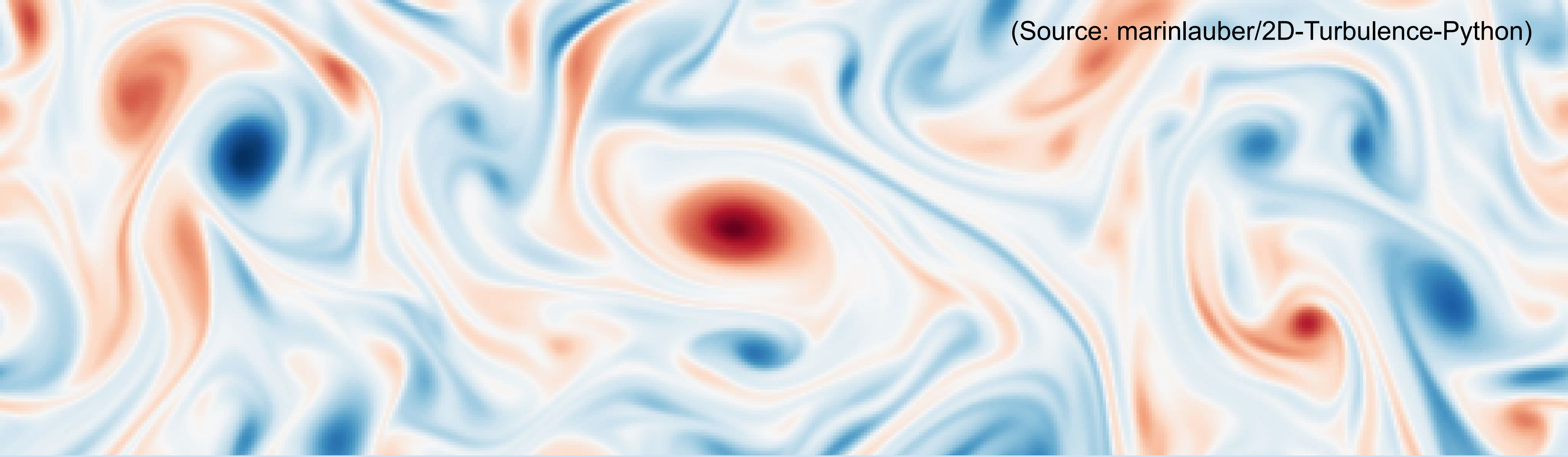

(Source: marinlauber/2D-Turbulence-Python)

Capturing Fine-Scale Turbulence in Planet-Forming Disks Using CNN-Augmented Fluid Solvers

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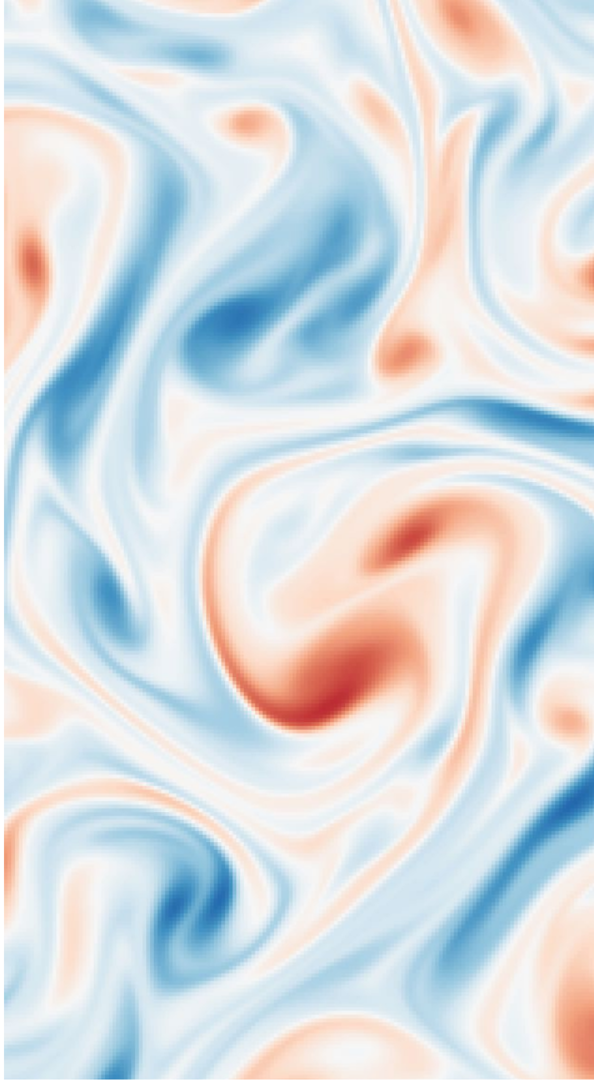
ASNUM 15/12/2025

Outline

1. Problem Setup
2. Methodology
3. Metrics and Results
4. Conclusion



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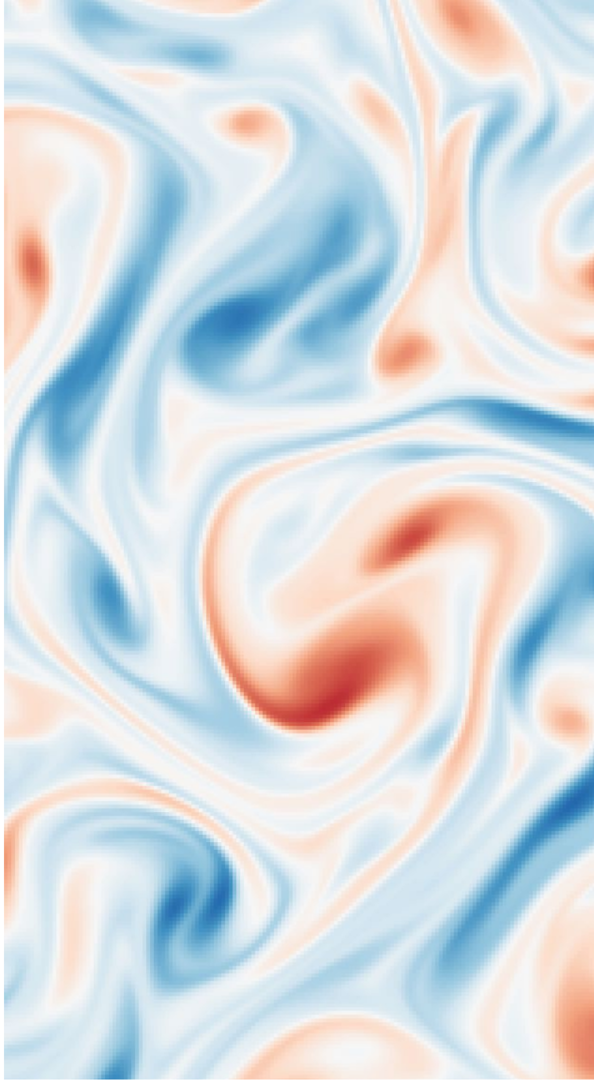
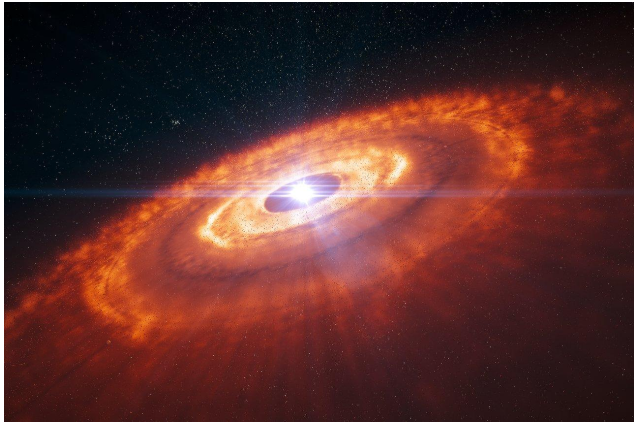
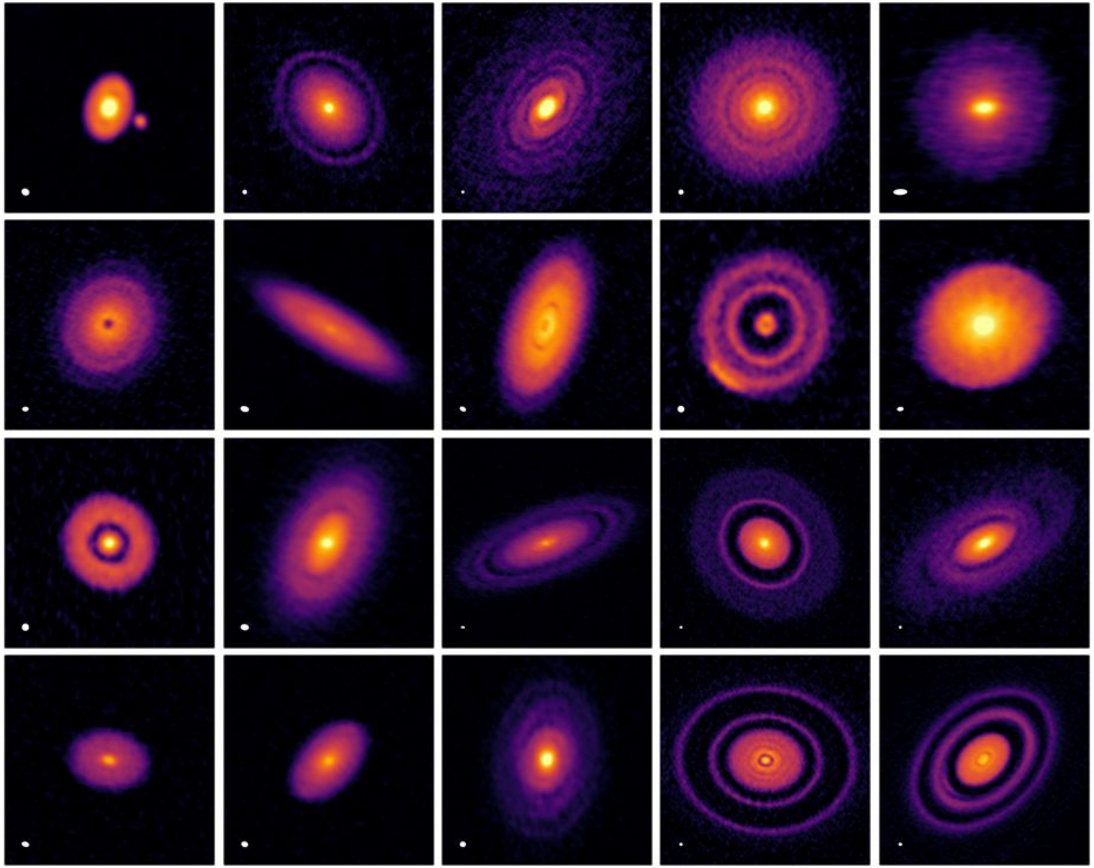


Planet-Forming Disk

- Keplerian disk around young star
- 99% gas, 1% dust



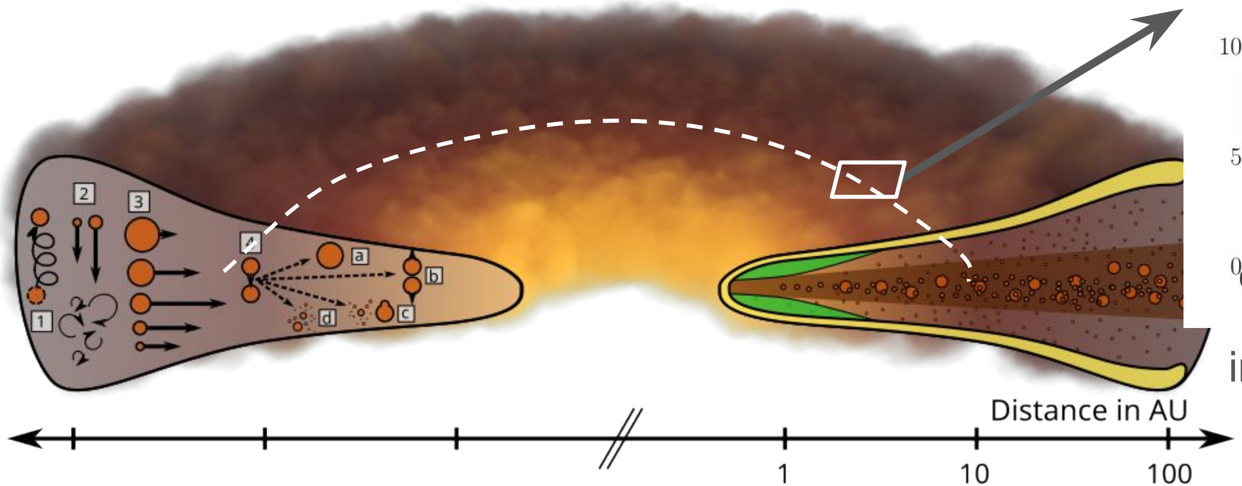
(Artist's Impression / ESO)



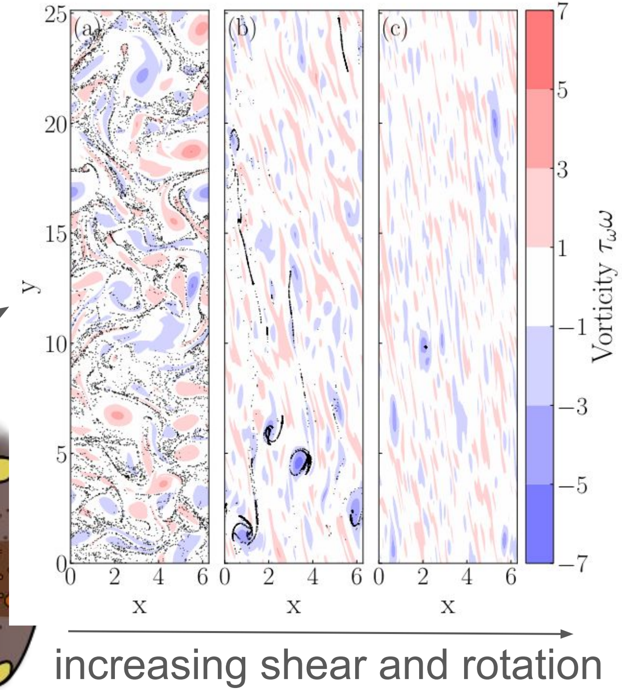
(Sean Andrews / DSHARP / ALMA)

Turbulence in Planet-Forming Disk is a Multiscale Problem

$$\boxed{\nu_T = \alpha c_s H}$$

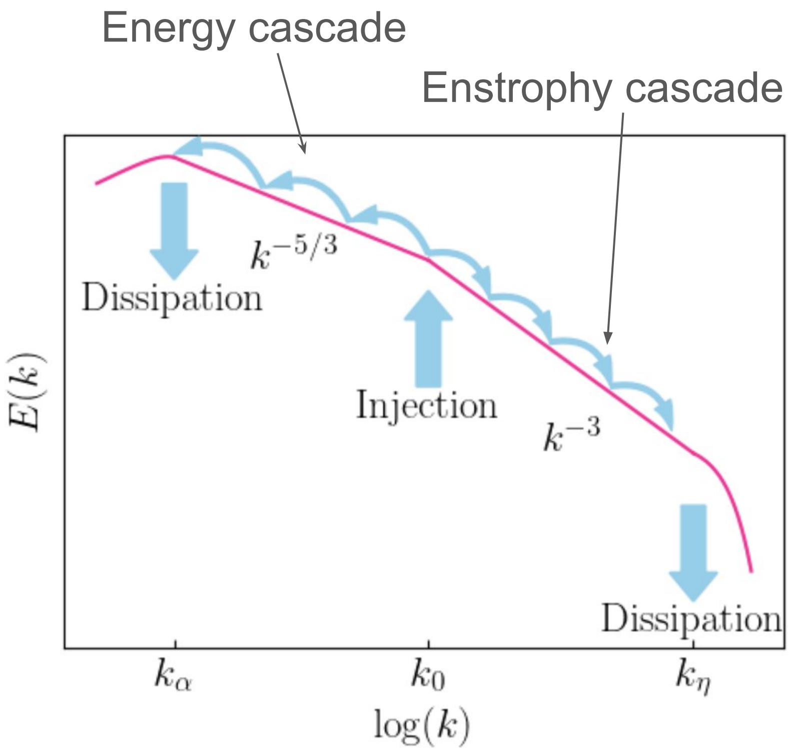


(Modified from Testi et al. 2014)



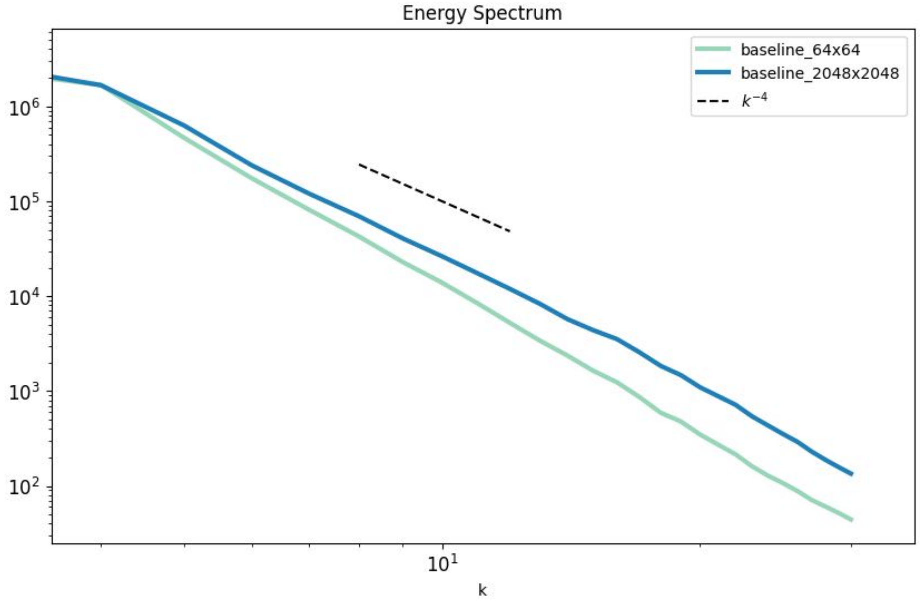
(Gerosa et al. 2023)

Turbulence Cascade



High Resolution —

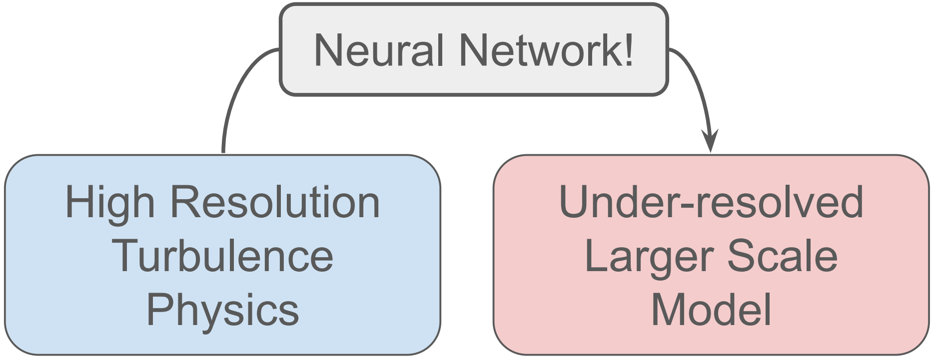
Low Resolution —



(Modified from Kochkov et al. 2021)

What we want to do?

1. Utilise suitable deep learning technique to capture small scale effect of turbulence inside a numerical solver
2. Produce fluid simulations that can resolve the effect of turbulence
3. Reduce computation cost



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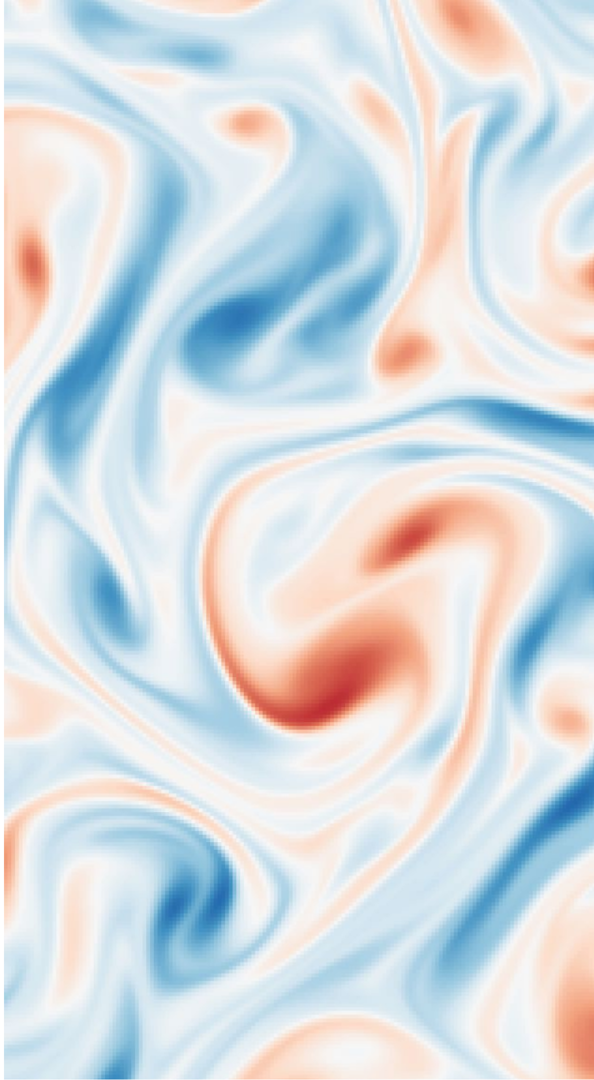
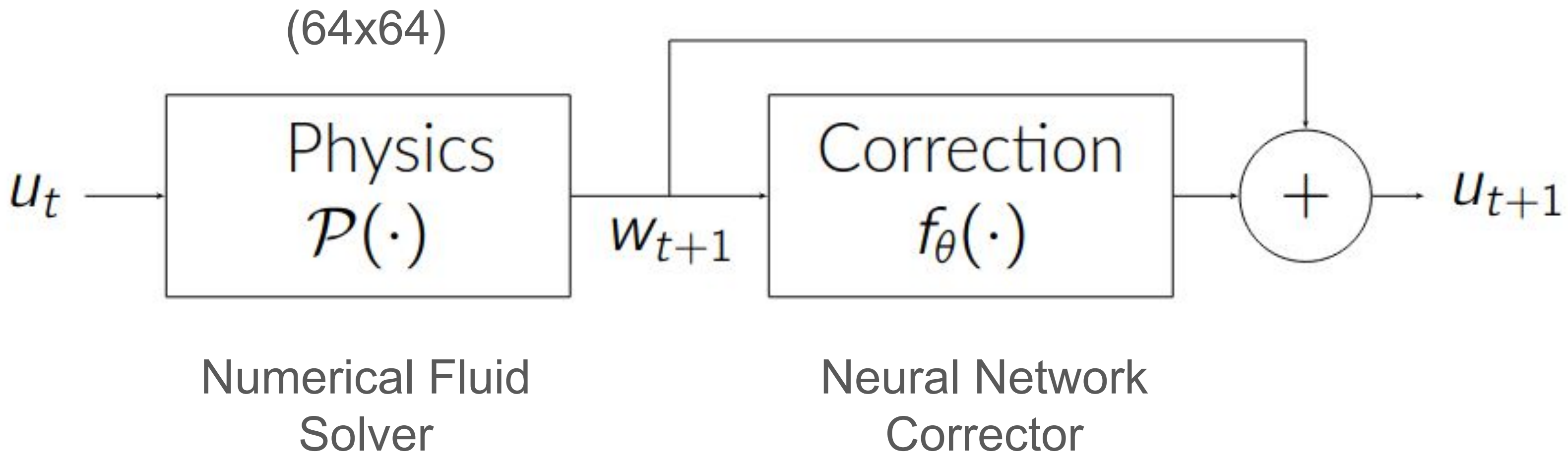


Our Proposed Solution

Inspired by Kochkov et al. 2021

For each timestep: $$u_{t+1} = \mathcal{P}(u_t) + f_\theta(\mathcal{P}(u_t))$$



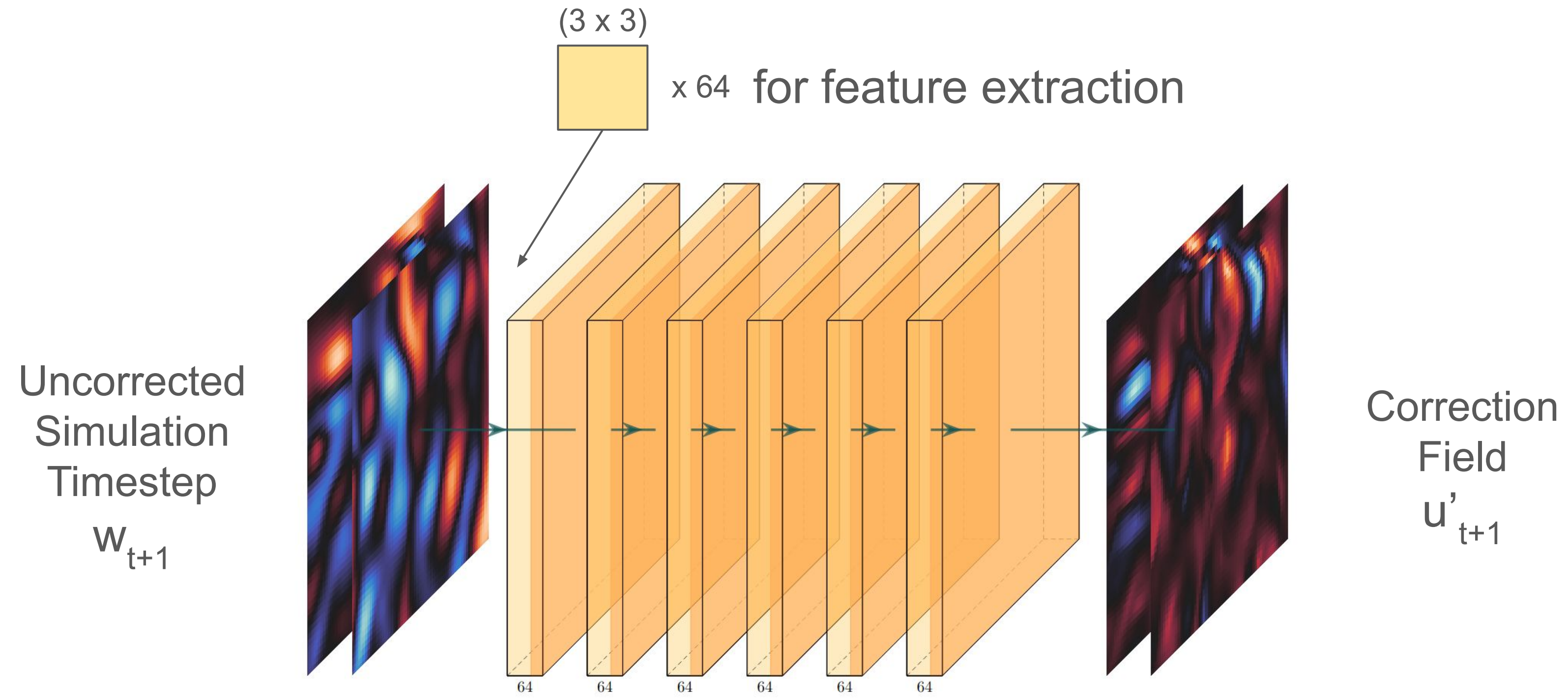
To model subgrid information and speed up simulation

What is important in a dynamic system?

Space! Time! Physics!

Space!

Convolutional Neural Network Corrector



Parameter count: 225K

How can we “teach” the neural network the correct dynamics?

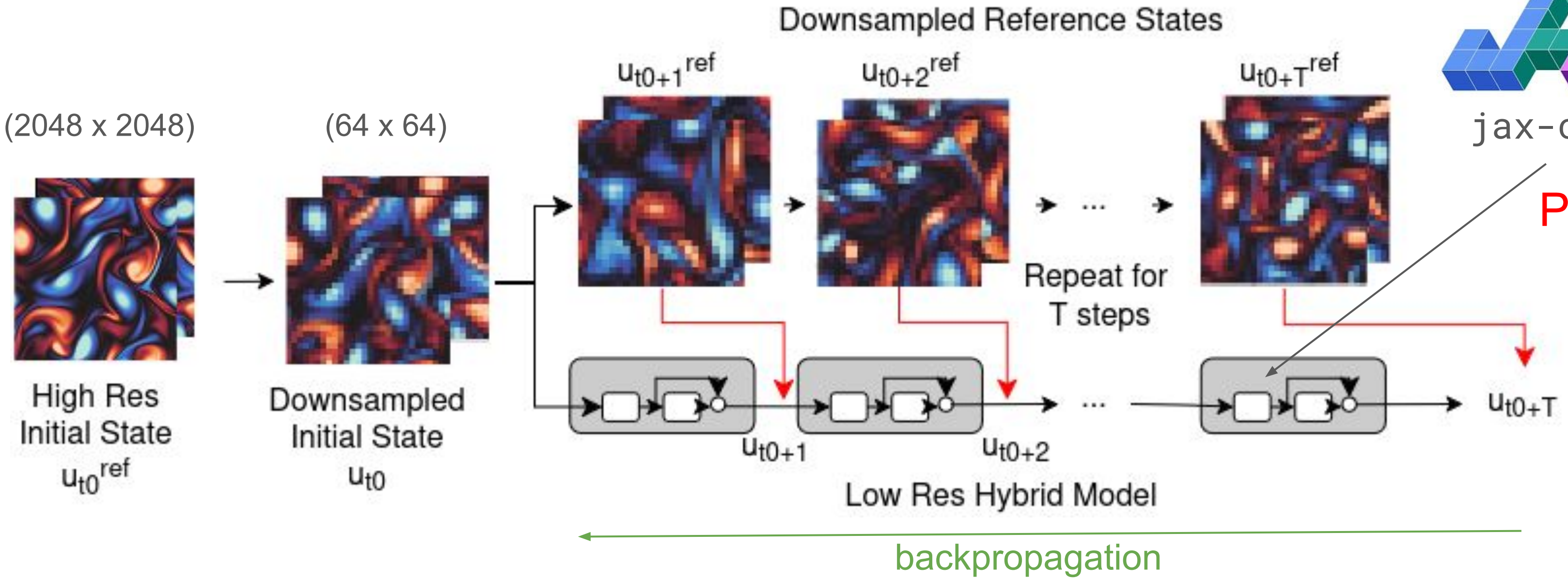
Time!

Optimizing over $$\mathcal{L}(\theta) = \sum_{\ell=1}^{M} \sum_{n=1}^{N-T} \sum_{i=n}^{n+T} (u_{i,\ell} - u_{i,\ell}^{\text{ref}})^2$$

“Solver-in-the-loop”

jax-cfd

Physics!



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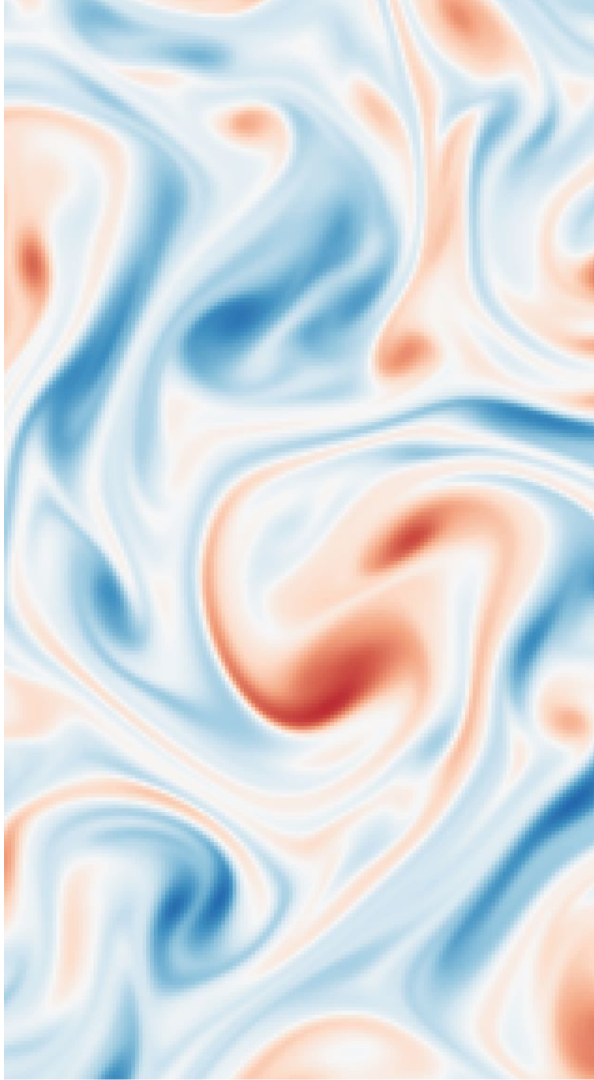
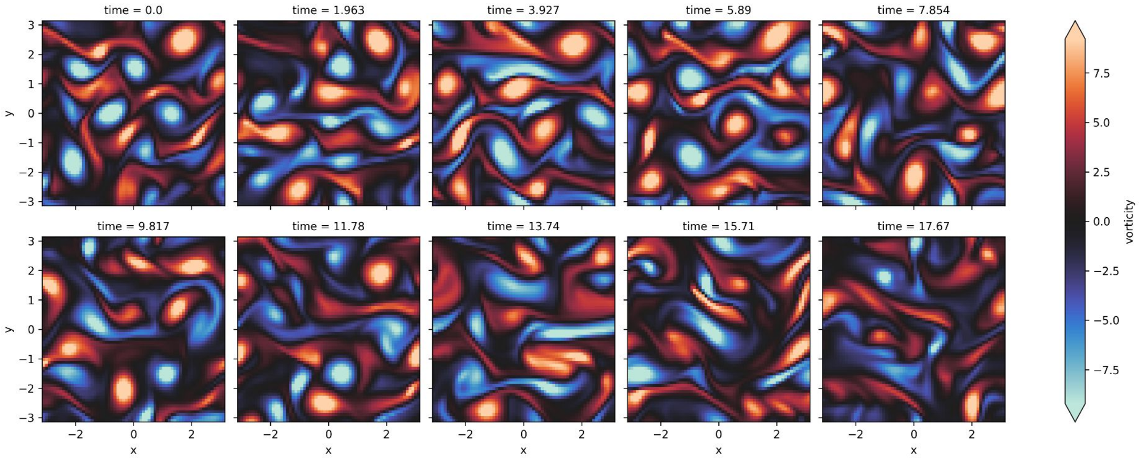


Test

Case Study: forced 2D incompressible homogeneous isotropic turbulence (HIT)

Dataset: 8 simulations of 500 timesteps initiated with different seeds (~7500 training samples)

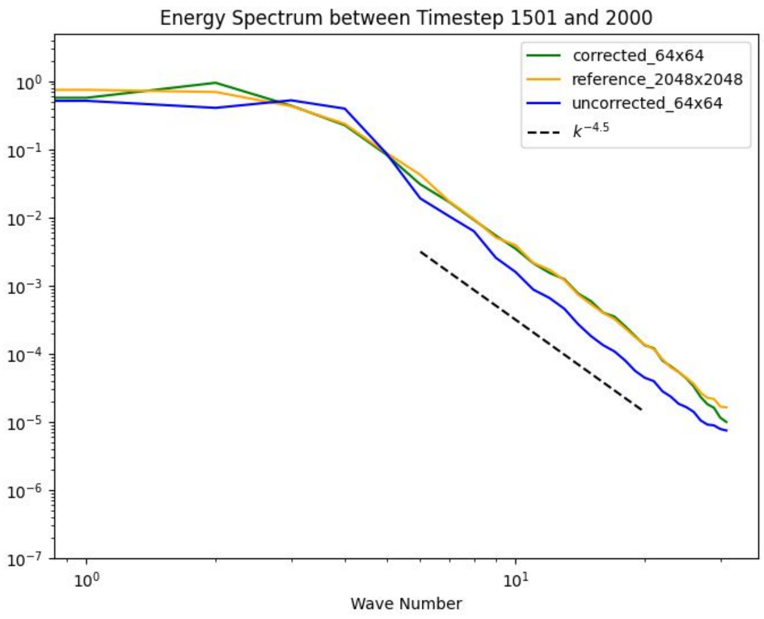


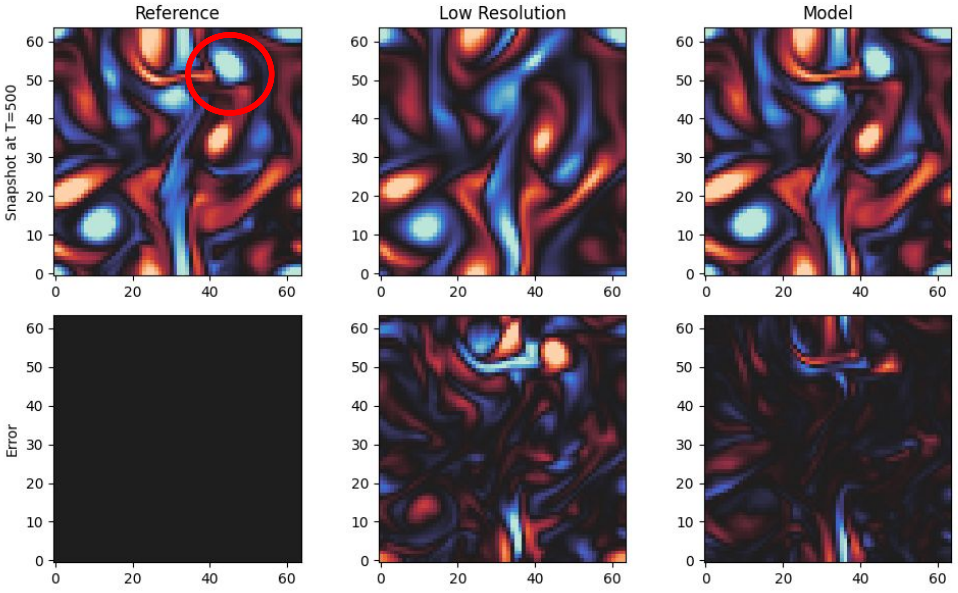
Test: simulations ran for 2000 steps (>> T)

Metrics: vorticity correlation, energy spectrum, vorticity field visualisation

Results

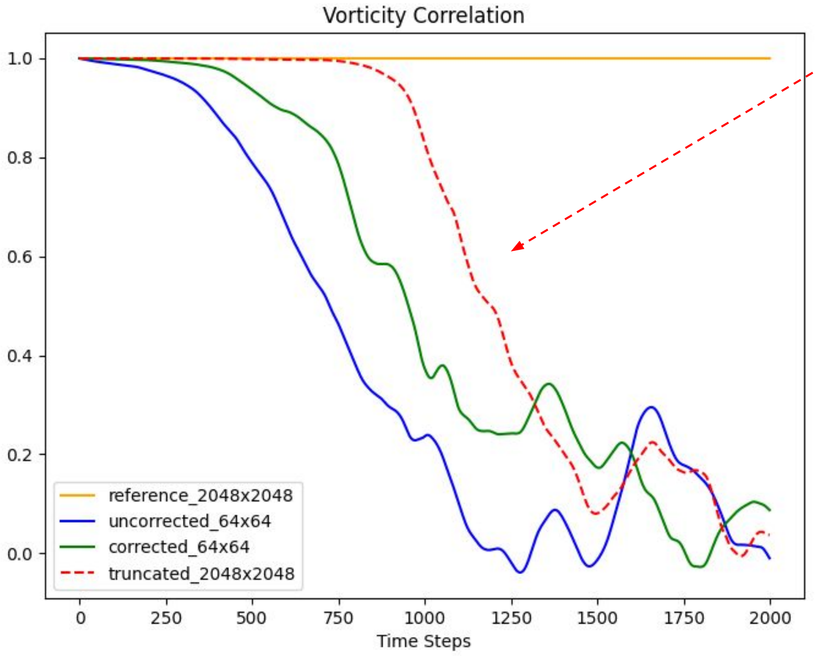
T=32, Epoch=400

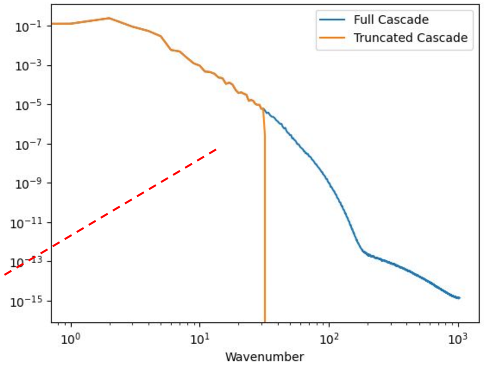


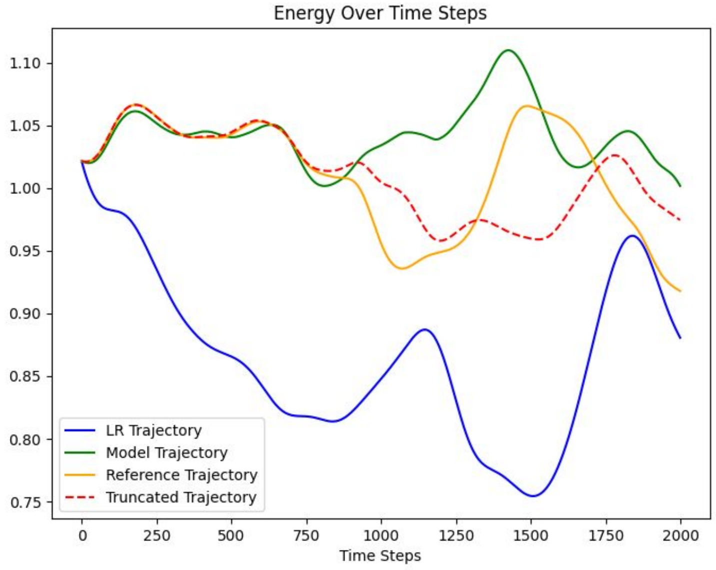


Timestep t=500

Results


Vorticity Correlation
1.0
0.8
0.6
0.4
0.2
0.0
0
250
500
750
1000
1250
1500
1750
2000
Time Steps
reference_2048x2048
uncorrected_64x64
corrected_64x64
truncated_2048x2048


Full Cascade
Truncated Cascade
Wavenumber


Energy Over Time Steps
1.10
1.05
1.00
0.95
0.90
0.85
0.80
0.75
0
250
500
750
1000
1250
1500
1750
2000
Time Steps
LR Trajectory
Model Trajectory
Reference Trajectory
Truncated Trajectory

Computation Time

Model training Time: ~6 hours

Type of Simulation	Computation Time to Reach Simulation Time t = 70
High Resolution (2048 x 2048)	~ 7 minutes
Low Resolution (64 x 64)	~ 2 seconds
Low Resolution with Correction	~ 6 seconds

speedup
~x70

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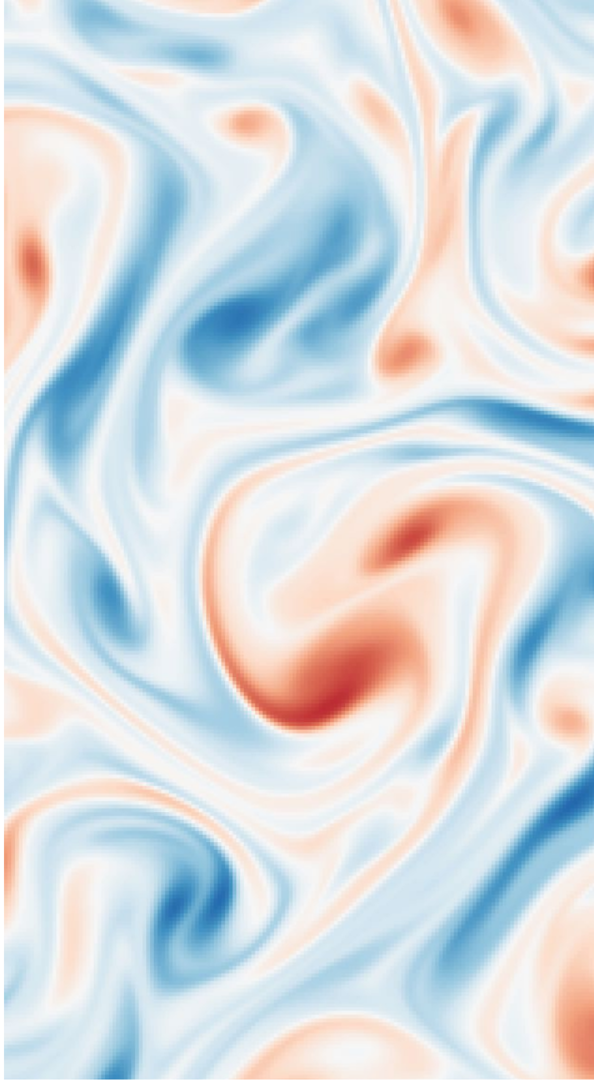

Conclusion

- Neural network is able to supply fluid solver with subgrid information
- Approach made possible with differentiable fluid solver
- Achieved a speed-up of ~x70 from high resolution simulations

Next steps:

- Modify fluid solver to enable shearing box simulations
- Improve neural network architecture
- Add particles into current framework
- Deploy model to existing codes


Thank you for listening!