Internal tidal extraction:

- Challenges: when/why is extracting the IT difficult? (motivation from idealized simulations) -- 3 min

Jeffery Uncu, Nicolas Grisouard

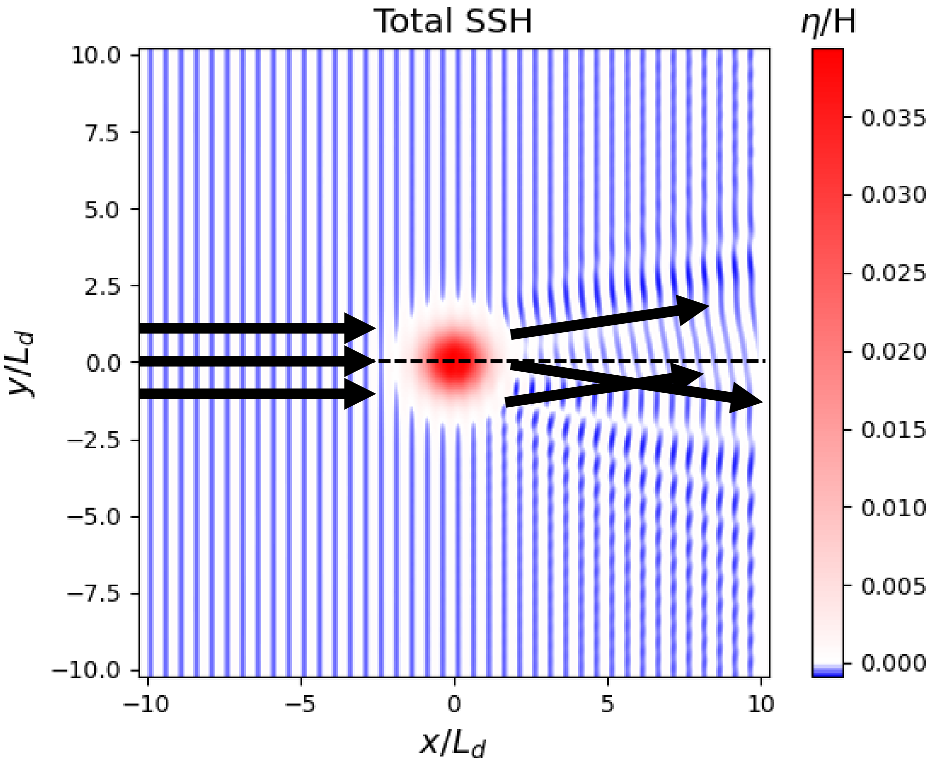
- Hopes:Deep learning method -- 5 min

Han Wang, Nicolas Grisouard, Hesam Salehipour, Alice Nuz, Michael K.M. Poon, Aurélien L.Ponte, Brian Arbic

Parameter sweep of $\boldsymbol{Ro, Bu, \Lambda}$

Experiments Conducted

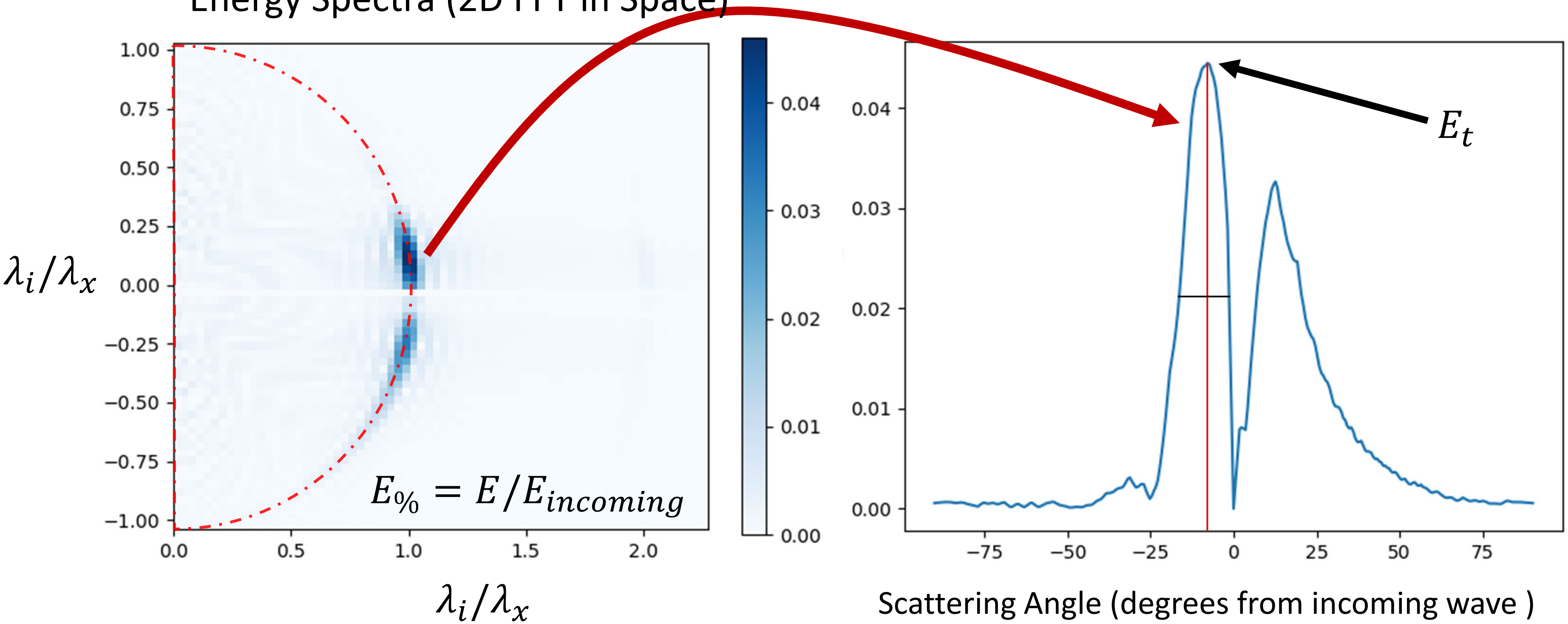
Ro	$U_v/(Lf)$ ζ_{max}/f	0.01/0.10 0.02/0.22 0.04/0.53 0.08 /1.27
Λ	L/λ	1,1.5,2,3,4
Bu	$(L_d/L)^2$	0.9, 1, 1.1, 1.5



One Layer Shallow Water Model

Redistribution of wave energy

Energy Spectra (2D FFT in Space)



Energy Transfer Function

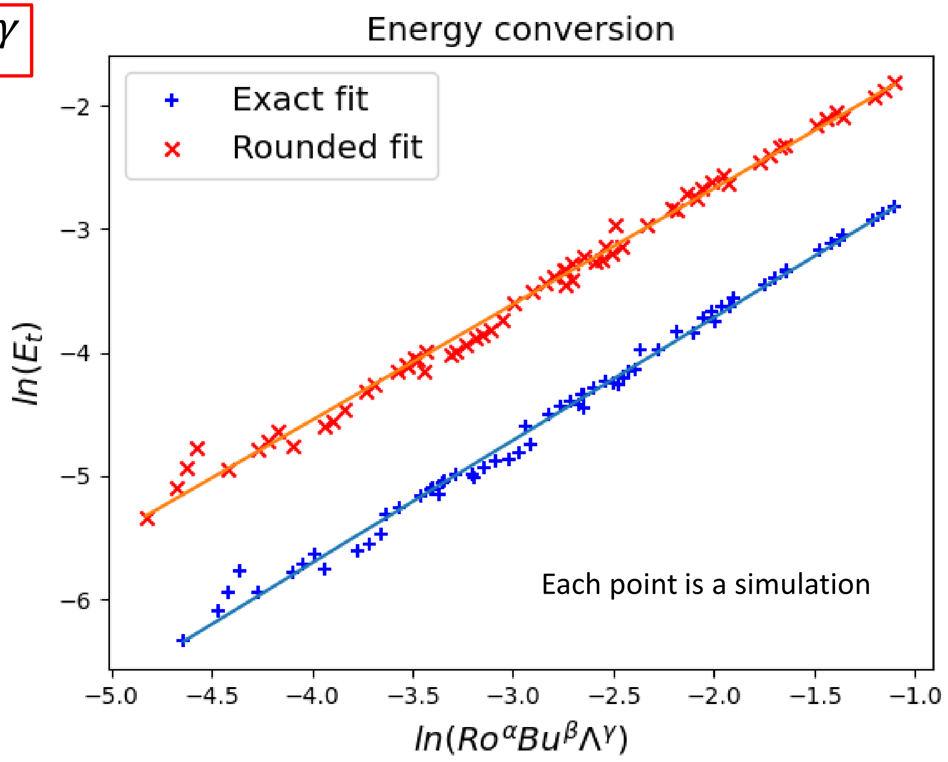
$\boxed{\text{Guess Power Law, } E_t = A Ro^{\alpha} Bu^{\beta} \Lambda^{\gamma}}$

$$\alpha = 0.96 \pm 0.01,$$
$$\beta = -0.54 \pm 0.02$$
$$\gamma = 0.91 \pm 0.01$$

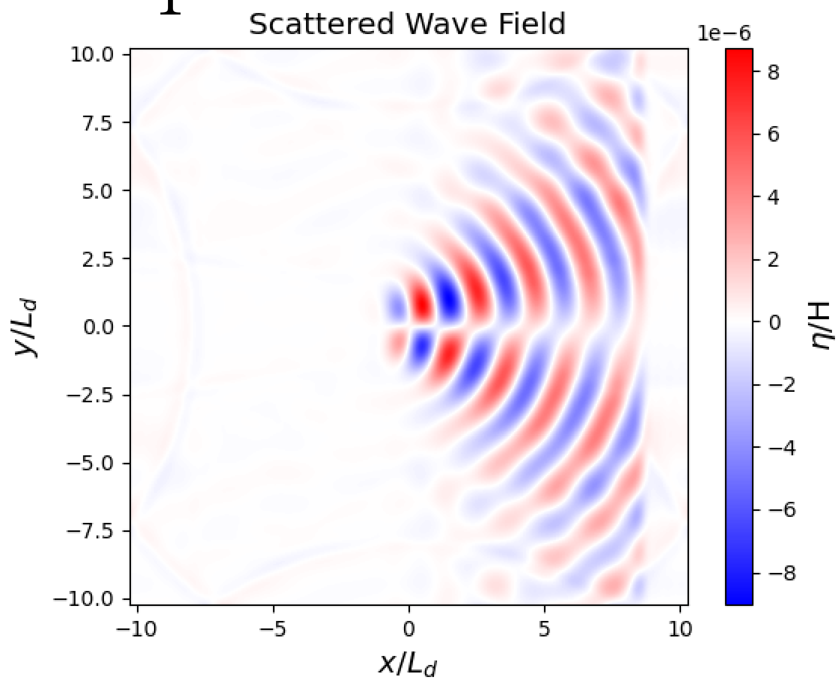
$\alpha = 1, \beta = -0.5 \quad \gamma = 1,$

then

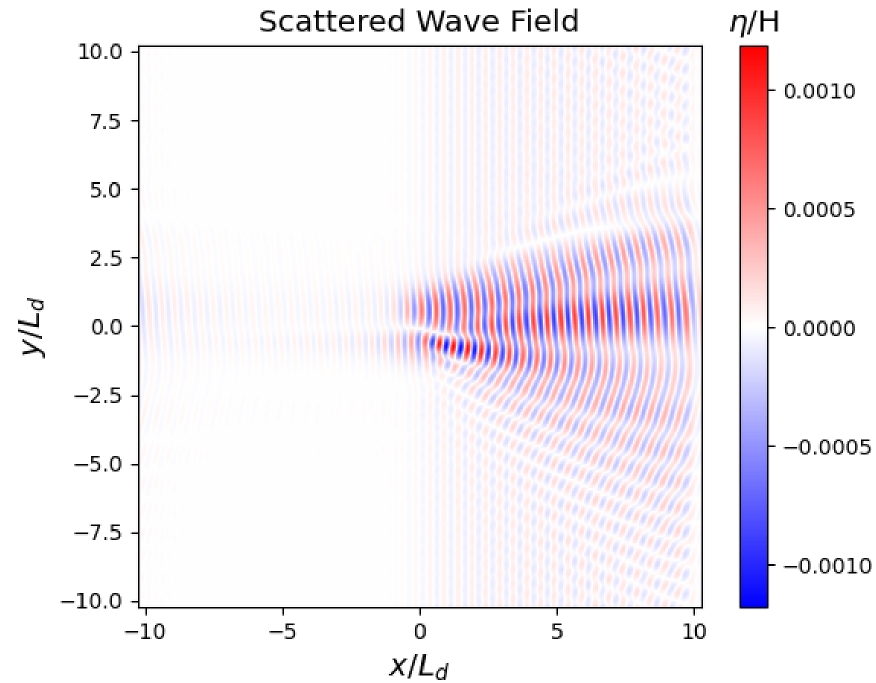
$$E_t \propto \frac{Ro\Lambda}{\sqrt{Bu}} = \mathrm{Fr}\,\Lambda$$



$Ro = 0.04/0.53, \Lambda = 1$



$Ro = 0.15/2.1, \Lambda = 4$



- Phase dislocation
- Scattering pattern changes with Ro

When/Why is extracting the IT difficult?

Stronger energy transfers $E_t \propto \frac{Ro\Lambda}{\sqrt{Bu}}$, should translate to more incoherence

Scattering patterns can become complicated with stronger vortices

Phase dislocation may hinder wave extraction

SWOT will reach submesoscale regimes

One way to get around these problems…
Machine Learning!

A machine learning approach

- Spatially 2D snapshots of SSH (50 km wide swaths) -> image-based methods to extract ITs
- Machine learning algorithm: conditional Generative Adversarial Network (cGAN)
- With SWOT in mind, but working on idealized simulations

Published (GRL): 10.1029/2022GL099400
"A Deep Learning Approach to Extract Internal Tides Scattered by Geostrophic Turbulence"

conditional Generative Adversarial Network

cGAN in a nutshell

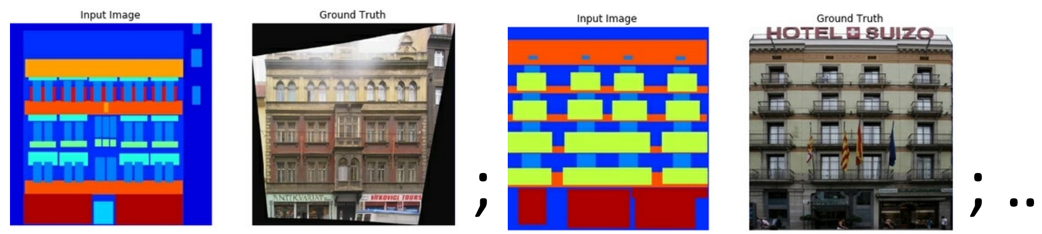
- Learns to generate an image conditioned on an input image

  (“conditional Generative”)

- Generator and Discriminator fight against each other (“Adversarial”)

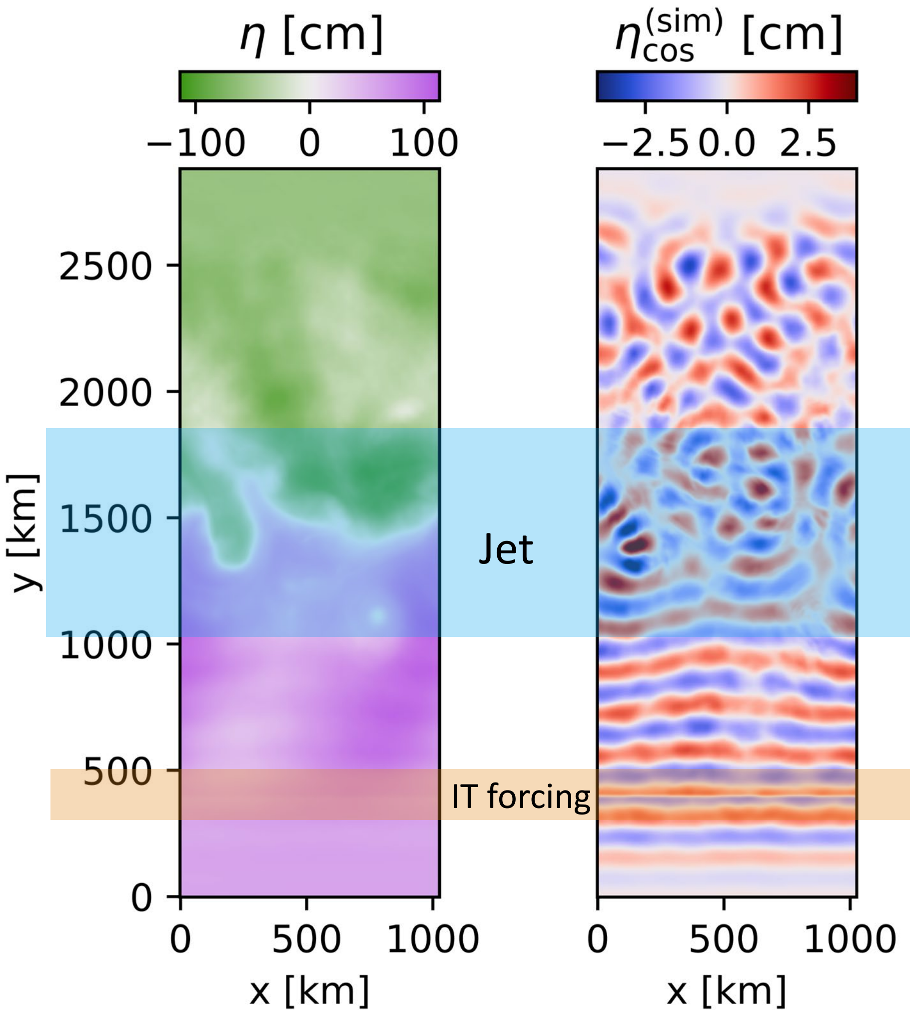
- The type of cGAN we use is based on “Pix2Pix”

Training



Testing

Isola et al. 2017

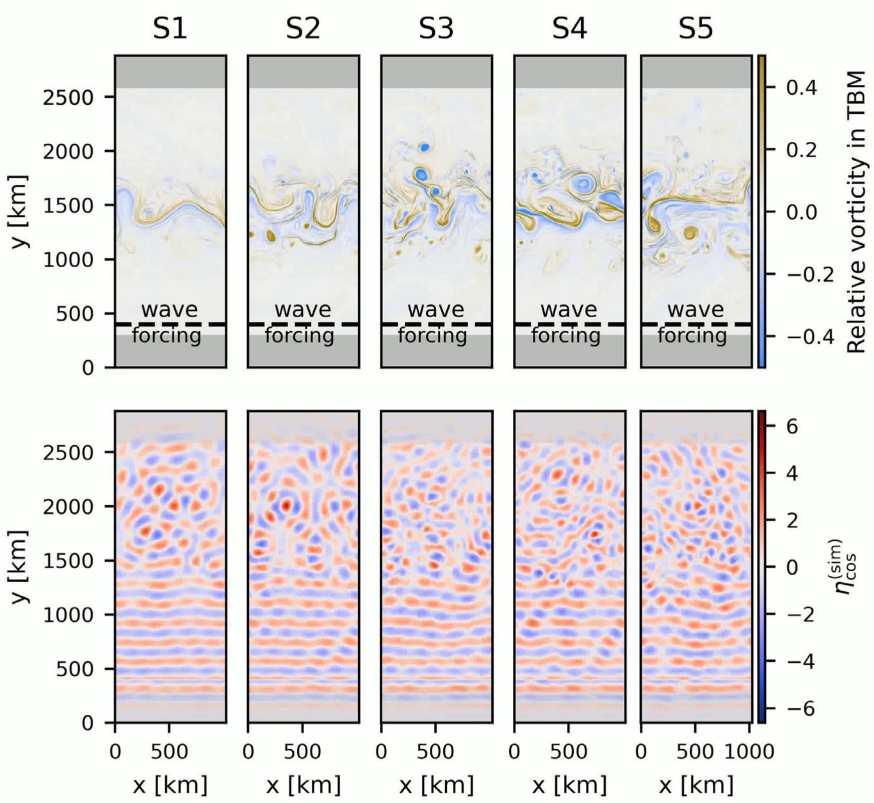


Dunpy et al. Simulation

- Low-mode IT propagate through geostrophic turbulence
- Left: η (raw SSH: all frequencies)
- Right: $\eta_{\cos}^{(\mathrm{sim})}$ SSH induced by ITs at a fixed period
- Train Pix2Pix cGAN to learn the mapping from η to $\eta_{\cos}^{(\mathrm{sim})}$
- Purely an 2D image translation problem

Dunpy, Ponte, Klein and Le Gentil, 2016

Division of train/test data



- Simulations run on different turbulence levels (S1-5)
- Train and test data contain different turbulence levels

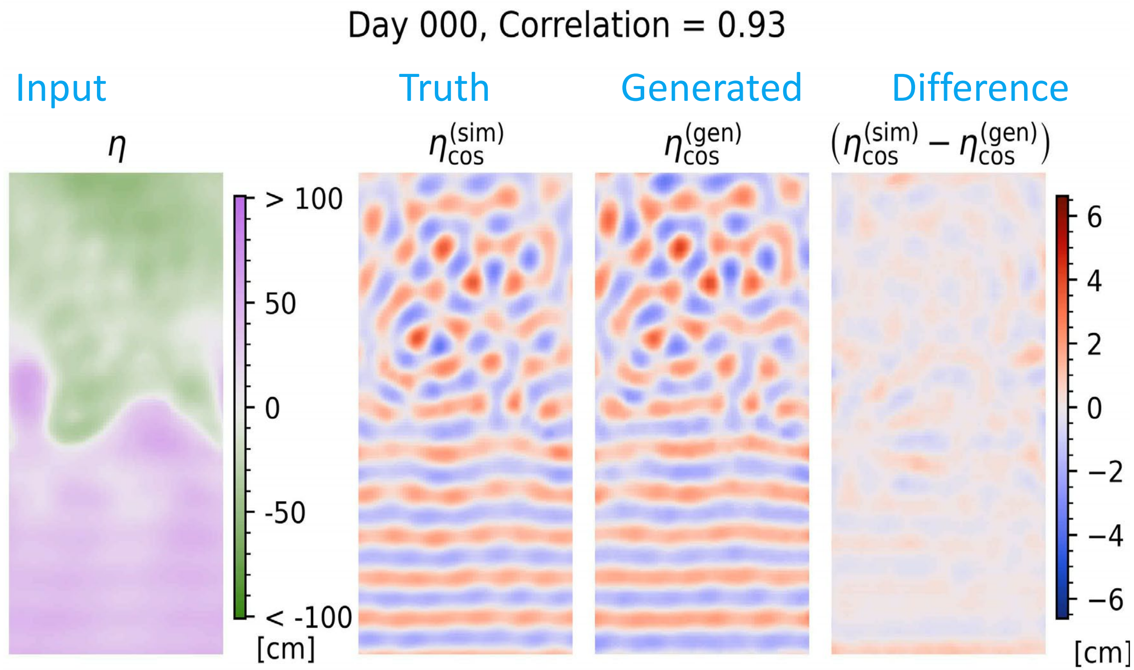
E.g. "ES1" run

Test data: S1

Train data: S2, S3, S4, S5

Repeat for ES2, ES3, ES4, ES5

Re-ordered by time: best run

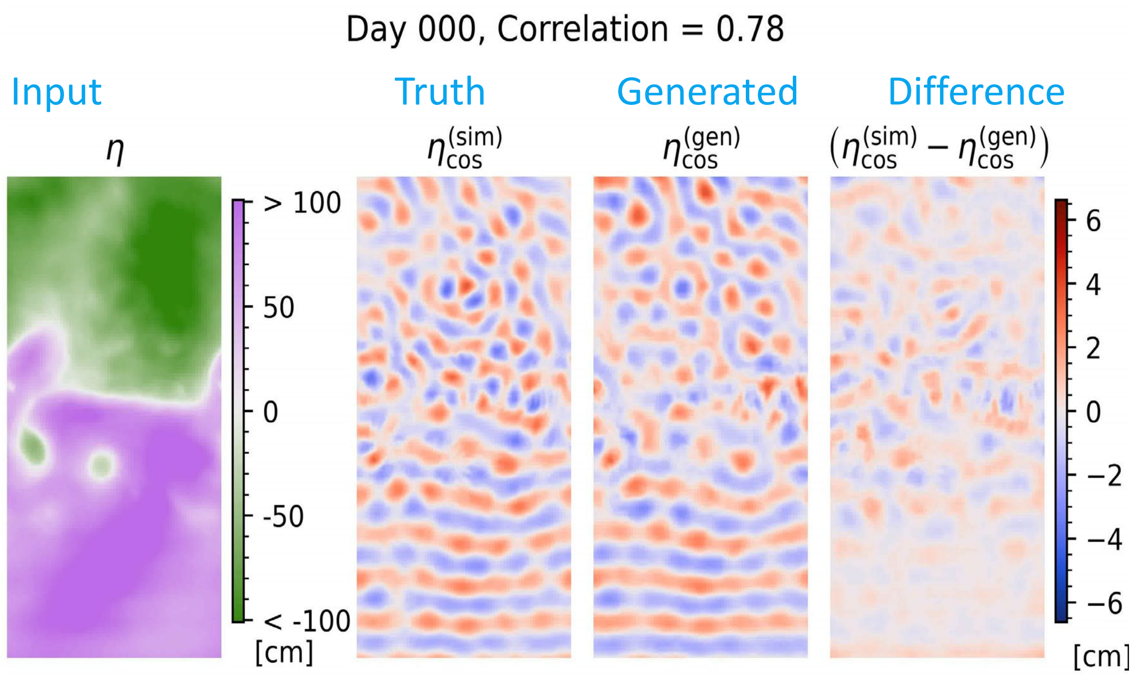


Notations:
"sim" = "from simulation" (ground truth)

"gen" = "generated" (by neural network)

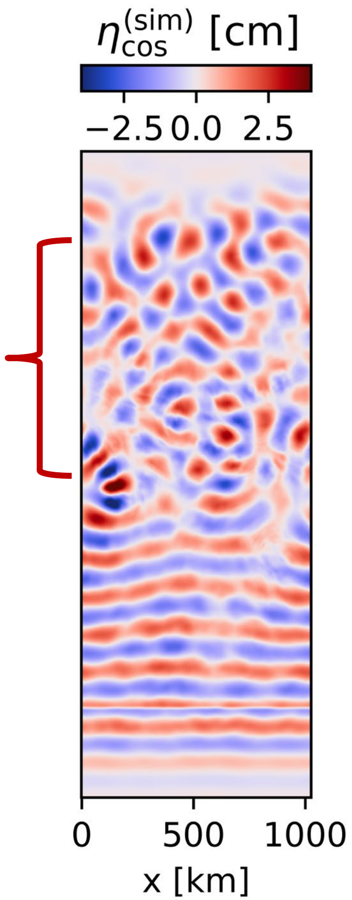
ES1: Train on S2, S3, S4, S5.
Tested on S1

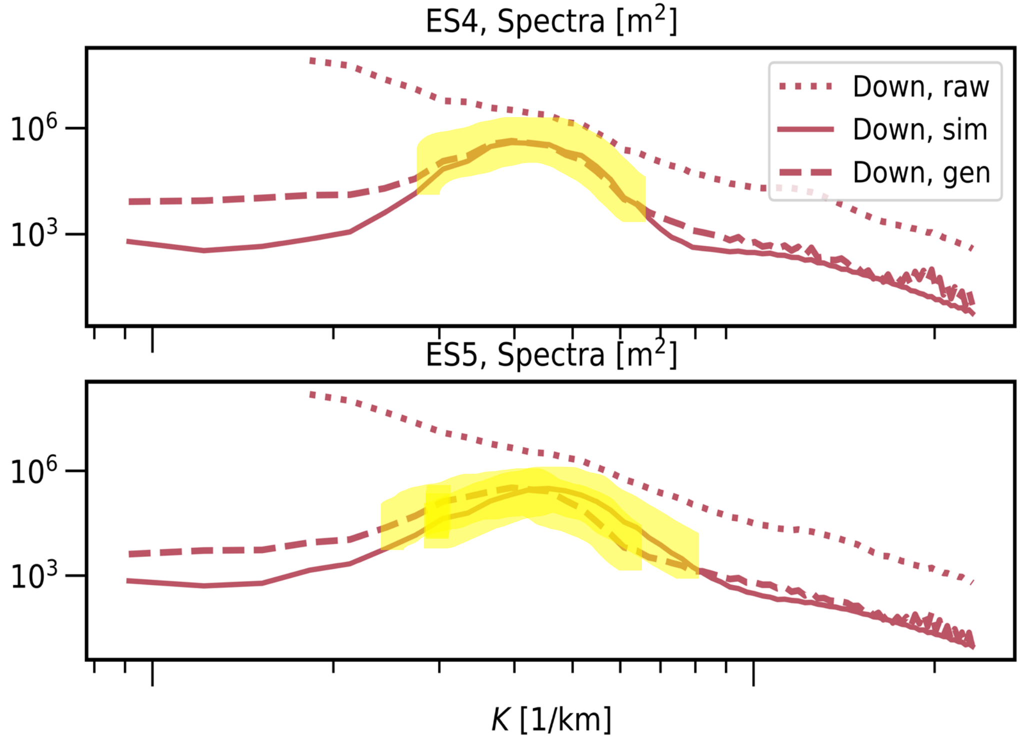
Re-ordered by time: worst run



ES5: Train on S1, S2, S3, S4.
Tested on S5 (extreme case)

ES4 v.s. ES5





The only run where the bump shifts (qualitative difference)

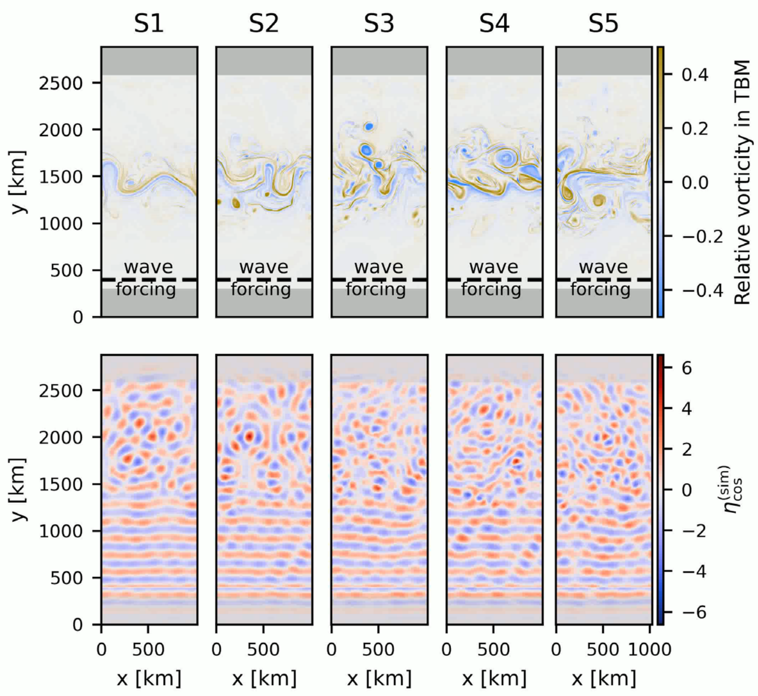
Causes and solutions

- Main cause: Complexity of patterns as turbulence levels increases
- ES4 performs much better than ES5

as it contains overly turbulent data during training

Test data: S4

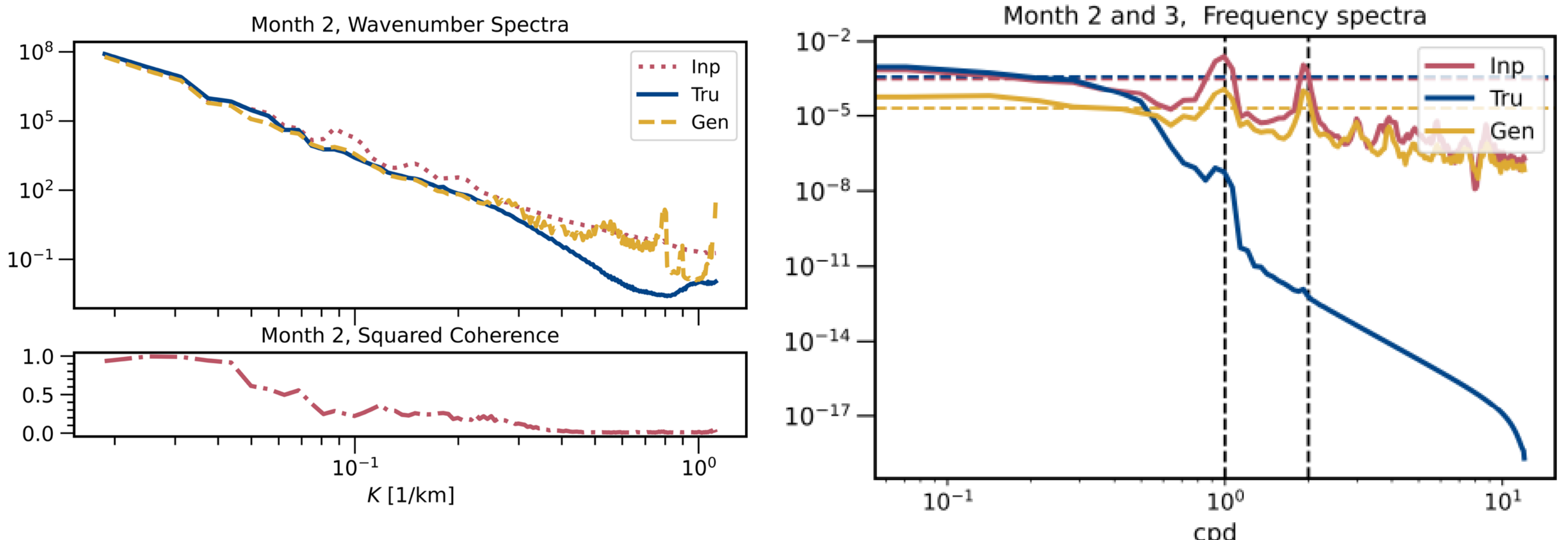
Train data: S1, S2, S3, S5



Application to HYCOM outputs

- Work in progress
- Current results: wavenumber spectra good, frequency spectra bad

Test data behavior in Southeast Pacific (28S, 90 W); Truth=low-pass field



- Trying: include Barotropic tides in inputs; wavenumber forcing; other cGANs; other regions in HYCOM,……

Summary

- Neural network to extract ITs from an idealized numerical simulation
- Great on Dunpy et al. simulations even without temporal info
  - Tested on turbulence levels not seen during training
  - High performance in both deterministic and statistical metrics
  - Worse at ES5; possible fix proposed
- Work in progress: HYCOM simulations

Thank you!

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