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ARTIFICIAL INTELLIGENCE FOR MARITIME SAFETY AND ENVIRONMENTAL SURVEILLANCE IN INDONESIA: AN OFFICIAL-STATISTICS BASELINE

Ifan Widayatullah
Dept of Civil Engineering, Faculty of Engineering, Narotama University, Surabaya, Indonesia

Muhammad Ikhsan Setiawan
Faculty of Engineering, Narotama University, Surabaya, Indonesia
ikhsan.setiawan@narotama.ac.id

Mohd Haziman Wan Ibrahim
Universiti Tun Hussein Onn, Parit Raja, Johor, Malaysia

ABSTRACT

Maritime safety and environmental surveillance in Indonesia depend on the reliability of official data supporting artificial intelligence (AI). This study establishes an official-statistics baseline using BPS-Statistics Indonesia's Marine and Coastal Resources Statistics 2023. It examines fishing-vessel fleets for 2021–2022 (34 provinces; 1,004,060 and 893,258 vessels), 118 classified fishing ports, 41 recorded oil-spill incidents (1999–2023), port-water monitoring at 27 sites and fisheries patrol records. Methods include concentration indices, k-means clustering with silhouette selection, principal component analysis, modified z-scores and Isolation Forest screening. In 2022, 88.8% of the recorded fleet was motorised; provincial distribution showed a Gini coefficient of 0.41. Three fleet typologies were identified: outboard-dominated, inboard-dominated and non-motorised-heavy. Ten of 94 provincial vessel-type changes were flagged as statistical outliers, while 10 of 27 water-monitoring sites reported none of three core parameters. In 2021, there was approximately one recorded inspection per 385 fishing vessels. These descriptive findings inform candidate AIS trajectory analytics, SAR oil-spill detection, optical satellite monitoring and smart-port planning. The study proposes a phased, data-first roadmap; it does not estimate the performance of operational AI systems in Indonesian waters.

Keywords: Artificial Intelligence; Indonesia; K-Means Clustering; Maritime Transport; Official Statistics; Oil-Spill Detection; Vessel Monitoring

1. Introduction

Maritime transport is crucial for global trade and, in an archipelagic state such as Indonesia, also underpins domestic connectivity, fisheries logistics and coastal livelihoods. Safe and environmentally responsible operation increasingly relies on data-driven decision support. Research shows that machine learning (ML) and deep learning (DL) applied to Automatic Identification System (AIS) data can predict vessel trajectories and help prevent collisions and navigational conflicts [1], [2], while AI in seaports spans many operational modules [3], [4]. In parallel, DL methods applied to synthetic aperture radar (SAR) images support oil-spill detection [5]–[8], while satellite optical imagery has also been investigated for oil-spill detection and concentration estimation [9].

These advances are, however, algorithm-centric: they presuppose that vessel registries, port inventories, incident records and environmental monitoring data are complete, consistent and representative. Whether national official statistics satisfy these presuppositions, and where AI should be prioritised given the structure of the fleet and the monitoring baseline, receives far less attention. For Indonesia, BPS-Statistics Indonesia compiles official tables on the vessel fleet, fishing ports, oil-spill incidents, port-water quality and fisheries surveillance in the *Marine and Coastal Resources Statistics 2023* [10], while its *Sea Transportation Statistics 2023* reports vessel calls, cargo handling and passenger movements at seaports in 36 provinces [11].

This study therefore builds a reproducible, official-statistics baseline for AI-enabled maritime transport safety and environmental surveillance. It makes four contributions: (i) it quantifies the structure, trend and spatial concentration of the vessel fleet; (ii) it derives a data-driven provincial typology to differentiate AI deployment; (iii) it applies unsupervised anomaly detection as a data-quality audit of the official tables; and (iv) it characterises port, surveillance and environmental-monitoring baselines and maps them to AI use cases validated in recent literature. The scope is deliberately bounded: the source

publication describes marine fishing vessels and fishing ports rather than cargo or passenger shipping, and no AI model is trained here.

2. Literature Review

2.1 AI for Vessel Traffic and Trajectory Prediction

Li et al. [1] systematically classify ML and DL approaches to AIS-based ship trajectory prediction, summarising twelve advanced methods published between 2000 and 2022 and establishing a benchmark. They report that support vector regression outperformed several alternatives in short-term prediction in their cases, whereas sequence-to-sequence models performed less well than in other application domains. A companion systematic review [2] motivates trajectory prediction as a means of preventing collision accidents and eliminating potential navigational conflicts, and Liu et al. [12] extend this logic with a multi-task DL model that jointly predicts ship trajectories and collision risk. Taken together, these studies suggest that AIS availability and quality are the binding preconditions of traffic-safety AI.

2.2 AI in Seaports

Liu and Yuen [3] review AI applications in seaports using Scopus and Web of Science records and network analysis, and identify three gaps: advanced techniques such as computer vision and artificial neural networks are notably absent in wave forecasting; quay-crane optimisation is lacking and deep reinforcement learning is underused in truck and route management; and neural networks and big-data analytics could be better exploited in vessel management for safety, security and operations. Li et al. [4] offer a bibliometric review of smart-port research and future directions. These reviews organise knowledge by technology and operational module; the present study complements them by asking what national official statistics can, and cannot, support.

2.3 AI for Oil-Spill and Environmental Monitoring

Recent studies examine both SAR-based oil-spill detection and satellite optical-imagery analysis. Huang et al. [5] propose a DL method for C-band SAR imagery with precision and recall of 89.23% and 89.14%, respectively. Dehghani-Dehcheshmeh et al. [6] combine convolutional neural networks and transformers for Sentinel-1 SAR imagery, reporting improvements in noisy images. Hasimoto-Beltrán et al. [8] introduce a multi-channel deep neural network for semantic segmentation of oil on the ocean surface, and Li et al. [7] develop a self-evolving algorithm that automatically generates new training data and re-learns, progressively improving performance. By contrast, Trujillo-Acatitla et al. [9] use machine learning and optical satellite imagery to examine oil detection and concentration estimation.

2.4 Synthesis and Research Gap

Table 1. summarises the ten studies reviewed. Within this selected set, three research opportunities emerge: published algorithm performance is rarely evaluated against the completeness of national statistical baselines; deployment priorities across heterogeneous fishing fleets receive limited attention; and the reliability of official input records is not always explicitly audited. This study examines these issues for Indonesia using publicly reported statistics.

Table 1. Summary of the ScienceDirect studies reviewed (2022–2025)

Study	Source	Focus	Relevance here
Li et al. [1]	Transp. Res. E 175, 103152 (2023)	ML/DL AIS-based ship trajectory prediction; twelve methods	Taxonomy of vessel-traffic AI
Li et al. [2]	Eng. Appl. Artif. Intell. 126, 107062 (2023)	Systematic review of AIS trajectory prediction	Collision-prevention use case
Liu et al. [12]	Ocean Eng. 287, 115870 (2023)	Multi-task DL: trajectory and collision risk	Integrated safety modelling
Liu & Yuen [3]	Expert Syst. Appl. 289, 128309 (2025)	Systematic review and network analysis of AI in seaports	Three gaps in port AI
Li et al. [4]	Transp. Res. E 174, 103098 (2023)	Bibliometric review of smart ports	Smart-port agenda
Huang et al. [5]	Mar. Pollut. Bull. 179, 113666 (2022)	DL spill detection, C-band SAR (P = 89.23%, R = 89.14%)	Detection benchmark

Study	Source	Focus	Relevance here
Dehghani-Dehcheshmeh et al. [6]	Mar. Pollut. Bull. 190, 114834 (2023)	Hybrid CNN–vision transformer, Sentinel-1	Boundary delineation, noisy SAR
Li et al. [7]	Remote Sens. Environ. 299, 113872 (2023)	Self-evolving DL with automatic training-data generation	Label-scarce settings
Hasimoto-Beltrán et al. [8]	Mar. Pollut. Bull. 188, 114651 (2023)	Multi-channel DNN semantic segmentation of SAR	Segmentation approach
Trujillo-Acatitla et al. [9]	Mar. Pollut. Bull. 184, 114132 (2022)	ML detection and concentration estimation from optical satellite imagery	Complementary optical-image monitoring

3. Materials and Methodology

3.1 Official Data

All quantitative inputs are taken from the BPS publication [10], whose tables cite the Ministry of Marine Affairs and Fisheries (KKP) and regional environmental agencies (Table 2). Provincial fleet records for 34 provinces reproduce the published national totals exactly for all three vessel types in both years (difference = 0), confirming extraction fidelity. Two internal inconsistencies of the source were retained and reported rather than corrected: private fishing-port rows by fisheries management area (WPP-RI) sum to five whereas the class total is four, and patrol vessels of Classes I–V number 35 in the vessel list but 34 in the operational table. The fleet table gives no gross tonnage, length or equipment carriage, so AIS or VMS capability cannot be observed directly.

Table 2. Official data used in this study

Variable	BPS table	Coverage	Source cited by BPS [10]
Fishing vessels by propulsion type	3.7	34 provinces, 2021–2022	KKP, Pusat Data, Statistik dan Informasi
Fishing ports by class and WPP-RI	4.3	National, 2022	KKP, Pusat Data, Statistik dan Informasi
Oil-spill incidents	5.13	41 incidents, 1999–2023	Compiled from various sources
Port-water quality	5.14	27 sites, 2022	Regional environmental impact control agencies, 2023
Fisheries patrol vessels; operation results	6.9; 6.10	2021; 2017–2021	KKP, Kelautan dan Perikanan Dalam Angka 2022

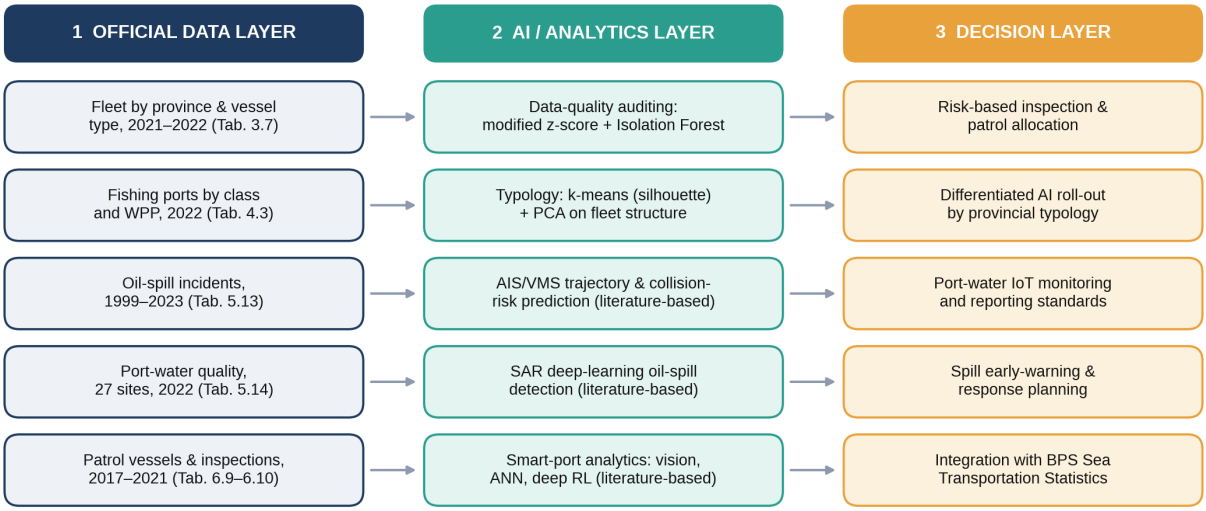


Figure 1. Analytical framework linking official data, AI/analytics methods and decisions. Methods marked literature-based are not trained in this study.

3.2 Analytical Methods

Concentration. For each vessel type, the Herfindahl–Hirschman Index (HHI) and the Gini coefficient were computed across provinces, with s_i the provincial share of the national fleet:

$$HHI = 10{,}000 \times \Sigma\, s_i^2 \quad (1)$$

Typology. Provinces were clustered on four standardised features of the 2022 fleet: $\log_{10}$ of total vessels and the shares of non-motorised, outboard-motor and inboard-motor vessels. K-means (50 initialisations, seed 42) was run for k = 2–6 and k was selected by the mean silhouette coefficient [13]; principal component analysis (PCA) was used only for visualisation. **Anomaly detection.** For province–vessel-type pairs with at least 100 vessels in both years (n = 94), the year-on-year log-ratio and the modified z-score [14] were computed, and pairs with |M| > 3.5 were flagged; an Isolation Forest [15] (500 trees, contamination 0.05) served as a second detector. Implementation used scikit-learn [16].

$$r_{ij} = \ln(x_{ij,2022} \,/\, x_{ij,2021}), \quad M_{ij} = 0.6745\,(\,r_{ij} - \text{median}\; r\,) \,/\, \text{MAD}(r) \quad (2)$$

Environmental and surveillance data. Oil-spill records were classified by rule from the incident description into vessel-related, fixed-facility or pipeline, and unspecified. In the port-water table, values of 0.00 for temperature, pH and salinity are physically implausible for seawater and were treated as not reported; the same rule was applied to total suspended solids (TSS) and oil and grease for completeness counts only. No comparison with regulatory seawater-quality limits is made. Patrol capacity was expressed as recorded vessels per patrol vessel and inspections per recorded vessel; these are scale indicators, not performance measures.

4. Results

4.1 Fleet Structure, Trend and Concentration

The recorded national fleet fell by 11.0%, from 1,004,060 vessels in 2021 to 893,258 in 2022 (Figure 2a). Non-motorised vessels declined most (−26.8%), followed by outboard (−9.9%) and inboard vessels (−6.8%); the motorised share therefore rose from 86.4% to 88.8%. The fleet is moderately concentrated across provinces (Gini = 0.41; HHI = 459), with the five largest provinces holding 35.5% (Table 3). Inboard vessels are markedly more concentrated (Gini = 0.51; top five = 42.6%, led by Sumatera Utara at 11.1%), and Java hosts the largest outboard fleets (Figure 2b). The 793,149 motorised vessels compare with 118 classified fishing ports, about 6,700 per port; because the tables do not link vessels to ports, this is an order-of-magnitude indicator only.

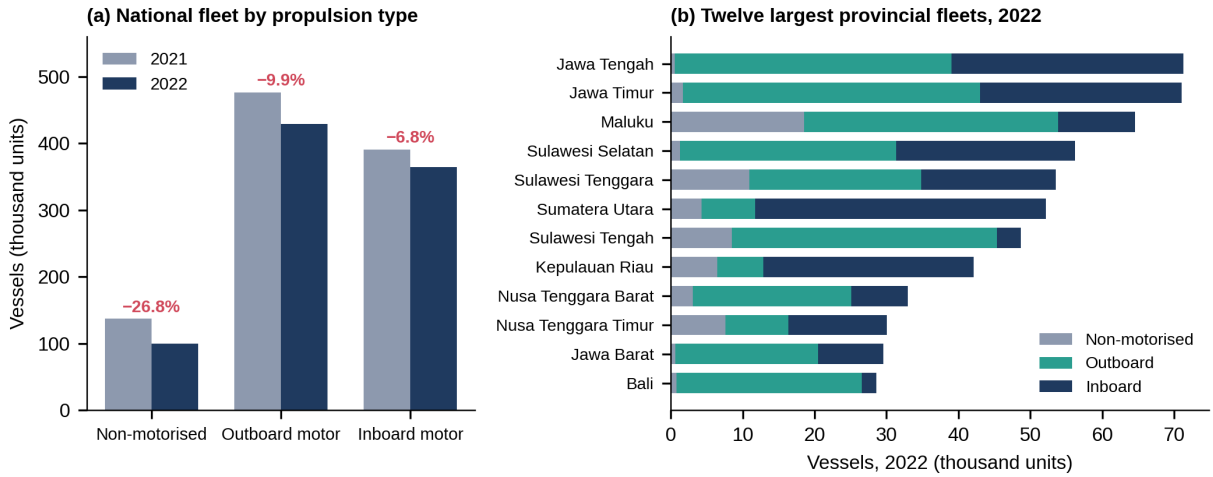


Figure 2. National fleet by propulsion type, 2021–2022, and the twelve largest provincial fleets in 2022. Source: author's calculation from BPS [10], Table 3.7.

Table 3. Key official indicators derived from BPS [10]

Indicator	Value	Note
Recorded fleet, 2021 → 2022	1,004,060 → 893,258	−11.0%
Motorised share, 2021 → 2022	86.4% → 88.8%	Outboard + inboard
Gini; HHI (total fleet, 2022)	0.41; 459	34 provinces
Top-five share: total / inboard / outboard	35.5% / 42.6% / 42.4%	Province-level
Classified fishing ports (PPS/PPN/PPP/PPI/private)	118 (7/18/42/47/4)	Rows sum to 119
Patrol vessels, 2021	95 (35 Classes I–V; 60 smaller)	1 per 10,569 recorded vessels
Inspections of Indonesian fishing vessels	3,882 (2017) → 2,606 (2021)	−32.9%; 1 per 385 vessels
Recorded oil-spill incidents, 1999–2023	41	25 vessel / 10 facility / 6 unspecified
Sites reporting all of temperature, pH, salinity	15 of 27 (55.6%)	None reported: 10 (37.0%)

4.2 Provincial Typology

The silhouette coefficient peaked at k = 3 (0.378, against 0.330, 0.359, 0.356 and 0.367 for k = 2, 4, 5 and 6), and the first two principal components explain 81.8% of feature variance (Figure 3a). Typology A is outboard-dominated (14 provinces, 41.1% of vessels, mainly Java, Sulawesi Selatan, Nusa Tenggara Barat and Bali). Typology B is inboard-dominated (13 provinces, 29.9%), including provinces that border major straits such as Aceh, Sumatera Utara, Riau and Kepulauan Riau. Typology C comprises seven eastern provinces with the largest median fleets and a non-motorised share of 26.3% (Table 4). The solution is robust: Ward hierarchical clustering reproduced it closely (adjusted Rand index, ARI = 0.92), omitting fleet size and clustering on shares alone gave ARI = 0.85, and 1,000 random 80% subsamples gave a mean ARI of 0.77 (5th percentile 0.56). Mean silhouette widths were 0.33, 0.44 and 0.37 for typologies A, B and C, with no negative values, although the modest overall value (0.378) indicates overlapping rather than sharply separated groups.

Table 4. Provincial fleet typologies, 2022 (k-means, k = 3)

Typology	n	Vessels (share)	Non-mot. / outboard / inboard (%)	Median fleet	Example provinces
A Outboard-dominated	14	367,456 (41.1%)	3.4 / 65.0 / 31.6	15,800	Jawa Tengah, Jawa Timur, Sulawesi Selatan, NTB, Jawa Barat, Bali

Typology	n	Vessels (share)	Non-mot. / outboard / inboard (%)	Median fleet	Example provinces
B Inboard-dominated	13	266,854 (29.9%)	7.3 / 21.4 / 71.3	17,971	Sumatera Utara, Kepulauan Riau, Aceh, Kalimantan Timur, Kalimantan Selatan
C Non-motorised-heavy	7	258,948 (29.0%)	26.3 / 51.5 / 22.2	30,013	Maluku, Sulawesi Tenggara, Sulawesi Tengah, NTT, Sulawesi Utara, Maluku Utara, Papua Barat

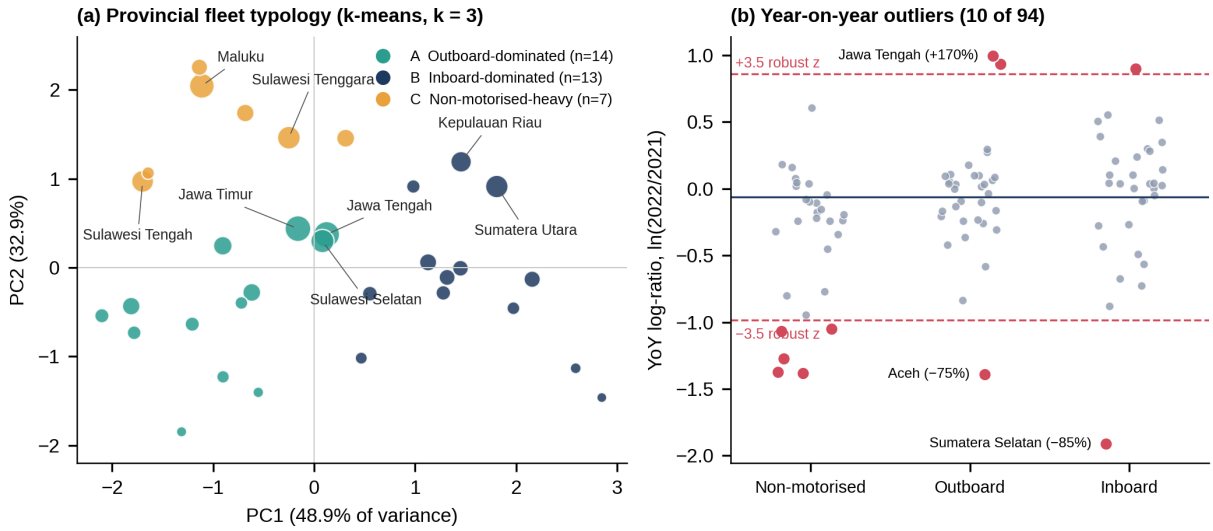


Figure 3. Provincial fleet typology in principal-component space (marker size proportional to fleet) and year-on-year outliers by vessel type. Source: author's analysis of BPS [10], Table 3.7.

4.3 Data-Quality Audit by Anomaly Detection

The median year-on-year log-ratio was −0.064 (MAD = 0.178). Ten of 94 pairs (10.6%) exceeded the modified z-score threshold, and the Isolation Forest independently confirmed five of them (Figure 3b). The most extreme were Sumatera Selatan inboard vessels (5,095 → 754; −85%), Aceh outboard vessels (33,055 → 8,212; −75%) and Jawa Tengah outboard vessels (14,252 → 38,492; +170%); non-motorised fleets fell by 65–75% in Jawa Timur, Papua, Jawa Tengah, Aceh and Sumatera Barat. In Sumatera Selatan, a fall in inboard and a rise in outboard vessels (1,375 → 3,496) is consistent with possible reclassification between categories. Flags identify records warranting verification; they are not evidence of error.

4.4 Ports and Surveillance Capacity

The 118 classified fishing ports comprise 7 ocean fishing ports (PPS), 18 archipelagic ports (PPN), 42 coastal ports (PPP), 47 landing bases (PPI) and 4 private ports. Port-by-area rows concentrate in WPP-RI 712, with 36 of 119 records (30.3%). In 2021 the fisheries patrol fleet comprised 95 vessels, equivalent to one patrol vessel per 10,569 recorded fishing vessels. Inspections of Indonesian fishing vessels fell by 32.9% between 2017 and 2021 (3,882 to 2,606), or approximately one recorded inspection per 385 vessels; 117 Indonesian and 66 foreign vessels were apprehended in 2021 (Figure 4).

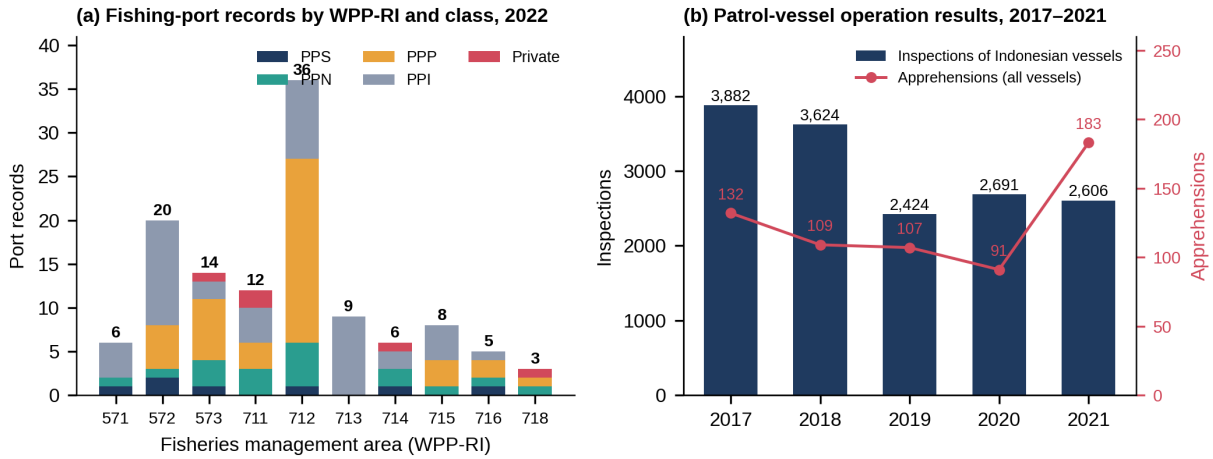


Figure 4. Fishing-port records by management area and class (rows sum to 119; the published class total is 118), and fisheries patrol inspections and apprehensions. Source: BPS [10], Tables 4.3, 6.10.

4.5 Environmental Baseline

Of 41 recorded oil-spill incidents, 25 (61.0%) were vessel-related, 10 (24.4%) involved fixed facilities, wells or pipelines, and 6 (14.6%) were unspecified (Figure 5a). All 19 incidents of 1999–2004 were vessel-related, whereas all nine entries since 2016 are facility-related or unspecified. Because the table is compiled from various sources, these counts are not a systematic time series. Port-water monitoring is incomplete (Figure 5b): 15 of 27 sites (55.6%) reported temperature, pH and salinity, two reported some, and 10 (37.0%) reported none. Site-level maximum TSS ranged from 2.0 to 796 mg/L (median of reported values 15.1 mg/L), with the highest values at Laut Selatan (DI Yogyakarta, 796 mg/L) and Minahasa Utara (456 mg/L); maximum oil and grease reached 37.70 mg/L at Laut Selatan and 18.82 mg/L at Lhoknga (median of reported maxima 0.70 mg/L).

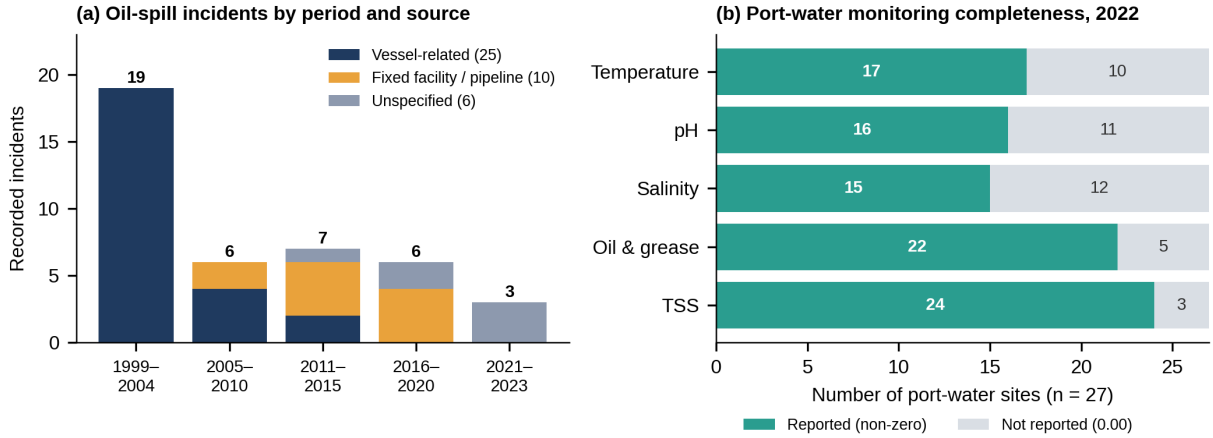


Figure 5. Recorded oil-spill incidents by period and source, and completeness of port-water parameters across 27 sites. Source: author's classification of BPS [10], Tables 5.13–5.14.

5. Discussion

5.1 Data Readiness as the First Constraint

Within the official datasets examined, data readiness emerges as an important early constraint on operational AI deployment. Ten flagged year-on-year changes, two reported source-table inconsistencies and the absence of core port-water parameters at 37.0% of sites indicate that subsequent modelling would require additional data-quality checks. Anomaly screening can be applied to annual releases and its flagged cases referred to data owners for verification; flags alone do not prove data error.

5.2 Typology-Differentiated AI Deployment

The typology supports differentiated deployment (Table 5). Where fleets are inboard-dominated (B), the AIS-based trajectory and collision-risk methods of [1], [2], [12] are the most natural candidates,

on the assumption, not observable in Table 3.7, that inboard vessels more often carry electronics. Outboard-dominated provinces (A) hold 41.1% of vessels in small boats, which favours landing-site and port-centric monitoring over on-board systems; this is a hypothesis to test, as are the computer-vision opportunities that [3] identifies in port operations. Typology C combines the largest median fleets with the highest non-motorised share, so data infrastructure and satellite-based approaches that need no on-board equipment should precede vessel-level AI.

Table 5. Mapping of the official-data baseline to AI use cases

Domain	Evidence from official data	Candidate AI application	Literature / prerequisite
Typology B: traffic	71.3% inboard; includes strait-adjacent provinces	AIS/VMS trajectory and collision-risk prediction	[1], [2], [12]; verified equipment carriage
Typology A: landing sites	65.0% outboard; 41.1% of fleet	Landing-site vision and low-cost tracking (hypothesis)	[3]; landing-site registry
Typology C: data-poor east	26.3% non-motorised; largest median fleet	Satellite-based monitoring; data infrastructure first	Fleet census with GT classes
Ports	118 classified ports; 30.3% in WPP-RI 712	Smart-port analytics, prioritised by area	[3], [4]; BPS port statistics [11]
Oil spills	41 incidents; nine since 2016 non-vessel or unspecified	SAR deep-learning detection over shipping lanes and facility corridors	[5]–[8]; [9] (optical); SAR archive, labelled events
Port water	37.0% of sites report no core parameter	IoT sensing with automated quality control	Common monitoring protocol
Enforcement	One inspection per about 385 vessels	Risk-based targeting using anomaly scores	Linked vessel registry

For environmental surveillance, the composition of recorded incidents suggests that SAR-based detection [5]–[8] could cover offshore facilities and pipelines as well as shipping lanes; optical-image approaches [9] may provide complementary observations when suitable imagery is available. The compiled, non-systematic incident records do not establish a time trend. The recorded inspection-to-fleet ratio (approximately one inspection per 385 vessels) suggests that risk-based targeting merits evaluation, but does not itself establish surveillance effectiveness or vessel-level coverage.

5.3 A Phased, Data-First Roadmap

The baseline implies a sequence in which analytics follow data quality (Table 6). Each phase is paired with an indicator that can be recomputed from the same official tables, so that progress is measurable without new surveys. The targets are proposals for discussion, not forecasts.

Table 6. Proposed phased roadmap with indicators measurable from official statistics

Phase	Actions	AI / analytics component	Baseline → proposed indicator
Data readiness	Publish fleet by gross-tonnage class and equipment flags; reconcile table totals; adopt a common port-water protocol	Anomaly screening on every annual release; automated quality control	Outlier pairs 10 of 94 → all verified; sites with core parameters 55.6% → 100%; source inconsistencies 2 → 0
Targeted pilots	AIS/VMS analytics in Typology B provinces; SAR spill detection over shipping lanes and facility corridors	Trajectory and collision-risk models [1], [2], [12]; SAR deep learning [5]–[8]; [9] (optical)	Share of Typology B provinces with a pilot; recorded spills with satellite-based detection
Integration and scale	Link fleet, port and Sea Transportation Statistics [11]; risk-based inspection	Risk scoring from anomaly and trajectory signals; smart-port analytics [3], [4]	Inspections per recorded vessel (1 in 385) → share of inspections risk-targeted

5.4 Limitations

The fleet table lacks gross tonnage and equipment fields; ports are reported by fisheries management area rather than province, preventing vessel-per-port analysis by province; and the spill

table is compiled rather than systematically observed. Zero entries in the water-quality table are interpreted as missing, not confirmed as such, and the analysis covers only two fleet years. No cargo or passenger movements are analysed. Although unsupervised clustering and anomaly detection were applied, no operational AIS-based or SAR-based predictive AI model was trained or evaluated on Indonesian observations. Integrating the BPS Sea Transportation Statistics [11] is a possible next step.

6. Conclusion

Using official BPS statistics, this study shows that Indonesia's recorded fleet is predominantly motorised (88.8% in 2022), moderately concentrated and divisible into three provincial typologies that call for different AI strategies. It also shows that the data pipeline needs strengthening: statistical outliers in year-on-year fleet records, inconsistencies in two source tables, incomplete port-water monitoring and a very low inspection ratio all limit the value of AI built directly on current records. We recommend (i) publishing fleet data with gross-tonnage classes and equipment-carriage flags, (ii) adopting a common port-water monitoring protocol with automated quality control, (iii) linking fleet, port and Sea Transportation Statistics records, and (iv) piloting AIS-based analytics in Typology B and SAR-based spill detection over facility corridors. Future work should add AIS, SAR and port-throughput data to estimate AI performance in Indonesian waters.

Data Availability

All data are from the publicly available BPS publication [10]; derived tables, classification rules and code can be provided on request.

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Author Contributions

[The authors must provide a verified individual contribution statement; no roles have been assumed.]

Competing Interests

[The authors must provide their declaration of financial and non-financial competing interests.]

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