

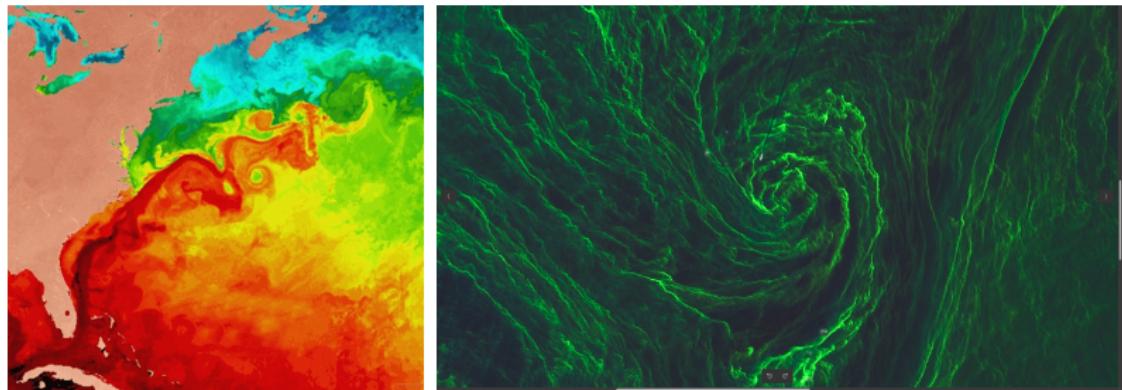
# Differentiable ocean models from large to small scales

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**Louis Thiry**  
INRIA Paris, ANGE team



# Ocean dynamics: a large range of scales



$10^6$  m to  $10^2$  m

# Hierarchy of dynamical equations

**Quasi-geostr.**

$\mathbf{q}$

slow  
dynamic

**Shallow-water**

$\mathbf{u}, \mathbf{v}, \eta$

constant density  
horizontally

**Primitive Eq.**

$\mathbf{u}, \mathbf{v}, \eta, T, s$

hydrostatic  
equilibrium

**Boussinesq NH**

$\mathbf{u}, \mathbf{v}, \mathbf{w}, \eta, T, s$

$$\rho(T, s) \sim \rho_0$$

Physical phenomena variety

Simplifications

## I. Dynamical core

- *high-order non-linear advection schemes*
- *prognostic variables continuity*
- *automatic differentiation*



## II. Data assimilation

- *4D Var*
- *deep denoiser priors*

## III. Machine learning

- *emulators*
- *physical params*

# Starting from simple models...

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# Quasi-geostrophic equations

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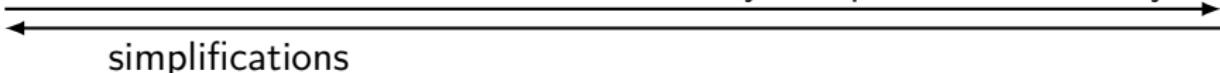
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Physical phenomena variety



## Quasi-geostrophic scaling of Shallow-water eqs

- $\mathbf{q}$ : potential vorticity
- $\mathbf{u}, \mathbf{v}$ : horizontal velocity
- $\mathbf{u}, \mathbf{v} = \nabla^\perp (\Delta - \lambda I d)^{-1} \mathbf{q}$  (elliptic eq.)

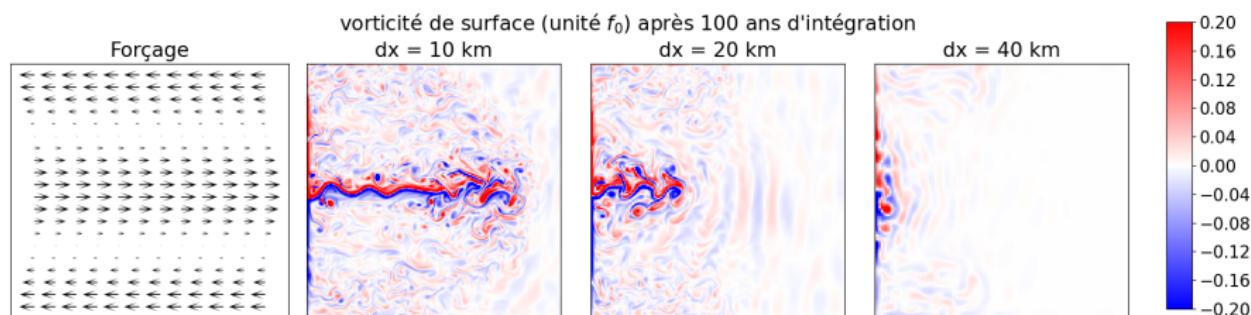
$$\partial_t \mathbf{q} + \nabla \cdot \left( \mathbf{q} \begin{bmatrix} \mathbf{u} \\ \mathbf{v} \end{bmatrix} \right) = Q_{\text{forcing}}$$

# Quasi-geostrophic equations

Usual discretization (Uchida et al. 2022)

- Advection: second order linear Arakawa (1981)
- Additional bilaplacian dissipation (hand-tuned coefficient)
- [github.com/louity/qgm\\_pytorch](https://github.com/louity/qgm_pytorch) (400 lignes)

Idealized Gulf-stream configuration,  $R_d = 40$  km.

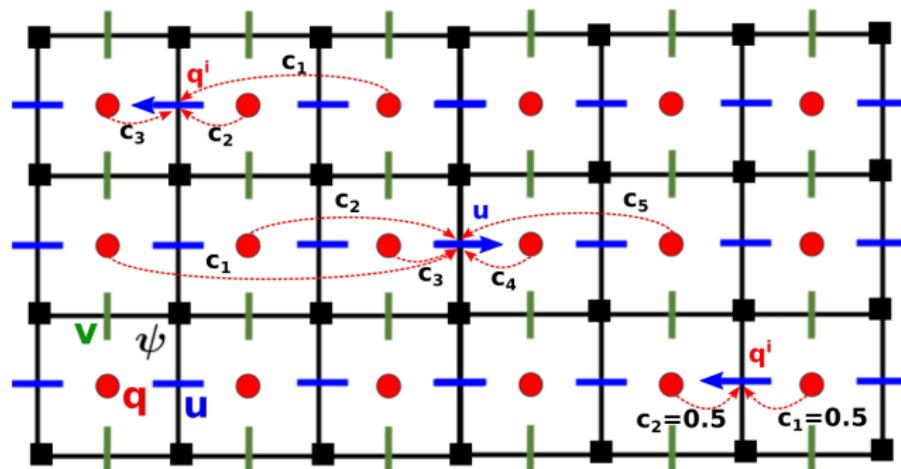


$dx \longrightarrow R_d$ : Gulf-stream severely impacted

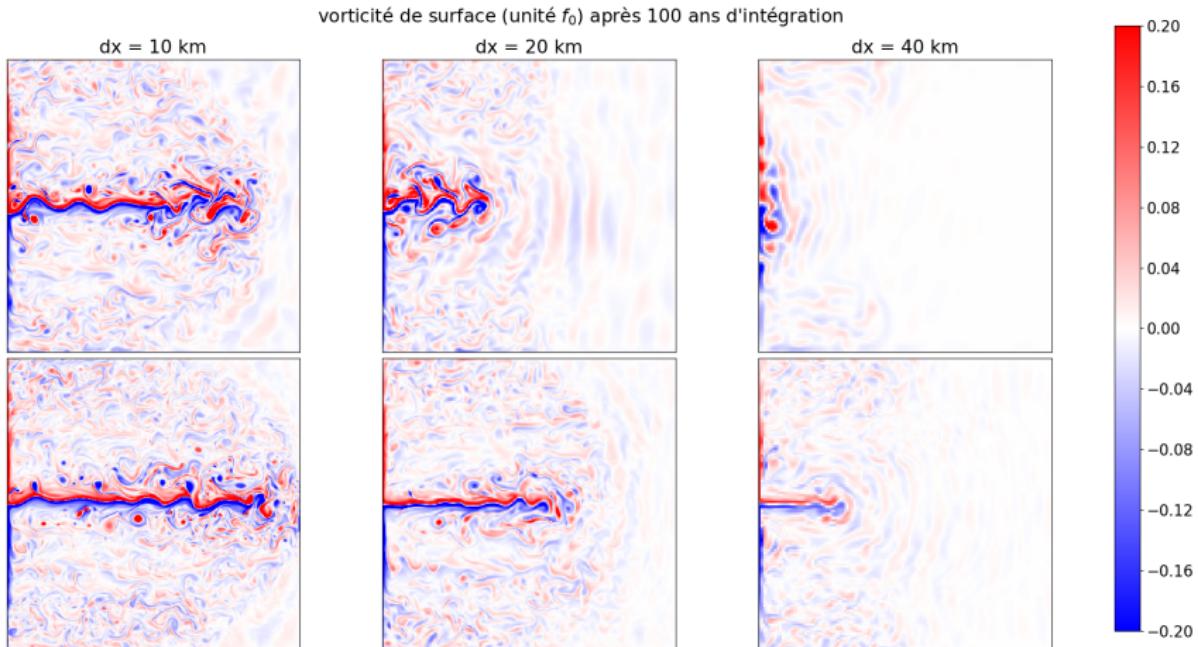
# Quasi-geostrophic equations

Working on the advection scheme (Thiry et al., 2023)

- Finite-volume, staggered grid
- Second-order discretization for  $\nabla \cdot$ ,  $\nabla \wedge$ ,  $\nabla^\perp$
- Flux: non-linear order 3/5 WENO (Borges et al., 2008)
- Implicit dissipation  $\implies$  **no explicit dissipation, no tuning**



# Quasi-geostrophic equations

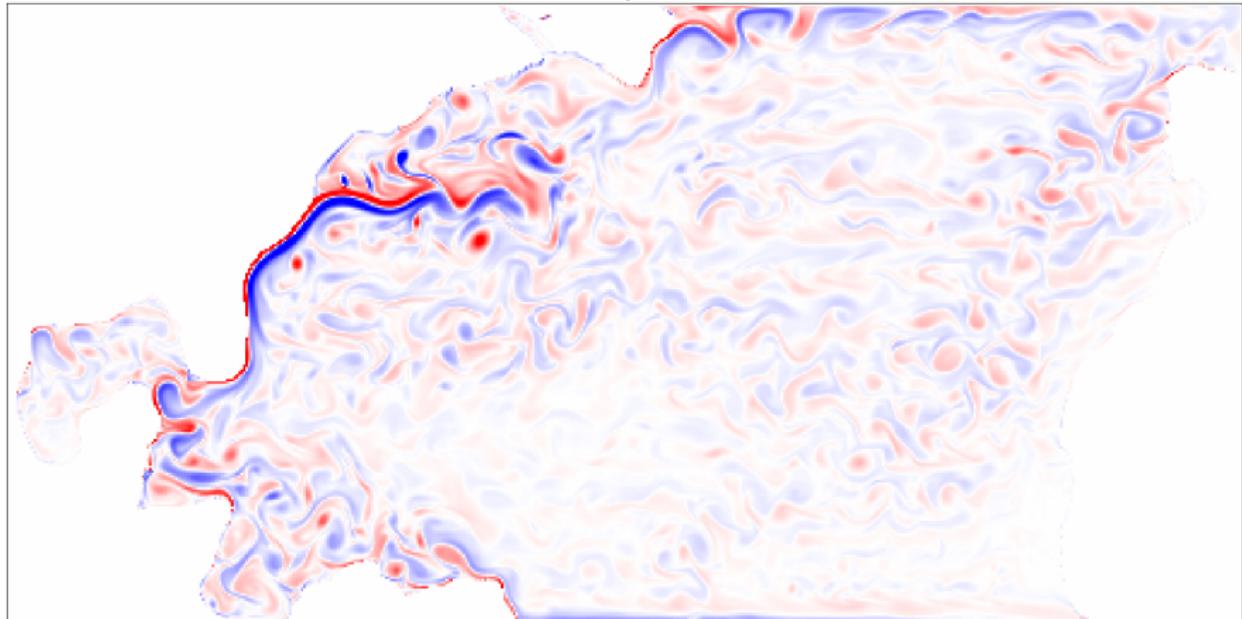


Usual (top) vs. our (bottom) QG discretization on idealized Gulf-stream config  
(ours costs  $\sim 2\times$  usual)

# Quasi-geostrophic equations

Non-rectangular domain with capacitance matrix method

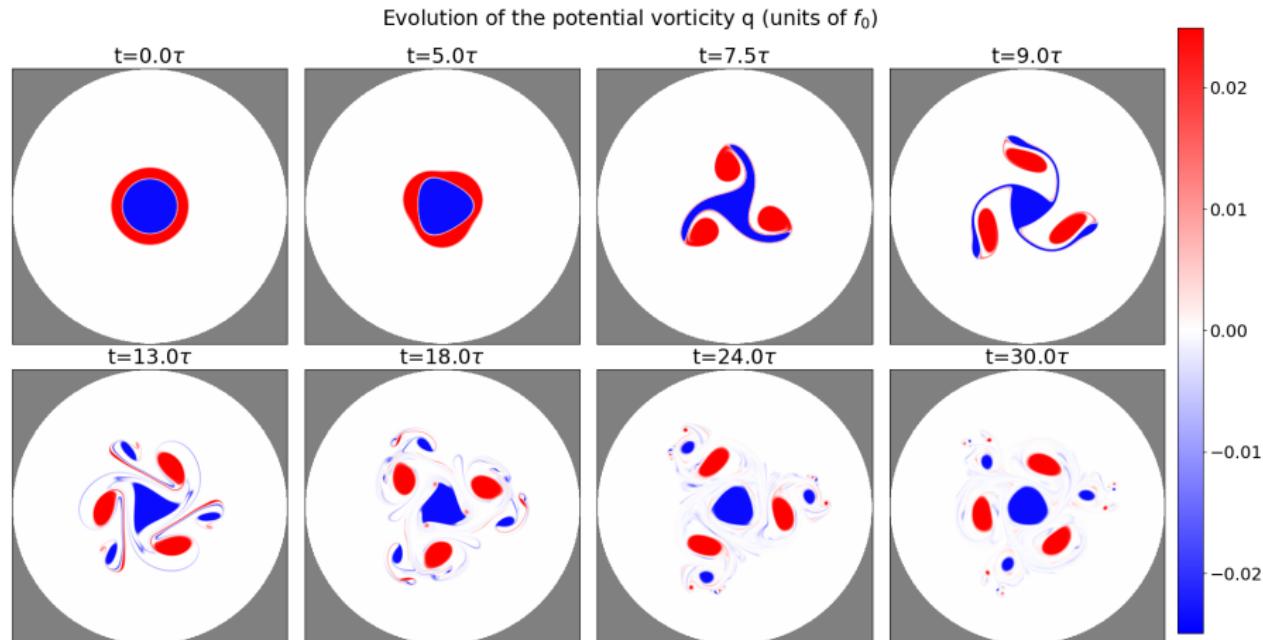
2 yrs, 245 days



Realistic Gulf-stream simulation (20min runtime)

# Quasi-geostrophic equations

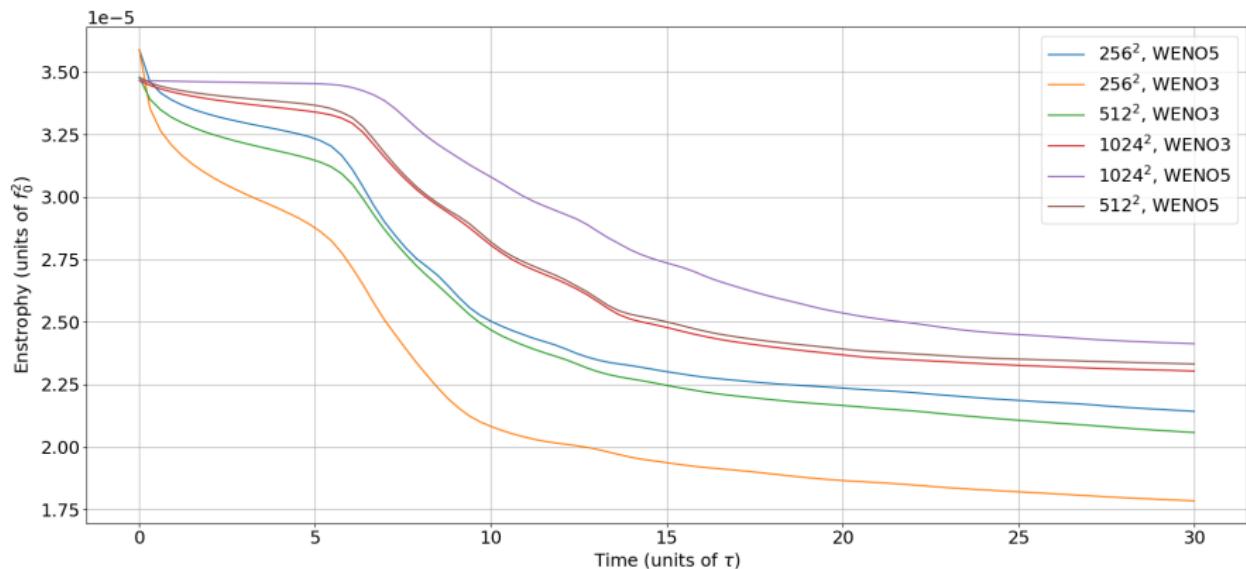
Non-rectangular domain with capacitance matrix method



Rankine vortex shear instability resolved in tripole

# Quasi-geostrophic equations

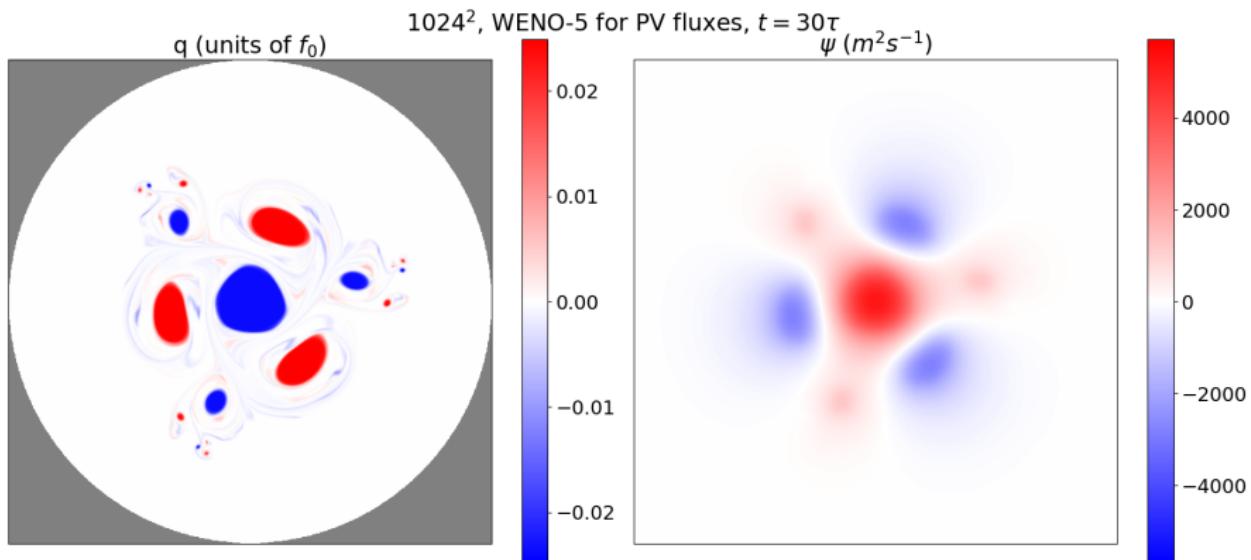
What is the point of WENO-5 vs WENO-3 ?



Evolution of  $\|\mathbf{q}\|_2$  at different resolution using WENO-3/5

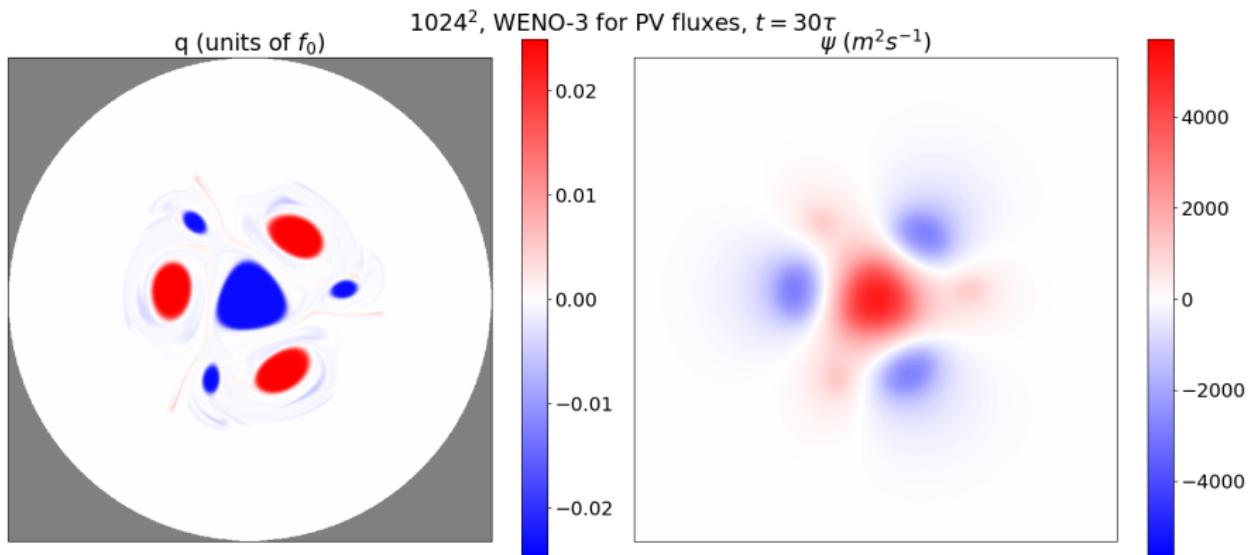
# Quasi-geostrophic equations

WENO-5 vs WENO-3



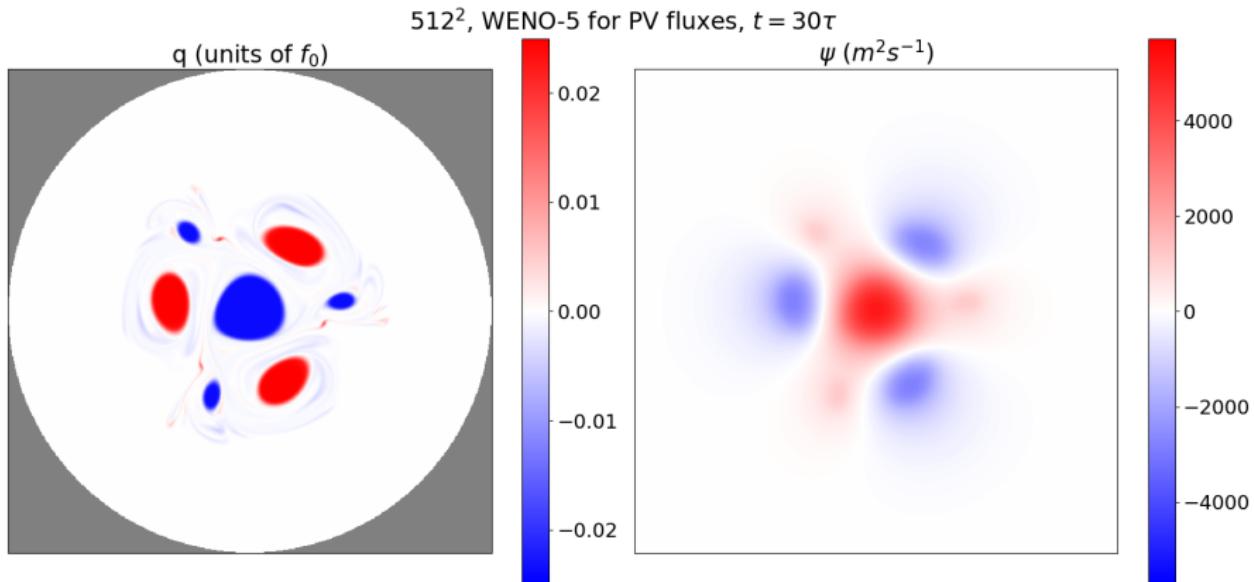
# Quasi-geostrophic equations

WENO-5 vs WENO-3



# Quasi-geostrophic equations

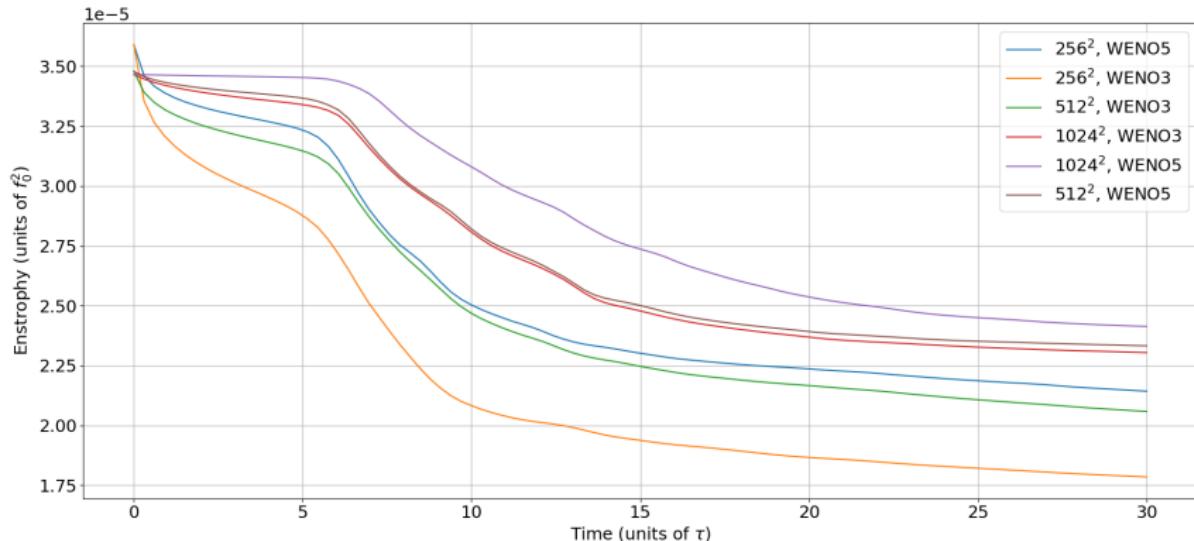
WENO-5 vs WENO-3



Final state, 512<sup>2</sup> WENO-5, 1min runtime

# Quasi-geostrophic equations

$$\partial_t \mathbf{q} + \nabla \cdot \left( \mathbf{q} \begin{bmatrix} \mathbf{u} \\ \mathbf{v} \end{bmatrix} \right) = 0$$



Why does the enstrophy decrease ? → **numerical dissipation**

# Lessons from our QG new implementation

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slow  
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constant density  
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$\rho(T, s) \sim \rho_0$

Physical phenomena variety

← simplifications →

- Benefits of high-order non-linear advection scheme
  - ▶ Large-scale structures (Gulf-stream)
  - ▶ Small-scale structures (Eddies and filaments)
  - ▶ No parameter tuning (Bilaplacian eddy viscosity)
- Extension to non-rectangular geometries → realistic Gulf-stream
- Implicit dissipation diagnostic (G. Roullet)

# Moving to the right...

QG variable:  $\mathbf{q} \neq$  Shallow-water variables:  $\mathbf{u}, \mathbf{v}, \eta$  (free-surface)

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## A new formulation of Shallow-water equations

$$\partial_t^{\text{qg}}(\mathbf{u}, \mathbf{v}, \eta) = P(\partial_t^{\text{sw}}(\mathbf{u}, \mathbf{v}, \eta))$$

$$P = G \circ (Q \circ G)^{-1} \circ Q$$

(projecteur QG)

Continuous version in Frederic Charve Thesis.

# Benefits for implementation

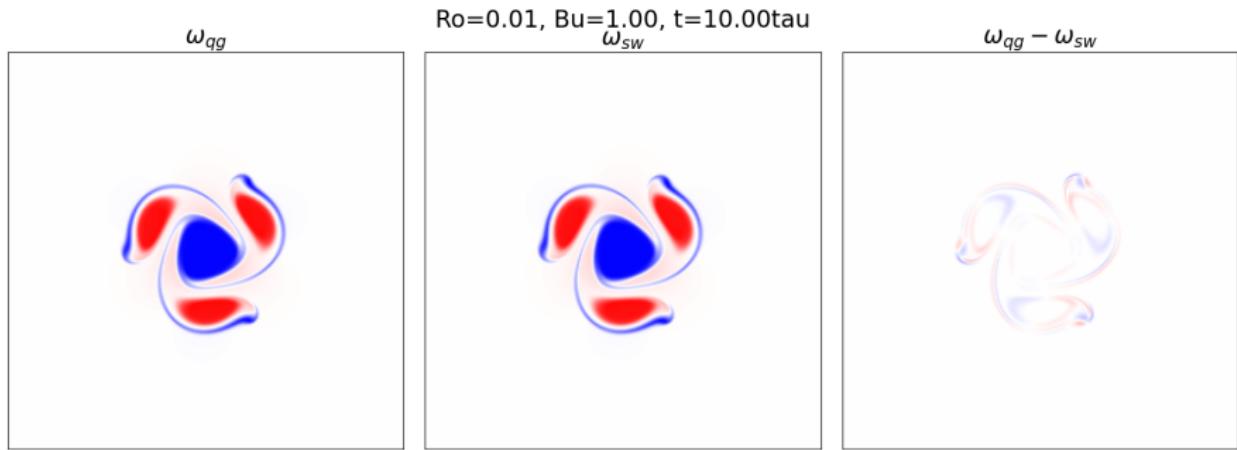
Quasi-Geostrophic scaling  $\iff$  class inheritance

```
class SW:
    """Concise implementation of multilayer shallow-water model."""
    def __init__(self, param):
        ...
    def compute_time_derivatives(self):
        self.compute_diagnostic_variables()
        dt_h = self.advection_h()
        dt_u, dt_v = self.advection_momentum()
        return dt_u, dt_v, dt_h

class QG(SW):
    """QG as projected SW."""
    def __init__(self, param):
        super().__init__(param)
        ...
    def compute_time_derivatives(self):
        dt_u_sw, dt_v_sw, dt_h_sw = super().compute_time_derivatives()
        self.dt_u_sw, self.dt_v_sw = dt_u_sw, dt_v_sw
        dt_u_qg, dt_v_qg, dt_h_qg = self.compute_qg_projection(dt_u_sw, dt_v_sw, dt_h_sw)
        return dt_u_qg, dt_v_qg, dt_h_qg
```

## Comparing QG and SW on a small system

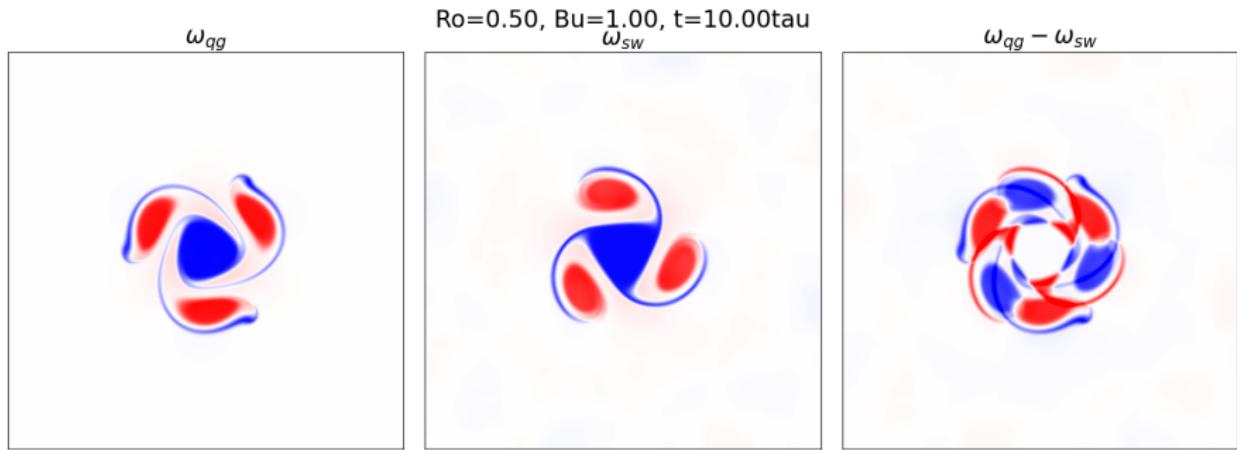
QG equations valid for  $Bu \leq 1$  and  $Ro \ll 1$ .



Vortex shear instability  $Ro = 0.01$  and  $Bu = 1$

# Vortex shear instability $Ro = 0.5$ and $Bu = 1$

QG equations valid for  $Bu \leq 1$  and  $Ro \ll 1$ .



Vortex shear instability  $Ro = 0.5$  and  $Bu = 1$

# Lessons from our SW new implementation

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Physical phenomena variety

simplifications

- Restoring the continuity in variables
- QG implementation via class inheritance, simply with a projection
- Compare QG and SW physics with same numerics

# Data assimilation

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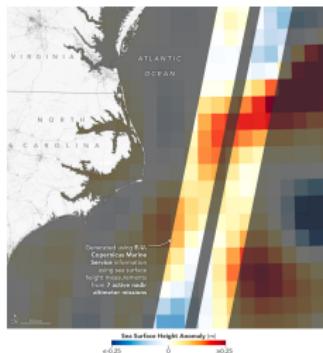
## III. Machine learning

- *emulators*
- *physical params*

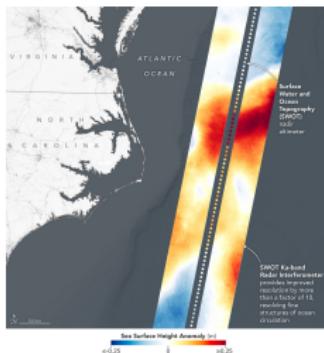
# Data assimilation

## Ocean observations

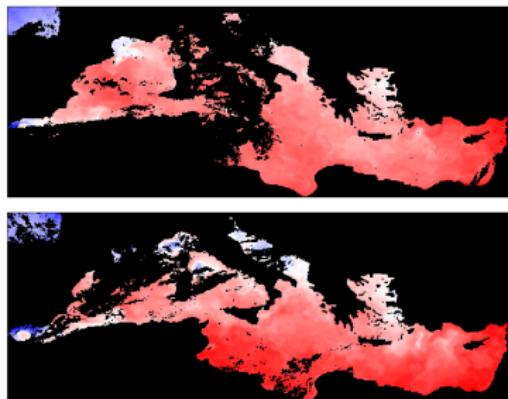
- Sea surface height (SSH)
- Sea surface temperature (SST)



(a) SSH NADIR



(b) SSH SWOT



(c) SST les 1 et 30 sept. 22

Source: NASA earth observatory, Copernicus Marine.

# Data assimilation with 4D Var

Quasi-geostr.  
 $\mathbf{u}, \mathbf{v}, \eta$  ( $\mathbf{q}$ )

Shallow-water  
 $\mathbf{u}, \mathbf{v}, \eta$

Primitive Eq.  
 $\mathbf{u}, \mathbf{v}, \eta, T, s$

Boussinesq NH  
 $\mathbf{u}, \mathbf{v}, \mathbf{w}, \eta, T, s$

←  
lower dimension

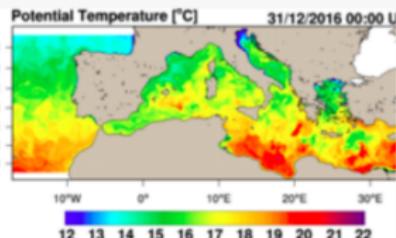
$$\mathbf{X}^* = \underset{\mathbf{X}_{t_0}}{\operatorname{argmin}} \|\mathcal{H}(\mathbf{X}) - \mathbf{y}\|^2 + \mathcal{L}_{\text{prior}}(\mathbf{X})$$

- $\mathbf{X}_{t_0} \rightarrow \mathbf{X}$  with the model
- $\operatorname{argmin}$  ? automatic differentiation (PyTorch)

Simple models (QG, SW)  $\implies$  low-dimension , strong regularization

# Current products on copernicus marine

## Products 3



Mediterranean Sea Physics Analysis and Forecast

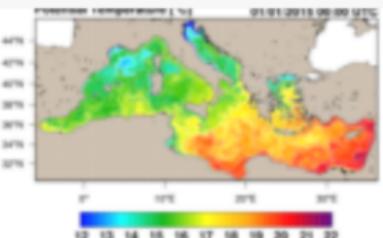
MEDSEA\_ANALYSISFORECAST\_PHY\_006\_013

Models

Med Sea,  $0.042^\circ \times 0.042^\circ \times 141$  levels

Since 29 Nov 2020, sub-hourly, **hourly**, daily,...

Mixed layer thickness, salinity, sea surface height, **temperature**, velocity



Mediterranean Sea Physics Reanalysis

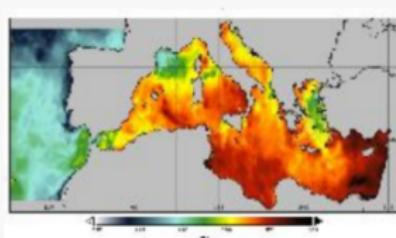
MEDSEA\_MULTIYEAR\_PHY\_006\_004

Models

Med Sea,  $0.042^\circ \times 0.042^\circ \times 141$  levels

Since 1 Jan 1987, **hourly**, daily, monthly, yearly...

Mixed layer thickness, salinity, sea surface height, **temperature**, velocity



Mediterranean Sea - High Resolution Diurnal Subskin Sea...

SST\_MED\_PHY\_SUBSKIN\_L4\_NRT\_010\_036

Satellite (**L4**)

Med Sea,  $0.0625^\circ \times 0.0625^\circ$

Since 1 Jan 2019, **hourly**

Temperature

- Observation: 6km, surface only
- Reanalysis: primitive equations,  $4\text{km} \times 141$  vertical levels (!!!)

# Machine learning

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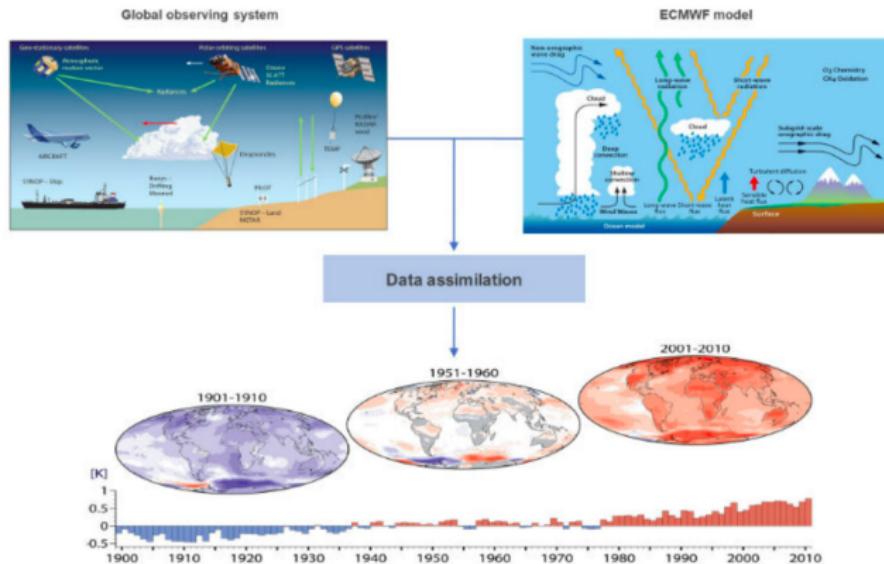
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# Available Data for Machine Learning

**Ocean:** only surface observations, Copernicus poor quality reanalysis

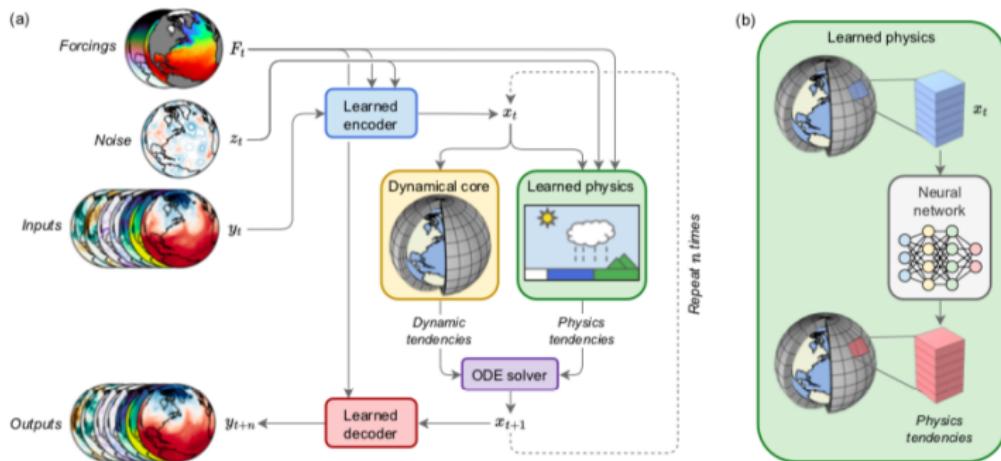
**Atmosphere:** lots of observations, ECMWF ERA5 high-quality reanalysis



- january 1940 to present
- whole atmosphere, res. 25km, 137 vertical levels
- time resolution: 1h

# NeuralGCM: hybrid physics + ML model

Differentiable physical dynamical core + machine learned physics on the vertical



<https://github.com/google-research/dinosaur> , 8609 of Python-JAX code.

# Questions ?

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## References I

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