EGU26-17936, updated on 22 Oct 2026
https://doi.org/10.5194/egusphere-egu26-17936
EGU General Assembly 2026
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Partial Emulation of Simulated Sea-Surface Currents in the Baltic Sea: An Assessment of Explainability and Potential Forecast Skill

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Marine research and operational services require accurate sea-surface current (SSC) data. Because direct observations are sparse and spatially incomplete, spatially consistent SSC fields are most commonly obtained from numerical ocean models. These models are physically comprehensive but computationally expensive, as they integrate the full three-dimensional ocean state even when only surface currents are required. This makes their routine use inefficient for applications that primarily need surface information.

Here we develop a convolutional U-shaped neural network to partially emulate daily-mean SSC variability in the Baltic Sea. The emulator is formulated as a one-day state-update operator that predicts next-day zonal and meridional SSC components from the previous-day SSC field and prescribed near-surface atmospheric forcing. The network is trained on nine years (2015–2023) of SSC fields from the Copernicus Marine Service Baltic Sea Physical Reanalysis, together with near-surface atmospheric forcing from the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA5), interpolated to the SSC grid. Both datasets are used at 1-nautical-mile spatial resolution and daily temporal resolution. Predictive performance is evaluated on an independent test year (2024).

Occlusion sensitivity-based input selection indicates that SSC persistence (SSC on day t) and near-surface wind forcing (wind on day t+1) capture the dominant controls on day-to-day SSC evolution (SSC on day t+1), allowing the input space to be reduced to four channels by excluding additional atmospheric variables. One-day emulation achieves high skill across most of the basin, with spatially averaged vector errors of 2.4–2.6 cm s^{-1} and correlations exceeding 0.9. When deployed in an autoregressive mode, errors increase smoothly with lead time and correlations decrease to approximately 0.65 by day 21. However, large parts of the coastal and interior Baltic Sea retain correlations above 0.9 and vector errors below 10 cm s^{-1} even at multi-week lead times, indicating stable and spatially localized error growth.

To interpret the learned dynamics, we apply two explainability analyses: layer-wise relevance propagation (LRP) and diagonal Jacobian elasticity (DJE). LRP identifies which input information supports the formation of the forecast by propagating the predicted output backward through the

network and assigning each input grid point a relevance score that reflects its contribution to the forward computation, independent of local sensitivity or numerical scaling. DJE, which we term here, characterizes how the forecast responds to small input perturbations by using the model's Jacobian—the set of partial derivatives linking outputs to inputs—to quantify local, co-located sensitivities. The results show that SSC persistence provides the primary structural support for predictions in energetic boundary and strait regions, while wind forcing dominates the local sensitivity of predicted SSC over the interior basin and offshore waters. These diagnostics indicate that the network learns physically plausible state-memory and wind-driven adjustment patterns rather than relying on diffuse, non-local correlations.