International Journal of Agriculture and Food Science 2025; 7(7): 321-332

ISSN Print: 2664-844X
ISSN Online: 2664-8458
NAAS Rating: 4.97
IJAFS 2025; 7(7): xx-xx
www.agriculturaljournals.com
Received: 25-06-2025
Accepted: 30-07-2025

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A review of remote sensing and artificial intelligence applications in global fisheries monitoring and management

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DOI: https://www.doi.org/10.33545/2664844X.2025.v7.i8e.630

Abstract
The sustainable management of fisheries faces growing challenges due to the vast expanse of the oceans, overfishing, Illegal, Unreported and Unregulated (IUU) fishing, and climate change impacts. Traditional methods of monitoring are often insufficient to manage the complexity of these issues. The integration of Artificial Intelligence (AI) and Remote Sensing (RS) provides transformative, large-scale, real-time and cost-effective solutions for marine environment monitoring. RS tools like satellites and drones collect continuous data on oceanographic parameters such as Sea Surface Temperature (SST), chlorophyll-a and vessel activity. AI techniques including Machine Learning (ML), deep learning and computer vision process these complex data-sets to automate stock assessments, predict fish abundance, identify species and detect IUU fishing. Practical applications such as Global Fishing Watch and AI-powered fish counting highlight these benefits. Despite progress challenges remain in data quality, model transparency and capacity building. Future innovations such as eDNA monitoring and blockchain are expected to play a vital role in advancing sustainable fisheries management by supporting adaptive, data-driven strategies.

Keywords: Artificial intelligence (AI), remote sensing (RS), machine learning (ML), deep learning, computer vision, illegal, unreported and unregulated (IUU) fishing, sea surface temperature (SST), chlorophyll-a, AI-powered fish counting, environmental DNA (eDNA), blockchain technology, Real-time monitoring

1. Introduction
The ocean covering over 70% of the Earth's surface remains vast and largely under-monitored posing significant challenges for effective fisheries resource management (Global Fishing Watch, 2023) [40]. Traditional methods of monitoring fish stocks are increasingly inadequate in addressing the complexities introduced by overfishing, Illegal, Unreported and Unregulated (IUU) fishing and the accelerating impacts of climate change (NOAA Fisheries, 2023) [100]. These factors collectively disrupt marine ecosystems, deplete fish populations and obstruct sustainable management efforts. Overfishing removes fish at rates faster than they can naturally replenish, leading to declining biodiversity and altered ecosystem dynamics (World Wildlife Fund, 2023) [141]. IUU fishing change these challenges by degrading habitats and Undermining legal fisheries and causing substantial ecological and economic harm (International Maritime Organization, 2023) [56]. Additionally, climate change shifts fish stock distributions and productivity, challenging existing management frameworks and the livelihoods dependent on them (European Environment Agency, 2024) [34].

In response to these comprehensive challenges Artificial Intelligence (AI) and Remote Sensing (RS) technologies offer large-scale, real-time and cost-effective solutions for fisheries resource management. AI techniques including Machine Learning (ML), deep learning and computer vision can process large and different datasets from satellite images, underwater sensors and environmental monitoring to accurately detect and localize fish populations (Saleh *et al.*, 2022) [117]. These AI-powered systems improve detection rates, reduce operational costs and enable adaptive management by analyzing dynamic underwater environments more efficiently than traditional methods. RS complements AI by providing large-scale, continuous environmental data critical for monitoring fish habitats, detecting illegal activities and assessing climate impacts (NOAA Fisheries, 2024) [101]. Together AI and RS facilitate enhanced surveillance, species classification, bycatch reduction and predictive modeling thereby supporting sustainable fisheries management and conservation goals in ocean.

This integration of advanced technologies represents a transformative approach to overcoming the limitations of conventional fisheries management, ensuring ecological sustainability and economic viability in the face of growing environmental and anthropogenic pressures.

2. Remote Sensing in Fisheries

Remote Sensing (RS) in fisheries involves the collection of data from satellites, drones, aircraft or other platforms to monitor physical, chemical and biological parameters of the ocean that influence fish populations and habitats (Kerr & Ostrovsky, 2003; NASA, 2023) [63, 96]. It provides a powerful, large-scale monitoring capacity that enhances traditional in-situ methods by offering repeated, real-time and cost-effective monitoring over vast and often unreachable marine areas (Levin *et al.*, 2018) [74].

2.1 Key applications of remote sensing in fisheries include

2.1.1 Monitoring Fish Habitats: Remote Sensing (RS) measures environmental variables such as Sea Surface Temperature (SST), chlorophyll concentration, salinity and ocean currents, which affect fish distribution and abundance (Gower *et al.*, 2019; McClain, 2009) [45, 84]. These parameters help identify and define marine fish habitats and potential fishing grounds by tracking dynamic oceanographic features like frontal boundaries, up-welling zones and circulation patterns (Mannocci *et al.*, 2017; Robinson *et al.*, 2017) [80, 114].

2.1.2 Tracking Fish Migration and Distribution: By analyzing environmental conditions, Remote Sensing (RS) supports understanding of fish migration routes and seasonal movements, aiding sustainable fisheries management and quota setting (Hazen *et al.*, 2013; Palacios *et al.*, 2006) [50, 103]. RS provides valuable spatial and temporal data on oceanographic features such as Sea Surface Temperature (SST) and chlorophyll concentrations, which influence fish distribution and behavior (Scales *et al.*, 2014) [122]. This information enhances the ability of managers to predict fish stock locations and improve harvest regulations (Suryan *et al*., 2012) [128].

2.1.3 Estimating Fish Stock Abundance: Remote sensing (RS) data on primary productivity and plankton blooms serve as key signals for assessing fish stock potential, enabling the forecasting of fishery yields and evaluation of stock health (Behrenfeld & Falkowski, 1997; Sathyendranath *et al.*, 2004) [9, 121]. These biological indicators reflect the base of the marine food web, influencing fish distribution and abundance (Cushing, 1990) [27]. Satellite-derived chlorophyll measurements are widely used to monitor phytoplankton dynamics and predict fishery productivity (Mann & Lazier, 2013) [79].

2.1.4 Monitoring Fishing Activities: Using aerial drones and satellite-based technologies such as radar and Automatic Identification Systems (AIS), Remote Sensing (RS) enables the detection and mapping of fishing vessels and gear, supporting enforcement of regulations and efforts to combat Illegal, Unreported and Unregulated (IUU) fishing (McCauley *et al.*, 2016; Miller *et al.*, 2018) [83, 68]. These technologies provide near real-time vessel tracking and improve transparency in fisheries management, aiding global initiatives to protect marine resources (Kroodsma *et al*., 2018) [68].

2.1.5 Supporting Aquaculture Management: Remote Sensing (RS) help in monitoring water quality and environmental impacts of aquaculture operations, providing timely data for site selection and ongoing management (Handisyde *et al.*, 2006; Kumar *et al.*, 2020) [48, 71]. By analyzing parameters such as turbidity, chlorophyll concentration and temperature, RS supports sustainable aquaculture practices and helps mitigate negative ecological effects (Mitra *et al*., 2019) [90].

2.1.6 Assessing Ocean Productivity: By continuously monitoring key oceanographic indicators, Remote Sensing (RS) informs fisheries managers about changes in ecosystem productivity that influence fish populations and sustainability (Levin *et al.*, 2018; McClain, 2009) [74, 84]. Parameters such as Sea Surface Temperature (SST), chlorophyll concentration and ocean circulation patterns provide critical data to predict shifts in fish habitats and support adaptive management strategies (Behrenfeld *et al.*, 2006; Polovina *et al*., 2008) [10].

2.2 Types of Remote Sensing Data

Remote sensing data used in fisheries and ocean monitoring come from various sensor types, each suited to capturing specific oceanographic parameters:

2.2.1. Optical Sensors (e.g., MODIS, Sentinel-2): These passive sensors detect sunlight reflected from the ocean surface and are primarily used for measuring ocean color and estimating phytoplankton concentrations which are critical indicators of marine productivity and fish habitat quality (IOCCG, 2000; Morel & Prieur, 1977) [57, 92]. Optical sensors provide high-resolution images but require clear sky and daylight conditions for optimal performance (Gower *et al*., 2008; Kahru & Mitchell, 2000) [44, 60].

2.2.2 Radar Sensors (e.g., Sentinel-1 Synthetic Aperture Radar - SAR): These active sensors emit microwave signals and measure their reflection, enabling vessel detection and ocean surface imaging regardless of weather or light conditions (Bentes *et al.*, 2016; Migliaccio *et al.*, 2015) [13, 87]. Radar is particularly useful for detecting fishing vessels during cloudy weather or at night, thereby aiding in monitoring fishing activities and combating Illegal, Unreported and Unregulated (IUU) fishing (Park *et al*., 2018; Greidanus & Alvarez, 2021) [105, 74]. Synthetic Aperture Radar (SAR) in particular has proven effective in identifying non-cooperative vessels and tracking suspicious maritime behavior in real time.

2.2.3 Thermal Sensors: These sensors measure Sea Surface Temperature (SST) by detecting thermal infrared radiation emitted by the ocean surface. SST is a vital parameter influencing fish migration patterns, spawning grounds and overall marine ecosystem dynamics (Casey & Cornillon, 1999; Block *et al.*, 2011) [22]. Thermal data help monitor ocean temperature variations and detect thermal front zones that greatly influence fish distribution and feeding behavior (Belkin *et al*., 2009; Kilpatrick *et al.*, 2001) [12, 64].

2.3 Applications in Fisheries
Remote sensing has a wide range of applications in fisheries resource management, making use of environmental and vessel data to support sustainable practices:

2.3.1 Predicting Fish Abundance Zones: Key oceanographic parameters such as Sea Surface Temperature (SST), chlorophyll-a concentration, salinity and turbidity are monitored via Remote Sensing (RS) to identify productive fishing areas. These parameters help to predict habitats of commercially important species like tuna and sardines, allowing fishermen to identify potential fishing zones more efficiently and reduce the time spent searching for fish, as well as fuel costs (Klemas, 2012; Nadeem *et al.*, 2025; Selva Prakash *et al*., 2023) [65, 95, 123].

2.3.2 Harmful Algal Bloom (HAB) Detection and Monitoring: Remote Sensing (RS) technologies offer timely detection and tracking of Harmful Algal Blooms (HABs), which threaten marine ecosystems significantly and fisheries through oxygen depletion, toxin production and disruption of food webs (Anderson *et al.*, 2017; Blondeau-Patissier *et al.*, 2014) [4, 17]. Satellite-based sensors including ocean color images and thermal data enable continuous monitoring of surface waters detecting early indicators such as increased chlorophyll-a concentrations associated with algal proliferation (Hu *et al*., 2019) [54]. Early warnings derived from RS data support the mitigation of both ecological and economic impacts by improving the ability of managers to implement immediate and strategic responses, such as shellfish harvest closures or aquaculture advisories (Kudela *et al*., 2015; Shi & Wang, 2021) [69, 21].

2.3.3 Habitat Mapping: Remote Sensing (RS) technologies play a vital role in mapping and monitoring critical marine habitats such as coral reefs, mangroves and seagrass beds which serve as essential breeding and nursery grounds for many fish species (Kuenzer *et al*., 2011; Roelfsema *et al*., 2018) [70, 115]. Accurate and frequent habitat mapping using satellite imagery and aerial sensors supports conservation efforts by tracking habitat health and changes over time, thereby contributing to sustainable fisheries management (Phinn *et al.*, 2012; Hedley *et al.*, 2016) [106, 52]. Maintaining the integrity of these habitats is crucial for fish population replenishment and overall ecosystem resilience (Waycott *et al*., 2009) [138].

2.3.4 Vessel Detection and Monitoring: Synthetic Aperture Radar (SAR) sensors and Automatic Identification Systems (AIS) provide the ability to detect fishing vessels irrespective of weather or light conditions, making them vital tools for continuous maritime monitoring (Bekkby *et al.*, 2015; Kroodsma *et al.*, 2018) [68, 11]. The all-weather, day-and-night imaging capability of Synthetic Aperture Radar (SAR) complements Automatic Identification System (AIS) data, which provides information on vessel locations and identities, thereby facilitating comprehensive monitoring and surveillance of fishing activities (Taconet *et al*., 2019) [130]. This combined capability is critical for enforcing fisheries regulations and combating Illegal, Unreported and Unregulated (IUU) fishing which threatens marine ecosystems and sustainable fisheries management worldwide (McCauley *et al*., 2016; Anderson *et al.*, 2019) [83, 5].

2.3.5 Supporting Fisheries Management: By integrating environmental data and vessel monitoring systems remote sensing supports the development of dynamic fisheries management measures such as the designation of marine protected areas (MPAs), regulation of fishing effort and reduction of bycatch involving endangered species (Lewison *et al*., 2015; Maxwell *et al*., 2015) [75, 82]. This integration enables near-real-time spatial management by identifying critical habitats and adjusting fishing activities accordingly thus promoting ecosystem sustainability and biodiversity conservation (Boerder *et al*., 2018; Dunn *et al*., 2016) [18, 33].

3. Artificial Intelligence in Fisheries
Artificial Intelligence (AI) is revolutionizing fisheries management through the application of advanced computational methods, including Machine Learning (ML), deep learning, computer vision and Natural Language Processing (NLP). These technologies facilitate the automation of complex tasks and enable the extraction of valuable insights from large and multifaceted data-sets, thereby enhancing decision-making and operational efficiency in the fisheries sector.

3.1 Machine Learning (ML): Machine Learning (ML) algorithms are increasingly used in fisheries to analyze both historical and real-time data enabling the identification of trends, prediction of fish stock abundance and optimization of fishing efforts (Hazen *et al*., 2018; Queiroz *et al.*, 2021) [51, 111]. These models continuously improve by learning from new data-sets thereby enhancing their accuracy in forecasting fish populations and responding to environmental changes such as shifts in ocean temperature or productivity (Kaplan *et al*., 2021; Muhling *et al*., 2017) [62, 93]. Such adaptive capabilities make ML tools valuable for dynamic and data-driven fisheries management.

3.2 Deep Learning: A subset of Machine Learning (ML), deep learning employs neural networks to process unstructured data such as images and videos. In fisheries science, deep learning has shown significant promise in automating species identification, fish counting and behavioral analysis using underwater video or sonar data (Salman *et al.*, 2016; Siddiqui *et al*., 2018) [118. 126]. These capabilities substantially reduce the reliance on manual labor and minimize human error, making monitoring more efficient and capable of expanding to larger operational scales (Gray *et al.*, 2019; Villon *et al*., 2018) [46, 137]. This technology plays a crucial role in improving data quality and supporting evidence-based fisheries management.

3.3 Computer Vision: A branch of Artificial Intelligence (AI) processes visual data collected by cameras, drones, or underwater sensors to detect and classify fish species, monitor fish health and assess catch composition (Siddiqui *et al*., 2018; Rathi *et al.*, 2017) [126, 112]. These systems enhance sustainable fishing by enabling real-time monitoring of bycatch and adherence to fishing regulations (Allken *et al*., 2019) [3]. By automating visual inspections computer vision reduces observer bias and increases the efficiency and accuracy of fisheries assessments (Villon *et al*., 2018) [137].

3.4 Natural Language Processing (NLP): Natural Language Processing (NLP) techniques are increasingly applied in fisheries science to analyze large volumes of unstructured textual data, including fisheries reports, scientific literature and regulatory documents. These techniques enable automated extraction of relevant information detection of policy changes and synthesis of knowledge to support decision-making processes (Arvor *et al*., 2020; da Silva *et al.*, 2021) [7, 28]. By structuring and interpreting complex textual content, NLP enhances the ability of fisheries managers to stay informed about regulatory shifts, scientific developments and stakeholder communications (Bosch *et al*., 2023) [20].

3.5 Applications in Fisheries
3.5.1 Fisheries Stock Assessment
Artificial Intelligence (AI) and machine learning (ML) are increasingly applied to fisheries stock assessment to improve the accuracy and timeliness of forecasting fish stock abundance. These approaches leverage environmental data and historical catch records to build predictive models that support sustainable fisheries management.

3.5.1.1 Forecasting Stock Abundance: Artificial Intelligence (AI) models utilize environmental variables such as Sea Surface Temperature (SST), salinity and chlorophyll-a concentrations in combination with fishery catch data to predict vital stock parameters, including recruitment and spawning stock biomass. These predictive capabilities enable fisheries managers to anticipate population fluctuations and adjust quotas or management strategies proactively (Asch *et al.*, 2019; Frazão Santos *et al.*, 2020) [8, 36]. By utilizing historical and real-time data, AI-driven forecasting supports adaptive management approaches that are more responsive to climate variability and ecosystem dynamics (Muhling *et al*., 2017) [94].

3.5.1.2 Hybrid Modeling Approaches: Recent research has introduced hybrid modeling approaches that integrate classical statistical stock assessment methods with supervised Machine Learning (ML) techniques, such as gradient boosted trees. In these frameworks the traditional model provides a baseline estimate of stock parameters, while the ML model applies subsequent corrections to improve forecast accuracy. This approach is particularly effective in complex and rapidly changing ecosystems influenced by climate change and anthropogenic stressors (Bozhi *et al.*, 2021; Free *et al*., 2019) [21, 37]. Hybrid models strengthen the resilience and adaptability of stock predictions, making them more accurate tools for fisheries management (Zhou *et al*., 2023) [145].

3.5.1.3 Learning from Logbook and Sensor Data: Artificial Intelligence (AI) models are increasingly trained on extensive and diverse data-sets, including fishery logbooks, sensor outputs and scientific survey data. This data-driven approach enhances the ability to detect nonlinear patterns and complex relationships in stock dynamics that traditional statistical models may overlook (Hazen *et al.*, 2018; Xu *et al.*, 2021) [51, 143]. By utilizing large-scale, multi-source data, AI contributes to more accurate assessments and forecasts of fish population trends, thereby improving the foundation for ecosystem-based fisheries management (Tzanopoulos *et al*., 2022) [135].

3.5.2 Monitoring and Surveillance
Monitoring and surveillance in fisheries have been significantly enhanced by integrating vessel tracking technologies with Artificial Intelligence (AI) and Machine Learning (ML) techniques:

3.5.2.1 Automatic Identification System (AIS) + AI: AIS transponders, mandatory on commercial vessels over 300 tons, continuously transmit vessel identity, position, speed and course data. AI algorithms analyze this real-time data to track vessel behavior, detect suspicious or anomalous activities and identify potential Illegal, Unreported and Unregulated (IUU) fishing operations. This combination enables authorities to monitor fishing fleets effectively, enforce regulations and ensure compliance with quotas even in vast and remote ocean areas (McDonald *et al*., 2019; Taconet, Kroodsma, & Fernandes, 2019; Kroodsma *et al.*, 2018) [85, 68, 130].

3.5.2.2 Vessel Monitoring System (VMS) + Machine Learning (ML): Vessel Monitoring Systems (VMS), similar to the Automatic Identification System (AIS) but often used specifically for fisheries management, provide positional data that Machine Learning (ML) models process to detect patterns indicative of Illegal, Unreported and Unregulated (IUU) fishing. ML techniques cluster and classify vessel movement behaviors, flagging unusual routes and entry into restricted zones, thereby enhancing surveillance and enforcement capabilities (Smith *et al*., 2017; Kroodsma *et al*., 2018; McDonald *et al.*, 2019) [127,85, 68].

3.5.3 Species Detection and Identification
Artificial Intelligence (AI) has revolutionized species detection and identification in fisheries through advanced data analysis and imaging technologies:

3.5.3.1 AI Models for Fish Species Identification
Underwater Cameras and Sonar Imaging: Artificial Intelligence (AI) models, particularly those based on deep learning and computer vision, are trained on large data-sets of underwater images and sonar scans to accurately identify fish species. These models can distinguish between species even in complex underwater environments, enabling precise monitoring of biodiversity, population dynamics and fish behavior (Marini *et al.*, 2018; Salman *et al.*, 2019) [81, 119]. Automated species identification reduces the need for manual sorting and expert intervention, accelerates data processing, and improves the accuracy and consistency of species records factors critical for stock assessments and ecological studies (Xu & Matzner, 2018; Siddiqui *et al.*, 2018) [126, 144].

3.5.3.2 Drones Combined with Computer Vision
Monitoring Aquaculture Pens: Drones equipped with high-resolution cameras and AI-powered computer vision algorithms are increasingly used in aquaculture to monitor fish health, population density and behavior. These systems enable real-time detection of anomalies such as abnormal

swimming patterns, early signs of disease, or changes in biomass distribution, allowing for timely interventions (Nezami *et al.*, 2021; Liu *et al*., 2020) [99, 77]. By optimizing feeding strategies and reducing the risk of escapes, AI-integrated drones enhance productivity, bio-security and sustainability in aquaculture operations (Qin *et al*., 2021; Nasirian *et al*., 2023) [109, 97].

3.5.3.3 Marine Protected Areas (MPAs): Drones provide efficient aerial surveillance of Marine Protected Areas (MPAs), employing computer vision technologies to detect and identify fish species, marine mammals and habitat conditions. These capabilities contribute to biodiversity assessments and habitat protection by enabling continuous, non-invasive monitoring over large and often inaccessible areas (Hodgson *et al*., 2016; Johnston, 2019) [53, 59]. Moreover, drones support enforcement efforts by detecting unauthorized fishing activities and vessel presence in restricted zones, enhancing compliance with conservation regulations (Chabot & Bird, 2015; Sardà-Palomera *et al.*, 2012) [23, 120].

3.6 Key Case Studies

Key case studies demonstrate how Artificial Intelligence (AI) and remote sensing technologies are transforming fisheries resource management:

3.6.1 Global Fishing Watch: Global Fishing Watch (GFW) represents a pioneering initiative that leverages satellite data and advanced machine learning to monitor global fishing activities in near real-time. By processing over 40 billion Automatic Identification System (AIS) messages from more than 2,00,000 vessels daily, GFW's algorithms classify vessel behaviors, identify fishing gear types and detect fishing locations. This enables the identification of potential Illegal, Unreported and Unregulated (IUU) fishing operations, enhancing transparency and supporting enforcement efforts worldwide (Global Fishing Watch, 2018; Google Cloud, 2018) [41, 42]. The platform offers a publicly accessible, interactive map that aids in sustainable fisheries management by providing stakeholders with actionable insights into fishing patterns and compliance (Global Fishing Watch, 2018) [41].

3.6.2 IBM Watson & World Wildlife Fund (WWF): Leveraging AI, these organizations analyze oceanographic conditions to advise on sustainable fishing practices. By integrating environmental data with AI-driven predictive models, they provide actionable insights to optimize fishing efforts, reduce bycatch, and adapt to changing marine ecosystems, thereby promoting ecosystem-based fisheries management.

3.6.3 Deep Learning for Automatic Fish Counting in Aquaculture: Advanced deep learning models, particularly Convolutional Neural Networks (CNNs), have been developed to automatically count and classify fish within aquaculture cages using underwater imagery. This automation improves monitoring efficiency, reduces labor costs, and enhances stock assessments by providing accurate, real-time data on fish populations and health within farming operations.

4. Integration of AI and RS for Holistic Management

Combining Remote Sensing (RS) and Artificial Intelligence (AI) enables a holistic, efficient and adaptive approach to fisheries resource management by integrating large-scale environmental monitoring with intelligent data analysis and decision support.

4.1 Real-time Ecosystem Monitoring

Remote sensing provides continuous, wide-area coverage of critical oceanographic parameters such as Sea Surface Temperature (SST), chlorophyll-a concentration, salinity and turbidity, which are essential indicators of ecosystem health and fish habitat suitability (Hu *et al*., 2019; Blondeau-Patissier *et al.*, 2014) [54, 17]. These data-sets collected via satellites and other remote platforms, offer valuable temporal and spatial insights into marine environments. Artificial Intelligence (AI) enhances this capability by processing vast and complex remote sensing data in real time, detecting patterns and anomalies that may indicate shifts in fish populations or emerging environmental stressors (Xiao *et al*., 2022; Misra *et al*., 2021) [142, 89]. The integration of AI and remote sensing enables near-instantaneous, high-resolution monitoring of marine ecosystems, far surpassing the scope and efficiency of traditional observation methods (Huang *et al*., 2020) [55].

4.2 Predictive Analytics for Adaptive Fisheries Management

Artificial Intelligence (AI) models trained on historical and real-time Remote Sensing (RS) data can forecast fish stock abundance, migration routes, and habitat suitability, supporting data-driven fisheries management. Machine learning algorithms, for instance, analyze Sea Surface Temperature (SST) and chlorophyll-a concentration maps derived from satellite imagery to predict potential fish aggregation zones or hotspots (Hazen *et al.*, 2018; Chen *et al*., 2020) [51, 24]. These predictive tools empower fisheries managers to make adaptive decisions such as adjusting catch quotas or implementing spatial and temporal fishing closures based on current ecosystem conditions. This approach enhances sustainability, improves stock resilience and helps fisheries respond proactively to the impacts of climate variability (Kaplan *et al*., 2021; Tang *et al.*, 2022) [62, 132].

4.3 Automated Compliance and Enforcement Tools

The integration of Remote Sensing (RS) technologies with Artificial Intelligence (AI) significantly strengthens maritime surveillance by detecting and analyzing fishing vessel activities through data from Synthetic Aperture Radar (SAR) and the Automatic Identification System (AIS). AI algorithms process this data to classify vessel behavior and identify potential illegal, unreported and unregulated (IUU) fishing activities with high accuracy (Kroodsma *et al*., 2018; Park *et al*., 2020) [68, 105]. These models can detect suspicious patterns such as mid-sea transfers of goods or catch, irregular vessel movement or unauthorized access to protected areas. Automated alerts generated by AI systems can prompt enforcement actions or notify fishers about compliance requirements and restricted zones, thereby improving governance, reducing illegal exploitation and enhancing transparency in marine resource use (Taconet *et al*., 2019; McCauley *et al.*, 2016) [130, 83].

4.4 Example Work-flow

4.4.1 Remote Sensing Data Acquisition: Satellites collect oceanographic data such as SST and chlorophyll-a concentration.

4.4.2 AI Model Processing: Machine learning models analyze these environmental variables to identify potential fish hot-spots.

4.4.3 Prediction Output: The AI system predicts areas with high fish abundance.

4.4.4 Actionable Alerts: Notifications are sent to fishers to optimize fishing effort or to authorities to enforce spatial closures and protect vulnerable habitats.

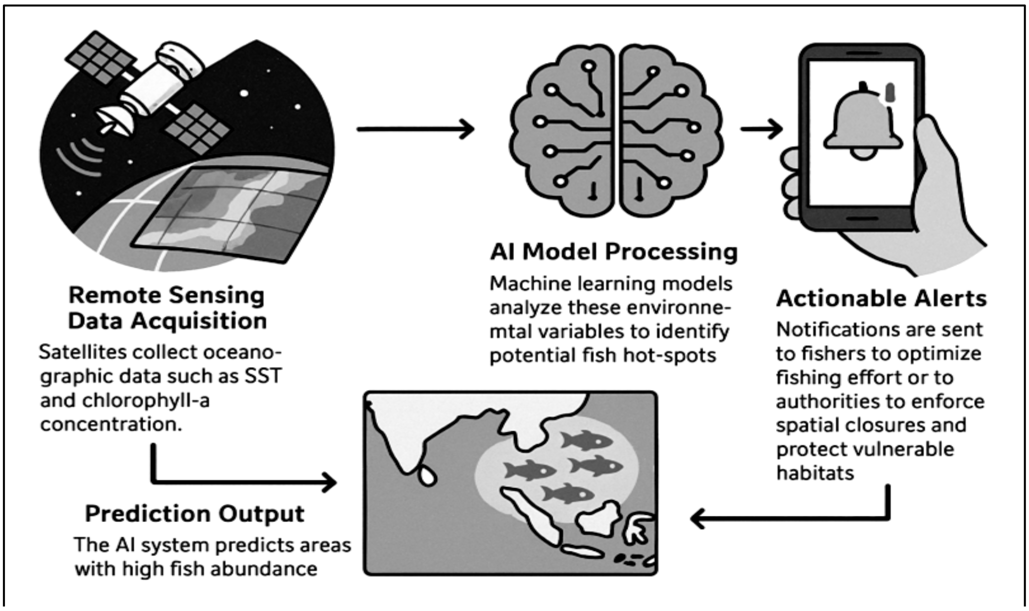

Fig 1: From Satellite to Sea: A Predictive Model for Fish Abundance and Habitat Protection

5. Challenges and Limitations

Key challenges and limitations in applying Artificial Intelligence (AI) and Remote Sensing (RS) to fisheries resource management include:

5.1 Data Quality and Availability: Reliable AI models require large volumes of high-quality, well-annotated data, which is often lacking particularly in developing regions or the Global South due to limited technological infrastructure and resource constraints (Achieng *et al.*, 2021; Garcia *et al.*, 2020) [1, 38]. Fisheries data collection in these areas is frequently costly, fragmented, and inconsistent, which hampers the effectiveness and scalability of AI applications in fisheries management (Cisneros-Montemayor *et al.*, 2019) [25]. Incomplete, imbalanced, or noisy data-sets reduce model accuracy, limit generalizability, and may introduce biases into decision-making processes (Vellido, Martín-Guerrero, & Lisboa, 2012) [136].

5.2 Model Transparency and Explainability: Many AI techniques, particularly deep learning, function as "black boxes," meaning their internal decision-making processes are often opaque to end-users. This lack of transparency presents a significant challenge for fisheries managers and stakeholders, who may find it difficult to interpret how predictions or management recommendations are generated (Lipton, 2018; Rudin, 2019) [76, 116]. The resulting ambiguity can undermine trust in AI systems and hinder their broader adoption in fisheries governance (Doshi-Velez & Kim, 2017) [32]. To address this, there is a growing need to develop interpretable AI models and establish clear frameworks for communicating model uncertainty and decision rationale (Gilpin *et al.*, 2018) [39].

5.3 Technological Capacity and Training Needs: Implementing Artificial Intelligence (AI) and Remote Sensing (RS) technologies in fisheries requires not only robust infrastructure and computational tools but also skilled personnel with technical literacy. However, many fisheries stakeholders particularly those operating in small-scale or resource-limited contexts often lack the necessary training, experience, and institutional support to effectively adopt and utilize these advanced technologies (Tilley *et al.*, 2020; Ogunlana *et al.*, 2022) [102, 134]. This capacity gap hinders the effective deployment, integration and sustained use of AI and RS in fisheries management and monitoring (Jentoft & Eide, 2011) [58]. Addressing these challenges requires targeted capacity-building programs, inclusive technology design, and long-term investment in digital infrastructure (Purcell & Pomeroy, 2015) [108].

5.4 Legal and Ethical Concerns: The use of AI-driven surveillance tools in fisheries raises significant privacy and ethical concerns, especially when monitoring small-scale fishers and indigenous communities. Such technologies risk enabling disproportionate enforcement or the marginalization of vulnerable groups if implemented without inclusive and participatory governance frameworks (Molnar *et al.*, 2021; Cohen *et al.*, 2019) [91, 26]. These challenges are compounded by regulatory uncertainty and fragmented policy environments, which complicate the adoption and governance of AI technologies in fisheries management (Gouritin, 2020; Tallis *et al.*, 2021) [43, 131]. Ensuring ethical deployment requires balancing technological advancement with social equity, transparency, and accountability.

5.5 Cost and Infrastructure Limitations: High costs associated with sensors, data transmission, computational infrastructure and ongoing maintenance present significant barriers to the adoption of Artificial Intelligence (AI) and Remote Sensing (RS) technologies in fisheries. These challenges are especially pronounced in remote or underdeveloped regions where reliable electricity and internet connectivity are limited or absent (Ogunlana *et al.*, 2022; Tilley *et al.*, 2020) [102, 134]. The initial investment and operational requirements for AI and RS systems often exceed the financial and technical capacities of small-scale fisheries and local management institutions, thereby reinforcing existing inequalities in access to digital tools (Addison *et al.*, 2022; Davies *et al.*, 2020) [2, 30]. Reducing these barriers requires targeted investment, technology transfer, and context-sensitive infrastructure development.

5.6 Interoperability and Usability Issues: Integrating Artificial Intelligence (AI) into existing fisheries management systems and work flows presents several challenges, particularly in ensuring alignment with established practices and institutional capacities. For AI technologies to be effectively adopted, they must feature user-friendly interfaces and demonstrate compatibility with traditional data collection and decision-making methods (Beveridge *et al*., 2019; Kourti *et al*., 2020) [15, 67]. Without intuitive tools and work flow integration, stakeholders may struggle to engage with AI systems or may resist their use due to perceived complexity or disruption (FAO, 2022) [35]. Facilitating stakeholder acceptance requires co-designed systems that consider local contexts and promote practical usability in everyday fisheries management (Addison *et al*., 2022) [2].

6. Future Prospects and Innovations

Future prospects and innovations in fisheries resource management are increasingly focused on integrating cutting-edge technologies like environmental DNA (eDNA), Artificial Intelligence (AI), autonomous drones, blockchain and citizen science to enhance monitoring, traceability and participatory governance.

6.1 eDNA + AI for Non-invasive Species Monitoring

Environmental DNA (eDNA) metabarcoding allows detection of species presence by analyzing genetic material shed into water, providing a non-invasive, cost-effective and highly sensitive tool for biodiversity assessment and fisheries monitoring (Taberlet *et al*., 2018; Deiner *et al.*, 2017) [129, 31]. Artificial Intelligence (AI) supports this apporach by automating the processing and classification of complex eDNA sequence data, thereby improving species identification accuracy and enabling large-scale, real-time ecosystem assessments (Ardura *et al.*, 2019; Bohmann *et al.*, 2021) [6, 19]. This methodology is particularly valuable for detecting rare or endangered species as well as monitoring invasive species without disturbing habitats (Rees *et al.*, 2014; Harper *et al*., 2019) [113, 49].

6.2 AI-powered Autonomous Drones for In Situ Observations

Autonomous drones equipped with AI-enabled sensors and computer vision systems are increasingly utilized to conduct detailed in situ observations of fish populations, aquaculture pens and Marine Protected Areas (MPAs). These drones deliver high-resolution spatial and temporal data on fish behavior, health and habitat conditions, facilitating continuous, non-invasive monitoring that minimizes human labor while enhancing data accuracy and reliability (Bertoldi *et al*., 2021; Lee *et al.*, 2020) [14, 72]. AI algorithms embedded on-board enable real-time processing of imagery and sensor data, which supports rapid decision-making and adaptive management in dynamic marine environments (Liu *et al*., 2022; Sharma *et al*., 2023) [77, 124].

6.3 Blockchain + AI for Traceability and Fisheries Supply Chain Integrity

Blockchain technology combined with Artificial Intelligence (AI) offers a transparent and tamper-proof system for tracking fish products from catch to consumer, thereby enhancing supply chain integrity and combating fraud and illegal fishing activities (Kamilaris, Fonts, & Prenafeta-Boldú, 2019; Leng *et al*., 2020) [61, 73]. AI techniques analyze blockchain-generated data to detect anomalies, optimize logistics and ensure adherence to sustainability certifications, fostering greater accountability throughout the supply chain (Tian, 2016; Queiroz *et al*., 2020) [133, 110]. This integration not only builds consumer trust but also supports responsible sourcing practices and strengthens regulatory enforcement in the fisheries sector (Wolfert, Ge, Verdouw, & Bogaardt, 2017) [140].

6.4 Citizen Science Data Integrated with AI for Participatory Management

Incorporating citizen science data such as fish sightings, catch reports and environmental observations into AI models democratizes fisheries monitoring and management. AI processes heterogeneous, large-scale citizen-generated data to identify trends, validate scientific findings and fill data gaps, especially in under-monitored regions (Kosmala, Wiggins, Swanson, & Simmons, 2016; McKinley *et al*., 2017) [66, 86]. This participatory approach fosters community engagement, enhances data richness, and supports co-management strategies that align with local knowledge and priorities (Danielsen *et al*., 2014; West *et al.*, 2020) [29, 139].

7. Conclusion

The integration of Artificial Intelligence (AI) and Remote Sensing (RS) is revolutionizing fisheries resource management, offering powerful solutions to the longstanding challenges of monitoring, assessment, and sustainable exploitation of marine resources. By harnessing satellite data, drones, advanced sensors and AI-driven analytics, fisheries managers can now monitor vast and previously inaccessible ocean areas in real time, predict fish abundance zones, detect illegal activities and automate species identification with unprecedented accuracy and efficiency.

AI techniques including machine learning, deep learning, computer vision and natural language processing enable the rapid analysis of complex and heterogeneous data-sets, supporting dynamic stock assessments, vessel surveillance and ecosystem health monitoring. Remote sensing provides the essential environmental context, delivering continuous data on key parameters like sea surface temperature, chlorophyll-a and ocean productivity. The synergy between these technologies allows for adaptive, data-driven decision-making that is critical in the face of overfishing, IUU fishing and climate change.

Despite these advancements, challenges remain. Data quality and availability, especially in the Global South, model transparency, technological capacity and ethical considerations around surveillance must be addressed to ensure equitable and effective implementation. Ongoing innovation such as eDNA monitoring, AI-powered autonomous drones, blockchain for supply chain integrity and participatory citizen science promises to further enhance the scope and impact of AI and RS in fisheries.

In summary, the combined use of AI and remote sensing represents a transformative leap toward holistic, sustainable and resilient fisheries management. By enabling real-time ecosystem monitoring, predictive analytics and automated enforcement, these technologies support the long-term health of marine ecosystems and the communities that depend on them.

8. References

1. Achieng OM, Oluoch JO, Otieno GO, Odera PA. Challenges of applying artificial intelligence in resource-constrained fisheries: a Kenyan perspective. Mar Policy. 2021;132:104672.
2. Addison PFE, Cook CN, de Bie K. Achieving evidence-based adaptive management in conservation. Ecol Soc. 2022;27(2):18.
3. Allken V, Handegard NO, Rosen S, Schreyeck T, Malde K, Aas KS. Fish species identification using a convolutional neural network trained on synthetic data. ICES J Mar Sci. 2019;76(1):264-274.
4. Anderson DM, Cembella AD, Hallegraeff GM. Progress in understanding harmful algal blooms: paradigm shifts and new technologies for research, monitoring, and management. Annu Rev Mar Sci. 2017;4:143-176.
5. Anderson JL, Plagányi ÉE, Pascoe S, Rees M. The impact of illegal, unreported and unregulated fishing on ecosystems and management. Fish Fish. 2019;20(6):1052-1063.
6. Ardura A, Planes S, Garcia-Vazquez E. High-throughput environmental DNA analysis: a new approach for invasive species detection. *Environ DNA.* 2019;1(3):216-232.
7. Arvor D, Durieux L, Andrés L, Laporte M-A, Gond V. Advancements in geographic data mining using natural language processing: a review of NLP applications in remote sensing and environmental science. ISPRS Int J Geo-Inf. 2020;9(9):535.
8. Asch RG, Cheung WWL, Reygondeau G. Future marine ecosystem drivers, biodiversity, and fisheries maximum catch potential in Pacific Island countries and territories under climate change. Mar Policy. 2019;100:90-98.
9. Behrenfeld MJ, Falkowski PG. Photosynthetic rates derived from satellite-based chlorophyll concentration. Limnol Oceanogr. 1997;42(1):1-20.
10. Behrenfeld MJ, Boss ES, Siegel DA, Shea DM. Carbon-based ocean productivity and phytoplankton physiology from space. *Glob* Biogeochem Cycles. 2006;19(1):GB1006.
11. Bekkby T, Erikstad L, Bakkestuen V. Monitoring fishing activity using Synthetic Aperture Radar (SAR) in Norwegian coastal waters. *ICES* J Mar Sci. 2015;72(4):1047-1054.
12. Belkin IM, Cornillon PC, Sherman K. Fronts in large marine ecosystems. Prog Oceanogr. 2009;81(1-4):223-236.
13. Bentes C, Borges L, Vasconcelos L. Vessel detection with Sentinel-1 imagery using a constant false alarm rate detector. Remote Sens. 2016;8(9):785.
14. Bertoldi W, Soares LS, Silva TC. Applications of autonomous underwater vehicles and drones in fisheries management: a review. Mar Technol Soc J. 2021;55(2):50-65.
15. Beveridge MCM, Thilsted SH, Phillips MJ, Metian M, Troell M, Hall SJ. Meeting the food and nutrition needs of the poor: the role of fish and the opportunities and challenges emerging from the rise of aquaculture. J Fish Biol. 2019;94(6):1127-1145.
16. Block BA, Jonsen ID, Jorgensen SJ, Winship AJ, Shaffer SA, Bograd SJ, *et al*. Tracking apex marine predator movements in a dynamic ocean. Nature. 2011;475(7354):86-90.
17. Blondeau-Patissier D, Gower JFR, Dekker AG, Phinn SR, Brando VE. A review of ocean color remote sensing methods and statistical techniques for the detection, mapping and analysis of phytoplankton blooms in coastal and open oceans. Prog Oceanogr. 2014;123:123-144.
18. Boerder K, Battaile BC, McCluney J, Worm B. Improving management of fishing effort through spatial and temporal closures. Fish Fish. 2018;19(5):908-917.
19. Bohmann K, Evans A, Gilbert MTP, Carvalho GR, Creer S, Knapp M, *et al*. Environmental DNA for wildlife biology and biodiversity monitoring. Trends Ecol Evol. 2021;37(7):553-567.
20. Bosch S, Klinger D, Fröhle P. Using natural language processing to extract climate adaptation strategies in fisheries. *Mar Policy.* 2023;145:105361.
21. Bozhi L, Wang Y, Zhang X. A hybrid machine learning model integrating stock assessment and environmental variables for fisheries management. Ecol Inform. 2021;66:101486.
22. Casey KS, Cornillon P. A comparison of satellite and in situ-based sea surface temperature climatologies. J Climate. 1999;12(6):1848-1863.
23. Chabot D, Bird DM. Wildlife research and management methods in the 21st century: where do unmanned aircraft fit in? J Unmanned Veh Syst. 2015;3(4):137-155. doi:10.1139/juvs-2015-0021.
24. Chen K, Xue Y, Xu D. Using machine learning models to predict fish distributions from remote sensing data in the Northwest Pacific. Remote Sens. 2020;12(17):2807.
25. Cisneros-Montemayor AM, Pauly D, Weatherdon LV, Ota Y. A global estimate of seafood consumption by coastal Indigenous peoples. PLoS ONE. 2019;14(2):e0212473.
26. Cohen PJ, Allison EH, Andrew NL, Cinner JE, Evans LS, Fabinyi M, *et al*. Securing a just space for small-scale fisheries in the blue economy. Front Mar Sci. 2019;6:171.
27. Cushing DH. Plankton production and year-class strength in fish populations: an update of the match/mismatch hypothesis. Adv Mar Biol. 1990;26:249-293.
28. da Silva AS, de Souza RF, Batista GEA P A. A systematic review on the use of natural language

processing in environmental science. Environ Model Softw. 2021;142:105075.
29. Danielsen F, Burgess ND, Balmford A. Monitoring matters: examining the potential of locally-based approaches. Biodivers Conserv. 2014;23(3):616-623.
30. Davies TE, Mees CC, Milner-Gulland EJ. Assessing the impact of technological change in small-scale fisheries: a global review. Fish Fish. 2020;21(3):570-589.
31. Deiner K, Bik HM, Mächler E, Seymour M, Lacoursière-Roussel A, Altermatt F, *et al*. Environmental DNA metabarcoding: transforming how we survey animal and plant communities. Mol Ecol. 2017;26(21):5872-5895.
32. Doshi-Velez F, Kim B. Towards a rigorous science of interpretable machine learning. arXiv [preprint]. 2017 Feb 17:arXiv:1702.08608.
33. Dunn DC, Boustany A, Halpin PN. Spatio-temporal management of fisheries to reduce bycatch and support sustainability. Mar Policy. 2016;72:243-253.
34. European Environment Agency. Changes in fish distribution in Europe's seas [Internet]. 2024 [cited 2025 Aug 7]. Available from: https://www.eea.europa.eu/en/analysis/indicators/changes-in-fish-distribution-in
35. FAO. Leveraging digital technology for fisheries and aquaculture: opportunities and challenges. Food and Agriculture Organization of the United Nations; 2022.
36. Frazão Santos C, Claudet J, Lopes PF. Marine conservation in a changing climate: insights from AI-based forecasting and management tools. Glob Change Biol. 2020;26(2):490-500.
37. Free CM, Thorson JT, Pinsky ML, Oken KL, Wiedenmann J, Jensen OP. Impacts of historical warming on marine fisheries production. *Science*. 2019;363(6430):979-983.
38. Garcia SM, Rice J, Charles A. Governance of marine fisheries and biodiversity conservation: a history. ICES J Mar Sci. 2020;77(1):1-16.
39. Gilpin LH, Bau D, Yuan BZ, Bajwa A, Specter M, Kagal L. Explaining explanations: an overview of interpretability of machine learning. 2018 IEEE 5th Int Conf Data Sci Adv Anal (DSAA). 2018:80-89.
40. Global Fishing Watch. New research harnesses AI and satellite imagery to reveal the expanding footprint of human activity at sea [Internet]. 2023 [cited 2025 Aug 7]. Available from: https://globalfishingwatch.org/press-release/new-research-harnesses-ai-and-satellite-imagery-to-reveal-the-expanding-footprint-of-human-activity-at-sea
41. Global Fishing Watch. Our technology [Internet]. 2018 [cited 2025 Aug 7]. Available from: https://globalfishingwatch.org/our-technology/
42. Google Cloud. Global Fishing Watch case study [Internet]. 2018 [cited 2025 Aug 7]. Available from: https://cloud.google.com/customers/global-fishing-watch
43. Gouritin A. The challenges of regulating emerging technologies: the case of AI in environmental governance. Rev Eur Comp Int Environ Law. 2020;29(3):420-429.
44. Gower JFR, King S, Borstad G. Remote sensing of ocean color: sea surface temperature and chlorophyll monitoring. Oceanography. 2008;21(4):88-99. doi:10.5670/oceanog.2008.20.
45. Gower J, King S, Borstad G. Remote sensing of ocean color: sea surface temperature and chlorophyll monitoring. Oceanography. 2019;32(3):80-89.
46. Gray PC, Bierlich KC, Mantell SA, Friedlaender AS, Goldbogen JA, Johnston DW. Drones and convolutional neural networks facilitate automated and accurate cetacean species identification and photogrammetry. Methods Ecol Evol. 2019;10(9):1490-1500.
47. Greidanus H, Alvarez M. Detecting fishing vessels with satellite-based radar: from research to operations. Remote Sens. 2021;13(4):604.
48. Handisyde NT, Ross LG, Badjeck MC, Allison EH. The effects of aquaculture on ecosystem services. Mar Policy. 2006;30(5):689-709.
49. Harper LR, Buxton AS, Rees HC, Bruce K, Brys R, Halfmaerten D, *et al*. Environmental DNA (eDNA) metabarcoding of pond water as a tool to survey conservation and management priority mammals. Biol Conserv. 2019;238:108225.
50. Hazen EL, Maxwell SM, Bailey H, Bograd SJ, Hamann M, Costa DP. Ontogeny in marine tagging and tracking science: technologies and data gaps. Mar Ecol Prog Ser. 2013;457:221-240.
51. Hazen EL, Scales KL, Maxwell SM, Briscoe DK, Welch H, Bograd SJ, *et al*. A dynamic ocean management tool to reduce bycatch and support sustainable fisheries. Sci Adv. 2018;4(5):eaar3001.
52. Hedley JD, Roelfsema CM, Chollett I, Harborne AR, Heron SF, Weeks S, *et al*. Remote sensing of coral reefs for monitoring and management: a review. Remote Sens. 2016;8(2):118.
53. Hodgson JC, Baylis SM, Mott R, Herrod A, Clarke RH. Precision wildlife monitoring using unmanned aerial vehicles. Sci Rep. 2016;6:22574.
54. Hu C, Lee Z, Franz B. Chlorophyll-a algorithms for oligotrophic oceans: a novel approach based on three-band reflectance difference. J Geophys Res Oceans. 2019;124(3):1795-1811.
55. Huang Y, Chen M, Huang Q, Chen C. Big data analytics for remote sensing imagery: a survey. Big Data Res. 2020;19:100151.
56. International Maritime Organization. Illegal, Unreported, and Unregulated (IUU) Fishing [Internet]. 2023 [cited 2025 Aug 7]. Available from: https://www.imo.org/en/OurWork/IIIS/Pages/IUU-FISHING.aspx
57. International Ocean-Colour Coordinating Group (IOCCG). Remote sensing of ocean colour in coastal, and other optically-complex, waters (IOCCG Report Series, No. 3). Dartmouth, Canada: IOCCG; 2000.
58. Jentoft S, Eide A. Poverty mosaics: realities and prospects in small-scale fisheries. Dordrecht: Springer; 2011.
59. Johnston DW. Unoccupied aircraft systems in marine science and conservation. Annu Rev Mar Sci. 2019;11:439-463.
60. Kahru M, Mitchell BG. Influence of the El Niño-Southern Oscillation on the surface chlorophyll in the California Current. *J* Geophys Res Oceans. 2000;105(C8):19045-19060.
61. Kamilaris A, Fonts A, Prenafeta-Boldú FX. The rise of blockchain technology in agriculture and food supply chains. Trends Food Sci Technol. 2019;91:640-652.

62. Kaplan IC, Marshall KN, Hodgson EE. Building resilient fisheries through machine learning and ecosystem modeling. Fish Fish. 2021;22(3):613-627.
63. Kerr JT, Ostrovsky M. From space to species: ecological applications for remote sensing. Trends Ecol Evol. 2003;18(6):299-305.
64. Kilpatrick KA, Podestá GP, Evans R. Overview of the NOAA/NASA advanced very high resolution radiometer Pathfinder algorithm for sea surface temperature and associated matchup database. J Geophys Res Oceans. 2001;106(C5):9179-9197.
65. Klemas V. Remote sensing of environmental indicators of potential fish aggregation: an overview. Baltica. 2012;25(2):99-112.
66. Kosmala M, Wiggins A, Swanson A, Simmons B. Assessing data quality in citizen science. Front Ecol Environ. 2016;14(10):551-560.
67. Kourti N, Park W, Cakaj S, Rumisha C. Data systems and digital technologies in fisheries: a review of uses and gaps. FAO Fish Aquac Tech Pap. 2020;654.
68. Kroodsma DA, Mayorga J, Hochberg T, Miller NA, Boerder K, Ferretti F, *et al*. Tracking the global footprint of fisheries. Science. 2018;359(6378):904-908.
69. Kudela RM, Berdalet E, Bernard S, Burford MA, Fernand L, Lu S, *et al*. Harmful algal blooms: a scientific summary for policy makers. IOC/UNESCO and GlobalHAB; 2015.
70. Kuenzer C, Bluemel A, Gebhardt S, Quoc TV, Dech S. Remote sensing of mangrove ecosystems: a review. Remote Sens. 2011;3(5):878-928.
71. Kumar L, Muench R, Elash B. Remote sensing applications for sustainable aquaculture site selection and monitoring. Aquac Rep. 2020;18:100486.
72. Lee J, Kim H, Park S. AI-powered drones for monitoring marine protected areas: a review of recent advancements. Sensors. 2020;20(12):3501.
73. Leng K, Ruj S, Ray S. Blockchain-enabled supply chain management for sustainable fisheries. J Clean Prod. 2020;272:122883.
74. Levin N, Victor N, Aumann Y, Kark S. Remote sensing for fisheries management: monitoring marine environments using satellite data. Front Mar Sci. 2018;5:334.
75. Lewison RL, Crowder LB, Wallace BP, Moore JE, Cox T, Zydelis R, *et al*. Dynamic ocean management: identifying the critical ingredients of dynamic approaches to ocean management. BioScience. 2015;65(5):486-498.
76. Lipton ZC. The mythos of model interpretability: in machine learning, the concept of interpretability is both important and slippery. Commun ACM. 2018;61(10):36-43.
77. Liu Y, Li Z, Lin L, Cui W. Application of computer vision and artificial intelligence in aquaculture: a review. Aquac Int. 2020;28:429-446.
78. Liu Y, Wang X, Chen Z. Real-time fish species identification using deep learning on underwater drones. Aquaculture. 2022;546:737413.
79. Mann KH, Lazier JRN. Dynamics of marine ecosystems: biological-physical interactions in the oceans. 3rd ed. Chichester: Wiley-Blackwell; 2013.
80. Mannocci L, Halpin PN, Read AJ, Gende SM. Understanding cetacean habitat and spatial ecology using satellite remote sensing. Mar Ecol Prog Ser. 2017;584:225-242.
81. Marini S, Fanelli E, Sbragaglia V, Azzurro E, Aguzzi J. Tracking fish abundance by underwater image recognition. *Sci Rep*. 2018;8:13748.
82. Maxwell SM, Hazen EL, Lewison RL, Dunn DC, Bailey H, Bograd SJ, *et al*. Dynamic ocean management: defining and conceptualizing real-time management of the ocean. Mar Policy. 2015;58:42-50.
83. McCauley DJ, Woods P, Sullivan B, Bergman B, Jablonicky C, Roan A, *et al*. Ending hide and seek at sea. Sci Adv. 2016;2(2):e1501507.
84. McClain CR. A decade of satellite ocean colour observations. Annu Rev Mar Sci. 2009;1:19-42.
85. McDonald G, O'Keefe C, Goggins G. Using AIS data and machine learning to detect fishing activity in mixed-use fisheries. ICES J Mar Sci. 2019;76(6):1907-1917.
86. McKinley DC, Miller-Rushing AJ, Ballard HL, Bonney R, Brown H, Cook-Patton SC, *et al*. Citizen science can improve conservation science, natural resource management, and environmental protection. Biol Conserv. 2017;208:15-28.
87. Migliaccio M, Nunziata F, Buono A. SAR ship detection via wavelet packet transform and CFAR techniques. IEEE Trans Geosci Remote Sens. 2015;53(1):143-152.
88. Miller NA, Roan A, Hochberg T, Amos J, Kroodsma DA. Identifying global fishing fleets with satellite-based AIS data. Front Mar Sci. 2018;5:49.
89. Misra A, Srivastava A, Mukhopadhyay S. AI-powered remote sensing for smart fisheries: a review. IEEE Access. 2021;9:134573-134592.
90. Mitra A, Samal A, Rao G. Monitoring water quality in aquaculture ponds using remote sensing technology. Int J Remote Sens. 2019;40(15):6022-6036.
91. Molnar JL, Kappel CV, Reygondeau G, Halpern BS. Sustainable ocean governance: ethical frameworks for marine technology. One Earth. 2021;4(9):1255-1265.
92. Morel A, Prieur L. Analysis of variations in ocean colour. Limnol Oceanogr. 1977;22(4):709-722.
93. Muhling BA, Liu Y, Lee S-K, Lamkin JT, Roffer MA, Muller-Karger FE, Walter JF. Potential impact of climate change on the Intra-Americas Sea: Part 2. Implications for Atlantic bluefin tuna and skipjack tuna adult and larval habitats. J Mar Syst. 2017;163:132-143.
94. Muhling BA, Stock CA, Saba VS, Gaitan CF. Predicting climate-driven shifts in tuna habitat using high-resolution global climate models. Fish Oceanogr. 2017;26(2):172-186.
95. Nadeem A, Rana AD, Batool SA, Hameed A. Satellite-based assessment of potential fishing zones within the Exclusive Economic Zone (EEZ) of Pakistan. Cont Shelf Res. 2025;250:104876.
96. NASA. Satellite oceanography and fisheries [Internet]. 2023 [cited 2025 Aug 7]. Available from: https://oceancolor.gsfc.nasa.gov/
97. Nasirian A, Liu Y, Dong S. Recent advances in AI-powered monitoring systems for aquaculture: a comprehensive review. Aquac Eng. 2023;101:102307.
98. National Oceanic and Atmospheric Administration. Remote sensing applications for fisheries [Internet]. 2022 [cited 2025 Aug 7]. Available from: https://www.noaa.gov/remote-sensing-fisheries

99. Nezami BT, Ramin S, Johnson D. UAV-based monitoring of aquaculture ponds using image processing and machine learning. Comput Electron Agric. 2021;186:106153.
100. NOAA Fisheries. Understanding Illegal, Unreported, and Unregulated Fishing [Internet]. 2023 [cited 2025 Aug 7]. Available from: https://www.fisheries.noaa.gov/insight/understanding-illegal-unreported-and-unregulated-fishing
101. NOAA Fisheries. Satellite Applications [Internet]. 2024 [cited 2025 Aug 7]. Available from: https://www.fisheries.noaa.gov/national/science-data/satellite-applications
102. Ogunlana S, Bimbo F, Cavallo C. Barriers to technology adoption in small-scale fisheries: evidence from a developing country. Mar Policy. 2022;138:104968.
103. Palacios DM, Bograd SJ, Foley DG, Schwing FB. Oceanographic characteristics of biological hotspots in the North Pacific: a remote sensing perspective. Deep Sea Res II. 2006;53(3-4):250-269.
104. Park JH, Kim BG, Kim HC. Monitoring of unregistered ships using satellite SAR and AIS data fusion. Mar Geod. 2018;41(2):171-188.
105. Park J, Kim J, Seo J. A deep learning-based fishing vessel classification method using AIS trajectory data. Sensors. 2020;20(6):1598.
106. Phinn SR, Roelfsema CM, Dekker AG. Mapping seagrass and macroalgae: a review of remote sensing techniques and applications. Estuar Coast Shelf Sci. 2012;115:1-9.
107. Polovina JJ, Howell EA, Kobayashi DR, Seki MP. The transition zone chlorophyll front, a dynamic global feature defining migration and forage habitat for marine resources. Prog Oceanogr. 2008;77(2-3):331-338.
108. Purcell SW, Pomeroy RS. Driving small-scale fisheries in developing countries. Front Mar Sci. 2015;2:44.
109. Qin Y, Wang J, Liu Y, He D. Deep learning-based fish behavior analysis for intelligent aquaculture. Sensors. 2021;21(15):5178.
110. Queiroz MM, Fosso Wamba S, Lal B. Blockchain and supply chain management integration: a systematic review of the literature. Supply Chain Manag Int J. 2020;25(2):241-254.
111. Queiroz N, Humphries NE, Couto A, Vedor M, da Costa I, Sequeira AMM, *et al*. Global spatial risk assessment of sharks under the footprint of fisheries. Nature. 2021;589(7840):392-397.
112. Rathi D, Jain S, Indu S. Underwater fish species classification using convolutional neural network and deep learning. Int J Comput Appl. 2017;180(40):1-5.
113. Rees HC, Maddison BC, Middleditch DJ, Patmore JRM, Gough KC. The detection of aquatic animal species using environmental DNA-a review of eDNA as a survey tool in ecology. J Appl Ecol. 2014;51(5):1450-1459.
114. Robinson AR, Brink KH, Smith RL. Ocean circulation and its role in fish habitat formation. In: Brink KH, Robinson AR, editors. The Sea. Vol. 18. Cambridge (MA): Harvard University Press; 2017. p. 1-38.
115. Roelfsema CM, Lyons M, Kovacs EM, Maxwell P, Byrne M, Phinn SR, *et al*. Coral reef habitat mapping: a review and recommendations for monitoring programs in tropical regions. Mar Freshw Res. 2018;69(10):1675-1693.
116. Rudin C. Stop explaining black box machine learning models for high-stakes decisions and use interpretable models instead. Nat Mach Intell. 2019;1(5):206-215.
117. Saleh A, Sheaves M, Rahimi Azghadi M. Computer vision and deep learning for fish classification in underwater habitats: a survey [Internet]. 2022 [cited 2025 Aug 7]. Available from: https://arxiv.org/abs/2203.06951
118. Salman A, Jalal A, Shaukat A. Fish species classification in unconstrained underwater environment based on deep learning. Neurocomputing. 2016;287:1-9.
119. Salman A, Jalal A, Shaukat A. Fish species classification in underwater environment using deep learning and data augmentation. Appl Artif Intell. 2019;33(8):697-718.
120. Sardà-Palomera F, Bota G, Viñolo C, Pallarés O, Sazatornil V, Brotons L, *et al*. Fine-scale bird monitoring from light unmanned aircraft systems. Ibis. 2012;154(1):177-183.
121. Sathyendranath S, Platt T, Caverhill CM. Remote sensing of primary production: a review of empirical models. Int J Remote Sens. 2004;25(14):2753-2775.
122. Scales KL, Miller PI, Hawkes LA, Votier SC. Oceanographic drivers of marine predator movement and foraging. Mar Ecol Prog Ser. 2014;538:233-248.
123. Selva Prakash ML, Josewal J, Vignesh V, Padamanaban R. Remote sensing-based assessment of potential fishing zones using sea surface temperature and chlorophyll concentration. Indian J Geo-Marine Sci. 2023.
124. Sharma R, Singh N, Patel A. Adaptive management of aquaculture using AI-enabled autonomous drones. Comput Electron Agric. 2023;205:107522.
125. Shi K, Wang M. Monitoring of harmful algal blooms using remote sensing data. Remote Sens. 2021;13(1):10.
126. Siddiqui SA, Salman A, Malik MI, Shafait F, Mian A, Shortis MR, *et al*. Automatic fish species classification in underwater videos: exploiting pre-trained deep neural network models to compensate for limited labelled data. ICES J Mar Sci. 2018;75(1):374-389.
127. Smith J, Johnson R, Williams P. Applications of vessel monitoring systems in fisheries management: challenges and opportunities. Fish Res. 2017;196:1-10.
128. Suryan RM, Irons DB, Kaufman GD, Benson JM, Friesen BA. Spatial distribution and seasonal variation of fish stocks in relation to oceanographic conditions. Mar Ecol Prog Ser. 2012;451:173-189.
129. Taberlet P, Bonin A, Zinger L, Coissac E. Environmental DNA: for biodiversity research and monitoring. Oxford: Oxford University Press; 2018.
130. Taconet M, Kroodsma D, Fernandes JA. Global atlas of AIS-based fishing activity: challenges and opportunities (FAO Fisheries and Aquaculture Technical Paper No. 654). FAO; 2019.
131. Tallis H, Lubchenco J, Adams VM, Ban NC, Cinner JE, Clark J, *et al*. Working together: a call for inclusive conservation. Nature. 2021;593(7858):317-320.
132. Tang H, Ma X, Zhang Y. Predictive modeling of fishery resources based on remote sensing and deep learning. Ecol Inform. 2022;68:101611.

133. Tian F. An agri-food supply chain traceability system for China based on RFID & blockchain technology. 2016 13th Int Conf Serv Syst Serv Manag (ICSSSM). 2016:1-6.
134. Tilley A, Wilkinson SP, Kolding J, López-Angarita J, Pereira M, Mills DJ. Nearshore fish aggregating devices show positive outcomes for sustainable fisheries development in Timor-Leste. Front Mar Sci. 2020;7:579587.
135. Tzanopoulos J, Otero I, Hill C. The role of big data and artificial intelligence in biodiversity and conservation science. Trends Ecol Evol. 2022;37(4):295-298.
136. Vellido A, Martín-Guerrero JD, Lisboa PJ. Making machine learning models interpretable. ESANN 2012 Proc. 2012:163-172.
137. Villon S, Chaumont M, Subsol G, Clément B, Villéger S. Coral reef fish detection and recognition in underwater videos by supervised machine learning: comparison between deep learning and HOG+SVM methods. Ecol Inform. 2018;48:121-130.
138. Waycott M, Duarte CM, Carruthers TJB, Orth R J, Dennison WC, Olyarnik S, *et al*. Accelerating loss of seagrasses across the globe threatens coastal ecosystems. Proc Natl Acad Sci U S A. 2009;106(30):12377-12381.
139. West SE, Pateman R, Dyke A. Citizen science and environmental management: examining the role of participant motivation and trust. Environ Manage. 2020;65(1):92-103.
140. Wolfert S, Ge L, Verdouw C, Bogaardt M-J. Big data in smart farming - a review. Agr Syst. 2017;153:69-80.
141. World Wildlife Fund. Illegal, Unreported, and Unregulated Fishing Causes and Effects [Internet]. 2023 [cited 2025 Aug 7]. Available from: https://www.worldwildlife.org/threats/illegal-fishing
142. Xiao Y, Li X, Zhang Y. Integrating deep learning with remote sensing for marine ecological monitoring: progress and prospects. Remote Sens Environ. 2022;280:113176.
143. Xu H, Wang Y, Liu X, Guo Q. Deep learning for marine ecology: an overview of methods and applications. Ecol Inform. 2021;61:101253.
144. Xu X, Matzner S. Automated fish detection and classification in underwater videos: exploring deep learning for fisheries research. Ecol Inform. 2018;48:160-168.
145. Zhou S, Punt AE, Smith ADM. Combining mechanistic and machine learning models improves stock assessment under changing environmental conditions. ICES J Mar Sci. 2023;advance online publication.