Robust Ocean Subgrid-Scale Parameterizations Using Fourier Neural Operators (NeurIPS 2023, ML4Science)

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Motivation

In climate simulations, **small-scale processes shape ocean dynamics** but remain computationally expensive to resolve directly. For this reason, **their contributions are commonly approximated using empirical parameterizations**, which lead to significant errors in long-term projections.

Example

A 1-year long **simulation** of **Black Sea physics** (CPU time):

- ≈ 14.5 years at high-resolution (~300m);
- ≈ 0.5 years at low-resolution (-3km).

Model and parameterization

- The mid-latitude ocean is approximated with a **2-layers quasigeostrophic model** (from *PyQG*). There exist two flow regimes: eddy- and jet-driven flows.

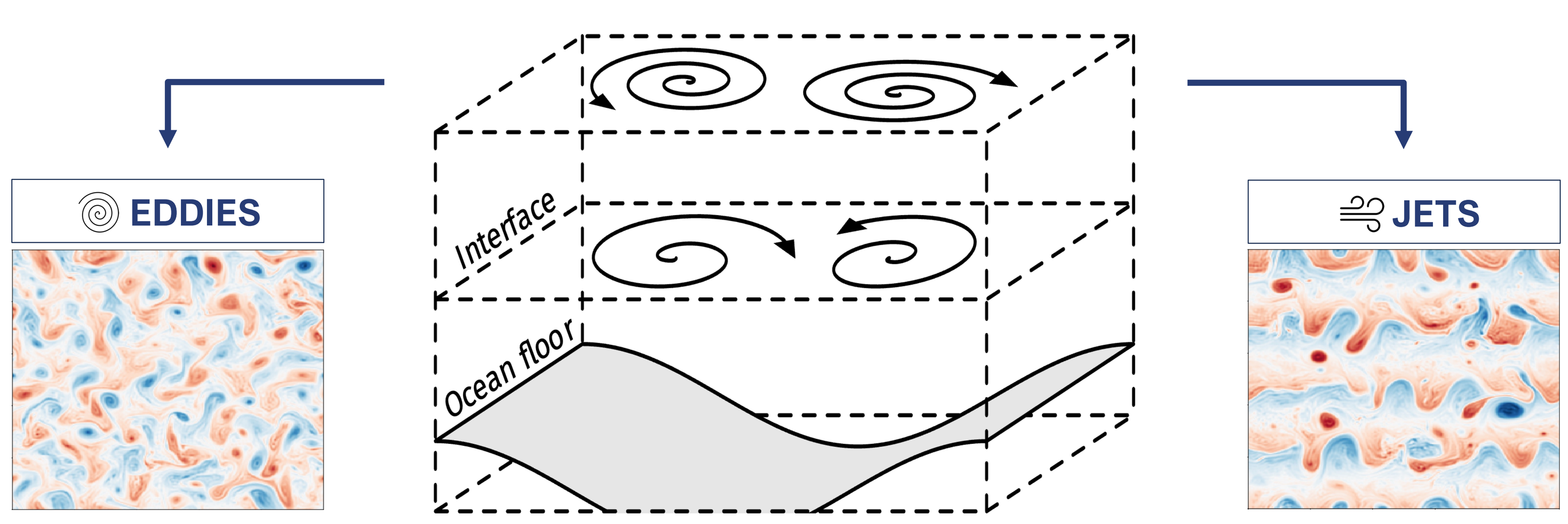

Figure 1: Illustration of the 2-layers quasigeostrophic model. The eddy-driven flow corresponds to a chaotic flow with lots of swirls, whereas for the jet-driven regime, the flow is more structured, and the fluid is moving in one main direction.

- The **quasigeostrophic equation** solved is:

$$\frac{\partial \bar{\mathbf{u}}}{\partial t} + (\bar{\mathbf{u}} \cdot \nabla)\, \bar{\mathbf{u}} = \bar{\mathbf{F}} + \bar{\mathbf{D}} + \bar{\mathbf{S}}$$

where the missing contributions $\bar{\mathbf{S}}$ are **approximated accurately and efficiently** using a parameterization.

Factorized Fourier Neural Operator (FFNO)

We want to **explore FFNO based parameterizations!**

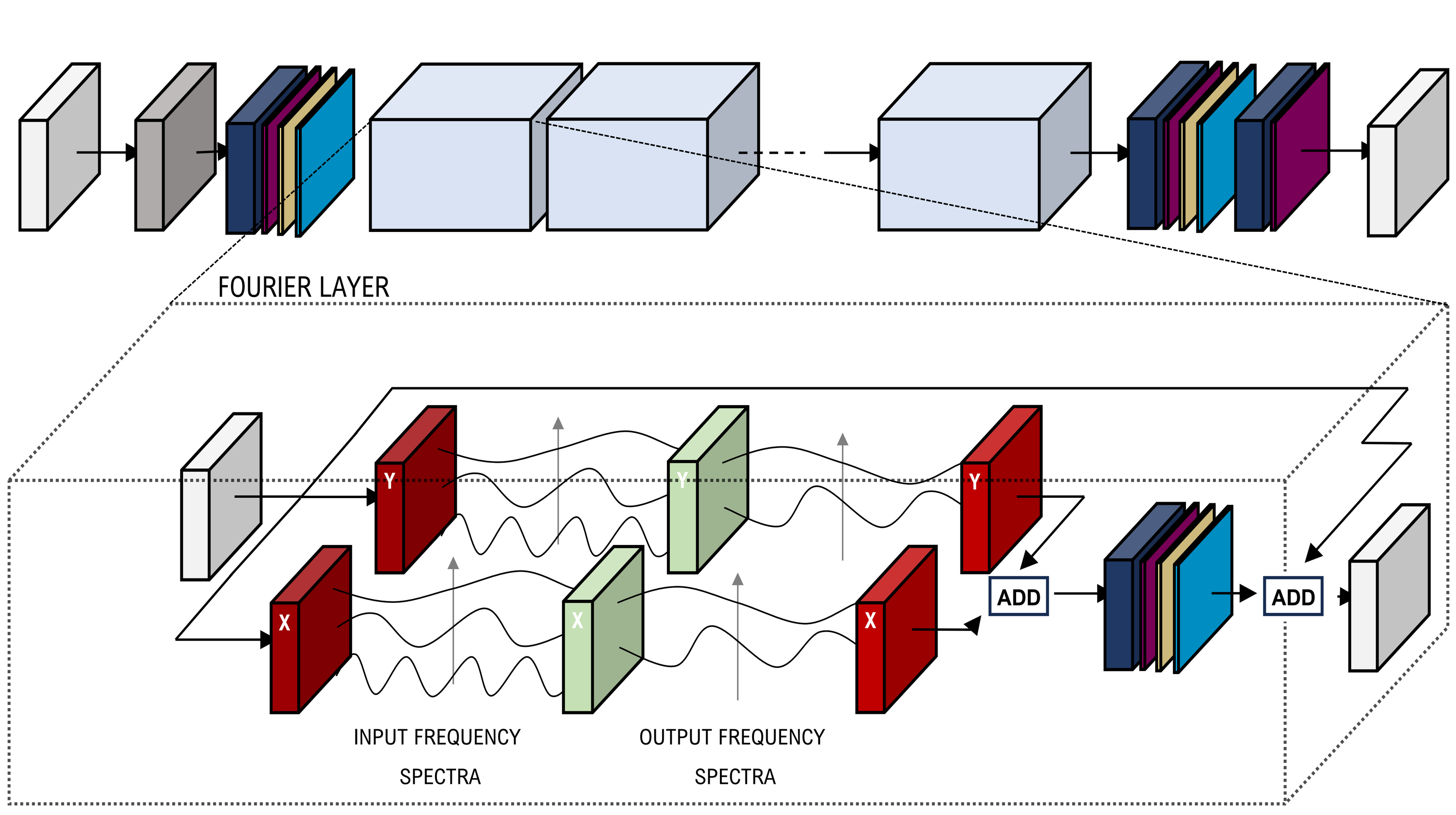

Figure 2: Illustration of the Factorized Fourier Neural Operator (Tran, Alasdair, et al. 2021)

Results

- The parameterization **accuracy** is assessed by computing the coefficient of determination $R^2 \in [-\infty, 1]$ on both layers. A value closer to 1 indicates better approximation of $\bar{\mathbf{S}}$.

TRAIN \ TEST	JETS				
	FCNN	UNET	FNO	FFNO	FFNO*
EDDIES	-0.34	-0.43	0.41	0.86	-
	-15.20	-14.40	-0.34	0.37	-
	FCNN	UNET	FNO	FFNO	FFNO*
EDDIES AND JETS	0.40	0.32	0.49	0.83	0.99
	-5.75	-4.91	0.13	0.49	0.93

Figure 3: Coefficient of determination R^2 results for neural network parameterizations show that FFNO is the only one generalizing on both layers, in contrast to FCNN, U-NET, and the original FNO architecture (line 1). When trained on both types of flow, only FNOs achieve positive scores in both layers, demonstrating their superior performance (line 2).

- The parameterization **efficiency** is evaluated by comparing the speed-up against a high-resolution simulation.

	FCNN	UNET	FNO	FFNO	FFNO*
SPEEDUP [-]	2.00	1.70	1.95	0.47	0.36

Figure 4: Computational time for a 10-year jets-driven flow scenario is simulated. The higher the speedup (>1) compared to the high-resolution simulation, the better. FFNO is inefficient in contrast to other architectures.

- Parameterization **robustness** is assessed by conducting a simulation and verifying the accurate correction of spectra for various physical quantities.

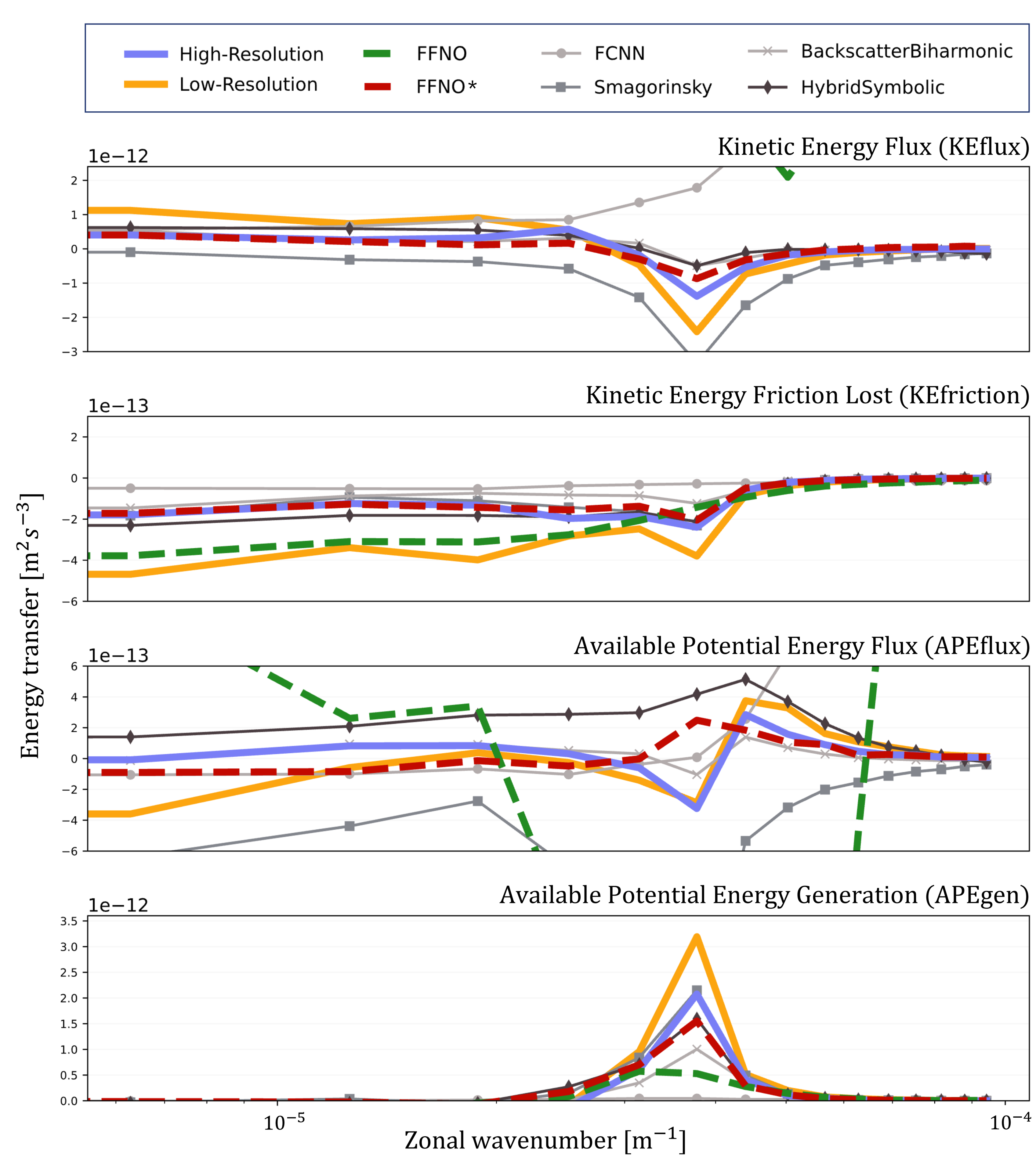

Figure 5: Energy spectrum comparison of different flow quantities in a jets-driven flow simulation. The closer a spectra is to the high-resolution spectra (blue) the better. FFNO* (fine-tuned FFNO) matches the best the high-resolution spectra except for the available potential energy flux (APEflux).