NASS
NAN YANG ACADEMY OF SCIENCES

Sustainable Marine Structures
https://journals.nasspublishing.com/index.php/sms

ARTICLE

Data-Driven Environmental Monitoring Using Autonomous Underwater Vehicles: Adaptive Sampling in The Al Hoceima Marine Protected Area

Hasna Bouazzati [1], *Asma Damghi* [1], *Xiang Gao* [2*], *Souhail Karim* [3,4], *Abdelmounaim El M'rini* [1]

[1] *Research Laboratory in Applied and Marine Geosciences, Geotechnics, and Geohazards (LR3G), Faculty of Sciences, Abdelmalek Essaadi University, Tetouan 93030, Morocco*

[2] *National Deep Sea Centre, Qingdao 266061, China*

[3] *Research Laboratory in Applied and Marine Geosciences Research and Development, Faculty of Sciences and Techniques, Abdelmalek Essaadi University, Al Hoceima 32003, Morocco*

[4] *National Park of Al Hoceima, Head Office, Al Hoceima 32000, Morocco*

ABSTRACT

In this research, we examine how the Al Hoceima Marine Protected Area (MPA), located in the southwest Mediterranean Sea, can be effectively monitored using the SeaExplorer glider—an advanced autonomous underwater vehicle (AUV) designed for long-duration oceanographic missions. The study focuses on the glider's ability to simultaneously observe a variety of environmental parameters, including temperature, conductivity, oxygen, and chlorophyll, during its deployment across multiple transects. The primary objective of the mission is to improve understanding of the vertical thermal structure and seasonal dynamics of the water column in this ecologically significant region. To achieve this, we apply Gaussian Process (GP) regression techniques to the glider-derived temperature data. This statistical method enables the smoothing and interpolation of irregularly spaced in situ measurements, thereby improving the visibility and interpretation of stratification patterns throughout the water column. Although the glider followed a predetermined course, the data-driven analysis suggests that adaptive sampling strategies—such as adjustments based on real-time outliers—could be valuable in future missions. Our

*CORRESPONDING AUTHOR:
Xiang Gao, National Deep Sea Centre, Qingdao 266061, China; Email: gaox@ndsc.org.cn

ARTICLE INFO
Received: 16 May 2025 | Revised: 28 May 2025 | Accepted: 18 June 2025 | Published Online:30 June 2025
DOI: https://doi.org/10.36956/sms.v7i3.2162

CITATION
Bouazzati, H., Damghi, A., Gao, X., 2025., et al., 2025. Data-Driven Environmental Monitoring Using Autonomous Underwater Vehicles: Adaptive Sampling in The Al Hoceima Marine Protected Area. Sustainable Marine Structures. 7(3): 1–16. DOI: https://doi.org/10.36956/sms.v7i3.2162

results, which show distinct thermal layering and seasonal variability, are crucial for informing ecosystem function assessments and climate resilience planning. This study also discusses how integrating machine learning into glider-based monitoring could enhance MPA observation systems and promote adaptive, evidence-based management.

Keywords: Marine Protected Area; SeaExplorer Glider; Gaussian Processes; Remote Sensing

1. Introduction

Marine protected areas, or MPAs for short, are recognized as vital tools for the conservation of marine biodiversity. especially in light of the increasing pressures from climate change and anthropogenic activities [1]. The MPA of Al Hoceima, located in the waters of the Mediterranean Sea, is crucial for the protection of marine species and habitats; however, its resilience to environmental changes is jeopardized [2]. Factors induced by climate change, including elevated sea temperatures, ocean acidification, and heightened microplastic pollution, are disrupting the fragile equilibrium of these ecosystems. Therefore, ongoing environmental monitoring of MPAs is essential to evaluate the effects of these threats, assess ecosystem health, and inform effective management strategies [3].

Autonomous underwater vehicles (AUVs), specifically gliders, are increasingly recognized for their ability to perform integrated and dynamic environmental monitoring, collecting high-resolution data across spatial and temporal scales [4]. The SeaExplorer glider is a buoyancy-driven autonomous underwater vehicle (AUV), commonly categorized under AUVs due to its autonomous mission capabilities, albeit without real- time navigation. Our work presents the results of Alseamar AUV deployment in the Al Hoceima MPA to monitor essential environmental parameters, including temperature, conductivity, oxygen, chlorophyll, and microplastic, and discusses the role of such technology in assessing the resilience of MPAs to climate change [5].

Integrated environmental monitoring systems utilizing autonomous underwater vehicles (AUVs) significantly enhance the understanding of marine ecosystems by providing high-resolution, real-time data on various ecological parameters [6]. These systems provide a comprehensive way to assess marine biodiversity, environmental conditions, and the impacts of human activity, leading to more effective management strategies. By integrating advanced sensors and data analytics, these AUVs offer unparalleled insights into underwater ecosystems, allowing researchers to monitor changes over time and respond swiftly to emerging threats. This is especially important for tackling challenges like climate change, pollution, and habitat destruction. Ultimately, these technologies play a key role in conserving marine resources and encouraging sustainable practices in ocean management. As these instruments advance, they possess the capacity to revolutionize marine study and conservation, offering innovative solutions to reduce human impact on vulnerable ocean ecosystems [7].

1.1. Enhanced Data Collection

High-Resolution Monitoring: AUVs can collect data on physical, biogeochemical, and biological parameters simultaneously, offering a detailed view of ecosystem dynamics [8]. This comprehensive data collection enables scientists to identify trends and correlations that were previously difficult to discern, thereby enhancing our understanding of the complex interactions within marine environments [9].

Prolonged Monitoring: Sustained observation over extended durations facilitates the detection of trends and alterations in marine populations and ecosystems, essential for comprehending climate effects [10].

1.2. Cost-Effectiveness and Efficiency

Decreased Operational Expenses: AUVs are typically more economical than conventional vessel-based approaches, facilitating wider geographic reach and increased frequency of data acquisition [11].

Automation and Velocity: Automated data processing protocols augment the rapidity of data analysis, facilitating prompt reactions to ecological alterations.

2. State-of-the-Art

The application of autonomous platforms for monitoring the marine environment has made great strides in recent years. Among these, underwater gliders like the SeaExplorer have proven to be valuable instruments for gathering detailed oceanographic information over extended periods of time and across different geographical regions. Gliders offer a more efficient and economical alternative to ship-based surveys for monitoring physical, chemical, and biological data both on-site and at depth [12, 13].

Gliders have been shown in multiple studies to be effective at identifying salinity fronts, thermoclines, and upwelling occurrences, all of which are important for elucidating ecosystem structure and guiding conservation efforts [14, 15]. Data on circulation patterns, climatic trends, and ecological responses have been greatly enhanced by glider missions in the Mediterranean Sea, which have aided basin-wide initiatives such as the MOOSE network and the ODYSSEA project [16, 17].

At the same time, data science methods are being used more and more to make big oceanographic datasets easier to understand. For instance, a non-parametric and highly adaptable method for producing smooth profiles with quantifiable uncertainty from sparse in-situ observations is Gaussian Process (GP) regression. In oceanography, GP applications have demonstrated potential for re-creating dissolved oxygen, salinity, and temperature profiles in situations with high dynamic variability [18, 19].

Although there has been some progress, there has been a dearth of research that specifically includes glider data and Gaussian Process (GP) modeling into MPA contexts, particularly in the southern Mediterranean. Logistics for glider deployment and interpolation algorithm improvement have received the bulk of the prior literature [12–20], instead of investigating how ecological interpretation and in situ data collection work together. Given the constraints of current hardware and communication, adaptive sampling—in which the glider's mission path or sampling frequency dynamically responds to environmental signals—remains mainly hypothetical [13–21].

In order to fill this knowledge gap, this work used GP-based modeling to examine thermal stratification in the Al Hoceima MPA using a SeaExplorer glider that was outfitted with multi- parameter sensors. Although adaptive sampling was not used in real time, the analytical benefits that such approaches potentially provide were simulated in the mission design and post-processing. Therefore, decision-makers involved in climate-resilient MPA management can benefit from this work's improved methodological understanding and its practical recommendations.

3. Materials and Methods

3.1. Study Area

Situated on the Mediterranean coast of Morocco, the Al Hoceima Marine Protected Area (MPA) encompasses a region of the Alboran Sea renowned for its unique ecological and oceanographic characteristics (**Figure 1**). Critical to the preservation of marine biodiversity are the several marine ecosystems that the MPA safeguards. These include pelagic zones, seagrass meadows, and rocky reefs [2–12].

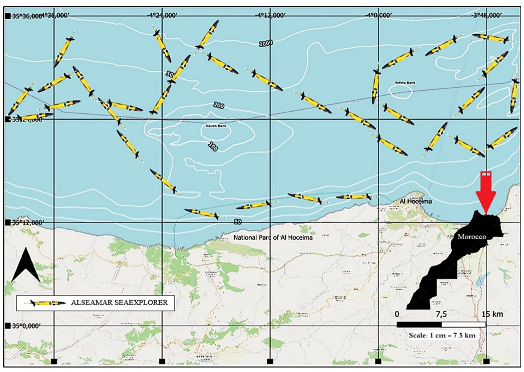

Figure 1. Trajectory Map of the SeaExplorer Glider During the First Mission in the Alboran Sea and near the Marine Protected Area of Al Hoceima (November–December), Generated by QGIS.

Additionally, worldwide studies have shown that MPAs are important in lessening the effects of climate change, which is why we chose the Al Hoceima MPA. Development along the shore, fishing, and other possible pollution sources all pose threats to the ecosystem in this area; therefore, constant monitoring and assessment are essential [2–20].

3.2. Autonomous Underwater Vehicle (AUV) Deployment

The ALSEAMAR SeaExplorer glider was deployed in the Al Hoceima MPA for a three-month period as a part of the ODYSSEA project [2, 13–20], covering two distinct periods: November to December and February to March of the following year. The SeaExplorer glider, built and sold in France by ALSEAMAR, went through 873 cycles every 682.67 kilometers, sampling at a rate of 4 seconds, from the surface to about 500 meters depth on the first trip. Equipped with sensors to evaluate various environmental conditions, the glider was programmed to navigate selected transects and collect data at multiple depths [14–18].

As previously mentioned in the Introduction, the SeaExplorer glider satisfies the functional requirements of an AUV because of its sensor-guided data collection capabilities and autonomous mission planning, even though it uses buoyancy-driven propulsion instead of active thrusters.

ALSEAMAR utilizes proprietary adaptive sampling methodologies for its SeaExplorer glider, enabling real-time modifications of the glider's trajectory in response to environmental conditions [15]. These techniques enhance data collection by concentrating on regions of significant variability, hence enhancing the data's quality. Still, specifics of how ALSEAMAR's exclusive procedures are put into action are unclear.

undisclosed to the public. This research proposes Gaussian Processes (GPs) as a viable correction method for adaptive sampling, offering a probabilistic framework for decision-making and data assimilation that may improve the efficiency and accuracy of data collection [16].

3.3. Data-Driven Sampling with AUV

The AUV can overcome the drawbacks of conventional survey methods by being able to use the data it collects (hence the name ”data-driven”) to adjust its objective. The capacity to conduct more sophisticated surveys, shorten mission duration, and decrease the volume of redundant data collected incentivizes the adoption of more advanced control strategies.

Enabling the AUV to employ obtained data—thus the term ”data-driven”—and adjust its mission accordingly allows it to address the constraints of traditional survey approaches, with various methodologies explored across fields such as robotics, statistics, geology, and atmospheric science, all aimed at enhancing information acquisition. Furthermore, in conjunction with Gaussian processes (GPs) [17], other methods such as Kalman filtering [18], Markov decision processes [19], and reinforcement learning have been used for adaptive sampling and decision-making in similar contexts [20]. A Gaussian process is a collection of random variables, any finite number of which have (consistent) joint Gaussian distributions. Kalman filtering plays a pivotal role in enhancing the performance of robotics and autonomous systems through effective state estimation and sensor fusion. Its applications span various domains, including mobile robot localization, simultaneous localization and mapping (SLAM), and underwater vehicle control. These methods provide different frameworks for data assimilation and mission planning, depending on the specific requirements of the study [21]. While the current deployment did not employ real-time adaptive sampling, the glider collected high-resolution environmental data along predefined transects [12–21]. Gaussian Process modeling was then applied post-mission to assess spatial patterns and thermal variability, allowing for retrospective optimization of sampling coverage. This contributes to a data- driven environmental monitoring framework, supporting future implementation of adaptive control and decision-making in similar MPAs.

The SeaExplorer glider employs adaptive sampling techniques that enhance data assimilation and decision-making in oceanographic research. By integrating real-time data with operational forecasts, the glider can optimize its sampling paths, leading to improved environmental monitoring and predictive capabilities (**Figure 2**) [22].

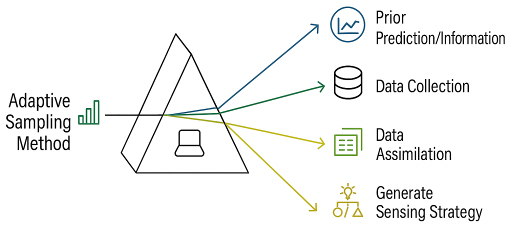

Figure 2. Enhancing Data Collection with Adaptative Sampling the World Model Incorporated by the Glider Acted as a Knowledge Base, Containing All Relevant Environmental Information, Including Initial States, Model Descriptions, and Mission-Specific Expertise.

This knowledge base supported functions such as path planning, collision avoidance, and cooperative planning.

The process commenced using a predetermined data collection strategy based on a predictive model. Although initiating without a predetermined plan is feasible, supplying an initial array of waypoints assists in directing the AUV during the initial stages of the mission. As the glider collected data, it continuously updated its understanding of the environment using adaptive sampling techniques. This allowed for effective reconciliation of newly collected data with prior information, ensuring that the AUV could adapt its strategy for information recovery in real time [23].

Data assimilation was performed in parallel with data collection, using statistical update procedures based on Bayesian approaches [24]. This iterative process ensured that the AUV remained responsive to changes in environmental conditions, optimizing its sampling strategy to enhance the relevance and accuracy of the collected data [25].

3.4. Data-Driven Sampling Using GPs

Before presenting the example, we need to delineate the foundational theory regarding GPs and spatial interpolation via Kriging [24–26]. Gaussian processes (GPs) are used in Python to model data-driven sampling and make predictions about unobserved data points by fitting a probabilistic model based on observed data. Python libraries like Scikit-Learn provide tools for implementing GPs through the GaussianProcessRegressor class, allowing users to perform regression tasks with an underlying kernel to specify how points in the input space relate to one another [27].

This approach facilitates the identification of intricate patterns in environmental data, providing both an average prediction and a quantification of uncertainty via confidence intervals. Kriging, a method associated with Gaussian Processes, is frequently employed for spatial interpolation, especially in the context of geospatial data [26].

3.5. Gaussian Processes and Interpolating with Kriging in Oceanography

Gaussian processes are an essential device in statistical modeling, widely applicable and frequently employed to represent natural events, for the ranges of numerous natural occurrences remain no less than roughly typical scattered [28]. Collaboration using GPs offers conceptual clarity, as a finite portion of GP- generated material within a specific field adheres to a multidimensional Gaussian pattern. As a result, it is easy to carry over the concepts of a Gaussian process into a multivariate Gaussian distribution. Multivariate GPs extend the concept of GPs to vector-valued functions, where each output can be correlated with others, necessitating a multivariate Gaussian distribution [29].

A Gaussian Process is a specific category of randomly generated process or random function, where the examined set of unknown functions contains specific metrics of "uniformity" derived from the defined correlation between the function's values. Gaussian Processes are consequently intricately associated with the examination of covariance functions, commonly referred to as functions of the kernel [27–30]. A kernel function tool used in computer science to increase the capacity for separating patterns in the attribute space.

One prevalent problem in environments with limited sampling is estimating values at unobserved locations to achieve the comprehensive perspective required for planning. Kriging is an interpolation technique frequently utilized in a spatial perspective [28], originating from geostatistics and named in recognition of Danie G. Krige, who initially utilized it for estimating gold reserves [31]. Kriging, in conjunction with simple least-squares methods, offers the optimal continuous unbiased estimation for quantities at unobserved sites [31].

Estimating the functional worth at a precise place using a weighted median of the surrounding values, the interpolated values are derived from predictions provided by the combination of covariance processes [32, 33]. The most effective prediction at an unknown point is a linear sum of the values that were observed, using varying degrees of trust assigned to every adjacent location within the regression model [34, 35].

Using the Gaussian Process model first, a specific covariance value is defined by a predetermined set of hyperparameters, articulating a notion regarding the covariance of functional values and connecting locations in the GP and drawing out their spatial relationships. That is not all; a positive definite covariance function is required. Following this, a sequence of observations is carried out, denoted as value of location pairs, which might generate new data at any point inside a certain typical distribution (GP) by integrating into the previous GP prior to generating an updated GP posterior. Diverse kriging approaches exist, dependent on the stationary properties that determine the comparison ability and behavior (a covariance characterization) associated with the random field. The notion of isotropy is important to recognize in this context. Isotropy as described in detail below, must be satisfied for the random field to be stationary or weakly stationary. A covariance function which is isotropic, is invariant to translations in the input space; only being a function of ||s – s'||, where s – s' is a distance metric.

Multiple dimensions of uncertainty regarding the latent process are created by the sea's spatio- temporal dynamics. Choosing a GP description is a calculated move; in a spatial setting, you can use the variogram to assess spatial dependency. Due to the inability to directly integrate time-varying uncertainty with a Gaussian Process without compromising its fundamental properties, it is necessary to assume stationarity or weak stationarity over a finite horizon, implementing corrective measures to assess the time-varying patterns [36].

3.6. GPs calculation

A Gaussian process is entirely defined by its standard deviation equation m(s) associated with the covariance value [37]:

$$k(s, s'\ ) \equiv conv\ (f(\ s), f(s'\ ))\tag{1}$$

at location s= (east, north) that constitutes a modification of the Gaussian pattern defined by the variance vector μ and a matrix of covariance Σ. In accordance with the nomenclature provided by [38], equation f that follows a Gaussian Process could possibly be represented as:

$$f = GP(m, k)\tag{2}$$

When you have decided on f as your explanatory function, the following step is to use training data, namely a numerical model, to begin modeling a Gaussian Process, **Figure 3** illustrates the computed surface temperature in the coastal area. Equation m(s) is derived through several linear analyses of regression applied to the temperature dataset presented in **Figure 3**, resulting in the following outcome:

$$\beta - vector\ (coefficients)\ \ = [0.01085714]\ intercept = 11.95238095238095\tag{3}$$

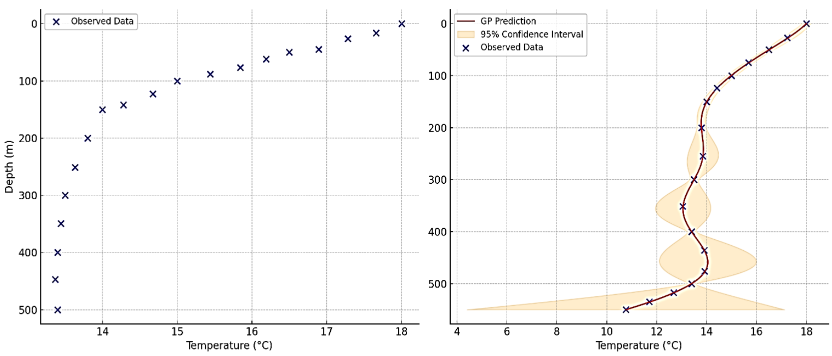

Figure 3. Temperature Pattern in a Glider Cycle During Descent: Observed Data and GP Smoothing. (**A**) The Observed Temperature Pattern During the Glider's Descent Cycle. (**B**) The Gaussian Process (GP) Smoothing Applied to the Observed Data, Highlighting the Prediction and the 95% Confidence Interval.

The intercept represents the expected value of the temperature when the depth is 0. In this case, the predicted temperature at a depth of 0 is approximately 11.95°C.

Examine the process defined in equation (1) then:

$$m\,(s) = \beta intercept = 0.0109e + 11.9524 \tag{4}$$

$$k\,(s,\ s') = \sigma 2\,exp\,(-\gamma||s–s'\,||) \tag{5}$$

where s is the location tuple s= (east north), β is the regressed mean vector, σ and γ are covariance design parameters. and ||s–s'|| may be recognized as a Euclidean distance between point s and s ' [37].

A variogram analysis is performed to obtain the precise correlation range. A variogram is a graphical representation that elucidates the relationship between spatial distance among points and the variance of those points, typically demonstrating that variance increases with distance unless a threshold is achieved. Beyond this point, the variables cease to exhibit a correlation according to their numerical values; hence, the variability might hardly increase. The outer layer temperature indicates an associated distance of approximately 7 km given this specific temperature simulation.

3.7. Updating the General Practitioner with Observations

To enhance the interpretability of environmental data collected by the SeaExplorer glider, Gaussian Process (GP) regression was applied to estimate continuous temperature fields across depth and time. This probabilistic approach allows the integration of sensor observations with prior distributions to infer smoothed environmental patterns while quantifying uncertainty.

Let f be the temperature measurements collected at known positions s, and f∗ the predicted values at new positions s∗. Assuming a prior joint Gaussian distribution:

$$\begin{bmatrix} f \\ f^{*} \end{bmatrix} \sim N\left(\begin{bmatrix} \mu \\ \mu^{*} \end{bmatrix},\ \begin{bmatrix} \Sigma & \Sigma_{*} \\ \Sigma_{**}^{T} & \Sigma_{**} \end{bmatrix} \right) \tag{6}$$

Let s$_i$ (for i=1,...,n) denote the observed locations, and let s_{*}^{k}(for k=1,...,p) represent the unobserved or prediction locations. The mean function evaluated at the observed locations is denoted by μ=m(s$_i$) and similarly, the mean at the unobserved locations is given by μ∗=m (s_{*}^{k}).

The covariance matrix of the observed data points is denoted by $\Gamma = Cov\,(f(\,s), f(s\,))$, while $\Gamma* = Cov\,(f(\,s*), f(s\,))$ represents the cross-covariance between the observed and unobserved points. The number of observations is n, and the number of prediction points is p [38].

The posterior distribution of the function values at the unobserved locations f*, conditioned on the observed data f, follows a multivariate normal distribution.

$$f * If \sim N\,(\mu * + \Sigma\Sigma - 1(f - \mu),\ \Sigma * * - \Sigma\Sigma - 1\Sigma*) \tag{7}$$

where $\Gamma * * = Cov\,(f(\,s*), f(s\,*\,))$ is the covariance among unobserved locations. This formulation provides a linear combination model for predicting values at new locations based on the observed data.

A radial basis function (RBF) kernel was chosen for the GP model's Python implementation using the scikit-learn package because of its ability to represent smooth spatial fluctuations in ocean temperature. Pandas and NumPy were used to clean and organize the glider's raw data, which was exported as CSV, before modeling. Using metadata such as timestamps and position coordinates, filtering and interpolation were used to control noise, missing values, and outliers.

Sharp gradients and noise abnormalities, which are frequently caused by vertical navigation shifts and transient ambient turbulence, were seen in the raw profiles' initial display. By creating a continuous temperature field and improving the transparency of thermal stratification, the GP smoothing resolved these variations.

Using a combination of estimated dive trajectories based on mission waypoints and depth sensors and surfacing GPS fixes, the glider's position was tracked. The GP framework's use of 4D coordinates (latitude, longitude, depth, and time) to associate temperature values was based on this spatial data.

The resulting posterior temperature field, as illustrated in **Figure 2**, records the horizontal advancement of thermal gradients throughout the mission cycle as well as their vertical structure. This method provides insights into the physical processes in the MPA by allowing for the retrospective adaptive study of significant environmental patterns.

4. Visualization of Results

The results of the Gaussian Process smoothing were then visualized using Matplotlib. (Matplotlib was used extensively for creating clear visualizations of the temperature profiles. The library's flexibility allowed us to produce both raw and smoothed visual representations of the data. which facilitated comparisons and highlighted the effects of Gaussian Process smoothing.) The visualization involved generating two main types of graphs: the raw temperature profile (before GP smoothing) and the smoothed temperature profile (after GP smoothing). The raw profile graph illustrated the initial state of the data with visible noise and gaps, while the smoothed profile presented a cleaner, more interpretable temperature distribution across time and depth. The application of Gaussian Processes helped highlight key features, such as the thermocline, by reducing noise and creating a clear gradient from warm surface waters to cooler deep waters.

Provide a concise and precise description of the experimental results, their interpretation, and the experimental conclusions that can be drawn.

The application of Gaussian Processes in this context significantly improved the quality of the temperature profile data, facilitating the identification of essential oceanographic features, such as thermal stratification, and elucidating their effects on the ecosystem within the MPA. The smoothed data revealed insights not readily apparent in the raw dataset, enhancing comprehension of the water column's physical structure and aiding subsequent analyses concerning ecological and conservation results.

Among all the parameters collected by the glider, such as chlorophyll concentration, microplastics, oxygen, and conductivity, temperature was chosen as a key focus for this analysis. Temperature is a fundamental physical property that directly influences a wide range of marine processes, including density- driven circulation, stratification, and the distribution of nutrients. Additionally, it is an important factor in deciding whether or not maritime ecosystems are biologically productive and whether or not certain marine species have suitable habitats. Understanding temperature variations and thermal gradients helps in identifying phenomena like thermoclines, which are essential for understanding nutrient mixing and primary productivity. Unlike chlorophyll, which is a proxy for biological productivity, or microplastic concentrations that indicate pollution levels, temperature provides a baseline physical context for interpreting other parameters. Moreover, temperature profiles are generally more stable and have a clear seasonal signal, making them ideal for illustrating the application of advanced smoothing techniques like Gaussian Processes.

This entire workflow—from data collection by the glider, CSV transformation, data cleaning and analysis in Python, and the application of Gaussian Processes for interpolation—demonstrates the value of combining autonomous technology and advanced statistical techniques to improve marine environmental monitoring and decision-making.

Figure 4 presents the temperature profile in a 2D format. **Figure 4**(**A**) and (**B**) represent the temperature before applying Gaussian Processes, while **Figure 4**(**C**) shows the smoothed temperature profile after applying Gaussian Processes. In **Figure 4**(**A**) and (**B**), the data points are irregular, and there is visible noise and gaps throughout the depth and time dimensions. The lack of continuity in temperature values highlights issues such as data sparsity and sensor noise, which could hinder further ecological interpretation.

Conversely, **Figure 4**(**C**) exhibits a more sophisticated temperature distribution. The utilization of Gaussian Processes mitigates sudden fluctuations, bridging the gaps and facilitating a seamless depiction of temperature variations across time and depth. Thermoclines are typically observed in graphs that depict only temperature and depth variations, as shown in **Figure 3**. However, in this case, where time variation is also included, the thermocline is represented by specific points. **Figure 4**(**C**)'s temperature profile distinctly illustrates the stratification within the water column, although it does not explicitly highlight the abrupt temperature changes with depth that define thermoclines. This enhanced visualization, which incorporates time as a variable, is crucial for comprehending thermal dynamics and their temporal impacts on marine ecosystems. The temperature profile illustrated in the graph is based on a data-driven methodology utilizing Gaussian Processes (GPs) to examine temperature variations at different depths over several weeks. Over the course of a day, this graph shows the temperature changes from the surface all the way down to 140 meters. The utilization of Gaussian Processes in this analysis enhances the interpretation of collected data by smoothing temperature profiles and providing reliable estimates, even when direct measurements are limited or unavailable.

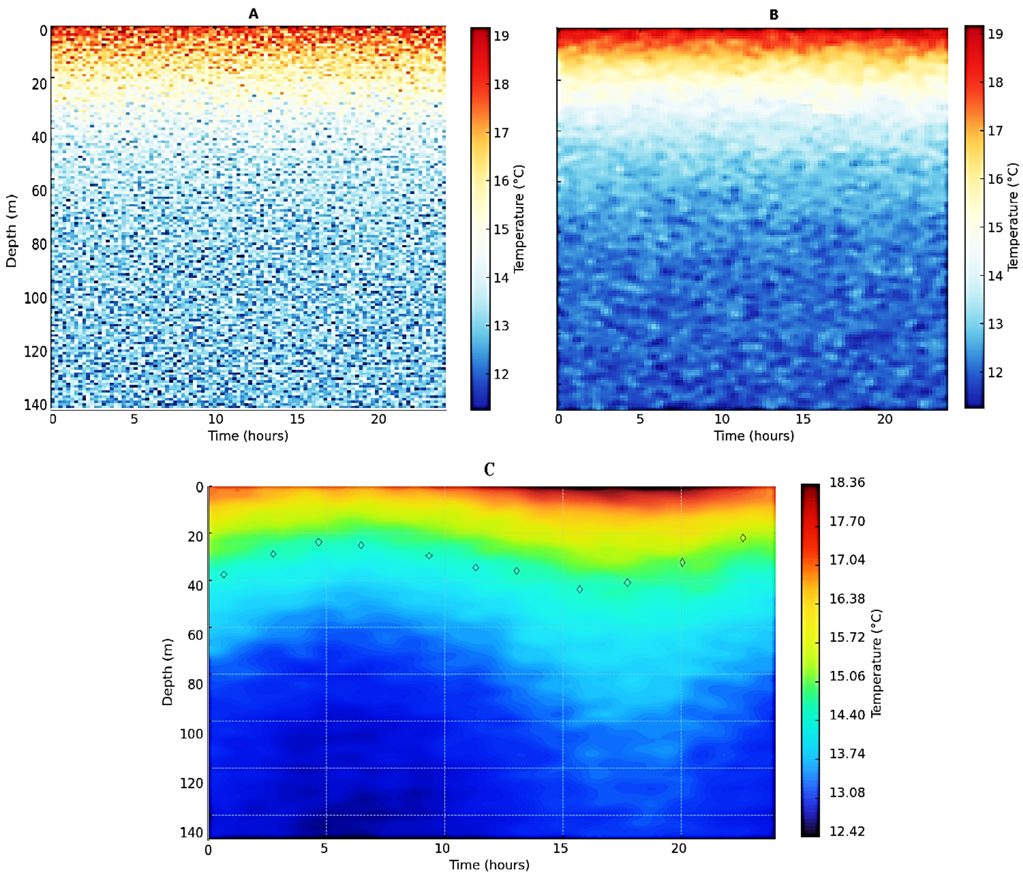

Figure 4. Three Distinct Water Column Temperature Profiles Displayed as a Function of Time. These Profiles Represent Different Stages of Temperature Data Processing, Specifically Before and After the Application of Gaussian Processes (GPs). (**A**) Raw or Initial Temperature Data, (**B**) Partially Processed Temperature Data, (**C**) Gaussian Process Smoothed Data.

Figure 5 provides insights into the temperature profiles from an alternative perspective. **Figure 5**(**A**) displays a dispersed, sparse dataset prior to Gaussian Process smoothing, with each data point indicating the temperature gradient at various depths and times. This graph illustrates the irregularity and scarcity of the raw data, complicating the identification of coherent patterns in the thermal structure of the water column. **Figure 5**(**B**) illustrates the scatter plot subsequent to preliminary processing but prior to complete Gaussian smoothing. It demonstrates a partial enhancement in which certain patterns are more discernible, yet the data remains deficient in complete coherence. The 3D scatter plots visually illustrate the chaotic characteristics of the raw dataset. **Figure 5**(**C**), conversely, illustrates the smoothed data subsequent to the application of Gaussian Processes in a surface plot configuration. The refined surface offers enhanced comprehension of temperature gradients and transitions across time and depth, highlighting essential oceanographic characteristics like thermoclines. The surface plot enables a clearer observation of the periodic variations and overall thermal distribution within the MPA, which were obscured in the dispersed data.

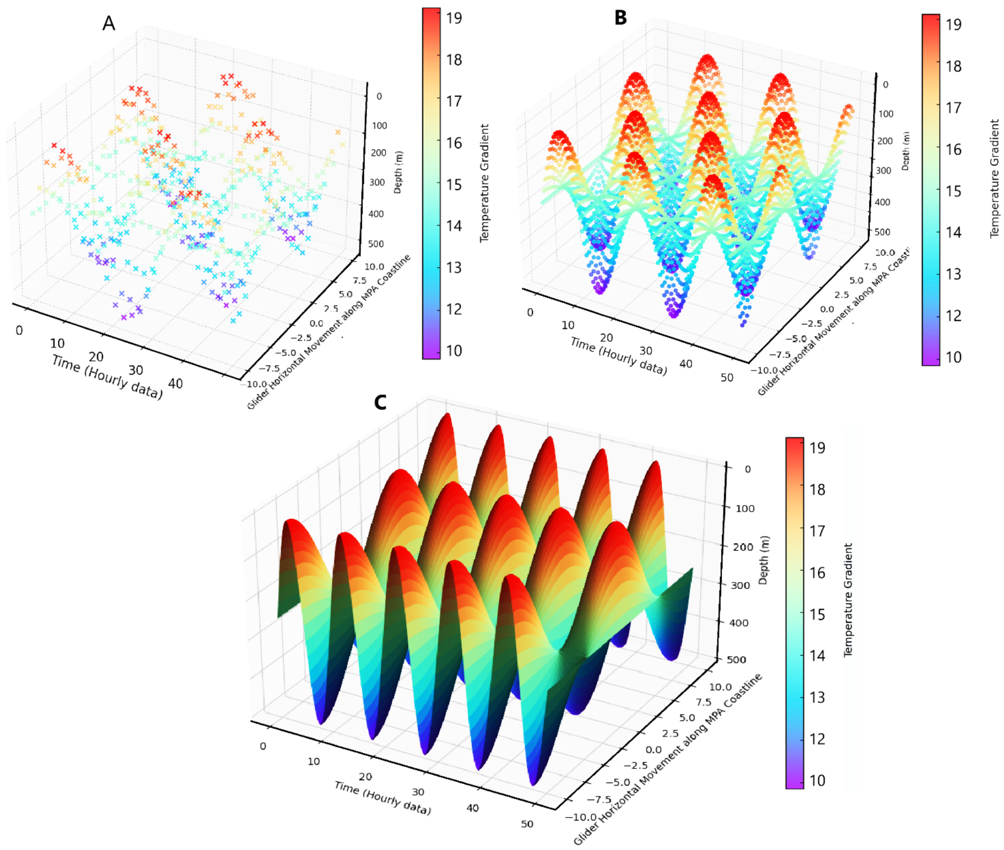

Figure 5. 3D Scatter and Surface Temperature Profiles of the Water Column Plotted Over Time and Space.(**A**) Raw or Initial Temperature Data, (**B**) Partially Processed Temperature Data, (**C**) Gaussian Process Smoothed Data.

The present paper employs both 2D and 3D representations of temperature for distinct analytical objectives. The 2D profiles facilitate the examination of specific temperature fluctuations over time and depth, thereby simplifying the identification of trends and stratifications. The 3D scatter and surface plots offer a more thorough spatial representation of the data, facilitating enhanced visualization of intricate relationships among variables.

We employed Gaussian Processes on these datasets to address the difficulties presented by noisy and incomplete data. The smoothed representations provide profound insights into the thermal structure of the Al Hoceima MPA, illustrating the impact of temperature variations on marine conditions. This method underscores the significance of Gaussian Processes in improving oceanographic data quality, facilitating more dependable interpretation, and guiding decision-making for conservation initiatives in marine protected areas.

The application of Gaussian Processes in this context significantly improved the quality of the temperature profile data, facilitating the identification of critical oceanographic features [9], such as thermal stratification, and elucidating their effects on the ecosystem within the MPA. The smoothed data revealed insights that were not readily apparent in the raw dataset, enhancing comprehension of the water column's physical structure and aiding subsequent analyses concerning ecological and conservation results [7].

The results obtained through the application of Gaussian Processes offer several valuable insights into the thermal dynamics of the Al Hoceima MPA. First, the identification of thermoclines provides critical information on the layering of the water column, which directly impacts nutrient availability and the distribution of marine life. By clearly defining these thermal boundaries, we can better understand the potential habitats of different species, especially those that prefer specific temperature ranges [39].

Moreover, the enhanced visualization after Gaussian smoothing provides a clearer picture of the temporal variability in temperature, which is essential for understanding seasonal changes and their ecological implications [28]. The capacity to forecast temperature at unmeasured depths and times enables researchers and policymakers to attain a more thorough comprehension of the MPA, even in regions where direct measurements were impractical. This enhanced coverage can substantially improve decision-making regarding marine conservation and resource management [2].

The insights derived from Gaussian Process smoothing can be pivotal in climate change research.

Comprehending temperature fluctuations in the MPA enables the monitoring and forecasting of global warming's impact on marine ecosystems [40]. The existence of stable thermoclines or the detection of periods of enhanced mixing may act as indicators of altering oceanographic conditions, offering early alerts for changes in ecosystem health [41].

This entire workflow—from data collection by the glider, CSV transformation, data cleaning and analysis in Python, and the application of Gaussian Processes for interpolation—demonstrates the value of combining autonomous technology and advanced statistical techniques to improve marine environmental monitoring and decision-making [42].

5. Discussion

The deployment of the ALSEAMAR SeaExplorer glider during the Odyssea project campaign in Al Hoceima's MPA effectively showcased the capabilities of autonomous underwater vehicles (AUVs) for adaptive, data-driven environmental monitoring [23]. This mission occurred from November to December and subsequently from February to March [2, 13], emphasizing the significance of ongoing environmental monitoring to comprehend seasonal variations in essential oceanographic parameters, such as temperature [43].

The implementation of data-driven methodologies, particularly Gaussian Processes for adaptive sampling, a technique evaluated and enhanced during the Odyssea project, enabled the glider to modify its mission strategy in real time. This data-centric methodology exhibited considerable benefits compared to conventional survey techniques [44]. By concentrating on regions of significant variability, the glider optimized data relevance and reduced redundancy, resulting in an efficient and accurate evaluation of the environmental condition. The capacity to perpetually revise the sampling plan according to incoming data facilitated a deeper comprehension of spatial and temporal variations within the Al Hoceima MPA [45].

The study identified notable variations in temperature, linked to physical processes such as coastal upwelling and other dynamics in the Alboran Sea [46]. The glider's capacity to consistently sample various depths provided understanding of the vertical organization of the marine ecosystem [13]. These observations are crucial for comprehending the resilience of the MPA amid changing climate conditions, as they facilitate the identification of heat distribution patterns and potential regions affected by ocean warming [47].

A primary benefit of utilizing Gaussian Processes is their capacity to deliver predictions along with corresponding uncertainties [34]. The GP model provided a precise depiction of environmental conditions and identified areas where further data collection would be advantageous [26]. The ability to integrate new observations into the model in real time rendered GPs an invaluable instrument for improving the accuracy and relevance of the data gathered during the mission [48].

While GPs are effective, the study also noted some of their inherent challenges. High computational demand for covariance matrix inversion was a key limitation [32], suggesting that further research should explore optimized algorithms or alternative adaptive sampling. Nonetheless, this study illustrates how probabilistic models can facilitate real-time decision-making for autonomous platforms, enhancing their capacity to collect ecologically significant data [6].

Another topic of discussion is the proprietary adaptive methodologies employed by ALSEAMAR, which remain undisclosed in their entirety. Integrating GPs as a supplementary or corrective technique could further augment the adaptive capabilities of the glider, facilitating a more precise sampling methodology [39–49]. Alternative methodologies for adaptive sampling, including Kalman filtering, Markov decision processes, and reinforcement learning, have been tested and refined and may be utilized to enhance the efficacy of Gaussian processes, contingent upon specific mission requirements and environmental conditions [27–38].

6. Conclusion

The deployment of the ALSEAMAR SeaExplorer glider at the Al Hoceima Marine Protected Area as part of the Odyssea project highlights the immense promise of AUVs for ecological surveillance, especially when combined with data-driven adaptive sampling methodologies that were tested and refined throughout the Odyssea project [2–17]. The deployment demonstrated that integrating AUV technology with Gaussian Process modeling for adaptive mission planning [50], akin to the methodologies employed in the Odyssea project, can produce high-resolution, spatially continuous datasets essential for comprehending marine ecosystem dynamics [51, 52].

The mission effectively recorded both spatial and temporal shifts in temperature and conductivity, yielding significant insights into the environmental condition of the Al Hoceima MPA. The integration of GPS allowed the glider to enhance its sampling strategy in real time, facilitating efficient data collection and minimizing redundancy [53]. This method aids in establishing a thorough baseline of marine environmental health, crucial for assessing the threats to marine life caused by human activities and the changing climate [47–53].

This study's findings illustrate the necessity for additional research on optimizing adaptive sampling, a methodology evaluated and enhanced during the Odyssea project for AUVs, in light of the computational challenges presented by GPs [54, 55]. Future research may investigate the integration of probabilistic models with alternative adaptive control strategies to enhance the robustness and efficiency of AUV-based environmental monitoring.

The methodology described here may be expanded to include chlorophyll-a, conductivity, oxygen, and microplastics in a single framework, building on our previous work in the Al Hoceima MPA employing glider platforms to monitor these parameters [2–20]. Predictive modeling and multi-parameter ecosystem evaluations would be made possible by this integration, offering more comprehensive insights into the resilience of the MPA and guiding adaptive conservation strategy [13].

By demonstrating the revolutionary potential of autonomous systems to monitor, understand, and administer Marine Protected Areas more effectively in the face of changing climate concerns, this study highlights the critical role that technological innovation plays in marine conservation.

Author Contributions

Conceptualization, H.B.; methodology, H.B.; software, H.B.; validation, H.B., A.E.M., and X.G.; formal analysis, H.B.; investigation, H.B. and A.D.; resources, A.D. and H.B.; data curation, H.B.; writing—original draft preparation, H.B.; writing—review and editing, A.D., X.G., and A.E.M.; visualization, H.B.; supervision, A.E.M.; project administration, A.E.M. All authors have read and agreed to the published version of the manuscript. Conceptualization, H.B.; methodology, H.B.; software, H.B.; validation, H.B., A.E.M., and X.G.; formal analysis, H.B.; investigation, H.B. and A.D.; resources, A.D. and H.B.; data curation, H.B.; writing—original draft preparation, H.B.; writing—review and editing, A.D., X.G., and A.E.M.; visualization, H.B.; supervision, A.E.M.; project administration, A.E.M. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable. This study did not involve human or animal subjects.

Data Availability Statement

The data supporting the findings of this study are not publicly available, as they are under the intellectual property rights of the ODYSSEA project. Access to the datasets used and analyzed during the current study is restricted and may be available from the corresponding author upon reasonable request and with permission from the ODYSSEA consortium.

Acknowledgments

We extend our heartfelt appreciation for the assistance and collaboration of Association AGIR. Their dedication and insightful perspectives significantly enhanced this research, and we are grateful for the resources they supplied. The ODYSSEA project and ALSEAMAR were instrumental in making this research a success, and we are grateful to them. The ODYSSEA platform allowed for the smooth integration of glider data with satellite observations by providing the necessary tools and infrastructure for data processing and analysis. Our capacity to track and evaluate environmental shifts in marine ecosystems has been greatly enhanced by our partnership. Thanks to ALSEAMAR's substantial assistance and wealth of knowledge, the autonomous underwater glider was successfully deployed. The united efforts of these institutions made this research possible, proving once again how crucial partnerships are for solving environmental problems and expanding our scientific knowledge for the sake of all generations.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Benedetti-Cecchi, L., Bates, A.E., Strona, G., et al., 2024. Marine protected areas promote stability of reef fish communities under climate warming. Nature Communications. 15(1), 1822-1832. DOI: https://doi.org/10.1038/s41467-024-44976-y

[2] Bouazzati, H., Damghi, A., El M'rini, A., et al., 2024. Water quality and environmental resilience to climate change: A comprehensive analysis of the Al Hoceima Marine Protected Area. Journal of Coastal Research. 113(SI), 1049-1053. DOI: https://doi.org/10.2112/JCR-SI113-205.1

[3] Dar, A.A., Chen, Z., Sardar, M.F., et al., 2024. Navigating the nexus: Climate dynamics and microplastics pollution in coastal ecosystems. Environmental Research. 252(3), 118971. DOI: https://doi.org/10.1016/j.envres.2024.118971

[4] Cauchy, P., 2024. Marine soundscape monitoring from underwater autonomous vehicles—passive acoustic monitoring gliders. Journal of the Acoustical Society of America. 155(3_Supplement), A184-A184. DOI: https://doi.org/10.1121/10.0027249

[5] Lopazanski, C., Foshay, B., Couture, J.L., et al., 2023. Principles for climate resilience are prevalent in marine protected area management plans. Conservation Letters. 16(3), e12972. DOI: https://doi.org/10.1111/conl.12972

[6] Pampalone, V., Milici, B., 2015. High spatial resolution mapping of water quality and bathymetry with an autonomous underwater vehicle. AIP Conference Proceedings. 1702(1), 180006. DOI: https://doi.org/10.1063/1.4938955

[7] Davis, A., Paneerselvam, S., 2023. Design and Development of AUV for Coral Reef Inspection and Geotagging Using CV/ML. In: Bhattacharya, A., Dutta, S., Dutta, P., et al. (eds.). Advances in Intelligent Systems and Computing. Springer: Singapore. pp. 595-610. DOI: https://doi.org/10.1007/978-981-99-0550-8_47

[8] Seto, M.L. (ed.), 2013. Marine Robot Autonomy. Springer: New York, NY, USA. DOI: https://doi.org/10.1007/978-1-4614-5659-9

[9] Ferrari, R., Marzinelli, E.M., Ayroza, C.R., et al., 2018. Large-scale assessment of benthic communities across multiple marine protected areas using an autonomous underwater vehicle. PLOS ONE. 13(3), e0193711. DOI: https://doi.org/10.1371/journal.pone.0193711

[10] Liu, Y., Anderlini, E., Wang, S., et al., 2022. Ocean explorations using autonomy: Technologies, strategies and applications. In: Su, S., Wang, N. (eds.). Offshore Robotics. Springer: Singapore. pp. 35-58. DOI: https://doi.org/10.1007/978-981-16-2078-2_2

[11] Llewellyn, L.E., Bainbridge, S.J., 2015. Getting up close and personal: The need to immerse autonomous vehicles in coral reefs. Proceedings of the OCEANS 2015 - MTS/IEEE Washington; 19-22 October 2015; Washington, DC, USA. pp. 1-9. DOI: https://doi.org/10.23919/OCEANS.2015.7404565
[12] Rudnick, D.L., Davis, R.E., Eriksen, C.C., et al., 2004. Underwater gliders for ocean research. Marine Technology Society Journal. 38(2), 73-84. DOI: https://doi.org/10.4031/002533204787522703
[13] International Union for Conservation of Nature (IUCN), 2012. Marine Protected Areas: Global Experience. IUCN: Gland, Switzerland. Available from: https://portals.iucn.org/library/efiles/documents/2010-053.pdf (accessed 15 March 2025).
[14] Von Oppeln-Bronikowski, N., de Young, B., Belzile, M., et al., 2023. Best practices for operating underwater gliders in Atlantic Canada. Frontiers in Marine Science. 10, 1108326. DOI: https://doi.org/10.3389/fmars.2023.1108326
[15] Puillat, I., Farcy, P., Durand, D., Karlson, B., Petihakis, G., Seppälä, J., Sparnocchia, S., 2016. Progress in marine science supported by European joint coastal observation systems: The JERICO-RI research infrastructure. Journal of Marine Systems. 162, 1-3. DOI: https://doi.org/10.1016/j.jmarsys.2016.06.004
[16] Testor, P., de Young, B., Rudnick, D.L., et al., 2019. OceanGliders: A component of the integrated GOOS. Frontiers in Marine Science. 6, 422. DOI: https://doi.org/10.3389/fmars.2019.00422
[17] Sylaios, G., Papadopoulou, A., Tsikliras, A., et al., 2018. ODYSSEA Deliverable 13.2: Data post-processing procedures (Final operational report). Democritus University of Thrace. Available from: https://odysseaplatform.eu/download/deliverables/ODYSSEA_Deliverable-13.2.pdf (accessed 10 December 2024).
[18] Kokkos, N., Papadopoulou, A., Zachopoulos, K., Zoidou, M., Beguery, L., Margirier, F., Sylaios, G., 2023. Hydrography and deep chlorophyll maximum patterns of the Athos Basin and the Thracian Sea continental shelf (North Aegean Sea) combining glider and satellite observations. Continental Shelf Research. 262, 105029. DOI: https://doi.org/10.1016/j.csr.2023.105029
[19] Donnelly, J., Abolfathi, S., Pearson, J., Chatrabgoun, O., Daneshkhah, A., 2022. Gaussian process emulation of spatio-temporal outputs of a 2D inland flood model. Water Research. 225, 119100. DOI: https://doi.org/10.1016/j.watres.2022.119100
[20] Bouazzati, H., Damghi, A., El M'rini, A., Maanan, M., [Author 5], 2025. Evaluating microplastic concentrations in the Al Hoceima Marine Protected Area: Implications for identifying pollution hotspots and formulating conservation strategies. Sustainable Marine Structures. 7(2), April 2025. DOI: https://doi.org/10.36956/sms.v7i2.1809
[21] He, S., Jin, S., Chen, J., et al., 2022. Hydrodynamic design and analysis of a hybrid-driven underwater vehicle with an ultra-wide speed range. Ocean Engineering. 264, 112494. DOI: https://doi.org/10.1016/j.oceaneng.2022.112494
[22] Griffiths, G. (ed.), 2002. Technology and Applications of Autonomous Underwater Vehicles. Taylor & Francis: London, UK. DOI: https://doi.org/10.1201/9780203522301
[23] Nezhad, M.M., Neshat, M., Piras, G., et al., 2022. Marine online platforms of services to public end-users—The innovation of the ODYSSEA project. Remote Sensing. 14(3), 572. DOI: https://doi.org/10.3390/rs14030572
[24] Liang, L., Ma, H., Zhao, L., et al., 2024. Vehicle Detection Algorithms for Autonomous Driving: A Review. Sensors. 24(10), 3088. DOI: https://doi.org/10.3390/s24103088
[25] ALSEAMAR, 2022. Survey Missions – Oceans Science. Available from: https://www.alseamar-alcen.com/products/underwater-glider/seaexplorerhttps://www.alseamar-alcen.com/ocean-science-sector/survey-missions-oceans-science/ (cited 15 June 2024).
[26] Barrett, T., Mishra, A., 2025. Statistical study of sensor data and investigation of ML-based calibration algorithms for inexpensive sensor modules: Experiments from Cape Point. arXiv preprint, arXiv:2503.13487. DOI: https://doi.org/10.48550/arXiv.2503.13487 (accessed 15 March 2025).
[27] Wang, B., Sun, Z., Jiang, X., et al., 2023. Kalman Filter and Its Application in Data Assimilation. Atmosphere. 14(8), 1319. DOI: https://doi.org/10.3390/atmos14081319
[28] Lei, X., Zhang, Z., Dong, P., 2018. Dynamic Path Planning of Unknown Environments Based on Deep Reinforcement Learning. Journal of Robotics. 2018(1), 5781591. DOI: https://doi.org/10.1155/2018/5781591
[29] Nejatbakhsh Esfahani, H., Bahari Kordabad, A., Moreno-Salinas, D., 2024. Advanced Control Strategies for Autonomous Maritime Systems, Special Issue Call. Journal of Marine Science and Engineering. Available from: https://www.mdpi.com/journal/jmse/special_issues/9Q0Y5EOJ3B (accessed 15 March 2025).
[30] Ford, D.A., Grossberg, S., Rinaldi, G., et al., 2022. A Solution for Autonomous, Adaptive Monitoring of Coastal Ocean Ecosystems: Integrating Ocean Robots and Operational Forecasts. Frontiers in Marine Science. 9, 1067174. DOI: https://doi.org/10

.3389/fmars.2022.1067174

[31] Amavasai, A., Tahershamsi, H., Wood, T., et al., 2024. Data assimilation for Bayesian updating of predicted embankment response using monitoring data. Computers and Geotechnics. 165, 105936. DOI: https://doi.org/10.1016/j.compgeo.2023.105936

[32] Zhou, H., Zeng, Z., Lian, L., 2017. Adaptive replanning of AUVs for environmental sampling missions: A fuzzy decision support system based on multi-objective particle swarm optimization. International Journal of Fuzzy Systems. 20, 650-671. DOI: https://doi.org/10.1007/s40815-017-0398-7

[33] Bogomolov, V., 2023. AUV positioning by the ranges to less than three acoustic beacons based on recursive Bayesian estimation. Proceedings of the 2023 International Conference on Ocean Studies (ICOS); 03-06 October 2023; Vladivostok, Russia. pp. 037-040. DOI: https://doi.org/10.1109/ICOS60708.2023.10425637

[34] Nag, P., Sun, Y., Reich, B.J., 2023. Spatio-temporal DeepKriging for interpolation and probabilistic forecasting. Spatial Statistics. 57, 100773. DOI: https://doi.org/10.1016/j.spasta.2023.100773

[35] Chen, W., Li, Y., Reich, B.J., et al., 2020. DeepKriging: Spatially dependent deep neural networks for spatial prediction. arXiv preprint arXiv:2007.11972. DOI: https://doi.org/10.48550/arXiv.2007.11972

[36] Cui, T., Pagendam, D.E., Gilfedder, M., 2021. Gaussian process machine learning and Kriging for groundwater salinity interpolation. Environmental Modelling & Software. 144, 105170. DOI: https://doi.org/10.1016/j.envsoft.2021.105170

[37] Marinescu, M., 2024. Explaining and Connecting Kriging with Gaussian Process Regression. arXiv preprint arXiv:2408.02331. DOI: https://doi.org/10.48550/arXiv.2408.02331

[38] Papritz, A., Stein, A., 1999. Spatial Prediction by Linear Kriging. In: Stein, A., van der Meer, F.D., Gorte, B. (eds.). Spatial Statistics for Remote Sensing. Springer: Dordrecht, Netherlands. pp. 83-113. DOI: https://doi.org/10.1007/0-306-47647-9_6

[39] Ponnuru, A., Madhuri, J., Saravanan, S., et al., 2025. Data-driven approaches to water quality monitoring: Leveraging AI, machine learning, and management strategies for environmental protection. Journal of Neonatal Surgery. 14(5S), 664-675. DOI: https://doi.org/10.52783/jns.v14.2107

[40] García Molinos, J., Halpern, B.S., Schoeman, D.S., et al., 2016. Climate velocity and the future global redistribution of marine biodiversity. Nature Climate Change. 6(1), 83-88. DOI: https://doi.org/10.1038/nclimate2769

[41] Barton, A.D., Irwin, A.J., Finkel, Z.V., et al., 2016. Anthropogenic climate change drives shift and shuffle in North Atlantic phytoplankton communities. Proceedings of the National Academy of Sciences. 113(11), 2964-2969. DOI: https://doi.org/10.1073/pnas.1519080113

[42] Rasmussen, C.E., Williams, C.K.I., 2006. Gaussian Processes for Machine Learning. MIT Press: Cambridge, MA, USA. DOI: https://doi.org/10.7551/mitpress/3206.001.0001

[43] Vargas-Yáñez, M., Plaza, F., García Lafuente, J., et al., 2002. About the seasonal variability of the Alboran Sea circulation. Journal of Marine Systems. 35(3-4), 229-248. DOI: https://doi.org/10.1016/S0924-7963(02)00128-8

[44] Qiu, H., Li, T., Zhang, B., 2024. The impact of climate change on the earth system and its simulation predictions: Progress, challenges, and future directions. Geographical Research Bulletin. 3, 231-246. DOI: https://doi.org/10.50908/grb.3.0_231

[45] Zhang, J., Liu, M., Zhang, S., et al., 2022. Multi-AUV adaptive path planning and cooperative sampling for ocean scalar field estimation. IEEE Transactions on Instrumentation and Measurement. 71, 9505514. DOI: https://doi.org/10.1109/TIM.2022.3167784

[46] Chang, N.-B., Bai, K., 2018. Multisensor data fusion and machine learning for environmental remote sensing. CRC Press: Boca Raton, FL, USA. DOI: https://doi.org/10.1201/b20703

[47] Lacava, T., Bernini, G., Ciancia, E., et al., 2014. Integration of satellite data and in situ measurements for coastal water quality monitoring: Preliminary results of the first IOSMOS (Ionian Sea Water Quality Monitoring by Satellite Data) campaigns. Proceeding of the 2014 EUMETSAT Meteorological Satellite Conference; 22-26 September 2014; Geneva, Switzerland. DOI: https://doi.org/10.13140/2.1.4039.2487

[48] Chen, Z., Fan, J., Wang, K., 2020. Remarks on multivariate Gaussian processes. arXiv preprint arXiv:2010.09830. DOI: https://doi.org/10.48550/arXiv.2010.09830

[49] Zhuang, X., Hu, Y., 2017. Statistical deformation model: Theory and methods. In: Zheng, G., Li, S., Székely, G. (eds.). Statistical Shape and Deformation Analysis: Methods, Implementation, and Applications. Academic Press: Cambridge, MA, USA. pp. 33-65.

[50] Yi, C., Zhang, K., Peng, N., 2019. A multi-sensor fusion and object tracking algorithm for self-driving vehicles. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering. 233(9), 2293-2300.

[51] Fiorelli, E., Bhatta, P., Leonard, N.E., et al., 2003. Adaptive sampling using feedback control of an au-

tonomous underwater glider fleet. Proceedings of the 13th International Symposium on Unmanned Untethered Submersible Technology (UUST); 1 January 2003; Durham, NH, USA. pp. 1-16.

[52] Clemens, J., Wellhausen, C., Koller, T.L., et al., 2020. Kalman filter with moving reference for jump-free, multi-sensor odometry with application in autonomous driving. Proceedings of the 2020 IEEE 23rd International Conference on Information Fusion (FUSION); 6-9 July 2020; Rustenburg, South Africa. pp. 1-9. DOI: https://doi.org/10.23919/FUSION45008.2020.9190464

[53] Liu, L., Sukhatme, G.S., 2016. Making decisions with spatially and temporally uncertain data. arXiv preprint arXiv:1605.01018v1. DOI: https://doi.org/10.48550/arXiv.1605.01018

[54] Lin, Z., Yin, F., Maroñas, J., 2023. Towards flexibility and interpretability of Gaussian process state-space model. arXiv preprint arXiv:2301.08843. DOI: https://doi.org/10.48550/arXiv.2301.08843

[55] Cressie, N., Wikle, C.K., 2011. Statistics for Spatio-Temporal Data. John Wiley & Sons: Hoboken, NJ, USA.