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Machine Learning Applications for Fisheries—At Scales from Genomics to Ecosystems

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ABSTRACT

Fisheries science aims to understand and manage marine natural resources. It relies on resource-intensive sampling and data analysis. Within this context, the emergence of machine learning (ML) systems holds significant promise for understanding disparate components of these marine ecosystems and gaining a greater understanding of their dynamics. The goal of this paper is to present a review of ML applications in fisheries science. It highlights both their advantages over conventional approaches and their drawbacks, particularly in terms of operability and possible robustness issues. This review is organized from small to large scales. It begins with genomics and subsequently expands to individuals (catch items), aggregations of different species *in situ*, on-board processing, stock/populations assessment and dynamics, spatial mapping, fishing-related organizational units, and finally ecosystem dynamics. Each field has its own set of challenges, such as pre-processing steps, the quantity and quality of training data, the necessity of appropriate model validation, and knowing where ML algorithms are more limited, and we discuss some of these discipline-specific challenges. The scope of discussion of applied methods ranges from conventional statistical methods to data-specific approaches that use a higher level of semantics. The paper concludes with the potential implications of ML applications on management decisions and a summary of the benefits and challenges of using these techniques in fisheries.

KEYWORDS

Marine science; monitoring; management

1. Introduction

Fisheries science needs extensive amounts of data to monitor and manage marine natural resources that provide ecological, social, and economic benefits. Data collection and data processing are among the most labor-intensive and costly aspects of fisheries science (Dennis et al. 2015), leading, for example, to the use of vessels of opportunity (Uriondo et al. 2024), reductions in fishery-independent surveys (DeFilippo et al. 2023), and transitions from human observers to electronic monitoring (van Helmond et al. 2020). Resource-intensive and critical data tasks include the aging of fish using otoliths/statoliths, gonad analysis, egg counting and identification, recording of catches at sea, analysis of vessel location data, video and image processing, genetic analysis of population

structures, use of acoustic data in fish stock assessment, analysis of environmental conditions and sampling for other biological parameters (e.g., to derive length-weight relationships). Meanwhile, fisheries management is moving toward more holistic ecosystem-based approaches that require consideration of all human activities, including the impacts of activities on non-target species and habitats (Pedreschi et al. 2019; Link and Marshak 2022).

Rapid technological developments have enabled extensive amounts of data to be collected through innovative and affordable sensor technology, while data storage capacity has become less expensive and computational power has expanded. Processing and analyzing these vast amounts of data presents a bottleneck requiring new and automated workflows (Malde et al. 2020; Rubbens et al. 2023). The upsurge

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of machine learning (ML) methods carries a promise of automating cumbersome steps in the analysis of fisheries data. Setting up ML systems and automated workflows requires substantial initial investment but can considerably alleviate resource limitations in the long run (Irigoien et al. 2008; Taconet et al. 2019), improve consistency and address the increasingly complex ecological processes considered in management decisions (Fernandes-Salvador et al 2022).

ML refers to mathematical models that can perform a specific task without explicit instructions. ML tasks can be broadly divided into unsupervised, supervised, and reinforcement learning (Figure 1). Unsupervised learning focuses on finding patterns in unlabeled input data (e.g., finding clusters of similar data),

whereas supervised learning requires labeled input data which is mapped to output data (e.g., identifying species from photographs, having seen other photographs with the correct identification). In reinforcement learning, an agent can learn a strategy via feedback mechanisms, without having received explicit instructions (e.g., a robot finding its way through a maze). Deep learning (DL) is a subset of ML that utilizes artificial neural networks (ANN) with a high number of layers, allowing them to learn complex patterns from large unstructured or newly added data. DL is particularly popular in the form of convolutional neural networks (CNN), which can learn spatial and temporal dependencies through a series of context-dependent filters (convolution). Shallow learning, as opposed to deep learning, is used to refer to other ML approaches not able to utilize the higher order of semantics that DL can use.

This article provides a review of existing ML applications in fisheries science to enhance the use of ML methods by providing discipline-specific examples within the field. Challenges and opportunities posed by ML in the context of the peculiarities of fisheries science problems and data are also discussed. Instead of organizing the paper by ML methodologies, it is organized around fisheries science sub-disciplines where ML has been used or has the potential to be used. This allows readers to explore examples of applications within topical areas of their interest. Therefore, this review is organized into two broad categories (Figure 2), orientating on the core realms of fisheries sciences: “Analysis of Samples” (section 2), which deals with the collection, processing and categorization of samples collected on research and fishing vessels; and “Analysis of Dynamics” (section 3), which compiles these data to infer dynamics on the state of the stock, metier/fleet, and ecosystem to inform management (Lackey 2005; Hart and Reynolds 2008). Within these

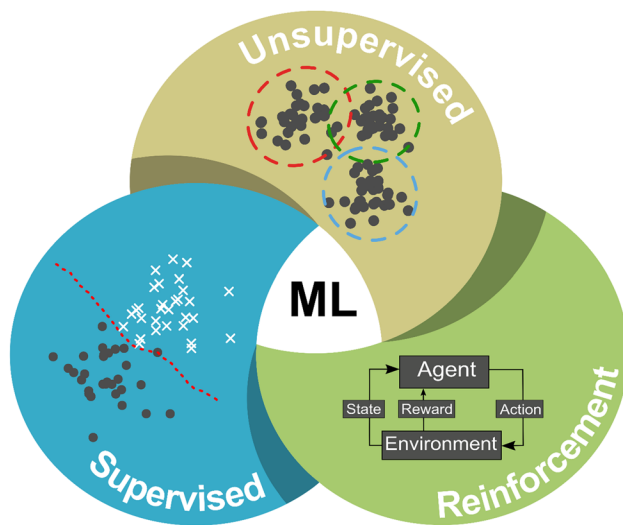


Figure 1. Schematic showing the three divisions of Machine Learning (ML): Unsupervised Learning – finding patterns in unlabeled data aka clustering, Supervised Learning - finding a mapping of the input to a labeled output, e.g., discriminating between two categories and Reinforced Learning – learning a strategy *via* interaction with an environment and a reward/penalty system.

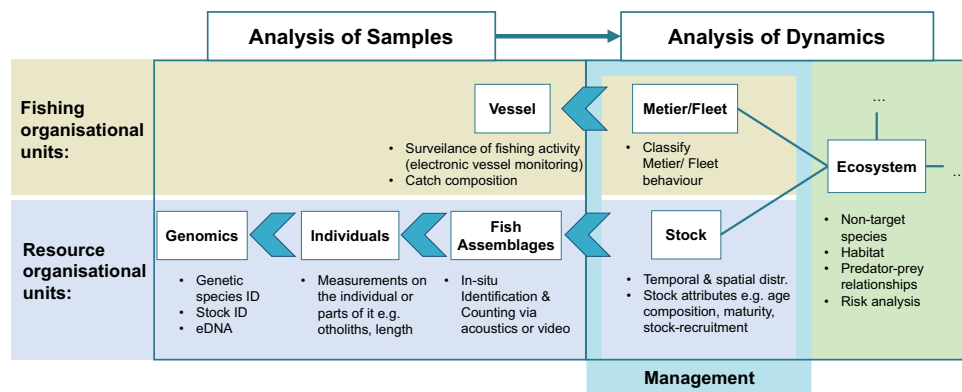


Figure 2. Graphical summary of the topics covered in this review organized at different hierarchical levels from small to large revolving around important realms in fisheries science.

broader categories, this work looks at different scales where ML is applied from small to large. The analysis of samples section focuses on genomic analysis, biometric data of individual fish, in-situ monitoring of fish shoals and onboard vessel monitoring. Meanwhile, the analysis of the dynamics section ranges from inferring dynamics at the stock level, and characterization of different fishing styles (metiers) and fleets up to the ecosystem level. The article ends with the fisheries management implications of ML applications, as well as the potential pitfalls and future directions. Table 1 gives an overview of the studies that are discussed in this article.

2. Analysis of fish samples

2.1. Genomics

Genomics technology is used in numerous fisheries applications (Mohanty et al. 2019) such as species identification for seafood authentication and traceability (Kusche and Hanel 2021), post-harvest value addition, monitoring invasive species, and improved fisheries management (Goodwin et al. 2017; Hansen et al. 2018; Martinsohn et al. 2019). Fisheries science also utilizes genetics to answer questions of population genetics for fisheries management advice (Valenzuela-Quinonez 2016), e.g., identifying the degree of connectivity, migration patterns and stock mixing in time and space, evolution due to fishing pressure acting as a selective force, or seascape genetics which link environmental factors to genetic differences found across ocean regions (Galindo et al. 2006; Selkoe et al. 2016). The field quickly transformed from studying a few neutral markers to the analysis of single nucleotide polymorphisms (SNP) across the whole genome (Valenzuela-Quinonez 2016). Targeting a larger number of loci across the whole genome allows for greater sensitivity in detecting genetic differences between populations (Luikart et al. 2003). Identifying markers with high discriminatory power is particularly needed in situations where management units do not match the natural population boundaries (Hemmer-Hansen et al. 2019; Weist et al. 2019; Wenne et al. 2020). Identifying a small set of discriminative markers is difficult when dealing with 1000 to millions of SNP, however (Kavakiotis et al. 2015). A common approach with large genomic datasets is to first use dimensionality reduction such as principal component analysis (PCA) (Chen et al. 2018). Correlations and higher-order interactions among genes pose additional challenges for identifying a small set of unique genetic markers, so several studies utilize Random Forest

modeling (RF) (Chen and Ishwaran 2012; Brieuc et al. 2018), as it can deal with multicollinearity, interactions, a large number of features, and it includes variable-importance metrics. For example, Sylvester et al. (2018) used RF for the selection of SNP for population assignment in Atlantic salmon and Alaskan Chinook salmon. Similarly, Sinclair-Waters et al. (2018) identified markers *via* regularized RF for estimating the proportion of Gilbert Bay cod stemming from a distinct population in a marine protected area (MPA) in fisheries catches. In *Sebastes mentella* (beaked redfish), a screening procedure of SNP via RF identified 21 loci to discriminate between different ecotypes of the species (Saha et al. 2021). The R-package “assignPOP” implements several common ML classifiers which incorporate both genomic and non-genomic information into population assignment (Chen et al. 2018).

A further revolution in genomics emerged through simultaneous sequencing of the DNA of different species within environmental samples, termed metagenomics or environmental DNA analysis (eDNA). This analysis often detects species' presence in aquatic environments with higher sensitivity than previous sampling methods (Bergman et al. 2016; Thomsen et al. 2016). Recent studies have also found a positive correlation between eDNA concentration in water and species biomass useful for fisheries management (Lacoursière-Roussel et al. 2016; Yamamoto et al. 2016; Rourke et al. 2022). The comparison of DNA sequences in the sample with those of a reference database is a critical step in metabarcoding, where several traditional bioinformatics sequence alignment-based classifiers (Bokulich et al. 2018; Mathon et al. 2021) and ML classifiers such as neural networks (Nugent and Adamowicz 2020) or naïve Bayes (Bokulich et al. 2018) can be deployed to find the correct taxon or the nearest taxonomic lineage (Bokulich et al. 2018). Speed and accuracy are key requirements for such algorithms (Bokulich et al. 2018; Flück et al. 2021). The first attempts of deploying deep learning to a taxonomic assignment of short eDNA sequences for tropical freshwater fish were promising with similar accuracy but 150 times faster (Flück et al. 2021). ML also offers the opportunity to avoid the work of taxonomic identification by collecting eDNA and inferring the species composition from that data. This allows inferring the environmental status and the effects of a certain stressor level on community composition (Cordier et al. 2017, 2018, 2019). This approach allows including taxa which are difficult to identify and are not regularly used in the derivation of biological indices. Although this

Table 1. Overview of studies mentioned in the main text utilizing ML in the different fields.

	Section	Objective	Data	Algorithm	Study
Analysis Samples	Genomics	Identification of genetic markers	Sequencing output	RF	Chen and Ishwaran, (2012) Brieuc et al. (2018) Sylvester et al. (2018) Sinclair-Waters et al. (2018) Saha et al. (2021)
		Taxonomic alignment in metabarcoding	Sequencing output	ANN Naïve Bayes CNN	Nugent and Adamowicz (2020) Bokulich et al. (2018) Flück et al. (2021)
		eDNA for biomonitoring	Sequencing output	RF/ SOM CNN	Cordier et al. (2017, 2018, 2019) Park et al. (2023)
	Biometrics	On-board Fish identification & counting	Images	CNN	French et al. (2015) French et al. (2020)
		Fish length estimation	Images	CNN	Monkman <i>et al.</i> (2019) Garcia <i>et al.</i> (2020) Álvarez-Ellacuría et al. (2020) Yu et al. (2020)
		Age reading from otoliths	Images	SVM/ANN SVM CNN Transformers	Fablet and Le Josse (2005) Bermejo et al. (2007) Moen et al. (2018) Moore et al. (2019) Ordoñez <i>et al.</i> (2020) Politikos et al. (2021a) Ordoñez et al. (2022) Martinsen et al. (2022) Moen <i>et al.</i> (2023) Bojesen <i>et al.</i> (2024) Cayetano <i>et al.</i> (2024) Sigurðardóttir et al. (2023)
	Fish Assemblages	In-situ fish identification	Hydroacoustic data	SVM/MLP/PNN	Robotham et al. (2010)
		In-situ fish identification and abundance estimation	Hydroacoustic data	RF/ MLP/ Nearest Neighbour/ Decision Trees	Uranga et al. (2017) Baidai et al., (2020)
		In-situ fish identification	Images	RF	Villon et al. (2016)
	Electronic monitoring	In-trawl catch identification	Images	SVM/CNN CNN	Ditria et al. (2020) Garcia et al. (2020) Allken et al. (2021) Sokolova et al., (2021b, 2021a) Yu et al. (2022)
		Fish identification and counting in a commercial environment	Images	CNN	French et al. (2015,2020) Lu et al. (2020) Tseng and Kuo, (2020) Qiao et al. (2021) van Essen et al. (2021) Lekunberri et al. (2022) Ovalle et al. (2022) Khokher et al. (2022) Sokolova et al. (2023)
		Identification of catch/ bycatch events	Images	CNN	Pierre (2018) Qiao et al. (2021) Khokher et al. (2022) Acharya et al. (2024) Saqib et al. (2024)

(Continued)

Table 1. Continued.

	Section	Objective	Data	Algorithm	Study
Analysis Dynamics	Stock/Population	Inferring life-history parameters	Tabular data of life history parameters	Factor Analysis/Major axis regression ANN BRT Decision Trees/RF/BRT	Thorson et al. (2017) Benzer and Benzer (2016, 2019) Morais and Bellwood (2018) Liu et al. (2020)
		Stock-recruitment modeling	Stock assessment model output/ Survey data	ANN Naïve Bayes RF	Chen and Ware (1999) Chen et al. (2000) Huse and Ottersen (2003) Megrey et al. (2005) Fernandes et al. (2010) Smoliński, 2019 Kühn et al. (2021)
		Species-distribution modeling	Spatial/ Spatio-temporal data	Various (BRT, RF, BART, ANN, MaxEnt,)	Muhling et al. (2020) Palacios-Abrantes et al. (2020) Stock et al. 2020 Costa et al. (2023)
		Enhance Process-based population/stock assessment models	Tabular data of temporal dynamics	Physics-informed ANN BRT	Rackauckas et al. (2020) Karniadakis et al. (2021) Lüdtke and Pierce (2023)
	Metier/Fleet	Identification of métiers and vessel behavior	AIS/ VMS data	ANN	Joo et al. (2011)
		Improve fishing effort estimates	AIS/ VMS data	CNN	Russo et al. (2011) Kroodsmas et al. (2018)
		Spatial mapping of fishing grounds	AIS/ VMS data	CNN	Kroodsmas et al. (2018) Taconet et al. (2019)
		Route optimization	Spatial data	Genetic algorithm	Granado et al. (2021, 2024)
	Ecosystem	Inferring illegal activity	AIS/ VMS data + auxiliary data	CNN	Belhabib et al. (2020) Park et al. (2020) Seto et al. (2022, 2023) McDonald et al. (2021a)
		Infer human right abuse	AIS/ VMS data + auxiliary data	CNN/RF/SVM	
		Identify risk hotspots for bycatch	AIS/ VMS data + auxiliary data	CNN Naïve Bayes/MLP/RF/ SVM	Queiroz et al. (2019, 2021) Goikoetxea et al. (2024)
		Spatial distribution maps and risk assessment	Spatial/ Spatio-temporal data	Various (BRT, RF, ANN, MaxEnt,)	Brownscombe et al. (2020) Griffin et al. (2022) Politikos et al. (2021b) Friedland et al. (2021)) Cheung et al. (2021) Breen et al. (2017) Cleasby et al. (2022)
	Management	Identify ecosystem dynamics, risk assessment and testing of “what if” scenarios	Various data types (quantitative/ qualitative)	Bayesian Network	Trifonova et al. (2017, 2019, 2021) Uusitalo et al. (2018) Maldonado et al. (2019) Tucker and Duplisea (2012)
		Scenario analysis in the context of marine spatial planning (MPA, windparks, ...)	Various data types (quantitative/ qualitative)	Spatial Bayesian Network	Coccoli et al. (2018) Pinarbaşı et al. (2019) Maldonado et al. (2022)
		MSE-type simulations via agent-based modeling	Various data types	Shallow RL Deep RL	Dreyfus-Leon (1999), Dreyfus-Leon and Kleiber (2001) Dreyfus-Leon and Gaertner (2006) Russell and Zimdars (2003) Bouton et al. (2019) Bailey et al. (2019)
		Testing of spatial management strategies	Various data types	Shallow RL	
		Dynamic ocean management via Spatial distribution models	Spatio-temporal data	BRT	Hazen et al. (2018) Breece et al. (2021) Welch et al. (2020)

ANN: artificial neural network; BART: Bayesian additive regression trees; BRT: boosted regression trees; CNN: convolutional neural network; MLP: multilayer perceptron; PNN: probabilistic neural network; RL: reinforcement learning; RF: random forest; SVM: support vector machines.

ML-based approach for biomonitoring (Cordier et al. 2021) is not yet frequently applied, it can further facilitate eDNA-based monitoring of fish communities in response to fishing pressure, e.g., in the context of MPA (Bani et al. 2020; Boulanger et al. 2021; Gold

et al. 2021), which currently rely on taxonomic assignment. Most recently Park et al. (2023) investigated ML algorithms for taxonomic classification of marine metagenomes. They applied DL and a novel Residual Network architecture that leverages natural language

processing and CNN architectures to map input sequence data (k-mers) to taxonomic groups without reliance on a curated taxonomic tree. The results suggested that high genome coverage and rectification of class imbalance (i.e., highly uneven number of observations in the different classes) are prerequisites for a well-trained model and, therefore, should be a major consideration in future ML work.

2.2. Biometrics

Collection and analysis of fish biometric data can be divided into two categories: (1) species identification and collection of data on morphological features such as body measurements, and (2) the inference of indirect features such as age and growth rates. The measurement of external features can be completed on a vessel, at the harbor or from previously collated samples in a lab setting, often involving multiple staff members identifying, counting, weighing, and measuring the specimens whilst noting the information before uploading the data into a suitable database. This is often facilitated by technology such as electronic measuring boards and calipers with some form of automated data transfer. To automate the data collection process, the individual fish in a sample would need to be recognized and identified successfully, a task referred to as “sorting,” before the measurement was taken.

The process of sorting is particularly challenging in a commercial environment, in comparison to a scientific survey, as conveyor belts are often used to move samples. As a result, sample images often include other objects and artifacts. The work done by Strachan (1993) represents some of the early attempts to automate the process of sorting using descriptors. Later, White et al. (2006) utilized an image processing algorithm to identify and measure fish on a conveyor belt. Their approaches rely on traditional image processing techniques and require a clear image of the individual fish to be identified. The quickly developing DL techniques, particularly region-based CNN (R-CNN) methods such as Fast R-CNN (Girshick 2015), Faster R-CNN (Ren et al. 2016), and Mask R-CNN (He et al. 2017) can speed up the recording of morphological features. As a notable example, Monkman et al. (2019) proposed standard regional CNN implementation to perform the task of fish detection and length estimation from raw input images. The approach has the advantage of being robust to horizontal flipping and downsampling, but falling short when the image orientation is subjected to a significant degree of rotation. French et al. (2015)

utilized CNN to successfully isolate and count discarded fish in footage from an operational trawler, becoming one of the earliest studies that utilized a CNN-based approach on a low-resolution setting and without requiring well-defined image capture techniques. More recently, French et al. (2020) trained a multi-class Mask R-CNN model to segment objects of a single fish class and identify species. An advantage of the Mask R-CNN-based approach is that it performs both the detection and segmentation tasks simultaneously, removing the need to isolate the fish from background objects. Several related studies (Álvarez-Ellacuría et al. 2020; Garcia et al. 2020; Yu et al. 2020) applied Mask R-CNN to improve fish detection performed as part of the biometric analysis.

The second category of studies involving biometric data aims to infer certain indirect characteristics such as age and growth rate. The age of fish is determined by counting the yearly ring patterns in the otoliths (Choat and Axe 1996). Though the collection of otoliths cannot be improved through ML, processing and counting the rings could be significantly expedited with successful image analysis. Early attempts of ML to automate age estimation formulated the problem as a classification task, with Fablet and Le Josse (2005) using both support vector machines (SVM) and artificial neural networks to classify plaice (*Pleuronectes platessa*) otolith images into 5 distinct age groups. Bermejo et al. (2007) also attempted to automate aging otoliths using SVM. In this approach, both PCA and hand-crafted morphological feature extraction were applied to a database of images focusing primarily on the shape of otoliths. The study relied heavily on the assumption that the outer otolith shape changes distinctively in relation to the fish age. This can be problematic when considering fish species such as eel that exhibit high otolith shape variability among individuals of the same age (Hamrin and Doering-Arjes 2002). Formulating the problem as a regression task (no predefined discrete set of ages), Moen et al. (2018) and Moore et al. (2019) adapted pre-trained CNN designed for object recognition to estimate the age of fish from otolith images. In Moen et al. (2018), the image dataset included Greenland halibut (*Reinhardtius hippoglossoides*) with ages up to 26 years. Age estimates were correct in 29% of cases and an additional 38% of cases had an error of only one year. A similar approach (Moore et al. 2019) used New Zealand snapper (*Chrysophrys auratus*) and hoki (*Macruronus novaezelandiae*), with ages up to 27 and 18, respectively, obtaining an accuracy of 47% with an additional 35% having only an error of one year. One notable advantage of this method was that the

CNN in these cases were previously designed and then adapted to the task, removing the need to design a CNN from scratch – an advantage for fisheries scientists without a computer vision background. More recently, a multi-task learning approach was developed by Politikos et al. (2021a) where a CNN was constructed to predict both fish age and length from otolith images of red mullet (*Mullus barbatus*). Applying a trained algorithm from one institution/working group to otolith images acquired at a different place with the goal of inter-institutional standardization is still considered an issue. For this reason, Ordoñez et al. (2022) modified a CNN originally trained on Norwegian Greenland halibut otolith images to classify the ages of Greenland halibut otoliths acquired in Iceland *via* domain adaptation, stressing the fact that the domain shift cannot be adequately handled by simple preprocessing alone. Apart from domain adaptation, there are also recent improvements in other implementation aspects such as the use of ensemble learning (Moen et al. 2023) and transformers (Sigurðardóttir et al. 2023) as well as several works addressing the lack of explainability of the DL-based approaches (Ordoñez et al. 2020; Martinsen et al. 2022; Bojesen et al. 2024; Cayetano et al. 2024).

1.3. *In situ* fish aggregations

Dynamic (e.g., sea surface temperature) and static (e.g., depth, latitude, longitude, seafloor habitat) characteristics of a particular location can drive spatial distributions of fish in a variety of ways (e.g., seasonal spawning events) among different species. Trying to quantify and assess species and the conditions they live in with minimal disturbance has become more feasible with technologies such as hydroacoustic, underwater visual monitoring and machine learning-based data analysis.

Identifying different species in hydroacoustic data started by utilizing standard statistical methods (LeFeuvre et al. 2000; Lawson et al. 2001), but has transformed toward the use of ML. For example, Robotham et al. (2010) identified schools of anchovy, jack mackerel and sardine using SVM, multi-layered perceptron (MLP), and probabilistic neural networks (PNN), with better performance from the SVM and MLP techniques. Image processing techniques and ML were also used to automate the analysis of commercial medium-range sonar on fishing vessels to detect the presence/absence of bluefin tuna (*Tunnus thynnus*) in the Bay of Biscay (Urange et al. 2017). More recently, ML methods were applied to acoustic data gathered by a commercial echosounder buoy to identify tropical

tuna aggregations (Baidai et al. 2020). Meanwhile, hydroacoustic data analysis has been streamlined through the development of CNN to aid in the task of labeling data (Sarr et al. 2020). Underwater *in situ* species identification can be carried out—in a labor-intensive and expensive manner—by divers, with minimal impact on sensitive communities. The use of underwater HD videos and still images are cost-efficient alternatives, but they generate large data-sets (>100 TBs) that need to be processed and classified afterwards. Applying two supervised ML methods (SVM and CNN) to automatically detect and recognize coral reef fishes in underwater HD, Villon et al. (2016) found that DL CNN were more efficient but were also more likely to misclassify background habitats than SVM.

An increasingly important noninvasive method for monitoring fish populations of both pelagic (Rosen and Holst 2013) and demersal (DeCelles et al. 2017) species is attaching underwater cameras to fishing gear. This approach allows fish monitoring without catching the target species (the net is equipped with an open codend), therefore avoiding unnecessary mortality. Several studies demonstrate various automated video processing approaches, primarily based on CNN applications (Ditria et al. 2020; Allken et al. 2021; Yu et al. 2022), which consequently lead to reduced demand for manual identification and count of species where the processing of one hour of video can require 10h of human labor (Rosen and Holst 2013; DeCelles et al. 2017). The use of underwater cameras in regular commercial fishing gear may serve as a decision-support tool for the fishers. By implementing such systems in fishing nets—particularly trawls, which are the type of gear typically used in mixed-species fisheries—fishers will be able to improve selectivity (i.e., catching target species and avoiding unwanted species).

Trawling typically lasts for several hours, resulting in significant amounts of data, which are often complicated to analyze and infeasible to analyze manually. Thus, the automation of video data analysis is a critical focus in fisheries (Garcia et al. 2020; Sokolova et al. 2021a, 2021b). The promise of automated processing pipelines lies in the field of deep learning, specifically CNN, and in traditional computer vision approaches that require feature engineering (Sokolova et al. 2021a). Meanwhile, particular challenges for catch monitoring in demersal trawl video are caused by a lack of light, poor visibility caused by suspended sediments, and mixed species catch composition (Krag et al. 2009; DeCelles et al. 2017). Nonetheless, optical devices can facilitate species identification if quality images can be obtained. Sokolova et al. (2021a, 2022)

developed an in-trawl image acquisition system for *Nephrops norvegicus* trawl fisheries applied during demersal trawling. The system reduces sediment in the camera field of view and assists automated processing of the target species by means of contrast enhancement.

2.4. Electronic monitoring

Electronic monitoring (EM) is an evolving tool utilized by managers and fisheries scientists to remotely monitor the catches and bycatch onboard commercial vessels. EM is typically associated with an extensive collection of video recordings (1–2 TB per month, EPFA 2019; Román et al. 2020) and manually reviewing video footage is expensive and time-consuming, which fostered recent developments in automated video processing via ML. Many studies concentrate on species separation, identification, and counting of catches while fish are on a conveyor belt. The working environment aboard a fishing vessel provides unique challenges that can affect classification accuracy including difficult camera mounting locations, highly variable illumination (e.g., due to weather or below-deck lighting conditions), or fouling of the camera lens by dirt or water (Tseng and Kuo 2020; Lekunberri et al. 2022). A strategy to overcome the latter would be to train an algorithm to detect dirt and water droplets on the lens and give an audible cue for the crew to clean the camera as necessary (Lekunberri et al. 2022). EM systems often deploy wide-angle fisheye lenses mounted in corners to monitor the largest spaces possible, ideal for man-made reviewing of video footage, but leading to distortion of objects in the image. For automated algorithms, a calibration process like placing a checkerboard pattern with known physical properties on a conveyor belt (French et al. 2020) can transform video images to their correct physical dimensions. Lekunberri et al. (2022) corrected a sub-optimal camera position above a conveyor belt via a simple transformation to rectify the skewed angle to obtain a zenith-angle position. This is particularly important if length measurements of individuals are estimated automatically via pixels to real length (in cm or mm) proxy, although this is yet only possible in a highly controlled environment with almost no overlap between fish individuals (Ovalle et al. 2022). Alternatively, the lens bias can be accounted for in automated length estimation. Training an algorithm on stereo vision cameras (two neighboring cameras with overlapping fields of view), which are frequently used in noninvasive underwater monitoring of fish (Boldt et al. 2018; Muñoz-Benavent

et al. 2018; Baker et al. 2021), might be an additional way to improve length measurements as well as enabling algorithms to remove artifacts. In addition to automated length estimation, there is a recent study devoted to weight estimation. Sokolova et al. (2023) present an end-to-end approach to predict the weight of an individual in parallel with species prediction and fish location in the 2D RGB image. The method is based on a YOLOv5 CNN with an additional output for weight prediction and is developed for discard registration onboard Dutch beam trawlers.

Current challenges are strongly associated with the respective fishery and the deployed gear types. A typical high-seas longline fishery targeting tuna or swordfish only catches a limited number of individuals at a time (Lu et al. 2020; Tseng and Kuo 2020; Qiao et al. 2021). Since few fish are handled on deck simultaneously, counting can be achieved with time thresholding (minimum number of subsequent images with a fish identified to be counted) and distance thresholding (individuals with a certain distance of their centroids are counted as separate). Here, the movement of the crew covering the field of view, highly variable illumination due to day-night cycles and weather, as well as miscellaneous objects on deck pose a challenge for the algorithms. Applying a ResNeXt with a cascade RCNN in a Patagonian toothfish longline fishery below deck, Khokher et al. (2022) found that camera positioning, image resolution, light conditions, and limited training data complicated the detection of some bycatch species, whereas the target species and those with a unique appearance could be identified with greater success.

Aboard mixed trawlers, automated computer vision for fish identification and enumeration is additionally complicated by the large variety of target and bycatch species. Thus, a successful segmentation of relatively similar individuals on top of a conveyor belt is a crucial task. A first attempt within the complex commercial environment was described by French et al. (2015) who proposed foreground segmentation of individuals in discards via the N^d —Fields algorithm (Ganin and Lempitsky 2014). Drawbacks include the need to train the algorithm for each belt separately, and the system only working with low resolution VGA footage as the segmentation becomes unreliable with higher resolution HD recording (French et al. 2020). Subsequent work (French et al. 2020) deployed a Mask-R-CNN for both object detection and segmentation and a separate 50-layer ResNet for fish classification in various settings on research and commercial vessels, experiencing difficulties in across-vessel operationalization. Ovalle et al. (2022) tested increasing

degrees of overlap between fish on a conveyor belt and obtained higher misclassification from a low overlap to a moderate overlap setting, and no reliable estimates of fish ID and counts in a typical high overlap situation common on commercial trawlers. Similarly, van Essen et al. (2021) found a negative correlation between increasing levels of occlusion (10%–85%) and the classification performance of a trained YOLO v3 model using video footage of discard catches and debris from a North Sea beam trawler. These findings are supported by Sokolova et al. (2023), who reported that the detection performance of discarded fish overall decreased with the increasing occlusion levels, specifically, when the occlusion exceeded 30%. Hoppers to reduce crowded environments have been suggested (Lekunberri et al. 2022); however, such mechanical devices can be misused for illegal discards (Fernandes-Salvador et al. 2022).

While automation of fish ID and counting via DL is possible in less crowded environments, it still lacks the necessary accuracy to be considered operational in a highly mixed setting with frequent occlusion, large size variation, similar looking species, and the presence of debris. Admittedly, this is also a challenging setting for human reviewers of EM footage as especially small fish in discards were frequently underestimated in various EM trials of the European mixed fishery (van Helmond et al. 2020). Therefore, future applications in automating the EM review process should not only focus on optimizing algorithms but also standardizing the working environment, e.g., via controlling the flow of individuals on the conveyor belt with hoppers to reduce overlap (Khokher et al. 2022; Lekunberri et al. 2022). For individual counting, tracking fish in subsequent images is often challenged by irregular conveyor belt movement. Tracking individual objects in subsequent frames can be done *via* a combination of correlating RGB pixels and deep neural network features from the pooling layers of subsequent images (French et al. 2020), applying an intersection-over-union tracker with a correlation filter for interpolating discontinued tracks (Khokher et al. 2022) or using a Kalman filter to track detections between images (van Essen et al. 2021). Tracking fish for counting provides additional challenges and is largely reliant on the performance of the fish detector, leading to double counts if the tracker aborts prematurely, ghost counts of tracked background over missed tracks of small or rare fish, and overestimation of abundant fish (van Essen et al. 2021). Alternatively, the raw video frames can be used to generate semi-linescan images, which eliminates the problem of the same fish individuals being present in multiple

images (Sokolova et al. 2023) reducing the potential sources of error.

Despite these advances in computer vision for species ID and counting, fewer studies applied ML to other important tasks in EM systems. Qiao et al. (2021) investigated how to identify catch events in video footage of a longline fishery using a CNN for object detection (simultaneous occurrence of fishers and fish in a frame) and a temporal filter for catch event detection, comparing the performance of several architectures including ResNet, GoogLeNet, DenseNet and YOLO. Such approaches significantly reduced the volume of video segments for manual reviewing, even if no additional ML tools for ID or counting were applied. Khokher et al. (2022) discussed the use of ML to identify anomalies in fishers' behavior e.g., in handling bycatch species if the movements of crew members were sufficiently distinct (like leaning over the vessel to cut a line in a longline fishery). Especially for protected species, which are removed before being visible in the camera field of view, crew behavior could be indicative of the occurrence of such an event (Pierre 2018). If EM is also used to monitor compliance, where the fishers' behavior—not only the catch—is subject to analysis, ethical issues might hinder implementation. Deploying automated analysis of fishers' behavior for anomaly detection on-board can already collide with article 1 “right to human dignity,” article 8 “protection of personal data” and article 48 “presumption of innocence and right of defence” of the EU Charter of Fundamental Rights and be considered a high-risk AI system (article 6(2) of the EU AI Act 2021) if it is “intended to be used for crime analytics regarding natural persons, allowing law enforcement authorities to search complex [...] data sets [...] in order to identify unknown patterns or discover hidden relationships in the data” (EU AI Act 2021, Annex III).

3. Analysis of fish and fisheries dynamics

3.1. Stock/population level

To determine the status of fish stocks and their future development for sustainable harvesting, data sources from previous organizational levels (above) are aggregated to derive estimates of important life cycle characteristics, which are fed into stock assessment models for use in management. ML approaches are either used to derive estimates of these life-history parameters or directly used to model/forecast stock dynamics. Additionally, if spatially resolved data are available, ML is used to infer the spatio-temporal

dynamics of different life stages through species-distribution modeling (SDM).

Differences in average biological traits among species can be summarized in a few sets of life history parameters (e.g., growth, mortality, maturity) crucial to distinguishing stock boundaries (Begg et al. 1999) and estimating sustainable harvest levels (Quinn and Deriso 1999). Some life history parameters cannot be directly measured without considerable cost and effort, and are often inferred from other more easily accessible life history parameters (Thorson et al. 2017). Many such life history parameters are derived from classical statistical mechanisms, deeply embedded in ecological/physiological theory, e.g., describing the growth of fish via a von Bertalanffy growth function (VBGF) or relating length to weight via a power law (Quinn and Deriso 1999). Attempts to replace these rather deterministic relationships with ML are limited (Benzer and Benzer 2016, 2019), but ML can build on mechanistic relationships (e.g., VBGF) for deriving general patterns in life history parameters over a broad range of species. Although not ML, the work of Thorson et al. (2017) set the stage by relating seven life history parameters (natural mortality, growth, asymptotic maximum length and bodyweight, length and age at maturity, maximum age) of 32,000 fish species and their temperature ranges, together with taxonomic dependencies *via* a combination of factor analysis with an extension of major axis regression. Liu et al. (2020) used tree-based learners (comparison of decision trees, bagged decision trees, RF and Boosted Regression Trees (BRT)) to infer natural mortality from other estimates of 256 records of life-history parameters (K , L_{∞} , $t_{\max}$) for Chondrichthyes and Osteichthyes. BRT performed better relative to the fit of established empirical relationships, readily incorporating categorical taxonomical information and allowing for non-linear relationships. In a different example, Morais and Bellwood (2018) used BRT to model growth rates ($K_{\max}$) of reef fishes as a function of various traits (body size, diet, distance to reef) and their thermal environment. The authors asserted that this is particularly useful to assess the growth pattern of unmeasured reef species and allow analysis of community-level growth patterns.

Modeling the stock-recruitment relationship is highly important for fisheries management (Houde 2008). Ecological theory provides various mechanistic functional forms (such as Beverton-Holt, Cushing, Ricker) to relate spawning stock biomass (SSB) to the number of offspring recruiting to the fishery, but environmental variability acting on various temporal and spatial scales can largely obscure this relationship.

The use of ML approaches was motivated by their ability to model non-linear relationships, and flexibility in their functional form without the need to define a relationship *a priori* and/or taking interactions into account (Chen and Ware 1999; Megrey et al. 2005; Smoliński 2019). Most of the earlier work exclusively focused on deploying neural networks (Chen and Ware 1999; Chen et al. 2000; Huse and Ottersen 2003; Megrey et al. 2005). In general, there is a rather narrow focus on applying established methods like neural networks, RF (Smoliński 2019; Kühn et al. 2021) and Naïve Bayes (Fernandes et al. 2010, 2015). Fernandes et al. (2010) compared several machine learning methods (Naïve Bayes, Tree augmented Naïve Bayes, SVM, MLP, and Decision trees) without any outperforming the Naïve Bayes model. As a probabilistic model with graphical representation, Naïve Bayes is appropriate for communication to end-users, contrary to black box approaches. Fernandes et al. (2015) combines the benefits of Naïve Bayes with kernels (usually used in SVM) to get the advantages of Bayesian networks and the flexibility of SVM. Looking forward, a newly emerging field called “scientific ML” (Rackauckas et al. 2020) or “physics-informed ML” (Karniadakis et al. 2021) generates hybrid models substituting part of a dynamical system/mechanistic model (a set of differential equations) with a ML model. Constraining the ML model by known mechanistic relationships allows harnessing advantages of both worlds – the data-driven universal approximation ability of ML and the mechanistic understanding and traceability that mathematical models provide. The combination allows for improved extrapolation ability of the model under a data-limited setting where pure ML approaches have a hard time. Various successful applications span a variety of disciplines ranging from climate/earth-system science (Reichstein et al. 2019; Kashinath et al. 2021), epidemiology (Dandekar et al. 2020) and biomedicine (Lagergren et al. 2020; Sahli Costabal et al. 2020). For example, Rackauckas et al. (2020) demonstrated the approach using the Lotka-Volterra predator-prey system from theoretical ecology. In this example, the authors had only a short time series of known prey birth rates and predator death rates, and they substituted the unknown degree of interactions between predator and prey with a neural network (neural differential equations). They replicated the unknown dynamics and extrapolated further in time, even though the training data did not include a full cycle of the unfolding dynamics. Population models in fisheries science, ranging from relatively simple surplus production models to fully age-structured models could also benefit from an incorporation of ML, to

approximate unknown hidden dynamics of hard-to-measure biological parameters or environmental forcing. An attempt in this direction was made by Lüdtke and Pierce (2023) combining a stock assessment model with a BRT for post-hoc corrections.

The spatial distribution of species is regularly sampled through research surveys and commercial catches. Spatially resolved data can help to identify important life history events like spawning aggregations (González-Irusta and Wright 2016; Miesner and Payne 2018), resolve nursery and feeding grounds relevant to conservation and management needs (Katara et al. 2021) or infer stock/population boundaries (Palacios-Abrantes et al. 2020). Additionally, spatially resolved data can inform estimates of bycatch (Stock et al. 2020) or reduce the impacts of choke species *via* optimization of species-specific catch ratios in mixed species fisheries (Dolder et al. 2018). The spatial data can be used to inform species distribution models (SDM). The use of ML methods in SDM modeling is widely established, which is in part attributed to a series of papers providing a tutorial-like introduction to the use of BRT (Elith et al. 2008) and MAXENT (Elith et al. 2011) for SDM. The emergence of an easy-to-use implementation of a variety of ML algorithms and model ensembles in R *via* packages like “BIOMOD” (Thuiller et al. 2009), “dismo” (Hijmans et al. 2020) or “sdm” (Naimi and Araújo 2016), facilitated the widespread use of ML for SDM.

Some challenges in SDM are specific to the marine/fisheries realm and are pertinent to the successful usage of ML. Species and environmental data are often not sampled at the same spatial resolution, as the former often originates from monitoring programmes with scarce spatial resolution, whereas the latter can be a highly resolved output from biogeochemical or ocean models as well as remote sensing (satellite) data products. Data matching at a common spatial resolution before modeling are, therefore, needed and is often done at the highest spatial scale possible. This is not necessarily the best practice, however, as Núñez-Riboni et al. (2021) reported lower prediction errors if both the environmental dataset and the biological dataset were downsampled to an intermediate spatial resolution. Additionally, the choice of model validation greatly affects the generalizability of the model. Cross-validation approaches are typically employed to evaluate model fit and predictive performance. Random cross-validation (randomly dividing the data into a train and test set) without considering spatial and temporal autocorrelation can greatly overestimate model generalizability. Several authors therefore suggest a form of blocked cross-validation (Hijmans 2012;

Boria et al. 2014; Roberts et al. 2017; Valavi et al. 2019), dividing the study area into different spatial (or spatio-temporal) strata. The challenge here lies in the careful selection of strata to avoid unintended extrapolation and therefore, overestimation of interpolation error (Roberts et al. 2017). On the other hand, if extrapolation is the goal, blocked cross-validation can be used to measure extrapolation error. This is particularly important when projecting a species outside its historical home range and time, as is frequently done to assess invasion potential or changes in species distributions under climate change. De la Hoz et al. (2019) argue that only assessing internal validation does not necessarily result in models that can be transferred in space and time, raising concerns about modeled future distributions of a species and derived management needs. If climate change effects are evaluated, model building should include transfer in time as well as assessing the overlap between fitted and projected environmental variables. Muhling et al. (2020) found that SDM (BRT, RF, ANN, GAM) for Pacific anchovy and sardine lost considerable predictive power if tested during a marine heat-wave event, representing a strong shift in an environmental covariate that is likely occurring to play a greater role under ongoing climate change.

3.2. Metier and fleet

How, when and where fishers fish are key questions to track changes in fishing distribution, monitor the effectiveness as well as enforcement of spatial management (e.g., MPA) or assess the impacts of fishing on other parts of the ecosystem. A recent proliferation of remotely collected locations of fishing and non-fishing vessels at sea has created vast new opportunities for exploring the behaviors of vessels, identifying metiers (Joo et al. 2011; Russo et al. 2011, 2016), improving estimates of unobserved fishing effort (Kroodsma et al. 2018), mapping the spatial extent of fishing grounds (Kroodsma et al. 2018; Taconet et al. 2019), comparing fishery carbon footprints (McKuin et al. 2021), inferring illegal fishing activities (Belhabib et al. 2020; Park et al. 2020; Seto et al. 2022), and even elucidating human rights abuses at sea (McDonald et al. 2021a)

In the last two decades, there has been a rapid expansion in the use of Automatic Identification Systems (AIS) for collision avoidance and Vessel Monitoring Systems (VMS) for fisheries enforcement. Fundamentally, these data sets have a set of latitude and longitude spatial coordinates, a unique identifier for an individual vessel, and a time stamp. The AIS

and VMS data are transmitted at regular intervals - nearly continuously in the case of AIS and ranging from minutes to hours for VMS. Analyzing this vast resource of data can be cumbersome with traditional methods, and underscores the computational gains from ML. Initially, many studies with AIS and VMS data had a similar approach to their analysis as studies analyzing satellite tag data from biological tagging projects. Analytical approaches often include examining vessel speeds, turning behaviors, geospatial attributes (e.g., distance from shore, bathymetry), environmental data (e.g., sea surface temperature), and other features that can be used as inputs to AI models for classification of vessel behaviors (e.g., transiting, fishing, searching for fish, trans-shipping). Kroodsmas et al. (2018) as well as Taconet et al. (2019) published a seminal application of neural networks to these data enabling the classification of vessel types and facilitating the mapping of fishing areas globally in comparison with catch distribution (Watson 2017). Moreover, the AI analyzed data set from this work has been made publicly available and is updated regularly, facilitating several of the other vessel analyses mentioned above (e.g., Park et al. 2020; White et al. 2020). A major challenge with using VMS and AIS data is the quality and frequency of transmissions. Some of the more elaborate illegal fishing efforts include spoofing (intentionally altering, disabling, or otherwise obfuscating) their AIS location signals (Welch et al. 2022). Meanwhile, with VMS data, the transmission intervals in some cases can either be inconsistent or simply infrequent enough that gaps in data sets can diminish the accuracy of models due to missing some fishing events (Watson and Haynie 2016). Finally, another challenge is the lack of labeled data available to many analysts for training models. Without EM or observer data associated with VMS or AIS data, it can be difficult to match vessel behaviors precisely with the activities associated with their different movements. When it comes to inferring unmeasured attributes with high ethical and political implications from vessel tracks like forced labor or illegal fishing activity, attention should be given to the occurrence of false positives. Identification of a class membership, when in fact there is none, can result in unjust sanctioning and discrimination of affected vessels (see the discussion around McDonald et al. (2021a) in McDonald et al. (2021b) and Swartz et al. (2021)). A similar issue is the possible scale dependency in the analysis of fishing pressure. Queiroz et al. (2019) resolved the global overlap between pelagic longline fisheries identified *via* ML by Kroodsmas et al. (2018) and the spatial distribution

of pelagic sharks to identify risk hotspots of shark bycatch and intentional catches. Even if results are correct at a global scale and are looked upon at a regional level by experts, the enormity of the data set (>70k AIS tracked vessels in this case) can result in misidentification on a localized scale (Queiroz et al. 2019, 2021). Harry and Braccini (2021) identified false positives in this classification of pelagic longliners leading to an overestimation of fishing pressure hotspots in certain regions in Australian waters with likely implications for conservation and management. Still, by refining classification algorithms, some of these problems could be resolved (Queiroz et al. 2021). In summary, a better balance of positive and negative cases in training data (Swartz et al. 2021), ground-truthing of model results (Harry and Braccini 2021; Queiroz et al. 2021; Swartz et al. 2021), awareness of scale-dependency (Harry and Braccini 2021) and reporting and propagating the uncertainty of class membership in the model pipeline (Swartz et al. 2021) can help to alleviate these problems and improve trust in using ML for law enforcement, conservation, and management. ML has been also used for fishing grounds identification for tuna species that reduces the chances of incidental fishing of sharks (Goikoetxea et al. 2024). Recent work has combined ML forecasts of the presence of high biomass species and fuel consumption with route optimization metaheuristics to reduce fuel consumption and consequent emissions (Granado et al. 2021, 2024).

3.3. Ecosystem

Understanding interactions among species and the environment has significant ecological and societal implications for predicting nature's response to natural and anthropogenic changes. Such interactions are further exacerbated by spatial and temporal variation of the ecosystem and its components (Polis et al. 1996; Hunsicker et al. 2011; Doney et al. 2012). Stressors such as climate change, fishing, and resource exploitation have been shown to drive ecosystem dynamics (Blanchard et al. 2012; Lotze et al. 2019).

ML has been used to examine ecosystem-level challenges for assessing the effects of fishing on non-target species in the form of risk analysis, delineating key habitats of target or vulnerable species (Brownscombe et al. 2020), assessing the degree of predator-prey interactions in time and space (Griffin et al. 2022), identifying drivers of ecosystem change, predicting ocean states (e.g., hypoxia, algae blooms) with implications on fisheries (Politikos et al. 2021b) or evaluating the impact of regional (e.g., wind farms

(Friedland et al. 2021)) and global (climate change (Cheung et al. 2021)) changes on fish and fishing opportunities. Spatial risk assessment on non-target species like marine mammals (Breen et al. 2017), sea turtles or birds (Cleasby et al. 2022) is predominantly done *via* SDM by examining the overlap of modeled species distributions with indicators of fishing pressure (e.g., effort maps). While distribution models would be ideal for the prediction of population dynamics in the face of multiple stressors, these are constrained due to habitat heterogeneity and plasticity in animal abundance and behavior across space and time (Matthiopoulos et al. 2022). Therefore, a pragmatic approach for risk assessment to support Ecosystem Based Fisheries Management (EBFM) under heterogeneous data, including data with different spatial or temporal resolution and of both quantitative and qualitative nature, are probabilistic ML methods such as Bayesian networks (Uusitalo 2007; Hart and Pollino 2008; Kaikkonen et al. 2021).

As applied in ecology, Bayesian networks represent probabilistic dependencies among species and ecosystem factors that influence variables' likelihood in an intuitive, graphic form (Jensen 2001); therefore, different expertise can provide quantitative indicators for a range of possible scenarios in support of strategic advice on potential ecosystem responses. Contrary to black-box ML approaches, the visual nature of Bayesian networks can help to communicate modeling results and allow a variety of perspectives of natural and anthropogenic effects to be represented (Levontin et al. 2011), while explicitly handling uncertainty associated with predictions (Fernandes et al. 2010). With the recent adoption of Bayesian Networks in predictive ecology, few assumptions can be made about the data and complex, spatially varying interactions can be recovered from collected field data (Trifonova et al. 2015).

Bayesian networks have been proposed as a method to formalize conceptual models of social-ecological systems and project system responses to environmental management interventions (McCann et al. 2006; Landuyt et al. 2013; Reum et al. 2021). By integrating spatial relationships, Bayesian networks have been used to resolve conflicts in the context of marine spatial planning between fisheries and aquaculture which revealed alternative fishing locations (Coccoli et al. 2018). Similarly, the approach has been used to identify suitable areas for offshore wave and wind energy sites (Pınarbaşı et al. 2019; Maldonado et al. 2022). The spatially explicit Bayesian network models and the resulting suitability maps demonstrated the feasibility of using such techniques during site

identification processes across different activities, environmental challenges and technological constraints.

Bayesian network ecosystem models can be used to explore a range of “what-if?” scenarios, based on potential physical changes (e.g., increase in temperature) or anthropogenic marine use (increase vs decrease in fishing), and the specific trends (increases or declines) of different ecosystem components in response to these changes can be explored. For example, Trifonova et al. (2017) used a Dynamic Bayesian Network model with a hidden variable and spatial autocorrelation to explore the future of different fish and zooplankton species, given alternate scenarios, and across spatial scales within the North Sea. They were able to predict for most fish species a trend of increasing or decreasing abundance in response to changes in fisheries catches. This varied across space, outlining the importance of trophic interactions and the spatial relationship between neighboring areas. They were also able to predict trends in zooplankton biomass in response to temperature change, with the spatial patterns of these effects varying by species. Crucially, dynamic Bayesian network models allow for both species-specific population trends at an ecosystem-wide scale in different habitat types to be predicted, as well as for the main indicators of strong changes in any of these trends to be identified (Trifonova et al. 2021). Most importantly, Trifonova et al. (2021) showed that the strength of such indicators (i.e., ecosystem components or variables) may also vary over time, thus the need to consider both the spatial and temporal variability of indicators throughout the trophic chain is critical to ensuring that the strongest and most consistent, highly predictable indicators, of ecosystem change, are used. Uusitalo et al. (2018) and Maldonado et al. (2019) fitted a series of Dynamic Bayesian Networks with different models and hidden variable structures to a system known to have undergone a major structural change, i.e., the Baltic Sea food web. The authors found that the exact configuration of the model or its hidden variables did not considerably affect the result, and the hidden variables detected a pattern that agreed with previous research on the system dynamics. The models used observed data, but relied on ecological knowledge on the species relationship, reducing the requirement for data. The models are not transferable from one area to another, however, and must be designed specifically for each case study.

The success of using a hidden variable to identify indicator species of key importance to the ecosystem dynamics has also helped illuminate the possible mechanisms behind functional ecosystem changes in

the North Sea (Trifonova et al. 2015) and Gulf of Mexico (Trifonova et al. 2019). Hidden variables can detect ecological patterns in the data that agree with ecosystem change that might not be strictly represented within the model structure and can reduce the likelihood of introducing spurious interactions that allow for more plausible modeling network structures (Tucker and Liu 2004). This is useful in ecosystem modeling where complex ecological interactions change in time due to changing pressures at different levels of the trophic chain. Using dynamic Bayesian network models with hidden variables, (Tucker and Duplisea 2012) predicted functional collapse across three different geographical regions (I.e., Georges Bank, East Scotian Shelf and North Sea). Specifically, a range of ML techniques (wrapper feature selection, classification and a functional equivalence algorithm which used a simulated annealing approach) were applied to fisheries data to identify species that perform similar functional roles in different fish communities. The study provided real insights into why fished ecosystems collapse and why they sometimes do not recover when a perturbation stops.

3.4. Fisheries management

Successful fisheries management often involves creating a model of a system, including the harvested resource and the fishing agents, and delivering recommendations on a level of harvesting to sustain the system in the long run. Taking out the maximum yield while leaving enough for sustainable regrowth is often defined as the goal (i.e., Maximum Sustainable Yield). Other goals such as Maximum Economic Yield or additional objectives within an ecosystem perspective (e.g., minimum seafloor disturbance) might also be of interest. A valuable tool for fisheries management is Management Strategy Evaluation (MSE), simulating various levels of exploitation within the perceived system often in the form of harvest-control rules trying to find the optimal harvesting strategy (Punt et al. 2016). MSE is similar to a type of ML called reinforcement learning, aiming to learn a strategy (or policy) by itself *via* positive or negatives incentives. Recent prominent examples of this learning type comprise algorithms like Alpha Go Zero (Silver et al. 2017) that surpassed the best human player in the complex board game Go in 2017 or an AI that plays several Atari games (like space invaders) at a superhuman level (Mnih et al. 2015). In reinforcement learning, a learning agent interacts with an environment through the perception of the environment's state. Based on the state, an agent can select an action

and enter a new state, receiving a delayed reward as a consequence of one or several of its actions. The goal is to learn a strategy to best interact with the given environment to maximize the total amount of reward earned (Sutton and Barto 2018). A simple formulation of fisheries management as a reinforcement learning problem, with the objective of maximizing the aggregated reward over time, would involve the distribution of a fish stock within the ocean as environment, fishers moving around and harvesting this resource as agents, fisheries yield or revenue as rewards and fuel costs as negative incentives. One of the first attempts using reinforcement learning to explore fishing patterns and their changes due to management regulations was made by Dreyfus-Leon (1999). The author used two shallow neural networks guiding the decisions of a vessel moving within or between fishing locations. The model was extended to multiple agents and applied to the east Pacific yellowfin tuna fishery in Dreyfus-Leon and Kleiber (2001) as well as aspects of information sharing between vessels in a more theoretical approach (Dreyfus-Leon and Gaertner 2006). Similarly Russell and Zimdars (2003), later updated with a DL approach (Deep Q-Learning) by Bouton et al. (2019), explored how to manage multiple agents (fishers) to harvest a common resource sustainably in analogy to a fisheries commissioner finding an optimal quota distribution among fleets. Bailey et al. (2019) explored various management policies ranging from an open-access situation to fishery-wide quotas *via* total allowable catch and individual tradable quotas, and amidst spatial closures/reserves with their agent-based model POSEIDON. The fishers' decisions in this scenario were modeled as a multi-armed bandit problem (Sutton and Barto 2018), a classic reinforcement learning type formulation in situations where agents are allowed to choose an option among several finite ones to maximize their reward. In large environments with many agents, reinforcement learning is hampered by the curse of dimensionality with an increasing number of possible actions. Here, heuristic search algorithms can be used to explore possible multi-faceted actions (Carrella et al. 2019) or a decomposing state space and approximate more complex actions *via* DL (Bouton et al. 2019). The presented approaches summarize attempts in the development of agent-based fisheries ML models to understand fishing patterns and to derive new effective policies (e.g., quota allocations among multiple fleets with multiple objectives). Although reinforcement learning for management and decision-making is currently more of a theoretical exercise in conceptual models that lack

real-life implementations (Chapman et al. 2021), their close resemblance to the iterative approach of adaptive management and MSE shows potential for the future of fisheries management.

Dynamic ocean management approaches have been increasingly explored in recent years to rapidly incorporate the latest environmental information into existing ML approaches and generate spatially explicit forecasts for species targeting or avoidance (e.g., Hazen et al. (2018); Breece et al. (2021)). Many such approaches are operated by BRT (Elith et al. 2008) that are trained on historic data and then implemented on new data as they are acquired from satellites or other sources, often in near real-time. In the EcoCast application (Welch et al. 2020), BRT generate SDM for both target species (swordfish) and bycatch species (turtles, sharks, sea lions) as functions of satellite data (e.g., sea surface temperature, chlorophyll) and produce pixelated maps for which each pixel is colored based on predicted ratios between these target and bycatch species. This near real-time tool is updated daily online, providing fishers with a decision analysis tool to help them avoid bycatch. Many fisheries lack sufficient observer and other spatially explicit data to support such tools, but EcoCast is illustrative of the types of operations that AI/ML approaches will increasingly facilitate.

4. A Way forward: trustworthy AI

While ML in fisheries bears various opportunities, precautionary measures must be taken to avoid undermining the trust of scientists, fishers, managers and stakeholders (Sohns et al. 2022). First and foremost, privacy issues and ethical concerns of fishers need to be taken seriously, especially when it comes to video surveillance on board vessels. Data use should be stated beforehand, and permissions renewed if additional use within ethical boundaries and legislations is desired, especially if human images or behaviors can be identified or inferred. Lack of transparency regarding the extent of data use could greatly decrease trust in ML applications.

Additional concerns exist around biases in training data and algorithms leading to predictive profiling – suspecting a certain behavior (e.g., illegal fishing) from an individual based on past experiences or close resemblance to other individuals exerting this behavior (Probst 2020). False positives in this regard are particularly detrimental in automated vessel classification, if certain behaviors may trigger sanctions or enforcement actions. In addition, biases in fully automated biological sampling and analysis can be greatly

amplified with effects on stock assessment and management. Practitioners should be aware of potential pitfalls regarding domain shifts, in which discrepancies arise between model training data versus data with which models are deployed, leading to unintended extrapolation of algorithms. Such failures, together with the perception of ML as a black box could lead to misperceptions or distrust by stakeholders around stock quotas and management rules (Sohns et al. 2022).

Critiques on the black-box nature of ML may be justified when it comes to adversarial attacks—intentional modifications of data/imagery that are meant to break a classifier, *via* exploiting the classification boundaries and provoking a completely opposite classification. Prominent examples include stickers being placed on an object, e.g., resulting in misclassifying a stop sign as a speed sign (Eykholt et al. 2018), images that are always classified as a toaster (Brown et al. 2018), or a 3D-printed turtle that is seen as a harmful rifle (for an overview see Akhtar and Mian 2018). Although examples from fisheries are yet hard to imagine, Global Fishing Watch reported several artificially simulated AIS tracks that were fed to a public AIS web page and picked up in analysis for marine monitoring (Bergman 2021). Systematic data analysis and careful cross-referencing with additional data sources like satellite imagery made it possible to identify these tracks. Nonetheless, without careful review, it is possible for publicly available data to include adversarial or malicious examples capable of shifting the decision boundaries of a classifier. Although manipulation of AIS signals and data sets to such an extent is an exception rather than a rule, it is a notable example of potential problems that intelligent systems can face. This example highlights the importance of good knowledge of the data being used by using checks (manual and/or automated) and revisiting the data in contrast with other data (e.g., AIS vs VMS and Catches in Taconet et al. 2022).

When using confidential data, e.g., georeferenced data that allows for identifying individual vessels and exposing their fishing locations, scientists typically aggregate analysis steps to cautiously anonymize results. Often, this is done manually before any statistical model is applied. The introduction of DL methods, working best on raw, disaggregated data bears the risk of breaching confidential information. Even if ML practitioners guard against a negligent breach, confidential information can still be inferred *via* a malicious attack on the trained model. The flow of information in a ML model is not one-way but can be reversed, reconstructing the raw training data or some subset from a trained

model, called model inversion (Veale et al. 2018). The possibility of model inversion and membership inference attacks, the latter seeking to identify an individual as part of the training set, suggests that some models themselves may warrant considerations as confidential data. This finding has implications for reporting results, the ever-growing open accessibility of models, and the possibility for new users to openly apply existing models to their own data. To remedy this, data can be anonymized before any processing.

5. Conclusion and outlook

ML is transforming fishery science and management in various ways, ranging from automation of data sampling and simplification of labor-intensive tasks to inference of stock and fleet dynamics to a higher level of individual guidance in management systems. Notably, the automation of biometric measurements from fish drives expectations of standardization across institutes/working groups to reach a level of independence from various human biases. The utilization of transfer learning, simply modifying (e.g., training only the last layer of a complex CNN) a pre-trained model to a new task or situation is a cost-effective approach that can accelerate data collection. Similarly, ML offers various opportunities for inference and analysis, enabling the utilization of large data sets from different sources where human experience may be limited or where relationships are poorly understood. It must be remembered, however, that systems, methods, and applications are at different stages of operational readiness. In recent years, with the advent of DL, numerous studies sought to automate steps in the data collection pipeline, with most of them still considered under development, before being readily deployed in the field/industry. One of the main challenges remains to reach an adequate level of generalization under nonstandardized conditions in different environments. When it comes to inferring stock dynamics, there is already a wider use of traditional ML, but DL applications are still limited. Meanwhile, overcoming the challenges of AIS/VMS data, especially around data sizes, is a perfect application for ML. ML applications in stock assessment and management are currently only rarely considered, but they show great promise for the future if they gain trust, despite their black-box nature. Finally, as more ecosystem models use ML techniques, it is important to exploit the strengths of each model type, while understanding how they differ and finding ways to generalize their outcomes to

strengthen projections under a range of natural and anthropogenic scenarios.

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