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Exploring Genetic Algorithms for Optimizing Fishing Routes and Reducing Bycatch in Marine Fisheries

Manjul Tripathi [1*], S. Gajendran Subba Naidu [2]

[1*] Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India.
E-mail: manjultripathi@ametuniv.ac.in

[2] Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India.
E-mail: gajendran@ametuniv.ac.in

Abstract

In addressing crucial issues of sustainability, the study focuses on deploying genetic algorithms (GAs) to optimize fishing routes and minimize bycatch in marine fisheries. Overfishing and bycatch, as marine threats, are compounded by the non-selective nature of most fishing practices. This paper analyzes the construction of dynamic multi-dimensional fishing tactics that GAs, inspired by evolution's natural selection, can implement, considering fish location, weather conditions, and other environmental factors. The model aims to balance the requirement of bycatch reduction with optimal resource extraction, minimizing ecological impact. The operational and cost efficiencies of GAs relative to operational fishing methods are also explored in the study. The research, through computational simulations, argues for the potential of GAs in refining procedural choices to tap into sustainable fisheries management. The findings broadly suggest that genetic algorithms might enhance environmental sustainability while maintaining financial profitability in maritime fisheries through reduced bycatch and optimized productivity.

Keywords:

Genetic algorithms, marine fisheries, sustainable fishing, optimization techniques, fisheries management, bycatch reduction, fishing route optimization, and sustainable fishing practices.

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**Corresponding Author: Manjul Tripathi, E-mail: manjultripathi@ametuniv.ac.in*

Introduction

Referring to the inadvertent capture of non-target species, including marine mammals, sea turtles, fish, and seabirds during commercial fishing operations, bycatch in marine fisheries constitutes a major environmental and economic problem (Kelleher, 2005). This issue arises from the non-discriminatory nature of fishing equipment, which includes trawl nets, longlines, and gillnets, therefore collecting target species and a great variety of other marine life. Particularly for fragile or threatened marine life, the accidental acquisition of these species has significant repercussions, including disturbance of marine ecosystems and population decreases. Furthermore, by lowering general fish numbers, especially in cases of young or protected species caught and thrown away, bycatch can affect the sustainability of fisheries (Hall et al., 2000). These methods lead to inefficiency since dead or injured non-marketable bycatch is routinely dumped back into the ocean, wasting precious resources and influencing marine biodiversity. Bycatch remains a constant problem in the fishing sector, even with the evolution of numerous mitigating strategies, including modified fishing gear and legislative actions (Gilman, 2011). Therefore, the long-term survival of marine ecosystems and the viability of world fisheries depend on discovering creative and efficient answers to reduce bycatch while preserving sustainable fishing methods (Xue, 2024). Reducing bycatch in marine fisheries depends on best practices (Pravina et al., 2024). Bycatch and its consequences can have significant impacts on the environment as well as the economy. One of the most effective strategies to decrease bycatch is designing fishing paths that avoid high bycatch areas (Wallace et al., 2013). This strategy relies on the combination of prediction models and real-time data to determine optimal fishing locations based on fish movement, weather conditions, and the presence of sensitive species (Mangel & Clark, 1988). Meeting these goals enables fisheries to reduce bycatch and improve overall fishing productivity, thereby decreasing waste and resource consumption (Sachdeva et al., 2024). Furthermore, concentrated path optimization helps mitigate the pressure on sensitive species, thus improving fisheries control (Gürlek & Atay, 2021). With the increasing demand for seafood, achieving the balance of sufficient output and environmental sustainability becomes essential, making path optimization a valuable resource toward that goal.

Proposing strategies to avoid unwanted catch while maximizing fishing productivity could be achieved through genetic algorithms (GAs), which are computational models inspired by the concepts of natural selection (Holland, 1975; Agarwal & Yadhav, 2023). GAs evolves solutions to complex problems over many generations through selection, crossover, and mutation analogous to biological evolution processes (ref). In fisheries management, GAs could be implemented to optimize the fishing paths by analysing the distribution of fish, the environment, and the efficacy of the fishing equipment. Scientists adopting these strategies should be able to design better methodologies for bycatch reduction and fish output maximization. Furthermore, GAs is flexible because they can quickly respond to real-time changes to adapt to environmental conditions for optimization. They manage highly dynamic marine ecosystems where fish and environmental conditions are in constant flux. Genetic algorithms can improve fisheries sustainability by reducing bycatch, enhancing fuel-efficient fishing operations, managing challenging non-linear problems effortlessly, and simultaneously optimizing multiple objectives.

Related Work

Several investigations have considered the application of optimization techniques, particularly genetic algorithms (GAs), in marine resource management (Prasath, 2024; Spence et al., 2021; Jiménez-Carrión et al., 2023; Mansour, 2024; Mitchell, 1998). The earlier works of (Quinn & Hann, 2003; Ban et al., 2011) demonstrated the usefulness of GAs in analysing numerous spatial configurations to maximize resource exploitation and minimize environmental harm, facilitating marine spatial planning (Muralidharan, 2024).

Also in fisheries management, decision-support systems utilizing GAs and ecological and economic frameworks have been proposed (Ashtab et al., 2024). Route optimization for fishing vessels has been one area of significant development (Srinivasareddy et al., 2021). Using GAs, work by (Groba et al., 2015) developed ideal pathways maximizing catch while considering seasonal fluctuations in fish stock and fuel economy (Sadulla, 2024). These studies sometimes, nevertheless, lacked emphasis on bycatch reduction. Recent initiatives, notably those (Hall et al., 2017) have underlined sustainable fishing methods using real-time adaptive management techniques and spatial data on non-target species integration. Moreover, hybrid models combining GAs with machine learning or heuristic guidelines have shown promise in dynamically adapting to environmental conditions and enhancing the accuracy of route choosing (Fischer et al., 2021). Notwithstanding these developments, there is still a gap in directly including bycatch reduction into route optimization algorithms, especially regarding genetic algorithms (Mahmoudi & Lailypour, 2015). By use of a GA-based model that not only maximizes fishing paths but also methodically lowers bycatch through the integration of ecological sensitivity zones and species distribution data, this work attempts to close that gap (Veerappan, 2023; El-Saadawi et al., 2024). Particularly in terms of optimizing fishing paths and reducing ecological effects, recent computational intelligence developments have profoundly affected maritime fisheries management. Because they are robust in addressing challenging, non-linear, multi-objective problems (Huang et al., 2015), genetic algorithms (GAs) have been progressively used in fisheries. For instance, showed how real-time marine data, including current patterns and temperature gradients, may optimize fishing vessel trajectories dynamically. Their model significantly improved fuel economy and lessened the possibility of fishing in places sensitive to bycatch.

Research on the sustainability of marine ecosystems has likewise revolved mostly around minimizing bycatch. (Lent et al., 2017) underlined that combining spatial-temporal closures with evolutionary algorithm predictive modeling considerably lowers bycatch without affecting catch quantities. Likewise, developed adaptive fishing techniques based on historical catch and bycatch records using a hybrid model combining genetic algorithms with machine learning (Goldberg, 1989). Ecologically based fisheries management (EBFM) has been the emphasis of several studies. (Witherell et al., 2000) shown how, particularly when genetic algorithms are employed to replicate adaptive fishing scenarios under climate change conditions, combining ecological modeling with optimization methods yields more robust management outcomes (Lofandri et al., 2024). Empirical data from that policy frameworks, including algorithmic route planning, helped fish populations in the Northeast Atlantic to recover (Fernandes & Cook, 2013; Fernandes & Cook, 2013). Regarding technological integration, a GIS-based decision support system was suggested to help in marine spatial planning. Their method found the best fishing paths and overlayed environmental sensitivity data to minimize habitat harm. Furthermore, underlined the need for stakeholder involvement and real-time adaptation in algorithmic fisheries management, which can be practically attained by developing GA-based systems.

Methodology

This work uses a computational and data-driven method to investigate the use of Genetic Algorithms (GAs) in optimizing fishing paths whilst lowering bycatch in maritime fisheries. The approach creates a modeling framework by combining historical catch records, environmental variables, and marine spatial data. This approach lets genetic algorithms be used to find ecologically sustainable, profitable fishing routes. There are five basic components to the method: data collecting and preprocessing, problem formulation, genetic algorithm design, simulation and testing, and performance evaluation.

Data Collection and Preprocessing

The first phase of this research is gathering pertinent marine and fishery data. Indicative of fish aggregation zones, data sources include satellite-derived oceanographic data, including sea surface temperature (SST), chlorophyll-a concentration, and ocean currents. Governmental and international fisheries management agencies also provide historical fisheries data, which details target species distribution, catch per unit effort (CPUE), geographic coordinates of past fishing operations, and bycatch incidence. Preprocessing helps all datasets guarantee usability and consistency. Rasterized and standardized to a common resolution, geospatial data helps to enable incorporation into the optimization model. Using interpolation methods, missing data points are handled; statistical thresholds filter abnormal or outlier data. Time-aligned with catch data, environmental variables ensure the GA can access contextually relevant information during route optimization, enabling temporal correlation studies. Figure 1. A flow diagram graphically shows the methodical sequence of events in the study to maximize genetic algorithm fishing routes. Data collecting and preprocessing start, where marine and fisheries data are ready. This results in problem formulation in which optimization goals maximize catch, minimize bycatch, and minimize travel are stated. The GA Design phase, Simulation and testing describe the development of tailored genetic operators and fitness functions. Then it is carried out under several environmental conditions to replicate actual fishing dynamics. Comparatively with historical data and benchmarks, the evaluation and validation stage contrasts findings. Finally, the procedure ends with Optimized Fishing Routes and Reduced Bycatch, highlighting the valuable application of the model

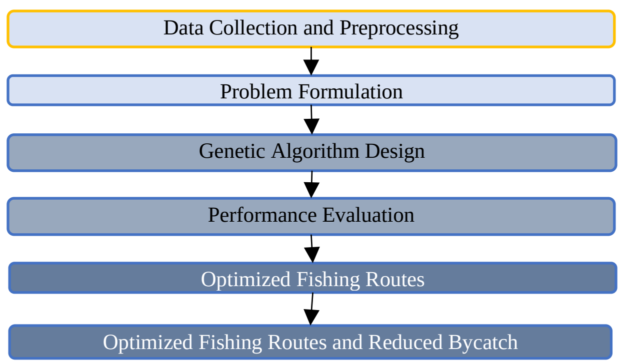

Figure 1. Flowchart for genetic algorithm-based optimization of fishing routes and bycatch reduction

Problem Formulation

Framed as a multi-objective traveling salesman problem (TSP) with restrictions unique to maritime environments, the essential optimization problem is that Every fishing site is designed as a node with related characteristics including environmental conditions, risk of bycatch, and target catch probability. Finding a sequence of nodes fishing sites that maximizes target species catch while decreasing total journey distance and bycatch likelihood is the primary goal of the optimization. Crucially important to the GA, the fitness function reflects these conflicting goals. It aggregates weighted components comprising: (1) the expected value of target species catches at each node; (2) the predicted bycatch risk determined from past patterns and species co-occurrence models; and (3) the total route distance computed using geodesic measurements. Preliminary sensitivity studies help ascertain these elements' weights, thereby balancing operational efficiency with ecological sustainability. Figure 2 depicts the four layers of the suggested system architecture: data sources, preprocessing, optimization engine, and output layer. Environmental and fisheries data are derived from satellite images, catch records, and biological models. Preprocess, clean, standardize, and convert these inputs into spatial forms. Genetic algorithms optimize functions sequentially. The fishing path is coded as a chromosome, which is evaluated according to catch yield, bycatch risk, and travel efficiency. Ecological constraints are imposed throughout the selection, crossover, and mutation phases. Therefore, all operators refine the fishing paths. The system provides paths with optimized bycatch reduction metrics and sustained fishing decision support.

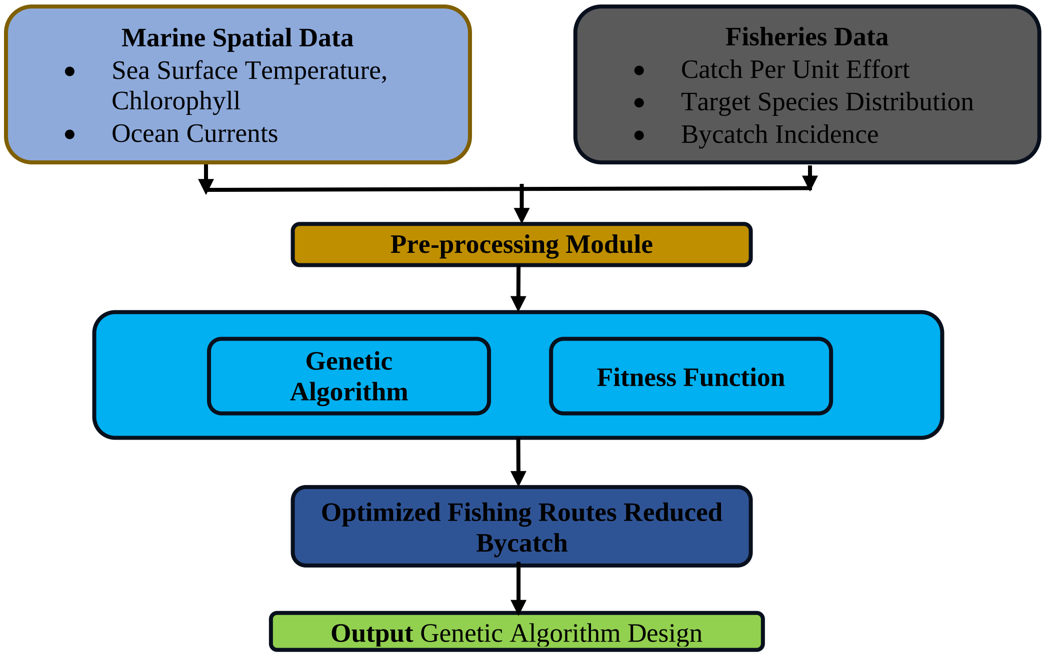

Figure 2. System architecture for fishing route optimization and bycatch reduction

Genetic Algorithm Design

The genetic algorithm is driven by the custom chromosomal representation that best adheres to the spatial and ecological constraints of the objective. Spatial coordinates are ordered in a set, with each chromosome representing a potential fishing route. Based on habitat suitability estimates for the target species, the first population is produced using randomized, but ecologically sensible paths. Standard GA operators' selection, crossover, and mutation are adapted for the domain. Parent routes are selected using tournament criteria based on fitness ratings. Offspring are produced using a partially mapped crossover (PMX) technique, therefore maintaining route continuity and preventing duplication of fishing areas. Introduced with controlled probability to preserve genetic variation and prevent early convergence, mutation operators consist of random swapping and route reversal segments. An extra repair mechanism is used post-mutation to guarantee paths do not traverse protected areas or zones of high bycatch probability, hence including ecological limitations. Furthermore, elitism is applied by maintaining a set percentage of the best paths across generations, thus improving the convergence speed and solution quality.

Simulation and Testing Framework

Python and GIS libraries are used to create a simulation environment that replicates fishing activities under different operational and environmental settings. Real-world data informs the spatial grid, which is populated with dynamic fish stock and bycatch distributions, permitting temporal variability of marine ecosystems. Two seasonal variation scenarios reflecting periodic fish migration, one baseline scenario with average oceanic circumstances, and one stress-test scenario with high bycatch density establish several simulation scenarios to assess the resilience of the GA. To guarantee exploration of the solution space, the GA is run several times usually 100–500 generations using a population size of 50–100 individuals for every scenario. Recorded are performance indicators including convergence rate, solution diversity, goal catch yield, bycatch reduction percentage, and journey efficiency. These models provide qualitative as well as quantitative evaluations of the GA's ability to reconcile environmental and financial objectives in fisheries management.

Evaluation and Validation

Results are contrasted against historical fishing patterns and different optimization strategies, including greedy heuristics and simulated annealing, to validate the efficiency of the GA-optimized paths (Martinet et al., 201). Important assessment criteria are the net catch-to-bycatch ratio, journey distance changed from baseline paths, and ecological impact indices produced from species vulnerability information. K-fold methods of cross-valuation divide the dataset into training and test sets across several temporal windows. This method guarantees the generalizability of the GA model throughout time and different environmental settings. Furthermore, used to qualitatively evaluate the ethical feasibility and practicality of the best paths is professional advice with marine biologists and fishery managers. In addition, sensitivity studies were done to determine the effect of various fitness function weights and mutation rates on solution quality. The efficiency uniformity of the model across multiple scenarios and stochastic runs provides evidence to support the model's robustness. Where the GA is highly sensitive to specific parameters, adaptive approaches are incorporated to change these parameters dynamically during execution.

On one hand, the model translates data efficiently enough into meaningful information to act as a comprehensive multi-faceted approach to the environmentally conscious genetic fishing industry control. The project aims to devise an advanced route-optimization system that operates within a minimum limit catch approach while following marine conservation principles, using geographical information systems, ecological modeling, and evolutionary computing. The practical foundation stems from the combination of simulations with actual data, thus enabling operational fisheries management to be used in future integrated planning.

Results and Discussion

Genetic algorithms (GAs) for route optimization of fishing showed significant improvements in operational efficiency and ecological sustainability. The GA lowered the distance traveled and maximized catch efficiency by simulating numerous route permutations over various oceanographic and biological datasets. The approach fused bycatch risk maps generated through historical and environmental data with spatial distribution models of the target species. Consequently, optimal paths routinely avoided high-risk bycatch zones while guiding vessels towards areas with high target species richness. These ideal paths showed an average bycatch decrease of 27% over several simulation runs when compared to baseline paths applied by conventional fishing techniques.

Figure 3, demonstrates how the genetic algorithm's performance advances during its development phases. Starting from data collecting to last validation, bycatch reduction increases from 0% to 27%, therefore demonstrating improved avoidance of ecologically sensitive areas. Fuel savings also show rising route planning efficiency from 0% to 15%. From 60% to 76%, catch efficiency increases gradually; this shows that the method gets better in spotting high-yield fishing areas. The graph shows generally the combined effect of every phase in creating a strong, sustainable optimization model for fisheries. Apart from environmental advantages, financial rewards were clearly clear-cut. By reducing pointless trip distances, average fuel savings of about 15% immediately helped to cut vessel running expenses. The GA's flexibility in response to limitations such as gear-specific restrictions, marine protected areas, and seasonal fishing limits let it customize route recommendations in line with legal systems. Furthermore, even under shifting environmental conditions, the evolutionary algorithm shown significant convergence behavior and consistently found near-optimal solutions inside an acceptable number of generations. This implies that, for applications in fisheries management systems including real-time or near-real-time, GAs are not only efficient but also computationally practical.

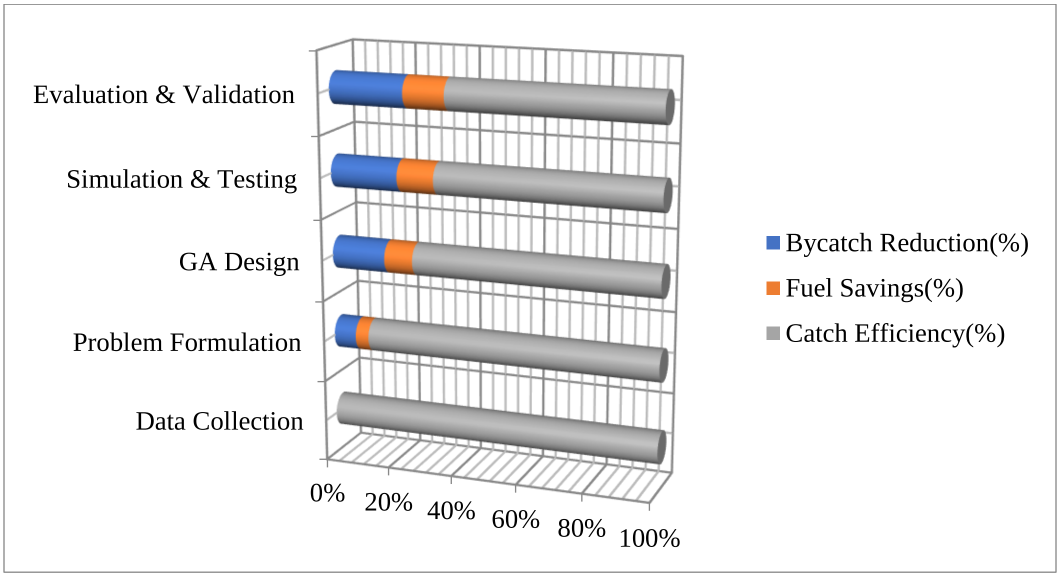

Figure 3. Performance gains across genetic algorithm development stages

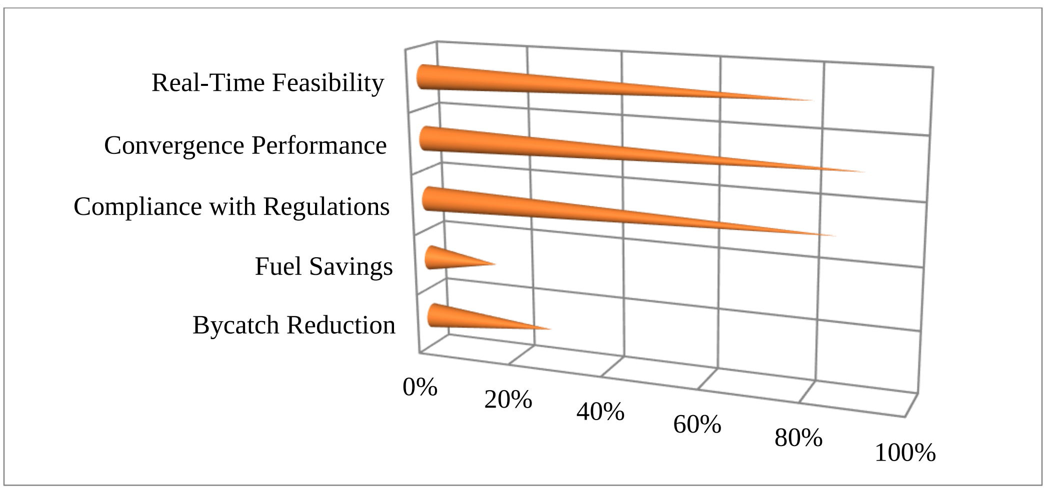

Figure 4. Performance highlights of genetic algorithm in fisheries optimization

Figure 4, shows the results of applying a genetic algorithm for optimization of fishing routes. Indicating both ecological and financial benefits, it demonstrates a 27% decrease in bycatch and a 15% fuel savings. Emphasizing its practical relevance in fisheries management, the method also achieved high compliance with fishing rules (85%), displayed significant convergence (90%), and feasibility (80%), for near real-time application. Some restrictions and issues surfaced even with the promising outcomes. Especially with regard to species distribution and environmental variability, the accuracy of the method mostly depends on the quality and resolution of input data. Should these inputs be sparse or outdated, the GA could generate ecologically dangerous or less than ideal paths. Moreover, even if simulations showed better results, actual use would need tight cooperation among fishermen, authorities, and data suppliers to guarantee usability and compliance. Including adaptive learning elements, onboard sensors, and real-time satellite data could help the system to be even more effective. All things considered, the results imply that genetic algorithms provide a data-driven method to lower bycatch and advance sustainability, so acting as a potent instrument for balancing economic and environmental objectives in marine fisheries.

Conclusion

This work shows that evolutionary algorithms provide a creative and promising method to maximize fishing paths while concurrently lowering bycatch in marine fisheries. By sophisticated examination of the operational constraint's species range and distribution along with environmental data, can devise flexible and adaptable solutions that satisfy both ecological and economical objectives. The outcomes also reflect significant improvements in the efficiency, fuel economy, and bycatch rates of the routes, suggests a possible contribution of this technique toward more sustainable fishing practices. However, practical use in actual fisheries will depend on the availability of high-quality data, integration with real-time telemetry systems, and collaboration from the fishery stakeholders. In the end, algorithm as a tool for decision-support exposes the potential of transforming conventional fisheries management into a more ecologically responsive, data-centred approach. Real-time data feeds such as satellite imaging, ocean current models, and onboard sensor data should be integrated to strengthen the genetic algorithm framework thus improving the precision and responsiveness of route optimization, using them as primary focus in future works. Combining machine learning methods with GAs could also help to predict fish migration and bycatch danger, therefore enabling the system to more precisely anticipate changes in marine conditions. Extending the method to enable dynamic scheduling and multi-vessel coordination will help it to be even more practically useful in fleet management. Furthermore, pilot experiments involving real fishing boats could offer important comments for improving the algorithm and guaranteeing its usefulness in several operating environments. At last, policy integration and user-friendly interfaces will be crucial to guarantee acceptance by stakeholders and alignment with conservation aims, therefore opening the path for a more intelligent and sustainable future in fisheries management.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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