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REAL-TIME VALIDATION OF OPERATIONAL OCEAN MODELS VIA EDDY-DETECTING DEEP NEURAL NETWORKS

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ABSTRACT

Surface currents provided, in real time, by operational ocean models often differ from each other but also from satellite altimetry observations, especially in terms of mesoscale dynamics. Eddies, which play a dominant role on circulation at the regional scale, have a signature on both altimetry maps and satellite imagery, such as sea surface temperature. Combining these independent signatures allows for a highly reliable detection of reference eddies. To this end, we build a convolutional neural network capable of detecting the contours of mesoscale eddies on SST maps in real time. Combined with a standard eddy detection algorithm applied to altimetry maps, we were able to locate and identify with high accuracy more than 900 eddies, in the Mediterranean Sea, over a period of 6 months, and use them as a reference for numerical model validation. We compare as a case study the performance of two operational models: MERCATOR and MFS.

Index Terms— Model Validation, Remote Sensing, Deep Learning, Mesoscale Eddies

1. INTRODUCTION

Operational ocean numerical models simulate, in real-time, the physical state and the dynamical properties of oceans, forecasting also their future state. Validation of ocean models consists of a quality assessment of their operational output. The quantification of model error is performed by comparing model outputs with observations, from satellite or in-situ source.

Assimilation of numerical models, seeks to integrate these observations to produce an optimal estimate of the evolving state of the system. The mesoscale dynamics, partially observed through different measured variables, can be thus assimilated by the numerical model. Albeit the important improvements brought by data assimilation methods, the results of different operational models in the same period and region can vary significantly on the level of mesoscale dynamics.

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Eddies are coherent structures, that can survive several weeks or months, with a prevalent role at mesoscale or submesoscale ocean circulation. These structures can have a signature on satellite observations such as altimetry, but also on visible imagery or synthetic aperture radar. Many algorithms use geometrical properties of the Sea Surface Height (SSH) field and/or the streamlines of the derived velocity field to detect and track in time vortex structures. However, standard altimetry (AVISO/CMEMS) products contain large uncertainties due to the spatio-temporal interpolation between satellite tracks, limiting the reliability of these algorithms [1].

Satellite imagery provides independent observations of mesoscale structures. In spite its high resolution, their patterns are too complex for standard geometric methods to process. Besides, Convolutional Neural Networks (CNNs) with deep architectures have proven very efficient in detecting eddy signatures on visible imagery such as Sea Surface Temperature [2], marking the potential of Deep Learning methods for this task.

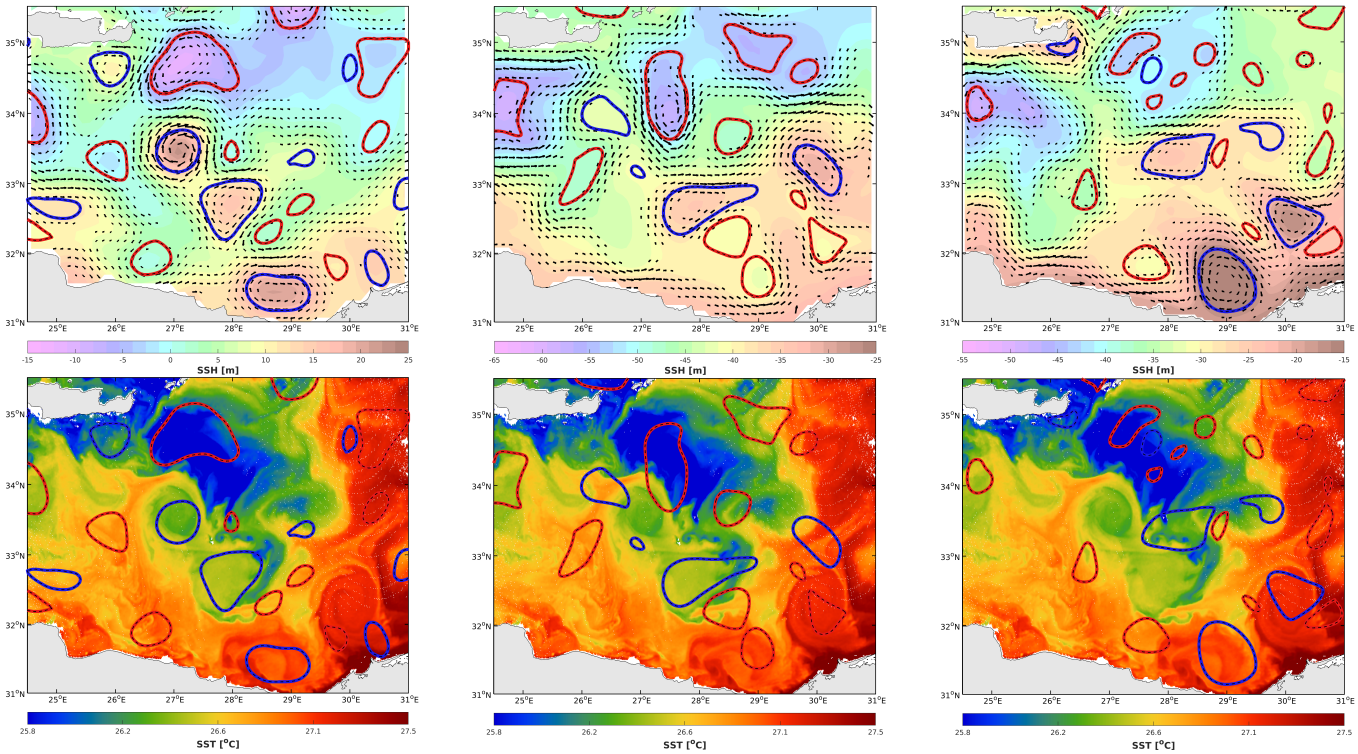
We present a novel methodology which employs an Eddy-Decting Convolutional Neural Network on SST maps, combined with an Altimetric Eddy Tracking Algorithm to provide a set of highly reliable eddy detections. These reference detections are used to validate the operational output of different numerical models and serve as a basis for an operator to pick-and-choose between available models on a certain region.

2. SATELLITE AND MODEL DATA

Working on the Mediterranean Sea as a case study, we use near real-time altimetry and SST satellite data to validate the real-time output of two operational numerical ocean models: MERCATOR and MFS.

Daily, 1/120°resolution, multi-sensor SST maps of the Mediterranean Sea are received from the CMEMS Ultra High Resolution L3S SST Dataset and are representative of night time SST. We also utilize daily SSH and derived geostrophic velocity fields from AVISO/DUACS altimetry products at 1/8°resolution from the CMEMS L4 Sea Level dataset.

To retrieve the eddy centers, their corresponding contours and dynamical properties we use the AMEDA algorithm [3]



(a) AVISO (Satellite) (b) MERCATOR (Model) (c) MFS (Model)

Fig. 1. Comparison of satellite altimetry (a) and two numerical models (b,c) on the eastern Mediterranean sea on the 22/08/2021. Sea Surface Height (SSH) obtained by the models and observed by satellite correspondingly is shown on the topmost panels along with the derrived geostrophic velocity vectors. The eddy contours (blue=anticyclonic, red=cyclonic) detected by AMEDA on each field are superimposed on the SSH panels. The bottom panels all show the Sea Surface Temperature (SST) measured by satellite on the same day, on which the aforementioned eddy contours corresponding to each SSH output are superimposed.

applied on the geostrophic velocity field. Daily eddy contours derived from the geometrical and dynamical properties of the velocity field are then integrated into eddy tracks which follow the lifetime of an eddy. The contours shown in this work correspond to the closed streamline of maximum velocity of the eddy.

Two operational models are considered in this study. The Operational Mercator global ocean analysis and forecast system (MERCATOR) is routinely operated in real time since early 2001 and updated daily [4]. The Mediterranean Forecasting System (MFS) is a second operational model providing nowcasting and forecasting specific to the Mediterranean Sea dynamics (Med-Currents) [5]. Both models run on a rectangular grid with unevenly spaced vertical levels and use data assimilation schemes: reduced-order Kalman filter for the MERCATOR and 3DVAR for MFS. Table 1 summarizes the differences in the parameters of the two operational models. The nowcast output of these models was downloaded in real-time from the CMEMS database.

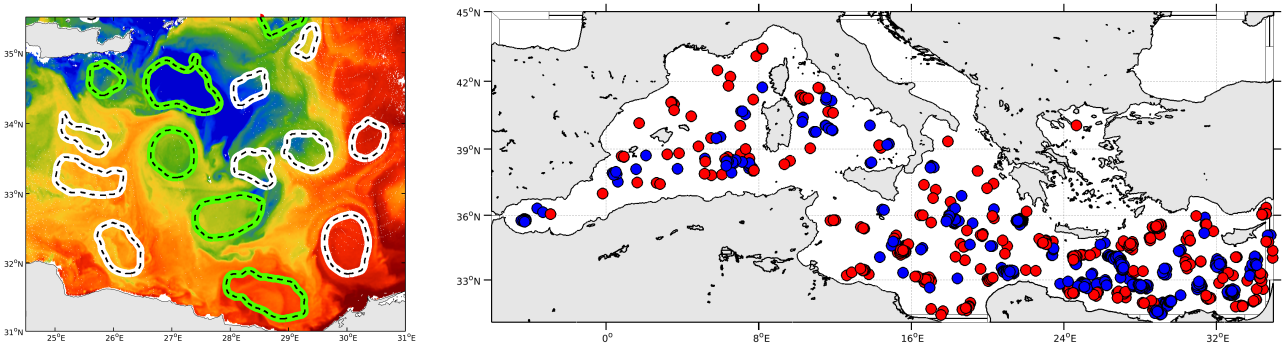
In Figure 1 the real-time data available from the MERCATOR Model, the MFS Model and Satellite Altimetry are compared on a certain day (22/08/2021) in the Eastern Mediterranean Sea region. The difference between the eddy contours obtained through the geostrophic velocity field of the two models and the observations are evident. Through SST images, an independent validation of the eddy position can be performed (Figure 1 bottom panels). Both models seem to miss many eddies with a signature on SST, while also the eddy contours from the more accurate satellite AVISO fields on Figure 1 (a) are not aligned with the SST gradients.

Model	Resolution		Assimilation		
	Horiz.	Vert.Lev.	In-Situ	SSH	SST
MERCATOR	$1/12°$	50	✓	✓	✓
MFS	$1/24°$	141	✓	✓	

Table 1. Main properties of the two operational models

3. EDDY-DETECTING CNN ON SST IMAGES

Convolutional Neural Networks (CNNs) have been successfully employed in the semantic segmantation of eddies [6]. However, most of the methods in the bibliography train and



(a) Example on 22/08/2021

(b) Reference eddies (900) in Summer-Spring 2021

Fig. 2. CNN Reference Eddies: (a) An example of CNN eddy detection on the SST on the 22/08/2021. White contours are CNN detections on the SST with no corresponding SSH AMEDA detection. Green contours are CNN detections with an overlapping SSH detection (criterion 1), and retained as reference eddies (b) Positions of 600 anticyclonic (blue dots) and 300 cyclonic (red dots) reference eddies retained on Spring-Summer 2021.

evaluate the performance of these CNNs on satellite altimetry data (SSH) which contain inherent uncertainty biases. Thus, the best of CNNs trained this way will only manage to replicate the best of the standard eddy detection models.

In this work, we introduce a CNN able to detect the position, size and form of eddies via a contour, on Sea Surface Temperature (SST) images. To perform this semantic segmentation task, we construct a U-Net type architecture with an upsampling and a downsampling branch composed by convolution and pooling operations. A dataset of more than 100,000 distinct eddy signatures on SST images are used to train the network by minimizing cross entropy loss on masks stemming from the AMEDA contours of maximal velocity. Three prediction channels (No Eddy, Anticyclone, Cyclone) are used to segment the output map and retain SST contours.

To evaluate the performance of the trained CNN we use a sample of 30,000 SST patches retained on distinct years from the ones used for training. Our test is performed on mesoscale eddies with radii larger than 20km and with a cloud coverage in the patch of less than 10 %. A comparison between the performance of the eddy-detecting CNN applied on SST images and that of standard detection methods applied on the geostrophic field derived by the SSH (as described in [1]) is given in Table 2. The Neural Network on SST overperforms standard detection on SSH both by a much lower Missed Eddies and Ghost (False Positive) Rate but also through the precision on the position and the size of detect eddies. This difference is even more pronounced for cyclonic eddies, which are less accurately detected on altimetry [1].

Method / Data	Miss	Ghost	Position	Size
Standard / SSH	34 %	10 %	7-20 km	15-50 %
CNN / SST	3 %	<1 %	7km	20%

Table 2. Error comparison on SSH and SST detection

4. REFERENCE EDDIES

Detections on SSH derived products (velocity) by the AMEDA are combined with the detections on the SST images by the Convolutional Neural Network (CNN). We define the agreement of the two detections on independent satellite observations with a simple Intersection over Union (IoU) threshold:

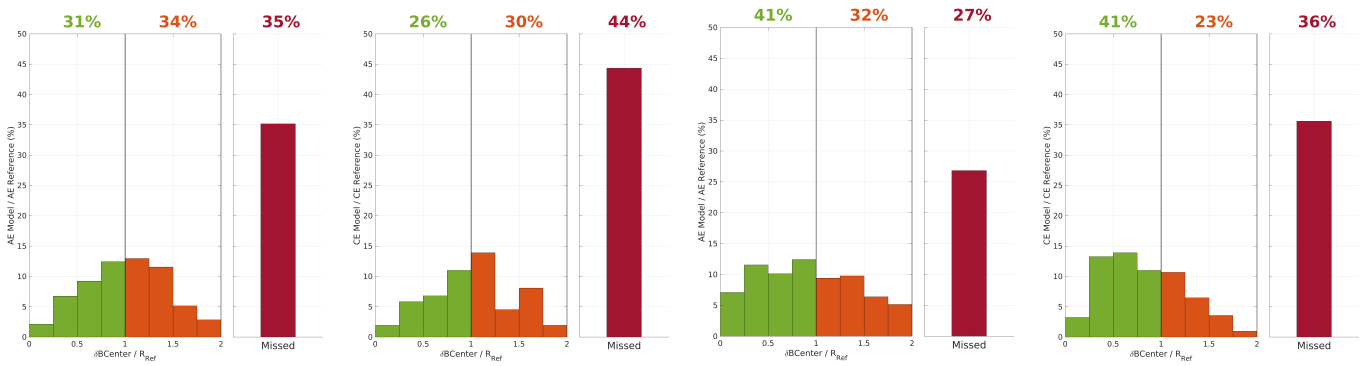
$$\frac{SSH \cap SST}{SSH \cup SST} > 0.5 \tag{1}$$

The outputs of the eddy detecting CNN on the SST are shown on Figure 2 (a). SST detections with no corresponding AMEDA detection on the SSH are shown with a white contour. SST detections with an overlapping SSH detection above the IoU threshold of criterion 1 are shown with a green contour and are retained as reference eddies. A total of 900 reference eddies shown in Figure 2 (b), of which 600 anticyclones and 300 cyclones, were retained in real-time on Spring-Summer 2021 by applying the CNN and AMEDA detection tools, spanning all the Mediterranean sea.

5. MODEL VALIDATION

The reference eddies, cross-detected in real-time on both SSH and SST observations, serve to validate the accurate reproduction of mesoscale dynamics of operational models in real-time. To retrieve the numerical model eddy contours we apply the AMEDA algorithm to the geostrophic velocity derived from the operational model in real-time. As seen in Figure 1 (b) and (c), the MERCATOR and MFS model show diverging results on the mesoscale field.

To apply our validation scheme we search for a corresponding numerical model contour for each reference eddy contour. To perform a colocalization, the distance of the barycenters of



(a) MERCATOR (AE) (b) MERCATOR (CE) (c) MFS (AE) (d) MFS (CE)

Fig. 3. Validation of two numerical models on the accuracy of reproduction of anticyclonic (AE) and cyclonic (CE) eddies. Green bins show accurately detected eddies, orange bins show erroneously detected eddies and red bins show missed eddies.

the two contours should not be bigger than the sum of their radii:

$$d_{bar}^{(Ref,Mod)} < R_{Ref} + R_{Mod} \tag{2}$$

If a contour is colocalized, the distance $d_{bar}^{(Ref,Mod)}$ normalized by the reference eddy radius R_{Ref} represents its positioning error, plotted on the x axes of Figure 3. When this error is smaller than the reference radius (R_{Ref}) then the eddy is considered as accurately detected (green bins). When the error is between R_{Ref} and $2R_{Ref}$ the eddy is considered as erroneously detected (orange bins). If no model contour in the vicinity of the reference contour surpasses the criterion 2, then the eddy is characterized as "missed" by the model.
As seen in Figure 2, the MFS model outperforms the Mercator model with a 41% of accurate detections both for AE and CE. However both models have a high miss rate of a third or more of the eddies (higher for CE than AE) and another third which is erroneously detected.

6. CONCLUSION

Operational oceanic model nowcast errors on mesoscale dynamics can be important, despite the assimilation of observations. Here, we propose a novel scheme to validate operational models in real-time. The eddy detections of a Convolutional Neural Network on SST satellite maps are coupled with those of standard methods on SSH maps to provide a sub set of highly reliable reference eddies. The later are then used to quantify, in real time, the accuracy of different operational models in the Mediterranean Sea. We show here that reliable eddy contours can act as topological information for the validation of numerical models, as also recently shown in [7].
Our CNN detecting eddies on SST images has a very low false negative (3%) and false positive ($< 1\%$) rate compared that of standard detection methods. CNNs have proven robust in processing cloud coverage [8], and can be thus trained to provide with reference eddy detections when the local region is covered with less than $< 50\%$ of clouds. Besides, the inclusion of other visible (CHL) or radar (SAR) observations could significantly increase the number of reference eddies. Harnessing data fusion and deep neural networks to validate operational ocean models can provide maritime stakeholders with reliable and accurate nowcast and forecast data.

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