We thank the reviewers for their positive and constructive comments. We have addressed all comments as detailed below.

@#R1

The manuscript by Picard et al. evaluates the catchment area of the ST moored 3000 meters below the seafloor. The authors employ machine learning technology to predict this catchment area based on the input of Sea Surface Height (SSH) and Sea Surface Temperature (SST). This study offers a valuable tool for the observational community, and the methodology and results appear convincing. Therefore, I recommend a minor revision with the following suggestions:

1. The authors should address the uncertainty associated with the backward tracing technique. Specifically, how is the confined interval of the backward tracing method evaluated? Since the CNN method is trained using the backward tracing results, a discussion on the propagation of uncertainty and its potential impact on the predictions would enhance the robustness of the approach.

In order to ensure the robustness of the Lagrangian backwarding method, sensitive tests were conducted in Wang et al. 2022 and Picard et al. 2024. In particular, we evaluated the influence of the final PDF depending on the size of the released patch and the number of particles considered. No significant change was observed. However, these observations are directly limited by the simulation resolution (2 km here). Indeed, a finer resolution may lead to different results by enhancing chaotic situations and divergent flows above the trap.

Presently, evaluating the associated uncertainties with a high degree of precision is challenging, given the lack of available numerical simulations at finer scales in the region, which would facilitate such an evaluation. However, one potential solution that avoids the use of an additional simulation is to adopt a stochastic approach (https://doi.org/10.1175/1520-0485(2002)032<0797:MTIOGP>2.0.CO;2), whereby random noise is introduced during the particles' trajectories to account for the absent diffusion processes. The random noise can be, for instance, parameterized based on the local dynamics. Unfortunately this stochastic Lagrangian modelling is not yet incorporated in our Lagrangian tool (i.e, Pyticles ;https://doi.org/10.5281/zenodo.4973786).

Nevertheless, in order to provide an example of the aforementioned method and to illustrate the associated uncertainties, we implemented a simplified Markov model at order 0 in Pyticles. The trajectory x_n of the particles can thus be described as follows:

$$x_{n+1} = x_n + \Delta t\, u(x_n, t_n) + \mathcal{R}(2K\Delta t)^{1/2}$$

The final term is associated with the stochastic implementation, whereby $\mathcal{R}$=N(0,1) denotes a random number sampled according to a normal distribution and K represents the diffusivity associated with subgrid scale turbulence. For this example, we chose two constant diffusivities $K = 0.1\, m^2 s^{-1}$ and $K = 1\, m^2 s^{-1}$. Considering a $\Delta t = 120s$, this leads roughly to typical horizontal speed of 0.04 $m\,.\,s^{-1}$ and 0.13 $m\,.\,s^{-1}$.

Two distinct periods are considered in the following: In the first example (Figure 1), the majority of particles are contained within an eddy. In the second example (Figure 2), the flow is more chaotic and the particle source area is more spread out. For each example, the following plots are presented: the original particle PDF without K diffusion, and the Gaussian filtered PDF that was utilised in this study. For each Kdiff, we have conducted ten experiments for each period, and four of them have been plotted. The resulting PDFs are then averaged, and a comparison is drawn between the averaged PDF and the Gaussian-filtered PDF.

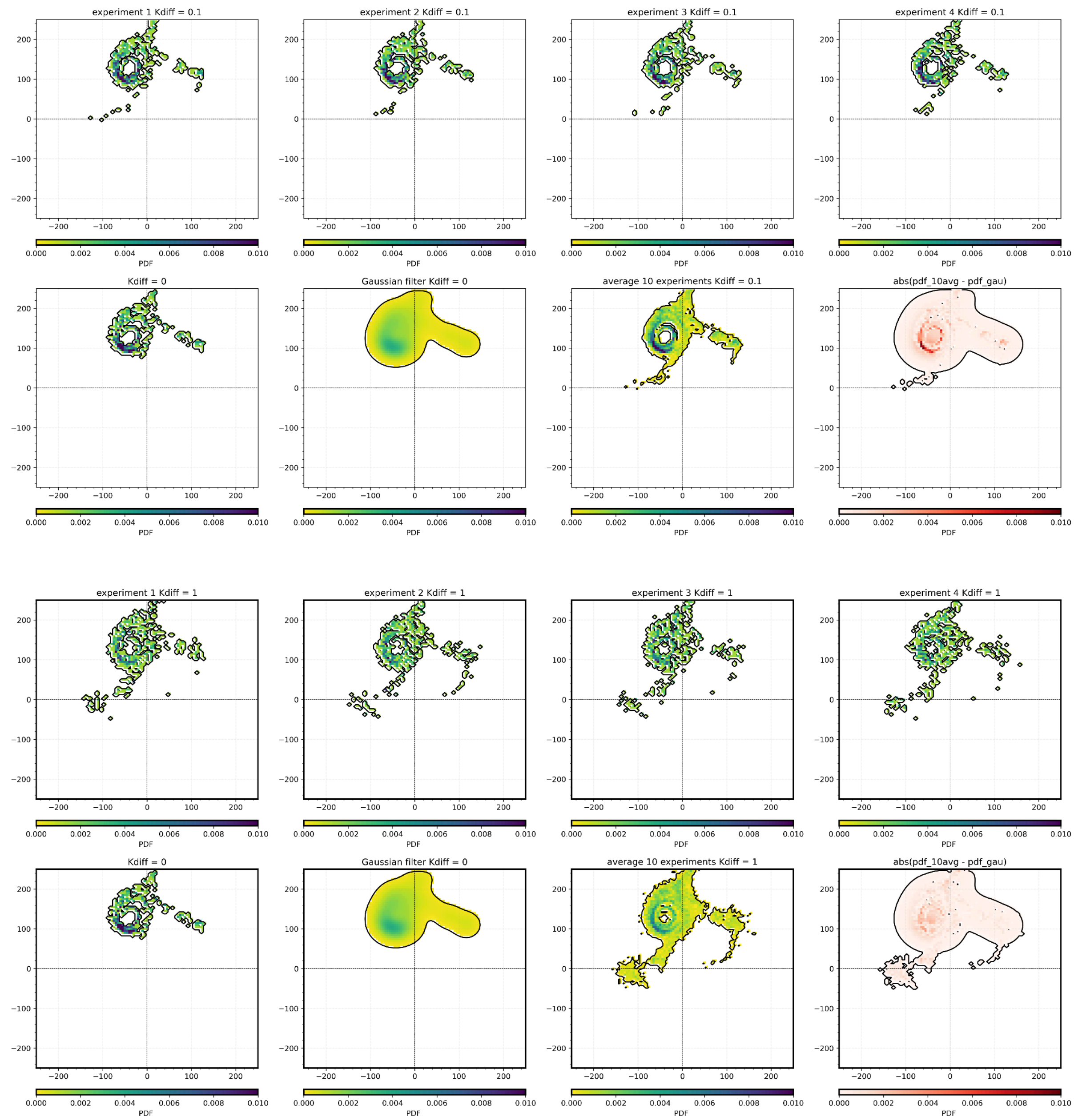

Figure 1: Eddy case. First row : 4 examples of PDF with Kdiff = 0.1. Second row respectively from left to right : PDF with Kdiff = 0, PDF Kdiff = 0 after gaussian filter, average of 1 PDF with Kdiff = 1, absolute error between the two previous PDF. Last two rows : Same with

Kdiff= 1.

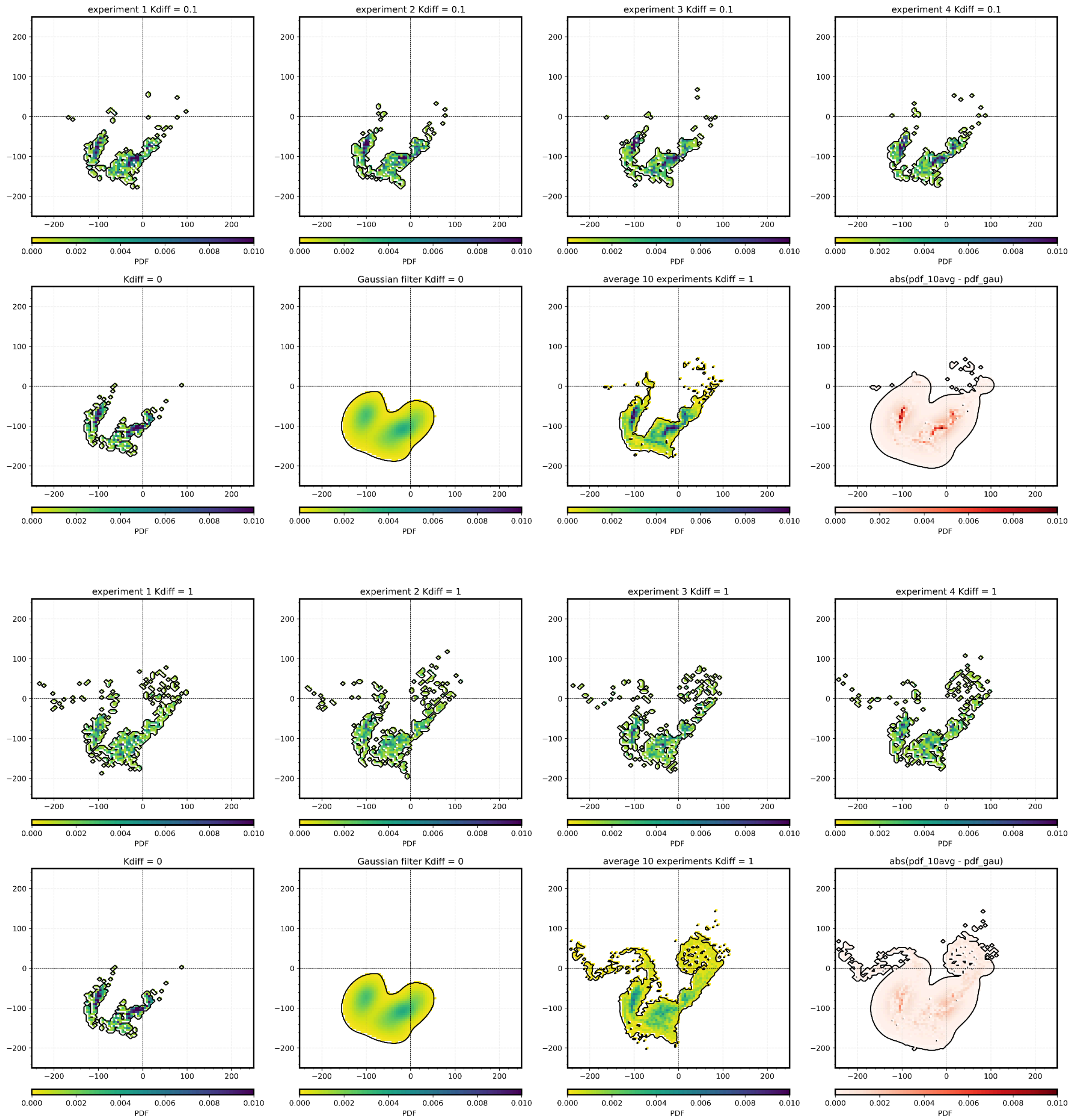

Figure 2: Chaotic case. First row : 4 examples of PDF with Kdiff = 0.1. Second row respectively from left to right : PDF with Kdiff = 0, PDF Kdiff = 0 after gaussian filter, average of 10 PDF with Kdiff = 1, absolute error between the two previous PDF. Last two rows : same plots with Kdiff = 1.

As shown in the two examples, when Kdiff is set to 0.1, the area of the averaged PDF appears to be comparable to the gaussian-filtered PDF in both cases. However, when Kdiff is set to 1, the averaged PDF is distributed over a larger area and may reveal new potential source regions, especially for chaotic situations (see the new particle patch in the middle left of Figure 1 and around the mesoscale eddy in the upper right of Figure 2). Consequently, a precise parameterization of Kdiff is likely to be of significance in this study and in future research. It would be worthwhile to further investigate this approach with a more complex diffusion model that parametrizes Kdiff with the local dynamics.

We have therefore added an Appendix D to present the second case and the following point has been added at the end of the discussion:

"***Finally, questions remain about the uncertainties associated with the Lagrangian method. It is clear that the uncertainty associated with the Lagrangian method has a direct impact on the predictions, since the network is trained directly with the backtracked particles. Although sensitivity tests have been carried out (changing the number of particles and the size of the released patch) to ensure that the particle sources are not affected, some diffusion processes are not represented in the numerical simulation and consequently in the propagation of the particles. To evaluate potential biases, it would be necessary in the future to adopt a stochastic approach \citep{Minguez2012}, where random noise is introduced into the particle trajectories to account for subgrid scale diffusion processes. These processes have the potential to influence the results of the Lagrangian analysis (see Appendix D for an example). Consequently, the diffusion parametrization should be carefully defined, taking into account local dynamics. This approach would facilitate the establishment of a confidence interval for the source areas.***"

2. I suggest discussing the regional dependence of the Unetsst−ssh method in greater detail. In particular, it is my understanding that surface data-based training may be more applicable in regions dominated by geostrophic or quasi-geostrophic currents. In areas with strong submesoscale processes, the bias of the model may increase, and it would be valuable to address this limitation in the context of the study.

Given that SSH is the main driver of the network score (figure 3), we can indeed reasonably assume that the network relies on geostrophic currents for its predictions. As a result, we believe that regions dominated by geostrophic or quasi-geostrophic currents should perform better with this network than, for example, regions with strong submesoscale processes, and this should be evaluated in the future.

We have modified the discussion at the end as follows:

"It is also possible to consider the deployment of sediment traps in a region where the deep dynamics are even weaker and unaffected by the near-topography, which is typically the source of deep eddies and instabilities (Smilenova et al., 2020). A numerical simulation such as the one used here can be used to identify the weakest dynamical regions, where particle pathways below the mesopelagic layer are unlikely to be affected. Nevertheless, 3D numerical simulation remains one of the most effective methods for studying deep ocean dynamics and further efforts are required to validate the accuracy of simulations of deep ocean currents. ***In addition, given that SSH is the main driver of the network score (see Figure 3), we hypothesise that the network relies predominantly on geostrophic currents to perform its prediction. Consequently, it would be worthwhile to compare the efficiency of the model in regions with varying degrees of geostrophic current dominance."***

3. The manuscript refers to the POF index, but the definition of this index is not provided in the main text. I recommend including a clear definition of the POF index to ensure that readers unfamiliar with the term can follow the methodology and results effectively.

As far as we know, there is no mention of the words “POF” or “index” in the manuscript.