Big Data-Based Literature Study on Automatic Identifition System Data and Synthetic Aperture Radar Image Integration for Illegal Fishing in Maritime Awareness

Fifi Fitriah[1], *Adi* Novitarini Putri[1], and *Totok* Yulianto[1*]

[1]Department of Naval Architecture, Institut Teknologi Sepuluh Nopember, Surabaya, East Java, Indonesia

Abstract. Illegal, unreported, and unregulated (IUU) fishing remains a persistent threat in Indonesian waters, causing substantial economic losses and long-term ecological damage. This review synthesizes methods for fusing Automatic Identification System (AIS) data with Synthetic Aperture Radar (SAR) imagery to enhance maritime surveillance. AIS conveys vessel identity and reported position, whereas SAR detects vessels operating without AIS ("dark" vessels). The review covers approaches to spatiotemporal synchronization, data association, and machine-learning models that jointly exploit both modalities. In addition, this study provides a systematic mapping of recent AIS–SAR fusion methods and proposes a conceptual big data framework tailored to Indonesia's maritime surveillance context. According to the surveyed literature, AIS–SAR fusion has been reported to improve the identification of non-cooperative vessels, reduce false alarm and missed detection rates, and shorten response times. Effective implementation requires reliable spatiotemporal alignment, adequate computing resources for large-scale processing, and interagency data-sharing mechanisms. Collectively, the evidence indicates that large-scale AIS–SAR fusion can enhance maritime awareness and support Indonesia's efforts to counter IUU fishing.

1 Introduction

Illegal, unreported, and unregulated (IUU) fishing remains a major concern for coastal states because it erodes state revenue, distorts fishing efforts, and accelerates the degradation of marine ecosystems [2]. For Indonesia, an archipelagic country where more than two-thirds of the territory is ocean and national welfare is closely linked to the marine and fisheries sector, these pressures are particularly acute [12]. Monitoring such vast maritime areas using conventional patrols alone is costly and uneven, which motivates the use of technology-supported surveillance to complement existing enforcement tools [1].

In recent years, maritime monitoring has increasingly drawn on a combination of automatic vessel reporting systems and satellite remote sensing. The Automatic Identification System (AIS) provides vessel identity, position, and basic kinematic information broadcast at regular intervals, which can be used to reconstruct traffic patterns

* Corresponding author: tyulianto1970@its.ac.id

and fishing activity over time [6]. Synthetic Aperture Radar (SAR) imagery offers a complementary view: it records the sea surface day and night and under a wide range of weather conditions, enabling the detection of vessels that do not transmit AIS signals or purposely switch them off to avoid scrutiny [1], [9]. Together, AIS and SAR form a paired information source that can, in principle, reveal both declared and hidden activities in fishing grounds [1].

A growing body of work has explored different ways to use these data. Some studies focus mainly on AIS-based behavioral analysis, for example, by deriving indicators of fishing effort, loitering, or encounters at sea [6], [7]. Others concentrate on SAR-based ship detection and small-vessel monitoring, often highlighting the importance of sensor characteristics such as band, resolution, and polarization [4], [9]. Recent studies have combined AIS and SAR to spot non-cooperative vessels, characterize trawl activity, and follow offshore fleets in selected regions, and these works indicate that using both data sources together provides a clearer picture than treating them separately [1], [2], [3].

Despite this progress, several gaps remain in the literature. Many studies have been organized around particular case areas or sensor configurations, making it difficult to see how the methods relate to one another in the broader literature [1]. There is also limited synthesis of how choices about SAR band, polarization, revisit time, AIS reception (terrestrial versus satellite), and spatial–temporal matching windows interact in practice, especially for IUU fishing detection rather than general traffic analysis [3], [9]. In parallel, developments in large-scale SAR constellations, public benchmark datasets for dark vessels, and national initiatives on data sharing and interoperability suggest that technical and institutional landscapes are changing rapidly [5], [12].

This paper responds to these gaps by presenting a literature-based study of AIS and SAR integration for IUU fishing detection, with a focus on publications from 2021 to 2025. This review compiles and organizes recent research that combines AIS and SAR, examines how data sources, sensor settings, and association strategies are used in practice, and summarizes emerging patterns relevant to fisheries monitoring [1], [2], [3]. Building on this synthesis, this paper also outlines a conceptual big data framework for AIS–SAR fusion that is tailored to Indonesia's maritime surveillance context, including its emphasis on interagency coordination and accountable data governance [11], [12].

2 Theoretical and Literature Framework

2.1 Literature Search

This review focuses on publications from 2021 to 2025 that examine how AIS and SAR can be used together to detect illegal, unreported, and unregulated (IUU) fishing [1]. The time window was chosen to capture the recent growth in satellite constellations, public datasets, and operational interest in AIS–SAR fusion, while still keeping the number of studies manageable for detailed analysis. A small number of earlier, clearly foundational papers were retained when they helped clarify concepts or workflows that were still used in more recent work.

To identify relevant studies, we searched Google Scholar, Scopus, IEEE Xplore, MDPI (Remote Sensing), Frontiers, and arXiv.We combined keyword sets for AIS and SAR with terms for illegal or dark fishing, vessel or boat detection, and fishing behaviour when constructing the search queries [5].Boolean operators AND and OR were used to link these terms so that the search remained broad enough to capture different approaches, but narrow enough to avoid large volumes of obviously irrelevant material [5]. The main databases, time window, and keyword groups are summarized in Table 1.

The screening process was conducted in several stages. First, duplicate records across the databases were removed. Next, titles and abstracts were read to exclude studies that were clearly outside the scope, such as work that did not involve AIS or SAR, focused only on wake or speed without vessel detection, or relied on non-satellite sensors. For the remaining items, the full texts were examined to check whether AIS or SAR data were used, whether some form of fusion or spatiotemporal association was present, and whether the study contained a methodological contribution rather than being purely descriptive. Articles that appeared as both preprints and final journal versions were consolidated so that only the most complete version was retained.

Finally, additional eligibility criteria were applied to meet the objectives of this review. We included papers that discussed AIS–SAR integration, detection of IUU or dark vessels, or AIS-based behavior analysis with relevance to maritime surveillance in Indonesia or comparable settings [1]. Studies were excluded if the full text was not available in Indonesian or English, if they were review papers without new methodological content, or if they introduced a dataset without any analysis. The resulting set of studies obtained through this identification and screening process forms the basis for the synthesis presented in the following sections.

Table 1. Literature identification, screening, and eligibility criteria for AIS–SAR for IUU (2021-2025)

Section	Item	Content
Literature identification	Databases	Google Scholar; Scopus; IEEE Xplore; MDPI (Remote Sensing); Frontiers; arXiv
	Publication time period	2021–2025 (with exceptions for a small number of relevant foundational studies before 2021)
	Keywords A	AIS AND SAR AND "data fusion" AND ("illegal fishing" OR IUU OR "dark ships")
	Keywords B	("ship detection" OR "boat detection") AND SAR AND (VV OR VH OR polarimetric)
	Keywords C	AIS AND (behaviour OR behavior) AND (loitering OR transshipment)
	Keywords D	("xView3" OR "dark vessel") AND SAR AND ("machine learning" OR "deep learning")
Literature screening	Inclusion criteria (abstract reading)	Topics on AIS and SAR integration in remote sensing; detection of IUU

		or dark ships; or AIS behaviour analysis relevant to maritime surveillance in Indonesia or comparable regions.
Literature eligibility (full-text reading)	Exclusion criteria (general)	Full text not available; not written in Indonesian or English; duplicate preprint versus final version (only the most complete version retained).
Papers included in the systematic review	Exclusion criteria (detailed)	Review article without methodological contribution; no AIS or SAR data; dataset-only paper with no detection method; focus only on wake or speed without vessel detection; no fusion or spatiotemporal association; not based on satellite remote sensing.

2.2 Inclusion Criteria

The search results from all databases were first combined, and duplicate records were removed. Titles and abstracts were then screened to retain articles that dealt with the integration of AIS and SAR, or more broadly, satellite remote sensing, for the detection of illegal, unreported, and unregulated fishing [1]. At this stage, we set aside clearly unrelated material, such as work on non-maritime topics or studies that did not involve vessels at all.

The full text of the remaining studies was retrieved. Only papers available in Indonesian or English were retained so that the methods and results could be assessed in a consistent way. At the eligibility stage, we focused on studies that used satellite sensors, active or passive, such as SAR or optical imagery, together with AIS data, reflecting the idea that AIS and satellite observations provide complementary information on vessel identity, position, and visibility at sea [1], [9].

We further required that a study describe some form of fusion or association between AIS and satellite detections in space and time, report explicit vessel detection rather than only tracks or wake patterns, and provide at least one quantitative evaluation metric (for example, accuracy, precision, recall, F1, or mean average precision) [9]. Papers were excluded if they were purely review articles, if they released datasets without any accompanying detection method, or if they focused only on speed or wake characteristics without identifying vessels, as such work does not offer a technical basis for comparing AIS–SAR fusion approaches [5].

2.3 Data Analysis

The selected studies were then analyzed to identify broad patterns in methods, sensor use, and reported outcomes for AIS and SAR integration in the context of IUU fishing. For each study, we noted the satellite sensor families employed (for example, C-band versus X-band systems and the use of single or dual polarization), the type of AIS reception (terrestrial or satellite), the general strategy used to associate AIS tracks with satellite detections, and the evaluation measures reported for vessel detection or classification [9].

To make the comparison easier, the studies were grouped into a small number of categories. One set of groups reflected sensor characteristics (such as band and polarization), while another reflected application focus, for example, dark-vessel detection in open water, large-area association along shipping routes, or monitoring of dense coastal traffic. These groupings made it possible to relate design choices to practical drivers, such as image resolution, revisit rate, and traffic density [4], [9].

Where it was reasonable to do so, simple counts and summary tables were produced to show how often particular sensor types, fusion strategies, and evaluation practices appeared across the corpus. The narrative synthesis then drew attention to differences that matter for fisheries monitoring, including which configurations seem most promising for detecting small vessels, and which studies discuss issues that can be transferred to the Indonesian context, such as data latency, coverage gaps, and institutional arrangements for sharing information [3], [12].

3 Overview of The Research Items Retrieved

This section provides an overview of the studies retained in the review and shows how data sources, sensor choices, and fusion strategies are used in practice. Table 2 summaries the main characteristics of each article, including the year of publication, type of data, focus, method highlight, study region, and short notes on the contribution.

Across these studies, AIS is primarily used for vessel identification and tracking over time, allowing analysts to infer behavioral patterns such as loitering, hidden trawling, or encounters at sea [6]. SAR imagery, in turn, contributes direct evidence of vessel presence even when transponders are switched off, so that non-cooperative vessels remain observable in busy waters [1]. Several papers also make use of optical or multispectral sensors, but in most cases these play a supporting role compared with SAR.

On the sensor side, Sentinel-1 C-band is by far the most frequently used platform, reflecting its wide geographic coverage, regular revisit, and open data policy [9]. Small-vessel detection is a recurring challenge, and many authors report that using dual polarization (VV and VH) helps to increase the contrast between vessels and the surrounding sea surface in Sentinel-1 imagery, making it easier to separate small targets from sea clutter [4]. X-band sensors appear less often, but they tend to be selected in dense traffic or coastal areas where higher spatial resolution is required [9].

Table 2. Overview of retrieved research items (AIS–SAR for IUU)

Ref	Year	Data and sensors	Focus	Method highlight	Region or sea	Notes
[1] Galdelli et al.	2021	AIS and SAR	Suspicious activity and fisheries	AIS to SAR association, point to point	Adriatic Sea	Integration of AIS and SAR for non-cooperative vessels
[2] Marsaglia et al.	2025	AIS and optical or SAR	Hidden trawl fishing	Remote sensing fusion with AIS	Mediterranean	Distribution and intensity of fishing

[3] Li et al.	2024	Satellite AIS and remote sensing	Offshore fisheries monitoring	Satellite AIS analysis with imagery	Northern Indian Ocean	Offshore fleet monitoring
[4] Shin et al.	2024	SAR Sentinel-1 with VV and VH	Small vessels	Dual polarisation to raise target–sea contrast	General	Improved small-vessel detection
[5] Paolo et al. (xView3 SAR)	2022	SAR multi-mission dataset	Dark-vessel benchmark	Annotation scheme and evaluation protocol	Global	Public benchmark and dataset
[6] Zhou et al.	2025	AIS	IUU behaviour from AIS tracks	Behaviour features such as loitering and rendezvous	General	Indicators of IUU from AIS trajectories
[7] Han et al.	2025	AIS	Classification of behaviour and vessel type	Behaviour feature-based classifier	General	High accuracy for vessel type
[8] Li et al.	2021	AIS and single-channel SAR	Early integration	Single-channel SAR fusion with AIS	General	Foundational integration
[9] Lee et al.	2024	SAR X-band with AIS and V-Pass	Detection and tracking in dense traffic	Multi-sensor tracking	High-traffic areas	TerraSAR-X, KOMPSAT-5, Capella
[11] Nikitakos et al.	2021	Sentinel-1 dual polarisation with AIS	Large-scale monitoring	Dual polarisation with AIS	General	C-band with AIS
[12] BRIN, KKP, Bakamla	2025	Governance and policy	Open maritime data and interagency access	Framework for data exchange and audit	Indonesia	Supports interoperability for AIS and SAR integration

Figure 1 then groups the studies by sensor or data category and shows how often each category appears in the corpus. The distribution highlights the dominance of Sentinel-1 C-band and the complementary role of X-band SAR and other sensors, such as KOMPSAT-5 and Capella, in high-traffic environments.

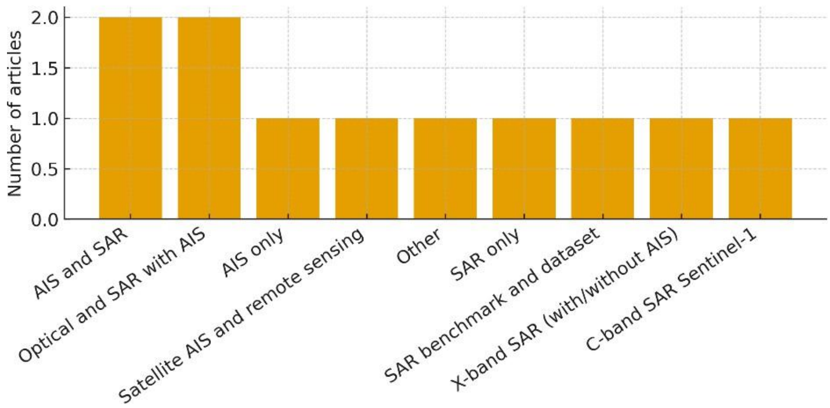

Fig. 1. Distribution of sensor categories in the collected articles

A synthesis of the retrieved literature points to several consistent patterns over the 2021–2025 period. First, cross-source fusion that combines AIS with SAR is now the dominant approach for monitoring fishing and other maritime activity, rather than relying on a single source alone [1], [3]. Second, two broad families of fusion strategy can be distinguished: point-to-point matching, which links individual SAR detections to AIS positions within a time–space window, and multi-feature association, which augments this with information such as target size or shape and is generally preferred in complex or crowded scenes [10].

Third, benchmark resources and shared protocols are beginning to emerge. The xView3 SAR mission, for example, is often used as a reference dataset for dark-vessel detection and as a way to compare annotation and evaluation practices across methods [5]. Performance is commonly reported using accuracy, precision, recall, F1 score, or mean average precision with Intersection-over-Union thresholds, which facilitates comparison among studies [9]. Taken together, these patterns provide a useful starting point for designing AIS–SAR fusion frameworks in Indonesia that emphasise robust time alignment, scalable processing for large data volumes, and coordinated data exchange across agencies [12].

4 Methods & Data Fusion

4.1 General Flow of AIS-SAR Integration

The overall workflow begins with two complementary data sources. AIS messages are processed to construct vessel tracks that record position, speed, and heading over time, whereas SAR images provide snapshots of vessel locations on the sea surface at specific acquisition times [1]. In the first stage, the AIS data are cleaned to remove duplicate messages and implausible position jumps, and the timestamps are converted to a common time standard so that they can later be aligned with satellite overpasses [6]. SAR scenes are calibrated and filtered to reduce speckle, producing stable backscatter values for ship detection [5]. The aim of this preparation step is to place both sources in a form that is suitable for matching, recognising that AIS represents continuous motion while SAR captures discrete scenes when the satellite passes over an area [1].

After preprocessing, analysts align AIS reports with SAR acquisitions within a practical time window so that vessel positions inferred from AIS remain plausible at the time the SAR image was recorded [1]. The spatial buffer around each AIS track segment is scaled to the image resolution and to local sea conditions rather than treated as a fixed distance because traffic density and message cadence differ between coastal and offshore regions and between terrestrial and satellite AIS reception [3]. Within these windows, candidate links between AIS tracks and SAR detections can be identified and passed to the association stage.

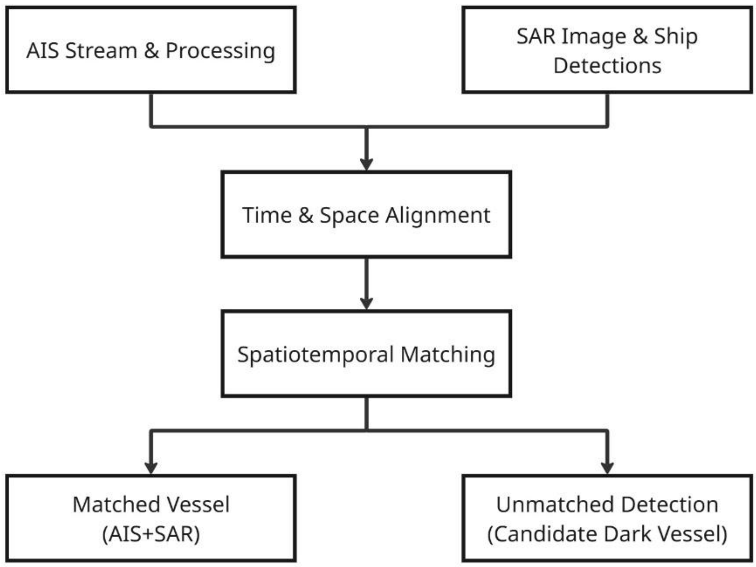

Fig. 2. Simplified AIS–SAR fusion workflow for identifying candidate dark vessels.

4.2 AIS Processing and SAR Detection

AIS processing consolidates the messages into coherent vessel trajectories. After duplicates and obvious outliers are removed, messages for each MMSI are ordered in time, and basic kinematic quantities, such as speed over ground, course, heading changes, and dwelling time, are computed [6]. In offshore areas, satellite AIS reception often results in larger gaps than terrestrial reception; therefore, short gaps may be bridged with simple interpolation or by using tighter time windows around SAR acquisitions [3]. Behavioral indicators such as prolonged loitering, rendezvous, and possible transshipment events can then be derived from these trajectories and later combined with SAR-based evidence [6].

On the SAR side, the imagery is radiometrically calibrated and filtered to reduce speckle so that the vessel targets stand out more clearly from the sea background [5]. Ship detection is then performed using a mixture of classical image-processing approaches and learning-based detectors to obtain bounding boxes and confidence scores for each object. The sensor configuration plays a central role in the quality of these detections. Dual polarization with VV and VH is frequently used because VV tends to capture strong reflections from vessel structures, while VH suppresses much of the sea clutter; together, they increase vessel-to-sea contrast and improve the detection of small boats [4]. X-band systems are often preferred in congested waters where finer spatial resolution is needed, with the Sentinel-1 C-band continuing to serve as a wide-area backbone sensor [4], [9]. The result of these preparations is two aligned products: a set of AIS trajectories enriched with behavioral features and a set of SAR-based vessel detections on a georeferenced scene. Both are ready for spatiotemporal association in the next step [1].

4.3 Data Association and Operational Evaluation

Spatiotemporal association links SAR detection with AIS position reports within the time window around each SAR acquisition, so that the inferred motion between successive AIS messages remains reasonable [1]. The spatial buffer used for matching is again scaled to image resolution and local conditions, for example, narrower buffers in calm, low-traffic waters, and slightly wider buffers in rough seas or busy shipping lanes [3].

In point-to-point association, candidate pairs are selected based on the nearest distance between an AIS track and SAR detection combined with the smallest time difference, after which simple physical checks on course and speed are applied to filter unlikely matches [1]. When traffic is dense or there are indications that AIS transponders may be switched off, studies increasingly rely on multifeature association. In this case, spatial and temporal proximity are combined with movement direction and attributes of SAR detection, such as bounding-box size and orientation, and, when available, supporting information from optical imagery [10]. These richer feature sets help reduce ambiguity when many vessels are present, or when dark targets are expected.

To support comparisons across studies, evaluation is usually reported using standard metrics such as accuracy, precision, recall, F1 score, and mean average precision with intersection-over-union thresholds [9]. Several papers have also reported the proportion of SAR detections that can be matched to AIS tracks within the chosen windows, which provides an operational indicator of how well the fusion works under different traffic and sensor conditions [3], [9]. Across the reviewed studies, initial parameter choices for time windows, spatial buffers, and validation checks are typically tuned to the sensing modality and traffic density, spanning low and medium traffic in C-band scenes, dense traffic in X-band scenes, and offshore situations dominated by satellite AIS [1], [3], [10].

4.4 Big Data for AIS-SAR Integraton

AIS and SAR integration benefits from big data architecture because the two data sources arrive in different forms. AIS messages form a continuous stream with a cadence of seconds to minutes, whereas SAR scenes arrive in batches that follow satellite revisit cycles [1]. In the ingestion layer, AIS streams are buffered and stored together with metadata such as the reception source, whereas SAR scenes are archived with orbit time, imaging mode, and polarization [4]. Both sources were written into a shared data lake using a common time standard and coordinate reference system so that they could later be merged, reprocessed, and audited [1].

The processing layer typically separates stream processing for AIS from batch processing for SAR. AIS streams are cleaned, trajectories are built, and behavioral features are extracted, while SAR batches undergo calibration, speckle reduction, and ship detection using the chosen sensor settings and polarization combinations [4]. Features from both sides are consolidated in a central repository of engineered variables, which allows experiments and models to be consistently reused across different tasks [9].

In the fusion layer, a spatiotemporal join is executed, and the association engine applies the point-to-point or multi-feature strategies described earlier [1], [10]. For training and validation, public benchmarks such as xView3 SAR are often used so that the methods can be tested under similar conditions before being adapted to local data [5]. Operationally, orchestration tools schedule various processing jobs, monitor latency and throughput, and log evaluation metrics, while the data lake maintains an audit trail so that each decision can be traced back to its inputs [9]. In the Indonesian context, this architecture must be complemented by governance arrangements and open maritime data policies that allow BRIN, KKP, and Bakamla to share AIS and SAR data transparently and accountably [12].

4.5 Method Summary

In summary, the methods reviewed in this paper combine behavioral information derived from AIS trajectories with visual evidence from SAR imagery to improve the detection of IUU-related activity. AIS processing yields clean tracks and indicators, such as loitering, rendezvous, and potential transshipment events, whereas SAR processing provides geo-located vessel detections under day-night and all-weather conditions [6]. Spatiotemporal association links these two views of maritime activity by aligning AIS and SAR in space and time and then applying point-to-point or multi-feature matching strategies adapted to local traffic and sensor settings [1], [10].

Embedding this workflow in a big data pipeline allows continuous AIS streams and batch SAR scenes to be handled at scale, with standard evaluation metrics and auditable processing steps. In the Indonesian setting, this type of architecture makes it easier to monitor activity almost in real time and gives the main maritime agencies a shared technical basis for working together in a transparent way [9], [12].

5 Findings

The reviewed studies converge on a consistent conclusion: fusing AIS tracks with SAR detections improves the ability to detect non-cooperative vessels (e.g., “dark” vessels) compared with relying on either data source alone. In low-traffic settings, straightforward point-to-point matching between AIS positions and SAR detections can be effective because the number of plausible candidates is small [1]. In higher-density scenes, however, association methods that incorporate additional cues—temporal offset, spatial distance, course/velocity consistency, and SAR-derived attributes—yield more robust matches and better separate true associations from false alarms [3], [10]. Benchmark datasets such as xView3 SAR further support method development by providing common data and evaluation protocols for dark-vessel detection before deployment on operational AIS streams [5].

From a sensor standpoint, Sentinel-1 C-band is the predominant backbone for AIS–SAR fusion due to its broad coverage, frequent revisit, and open-access policy [9]. Higher-resolution X-band sensors (e.g., TerraSAR-X, KOMPSAT-5, Capella) are used less often but are typically selected for congested coastal zones where resolving closely spaced targets is critical [9].

Multiple studies also report that combining Sentinel-1 VV and VH polarizations increases vessel–sea contrast, improving small-vessel detectability that is particularly relevant to fisheries monitoring [4]. These results indicate that sensor configuration materially affects the achievable performance of AIS–SAR fusion for IUU applications.

A complementary thread focuses on AIS-based behaviour analytics. Indicators such as sustained loitering, repeated returns to offshore hotspots, close-proximity encounters, and suspected transshipment are repeatedly highlighted as signals of potential IUU activity [6]. When coupled with SAR evidence, these behavioural flags help differentiate routine traffic from cases that merit follow-up. In several studies, behaviour-based classifiers are used to rank vessels by risk level, and the resulting candidates are cross-checked against SAR scenes to assess consistency between declared vessel type/activity and observed behaviour [7], [1].

Finally, the literature points to an operational blueprint: a big-data pipeline that ingests streaming AIS and batch SAR, performs cleaning and preprocessing, aligns both sources in space and time, and outputs fused vessel lists, risk scores, and maps of suspicious activity [1], [9]. For Indonesia, the reviewed work underscores that algorithmic advances must be paired with reliable data access and interagency governance; coordinated AIS and SAR sharing is as important as the detection method itself [12].

6 Conclusions

This review has examined recent work on the integration of AIS and SAR for monitoring illegal fishing, particularly illegal, unreported and unregulated (IUU) fishing, and related non-cooperative behavior at sea. Across the studies considered, AIS provides information on vessel identity and longer-term movement patterns, whereas SAR offers weather-independent snapshots of vessel presence at particular points in time [1]. When these two views are brought together through careful spatial and temporal alignment, dark vessels (vessels that disable or manipulate AIS) and other forms of unusual activity commonly associated with illegal fishing (e.g., AIS gaps, suspicious rendezvous/transshipment, loitering near boundaries, or irregular movement patterns) become easier to detect than with either data source alone [10]. The quality of the results depends on several factors: sensor choice and configuration, the way AIS and SAR are preprocessed, and the strategy used to associate detections with the tracks [9].

The literature suggests a gradual route towards implementation. In settings with moderate traffic, conservative point-to-point associations with well-chosen time windows and spatial buffers can provide useful starting points [1]. In more complex environments, multi-feature associations that also consider motion direction, bounding-box size, or supporting imagery appear to be more reliable [3], [10]. The Sentinel-1 C-band is likely to remain the backbone sensor for many countries, while X-band acquisitions and dual-polarization modes can be reserved for areas where small vessels and busy lanes create additional challenges [4], [9]. Reporting standard metrics such as accuracy, precision, recall, F1 score, and mean average precision with Intersection-over-Union thresholds helps to keep future work comparable and track progress over time [9].

For Indonesia, the main message from this review is that technical and institutional designs need to move together. A documented big data pipeline for AIS and SAR, paired with clear rules for data access and interagency cooperation, can support faster detection and enforcement of illegal fishing (IUU) by turning indicators such as dark vessels and unusual activity into actionable alerts for inspection and intervention.

References

1. Galdelli et al., A synergic integration of AIS data and SAR imagery to monitor fisheries and detect suspicious activities. Remote Sens. 13, 2455–2469 (2021).
2. M. Marsaglia et al., Shedding light on trawl fishing activity in the Mediterranean Sea with remote sensing data. ICES J. Mar. Sci. 82, 525–540 (2025).
3. J. Li, Q. Xing, X. Li, M. Arif, J. Li, Monitoring off-shore fishing in the Northern Indian Ocean based on satellite Automatic Identification System and remote sensing data. Sensors 24, 350–364 (2024).
4. H. Shin et al., Enhancement of small ship detection using polarimetric combination from Sentinel-1 imagery. Remote Sens. 16, 205–217 (2024).
5. F. Paolo et al., xView3-SAR: Detecting dark fishing activity using synthetic aperture radar imagery. arXiv (2022).
6. Y. Zhou et al., Identifying behaviors indicative of illegal fishing activities in Automatic Identification System data. J. Mar. Sci. Eng. 13, 34–49 (2025).
7. X. Han, Y. Zhou, J. Weng, L. Chen, K. Liu, Research on fishing vessel recognition based on vessel behavior characteristics from AIS data. Front. Mar. Sci. 12, 1–10 (2025).
8. J. Li et al., Integration of Automatic Identification System data and single-channel Synthetic Aperture Radar images. Ocean Coast. Res. 29, 189–202 (2021).
9. S. Lee et al., Assessment of maritime vessel detection and tracking using integrated SAR imagery and AIS/V-Pass data. J. Navig. 78, 305–321 (2024).
10. X. Li et al., Dark ship detection via optical and SAR collaboration: An improved multi-feature association method between remote sensing images and AIS data. Remote Sens. 17, 101–115 (2025).
11. N. Nikitakos et al., Large-scale automatic vessel monitoring based on dual-polarization Sentinel-1 and AIS data. Remote Sens. Lett. 14, 832–841 (2021).
12. BRIN, KKP, Bakamla, Open maritime data policy framework for Indonesia. Natl. Marit. Res. Bull. (2025).