One Earth

Primer

Harnessing AI to map global fishing vessel activity

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SUMMARY

Describing the sheer scale of the global fishing industry necessitates a lot of zeros: 4,900,000 fishing vessels, 40,000,000 million workers, and an annual production of 80,000,000 tonnes of seafood valued at $141,000,000,000. Effective management of the fishing industry requires crunching these big data—while the human mind balks at such a task, the artificial mind does not. Artificial intelligence (AI) is a family of systems that allow computers to simulate human behaviors, such as learning from experience and recognizing visual patterns. This primer explains how AI is used to monitor and surveil fishing vessels from space, shore, and the seafloor and then how it is applied to process this information to meet fisheries management goals, like combating illegal fishing. The exponential rise of AI in fisheries applications over the past decade shows no signs of slowing. We reflect on how the AI of tomorrow may improve fisheries' sustainability and transparency while emphasizing the sustained need for human oversight in an increasingly automated future.

INTRODUCTION

Imagine a world in which the locations of a significant portion of airplanes were unknown. Nations would struggle to track or identify the aircrafts entering their airspaces, with limited ability to enforce airspace violations. The regulatory oversight that ensures safe onboard working conditions and equipment would be non-existent. Without information on where planes are landing, the transport of cargo would go unmonitored, creating blind spots that allow contraband smuggling and human trafficking to proliferate. While this aviation scenario is fortunately just a thought exercise, it is a harsh reality in the global fishing industry.

Roughly 98% of the 4.9 million vessels in the global fishing fleet do not publicly broadcast their locations. The lack of transparency created by these missing data poses significant challenges for fisheries sustainability. Fishing vessels move through a complex patchwork of governance spanning waters managed by regional fisheries management organizations, national governments, and local territories without contiguous information on where they are fishing or what they are catching. Poor information on the catch can prevent accurate assessments of overfishing of target species like tunas and the incidental catch (i.e., bycatch) of threatened and protected species, like marine mammals and turtles. This lack of oversight creates blind spots that allow illegal, unreported, and unregulated (IUU) fishing activity to operate on a large, systemic scale. IUU fishing results in up to $25 billion in annual economic losses, and fishing vessels engaged in IUU often commit human rights violations like human trafficking and modern slavery. It is estimated that 128,000 fishermen worldwide are trapped in forced labor onboard these vessels.

In recognition of these issues, a suite of global mandates have been ratified to improve fisheries sustainability, for example, the Convention on Biological Diversity, the Sustainable Development Goals, the Port States Measures Agreement, and Biodiversity Beyond National Jurisdictions. Improving fisheries sustainability requires better data on the global and dynamic footprint of fishing. Artificial intelligence (AI) has emerged as a critical tool for mapping fishing fleets, improving the quality, volume, and immediacy of data on where vessels are fishing and what they are catching. In this primer, we overview how AI is revolutionizing fisheries monitoring and surveillance, beginning with the story of AI's rapid proliferation into most aspects of modern life and an explanation of AI systems. We also elaborate on how AI reveals where fishing vessels operate and how AI translates this information in support of fisheries efficiency, enforcement, and conservation. Lastly, we reflect upon how the next decade of AI advancements will enhance our understanding of how fisheries operate across our vast marine global commons, guiding their sustainable use for future generations.

The rapid rise of AI

AI has undergone a Cambrian-like explosion over the past several decades, rapidly diversifying, proliferating, and complexifying

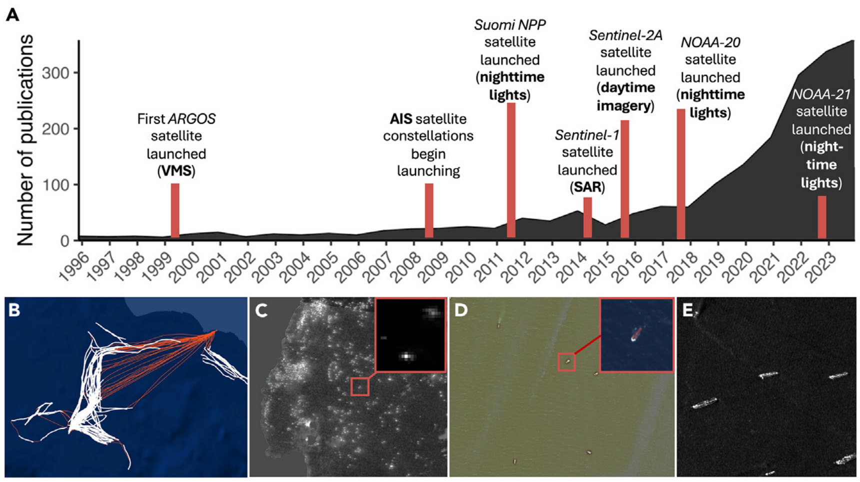

Figure 1. The rapid rise of artificial intelligence in fisheries monitoring and surveillance

(A and B) Number of peer-review publications per year that mention AI and fisheries tracking and select launch dates for satellites used to observe fishing vessels from space. Images: (B) automatic identification system (AIS) tracks from a bottom trawler off the coast of Italy, colored by fishing activity (white) and transiting (orange). Vessel monitoring system (VMS) tracks are similar in appearance but cannot be publicly mapped due to confidentiality restrictions.
(C) Nighttime lights in the Gulf of Thailand.
(D) Daytime imagery of five trawlers.
(E) Synthetic aperture radar (SAR) image of five vessels.
Image credits: (B) Global Fishing Watch, (C) NASA, (C, inset) Skylight and NOAA, (D) Global Fishing Watch, (D, inset) European Space Agency and Sentinel Hub, and (E) https://github.com/chaozhong2010.

from the early checkers-playing programs of the 1950s. Today, AI has expanded into nearly all major industries: streamlining the scouting process in major league sports, identifying cancers in tissue samples, and putting on the brakes in self-driving cars. Fisheries monitoring and surveillance has a similar AI trajectory, with less than 10 scientific papers published on the topic in 1995 to over 300 published in 2023 (Figure 1A). The rapid rise of AI coincides with exponential growth in computing power, power that is critical to run AI's intricate instructions and algorithms. Personal laptops today are five orders of magnitude faster than the early computers of the 1960s. Increases in the volume and speed of data transfer over the internet spurred advances in cloud computing. Cloud computing spreads out processing tasks across multiple remote servers, effectively scaling up computing power without the need for additional hardware. As computing power increased, so too did computer literacy, open-source frameworks, and educational resources, making AI easier to use and accessible to a broader range of users. With more people building and testing, AI products became increasingly accurate—consider, for example, the collective global awe when ChatGPT, a virtual chatbot that can rapidly process natural language to formulate informative human-like conversations, was rolled out in late 2022.

The final component of AI's rapid rise is big data, which are data on the scale of terabytes to exabytes. In fisheries monitoring and surveillance, big data have rapidly expanded due to satellites. Reduced launch and hardware costs have led to a massive increase in the number of satellites orbiting the Earth (Figures 1B–1E). Satellites capture a suite of geospatial information on fishing vessels: GPS-based vessel position information from vessel monitoring systems (VMS) and automatic identification systems (AIS), low-light emissions or "nighttime lights" from vessels at night, radar signal reflections from vessels captured by synthetic aperture radar (SAR), and daytime imagery of vessels. These datasets are too large, complex, and rapidly generated to process manually and require the automation, advanced pattern recognition, and real-time processing afforded by AI. A lack of training data has historically been a significant barrier to applying AI at scale—AI systems must be trained over large volumes of data to produce accurate results. Thus, the same big data that required AI to be processed have also enabled AI systems to improve.

AI-enabled machine learning to analyze fishery data

AI is the simulation of human intelligence in machines and computers that are programmed or trained to mimic human behaviors, like learning from experience and recognizing visual patterns. In this section, we aim to provide a brief explanation of how AI works, specifically focusing on a vital subfield of AI called machine learning (Figure 2). We do not cover all subfields of AI, such as swarm intelligence, evolutionary algorithms, or natural language processing, but readers can explore these notions further in Dong et al. and MahmoudZadeh et al. in the recommended reading section. Broadly, machine learning systems learn from data without needing explicit instructions from a human by using one of three learning paradigms: supervised, unsupervised, or reinforcement.

The three learning paradigms (supervised, unsupervised, and reinforcement) can use shallow and deep learning. Shallow learning algorithms have a simple structure, do not require much training data, and generally perform best on tabular datasets. Shallow learning algorithms are various, and their applications can be case specific, which we will touch upon below. Deep learning leverages neural networks, which are a family of algorithms inspired by the structure and functioning of the human brain; examples include multilayer perceptron network (MLP), convolutional neural network (CNN), and transformer-based models. Deep learning requires significantly more training data compared to shallow learning, but it can learn from a wide range of data types, such as image, video, audio, and text, as well as tabular datasets.

In supervised learning, the system is trained on a labeled dataset, and the goal is to predict a specific output. Take, for example, a supervised system designed to predict how at risk certain areas are for illegal fishing as an output. The system is trained on a dataset of area features (e.g., number of patrol vessels, marine productivity, the dollar value of species that frequent the area, and the financial health of the nation that controls the area) labeled by the area's corresponding risk of illegal fishing. The system learns relationships within the dataset to create an

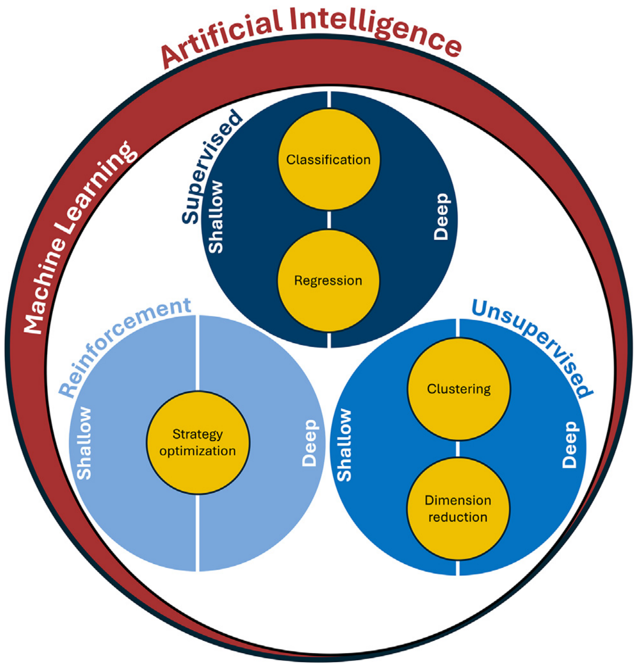

Figure 2. AI systems commonly used in fisheries monitoring and surveillance
Machine learning (white circle) is a subfield of AI characterized by algorithms that learn from data without needing explicit instructions from a human. Learning paradigms within machine learning include supervised, unsupervised, and reinforcement learning (blue circles). Within each learning paradigm, shallow and deep learning algorithms are applied to power tasks such as classification, regression, clustering, dimension reduction, and strategy optimization (yellow circles).

algorithm that accurately predicts illegal fishing risk as a function of these features. If the goal is to predict low-risk versus high-risk areas (a binary output), then it is a classification task; if the goal is to predict the degree of riskiness (a continuous output), then it is a regression task. Examples of shallow supervised learning algorithms include random forest (RF), gradient boosting (GB), naive Bayes, and support vector machine (SVM).

In contrast, an unsupervised learning system is trained on unlabeled data, and the goal is to identify patterns as opposed to predicting a specific output. In the illegal fishing example, the system is trained on the dataset of area features, but the areas are not labeled by their corresponding risk of illegal fishing. Dimension reduction compresses datasets by finding a smaller, summarized set of representative features that preserve the maximum amount of information in the full dataset. For example, it might be applied to the illegal fishing dataset to find that the number of patrol vessels and financial health can be described as a single feature, and that marine productivity does not vary much across areas and is therefore unimportant. Examples of shallow algorithms include principal-component analysis (PCA), factor analysis, and forward/backward model selection. Clustering partitions data into groups that have high within-group similarity and high between-group dissimilarity; examples of shallow algorithms include k-means, partitioning around medoids (PAM), and Gaussian mixture models (GMMs). In the illegal fishing example, clustering may partition the areas into low and high risk, but because the system is not trying to predict a specific output, it may also partition the areas into productive and unproductive or waters controlled by wealthy and developing nations. It is also worth noting that an algorithm can use a mix of supervised and unsupervised learning, a category known as semi-supervised learning, in which the algorithm is trained on a usually small amount of labeled data and a larger amount of unlabeled data.

The goal of reinforcement learning is to optimize a specific strategy. An agent interacts with a virtual environment, and its actions are either rewarded or punished. The agent self-learns from this feedback to discover the optimal strategy to maximize the rewards (or minimize punishment) over time. In the illegal fishing example, the goal of a reinforcement learning system is to optimize the route a patrol vessel (the agent) takes across a crowded seascape (the virtual environment). The patrol vessel is penalized when it collides with another vessel and rewarded when it transits around the vessel. By simulating the trial-and-error process humans use to learn, over time, the patrol vessel learns the most efficient way to move across the water.

Fishing vessel tracking and detection

Monitoring the global fishing fleet requires observing the movements of nearly 5 million vessels across 360 million km^2 of ocean surface. This significant undertaking relies on a constellation of technologies and AI systems (as well some non-AI techniques) to overcome challenges such as bad weather, cloud cover, darkness, and vessel operators who may not want their movements observed (Figure 3). In this section, we provide an overview of the tech-AI systems that track and detect fishing vessels from space, shore, and the seafloor.

Identifying fishing activity in vessel tracking data

Shipboard VMS and AIS transponders use GPS satellites to determine vessel positions, which are then relayed to satellite and terrestrial receivers. Although the two systems have similar functionality, the VMS was designed for surveilling commercial fishing vessels and is usually confidential, while the AIS was designed for collision avoidance and is publicly accessible. A primary use of AI in fisheries tracking is the identification of fishing versus non-fishing activities (Figure 1B); understanding when and where vessels fish is essential for monitoring fishing effort and enforcing regulations. Vessels exhibit distinctive movement patterns that allow for the classification of their activities into categories such as fishing, resting, and transiting. Unsupervised learning can be used to categorize activities based on patterns in VMS and AIS data without the prior labeling of fishing activity. However, supervised learning methods trained on labeled data can identify fishing activity with greater accuracy. Labeling is done manually by expert review or cross-referencing tracking data to other fishery datasets in which fishing activity is recorded, such as observer, logbook, or electronic monitoring data. Electronic monitoring involves the use of vessel-mounted cameras to record key operational activities like gear deployment and catch handling. Traditionally, these activities have been identified through manual review of the footage, but computer vision is increasingly being applied to automate the identification process. Computer vision is an AI application that leverages deep learning to interpret visual data from images and videos, akin to human visual perception. Electronic monitoring

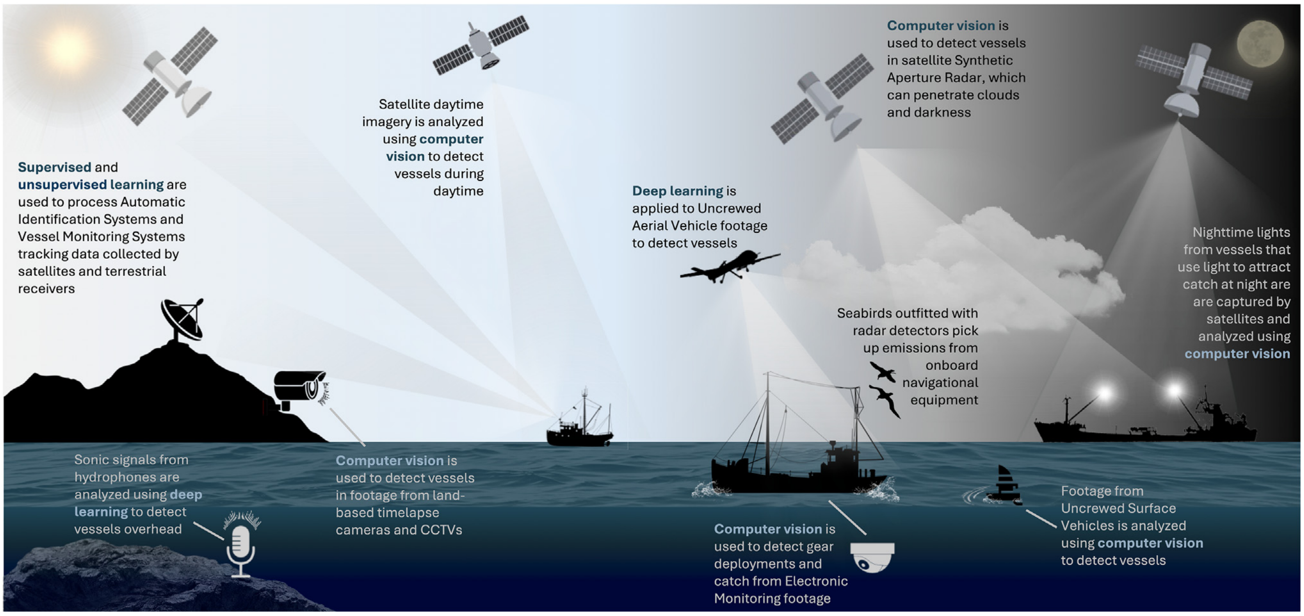

Figure 3. The constellation of tech-AI systems used to track and detect fishing vessels
Data are collected by satellites, uncrewed vehicles, seabirds, and fixed sensors like time-lapse cameras and hydrophones. AI systems are then used to identify vessels and observe their movements.

data are matched to VMS data to produce geospatial information on fishing activity and catch. In addition to fishing versus non-fishing activities, unsupervised and supervised learning techniques are used to categorize vessels by fishing gear type and estimate vessel length.

Detecting fishing vessels from space
AIS and VMS are powerful tools for tracking fishing fleets; however, many vessels are not equipped with either system. Globally, an estimated 52%–85% of vessels larger than 24 m are equipped with AIS. A comparable global statistic has not been estimated for VMS, but roughly 5% of US and 14% of European commercial fishing vessels are equipped with VMS. Public satellite-based optical imagery and SAR provide a means of detecting untracked fishing vessels. Optical imagery consists of daytime imagery and nighttime lights and can identify the location of vessels as long as clouds are not present. Daytime imagery can detect individual vessels on the water during the day, while nighttime lights can detect where there are vessels that use light, a common fisheries practice to attract catch like squid. Using radar waves, SAR captures radar signal reflections from vessel surfaces. It penetrates through clouds and operates both day and night, making it highly effective in all weather conditions. Computer vision is used to detect vessels in daytime imagery, nighttime lights, and SAR and then categorize fishing gear types and estimate vessel length. Detected vessels are then cross-referenced against vessel tracking data to identify untracked or "dark" fishing vessels—those that are not tracked by AIS or VMS. Despite the large increase in the number of satellites orbiting the earth, it is still difficult to repeatedly detect—i.e., track—dark vessels across time due to low revisit rates (how often satellites return to observe the same point on the Earth), particularly offshore, where public satellite coverage is more limited.

Detecting fishing vessels using local technologies
Nearly a third of the world's seafood is captured by small-scale fisheries, yet these vessels are significantly underrepresented in fisheries tracking and satellite datasets. VMS and AIS are biased toward larger vessels, with less than 1% of vessels under 12 m equipped with AIS. Public satellite imagery struggles to resolve objects smaller than 10 m and distinguish vessels from rocks and manmade objects in nearshore waters, where small-scale fisheries primarily operate. In contrast, local technologies allow for high-resolution vessel detection over small, discrete portions of the ocean. Harbor-mounted time lapse cameras and closed-circuit television (CCTV) continuously monitor vessel traffic entering and leaving port. These photo and video streams are analyzed using computer vision to detect vessels at high enough resolutions to identify vessel ID plates. Seafloor-mounted hydrophones listen for vessel engine noise, using deep learning to track the amount of vessel traffic overhead. Uncrewed aerial and surface vehicles survey fishing vessels from the air and ocean surface using deep learning and computer vision. Onboard these uncrewed vehicles, operational activities like obstacle avoidance and path planning are also governed by AI systems, such as swarm intelligence and evolutionary algorithms. The propensity of seabirds to follow fishing vessels has also been harnessed for vessel detection: albatross fitted with radar detectors are used to detect radio emissions from navigational equipment onboard vessels (although AI is not currently integrated into this technology). Like satellite-based detections, these local detections are cross-referenced against vessel tracking data to identify dark vessels.

Toward transparent fisheries
Fisheries transparency refers to the open and accessible sharing of information related to human activities at sea. Here, we

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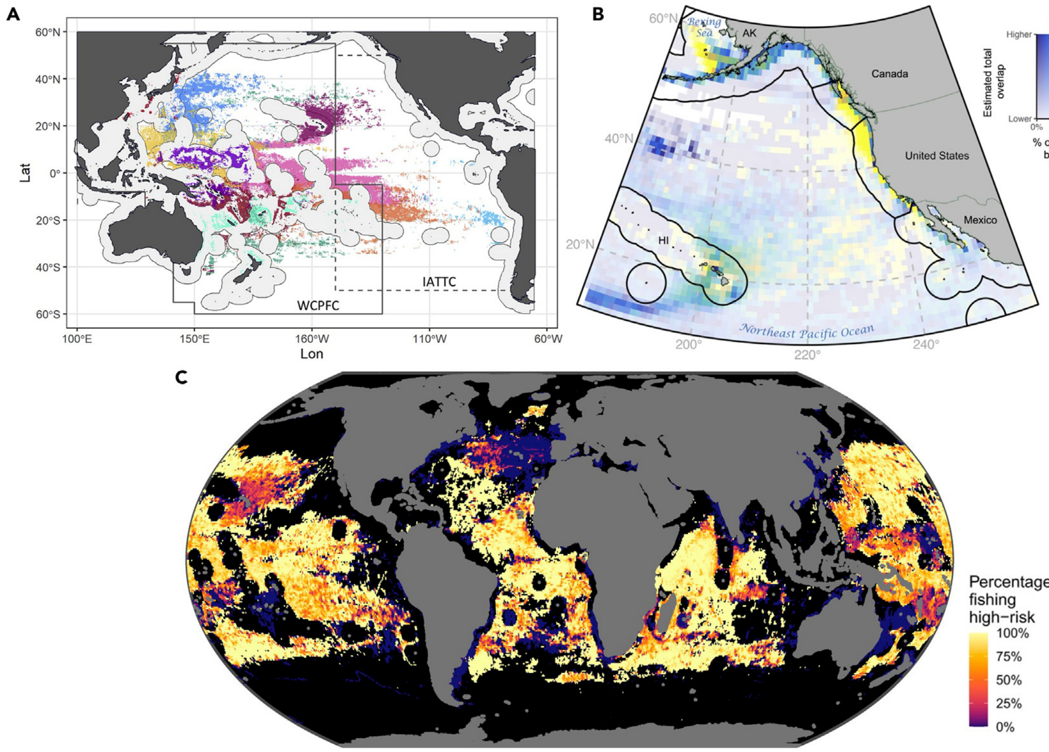

Figure 4. Using AI to integrate AIS data with value-added products to meet fisheries management goals

(A) Decoding fishing behaviors: unsupervised learning is applied to AIS and target species data to identify functional fishing groups; each color represents a unique group.

(B) Mapping resources: human-wildlife risk is estimated by applying supervised learning to satellite tagging data from marine predators and then overlapping AIS data; unseen activity represents vessels that are equipped with AIS but are not broadcasting their locations.

(C) Combating illegal fishing: supervised learning is applied to AIS and vessel registry data to model forced labor risk; map shows the percentage of longliner activity predicted to be high risk for forced labor.

Image credits: (A) Frawley et al. in the recommended reading section, https://creativecommons.org/licenses/by/4.0/; modifications: figure cropped. (B) Welch et al. in the recommended reading section, https://creativecommons.org/licenses/by/4.0/; no modifications. (C) McDonald et al. in the recommended reading section, https://creativecommons.org/licenses/by-nc-nd/4.0/; modifications: figure cropped and legend relocated.

overview how AI is applied to promote transparency by integrating fisheries tracking and detection data with value-added datasets that describe the ecological, social, and economic conditions of our seascapes (Figure 4).

Decoding fishing behaviors

Understanding vessel-level and fleet-level dynamics is important for effectively designing fishery regulations, as well as predicting the impact of proposed regulations. Deep learning is applied to fisheries tracking data to forecast vessel trajectories in order to reduce maritime risks, such as collision and stranding. Reinforcement learning is used to optimize vessel voyage planning, improving fishing efficiency and profitability while reducing risks from adverse weather conditions. Functional fishing groups—or métiers—are fishing units with similar size and common exploitation patterns. Supervised and unsupervised learning is used to predict and cluster fisheries tracking data into métiers based on attributes such as gear types, fishing ground locations, and target species (Figure 4A). Supervised learning is also applied to fisheries tracking data to evaluate the impacts of regulatory changes on fleets and forecast fleet responses to proposed marine protected areas up to 3 years in the future. Supervised learning can be directly applied to fisheries tracking data to understand what drives vessels to fish or disable their transponders. Fisheries tracking data, associated with economic information from the World Bank and vessel registries, provide insights into how wealth and corporation ownership drives fishing behaviors. This information can guide policy to support the economic growth of developing countries and prevent industry consolidation.

Mapping resources

Fisheries tracking and detection data offer valuable information on the locations where vessels are fishing, but they provide little insight into which species the vessels are targeting and catching. While VMS-associated electronic monitoring data contain information on catch, electronic monitoring has been implemented on less than 1,000 vessels. A broadscale understanding of the spatial patterns of targeted and protected resources is essential to prevent overfishing, reduce bycatch of threatened and protected species, and assess the impact of regulatory actions on fishermen's economic opportunities and livelihoods. Geospatial records of targeted and protected species, drawn from logbooks, observer datasets, and satellite tagging programs, are integrated with environmental data. Supervised learning is then used to map the biomass, abundance, or distribution of targeted and protected species. Fishing vessel activity can be overlaid on these maps, providing estimates of the risk of human-wildlife interactions, such as catch, bycatch, ship strike, and noise pollution (Figure 4B). Information on interaction risk is integrated into stock and mortality assessments and then used to inform management levers, such as gear modifications and fishery closures. Revenue is mapped by linking VMS fishing activity to data on shoreside deliveries. These spatial descriptions of fishing activity and revenue are used to guide marine spatial planning, an essential tool to navigate trade-offs between industries like fishing and offshore wind development in our increasingly crowded oceans.

Combating illegal fishing

Illuminating the locations and activities of untracked vessels—particularly those equipped with vessel tracking systems that then go dark—is a powerful first step toward identifying instances of IUU. Although untracked vessels are not necessarily engaged in illegal activities, this information narrows the needle-in-haystack problem of focusing finite enforcement resources across large numbers of vessels. Insights into dark vessels are used by enforcement agencies to position patrol assets and schedule port inspections to target vessels with the highest risk of IUU. High-resolution optical satellites (usually run by private companies) can be cued to capture detailed imagery of individual dark vessels for one-tenth of the cost of deploying a patrol vessel. Successful enforcement response to suspected IUU requires information on dark vessels to be available in as close to real time as possible. At present, this information can be produced in 4–6 h, with most of the delay due to the time it takes to receive the data from satellites (AI processing takes minutes, at most). Supervised and unsupervised learning is applied to fisheries tracking data linked to value-added datasets, (e.g., ownership databases, vessel registries, and forced labor reports) to map IUU risk near ports, forced labor risk, transshipment risk, and the activities of unidentified or unauthorized vessels (Figure 4C). Vessel tracking data are compared against these maps to reveal if vessels have been operating in risky waters—further focusing enforcement actions. Supervised learning is used to predict the footprints of dark fleets and when vessels are illegally fishing in unauthorized waters. A growing body of research uses supervised and unsupervised learning to detect anomalies in vessel tracking data to reveal potential instances of IUU: vessels fishing using different methods than their declared gear type, vessels fishing with their transponders disabled, and vessels spoofing (deliberately falsifying or manipulating) their locations.

Outlook

Over the past decade, AI has become deeply embedded in fisheries monitoring and surveillance, translating the big data generated therein into practical, actionable information. The rapid rise of AI shows no sign of plateauing. Global competitions, backed by monetary rewards, have emerged as vehicles of AI advancement. One such competition spurred the next generation of computer vision algorithms for vessel detection. Others are advancing AI for the identification of species in electronic monitoring footage and navigation in uncrewed surface vehicles. Currently, the constellation of tech-AI systems allows for the identification of potential IUU in near real time; one ongoing competition challenges participants to forecast potential IUU before it occurs.

AI systems from other industries are being adapted to achieve fisheries monitoring and surveillance goals. The same blockchain technology that records cryptocurrency transactions is being explored to improve the traceability and transparency of the seafood supply chain. AI-identified catch information will be recorded in the blockchain and preserved during each transaction, from the ocean to hors d'oeuvre. Consumers will access this information by scanning QR codes using the built-in computer vision apps in their phones to learn about the sustainability of their selection. Non-governmental organizations like Skylight and Global Fishing Watch serve AI-processed fisheries tracking and detection data in public portals. Large language models, such as the one powering ChatGPT, are under consideration to assist end users in asking the right questions to achieve their management objectives.

Like all industries, fisheries will feel the effect of our changing climate. AI is increasingly harnessed to forecast global atmospheric and marine weather patterns. These physical forecasts, paired with machine learning models, can provide insights into how fisheries and the species they catch will redistribute as the oceans warm. Future exploitation of an increasingly ice-free Arctic is being forecast to inform proactive policy. Forecasts of transboundary shifts of target stocks provide early-warning systems to forewarn the social conflicts that can occur when one country's fish ends up in another country's waters. Mobile marine protected areas—informed by machine learning models of species distributions—are under exploration as a solution to reduce bycatch of protected species as they redistribute during extreme weather events, such as marine heatwaves.

AI is, in turn, highly capable and highly capable of making mistakes. Earlier this year, Google's AI-enhanced search infamously recommended users put glue on pizza and consume one small rock a day. More seriously, AI-powered cancer detection and facial recognition software have shown racial biases. Fisheries tracking and detection data are biased to large vessels from wealthy countries. The AI systems that ingest these data to inform policy, develop decision support tools, and guide regulation may perpetuate or even amplify these biases. AI-based IUU detection may unfairly flag certain vessels, ports, or gear types based on prior interactions with law enforcement. To minimize harm, AI should enhance, rather than replace, human capabilities. Human oversight in the decision-making process remains essential for developing ethical AI systems, particularly with regard to value judgements. This human-in-the-loop approach involves a diverse set of voices guiding decisions about which data AI systems are presented with, which outcomes AI systems are optimized to achieve, and who is accountable when negative outcomes occur. In other words, use AI to determine if a vessel is at high risk for IUU, but perform a cargo inspection before prosecuting it.

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DECLARATION OF INTERESTS

The authors declare no competing interests.

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