A data-driven method for modelling dissipation rates in stratified turbulence

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We present a deep probabilistic convolutional neural network (PCNN) model for predicting local values of small-scale mixing properties in stratified turbulent flows, namely the dissipation rates of turbulent kinetic energy and density variance ε and χ. Inputs to the PCNN are vertical columns of velocity and density gradients, motivated by data typically available from microstructure profilers in the ocean. The architecture is designed to enable the model to capture several characteristic features of stratified turbulence, in particular the dependence of small-scale isotropy on the buoyancy Reynolds number $Re_b := \varepsilon/(\nu N^2)$, where ν is the kinematic viscosity and N is the background buoyancy frequency, the correlation between suitably locally averaged density gradients and turbulence intensity, and the importance of capturing the tails of the probability distribution functions of values of dissipation. When trained and tested on a simulation of stratified decaying turbulence which accesses a range of turbulent regimes (associated with differing values of Re_b), the PCNN outperforms assumptions of isotropy significantly as Re_b decreases, and additionally demonstrates improvements over fitted empirical models. A differential sensitivity analysis of the PCNN facilitates a comparison with theoretical surrogate models and provides a physical interpretation of the features enabling it to make improved predictions.

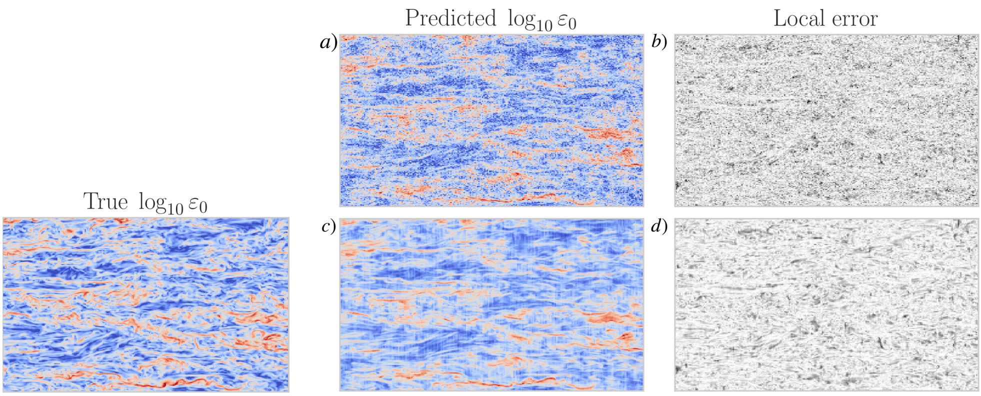

Figure 1: The left panel shows a 2D vertical snapshot of kinetic energy dissipation ε_0 from the DNS where red and blue colours represent higher and lower values of dissipation, respectively. The middle and right panels show values of ε_0 predicted by the PCNN and their corresponding local errors. *a*) and *b*) are predictions for a single sample of outputs from the PCNN; *c*) and *d*) are mean values calculated over an ensemble of 50 predictions.

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