

Figure 1: Drifter trajectories over 30 days, included in our benchmark.

DRIFT-NCRN: A BENCHMARK DATASET FOR DRIFTER TRAJECTORY PREDICTION

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Paper under double-blind review

ABSTRACT

Influenced by complex interactions at the intersection of air and water, the fate of objects floating in the ocean is difficult to predict even a few days into the future (DARPA-FFT, 2021). Despite the complexity of long-term drifter trajectory forecasting, accurate predictions are critically important for missions such as search and rescue, ecological studies, and disaster remediation. Inspired by the DARPA Forecasting Floats in Turbulence (FFT) Challenge (DARPA-FFT, 2021), we present an open-source machine learning benchmark dataset for measuring progress in ocean trajectory modelling based on a collation of drifter trajectories and archival weather and ocean forecasts. Given recent success in deep generative models (Ravuri et al., 2021; Erichson et al., 2019; Sosanya & Greydanus, 2022) for forecasting physical processes, we hope that a formal dataset will enable further development of models tuned for the complexities of drifter trajectory forecasting. In addition to introducing benchmarks for drifter forecasting, we provide baseline solutions built off of OpenDrift (Dagestad et al., 2018) an open-source software package for modeling the fate of objects in the ocean or atmosphere.

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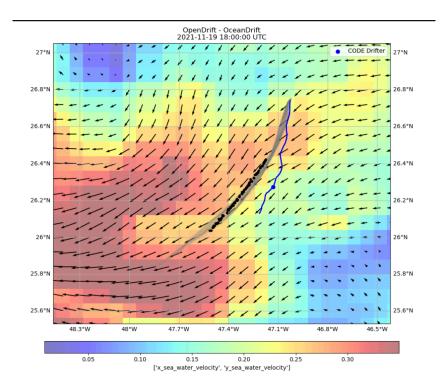


Figure 2: Baseline prediction of FFT drifter using Dagestad et al. (2018).