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Review Article

The potential of video imagery from worldwide cabled observatory networks to provide information supporting fish-stock and biodiversity assessment

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Seafloor multiparametric fibre-optic-cabled video observatories are emerging tools for standardized monitoring programmes, dedicated to the production of real-time fishery-independent stock assessment data. Here, we propose that a network of cabled cameras can be set up and optimized to ensure representative long-term monitoring of target commercial species and their surrounding habitats. We highlight the importance of adding the spatial dimension to fixed-point-cabled monitoring networks, and the need for close integration with Artificial Intelligence pipelines, that are necessary for fast and reliable biological data processing. We then describe two pilot studies, exemplary of using video imagery and environmental monitoring to derive robust data as a foundation for future ecosystem-based fish-stock and biodiversity management. The first example is from the NE Pacific Ocean where the deep-water sablefish (*Anoplopoma fimbria*) has been monitored since

2010 by the NEPTUNE cabled observatory operated by Ocean Networks Canada. The second example is from the NE Atlantic Ocean where the Norway lobster (*Nephrops norvegicus*) is being monitored using the SmartBay observatory developed for the European Multidisciplinary Seafloor and water column Observatories. Drawing from these two examples, we provide insights into the technological challenges and future steps required to develop full-scale fishery-independent stock assessments.

Keywords: cabled video observatories, ecosystem services, fishery-independent assessment, monitoring, Norway lobster, sablefish

Introduction

The monitoring of marine biodiversity at different spatio-temporal scales is a key aspect for the conservation of marine ecosystems, as it serves as a proxy for ecosystem functioning and services (e.g. Tittensor *et al.*, 2010; Costello and Chaudhary, 2017). There is growing awareness of the importance of biodiversity in deep benthic marine habitats, which are exposed to multiple impacts, spanning from direct physical disturbance (e.g. mining, bottom contact fisheries, litter, noise, and contaminants) to indirect effects related to climate change such as deoxygenation and acidification (Ramirez-Llodra *et al.*, 2011; Sato *et al.*, 2017; Jamieson *et al.*, 2019; Levin *et al.*, 2019; Costa *et al.*, 2020). The quantification of megafauna (i.e. animals larger than 2 cm; Moleón *et al.*, 2020) as major ecosystem service providers and the extraction of ecological indicators for its monitoring is about to be prioritized in major international management and conservation policy programmes (Danovaro *et al.*, 2020).

The identification of new monitoring tools and optimal sampling practices for the assessment of environmental status is at the core of important international management policies. These include the Marine Strategy Framework Directive (EC, 2008) of the European Union, and the Integrated Ecosystem Assessment, which supports Ecosystem-Based Management programmes in the United States (Samhouri *et al.*, 2014), as well as for the recent Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (Díaz et al., 2019), the Intergovernmental Panel on Climate Change (Bindoff *et al.*, 2019), and the Deep-Ocean Observing Strategy (Levin *et al.*, 2019).

Fishing activities are chiefly carried out in highly productive deep-water and deep-sea continental margin areas of the planet (i.e. from shallow shelves to lower slopes, Pauly and Zeller, 2016). The fishing industry, together with the aquaculture industry, will likely become an increasingly important source of animal protein for human and livestock consumption in coming decades (Food and Agriculture Organization of the United Nations, 2019; Lynch and MacMillan, 2020). These and other industrial activities (e.g. drilling and mining) will increase in the future, along with the social and economic conflicts arising from the exploitation of these resources. The development and implementation of novel monitoring sensors and platforms, which provide accurate data on living resources, will be crucial to develop better management strategies (Danovaro *et al.*, 2017, 2020), and for documenting and monitoring change. The operational range of these technologies will also increase along with their development, either in time or in space, thanks to the implementation of autonomous solutions (Aguzzi *et al.*, 2019). Two main challenges for this technological development are (i) the ability to track bio-ecological variables from coastal areas to the abyss and (ii) the ability to track and quantify individuals at all life stages (Rountree *et al.*, in press).

Seafloor multiparametric cabled observatories represent a well-established solution for the remote and continuous monitoring of the marine environment (Favali and Beranzoli, 2006; Ruhl *et al.*, 2011; De Leo *et al.*, 2018; Aguzzi *et al.*, 2019; Dañobeitia *et al.*, 2020; Rountree *et al.*, 2020). These permanent seafloor infrastructures host complex and multidisciplinary sets of physical, chemical, and geological sensors designed to meet the challenges of integrated and large-scale oriented basic and applied science. The European Multidisciplinary Seafloor and water column Observatory (EMSO; http://emso.eu), Ocean Networks Canada's NEPTUNE and VENUS observatories (ONC; www.oceannetworks.ca/), the cabled array of the American Ocean Observatory Initiative (OOI; https://ooinet.oceanobservatories.org/; Smith *et al.*, 2018), and the Japanese Dense Oceanfloor Network System for Earthquakes and Tsunamis (DONET; http://www.jamstec.go.jp/donet/e/) are presently the largest existing networks of observing seafloor cabled stations. DONET was specifically designed as a seismic geohazard early-warning system (Kasaya *et al.*, 2009), whereas EMSO, ONC, and OOI were designed for multidisciplinary monitoring and research in the fields of geology, physical oceanography, and ecology (e.g. Barnes and The NEPTUNE Canada Team, 2007; Service, 2007; Taylor, 2009; Ruhl *et al.*, 2011; Aguzzi *et al.*, 2012; Witze, 2013; Moran *et al.*, 2019).

Deployment and maintenance costs for such marine observatory infrastructures are high because they require extensive ship assets and specialized equipment (e.g. cable laying ships or the use of Remotely Operated Vehicles—ROVs), a wide range of dedicated personnel including mechanics, engineers, marine scientists, data analysts, and an extensive shore-based data distribution platform (Pirenne and Guillemot, 2009; Cristini *et al.*, 2016). For example, the cost to operate ONC's observatories since the deployment of its first seafloor monitoring assets in 2003 has been in excess of 114 M CA$ (https://www.oceannetworks.ca/about-us/funders-partners/funders). Such seemingly high operational costs are justified by the multi-use and multi-stakeholder nature of ocean observatories, providing curated data and services to scientists, government agencies, policy-makers, and society as a whole (Moran *et al.*, 2019). In this context, ocean cabled observatories should also align their strategic planning with the Sustainable Development Goals set by the United Nations (European Multidisciplinary Seafloor and water column Observatory, 2020), which call for the monitoring of essential ecosystem services, which include healthy fish stocks and sustainable fisheries. Therefore, it becomes crucial to develop standardized monitoring programmes specifically dedicated to the production of real-time biological and environmental data assisting fishery-independent stock assessments (Aguzzi *et al.*, 2015, 2019; Rountree *et al.*, 2020).

The installation of video cameras on cabled instrument platforms is a breakthrough for marine ecology and associated monitoring programmes and policies (Bicknell *et al.*, 2016; Aguzzi *et al.*, 2019; Rountree *et al.*, 2020). Biodiversity of megafauna can be assessed and quantified using time-lapse imaging at frequency intervals as short as minutes and for the duration of multiple year periods (Aguzzi *et al.*, 2012, 2015; Lelièvre *et al.*, 2017), when video data are adequately cross-referenced with physical samples for taxonomic determination (Howell *et al.*, 2019). When the image acquisition is coupled with physical, chemical, and geological monitoring (*via* a multiparametric set of sensors installed alongside the cameras), it is possible to quantify potential cause–effect relationships between community abundance and composition and environmental changes (e.g. Burrows *et al.*, 2011; Chauvet *et al.*, 2018), focusing the analyses on commercially key species (Chauvet *et al.*, 2019).

At this stage, it is worth mentioning that a comprehensive monitoring approach should focus not only on the commercially important species but also on populations of other ecological indicator species within its community, potentially interacting through predator–prey relationships, resource competition, and temporal niche partitioning/spatial exclusion (Lima, 1998; Fock *et al.*, 2002; Aiken and Navarrete, 2014; Choy *et al.*, 2017; Baltar *et al.*, 2019). Therefore, in order to develop the goal of monitoring the stock of this important fish from an ecosystem point of view, the acquisition of local data on size distribution and population abundance for all species sharing the same habitat of sablefish will extend the spatiotemporal knowledge of ecological interactions (e.g. predators, prey, and competitors).

Vessel-assisted and mobile sampling tools (e.g. *via* trawl, ROV, or Autonomous Underwater Vehicle video surveys) can typically collect data that are representative of a relatively large study area. Unfortunately, these type of survey methods are also costly and logistically challenging, and often not temporally representative, because of seasonal or sporadic sampling (National Research Council, 2009). In contrast, a network of fixed cameras can deliver observations at high frequencies, continually and over long time periods, but with a rather limited spatial coverage in terms of any singular species' natural habitat. In other words, a video camera has a field of view limited to few cubic metres (depending on intrinsic and/or environmental conditions).

A network of seafloor cameras can still be set up to ensure a representative observation coverage of the surrounding geographic area (e.g. Campos-Candela *et al.*, 2018), but the technological requirements for spatial data integration are still challenging (Aguzzi *et al.*, 2020b). For instance, underwater imagery quality can be compromised by suspended particles such as sediment and organic matter, variable and uncontrolled lighting conditions, or even by inappropriate resolution of the imaging sensors (Sun *et al.*, 2016; Zhang *et al.*, 2017; Li *et al.*, 2018). In addition, camera illumination systems can have a negative impact on the environment caused by photic contamination that may cause the avoidance or attraction of particular taxa, thus potentially biasing abundance and community composition estimations (Longcore and Rich, 2004; Trenkel *et al.*, 2004; Widder *et al.*, 2005; Doya *et al.*, 2014). Moreover, the observatory network spatial set-ups and placement need to be carefully considered in relation to the range of species displacements within heterogeneous habitats (Aguzzi *et al.*, 2019). In other words, fixed cameras might be installed in places of operational convenience rather than ecological relevance, and also without a coherent sampling scheme (Thompson, 2012). Therefore, under these undesirable circumstances, the acquired video imagery data may not be suitable for extrapolation to the actual environmental state of a target species geographic range or stock area.

Despite such technical particularities of observatory infrastructures and elevated operational and maintenance costs compared with simpler and potentially more flexible monitoring schemes (e.g. low-cost, retrievable stand-alone monitoring units), the (near) real-time output of observatories offers important advantages for stock management. Any sharp changes in stock levels, distribution, or behaviour could be detected almost instantly (i.e. in a matter of days or weeks), based on multiple-years averaged data and new appearing and persistent outlier values (i.e. an alarm system; Aguzzi *et al.*, 2019) either allowing for a quick reaction by the authorities and relevant management entities. The capability to set stationary state values (i.e. averages) for ecological data (including population indicators) would provide valuable tool to set a surveillance system allowing management strategies to be developed or adjusted in short time, whereas continuous, real-time data can also serve the evaluation of the representativeness of other data sources. In addition, seafloor observatories are already utilized in numerous multidisciplinary projects (e.g. geology, physical oceanography, ecology, and other fields mentioned above), which already require real-time data flow. In this way, an additional societal service (i.e. fishery-independent stock assessment) improves the allocation of resources when compared to individual deployments, which can be nevertheless useful and complementary for a more complete spatial resolution (see "Spatial organization" section).

There are still technological and methodological milestones to be achieved before a network of cabled cameras can be considered as a reliable tool to track and collect biological and ecological data relevant to broad spatial scales, which is the pre-requisite to accurately infer relevant ecological indexes, such as species richness and abundance, and their possible drivers [see review by Rountree *et al.* (2020)]. In the present paper, we outline a strategic pathway for a global effort to develop networks of key observatory infrastructures and associated technologies that are focused on economically valuable species. First, we define specific aspects to help make observatory networks infrastructures of more scientific and socio-economic utility in relation to their spatial organization and data interpolation. Next, we describe two pilot projects that have begun to implement these strategies as part of an effort to assess their efficacy and relevance to fishery stock assessment programmes.

Strategic pathway for the establishment of cabled observatories' monitoring programmes

We have identified two main aspects of strategic relevance for the development of cabled observatory networks, as the pre-requisite to obtain reliable data on fishery targeted species. These are

(1) network spatial organization allowing data interpolation to derive demographic indices (e.g. size, density, and biomass) and behavioural information and

(2) Artificial Intelligence (AI) assistance in data collection and processing.

Note that the typical goal is to link AI-based animal counts to water temperature, salinity, turbidity, and so on. However, here, we do not focus on this stage of analysis, because multiparametric data processing at cabled video observatories has been extensively treated elsewhere (Aguzzi *et al.*, 2012, 2015, 2019, 2020a, b). Instead, we elaborate on the strategic aspects of spatial organization and AI for video surveillance.

Spatial organization

Development of a cabled observatory network, as a data collection technology, faces two basic issues at the spatial scale: sample bias and missing data. Traditional data collection occurs during surveys (e.g. trawling), that are designed to minimize sample bias and increase sample representativeness. This is generally not the case with cabled observatories, which are typically installed at fixed points of convenience, with a spatial organization that may not follow relevant ecosystem structures. As a result, data collected in such a way are often not representative of true population or community dynamics. Moreover, because observatory installation cannot be ubiquitous, there are vast areas from which data are missing. In these cases, we typically proceed with interpolation (prediction) of non-available data, which is also largely influenced on how the observatory network is arranged. Thus, although data representativeness and missing data are two separate problems, the approach to address these problems is subtly interrelated, because it depends on the network's spatial arrangement. As a result, observatory installations should be carefully preplanned to best address both problems. Finally, depending on the type of targeted stock, a certain level of flexibility and adaptability of the specific location for some sites might be required, given the possible changes in distribution of fish stocks because of natural and/or anthropogenic factors.

Marine observatories should be arranged into integrated geographic networks (at relevant spatial scales) to efficiently monitor targeted fish stocks (*sensu* Rountree *et al.*, 2020). Such an arrangement can lead to a spatially coordinated inventory of organisms and environmental conditions at all observatories within the network. Information could be subsequently interpolated at different spatial scales, from local (m^2 effective field of view coverage at each observatory) to large spatial scales (km^2 effective area coverage of the network), using spatial distribution modelling approaches (Hengl, 2009; Di Piazza *et al.*, 2011; Li and Heap, 2011). If the arrangement of the network and observation protocols are well designed and planned in consultation with statisticians (Foster *et al.*, 2018), they could possibly be used akin to Baited Remote Underwater Video Systems (BRUVS) to collect video estimates of biodiversity metrics such as relative abundance and size structure (Cappo *et al.*, 2007; Langlois *et al.*, 2012, 2018; Hill *et al.*, 2014, 2018; Whitmarsh *et al.*, 2017). Fish-stock assessment metrics have been successfully obtained with BRUVS (e.g. Langlois *et al.*, 2018). Cabled observatories could be used in a similar fashion to BRUVS, albeit not baited, to provide an inexpensive non-invasive method complementary to direct sampling (e.g. trawling). Thus, ultimately they could yield results comparable to experimental fishery surveys, as advocated by experts of the International Council for the Exploration of the Sea—ICES (WKPICS2 report; ICES, 2013).

In this scenario, a spatial network could be conceived to have a fixed framework of nodes and a group of mobile units in-between, which could include BRUVS (Rountree *et al.*, 2020). The use of autonomous mobile platforms such as stand-alone (non-cabled) lander-nodes (Corgnati *et al.*, 2016; Marini *et al.*, 2018a) as well as remotely operated underwater crawlers (Aguzzi *et al.*, 2019; Chatzievangelou *et al.*, 2020), in concert with cabled observatories, would permit some flexibility with regard to a maximizing power within a statistically sound survey design (*sensu* Hill *et al.*, 2018) and, if necessary, spatially adaptive adjustments of monitoring in response to changing fishery stock distributions. Stand-alone repositionable landers, equipped with mobile underwater crawlers, will be used in future to enforce different nesting routines for image sampling around fixed platforms, hence providing important spatial data according to different scales of seafloor heterogeneity (Aguzzi *et al.*, 2020a).

The observatory mechanical eye is the camera, which, if endowed with enough measuring functionalities (AI), could be an effective automatic replacement to physical catch and manual measurement. Spatial coverage remains a relevant issue (Aguzzi *et al.*, 2019). A well-planned arrangement of a network of such cameras, possibly including small mobile platforms, could be a similarly beneficial replacement to costly and temporally scarce survey missions (Rountree *et al.*, 2020).

Artificial video intelligence

An AI upgrade for the processing of video data is required to transform cameras into true ecological effective sensors, operative in fully natural environments, and capable of autonomous classification and enumeration of individuals of key target species (MacLeod *et al.*, 2010; Dell *et al.*, 2014; López-Vázquez *et al.*, 2020), alongside the estimation of individual animal characteristics like body size and behaviour (Aguzzi *et al.*, 2020b). To fully address measuring functionalities, cameras still need a level of advancement in integration between hardware (e.g. stereo vision) and software (e.g. image-analysis programmes) components that are not yet standardized. An increase in classification efficiency could be achieved by defining appropriate training datasets, in which experts manually classify animals and AI approaches automatically learn how to detect and discriminate among species (Moniruzzaman *et al.*, 2017; Malde *et al.*, 2020).

The Lofoten-Vesterålen (LoVe) observatory, located in a rich Cold-Water Coral area dominated by the deep-water coral *Lophelia pertusa* (Figure 1), provides an example of developed procedures for implementing a fully automatic underwater video-surveillance system for deep-sea commercial species such as rockfish (*Sebastes* sp.) (Pampoulie *et al.*, 2009). Automation in fish tracking and counting is being implemented in order to produce information on population activity patterns at diel and seasonal scales, in relation to oceanographic cycles (Aguzzi *et al.*, 2020a). To this end, the establishment of large open-access repositories of labelled images of fish should be encouraged, because the precision of classification depends on the level of representativeness of that set (e.g. Bird *et al.*, 2014; Matabos *et al.*, 2017; Konovalov *et al.*, 2019). Such collaboration could be also envisaged with the BRUVS Community as operators have a need for similar AI development related to the creation of a centralized data repository of ecological annotation data (https://globalarchive.org).

To date, popular AI approaches (e.g. based on deep learning) are rarely used as stand-alone vision algorithms, but rather in conjunction with more classic imaging, classification, and prediction approaches (Qin *et al.*, 2016; Sun *et al.*, 2016). For instance, Convolutional Neural Networks (CNNs), a popular deep-learning approach, typically require some image pre-processing for good classification performances (Ali-Gombe *et al.*, 2017; Villon *et al.*, 2018). Recent CNN applications are often performed under controlled conditions, where image content is mostly unambiguous and the overall number of training examples is relatively high (Siddiqui *et al.*, 2018; Álvarez-Ellacuría *et al.*, 2020;

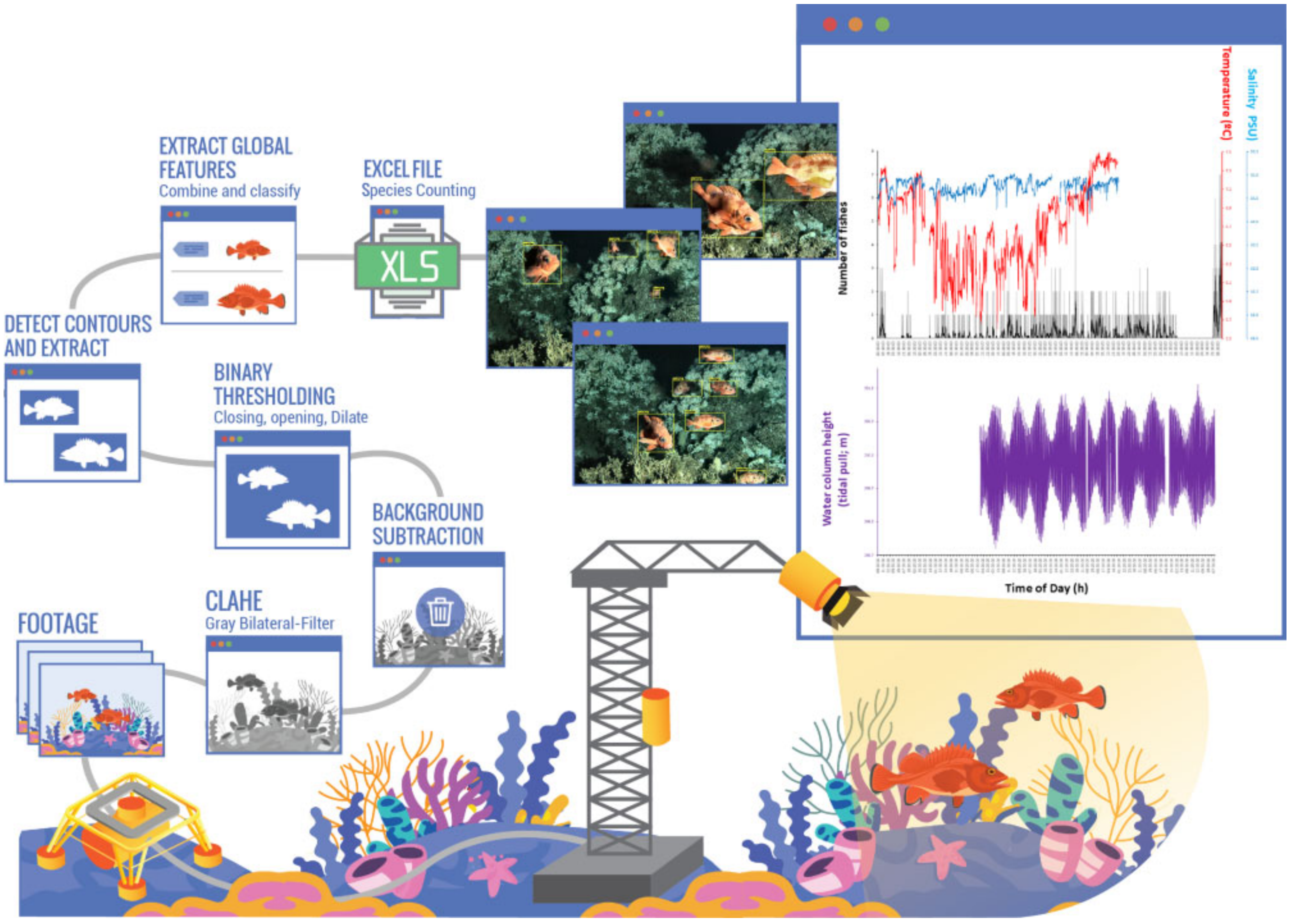

Figure 1. Pipeline for the automated rockfish tracking and counting at the LoVe ocean observatory (https://love.statoil.com/) (López-Vázquez *et al.*, 2020). Video counts (light grey, row output; bold black the three-step moving averaged tendency) were obtained form 17 November 2017 to 27 June 2018, along with environmental parameters (temperature, salinity, and depth of the water column—a proxy for the local internal tidal regime). First, various filters are applied to the original images and then the background is subtracted. With the help of binary thresholding, contours are detected and extracted. Afterwards, the global characteristics are extracted for classification. Finally, the rockfish count per hour (grey plus three-step moving average in bold black) is extracted in order to analyse their diel activity.

Hu *et al.*, 2020). However, deployed cabled cameras should operate in natural uncontrolled conditions (Spampinato *et al.*, 2010), where underwater equipment is often subject to power supply limitations when deployed in a stand-alone mode. However, such deployments could execute image-analysis operations on board. The computational costs of trained CNNs could be too high to sustainably operate inside such underwater equipment. To this end, synthetic image-representations based on trained evolutionary algorithms (Marini *et al.*, 2018b) have been proposed to more cost-effectively operate inside underwater stand-alone cameras. Regardless of the AI method used, the recognition and classification problem in underwater imaging remain unresolved to date, especially as an automated tool for stand-alone and networked observatories (Aguzzi *et al.*, 2020b).

Interestingly, the problem of data representativeness also applies to camera equipment and computer vision (Aguzzi *et al.*, 2020b) that are ultimately responsible for data recording. Here, to effectively replace human intervention, a comparable level of visual comprehension and detail is needed. This requires an ideal level of automation, which is presently hindered by camera and AI technological limitations (see above), and high costs in planning and deployment of a camera network. At present, a more realistic configuration is to have a patchy network of conveniently arranged cameras with heterogeneous imaging capabilities (e.g. some yielding only counts, others yielding counts-by-class plus individual fish lengths, and so on), reflecting the compromise between practical/cost-related issues (e.g. finite number of nodes within the observatory network, selection of sites based on seabed geo-morphology and habitat heterogeneity, and adequacy for connectivity/maintenance) and the optimal spatial arrangement based on ecological representativeness for each targeted species or community. On an equally important note, because of the lack of a globally standardized methodological approach, we are likely to see different projects having different infrastructure set-ups and sensing/measuring resolutions. One should expect considerable effort in developing AI and statistical corrections to address this less-than-ideal configuration. For instance, one should practically consider ways to integrate heterogeneous imaging outputs at different degrees of individual fish detail.

When possible, one should assess the level of data representativeness by comparing camera outcomes with data from nearby commercial fleet landings (or survey missions) carried out in the same time windows, assisted by the use of electronic logbook data with potentially better spatial resolution of catches. Furthermore, new -omics technologies based on eDNA specific markers traceability and quantification could be used (Knudsen *et al.*, 2019). Interesting initiatives in this sense are the creation of robotic *in situ* omics sensors for water time-lapse collection, fixation, and markers presence determination (e.g. https://www.aqua.dtu.dk/english/news/2018/10/robot-tracks-environmental-dna-from-fish-on-seabed? id=a0d7fd91-b2d7-422f-bb3c-1ddd08acf4a2). Unfortunately, currently calibration actions are envisaged as the cross-reference of detected eDNA markers for targeted species upon images in extensive video-richness data banks form cabled observatories and stand-alone units (Aguzzi *et al.*, 2019). Such a cross-validation would also need to be foreseen in terms of markers' signal intensity vs. video-reported counts as another way to get to comprehensive evaluations of abundances. Various studies suggest potential calibration methods to inter-calibrate camera-collected data with more accurate field-survey measurements (Deville and Särndal, 1992; Valliant and Dever, 2011; Baker *et al.*, 2013). For instance, propensity models (Valliant and Dever, 2011) could use individual fish features to calibrate camera data with field-survey counts. The idea is to calculate the individuals' propensity to be included in a camera sample, by using fish counts and features from both reference population survey data and camera data. Next, camera counts are re-weighted with those propensity scores to obtain more representative count estimates. Generally, these correction techniques are popular in statistical surveys, but their application seems not yet standardized in fishery science, probably because of the difficulty of intensive spatio-temporal data collection. As finer the sampling in relation to space and time (sizing, sex/age recognition by specific markers or length, all the way up to biomass calculation as a function of three-dimensional volume of individuals etc.; *sensu* Aguzzi *et al.*, 2020b) and more data are available through camera sensing, more those statistical methods could become appealing in fishery applications. More methodological research might be needed to better tailor these techniques to monitoring by cabled observatories. Here, the more individual fish features that are determined (both from cameras and from surveys), the better the calibration will be. Interestingly, as a result, finer camera functionalities can be exploited to correct (to a certain degree) the negative impact of a poor arrangement of the camera network by using *post hoc* statistical techniques. Therefore, one of the most urgent current goals is to rapidly develop AI vision methodologies to empower general measuring capabilities of cameras that are yet lacking.

Pilot examples that provide a roadmap for cabled observatory monitoring of fishing stocks

We now present two strategically and operationally relevant pilot projects that are ready to immediately begin biological (i.e. image-based) and environmental monitoring of commercially relevant fishery resources. These projects are set at two existing major observatories: ONC for sablefish (*Anoplopoma fimbria*) and EMSO for Norway lobster (*Nephrops norvegicus*).

Study case 1: fishery-independent assessment of sablefish in the NE Pacific

Sablefish is a soniferous, long-lived, deep-sea demersal fish species, found at depths from 300 to 3000 m, which supports important commercial fisheries over its broad distribution in the Pacific Ocean (Wilkins and Saunders, 1997; Warpinski *et al.*, 2016; Riera *et al.*, 2020). Sablefish populations include migratory and resident individuals (Chapman *et al.*, 2012), with complex geographic movements occurring at small and large basin-scale ranges (i.e. Pacific coast of North America; Orlov, 2003). Their complex biological cycle is characterized by horizontal and vertical movements, which vary with sex and maturity (Beamish and McFarlane, 1988; Sogard and Olla, 1998; Ryer and Olla, 1999; Jacobson *et al.*, 2001; Maloney and Sigler, 2008; Morita *et al.*, 2012; Hanselman *et al.*, 2015). Recent studies have proposed different mechanisms for controlling the temporal patterns of sablefish movements along the seafloor and through the water column. Although in Barkley Canyon, British Columbia, sablefish movements seem to be ruled mainly by tidal cycles (Doya *et al.*, 2014; Matabos *et al.*, 2014; Chatzievangelou *et al.*, 2016), in other regions of the NE Pacific, diel vertical migrations of subpopulations have been attributed to the displacement patterns of their prey (Goetz *et al.*, 2018) and also to the intensity of their near-bottom foraging behaviour (Sigler and Echave, 2019). However, other studies have not identified a single major environmental control over sablefish population movements (Orsi *et al.*, 2006). The sablefish fishery is an economically important fishery in the north Pacific (Wilkins and Saunders, 1997; Warpinski *et al.*, 2016; in 2018, US commercial catches were 17.6 thousand metric tons valued at US$110.4 million, National Marine Fisheries Service, 2020) and is currently managed based on fishery-dependent survey data conducted on board commercial fishing vessels employing either creels or pots, and on independent trawl survey data collected by Fisheries and Oceans Canada (DFO) (Cox *et al.*, 2011) and NOAA Fisheries. However, as with other demersal trawl fisheries, there are concerns about the potential impacts of trawl surveys on deep-sea habitats (Clark *et al.*, 2016; Hiddink *et al.*, 2017).

The NEPTUNE cabled observatory operated by ONC presently represents the best equipped network for a truly technologically oriented fishery-independent monitoring of sablefish stocks along the Pacific coast of North America (map inset in Figure 2). One of its nodes, located in Barkley Canyon, consists of several cabled instrument platforms that span a maximum linear distance of ~15 km, and a depth range of 400–985 m, which overlaps with the depth of greatest abundance for sablefish (Goetz *et al.*, 2018; Kimura *et al.*, 2018). The total of five fixed instrumented platforms and a mobile crawler (with a 70-m radius range) are equipped with a suite of oceanographic and biogeochemical sensors in addition to the video cameras mounted on pan and tilt units. This combined scheme of fixed and mobile platforms can increase the spatial and ecological representativeness of data, tackling distinct challenges posed by different levels of motility among targeted species in the monitored community (e.g. highly motile vs. more sedentary or even sessile animals). The crawler is able to cover a substantially greater area than the standard field of view of the fixed platforms and, provided that statistical challenges of standardizing data from a diverse monitoring setting are overcome, that platform can help to extrapolate local (site-specific) results to a broader scale (e.g. more reliable calculations of densities over a greater surface). The broad range of oceanographic and biogeochemical sensors are set to measure parameters such as temperature, salinity, pressure, dissolved oxygen, current speeds and direction, acoustic backscatter, turbidity, chlorophyll, pCO_2, pH, and ambient noise. All of these parameters, sampled at high (0.1 Hz) frequencies are instrumental for

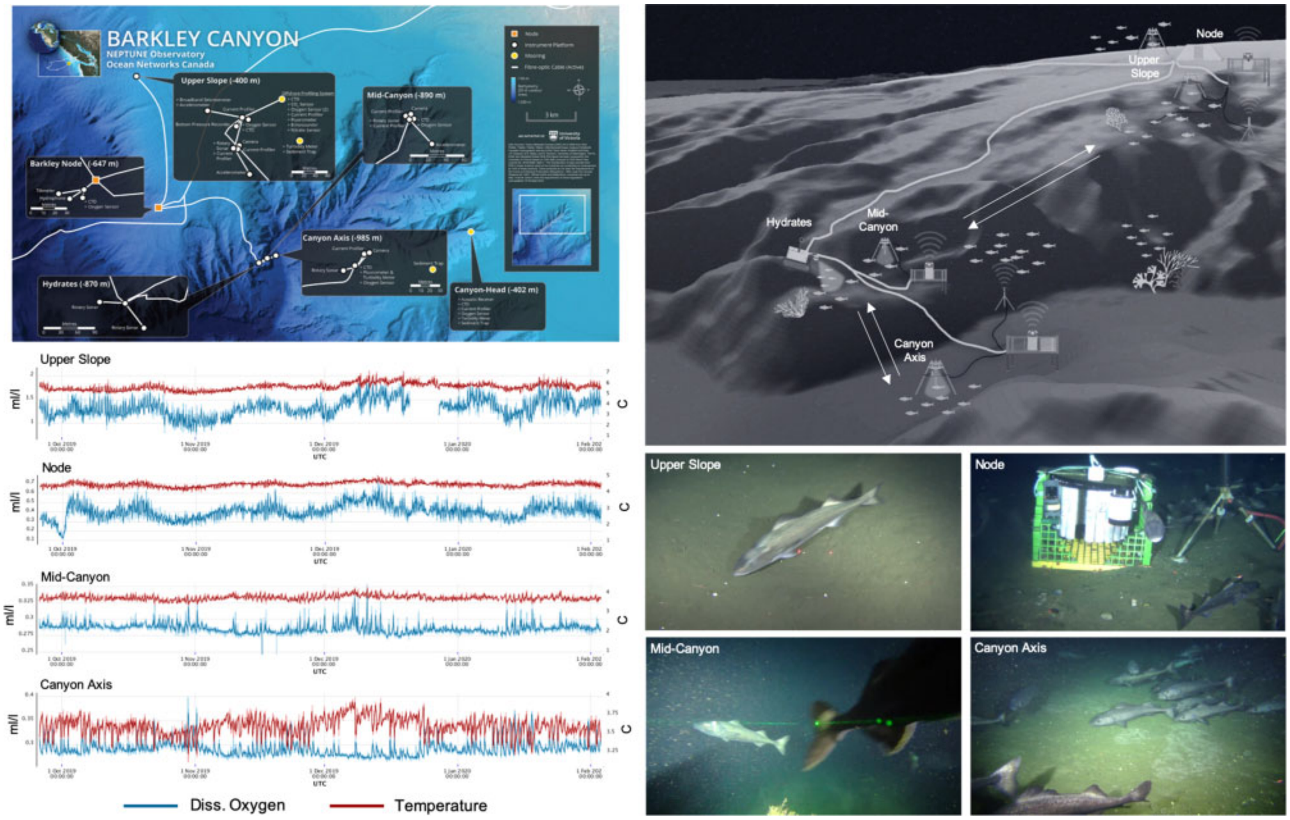

Figure 2. A ONC cabled observatory in the NE Pacific depicting the seafloor infrastructure in Barkley Canyon allowing fishery-independent monitoring of sablefish (*Anoplopoma fimbria*). Top left: map showing the locations of the instrument platforms in the canyon and adjacent slope: Barkley Upper Slope (400 m), Node (647 m), Hydrates (870 m), Mid-Canyon (890 m), and Canyon Axis (985 m). Bottom left: temporal variability in dissolved oxygen and temperature data from four of these locations from 27 September 2019 to 3 February 2020. Top right: schematic showing a three-dimensional bathymetric map with observing locations in Barkley Canyon and depicting some of the known population moments of sablefish (white arrows—Doya *et al.*, 2014). Bottom right: field of view of seafloor cameras installed in four of these locations in a depth gradient and inside and outside the submarine canyon depicting large densities of sablefish. The collocated environmental sensors with the seafloor video cameras are nested in spatial scales from 100s of metres up to ∼15 km, and in a depth gradient spanning ∼600 m. This allows for deriving individual species population metrics such as abundance and size–class distributions, and also entire community parameters such as species richness and diversity, in all the locations with potential extrapolation for the entire region.

determining environmental fluctuations at multiple temporal scales, which combined with time-lapse imagery and passive acoustics may enable the constraining of cause–effect relationships determining temporal and spatial changes of sablefish abundances and size–frequency distributions. However, what remains to be assessed is how effectively the video and ancillary environmental data from these five different locations can be combined to generate reliable and complementary information for sablefish fishery stock assessment representative of a much larger area. A clear first step for a "proof of concept" of this application would be to compare the accumulated ∼10 years of video and environmental data available from the various installations in Barkley Canyon with regional fishery statistics available for sablefish (e.g. fishery catch/landings data).

Inferring true density estimations of freshwater and marine fish populations has been explored based on individual counts, species' home ranges, and movement patterns (Campos-Candela *et al.*, 2018). In addition, population density estimations have been assessed by using simultaneous reference time-series (Follana-Berná *et al.*, 2019, 2020), individuals' arrival times at and geometry of baited cameras (Farnsworth *et al.*, 2007), and by using stereo vision imagery (Denney *et al.*, 2017). Species home range was used by Palmer *et al.* (2011) and Alós *et al.* (2016, 2019) as the area with 95% probability of finding an individual during an extended period of time. In applying this interpretation to our "proof of concept", the assumption of fixed, homogeneously distributed home ranges for sablefish individuals in Barkley Canyon could be challenged because of the existing knowledge of the species' population dynamics around Vancouver Island. For example, the species is known to be highly mobile and migratory, albeit with high proportions of resident individuals (Kimura *et al.*, 2018). Furthermore, individuals may move either independently at small spatial scales, without aggregation, or rather in large dispersed shoals, and therefore the presence of an individual is often correlated to other individuals nearby, swimming at a certain distance (Krieger, 1997). To account for the intrinsic variability within the population, tackling uncertainties of the demographic models, fisheries, and independent survey data must be used as a reference, in addition to the systematic tracking of sablefish individuals in Barkley Canyon (e.g. by using large-scale acoustic tag tracking). At the same time, one should bear in mind that cabled observatory network nodes can be also established in key areas for more direct demographic monitoring such as nurseries.

The first preliminary step towards the development of a model for the estimation of sablefish density and, subsequently, biomass in Barkley Canyon is the establishment of an expected number of counts per observing platform and temporal window, based on Poisson probabilities and movement patterns of known rhythmic typology and use them to create baseline simulated time-series. An example analysis was conducted based on the sablefish counts recorded every 30 min at three Barkley Canyon video platforms, between mid-October and mid-November 2011 (PODs 1, 3, and 4; Doya *et al.*, 2014). For a detailed description of the methodology and results see Supplementary Appendix 1. Briefly, the expected count rate λ was calculated for each platform as a function of time, and it was subsequently used to simulate time-series (Supplementary Appendix Figure A1). The next steps would involve the development of a model-scenario for better describing the movements of sablefish within a wide range of habitats within Barkley Canyon (based on a constrained distribution, without accounting for individuals entering or leaving the canyon from or towards the surrounding areas).

Data derived from ONC's archived video imagery in Barkley Canyon have already provided valuable information on sablefish ecology with relevance to fishery-oriented monitoring. Video counts of sablefish are, at certain periods of the annual cycle, the highest of all species within the local community, only second to the also commercially important tanner crab (*Chionoecetes tanneri*) (Matabos *et al.*, 2014; Doya *et al.*, 2017; Chauvet *et al.*, 2018, 2019). Fish counts vary over the topography at small scales within different camera views (Doya *et al.*, 2014, 2017; Chatzievangelou *et al.*, 2016), while sizes range from 35 to 95 cm with an average ($\pm$standard deviation) length of 63.6 $\pm$ 10.4 cm, indicating that video counts at depths of $\sim$850–900 m mostly include adults (Doya *et al.*, 2014).

The benthic faunal assemblages within Barkley Canyon, also studied in the ONC network area exhibits distinct seasonal patterns, related to environmental variation (Juniper *et al.*, 2013). Sablefish counts increase in spring–summer (Doya *et al.*, 2017) at the hydrate site in the Barkley canyon wall (see the map inset in Figure 2), but not in the Mid-Canyon and Canyon Axis sites (Juniper *et al.*, 2013; Matabos *et al.*, 2014; Chauvet *et al.*, 2018), supporting the need for monitoring the Barkley Canyon population using various, extensively arranged in space, imaging sources. The relationship of the observed seasonal trends with the local spring–summer upwelling (depth limit 250 m) is uncertain (Chauvet *et al.*, 2018), whereas stochastic meteorological events (e.g. storms) can also indirectly influence fish counts, through variation in water mass properties that affect predator and prey abundances in the water column (Matabos *et al.*, 2014). At aphotic depths, fish counts drop when tidal flow speed increases in the Benthic Boundary Layer (Doya *et al.*, 2014; Matabos *et al.*, 2014; Chatzievangelou *et al.*, 2016) with the dominant current oriented down-canyon at mean speeds of 2–4 cm/s and peaks of up to 30–70 cm/s (Chauvet *et al.*, 2018). Based on successive peaks in counts from video platforms at different depths, Doya *et al.* (2014) hypothesized that sablefish perform diel vertical migrations through Barkley Canyon related to feeding and predator avoidance strategies. In particular, adults show 24-h based vertical water column migrations in combination with bathymetric axis-oriented displacements over the seabed when entering the canyon. Seabed movements into the canyon could be performed to avoid large pelagic predators (e.g. cetaceans; e.g. Mathias *et al.*, 2012), although no proof for that has been yet provided. Chatzievangelou *et al.* (2016) expanded on this observation, suggesting that sablefish may synchronize their displacement according to weak tidal flows to disperse long distances through the hypoxic waters of Barkley Canyon at low energetic costs.

Automated scripts for counting of individuals (Qin *et al.*, 2016; Marini *et al.*, 2018a, b; López-Vázquez *et al.*, 2020) should be at the core of any established video-monitoring programme at ONC. Those scripts could be implemented by focusing on the development of the recognition, counting, and size–class measuring of fishes (Fier *et al.*, 2015). Count results obtained at each single node could be extrapolated over the whole network area (see Figure 2), for instance using kriging regression techniques (Hengl, 2009), and then compared and validated with those derived from commercial pot fishing and trawling, using propensity modelling (Valliant and Dever, 2011). Here, trawling surveys would produce the reference data with which non-probability sampling camera data could be calibrated, as described above. Alternatively to kriging regression for inter-node extrapolation, one could also use a combination of Poisson modelling of all locally derived (i.e. site-specific) count data, individual arrival patterns, the available or inferred information on sablefish home range, displacement pattern, and movement speed within Barkley Canyon, to estimate regional abundances through Bayesian-based simulations (Follana-Berná *et al.*, 2019, 2020).

Such an approach could be further strengthened by combining video imaging with high-frequency acoustic cameras, which have greater projection range into the water column and are not dependent on light or water clarity (Rountree *et al.*, 2020), as well as passive acoustics, given that sablefish sounds have recently been described (Riera *et al.*, 2020). Species morphometric characteristics in three-dimensional-image outputs and their traceability based on sound markers, may complement image counting capacity as well the computing of other demographic indicators as class–size distribution frequencies (Aguzzi *et al.*, 2019). Acquisition of size–class frequencies (Beamish and Chilton, 1982) and the assessment of the role of canyon morphology on population dynamisms (e.g. the presence of adults and juveniles in different areas) is an ongoing effort, as a proof of concept of potential services ONC may provide to Fisheries and Oceans Canada (DFO) and the Canadian Fishery Associations.

Study case 2: fishery-independent assessment of Norway lobster in Galway Bay, Ireland

In the European Union, the EMSO network relies on the previous successful experiences and know-how from ONC in setting a guideline for its service-oriented installations in the Atlantic and Mediterranean, which host fully developed fishery industries. The Norway lobster is one of the most important commercial fishery resources in Europe (Ungfors *et al.*, 2013). European landings of Norway lobsters were around 44 000 tonnes valued at $\sim$360 million EUR in 2016 (EUROSTAT, ec.europa.eu/eurostat/web/fisheries/data/database). Norway lobsters dig and inhabit complex burrow systems in muddy habitats used for shelter and for territorial control, from which they emerge to find food (Sbragaglia *et al.*, 2017). Burrow emergence patterns differ with relation to depth and time of the day (Aguzzi and Sardà, 2008): from nocturnal to crepuscular on upper and lower shelves to diurnal on slopes. Emergence is modulated not only by the stage of the reproductive cycle but also by size and other more contingent ecological factors (e.g. the presence of predators or prey; Sbragaglia *et al.*, 2017). Such modulation represents a behavioural mechanism that protects this commercially exploited population from trawling because when individuals are in their burrows they are inaccessible to trawling.

The behaviour of free-living Norway lobster individuals has never been monitored over time with video-cabled observatory technology. Continuous video tracking of populations would be highly informative for fishery assessment and management in both the Atlantic Ocean and Mediterranean Sea (Morello *et al.*, 2007). Trawling surveys have been used to provide indirect biomass estimates by means of abundance indices derived from surface density data (i.e. the number of animals per swept area; Maynou *et al.*, 1998). However, this method does not account for temporal and spatial changes in susceptibility to trawl capture because of the lobster's burrowing behaviour (Sardà and Aguzzi, 2012). In part because of the inherent bias of trawl data, video surveys were first instituted for Norway lobster assessment in the 1970s (Leocádio et al., 2018). The visual direct method of assessment counts burrows (and thus inhabiting individuals) based on the characteristic morphological traits of these structures within the substrate (Campbell *et al.*, 2009). The video, or "Under Water TeleVision" (UWTV), survey is a less invasive methodology compared to trawling and is conducted using towed camera-sledges (Leocádio *et al.*, 2018). A comprehensive monitoring and a UWTV-based stock assessment programme have been developed in several European countries coordinated by ICES, which hosts the Working Group on *NEPhrops* Surveys (WGNEPS; ICES, 2019).

Three major uncertainties have been identified with UWTV methodology (Leocádio *et al.*, 2018). Current stock assessment procedures make assumptions to address these uncertainties. The first relates to burrow occupancy, which is currently assumed to be that one individual >17-mm carapace length occupies one identifiable burrow system. The second relates to burrow system size and the "edge effect" (i.e. burrows systems only partially included in the field of view, leading to errors in counting), both biasing the density estimates of the effective area surveyed. The third relates to the accuracy of burrow identification because other sympatric fish and decapod species construct tunnels with morphology similar to those of *Nephrops* and may bias assessment by underwater photography (Sardà and Aguzzi, 2012).

UWTV surveys have seldom been used to derive behavioural information on burrow emergence rhythms as a source of animal availability to capture. A fixed-point-cabled camera installed on the SmartBay observatory (https://www.smartbay.ie/) as an EMSO testing site, may help in gathering those behavioural data as ancillary information to stock assessment. This cabled observatory presently operates at a depth of 20 m in the Galway Bay area, within an important fishing ground for Norway lobsters (Gaughan and Kolar, 2010). Technological platforms like this one can provide critical information on burrow usage by several individuals at once, including temporal patterns in emergence, occupancy, and changes in the visual signature of the burrows (Figure 3). The burrowing emergence behaviour of several individuals could then be monitored by means of continuous day–night video and multiparametric environmental data collection, to assess the control of ecological (e.g. presence of predators and prey) and environmental (oceanography and meteorology with special focus on light) factors in modulating individual variable predisposition towards burrow emergence. At the same time, the role of social aggressive interactions in modulating emergence timing and duration in a group of neighbours could be evaluated (Sbragaglia *et al.*, 2017).

SmartBay monitoring could be spatially facilitated by using stand-alone camera set-ups for long-lasting deployment, following BRUV sampling strategies (e.g. GUARD1/DeepEye; Marini *et al.*, 2018a) as well as coastal crawlers (Aguzzi *et al.*, 2015, 2020a). Recently, both technological platforms have been installed at the Mediterranean OBSEA cabled observatory (https://obsea.es) (Aguzzi *et al.*, 2018), that like SmartBay, is an EMSO technology testing site (Del Río *et al.*, 2020). A coastal crawler is being used to scale local camera information to larger video-transect areas (Aguzzi *et al.*, 2015). Moreover, preliminary trials on *Nephrops* behavioural tracking by cabled observatory cameras have already started. During 2019, a first trial to evaluate the technology and the use of a video camera to study the behaviour of *Nephrops* was executed. A 3×3 m cage was built and deployed on the seabed close to OBSEA, where the real-time video camera is installed (Figure 4). Artificial burrows were also installed inside the cage. By using the video camera, the movement of the animals was recorded in relation to the establishment of deep-water pot fishing and release (i.e. as required in fishery no-take zones) procedures. Time-lapse image monitoring, animal confinement, and *in situ* caging are helping to establish similar procedures at the SmartBay observatory (see Figure 3).

As for sablefish, the establishment of an automated video-imaging protocol would be required to achieve the status of an autonomous monitoring programme useful on a stock assessment scale. In the case of lobsters, this would encompass AI-aided detection of burrow emergence, tracking of animal movement, and identification of social interactions (García *et al.*, 2019), altering burrow emergence behaviour (Sbragaglia *et al.*, 2017). Such long-term *in situ* observations will be particularly informative in addressing the burrow occupancy assumption used in the UWTV-based stock assessment. Refining the automation of burrow counting on the UWTV surveys through AI or deep learning could also greatly improve the quality and reproducibility of what is currently a subjective process, albeit based on the judgement of trained experts, overcoming challenges such as the capability of the algorithms to distinguish between burrows of different species and the lack of appropriate ground truth for their training (Lau *et al.*, 2012; Sooknanan *et al.*, 2013, 2014; Corrigan *et al.*, 2019).

Conclusions

In the near future, the growing demand for the implementation of strategic marine habitat conservation areas and the ensuing debate surrounding their exploitation will encourage a multidisciplinary dialogue between oceanographers, geologists, ecologists, fishery biologists, policy-makers, and the public. Advancements in biological and environmental automated data collection *via* cabled digital cameras, environmental sensors, and probes, AI vision and data processing promise to revolutionize how such marine zones might be monitored and managed. However, to date, the ideal level of required automation is a long way from reaching a development stage suitable for fisheries applications. This is because of intrinsic limitations in automatic imaging (in both camera

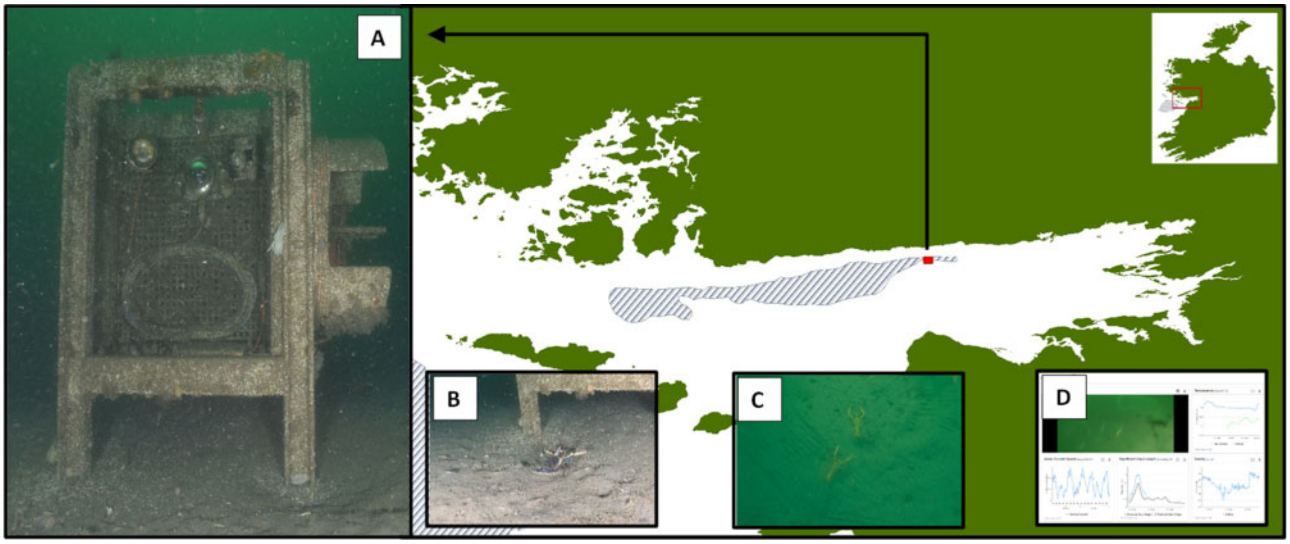

Figure 3. The ESMO SmartBay observatory location within Galway Bay (Ireland) in relation to the Norway lobster (*Nephrops norvegicus*) fishery grounds. The node infrastructure is visible over the muddy seabed area (a), where an individual clawed lobster (*Homarus gammarus*; b) is depicted in relation to the node infrastructure. Two specimens of *Nephrops* (c) are depicted from another angle of view. Time-series graphs of multiparametric environmental data are shown from the observatory web interface for data management and visualization (d).

Figure 4. The OBSEA trials (Vilanova i la Geltrú, Spain) for the video monitoring of Norway lobster (*Nephrops norvegicus*) behaviour. Top left: cage to prevent animals escaping form the camera field of view. Top right: deployment and installation of the cage in front of the video camera. Bottom right: animal inside the cage with a plastic tag used for its identification. Bottom left: animal inside the artificial (PVC plus concrete) burrow.

and AI) and the lack of strategic planning of the arrangement of cameras into a useful network with adequate observation coverage.

Here, we have provided two cases where existing infrastructures (and their data collections) may be used for the development and testing of methods and strategies for automated marine observation in relation to potential fishery-independent stock assessment of key commercial species. A highly integrated spatial network containing fixed nodes and a group of mobile units operating in-between could be the most appropriate set-up for deriving fish-stock assessment information and an ecosystem-based monitoring of biodiversity. Such a framework would enable the non-invasive acquiring of local data on size distribution and population abundance for all species sharing the same habitat regardless of their motility, to extend the spatiotemporal knowledge of ecological interactions and other highlighted ecological indicators along time.

The development of the AI vision capabilities and a more integrated collection and exchange of information at an adequate spatial scale between cabled observatories will expand this potential. If proven feasible, implementation of these actions will be expensive. Therefore, there is need for a timely debate of socio-economic relevance and benefit of extending fixed camera observatory networks and their capabilities to produce spatially reliable and efficient biodiversity monitoring programmes and fish-stock assessments.

Data availability

There are no new data associated with this article. No new data were generated or analysed in support of this research.

Supplementary data

Supplementary material is available at the *ICESJMS* online version of the manuscript.

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Author Contributions

All the authors equally contributed to the conception of the paper. All the authors contributed to writing and editing the manuscript and approved the final draft.

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