Drift Trajectory Predictions using Massive Ensembles of Simplified Ocean Models

SINTEF

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Problem description

Short-term drift trajectory prediction is an important tool for, e.g., search and rescue operations, oil-spill cleanup, and decision making for avoiding collisions between icebergs and offshore installations. Traditionally, such forecasts are made from a small ensemble of advanced 3D ocean circulation models, with drift prediction as a post-processing step. Herein, we investigate in using simplified ocean models, which can be implemented to efficiently run on graphics processing units (GPUs). This enables us to run large ensembles of simplified ocean models with integrated drift simulations. Furthermore, we use past observations of the drifting object to improve the ocean initial conditions through data assimilation. As the ocean is dominated by highly nonlinear dynamics and we have few observations, we use a particle filter based on sequential importance resampling (SIR). In our experiments, we apply up to 10 000 ensemble members. Fig. 1 shows the initial conditions and synthetic true drifters used in our forecast experiments.

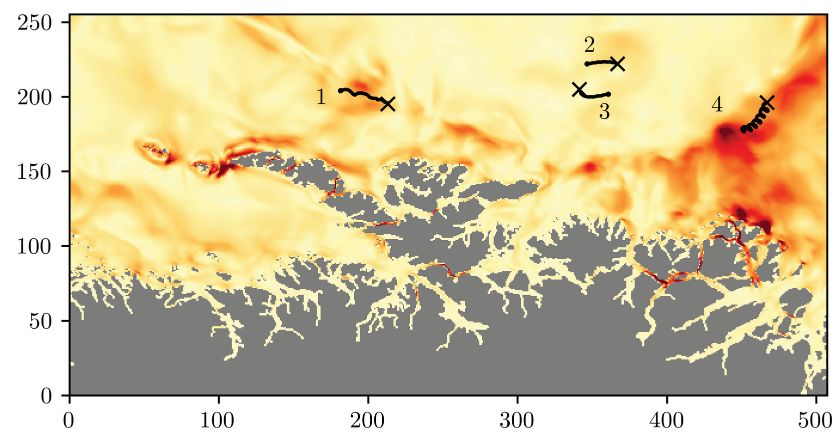

Figure 1: Synthetic observed drift trajectories used in the forecast experiments. The color map shows initial particle velocity.

Simulation of simplified ocean models

We consider the rotating shallow-water equations as a simplified ocean model, given by

$$\begin{bmatrix}\eta\\ hu\\ hv\end{bmatrix}_t + \begin{bmatrix}hu\\ hu^2+\frac{1}{2}gh^2\\ huv\end{bmatrix}_x + \begin{bmatrix}hv\\ huv\\ hv^2+\frac{1}{2}gh^2\end{bmatrix}_y = \begin{bmatrix}0\\ fhv\\ -fhu\end{bmatrix} + \begin{bmatrix}0\\ ghH_x\\ ghH_y\end{bmatrix}.$$

It is a hyperbolic conservation law with the conserved state $\boldsymbol{\psi} = [\eta, hu, hv]^T$ representing the surface elevation and volume transport in x- and y-direction. Furthermore, g is the gravitational force, f is the Coriolis parameter, and $H(x,y)$ describes equilibrium depth so that the total ocean depth becomes $h = H + \eta$.

We have developed a simulation framework [1] based on an explicit, high-resolution finite-volume scheme [2], which is extended to account for all aspects required to run simulations directly from operational ocean forecasts issued by MET Norway.

Our extensions to the numerical scheme are:

- Reconstruction of bathymetry at cell intersections from cell centers (Fig. 2),
- Coriolis force when north is not aligned with the y-axis (Fig. 3),
- Boundary condition with static land mask,
- Support of dry zones,
- Nested boundary conditions from external model,
- Wind-forcing and bed friction source terms,
- Grid refinement/coarsening,
- Algorithmic improvements to make the scheme suitable for GPU implementation.

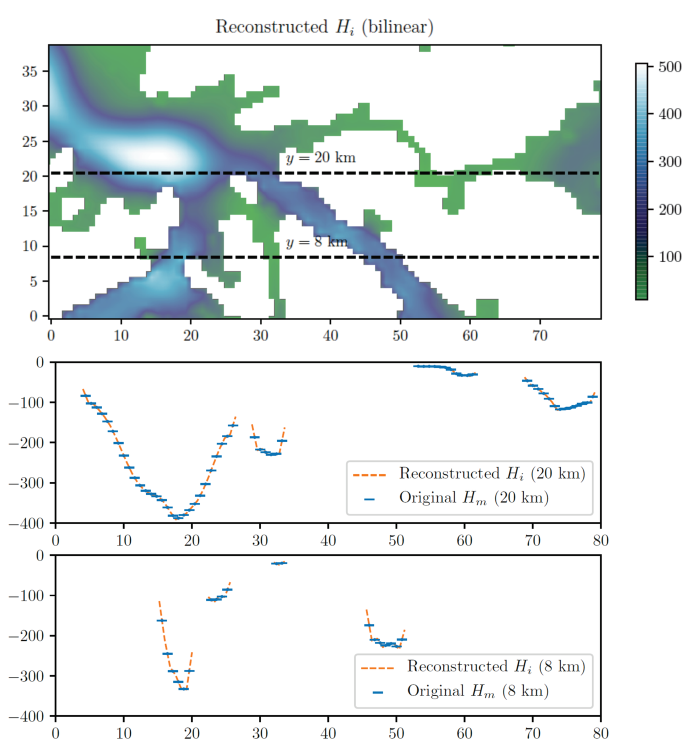

Figure 2: Reconstruction of bathymetry.

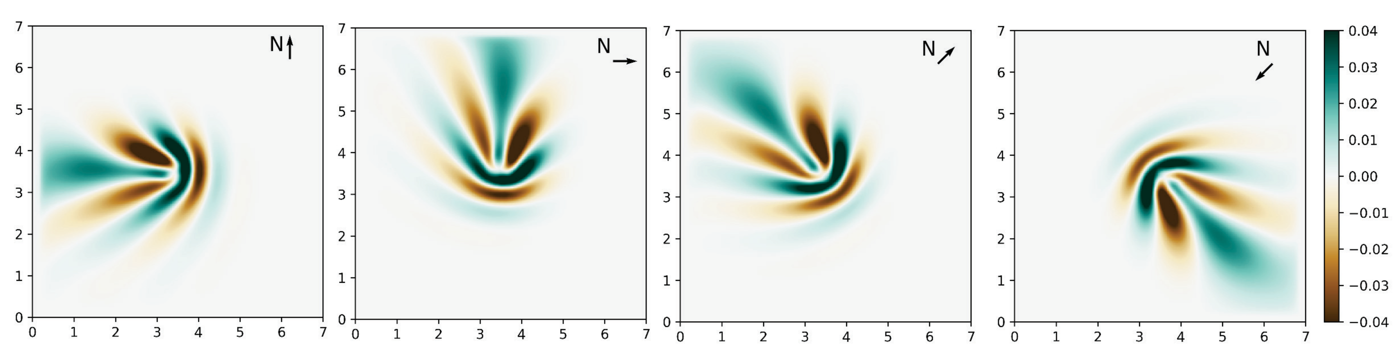

Figure 3: Planetary Rossby waves for various grid orientations relative to north.

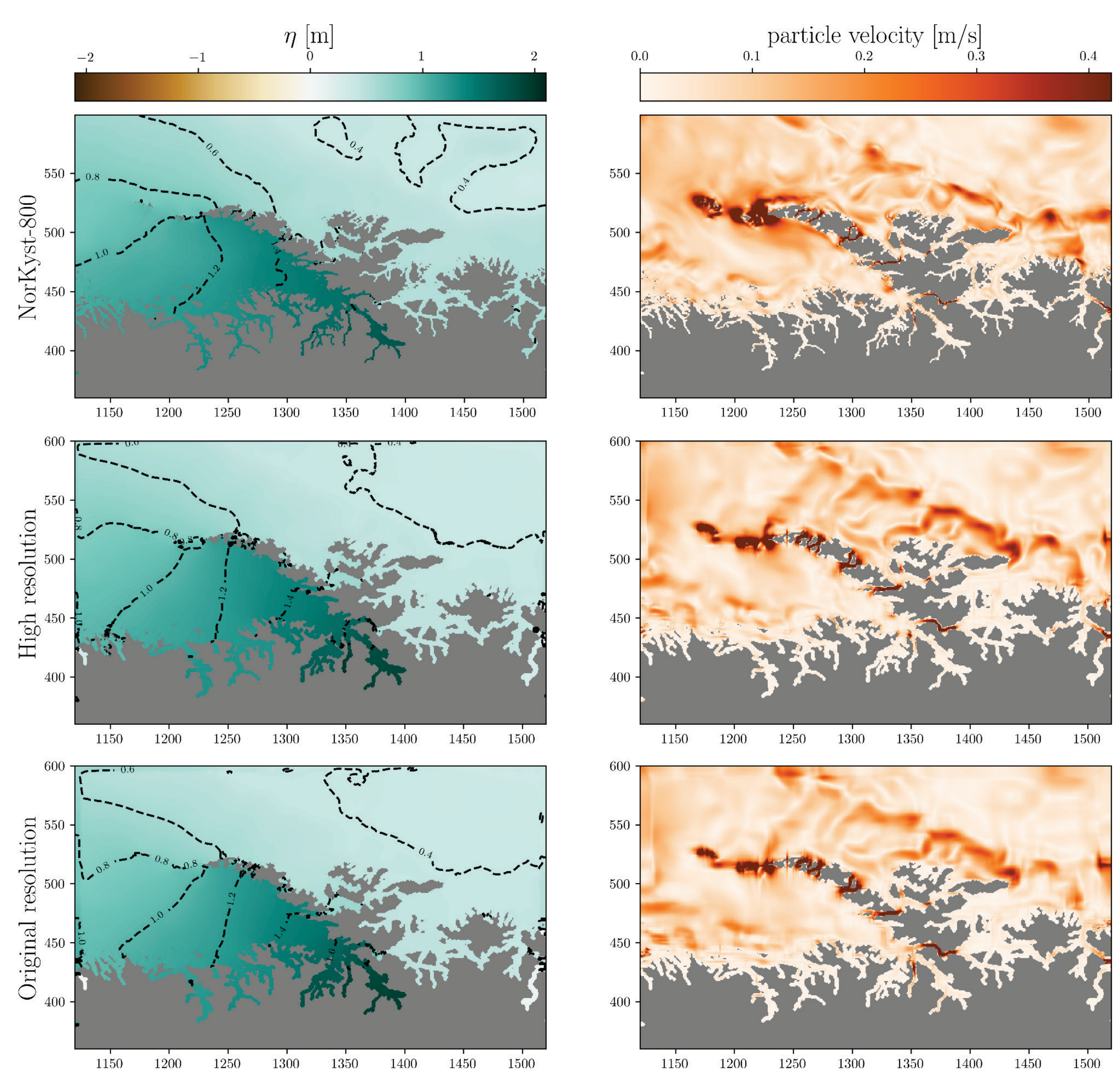

Figure 4: The operational ocean forecast and simulation results using the simplified ocean model after 23 hours.

Nonlinear data assimilation with massive ensemble

Before starting the drift trajectory forecast, we run ensemble-based data assimilation to improve our initial conditions based on estimates of the ocean currents obtained from positional observations of the drifters. With imperfect observations $\boldsymbol{y}^n$ at times $t^n \in \{t^1_{obs}, t^2_{obs}, \dots, t^K_{obs}\}$, we first evolve the ensemble $\{\boldsymbol{\psi}^n_i\}_{i=1,\dots,N}$ to t^n. We then apply Bayes theorem to the ensemble to get an improved probability estimate of the ocean state in the form of a weighted ensemble:

$$p(\boldsymbol{\psi}^n|\boldsymbol{y}^n) \propto \sum_{i=1}^{N} \frac{p(\boldsymbol{y}^n|\boldsymbol{\psi}^n_i)}{\sum_{j=1}^{N} p(\boldsymbol{y}^n|\boldsymbol{\psi}^n_j)} \delta(\boldsymbol{\psi}^n - \boldsymbol{\psi}^n_i) = \sum_{i=1}^{N} w^n_i\, \delta(\boldsymbol{\psi}^n - \boldsymbol{\psi}^n_i)$$

As ensemble members with low weights have negligible contribution to the ensemble we use a SIR particle filter (see [3]) to resample the ensemble members based on their weights.

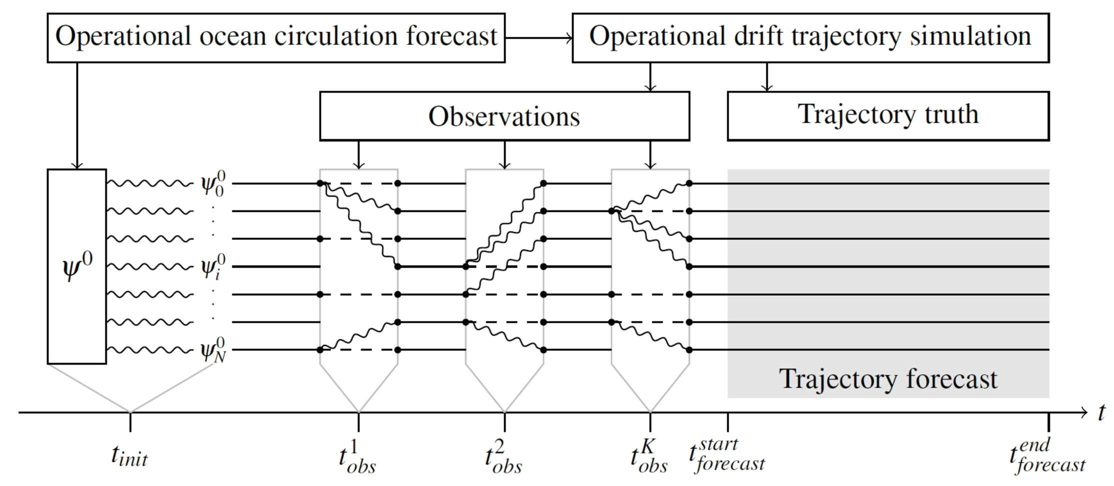

Figure 5: Experiment setup. We initialize the ensemble from an ocean forecast and assimilate observations into the ensemble using a SIR particle filter. Straight lines are deterministic simulation, whereas wiggly lines represents perturbations.

In our experiments [4] we run 48 hours of data assimilation before a 24 hour drift trajectory forecast. The experiments are run on a Nvidia DGX-2 server containing 16 Tesla V100 GPUs. Fig. 6 shows ensemble forecasts for drifter 2 from Fig. 1, with the following configurations:

a) $N = 1000$, pure Monte Carlo simulation using no observations,
b) $N = 1000$, SIR particle filter with observations every 30 mins,
c) $N = 1000$, SIR particle filter with observations every 5 mins,
d) $N = 10\,000$, SIR particle filter with observations every 5 mins,

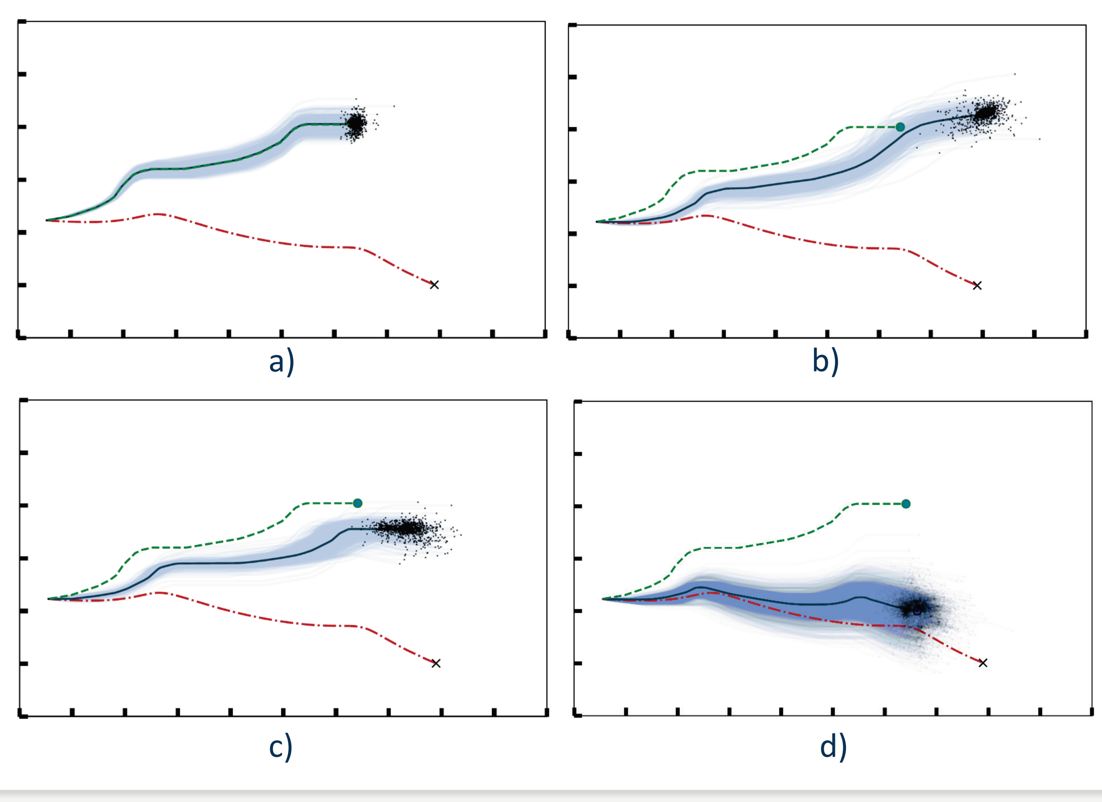

Figure 6: Resulting drift trajectory forecasts.

Light blue: Ensemble members, Dark blue: Ensemble mean, Green: Single deterministic forecast, Red: Synthetic truth.

Further reading

[1] A. Brodtkorb, H. Holm "Real-world oceanographic simulations on the GPU using a two-dimensional finite-volume scheme", in review, 2020. Preprint: arXiv:1912.02457

[2] A. Chertock, M. Dudzinski, A. Kurganov, M. Lukácová-Medvidová "Well-balanced schemes for the shallow water equations with Coriolis forces", *Numerische Mathematik*, 2017. DOI: 10.1007/s00211-017-0928-0

[3] P. van Leeuwen, L. Nerger, R. Potthast, S. Reich, and H. Kunsch "A review of particle filters for geoscience applications", *Quarterly Journal of the Royal Meteorological Society*, 2019. DOI: 10.1002/qj.3551

[4] H. Holm, M. Sætra, A. Brodtkorb "Data Assimilation for Ocean Drift Trajectories Using Massive Ensembles and GPUs", in review, 2020.

Source code: https://github.com/metno/gpu-ocean/ Project website: https://www.met.no/en/projects/gpu-ocean

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