Reconstructing dynamics from sea surface height using neural networks

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Goal

Develop methods to infer vertical transport from SWOT SSH: need wave-free frontal divergence

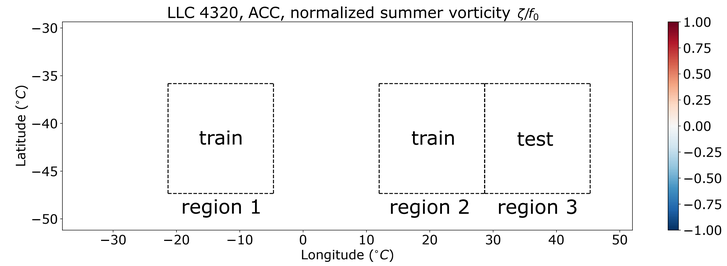
Results & Approach

- SWOT is beating expectations, observing true submesoscale
- At these scales, inertia-gravity waves (IGWs) and frontogenetic (FG) flows reduce the accuracy of geostrophy
- IGWs don't contribute to vertical transport [B18]
- FG flows do contribute to vertical transport [B18, B21]
- Lack dynamics-based model to infer FG flow from SSH
- But if vorticity ζ, strain σ, divergence δ are known, JPDFs parse flows into structures [B21]

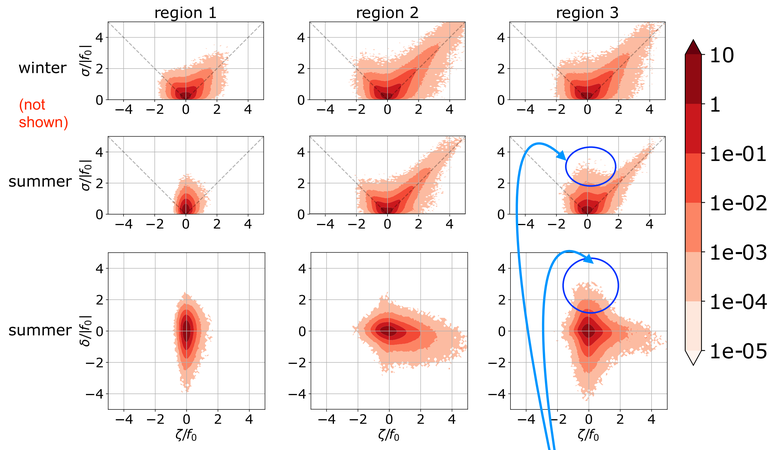
Strain:	$\sigma = \sqrt{(u_x - v_y)^2 + (u_y + v_x)^2}$
Vorticity:	$\zeta = v_x - u_y$
Divergence:	$\delta = u_x + v_y$

➜ Use Convolutional Neural Networks (CNN) to learn velocity statistics directly from SSH [X23]

Region from LLC4320 used for CNN



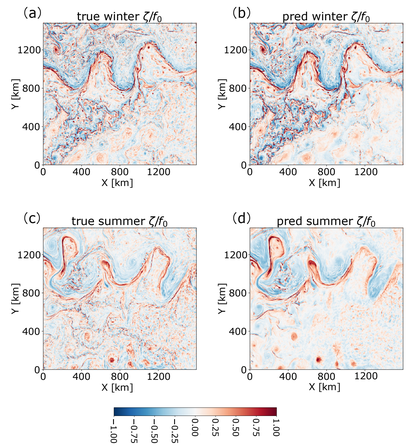
Vorticity, strain and divergence from "train" regions used in UNET



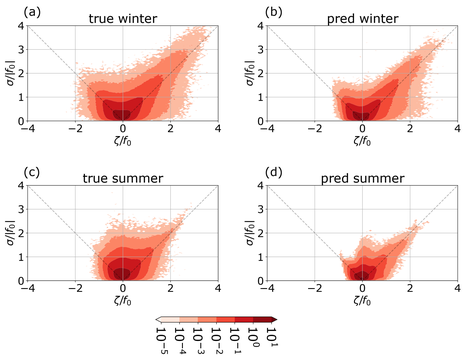
JPDFs of vorticity, strain, divergence from 3 regions for summer (shown above) and winter (not shown, but same regions), from LLC4320 simulation

True vs UNET predicted ζ & σ

True and UNET-predicted fields for region 3 (test), in summer (wavier) and winter (less wavy)

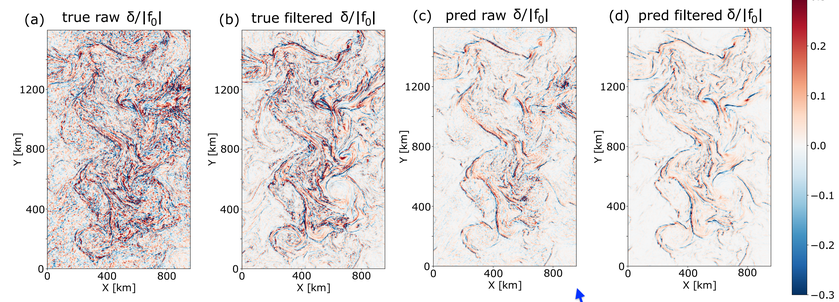


Vorticity-strain JPDFs, true and predicted, for summer and winter in region 3



True vs UNET predicted δ

True and UNET-predicted divergence in winter for region 3, using both raw input and Lagrangian-IGW-filtered velocities ([J23] and next poster!)

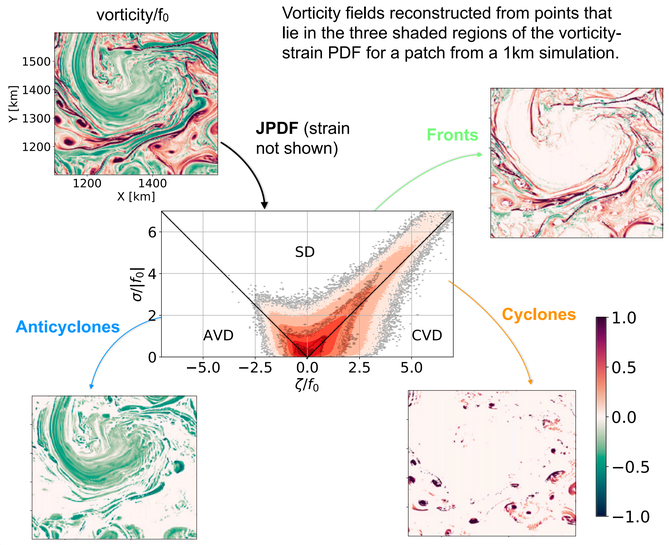


Can be seen from divergence computed from SW dispersion relation for IGWs: two branches (+/-) of frequency selected randomly result in unlearnable random field

$$\delta = -\frac{\omega m^2}{N^2}\hat{p}\sin(kx + ly + mz - \omega t)$$

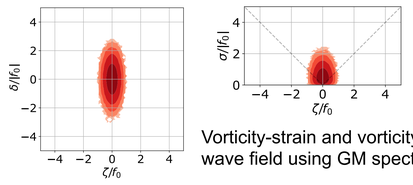
Even without pre-filtering waves, UNET learns nearly IGW-free divergence field!

Structure from ζ & σ



Vorticity fields reconstructed from points that lie in the three shaded regions of the vorticity-strain PDF for a patch from a 1km simulation.

Synthetic wave field JPDFs

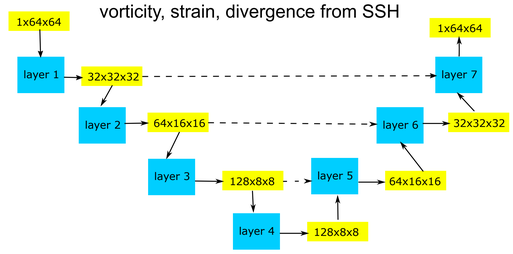


Vorticity-strain and vorticity-divergence JPDFs from synthetic surface wave field using GM spectrum and local stratification

Summer fields with shallower mixed layer have stronger IGW signal. Appears as high strain/low vorticity bump in JPDFs.

UNET Neural Network

Network architecture used to learn vorticity, strain, divergence from SSH



Blue: convolutional layers

Yellow: input, intermediate and final outputs;

Numbers: channels, height, width;

Solid lines: delivery of data to next layer;

Dashed lines: data is re-used

References

- [X23] Xiao, Q., D. Balwada, S. Jones, M. Herrero-Gonzalez, S. Smith, R. Abernathey, 2023: "Reconstruction of Surface Kinematics from Sea Surface Height Using Neural Networks". Accepted for *JAMES*.
- [J23] Jones, S., Q. Xiao, R. Abernathey, and S. Smith, 2023: Using Lagrangian filtering to remove waves from the ocean surface velocity field. *JAMES*, **15**
- [B21] Balwada, D., Q. Xiao, S. Smith, R. Abernathey and A. Gray, 2021: Vertical fluxes conditioned on vorticity and strain reveal submesoscale ventilation. *J. Phys. Oceanogr.*, **51**, 2883-2901
- [B18] Balwada, D., S. Smith, and R. Abernathey, 2018: Submesoscale vertical velocities enhance tracer subduction in an idealized Antarctic Circumpolar Current. *Geophys. Res. Lett.*, **45**