Species Recognition using Artificial Intelligence

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Supporting offshore wind farms

Who should read this paper?

This paper is intended for offshore wind practitioners, marine ecologists, regulators, and technology developers involved in biodiversity monitoring and environmental management. It will also be relevant to researchers and policy-makers working at the interface of marine science, digital monitoring, and governance.

Why is it important?

The rapid expansion of offshore wind is creating a growing mismatch between the scale of development and the capacity of traditional biodiversity monitoring approaches. This paper addresses that gap by critically examining how real-time Artificial Intelligence (AI) species recognition can support more responsive, transparent, and credible marine monitoring without overstating current capabilities. It offers a balanced perspective that integrates ecological science, operational reality, and governance considerations, which are increasingly central to ocean management decisions.

This is a synthesis and perspective paper grounded in peer-reviewed literature, emerging offshore wind practice, and practitioner experience. Rather than presenting AI as a standalone solution, the paper reframes real-time species recognition as a screening and prioritization tool embedded within hybrid human-AI monitoring systems. By focusing on how AI outputs are interpreted, validated, and used, the paper moves the discussion beyond algorithm performance toward decision-relevant application.

It provides a practical framework for deploying AI-enabled monitoring in ways that enhance learning without undermining scientific or regulatory credibility. It helps practitioners and regulators distinguish between exploratory signals and evidence suitable for decision-making, reducing the risk of misinterpretation or over-claiming. More broadly, it supports the development of monitoring approaches that can keep pace with offshore renewable energy expansion while maintaining trust and ecological rigour.

About the author

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REAL-TIME ARTIFICIAL INTELLIGENCE SPECIES RECOGNITION FOR MARINE BIODIVERSITY MONITORING: A TRANSFORMATIVE APPROACH FOR OFFSHORE WIND MANAGEMENT

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ABSTRACT

The rapid global expansion of offshore wind is critical for meeting net-zero targets but presents distinct ecological management challenges. Effective biodiversity monitoring around marine renewable installations traditionally involves intermittent, costly methods with significant data gaps, limiting robust ecological assessments and adaptive management responses. Recent advancements in real-time Artificial Intelligence (AI) species recognition technology represent a transformational shift, providing continuous, high-resolution biodiversity data. This research highlights practical applications and validations of AI-driven underwater monitoring systems within offshore wind farms. Notably, initiatives such as The Rich North Sea Program (Netherlands) and RWE's SeaMe project have successfully implemented AI monitoring technologies, significantly enhancing our understanding of ecological interactions and biodiversity outcomes associated with marine structures. Canadian initiatives, including those by Ocean Networks Canada and Fundy Ocean Research Centre for Energy, further validate the role of AI monitoring in ecological understanding and adaptive management of marine renewable projects.

Real-time AI monitoring fosters unprecedented stakeholder engagement through live-streaming biodiversity data, creating transparency and enhancing public support and education, particularly within local communities and educational institutions. This approach is critical for generating social licence and community collaboration in marine renewable developments.

By harnessing the power of real-time AI monitoring, marine renewable projects substantially improve ecological outcomes, effectively meet regulatory demands, and authentically engage communities. This paper discusses the scalability of AI-driven monitoring solutions, integration into adaptive management frameworks, and their role in shaping policy and operational decisions within the offshore wind sector.

Keywords: AI species recognition, adaptive management, ecological impact, marine artificial structures, offshore wind, real-time biodiversity monitoring, stakeholder engagement

1. INTRODUCTION

Offshore wind is expanding at a pace and scale unprecedented in the marine environment. Across European, North American, and Asia-Pacific waters, projects are moving rapidly from single-site developments to large, multi-array offshore wind farms, often in ecologically complex and socially contested seascapes. This acceleration is driven by climate and energy security imperatives, yet it has also intensified scrutiny of offshore wind's environmental footprint, particularly in relation to biodiversity impacts, cumulative effects, and long-term ecosystem change. Regulators, developers, and stakeholders are increasingly required to demonstrate not only compliance with environmental conditions, but credible evidence that monitoring and management approaches are keeping pace with the operational realities of offshore infrastructure [1], [2].

Marine biodiversity monitoring has long relied on a combination of diver surveys, vessel-based observations, fisheries data, and periodic remote sensing. While these methods remain scientifically robust, they are constrained by cost, spatial coverage, temporal resolution, and human availability. As offshore wind arrays extend further offshore, into deeper waters, traditional monitoring approaches are increasingly stretched beyond their practical limits. Monitoring programs are often episodic rather than continuous, spatially restricted rather than system-wide, and slow to translate data into operational decision-making. This mismatch between the tempo of industrial activity and the tempo of ecological observation has become one of the defining challenges of contemporary marine environmental management [3], [4].

Recent advances in Artificial Intelligence (AI), particularly in computer vision and machine learning, have been proposed as a means to address this growing monitoring gap. In aquatic and marine sciences, AI-enabled approaches are increasingly applied to species identification and automated image analysis, with reviews highlighting substantial gains in processing speed and classification accuracy for visually detectable taxa compared to manual methods [5]. At the same time, studies focused on underwater imagery demonstrate that performance remains strongly constrained by environmental conditions such as turbidity, variable lighting, and imbalanced training datasets, particularly for rare or visually difficult-to-detect species [6].

Within the offshore wind sector, interest in real-time or near real-time AI-based monitoring has grown rapidly. Fixed and mobile camera systems, Autonomous Underwater Vehicles (AUVs), and Remotely Operated Vehicles (ROVs) increasingly generate volumes of visual data that far exceed the capacity of human analysts to process manually. Automated species recognition offers an apparent solution: continuous monitoring at scale, rapid detection of ecological signals, and the potential to inform adaptive management measures within operational timeframes. However, conservation literature cautions that the use of AI in ecological monitoring carries risks of overconfidence, bias, and inappropriate application if deployed without sufficient oversight, particularly in complex ecological systems [7].

Crucially, the application of AI in marine monitoring is not a purely technical challenge. Decisions about what is monitored, how data are interpreted, and how outputs are used carry governance implications that extend beyond model performance. In offshore wind contexts, where monitoring data may inform licensing compliance, mitigation triggers, or stakeholder trust, the legitimacy of AI-derived evidence becomes as important as the accuracy of the underlying technology.

This paper sets out how real-time AI species recognition can support offshore wind biodiversity monitoring when embedded within ecological study design and human decision-making processes. Rather than replacing established methods or expert judgement, AI is positioned as a screening and prioritization tool that enhances human capacity while retaining expert oversight, consistent with emerging concepts of hybrid intelligence [8].

Drawing on peer-reviewed literature and emerging offshore practice, the paper examines how AI-enabled species recognition can contribute to more adaptive and transparent monitoring, while explicitly addressing technical constraints and uncertainty, and asking under what conditions real-time detection meaningfully improves ecological understanding, regulatory confidence, and environmental outcomes [7], [9].

2. THE MONITORING GAP IN OFFSHORE WIND

The rapid expansion of offshore wind has exposed structural limitations in how marine biodiversity is currently monitored, assessed, and governed. While monitoring requirements have increased in scope and ambition – driven by cumulative impact assessment, biodiversity policy, and stakeholder expectations – the underlying methods and delivery models have remained largely unchanged. This has created a widening gap between what monitoring is expected to achieve and what it can realistically deliver under existing paradigms [10], [11].

2.1 Temporal Mismatch: Episodic Surveys in Dynamic Systems

Marine ecosystems are inherently dynamic. Species distributions, behaviours, and interactions vary across daily, seasonal, and interannual timescales, and can respond rapidly to anthropogenic pressures such as noise, vessel activity, and habitat alteration. Conventional offshore monitoring programs, however, are typically structured around survey windows, often constrained to a small number of campaigns per year. These surveys provide valuable snapshots, but they may not capture short-term dynamics needed for adaptive management.

As a result, monitoring outputs are frequently retrospective. Data are collected, processed, quality-assured, and reported months after the ecological conditions of interest have occurred.

By the time evidence reaches regulators or project operators, opportunities for adaptive management – such as modifying operational timing or testing mitigation measures – have often passed. This temporal lag can limit the utility of traditional monitoring in fastmoving industrial contexts.

2.2 Spatial Constraints

Offshore wind farms occupy large spatial footprints, often spanning tens to hundreds of square kilometres. Yet monitoring effort within these areas is necessarily selective, constrained by vessel time, weather windows, and cost. Survey designs typically prioritize statistically representative sampling over comprehensive coverage, leaving substantial portions of project areas unobserved at any given time.

This uneven spatial coverage is particularly problematic when monitoring aims to detect rare events, low-abundance species, or localized ecological responses to infrastructure. For visually detectable taxa, such as demersal fish or mobile invertebrates, detection probability is strongly influenced by survey timing, visibility conditions, and observer effort. Studies in aquatic biology have repeatedly highlighted that nondetections should be interpreted cautiously.

2.3 Cost and Logistical Constraints

Marine surveys are resource intensive. Vessel day rates, specialist equipment, and the need for trained personnel limit how frequently monitoring can be undertaken. As offshore wind projects move further offshore and into more challenging environments, costs increase without necessarily delivering proportionate gains in ecological understanding. In practice, monitoring effort may change postconstruction, even as processes such as colonization, attraction, or displacement continue to develop [12].

The result is that monitoring data may be too infrequent or delayed to meaningfully inform management decisions. From a practitioner perspective, this raises practical questions about whether existing monitoring approaches remain appropriate for the scale and pace of offshore renewable energy development.

2.4 Monitoring as Evidence in Decision-making

Beyond its scientific role, biodiversity monitoring underpins how offshore wind projects are assessed, regulated, and discussed. Monitoring data are used to demonstrate compliance with licence conditions, inform regulatory decisions, and support engagement with fisheries stakeholders and the wider public. Where evidence is perceived as incomplete, outdated, or difficult to interpret, confidence in monitoring outcomes can be undermined, even where substantial effort has been invested [9], [13].

Research on marine governance highlights that monitoring systems shape how information is accessed, interpreted, and communicated, rather than functioning as neutral data pipelines [9]. In offshore wind contexts, this places emphasis on monitoring approaches that are transparent, interpretable, and proportionate to the decisions they are expected to inform.

3. REAL-TIME AI SPECIES RECOGNITION: TECHNICAL FOUNDATIONS AND CONSTRAINTS

Real-time AI species recognition refers to the application of machine learning models – most commonly deep learning-based computer vision – to detect and classify organisms in visual data streams as imagery is collected. In marine settings, this typically involves underwater cameras deployed on fixed infrastructure (such as turbine foundations or scour protection), mobile platforms including ROVs and AUVs, or hybrid systems combining visual sensors with acoustic or environmental metadata. The defining feature of real-time application is not automation alone, but the ability to move more quickly from observation to interpretation, allowing ecological signals to be identified within operationally relevant timeframes.

3.1 Core Technical Approach

Most AI-based species recognition systems are trained to identify organisms in images by learning recurring visual features such as shape, contrast, and movement. In aquatic biology, these approaches have been shown to work best for visually distinctive and frequently observed species, including many fish, crustaceans, and larger mobile fauna. Reviews of AI applications in aquatic biology show that automated classification can be useful in suitable conditions, particularly where large volumes of imagery need to be processed [5].

In offshore wind monitoring, the primary value of these systems lies in their ability to process continuous image streams that would be impractical to analyze manually. Automated detection provides an initial screening layer, allowing species presence or unusual activity to be flagged quickly and directing human effort to where it is most needed.

3.2 Environmental Constraints

Underwater imagery is highly sensitive to environmental conditions. Turbidity, suspended sediments, biofouling, variable light conditions, and camera orientation all influence image quality and, by extension, model performance. Even modest changes in these conditions can reduce detection probability or increase false positives. As a result, some species or size classes may be detected more readily than others, rather than reflecting true ecological patterns.

Training datasets are often dominated by common, easily observed species, while rarer or protected taxa are underrepresented. Automated detection may be less reliable for rare or visually cryptic species [5].

Performance can also vary between locations. Models trained in one area may not transfer well to different habitats or conditions, making site-specific testing and cautious interpretation essential in offshore wind monitoring.

3.3 Real-time Detection and Decision-making

For offshore wind practitioners, it is important to distinguish between real-time detection and decision-ready evidence. Automated outputs indicate possible presence, not confirmed ecological conclusions. Without context – such as monitoring effort, visibility conditions, or environmental variability – detections, and equally non-detections, can be misinterpreted.

Effective use of AI, therefore, relies on combining automation with expert review. Automated systems can screen large volumes of imagery and flag material of interest, but human expertise remains essential to verify detections, interpret ecological relevance, and judge whether evidence is sufficient to inform management or regulatory reporting [8]. Used in this way, AI improves efficiency and responsiveness without removing accountability or ecological understanding.

3.4 Implications for Offshore Wind Monitoring Design

For offshore wind practitioners, the technical foundations of AI species recognition bring both opportunity and responsibility. Continuous automated monitoring can greatly increase the amount of data collected and improve temporal coverage, but it also introduces new sources of uncertainty that need to be managed consciously. Choices about where and how cameras are deployed, what species the system is trained to recognize, how outputs are checked, and when results are reviewed all affect how reliable and useful AI-derived evidence will be.

Recognizing these constraints does not weaken the case for AI-enabled monitoring. On the contrary, it clarifies the conditions under which such systems add value. When deployed as part of a structured monitoring framework – rather than as a standalone technological solution – real-time AI species recognition can support more responsive, transparent, and informative biodiversity monitoring around offshore wind infrastructure. The following sections build on this foundation, examining how hybrid intelligence workflows, governance arrangements, and complementary tools are required to translate technical capability into credible environmental evidence.

4. HYBRID INTELLIGENCE

The practical value of real-time AI species recognition in offshore wind monitoring depends less on algorithmic sophistication than on how automated outputs are integrated into human decision-making. Environmental monitoring and decision-support literature cautions against fully automated approaches in complex ecological settings, emphasizing instead the value of hybrid systems in which automation supports, rather than replaces, expert interpretation and accountability [8].

4.1 Hybrid Intelligence in Marine Monitoring

Marine biodiversity monitoring presents conditions that favour combined human and automated approaches. Ecological signals are variable, detection depends on environmental conditions, and many species of regulatory concern are rare or difficult to identify visually. Automation performs well at scale and speed but is limited in contextual interpretation and accountability. Human expertise remains essential for assessing ecological significance, resolving uncertainty, and supporting defensible decisions.

Hybrid intelligence literature emphasizes allocating tasks according to these strengths: automated systems handle high-volume screening, while human experts retain responsibility for validation, interpretation, and action [8]. In offshore wind monitoring, this positions AI as a screening and prioritization tool, rather than an autonomous decision-making system.

4.2 Hybrid Use, Uncertainty, and Interpretation

AI-enabled monitoring produces early signals that require validation and context before being used for management or regulatory purposes. In offshore wind monitoring, where outputs may influence compliance assessments or stakeholder confidence, it is important to distinguish clearly between exploratory observations and evidence that has been reviewed and interpreted.

Combining automation with expert review helps manage uncertainty rather than eliminate it. Automated outputs reflect limits in training data and environmental conditions, while human interpretation introduces judgement and potential bias. Being explicit about how outputs are reviewed and used allows projects to benefit from automation without overstating certainty or undermining credibility [8].

4.3 Implications for Offshore Wind Practitioners

For offshore wind developers and regulators, adopting hybrid intelligence approaches has practical implications for resourcing, governance, and expectations. Automation does not remove the need for human expertise; instead, roles shift toward validation and decision support, with associated cost and capacity considerations that need to be recognized early in project design.

At the same time, hybrid systems provide a pathway to scale monitoring without sacrificing credibility. By combining automated screening with expert oversight, projects can increase temporal coverage, respond more rapidly to emerging issues, and communicate evidence more transparently. In offshore wind contexts, hybrid intelligence should be understood as a deliberate design choice that reflects the realities of marine ecosystems and environmental governance, rather than a compromise between technology and expertise.

5. EVIDENCE FROM EMERGING OFFSHORE PRACTICE

The application of real-time or near real-time AI species recognition in offshore wind is no longer purely conceptual. While few projects yet rely on AI-derived outputs as primary decision-grade evidence, a growing number of monitoring programs are using automated image analysis to augment traditional surveys, increase temporal coverage, and improve situational awareness. These early applications provide important lessons about what AI-enabled monitoring can realistically deliver, and under what conditions it adds value.

5.1 Fixed Infrastructure and Continuous Observation

One of the most promising emerging applications of AI species recognition in offshore wind involves the use of fixed camera systems on turbine foundations, substations, and associated scour protection. These installations provide relatively stable viewpoints and long operational lifetimes, making them well suited to continuous or high-frequency observation where monitoring objectives justify it.

Across a small number of European offshore wind projects and research-led trials, fixed cameras have been used to document fish and invertebrate presence around foundations, offering insights into colonization and localized use of structures that are difficult to capture through periodic surveys alone. In most cases, analysis has relied primarily on manual review, reflecting both the exploratory nature of these deployments and the need for caution in interpreting results.

Where AI tools have been trialled alongside fixed camera systems, they have generally been framed as supporting data screening rather than automated reporting. In these cases, automated methods are used to identify imagery that may warrant further attention, while interpretation and reporting remain subject to expert review.

5.2 Mobile Platforms and Operational Monitoring

AI-enabled species recognition has also been explored on mobile platforms, including ROVs and AUVs used for inspection, maintenance, and environmental surveys. These platforms generate large volumes of video footage during routine operations, much of which has historically been underutilized for ecological analysis due to the effort required for manual review.

In offshore wind, interest has focused on whether automated screening could support opportunistic biodiversity monitoring from inspection footage, allowing ecological observations to be extracted without dedicated survey time. This approach remains limited in scope and is not yet widespread and has so far been explored primarily through research-led initiatives and the opportunistic use of inspection footage, including programs such as SeaMe.

Where considered, the appeal lies in closer alignment between engineering and environmental activities: inspections undertaken for asset integrity may also provide ecological insight, provided that data quality, metadata, and validation requirements are addressed. However, footage collected on mobile platforms varies substantially in camera angle, speed, lighting, and proximity to structures. This variability introduces additional uncertainty for automated detection and reinforces the need for cautious interpretation and expert review.

5.3 Regional Initiatives and Collaborative Programs

Beyond individual projects, there is growing interest in whether AI-enabled monitoring could support learning at broader spatial scales. In European waters, research consortia and offshore renewable energy test sites have begun to explore combinations of fixed sensors, automated analysis, and shared data approaches to better understand habitat use and potential cumulative effects. These efforts remain exploratory, reflecting recognition that single project monitoring is often insufficient to capture broader ecological patterns.

Practical examples of this approach are already emerging within European offshore wind. The Rich North Sea Programme in the Netherlands has applied long-term, camera-based ecological monitoring around offshore energy infrastructure to support learning on habitat use and ecological function at program scale. Similarly, RWE's SeaMe initiative integrates underwater camera systems and digital monitoring tools across offshore wind assets to improve understanding of species-structure interactions and to inform adaptive environmental management. In both cases, AI-assisted analysis has been explored to support data screening and interpretation [14], [15].

Such initiatives highlight both the potential and the challenges of scaling AI-enabled monitoring. Shared datasets improve model training and benchmarking, but raise questions about data ownership, access, and standardization. Moreover, while regional analyses can reveal trends not apparent at site level, they also amplify the consequences of bias or error if validation is inconsistent. Early experience suggests that governance arrangements are as critical as technical capability in determining the success of these approaches.

5.4 What Practice Reveals about Limits

Across these emerging applications, several consistent limitations are evident. First, systems that perform well on fixed installations with stable conditions may struggle in turbid waters, during storm events, or on highly mobile platforms. Second, rare or cryptic species continue to require expert attention, limiting the extent to which automation can reduce human involvement. Third, the interpretive value of AI-derived indicators depends heavily on accompanying information about detection effort, environmental conditions, and system performance.

Practitioners also report a learning curve in organizational adoption. Integrating AI outputs into established monitoring and reporting workflows requires changes in roles, expectations, and quality assurance processes. Where these changes are not explicitly managed, AI risks being treated as an experimental add-on, rather than as a meaningful component of the monitoring system.

5.5 Lessons for Offshore Wind Monitoring

Taken together, emerging offshore practice suggests that real-time AI species recognition is most effective when deployed incrementally and transparently. Successful applications share several characteristics: clear articulation of what AI outputs are – and are not – used for; explicit separation between screening and decision-grade evidence; and early engagement with regulators and stakeholders to build understanding of methods and limits.

These lessons reinforce the argument that AI-enabled monitoring should be evaluated not solely on technical performance, but on its contribution to better environmental decision-making. In offshore wind, where monitoring serves scientific, regulatory, and social functions simultaneously, credibility depends on aligning automation with governance and expertise. The following section examines how these considerations intersect with ecological study design, and how AI-enabled systems can be integrated without undermining statistical robustness or interpretability.

6. INTEGRATING AI MONITORING WITH ECOLOGICAL STUDY DESIGN

The integration of AI-enabled species recognition into offshore wind monitoring does not remove the need for robust ecological study design. On the contrary, the increase in data volume and temporal resolution intensifies the importance of clearly articulated hypotheses, sampling logic, and analytical frameworks. Without these foundations, AI risks amplifying noise rather than improving ecological insight. For practitioners, the challenge is, therefore, not whether AI can collect more data, but how those data are structured, interpreted, and linked to meaningful ecological questions.

6.1 AI as an Extension, not a Replacement, of Study Design

Established approaches to impact assessment in marine environments – such as Before-After-Control-Impact (BACI) and related beyond-BACI frameworks – remain relevant in AI-enabled monitoring contexts. These frameworks provide the logic needed to distinguish project-related effects from natural variability, a distinction that automation alone cannot achieve. Continuous observation does not inherently resolve issues of confounding, pseudo-replication, or baseline selection; these must still be addressed through design.

AI can, however, extend the practical application of such frameworks. High-frequency data allow practitioners to characterize baseline variability more comprehensively, explore temporal patterns at finer resolution, and test assumptions that would otherwise remain implicit. For example, continuous imagery can reveal whether short survey windows are representative of broader conditions, informing decisions about survey timing and effort.

6.2 Detection Probability and Effort Standardization

A central issue in integrating AI outputs into ecological analysis is detection probability. Automated species recognition does not observe organisms directly; it detects visual signals that are themselves influenced by environmental conditions, camera performance, and model characteristics. Changes in detection rates may, therefore, reflect shifts in visibility, fouling, or system configuration rather than ecological change.

To address this, AI-enabled monitoring programs must explicitly define and document unit effort. This may include camera uptime, field of view, lighting regime, and environmental context (e.g., turbidity or current strength). Detection metrics should be normalized against these factors wherever possible, allowing practitioners to distinguish true biological patterns from artifacts of observation. The aquatic AI literature consistently emphasizes that failure to account for detection bias can lead to misleading conclusions, regardless of analytical sophistication [5].

6.3 Indicator Selection and Ecological Relevance

The availability of large volumes of automated detections can tempt analysts to focus on easily quantifiable metrics rather than ecologically meaningful ones. Counts of detections, for example, may be influenced by repeated observations of the same individuals or by behavioural responses to infrastructure. Integrating AI monitoring into study design, therefore, requires careful consideration of what indicators are intended to represent.

In offshore wind contexts, useful indicators may include presence-absence over defined temporal windows, relative activity levels of functional groups, or colonization trajectories on nature-inclusive design features. Importantly, indicators should be specified a priori, linked to management or learning objectives, and interpreted cautiously. AI-derived metrics gain value when they are clearly tied to hypotheses about habitat use, attraction, or avoidance, rather than treated as descriptive outputs.

6.4 Baselines, Controls, and Comparability

AI-enabled monitoring can strengthen baseline characterization by extending observations over longer periods and across a wider range of conditions. However, baseline data are only meaningful if they are comparable to subsequent observations. Changes in camera hardware, software updates, or model retraining can introduce discontinuities that complicate temporal comparisons.

Practitioners must, therefore, manage change carefully. Where system modifications are unavoidable, overlapping datasets or calibration exercises should be used to assess comparability. Similarly, where control sites are employed, consistency in sensor configuration and analytical workflows is essential. These considerations are familiar from traditional monitoring, but their importance is magnified when automated systems are involved.

6.5 From Data to Inference

Integrating AI monitoring into ecological study design ultimately concerns inference: what conclusions can legitimately be drawn from the data. Continuous automated observation can improve sensitivity to change, but it does not remove uncertainty. Statistical analysis must still account for variability, autocorrelation, and imperfect detection. Hybrid intelligence approaches, in which expert judgement informs interpretation, remain essential for translating patterns into understanding.

For offshore wind practitioners, the implication is clear. AI-enabled monitoring can enhance study design by expanding observational capacity, but it cannot substitute for ecological reasoning. When embedded within well-defined analytical frameworks, AI outputs can support more nuanced and responsive assessments of ecological change. When divorced from such frameworks, they risk becoming data-rich but insight-poor. The following section, therefore, turns to governance and data stewardship, examining how design, interpretation, and accountability intersect in AI-enabled monitoring systems.

7. GOVERNANCE AND DATA STEWARDSHIP

As AI-enabled monitoring becomes more common in offshore wind, governance and data stewardship move from supporting considerations to core design issues. Monitoring data inform regulatory decisions, influence stakeholder confidence, and shape how environmental performance is understood. In this context, the value of AI-derived evidence depends not only on technical performance, but on how data are managed, interpreted, and used in practice.

7.1 Governance beyond Technical Performance

AI-based monitoring systems influence what is detected, prioritized, and reviewed. Choices around training data, confidence thresholds, and validation protocols affect which signals are visible and which are missed. Research on so-called "smart ocean" governance – the growing use of digital and automated technologies in marine monitoring and management – shows that, without clear roles and accountability, such systems can shift decision-making authority away from regulators and subject-matter experts toward technology providers or data owners [9].

In offshore wind monitoring, this matters once automated outputs start to influence compliance or management decisions. Governance arrangements should clearly set out who interprets AI outputs, how uncertainty is addressed, and who is responsible if results are misunderstood.

7.2 Data Ownership, Access, and Transparency

Offshore wind monitoring typically involves multiple actors, including developers, consultants, regulators, and technology providers. AI-enabled systems generate large datasets that raise practical questions around ownership, access, and reuse. Clear data stewardship arrangements are essential to avoid disputes and maintain confidence in monitoring outcomes.

Data management principles such as accessibility, consistency, and reusability are increasingly referenced in environmental monitoring, but must be applied pragmatically in commercial and regulatory settings [16]. In practice, this often means tiered access to raw data, processed outputs, and visual summaries, depending on purpose and audience. Where AI is involved, transparency around how data are processed and reviewed is particularly important.

7.3 Communicating Uncertainty

Automated monitoring outputs can appear precise, especially when presented through annotated imagery or summary metrics. However, they inevitably reflect assumptions, detection limits, and environmental variability. If uncertainty is not communicated clearly, outputs may be over-interpreted or misused.

For practitioners, this places responsibility on how results are presented. Distinguishing screening information from evidence used to support decisions, documenting validation steps, and explaining known limitations are all essential. Visual outputs can support engagement, but only when accompanied by clear explanation of what they do – and do not – show [7], [9].

7.4 Regulatory Engagement and Learning

Early engagement with regulators is one of the most effective governance measures. When monitoring approaches are discussed during design, rather than after data have been collected, there is greater scope for shared understanding and improvement over time. Experience from marine governance shows that confidence in new monitoring methods benefits from transparent evidence and stakeholder engagement [9].

In offshore wind contexts, AI-enabled monitoring is most effective when positioned as a complementary tool that supports existing regulatory frameworks. Clear governance arrangements, transparent data handling, and accountable interpretation allow innovation to add value without undermining confidence in the monitoring process.

8. RISKS, LIMITS, AND RESPONSIBLE USE

Real-time AI species recognition can add value to offshore wind monitoring, but only if applied with care. The main risks are not technological failure, but misinterpretation, overconfidence, and inappropriate use of automated outputs in decision-making.

AI-derived observations can appear precise, particularly when visualized, yet they remain indicators rather than conclusions. Without context, detections – or absences – may be over-interpreted. Uneven performance across species further complicates interpretation, as automated systems tend to be least reliable for rarer or visually difficult-to-detect taxa, including those of regulatory importance.

Ultimately, AI-enabled monitoring is most effective when used as a complementary tool that supports expert assessment and learning. Applied correctly, it can strengthen evidence and responsiveness in offshore wind management.

9. CONCLUSION

Offshore wind development is entering a phase where expectations around environmental evidence are rising as quickly as installed capacity. Biodiversity monitoring is no longer judged solely on scientific adequacy, but on its ability to provide timely, credible, and interpretable information that supports regulatory confidence, operational decision-making, and stakeholder trust. Within this context, real-time AI species recognition offers a meaningful opportunity – but only if its role is clearly defined and responsibly governed.

This paper has shown that AI-enabled species recognition can address long-standing weaknesses in offshore wind monitoring, particularly gaps in temporal coverage and data processing capacity. Continuous visual observation, combined with automated screening, allows practitioners to move beyond episodic snapshots toward a more dynamic understanding of how organisms interact with offshore infrastructure. Used appropriately, this capability supports earlier detection of patterns, more responsive adaptive management, and improved learning about ecological responses around offshore structures.

The paper also sets out clear limits to what AI-based monitoring can and cannot do. AI outputs are sensitive to conditions and species characteristics. They do not constitute decision-grade evidence without validation, interpretation, and governance. The distinction between screening information and verified evidence is, therefore, central to maintaining credibility. Hybrid intelligence – where automation augments rather than replaces expert judgement – emerges as a practical and defensible model for offshore wind monitoring.

Equally important are the institutional dimensions of AI deployment. Data ownership, transparency, accountability, and communication of uncertainty shape whether AI-enabled monitoring strengthens or undermines trust. Governance frameworks that treat AI as a socio-technical system, rather than a neutral tool, are essential if automated monitoring is to contribute positively to environmental management and social licence.

In conclusion, real-time AI species recognition should not be framed as a technological solution in search of a problem. Its value lies in how it is integrated into well-designed monitoring programs, aligned with ecological objectives, and embedded within clear governance structures. When applied with realism and restraint, AI can help offshore wind monitoring evolve from retrospective compliance toward adaptive, evidence-informed practice – supporting both biodiversity outcomes and the responsible delivery of offshore renewable energy.

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REFERENCES

[1] E. S. Brondízio et al., Global Assessment Report on Biodiversity and Ecosystem Services, Intergovernmental SciencePolicy Platform on Biodiversity and Ecosystem Services, Bonn, Germany, 2019. doi: 10.5281/zenodo.3831673.

[2] Convention on Biological Diversity, "Kunming-Montreal Global Biodiversity Framework," CBD/COP/15/L.25, Dec. 18, 2022. [Online]. Available: https://www.cbd.int/gbf

[3] M. Elliott, Marine science and management means tackling exogenic unmanaged pressures and endogenic managed pressures – A numbered guide, *Marine Pollution Bulletin*, vol. 62, no. 4, pp. 651–655, 2010. doi: 1016/j.marpolbul.2010.11.033.

[4] A. Borja et al., "Moving Toward an Agenda on Ocean Health and Human Health in Europe," *Frontiers in Marine Science*, vol. 7, art. 37, 2020. doi: 10.3389/fmars.2020.00037.

[5] K. Malde, N. O. Handegard, L. Eikvil, and A.-B. Salberg, "Machine intelligence and the data-driven future of marine science," ICES *Journal of Marine Science*, vol. 77, no. 4, pp. 1274–1285, 2020. doi: 10.1093/icesjms/fsz057.

[6] S. Villon et al., "A deep learning method for accurate and fast identification of coral reef fishes in underwater images," *Ecological Informatics*, vol. 48, pp. 238–244, 2018. doi: 1016/j.ecoinf.2018.09.007.

[7] S. A. Reynolds et al., "The potential for AI to revolutionize conservation: a horizon scan," *Trends in Ecology & Evolution*, 2024. Advance online publication. doi: 10.1016/j.tree.2024.11.013.

[8] D. Dellermann, P. Ebel, M. Söllner, and J. M. Leimeister, "Hybrid Intelligence," *Business and Information Systems Engineering*, vol. 61, no. 5, pp. 637–643, 2019. doi: 10.1007/s12599-019-00595-2.

[9] K. Bakker and M. Ritts, "Smart oceans: artificial intelligence and marine governance," *Earth System Governance*, vol. 13, 2022, art. 100141. doi: 10.1016/j.esg.2022.100141.

[10] European Commission, Guidance Document on Wind Energy Developments and EU Nature Legislation, Brussels, Belgium, Nov. 18, 2020. [Online]. Available at: https://op.europa.eu/en/

publication-detail/-/publication/2b08de80-5ad4-11eb-b59f-01aa75ed71a1
[11] The Crown Estate, Offshore Wind Evidence and Change Programme, 2021. [Online]. Available at: https://www.thecrownestate.co.uk/our-business/marine/offshore-wind-evidence-and-change-programme
[12] S. Degraer, R. Brabant, B. Rumes, and L. Vigin, (eds.), Environmental Impacts of Offshore Wind Farms in the Belgian Part of the North Sea: Attraction, avoidance and habitat use at various spatial scales. Memoirs on the Marine Environment. Brussels: Royal Belgian Institute of Natural Sciences, OD Natural Environment, Marine Ecology and Management, 104 pp., 2021. [Online]. Available: https://tethys.pnnl.gov/sites/default/files/publications/winmon_report_2021_final.pdf
[13] R. Kelly, A. Fleming, and G. T. Pecl, "Social licence for marine conservation science," *Frontiers in Marine Science*, vol. 5, 2018. doi: 10.3389/fmars.2018.00414.
[14] The Rich North Sea Programme, "Monitoring and ecological research." Accessed: Sep. 2025. Available at: https://www.therichnorthsea.com
[15] RWE Renewables, "SeaMe – Sustainable ecological monitoring." Accessed: Sep. 2025. Available at: https://www.rwe.com/en/the-group/sustainability/biodiversity/seame
[16] M. D. Wilkinson et al., "The FAIR Guiding Principles for scientific data management and stewardship," *Scientific Data*, vol. 3, 2016. doi: 10.1038/sdata.2016.18.