From Ambition to Action

Human-Led Artificial Intelligence in Marine Planning and Governance

The Coastal Futures 2026 call to action provided a timely opportunity to reflect on the growing complexity of marine planning and governance in UK waters. This article explores how human-led artificial intelligence can help policymakers and practitioners keep pace by using evidence more effectively and make more informed decisions.

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Introduction

Marine planning and governance have expanded rapidly in scope and complexity as UK seas become increasingly congested [1, 2]. Yet the gap between policy ambition and the capacity for action has widened. Policymakers and practitioners face mounting pressure to make high-stakes trade-offs across a dense seascape of competing interests [3, 4]. These decisions determine who gets access to space, resources and environmental protection. Every decision or prolonged indecision now attracts greater public and political scrutiny, creating governance risks.

While managing the marine space has always involved balancing priorities and negotiating compromises [5, 6], there has been a step change in the nature of decision-making itself [7]. It has shifted from a largely sectoral perspective to one that is more interdependent and system-wide, making the marine space not just busy but contested.

The complexity of interdependencies shaping decision-making is beginning to outpace the capacity of institutions to process them effectively [8,9]. While conventional decision-making

processes remain essential, they are increasingly tested by rising data volumes, growing uncertainty and the urgency to act. This has driven a growing interest in artificial intelligence (AI) as a means of extending analytical capacity while keeping human judgement at the centre of consequential decisions [10, 11, 12].

At Coastal Futures, discussions around AI were present but not prominent, reflecting its early adoption in the marine sector rather than a lack of relevance. While tools such as ChatGPT and Copilot are becoming commonplace for individual productivity, more advanced applications, such as machine learning and generative AI, still remain unfamiliar to many policymakers and practitioners. Yet these tools are well suited to the scale, pace and complexity now facing marine planning and governance.

Division of Labour

Because planning and governance decisions are not purely technical, understanding AI's strengths and limitations is critical to its effective deployment. AI cannot determine what constitutes an acceptable trade-off, resolve stakeholder disagreements nor make ethical judgements. These choices demand human input and legitimacy [13,14,15]. However, AI's real value lies in enhancing human decision-making through deeper analysis and the integration of evidence [16]. This approach underpins the "human-in-the-loop" AI systems, which ensure outputs are reviewed, validated and, where necessary, corrected by human oversight (see illustration below).

Human oversight also improves reliability and contextual alignment, helping AI models respond to real-world complexity, ethical considerations and transparency requirements. This enhances decision-making meaningfully while preserving accountability [17]. In effect, it creates a deliberate division of labour, where AI compresses complexity upstream while humans retain authority downstream [17].

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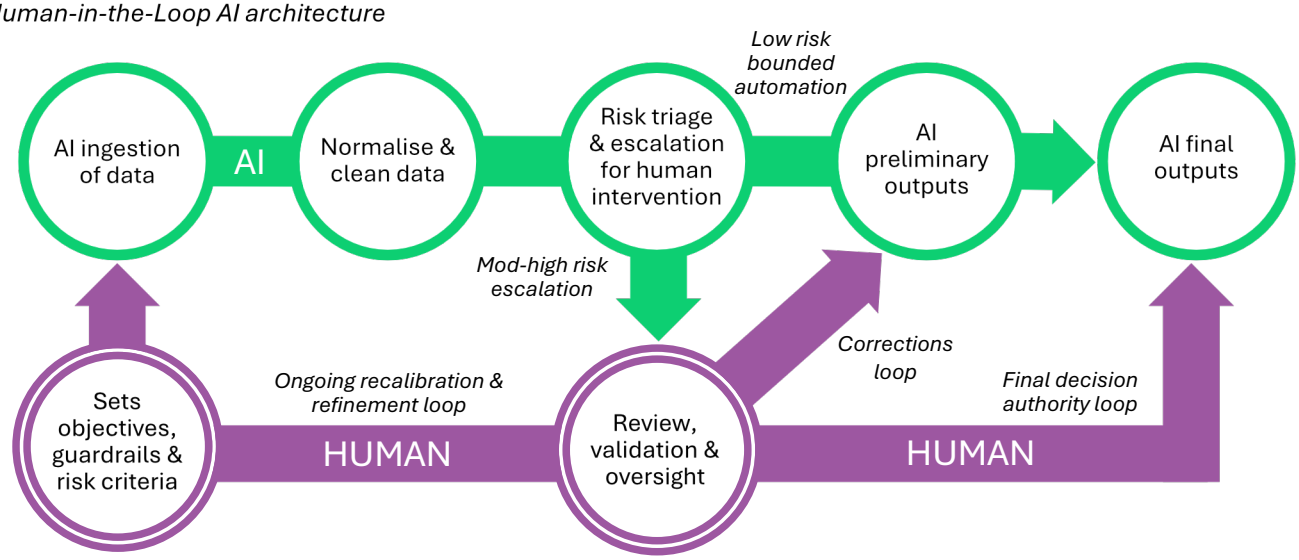
For decision support, augmenting human judgement rather than automating it is essential to maintaining public trust. Nowhere is that legitimacy more tangible than in coastal communities directly affected by marine planning decisions [5, 18]. For them, governance is not an abstract principle but an immediate and personal reality. Fishing livelihoods, cultural identity and local economies are all shaped by national-level planning and regulatory frameworks designed to balance competing interests at scales beyond any single community [6].

This makes transparency not just a procedural requirement but a condition of trust. The Crown Estate has developed a public-facing Marine Delivery Routemap platform to demonstrate how it intends to manage contested priorities through greater transparency and shared evidence [19]. The initiative provides public access to cross-sector

Human-in-the-Loop AI architecture



data on resource use, nature conservation, risks and opportunities.

The platform reflects a broader recognition that effective governance increasingly depends on synthesising information in ways that are both rigorous and accessible. In such data-intensive settings, human-led AI systems could further strengthen analytical capacity and scenario evaluation while preserving institutional accountability.

Making Sense of AI

Artificial intelligence refers to computer systems that learn statistical patterns from data rather than relying on fixed, rule-based instructions. It encompasses a range of tools and techniques that are being used in decision-support, planning and governance (see examples below). Unlike conventional software, AI systems learn to identify patterns across large datasets, generating predictions and recommendations, and apply them to new situations.

AI does not exercise judgement, but its outputs can extend analytical capacity by enabling inference and the synthesis of complex information at speed and scale. In turn, it provides a powerful means of exploring trade-offs across competing priorities and supporting decision-makers navigating complex systems.

The pace of AI development is accelerating on timescales measured in months rather than years [20]. Advances in computing power, data availability, and model architecture are driving rapid gains in technical capability. However, technological progress does not equate to institutional readiness. Building systems that policymakers, practitioners and stakeholders can trust requires human-in-the-loop validation and assurance.

In regulated, safety-critical and environmentally sensitive domains, responsible adoption doesn't mean slowing innovation, but embedding it within robust governance frameworks that preserve public legitimacy.

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Deploying AI

AI has become embedded across everyday technologies, from digital services and consumer applications to transport, infrastructure and industrial operations. These capabilities are increasingly being deployed in marine science and management, where they can uncover system-level patterns and insights that are difficult or impossible to identify using conventional analytical techniques [21].

Practical applications are advancing quickly, especially in remote sensing, species identification and site screening [22]. Their effectiveness is in

Commonly deployed AI tools in decision-support

Machine learning	The most widely deployed form of AI to applications such as risk prediction, anomaly detection and spatial suitability modelling.
Deep learning	A more specialised subset analysing high-dimensional data such as imagery and acoustic signals for tasks such as species detection and remote sensing.
Generative AI	Produces new content such as code, images, and structured analyses by learning from large datasets, and is used in scenario analysis and the synthesis of data in complex environments.
Multi-criteria techniques	Play a critical role in evaluating trade-offs across complex spatial & regulatory constraints in marine planning.

strengthening the analytical foundations that support decision-making. The following examples illustrate how AI is already being deployed in marine domains and highlight implications for marine planning and governance.

Early Screening

AI-enabled early screening enhances spatial precision, strengthens ecological risk detection, and improves transparency in offshore development decision-making. At the earliest stages of marine development, screening requires assessing large and complex areas to identify potentially suitable locations.

Traditional screening approaches typically rely on manual Geographic Information System (GIS) overlays and expert interpretation. By contrast, AI systems can operationalise large-scale geospatial analysis using machine learning, remote sensing and ecological modelling to generate more consistent site assessments with stronger scientific foundations.

Established screening and spatial modelling frameworks demonstrate the value of integrating remote sensing, acoustic monitoring, species distribution and multi-criteria decision analysis to support site-selection. AI techniques (e.g. Boosted Regression Trees and Maximum Entropy models) can deepen these capabilities by automating pattern recognition, scaling analysis across larger datasets, and improving predictive performance [23, 24, 26].

Machine learning models, for example, can rapidly screen large marine areas by combining wind or tidal resource estimates, seabed characteristics, grid proximity, and environmental sensitivities to identify suitable development and design options (e.g. VindAI, RESSAIG).

These approaches enhance the integration of longitudinal ecological datasets, enabling more robust predictions of seasonal and interannual variability [25, 26, 27]. By transforming previously labour-intensive assessments into AI-based screening processes, they reduce timescales while improving output consistency and scientific defensibility [28]. This lowers regulatory risk and strengthens stakeholder confidence.

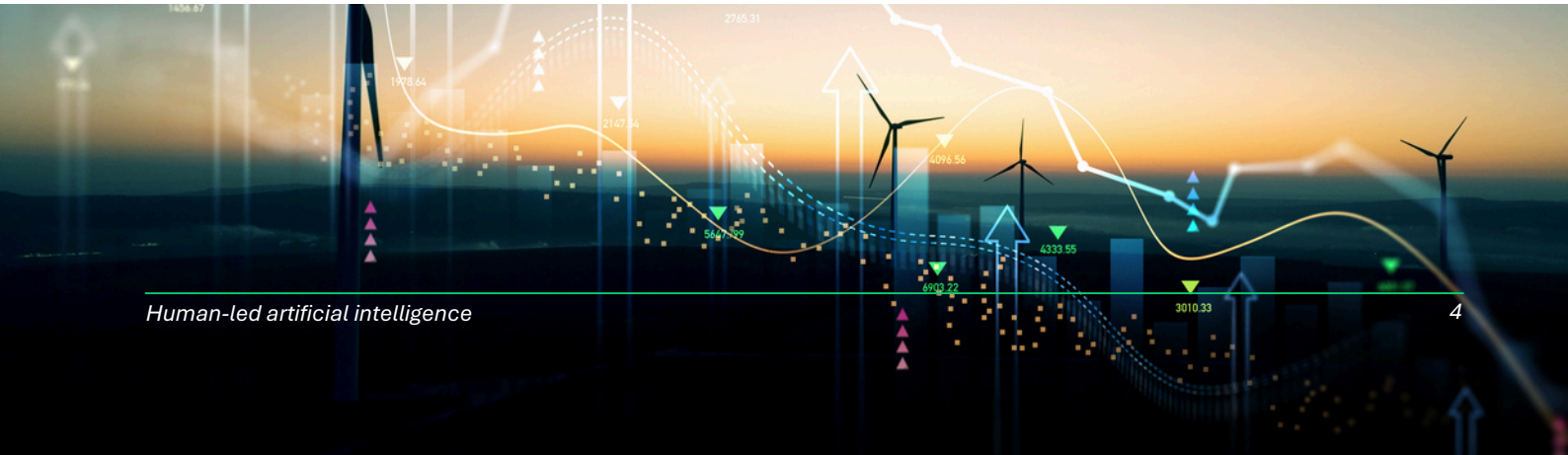
> *" AI-enabled optimisation is increasingly shaping how development options are assessed under competing regulatory, ecological and operational constraints."*

Marine Spatial Planning and Trade-Off Analysis

Within formal marine spatial planning, AI-enabled optimisation is increasingly shaping how development options are assessed under competing regulatory, ecological and operational constraints [29]. Traditional planning processes rely on digital mapping, scenario development and multi-stakeholder negotiation to navigate trade-offs, but can struggle to systematically evaluate the full combinatorial complexity of spatial configurations.

Recent advances in data-driven spatial optimisation, probabilistic modelling and model ensembling have improved the robustness of offshore marine planning under uncertainty [30, 31]. Building on established optimisation approaches used in conservation and spatial planning, machine learning techniques now allow planners to explore a wider range of scenarios and sensitivity conditions efficiently.

Artificial neural networks have also been integrated into offshore renewable energy modelling, including wind resource prediction, scenario generation and geospatial clustering of high-potential regions [32]. These approaches support a shift from individual site assessment toward portfolio-level and strategically clustered deployment across broader maritime areas.



Adaptive Management

Post-consent, AI-enabled monitoring systems are increasingly being piloted or deployed to integrate data from sensor networks, satellite observation, acoustic arrays and, in some cases, Supervisory Control and Data Acquisition (SCADA) systems [33]. These data streams can be integrated into digital twin models of offshore assets and their surrounding marine environments to support regulatory and operational oversight. When implemented, such systems combine real-time environmental observations, operational performance data and compliance indicators within continuously updated digital models [34]. However, their systematic adoption within post-consent regulatory frameworks remains limited.

Rather than replacing regulatory judgement, digital twins extend conventional monitoring by enabling structured scenario testing and predictive modelling. Machine-learning algorithms can identify anomalies in environmental or operational data streams, surface potential compliance risks and model cumulative environmental pressures under alternative operating regimes. Agent-based and simulation models can also be used to explore stressors, such as extreme weather events or seasonal ecological variability, prior to operational adjustments. This provides decision-makers with tools to evaluate trade-offs under uncertainty.

By enabling earlier detection of risks and allowing operational changes to be stress-tested against environmental thresholds, such systems have the potential to strengthen adaptive management within marine governance frameworks, consistent with ecosystem-based principles [19]. Importantly, they generate auditable data trails and transparent performance metrics that can be scrutinised by regulators and shared with stakeholders. This enhances regulatory oversight and accountability while maintaining human authority over consequential decisions.

Stakeholder Engagement and Conflict Mapping

AI–enabled text analytics can strengthen stakeholder engagement processes by systematically analysing large volumes of consultation submissions, public comments and policy responses. Using natural language processing techniques including topic modelling, semantic clustering and sentiment analysis, unstructured textual data can be synthesised into structured representations of recurring themes, value conflicts and areas of concern [25, 26].

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In large-scale marine consultations, where responses may number in the thousands, manual review can be time-consuming, inconsistent and vulnerable to selective interpretation [35]. AI-supported analytics can cluster submissions based on shared narratives, detect emerging patterns of opposition or support, and map the distribution of concerns across geographic, sectoral, or institutional boundaries. Crucially, these systems do not determine whose interests prevail - rather they provide decision-makers with greater situational awareness of the structure and intensity of stakeholder perspectives [17, 36].

Beyond simple sentiment scoring, more advanced techniques such as argument mining and stance detection can identify the reasoning underlying objections. This includes distinguishing ecological concerns from questions of fairness, economic impact or local anxiety. When integrated with spatial data layers, such tools can also support conflict mapping by linking textual concerns to defined planning areas or development zones.

By making areas of consensus and disagreement more transparent, AI-enabled engagement analytics can improve the clarity, consistency and auditability of consultation processes [13]. This contributes to procedural legitimacy by demonstrating that submissions have been systematically considered, while preserving the deliberative role of human judgement in resolving trade-offs. Enabling AI to augment institutional capacity for engagement without replacing the normative and political dimensions of governance.

Ethics and Guardrails

Ethics and guardrails are closely related but serve distinct functions. Ethics define the values and priorities that should guide AI decision support. Guardrails translate those ethical boundaries into technical, procedural and governance constraints that control how AI systems are used. Together, they help ensure AI outputs remain safe and align with human-defined legal and regulatory standards - particularly where decisions affect livelihoods, communities and fairness.

Most contemporary AI systems learn from historical data, which can provide powerful insights. However, they can also reflect past inequalities. In marine planning and governance, this means care is needed to check data quality, recognise potential biases and ensure different perspectives are represented.

Such safeguards ultimately depend on institutional judgement. Human oversight is central to contextualising AI outputs, testing assumptions and ensuring analysis informs judgement rather than pre-determining outcomes. This requires a willingness to challenge outputs and refine them to improve the quality and robustness of AI systems over time.

Embedding such scrutiny requires design choices that prioritise transparency and interpretability from the outset, rather than treating them as an afterthought. The table below outlines practical measures for policymakers and practitioners seeking to deploy AI responsibly.

Conclusion

AI cannot resolve the fundamental tensions at the heart of marine planning and governance. Trade-offs between development and conservation, national priorities and community interests, and short-term returns versus long-term environmental obligations require human judgement, political decision-making and democratic accountability.

Measures	Description
Documentation	Clear documentation of objectives, constraints, datasets and model limitations (for example, model cards and data sheets) to enable internal and external scrutiny.
Proportional Oversight	Standards for validation, version control and performance monitoring, with oversight proportionate to the potential impact of the system.
Accountability & Auditability	End-to-end auditability, linking data inputs to analytical outputs so that decisions can be reviewed, challenged and justified.
Participatory Workflows	Role-based, participatory workflows, including decision-maker sign-off, expert reviews and community engagement where outcomes affect local or indigenous interests.
Capability & Literacy	Investment in digital literacy and AI assurance capability across regulators, planning authorities and project sponsors.
Governance & Decision Rights	Clear governance structures, defining decision rights, escalation pathways and responsibility for model ownership and updates.
Security & Privacy Controls	Minimise unnecessary data collection, control access and stress-test compliance with legal, regulatory and policy obligations when conditions change or operate unexpectedly.

What AI can do is strengthen the institutional systems through which those judgements are made. It can enhance evidence synthesis, enable structured scenario testing, support adaptive management and improve transparency across complex spatial and regulatory decisions. Used deliberately, AI makes delivery at pace more achievable without sacrificing analytical rigour or public legitimacy.

The organisations best equipped to manage this complexity will not be those that adopt AI the fastest, but those that integrate it most thoughtfully. This means clear governance, transparency, robust oversight and sustained investment in digital literacy and a commitment to keeping human judgement at the centre of consequential decisions.

The question is no longer whether AI has a role in marine planning and governance, but whether institutions are building the literacy, frameworks and organisational culture needed to use it responsibly.

As UK seas become more congested and decisions more contested, the delivery gap will continue to widen without stronger decision support. The AI toolbox already exists and is advancing rapidly, but uncertainty and hype risk slowing adoption. Policymakers and practitioners who focus less on technological novelty and more on deliberate integration into existing governance practices will be best placed to bridge this gap.

About the Author

Dr Steve Freeman is the founding director of REP and has over 30 years' experience in marine management, offshore wind, energy policy, strategy, and stakeholder engagement.

He has advised governments and senior industry leaders globally on markets and infrastructure delivery. Over the past two years, Steve has worked closely with AI technology and consulting firms to support the application of AI in the energy transition, and human-led decision-support to advance renewables deployment and marine governance.

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