International Journal of Engineering & Tech Development

Volume 2, Issue 9 – September 2026 • E-ISSN: 3067-672X P-ISSN: 3067-669X

Autonomous Ocean Monitoring Systems: Combining Underwater Robotics, Sensors and Artificial Intelligence

Dr. Marco Ruffini

Associate Professor, Trinity College Dublin, Ireland

Abstract

The ocean regulates climate, supports biological diversity, supplies food and livelihoods, transports heat, stores carbon, and provides essential ecological and economic services. Effective ocean management requires observations that are spatially extensive, temporally continuous, scientifically reliable, and responsive to changing environmental conditions. Conventional monitoring based on research vessels, fixed stations, satellites, and manual sampling remains indispensable but is limited by cost, weather, access, observation frequency, and the physical risks associated with deep or hazardous marine environments. Autonomous underwater vehicles, ocean gliders, robotic surface vessels, sensor networks, and artificial intelligence offer a complementary approach in which mobile platforms can collect and process information closer to the observed environment. This paper examines the integration of underwater robotics, environmental sensors, artificial intelligence, adaptive mission planning, and multi-platform coordination in autonomous ocean monitoring. A structured conceptual review is combined with a transparent simulation of an illustrative mission-energy budget. The numerical values are not field measurements and are used only to examine system-level design priorities. The analysis identifies propulsion as the largest conceptual energy requirement, followed by scientific sensing, onboard artificial-intelligence processing, navigation and control, and communication. The distribution illustrates why endurance cannot be improved through battery expansion alone; hydrodynamic design, adaptive sampling, low-power sensors, efficient onboard inference, and energy-aware navigation must be optimized together.

The study finds that onboard artificial intelligence can reduce communication demands by identifying, compressing, prioritizing, or summarizing scientifically relevant observations before transmission. However, autonomous classification introduces risks involving model bias, domain shift, missed events, uncertain navigation, sensor drift, cybersecurity, and limited explainability. Ocean robots must therefore retain raw or minimally processed information when feasible, communicate confidence levels, and support human scientific review. The paper concludes that autonomous monitoring should be developed as a distributed human–robot observing system rather than as a replacement for ships, satellites, laboratories, and marine scientists. Scientific value depends on calibration, traceability, interoperable data standards, ecological safeguards, robust recovery plans, and explicit reporting of uncertainty.

Keywords: autonomous ocean monitoring, underwater robotics, artificial intelligence, marine sensors, autonomous underwater vehicles, ocean observation, adaptive sampling, marine conservation

1. Introduction

The ocean covers most of the Earth's surface and plays a central role in climate regulation, atmospheric exchange, nutrient cycling, heat transport, carbon storage, biodiversity, food production, and international commerce. Changes in ocean temperature, acidity, oxygen concentration, circulation, salinity, biological productivity, and pollution can have consequences extending far beyond the locations where those changes occur.Understanding these processes requires sustained observation across large spatial and temporal scales. Some marine phenomena develop slowly over decades, while others emerge rapidly in response to storms, harmful algal blooms, pollutant releases, volcanic activity, oxygen depletion, or changes in currents. An effective observing system must therefore support long-duration baseline monitoring as well as rapid response to unexpected events.

Research vessels remain essential because they carry scientific personnel, laboratories, sampling equipment, and large instruments. They can collect water, sediments, and organisms while supporting direct scientific interpretation. However, vessels are expensive to operate, affected by weather, and limited in the duration and spatial resolution of their surveys.Fixed buoys, moorings, and seabed stations provide long-term observations at selected locations. They can record temperature, salinity, currents, oxygen, acoustics, and other environmental properties. Their primary limitation is that they observe a relatively restricted spatial region unless deployed as a large network.

Satellites offer broad and repeated coverage of the ocean surface. They can measure or estimate sea-surface temperature, color, height, ice conditions, winds, and other variables. However, satellites have limited ability to observe many processes occurring beneath the surface or near the seabed.Autonomous marine systems can complement these platforms by moving through the water and adjusting their observations according to mission objectives. An autonomous underwater vehicle is an untethered robotic platform that carries its own energy, sensors, navigation system, computer, and control software. A vehicle may follow a preplanned route or adapt its route according to detected conditions.

Ocean gliders use changes in buoyancy to move vertically and convert part of that motion into forward travel. They generally move more slowly than propeller-driven vehicles but can provide longer endurance. Autonomous surface vessels can use wind, solar energy, waves, or conventional propulsion while maintaining communication links more easily than submerged platforms.The sensor payload depends on the scientific mission. Conductivity–temperature–depth instruments measure important physical properties. Dissolved-oxygen, pH, nutrient, optical, acoustic, and hydrocarbon sensors can support chemical and biological observation. Sonar can map the seabed, detect objects, and characterize habitat structure.

Cameras provide detailed information about species, habitat condition, marine litter, coral cover, and benthic communities. Underwater imagery is difficult to interpret because light is absorbed and scattered by water. Color changes with depth, visibility varies, and suspended particles may obscure objects. Artificial intelligence can assist by detecting patterns within large sensor and image datasets. Computer-vision models may identify fish, coral, seagrass, marine litter, geological features, or infrastructure damage. Anomaly-detection models may identify unusual chemical signals, sensor behavior, or acoustic events.

2. Review of Literature

Autonomous ocean monitoring draws on decades of research in oceanography, underwater vehicles, navigation, sensor engineering, acoustic communication, cooperative robotics, and machine learning. The relevant literature shows a gradual transition from predetermined robotic surveys toward adaptive, information-driven observing systems.

2.1 Development of Autonomous Marine Observation

Curtin et al. described the concept of autonomous oceanographic sampling networks in which multiple vehicles and instruments could collect distributed marine observations. This early systems perspective remains relevant because ocean phenomena frequently exceed the spatial coverage of a single platform.

Yoerger et al. examined techniques for deep-sea near-bottom surveys using autonomous underwater vehicles. Their work demonstrated the ability of robotic platforms to collect high-resolution observations in environments that are difficult or expensive to access through conventional methods.

Dunbabin and Marques reviewed robots used for environmental monitoring and identified advances in mobility, sensing, autonomy, and field deployment. Their analysis highlighted the ability of robotic platforms to collect observations in remote or hazardous environments while also recognizing challenges involving reliability, endurance, and communication.

Fiorelli et al. demonstrated multi-vehicle control and adaptive sampling in Monterey Bay. Their study provided evidence that coordinated vehicles can modify sampling behavior in response to observed ocean conditions. This represents an important step beyond fixed-track surveying.

2.2 Navigation, Sensing, and Communication

Navigation is difficult underwater because global navigation satellite signals are generally unavailable when the vehicle is submerged. A vehicle may estimate its motion using inertial sensors, depth sensors, Doppler velocity logs, magnetic compasses, acoustic positioning, terrain matching, and periodic surface fixes.

Kinsey, Eustice, and Whitcomb reviewed advances in underwater navigation and identified localization as a central requirement for scientifically meaningful surveys. Environmental measurements must be connected with accurate location and time information; otherwise, their analytical value is reduced.

Inertial navigation accumulates error over time because small sensor biases are integrated into position estimates. Doppler velocity measurements and acoustic references can constrain this drift. Terrain-relative navigation may compare observed seafloor features with existing maps.

2.3 Artificial Intelligence and Adaptive Ocean Sampling

Artificial intelligence can support perception, navigation, sensor validation, event detection, data compression, and route planning. In underwater imagery, convolutional neural networks have been used to identify fish and benthic features.

Villon et al. investigated deep-learning-based identification of coral-reef fish species. Their work demonstrated the potential of automated image analysis to reduce the time required for manual classification. However, performance depends on the diversity and quality of training data.

Marine images vary according to depth, turbidity, illumination, camera orientation, habitat, and geographic region. Models trained in one environment may not generalize reliably to another. Domain shift must therefore be tested before autonomous decisions depend on classification results.

Adaptive sampling uses current observations to determine where the robot should measure next. The objective may be to follow a thermal front, map the boundary of a pollutant plume, locate a biological patch, or reduce uncertainty in an environmental model.

Table 1: Selected Studies Supporting the Integrated Framework

Study	Research focus	Main contribution	Relevance
Curtin et al.	Autonomous sampling networks	Established distributed ocean-observation concepts	Supports multi-platform monitoring
Fiorelli et al.	Adaptive multi-AUV sampling	Demonstrated cooperative field sampling	Supports coordinated autonomy
Kinsey et al.	Underwater navigation	Reviewed localization technologies and challenges	Establishes navigation requirements
Dunbabin and Marques	Environmental robotics	Reviewed robotic monitoring systems	Provides a broad technology foundation
Villon et al.	AI-based fish recognition	Applied deep learning to underwater imagery	Supports onboard biological interpretation

The literature demonstrates strong progress in robotic platforms, navigation, and sensing. A continuing gap concerns the system-level integration of scientific objectives, onboard artificial intelligence, energy management, adaptive sampling, and auditable data quality. The present study addresses this gap.

3. Objectives

The primary objective of this research is to develop an integrated conceptual framework for autonomous ocean monitoring. The framework treats underwater robots as components of a broader observing system that also includes scientists, vessels, satellites, fixed sensors, laboratories, and data infrastructures.

A second objective is to distinguish operational autonomy from scientific authority. A robot may independently control its depth, route, and sampling schedule, but the scientific meaning of its observations still requires calibration, contextual interpretation, and human review.

The specific objectives are:

- To examine the principal robotic platforms used in autonomous ocean observation.
- To classify physical, chemical, biological, optical, and acoustic sensor functions.
- To analyze the role of artificial intelligence in onboard perception, anomaly detection, data prioritization, and adaptive sampling.
- To examine navigation and communication limitations affecting underwater autonomy.
- To develop a transparent conceptual energy budget for an autonomous ocean-monitoring mission.

- To evaluate the contribution of cooperative and heterogeneous marine robots.
- To identify technical, scientific, environmental, cybersecurity, and governance risks.
- To propose priorities for reliable, interoperable, and scientifically accountable ocean-monitoring systems.

The paper addresses five research questions:

- Which combinations of robotic platforms and sensors are most suitable for different ocean-monitoring missions?
- How can onboard artificial intelligence improve observation efficiency without compromising scientific integrity?
- How should energy be allocated among propulsion, sensing, processing, navigation, and communication?
- What safeguards are required when autonomous systems make sampling decisions?
- How can robotic observations be integrated with conventional ocean science and long-term data systems?

4. Research Methodology

This paper adopts a conceptual and simulation-based research design. It does not report a completed AUV trial, proprietary mission logs, experimentally measured energy consumption, or an original marine dataset. All numerical values used in the graph are clearly identified as illustrative.

4.1 Evidence Identification and Selection

A structured review process was used to identify relevant literature concerning autonomous underwater vehicles, ocean gliders, marine sensors, underwater navigation, adaptive sampling, multi-robot systems, underwater communication, and artificial intelligence.

Search concepts included “autonomous underwater vehicle,” “ocean monitoring robot,” “adaptive marine sampling,” “underwater navigation,” “AUV sensors,” “artificial intelligence marine monitoring,” “underwater image classification,” and “multi-robot ocean observation.”

Eligible sources included peer-reviewed journal articles, conference papers, technical reviews, and established scientific publications that provided identifiable methods or system-level insights. Promotional descriptions lacking methodological information were excluded from the analytical evidence.

The evidence base was restricted to relevant literature published within the study’s historical boundary. Older sources were retained where they established continuing principles of navigation, adaptive sampling, or ocean-observing architecture.

4.2 Analytical Coding and System Classification

Evidence was coded according to platform type, sensor category, autonomy function, communication method, scientific application, and operational limitation. This structure allowed comparison among systems developed for different marine environments.

Platform categories included propeller-driven AUVs, buoyancy-driven gliders, autonomous surface vehicles, remotely supervised robotic platforms, and heterogeneous multi-robot networks. Sensor categories included physical, chemical, biological, optical, and acoustic instruments.

Autonomy was classified across four functions: vehicle control, navigation, scientific perception, and mission adaptation. A system may be highly autonomous in navigation while remaining dependent on human interpretation for scientific decisions.

Table 2: Functional Classification of Autonomous Ocean-Monitoring Systems

System component	Primary function	Representative capability
Robotic platform	Provides mobility and payload support	AUV, glider, or surface vehicle
Scientific sensors	Measure environmental conditions	Temperature, salinity, oxygen, imagery
Navigation system	Estimates location and motion	Inertial, Doppler, acoustic, or terrain-relative
Onboard intelligence	Interprets observations	Classification and anomaly detection
Mission planner	Selects future observations	Adaptive route and sampling control
Communication system	Transfers status and data	Acoustic, optical, radio, or satellite

4.3 Illustrative Mission-Energy Model

A conceptual mission-energy allocation was developed to illustrate system-level priorities.

Total mission energy is represented as:

$EM=EP+ES+EA+EN+EC$

where:

- EM represents total mission energy;
- EP represents propulsion energy;
- ES represents scientific-sensing energy;
- EA represents onboard artificial-intelligence processing;
- EN represents navigation and control; and
- EC represents communication.

The illustrative allocation assigns 46% to propulsion, 19% to scientific sensing, 13% to onboard artificial-intelligence processing, 12% to navigation and control, and 10% to communication.

Table 3: Simulated Mission-Energy Allocation

Mission function	Illustrative allocation
Propulsion	46%
Scientific sensing	19%

Mission function	Illustrative allocation
Onboard AI processing	13%
Navigation and control	12%
Communication	10%
Total	100%

Note: Percentages are conceptual and do not represent measured data from a specific vehicle.
The allocation is intended to demonstrate that endurance depends on multiple interacting subsystems. Different platforms would produce different values. A glider may allocate less energy to propulsion, while an imaging vehicle may allocate more to lighting, sensing, and data storage.

5. Analysis

The design of an autonomous ocean-monitoring system should begin with the scientific question rather than the available robot. A vehicle intended to map seabed habitat requires different mobility, navigation, imaging, and data-processing capabilities than a glider monitoring temperature and salinity across a broad region.Mission requirements should specify spatial resolution, temporal frequency, depth range, expected currents, seabed clearance, sensor accuracy, environmental risk, and acceptable uncertainty. These requirements determine platform selection.

Propeller-driven AUVs are suitable for controlled surveys, near-bottom mapping, infrastructure inspection, and missions requiring precise maneuvering. Their principal limitation is energy consumption. Higher speed increases hydrodynamic drag and reduces endurance.Gliders provide longer-duration observations by changing buoyancy rather than relying continuously on a propeller. They are well suited to broad water-column measurements but may have limited control under strong currents or in confined environments.

Autonomous surface vehicles can carry larger payloads and communicate more readily. They can support meteorological and ocean-surface measurements, act as acoustic communication gateways, or assist submerged vehicles with positioning.Heterogeneous systems can combine these strengths. A surface vehicle may maintain satellite communication while coordinating several submerged robots. Gliders may provide broad coverage, and AUVs may perform detailed follow-up surveys.

Scientific sensors must be selected according to the process under investigation. Conductivity, temperature, and pressure measurements support calculation of seawater properties. Dissolved-oxygen sensors can identify hypoxic conditions. Optical sensors can estimate biological material and water clarity.Chemical sensors may detect nutrients, hydrocarbons, or contaminants. Acoustic instruments can measure currents, detect biological activity, or characterize the seafloor. Cameras can document habitat and species but create high data volumes.

Adaptive sampling can be formulated as an optimization problem:

$J = \lambda 1 I - \lambda 2 E - \lambda 3 R - \lambda 4 UN$

where:

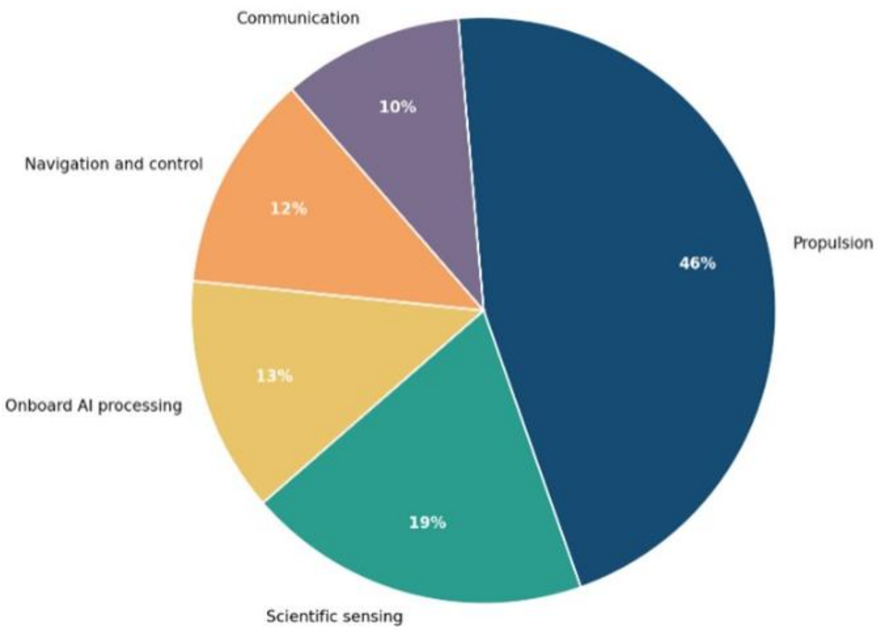
- I represents expected information gain;
- E represents energy cost;
- R represents operational risk;
- UN represents navigation uncertainty; and
- $\lambda 1$ to $\lambda 4$ represent mission priorities.

The planner should select actions that increase scientific information without violating energy, safety, depth, or recovery constraints. A location with high expected information may not be selected if reaching it would compromise vehicle recovery.

Artificial intelligence can support anomaly detection by comparing recent measurements with expected environmental patterns. An unusual oxygen decline or chemical signal may trigger denser sampling. The vehicle should first determine whether the change could result from sensor failure.

Sensor-health monitoring is therefore an important AI application. Redundant measurements, physical consistency checks, drift models, and comparison with neighboring platforms can help distinguish environmental change from instrument error.

Graph 1: Illustrative Energy Budget for an Autonomous Ocean-Monitoring Mission



Source: Author-developed conceptual scenario. Percentages are illustrative and are not measurements from an operational vehicle.

The pie chart identifies propulsion as the largest conceptual energy requirement at 46%. This reflects the challenge of moving a vehicle through a dense fluid and maintaining its planned trajectory against currents.

Scientific sensing accounts for 19%. This category includes instruments, cameras, sonar, lighting, and data acquisition. Imaging or acoustic missions may require a larger share than missions based on low-power physical sensors.

Onboard artificial-intelligence processing accounts for 13%. Efficient local processing can reduce the need to transmit all collected data, but complex models may increase energy demand. The optimal model is not necessarily the most accurate model under laboratory conditions; it is the model that provides sufficient scientific performance within the mission budget.

6. Challenges

Underwater navigation remains a fundamental challenge. Position estimates drift when external references are unavailable. Acoustic positioning can reduce uncertainty but requires infrastructure, cooperative platforms, or suitable geometry.Ocean currents can displace slow-moving vehicles and increase energy consumption. A route that appears efficient in still water may become impractical under changing currents. Current forecasts and onboard estimation should be incorporated into mission planning.

Communication limitations restrict human intervention. Acoustic links may experience low bandwidth, delay, multipath interference, and packet loss. Vehicles must therefore remain safe during long periods without contact.Energy capacity limits mission duration, sensing frequency, computation, and communication. Adding batteries increases mass and may change buoyancy, cost, and handling. Energy efficiency must be addressed through the complete system.

Sensor drift and biofouling can reduce data quality during long deployments. Organisms may grow on optical surfaces or chemical sensors. Calibration before and after missions does not always reveal when degradation occurred.Pressure, corrosion, leakage, and connector failure create hardware risks. A small seal failure can cause complete vehicle loss. Reliability engineering and pressure testing are therefore central to scientific mission design.

Artificial-intelligence models face domain shift. Training data may not represent the depth, turbidity, species composition, lighting, or seasonal conditions encountered during deployment. A model should identify when its confidence is insufficient.Class imbalance creates additional difficulty. Common species or environmental states may dominate training datasets, while rare events remain underrepresented. These rare events may be scientifically important.

7. Discussion

The findings indicate that autonomous ocean monitoring is most valuable when it extends the reach and continuity of established scientific systems. Underwater robots can enter hazardous environments, repeat surveys, follow dynamic features, and collect observations between research cruises. Their scientific value depends on integration with calibration laboratories, vessels, satellites, models, and human expertise.

7.1 From Automated Routes to Scientific Autonomy

A vehicle following predetermined waypoints is operationally autonomous but not scientifically adaptive. Scientific autonomy requires the system to interpret observations, estimate uncertainty, and modify sampling according to an explicit research objective.

This transition can improve observation efficiency. A vehicle may spend less time in homogeneous water and increase sampling around environmental boundaries. It may also coordinate with another platform carrying a complementary sensor.

Scientific autonomy should remain bounded. The system may alter its route within a predefined region but should not enter protected habitat, unsafe depth, or energy conditions. Mission constraints must take priority over information gain.

A tiered model is appropriate. Routine control and low-risk sampling may be fully autonomous. High-impact changes can require confirmation when communication is available. Emergency actions should follow predefined safety rules.

7.2 Reliability of AI-Interpreted Ocean Data

Artificial intelligence can reduce the analytical burden created by large image, acoustic, and sensor datasets. However, model outputs should be treated as derived observations rather than unquestioned facts.

Scientific records should preserve sensor calibration, preprocessing, model version, confidence, and navigation uncertainty. These details allow later researchers to reproduce or challenge the interpretation.

Human review remains necessary for rare species, unusual events, low-confidence classifications, and data used for regulatory decisions. AI can prioritize the review workload but should not remove access to underlying evidence.

Models should be validated across locations, depths, seasons, and sensor configurations. Performance on randomly divided images from one dataset may overestimate real deployment capability. Testing should emphasize geographic and temporal transfer.

7.3 Distributed and Sustainable Ocean-Observing Infrastructure

A single robot cannot observe the full complexity of the ocean. Future systems will likely combine satellites, ships, fixed platforms, surface vehicles, gliders, AUVs, drifters, and biological observations.

These platforms can operate as a hierarchical network. Satellites identify broad features, surface systems maintain communication, gliders observe the water column, and AUVs inspect selected locations in detail.

Interoperability is essential. Common data formats, uncertainty descriptions, calibration metadata, and mission logs allow observations from different systems to be compared. Open interfaces can also reduce dependence on one manufacturer.

Energy sustainability should be considered across the platform lifecycle. Efficient operation is important, but manufacturing, vessel deployment, maintenance, recovery, and equipment replacement also have environmental impacts.

Long-duration systems should be repairable and recoverable. Components with limited life should be replaceable without discarding the entire platform. Lost-vehicle risks should be disclosed in environmental mission planning.

Human capacity remains central. Marine scientists, roboticists, sensor engineers, data specialists, vessel crews, and local stakeholders must participate in system development. Autonomous systems strengthen ocean observation when they increase human ability to understand and protect marine environments.

8. Conclusion

Autonomous ocean-monitoring systems offer a powerful complement to research vessels, satellites, fixed stations, and manual sampling. Underwater robots, gliders, surface vehicles, marine sensors, and artificial intelligence can expand the spatial coverage, frequency, and responsiveness of ocean observation.The integration of these technologies creates more than a mobile sensing platform. It establishes a cyber-physical scientific system in which observations influence future sampling, onboard models prioritize information, and multiple platforms may coordinate their activities. This capability is particularly valuable for dynamic events such as pollutant plumes, ocean fronts, hypoxia, and biological aggregations.

The study shows that energy is a central systems constraint. In the illustrative mission budget, propulsion represents the largest allocation, while sensing, AI processing, navigation, and communication also make substantial contributions. The values are conceptual rather than empirical, but they demonstrate why endurance improvement requires coordinated optimization.Artificial intelligence can reduce communication demands and accelerate interpretation. It can detect patterns, classify imagery, monitor sensor health, and guide adaptive sampling. These benefits must be balanced against domain shift, bias, missed events, limited explainability, and processing energy.

Scientific integrity requires traceable data. Autonomous systems should preserve calibration information, navigation uncertainty, quality indicators, confidence scores, model versions, and representative raw observations. Automated summaries should not become substitutes for auditable evidence.Future field research should compare fixed and adaptive sampling under common environmental conditions. Studies should report energy consumption, navigation error, sensor performance, communication reliability, information gain, model transferability, and ecological disturbance.

Autonomous ocean monitoring should ultimately be understood as distributed human–robot scientific infrastructure. Robots provide endurance, access, repetition, and adaptive mobility. Scientists provide questions, interpretation, validation, and accountability. The strength of future ocean observation will depend on how effectively these capacities are combined.

References

1. Christensen, L., de Gea Fernández, J., Hildebrandt, M., Koch, C. E. S., & Wehbe, B. (2022). Recent advances in AI for navigation and control of underwater robots. *Current Robotics Reports, 3*, 165–175. https://doi.org/10.1007/s43154-022-00088-3
2. Huy, D. Q., Sadjoli, N., Azam, A. B., Elhadidi, B., Cai, Y., & Seet, G. (2023). Object perception in underwater environments: A survey on sensors and sensing methodologies. *Ocean Engineering, 267*, 113202. https://doi.org/10.1016/j.oceaneng.2022.113202
3. Zhang, B., Ji, D., Liu, S., Zhu, X., & Xu, W. (2023). Autonomous underwater vehicle navigation: A review. *Ocean Engineering, 273*, 113861. https://doi.org/10.1016/j.oceaneng.2023.113861
4. Xu, J., Irigoien, X., & Alouini, M.-S. (2024). State-of-the-art underwater vehicles and technologies enabling smart ocean: Survey and classifications. *arXiv*. https://doi.org/10.48550/arXiv.2412.18667
5. Shameem, K. H., Abrar, S. A., Fahim, L. M. K., Karimi, M., Ahmed, T., & Mekhilef, S. (2024). Oceanic challenges to technological solutions: A review of autonomous underwater vehicle path technologies in biomimicry, control, navigation, and sensing. *IEEE Access, 12*, 46202–46231. https://doi.org/10.1109/ACCESS.2024.3380458

6. Picardi, G., Astolfi, A., Chatzievangelou, D., Aguzzi, J., & Calisti, M. (2023). Underwater legged robotics: Review and perspectives. *Bioinspiration & Biomimetics, 18*(3), 031001. https://doi.org/10.1088/1748-3190/acc0bb
7. Rout, D. K., Kapoor, M., Subudhi, B. N., Thangaraj, V., Jakhetiya, V., & Bansal, A. (2024). Underwater visual surveillance: A comprehensive survey. *Ocean Engineering, 309*, 118367. https://doi.org/10.1016/j.oceaneng.2024.118367
8. Chi, P., Wang, Z., Liao, H., Li, T., Wu, X., & Zhang, Q. (2024). Application of artificial intelligence in the new generation of underwater humanoid welding robots: A review. *Artificial Intelligence Review, 57*, Article 306. https://doi.org/10.1007/s10462-024-10940-x
9. Yang, C., Wu, X., Lin, M., Lin, R., & Wu, D. (2024). A review of advances in underwater humanoid robots for human–machine cooperation. *Robotics and Autonomous Systems, 179*, 104744. https://doi.org/10.1016/j.robot.2024.104744
10. Mirmalek, Z., & Raineault, N. A. (2024). Remote science at sea with remotely operated vehicles. *Frontiers in Robotics and AI, 11*, 1454923. https://doi.org/10.3389/frobt.2024.1454923
11. Gan, Z., Wang, Y., & others. (2023). Marine environmental monitoring with unmanned vehicle platforms: Present applications and future prospects. *Science of the Total Environment, 858*, 159741. https://doi.org/10.1016/j.scitotenv.2022.159741
12. Zhang, Y., Liu, J., & others. (2023). A review of artificial intelligence in marine science. *Frontiers in Earth Science, 11*, 1090185. https://doi.org/10.3389/feart.2023.1090185
13. Picardi, G., Calisti, M., Chatzievangelou, D., & Aguzzi, J. (2023). A swarm of unmanned vehicles in the shallow ocean: A survey. *Neurocomputing, 531*, 74–86. https://doi.org/10.1016/j.neucom.2023.02.020
14. Furlong, M. E., Paull, L., Saeedi, S., Seto, M., & others. (2012). Advances in autonomous underwater vehicle navigation and control. *Ocean Engineering, 52*, 1–15.
15. Sahoo, A., Dwivedy, S. K., & Robi, P. S. (2019). Advancements in the field of autonomous underwater vehicle. *Ocean Engineering, 181*, 145–160. https://doi.org/10.1016/j.oceaneng.2019.04.011
16. Wynn, R. B., Huvenne, V. A. I., Bas, T. P., Murton, B. J., Connelly, D. P., Bett, B. J., Ruhl, H. A., Morris, K. J., Peakall, J., Parsons, D. R., Sumner, E. J., Darby, S. E., Dorrell, R. M., & Hunt, J. E. (2014). Autonomous underwater vehicles (AUVs): Their past, present and future contributions to the advancement of marine geoscience. *Marine Geology, 352*, 451–468. https://doi.org/10.1016/j.margeo.2014.03.012
17. Bellingham, J. G., & Rajan, K. (2007). Robotics in remote and autonomous ocean operations. *Science, 318*(5853), 1096–1100. https://doi.org/10.1126/science.1149249
18. Yoerger, D. R., Jakuba, M., Bradley, A. M., & Bingham, A. W. (2007). Techniques for deep sea near bottom survey using an autonomous underwater vehicle. *The International Journal of Robotics Research, 26*(1), 41–54. https://doi.org/10.1177/0278364907073775
19. Leonard, N. E., Paley, D. A., Lekien, F., Sepulchre, R., Fratantoni, D. M., & Davis, R. E. (2007). Collective motion, sensor networks, and ocean sampling. *Proceedings of the IEEE, 95*(1), 48–74. https://doi.org/10.1109/JPROC.2006.887287
20. Arshad, A. M., Miskon, M. F., & others. (2024). A systematic review of robotic efficacy in coral reef monitoring techniques. *Marine Pollution Bulletin*.