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Echogram Image Analysis for Pelagic Fish School Classification in Bungus Waters, West Sumatra

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Abstract

Tropical marine fisheries are characterized by high species diversity but low individual abundance per species within the same water column, making the detection of distinct fish schools challenging using hydroacoustic technology. However, a hydroacoustic survey conducted in Bungus, West Sumatra, in October 2023 revealed the presence of approximately 24 identifiable fish schools of varying sizes, indicating the potential for further analytical investigation. This study aims to characterize and classify fish schools by analyzing echogram imagery and extracting key acoustic parameters through a statistical multivariate approach. Acoustic data were collected using a Simrad EK-15 echosounder operating at 200 kHz. Subsequent data processing was performed in Echoview, followed by multivariate analysis. From an initial dataset of 24 detected schools, 12 parameters were retained for analysis. These parameters were categorized into three groups: (1) energetic parameters, including target strength (TS), volume backscattering strength (Sv), area backscattering strength (Sa), skewness, and kurtosis; (2) morphometric parameters, consisting of school height, length, perimeter, and area; and (3) bathymetric parameters, represented by average school depth. Latitude and longitude were included as supplementary spatial descriptors. Among the 12 parameters, latitude did not contribute to school characterization and was therefore excluded from further analysis. Multivariate results indicated that morphometric parameters (particularly school height and area) and energetic parameters (Sa and TS) were the most influential in differentiating school structure. Cluster analysis based on the remaining 11 parameters identified two distinct groups of fish schools: Group 1, comprising 14 schools (58.3%), and Group 2, comprising 10 schools (41.7%). These findings demonstrate that integrating hydroacoustic metrics with multivariate statistical methods provides an effective framework for identifying and characterizing fish schools in tropical waters with inherently complex species assemblages.

Keywords: Bungus, fish school, kurtosis, skewness, volume backscattering strength

1. Introduction

Pelagic fisheries are an important part of Indonesia’s marine sector, supporting both the national economy and many coastal communities (Bafagih, 2015). Because these fisheries play such a large role, managers need reliable information about fish stocks to guide sustainable harvesting. Stock assessments depend on methods that can observe fish abundance and distribution with enough accuracy to reflect what is happening in the water.

One method that has become widely used for this purpose is hydroacoustics. By transmitting sound waves into the water and reading the returning echoes, researchers can detect fish quickly and without disturbing them (Manik and Ma’mun, 2009). The method works in real time and covers large areas efficiently, which is particularly useful for pelagic fish that often form moving and unevenly distributed schools.

Hydroacoustic surveys produce echograms, which are visual displays of the returning echoes. These images show the shape, size, and general structure of fish schools. Many aspects of these schools can be measured directly from the echograms using simple image-analysis approaches (Reid and Simmonds, 1993). Since pelagic fish tend to gather in schools, the information in echograms is helpful for understanding where these schools are located and how they behave.

The identification of fish schools can be improved further by examining parameters derived from the acoustic signal. These parameters describe both the internal structure and the outer shape of the schools, and they make it possible to distinguish one type of school from another (Lu and Lee, 1995; Diner et al., 1989). For fisheries that target schooling species, such information helps produce better estimates of stock density and movement patterns.

This study focuses on the waters off Bungus in Padang, West Sumatra. The area faces the Indian Ocean and is known for productive pelagic fisheries, including skipjack tuna and yellowfin tuna (Hutauruk and Rengi, 2017; Siregar et al., 2018). Bungus also has an active Ocean Fishery Port, which makes it an important landing site and distribution point for tuna. Understanding the school characteristics of pelagic fish in this region can support more accurate assessments and improve management efforts.

The purpose of this study is to examine echogram images from Bungus waters and identify parameters that can be used to describe and classify pelagic fish schools. By analyzing the relationships among these parameters, this research aims to improve the use of hydroacoustic data for identifying fish schools in a tropical environment. Based on this background, the study tests two main hypotheses: (1) echogram-derived acoustic and morphometric parameters differ significantly among pelagic fish schools in Bungus waters and can be used to distinguish distinct school types; and (2) the combined use of energetic and morphometric parameters enhances the characterization of pelagic fish school structure and spatial distribution.

The classification of pelagic fish schools proposed in this study is intended to support practical applications in fisheries assessment. Separating schools based on their acoustic and morphometric characteristics can help improve estimates of fish density and biomass by reducing uncertainty caused by differences in school size and structure. This approach can filter the fish school by size class, making it easier to distinguish between juvenile and adult components of the stock.

2. Materials and Methods

2.1. Time and Location of The Study

The survey was conducted in the coastal waters of Bungus, Padang, West Sumatra, where depths generally remain below 100 m. Hydroacoustic data were collected on 31st October 2023. The survey was planned using a parallel transect design, but the rough sea conditions made it difficult for the vessel to stay precisely on course. As a result, the final track followed a semi-parallel pattern. Despite these conditions, the survey successfully recorded 24 pelagic fish schools within the study area. **Figure 1** shows the research location map.

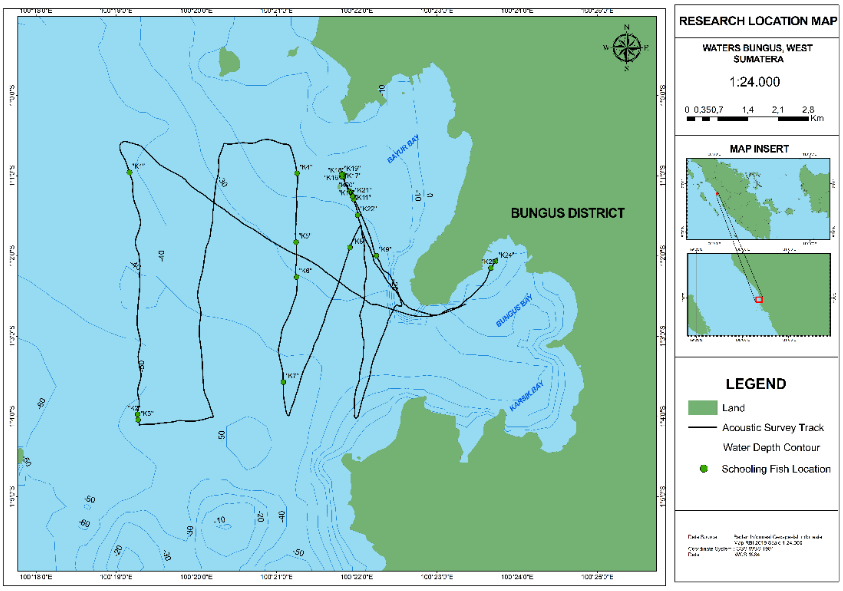

Figure 1. The research location map. The black lines show the acoustic survey track and the green circles show the schooling fish location.

2.2. Tools and Materials

The tools used in this study consisted of a laptop device that had been installed with several software. The materials used were recorded data from the Single beam Echosounder Simrad EK-15 at a frequency of 200 kHz with the data extension *raw and capture fisheries production data with the extension *xls.

2.3. Data Collection

This study used two main types of data: hydroacoustic measurements and fisheries landing records. The acoustic data were collected using Simrad EK-15 single-beam echosounder with the frequency of 200 kHz. Information on fish catch was taken from the reports of the Bungus Ocean Fisheries Port (PPS Bungus). These landing data were gathered using a purposive sampling approach, focusing on the fish brought into the port to capture the species composition and catch patterns that were relevant to this study. Nevertheless, these landing data are used only as an interpretive support for the acoustic clusters.

2.4. Data Processing

The first step in processing the data was to open the raw Simrad EK-15 files in Echoview 4.8, using the licensed dongle provided by the Ministry of Marine Affairs and Fisheries. The acoustic records were displayed as color echograms showing the distribution of volume backscattering strength (Sv). Each echogram was then examined to identify potential fish schools, and a threshold of −70 to −34 dB was applied, following the range reported by Manik and Nurkomala (2016) for pelagic species. After the schools were identified, they were digitized and exported using the analysis-by-region function. The exported files were saved in ASCII (.csv) format and compiled into a Fish School Data Matrix, which contained the full set of parameters for each school. An overview of these parameters is presented in **Table 1** and illustrated **in Figure 2**.

Table 1. Parameters for identifying pelagic fish schools according to Lawson (2001)[1)], Coetzee (2000)[2)], and Fauziyah (2005)[3)]

Set of Parameter		Parameter
A	Energetic:	*Backscattering volume* (dB)
		Target strength (dB)
		Backscattering area (dB)
		Skewness [1) 2)]
		Kurtosis [1) 2)]
B	Morphometric	Height (m) [2)]
		Length (m) [2)]
		Perimeter (m) [3)]
		Area (m^2) [3)]
C	Biometric	Average depth of fish school (m) [1)]
D	Support	Longitude

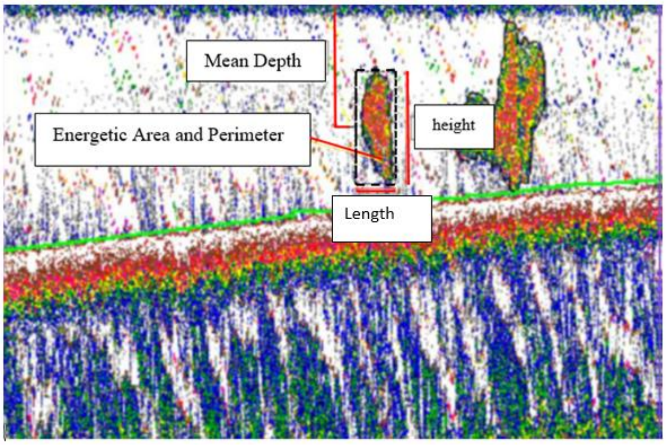

Figure 2. Fish school parameters' sample used in this research. It shows the illustration of the mean depth of the schooling, energetic area and perimeter, and the length and height of the schooling.

2.5. Data Analysis

The acoustic data were examined using several statistical approaches to help describe how the parameters relate to one another and to identify patterns within the fish school dataset. The analysis began with a correlation test to see the strength and direction of relationships among the measured parameters. After that, a set of multivariate methods was applied to explore the data more thoroughly. These included factor analysis, cluster analysis, and discriminant analysis. Factor analysis helped reveal groups of parameters that tended to behave similarly, and the resulting components were displayed using rotated plots. Cluster analysis was then carried out using a hierarchical method, allowing the fish schools to group naturally based on similarity without setting the number of clusters in advance (Santoso, 2010). The resulting dendrogram showed how the schools were related in terms of their acoustic characteristics. Finally, the cluster results were used in a discriminant analysis to determine which parameters played the strongest roles in separating the different fish school groups, following the procedure outlined by Muhiddin (2007).

3. Results and Discussion

Fish catch records from the PPS Bungus for October 2023 (**Figure 3**) show that 24 fish species were caught in that month, with a total catch of about 513 tons. Anchovies (*Stolephorus* spp.) dominated the records. The five pelagic species that appeared most often are shown in Figure 3, and the pattern aligns with what is commonly seen in tropical seas—many species present, but each usually in smaller groups (Achmadi, 2015).

Anchovies have an important role in the small pelagic community and are usually found in shallow coastal waters. Their high numbers in Bungus are closely related to the fishing gear used by local fishers, especially the bagan lift-net. This gear works well for anchovies because they tend to gather in compact schools and respond strongly to light, which is exactly what the bagan method takes advantage of (Rudin et al., 2017).

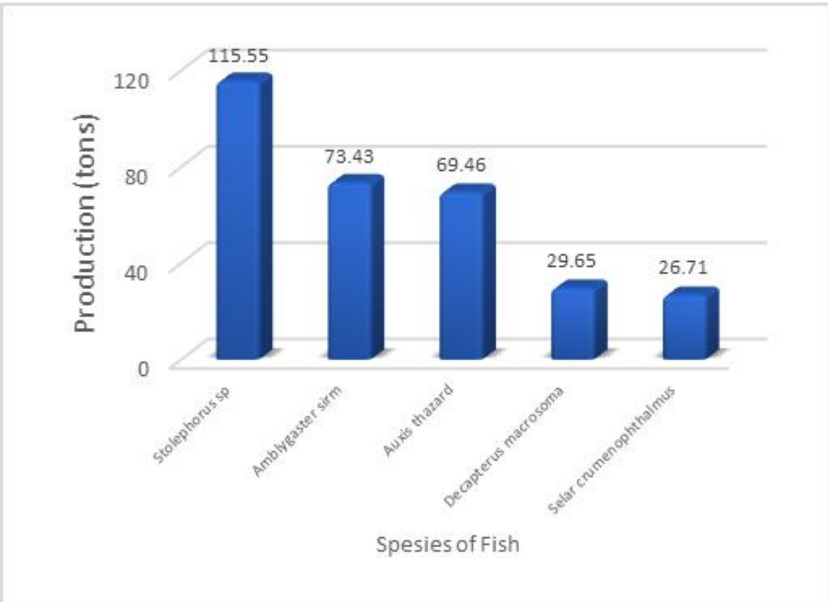

Figure 3. Composition of pelagic fish catch. The data were from PPS Bungus' fish catch records.

3.1. Pelagic Fish School Analysis

Processing of the echogram data resulted in the identification of 24 pelagic fish schools, each described using 11 acoustic and spatial parameters. For clarity, these parameters were grouped into four categories:

(1) energetic parameters, which included TS, Sv, Sa, skewness, and kurtosis;

(2) morphometric parameters, such as school height, length, perimeter, and area;

(3) bathymetric parameters, represented by the average depth; and

(4) spatial descriptors, namely longitude for each school.

When the relationships among parameters were examined, a clear link appeared between the energetic and bathymetric groups—most notably between TS and average depth (Farhan et al. 2022). This matches the findings of Setiadi *et al*. (2015), who showed that TS increases with body size and can influence where fish position themselves in the water column. Several energetic parameters, including skewness and kurtosis, also showed strong correlations with many of the morphometric measurements. This suggests that the structure of a school affects how acoustic energy is returned, an idea also noted by Fauziyah (2005). In addition, morphometric features such as length, perimeter, and area showed consistent relationships with depth, indicating that school shape and size shift with depth due to behavior related to foraging and social organization.

After the correlation analysis, factor analysis was used to identify which parameters contributed the most to the overall variation in the dataset. Following Santoso (2017), parameter screening was based on the Measure of Sampling Adequacy (MSA). Latitude had the lowest MSA value (<0.5) and was removed, which is reasonable given the small spatial extent of the study area. Most of the remaining parameters showed communalities above 0.5, meaning they were strongly represented in the extracted factors.

From the factor extraction, 11 components were produced (**Table 2**), but only two had eigenvalues greater than 1 and were kept for interpretation. These two components explained 85.98% of the total variance, showing that they captured most of the meaningful differences among the fish schools.

Component loading patterns indicated that the first component was influenced mainly by TS, Sa, and the morphometric features (length, height, perimeter, and area), along with average depth. This component seems to reflect combined energetic and structural traits of the schools. The second component was shaped by Sv, skewness, kurtosis, and longitude, suggesting it represents variation linked to signal shape and spatial spread. These relationships are illustrated in the rotated principal component plot (**Figure 4**), which shows how the parameters cluster and how strongly each one contributes to the two major components.

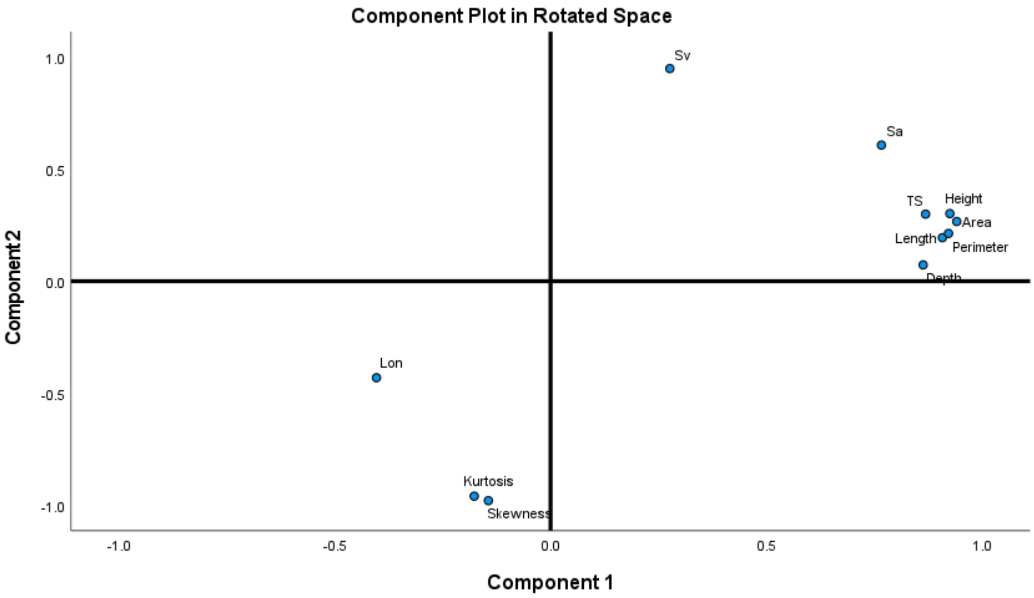

Figure 4. Plot of principal components in rotated space. The figure shows the relationships between the Component 1 and the Component 2.

Table 2. Principal component matrix with varimax rotation. There are 11 components used in this research

	Component	
	1	2
Sv	.28	**.95**
TS	**.87**	.30
Sa	**.77**	.61
Skewness	-.14	**-.98**
Kurtosis	-.18	**-.96**
Long	**.91**	.19
Height	**.92**	.30
Perimeter	**.92**	.21
Area	**.94**	.27
Depth	**.86**	.07
Lon	-.40	**-.43**

3.2. Fish School Clustering Analysis

Cluster analysis is a multivariate approach used to group observations that share similar characteristics, producing clusters that are relatively uniform within each group and clearly distinct from one another (Santoso, 2017). In this study, hierarchical clustering was applied using Ward's method, which aims to reduce variation within each cluster, so the resulting groups are more compact and easier to interpret (Shalsadilla et al., 2023). The analysis was carried out using the component scores obtained from the earlier factor analysis.

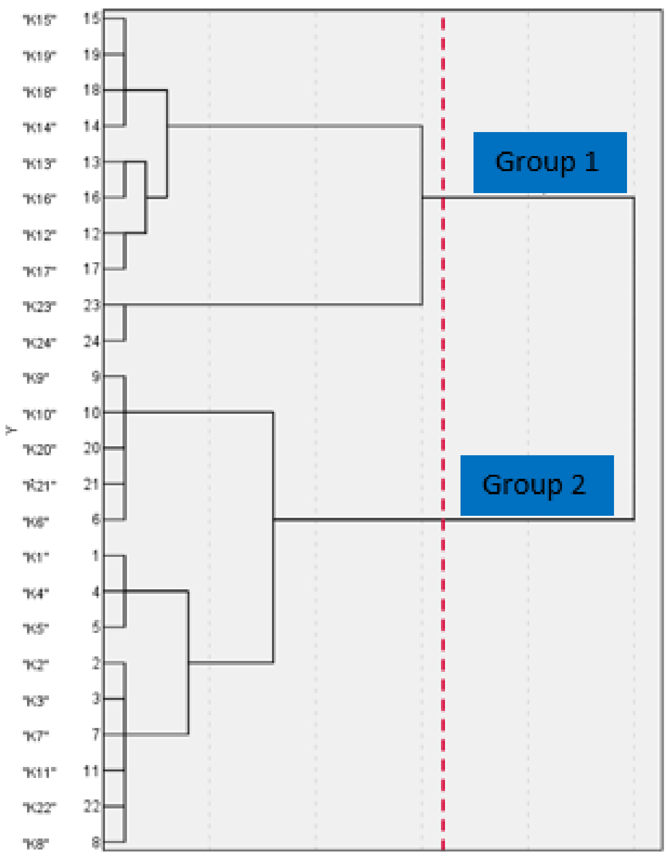

Figure 5. Dendogram of a school of fish. The dendogram divides the schooling into two clusters.

The dendrogram in **Figure 5** shows that several of the fish schools' group together at short linkage distances, roughly between 1 and 2. This indicates that many of the schools share similar acoustic or structural properties. Cutting the dendrogram at the widest linkage distance (16) divides the set into two clear clusters. Fourteen of the 24 schools (58.3%) fall into Cluster 1, while the remaining ten (41.7%) form Cluster 2.

The two clusters differ most noticeably in the energetic parameters. Target strength (TS) provides the clearest separation. TS values for Cluster 1 range from −55.52 to −39.22 dB, with an average of −49.42 dB. Schools in Cluster 2 show lower TS values, between −73.19 and −57.81 dB (mean −66.67 dB). Applying the TS–length conversion formula for pelagic fish ($TS = 20 \log L - 73.97$; Natsir et al., 2005) produces distinct length ranges. Cluster 1 schools correspond to fish between 8.3 and 54.6 cm (mean 16.8 cm). Cluster 2 corresponds to fish between 1.1 and 6.4 cm (mean 2.3 cm). Schools in Cluster 1 also show higher backscatter levels and larger morphometric measurements (height, length, perimeter, area) and occur at greater average depths than schools in Cluster 2. These patterns collectively indicate that Cluster 1 reflects adult or larger-bodied pelagic fish, while Cluster 2 represents juvenile fish or small pelagic fry.

The depth differences seen between the two clusters are consistent with what is generally known about how pelagic fish change their habitat use as they grow. Larger or adult individuals usually stay in deeper layers, while juveniles are more common in shallower water. Their vertical and horizontal patterns also tend to follow feeding behaviour. Zooplankton—both the groups that feed on phytoplankton and the higher trophic plankton—has a major influence on where fish are found in tropical systems (Nontji, 2008).

Schooling behaviour itself reflects additional ecological and evolutionary pressures. Weihs (1973) pointed out that predation, social interactions, genetic tendencies, and hydrodynamic considerations all contribute to the way pelagic fish form and maintain schools. Schools often contain fish of roughly similar size, which helps them keep comparable swimming speeds and maintain coordinated movement based on body length. These coordinated swimming patterns support migration, improve group stability, and reduce the chances of being caught by predators.

3.3. Analysis of the Influence of Fish School Parameters

Discriminant analysis was carried out to identify which parameters had the strongest influence on separating the two fish-school clusters. This technique follows a dependence-based multivariate approach, where the distinction between predefined groups is interpreted through the relationships between the independent variables (acoustic and morphometric parameters) and the dependent variable, namely cluster membership (Santoso, 2017).

Table 3 presents the significance tests for each parameter and shows whether the differences between the two clusters are statistically meaningful. Parameters with significance values (Sig.) below 0.05 are considered to contribute to the separation of fish-school groups, while parameters with Sig. ≥ 0.05 do not play a discriminating role (Santoso, 2017). In this study, all parameters showed significant differences, indicating that each contributed to distinguishing the two groups.

Table 3. Test of equality of means of parameter groups. The table tests for significant differences between groups on each variable based on its significance value.

Parameter	Wilks' Lambda	F	df1	df2	Sig.
Sv	.60	14.78	1	22	.00
TS	.23	72.96	1	22	.00
Sa	.18	97.42	1	22	.00
Skewness	.70	9.46	1	22	.01
Kurtosis	.66	11.17	1	22	.00
Length	.34	41.97	1	22	.00
Height	**.18**	**103.26**	1	22	.00
Perimeter	.29	54.17	1	22	.00
Area	.21	81.51	1	22	.00
Depth	.42	30.42	1	22	.00
Longitude	.78	6.14	1	22	.02

To understand which parameters exerted the strongest influence on group separation, Wilks' Lambda values and F-statistics were examined. Parameters with Wilks' Lambda values closer to zero and larger F-statistics provide the greatest discriminating power. Based on these criteria, ten parameters were identified as the most influential, listed here in decreasing order: school height, Sa (area backscattering strength), school area, TS (target strength), perimeter, school length, average depth, Sv (volume backscattering strength), kurtosis, skewness, and longitude. The prominence of both morphometric and energetic parameters as primary discriminators is consistent with the findings of Fauziyah et al. (2010), who reported that structural (morphometric) and acoustic-energetic attributes play central roles in fish-school identification and classification.

4. Conclusions

The statistical analyses in this study indicate that acoustic-free parameters can serve as a useful basis for identifying and describing pelagic fish schools. Of the 12 parameters considered, latitude was removed because it did not help distinguish school structure within the relatively small study area. The multivariate results show that several morphometric variables (school height and area) along with two energetic parameters (Sa and TS), played the strongest roles in separating the schools into different groups. Using the remaining 11 parameters, the cluster analysis produced two clear groups: 14 schools (58.3%) in Group 1 and 10 schools (41.7%) in Group 2. Overall, the results suggest that combining morphometric information with energetic acoustic measures provides a practical and effective way to identify fish schools in tropical waters. At the same time, the findings of this study should be interpreted in light of several limitations. The number of detected schools was relatively small (24 schools), and species composition within each school could not be directly validated due to the absence of biological sampling. In addition, sea-state conditions during the survey affected vessel manoeuvrability and transect precision, which may have influenced school detection and spatial representation. Acknowledging these constraints, the results provide an initial framework for fish school classification in Bungus waters, which can be strengthened in future studies through increased sampling effort, improved survey conditions, and direct biological validation.

Conflicts of Interest

There are no conflicts to declare

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AI Writing Statement

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) for language editing and stylistic improvement. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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