Rapid 3D Seismic Waveform Modeling using Fourier Neural Operator

Qingkai Kong[1], Arthur J. Rodgers[1]
Yan Yang[2], Zachary E. Ross[2] Kamyar, Azizzadenesheli[3], Robert W. Clayton[2]

This work is funded by LLNL's
Lab Directed Research and Development Program
23-FS-021

1 – Lawrence Livermore National Laboratory
2 – Caltech
3 – Nvidia

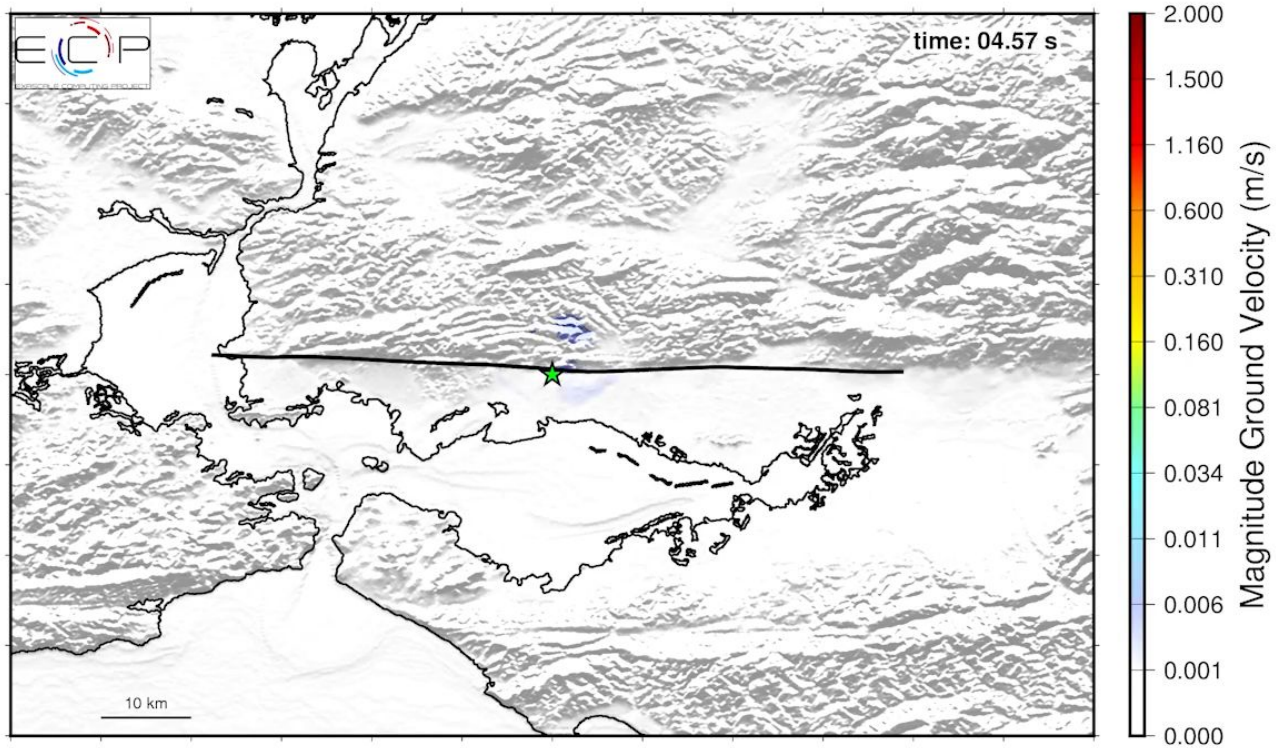
LLNL-PRES-852188
This work was performed under the auspices of the U.S. Department of Energy by Lawrence Livermore National Laboratory under contract DE-AC52-07NA27344. Lawrence Livermore National Security, LLC

Lawrence Livermore National Laboratory

Scientific simulations are important

- Full physics PDE solvers
  - e.g. wave equation, fluid dynamics
- High computational cost prohibit
  - uncertainties & parameter sensitivities
  - Difficult for real-time applications

12 hours, 450,000 cores Up to 5 Hz

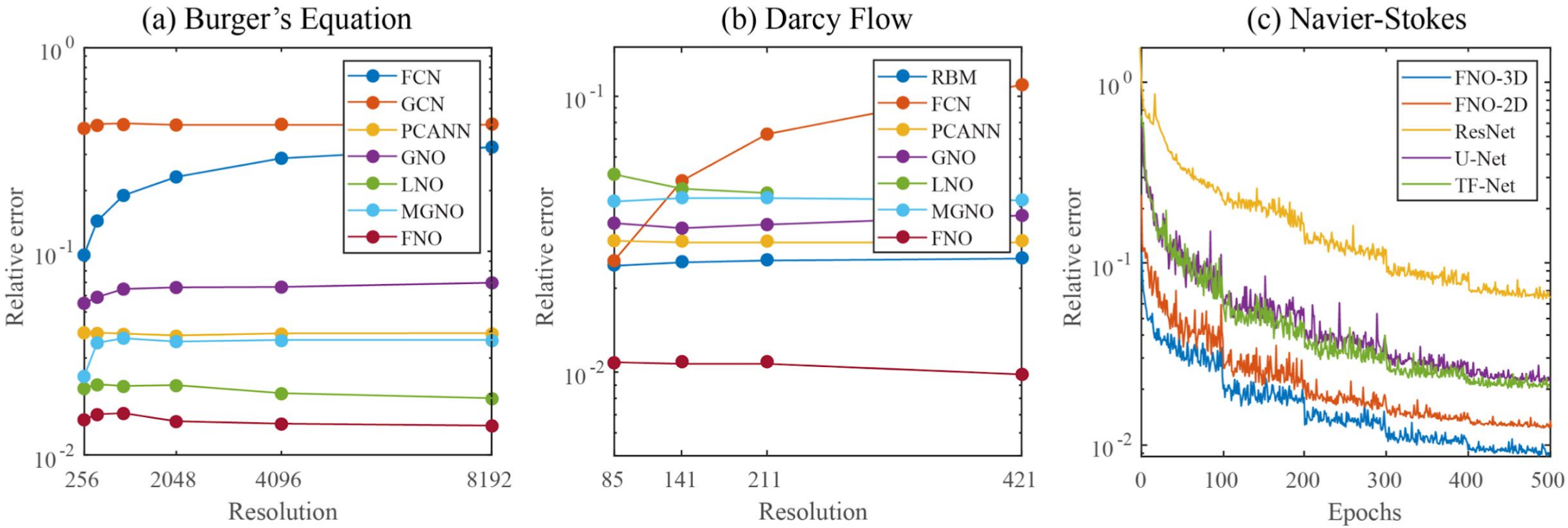


M7.0 Hayward Fault Earthquake Simulation

Rodgers et al., 2019

Potential solution – Fourier Neural Operator (FNO)

A new data driven Partial Differential Equations (PDE) solver that can change the way we do simulations



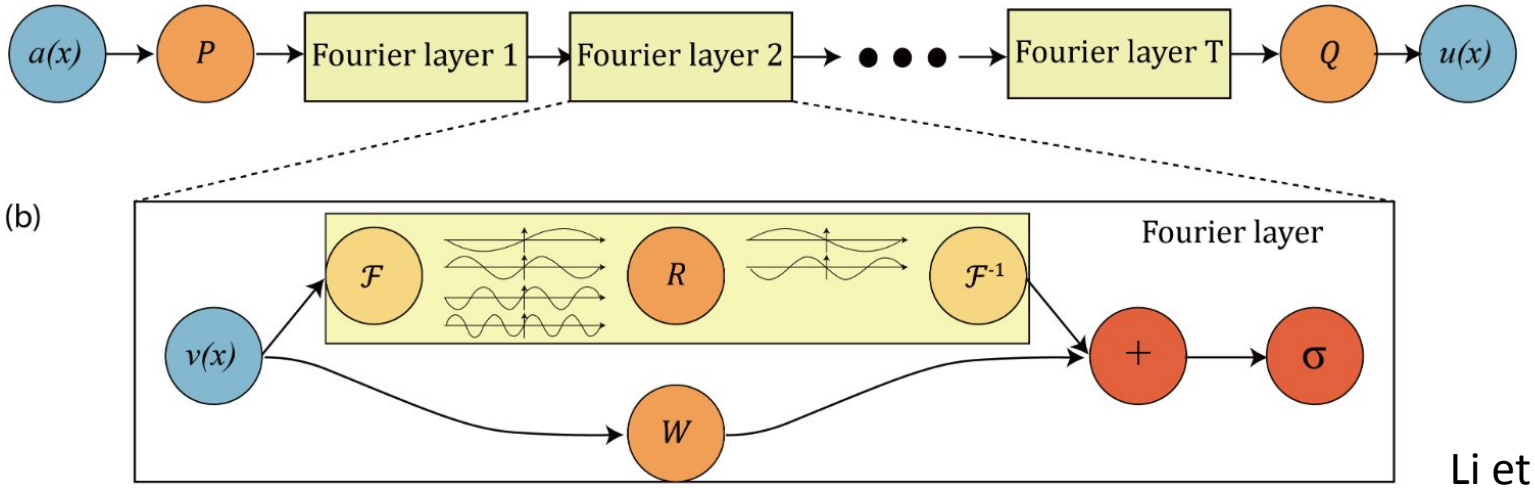
FNO achieves better performance

Li et al., 2021

Basics of FNO

Benefits of using FNO

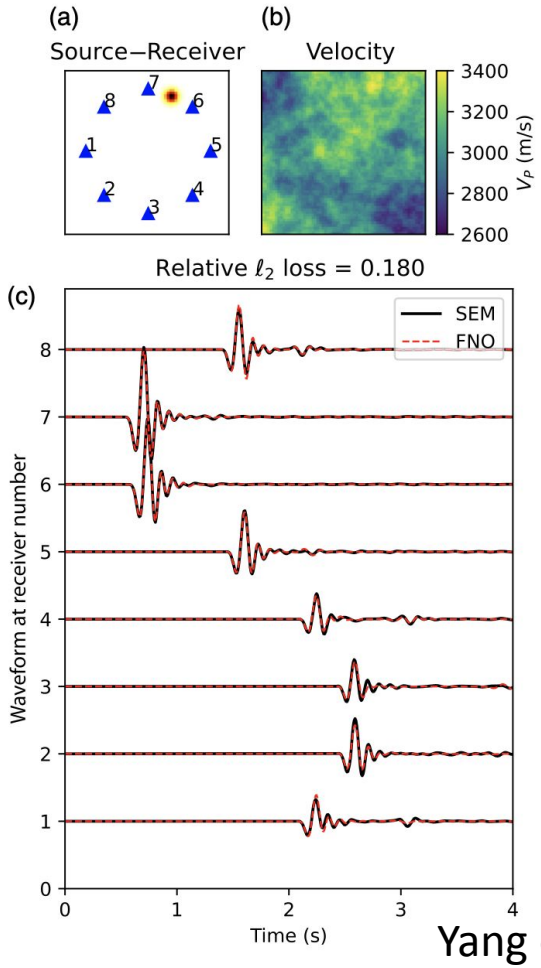
- Learning integral operator behind PDE
  - Different from neural network-based models
- Computationally fast
  - Can be orders of magnitude faster
- Grid independent
  - Train on coarse grid, use on higher grid



Li et al., 2021

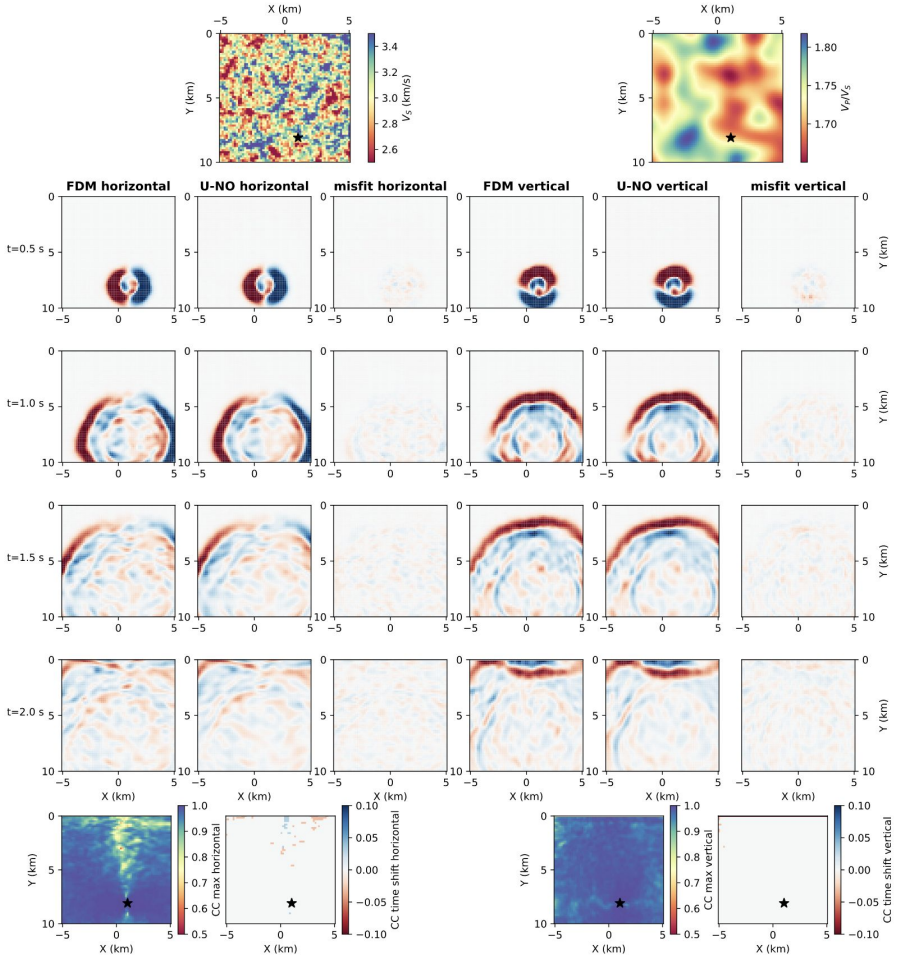
https://www.quantamagazine.org/latest-neural-nets-solve-worlds-hardest-equations-faster-than-ever-before-20210419/

Applied in solving the 2D wave equations



Yang et al., 2021

2D Acoustic Wave Equation



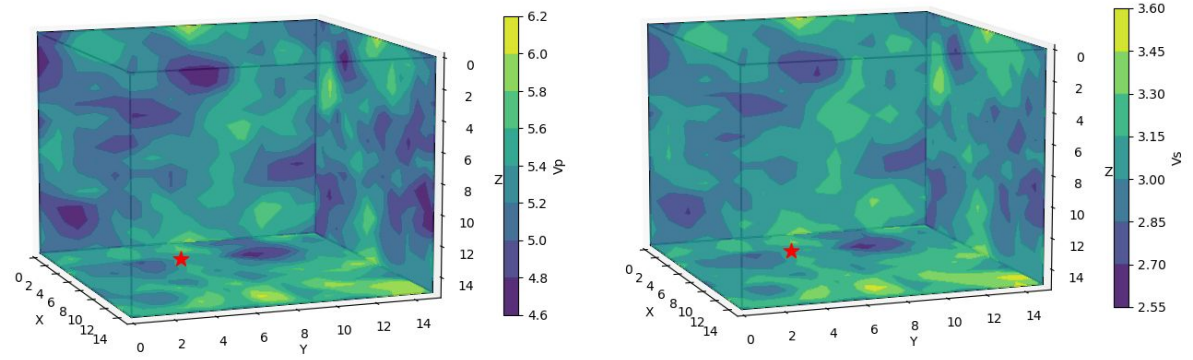
Yang et al., 2022

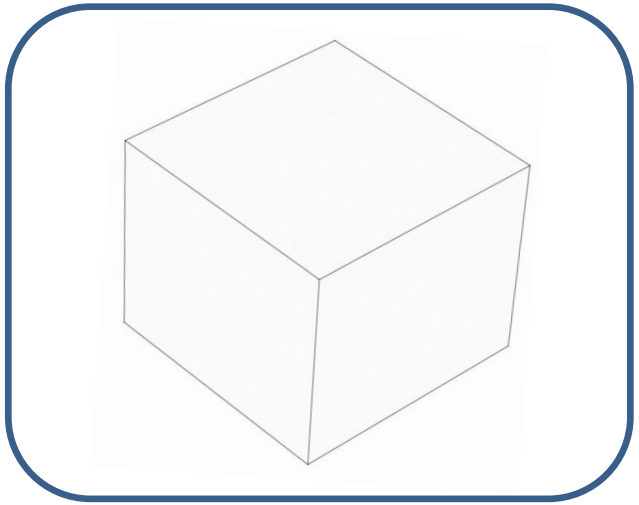
2D Elastic Wave Equation

Our collaborator initialized this research and now we work together to expand it to the more complicated 3D simulations

We explored the potential of the FNO calculation in a recent feasibility study

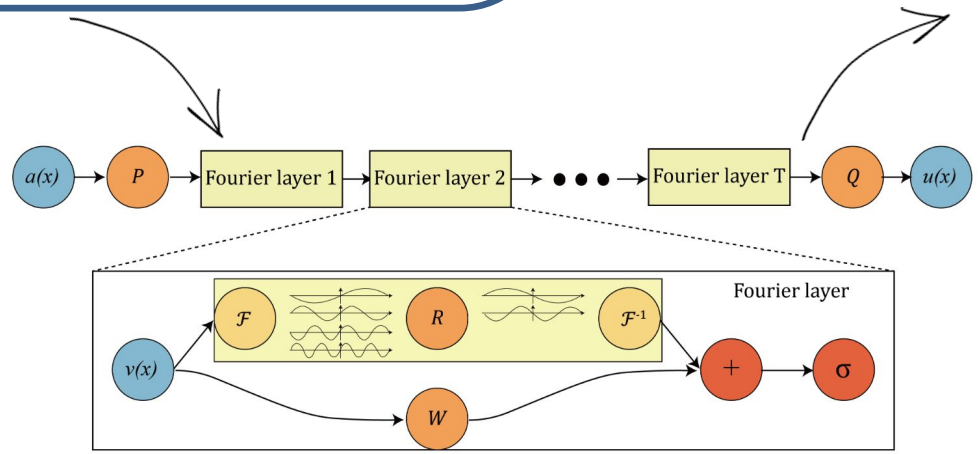
P velocity + S velocity + Source



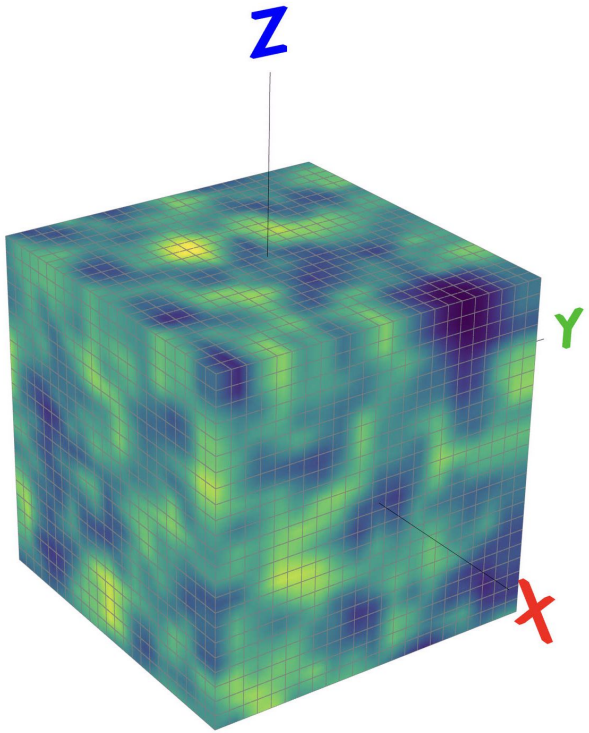


16x16x16x64

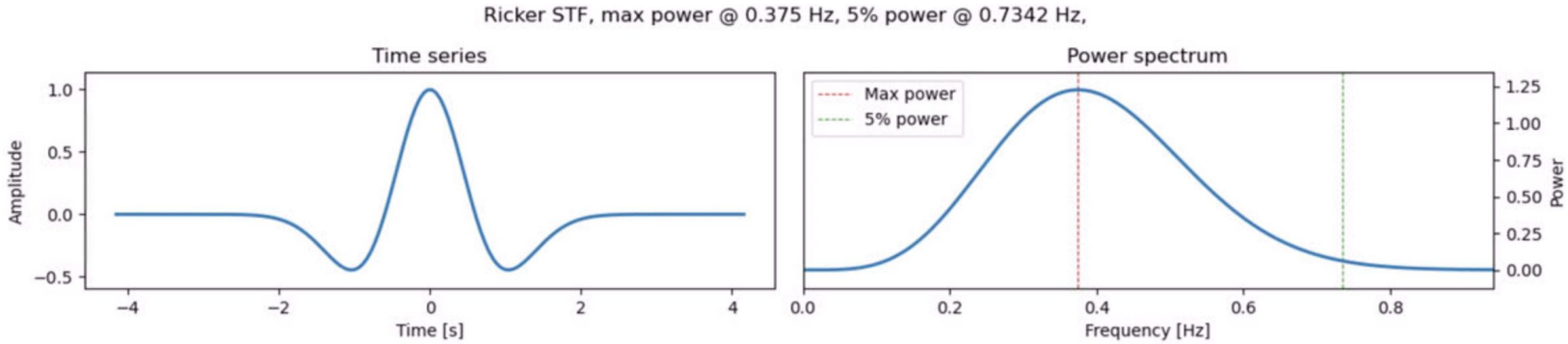
x y z t



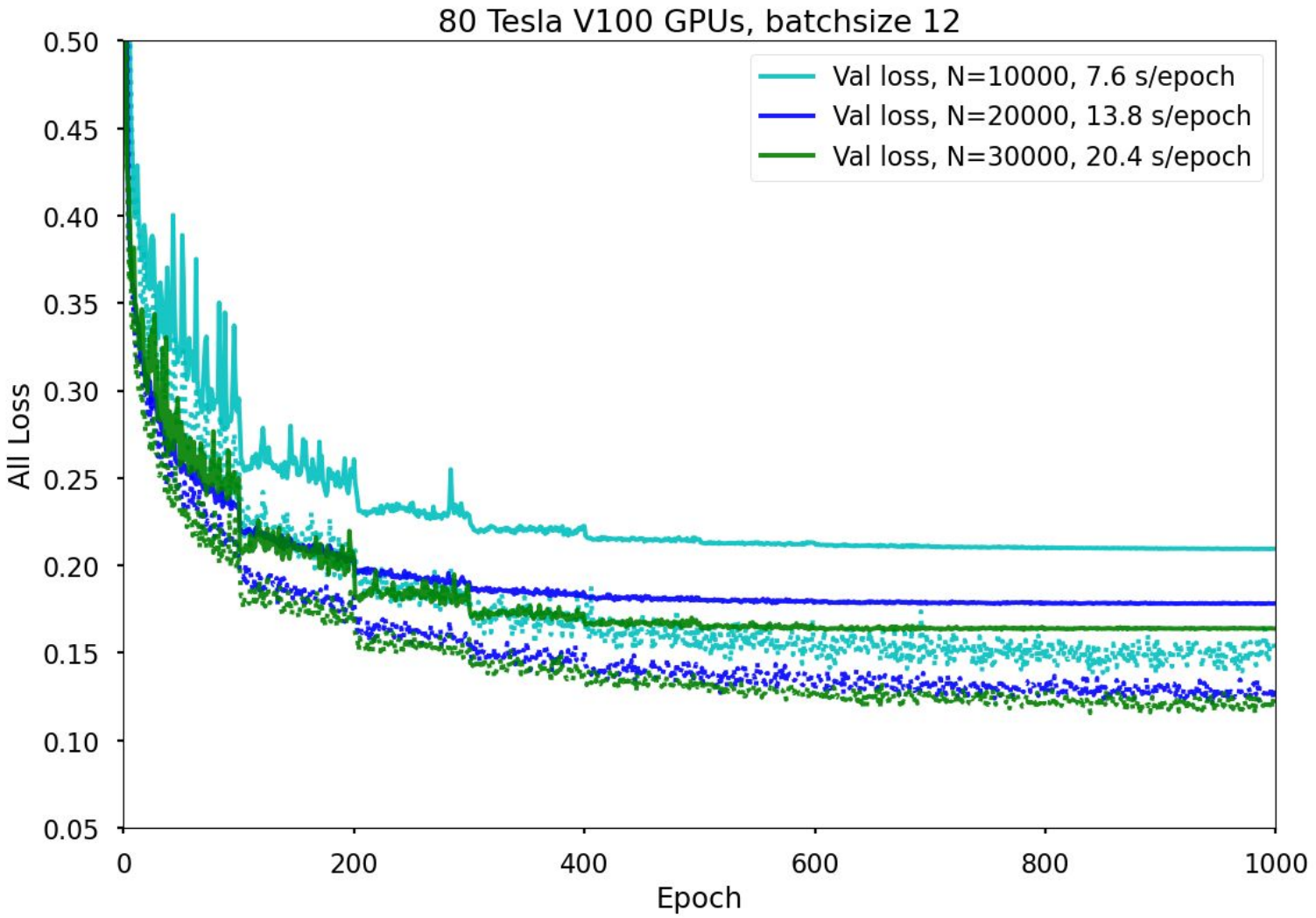
Simulation Details



- Domain: 16 km x 16 km 16 km
- Station spacing, H = 1 km
- Background model: VS=3 km/s; VP=5.2 km/s; RHO=2632 kg/m^3
- Elements/wavelength = 2; freq_max = 1.5 Hz
- Source freq = 0.375 Hz; source width = 2 km
- VK a = 8*H = 8 km; std = 5%

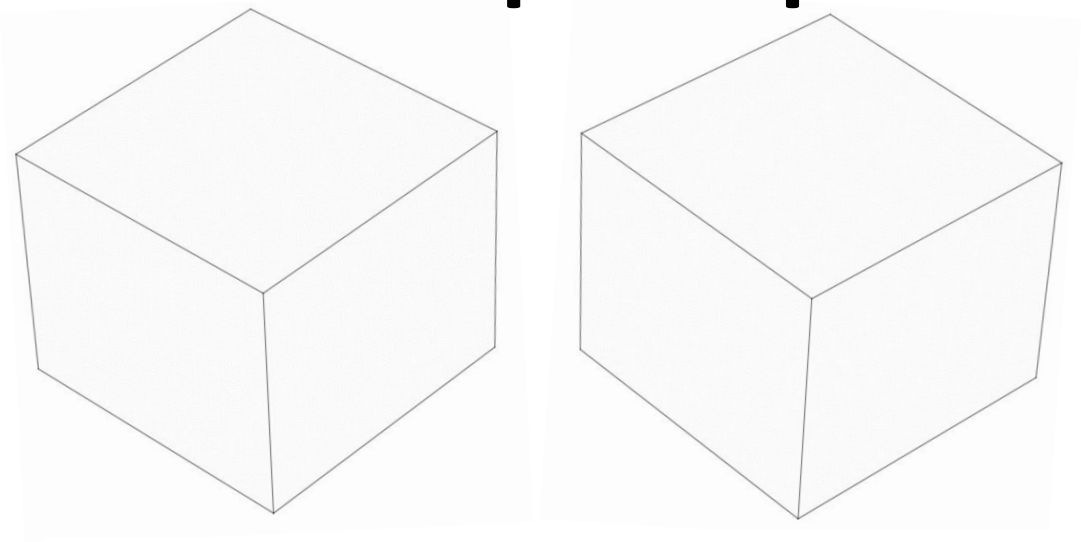


Training


80 Tesla V100 GPUs, batchsize 12
Val loss, N=10000, 7.6 s/epoch
Val loss, N=20000, 13.8 s/epoch
Val loss, N=30000, 20.4 s/epoch
All Loss
0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0
200
400
600
800
1000
Epoch

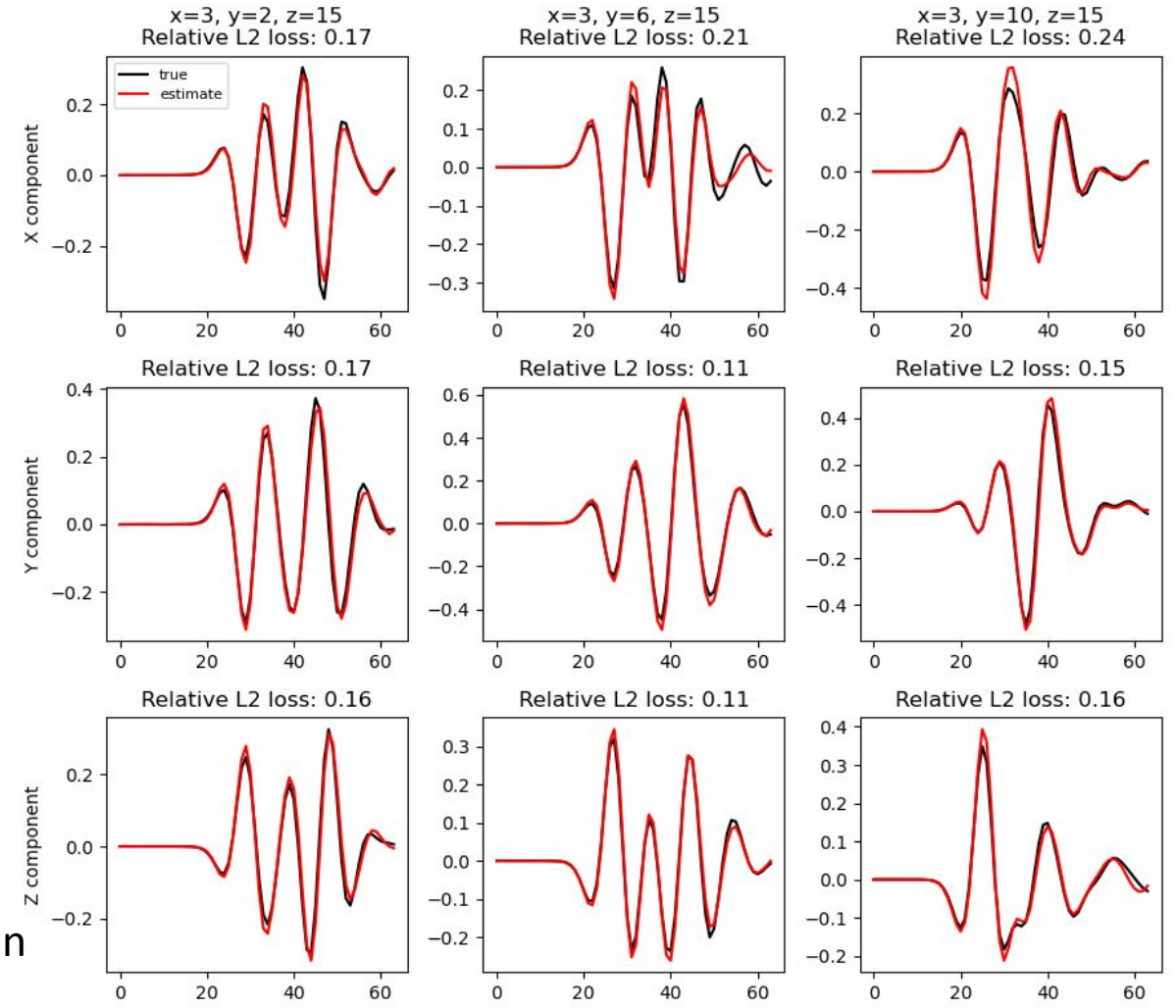
Comparison to traditional methods demonstrates a 32x speedup

32x Speedup



Physics Simulation
3.61s

NeurOp Estimation
0.11s



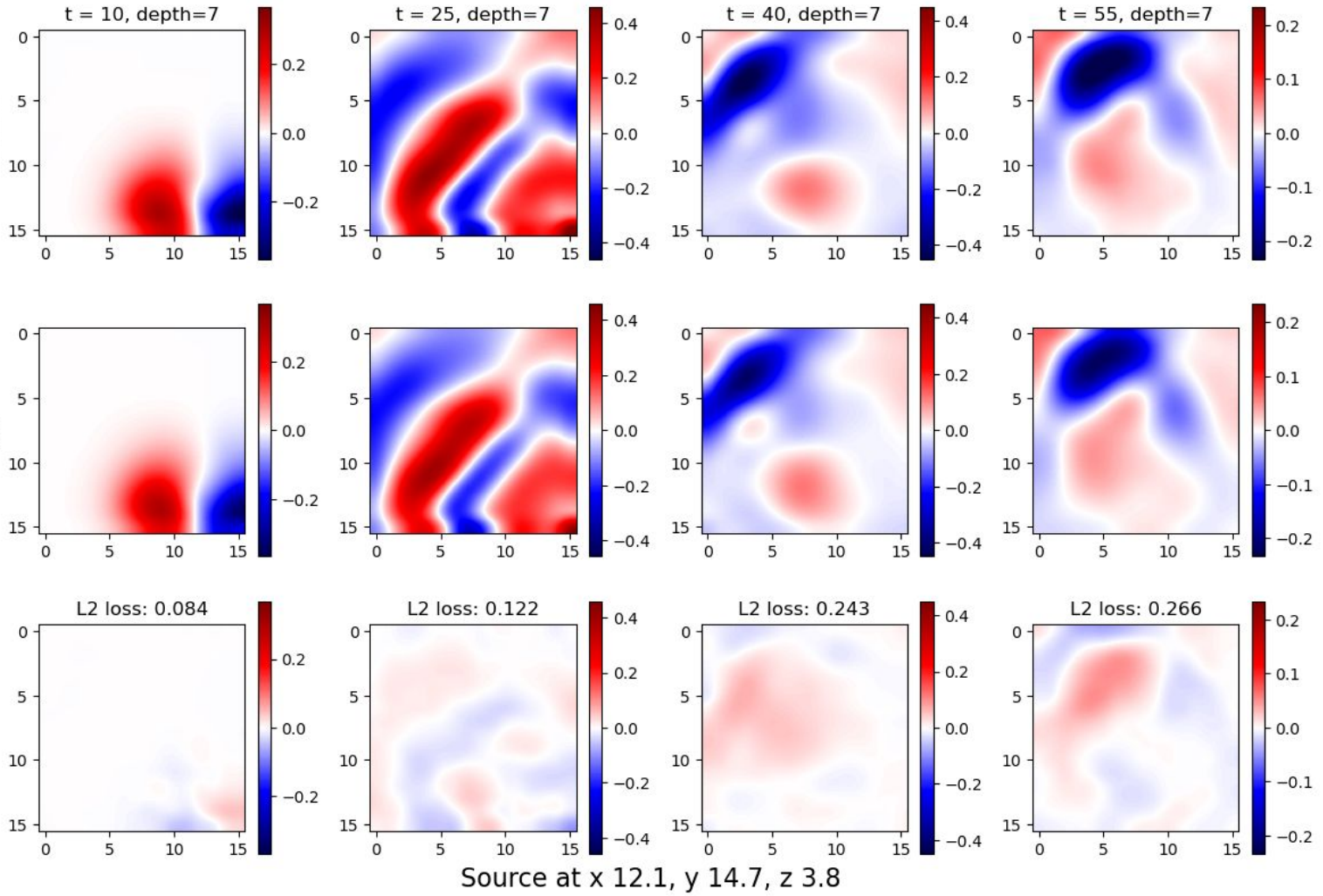
This example is generated using one Nvidia RTX 6000 GPU, which on average, we see about 32 times speedup for one simulation.

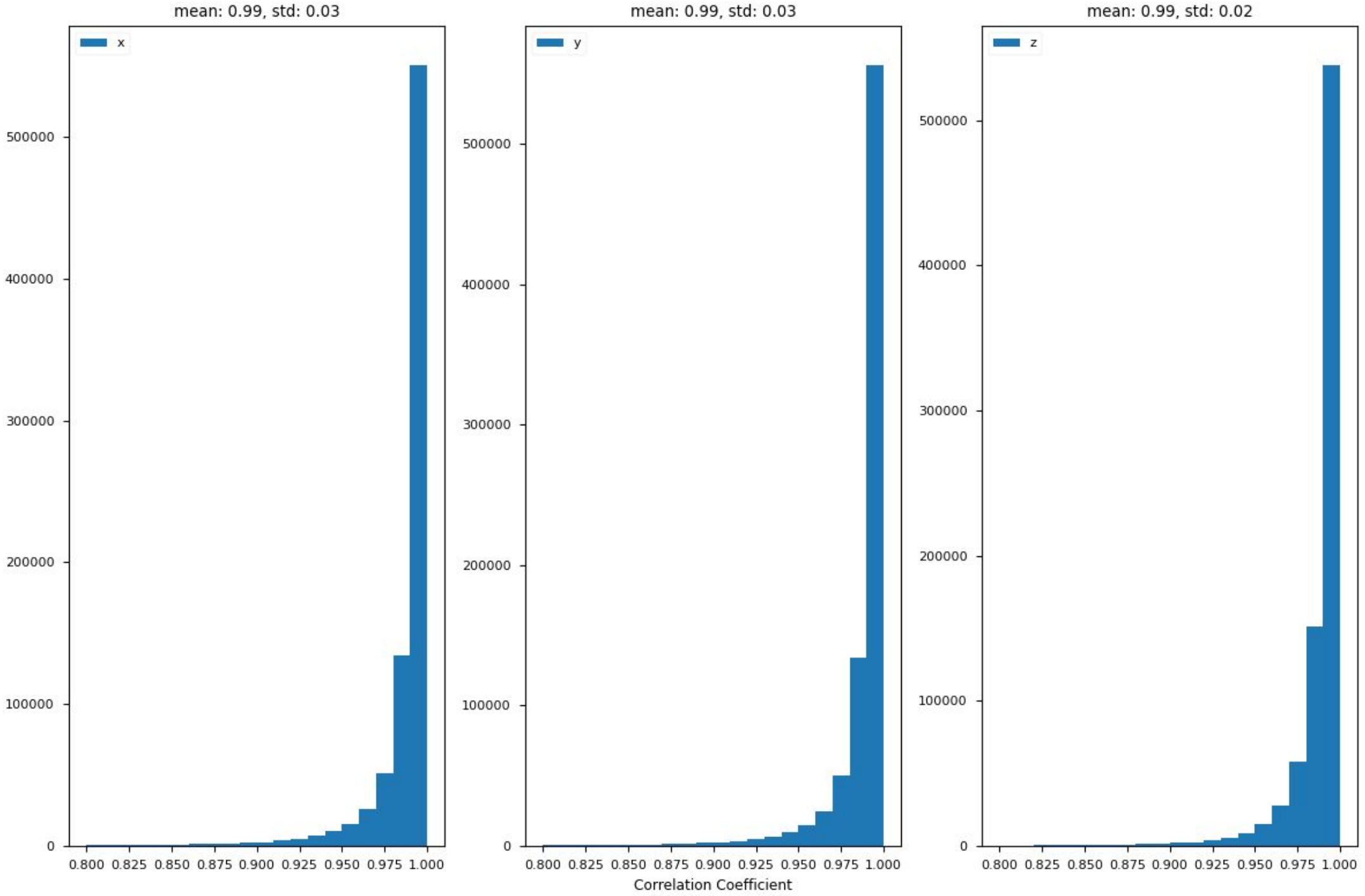
FNO estimated wavefield shows high fidelity to the exact result

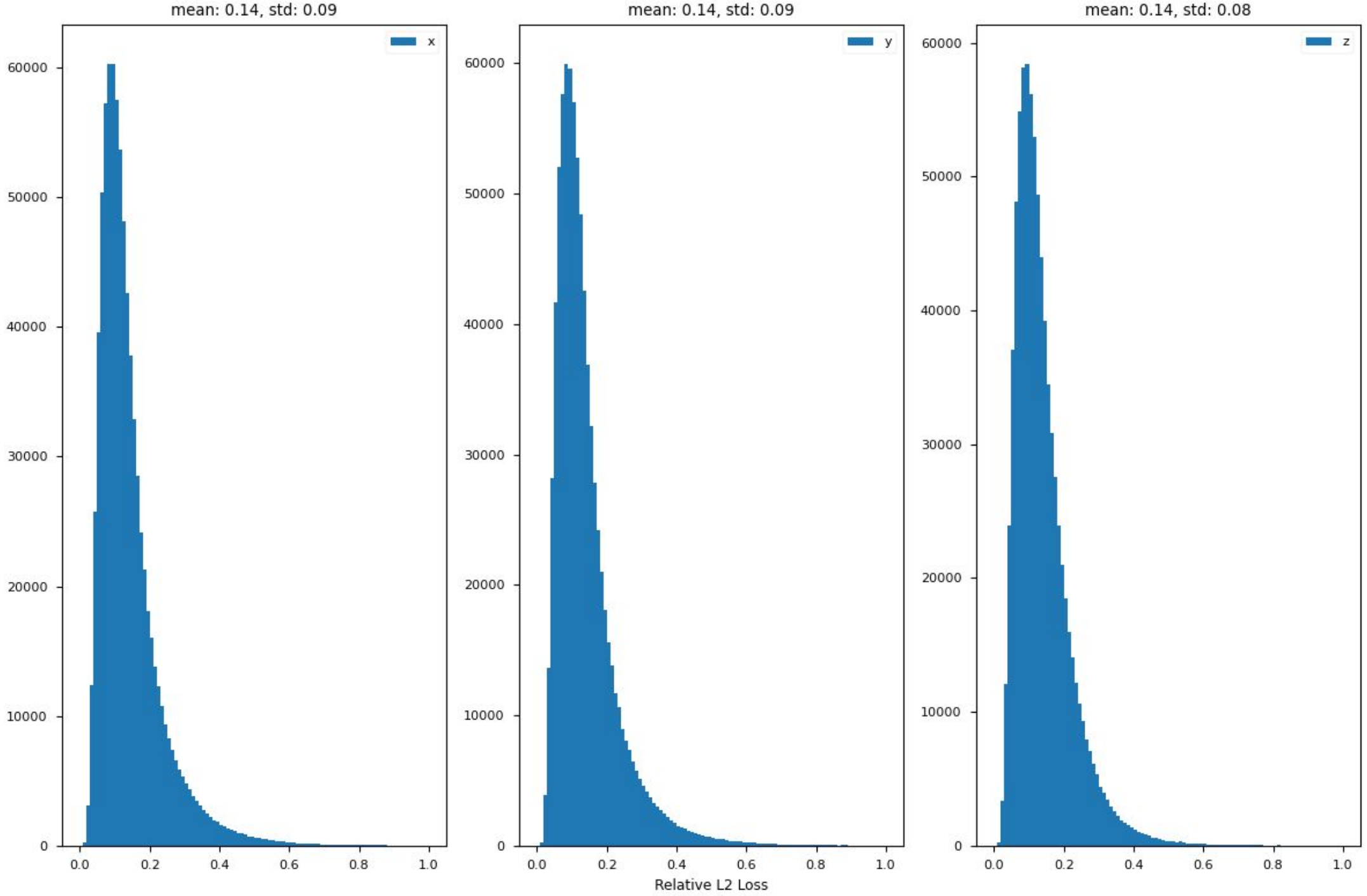
FNO

Physics solver

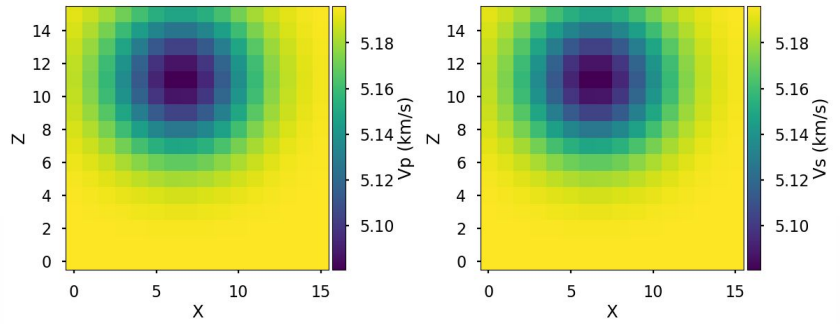
Difference

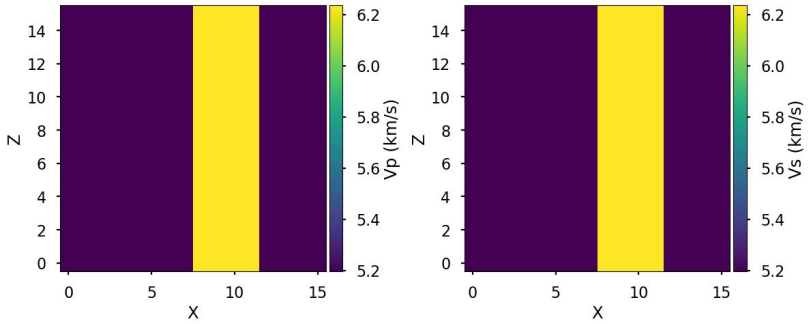


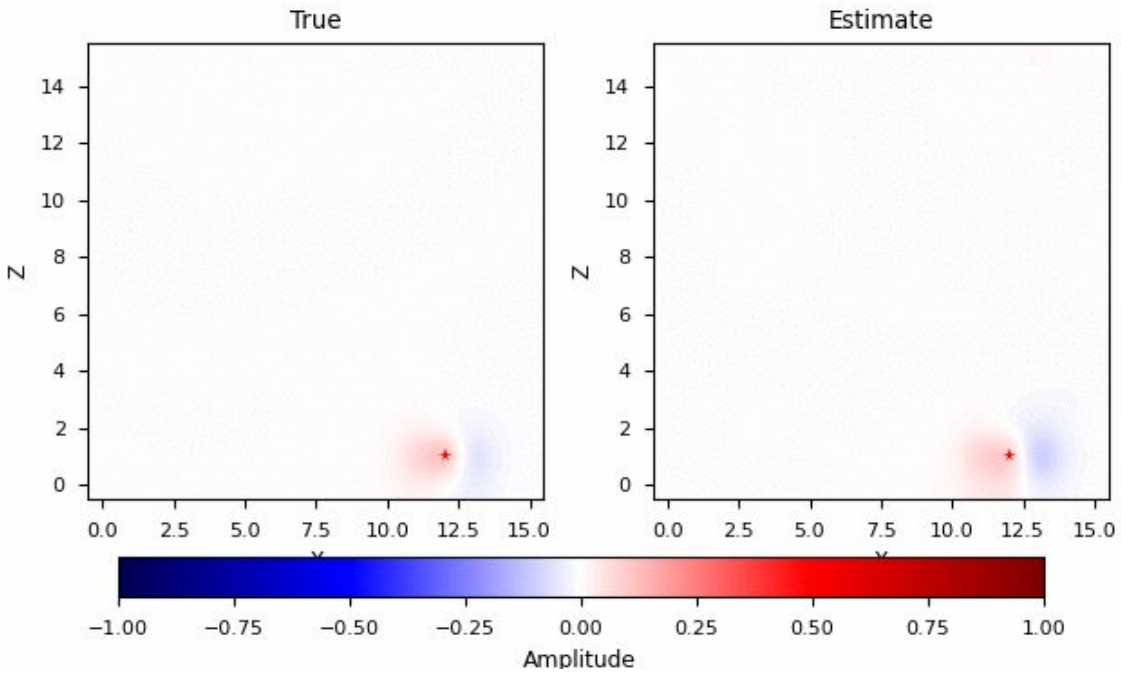

mean: 0.99, std: 0.03
x
mean: 0.99, std: 0.03
y
mean: 0.99, std: 0.02
z
500000
400000
300000
200000
100000
0
0.800 0.825 0.850 0.875 0.900 0.925 0.950 0.975 1.000
Correlation Coefficient

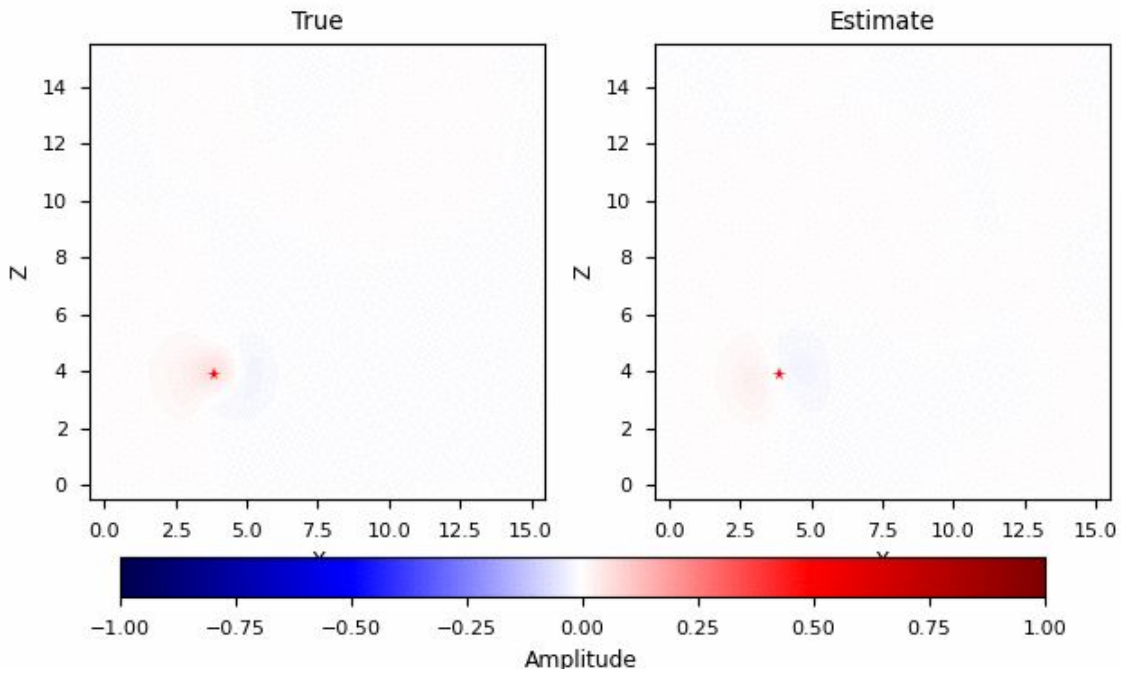

mean: 0.14, std: 0.09
x
mean: 0.14, std: 0.09
y
mean: 0.14, std: 0.08
z
60000
50000
40000
30000
20000
10000
0
0.0
0.2
0.4
0.6
0.8
1.0
Relative L2 Loss

Apply on different cases





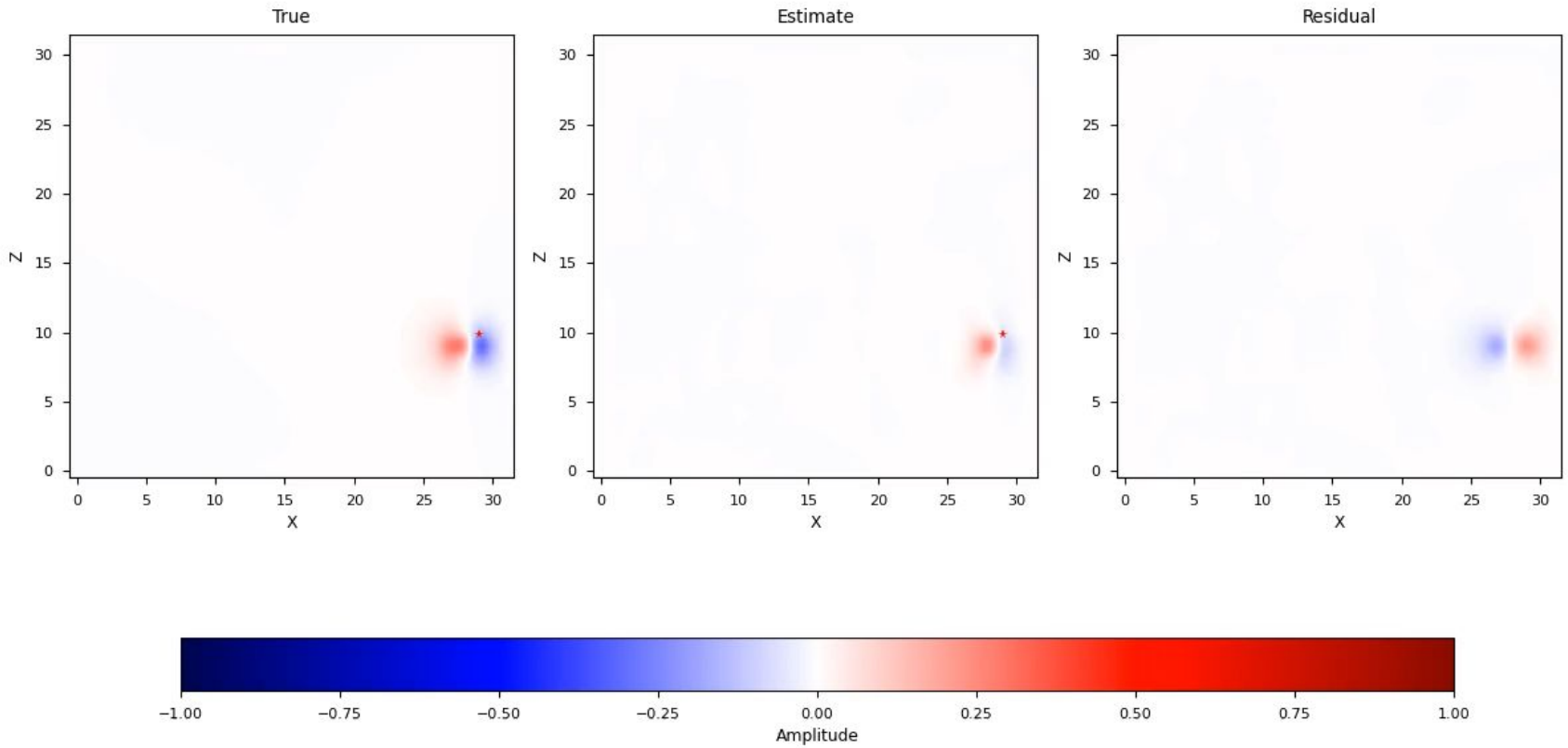




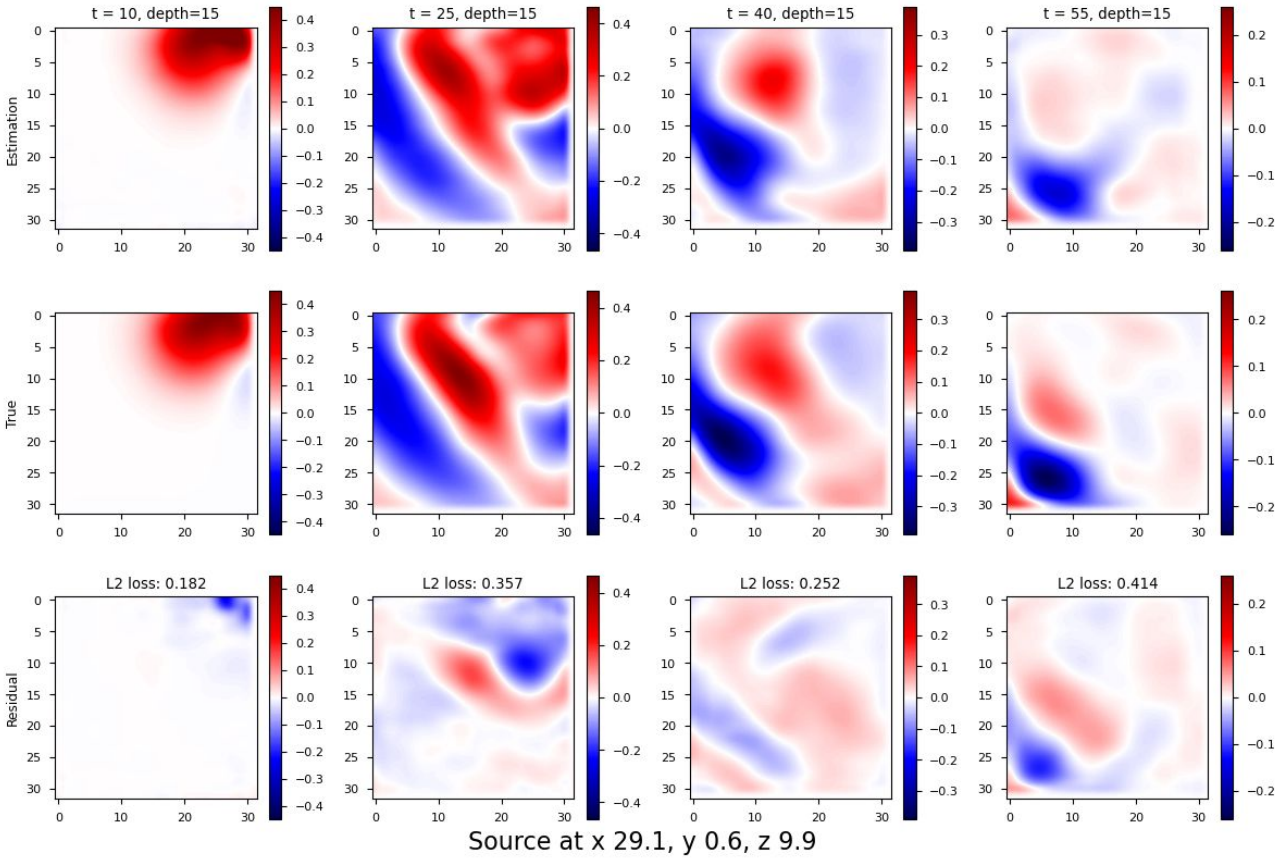
Apply to higher-resolution data

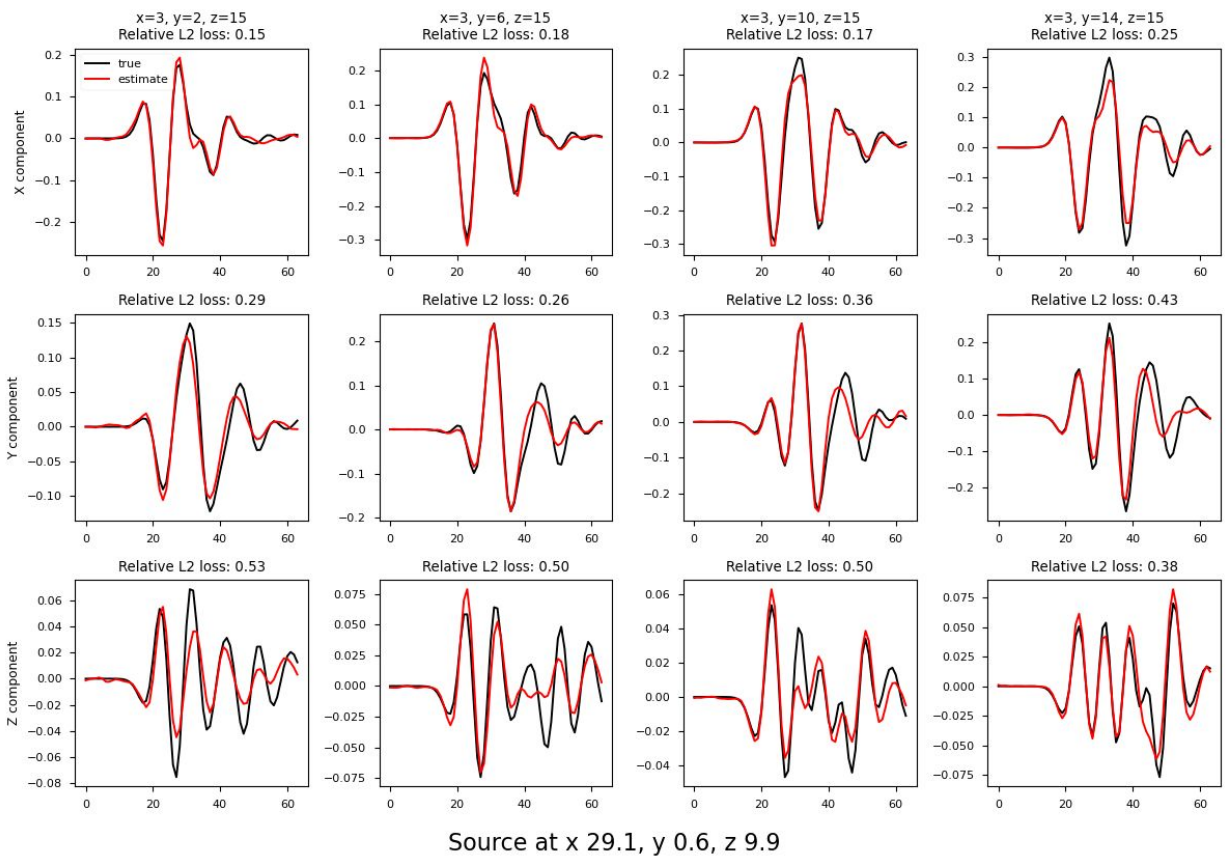
- Using the base model trained on 16x16x16x64 (30,000)
- Finetune with 32x32x32x64 (1800 training + 200 Val)
- Test on 32x32x32x64 (200 simulations as test)

Apply on higher resolution grids (2x)

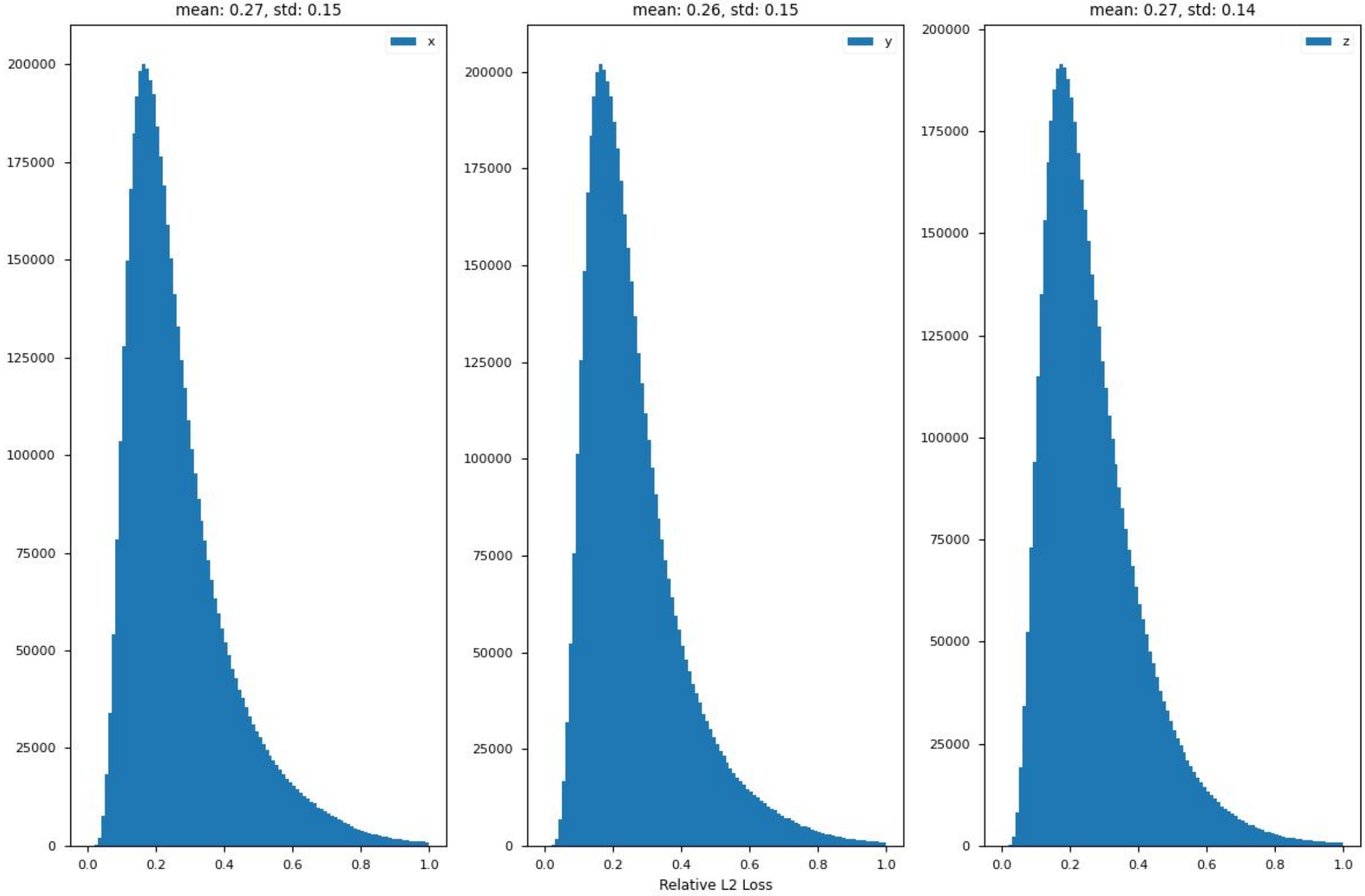


Performances





FNO Physics


mean: 0.27, std: 0.15
x
mean: 0.26, std: 0.15
y
mean: 0.27, std: 0.14
z
200000
175000
150000
125000
100000
75000
50000
25000
0
0.0
0.2
0.4
0.6
0.8
1.0
Relative L2 Loss

Conclusion and Future work

- Working in progress, we still see potential to improve
- Higher grid resolution
- Earthquake sources

Thank you so much