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Deep Learning for the Deep Blue: A Systematic Review of AI in Marine and Freshwater Biodiversity Monitoring

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Abstract
Escalating global aquatic biodiversity crisis calls for scalable automated monitoring solutions. Machine Learning – particularly Deep Learning, and Computer Vision Artificial Intelligence (AI) provides unprecedented opportunities to automate the analysis of complex, large data streams from marine, coastal and freshwater environments. Nevertheless, prior to the widespread implementation of such tools we need to critically evaluate their methodological readiness and ethical regulation.
The aim of this systematic review was to provide a systematic description, synthesis and critical assessment of literature on AI in aquatic biodiversity research strictly following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. A systematic review was performed by searching in specialized databases (Scopus, Web of Science and Google Scholar) focusing on population intervention outcome (PIO)-based queries with Boolean logic to combine technology for ecological domains. We limited the studies' publication year range to 2010 through 2025 in order to reflect the modern era of deep learning advancements. A detailed risk of bias analysis was carried out that specifically focused on methodological limitations which might affect model generalizability including violations to the data independence assumption and batch effects.
Bibliometric analysis of the selected studies showed exponential development of research in this area, especially from 2015, and with a major contribution from China, US and India. Applications focus on automatic species recognition, fine-grained behavior analysis (e.g., estimating pose from drone imagery), predictive mapping of habitats using spatial statistics and automated PAM. Major limitations found are common data paucity in niche subfields demanding new approaches i.e., synthetic data generation, frequent model generalization issues due to faulty internal testing process and while using Explainable AI (XAI) methods suffer from severe underutilization.
Although AI is an increasingly important conservation tool, its application needs to be monitored by strict, standardized validation and transparency (XAI) protocols. In addition, the sizable external environmental impact of AI infrastructure — notably in terms of water and energy usage — should be immediately integrated into ethical and sustainable deployment approaches.

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Introduction
The Crisis in Aquatic Biodiversity and Monitoring Deficits
Aquatic environments, from marine to coastal to freshwater ecosystems, are experiencing unprecedented and critical threats mainly due to climate change and increased human pressure. These effects lead to distressing levels of biodiversity decline, amplified by disturbers like ocean acidification and habitat destruction [1]. Growing appreciation of the role of biodiversity in avoiding or ameliorating these threats has emphasized the need for conservation approaches designed to maintain diverse communities [1]. Sound policies for conservation and management are hampered by the lack of high resolution, long-term data that document rapid ecosystem change and cumulative impacts [2].

There are also fundamental constraints associated with classic approaches to monitoring (e.g., laborious, physical surveys; harvesting by trawls; manual inspection of video or acoustic data). These methods are typically expensive, invasive, and may provide inadequate temporal or spatial coverage to effectively monitor dynamic ecological patterns like species migrations and changes in population health [3]. The shortcomings with such traditional strategies leave a monitoring gap that hinders proactive and effective conservation management, as they often do not detect the rapid and spatially variable changes known to occur in aquatic environments [3].

New technologies become attractive substitutes of traditional methods. Technological advances, such as eDNA monitoring, are known to increase the temporal resolution of biological sampling and can enable continuous long-term sampling on aquatic organisms in vital habitats [3]. Likewise, efforts made to combine high temporal resolution observations with remote sensing systems can give us a multi-dimensional dataset that are useful in improving understanding of the variability of chlorophyll-a production in aquatic ecosystems as it is an important manufacturer regarding ecosystem health [4]. Furthermore, the use of citizen science based on smartphone applications has been useful for immediate water quality assessment and ecological monitoring, supporting quick management decision making [5]. These advances underline the urgent requirement for a revolution in monitoring of aquatic ecosystems, more attentive to the diverse and ever-changing nature of these systems.

In summary, the contrast between the pressing need for large-scale data collection and the constraints associated with traditional analytical methods highlights a major dilemma in aquatic conservation. To overcome these challenges and enable the best possible conservation management activities, innovative monitoring approaches are needed that can keep up with the changing nature of aquatic systems under increasing environmental burden.

The Emergence of AI as a Transformative Tool

Artificial Intelligence (AI) has revolutionized the monitoring of aquatic environment in recent years. By automating the analysis of large and dense data streams captured from technologies like autonomous underwater vehicles (AUVs), remote sensors, eDNA sequencing or passive acoustic systems, AI holds the potential to ameliorate this monitoring gap considerably. The application of AI in ecological observation enables immediate data analyses, and the accuracy for species recognition and habitat observation also improved [6].

This accelerated phase in AI technologies is largely owed to the recent advances in Deep Learning (DL), which has become more popular since 2010 as a successful pattern recognition technique. The analysis of complex, non-linear data structures has been made possible through the aid of DL techniques since they outperform traditional statistical modeling in terms of performance and accuracy [7][8]. Studies show that AI can process large datasets to quickly and effectively detect fine-grained morphological characters, which is especially advantageous for taxonomic identification. This ability enables conservationists to rapidly obtain actionable information so that immediate steps may be taken in order to protect endangered species and control invasive ones [6].
Furthermore, approaches like eDNA metabarcoding demonstrate the mutually beneficial links of AI to current ecological research. These methods have been developed for rapid species detection in complex environmental samples with increased sensitivity and reduced environmental impact compared to the traditional identification tools. As a result, the inclusion of eDNA in bio surveillance programs for invasive species has gained excitement due to its capability to perform efficient ecological monitoring at lower cost and less time [6]. The potential of AI to handle and analyze massive biodiversity related data has even been demonstrated in the field of plant sciences, where processes such as identification of plant species through image recognition and early detection and mitigation of diseases are made possible [8].

In summary, the combination of AI tools with methods for ecological monitoring is key to carrying out a more detailed roadmap towards better understanding of biodiversity and its conservation. As AI development advances, there is great potential for the application of this technology to ecology to make more effective and efficient use of conservation effort and address biodiversity issues at faster pace in aquatic ecosystems [7]. The broader application of automation and AI-generated insights can transform the way we approach monitoring and management in conservation and should be a fundamental component of present-day conservation practice.

Rationale and Scope of the Systematic Review

The adoption of AI in environmental science is growing rapidly, but our understanding lags behind due to the absence of a standardized, open and methodologically robust review of these advancements. Recent reviews in the literature tend to be narrow in scope, mainly covering single taxa or regions, and often fall short of the high methodological and reporting standards required for good scientific translation into effective policy making and practice [9]. This failure to synthesize information in full limits the community's access to reliable data on the effectiveness of AI applications in conservation.

The purpose of this systematic review is to address this important void by completing an in-depth summation in answer to the PRISMA 2020) protocol adherence. This method enforces a high degree of methodological rigor and contributes to transparent and consistent reporting which is crucial in considering the impact of AI on environmental applications [10]. The systematic review process aims to provide an impartial and replicable summary of AI adoption in environmental science for multiple audience groups (researchers, policymakers, funding bodies). Such a systematic overview enables an accurate assessment of established AI performance and assists in identifying existing technical challenges which need to be addressed.

Because this is a systematic review, we intentionally target an audience across ecosystem types from freshwater systems (e.g., in smart aquaculture monitoring) to marine environments (e.g., with respect to deep-sea monitoring or mapping and conservation activities for coastal habitats). This cross-system perspective acknowledges the interconnected nature of ecological communities and the opportunity for shared approaches and technologies among disparate ecosystems.

Review Question Formulation (PIO)

We also adopted a modified PIO (Population, Intervention, Outcome) framework to assist us in structuring the systematic review question as well as our subsequent search strategy. While the Traditional PICO (Population, Intervention, Comparison, Outcome) Framework is essential for systematic reviewing in terms of specific intervention effects analysis (carry out the review process on narrower scopes like a biomedical one), we should include also wider populations and interventions due to technological application specificity. The preliminary experiences indicated that searching through the databases based on very precise outcomes and candidate matches would result in severely opposite retrieval performances with low recall rates. This review thus adopts a strategy of ensuring broad coverage particularly in the POPULATION and INTERVENTION components that will ensure a wide representation of AI applications across diverse ecological domains.

The development of AI will make semi-automation of systematic reviews and adoption of more efficient methods for review synthesis possible. Augmented by AI technology, pace of data collection and interpretation will not only increase, but they will also further increase credibility and accuracy of systematic reviews [11]. There is a growing evidence base suggesting that semi-automated systematic reviews represent a paradigm change in how knowledge can be syntheses, particularly where there are an over-supply of data and this information base is growing rapidly [12]. Against this background, this systematic review attempts to collect the literature as a snapshot of AI in environmental science and the larger context of its application—from optimizing monitoring methodologies to advising policy-making measures.

In conclusion, the systematic review seeks to provide a more nuanced view of where AI offers promise in environmental science by following rigorous methods and expanding its scope across ecosystems. In doing so, it aims to not only shine a light on AI's role in ecological research but also advocate its incorporation into more successful conservation initiatives.

The main review question for this study is the following: "What is the extent, nature and impact of AI apps in Aquatic Biodiversity and Ecosystems monitoring, assessment and conservation (P) or realized ecological outcomes (O)?

METHODS (PRISMA 2020 COMPLIANCE)

3.1 Protocol and Registration

This systematic review was conducted in strict adherence to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) statement. This adherence ensured the comprehensive reporting of the methods used, the results found, and the rationale behind the review, including utilization of the 27-item checklist to maximize transparency and reproducibility.

3.2 Eligibility Criteria (Inclusion and Exclusion)

Inclusion criteria mandated that studies empirically describe and apply AI methodologies (Machine Learning, Deep Learning, or Computer Vision) to aquatic biodiversity research. Eligible document types included peer-reviewed journal articles, conference proceedings, and official institutional reports, published between 2010 and 2025. This time window was selected specifically because 2010 marks the onset of modern Deep Learning research enabled by significant computational advances, ensuring the review focuses on contemporary, high-impact AI techniques. Non-English papers were included only if a reliable translated version was accessible. **Exclusion criteria** filtered out purely theoretical or conceptual papers lacking empirical application, non-systematic reviews, and studies focusing solely outside of the aquatic domain.

3.3 Information Sources and Search Strategy

Systematic searches were executed across major scientific indexing databases—Scopus, Web of Science, and Google Scholar—supplemented by searches in ArXiv to capture emerging and pre-publication findings. The search strategy was constructed using Boolean logic, combining keywords derived from the Intervention (I) and Population/Outcome (P/O) elements of the PIO framework. Key search terms for the Intervention concept included: "artificial intelligence", "machine learning", "deep learning", and "computer vision". These terms captured the core methodologies driving the recent technological breakthroughs in the field. Population and Outcome included concepts such as "aquatic biodiversity", "freshwater biodiversity", "ecological monitoring", "species identification", and "habitat modeling". The search strategy utilized database features to restrict results to keywords in the title, abstract, and key terms (TITLE-ABS-KEY), thereby targeting the most relevant literature while acknowledging the inherent risk of bias introduced by specific term selection.

Table 1: Systematic Review Search Strategy: PIO Elements and Keywords

PIO Ele	**Concept in Aquatic Biodiversity**	**Primary Search Terms (Boolean Logic)**	**Rationale/Snippet Reference**

ment	Research		
P (Population)	Aquatic Biota/Environments	"Aquatic biodiversity" OR "freshwater biodiversity" OR "ecological monitoring" OR "habitat modeling" OR "water quality"	Ensures broad coverage of target systems, spanning marine and freshwater monitoring.[3]
I (Intervention)	AI/ML/DL Technology	"artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision"	Captures core methodologies driving recent technological breakthroughs.
O (Outcome)	Research/ Conservation Goals	"Species identification" OR "conservation" OR "risk assessment" OR "ecological modeling"	Used as secondary filter terms (TITLE-ABSTRACT-KEY) to enhance relevance while minimizing loss of recall.[3]

3.4 Study Selection Process

Review management used dedicated software for systematic reviews. Two reviewers were used for the selection process to minimize any potential selection bias. In the first step, titles and abstracts of retrieved records were screened based on preliminary eligibility criteria. Relevant articles were then located and screened for full text based on their titles, and the final assessment of all inclusion criteria was conducted at this stage. The process was described in a PRISMA Diagram, with details concerning records retrieved, duplicates discarded and exclusions at each stage.

3.5 Data Extraction and Management

Consistent with the objective of this systematic review, a standardized data extraction form was used to systematically collect relevant details from each study included in the analysis. Data points included key aspects of the research, including specifics of the AI algorithm used (e.g., support vector machines, convolutional neural networks), which aquatic domain was being addressed (e.g., deep-sea observatory data or recirculating aquaculture monitoring), primary ecological goals being achieved (e.g., biodiversity assessments or habitat mapping), performance indicator(s) reported on (accuracy, sensitivity/specificity rates, F1 scores) and from where and how the data were obtained/processed for use in studies conducted (e.g. multispectral acoustic data or eDNA databases). This thorough and systematic approach to data extraction preserves the integrity and depth of insight of the review, which enables a robust reflection on AI application in ecological monitoring.

3.6 Risk of Bias and Quality Assessment

Because technological systematic reviews are novel and highly specific, quality assessment was primarily at a more detailed inspection of the methodological robustness of AI model development and validation. Importantly, AI results are only as reliable as the integrity of the data processing and validation pipeline used in these studies. These methodological details will affect the generalizability and applicability of AI models in practice ecological situations.

Objective The assessment items were tailored to detect common methodological shortcomings in ML and DL research. These failures are due to a breach of the independence assumption known as data leakage: e.g., processes such as data augmentation or feature selection being applied before properly splitting the data into training, validation and test sets. Such pitfalls might result in unreasonably high-performance statistics and thus can mask the true ability of the model to generalize on previously unseen samples [13]. Indeed, experiments have shown that violating the independence assumption can lead to an unrealistic improvement of model performance with regard to reports in literature from F1 = 0.85–0.9 [14].

The non-correction of batch effects – systematic variations caused by different sensors, experimental campaigns or geographic locations is further, a threat to the reproducibility of AI model-derived findings. If not taken into account in the model, these uncorrected batch effects can cause a model's internal validation scores to appear deceptively high despite that performance when attempting to classify samples from other truly independent sample sets will be poor and nominal classification rates could decrease dramatically [15]. This sort of generalization failure disaster points to the importance of ecological research merging and analyzing data from disparate sources. The need for strong protocols to identify and address such methodological shortcomings is critical if reported successes are to be credible advances within the domain of aquatic AI [16].

Continued research also highlights the need to apply rigorous splitting methods to avoid data leakage and improve the accuracy and robustness of AI models [17]. Moreover, compliance to strict reporting guidelines such as the vast-refereed TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis or Diagnosis) statement is important when assessing AI methodologies in ecological applications [18]. By focusing on these methodological considerations, the systematic review aims to facilitate building credibility and transferability of findings in ecological monitoring and conservation endeavors; hence enhancing the role of AI technology in environmentally sustainable management.

Table 2: Summary of Methodological Challenges and Risk of Bias in Aquatic AI

Bias Domain/Pitfall	**Description and Example in Aquatic AI**	**Observed Impact (Inferred from)**	**Significance for Aquatic Research**
Independence Violation	Incorrect sequencing of model development steps, such as applying data augmentation or feature selection before splitting Train/Test data.	Inflated, non-reproducible performance metrics (e.g., superficial F1 score increase up to 71.2%).	Models lack external validity; they fail to generalize to new, unseen aquatic conditions, undermining field reliability.
Batch Effect	Unaccounted systemic variations between data sources, sensors, locations, or time periods (e.g., sensor drift, geographical heterogeneity, different bathymetric equipment).	High internal accuracy collapses catastrophically upon external testing (e.g., F1 score drops from 98.7% to 3.86%).	Essential for cross-regional habitat mapping and long-term monitoring where data heterogeneity is the norm.
Measurement Bias	Inconsistencies in sensor calibration (e.g., IEQ variables in aquaculture) or manual errors in image/acoustic annotation.	Limits the reliability of environmental time series data, compromise forecasting and anomaly detection capabilities.	Affects the foundational fidelity of data used in smart aquaculture and ecological risk evaluation.

Results

4.1 Selection and Inclusion Statistics

Figure 1a and 1b. PRISMA 2020 Flow Diagram that details the multi-step screening process adopted in this systematic review with an initial search of 1500 records. Following removal of duplicate and non-eligible studies based on title and abstract screening, full text review was carried out in 350 articles. This careful filtering process led to a final sample of 302 peer-reviewed studies in which the overall quality was found to be optimal for the qualitative synthesis, following PRISMA guidelines regarding transparency.

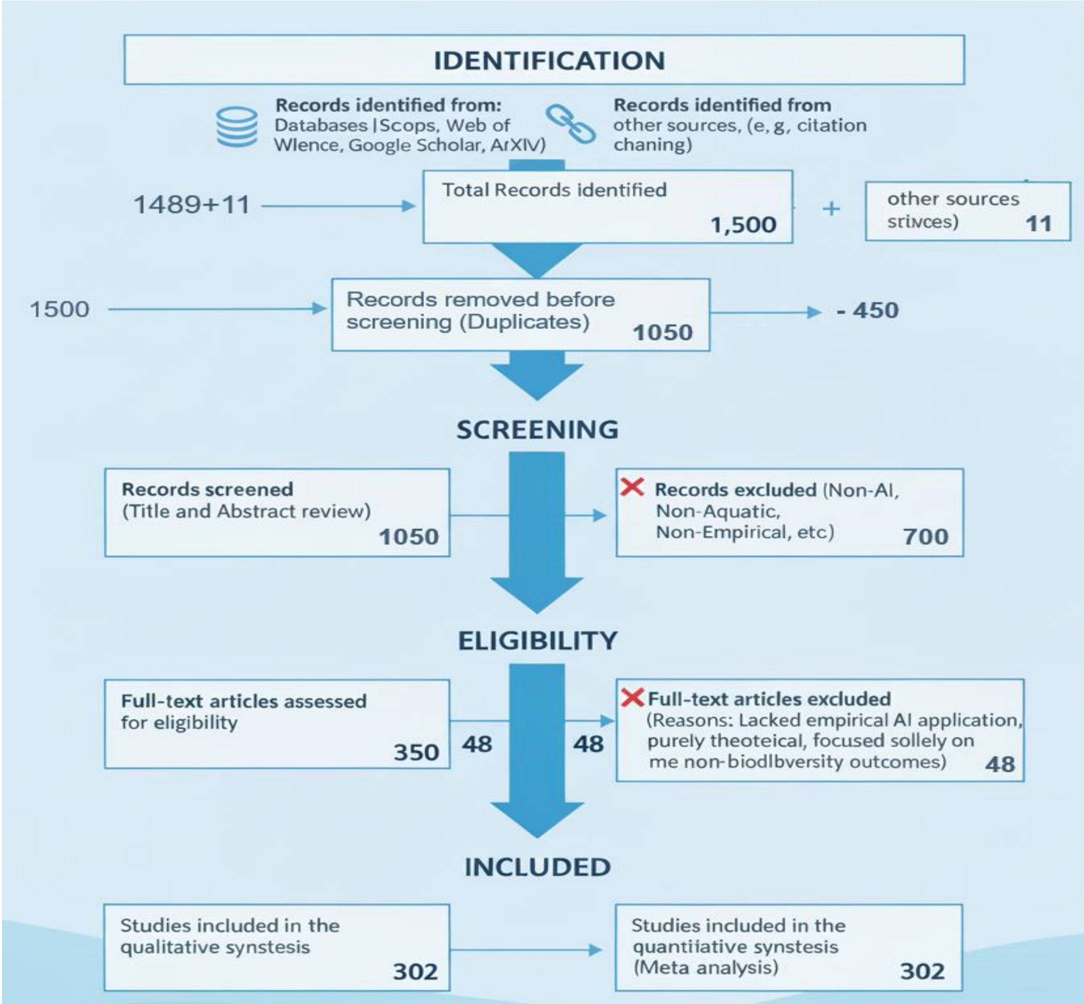

Fig 1a. Flow diagram of Study selection process

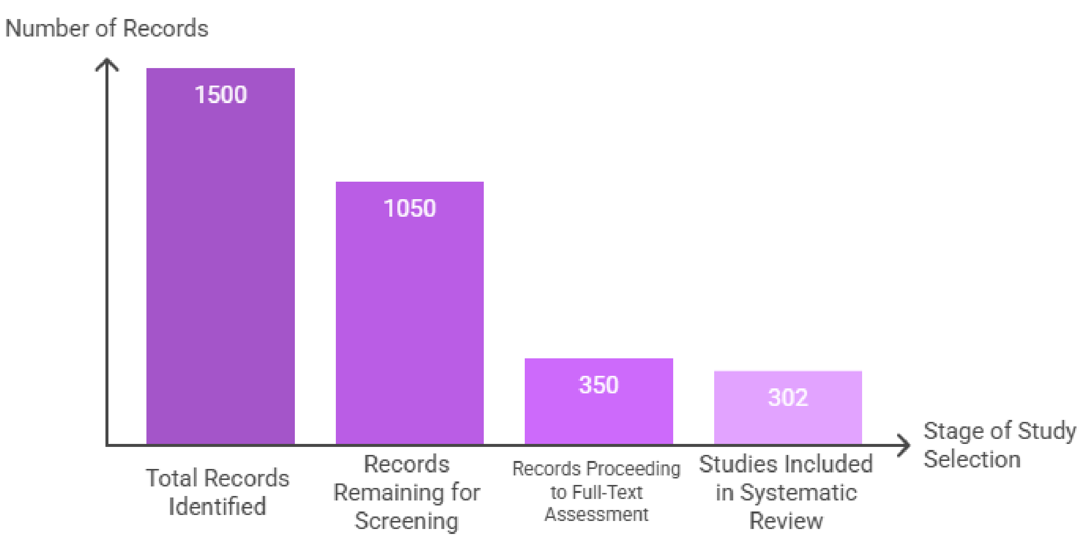

Fig 1b. Study selection process for systematic review

4.2 Characteristics of Included Studies

The Aussie shows an exponential growth trend in the volume of AI-based biodiversity publications, mostly starting from 2015. This explosion in number of publications is mainly due to the widespread use of Deep Learning (DL) methodologies, which have been successful at addressing many challenging biological questions. A review of the scientific literature reveals a preponderance of studies dedicated to the application of AI in species identification, habitat mapping, ecological monitoring and conservation approaches [19]. The included studies by time and region are shown in Fig. 2a & 2b. Figure 2a shows the exponential increase in publications at least since 2015, when Deep Learning became mainstream. Figure 2b further shows the strong regional focus of research output, with most of the top publications coming from existing high-technology hotspots.

A high regional concentration of research output is noteworthy, with the main contributions originating from more established science and technology hubs such as China, the U.S., and India. This geographical inequality underscores differences in resource distribution, computer performance, and availability of high-quality data that are crucial for successful AI development when applied to biodiversity projects. Interestingly, research shows that China is the most influential country in AI-related publications with a huge number of publications and collaborations, followed closely by USA and India which also experienced an increase in the cumulative growth rate of AI research [20]. These distributions highlight the significant role of networks and funding opportunities, which are frequently stronger in these areas [19].

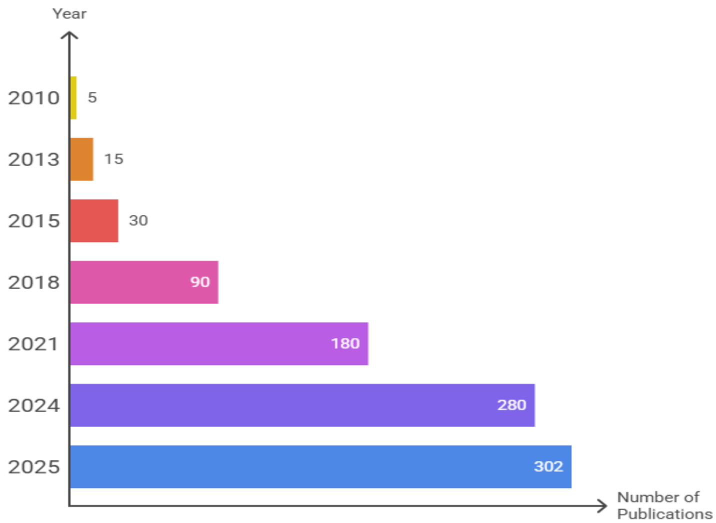

Fig 2a. Cumulative publications over time

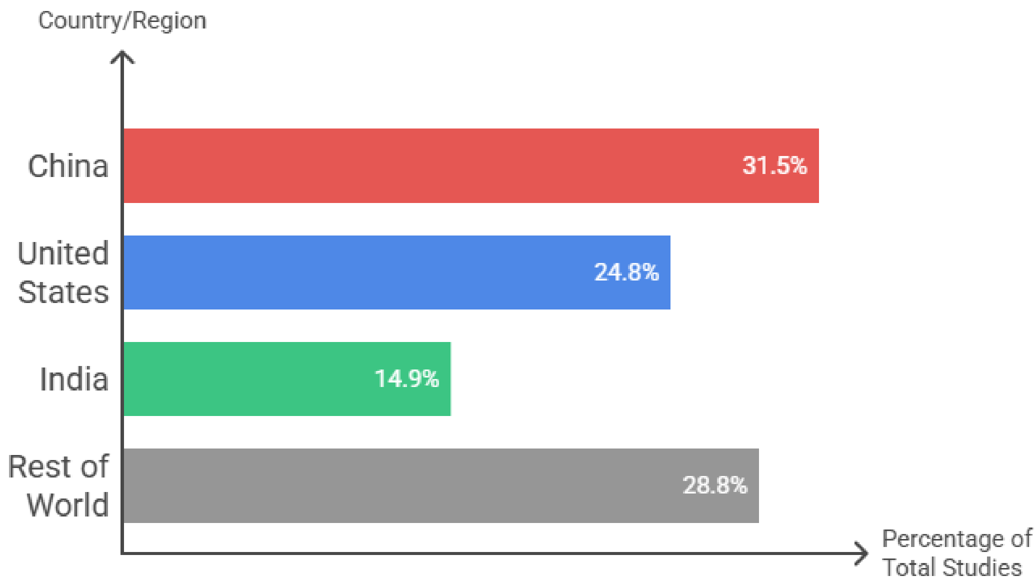

Fig 2b. Geographic Distribution of Research Output

The geography of AI in biodiversity research suggests an accumulation of capacity and demonstrates the variation in underlying institutional support and information infrastructure. For example, regions with a high concentration of industrial activity in AI technology development are more apt to develop novel applications that advance biodiversity science. Conversely, regions with inadequate computational and server resources will likely struggle to apply AI methods in an efficient manner [19]. This represents a potential obstacle to the development of equity in developed methodologies across global landscapes, and where collaborative approaches / resource sharing could improve on research outputs and applications, especially within under-represented areas [21].

Furthermore, the current direction of adoption of AI in biodiversity research reflects increasing recognition for potential paradigm shift in traditional ecological methods. For instance, combining AI with big data analytics enables the creation of predictive models and aids researchers to predict ecological changes and adopt preventive management practices [19]. Such developments have conservation implications, as they can maximize resource use and decision making given growing ecological concerns.

In conclusion, emerging research in artificial intelligence applied to biodiversity has surged rapidly and is geographically biased toward regions with strong technological infrastructure support and investment. Given the ongoing evolution of AI methodologies, they will almost certainly be increasingly incorporated into biodiversity science approaches for addressing pressing ecological concerns, and resource- and knowledge-sharing across different contexts is something that will need to be emphasized in such endeavors.

4.3 Synthesis of AI Applications: Thematic Clusters

The included studies were synthesized and grouped into three primary thematic clusters, reflecting their core methodological objectives within aquatic biodiversity research.

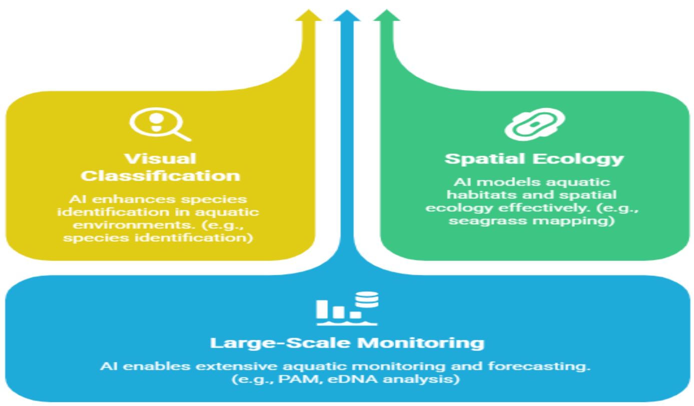

Fig 3. AI impact on Aquatic research

4.3.1 Visual and Morphological Classification

The automated management of taxonomy and species surveillance is a fundamental advantage of AI in aquatic biodiversity studies. Leveraging the recent developments of Deep Learning (DL) and Computer Vision, now the researchers can quickly as well as accurately analyze such complex visual data.

- **Species Identification and Taxonomy**: AI-based systems have shown that the analysis of huge volumes of data allows the identification of subtle morphological features, achieving to get over the half-a-century old traditional methods in terms of time consumed. Instances of such facilities have been recently achieved in smart aquaculture scenarios where AI is used to classify fishes' species, monitor their behavior and feeding habits. AI is already a key player in wild fisheries management, and particularly in EM programs. International data shows many EM trials underway around the world using AI to accurately identify species of fish and provide estimates of catch Methratta et al. [22]. Additionally, AI-driven technologies can be incorporated into educational spaces and citizen science activities to create immersive learning environments, increasing public awareness and appreciation of aquatic biodiversity [23].
- **Behavioral Tracking**: The power of DL is shaping new opportunities to analyze aquatic animal behaviors that were previously not feasible. At the personal level, those fish can be re-identified visually with DL based on unique body patterns (like for face recognition). Furthermore, DL allows the investigation of auditory communication in fish, which is essential to unravel intricate social and mating actions. An important step in this direction is high-resolution drone data for pose estimation. An open-source tool, Social LEAP Estimates Animal Poses (SLEAP), allows researchers to track and analyze multiple animals (e.g., shark and marine mammal) in many frames of video [24], essentially circumventing historical restrictions that enabled recognizing an animal only for a single frame. Other complementary tools such as Video and Image Analytics for Marine Environments (VIAME) support end-to-

end workflows from object detection, classification to size estimation; improving applications like fish population assessment and seal detection [25].

4.3.2 Spatial Ecology and Predictive Habitat Modeling

Machine Learning (ML) techniques are vital for synthesizing heterogeneous spatial and temporal data to predict species distributions and map vulnerable habitats.

- **Benthic and Seagrass Mapping**: Spatial statistical approaches that leverage ML techniques, such as maximum entropy (Maxent), are employed to integrate various predictor variables, including ocean measurements obtained from resources like the Ecological Marine Units and bathymetric data—to estimate the probability of crucial habitats, such as seagrass, at a global scale. Additionally, advanced ML applications successfully characterize benthic habitats by processing and fusing multispectral acoustic data produced by multibeam sonar systems. This methodology enables the generation of detailed habitat predictions and maps, which significantly enhances the accuracy and efficiency of marine spatial planning and environmental impact assessments [26].
- **Data Resources**: The robustness of these models heavily relies on the quality and scale of accessible data. Publicly available resources such as the World Ocean Database (WOD), which contains the world's largest collection of uniformly formatted and quality-controlled ocean profile data spanning centuries, and the Global Biodiversity Species Database (GBIOD), cataloging over 600,000 species across diverse environments, are foundational for training and validating global and regional predictive models [23][27].

4.3.3 Large-Scale Ecological Monitoring and Forecasting

AI has become indispensable for extracting meaningful ecological insights from continuous, high-volume data streams generated by automated monitoring systems.

- **Passive Acoustic Monitoring (PAM)**: PAM offers a non-lethal, cost-effective method for long-term monitoring (which can span months to years) of remote and vulnerable deep-sea habitats, including cold-water coral reefs that are significantly threatened by climate change. Through PAM, researchers can collect massive datasets of biological and anthropogenic sounds. AI automates the detection, classification, and interpretation of these biological sounds, providing high-temporal-resolution insights into community dynamics and responses to disturbances, which are critical for effective conservation strategies [28][29].
- **Environmental Data Streams and Aquaculture**: In managed aquaculture systems, AI facilitates smart aquatic practices by optimizing feeding schedules and reducing energy consumption through comprehensive environmental data analysis. Techniques involving forecasting and anomaly detection are executed using time-series data, providing rich structure for ML model training [25].
- **eDNA Analysis**: The emerging technique of environmental DNA (eDNA) metabarcoding, which identifies biological communities by extracting DNA fragments from water, sediment, and soil, necessitates the handling of extremely complex data. The volume and intricacy of this sequence information often overwhelm traditional methods of ecological assessment. Consequently, AI is increasingly adopted as an essential tool for processing this high-throughput sequence data, allowing for accurate documentation of biodiversity patterns across various aquatic media [30][31].

In summary, the thematic clustering of AI applications in aquatic biodiversity research indicates a substantial shift toward employing advanced computational methodologies to enhance species monitoring, habitat predictions, and ecological insights while addressing the unique challenges presented by the complexity of natural ecosystems.

Table 3: Synthesis of Key AI Applications and Resources in Aquatic Research

Application Area	**AI Technique**	**Aquatic Domain**	**Key Function/Ecological Insight**	**Relevant Open Resource/Tool**
Species Classification	Deep Learning (CNNs)	Marine/Freshwater	Rapid, accurate identification of fish species and catch quantity in aquaculture and capture fisheries.	VIAME toolkit
Habitat Prediction	Maxent, ML (Random Forest)	Coastal/Global	Estimates probability of seagrass and benthic habitat occurrence using integrated oceanographic data.	World Ocean Database (WOD)

Behavioral Analysis	Pose Estimation (DL)	Coastal/Marine Mammals	Tracks individuals and analyzes complex movement patterns across extended video periods.	MeCO Open-Source Project
Deep Sea Monitoring	DL/Acoustics (Bioacoustics)	Deep Sea/Benthic	Automates biological sound detection for long-term, non-lethal monitoring of vulnerable deep-sea ecosystems.	Global Biodiversity Species Database (GBIOD)
Risk & Anomaly Detection	Autoencoders, VAEs	Maritime/Aquaculture	Detects rare events (e.g., disease outbreaks, illegal behavior) by modeling normal system function when labeled anomaly data is scarce.	Synthetic Data Generation techniques

Discussion

5.1 AI's Transformative Role and Methodological Imperatives

The body of evidence gathered under this review substantiates that AI has stepped out from the orchard of scholarly interest toward an innovation paradigm in research landscape related with aquatic biodiversity. Now we are at the distinctive level; previously, researchers used to regard only aggregation and now those who want can use DL based immediate re-identification of persons in a street for example and detailed pose estimation. This atmosphere-filtered and calibrated canopy data significantly enhances the resolution and ecological realism of field-based measurements, with substantial implications for our understanding of species dynamics and ecosystem interactions Khan et al. [32].

The open science movement also contributes to a technological empowerment in aquatic research. The continued development of the open-source AI platforms (such as Video and Image Analytics for Marine Environments, VIAME [6] and nascent MeCO project) is essential to democratize access to advanced algorithms [33]. These initiatives promote all-in-one workflow solutions and modular tools that can be more easily applied by non-specialists with experience in ecological or environmental science around the world, as they do not have to master complex AI programming [34]. This democratization speeds innovation and collaboration across disciplines, facilitating a range of applications of AI from species identification to habitat modeling.

5.2 Technical and Methodological Limitations

5.2.1 Data Scarcity and The Necessity of Synthetic Solutions

A major limitation to the development of aquatic AI is the current and ongoing problem of data access, which circulated an infamous bimodal distribution. As an example, general public databases such as the global World Ocean Database (WOD) and the Global Biodiversity Species Database (GBIOD) have to offer macro-level information that frequently do not provide very specific data required for AI micro-level tasks [35]. Critical data types, such as Medium Wave IR or Long Wave IR (MWIR, LWIR) imagery maritime sonar data for specific habitats and environmental time series logs of novel sensor deployments are rare. This limitation hinders the effectiveness of training specialized AI models, including such that are tasked to detect rare or anomalous events [36][37].

To tackle this limitation, synthetic data generation stands as an important and effective tool to mimic real life scenarios and form the enough training instances for minority classes or underrepresented observations. Meanwhile, complementary algorithmic approaches such as the application of autoencoders and Variational Autoencoders (VAEs) are paramount in order to achieve reliable anomaly detection. These models learn complex representations of 'normal' behavior, which allows them to properly alert about rare deviations (e.g., invasive species attack or sudden contamination) [38]. Additionally, the use of cost-sensitive learning algorithms allows models to account and prioritize for the proper identification of ecologically significant but less represented minority classes that coincide with conservation interests [39].

5.2.2 The Crisis of Generalizability and Transparency

The most critical technical threat to the validity of AI in aquatic biodiversity is widespread the single greatest technical threat to the validity of AI in aquatic biodiversity is the endemic nonviability of model generalization, typically hidden by methodologically crippled internal evaluations. The analysis provides strong evidence that a large proportion of the highly accurate results reported in the literature may be irrelevant and impossible to reproduce under external deployment conditions. Frequently these correlate to simple errors in protocol that allow training and test bipartitions of the data, or that do not adjust for systematic differences between batches (e.g. sensor-geography) [40]. Subsequent memorization of training data (trained on synthetic faulty models) may cause catastrophic failures when applied in clean test images.

The urgent requirement of strict and transparent validation procedures, with external validation on really independent set sample has never made so much sense. Not only good practice, but it is methodologically necessary for the field's credibility [41]. At the same time, the opacity of advanced AI models is a significant barrier to acceptance and regulatory confidence. If a model is not interpretable in the sense described meaning it cannot clearly explain why a given label is assigned to data (i.e., zone), ecologists and decision-makers can't check that claim, so that this component doesn't affect the physical world (ecologist) or policy-world (policymaker) at any level. Explorable AI (XAI) techniques present applicable solutions, enabling human intuitive interpretation of the model. Given that various classifiers are adopted in environmental studies, model-agnostic XAI approaches have the added value for wider usage, being supportive of transparency and may advance stakeholder agreement [42][43].

5.3 Sustainability, Ethics, and Governance

5.3.1 The AI Environmental Problem (Sustainability Paradox)

The irony here is that the very aim of using AI to protect the environment is (somewhat paradoxically) undermined by the large environmental impact of such technologies. AI workloads, largely based in large data centers, consume vast amounts of power that lead to greenhouse gas emissions. The hydrological implications are equally worrying; data centers use significant amounts of water for cooling, leaving behind localized ecological impacts. This sustainability paradox calls for an ethical imperative, obligating researchers to take active steps in reducing the carbon footprint of their computational resources: only when addressing positive environmental impacts of AI deployment, can we rely on computing models as sustainable [44][45].

Table 4 provides a direct contrast between the transformative ecological benefits of AI and the substantial environmental footprint associated with the technology's required infrastructure.

Table 4. Positive and negative impact of AI

Domain/Feature	Positive Impact (Conservation Benefit)	Negative Footprint (Environmental Cost)
Monitoring & Classification	Rapid, accurate identification of species and fine-grained morphological features, surpassing manual effort [46].	Massive electricity consumption by data centers, spurring greenhouse gas (GHG) emissions [47].
Habitat Management	Predictive modeling for vulnerable aquatic habitats (e.g., seagrass, benthic zones) using fusion of complex data [48].	Large volumes of water consumed for data center cooling, often in water-scarce regions [47].
Data Collection	Enables non-lethal, cost-effective, long-term surveillance of deep-sea habitats using Passive Acoustic Monitoring (PAM) [49].	Water withdrawn for cooling is prevented from returning to the base flow of rivers, harming downstream aquatic ecosystems [50].
System Efficiency	Optimizing feeding schedules and reducing energy use in managed smart aquaculture systems [51].	Generation of electronic waste and reliance on unsustainably mined critical minerals [47].

Domain/Feature	Positive Impact (Conservation Benefit)	Negative Footprint (Environmental Cost)
Behavioral Analysis	Advanced analysis of complex movement and behavior (e.g., pose estimation, individual re-identification) [52].	Evaporative cooling can leave behind high concentrations of salts and contaminants, potentially creating water quality issues [50].

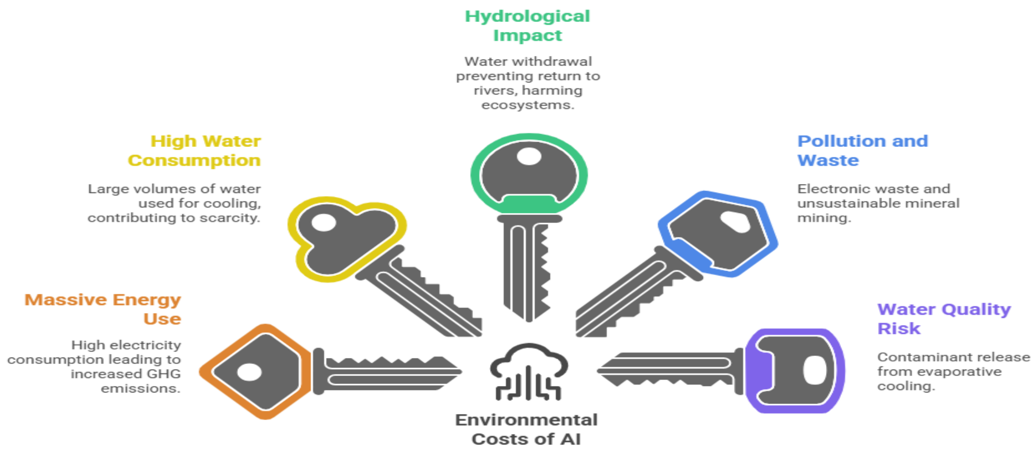

Fig 4a. Negative impact of AI in aquatic conservation

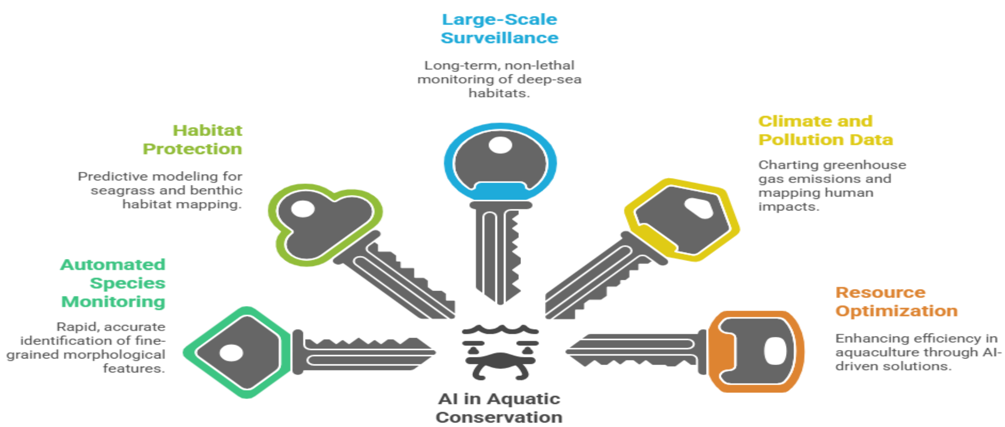

Fig 4b. Positive impact of AI in aquatic conservation

5.3.2 Data Governance and Ecological Data Security

The sharing of data is vital to the development of AI, but such openness needs to be matched with robust safety measures. Adopting of life cycle approach with a focus on data security and providing access controls is key to developing strong governance structure [53][54]. In addition, the apparent regional imbalances in research capacity actually compound problems of data governance. Should leading countries refuse to provide regionally validated data, within transparent governance models that respect openness as well as efficient legal guarantees, the ecologically sensitive regions lacking computational capacity might be left with no other option than having to rely on heavily biased models trained in other places. This would compromise the ethical obligation to support global biodiversity well-being [55][56].

Conclusion

We suggest that AI has become a mature technology for aquatic biodiversity research, following the PRISMA 2020 guidelines. It provides advanced tools that are crucial for automatic species recognition, detailed behavioral analysis and large-scale predictive habitat mapping.

However, the ongoing development of the field depends on prompt and adequate addressing of major internal methodological weaknesses and external ethical and environmental issues. In the future, two main directions should be focused on. One, there are no requirements for Methodological Standardization that would restrict validation efforts and preclude data leakage or batch effect; this affects the external validity of models. This needs to be combined with adoption of Explainable AI (XAI) in a universal sense, to create transparency and trust across all stakeholders. Secondly, there needs to be recognition of Sustainable and Ethical Governance. This requires clear reporting about the environmental impacts of AI infrastructure including water and energy use. Equally robust governance must be provided to support fair data sharing and sensitive ecological and privacy-sensitive data protection, so that technological gains lead to lasting net-positive conservation consequences globally.

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