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BIBLIOMETRIC ANALYSIS OF MACHINE LEARNING APPLICATIONS IN FISHERIES MANAGEMENT (2010-2023)

TRI PRATIWI HANDAYANI[1], DIAN PAMULARSIH ANGGRAENI[2]*, MUHAMMAD ALI[2] AND MEIKA PUSPITA SARI[3]

[1]Department of Information System, Muhammadiyah University of Gorontalo, Pentadio Timur, 96181 Gorontalo, Indonesia.
[2]Research Centre for Biota Systems, National Research and Innovation Agency, 16911 Cibinong, West Java, Indonesia.
[3]Department of Aquaculture, Muhammadiyah University of Palembang, 30263 Palembang, South Sumatra, Indonesia.

*Corresponding author: dian092@brin.go.id
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Abstract: This study presents a bibliometric analysis of machine learning applications in fisheries management from 2010 to 2023. Using the Scopus database, 183 publications were identified with the keywords "machine learning" and "fisheries management". Bibliometric analysis was conducted using Microsoft Excel and VOSviewer (version 1.6.18) to examine publication trends, including country, author, and keyword distributions. The results show a steady increase in machine learning applications during the studied period, with contributions from more than 50 countries, highlighting its global significance. The United States leads in institutional contributions, with Pittman and Brown, cited 202 times, standing out as the most influential work. Frequently occurring terms such as "machine learning" (64 occurrences) and "fisheries management" (20 occurrences) illustrate the central themes and research focus areas. This study offers valuable insights into research trends, key contributors, and thematic developments, enabling researchers to identify deep learning topics and gaps in machine learning applications for fisheries management. By mapping the evolution of this field, it enables academics and policymakers to align future research with practical challenges, thereby enhancing data-driven decision-making in fisheries management. The findings serve as a foundational reference for advancing sustainable fisheries practices through artificial intelligence and support interdisciplinary collaboration for addressing critical global fisheries challenges.

Keywords: Artificial intelligence, bibliometric, fisheries management, machine learning, occurrences.

Introduction

Fisheries management plays a pivotal role in ensuring the sustainability of marine and freshwater ecosystems, which are vital for global food security and biodiversity conservation. However, increasing pressures from overfishing, climate change, and habitat destruction have highlighted the need for innovative solutions. Traditional fisheries management often relies on historical data and expert judgement, which may not be sufficient to handle the complexity and dynamism of aquatic ecosystems. Conventional models struggle to account for changing ecological conditions, environmental drivers, and human impacts (Collier *et al*., 2016; Ramos Martins *et al*., 2021). In response, Machine Learning (ML) has emerged as a transformative tool, offering data-driven solutions to enhance decision-making processes.

The integration of ML represents a significant advancement in fisheries management, enabling the analysis of large and complex datasets from diverse sources, including satellite imagery, acoustic sensors, and environmental monitoring systems. As a subset of artificial intelligence, ML encompasses various methods such as deep learning (convolutional neural networks and recurrent neural networks), decision trees (random forests and XGBoost), Support Vector Machines (SVMs), and reinforcement learning, all of which have shown promise in fisheries applications (Coro *et al*., 2022). These techniques are particularly useful for automating stock assessments, monitoring illegal, unreported, and unregulated (IUU) fishing activities, and predicting changes in fish distribution based on environmental variables.

Recent studies have demonstrated the efficacy of ML in various fisheries-related applications. Deep learning models, for instance, have been used to classify fishing vessels via satellite imagery, supporting real-time enforcement of fishing regulations. Similarly, predictive modelling techniques such as random forests and XGBoost have been applied to estimate fish stock levels and forecast distribution patterns, aiding in sustainable resource allocation. While these advancements contribute to improved fisheries assessments, challenges remain in terms of data quality, accessibility, and model transparency.

Despite its potential, the widespread adoption of ML in fisheries management is hindered by several factors. Data limitations, particularly in developing regions, constrain the effectiveness of ML models. Additionally, the complexity of some ML techniques—the so-called "black box" problem—raises concerns regarding transparency and interpretability, making it difficult for stakeholders to fully trust and integrate these models into policy decisions. Addressing these challenges requires a collaborative, interdisciplinary approach involving fisheries scientists, data engineers, and policymakers to ensure that ML solutions are both scientifically rigorous and practically implementable.

This study aims to provide a comprehensive bibliometric analysis of ML applications in fisheries management from 2010 to 2023, examining key research trends, influential contributors, and thematic developments. By mapping the evolution of ML in this domain, we offer insights into emerging research areas and identify opportunities for interdisciplinary collaboration. Moreover, this study goes beyond traditional bibliometric analyses by critically evaluating the implications of ML for sustainable fisheries management. As climate change and population growth continue to exert pressure on global fisheries, the findings of this research will support the development of adaptive, data-driven management systems that promote long-term ecological and economic sustainability.

Literature Review of Machine Learning Algorithms in Fisheries Management

This bibliometric research reveals notable developments in the utilisation of ML in fisheries management from 2010 to 2023. This work offers significant insights into publication trends, keyword analysis, and collaboration patterns. Nevertheless, it is also crucial to examine the practical ramifications and real-world uses of ML in fisheries management. This section examines these elements, responding to the reviewer's suggestion for increased focus on practical applications and case studies.

Practical Implications of Machine Learning in Fisheries Management

ML has shown enormous potential for addressing complicated issues in fisheries management. For example, ML algorithms have been used to forecast fish stock levels and catch patterns by analysing historical data on environmental conditions, fishing effort, and species dynamics (Pittman & Brown, 2011). These estimates allow fishery managers to proactively change rules, ensuring the long-term viability of fish stocks.

A significant application is the utilisation of computer vision and sensor technology to oversee fishing activities. For instance, systems integrated with ML may identify and categorise fishing vessels, assess catch composition, and detect occurrences of IUU fishing in real time (Gladju & Kanagaraj, 2021). These instruments deliver actionable data that augment enforcement skills and aid in the preservation of marine habitats.

In aquaculture, ML has been utilised to enhance operations like fish biomass monitoring, production environment regulation, and disease prevention. The Food and Agricultural

Organisation (2013) devised a methodology that integrates remote sensing and ML to map and forecast fish distribution in inland waters, providing cost-effective management solutions for aquaculture practitioners. These developments demonstrate the revolutionary effect of ML in enhancing efficiency, lowering costs, and promoting sustainability in aquaculture methods.

Case Studies of Machine Learning Applications in Fisheries Management

The application of ML in fisheries management has redefined approaches to sustainability, resource optimisation, and ecosystem conservation. By leveraging its ability to process vast and complex datasets, ML enables predictive modelling, automated monitoring, environmental analysis, and aquaculture optimisation, offering innovative solutions to longstanding challenges in the fisheries sector.

Predictive Modelling and Stock Assessment

ML's capacity for analysing historical and real-time data has significantly advanced stock assessment and forecasting methods. Pittman and Brown (2011) provided a seminal example by using a multi-scale analytical approach to predict fish distributions across coral reef seascapes, emphasising its utility in marine spatial planning and the establishment of marine protected areas. Similarly, Fernandes *et al.* (2010) employed robust supervised classification techniques to predict fish recruitment, highlighting the role of ML in informing sustainable harvest levels.

Case study: In the Northern Adriatic Sea, ML-based trajectory analysis was utilised to predict fishing vessel activities, which improved the management of overfished species and optimised conservation strategies (Brandoli *et al*., 2022).

Automated Monitoring and Surveillance

Advancements in ML-powered computer vision and sensor systems have revolutionised the monitoring of fisheries. Automated tools detect IUU fishing and classify vessel activities with high accuracy. Salman *et al.* (2019) showcased the use of deep learning for fish detection in underwater videos, enabling cost-effective and efficient monitoring solutions.

Case study: In Chile, the integration of satellite data with ML algorithms significantly reduced IUU fishing by enabling authorities to monitor artisanal fisheries effectively, as reported by the Food and Agriculture Organisation (2020).

Environmental Monitoring and Climate Resilience

ML has become indispensable in understanding the effects of climate change on fisheries. Algorithms analyse water temperature, salinity, and nutrient cycles, predicting shifts in fish distribution and productivity. Malde *et al.* (2020) advocated for the integration of high-resolution satellite imagery with ML models to predict and mitigate climate impacts.

Case study: In the Gulf of Maine, ML algorithms were used to analyse the shifting distribution of lobster populations due to warming waters, allowing fishery managers to adapt quotas and spatial regulations (Pershing *et al*., 2021).

Integration with Aquaculture Systems

In aquaculture, ML contributes to optimising productivity and sustainability through precise monitoring of fish health, feed efficiency, and environmental parameters. Gladju and Kanagaraj (2021) reviewed the role of ML in automating disease detection and improving feed utilisation in fish farms.

Case study: Norway's aquaculture sector leveraged ML models, combined with Internet of Things (IoT) sensors for real-time monitoring of salmon farms, reducing disease outbreaks by 30% and improving feed conversion ratios. This was detailed in a study by O'Donncha and Grant (2019).

Multidisciplinary Collaboration and Global Impact

The application of ML in fisheries management is marked by its multidisciplinary scope, integrating environmental science, engineering, and policy studies. Collaborative efforts among nations, including the United States, China, and Australia have driven innovation in the field. For instance, Sala *et al*. (2018) employed ML to assess the economic costs and benefits of high-seas fishing, influencing global policy discussions on sustainable fisheries.

Case study: Indonesia's Ministry of Marine Affairs and Fisheries implemented ML-powered platforms to analyse vessel movement data, leading to a significant reduction in IUU fishing and enhanced maritime governance (Satria *et al*., 2022).

To provide context for these applications, notable studies that demonstrate the practical use of ML in fisheries management are highlighted:

(1) *Fishing Vessel Detection:* Souza *et al*. (2016) applied ML to satellite Automatic Identification System (AIS) data to improve fishing pattern detection. This method allowed for high-resolution spatial and temporal monitoring of fishing efforts, contributing to more precise regulatory measures.

(2) *Fish Stock Prediction:* Fernandes *et al.* (2015) utilised supervised classification techniques to forecast recruitment levels of seven North Atlantic fish species. Their approach demonstrated how ML could improve the accuracy of fishery models, aiding in the development of sustainable harvesting strategies.

(3) *Environmental Monitoring:* Salman *et al*. (2019) integrated deep learning into underwater video analysis to automate fish detection. This innovation has significant implications for biodiversity conservation and the assessment of marine habitats.

These examples underscore the diverse ways ML is being deployed to address critical issues in fisheries management, bridging the gap between theoretical research and practical implementation.

Integrating Bibliometric Findings with Practical Insights

The bibliometric trends identified in this study can inform future research directions and policy decisions. The frequency of terms such as "machine learning", "fisheries management", and "climate change" indicates a growing emphasis on integrating advanced computational techniques with objectives of environmental sustainability. The geographic concentration of research outputs in countries like the United States and China underscores the need for more international collaboration to address global fisheries management issues.

Methodology

Data Source

The methodology includes a bibliometric review of the most widely cited research on the application of machine learning in fisheries management. This approach is intended to evaluate scientific productivity (Fernandes *et al*., 2015), synthesise key findings from a collection of bibliographic records (Martínez-Climent *et al.*, 2018), identify new research trends, and foster interdisciplinary collaboration. This method is also useful for organising knowledge within a given academic discipline (Albort-Morant & Ribeiro-Soriano, 2016).

Descriptive data include details about the main authors, publication years, and journals of publication (Wu & Wu, 2017). More advanced techniques such as document co-citation may also be employed. An effective literature review involves selecting appropriate keywords, conducting a literature search, and closely examining the findings (Fahimnia *et al*., 2015). To ensure reliable results, this process must be repeated several times. Consequently, the study focuses on high-calibre publications, as these provide valuable insights into the theoretical perspectives shaping the development of the field.

Several bibliographic databases are available besides Scopus, including Web of Science, Dimensions, Google Scholar, and PubMed. For this study, data were extracted from Scopus to ensure accuracy and reliability (di Stefano *et al*., 2010; Khiste & Paithankar, 2017; Al-Khoury *et al*., 2022). To maintain rigour, only peer-reviewed journal articles were included while books and lecture notes, which typically undergo less rigorous review processes were excluded (Gu *et al*., 2019). Scopus offers significant advantages, including access to high-quality indexed publications across multiple disciplines (Ellegaard & Wallin, 2015; Shah, 2019), reliable data, robust citation analysis, and compatibility with bibliometric tools, making it the preferred choice for comprehensive research. For specialised purposes such as medical or health literature analysis, PubMed may be more appropriate. In contrast, Google Scholar provides free and extensive coverage, but has limitations in data quality assurance, which can affect the reliability of bibliometric studies.

Data Search

The documents search was conducted on June 16, 2024, with the keywords "machine" and "learning" and "fisheries" and "management". The vast majority of the journals in this index are published in English, which is considered an advantage over other well-known indexing organisations (Van Eck & Waltman, 2010; Ma *et al*., 2018). Figure 1 illustrates the document selection process used in this study, showing the steps for obtaining articles and applying filtering settings during the search.

There were 204 documents in the Scopus search covering a 10-year period. He results were then limited to English-language publications, yielding 198 items. Journal articles were selected on the assumption that they offer higher quality than other types of materials and to ensure high-quality data, making them the focus of analysis in this study. Using the Scopus filtering tool, additional keyword filtering was applied based on the finding of the first phase, excluding terms unrelated to fisheries and water management. This process resulted in 183 articles.

All search results were saved as an Excel file and processed using the VOSviewer programme (version 1.6.18). VOSviewer was chosen for its ease of use and flexibility, which significantly reduces opportunity costs, especially for new users. Since its introduction

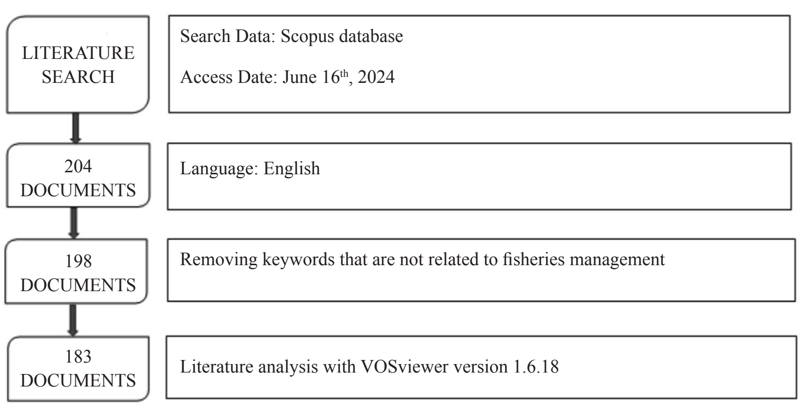

Figure 1: Data collection process

in 2010, the number of papers produced using software such as VOSviewer has grown exponentially (Van Helmond *et al.*, 2020). De Souza *et al.* (2016) described VOSviewer as a tool for bibliometric map trend analysis and visualisation. Such programmes can display and illustrate bibliometric visual maps using unique datasets.

Results

The application of ML in fisheries management has transformed traditional approaches to sustainability, resource optimisation, and ecosystem conservation. Leveraging its ability to process vast and complex datasets, ML enables predictive modelling, automated monitoring, environmental analysis, and aquaculture optimisation, addressing long-standing challenges in the fisheries sector. Recent research highlights the diverse applications of ML algorithms, each offering unique advantages based on their specific strengths and domains, as shown in Figure 2.

The bar chart illustrates the frequency of various ML algorithms mentioned in the abstracts of research papers. Key insights include:

(1) Popular algorithms

Algorithms like "deep learning", "neural networks", and "convolutional neural networks" or "CNN" appear to be the most frequently mentioned, indicating their widespread application in the analysed studies.

(2) Moderately mentioned algorithms

Techniques such as "random forests", "support vector machines" or "SVM", and "gradient boosting" are referenced with moderate frequency, reflecting their significance in specific problem domains.

(3) Less common algorithms

Approaches like "naive Bayes", "K-nearest neighbours" or "KNN", and "reinforcement learning" are less frequently discussed, suggesting either niche applications or declining popularity compared to more advanced methods.

(4) Emerging trends

The presence of terms like "transformer" and "BERT" indicates growing interest in advanced natural language processing techniques within the research community.

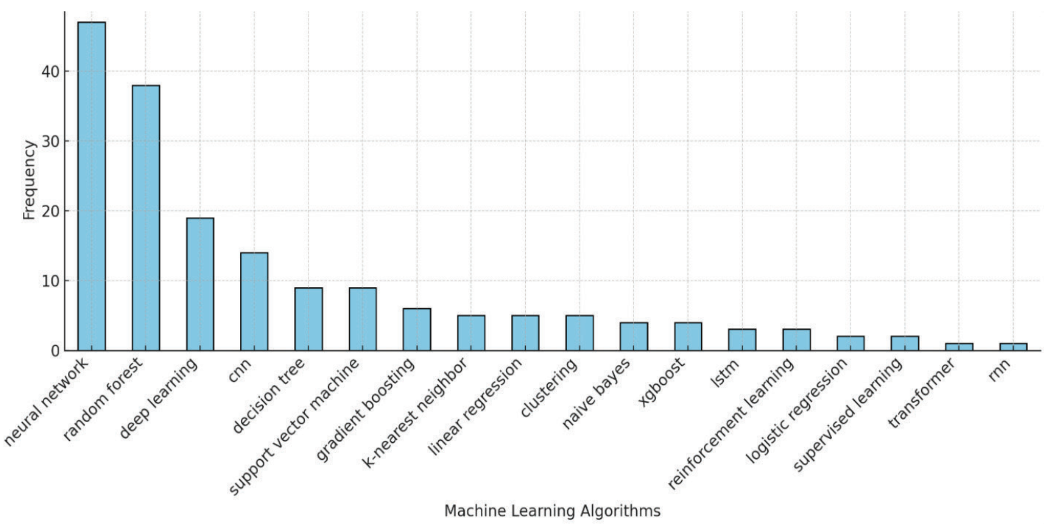

Figure 2: Frequency of mentions of machine learning algorithms

Deep learning methods, particularly Convolutional Neural Networks (CNNs), excel at processing and analysing high-dimensional data such as images and videos. They are widely used for tasks like image recognition, object detection, and natural language processing. For example, Zouin *et al.* (2024) employed CNNs for fish detection and classification with tracking and Bravata *et al*. (2020) demonstrated their robustness in predicting fish length, circumference, and weight from images. These applications exemplify the algorithm's capacity to enhance fisheries monitoring and prediction systems.

Random forests and decision trees, known for their interpretability and robustness are commonly applied in classification and regression tasks. Meeanan *et al.* (2023) used decision trees to estimate the spatiotemporal distribution of marine resources while Smoliński *et al.* (2020) employed random forests to assess fish stock discrimination. Burns *et al*. (2023) further highlighted the algorithm's efficacy in estimating shark catch risk in longline fisheries, showcasing its role in ecological risk assessment and resource management.

Support Vector Machines (SVMs) have proven effective in binary and multiclass classification tasks by maximising class margins. Marrable *et al.* (2023) utilised SVMs in semi-automated ecological modelling while Lazuardi *et al*. (2021) combined SVMs with linear regression to map coral and seagrass cover. These studies underscore the versatility of SVMs in handling ecological and environmental data.

Gradient boosting, particularly XGBoost has emerged as a powerful tool for predictive modelling by converting weak learners into strong predictors. Jafari *et al.* (2022) applied XGBoost to distinguish between wild and farmed common carp while Kaemingk *et al.* (2020) used it to predict angler harvest-release decisions, leveraging extensive fishery datasets. Such applications highlight the algorithm's capability to support decision-making in complex ecological scenarios.

ML's potential extends beyond traditional algorithms. Salman *et al.* (2019) showcased the use of deep learning in detecting fish in underwater videos, enabling cost-effective and efficient monitoring solutions. Similarly, Gladju and Kanagaraj (2021) reviewed the role of ML in automating disease detection and optimising feed utilisation in aquaculture. Norway's aquaculture sector leveraged ML models and IoT sensors for real-time monitoring, reducing disease outbreaks by 30% and improving feed conversion ratios (O'Donncha & Grant, 2019).

ML's capacity to integrate environmental data has proven indispensable in understanding climate impacts on fisheries. Malde *et al*. (2020) advocated for the use of high-resolution satellite imagery with ML models to predict and mitigate climate-driven changes. In the Gulf of Maine, ML algorithms analysed lobster population shifts due to warming waters, enabling adaptive management strategies (Pershing *et al*., 2021). Indonesia's Ministry of Marine Affairs and Fisheries implemented ML-powered platforms for vessel movement analysis, reducing IUU fishing and enhancing maritime governance (Satria *et al*., 2022).

Emerging trends in fisheries management demonstrate the increasing role of neural networks and ensemble models like boosted regression trees, which enhance predictive analytics and decision support. Integrating these models with global datasets, including satellite imagery and in situ observations improve the precision and scalability of ML applications. As Sala *et al*. (2018) illustrated by assessing the economic costs and benefits of high-seas fishing, ML-driven insights are shaping global policy discussions on sustainable fisheries.

By redefining approaches to stock assessment, monitoring, and aquaculture optimisation, ML continues to drive innovation in fisheries management. Its multidisciplinary scope, incorporating environmental science, engineering, and policy studies highlights its transformative impact and underscores the need for continued exploration of emerging technologies and collaborative frameworks.

In summary, recent research highlights the increasing role of neural networks and ensemble models in fisheries management. Advanced algorithms such as CNNs and boosted regression trees are being utilised for predictive analytics and decision support. The integration of these models with global datasets, including satellite imagery and in situ observations continues to enhance the precision and scalability of ML applications in fisheries.

Study Characteristics

Publishing trends from 2010 to 2023 in the area of ML applications in fisheries management show interesting developments. Plotting the number of publications over these years reveals a clear upward trend, suggesting increased interest and research activity in this multidisciplinary topic.

This study examined 183 papers on the use of ML in fisheries management over the 13-year period, showing an average annual increase in publications. Researchers have explored the application of ML in fisheries management since 2010, with a marked rise in output in 2017 (n = 5, 2.73%), despite dips in 2013 (n = 0), 2014 (n = 1, 0.55%), and 2016 (n = 2, 1.09%). The most striking growth occurred between 2022 and 2023, with publications surging from 36 to 56. This significant increase indicates a period of intensified scholarly focus, underscoring the growing importance of ML as a tool for addressing complex fisheries challenges. The publication output between 2010 and 2023 is shown in Figure 3.

Country Analysis

Articles on the use of ML in fisheries management were published across 56 countries. The majority originated from the United States (n = 42, 15.05%), China (n = 24, 8.60%), Australia (n = 20, 7.17%), Canada (n = 19, 6.81%), and the United Kingdom (n = 13, 4.66%). Table 1 presents the number of articles and citations by countries with at least 20 publications. Australia ranked first in total link strength while the United States had the highest number of citations per article (18.57). Co-authorship analysis showed that the most active collaborators in this field were Australia (TLS = 19), the United States (TLS = 13), Germany (TLS = 6), France (TLS = 5), and Pakistan (TLS = 5). Total link strength reflects the strength of connection between researchers who have co-authored publications (Van Eck & Waltman 2010; Van Helmond *et al.*, 2020).

The highest number of citations was recorded in 2018 at 508, followed by 2011 at 415, and 2020 at 356. Figure 4 presents a line graph with two curves, showing the annual total publications and citations. No significant

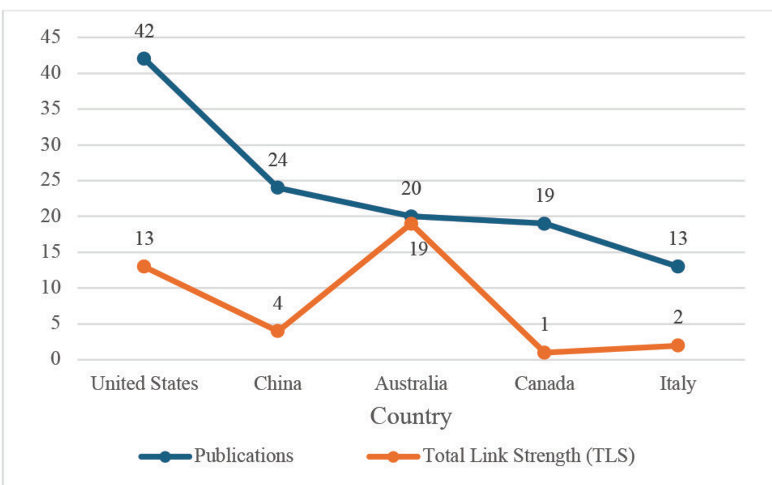

Figure 3: Top countries according to number of publications and total link strength

Table 1: Publication metrics for machine learning applications in fisheries management

Year	Quantity of Publications	Quantity of Citations	Average Citation Per Publication	Percentage of Publication
2010	3	60	20.00	1.64
2011	3	415	138.33	1.64
2012	2	44	22.00	1.09
2013	0	0	0.00	0.00
2014	1	2	2.00	0.55
2015	3	237	79.00	1.64
2016	2	197	98.50	1.09
2017	5	45	9.00	2.73
2018	11	508	46.18	6.01
2019	13	148	11.38	7.10
2020	20	356	17.80	10.93
2021	28	236	8.43	15.30
2022	36	275	7.64	19.67
2023	56	131	2.34	30.60

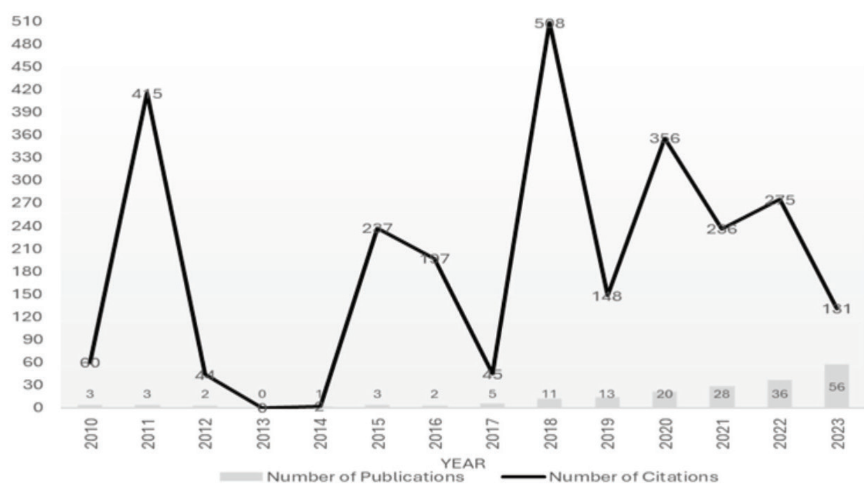

Figure 4: Publications and citations on machine learning applications in fisheries management (2010-2023)

correlation was observed between the number of publications in a given year and the total citations across all works.

The co-authorship network reveals strong collaboration patterns among researchers, with key clusters indicating frequent partnerships. When common interests and a convergence of concerns encourage cooperation between multiple countries, international collaborations tend to increase.

The integration of advanced ML systems in fisheries management necessitates collaboration between marine scientists and data scientists. However, there is often a gap in technical knowledge among stakeholders in fisheries management, which could hinder the deployment of such technologies. Capacity-building initiatives and interdisciplinary collaborations will be crucial in bridging this gap.

The country visualisation produced by VOSviewer, which depicts the co-authorship relationships between various nations in the subject of fisheries management research is shown in Figure 5. The colour gradient from blue (representing older publications) to yellow (representing more current publications) depicts the collaborative landscape and shows how international cooperation has evolved over time.

The central node of the visualisation is occupied by the United States, which indicates its position as the country with the highest number of collaborations. It is connected to a wide range of countries, including Germany, China, Australia, Canada, and France. This central position underscores the United States' significant role in fostering international partnerships in fisheries management research. China and Japan are also prominent in the network, with China showing extensive connections to other countries, including the United States, Germany, and France. Japan, on the other hand, appears to have more recent collaborations, as indicated by its yellow-green hue. This suggests an increasing trend in Japan's participation in international fisheries management research over the past few years.

European countries such as Germany, France, and Norway also play key roles in the collaborative network. Germany and France are notably well-connected, indicating their active involvement in multinational research projects. Norway, although smaller in node size, also demonstrates significant connections, particularly with other European nations and the United States.

India and Australia are other notable players in this network. India's collaborations are marked with more recent colours, indicating a growing involvement in international research efforts. Australia's connections, while spread out, show significant collaborations with countries like the United States and Canada, highlighting its role in the global fisheries research community.

The visualisation also highlights the involvement of smaller countries such as Greece, Pakistan, Saudi Arabia, and Estonia. These countries, while having fewer connections, still contribute to the global research network, indicating the widespread interest and collaborative efforts in fisheries management research across different regions.

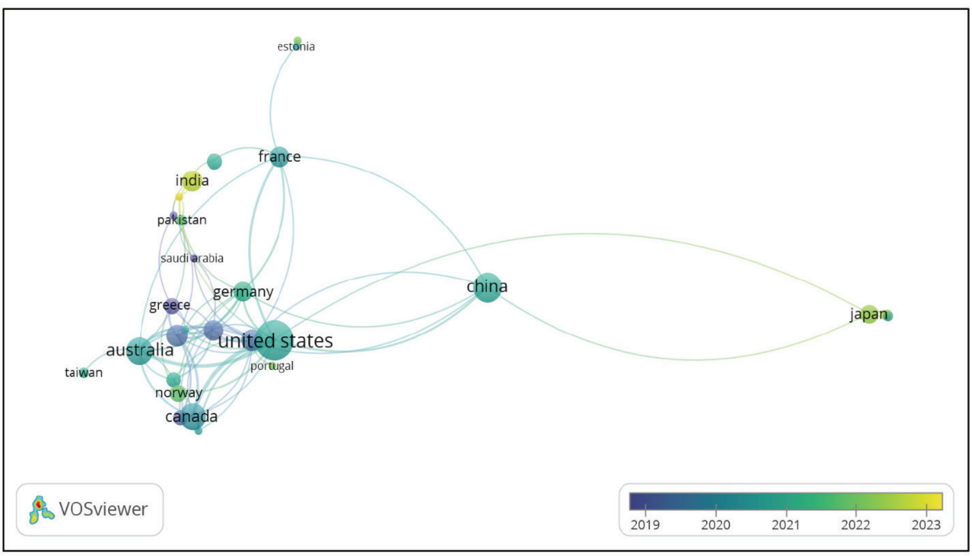

Figure 5: Country visualisation of co-authorship in fisheries management research

Most Prolific Authors

Among the 183 publications between 2010 and 2023, several authors have been notably prolific in this academic field. The leading contributors are highlighted in Figure 6.

Table 2 presents the publication titles and citation counts for these authors. Stan Matwin (De Souza *et al*., 2016; Adibi *et al*., 2020; Brandoli *et al*., 2022), Dadong Wang (Lopez-Marcano *et al*., 2021; Qiao, 2021; Khokher, 2022), Yuki Takahashi (Khiem, 2022; Khiem *et al.*, 2023; Meeanan, C., 2023), and Fabio Pranovi (Vincenzi, S., 2011; Adibi *et al*., 2020; Brandoli *et al.*, 2022) have each authored three significant papers in this field. Among them, Stan Matwin's (2016) paper on improving fishing pattern recognition from satellite AIS using data mining and ML has received the highest number of citations, with 192 to date. These authors have made substantial contributions to advancing ML research in fisheries management.

Table 2 also reveals instances of author collaboration on specific articles. For example, Stan Matwin and Fabio Pranovi both contributed to the article "From multiple aspect trajectories to predictive analysis: A case study on fishing vessels in the Northern Adriatic Sea". Similarly, Nguyen Minh Khiem and Yuki Takahashi contributed jointly to two studies: "A novel machine learning approach to predict the export price of seafood products based on competitive information: The case of the export of Vietnamese shrimp to the US market" and "A machine learning ensemble approach for predicting growth of abalone reared in land-based aquaculture in Hokkaido, Japan". Likewise, Jose A. Lozano, Jose A. Fernandes, and Xabier Irigoien collaborated on the papers "Evaluating machine-learning techniques for recruitment forecasting of seven North East Atlantic fish species" and "Fish recruitment prediction, using robust supervised classification methods".

Top Cited Papers

Table 3 presents the most cited articles, both in absolute terms and relative to citations per year. The study by Pittman and Brown (2011), which offers a multi-scale approach to predicting fish species distribution, ranks highest in total citations. Since its publication in 2011, this paper has been widely cited due to its introduction of an innovative and cost-effective tool—the multi-scale analytical approach. This method enables precise characterisation of key fish habitats, thereby supporting conservation goals in marine protected area development, marine spatial planning, and ecosystem-based fisheries management.

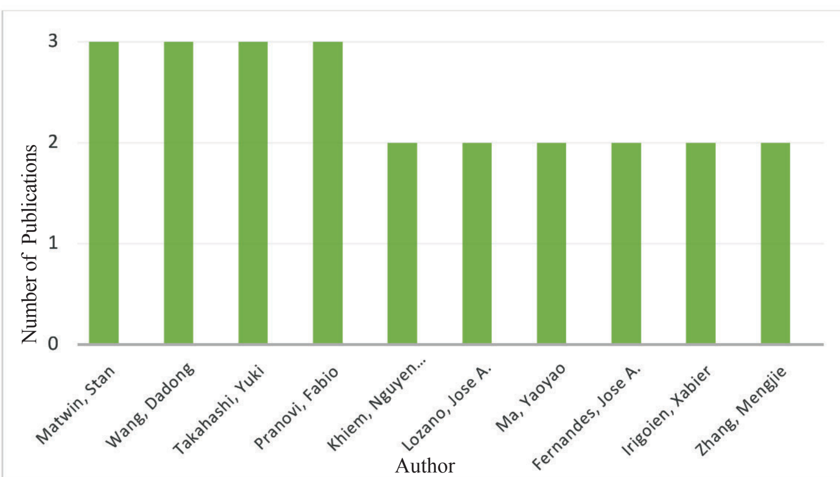

Figure 6: Most prolific authors

Table 2: Prolific authors and their contributions

Author	Title	Year	Citations
Matwin and Stan	Improving fishing pattern detection from satellite AIS using data mining and machine learning (De Souza *et al*., 2016)	2016	192
	Predicting fishing fffort and catch using semantic trajectories and machine learning (Adibi *et al*., 2020)	2020	21
	From multiple aspect trajectories to predictive analysis: A case study on fishing vessels in the Northern Adriatic sea (Brandoli *et al*., 2022)	2022	8
Wang and Dadong	Automatic detection of fish and tracking of movement for ecology (Lopez-Marcano *et al*., 2021)	2021	40
	Deep learning methods applied to electronic monitoring data: Automated catch event detection for longline fishing (Qiao *et al*., 2021)	2021	8
	Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: Where machine learning meets commercial fishing (Khokher *et al*., 2022)	2022	8
Takahashi and Yuki	A machine learning ensemble approach for predicting growth of abalone reared in land-based aquaculture in Hokkaido, Japan (Khiem *et al*., 2023)	2023	1
	A novel machine learning approach to predict the export price of seafood products based on competitive information: The case of the export of Vietnamese shrimp to the US market (Khiem *et al*., 2022)	2022	8
	Estimation of the spatiotemporal distribution of fish and fishing grounds from surveillance information using machine learning: The case of short mackerel (Rastrelliger brachysoma) in the Andaman Sea, Thailand (Meeanan *et al*., 2023)	2023	2
Pranovi and Fabio	Application of a random forest algorithm to predict spatial distribution of the potential yield of Ruditapes philippinarum in the Venice lagoon, Italy (Vincenzi *et al*., 2011)	2011	181
	Predicting fishing effort and catch using semantic trajectories and machine learning (Adibi *et al.*, 2020)	2020	21
	From multiple aspect trajectories to predictive analysis: A case study on fishing vessels in the Northern Adriatic sea (Brandoli *et al.*, 2022)	2022	8
Khiem and Nguyen M.	A novel machine learning approach to predict the export price of seafood products based on competitive information: The case of the export of Vietnamese shrimp to the US market	2022	8
	A machine learning ensemble approach for predicting growth of abalone reared in land-based aquaculture in Hokkaido, Japan	2023	1
Lozano and Jose A.	Fish recruitment prediction, using robust supervised classification methods (Fernandes *et al.*, 2010)	2010	54
	Evaluating machine-learning techniques for recruitment forecasting of seven North East Atlantic fish species (Fernandes *et al.*, 2015)	2015	17
Ma and Yaoyao	Real-time automated identification of algal bloom species for fisheries management in subtropical coastal waters (Guo *et al*., 2021)	2021	12
	Dynamics of algal blooms as revealed by continuous machine- learning based automatic species detection and water quality monitoring in sub-tropical marine fish culture zone (Ma *et al.*, 2022)	2022	0

Fernandes and Jose A.	Fish recruitment prediction, using robust supervised classification methods (Fernandes *et al.*, 2010)	2010	54
	Evaluating machine-learning techniques for recruitment forecasting of seven North East Atlantic fish species (Fernandes *et al.*, 2015)	2015	17
Irigoien and Xabier	Fish recruitment prediction, using robust supervised classification methods (Fernandes *et al.*, 2010)	2010	54
	Evaluating machine-learning techniques for recruitment forecasting of seven North East Atlantic fish species (Fernandes *et al*., 2015)	2015	17
Zhang and Mengjie	Deep convolutional neural networks for fish weight prediction from images (Yang *et al.*, 2021a)	2021	5
	Genetic programming for symbolic regression: A study on fish weight prediction (Yang *et al.*, 2021b)	2021	5

Table 3: Top cited papers

Author	Title	Total Citations	Citations Per Year	Primary Institution
Pittman and Brown (2011)	Multi-scale approach for predicting fish species distribution (Pittman & Brown, 2011)	202	15,54	Biogeography Branch, Center for Coastal Monitoring and Assessment, USA
Oliver *et al*. (2015)	Global patterns in the bycatch of sharks and rays (Oliver *et al*., 2015)	202	22,44	The School of Plant Biology, The University of Western Australia, Australia
De Souza *et al*. (2016)	Improving fishing pattern detection from satellite data using machine learning (De Souza *et al*., 2016)	193	24,13	Big Data Analytics Institute, Faculty of Computer Science, Dalhousie University, Canada
Sala *et al*. (2018)	The economics of fishing the high seas (Sala *et al.*, 2018)	182	30.33	National Geographic Society, Washington, 20036, DC, USA
Vincenzi *et al*. (2011)	Application of a random forest algorithm to predict fishery yields (Vincenzi *et al.*, 2011)	181	13,92	Dipartimento di Scienze Ambientali, Università Ca' Foscari Venezia
Salman *et al*. (2019)	Automatic fish detection in underwater videos using deep learning (Salman *et al*., 2019)	123	30,75	School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan
A. Sylvester *et al*. (2018)	Applications of random forest feature selection in fisheries management (Sylvester *et al.*, 2018)	94	15,67	Faculty of Computer Science, Dalhousie University, Canada
Sun *et al*. (2018)	Transferring deep knowledge for object recognition in low-quality underwater videos (Sun *et al*., 2018)	69	11,50	College of Information Science and Engineering, Northeastern University, China
Gladju *et al*. (2022)	Applications of data mining and machine learning framework in aquaculture and fisheries: A review (Gladju *et al.*, 2022)	57	28,50	Nallamuthu Gounder Mahalingam College, Department of Computer Science, Pollachi, India
Fernandes *et al*. (2010)	Fish recruitment prediction, using robust supervised classification methods (Fernandes *et al*., 2010)	54	3,86	AZTI - Tecnalia, Marine Research Division, Herrera Kaia z/g, E-20110 Pasaia, Spain

In relative terms, Salman *et al*. (2019), which summarises automatic fish detection in underwater videos using deep learning is the most highly cited study, with 30 citations per year. Notably, one of the most cited bibliometric studies on ML in fisheries management proves that the multi-scale method is an affordable means of precisely defining vital fish habitats and helping to prioritise conservation in the establishment of marine protected areas, marine spatial planning zoning, and ecosystem-based fisheries management.

Other significant bibliometric reviews include analyses of elasmobranch bycatch (Oliver *et al*., 2015) trawl, purse-seine, and gillnet fisheries in order to obtain a general perspective of bycatch patterns and to expose knowledge gaps and identify management and research priorities. Two bycatch ratios were considered: The number and the weight of elasmobranch bycatch relative to that of the target species captured. Patterns were determined through machine learning algorithms with gear type, oceanic region, habitat, and the presence or absence of bycatch management measures as candidate predictors. There are considerable information gaps. Most of the current information on elasmobranch bycatch is for the North Atlantic, which is not where the greatest fishing pressure is exerted, so, several fisheries were largely under-represented.

Overall for sharks, gear type was the most important predictor with pelagic longline fisheries in the South Atlantic displaying the highest bycatch ratios. No patterns were found for ray bycatch ratios. For the fisheries considered in this study, pelagic longlines and deep-sea, and coastal trawl fisheries had the largest total annual shark and ray bycatch, respectively. Blue sharks Prionace glauca, Carcharhinidae, methods to recognise and identify fishing behaviour (De Souza *et al*., 2016) such as fishing. While coastal fisheries in national waters are closely monitored in some countries, existing maps of fishing effort elsewhere are fraught with uncertainty, especially in remote areas and the High Seas. Better understanding of the behaviour of the global fishing fleets is required in order to prioritise and enforce fisheries management and conservation measures worldwide. Satellite-based Automatic Information Systems (S-AIS, modelling framework combining ML and geographic information system for aquaculture species (Vincenzi *et al*., 2011) and the use of satellite data and ML for real-time tracking of fishing vessels, quantifying effort, costs, and benefits (Sala *et al*., 2018). Salman *et al.* (2019) also explored approaches to using motion information from videos and raw images to generate fish-dependent candidate regions.

Most papers have relatively low citation counts (between 0 and 10, which is typical in academic research, where only a minority of papers achieve substantial influence and visibility). However, some studies, with citation counts between 50 and 100 have had moderate to high impact in the field. A small number of papers have exceptionally high citations, exceeding 100, and are often considered seminal works that have significantly advanced the discipline.

This citation distribution reflects a common academic pattern, where a few highly cited papers coexist alongside many with fewer citations. Understanding this pattern helps identify influential research and highlights potential directions for future investigation in the application of ML and fisheries management.

Top Sources

Figure 7 shows the leading sources of publications in the field of ML and fisheries management, along with the number of articles from each source.

The bar chart in Figure 7 illustrates the distribution of fisheries management publications across various scholarly journals. Each bar represents a distinct journal, with its length corresponding to the number of publications in that journal.

Frontiers in Marine Science leads the chart with nine publications, highlighting its role as a prominent platform for researchers to disseminate fisheries management work.

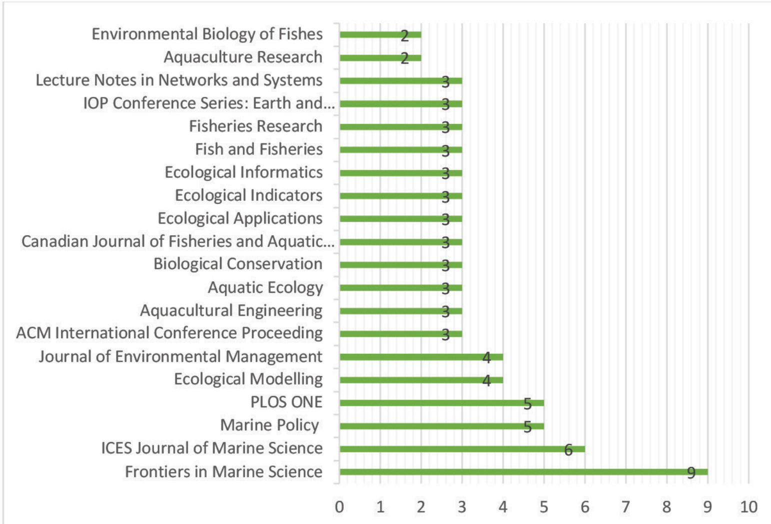

Figure 7: Top sources of publications in machine learning applications in fisheries management

Its focus on marine science makes it an ideal outlet for a wide range of studies in this field. Following closely is the *ICES Journal of Marine Science*, with six publications, known for its comprehensive coverage of marine science and fisheries research.

PLOS ONE and *Marine Policy* each account for five publications. *PLOS ONE*'s broad interdisciplinary scope supports diverse studies, including those related to fisheries management while *Marine Policy* emphasises research at the intersection of marine science and policy, attracting work focused on fisheries management practices.

Journals such as the *Journal of Environmental Management* and *Ecological Modelling* each have four publications. Others, including *Ecological Indicators* and *Ecological Informatics* contribute three publications apiece. These journals underscore the multidisciplinary nature of fisheries management research, emphasising environmental and ecological perspectives.

Specialised journals like the *Canadian Journal of Fisheries and Aquatic Sciences*, *Fish and Fisheries*, *Aquacultural Engineering*, and *Fisheries Research* each feature three publications, offering targeted insights into fisheries and aquaculture. Meanwhile, *Aquaculture Research* and *Environmental Biology of Fishes* have two publications each.

Additionally, journals such as *Biological Conservation*, *Lecture Notes in Networks and Systems*, and *IOP Conference Series* appear in the chart with three publications each, reflecting the diverse methodologies and conservation efforts within fisheries management research. Although not primary outlets, these journals contribute to the dissemination of important in this area.

Content Analysis

The top keywords in the dataset reveal the terms most frequently appearing in titles of works on ML and fisheries management. These keywords highlight the main themes and focus areas within the research field. Figure 8 lists the main keywords that define the core themes and areas of concentration.

Figure 8 shows that of the term "machine learning" occurs 64 times while "deep learning" occurs 21 times. The frequent presence of these keywords indicates a strong research focus on learning strategies, particularly machine learning and deep learning. This suggests many studies employ these algorithms to analyse data,

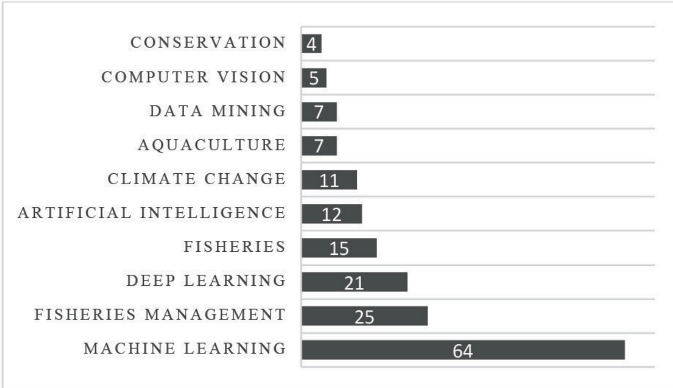

Figure 8: Top keywords

predict outcomes, or automate fisheries-related tasks, highlighting their central role in a sizable percentage of the research in addressing fisheries management challenges.

The keyword "fisheries management" appears 20 times, drawing attention to the broader context of sustainable use, conservation, and management of fisheries resources. This suggests that a significant number of studies concentrate on fisheries-related issues rather than on just a specific species. Similarly, the keyword "fisheries" occurs 15 times, reflecting studies centred on fish species and fishery-level issues, including designated waters or collections of fishing activities.

"Artificial intelligence" appears 14 times in the dataset. While closely related, Artificial Intelligence (AI) and ML are distinct; ML is a subset of AI. These two terms are often used interchangeably, despite representing two distinct concepts. Their presence highlights the prominent technological approaches in this research area.

The keyword "climate change" occurs 11 times, underscoring its recognised impact on fisheries in various ways. "Aquaculture", with seven occurrences, represents studies focused on fish farming activities and related issues. Likewise, "data mining", a process of discovering patterns in large datasets and integral to data science, appears seven times. Data mining supports accurate forecasting and informed decision-making in fisheries management.

Figure 9 shows the network visualisation produced by VOSviewer that illustrates the co-occurrence of key terms in fisheries management research. The graphic aids in determining the primary subjects and their interrelationships, offering insights into the study domain's thematic organisation. The network demonstrates the multidisciplinary nature of fisheries management research, showing connections among terms from AI, computer science, and environmental science, reflecting collaborative efforts across disciplines to address complex challenges.

Each node represents a distinct keyword. The frequency with which each term appears in the dataset is reflected in the size of the node. Larger nodes indicate more frequent occurrences. Links between nodes represent the co-occurrence of terms within the same publications; thicker lines denote stronger associations and higher co-occurrence frequency.

The term "machine learning" appears frequently in the network's core, highlighting its vital importance in fisheries management studies. Its numerous connections to other keywords underscore its application across various aspects of the field. The terms "artificial intelligence" and "deep learning" are strongly associated with machine learning, indicating the increasing demand for sophisticated computational methods in fisheries studies.

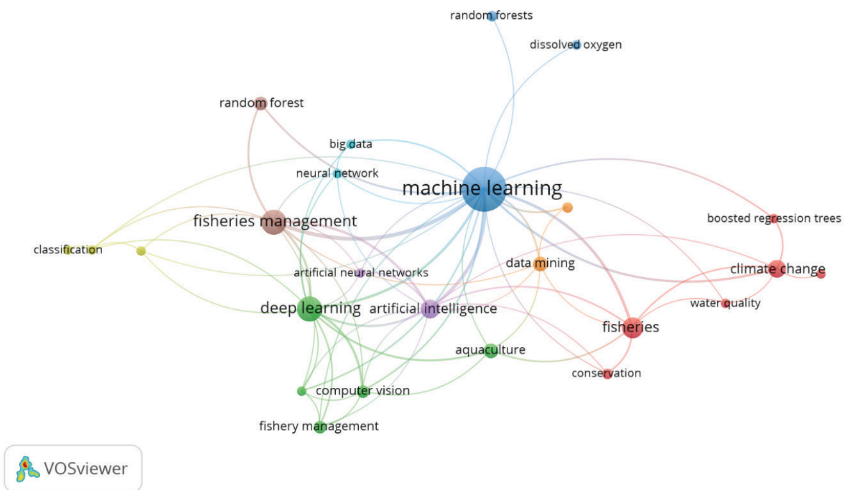

Figure 9: Keyword analysis

The visualisation identifies distinct clusters representing sub-themes within the research domain. The blue cluster includes terms like "machine learning", "data mining", and "dissolved oxygen", emphasising the connection between environmental monitoring and ML applications. The green cluster, featuring the terms "deep learning", "computer vision", "aquaculture", and "fishery management" highlights the application of cutting-edge AI in fisheries and aquaculture management. The red cluster contains terms like "climate change", "water quality", and "boosted regression trees" reflecting a focus on predictive modelling and environmental impacts. The yellow cluster, with keywords such as "classification" and "random forest" illustrates the use of specific ML methods in fisheries research.

Emerging topics are indicated by terms like "big data", "neural network", and "conservation", pointing to future trends, where large datasets and sophisticated algorithms enhance conservation efforts and sustainable fisheries management.

In summary, the network visualisation offers a comprehensive overview of key concepts and their relationships in fisheries management research. It highlights the pivotal role of linked technologies and ML, the multidisciplinary collaborations they enable, and emerging trends shaping the field's future.

Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (LDA) is a topic modelling technique used to identify abstract subjects within a set of documents. In this study, the titles of publications related to ML and fisheries management were analysed using LDA. The resulting topics reveal recurring patterns and thematic areas within the dataset.

The LDA analysis identified five distinct topics, each representing a specific aspect of research in the intersection of machine learning and fisheries management, which are presented in Table 4. The topics are characterised by associated keywords and interpreted to reflect their research focus.

Each LDA-identified topic sheds light on different facets of research within the intersection of ML and fisheries management. These topics help to pinpoint key research themes, trends, and areas of focus, providing a comprehensive overview of how machine learning techniques are being applied to fisheries management.

The ability of LDA to distil large datasets into coherent topics makes it a valuable tool for understanding the research landscape. By

Table 4: LDA-identified topics in the dataset

Topic	Keywords	Interpretation
Topic 1	data, fishing, based, neural, fisheries, convolutional, sea, detection, using, global	Focuses on the use of neural network models, including CNNs, and data in fisheries management. Applications include fish detection and fishing operations, often at a global scale, with emphasis on data-driven decision-making.
Topic 2	learning, machine, fish, using, based, management, data, species, deep, fisheries	Centres on the use of ML in fishing applications, especially on how fisheries and fish species are managed through the application of ML techniques. Terms like "deep" indicate the use of deep learning models to species management and data analysis.
Topic 3	study, approach, fishing, analysis, case, fish, distribution, science, fishery, conservation	Encompasses methodological approaches, case studies, and scientific analyses related to fish distribution and conservation within fisheries research.
Topic 4	fish, shark, ocean, method, prediction, based, bangladesh, freshwater, aquaculture, using	Relates to specific species and marine organisms (e.g., sharks) and predictive modelling techniques. Includes geographic and habitat-specific contexts such as Bangladesh, freshwater systems, oceans, and aquaculture.
Topic 5	species, fisheries, age, using, fishing, model, conservation, management, deep, climate	Concerns fisheries and species management, incorporating conservation and age modelling, with attention to deep-water habitats, climate impacts, and environmental factors.

examining keyword associations, researchers can gain insights into the prevalent methodologies, geographical focuses, and specific species or environments that are of interest within the field. This analysis not only highlights current research trends, but also helps identify potential areas for future investigation, facilitating a deeper understanding of how ML can contribute to effective fisheries management.

Research Gaps and Future Directions in Machine Learning Applications for Fisheries Management

Despite significant advancements in the application of Machine Learning (ML) to fisheries management, several critical research gaps remain. Addressing these gaps is essential for enhancing the effectiveness, scalability, and trustworthiness of ML-driven solutions in this field.

Identified Research Gaps

There are several research gaps, which can be outlined as follows:

(1) Understanding angler behaviour

While predictive models such as XGBoost (Kaemingk *et al*., 2020) have been employed to forecast angler decisions, existing approaches lack insights into the psychological and social factors influencing fish harvest and release behaviours. A deeper understanding of these factors could refine fisheries management strategies.

(2) Data quality and accessibility

The accuracy and generalisability of ML models heavily depend on the quality of input data. However, inconsistent, sparse, or biased datasets remain a major limitation (Xie *et al*., 2023). Ensuring the availability of standardised, high-quality datasets across regions is critical for robust ML applications.

(3) Algorithm transparency and interpretability

The lack of transparency in ML models, particularly those predicting illegal fishing activities, poses challenges for regulatory adoption and stakeholder trust (Watson, 2023). Developing explainable

AI frameworks is necessary to enhance interpretability and compliance with fisheries management policies.

(4) Integration of environmental factors

ML models often fail to incorporate ecological and climatic variables that influence fish stock distribution and population dynamics. Coro *et al*. (2022) highlighted the need for integrating environmental parameters such as temperature, salinity, and ocean currents, into predictive models to improve stock assessments.

(5) Species identification and classification

While ML techniques have demonstrated high accuracy in distinguishing between wild and farmed species (Jafari *et al*., 2022), their application remains limited to a subset of well-studied taxa. Expanding automated identification systems to under-researched species would enhance biodiversity monitoring and conservation efforts.

(6) Longitudinal data analysis

Many existing ML models rely on static datasets, limiting their ability to capture temporal variations in fish populations and habitat conditions. Zhang (2023) emphasised the importance of incorporating time-series and multimodal data to improve adaptive fisheries management.

(7) Socio-economic implications

The economic dimensions of ML applications in fisheries remain underexplored. While Sun and Yang (2023) introduced cost modelling for fishing trips, comprehensive studies linking ML predictions with socio-economic impacts are needed to inform data-driven policymaking.

(8) Interdisciplinary integration

The intersection of ML with fisheries science, environmental economics, and conservation biology remains underdeveloped. Syed and Weber (2018) emphasised that a multidisciplinary approach is crucial for addressing the complex interactions between ecological and economic factors in fisheries management.

Future Research Directions

To advance ML applications in fisheries management, future research should prioritise the following key areas:

(1) Scalability of ML models

Expand ML frameworks to accommodate large-scale fisheries and diverse marine ecosystems, ensuring adaptability across different regulatory and environmental contexts.

(2) Multimodal and local knowledge integration

Combine satellite imagery, sensor data, and traditional ecological knowledge with ML models to improve predictive accuracy and decision-making (Zhang, 2023).

(3) Predictive modelling for environmental factors

Develop ML-driven forecasting models to analyse how environmental changes such as ocean acidification and climate variability affect fish behaviour and habitat suitability (Qiong *et al*., 2024).

(4) Automated vessel and bycatch monitoring

Leverage ML algorithms for real-time vessel detection, bycatch analysis, and compliance monitoring through satellite and video surveillance (Tsuda *et al*., 2023; Prior *et al*., 2023).

(5) Smart aquaculture systems

Enhance automation in aquaculture through ML-based optimisation of feeding regimes, disease prediction, and water quality control to improve sustainability and productivity (Matondang *et al*., 2022).

(6) Economic modelling and policy integration

ML models such as the bidirectional long short-term memory recurrent neural network have demonstrated higher prediction accuracy and stability for forecasting fishery import and export trade data compared with traditional models. This can aid in formulating effective policies and regulations for sustainable fishery development (Sun & Yang, 2023).

(7) Interpretable AI for fisheries management

Develop explainable ML models that provide transparent and justifiable recommendations, facilitating adoption by policymakers and industry stakeholders (Watson, 2023).

(8) Reinforcement learning for adaptive fisheries governance

Explore deep reinforcement learning for dynamic fisheries management, enabling real-time policy adjustments based on changing ecological and economic conditions (Lapeyrolerie *et al*., 2022).

(9) Cross-disciplinary collaborations

Strengthen partnerships between ML researchers, marine biologists, economists, and policymakers to develop holistic, science-driven fisheries management solutions.

The application of machine learning in fisheries management has demonstrated considerable potential, yet critical research gaps persist. Addressing these challenges through interdisciplinary collaboration, scalable data integration, and enhanced model transparency will be essential for advancing sustainable fisheries practices. By incorporating emerging technologies and refining current methodologies, future research can bridge these gaps, paving the way for innovative, effective, and equitable fisheries management solutions.

Conclusions

This study presents a comprehensive bibliometric analysis of Machine Learning (ML) applications in fisheries management from 2010 to 2023, examining key research trends, influential contributors, and emerging themes in the field. The bibliometric findings indicate a growing body of research, with a sharp increase in publications in recent years, reflecting the increasing relevance of ML in fisheries science. The United States, China, and Australia emerge as the most active contributors, with significant international collaborations shaping the advancement of ML-driven fisheries management.

From a bibliographic perspective, this study identified the most cited papers, prolific authors, and influential journals in the domain. Pittman and Brown (2011) stood out as the most cited work, emphasising ML's role in stock assessments and spatial modelling. Leading authors such as Stan Matwin, Fabio Pranovi, and Jose A. Fernandes have contributed multiple high-impact studies, demonstrating strong expertise in fisheries resource modelling and predictive analytics. The top publication sources, including *Frontiers in Marine Science* and *ICES Journal of Marine Science* highlight the interdisciplinary nature of this research field, merging marine science, artificial intelligence, and environmental policy.

Keyword analysis reveals that "machine learning", "fisheries management", and "climate change" are dominant themes, indicating a strong emphasis on sustainability, stock prediction, and environmental impact assessment. However, certain research areas such as interpretable AI, multimodal data integration, and real-time ML applications remain underexplored, representing opportunities for future investigation.

Beyond bibliometric trends, this study also discusses practical implications and case studies, illustrating how ML enhances fisheries management through automated vessel monitoring, fish stock prediction, aquaculture optimisation, and conservation planning. While ML offers significant advancements, challenges such as data quality, model transparency, and stakeholder trust must be addressed for broader adoption in fisheries governance.

This study highlights several critical research gaps that need to be addressed:

- Enhancing ML interpretability to improve stakeholder trust and regulatory acceptance.

- Developing standardised datasets for fisheries monitoring, enabling more robust ML training.
- Integrating socio-economic and environmental factors into ML models for a more holistic approach to fisheries management.
- Expanding ML applications to low-resource regions, ensuring equitable access to technology-driven fisheries solutions.

By addressing these gaps, ML can significantly contribute to the long-term sustainability of global fisheries, supporting evidence-based policy decisions, ecosystem resilience, and improved resource management. This bibliometric analysis serves as a foundational reference for researchers, policymakers, and practitioners, guiding future studies and fostering interdisciplinary collaboration in AI-driven fisheries management. As ML technologies continue to evolve, their role in safeguarding marine biodiversity and optimising fisheries sustainability will become increasingly crucial.

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Conflict of Interest Statement

The authors declare that they have no conflict of interest.

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