Artificial Intelligence and Machine Learning for Australian Marine Science

NMSC White Paper – 2025-2035

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1 Executive summary

Australia's vast marine territories and growing ocean data collections require Artificial Intelligence (AI) and Machine Learning (ML) to overcome data processing bottlenecks, extract meaningful insights, and support timely, data-driven decision-making. These technologies can automate routine tasks, enable real-time analysis and support integrated modeling and sampling design, ultimately shifting from reactive to proactive management. The strategic imperative to adopt AI/ML is clear — with increasing environmental pressures and growing data demands, AI/ML is essential for unlocking the full value of marine data, enabling effective conservation, sustainable resource use and climate resilience.

This paper identifies numerous stakeholders who stand to benefit from AI/ML in marine science, including government agencies, researchers, industry, Indigenous custodians, policymakers and the general public. A national survey of 42 projects across 18 institutions reveals a diverse range of applications in marine biodiversity conservation, ocean monitoring, fisheries and climate science. However, the survey also highlights critical dependencies, barriers and capability gaps, including funding uncertainty, personnel shortages, infrastructure constraints, data issues and regulatory complexities.

To overcome these challenges, the paper recommends several key actions. These include strengthening human capital through interdisciplinary training and new roles, investing in high-performance computing and data storage, improving data availability and quality through standardized metadata and sharing mechanisms, addressing structural funding barriers with multi-year funding streams and building strategic partnerships across sectors. The implementation strategy emphasizes scaling up through targeted funding, recruiting cross-disciplinary experts, developing collaborative partnerships and establishing regulatory frameworks that support innovation while providing clarity. It also calls for consolidating related initiatives under larger, coordinated programs to reduce redundancy and facilitate data flow.

Ensuring responsible and effective AI/ML use is paramount, requiring trust, transparency, human-centric design and ethical frameworks. This includes proactively managing ethical and transparency concerns, establishing governance frameworks and institutional policies for responsible use and prioritizing explainability in AI/ML outputs. Measuring progress will involve defining clear impact metrics, establishing baseline data, engaging stakeholders and tracking downstream use.

Australia possesses good foundational data resources but must address funding, personnel and government staffing challenges to fully leverage AI/ML for marine science. Strategic investment and enhanced collaboration has the potential to establish Australia as a global innovator, effectively addressing the complex challenges facing its marine environments and positioning itself as a leading contributor to global efforts in marine AI.

2 Relevance – Societal Benefits

2.1 Why does Australia need to pursue AI/ML in marine science?

2.1.1 An Island Nation

Australia, a nation intrinsically linked to its vast marine estate, has one of the world's largest ocean territories, stretching from the tropics to the sub-Antarctic (Geoscience Australia, 2022). Our marine ecosystems are biologically rich, economically valuable and culturally significant. This extensive marine estate underpins Australia's "blue economy", a sector encompassing activities such as fishing, aquaculture, tourism, offshore oil and gas and naval operations. It contributes over $100 billion annually to Australia's Gross Domestic Product (GDP), positioning it as the 12th largest industry in the Australian economy (Australian Institute of Marine Science, 2023). The health and resilience of these marine ecosystems are therefore critically important for sustained national prosperity (Australian Institute of Marine Science, 2023). Much of our scientific understanding of these environments ultimately depends on the interpretation of ocean observations and environmental data (Brett et. al. 2022). These data are critical to inform effective decision-making in the designation and assessment of marine protected areas, establish environmental baselines and to assess human impacts, such as fishing, offshore energy generation and climate change (Ditria et al., 2022). As these pressures increase, timely, data-driven decision-making is more critical than ever (Ditria et al., 2022).

2.1.2 Growing Data, Growing Demands

Australia has made significant investments in ocean data collection through marine research programs and national facilities like IMOS, AIMS and CSIRO (Proctor et al., 2010; Vercelloni et al., 2025; Lynch et al., 2014; Lara-Lopez et al., 2016). These efforts have resulted in vast quantities of marine data – from imaging and video to sensor-based environmental readings. However, the rapid growth in data has outpaced our capacity to efficiently analyse and extract meaningful insights from it (Durden et al., 2016).

For example, in the domain of marine imaging, the IMOS Understanding Marine Imagery Facility (IMOS 2025) has approximately 10 million images from almost 20 thousand deployments across various platforms and institutions (Friedman et al., in-prep). All these data are available for exploration and analysis, but less than 3% have been annotated. This represents a huge deficit in image processing, which is compounded by the considerable cost and time-consuming nature of manual image annotation. With an estimated cost of AU$3-$15 per manually annotated image (Katija et al., 2022), this represents up to AU$30-150 million worth of investment that would be required to manually analyse all the collected image data.

The time and expertise required for manual data collection, extraction, annotation and identification across various data types represent a significant financial burden and a major constraint on research productivity. This burden is amplified by the sheer volume of data being generated.

2.1.3 The Role of AI/ML in Overcoming Bottlenecks

The rapid growth of marine data collection has created a critical gap between data acquisition and our ability to extract meaningful insights. Traditional manual analysis methods cannot scale to meet current demands, creating bottlenecks that delay scientific progress and decision-making. When properly developed, validated, and governed, Artificial Intelligence (AI) and Machine Learning (ML) can:

- Dramatically reduce the time and cost of data processing (e.g., image annotation, habitat mapping).
- Enable new lines of enquiry by offering previously impractical or unattainable data products (e.g., accurate size information, through segmentation of mosaics and images).
- Enhance the accuracy, speed, temporal and spatial extents of marine monitoring and forecasting.
- Provide tools for understanding species distributions, ecosystem dynamics and environmental change.
- Reduce the need for direct human intervention in hazardous environments by enabling smarter and more adaptive autonomous systems and decision-making for complex tasks, improving safety and reducing reliance on divers and manned submersibles.

These capabilities represent a fundamental shift in how we approach marine data analysis, moving from labor-intensive manual processes to intelligent systems that can process information at unprecedented scale while maintaining scientific rigor. By addressing these bottlenecks, AI/ML will enable marine science to fully capitalize on the wealth of data now being collected.

2.1.4 Advancing Marine Science and Innovation

These technologies enable a transition from reactive to proactive management by delivering timely, data-driven insights at scale. AI/ML technologies can accelerate the pace of scientific discovery and enable new lines of enquiry by:

- Automating routine and complex tasks in research workflows.
- Enabling real-time data analysis for rapid environmental response.
- Supporting integrated modelling for cumulative impact assessments.
- Providing new ways to synthesise multidisciplinary data sources.

This transformation also allows marine scientists to focus more on interpretation and high-level decision-making, while machines handle repetitive processing tasks.

2.1.5 A Strategic Imperative

The integration of AI/ML into marine science is not merely an incremental improvement but represents a fundamental shift required to achieve national marine science goals. This is particularly true for objectives related to large-scale monitoring and developing predictive capabilities in the face of escalating environmental pressures. National marine science plans, such as AIMS Strategy 2030, Geoscience Australia Strategy 2028 and the National Marine Science Plan 2015–2025, consistently emphasise the need for long-term monitoring, understanding climate change impacts and sustainable management (Australian Institute of Marine Science, 2023; Geoscience Australia, n.d.; National Marine Science Committee, 2015). The adoption of AI/ML in marine science represents a significant opportunity to address growing data challenges. These technologies help to maximise the utility of existing and future marine data collections, potentially supporting conservation efforts, resource management and climate adaptation strategies. Strategic investment in responsible AI/ML applications can enhance Australia's capacity to monitor and understand its marine environments while contributing to global marine science advancements.

2.2 Who will benefit from AI/ML in marine science?

AI/ML technologies offer transformative potential for a wide range of beneficiaries in the marine science ecosystem. These tools enhance the ability to collect, interpret and act on marine data – benefiting decision-makers, users of the marine environment and those working to protect it.

1. **Government Agencies:** Government bodies, including fisheries departments, environmental agencies and regulators, stand to derive significant benefits from the adoption of AI/ML technologies, with application in areas such as stock assessment, resource management and monitoring. AI/ML tools can inform crucial decisions like offshore infrastructure decommissioning and support evidence-based policy development through enhanced data quality, spatial information and predictive modelling for climate change and species distribution. Efficiency gains through automation in areas like electronic monitoring review reduce costs and provide greater surety of catch statistics and bycatch knowledge, supporting regulatory roles and social license. Data also informs infrastructure planning and management.

2. **Marine Science Researchers:** Academic and applied research institutions benefit significantly from access to extensive, high-quality and often unique datasets and large annotated data collections. AI/ML methods represent powerful new tools, models and platforms that accelerate research, improve efficiency and enable new lines of enquiry. These advancements enhance understanding of complex marine processes, ecosystems and species, foster national and international collaboration and build capacity in cutting-edge research areas like AI-driven marine science and ecology.

3. **Research and Academia:** The Research and Academia sector broadly benefits from the generation of new knowledge, advanced methodologies and valuable datasets across numerous marine science disciplines. AI/ML projects provide access to state-of-the-art tools (algorithms, models, software) and data resources (annotated imagery, curated databases) that support further research, comparative studies and the development of transferable knowledge. These initiatives foster collaboration, enhance research capacity, provide training

opportunities, democratise complex fields like ecosystem modelling and contribute to Australia's reputation as a leader in marine science.

4. **Industry and Businesses:** Sectors such as commercial fisheries, aquaculture, tourism and offshore energy benefit from improved environmental intelligence that reduces operational risk, supports compliance and enhances sustainability. AI-powered early warning systems (e.g. for harmful algal blooms) can help protect assets, while better stock assessments and habitat monitoring would support more resilient planning and resource use. The oil and gas industry benefits from science informing decommissioning decisions and marine industries gain efficiencies in meeting environmental monitoring requirements. Automation in data collection and analysis offers cost reductions and supports sustainable resource management, while enhanced conservation and understanding of marine ecosystems can boost eco-tourism and maintain social license.

5. **Traditional Owners and Indigenous Custodians:** Local communities and Indigenous ranger groups benefit from tailored, accessible data that enhances stewardship of Sea Country and community-based monitoring. By investigating ways to integrate traditional knowledge into AI/ML workflows and generating useful, culturally aware outputs, there is potential to strengthen cultural and environmental outcomes, supporting equity and self-determination in marine management.

6. **Policy Makers:** Government and intergovernmental policy makers benefit from improved access to robust, science-based evidence, enhanced data quality and predictive models to support informed decision-making across various marine domains. AI/ML projects can provide critical information for climate change adaptation planning, fisheries management (including regulations and quotas), spatial planning, habitat protection and managing impacts. Automation and improved monitoring techniques offer more responsive data outputs, potentially shortening research-to-policy timelines and enabling more targeted and effective management strategies. The development of accessible reporting tools also aids policy application.

7. **International Organisations:** Outputs can also support global efforts to identify and protect Vulnerable Marine Ecosystems (VMEs) and align with UN Sustainable Development Goals. Access to global datasets, platforms and improved monitoring techniques enhances international collaboration and reporting on the status of marine environments like coral reefs.

8. **Education and Training Sectors:** Universities, vocational training providers and educators benefit from the creation of new interdisciplinary pathways that integrate marine science, AI and data analytics. These emerging domains foster skills that are increasingly critical for future research, management and industry innovation.

9. **General Public:** The public benefits broadly across numerous projects, primarily through advancements in habitat and biodiversity conservation and the protection of fishery resources. They gain from improved understanding and management of marine environments, access to more robust climate projections for informed decision-making and enhanced public health protection via better monitoring of risks like harmful algal blooms and associated seafood safety. Furthermore, public interest is captured by projects focusing on charismatic species and they benefit from restored ecosystems (like coral reefs), access to information via reporting tools and sustainable management of recreational activities and resources.

2.3 Challenges and Opportunities

The NMSC has outlined several key focus areas, drawing from the SOP, Australia's National Science and Research Priorities and the UN Ocean Decade Challenges, among other sources, to guide the development of the new National Marine Science Strategy (NMSS). Topics to address include:

1. **Enabling a Sustainable Blue Economy:** This challenge centres on the sustainable use of ocean resources to foster economic growth, environmental health and social equity. AI/ML can contribute by improving fisheries management through more precise biomass estimation, aiding in sustainable catch limits and long-term fish stock viability; supporting the development of resilient coastal infrastructure that benefits local economies; creating tools and frameworks for effective conservation management; and striving to balance economic activities with the imperative to maintain healthy marine ecosystems, recognising that a thriving ocean underpins a sustainable blue economy.

2. **Integrated Ocean Management:** This challenge involves a holistic approach to managing human activities in the ocean for long-term environmental health and productivity. AI/ML can support this by developing conservation tools applicable across jurisdictions, creating dynamic predictive models to assess ecosystem risks and promoting coordinated strategies to address complex and interconnected marine challenges.

3. **Maintaining Food Security:** This challenge focuses on ensuring a reliable and sustainable food supply from the ocean. AI/ML can support the sustainable management of commercial and recreational fisheries, vital to many communities and assess and mitigate human impacts on coastal fish populations, which are especially important for local food security.

4. **Optimizing Resource Allocation and Management:** This challenge is about making informed decisions on marine resource use to maximise benefits while minimising harm. AI/ML can contribute by delivering essential data and decision-support tools for fisheries management and assessing fish population health and status to guide sustainable resource allocation.

5. **Protecting Biodiversity and Ecosystem Health:** This challenge centres on conserving marine species and habitats. AI/ML can promote the protection of diverse ecosystems and their biodiversity, assess and mitigate human impacts on marine life and ecological processes, develop tools for environmental impact assessments and enhance understanding of species distribution, behaviour and relationships.

6. **Climate and Oceans:** This challenge addresses the ocean's role in regulating climate and the impacts of climate change on marine systems. AI/ML can promote conservation under climate stress, improve climate predictions through high-quality ocean data, assess and mitigate adverse climate impacts on marine ecosystems and study key oceanographic and biological variables to better understand climate-related changes.

7. **First Nations and Sea Country:** This challenge involves integrating traditional knowledge and the rights of First Nations people in marine management. AI/ML can support biodiversity and habitat conservation through meaningful collaboration with First Nations communities, recognising and respecting their deep cultural connections to Sea Country.

8. **Ecosystem Restoration and Repair:** This challenge is focused on reversing damage to marine ecosystems to restore their health, resilience and productivity. AI/ML can contribute by promoting habitat restoration and supporting biodiversity recovery in degraded marine areas.

9. **Energy Security, Diversification and Achieving Net-Zero:** This challenge explores the ocean's potential for sustainable energy and climate mitigation. AI/ML can support this by developing tools to assess and manage the environmental impacts of marine energy activities.

10. **Planning Urban and Coastal Development, Infrastructure and Services:** This challenge ensures development is sustainable and minimises marine impacts. AI/ML can provide key data and tools for coastal monitoring, reporting and management and assess potential impacts of infrastructure projects on ecosystems and vulnerable species.

11. **Maintaining Sovereignty, Securing and Defending Australia:** This challenge highlights the need to use marine resources and spaces in ways that uphold national security. AI/ML can support enhanced monitoring and surveillance of Australian waters to safeguard national interests and maritime security.

12. **Protecting Australia's Cultural Heritage:** This challenge is about preserving culturally significant marine sites and resources. AI/ML can develop adaptable tools and approaches for marine management that include protecting cultural heritage.

13. **Climate and Green Engineering:** This challenge encourages the use of eco-friendly technologies in the marine sector to minimise environmental harm. AI/ML can contribute by

developing tools and methods that promote green engineering across marine management domains.

14. **Ocean Accounting:** This challenge focuses on valuing the ocean's economic, social and environmental contributions. AI/ML can support the development of tools and methodologies applicable to marine management, including ocean accounting practices.

15. **Safety at and from, the Sea (Natural Hazards and Early Warning Systems):** This challenge seeks to enhance safety and preparedness for natural hazards in marine environments. AI/ML can help by developing versatile tools and approaches for marine safety, monitoring and early warning systems.

3 Current State of the AI/ML in marine science

3.1 AI+ML project survey results

A survey was conducted to collect input from a targeted focus group on the current state of AI / ML in Australian marine science. There were 31 participants who contributed data on 42 projects across 17 different institutions (Table 1).

Table 1: *Titles, summaries, partners, funding and subjective Technology Readiness Level (TRL) (Mankins, 1995) for each AI/ML project submission. The # column denotes the project ID which will be referred to throughout this document.*

#	Project Info	$ / [TRL]
11	**Esso Offshore Decommissioning Research**: Investigates influence of offshore oil/gas structures on marine ecosystems for sustainable decommissioning. Uses ML, statistical modeling, computer vision and AI visualization for species identification and dispersal pathway modeling. *Partners: Industry Partner, University/Research Institute*	$1M+ [9]
31	**ReefCloud**: Platform facilitating global coral reef monitoring and preservation. Its ML backend scales image-based sampling by reducing manual annotation and centralizing datasets. *Partners: University/Research Institute, Government Agency, Non-profit/NGO*	$1M+ [9]
45	**SQUIDLE+:** Software platform for managing, discovering and annotating marine imagery. Offers exploration interfaces, annotation workflows, reporting and analytics using human and/or automated ML annotation. *Partners: University/Research Institute, Government Agency, Industry Partner, Non-profit/NGO*	$1M+ [8]
28	**Flying Fish Marine Data Collection:** Utilizes breakthrough technology and AI/ML to generate actionable insights from large marine visual datasets for national scale conservation impact. Offers efficient and scalable marine surveys. *Partners: Industry Partner*	$1M+ [6]
30	**HAB Species Detection System**: Develops advanced ML detectors for identifying harmful algal bloom species in microscope imagery to support critical early warning systems. Enhances monitoring and minimizes economic losses. *Partners: Government Agency*	$1M+ [6]
32	**Strategic AIML for Tuna Fishery**: Delivers cost-efficiencies using AI/ML to identify and count fish catch and bycatch from electronic monitoring video in Australia's tuna fishery. Reduces costs and increases coverage. *Partners: Government Agency*	$1M+ [6]
40	**Multi-species Seagrass Detection**: Introduces first multi-species detector/classifier for seagrasses based on deep CNN. Enables automated broad-scale mapping of critical seagrass ecosystems needing protection. *Partners: Government Agency*	$50K-$100K [5]

39	**Weakly Supervised Coral Reef Segmentation**: Proposes approaches for coral reef imagery to reduce costly manual labelling. Enables high-resolution coral species monitoring for climate threats and bleaching events. *Partners: Government Agency*	$50K-$100K [3]
24	**LLM for Bespoke Reporting**: Leverages LLMs to make large, comprehensive reports more accessible and useful. Facilitates real-time, science-informed decision-making through improved reporting pipelines. *Partners: University/Research Institute, Government Agency, Industry Partner*	$1M+ [2]
12	**Global Library of Underwater Sounds**: Creates reference library of aquatic fauna sounds and datasets to develop AI detectors for mapping distribution, biodiversity and health. Enables fast, low-cost analysis and potential real-time detection of changes. *Partners: University/Research Institute, Government Agency*	$50K-$100K [1]
29	**Benthic Vision Architecture**: Develops advanced transformer-based classification systems using ML for benthic substrates to support spatial management and protection of vulnerable marine ecosystems in Australia and NZ. *Partners: Government Agency, Industry Partner*	$1M+ [0]
14	**WA Temperate Shark Fisheries AI**: Collaboration between WAFIC and WA Government developing AI algorithm for species identification in gillnets used by commercial shark fishing vessels to speed up electronic monitoring. *Partners: Industry Partner*	$500K-$1M [7]
25	**Ningaloo Climate Vulnerability Assessment**: Co-produces preliminary climate vulnerability assessment of Ningaloo Coast World Heritage Area. Provides high-quality local climate information for planning ecosystem resilience under climate change. *Partners: University/Research Institute*	$500K-$1M [6]
33	**AIML for Sub-Antarctic Fisheries**: Delivers cost-efficiencies using AI/ML to identify and count fish catch and bycatch from electronic monitoring video in Australia's sub-Antarctic fishery. Improves sustainable and profitable operations. *Partners: Government Agency*	$500K-$1M [6]
10	**GBR Climate Impact Modeling**: Applies Super Resolution CNN and GAN to downscale future climate projections for the Great Barrier Reef. Provides robust, improved climate projections for adaptation and mitigation planning. *Partners: University/Research Institute, Government Agency*	$500K-$1M [5]
23	**Thermal Coral Prediction Models**: Uses ML to build predictive models for selecting thermally tolerant corals based on offspring survival under climate change. Enhances reef protection supporting tourism, fisheries and coastal protection. *Partners: University/Research Institute, Industry Partner*	$500K-$1M [2]
17	**Automated Fish Counts on Shellfish Reefs**: Uses AI data extraction from unbaited underwater videos for automated fish counts and sizing on restored shellfish reefs. Provides robust measures of fisheries production enhancement. *Partners: University/Research Institute, Non-profit/NGO*	$100K-$500K [9]
20	**Northern Australian Marine Monitoring Alliance**: Collaboration supporting Indigenous Rangers and Traditional Owners in sustainably managing Sea Country using modern scientific methods for monitoring marine environments in Indigenous Protected Areas. *Partners: Government Agency, PBCs*	$100K-$500K [8]
19	**CuCount Software**: Software and reporting dashboard for automated sea cucumber counts in ROV survey videos. Makes benthic surveys for harvested species more efficient and reliable for decision making. *Partners: University/Research Institute, Industry Partner*	$100K-$500K [7]
26	**Reef Guidance Systems**: Develops real-time, edge-in-field decision-making to guide coral recruit deployment for reef restoration. Enables scaling restoration by automating deployment and improving recruit survival. *Partners: University/Research Institute, Government Agency*	$100K-$500K [7]
5	**Pygmy Blue Whale Distribution Modeling**: Uses AI/ML on 30 years of acoustic recordings to identify blue whales and model distribution against environmental factors. Critical for marine spatial planning to avoid disturbing feeding/breeding areas. *Partners: University/Research Institute*	$100K-$500K [6]
43	**Targeted Knowledge Extraction for AMPs**: Used SQUIDLE+ to develop ML models converting low-level annotations into high-level Essential Ocean Variables. Streamlines and standardizes benthic imagery interpretation for Australian Marine Parks. *Partners: University/Research Institute, Government Agency*	$100K-$500K [6]
4	**GNN-Based Coastal Sediment Dynamics**: Advances understanding in Darwin Harbour using Graph Neural Networks to study wave-current interactions and sediment processes. Informs engineering and design by forecasting beach morphology, promoting sustainable infrastructure. *Partners: University/Research Institute*	$100K-$500K [4]
27	**Automated Scallop Detection**: Develops ML solutions for automating scallop detection and sizing in underwater towed camera footage. Provides critical data for sustainable fisheries management and stock assessment. *Partners: University/Research Institute, Government Agency*	$100K-$500K [4]
6	**MegaMove - Marine Megafauna Movement**: Global effort for marine megafauna conservation, mitigating threats using innovative science and leveraging movement/environmental data. Uses ML and statistical modeling to understand animal patterns. *Partners: University/Research Institute, Government Agency, Non-profit/NGO*	$100K-$500K [3]

7	**Marine Ecosystem Modeling**: Explores generative AI for marine ecosystem modeling including validation and best practices. Seeks to democratize modeling for stakeholders with application-agnostic approaches for whole-of-system models. *Partners: Government Agency, University/Research Institute*	$100K-$500K [2]
41	**Self-supervised Marine Feature Learning**: Develops techniques using unlabelled data to enhance ML for rapid marine imagery processing using SQUIDLE+. Addresses challenge of limited expert annotations for Australia's vast marine territory. *Partners: University/Research Institute, Industry Partner*	$100K-$500K [0]
3	**ML Toolkit for Sea Urchin Impact Assessment**: Supervisory role using ML tools to assess long-spined sea urchin impacts across SE Australia and NZ. Focuses on habitat loss affecting conservation and fisheries. Uses object detection and habitat classification through SQUIDLE+. *Partners: University/Research Institute*	<$50K [8]
42	**SQBOT**: Toolchain streamlining ML tool integration into SQUIDLE+, connecting ML researchers with training data and marine scientists with ML outputs. Streamlines development, deployment and access to models. *Partners: University/Research Institute, Government Agency, Industry Partner, Non-profit/NGO*	<$50K [8]
35	**RapidBenthos**: AI tool integrating SAM and ReefCloud annotation to automate ecological information extraction from orthomosaics. Provides rapid assessment of coral community composition for timely detection of ecosystem changes. *Partners: University/Research Institute, Government Agency, Industry Partner*	<$50K [7]
18	**Automated Estuarine Fish Monitoring**: Uses automated data extraction from remote underwater video stations to identify and count fish species indicating ecosystem health. Improves robustness and efficiency in estuarine health assessments. *Partners: University/Research Institute, Government Agency*	<$50K [6]
13	**Remote Camera Vessel Retrieval Automation**: Implements detection, tracking and counting of recreational vessel retrievals in Western Australia via camera network. Uses YOLO v11 and statistical modeling to scale recreational survey data. *Partners: Government Agency*	<$50K [5]
8	**AI Fish Length Estimation**: Explores AI to estimate fish sizes from angler photos, providing valuable data for assessing recreational fish species. Addresses assessment issues, conservation and management priorities. *Partners: University/Research Institute, Non-profit/NGO, Industry Partner*	<$50K [4]
22	**SealSpotter**: Uses ML to count fur seals from drone images, leveraging citizen science to train algorithms. Algorithms highly transferable for counting camouflaged and entangled seals. *Partners: University/Research Institute*	<$50K [4]
9	**IQuOD Database**: Creates a climate-quality database of historical ocean temperature profiles with consistent quality control and uncertainties. Uses basic ML for quality control and metadata estimation. *Partners: University/Research Institute, Government Agency, Industry Partner, Non-profit/NGO*	<$50K [3]
21	**AI for Marine Fauna Detection**: Uses AI for marine fauna detections from acoustic receivers, underwater video and aerial imagery. Expedites data processing to understand species occurrence and distribution in remote areas. *Partners: Industry Partner, University/Research Institute*	<$50K [3]
34	**Marine Protected Species Management**: Uses AI/ML to detect wildlife as part of a deterrent device to reduce harmful interactions between seabirds and humans. Addresses changes in species distribution and abundance. *Partners: Government Agency*	<$50K [3]
15	**Automatic Crustacean Sizing**: Focuses on automated sizing of crustaceans onboard commercial vessels using video footage. Mitigates need for onboard observers and facilitates logbook data validation using segmentation masks. *Partners: Government Agency*	<$50K [2]
16	**LLM for Fishing Survey Text Analysis**: Leverages language-based modeling to process free text responses from recreational fishing surveys. Enables improved survey design and insights into participant satisfaction and issues. *Partners: Government Agency*	<$50K [2]
44	**Enhancing Marine Habitat Observations**: Doctoral thesis research adapting and enhancing ML for marine species detection in underwater imagery. Focuses on compensating for limited labelled data to increase marine scientists' productivity using SQUIDLE+. *Partners: University/Research Institute*	<$50K [2]
38	**Auto-Labeling for Marine Images**: Combines human and machine labelling with context knowledge for large-scale, accurate interpretation of benthic images with minimal human effort. Leverages large models adapted to marine science. *Partners: University/Research Institute*	<$50K [1]
36	**Reef Life Survey Habitat Reporting**: Uses ML algorithms in SQUIDLE+ to efficiently deduce changes across broad scales for shallow reef habitat cover. Provides standardized data source for large-scale reporting. *Partners: University/Research Institute*	<$50K [0]

Most AI/ML projects surveyed originate from University / Research Institutes and Government Agencies. Figure 1 shows a breakdown of project partners by organisation type.

Figure 1: *Breakdown of projects partners by organisation type*

Projects were spread across several marine science applications, with the top three domains being Marine Biodiversity & Conservation, Ocean Monitoring & Observation and Fisheries & Aquaculture. Figure 2 shows the breakdown of projects across the marine science application domains.

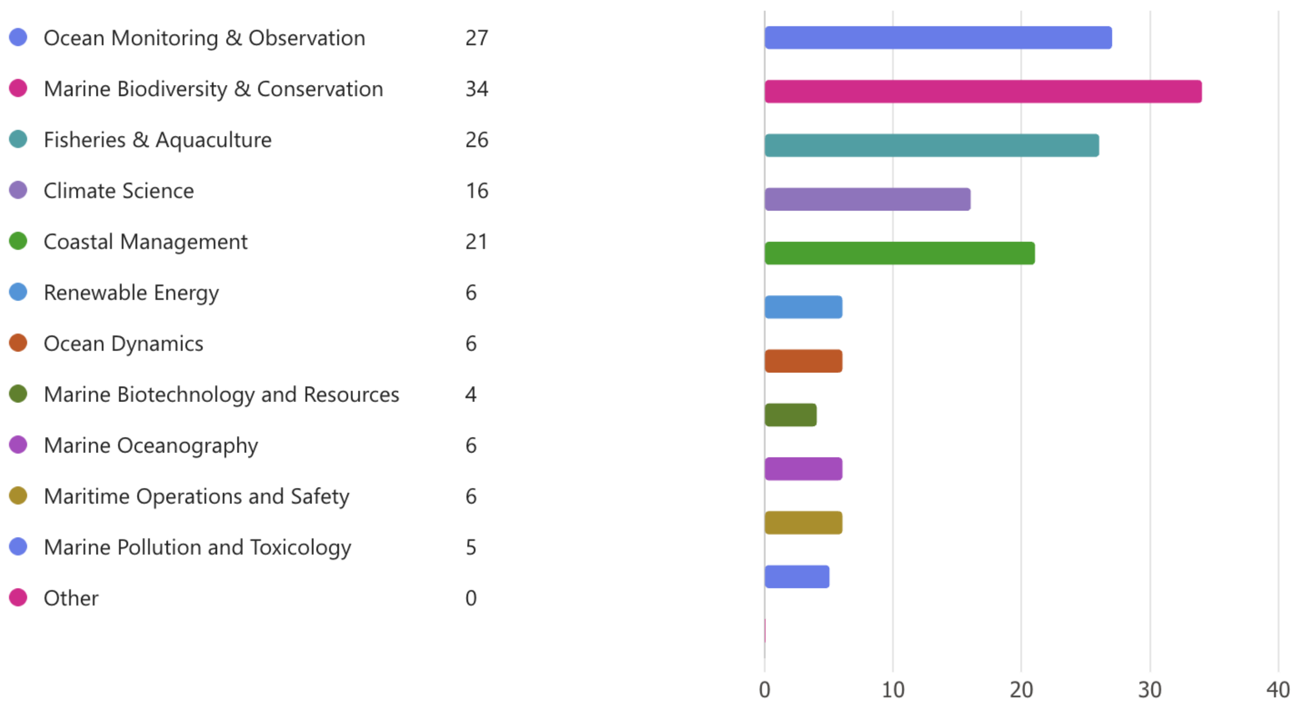

Figure 2: *Breakdown of projects by marine science application domains*

Based on the Challenges and Opportunities introduced in Section 2.3, respondents' projects covered a wide swath of topics, with the largest number of projects addressing 'Protecting Biodiversity and Ecosystem Health' followed by 'Enabling a Sustainable Blue Economy'. Figure 3 shows a breakdown of projects across the identified Challenges and Opportunities.

Figure 3: *Breakdown of projects across marine science Challenges and Opportunities*

Of the beneficiaries that were discussed in Section 2.2, the respondents' projects were quite evenly distributed, with the most common being Government and Marine Science Researchers followed by Industry & Business. Figure 4 provides a breakdown of beneficiaries across the projects.

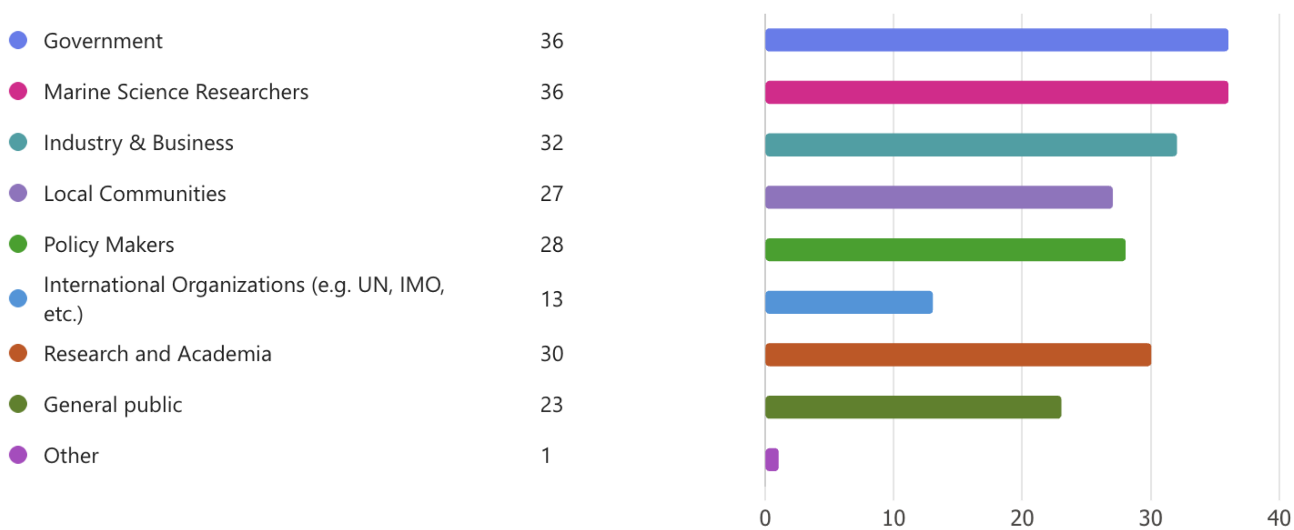

Figure 4: *Breakdown of project beneficiaries*

3.2 Project Applications and Potential Impacts in Marine Science

This section presents the findings of our survey on the application of AI and ML across various domains within marine science. The surveyed projects demonstrate a significant trend towards leveraging these technologies to enhance monitoring capabilities, improve data analysis and support more informed decision-making for the health and sustainable use of our oceans. The projects are referenced by the # ID in Table 1.

3.2.1 Enhancing Ocean Monitoring and Observation

AI and ML have the potential to revolutionise how we observe and understand the marine environment. Several projects focus on automating species assessment, offering more efficient and scalable alternatives to traditional methods. For example, machine learning is being implemented for urchin impact assessment (#3), providing rapid quantification of grazing effects. Similarly, automated fish counts (#17, #18) and seal counts from drone imagery (#22) allow broader spatial and temporal coverage in population monitoring. These advancements benefit researchers, conservationists and policymakers by providing more timely and accurate data on species populations and distributions.

Furthermore, the development of AI-powered underwater image analysis tools, such as ReefCloud (#31), RapidBenthos (#35) and SQUIDLE+ (#45), significantly accelerates the processing and improves the quality of visual data for benthic habitat characterization. Similarly, passive acoustic monitoring, exemplified by the Global Library of Underwater Biological Sounds (#12), combined with AI, enables the modelling of species distribution, such as for pygmy blue whales (#5). These tools enhance the work of marine biologists, ecologists and environmental managers.

AI/ML also contributes to improved data management and analysis, as seen in IQuOD (#9) for ocean temperature profiles and the support provided to Indigenous Rangers by the Northern Australian Marine Monitoring Alliance (#20). In fisheries management, AI is being applied to electronic monitoring (#32, #33), sizing (#8) and vessel tracking (#13). Finally, emerging survey technologies (#28) promise to dramatically increase the speed and precision of marine data acquisition. These improvements serve the needs of fisheries managers, researchers and indigenous communities.

Potential Impacts:

- More efficient and scalable data collection
- Enhanced accuracy and coverage of marine surveys
- Improved understanding of species distribution and abundance
- Faster and more detailed analysis of complex datasets
- Better support for sustainable fisheries management and marine conservation efforts

3.2.2 Advancing Marine Biodiversity and Conservation

Marine biodiversity and conservation represents the most active domain in our survey. AI and ML are being widely adopted for monitoring species and habitats at risk. Projects focus on tracking invasive and endangered species (#3, #5, #6) and classifying critical habitats through automated fish monitoring (#18), SQUIDLE+ (#45) and marine fauna detection systems (#21). These efforts aid conservation organizations, wildlife managers and researchers.

Coral reef assessment is another key area, with projects like ReefCloud (#31) and RapidBenthos (#35) providing tools for large-scale health assessments, including the identification of thermally tolerant corals (#23). The classification of benthic habitats is being enhanced by initiatives like the Benthic Vision Architecture (#29) and multi-species seagrass detection (#40). Notably, the Northern Australian Marine Monitoring Alliance (#20) integrates Indigenous knowledge with AI-driven monitoring. AI/ML is also enabling monitoring in challenging environments, such as harmful algal bloom detection (#30) and deep-sea coral identification (#29). These projects provide critical information to policymakers, conservationists and local communities for effective reef management and protection.

Potential Impacts:

- Enhanced capacity for monitoring and managing marine biodiversity
- Improved understanding of habitat health and the impacts of threats
- More effective conservation strategies for endangered species and critical ecosystems
- Greater involvement of Indigenous communities in Sea Country management

3.2.3 Supporting Sustainable Fisheries and Aquaculture

AI and ML are providing valuable tools for the sustainable management of fisheries and aquaculture operations. Electronic monitoring of commercial fisheries (#32, #33) offers a cost-effective way to increase compliance and data collection. Automated detection and sizing of commercial and recreationally targeted species (#27, #8, #15) improves the efficiency and accuracy of stock assessments. Projects like automated fish counts on restored shellfish reefs (#17) and sea cucumber counts (#19) demonstrate the utility of AI in evaluating restoration success. These tools benefit fisheries managers, commercial fishermen and aquaculture operators.

AI/ML is also being applied to minimize bycatch (#14) and protect aquaculture from harmful algal blooms (#30). Furthermore, leveraging user-generated data through LLM analysis (#16) and automated vessel monitoring (#13) offers new avenues for scaling recreational fisheries data collection. This data is valuable to fisheries researchers and regulatory agencies.

Potential Impacts:

- Improved data for sustainable fisheries management
- Enhanced efficiency and compliance in fishing operations
- Reduced bycatch of non-target species

- Minimized economic losses in aquaculture due to harmful algal blooms
- Better integration of recreational fishing data into management strategies

3.2.4 Informing Climate Science and Adaptation

The survey reveals a growing use of AI and ML to understand and respond to climate change impacts on marine systems. Projects are employing these technologies for downscaling climate projections (#10), analyzing historical ocean temperature data (#9) and modelling marine ecosystems (#7). Identifying thermally tolerant corals (#23) and monitoring climate change impacts on indicator species (#22) are crucial for developing adaptation strategies. This research supports the work of climate scientists, policymakers and coastal communities.

Furthermore, multi-species seagrass detection (#40) supports the monitoring of blue carbon sequestration and the MegaMove project (#6) uses AI to assess risks to marine megafauna under changing climate conditions. These efforts provide critical data for international climate initiatives and conservation efforts.

Potential Impacts:

- Enhanced understanding of climate change impacts on marine ecosystems
- Improved accuracy of climate projections at regional scales
- Identification of climate-resilient species and habitats
- Better monitoring of blue carbon sequestration
- Development of more effective climate adaptation strategies

3.2.5 Enhancing Coastal Management and Planning

AI and ML are providing valuable insights for sustainable coastal decision-making and resource protection. Projects focus on habitat monitoring (#18, #40, #21), understanding climate impacts on coastal environments (#25, #4) and linking environmental changes to indicator species (#22). The integration of Indigenous knowledge (#20) is also a key aspect. These projects assist coastal planners, government agencies and indigenous communities in making informed decisions.

Furthermore, harmful algal bloom detection (#30) supports coastal management decisions and improved biodiversity monitoring (#36, #41) provides a stronger evidence base for planning.

Potential Impacts:

- More informed and sustainable coastal development decisions
- Improved understanding of coastal ecosystem dynamics and vulnerabilities
- Enhanced protection of coastal biodiversity
- Greater inclusion of Indigenous perspectives in management
- Better preparedness for and response to coastal hazards

3.2.6 Supporting Renewable Energy Development

AI and ML are playing a role in facilitating the sustainable development of renewable energy in marine environments. Projects like the application of AI to downscale climate projections (#10) provide high-resolution oceanographic information relevant to renewable energy development. The Global Library of Underwater Biological Sounds (#12) supports renewable energy through on-board processing for real-time assessment of species and habitats, particularly for detecting disturbance events. The Esso Offshore Decommissioning Marine Research project (#11) transfers knowledge about the impact of artificial structures to the offshore renewable energy sector. SQUIDLE+ (#45) provides valuable ground-truthing information on marine habitat distribution for renewable energy site selection and impact assessment. The Flying Fish Technologies project (#28) offers rapid marine surveys that can support renewable energy planning. These applications benefit renewable energy companies, environmental regulators and local communities.

Potential Impacts:

- Enhanced sustainability of renewable energy development
- Improved site selection and impact assessment for projects
- Better understanding of potential environmental impacts

3.2.7 Advancing Understanding of Ocean Dynamics

AI and ML are being leveraged to enhance our understanding of physical oceanographic processes. The GNN-based Wave-Current Interaction Modelling project in Darwin Harbour (#4) focuses on comprehending wave-current interactions and sediment processes in coastal waters. IQuOD (#9) provides high-quality historical ocean profile data essential for understanding ocean dynamics and climate modelling. The climate vulnerability assessment of the Ningaloo Coast World Heritage Area (#25) includes analysis of ocean dynamics and ecological responses under climate change. The Marine Ecosystem Modelling with Collaborative Intelligence project (#7) develops methods for whole-of-system models applicable to ocean dynamics. The use of Super Resolution CNN and Generative Adversarial Networks (#10) provides high-resolution oceanographic information. These advancements serve the needs of oceanographers, climate scientists and coastal engineers.

Potential Impacts:

- Deeper insights into complex ocean dynamics
- Improved predictive capabilities for ocean management
- Advancements in oceanographic research and modeling

3.2.8 Enhancing Marine Biotechnology and Resource Management

AI and ML are being employed to enhance resource utilization and biological understanding in the context of marine biotechnology and resources. The automated fish counts on restored shellfish reefs project (#17) provides measures of fisheries enhancement resulting from restoration. The Marine

Ecosystem Modelling with Collaborative Intelligence project (#7) develops methods applicable to marine biotechnology and resource management. Research on thermally tolerant corals (#23) aims to identify heat-resistant coral populations. The Leveraging LLM for bespoke reporting project (#24) facilitates access to information relevant to marine biotechnology. These efforts benefit marine biotechnology companies, resource managers and conservationists.

Potential Impacts:

- Improved understanding and management of marine biological resources
- Enhanced data analysis and modeling capabilities
- Support for marine resource conservation and restoration

3.2.9 Advancing Marine Oceanography

AI and ML are contributing to advancements in understanding oceanographic processes and systems. IQuOD (#9) maximizes the potential of historical ocean temperature profiles. The climate vulnerability assessment of Ningaloo Coast World Heritage Area (#25) and the Coastal Sediment Dynamics (#4) projects incorporate oceanographic analysis. The Flying Fish Technologies project (#28) generates rich datasets with oceanographic metadata. The Benthic Vision Architecture project (#29) links seafloor classification outputs with oceanographic data. The use of Super Resolution CNN and Generative Adversarial Networks (#10) provides high-resolution oceanographic projections. These advancements benefit oceanographers, climate researchers and marine scientists.

Potential Impacts:

- Improved data quality and enhanced analytical capabilities
- Better integration of physical and biological oceanographic information
- Advancements in oceanographic research

3.2.10 Improving Maritime Operations and Safety

AI and ML are enhancing maritime activities and safety measures. The Remote Camera Network Vessel retrieval automation project (#13) provides continuous monitoring. LLM analysis of recreational fishing survey responses (#16) supports enforcement. The management of marine threatened species project (#34) develops systems to deter wildlife-human interactions. The harmful algal bloom detection system (#30) supports early warning systems. The GNN-based Wave-Current Interaction Modelling project (#4) contributes to improved forecasting. The Flying Fish Technologies project (#28) provides rapid marine surveys. These improvements benefit maritime authorities, shipping companies and recreational users.

Potential Impacts:

- Enhanced maritime domain awareness
- Improved safety through better monitoring, forecasting and early warning systems

- Support for enforcement and regulatory activities

3.2.11 Addressing Marine Pollution and Toxicology

AI and ML are being applied to monitor and mitigate pollution impacts. The machine learning-based seal counting project (#22) links contaminant levels and entanglement in marine plastic / fishing materials to seal mortality. The harmful algal bloom detection system (#30) identifies potential toxin-producing phytoplankton. The Esso Offshore Decommissioning Marine Research project (#11) investigates contaminant levels around offshore structures. The Leveraging LLM for bespoke reporting project (#24) facilitates access to pollution and toxicology information. These applications aid environmental agencies, researchers and industries in managing and mitigating pollution.

Potential Impacts:

- Enhanced ability to monitor and respond to marine pollution
- Improved detection, analysis and reporting systems
- Support for mitigating toxicological threats

3.3 Summary of ML Methods Across Projects

Figure 5 shows a breakdown of AI/ML methods used across the surveyed projects.

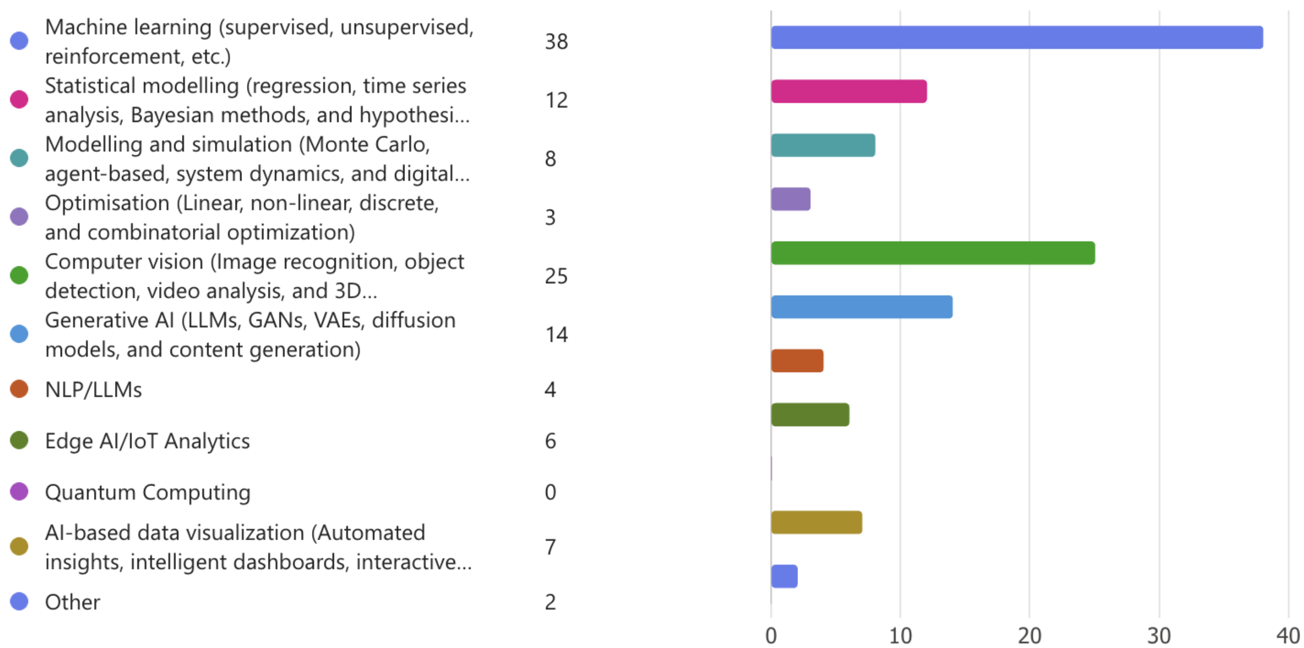

Figure 5: *AI/ML methods used across surveyed projects*

The surveyed projects utilise a range of machine learning methods:

- **Supervised, Unsupervised and Reinforcement Learning:** Used extensively across projects (e.g., #3, #4, #6, #8, #13, #14, #15, #23, #31, #32, #33, #34, #45) for tasks like species detection, habitat classification and environmental modelling.
- **Computer Vision:** Techniques like image recognition, object detection and video analysis are applied in projects such as #18, #19, #22, #27, #29, #31, #35, #40 and #42 for automating the detection, classification and measurement of marine organisms and habitats.
- **Statistical Modelling:** Employed in projects like #4, #5, #6, #7 and #13, often in conjunction with machine learning, for tasks like species distribution modelling and validating AI-generated outputs.
- **Generative AI:** Emerging techniques like LLMs, GANs and VAEs are used in projects such as #7, #10, #39, #40 and #12 for synthetic data generation, downscaling climate projections and assisting in ecosystem modelling.
- **Modelling and Simulation:** Techniques such as Monte Carlo and agent-based modelling are applied in projects like #4, #6, #7, #11 and #19 for understanding complex ecosystem dynamics and predicting future states.
- **NLP/LLMs:** Natural language processing and large language models are used in projects #7, #16, #24 and #40 for extracting information from unstructured data and enhancing reporting.
- **Edge AI/IoT Analytics:** Emerging in projects like #26, #28, #32, #33 and #12 for real-time data processing in field conditions.
- **AI-Based Data Visualization:** Used in projects #7, #11, #24 and #28 to transform complex datasets into actionable insights.
- **Optimization Techniques:** Applied in projects #7, #22 and #28 to fine-tune models and search for optimal parameter values.
- **Synthetic Data:** Generation of synthetic data, for example in project #44, to augment training datasets.

3.4 Project TRL assessment

A review of the provided survey data reveals a diverse distribution of Technology Readiness Levels (TRLs) across Australian marine science projects, with a notable ambition for advancement. Figure 6 shows the AI/ML TRL scale, for each of the surveyed projects with IDs as per Table1. The majority of projects currently sit in the lower to mid-TRL range, with an average current TRL of approximately 4.2 and a target TRL at project completion of approximately 8. This indicates a strong intent to transition research prototypes and laboratory concepts into operational systems and applications. However, a significant number of projects (approximately 36%) report being off-track or uncertain about achieving their target TRL, with the most frequently cited blockers being a lack of sufficient funding (mentioned by 18 projects), skilled personnel (16 projects) and adequate infrastructure (12 projects). Data-related issues, such as insufficient training data or data accessibility, also appear as blockers for some projects. When barriers are removed, many projects express a desired TRL of 9, suggesting that with adequate resources and support, these innovations could reach full operational deployment. This highlights a clear resource gap preventing the full realization of these projects' potential.

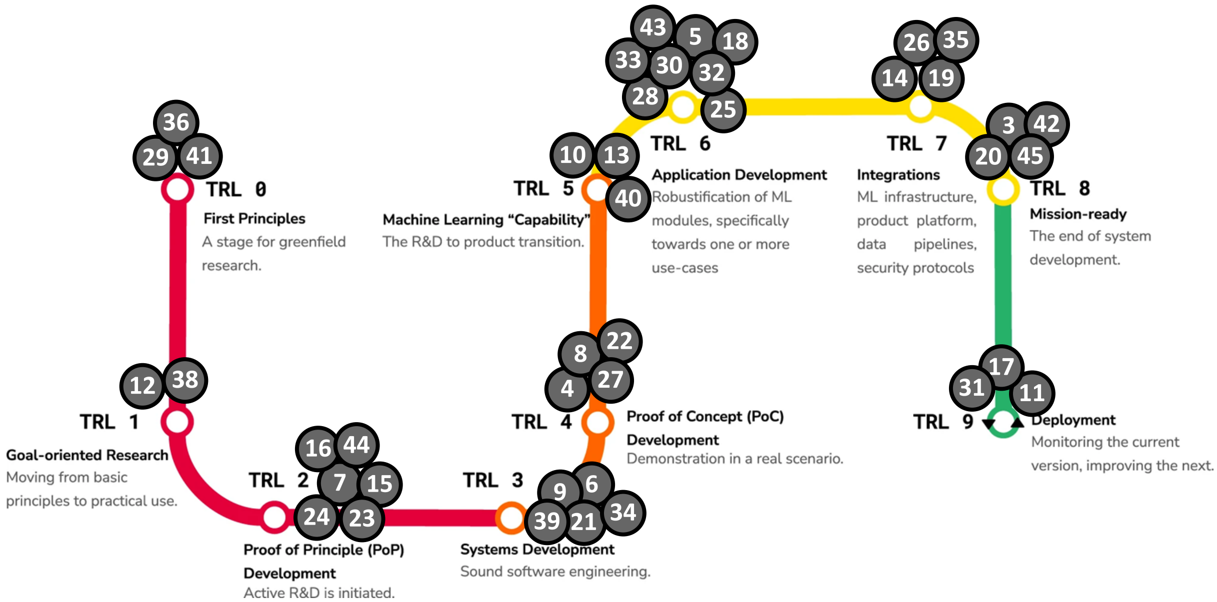

Figure 6: *Surveyed projects on AI/ML TRL scale. The numbers in the grey circles refer to the project #IDs in Table1.*

3.5 Future Trajectory

A notable portion of projects are progressing as planned. However, a significant number report being uncertain or off track, often citing common barriers (discussed in Section 4). This suggests that while there is strong interest and initial success in applying AI/ML to marine science in Australia, scaling these efforts requires addressing systemic issues.

While Australian marine scientists are actively embracing AI/ML and demonstrating innovative applications, the speed and scale of future progress will largely depend on overcoming current blockers related to funding, workforce capacity and infrastructure. Strategic investment and enhanced collaboration have the potential to unlock significant additional capabilities and benefits, positioning Australia to make substantial advancements in utilizing AI/ML for understanding, managing and protecting its marine environment.

3.6 How is Australia placed on the world stage?

The general sentiment across survey respondents is that while Australia possesses good foundational data resources, its ability to be "well-placed" both now and in 2035 is contingent on addressing challenges related to funding, ensuring sufficient and appropriately skilled personnel are available and dedicated to the task and potentially reforming government staffing approaches in relevant areas.

Australia has shown strength in specific applications of AI/ML to marine science, particularly in environmental monitoring of complex ecosystems like coral reefs and in developing practical AI solutions for sustainable marine resource management. Its research institutions are contributing to advancements in areas like automated image analysis for marine data.

However, when compared to the sheer scale of investment and the breadth of fundamental AI research happening in countries like the US and China, Australia's overall AI ecosystem is small. While Australia has a national AI strategy and is increasing investment, some reports suggest it lags behind other developed nations in overall AI investment and in creating globally competitive foundational AI models.

The AI Index (Maslej et al., 2025) provides a comprehensive evaluation of the AI standing for 36 nations. While not specifically focussed on marine science applications, it identifies key national indicators to guide policy decisions and highlights centers of AI excellence in advanced and emerging economies. Figure 7 shows the weighted index scores of the Global AI Vibrancy Ranking (derived from 2023 data). Australia is ranked just 28th across the globe placing Australia in the bottom quarter of nations for AI vibrancy. Adjusted for population, Australia rises to 16th out of 36 measured per capita.

Figure 8 shows the AI Innovation index, which measures a country’s innovation potential by assessing its research and development (R&D) activities, academic output, technological advancements, intellectual property generation and supporting technological infrastructure. It highlights a country’s capacity to produce new knowledge, innovate and contribute to global AI advancements. Australia ranks 29th in absolute terms and 15th if adjusted per capita.

In AI patents filed globally, Australia was 14th with 0.38 per 100,000 inhabitants, compared to the top 5 countries which ranged from 4.58 to 17.27 as shown in Figure 9. From Figure 10, we can see that Australian private investment in AI over the last decade (US$3.99 billion) lags behind leaders like the United States (US$470.92 billion), China (US$119.32 billion) and the United Kingdom (US$28.17 billion) by orders of magnitude. Australia’s 2024 federal budget, for instance, allocated $39.9 million over five years for AI, which is only $8 million annually, a figure generally considered to be meagre.

The observation that Australia's AI investment is small compared to global leaders jeopardises its economic and strategic standing. This risk implies that a lack of sovereign AI capability will result in Australia becoming dependent on foreign technology providers like Microsoft, Google and Amazon for critical technologies. Such dependency not only poses national security risks but also stifles local innovation. This systemic underinvestment extends to specialized domains such as marine science.

Despite this, Australia's focused approach to applying AI to its unique marine environments and challenges, coupled with strong research capabilities in relevant AI subfields like computer vision and machine learning, positions it as a significant contributor to the global marine AI landscape, particularly in areas related to environmental sustainability and monitoring. Australia possesses world-class marine expertise and is actively collaborating internationally and leveraging global AI advancements for its marine science objectives.

Australia is a capable and active player in the field of AI/ML in marine science, with notable strengths in applying these technologies to environmental monitoring, conservation and sustainable resource management. While not having the largest overall AI ecosystem globally, its targeted investments and strong research in specific marine applications place it among the significant contributors to this growing field.

Weighted Index Score | Source: 2025 AI Index

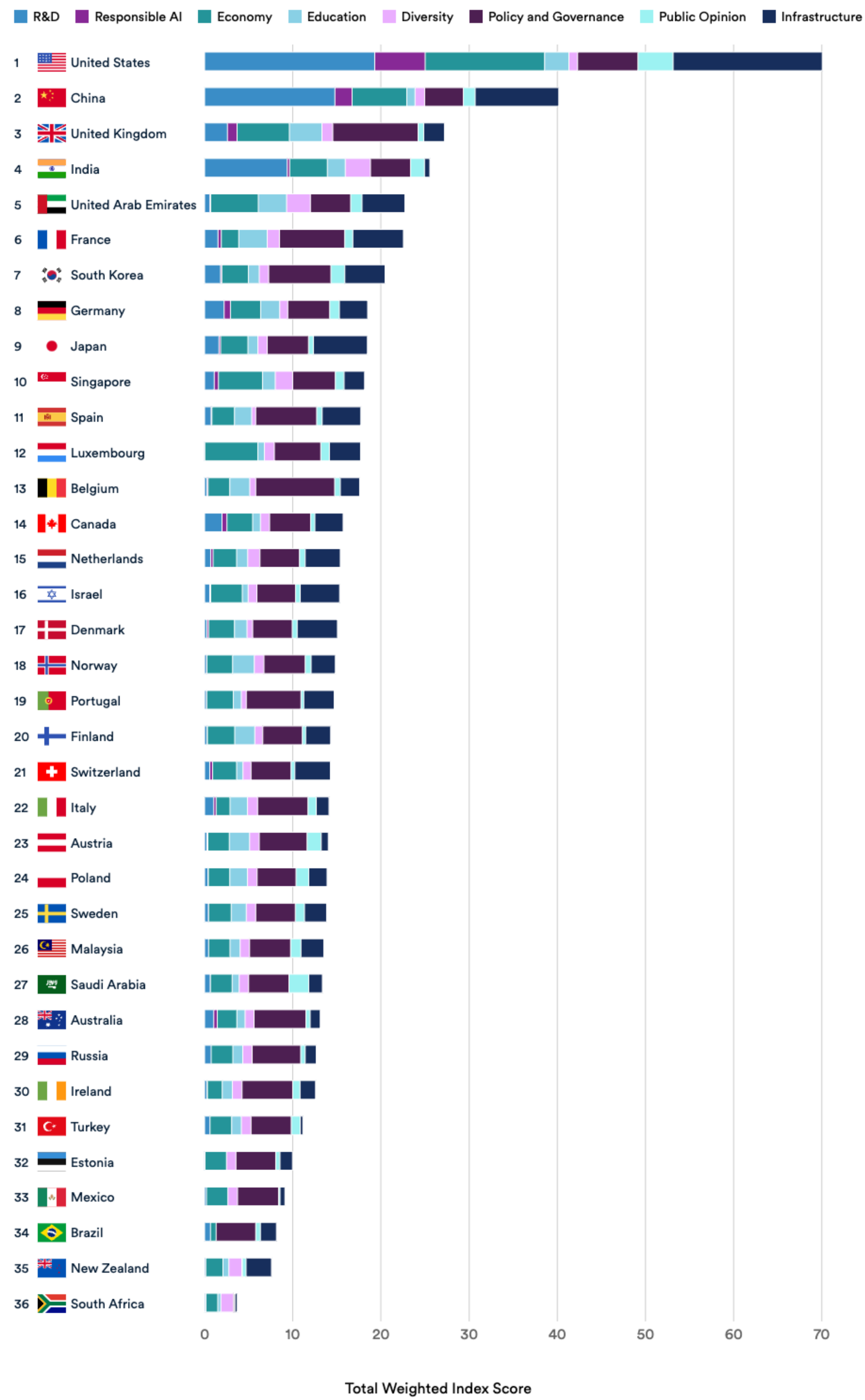

Figure 7: *2023 Global AI Vibrancy Ranking, source: 2025 AI Index (Maslej et al., 2025)*

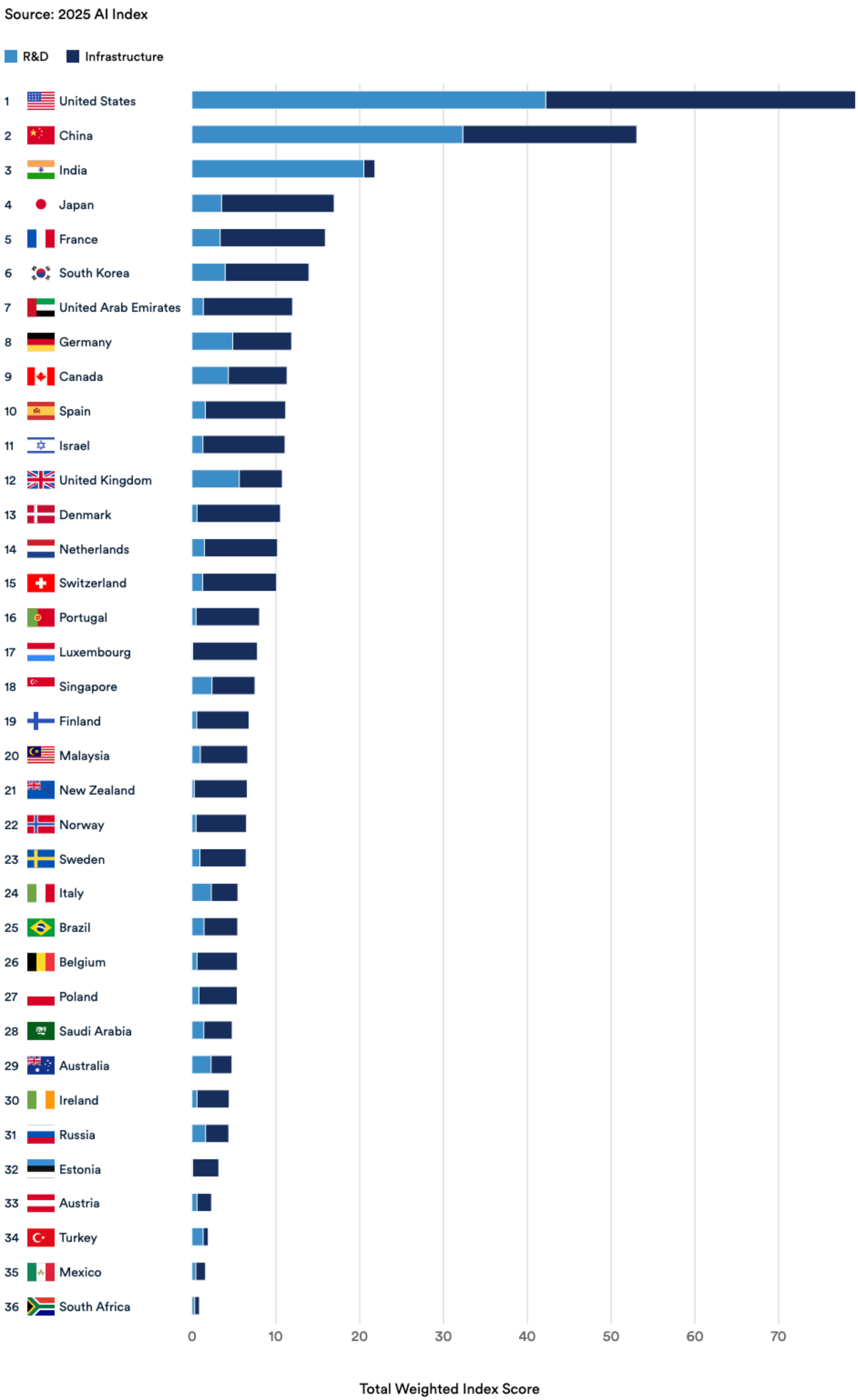
Source: 2025 AI Index
R&D
Infrastructure
1 United States
2 China
3 India
4 Japan
5 France
6 South Korea
7 United Arab Emirates
8 Germany
9 Canada
10 Spain
11 Israel
12 United Kingdom
13 Denmark
14 Netherlands
15 Switzerland
16 Portugal
17 Luxembourg
18 Singapore
19 Finland
20 Malaysia
21 New Zealand
22 Norway
23 Sweden
24 Italy
25 Brazil
26 Belgium
27 Poland
28 Saudi Arabia
29 Australia
30 Ireland
31 Russia
32 Estonia
33 Austria
34 Turkey
35 Mexico
36 South Africa
0
10
20
30
40
50
60
70
Total Weighted Index Score

__Figure 8:__ 2023 Innovation Index, source: 2025 AI Index (Maslej et al., 2025)

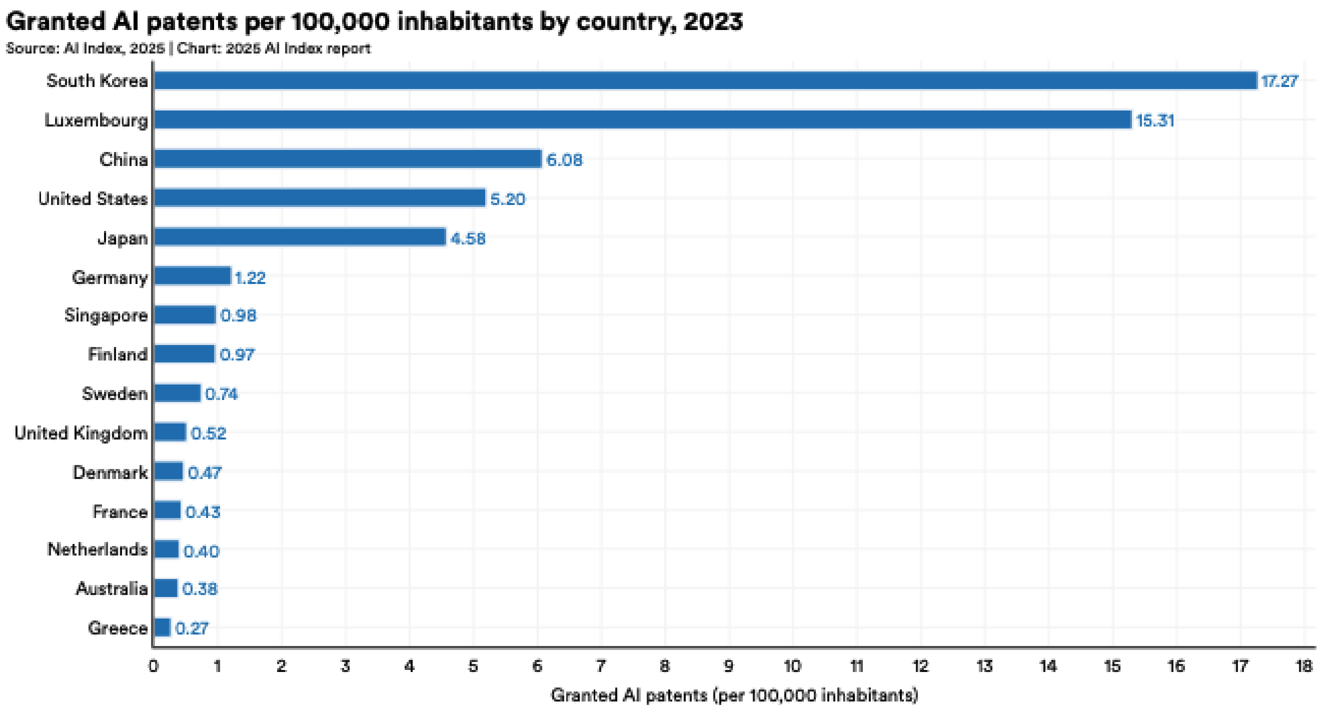

__Figure 9:__ Granted AI patents by country, source: 2025 AI Index (Maslej et al., 2025)

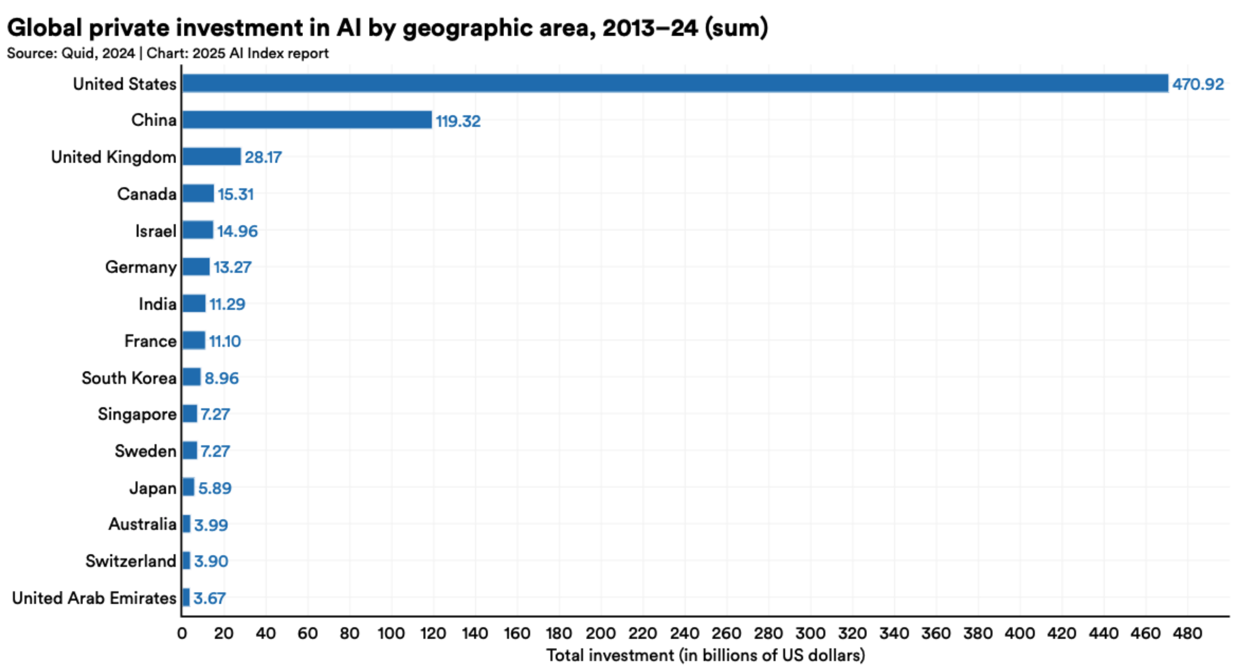

__Figure 10:__ Global private investment in AI by country, source: 2025 AI Index (Maslej et al., 2025)

4 Dependencies, Barriers and Capability Gaps

Australia’s capacity to develop, scale and sustain AI and ML applications for marine science is heavily shaped by the maturity of its infrastructure, availability of skills, access to data and strength of partnerships. This section outlines the key enablers, capability gaps and barriers identified across current projects and proposes strategies to address them.

4.1 Foundational Dependencies

Several foundational enablers are necessary to support the successful development and deployment of AI/ML systems in the marine domain. These enablers span technical, organisational and financial dimensions and are often interdependent. The following core dependencies have been identified:

4.1.1 Skilled Personnel

The availability of staff with appropriate expertise in AI/ML, marine science and data engineering is a key determinant of project success. Interdisciplinary skillsets are especially valuable, yet remain scarce.

- High demand for individuals with cross-disciplinary training in AI and marine science.
- Mentoring and skill-sharing mechanisms remain underdeveloped.
- Expert input is required for generating training data, validating outputs and ensuring problem definitions align with overarching science objectives.

4.1.2 Computational Infrastructure

Modern AI models require high-performance computing and large-scale data storage, both of which are frequently lacking, insufficient or prohibitively expensive to access.

- High-performance computing (HPC) access is limited or externally dependent.
- Internal storage often cannot accommodate high-resolution imagery or model outputs.

4.1.3 Data Availability

Progress depends on access to well-curated datasets, particularly for rare or threatened marine species. Data sharing is still uneven and lacks national coordination.

- Legal, ethical and technical barriers constrain sharing.
- Inconsistent metadata and formats limit discoverability and reuse.

4.1.4 Organisational IT Support

Effective AI workflows often require agile support for model development, testing and deployment — support that is often unavailable or slow to respond in institutional settings.

- Legacy IT systems can be a barrier to deploying AI systems in production environments.

- Research workflows are often unsupported by institutional IT teams.

4.1.5 Funding and Partnerships

AI innovation depends on sustained funding and co-investment from research, industry and government. Funding gaps create delays, while lack of stable partnerships reduces long-term impact.

- Short-term funding cycles disrupt continuity and inhibit planning.
- Projects with co-investment tend to progress faster and scale more effectively.

4.2 Systemic Barriers

Despite interest and activity in AI/ML for marine science, several systemic and practical barriers slow progress. These barriers cut across institutions, projects and stages of development.

4.2.1 Funding Uncertainty

Many projects operate on short-term or piecemeal funding, making it difficult to attract and retain staff, invest in infrastructure, or plan for scale.

- Staffing is often insecure due to year-by-year budget cycles.
- Funding gaps delay research and model validation.

4.2.2 Personnel Shortages

AI/ML expertise is in high demand and many organisations struggle to attract or maintain skilled staff, especially those with experience in ecological domains.

- Government agencies and smaller research groups are particularly affected.
- Loss of key staff can halt project momentum entirely.

4.2.3 Infrastructure Constraints

Projects frequently hit limits on their ability to compute, store, or process data at the scale required for model development and deployment.

- Limited access to high-performance computing stalls training and validation.
- Model deployment often depends on overseas infrastructure.

4.2.4 Data-Related Issues

Training data is either unavailable, incomplete, poorly labelled or inconsistently labelled between different projects. Data preparation is underfunded and rarely prioritised and marine datasets are often tiny when compared with larger, terrestrial datasets.

- Inconsistent metadata along with differences in labelling and science objectives, make datasets difficult to integrate. This diversity poses a considerable barrier to data reuse, syntheses between projects and the large-scale training of ML algorithms.

- Efforts to clean and harmonise data are resource-intensive and often duplicated.
- The inherent variability of marine data and the complexities of acquisition (e.g., lighting, colour attenuation, turbidity, lack of GPS under water) introduces complexities that affect data quality and volume, which can vary across sites and environments. This in turn can impact the generalisability of ML models.

4.2.5 Regulatory Complexity

Navigating approvals, permits and data-sharing restrictions introduces delays, especially in projects involving sensitive data or Indigenous knowledge.

- Legal and ethical approval processes can take months or longer.
- Unclear or conflicting policies around data ownership create uncertainty.
- Unwillingness to share datasets can reduce the amount of data available for training AI/ML models, potentially hindering their effectiveness and development.

4.2.6 Project Fragility

Dependence on individual contracts, pilots, or partnerships makes many projects fragile. If a single element fails, projects can stall or collapse entirely.

- Project milestones tied to single funders or deliverables increase risk.
- Lack of continuity in staff or leadership compounds this vulnerability.

To accelerate R&D and transition to operational capability, these barriers must be addressed through targeted investment, reforms to funding mechanisms and stronger coordination across sectors.

4.3 Capability Gaps

Despite growing interest and effort, significant capability shortfalls are hindering progress:

4.3.1 People, Skills and Expertise

There is an acute shortage of skilled personnel with AI/ML expertise, particularly those who can operate across disciplinary boundaries. This shortage affects not only research quality but the ability to operationalise models at scale.

- Government agencies often lack internal data science expertise.
- The development and deployment of AI/ML tools often suffer from poor coordination and limited interdisciplinary collaboration.
- Mentorship and knowledge-sharing across projects are limited.
- Maintaining AI/ML capability in smaller organisations is particularly challenging.
- Researchers have focussed on development of AI/ML, but have historically struggled with making tools accessible to non-specialist end users

4.3.2 Infrastructure

Projects frequently report limitations in both computational power and data management:

- Many lack access to HPC resources necessary for model training.
- Inadequate storage capacity and weak internal IT support hamper data handling and model deployment.
- Dependence on overseas infrastructure for running advanced models is seen as a vulnerability.

4.3.3 Data

A lack of well-labelled training data, is a recurring issue:

- Data collection, cleaning and metadata completion are time-consuming and under-resourced.
- There is often a lack of consistency between the tools being used for managing, analysing data and processing the data.
- Sharing practices are inconsistent and often ad hoc.

4.3.4 Funding and Other Constraints

Across the board, respondents cited funding shortfalls as a persistent constraint:

- Insufficient resources delay progress, restrict staffing and limit access to infrastructure.
- Regulatory requirements and project approval processes can also slow innovation.

5 Recommendations & Implementation

The application of AI and ML in marine science offers transformative potential. However, realising this potential requires coordinated investment, targeted capability development and inclusive, transparent governance. Drawing on diverse insights and experiences highlighted in the project survey as well as the National Science and Research Priorities (Australian Research Council, n.d.), this section outlines key priorities, enabling conditions and recommendations for effective and responsible AI/ML deployment.

5.1 Guiding principles

The priorities and recommendations below are driven by several overarching imperatives:

- **Trust and Transparency:** Build public and stakeholder confidence through explainable, ethical systems.
- **Human-Centric Design:** Support, rather than replace, expert judgment—especially in high-stakes contexts. Complement expertise rather than automate decisions inappropriately. This includes incorporating Indigenous perspectives into the design process.
- **Sustainability and Scalability:** Ensure long-term viability via interoperable tools, shared resources and standardisation.

- **Agility and Responsiveness:** Promote environments that support rapid experimentation and iteration.
- **Pragmatism and Impact:** Prioritise the low-hanging fruit—ML applications that are relatively easy to implement yet offer high returns—so that early successes can build momentum and confidence. However, it is also important to assess the potential impact of project outcomes when considering funding and investment decisions.

5.2 Key Enablers

Several enablers are necessary to accelerate and scale AI/ML-enabled marine science. These fall into four interrelated domains:

5.2.1 AI/ML Capability and Model Development

Improving AI/ML performance remains a central priority. Key innovation areas include:

- AI across ecosystem modelling pipelines as assistive systems.
- AI deployment in the field and/on edge devices to enable real-time field applications to streamline operations and reduce human error.
- Automated quality control using AI models trained and validated on expert review patterns.
- Enhanced taxonomic and ecological coverage, including detection of rare species, ecological indicators, estimation of animal condition and accurate size measurements.
- Integration with operational systems, including fisheries data systems and marine agency workflows.
- Rapid development platforms, connecting ML developers with marine scientists to prototype, test and deploy tools efficiently.
- Cross-institutional model benchmarking, to ensure robust evaluation and encourage best-practice sharing.
- Explainable AI models grounded in geophysical and oceanographic applications.

5.2.2 Data Quality and Availability

The effectiveness of AI/ML tools is fundamentally dependent on the quality and quantity of data:

- Creation and curation of large, standardised, annotated datasets, in an appropriate level of detail that balances science priorities with AI/ML capabilities.
- Implementation of quality control pipelines and standardised metadata protocols to ensure quality assessments and that data are fit for purpose.
- Improved data sharing mechanisms, including federated or centralised repositories that support interoperability and standardisation.
- Integration of diverse data sources (e.g. satellite, sensor, citizen science) to enhance model context and predictive capacity.
- Defined data provision and storage rules that support sustainable, secure infrastructure use.

5.2.3 Infrastructure and Resourcing

Computational infrastructure and personnel remain significant bottlenecks:

- Access to high-performance computing environments for AI training and deployment.
- Expanded storage and cyberinfrastructure for handling large-scale datasets.
- Investment in skilled personnel, including interdisciplinary staff combining AI/ML expertise with domain knowledge.
- Bridge funding to sustain momentum between funding cycles to maintain capabilities.

5.2.4 Collaboration and Integration

Effective integration across disciplines, institutions and jurisdictions is critical:

- Stronger collaboration between marine science and AI/ML specialists through joint projects and shared development environments.
- Cross-sector partnerships with government, industry and community stakeholders to ensure tools meet operational needs.
- Alignment with international initiatives to build globally relevant datasets and tools.
- Promotion of Australian-developed software globally, to support uptake, sustainability and innovation exchange.

5.3 Implementation Strategy

Addressing the capability gaps and barriers identified above will require more than ad hoc solutions – it calls for coordinated investment, policy support and sustained effort across domains. This section outlines targeted strategies for strengthening human capital, infrastructure, data quality, funding structures and partnerships. While some initiatives are already underway, scaling them to national impact will require system-wide planning and cross-discipline commitment.

5.3.1 Strengthening Human Capital

A persistent shortage of skilled personnel, particularly those with AI/ML and interdisciplinary expertise, undermines Australia's ability to build and maintain capability in this domain. Efforts to fill this gap should focus not just on new hires, but on developing systems for knowledge transfer, retention and cross-disciplinary collaboration.

- Fund new full-time equivalent (FTE) roles across research institutions and public agencies, with a focus on AI/ML and marine science integration.
- Support multi-disciplinary workshops to facilitate skill transfer across institutions and domains.
- Encourage secondments or industry exchanges to expose AI specialists to real-world marine science applications and broaden their domain knowledge.
- Consider establishing a dedicated, cross-agency body, involving key stakeholders to be responsible for coordinating investment, setting strategic priorities and overseeing the comprehensive implementation of a national marine AI/ML roadmap.

5.3.2 Investing in Infrastructure

Infrastructure gaps, particularly in computing and data handling, limit Australia's ability to scale AI/ML applications. These challenges are most acute in smaller organisations and projects operating without access to shared facilities. Strategic national investment is required to build a robust foundation for long-term capability.

- Invest in shared national infrastructure to support smaller research groups and reduce duplication. Prioritise investment in national high-performance computing (HPC) and storage infrastructure, with access pathways for marine science applications.
- Improve internal institutional IT support to align with modern, agile research workflows.
- Invest in centralised data portals that facilitate cross-disciplinary collaboration between science users and AI/ML practitioners by standardising datasets and streamline the training, deployment, accessibility and validation of AI/ML algorithms.
- Develop intuitive, user-oriented platforms and interfaces that help promote transparency and trust through improving model accuracy, reliability and explainability, through iteration and validation.
- Develop foundational infrastructure, such as data pipelines, cloud services and secure platforms.
- Consider establishing a dedicated Marine AI/ML Centre of Excellence to drive game-changing innovations tailored to marine challenges with cross-domain expertise.

5.3.3 Improving Data Availability and Quality

Data is the fuel of AI/ML, yet critical datasets remain inaccessible, poorly labelled, or inadequately curated. Addressing this requires both technical solutions and organisational reform to make data collection, cleaning and sharing more sustainable and interoperable.

- Facilitate data integration across formats and sources with validation. Launch targeted data rescue and curation programs, with a focus on high-value or at-risk marine datasets.
- Fund the integration of data managers into research teams to improve metadata quality and support long-term reuse.
- Develop lightweight, streamlined legal and ethical frameworks to encourage data sharing across institutions.
- Develop and enforce national standards for marine data collection, curation and sharing to facilitate high-quality, AI-ready datasets that are consistently available and accessible across the entire research and industry ecosystem.

5.3.4 Addressing Structural Funding Barriers

Fragmented and short-term funding continues to impede progress, particularly for long-term model development, staff retention and infrastructure maintenance. Reforming funding models is essential to support innovation, scale and sustainability.

- Establish multi-year funding streams for research infrastructure, staffing and model lifecycle support.

- Create mechanisms to fund early-stage, low-TRL (Technology Readiness Level) innovation and de-risk future operational systems.
- Fund national coordination efforts to minimise duplication, facilitate collaboration and support strategic planning.
- Allocated bridge funding to sustain momentum between funding cycles to maintain capabilities.
- Prioritize long-term, programmatic funding over fragmented, short-term project grants to support sustained, multi-year funding projects.

5.3.5 Building Strategic Partnerships

Partnerships, domestic and international, are essential for addressing capability gaps and sharing costs, expertise and infrastructure. A coordinated partnership approach can improve alignment between existing efforts and amplify their collective impact.

- Foster cross-sector collaboration between academia, government and industry to jointly fund infrastructure and workforce development.
- Promote cross-disciplinary collaboration between machine learning experts and marine scientists to ensure effective application of AI/ML, facilitate knowledge transfer and drive innovation.
- Develop international linkages through shared research challenges, data exchanges and capability-building programs.
- Support national coordination bodies or frameworks to align dispersed efforts, promote interoperability and scale successful pilot projects.

5.3.6 Scaling Up

To effectively scale AI/ML efforts, several enabling conditions must be advanced concurrently:

- Targeted funding for infrastructure, personnel and long-term operations.
- Recruitment of cross-disciplinary expertise, bridging marine science and AI/ML.
- Accessible computing and storage infrastructure, capable of supporting big data analytics.
- Standardised, high-quality datasets representing diverse environments and use cases aligned to science objectives.
- Collaborative partnerships to enable data and tool sharing across institutions.
- Regulatory frameworks that provide clarity while supporting innovation.
- Consolidate related initiatives under larger, coordinated programs.

Progress in one area often depends on others. Gaps in infrastructure, data quality, or staffing can significantly undermine system effectiveness.

5.4 Improving Communication, Collaboration and Uptake

Enhanced communication and collaboration are critical to accelerating adoption and coordinating dispersed efforts:

- Ensure outputs are accessible, interpretable and usable by non-specialists.
- Project integration under coherent national or regional programs can reduce redundancy and facilitate data flow.
- Lowering barriers to adoption by ensuring tools are intuitive, well-documented and designed with end-user needs in mind.
- Publicly accessible outputs, including APIs, visualisations and simplified interfaces, increase uptake.
- Ethical transparency and interpretability are essential to build trust in AI/ML outputs.
- Knowledge exchange mechanisms, including mentoring, industry secondments and government training workshops, can support long-term capability development.
- Case studies and metrics highlighting real-world impact help to demonstrate value and encourage adoption.
- Promote successful outcomes through publications, presentations and knowledge-sharing platforms.

5.5 Responsible Use of AI/ML

The deployment of AI/ML in marine science must be guided by principles that ensure effectiveness, transparency and ethical integrity:

- Proactively manage ethical and transparency concerns.
- Establish governance frameworks and institutional policies for responsible use. These frameworks should cover data privacy, algorithmic bias, accountability and the societal impact of AI-driven decisions.
- Adopt trusted frameworks that include validation, uncertainty quantification and ethical oversight.
- Design AI/ML tools as assistive systems, augmenting—not replacing—expert human judgment.
- Support agile, low-barrier environments to foster experimentation and innovation.
- Prioritise explainability, allowing users to understand the rationale and limitations of AI/ML outputs.
- Engage diverse stakeholders including Indigenous communities, local populations, policymakers and the public in discussions about the ethical implications of marine AI, ensuring diverse perspectives are considered in its development and deployment.

These principles underpin trust, long-term adoption and integration into operational workflows.

5.6 Measuring Progress/Impact

To improve impact measurement in AI/ML projects within this field, several strategies can be implemented, drawing on principles of project evaluation and the context of the challenges and opportunities:

- **Define Clear and Measurable Impact Metrics:** Beyond technical validation metrics (e.g., model accuracy, precision), projects should define clear indicators of ecological, economic, social, or policy impact at the outset. For example, instead of just measuring the accuracy of a species detection model, measure its impact on the efficiency of monitoring programs, the cost savings achieved, or the improvement in conservation outcomes.
- **Establish Baseline Data:** To demonstrate impact, it is crucial to have baseline data against which changes can be measured. This allows for the assessment of the project's contribution to desired outcomes.
- **Incorporate Long-term Monitoring and Evaluation:** The true impact of many marine science and conservation projects, especially those involving AI/ML technologies, may not be immediately apparent. Long-term monitoring plans should be integrated into projects to track changes and assess sustained impact over time.
- **Engage Stakeholders in Defining and Measuring Impact:** Involving the stakeholders who are intended to benefit from the research (e.g., government, industry, local communities, policymakers) in defining what constitutes success and how impact should be measured can ensure that the evaluation is relevant and meaningful to end-users. This aligns with the emphasis on adoption mechanisms and stakeholder benefits seen in other parts of the data.
- **Develop Standardized Reporting Frameworks:** Adopting standardized frameworks for reporting on project outcomes and impacts can facilitate comparison across different projects and contribute to a broader understanding of the collective impact of AI/ML in the field.
- **Track Downstream Use and Influence:** Monitor how the outputs and findings of AI/ML projects are being used by end-users, whether they are informing policy decisions, changing management practices, or contributing to further research. This can provide valuable qualitative and quantitative data on impact.
- **Assess Scalability and Adoption Rates:** As highlighted in the data regarding adoption barriers and mechanisms, the extent to which AI/ML technologies are adopted and scaled up is a key indicator of their potential for wider impact. Tracking adoption rates and identifying factors that facilitate or hinder scaling are crucial for evaluating the broader influence of the work.

5.7 Required investment

Despite world-leading capabilities and existing foundational AI/ML projects within marine science, it is clear from the discussion in Section 3.6 that a significant disparity exists in the overall strategic investment in AI at the national level. The current fragmented project funding is insufficient to build a comprehensive, sovereign AI ecosystem for marine science. This suggests a broader lack of coordinated, large-scale federal backing for AI as a critical enabler across all sectors, including the vital marine domain.

To meet national priorities—such as safeguarding the Great Barrier and Southern Reefs, managing marine ecosystems, enhancing the blue economy, maintaining food security and improving climate resilience—and to elevate its global standing in the rapidly expanding maritime AI market, Australia requires a sustained, multi-billion dollar commitment over the next decade. This investment, averaging hundreds of millions annually, could be strategically allocated across four key pillars:

1. **Advanced Research & Development (R&D) and Innovation:** Suggest hundreds of millions annually to establish dedicated Marine AI/ML Centres of Excellence and drive game-changing innovations tailored to Australia's unique marine challenges.
2. **Critical Infrastructure & Data Ecosystems:** Suggest tens to hundreds of millions annually for high-performance computing, cloud AI infrastructure, national AI-ready marine data repositories and advanced sensing technologies like Autonomous Underwater Vehicles (AUVs), Autonomous Surface Vessels (ASVs), etc.
3. **Talent Development & Workforce Capacity Building:** Suggest tens of millions annually for specialized education, training pathways and retention strategies to cultivate a skilled AI/ML workforce for the marine sector.
4. **Technology Adoption & Integration:** Suggest tens of millions annually to foster collaborations, commercialization and integrate AI solutions into marine industries and management frameworks.

This strategic investment is expected to yield substantial benefits, including vastly enhanced environmental management, significant economic growth in the blue economy, strengthened national security through sovereign AI capabilities, improved climate resilience and substantial operational efficiencies and cost savings (e.g., reef monitoring analysis accelerated by hundreds of times at a fraction of the cost). Ultimately, it will position Australia as a global leader in sustainable ocean management, influencing international agendas and becoming a partner of choice. Realizing this potential necessitates a national strategy, long-term

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