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1 **Neural prediction of Lagrangian drift trajectories on the sea surface**

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8 ABSTRACT: We simulate Lagrangian drift on the sea surface and investigate deep learning ap-
9 proaches to address the shortcomings of current model-based and Markovian approaches, particu-
10 larly concerning error propagation and computational complexity. We present a novel deep learn-
11 ing framework, referred to as DriftNet, inspired by the Eulerian Fokker-Planck representation of
12 Lagrangian dynamics. Through numerical experiments for simulated and real drift trajectories on
13 the sea surface, we illustrate the effectiveness of DriftNet compared to existing state-of-the-art
14 schemes. We also delve into the influence of diverse geophysical fields, whether derived from
15 models or observations, used as inputs by DriftNet on drift simulation. Our objective is to assess
16 the amount of dynamic information required to accurately simulate realistic trajectories.

17 SIGNIFICANCE STATEMENT: We propose a novel Deep Learning model, DriftNet, for con-
18 ditional generation of Lagrangian trajectories on the sea surface. Our model is based on Eulerian
19 Fokker-Planck formalism and can be conditioned by multiple geophysical fields. We highlight the
20 overall over-performance of DriftNet compared to the baseline model-based and learning-based
21 approaches. We put in evidence the capacity of the proposed method to extract pertinent infor-
22 mation from various geophysical fields, both from modeled and observed data. We highlight the
23 significant impact of the observed sea surface height when combined to sea surface currents in the
24 quality of the generation of Lagrangian trajectories.

25 1. Introduction

26 The modeling and simulation of Lagrangian drift on the sea surface holds relevance for various
27 applications such as tracking of plastics and other debris [Maximenko et al. (2012)], the study of
28 algae and plankton dynamics [Son et al. (2015)], or the prediction of future locations of drifting
29 objects that is crucial for search and rescue operations [Breivik et al. (2013)]. Furthermore, the
30 analysis of Lagrangian drifts serves as a valuable tool for diagnosing ocean numerical models
31 in their capability for reproducing small-scale dynamics [Barron et al. (2007)]. However, repro-
32 ducing realistic Lagrangian trajectories on the sea surface poses a significant scientific challenge
33 within operational oceanography [Röhrs et al. (2021)].

34 From a methodological standpoint, we can distinguish three main categories of approaches for
35 Lagrangian drift simulation: model-based approaches [Liubartseva et al. (2018); Zambianchi et al.
36 (2017)], probabilistic data-driven schemes [Visser (2008)], and more recent deep learning tech-
37 niques [Botvynko et al. (2023); Jenkins et al. (2023)]. Model-based approaches involve a sequen-
38 tial advection process based on known sea surface velocity fields [Lange and van Sebille (2017)].
39 However, small errors in the underlying velocity fields or velocity fields without very fine spa-
40 tial resolution may lead to unrealistic Lagrangian trajectories [Callies et al. (2021)]. This often
41 impedes their operational usefulness due to significant uncertainties in the forecasting and recon-
42 struction of sea surface dynamics, especially regarding mesoscale ocean dynamics [Prants et al.
43 (2017)]. Due to their sequential nature, these schemes also face scalability challenges when simu-
44 lating large ensembles of drift trajectories. By contrast, probabilistic data-driven schemes usually
45 leverage first-order Markovian models and naturally account for uncertainties in the drift process.

46 However, they are primarily suited for relatively coarse space-time resolutions. Extending these
47 schemes to capture fine-scale patterns poses a challenge [Fine et al. (1998)]. For these two first cat-
48 egories, the simulation of the Lagrangian drift relies on location-wise velocities at each time step,
49 which may only be applicable for smooth velocity fields. Deep Learning has recently emerged as
50 a novel class of numerical tools for the learning-based simulation of movement patterns. We may
51 cite applications to pedestrians [Korbmacher and Tordeux (2022)], seabirds [Roy et al. (2022)],
52 cars [Jiang et al. (2019)] or maritime vessels [Nguyen and Fablet (2024)]. These applications
53 leverage state-of-the-art recurrent neural networks, such as Long Short-Term Memory (LSTM)
54 networks [Yu et al. (2019)], as well as deep generative schemes [Goodfellow et al. (2020); Roy
55 et al. (2022); Ma et al. (2019); Gan et al. (2020); Julka et al. (2021); Paz et al. (2021)]. Most of
56 these studies can be regarded as neural extensions of probabilistic Markovian schemes.

57 In this context, we present an innovative Deep Learning framework, referred to as DriftNet, for
58 simulating Lagrangian trajectories at the sea surface. The proposed neural model takes as input
59 geophysical fields characterizing the ocean dynamics in a spatio-temporal region and produces
60 the associated Lagrangian trajectory. Our approach is fully-convolutional and features a spatially-
61 explicit latent representation, drawing inspiration from Eulerian Fokker-Planck representations of
62 drift processes [Botvynko et al. (2023)]. From numerical simulation datasets, we demonstrate
63 DriftNet to outperform state-of-the-art neural schemes for the simulation of Lagrangian trajec-
64 tories, including when considering degraded sea surface velocities. The application to real sea
65 surface drifters' datasets further supports the relevance of DriftNet to improve the simulation of
66 Lagrangian drift on the sea surface compared with model-driven simulations. This last experiment
67 also illustrates how DriftNet can exploit additional data sources, besides sea surface velocities,
68 here satellite-derived sea surface height fields.

69 This paper is organized as follows: section 2 focuses on the problem description; we introduce
70 DriftNet in section 3 and the considered experimental setup in section 4; section 5 details our
71 results and section 6 discusses key aspects of this study.

72 **2. Problem statement**

73 In the context of Lagrangian fluid dynamics¹, one may describe a flow by following the mo-
74 tion of an ensemble of individual particles [Davis (1991)]. In order to describe the flow in the

¹From now on, the Lagrangian notations are presented with \rightarrow symbol, and the Eulerian notations are in **bold**.

75 Lagrangian framework, an ordinary differential equation defines the particle's trajectory :

$$\frac{\partial \vec{r}(\vec{r}_{i_0}, t)}{\partial t} = \vec{v}(\vec{r}_{i_0}, t) = \mathbf{u}(\vec{r}(t), t) \quad (1)$$

76 where $\vec{r}(\vec{r}_{i_0}, t)$ and $\vec{v}(\vec{r}_{i_0}, t)$ are respectively the position and velocity at time t of the particle situated
77 at \vec{r}_{i_0} at $t = 0$, and $\mathbf{u}(\vec{r}(t), t)$ is the Eulerian velocity of the underlying flow given position $\vec{r}(t)$ and
78 time t . Classical model-driven approaches simulate Lagrangian drift dynamics through explicit
79 time and space integration methods such as Runge-Kutta 4. Thus, the integration of eq.(1) leads
80 to :

$$\vec{r}(\vec{r}_{i_0}, t + \Delta t) = \vec{r}(\vec{r}_{i_0}, t) + \int_t^{t+\Delta t} \vec{v}(\vec{r}_{i_0}, \tau) d\tau \quad (2)$$

81 The sequential nature of this equation introduces important propagation of errors when the under-
82 lying velocities are not accurately known [Callies et al. (2021)].

83 Interestingly, we can also derive an Eulerian formulation of Lagrangian dynamics. Through
84 Fokker-Planck formalism [Visser (2008)], we can generalize eq.(2) to the time propagation of the
85 Probability Density Function (PDF) of the moving particle as follows:

$$\frac{\partial}{\partial t} p_{\vec{r}}(x, t) = -\frac{\partial}{\partial x} [\mu(x, t) p_{\vec{r}}(x, t)] \quad (3)$$

86 where x represents spatial position in the Eulerian framework, t the time, $p_{\vec{r}}(x, t)$ the PDF of the
87 particle at position \vec{r} and $\mu(x, t)$ a drift field. In our case, this drift term relates to the underlying
88 Eulerian velocity field $\mathbf{u}(x, t)$. Solving eq.(3) relies on a time integration scheme from the initial
89 PDF $p_{\vec{r}}(x, t = 0) = p_{\vec{r}_{i_0}}(x, 0)$.

90 Here, we rely on this Eulerian Fokker-Planck representation of Lagrangian dynamics to explore
91 convolutional neural architectures for the simulation of individual drift trajectories.

92 **3. DriftNet for Lagrangian drift simulation**

93 This section introduces the mathematical framework and the architecture of the proposed neural
94 network model, called DriftNet, along with the considered learning scheme.

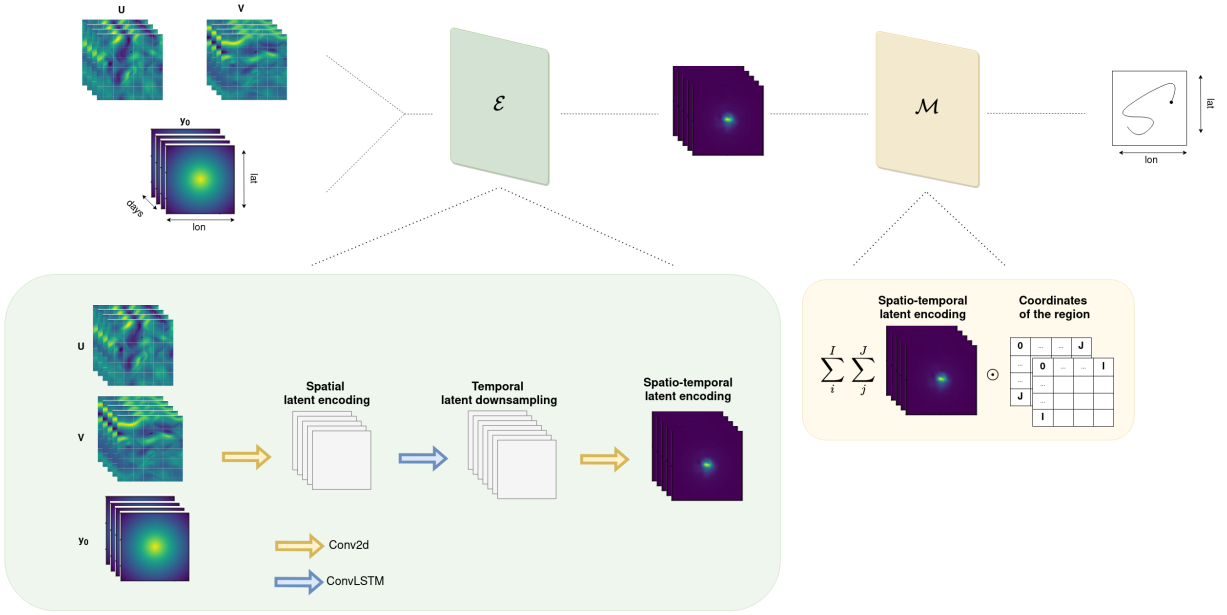


FIG. 1: **DriftNet architecture:** The input geophysical fields over 9-day (here zonal \mathbf{U} and meridional \mathbf{V} components of the velocity field) coupled to the initial spatio-temporal positional encoding \mathbf{y}_0 are first passed to the encoding block \mathcal{E} and output a spatio-temporal latent encoding. The second block of DriftNet \mathcal{M} maps this latent representation to a 1D trajectory, *i.e.* a time series of positions on the sea surface.

95 *a. Proposed neural scheme*

96 Given a spatial domain of interest \mathcal{D} defined as a regularly-gridded domain of size $I \times J$, we
 97 define the associated sequence of velocity fields $\mathbf{u} = \{\mathbf{u}_{t_0}, \mathbf{u}_{t_0+\Delta}, \dots, \mathbf{u}_{t_0+K\Delta}\}$ from time t_0 to $t_0 +$
 98 $K\Delta$, where Δ is the time sampling and K the number of time steps, and the trajectory of a particle as
 99 a time series of locations $\vec{r} = \{\vec{r}_{t_0}, \vec{r}_{t_0+\Delta}, \dots, \vec{r}_{t_0+K\Delta}\}$ in \mathcal{D} from t_0 to $t_0 + K\Delta$, where \vec{r}_{t_0} corresponds
 100 to the initial position of the particle.

101 Inspired by Fokker-Plank eq.(3), we consider the following latent representation for a simulated
 102 Lagrangian drift \vec{r} :

$$\begin{cases} \mathbf{y} &= \mathcal{E}(\mathbf{u}, \mathbf{y}_0) \\ \vec{r} &= \mathcal{M}(\mathbf{y}) \end{cases} \quad (4)$$

103 where $\mathbf{y} = \{\mathbf{y}_{t_0}, \mathbf{y}_{t_0+\Delta}, \dots, \mathbf{y}_{t_0+K\Delta}\}$ is a space-time-explicit latent embedding of \vec{r} , and $\mathbf{y}_0 =$
 104 $\{\mathbf{y}_{0,t_0}, \mathbf{y}_{0,t_0+\Delta}, \dots, \mathbf{y}_{0,t_0+K\Delta}\}$ some initial encoding of the initial position \vec{r}_{t_0} . In particular, we define
 105 \mathbf{y}_{0,t_0} by assigning to each spatial pixel of the grid a value corresponding to the normalized distance

106 to the initial position of the particle eq.(5).

$$d = -\sqrt{\sum_{x \in \mathcal{D}} (\vec{r}_{t_0} - x)^2} \quad (5)$$

$$\mathbf{y}_{0,t_0} = \frac{d + |\min d|}{\max(d + |\min d|)} \quad (6)$$

107 while the other time steps of \mathbf{y}_0 are initialized as all-ones matrix of the same dimension as \mathcal{D} .

108 The operator \mathcal{E} computes a latent embedding \mathbf{y} given velocity conditions \mathbf{u} and initial repre-
 109 sentation \mathbf{y}_0 , as introduced in eq.(3). And, the operator \mathcal{M} maps latent representation \mathbf{y} to the
 110 targeted Lagrangian drift \vec{r} . In other words, it maps a multi-dimensional tensor to a time series of
 111 locations in \mathcal{D} . The analytical expression of the operator \mathcal{M} for a given time step t grounds on the
 112 Hadamard product between the spatially-explicit encoding x of the space \mathcal{D} and \mathbf{y}_t field:

$$\mathcal{M} = x \cdot \mathbf{y}_t \quad (7)$$

113 where $\mathbf{y}_t \in \mathbf{y}$, a sample of \mathbf{y} at a time step $t \in [t_0, \dots, t_{0+K\Delta}]$.

114 Regarding the operator \mathcal{E} , we consider the architecture sketched in Figure 1 and composed of:

- 115 1) a 2D convolutional layer increasing the number of channels from 3 (zonal and meridional
 116 components of \mathbf{u} coupled to \mathbf{y}_0) to 64, followed by a LeakyReLU activation function.
- 117 2) 2D convolutional LSTM block [Shi et al. (2015)].
- 118 3) 2D convolutional layer decreasing the number of channels from 64 to 2, followed by 2D
 119 Softmax function.

120 Since our model is mainly based on 2D convolutional layers, we expect the resulting architecture
 121 to capture relevant information at different space-time scales, and not only in a point-wise manner,
 122 as it would be the case for the straightforward implementation of Fokker-Plank representation
 123 eq.(3). Thus, our network can leverage non-local physical information explaining the particle's
 124 motion and processes it to propagate the latent representation of particle's positions through time.

125 Interestingly, the proposed architecture easily generalizes to multi-source input data. Gridded
 126 fields such as SSH fields with the same space-time resolution as the sea surface velocities convey
 127 relevant information on sea surface dynamics. Stacking SSH and sea surface velocities, we may

128 apply the same neural architecture, just increasing the number of channels of the input fields. The
 129 same applies for a prior on the diffusivity from the initial location of a particle in the field, that can
 130 be also included by stacking with the temporal evolution of the initial condition \mathbf{y}_0 .

131 *b. Learning scheme*

132 We consider a supervised training of the proposed neural architecture according to the following
 133 two losses:

- 134 1. the Mean Square Error (MSE) between the reference and simulated trajectories for the K -step
 135 simulation of N_T particles

$$\mathcal{L}_{MSE} = \frac{1}{N_T K} \sum_{i=0}^{N_T} \sum_{j=0}^K (\vec{r}_R(\vec{r}_{0,i}, j\Delta) - \vec{r}_S(\vec{r}_{0,i}, j\Delta))^2 \quad (8)$$

136 where \vec{r}_R and \vec{r}_S are the vector of positions of the reference and simulated trajectories respec-
 137 tively.

- 138 2. Liu index between the reference and simulated trajectories [Liu and Weisberg (2011)]

$$\mathcal{L}_{Liu} = \frac{1}{N_T} \sum_{i=1}^{N_T} \frac{\sum_{j=1}^K d_{ij}}{\sum_{j=1}^K l_{ij}} \quad (9)$$

139 where

$$d_{ij} = \sqrt{(\vec{r}_R(\vec{r}_{0,i}, j\Delta) - \vec{r}_S(\vec{r}_{0,i}, j\Delta))^2} \quad (10)$$

140 is the Euclidean distance between the reference and the simulated trajectories number i at
 141 time step j and l_{ij} is the length of reference trajectory i between the initial position and the
 142 position at time step j .

143 Overall, the training loss \mathcal{L} is a weighted sum: $\mathcal{L} = \alpha \cdot \mathcal{L}_{MSE} + \beta \cdot \mathcal{L}_{Liu}$. From cross-validaton
 144 experiments, we set α and β to 0.6 and 0.4. Using Pytorch², our learning setup relies on Adam
 145 optimizer with a learning rate of 5e-4 over 750 epochs.

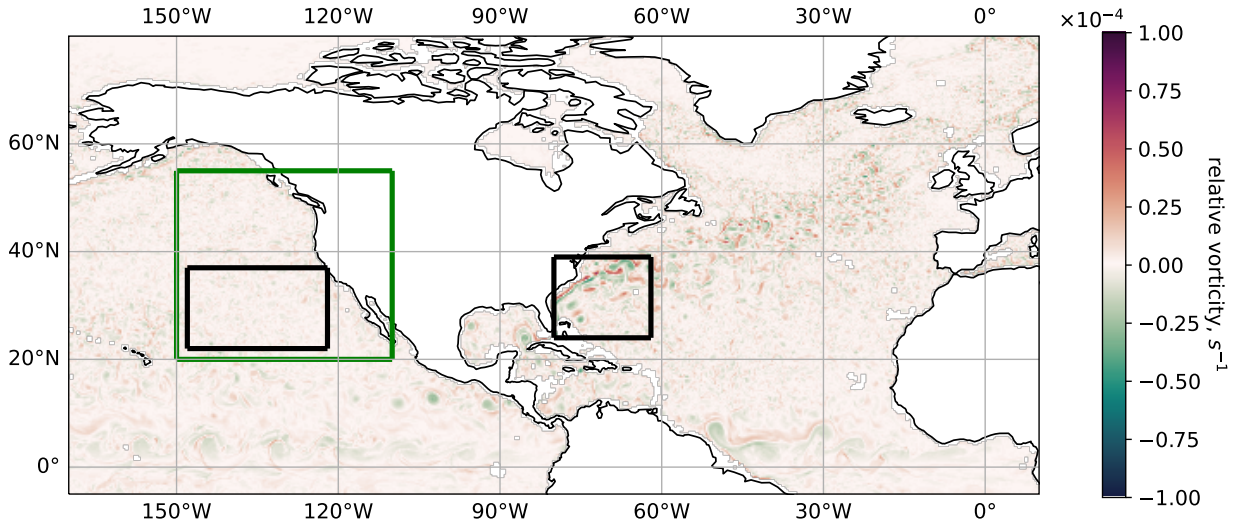


FIG. 2: **Study cases delineation:** Relative vorticity of North East Pacific and North Atlantic oceans from E1 simulation of 01/10/2015. The two black boxes indicate the North East Pacific and Gulf Stream case study regions for benchmarks B1 and B2. The green box defines the North East Pacific region of study for benchmark B3.

146 4. Experimental workflow

147 Section 4.a details the two case-study regions considered because of their contrasting turbulent
 148 activity: the Gulf Stream and the North-East Pacific region, see Figure 2. We describe the different
 149 datasets used in our experiments in section 4.b, see Table 1, and the metrics used to evaluate
 150 performance in section 4.c. In section 4.d we present the benchmarked deep learning models. We
 151 perform three different experiments: two relying on numerical simulation datasets such that the
 152 full sea surface velocity field is known, and a last experiment dealing with real drifters in the sea
 153 surface. These three benchmarks are explained in section 4.e.

154 a. Case-study Regions

155 **The Gulf Stream** is a Western boundary current system characterized by a fast flowing jet that
 156 originates in the Gulf of Mexico and flows into the North Atlantic [Gula et al. (2015); Dewar and
 157 Bane (1989)], becoming a part of it’s anticyclonic subtropical gyre [Talley (2011)]. Surface
 158 velocity can exceed $2 \text{ m} \cdot \text{s}^{-1}$ and the current is characterized by high eddy variability. Exhibiting
 159 strong velocities for hundreds of kilometers, the Gulf Stream transports warm saline water from
 160 lower latitudes north-eastward. The Gulf Stream plays a crucial role in redistributing heat and

²DriftNet code is available at <https://github.com/CIA-Oceanix/DriftNet>

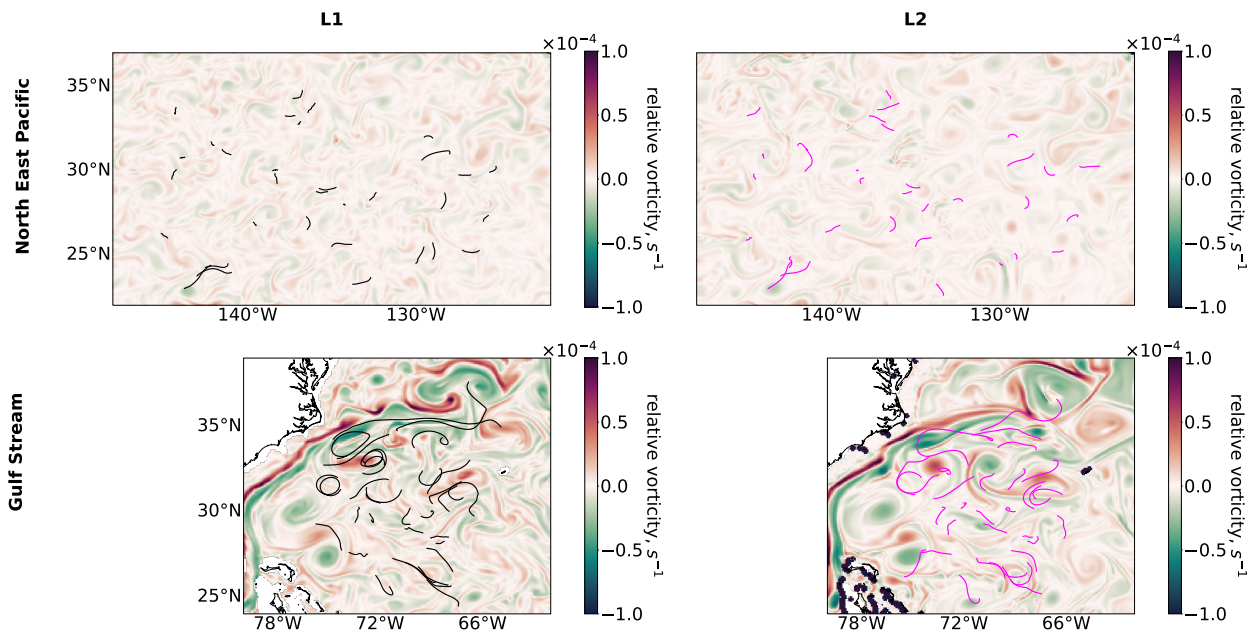


FIG. 3: **Examples of trajectories:** Trajectories from dataset L1 and dataset L2 superimposed respectively to the E1 and E2 relative vorticity fields of 2015/01/01.

161 influencing climate patterns and the surrounding marine ecosystem [Gula et al. (2015)], [Wills
 162 et al. (2016)].

163 **The North East Pacific** is a vast oceanic region extending from the western coast of North
 164 America to the central Pacific. It is influenced by various ocean currents, including the California
 165 Current and North Pacific Current. The California Current System (CCS) is an eastern boundary
 166 of the slow ($0.1 \text{ m} \cdot \text{s}^{-1}$) eastward North Pacific Current. It is a cold, nutrient-rich current that
 167 flows southward along the Western coast of North America [Checkley and Barth (2009); Aua
 168 et al. (2011)], impacting marine ecosystems and fisheries. The CCS is an upwelling region due to
 169 Ekman transport, spinning up eddies westward offshore. It has a mean surface velocity of $0.4 - 0.8$
 170 $\text{m} \cdot \text{s}^{-1}$. Due to the baroclinic instability of the coastal upwelling current, the CCS contains high
 171 mesoscale eddy activity, associated with the highly variable sea-surface height [Talley (2011)].

172 *b. Datasets*

173 Our study involves three different Eulerian datasets used as input data for the benchmarked
 174 models:

TABLE 1: **Summary description of the Eulerian and Lagrangian datasets used in the current study:** *Source* makes reference to the used numerical or satellite product, *Variable* indicates the physical quantity of interest, *Period* the studied years. The spatial and temporal resolutions of each product are also indicated. SSC - sea surface currents. SSH - sea surface height.

<i>Name</i>	<i>Source</i>	<i>Variable</i>	<i>Period</i>	<i>Spatial resolution</i>	<i>Temporal resolution</i>
Eulerian					
E1	Nature Run	SSC and SSH	2015	1/12°	1 day
E2	OSSE-based assimilated free run	SSC	2015	1/12°	1 day
E3	Operational assimilated reanalysis GLORYS12	SSC	1992 - 2020	1/12°	1 day
E3	DUACS	SSH	1992 - 2020	1/4°	1 day
Lagrangian					
L1	Ocean Parcels simulation on E1 SSC	Position	2015	-	6 hours
L2	Ocean Parcels simulation on E2 SSC	Position	2015	-	6 hours
L3	CMEMS drifters	Position	1992 - 2020	-	6 hours
L4	Ocean Parcels simulation on E3 SSC	Position	1992 - 2020	-	6 hours

- 175 • **Eulerian dataset E1:** This Eulerian dataset contains the sea surface current (SSC) velocity
176 and sea surface height (SSH) fields. Both fields are obtained from a high-resolution free
177 simulation of the NEMO ocean model without any data assimilation [Benkiran et al. (2021b)].
178 Those are regularly-gridded products with a horizontal spatial resolution of 1/12° and a daily
179 time resolution. This study involves the entire year of 2015.
- 180 • **Eulerian dataset E2** This dataset contains the SSC fields from a data assimilated run, which
181 dynamically reconstructs the ocean state using pseudo observations from E1 which mimic
182 the current observational network (satellite altimetry tracks). Those fields are at the same
183 1/12° and daily space-time resolution as the E1 dataset. As in the previous E1 dataset, we
184 equivalently use the complete 2015 year.
- 185 • **Eulerian Real-world dataset E3:** this real-world dataset combines the SSC from the opera-
186 tional ocean reanalysis GLORYS12 [Lellouche et al. (2021)] and the optimally-interpolated
187 altimetry-derived SSH product DUACS [Pujol et al. (2016)]. The GLORYS12 velocity fields
188 are provided on the regular grid with spatial resolution of 1/12° and temporal resolution of
189 1 day. We re-interpolate the SSH fields on the same 1/12° regular grid at daily temporal
190 resolution.

191 For each individual trajectory, the considered spatial domain of the Eulerian conditional fields is
192 equal to, $4^\circ \times 4^\circ$ window for the North East Pacific and $10^\circ \times 10^\circ$ for the Gulf Stream. The size of
193 the domains corresponds to the furthest displacement from a given particle’s deployment location
194 in each case study region.

195 Our benchmarks involve four different Lagrangian datasets:

196 • **Lagrangian Dataset L1:** this dataset is composed of 9-day trajectories of virtual particles
197 advected by the sea surface velocities from dataset E1 using Ocean Parcels, a state-of-the-art
198 tool for model-based Lagrangian drift simulation [Lange and van Sebille (2017)]. Around 20
199 particles were randomly seeded every day across the domain and the studied period, amount-
200 ing to a total of 7900 particles.

201 • **Lagrangian Dataset L2:** this dataset contains 9-day trajectories of virtual particles advected
202 by the SSC of the E2 dataset with Ocean Parcels. It contains 7900 particles deployed at the
203 exact same locations and times as in the Lagrangian Dataset L1 described above, see Figure 3.

204 • **Lagrangian Dataset L3** This dataset contains trajectories from CMEMS drifters [Etienne
205 et al. (2023)] in the North East Pacific region, from 1992 to 2020. Those drifters are a part
206 of the Surface Velocity Program (SVP) and are built of 1-m long floating buoy attached to
207 a “drogue” deployed at 15 meters depth in order to reduce the windage slip [Lumpkin et al.
208 (2017)]. Drifters positions are subject to a quality control and editing procedures before
209 being operational. Subsequently, trajectory positions undergo regular reinterpolation using
210 the Kriging technique at 6-hour intervals [Etienne et al. (2023)]. For this study, we refer
211 to drogued-only drifters which are representative of the ocean currents at 15 meters depth
212 and are widely used in various application domains [Lumpkin et al. (2012); Koszalka et al.
213 (2011); Lumpkin and Flament (2013); Kaplan et al. (2005); Lumpkin and Garzoli (2011)].

214 This dataset contains 12.785 9-day trajectories in the North East Pacific case-study region,
215 green box in Figure 2. These trajectories are obtained by dividing the whole drifter trajectories
216 of the region in 9-day long non-overlapping segments.

217 • **Lagrangian Dataset L4:** this dataset contains 9-day trajectories of virtual particles advected
218 by the velocity fields from E3 with Ocean Parcels. We use the same initial deployment posi-
219 tion and time of the trajectories as in dataset L3.

220 *c. Performance metrics*

221 As evaluation metrics, we consider

- 222 • the mean Euclidean distance at the last time step (9-th day) in kilometers, that we denote D :

$$D = \frac{1}{N_T} \cdot \sum_{i=0}^{N_T} d_{i_9} \quad (11)$$

223 with N_T the number of trajectories and d_{i_9} defined in eq.(10) with $j = 9$ days.

- 224 • the mean Liu index \mathcal{L}_{Liu} without units, see eq.(9).
- 225 • the mean error between autocorrelation functions, $R_{\vec{u}}(\tau)$ and $R_{\vec{v}}(\tau)$ respectively for zonal
226 and meridional components of trajectories' velocities [Krauß and Böning (1987); Kang et al.
227 (2005); Wunsch (1999)]:

$$\Delta R_{\vec{u}} = \langle |\bar{R}_{\vec{u}_R}(\tau) - \bar{R}_{\vec{u}_S}(\tau)| \rangle \quad (12)$$

228 where $\langle \rangle$ is the average across temporal dimension, $\bar{R}_{\vec{u}_R}(\tau)$ and $\bar{R}_{\vec{u}_S}(\tau)$ are respectively the
229 ensemble mean of the reference and simulated normalized autocorrelation functions of the
230 Lagrangian velocity, defined as: $R_{\vec{u}}(\tau) = \frac{1}{9 \cdot \Delta} \cdot \sum_{t=0}^9 \vec{u}(t\Delta + \tau) \vec{u}(t\Delta)$. The same definition is
231 used for the meridional velocity.

232 The mean euclidean distance and the mean Liu index are computed between the reference and
233 generated trajectories and averaged over the whole ensemble of studied trajectories.

234 *d. Benchmarked deep learning models*

235 To evaluate the performance of DriftNet, we compare it to the following CNN and LSTM base-
236 lines inspired by [Zheng et al. (2022); Ma et al. (2019)]:

- 237 • Convolutional Neural Network (CNN): a 2D convolutional block varying the number of chan-
238 nels from 27 (\mathbf{u} and \mathbf{y}_0 concatenated along the time dimension) to $8 \rightarrow 16 \rightarrow 32 \rightarrow 35$. Each
239 convolution layer has a kernel of size 5 and is followed by a LeakyReLU activation function
240 with a slope of 0.2 for negative inputs. The output of this convolutional block is introduced

241 by a reshape, where the two spatial dimensions of initial 3d matrix are flattened together,
242 and the output is passed to a fully connected layer with 256 and 128 neurons decreasing the
243 mentioned spatial dimension to 2.

- 244 • Long Short-Term Memory (LSTM): a 5-layer LSTM block with hidden size 96, followed by
245 a ReLU activation function, then two fully connected layers with a ReLU in between. Each
246 dense layer contains 864, and 128 neurons respectively, reducing the latent space to 2·35.
247 This output is then reshaped so to contain the spatial dimension 2 and temporal one 35.

248 We also explore different configurations of DriftNet. In order to investigate the impact of each
249 component of the model on the evaluation metrics, we modify its inner architecture, see section
250 3. a and Figure 1, and assess the performance of the following three architectures:

- 251 • DriftNet without the ConvLSTM block in the encoding operator \mathcal{E} ;
- 252 • DriftNet without the CNN block in the encoding operator \mathcal{E} ;
- 253 • a DriftNet-U-Net architecture, referred to as DriftNet_U : in this architecture, we replace the
254 CNN block in the encoding operator \mathcal{E} by a U-Net block. The latter is composed of three
255 2D Conv-MaxPool-ReLU layers with kernel size 3 and channels evolving from 27 to 256 and
256 three 2D ConvTranspose-Upsample-ReLU layers with kernel size 3 and channels evolving
257 from 256 to 27.

258 *e. Benchmarks*

259 This section presents the experimental setups that we employ to assess the performance of Drift-
260 Net in both virtual and real-case scenarios.

261 **Benchmark B1** This benchmark B1 aims to assess the reliability and accuracy of learning-
262 based schemes in reproducing Lagrangian drift trajectories given fully-known underlying dynam-
263 ics. This benchmark uses the Eulerian velocity field extracted from the dataset E1 and the trajec-
264 tories from the Lagrangian Dataset L1. The resulting dataset is randomly splitted into train (80%),
265 validation (10%) and test (10%) datasets. DriftNet is fed with E1 velocity fields and trained to
266 reproduce reference trajectories from the L1 dataset. For benchmarking purposes, we consider the
267 CNN and LSTM baselines trained following the same strategy as DriftNet.

268 **Benchmark B2** This benchmark aims to assess from simulation data the ability to predict accu-
269 rately Lagrangian drift trajectories when the sea surface velocities are imperfectly known. We use
270 E2 velocity fields and L1 trajectories as reference. Similarly to Benchmark B1, we randomly split
271 the resulting dataset into train (80%), validation (10%) and test (10%) datasets. For benchmarking
272 purposes, we consider the state-of-the-art model-based method corresponding to trajectory dataset
273 L2 as well as the CNN and LSTM baselines trained following the same strategy as DriftNet.

274 Benchmark B2 also assesses the ability of DriftNet to exploit multi-source geophysical data.
275 Here, we complement the data with the Sea Surface Height (SSH) from Dataset E1. In this con-
276 figuration, DriftNet is fed with E2 velocity fields and E1 SSH fields to reproduce L1 trajectories.

277 **Benchmark B3** This benchmark addresses a real-case scenario with real drifters' trajectories
278 and operational ocean reanalyses. We use E3 velocity and SSH fields and real trajectories from
279 L3 dataset as reference. Similarly to Benchmark B1, we randomly split the resulting dataset into
280 train (70%), validation (10%) and test (20%) datasets.

281 For benchmarking purposes, we consider the state-of-the-art model-based method correspond-
282 ing to trajectory dataset L4 as well as the CNN and LSTM baselines trained following the same
283 strategy as DriftNet. This benchmark assesses a DriftNet using solely E3 velocity fields and a
284 DriftNet using jointly E3 velocity and SSH fields.

285 5. Results

286 This section reports our numerical experiments for the three benchmarks introduced in the pre-
287 vious section, namely benchmark B1 (section 5.a), benchmark B2 (section 5.b) and benchmark
288 B3 (section 5.c).

289 *a. Results for Benchmark B1*

290 DriftNet presents the best performance for all metrics and significantly outperforms the CNN
291 and LSTM baselines, see Table 2. For the North East Pacific, the separation distance of 5.3km
292 after 9 days is about one order of magnitude smaller than the baseline CNN and LSTM models.
293 Similar performances are noted for Liu index, 0.06, and for the autocorrelation functions errors
294 in both zonal and meridional components, 0.0103 and 0.0145. For the Gulf Stream, the overall
295 accuracy is lower (separation distance after 9 days of 91.1km, Liu index 0.26 and autocorrelation

TABLE 2: **Performance of DriftNet for Benchmark B1:** we report the performance metrics for DriftNet and classical learning-based approaches for benchmark B1 in the two study regions: North East Pacific and Gulf Stream. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and error between autocorrelation functions ($\Delta R_{\vec{u}}$ and $\Delta R_{\vec{v}}$). Bold indicates the best performance. We refer the reader to section 4.d for the details of the benchmarked architectures.

Method	North East Pacific				Gulf Stream			
	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$
DriftNet	5.3	0.06	0.0103	0.0145	91.1	0.26	0.0405	0.0348
CNN	43	0.5	0.1076	0.1379	151.85	0.63	0.229	0.2173
LSTM	30.6	0.4	0.2136	0.2283	188	0.77	0.2244	0.2123

errors 0.0405 and 0.0348), outperforming the baselines. These experiments support the proposed Eulerian Fokker-Plank-inspired architecture.

DriftNet simulation error is larger for the Gulf Stream region. This is consistent with the resolution error in encoding initial positions, as evidenced in [Callies et al. (2021)]. Here, Lagrangian trajectories simulated with an error corresponding to the resolution of the grid (*i.e.*, $1/12^\circ$) leads to a separation distance after 9 days of 20km (resp. 94km) for the North East Pacific region (resp. the Gulf Stream region). The larger sea surface velocities and sharper associated spatial gradients in the Gulf Stream region explains the larger separation distance after 9 days.

Impact of DriftNet components We compare DriftNet in its original configuration to three variations presented in section 4.d namely a configuration combining two commonly used U-Net models separated by one ConvLSTM block, a second one containing the ConvLSTM block only, and finally one composed of 2D convolutional layers only.

Removing the CNN or ConvLSTM blocks from the DriftNet architecture impacts the simulation performance, see Table 3. The separation distance increases from 5.3km to 36.2km (resp. 57.1km) for the North East Pacific region when we remove the CNN (resp. ConvLSTM) block. Similarly, the U-Net version of the DriftNet does not lead to a better simulation performance. This likely relates to some overfitting in our training schemes due to the greater complexity of this U-Net configuration. Same qualitative results are found in the Gulf Stream region.

Impact of the resolution of the conditioning velocity fields. Coarsening the resolution of the conditioning fields leads to degrading the performance, see Table 4. For both regions, the impact is significant in the mean separation distance and the Liu index. Interestingly, the error between

TABLE 3: **Ablation study of DriftNet**: we compare the metrics of different configurations of DriftNet for benchmark B1: namely, the reference DriftNet, DriftNet_U with a U-net block instead of CNN, a DriftNet without the CNN block and DriftNet without ConvLSTM. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and error between autocorrelation functions ($\Delta R_{\vec{u}}$ and $\Delta R_{\vec{v}}$). Bold indicates best performance.

Method	North East Pacific				Gulf Stream			
	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$
DriftNet	5.3	0.06	0.0103	0.0145	91.1	0.26	0.0405	0.0348
DriftNet _U	16.1	0.21	0.1552	0.1694	96.4	0.32	0.0573	0.0432
DriftNet without CNN	36.2	0.39	0.0299	0.0379	163	0.68	0.0834	0.1035
DriftNet without ConvLSTM	57.1	0.72	0.0846	0.1093	177	0.73	0.1568	0.1592

TABLE 4: **Impact of spatial resolution on DriftNet performance** Performance of DriftNet in function of the spatial resolution of the input Eulerian velocity field for benchmark B1 in both study regions: North East Pacific and Gulf Stream. Each line corresponds to a different spatial resolution of the input E1 field. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and error between autocorrelation functions ($\Delta R_{\vec{u}}$ and $\Delta R_{\vec{v}}$). Bold indicates best performance.

Resolution	North East Pacific				Gulf Stream			
	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$
$1/12^\circ \times 1/12^\circ$	5.3	0.06	0.0103	0.0145	91.1	0.26	0.0405	0.0348
$1/6^\circ \times 1/6^\circ$	8.7	0.15	0.0162	0.0152	102.3	0.35	0.0377	0.0255
$1/3^\circ \times 1/3^\circ$	17.9	0.27	0.0272	0.034	109.4	0.47	0.0376	0.0313
$1/2^\circ \times 1/2^\circ$	28.2	0.40	0.0768	0.0995	115.9	0.46	0.048	0.0448

317 the autocorrelation functions in the Pacific region increases when the input resolution is coarsen,
318 while in the Gulf Stream a lower input resolution allows to slightly improve the estimation of the
319 zonal component for $1/3^\circ \times 1/3^\circ$ and the meridional component for $1/6^\circ \times 1/6^\circ$. Resolution is
320 thus an important characteristic of the input fields.

321 *b. Results for Benchmark B2*

322 Table 5 illustrates the performance of the simulation of Lagrangian trajectories using degraded
323 velocity fields instead of the true velocity fields. Similarly to Benchmark B1, we compare DriftNet
324 to CNN and LSTM baselines. Here we also benchmark DriftNet with respect to the Lagrangian
325 simulations with Ocean Parcels [Lange and van Sebille (2017)].

TABLE 5: **Performance metrics for Benchmark B2 experimental framework.** We report the performance metrics for DriftNet and baseline models, all supplied with velocity fields from E2 and trained to generate trajectories from reference Dataset L1 in the two study regions: North East Pacific and Gulf Stream. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and error between autocorrelation functions ($\Delta R_{\bar{u}}$ and $\Delta R_{\bar{v}}$). Bold indicates the best performance.

Method	North East Pacific				Gulf Stream			
	D , km	\mathcal{L}_{Liu}	$\Delta R_{\bar{u}}$	$\Delta R_{\bar{v}}$	D , km	\mathcal{L}_{Liu}	$\Delta R_{\bar{u}}$	$\Delta R_{\bar{v}}$
Ocean Parcels	53.6	0.87	0.0086	0.016	168.3	0.75	0.0084	0.0212
DriftNet	45.4	0.7	0.1212	0.1202	154.6	0.63	0.1623	0.135
CNN	51.7	0.72	0.1492	0.1807	184.1	0.67	0.1603	0.1574
LSTM	47.9	0.69	0.2281	0.237	163.2	0.67	0.1742	0.157

326 DriftNet presents smaller D 45.4 km (154.6 km), $\Delta R_{\bar{u}}$ and $\Delta R_{\bar{v}}$ than the other learning-based
327 models, and smaller D , \mathcal{L}_{Liu} than Ocean Parcels, thus consistently outperforming the baseline ap-
328 proaches. The \mathcal{L}_{Liu} for the North East Pacific region is of 0.7 and is smaller than the most baseline
329 approaches, except the LSTM model (0.69) slightly outperforming the proposed method. While in
330 the Gulf Stream the \mathcal{L}_{Liu} (0.63) is smaller than all the other approaches. The autocorrelation errors
331 is smaller for the proposed method than the other learning-based approaches in the North East Pa-
332 cific region. In the Gulf Stream, the autocorrelation error in the meridional component is smaller
333 than the other learning-based methods. For both regions, the proposed method’s autocorrelation
334 errors are larger than for the Ocean Parcels.

335 **Impact of auxiliary variables** Table 6 assesses how the availability of the SSH fields could
336 improve the simulation of Lagrangian drift trajectories. Whereas Lagrangian model eq.(1) solely
337 depends on the sea surface velocities, deep learning schemes can easily extend to multiple condi-
338 tioning fields. Among the observed satellite-derived tracers on the sea surface, the SSH explicitly
339 seems appealing as it informs the geostrophic component of sea surface currents [Taqi et al. (2019);
340 Ballarotta et al. (2022)]. In an idealized setting, we evaluate the potential added value of the true
341 SSH fields provided as inputs to DrifNet either in place of E2 velocity fields or to complement
342 them, see Table 6.

343 These results emphasize the synergistic potential of SSH observations and E2 velocity fields
344 compared with using only one of these two input data. In the North East Pacific region, D is
345 reduced by over 55%, \mathcal{L}_{Liu} by over 60%, $\Delta R_{\bar{u}}$ and $\Delta R_{\bar{v}}$ by over 60% and 50%. Similarly in

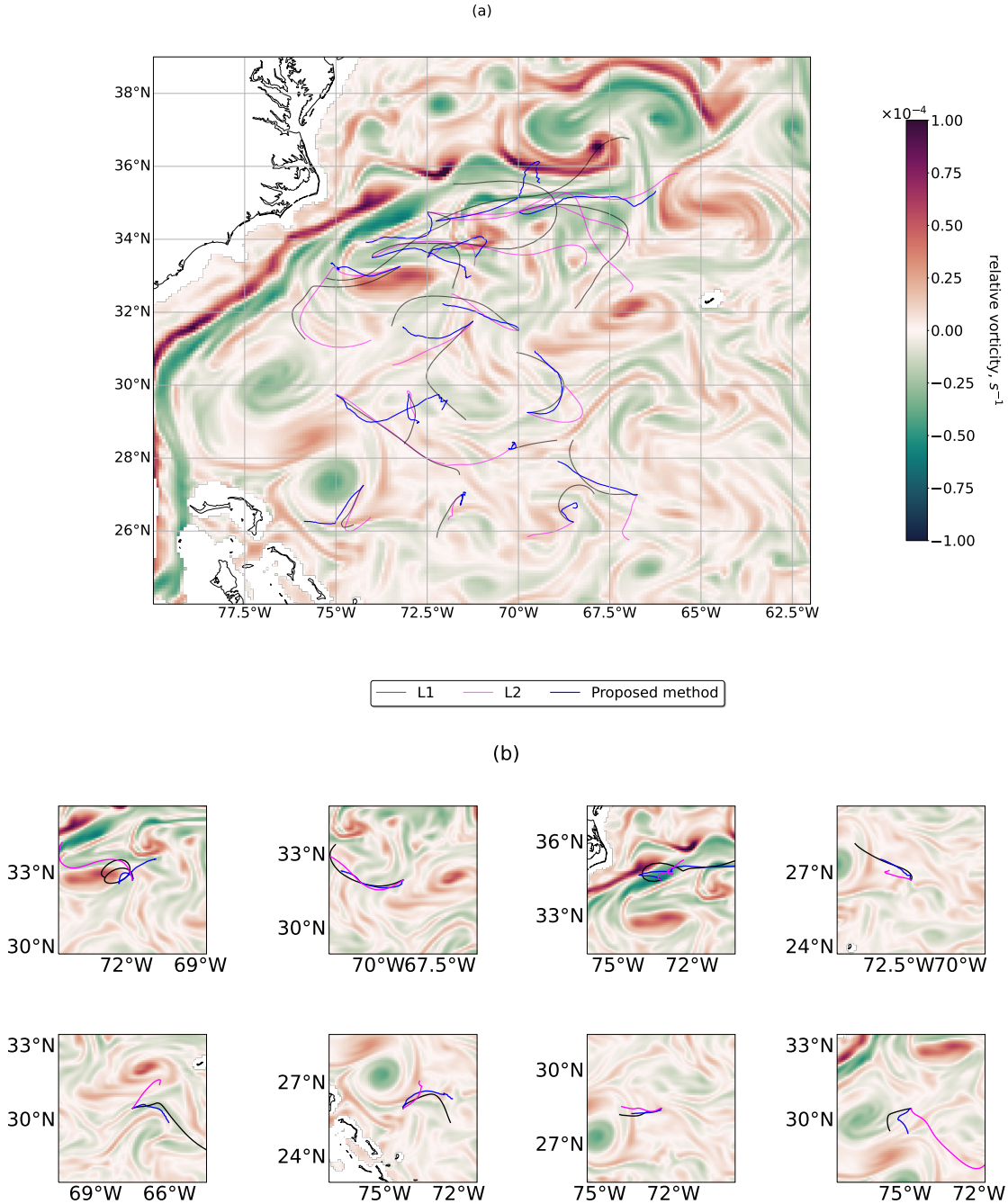


FIG. 4: **Trajectories for Benchmark B2 in the Gulf Stream** Lagrangian trajectories from Dataset L2 are depicted in magenta, trajectories simulated with DriftNet conditioned with SSC from E2 and SSH from E1 in blue, and trajectories from Dataset L1 in black. For better visual appreciation panel a) shows 16 randomly picked trajectories for the whole region while b) shows 8 random trajectories zoomed. All superimposed to the mean relative vorticity field of E1.

346 the Gulf Stream, we report a relative gain greater than 25% for D , 30% for \mathcal{L}_{Liu} . The $\Delta R_{\vec{u}}$ and
 347 $\Delta R_{\vec{v}}$ however are reduced by over 56% and 57% for the case of SSH fields input only. These

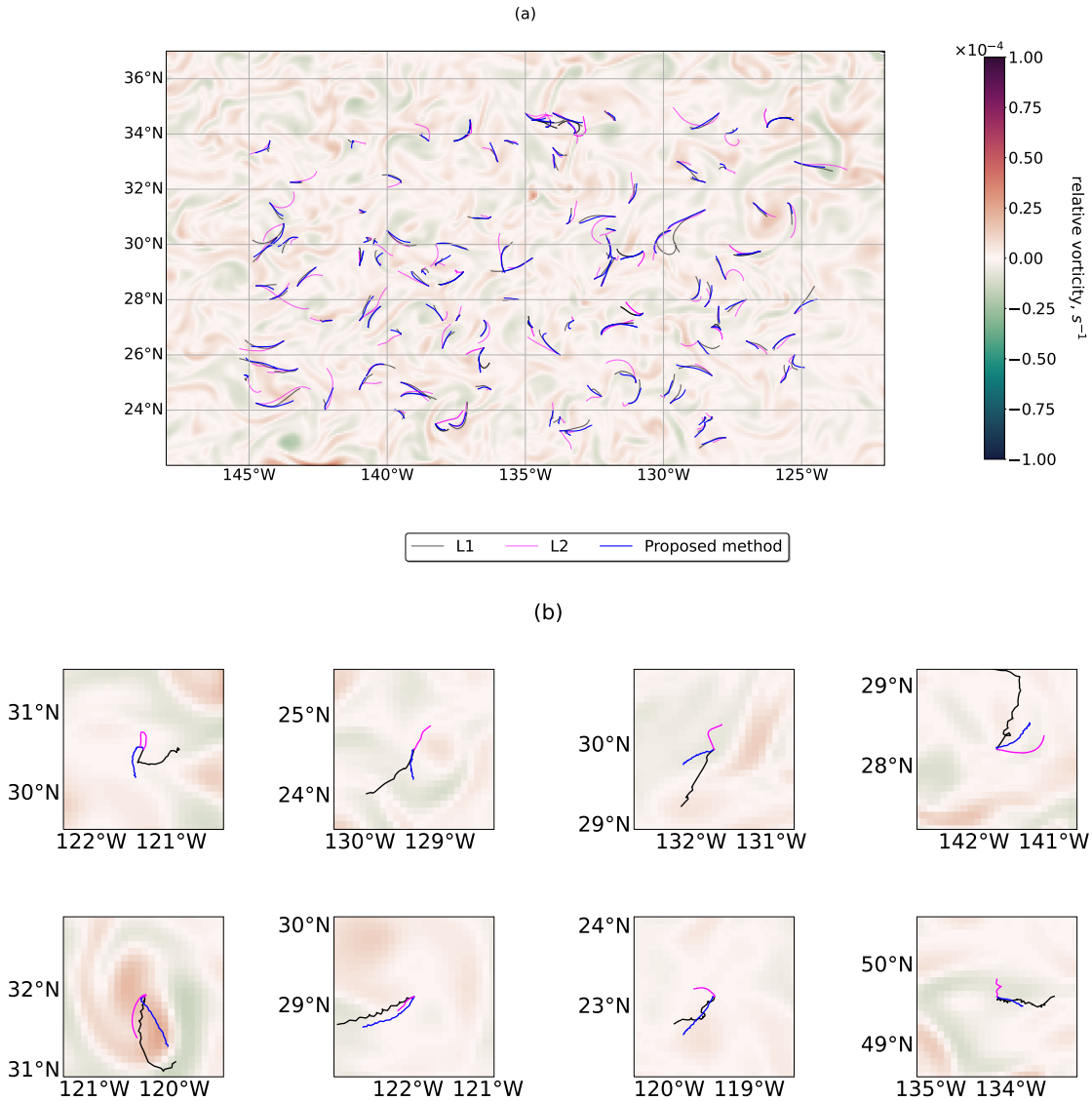


FIG. 5: **Trajectories for Benchmark B2 in the North East Pacific** Lagrangian trajectories from Dataset L2 are depicted in magenta, trajectories simulated with DriftNet conditioned with SSC from E2 and SSH from E1 in blue, and trajectories from Dataset L1 in black. a) shows 128 randomly picked trajectories for the whole region while b) shows 8 random trajectories zoomed. All superimposed to the mean relative vorticity field of E1.

TABLE 6: **Synergistic use of SSH observations and data-assimilation-based velocity fields in Benchmark B2.** We benchmark DriftNet schemes using as inputs data-assimilation-based velocity fields from dataset E2 and idealized perfectly-observed Sea Surface Height (SSH) fields (i.e., SSH fields from dataset E1). We illustrate performance in the two study regions: North East Pacific and Gulf Stream. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and error between autocorrelation functions ($\Delta R_{\vec{u}}$ and $\Delta R_{\vec{v}}$). Bold indicates the best performance.

Method(Variable)	North East Pacific				Gulf Stream			
	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$
DriftNet	45.4	0.7	0.1212	0.1202	154.6	0.63	0.1623	0.135
DriftNet (SSH)	31.2	0.32	0.059	0.0672	160.3	0.7	0.0709	0.057
DriftNet (U, V, SSH)	22.2	0.29	0.0456	0.0579	127	0.52	0.0833	0.0616

TABLE 7: **Performance metrics for Benchmark B3.** Performance of different Lagrangian simulation schemes for Benchmark B3 which involves real data. For each scheme, we detail the considered input data: namely the velocity fields U and V from the GLORYS12 reanalysis [Lellouche et al. (2018)] possibly complemented by satellite-derived optimally-interpolated SSH fields [Pujol et al. (2016)]. We report the performance metrics in the two study regions: North East Pacific and Gulf Stream. The evaluation metrics are the last time step mean separation distance (D), mean Liu index (\mathcal{L}_{Liu}) and mean absolute error between autocorrelation functions ($\Delta R_{\vec{u}}$ and $\Delta R_{\vec{v}}$). Bold indicates the best performance.

North East Pacific				
Method(Variable)	D , km	\mathcal{L}_{Liu}	$\Delta R_{\vec{u}}$	$\Delta R_{\vec{v}}$
Ocean Parcels (U, V)	73.77	0.65	0.1374	0.1471
DriftNet (U, V)	62.4	0.55	0.0522	0.0315
CNN (U, V)	68.64	0.57	0.0466	0.0621
LSTM (U, V)	64.3	0.55	0.0982	0.0893
DriftNet (U, V, SSH)	60.2	0.52	0.0296	0.034

353 For both regions the trajectories are visualised at the Figure 4 and Figure 5 which show that
354 DriftNet generates trajectories closer to the ground truth from L1 than the baseline L2.

355 *c. Results for Benchmark B3*

356 In this real case situation, DriftNet outperforms the classical advection method, see Table 7 and
357 Figure 6. Compared to the model-based baseline, the mean separation distance is reduced by
358 around 15% to 62.4km, the Liu index by 15% to 0.55. Unlike previous B2 experiment, the auto-
359 correlation errors are significantly reduced to 0.0522 and 0.0315 compared to Ocean Parcels. As

360 in benchmark B2, we observe a significant impact of the observed SSH fields in the quality of the
361 simulation of the Lagrangian trajectories. The combination of GLORYS12 velocities and satellite-
362 derived SSH fields leads to a reduction of the mean separation distance by almost 4% compared to
363 the baseline DriftNet and by over 18% compared to the baseline model-based advection method.
364 The Liu index is also reduced by more than 5% compared to the DriftNet baseline and by over
365 20% compared to the baseline advection method. The autocorrelation error in the zonal compo-
366 nent is reduced by more than 43% compared to the DriftNet baseline and by over 78% compared
367 to the baseline model-based approach.

368 **6. Conclusions and Discussion**

369 In this study, we presented a novel deep learning framework, called DriftNet, for the condi-
370 tional simulation of Lagrangian drift trajectories on the sea surface. We drew inspiration from the
371 Fokker-Planck equation to explore a spatially-explicit Eulerian latent representation of the trajec-
372 tories in the proposed neural architecture. We evaluate DriftNet on three different benchmarks
373 using synthetic and real-world datasets. Our experiments support the relevance of DriftNet to ad-
374 vance Lagrangian drift simulations on the sea surface and better exploit available reanalysis and
375 observation datasets.

376 DriftNet consistently demonstrated a better performance than state-of-the-art model-based and
377 learning-based approaches, with respect to the following Lagrangian metrics: mean separation
378 distance, Liu index and autocorrelation error between the ground-truth trajectories and the simu-
379 lated ones. When DriftNet is provided with fully known velocity fields from Nature Run simula-
380 tion (Benchmark B1), it reduces the overall error by more than 80% compared to the state-of-the-
381 art learning-based approaches. Moreover, when DriftNet is provided with degraded velocity fields
382 from OSSE-based assimilated simulation (Benchmark B2), it reduces the overall error by over
383 15% compared to conventional point-wise schemes. These results are consistent for the two case-
384 study regions, even if they are characterized by notably different dynamical regimes. Interestingly,
385 we draw similar conclusions between synthetic and real datasets.

386 The performance of DriftNet exhibits variabilities across the two different regions. It likely un-
387 derscores the importance of region-specific adaptations in trajectory simulation models. As such,
388 the deployment of DriftNet on a global scale may require retraining the model to accommodate

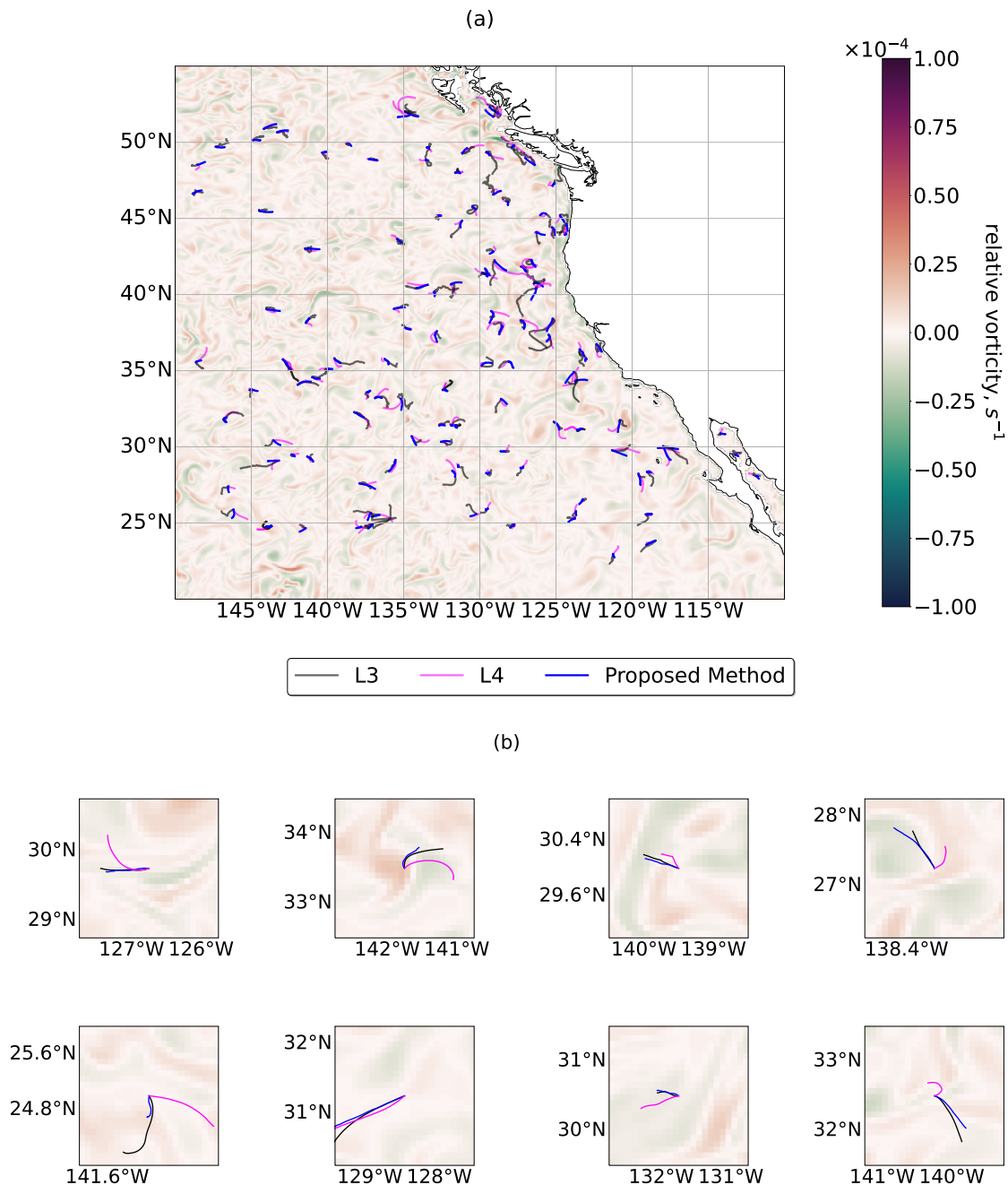


FIG. 6: **Examples of simulated trajectories for Benchmark B3:** we depict real drifters trajectories in black (L3), trajectories simulated with Ocean Parcels using GLORYS12 velocity fields in magenta (L4) and trajectories simulated with DriftNet using both GLORYS12 velocity fields and satellite-derived optimally-interpolated SSH fields in blue. Panel (a) illustrates trajectories from the whole region. Panel (b) zoom on a subset of randomly-selected trajectories. All superimposed to the mean relative vorticity of the GLORYS12 velocity fields.

389 the diverse dynamics in various oceanic regions [Miao et al. (2023)]. While we expect the pro-
390 posed neural architecture to be generic, fine-tuning its parameters to align with the characteristics
391 of a given region seems crucial for the relevance of the simulations. This approach allows for the
392 incorporation of region-specific features, thereby enhancing the model’s predictive capabilities
393 across diverse geographical regions. Furthermore, leveraging transfer learning techniques to capi-
394 talize on the knowledge gained from training in one region to inform model adjustments in others
395 holds promising avenue. By iteratively refining DriftNet through region-specific training and fine-
396 tuning iterations, we hope to develop a robust trajectory simulation tool capable of capturing the
397 intricacies of oceanic dynamics on a global scale.

398 Our benchmarks highlight the relevance of the SSH fields to improve the prediction of La-
399 grangian drifts on the sea surface both in synthetic and real case-studies, *i.e.* Benchmarks B2 and
400 B3. We report a significant improvement for all the considered metrics when we complement
401 reanalysis velocity fields with SSH fields. The SSH informs the geostrophic component of the
402 sea surface currents, which is important for the two case-study regions for horizontal scales above
403 100km [Checkley and Barth (2009); Thomas and Joyce (2010); Johns et al. (1989)]. As ocean
404 reanalysis datasets can usually retrieve sea surface currents for horizontal scales above a few hun-
405 dred of kilometers [Benkiran et al. (2021a); Lellouche et al. (2021)], the learning schemes likely
406 benefit from the SSH fields to recover a more robust representation of the sea surface dynamics
407 and improve the simulation of Lagrangian drift on the sea surface. The advent of wide-swath satel-
408 lite altimeters [Benkiran et al. (2021b); Tchonang et al. (2021)], possibly combined with neural
409 mapping schemes [Martin et al. (2023); Beauchamp et al. (2022); Fablet et al. (2023)], will lead
410 to a better reconstruction of satellite-derived SSH fields, which could in turn result in improved
411 learning-based Lagrangian simulations for real drifters on the sea surface.

412 Beyond the exploraton of satellite-derived SSH fields, the use of additional geophysical variables
413 to enhance trajectory generation offers another interesting approach to improve the simulation
414 performance. Future studies could investigate other variables such as Sea Surface Temperature
415 [Ciani et al. (2020)], Ocean Color [Yang et al. (2015); Liu et al. (2017)], Winds [Cucco et al.
416 (2016); Solanlki et al. (2001)] or Waves Tang et al. (2007) to refine trajectory simulations and gain
417 deeper insights into oceanic processes. By leveraging these variables, the proposed method could

418 not only improve trajectory accuracy but also facilitate comprehensive analysis of the underlying
419 ocean dynamics.

420 Inspired by established initiatives such as WeatherBench [Rasp et al. (2020)] and OceanBench
421 [Johnson et al. (2024)], we propose a new benchmark for a standardized assessing and compar-
422 ing Lagrangian trajectory simulation models <https://github.com/CIA-Oceanix/DriftNet>. Through
423 proposed datasets and evaluation metrics, this framework seeks to foster collaborative frameworks
424 involving ocean scientists and ML practitioners. In this context, future work could explore new
425 evaluation metrics and extend the proposed benchmarks to a broader array of oceanic regions.

426 From a methodological point of view, it seems appealing to extend the DriftNet to a proba-
427 bilistic framework with a view to sampling ensembles of realistic drift trajectories. Conditional
428 Generative Adversarial Networks (GAN) [Roy et al. (2022)] naturally arise among the promising
429 solutions. Other generative models such as diffusion models [Tashiro et al. (2021)] could also be
430 explored. Regarding real-time operational applications, such as search and rescue operations, or
431 iceberg drifts, such generative schemes would also naturally apply to the short-term forecasting of
432 Lagrangian trajectories on the sea surface using sea surface conditions issued from short-term fore-
433 casts. This research direction would likely benefit from the development of neural ocean forecasts
434 [Wang et al. (2024); Xiong et al. (2023)] to advance model-based operational forecasts [Drévil-
435 lon et al. (2008); Benkiran et al. (2024)].

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445 *Data availability statement.* The data used in this study, including ocean currents and sea surface
446 height are openly accessible through the Copernicus Marine Environment Monitoring Service
447 (CMEMS). The data from the B1 and B2 benchmarks are subject to access restriction, one should
448 refer to Mercator Ocean International in order to claim the access rights. Additionally, the code
449 implemented for the evaluation of the methods discussed in this article is available as an open-
450 source project on GitHub: <https://github.com/CIA-Oceanix/DriftNet>.

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