On Model-Driven Ocean Exploration

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Introduction

The coastal ocean, the marine area extending from the coastline to the continental slope, encompassing the continental shelf, constitutes one of the most dynamic and complex regions of the ocean. These areas are characterized by highly variable forcing mechanisms, intricate topographies, and coastline geometries. They are forced by a wide range of physical and biogeochemical processes which occur across diverse spatial and temporal scales. They are among the most productive and economically significant areas of the world's oceans, benefiting from terrestrial inputs via river discharges and nutrient renewal driven by upwelling processes. As a result and in part, coastal areas concentrate a great proportion of human maritime activities, from fisheries and offshore aquaculture to renewable energy exploitation. Moreover, the coastal ocean acts as an interface between deep-ocean processes and coastal environment, modulating how large-scale phenomena — such as climate-driven changes or extreme weather events — impact coastal populations. It also regulates, for example, how anthropogenic influences originating on land are redistributed and affect marine ecosystems.

The complex interplay between physical, chemical, and biological processes in the coastal ocean can rapidly amplify or modulate the impacts of extreme events such as storms, flooding, or pollution incidents. Furthermore, the coastal ocean serves as a key interface where large-scale oceanic and atmospheric changes manifest their consequences for coastal ecosystems. Accurately forecasting the state of the coastal ocean is therefore essential not only for safeguarding environmental and economic interests, but also for enhancing resilience to climate variability, natural hazards, and human-induced pressures. Achieving this, however, remains a major scientific and technological challenge, given the high variability, rapid dynamics, and observational constraints inherent to these regions.

Ocean models have become essential tools for predicting the ocean state and underpin a wide range of societal applications, from climate forecasting to pollution monitoring and resource management. However, these models are inherently imperfect representations of complex reality. Data assimilation techniques — where observational data are integrated into models — play a critical role in correcting or adjusting model errors and improving their forecasting capabilities. Yet, the success of data assimilation depends heavily on the availability, quality, and relevance of observations.

Observations of the ocean are obtained through multiple sources. Satellite remote sensing offers extensive spatial coverage but is limited to surface measurements with usually low spatial resolution and often compromised by atmospheric conditions. In situ observations, whether from ships, moorings, or drifting platforms, provide higher accuracy but suffer from limited spatial and temporal coverage, high operational costs, and logistical constraints — particularly high in coastal regions. Recent technological advances have enabled the use of autonomous underwater vehicles (AUVs) and other robotic platforms, offering flexible, mobile, and increasingly autonomous means of sampling ocean properties with high spatiotemporal resolution and low logistic footprint [1, 2, 3, 4, 5, 6, 7, 8, 9].

However, even with these new tools, efficiently gathering data at the right spatial and temporal scales remains a complex challenge. AUVs are constrained by endurance, communication bandwidth, and operational risks such as high currents and bathymetry even as the ocean itself remains highly dynamic with key processes often evolving faster than traditional sampling strategies can capture. This opens the door to adaptive sampling strategies, where observation efforts are guided by model outputs and uncertainty estimates to maximize the relevance of collected data. Adaptive sampling [10, 11, 12, 13] represents a fundamental shift: instead of executing pre-planned missions, autonomous vehicles dynamically prioritize areas for observation.

One approach that we articulate here is combining model predictions with adaptive AUV sampling. Doing so combines predicted model uncertainties in comparison with prior data assimilation process with availabe obervations. Model forecasts identify where uncertainty is highest or where new observations are expected to have the greatest impact in reducing forecast errors. Vehicles are then directed to sample these areas, and their data are in turn assimilated back into the models, generating improved forecasts for subsequent adaptive planning as a virtuous cycle. Doing so closes a critical feedback loop between models and observations; model prediction generates a forecast and associated uncertainty field while adaptive sampling targets areas of maximum predicted uncertainty. Data assimilation from these high uncertainty regions are then incorporated into the model such that new predictions benefit from improved in-situ data, closing the loop. Such a *data cycle* approach promises to significantly enhance the skill of ocean forecasts, especially in the complex coastal environment where processes occur over a wide range of scales and where human and environmental stakes are high. It also has the potential to improve operational efficiency by optimizing the deployment of costly and resource-constrained observational assets.

In this study, we address the challenge of such loop closure by implementing and evaluating a complete data cycle — from model prediction, to uncertainty projection, to adaptive sampling and data assimilation — in a coastal ocean environment. The work was conducted within the framework of **FRESNEL** (**F**ield expe**R**iments for mod**E**ling, a**S**similatio**N** and adaptiv**E** samp**L**ing), a project specifically designed to explore and test model-driven robotic exploration strategies. **FRESNEL** provided the experimental setting and operational assets to demonstrate how model-based uncertainty fields can drive adaptive sampling missions aimed at improving ocean model predictive skills to enhance ocean forecasts in highly dynamic coastal environments (Fig. 1). The experi-

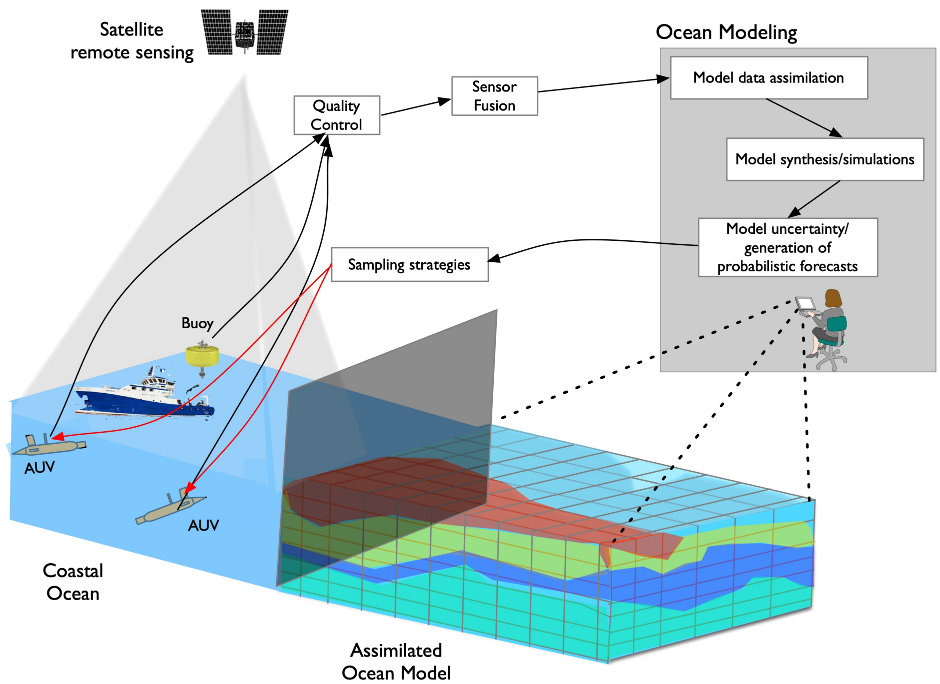


Figure 1: **FRESNEL** demonstrates the value of integrating ocean models with adaptive robotic vehicles in the coastal ocean, to increase model skill while increasing model accuracy and prediction within a tight control loop.

mental results obtained within **FRESNEL** serve to illustrate and validate the proposed approach, highlighting the practical benefits and challenges of real-world adaptive ocean exploration.

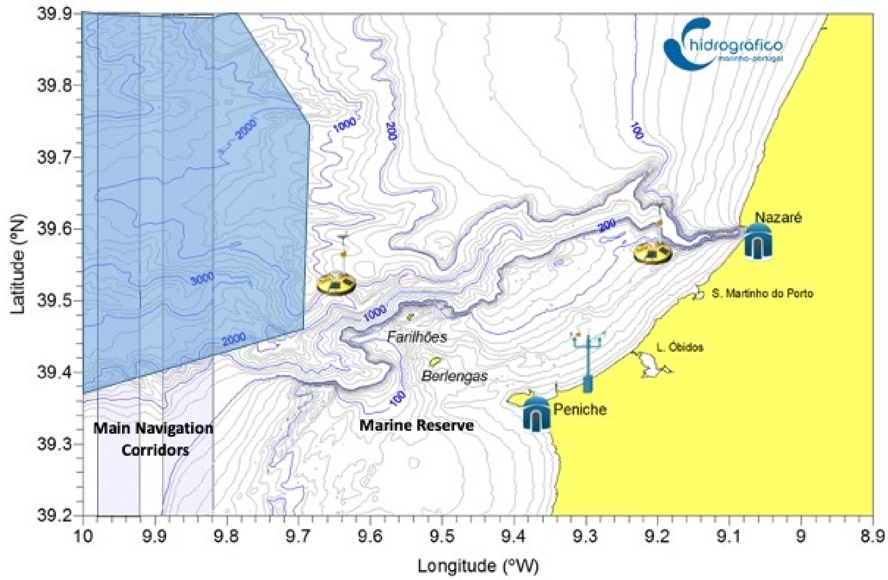
Study Area

The study was conducted in the coastal ocean off central Portugal, focusing on the region influenced by the Nazaré Canyon (39.2° -39.9°N) (Fig. 2) in the Fall of 2024. While the experiment considered the measurable impact of model driven robotic sampling to both the bio-geochemistry of the the canyon region, this manuscript is focused on the implications of such *sample-assimilate-predict-direct* loop closure (Fig. 3).

Implementing such a system in the dynamic real world of the coastal region presents substantial challenges requiring high-resolution numerical models capable of rapidly generating uncertainty projections, robust algorithms for exploration under a range of constraints, reliable communication links for mission updates, and assimilation frameworks able to integrate heterogeneous, real-time data streams. Furthermore, the logistical risks and communication limitations inherent in marine operations — low bandwidth, intermittent connections, unpredictable weather conditions — impose additional constraints on the practical execution of adaptive sampling missions.

The Nazaré area is shaped by strong topographic contrasts, including the transition from the wide Estremadura Plateau to the narrower shelf to the north, the long and narrow Nazaré submarine canyon that incises the shelf and extends more than 200 km offshore, and the Berlengas archipelago, a UNESCO Biosphere Reserve with high ecological value. These features contribute

(a) Map of Portugal and the study area highlighted with the red rectangle.



(b) Zoomed in bathymetry showing the Nazaré canyon-Berlengas area (isobaths with depth in meters) and its environment including the placement of buoys.

Figure 2: (a) & (b) show detailed views of the study area for **FRESNEL** off the coast of mainland Portugal. The Nazaré Canyon is a significant feature of this area and a driver for the bio-geophysics of the domain.

to enhanced biological productivity and biodiversity, and strongly modulate physical and biogeochemical processes in the region.

Freshwater inputs from major rivers, such as the Tagus, have only a limited direct impact on the area. In contrast, smaller rivers and the Óbidos lagoon can episodically deliver low-salinity, nutrient-rich plumes to the shelf. Circulation is controlled by seasonal wind forcing associated with the Azores High, with persistent upwelling-favorable northerly winds in summer and frequent downwelling episodes in winter under southerly winds. The interplay between canyon topography, shelf circulation, and atmospheric forcing generates complex mesoscale dynamics, intensified tidal currents, and internal wave activity that promote strong vertical mixing and cross-shelf exchanges [14, 15].

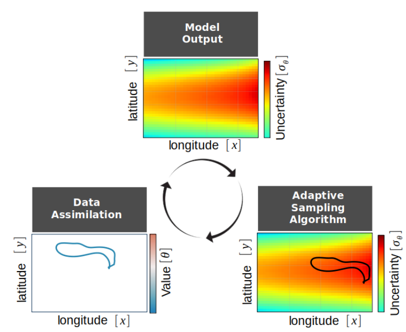


Figure 3: **FRESNEL** attempts to close the *sample-assimilate-predict-direct* loop using data obtained from robotic vehicles assimilated into a model which generates a prediction which in turn targets where the robotic vehicles can be repositioned to better address model uncertainty.

The combination of sharp bathymetric gradients, variable forcing, and rich physical–biogeochemical interactions makes the Nazaré Canyon region an ideal natural laboratory to test adaptive observation strategies. In particular, its dynamic environment posed both opportunities and challenges for the **FRESNEL** experiment, providing a representative coastal setting in which to evaluate how model-based uncertainty projections can guide adaptive sampling and assimilation to improve ocean model predictive skill.

Methods

Our methodology is based on the implementation of a complete data cycle to enhance model predictions in a coastal ocean domain through robotic adaptive sampling and data assimilation. The approach consists of three fundamental steps, executed iteratively on a daily basis:

Model Forecast and Uncertainty Projection : A numerical ocean model provides a daily one-step forecast $\hat{\theta}(k+1, x, y)$ of a target oceanic variable θ, along with an associated uncertainty field $\sigma_{\hat{\theta}}(k+1, x, y)$, where k represents the current day and (x, y) denote the geographical coordinates. These outputs are organized into discrete spatial maps, $M_{\hat{\theta}}(x, y)$ and $M_{\sigma_{\hat{\theta}}}(x, y)$, representing, respectively, the predicted state and its uncertainty over a predefined grid covering the study area.

Target Sample Planning: Using the uncertainty map $M_{\sigma_{\hat{\theta}}}(x, y)$ as input, a targeted sampling algorithm determines the set of trajectories for a fleet of N AUVs for the next operational cycle. The goal is to maximize the accumulated uncertainty sampled along the vehicle paths, while satisfying vehicle-specific constraints. The planned trajectories are transmitted to the vehicles for execution.

Data Collection and Assimilation: Throughout the operational period, each AUV collects measurements of the target variable θ along its assigned path. After the mission is completed, the collected measurements are assimilated into the numerical model using an appropriate data assimilation scheme. This updated model state serves as the new initial condition for the next forecasting cycle, closing the loop.

While previous efforts have concentrated on a form on embedded automated decision-making on AUVs [16, 17, 18, 19, 20, 1, 3, 21] to demonstrate adaptive sampling, here we AUV trajectories are defined by human-in-the-loop decisions apriori, with adaptation focused on deployment based on $M_{\sigma_{\hat{\theta}}}(x, y)$. No automated decisions were made on the AUVs. Loop closure in this work, refers to the *sample-assimilate-predict-direct* process as shown in Fig. 3.

Model Forecast and Uncertainty Projection

Sampling strategies rely on timely information about the spatial variability of ocean properties. However, conventional numerical ocean models are computationally intensive, and their runtime makes them impractical for use in near-real-time mission planning KR: Need a citation here. While similar assimilation cycles could, in principle, be implemented directly within deterministic numerical models, this would require either substantially higher computational resources or larger temporal horizons. As a more practical alternative, we employ geostatistical stochastic sequential simulation as a computationally efficient surrogate, producing short-term spatial predictions of ocean temperature together with estimates of spatial uncertainty [22]. This approach captures the essential variability of local ocean dynamics, based on calibrated dynamic ocean models, at a fraction of the computational cost of full numerical models, while remaining flexible enough to assimilate new in situ observations quickly [23] and coherent with the scope of the work approach.KR: But what do we loose in turn? Resolution? Need to state that.

The methodology relies on ensembles of geostatistical realizations, each representing a state of the ocean temperature field conditioned by *a priori* deterministic ocean models [24] and direct observations. By computing the pointwise standard deviation across the ensemble, we obtain spatial uncertainty maps that highlight regions where predictions are less constrained and/or more variable and potentially more informative for sampling. These maps serve as the basis for identifying areas where new measurements are expected to maximize the reduction of forecast error. In the field application example shown here, the geostatistical realizations are produced using direct sequential simulation [25], a stochastic method that draws values from conditional probability distributions defined by kriging estimates and variances and conditioned to existing direct measurements and a spatial covariance matrix. The continuity of the temperature field in space and time is characterized by variogram models fitted to long-term calibrated ocean model data from E.U. Copernicus Marine Service (CMS) [24]. At each depth of the numerical ocean model, geostatistical simulations are carried out independently, using a moving temporal window of fourteen previous KR: why 14? Where did this specific number come from? days as conditioning data (i.e., experimental data) to predict the subsequent day. This sliding-window strategy strikes a balance between forecast skill and computational feasibility, and can be adapted according to the complexity of the oceanographic conditions.

The ensemble of realizations provides both a forecast of ocean temperature and a quantitative assessment of the prediction uncertainty. By updating the forecasts with new AUV measurements through sequential assimilation, the method progressively refines the temperature field while maintaining consistency with prior model dynamics. The resulting forecasts and uncertainty maps form the input for the target sampling algorithm, guiding the allocation of AUV trajectories towards regions of greatest expected information gain. More details about the model, its development, and application during the **FRESNEL** experiment can be found in [23].

Target Sampling Algorithm

The adaptive sampling problem here is posed as the design of vehicle trajectories that maximize information gain [26, 8] extracted from a model-derived uncertainty map, while satisfying operational AUV constraints. Each day, the models provide both a forecast field and its associated uncertainty distribution, which together define the reward landscape for the planner. The task is then to generate, for each vehicle, a path composed of waypoints that accumulates the highest possible uncertainty values.

To address this, the problem is cast as a graph theoretic problem. The spatial uncertainty map is first pre-processed to remove obstacles and smoothened to highlight large-scale features. Candidate waypoints are then identified from the map and used to build a weighted graph, where nodes carry a reward proportional to their uncertainty value and edges represent travel costs. The trajectory planning task is posed as a vehicle routing problem where routes must balance the rewards obtained from visiting nodes with associated costs of traveling between them [27, 28]. By solving this, the algorithm returns a set of near-optimal trajectories that prioritize regions of greatest uncertainty, while ensuring vehicle endurance and safety constraints. This provides a principled way of steering autonomous platforms toward the most informative sampling locations, forming a key component in the daily cycle of forecast, adaptive sampling, and data assimilation. Additional insights into the algorithm and its deployment during **FRESNEL** are reported elsewhere in [29].

Figure 4: AUVs deployed in the **FRESNEL** experiment.

Data Collection

In-situ data collection process involved a number of upper water-column AUVs designed and developed in-house at the University of Porto [30].Each AUV comes equipped with a range of sensors including a CTD (Fig. 4). Some have in addition other sensors including fluorometers, turbidity, Oxygen, DVL/ADCP and all come equiped with WiFi and Iridium satellite communications, acoustic modems, and battery packs enabling 60h+ endurance. The CTDs mounted on the AUVs were cross-calibrated to ensure consistency across all vehicle measurements. In addition to the hardware involved, an extensive suite of mature advanced mission planning and command/control tools were used – discussion of these is outside the scope of the paper and can be referenced at [31, 32, 33, 34, 35].

Field deployment: planning and preparation

IH contributed the NRP D. Carlos for 5 days during one of the planned offshore buoy maintenance missions taking place annually in April or in October. The October period was selected for the **FRESNEL** deployment. The meteorological and ocean conditions are typically not significantly different in these periods and may be affected by distant storms taking place in the Atlantic.

The planned time window for the **FRESNEL** deployment with NRP D. Carlos was the second week of October. However, this time window had to be shifted by one week, to start October 20th, because of challenging meteorological and ocean conditions. The AUV deployments were planned to start the first week of October but were delayed starting October 14th and end October 31st. The decisions to delay both the ship and AUV deployments proved to be adequate and made it possible to have 5 days of ship time and 7 days of AUV operations. This also enabled concurrent operations of the ship, glider, and AUVs. The AUVs collected data one week in advance of the ship's arrival and kept running the developed algorithms during the third week of the deployment. The planned areas of operation for NRP D. Carlos (large rectangle) and for the AUVs (smaller rectangle) are depicted next.

These areas have intense ship traffic, particularly from fishing vessels, that presents added collision risks to AUVs at surface or when surfacing, as well as potential encounters with bottom trawling fishing nets. In addition, because Nazaré is a fishing harbor there is the added challenge of AUV encounters with fishing nets.

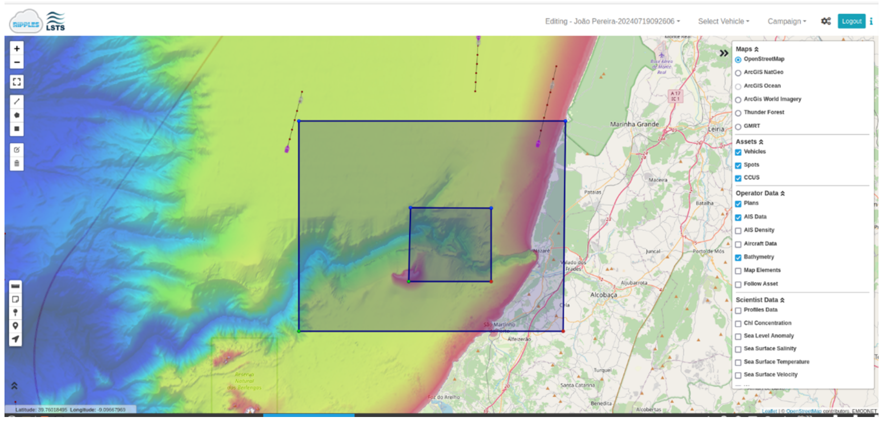


Figure 5: Areas of operations for NRP D. Carlos and for the AUVs.

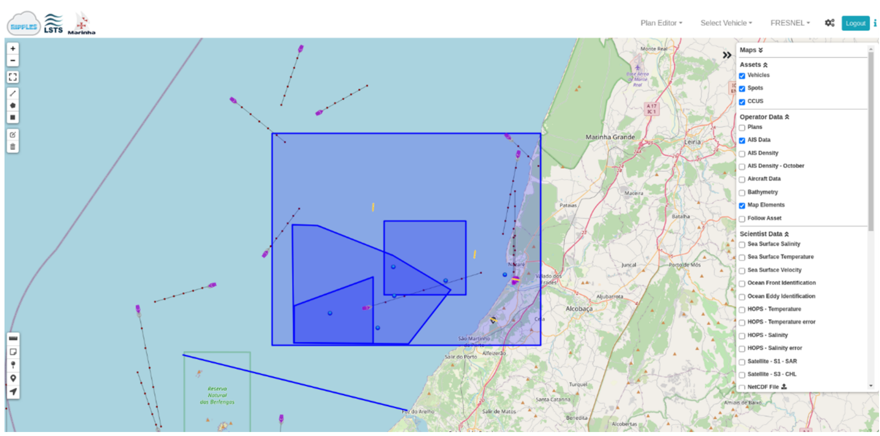


Figure 6: The operational area was partitioned into 3 areas with different levels of risk

XXX PLACE RISK MAP SIDE BY SIDE

To address these challenges we started by meeting fisherman associations with the support of the city hall to engage the community, understand their fishing procedures and the probable locations of fishing nets. Second, we studied AIS patterns and densities, first for one year, then for one month, and finally for each week in October. This enabled us to partition the operations area into 3 areas with increasing risk levels 6. We focused our operations on the first two areas, starting operations at the one where risk was lower. Finally, by studying daily patterns we were able to establish temporary areas for operations with acceptable risks. We have distilled this knowledge into operational procedures and automated decision aids and alerts.

Field operations were organized into two concurrent activities:

- NRP *D. Carlos* campaign taking place October 20th – 24th. Team members from the University of Aveiro were onboard NRP D. Carlos to support operations with the UVP and wet laboratory operations. In addition to the rosette casts a glider was also deployed from the ship. The deployment of the glider along the western boundary of the operations area provided some of the initial conditions for the HOPS model. The rosette casts provided a course description of essential ocean variables in the larger area of operation. XXX Detailed descriptions of these activities are presented in Annexes E - H.

- AUV deployments taking place October 14th - 31st. These deployments were supported by two boats rented in Nazaré. In addition to the AUV deployments by LSTS-UPorto, water samples were collected by researchers from Columbia University. These data collection activities provided a dense grip of data collection points. XXX Detailed descriptions of these activities are presented in Annexes D, F, G.

These two activities were conducted in coordination, namely in what concerns water space management and sharing of model predictions, done with the help of the LSTS toolchain and the underlying communication infrastructure. Both activities run 24/x. In the case of the AUV deployments the LSTS-UPorto team operated in 4 6-hour long shifts with minimal operator's footprint (one active and one backup operator). Operations were run from a house rented in Nazaré and from LSTS in Porto.

Field deployment: summary of AUV and ship operations

Questions:

- explain yoyos
- include a more detailed description of daily ops with tables?

AUV daily operations started with the analysis of remote sensing data, data collected during the previous 24h, forecasts of meteorological and ocean condition, performance of the planning and execution control algorithms, performance of the modeling-sample-assimilation-tasking cycle (this was done during the last week of operations), and mission updates provided by the operators in charge of the night shifts.

AUV operations' planning then proceeded in 2 different time horizons:

- Plan for the day, including launch and recovery of vehicles, as well as boat operations.
- Plan for next 2-3 days (3 AUVs could operate for 50h+). This was particularly challenging because it included calculating time of recovery and making sure that the meteorological and ocean conditions were feasible for these operations. AUV execution control was focused on addressing alerts (e.g., ships crossing the area of operations), coordinating launch and recovery of AUVs with the help of the two boats, and re-tasking the vehicles in case a significant change in the planning assumptions occurred.

FRESNEL operations started spanned October 14th - 31st period. We took a risk-minimizing incremental approach to operations planning and execution control. The first week was about getting acquainted with the new area of operations and evaluating, testing, and improving operational procedures. The second week was about deploying the whole approach and learning from it. The third week focused on running AUV operations to further evaluate and test the approach, namely in what concerned simultaneous deployments and persistent observation.

The first week was about AUV and small boat operations (including collecting water samples). The focus was on testing the validity of the risk management approach (including the partition of the operations area) and on evaluating and testing the operation of the AUVs in this new area. AUV missions were already spanning at least 2-day durations.

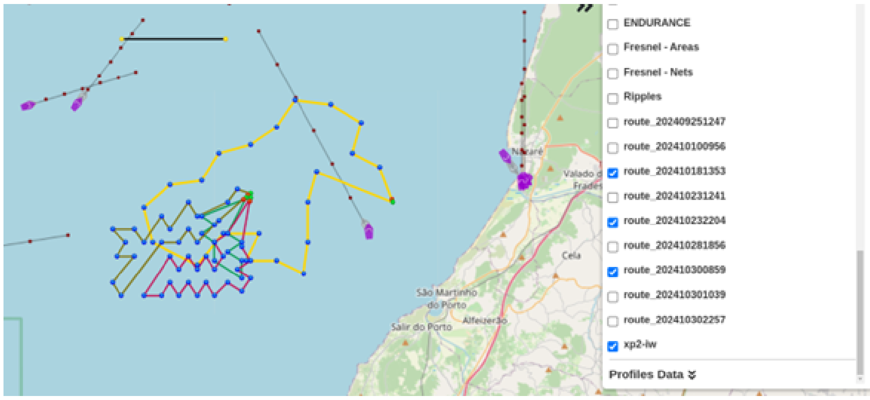


Figure 7: Example of mission plans (tours) to be executed by 3 AUVs.

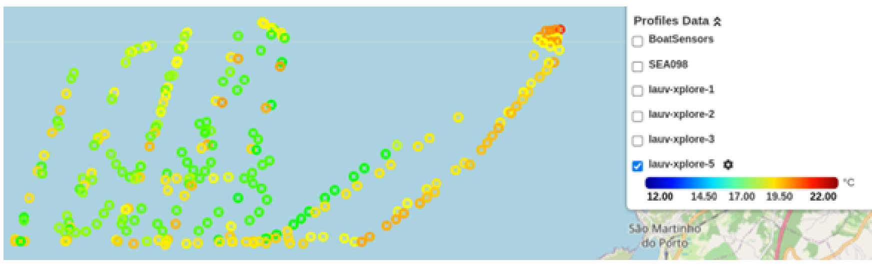


Figure 8: AUV path color-coded by levels of temperature at surfacing points.

The second week involved the 5-day long NRP *D. Carlos* campaign together with AUV operations with boat support for launch and recovery and water sampling. Coordination of these concurrent operations involved water space management, to prevent collisions, and ingestion of data provided by the ship and AUVs for analysis and assimilation. The experience acquired during this week was invaluable and provided the templates for AUV operations taking place the following week. Over these two weeks the AUVs were impacted several times by strong vertical currents in areas of significant stratification. Our preliminary analysis pointed to internal waves as the most probable cause of these currents. The area is known for internal wave activity and remote sensing data provided evidence of the presence of internal waves during the same days.

The final week focused on AUV operations only. Multi-day AUV deployments provided additional data about the modeling-sample-assimilation-tasking cycle (executed several times). In addition, AUVs were deployed concurrently not only in the area surveyed the previous week (to minimize risk) but also in areas with higher risk of collisions in which short time windows limited the duration of these deployments. This required tighter planning and execution control procedures for the two operators in charge of the concurrent operations. This is illustrated with mission plans depicted in Figure 7. One AUV was tasked to perform yo-yos along straight line (line in black) in an area in which trawlers run North-South transects, while two others performed the adaptive sampling algorithm further South in a safer area.

The AUV operators were provided with close to real-time information about the data collected by the AUVs, as depicted in Figure 10(b) showing surfacing points for one mission color-coded by temperature. The operator could click in any of these points to get a temperature profile for the previous dive.

Despite the challenging meteorological and ocean conditions, that strongly constrained the overall deployment, the **FRESNEL** team was able to demonstrate the overall approach during these 3 weeks (out of which only 7 days of operation were possible). The team operating the AUVs spent these 3 weeks on site and on call to rapidly deploy or recover the AUVs as dictated by meteorological and ocean conditions or forecasts.

Field Experiment Analysis and Evaluation

Although the FRESNEL field campaign extended over a longer period, for the purpose of this paper, only a three-day sequence of consecutive experiments (29–31 October) is considered, as it provides a representative demonstration of the proposed framework and its operational workflow.

The evaluation of the framework was carried out during the FRESNEL field campaign through a series of consecutive daily experiments designed to test the integration of model forecasts, target sampling planning, and data assimilation. All of these components were previously described. The analysis aimed to quantify the impact of assimilating AUV-acquired temperature data on the predictive performance of the statistical model and to assess the operational feasibility of the data cycle approach in a real-world coastal setting.

Each experimental day followed a structured cycle involving: (i) the generation of a statistical model forecast and its associated ¡¡¡¡¡¡¡ HEAD uncertainty field based on Copernicus Mar data available up to the previous ======= uncertainty field based on Copernicus Marine Serice) data available up to the previous ¿¿¿¿¿¿¿ remotes/origin/overleaf-2025-10-16-1655 day; (ii) the execution of the target sampling algorithm to plan the next-day missions; and (iii) in situ data collection by the AUV fleet following the planned routes. The data collected within the previous day (0–24 h) were subsequently assimilated into the statistical model to produce updated forecasts, enabling comparisons between forecasts with and without data assimilation.

The campaign involved three Light Autonomous Underwater Vehicles (LAUVs) — Xplore2 (XP2), Xplore3 (XP3), and Xplore5 (XP5), which alternated daily in performing target sampling missions over the Nazaré Canyon region. On 29 October, the statistical model produced the initial forecast solution (A), which was used to plan the mission executed by XP2. The resulting in situ temperature data were later assimilated offline to produce an updated statistical model solution (B1) for 30 October. Although operational real-time assimilation was initially planned, logistical constraints prevented its implementation. Consequently, all assimilation cases were performed offline after mission completion. The target sampling algorithm, therefore, relied on statistical forecasts without assimilation (B), using pre-existing data as input for daily mission planning. This limitation is not expected to have significantly affected the experimental outcomes, as the operational area was spatially compact and the predicted variability field remained consistent between consecutive days. In future implementations, on-board or near-real-time assimilation should be considered to fully exploit the adaptive potential of the framework.

Data collected by XP3 and XP5 on 30 October were assimilated offline to generate new model solutions for 31 October (C1, C2, C3, C4), along with a non-assimilated reference case (C). The configurations were as follows:

- C1 – assimilation including only XP2 data from 29 October;
- C2 – assimilation including XP2 (29 October) and XP5 (30 October) data;

Figure 9: INSERT schematic about the 3-day loop

- C3 – assimilation including only XP5 data from 30 October;
- C4 – assimilation including all available data from 29 and 30 October (XP2, XP3, and XP5).

An analogous setup was used for scenario D, in which the difference from case C is that the statistical predictions for 31 October were generated using CMEMS data available up to different cutoff dates:

- D – forecast for 31 October based on CMEMS data available until 29 October;
- D1–D4 – corresponding to the same assimilation configurations as C1–C4, but using CMEMS data available until 30 October.

D1–D4 – corresponding to the same assimilation configurations as C1–C4, but using CMEMS data available until 30 October.

Model performance was evaluated by comparing predicted and observed temperature data along the AUV trajectories using the root-mean-square error (RMSE) as the primary performance metric for 31 October.

Results

This section presents the main results of the FRESNEL field campaign, focusing on the integration of model forecasts, target sampling, and data assimilation using autonomous underwater vehicles (AUVs). The analysis combines CMS and statistical model forecasts (as described in the Methods section) with in situ observations to assess how the proposed data-cycle approach can enhance short-term ocean prediction in a dynamic coastal environment.

Fig. 10(a) provides an overview of the environmental conditions observed during the three-day experimental window considered in this study (29–31 October). The background fields correspond to the Level-3 Sea Surface Temperature (SST) product from Copernicus Marine Service (`DOI: 10.48670/moi-00310`). The operational area was relatively compact, covering approximately 100 km^2 south of the Nazaré Canyon, where the AUVs executed the planned target sampling missions. All missions were planned using the target sampling algorithm to explore the temperature variability predicted by the statistical model. On 31 October, however, XP2 performed a different mission, following a cross-shore transect of approximately 13 km instead of a target-driven pattern north of the canyon. This mission was designed to sample an internal wave hotspot, but, for the purpose of this study, it serves as an independent ground-truth dataset, collected in a distinct subregion relative to where the data assimilation was applied. The XP2 observations are thus used as a reference for evaluating the forecast cases (C–C4 and D–D4).

During this period, the coastal ocean was influenced by a late-season upwelling–relaxation cycle. At the beginning of the sequence (29 October), the SST field reveals the characteristic signature of coastal upwelling, with colder water masses extending offshore due to wind-driven Ekman transport that brings subsurface, nutrient-rich waters to the surface. In the following days (30–31 October), the weakening of upwelling-favorable winds led to a relaxation phase, during which warmer offshore waters gradually advanced toward the coast. This transition is reflected in the SST maps by an overall warming trend in the nearshore region, particularly evident on 1st October.

It is important to note that the SST imagery is partially affected by cloud coverage, which limits the availability and accuracy of satellite-derived temperature data. These gaps arise from the radiometric constraints of indirect SST retrieval, resulting in reduced spatial continuity and increased uncertainty near cloudy regions. Despite these limitations, the SST patterns clearly capture the dominant mesoscale features and coastal processes driving the observed variability during the experiment.

These evolving conditions provided an ideal natural setting for testing the adaptive sampling and data assimilation framework developed in FRESNEL. The pronounced temperature gradients associated with the upwelling front generated well-defined spatial and temporal variability, allowing the evaluation of how AUV-based targeted observations can improve the predictive skill of the statistical model in a real-world coastal scenario.

Following the overview of the surface conditions, Fig.10(b) presents the vertical temperature distribution recorded by the LAUVs XP2, XP3, and XP5 during their respective missions between 29 and 31 October. The panels show temperature as a function of time and depth, illustrating the temporal and vertical structure of the coastal water column throughout the three-day experimental sequence.

XP2 operated on 29 October, XP5 on 29, 30, and 31 October, and XP3 on 30 and 31 October, with all vehicles capable of sampling the upper 100 m of the water column. However, this depth range was not always achieved due to logistical and bathymetric constraints. The temperature fields reveal a thermocline and a progressive warming of the surface layer down to approximately 40 m depth, with temperatures ranging from around 14 °C in deeper layers to about 18 °C near the surface, reaching their maximum on 30 October afternoon during XP5's mission.

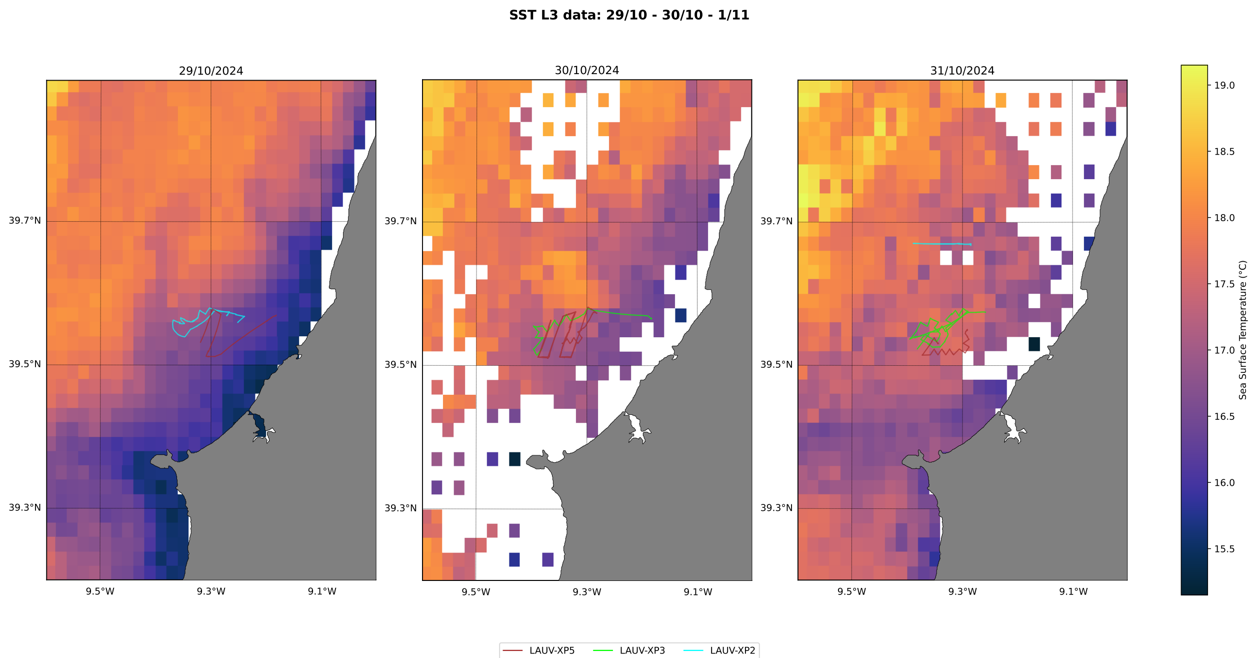
It is important to note that the trajectories shown in the previous figure might suggest that the AUVs remained continuously at sea for 24 hours each day. However, as Fig. 10(b) demonstrates, this was not the case. The vehicles can be deployed and recovered multiple times per day, with operational windows limited by logistics, weather, and available support assets. This figure, therefore, also highlights the non-linear nature of field logistics in multi-vehicle operations, where dynamic scheduling, resource allocation, and environmental constraints determine the actual temporal coverage of the missions.

This section presents the main results of the FRESNEL field campaign, focusing on the integration of model forecasts, target sampling, and data assimilation using autonomous underwater vehicles (AUVs). The analysis combines CMEMS and statistical model forecasts (as described in the Methods section) with in situ observations to assess how the proposed data-cycle approach can enhance short-term ocean prediction in a dynamic coastal environment.

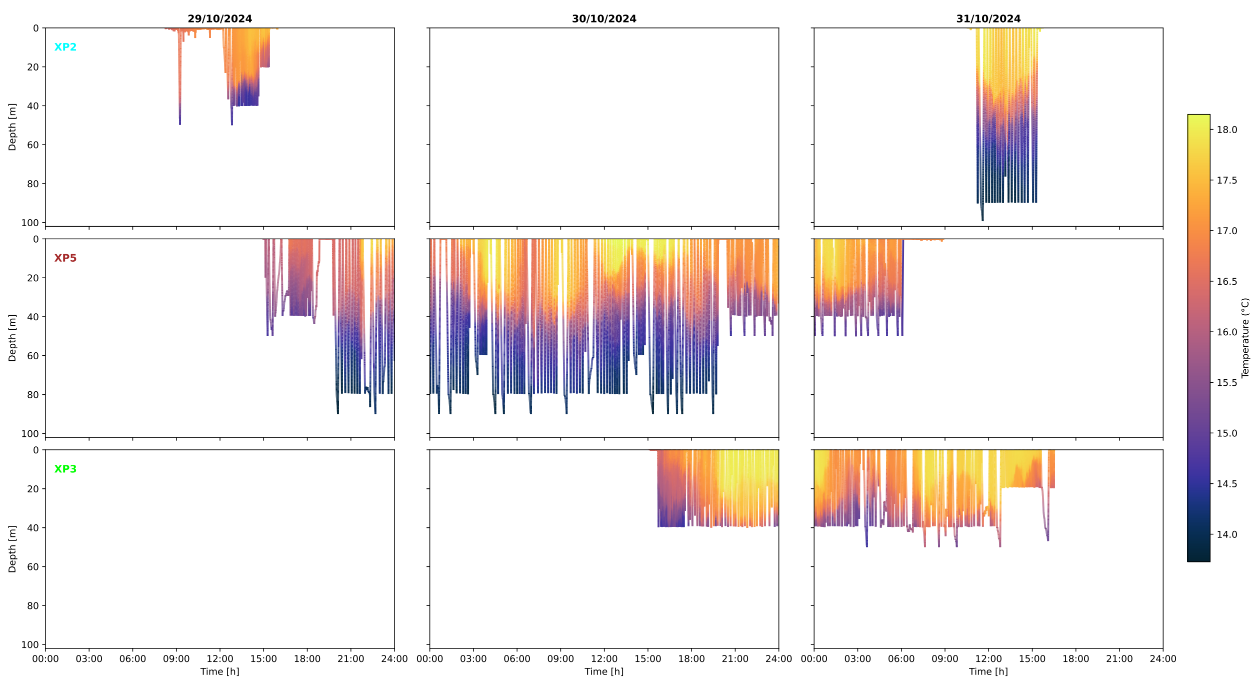
Fig. 10(a) provides an overview of the environmental conditions observed during the three-day experimental window considered in this study (29–31 October). The background fields correspond to the Level-3 Sea Surface Temperature (SST) product from the E.U. Copernicus Marine Service Information (urlDOI:10.48670/moi-00310)

- Environmental context
- RMS table (all cases) + rms figure (just A+D cases)

*- Use **subheadings** to organize different experiments or analyses.*



(a) Sea surface temperature (SST) and XP2, XP3 and XP5 trajectories during the FRESNEL field campaign (29–31 October).



(b) Time–depth temperature evolution observed by XP2, XP3, and XP5 during the FRESNEL field campaign (29–31 October).

Discussion

The challenging ocean and meteorological conditions faced as part of this experiment precluded cycles of week-long operations, as planned. Nevertheless, we were able to operate for 7 days during the 3-week long deployment. We demonstrated the overall integrative overall approach to close modeling-sampling-assimilation-tasking cycle with the goal of improving the skill of oceanographic models by leveraging observations from AUVs, traditional methods such as ship-based measurements and opportunistic measurements using low-cost sensors, and by exploring synergies between dedicated surveys and opportunistic observations.

Full integration of command and control strategies comprising modeling, assimilation and adaptive sampling algorithms was demonstrated with the help of the advanced LSTS software toolchain enabling 24/x operations with minimal operator's support. The deployments were performed to evaluate and test the overall approach in an incremental fashion. The last days of the deployment demonstrated several iterations of the closed modeling-sampling-assimilation-tasking cycle. The accuracy of the predictions of the geostatistical model increased after several cycles, while the overall prediction errors decreased. However, these results still lack statistical significance because of the few consecutive cycles in which the overall approach was tested. We observed that we never had more than 3 consecutive days of operation.

The dense grid of AUV observations enables post-experiment evaluation and testing of the assimilation schemes and of the geostatistical model. While we are still lacking the desired statistical significance of a long series of consecutive cycles, these post-experiment activities will lead to a better understanding of the overall procedures and the identification of improvements, namely the optimization of the parameters used for the coordinated integration of the algorithms used in the modeling-sample-assimilation-tasking cycles. We will further investigate the selection of representative depths for the application of the sampling algorithm used to find the horizontal projection of the AUV paths.

This field study provided invaluable lessons in operational procedures, refinement of adaptive sampling and algorithms, and risk minimization to operate in an area with dense ship traffic and fishing nets. Our AUVs were occasionally impacted by strong vertical currents that may have resulted from the impact of internal waves that are common in the area, namely in stratified regions (which was the case) and that were observed with the help of remote sensing imagery during the deployments. Finally, the results achieved with this deployment provided additional insights and the motivation to further advance the state of the art in refining the modeling-sampling-assimilation-tasking cycle with the goal of improving the skill of oceanographic models. Furthermore, dense grids of sampled oceanographic data have the potential to fuel developments targeting existing gaps in modeling skill when different levels of spatial and temporal resolution are considered [36].

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