Towards Physics-Informed Deep Learning for Turbulent Flow Prediction


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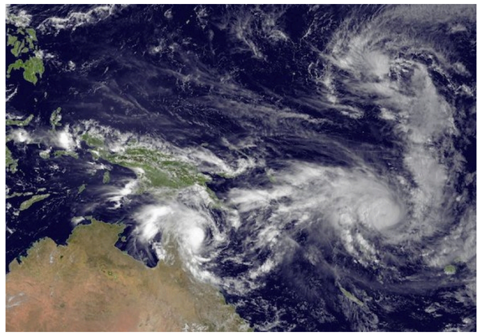
Introduction

- Turbulence modeling: fundamental task in science
- No analytical theory to predict the evolution
- Computational prohibitive to simulate



atmospheric science

marine science

aerodynamics

Rayleigh-Bénard convection[1]

1. Visualization and simulation by: Erwin P. van der Poel & Rodolfo Ostilla Mónico.

Related Work

- **Turbulence Modeling** [Ling et al. 2016, Raissi et al. 2017, Fang et al. 2018, Kim and Lee 2019, Mohan et al. 2019, Wu et al. 2019]
    - no external force, spatial modeling
    - require boundary condition inputs
- **Fluid Animation** [Tompson et al. 2017, Chu and Thuerey, 2017, Xie et al. 2018, Thuerey et al. 2019]
    - emphasize simulation realism
    - lack physical interpretation
- **Video Prediction** [Wang et al. 2015, Finn et al. 2016, Xue et al. 2016]
    - complex noisy data
    - unknown physical processes

Governing Equations

- Navier-Stokes equations: describe the motion of viscous fluids

- Variables velocity $\mathbf{w} = (u, v)$ pressure p
  temperature T density ρ_0 force f

continuity $\nabla \cdot \mathbf{w} = 0$

momentum $\frac{\partial \mathbf{w}}{\partial t} + (\mathbf{w} \cdot \nabla)\mathbf{w} = -\frac{1}{\rho_0} \nabla p + \nu \nabla^2 \mathbf{w} + f$

energy $\frac{\partial T}{\partial t} + (\mathbf{w} \cdot \nabla)T = \kappa \nabla^2 T$

Hybrid Learning Framework

- Reynolds Averaging (RANS)

$$\mathbf{w}(\mathbf{x}, t) = \bar{\mathbf{w}}(\mathbf{x}, t) + \mathbf{w}'(\mathbf{x}, t)$$

$$\bar{\mathbf{w}}(\mathbf{x}, t) = \frac{1}{T}\int_{t-T}^{t} G(s)\boldsymbol{w}(\mathbf{x}, s)ds$$

- Large Eddie Simulation (LES)

$$\mathbf{w}(\mathbf{x}, t) = \tilde{\mathbf{w}}(\mathbf{x}, t) + \mathbf{w}'(\mathbf{x}, t)$$

$$\tilde{\mathbf{w}}(\mathbf{x}, t) = \int G(\mathbf{x}\,|\,\xi)\mathbf{w}(\xi, t)d\xi$$

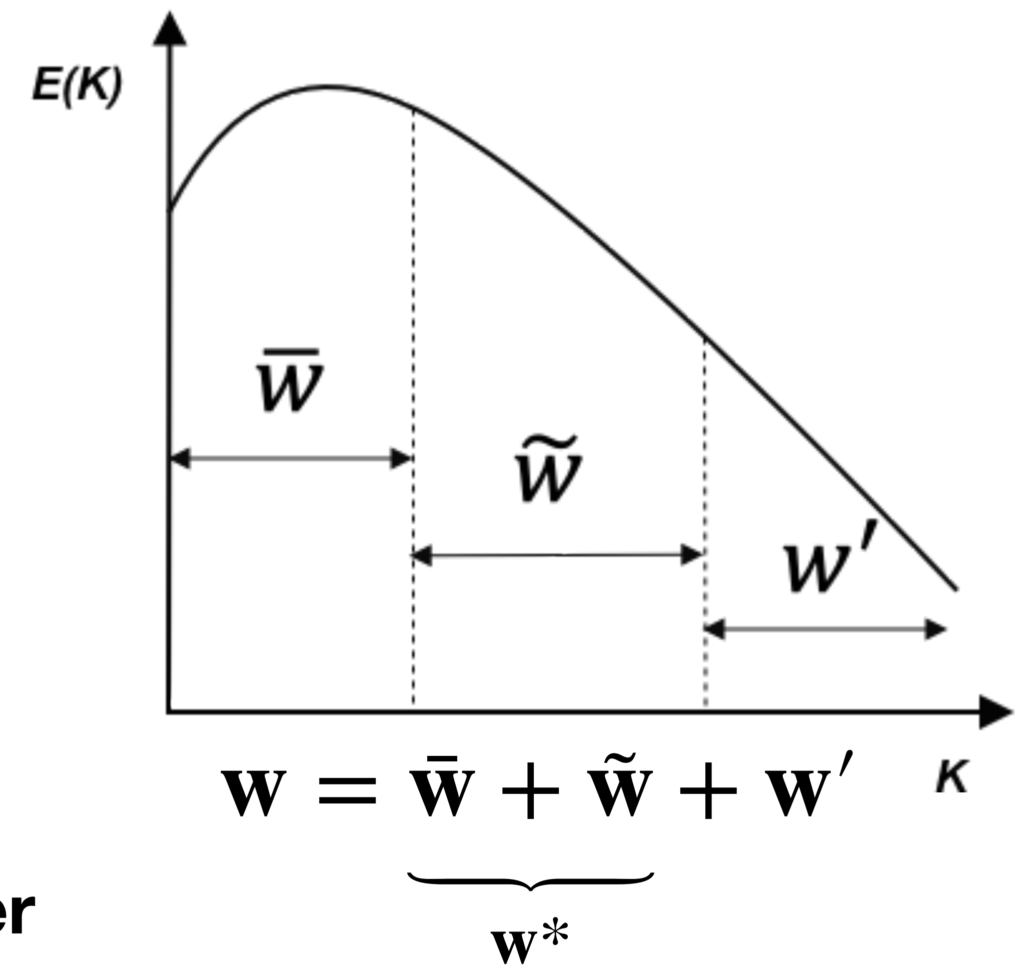
- RANS-LES Coupling

Spatial Filter

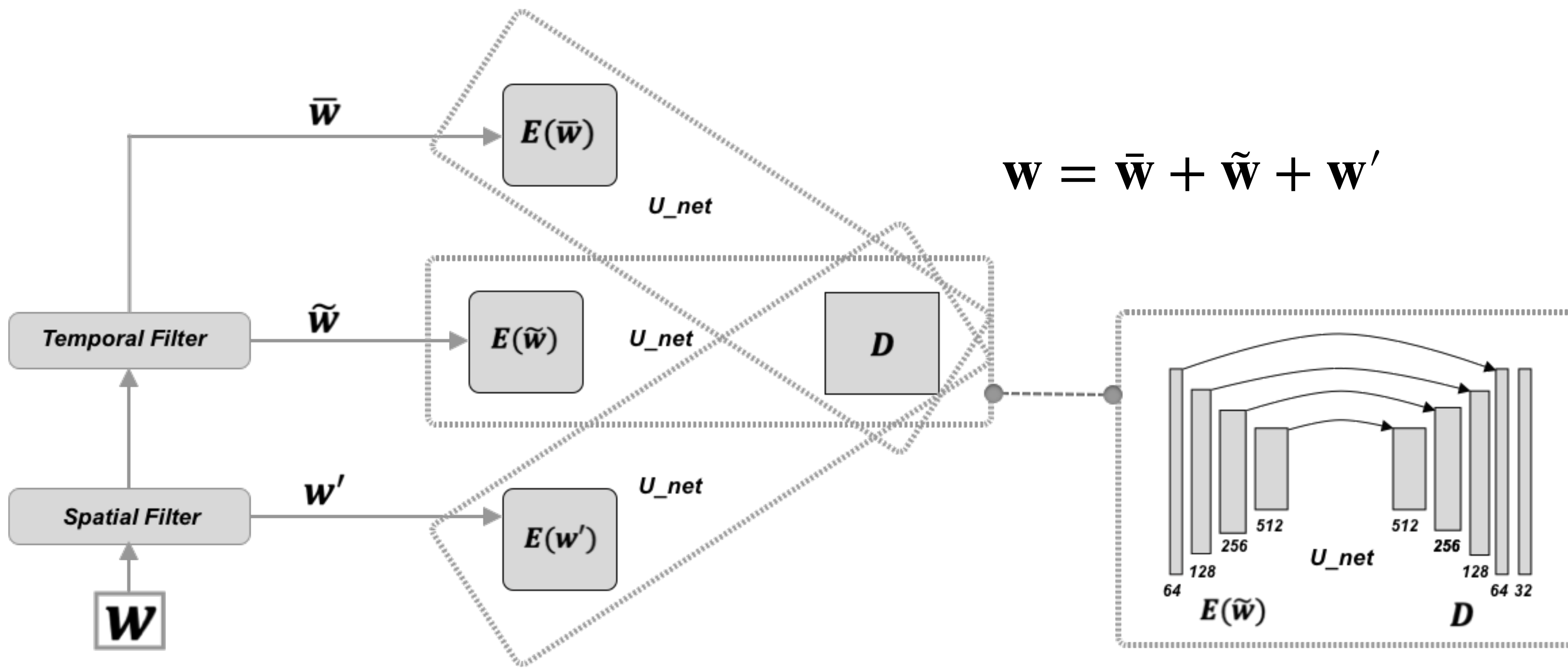
$$\mathbf{w}^*(\mathbf{x}, \mathbf{t}) = G_1(\mathbf{w}) = \sum_{\xi} G_1(\mathbf{x}\,|\,\xi)\mathbf{w}(\xi, t)$$

Temporal Filter

$$\bar{\mathbf{w}}(\mathbf{x}, \mathbf{t}) = G_2(\mathbf{w}^*) = \frac{1}{T}\sum_{s=t-T}^{t} G_2(s)\mathbf{w}^*(\mathbf{x}, s)$$



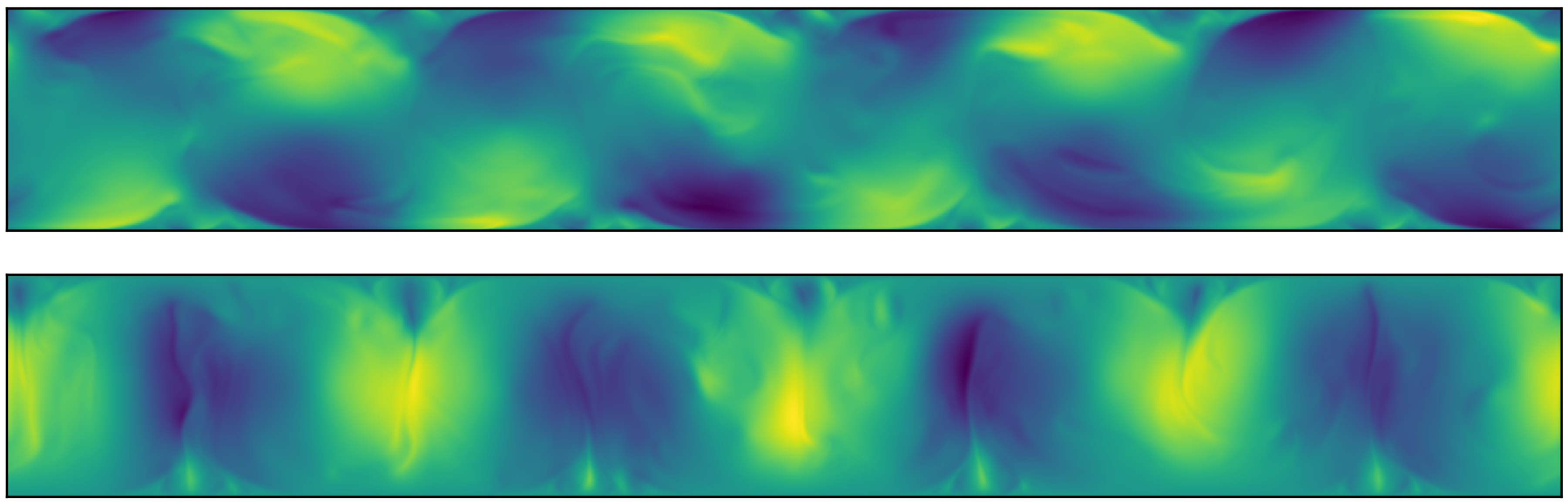
Turbulent-Flow Net



$$\mathbf{w} = \bar{\mathbf{w}} + \tilde{\mathbf{w}} + \mathbf{w}'$$

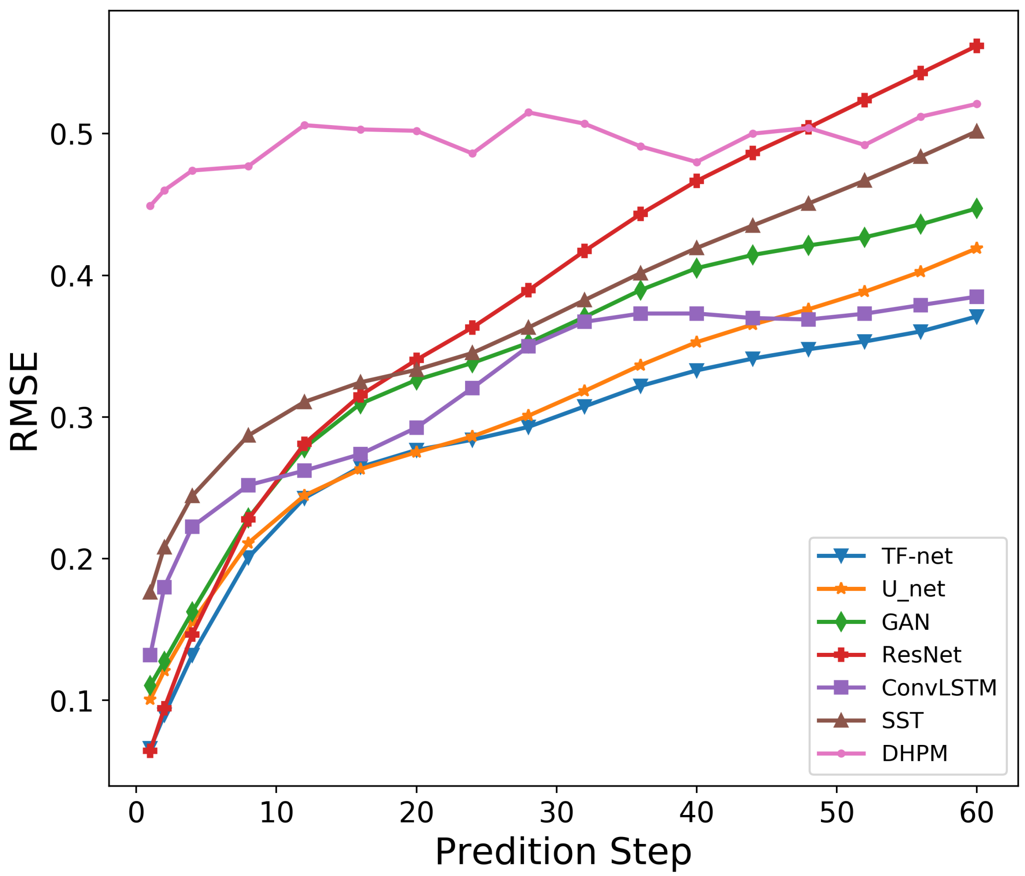
- Multi-scale spectral decomposition with **spatial** and **temporal** filters
- Unifying CFD techniques (RANS-LES coupling) and deep generative models
- Each encoder-decoder can be viewed as a U-net without duplicate layers and middle layer.

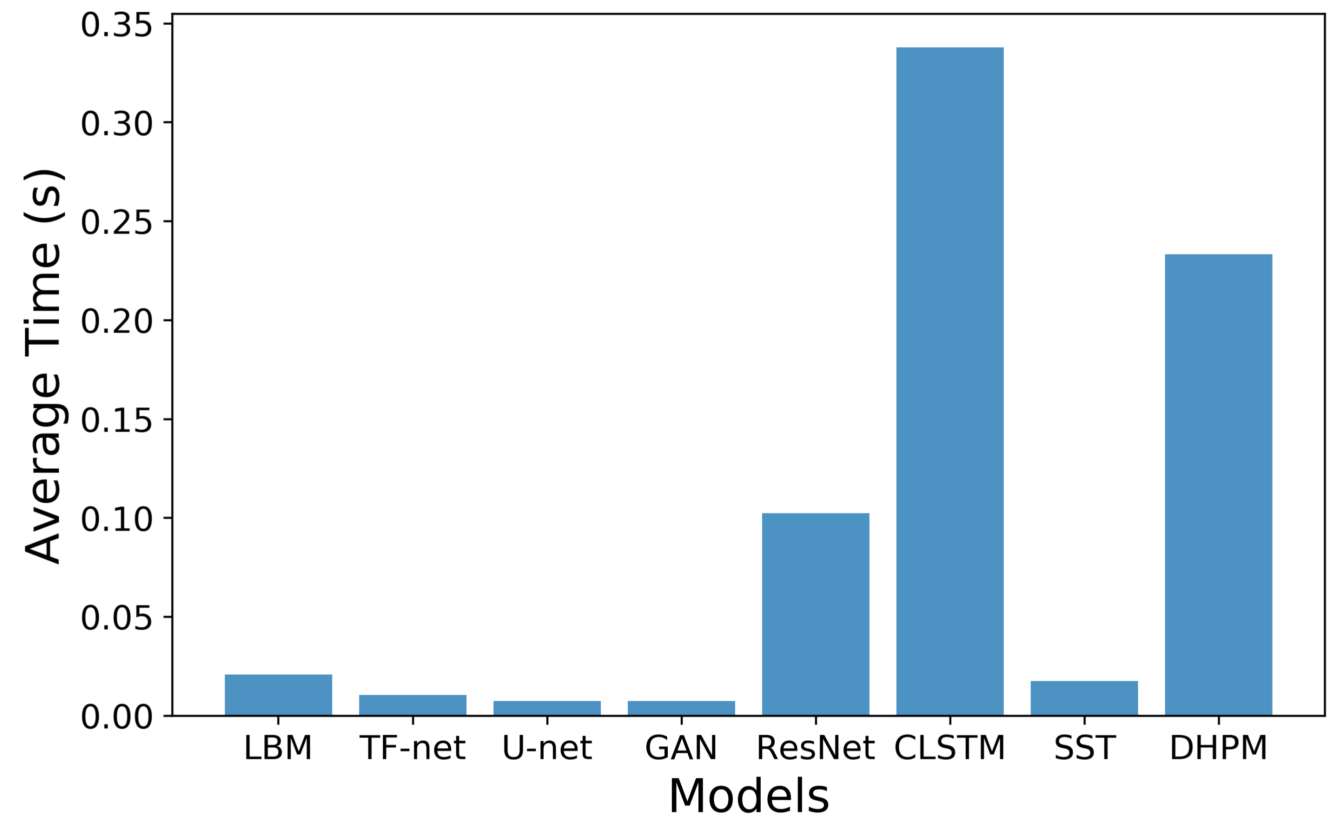
Data Description



- RBC simulation with Prandtl number 0.71 and Reynolds number 2.5 x e8
- ~10k sequences, spatial resolution 64x64, time length 90
- 60 time step ahead prediction, results averaged over three runs

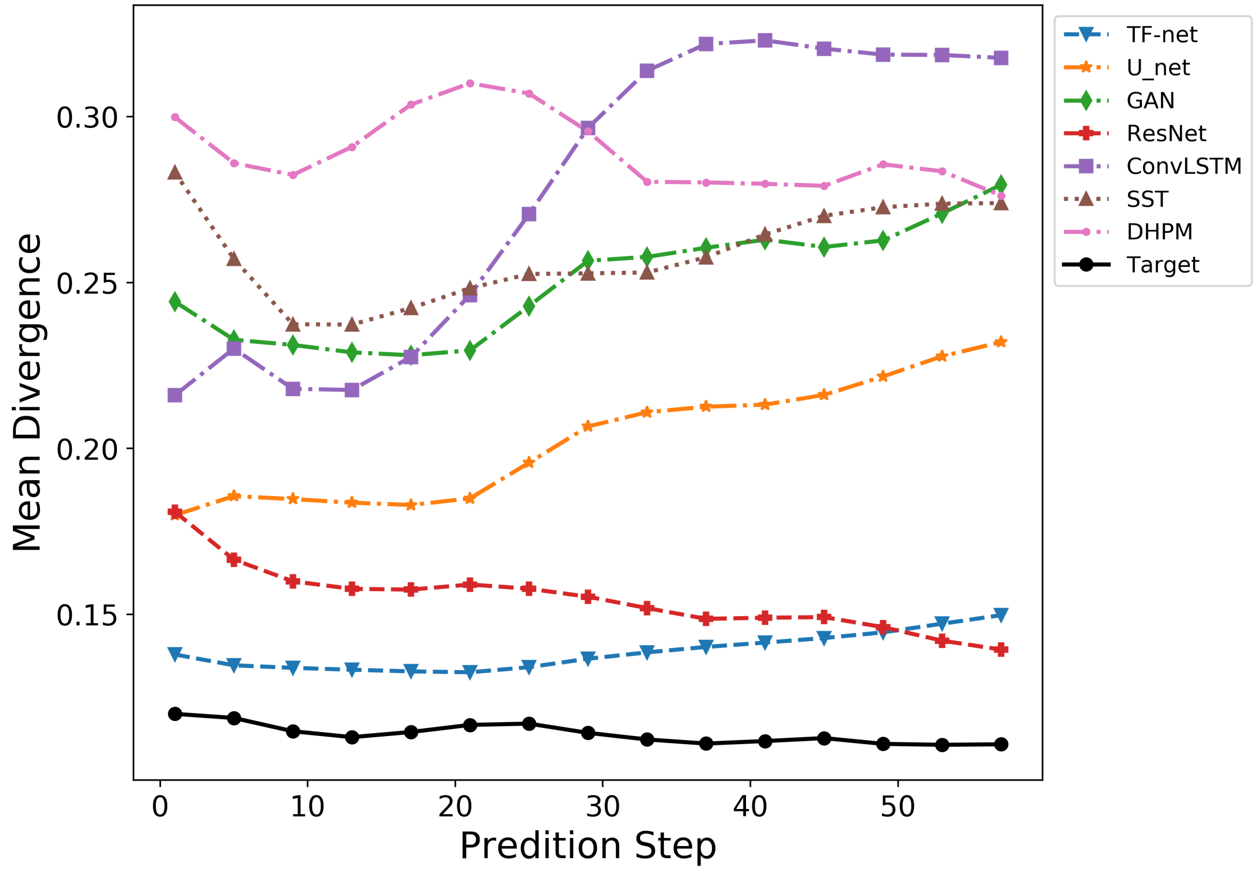
Prediction Performance

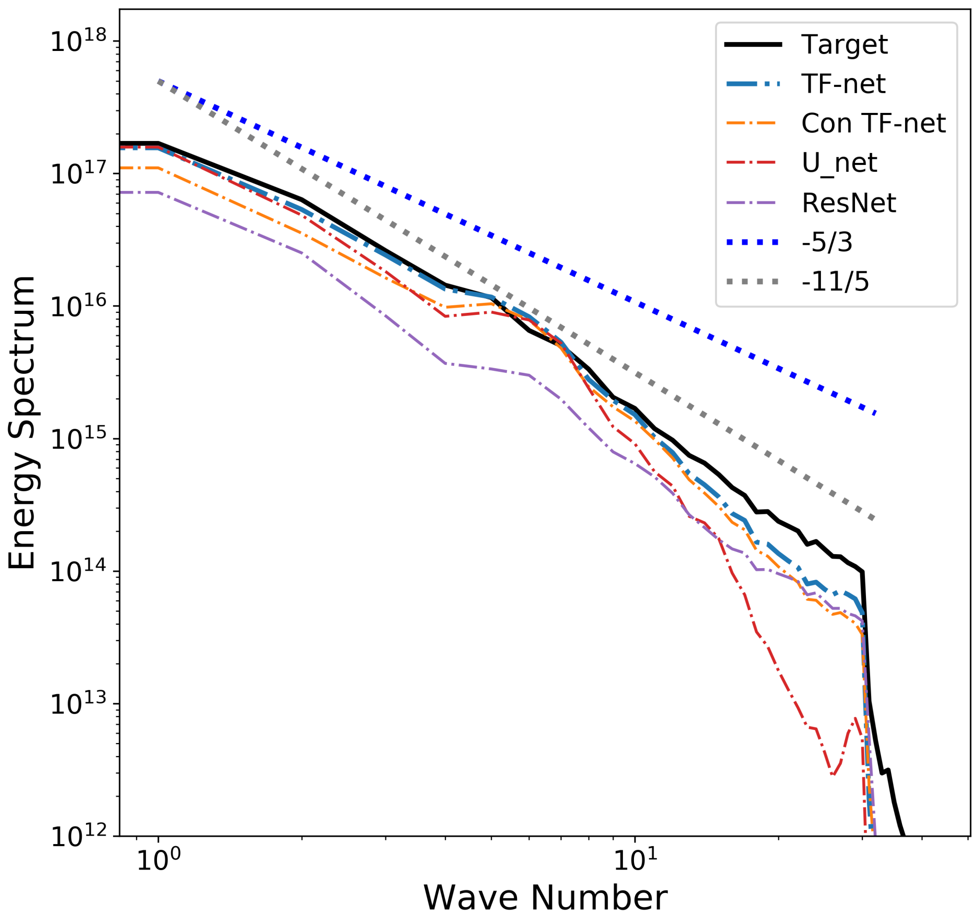




- TF-Net consistently outperforms baselines on prediction RMSE
- Faster than Lattice Boltzmann method (LBM) by 2X

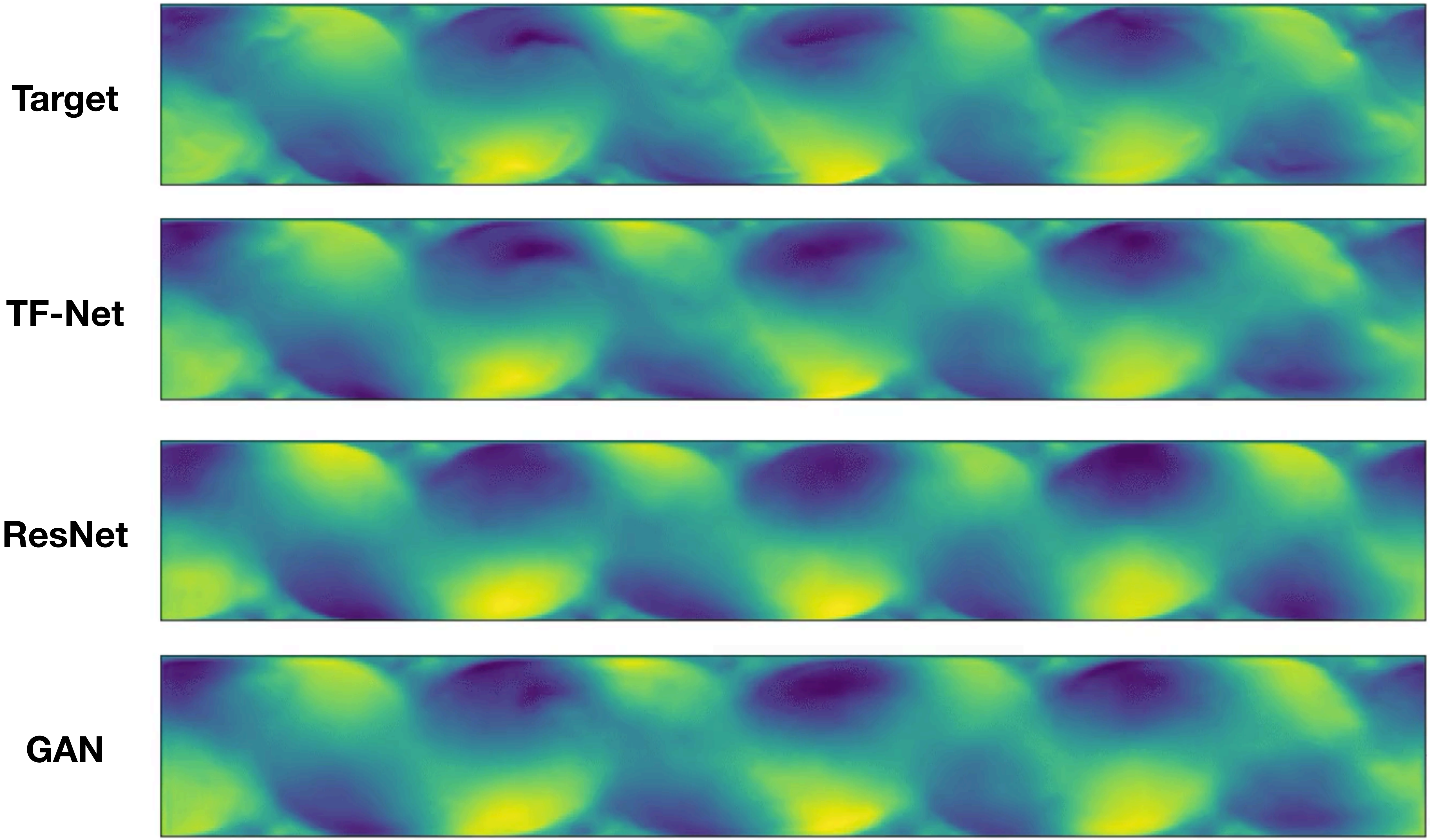
Turbulent Kinetic Energy





- TF-net predictions are closest to the target w.r.t. kinetic energy
- Video forward predictions methods (e.g. Unet, ConvLSTM) cannot capture physical properties

Prediction Visualization



Ablation Study