Assessing data assimilation techniques with deep learning-based eddy detection

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I - INTRODUCTION

In this study, we introduce a method for detecting eddies using deep learning, which we evaluate against the traditional Py-Eddy-Tracker algorithm within the framework of dynamical Observing System Simulation Experiments. Our reference standard comprises eddy maps produced by an unconstrained model utilizing Py-Eddy-Tracker. The goal is to train a deep learning model on data from a degraded model to accurately replicate the eddy patterns identified by the free-run model. This approach serves as a means to assess the quality of data assimilation from degraded models and to gauge the impact of such assimilation on eddy detection capabilities.

II- EDDIES, THEIR DETECTION AND LIMITATIONS

What are eddies?

- Swirling masses of water formed by ocean currents.
- Range from small-scale features to large vortices spanning hundreds of kilometers.

Types:

- **Cyclonic eddies**: Cooler water, spin counterclockwise in the Northern Hemisphere.
- **Anticyclonic eddies**: Warmer water, spin clockwise in the Northern Hemisphere.

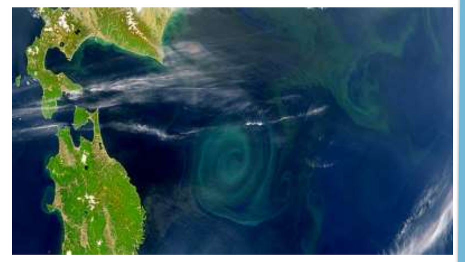

Fig 1 : Ocean eddy. Credits : **Provided by the SeaWiFS Project, NASA/Goddard Space Flight Center, and ORBIMAGE**

Importance of eddy detection and forecast:

- **Climate impact:** Influence global climate patterns by transferring heat and carbon between ocean layers.
- **Marine Ecosystems:** Affect nutrient distribution, essential for marine biodeversity and fisheries.
- **Energy transfer:** Play a crucial role in the mixing and energy transfer across ocean basins.

Traditional Sea level anomaly-based algorithms:

- SLA based algorithms, such as py-eddy-tracker, detect closed contours of SLA levels.

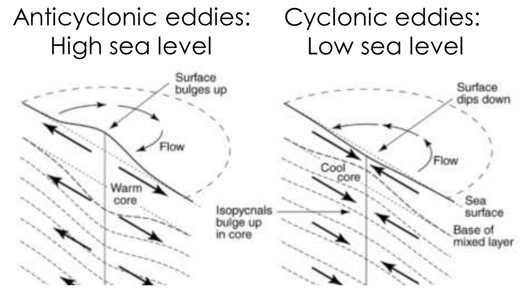

Fig 2 : Eddies and sea level

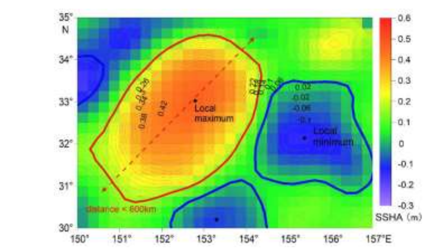

Fig 3 : SSHA map and eddies. Illustration from: **Oceanic Eddy Detection and Analysis from Satellite-Derived SSH and SST Fields in the Kuroshio Extension**

- Interpolation from 1D tracks to 2D maps induces a noisy reconstruction of the SLA field, and thus error in recovering the eddy field.

Limitations:

- Classical SLA-based eddy detection algorithms suffer from the **low coverage** of the current **altimetry network**.
- Interpolation from 1D tracks to 2D maps induces a noisy reconstruction of the SLA field, and thus **errors** in recovering the eddy field.

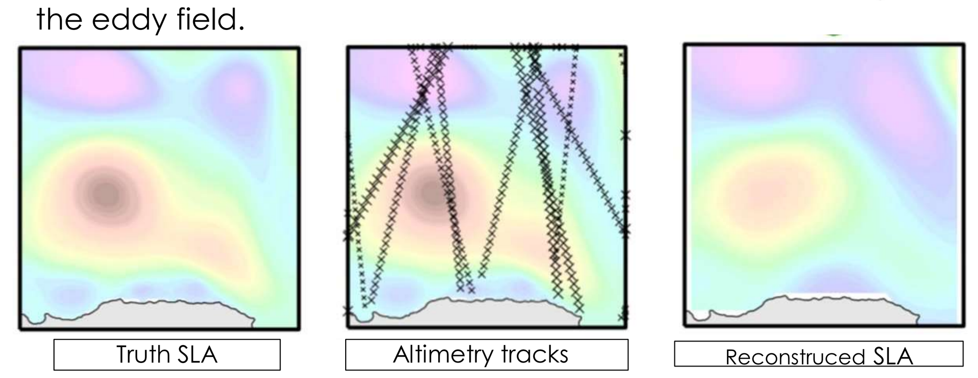

Fig 4 : Illustration of the impact of satellite altimetry network on the reconstruction of SLA (From Stegner et al. 2021)

III – SETUP AND OBJECTIVE

Data:

Two high resolution **(1/12°)** models from a **dynamical** Observing System Simulation Experiments (**OSSE**):

- **Free unconstrained model:** a free-run ocean circulation model representing the 'truth'.
- **Degraded model:** ocean circulation model constrained by synthetic observations from the 'truth' model mimicking the altimetry network through **data assimilation** techniques, to approximate the state of the 'truth' model

Variables : SSH, SST, U and V currents.

Focus region : **Gulf Stream**

Year of study : **2015** (daily data)

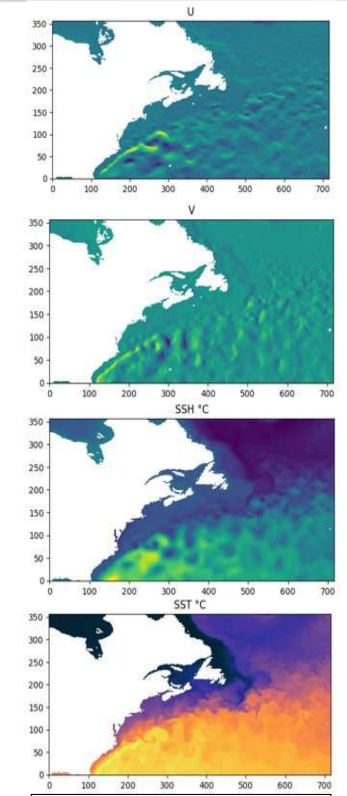

Fig 5 :U, V, SSH and SST from degraded model

Objective : overcome the limitations of traditional algorithms using deep learning.

When attempting to **recover** the 'true' eddy field from the **free model** using data from the **degraded model**, various types of errors can occur, making the accurate reproduction of the true swirling landscape challenging.

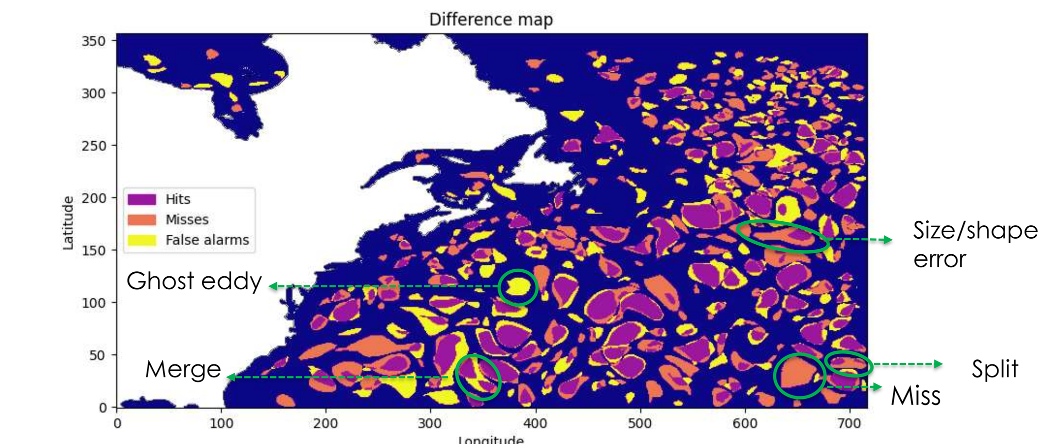

Fig 6: **Categorical difference map** between eddies detected with py-eddy-tracker on the free-model and the degraded model, and **possible errors to overcome.**

IV – PROBLEM FORMULATION AND PARAMETERS

- We aim to **detect eddies** of the **free-run model** using **degraded model data**. Eddy detection using deep learning is frequently linked with **U-shaped** architectures, since their detection can be formulated as a **semantic segmentation** problem.
- **Each pixel** of the output eddy maps is to be classified into one of **four classes**: Non-Eddy, Cyclonic Eddy, Anticyclonic Eddy, or Land (Land class is introduced to handle nan values).
- Our U-Net architecture takes **SST**, **SSH**, **U** and **V** maps from the **degraded** model and produces corresponding eddy maps with the same spatial dimensions, enabling direct **pixel-to-pixel mapping** for accurate eddy detection.
- We split our dataset into **training** (70%), **test** (15%) and **validation** (15%), and use a **weighted cross-entropy loss** to tackle **class imbalance** $-\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} w_c . y_{i,c} . \log(\hat{y}_{i,c})$, where :
  - C is the number of classes
  - $y_{i,c}$ is a binary indicator for observation i being of class c
  - $\hat{y}_{i,c}$ is the predicted probability of observation i being of class c.
  - w_c is the weight for class c.
- The **batch size** for training is **32**, and **16** for validation and test, the training was completed over **65 epochs**, with a **learning rate** of **7,5e-4**.

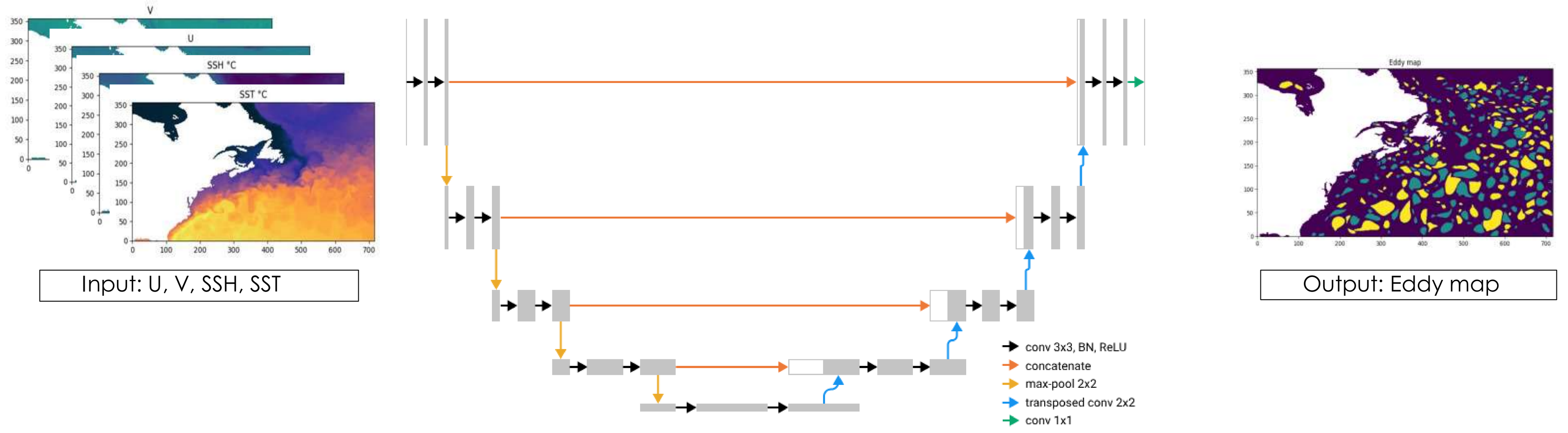

Fig 7: UNET architecture

V – RESULTS

Deep learning model performance

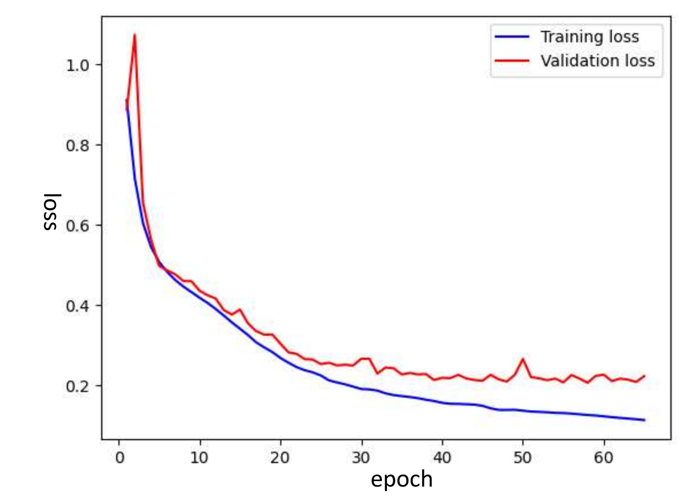

Fig 8 : Training and validation loss over epochs: **no overfitting**

	Anticyclonic Eddy	Cyclonic Eddy	Non-Eddy
UNET	**83,95%**	**85,10%**	91,39%
Py-Eddy-Tracker	48,75%	45,70%	84,74%

Table 1 : Accuracy for each class over the test dataset. We achieve **high pixel-wise accuracy for eddy classes.**

Visual analysis of the predictions

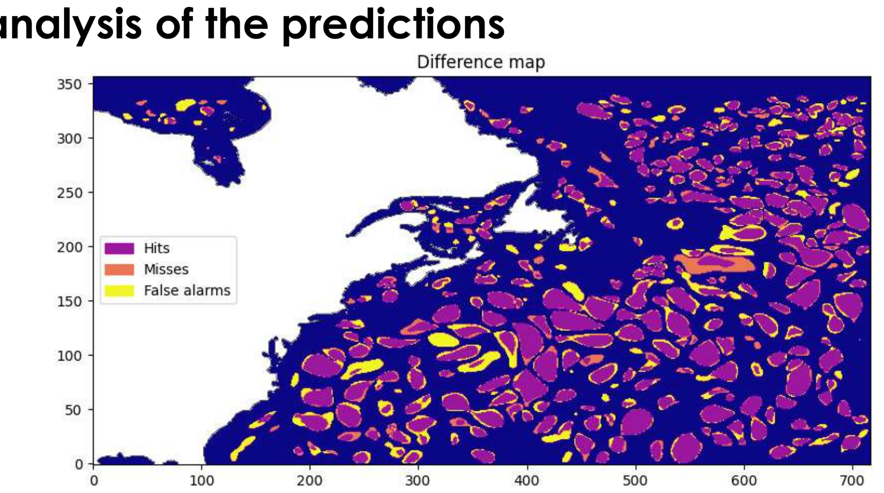

Fig 9 : Example of **categorical difference map**, free model as truth and unet predictions on degraded model, from **test dataset.**

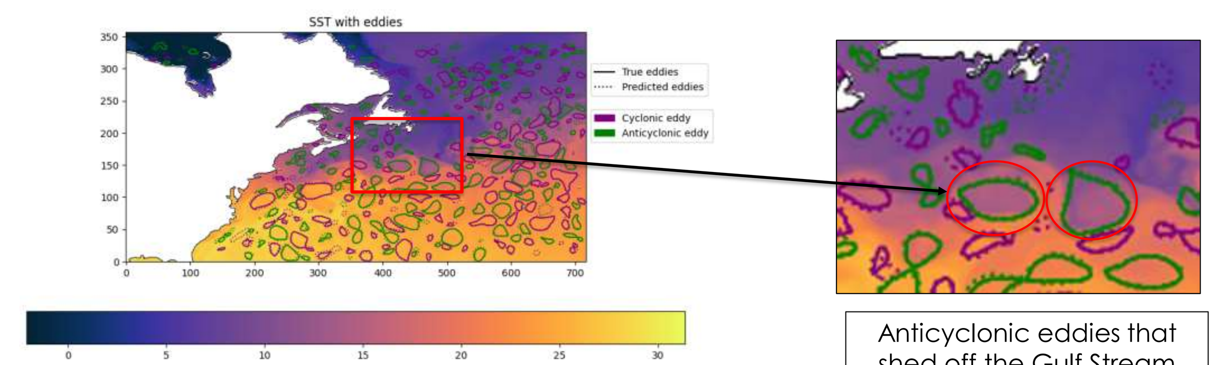

Fig 10 : Example **sea surface temperature** map with true and predicted eddies, from test dataset.

Anticyclonic eddies that shed off the Gulf Stream with **visible cold cores** on SST map.

Statistical analysis of detected eddies

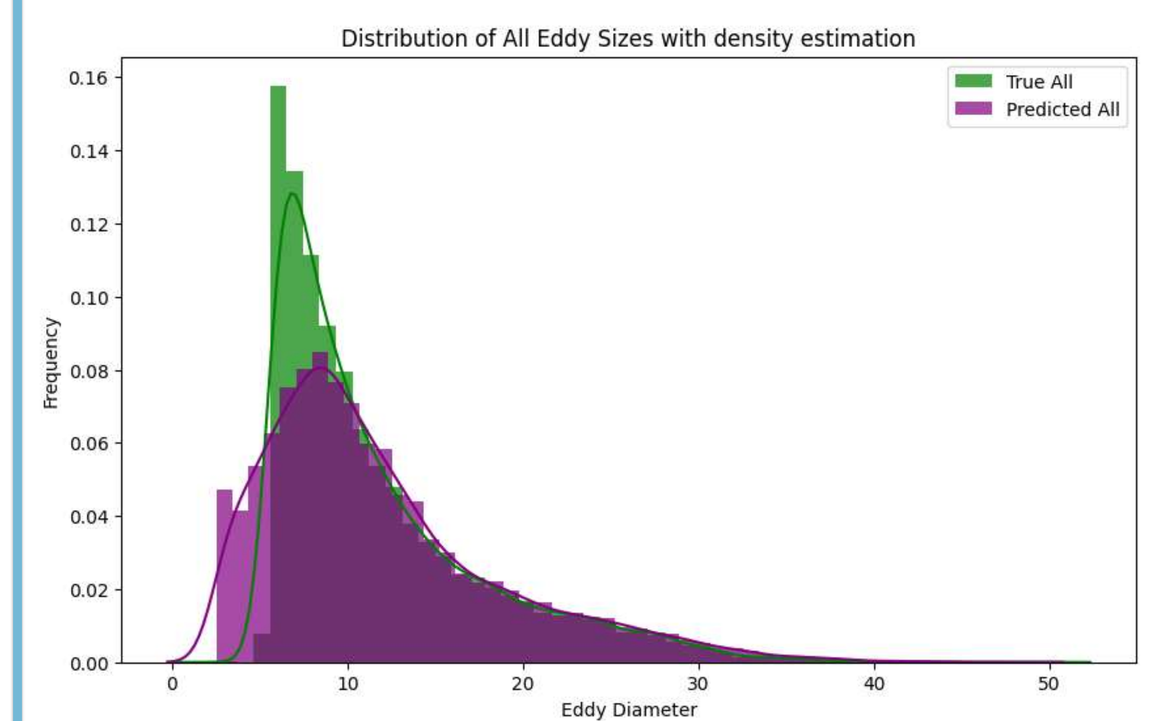

Fig 11 : **Distribution** of all eddy (cyclonic and anticyclonic) **sizes** with density estimation, for the test dataset.

CONCLUSION & PERSPECTIVE

Deep learning techniques have demonstrated skill in emulating the eddy patterns observed in the unconstrained model by utilizing data from the assimilated model, outperforming the standard algorithm in terms of accuracy. To broaden the scope of our insights on the applicability of these findings, future work will extend the study across multiple years and various oceanic regions. Furthermore, we are currently developing an eddy-tracking methodology informed by this deep learning approach. Preliminary applications of this eddy detection framework to **operational** models have yielded promising outcomes. This research paves the way for ongoing improvements in the field of eddy detection and the enhancement of ocean modeling capabilities through the integration of data assimilation and advanced deep learning techniques.

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