Learning submesoscale flow and wave-balance separation from surface vorticity, strain and divergence statistics

SWOT Science Team Meeting
Chapel Hill, June 2022

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... and Mario Herrero-González**
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working on data assimilation and ML to improve interpolation

*credit to Qiyu & Dhruv & Spencer!

Goal: Estimate transport-active flow from SWOT SSH

$$u_{\text{surface}} = \boxed{u_g} + \boxed{u_a} + \boxed{u_w}$$

$$h_{\text{surface}} = \boxed{h_g} + \boxed{h_a} + \boxed{h_w}$$

geostrophic (easy if only!)

balanced ageostrophic (e.g. fronts)

wave (IGW + tide)

want these transport-active parts

no transport, multiple sources, aliased onto balanced flow 😩

AND no general method to separate parts 😩

no simple diagnostic inversion from SSH 😩

Outline / Approach

- [Balwada et al 2021] Vorticity, strain, divergence (surface, snapshot) JPDF

  $\Longrightarrow$ feature identification, lateral scale: **quantifies vertical flux in fronts**

- [New] JPDF also identifies wave signature

  $\Longrightarrow$ suggests way to estimate submesoscale flux from (wavy) SWOT SSH

- [Jones et al 2022] Used Lagrangian filtering to filter waves from LLC4320 surface data near Agulhas (winter)

  $\Longrightarrow$ "truth" signal on which to train CNN to filter waves

- [New] Training CNN to estimate vort, strain, div from ≈ wave-free data

  $\Longrightarrow$ get transport-active flow directly from SSH

- [Hope] Learn dynamical balance governing $\mathbf{u}_a$ and $\mathbf{h}_a$, add to cost function

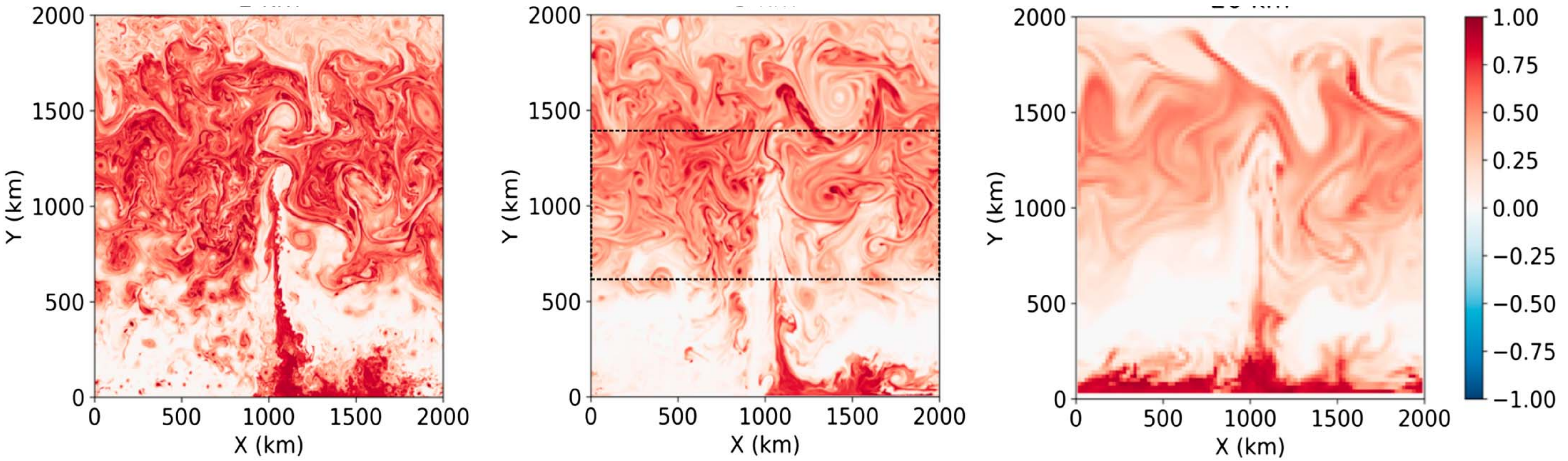
  $\Longrightarrow$ **robust, transferable algorithm to extract transport from SWOT SSH**

Experimental Setup

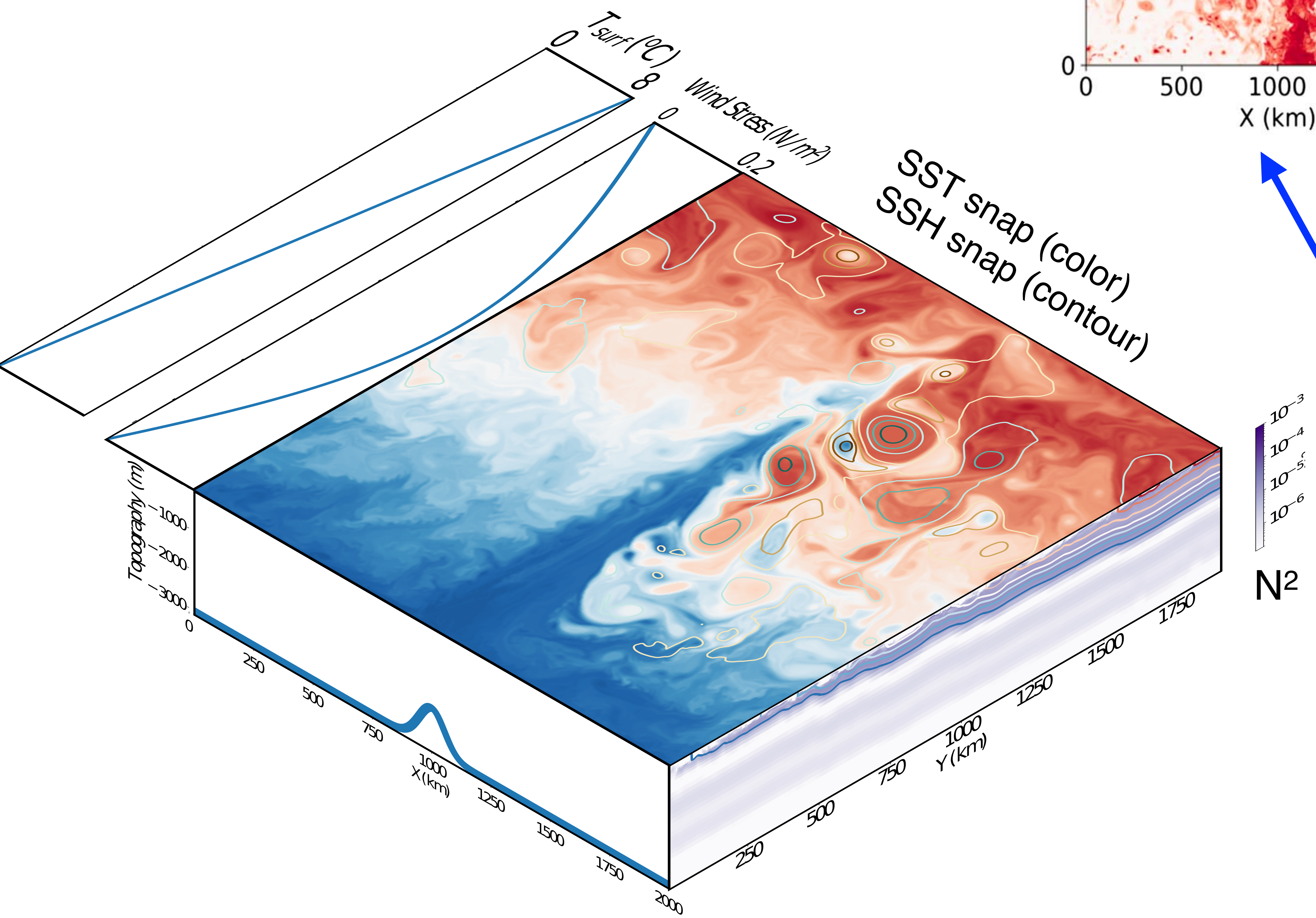
After spin up, **passive tracer forced at top boundary**

Channel, 2000^2 x 3 km, 1 km ridge
Constant wind, buoyancy forcing
LLC closures, 76 levels

Res: **20km, 5km and 1km**



Tracer @ z = MLD+100m, t = 1 year



Tracer accumulation below ML **is much higher in 1km run** (after 1 year)

Why? Strengthening of **large fronts**? Or do **small-scale, fast fronts** contribute significantly?

Submesoscale Vertical Velocities Enhance Tracer Subduction in an Idealized Antarctic Circumpolar Current

Geophysical Research Letters 2018

Dhruv Balwada[1], K. Shafer Smith[1], and Ryan Abernathey[2]

A statistical approach

Vertical Fluxes Conditioned on Vorticity and Strain Reveal Submesoscale Ventilation
DHRUV BALWADA,[a] QIYU XIAO,[b] SHAFER SMITH,[b] RYAN ABERNATHEY,[c] AND ALISON R. GRAY[a]
JOURNAL OF PHYSICAL OCEANOGRAPHY SEPTEMBER 2021

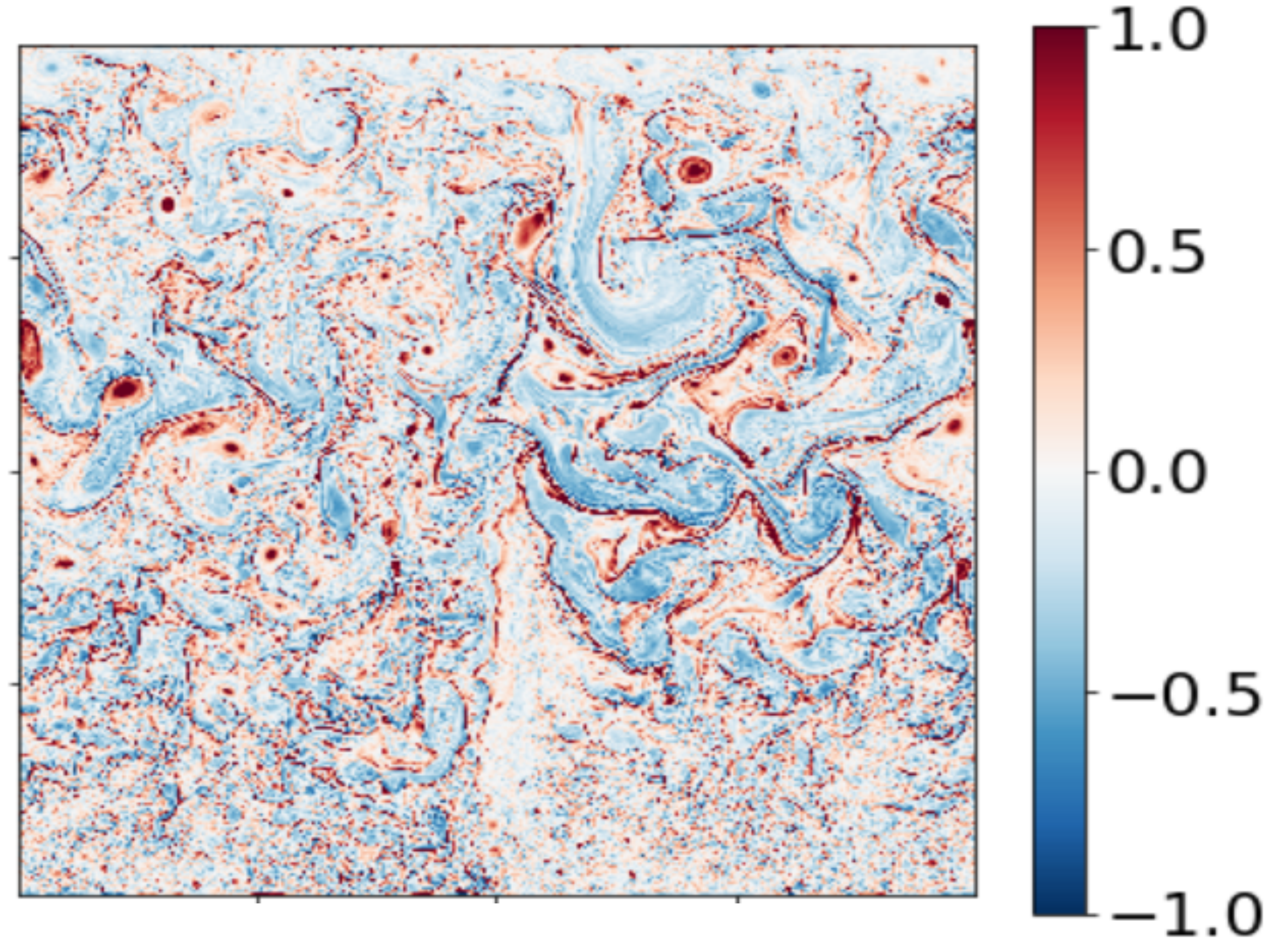
[see also Shcherbina et al (2013 GRL)]

Can the statistics of the flow cleave the flux by process and scale? **

Consider **vorticity, strain, divergence**

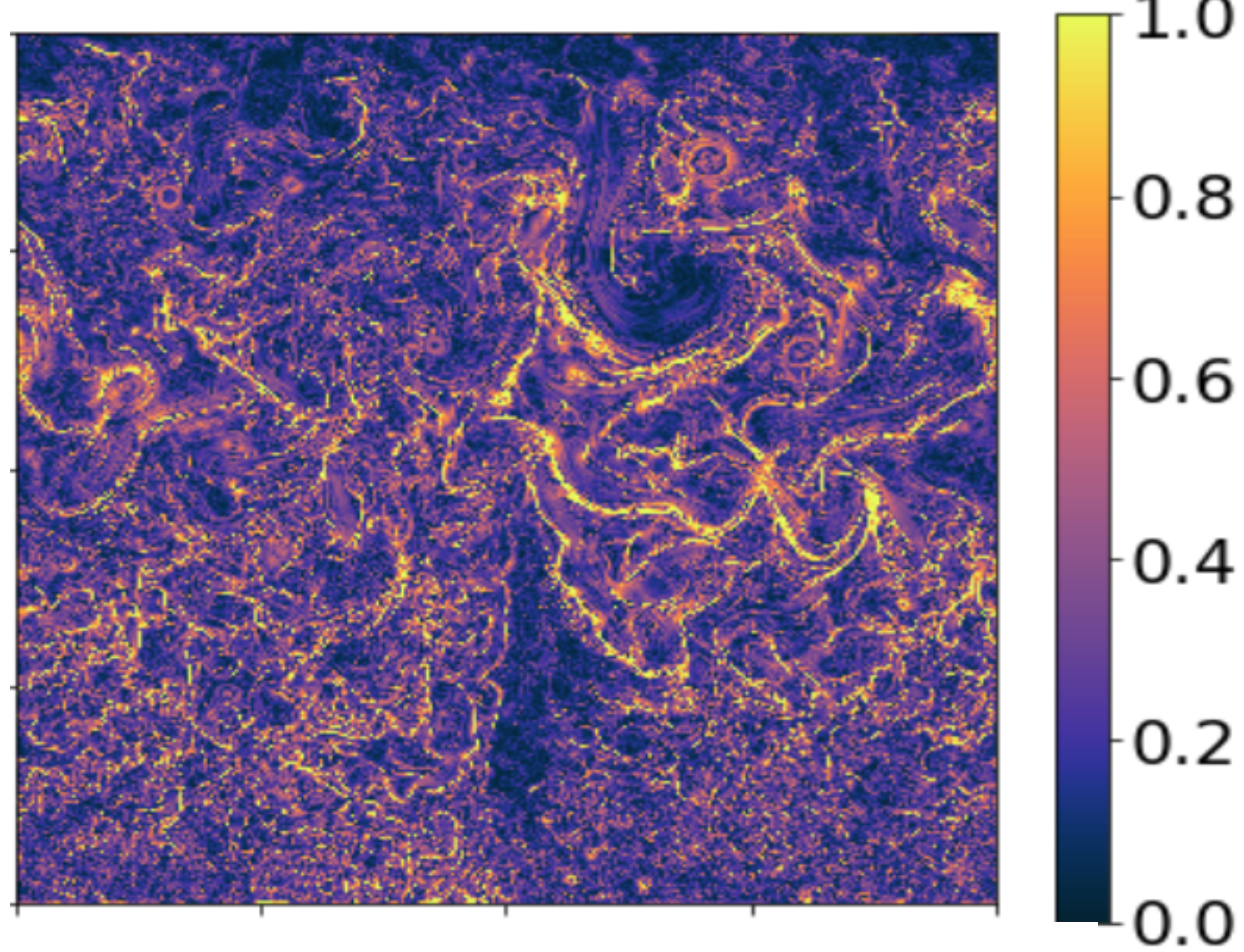
1 km
z = 0

Vorticity ζ/f_0



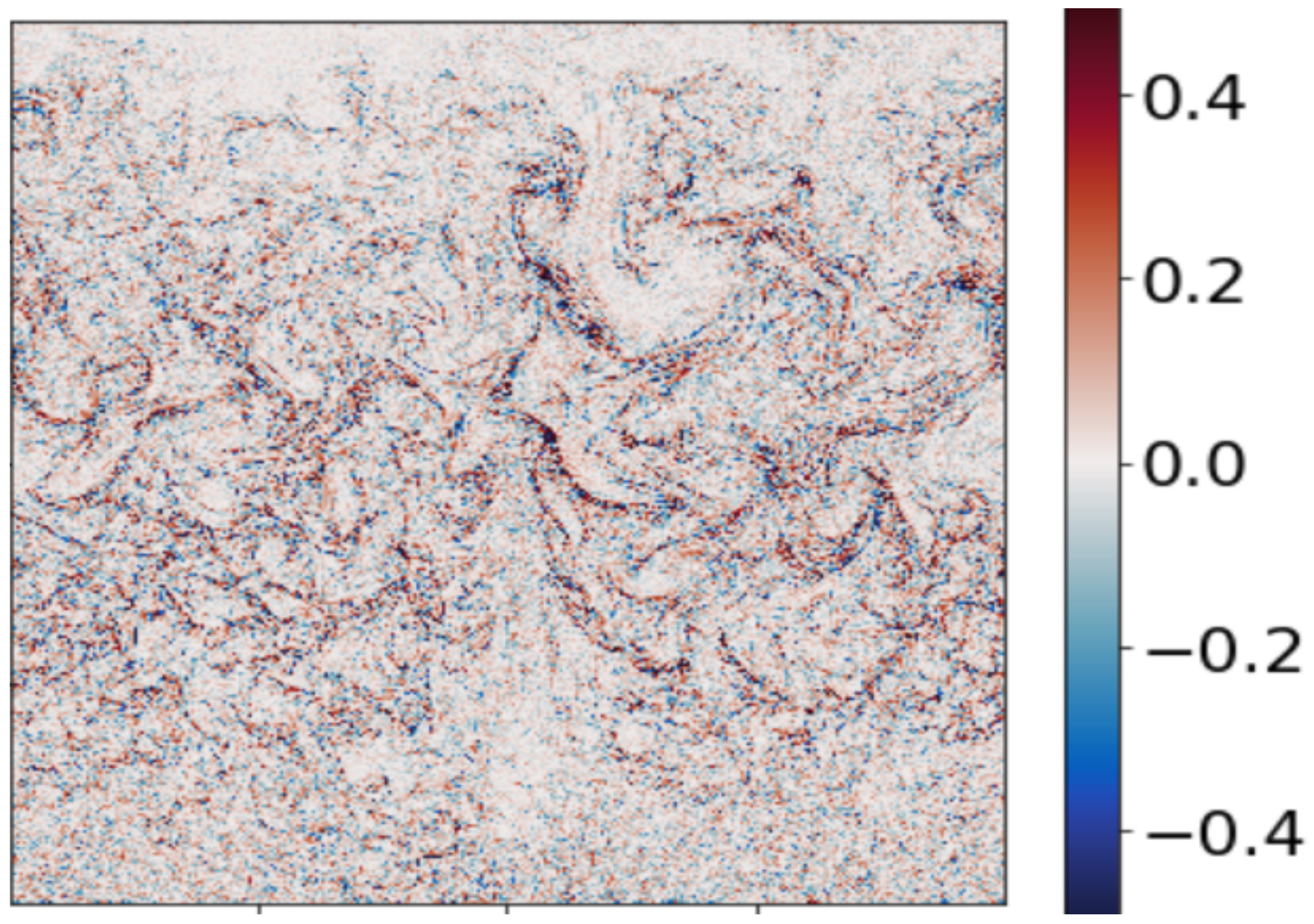
$$\zeta = v_x - u_y$$

Strain $\sigma/|f_0|$



$$\sigma = \sqrt{(u_x - v_y)^2 + (u_y + v_x)^2}$$

Divergence $\delta/|f_0|$



$$\delta = u_x + v_y$$

** (Alternative to coherent structure identification or single-front modeling).

A statistical approach

Vertical Fluxes Conditioned on Vorticity and Strain Reveal Submesoscale Ventilation

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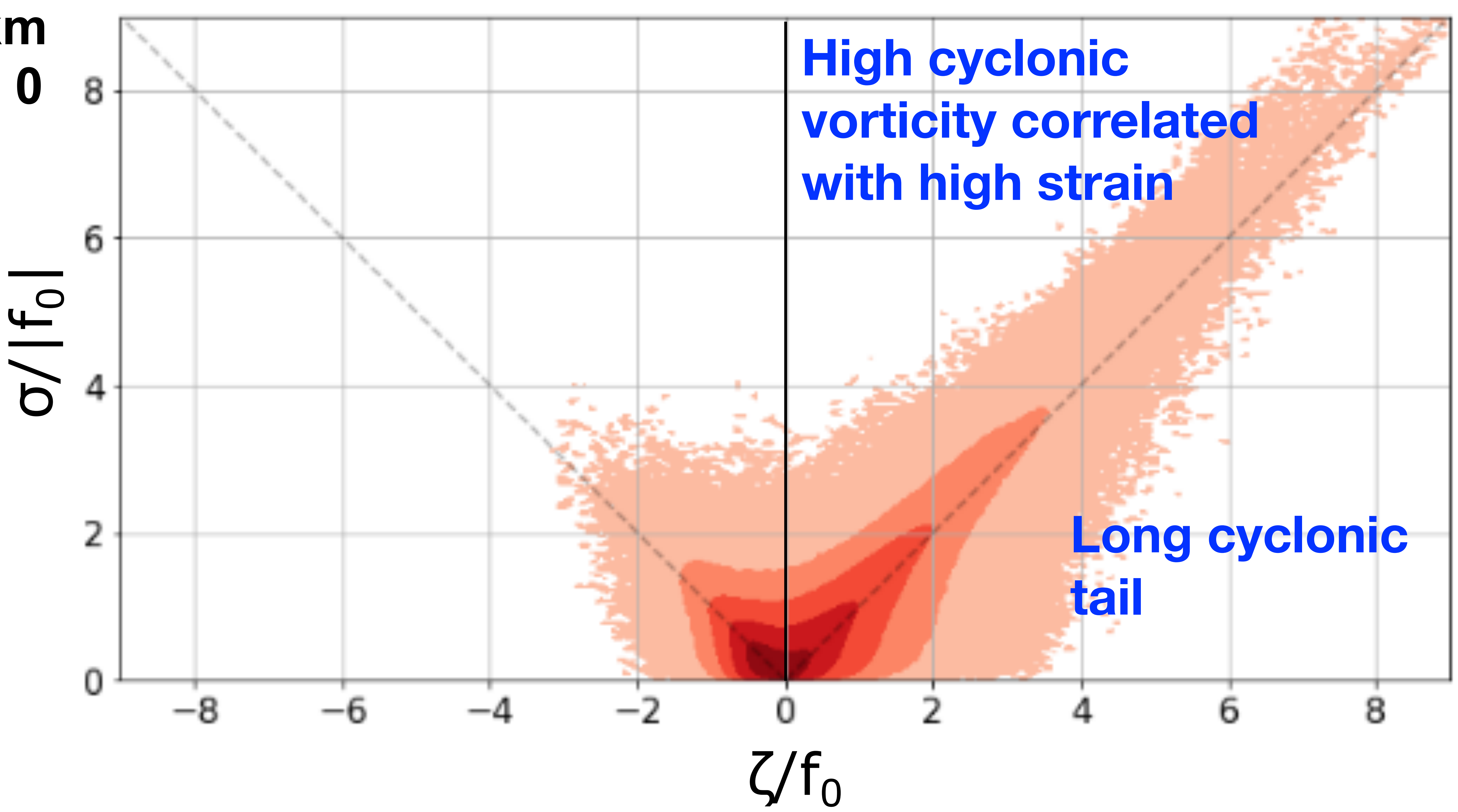
JOURNAL OF PHYSICAL OCEANOGRAPHY SEPTEMBER 2021

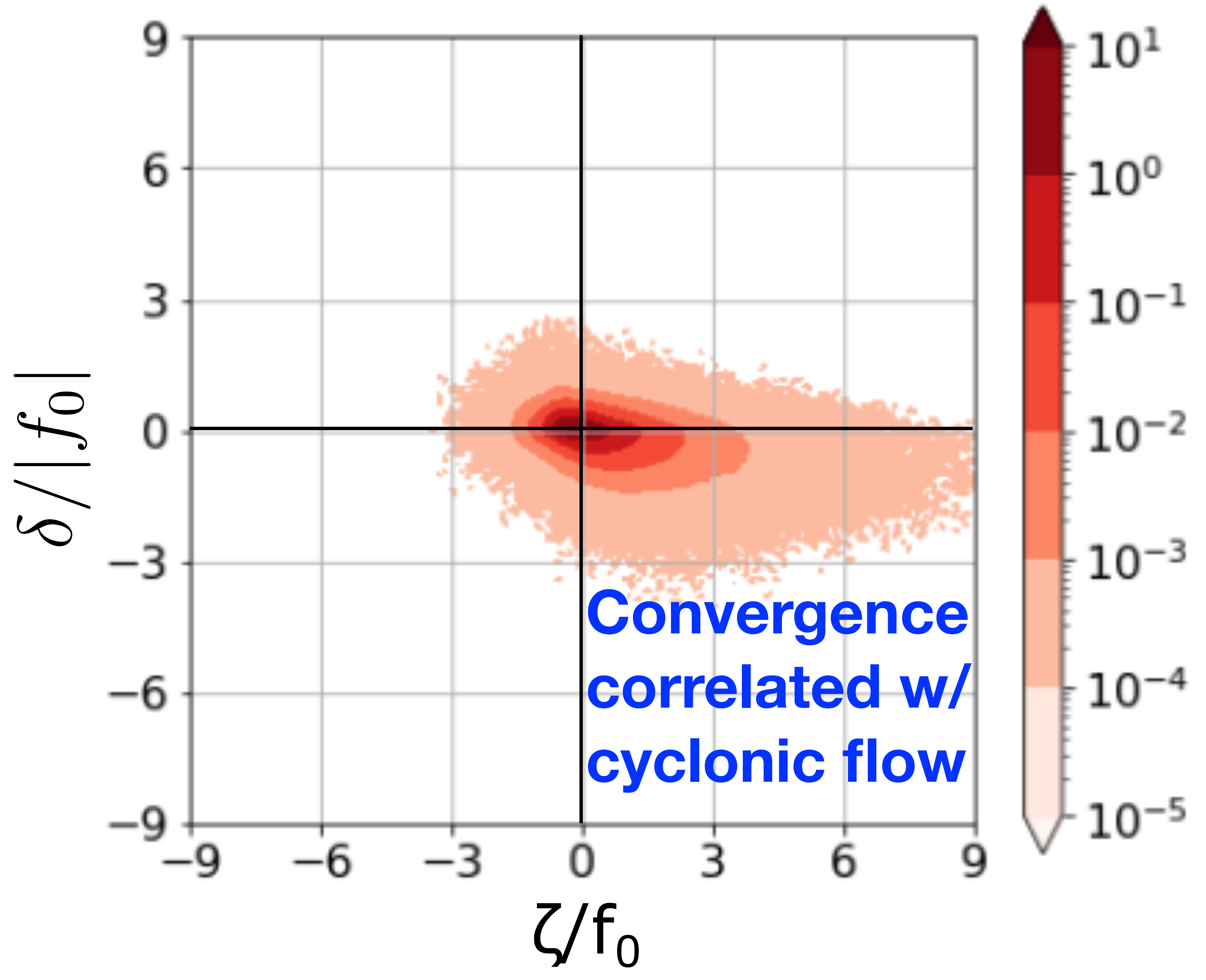
Can the statistics of the flow cleave the flux by process and scale?

[see also Shcherbina et al (2013 GRL)]

Better: consider JPDFs **vorticity, strain, divergence**

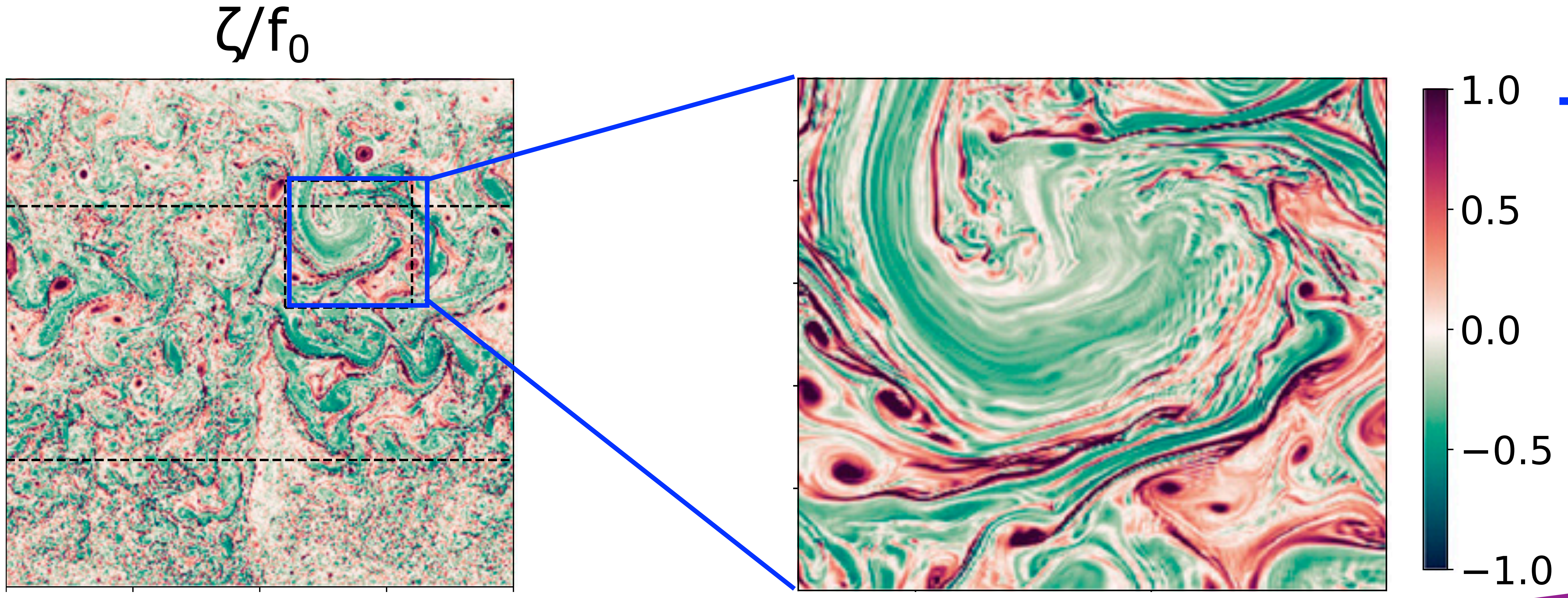
1 km
z = 0



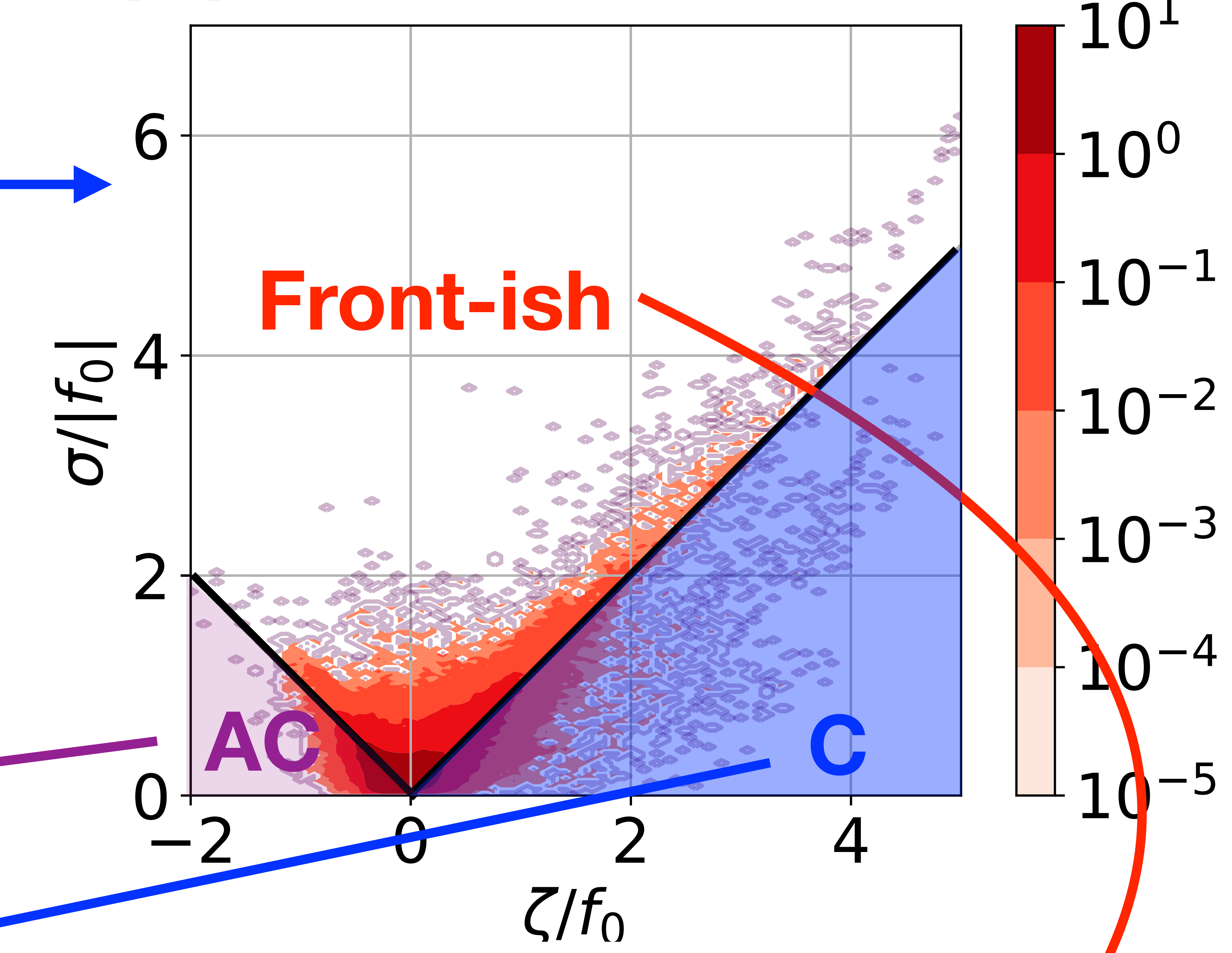


What gives rise to these shapes? Why asymmetric?

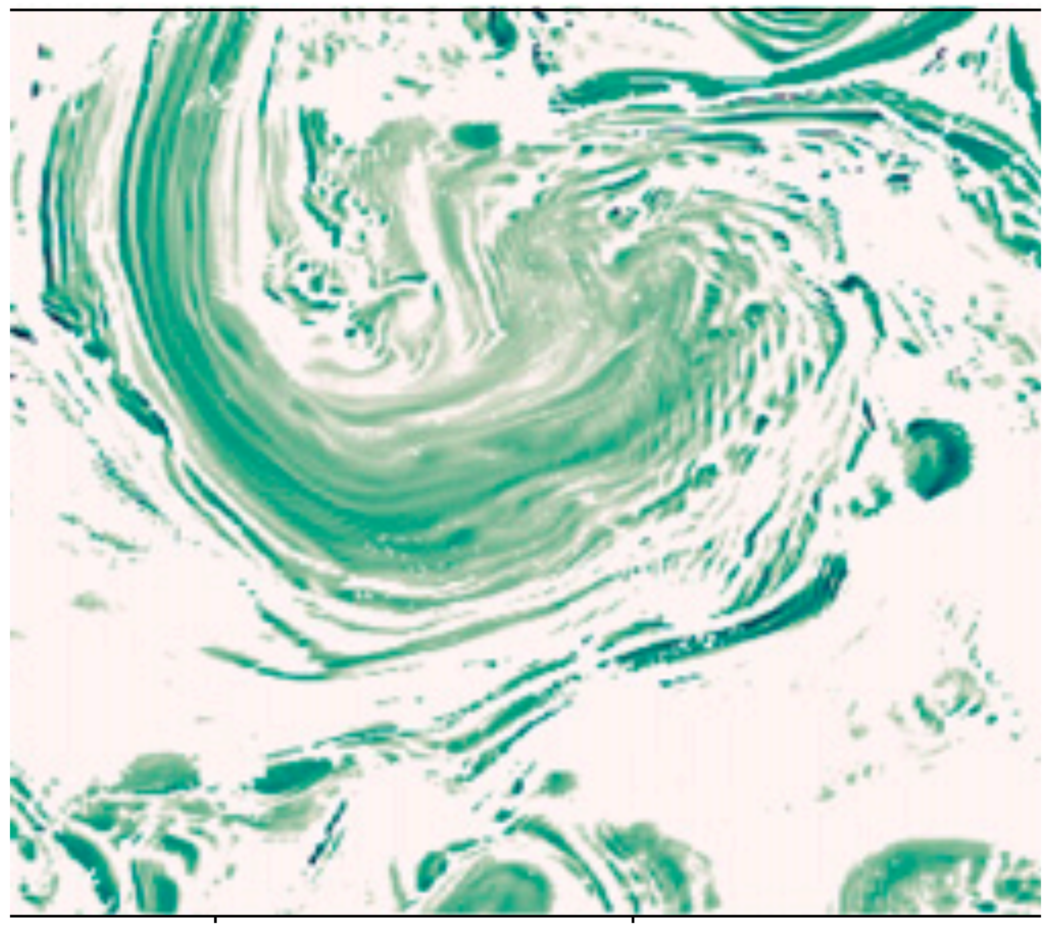
Feature separation



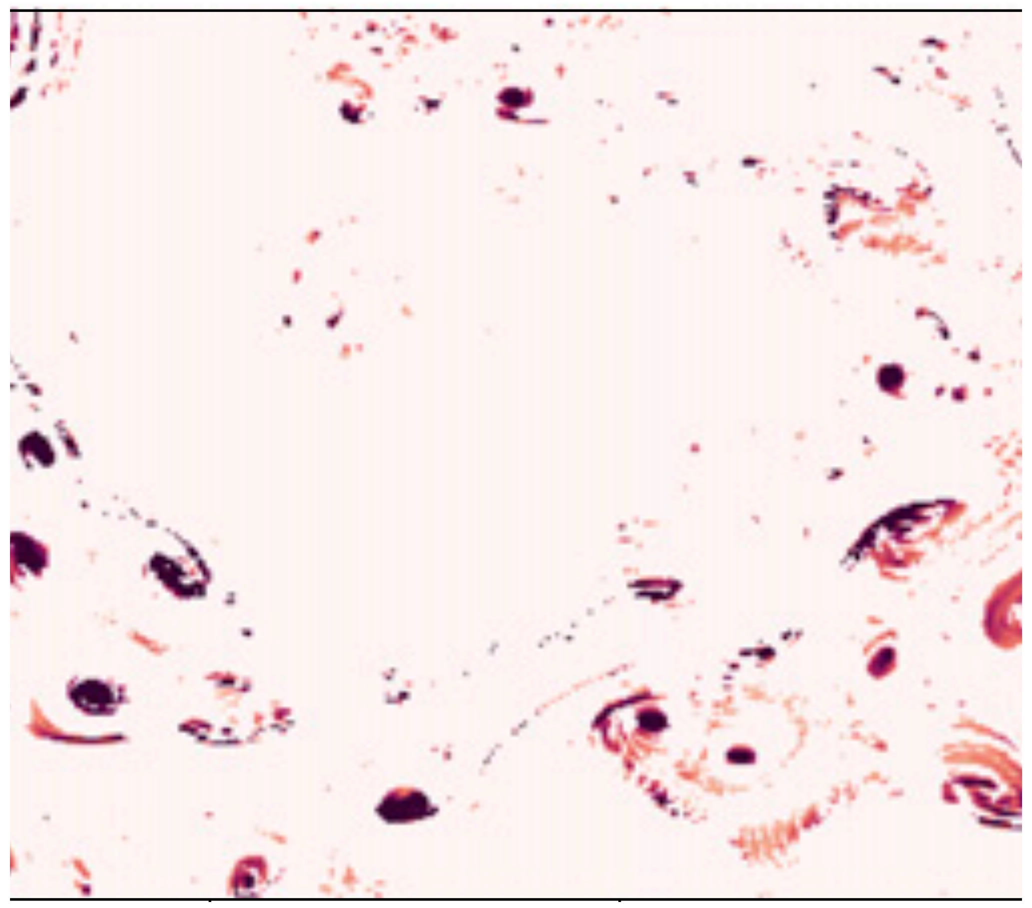
Vorticity-strain JPDF of sub-region



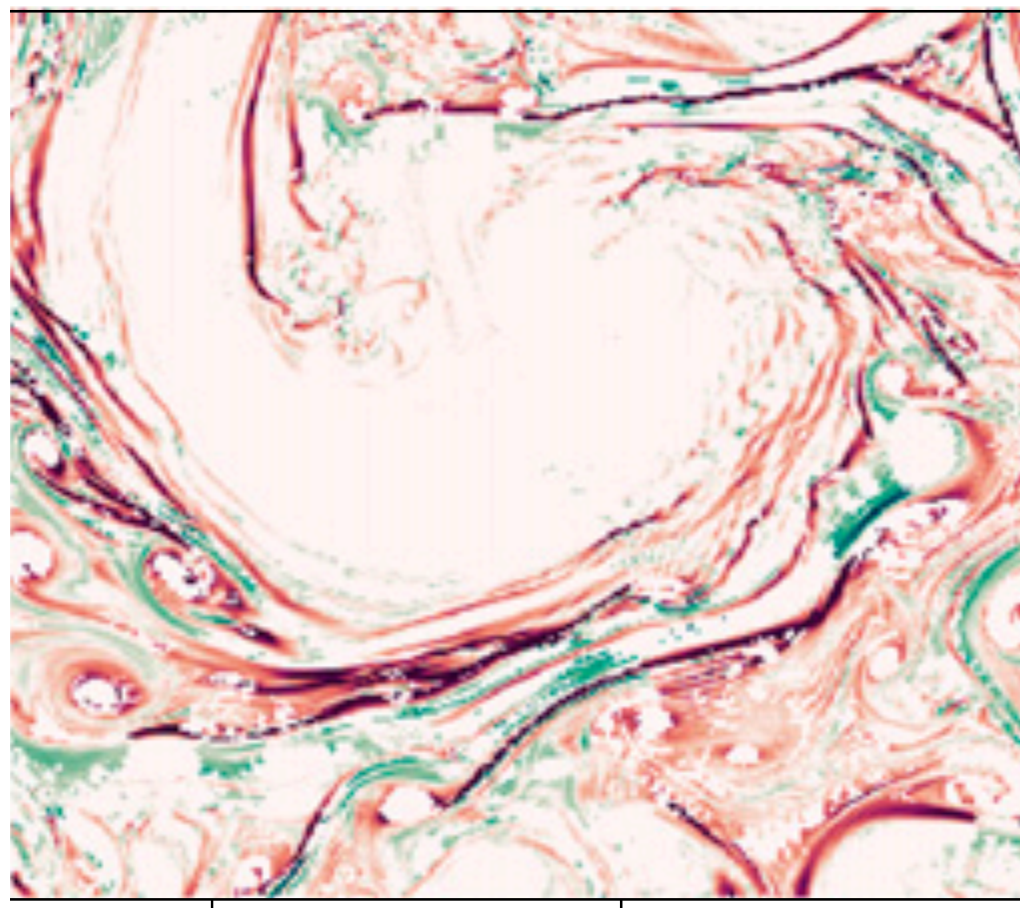
AC



C



Front-ish

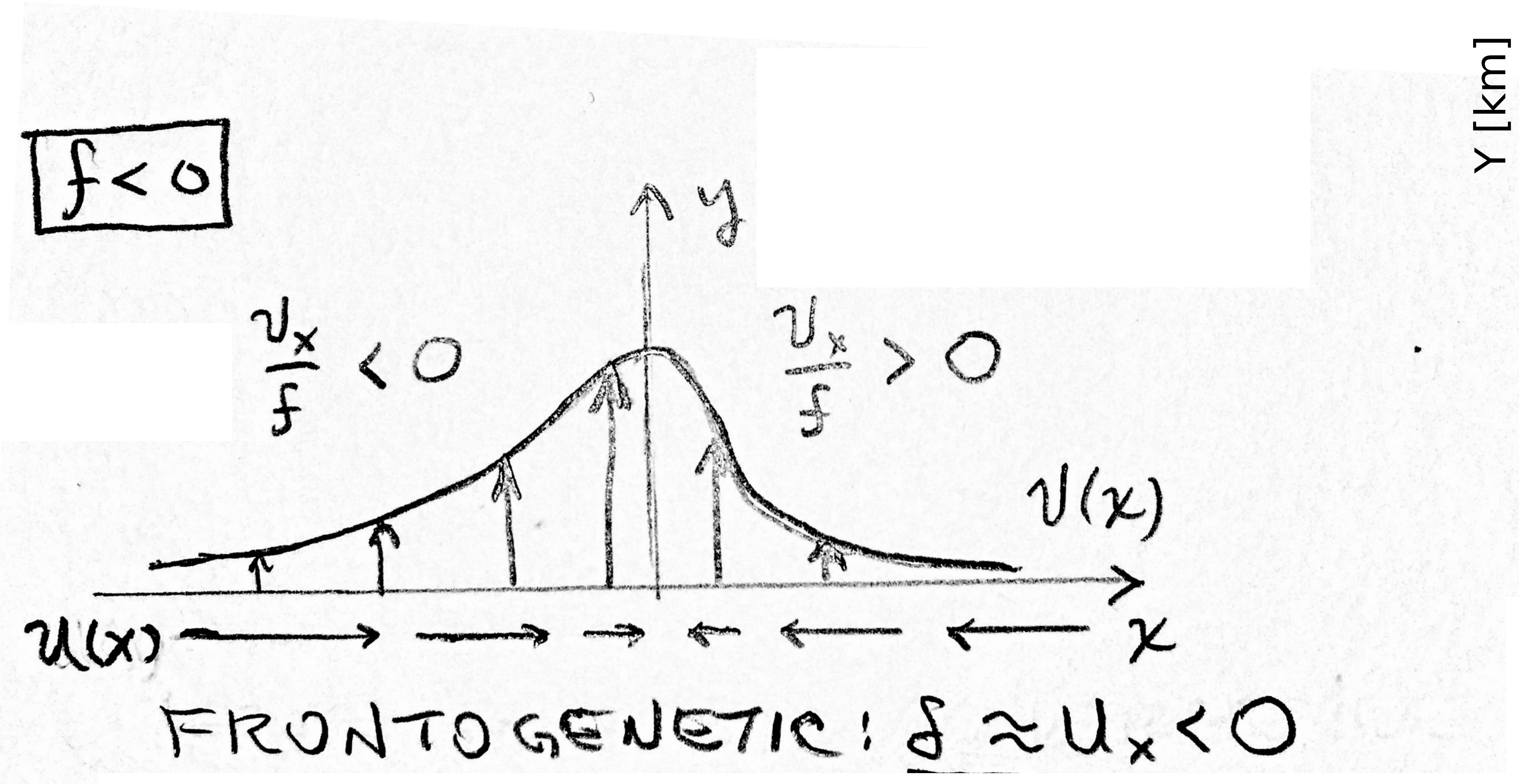


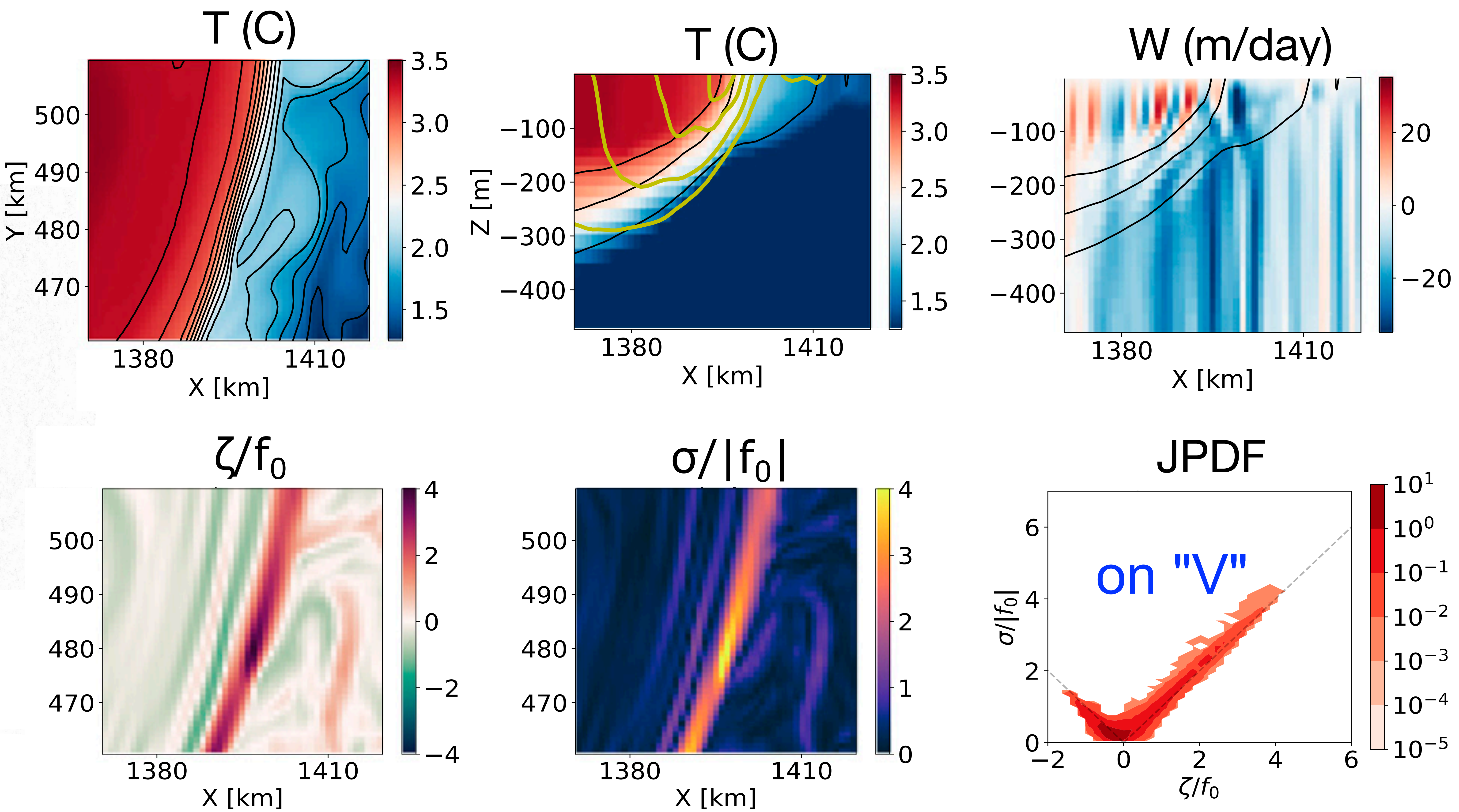
Why fronts along strain ~ vorticity line?

Submesoscale fronts

Typical small front in 1km run

Consider a straight front in y-direction:





$$\zeta = v_x \qquad \text{and} \qquad \delta = u_x$$

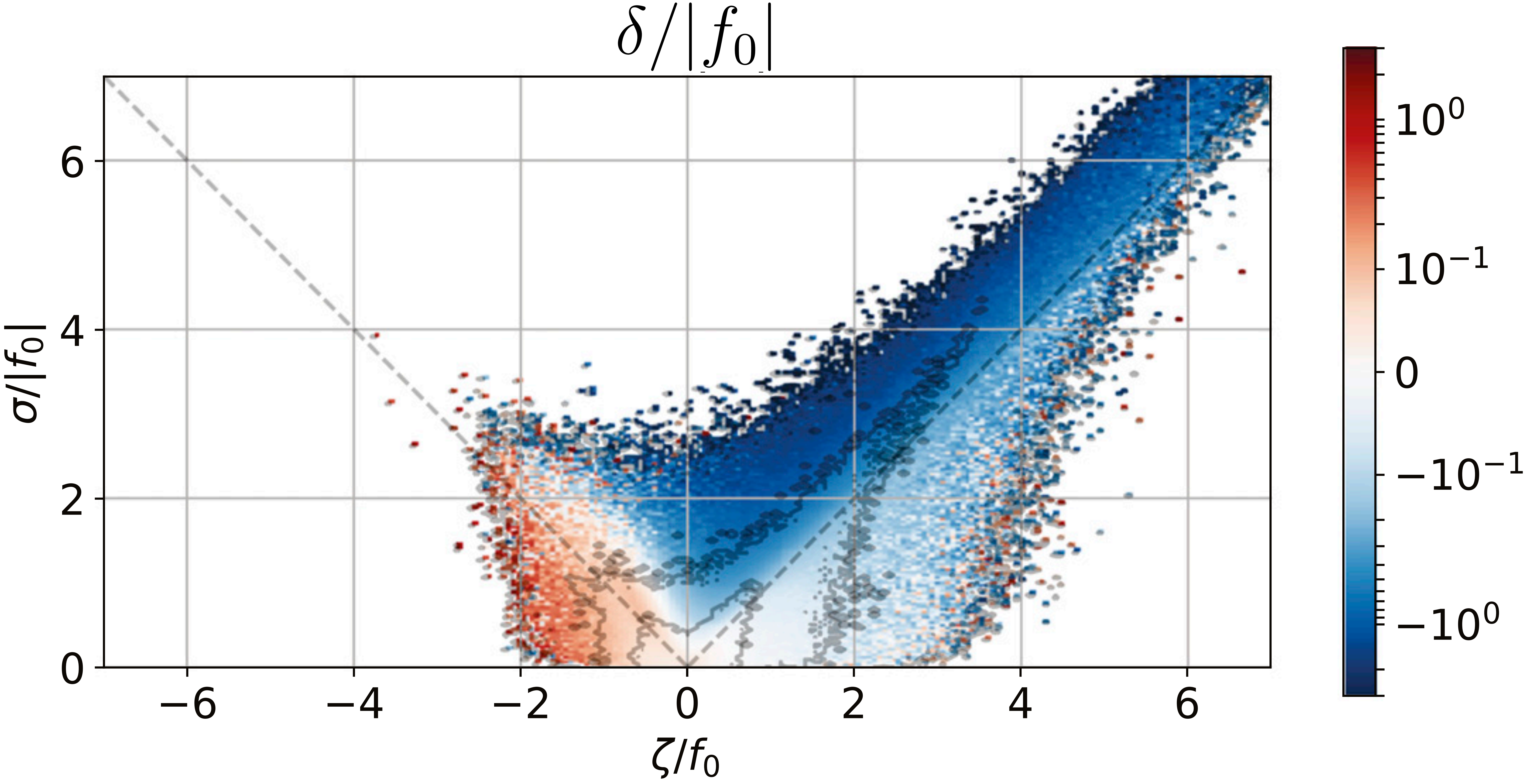
so

$$\sigma = \sqrt{u_x^2 + v_x^2} = \sqrt{\zeta^2 + \delta^2} > |\zeta|$$

- Convergent (δ < 0), and
- Strongly cyclonic (ζ > 0) on downwelling, cold side
- Strong submesoscale upper ocean fronts have |δ| ~ |ζ| (Barkan 2019) so max strain like

$$\sigma \approx \sqrt{2}|\zeta|$$

Divergence and flux binned by vorticity & strain



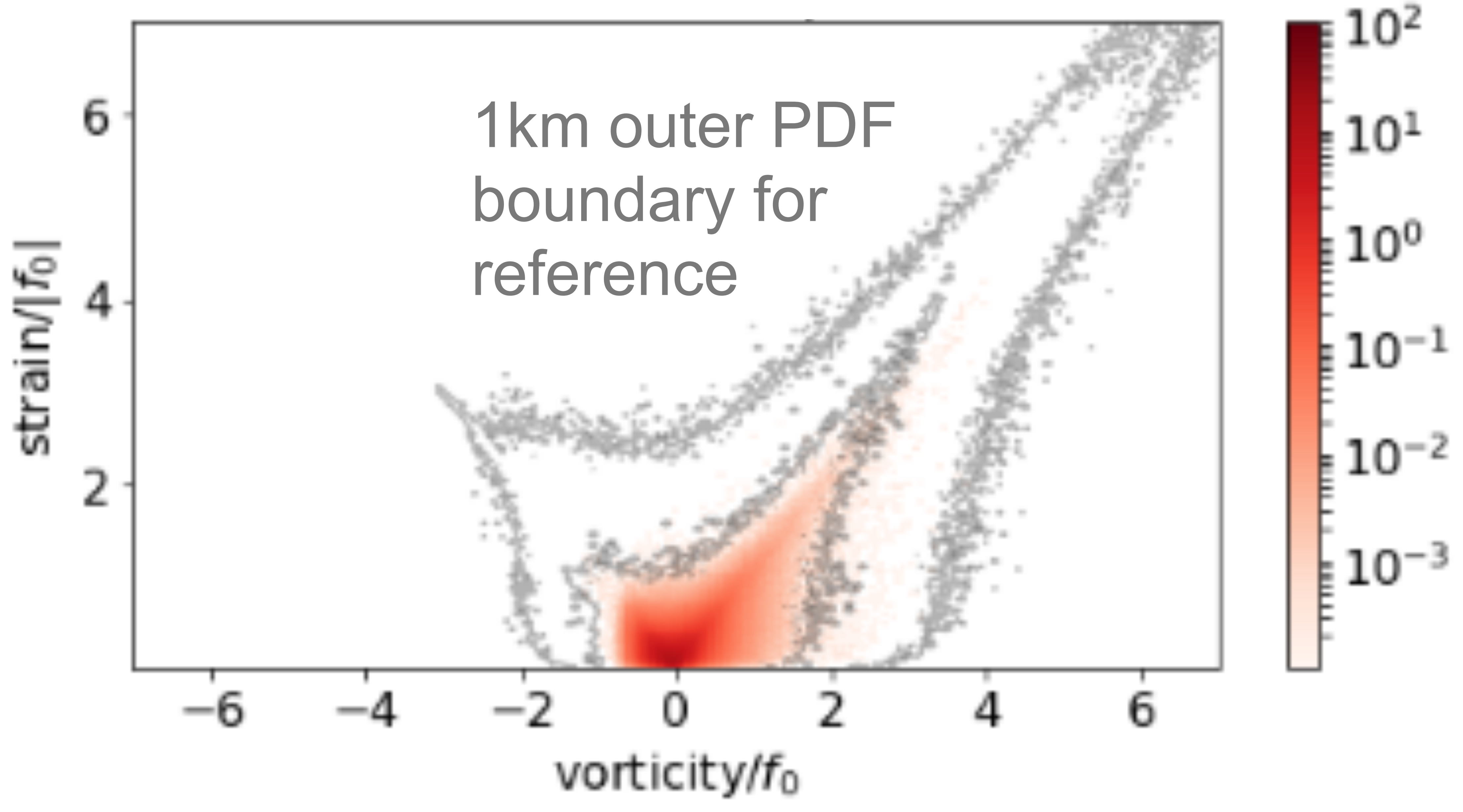
Regions with strong convergence correspond to high strain and vorticity

$\Longrightarrow$ high downward flux

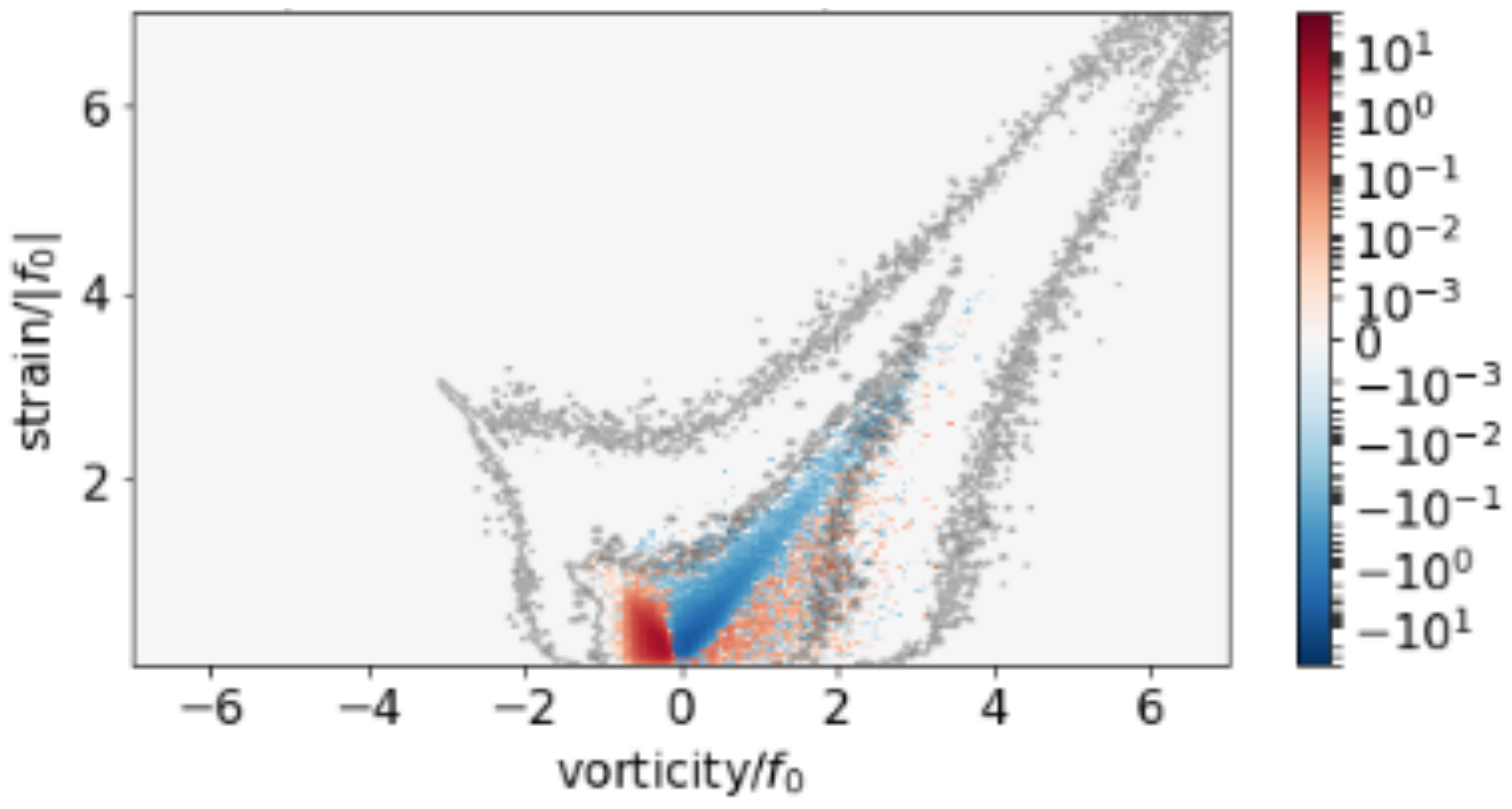
Scale dependence

1 km results coarsened to 5 km

JPDF



Flux



Filters same points removed by lowering resolution

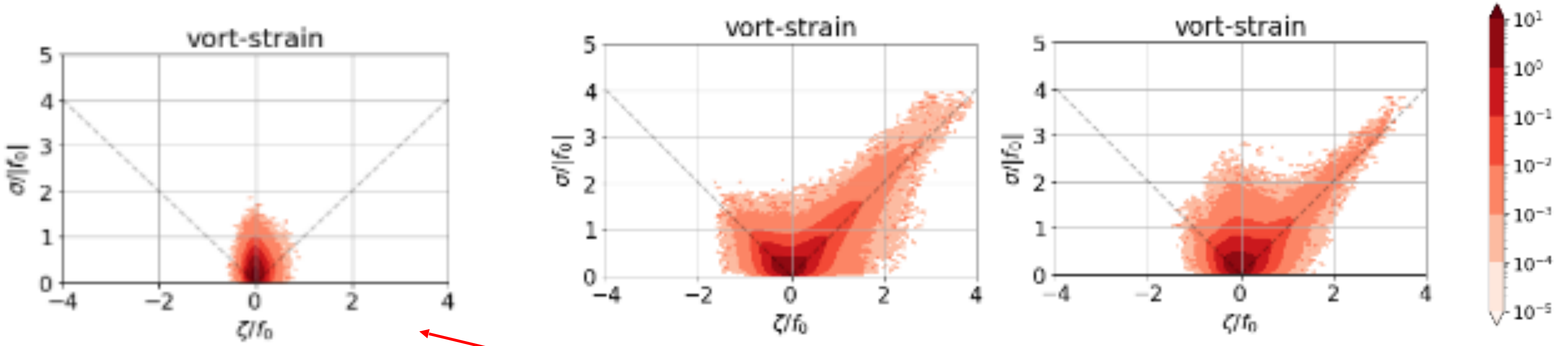
$\Longrightarrow$ JPDF contours denote scale selection

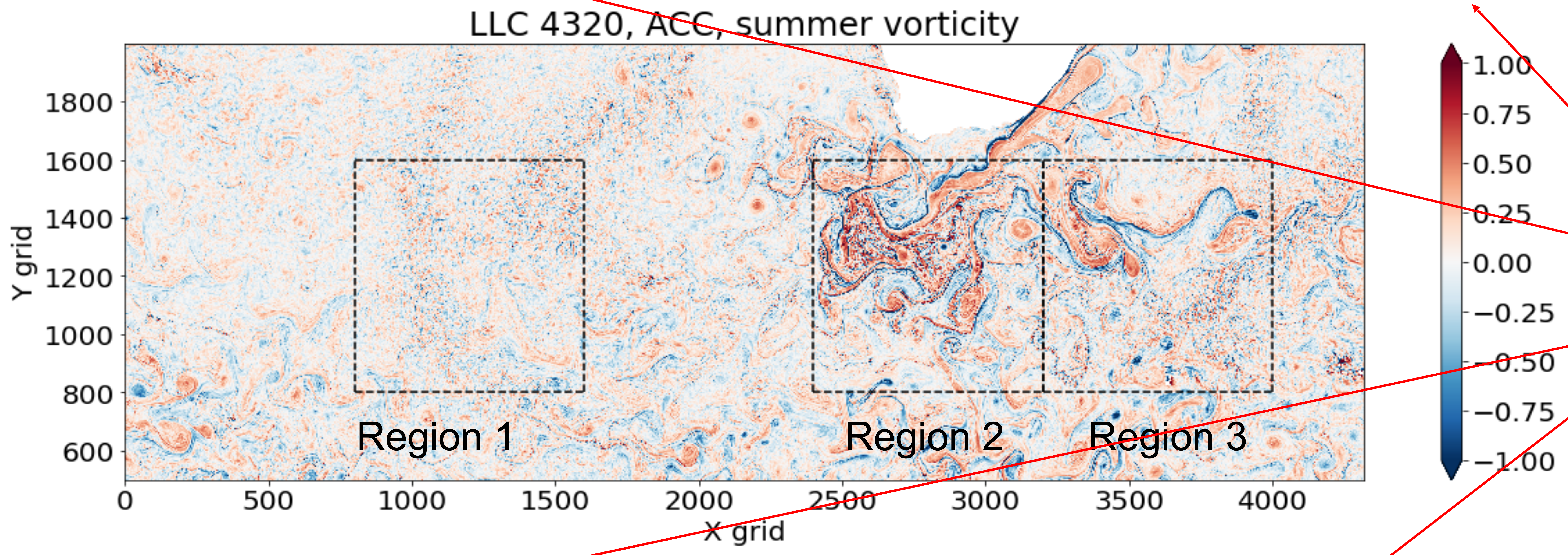
$\Longrightarrow$ Features and fluxes lying in outer-most contour are submesoscale

What is signature of waves on JPDF?

We computed JPDFs of vorticity and strain for regions near South Africa in the LLC4320 simulation:

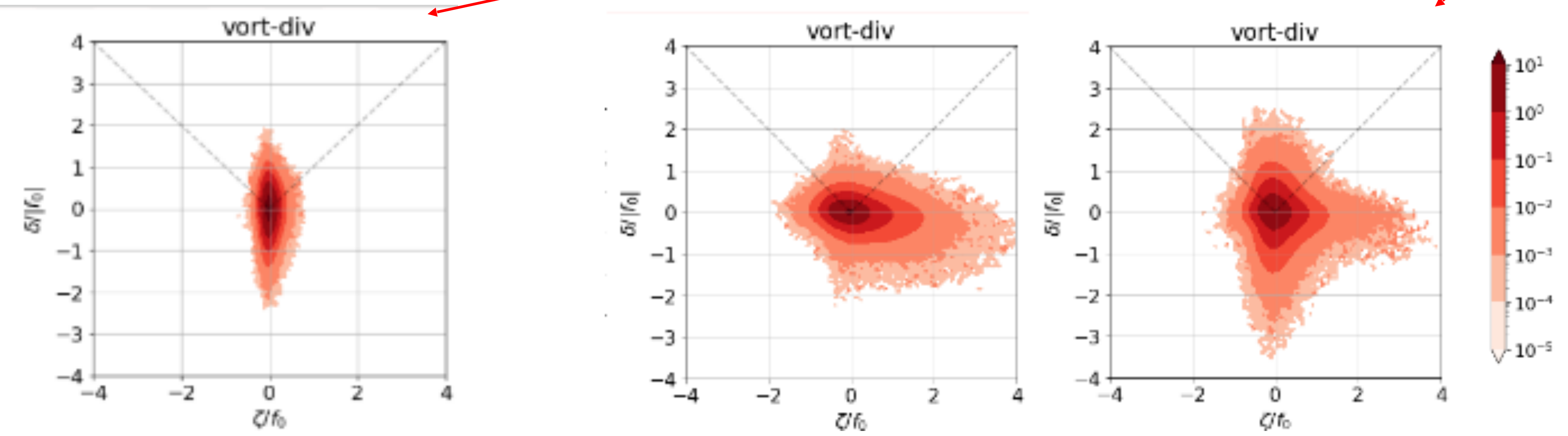
Vorticity-Strain JPDF





Why do these look so different?

Vorticity-Divergence JPDF

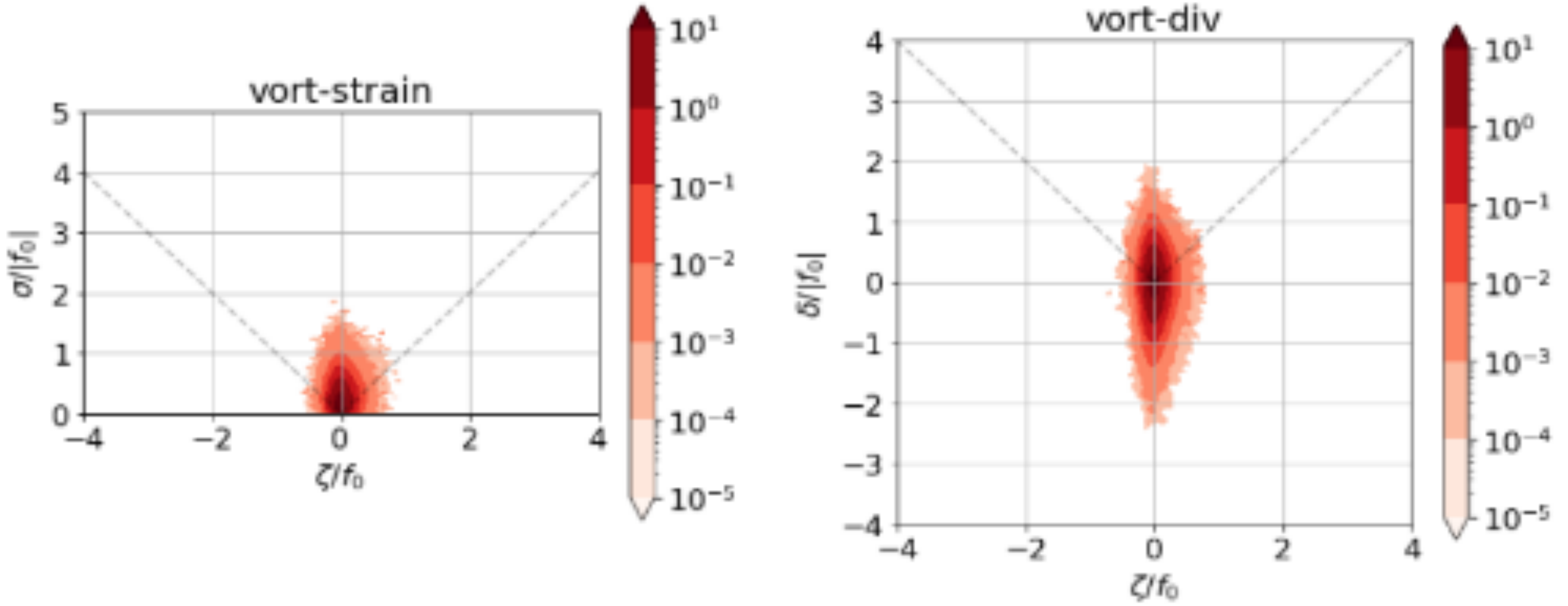


SH SUMMER

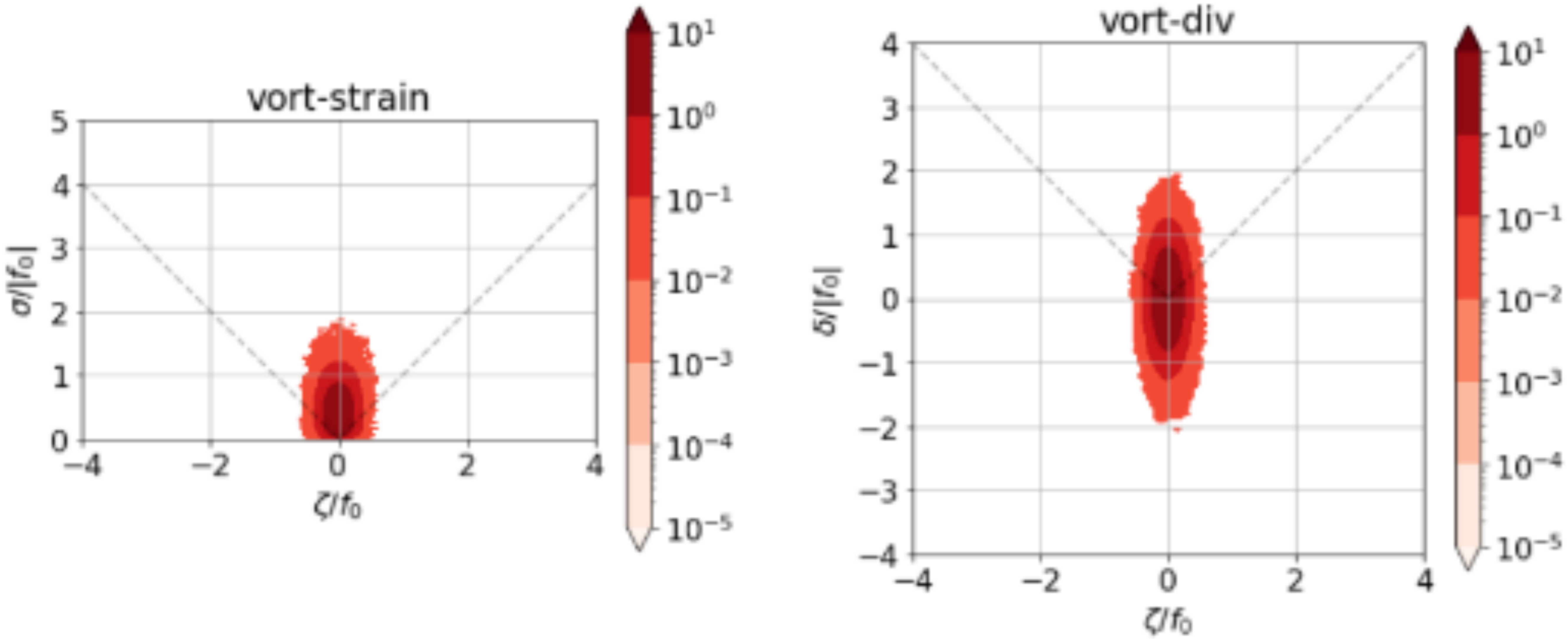
thin ML
$\Longrightarrow$ strong NIWs

JPDF for wavy flow

LLC 4320 summer Region 1



IGW surface field from GM spectrum



[made from velocity field of a superposition of IGWs following the GM spectrum, using code from Jeffrey Early: https://github.com/Energy-Pathways-Group/GLOceanKit]

Why this structure?

Consider plane IGW:

$$\zeta = \frac{f}{\omega} K \cos\left(kx + ly - \omega t + \phi\right)$$

$$\delta = K \sin\left(kx + ly - \omega t + \phi\right)$$

$$\implies \quad \zeta/\delta \approx \frac{f}{\omega}$$

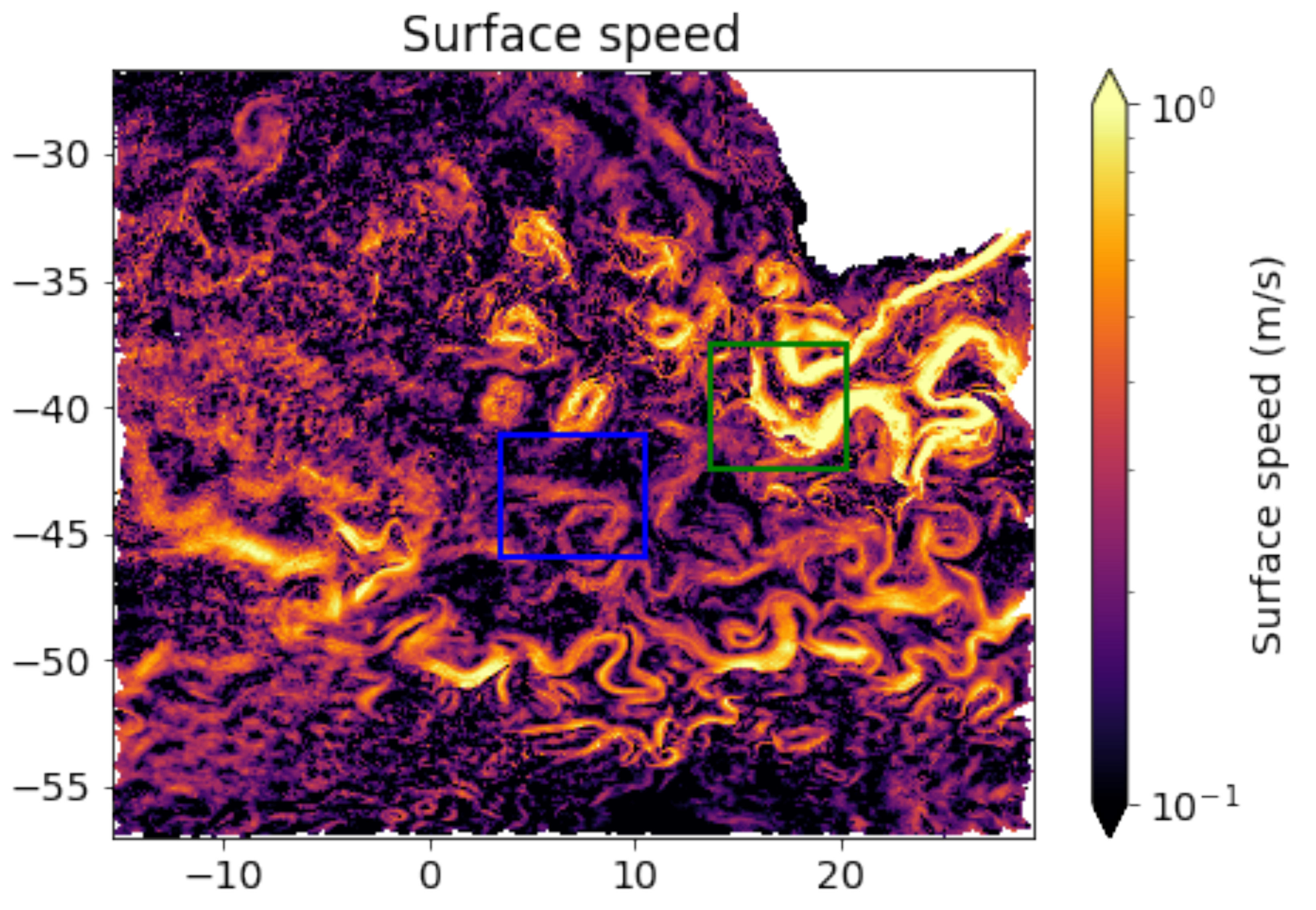
$$\omega \gg f \implies \zeta \ll \delta$$

$$\sigma = \sqrt{\zeta^2 + \delta^2} \approx |\delta|$$

(For balanced flow: $\sigma \sim \zeta > \delta$)

How to create a wave-free truth signal on which to train methods?

Lagrangian filtering of LLC4320



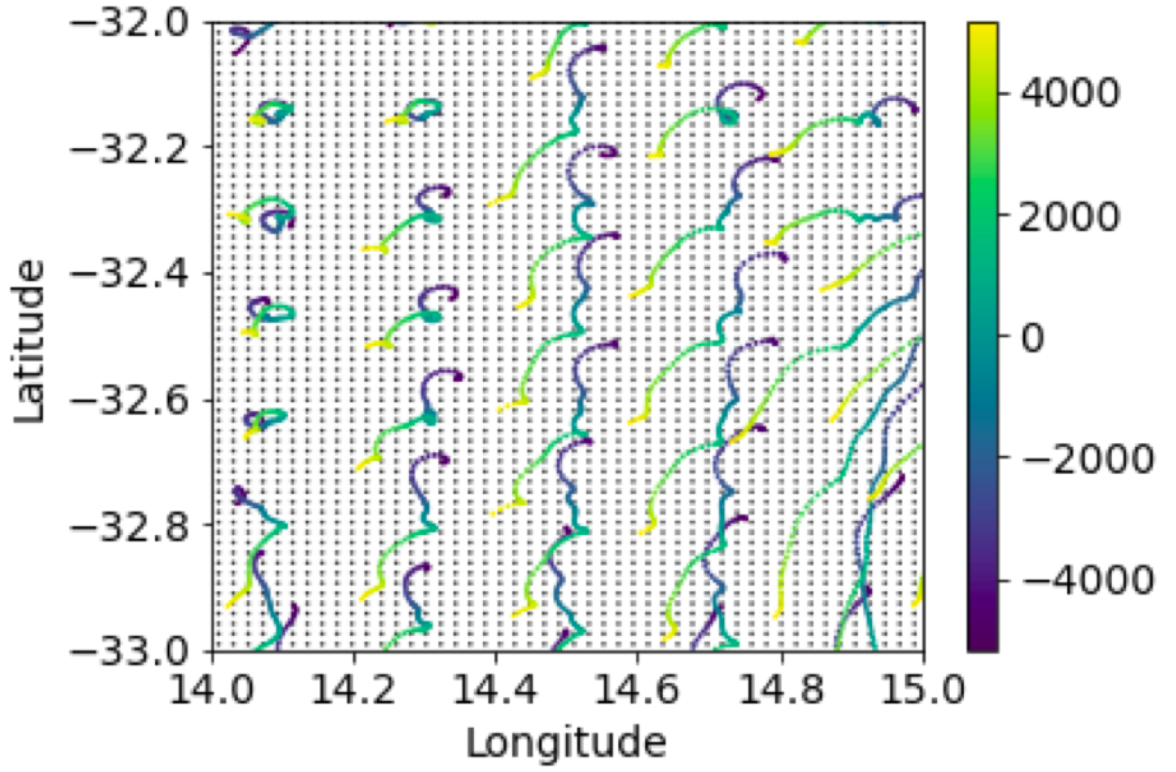
Surface speed in analysis domain (SH Winter)

Separating balanced and unbalanced flow at the surface of the Agulhas region using Lagrangian filtering

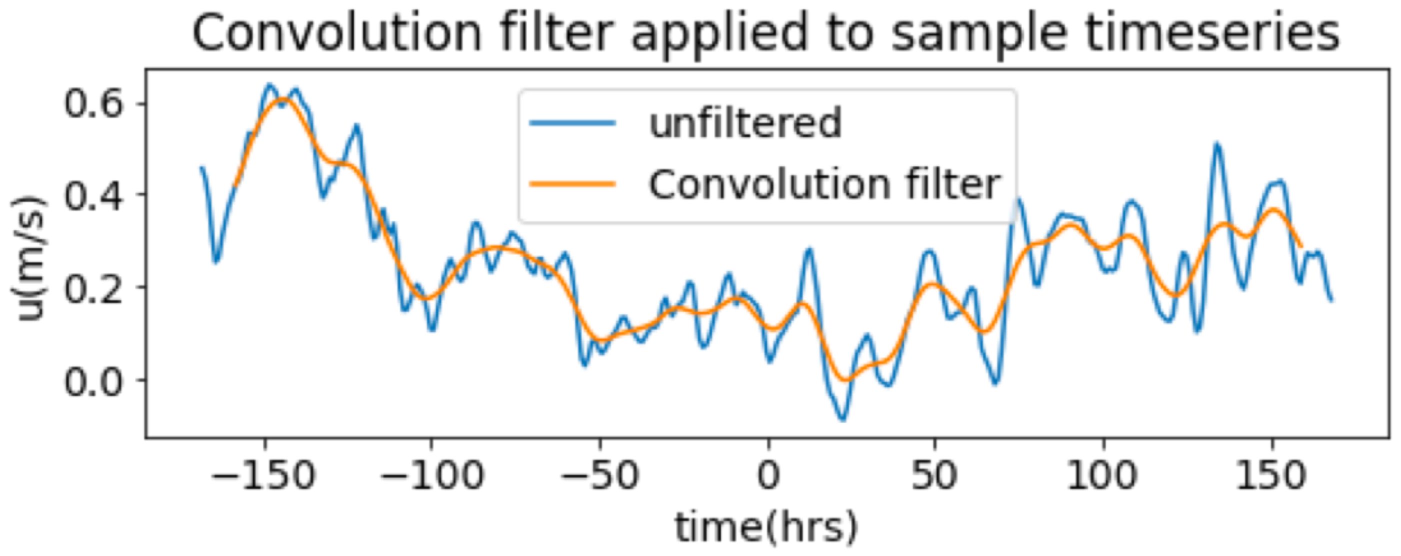
Jones, C. Spencer, Q. Xiao, R. P. Abernathey, & K. Smith

[Submitted to ***JAMES***]

STEP 1: Seed model with grid of particles, run them forwards and backwards in time for 36hrs.



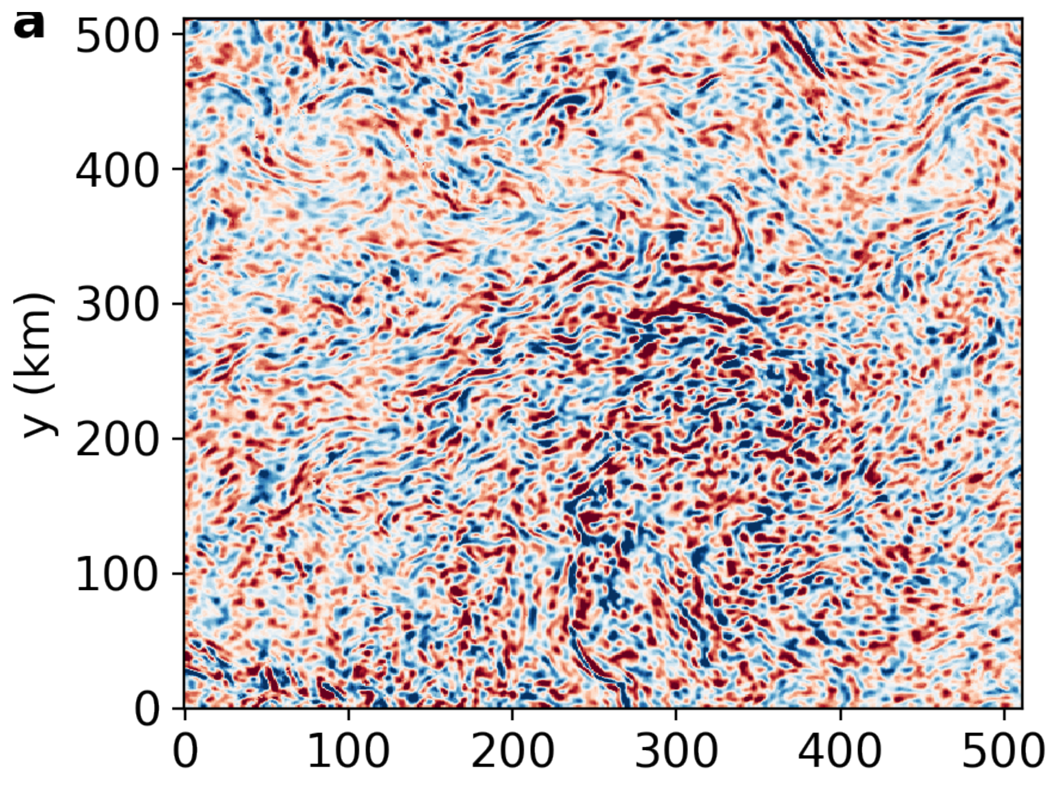
STEP 2: Convolution filter in Lagrangian space - remove high frequencies in Lagrang velocities



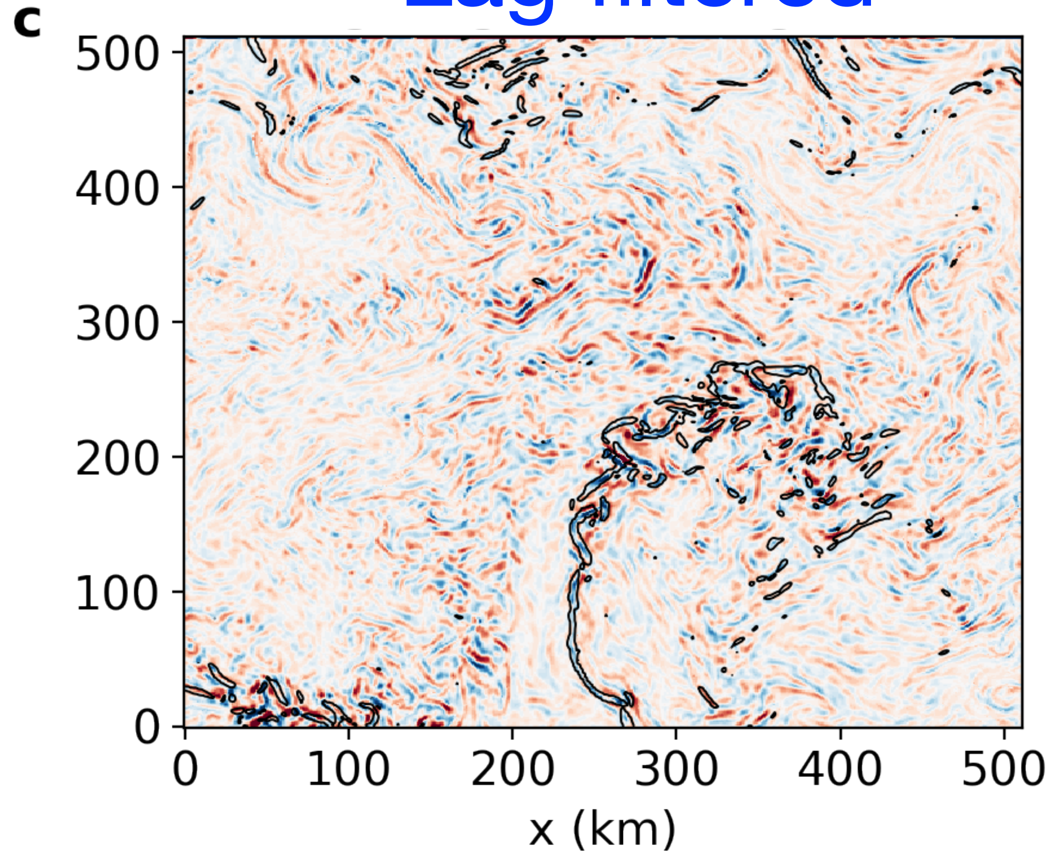
STEP 3: Interpolate the filtered velocities back to Eulerian space.

Divergence

unfiltered

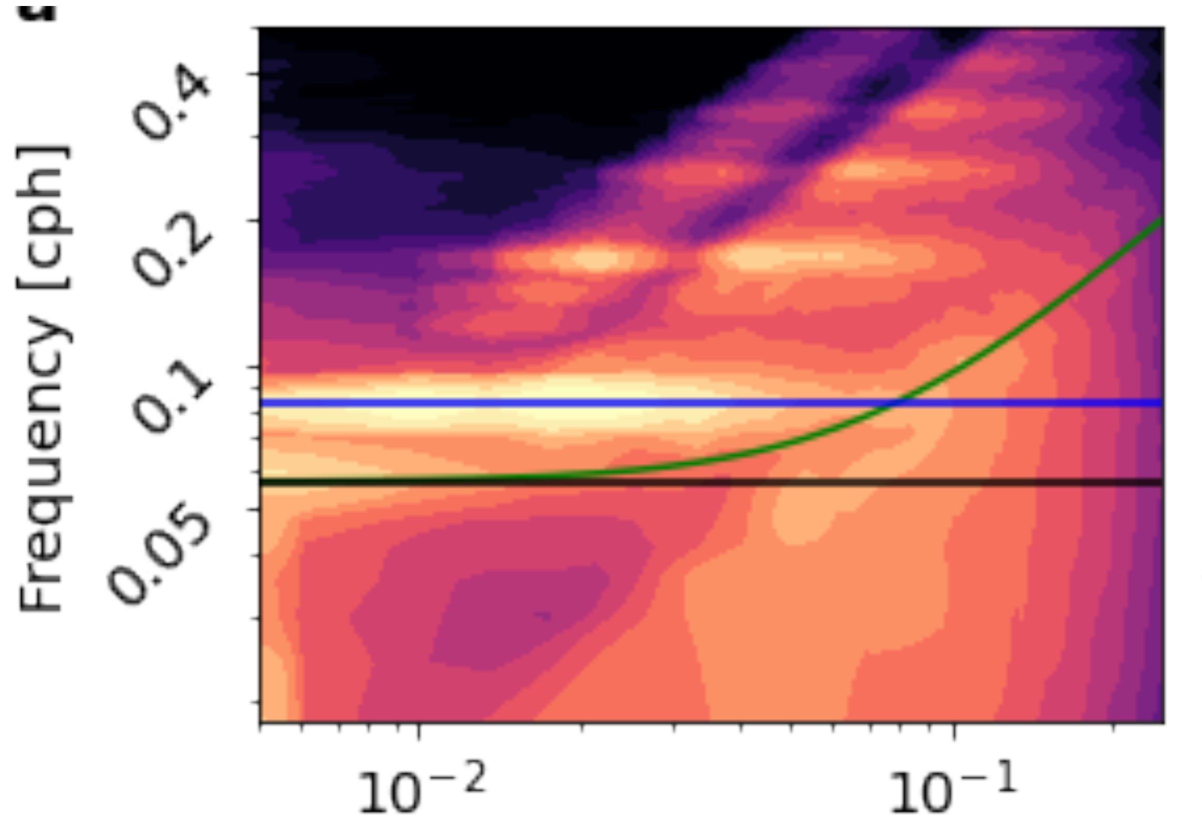


Lag filtered

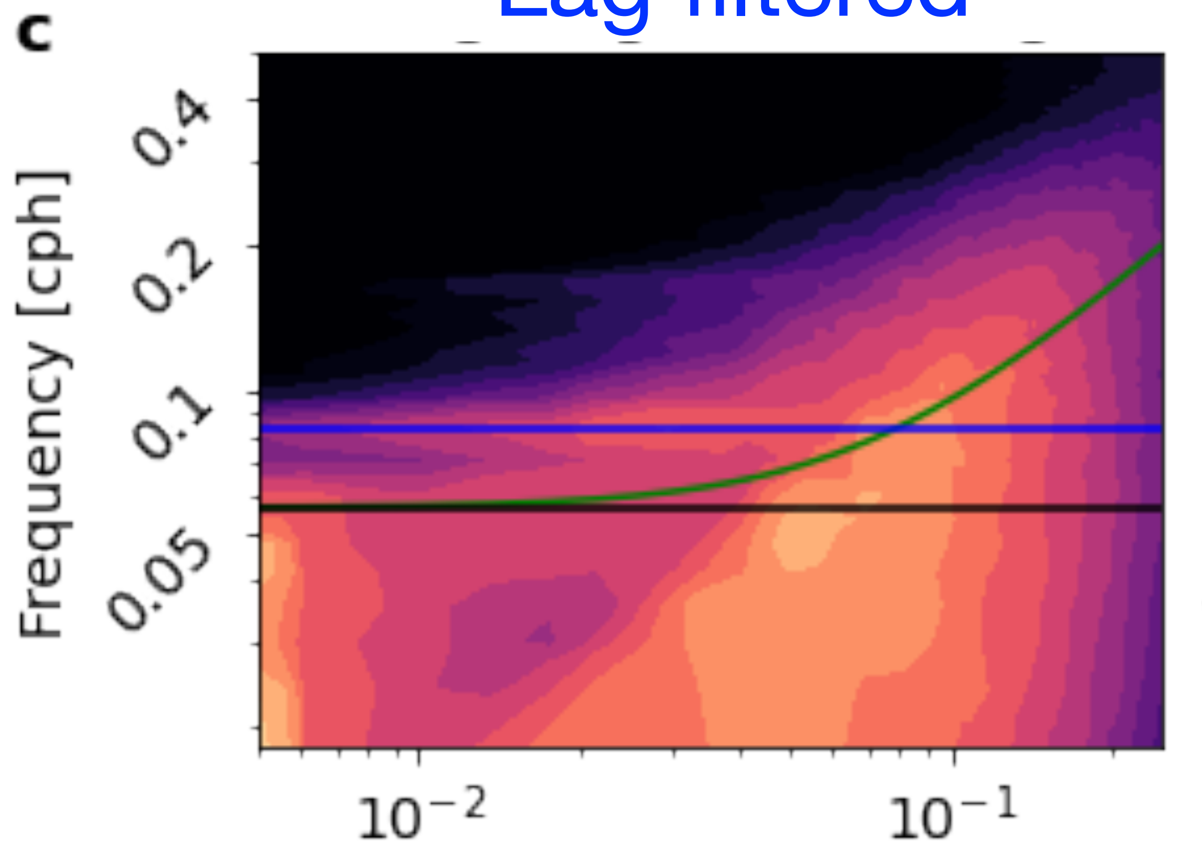


KE spectrum

unfiltered



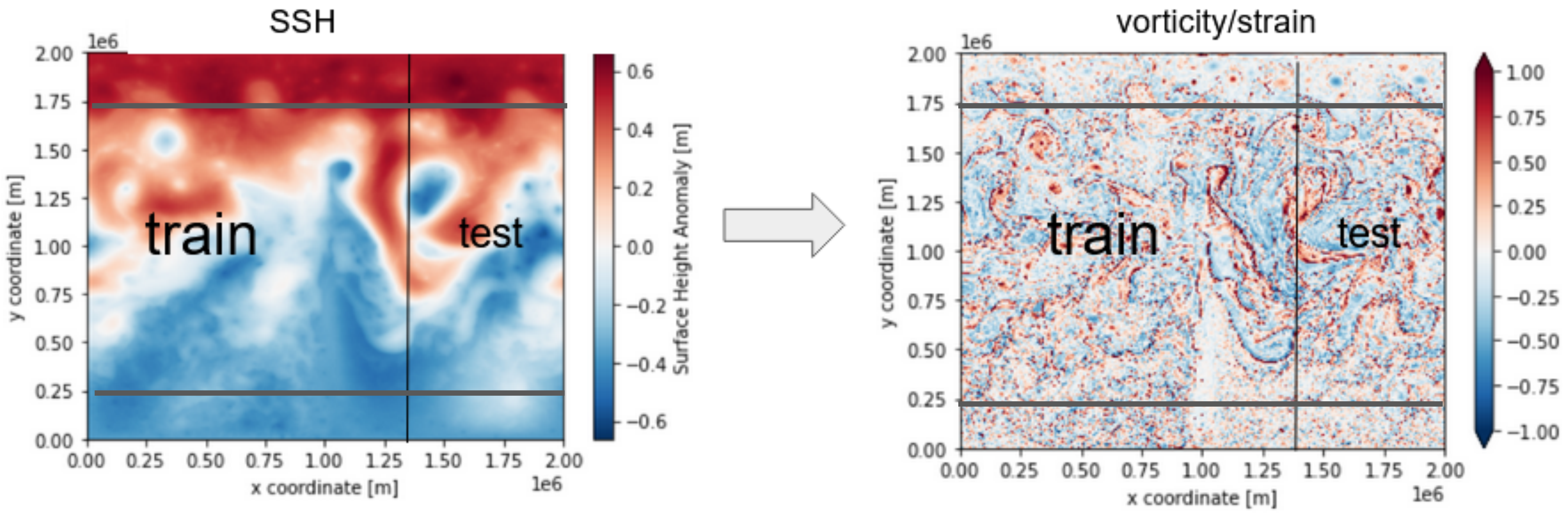
Lag filtered



Recent ML attempts by Qiyu:

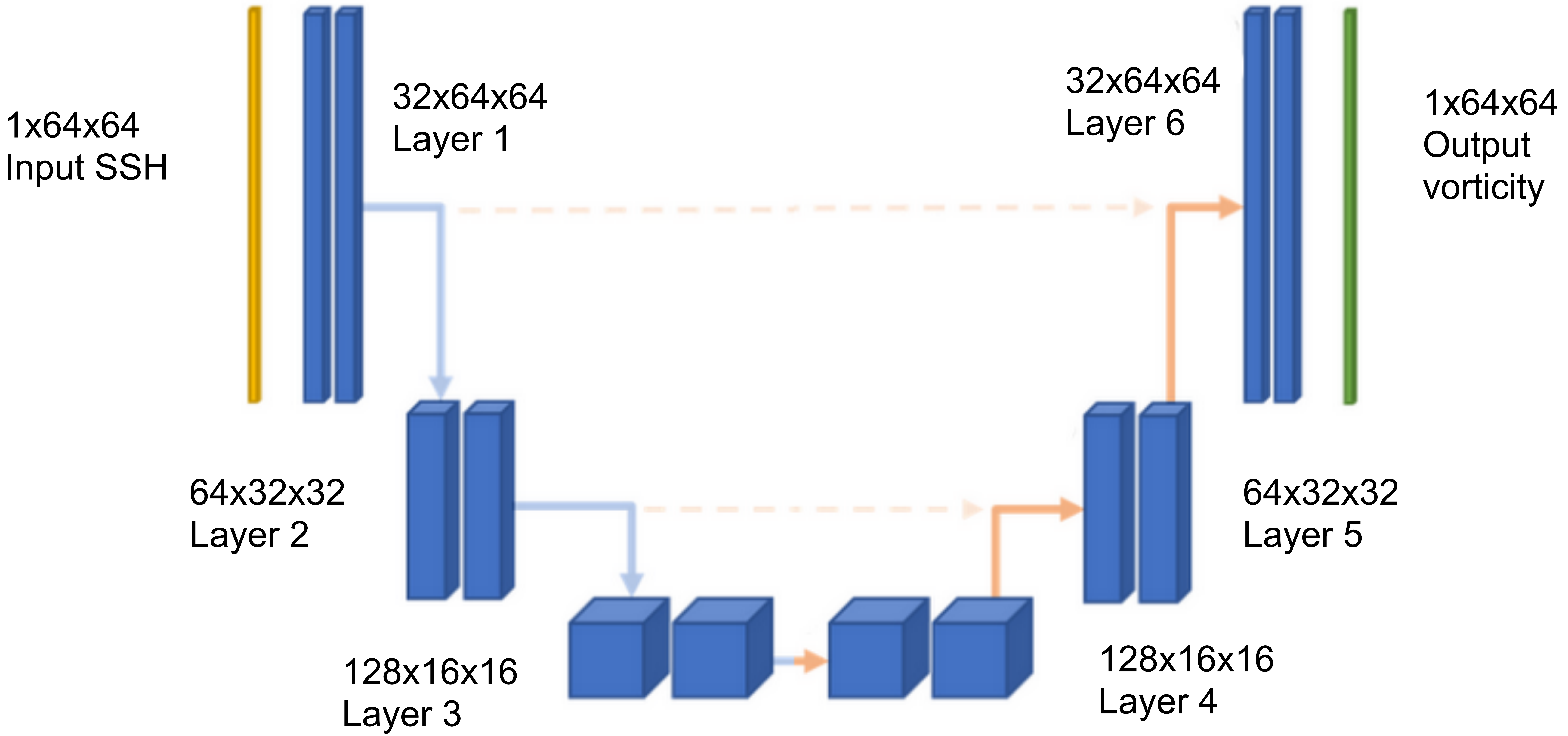
Using UNET CNN to learn vorticity, strain, divergence from SSH in channel simulation (not very wavy)

Better: use Lagrangian filtered data for LLC summer data (TBD)



- 3 month of 6 hourly snapshot data from 1km channel simulation (randomly shuffled when training, so assume no time information learned)
- South and north boundaries excluded
- Day 1~75 for training, day 80~90 for testing
- X<=1.25km for training, X>=1.35km for testing
- Split to 64x64 non overlap regions for training
- During prediction, predict every 64x64 regions but with overlap

Unet structure



Blue Cuboids represent convolution layers. C x H x W = channels x height x width.
Around 380000 parameters.

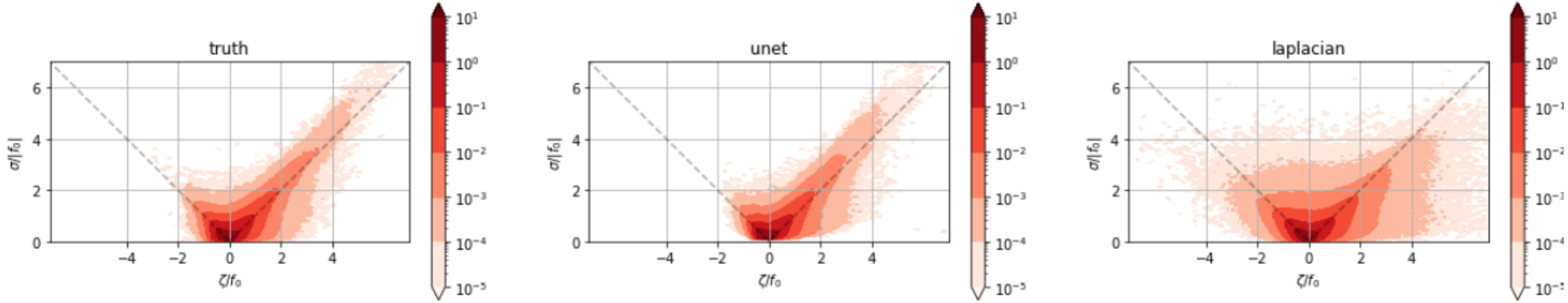
Comparison between true and predicted surface vorticity

$$Skill = 1 - \left(\frac{\overline{|\, SSH_{predicted} - SSH_{true} \,|^2}}{\overline{|\, SSH_{true} \,|^2}} \right)^{\frac{1}{2}}$$

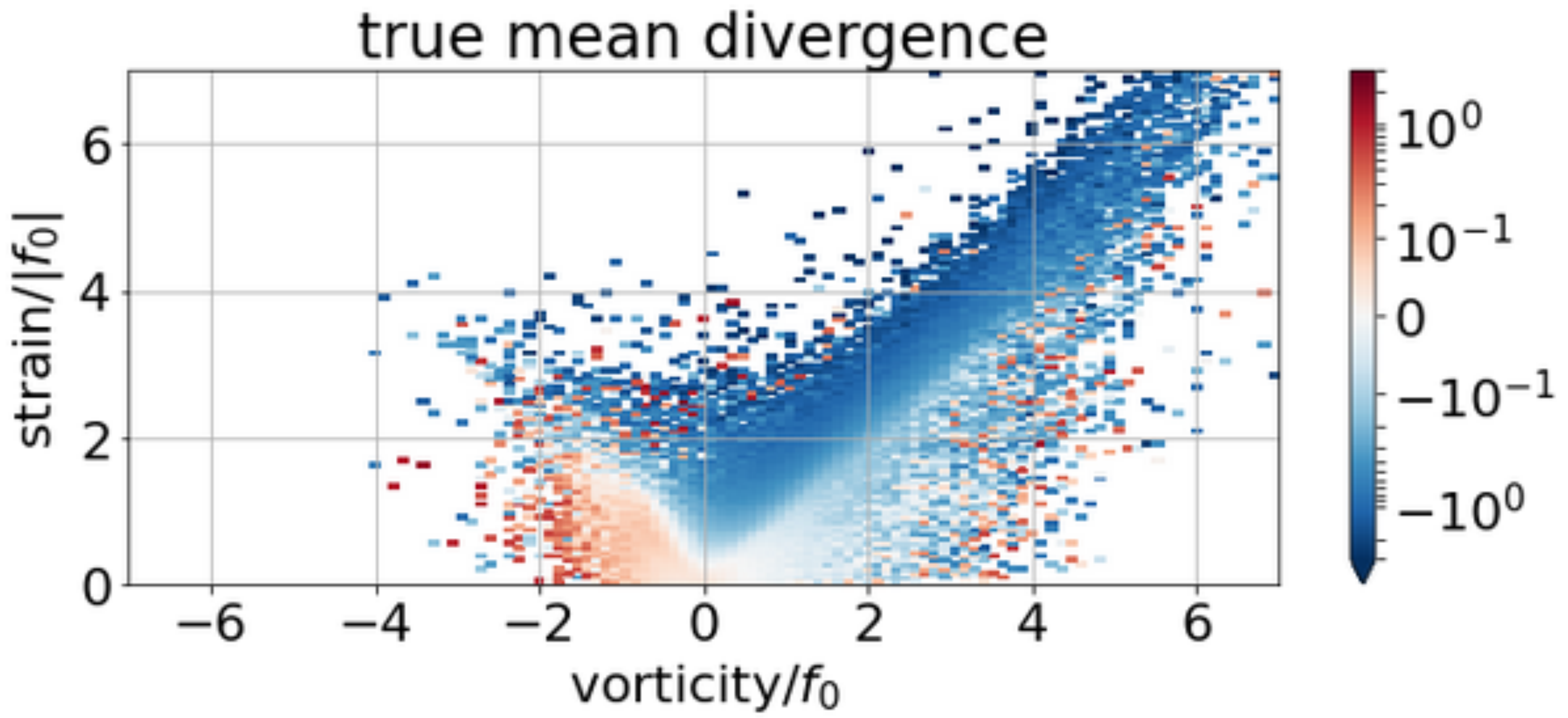
Correction with true: 0.95
Skill: 0.69

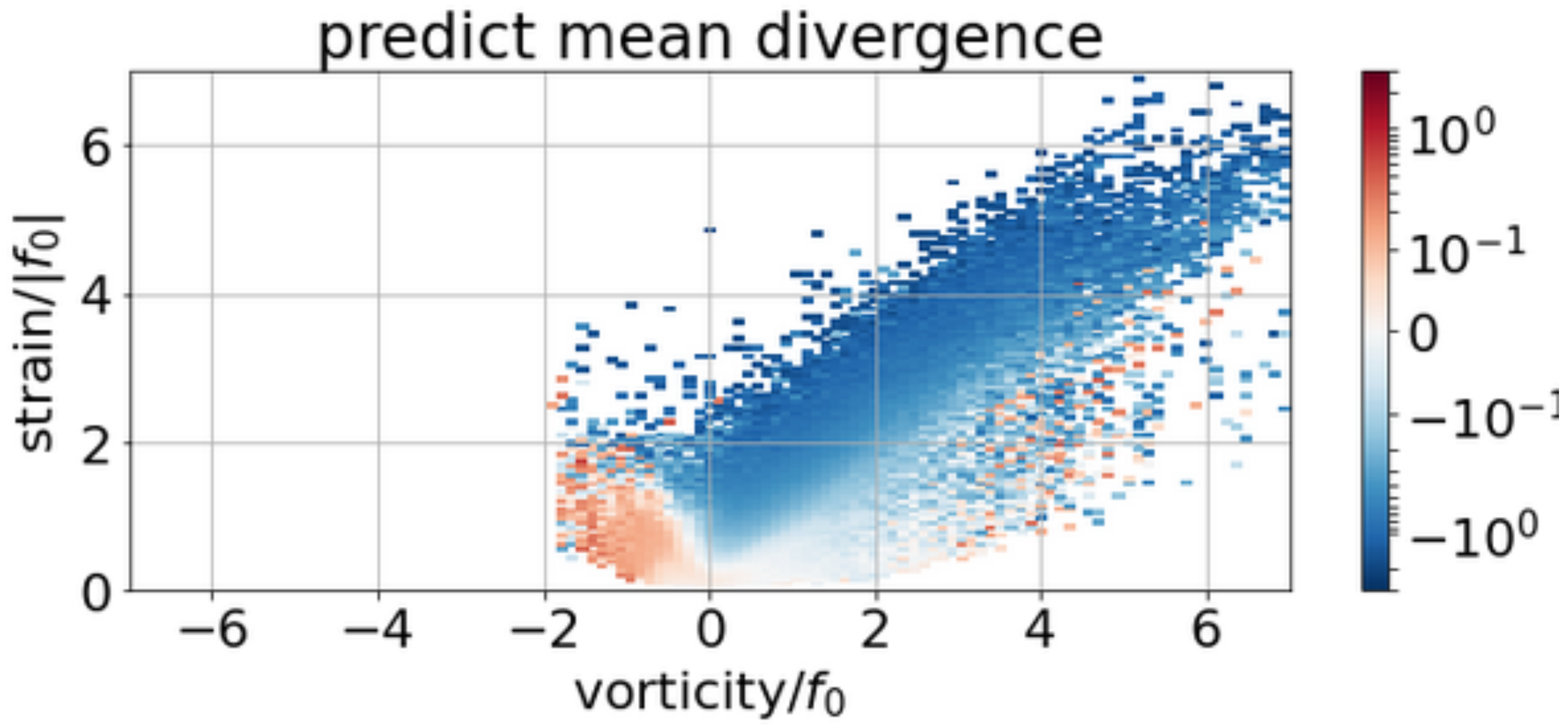
Correlation with true: 0.8
Skill: 0.2

Comparison between true and predicted surface vorticity-strain JPDF

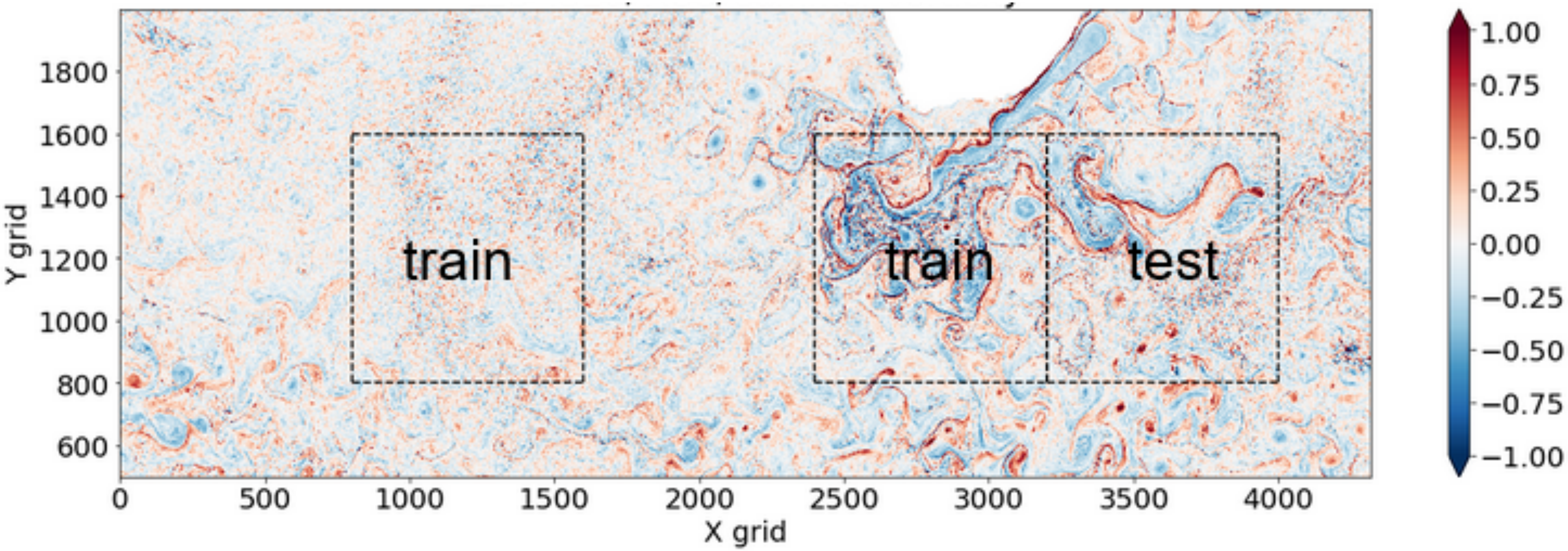


Comparison between true and predicted mean surface divergence (conditioned on surface vorticity and strain)





Try it with LLC4320 winter data (from Spencer et al)



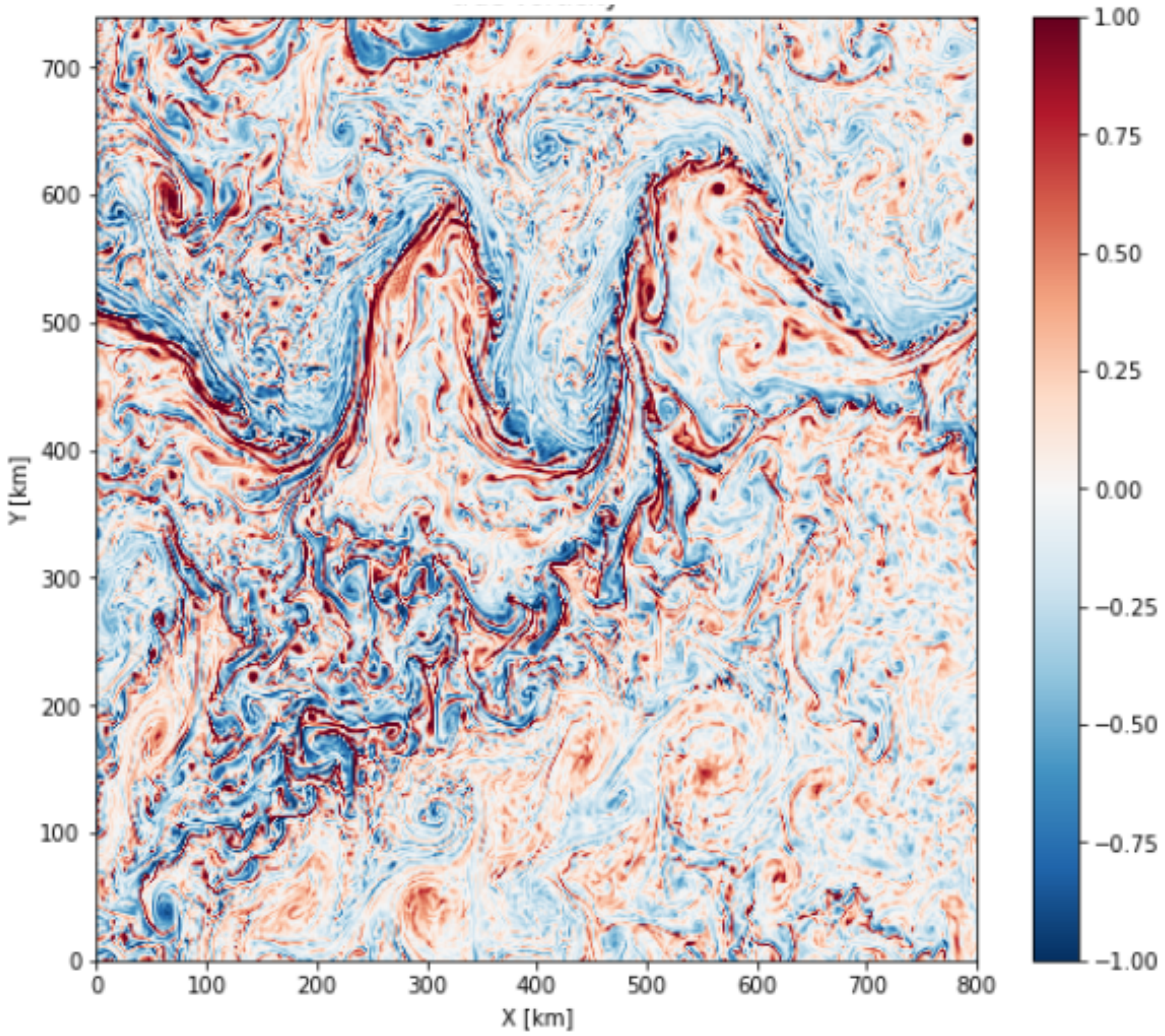
- 1 month of hourly snapshot data from LLC 4320 winter (randomly shuffled when training, so assume no time information learned)
- Day 0~25 for training, day 26~30 for testing
- Each box around 20 degree by 20 degree (800x800 grid points)
- No latitude/longitude information used during training
- Split to 64x64 non overlap regions for training
- During prediction, predict every 64x64 regions but with overlap

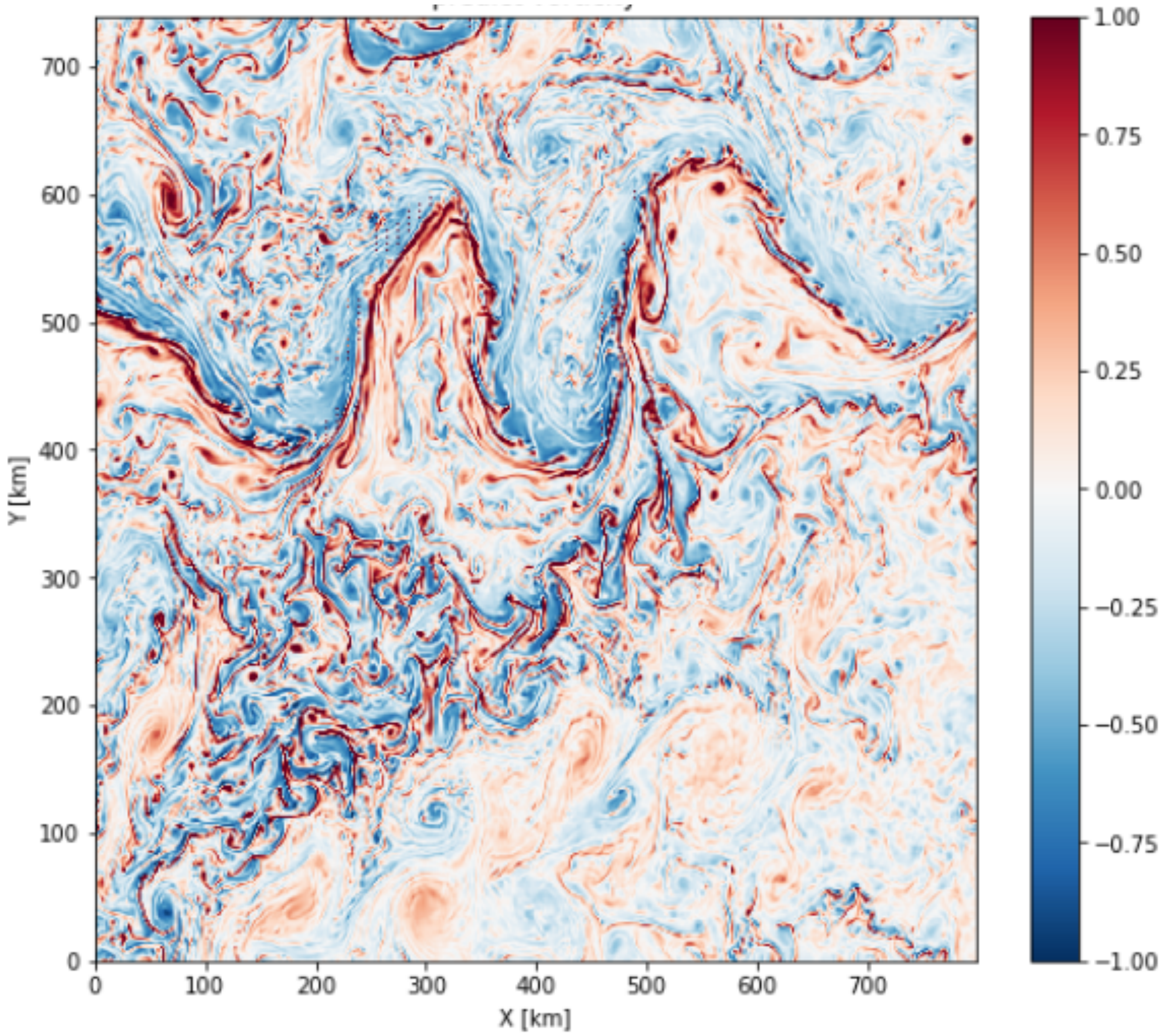
Results

True

Predicted

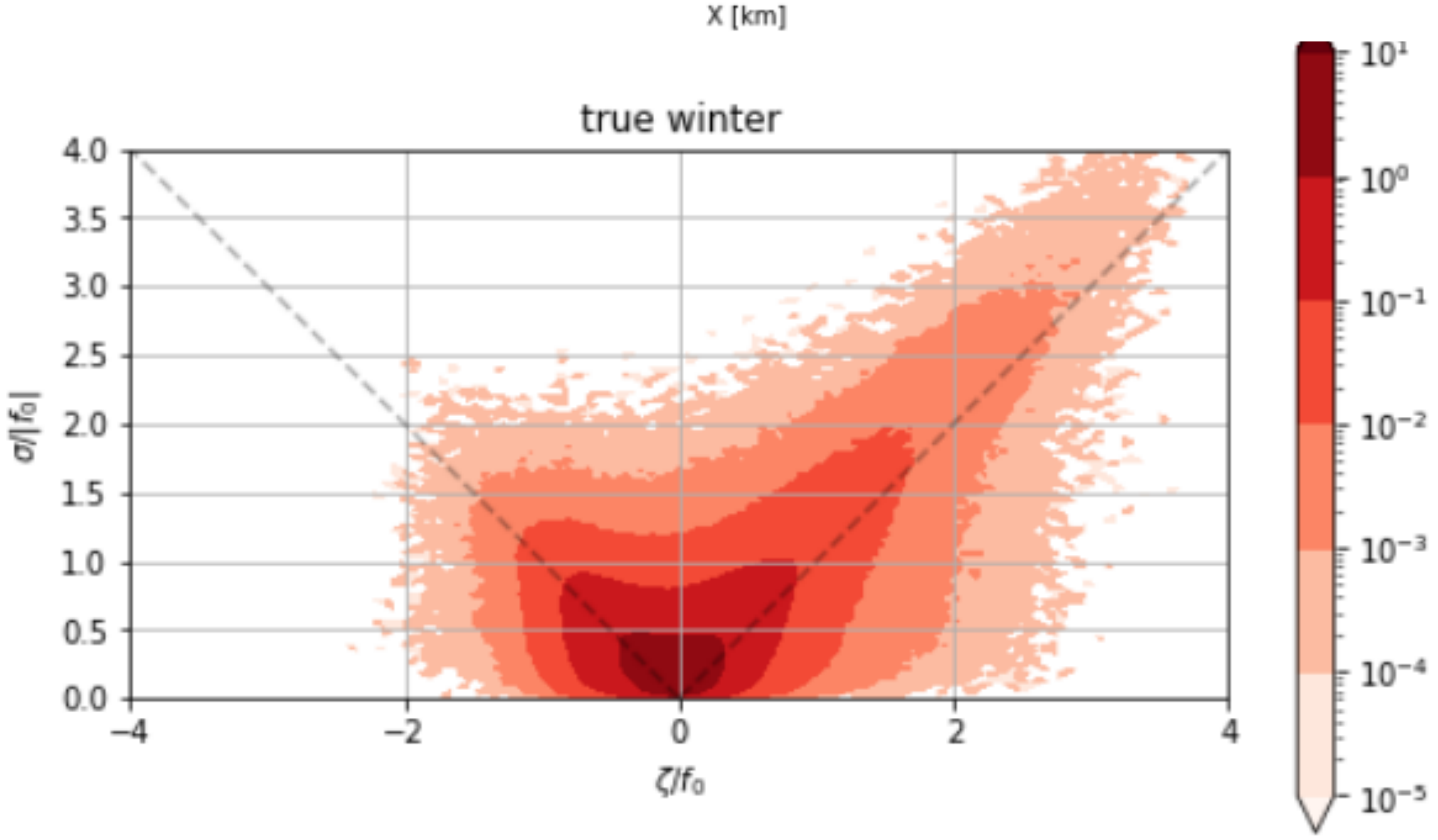
Vorticity

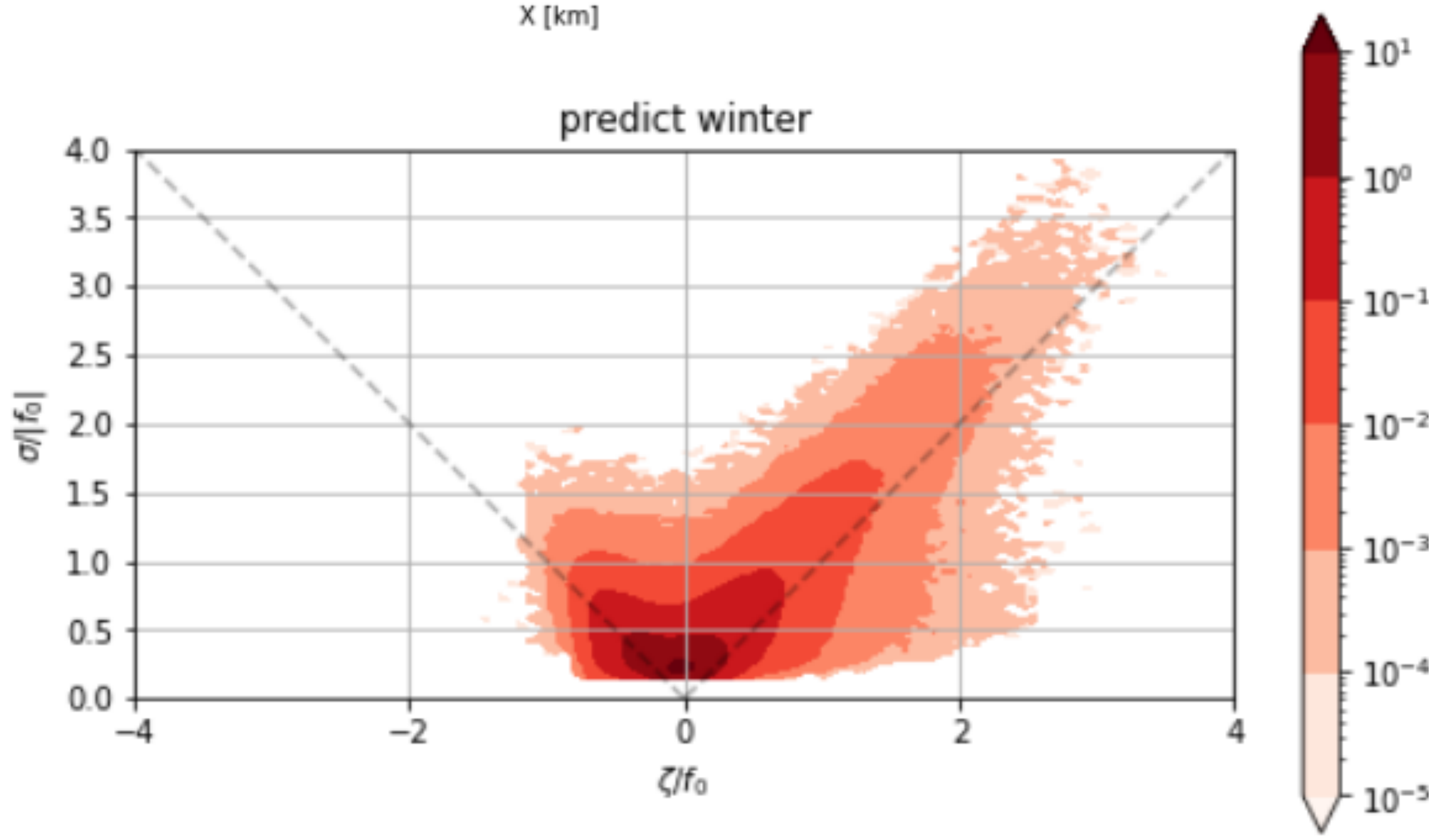




Correlation: 0.9
Skill: 0.54

Vort-strain JPDF





Summary

- Vorticity-strain joint PDF **increasingly asymmetric as resolution is increased**
- Additional high-strain, high-vorticity points due to **new small-scale features**
- Vertical flux below ML, conditioned on vorticity & stain, is **increasingly downward as resolution is increased**
- Taxonomy and scale dependence of vorticity-strain-divergence statistics indicates **this additional downward flux is due to small-scale convergent fronts that penetrate ML base, despite high stratification**
- Distinct signature of waves on JPDFs suggests they may be useful in extracting transport-active flow from surface observations (if we have velocity...)
- CNNs show skill in recovering surface velocity statistics from SSH, when waves are minimal, or filtered
- **Need new postdoc**