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JERICO-S3 DELIVERABLE

Joint European Research Infrastructure network for Coastal Observatory Science, Services, Sustainability

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EXECUTIVE SUMMARY

Deliverable D1.4 of the JERICO-S3 project intends to draw a picture of what could and should be the coastal observing system of the future (with a 20-year perspective), and its implication for the future European research infrastructure for coastal observation – JERICO, based on an analysis of the main drivers that will lead the evolution of coastal observation. The key drivers considered in this study are (1) the evolution of the policy framework to answer emerging new societal needs, (2) the state-of-the-art in coastal observation, supporting science, and (3) ongoing technological game changers related to the industry 4.0 revolution and the rise of bio-based technology. The aim is to propose a vision that can trigger further discussion within the science community, and between research, industry and policymakers, to support the elaboration of dedicated ambition action plans for its implementation.

The concomitant societal needs for protection and exploitation of coastal resources are investigated, as the expectations from the main policy initiatives addressing them (i.e., UN Sustainable Development Goal #14, UN Ocean decade, European Green Deal, Mission Restoring water and ocean 2030, Sustainable blue economy partnership). Conclusions on emerging scientific challenges and their implications on new requirements for coastal observations are drawn. Maintaining the provision of ecosystem services is seen as a keystone, leading to the need for Fit-for-purpose observing systems are needed for comprehensive observation/understanding of ecosystem across compartments, as well as integrated observing strategy between scientific domains, between observing technologies, and with strong benefit for simulation and forecasting services.

An in-depth state-of-the-art on coastal observation is provided, through a review of scientific questions and technologies for observing physical, biogeochemical, biological and chemical EOVs in coastal regions. An extensive and recent bibliography is provided, and conclusions are drawn on the need for integrated observations and integration of data supporting a comprehensive understanding of the dynamics and variability of coastal ecosystems under multiple pressures.

Key ongoing technological revolutions are investigated, with focus on the digital revolution, encompassing IoT-enabled AI, edge computing, automation and robotics, and on the biotech revolution and omics-based techniques and technologies.

Based on the investigation of these main drivers, a prospective vision of the coastal observation of the future is presented. By 2040, coastal ocean observing systems will be vastly more sophisticated, integrated, and inclusive, leveraging cutting-edge technologies to provide detailed, real-time insights into coastal environments. Citizen empowerment will provide a new momentum in observation, densifying the coverage in space and time, contributing to early identification of environmental

changes and threats. The concept of FAIR-2 answering to the emerging requirement for FAIR and AI-Ready data is introduced. AI-ready data is a cornerstone for advancing ocean observation systems, enabling the deployment of sophisticated machine learning and AI techniques (including Digital Twins) to enhance our understanding and management of marine environments.

These transformations will enhance our ability to protect and manage these vital ecosystems, ensuring their sustainability for future generations. JERICO ambitions to be a pro-active actor of these changes through its own expertise on science and technology related to coastal observations.

1 Emerging Scientific Challenges – Horizon 2030 and beyond

1.1 The societal and political context

In recent years, the global community has increasingly recognized the urgent need for concerted action to address the mounting environmental challenges facing our planet's oceans. Many large international initiatives have emerged, each aiming to tackle specific aspects of ocean conservation, restoration and sustainable blue economy. These initiatives represent collaborative efforts involving governments, intergovernmental organisations, non-governmental organisations, academia, and the private sector, with the shared goal of safeguarding the health and resilience of our oceans for future generations, and with demonstrating major progress by 20230.

At the global level, **Sustainable Development Goal** 14 (SDG 14) calls for the conservation and sustainable use of oceans, seas, and marine resources. Adopted by all United Nations Member States as part of the 2030 Agenda for Sustainable Development, SDG 14 encompasses targets related to marine biodiversity conservation, pollution reduction, sustainable fisheries management, and the protection of marine ecosystems and coastal habitats. SDG 14 serves as a guiding framework for international cooperation and action to address the interconnected challenges facing our oceans.

Aligned with SDG 14, the **United Nations Decade of Ocean Science for Sustainable Development** (the Ocean Decade) seeks to mobilise the global ocean science community to generate the knowledge and solutions needed to achieve ocean sustainability. Launched in 2021, the Ocean Decade provides a platform for collaborative research, capacity-building, and innovation to address priority areas such as marine pollution, ocean acidification, ecosystem restoration, and the impacts of climate change on oceans. By fostering interdisciplinary collaboration and knowledge exchange, the Ocean Decade aims to support evidence-based decision-making and transformative actions for ocean conservation and sustainable development.

In Europe the overarching framework is the **European Green Deal**, which stands as a comprehensive roadmap for the European Union's transition to a sustainable and carbon-neutral economy. Central to this initiative is the recognition of the critical role that oceans play in regulating the Earth's climate, supporting biodiversity, and providing essential ecosystem services. The European Green Deal outlines ambitious targets and policy measures to support the transition towards more sustainable and renewable energy systems and food systems, and the fostering of the development of blue economy sectors in a manner that respects ecological boundaries and safeguards marine ecosystems.

From a science perspective, the European Green Deal is implemented through the **Mission Restoring the Ocean 2030**, which is an ambitious initiative launched under the European Union's Horizon Europe framework. The mission aims to restore ocean health and biodiversity by 2030 through a combination of targeted research, innovation, and policy actions. Key objectives include reducing marine pollution, restoring degraded marine habitats, enhancing sustainable fisheries management, and fostering the resilience of coastal communities in the face of climate change impacts.

Complementary to the Mission, the **Sustainable Blue Economy Partnership** brings together governments, international organisations, and stakeholders from the private sector and civil society to promote the sustainable use of marine resources for economic development. Through collaborative initiatives and investments in blue economy sectors such as fisheries, aquaculture, tourism, renewable energy, and maritime transport, the partnership seeks to unlock the economic potential of oceans while safeguarding their ecological integrity and resilience.

In connection to these ambitious objectives of sustainability (economical, environmental and political), the necessity of robust tools for simulating so-called "what if" scenarios, has become a keystone for decision-making, especially with regards to the billions of Euros investment to be deployed in support to the marine-based energy transition. This has crystallised into the concept of **Digital Twin of the Ocean** (DTO).

1.2 Emerging societal needs and requirements

1.2.1 Sustainable exploitation of the coastal ocean

The increasing promotion by governments of the so-called "**Blue Economy**," which includes both traditional (e.g., fisheries, Aquaculture, coastal tourism) and emerging activities (e.g., renewable energies, blue biotechnology,), either marine-based or marine-related, brings many benefits but also many socio-ecological and socio- economic challenges that can compromise a sustainable use of the ocean (Lubchenco et al., 2020).

The Ocean Conference in Lisbon 2022 highlighted the growing demand for renewable energy, linked to the transition from *black* to *green* energy, with projections indicating a need for 40 times more energy production from marine sources in the coming years. Likewise, it highlighted the need for six times more food from the sea. These societal and political demands are also at the heart of the European Green Deal.

a) More energy from the sea

Meeting this demand requires a deep understanding of marine environments and the development of robust coastal observing systems to support sustainable and efficient energy extraction with minimise environmental impacts.

Sustainably achieving this goal sets specific requirements and constraints on the services to be delivered by a coastal observing system. From an environmental assessment perspective, the expansion of marine energy infrastructure can have significant environmental impacts on coastal ecosystems, including changes in hydrodynamics, sediment transport, and habitat disturbance. Observational systems should support the knowledge building needed to achieve environmental sustainability, as well as provide cEOVs and integrated multidisciplinary datasets, at the appropriate frequency (in space and time) and scales in support to all operation phases (exploration (Baseline, identification and characterisation of sites), implementation (building of energy production systems), exploitation and decommissioning).

In-situ sensor networks, deployed on buoys, moorings, FerryBox, and autonomous and underwater platforms, offer high-resolution measurements of physical, biogeochemical, and biological parameters in coastal waters. These platforms and sensors, when appropriately managed, can provide the needed cEOVs and integrated datasets.

Autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) equipped with imaging systems and environmental sensors can conduct detailed surveys of benthic habitats, marine fauna, and water column properties in coastal waters. These vehicles offer flexibility and precision in data collection, allowing for targeted sampling and monitoring of specific environmental parameters.

During early investigation and characterisation of the potential of a site, environmental data are needed to support simulation of "what if" scenarios, filling in scientific knowledge and understanding gaps, elaborate environmental baseline, and support decision-making and unlocking of investments.

During operation, observational systems should provide monitoring data on device performance, structural integrity, and environmental conditions to support efficient operation and maintenance.

b) More food from the sea

The European Green Deal and related Farm to Fork Strategy underscore the urgent need to transform the EU's food systems to ensure sustainability, resilience, and health. As the world faces increasing pressure from climate change, population growth, and land scarcity, the ocean and coastal regions present an untapped resource for sustainable food production. Expanding aquaculture and sustainable fisheries is vital to meeting the EU's food security goals while minimising environmental impact.

Aquaculture, the farming of fish, shellfish, and aquatic plants, can significantly contribute to the EU's protein supply. Unlike terrestrial agriculture, aquaculture requires less land and freshwater, and certain species, like shellfish and seaweed, can even improve water quality and sequester carbon. By diversifying and increasing aquaculture production, the EU can reduce its reliance on imported seafood, decrease pressure on wild fish stocks, and create new economic opportunities in coastal communities.

Sustainable fisheries also play a crucial role in the Farm to Fork Strategy. Implementing science-based management plans, reducing bycatch, and protecting critical habitats are essential to maintaining fish populations and ecosystem health. Improved monitoring and enforcement of fishing regulations can help prevent overfishing and ensure that fish stocks are harvested at sustainable levels. Additionally, promoting the consumption of under-utilised species can alleviate pressure on overexploited stocks and diversify consumer diets.

Integrating seaweed into the food system offers another promising avenue. Seaweed is a nutritious, low-impact crop that can be used as food, animal feed, and even bioplastics. Expanding seaweed cultivation can enhance food security, reduce agricultural runoff, and provide a sustainable source of biomass for various industries.

To best support the environmental sustainability of the required growth of the aquaculture industry, several new observation capacities are needed, including advanced observing platforms and sensors that provide comprehensive environmental monitoring. Several specific parameters that are currently poorly measured but critical for effective monitoring and management are required (e.g., oxygen and nutrients concentrations, DOC, sediment quality pH, pCO_2, biological activity (algae, pathogens, bacteria). Enhancing the measurement of these parameters would provide deeper insights into the environmental impacts and ensure sustainable and resilient aquaculture practices.

1.2.2 Conserving/restoring the coastal ocean under climate change

The political context discussed above requires additional efforts on understanding coastal processes so that environmental sustainability targets may be reached, ensuring the conservation and the good environmental status of coastal ecosystems. Furthermore there are pressing challenges of conserving and restoring coastal ecosystems amid climate change. The EU Mission "Restore our Ocean and Waters by 2030" aims to address this. Coastal ecosystems are vital for biodiversity, carbon sequestration, and coastal protection. However, climate change exacerbates threats like sea-level rise, ocean acidification, and increased frequency of extreme weather events, which contribute to habitat loss and degradation.

Restoration efforts face multiple challenges, including the need for large-scale habitat restoration projects that are resilient to future climate impacts. This requires advanced scientific understanding and innovative techniques to enhance ecosystem resilience. Monitoring and adaptive management are essential to track the success of restoration efforts and adjust strategies in response to changing conditions. The EU Mission emphasises the importance of leveraging advanced technologies, such as observing systems and ecological modelling, to improve the effectiveness of conservation initiatives.

1.3 Associated scientific challenges and observational needs

Most of the abovementioned human activities can introduce contaminants into the ocean, either "classical" (e.g., metals, hydrocarbons, nutrients, radioactivity, etc.) or "emergent" (e.g., plastics, noise, pharmaceuticals, etc.). A synthesis on Grand challenges in ocean sustainability has been proposed by Borja (2023), concluding on the need for a holistic interdisciplinary and transdisciplinary approach (Lang et al., 2012), based on an ecosystem-based management (Kirkfeldt, 2019) for addressing the multiple uses of coastal ocean space and providing data, knowledge and guidance allowing policy-makers to investigate solutions to the problems the coastal ocean is facing, and ensuring that activities at sea are sustainable while achieving at the same time a healthy status of the ocean, able to maintain the provision of ecosystem services (Gilbert et al., 2015). The ecosystem-based approach requires tools to assess the health status of ocean, considering multiple components, multiple activities, multiple pressures and multiple impacts on the environment and the ecosystem services provided.

To monitor this provision, an integrating observing approach addressing both the environmental and biotic ecosystem components and processes is required. Fit-for-purpose observing systems are needed for comprehensive observation/understanding of ecosystems across compartments.

Furthermore, developing integrated observing strategy between scientific domains, between observing technologies (in-situ and satellite), and with strong benefit for simulation and forecasting services is needed. This is presently pursued in several initiatives in Europe such as the European HORIZON-CL6-LandSeaLot project, which focuses on the land-sea interface and continuum.

Modelling coastal physical and biogeochemical processes, and their coupling, represent a major challenge when compared to open water due to the limited knowledge of physical and biogeochemical constraints as the bottom and coastline, or the lack of high-quality temporal and spatial data needed for models to resolve fine scale processes. In this regard, observations become imperative for calibrating and validating these numerical models but also to accurately represent the dynamics once they are assimilated into the model. Applying numerical models together with high quality temporal and spatial field observations can enhance the understanding of observed processes but also improve the quantification of the future changes and impacts on the coasts. Regarding satellite data, in-situ observations, are also key for calibration, quality control, spatio-temporal gap-filling (with some satellite technologies having reduced coverage/accuracy close to the land) and monitoring fine-scale variability related to physical variables like sea level, temperature, salinity or surface currents.

Modelling biological processes is still at a much lower level of maturation. It is a common understanding that in-situ observations will be paramount for progressing in developing biological modelling, and that Machine-learning and other AI approaches might be the most promising techniques for deploying DTOs supporting the ecosystem-based approach.

The JERICO science strategy is designed for implementing such an approach (see Deliverable D1.5).

2 State-of-the-art in coastal observation

The GOOS Expert Panel has identified the Essential Ocean Variables (EOVs) based on the following criteria (Miloslavich *et al.,* 2018):

- Relevance: the variable is effective in addressing the general GOOS issues of climate, ocean operative services and ocean health.
- Feasibility: the observation or calculation of the variable on a global scale is technically feasible using proven and scientifically valid methods.
- Cost-effectiveness: generating and storing variable data is convenient and relies mainly on coordinated observation systems that use proven technology, exploiting, where possible, historical datasets

While, this list is applicable globally, coastal regions may required the observations of additional variables (e.g., anthropogenic stresses, land-sea interactions, benthic-pelagic interactions, coastal geomorphology.), for appropriately describing the dynamic interfaces between land and open-sea, which host diverse ecosystems, support human livelihoods, and face mounting environmental pressures. Understanding and managing these complex coastal systems necessitate a focused approach that incorporates Essential Coastal Ocean Variables (cEOVs), which have a pivotal role in building new knowledge on and improving the understanding of coastal processes, and subsequently in enhancing coastal resilience, resource management, and sustainable development efforts. CEOVs can be seen as bridging the EOV concept with the Essential Ecosystem Service Variables introduced by Balvarena et al. (2022).

2.1 Essential Coastal Ocean Variables

Essential Coastal Ocean Variables encompass a suite of key parameters (EOVs and complementary variables) that capture the essential aspects of coastal environments, including physical, chemical, biogeochemical and biological indicators. These variables are carefully selected to reflect the unique characteristics and dynamics of coastal systems, emphasising their role in driving ecological processes, and supporting sustaining ecosystem services. By standardising the observation and monitoring of cEOVs, coastal scientists and stakeholders gain valuable insights into coastal dynamics, identify emerging trends, and inform evidence-based decision-making.

Several guiding principles inform the selection and definition of Essential Coastal Ocean Variables:

1. Relevance to Coastal Processes: cEOVs should directly relate to key coastal processes such as water quality, shoreline dynamics, habitat integrity, and ecosystem productivity, ensuring their significance in assessing coastal health and resilience.
2. Spatial and Temporal Variability: cEOVs should capture the spatial and temporal variability inherent in coastal systems, accounting for dynamic interactions between land, sea, and atmosphere across different scales.
3. Interdisciplinary Perspective: cEOVs should integrate physical, chemical, biological, and socio-economic indicators, reflecting the interconnected nature of coastal environments and the diverse range of human activities occurring within these regions.
4. Stakeholder Engagement: The selection of cEOVs should involve active engagement with coastal communities, resource managers, policymakers, and other stakeholders to ensure that key concerns and priorities are adequately addressed.

Those directly relate to the 5 pillars of the JERICO Science strategy (Figure 1):

Pillar 1: Developing innovative technologies mostly because of: (1) between discipline differences in Technology Readiness Levels, and (2) the need/interest of developing multidisciplinary platforms to enhance the emergence of holistic observation.

Pillar 2: Enhancing integrated Coastal Ocean Monitoring to account for the strong interactions between marine coastal compartments and processes within coastal marine systems since the effective implementation of multi-disciplinarity within JERICO-NEXT Joint Research activity Projects was overall considered unsatisfactory.

Pillar 3: Interfacing with other ocean observing initiatives because of the necessity of coordinating the observation strategy of coastal marine systems with those of external ones monitoring potential controlling factors.

Pillar 4: Fostering societal impact for a larger community of stakeholders because of the necessity of taking into account the diversity of the concerns of users and to involve them deeper in the design and the functioning of a dedicated research infrastructure so that derived products better suit their expectations.

Pillar 5: Establishing observing objectives, strategy and implementation at the regional level since this spatial scale is likely the most suitable for both: (1) defining sets of functionally linked subsystems, and (2) constituting the individual units of a future coordinated pan-European Research Infrastructure.

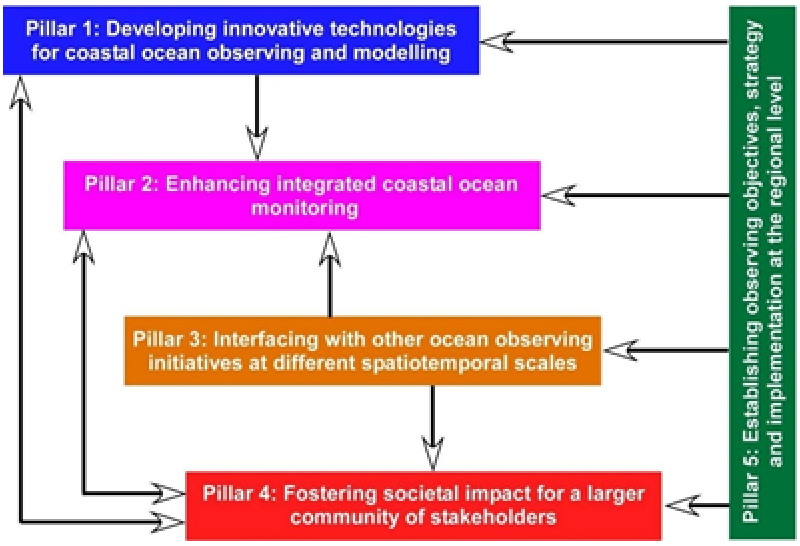


Figure 1 - General structuration of the science strategy elaborated during JERICO-NEXT (Taken from Grémare et al 2019).

Essential Coastal Ocean Variables find diverse applications across the KSCs sand SSCs addressed by JERICO (

Table 1):

Table 1 – Key scientific challenges, Specific Scientific challenges and research areas addressed by the JERICO RI.

Key Scientific Challenges	Specific Scientific Challenges	Research axes
Assessing changes under the combined influence of global and local drivers	Land Sea Ocean continuum. Impacts of land-derived discharges and exchanges with open ocean	Nutrients, particles and organic matters, inorganic carbon, litter and contaminants
	Sea-atmosphere interface. Quantification of inputs	Particles, nutrients, contaminants
	Connectivity and transport. Pathways of water masses and materials	
	Biodiversity trends	Phytoplankton, zooplankton, benthos
	Ecosystem biogeochemical processes and interactions	Pelagic, benthic, pelagic/benthic coupling
	Carbon budget and carbonate system	Carbon fluxes and budget, carbonate system trends, effects of acidification
Assessing the impacts of extreme events	Impacts of rare and extreme events	Floods, storms/large waves, heat waves, landslides/sudden erosion, HAB, accidental pollution
Unravelling and predicting the impacts of natural and anthropogenic changes	Resolving climate change impacts	Temperature, salinity, currents, sea level, waves, biological productions, species distribution ranges, nutrients
	Resolving anthropogenic impacts	Eutrophication, habitat and biodiversity loss, contamination, coastal engineering, use of marine space, use of marine non-living resources, use/cultivation of living resources, invasive species, maritime traffic, underwater noise
	Disentangling impacts	Meta analysis, coupled modelling

Despite their importance, the effective implementation of Essential Coastal Ocean Variables faces various challenges, including data gaps, spatial heterogeneity, and limited capacity in coastal monitoring and research. Addressing these challenges requires enhanced collaboration among scientists, policymakers, and stakeholders, as well as investments in coastal observational infrastructure, data management systems, and capacity-building initiatives.

Looking ahead, the evolution of Essential Coastal Ocean Variables will involve refining existing indicators, integrating new technologies and citizen science, and enhancing interdisciplinary approaches to coastal research and management. Moreover, fostering community engagement and promoting participatory approaches is considered as essential for empowering coastal stakeholders and ensuring the relevance and usability of cEOV datasets in decision-making processes.

The following sections provide an overview of the state-of-the-art on observing physical, biogeochemical, biological and chemical cEOVs.

2.2 Physics

Coastal processes shape the physical environment in the coastal zone on a wide range of spatial and temporal scales. Temperature, precipitation, and winds as waves and tides, together with water temperature and salinity represent the major marine and atmospheric physical variables governing coastal morpho-dynamics. The physical observation of the coastal zone relies on marine infrastructures, comprising marine technologies such as fixed (cabled) stations, moorings, gliders, HF radars, FerryBox, and shallow water Argo floats, allow for generating data products to support responses for short-term coastal events (e.g. storms) and to long-term changes (e.g. shoreline changes derived from climatic change processes). Such products are also pivotal inputs to enhance the performance of many ocean and atmospheric models, and their downscaling to the coastal domain. A more comprehensive and in-depth knowledge of coastal processes measured by these variables and products is essential to understand both spatial and temporal changes which eventually determine the appearance and functioning of the coasts. The main physical variables commonly measured in coastal areas and integrated into JERICO are summarised in Table 2.

Table 2 - Summary of the main measured physical variables in coastal areas

Main physical variables		
Name	Units	Relevance
Temperature at the surface (SST) and water column	ºC	Coastal areas are particularly vulnerable to the effects of **climate change**. Measuring coastal sea-surface and sub-surface temperature provides essential data for assessing the impact of rising sea levels, ocean acidification, and other climate-related changes. Surface temperature measurements contribute to the **weather and climate prediction** since they provide valuable data for understanding local weather patterns (e.g., storms, fog). Coastal waters also play a significant role in **oceanographic processes** such as the movement of surface currents, upwelling, downwelling, and thermohaline circulation. Surface and sub-surface temperature measurements help in comprehending these dynamics. Monitoring temperature in coastal areas also helps in understanding how changes in temperature might impact the **life cycles and behaviours** of fish, plankton, corals, and other organisms crucial to the coastal ecosystem.
Salinity in the surface (SSS) and in the water column	PSU	In coastal areas, salinity levels can fluctuate due to various factors such as freshwater influx from rivers, precipitation, evaporation, and proximity to the open ocean. Monitoring salinity helps in understanding the **composition and variability** of coastal water bodies and the dynamics of transitional zones as estuaries. Monitoring salinity helps in understanding the density-driven circulation and mixing of water masses, which in turn impacts nutrient cycling, primary productivity, and overall **water quality** in these regions. Like temperature, salinity measurements are critical for

		detecting climate change effects, and supporting various human activities in these regions.
Surface currents	cm s^{-1}	Measuring sea surface currents is crucial for understanding coastal ocean physical processes, connectivity, divergence/convergence and in general and transport patterns. It has direct applications in **search and rescue operations** and **safe navigation**, especially in coastal areas where currents can be highly variable and affect the movement of individuals, vessels and other objects. Understanding current patterns is crucial for an efficient and sustainable **fisheries management, aquaculture** and **engineering** projects to ensure their stability and functionality. Studying surface currents provides insights into the **movement of water masses**, upwelling events, mixing processes, and the exchange of water between coastal and open ocean areas. Accurate knowledge of sea surface currents helps in understanding the transport of heat, nutrients, pollutants, and marine organisms, which is crucial for environmental assessments and **managing pollution** or **invasive species.**
Water clarity/Turbidity	NTU	Measuring water clarity in coastal waters is essential for assessing **ecosystem health** since the amount of suspended particles directly influences light penetration, which is crucial for photosynthesis and the growth of aquatic plants. Turbidity measurements provide valuable information about **water quality** in coastal areas. High turbidity or reduced water clarity can indicate increased sedimentation, nutrient runoff, or pollution, which can negatively impact the health of the ecosystem and aquatic life. Monitoring water clarity is important for facilitating **recreational activities** and for understanding the **impacts of human interventions** on coastal ecosystems.
Sea level	m	Sea level rise is a significant indicator of global **climate change**. Monitoring sea level in coastal areas helps track changes over time, providing essential data for understanding the impact of climate change on coastlines, communities, and ecosystems. Sea level measurements provide valuable information on **ocean dynamics**, including tides, currents, and the movement of water masses, crucial for a better understanding of coastal processes and their interaction with the larger oceanic systems. Accurate sea level measurements are also essential for **coastal planning, infrastructure development, engineering design,** and **land-use decisions** as well as for informing policy decisions aimed at **mitigating the risks** associated with sea level rise in coastal regions.
Waves	m, s	Coastal observatories measure wave height, period, and direction to understand wave dynamics, which influence **coastal erosion**, **sediment transport**, and the **dynamics of nearshore processes**. Accurate wave

		measurements help in predicting and assessing conditions for **safe navigation**, **port operations**, and **recreational** and **tourism activities**. Wave data aids in managing and **preserving coastal zones** affected by wave action.
Wind	m s^{-1}	Monitoring wind conditions near the coast, and particularly wind speed and direction parameters, helps to understand **atmospheric interactions with the ocean**, influencing currents, wave patterns, and weather events. Timely and accurate wind data are important for predicting and preparing for **weather-related hazards**, and for planning safely and efficiently recreational and maritime activities. Measuring wind parameters helps in assessing the **wind energy potential** in coastal areas and optimising the placement and operation of wind turbines.
Other atmospheric and meteorological parameters	ºC, RH, Pa (mb), W/m²	Coastal regions often experience unique weather patterns and have distinct microclimates affected by proximity to the ocean, land-sea temperature contrasts, and sea breezes. Thus, atmospheric and meteorological parameters such as air temperature, humidity, pressure or solar radiation aids in understanding **coastal climate** and supports **local weather forecasting**. Measuring atmospheric parameters are crucial for early detection and prediction of **weather-related hazards** like storms or hurricanes and for engineering resilience designs of coastal infrastructures. Accurate meteorological data also supports safe maritime operations.

Coastal ocean physical variables are typically collected using a combination of in-situ sensors, buoys, moorings, autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs), and other data collection instruments. The coastal in-situ component of the ocean observations has the specificity of partially relaying on land-based or on-land solution, like tide gauges, fixed platforms, and HF radars (El Serafy *et al*. 2023).

Fixed platforms, including cabled stations, benthic landers, buoys, and moorings, contribute significantly to the coastal network, providing multiparameter measurements. JERICO is a major contributor to this effort for coastal regions. **High-frequency (HF) radars** offer a cost-effective solution, providing real-time, high-resolution ocean surface current maps for coastal management. While the EuroGOOS HF radar Task Team (https://eurogoos.eu/high-frequency-radar-task-team/) and the European HF radar node (https://www.hfrnode.eu/), promotes the use of this technology, it development and operational implementation is coordinated by JERICO. Although real-time HF radar data is often emphasised for operational applications, long-term data series are crucial for comprehensively studying coastal ocean processes, their interactions, air-sea dynamics, and the connectivity among marine areas (Rubio et al., 2017). **Coastal profilers (coastal Argo floats)**, build upon the expertise from Euro-ARGO ERIC, for monitoring physical variables at both surface and depth in coastal areas. Finally, in-situ data from **monitoring ship campaigns** under European directives (e.g., MSFD, WFD) also complement the existing operational observations. In addition to all the solutions listed above, JERICO encompasses other platforms such as Ferrybox, VM ADCP, CTP profiles, and autonomous vehicles (AUVs and gliders).

The European tide gauge network is operated separately of JERICO, and provide continuously record sea level elevations along coastlines, traditionally situated in ports or urbanised areas for navigation purposes and have today an extended coverage (the EuroGOOS Tide Gauge Task Team manages an inventory of tide gauge metadata for European and adjacent seas).

Among the gaps in terms of monitoring of coastal ocean physical variables, we can include lack of continuity in space and/or time of observations, reduced spatio-temporal resolution for some of the variables, reduced coverage at subsurface levels and even at surface levels for some relevant variables (like turbidity). It is worth highlighting that enhancing the land-ocean continuum description requires improved data on river inputs, emphasising the need for better quality and integration of river runoff data within European marine data services. Also, as an emerging technology (with not yet coordination at European level), video-monitoring solutions (using high-resolution operational cameras) can contribute to beach morphology and coastline evolution studies, and to building services for rip current monitoring or emergency response during extreme wave events, monitoring flooding and wave overtopping on coastal infrastructures.

2.3 Biogeochemistry

2.3.1 Coastal water biogeochemistry

International efforts to coordinate ocean biogeochemistry (BGC) observations, including ship-based, fixed-point, and autonomous methods, have significantly advanced over the past decade, particularly in meeting Essential Climate Variables (ECV) requirements (Zemp, 2021). While surface ocean pCO2 observations are well-covered in the northern hemisphere's open ocean, coverage is lacking in the southern hemisphere and in coastal zones. The latter concerns in particular observations of BGC variables (Table 3) to understand how climate change could impact physical-biogeochemical interactions and the role played by these regions acting as sink or sources of CO2 (Farcy *et al.*, 2019)

a) Scientific issues in coastal waters

Scientific research on coastal waters addresses key issues such as CO2 fluxes and acidification, eutrophication, deoxygenation, river runoffs, and many different chemical pollution (Cooley et al., 2022). Monitoring these variables is vital for sustainable coastal management, ensuring the preservation of diverse marine ecosystems and the well-being of coastal communities.

The coastal waters play a crucial role in the global carbon cycle. The increase of atmospheric CO2 with penetration to the surface ocean leads to acidification, impacting marine ecosystems. In this context, carbonate variables (e.g., pH, alkalinity) are essential for understanding the dynamics of acidification and its effects on marine life. Excessive nutrient inputs, often from human activities, can lead to eutrophication, a process causing algal blooms and oxygen depletion. The observation of the nutrient levels (nitrogen, phosphorus) helps assess and manage eutrophication, preserving the health of coastal ecosystems. Deoxygenation, or oxygen depletion, is a critical issue affecting coastal waters, threatening marine life and ecosystem balance. To observe and estimate the trend of deoxygenation, regular measurement of dissolved oxygen levels provides insights into the health of coastal waters and potential impacts on aquatic organisms. Rivers contribute various substances to coastal waters, influencing water quality and ecosystem dynamics. Monitoring river inputs involves assessing variables like organic matter, turbidity, and nutrient content, crucial for understanding the coastal environment. Finally, accidental oil spills and pollution from various sources pose significant threats to coastal ecosystems. Monitoring and mitigating pollution involves tracking heavy metal concentrations, plastic accumulation, and hydrocarbon levels to safeguard coastal biodiversity and human health.

Table 3 - Main biogeochemical variables measured in coastal waters

Names	Units	Relevance
Dissolved oxygen DO	µmol/kg	Oxygen is essential for the growth and survival of marine organisms. Decreasing oxygen levels can cause complex changes in marine ecosystems, intensifying the effects of **warming ocean temperatures, acidification, and pollution on species abundance and diversit**y. Climate change significantly contributes to the **reduction of oxygen** in seawater. Globally, rising ocean temperatures drive this process, as warmer water holds less oxygen, increases stratification, reduces oxygen mixing between depths, and elevates oxygen consumption by organisms.
Total Alkalinity TA	µmol/kg	Total alkalinity (AT) is one of four measurable parameters for characterising the marine carbonate system. Monitoring AT helps in assessing the buffering capacity of coastal waters against **acidification**, which is critical as increasing atmospheric CO2 levels dissolve in seawater, forming carbonic acid and lowering the pH. AT is directly related to the availability of these carbonate ions. It provides information on the potential impacts of changing carbonate chemistry on some organisms, which are vital to marine ecosystems. Changes in AT can indicate alterations in water chemistry due to these factors (freshwater input with lower alkalinity).
Dissolved Inorganic Carbon DIC	µmol/kg	Understanding the concentrations and fluxes of DIC helps to track **carbon exchange** between the ocean and atmosphere, as well as the processes of carbon storage in the ocean. DIC is a direct indicator of **ocean acidification**. As atmospheric CO2 levels rise, more CO2 dissolves in seawater, increasing the DIC and forming carbonic acid. DIC levels affect the availability of carbonate ions, which are necessary for the **calcification processes** in marine organisms like corals, shellfish, and some plankton. DIC is closely linked to **primary production and respiration processes** in marine ecosystems. Phytoplankton photosynthesis consumes CO2, reducing DIC, while respiration by marine organisms releases CO2, increasing DIC.
pH		The pH of seawater is a direct indicator of its acidity. With the increasing absorption of atmospheric CO2 by oceans, pH levels are decreasing, leading to **ocean acidification**. Lower pH levels can affect the availability of carbonate ions needed for **calcification**, impacting the growth and survival of these organisms. Measuring pH provides insights into the conditions that support or threaten these species. Regular monitoring of pH can help identify **contamination source**s and guide remediation efforts to maintain healthy coastal environments and to ensure that

		conditions remain suitable for the species being cultivated or harvested (aquaculture)
pCO_2	µatm	Partial pressure of CO2 provides information on **air-sea CO2 flux** in coastal waters which help to observe if the ocean is acting as a **source or a sink of atmospheric CO2**. The levels of pCO2 in seawater are directly related to ocean **acidification**. Higher pCO2 leads to the formation of carbonic acid, which lowers pH and alters the carbonate chemistry of the water. pCO2 levels are influenced by the balance between **primary production** (photosynthesis) and **respiration** in marine environments.
Nutrients	µmol/L	Nutrients such as nitrogen (N), phosphorus (P), and silicon (Si) are essential for the **growth of phytoplankton**. Measuring nutrient concentrations helps in understanding **primary production** rates, which directly influence the health and productivity of marine ecosystems. Excessive nutrient inputs, often from agricultural runoff, sewage discharge, and industrial pollution, can lead to **eutrophication** resulting in harmful **algal blooms, hypoxia** and the subsequent death of marine life. High levels of nutrients can signal **pollution** and deteriorating water conditions. Different nutrient levels can influence species composition and **biodiversity** in coastal waters. Some species thrive in nutrient-rich environments, while others may be outcompeted or suffer from nutrient imbalances. Optimal nutrient levels are crucial for **aquaculture** operations. Excessive or insufficient nutrients can impact the growth and health of farmed species.

b) Existing biogeochemical sensors for coastal waters observation

Biogeochemical (BGC) sensors play a pivotal role in advancing our understanding of marine coastal waters by providing real-time data on key environmental variables. Electrochemical sensors allow measuring parameters like dissolved oxygen (DO), pH, and nutrient concentrations. These sensors operate by leveraging electrochemical reactions to generate signals corresponding to specific chemical concentrations. However, these sensors are very sensitive to biofouling, which is a major challenge in most coastal waters. Even if some anti-fouling systems exist (e.g., copper foil, TBT, electrolyse, UV), they consume a lot of energy and they need technical support for maintenance (Lorenzoni et al., 2015)

Optical sensors, on the other hand, utilise light properties to measure parameters such as dissolved oxygen, nitrate, chlorophyll levels, turbidity, and organic matter content. These sensors can capture intricate details about the biological and chemical composition of coastal waters with high precision and sensitivity. The integration of these sensor technologies enables scientists to monitor changes in the coastal environment, identify trends, and respond promptly to emerging challenges, contributing to more effective coastal management strategies. These sensors are less power-hungry, more reliable for long term observations (less sensitive to sensor drift) but their costs could be high (e.g., UV for nitrate) and the data processing for adjusting the values is not mature yet for some variables and sensors (e.g., need adaptation of the sensor's calibration procedures, regular in situ sampling…).

Thanks to previous European projects and experiments (e.g., GOOS, OOI, FIXO3, EUROSEA, JERICO-NEXT, …), a list of recommended BGC sensors can be established depending on the techniques and maturity (data quality and maintenance) (Palevsky et al., 2022)

Table 4 - Current list of recommended BGC sensors to measure chemical variables (colour indicated the degree of robustness: green = robust, yellow = need more validation, red = need more deployment and test).

Variables	Recommended technique	Sensor 1	Sensor 2	Sensor 3	Sensor 4
DO	Luminescence lifetime optode sensor	AADI 4330	Seabird 63	JFE RINKO	RBR CODA
Nutrients	Ultraviolet spectrophotometer; wet chemistry	Seabird SUNA	Trios OPUS	Chemini, WIZ, …	
pCO2	NDIR, spectrophotometry	4H-JENA HYDRO-C	Pro-Oceanus CO2-Pro	Sunburst SAMi-CO2	NKE CARIOCA
pH	Ion-sensitive field-effect transistor	Seabird SEAFET	SAMI-pH	Chemini	Clearwater LoC

c) Challenges

Several technical challenges persist in the field of biogeochemical sensors in oceanography. Achieving high accuracy and precision in measurements, especially for parameters with low concentrations, remains a challenge. Calibration and quality control methods need continuous improvement to ensure reliable data. Such progress is a long-term process but necessary for the scientific community (e.g., the maturity of Optode for oxygen took over 10 years to adapt and improve the calibration procedure). Biofouling, the accumulation of organic and inorganic material on sensor surfaces, can degrade sensor performance over time. Developing antifouling strategies or materials is essential to maintain sensor accuracy during long-term deployments. Harsh marine environments, including high pressures, corrosive seawater, and bio-corrosion, can affect the durability of sensors. Enhancing the robustness of sensor designs and materials is crucial for prolonged deployments in challenging conditions. Many biogeochemical sensors are deployed on autonomous platforms (e.g., gliders) with limited power resources. Developing sensors that are energy-efficient and can operate for extended periods without frequent battery changes is a persistent challenge. Integrating multiple sensors to measure different parameters on a single platform (e.g., fixed buoys or Ferrybox) can be challenging due to issues related to space, power requirements, and potential interference between sensors. Developing compact, integrated sensor packages is essential for facilitating sensor integration on autonomous platforms. While sensor technology has advanced, the cost of some high-quality sensors can be a barrier. Ensuring affordability without compromising data quality is important for broader accessibility to these technologies. Finally, continuous research and innovation in sensor technology (e.g., lab-on-chip sensors using microfluidics technology), collaboration among scientists and engineers, and addressing these technical challenges are essential to advancing our understanding of marine biogeochemistry and effectively monitoring the marine coastal ecosystems.

While the observation of key BCG variables (Table 3) seem to have reached a level of maturity that enable the operationalisation of measurements at the appropriate sampling frequency (in space and time) for describing coastal BGC processes, their variability and their dynamics, measurement of anthropogenic chemicals (pollutants) is still not based on observation but on water sampling and lab analysis, with major barriers regarding the assessment of their concentrations, distribution, fate, bio-uptake and degradation in the ocean and not least, in the coastal environment. Recent development of auto-samplers and technology for preserving samples onsite can be seen as an important, while small, step for densifying measurements towards a better understanding and description of pollutant related processes. Technologies and approaches for observing or measurement of pollutants on sites have still to emerge. Revolutions in digitising, robotics, autonomous lab facility, and biotechnology may provide in the future solutions to the current critical limitation.

2.3.2 Benthic & sediment biogeochemistry

Biogeochemical observations at the sediment-water interface are mostly dedicated to processes linked to organic matter remineralization, which is mostly achieved by microorganisms but also partly result directly (through nutrition) and indirectly (through bioturbation) from meio- macrofauna activity. Remineralization processes in the upper sediment column involve a series of final electron receptors, which are used by microorganisms following a sequence corresponding to decreasing energy gain (Froelich et al., 1979). The oxidation/reduction of these electron receptors induces: (i) transfers between particulate/dissolved forms, and (ii) the formation of concentration gradients from which the pathways and intensities of organic matter mineralization can be derived using specific models.

Concentration gradients of oxidising/reducing compound in the top sediment column can be assessed using a large variety of approaches including: (i) direct pore water measurements, (ii) diffusive gels (i.e., DET and DGT) with various integration periods, and (iii) microelectrode profiling. Oxygen is the most efficient final electron receptor. It is also used in re-oxidising the reduced forms of other final electron receptors. Moreover, because of the usually tight 1:1 relationship between rates of benthic mineralisation and photosynthetic production and the parallel uptake or release of O_2 (see Berg et al. 2022 for a more detailed review), the net balance between these two opposite processes can be assessed by measuring benthic O_2 exchange rates at the sediment-water interface.

Biodiffusive benthic O_2 fluxes mostly account for remineralization by microorganisms in relation with the availability of final electron receptors, which is itself cued by diffusion processes. Their assessment is based on O_2 concentration vertical micro-profiles in the top sediment column, which are typically acquired using O_2 microprofilers, which include a 2D translator and provide repeated micro-profiles over small scale soft-sediment surface and during limited time periods due to the fragility of microelectrode tips (typically <200µm in diameter). These profiles are then modelized to quantify biodiffusive oxygen fluxes.

Biodiffusive benthic O_2 fluxes do not account for respiration and bioturbation by meio- and macrofauna; two processes, which also contribute to total organic matter remineralization. Total benthic O_2 fluxes have first been measured in recovered sediment cores incubated in controlled environments mimicking *in situ* conditions. They can now be quantified *in situ* using two main approaches: (i) incubation chambers, and (ii) eddy covariance. Incubation chambers consist in the in situ enclosing of a given surface of sediment and a known volume of overlying water and measuring the kinetics of O2 concentration decrease in the overlying water. These devices have been integrated on benthic landers for the study of deep-sea sediments and have been used in simpler forms for the quantification of the balance between primary production and remineralization in a large variety of coastal habitats. Here again, incubation chambers only allow for flux measurements over a small sediment surface. Another drawback is that they may disturb the substrate and alter the natural drivers of O_2 flux (Berg et al. 2022). Finally, the incubation approach also suffers from difficulties in achieving sound replicated measurements (i.e. over the same sediment surface) due to imperfect water renewal between successive incubations, although this last issue was efficiently tackled within JERICO-S3 WP7 (see the ACOBS sections of D7.7 and D7.9 for details).

Aquatic eddy covariance has been introduced to overcome these drawbacks. Its principle consists in deriving vertical O_2 fluxes by averaging the product of fluctuations in vertical current velocities and O_2 concentrations at a given point in the water above a studied sediment habitat. Aquatic eddy covariance systems associate an ADV for the assessment of the vertical component of turbulence and O_2 micro electrode/Optode for the assessment of high frequency fluctuations in O_2 concentrations. Data processing involves sophisticated procedures, which allow for the computation of total fluxes. The ecological interpretation of these fluxes and the identification of their potential controlling factors both require determining the exact location and the spatial limits of the "footprint" (i.e., the substrate area over which measured fluxes are integrated). The area of the footprint depends on the location of the eddy covariance system and on current patterns. In any case, it is much larger (i.e., several m^2) than the surfaces associated with micro-profiling and incubation chambers. Another advantage of the eddy covariance approach is that its deployment is not limited to soft sediments. Although, this approach has been used for assessing total O2 fluxes in a large variety of environments (Berg et al. 2022) including decadal monitoring (Berger et al 2020), its applications remain somehow limited due to the high level of technicity required during deployment and data processing.

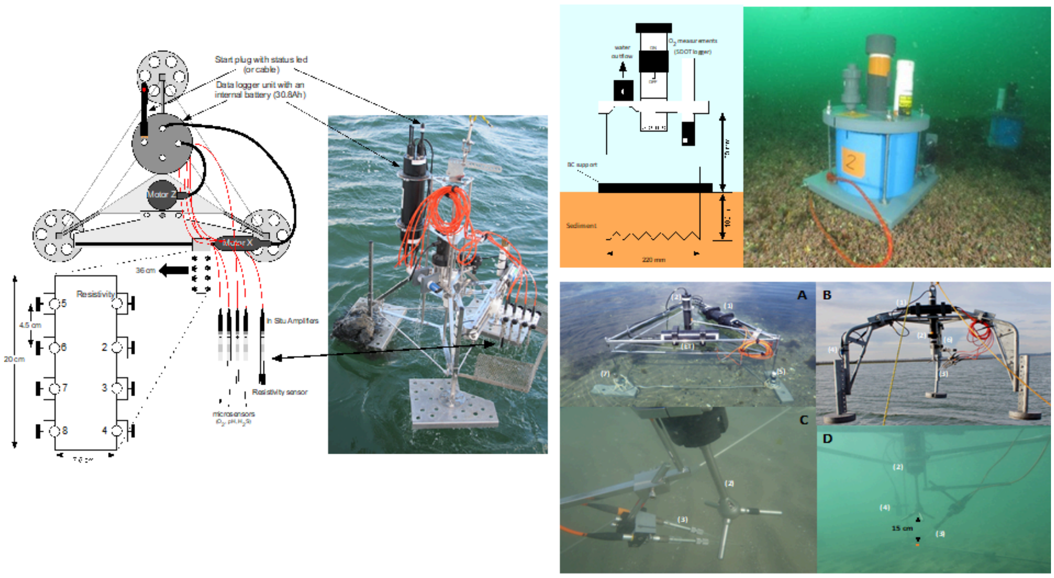


Figure 2 - Benthic O_2 fluxes: Sediment microprofiler for the assessment of diffusive fluxes (Left), benthic chamber (Top right) and eddy covariance system (Bottom right) for the assessment of total fluxes. Modified from JERICO-Next D3.10.

2.4 Biology

2.4.1 Pelagic communities

Traditional methods for pelagic marine observations (phytoplankton to macropelagos) often consume a lot of resources and leave large knowledge gaps on both temporal and spatial scales. Emerging, autonomous in situ technologies are capable of filling some of those gaps. Deploying compact, light, low-cost sensors on platforms such as moorings, buoys and autonomous vehicles enables the monitoring of areas that are otherwise hard to reach due to distance and/or conditions. The implementation of autonomous monitoring tends to have high initial costs, but it decreases the costs in the long run. Autonomous technologies allow for the possibility of adaptive sampling which in turn helps to optimise the use of resources. These technologies include bio-optics, bioacoustics, imaging and genetics. Some of these are already in operational use while others are in the developing stages. In the future, they should be included in routine monitoring programmes.

Many of these technologies have the capability of continuously transmitting data in real time or near real-time, significantly increasing the temporal coverage of observations, as well as the amount of incoming data. Optimising the dataflow, storing large amounts of data and performing analyses on it in real-time are challenges requiring new developments, and have led to increased use of artificial intelligence. An important requirement is that the data corresponds to the FAIR principles so that it is accessible, appropriately formatted, documented and quality assured. Multi-instrumentalisation i.e. deploying multiple sensors of various technologies that support each other allows for a more holistic dataset, which is potentially fit for multiple different purposes.

Below are categorised the key autonomous technologies some of which are already in operational use, and some that are emerging.

a) Imaging

Imaging (in situ and ex situ) is facilitating consistent observations of plankton and particle dynamics in marine ecosystems (Lombard et al. 2019). One of the technologies with multiple examples of autonomous instruments in operational use is imaging flow cytometry. Imaging flow cytometers such as the Imaging Flow CytoBot (IFCB) and Cytosense can be deployed on multiple platforms; there are examples of deployment on land and on different moorings (Ruiz-Villareal et al., 2022; Kraft et al., 2022). Data from these instruments can be transmitted in near real-time. Another possibility for imaging is different cameras, such as the Underwater Vision Profiler (UVP6, Picheral et al. 2022) which can be deployed on multiple autonomous platforms such as floats, gliders, and moorings. It is a miniaturised version of UVP5 (Picheral et al. 2010), and capable of continuous recording. The TechOceanS project[1] is also developing a miniaturised variant of the UVP6 called UVP6m, designed for the detection and classification of smaller particles. It is not yet commercially available. Holographic imaging systems, although becoming lighter and more compact, are still very data-intensive and in need of further technical developments before near real-time data transmissions and image processing are feasible. Complementary imaging techniques covering a wide range in object sizes allow to assess size distributions of both particles and plankton, with powerful derived estimates of e.g. carbon export flux and trophic transfer efficiency on marine food webs. Efforts are underway to harmonise such efforts and inter-calibrate instruments (Dugenne et al. 2023).

[1] https://techoceans.eu/

The imaging instruments are often quite expensive and require expertise from the user. Transmitting and analysing image and video data also does require a lot of power which means that often there is a need for high-performance computing infrastructure. Using machine learning to process e.g. classify image data increases the efficiency of data analysis significantly. Convolutional neural networks (CNN) are increasingly popular and the most commonly used classification algorithm in new marine ecological publications. There are multiple examples of using CNNs to classify IFCB image data, but they are suitable for many different types of data. It would be good to build adaptable data pipelines that could be used with multiple imaging instruments, as Schmid et al. (2023) did with In-situ Ichthyoplankton Imaging System-3 (ISIIS-3) images.

b) Bio-optics

Optical devices can measure abundance, size, and type or marine particles, and cover a range of technologies including fluorescence, scattering and absorption sensors and spectral sensors. One of the potential technologies for future sensors is Single-Turnover Variable Chlorophyll Fluorescence (ST-ChlF) which is a tool for assessing phytoplankton photosynthetic physiology. ST-ChlF instruments can be deployed on autonomous platforms as e.g. Carvalho et al. (2020) have demonstrated by integrating a fluorescence induction and relaxation sensor into a glider. They have the potential for advancing our understanding of phytoplankton primary productivity but the current practices concerning the instruments, quality control and data reporting and archiving are inconsistent and therefore hinder inter-comparability of data. Schuback et al. (2021) have worked towards common guidelines and recommendations.

New ST-ChlF sensors are in development. TechOceanS project is developing an in-situ prototype sensor called MicroSTAF that measures phytoplankton primary productivity and has lower power requirement, decreased volume and increased pressure rating compared to UK Oceanids project's AutoSTAF. TechOceanS has also designed a microcytometer that uses impedance and fluorescence measurements to autonomously measure phytoplankton biomass and diversity across a multi-day deployment. Spectromarine[2] is a company currently developing autonomous optical sensor for measuring e.g. Chl-a and phycocyanin. Their technology is currently at TRL 6. Manufactures of established optical sensors include bbe Moldaenke (e.g., FluoroProbe III), Chelsea Technologies (e.g., VLux TPro) and TriOS (e.g., matrixFlu VIS). JERICO-S3 project's WP7 has included collecting information on innovative sensors and systems. One of them is the Hyperspectral Absorption Sensor[3] (HyAbs) that can be used to assess e.g. phytoplankton biomass through Chl-a, and algal groups. It is a custom-made prototype sensor modelled after PSICAM and can be connected to e.g. FerryBox systems.

c) Bio-acoustics

Acoustic information benefits from being combined with other types of sensors that give complementary information. There are echo sounders that take measurements autonomously and can be deployed on a variety of platforms such as the EK80 sensors manufactured by Kongsberg[4]. Schmid et al. combined such an echo sounder with ISIIS-DPI imagery and a deep learning data pipeline to observe diel vertical migration of zooplankton.

[2] https://spectromarine.com/
[3] https://docs.google.com/document/d/1YVJbX8l_i-CZMWWykIK8wrweFZk6NzCV/edit
[4] https://www.kongsberg.com/ek80

d) *Metabolism and rates*

Methods assessing phago-mixotrophy in aquatic organisms exist but are not yet ready for autonomous monitoring. There are, however, emerging techniques for in situ analyses such as meta-transcriptomic analyses and utilising cell staining together with imaging flow cytometry. One example of the latter would be the use of a Cytosense[5] device coupled to a BSM (Bacterial Staining Module)[6].

e) *Toxins*

Environmental Sample Processor (ESP) is a system that automates the in-situ sampling, concentration and analysis of HABs and their toxins (Moore et al., 2021). It is a commercially available autonomous platform that can be deployed for up to three months. It is not capable of continuous measurements due to a limited sample capacity, but the data can be retrieved in near real-time. TechOceanS project is developing in situ immunoassays that are based on antibodies and can be deployed to detect HAB toxins or other contaminants. The same project is also developing a nucleic acid sensor for microbial nucleic acids that is currently at TRL 4. One focus for the sensor is the early detection of toxic phytoplankton blooms.

f) *Environmental DNA*

See section 3.2.1

2.4.2 Benthic communities

Benthic communities are key components of the structuration and functioning of coastal ecosystems. They are key elements of coastal marine food chains and, for example, constitute a major food source for many exploited fish species (Petersen and Jensen 1911). Continental margins constitute the main zone of the world ocean where organic carbon is buried in marine sediments and thus preserved for remineralisation over geological time periods (McKee et al. 2004). Marine benthic organisms largely control the intensity of this sink either directly through its nutrition and respiration, and indirectly through bioturbation. Large proportions of meio- macrobenthic organisms is sessile and long-living. They therefore: (i) cannot escape man-induced disturbances, and (ii) are able to integrate the adverse effects induced by those disturbances over various time durations. This explains why meio- macrobenthos is currently used to describe the Ecological Quality status of marine waters within the framework of both the WFD and the MSFD (e.g., Borja et al. 2000, Rosenberg et al. 2004, Labrune et al. 2021 for macrobenthos). Based on these rationales, there are thus major needs in assessing benthic species composition, abundance/biomass, activity and impacts on key biogeochemical processes affecting the fate of particulate organic matter at the sediment-water interface.

a) *Assessments of benthic community compositions*

Classical approaches

The classical scheme for benthos analysis is based on (i) punctual sampling, ii) sorting of living organisms from the sediment, and iii) identification of living organisms. There is currently no available fully automated process to generate taxa-abundances tables for benthic fauna. The selected sampling device is first depending on the willingness to assign collected numbers to a given sediment surface (i.e., quantitative sampling) or not (i.e., qualitative sampling). It also depends on i) the component of the benthos to be addressed: grab for macrobenthos, box or multicorer for

[5] https://docs.google.com/document/d/1y33edI_EtsagNjKnphpGXYVVRBoliQec/edit#heading=h.gjdgxs
[6] https://precym.mio.osupytheas.fr/a-new-automated-staining-module-to-study-aquatic-microbes/

meiobenthos and bacteria. In the two later cases, the vertical zonation of the collected organisms is most often assessed through the slicing of collected cores. The number of replicates to be collected is usually determined from accumulation curves. For macrobenthos, sorting consists in sieving (over a 1 or 0.5mm mesh). For meiobenthos, it mainly consists in a combination of agitation, decantation, sieving (typically over a 63µm mesh) and centrifugation in a gravity (diluted ludox) gradient (Burgess 2001).

Up to the 1980s total benthic microfauna/bacteria were classically counted using epifluorescence microscopy and/or flow cytometry after sediment extraction (e.g. through sonication). Living microfauna/bacteria were classically counted using dilution/cultivation approaches. Taxonomic assessment was limited to broad categories and mostly achieved through the assessments of physiological capacities (i.e. ability to grow on different poor/deficient media).

Either before or after sorting, meio- and macrofauna samples are usually fixed using (4-5% formaldehyde) and later preserved in 70% ethanol. Each collected macro/meio benthic individual organism is then identified through morphological analyses achieved under a stereomicroscope and possibly specific dissections together with microscopic observations. Organisms of the same species are then pooled, counted and eventually weighed. Morphological taxonomic identification most often relies on the expertise of taxonomists specialised on the local biota and/or specific taxonomic groups, which complicates comparisons between studies. Morphological identification is also time consuming, which: i) limits both the number of observations that can be practically performed, and ii) increases the delay (up to several years!) between sampling and data availability (Rey et al. 2020). It nevertheless still constitutes the reference methodology for the analysis of benthic meio- and macrofauna.

Figure 3 - Classical scheme for soft bottom macrofauna analysis: Sampling (A), sieving and sorting (B) and fauna identification (C). (A) is taken from Grall & Hily (2003).

<u>Environmental DNA metabarcoding</u>

Metabarcoding (Taberlet *et al.,* 2012) is a commonly used term for the study of genetic material obtained directly from environmental samples. The perspective of the simultaneous identification of taxa present in a complex environmental sample through a fully automated process is currently revolutionising traditional biodiversity monitoring. Environmental (e)DNA metabarcoding is currently considered as a cost-effective complementary or even as an alternative approach to classical morphological identification (Rey et al. 2020). Up to now most metabarcoding studies achieved on aquatic ecosystems have focused on water column samples. However, eDNA metabarcoding has also been applied to soft sediments (Pawlowski et al 2022).

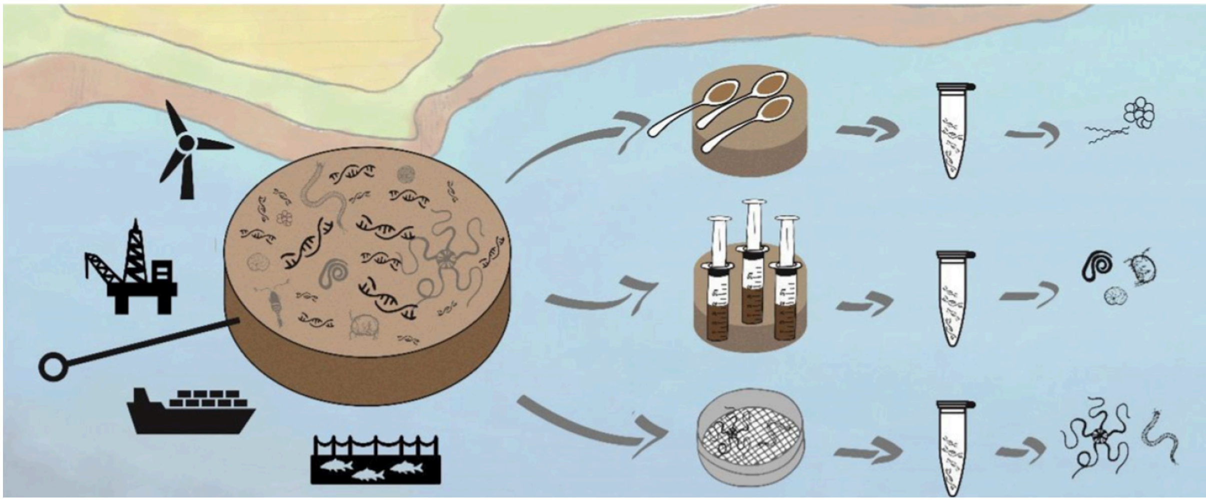


Figure 4 - Environmental DNA metabarcoding: General schemes for the assessments of the compositions of benthic micro-, meio- and macrofauna soft bottom communities. Taken from Pawlowski et al. (2022).

Marine sediment eDNA metabarcoding has clearly revolutionised the study of microbial diversity in benthic ecosystems. Due to the very small fraction of benthic microorganisms that could be cultivated using standard techniques, marine sediment eDNA has revealed a huge and largely undescribed diversity of microorganisms including virus, archaea, fungi and protists (Pawlowski et al 2022 and references therein). This is also true, although to a lesser extent (since classical taxonomy was more advanced) for meiofauna (Pawlowski et al. 2022 and references therein). it should, however, be stressed that: (i) methods and protocols used for sediment eDNA metabarcoding are not fully stabilised yet, and (ii) standardisation efforts are needed to improve their robustness, comparability and use within regulatory monitoring frameworks (Aylagas et al. 2016 & 2018). The main points still to be addressed include: (i) sediment extraction protocols (Pawlowski et al. 2022), (ii) reference databases to convert barcodes in taxonomic information, (iii) the nature and processing of the so-derived taxonomic information, and (iv) the current impossibility to derive sound INDIVIDUAL abundance assessments due to DNA extraction and PCR amplification biases. Such current difficulties/imperfections may explain why the inputs of sediment eDNA metabarcoding in assessing benthic fauna compositions are somehow less obvious for macrofauna (e.g. Lanzen et al. 2021).

Underwater video imagery

As already stated above, the classical procedure for analysing macrobenthos is time consuming, which limits the number of samples that can be processed and thus both the spatial and temporal resolutions of community composition assessments. Another point to be mentioned is that grabs and sediment corers are not fully efficient in quantitatively collecting: (1) benthic megafauna, and (2) endofauna living deep in the sediment column. The descriptions of benthic communities therefore remain most often incomplete (to an unknown extent, which is likely to vary depending on habitats and communities). This explains why underwater video imagery has been developed for megafauna living at the sediment-water interface. Towed-video imagery consists in placing a video camera on a device (i.e., a sledge, a ROV and AUV or a glider), which is towed on or circulating over the sediment surface (Sheehan et al. 2014). In coastal soft bottom habitats, sledges are most commonly used.

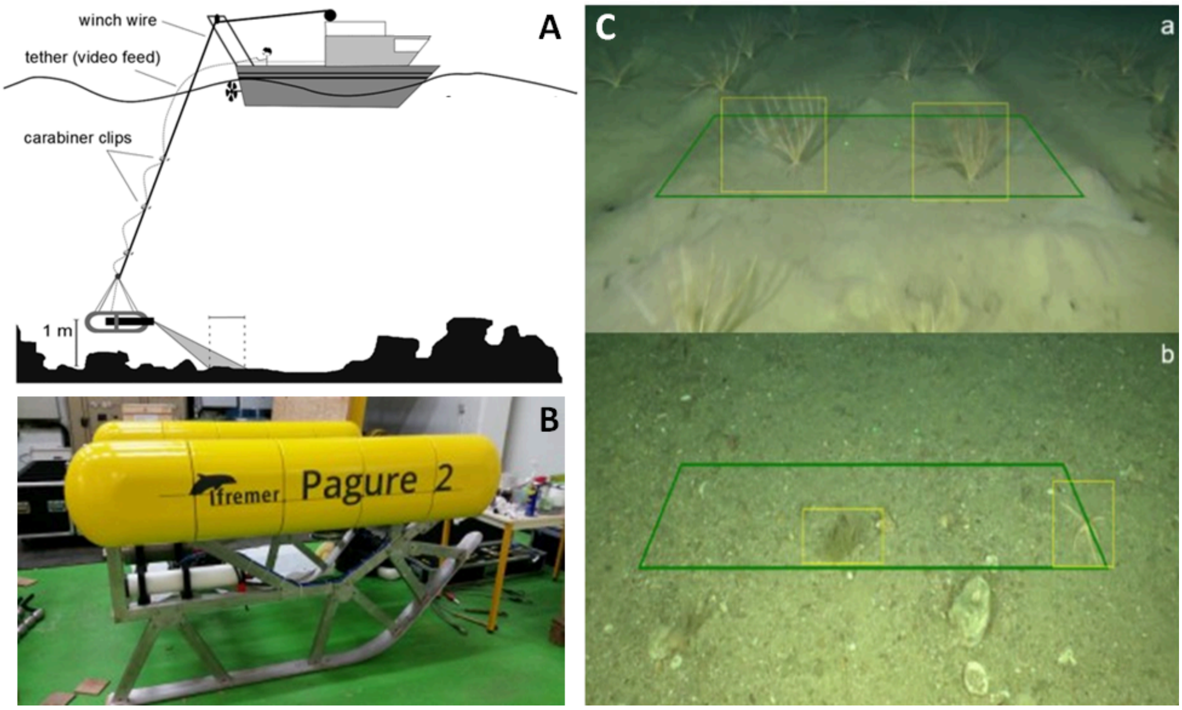


Figure 5 - Underwater video imagery: General principle (A), Example of a towed underwater video system mounted on a sledge (Ifremer Pagure 2) (B) and acquired images (C). Modified from Lindholm et al. 2014, https://www.jerico-ri.eu/2016/11/17/pagure-ii-device-was-tried-out-in-the-bay-of-brest/ and Jac et al. 2021.

This allows for the acquisition of image time series of the sediment-water interface. Benthic megafauna are identified and counted on each individual image. The so-generated data set is then combined with the georeferencing of individual images to map habitats and benthic megafauna in the surveyed area. Together with his approach has been and still is largely used to map benthic habitats (Siaulys et al. 2024) and to address the effect of bottom trawling on benthic communities (Jac et al. 2021). Current limitations are dealing with: (i) the low quality of collected images especially in turbid areas, (ii) associated difficulties in megafauna identification, (iii) the time duration requested for the visual analysis of collected video sequences, (iv) the necessity of counting only once the same organism present in consecutive images, and (v) the necessary correction for the tilt of the video camera when expressing abundances relative to a given sediment surface and measuring the size of observed megafauna. Significant progresses regarding these different points have been achieved within the different JERICO projects. This includes the developments of: (1) the Pagure 2 sled by Ifremer which allows for the acquisition of better-quality images with a restricted impact on the sediment, and (2) a dedicated image analysis software (AviExplore, Romero-Ramirez et al. 2016). Current ongoing efforts consist in developing annotated databases allowing for the development of a new generation of dedicated software based on the use of Artificial Intelligence (e.g. Siaulys et al. 2021 and 2024).

b) Benthic biological activity

Through bioturbation, macrobenthos is a key actor in controlling the fate (i.e., resuspension, remineralization or burial) of sedimented Particulate Organic Matter. Bioturbation mainly results from two different types of activities: (i) sediment reworking, which induces displacements of sediment particles, and (ii) bio-irrigation, which corresponds to changes in sediment oxygenation through biologically induced water exchanges between the sediment and the water column. Benthic biological activity can be assessed based on fixed time lapse/video imagery, which can be deployed either over the sediment-water interface (Maire et al. 2006 & 2007) or on top sections of the sediment column including the sediment-water interface (Solan & Kennedy 2002). In both cases, the quantification of biological activity is either derived from direct visual examination or from the pixel-by-pixel comparison of consecutive images, using dedicated software such as AviExplore (Romero-Ramirez et al. 2016).

The deployment of fixed video imagery for acquiring video sequences over a given sediment surface. has been successfully used in the deep sea in association with bait experiments allowing for the identification of "opportunistic" species responding to dead organic matter inputs. This approach has also been used in soft bottom coastal sediments for the assessment of temporal changes in the nature and the intensity of macrobenthos activity (Maire et al. 2006 & 2007). Benthic biological activity at the sediment water interface can also be assessed through the deployment of Sediment Profile Imagers, which are designed to acquire *in situ* images of 2D sections of the top sediment column (Rhoads and Young, 1970). Sediment Profile Imagers function as inverted periscopes with a down pointing camera capturing an image of a 2D top-sediment section reflected by a 45° oriented mirror. When used in time lapse/video mode, sediment Profile Imaging can be used to acquire image time series that can be processed as described above to infer biological activity at the sediment-water interface (Solan & Kennedy 2002, see the ACOBS section of D7.9 for a more recent example with a higher temporal resolution documented within JERICO-S3 WP7).

Sediment Profile Images contain a complex set of information such as: (1) the thickness of the apparent Redox Potential Discontinuity (aRPD),which corresponds to the limit between oxic and suboxic mineralization processes, (2) the numbers of epi and endofauna, (3) the number and size of tubes, (4) the number and depth of burrows and oxic voids within the sediment column, and (5) the presence of faecal pellets and feeding structures at the sediment-water interface. This information can be interpreted in terms of: (1) habitat Ecological Quality status, using specific indices such as OSi (Rhoads & Germano 1986) and BHQ (Nilsson & Rosenberg 1997), and (2) animal sediment relationships including bioturbation processes through which macrobenthos affects sediment biogeochemistry.

Sediment Profile imaging has proven its ability to detect a large variety of anthropogenic impacts. It has thus been and is still used as a monitoring tool of benthic environments habitat ecological quality (see Germano et al. 2011 for a review). Sediment Profile Imaging also allows for the 2D characterization and quantification of integrated biological activity traces, which can then be put in correlation with sediment reworking during either field (Teal et al. 2013) or laboratory (Maire et al. 2007) experiments. The main difficulties associated with the acquisition of sediment profile images are: (1) the cost of the sediment profile imager (i;e., around 60 k€) explaining the few number currently in academic use worldwide (Germano et al., 2011); and (2) the low representativity of single sediment profile images due to the small size (i.e., close to a A4 format) of the observation window. Moreover, the visual analysis of sediment profile images is time consuming, requires a specific expertise and remains highly operator dependent. Although significant progress has been achieved recently through the development of dedicated software (e.g. SPIArcBase, Romero-Ramirez et al. 2013), the situation is not fully satisfactory and new developments based on Artificial Intelligence are foreseen.

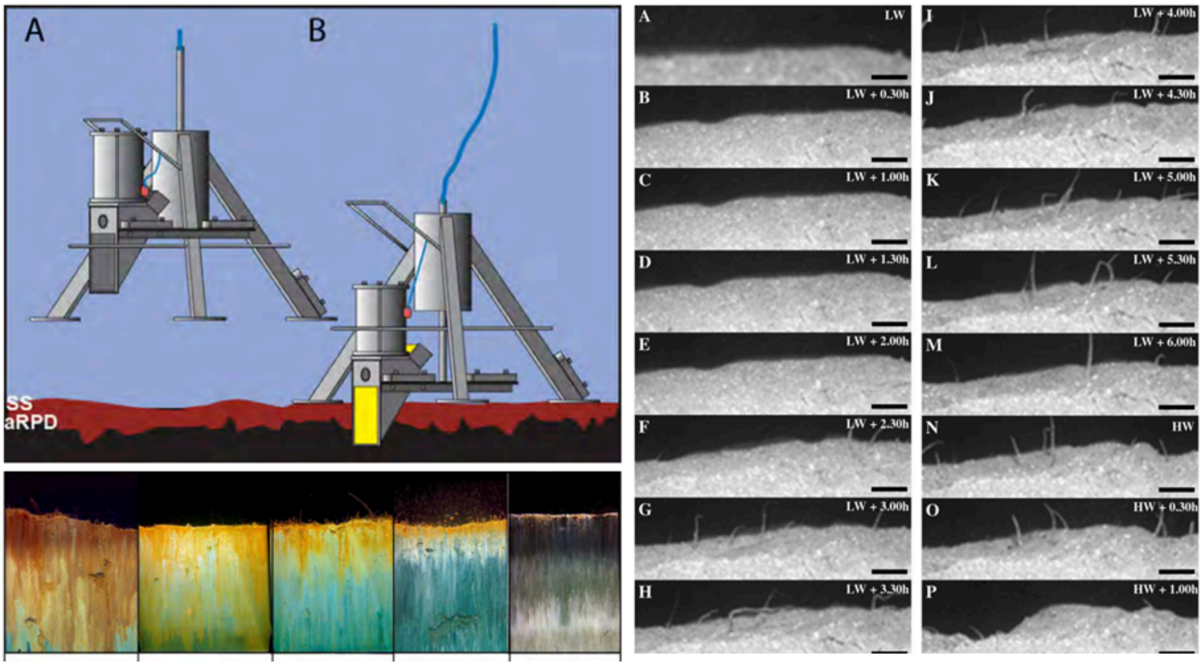


Figure 6 - Sediment Profile imagery: General principle (Top left), Example of sediment profile images collected along an oxygen depletion gradient (Bottom left) and time lapse sediment profile images allowing for the assessment of in Galway Bay (Right). Modified from Nilsson & Rosenberg (2006) and Solan & Kennedy (2002).

c) *Synthesis and perspectives*

Overall, and despite recent/current progress for some achieved within the JERICO framework, available techniques for achieving automated or semi-automated observation of benthic biological compartments and processes remain limited. There is clearly a lack of long-term deployment of automated sensors. direct observations thus mostly consist in snapshot measurements in both space and time, which limits the spatial and temporal extensions over which direct field observations can be achieved. This drawback is especially pronounced when studying the coastal ocean where benthic systems are highly heterogeneous and dynamic. There is thus a clear need in developing a "continuity" between direct field observations through upscaling *sensus largo*.

A first way forward consists in increasing the number and the comparability of direct field observations. The development of metabarcoding and imaging approaches constitute a key step forward for the observation of benthic systems. They, however, still present significant imperfections (i.e., the difficulty in relating biodiversity to a given sediment area and in generating quantitative data for benthic metabarcoding; the low taxonomic resolution and the absence of fully automated image processing procedures for benthic image analysis). The incorporation of Artificial Intelligence (AI) clearly constitutes a major element of current development as well as a highly promising perspective regarding this last aspect.

The use of AI to describe and extrapolate temporal sequences of direct field observations is also currently emerging. This approach is clearly more powerful than classical analysis procedures to describe the behaviour of complex time series. It therefore also constitutes a sound perspective for generating prediction (i.e., temporal upscaling). It should nevertheless be underlined that the enhanced (i.e., relative to classical approaches) power of AI to fully describe a time series, even when not fully considering its controlling factors, may instead be misleading. This potential bias should explicitly be considered when performing predictions based on AI generated procedures.

When direct observations remain scarce, which is likely to be the case for benthic ones, spatiotemporal upscaling relies on a sound understanding of the factors/processes controlling the component to be upscaled. The control of benthic biological compartments and biogeochemical processes, rely on complex interactions between physicochemical, biogeochemical and biological variables taking place over various spatiotemporal scales both in the water column and in the sediment. These interactions can be addressed through observation providing that a true interdisciplinary approach is deployed according to an *a priori* defined strategy designed to optimise the crossing of physical, biogeochemical and biological variables/processes. the JERICO community has clearly adopted this interdisciplinary perspective and started to contribute to its field implementation through (i) the developments of integrated equipment (e.g. ACOBS for the observation of benthic systems during JERICO-S3), and (ii) the tackling of specific research axes in JERICO-S3 Pilot Super Sites. Within JERICO-S3, these research axes, however, have mostly dealt with the water column and have not explicitly taken in consideration the tight interactions linking benthic and pelagic coastal systems. The *a priori* definition of a sampling strategy in response to a more holistic perspective thus certainly still constitutes a major (if not the key!) challenge for the improvement of the identification of the controlling factors of spatiotemporal changes in (benthic) compartments and processes and thus to their upscaling.

2.5 Chemicals and contaminants

Coastal monitoring of chemical contaminants serves several purposes including (1) detecting and tracking pollutants to understand their fate and distribution in the marine environment, (2) ensure the safety of coastal waters for recreational activities and the consumption of seafood, (3) compliance with regulatory guidelines and quality standards, including for industrial discharges at sea, (4) early warning system to identify the emergence of potential contaminants of interest for timely mitigation measures, and (5) to evaluate the exposure and impact of chemicals on marine organisms. Overall, coastal and marine monitoring plays a crucial role in maintaining the well-being of both ecosystems and human populations.

The regulatory context for the assessment of anthropogenic contaminants presence and impact on the marine environment (coastal and territorial waters) includes two European directives, the Water Framework Directive (WFD) and the Marine Strategy Directive (MSFD)[7]. Specifically, the MSFD requires European member states to demonstrate through GES descriptor 8 that "Concentrations of contaminants are at levels not giving rise to pollution effects". It has been proposed that chemical and biological effects procedures developed in monitoring programmes under the guidance of the Convention for the Protection of the Marine Environment of the North- East Atlantic (OSPAR), Baltic marine Environment Protection Commission (HELCOM) and Convention for the Protection of the Mediterranean Sea Against Pollution (MEDPOL) be used as starting point for the assess GES descriptor 8.

Presently no chemical contaminants are measurable automatically by dedicated sensors, and sampling for contaminants assessment in the lab is mostly done using ships and costly time at sea.

New approaches for automatic sampling have recently appeared and are either based on passive sampling or on water sampling and preservation methods.

[7] https://environment.ec.europa.eu/system/files/2023-04/C_2023_2203_F1_COMMUNICATION_FROM_COMMISSION_EN_V5_P1_2532109.PDF

2.5.1 Passive sampling of contaminants:

In this context, observational marine infrastructure and platforms such as buoys, gliders or Ferrybox systems have been used for the measurement of contaminant levels in the marine environment. Fixed infrastructure such as buoys and moorings, particularly those in remote areas or for sampling at great depths, can be used for time-integrated measurements through the deployment of **passive sampling devices**. These devices are designed to accumulate over time contaminants from the water they are exposed to. Samplers are then brought back to the laboratory where these are extracted and analysed for chemicals of interest. It is then possible with appropriate calibration to estimate freely dissolved concentrations of contaminants in water. For example, within this project and through the 2nd TA call, access to moorings (HCMR Buoy & HCMR POSEIDON calibration Lab, Greece) in the Mediterranean Sea was provided to RECETOX/Masaryk University (Czech Republic) for the deployment of passive sampling devices (project *ASE-NOPAH: Levels and air-sea exchange of nitrated and oxygenated polycyclic aromatic hydrocarbons in the marginal sea of Europe*). In this case contaminant measurements were made in air and in water allowed to calculate air-water concentration gradients.

Routine passive sampler deployments onto buoys and moorings can easily be integrated into larger monitoring networks such as within the AQUA-GAPS initiative (Lohmman et al., 2017; Lohmann et al. 2023). Passive samplers provide an excellent approach for standardising contaminants measurements in the aquatic environments enabling mapping concentrations of chemicals on a large spatial scale or with depth (Lohmann et al., 2023; Allan et al., 2021; Booij et al., 2014). Challenges with deployments on fixed structures include for example the possible contamination of the samplers during deployment and retrieval operations onboard vessels. Some progress has been made regarding deployment cage design and procedures to limit the possibility of contamination.

While fixed infrastructure is ideal for passive sampler exposures, proposals and trials of the use of ships of opportunity and (custom-made) online Ferrybox systems or gliders have been conducted for deploying passive samplers (Allan et al., 2011; Suberg et al., 2014; Vrana et al., 2018). These original tests undertaken during a cruise on the Danube River were followed by the use of a similar system on board research vessels in the Black Sea and the Southern Atlantic Ocean (Sobotka et al., 2021). Passive sampler deployments on fixed structures in the marine environment are generally undertaken for periods of months to years. Exposure procedures have had to be modified in order to obtain meaningful data based on a ship's movement by shortening exposure times substantially. The data become spatially integrated rather than time-integrated. While these systems have been successful on an individual sampling campaign basis, they have yet to be integrated formally into Ferrybox units.

2.5.2 Water sampling and preservation

Mobile platforms such as Ferrybox systems or gliders are generally more amenable to the automatic collection of discrete samples such as with the use of the **WASP** (Water Sample filtering and Preservation device) enabling non-realtime high frequency measurements through automated sample filtering and preservation of water samples for further lab analysis (Task 7.3.3). Discrete, high frequency seawater sampling making use of ship's pumped intake seawater to obtain samples for organic contaminant measurements back at the laboratory to be able to investigate the spatial distribution of contaminants over wide spatial scales (Brumovský et al., 2017; Brumovský et al., 2016; Brumovský et al., 2022). However, some challenges remain since in many cases some human manipulation is needed in the process, only limited levels of sample processing is possible onboard the ship, some preservation is needed to avoid the degradation of the chemicals of interest between sample collection and extraction/analysis, and possible sample contamination from the ship's seawater intake. Unless some sample filtration or pre-concentration on-site/online is possible, sample volumes remain limited and this can limit the sensitivity of the analysis, which needs to be optimum for seawater conditions with low contaminant concentrations expected in the remote marine environment. Not mentioned so far, mobile structures such as Ferrybox can be used for sampling microplastic contamination in surface seawater. Systems are based on integrating filtering units into Ferrybox that can allow the processing of the substantial volumes of water (10s m^3 level) needed to obtain representative data.

2.6 *Needs for integration of data*

Effectively observing and describing coastal processes requires a holistic approach that integrates physical, biogeochemical, and biological observations across multiple spatial and temporal scales. integrating observations is essential for gaining a comprehensive understanding of the complex interactions and processes occurring within coastal ecosystems. The integration of these different observational domains allows researchers to unravel the interconnectedness of physical drivers, biogeochemical cycles, and biological responses, providing valuable insights into the functioning and resilience of coastal marine systems. It allows us to better understand and describe the complex interactions and feedback between different components of coastal marine systems.

Achieving a comprehensive understanding requires careful consideration of spatial and temporal sampling strategies, as well as the transfer of scales between different observational domains. Coastal environments exhibit considerable spatial heterogeneity due to variations in bathymetry, coastline morphology, and hydrodynamic processes. As a result, observation strategies must account for this spatial variability by strategically deploying observation platforms such as buoys, moorings, Ferrybox, gliders across different coastal zones.

Furthermore, coastal systems are characterised by dynamic temporal variability, driven by factors such as tides, seasonal changes, and episodic events like storms and heatwaves. Effective temporal sampling involves conducting observations over multiple time scales, ranging from high-frequency measurements to long-term monitoring programs. By capturing temporal variations in physical, biogeochemical, and biological parameters, one can elucidate the underlying drivers of ecosystem dynamics and assess their response to environmental change.

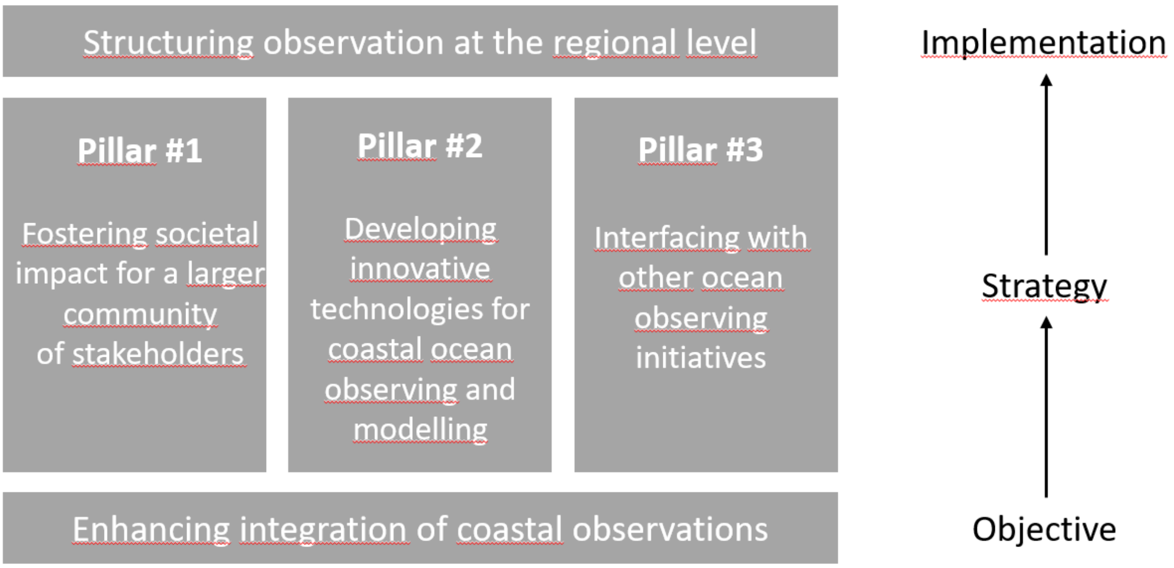
Moreover, integrating observations across different spatial and temporal scales is essential for understanding the transfer of processes and phenomena within coastal marine systems. For instance, physical processes such as coastal upwelling and estuarine circulation can influence the distribution and transport of nutrients and organic matter, which in turn regulate biogeochemical cycling and primary production. Similarly, biological processes such as phytoplankton blooms and larval dispersal can impact ecosystem structure and function at local and regional scales, affecting nutrient dynamics and ecosystem services.

Achieving seamless integration across scales requires innovative approaches such as hierarchical sampling designs, nested observation networks, and data assimilation techniques. Hierarchical sampling designs involve collecting data at multiple spatial and temporal resolutions, with finer-scale observations nested within broader-scale monitoring efforts. This approach allows researchers to examine processes occurring at different scales simultaneously, facilitating the identification of cross-scale interactions and feedback within coastal systems.

Data assimilation techniques aim to integrate observational data with numerical models, providing a consistent framework for analysing and interpreting coastal processes across scales. By assimilating observations into model simulations, one can improve the accuracy of model predictions, constrain uncertainties, and enhance our understanding of complex coastal dynamics.

By strategically sampling coastal environments and transferring scales between different observational domains, researchers can gain insights into the drivers and dynamics of coastal ecosystems, informing management and conservation efforts aimed at preserving these valuable and vulnerable habitats. Embracing interdisciplinary collaboration, technological innovation, and data-driven approaches is a keystone for advancing our understanding of coastal marine systems and ensuring their long-term sustainability.

The development of digital twins of coastal marine systems represents an emerging approach to integrate and simulate the complex interactions between physical, biogeochemical, and biological processes in coastal environments. Digital twins are computational models that replicate the behaviour and dynamics of real-world systems, incorporating data from diverse observational sources to provide a virtual representation of coastal marine ecosystems.



By developing digital twins of coastal marine systems, researchers can simulate and predict the response of coastal ecosystems to environmental changes, anthropogenic stressors, and management interventions. These models enable scenario testing, risk assessment, and decision support for coastal management and policy-making, helping to optimise conservation strategies, mitigate impacts, and enhance the resilience of coastal ecosystems to future challenges.

The requirement for integration of data to better address scientific and societal needs is at the heart of the JERICO Science strategy (Figure 7). But both the societal, political and technological contexts around the development of JERICO have very much evolved the last years, bringing new expectations on the contributions and services to be provided by the RI, as well as new opportunity in terms of the applications of emerging enabling and disruptive technologies for the observation of coastal ocean. These are topics discussed in the following sections.

3 Technology revolutions

We foresee a revolution in the way we observe, connect, share and utilise ocean data (EMB, 2019).

Novel technologies and data handling methods are transforming our daily lives. We live in the Fourth Industrial Revolution defined by a holistic technological momentum that integrates a physical, digital revolution (digitising, automation and robotics, smart solutions, IoT-enabling AI, imagery and visualisation) and a biological revolution (biotechnology revolution including the bacterial factory, DNA-based technology, and omics at large). The following sections, not trying to be exhaustive, provide some key elements on what these two revolutions could be game changers in the way one observes the coastal ocean, and current barriers that are foreseen to be removed through the implementation of these technologies.

3.1 *The Digital revolution*

The digital revolution encompasses several key technological breakthroughs such as the development of the Internet-of-Things framework (IoT), the emergence of Artificial Intelligence (AI), both having significant impact on robotics and automation, and edge computing. These technologies represent a transformative leap in marine data collection and analysis for experts in the field. **IoT** enables creating an extensive network of interconnected systems and sensors, capable of providing high-resolution spatial and temporal data critical for comprehensive coastal research. **AI-driven analytics** significantly may enhance the ability to process and interpret the massive datasets generated by these IoT networks. Machine learning algorithms are particularly adept at recognizing patterns, detecting anomalies, and making predictive analyses, which may become crucial for anticipating and mitigating events like harmful algal blooms, marine heatwaves, and shifts in biodiversity. The application of AI is expected to enable researchers to extract actionable insights from complex datasets, fostering a deeper understanding of marine processes and improving the accuracy of predictive models. **Edge computing** may further optimise ocean observing systems by processing data locally at or near the data source. This approach minimises latency, reduces bandwidth requirements, and ensures real-time data analysis and decision-making, even in remote or harsh marine environments where connectivity may be limited. Moreover, Edge devices can preprocess and filter data, sending only the most critical information to central servers, thus enhancing the efficiency and reliability of the data collection process.

3.1.1 How IoT and undersea communication can support coastal observation

The Internet of Things (IoT) and improved undersea communication technologies are enabling a new era of coastal ocean observation. Cost-effective sensor systems, platforms and communications are allowing for distributed observation systems that provide data on areas previously poorly monitored, by addressing e.g., connectivity, self-described sensor systems, self-awareness, interoperability standards. These systems will soon be able to quickly adapt to changing stakeholder needs and environmental conditions (Mariani 2021). IoT platforms for ocean observation buoys that integrate various sensors and communications interfaces are being developed. These platforms support sensor registration and management, and multi-hop relay networks that provide greater communication coverage than previous systems. Experiments show these networks can accurately collect and transmit data (Kim 2017). There is a push toward co-designing modular, low-cost instrument architectures for coastal observation that leverage available technologies. These instruments could meet the needs of researchers, stakeholders and educators, providing data for model calibration, validation and monitoring (Marcelli 2021). Low-cost "IoT" tide gauge networks that provide real-time and delayed sea-level data are being tested to support coastal monitoring (Knight 2021).

In Delory & Pearlman (2019) several methods have also been documented to enhance the connectivity of sensors and platforms, most being still at a maturity level (a.k.a Technology Readiness Level - TRL) that has not allowed for full adoption by the research community, while the industrial sector is still in an exploratory phase, a phase before evolving from conventional technologies that deliver on some objectives (e.g. reliable data and command communication) to more advanced technologies (i.e. semantically rich) that have not fully developed or been agreed upon.

Sensor Web Enablement (SWE) standards and related are yet to be implemented at observatory (not only marine) and sensor level (Kotsev et al., 2018). IoT standards also evolve in the computing and consumer market industry, offering new opportunities and challenges for observing system operators and developers. These developments can be a source of inspiration for the design of underwater communication between autonomous systems. An overview of the potential has been addressed in a so-called *smart-ocean*, based on an underwater Internet of Things in Qiu et al. (2020).

New instruments for BGC and biology are continuously being developed, responding to the need for more data in order to better understand and manage ecosystems. These sensors, some being bulky and power hungry, will benefit from developments in miniaturisation, interoperability, self-awareness (adaptive sampling), and, consequently, greater autonomy for longer term missions.

Recent progress has also been made in integrating sensor data in ERDDAP[8] in near real-time, which will certainly offer an interesting path for connecting sensor data to oceanographic data services, with the derived benefit of having both historical and real-time data available from a single interface.

To respond to new requirements, the JERICO community, through the JERICO-S3 project, has built a system based on a generic instrumentation module (EGIM) developed in EMSO-ERIC (Lantéri et al. 2022). A coastal module was derived, with enhanced interoperability and sensor integration for biology and BGC, and adaptive sampling. While several issues remain, such as the maintenance, autonomy and reliability of autonomous systems, these advances are setting new paths that will require collaboration between operators and developers for co-design, co-development and validation.

3.1.2 AI and smart systems

The recent advances in Artificial Intelligence (AI) are having a positive impact on the scientific discoveries (e.g., supporting scientists generating new hypotheses and designing experiments), and new advanced data analysis tools. They have also promising applications in the field of automation and steering of complex IoT-based observing systems, allowing the acquisition of large datasets and providing their interpretation as well as providing insights that might not have been possible using traditional scientific methods alone (Wang et al 2023).

As AI needs a vast amount of data for training, data-rich environments provide for more opportunities to advance their domain of knowledge and allow AI based approaches to perform autonomous intelligent actions. This is true especially for the Machine Learning approaches (ML) where algorithms are designed to learn patterns in the available data and then apply this knowledge to new data (EC 2018).

[8] https://coastwatch.pfeg.noaa.gov/erddap/index.html

The huge amount of data produced by underwater observatories is fostered by the complexity of the coastal environment, from which heterogeneous biological and environmental measurements are acquired for explaining the physical characteristics and the functioning of the marine ecosystems (Orr et al. 2020, Griffiths et al. 2020). Consequently, a variety of sensors have been developed for acquiring different environmental parameters and a variety of platforms have been also developed for hosting these sensors (Aguzzi and Marini et al. 2019, Aguzzi and Marini et al. 2022). Nevertheless, the marine science community urges novel and effective observing technologies beyond the traditional vessel-assisted, time-consuming and high-cost sampling surveys allowing the acquisition of large datasets distributed in space and extended in time (Farcy et al. 2019, Aguzzi and Marini et al. 2019, Dañobeitia et al. 2020). To achieve fully operational intelligent services for the marine science community, IoT and SWE compliant observatories need to be improved with AI-based methodologies capable to capture and manage the complexity and the non-linear dynamics typical of marine environment (Jahanbakht et al. 2021, Delory et al. 2021, Marini et al. 2022). At the same time data analysis techniques based on AI have to be used to bridge ocean data and knowledge exploiting the large scientific data repositories collecting the "Blue Big Data" (Ge Chen et al. 2022, Han et al. 2023).

While several survey publications listed the current status of AI methodologies used by the marine science community (Malde 2020, Beyan and Browman 2020, Jiang and Zhu 2022, Rubbens et al, 2022, Song et al. 2023), many other AI topics are not yet in use in the marine domain and need to be included to advance the current observing systems and data analysis procedures. A synergistic future for AI and ecology is discussed in (Han et al 2023), while many relevant topics dealing with the use of AI for data generation, representation and annotation, as well as generation of scientific hypotheses and AI-driven experimentation and simulation are summarised in (Wang et al. 2023). Also, AI-based data processing tools for ocean variable forecasting, like for example biogeochemical variables (e.g., CANYON ANN from Sauzède et al., 2017; Fourrier et al., 2020), sea currents, larval or pollutant dispersion and harmful algal blooms occurrence, can support coastal stakeholders in making decisions with high social impact. Nevertheless, decisions based on "black box" AI tools, like for example Convolutional Neural Network (CNN), cannot be considered fully reliable. This limit can be overcome by using methodologies based on eXplainable Artificial Intelligence (XAI) as discussed in (Guidotti et al. 2018, Dwivedi et al. 2023). Other AI-based approaches deal with the capability to process the data on board the observing system, as close as possible to the source that originated the data, as described in the context of Edge Computing (Zhang and Tao 2021). These approaches allow the development of underwater observing systems capable of sensing the surrounding environment and to adapt their behaviour according to dynamics of the water parameters and to user defined missions (Delory et al. 2021, Marini et al. 2022). Ditria & Connolly (2002) has provided a synthesis of research and application areas that could benefit from AI-enabled automation (Table 5).

Table 5 - Summary of areas of research that have substantial gaps and challenges in marine ecosystems that require further research to create useful tools to assist conservation management through automated monitoring facilitated by artificial intelligence (Ditria et al, 2022).

	Process step	AI/Automation technology	Gaps	Challenges
Monitoring	Data collection	Cameras UAVs eDNA Remote sensing	•Collecting big data on animal response to restoration efforts across appropriate spatial and temporal scales	•New technologies may be prohibitively expensive: eg eDNA •Processing bottlenecks •Cost results in inappropriate monitoring designs implemented
	Data transfer	Edge computing, underwater networks, cabled observatories	•Scalability and feasibility of edge computing in marine environments	•Infrastructure is costly to implement •Marine-specific environmental challenges eg short transfer distance •Big data transfer and storage needs
	Data processing	Computer vision/Deep learning	•Scalability and accuracy of models to answer ecological questions by integrating deep learning model outputs •Investigating alternative solutions to marine-specific challenges such as varying water visibility •Automated sizing using stereo-cameras	•Limitations of small training datasets •Marine-specific environmental challenges •Cost of marine-related site accessibility restricting the breadth of studies eg boating and diving costs.
Evaluation and decision support	Data summary and analysis	Data visualisation	•Data-driven modelling for analysis of true "big data" from raw data inputs •Exploiting newly available capabilities of big data analysis	•Biases in big data collection can lead to misleading results •Requires the possible creation of new metrics and methods of data analysis
	Predictive models and adaptability	Data driven modelling and reinforcement learning	•"Opening the black box" for ML model interpretability •Reinforcement learning using continuous streaming of raw data	•ML model interpretability may be difficult depending on the complexity of the data input •RL is computationally challenging and expensive •Lack of 'true' big data to implement RL effectively
	Decision making support	Adaptable user interfaces	•Easily interpretable information *via* user interfaces to facilitate decision making	•Possibly expensive and outside project budget •May need ongoing maintenance and flexibility for adaptive management approach
Other	Social challenges	NA	•Education on AI technologies and capabilities •Appropriate upskilling of staff	•Wariness of new technology and implications for jobs •Possible high initial costs associated with upskilling staff
	Centralisation of data and data sharing	Data integration	•Creation and implementation of standardised reporting frameworks •Democratisation of data	•Lack of global-cooperative efforts in standardisation due to varying opinions and resources •Organisation intellectual property rules and lack of centralised databases and frameworks for effective data sharing

The European Marine Board advocated for a continued development of automated smart ocean sensors to work towards creating an *Ocean Internet of Things*, particularly for biological parameters (e.g. automated optical sensors), which are typically less well suited for automation. This will enable the collection of truly big data sets for which more complex analyses can be carried out (EMB, 2020).

3.1.3 Edge computing

Edge computing is all about placing workloads as close as possible to where data is being created or where the end user needs it. It seeks to address the problems of data in motion by limiting the need for long-distance transfers. Rather than backhauling large amounts of raw data to be processed in the cloud or data centre, computing occurs on-site. This reduces strains on centralised networks, which can lead to delays and service disruptions. Depending on the use case, edge computing can involve data storage for later analysis, purging irrelevant data and running applications to synthesise insights and inform real-time decisions by machines or operators.

An ocean observing system is a typical edge device. It is remote, often disconnected from a data centre (except for cabled observatories) and generates loads of data. Outfitting it to function as an edge device, with local compute, unlocks a host of operational benefits, including reduced latency, greater security and lower transport costs. The idea behind edge-hosted payloads is to reduce the need for data to make multiple round trips to a terrestrial-based cloud.

- Edge computing may enable reducing the time between sensor measurement and decision-making, which is critical to latency-sensitive applications, like communication and autonomous systems. This feature is critical in the growing field of onboard AI/ML applications, such as AUV navigation, analysis of environmental or technical situational awareness (e.g., condition-based monitoring. condition-based maintenance), and adaptive sampling.

The synergy of IoT, AI, and edge computing is expected to empower operators of coastal observing systems and coastal researchers with robust tools for real-time environmental monitoring, rapid response to ecological changes, and enhanced data-driven decision-making.

3.2 The genomics and biotech revolution

3.2.1 Molecular ecology & genetic biodiversity

One of the most recent progresses in tackling marine biodiversity has been through omics. By using cellular-level molecular biology to investigate DNA, RNA, proteins, and metabolites, researchers can identify and quantify life in the ocean — from tiny toxic algae and microorganisms to the largest whales. Environmental omics provides a picture of ecosystem health and set the stage for more comprehensive water safety management, fisheries management, biodiversity monitoring, and large-scale conservation habitat efforts.

Any seawater sample contains Environmental DNA (eDNA). The analysis of eDNA allows for studying the community present in a given water mass and to detect presence and abundance of a target species. There are several steps involved in an eDNA analysis project on which the accuracy of the results depends (Figure 8)

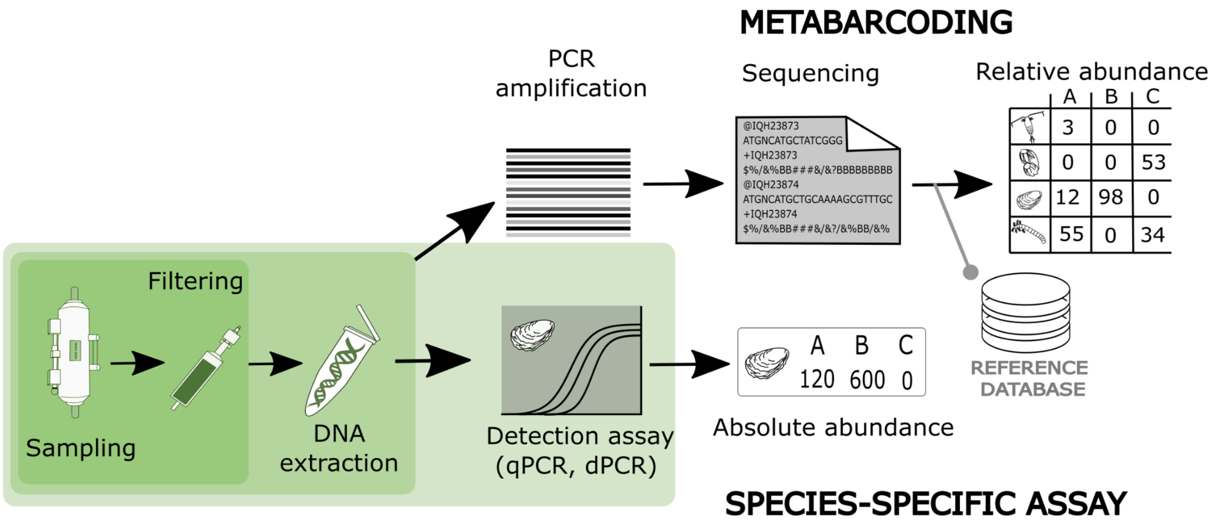


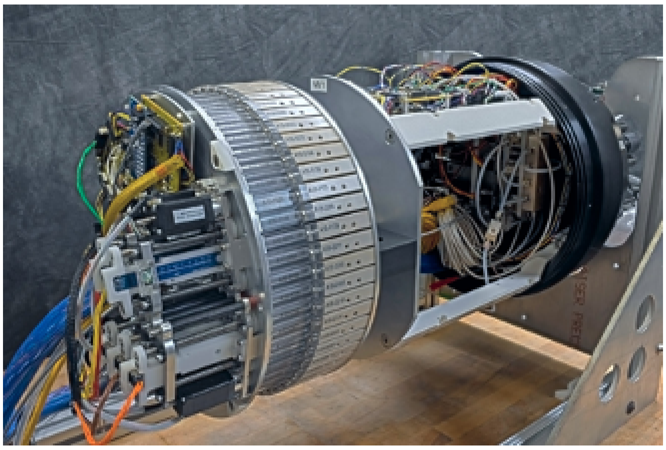
Figure 8 - Steps involved in any eDNA analyses. The green squares indicate the processes that can be covered by the automated samplers which can be only designed to filter water and store filters, to filter water and extract and store DNA or to filter water, extract DNA and perform qPCR assays for species detection.

a) Automatic sampling for omics analysis

There are different autonomous samplers that can take water samples that can then be analysed later when the samples are retrieved. The limiting factor is the sample capacity. Phytoplankton Sampler by McLane has the capacity for 24 water samples and can be deployed for 14 months. The Mclane device has been the basis for the WASP device, developed for eDNA sampling and preservation and integrated to Ferrybox system in the context of JERICO-S3 (WASP). There are several other devices and initiatives, such as the TechOceanS project[9], which has developed an eDNA sampler called Robotic Cartridge Sampling Instrument (RoCSI), collecting and preserving at least 50 samples, also commercially launched by McLane Labs. Hendricks et al. (2023) also describe an autonomous eDNA sampler that is commercially available through Dartmouth Ocean Technologies Inc., capable of storing 9 samples on a cassette that is easy to remove and change on site.

b) Onsite eDNA analysis

Although most studies performed so far require an active sample acquisition and processing, there are several ongoing initiatives which have made significant progress towards automated sampling and analysis of eDNA. One of the pioneers on the development of such devices is the Monterey Bay Aquarium Research Institute (MBARI), which developed the Environmental Sample Processor (**Error! Reference source not found.**) which is commercially available through McLane Labs.



The status of these technologies and future avenues was thoroughly discussed during a Workshop at MBARI on Marine Omics Technology and Instrumentation. The workshop joined together technology developers and users and several of the available and in development samplers were presented such as the RoCSI (by Julie Robidart), Smith Root (Austen Thomas), Pufferfish from Aquatic Labs (Allan Adams), SADIe (Kim Parsons), among others. During the three-day workshop several aspects for the future of autonomous samplers for omic technologies were discussed and by the end it was evident for everyone that a sentence raised by MBARI president and CEO Chris Scholin still holds: "There's no single sensor or sampler technology that can solve all of our problems. The future lies in finding the right combination of devices and the platforms on which they are deployed to address specific use cases.". Yet, this does not prevent the need for developing standardising processing pipelines and harmonising data acquisition, for which initiatives are currently ongoing such as the Ocean Best Practices Task Team on Omics/eDNA Protocol Management[10].

3.2.2 Bio- and Genosensors

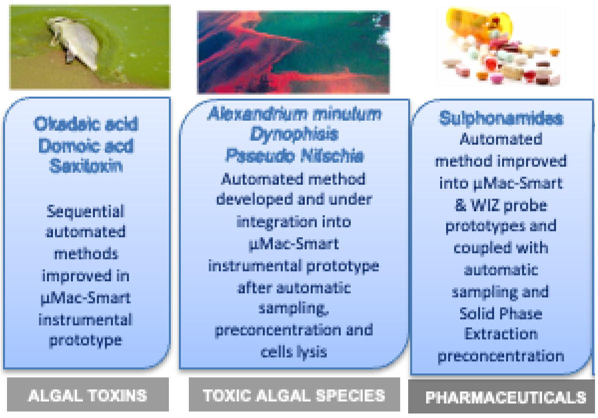
a) Innovation in emerging pollutants using biosensors

In section 2.5, we presented the state-of-the-art in pollutant measurements, for which only sampling techniques are available with the aim of increasing the frequency of measurement in space and time, and of reducing the costly time at sea. Omics-based biotechnologies have the potential to revolutionise the quantification of pollutants in-situ (i.e., directly at the site of interest) and

[9] Announcing RoCSI eDNA Sampler - McLane Labs

[10] https://www.oceanbestpractices.org/ocean-best-practices-systems/our-work/task-teams/omics/

automate this process in the future. Here the term "Pollutants" encompass both chemical contaminants (e.g., heavy metals, Persistent organic pollutants – POPs, pharmaceuticals, hydrocarbons) and biological substances considered as contaminants (e.g., algal toxin, toxic algae, pathogens).



Biosensors and Environmental Genomics: Omics techniques, particularly genomics and proteomics, can be integrated into biosensor platforms for real-time detection of pollutants. Biosensors utilise biological components such as enzymes, antibodies, or whole cells to recognize and bind to specific pollutants, triggering a measurable response. By incorporating genomic information into biosensor design, researchers can engineer biosensors with enhanced specificity and sensitivity. For example, synthetic biology (bacterial factory) approaches can be used to sensorise modified microbial communities into biosensors that express specific genes in response to pollutant exposure, producing a detectable signal. This integration of genomics with biosensors enables rapid and accurate quantification of pollutants directly in the environment.

Metagenomics for Environmental Monitoring: Metagenomics, which involves the study of genetic material recovered directly from environmental samples, provides a powerful tool for assessing microbial communities and their responses to pollution. Metagenomic analysis can reveal the presence of pollutant-degrading microorganisms and their functional genes within a given ecosystem. By monitoring changes in the abundance and activity of these microbial populations over time, researchers can infer the level of pollutant contamination and the effectiveness of remediation strategies. Advances in sequencing technology, such as portable nanopore sequencers, enable on-site metagenomic analysis, allowing for real-time monitoring of microbial diversity and function in response to environmental perturbations.

Metabolomics for Pollutant Detection: Metabolomics, the study of small molecules or metabolites within cells or organisms, offers a complementary approach to omics-based pollutant quantification. Exposure to pollutants can induce changes in the metabolic profiles of organisms, leading to the production of specific metabolites as biomarkers of contamination. By analysing the metabolome of organisms or environmental samples, researchers can identify signature metabolites associated with pollutant exposure. Metabolomics techniques, such as mass spectrometry and nuclear magnetic resonance spectroscopy, can be applied in-situ to quantify pollutant metabolites rapidly and accurately, providing valuable insights into environmental pollution levels.

Integration with Remote Sensing Technologies: Omics data can be integrated with remote sensing technologies, such as satellite imagery and unmanned aerial vehicles (UAVs), to monitor pollutant distribution and dynamics over large spatial scales. Remote sensing allows for the detection of physical and chemical parameters indicative of pollutant presence, such as water turbidity, chlorophyll concentration, and surface temperature. By combining omics-derived information on pollutant sources and microbial responses with remote sensing data, researchers can develop predictive models to estimate pollutant loads and track their movement in coastal waters in real-time.

Omics technologies hold great promise for advancing the quantification of pollutants in-situ and automating this process in the future. By integrating genomics, metagenomics, proteomics, and metabolomics with innovative sensing platforms and remote monitoring technologies, we can develop robust tools for assessing environmental pollution levels, guiding remediation efforts, and safeguarding coastal ecosystems

3.3 *Promising approaches and innovations*

Lab-on-Chip (LoC) technology represents a significant advancement in the field of environmental monitoring, offering the potential for rapid, on-site analysis of water samples with high sensitivity and specificity. LoC devices, also known as microfluidic chips, miniaturise and integrate multiple laboratory functions onto a single chip-scale platform, enabling the automation of complex analytical processes.

In the context of coastal water monitoring, LoC technology holds immense promise for the detection and quantification of pollutants, pathogens, and other environmental parameters. Here's how LoC technology works and its relevance to coastal water monitoring, with reference to the technology developed, especially, at the NOC (Southampton) for nutrients and carbonate system variables, Monterey Bay Aquarium Research Institute (MBARI).

Miniaturization and Integration: LoC devices consist of microchannels, chambers, valves, and sensors fabricated on a small chip, typically made of materials such as glass, silicon, or polymer. These microfluidic components are designed to perform specific analytical tasks, such as sample preparation, chemical reactions, and detection, in a highly controlled and efficient manner. By integrating multiple functions onto a single chip, LoC devices streamline the analytical workflow, reduce sample and reagent consumption, and minimise the risk of contamination.

High Sensitivity and Specificity: LoC devices leverage miniaturised sensing technologies, such as fluorescence, electrochemical, and optical detectors, to achieve high sensitivity and specificity in pollutant detection. For example, MBARI researchers have developed LoC-based biosensors capable of detecting marine toxins, heavy metals, and organic pollutants at trace levels in seawater samples. These biosensors utilise specific biomolecules, such as antibodies or DNA probes, to selectively capture and quantify target analytes, enabling rapid and accurate detection without the need for extensive sample processing or laboratory infrastructure.

Figure 10 - Optical biosensor scheme strategies for heavy metal (HM) ion detection in water (Aloisi et al., 2019).

Real-time Monitoring: One of the key advantages of LoC technology is its capability for real-time, continuous monitoring of environmental parameters. LoC devices can be deployed directly in coastal waters or integrated into autonomous underwater vehicles (AUVs) and remote sensing platforms for in-situ analysis. By interfacing LoC sensors with wireless communication systems, researchers can transmit data in real-time to shore-based laboratories or decision-makers, facilitating timely responses to environmental threats and informing adaptive management strategies.

Customization and Scalability: LoC technology offers flexibility for customization and scalability to address specific monitoring needs and environmental challenges. Researchers can tailor the design of LoC devices and the selection of sensing elements to target a wide range of pollutants and environmental parameters relevant to coastal water quality. Furthermore, advances in manufacturing techniques, such as 3D printing and soft lithography, enable rapid prototyping and mass production of LoC devices at relatively low cost, making them accessible for widespread deployment in coastal monitoring networks.

MBARI's contributions to LoC technology for coastal water monitoring have been significant, with research initiatives focused on developing portable, field-deployable biosensors and microfluidic platforms for detecting harmful algal blooms, marine pollutants, and microbial contaminants. For example, MBARI scientists have demonstrated the use of LoC-based PCR (polymerase chain reaction) assays for the rapid detection of genetic markers associated with harmful algal species, allowing for early warning of bloom events and proactive management measures.

In conclusion, Lab-on-Chip technology represents a transformative approach to coastal water monitoring, offering the potential for high-sensitivity, real-time analysis of pollutants and environmental parameters in situ. Through continued innovation and collaboration between researchers, technologists, and stakeholders, LoC devices have the capacity to revolutionise our understanding of coastal ecosystems and support sustainable management practices for coastal waters worldwide.

4 Prospective 2040 for coastal observation

In 20 years, coastal ocean observing systems are poised to undergo a significant transformation driven by advancements in technology, including the Internet of Things (IoT), artificial intelligence (AI), automation, and biotechnology. These innovations will revolutionise how we monitor, understand, and manage coastal environments.

Based on the above overview, a prospective view of the coastal observation at the horizon 2040 is drawn. The result of such an exercise is by essence subjective, and in our case is very much related to the nature and strategy pursued by JERICO.

We hope that these conclusions may lead to fruitful discussion in the coastal observation community at large, and help converging on priorities to be addressed on the short-, medium- and longer terms.

4.1 *The coastal observing systems of the future*

The future coastal observing system will be an integrated network combining IoT, AI, automation, and biotechnology to provide a holistic view of coastal ecosystems. Key features will include:

1. **Real-Time Monitoring**: Continuous, high-resolution data streams from a multitude of sensors will provide an up-to-the-minute picture of coastal conditions. This data will be accessible to scientists, policymakers, and the public through user-friendly platforms and mobile apps.
2. **Predictive Analytics**: AI-driven models will predict environmental changes, allowing for proactive management strategies. These models will integrate data from various sources, including satellite observations, weather forecasts, and historical records, to provide comprehensive predictions.
3. **Automated Data Collection**: AUVs, drones, and robotic platforms will autonomously collect data, reducing the need for manual sampling and increasing the efficiency and coverage of monitoring efforts. These systems will operate around the clock, providing continuous insights into coastal dynamics.
4. **Biotechnological Innovations**: eDNA analysis and biosensors will offer new ways to monitor marine life and ecosystem health. These technologies will provide detailed information on species diversity, population dynamics, and ecological interactions, contributing to conservation efforts and biodiversity management.
5. **Community Engagement and Citizen Science**: Advances in technology will also empower citizen scientists to contribute to coastal monitoring. Affordable, user-friendly sensors and mobile apps will enable individuals to collect and share data, enhancing the overall observation network and fostering a greater connection between communities and their coastal environments.

The following game changers are expected to happen in the next 20 years:

The integration of **IoT** will enable the deployment of a vast network of interconnected sensors and devices in coastal regions. These sensors will continuously monitor a wide array of physical, biogeochemical, but also biological parameters. IoT-enabled devices will provide real-time data streams, allowing for continuous and comprehensive environmental monitoring. This real-time data will be crucial for early detection of ecological changes, pollution events, and natural disasters, facilitating prompt responses and mitigation efforts.

AI will play a pivotal role in processing and analysing the massive volumes of data generated by IoT devices. Machine learning algorithms will identify patterns and trends that human analysts might overlook, providing deeper insights into coastal ecosystem dynamics. AI-driven predictive models will forecast changes in water quality, fish populations, and the impacts of climate change with greater accuracy. These models will support decision-making processes for environmental management and policy development.

Automation will enhance the capabilities of ocean observing systems by deploying autonomous underwater vehicles (AUVs), drones, and robotic platforms for data collection. These automated systems will operate continuously, even in harsh or remote environments, ensuring consistent data acquisition. Swarm robotics, where multiple autonomous units work in coordination, will enable large-scale monitoring efforts, such as tracking marine species, and surveying underwater habitats.

Advances in **biotechnology** will introduce novel methods for monitoring and assessing coastal ecosystems. Environmental DNA (eDNA) analysis will allow for the detection and identification of marine organisms through genetic material found in water samples. This technique provides a non-invasive way to monitor biodiversity and track the presence of endangered or invasive species. Additionally, biosensors embedded in marine organisms or artificial substrates will detect changes in water quality and ecosystem health, offering real-time biological indicators.

Some highlights and examples are given in the next sessions concerning expected progress on sensors, platforms and exploitation of data.

4.1.1 Integrated, interoperable and smart observing platforms

For appropriately describing coastal processes and environmental conditions, coastal observing systems, such as JERICO, have implemented a multi-platform approach, recognising the value and complementarity of various observing platforms for accessing the four dimensions of these very dynamic and highly variable environments. For example, while FerryBox and HF-radar provide high frequency observation of the sea surface and upper layer, mooring and coastal profilers provide the vertical dimensions, with gliders connecting the four dimensions along specific transects.

The development of complex multi-sensor platforms is a first step towards addressing an ecosystem-based approach. Together with the development of IoT standards and edge computing, it opens for a new world of automation of specific tasks onboard those platforms, related for example to automatic maintenance (e.g., cleansing of biofouling on optical sensors, programming and adjustment of sensor setups, etc. However, one can expect IoT and progress in underwater communication to open new possibilities for interacting, not only between sensors pertaining to one complex system, but also between platforms of different natures. For example, communication between mobile platforms (e.g., FerryBox, UAVs) as they cross or when they are in the vicinity of a fix-platform, pertaining to the same observing systems. Such capability will open for brand-new fields of application and provide new capabilities for optimising observation in space and time. Such capability can be drastically enhanced if edge computing and AI-tools are also available.

IoT, together with automation and robotics is presently unleashing the field of drone applications. In coastal regions, both aerial (Unmanned Aerial Vehicles - UAV), sea-surface (Unmanned sea-surface vehicle, ASV, e.g. SailBuoy, Saildrone) and underwater drones (Autonomous and/or unmanned Underwater vehicles) are being considered for increasing the observation capacity. Energy islands (for instance based on the decommissioning and re-use of offshore platforms) could serve as harbour/airport for those technologies, which would support the autonomous observation of coastal and shelf-seas, far from land.

4.1.2 Accessing poorly observed variables and sensor innovation

While the observation of physical and biogeochemical cEOVs has reached a rather high level of maturation, progress can be expected on cost, energy consumption and interoperability.

Major progresses are expected in the field of **in-situ observation of chemicals and biological variables**, through the maturation of biotechnological solutions based on e.g., omics. The field of environmental biotechnology is just emerging. Prototypes of biosensors and genosensors measuring various chemicals, algal toxins, pathogens or specific species exist, paving the way for future innovations. However, this field of research, development and innovation is just emerging and will benefit from the blooming field of biotechnological applications to environmental issues.

Considering the infinite possibilities arising for the manufacturing of specialised microorganisms for detecting specific substances, one can think that biotechnology will take a prominent role in future environmental sensors. If such technology is generally difficult to put in place (costly investments for the R&D phase), they can be rather inexpensive to produce and to operate while mature.

One can expect such biosensors to make a leap in accessing information on the biotic environment in coastal regions, with fit-for-purpose (operational) observation frequency, or even in realtime, through synergy with other communication and processing technologies (see next section).

The existing prototypes of biosensors mentioned above, are all based on microfluidics and bioassays, and therefore presently limited in terms of number of samples to be processed before maintenance. This is a major limitation that one can expect to be overcome in the next ten years. Meanwhile the development of IoT-enabled AI and edge computing will soon allow unmanned steering of sensors based on smart solutions. For instance, one can foresee that, in the future, biosensors integrated into an IoT-based observing system will be piloted by the system itself and triggered only when the environmental conditions determined in realtime by observations from physical and biogeochemical variables, processed through AI-tools, will indicate that the likelihood for occurrence of a biological phenomenon is significant. Such capability, very much linked to the field of adaptive sampling, will allow longer term deployment of biosensors by optimising the use of the onboard bioassays. One can also think that solutions for renewing (cleaning, etc.) of bioassay plates will become available, as well as lab-on-chip solutions miniaturised enough to fit into easy-to-handle sensors.

The development of the environmental biotechnology is foreseen to be a game changer for the observation of the dynamics, distributions and fate of chemical and biological contaminants, thereby providing improved understandings of the processes they contribute to, crucial contributions to ecosystem-based DTOs, and to the management of environmental threats in coastal regions.

4.1.3 Accessible sensors and citizen empowerment

In the years to come, citizen science is expected to play a transformative role in coastal observation and observing systems, bringing numerous benefits that enhance scientific research, environmental monitoring, and community engagement.

The most obvious impact of citizen empowerment is related to **expanded data collection**: Citizen scientists can greatly expand the spatial and temporal coverage of data collection. With widespread use of smartphones, drones, and affordable sensors, citizens can gather data on water quality, biodiversity, pollution, and coastal changes. This extensive data collection network will fill gaps in existing observation systems, providing a more comprehensive picture of coastal environments. Furthermore, citizens can help monitor the impacts of climate change, such as sea-level rise, coastal erosion, and extreme weather events. Real-time reporting of these changes through apps and online platforms may allow for quicker response and adaptation measures.

As citizen science projects grow, so will the emphasis on data quality and validation. Standardised protocols should ensure that the data collected by citizens is reliable and scientifically robust. This collaborative approach will help integrate citizen-generated data with traditional scientific datasets, enriching the overall data pool used for coastal management and research. It is foreseen that citizen science may spur innovation in data collection and analysis technologies. The need for user-friendly tools and platforms can lead to the development of **novel and affordable sensors**, mobile applications, and data processing software. For citizen science to effectively contribute to coastal observation and environmental monitoring, the availability of affordable and easy-to-use sensors is paramount. These sensors should empower individuals and communities to collect valuable data, which can be integrated into larger scientific efforts. Affordable sensors lower the barrier to entry for citizen scientists, allowing more people to participate. This democratisation of science will lead to broader data collection efforts, which are essential for comprehensive environmental monitoring. Furthermore, sensors with intuitive interfaces ensure that people with little to no technical background can effectively use them. This simplicity encourages more widespread participation and ensures data collection is not limited to experts.

While the current effort on low-cost sensor is mostly focused on the observation of physical variables, and in particular sea temperature, Citizen science will, in the future, benefit from multi-functional sensors that can measure various parameters such as water quality, temperature, salinity, and pollution levels, hence enhancing the efficiency of data collection efforts and provide more comprehensive environmental insights. Coupling sensors with mobile applications will allow for immediate data logging, visualisation, and analysis, as well as data transmission in real-time to centralised databases or cloud platforms. Users will easily be able to upload data, receive feedback, and participate in broader citizen science networks.

4.2 Better integration and exploitation of existing data

AI is on the path of becoming a major approach for analytics of complex patterns in datasets, for automatic image-based recognition, and for integration of multi-sources, multi-type data.

It is recognized that there is no success with AI without AI-ready data This is often stated in the popular form "Garbage in – Garbage out".

Ocean data will therefore evolve from complying to the FAIR principle to the FAIR-2 principle, meaning FAIR and AI-Ready data. Data readiness for AI is the process of preparing your data for generative AI. For generative AI to be effective, your data must be:

- Understandable with the right context
- Of high-quality - accurate, complete, consistent, timely, unique, free of bias, enriched,
- Well governed to support ethical and compliant use of data
- Available, discoverable and accessible (FAIR)

AI-ready data is a cornerstone for advancing ocean observation systems, enabling the deployment of sophisticated machine learning and AI techniques to enhance our understanding and management of marine environments. For data to be AI-ready, several critical attributes must be met:

1. **High Data Quality**: Ensuring data accuracy, precision, and consistency is paramount. This involves rigorous validation and calibration of sensors, standardising data collection protocols, and maintaining high-resolution temporal and spatial data. High-quality data minimises noise and errors, which are crucial for training robust AI models.
2. **Data Volume and Variety**: AI models thrive on large, diverse datasets. Integrating various types of oceanographic data, including physical (e.g., temperature, salinity), biogeochemical (e.g., nutrient concentrations), biological (e.g., species abundance), and geological (e.g., seafloor topography) data, enhances model training and performance. Comprehensive datasets enable the development of more accurate and generalizable AI applications.
3. **Real-Time Data Accessibility**: Real-time data availability is essential for dynamic applications such as forecasting ocean conditions and detecting anomalies. Autonomous platforms, including gliders, FerryBox, smart buoys, equipped with real-time communication capabilities, ensure timely data acquisition and processing.
4. **Detailed Metadata and Provenance**: Comprehensive metadata, including information on data sources, collection methodologies, and processing steps, is critical for transparency and reproducibility. Well-documented data provenance ensures that AI models can be trusted, and their outputs validated.
5. **FAIRness**: The importance of FAIR (Findable, Accessible, Interoperable, Reusable) data principles for AI-readiness in ocean observation cannot be overstated. These principles ensure that data is structured in a way that maximises its utility for AI applications.
6. **Interoperability and Standardization**: Utilising interoperable data formats and adhering to international data standards (e.g., ISO, OGC) facilitate seamless data integration and sharing among researchers and stakeholders. This enhances collaborative efforts and maximises the utility of datasets across different AI applications.

By focusing on these attributes, the ocean observation community can prepare datasets that are not only ready for AI analysis but also enhance the development of AI-driven tools and solutions, leading to more effective and informed ocean management practices.

This step is paramount for the effective development of Digital Twins of the Ocean, answering to the need for comprehensive ecosystem-based approach, hence

5 Conclusions

By 2040, coastal ocean observing systems will be vastly more sophisticated and integrated, leveraging cutting-edge technologies to provide detailed, real-time insights into coastal environments. This transformation will enhance our ability to protect and manage these vital ecosystems, ensuring their sustainability for future generations.

JERICO intends to be a pro-active actor of these changes through its own expertise on science and technology related to coastal observations. It is foreseen that, as part of its services, JERICO will establish a Technology Oversight service, aiming at being appropriately informed about technological innovation and trends (not limited to coastal oceanography) which could benefit the development, capability and efficiency of the research infrastructure. We anticipate that the full implementation of the JERICO Service: will require yearly evaluation of the prospective view by an ad-hoc multidisciplinary expert committee, supported by an external stakeholder group.

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