INNOVATIONS IN MARINE DATA COLLECTION

CONSEQUENCES FOR ADVICE AND MANAGEMENT

European Fisheries and Aquaculture
Research Organisations

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Preamble

During 2019 an EFARO working group was established to draft a discussion paper on technological developments and innovations in data collection and processing, and potential consequences these may have on the scientific advisory system and marine resource management practices.

We are very grateful to the members of the WG for their time, effort and input.
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Glossary

ABM	Agent-Based Model
AI	Artificial Intelligence
AIS	Automatic Identification System of vessels
AUV	Autonomous Underwater Vehicle
BN	Bayesian networks
CCTV	Closed-circuit television
CFP	Common Fisheries Policy
CKMR	Close Kin Mark Recapture
CS	Citizen Science
EAF	Ecosystem Approach to Fisheries
EBM	Ecosystem Based Management
eDNA	environmental DNA
ERA	Ecosystem Risk Assessments
FAIR	Principles for data to be Findable, Accessible, Interoperable and Reusable
FDF	Fully Documented Fisheries
GES	Good Environmental Status
GFCM	General Fisheries Commission for the Mediterranean
GPS	Global Positioning System
ICES	International Council for the Exploration of the Sea
ISSF	Information System on Small-scale Fisheries
ML	Machine Learning
MSFD	Marine Strategy Framework Directive
NGO	Non-Governmental Organisation
PGMs	Probabilistic Graphical Model
qPCR	quantitative Polymerase Chain Reaction
REM	Remote Electronic Monitoring
SAC-GFCM	Advisory Committee on Fisheries of the General Fisheries Commission for the Mediterranean
SSF	Small Scale Fisheries
VMS	Vessel Monitoring System
VSAT	Very Small Aperture Terminal

1. Introduction

Recent developments in the technology and know-how available to collect, manage and analyse fishery-relevant data provide a suite of possible solutions to update and modernize fisheries data systems and greatly increase the quantity and quality of data collection and analysis (Bradley et al., 2019), and as a consequence scientific advice.

Development of a new generation of multifunctional sensor systems is underway to address ocean monitoring challenges. These range from more precise and accurate monitoring of physical, chemical and biological parameters of the marine environment to the provision of an improved database for management of fisheries and, among other things, to address improved life cycle cost-efficiency. These advances will be achieved through innovations such as multi-platform integration, greater reliability through better antifouling management of underwater sensors and greater sensor and data interoperability (Pearlman et al., 2014).

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The use of animals as platform for ocean data collection can provide new information on ecosystem state as well as animal behaviour (Fedak, 2004). However, potential for telemetry data to answer complex questions about aquatic animals and their interactions with the environment is limited by the capacity to store, manage, share and access data across the research community. Large telemetry networks and databases exist, but are limited by the actions of researchers to share their data. Promoting data sharing and understanding researchers' views on open practices is a major step toward enhancing the role of Big Data in ecology and resources management (Nguyen et al., 2017). In addition, data originating from, for example, control activities in fishery (e.g. VMS) are often not available for (all) research activities and research institutes.

Modernising data systems

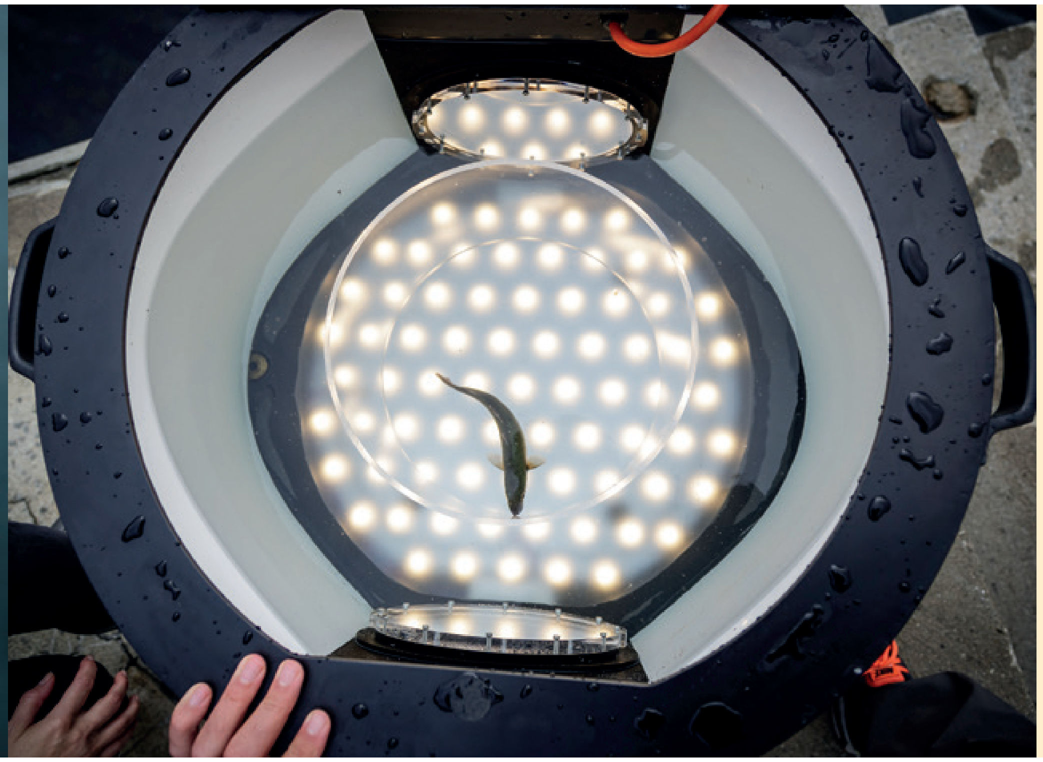
Modernising data systems to inform collaborative management is critical to adaptively managing fisheries in an era of rapid climate change (Merrifield et al., 2019). The need for sound ecological science has escalated alongside the rise of the information age and "Big Data" across all sectors of society. Big data generally refer to massive volumes of data from various sources not readily handled by the usual tools and practices and present unprecedented opportunities for advancing science and informing resource management through data-intensive approaches (Hampton et al., 2013). Although Big Data technology is perhaps the most important innovation that can play a role in fishery sustainability, it will not solve all challenges in global fisheries. Threats such as climate change and poor governance on the high seas can only to some degree be neutralized by modern fishery management informed by Big Data technologies (Costello and Ovando, 2019). In fact, innovation in fisheries at times is stagnating as a result of lack of trust and cooperation between fishers and managers (Bradley et al., 2019).

Existing fisheries information systems fail to fully capture e.g. the characteristics and essence of Small Scale Fisheries (SSF), resulting in a lack of integrated and up-to-date data, which further marginalizes the sector in policy making and governance. To help rectify the situation, the Too Big To Ignore project developed the Information System on Small-scale Fisheries (ISSF), a Web-based, open data portal to collect and disseminate knowledge on various aspects of SSF (Chuenpagdee et al., 2019). eCatch built successive software prototypes that leveraged location-aware mobile devices, cloud-based computing, and visualization and query of geographic data over the web. The resulting software, eCatch, enabled avoidance of sensitive species and habitats and quantitative reporting on performance metrics related to those activities. What started as a technology solution to a problem of timely scientific monitoring revealed collateral benefits of collaboration with the fishing industry and markets that support sustainable activities (Merrifield et al., 2019).

Reading guide

Below in section two a selection of developments and innovations in data collection and data processing and novel concepts of obtaining, analysing and perceiving data is presented. In section three a number of scenarios will be developed that will try and capture the consequences of these developments both in the way the science advisory system operates and/or will change and the consequences these developments may have for the marine resource management system. In section four conclusions and recommendations will be presented.

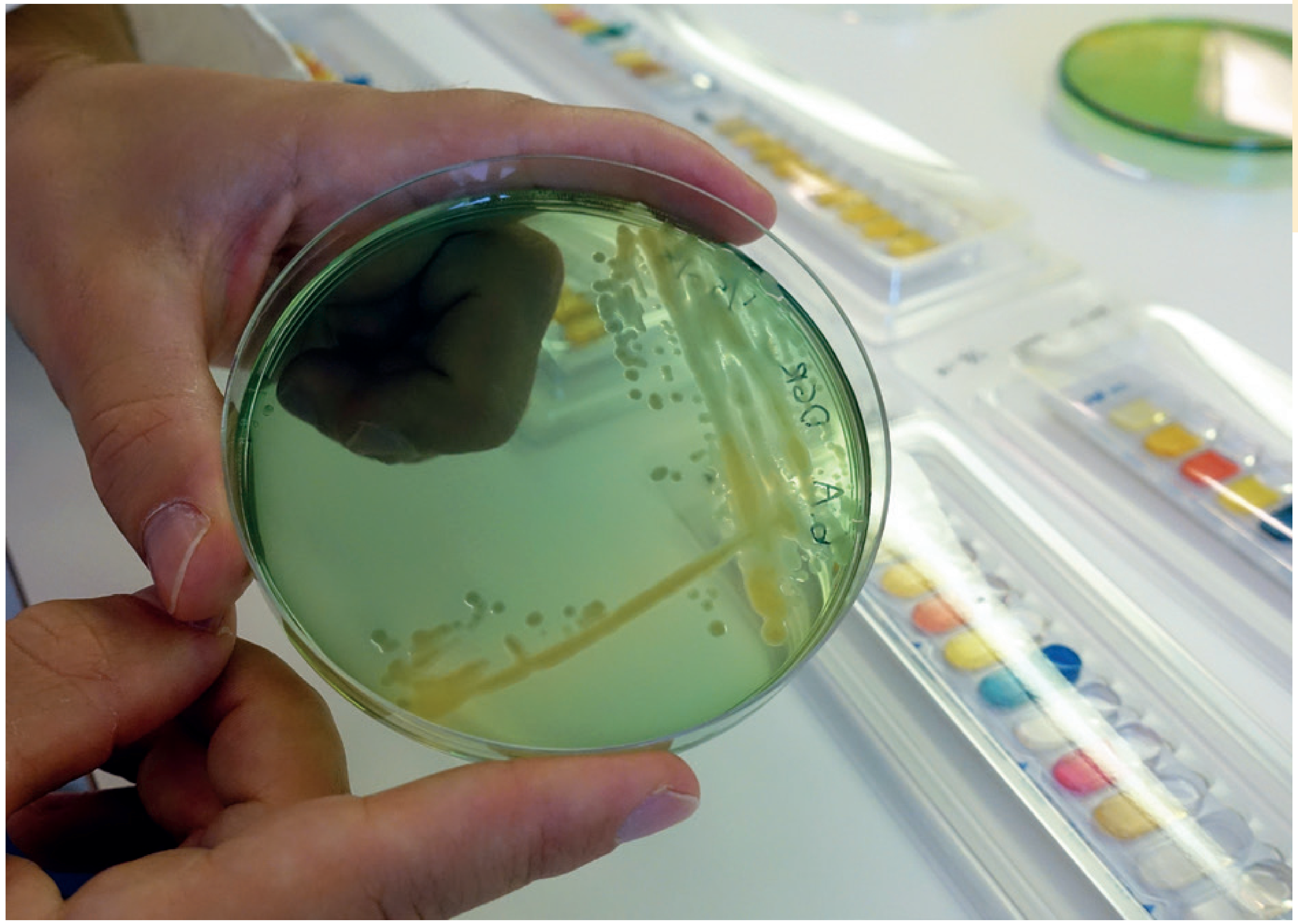
In section five we present the results of an online discussion held with representatives of EFARO and invited experts from DGMARE, DGRTD, PFA and ICES on the findings of this report.



2. New approaches to collect data

2.1 Genetics-based tools

Genetics-based tools are, particularly due to the advent of high-throughput sequencing technologies, considered amongst the most promising alternatives to improve and ease marine ecosystem monitoring and resources management as they allow measuring variables that cannot be measured otherwise and, in some cases, provide cost-effective alternatives to traditional approaches.



Several studies have highlighted the potential of genetic methods for improving marine monitoring and fisheries management in response to the need for implementing directives and policies such as the MSFD (Bourlat et al. 2013) or the CFP (Casey et al. 2016). The vast panoply of genetic methods can be categorized into those looking at the taxonomic composition of a given sample, those studying intraspecific genetic variation to infer connectivity, diversity, and abundance, and those using genomic markers to deduce individual features such as age or sex.

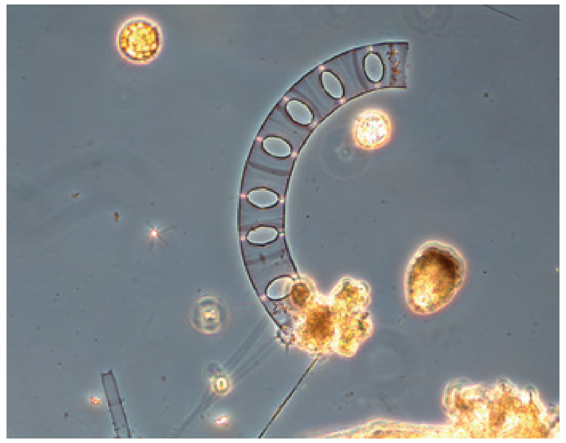
Available DNA-based approaches with application for marine management

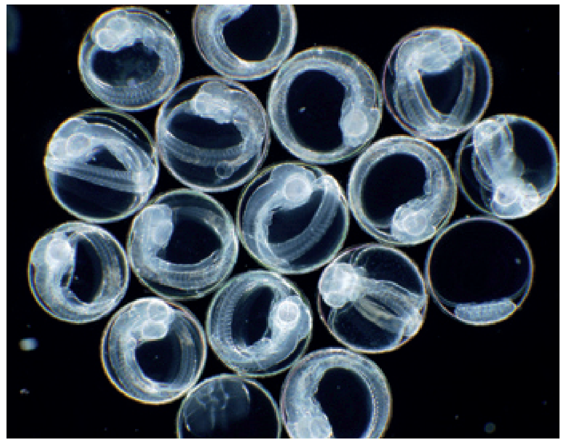
Methods looking for species identification (DNA barcoding) or detection (qPCR) are particularly relevant, and their applications range from detecting invasive species or pathogens to reporting Illegal, Unreported and Unregulated (IUU) fishing. Recently, the advent of DNA metabarcoding, which consists of the simultaneous taxonomic assignment of the organisms present in a given sample based on a small DNA fragment that is unique to each species, has allowed the characterization of entire communities, and has shown a great potential for biodiversity assessments (Taberlet et al. 2012), calculating biotic indices (Aylagas et al. 2018) or studying trophic relationships by analysing stomach contents (Albaina et al. 2016). Of particular interest is the application of two of these techniques (qPCR and metabarcoding) to environmental DNA (eDNA). eDNA is the genetic material released to the environment by macro-organisms by way of e.g. faeces and mucus exfoliation, and has been shown as a potential new source of information for assessing biodiversity of large animals without the need of seeing or sampling them, suggesting that a new, reliable, non-invasive and cost-effective method to collect information regarding the distribution of fish species in large oceanic environments could be possible (Klitgaard-Hansen et al. 2018).

Methods looking at genetic variation within species are those that make use of genetic markers such as microsatellites or, more recently, Single Nucleotide Polymorphisms (SNPs). Using these markers, it is possible to assess population connectivity, which is crucial for stock delimitation (Leone et al. 2019), to assign individuals to their population of origin, which is relevant for resolving mixed-stock fisheries

(Rodriguez-Ezpeleta et al. 2019) and to detect IUU. Additionally, analyses of intraspecific variability can help understand population abundance and genetic diversity which, together with information about population connectivity are relevant to understand evolutionary responses and potential resilience to impacts such as fishing pressure or climate change. Finally, a recent avenue in genetic research is the identification of adaptive genetic variation to anticipate species range projections in response to climate change (Razgour et al. 2019).

Genetic methods can also be used to obtain information to be included in stock assessment models such as individual age or sex. Whereas methods for inferring age (based on telomere length or on changes in DNA methylation over time) are still incipient, methods for inferring sex from genetic markers are already available (Kirubakaran et al. 2019). Yet, these depend on the species sex determination system, which is complex in fish and does not always allow for a genetic assay development. A promising method that can revolutionize stock-assessment by providing fishery-independent spawning stock biomass estimates is the Close Kin Mark Recapture (CKMR). This method consists of taking a random sample of fish and finding, based on their genetic make-up, pairs of related individuals. The larger the population size, the lower the probability of finding related pairs, and vice versa (Bravington et al. 2016). Yet, although the potential of the method seems clear, its viability needs to be considered for each case considering the biological knowledge available, population connectivity and potential uncertainties.





From technical developments to practical application

Several studies have highlighted the potential of genetic methods for improving fisheries management in general (Ovenden et al. 2013) and for the application under the EU CFP in particular (Casey et al. 2016); yet, comprehensive studies using real case studies that perform Strengths, Weaknesses, Opportunities and Threats (SWOT) analyses, examine cost-effectiveness and identify cases where genetic based approaches are most beneficial are scarce. These analyses should be performed by e.g. examining the appropriateness for stock assessment and biodiversity monitoring considering the required needs for each case, the necessary equipment and expertise, the potential for standardization, associated risks, robustness and accuracy, power to detect the desired biological measure. It is also important to consider the transferability of basic scientific knowledge to the benefit of developing improved management strategies for marine resources. Also, socio-economic criteria are to be included in the cost-benefit analysis of each method for a given purpose as well as jobs lost and/or created by replacing "traditional" with genomic based methods.

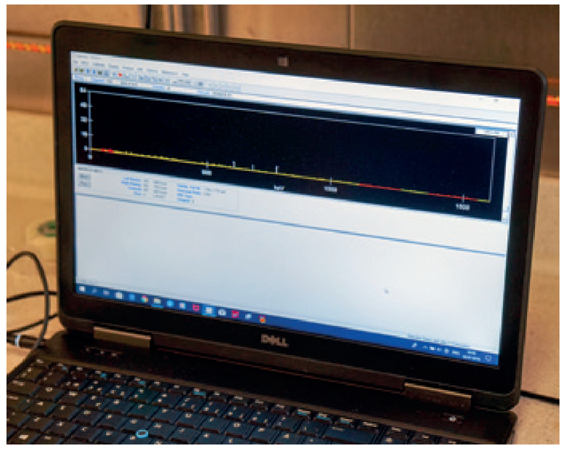
2.2 Improved acoustic sensors

Acoustic sensing is a central component of ocean exploration and in-situ observations at all scales including geological, ecological, naval and engineering applications (Etter, 2018). Active acoustic methods are regularly used to monitor marine life from plankton to whales and they constitute a key component for the regular assessment of several fish stocks, especially small pelagics.

This widespread use is the result of the long-distance propagation of sound waves in water, which enables distant underwater object detections by recording backscatter signals. The integrated data processing allows visualization of underwater objects in near real-time and it does support fishing practises from small to large scale vessels.

New developments and trends in acoustic sensing technologies to study life in the ocean include advances in multibeam systems (Mosca et al., 2016), omni-directional sonars (Vatnehol et a.,l 2018), broadband signal analyses (Korneliussen et al., 2009) and miniaturized transducers that can be mounted on a multitude of manned and unmanned platforms (De Robertis et al., 2019). Additionally, the combined effects of increased local data processing capacity and miniaturization of electronic components could give opportunities to establish underwater acoustic networks to make simultaneous observation of environmental processes over large scales (e.g. Felemban et al., 2015).

A variety of scientific and commercial products exist for fishery acoustics with e.g. varying capabilities for single-target detection (single beam and split-beam), range and size resolution (single-frequency, multi-frequency, broadband tools), and endurance and autonomy (e.g., wide-band autonomous transceiver). In recent years compact and highly capable echo-sounders with low power requirements



have become available (Benoit-Bird et al 2016), which, combined with recent advances in autonomous vehicles (Ludvigsen et al., 2016, Verfuss et al., 2019), have shown potential to make long-term acoustic measurements of fish abundance more accessible (De Robertis et al., 2019).

Opportunities and risk of big data and Artificial Intelligence

The use of specific technologies will depend on the particular organisms and questions targeted and will trade-off between data quality, data processing and costs (Benoit-Bird et al., 2016). Nonetheless, independent of the specific system used, a substantial amount of effort is required for calibration of the device, as well as for the integration and processing of the acoustic signal. A number of solutions have been recently proposed to partially automate this phase, including both supervised and unsupervised machine learning methods (see Brautaset et al., 2020 for a short review). But still new methods and tools are needed in acoustic data processing to fully benefit of the rapid expansion in the use of underwater acoustic technologies in marine biological research and to accelerate the transition into increased ocean digitalization and big data analyses (Guidi et al., 2020).

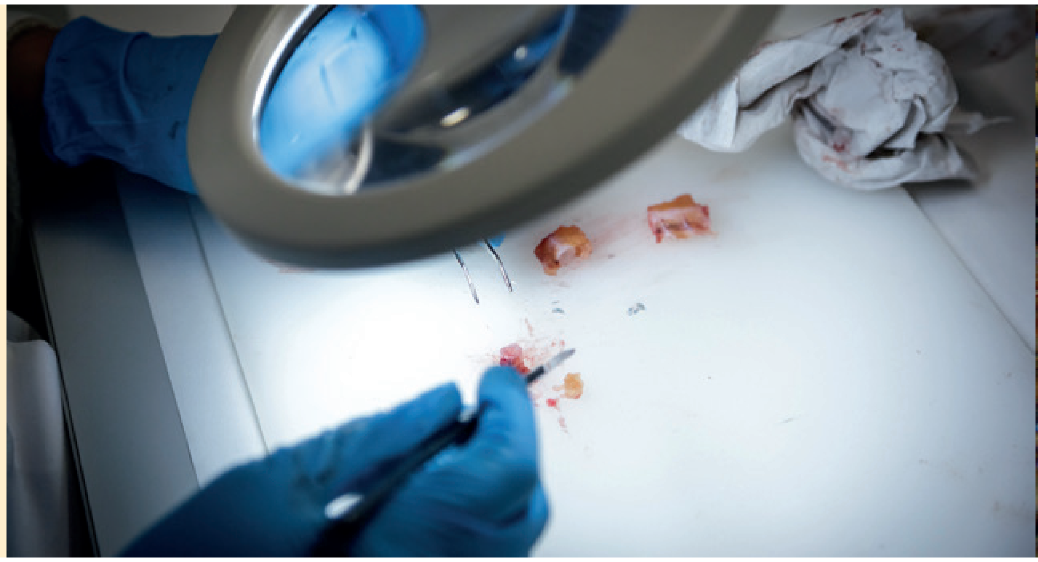
In parallel to the development of active acoustic solutions for fishery applications, passive methods (e.g. hydrophones) and methods for underwater acoustic communications, and seafloor explorations have advanced as well. The widespread use of acoustic technologies has raised questions about the disruption of the natural acoustic environment resulting in underwater noise pollution. Changes in ocean soundscape due to natural effects and anthropogenic activity (e.g. naval-sonar systems, seismic-exploration activity, maritime shipping, and windfarm development) are concerns.

2.3 From snapshots to real-time monitoring

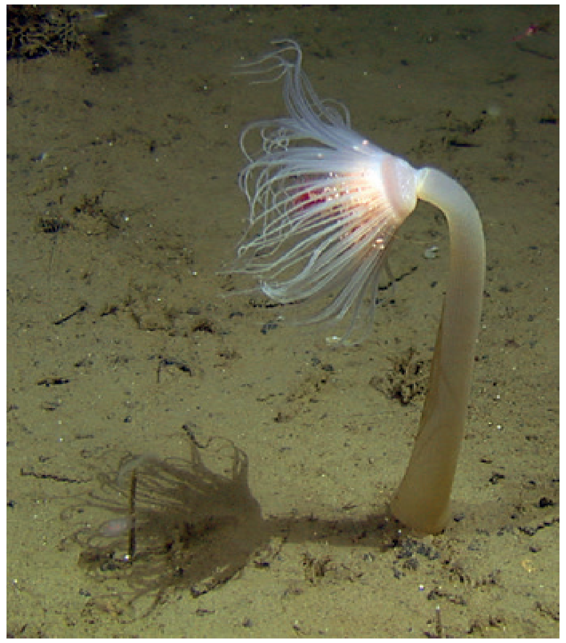
Marine biological and environmental monitoring provides context to marine science and over the last century has allowed development of a critical scientific understanding of the marine environment and the impacts that humans are having on it. Most of the national biological monitoring programmes entirely rely on research vessels surveying either a fixed station grid, a set of randomly distributed survey stations or any combination of both approaches (e.g. van der Meer, 1997).

Typically, at each survey station the ships stop and a set of measurements, such as abundance of individuals from sediment cores, dredging, or trawling samples is taken yielding a series of snapshots. The snapshot approach provides however an incomplete picture of the true situation underwater. Moreover, these programs and traditional methods are labour intensive per unit area/time that they cover. Since the number of ships and labour time are limited, information needs to be interpolated over space and time to yield a synoptic picture. So far, a deeper understanding of spatio-temporal trends remains limited since continuous measurements of biological properties are difficult to obtain compared to e.g. physico-chemical parameters. As we enter the big data era, the traditional methods need to be complimented with new biological data sources, including high-definition optical imagery, hydro-acoustics and genetic sequences.

The recently developed novel monitoring technologies present a wide array of advantages including a higher taxonomic resolution and the capability to rapidly provide, often in near real-time, information regarding wide geographic areas, e.g. from remote sensing, or large temporal scales (e.g. autonomous observation platforms such as buoys, moorings or ships-of-opportunity). Technology is evolving in two main directions: (i) innovative molecular approaches (paragraph 2.1 above); and (ii) autonomous and



sensitive (e.g. optic and acoustic) sensor systems (paragraph 2.2 above), which allow operating and collecting data in situ over wide spatial and temporal scales (She et al., 2016). Data obtained from new sensors and in situ technologies such as high-definition optical imagery coming from Remotely Operated Vehicles (ROVs), autonomous underwater vehicles (AUVs), drop-cameras, video plankton recorders, or drones combined with hydro-acoustic data coming from either passive hydrophones that collect data on underwater soundscapes, or active sonars, single- and multi-beam echo-sounders will disrupt current marine ecological research in the near future and calls for a redesign of marine ecological research. The full integration of hydro-acoustic and camera-based systems will allow for non-invasive extraction of biological information from marine ecosystems with unprecedented quantity and quality and open up completely new information dimensions and substantially enhances our understanding of biological processes in the oceans across all trophic levels.



2.4 Use of robotics, miniaturisation, autonomous vessels (drones) and machines, and observation system integration

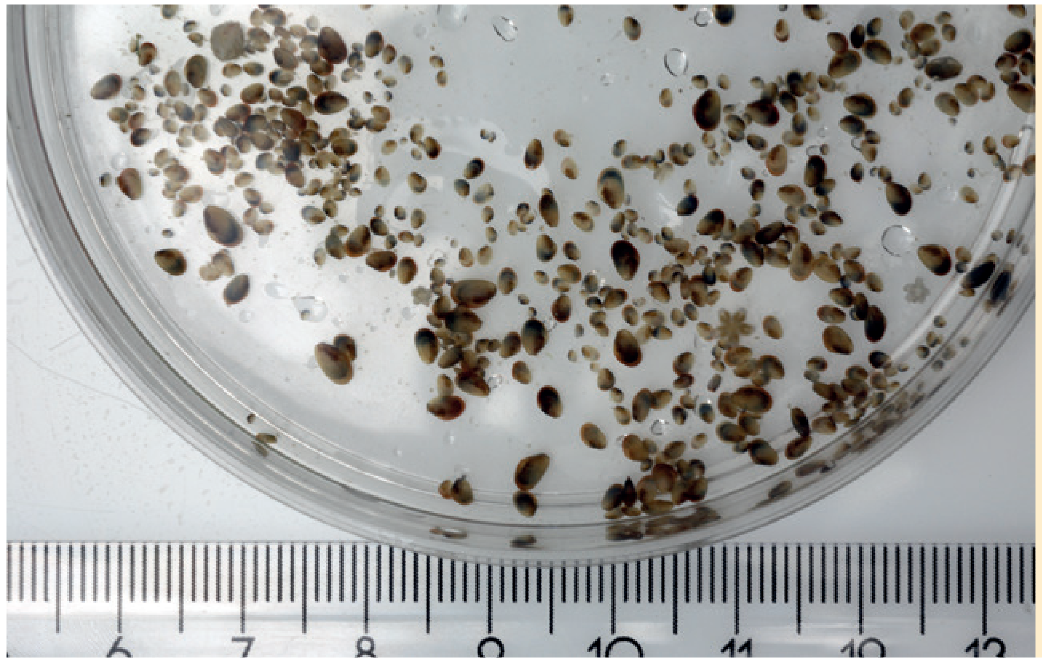
Recent marine platforms (e.g. underwater manned or unmanned vehicles, smart buoys and mooring systems, underwater cabled observatories) can provide unprecedented opportunities for data collection at sea, even in remote places and under extreme conditions.

This new data can support fishers in for example better management and planning of fishing activities, as well as providing resource managers with a more effective monitoring of marine resources. Promising results have been already obtained using autonomous surface vehicles in monitoring programmes mapping distribution of fish (Chu et al., 2018; NOAA, 2018) and plankton (Pedersen et al., 2019) over large scales and at high resolution in time and space. Commercial shrimp fishery in the Southern Ocean are using small fleets of autonomous surface vehicles equipped with acoustic devices to extend their research areas during fishing operations. Another example is the tuna fisheries starting to use smart buoys and decision support systems (Groba et al., 2015; Groba et al., 2018).

Observation systems

Improved underwater vision sensors can provide real-time information on catches and, if integrated with autonomous devices, can help reduce bycatch and discards. Ongoing research projects are developing automated catch information systems to provide detailed information on e.g. the Nephrops fishery. The system will detect, identify and track all individuals captured by the trawl to provide real-time information on catch composition to the fishermen enabling them to make informed decisions on the catching process. This system benefits from advances in optical sensors to obtain improved underwater image acquisition, and will exploit artificial intelligence (AI) in computer vision algorithms. Additionally, new sensor fusion protocols, merging GPS information with images and counting of the catch, will enable near-real-time geographical mapping of the resources.

Merging computer vision software with autonomous underwater vehicles can provide effective solutions to map at high definition large marine areas. As an example, interesting solutions have been developed to help identify species composition in the purse-seine fishery before closing the net, hence avoiding unwanted catches and discards (Haahr Christensen et al., 2018). The system is small and can be easily deployed in the water, it can navigate autonomously in the net collecting images with a set of cameras, classifying species and providing the statistical composition of the catches.



The management systems of the USA and Australia offer examples of methodologies able to provide a view of the climate and fishing effects on the ecosystem, used to recommend precautionary thresholds to ensure sustainable fishing yields while also protecting ecosystem integrity. These methodologies have different levels of complexity, based on both the number of system interactions under consideration and the analytical approach, spanning from quantitative food-web assessment (Holsman et al., 2019) to qualitative expert opinions (Morzaria-Luna et al., 2014). Quantitative results are very useful to managers, however elaborating such complex models causes high requirements in terms of data and computational power (Plagányi et al., 2014).

Ecosystem Risk Assesment

A more pragmatic step toward an Ecosystem Based Management (EBM) for fisheries is the Ecosystem Risk Assessments (ERA), able to characterize impacts of multiple pressures and associate risk of these impacts to the key components of the fishery exploited communities (Holsman et al., 2017; Pecl et al., 2014). ERA have already been used to adjust the stock assessment results for fisheries (Thompson and Palsson, 2018).

The awareness of climate change impact on fisheries is a major topic also in the EU. During the last decade, several studies addressed the detrimental combined effect of fishing pressure and changing environment on the North Atlantic and Mediterranean ecosystems (e.g.: Coll et al., 2009; Hollowed et al., 2013; Piroddi et al., 2017). The increase of the availability of integrated and standardized data across Europe is allowing the verification of current ecosystem models and past forecasts beyond single stocks assessments (Baudron et al., 2020; Fernandes et al., 2020). The new frontiers in technologies available to collect, manage and analyse fishery-relevant data can represent the right pathway in the EU context to implement a formal ERA with the final aim of improving management and exploitation of fishery resources.

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2.5 Collecting and using data from fully documented fisheries

The monitoring of fisheries activities has been of great importance to tackle the problem of unreported and illegal catches globally, especially since 11-26 million tons of seafood per year are of such nature (Agnew et al., 2009).

For long, monitoring of fisheries activities has been conducted by onboard observers who would track and document the fishing activities of commercial vessels on a standardised way and for a selected number of fishing trips. Quiet often this method has been the source of biased data due to observer effects as well as deployment effects (Benoît & Allard, 2009). Furthermore, the cost efficiency of this monitoring method is low, and not many countries suffice to conduct a full monitoring of their entire fleet (McCluskey and Lewison, 2008).

An alternative to onboard observers has been the use of Vessel Monitoring Systems (VMS). These system include a combination of GPS systems and other technologies to follow up the fishing activities at a high spatial and temporal scale (Gerritsen and Lordan, 2010). An improved version of the VMS includes the use of Closed-circuit television (CCTV) technologies. This is generally named Remote Electronic Monitoring (REM), whereby cameras are positioned at well-defined places onboard where the majority of fishing activities are taking place (deck, conveyor belts) (Bartholomew et al., 2018).

The introduction of REM technologies in the fisheries sector has led to a better documentation of commercial catches and bycatch and has a great potential to establish a full documentation of fishery activities and catches (Mangi et al., 2013). The use of such camera systems in combination with smart software (i.e. artificial intelligence (AI) and machine learning (ML)) has already proven to be of significant importance in the collection of high quality data. Onboard conveyor belts can be equipped with such camera systems that, in combination with species identification and length measurement software, can deliver a full documentation of the commercial catches and bycatch (Storbeck and Daan, 2001;

White et al., 2006). Such technologies have already found their way into the fisheries industry but are still lacking to fully identify both the commercial catch and the bycatch species, more specifically in the trawling fisheries, where large fractions of unwanted non-target species may be present. It is yet not unimaginable that in future, a combination of cameras and smart software will be able to measure and identify the entire catch of such fishing vessels before they are sorted by the crew onboard the ship.

Fully Documented Fisheries

Since increasingly vessels are being equipped with VSAT (Very Small Aperture Terminal) technology, unlimited data transfer from REM systems can provide a continuous transfer of data (i.e. catch- and location data) from the sector to the user (i.e. Scientific community & management). The data that Fully Documented Fisheries (FDF) provides will have a high potential for the fishing community to provide data for scientific purposes as well as for management purposes. But also the fishing industry can benefit from the use of REM technologies to provide a fully documented fisheries, for example in cases where exemptions on strict management measures can be put into place.

2.6 Agent based approaches

Advances in computation have made it possible to construct agent-based models (ABMs), which explicitly simulate the behaviour of individual people, firms, or vessels in order to understand and predict their single or aggregate behaviour (Bousquet and Le Page, 2004). Also ABMs can be directly applied to the marine fish resource with the aim to understand population dynamics.

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Stock probabilistic agent-based simulators can help to investigate and understand sustainability in the exploitation of fishery resources by exploring different fishing scenarios (Bastardie et al., 2013; Bastardie et al, 2017; Minelli et al., 2017; Lindkvist et al., 2020). ABMs are therefore well suited to understand emergent consequences of resource, environment and fisher interactions, heterogeneity, and bounded rationality, especially in the complex ecological, social, and institutional context of fishery management (Guyot et al., 2006). In particular, ABMs can represent a powerful and flexible tool to the micro-level complexities of small scale fisheries, because they are able to fully characterise both the multispecies/multigear of SSF as well as its complex social dimension.

There are a number of advantages to using ABMs over traditional fisheries or stock assessment models. ABMs enable qualitative and quantitative data to be combined to understand the underlying processes of empirical active and collaborative engagement and have the potential to bring together different stakeholder views. More importantly, ABMs allow the integration of diverse knowledge to ask questions about how particular behaviour at the individual level could give rise to patterns at larger scales and help investigate what interactions and processes may have produced a given outcome or pattern.

Modelling uncertainty

On the other hand, if it is true that we can detail agents' behaviour as much as we want, yet it is important to consider that we cannot model all the occurrences and we must make some assumptions on what we cannot foresee. Since these assumptions affect the model outcomes at different levels of simulation, a crucial point to take into account when working with ABMs is that uncertainty must be simulated as well and introduced into the model with the appropriated instruments.

2.7 Social and technical innovation: Citizen science and self-sampling in fisheries

One of the greatest weaknesses of the current research system is that it remains fragmented, introspective and lacking in creative connectivity, both between the participating disciplines and with wider sources of knowledge and expertise (Phillipson and Symes, 2013).

On the one hand technical innovation makes it possible to collect data faster, in larger quantities and from more different sources and make this data available to a wider audience. On the other hand this audience of policy makers, fishers and other stake-holders is increasingly being invited to participate in the decision-making process so that adopted measures will better reflect local circumstances (Garza-Gil et al., 2020). A wider trend of social change in which, following Van Deth (2014), an increase of opportunities for political involvement is witnessed with a changing nature of participation and changes in the style of political action (Van Deth, 2014).

Scientific debates often revolve around the issues of 'unbiased science' with the majority of scientists keeping themselves at arm's length from policy-making to ensure their credibility. Participatory research has been shifting these dynamics and has led to the emergence of research practices and advice frameworks that allow co-creation of common knowledge bases for management (Holm et al., 2020). Citizen Science (CS) has been emerging in the last decade as a new field of environmental monitoring involving a direct collaboration between everyday citizens and scientists (Fehri et al., 2020). CS is not a new phenomenon as, following Lakshminarayanan (2007), using a distributed network of data gatherers, such as field collectors or ornithologists, has been used already for decades (Lakshminarayanan, 2007). What is new in this development of action research is the development towards treating citizens as scientists on equal terms. As such it simultaneously assists in practical problem-solving and expands scientific knowledge, as well as enhances the competencies of the respective actors, being performed collaboratively in an immediate situation using data feedback in a cyclical process aiming at an increased understanding of a given social situation, primarily applicable for the understanding of change processes in social systems and undertaken within a mutually acceptable ethical framework (Hult and Lennung, 1980).

However, this citizens' contribution is not without critique. Those who plan, codesign and facilitate participation in sustainability science need to a) be aware of possible opportunities and challenges concerning the conflicting rationales of participation, such as normative ideals dominating the conceptual background versus effectiveness-oriented rationales while implementing participation, b) value possible tensions and conflicts, by involving 'experts' and 'lay people' or actors with fundamentally different experiences, but at the expense of immediately deliverable outputs, and c) be honest and realistic about project effects with scarce available time and human resources (Musch and von Streit, 2020).

Self-sampling

A specific case of CS is self-sampling by fishers. Following Kraan et al. (2013) sampling of commercial fishery catches by observers is a relatively expensive exercise (also see 2.5 above). Sampling by fishermen themselves (self-sampling) is an attractive alternative, because a larger number of trips can be sampled at lower cost. Self-sampling should not be used too casually, however, as there are often issues of data-acceptance related to it, which are not easily dealt with in a statistical manner (Kraan et al., 2013). One example of this type of gathering information directly from the fishers is the Fishers' North Sea Stock Survey which has been carried out annually since 2003 with the aim of making fishermen's knowledge of the state of fish stocks available to fisheries scientists and fisheries managers (Napier, 2012). The questionnaire-based survey collects information on vessel size and fishing gear type, on the status of key fish species, and on economic circumstances.

Another example of using fishers' collected data can be found in the employment of fisheries scientists by fisheries organisations to collect and analyse data of the fishing fleet. For example the Pelagic Freezer-Trawler Association has implemented a self-sampling programme since 2014, which builds on the capacity already available within the industry to sample fish. The primary objective of that monitoring programme is to assess the quality of fish. The expansion in the self-sampling programme consists of recording of haul information, recording the species compositions per haul and regularly taking random length-samples from the catch. The self-sampling is carried out by the vessel quality managers on board of the vessels, who have a long experience in assessing the quality of fish, and by the skippers/officers with respect to the haul information. The scientific coordination of the self-sampling programme is carried out by the PFA chief science officer with support of an independent contractor (Pastoors and Quirijns, 2020).

2.8 Develop fit for purpose AI methods and algorithms that make use of existing and newly available big data

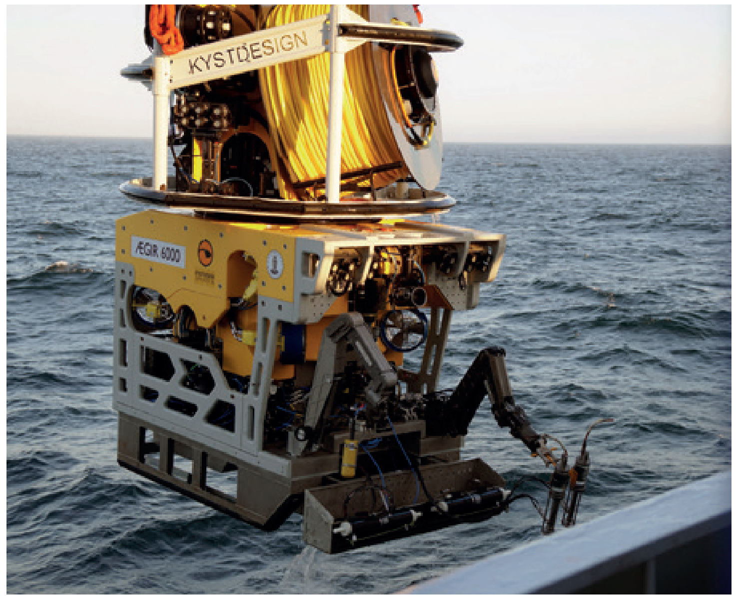
Ocean monitoring through satellite and in situ platforms have increased exponentially during the last decades (Longhurst et al., 1995). The lack of integration of multiple observational platforms at the right scale and real-time processing capacity has prevented the development of an effective forecasting system. The term Big Data was coined to capture the meaning of this emerging trend (Hu et al., 2014). In addition to its sheer volume, big data exhibits other unique characteristics as compared with traditional data.

For instance, Big Data is commonly unstructured and requires real-time analysis. The need for real-time storage, processing and visualization is crucial for an effective system beyond previous proofs-of-concept. This development calls for new system architectures for data acquisition, transmission, storage, and large-scale data processing mechanisms from computer science (LeCun et al., 2015).

Machine learning

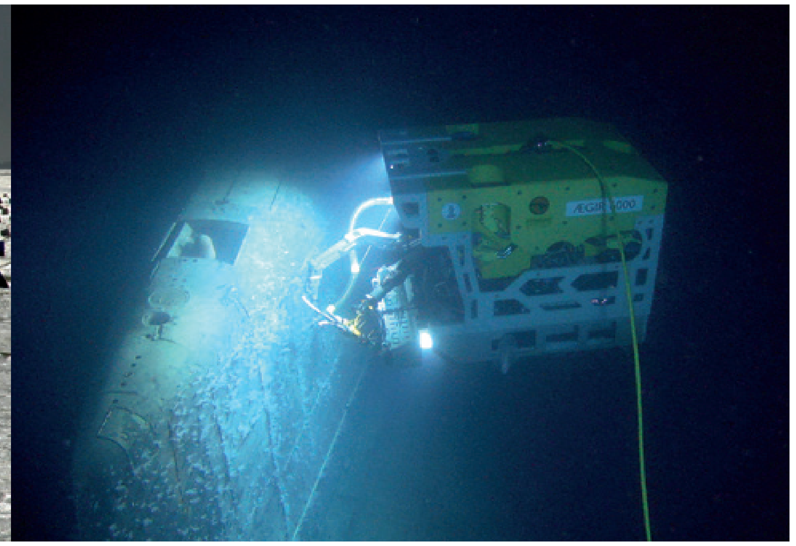
Big Data techniques enhanced by machine learning methods can increase the value of such data and its applicability to society, industry and management challenges. Machine learning has already proven its potential in marine sciences applied to fisheries forecasting (Fernandes et al., 2010) and automatic classification of zooplankton samples (Fernandes et al., 2009). One machine learning modelling paradigm based on probability theory and graph theory (Buntine, 1991) is the Probabilistic Graphical Models (PGMs) paradigm (Pearl et al., 1988, Castillo et al., 1997). PGMs include the cases of Bayesian networks (BNs; Jensen and Nielsen, 2001), that provide a paradigm suitable to deal with uncertainty, offering an intuitive interface to data without being a black box approach. These intuitive properties of Bayesian networks and their explicit consideration of uncertainties enhance the confidence of domain experts on their forecasts (Fernandes et al., 2010; 2013; 2015).

Although there is a large body of literature on probabilistic models, its application in marine research is sparse. Weakly supervised methods (Hernández-González et al., 2016) from machine learning discipline have been used in the past in other domains of similar characteristics, but rarely in marine science domains (Hernández-González et al., 2019). Recent machine learning methods have aimed at providing earliest possible forecast with evaluation of the impact on the model reliability (Mori et al., 2016) or forecast multiple targets (e.g. species) simultaneously (Fernandes et al., 2013). Therefore, there are state-of-the-art methodologies developed by experts in machine learning that would be beneficial to test and integrate into real-time forecasting systems which reduce uncertainty.



A first approach in developing a fit for purpose AI model for Big Data is obviously to use a battery of existing methods to a dataset to explore the feasibility of AI methods to a problem (Grosjean et al., 2004). However, there are several risks associated with this approach. For example, if AI methods are not fit for purpose, then higher performances can be missed (Fernandes et al., 2009) or overfitting can lead to over confidence on AI capacity (Fernandes et al., 2010) if proper validation is not performed. In addition, the lack of fit for purpose can lead to conclusions of AI not fitting for purpose (Uusitalo et al., 2007) when a fit for purpose adapted AI methodology can overcome successful initial barriers (Fernandes et al., 2010).

A multi-disciplinary approach, where the domain experts and AI experts work together, is key for allowing this fit for purpose that can go beyond the state-of-the-art in more than one discipline (Fernandes et al., 2013; Hernández-González et al., 2019). A person-in-the-middle approach can be key for a successful process. This can be an ecologist with interest in statistics and machine learning (Grosjean et al., 2004; Fernandes et al., 2012; Trifonova et al., 2015; Uusitalo et al., 2016), or a person with computing or statistical background with interest in not only developing new algorithms and find any kind of problem to test them, but orientated into another discipline such as oceanography or marine sciences. This is particularly important not to get overconfident on the capacity of algorithms within a limited dataset (Kroodsma et al., 2019) when the broad picture of the domain to address can be missed and their applicability limited without proper domain testing beyond statistical validation (Taconet et al., 2019).



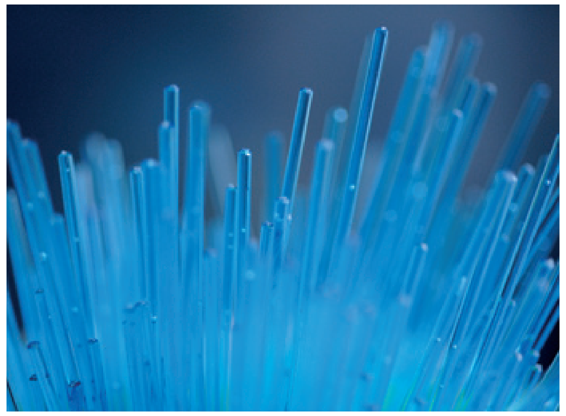
2.9 Advance knowledge on ecological processes and new ecosystem models

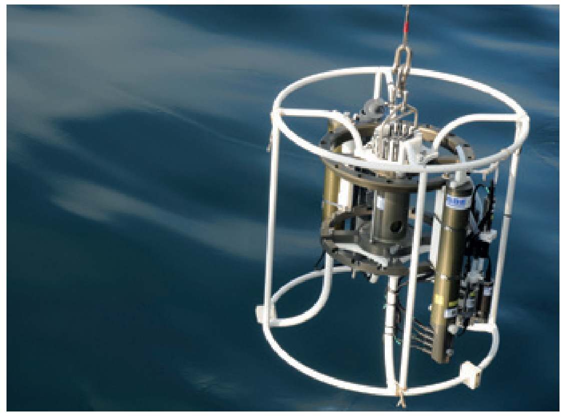
The increase in the amount of data collected at sea should go hand-in-hand with an equal increase in information and knowledge on critical marine processes that have been historically overlooked for the lack of accurate observations.

The role of social information transfer and group dynamics in fish communities is a major knowledge gap in marine ecology, although it might have important implications in spatial and temporal distributions of the species (e.g. schooling, migrations, fear ecology) and have effects on functional responses between predator and prey.

The individual behavioural traits regulating the ability of marine organisms to migrate are largely unknown, but are most likely resulting from the balance between individual preferences and collective decisions processes. Migrations between widely separated but geographically stable locations of spawning and feeding sites raise several questions about how marine animals manage to learn and remember these often-complex migration routes. Where is the information on the path stored? How is it retrieved, shared and elaborated by a migrating group? Are the tasks significantly better when performed by the group than by isolated individuals? Examples of such a complex decision-making problem can be found in the structure of the migration routes of several species of crustaceans (e.g. crabs), fish (e.g. tunas, mackerels) and marine mammals (e.g. cetaceans).

For example, large numbers of Bluefin tunas used to migrate into the Norwegian and North Seas, but the species has become extremely rare in these regions since the mid-1960s and 1970s (Tiews, 1978; Fromentin and Powers, 2005, Mariani et al., 2017). Reasons for the disappearance are still unknown but the loss of collective memory within tuna schools caused by heavy fishery has been suggested as a possible mechanism triggering a sudden shift in migrations and hence loss of habitat





connectivity (De Luca et al., 2014). Breakdown of social traditions, due to selected fishing on older informed individuals, has been hypothesized to have contributed to stock collapses in several large commercially important fish populations. But little and sparse data exist on these important processes (Brown and Laland, 2003, Petigas et al., 2010). Recently, there are reasons to believe that after several years of conservative stock management, large groups of Bluefin tuna have re-entered the Nordic seas (MacKenzie et al. 2020). This supports the hypothesis that collective memory of specific regions could also be restored in a fish group when population density is high enough to allow large vagrant species to transfer the information back to the group.

Highly migratory species

The functional role and behaviour of several marine highly migratory species is unknown. This includes large groups of marine mammals (e.g., whales, dolphins, and seals), fish (e.g., large tunas, sharks and rays), reptiles (e.g., sea turtles) and seabirds. Many populations are still impacted by both historical and present day human exploitation for food, fuel and fashion, leading to low abundances. Most species occupy higher trophic levels in food webs and play important roles via (direct and indirect) cascading effects on the biomasses of lower trophic level species, thus controlling flows of energy, carbon and nutrients through the food webs.

Furthermore, many of these species transit annually large areas of the global ocean, including areas beyond national jurisdictions, in search of prey or suitable places to reproduce. They are therefore potentially important and highly mobile agents affecting the functional and taxonomic diversity of food webs in different areas and times of the year, as well as the transfer among regions (e.g., trans-Atlantic east-west or north-south) of energy, biomass, nutrients and pathogens. However, for most mega-fauna species, their provisioning of ecosystem services is unclear and in particular the role of their migratory behaviour for ocean ecosystem functioning and biodiversity maintenance. Similarly, is it largely unknown how sensitive their migratory behaviour and other life history strategies are to changing ocean conditions (e.g. temperatures, oxygen conditions, currents, stratification), human pressures (e.g. overfishing, disturbance, pollutants incl. noise, hormonal disruptors and chemical substances) and e.g. naturally occurring outbreaks of diseases.

These knowledge gaps thus pose a significant challenge for the operationalisation of ecosystem-based management of marine stocks. New data and new knowledge is needed to improve the ability to manage marine resources at sustainable levels and to enable a healthy and resilient ocean supporting a healthy human society.

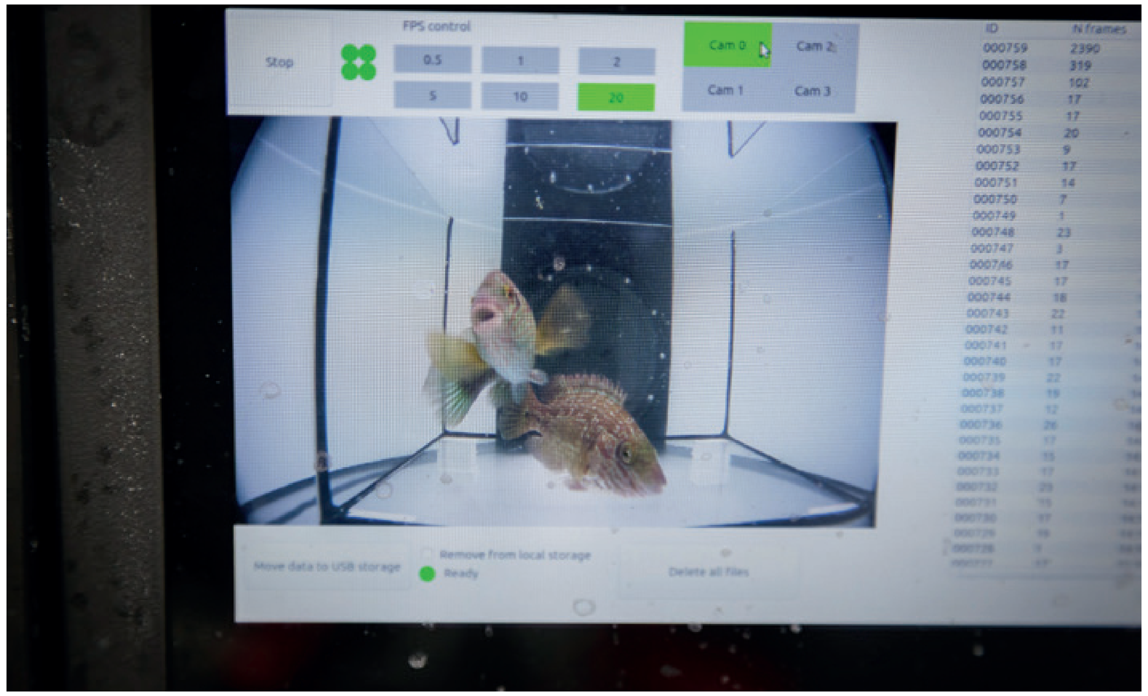
2.10 From Real-time Monitoring to Real-time Advice

A good example for real-time advice is a tool called ECOCAST, which shows fishermen a daily map where there are more swordfish than bycatch. The maps are based on statistical models of target (swordfish) and bycatch (turtles) species distributions and meteorological and oceanographic data through remote sensing.

With the remotely sensed data, species distributions are forecasted and can be used in real-time by fishermen to adjust their fishing behaviour. Getting swordfish-fishers to actually use the tool is another question—so far, its data is advisory-only.

Probably the most prominent example for a real-time advice application is the “Global Fishing Watch” tracking tool. Global Fishing Watch provides near real-time tracking of global commercial fishing activity using information from the automatic identification system of the vessels (AIS) to advance ocean sustainability and stewardship through increasing transparency.

While the ECOCAST tool as a science product and Global Fishing Watch as an initiative initiated by NGOs produce unsolicited advice to everyone who is interested in the product, or even just the scientific basis to formulate advice upon, there are also applications of real-time advice in real world fisheries management. For example, in the East Australian multi-species longline fishery, managers regulate fishing effort and allocate observer coverage for quota-managed southern bluefin tuna (Thunnus maccoyii) using real-time habitat predictions based on tuna’s temperature-dependent habitat preferences (Hobday and Hartmann, 2006). In Icelandic fisheries management, online logbook information is used to avoid areas of high juvenile bycatch. If monitoring reveals that the percentage of



small fish in the catch or the bycatch exceeds guideline limits, the Icelandic Marine Research Institute may close the relevant fishing area for a period of time. Such a fishing prohibition enters into force within a few hours. If small fish or bycatch repeatedly exceeds guideline limits, the relevant area is closed for a longer period of time.

Recently a framework integrating real-time advice into a so called dynamic ocean or fisheries management has been established (Maxwell et al., 2105). Maxwell et al. (2015) state: "In dynamic management approaches, we can integrate: (1) existing datasets, such as remote sensing, animal tracking or fisheries observer data, (2) advanced analytical processing and modelling techniques that allow us to predict key species distributions, user behaviour or oceanographic habitats in space and time, and (3) rapid data-sharing technology such as handheld devices to implement dynamic tools that respond at finer scales than have been implemented in the past. This kind of approach has only become practical in recent decades due to improvements in related technology, and due to long-term datasets on which models can be based, and datasets that will be reliably collected into the future, via e.g. remote sensing. While dynamic management does not necessarily require a full suite of advanced technology, the capacity exists to integrate multiple data types and technology platforms."

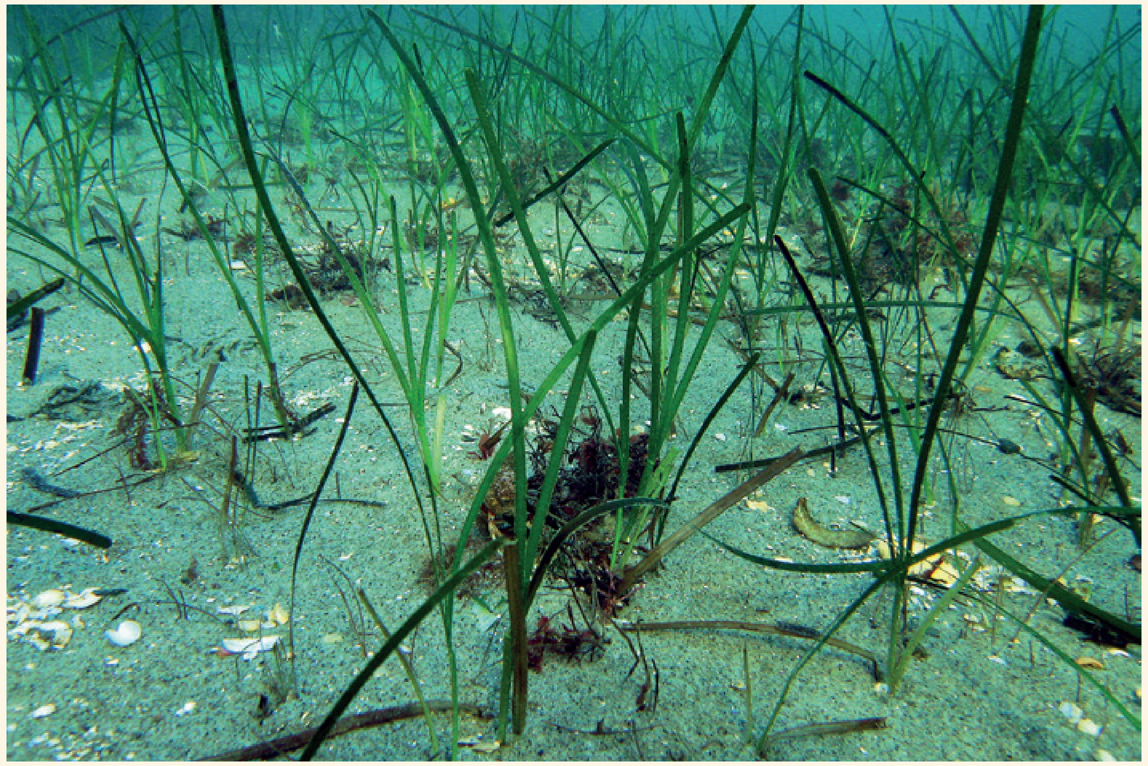
Real-time advice

These deliberations show the huge potential to generate and integrate real-time advice into fisheries management. Following up on that, Dunn et al. (2016) showed that the efficiency of fisheries management could be increased by using dynamic management. Presently however, real-time advice is mostly used to avoid regions of high juvenile or sensitive species bycatch. While approaches based on species distribution modelling are still mostly scientific exercises with limited applications in fisheries management, applications based on near real-time monitoring of catch compositions from e-log-books are already widely applied in fisheries management, e.g., in the North Atlantic region (Iceland, Norway, EU), when executing so called real-time closures. Following the advice of Maxwell et al. and Dunn et al. there are plenty of possibilities to integrate novel data sources into the generation of real-time advice going along with a huge potential to increase the efficiency and precision of fisheries management based on real-time advice.

1 https://coastwatch.pfeg.noaa.gov/ecocast
2 https://globalfishingwatch.org

3. How can the scientific advisory system and the management system deal with this new situation

As a result of new technologies, new ways of collecting and analysing data and timing and quantity of information coming available, the scientific advisory system and the management system are challenged to accommodate these changes (see section 2.10). These changes can range from adapting protocols to wider institutional, governance and systemic adaptation. In order to grasp some of these changing modalities below three 'what-if' scenarios are being developed. These scenarios are not exhaustive nor mutual exclusive; they are an attempt to grasp some of the changes that may occur. The scenarios deal with changes in shifting frameworks, shifting responsibilities and shifts in actors.



3.1 *SCENARIO I*: MSFD in full implementation - Potential for an integrated advisory and management system on fisheries and the marine environment

Currently the MSFD is still in development. Especially the operationalisation of the eleven qualitative descriptors which describe what the environment will look like when Good Environmental Status has been achieved, is still an ongoing process. When the descriptors are operationalised and being made concrete there will be a need for targeted monitoring on the indicators of these descriptors.

Already today some MSFD related data is being collected, usually as an addition to already running monitoring programmes such as for example under the CFP Data Collection Framework. In addition, adjacent data are being collected by a wide array of institutions spanning marine and maritime research organisations to specific university groups. When MSFD monitoring becomes fully operational this may well call for the extension of current monitoring programmes and even for the establishment of additional dedicated MSFD data collection programmes.

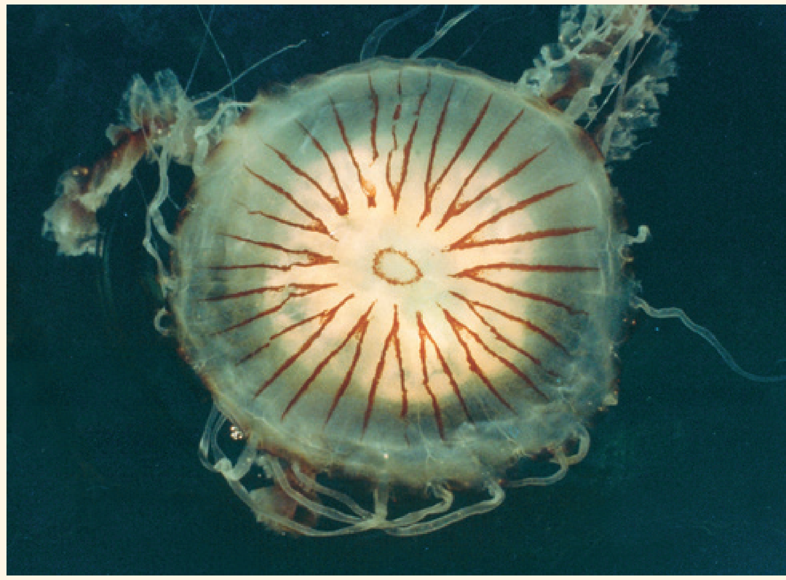
The NeXOS project might serve as an example how progress could be made towards an innovative and efficient monitoring program for the MFSD including some of the above mentioned novel technologies. The project aims to develop new multifunctional sensor systems supporting a number of scientific, technical and societal objectives, ranging from more precise monitoring and modelling of the marine environment to an improved management of fisheries. Several sensors will be developed, based on optical and passive acoustics technologies, addressing key environmental descriptors identified by the European Marine Strategy Framework Directive (MSFD) for Good Environmental Status (GES). Two of the new sensors will also contribute to the European Union Common Fisheries Policy (CFP), with a focus on variables of interest to an Eco-system Approach to Fisheries (EAF). An objective is the improved cost-efficiency, from procurement to operations, via the implementation of several innovations, such as multiplatform integration, greater reliability through better antifouling management, greater sensor and data interoperability and the creation of market opportunities for European enterprises. Requirements will be further analysed for each new sensor system during the first phase of the project. Those will then be translated into engineering specifications, leading to the development phase. Sensors will then be tested, calibrated, integrated on several platform types, scientifically validated and demonstrated in the field (Delory et al., 2014).

Coordinating monitoring programmes

In order to establish a unified and coherent monitoring program for the MFSD, all current approaches need to be combined into a common framework including novel sensor applications described in chapter 2. Coordinating both data collection, bringing data together and data processing is and will remain a major challenge, but institutional coordination might even be a larger challenge. This concerns the coordination of data collection programmes, which among others will raise the question whether MSFD monitoring should be embedded in current programmes or separate programmes should be developed. Similarly to this is the question whether MSFD monitoring should be included in current survey programmes or should develop separate programmes with dedicated resources such as manpower and ship-time. But it also requires institutional coordination between the institutes collecting, processing and analysing the data and the relevant government agencies involved. In quite a number of Member States a number of research organisations are involved in fisheries and MSFD data collection. In addition quite often responsibilities for fisheries monitoring (CFP) and environmental status monitoring (MSFD) are with different ministries.

Whereas collecting additional and larger quantities of data may well be addressed by future technological possibilities as described above, the shifting frameworks render institutional coordination to remain a major challenge for the scientific advisory and management system. EFARO could play a role in this by developing the platform function for coordination at the European level while facilitating similar developments at the National level.

This development could, if properly implemented, in the longer run result in an integrated advisory and management system on fisheries and the marine environment.



3.2 *SCENARIO II*: Industry as main driver for collecting data

As described above (section 2.7) increasingly data are being collected and being made available by the fishing industry. What if this development of citizen data collection progresses further and more date from more fleets and métiers becomes available?

We already see this development taking place today. And scientists employed by fisheries organisations produce scientific evidence underpinning management and policy recommendations of the fisheries organisations. In fact, with more date collected the industry could in the longer term perform its own stock assessments and produce its own catch advises.

Of course a major challenge will be the quality control of data and information. Hence for both the science institutes as for policy makers less effort would be required in data collection but an extensive effort would be required on validation and control.

This also raises governance concerns on the ownership of data. In addition, will in future the funding of data collection be extended to fishers making data available? Or are only those allowed to fish that make data available?

With more and more real-time catch data being available the quality of the management system could be improved. This however would require a major institutional change of the scientific advisory system and the management system, with scientists taking on a novel position.

With Fully Documented Fisheries and fishers making data available to science and management the rate of successful implementation of management and compliance to management measures could increase. In fact this could be a development towards more co-management in which the industry takes on the responsibility of sustainable management of marine resources. Through documentation of fishing operations and fishers sharing management responsibility in peer groups, accountability could be improved, both between the resource managers and the industry as well as among the fishers. With improved accountability compliance with management measures would increase.

3.3 *SCENARIO III*: Towards Citizen's Science - NGO monitoring

Related to the scenario 3.2 above, if in addition to fishing fleets also other civic entities (such as individual citizens but also NGOs) start to collect and make marine data available. On the one hand this would imply that even more data are becoming available. This, as we have seen above, raises issues of (institutional) coordination and control of data and information quality.

On the other hand it raises the issue of making data available and publicly assessible. Already today within the EU the FAIR principles for data prevail: data collected to be findable, accessible, interoperable and reusable. With new and additional data becoming available the FAIR principles become even more important.

In order to secure data and information Block-chain technology could be used. This technology allows for the management of trusted information, making it easier to access and use data while maintaining the security of this information by using an encoded digital ledger that is stored on multiple computers in a public or private network (McKinsey Digital, 2017). This will allow the owner of the data to remain custodian of the data and determine the way in which data is being made available.

Of course a major challenge will be to connect the different sources of data and secure interoperability. Also the institutional setting and governance of data use needs to be developed.

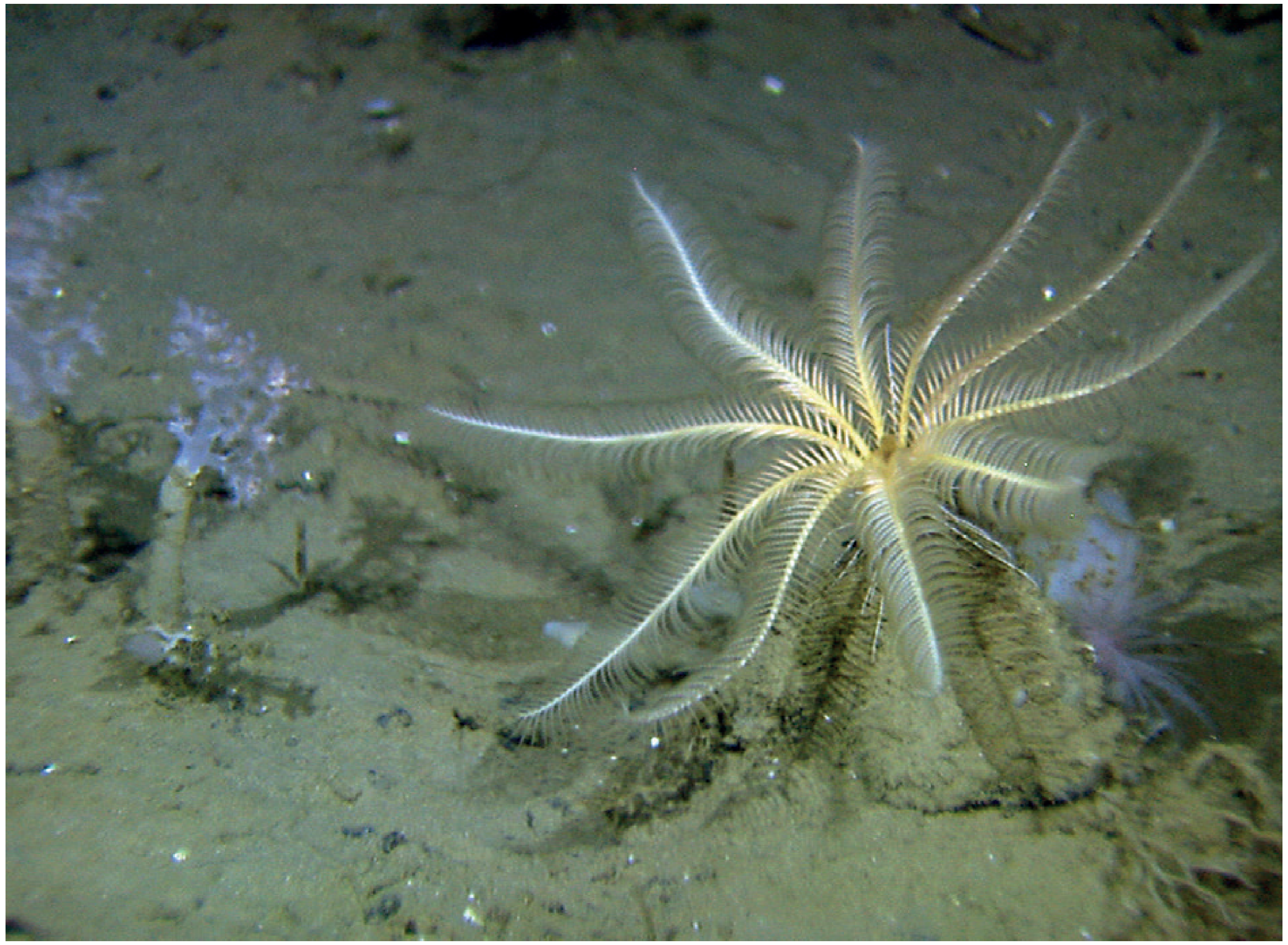
With more data being publicly available the public understanding of the marine environment and its resource use may well increase. This will allow other actors than the traditional science community and resource managers to develop plans and ideas on resource management. This could be very beneficial for the openness, transparency and legitimacy of the resource management discourse. And would allow for example for the fishing industry together with NGOs and perhaps even other actors in the market chain to jointly develop management plans for resource use.

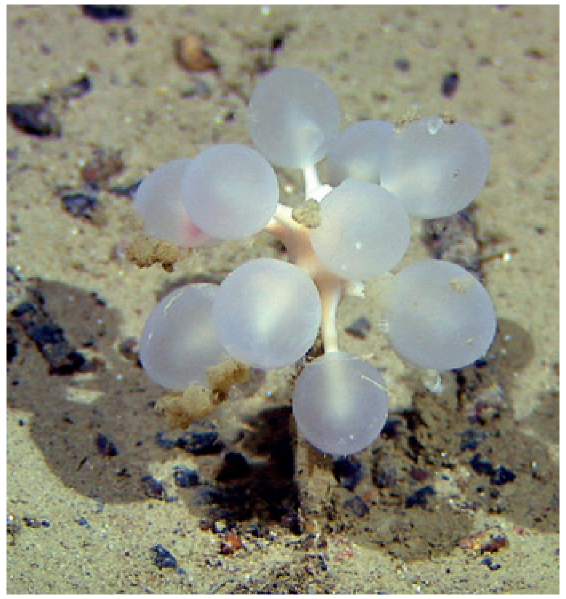
On the other side, with more data being available and more parties that can freely develop alternative interpretations and policy suggestions there is a danger of a polarisation in debate. Already in today's analyses advice requires thorough (peer) scrutiny as the knowledge of the complex marine ecosystem is rather limited. With more data being publicly accessible there will be an increased risk of actors seeking to develop 'alternative facts' to skew the debate.

Indeed this will require for the traditional science community and resource managers to reconsider their role in the data collection-information-advise-management sequence. A major role in this process will be for defining the institutional authority that will guarantee both quality of data and information and coordinating the process of interpretation, truth finding and advise. EFARO and also ICES and SAC-GFCM can and should play a role in this development.

4. Conclusion

A large number of new technologies to obtain and analyse data have become available in the marine domain and to marine science and management. This development has gained momentum over the past decades and is still rapidly progressing in terms of hardware (as in physical equipment), software (as in programmes and models) and understanding, in terms of information, knowledge and insights.





Technical innovation makes it possible to collect data faster, in larger quantities and from more different sources and make this data available to a wider audience. This requires also for the system of data analysis that it has to be in sync with these developments. On the one hand by developing (AI) data processing technology and models. And on the other hand by further developing the understanding of the underlying socio-ecological marine system.

This new data and data sources can support for example fishers in better management and planning of fishing activities, as well as providing resource managers with a more effective monitoring of marine resources and fishing activities. In addition, with a further development of citizens' science, in which for example the fishing industry but also NGOs contribute to data collection, additional platforms for data collection become available.

There are many possibilities to integrate these novel data sources providing a huge potential to increase the efficiency and precision of fisheries management by providing a real-time monitoring and advisory system. Also with fully documented fisheries the monitoring of activities can improve, resulting in more successful resource management and a reduction in control effort required. This would call for the marine advisory and management system to line up with this development.

However, with more data being available and increased transparency more parties can access data and freely develop alternative interpretations and policy suggestions increasing the danger of a polarisation in debate. Already in today's analyses advice requires thorough (peer) scrutiny as the knowledge of the complex marine ecosystem is rather limited. With more data being publicly accessible there will be an increased risk of actors seeking to develop 'alternative facts' to skew the debate.

Hence a new governance system for marine data is needed. Who keeps track of all the new marine data streams, how can it be organized that innovative advisory and management systems are always up to date regarding data and data products and make best possible use of it? How should a required infrastructure look like? Who owns data, how is access ensured and misuse prevented (important when it comes to industry data)?

5. Consultation Results

On the 10th of September 2020 an online discussion was organised which was attended by representatives of EFARO, and invited experts from DG MARE, DG RTD, PFA and ICES. The meeting started with a video presentation of the EFARO Innovation report (which can be found on the EFARO website: www.efaro.eu) after which the findings in the report were discussed. Below the main items that surfaced during the discussion.

It was noted that a large share of the innovations presented in the report are not really new but have been around for already quite some time. Some of the technology and engineering, for example in genomics, have been around already for a few years. Yet quite a few of these break throughs in science struggle to pass the valley of death: the stage after the first test phase of the innovation in which the technology or process has to be scaled up and become commercially available. Some of the known innovations currently simply lack industrial suppliers. In addition there is also an apparent valley of death between the results from science and the uptake by policy. The transfer of knowledge cannot be expected to occur immediately nor extremely fast. Real life demonstrators can assist in identifying and overcoming bottlenecks and help validate new technologies on a larger scale.

In addition, also the governance questions of *Which data do we need for which purpose? Who owns the data? Who has access to the data? And do new technologies change the answers?* are not new questions. In general the purpose of data collection is not to collect more data as such; it is important to identify which data is needed for which purpose. Yet indeed the (technical) possibilities in data collection should be explored along with the way our understanding of managing the marine ecosystem and fisheries can be advanced.

A trade-off has to be considered between data quality, the amount of data gathered and the time and costs involved. On the one hand, new technology may alter such trade-off limits. On the other hand, it also raises the (governance) question of who are the actors in the new system? For example currently the classical setup of national ministries, with a division between Environment and Fisheries, hampers the collection of the necessary information needed for implementation of the MSFD. It appears that only an EU wide initiative to point at the European Commission to try to push Member States to implement the operational program may address this challenge.

With more and new sources of data becoming available, these governance questions become even more pressing. For all data collected the issue of ensuring the quality of the data is relevant. It is essential to build in methods to show how data has been collected, and to be transparent on methods applied. In order to get the scientific community, the management fraternity and the Advisory Bodies to adopt new forms of data collection and processing there is still a lot of ground to cover in order for the advisory systems to open up for the new ways to collect data.

Especially the issue of Citizens' Science (CS) adds to this debate. CS can make more data available from more different and new sources. It is argued that industry and citizen science cannot replace the dedicated bodies that presently provide data collection. However, the additional data collected can of course be complementary. Yet it is perceived that when industry/citizens collect data, it will be based on interest and activity of the particular data collector (for example, on large scale vs. small scale fisheries, northern vs. southern areas, etc.) and hence will have the risk of being biased. In addition, when moving towards new data methods or sources, solutions must be found for maintaining the timeseries we have now.

In Spain AZTI is pushing small fleets to collect their own data. These data are useful for the fishermen as prove of their activities when in conflict with other parties and useful for the scientific community as it provides real-time data on what they are fishing. What is interesting in self-sampling is not so much the added data, but a shift in responsibility towards the industry, not only in collecting data but also in advise. The challenge is how to organize the trust needed to implement this. How to organise trust in a situation where trust does not always comes naturally.

Although there is a lot of marine research being implemented, there are still fundamental topics we have no knowledge about, yet this knowledge is dearly needed for proper fisheries management (e.g. basic ecological knowledge of certain species or habitats). In addition it is noted that the gap between northern European countries and southern European countries in both development and proliferation of new technologies appears to be widening. It is important to assist the flow of technical developments made in the north to the south. This can for example be facilitated through capacity building in the southern countries (Mediterranean/Black Sea) in developing new technologies.

As for future innovations, a much needed application is the merger of all ocean data, information and knowledge available in the EU (ranging from physics up to governance) into a digital twin of the ocean, a simulation environment. In addition the development of innovations in global ocean governance is required.

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