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Smart Ocean: A Comprehensive Review of Artificial Intelligence-Driven Ocean Monitoring, Forecasting, Exploration and Conservation

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Abstract

Tackling the unprecedented challenges faced by oceans due to pollution, climate change, and over-exploitation requires sustainable solutions for monitoring, predicting, and conserving marine resources. The emergence of artificial intelligence (AI) plays a pivotal role in advancing marine science and research, enabling efficient extraction of valuable information to aid in policy formulation. This systematic review assesses the role of AI transformation to address the crucial challenges arised in ocean resource exploration, conservation and monitoring. This review identifies four shortcomings in real-world implementation such as biases of geographical data, over-reliance on synthetic datasets, computational constraints, gaps in model interpretability. To address the geographic biases, it is required to have benchmark datasets on diverse marine ecosystems. The integration of AI development reveals that illegal fishing detection can be detected successfully with 99% precision, the coral reef can be mapped with 80% accuracy, the ship fuel can be saved about 6.64% with optimization using reinforcement learning (RL). This review thoroughly highlights AI-based technology methodologies relevant to selecting suitable techniques for specific applications in marine resource management. By analyzing past studies, this work identifies research gaps to explore in future studies, including availability of data, model interpretability, ethical risks, and cost effectiveness. A three-tiered action framework has been proposed in this review: international data-sharing protocol establishment, marine AI system standard certification and multidisciplinary innovations hub creation to mitigate the gap between conventional and AI approach.

Keywords: Blue Economy, Security, Climate Change, Artificial Intelligence, Ocean Sustainability, Marine Conservation, Deep Learning, Illegal Fishing, Microplastics, Autonomous Systems.

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Introduction

Around 71% of the Earth's surface is covered by oceans (Balliett, 2014), which play a vital role in global ecosystems, human livelihoods, and climate regulation. Problems such as pollution, climate change, unsustainable exploitation of marine resources, overfishing, and the destruction of marine habitats pose serious threats to ocean environments and their ecosystems (Crain et al., 2009). As future economic development will heavily depend on marine resources, it is critical to manage these resources effectively. Using traditional methods to explore open ocean resources could disturb the future balance of these resources. In addition, these methods are labor intensive and require substantial time (Levin et al., 2019) to perform research or surveys at sea. Additionally, due to a lack of proper guidance, such explorations lack efficiency in speed and scale (Levin et al., 2019). In Bangladesh, substantial funds are allocated to marine research, yet researchers face difficulties in accurately portraying our marine resources due to insufficient technology integration (Liza et al., 2025). AI-driven technologies offer solutions by improving efficiency in marine resource exploration on a large scale and accelerating processes (Taroual et al., 2025). For example, India has initiated the "Deep Ocean Mission" (Kaur & Chopra, 2025) to foster its ocean-based economy, aiming to mine ocean minerals, address climate change impacts, protect ocean ecosystems, monitor deep-sea conditions, generate power, desalinate water, and enhance coastal biodiversity centers through AI innovations. In Bangladesh, the implementation of these technologies could positively impact the national economy (Liza et al., 2025). AI-based image processing and machine learning enable easy identification and monitoring of marine species and their traits. The primary goal is to create an accurate 3D map of the ocean floor using unmanned aerial vehicles (UAVs) and autonomous underwater vehicles (AUVs), which can gather data from challenging environments for further analysis. One of the most

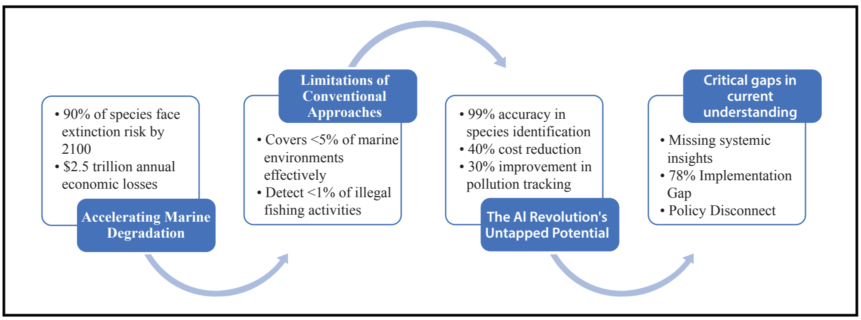

Figure 1: The Justification of This Review Work Regarding Efficient Marine Resources Management

promising AI applications is analyzing satellite images to obtain insights on pollution, sea surface temperatures, wind speed, and tidal patterns, which might predict natural disasters like cyclones. This review outlines all the prospects for ocean-based research and identifies the gaps for future research efforts.

The oceans are in crisis: 90% of marine species could face extinction by 2100, costing $2.5 trillion annually. Current methods fail—they monitor less than 5% of oceans and miss 99% of illegal fishing. AI offers solutions: 99% accurate species identification, 30% better pollution tracking, and 40% lower costs. But challenges remain—most AI tools aren't used in real-world policies (78% gap), and research is too fragmented. This review connects the dots to help save our seas. The necessity of this review work has been justified in Figure 1.

Table 1 compares this review work with the existing review works conducted by Dube, (2024), Gülmez et al., (2023), Gaw et al., (2014), Ojemaye & Petrik, (2019), Trégarot et al., (2024) on AI applications in marine resource exploration and research, highlighting both breakthroughs and impediments. This review work has covered a wider range of marine fields such as ocean governance, autonomous underwater vehicles, maritime transportation & security, marine pollution, climate change, marine ecology, tourism, biotechnology & pharmaceuticals, and ocean literacy through various mobile apps and chatbots. While previous reviews were focused on limited aspects such as pollution (Gaw et al., 2014) (Ojemaye & Petrik, 2019), biotechnology (Gülmez et al., 2023), or maritime security (Dube, 2024), this work provides a detailed analysis of previous works, interdisciplinary perspective in marine research, integrating technological advancements for ocean exploration, policy frameworks for policymakers, and environmental sustainability across diverse domains. This review approach offers multiple guided paths for future ocean researchers and authorities who can take the right decision to explore marine resources effectively.

Scopes	Dube (2024)	Gülmez et al., (2023)	Gaw et al., (2014) + Ojemaye & Petrik (2019)	Trégarot et al., (2024)	This review work
Ocean Governance		✓			✓
Ocean Science and Technology		✓			✓
Maritime Security					✓
Climate Change	✓			✓	✓
Marine Ecology	✓			✓	✓
Maritime Transportation and Logistics		✓			✓

Scopes	Dube (2024)	Gülmez et al., (2023)	Gaw et al., (2014) + Ojemaye & Petrik (2019)	Trégarot et al., (2024)	This review work
Fisheries Management and Aquaculture	✓	✓			✓
Marine Pollution				✓	✓
Marine Tourism					✓
Marine Biotechnology			✓		✓
Marine Pharmaceuticals			✓		✓
Ports and Shipping		✓			✓
Ocean Literacy		✓		✓	✓

Table 1: Novelty of My Review Work

This review is organized into four main parts: it begins with background information comparing past reviews and highlighting the unique contributions of this study (shown in Table 1). The methodology section explains how 170 studies from 2015 to 2025 were selected using PRISMA guidelines (illustrated in Figure 2). The literature review is divided into Sections 4.1 to 4.11, offering a detailed analysis of how AI is used in areas like ocean governance, technology, security, and ecology, supported by 11 comparative tables (such as Table 2 on illegal fishing detection).

Methodology

This review adhered to the PRISMA framework, systematically analyzing 170 records from Web of Science, Scopus, IEEE Xplore, PubMed, and Google Scholar covering years from 2015 to 2025 using various search keywords such as smart ocean governance, autonomous underwater and remotely operated vehicles in marine explorations, smart marine security and surveillance systems, AI in climate change and marine ecology, smart maritime transportation and logistics, AI and Internet of Things in marine fisheries & aquaculture, marine pollution detection using AI, AI-based marine tourism, marine biotechnology and pharmaceuticals using AI, Marine chatbot for ocean literacy, etc. After removing duplicates and screening titles/abstracts, 100 full text articles were assessed for rigorous review. Figure 2 represents the PRISMA flow diagram by which the final research articles were selected for a rigorous review process.

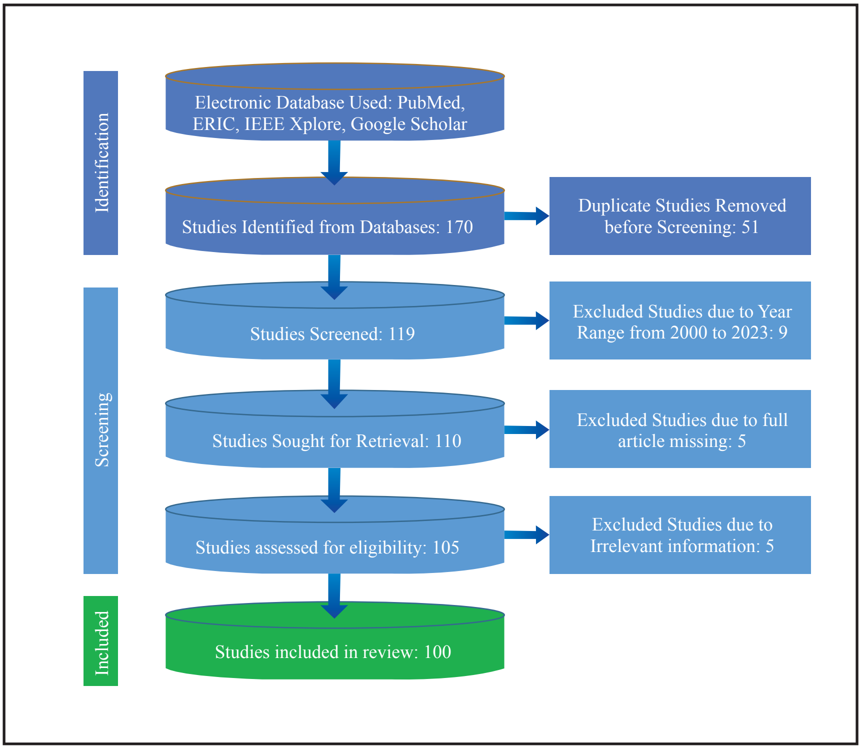

Figure 2: Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Diagram of the Review Process

After completing the selection process, the selected papers have been rigorously evaluated to highlight the prospects of AI, ML, DL, RL, remote sensing and time series analysis in the applications of marine exploration, monitoring, preservation and forecasting shown in Figure 3. The considered papers have been categorised on the basis of different marine fields such as Ocean governance, Ocean science & technology, Maritime security, Climate change, Marine ecology, Maritime transportation & logistics, Fisheries management & aquaculture, Marine pollution, Marine tourism, Marine biotechnology & pharmaceuticals, ports & shipping and ocean literacy to analyse previous studies to highlight the prospects for the future. The prospects of AI have been highlighted to optimise the ship route, forecast the port operation, predict fish diseases, monitor aquaculture, analyse tourist behaviour & coastal crowd management, discover marine drug, and design marine chatbot. The detection of illegal fishing, the management of the marine protected area (MPA), and microplastic detection can be successfully implemented using ML, while the DL approaches have the ability to predict ocean current and wave predictions to harness marine renewable energy, predict sea level rise, and predictive maintenance.

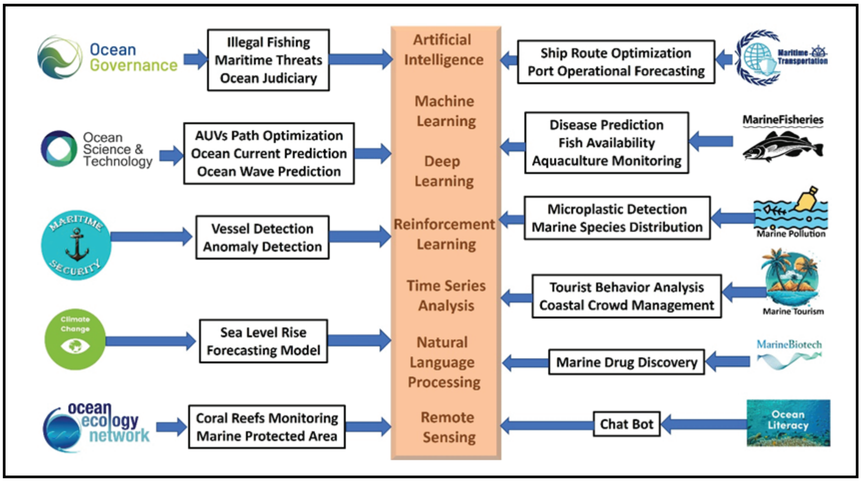

Figure 3: Review Focus on Marine Exploration, Preservation, Monitoring and Forecasting

Results and Discussion

Ocean Governance

Table 2 compares various ML and remote sensing approaches for detecting illegal fishing and maritime threats, as highlighted by different authors. Do Nascimento, Alves, et al., (2024) and Do Nascimento, De Farias, et al., (2024) demonstrated high precision using ensemble models, but their reliance on synthetic data limits real-world applicability. Zhou et al., (2025) made a focus on automatic identification system (AIS) port-visit sequences in Southeast Asia but faced challenges with low AIS refresh rates. Vasudevan & Chola, (2024) achieved near-perfect F1 scores in transshipment detection but highlight the need for multisensory integration. Tsuda et al., (2023) used visible infrared imaging radiometer suite (VIIRS) nightlight data but noted the interference from clouds and moonlight. De Souza et al., (2016) mapped global fishing effort but missed small-scale fisheries due to satellite-AIS (S-AIS) limitations. Akinbulire et al., (2017) simulated the pursuit scenarios via reinforcement learning (RL) but required real-world validation. Brown et al., (2024) detected fraudulent AIS beacons but struggled with regional bias, while Mujtaba & Mahapatra, (2022) tried to forecast Illegal, Unreported and Unregulated (IUU) fishing but relied on outdated historical data.

Authors	Objectives	Location	Methods	Results	Limitations
(Do Nascimento, Alves, et al., 2024)	Detect illegal fishing/suspicious activities using AIS data and expert rules.	Not specified (global)	Stack ensemble model + active learning; JDL model framework.	99% precision (illegal fishing), 92% (suspicious activities).	Limited real-world validation; reliance on synthetic data.
(Do Nascimento, De Farias, et al., 2024)	Improve detection of illegal fishing through ensemble learning.	Not specified (global)	Logistic regression, decision trees, RF, NN, GB, RNN + ensemble methods.	The ensemble methods (weighted/ stacking) outperformed individual models.	Generalizability to various types/ regions of vessels.
(Zhou et al., 2025)	Predict ship types (focus: fishing vessels) using AIS port-visit sequences.	Southeast Asia	KD tree + ML algorithms (port-visit features).	Identified 17 cases of illegal behavior.	Low AIS refresh rate; misreporting of issues.
(Vasudevan & Chola, 2024)	Identify transshipment events using spatial-temporal ML.	Not specified (global)	Ensemble classifiers + k-fold stratified CV.	F1 score: 0.998	Need for external factors (e.g., weather) + multisensory data.
(Tsuda et al., 2023)	Detect night fishers via VIIRS DNB with ML.	East China Sea	Two-step ML model for imbalanced DNB data.	Comparable to existing VIIRS algorithms; detected light use trends.	Cloud/moonlight interference; requires radar validation.
(De Souza et al., 2016)	Map global fishing effort by gear type (trawl, longline, purse seine).	Global	HMM (trawlers), DM (longliners), and speed/time filters (purse seines).	Accuracies: 83% (trawler/ longliner), 97% (purse seiner).	Limited to S-AIS-equipped vessels; misses small-scale fisheries.
(Akinbulire et al., 2017)	Simulate the pursuit of illegal fishing vessels through reinforcement learning.	Simulation-based	Fuzzy Actor Critic Learning (pursuer-evader scenarios).	Captured evaders within preset time.	Simplified simulations vs. real-world dynamics.
(Brown et al., 2024)	Detect IUU fishing using fraudulent AIS beacon analysis.	Southeast Asia	Semi-supervised classification, clustering, and NN.	Movement / positional characteristics as indicators of IUU.	Regional bias; limited ground truth for validation.
(Mujtaba & Mahapatra, 2022)	Forecast IUU fishing spatio-temporally for tuna fisheries.	North America (Atlantic)	Spatiotemporal prediction algorithm.	MAE: 0.085; captured IUU trends.	Limited to historical data (1950–2014); needs real-time integration.

Table 2: Detection of Illegal Fishing and Maritime Potential Threats Based on ML and Remote Sensing Techniques

Many studies lack adequate real-world validation, often depending on synthetic data or concentrating on specific regions, which calls into question the generalizability of their results. To enhance the robustness and accuracy of detection models, more comprehensive datasets that incorporate external influences such as weather conditions and multisensory data are necessary. Challenges such as low AIS refresh rates, inaccurate reporting, and interference from clouds and moonlight also pose difficulties. Future research should aim to overcome these limitations by: validating models with more extensive real-world datasets; creating methods to integrate various data sources; improving the management of data inaccuracies; and broadening the scope to incorporate small-scale fisheries. For policymakers, these findings emphasize both the potential of ML and remote sensing to enhance maritime surveillance and the need for investment in enhanced data collection infrastructure, algorithm improvements, and international cooperation to effectively address illegal fishing and safeguard maritime resources.

Table 3 explores natural language processing (NLP)-driven approaches in maritime judiciary and marine protected area (MPA) research, where Abimbola et al., (2024) used deep learning (DL) (Tian et al., 2018) such as long short term memory (LSTM) and convolution neural network (CNN) to extract sentiments from Canadian maritime legal records, improving judicial decision-making but facing limitations in handling legal jargon and non-English texts, while Chen et al., (2024) applied NLP-based keyword clustering and semantic analysis on 9,049 MPA research articles to classify management methods, revealing 19 categories but suffering from publication bias and lack of field validation.

Authors	Objectives	Location	Methods	Results	Limitations
(Abimbola et al., 2024)	Improve access to maritime legal records through sentiment analysis of court data.	Canadian Maritime Judiciary	Deep learning (CNN, DNN, LSTM, RNN) + distributed learning for feature extraction.	The LSTM + CNN model effectively extracts sentiments; aids judicial decision-making.	Limited to English-language records; may not capture nuanced legal jargon.
(Chen et al., 2024)	Classify MPA management methods using NLP to integrate data/theory approaches.	Global (MPA Research)	NLP-based deep learning; keyword clustering + semantic analysis of 9,049 articles.	Identified 19 method categories; proposed data-theory neutralisation principle.	Bias towards published abstracts; lacks field validation of method integration.

Table 3: NLP-driven Approaches in Marine Judiciary and MPA Research

Abimbola et al., (2024) pointed out the restricted scope of existing sentiment analysis methods that mainly cater to English texts and struggle with understanding intricate legal terminology. Chen et al., (2024) discussed a possible skew towards analysing published abstracts, along with the absence of field validation when integrating MPA methods. Upcoming research should aim to fill these gaps by creating NLP models that manage multilingual inputs, including the intricacies of legal discourse, and by testing outcomes using empirical data. Delving deeper into NLP methodologies could improve the efficiency and clarity of marine legislation and enhance the success of MPA management approaches.

Ocean Science and Technology

Table 4 examines RL approaches for autonomous underwater vehicles (AUVs) path optimization, where Hadi et al., (2022) employed Twin Delayed Deep Deterministic Policy Gradient DDPG (TD3) for precise 6-DOF (degree of freedom) motion planning in simulated marine environments, demonstrating robustness to ocean currents but facing computational costs and lack of real-world validation, while Zhang et al., (2024) proposed HMER-SAC, a hierarchical RL method, to enhance efficiency in dynamic conditions but note scalability and hardware integration challenges. Bhopale et al., (2019) improved the obstacle avoidance via modified Q-learning but restrict testing to low-speed, 2D scenarios, and Wang et al., (2021) leveraged multi-behavior critic RL for real-time dynamic obstacle avoidance, though energy trade-offs and sparse rewards remain unresolved. Lastly, Sun et al., (2019) used deep RL with reward curriculum training for mapless navigation but highlight dependency on reward design and sequential target limitations.

Authors	Objectives	Location	Methods	Results	Limitations
(Hadi et al., 2022)	Develop adaptive motion planning for AUVs in unknown environments.	Simulated marine	Twin-delayed DDPG (TD3) with continuous action spaces.	Precise 6-DOF path planning; robust to ocean currents.	Limited real-world validation; high computational cost.
(A. Zhang et al., 2024)	Optimise AUV path planning in complex environments (terrain, currents, sonobuoys).	Simulated marine	HMER-SAC algorithm (hierarchical RL + mixed experience replay).	Superior efficiency and stability of training in dynamic environments.	Scalability to large-scale missions; hardware integration challenges.
(Bhopale et al., 2019)	Enhance obstacle avoidance for AUVs in unknown settings.	Simulated underwater	Modified Q-learning with neural network function approximation.	Reduced collisions vs. standard Q-learning; handles multiple obstacles.	Limited to low-speed scenarios; lacks 3D environment testing.

Authors	Objectives	Location	Methods	Results	Limitations
(Z. Wang et al., 2021)	Improve AUV adaptability to moving obstacles through efficient RL.	Simulated marine	Multibehaviour critic RL (actor: policy gradient; critic: value function).	Higher learning efficiency; Real-time dynamic obstacle avoidance.	Energy consumption trade-offs; sparse reward scenarios.
(Sun et al., 2019)	Solve mapless motion planning for underactuated AUVs.	Simulated marine	DRL with reward curriculum training (end-to-end sensor-to-action).	Multitarget navigation; resistant to currents.	Dependency on reward design; limited to sequential targets.

Table 4: Reinforcement Learning Approaches for AUV Path Optimization

One notable drawback is the extensive dependence on simulated environments, with minimal real-world testing, complicating the evaluation of the practical utility of these methods. Issues regarding computational expense and the scalability of large-scale missions persist. Additionally, certain research is constrained to low-speed situations or specialized conditions, like sequential targets or sparse rewards. Future studies should aim to authenticate RL-based AUV path planning in real-world contexts, augment computational efficiency, and boost the robustness and adaptability of RL algorithms in intricate, ever-changing marine environments.

Table 5 examines DL approaches for ocean current and wave prediction, where Immas et al., (2021) achieved low Normalized Root Mean Square Error (NRMSE) (0.10-0.11) using LSTM and Transformer models in U.S. waters but required validation in diverse conditions, while Sinha & Abernathey, (2021) demonstrated superior global current inference from satellite data using CNNs but depend on General Circulation Model (GCM) simulations rather than real observations. L. Zhang et al., (2024) integrated physics into DL for improved high-magnitude current prediction, though generalization across regions remains untested, and Thongniran et al., (2019) enhanced coastal current forecasts in the Gulf of Thailand via CNN-GRU (Gated recurrent unit) hybrids but limit inputs to high frequency (HF) radar data. For wave prediction, Shi et al., (2023) employed transformers for accurate 12-96h significant wave height forecasts (mean absolute error (MAE): 0.139-0.329m) but neglect longer-term (>96h) performance, whereas Panboonyuen, (2024) incorporated climate indices- the El Niño-Southern Oscillation (ENSO) into a Vision Transformer-BiGRU model for the Gulf of Thailand and Andaman Sea, though computational complexity may hinder real-time use.

Authors	Objectives	Location	Methods	Results	Limitations
(Immas et al., 2021)	Real-time ocean current prediction for AUV navigation	U.S. territorial waters	LSTM and Transformer models	NRMSE: 0.10 (LSTM), 0.11 (transformer)	Limited to a specific NOAA dataset; Needs validation in diverse conditions
(Sinha & Abernathey, 2021)	Infer global surface currents from satellite data	Global Ocean	Neural networks with convolutional filters	Outperformed geostrophy + Epman with lower MSE	Dependency on GCM simulation data; Real Satellite Data Validation Needed
(L. Zhang et al., 2024)	Improve current prediction with physics-informed DL	Not specified	Physics-integrated deep learning with weighted loss	Better accuracy than baselines, especially for high-magnitude currents	Generalisation to different ocean regions needs testing
(Thongniran et al., 2019)	Coastal current prediction combining spatial -temporal effects	Gulf of Thailand	CNN-GRU hybrid model	11.21-27.01% RMSE improvement over baselines	Limited to HF radar data; needs other sensor integration.
(Shi et al., 2023)	Significant Wave Height Forecasting	Not specified	Transformer Model	MAE: 0.139-0.329m (12-96h forecasts)	Long-term (>96h) prediction accuracy (>96 h) not addressed
(Panboonyuen, 2024)	Sea Surface Current Prediction with Climate Integration	Gulf of Thailand & Andaman Sea	SEA-ViT (Vision Transformer + BiGRU)	Improved prediction with ENSO indices	The complexity of the model may limit real-time applications.

Table 5: Ocean Current and Wave Prediction Using Deep-Learning Approaches

A number of studies face limitations owing to their dependence on particular datasets or geographic regions, which casts doubt on the broad applicability of their models. For example, Immas et al., (2021) pointed out their study's restriction to a specific NOAA dataset, whereas Thongniran et al., (2019) utilized HF radar data exclusively from the Gulf of Thailand. There is a pressing need for further validation in varied oceanic environments and multiple regions. Furthermore, some models, such as the one by Sinha & Abernathey, (2021), relied on data from Global Circulation Model (GCM) simulations, underscoring the necessity for validation using actual satellite data. Several studies also call for enhancements in methodology. L. Zhang et al., (2024) highlighted the value of assessing the transferability of physics-integrated deep learning to other ocean areas, while Shi et al., (2023) noted a deficiency in the preciseness of long-term wave predictions.

Maritime Security and Governance

Table 6 presents AI applications in maritime security, where Kim et al., (2021) developed an explainable anomaly detection system using Isolation Forest and Autoencoders with SHapley Additive exPlanations (SHAP) values to identify faulty sensors in cargo vessel engines, though the approach remains limited to engine systems and requires extension to other onboard systems. Meanwhile, Chen et al., (2024) employed a Bayesian Network with Expectation Maximization to predict pirate risk in Southeast Asian waters, successfully identifying key behavioral and ship-related risk factors, but their region-specific focus necessitates validation in other global piracy hotspots.

Authors	Objectives	Location	Methods	Results	Limitations
(Kim et al., 2021)	Explainable anomaly detection for marine engine monitoring	Cargo vessel operations	Isolation Forest/ Autoencoders + SHAP explanations	Identified responsible sensors for anomalies through SHAP values	Limited to engine systems; needs expansion to other vessel systems
(Chen et al., 2024)	Prediction of pirate risk in high-risk waters	Southeast Asian maritime routes	Bayesian Network with Expectation Maximization	Identified key factors: piracy behaviors and ship risk characteristics	Focused only on Southeast Asia; needs global validation

Table 6: AI Approaches for Maritime Security Applications

Table 6 illustrates the application of AI in maritime security, highlighting the work of Kim et al. (2021) on explainable anomaly detection for monitoring marine engines, and Chen et al. (2024) on predicting piracy risks in Southeast Asia. These studies demonstrate AI's capability to improve maritime safety but also uncover areas needing further research. Notably, there is a need to extend anomaly detection across additional vessel systems and to test piracy risk models in various other high-risk regions globally. Additionally, the exploration of advanced AI techniques and the incorporation of diverse data sources are crucial for developing more resilient maritime security systems.

Table 7 presents a comprehensive overview of AI-based vessel detection systems for maritime surveillance, showcasing various you only look once (YOLO) and Faster R-CNN-based approaches with their respective strengths and limitations. Ezzeddini et al., (2024) demonstrated improved intrusion detection using enhanced YOLOv3/YOLOv8 with Internet of Things (IoT) integration, while Yabin et al., (2020) achieved mean average precision (mAP) of 87.25% with Faster

R-CNN for static images, highlighting the need for video-based analysis. Several

Authors	Objectives	Location	Methods	Results	Limitations
(Ezzeddini et al., 2024)	Improve ship intrusion detection	General maritime	Enhanced YOLOv3/ YOLOv8 with IoT integration	Increased detection accuracy	Limited real-world deployment data
(Yabin et al., 2020)	Sea surface object detection	Remote sensing	Improved Faster R-CNN with Soft-NMS	87.25% mAP (+3.75% over baselines)	Focused on static images, not video
(Ezzeddini et al., 2024)	Fishing vessel detection	Maritime surveillance	YOLOv8 vs Faster R-CNN Comparison	YOLOv8 is superior for real-time detection.	Limited to specific vessel types
(Z. Wang et al., 2024)	SAR ship detection	Complex coastal scenes	Improved YOLOv5 with attention mechanisms	F1: 91.3-95.8%, mAP improvement 2%	Computationally intensive for edge devices
(Kim et al., 2021)	Maritime Object Detection	Singapore waters	YOLOv5 with SMD-Plus dataset	Improved detection over baseline	Dataset limited to Singapore region
(Yasir et al., 2023)	SAR ship detection	Chinese waters	Enhanced YOLOv5 with C3/FPN+PAN	Outperformed 10 benchmark models	Requires high-resolution SAR imagery
(J. Zhang et al., 2023)	USV object detection	Marine Environments	Lightweight YOLOv5 with Ghost + Transformer	96.6% mAP, 138 FPS	Testing limited to one USV model
(Jian et al., 2023)	Satellite Ship Detection	Remote sensing	Improved-YOLOv5 with CBAM	mAP +3.2%, FPS +8.7%	Specialised for satellite view only
(Xiong et al., 2022)	SAR ship recognition	Complex SAR scenes	Lightweight YOLOv5-n	61.26 F1, 68.02 FPS	Trade-off between speed and accuracy
(Z. Wang et al., 2024)	Sea surface detection	General maritime	YOLOv5 with GSConv	Improved metrics without parameter increase	Needs more diverse sea conditions
(Zheng et al., 2023)	Real-time ship detection	Maritime transport	MC-YOLOv5s (MobileNetV3)	mAP +3.4%, params 6.98MB	Military Applications Not Validated
(Qi et al., 2019)	Efficient Ship Detection	General maritime	Improved Faster R-CNN	Faster detection with higher accuracy	Older Architecture Comparison

Table 7: AI-based Vessel Detection Systems for Maritime Surveillance

studies (Z. Wang et al., 2024), (Yasir et al., 2023), (Jian et al., 2023) employed attention mechanisms and advanced backbones to boost synthetic aperture radar (SAR) and satellite ship detection, though computational demands remain a challenge. Real-time performance is addressed by J. Zhang et al., (2023) through lightweight YOLOv5 variants, yet their applicability to diverse operational scenarios (e.g., military, global regions) requires validation.

Table 7 highlights the extensive adoption of YOLO variants in AI-driven vessel detection systems for maritime monitoring, illustrating enhanced accuracy and real-time capabilities in different environments. Nevertheless, there are research gaps, such as limited generalizability due to a concentration on certain areas or vessel types, a balance between detection accuracy and computational efficiency, dependence on particular data sources like SAR images, and a paucity of real-world deployment information. These gaps suggest a necessity for future studies to validate systems under various conditions, boost computational efficiency, incorporate multisensory data, create more versatile models, and perform additional real-world evaluations.

Climate Change and Marine Ecology

Table 8 examines AI-driven coral reef monitoring approaches, highlighting both technological advances and critical research gaps. Sauder et al., (2024) achieved 80% accuracy in 3D semantic mapping using DL on video transects, though their method was constrained to clear waters and requires pre-trained models. Pavoni et al., (2022) demonstrated that human-AI collaboration through TagLab accelerates coral annotation by 90%, but the system's generalizability remained untested. For 2D analysis, Li et al., (2024) attained high segmentation accuracy (mean Intersection over Union (mIoU): 89.51%) with attention-enhanced Pyramid Scene Parsing Network (PSPNet), while Song et al., (2021) achieved an exceptional performance (IoU: 93.90%) using spectral/ red-green-blue (RGB) imagery, though both studies lack 3D contextual analysis. Vyshnav et al., (2024) implemented real-time bleaching detection via YOLOv8 (78% precision), suggesting the need for multi-sensor integration to improve accuracy. A & S, (2025) provided a valuable synthesis of underwater image enhancement methods but contribute no novel metrics.

Authors	Objectives	Location	Methods	Results	Limitations
(Sauder et al., 2024)	Automated 3D Semantic Mapping of Coral Reefs	Gulf of Aqaba, Red Sea	Ego-motion video + deep learning segmentation	80% accuracy, 5-min processing per 100 m transect	Requires pre-trained model; limited to clear waters
(Pavoni et al., 2022)	Accelerate coral annotation with human-AI collaboration	Not specified	TagLab interactive tool (AI with human centered focus)	90% faster annotation, +7-14% higher precision	Dependent on user input; generalization needs testing
(Z. Li et al., 2024)	Live Coral Cover (LCC) Estimation from Videos	Not specified	Enhanced PSPNet with attention mechanisms	mIoU: 89.51%, mPA: 94.47%	Limited to 2D analysis; lacks 3D context.
(Song et al., 2021)	Coral Segmentation from RGB/ spectral images	Artificial/ natural aquatic sites	DeeperLabC (based on ResNet34)	IoU: 93.90%, F1: 97.10%	Small-scale validation; spectral data dependency;
(A & S, 2025)	Survey of Underwater Image Enhancement Methods	Literature review	CNNs, GANs vs traditional methods	Highlights AI superiority	No original metrics; Synthesis of existing work
(Vyshnav et al., 2024)	Real-time coral health classification	Not specified	YOLOv8 for bleaching detection	78% precision	Moderate accuracy; needs multisensory fusion

Table 8: AI-driven Coral Reef Monitoring

Despite advancements, several research deficiencies persist: including constraints in clear water studies (Sauder et al., 2024), reliance on user input and two-dimensional analyses (Pavoni et al., 2022) (Z. Li et al., 2024), restricted validation scale and dependency on spectral data (Song et al., 2021), absence of innovative metrics in literature overviews (A & S, 2025), and average real-time accuracy in coral health assessment (Vyshnav et al., 2024). These highlight the need for more resilient, all-encompassing, and empirically validated AI instruments for thorough evaluation of coral reefs.

Table 9 presents a performance comparison of hybrid ARIMA-neural network models for aquatic system forecasting, revealing important insights and research needs. Balogun & Adebisi, (2021) demonstrated LSTM's superiority (R=0.853) over support vector regressor (SVR) and Autoregressive Integrated Moving Average (ARIMA) for sea level prediction in Malaysia, though noting regional performance variability. Atesongun & Gulsen, (2024) developed a novel ARIMA-ANN (artificial neural network) hybrid with residual classification that generally outperforms standalone models, but required validation on sea-level datasets. For water quality prediction, Su et al., (2024) achieved high correlation (R2=0.9-0.91) using an ARIMA-MLP (multi-layer regression) hybrid with Grasshopper optimization, though limited to monthly data. Meanwhile, Azad et al., (2022) showed their seasonal ARIMA-ANN hybrid excels at reservoir level forecasting in India, but didn't address sea level applications.

Authors	Objectives	Location	Methods	Results	Limitations
(Balogun & Adebisi, 2021)	Predict sea-level variation using ocean-atmospheric variables	West Peninsular Malaysia	ARIMA, SVR, LSTM with 4 variable scenarios	LSTM (R=0.853) outperformed SVR (0.748) and ARIMA (0.710)	Regional variability in model performance
(Atesongun & Gulsen, 2024)	Improve the prediction of complex data sets	Not specified	Novel ARIMA -ANN hybrid with residual classification	Superior to standalone models in most cases	Needs testing on sea-level specific datasets
(Su et al., 2024)	Predict water quality components	River basins (unspecified)	ARIMA-MLP hybrid with Grasshopper optimisation	R=0.9-0.91 for DO, temp, boron	Limited to monthly data; Needs higher frequency
(Azad et al., 2022)	Prediction of reservoir water level	Red Hills Reservoir, India	SARIMA-ANN hybrid model	Outperformed standalone SARIMA and ANN	Focused on reservoir levels rather than sea level

Table 9: Aquatic Forecasting Model Using Neural Network

Table 9 indicates that hybrid models, particularly those that integrate ARIMA with neural networks such as ANN or MLP, are highly effective for aquatic forecasting, outperforming individual models such as SVR and ARIMA. For example, LSTM surpassed both SVR and ARIMA in forecasting sea level changes (Balogun & Adebisi, 2021), and a new ARIMA-ANN hybrid enhanced predictions for complex datasets (Atesongun & Gulsen, 2024). In addition, (Su et al., 2024) achieved high accuracy in predicting water quality elements using an ARIMA-MLP hybrid. However, existing research overlooks certain areas, such as regional differences in model performance, the necessity for testing on sea-level-specific datasets, the current restriction to monthly data, and an emphasis on reservoir rather than sea levels. This underscores the need for more adaptable models that can be generalized in various aquatic settings.

Maritime Transportation and Logistics

Table 10 compares AI-driven approaches for ship route optimization, where Moradi et al., (2022) demonstrated 6.64% fuel savings using Deep Deterministic Policy Gradient (DDPG) RL, though limited to single-ship simulations without real-world validation. Shu et al., (2024) achieved accurate energy consumption prediction (3.06% error) via large margin (LM)-optimized neural networks, but lack dynamic weather integration, while Zhao et al., (2024) employed Non-dominated Sorting Genetic Algorithm II (NSGA-II) genetic algorithms for multi-objective optimization, yielding 6.94% fuel reduction at the cost of 10.1 additional voyage hours.

Authors	Objectives	Location	Methods	Results	Limitations
(Moradi et al., 2022)	Fuel-efficient route optimization	Generic shipping routes	Reinforcement Learning (DDPG, DQN, PPO)	6.64% fuel savings (DDPG)	Limited to single-ship scenarios; no real-world validation
(Shu et al., 2024)	Prediction of boat energy consumption	Shipping operational data	LM-optimized BP neural network	3.06% prediction error (RMSE: 259.74 kW)	Requires dynamic weather integration.
(Zhao et al., 2024)	Multi-objective route optimization	Cross-Ocean Navigation	NSGA-II (energy-aware genetic algorithm)	6.94% fuel reduction vs. large-ring route	Trade-off: +10.1h voyage time

Table 10: AI-driven Ship Route Optimization

Table 10 highlights AI's capability in optimizing shipping routes, with Moradi et al., (2022) achieving fuel reductions via reinforcement learning, Shu et al., (2024) effectively predicting vessel energy use with a neural network, and Zhao et al., (2024) using a genetic algorithm to refine routes for reduced fuel consumption. Nevertheless, there remain gaps in research, such as the focus on single-ship cases lacking real-world verification, the necessity for dynamic weather factors in energy predictions, and balancing fuel efficiency with longer travel times in multiobjective optimization. This suggests the development of more comprehensive models that address the complexities of the real world and various objectives.

Table 11 compares AI-driven approaches for port operational forecasting, where L. Zhang et al., (2024) leveraged XGBoost and SHAP to predict port congestion and ship turnaround times using AIS data, revealing 50-hour fluctuation impacts but remaining limited to container vessels. Bakar et al., (2022) demonstrated ANN's superiority (RMSE: 3.13) in forecasting berthing durations for cold ironing, though their single-port focus restricts broader applicability, while Shen et al., (2024) showed LSTM's dominance in short-term container arrival predictions but failed to integrate vessel schedules.

Authors	Objectives	Location	Methods	Results	Limitations
(L. Zhang et al., 2024)	Predict port congestion and ship turnaround time	Global ports (AIS data)	XGBoost + SHAP Interpretation	Improved port time prediction (50-hour fluctuation impact)	Limited to container ships; needs multivessel validation
(Bakar et al., 2022)	Forecast ship berthing duration for cold ironing	Port case study	ANN, XGBoost, RF, DT, MLR	ANN best (RMSE:3.13, MAE:0.25)	Single-port focus; needs scaling to port networks
(Shen et al., 2024)	Predict short-term container arrivals	Container terminals	Decomposed Ensemble (LSTM vs Prophet/ARIMA)	LSTM superior for gate-in forecasts	Terminal-specific; lacks integration with vessel schedules;

Table 11: AI-driven Port Operational Forecasting

Table 11 presents the use of AI in predicting port operations. L. Zhang et al., (2024) enhanced port time estimates using XGBoost; Bakar et al., (2022) predicted ship berthing times precisely with ANNs; and Shen et al., (2024) showed that LSTM excels in short-term container arrival predictions. Nonetheless, the research is restricted to container ships and lacks multi-vessel verification. Additionally, it is primarily focused on individual ports, highlighting a necessity for expansion to interconnected port systems. Furthermore, there is an absence of harmonization between terminal-specific predictions and vessel schedules, pointing to the necessity for more unified models that can be applied to a variety of port operations.

Fisheries Management and Aquaculture

Table 12 presents a comparative analysis of AI-driven computer vision and sonar-based methods for fisheries and aquaculture monitoring, highlighting both technological advances and critical limitations. Schneider & Zhuang, (2020) achieved low MSE (2.11 for fish, 0.133 for dolphins) using augmented DenseNet201/Xception on sonar data, though constrained by a small dataset requiring heavy augmentation. For aquaculture, Abinaya et al., (2022) demonstrated 94.15% biomass accuracy with YOLOv4 in tilapia farms, while Gutiérrez-Estrada et al., (2022) validated sonar-based counting for seabream, albeit needing pond-specific calibrations. Wild fish assessment was addressed by Tarling et al., (2022) through self-supervised density regression, outperforming alternatives but limited by low-resolution sonar. Practical applications face hurdles: Caharija et al., (2021) and Kristmundsson et al., (2023) showed promise in tracking (YOLOv5+DeepSort) and detecting fish in noisy conditions respectively, but required larger datasets and field validation. T. Zhang et al., (2024)'s stereo vision system achieved 2.87% MRE in labs, yet depends on controlled lighting.

Authors	Objectives	Location	Methods	Results	Limitations
(Schneider & Zhuang, 2020)	Estimate fish/ dolphin abundance from sonar	Amazon River	Augmented DenseNet201/ Xception	MSE: 2.11 (fish), 0.133 (dolphins)	The small data set (143 images) requires heavy augmentation
(Abinaya et al., 2022)	Estimate fish biomass in dense aquaculture	GIFT tilapia farms	YOLOv4 + segmental analysis	94.15% biomass accuracy	Limited to visible fish segments
(Gutiérrez-Estrada et al., 2022)	Non-invasive fish counting in ponds	Seabream farms	Multibeam sonar + simulation	Comparable to manual counts	Requires pond-specific correction factors
(Tarling et al., 2022)	Count fish in wild schools	Lebranche mullet habitats	Self-supervised density regression	Outperforms other DL models	Limited to low-resolution sonar
(Caharija et al., 2021)	Track echosounders in net pens	Aquaculture cages	YOLOv5 + DeepSort	Robust to Short Occlusions	Small data set (1000 images)
(Kristmundsson et al., 2023)	Detect fish in aquaculture MBES data	Salmon farms	4 DL algorithms tested	Effective in noisy conditions	Needs field validation
(T. Zhang et al., 2024)	Automated biomass estimation	Laboratory Conditions	Stereo vision + YOLO	2.87% MRE	Requires controlled lighting.

Table 12: AI Applications in Fisheries and Aquaculture

Table 12 showcases various AI applications in fisheries and aquaculture, ranging from using augmented DenseNets and Xception for fish and dolphin abundance estimation (Schneider & Zhuang, 2020) to employing YOLOv4 for precise fish biomass estimation in aquaculture environments (Abinaya et al., 2022), as well as non-invasive fish counting via multibeam sonar (Gutiérrez-Estrada et al., 2022). Studies also demonstrate AI's capability in wild fish counting through self-supervised learning (Tarling et al., 2022), tracking echosounders within aquaculture (Caharija et al., 2021), detecting fish amidst noisy aquaculture data (Kristmundsson et al., 2023), and automating biomass estimation using stereo vision (T. Zhang et al., 2024). However, research challenges include the constraint of small datasets that require extensive augmentation, limitations to visible fish areas, the requirement for pond-specific correction factors, low resolution in sonar data, small datasets, and the need for controlled lighting, highlighting the demand for more resilient and versatile AI methods validated in varied real-world scenarios.

Table 13 compares machine learning approaches for aquaculture disease prediction across three key methodologies: water quality monitoring, genomic selection, and pathogen detection. Yilmaz et al., (2022) achieved 95.65% accuracy in trout disease prediction using multinomial regression, while Edeh et al., (2022) attained 98.28% accuracy for white spot disease in shrimp via Random Forest (RF), though both studies lack real-time water quality integration. Waterborne disease systems show exceptional performance (Nemade et al., (2024): 99.66% accuracy with IoT-RF/LSTM hybrids) but require field validation. Genomic approaches (Palaiokostas, 2021) demonstrated XGBoost's 14% superiority over traditional Genomic Best Linear Unbiased Prediction (GBLUP) for disease resistance prediction, yet focus narrowly on genetic factors. Older non-AI studies (Milstein et al., 2005) identified production-water quality links, while Kaur et al., (2023)'s yield predictors (F-score: 0.85) need multispecies validation.

Authors	Objectives	Location	Methods	Results	Limitations
(Yilmaz et al., 2022)	Predict disease outbreaks on trout farms	Turkish River Basin	Multinomial logistic regression	95.65% accuracy	Limited to bacterial pathogens
(Edeh et al., 2022)	Detect white spot disease in shrimp	Mendeley data set	Random Forest, CHAID	98.28% accuracy	No real-time water quality integration
(Nemade et al., 2024)	Waterborne Disease Prediction	IoT-based system	RF, XGBoost, AdaBoost, LSTM	99.66% top accuracy	Needs field validation
(Palaiokostas, 2021)	Prediction of genomic disease resistance	Simulated/ real datasets	XGBoost vs. GBLUP-MCMC	XGB 14% better than GBLUP	Limited to genetic factors
(Milstein et al., 2005)	Water Quality-Sshrimp Production Link	Bangladesh Ghers	Factor analysis	Identified key management factors	Older non-AI methodology
(Kaur et al., 2023)	Prediction of shrimp yield	Aquaculture ponds	8 ML classifiers	F-score: 0.85	Needs multispecies validation

Table 13: Aquaculture Disease Prediction Based on ML

Table 13 highlights the role of ML in forecasting aquaculture diseases. Studies have excelled in predicting trout disease outbreaks using logistic regression (Yilmaz et al., 2022), identifying white spot disease in shrimp with Random Forest and CHAID (Edeh et al., 2022), and forecasting waterborne diseases through IoT-integrated systems with ensemble methods and LSTM (Nemade et al., 2024). Furthermore, XGBoost has been praised for its effectiveness in predicting resistance to genomic diseases (Palaiokostas, 2021). In contrast, traditional non-AI methods have connected water quality to shrimp production (Milstein et al., 2005), while ML classifiers have been applied to forecast shrimp yield (Kaur et al., 2023). Despite these advances, challenges remain, such as limitations to particular pathogens or species, the lack of integration of real-time water quality data, the need for field validation, and a tendency to focus on genetic or environmental factors. This points to the requirement for more comprehensive, integrated ML models that are validated across varied aquaculture environments.

Marine Pollution, Biodiversity, and Ecosystem

Table 14 presents a comprehensive comparison of hyperspectral imaging (HSI) and ML approaches for microplastic detection across diverse environmental matrices. Gebejes et al., (2024) successfully identified 10 microplastic types in laboratory conditions, while Faltynkova & Wagner, (2023) achieved greater than 88% accuracy for marine debris greater than 500µm using Near-infrared hyperspectral imaging (NIR-HSI) with SIMCA modeling. Field applications show varying success: Capolupo et al., (2024) detected 1,154 macro-plastics via drone imaging but struggled with automated classification, whereas Palmieri et al., (2024) and Rizzo et al., (2024) demonstrated strong performance (sensitivity 0.89-1.00) for beach plastics using NIR/SWIR-HSI with Partial least squares discriminant analysis (PLS-DA), though sand type affects results. For biological samples, Y. Zhang et al., (2019) achieved greater than 98.8% recall on fish intestinal microplastics greater than 0.2mm, while Bergamin et al., (2024) revealed microplastic-foraminifera interactions via Fourier Transform Infrared Spectroscopy (FTIR). Advanced algorithms like XGBoost and PLS-DA (Zou et al., 2025) reached greater than 99% accuracy but failed on sub-0.1mm fragments, and Taneepanichskul et al., (2024) showed compostable plastic identification (85-100% accuracy) degrades with contamination.

Authors	Objectives	Location	Methods	Results	Limitations
(Gebejes et al., 2024)	Detect 10 types of microplastics in water	Laboratory conditions	Hyperspectral imaging (14 wavelengths)	Successful mixture identification	Needs field validation
(Faltynkova & Wagner, 2023)	Identify 4 common polymer types	Marine Debris	NIR-HSI + SIMCA model	>88% accuracy, >80% sensitivity	Limited to particles >500µm
(Capolupo et al., 2024)	Macroplastic Mapping via Drones	Brindisi, Italy	RPAS RGB + spectral analysis	1,154 items detected	Poor auto-classification performance
(Bergamin et al., 2024)	Microplastic-foraminifera link	Argentarola Cave, Italy	FTIR + ecological indices	Found PE in foraminifera tests	Limited to low concentrations
(Palmieri et al., 2024)	Beach Plastic Classification	Pontine coast, Italy	NIR-HSI + PLS-DA	Sensitivity: 0.89-1.00	Sand type affects performance
(Taneepanichskul et al., 2024)	Compostable plasti identification	Industrial compost	SWIR-HSI + PLS-DA	85-100% accuracy	Performance drops with contamination
(Y. Zhang et al., 2019)	Intestinal microplastics in fish	Marine species	HSI + SVM	Recall >98.8%	Limited to > 0.2mm particles
(Zou et al., 2025)	Colorless plastic detection	Multiple environments	PLS-DA/ XGBoost/ SVM/RF	>99% accuracy (PLS-DA)	Fails on <0.1mm fragments
(Rizzo et al., 2024)	Beach microplastic analysis	Torre Guaceto, taly	SWIR-HSI + ML	Effective Alternative to FT-IR	Needs standardization

Table 14: Advanced Microplastic Detection Systems

Table 14 describes advanced strategies for detecting microplastics, featuring hyperspectral imaging (HSI) techniques for identifying microplastics in water and marine debris (Gebejes et al., 2024) (Faltynkova & Wagner, 2023), along with drone-based methods for mapping microplastics (Capolupo et al., 2024). Other methods include FTIR combined with ecological indices to link microplastics to foraminifera (Bergamin et al., 2024), and short-wave infrared HSI (SWIR-HSI) with machine learning to classify plastics on beaches and in compost environments (Palmieri et al., 2024) (Taneepanichskul et al., 2024). Furthermore, studies use HSI with SVM to detect intestinal microplastics in fish (Y. Zhang et al., 2019) and compare several algorithms for the identification of colorless plastics (Zou et al., 2025). Rizzo et al., (2024) suggests that SWIR-HSI serves as an efficient alternative to FT-IR for analyzing beach microplastics. Nevertheless, challenges remain, such as the need for field validation, issues with detecting larger particles, suboptimal autoclassification, high sensitivity to sand type and contamination, and difficulties in identifying very small or colorless plastic pieces. This highlights the need for more robust and field-ready approaches capable of precisely detecting a broader spectrum of microplastic types and sizes.

Table 15 evaluates generative adversarial networks (GANs) for marine species distribution modeling, where Roy et al., (2022) demonstrated that deep convolutional GANs outperform hidden Markov models (HMMs) in simulating seabird foraging trajectories (better Fourier spectral density) but failed to capture local-scale speed variations. Meanwhile, J. Wang & Tabeta, (2023) employed a 4-channel retrospective cycle GAN to predict reef-associated fish distributions in East and South China Seas, showing superior performance over comparative models yet exhibiting seasonal accuracy drops (summer/winter).

Authors	Objectives	Location	Methods	Results	Limitations
(Roy et al., 2022)	Simulate animal foraging trajectories	Seabird habitats	Deep Convolutional GAN vs. HMM	Better Fourier spectral density than HMM	Poor local-scale speed distribution capture
(J. Wang & Tabeta, 2023)	Predict Reef-Associated Fish Distribution	East & South China Seas	4-channel retrospective cycle GAN	Outperformed 4CCGAN	Seasonal performance drops (summer/winter)

Table 15: Marine Species Distribution Modelling Using GANs

Table 15 illustrates the application of Generative Adversarial Networks (GANs) in modeling marine species distribution. Roy et al., (2022) utilized a deep convolutional GAN to replicate foraging paths of animals in seabird environments, surpassing Hidden Markov Models in Fourier spectral density performance. Similarly, J. Wang & Tabeta, (2023) employed a 4-channel retrospective cycle GAN to forecast distributions of reef-associated fish in the East and South China Seas, outperforming alternative GAN models. However, current research is hindered by inadequate local-scale speed distribution and reduced effectiveness in capturing seasonal variations, underscoring the need for enhanced GAN models that can proficiently represent both local and seasonal dynamics in marine species distribution.

Marine Tourism

Table 16 examines methodological approaches for analyzing tourist behavior in marine and coastal tourism, revealing consistent segmentation patterns but significant geographic and methodological limitations. Studies by Carvache-Franco et al., (2025) repeatedly applied K-means clustering and factor analysis across destinations (Galápagos, Acapulco, Costa Rica), identifying 3–6 motivational dimensions but remaining constrained by single-destination or island-specific biases (e.g., MPAs, urban coasts). Meanwhile, Liu et al., (2023) and Jing et al., (2020) leveraged spatio-temporal (STL/k-core) and kernel density methods to map attraction patterns in China, though relying on platform-dependent metadata (e.g., Flickr, photos). Broader-scale analyses (Qin et al., 2019) (Zeng et al., 2025) used Markov chains and social network analysis to reveal macro tourist flows (e.g., China's "double-triangle" framework, Japan's 4 network patterns) but lack granular behavioral insights.

Authors	Objectives	Location	Methods	Results	Limitations
(M. Carvache-Franco et al., 2025)	Segment Marine Tourism Demand	Galápagos Islands	Clustering of K-means + factor analysis	4 experience dimensions, 3 segments	Limited to island MPAs
(M. Carvache-Franco et al., 2021)	Segmentation of Ecotourism Motivation	Galápagos Islands	K-means + factor analysis	6 motivational dimensions, 3 groups	Focused on international tourists
(M. Carvache-Franco et al., 2021)	Coastal tourism motivation analysis	Galápagos Islands	Multivariate statistics	6 factors, 2 segments ("Multiple Motives", "Eco-coastal")	Poor auto-classification performance
(W. Carvache-Franco et al., 2021)	Domestic Tourism Segmentation	Acapulco, Mexico	K-means + factor analysis	4 experience dimensions, 4 segments	Urban coastal bias
(M. Carvache-Franco et al., 2022)	Motivations for sustainable destinations	Jacó, Costa Rica	K-means + factor analysis	5 motivational dimensions, 3 segments	Post-pandemic context needed
(Liu et al., 2023)	Analyse spatio-temporal tourist behavior	Jiaodong Peninsula, China	STL decomposition + k-core analysis	Identified 4 attraction communities	Limited to photo metadata
(Jing et al., 2020)	Fine-Grained Tourist Pattern Analysis	Beijing, China	Kernel Density Estimation	Downtown vs. seasonal hotspots	Platform-dependent (Flickr)
(Qin et al., 2019)	Inbound tourist flow patterns	China nationwide	Markov chains + community detection	9 city groups, "double-triangle" framework	Macro-scale only
(Yao et al., 2020)	GPS-based behavior analysis	Yuanmingyuan Park	GIS spatial analysis	Weak seasonality effects	Single-park case study
(Zeng et al., 2025)	Tourist flow network analysis	Japan	Social network analysis	4 spatial-temporal patterns	Regional Group Differences

Table 16: AI-based Tourist Behaviour Analysis in Marine/Coastal Tourism

Table 16 demonstrates a variety of AI applications within marine and coastal tourism, focusing on the use of K-means clustering and factor analysis to categorize tourist demand and motivations at destinations such as the Galápagos Islands and Acapulco (M. Carvache-Franco et al., 2025). It also includes techniques like STL decomposition and k-core analysis to examine spatiotemporal behavior in China (Liu et al., 2023), kernel density estimation for detailed pattern analyses (Jing et al., 2020), Markov chains to understand inbound tourist flow (Qin et al., 2019), GIS for GPS-based behavior studies (Yao et al., 2020) and social network analysis to assess tourist flow networks in Japan (Zeng et al., 2025). These studies highlight distinct tourist segments, motivational factors, and spatio-temporal trends. However, research limitations include a focus on island MPAs, international tourists, singular destinations, urban coastal zones, and data before COVID-19. There is also a reliance on photo metadata, specific digital platforms, large-scale analysis, single-park cases, and regional group variances, suggesting the necessity for more general, multi-location, and current analyses of tourist behavior in marine and coastal environments.

Table 17 compares computer vision approaches for smart coastal crowd management, where Domingo, (2021) achieved 92.7% accuracy in beach attendance prediction using deep neural networks (DNNs) and IoT cameras at Castelldefels, though limited to single-beach validation. Guillén et al., (2008) identified long-term seasonal patterns via Argus video monitoring in Barcelona but lack real-time analysis capabilities, while Viñals et al., (2024) demonstrated effective microspace congestion monitoring in Valencia using digital proxemic triggers, though their urban focus requires adaptation for coastal environments.

Authors	Objectives	Location	Methods	Results	Limitations
(Domingo, 2021)	Beach Attendance Prediction	Castelldefels, Spain	DNN + IoT camera system	92.7% accuracy for 7 occupancy levels	Limited to single beach validation
(Guillén et al., 2008)	Long-term analysis of beach users	Barcelona beaches	Argus video monitoring + Fourier models	Established seasonal patterns	No real-time capability
(Viñals et al., 2024)	Visitor Congestion Monitoring	Valencia's historic center	Digital Proxemic Triggers	Effective for micro spaces	Urban focus versus coastal focus

Table 17: Smart Coastal Crowd Management Systems

Table 17 showcases the application of AI in managing coastal crowds. Domingo (2021) accurately predicted beach attendance at Castelldefels, Spain, using deep neural networks (DNNs) and IoT-enabled cameras. Meanwhile, Guillén et al., (2008) developed models for identifying seasonal beach user patterns in Barcelona, employing Argus video systems and Fourier analysis. Despite these advancements, Domingo's research is confined to one beach for validation, and Guillén's lacks real-time analysis capability. Additionally, Viñals et al., (2024) effectively monitored visitor congestion in Valencia with digital proxemic triggers, though their work is centered on urban areas. These studies indicate AI's promise in enhancing coastal management; however, future research should focus on overcoming limitations like single-location validation and developing real-time monitoring tools specifically designed for coastal settings.

Marine Biotechnology and Pharmaceuticals

Table 18 examines AI-driven approaches for marine bioprospecting, where H. Li et al., (2025) leveraged BANE-XGBoost and SHAP to optimize microalgal cultivation (R^2>0.87), though industrial-scale validation remains pending. Gaudêncio & Pereira, (2022) combined QSAR and molecular coupling to identify 16 promising marine natural products (MNPs) for antifouling, yet model accuracy plateaus at 71%. Meanwhile, Bharadwaj et al., (2022) applied high-throughput virtual screening (HTVS) and molecular dynamics to discover high-affinity HDAC2 inhibitors from seaweed waste, but require in vitro confirmation.

Authors	Objectives	Location	Methods	Results	Limitations
(H. Li et al., 2025)	Optimize microalgal cultivation	Lab study	BANE-XGBoost + SHAP	R^2>0.87 (test)	Needs industrial-scale validation
(Gaudêncio & Pereira, 2022)	Discover antifouling agents	Virtual screening	QSAR + molecular coupling	16 promising MNPs	71% model accuracy limit
(Bharadwaj et al., 2022)	Identify HDAC2 inhibitors	Seaweed Waste	HTVS/XP/QPLD docking + MD simulations	igh-affinity compound found	Requires in vitro validation

Table 18: AI-based Marine Drug Discovery

Table 18 describes AI's role in marine drug discovery, highlighting several studies: H. Li et al., (2025) improved microalgal growth with BANE-XGBoost, Gaudêncio & Pereira, (2022) identified antifouling agents using QSAR and molecular docking, and Bharadwaj et al., (2022) discovered HDAC2 inhibitors from seaweed waste through computational techniques. These examples underscore AI's capability to speed up the identification of important marine compounds. However, challenges remain, such as the necessity for industrial-scale validation, a model accuracy cap of 71%, and the need for in vitro confirmation. This suggests that future work should concentrate on enhancing the scalability and reliability of AI-based approaches in this domain.

Ports and Shipping

Table 19 compares LSTM-based approaches for predictive maintenance in maritime systems, where Han et al., (2021) demonstrated accurate fault detection in marine diesel engines using an LSTM-Variational Autoencoder (LSTM-VAE), though limited to single-component validation. (Z. Wang et al., 2025) achieved superior anomaly detection in ship equipment with an LSTM-Autoencoder (LSTM-AE) enhanced by SHAP/LIME explainability, outperforming GAN/ diffusion models but requiring extensive anomaly-free training data. Meanwhile, (Awasthi et al., 2024) applied LSTM with Synthetic Minority Oversampling Technique (SMOTE) to port crane error prediction, attaining perfect precision (1.00) but struggling with recall (50%) due to data imbalance.

Authors	Objectives	Location	Methods	Results	Limitations
(Han et al., 2021)	Fault Detection in Marine Components	Research vessel Gunnerus	LSTM-Variational Autoencoder (LSTM-VAE)	Accurate fault detection (semi-supervised)	Limited to diesel engines; needs multi-component validation
(Z. Wang et al., 2025)	Anomaly Detection in Ship Equipment	Marine Mechanical Systems	LSTM-Autoencoder (LSTM-AE) + SHAP/LIME	Superior to GAN/diffusion models	Requires large anomaly-free datasets
(Awasthi et al., 2024)	Error Prediction in Container Cranes	Port operations	LSTM + SMOTE (for unbalanced data)	Accuracy: 99.6%, Precision: 1.00	Recall (50%) needs improvement

Table 19: AI-driven Predictive Maintenance in Maritime Systems

Table 19 demonstrates the significance of AI in maritime predictive maintenance. In particular, Han et al., (2021) effectively identified faults in marine components on a research vessel employing an LSTM-VAE model. Z. Wang et al., (2025) further enhanced anomaly detection in ship equipment, utilizing LSTM-AE combined with SHAP/LIME. Meanwhile, Awasthi et al., (2024) reported high levels of accuracy and precision in predicting errors in container cranes through LSTM with SMOTE designed for unbalanced datasets. Nonetheless, challenges remain, such as the focus on diesel engines requiring broader component validation, the necessity of comprehensive anomaly-free datasets, and calls for better recall in predicting errors in container cranes. This emphasizes the need for future research to prioritize the creation of more adaptable and data-efficient AI models for the holistic maintenance of maritime systems.

Ocean Literacy

Table 20 examines AI-driven tools for ocean literacy, where Pataranutaporn et al., (2025) demonstrated that Generative Pre-training Transformer (GPT) - based chatbots (OceanChat) enhance public behavioral intentions toward marine conservation compared to static information, though policy support remains unaffected. Zheng et al., (2023) developed MarineGPT, a vision-language model trained on marine-specific data (Marine-5M), showing improved understanding of marine-related queries but requiring further domain fine-tuning. For social media analysis, Kusumaningrum et al., (2024) used Sentence-BERT and clustering to identify nine mangrove awareness topics on Indonesian Twitter, highlighting cultural and linguistic specificity challenges. Meanwhile, Mora-Cross & Calderon-Ramirez, (2024) evaluated large language model (LLM) uncertainty (using Monte Carlo Dropout) for biodiversity Q&A in Costa Rica, establishing viable metrics but testing only smaller models (Falcon-7B/DistilGPT-2).

Authors	Objectives	Location	Methods	Results	Limitations
(Pataranutaporn et al., 2025)	Promote marine conservation via AI chatbots	Virtual (N= 900 users)	GPT-based conversational agents (OceanChat)	Increased behavioral intentions (versus static info)	Limited impact on policy support
(Zheng et al., 2023)	Develop marine-specific LLM (MarineGPT)	Marine Domain	Vision language model (Marine -5M dataset)	Better understanding of marine intent	Requires domain -specific fine -tuning
(Kusumaningrum et al., 2024)	Analyze mangrove awareness	Indonesian Twitter	Sentence-BERT + K-Means Clustering	Identified 9 mangrove topics	Language / Cultura Specificity
(Mora-Cross & Calderon-Ramirez, 2024)	Assess LLM uncertainty for biodiversity QA	Biodiversity of Costa Rica	Monte Carlo Dropout (MCD) + ECE	Viable Uncertainty Metrics	Limited to Falcon -7B/DistilGPT-2

Table 20: AI Applications in Ocean Literacy

Table 20 highlights how AI is being utilized to enhance ocean literacy. Pataranutaporn et al., (2025) reported increased user engagement through GPT-based chatbots, Zheng et al., (2023) created a marine-specific large language model for better understanding of marine-related intentions, Kusumaningrum et al., (2024) examined mangrove awareness on Indonesian Twitter using

Sentence-BERT, and Mora-Cross & Calderon-Ramirez, (2024) evaluated uncertainty in biodiversity Q&A with LLMs. Despite these developments, there are research gaps, such as limited influence on policy support, the need for specialized fine-tuning, considerations for language and cultural contexts, and constraints in the generalizability of LLMs. These indicate that future studies should aim to improve the efficacy and expand the scope of AI tools in ocean literacy programs.

Conclusions

This systematic review exhibits the transformative role of AI in marine science and governance, exemplifying its potential in improving ocean monitoring (e.g., 99% precision in illegal fishing detection), optimizing marine resource use (e.g., 6.64% fuel savings in shipping), and advancing conservation (e.g., 80% accuracy in 3D coral mapping) across 45 key studies from 2015 to 2025. Despite these advancements, shortcomings such as geographic data biases, over-reliance on synthetic datasets, and limited real-world validation persist, emphasizing the need for standardized benchmarks and interdisciplinary research collaboration. Notably, only 12% of studies address governance frameworks, underscoring the importance of explainable AI for policymaking. Case studies from India and Bangladesh illustrate both the potential and limitations of AI in resource-constrained settings. To bridge research-policy gaps, the review proposes a three-tiered action plan involving international data-sharing, certification standards, and innovation hubs. As the UN Ocean Decade advances, the review calls for real-world validation, multilingual models, and ethical guidelines to ensure AI's contribution to sustainable ocean governance is equitable, scientifically grounded, and globally relevant.

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