INTEGRATION MODEL OF AUTONOMOUS UNDERWATER VEHICLES AND UNMANNED AERIAL VEHICLES FOR COMBATING ILLEGAL, UNREPORTED AND UNREGULATED FISHING

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Summary

Illegal, unreported and unregulated (IUU) fishing can pose a serious threat to biodiversity, maritime ecosystem and fish fonds that otherwise can be exploited in a more adequate and economical manners. Advanced fishing management techniques, enhanced algorithms, and newly developed technologies, more specifically the upswing of unmanned aerial vehicles (UAV) and autonomous underwater vehicles (AUV), can help provide new solutions to combat the illegal activities at sea. This paper aims to explore the current findings regarding usage of UAVs and AUVs for abundance assessments and direct and indirect prevention of illegal, unreported, and unregulated (IUU) fishing by applying thorough analysis, compilation, systematic comparison and evaluation of methods and technologies indispensable for creating a modern fishery management system supported by AUVs and UAVs. As the contribution, the paper proposes an integrated model for deterrence of maritime misconduct by combining UAV and AUV systems, as well as using them for localizing high-risk areas according to depletion of fish stock. In that way distributing resources in the appropriate areas for maximizing the efficiency of law enforcement efforts by various agencies operating underwater and aerial maritime drone systems. In addition, possible challenges and drawbacks of the system that will have to be addressed are also examined and explained. Limitations of the study include the fact that the model has not been implemented in practice, which opens the gates to further research and possible continuation and expansion of proposed integrated UAV and AUV IUU fishing prevention model.

Key words: IUU fishing, sustainable fishing, AUV, UAV

1. INTRODUCTION

Illegal, unreported, and unregulated (IUU) fishing has been shown to have an increasingly detrimental impact on fish population abundance across various geographic regions. This escalating issue presents a significant challenge to traditional IUU combating methods, which may no longer be sufficient to address the complexity and scale of the problem [1–6]. In light of this, the current paper aims to examine the latest technological advancements, with a primary focus on the development and implementation of autonomous underwater vehicles (AUVs) and unmanned aerial vehicles (UAVs). These technologies are explored both in the context of fish stock abundance assessment and in the direct identification and catching of IUU vessels. Furthermore, this paper proposes a threshold-based algorithm designed to underpin an integrated operational model. This model links ecological data acquisition with enforcement actions, using the capabilities of AUVs and UAVs to create a responsive, data-driven system for monitoring and combating IUU fishing. The authors suggest this model as a means of improving efficiency and effectiveness in the deployment of available resources. The structure of the paper is organized into four main chapters, each addressing a key component of the proposed approach. The first chapter provides a detailed examination of fish stock population growth models and explores how these models relate to IUU catch estimation. It also delves into the role of AUVs and UAVs in conducting fish stock assessments, highlighting their contribution to the data needed for both population modelling and catch analysis. By establishing this foundation, the chapter emphasizes the importance of accurate, autonomous data collection as a basis for effective fisheries management and IUU monitoring. The second chapter shifts focus to the technological side of enforcement, exploring various emerging technologies used in the direct identification of IUU vessels. Special attention is given to advancements in computer-enhanced vision systems and vessel recognition models, which are proving to be increasingly useful in maritime surveillance. In addition, this chapter presents an overview of the unmanned platforms currently in operational use, detailing their technical characteristics in the context of maritime monitoring and enforcement missions. In the third chapter, the paper addresses the concept of maximum sustainable yield as a potential reference point for defining intervention thresholds within the proposed algorithm. It further elaborates on the design and theoretical structure of the algorithm itself, which is intended to serve as a flexible, scalable framework for integrating various unmanned and autonomous platforms. The aim of this integration is to enable a system capable of optimized resource allocation, deploying assets only when necessary and in areas where they will have the greatest impact, though this algorithm lacks practical implementation. Finally, the fourth chapter explores several challenges and limitations related to the real-world applicability of the technologies, models, and algorithms discussed throughout the paper. It acknowledges existing technical, logistical, and contextual constraints, and emphasizes the importance of continued research and development. The chapter concludes by outlining potential directions for future work, thereby opening the door for ongoing innovation and interdisciplinary collaboration in the field of sustainable fisheries management and IUU fishing prevention.

2. CONDUCTED RESEARCH ON FISH STOCK CONTROL

This chapter will examine the relation between fish stock population depletion and illegal and uncontrolled (IUU) fishing, as well as usage of unmanned aerial vehicles (UAVs) and autonomous underwater vehicles (AUVs) in determination of fish population quantity and in turn correlate the two phenomena whereby fish stock assessment can be used in IUU intensity assessment as well, providing state authorities with information for necessary reactive action-taking.

2.1. Impact of IUU fishing on fish stock

There are several examples of fish stock deterioration in certain geographical areas due to illegal and uncontrolled (IUU) fishing operations [1-6]. Examples of fish stock deterioration due to unlawful and uncontrolled activities mostly apply to the West and Central African coast, but there are also examples of this type of fishermen conduct affecting fish population in the Caspian Sea and Northern Africa [1-6]. Industrial IUU catching severely deteriorated fish stock population of Tunisia [3]. Stingrays and dolphins as well as other endangered species have also been noted to entangle in nets, while sea-grass beds are damaged from deep-water trawling [3]. In the Caspian Sea, the historically most important fish species, sturgeon, has been classified as critically endangered as a result of overfishing and destruction of spawning grounds [6]. IUU fishing has also had negative socio-economic impact on certain areas, for example in the case of Sierra Leone, artisanal fishing has been compromised by IUU fleet overexploitation of the area [1, 5]. In all cases, however, IUU fishing has negatively reflected on fish stock quotas and thus a correlation between stock depletion and an increase in IUU fishing activities can be drawn. Natural change of fish stock in one year in relation to quantifiable factors can mathematically be described using the following equation:

$$B_i = B_{i-1} e^{-F_{i-1} - M} + R, \tag{1}$$

where B_i is the calculated biomass quantity for the current year, B_{i-1} is the biomass quantity of the previous year, F_{i-1} is expected mortality rate due to fishing, M is the natural mortality rate and R is the natural biomass increase. If the calculated biomass of the current year deviates from the measured one such that $B_{icalculated} > B_{imeasured}$ this could indicate the rise of mortality in previous year due to IUU fishing. Thus, the catch for the previous year can be calculated as [7]:

$$C_{i-1} = \frac{B_{i-1} F_{i-1} (1 - e^{-F_{i-1} - M})}{F_{i-1} + M}, \tag{2}$$

Consequentially, if the fishing mortality rate and catch quantity increases above the threshold of sustainability, the information could serve as an alarm to the authorities to start taking measures against IUU fishing.

2.2. Fish stock assessment using autonomous underwater vehicles

As articulated in the previous subchapter, for correctly assessing the need to deploy measures against the IUU fishing, law enforcement authorities must firstly be acquainted with the current fish stock status which must be measured and assessed in real time. Assessment of fish population quantity can never be fully precise, nor can an exact biomass ever be known, but close approximations are achievable using proper sampling procedures when assessing the fish stock. Usual unbiased procedure includes choosing a specific sampling area or areas at random from all the possible sampling sites. Apart from probability assessment, non-probability assessment may also be used in case of specific areas to which certain rare species are either linked or the areas themselves are limited, such as lakes, so there exists no need for probability sampling [8]. After selecting the sampling area, there are number of methods of assessing population on the spot. One of them is using autonomous underwater vehicles (AUVs). For the purpose of fish stock assessment, AUVs can be differentiated by a few criteria in particular categories. One of them is detection equipment which can be either hydroacoustic or visual [9-11]. Experimental evidence has shown that video cameras have highly impaired effectiveness in turbid waters, while acoustic cameras are virtually unaffected by turbidity [9]. Acoustic cameras, on the other hand, lack the proper target strength to discriminate individual fish and are largely unable to determine their characteristics [10,11]. Therefore, when identifying species of the observed fish taxa, or their specific characteristics visual cameras provide a much better tool during assessment than their acoustic counterparts [10]. Another difference between two sensors also includes the fact that acoustic cameras use abundance models to assess the size of the biomass, rather than directly counting it [12]. Furthermore, AUVs can be used to observe fish taxa, individual fish or completely different organisms entirely [13-15]. For example, in protected waters archipelago in the Aegean Sea this method has been successfully utilized to identify 27 fish taxa, 21 of which have been categorized at the species level [13]. Along the Atlantic coast of Delaware and Maryland this technique allowed for counting of individual sharks to assess their population quantity, but more importantly, to even track their migration pattern [14]. Moreover, alongside fish, scallop population sizes and densities have also been successfully measured at the sea bottom [15]. While all these methods can be utilized even without the usage of remotely operated vehicles (ROVs) or AUVs, using human divers, applying new technologies removes safety risks, reduces the cost of conducting the operation, saves substantial amount of time and drops the possibility of human error [16]. AUVs have further advantage over ROVs since they have the ability to cover much larger areas and are therefore more suitable for conducting underwater surveys with the only real comparable disadvantage being the fact that the data is not transmitted in real time [17]. AUVs have pre-programmed tracks and are self-navigated using inertial navigation, to be precise, a system consisting of gyro compass, accelerometer, altimeter and other navigation sensors integrated to hold and change a pre-programmed track and in combination with data gathering system, i.e. video and acoustic cameras, can conduct a survey over a chosen area [18]. This allows for the AUV's full autonomy, as the name suggests, and thus longer surveying periods of larger areas. In addition, AUVs can be grouped together and a communication algorithm can be established between using acoustic communication systems, a technology still in development, which allow for better performance and efficacy [19]. Conclusively, AUVs serve as the most optimal platforms for conducting fish stock surveillance which is necessary for assessing the probable magnitude of IUU fishing operations and granting the law enforcement information for conducting further measures.

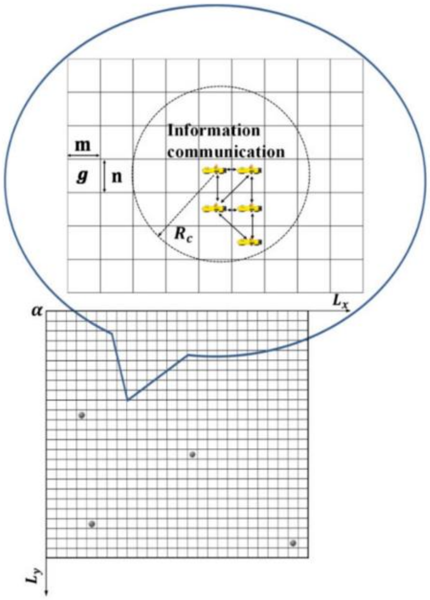

Figure 1 Search area model of multi-AUV system

Source: [19]

2.3. Fish stock assessment using unmanned aerial vehicles

Apart from AUVs, other forms of drone technologies can also be viably applied as an auxiliary system to the main AUV system of surveillance. One such form of drone technology is the usage of unmanned aerial vehicles (UAVs). Unlike the AUVs, UAVs are operated by a person, like the ROV control system, but, unlike it, conducted in aerial rather than maritime plane. Studies have shown that UAVs can indeed be used for abundance assessment [20, 21]. In addition, they can also be used for mapping of the fisheries geographic regions and assessment of the fish habitat [22].

3. OVERVIEW OF EFFECTIVE SEA AREA SURVEILLANCE

While unsustainability of keeping existing fisheries management models soared, sensor improvements opened discussion for broader surveillance applications of UAV in modern, overloaded environment [23, 24]. Their cost-to-benefit ratio surpassed that of traditional manned patrolling platforms [25]. Therefore new, highly autonomous UAV platforms, especially those combining advanced sensors and software become powerful tools for future IUU fishing prevention and catching. This chapter aims to summon development trends, validated scientific ideas and published operational applications of UAVs as a mean of effective sea area surveillance in environment overloaded with challenges [23]. Recommendations for UAV exploitation in the fish abundance assessment is also a valid path [25, 26]. However, although UAVs can be useful for abundance assessment, in this integration model, the role of fish abundance assessment is left to AUVs considering their advantages over UAVs at different depths and weather conditions [27, 28].

3.1. UAV for sea surveillance

Unmanned Aerial Vehicles (UAVs) or simply drones are defined as aircraft without a pilot and controlled from the ground or by a computer program [29]. They can be fixed-winged or rotary-winged. Also, they can further be divided by dimension cost, and the sensors they carry [25, 30]. Due to their and sensor improvements, UAVs pushed the boundaries of efficiency and affordability [31]. That also includes the maritime industry, where AUVs were already used for fauna surveying post-disaster assessment beach maintenance and litter classification platform for photogrammetry search and rescue actions UAVs have also capacity for IUU fishing prevention sea monitoring. Activity has been largely divided into suspecting ships detection, identification, localization, and tracking, and ghost fishing detection and removal [26, 30, 32-35]. According to that UAVs capabilities are:

3.1.1. UAVs for stationary target detection

Research was made on the UAVs detection of crab traps as one of mayor ghost fishing agent [27, 28]. It was stated that remote pilots can detect crab traps using cameras onboard small, non-specialized UAVs. While the detection rate depends on flight altitude, wind and precipitation, transparency of the sea, depth, and trap colour, it can greatly enhance IUU traps detection capability [27, 28]. Nevertheless, although the detection of stationary objects like gillnets and traps is the least complicated task; to make detection truly cost-effective it is necessary to automate it. Something that seems largely overlooked [30].

3.1.2. Trends in UAV fishing monitoring systems deployment

UAVs are very useful for first-view monitoring of a particular sea area and potential IUU fishing ship detection and identification, localization, and tracking [25, 28, 36-39]. Visual image monitoring by UAVs carrying cameras greatly helped Belize’s tiny fishery enforcement office Around 10 years ago they started using Solo Quadcopter by company 3DR carrying an onboard camera (few models can be fitted) with live video transmission [40]. At approximately the same time Jamaica led a similar project acquiring two UAVs one of which is X8 Skywalker [41]. Not long after that Jamaican official announced the procurement of new UAVs with greater reach [42]. In 2023. testing flights were conducted in French Guiana consisting of patrolling over an area of more than 70km in a radius with French-made long-range fixed-wing UAV BOREAL produced by French company BOREAL SAS [43]. Most recently, Palau has announced the acquisition of an advanced Matrice 350 RTK UAV for IUU fishing combating [44]. Chinese province of Zhejiang also started using long-range UAVs for combating IUU fishing a few years ago. Their JOUAV CW-25E with a powerful camera enhanced with computer vision software can automatically track and identify IUU fishing ships [45]. Systematic list of mentioned UAV systems is provided in the Table 1 below.

Table 1 UAVs for Maritime Surveillance

Model	Country	Producer	Type	Start of Deployment	Range	Max horizontal speed	Endurance	Sensors and software	Cost*
Scan Eagle-USCG 2017	USA	Boeing-Insitu	Fixed wing, heavy fuel or gasoline engine	2013.	60 NM	80 knots	Up to 18 h	EO telescope (high zoom day FMV), MWIR/EO dual sensor, ViDAR (maritime surface search)	Not announced officially Can be estimated to 1.4 million* (2023.-hole system)
SKYWALKER X8	Jamaica	UAV Model	Electric powered fixed wing	2015.	Up to 10 km	65-70km/h	25 min	Without frame, but carries up to 2kg	150-400
Solo Quadcopter	Belize	3DR	Small rotary-winged, quadcopter	2016.	800 m	55 mph	15-25 min*	Built-in GoPro frame, gimbal stabilised	800(2019)
TEKEVER AR5- EMSA	EU	CLS-TEKEVER consortium	medium-altitude, medium-endurance fixed-wing UAS	2021.	Up to 1000 km	100 km/h	Up to 9h	EO/IR cameras, AIS sensor, EPIRB, Satcom terminal, Maritime Radar, radar emitter detector, Mobile phone detector	Not announced officially
DJI Mavic Enterprise	Seychelles	DJI	Electric powered fixed wing	2021.-2022.	9-15 km	15 m/s	45 min	4/3 CMOS Wide Camera, 56× Hybrid Zoom, 640 × 512 px Thermal Camera, AI enhanced	3500 (2021.)
BOREAL ISR	France	BOREAL SAS	long-range, fixed wing drone	2022.	800 km	37-70 knots	Up to 8 h	E/O HD (IR) sensors, AI enhanced 360° day/night vision gimbal camera	Not announced officially
JOUAV CW-25E	China	JOUAV Unmanned Aircraft System	Long Endurance Electric Fixed-wing VTOL Drone	2023.	35-100 km	72 km/h	4 h	AI enhanced MG-150E gimbal camera	Not announced officially
AEROSONDE 4.7	Australia	Aerosonde Uncrewed Aircraft System	Hybrid Quadrotor,vertical takeoff and landing (VTOL) drone	2024.	140 km (75 NM)	45-65 kt	Up to 12	Full-Motion Video (FMV), Maritime Wide Area Search Synthetic Aperture Radar (SAR) Automatic Identification Systems (AIS), Light Detection and Ranging (LiDAR)	$25,610,000 (whole system-2022.)
Matrice 350 RTK	Palau	DJI	Small rotary-winged, quadcopter	2025.	8-20 km	23 m/s	Up to 55 min	-Directional Positioning, Night-Vision FPV Camera Night-Vision, Multi-Payload Support	From 13 789 €

*Cost is somewhere expressed for the sole drone and where it was possible for system as a hole.
Sources: [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64], [65], [66]

3.1.3. Spatial organization of UAV area surveillance

It is evident that although UAVs equipped with cameras can be very effective and affordable tools in expanding situational awareness and broadening areas of surveillance, their surveillance role can be greatly enhanced by combining their sensors with ground process centres where more powerful software can be employed. That ground station can be on cost guard ships, so they have even greater reach [67]. One ground station can, with raising automatization, launch big number of drones using swarm control, as described in [36]. Such an integrated system can take area surveillance and IUU fishing catching to another level. Moreover, number of UAV systems employed, positioning of the ground station and size and shape of area they survey or protect can impact surveillance effectiveness. For that reason, different positioning rules have been proposed for ground station in accordance with size and shape of marine protected area and number of UAVs available that can be seen in Fig. 2,3 [36].

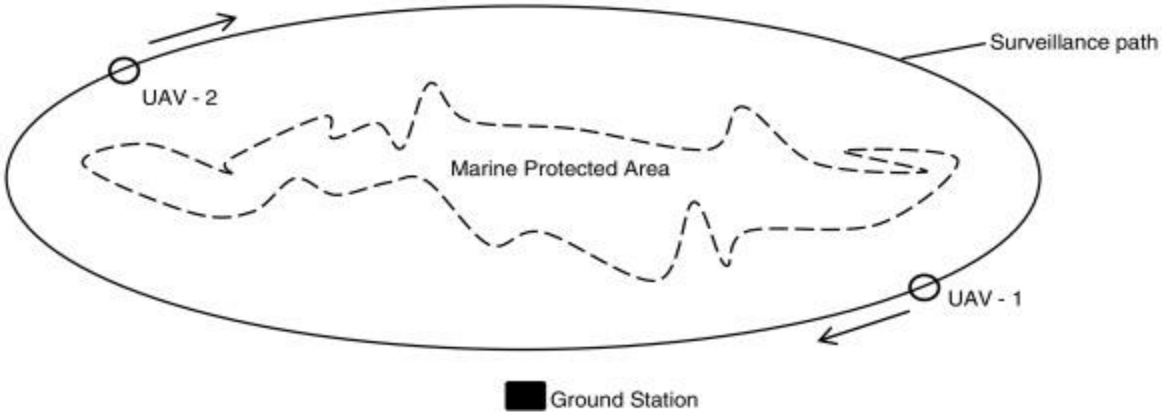

Figure 2 Elliptical planning of marine protected area surveillance

Source: [36]

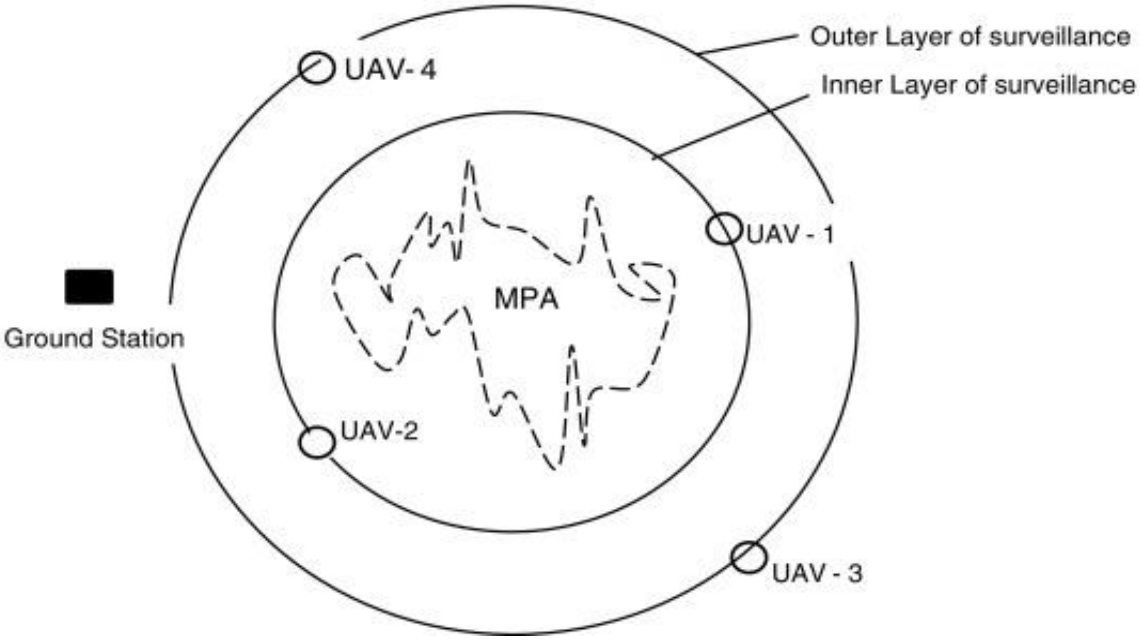

Figure 3 Circular planning of marine protected area surveillance

Source: [36]

4. PROPOSED INTEGRATION MODEL OF AUV AND UAV SYSTEMS AND ALERT THRESHOLD BASED ALGORITHM FOR COMBATING IUU FISHING

In previous chapters AUV and UAV fish stock assessment and catching methods have been discussed. Although UAVs with computer-enhanced photographic capabilities can be used directly, in patrol-like inspections, it might be more economically viable to hold them in passive rest until the proposed threshold-based algorithm raises an alert over a specific area based on fish stock reduction. It will also make concentration of UAVs extensive only over the areas where stock depletion has been detected, thus further optimizing the resource allocation as well as raising the probability and reducing the time needed to catch the IUU fishing vessels. This chapter will provide the necessary information about proposed model and algorithm.

4.1. Static and dynamic threshold algorithms

When discussing threshold-based algorithms, there are two types of such algorithms, namely static and dynamic algorithms. Static threshold algorithms use a constant value as a threshold, while dynamic threshold algorithms use a variable value [68]. Thus, dynamic threshold algorithms are more complex, however, as alert threshold alert algorithm is dependent on different fish species, geographical area and seasonal and periodical changes, so does the threshold vary based on these parameters, making it a dynamic one.

4.2. Maximum sustainable yield

In the first chapter of this paper, a thorough analysis of the monitoring of change in fishing activity through the assessment of fish stock has been presented. Accordingly, an increase or decrease in catch is calculated, however, stationary catch does not necessarily mean sustainability in the long run, nor does an increase in catch necessarily mean an inherent lack of it. Threshold for this algorithm therefore can not be taking the catch of the previous year as a maximum. Hence, maximum sustainable yield is introduced. As fish populations increase following the logistics curve or the “S” curve, since at first there is too little biomass to reproduce quickly, then it starts reproducing exponentially after a while and in the end, it hits the limit presupposed by the environment [69, 70]. The change of fish population over time can thus be described as the first derivative of the “S” curve and be expressed as:

$$\frac{dB}{dt} = \frac{rB_1 - B}{B_0 - pB}, \tag{3}$$

where $\frac{dB}{dt}$ is the change of biomass over time, r is the exponential growth factor, B_1 is the initial biomass, B_0 is the intersect and the stationary point of the population growth curve and p is the decline factor [49]. If plotted, the change in growth rate curve will resemble a pseudo-parabola as in Fig. 4:

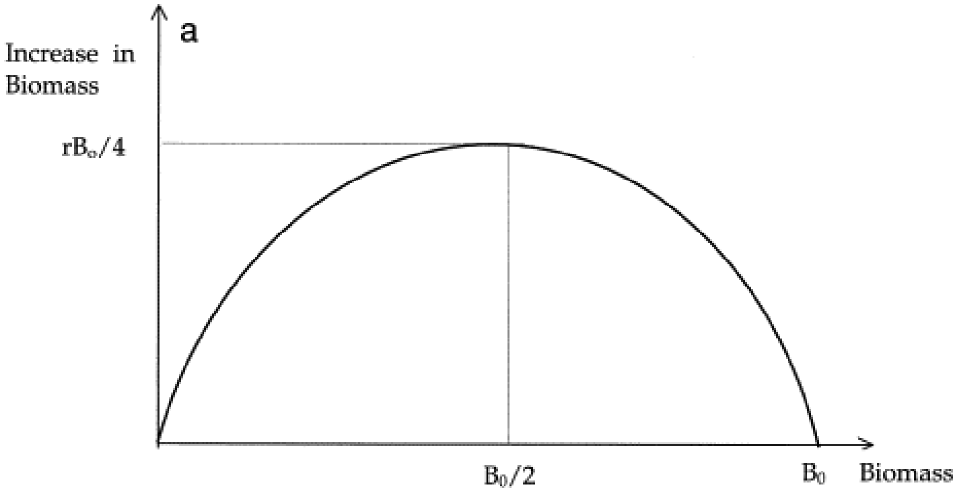

Figure 4 Change of growth rate of fish population

Source: [70]

From this relationship, it is apparent that biomass of the maximum sustainable yield, which is the maximal quantity of extracted biomass which will not cause the decrease in fish growth rate, is position at the maximum of the growth rate change curve and can be expressed as [71]:

$$B_{msy} = 0.5B_0, \tag{4}$$

to precisely calculate the maximum sustainable yield, statistical data of fish population over periods of time need to be collected and examined. Once obtained, the maximum sustainable yield can be used as a threshold for allowed and prescribed catch quantity and, consequently, a threshold for alarm after which UAV catching methods can be employed in order to combat IUU fishing activities.

4.3. UAV catching system's threshold alert algorithm

As expressed previously, in order to maximize the effectiveness of UAV catching by increasing their concentration in the areas with high alarm for biomass decrease due to IUU fishing and to optimize the resource allocation, maximum sustainable yield is used as a reference point and data collected by combined AUV and UAV fish stock surveillance is used as an input data for comparison with the reference point. Furthermore, if the fish mortality due to fishing does not increase above maximum sustainable yield no measures need to be taken and UAV systems for catching IUU fishing vessels can be held in passive, thus saving the resources and optimizing their allocation. Therefore, the final explanation of algorithm is as follows: AUV and UAV surveillance platforms collect data on fish stock; maximum sustainable yield is calculated; from data collected, catch quantity is calculated; catch quantity is compared to maximum sustainable yield; if the catch is smaller or equal to yield, no measures ought to be taken and UAV systems for catching IUU boats can stay at passive; if the catch is greater, UAV systems are activated over the alarmed area and help combat the IUU fishing. The algorithm is further described in Fig.5:

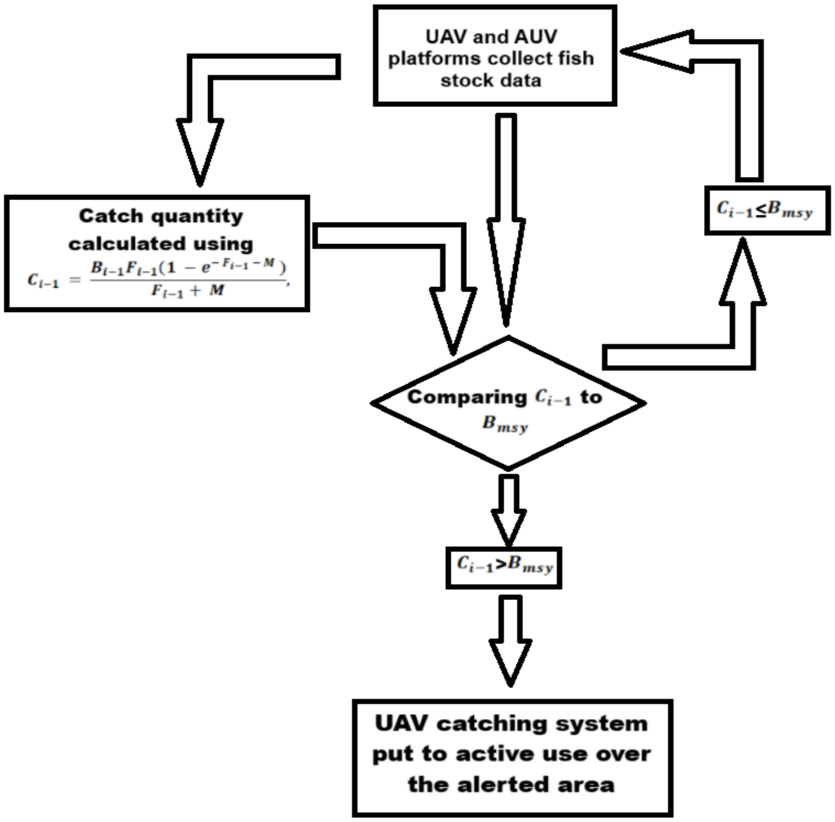

Figure 5 UAV catching system's threshold alert algorithm

Source: Authors' original work

5. CONCLUSION

To conclude, this paper has thoroughly examined the interconnected nature of fish stock depletion and the prevalence of IUU fishing activities. Through a multifaceted analysis, it has become evident that combating IUU fishing requires not only stricter enforcement mechanisms but also the integration of advanced technologies for monitoring, assessment, and intervention. The research has proposed a comprehensive framework that utilizes AUVs and UAVs for both fish stock abundance estimation and real-time surveillance of suspicious maritime activity. This dual use of autonomous platforms not only enhances operational efficiency but also minimizes human risk and cost. A central feature of the proposed model is a threshold-based algorithm that leverages periodically gathered fish stock data to determine optimal points for activating IUU intervention protocols. By deploying UAVs in swarm configurations only when certain ecological thresholds are breached, the system aims to concentrate resources in critical areas while avoiding unnecessary expenditures in regions with stable stock levels. This data-driven approach promises to increase the responsiveness and cost-efficiency of enforcement actions. However, the algorithm’s effectiveness is contingent upon the accuracy and timeliness of ecological data. Its periodic nature may delay action in fast-developing IUU scenarios, making it more suitable for addressing systematic or long-term exploitation patterns rather than urgent, short-term incidents. Furthermore, while the model assumes that a significant portion of fish stock decline is due to fishing pressure, it currently does not account for alternative mortality factors such as climate change-induced stress, pollution, disease outbreaks, or the introduction of invasive predatory species. This assumption could lead to misinterpretation of fish stock signals and potentially misguide the system's response if not cross-referenced with broader ecological datasets. In parallel, the paper has explored the emerging role of advanced sensory technologies in enhancing IUU detection capabilities. Recent advancements in computer vision and multisensory data fusion have enabled real-time vessel detection, localization, and identification. These systems have proven effective in identifying vessels based on visual cues such as hull shape, movement patterns, and even hull plate matching. Some researchers have successfully integrated dual-stage recognition systems that combine fast but less precise onboard detection with slower, high-accuracy processing on the ground. Nevertheless, these technological solutions are not without their limitations. Many systems still rely heavily on AIS (Automatic Identification System) data, which can be disabled by IUU vessels to evade detection. Hull plate recognition, while promising, depends on a robust and up-to-date database, and its effectiveness is reduced when dealing with unregistered or foreign vessels operating outside recognized standards. Additionally, environmental conditions such as fog, high seas, and poor lighting can impair sensor accuracy, while legal and jurisdictional constraints may limit enforcement capabilities in certain maritime zones. Looking ahead, the development of an effective IUU combating system must be seen as an evolving process—one that continually incorporates emerging scientific discoveries and technological innovations. It is crucial to adopt a modular, flexible architecture that allows integration of new detection tools, data sources, and intervention strategies as they become available. At the same time, every new solution must be evaluated not only for its technical capabilities but also for its economic viability, operational resilience, and legal compatibility across different regions and maritime frameworks. In summary, the future of sustainable marine resource management lies in the smart convergence of autonomous monitoring platforms, artificial intelligence, and ecological modelling. By adopting a holistic, adaptive, and data-informed approach, we can build a more robust and responsive system that not only deters IUU fishing but also ensures long-term preservation of marine ecosystems while maximizing the efficiency of resource utilization.

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