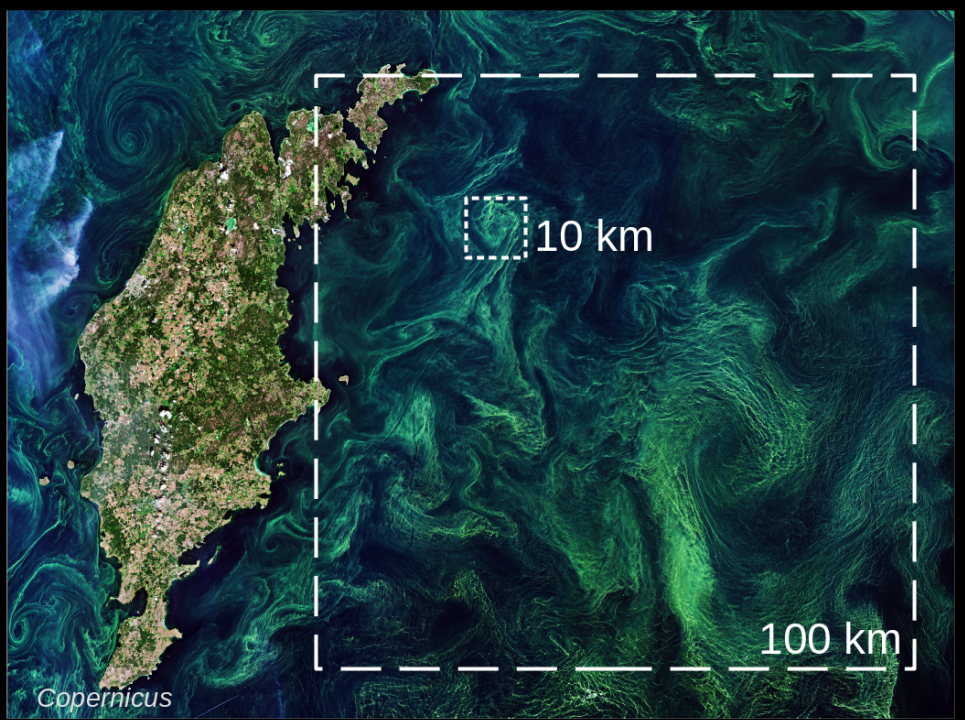


Fluids Under Location Uncertainty for surface layers

Groupe de travail AIRSEA – 11/02/2021

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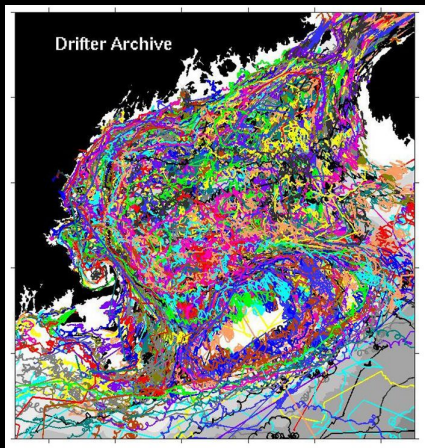
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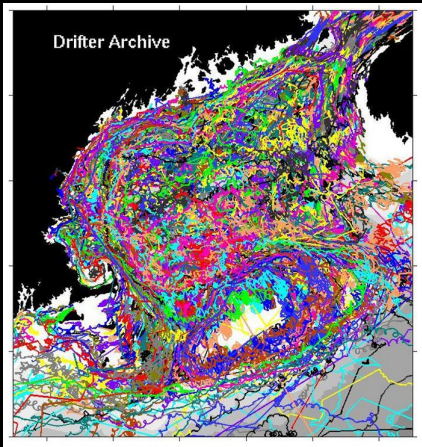
→ generate uncertainty

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How to introduce physically consistent uncertainty and parameterization ?



[Oceanic drifters, NOAA]



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trajectory = coherent + random

Fluid Under Location Uncertainty (ULU)

Assumptions:

[Resseguier, Mémin, Chapron 2017]

- slow/fast decomposition
- fast component modeled by Brownian motion

Fluid particle trajectory

$$\mathbf{X}_t = \mathbf{X}_0 + \underbrace{\int_0^t \mathbf{u}(\mathbf{X}_s, s) ds}_{\text{slow}} + \underbrace{\int_0^t \boldsymbol{\sigma}(\mathbf{X}_s, s) d\mathbf{B}_s}_{\text{fast (Brownian)}} \quad \text{Itô integral}$$

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$\boldsymbol{\sigma}$ spatial diffusion operator :

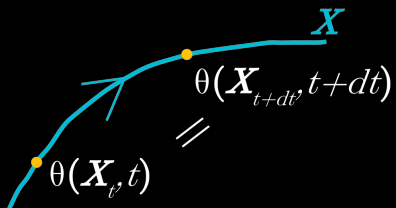
$$\boldsymbol{\sigma}(\mathbf{x}, t) d\mathbf{B}_t := \int_{\mathbb{R}^3} \check{\boldsymbol{\sigma}}(\mathbf{x}, \mathbf{y}, t) d\mathbf{B}_t(\mathbf{y}) d\mathbf{y}$$

$$\mathbb{E} [(\boldsymbol{\sigma}(\mathbf{x}, t)d\mathbf{B}_t)_i(\boldsymbol{\sigma}(\mathbf{x}, s)d\mathbf{B}_s)_j] = (\boldsymbol{\sigma}\boldsymbol{\sigma}^t)_{ij}(\mathbf{x}, t)\delta(t - s)dt$$

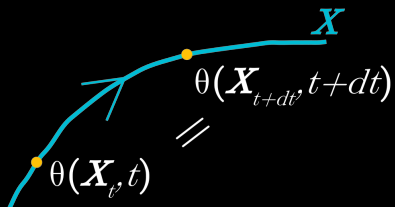
Spatial correlations: variance tensor $\mathbf{a}(\mathbf{x}, t) := \boldsymbol{\sigma}\boldsymbol{\sigma}^t(\mathbf{x}, t)$, generalized eddy-diffusivity

No time correlation

Transport of scalar field ULU



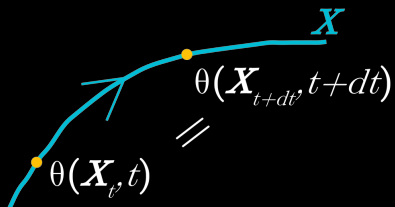
Transport of scalar field ULU



Deterministic transport: $d\mathbf{X}_t = \mathbf{u} dt$

$$D_t \theta := \partial_t \theta + \mathbf{u} \cdot \nabla \theta = 0 \text{ at } \mathbf{x}, t$$

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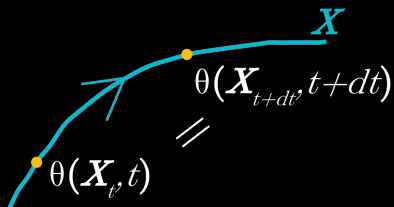
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Rigorous derivation of known parameterizations!

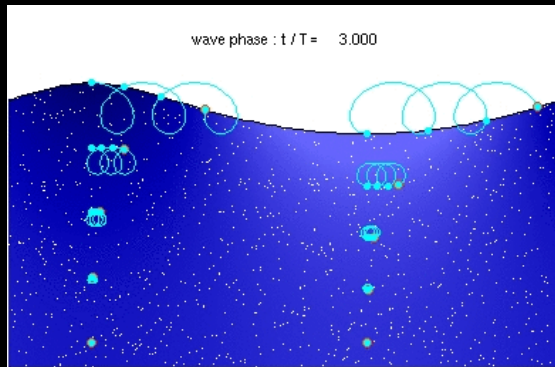
$$d_t\theta + \underbrace{\left(\mathbf{u} - \frac{1}{2}\nabla \cdot \mathbf{a}\right)}_{\mathbf{u}^*} \cdot \nabla\theta dt + (\boldsymbol{\sigma} d\mathbf{B}_t) \cdot \nabla\theta - \frac{1}{2}\nabla \cdot (\mathbf{a}\nabla\theta) dt = 0$$

Modified advection due to statistical inhomogeneity: Stokes drift (surface waves), eddy-induced velocity (ocean), turbophoresis

Physical interpretation

$$d_t\theta + \underbrace{\left(\mathbf{u} - \frac{1}{2}\nabla \cdot \mathbf{a}\right)}_{\mathbf{u}^*} \cdot \nabla\theta dt + (\boldsymbol{\sigma} d\mathbf{B}_t) \cdot \nabla\theta - \frac{1}{2}\nabla \cdot (\mathbf{a}\nabla\theta)dt = 0$$

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Subgrid diffusion:

Phenomenology of turbulent diffusion



Leonardo da Vinci, *Studies of Turbulent Water*,
Royal Collection Trust/©Her Majesty Queen Elizabeth II 2019

Phenomenology of turbulent diffusion

Large scale energy → Small scale energy
resolved unresolved



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Large scale energy → Small scale energy
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Modeled by diffusion of resolved scales!



ULU diffusion is natural

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Usual approach: **assume** turbulent diffusion $\nabla \cdot (\nu_{\text{turb}} \nabla \bar{\theta})$

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ULU: diffusion appears naturally

"turbulent diffusivity" tensor $\mathbf{a} = \boldsymbol{\sigma}\boldsymbol{\sigma}^\top$ directly related to statistics of the noise

Noise balances diffusion

Physical origin of the noise

⇒ Conservation of statistical energy (for $\nabla \cdot \mathbf{u}^* = 0$)

$$d_t \int_V \theta^2 = 0$$

Exact balance between diffusion and noise forcing!

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⇒ Statistical balance

$$\frac{d}{dt} \int_{\mathbf{V}} (\mathbb{E}[\theta])^2 = -\frac{d}{dt} \int_{\mathbf{V}} \text{Var}[\theta]$$

Mean energy decrease → variance increase

Newton second law:

$$\frac{d}{dt} \text{momentum} = \text{forces}$$

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Newton second law for deterministic fluids = Navier-Stokes

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Newton second law for fluids Under Location Uncertainty

$$\mathbb{D}_t \mathbf{u} = -\frac{1}{\rho} \nabla (p dt + dp_t) + \mathbf{F}(\mathbf{u} + \boldsymbol{\sigma} d\mathbf{B}_t)$$

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Time regularity assumption on $\mathbf{u} \implies$ LES-like deterministic model:

$$\partial_t \mathbf{u} + \left(\mathbf{u} - \frac{1}{2} \nabla \cdot \mathbf{a} \right) \cdot \nabla \mathbf{u} = -\frac{1}{\rho} \nabla p + \nu \nabla^2 \mathbf{u} + \frac{1}{2} \nabla \cdot (\mathbf{a} \nabla \mathbf{u})$$

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Summary on ULU

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- data assimilation
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- reduced-order models
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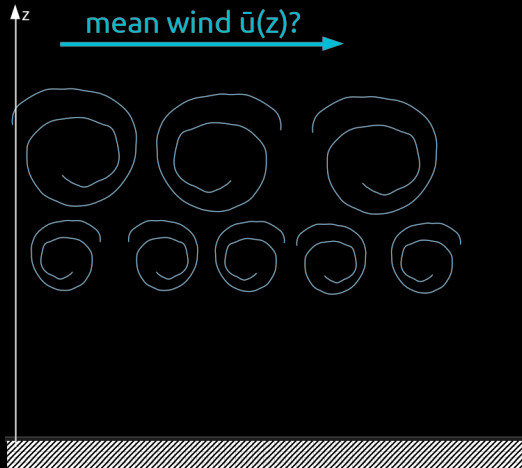
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What about Air-Sea interactions?

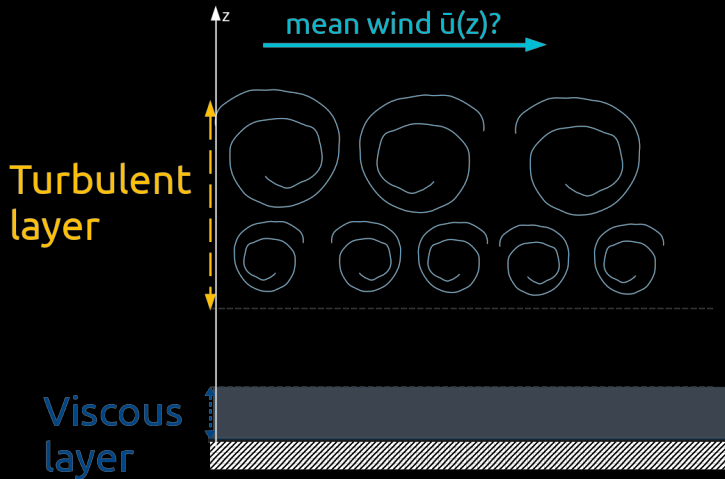
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Constant density fluid $\rho = \text{cte}$. Mean horizontal wind profile $\bar{u}(z)$?



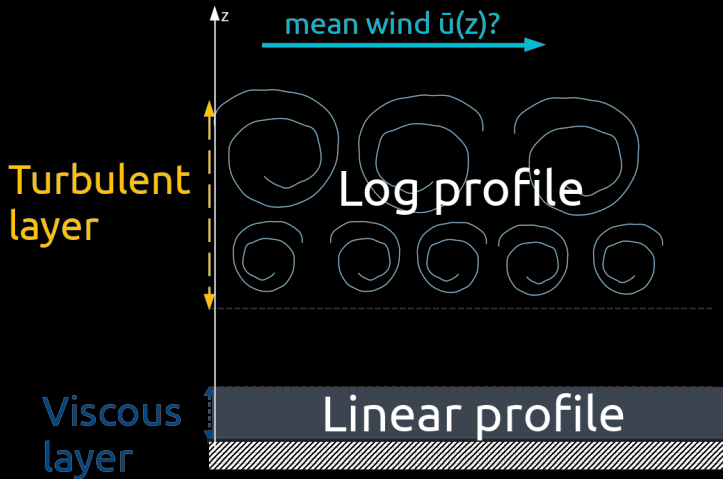
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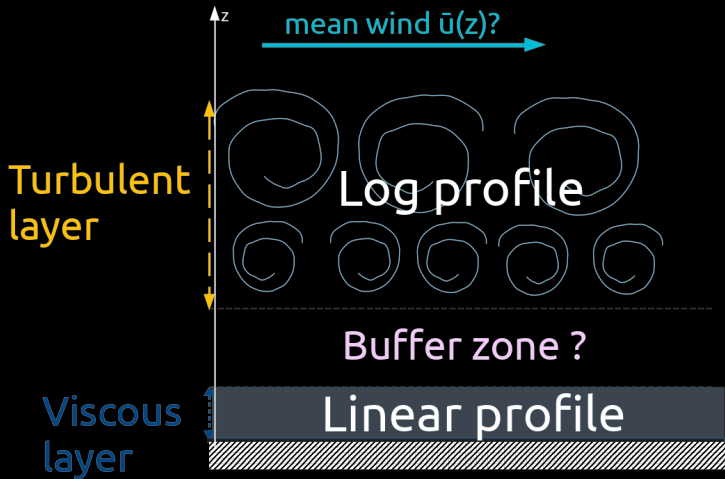
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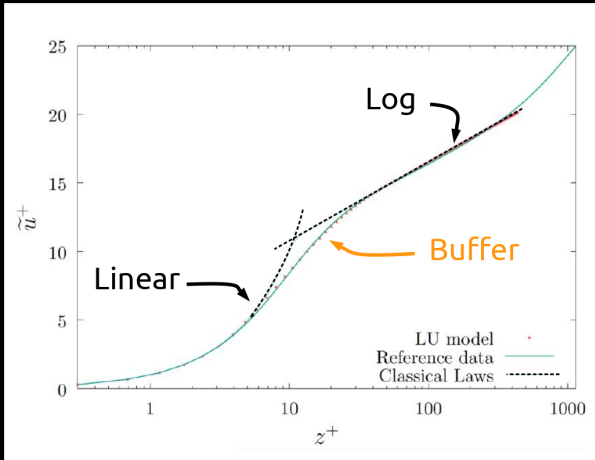
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ULU adresses buffer zone problem

[Pinier et al. 2019]

Assuming log profile in turbulent layer
ULU gives a model for buffer zone!



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data \rightarrow different turbulent diffusion

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ULU: same turbulent diffusion

$$\partial_z(a_{zz} \partial_z u), \partial_z(a_{zz} \partial_z \theta)$$

contradiction with data!

Why?

Why turbulent diffusion of momentum and heat are different?

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→ ULU: relax scale-separation hypothesis, consider time-correlated noise?

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