Navigating the Bay with Intelligence

Forward Guidance for Artificial Intelligence in Fisheries Governance in the Bay of Bengal Region

A LIVING STRATEGY DOCUMENT

Bay of Bengal Programme
Inter-Governmental Organisation

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Foreword

The evolving practice of the fisheries management is about solving multiple objectives of food security, livelihoods, empowerment, institutions while ensuring sustainability of the resources in an increasingly uncertain environment. Collection, collation and processing of information, is therefore, became the backbone of the modern fisheries management system. However, the process of an evidence-based decision making is also a challenge in itself especially for the developing countries as they are constrained by both human and financial resources.

The advent of artificial intelligence, an umbrella term for a broad suit of decision support technologies seems to be offering a viable solution in this regard. It can automate various processes while identifying patterns and predicting future trends thus freeing critical resources hence so far embedded in the system.

However, despite its rapid adoption in various economic and institutional processes, AI is not yet a perfected technology and need human in the loop to alleviate potential risks. It is at best can be seen as a smart collaborator, while the decision making still should be based on human judgement.

The Bay of Bengal rim countries are no stranger to this situation. The marine fisheries sector is reeling from various problems and untapped potentials. Over the years, the countries have built up their R&D capacities and information management system to support the fisheries. However, there is still gap in availability of actionable information and knowledge for decision-making.

This document comes at a timely moment especially when AI is developed to a point where a variety of AI-driven tools that range from satellite-based vessel tracking and automated anomaly detection to predictive analytics and decision-support systems are being developed and put to use. By enabling real-time data integration, improving risk profiling, and supporting evidence-based policymaking, AI has the potential to bridge longstanding gaps in enforcement and compliance as it can process large volumes of data rapidly.

I hope that this document will not only be a conversation starter but also a blueprint for taking advantage of the emerging technologies in a cooperative and collaborative manner. We are in a pragmatic but unforeseen world, and the best foot forward is to learn from each other!

Welcome to a new way of doing things, doing better!

(Dr. Abhilaksh Likhi)

About This Document

This living strategy document provides a framework for the adoption of artificial intelligence (AI) in fisheries governance for the Bay of Bengal rim countries. The document brings together four elements: a diagnosis of the structural information failures behind the current fisheries governance crisis; an assessment of relevant AI and digital technologies; a proposed regional cooperation architecture; and a strategic roadmap for implementation. It argues that while AI is not a stand-alone solution to the fisheries governance crisis, it can be effectively positioned as an enabling instrument to make existing governance frameworks work at the scale and with the consistency the BOBLME requires.

It also examines how these technologies, when designed with small-scale fisheries in mind, can strengthen the economic position of fishers and fishing communities by improving market access, reducing post-harvest losses, enabling access to financial services, and supporting more informed business decisions at the base of the fisheries value chain.

The 14th Steering Committee meeting of FAO's Fisheries and Resources Monitoring System (FIRMS) concluded on 04 July 2025 in Copenhagen constituted a Technical Working Group comprising FAO, ICES and BOBP-IGO to develop an approach paper for exploring the benefits, opportunities and challenges of using artificial intelligence (AI) in fisheries management. This document is a first step towards developing a global strategy on this fast-evolving dimension.

SUMMARY

Executive Summary

Oceans sustain life at planetary scale, regulating climate, supporting food systems, and underpinning livelihoods across the world. In the Bay of Bengal, fisheries are central not only to nutrition and employment, but also to coastal stability, trade, and regional cooperation. Yet fisheries governance in our region continues to operate under severe informational constraints. Governments are required to manage shared and heavily exploited resources in conditions where stock data remain incomplete, small-scale fishing activity is only partially visible, catch reporting is often weak, and supply chains remain difficult to verify. In such a context, fisheries sustainability depends not only on legal frameworks and scientific principles, but increasingly on the availability of timely, reliable, and actionable intelligence.

This challenge is particularly acute in the Bay of Bengal Large Marine Ecosystem (BOBLME). At its core, the Bay of Bengal reflects one of the central weaknesses of contemporary fisheries governance: the mismatch between ecological connectivity and political jurisdiction. The region is ecologically productive, economically significant, and socially dense, but it is also marked by overexploitation risks, transboundary fish stocks, fragmented governance arrangements, and uneven institutional capacity across member states. Over 4.5 million active fishers operate across the region, supporting tens of millions of dependents, while many of the most important commercial species move across national jurisdictions. Because these shared resources are harvested simultaneously across multiple national waters, no single member state can generate a complete picture of total fishing pressure or cumulative stock status. The effective stewardship of the Bay's most commercially important fisheries therefore requires coordinated, multi-country stock assessments and jointly agreed management measures — a structural imperative that the current governance architecture has yet to fully address.

> *The adoption of the Bay of Bengal Regional Plan of Action on IUU Fishing provides an important regional basis for cooperation, but its implementation will depend on whether member states can generate and use better information for monitoring, verification, planning, and enforcement. Critically, it will also depend on whether member states can move toward shared intelligence and joint assessment of the transboundary stocks that sustain the region's fisheries. Joint stock assessments and cooperative management frameworks are not optional add-ons; they are functional necessities for the entire BOBLME.*

In this framework, we do not present Artificial Intelligence (AI) as a solution in itself to these governance failures. Rather, we view AI as a practical and increasingly accessible set of tools that can help fisheries institutions close long-standing information gaps.

For example, intelligent vessel monitoring systems can detect dark vessels using satellite data; electronic monitoring can strengthen catch verification while reducing dependence on expensive observer coverage; machine learning can support stock assessment in data-limited fisheries; and AI-assisted traceability can strengthen legality assurance and reduce opportunities for catch laundering. Potentially, these tools can help shift information-deficit fisheries governance towards an evidence-based decision-making.

At the same time, we do not view AI in fisheries only as an instrument of surveillance or control. In the Bay of Bengal, fisheries are not only a governance challenge; they are also a livelihood system dominated by small-scale operators. The same data architecture that supports monitoring and management can also support fishers and fishing communities through better market intelligence, access to schemes and entitlements, reduction of post-harvest losses, cooperative-level business planning, and improved access to credit and insurance. Governance-oriented AI and livelihood-oriented AI must therefore be approached as two linked dimensions of the same transition. Any system that asks fishers to contribute data without returning visible value to them is unlikely to secure sustained adoption.

Our approach also rests on a clear institutional principle: AI should strengthen human decision-making, not replace it. We do not envisage displacement of enumerators, inspectors, analysts, or fisheries officers. Instead, we seek to augment their effectiveness by reducing routine data burdens, improving anomaly detection, and allowing scarce public capacity to be directed toward interpretation, enforcement follow-through, and management action. For that reason, technology adoption must be accompanied by investments in training, institutional adaptation, and legal preparedness.

Accordingly, we identify a set of priority technology domains for the region. These include vessel surveillance and dark-vessel detection; electronic monitoring and on-board data collection; smart and selective fishing gear; AI-assisted stock assessment and predictive analytics; automated species identification and biodiversity monitoring; supply-chain traceability and anti-fraud systems; A regional registry of fish stocks based on FAO standards for unique stock identifiers and fisher-facing business and support services. We do not propose that all domains be implemented at once. Instead, we recommend that member states and the Technical Advisory Committee (TAC) prioritise one or two near-term, operationally feasible application areas where lessons can be generated quickly and with limited institutional risk.

The case studies reviewed in this framework reinforce the practical relevance of this approach. Global and regional experience shows that conventional monitoring systems often understate the scale of fishing activity, catch misreporting, and supply-chain opacity. At the same time, newer digital systems show that where data tools are designed around the needs of fishers as well as regulators, they can generate both governance value and livelihood benefits. We also draw on BOBP-IGO's own evaluation experience under the Fisheries and Aquaculture Infrastructure Development Fund (FIDF), which showed that uptake of public support can remain low not because schemes are irrelevant, but because beneficiaries face information barriers, documentation burdens, language constraints, and administrative frictions. This strengthens the case for multilingual AI-assisted support services, including fisheries support bots, that can reduce the cost of accessing schemes and entitlements that already exist.

We build this framework on three broad premises. **First,** AI technologies are now sufficiently mature, affordable, and field-tested for carefully selected fisheries governance applications in the BOBLME. **Second,** the governance value of AI in the Bay of Bengal is inherently regional: fish stocks, IUU networks, and supply chains do not respect national boundaries, and isolated national systems will underperform where cooperation is absent. **Third,** successful deployment requires governance architecture, legal frameworks, data-sharing arrangements, institutional safeguards, and social inclusion measures to be built alongside the technology, rather than after it.

> *For BOBP-IGO, this leads to a clear institutional role. We do not envision BOBP-IGO becoming an operational technology agency. Instead, we see our role as that of a regional convenor, standards facilitator, pilot coordinator, and implementation support partner.*

To support this role, we propose establishing a light-touch Bay of Bengal Fisheries Information Coordination Hub (BOB-FICH) within BOBP-IGO to serve as the regional coordinating layer. Its functions would include technical standards-setting, support for data governance arrangements, coordination of bilateral and eventually broader data-sharing mechanisms, development of regional training and certification programmes, and preparation of an Annual Regional AI Fisheries Review focused on management value rather than technology deployment alone. Member states would retain operational control of national systems, while BOBP-IGO would provide the regional layer needed for interoperability, sequencing, and accountability.

THE REGIONAL ARCHITECTURE   FOUR LAYERS

Institutional	A Bay of Bengal Fisheries Information Coordination Hub (BOB-FICH) within BOBP-IGO staffed by data scientists, legal specialists, and governance experts sets standards, coordinates data-sharing, delivers training, and conducts the Annual Regional AI Fisheries Review. Not a parallel structure, but the AI dimension of work that BOBP-IGO is already doing.
Legal	Three instruments: a BOB Data Governance Framework with explicit sovereignty protections; model legislative provisions for AI evidence admissibility; and a Regional Fisheries Data Standard for interoperability. Developed by BOB-FICH with UNODC and national law universities.
Technical	Five components: a vessel monitoring data fusion platform (SAR/AIS/VMS); a shared species ID library for EM systems; a multilingual offline-capable artisanal catch reporting interface; and BOBSAN, the Bay of Bengal Stock Assessment Network and a Regional Fish Stock and Fishery Resource Registry
Operational	Joint MCS protocols with cross-jurisdictional evidence handoff; a cross-agency training and certification programme focused on real governance workflows; and an Annual Review that mandates failure analysis, not just success documentation.

The legal and political architecture proposed here is deliberately sovereignty-sensitive, but it must also be verification-ready. Fisheries data, especially vessel monitoring, catch documentation, stock assessment, and enforcement-related information, are politically sensitive and cannot be treated as ordinary technical data. We therefore recommend a sovereignty-protected data-sharing framework in which routine regional sharing is based primarily on derived intelligence products rather than the transfer of raw national datasets. However, this principle should not create a black-box system in which regional assessments cannot be verified. The framework should provide tiered access arrangements through which aggregated data, metadata, sample records, audit logs, and, where necessary, controlled inspection of selected raw or detailed data can be made available for validation, dispute resolution, and enforcement review under agreed safeguards. Every regional intelligence product should carry a clear data lineage statement covering source types, temporal and spatial coverage, processing steps, model or algorithm used, assumptions, limitations, confidence level, and known bias risks. Where raw data cannot be transferred, safe-room, joint technical review, or trusted third-party mechanisms should allow authorised experts to inspect sufficient underlying detail without compromising national sovereignty, confidentiality, or enforcement sensitivity. We also recommend early legal work to determine how AI-generated information can become admissible and usable in fisheries enforcement and administrative proceedings across the four member states, provided that provenance, uncertainty, quality controls, and validation status are visible to the responsible human authority.

The strategic roadmap for 2026–2030 presented here is incremental. It is conceived not as an immediate regional transformation programme, but as a structured learning programme that starts small, tests practical use cases, and scales only where evidence supports it. The first phase focuses on institutional preparation, limited pilots in selected sites, establishment of baseline indicators, and a mandatory TAC review using actual adoption and performance data. Subsequent phases are intended to validate workable approaches, embed them in national systems, and only then consider selective scale-up. This sequencing reflects a central judgment in our approach: in fisheries governance, technology should not be scaled ahead of legal readiness, institutional capacity, and demonstrated value.

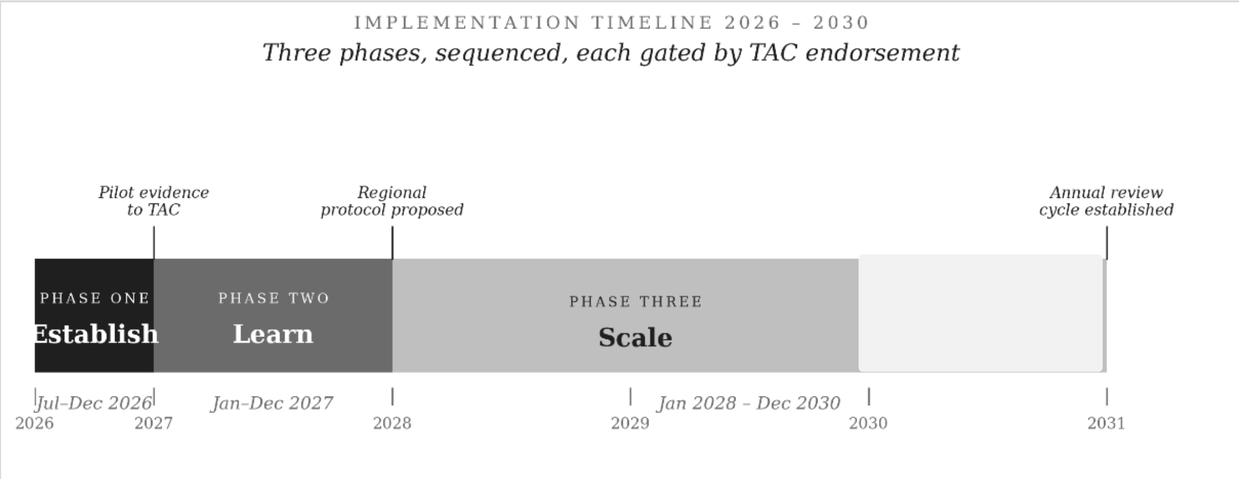
THE FIRST STEP A LEARNING PROGRAMME, NOT A PILOT

A twelve-month structured learning programme in two member states, generating evidence before any wider commitment. Both outcomes are wins confirmed or identified what to fix. The commitment made in advance, mandatory six-month review, evidence-driven scale decision, public reporting to TAC - is what makes it a learning programme.

Do more	Fisher cooperatives with low-cost GPS trackers and voice-based reporting cooperative as entry point, value to the fisher first. Even 40% adoption generates more small-scale data than currently exists.
Do better	One new KPI active vessel coverage percentage inserted into field officer performance frameworks. No new budget. AI automates the measurement. Both outcomes (improvement or identified blockage) are actionable.
Grow smarter	A bilateral data-sharing arrangement between two willing member states, scope-limited and sovereignty-protected, reviewed jointly at six months. Template for the regional architecture.

In essence, this framework rests on a simple but important proposition: the Bay of Bengal does not lack fisheries rules; it lacks the scale and quality of usable information required to make those rules work consistently across ecosystems, value chains, and jurisdictions. AI can help close that gap, but only if introduced through a phased, governed, and inclusive process. Our ambition is therefore not technological novelty for its own sake. It is to support a gradual transition from reactive, data-scarce fisheries governance toward a more evidence-driven, regionally coordinated, and socially grounded system that works for both institutions and fishing communities.

IMPLEMENTATION TIMELINE 2026–2030	
Phase 1 Establish *Jul–Dec 2026*	Confirm bilateral partner states and pilot districts. Establish BOB-FICH. Finalise data-sharing agreement. Deploy GPS trackers through cooperative networks. Insert vessel coverage KPI. Set baseline.
Phase 2 Learn *Jan–Dec 2027*	Analyse adoption rates. Run first bilateral transboundary stock intelligence products. Document legal gaps on AI evidence admissibility. Commission country-level implementation plans.
Phase 3 Scale *Jan 2028–Dec 2030*	Extend cooperative data model. Bring additional member states into bilateral data-sharing. Initiate legal reform on AI evidence admissibility. Position findings for GCF Phase 2 application.



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CHAPTER 01

1. A New Age is Looming

1.1. The year of 2020 is a watershed year in human history

This is the year when not only we witnessed a global shutdown, but we also graduated from an age of information to the age of intelligence. The emergence of the artificial intelligence is not only changing the way we do things, but it also has the potential to change our very institutions in an unknowable manner. It is an age of immense potential as well and unframed danger (OECD AI Futures Report (2024)).

> *For the fisheries sector, this intelligence revolution carries a dual perspective: it can transform how governments govern fisheries or choose to govern, and it can also transform how the fisheries business itself is carried out. Both these dimensions require attention. While it can be expected that the market evolve itself, from a sustainability perspective, the challenge is to ensure such evolution does not marginalize the vulnerable sections but create a level-playing field for all. Therefore, the Government intervention and integration of AI in system is largely about 1. Finding a balance between social and ecological objectives and 2. Balancing inter-social interests. An ecology-only or social-only framing risks repeating the historical pattern in which technology served the elites weakening both ecological and social institutions.*

1.2. The Ecological Balance: A Planet Under Human Pressure

The ocean covers 71% of Earth's surface, holds 97% of its water, absorbs most excess anthropogenic heat and a substantial share of CO_2 emissions, supports rich marine biodiversity, and underpins fisheries and aquaculture that provide vital nutrition to billions of people. Yet it is now under unprecedented, overlapping pressures: climate change is rapidly altering temperature, chemistry, circulation, and productivity; warming and acidification are shifting species distributions, disrupting key ecological processes, and damaging corals, shellfish, and plankton-based food webs; nutrient pollution is expanding coastal hypoxia, including in parts of the Bay of Bengal; and fishing pressure has reached unsustainable levels across much of the ocean.

However, the ongoing crisis is not due to the absence of governance frameworks, but to the lack of a crucial resource: reliable actionable information. We have built complex governance systems on data that is often too sparse, delayed, geographically incomplete, or easily manipulated, undermining the quality of decisions these frameworks are meant to support.

Sound governance depends on several interlinked categories of information. It requires stock abundance data derived from surveys or defensible models; catch and effort data disaggregated by species, gear, vessel, time, and place; biological sampling that enables assessment of population structure and exploitation patterns; spatial information on fishing effort and habitat interaction; ecosystem context that captures climate and environmental variability; and compliance data capable of showing whether rules are being followed in practice. These are not supplementary inputs. Together, they form the informational foundation of sustainable fisheries governance. Where they are incomplete or absent, management becomes reactive, uncertain, and vulnerable to both error and capture.

The Scale of the Global Information / Process Deficit

- "A majority of the world's fisheries remain unassessed or data-limited, particularly in developing regions.[1]
- Over 40% of global wild-caught landings are not reported to the species level preventing species-specific reference point calculation, the technical prerequisite for quota management.[2]
- Traditional vessel monitoring systems (VMS) and automatic identification systems (AIS) cover fewer than 15% of small-scale fishing vessels globally the sector responsible for most of the coastal fishing effort in many developing nations.[3]
- The independent monitoring of fishing operations at sea and human observer coverage averages 5–10% of commercial fishing trips in most regional fisheries and is zero in small-scale fisheries.[4]
- Post-harvest losses of 25–35% in tropical fisheries are driven partly by supply chain opacity that simultaneously enables seafood mislabelling and IUU product laundering at scale.[5]
- *IUU fishing is estimated to account for 11–19% of global catch in key fisheries, generating USD 10–23.5 billion annually in illegally extracted resource value much of it concentrated in developing-nation EEZs.*[6]

1.3. The Social Balance: Case of the Small-Scale Fisheries

The governance value of AI in fisheries is well established in the preceding analysis. But for the approximately 4.5 million active fishers in the Bay of Bengal region, most of whom operate small-scale, artisanal enterprises, the question is not only whether AI helps the state manage fisheries better, but whether it helps fishers' fish smarter, sell better, and build more resilient livelihoods.

This is not a secondary concern. In the BOBLME, fisheries are simultaneously a public resource governance challenge and a private enterprise reality. The fisher who lands catch at an informal site is both a data point the management system needs and an economic agent making daily business decisions about where to fish, when to sell, whom to sell to, whether to invest in ice or storage, whether a government scheme applies to them, usually under conditions of severe information asymmetry.

The AI architecture proposed in this document is to be designed from the outset to serve both governance and enterprise objectives. The data infrastructure required for vessel tracking, catch documentation, species identification, traceability also generates the informational raw material for fisher-level business services. The marginal cost of delivering business intelligence on top of governance intelligence is low. The marginal benefit, in terms of fisher adoption, political support, and poverty reduction impact, is high. A framework that asks fishers to contribute data to

[1] Costello, C., et al. (2012). "Status and solutions for the world's unassessed fisheries." *Science*, 338(6106), 517-520.
[2] Blasco, G. D., & Ferraro, D. M. (2020). "Substantial Gaps in the Current Fisheries Data Landscape." *Frontiers in Marine Science*, 7, 612831.
[3] Global Fishing Watch. (n.d.). "Our Technology."
[4] EU Regulation (EU) 2017/2107; Pew Charitable Trusts (2021).
[5] FAO & BOBP-IGO (2026). "Infra inefficacies cause wastage of 25 to 35 million tonnes of fish globally every year." *The Economic Times*.
[6] World Wide Fund for Nature. (2023). *Illegal, Unreported and Unregulated Fishing (IUU)*. Retrieved from https://www.wwf.org.uk

governance systems without returning business value to the fisher will face the same adoption failures that have plagued fisheries data collection for decades.

1.4. The Fisheries Information Deficit

The scale of the global fisheries information deficit remains substantial. Formal stock assessments cover only a fraction of the total stocks being harvested worldwide, and assessment effort remains biased toward larger, commercially dominant, and institutionally better-resourced fisheries. A large share of exploited stocks, particularly in tropical and developing-country contexts, remain either unassessed or data-limited. They are harvested, traded, and consumed without an adequate scientific basis for determining whether current extraction levels are sustainable. This is not merely a technical inconvenience. It is a governance risk built into the operation of the fishery itself.

Table 1. Global Stock Assessment Coverage and Status (FAO 2025)

Sources: FAO Review of State of World Marine Fishery Resources, November 2025; FAO SOFIA 2024

Indicator	Value	Implication for governance
Total stocks assessed in FAO 2025 review	2,685	Largest dataset ever, but still a fraction of total stocks harvested
Stocks within biologically sustainable limits	64.5%	Majority sustainable, but trend is downward
Stocks classified as overfished	34.5%	One in three assessed stocks at risk
Landings from sustainable stocks (production-weighted)	77.2%	Higher-volume fisheries tend to be better managed
Deep-sea species stocks that are sustainable	29.0%	Most vulnerable category, least managed
Tuna stocks globally that are sustainable	87.0%	RFMO management demonstrably effective
Northeast Pacific sustainability rate	92.7%	Benchmark for what strong governance achieves
Eastern Central Atlantic sustainability rate	47.4%	Low-capacity governance context BOB parallel
Rate of increase in overfished stocks (recent years)	~1% per year	Trend not encouraging
Wild-caught landings not reported to species level	>40%	Management blind spot of enormous scale

Ref: Sharma, R., Barange, M., Agostini, V., Barros, P., Gutierrez, N.L., Vasconcellos, M., Fernandez Reguera, D., Tiffay, C., & Levontin, P., eds. 2025. Review of the state of world marine fishery resources – 2025. FAO Fisheries and Aquaculture Technical Paper, No. 721. Rome. FAO. https://doi.org/10.4060/cd5538en

1.5. The Reporting Gap

The reporting gap is equally serious. Even where fish are landed in significant volumes, the data generated at landing sites are often incomplete, delayed, spatially narrow, or too aggregated to support stock-specific management. Small-scale and artisanal catches are especially prone to undercounting because they move through informal landing sites, dispersed markets, and fragmented value chains that fall outside formal enumeration systems. Where reported catch is aggregated into broad categories such as “mixed demersals” or “small pelagics,” managers lose the species-level resolution required for credible stock assessment and reference-point based management. The result is that total fishing mortality is often understated, species composition is poorly understood, and management action is taken under conditions of structural uncertainty.

1.6. The Small-Scale Fisheries Blind Spot

This deficit is most severe in small-scale fisheries, precisely where human dependence on marine resources is often greatest. Vessels under 12 metres constitute the overwhelming majority of fleet numbers in many developing-country fisheries, yet they remain largely invisible to vessel tracking systems such as AIS and, in many cases, VMS.

Without routine positional data, management agencies cannot accurately map small-scale fishing effort, assess spatial concentration, identify pressure on habitats, or understand overlap between artisanal activity and depleted or sensitive stock areas. This is not only a technical blind spot. It is also a legitimacy problem. When management decisions are built primarily on data from industrial or semi-industrial fleets, they implicitly govern artisanal fisheries through evidence that does not adequately represent them.

Table 2. AIS and VMS Coverage by Vessel Size: The Monitoring Gap

(Sources: Global Fishing Watch; FAO)

Vessel length category	AIS carriage globally	VMS carriage (typical)	Monitoring status	BOB relevance
>36 metres	High	Regulated in most jurisdictions	Well monitored	Industrial trawlers and carriers
24–36 metres	Moderate	Partial national regulation	Moderately monitored	Semi-industrial BOB fleet
12–24 metres	Low	Partial	Poorly monitored	Mixed BOB fleet
<12 metres (SSF)	<1%	<1%	Virtually invisible	Majority of BOB fishing fleet
Non-motorised traditional boats	0%	0%	Completely invisible	Significant share of Bangladesh, India inshore fleet

Vessel length category	AIS carriage globally	VMS carriage (typical)	Monitoring status	BOB relevance
Vessels with AIS	~100,000 (~2% of 4.9 million global fishing vessels)		Massive global gap	BOB gap proportionally larger

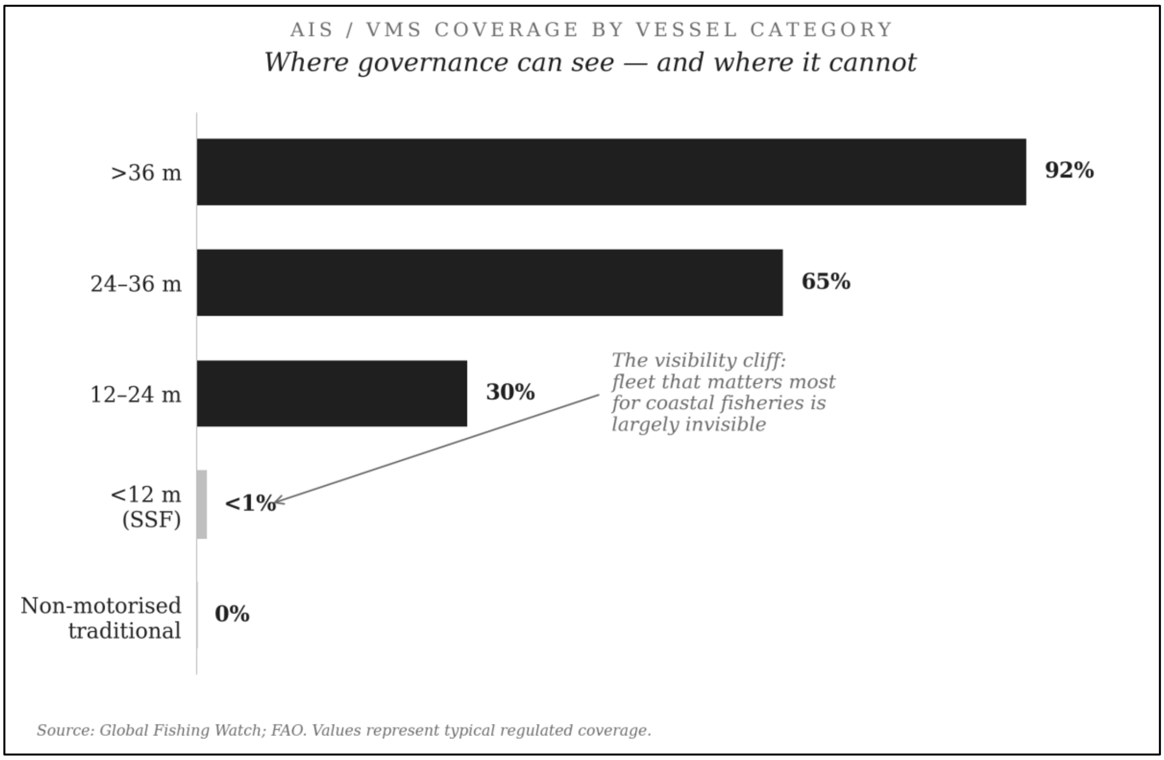


Figure 1: AIS/VMS Coverage by Vessel Category

1.7. Why Traditional Monitoring Methods Are Inadequate

Traditional monitoring methods designed around the 1980s, were from an era where scale of fisheries activities was limited and the management objectives were simpler. In that period, traditional fisheries monitoring faced limitations not only due to underinvestment but also a structural mismatch. The Bay of Bengal Large Marine Ecosystem spans about 6.2 million km^2, with roughly two-thirds inside member-state EEZs and the remainder on the high seas, making comprehensive patrol-based surveillance inherently difficult at regional scale.

Presently, AIS has improved vessel visibility, but intentional disabling remains a documented limitation: a global analysis found that AIS shutoffs obscured up to 6% of commercial fishing vessel activity, especially near EEZ boundaries and transhipment hotspots.[7] Catch monitoring faces similar constraints because fisheries data systems have historically relied on observers, landings reports, and self-reported paper logbooks, while electronic-monitoring audits show that logbook

[7] Welch, H., Clavelle, T., White, T.D., Cimino, M.A., Van Osdel, J., Hochberg, T., Kroodsma, D. and Hazen, E.L., 2022. Hot spots of unseen fishing vessels. *Science Advances*, *8*(44), eabq2109.

reporting can vary markedly across vessels and improves when independently validated.[8] Or in other words, advanced technologies layered over the traditional system is not producing the desired results.

These weaknesses help explain why reconstructed global marine catches for 1950–2010 were estimated to be about 50% higher than officially reported FAO data.[9] Taken together, the evidence suggests that conventional monitoring remains necessary but insufficient on its own, and that scalable digital surveillance, electronic monitoring, and AI-assisted analysis are increasingly being pursued as complements to close the fisheries data gap.[10]

1.8. From Data Scarcity to Decision-Grade Intelligence

The deeper lesson is that fisheries governance does not merely need more data. It needs better-governed information: data that are timely, comparable, verifiable, interoperable, and connected across science, monitoring, compliance, trade, and enforcement. The challenge is not only to observe more of the ocean, but also to transform fragmented observations into usable intelligence for public decision-making. This is where the integration between information and governance becomes critical. Data without integration do not produce accountability; reporting without verification does not produce trust; and legal frameworks without decision-grade evidence cannot deliver sustainability in practice.

This is the point at which artificial intelligence becomes strategically relevant. AI is not a substitute for institutions, legal frameworks, or scientific judgment. Its importance lies elsewhere: in its capacity to process large and heterogeneous data streams, support continuous observation, identify anomalies, strengthen verification, improve forecasting, and connect systems that would otherwise remain fragmented. In fisheries governance, its value is not simply technical efficiency. It is the possibility of shifting from partial visibility to integrated intelligence, and from reactive administration to more evidence-driven and anticipatory governance. The next chapter therefore examines AI not as a technological solution in itself, but as a strategic enabler of stronger fisheries governance in the Bay of Bengal region.

AI will not resolve the fisheries data problem unless the underlying data foundations are strengthened. In many fisheries, especially small-scale and artisanal fisheries, the limitation is not simply the absence of data, but the absence of data that are comparable, validated, representative, timely, and usable across institutions. Poorly harmonised landing records, incomplete species identification, uneven spatial coverage, weak effort data, and under-representation of informal landing sites can all be carried forward into AI systems. If these weaknesses are not addressed, AI may reinforce existing blind spots rather than close them. For this reason, the roadmap treats data quality, standardisation, validation, metadata, local participation, and representative coverage as preconditions for responsible AI-enabled fisheries governance, not as secondary technical tasks.

[8] Emery, T.J., Noriega, R., Parsa, M., Bromhead, D. and Timmiss, T., 2025. The capability of electronic monitoring to measure logbook reporting performance and improve data for scientific analyses. *Fisheries Research*, *291*, p.107518.

[9] Pauly, D. and Zeller, D., 2016. Catch reconstructions reveal that global marine fisheries catches are higher than reported and declining. *Nature communications*, *7*(1), p.10244.

[10] Welch, H., Ames, R.T., Kolla, N., Kroodsma, D.A., Marsaglia, L., Russo, T., Watson, J.T. and Hazen, E.L., 2024. Harnessing AI to map global fishing vessel activity. *One Earth*, *7*(10), pp.1685-1691.

1.9. The Depth of Socio-Economic Dependency

Human reliance on BOBLME fisheries is immense, both in scale and geographic concentration. In Bangladesh, more than 17 million people, over 10% of the population, work in fisheries-related livelihoods. This sector accounts for 3.57% of the country's GDP and over 24% of its agricultural GDP. Hilsa shad (*Tenualosa ilisha*), the national fish, alone contributes about 1% to GDP and makes up 12% of the entire country's fish production. Its cultural, economic, and nutritional significance is unmatched by any other species in the BOBLME region.

In India, 14 million livelihoods rely directly on fisheries, with marine fish production reaching 3.94 million metric tons in 2022–23. Seafood export (including produce from aquaculture) brought in about USD 7.7 billion, positioning India among the top five seafood exporters globally. In Sri Lanka, fisheries encompass both large-scale commercial operations and dense small-scale coastal fisheries, employing around 600,000 people directly. This sector is vital for rural coastal food security and contributes significantly to the country's export income. Meanwhile, in the Maldives, a small yet highly specialized tuna pole-and-line fleet plays an important role in supporting a notable portion of the national economy.

1.10. The Transboundary Stock Governance Challenge

The defining structural feature of fisheries governance in the Bay of Bengal is the transboundary distribution of commercially important fish stocks. Transboundary species account for a significant share of the Bay's catch and value, meaning that cooperative governance is not an optional add-on but a functional necessity. Some ecologically connected transboundary stocks cover other BoB rim countries, who are not part of BOBP-IGO. Hilsa shad migrates between marine and riverine systems across Bangladesh, India, and Myanmar. Indian mackerel is distributed across multiple littoral states. Commercial shrimps span contiguous EEZs across countries. Similar dynamics apply to croakers, anchovies, threadfin breams, sardinellas, and other economically important groups.

The governance implication is profound. Shared stocks can be intensively harvested by multiple countries without any one state having complete information on total fishing pressure, stock status, or risk. This means that purely national management frameworks, even when well-designed domestically, are often insufficient in ecological terms. A country may regulate responsibly within its own waters while still suffering the consequences of unsustainable practices elsewhere in the same biological system. The Bay of Bengal therefore exposes one of the central weaknesses of contemporary fisheries governance: the mismatch between ecological connectivity and political jurisdiction.

1.11. Exploitation, Uncertainty, and Weak Coordination

The Bay also illustrates the consequences of weak coordination over time. The transboundary stocks working document[11] shows that in the Eastern Indian Ocean, "developing" stocks declined sharply over the long term, while exploited, over-exploited, and collapsed categories increased. At the same time, a substantial share of stocks remained in the "Data Not Available" category

[11] Managing the Unmanaged Shared Resources: Policy Options for Managing the Transboundary Stocks in the Bay of Bengal", a working document was prepared by the BOBP-IGO team in response to the suggestion by the 12th Governing Council of BOBP-IGO.

because of inadequate information, inconsistent data, or non-reporting. These findings are important because they show that the problem is not only overfishing in a narrow biological sense. It is the combination of rising fishing pressure and persistent uncertainty. Shared resources can be intensively fished without any participating country having a complete and reliable understanding of the cumulative pressures being exerted.

Institutional developments in the Bay of Bengal reveal both progress and limitation. The adoption of the Bay of Bengal Regional Plan of Action on IUU Fishing by the member countries of BOBP-IGO, is a major regional milestone, but the real difficulty lies in operationalizing that agreement across four different legal and institutional systems. Digital traceability is the most practical near-term tool for advancing both IUU mitigation and value-chain upgrading, and there is a clear need for capacity development in vessel boarding, port inspection, port state measures, and data sharing.

> *These priorities underscore a broader reality: regional governance increasingly depends not only on policy intent, but on technical interoperability, institutional alignment, and the ability to act on shared information.*

1.12. The BoB's Triple Burden

The Bay of Bengal is a semi-enclosed tropical basin bordered by Bangladesh, India, Indonesia, Malaysia, Maldives, Myanmar, Sri Lanka, and Thailand (with BOBP focusing on the western arc). It is one of the most biologically productive yet politically complex marine regions on Earth. The region faces a triple burden:

1. **Ecosystem Overexploitation:** The commercial fishery in the BOB region is likely over-exploited. The catch data from eastern Indian Ocean show that more than one-third of the fish stock are over exploited. Hilsa shad (*Tenualosa ilisha*) the signature species of the northern BOB has seen catch declines of 40–60% in Myanmar and parts of India over two decades.
2. **Socio-Economic Dependence:** Over 4.5 million active fishers operate across the region, supporting an estimated 40–50 million dependents. Most are small-scale, artisanal fishers with vessels under 12 meters length that is almost entirely invisible to existing monitoring systems.
3. **Governance Fragmentation:** The Bay of Bengal governance landscape remains institutionally fragmented, with different bodies covering different species, functions, and legal mandates rather than a single comprehensive regional fisheries management architecture. Existing mechanisms including the Bay of Bengal Programme Inter-Governmental Organisation (BOBP-IGO), the Indian Ocean Tuna Commission (IOTC), and various bilateral agreements operate with overlapping mandates, weak enforcement, and no shared intelligence platform.

These three burdens become most visible through a series of recurring governance failures. Illegal, unreported, and unregulated fishing remains difficult to monitor consistently across EEZ boundaries, especially where vessels operate under flags of convenience or where tracking systems do not connect across jurisdictions. At-sea transshipment creates additional opacity by allowing catches to change hands before they reach shore, often without reliable linkage between vessel movements, cargo records, and landed product. Bycatch and discards continue at significant levels, but the absence of broad electronic monitoring coverage means that much of this activity remains weakly documented. Even where maritime boundaries are legally settled, operational ambiguity persists, and fishers may still be detained or penalized because there is no shared, real-time geofencing or alerting mechanism. In each case, the governance problem is inseparable from an information gap.

The BoB is not a special case; it is a representative case. This is the deeper meaning of the data dilemma. Fisheries governance does not merely need more data. It needs decision-grade information: data that are timely, comparable, verifiable, and connected across science, monitoring, compliance, and trade. Until that transition occurs, management will continue to rely on partial visibility and delayed interpretation.

> *AI becomes strategically relevant because it can help reduce this dilemma but only if deployed within an architecture capable of turning fragmented data into coherent governance intelligence.*

CHAPTER 02

2.AI in Fisheries: Evidences from the Oceans

The discussion so far has shown that the central weakness in contemporary fisheries governance is not simply the absence of rules, but the persistent gap between what institutions need to know and what existing monitoring and reporting systems are actually able to reveal. In the Bay of Bengal, AI has relevance in two closely connected domains: it can strengthen fisheries governance by improving visibility, verification, forecasting, and enforcement, and it can also support livelihoods and business performance by helping fishers, workers, and small enterprises make better decisions, access schemes and services, reduce losses, and participate more effectively in markets. In a region where small-scale fisheries dominate and information asymmetry is a major source of both ecological stress and economic vulnerability, governance-oriented AI and livelihood-oriented AI must be treated as two sides of the same policy challenge. This section shares lessons from selected case studies and operational illustrations drawn from global and regional experiences on how AI has already generated governance value and where it offers realistic strategic potential for the Bay of Bengal.

2.1. Case studies from around the oceans

01 ***VESSEL SURVEILLANCE***	**We Were Not Watching Most of the Ocean & the Fleet Knew It** **What governance assumed:** *AIS transponder data provides meaningful coverage of commercial fishing activity. Illegal operators who turn off their transponders are exceptions that enforcement can pursue case by case.* **What AI revealed:** Approximately 75% of the world's industrial fishing vessels are not publicly tracked. This is not an exception it is the norm. Untracked fishing is concentrated in the regions of highest governance need, including South Asia and West Africa. In 2017, Global Fishing Watch applied machine learning to SAR satellite imagery and AIS data to expose 900 Chinese vessels fishing illegally inside North Korean waters an entire fleet operating in plain sight of satellite sensors but invisible to any monitoring system that relied on transponder broadcasts. The vessels had simply switched off their AIS. A 2020 study in Science Advances confirmed the Galápagos case: 72% of vessels detected near a flagship Marine Protected Area were not transmitting AIS. Studies published in Science in July 2025, covering nearly 1,400 MPAs globally, confirmed this finding at scale three quarters of vessels detected by radar were not being tracked. In 2025, GFW published the first complete map of global industrial fishing activity, built from 2 million gigabytes of satellite imagery: the finding was that approximately 25% of total global fishing effort had been entirely absent from any official monitoring dataset.

02 ***CATCH DATA***	**Our Catch Records Were Not What We Thought They Were** **What governance assumed:** *Logbooks and landing declarations, even where compliance is imperfect, provide a broadly accurate picture of what is being caught. Observer coverage at 10–20% of trips provide adequate verification.* **What AI revealed:** Observer-verified fisheries with good logbook compliance still show systematic underreporting of discards and non-target species when EM cameras are installed. The misreporting is not exceptional it is structural, driven by incentives that operate consistently whenever fishing is unobserved. The NOAA West Coast Groundfish EM programme, implemented as mandatory full-fleet coverage from January 2024, one of the earliest fisheries to achieve near-comprehensive independent catch verification. What it found was that even in a well-monitored fishery with experienced operators and an active observer programme, EM-generated catch records identified systematic underreporting of discards absent from logbook data. The Pacific Islands EM programme, covering over 400 vessels in a USD 10 billion tuna fishery, reduced per-trip monitoring cost by 70% and simultaneously identified catch events that were underrepresented in voluntary reporting. *The conclusion is consistent across both programmes: it is not that fishers are uniquely dishonest. It is that any system in which the entity generating the primary data record has a financial incentive to misreport, and is unobserved most of the time, will produce systematically biased data regardless of the legal compliance framework surrounding it.*

03 ***STOCK ASSESSMENT***	**Useful Signals Where Conventional Assessment Cannot Reach** **What governance assumed:** *Stock assessment requires formal survey data: research vessel trawls, acoustic surveys, biological sampling. Without this infrastructure, data-poor fisheries cannot be meaningfully assessed.* **What AI revealed:** AI models that integrate satellite oceanographic data with historical catch, effort, and environmental records can generate management-relevant ecological and fishery signals for data-limited species. These outputs can help identify habitat shifts, aggregation patterns, catchability changes, and priority areas for sampling or management attention. However, they should not be treated as stand-alone stock assessments. Biological stock assessment still requires information on stock identity, population structure, biological sampling, size or age composition, recruitment, mortality, and standardised catch-effort data. AI-generated outputs are therefore positioned as inputs to FAO data-limited assessment approaches, not as substitutes for analytical stock assessment. This aligns the roadmap with current international stock-assessment practice and clarifies that AI outputs feed into, rather than replace,

	established assessment workflows. Where data are sparse, AI-derived signals may support indicator development, sampling prioritisation, trend interpretation, and data-limited assessment methods as one line of evidence among others, subject to human review and uncertainty reporting. India's INCOIS Potential Fishing Zone advisory system has been operational since 2002, enhanced with machine learning since 2015. It delivers probabilistic predictions of fish aggregation locations derived from satellite SST, chlorophyll-a, current velocity, and historical catch data directly to over 100,000 registered fishers by SMS in seven languages. Documented outcomes include 20–30% reductions in fuel cost and time-at-sea for users relative to non-users. The system demonstrates that oceanographic satellite data, processed by AI, can substitute survey vessel infrastructure in generating actionable fisheries information. In Bangladesh, AI models integrating Ganga-Brahmaputra-Meghna River discharge data with coastal salinity and catch records have enabled pre-season Hilsa abundance predictions 3–4 months ahead of the main fishing season providing advance evidence for setting ban duration and sanctuary boundaries.

04 ***SUPPLY CHAIN***	**Clean Supply Chains Were Not as Clean as the Documentation Suggested** **What governance assumed:** *Seafood export documentation like HACCP certification, catch certificates, species declarations provide meaningful assurance that certified products derive from legal, sustainable sources.* **What AI revealed:** Paper-based supply chain documentation is routinely falsified or manipulated. IUU fish enters certified supply chains at scale. The evidence only became visible when AI traceability systems created independent, tamper-evident verification of what the documentation claimed. Thailand's 2015 EU Yellow Card exposure was one of the most consequential regional examples of how traceability and compliance failures can trigger market and governance pressure. When the EU applied its IUU Fishing Regulation which requires exporting countries to demonstrate effective national control systems, Thailand's USD 1.5 billion EU seafood export sector was placed under formal scrutiny. The subsequent audit found systematic failures: vessels operating without documentation, catch entering supply chains without verifiable provenance, and paper certification systems that were structurally unable to verify the claims they were certifying. The cost of the four-year reform process, in market access restrictions, investment uncertainty, and compliance expenditure, is estimated by Thailand's fishing industry at approximately USD 500 million substantially more than proactive traceability investment would have required.

	In contrast, the Maldives which had invested in documented chain of custody for its pole-and-line tuna fishery commands a sustained 15–25% market premium over uncertified equivalent products, earning an estimated USD 20–30 million annually in premium value directly attributable to its traceability infrastructure. India's launch of a National Digital Traceability Framework, linking blockchain catch records to vessel registration, landing documentation, and export certification, represents an early example of a potential AI-supported digital chain-of-custody initiative in India's seafood export sector.

05 ***LIVELIHOODS***	**Digital Catch Records Were Worth More Than the Fish They Described** **What governance assumed:** *Catch documentation serves a monitoring function: it tells managers what is being caught and where. For small-scale fishers, market access and financial inclusion are separate problems, addressable through credit schemes or trader networks and not through data systems.* **What AI revealed:** ABALOBI's platform in South Africa demonstrated that the same mobile catch record species, location, gear, time simultaneously serves as fisheries monitoring data, provenance certificate for premium market access, and proof of income for financial institutions that have historically treated artisanal fishers as effectively undocumented. Fishers using the platform earned up to four times more revenue by bypassing intermediaries and selling directly through the "Fish with a Story" marketplace. Within three years, over 488 tonnes of fully traceable seafood had transacted through the system and 93 percent of listed catch met sustainability criteria. The platform has since expanded to 12 countries. The deeper finding is structural: governance data infrastructure and business service delivery can be run through the same system, and the catch record is the key that unlocks both. The model has now been replicated across Kenya, Seychelles, Palau, Madagascar, Chile, and the Comoros, among others.

6 ***COMMUNITY MOBILIZATION***	**A Country Had No Idea Where to get its data from and then the community stepped in** **What governance assumed:** *Fisheries monitoring is a state function, built from the top down through institutional investment in survey infrastructure, observer programmes, and official data systems. Community members at landing sites are data sources to be sampled, not partners in building the monitoring architecture itself. Without prior investment in government capacity, reliable fisheries data cannot be generated or sustained at scale.*

	What AI revealed: Peskas, developed by WorldFish in partnership with Timor-Leste's Ministry of Agriculture and Fisheries, inverted this assumption. The system combined GPS trackers mounted on artisanal fishing vessels with community members at landing sites collecting catch data and uploaded the results to a publicly accessible dashboard providing near real-time visibility into small-scale fisheries activity. Before 2016, the government had virtually no reliable information on where coastal fishers were operating or what they were landing. That invisibility was not merely a data problem: fishers who cannot be seen by management systems cannot be protected by them, and resources that are not counted cannot be managed for long-term yield. It was community-embedded data collection that closed the gap not a government survey programme. Peskas has since become Timor-Leste's official national fisheries monitoring system and directly informed the country's latest National Fisheries Strategy. Formal government adoption accelerated inter-agency collaboration and attracted new investment into the fisheries sector. The model is now being replicated across Kenya, Tanzania, and Mozambique through the WorldFish-led Asia–Africa BlueTech Superhighway project. The finding is structural: where state monitoring capacity is absent, communities can build the data infrastructure that states subsequently adopt and the legitimacy of community-generated data, when made publicly accessible and institutionally legible, proved sufficient to anchor national policy. A six-year impact assessment recorded one important limit. Peskas was highly effective at strengthening data flows, institutional coordination, and investment attraction. It had only limited effect on the development of new fisheries regulation. The binding constraint was not data it was an inadequate legal framework and broader institutional capacity. Community mobilisation can generate the evidence base that governance requires. It cannot substitute for the legal and institutional architecture through which that evidence must act.

2.2. What the Evidence Establishes

Across these six findings, the pattern is consistent. The gap between what official systems reported and what digital monitoring, AI-enabled observation, and community-based data collection revealed was not small. It was structural the product of governance architectures designed for a level of ocean transparency that was never achievable by the tools deployed to achieve it. Two of the findings add a further dimension: where data systems were redesigned from the ground up around the fisher rather than the regulator, they generated livelihood and financial outcomes that conventional monitoring infrastructure was never conceived to produce.

The table below summarises the scale of each governance gap and the livelihood implications where evidence exists.

Table 3. The quantified scale of each governance gap as revealed by AI evidence

Governance Domain	What Was Assumed	What the Evidence Revealed	Scale of Gap
Vessel Surveillance	AIS provides meaningful monitoring of commercial fleet activity	~75% of industrial fishing vessels not publicly tracked; 25% of global effort absent from all official datasets	Three-quarters of the fleet invisible
Catch Documentation	Logbooks + 10–20% observer coverage provides adequate catch data	EM systems in well-monitored fisheries reveal systematic discard underreporting even with active compliance frameworks	Catch data structurally biased toward under-reporting in all unobserved fisheries
Stock Assessment	Data-poor conditions prevent meaningful stock assessment without survey infrastructure	AI + satellite oceanographic data generates management-relevant stock signals for unassessed species; INCOIS PFZ demonstrates fisher-level applicability	33.8% of EIO stocks 'unassessable' but usable data already exists in satellite archives
Supply Chain Integrity	Certification and catch documentation provide meaningful assurance of product provenance	Paper supply chains are routinely manipulated; AI traceability reveals IUU product entering certified chains; Maldives premium vs Thailand penalty quantifies the market stakes	Provenance claims in paper-documented supply chains are unverifiable and frequently inaccurate
Livelihoods	Catch data serves a monitoring function; market access and financial inclusion are separate policy problems	The same digital catch record simultaneously functions as a fisheries monitoring instrument, a provenance certificate, and proof of income generating up to 4× revenue gains and financial identity for previously undocumented fishers (ABALOBI; 12 countries)	The separation of governance data and livelihood delivery was an assumption, not a necessity
Community mobilization	Monitoring and fisher welfare are addressed through separate instruments	Community-based GPS monitoring became a country's official fisheries management system within a decade, informing national strategy and attracting investment; fisher invisibility to management systems is itself a livelihood risk (Peskas, Timor-Leste)	Monitoring is a prerequisite for livelihoods protection; the binding constraint was legal framework and institutional capacity, not data

CHAPTER 03

3. AI as a Strategic Enabler: Technology-to-Governance Pathways

3.1. Technology Domains and BOBLME-Specific Applications

Seven Governance-AI domains have direct and high-impact application to the fisheries governance challenges identified in the BOBLME. Each domain is assessed below in terms of its technology maturity, BOBLME-specific application, demonstrated outcomes, and strategic priority for the region.

A framework of this kind must address a key institutional concern: whether AI-enabled monitoring will displace the human observers, inspectors, and enumerators on whom fisheries governance depends. Available evidence does not support that conclusion. AI-assisted monitoring reduces the volume of routine footage and records requiring manual review, but it does not remove the need for trained analysts, compliance officers, and port inspectors. Instead, it changes the nature of these roles, shifting effort from repetitive checking to anomaly interpretation, exception handling, and enforcement follow-through.

In the BOBLME context, where observer coverage and inspection capacity remain limited, the core constraint is not labour surplus but insufficient monitoring reach. AI therefore expands what a constrained workforce can see and verify, while increasing the importance of investment in trained analysts, empowered inspectors, and data-literate fisheries officers.

> *AI should be understood as a tool to augment human capacity in monitoring, analysis, and decision-making, not as a substitute for fisheries workers or institutional roles.*

Domain 1: Vessel Surveillance and Dark Vessel Detection

Satellite-based AI surveillance integrating SAR imagery, multispectral optical data, and AIS/VMS transponder data offers the most immediate and scalable application for BOBLME governance. Machine learning algorithms trained on vessel radar signatures can detect and classify fishing vessels regardless of transponder status, providing enforcement agencies with a comprehensive operational picture across national and international waters. Current SAR satellite constellations (including Sentinel-1, ALOS-2, and commercial operators) provide revisit times of 1–3 days over most of the BOBLME, sufficient for near-real-time monitoring of high-risk fishing areas and EEZ boundary zones.

For BOBLME member states, this technology is most valuable in the Bangladesh–India–Myanmar maritime boundary zone, the Malacca Strait approach, and the Andaman Sea. These areas are marked by intense fishing activity, and historically limited enforcement presence. Global Fishing Watch offers free or subsidised data access to eligible fisheries management authorities, providing an affordable entry point for member states with constrained surveillance budgets.

Domain 2: Electronic Monitoring (EM) and On-Board Data Collection

Electronic Monitoring systems including rugged cameras, GPS devices, and sensors recording catch data, gear deployment, and vessel positioning are the main way to close the data gap in both large-scale and, increasingly, small-scale fisheries. AI-powered EM systems can automatically identify species, estimate the size and weight of individual fish, and flag compliance issues (such as discarding or the use of prohibited gear) without needing human review of all video footage.

Demonstrated outcomes from EM programmes in North America, Australia, and New Zealand show that AI-assisted video review reduces analyst time by 60–80% while maintaining or improving data accuracy compared to human observers. A phased EM rollout targeting medium-scale vessels could be piloted in the member countries of BOBP-IGO.

Domain 3: Smart and Selective Fishing Gear

AI-integrated fishing gear represents a convergence of real-time computer vision, underwater robotics, and sensor technology to reduce bycatch, minimise habitat damage, and improve species selectivity. Underwater camera systems with onboard species identification algorithms can trigger mechanical sorting mechanisms to release non-target species before capture. Acoustic deterrents triggered by AI-detected marine mammal presence can reduce dolphin and cetacean bycatch. Variable-mesh trawl systems that adjust net geometry in response to real-time species composition data are in advanced field trial stages in multiple fisheries globally.

ICES reports bycatch reductions of 30–60% in temperate fisheries through the use of improved gear selectivity mechanisms. In the BOBLME context, where shrimp trawl fisheries produce some of the highest bycatch-to-target ratios in the world with ratios of 3:1 to 10:1 reported in some areas smart gear deployment represents both an ecological and economic priority.[12] The technology development costs for tropical, small-scale-compatible smart gear remain high, and regional investment in applied R&D is needed to adapt proven concepts to BOBLME conditions.

Domain 4: AI-Supported Stock Assessment and Predictive Analytics

Conventional stock assessment requires detailed time-series data on catches, effort, and abundance, together with biological sampling that supports inferences about population structure, recruitment, and age composition. Most BOBLME stocks lack at least one of these inputs, and many lack several. AI cannot manufacture biological information that has not been collected. What machine-learning approaches can do is extend the analytical reach of available data, for example, by combining catch and effort series with environmental covariates, by applying data-limited methods to fisheries with no formal assessment, or by transferring inferences from comparable well-studied stocks. The outputs of such methods are best understood as decision-support indicators, not stock assessments in the conventional sense. They are useful for precautionary management of stocks that would otherwise be unmanaged, for identifying emerging trends that warrant biological investigation, and for supporting joint regional analysis where national data alone are insufficient.

For Hilsa shad, the most economically and culturally significant transboundary species in the BOBLME, AI applications can be approached in two stages. First, environmental and

[12] Food and Agriculture Organization of the United Nations. *Tropical shrimp fisheries and their impact on living resources*. Rome: FAO; 2000.

oceanographic models combining river-flow data, sea surface temperature, salinity, and historical landings can support fishing-ground advisories and short-term forecasting useful to both managers and fishers. Second, with sustained investment in regionally coordinated biological sampling across Bangladesh, India, and Myanmar, AI methods can subsequently contribute to a joint, transboundary stock signal that supports cooperative management decisions. The framework does not claim that AI alone can produce a Hilsa stock assessment; it does propose that AI-supported analytical infrastructure, built jointly across the riparian states, is a necessary part of any credible future joint assessment. Predictive analytics built on oceanographic models and historical catch data can also generate dynamic fishing-ground predictions, enabling more efficient fleet deployment while reducing fuel consumption and pressure on vulnerable habitats; India's INCOIS Potential Fishing Zone advisory programme is the leading operational example in the region.

Domain 5a: Regional Fish Stock and Fishery Resource Registry

A foundational priority for the BOBLME is the establishment of a Regional Fish Stock and Fishery Resource Registry, aligned with FAO-FIRMS/GRSF standards for unique identification of fish stocks and fisheries. Such a registry would assign or map each recognized Bay of Bengal fish stock, assessment unit, fishery resource, or fishery unit to a standardized identifier, including where appropriate the GRSF UUID and Semantic Identifier.

This would address a major regional governance gap: the absence of a harmonized inventory of how many fishery resources are being reported, monitored, assessed, or managed across countries. At present, the same resource may be described differently across national systems, landing records, assessment reports, or regional documents. A regional registry would provide a common reference layer for stock reporting, catch documentation, biodiversity monitoring, traceability, and future joint assessments.

In the Bay of Bengal context, this registry would be especially important for transboundary and shared resources such as hilsa, mackerels, shrimps, croakers, anchovies, threadfin breams, sardinellas, tunas, and other commercially important groups. It would not imply that all stocks are already fully assessed. Rather, it would create a structured pathway from "identified and reported resource" to "harmonized regional stock record" and eventually to "jointly assessed and cooperatively managed stock."

Operationally, BOBP-IGO could facilitate this registry through its proposed regional coordination architecture, working with member states, FAO/FIRMS, national scientific institutions, and existing databases. The initial output could be a Bay of Bengal stock and fishery resource inventory with standardized species names, areas, national reporting references, known transboundary status, assessment availability, data gaps, and unique identifier mapping. This would support harmonized reporting immediately, while laying the foundation for future joint stock assessment and shared management.

Domain 5b: Automated Species / Group-level Identification and Biodiversity Monitoring

Deep learning models, particularly Convolutional Neural Networks (CNNs) trained on extensive image libraries, can identify fish species or family-level groups from photographs with high accuracy when trained on sufficiently representative regional datasets. Deployed at landing sites via mobile applications accessible to enumerators, these tools can transform the quality of species/family-level catch data without requiring specialist taxonomic training. Integration with fish market surveillance cameras can provide continuous automated monitoring of species composition and size distribution at major landing centres.

For the BOBLME, automated species identification has value in documenting the catch composition of data-poor fisheries. The usefulness of automated species identification in the Bay of Bengal will depend heavily on the creation of region-specific annotated image datasets, as many locally important species groups remain poorly represented in existing global training libraries. The FAO Fish Species Sheets, FishBase and iNaturalist databases provide foundational training data, and regional initiatives to extend training datasets to BOBLME-specific species would significantly improve identification accuracy.

Domain 6: Supply Chain Traceability and Anti-Fraud Systems

AI-powered supply chain traceability combines blockchain-based catch records, RFID tags, DNA barcoding, and machine learning anomaly detection to counteract governance failures that enable illegal, unreported, and unregulated (IUU) fish to be laundered into legitimate supply chains. Comprehensive traceability systems that connect catch data (vessel, location, gear, species) with landing records, processing documents, and retail certifications establish an auditable custody trail, making catch laundering economically and legally unviable.

Investing in traceability has a strong economic rationale. Premium markets in the EU, Japan, and the US increasingly demand documented sustainability credentials, and exporters without reliable traceability face rising market access challenges. India's shrimp aquaculture sector has already shown that investing in traceability yields market premiums that exceed implementation costs. Expanding traceability infrastructure to wild-capture fisheries, especially for high-value exports like tuna, grouper, and premium shrimp, would enhance both governance and market development.

Domain 7: AI as a Business Enabler: Technology-to-Livelihood Pathways

The governance value of AI in fisheries has already been established in the preceding discussion. For the nearly 4.5 million active fishers in the Bay of Bengal region, however most of whom operate in small-scale, artisanal enterprises the more immediate question is not simply whether AI can help the state manage fisheries better. It is whether AI can help the fishers fish more intelligently, sell more profitably, and build more resilient livelihoods.

Market intelligence and price discovery. AI-enabled platforms that combine real-time landing-centre prices, processor and export market demand signals, and transport cost information can shift bargaining power in favour of fishers. The INCOIS experience shows that fishers adopt advisory services when the value proposition is immediate and personal. Extending this logic from fishing-ground prediction to market-price prediction is technically feasible.

Access to schemes and entitlements. Across all four member states, fishers are potentially eligible for welfare schemes, insurance products, subsidies, and disaster relief. In practice, uptake is often constrained by information gaps, documentation burdens, and last-mile delivery failures. AI-assisted eligibility screening, multilingual chatbot guidance, and automated document preparation can reduce the transaction cost of accessing benefits that already exist.

Reduction of post-harvest losses. AI can support cold-chain optimisation, demand-matched harvest scheduling, and quality grading at landing sites. These interventions can directly reduce the 25–35 percent post-harvest losses documented in tropical fisheries. For a small-scale fisher, even a 10 percent reduction in such losses may produce an income gain equivalent to increasing catch without increasing fishing effort. This creates a rare alignment between economic and ecological benefit.

Financial inclusion and access to credit. Digital catch records generated through electronic monitoring or app-based reporting can create a transaction history that supports credit scoring, micro-insurance eligibility, and formal banking access. A fisher who participates in digital catch documentation gains not only governance visibility, but also a form of financial identity.

Cooperative-level business intelligence. When catch and market data are aggregated at the cooperative level, they can support collective bargaining, joint marketing, fleet-level fuel optimisation, and investment planning. In this way, the cooperative can evolve from an administrative intermediary into a data-enabled business institution.

The strategic implication is clear: the AI architecture proposed in this document should be designed from the outset to serve both governance and livelihood purposes. The same data infrastructure required for fisheries management vessel tracking, catch documentation, species identification, and traceability can also generate the raw material for fisher-facing business services. The marginal cost of layering business intelligence onto governance intelligence is relatively low. The marginal benefit, in terms of fisher adoption, political support, and poverty-reduction impact, is potentially high. Any framework that asks fishers to contribute data to governance systems without returning visible business value is likely to face the same adoption failures that have hindered fisheries data collection for decades.

FIDF Evaluation: Access Frictions in Fisheries Schemes and the Case for an AI Support Bot (India, 2022–2023)

The Fisheries and Aquaculture Infrastructure Development Fund (FIDF) provides a practical institutional case for understanding why fisheries schemes often underperform even when substantial public support is formally available. The evaluation of the scheme, undertaken by **BOBP-IGO** for the National Fisheries Development Board (NFDB), found that overall uptake was low: during the review period, the cumulative value of proposals received amounted to only 34 percent of the fund mobilization target, and the time taken from proposal submission to actual receipt of bank finance was particularly long.

The significance of the case lies in the reasons for this underperformance. The evaluation found that many eligible entities faced difficulty not because the scheme lacked relevance, but because access to it was administratively hard. Key constraints included lack of information on viable areas for investment, difficulty in preparing DPRs, delays in obtaining clearances, challenges in meeting collateral requirements, and weak understanding of scheme procedures. The report also notes that many stakeholders struggled with instructions delivered in English or Hindi, and specifically recommended stronger outreach, handholding through NFDB regional centres, and ready-to-use model DPRs to reduce applicant burden.

This case is especially relevant to the present document because the barriers identified in FIDF mirror the broader access problems faced by fishers in relation to welfare schemes, insurance, subsidies, and disaster relief. The bottleneck is often not the formal absence of entitlements, but the transaction cost of accessing them: understanding what one is eligible for, producing the necessary documents, interpreting the instructions, and moving the application through a fragmented administrative chain.

The FIDF evaluation is also notable because it points toward a digital remedy. Among its recommendations was an **AI-based immersive website and virtual assistant** that could answer queries, guide users through scheme features, and eventually help them plan a project and identify the most appropriate support window. This directly supports the AI bot proposed in the present framework. A multilingual fisheries-support bot could screen users for likely eligibility, explain schemes in local languages, generate personalized document checklists, assist in preparing draft applications or DPR inputs, and provide stepwise guidance until escalation to a human official is required.

The broader lesson is clear. The FIDF case shows that even well-funded fisheries support mechanisms can underperform when beneficiaries encounter information barriers, documentation burdens, language constraints, and last-mile delivery failures. It therefore supports the proposition that AI-assisted eligibility screening, multilingual chatbot guidance, and automated document preparation can materially reduce the cost of accessing benefits that already exist. In this sense, the proposed AI bot is not an ornamental digital feature; it is a response to a demonstrated implementation failure in fisheries scheme delivery.

Table 4. AI Technology Domains: Maturity, Application, and Strategic Priority for the BOBLME

Governance-Technology Domain	Maturity Level	Governance Application in the BOBLME	Livelihood / Business Application	Strategic Value	Priority
Vessel Surveillance (SAR/AI + AIS/VMS integration)	High deployable now	EEZ monitoring, dark vessel detection, hotspot surveillance, support to IUU enforcement and maritime domain awareness	Indirect livelihood benefit through safer fishing space, reduced conflict, and improved protection of inshore resources from illegal encroachment	Strongest immediate use case for improving visibility at scale	Critical
Electronic Monitoring (EM) and On-board Data Collection	High proven at scale	Catch verification, compliance monitoring, bycatch documentation, support to traceability and stock assessment	Digital catch history, improved credibility of landings, basis for access to formal markets, finance, and insurance	Foundational bridge between governance data and fisher-facing value	Critical

Governance-Technology Domain	Maturity Level	Governance Application in the BOBLME	Livelihood / Business Application	Strategic Value	Priority
Smart and Selective Fishing Gear	Medium field trial stage	Bycatch reduction, habitat protection, improved compliance with gear regulations	Higher target-species efficiency, lower waste, improved catch quality, reduced fuel and sorting losses	Strong ecological and economic co-benefit, but adaptation for tropical small-scale fisheries is still needed	High
AI-Powered Stock Assessment and Predictive Analytics	Medium emerging	Data-limited stock assessment, forecasting of stock movement, better evidence for management decisions and transboundary cooperation	Dynamic fishing-ground advisories, lower fuel use, shorter search time, reduced pressure on vulnerable habitats	Important for moving from data scarcity to decision support in stock-poor fisheries	High
Automated Species / Group-level Identification and Biodiversity Monitoring	High mobile deployable	Improved landing-site data, better catch composition records, biodiversity monitoring, support to assessment and compliance	Better sorting, grading, species-wise price realization, reduced dependence on specialist taxonomic expertise	Practical tool for improving routine fisheries data quality at scale	High
Supply Chain Traceability and Anti-Fraud Systems	Medium-High	Catch-to-market verification, anti-fraud control, prevention of IUU laundering, stronger export certification and legality assurance	Better market access, eligibility for premium markets, lower rejection risk, improved chain-of-custody confidence	Governance and market incentives align strongly in this domain	High
AI-based Livelihood and Business Support Services	Medium readily pilotable using existing	Improved public service delivery through scheme screening, advisory support, multilingual query	Market intelligence, price discovery, access to schemes and insurance,	Most important domain for ensuring that AI adoption is inclusive and	Critical

Governance-Technology Domain	Maturity Level	Governance Application in the BOBLME	Livelihood / Business Application	Strategic Value	Priority
	digital infrastructure	handling, and reduced administrative burden in accessing entitlements	document preparation, credit linkage, cooperative-level business planning, post-harvest loss reduction	politically legitimate among small-scale fishers	

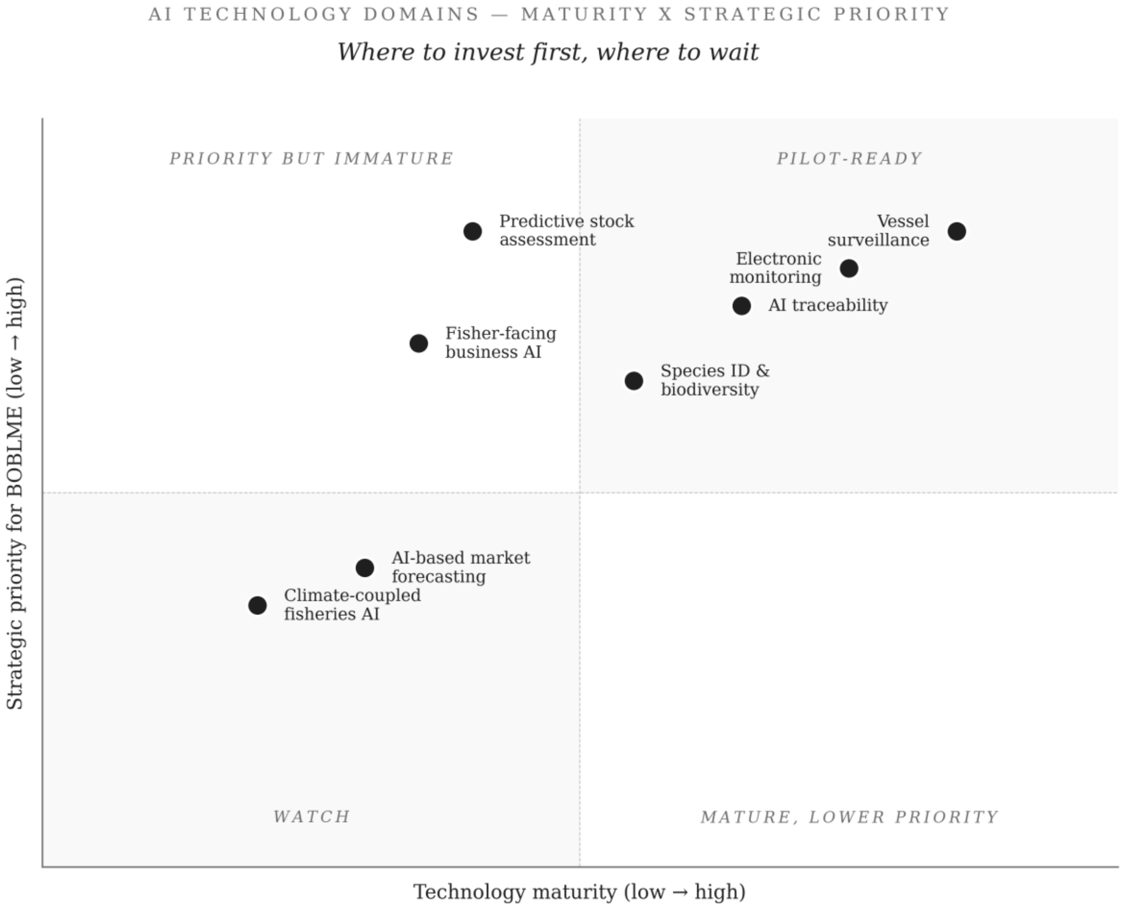


Figure 2: AI Technology Domains – Maturity versus Strategic Priority

3.2. From Data to Governance: How AI Strengthens Fisheries Management

AI is strategically important to fisheries governance because it enables a new relationship between data and decision-making. It turns raw information streams into interpretable signals, automates forms of detection and verification that were previously too costly or slow, and supports a shift from reactive oversight to predictive governance.

> *In this sense, AI should not be treated simply as a set of technical applications. It should be understood as a governance enabler - one that can strengthen how states observe, verify, predict, coordinate, and enforce*.

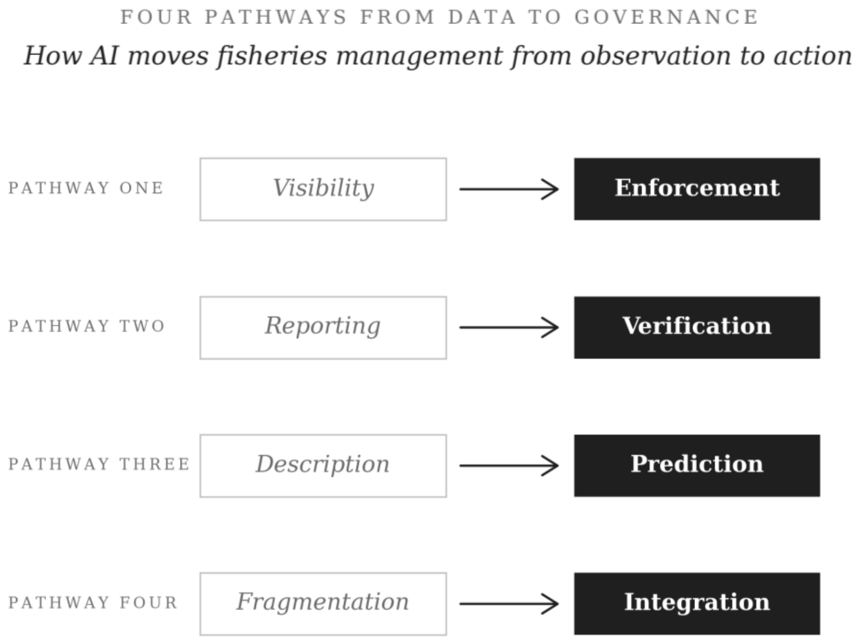


Figure 3: Four Pathways from Data to Governance

PATHWAY	EXPLANATION
The first pathway runs from visibility to enforcement.	AI can process satellite imagery, radar, AIS, VMS, and related data to detect dark vessels, anomalous movement patterns, suspicious loitering, incursions into protected areas, or possible illegal transshipment. This expands the practical visibility of public authorities. Instead of relying only on declared positions or sporadic patrols, agencies can use AI-supported systems to identify where risks are concentrated and where limited enforcement resources should be focused. The governance effect is not merely more data, but more targeted action.
The second pathway runs from reporting to verification.	In fisheries, reporting has historically depended on manual declarations, inspectors, and paper-based workflows. AI changes this by supporting onboard electronic monitoring, automated species recognition, catch counting, and data validation. Cameras equipped with machine learning tools can help document what is actually brought aboard. When linked to catch documentation systems and traceability platforms, such tools strengthen the evidentiary quality of compliance systems. This matters because the integrity of fisheries governance depends increasingly on whether catch can be trusted as both legal and accurately described.

PATHWAY	EXPLANATION
The third pathway runs from historical description to prediction.	Traditional fisheries management often looks backwards, using past catch and survey information to infer present conditions. AI expands the ability to look forward. By combining historical catch data, environmental variables, satellite signals, and effort patterns, predictive models can support stock forecasting, dynamic ocean management, climate risk assessment, and more flexible management strategies. In an era of shifting baselines and climate disruption, this predictive capability is one of AI's greatest governance contributions. It allows institutions to prepare for change rather than merely documenting it after the fact.
The fourth pathway runs from fragmented systems to integrated governance.	Fisheries management depends on multiple information domains: surveillance, science, ports, markets, traceability, and enforcement. AI can help connect these domains by linking and analysing data that would otherwise remain isolated. A vessel track can be examined alongside landing declarations; species recognition outputs can be compared with catch certificates; satellite detections can be matched with gaps in AIS. This is where AI's strategic value becomes most visible. It is not simply reducing manual workload. It is helping build an integrated governance system.

The strategic implication is clear. AI helps governments manage fisheries better when it is deployed in service of clearly defined governance problems: seeing the unseen, verifying the uncertain, predicting the emerging, and connecting the fragmented. That is why the future of fisheries AI lies not in scattered pilot technologies, but in pathways that connect technical systems to administrative processes, legal standards, and public-interest outcomes. AI matters when it strengthens governance, not when it operates in isolation from it.

Table 5. AI-to-Governance Pathway: Mapping Applications to Decisions & Institutional Gaps

AI Application	Data Produced	Decision Enabled	Institutional Step Required	Current BOB Gap
SAR dark vessel detection	Vessels in specific waters at specific times	Enforcement action against IUU vessels	Legal admissibility of satellite AI evidence; enforcement vessel dispatch	AI evidence not legally established; enforcement assets limited
EM catch recording	Verifiable species and volume data per trip	Catch limit compliance; bycatch management	EM data accepted as official catch record; data	EM data not in national reporting systems for BOB nations

AI Application	Data Produced	Decision Enabled	Institutional Step Required	Current BOB Gap
			flows to national database	
Predictive stock assessment	Stock status index with uncertainty bounds	Provisional catch limit; precautionary closure	Assessment outputs formally integrated into quota-setting process	BOBSAN outputs not formally integrated into any BOB member state quota process
PFZ advisory (INCOIS-type)	Predicted fish aggregation locations	Fisher decision on where to deploy effort	Last-mile delivery to fisher; fisher trust in system	India operational; Bangladesh, Sri Lanka, Maldives not yet receiving advisories
Supply chain traceability	Chain-of-custody documentation	Export market access; IUU exclusion	Importers require documentation; catch certificates legally recognised	Ongoing need to strengthen traceability and compliance systems to reduce market access risk

CHAPTER 04

4. Enabling Factors: Governance, Equity, and Capacity

4.1. Defining AI and Scope for This Framework

For the purpose of this framework, Artificial Intelligence is used as an umbrella term for computational methods that help institutions and communities convert large, diverse, and often fragmented data into decision-support intelligence. It includes techniques that can recognise patterns, classify objects or events, predict trends, detect anomalies, optimise operational choices, interpret language, and support evidence-based decisions. This functional, technology-neutral definition is intended to remain robust beyond the 2026–2030 horizon.

As of 2026, the operationally relevant AI families for fisheries governance include: (i) machine learning and predictive analytics for stock assessment support, fishing-ground advisories, risk forecasting, and climate/environmental interpretation; (ii) computer vision and image analysis for vessel detection, electronic monitoring, species or group identification, size estimation, and biodiversity monitoring; (iii) anomaly detection and risk scoring to flag AIS gaps, suspicious vessel movement, catch-reporting inconsistencies, traceability breaks, and potential IUU fishing risks; (iv) natural language processing and multilingual AI assistants to support scheme access, document preparation, fisher advisories, and communication in local languages; (v) optimisation and decision-support systems for patrol prioritisation, inspection planning, cold-chain management, post-harvest loss reduction, market intelligence, and cooperative-level business decisions; and (vi) AI-enabled traceability and verification systems that combine vessel identity, digital catch records, landing data, supply-chain documents, and anomaly detection to strengthen legality assurance. This list is treated as a 2026 operational snapshot rather than a fixed classification. The AI Coordination Unit will periodically review and update the recognised AI families as technologies, use cases, and governance needs evolve.

For governance purposes, the framework adopts a consequence-based scoping approach rather than a purely method-based one. AI applications are grouped into three tiers:

- **Advisory**: Supports information access, fisher advisories, planning, and awareness (e.g., fishing-ground alerts, language assistants).
- **Management-support**: Informs fisheries management, monitoring priorities, risk assessment, and programme implementation under human review (e.g., patrol prioritisation, inspection scheduling).
- **Enforcement-adjacent**: Where AI outputs support compliance monitoring, inspection targeting, traceability verification, or IUU fishing risk identification, potentially as evidence or triggers for sanctions.

Safeguards, validation, human oversight, and evidentiary standards scale proportionately: lighter for advisory, stricter for enforcement-adjacent. This framework also recognises enabling digital infrastructure such as satellite data, AIS/VMS/GPS data, electronic-monitoring cameras, mobile applications, sensors, databases, dashboards, cloud platforms, digital ledgers, and interoperable data standards. These are not all AI by themselves, but they generate the data environment in which AI tools can function.

4.2. Technology Domains and BOBLME-Specific Applications

In 2013, Indonesia equipped its fishing fleet with Vessel Monitoring Systems satellite tracking devices that broadcast a vessel's location in real time. On paper, this was a significant enforcement leap. In practice, the data piled up on servers inside the Ministry of Marine Affairs and Fisheries with almost no operational effect. Enforcement vessels were not dispatched. Prosecutions did not follow. Illegal fishing continued at roughly the same rate. The problem was not the technology. *The problem was that the institution receiving the data had no legal mandate, no trained staff, and no operational procedure to act on what the technology was telling it*.

This story is not unique to Indonesia. It has played out across dozens of fisheries programmes in the developing world over the past three decades different countries, different technologies, the same outcome. Hardware installed. Data generated. Governance unchanged.

It is the most important cautionary lesson for AI adoption in fisheries today. AI tools are now genuinely powerful. Satellite systems can detect vessels that have switched off their transponders. Camera systems on boats can automatically count and identify every fish brought on deck. Algorithms can flag suspicious catch certificates before fraudulent seafood enters a supply chain. None of this produces better fisheries governance on its own. It produces better data which is only useful if the laws, institutions, and people responsible for managing fisheries are equipped and empowered to act on it. That gap between data and action is where most technology-led fisheries reform has broken down. And it is where the strategic challenges addressed in this chapter are located.

4.3. When Detection Does Not Lead to Action: The Evidentiary and Procedural Gap

Consider a common enforcement scenario. A satellite monitoring system identifies a vessel apparently operating inside a protected area. The sensor record shows an object at a particular location and time. Additional data may link that object to a specific vessel, and an analyst may classify the activity as suspicious or potentially non-compliant. A case file is then prepared for enforcement review.

At that point, enforcement often slows down not necessarily because officials are indifferent, but because detection does not automatically translate into legally actionable proof. The core difficulty is not that satellite or AI-assisted data are inherently unusable in law. In many jurisdictions, digital imagery, electronic records, and expert interpretation may be admitted under general evidentiary rules. The real difficulty is whether the available material is sufficiently authenticated, reliable, and relevant to prove the specific fisheries offence alleged.

This distinction is important. A satellite image is not “AI-generated evidence”; it is sensor-generated data. AI may assist by detecting patterns, classifying vessel behaviour, enhancing imagery, or assigning risk scores. Legally, these elements may carry different evidentiary weight. The raw image, the processed output, the analyst’s interpretation, and the algorithmic flag are not the same thing. What a court or administrative authority will ask is more concrete: Can the vessel be reliably identified? Can the location and time be verified? Is there an unbroken record of how the data were obtained, stored, and analysed? Does the evidence show fishing activity, or only presence? Does it prove breach of a legally defined prohibition?

For that reason, the gap in many countries is better described as an evidentiary and procedural gap rather than a total legal vacuum. Fisheries legislation may prohibit unauthorized fishing, entry into closed areas, or misreporting, yet remain silent on how remote-sensing outputs, electronic monitoring records, or algorithm-assisted detections should be operationalised in inspection, prosecution, or administrative sanctioning. Even where general law allows electronic evidence, cases may still falter because sector-specific protocols are weak: chain-of-custody procedures are unclear, certification standards for monitoring systems are absent, analyst roles are undefined, and enforcement officers and prosecutors are not trained to convert technical detections into legally robust case files.

The same issue arises with electronic monitoring on fishing vessels. Camera systems and automated video review may greatly improve detection, coverage, and record quality. But better data do not by themselves resolve questions of legal use. Authorities still need rules or protocols on equipment integrity, tamper safeguards, metadata retention, access control, review procedures, evidentiary extraction, and the respective roles of automated screening and human verification. Without such safeguards, the defence need not prove that the system is useless; but it needs to raise reasonable doubt about integrity, attribution, or interpretation.

The policy implication is straightforward. The key legal task is not simply to “recognise AI-generated data” as a new category of evidence. What is needed is a more specific framework that clarifies how remote-sensing data, electronic monitoring records, and AI-assisted analytical outputs are to be authenticated, verified, stored, disclosed, interpreted, and used in administrative or judicial proceedings. This includes standards for system certification, metadata preservation, audit trails, human review, expert testimony, and disclosure of method where required. It also requires training for fisheries officers, prosecutors, and adjudicators so that technical detections can be translated into enforceable legal claims.

AI-generated outputs should not be treated as definitive evidence by themselves. They are model-based inferences produced from available data, and they carry uncertainty, error margins, assumptions, and possible bias. This is especially important where AI outputs are used in compliance, inspection, patrol prioritisation, or enforcement contexts. A vessel-risk score, dark-vessel alert, anomaly flag, species-identification result, or traceability warning should therefore be treated as decision-support information that requires human interpretation, validation, and corroboration with other evidence before formal action is taken. Clear procedures will be needed to define how AI-generated information is reviewed, validated, challenged, documented, and acted upon by responsible authorities.

This work is institutionally mundane but legally decisive. Without it, investments in AI-supported surveillance may still improve intelligence and targeting, but their conversion into sanctions, prosecutions, or compliance outcomes will remain uncertain. The central issue, therefore, is not whether technology can detect suspicious conduct. It is whether the legal and procedural system is prepared to convert that detection into defensible state action.

4.4. The Data Sharing Problem: Why Countries Hold Back

In 2020, a study published in the journal, Science Advances found that when researchers cross-referenced satellite radar imagery with publicly available vessel tracking data near the Galápagos Marine Reserve one of the world's most closely watched protected areas 72 percent of the vessels detected by radar were not transmitting any tracking signal at all. They were invisible to every national monitoring system in the region, because each country's system only tracked vessels it had licensed. No one was looking at the full picture.

The technical solution is straightforward: connect the national systems, share the data, and the dark vessels become visible. The political reality is harder.

> *Vessel tracking data tells you not just where illegal operators are fishing   it tells you where legal operators are fishing too. It reveals which fishing grounds a country's fleet depends on, where its vessels concentrate their effort, and how far they range. This is commercially and strategically sensitive information that governments are understandably reluctant to hand to neighbouring countries with competing fishing interests or unresolved maritime boundary disputes.*

This dynamic is relevant in sensitive cross-boundary fishing contexts, including the Palk Bay, where trust, data-sharing, and operational coordination remain essential. The lack of agreed rules for sharing data has also made it harder for countries to work together among Bay of Bengal member states, where shared fish stocks and unresolved maritime boundaries make data sharing politically sensitive.

It has limited the effectiveness of every regional fisheries body that has attempted to build shared surveillance infrastructure without first investing in the political architecture of trust that shared data requires.

There is no algorithmic solution to this. Regional AI governance will only work if the political groundwork   the bilateral agreements, the reciprocal commitments, the transparent governance structures   are built alongside the technical systems.

Countries will share data when they trust that it will be used for the agreed purpose, that it will not be shared further without their consent, and that they will receive something of genuine value in return. Building that trust is slower and less visible than building a data platform. It is also more important.

4.5. Who Benefits and Who Gets Left Behind

In 2019, Peru introduced one of the world's most sophisticated AI-powered vessel monitoring programmes for its anchovy fishery   one of the largest single-species fisheries on earth. The system tracked the industrial purse seine fleet in near real time, generating high-quality catch and effort data that dramatically improved stock assessment accuracy. It was, by any technical measure, a success.

What it did not do was monitor the thousands of small-scale artisanal boats working in the same coastal waters. Those vessels were too small for the system to cover cost-effectively. Their landings continued to go largely unrecorded. Their fishing effort remained invisible in the national database. And management decisions including catch limits and closed season dates continued to be set based on data that represented the industrial fleet, not the full fishery.

This is the equity problem that AI-enabled governance must confront directly. Globally, small-scale and artisanal fishers account for most people whose livelihoods depend on fisheries and a significant share of total coastal catch.

> *Small-scale fishers are most systematically excluded from the data systems on which fisheries management depends not by deliberate intent, but by practical logic of technology deployment, which follows the path of least resistance toward larger, better-connected, more commercially visible operators first.*

The consequences of this exclusion are not merely unfair. This is bad fisheries management. When the science underlying a closed season or a catch limit is built on data only from the industrial fleet, it does not reflect the full pressure being placed on the stock.

> *When traceability systems are designed for export-certified supply chains, they certify a fraction of total catch while leaving the majority undocumented. When AI advisory services are delivered by smartphone app, they reach fishers with smartphones and connectivity which in most low-income fishing communities is not available to many fishers*.

Fixing this requires deliberate design choices made before systems are built, not after.

- **Monitoring approaches need to include low-cost options** solar-powered (or powered by any alternate energy) trackers, community-based catch reporting tools, simple mobile applications that work on basic phones in low-connectivity environments that bring small-scale fishers into the data system rather than designing around them.
- **Advisory services need to be tested for last-mile delivery**: SMS in local languages, voice alerts, community radio, fisher cooperative networks.
- **Traceability frameworks need tiered compliance requirements** that do not impose the same certification burden on a canoe landing twenty kilograms of fish as on an industrial trawler landing twenty tonnes.

These are not small design details. They determine whether AI-enabled governance is a system that works for fisheries as a whole, or a system that works for the most powerful part of it.

4.6. Building Institutions, Not Just Installing Systems

In 2015, the European Union issued Thailand a Yellow Card under its IUU Fishing Regulation a formal warning that Thailand's fisheries governance was insufficiently robust to guarantee that its seafood exports were legally caught. What followed was one of the most consequential fisheries governance reform processes of the last decade. Thailand rewrote its fisheries law, restructured its monitoring systems, overhauled its port inspection procedures, and invested heavily in new technology. It took four years, cost an estimated USD 500 million in compliance investment and market disruption, and was completed only because the EU market access consequences made inaction economically untenable.

The Thailand Lesson:

The lesson is not that there should be external pressure for something to work, though in this case it did. The lesson is that technology - the vessel monitoring systems, the electronic logbooks, the port inspection software that Thailand deployed was the easy part. The hard part was building the institutional infrastructure to operate it: the trained inspectors, the legal frameworks, the inter-agency coordination between fisheries, customs, and coast guard, the administrative procedures connecting port inspection data to licensing decisions. None of that existed at the scale required before the reform process began. All of it had to be built from scratch, under severe time pressure, at enormous cost. This is the institutional capacity challenge facing fisheries governance globally.

> *AI tools do not govern fisheries. Institutions govern fisheries, using AI as an instrument. And in a large proportion of the world's fishing nations, the institutions are not yet equipped to use that instrument effectively, not because the will is absent, but because the ecosystem of skills, legal mandates, inter-agency relationships, and administrative procedures that effective AI deployment requires has not been built.*

Addressing this honestly means accepting that capacity development is not a workshop series or a study tour programme. It is a long-term investment in the governance infrastructure within which AI must operate, and it must be funded, sequenced, and evaluated.

Development partners and international institutions have a specific responsibility here: to support institutional development over the multi-year cycles it requires, rather than the short project periods that donor reporting structures tend to favour.

The countries that most need AI-enabled fisheries governance are, almost without exception, the countries least equipped to deploy it without sustained external partnership.

Recognising this not as a problem to be solved once but as a condition to be managed over time is the starting point for a capacity strategy that will work.

CHAPTER 05

5. Regional Cooperation in AI-Enabled Fisheries Governance: From Mandate to Action

The analysis in the preceding chapters has established that the main barriers to effective AI use in fisheries governance are not technological, primarily. They lie in evidentiary procedures, institutional readiness, politically sensitive data-sharing, the systematic exclusion of small-scale fisheries from monitoring architectures, and the absence of long-term capacity development systems. In this context, the most appropriate role for BOBP-IGO is not that of a regional technology operator. It is that of a regional convenor, standards facilitator, pilot coordinator, and implementation support partner. This section sets out how that role translates into action.

5.1. The Cooperation Imperative

No single BOBP-IGO member state can achieve AI-enabled fisheries governance of transboundary stocks alone. Fish populations that cross EEZ boundaries cannot be assessed, managed, or protected through unilateral national action   the management decisions of each state affect the stocks available to all others. IUU fishing vessels that move between national jurisdictions can evade enforcement systems that do not share intelligence across borders. Supply chains that pass through multiple national economies before reaching export markets cannot be made transparent through national traceability systems that are not interoperable.

Regional cooperation is therefore not an optional enhancement of national AI governance capacity. It is the precondition for that capacity producing outcomes proportionate to the scale of the challenge. Three conditions have converged to make this the right moment to act.

The first is the mandate. The 2025 adoption of the Bay of Bengal Regional Plan of Action on IUU Fishing gives the region a formal commitment it did not previously hold. That commitment has no delivery system. Every previous AI fisheries initiative in the region has encountered the same structural failure: technology was deployed before the governance layer was in place. Satellite monitoring systems produced intelligence that enforcement laws could not admit as evidence. Data-sharing platforms were built before the political agreements to fill them existed. Vessel monitoring systems were certified before inspectors were trained to interpret their outputs. The lesson is not that technology fails. It is that technology and governance cannot be solved sequentially. They must be built together, from the start, with accountability for both.

The second is the technology. The tools required are no longer expensive or experimental. A low-cost GPS tracker costs less than USD 100. Voice-based catch reporting works on a basic phone without internet. Satellite anomaly detection is available as a service. Small-scale fisheries governance no longer requires patrol vessels, dedicated enumerators, or new bureaucracies to generate decision-grade information.

The third is the institution. BOBP-IGO holds the regional legitimacy, the secretariat function, and with the RPOA-IUU the explicit mandate to anchor a governed regional AI architecture. No other institution in the region holds all three simultaneously. The window to establish this institutional role is open now.

5.2. The Institutional Layer

The core institutional requirement is a dedicated coordinating mechanism within BOBP-IGO with a clear mandate covering the AI and digital governance dimensions of the organisation's fisheries work. This document proposes the establishment of a Bay of Bengal Fisheries Information Coordination Hub (BOB-FICH) — a light-touch secretariat function, not a standalone agency — designed to provide the regional layer of coordination, standard-setting, and accountability that no individual member state can provide for itself. The rationale is straightforward: the technologies described in Chapter 5 generate data that crosses national boundaries, requires common standards to be interoperable, and demands legal and institutional arrangements that must be developed collectively. Without a designated coordinating unit, these requirements will be addressed ad hoc, inconsistently, or not at all — as the experience of previous regional technology initiatives in fisheries has repeatedly demonstrated.

The BOB-FICH would carry four standing functions. It sets and maintains technical standards for AI tools deployed under the regional architecture, ensuring that national systems meet the interoperability, open standards, and data quality requirements on which regional intelligence products depend. It coordinates data-sharing arrangements between national fisheries information systems, including the bilateral and eventually multilateral agreements through which shared surveillance intelligence is generated. It develops and delivers training and certification programmes that build the national institutional capacity among fisheries officers, analysts, inspectors, and prosecutors without which merely having better data cannot produce better decisions. And it conducts the Annual Regional AI Fisheries Review, presented to the BOBP-IGO Governing Council and submitted to FAO COFI as part of CCRF implementation reporting, creating the accountability mechanism that ensures AI investments are assessed against management outcomes rather than deployment metrics alone.

BOB-FICH is not envisaged as a parallel structure to BOBP-IGO's existing institutional work. It is the AI and digital governance dimension of that work operationally connected to FAO's FIRMS fisheries monitoring system, operationally connected to FAO's FIRMS fisheries monitoring system via the unique fish stock identifiers (UUIDs) established under the regional registry) IOTC for tuna species management, and to the BOBLME project's broader governance architecture. Its working relationships with UNODC on enforcement procedure and prosecution support, and with national law universities under BOBP-IGO's existing MoUs on legal research and comparative evidentiary review, are standing partnerships rather than project-specific arrangements.

BOBP-IGO may mobilise financial resources for BOB-FICH from national and multilateral funds including the Green Climate Fund and Blue Economy framework financing, in close cooperation with member states. Specific activities may be supplemented by the BOBLME-II project budget. The unit should be sized as a light-touch secretariat function sufficient to anchor coordination, set standards, and manage the review cycle rather than as an operational technology agency. Member states retain operational control of their national systems; BOB-FICH provides the regional layer that makes those systems interoperable and accountable.

5.3. The Legal Layer

Three legal instruments are needed to provide the foundation for regional AI fisheries governance. BOB-FICH would be responsible for the development, maintenance, and periodic review of all three, working through the partnerships identified above.

The first is a BOB Data Governance Framework a voluntary inter-governmental agreement establishing common standards for the collection, storage, access, sharing, and use of fisheries data generated by AI systems in member state waters. This framework must address data sovereignty concerns explicitly: specifying that vessel monitoring data from a member state's EEZ remains under that state's sovereign control; that data sharing for regional management purposes does not constitute a waiver of sovereignty; and that data shared for fisheries management purposes may not be used for other purposes without the explicit consent of the sharing state. BOB-FICH would serve as the custodian of the framework and the first point of contact for member states seeking guidance on its application.

The BOB Data Governance Framework should be designed not only to protect sovereignty, but also to ensure that regional AI outputs are transparent, verifiable, and usable for governance. Routine regional sharing may rely primarily on derived intelligence products rather than the transfer of raw national datasets. However, the framework should define tiered access conditions under which aggregated data, metadata, sample records, audit logs, and, where necessary, controlled access to selected raw or detailed data may be made available for validation, dispute resolution, and enforcement review under agreed safeguards.

To prevent black-box processing, every regional intelligence product generated under this framework should carry a data lineage statement describing the source types, time and area coverage, processing steps, model or algorithm used, version, assumptions, limitations, confidence level, and known bias risks. BOB-FICH should maintain audit trails, method documentation, model cards or data cards, uncertainty statements, and review logs so that member states can understand how an output was produced and challenge it where necessary.

Where raw or sensitive data cannot be transferred, the framework should provide for safe-room review, joint technical review, or trusted third-party mechanisms. These arrangements would allow authorised experts to inspect sufficient underlying detail for validation without compromising national sovereignty, confidentiality, or enforcement sensitivity. AI-derived intelligence should be used for decision support only when data provenance, quality controls, uncertainty, and validation status are visible to the responsible human authority.

The second is model legislative provisions for the admissibility of AI-generated evidence in fisheries enforcement proceedings provisions that each member state can adapt to its national legal context, but that establish a common baseline for the evidentiary standards that AI surveillance outputs must meet. As established in Section 6.2, the evidentiary challenge is not whether digital or AI-assisted data can in principle be admitted, but whether clear procedures exist for authentication, chain of custody, metadata retention, analyst roles, human verification, and case-file preparation. These provisions should address the chain of custody for satellite imagery and AIS data, the qualifications required of expert witnesses who interpret AI outputs, and the standards for algorithmic transparency that AI evidence must satisfy. BOB-FICH would develop these provisions in partnership with UNODC and with national law universities under BOBP-IGO's existing MoUs, drawing on their comparative review of evidentiary treatment across the four-member state jurisdictions.

AI-generated information should be legally framed as decision-support or evidentiary lead material, not as automatic proof of violation, unless supported by clear provenance, validation, uncertainty documentation, and corroborating evidence.

The third is a Regional Fisheries Data Standard: a technical specification for catch reporting formats, vessel identification codes, species classification systems, unique fish stock identifiers and data exchange protocols that national fisheries information systems must adopt to achieve interoperability with the regional platform. The inclusion of UUIDs means that even if member states continue to report catches under different national stock names or spatial definitions, the identifier provides a persistent, common reference – a necessary step toward formal recognition and eventual joint assessment of shared resources. BOB-FICH would set and maintain this standard, and its application would be a condition of participation in the regional architecture. Without it, the technical components described in Section 6.4 cannot function as a regional system.

Responsible AI considerations are acknowledged in this roadmap, although detailed protocols will need to be developed during the implementation phase by member states and BOB-FICH. Where GPS trackers, electronic monitoring systems, or mobile applications involve fishers and vessels, future pilots should include safeguards for individual data privacy, informed consent, data minimisation, purpose limitation, and digital rights, developed in consultation with fishers and relevant civil society actors. AI-based risk scoring or anomaly detection used for enforcement should be auditable, with model documentation and fairness checks to ensure that particular vessel types, gear groups, or communities are not unfairly profiled. The environmental footprint of AI, including energy used for large-scale satellite imagery processing, should also be monitored and reduced through efficient models and shared or green computing infrastructure. Finally, AI systems should be protected against adversarial risks such as GPS/AIS spoofing, model evasion, cyber intrusion, and data leakage through security assessments, redundancy, and audit trails.

5.4. The Technical Layer

The technical architecture for regional AI fisheries governance must be built around three principles that BOB-FICH sets and enforces: interoperability, open standards, and national capacity for independent operation. Interoperability means that data generated by national fisheries information systems can be accessed and analysed by the regional platform without manual extraction and reformatting. Open standards mean that AI tools used in regional governance are built on technologies that member states' technical staff can understand, audit, and modify not proprietary black-box systems that create permanent dependency on external vendors. National capacity for independent operation means that training and staffing investments are designed to enable member states to operate and maintain these tools without ongoing external technical assistance an outcome that BOB-FICH's certification programmes are specifically designed to achieve.

Five specific technical components are required. A regional vessel monitoring data fusion platform integrating SAR, AIS, and VMS data streams across all four member-state waters provides the surveillance backbone. A shared species identification library for onboard EM systems training data shared across member states to improve algorithm performance in the specific ecological context of Bay of Bengal fisheries addresses the regional dataset deficit identified in Section 4. A common catch reporting interface for artisanal fisheries, mobile and voice-enabled, multilingual, and offline-capable, brings small-scale fishers into the data system on terms they can actually use. A regional stock assessment data platform the infrastructure for a Bay of Bengal Stock Assessment Network (BOBSAN) to consolidate, harmonise, and jointly analyse stock assessment data from all four member states provides the scientific foundation for transboundary stock management, beginning with Hilsa shad and Indian mackerel. A Regional Fish Stock and Fishery Resource Registry, aligned with FAO-FIRMS/GRSF UUIDs and semantic identifiers, would provide the reference layer through which nationally reported resources are mapped, counted, compared, and progressively prepared for joint assessment and management. BOB-FICH would coordinate the development and governance of each component, while member states retain operational control of their national system nodes.

5.5. The Operational Layer

Technical architecture and legal frameworks only produce governance outcomes if they are operationalised through functioning procedures, trained personnel, and accountable institutions. Three operational elements are essential.

Joint MCS operations coordinated patrol and enforcement activities enabled by shared AI surveillance intelligence require agreed protocols for information sharing in real time, clear rules for which nation's authorities take the lead when a vessel is detected in or near a contested or boundary area, and pre-agreed procedures for evidence preservation and legal handoff when an enforcement action crosses jurisdictional boundaries. These protocols do not require full data pooling to function. As Section 6.3 establishes, the political architecture of trust must be built alongside the technical system and the operational protocols are where that trust is most rigorously tested. BOB-FICH would develop model joint MCS protocols in partnership with UNODC, drawing on the bilateral data-sharing arrangements established under 6.3.

A regional training and certification programme building standardised competencies in AI fisheries tools across all four member states ensures that technical capacity is distributed rather than concentrated. Delivered by BOB-FICH, this programme must be cross-agency in design, involving fisheries departments, MCS units, legal officers, prosecutors, and where relevant coast guard, customs, and port authorities. It must focus on real governance workflows detection-to-case-file preparation, inspection-to-sanction procedures, electronic monitoring review and evidentiary extraction, risk-flagging to administrative follow-up rather than generic technology exposure. UNODC is the appropriate partner for enforcement workflow and prosecution-oriented modules. FAO is the more suitable partner for fisheries management, EM systems, and small-scale fisheries integration.

The Annual Regional AI Fisheries Review, conducted by BOB-FICH and presented to the BOBP-IGO Governing Council, creates the accountability mechanism that prevents AI governance from becoming a compliance exercise. The Review should assess, for each AI tool in operational use, what data it produced, what management decision it informed, what the outcome of that decision was, and where the system failed to produce expected outputs. Failure analysis is as important as documenting successes. The Review is most valuable as a learning instrument, not a performance report. Its submission to FAO COFI as part of CCRF implementation reporting connects regional accountability to the global fisheries governance architecture within which BOBP-IGO operates.

5.6. The First Step: A Structured Learning Programme

The institutional, legal, technical, and operational architecture described above cannot be built simultaneously or at once. A regional readiness and sequencing framework, developed by BOB-FICH, should help member states assess legal and procedural readiness, institutional roles and mandates, data governance arrangements, inter-agency coordination capacity, small-scale fisheries inclusion, staffing requirements, and the sustainability of operating costs before major system investments are made. This framework is not a compliance instrument. It is a planning and prioritisation tool one that distinguishes between member states or sub-sectors ready for pilot deployment and those that first require preparatory legal, administrative, or institutional work.

The most appropriate first operational step within this framework is a structured twelve-month learning programme, piloted in selected sites across two member states, designed to generate practical evidence before any wider commitment is made. BOB-FICH would establish the baseline, receive the six-month review data, and present a scale recommendation to TAC grounded in evidence rather than projection.

The distinction between a learning programme and a conventional pilot is not semantic. In a conventional pilot, there are two outcomes: success or failure. Failure is visible and creates political exposure in a multilateral context. In a learning programme, both outcomes are wins: the programme either confirms what works, or it identifies precisely what needs fixing before scaling. The commitment made in advance that both outcomes will be reported publicly to TAC and that the scale decision will be evidence-driven is what makes it a learning programme. That pre-committed accountability is the structural difference.

The programme is structured around three pillars. Each tests a distinct hypothesis, addresses a different gap, and speaks to a different part of the TAC. Crucially, each produces value **r**egardless of whether the hypothesis is confirmed or refuted**.** There is no failure mode only evidence.

Table 6: The Three Pillars of the Programme

Pillar	Problem it addresses	What is tested	Why both outcomes are wins
Do More: **Expand what the ministry can see** *<u>Audience:</u> Scientists*	80% of fishing activity is invisible to governance. Small-scale fleets, night fishing, and informal landings are not captured.	Can fisher cooperatives, equipped with low-cost GPS trackers and a voice-based reporting tool, generate reliable fleet data without government infrastructure?	Even 40% adoption generates more small-scale data than currently exists. Any result is a finding. The question is what adoption level is achievable, not whether the tool works.
Do Better: **Improve the quality of decisions being made** *<u>Audience:</u> Officials*	Ministries make policy decisions closed seasons, catch limits, sanctuary boundaries on data that is years old and industrially biased.	Can one new performance measure active vessel coverage percentage improve monitoring outcomes in a pilot district within twelve months, with no new budget?	If coverage improves, the measure works scale it. If it does not, the specific blockage is identified fix it before scaling. Both outcomes are actionable.

Pillar	Problem it addresses	What is tested	Why both outcomes are wins
Grow Smarter: **Build regional cooperation that compounds** *Audience: Diplomats*	Regional cooperation on data has stalled because sharing feels like a sovereignty risk. Every member state knows shared intelligence would improve outcomes, but no one wants to go first.	Can a bilateral data-sharing arrangement between two willing member states limited in scope, sovereignty-protected, reviewed jointly at six months produce intelligence neither country could generate alone?	If the exchange works, regional momentum builds organically. If it surfaces sovereignty concerns, they are resolved at small scale before becoming regional flashpoints. Diplomats get credit either way.

5.7. Expected Outputs

1. Preparation of a diagnostic audit report assessing the need, scope, and priority entry points for the application of AI in fisheries governance in the Bay of Bengal region.
2. Preparation of a curated compendium of AI applications and use cases relevant to fisheries governance, including technology maturity, data requirements, governance function, and implementation risks.
3. Development/adaptation and pilot implementation of selected need-based AI applications in identified fisheries governance contexts in member countries.
4. Preparation of a strategic roadmap and recommendations for the phased integration of AI into fisheries governance at regional and national levels.

Indicative medium-term technical outputs

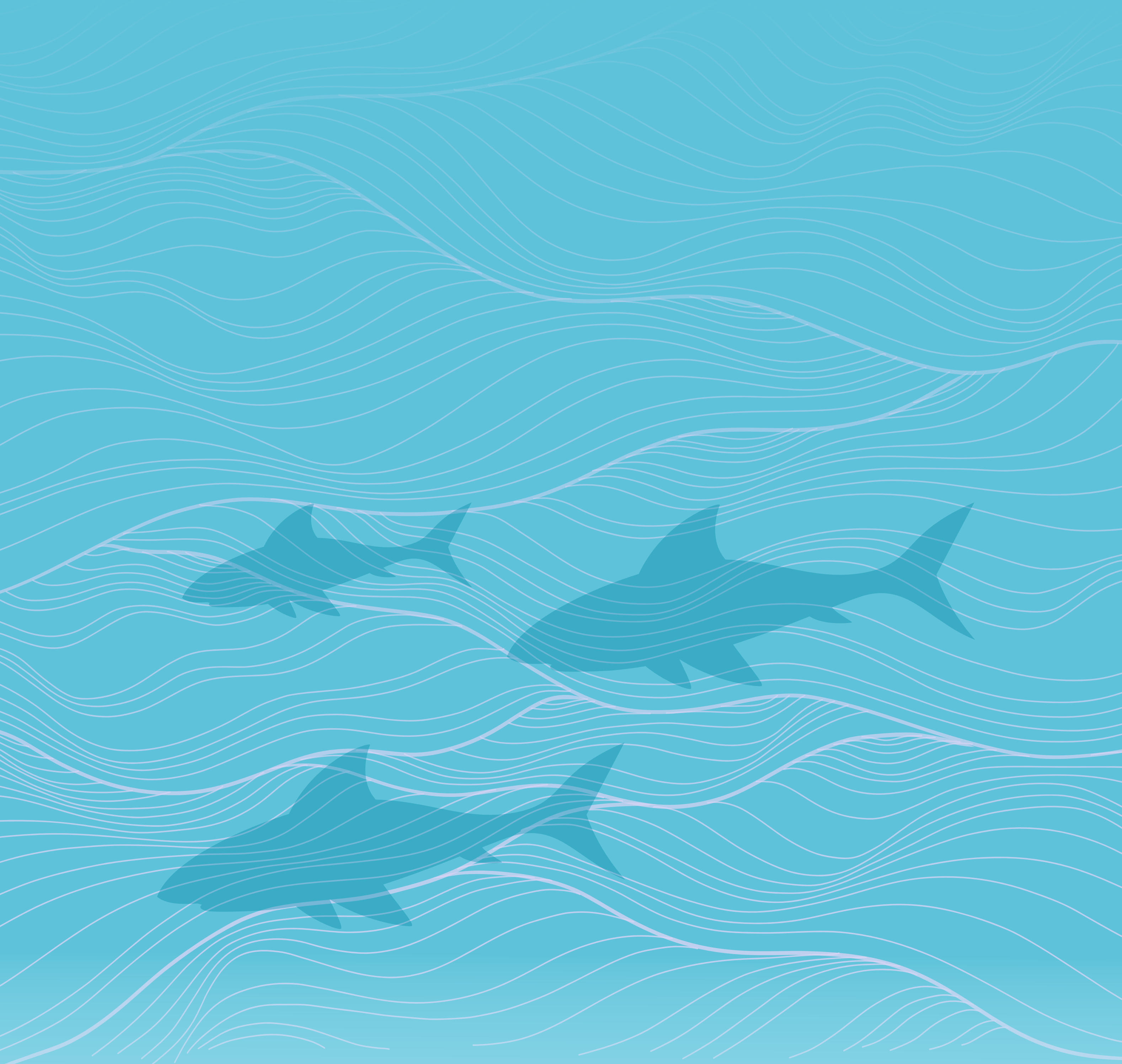
1. A regional vessel monitoring data fusion platform, integrating SAR, AIS, and VMS data streams across all four-member state waters;
2. A shared species identification library for onboard EM systems, training data that can be shared across member states to improve algorithm performance in the specific ecological context of BOB fisheries;
3. A common catch reporting interface for artisanal fisheries, mobile and voice-enabled, multilingual, offline-capable; and
4. A regional stock assessment data platform, the infrastructure for Bay of Bengal Stock Assessment Network (BOBSAN) to consolidate, harmonise, and jointly analyse stock assessment data from all four member states.

5.8. Expected Outcome

1. Stronger monitoring, verification, and forecasting capacity in Bay of Bengal fisheries governance;
2. Improved regional interoperability in data, surveillance, and stock assessment systems;
3. A more evidence-driven and anticipatory governance approach under BOBP-IGO.

5.9. Implementation Structure

Phase	Timeline	Key activities
Phase 1 Establish	Jul-Dec 2026	Confirm two bilateral partner states and pilot sites. Establish the regional coordinating unit within BOBP-IGO. Finalise data-sharing agreement with sovereignty protections. Deploy GPS trackers and catch reporting tools through cooperative networks. Insert vessel coverage measure into field officer performance frameworks. Set baseline data.
Phase 2 Learn	Jan-Dec 2027	Analyse adoption rates by cooperative type, district, and fisher profile. Run first bilateral transboundary stock intelligence products. Document legal gaps on AI evidence admissibility. Commission country-level implementation plans for all four member states.
Phase 3 Scale	Jan 2028-Dec 2030	Extend cooperative data model to additional districts. Bring additional member states into bilateral data-sharing on the sovereignty-protected template, while developing a limited open-data practice based on aggregated, anonymised, and non-sensitive regional outputs. This may include selected shared-stock indicators, species-level summaries, reporting coverage metrics, joint assessment outputs, and periodic public-facing regional fisheries intelligence products approved by participating member states. Initiate legal reform on AI evidence admissibility. Position learning programme findings for Green Climate Fund Phase 2 application.



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