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► **To cite this version:**

Pierre Garcia, Théo Archambault, Hannah Bull, Anastase Charantonis, Dominique Béréziat. Transfer-learning and data fusion for forecasting ocean surface currents. RFIAP 2024, Jul 2024, Lille, France. hal-04594549

HAL Id: hal-04594549

<https://hal.science/hal-04594549v1>

Submitted on 30 May 2024

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Transfer-learning and data fusion for forecasting ocean surface currents

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1 Summary

Short-term forecasting of ocean surface currents improves our understanding of ocean dynamics and has numerous applications such as planning ship routes over multiple days. Satellites measure various physical properties of the ocean in real-time. Observations such as sea surface temperature (SST), chlorophyll concentration, and sea surface height (SSH) provide indirect measurements of ocean surface currents. Direct measurement of ocean currents is possible using in-situ sensors, but these measurements are sparse and noisy. Due to lack of sufficient ground truth data, neural methods estimating ocean currents are often trained on synthetic data produced from physically realistic ocean simulations derived from fluid dynamics equations, with associated simulated satellite observations. Real satellite data can then be used to fine-tune or evaluate the model.

We use data from numerical simulations in conjunction with real-world satellite observations and in-situ measurements to train and validate a deep-learning model to forecast ocean currents on several days. Our model builds upon previous work by focusing on forecasting ocean surface current fields in addition to only SSH fields. Furthermore, this approach is observation-driven rather than an explicit physical forecast. In a first stage, we train a convolutional neural network to forecast currents using simulated satellite observations and ground truth data from a numerical model. In a second transfer-learning stage, we use real altimetric observations and in-situ measurements to fine-tune our model. We evaluate our ocean current forecast using both numerical simulations and real in-situ measurements from drifters and on-board instruments from ships.

2 State of the art

Far from the Equator, surface currents can be approximated from SSH using the geostrophic balance equation [1]. Altimetric satellites provide sparse along-track measures of sea surface height, which can then be optimally interpolated to provide a low-resolution dense map, as provided by DUACS [3]. Alternatively, several studies train deep learning models on simulated data to reconstruct SSH from sparse observations, and hence approximate currents [7, 9, 5]. Recent approaches by Archambault et al. [6] and Martin et al. [8, 12] inpaint SSH fields without simulated data, by computing loss along sparse SSH observation tracks. In [11, 10], the authors pre-train a model on simulated data and fine-tune the model on real data to reconstruct SSH. While the aforementioned methods can provide reasonably accurate predictions of ocean surface currents in real-time, further work is required to produce reliable forecasts.

Numerical simulations rely on physical equations to describe the ocean dynamics and provide forecasts of surface currents. Numerical models such as Mercator [2] are assimilated to real satellite observations in real-time, providing a nowcast and forecast of ocean currents. Nevertheless, the nowcast performance of Mercator for ocean surface currents is low [11]. In [14], the authors train a neural network to forecast ocean currents from initial conditions produced with an assimilated numerical model. This model strongly relies on numerical simulations, which limits its operational use. Hence, we further develop this work by forecasting ocean currents from only real-time satellite observations. The architecture in [10] can be adapted to forecast SSH fields, and our method expands upon this architecture to additionally forecast ocean currents.

3 Method

3.1 Data

To train and evaluate our model on simulated data, we use CROCO [4], a reanalysis of observations acquired over the Mediterranean Sea over the period 2015–2016. This dataset provides ground truth values of SSH and ocean currents at

1/60th of a degree (approx. 2km), as well as simulated satellite observations of SST, along-track sparse SSH observations imitating satellite altimetry, and a low-resolution simulated DUACS interpolated SSH product.

In the transfer-learning phase, used to fine-tune and evaluate our model on real data, we use input data from satellites and evaluation data from satellites and in-situ measurements. In particular, we use as inputs SST (1km resolution), chlorophyll concentration (300m resolution), along-track sparse SSH observations, and the interpolated SSH product from DUACS (12km resolution). As ground truth data, we use future along-track SSH observations as well as in-situ observations of ocean surface currents from drifters and from on-board instruments from ships.

3.2 Model

Let f_θ be a neural network forecasting SSH and currents from a temporal window of SSH and SST observations: $f_\theta(Y_{-T:0}) = \hat{X}_{1:\tau}$ where $Y_{-T:0}$ are past SSH and SST observations up to time $t = 0$ and $\hat{X}_{1:\tau}$ are estimations of the future SSH and current fields after time $t = 0$. Figure 1 illustrates our model inputs, outputs and architecture. Building upon the architecture used in [10] to reconstruct SSH, f_θ is an encoder-decoder model based on 3D convolutions (the dimensions being time, latitude, and longitude), temporal and spatial attention modules, upscaling, downscaling and activation layers. Each input and forecast is a spatial crop of 128×128 pixels. Physical models trained on multiple geographic regions are generally worse than region-specific models [13]. To address this, we provide our model with region-specific physical property fields: seafloor depth map, latitude and longitude (see Figure 1).

3.3 Transfer-learning from simulated to real data

We pre-train our network on simulated data and fine-tune it on real observations. In the first stage of training, our model inputs simulated observations from satellite altimetry and SST, as well as geographic information such as latitude, longitude, and ocean depth. Each sample consists of a random spatial crop of 128×128 pixels. We experiment on several resolutions: 1/60th, 1/30th and 1/15th of degree of latitude and longitude per pixel. We conduct experiments on the capacity of the model to forecast with 3 types of inputs: (i) simulated ground truth SSH and SST: this tests the model’s capacity to learn future ocean dynamics from past states; (ii) simulated interpolated low-resolution SSH observations and noisy high-resolution SST: this tests the model’s capacity to forecast high-resolution ocean currents from low-resolution or noisy approximations; (iii) simulated sparse SSH observations and noisy high-resolution SST: this tests the model’s capacity to jointly interpolate SSH as well as forecast ocean currents from realistic observations.

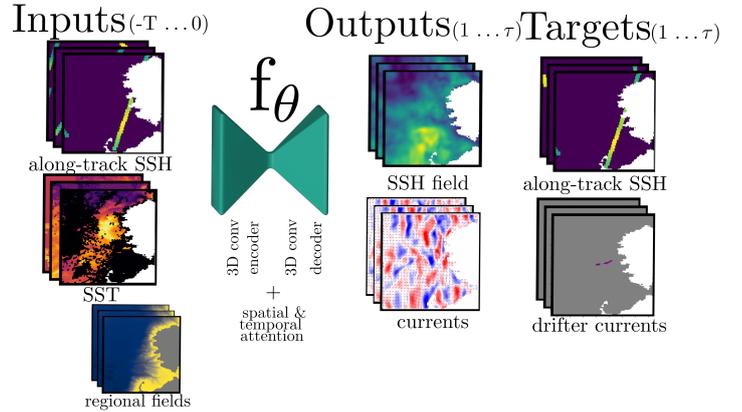


Figure 1: Our model is a 3D encoder-decoder neural network. **Inputs:** past SSH tracks, SST, and regional fields such as seafloor depth ($Y_{-T:0}$). **Outputs:** future SSH fields and ocean currents ($\hat{X}_{1:\tau}$). **Targets:** future SSH tracks and currents measured by in-situ observations. Cloudy pixels in the SST are masked in black, land masks are in white.

In the second transfer-learning phase of training, we input real satellite observations. Models (ii) and (iii) can be evaluated and fine-tuned using real satellite observations (see figure 1 for model (iii) setup). To fine-tune SSH predictions, we compute RMSE loss using sparse observations from satellite altimetry. We fine-tune predictions of ocean surface currents using sparse observations from drifters, as well as pseudo-labels from reliable predictions [11].

3.4 Evaluation

We have three sources of evaluation data: ground truth data from numerical simulations (ocean surface currents and SSH), sparse SSH observations from satellites, and sparse in-situ observations of ocean surface currents from drifters and ships. To compare the performance of our model in forecasting SSH, we use the RMSE metric. We compare to both ground truth data from simulations and sparse altimetric tracks from real observations. To evaluate our model’s performance in predicting ocean surface currents, our metrics are absolute angle and magnitude differences between our predictions and the ground truth. We use both simulated ground truth data and in-situ observations from drifters and on-board instruments from ships to evaluate the performance of our model in forecasting ocean currents.

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