# REVIEWER #1

In this paper the authors use different machine learning models to characterize near surface ocean dynamic. The authors launched several undrogued surface drifters in the North Sea released from the coast of Netherlands, tracking their position with GNSS. Then, several variables (including variables derived from wind, oceanic currents and waves) from different research products are used as inputs in three machine learning models (linear regression, random forest and support vector machine) to predict drifter velocities. Permutation feature importance and ALE plots are then used to explain the importance of the input variables in predicting the drifter velocities.

The authors claim two different results in the conclusions.

The first one is the efficacy of the proposed analysis method. The use of techniques of explainable machine learning to investigate surface ocean dynamic is interesting and sufficiently novel. I have no objections for this part.

The second one is the accuracy of the proposed method in inferring drifter trajectories. This is, in my opinion, the weakest part of the paper. Albeit the numerical results support the conclusions of the authors, the trajectory dataset is very small, consisting of twelve drifters, released the same day at 250 meters of distance. As can be seen from the figures in the paper, the trajectories are higly correlated, meaning that the dataset lacks the variety needed to ensure sufficient generalization. In this condition the risk of overfitting a model during training is very high, and this problem is neither mentioned nor addressed in the paper.

The reason why the trajectory integrated using the linear model outputs is much more different from the other might be because, due to being a simpler model, it overfitted less than random forest and support vector regression.

I still think that integrating the trajectories using the model outputs is a reasonable benchmark, if the scope of the models is to explain the correlations between input variables and predicted drifter velocities.
In order to claim that the model is able to generalize beyond the twelve drifters presented in the paper, a test using some other drifter release (from some other starting position, in some other period) should be necessary.

I understand that drifter release is a demanding task, and I am obviously not asking the authors to plan further releases. However, in order to better understand the generalization limits, if other surface drifter trajectories are available to the authors, I suggest to test the trained models to reproduce them. If this is not possible, I expect that these concerns are better addressed in the conclusions.

At the very least, the model-integrated trajectories should be compared with trajectories simulated using the ocean velocities given as input to the machine learning models, using some classical integration scheme such as RK4 or RK45.

As a last note, even if the models are actually overfitting the data, this is not an issue for the first scope of the paper (predictor-velocity analysis), since the analysis is focused on this particular dataset and has no claim of generalization. Some degree of overfitting might even be considered beneficial.

We are grateful to the reviewer for highlighting this point and we agree that the implication that these models are rigorous as a standalone forecasting mechanism and could be suitable to predict drifter velocities in other regions beyond the southern North Sea has not been supported with evidence.

While the full dataset was not available at the time of submission, we have since obtained measurements from a drifter campaign with the same surface drifters recovered from the North Sea experiment. A research team from the Department of Marine Animal Conservation at the *Stazione Zoologica Anton Dohrn Napoli,* led by Dr. Hochscheid, deployed six drifters off the coast of Napoli on 26 June 2025 to compare the drifting behaviour of buoyant objects and turtles (van Sebille, 2025). One of the drifters stopped transmitting after one day, while the remaining five drifted for at least 40 days in the Tyrrhenian Sea.

In the revised manuscript, we have applied the North-Sea-trained models to predict these unseen trajectories using the method and evaluation metrics described in Section 3.3. We also test the generalisability of the leeway method by applying the same windage coefficients derived from the North Sea data. Trajectories were reconstructed over 48h with predictions iteratively repeated along the full drifter trajectory to obtain 20 predictions per drifter. The choice of a 48h prediction window is motivated by the aim of comparing its performance with that reported in other studies that aim to forecast on unseen data: (Dagestad & Röhrs, 2019) reported 20-40km separation distance after 48h for CODE and iSphere drifters in the Norwegian coast using a physics-based linear model, while (Grossi et al., 2025) found 20-50 km RMSE between prediction and observation for an artificial neural network model of the Gulf of Mexico.

The random forest model achieves the best performance (separation distance of 17.4 km, RMSE of 12 km, Mean Cumulative Separation Distance of 9.6 km), followed closely by the support vector regression model (18.9 km, 11.2 km, 9.7 km). The linear regression performs slightly worse (19.1 km, 12.0 km, 10.5 km). We also observed this good performance of linear regression for short-term prediction (Fig. 8) but found that errors rapidly propagate for timescales greater than one week. Nevertheless, compared with values from literature studies using both physics-based and machine learning models, all models show good forecasting skill after 48h.

These results indicate that the machine learning models trained on the North Sea data can reproduce the drifter behaviour in the Tyrrhenian Sea despite the differences in the ocean dynamics between the two. The North Sea is a tidally dominated region, while the Tyrrhenian Sea is part of the Mediterranean Sea, a semi-enclosed basin with a thermohaline and wind-driven circulation with eddies as regular features (Buffett et al., 2017).

All this additional analysis and results have been included in an additional section called "4.2.2. Generalisability of prediction results" in the tracked-changed manuscript. The conclusion has also been changed accordingly to include these new insights.

We also appreciate the reviewer's concern regarding potential overfitting. We would like to clarify that the cross-validation framework is specifically designed to detect and prevent overfitting by evaluating the model on data that is not used for training. We further strengthened this procedure by implementing a block cross-validation strategy, which ensures that training and validation is temporally independent. This prevents information leakage between folds and avoids the optimistic bias that can arise from autocorrelated data. We have changed lines 215-216 to clarify this:
*"(…) ensuring that any two points separated by more than this time range can be considered statistically independent and thus suitable for validation* ***This approach substantially reduces the risk of overfitting, as it prevents information leakage between training and validation sets and ensures that model performance is assessed on truly unseen, time-independent samples****. For a detailed explanation …."*

However, the reviewer is right to highlight that there might still be spatial correlation between the training data and the test with the drifters in the Tyrrhenian Sea addresses this concern.

## REFERENCES


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