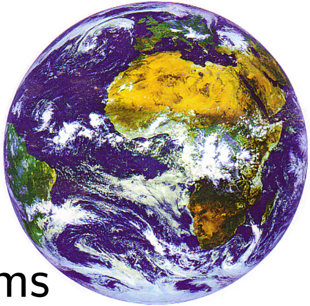
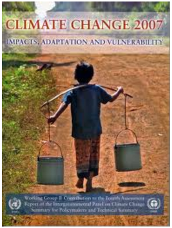


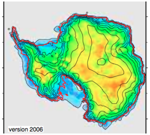
Numerical forecast systems for geophysical fluids and for climate

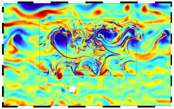
Eric Blayo and Laurent Debreu
Jean Kuntzmann Lab.
Univ. Grenoble Alpes and INRIA

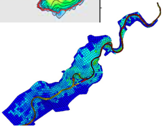
Context: understanding and forecasting geophysical systems

- Numerous disciplines: meteorology, oceanography, hydrology, glaciology, climatology…
- Huge societal impact



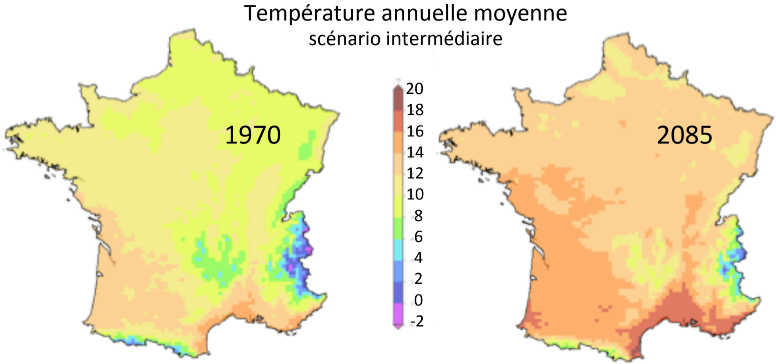






Numerical forecasts: important stakes

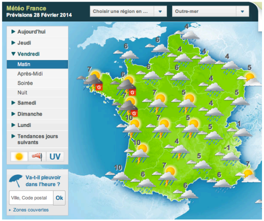
- Climate change



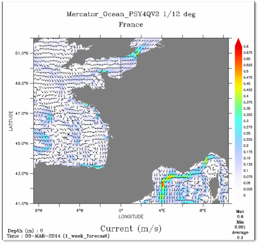
Source: DRIAS – Météo France, IPSL, CERFACS

Numerical forecasts: important stakes

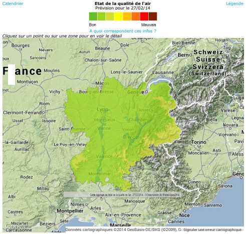
- Climate change
- Short term prediction



Météo France



Mercator Océan



Air Rhône-Alpes

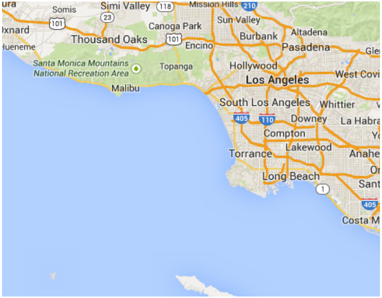
Numerical forecasts: important stakes

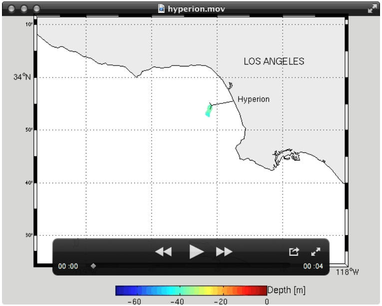
- Climate change
- Short term prediction
- Risk management, local planning...

Avalanches

Dam break

Flood


Somis
Simi Valley
Mission Hills
Sun Valley
Canoga Park
Thousand Oaks
Burbank
Altadena
Encino
Pasadena
Santa Monica Mountains
National Recreation Area
Topanga
Hollywood
Los Angeles
Malibu
South Los Angeles
Whittier
Downey
Compton
Lakewood
Torrance
Long Beach


hyperion.mov
LOS ANGELES
Hyperion
34°N
118°W
00 :00
00 :04
Depth [m]
-60
-40
-20
0

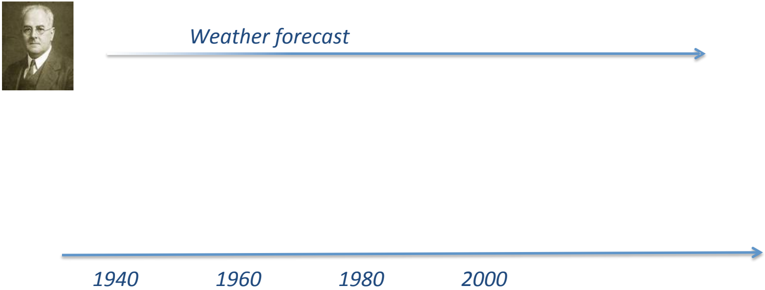
Numerical forecasts: important stakes

- Climate change
- Short term prediction
- Risk management, local planning...

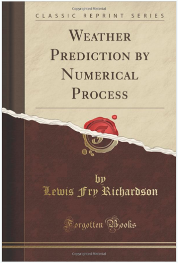
⟶ Numerical forecast systems are omnipresent and play a fundamental role when dealing with such issues.

A short history of numerical forecast systems

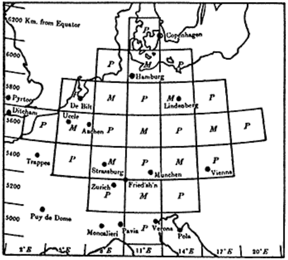
Numerical forecast systems have been developed progressively for all disciplines related to geophysical fluids.



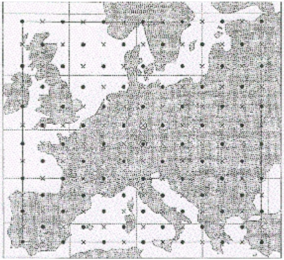
Richardson's forecast factory (1922)



Lewis F. Richardson (1881-1953)



Meteorological stations



Computation grid

Richardson's forecast factory (1922)

A myriad computers are at work upon the weather of the part of the map where each sits, but each computer attends only to one equation or part of an equation. The work of each region is coordinated by an official of higher rank. Numerous little "night signs" display the instantaneous values so that neighbouring computers can read them. Each number is thus displayed in three adjacent zones so as to maintain communication to the North and South on the map.


The forecast factory

From the floor of the pit a tall pillar rises to half the height of the hall. It carries a large pulpit on its top. In this sits the man in charge of the whole theatre; he is surrounded by several assistants and messengers. One of his duties is to maintain a uniform speed of progress in all parts of the globe. In this respect he is like the conductor of an orchestra in which the instruments are slide-rules and calculating machines.

A short history of numerical forecast systems

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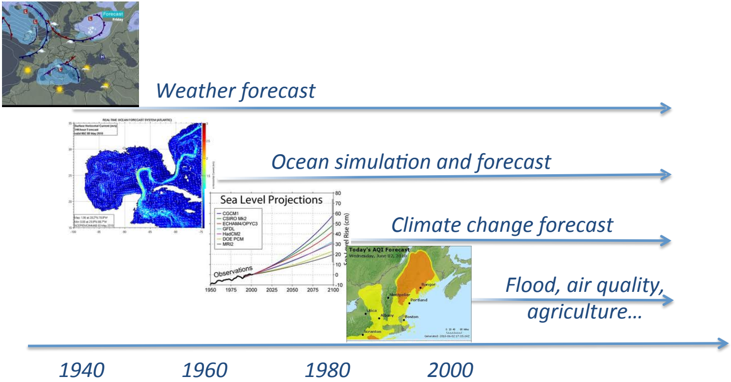
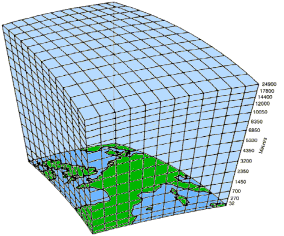


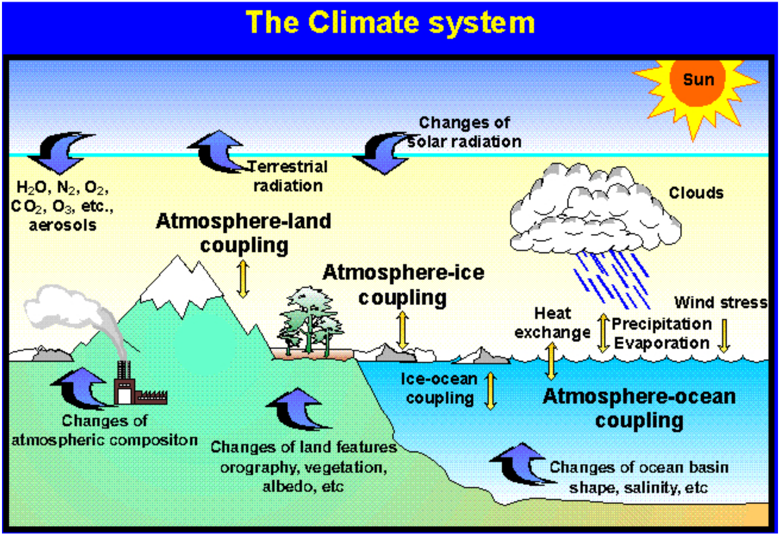
Building a numerical forecast system

- A numerical forecast system is the output of a multi-disciplinary effort.

- A three step construction:
  1. modeling (mathematics and numerics)
  2. calibration (data assimilation)
  3. uncertainty quantification



Step 1: translate reality into equations



Step 1 - Modeling: translate reality into equations

- Main physical laws: conservation of mass, energy, water...
- Boundary conditions: exchange fluxes (heat, mass...)
- Some specific aspects: boundary layers, micro-physics...

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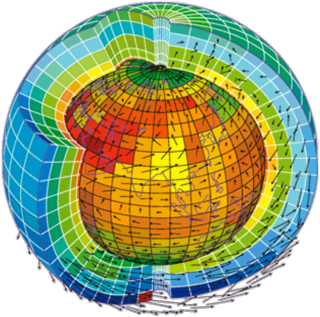
$$\frac{\partial u}{\partial t} + \mathbf{U}.\nabla u - fv + \frac{1}{\rho_0}\frac{\partial p}{\partial x} - \mathcal{F}(u) = 0 \qquad \frac{\partial T}{\partial t} + \mathbf{U}.\nabla T - \mathcal{D}_T(T) = 0$$

$$\frac{\partial v}{\partial t} + \mathbf{U}.\nabla v + fu + \frac{1}{\rho_0}\frac{\partial p}{\partial y} - \mathcal{F}(v) = 0 \qquad \frac{\partial S}{\partial t} + \mathbf{U}.\nabla S - \mathcal{D}_S(S) = 0$$

$$\frac{\partial p}{\partial z} = -\rho\, g \qquad \rho = \rho(T, S, p)$$

$$\mathrm{div}\ \mathbf{U} = 0 \qquad + \text{ conditions aux limites}$$

From infinite to finite dimension

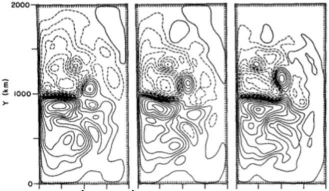


Approximated representation of:

- the geographical domain: mesh
- the equations: numerical schemes

This results in a (large) system of equations, the solution of which allows to compute a future system state starting from the present one. ($\simeq 10^6 - 10^9$ unknowns)

At this stage: a numerical model that is useful to understand the behavior of geophysical systems...



Holland (1978): evidence for intense meso-scale eddy activity in mid-latitude ocean

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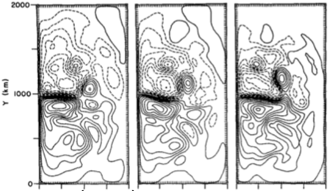

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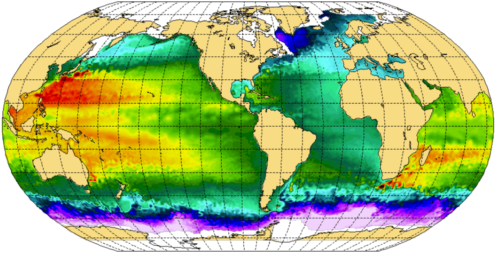

1/4° global ocean simulation (sea surface elevation)

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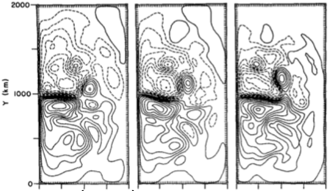

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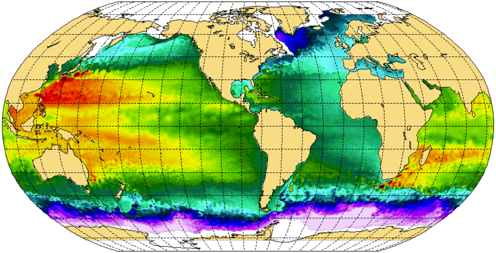
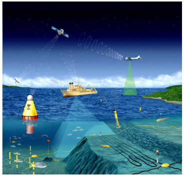


1/4° global ocean simulation (sea surface elevation)

...but is unable to produce forecasts.

Step 2: describe the present before forecasting the future

- Use all sources of information to reproduce the present state of the system:



past and present observations

$$
\left\{
\begin{aligned}
\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} + \dot\sigma\frac{\partial u}{\partial \sigma} - f(v - v_g) + \frac{\partial \phi}{\partial x}|_p + F_u = 0 \\
\frac{\partial v}{\partial t} + u\frac{\partial v}{\partial x} + v\frac{\partial v}{\partial y} + \dot\sigma\frac{\partial v}{\partial \sigma} + f(u - u_g) + \frac{\partial \phi}{\partial y}|_p + F_v = 0 \\
\frac{\partial \phi}{\partial (T/\theta)} = -C_p\theta(1 + 0.85 q_v) \\
\frac{\partial p_\star}{\partial t} = -\int_0^1 [\frac{\partial (p_\star u)}{\partial x} + \frac{\partial (p_\star v)}{\partial y}] d\sigma \\
\frac{\partial \sigma}{\partial t} = \frac{1}{p_\star}\{\sigma \int_0^1 [\frac{\partial (p_\star u)}{\partial x} + \frac{\partial (p_\star v)}{\partial y}] d\sigma - \int_0^\sigma [\frac{\partial (p_\star u)}{\partial x} + \frac{\partial (p_\star v)}{\partial y}] d\sigma\} \\
\frac{\partial \theta}{\partial t} + u\frac{\partial \theta}{\partial x} + v\frac{\partial \theta}{\partial y} + \dot\sigma\frac{\partial \theta}{\partial \sigma} + \frac{\partial R_{rad}}{\partial \sigma} + F_\theta + p_\theta = 0 \\
\frac{\partial q_v}{\partial t} + u\frac{\partial q_v}{\partial x} + v\frac{\partial q_v}{\partial y} + \dot\sigma\frac{\partial q_v}{\partial \sigma} + F_{q_v} + p_{q_v} = 0
\end{aligned}
\right.
$$

mathematical models

statistics

$\longrightarrow$ Data assimilation

Step 2: describe the present before forecasting the future

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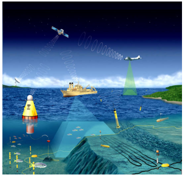

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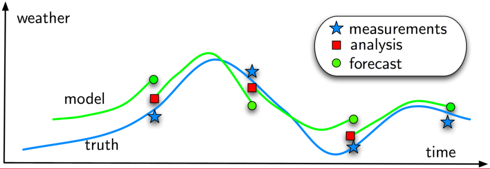
\right.
$$

mathematical models

statistics

$\longrightarrow$ Data assimilation

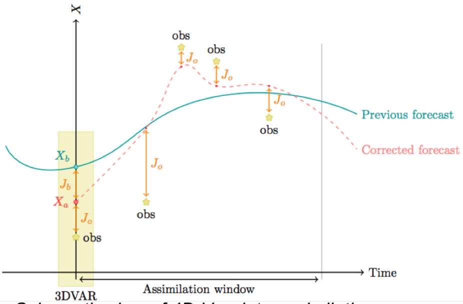
- You all already experienced data assimilation



From a mathematical point of view

- Mathematical techniques that combine different sources of information in an optimal way: optimal control, stochastic filtering. . .

$$\min_{u} \int_0^T \|\mathbf{y}^{obs}(t) - \mathcal{H}(\mathbf{x}(u,t))\| \, dt \quad ; \quad \max p(\mathbf{x}(t) \,|\, \mathbf{x}(t-1), \mathbf{y}^{obs}(t))$$

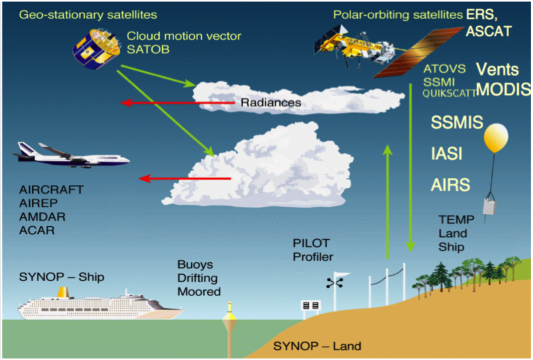


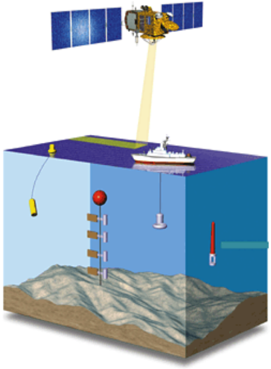
Schematic view of 4D-Var data assimilation

$$J(\mathbf{x}_0, \ldots) = \frac{1}{2}\|\mathbf{x}_0 - \mathbf{x}_0^b\|^2_{B^{-1}} + \frac{1}{2}\sum_{k=1}^{N}\|H(\mathbf{x}_k) - \mathbf{y}_k\|^2_{R^{-1}}$$

A wide variety of observations

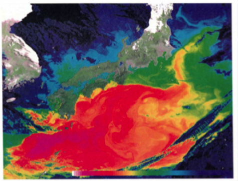
- in situ / satellite, quantitative / qualitative. . .





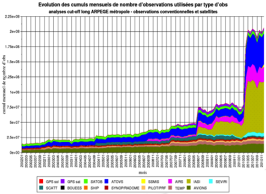
A wide variety of observations

- in situ / satellite, quantitative / qualitative...
- Earth observation from space has initiated a revolution in geophysical NFSs



sea surface temperature

satellite observations



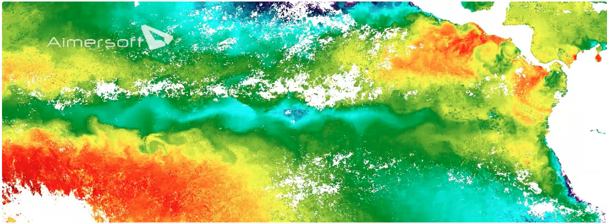
# of satellite obs in Arpege

A number of theoretical and practical difficulties

- management of nonlinearities
- huge dimension
- computation cost: $\times$ 10-50
- error statistics
- observation operators

A present challenge: assimilation of sequence of images

- Images are abundant and informative



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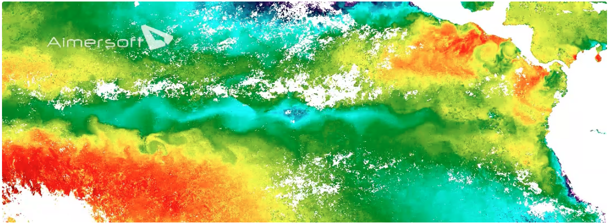
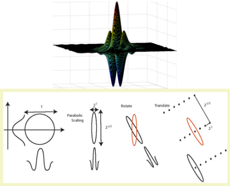


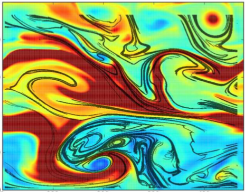
- How to link a photo and a numerical model ?

image analysis



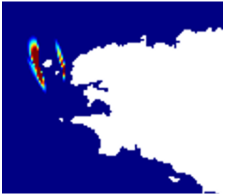
curvlet decomposition

dynamical systems



chlorophylle and Lyapunov exponents

optimal transport



optimal field with obstacles

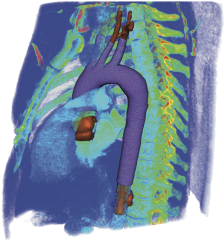
Data assimilation

- optimal control, stochastic filtering

$$\min_{u} \int_0^T \|\mathbf{y}^{obs}(t) - \mathcal{H}(\mathbf{x}(u,t))\| \, dt \quad ; \quad \max p(\mathbf{x}(t)|\mathbf{x}(t-1), \mathbf{y}^{obs}(t))$$

- A number of present challenges

- Methods that spread over numerous other applicative domains



Step 3: quantifying uncertainty

Prediction is very difficult, especially about the future. *(Niels Bohr)*

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- A prediction without an error bar is not so useful
- Prediction may be very sensitive to uncertainty on the present state: chaos, butterfly effect...

  $\longrightarrow$ ensemble and/or multi-model approaches

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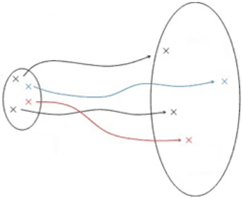
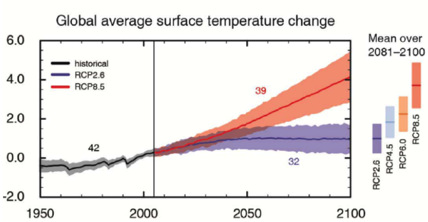
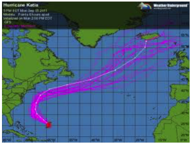
$\longrightarrow$ ensemble and/or multi-model approaches





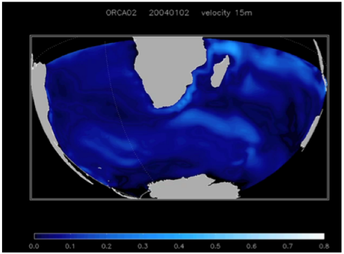


$\longrightarrow$ Providing meaningful error bars for such systems is really challenging.

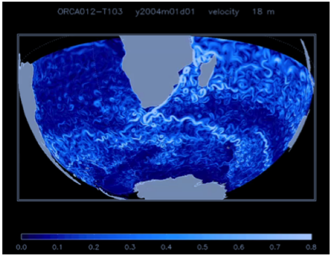
A massive use of supercomputers

- Increasing the resolution is often one of the key points for improving the quality of the model results (small scale activity + scale interactions).

ORCA model – 2° resolution



ORCA model – 1/12° resolution



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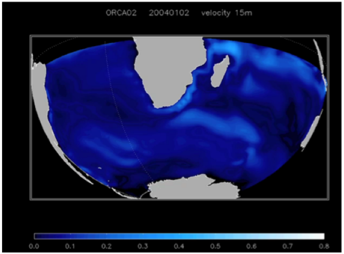

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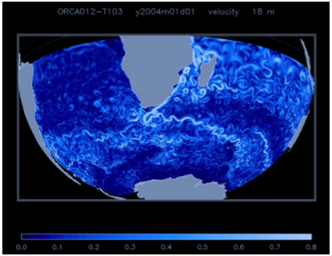
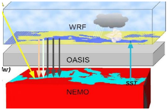


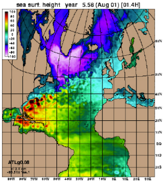
- Data assimilation: × one or two orders of magnitude
- Quantification of uncertainty: × several orders of magnitude

⟶ Numerical systems for ocean/atmosphere/climate simulations generally require huge computational costs.

Some issues related to HPC



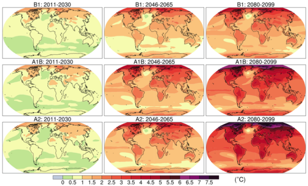
- Model coupling



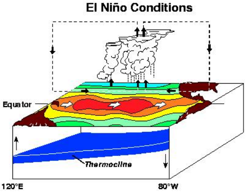
- Computational grids and methods

Ocean-atmosphere coupling

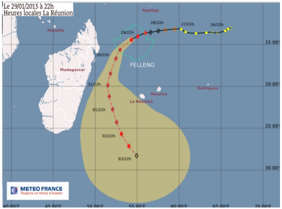
- Various applications require coupling an oceanic model and an atmospheric model.



climate modeling



seasonal forecasts



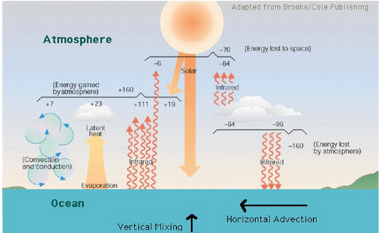
short term predictions

- **Objective:** revisit the coupling strategies presently used in such systems, in order to improve their mathematical properties (hence the quality of the model solutions ?)

Air-sea interactions

$$\begin{cases} \mathcal{L}_{\text{atm}}\, \boldsymbol{U}^{\text{a}} = f_{\text{atm}} & \text{in } \Omega_{\text{atm}} \times [0, T] \\ \mathcal{L}_{\text{oce}}\, \boldsymbol{U}^{\text{o}} = f_{\text{oce}} & \text{in } \Omega_{\text{oce}} \times [0, T] \end{cases}$$

$$\text{with } \boldsymbol{U}^{\text{a}} = \begin{pmatrix} \boldsymbol{u}_h^{\text{a}} \\ T^{\text{a}} \end{pmatrix} \quad \boldsymbol{U}^{\text{o}} = \begin{pmatrix} \boldsymbol{u}_h^{\text{o}} \\ T^{\text{o}} \end{pmatrix}$$

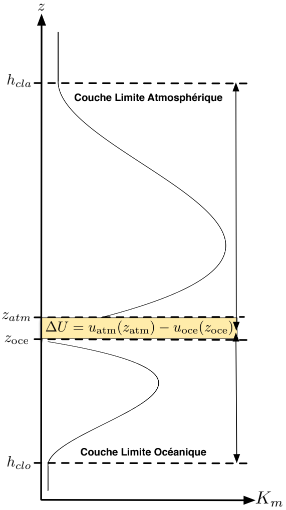


Interface conditions:

$$\text{momentum} \qquad \rho^{\text{a}} K_{\text{m}}^{\text{a}} \frac{\partial \boldsymbol{u}_h^{\text{a}}}{\partial z} = \rho^{\text{o}} K_{\text{m}}^{\text{o}} \frac{\partial \boldsymbol{u}_h^{\text{o}}}{\partial z} = \boldsymbol{\tau} \qquad \text{on } \Gamma \times [0, T]$$

$$\text{heat flux} \qquad \rho^{\text{a}} c_p^{\text{a}} K_{\text{T}}^{\text{a}} \frac{\partial T^{\text{a}}}{\partial z} = \rho^{\text{o}} c_p^{\text{o}} K_{\text{T}}^{\text{o}} \frac{\partial T^{\text{o}}}{\partial z} = Q_{\text{S}} + \mathcal{R} \qquad \text{on } \Gamma \times [0, T]$$

Boundary layer parameterization



Typical vertical viscosity profile

$$\begin{cases} \boldsymbol{\tau} = \rho^{\rm a}\, C_D\, \|\Delta \boldsymbol{u}\|\, \Delta \boldsymbol{u} \\ Q_S = \rho^{\rm a} c_p^{\rm a}\, C_H\, \|\Delta \boldsymbol{u}\|\, \Delta T \end{cases}$$

with:

$\Delta \boldsymbol{u}, \Delta T$ = jumps of $\boldsymbol{u}$ and T

C_D, C_H: exchange coefficients given by (quite complicated) bulk formulas $= f(\Delta \boldsymbol{u}, \Delta T, \Delta q, z_{\rm atm}, z_{\rm oce}, \ldots)$

Keywords: parameterization of Reynolds terms, K-profile schemes, Monin-Obukhov theory, bulk aerodynamic formulas...

In summary

We would like to solve:

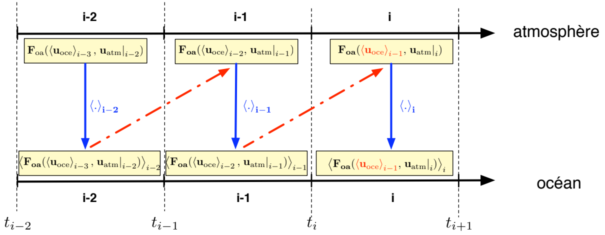
$$\begin{cases} \mathcal{L}_{\text{atm}}\, \boldsymbol{U}^{\text{a}} = f_{\text{atm}} & \text{in } \Omega_{\text{atm}} \times [0, T] \\ \mathcal{L}_{\text{oce}}\, \boldsymbol{U}^{\text{o}} = f_{\text{oce}} & \text{in } \Omega_{\text{oce}} \times [0, T] \\ \mathcal{F}_{\text{atm}}\, \boldsymbol{U}^{\text{a}} = \mathcal{F}_{\text{oce}}\, \boldsymbol{U}^{\text{o}} = F_{\text{OA}}(\boldsymbol{U}^{\text{a}}, \boldsymbol{U}^{\text{o}}, \mathcal{R}) & \text{on } \Gamma \times [0, T] \end{cases}$$

Usual approach: asynchronous coupling

$$\begin{cases} \mathcal{L}_{\text{atm}}\,\boldsymbol{U}^{\text{a}} = f_{\text{atm}} & \text{in } \Omega_{\text{atm}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\text{atm}}\,\boldsymbol{U}^{\text{a}} = F_{\text{OA}}(\langle \boldsymbol{U}^{\text{o}} \rangle_{i-1}, \boldsymbol{U}^{\text{a}}, \mathcal{R}) & \text{on } \Gamma \times [t_i, t_{i+1}] \end{cases}$$

then

$$\begin{cases} \mathcal{L}_{\text{oce}}\,\boldsymbol{U}^{\text{o}} = f_{\text{oce}} & \text{in } \Omega_{\text{oce}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\text{oce}}\,\boldsymbol{U}^{\text{o}} = \langle \mathcal{F}_{\text{atm}}\,\boldsymbol{U}^{\text{a}} \rangle_i & \text{on } \Gamma \times [t_i, t_{i+1}] \end{cases}$$



- $+$: balanced fluxes over each time window $[t_i, t_{i+1}]$
- - : synchrony issue

Usual approach: asynchronous coupling

- Current coupling methods are simple ad-hoc algorithms, in order to be computationally cheap.
- These methods are inadequate from a mathematical point of view.

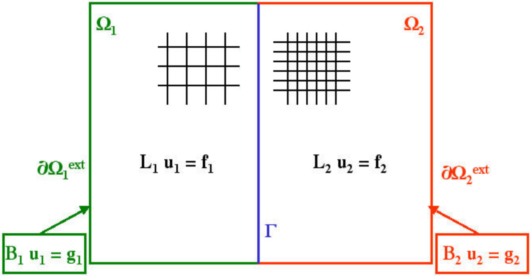
Usual approach: asynchronous coupling

- Current coupling methods are simple ad-hoc algorithms, in order to be computationally cheap.
- These methods are inadequate from a mathematical point of view.

Issues

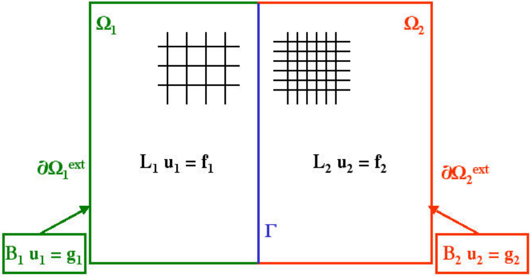
- Can we improve the coupling methods ?
- Does it improve the physics of the coupled solution ?
- Can this be done at a reasonable CPU cost ?

A convenient framework: Schwarz methods



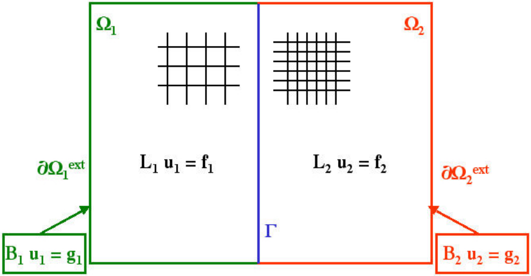
$$\begin{cases} L_1 u_1 = f_1 & \Omega_1 \times [0, T] \\ u_1 \ \text{given} & \text{at } t = 0 \\ B_1 u_1 = g_1 & \partial\Omega_1^{ext} \times [0, T] \\ C_1 u_1 = C_1 u_2 & \Gamma \times [0, T] \end{cases} \qquad \begin{cases} L_2 u_2 = f_2 & \Omega_2 \times [0, T] \\ u_2 \ \text{given} & \text{at } t = 0 \\ B_2 u_2 = g_2 & \partial\Omega_2^{ext} \times [0, T] \\ C_2 u_2 = C_2 u_1 & \Gamma \times [0, T] \end{cases}$$

A convenient framework: Schwarz methods



$$\left\{\begin{array}{lll} L_1 u_1^{k+1} & = f_1 & \Omega_1 \times [0,T] \\ u_1^{k+1} & \text{given} & \text{at } t=0 \\ B_1 u_1^{k+1} & = g_1 & \partial\Omega_1^{\text{ext}} \times [0,T] \\ C_1 u_1^{k+1} & = C_1 u_2^{k} & \Gamma \times [0,T] \end{array}\right. \qquad \left\{\begin{array}{lll} L_2 u_2^{k+1} & = f_2 & \Omega_2 \times [0,T] \\ u_2^{k+1} & \text{given} & \text{at } t=0 \\ B_2 u_2^{k+1} & = g_2 & \partial\Omega_2^{\text{ext}} \times [0,T] \\ C_2 u_2^{k+1} & = C_2 u_1^{k} & \Gamma \times [0,T] \end{array}\right.$$

A convenient framework: Schwarz methods



$$\begin{cases} L_1 u_1^{k+1} = f_1 & \Omega_1 \times [0,T] \\ u_1^{k+1} \text{ given} & \text{at } t=0 \\ B_1 u_1^{k+1} = g_1 & \partial\Omega_1^{ext} \times [0,T] \\ C_1 u_1^{k+1} = C_1 u_2^k & \Gamma \times [0,T] \end{cases} \qquad \begin{cases} L_2 u_2^{k+1} = f_2 & \Omega_2 \times [0,T] \\ u_2^{k+1} \text{ given} & \text{at } t=0 \\ B_2 u_2^{k+1} = g_2 & \partial\Omega_2^{ext} \times [0,T] \\ C_2 u_2^{k+1} = C_2 u_1^k & \Gamma \times [0,T] \end{cases}$$

- Present ocean-atmosphere coupling methods correspond to one single iteration of a Schwarz-like coupling method

Towards iterative ocean-atmosphere coupling

$$\begin{cases} \mathcal{L}_{\mathsf{atm}} \boldsymbol{U}^{\mathsf{a}} = f_{\mathsf{atm}} & \text{in } \Omega_{\mathsf{atm}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\mathsf{atm}} \boldsymbol{U}^{\mathsf{a}} = F_{\mathsf{OA}}(\boldsymbol{U}^{\mathsf{o}}, \boldsymbol{U}^{\mathsf{a}}, \mathcal{R}) & \text{on } \Gamma \times [t_i, t_{i+1}] \end{cases}$$

$$\begin{cases} \mathcal{L}_{\mathsf{oce}} \boldsymbol{U}^{\mathsf{o}} = f_{\mathsf{oce}} & \text{in } \Omega_{\mathsf{oce}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\mathsf{oce}} \boldsymbol{U}^{\mathsf{o}} = \mathcal{F}_{\mathsf{atm}} \boldsymbol{U}^{\mathsf{a}} & \text{on } \Gamma \times [t_i, t_{i+1}] \end{cases}$$

Towards iterative ocean-atmosphere coupling

Iterate until convergence

$$\left\{ \begin{array}{lcll} \mathcal{L}_{\text{atm}} \boldsymbol{U}^{\text{a}}_{k+1} & = & f_{\text{atm}} & \text{in } \Omega_{\text{atm}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\text{atm}} \boldsymbol{U}^{\text{a}}_{k+1} & = & F_{\text{OA}}(\boldsymbol{U}^{\text{o}}_{k}, \boldsymbol{U}^{\text{a}}_{k+1}, \mathcal{R}_{k+1}) & \text{on } \Gamma \times [t_i, t_{i+1}] \end{array} \right.$$

then

$$\left\{ \begin{array}{lcll} \mathcal{L}_{\text{oce}} \boldsymbol{U}^{\text{o}}_{k+1} & = & f_{\text{oce}} & \text{in } \Omega_{\text{oce}} \times [t_i, t_{i+1}] \\ \mathcal{F}_{\text{oce}} \boldsymbol{U}^{\text{o}}_{k+1} & = & \mathcal{F}_{\text{atm}} \boldsymbol{U}^{\text{a}}_{k+1} & \text{on } \Gamma \times [t_i, t_{i+1}] \end{array} \right.$$

Impact on the physics

Major difficulty There is no idealized coupled ocean-atmosphere testcase with a known reference solution.

Impact on the physics

Simulation of the tropical cyclone Erica (2003), by coupling

- ROMS: primitive equation ocean model (Shchepetkin-McWilliams, 2005)
- WRF: non hydrostatic atmospheric model (Skamarock-Klemp, 2007)

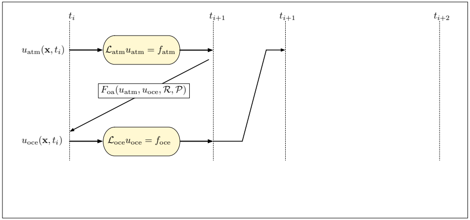
Δx_a = 35km, Δt_a = 180s
Δx_o = 18km, Δt_o = 1800s
15-day simulation

Interface conditions: vertical fluxes for momentum, heat and fresh water

Impact on the physics (cont'd)

15-day simulation (60 6-hour time windows)

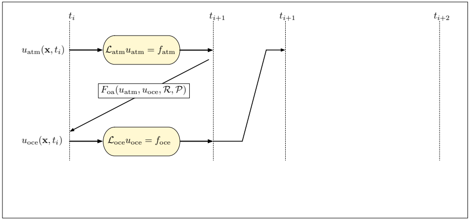
Usual method



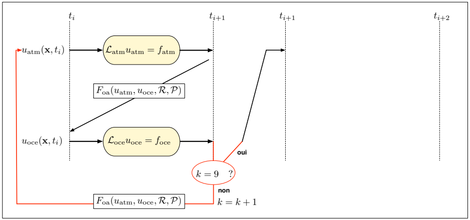
Impact on the physics (cont'd)

15-day simulation (60 6-hour time windows)

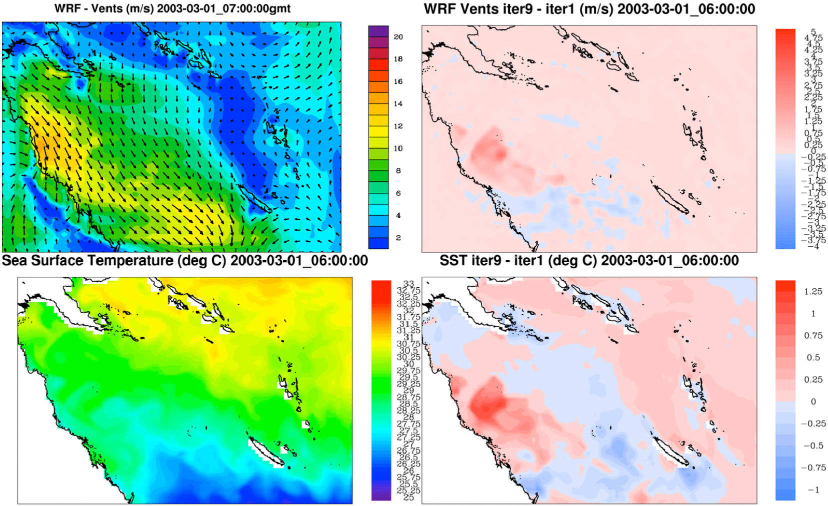
Usual method



Schwarz method



Impact on the physics (cont'd)



10-meter wind (m/s) and sea surface temperature (°C).

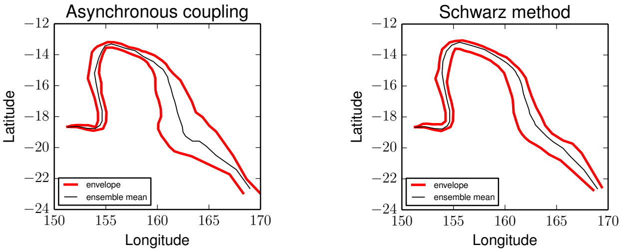
Impact on the physics (cont'd)

To assess the robustness of the coupled solution: ensemble simulations w.r.t. uncertain system parameters (initial conditions, length of the time windows)

Impact on the physics (cont'd)

To assess the robustness of the coupled solution: ensemble simulations w.r.t. uncertain system parameters (initial conditions, length of the time windows)

Trajectory of the cyclone



- The uncertainty on the cyclone trajectory and intensity is decreased by 30%-50%. (see Lemarié et al, 2014, for further details)

Work in progress

Major drawback: iterations !! $\longrightarrow$ decrease the computation cost

- decrease the amount of computations:
  - less iterations: optimize the interface conditions (theory of absorbing boundary conditions)
  - less computations / iteration: use reduced models
- better exploit the computers $\longrightarrow$ optimized algorithms and implementations