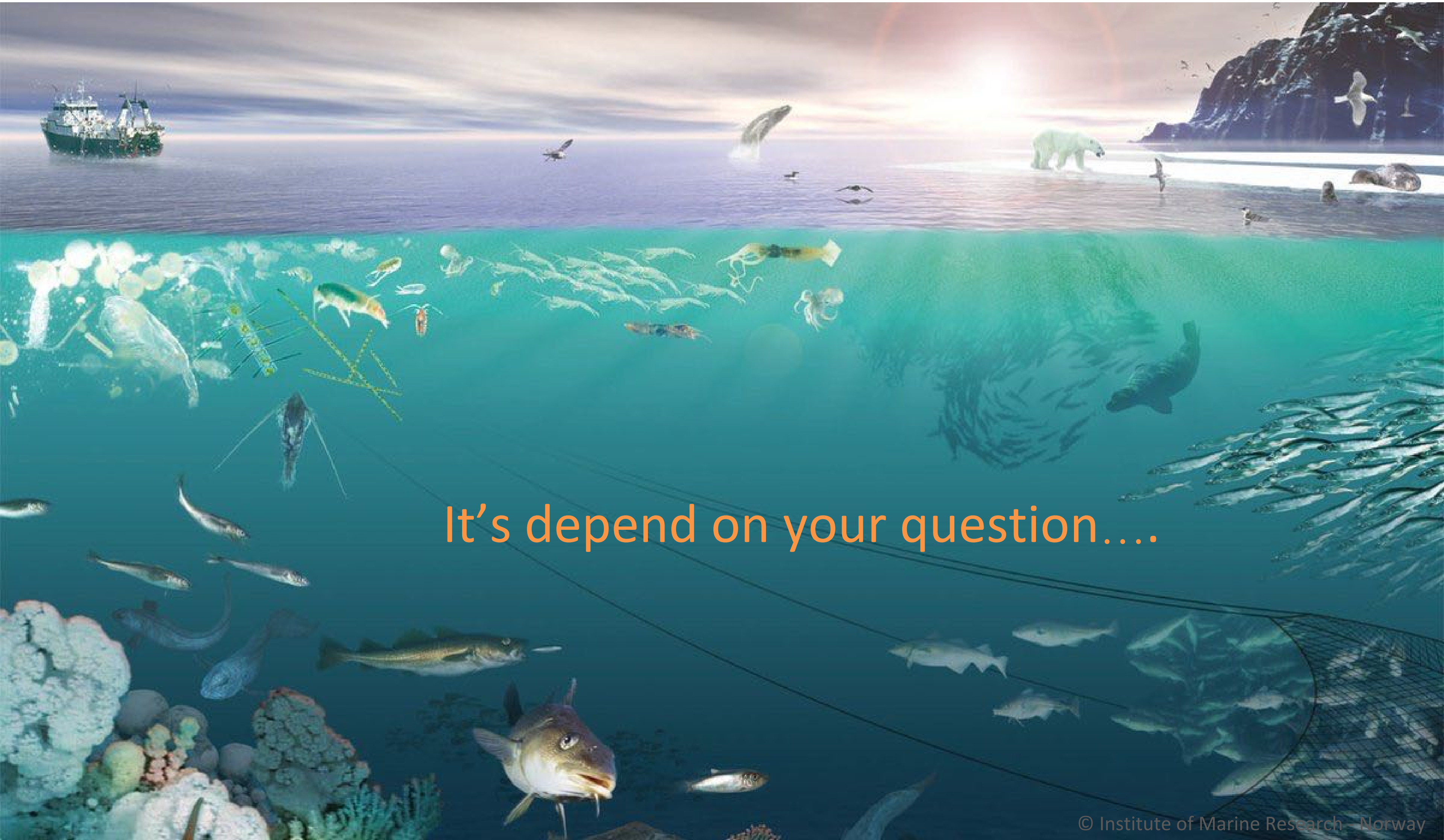
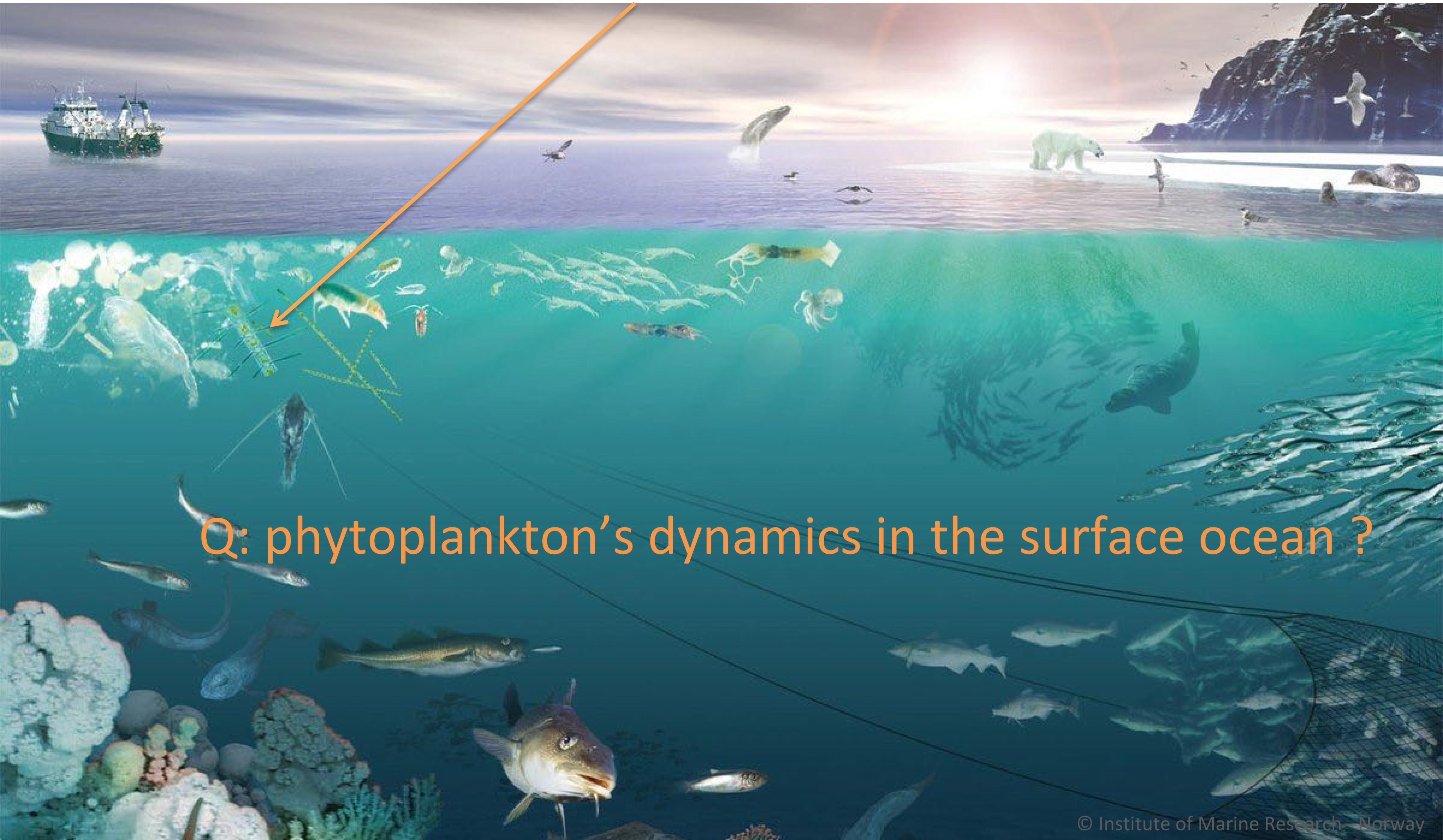
How can we model marine ecosystems?



How can we model marine ecosystems?

Let’s start by modelling one plankton population



Modelling one population

Dynamical model

Differential equation

P(t): state variable

$dP/dt = \text{source} - \text{sink}$

Modelling one population

Dynamical model

Constructing the model step by step!
From the most simple assumptions…

Differential equation

P(t): state variable

dP/dt = source − sink = birth - death

Modelling one population

Dynamical model

Constructing the model step by step!
From the most simple assumptions…

<u>**Case #1: linear processes**</u>

Differential equation

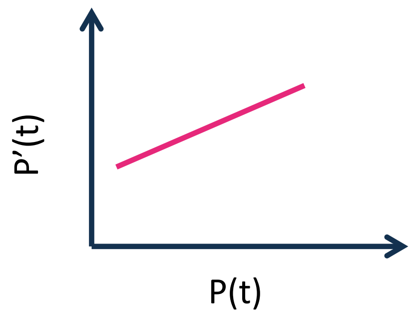
$P(t)$: state variable

dP/dt = source − sink = birth - death

Blackboard…

Modelling one population

- **Case #1: linear growth**



$$P'(t) = r.P(t)$$

This **differential equation** can be solved analytically

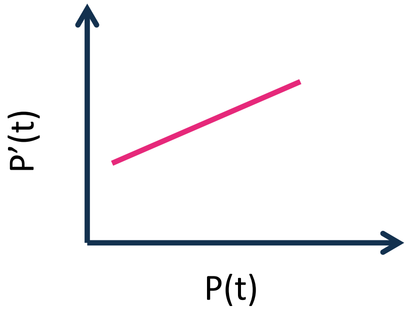
Analytical solution:

$$P(t) = P_0.e^{r.t}$$

Blackboard…

Modelling one population

- <u>Case #1: linear growth</u>



$$P'(t) = r.P(t)$$

This **differential equation** can be solved analytically

<u>Analytical solution:</u>

$$P(t) = P_0.e^{r.t}$$

<u>NB: "Solving the equation":</u>

- Find the analytical solution, when possible
- If not ? Compute an approximation

  $\Longrightarrow$ numerical integration!

ard…

Modelling one population

- <u>**NB : Numerical integration**</u>

  ≠ Finding the exact solution

  = Solving an equation using an approximation

It requires to:

⇒ Discretize the time into time steps Δt

⇒ Estimate state at time $P(t+\Delta t)$ from $P(t)$

<u>Principle</u> :

- Start from the initial condition
- Estimate the state after a very small time step, and so on (recursive)

On option is to use the Taylor's developments, e.g. at order 1 :

$$\mathbf{P(t+dt)} \approx \mathbf{P(t)} + \frac{d\mathbf{P(t)}}{dt} .dt$$

Making the hypothesis that the terms of higher order can be neglected

Modelling one population

- **NB : Numerical integration**

  ≠ Finding the exact solution

  = Solving an equation using an approximation

It requires to:

⟹ Discretize the time into time steps Δt

⟹ Estimate state at time $P(t+\Delta t)$ from $P(t)$

For the exponential growth of a population

$$\begin{cases} \dfrac{d\mathbf{P}}{dt} = r \,.\, \mathbf{P} \\ P(0) = P_0 \end{cases}$$

Numerical integration step by step:

$P(t_1=t_0+\Delta t) =$

$P(t_2=t_2+\Delta t) =$

$P(t_3=t_3+\Delta t) =$

$P(t_4=t_4+\Delta t) =$

…

Nota bene **: This integration method is called Euler's integration, but many more (complex one) exist! E.g. Runge-Kutta**…

Modelling one population

- **<u>NB : Numerical integration</u>**

  ≠ Finding the exact solution

  = Solving an equation using an approximation

It requires to:

$\Rightarrow$ Discretize the time into time steps Δt

$\Rightarrow$ Estimate state at time $P(t+\Delta t)$ from $P(t)$

<u>To keep in mind:</u>

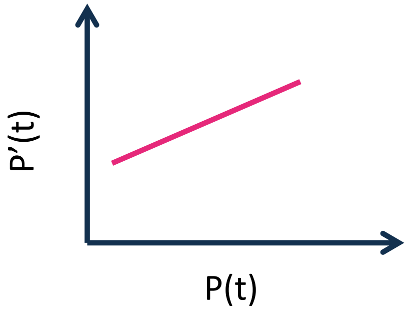
$\Rightarrow$ This is how dynamical model are simulated

$\Rightarrow$ Several integration methods exist (more or less costly/precise)

$\Rightarrow$ This can lead to numerical diffusion is the time step is too small

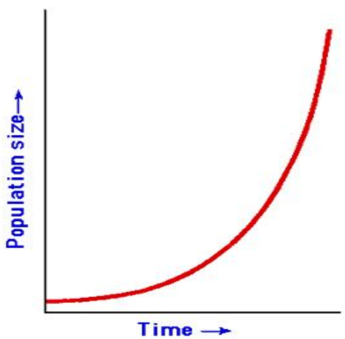
Modelling one population

- Case #1: linear growth



$$P'(t) = r.P(t)$$

This **differential equation** can be solved analytically



Analytical solution:

$$P(t) = P_0.e^{r.t}$$

Malthus model

If r >1: Exponential growth is unlimited…

Which is unrealistic…. !

Let's add a limitation term…

Blackboard…

Modelling one population

- <u>Case #2: density-dependant mortality</u>

Pierre-François Verhulst (1804–1849)

Limiting term to avoid unlimited growth:

The growth is negative when the concentration becomes too high

$$P'(t) = r.P(t).[1 - P(t)/k]$$

<u>Solution:</u>

$$P(t) = \frac{k}{1+(k/P_0-1).e^{-r.t}}$$

Logistic growth (Verhulst's model)

Modelling one population

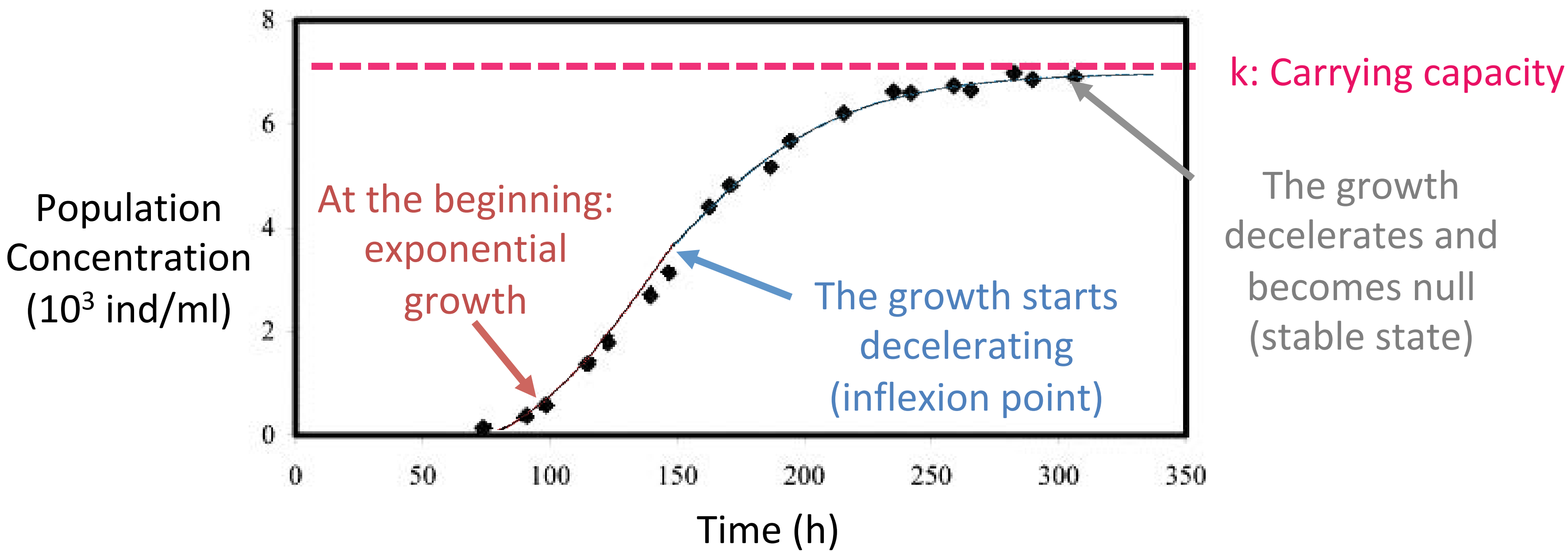
- <u>Case #2: density-dependant mortality</u>

Pierre-François Verhulst (1804–1849)

Limiting term to avoid unlimited growth:
The growth is negative when the concentration becomes too high

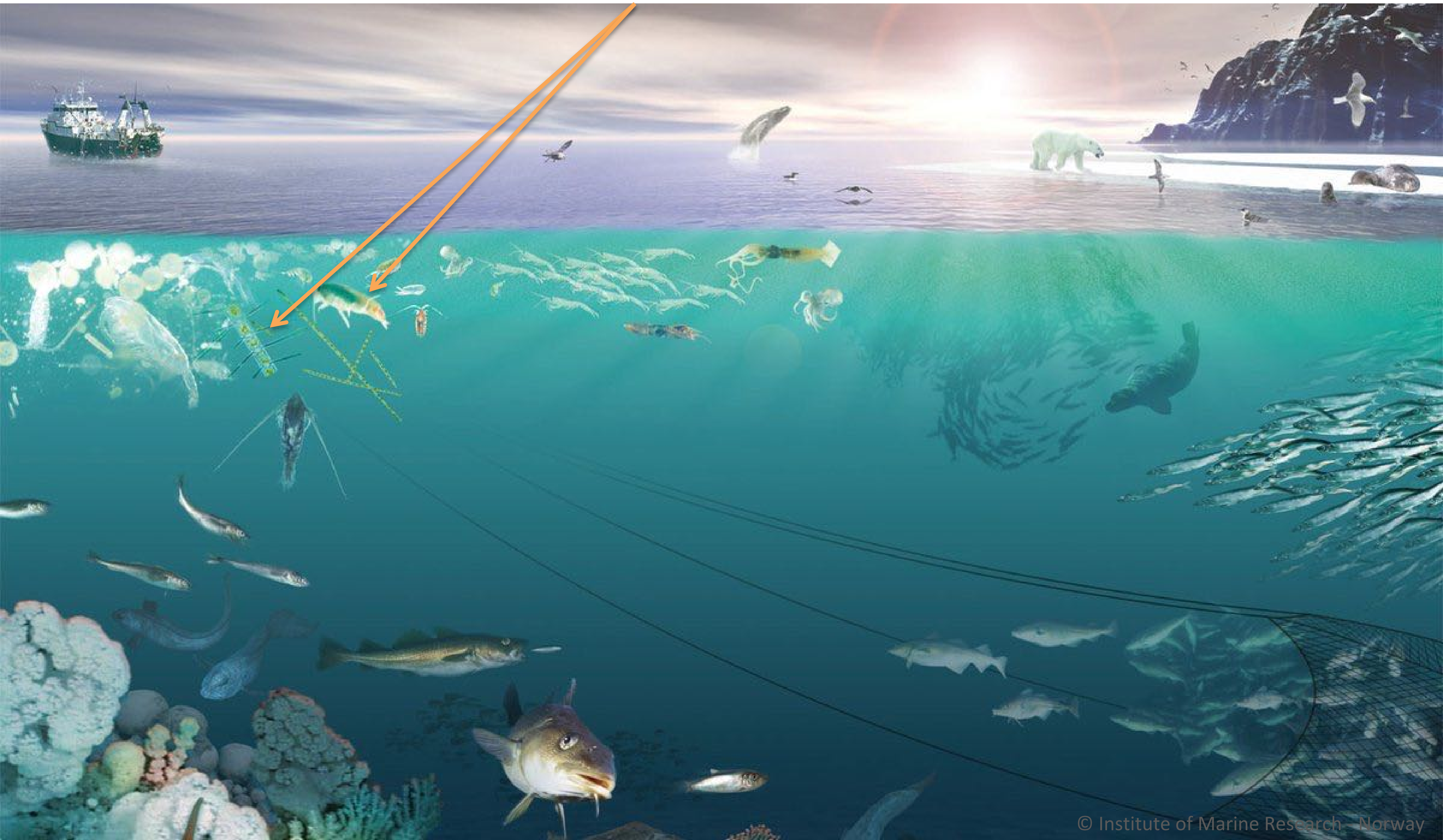
$$P'(t) = r.P(t).[1 - P(t)/k]$$

Much more realistic !

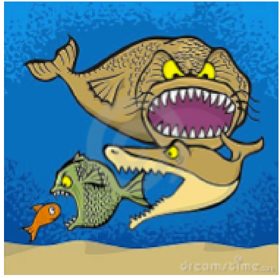


How can we model marine ecosystems?

Now, let's have two populations interacting

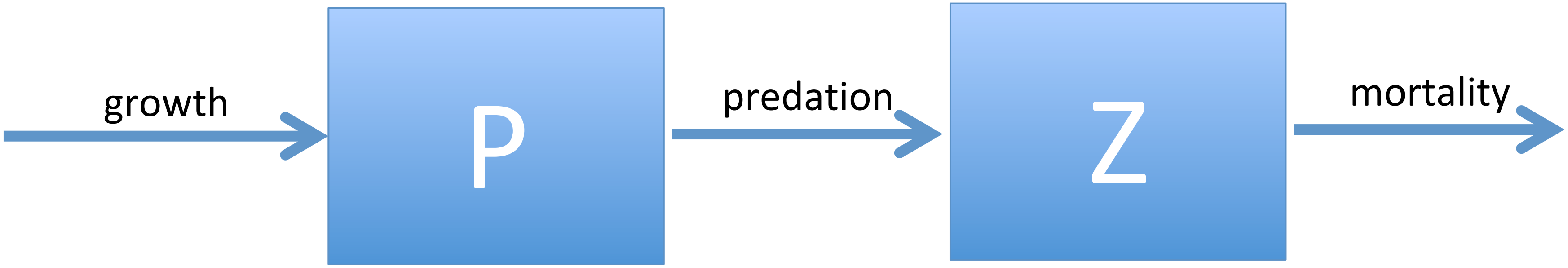


Modelling two populations



- <u>Predatory-prey relationships</u>

Again, constructing the model step by step!
From the most simple assumptions…



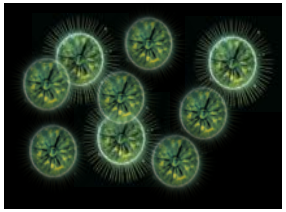
Simple case: linear processes only

r: growth rate
a: grazing rate
e: efficiency of biomass/energy conversion
m: mortality rate

Blackboard…

Modelling two populations

- <u>Predatory-prey relationships</u>



<u>Lotka-Volterra model</u>

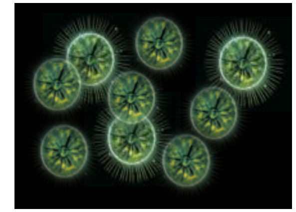
- Linear growth of the prey P (growth rate r)
- Linear predation by the predator Z (predation rate a)
- Growth of the predator proportional to the predation (factor e)
- Linear mortality of the predator Z (mortality rate m)

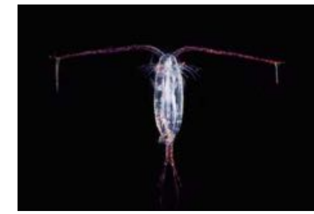
$$\begin{cases} \dot{P} = \dfrac{dP}{dt} = \text{Linear growth} - \text{linear death by predation} = r.P - a.P.Z = f(P,Z) \\ \dot{Z} = \dfrac{dZ}{dt} = \text{Growth by predation} - \text{linear mortality} = e.a.P.Z - m.Z = g(P,Z) \end{cases}$$

$\Rightarrow$ Analytical study of the model

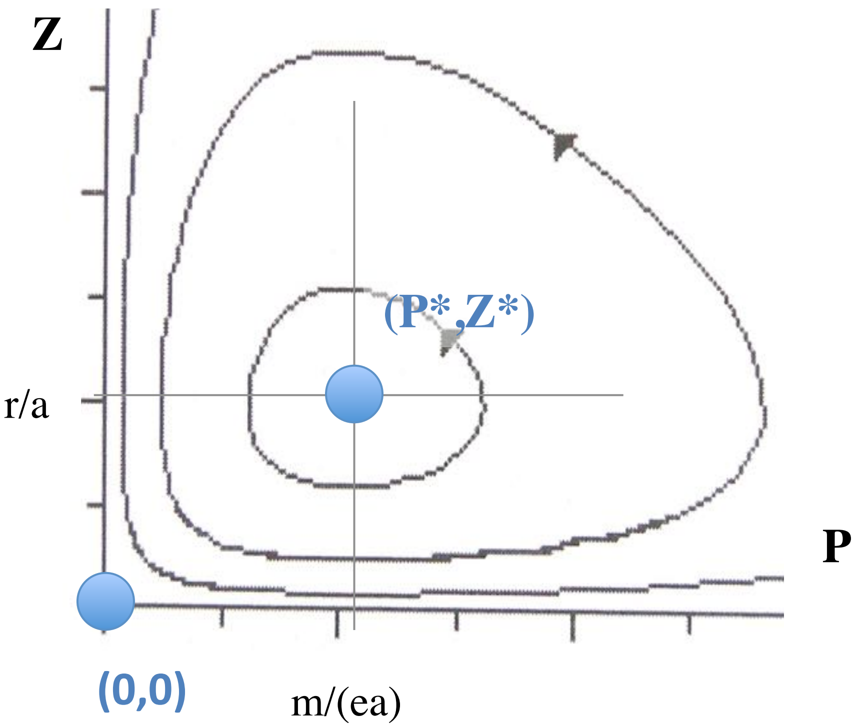
Modelling two populations

Analytical study of the Lotka-Volterra model

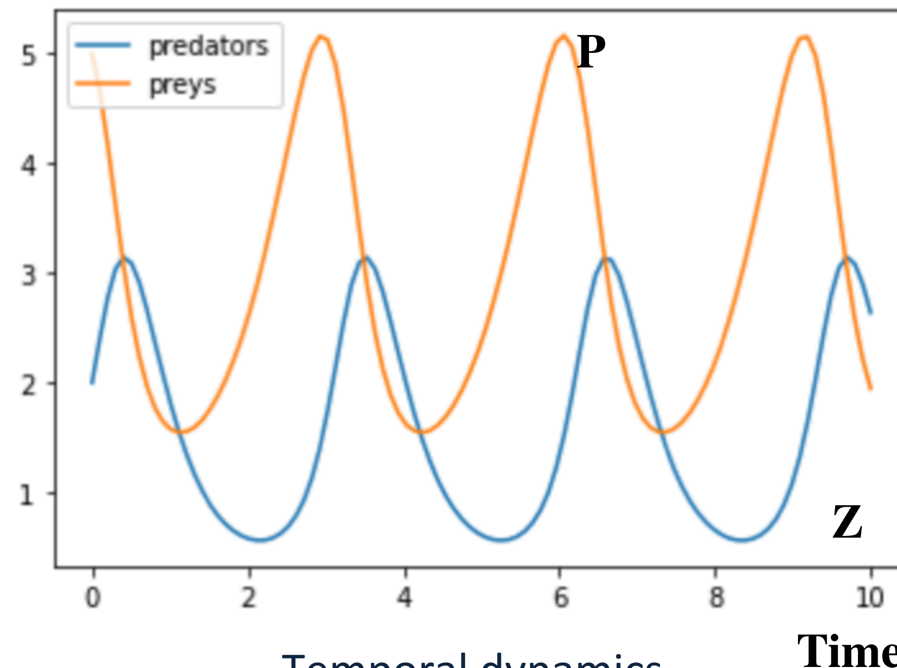




Two equilibriums



Phase portrait



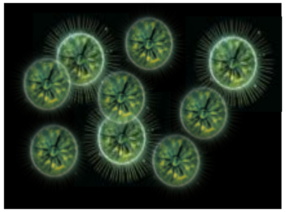
Temporal dynamics

Cf. this afternoon with Redouane

BUT: Biological/ecological processes are usually NOT linear

For instance:

Phytoplankton growth is limited,
especially by light and nutrient availability



Predation is not linear: it saturates

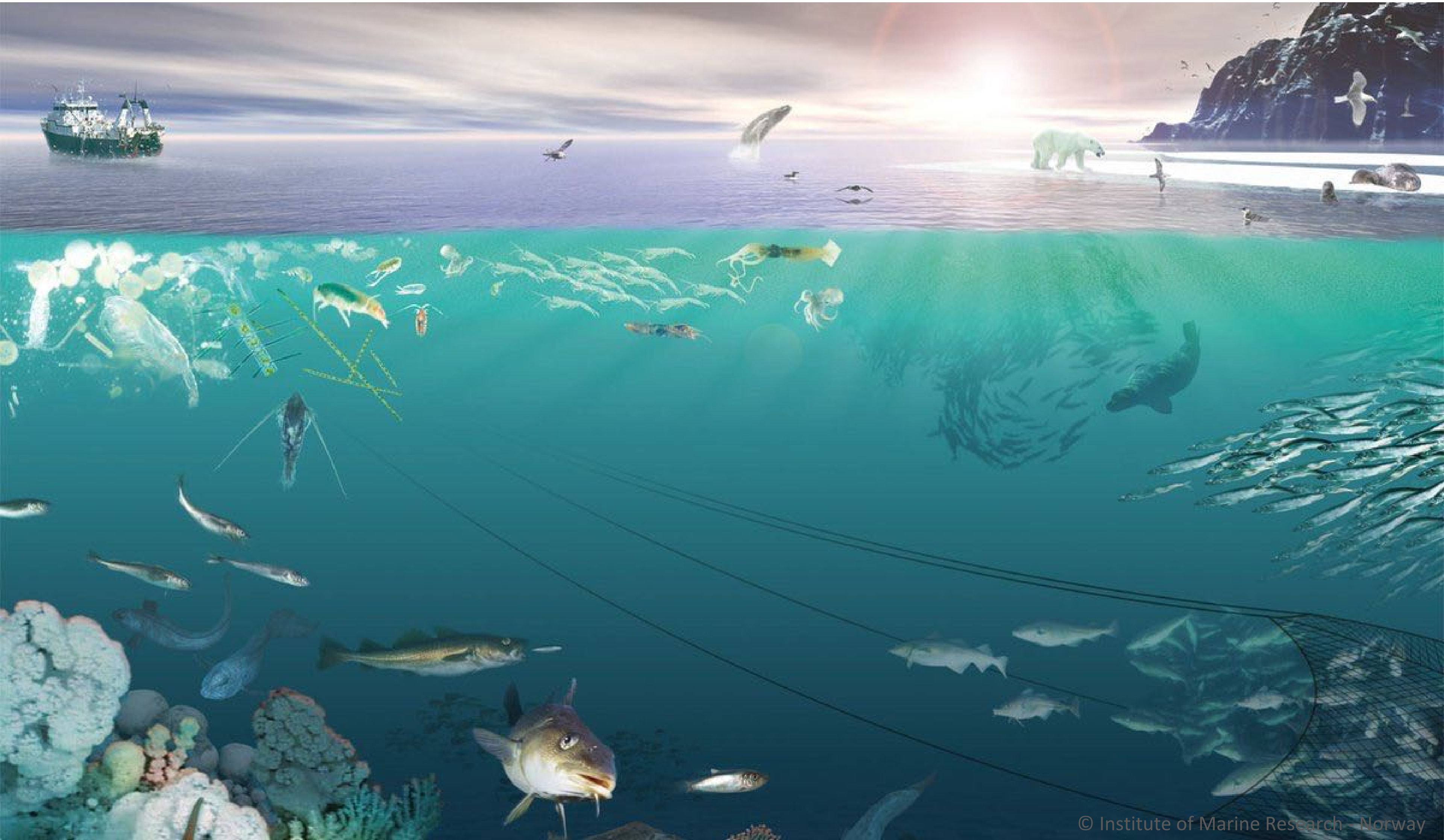
Most of the time, more complex functions are needed!

How do we chose them?

"Functional responses"
For instance: Holling-type I, II, III…

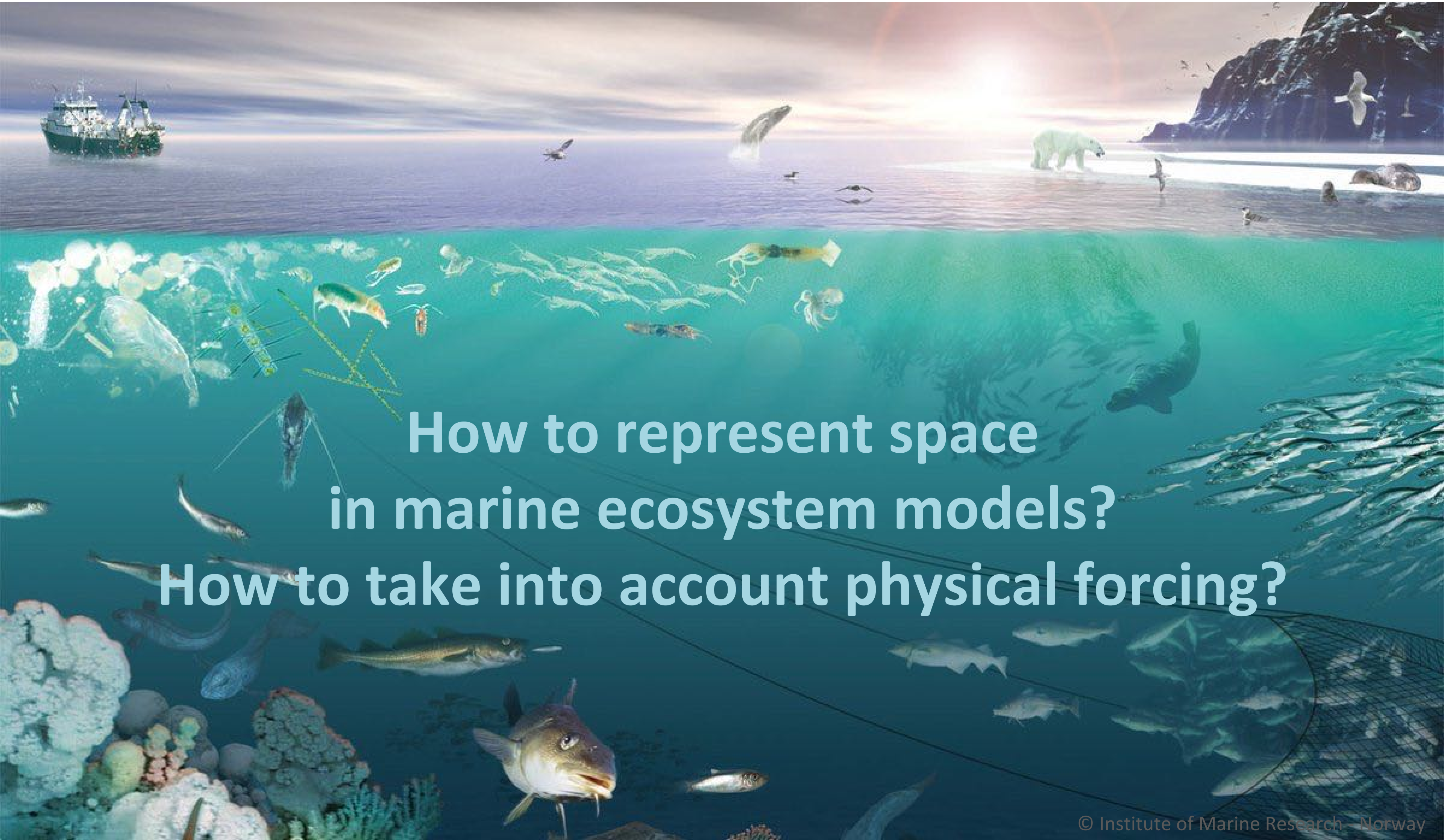
How can we model marine ecosystems?

3D ocean!



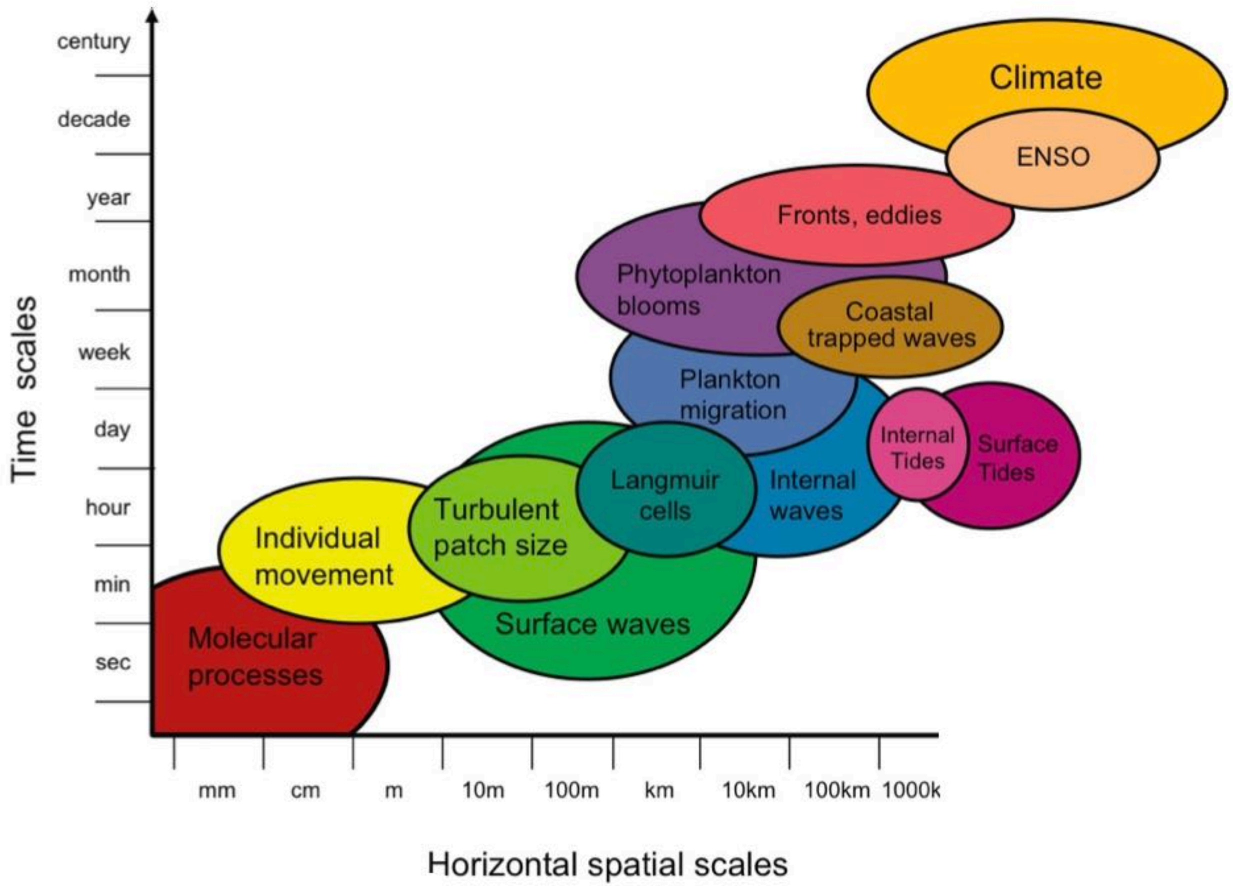
How can we model marine ecosystems?

3D ocean!



Representing space in models

Spatiotemporal scales

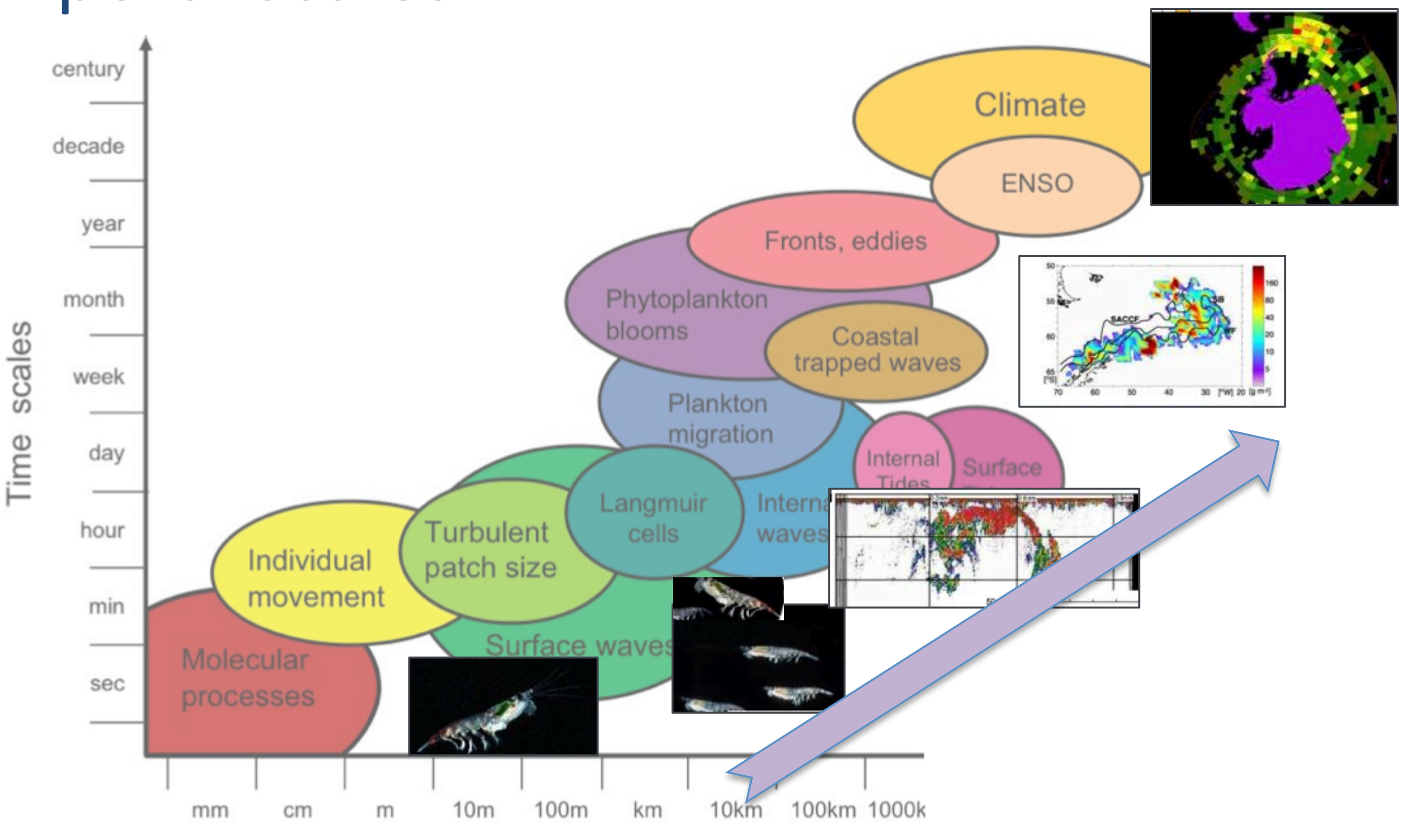


[Time scales and spatial scales of oceanic processes]()

Representing space in models

Spatiotemporal scales

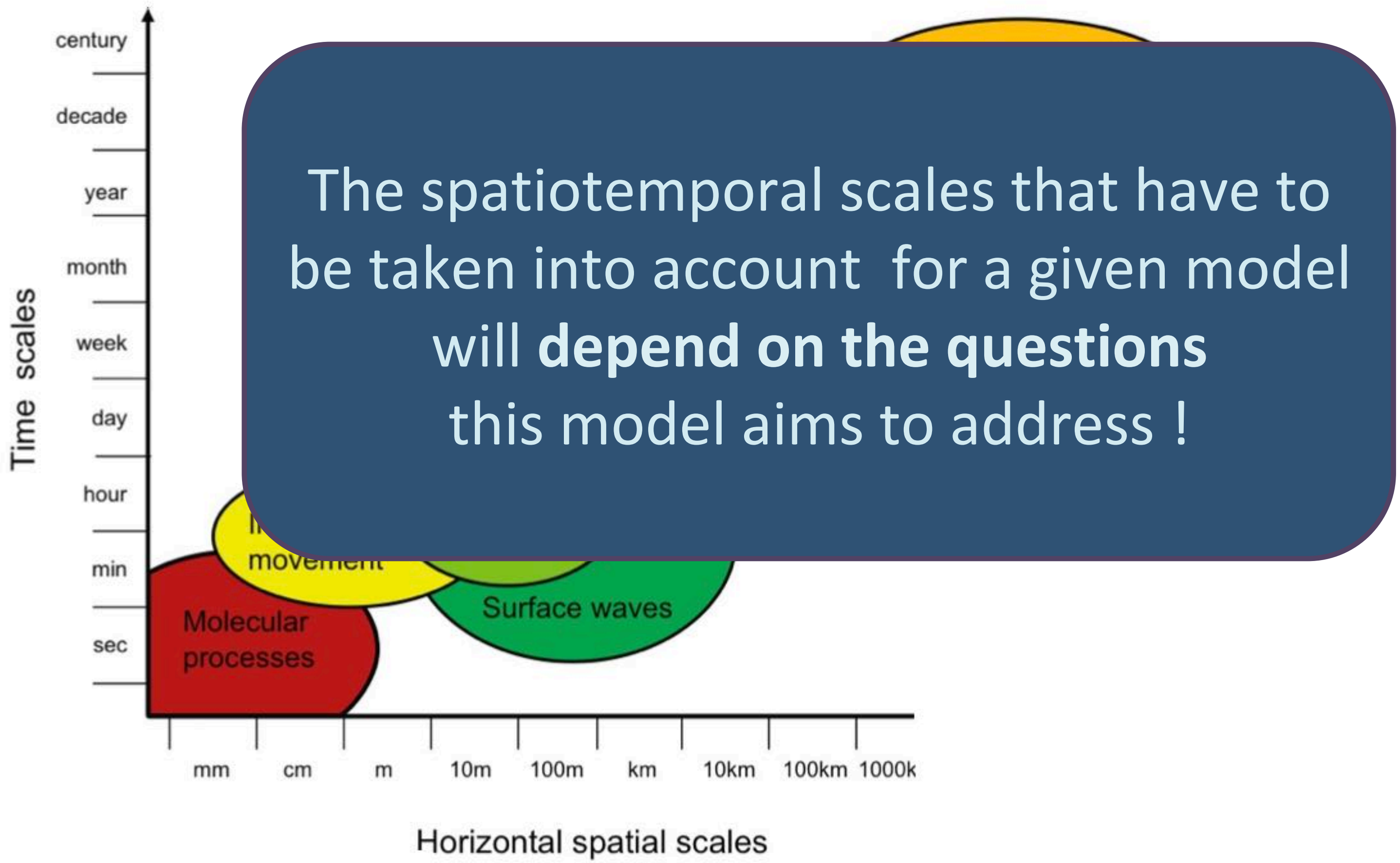
Example of zooplankton in the austral ocean



[Time scales and spatial scales of oceanic processes]()

Representing space in models

Spatiotemporal scales



The spatiotemporal scales that have to be taken into account for a given model will **depend on the questions** this model aims to address !

Time scales and spatial scales of oceanic processes

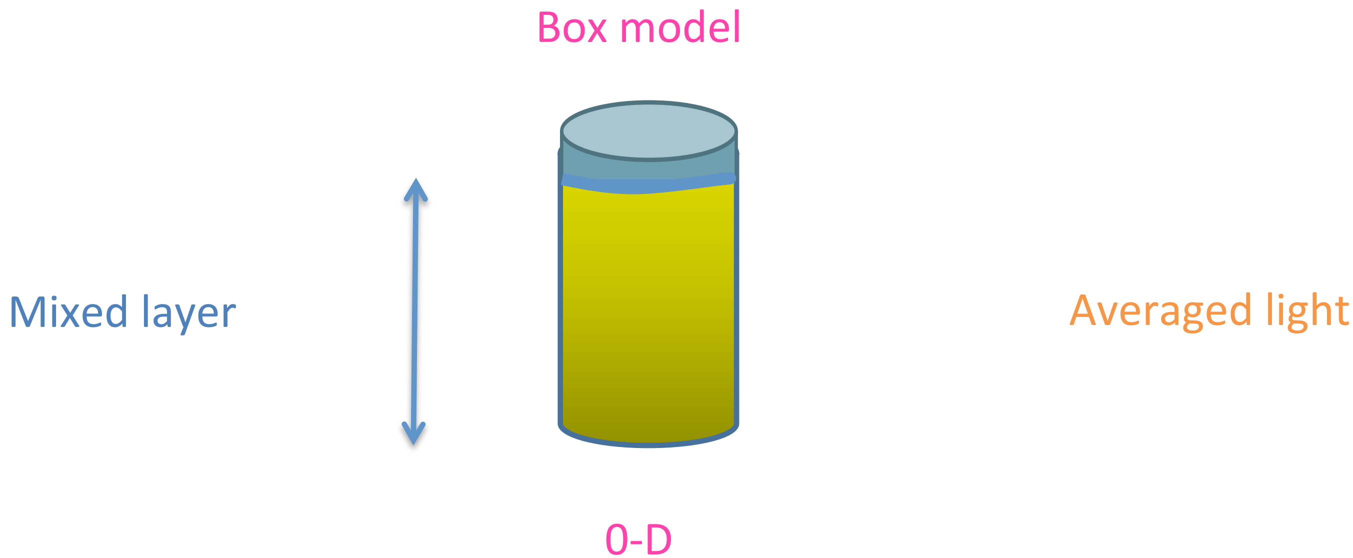
Spatial dimensions

Example: modelling phytoplankton growth in the ocean

Spatial dimensions

Example: modelling phytoplankton growth in the ocean

- 0D: homogeneous mixed layer (box model)

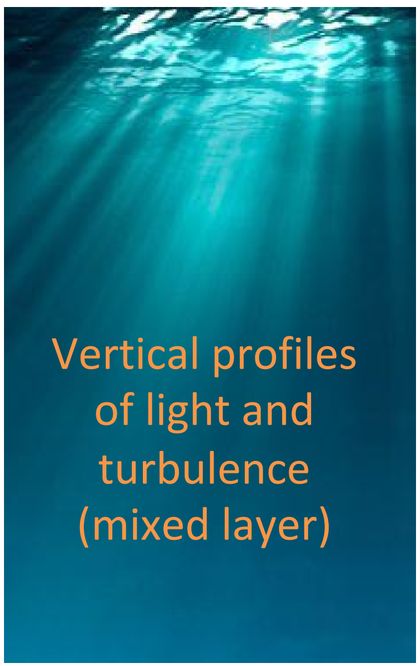


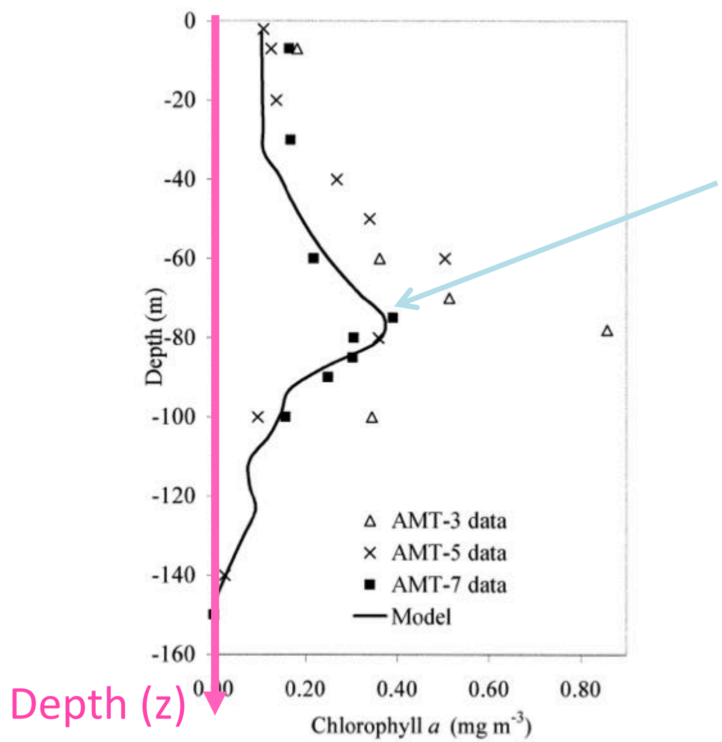
Concentration of phytoplankton in the mixed layer in a 0D model

Spatial dimensions

Example: modelling phytoplankton growth in the ocean

- 1D: vertical model of the water column





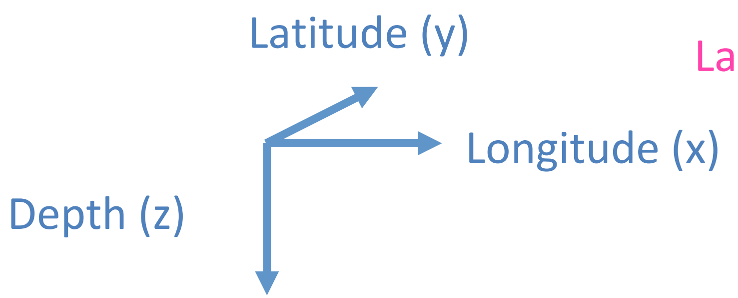
1-D

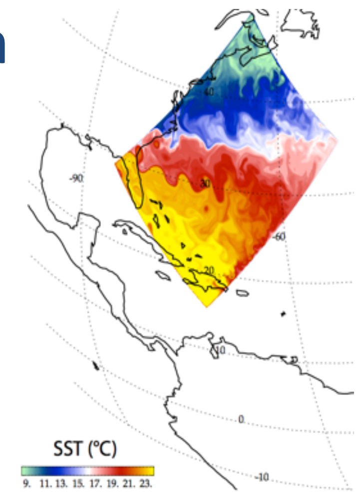
Vertical profile of chlorophyll concentration in the NE Atlantic (observed and modelled, Lefèvre et al. (2003).

Spatial dimensions

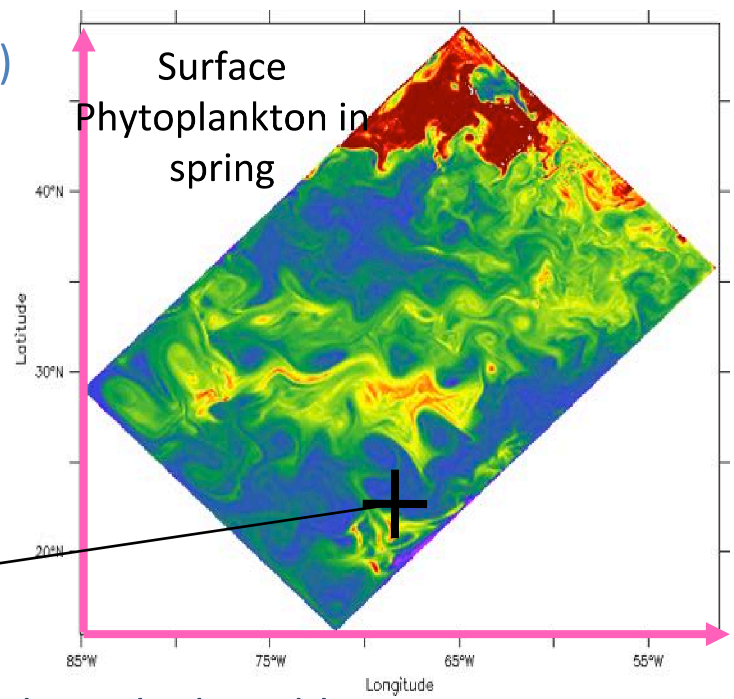
Example: modelling phytoplankton growth in the ocean

- Example of results from a 3D ocean model





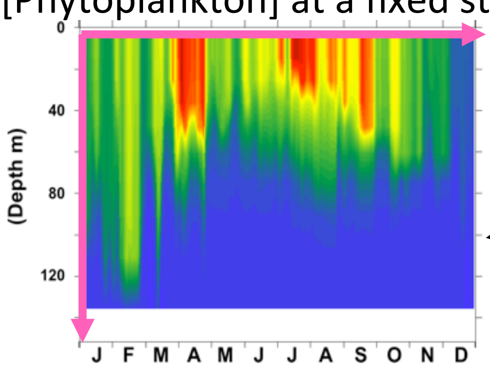
Latitude (y)



Longitude (x)

Mesoscale processes: eddies, filaments, jet…

Temporal evolution of vertical [Phytoplankton] at a fixed station



Time (t)

Depth (z)

Phytoplankton blooming in a 3D ocean model

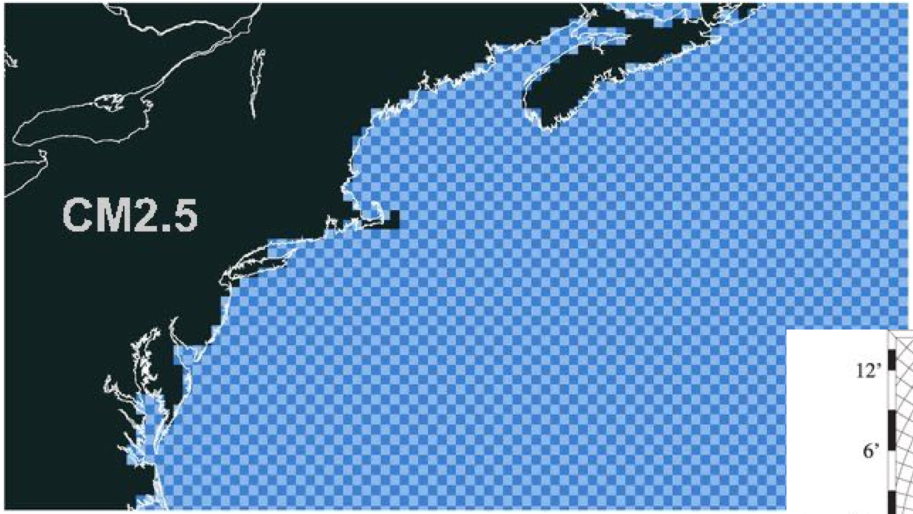
Ayata et al. 2014

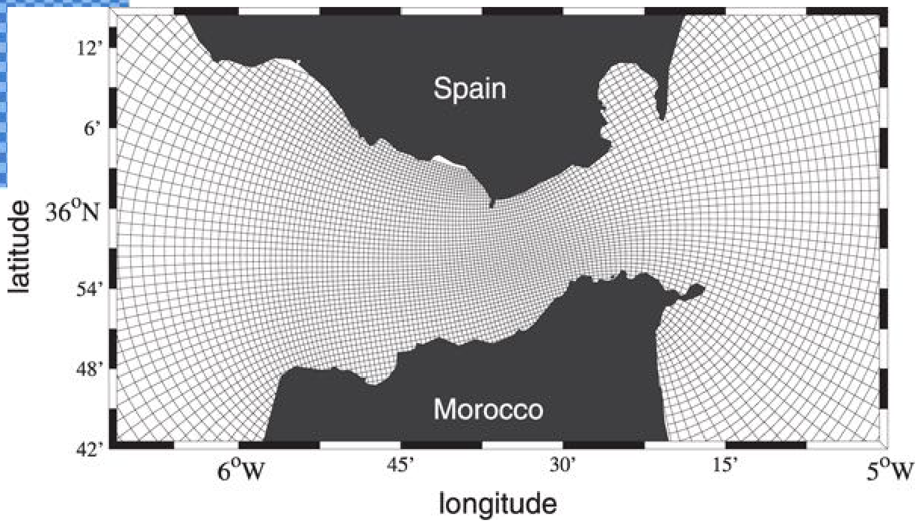
Discrete vs continuous spatial models

How can we discretize space?

Horizontal grid in ocean models

Several gridding type along the horizontal

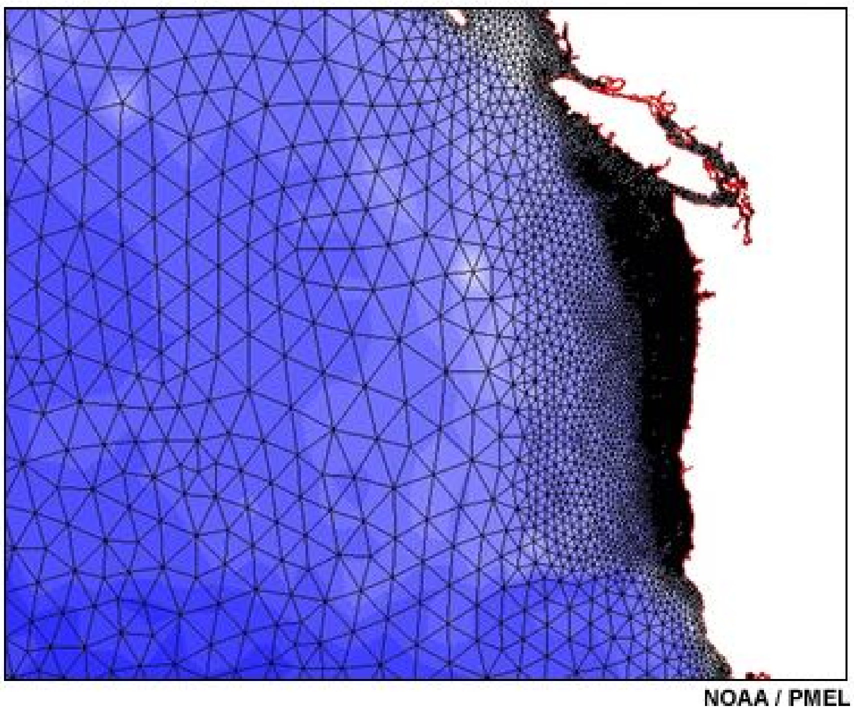


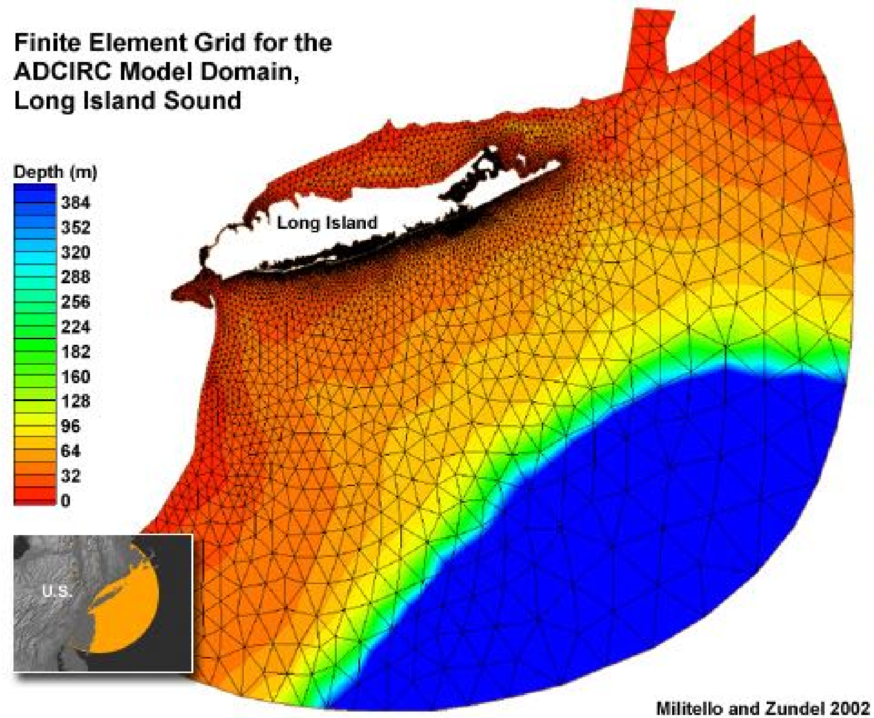


Regular vs. adaptive rectangular grids

Horizontal grid in ocean models

Several mesh sizes, with smaller grid cells close to the coast





Non-rectangular adaptive grids

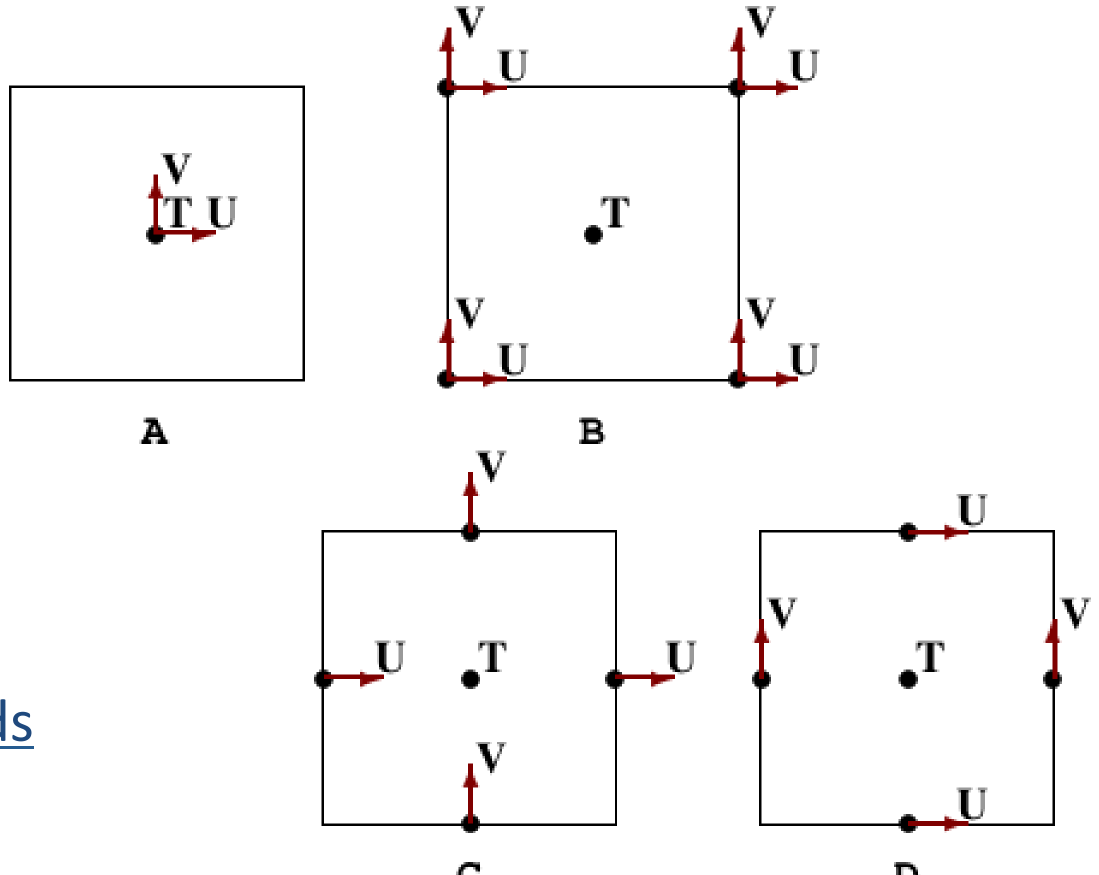
Horizontal grid for calculus

Arakawa horizontal grids for calculus

When shall we integrate the velocities U and V and the temperature T?

Different options

Arakawa horizontal grids

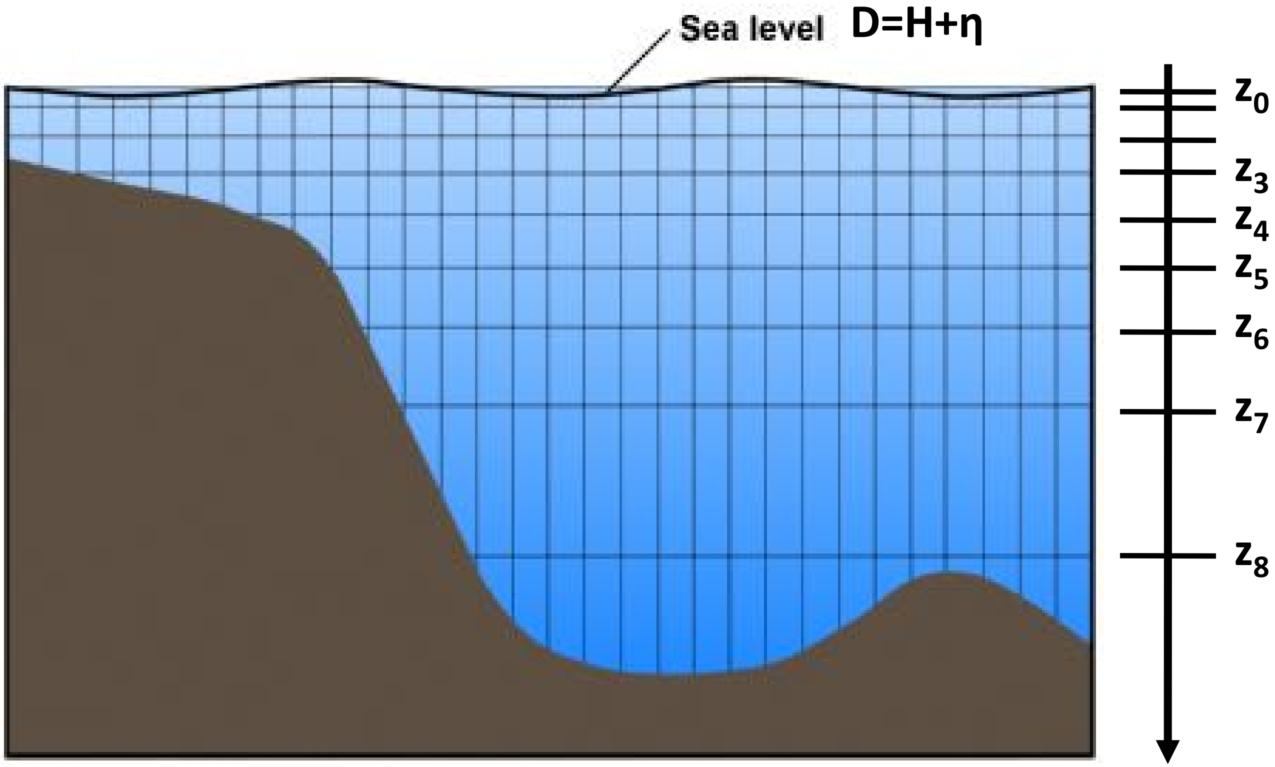


Vertical dimension

Several coordinates systems along the vertical

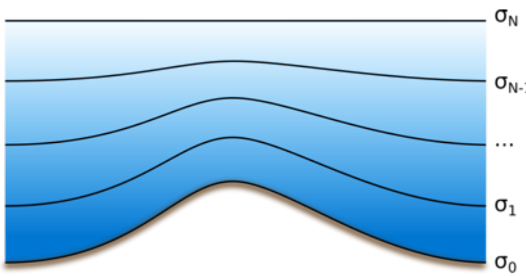
- Z-coordinates

Constant layer depth



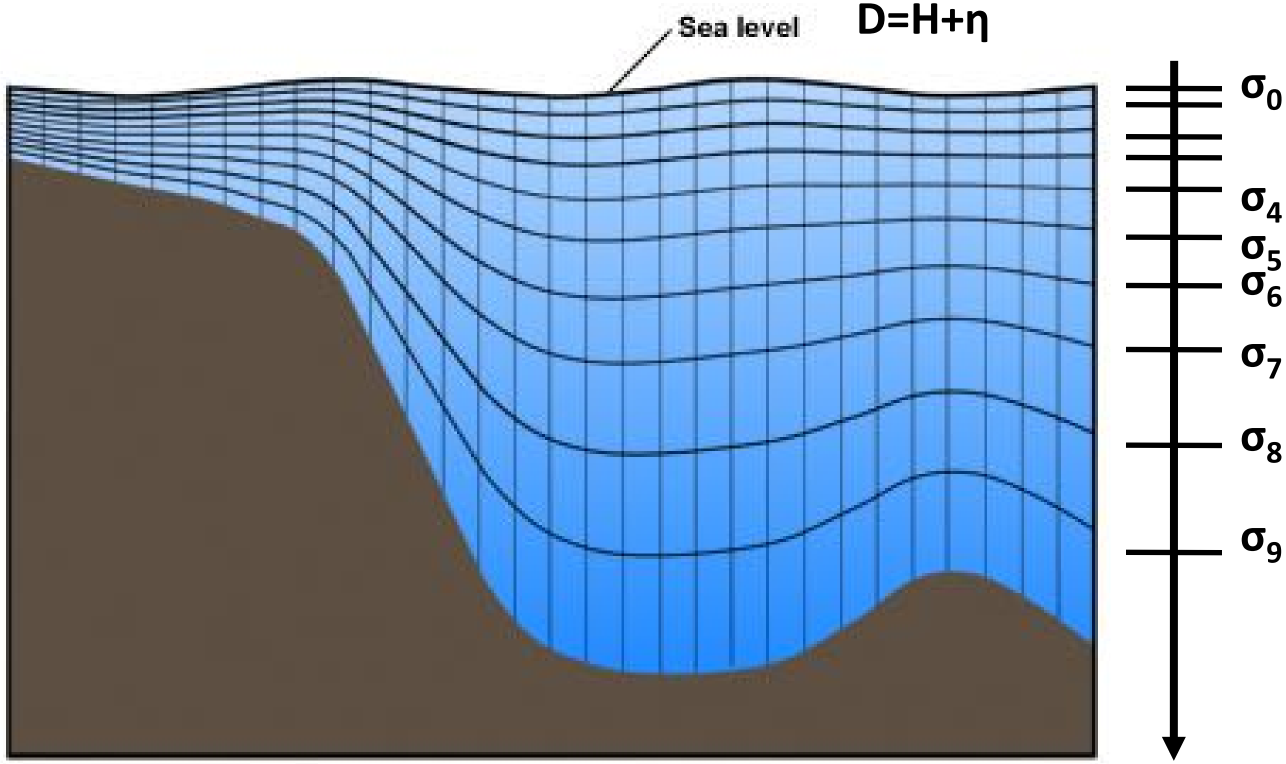
Z vertical coordinate system

Vertical dimension



Several coordinates systems along the vertical

- σ-coordinates (sigma)



Proportion

$$\sigma = \frac{z}{D}$$

$$\sigma = \frac{z}{H+\eta}$$

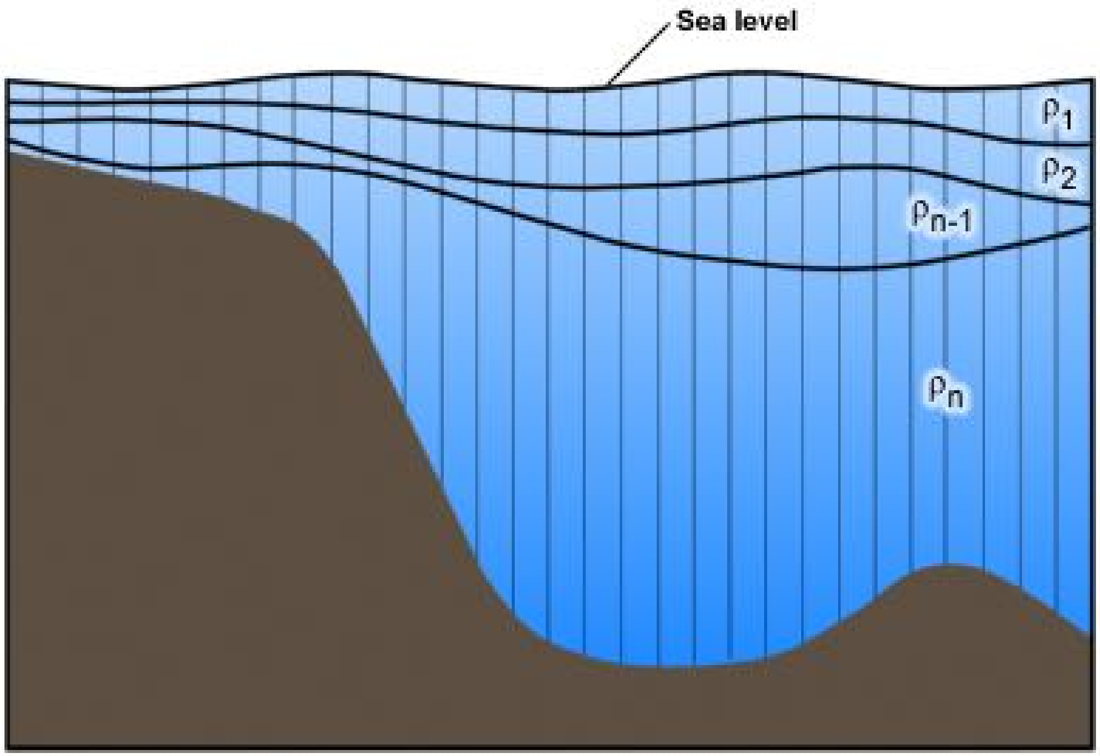
Sigma vertical coordinate system

Vertical dimension in the ocean

Several coordinates systems along the vertical

- Isopycnal-coordinates

Along density lines

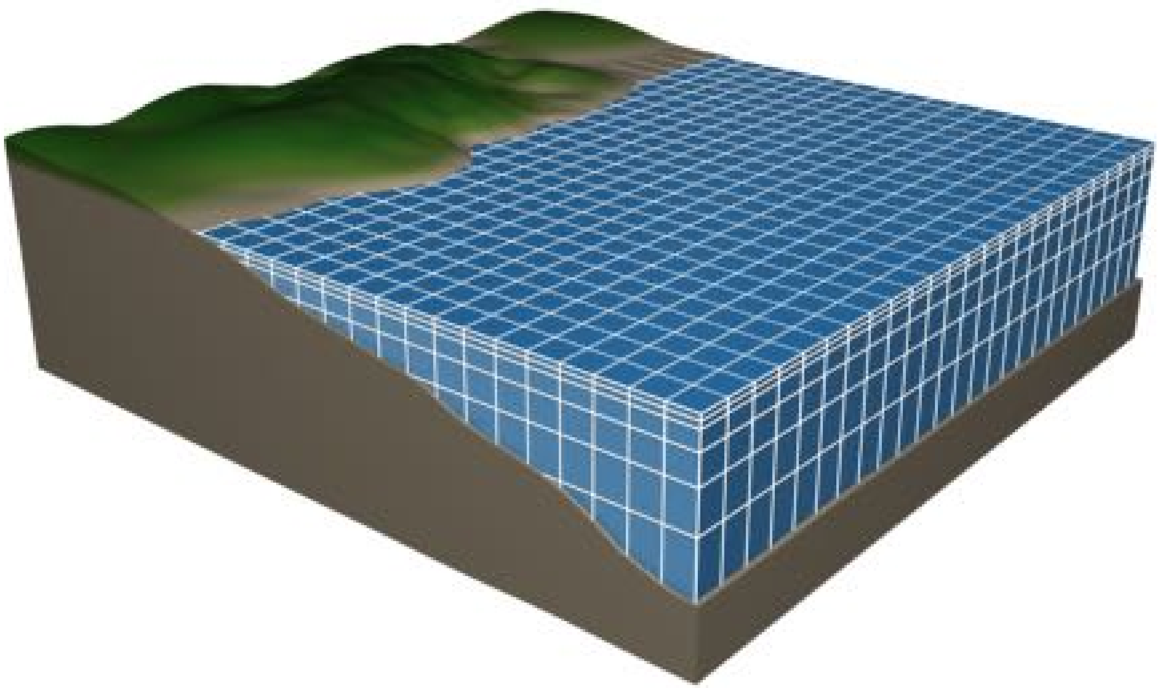


Density-layer (or isopycnal) vertical coordinate system

NB: hydrid models using different types of vertical coordinates exist…

3D modelling in the ocean

3D grid combining 1D vertical grid and 2D horizontal grid

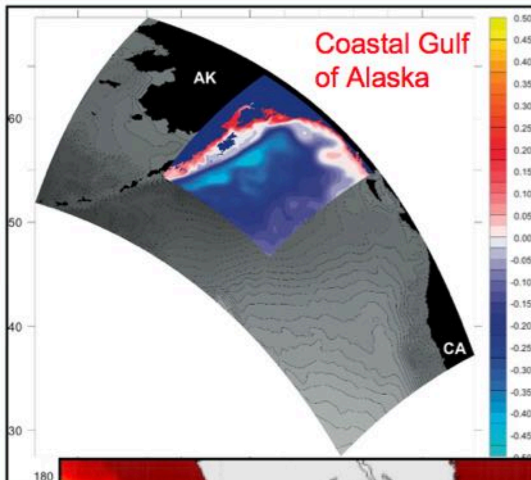


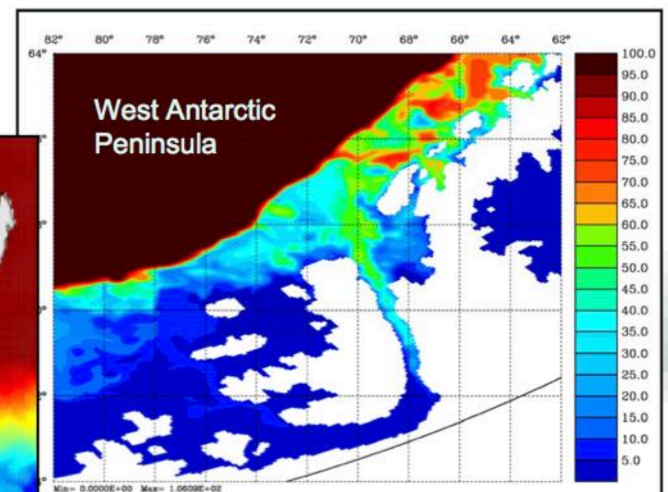
Example of a 3D grid in the ocean

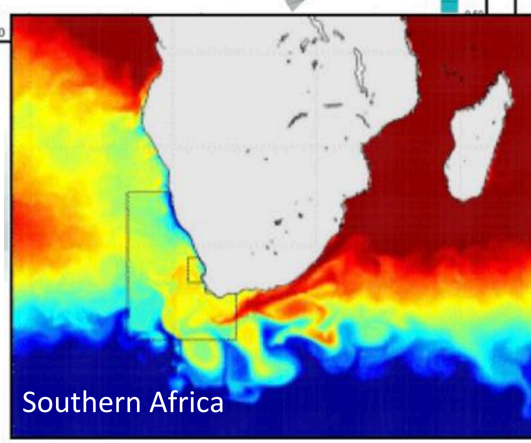
3D modelling in the ocean

Realistic regional circulation models are available

They can include sea ice, coupling to atmospheric models, and to larger scale models







Examples of realistic regional circulation models

Dynamical equations in biophysical models

General equation in 1D

The variable C varies with time t and space x: C(x,t)

The evolution of C(x,t) with time depends on physics and biogeochemistry

$$\frac{\partial C(x,t)}{\partial t} = \underbrace{P(C,x,t)}_{\text{Physical transport (advection + diffusion)}} + \underbrace{J(C,x,t)}_{\text{Biogeochemical source/sink transformation processes}}$$

Temporal evolution of the concentration of variable C (dye, plankton...)

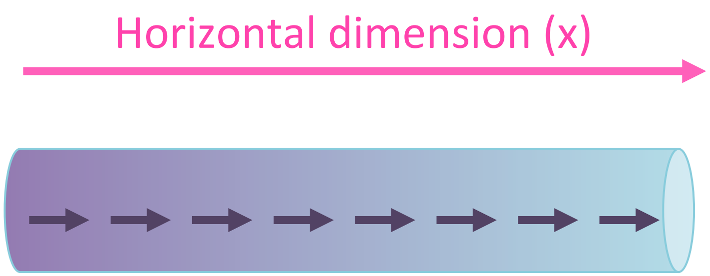
Equations for physical transport?

Transport model in 1D or more

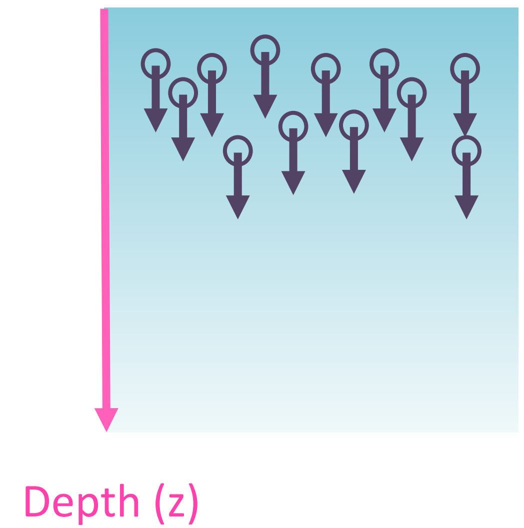
Physical processes affecting the transport: advection and diffusion

Advection

(transport due to mean flow)



Flow in a river



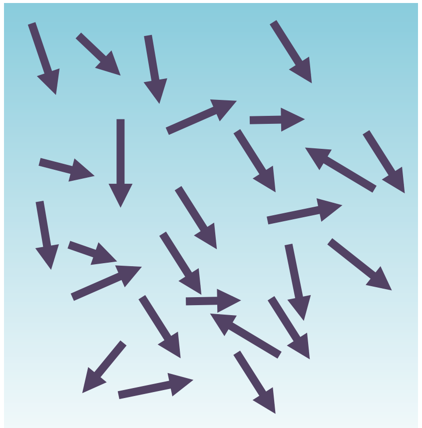
Sinking of particles in a water column

Transport model in 1D or more

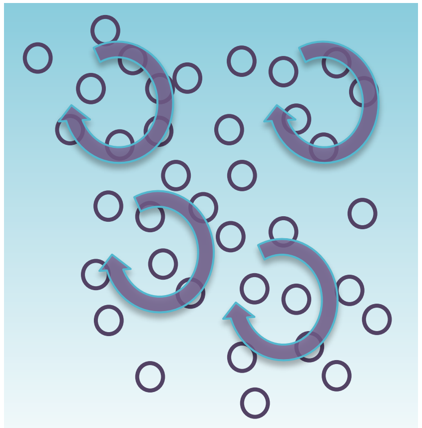
Physical processes affecting the transport: advection and diffusion

Diffusion

(transport due to flow's variability)



Molecular diffusion induced by random motion of particles



Eddy diffusion caused by turbulent mixing of particles

Temporal evolution of the concentration

Conservation of mass of a tracer C (here in 1D)

Advective flux

$$\frac{\partial C}{\partial t} = -\frac{\partial}{\partial x}(\boxed{uC}) + \frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right) + J$$

Temporal evolution of C

Advective flux divergence

Diffusive flux divergence

Biogeochemical source or sink processes

Contribution due to fluid flow (advection)
u: velocity of the flow
C: concentration

Temporal evolution of the concentration

Conservation of mass of a tracer C (here in 1D)

Diffusion

$$\frac{\partial C}{\partial t} = -\frac{\partial}{\partial x}(uC) + \boxed{\frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right)} + J$$

Temporal evolution of C

Advective flux divergence

Diffusive flux divergence

Biogeochemical source or sink processes

D: molecular diffusivity
(or K: eddy diffusivity)
(of the order of $10^{-9} m^2 s^{-1}$ for most substances in the ocean)

Follows the gradient of concentration
$\Rightarrow$ Second derivative!

Temporal evolution of the concentration

Conservation of mass of a tracer C (here in 1D)

Biogeochemistry

$$\frac{\partial C}{\partial t} = -\frac{\partial}{\partial x}(uC) + \frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right) + \boxed{J}$$

Temporal evolution of C

Advective flux divergence

Diffusive flux divergence

Biogeochemical source or sink processes

Biological production or consumption, Radioactive production or decay, …

Temporal evolution of the concentration

$$\frac{\partial C}{\partial t} = \underbrace{\boxed{-\frac{\partial}{\partial x}(uC)}}_{\text{Advection}} + \underbrace{\boxed{\frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}\right)}}_{\text{Diffusion}} + \underbrace{\boxed{J}}_{\text{Biogeochemistry}}$$

NB: Eulerian framework

$$\frac{\partial}{\partial t}$$

This equation is cast in terms of fixed-space frame of reference. It is equivalent to sitting in a particular spot in the ocean and making measurements over time, such as moorings and ship-based time series, or numerical models constructed on a fix geographic grid.

Temporal evolution in 3D

Let us consider the advection-diffusion equation in 3 spatial dimensions:

$$\frac{\partial C}{\partial t} = \boxed{-\nabla(\boldsymbol{u}C)} + \boxed{\nabla(\boldsymbol{\kappa}\nabla C)} + J$$

3D velocity field

3D turbulent diffusivity tension

with the operator ∇ the 3D gradient operator, given by:

$$\nabla = \hat{x}\frac{\partial}{\partial x} + \hat{y}\frac{\partial}{\partial y} + \hat{z}\frac{\partial}{\partial z}$$

wi $\hat{x}$ $\hat{y}$,$\hat{z}$,, z the unit-length vectors
and *x*, *y*, *z* the directions

Numerical diffusion

$$\frac{\partial C}{\partial t} = -\frac{\partial}{\partial x}\Big(uC\Big) - \frac{\partial}{\partial x}\Big(\kappa\frac{\partial C}{\partial x}\Big) + J$$

Pay attention when doing numerical integration!!

Attention must be paid to the integration time Δt and space Δx!

Indeed, the advection-diffusion equation can be used only under the following condition. If the current **u** or the diffusivity **K** are too big, then the matter in a given grid of the model will be completely advected or diffused to the adjacent grids, and the initial grid will be totally emptied! This is called **numerical diffusion**. You can detect it if you model calculates negative or infinite values for concentration.

Numerical diffusion

$$\frac{\partial C}{\partial t} = -\frac{\partial}{\partial x}\Big(uC\Big) - \frac{\partial}{\partial x}\Big(\kappa \frac{\partial C}{\partial x}\Big) + J$$

Pay attention when doing numerical integration!!

Conditions on the time step Δt and on the spatial resolution Δx

To avoid numerical diffusion, the following constraints must be verified in all directions:

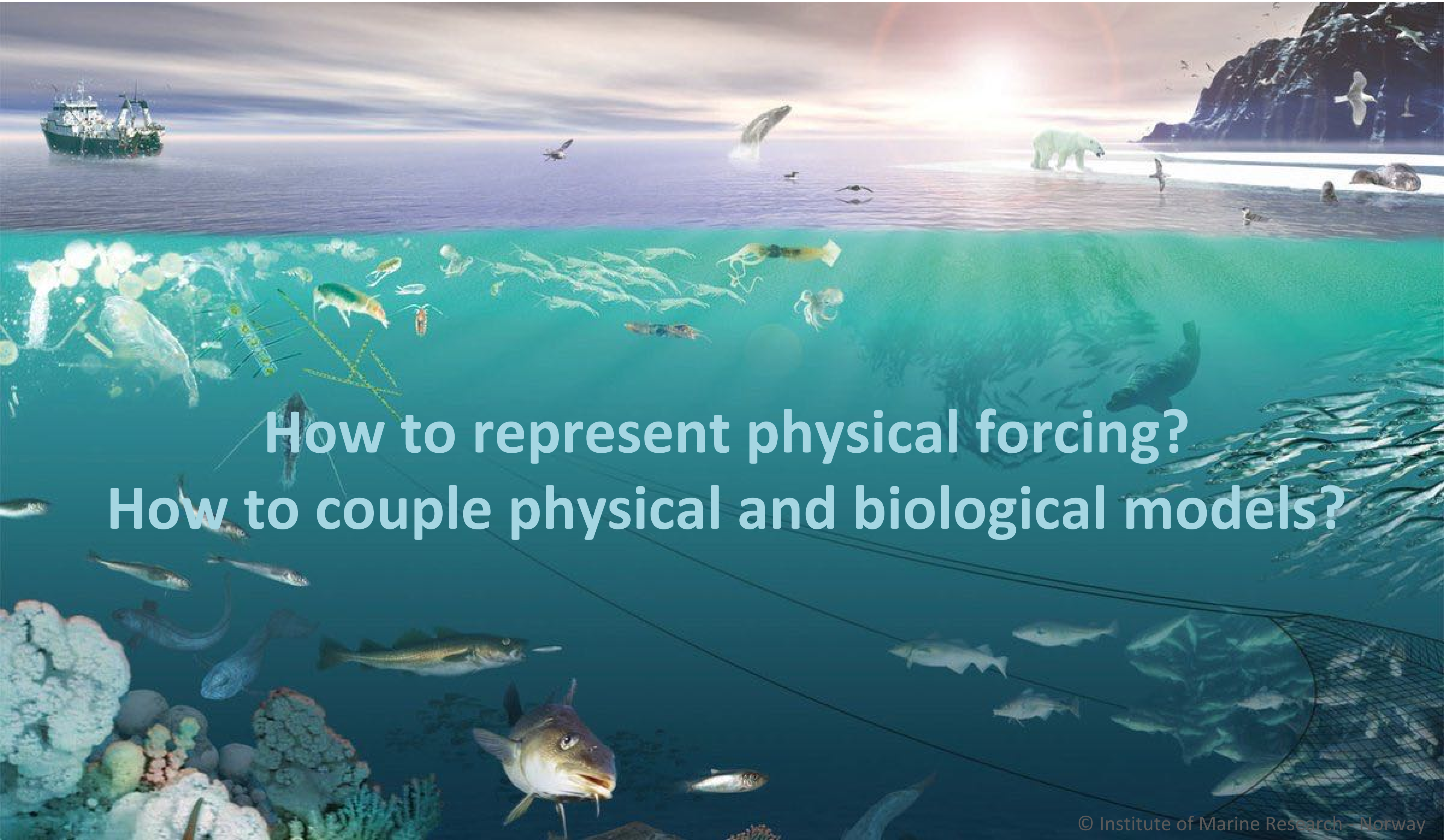
$$u_x << \frac{\Delta x}{\Delta t} \qquad K_x << \frac{(\Delta x)^2}{\Delta t}$$

$$u_x \Delta t << \Delta x \qquad K_x \Delta t << (\Delta x)^2$$

Otherwise the biological tracer of concentration C will be advected or diffused artificially because of the grid and time step that you have chosen are to small and to large, respectively.

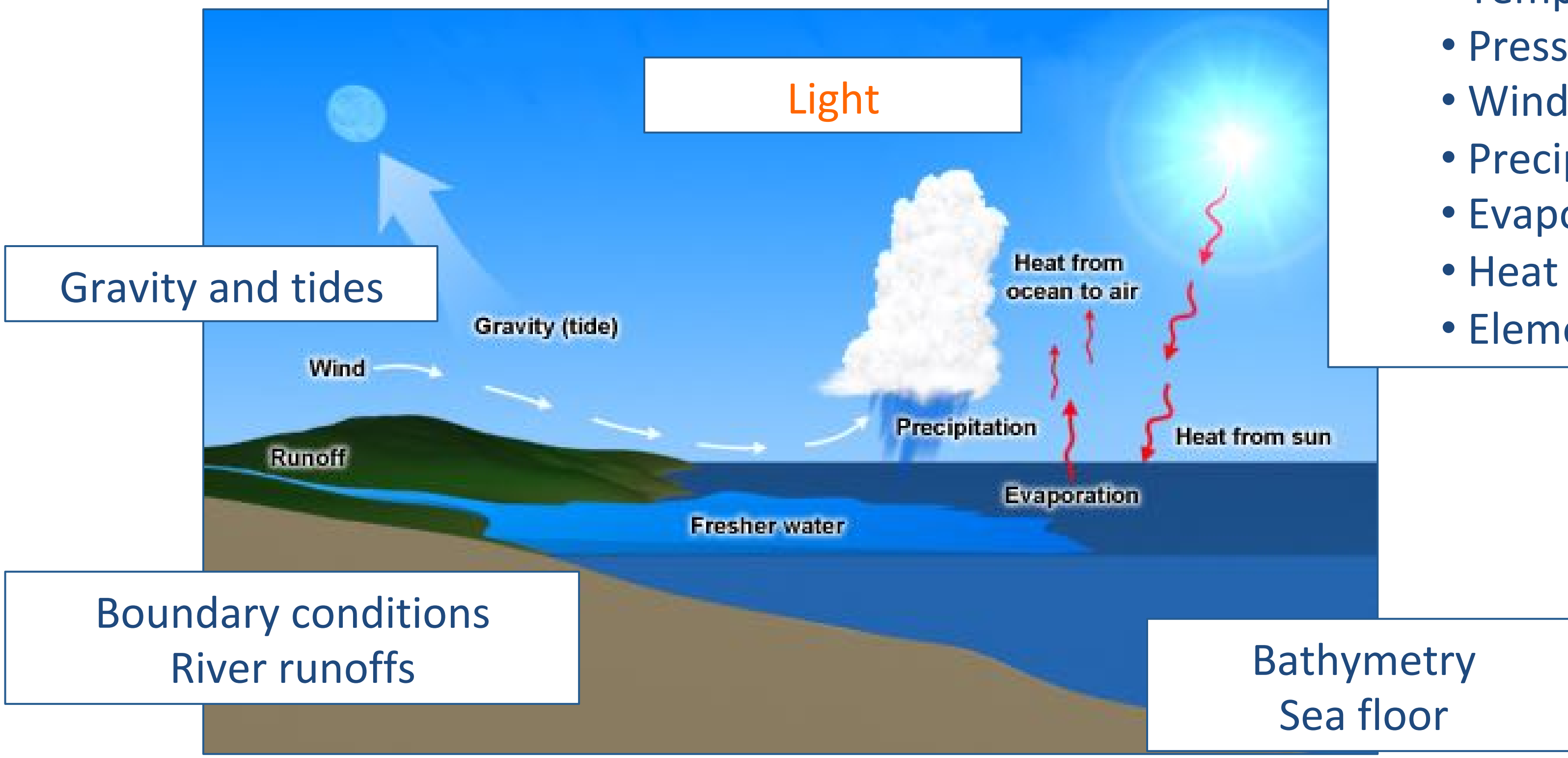
How can we model marine ecosystems?

Physical forcing



Physical forcing

Which physical forcing should be considered to model the marine ecosystem?

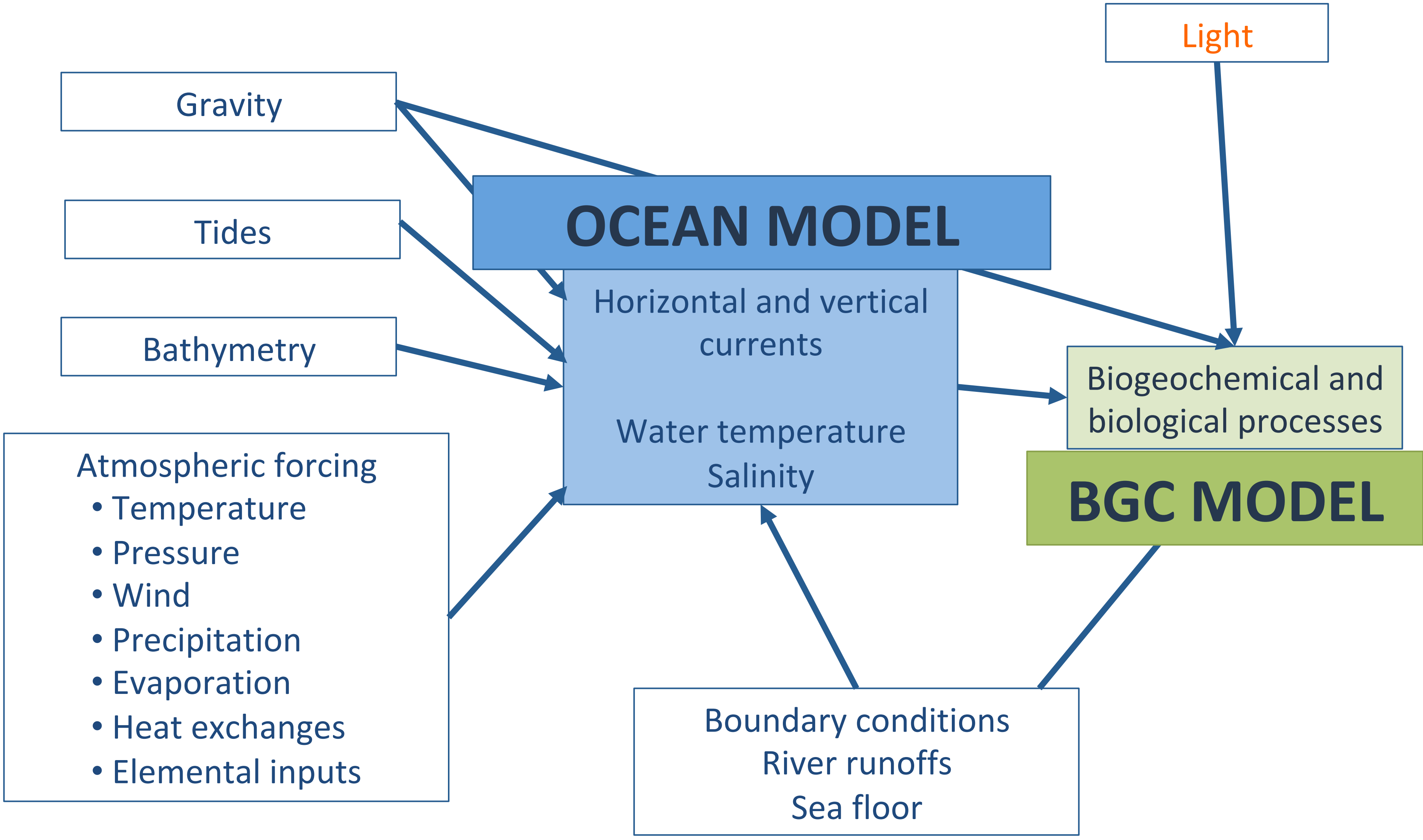


Atmospheric forcing

- Temperature
- Pressure
- Wind
- Precipitation
- Evaporation
- Heat exchanges
- Element inputs

Example of physical forcing in the ocean

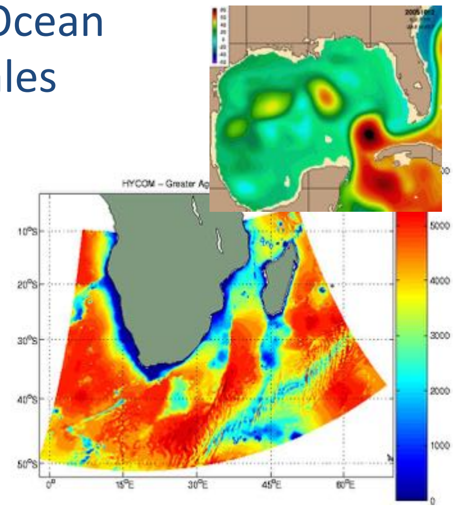
Coupled bio-physical modelling



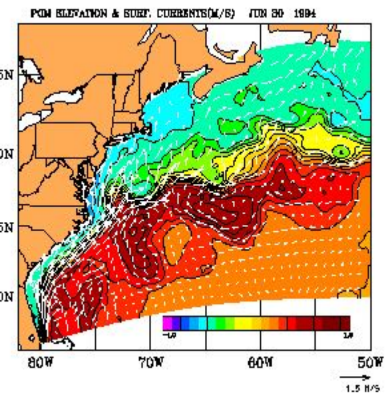
Example of ocean models

NEMO: Nucleus for European Modelling of the Ocean
MARS-3D: Model for Application at Regional Scales
ROMS: Regional Ocean Modeling System
POM: Princeton Ocean Model
HYCOM: Hybrid Coordinate Ocean Model
…

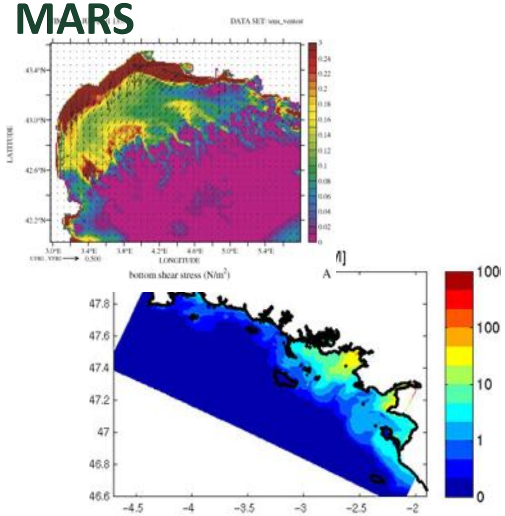
HYCOM



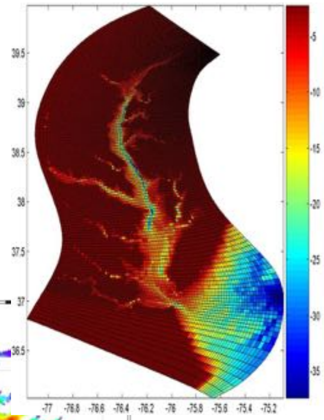
POM

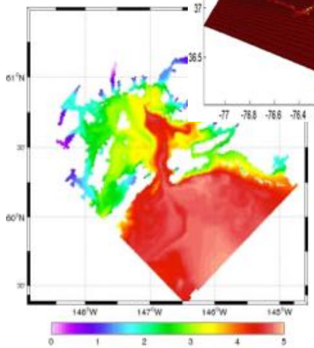


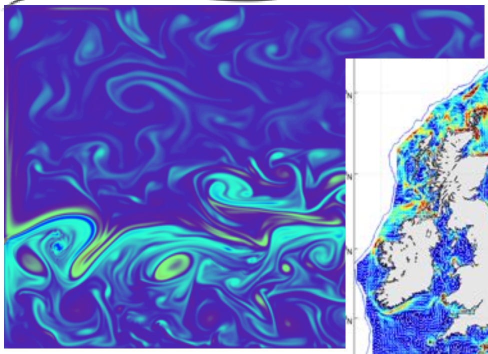
MARS

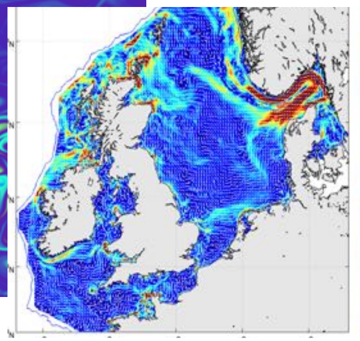


ROMS





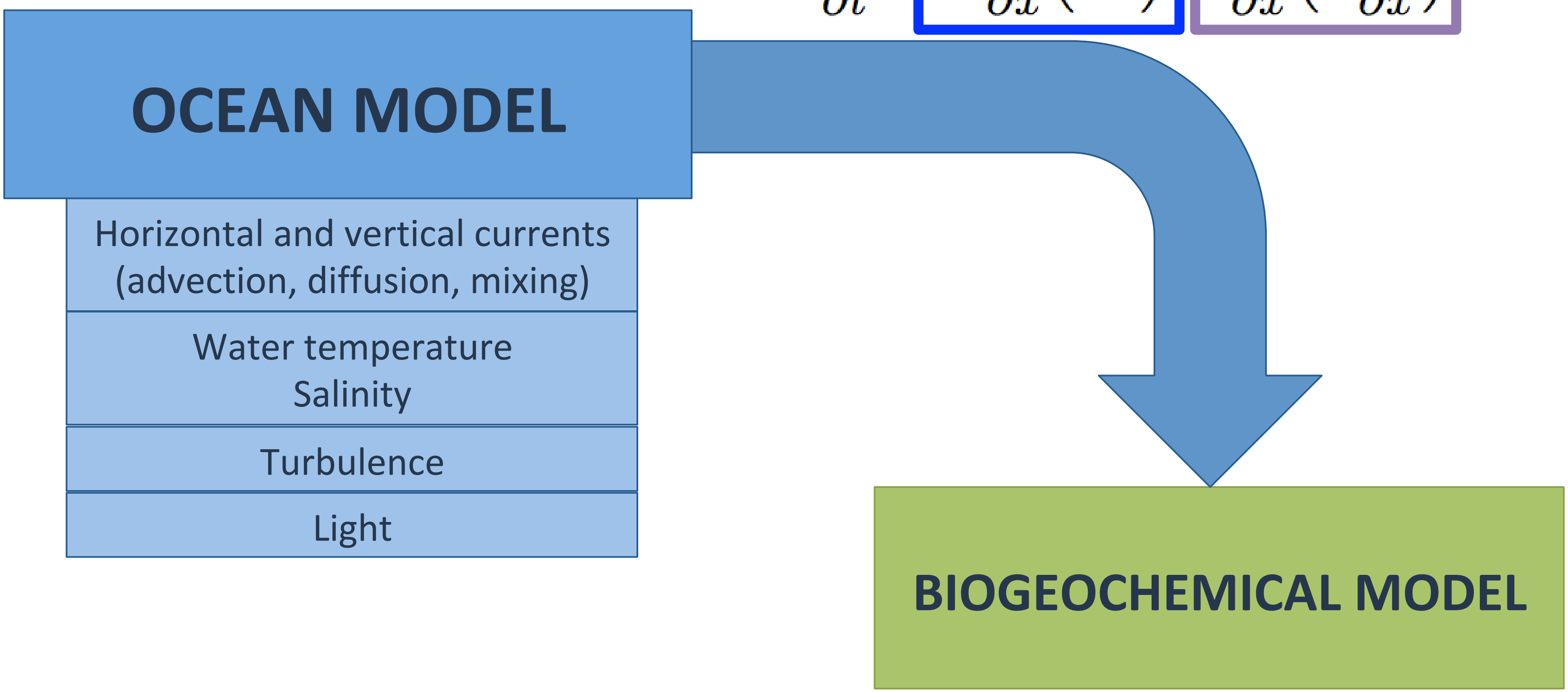




Bio-physical coupling

Biophysical coupling through the advection-diffusion equation of transport and biogeochemical source/sink terms

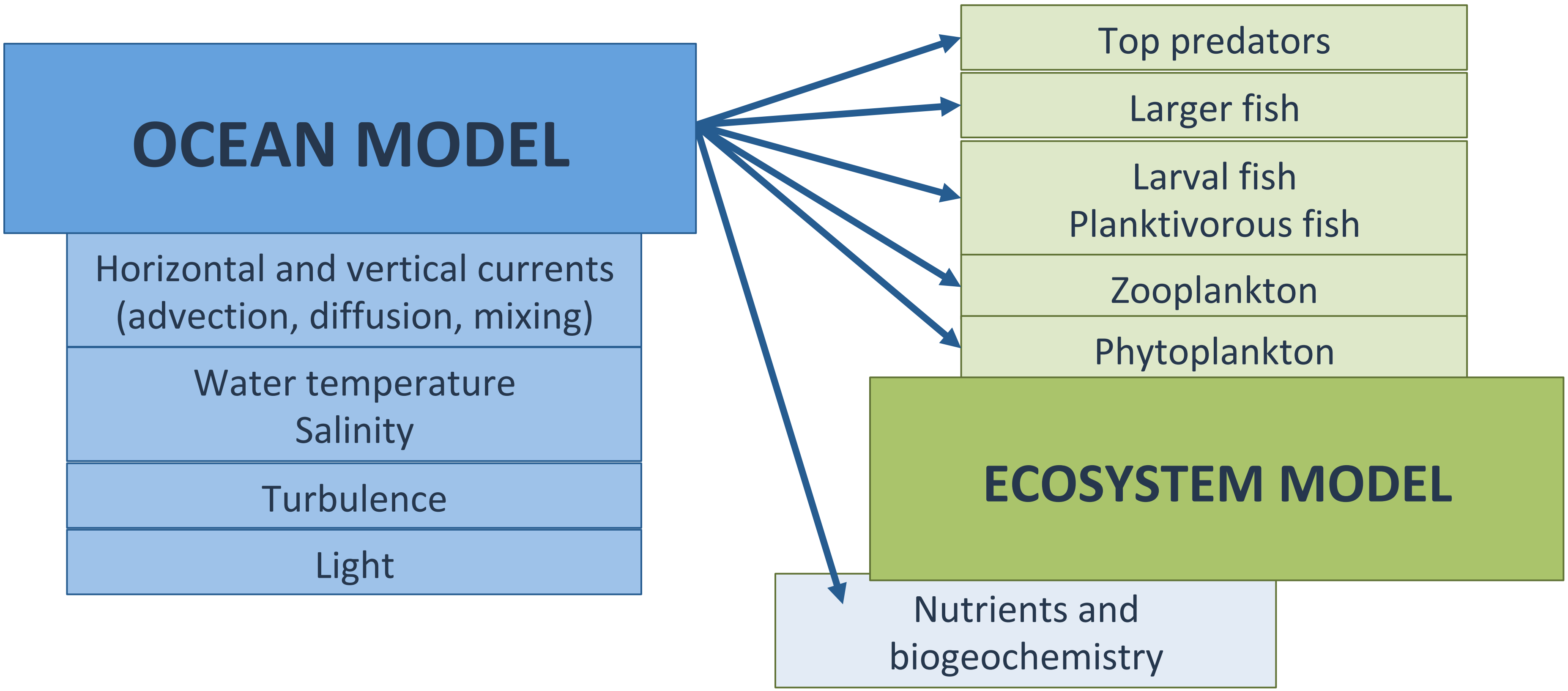
$$\frac{\partial C}{\partial t} = \boxed{-\frac{\partial}{\partial x}\left(uC\right)} + \boxed{\frac{\partial}{\partial x}\left(\kappa\frac{\partial C}{\partial x}\right)} + J$$



Bio-physical coupling

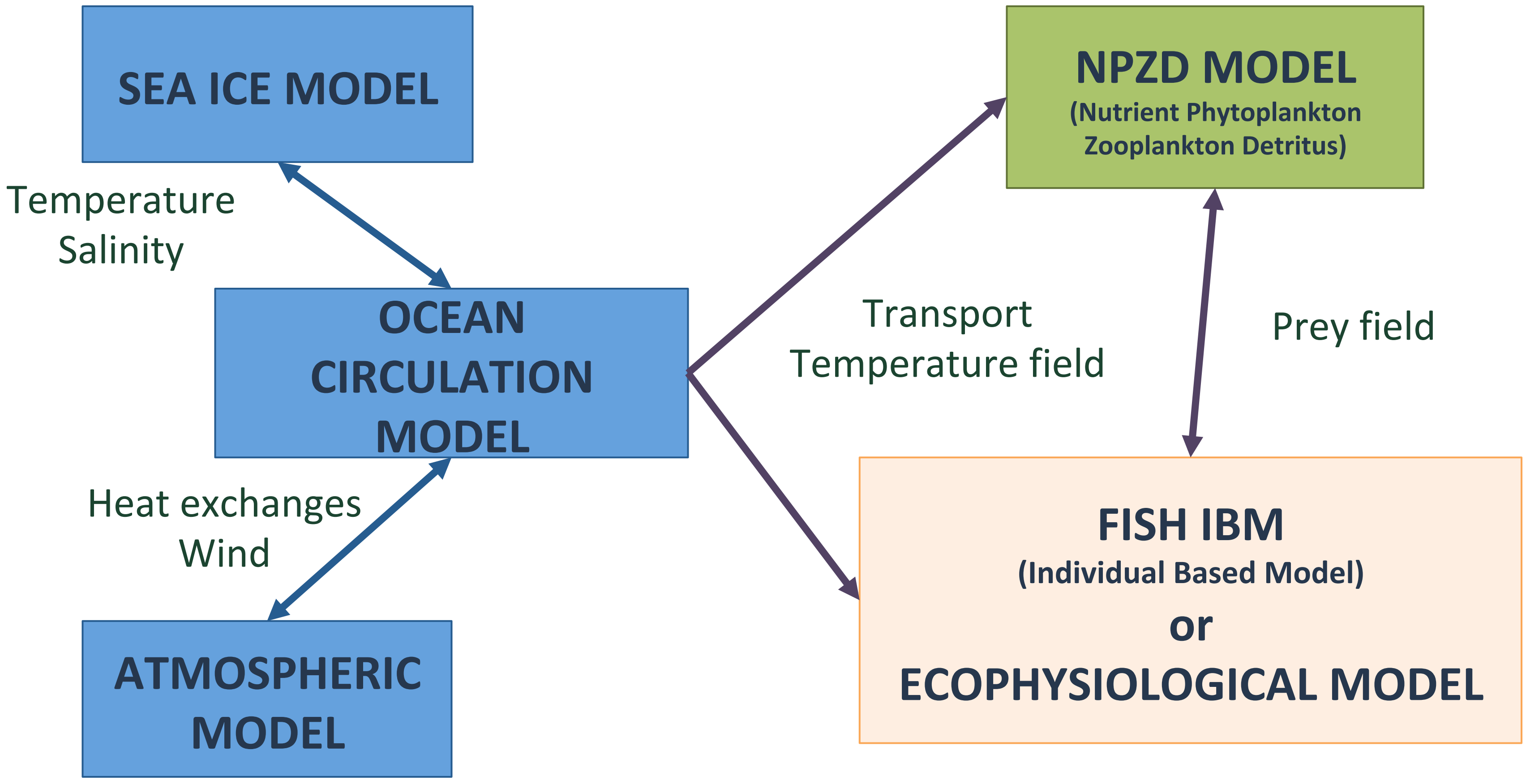
Biophysical coupling act at every scales of the marine ecosystems

$$\frac{\partial C}{\partial t} = \boxed{-\frac{\partial}{\partial x}\left(uC\right)} + \boxed{\frac{\partial}{\partial x}\left(\kappa\frac{\partial C}{\partial x}\right)} + J$$



Bio-physical coupling

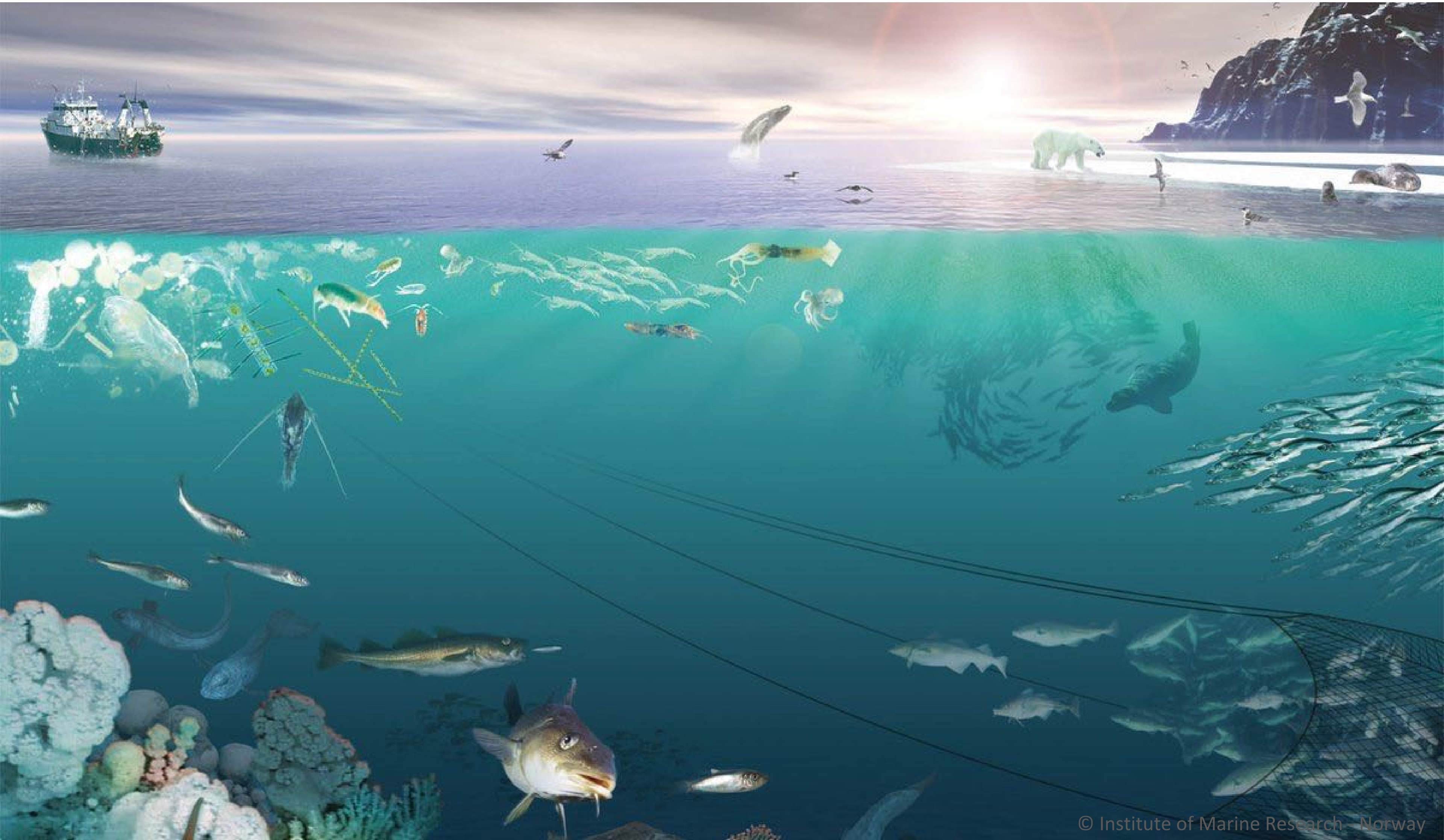
Biophysical models are systems of interconnected modules



Examples of a bio-physical model with interconnected modules

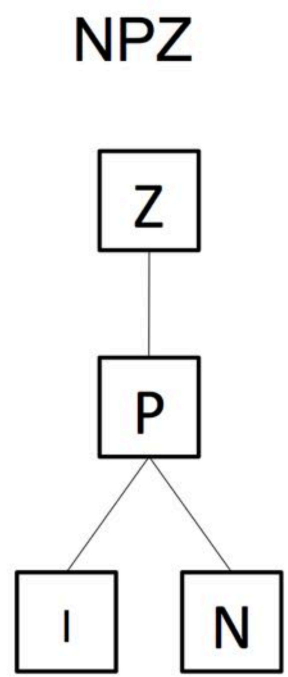
How can we model marine ecosystems?

Taking into account biodiversity…



Plankton functional types (PFTs)

Simple view of planktonic ecosystem



Zooplankton

Phytoplankton

Irradiance

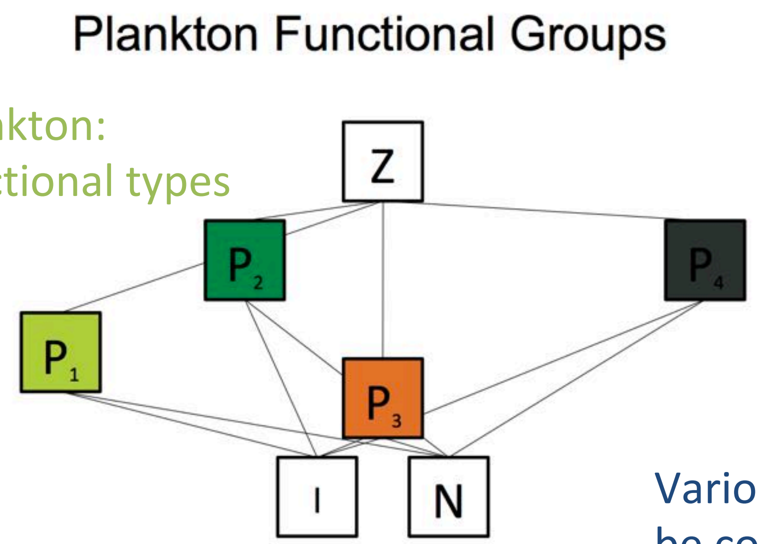
Nutrient

Figure from C. Klausmeier

Plankton functional types (PFTs)

Getting into more details…

Here focusing on phytoplankton:
Several phytoplankton functional types



Various phytoplankton types can be considered:

- cyanobacteria (prokaryotes)
- diatoms (Si)
- dinoflagellates
- calcifious ppk (Ca)
- picoplankton
- …

Different ecological and biogeochemical roles!

Figures from NASA & C. Klausmeier

Plankton functional types (PFTs)

Different equations for each type of phytoplankton!
(Le Quéré et al, 2005)

⇒**Traits of each PFT**

Global Change Biology (2005) **11**, 2016–2040, doi: 10.1111/j.1365-2486.2005.01004.x

Ecosystem dynamics based on plankton functional types for global ocean biogeochemistry models

CORINNE LE QUÉRÉ*[1], SANDY P. HARRISON*†, I. COLIN PRENTICE*‡, ERIK T. BUITENHUIS*, OLIVIER AUMONT§, LAURENT BOPP¶, HERVÉ CLAUSTRE‖, LETICIA COTRIM DA CUNHA*, RICHARD GEIDER**, XAVIER GIRAUD*[2], CHRISTINE KLAAS*††, KAREN E. KOHFELD*[3], LOUIS LEGENDRE‖, MANFREDI MANIZZA*‡‡, TREVOR PLATT§§, RICHARD B. RIVKIN¶¶, SHUBHA SATHYENDRANATH§§, JULIA UITZ‖, ANDY J. WATSON‡‡, and DIETER WOLF-GLADROW††

Table 1 Biomass and size distribution of Plankton Functional Types (PFT)

Size class	Biomass (Pg C)	PFT name	Cell Size (μm)
Bacteria			
Pico	0.35*	Pico-heterotrophs	0.3–1.0
Phytoplankton			
Pico	0.28†	Pico-autotrophs	0.7–2.0
		Phytoplankton N_2-fixers	0.5–2.0‡
Nano	0.39†	Phytoplankton calcifiers	5–10
		Phytoplankton DMS-producers	5§
		Mixed-Phytoplankton	2–200
Micro	0.11†	Phytoplankton silicifiers	20–200
Zooplankton			
Proto	0.16¶	Proto-zooplankton	5–200
Meso	0.10‖	Meso-zooplankton	200–2000
Macro	Unknown	Macro-zooplankton	> 2000

Plankton functional types (PFTs)

Different equations for each type of phytoplankton!

(Le Quéré et al, 2005)

$\Longrightarrow$**Parameters for each PFT**

Examples of PI curves

(Photosynthesis-Irradiance)

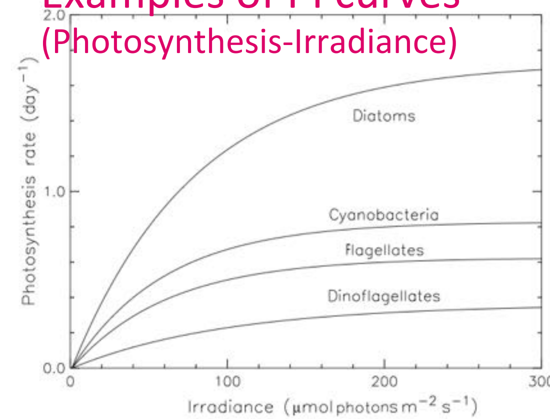


Fig. 2 Example of productivity vs. irradiance at 15–25 °C for different phytoplankton groups (Geider *et al.*, 1997). The diatoms

Table 2 Traits that characterize different Plankton Functional Types

			Light		Half–saturation			
	Max growth rate at 0 °C* (day^{-1})	Max mortality rate† (day^{-1})	Affinity‡	Stress§ 0 to 1	P¶ (nM)	Fe‖ (aM)	Si** (μM)	Other nutritional source††
Bacteria								
Pico-heterotrophs	2.1	No data						5 (DOM)
Phytoplankton								
Pico-autotrophs	0.6	0.05	3.2	0	19	No data		
Phytoplankton N_2-fixers	0.04	0.05	1.6	No data	75	120		0 (N_2)
Phytoplankton calcifiers	0.2	0.05	1.6	1	4	20		**1.9 (DOP)**
Phytoplankton DMS producers	0.6	0.05	1.6	No data	700	20		
Phytoplankton silicifiers	0.6	0.05	5.1	0	**75**	120	4	
Mixed-phytoplankton	0.6	0.05	1.6	0.5	19	20		
Zooplankton								
Proto-zooplankton	0.6	1e¶-proto						18
Meso-zooplankton	**0.24**	**0.058**						**0.29**
Macro-zooplankton	No data	No data						No data

Plankton functional types (PFTs)

Example of results from PFT global models

(Le Quéré et al, 2005)

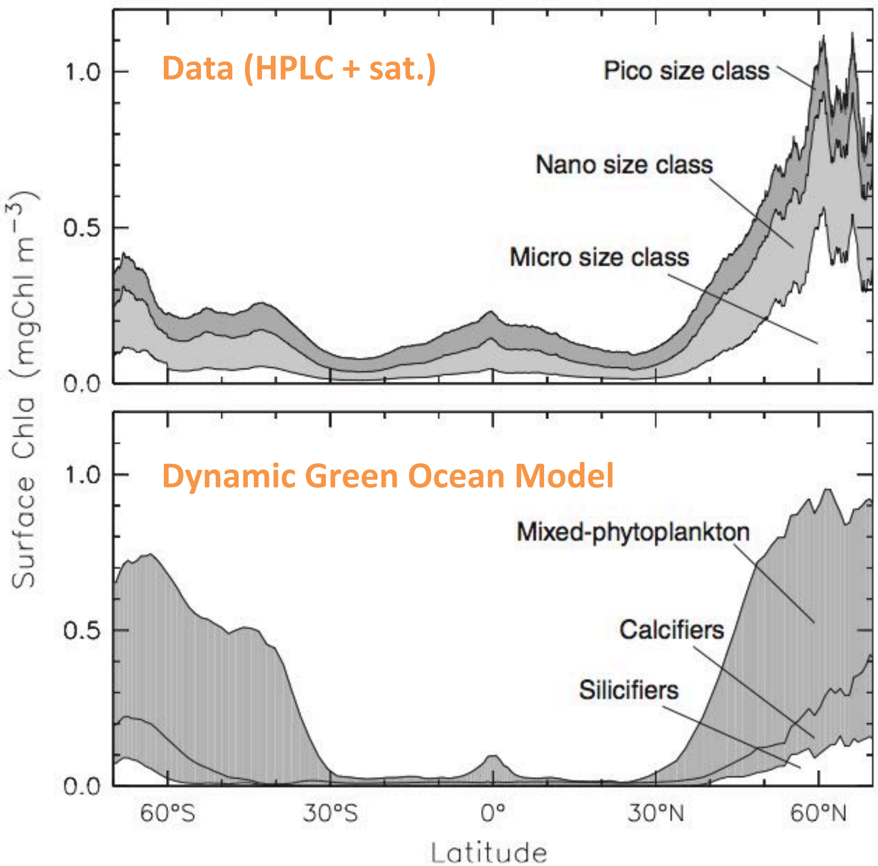
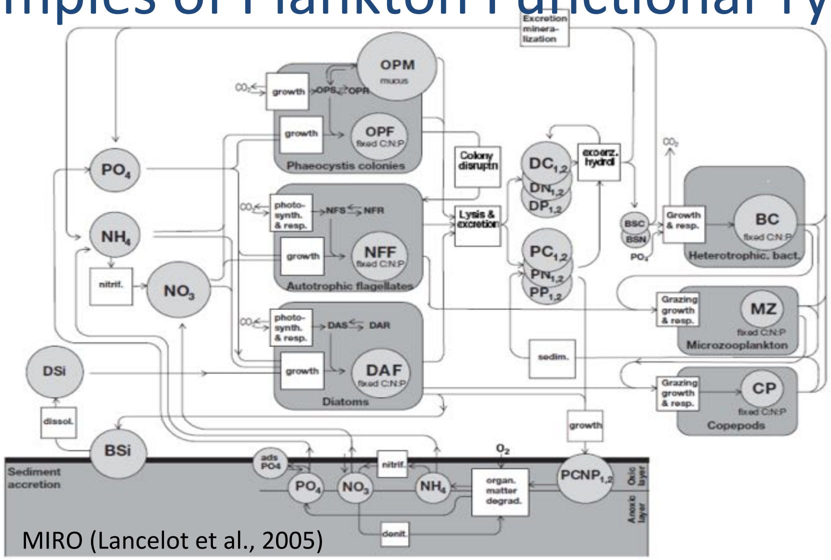


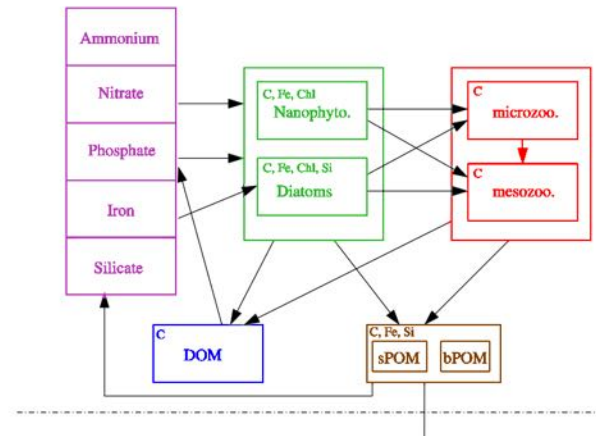
Fig. 4 Zonal average of the contribution of different phytoplankton plankton functional types to the total chl*a* (in mg Chl m^{-3}) for the (top) micro-, nano-, and pico-size classes estimated using the combination of the statistical analysis of an HPLC pigment database and monthly composite SeaWiFS scenes of the year 2000 (Uitz *et al.*, 2005) and (bottom) silicifiers, calcifiers, and mixed-phytoplankton estimated using a Dynamic Green Ocean Model.

Plankton functional types (PFTs)

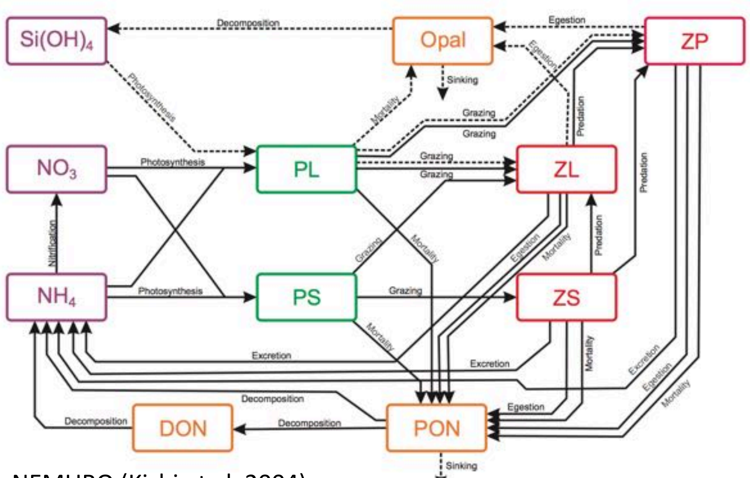
Examples of Plankton Functional Type models



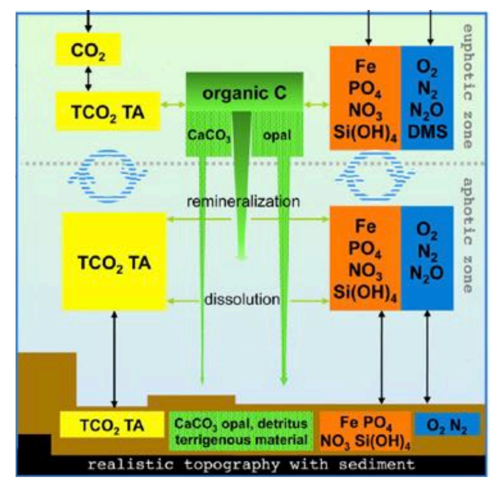
MIRO (Lancelot et al., 2005)



PISCES (Aumont et al. 2015)



NEMURO (Kishi et al, 2004)



HAMOCC (Maier-Reimer et al, 2005)

Figure from Ilyina et al (2013)

Plankton functional types (PFTs)

Solving Plankton Functional Type models

<u>Interests of modelling PFTs:</u>

- Even more mechanistic because resolving key functional groups and processes

BUT

- May require hundreds of empirical parameters!

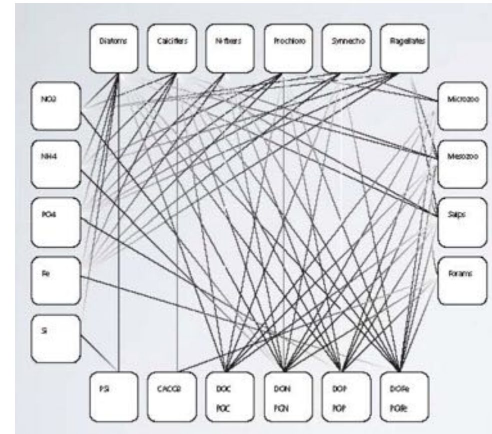
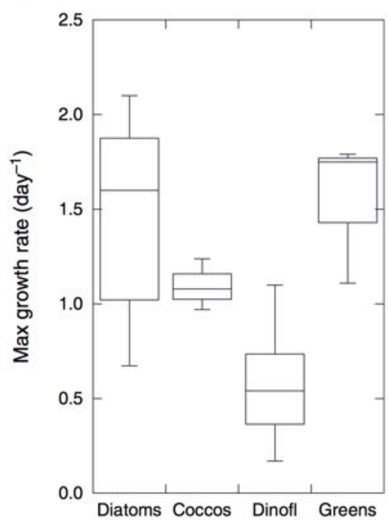


Figure from B. Ward

Growth rates of PFTs



Litchman et al (2007)

PFT models are based on community averages

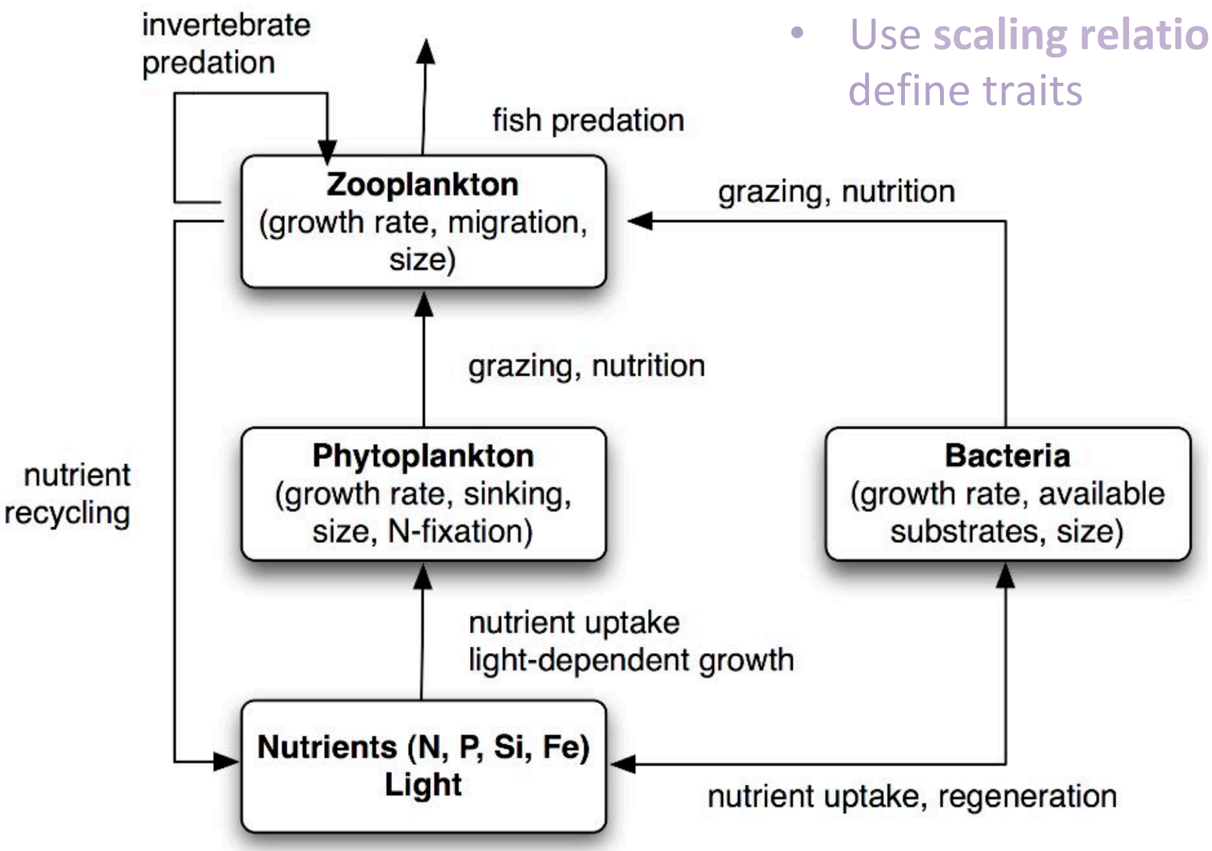
Still significant variability of traits within groups!

Trait-based models

Taking into account the variability of the "traits"

Defining traits for each component:

- Need to find ways to **reduce dimensionality** of traits that describe interactions **between trophic levels**
- Use **scaling relationships and stoichiometry** to define traits



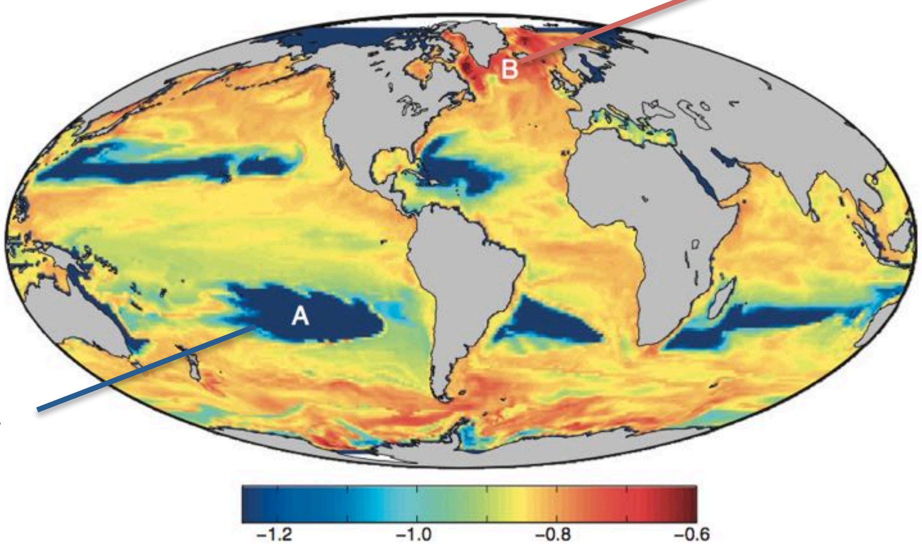
Litchman et al. (2010)

Trait-based models

Trait-based biogeography of plankton

Global size-structured plankton community model

Large-cell community



Small-cell community

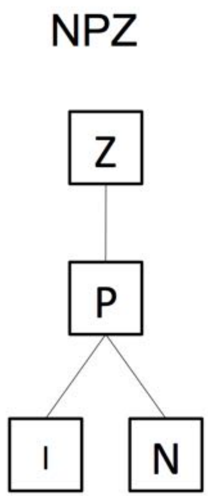
Figure 2 Size-spectral slope in a global size-structured plankton community model (data from Ward *et al.* 2012). 'A' indicates a subtropical location with relatively few large cells present (more negative slope), whereas 'B' indicates a subpolar location with a greater representation of large cells in the community (less negative slope).

Barton et al. (2013)

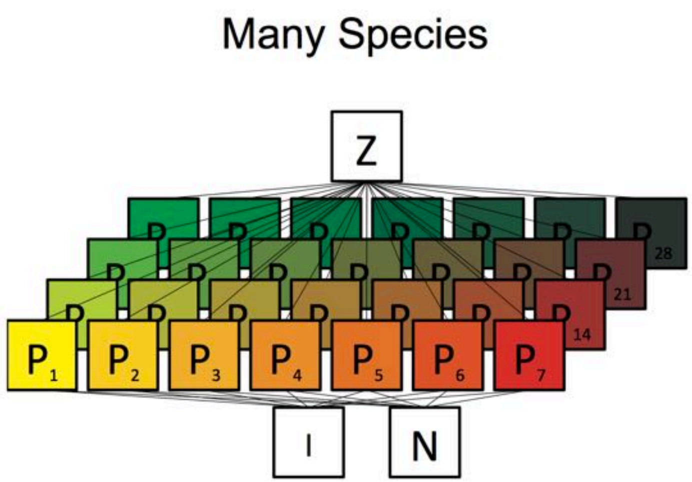
Trait-based and adaptive dynamic approach

May the best one win!

PFT model



Trait-based model



Figures from C. Klausmeier

Adaptive dynamic approach & Trait evolution

Example: biogeography of plankton communities

Modeling plankton communities using size-classes (trait-based approach + competition)

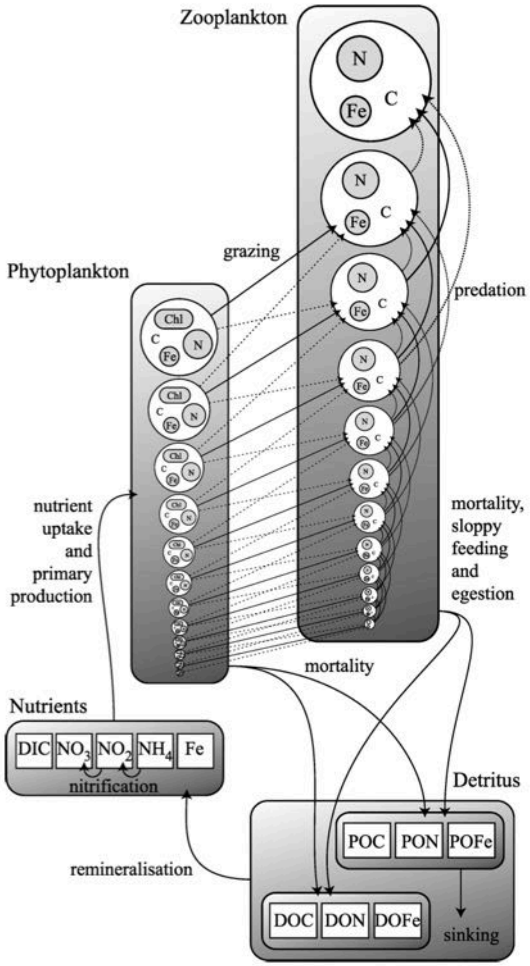


Fig. 2. Schematic representation of the ecosystem model. Not all size classes and not all predator–prey interactions are shown.

Size-classes

Competition for limited resources

Predator-prey interactions

Model structure : n times (NPZD) with quota

⇒ About 60 biogeochemical parameters

⇒ About 50 "species"

⇒ About 300 state variables

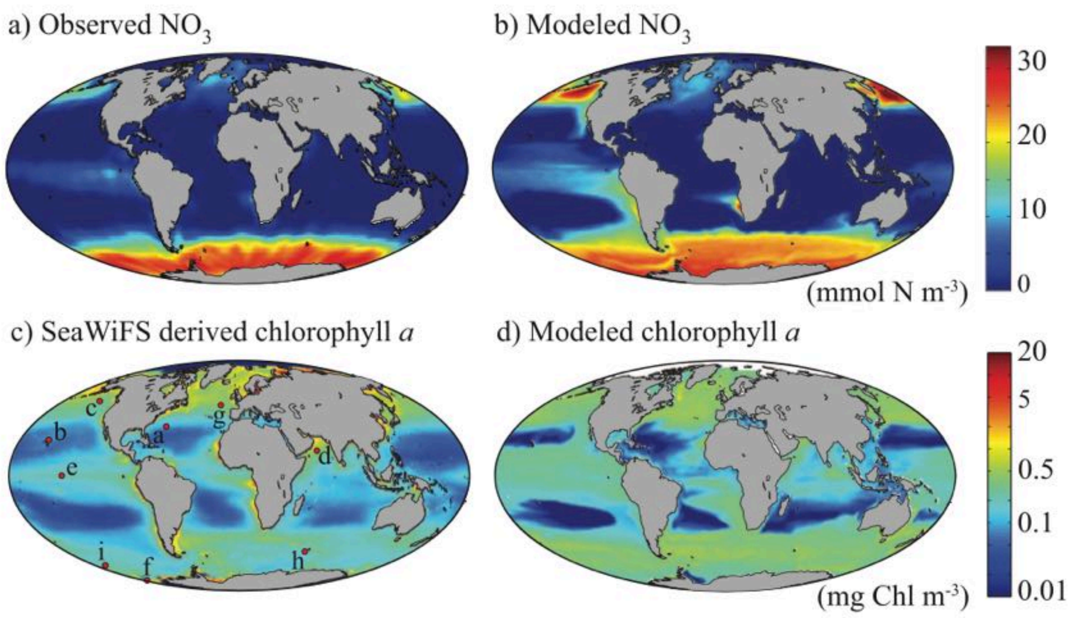
Ward et al 2012

Trait evolution

Example: biogeography of plankton communities

Modeling plankton communities using size-classes (trait-based approach + competition)

Example of results



Nitrate, chl a & primary production

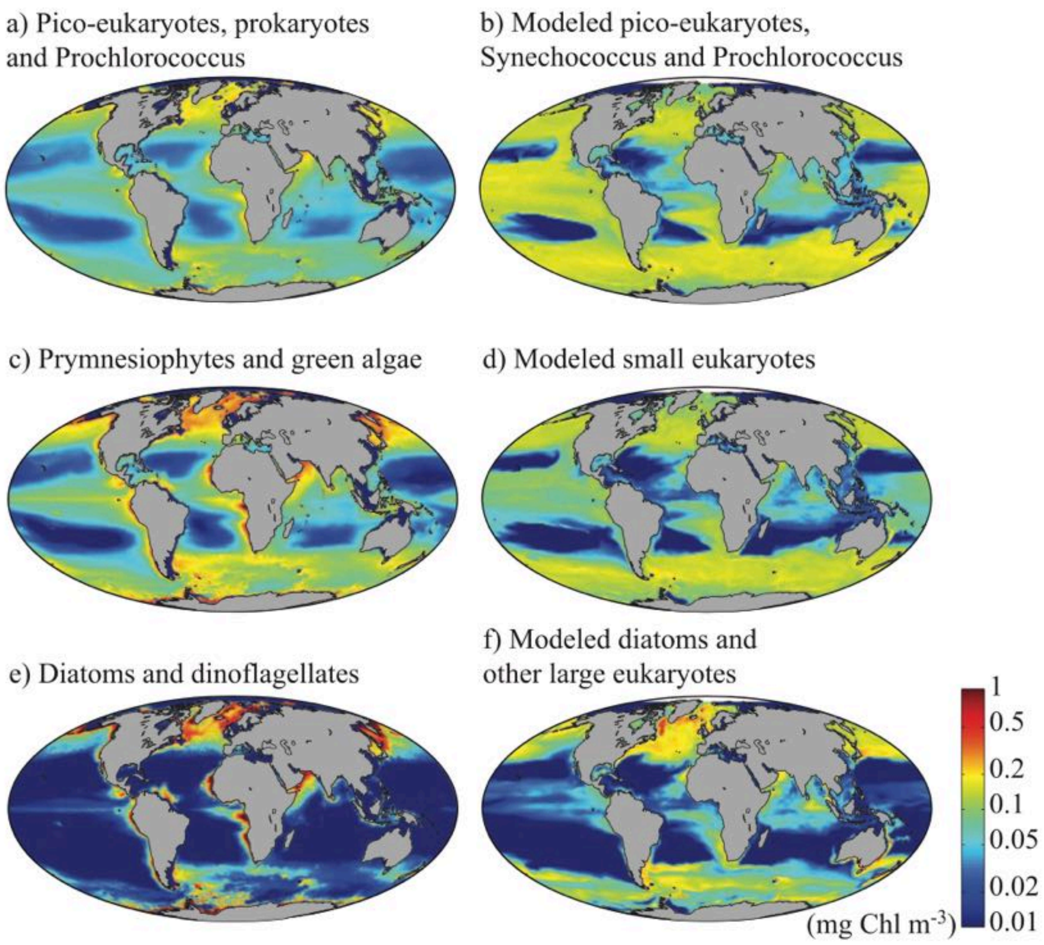
Cf. DARWIN's model (developed at MIT)

Ward et al 2012

Trait evolution

Example: biogeography of plankton communities

Modeling plankton communities using size-classes (trait-based approach + competition)



Example of results

Phytoplankton types' distribution

Ward et al 2012

Adaptive model

Other examples of adaptive dynamic approach

www.sciencemag.org SCIENCE VOL 315 30 MARCH 2007

Emergent Biogeography of Microbial Communities in a Model Ocean

Michael J. Follows,[1*] Stephanie Dutkiewicz,[1] Scott Grant,[1,2] Sallie W. Chisholm[3]

- **Bruggeman and Kooijman (2007) L&O**

  Light vs nutrient competitive ability in a seasonal 1D water column

- **Clark et al. (2013) L&O**

  Cell size in a global ocean model

- **Follows et al. (2007) Science**

  Optimum temperature and irradiance in a global ocean model

- **Dutkiewicz et al. (2013) Global Biogeochemical Cycles**

  Ecological and biogeochemical consequences of global warming

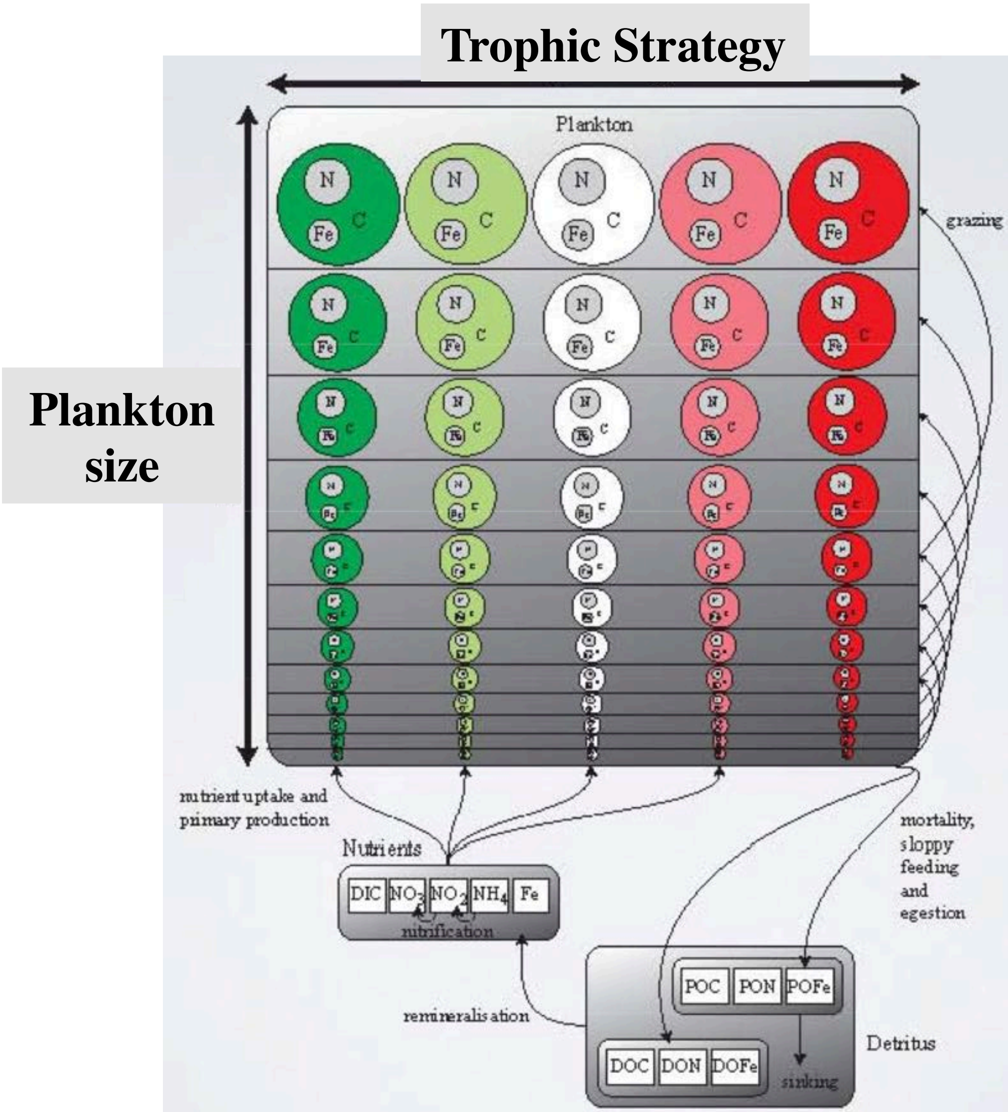
- **Sauterey et al. (2015)**

  When everything is not everywhere but species evolve

=> Emergent properties

Adaptive model

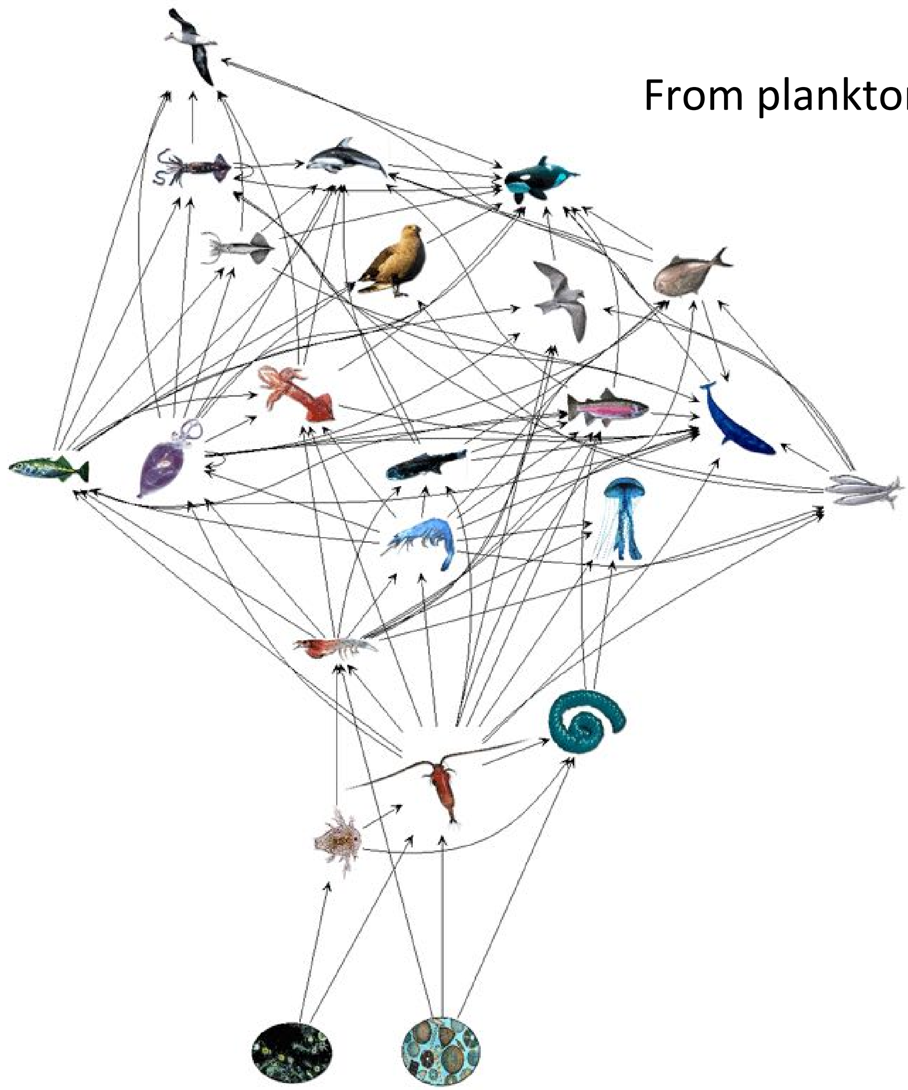
Going beyond the size axis...



⇒ Considering continuous trophic strategy

⇒ A way for solving the mixotroph problem!

End-to-end model

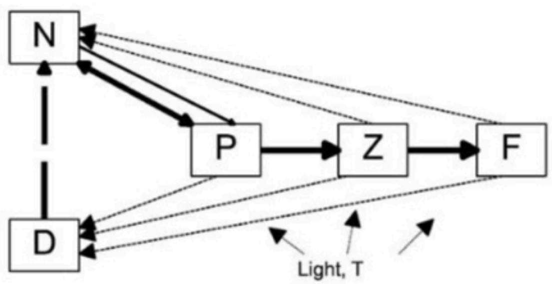


From plankton to top predators!

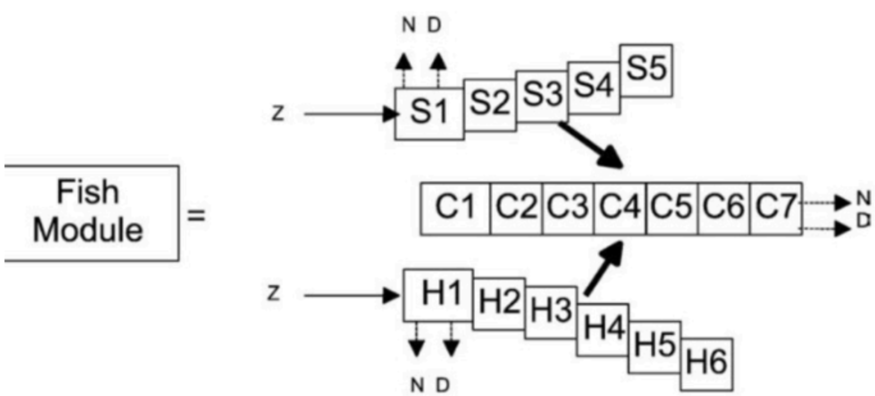
Figures from Kearney et al (2012)

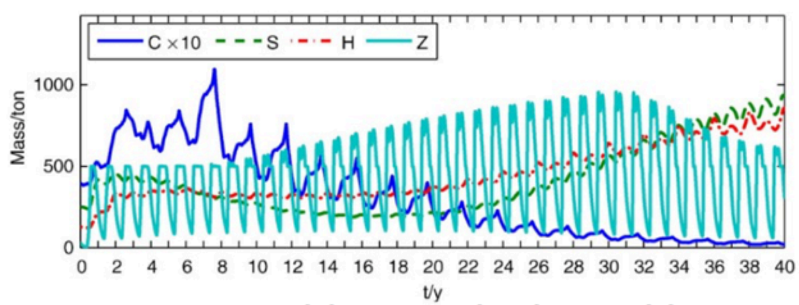
End-to-end model

Expending the NPZD model to fish



- Stock sizes and magnitude of change well simulated
- Responses time and phases of the variations not well reproduced



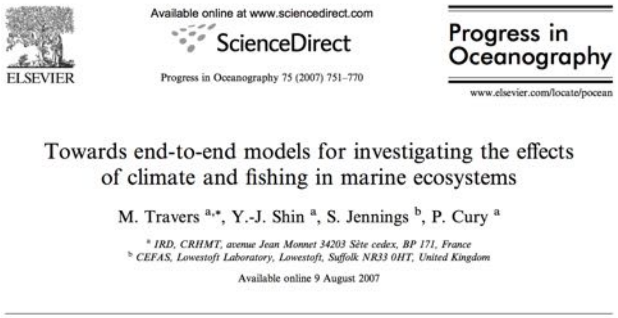


1963-2003 biomass in the Baltic Sea

Fennel, 2008;2009;2010

End-to-end model

What is end-to-end (e2e) modelling?


Available online at www.sciencedirect.com
ScienceDirect
Progress in Oceanography 75 (2007) 751–770
ELSEVIER
Progress in Oceanography
www.elsevier.com/locate/pocean

Towards end-to-end models for investigating the effects of climate and fishing in marine ecosystems

M. Travers [a,*], Y.-J. Shin [a], S. Jennings [b], P. Cury [a]

[a] IRD, CRHMT, avenue Jean Monnet 34203 Sète cedex, BP 171, France
[b] CEFAS, Lowestoft Laboratory, Lowestoft, Suffolk NR33 0HT, United Kingdom

Available online 9 August 2007

Lower trophic levels ⟷ Higher trophic levels (fishes) ⟷ Human societies

- Aims to represent the **entire food web** and the associated **abiotic environment**
  - Multiple species or functional groups are represented at each of the key trophic levels
  - Top predators in the system are also included

- Requires the integration of **physical** and **biological** processes at different **scales**

- Implements **two-way interactions** between ecosystem components (from higher to lower trophic levels and from lower to higher trophic levels)

- Accounts for the dynamic forcing effect of **climate and human impacts at multiple trophic levels** (represented in a dynamical manner)

End-to-end model

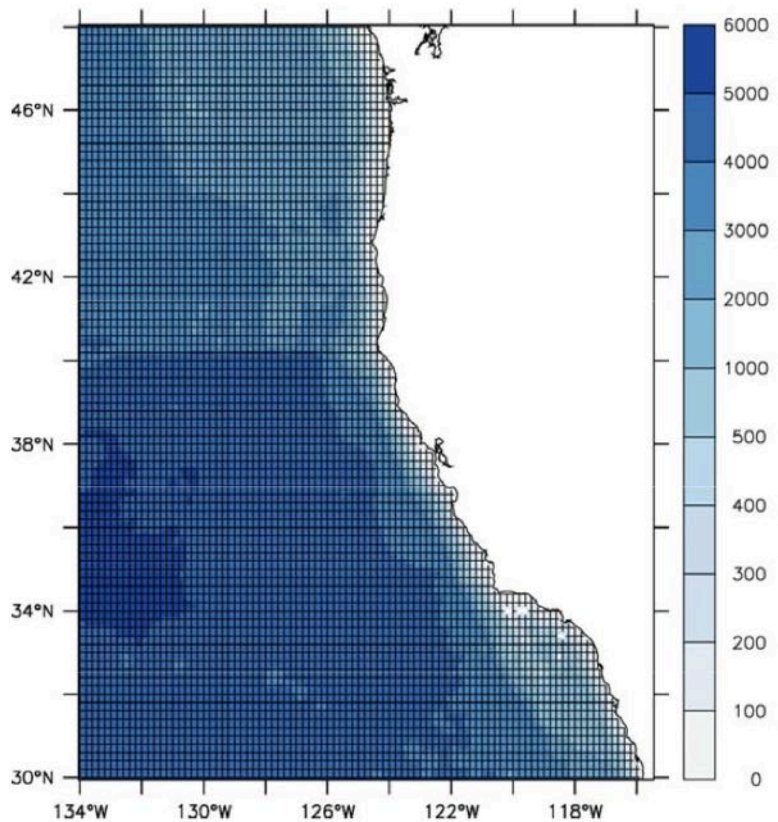
Example: Sardine & anchovy in the California current

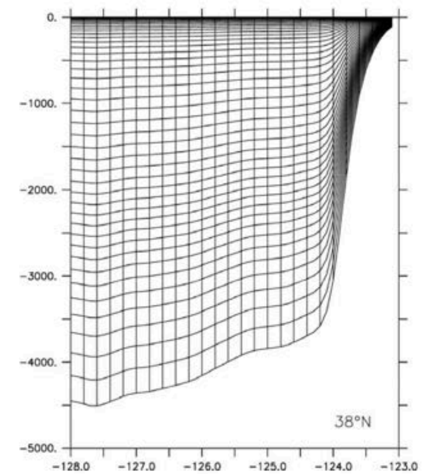
- Coupling of four models:
  1) Physical model: 3-dimensional ROMS
  2) Plankton model: NEMURO
  3) Fish model: multiple-species individual-based model
  4) Fishing fleet dynamics

End-to-end model

Example: Sardine & anchovy in the California current

1) Physical model: 3-dimensional ROMS





<u>Vertical layers</u>
42 sigma levels

<u>Horizontal grid</u>
10 km x 10 km

Run duration: 40 years (1958-2007)

End-to-end model

Example: Sardine & anchovy in the California current

2) Plankton model: NEMURO

NPZD-type model

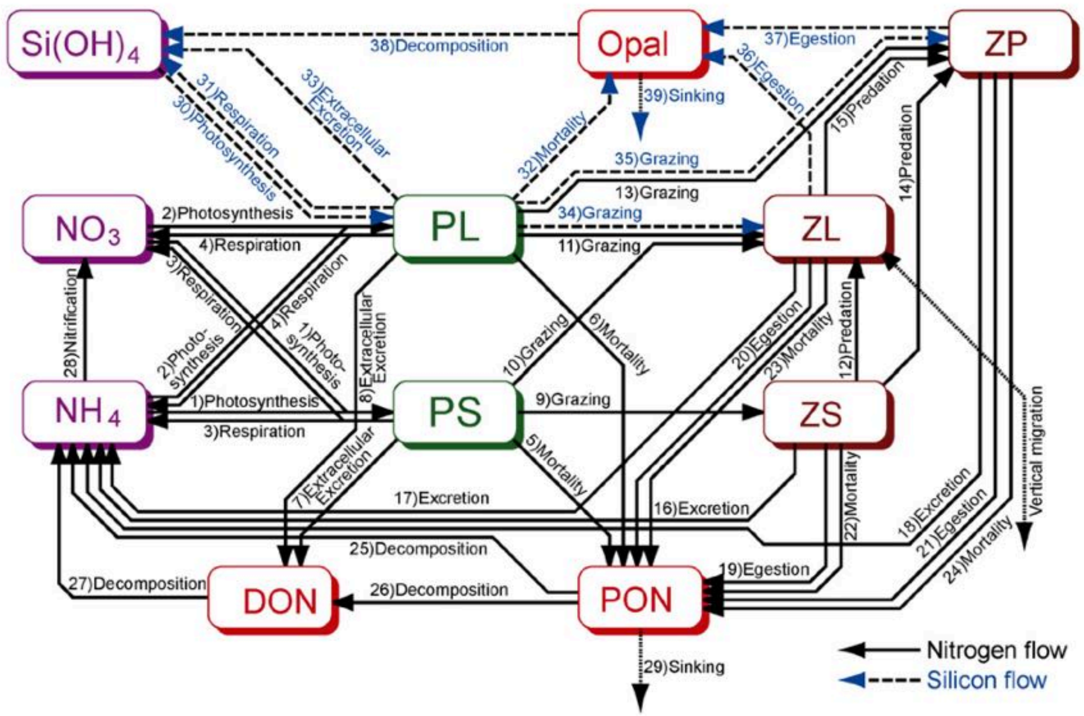


Fig. 1 – Schematic view of the NEMURO lower trophic level ecosystem model. Solid black arrows indicate nitrogen flows and dashed blue arrows indicate silicon. Dotted black arrows represent the exchange or sinking of the materials between the modeled box below the mixed layer depth.

Figure from Kishi et al (2007)

End-to-end model

Example: Sardine & anchovy in the California current

3) Fish model: multiple-species individual-based model (IBM)

Sardine

Anchovy

Both sardine and anchovy are fully modelled:
- Reproduction (T-dependant)
- Growth (T- and Plankton-dependant)
- Mortality: constant, starvation, predation, fishing
- Movement (T-dependant + transport + swimming)
- Competition (for food and space)
- Predators

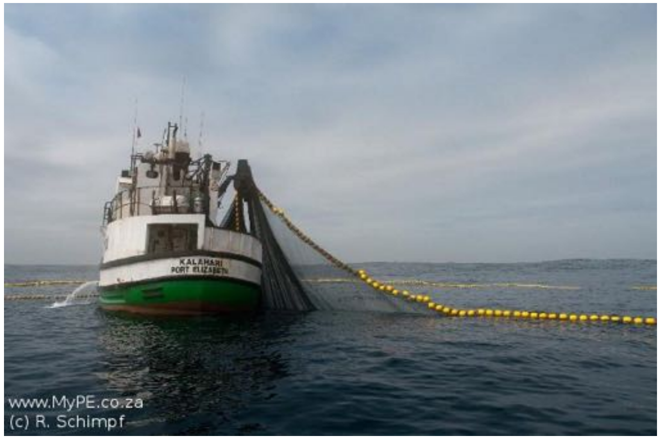
Migratory predators

Migratory predators are not fully modelled:
- Enter and exit the grid,
- Movement
- Consumption of sardine and anchovy only
- Typically : albacore tuna

End-to-end model

Example: Sardine & anchovy in the California current

4) Fishing fleet dynamics



Fishing fleet:

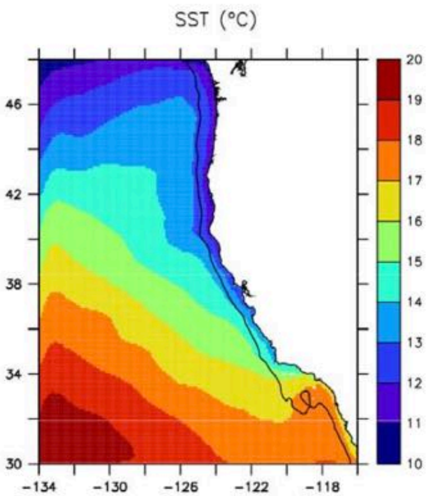
- 100 boats and 5 ports for fishing the sardine
- Day boats so complete a trip in 24 hours
- Daily evaluation
- Compute expected net revenue (ENR) based on:
    - Perceived CPUE (10-day average)
    - Price per pound
    - Cost per km
    - Return to nearest port

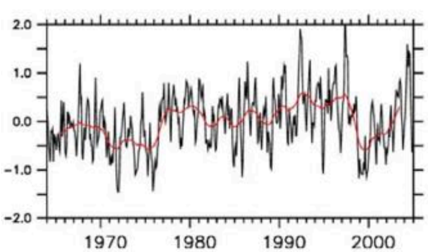
End-to-end model

Example: Sardine & anchovy in the California current

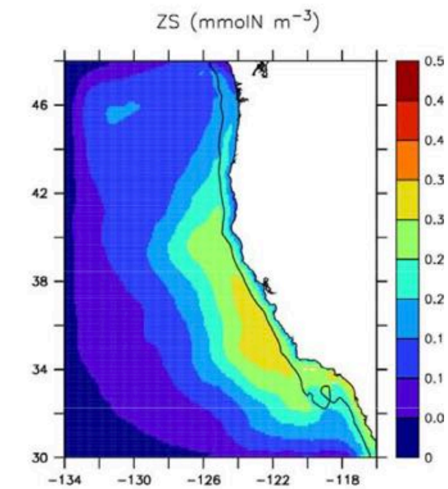
Examples of results

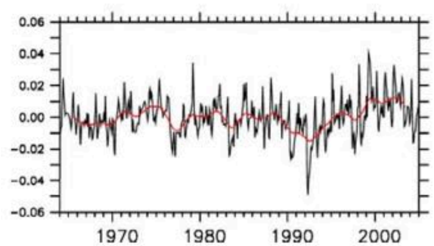
Surface temperature



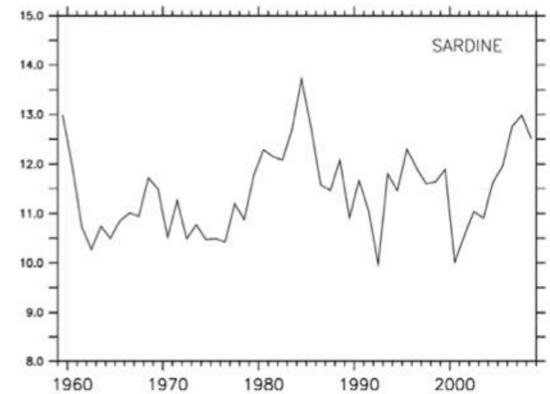


Phytoplankton





Abundance



Depth

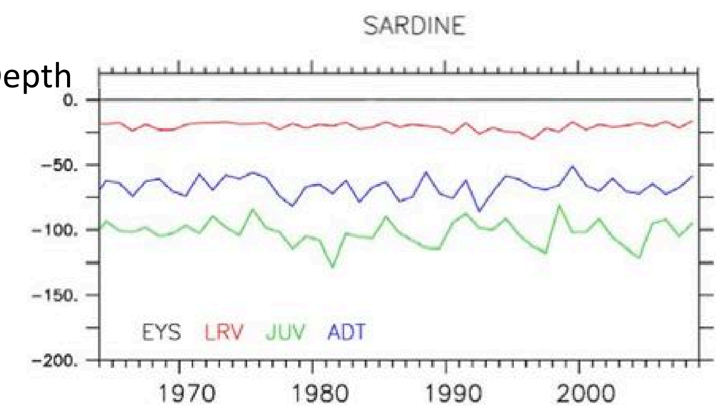


Figure from K. Rose

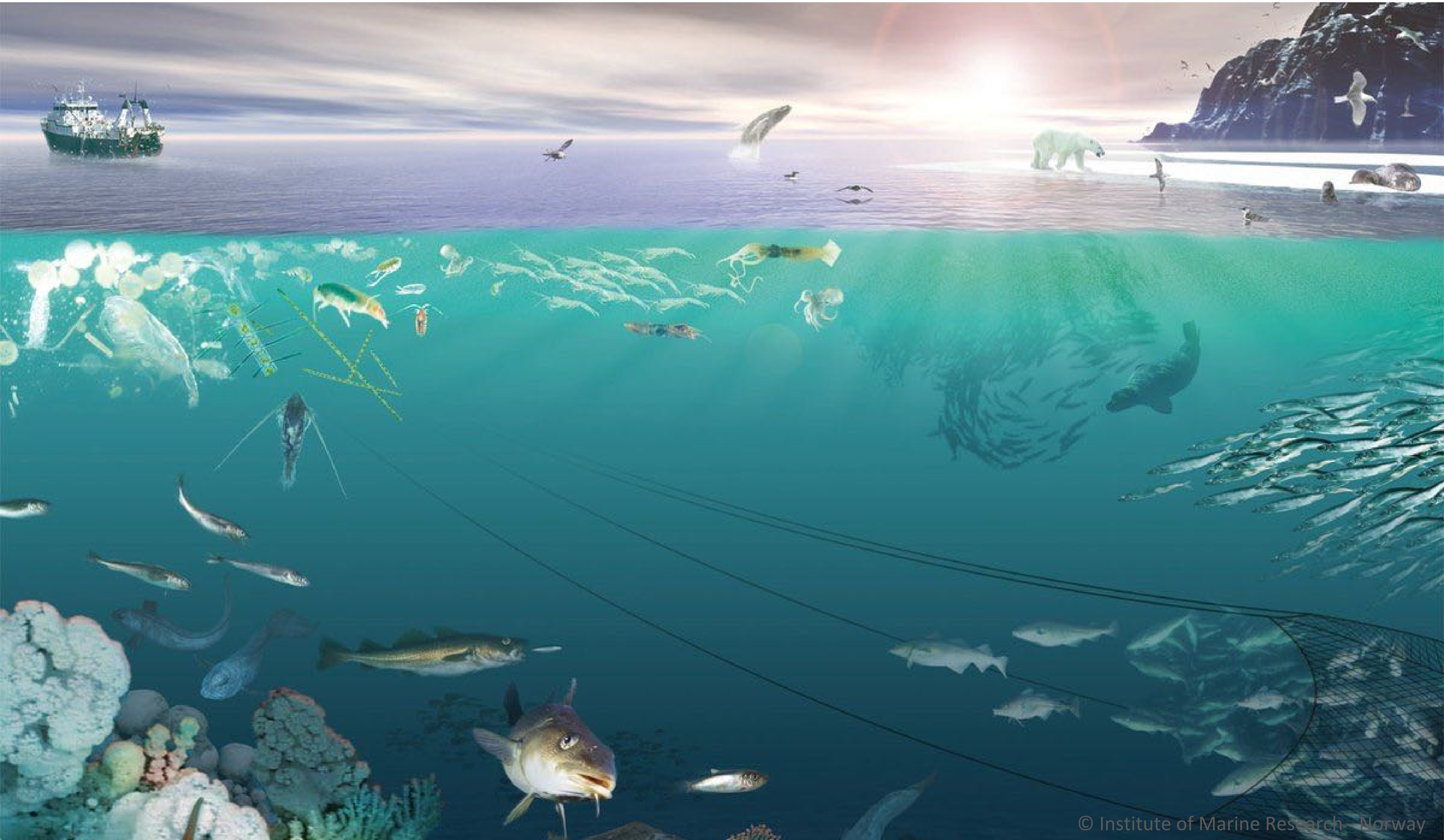
End-to-end model

Numerical challenges…

- Solving everything simultaneously
- Code is thousands of lines
- Computing speed
- Two-way coupling between fish and zooplankton
- Mass balance
- Eulerian with Lagrangian
- Full life cycle of fishes
- …

How can we model marine ecosystems?

And the machine learning in all of this?



Data assimilation in marine ecosystem models

Traditional methods:

e.g. using ocean color data, time-series data…

⟹ Parameter optimization, e.g. microgenetic algorithm (Ayata et al. 2013)

⟹Gradient descent/ variational methods (3D-VAR)

ML-based methods?

⟹ Used for physical models so far (e.g. high resolution)

⟹ Cf. Patrick Gallinari's lecture and Rédouane Lguensat's lab

An open field of research!

Using ML for marine ecosystem modelling

Examples of recent articles…??

Conference paper

Artificial Intelligence, Machine Learning and Modeling for Understanding the Oceans and Climate Change

Nayat Sanchez-Pi [1] , Luis Marti [1] , André Abreu [2] , Olivier Bernard [3] , Colomban de Vargas [4] , Damien Eveillard [5, 6] , Alejandro Maass [7] , Pablo A. Marquet [8] , Jacques Sainte-Marie [9] , Julien Salomon [9] , Marc Schoenauer [10] , Michele Sebag [10] Détails

ELSEVIER
Ecological Modelling
Volume 451, 1 July 2021, 109578

Global assessment of marine phytoplankton primary production: Integrating machine learning and environmental accounting models

F. Mattei [a, c, d], E. Buonocore [b, c], P.P. Franzese [b, c], M. Scardi [a, c]

Still a lot of opportunities!

Using ML for marine ecosystem modelling

Perspectives?

- Combining ML-based prediction with dynamical models
    - cf. Jean-Olivier Irisson's lecture and TD of Tuesday
- Using ML to represent unresolved process
    - cf. sub-grid dynamics in AI-informed physical models (next lecture)
- Symbolic AI? Hybrid AI?
    - cf. the ongoing ANR IA-Biodiv Challenge…

Thank you for your attention!