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## Digital Tech Interventions in Marine Ecosystem Monitoring: An Integrative Review

**Author: Amina Hassan**

Affiliation: Swiss International University (SIU)

ORCID ID: 0009-0005-7237-7565

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### Abstract

Marine ecosystems are changing faster than the observation systems designed to track them. This article presents an integrative review of digital technology interventions in marine ecosystem monitoring, synthesising peer-reviewed research on sensing platforms, molecular and acoustic methods, machine learning, and ocean data infrastructures published mainly between 2014 and 2026. The review addresses three questions: which classes of digital technology now support marine ecosystem monitoring and what ecological information each supplies; which recurring technical and institutional constraints limit their contribution to sustained, decision-relevant observation; and how these classes can be combined conceptually into an architecture linking sensing to management decisions. The synthesis shows that satellite remote sensing, autonomous platforms, environmental DNA, and passive acoustics have matured within largely separate research streams, each with distinctive observational strengths and each constrained by calibration demands, energy and sensor limits, interpretive

uncertainty, or fragmented data practices. Machine learning relieves an analysis bottleneck created by high-volume sensing but introduces its own validation requirements. Building on these findings, the article proposes a four-layer sensing-to-decision architecture that connects observation, analytics, data integration, and governance through explicit feedback loops, using essential ocean variables as the prioritisation logic that binds the layers together. The framework offers monitoring programme designers and ocean governance bodies a structured basis for investment and evaluation decisions, and it identifies cost-effectiveness evidence, cross-domain interoperability, and institutional data governance as priorities for future research.

**Keywords:** marine ecosystem monitoring, ocean observing systems, environmental DNA, passive acoustic monitoring, machine learning, digital twin, autonomous platforms

## **1. Introduction**

Societies depend on the ocean for food, climate regulation, and economic activity, and this dependence is intensifying at the same time as marine ecosystems come under growing anthropogenic pressure (Ryabinin et al., 2019). Warming, acidification, and deoxygenation are altering ocean biogeochemistry at scales that conventional observation struggles to detect (Chai et al., 2020). Decisions about fisheries, protected areas, pollution control, and climate adaptation therefore rest on the quality, coverage, and timeliness of ecological information about the sea. The United Nations Decade of Ocean Science for Sustainable Development (2021–2030) makes this link explicit by calling for a more complete and sustainable observing system whose outputs feed science-based decision making (Ryabinin et al., 2019).

The established toolkit for marine ecological observation was not designed for this task. Classical monitoring based on research vessels, towed nets, grabs, and diver surveys offers low spatial and temporal resolution and is labour-intensive for every unit of area and time surveyed (Danovaro et al., 2016). A review of monitoring practice in the United

Kingdom found that many techniques in routine use had changed little since the early 1900s (Bean et al., 2017). Ship-based programmes remain indispensable for calibration and for long-term comparability, but they cannot alone deliver the sustained, high-resolution, multi-variable coverage that ecosystem-based management requires.

Over the past decade a set of digital technologies has matured to the point where it plausibly changes what monitoring programmes can observe. Satellite ocean colour instruments track phytoplankton dynamics at seasonal and interannual scales (Groom et al., 2019). Autonomous floats, gliders, and underwater vehicles carry physical, biogeochemical, and imaging sensors into regions ships rarely reach (Roemmich et al., 2019; Testor et al., 2019; Wynn et al., 2014). Environmental DNA (eDNA) metabarcoding detects communities of organisms from water samples without capturing a single animal (Miya, 2022). Passive acoustic monitoring converts the ocean soundscape into biodiversity information (Mooney et al., 2020). Deep learning methods process the resulting volumes of imagery and audio (Goodwin et al., 2022; Stowell, 2022), and data infrastructures and digital twins promise to fuse these streams into decision-ready products (Miedtank et al., 2024; Tanhua et al., 2019).

The literature documenting these developments has a structural weakness: it is organised almost entirely within technology classes. Authoritative reviews exist for eDNA (Deiner et al., 2017), passive acoustics (Mooney et al., 2020), autonomous vehicles (Whitt et al., 2020; Wynn et al., 2014), satellite observation (Groom et al., 2019; Hedley et al., 2016), and deep learning in marine ecology (Goodwin et al., 2022), yet each stream defines its own problems, evaluates its own constraints, and rarely engages the others. The two broad cross-technology syntheses available are jurisdictionally bounded, one to European regulatory assessment (Danovaro et al., 2016) and one to the United Kingdom (Bean et al., 2017), and both predate the maturation of deep learning pipelines and marine digital twins. The literature on analytics and data governance, meanwhile, has developed separately from the literature on

sensing platforms (Malde et al., 2020; Tanhua et al., 2019). What the field has not resolved is how the technology classes relate to one another as components of a single observation-to-decision chain: which class supplies which ecological variables, which constraints recur across classes, and what an integrated architecture would need to look like for monitoring outputs to reach management. This unresolved question matters directly to the designers of national and regional monitoring programmes, to coordinating bodies for ocean observation, and to funders who must allocate resources across platforms, analytics, and data systems rather than within any single technology.

This article addresses that gap through an integrative review with a conceptual contribution. It synthesises verified peer-reviewed literature across four technology domains, sensing platforms, molecular and acoustic methods, machine learning analytics, and data integration and governance, and from that synthesis derives a layered sensing-to-decision architecture for digital marine ecosystem monitoring. The review answers three research questions:

RQ1. Which classes of digital technology now support marine ecosystem monitoring, and what ecological information does each class supply?

RQ2. Which recurring technical and institutional constraints limit the contribution of these technologies to sustained, decision-relevant monitoring?

RQ3. How can these technology classes be combined conceptually into an integrated architecture that links sensing to management decisions?

The remainder of the article proceeds as follows. Section 2 situates the review in the literature on sustained ocean observation and identifies the integration deficit in existing research. Section 3 sets out the integrative review protocol. Section 4 presents the findings in five subsections, including the synthesis table and the conceptual framework. Section 5

discusses theoretical, practical, and policy implications, states the limitations of the review, and outlines future research. Section 6 concludes.

## **2. Literature Review and Theoretical Framework**

### **2.1 From expeditions to sustained ocean observation**

The intellectual context for digital monitoring technology is the long transition from expedition-based oceanography to sustained, systematic observation. The Argo programme of profiling floats is the emblem of this transition, and its designers now propose extending the array beyond its original 2000 m depth limit toward a full-depth, multidisciplinary global system with improved coverage of equatorial and boundary regions (Roemmich et al., 2019). The biogeochemical extension of Argo equips floats with sensors for six variables, oxygen, nitrate, pH, chlorophyll a, suspended particles, and downwelling irradiance, and releases the data freely within 24 hours of transmission (Claustre et al., 2020). Underwater gliders acquired a comparable coordinating structure when the OceanGliders programme, established in 2016, organised glider observation of physical, biogeochemical, and biological processes within the Global Ocean Observing System (Testor et al., 2019).

Sustained observation requires agreement on what to measure. Miloslavich et al. (2018) derived a set of biological and ecosystem essential ocean variables (EOVs), including plankton biomass and diversity, the abundance and distribution of fish, turtles, birds, and mammals, and the cover of coral, seagrass, mangrove, and macroalgal habitats, selecting variables through a driver-pressure-state-impact-response logic weighted by impact and feasibility. The EOv concept supplies a shared prioritisation language across otherwise disparate observing communities, and it recurs throughout this review as the natural bridge between technology classes. At the policy level, the UN Decade frames the purpose of these

systems as feeding a science-based decision-making apparatus rather than accumulating data for its own sake (Ryabinin et al., 2019).

## **2.2 Technology-specific research streams**

Within this broad movement, distinct research streams have developed around individual technology classes. A robotics and platforms stream traces the contribution of autonomous underwater vehicles to seafloor science (Wynn et al., 2014), articulates a collective vision for autonomous observation (Whitt et al., 2020), and designs permanent deep-sea networks that combine cabled seabed platforms with mobile vehicles (Aguzzi et al., 2019). A remote sensing stream evaluates satellite ocean colour as the principal synoptic view of marine ecosystems (Groom et al., 2019), reviews reef-scale applications (Hedley et al., 2016), and specifies the sensor characteristics that coastal biodiversity observation would require (Muller-Karger et al., 2018). A molecular stream established environmental DNA as a conservation monitoring tool (Thomsen & Willerslev, 2015), codified the metabarcoding workflow (Deiner et al., 2017), and demonstrated its application to marine fish communities (Miya, 2022). An acoustics stream assesses passive listening as a biodiversity method (Mooney et al., 2020) against the backdrop of a rapidly changing ocean soundscape (Duarte et al., 2021), with computational bioacoustics supplying the analytical machinery (Stowell, 2022). A machine learning stream diagnoses the widening gap between data acquisition and analytic capacity (Malde et al., 2020) and maps deep learning applications across marine ecology (Goodwin et al., 2022). Finally, a data stream applies the FAIR principles of findability, accessibility, interoperability, and reusability to ocean data services (Tanhua et al., 2019) and, most recently, explores marine digital twins (Miedtank et al., 2024) following broader proposals for digital twins of the Earth system (Bauer et al., 2021).

Each stream is internally rigorous, and several include self-critical assessments of their own limits: acoustic researchers urge caution about current biodiversity indices (Mooney et

al., 2020), molecular ecologists document how protocol choices propagate into community-level conclusions (Deiner et al., 2017), and remote sensing scientists detail the calibration burden behind apparently effortless global imagery (Groom et al., 2019). What the streams share is an outward-facing claim, namely that their technology serves ecosystem monitoring, combined with limited analysis of how that service depends on the other streams.

## **2.3 The integration deficit**

Two earlier syntheses attempted a cross-technology view. Danovaro et al. (2016) reviewed molecular methods, in situ instrumentation, and remote sensing against European marine-status assessment obligations and concluded that recently developed technologies can offer advantages in accuracy, efficiency, and cost over classical methods. Bean et al. (2017) catalogued platforms and sensors used in United Kingdom monitoring and argued that integrating traditional techniques with technological and modelling innovation could yield data that are currently too difficult or expensive to gather. Both reviews are valuable precedents, and both are explicitly bounded: their organising questions are set by a specific regulatory regime, and both were written before deep learning pipelines, biogeochemical float networks at global scale, and digital twin initiatives reshaped the field.

The theoretical lens adopted here treats a monitoring system as a value chain in which raw signals become ecological variables, variables become synthesised knowledge, and knowledge becomes management action. This framing is implicit in the observing-system literature: the EOVS framework connects measurement to societal requirements (Miloslavich et al., 2018), FAIR data services connect measurement to reuse (Tanhua et al., 2019), and the Decade connects observation to decision making (Ryabinin et al., 2019). Making the chain explicit, and locating each technology class within it, is the conceptual work this review undertakes. The review is therefore built to answer the gap identified above: a technology-by-

technology synthesis oriented not toward any single class but toward the connective structure among classes.

### **3. Method**

#### **3.1 Review design**

The study follows the integrative review method, which is appropriate when a field's evidence is dispersed across heterogeneous literatures and the intended output is a new conceptual structure rather than a pooled effect estimate (Torraco, 2016; Whitemore & Knafl, 2005). Integrative reviews permit the combination of diverse source types, including empirical studies, methodological reviews, and programmatic position papers, under an explicit analytical framework (Whitemore & Knafl, 2005). Because the guiding questions span technical and institutional issues, an integrative design was preferred over a narrowly systematic one, consistent with guidance that the review form should match the research purpose (Snyder, 2019).

#### **3.2 Search strategy**

Literature was identified through structured searches of Scopus and the Web of Science Core Collection, supplemented by Google Scholar for forward and backward citation chasing. Example search strings included: ("marine monitoring" OR "ocean observing" OR "marine ecosystem" ) AND ("autonomous underwater vehicle" OR glider OR "profiling float" OR "remote sensing" OR "ocean colour"); ("environmental DNA" OR metabarcoding) AND (marine OR ocean) AND (monitor\* OR biodiversity); ("passive acoustic monitoring" OR soundscape OR bioacoustics) AND (marine OR ocean); ("machine learning" OR "deep learning") AND (marine OR ocean) AND (imagery OR acoustics OR ecology); and ("digital twin" OR "FAIR data" OR "essential ocean variables") AND ocean. The core search window was January 2014 to August 2026, reflecting the period in which the reviewed technologies

reached operational maturity, with older works admitted when they were methodologically foundational for the review design or for a technology class.

### **3.3 Inclusion and exclusion criteria**

Sources were included when they (a) were peer-reviewed journal publications in English; (b) addressed digital technologies for observing marine ecosystems, or the analytic and data infrastructures that such observation requires; and (c) operated at a synthesis, roadmap, or programme level capable of informing cross-technology comparison, rather than reporting a single-site engineering trial. Sources were excluded when they concerned exclusively freshwater systems, addressed digital twins of ships or industrial installations rather than of the marine environment, treated algorithms with no marine application, or could not be verified against the Crossref bibliographic record. Every retained source had its full bibliographic metadata confirmed against the Crossref application programming interface, and sources whose records could not be confirmed were discarded. Screening proceeded in two stages, first on title and abstract and then on full available text, against the criteria above. The final corpus comprises 30 sources: 27 substantive works on marine monitoring technology and infrastructure and three methodological anchors for the review design.

### **3.4 Analysis and framework derivation**

Retained sources were coded into an extraction matrix with fields for technology class, observed ecological properties, reported strengths, reported constraints, data practices, and stated links to management or governance. Synthesis followed the constant comparison logic recommended for integrative reviews, iterating between within-class summaries and cross-class comparison until stable themes emerged (Whittemore & Knafl, 2005). Four themes were retained: platform-based sensing, molecular and acoustic sensing, machine learning analytics, and data integration and governance. The conceptual framework was derived abductively: the

layered structure was proposed as the simplest arrangement that accounts for the relationships documented in the matrix, then tested against each source for contradiction and refined. Table 1 and Figure 1 are direct products of this process.

### 3.5 Rigor and trustworthiness

Several measures bound the trustworthiness of the review. All bibliographic records were verified against Crossref before citation, and an audit trail links every substantive claim to a logged source. The review does not claim exhaustiveness: integrative synthesis prioritises conceptual coverage over census-style completeness, and no article-count flow diagram is reported because the corpus was consolidated for conceptual saturation rather than enumerated through a preregistered protocol. Restricting the corpus to English-language, journal-published sources narrows the evidence base, and reliance on synthesis-level papers risks importing the optimism characteristic of community position statements; the findings sections counter this by giving constraints equal standing with capabilities. Screening and coding were performed by a single author, a limitation addressed through explicit criteria and the documented audit trail rather than through inter-coder statistics.

## 4. Findings

The four thematic subsections below answer RQ1 and RQ2 by technology class, and Section 4.5 answers RQ3. Table 1 summarises the synthesis: for each class it lists what is observed, the principal strengths reported in the reviewed literature, and the constraints that recur across sources.

**Table 1**

*Digital Technology Classes for Marine Ecosystem Monitoring: Observed Properties, Strengths, Constraints, and Sources*

| Technology class                      | Primary observed properties                                                                               | Principal strengths                                                                                    | Recurring constraints                                                                                      | Key sources                                                                              |
|---------------------------------------|-----------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| Satellite remote sensing              | Ocean colour and chlorophyll; phytoplankton dynamics; reef extent, benthic cover, sea surface temperature | Synoptic, repeated coverage; operational monitoring of blooms and eutrophication                       | Mission continuity and cross-sensor merging; stringent calibration; coastal resolution gaps                | Groom et al. (2019); Hedley et al. (2016); Muller-Karger et al. (2018)                   |
| Profiling floats and gliders          | Temperature and salinity; oxygen, nitrate, pH, chlorophyll a, particles, irradiance                       | Sustained interior observation; open data within 24 hours; float array building toward global coverage | Biogeochemical sensors at lower technology readiness; glider deployments largely regional and near-surface | Roemmich et al. (2019); Claustre et al. (2020); Testor et al. (2019); Chai et al. (2020) |
| AUVs and seafloor observatories       | Seafloor imagery and habitat maps; continuous deep-sea video and acoustic observation                     | High-resolution mapping of environments inaccessible to surface vessels; continuous presence           | Subsurface energy limits; biofouling; acoustic communication bandwidth; cost and expertise                 | Wynn et al. (2014); Aguzzi et al. (2019); Whitt et al. (2020)                            |
| Environmental DNA metabarcoding       | Multi-species community composition; marine fish richness and spatiotemporal dynamics                     | Noninvasive; cost-effective; multi-taxon detection amid declining taxonomic expertise                  | Relative abundance estimation unresolved; sensitivity to workflow choices from primers to bioinformatics   | Thomsen & Willerslev (2015); Deiner et al. (2017); Miya (2022)                           |
| Passive acoustic monitoring           | Vocalising species; anthropogenic noise; ocean soundscapes                                                | Long-duration listening in a medium where sound travels far                                            | Current biodiversity indices require caution; large archives depend on machine learning analysis           | Mooney et al. (2020); Duarte et al. (2021); Stowell (2022)                               |
| Machine learning analytics            | Detection, classification, tracking, segmentation of organisms in imagery and audio                       | Relieves the analysis bottleneck created by high-volume sensing                                        | Dependence on supervised training data; standardisation and validation across programmes                   | Malde et al. (2020); Goodwin et al. (2022); Lombard et al. (2019)                        |
| Data infrastructure and digital twins | Integrated essential-ocean-variable products; FAIR data services; marine digital twins                    | Reuse and comparability of observations; route from observation to decision support                    | Fragmented catalogues; uneven maturity across disciplines; sustained funding for data management           | Tanhua et al. (2019); Miloslavich et al. (2018); Miedtank et al. (2024)                  |

*Note.* Synthesis by the author from the sources cited in each row. Strengths and constraints are those reported in the cited literature; the table introduces no new empirical data. AUV = autonomous underwater vehicle; FAIR = findable, accessible, interoperable, reusable.

#### **4.1 Platform-based sensing from orbit to seafloor**

Satellite remote sensing supplies the only routinely synoptic view of marine ecosystems. Ocean colour radiometry underpins the study of phytoplankton dynamics at seasonal and interannual scales and supports operational monitoring of coastal eutrophication, harmful algal blooms, and sediment plumes (Groom et al., 2019). For structured habitats, satellite and airborne observation maps reef extent, benthic cover, and sea surface temperature, trading the point-level accuracy of field survey for complete spatial coverage (Hedley et al., 2016). The constraints of the class are equally well documented. The long-term ocean colour record is stitched together from a sequence of one-off missions whose merging risks artefacts, and retrieval is demanding because the water-leaving signal constitutes less than a tenth of what the sensor detects at the top of the atmosphere (Groom et al., 2019). For coastal biodiversity specifically, Muller-Karger et al. (2018) concluded that current and planned satellites are not designed to observe rapidly changing coastal essential biodiversity variables, and specified requirements, including pixel sizes of 30 to 100 m and revisit times of hours to days, that no operational system yet meets.

In the water column, autonomous platforms have converted what was once expedition sampling into sustained observation. The proposed extension of Argo toward a full-depth, biogeochemically instrumented global array (Roemmich et al., 2019), and the demonstrated capacity of biogeochemical floats to deliver six-variable profiles as open data within a day of collection (Claustre et al., 2020), define the current benchmark for scalable in situ observation. Reviews of this platform ecosystem argue that autonomous mobile assets combined with satellite data can provide the four-dimensional information needed to model and forecast ocean health under warming, acidification, and deoxygenation (Chai et al., 2020). Gliders contribute sustained sections through boundary currents and storm-affected regions under international coordination (Testor et al., 2019), while autonomous underwater vehicles

deliver seafloor imaging and habitat mapping at resolutions unattainable from surface vessels, including under ice and in the deep sea (Wynn et al., 2014). At the seafloor itself, proposed monitoring networks combine fixed cabled platforms with mobile vehicles carrying video, acoustic, and molecular payloads for continuous ecological observation (Aguzzi et al., 2019), aligned with proposals for globally coordinated deep-ocean monitoring variables (Danovaro et al., 2020).

The recurring constraints of the platform class are physical and economic. Subsurface energy availability fundamentally limits propulsion, sensing, and communication; biological and biogeochemical sensors mostly sit at lower technology readiness than their physical counterparts; biofouling degrades long deployments; underwater acoustic communication restricts data return; and acquisition and operation remain costly and expertise-intensive (Whitt et al., 2020). These constraints explain a pattern visible across the corpus: while the float network builds toward global biogeochemical coverage, glider and surface-vehicle deployments carrying such sensors have largely remained regional and near-surface (Chai et al., 2020).

## **4.2 Molecular and acoustic sensing**

Environmental DNA and passive acoustics extend monitoring to organisms and behaviours that platforms with cameras and physical sensors cannot efficiently capture. eDNA, defined as genetic material obtained directly from environmental samples, offers a noninvasive and standardisable survey approach at a time when taxonomic expertise for morphological identification is in decline (Thomsen & Willerslev, 2015). Metabarcoding of such samples surveys whole communities of animals and plants and has been applied across marine, freshwater, and terrestrial systems (Deiner et al., 2017). For marine fish specifically, eDNA metabarcoding detects multiple species simultaneously and resolves species richness and spatiotemporal community dynamics across spatial scales, at costs the review literature

characterises as low relative to conventional survey (Miya, 2022). The interpretive constraints are handled candidly in the same literature: estimating relative abundance from read counts remains problematic, and results are sensitive to choices along the entire workflow from primers and library preparation to bioinformatic filtering (Deiner et al., 2017). Integration with platforms is already envisaged, with in situ sequencing instruments included in deep-sea observatory designs to detect organisms, including prokaryotes, that imaging cannot record (Aguzzi et al., 2019).

Passive acoustic monitoring exploits the physics of the ocean, where sound travels faster and farther than in air and where marine organisms have evolved to rely on acoustic communication (Duarte et al., 2021). Passive recorders therefore capture vocalising species together with the anthropogenic sound, whose growth Duarte et al. (2021) document as a defining feature of the modern ocean soundscape. As a biodiversity method, however, the field's own assessment is cautious: Mooney et al. (2020) recommend restraint in applying current acoustic diversity indices while identifying machine learning and source separation as the most promising analytical directions. This caution matters for programme design, because it separates the mature use of acoustics for detecting target species and anthropogenic noise from the still-developing use of acoustics as a general biodiversity metric.

#### **4.3 Machine learning and the analysis bottleneck**

The sensing classes reviewed above share one systemic consequence: they generate data faster than conventional analysis can absorb. Malde et al. (2020) diagnose this directly, observing that modern sensor systems produce unprecedented data volumes while analytic capacity has not kept pace, and positioning deep learning as the most plausible response across marine science. The applications literature substantiates the response. Deep networks now perform detection, classification, tracking, and segmentation on marine imagery of plankton, fish, and marine mammals (Goodwin et al., 2022). In bioacoustics, deep learning

inherited its methods from speech and image processing, and the field faces problems distinct enough from those parent domains that Stowell (2022) proposes a dedicated research roadmap for computational bioacoustics. In plankton observation, imaging instruments and optical sensors are mature, but inconsistent and diverse methods across programmes obstruct the detection of global and long-term patterns, prompting calls for standardised, quality-controlled, automated pipelines integrated with existing observing infrastructure (Lombard et al., 2019).

Read across sources, the machine learning theme carries a double message. Analytics is the multiplier that makes high-volume sensing worthwhile; without it, imagery and audio accumulate as unprocessed archives. At the same time, the reviewed literature ties the value of these methods to conditions that are institutional as much as algorithmic: the applications surveyed rely largely on supervised learning, which binds performance to curated training data (Goodwin et al., 2022), and outputs only become comparable across programmes where processing and quality control are standardised (Lombard et al., 2019). The bottleneck, in short, moves rather than disappears: from analysing data to governing the analysis.

#### **4.4 Data integration, digital twins, and governance**

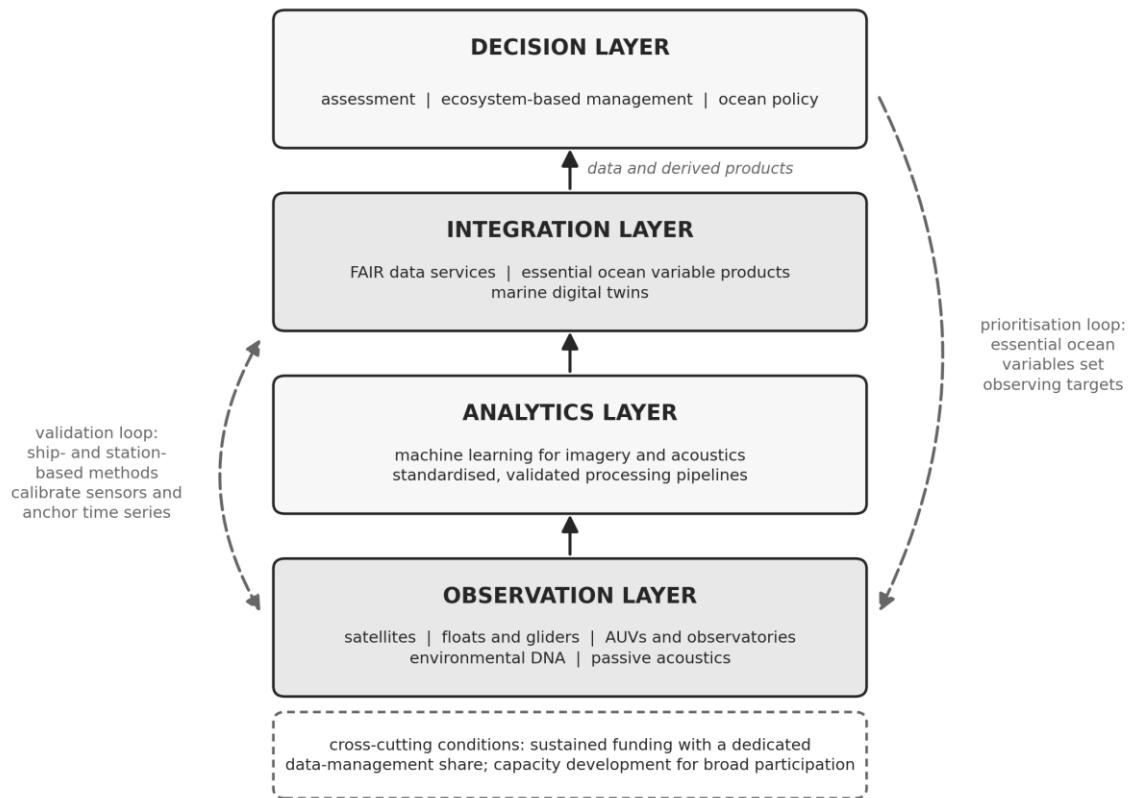
The final theme concerns the infrastructure through which observations become usable evidence. The FAIR framework, requiring ocean data to be findable, accessible, interoperable, and reusable, is the organising standard, and its application reveals uneven maturity: physical oceanography has advanced furthest, aided by the Argo data system's automated quality control and global assembly centres, while biological and biogeochemical data communities lag, and infrastructure remains fragmented, illustrated by the existence of more than 70 data catalogues for polar regions alone (Tanhua et al., 2019). The same source proposes a concrete governance norm, recommending that 5 to 10 percent of research funding be dedicated to data management (Tanhua et al., 2019). The EOVS framework complements FAIR by specifying

what merits sustained observation in the first place, derived from societal drivers and feasibility rather than disciplinary habit (Miloslavich et al., 2018).

Digital twins represent the most ambitious integration proposal in the corpus. Following the argument for a digital twin of Earth in support of the green transition (Bauer et al., 2021), marine digital twins are now advanced as a means of deepening ocean understanding (Miedtank et al., 2024). Within the sensing-to-decision chain, the twin concept occupies the apex: it presupposes interoperable data flows, validated analytics, and sustained observation, and its credibility therefore depends on every layer beneath it. The policy architecture for such integration exists in outline: the UN Decade explicitly aims to connect a more complete observing system to science-based decision making (Ryabinin et al., 2019), and national reviews argue that integrated deployment of old and new methods can satisfy legislative monitoring obligations at acceptable cost (Bean et al., 2017; Danovaro et al., 2016).

#### **4.5 An integrated sensing-to-decision architecture**

The synthesis supports a conceptual answer to RQ3, presented as Figure 1. The framework is interpretive: it is derived from the reviewed literature but is itself a proposal, not an empirical result. It arranges digital marine monitoring into four layers connected by two feedback loops, with two cross-cutting conditions.



**Figure 1.** A sensing-to-decision architecture for digital marine ecosystem monitoring. Solid arrows show the flow of data and derived products; dashed arrows show the prioritisation and validation feedback loops; the dashed bar lists cross-cutting enabling conditions. Original figure by the author; synthesised from the reviewed literature.

The observation layer comprises the complementary sensing classes established in Sections 4.1 and 4.2: spaceborne remote sensing for synoptic coverage, autonomous and fixed platforms for interior and seafloor observation, and molecular and acoustic methods for biological detail. The analytics layer converts raw signals into ecological variables through machine learning pipelines whose outputs are only as credible as their training data, standardisation, and validation (Goodwin et al., 2022; Lombard et al., 2019). The integration layer assembles validated variables into FAIR data services (Tanhua et al., 2019) and, at its most ambitious, into marine digital twins (Miedtank et al., 2024). The decision layer uses these products in assessment, management, and policy, the destination the Decade assigns to ocean observation (Ryabinin et al., 2019).

Two feedback loops make the architecture a system rather than a pipeline. A prioritisation loop runs from the decision layer back to observation: essential ocean variables, derived from societal requirements, determine what the observation layer should measure and which sensor investments matter most (Miloslavich et al., 2018). A validation loop runs between layers: legacy ship-based and station-based methods calibrate new sensors and anchor long-term comparability, a role the national syntheses identify as the enduring value of traditional monitoring (Bean et al., 2017; Danovaro et al., 2016). The cross-cutting conditions are sustained funding with an explicit data-management share (Tanhua et al., 2019) and capacity development so that participation in digitally intensive monitoring is not confined to wealthy programmes (Ryabinin et al., 2019; Tanhua et al., 2019).

The architecture answers RQ3 by specifying where each technology class sits, what it depends on, and where investment imbalances break the chain: sensing without analytics accumulates archives, analytics without data services produces incomparable outputs, and integration without decision-layer uptake produces infrastructure without consequence.

## **5. Discussion**

### **5.1 Theoretical implications**

The review's first implication is that marine monitoring technology is best theorised as a coupled system rather than a set of substitutable instruments. The technology-class literatures reviewed here each present their own tools as monitoring solutions, yet the constraints they report are almost always resolved in a different layer of the architecture: the platform literature's data-volume problem is addressed by analytics (Malde et al., 2020), the analytics literature's standardisation problem is addressed by data governance (Lombard et al., 2019; Tanhua et al., 2019), and the governance literature's prioritisation problem is addressed

by variable frameworks negotiated with decision makers (Miloslavich et al., 2018). Cross-layer dependence, not within-class capability, is the analytically productive unit.

Second, the EOVS framework functions in this synthesis as a boundary object: it is the one construct that every layer can address, from sensor design to data services to policy reporting (Miloslavich et al., 2018). Treating EOVSs as the binding logic of the architecture extends their original role in observing-system coordination into a general integration mechanism for digital monitoring.

Third, the framework extends the earlier cross-technology syntheses beyond their jurisdictional origins. Danovaro et al. (2016) and Bean et al. (2017) demonstrated integration arguments within specific regulatory settings; the architecture proposed here generalises the integration claim into a structure that is independent of any single regime and explicitly incorporates the analytics and integration layers that postdate those reviews.

## **5.2 Practical and policy implications**

For monitoring programme designers, the architecture converts a diffuse technology menu into a portfolio question: investments should be balanced across layers, because the marginal value of an additional sensor depends on the analytics, data services, and decision pathways available to absorb its output. The reviewed literature supplies concrete anchors for such portfolios: open release of float data within a day of collection as a benchmark for data latency (Claustre et al., 2020), a 5 to 10 percent share of research funding for data management (Tanhua et al., 2019), and continued operation of established methods alongside digital ones to preserve the comparability of long-term series (Bean et al., 2017).

For ocean governance bodies, two implications stand out. First, the caution voiced within the acoustic and molecular literatures (Deiner et al., 2017; Mooney et al., 2020) argues for standards that distinguish decision-grade applications, such as target-species detection,

from research-grade applications, such as community-level indices still under validation. Second, the Decade's window for coordinated investment (Ryabinin et al., 2019) makes the capacity dimension urgent: without deliberate transfer of tools, training data, and infrastructure, digitally intensive monitoring risks concentrating observational capability in already well-resourced regions, a concern consistent with the capacity-building emphasis in the ocean data literature (Tanhua et al., 2019).

### **5.3 Limitations**

The limitations of this review follow from its method. First, an integrative review is selective by design; although every source was verified and the corpus was assembled to cover the field's principal streams, other defensible corpora exist, and a different selection could weight the themes differently (Snyder, 2019; Whitemore & Knafl, 2005). Second, the corpus favours synthesis-level and programmatic publications, which document capabilities and roadmaps more readily than operational failures; the balance of strengths and constraints reported here is therefore only as honest as the self-assessment of the reviewed communities. Third, restriction to English-language journal literature excludes grey literature from monitoring agencies and non-English national programmes in which considerable operational experience resides. Fourth, screening and coding were conducted by a single author, and no inter-coder reliability can be reported. Finally, the field moves quickly; conclusions about maturity, particularly for machine learning and digital twins, carry short half-lives.

### **5.4 Future research**

Four directions follow directly from what the reviewed literature leaves open. First, comparative cost-effectiveness: the corpus contains claims of efficiency advantages for new methods (Danovaro et al., 2016; Miya, 2022) but no cross-class economic evidence base adequate for portfolio decisions; empirical cost-per-variable studies across technology classes

are needed. Second, interoperability of molecular and acoustic outputs with the EOVS framework: community-level eDNA and acoustic indices require the validation programmes that their own literatures call for before they can enter sustained observing systems (Deiner et al., 2017; Mooney et al., 2020). Third, the transferability of machine learning models across regions, instruments, and time, identified as a live problem in both marine imagery and bioacoustics (Goodwin et al., 2022; Stowell, 2022), warrants systematic evaluation under operational monitoring conditions. Fourth, the institutional side of the architecture, including who sustains data services, how the recommended budget shares fare in practice, and whether digital twins alter decisions rather than dashboards, is essentially unstudied in the reviewed corpus and requires governance-oriented empirical research.

Against the gap stated in the Introduction, the review closes the conceptual portion: it maps the technology classes onto a common architecture, identifies the cross-class constraints, and supplies the integration structure that the class-specific literatures lacked. The empirical portion of the gap, above all the comparative economics and the institutional performance of integrated systems, remains open and defines the agenda above.

## **6. Conclusion**

This integrative review synthesised the peer-reviewed literature on digital technology in marine ecosystem monitoring across four domains: sensing platforms from satellites to seafloor observatories, molecular and acoustic methods, machine learning analytics, and data integration and governance. The synthesis shows a field of individually maturing technology classes whose monitoring value is jointly determined: each class resolves its central constraint only through the layers around it. The proposed sensing-to-decision architecture organises these dependencies into four layers bound by prioritisation and validation feedback loops, with essential ocean variables as the connective logic and sustained funding and capacity development as enabling conditions. The framework gives programme designers a structured

basis for balancing investment across sensing, analytics, and data infrastructure, and gives researchers a map of the seams between literatures where the most consequential open questions, from cross-class cost-effectiveness to the institutional performance of digital twins, are located. Marine monitoring is becoming a digital system; understanding it, and funding it, as a system is the condition for that transition to serve ocean governance.

## **Declarations**

Funding: This research received no external funding.

Conflicts of Interest: The author declares no conflict of interest.

Ethics: This study is a review of published literature and did not involve human participants, animal subjects, or primary data collection; ethical approval was therefore not required.

Data Availability: No new data were created or analysed in this study. All sources synthesised are cited in the reference list and publicly identifiable through the digital object identifiers provided.

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