

Advancing artificial intelligence in fisheries requires novel cross-sector collaborations

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Abstract

Artificial intelligence, or AI, has the potential to dramatically improve our understanding and management of the ocean. For fisheries, these benefits could include greater monitoring coverage at lower costs, improved estimates of catch and bycatch, identification of illegal fishing, and seafood traceability throughout the supply chain. However, fisheries AI innovation and adoption faces substantial barriers from the highly regulated nature of fisheries and the complex overlap of government policies, diverse user needs, and market pressures. We argue that needed advances in fisheries AI require novel collaborations to share data and methods, encourage new and diverse entrants to the field, and increase baseline technical literacy across the global fisheries community. Unlocking fisheries data to power AI, particularly image data, can only be achieved through partnerships across government managers, AI developers, fishers and vessel owners, and technology service providers, which, in turn, requires a common vocabulary for policy and technical concepts. With a greater shared understanding across the field, fisheries AI providers can deliver desired results, and users can have confidence that systems are performing as advertised, ultimately meeting monitoring demand and sustainability goals.

Keywords: artificial intelligence; computer vision; electronic monitoring; policy; management

Ocean fisheries are a \$159 billion business employing more than 61 million people worldwide that provides food security and essential nutrition (FAO 2024). Where fish are caught, what species and fish sizes are kept or discarded, and fishing interactions with other ocean wildlife are critical data for managers and scientists working to maintain long-term fisheries and ocean sustainability, as well as for businesses seeking to meet seafood traceability standards. With 4.9 million fishing vessels (FAO 2024) and 360 million km² of ocean waters—two-thirds of which are more than 370 km from shore and beyond national jurisdictions—monitoring fishing activities requires covering an enormous area over time.

Technological advances in the last decade, including hardware and software innovations, now make it possible to collect and analyse fisheries data that were previously too expensive or impossible to obtain (Brett et al. 2020, Malde et al. 2020, Probst 2020). Because of the volume and complexity of this data, artificial intelligence (AI) is playing a growing role in handling these new data streams. For example, AI can combine data from location tracking devices, satellite imagery, and vessel transponders to provide a clearer picture of fishing vessel movements (Paolo et al. 2024). With as much as 80% of the world's fisheries targeting fish populations that are data-poor or unassessed (Costello et al. 2012), AI could have a transformative effect by bringing new information into monitoring and management. (Dowling et al. 2015, Bradley et al. 2019, Exeter et al. 2021),

In this paper, we use AI to refer to a branch of computer science that focuses on creating systems capable of performing tasks that historically have required human intelligence. These tasks are accomplished through algorithms and models

designed to process data, identify patterns, and achieve specific objectives without explicit human instruction. Both machine learning and computer vision fall under the general umbrella of AI (Beltzung et al. 2023, Rubbens et al. 2023). We are deliberately using a more general definition of AI distinct from 'AI models' or 'AI systems,' because the term 'AI' currently has a broad, colloquial use in many communities while 'AI systems' are specifically defined in policies such as the 2024 EU AI Act. We will also focus on vision and multimodal AI systems as a case study for overall fisheries AI innovation and adoption. In part, this is because the authors have spent the last decade working on design, engineering, product, deployment, and policy challenges around fisheries image data. Vision and multimodal models make up a small percentage of the AI revolution over the last 5 years (Epoch and Our World in Data 2024), but they are critical to the success of fisheries electronic monitoring systems. While there may be different barriers facing image and multimodal AI systems than other applications of AI in fisheries, we believe these lessons and recommendations are broadly applicable.

AI and electronic monitoring

Electronic monitoring systems, or EM, use on-vessel video cameras and activity sensors to record catch. EM can be installed on boats too small to accommodate a human observer and can operate continuously across the days and weeks of a full commercial fishing trip. This means that EM can potentially be applied to more of the world's fishing vessels than traditional human monitoring and collect more fishing activity information. This increased coverage comes with greater

data volumes, which need to be transmitted from the vessel, reviewed, and stored. A single 720p camera recording at 15 frames per second can produce a 1.5 GB file each hour, and many EM systems include multiple cameras, in addition to other sensor data (B. Woodward, personal communication). Even with recent expansions in ocean cellular coverage and satellite transmission, EM files can still be too large to upload remotely and require exchanging physical hard drives. Once files are received by the EM service provider, expert reviewers are faced with thousands of hours of video, the bulk of which may contain no relevant fishing activity, e.g. when a vessel is transiting between fishing areas.

The data volumes involved make EM a prime candidate for AI. On-vessel AI systems can trim non-fishing activity from video files, significantly reducing file sizes and the bandwidth needed to transmit data, and obfuscate vessel numbers or faces to meet privacy protection requirements. Once data are transmitted, AI can identify and flag video segments for human reviewers, reducing both cost and human fatigue. With certain camera configurations and catch handling procedures, AI can identify and measure individual fish, track discards, and record protected species interactions (van Helmond et al. 2020). Integrating AI into EM systems has the potential to make EM more affordable, increasing its adoption and, in turn, fueling EM improvements as the market expands.

To date, global EM adoption has been slow. After the technology's introduction in the British Columbia, Canada crab fishery in 1999, fewer than 2000 systems were installed worldwide in 2020 (McElderry 2006, Michelin and Zimring 2020). However, EM demand is growing, driven largely by government mandates. A total of 12 EM programs have been established across Canada, Spain, the USA, and Australia (van Helmond et al. 2020), and 11 of the 15 multi-national Regional Fisheries Management Organizations/Associations (RFMOs) are discussing EM requirements (Gilman 2023). This includes three of the major high seas management entities—the Indian Ocean Tuna Commission, the Inter-American Tropical Tuna Commission, and the International Commission for the Conservation of Atlantic Tunas—which govern a combined 23 600 fishing vessels across 75 countries. Interest is also growing in combining EM systems with other fisheries data collection and monitoring tools (Seraphin et al. 2016, Tickler et al. 2018, Haukebo et al. 2021, Signaroli et al. 2024), or expanding its use beyond its original design for commercial fisheries monitoring. For example, concerns about human rights abuses, labour violations, and worker safety are spurring research into using on-board camera systems to track people, not only (or instead of) fish (Boulais 2020, Moncada Pesantes 2022, Joo et al. 2023).

We see AI as essential to expanding EM coverage because of its potential for cost reductions, verifiable data streams, and improved analytics. However, if EM were mandated this year by all three of the RFMOs listed above, it is unlikely that the current supply of AI-supported EM systems could effectively meet that demand. Accelerating AI development and deployment is a people and policy issue more than a technical challenge, and policy changes will require a coordinated effort across members of the fisheries community to address.

Key partners in fisheries EM

An AI-supported EM system requires the active participation of four general groups:

1. The fishers and vessel owners who will carry the EM systems.
2. The EM service providers who design systems, install and support hardware, and often also supply video review services.
3. AI developers building models for EM systems.
4. The government managers/regulators who determine what data need to be reported and can set rules around any part of the system, from hardware specifications to how fishers handle catch on deck.

For the first group, cost is a major concern as many EM programs require fishers to pay all or part of the installation and operating costs as a fishing permit condition or to access certain fishing areas. Fishers have also expressed concerns around the privacy of personal data like facial images and the potential use of data for purposes other than fisheries monitoring (Mangi et al. 2015, Plet-Hansen et al. 2017).

There are approximately 13 EM service providers or vendors as of this writing, some of whom operate around the globe, while others focus on specific fisheries, gear types, or regions. Their core business is delivering EM systems and data to meet customer requirements; AI is only one part of that business. Like governments, EM service providers are competing for AI talent against high-paying jobs in the private sector (Stokel-Walker 2024). Some EM vendors have small internal AI teams, while others contract with external AI developers, both fisheries-focused and AI generalists. Fisheries-focused AI firms (e.g. ai.fish, ondeck.fish) tend to be small, but their teams have trusted relationships with data holders, including governments and EM service providers, and experience working with the challenges of EM image data, such as low lighting and water spots. General AI firms may have greater staff and compute capacity but lack access to training data.

Governments define the terms of how and where EM systems will operate and what they must deliver. For EM systems, the government may be a customer as well as a regulator. For fisheries managers, this can mean sorting through a thicket of technology options and jargon to map fisheries objectives onto tools and providers. Historically, regulators have struggled to set the appropriate level of specificity and performance standards in program designs and contracts, which can constrain innovation and adaptation to technological improvements (Garren et al. 2021).

Successfully deploying AI-supported EM requires the availability of systems that are affordable by fishers and governments, satisfy fisheries science and monitoring conditions, can be integrated with the hardware and review workflows of EM service providers, and are seen as trustworthy and reliable by all parties. A core element of achieving this success is increasing access to training data.

Data and capacity constraints

AI models are only as good as the data they are trained on. High-performing AI models require large amounts of data that are also high quality and relevant to the target use (Adhikarla et al. 2023, Orenstein et al. 2023, Yao et al. 2023). While enormous volumes of data can compensate for some quality issues, AI will not work well for users and use cases are not represented in the training data. Large language models like ChatGPT have been trained on the entire text corpus of the internet but can struggle with non-English languages

(Ahuja et al. 2023, Zhang et al. 2023, Hada et al. 2024). AI models for EM systems need to be trained on images from commercial fishing activities, ideally with the same gears and target species where the final systems will be used.

Large, publicly available, labelled image datasets, such as Imagenet and Microsoft Common Objects in Context, have very few images of fish; what images are publicly available are primarily underwater footage or of species not targeted by commercial fisheries. Underwater image datasets cannot train a model to find a fish on the deck of a vessel, in rainy conditions, surrounded by crew. In 2019, The Nature Conservancy released an open training dataset of labelled images from Pacific tuna fisheries, which has been used by both established monitoring companies and fisheries AI startups and remains the only public dataset of its kind (Kay and Merrifield 2021).

Creating that public dataset required The Nature Conservancy to negotiate data use agreements with individual governments and fishing vessel owners. This type of 1:1 data sharing is common for AI researchers and developers, who must invest in legal counsel and information security to support multiple data use agreements with multiple partners to get enough data to train a model (French et al. 2020). It is notable that Canada, the birthplace of modern EM, allows fishers to own the data collected about them, meaning they could share or sell data with AI developers. Some governments, such as in the USA and Australia, contract directly with service providers and own and control the data vendors collect, even in cases where fishing vessel owners must cover all or part of the monitoring costs (National Marine Fisheries Service 2022, Australian Fisheries Management Authority n.d.). Where EM data are treated as part of government monitoring, control, and surveillance (MCS) programs (Miller et al. 2013), data may be treated as classified or confidential information, unable to be shared at all or only under highly restrictive conditions and in aggregate or obfuscated formats. In countries where EM data are treated as confidential information, fishers cannot receive copies of data from technology installed on their vessels, nor can service providers or AI developers retain and reuse data from their own systems.

Policy changes could make greater volumes of training data available, but that data will benefit from expert review and annotation before being used by AI developers. An experienced fisheries observer may be able to distinguish between two species of tuna based on the placement or colour of a fin, with a speed and accuracy rate that fisheries AI has yet to attain. Attempts to use commercial data annotation firms, such as those working with self-driving car imagery, have had mixed results for fisheries datasets. Former observers and local fisheries experts can be trained as annotators, adding labels and bounding boxes to EM images, but these roles need appropriate salaries and working conditions to be ethical and attractive jobs. When data are scarce, companies that can access data and invest in data annotation have lower incentives to share their training data, while new companies have few options to obtain data to train their models.

In advancing AI-supported fisheries monitoring, we should also be mindful of the uneven distribution of data and AI capacity across fishing nations and fishing communities. While some countries in the Food and Agriculture Organization of the United Nations (FAO) list of top fishing producers (China, the USA, India, and Japan) are also well positioned to develop and deploy fisheries AI, other major fishing nations countries (Peru, Indonesia) score much lower on global in-

stances of AI readiness (FAO 2022, Cesareo et al. 2023). So-called 'small-scale fisheries' are significant sources of employment and subsistence in Bangladesh, Viet Nam, Myanmar, and Nigeria (FAO et al. 2023); these countries are parties to international agreements that may mandate the use of EM or other AI-supported technologies. Unequal access to AI research and development teams and tools, or to high-quality training data, could disadvantage these countries and communities.

Policy shapes the marketplace

Fisheries are a highly regulated market where government policies and requirements strongly control what products and services are available (Nevi et al. 2024). As of the writing of this paper, there are no full-scale EM programs that allow fishers to build their own EM system from off-the-shelf components or pick any service provider unless that vendor is on a government-approved list. Because there is no open market for EM systems, service providers are designing systems to meet the specifications of government contracting and procurement requests, which can be extremely specific about hardware, software, information security, data standards, and performance metrics. The government contracting process can be complex and arduous, favoring firms with the capacity to wait months between initial proposals and payments and to respond to multiple requests for information. Firms have little incentive or budget to invest in features without the promise of a government purchase, which means how government talks about the use of AI shapes what is available.

However, many government fisheries experts are not also technology experts. Certain terms, such as 'accuracy' and 'transparency,' can mean different things to computer scientists and fisheries scientists, which means they require careful consideration if used in a regulatory context or as a contract performance metric. Contracting rules can prohibit government staff from talking to potential bidders once a contract is out for consideration, so staff need avenues to gain insights about the performance and limitations of different technologies well in advance of releasing a bid request. It can also be valuable for managers to talk with their counterparts in other countries to understand what types of systems have performed well for both fishers and government analysts for certain fisheries or gears.

EM systems have had far more pilot projects than full-scale programs (van Helmond et al. 2020). Pilots allow service providers to test systems *in situ* and tailor their software and hardware configurations to specific operating conditions, making adjustments to meet the needs of fishers and government programs. Pilots can also be an opportunity to gather training data for AI, if the service provider has AI development capacity and the authorization to use data for that purpose. However, EM pilots often use only one service provider. Rather than translating the results of a pilot into general requirements for a larger program, government agencies may simply copy the exact specifications used by that service provider into the program requirements, potentially shutting out other service providers who do not use the same hardware, software, or review processes (CEA Consulting and Net Gains Alliance 2021). For AI-supported EM, if only the pilot service provider has access to training data for that fishery, other EM systems may not perform as well, making those service providers and the AI developers working with them less competitive.

Fisheries AI operates within the context of general AI and data policy

EM systems are used to monitor compliance with fisheries rules and regulations, such as prohibitions on discards at sea. When EM records a violation, there can be consequences for vessel owners and fishers, including fines and the loss of fishing access. Existing EM programs have had to address issues around compliance and law enforcement proceedings within the fisheries management context, such as maintaining a chain of custody for data that may become legal evidence. The introduction of AI into EM systems brings new policy considerations as more countries adopt general data and AI policies. Notably, the EU has proposed using EM systems for compliance with its landing obligation, and the EU has both the 2016 General Data Protection Regulation (GDPR) and the 2024 AI Act (European Parliament 2016, 2024). Other fishing nations have some similar frameworks in place, such as the UK's Algorithmic Transparency Recording Standard (Ada Lovelace Institute et al. 2021, UK Department for Science, Innovation and Technology 2023). In addition to handling the complexities of making AI-supported EM fit for purpose, fisheries experts will need to be mindful of these overarching policies to keep both EM systems and the AI supporting them compliant. We describe two relevant concepts below, with the caveat that these descriptions are not meant as, nor should they be taken as, legal advice.

Certain types of data are singled out for special treatment under these policies as 'sensitive data,' 'personal data,' or 'personally identifying information (PII).' These types of data could reveal the identity of an individual and may be subject to stricter rules around data protection and release, for both government agencies and businesses. Image data that include human faces, like the kind captured by EM cameras, often falls into these categories. Some countries, such as Australia, require EM vendors to blur out faces and other identifying features before video is submitted to the government. This is a task AI can assist with, particularly if AI developers could retain access to and reuse the unblurred video for further training. This might require developers and the EM service providers they work with to meet additional data security standards.

A second relevant concept is the treatment of AI systems that significantly impact public decision-making processes and the responsibilities of those who develop and use them. The exact language around what types of systems and decisions qualify for additional scrutiny vary by policy and statute. Annex III of the 2024 EU AI Act lists eight areas where AI systems are categorized as 'high risk,' including law enforcement, judicial proceedings, migration, and access to essential public benefits. The UK's Algorithmic Transparency Recording Standard requires reports for algorithmic tools that 'have a significant influence on a decision-making process with direct or indirect public effect.'

If AI-supported EM is used in any of these ways, directly or indirectly, it could be subject to additional requirements for reporting and disclosure. This might include the use of AI-supported EM data to deny fishing permits or assess compensation levels after a natural disaster. For the 2024 EU AI Act, responsibilities for high-risk systems are assigned both to AI developers and to AI 'deployers,' which include any 'natural or legal person, public authority, agency, or other body using an AI system' outside of personal use; this would seem to cover EM service providers, fisheries management

agencies using EM, and potentially also fishing companies that use AI-supported EM for business purposes. The degree to which AI is used to automate decision-making can be a factor in what policies are applied. A 'human-in-the-loop' EM system, where human reviewers check footage flagged as violations by AI and humans assess the severity of the violation, may be treated differently from a system that only uses AI models to automatically process data and impose fines.

Finally, general data and AI laws may include provisions for what data subjects can require around data collected about them and used in decisions about them, such as the GDPR's 'right to be forgotten' (Wolford 2018). How these laws would intersect with policies governing fisheries data as part of MCS programs is unclear, but it is worth noting that a national policy around AI or data transparency may create an expectation by fishers that EM data, and data around AI, will be treated similarly. Principle 7 of the UN Framework Principles on Human Rights and the Environment states that governments should provide public access to environmental information to any person upon request (Knox 2018). If AI-supported EM systems allow governments to gather and use more fisheries information, there will be new questions about the accessibility, confidentiality, and application of that information.

A path forward

The added costs, delays, and liabilities involved in capturing and transmitting fisheries data, accurately annotating it, storing and sharing it in compliant ways, and negotiating access across parties are hindering the ability of AI to better serve the sector.

We believe we are at a catalytic time for fisheries AI, where fishers, vessel owners, managers, AI developers, and monitoring companies all understand the potential of pushing through the thicket of policy and technical barriers. However, these barriers are too large for any one actor to overcome alone. Coordinated efforts are essential to progress at the rate we need. The following four recommendations reflect the cross-sector efforts we see as essential to building AI capacity, improving AI effectiveness and auditability, and increasing buy-in from across the fisheries community.

1. Support regular cross-sector discussions to create shared terminology and understanding of AI concepts

Fisheries is not a field with unlimited resources, and there are trade-offs involved in choosing priorities and approaches to develop and deploy AI. Understanding those trade-offs requires all participants to have a baseline understanding of technology concepts, fisheries management frameworks, and on-the-water constraints. This paper emerged from a series of annual meetings hosted by the Pew Charitable Trusts around fisheries AI, which bring together an international group of managers, policy experts, monitoring vendors, researchers, and AI developers. One product of these meetings has been a Fisheries AI glossary (The Pew Charitable Trusts 2024). Groups like SAFE-T, EM4Fish, and the Fish AI Consortium offer webinars and online discussion forums on fisheries technology. The annual meetings of both the North Pacific Marine Science Organization (PICES) and the International Council for the Exploration of the Sea (ICES) host AI-related sessions. These are important spaces where fisheries professionals in all roles can learn about AI, and EM service providers and AI

developers can learn about fisheries science and management needs. They also provide opportunities for government staff to explore discuss program designs and system limitations outside of a contracting process, when they may be prohibited from talking to developers or vendors to avoid the perception of bias (CEA Consulting and Net Gains Alliance 2021).

One topic that has been particularly valuable for cross-sector discussions is around the concepts of auditability and transparency, two English words that have more specific meanings in an AI context than they do in general use. In AI, auditability refers to the capability of an AI system to be examined and assessed by external or internal teams. Transparency refers broadly to the clarity and openness with which an AI system operates, beyond disclosures made in the context of a specific system assessment. This does not prohibit vendors from developing proprietary AI; a proprietary AI system can be considered transparent if it can be properly and credibly audited, preferably by an independent third party. Managers, vendors, and vessel owners benefit from having the vocabulary to ask better questions of AI developers and clarify expectations around system transparency, accuracy, and auditability.

Most of these cross-sector discussions have been hosted by non-governmental organizations and philanthropy to date, but governments could also support them, possibly as adjunct sessions to RFMO meetings or other international fisheries management fora. Governments are also essential for defining AI-related terms in fisheries regulations, which will benefit from being informed by these cross-sector dialogues and having consistent meanings across fisheries as much as possible (see also recommendation #4). As the 2024 EU AI Act is implemented, its technical terms and regulatory concepts will be translated into twenty-four languages, providing additional material for interdisciplinary, multi-lingual fisheries conversations.

2. Develop a library of model language for fisheries AI contracts and data use agreements

When contracting for AI development or AI-supported monitoring tools, government agencies and managers should have a library of template terms to draw from rather than starting from scratch for each project or program. The reference library would provide foundational terms and concepts, helping guide staff away from being overly prescriptive, such as requiring a certain brand of camera. It could also help reduce vendor 'lock-in,' where the first firm to provide services is able to influence the terms of future contracts to give their firm an advantage. By being able to review a range of terms and use cases, government contractors could better tailor requests to their fisheries needs and see what other agencies are pursuing for solutions.

There are existing examples of general model libraries for non-disclosure agreements and data collaborations (GovLab et al. n.d.; TLB n.d.). The ICES Working Group on Technology Integration for Fishery-Dependent Data has drafted model language for proposal requests (RFPs) and data specifications around EM, drawing largely on European examples (ICES 2023). In March of 2024, the Pacific Community, a scientific and development organization of 27 member countries and territories in the Central and Western Pacific, issued a Request for Quotations for firms to help them develop a shared image database to support fisheries AI development across the region (Pacific Community 2024). The RFP specifically calls out the need for both technical and policy activities to en-

able data sharing, labelling, and model training, acknowledging the transdisciplinary nature of fisheries AI development. More government agencies should publish their procurement and contract documents, including the language in completed contracts, redacting provisions only as needed to protect confidential business information.

The library could also support the inclusion of multi-party data-sharing provisions in fisheries AI data use agreements and contracts. If initial contracts and agreements describe the conditions under which data could be shared and allow for the possibility of future data sharing, they lay the groundwork for future data collaborations, even if those provisions are never exercised. For example, if an EM service provider finds that it needs additional data labelling to improve model accuracy and wants to bring in an outside expert annotation firm, would they need to get the agreement of every vessel owner to share that data, hold the data securely on their own servers so that the new firm never takes 'ownership' of the data, and/or renegotiate the contract with the government agency? These are the types of terms and conditions that are commonly addressed in data sharing agreements, and fisheries should have templates that include fisheries-specific considerations to support data collaborations across partners.

3. Create structures to safely share training data and increase fisheries AI capacity

The biomedical research field created collaborative research platforms like Terra.bio and Synapse.org to share highly sensitive data, such as individual patient health records and genetic samples (Field et al. 2009, Carey et al. 2020, Haendel et al. 2021). On these platforms, data access and use can be conditioned by both the type of user and the type of use. For example, some data may be accessible for a set period of time to authorized researchers who submit queries, receive model results, but never see the underlying datasets (Mangravite et al. 2020). Setting data permissions based on users allows data holders to comply with national policies on data protection (see Recommendation #4). Setting permissions based on use allows data owners to exercise data sovereignty and control commercialization. For example, Indigenous partners may choose to share data only with a project aligned with their priorities (Jennings et al. 2023), or a nonprofit may only be able to contribute data or code to open source AI models (Schmidt et al. 2016). Modern data management platforms can implement complex data permissioning and governance to enable collaboration and research while protecting sensitive data (Klievink et al. 2018, Ruijter 2021, Verhulst 2024).

Pooling data across different countries, fisheries, vessel types, and fishing conditions makes it possible to train models that can be applied across those operating environments. It would also be possible to create a 'testing set' of data separated out of the training datasets, which could be used by governments and other AI customers to evaluate how an AI model performs on data that was not used to build that model. In addition to granting access to pools of data, having developers come to a centralized data space in the form of privileged code sandboxes or development environments can greatly reduce some of the technical and economic challenges of storing and transmitting the large amounts of video data involved in training AI models for EM. These managed development spaces could support agreements between regional data holders to allow for pooled processing of data in a known environment, with stringent controls on access and acceptable use.

Platforms also provide a forum for developers to share code and collaborate on best practices (Lowndes et al. 2017). They can track data usage and produce Digital Object Identifiers (DOIs) for data products that can be shared more widely, giving credit to the original data owners and to anyone who contributed to the new products. Both commercially available and bespoke data platforms can serve as these types of data intermediaries and may be seen as more trustworthy options for governments and other data holders than signing one-to-one data agreements with individual AI or fisheries technology companies. While it may still take policy changes to move government-controlled data onto an independent research platform, a prototype would make benefits and security features visible, helping incentivize participation with a tangible product.

Finally, these types of data intermediaries and shared development environments can lower the barriers to entry for new participants in AI-supported EM or other fisheries monitoring, including service providers, AI developers, fisheries researchers, non-governmental organizations, and communities. While government mandates in larger fisheries have driven EM expansion to date, small-scale fisheries make up a significant proportion of fisheries participation, production, and economic impact in many countries (FAO et al. 2023). These fisheries may choose to voluntarily adopt AI-supported monitoring tools to comply with government reporting programs, document their activities, or meet third-party certification standards for sales and exports. As the costs of technology and data infrastructure continue to fall, a shared data and development platform could provide training and tools that allow any fishing community to create AI-supported data collection programs that meet their needs.

4. Bring lessons and resources from general AI and data policies into fisheries

Fisheries experts can look to existing AI and data policies as guidance for contracts and international agreements. Borrowing language around data privacy may help address concerns by fishers about the impacts of surveillance, especially if fishers are actively involved in the design of the AI application (Atske 2018, Khokher et al. 2022, Xu et al. 2023). Public transparency and ethics guidelines for automated algorithmic decision-making could potentially increase trust in fisheries AI (Ada Lovelace Institute et al. 2021) and human-in-the-loop systems could change which general AI policies are applied. If human-in-the-loop systems will be required for EM, this needs to be considered during program design and in the initial specifications. We also encourage governments and organizations to host dialogues like those in recommendation #1 around the legal and policy intersections across fisheries, data, and AI. AI and data policies are evolving quickly, and countries are staffing up agencies to interpret and enforce these policies; government fisheries experts should develop relationships with their counterparts at national data and AI agencies to draw on their knowledge and tools.

Conclusion

It is easy for fisheries managers, fishers and vessel owners, AI developers, and technology service providers to proceed in parallel tracks, only glancing over their shoulders at each other's work when it comes time to draft a contract or install monitoring devices. However, the innovations needed in fish-

eries AI will come from efforts at the intersections of those communities. When government agencies write policies focused on system performance that can adapt as technology improves, they provide regulatory certainty for software and hardware developers, which can open up the market to new service providers and stimulate investment in research and development. When fisheries data are treated as an asset to be stewarded and carefully shared, in the service of sustainability and traceability, it can improve AI performance and trustworthiness. All of these activities require cross-sector dialogue and coordination, as well as investment and action. We cannot afford to talk past each other and miss this moment in time to scale the use of AI in fisheries monitoring.

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Author contributions

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