

Extreme Event Prediction with Multi-agent Reinforcement Learning-based Parametrization of Atmospheric and Oceanic Turbulence

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Why Machine Learning?

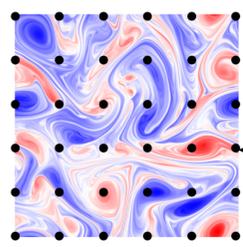
- Climate models are deficient in representing small scales and some physical phenomena
- Learn from observations to account for the sub-grid scale phenomena

Why Reinforcement Learning?

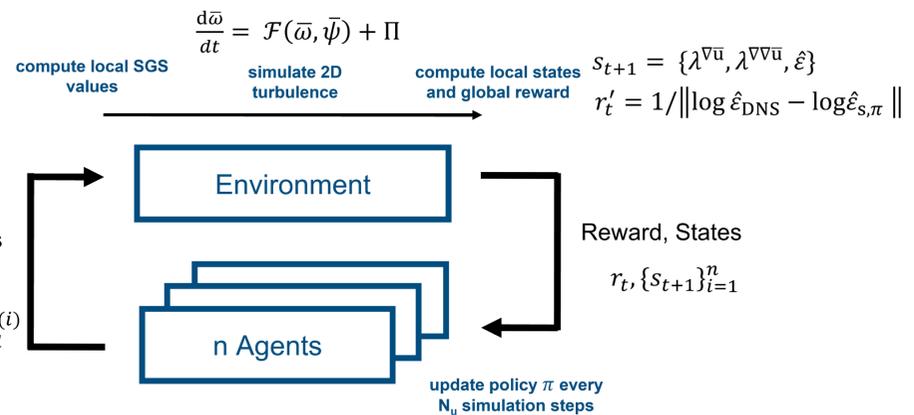
- Training in small data-regime
- Training on low-order statistics of the system (we do not have over-resolved snapshots of the states)
- Incorporating physics of sub-grid scale model for generalizability

Multi-Agent Reinforcement Learning

- **State:** Invariants of the state of the flow and instantaneous enstrophy spectrum
- **Action:** Empirical coefficients of physics-based models (Smagorinsky and Leith models)
- **Reward:** Inverse of deviation from the enstrophy of the target flow
- **Environment:** In-house spectral flow solver



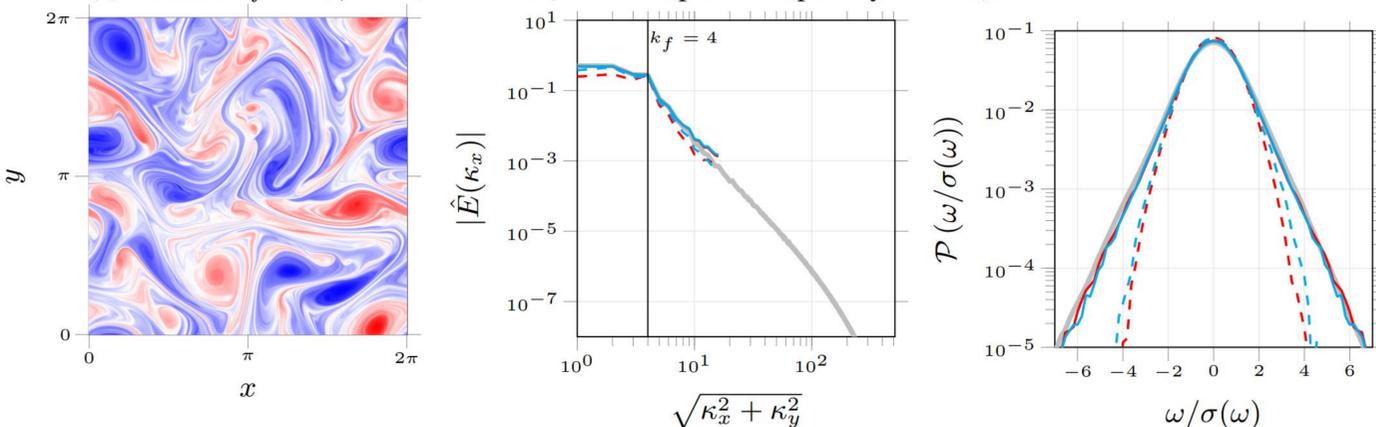
Actions
 $\{a_t^{(i)}\}_{i=1}^n$
 $a_t^{(i)} = c_s^{(i)}, c_l^{(i)}$



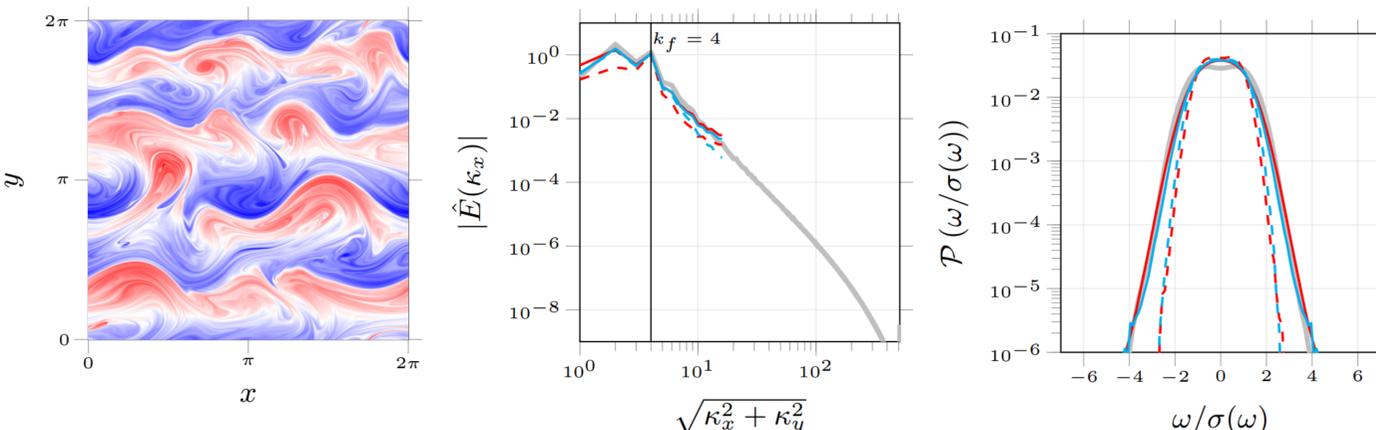
Results

— DNS - - - Dynamic Smag. - - - Dynamic Leith — RL Smag. — RL Leith

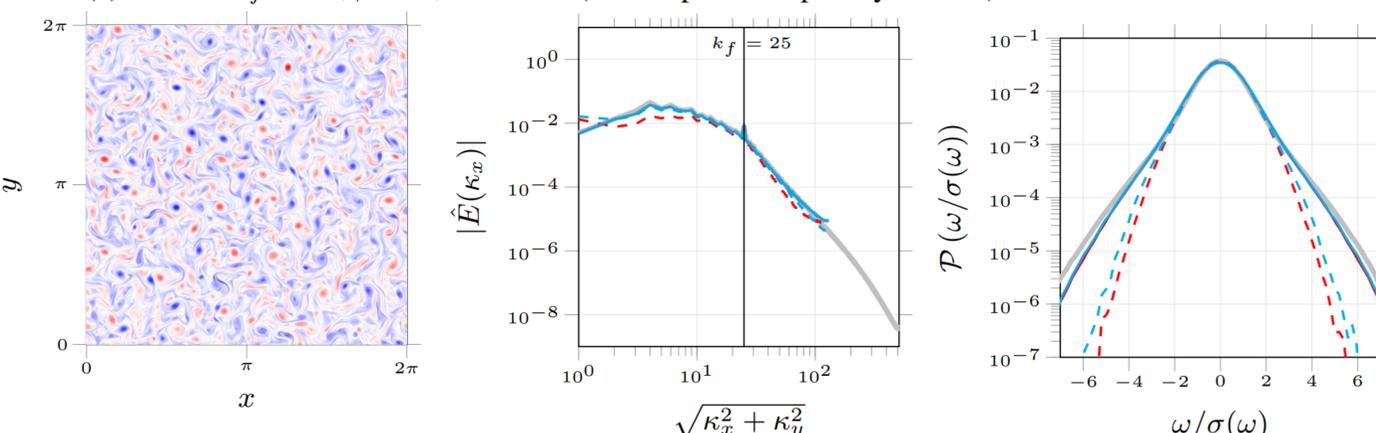
(a) Case 1: $\kappa_f = 4, \beta = 0, N = 32$ (10240× spatio-temporally coarser)



(b) Case 2: $\kappa_f = 4, \beta = 20, N = 32$ (10240× spatio-temporally coarser)

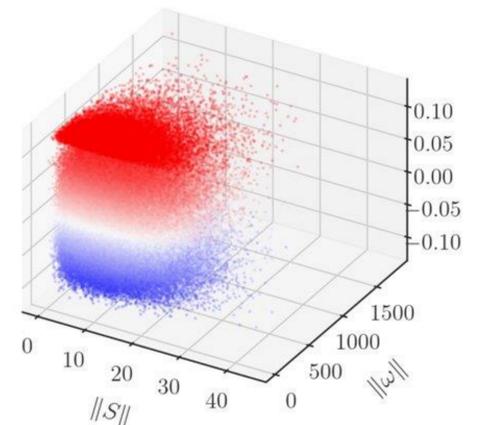


(c) Case 3: $\kappa_f = 25, \beta = 0, N = 256$ (160× spatio-temporally coarser)



Future Direction

- **Interpretation**
Low dimensional embedding of the learned actions



- **Generalization**
Which physical state can inform the generalization?
- **Training on a climate model**
Building up in the hierarchy of model complexity

Cite this work:

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