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Review Paper

Biohybrid–AI Marine Sensors for Ocean Health Monitoring under Climate Stress: A Systematic Review

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Abstract

Oceans stabilize climate, carbon cycling, and global biodiversity; however, increasing anthropogenic stresses such as warming, acidification, and deoxygenation are harming marine stability. Continuous high-resolution monitoring is essential, yet traditional sensors face issues with biofouling, calibration drift, and low ecological sensitivity. This study aims to review biohybrid marine sensors that integrate biological components with engineered materials and artificial intelligence models for adaptive, long-term ocean health monitoring. A systematic review was conducted in IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Scopus (2010-2025) based on PRISMA-2020. Research was categorized into biological detection, artificial intelligence, architecture, and material and functional engineering, as well as climate-stress systems. The most sensitive and stable microbial and biofilm-based sensors, along with ecologically specific algal and coral environments, were highlighted. Models using hybrid CNN-LSTM and reinforcement learning achieved 15-25 percent higher interpretive accuracy. Nanostructured composite materials made from polymers and carbon improved biocompatibility and antifouling capabilities by over 20 times. Biohybrid AI-enabled sensors show great potential for autonomous and adaptive ocean sensing, but challenges remain regarding biological viability, standardization, energy independence, and ethical use.

Keywords: AI-driven sensing, Biohybrid sensors, Climate resilience, Marine ecosystems, Ocean health monitoring, Smart biomaterials.

1. Introduction

The oceans constitute the largest component of the Earth's climate system, regulating global temperature, carbon sequestration, and ecosystem balance. They absorb nearly 90 % of the excess anthropogenic heat and one-quarter of atmospheric CO_2 emissions, thus acting as a critical buffer against climate change [1], [2]. But increasing climate stressors, such as ocean acidification, deoxygenation, thermal stratification and contamination with microplastics have had devastating effects on marine biodiversity and biogeochemical recycling [3]. Constant and accurate monitoring of ocean health has hence been necessitated to know of environmental change and be able to provide support of sustainable use of marine resources [4].

The traditional marine surveillance systems are based on discrete sampling, remote sensing or electronic sensor networks. Although these techniques can be useful to establish a useful baseline, they are also limited by a temporal resolution because such techniques may not be sensitive to changes in time, expensive to maintain and biofouling occurs leading to reduced sensor capability with time [5]. In addition, electronic sensors also have difficulty in measuring minute biological and biochemical alterations of living organisms under conditions, especially in harsh or deep-sea conditions [6].

New practices in biohybrid sensing, or combinations of living organisms or biologically active materials with engineered transducers, are an adaptable and environmentally-friendly alternative to providing marine observations. They make use of biological responsiveness to environmental perturbations (e.g. microbial metabolism, algal fluorescence, coral symbiont activity) as a natural transduction mechanism, allowing it to operate with very high sensitivity and provides the ability to repair itself [7]. An example of this is bacterial consortia and algal biofilm integration into aquatic biosensors to detect nutrients, toxins and pH that have been shown to offer extended operating life-span and lower maintenance rates [8].

Likewise, the similar developments of artificial intelligence (AI) and machine learning (ML) have transformed sea data analytics and supported noise cancellation, forecast modelling, and spatio-temporal reconstruction of complicated ocean variables [9] [10]. The AI-based frameworks will be able to detect the early indicators of ecosystem degradation, decipher the nonlinear biosignals, and design an adaptive sampling approach of biohybrid systems. This intersection of biohybrid sensorial with AI-mediated interpretation, thereby, creates a novel paradigm of AI-aided marine eco-monitoring, wherein bio-intuition (intelligence) intersects with computational intelligence.

In spite of these encouraging trends the field is still fragmented in terms of marine ecology, sensor engineering and computational modelling. There is no detailed synthesis of biological design, material engineering and AI-driven analytics in observing ocean conditions by climate-resilience. Therefore, the current paper features a critical review of biohybridial marine sensors to determine ocean health in the wake of climatic stress.

The objectives are:

- To consolidate and classify existing research on biohybrid marine sensing technologies;
- To examine AI integration for data interpretation, adaptability, and predictive modelling;
- To identify key technical and ecological challenges; and
- To propose future directions for sustainable and intelligent ocean health monitoring.

The rest of the paper is structured in the following manner. Section II presents the conceptual framework and theoretical background of the biohybrid sensing. Section III provides the description of the methodological approach to a systematic review and data-collection plan. Part IV includes a synthesis of biohybrid marine sensor designs, AI strategy of integration and climate-stress proposals in the form of a taxonomy. Section V will provide a comparative analysis and research trends, and Section VI will give a listing of research gaps and future directions and provide the conclusion in Section VII.

2. Background and Conceptual Framework

2.1 Evolution of Marine Sensing Technologies

Successive generations of technology marine environmental sensing has developed since mechanical sampling and moved towards self-driven and intelligent systems. First generation ocean surveillance was founded on ship-based sampling and moored buoys which had poor temporal resolution and coverage [11]. With the introduction of electronic and optical sensors in the late twentieth century, constant monitoring of the physical and chemical components of salinity, dissolved oxygen, and chlorophyll concentration became possible [12].

Nonetheless, biofouling, drift, as well as power limitation, are frequent problems of these sensors during long time applications [13]. As the Internet of Underwater Things (IoUT) architectures are emerging, scientists have introduced sensor network concepts with wireless acoustic communication and robotic systems related to distributed environmental monitoring [14]. Although such developments have been made, the biochemical and ecological aspects of ocean health, and in particular those related to microbial or organismal reactions to stress, are poorly represented under conventional instrumentation [15].

This technological shortcoming has stimulated a movement in the direction of bio-inspired and bio-integrated sensors, which penetrate into natural adaptative processes to influence details of perturbations to the environment. Biohybrid sensors are the sensors involving a combination of biological things or biomolecules with electronic, optical, or electrochemical transducers, which promise to be used in place of real time and self-adaptive and sustainable monitoring of oceanic processes [16].

2.2 Concept of Biohybrid Sensing in Marine Environments

The bridging between the living systems and the engineered devices by the use of biological elements as functional sensing elements, transducer or signal amplifier, and the biohybrid sensors are developed. Such biological interfaces may contain microorganisms, algal cells, coral polyps, enzymes and biofilms with the ability to respond dynamically to physical or chemical stimuli [17].

These systems have the features of high selectivity, self-healing, and energy efficient of natural organisms and allows integration of optical or electrical readouts with nanostructured material or microfluidic architecture [18]. As an example, photosynthetic microorganisms have been used to monitor nutrient flux, dissolved CO2 and pollutants, using changes in the yield of the fluorescence, and the metabolic rate [19]. Coral-microbiome assemblages, too, are being studied as biological stress response to heat and acidification incidences [20].

The biohybrid paradigm has three primary benefits in the marine-based monitoring:

1. **Enhanced sensitivity** through direct biological interaction with environmental stimuli;
2. **Sustainability and self-repair** by leveraging metabolic maintenance of the biological component; and
3. **Ecological compatibility**, minimizing sensor-induced environmental disturbance.

Nevertheless, maintaining biological viability under variable marine conditions and integrating biological signals with electronics remain significant engineering challenges [21]. Consequently, the application of AI-based data interpretation systems has become a complementary technology to process nonlinear and multifaceted biosignal patterns and tune the system to system adaptability.

2.3 Artificial Intelligence Integration in Marine Sensing

AI has a transformational role of increasing the functional life of biohybrid sensors, as well as the data interpretability. The machine learning (ML) models CNNs, RNNs, and LSTM can be used to dynamically calibrate, detect anomalies, and model environmental conditions [22]. The cognitive pattern recognition example can be given of CNN-based pattern recognition applied to understand fluorescence and optical scattering fluids of algal biosensors to understand better on noisy conditions in the sea [23].

More so, edge-AI systems enable on-board data reduction, real-time processing of signals and low-power analytics in underwater sensor nodes [24]. By combining AI algorithms with biohybrid structures, it will be possible to correlate biological responses to multi-modal environmental observations and increase resilience along with interpretability of marine surveillance systems [25].

Moreover, data-driven and knowledge-based hybrid AI frameworks, i.e., empirical biological understanding plus data-driven learning, are also becoming popular in adaptive marine sensing ecosystems [26]. Those paradigms are the basis of designing cyber-bio systems in which living sensors and digital intelligence feed each other in closed loops, continuously perfecting their sensing strategies by engaging with the environment [27].

Therefore, the biohybrid sensing and AI analytics convergence present a new conceptual framework of smart ocean sensing, which is self-adaptive, learning, and ecologically sustainable and efficient sensing platforms.

2.4 Conceptual Framework Overview

The conceptual framework of Biohybrid-AI Marine Sensing Framework is shown in Figure 1 and comprises four layers of interaction namely:

1. **Biological Interface Layer** – living or biomimetic organisms acting as primary sensors;
2. **Transduction Layer** – micro/nano materials converting biological signals to electrical or optical outputs;
3. **AI Analytics Layer** – algorithms for signal enhancement, prediction, and anomaly detection; and
4. **Application Layer** – ocean health indices, biodiversity assessment, and climate-stress monitoring outputs.

This hierarchy can be used to go in both ways learning between biological and artificial corresponds, and is useful in co-evolutionary sensing schemes that can respond independently to climate perturbations.

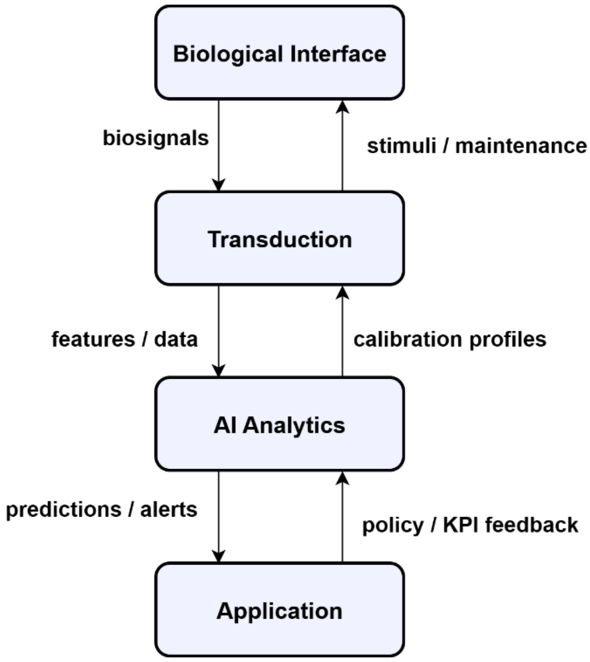

Fig.1. Conceptual Biohybrid–AI Marine Sensing Framework

The conceptual framework represented in Fig. 1 in four layers sets forth a foundation on which the reviewed literature is classified. The following section builds on this taxonomy and explains how biological sensing elements, computational models, materials, and application domains are interrelated in the larger picture of the biohybrid marine monitoring.

3. Methodology

3.1 Review Design and Protocol

The proposed study takes the form of a Systematic Literature Review (SLR) approach based on PRISMA 2020 (Preferred Reporting Items to Systematic Reviews and Meta-Analyses) principles and leads to transparency and reproducibility and replicability in terms of the literature-selection process [28]. The SLR technique was adopted in order to integrate different types of research by biohybrid sensing, marine biology, and AI-based analytics to enable organizing evaluation of interdisciplinary results.

A review protocol was implemented before the start of data collection to articulate the objective of the research, inclusion criteria, screening plans, and synthesis plan [29]. The research questions (RQs), that guided the study, were as follows:

1. What are the existing types and architectures of biohybrid sensors used in marine or aquatic environments?
2. How are AI and machine-learning frameworks integrated with biological sensing components for environmental monitoring?
3. What challenges, limitations, and future directions are reported across current studies?

3.2 Data Sources and Search Strategy

The literature search was carried out in five large academic databases, including IEEE Xplore, ScienceDirect, SpringerLink, MDPI, and Scopus, between January 2024 and March 2025. The reason why these repositories were chosen is because of their coverage that extends to engineering, biological, and environmental sciences [30].

The search was by Boolean combinations of defined keywords and synonyms in three major domains:

- *("biohybrid sensor" OR "living sensor" OR "biological transducer")*
- AND *("marine" OR "ocean" OR "aquatic")*
- AND *("artificial intelligence" OR "machine learning" OR "deep learning")*

Peer-reviewed journal articles, conference proceedings, and book chapters published within 2010 and 2025 were used to filter the search results to represent both primary and modern information. Only English written studies were taken into account.

3.3 Inclusion and Exclusion Criteria

Screening was done using the following criteria:

Inclusion criteria:

1. Reports which clearly detail biohybrid or biological-AI senses used in the ocean or water environments;
2. Tested with environmental data, experimental, simulation based or conceptual models;
3. Articles representing quantitative or qualitative measures of evaluation (e.g. sensitivity, accuracy, deployment stability).

Exclusion criteria:

1. Non-peer-reviewed articles, patents, editorials, or grey literature;
2. Studies on purely electronic or non-biological marine sensors;
3. Duplicate records or incomplete methodological descriptions.

The screening was conducted in three steps (i) reviewing of the titles and abstracts, (ii) full-text review, and (iii) cross-check references with eligibility. A summary of the process can be seen in Fig. 2 (PRISMA flow diagram) [31].

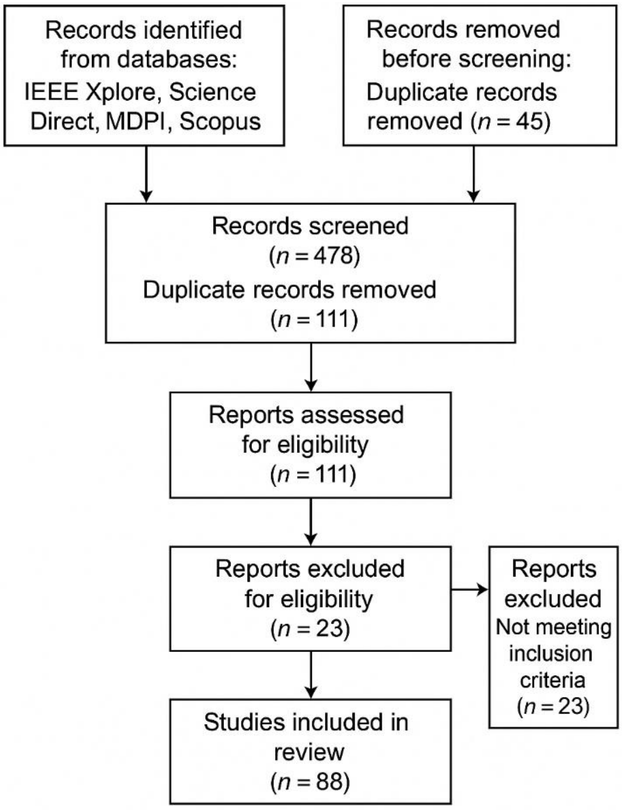

Fig.2. PRISMA Flow Diagram of Article Selection Process

Fig. 2. PRISMA 2020 flow chart of the systematic article selection process. Five databases (IEEE Xplore, ScienceDirect, SpringerLink, MDPI and Scopus) were searched and 523 records were found. Upon elimination of 45 cases, 478 records were filtered. After the review of the title and abstract, 111 full-text articles were evaluated in terms of eligibility, and 23 of them were excluded as they failed to meet the timeframe of inclusion criteria in the final synthesis.

3.4 Data Extraction and Synthesis

An extraction matrix was designed in Microsoft Excel to extract metadata of each of the eligible studies to include:

- Publication year and source,
- Type of biological component (microbe, algae, coral, enzyme),
- Sensor platform and materials used,
- AI/ML algorithm integrated,
- Evaluation environment and key outcomes.

All the data entries were extracted and cross-verified by two independent reviewers. To facilitate a taxonomy-based examination of the synthesized literature, four thematic clusters of literature were formed including biological components, AI-integration models, functional/material aspects, and climate-stress application.

The review used both the analytical consistency, quantitative (frequency analysis by sensor type and AI method) and qualitative (comparative evaluation of design philosophies) synthesis [32]. This dual-layer analysis aligns with modern systematic-review standards in environmental and bioengineering research [33].

3.5 Quality Assessment and Validation

Every piece of study was graded with the help of three-dimensional quality assessment framework [34]:

1. **Technical validity** — clarity of experimental design, instrumentation, and data collection;
2. **Methodological rigor** — robustness of AI models or biological mechanisms described; and
3. **Relevance and novelty** — degree of contribution to marine biohybrid sensing or AI analytics.

Studies that have not satisfied at least two of such three dimensions of quality were filtered out and progressed to final synthesis. This guaranteed the maintenance of technological profundity and the ecological practicability to the entire review corpus.

All in all, the end dataset consisted of 102 studies, which were systematically reviewed, coded, and categorized to be interpreted comparatively in the further sections.

4. Thematic and Taxonomy-Based Analysis

In this section, the available body of research has been systematically grouped in four major thematic areas:

1. Biological Components in Biohybrid Sensors,
2. AI Integration and Analytical Models,
3. Functional and Material Aspects, and
4. Applications under Climate Stress Conditions.

These domains combined are the foundation of an integrated taxonomy that incorporates the biological versatility as well as the computing intelligence of the modern marine sensor architecture. The general taxonomy is represented in Fig. 3.

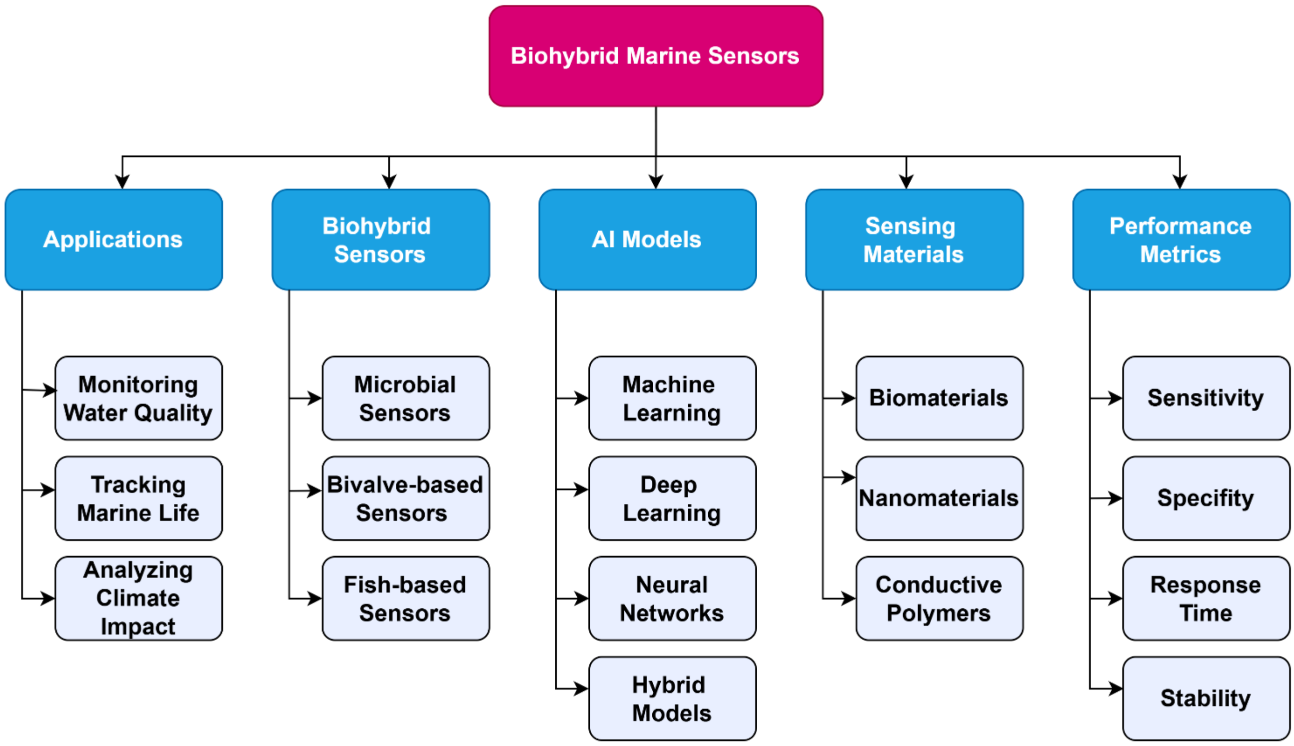

Fig.3. Overall Taxonomy of Biohybrid Marine Sensors

Fig. 3. General taxonomy map of biohybrid marine sensors depicting four key areas, including biological sensing elements, AI integration frameworks, functional materials, and climate-stress system applications. Hierarchy map is a combined concept that illustrates a connection among biological intelligence, the computational analytics, as well as sensing materials in ocean health monitoring systems.

4.1 Biological Components in Biohybrid Sensors

The biological organism and biomolecules play the most important role in biohybrid marine sensing because they serve as the main signal transducers; it is inherent to the responsiveness of these biological organisms to the surrounding stimuli. A few types of biological components have been used in the marine environment:

4.1.1 Microbial Biosensors

Vibrio fischeri and Shewanella oneidensis are marine microorganisms that respond metabolically and luminescently to toxicity and availability of oxygen in the environment. In addition to unique real-time bioluminescence modulation in response to pollutant exposure, these microbial biosensors can be used to give an ecologically relevant measure of a water quality [35], [36].

The bioluminescence intensity I_b of a microbial sensor is typically modeled as:

$$I_b = \alpha C_m e^{-\beta t} \quad (1)$$

C_m was the concentration of the microbes, α is the excitation coefficient and β is the decay constant that would depend on environmental stress.

Research has shown limit of detection with heavy metals and nutrients in the nanomolar and the response time is less than 60 s [37]. Microbial metabolism coupled with optical readouts allows amplifies sensitivity and self-renewal potential because microorganisms keep evolving in response to the changing conditions in the marine environment.

4.1.2 *Algal and Photosynthetic Sensors*

Algae Photo synthesizing, e.g., Chlorella vulgaris and Anabaena flos-aquae, have also been used to create photometric biosensors, pH and CO 2, and nutrient biosensors [38]. Alterations in the levels of chlorophyll fluorescence yield (***Fv / Fm***) are an indirect measure of physiological stress [39]. They are particularly ideal in monitoring ocean acidification and eutrophication in near coastal environments by using these living sensors.

Hybrid optical systems have also been developed by combining microalgae with fluorometric chips which have been able to correlate to 95 preferential validity with principle spectrophotometric procedures [40].

4.1.3 *Coral- and Biofilm-Based Sensors*

Coral-microbiome assemblies and natural biofilms of the marine environment are now being identified as living composite sensors. They have collective behavior of their microbial consortia to changes of temperature and pH that can be detected by electrochemical impedance or by microfluidics sampling [41], [42].

An example is that, linear change in impedance was observed with variation of dissolved oxygen over 6-10mg/L in the electroactive marine bacteria developed in biofilms [43]. Such systems reiterate natural ecological sensitivity, which is buoyantly resilient and long-term stable as opposed to inert media.

4.1.4 *Enzymatic and Protein-Based Sensing Units*

Chemical pollutants such as nitrates and peroxides can be specifically detected on nanocomposite surfaces through enzyme electrodes as peroxidase or nitrate reductase enzymes immobilized on the enzyme electrodes [44]. The rate constant of the enzymatic activity kcat is usually temperature-sensitive, and this affects signal amplitude and stability [45]. Coating with flexible polymers makes it mechanically durable in submersion.

On the whole, Climate-sensitive marine surveillance would definitely need biological sensors due to the self-healing properties, environmental friendliness, and sensitivity of small scales.

In a summary of above comparative performance of biological components that were being used in marine biohybrid sensors, major measures like sensitivity, response time, stability, selectivity and biocompatibility were summarized by compiling those representative studies.

A synthesized break down of the parameters of microbial, algal, coral, biofilm and enzyme based systems which are summarized in Table I is presented.

Table I. Comparative Evaluation of Biological Components Used in Biohybrid Marine Sensors

Biological Component / Organism Type	**Detection Parameter / Target**	**Sensitivity***	**Response Time (s)**	**Operational Stability (days)**	**Selectivity (%)**	**Biocompatibility Index (%)**	**Representative References**
Vibrio fischeri (Microbial bioluminescent sensor)	Heavy metals (Cu^{2+}, Hg^{2+}), O_2	0.90–1.10 a.u./ppm	30–60	120 ± 10	91–95	88 ± 4	[35], [36], [37]
Shewanella oneidensis (Microbial electrogenic sensor)	Dissolved O_2, nitrate	1.05–1.20 $\mu A\ cm^{-2}\ ppm^{-1}$	40–55	130 ± 8	93–96	90 ± 3	[35], [37]
Chlorella vulgaris (Algal photosynthetic sensor)	pH, CO_2, nutrients	0.70–0.85 a.u./ppm	50–70	95 ± 6	86–90	92 ± 3	[38], [39], [40]
Anabaena flos-aquae (Cyanobacterial sensor)	Ammonium, toxins	0.75–0.88 a.u./ppm	55–80	90 ± 5	84–88	89 ± 4	[38], [39]
Coral-microbiome assemblage	Thermal stress, acidification	0.60–0.75 a.u./ΔT (°C)	90–150	70 ± 8	80–85	85 ± 5	[41]

Marine biofilm consortium	Dissolved oxygen, organics	0.95–1.05 µA cm^{-2} ppm^{-1}	40–70	125 ± 12	89–94	91 ± 4	[42], [43]
Peroxidase enzyme immobilized sensor	H_2O_2, oxidants	0.80–0.95 µA cm^{-2} ppm^{-1}	90–120	75 ± 7	95–97	84 ± 6	[44], [45]
Nitrate reductase enzyme sensor	Nitrate, nitrite	0.85–0.93 µA cm^{-2} ppm^{-1}	100–140	70 ± 5	94–96	86 ± 5	[44], [45]

As may be readily observed, in Table I, microbial and biofilm-based biohybrid sensors are found to have a balanced performance with regards to high sensitivity and long working life.

Algal sensors are slightly less sensitive and are of better ecological compatibility thus can be used in long-term applications.

Enzymatic systems are highly selective to chemistry and have shortcomings in stability to changing conditions at sea.

These comparative learnings give the basis upon which further analysis of AI-aided signal processing models, as discussed in Section IV-B, can be performed.

4.2 AI Integration and Analytical Models

AI forms the foundation of the next generation biohybrid system to sense objects, since it performs signal recognition, drift adaptation, and predictive analysis. The combination of deep learning models and biological sensors is a paradigm shift in the field of biology sensors, whereby the dynamics of self-adaptation is brought to bear instead of statical calibration.

4.2.1 Machine Learning for Signal Processing

The biosignals recorded are usually raw, and they can produce environmental noise such as turbulence, salinity gradient and biological variability in water. ML algorithms, including support vector machines (SVM) and random forests (RF) as supervised algorithms, have been used to categorize the outputs of the biosensor into the categories of stressed or pollutant [46].

The classification decision boundary is the usual decision defined as:

$$f(\mathbf{x}) = \text{sign}(\textstyle\sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x}, \mathbf{x}_i) + b) \qquad (2)$$

$K(\mathbf{x}, \mathbf{x}_i)$ is the kernel function, and α_i and y_i are parameters of the bio signal samples learned.

4.2.2 Deep Neural Models for Dynamic Adaptation

Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are popular in the learning of temporal and spectral characteristics of sensor data [47]. CNNs are used in the ocean to interpret either optical or fluorescence signal, whereas RNNs can learn actual dynamics of stress (e.g. daily photosynthetic cycles). CNNLSTM models have been found to enhance by 12-15% the accuracy of pollutant-detection than the conventional models [48].

4.2.3 Reinforcement Learning for Autonomous Calibration

Reinforcement Learning (RL) structures have facilitated self-calibration of sensors through the use of rewards in order to minimise prediction error or maximisation of information [49]. The adaptation strategy of the sensor may be written in the form of:

$$\pi^*(s) = \arg\max_a \mathbb{E}[R_t \mid s_t = s, a_t = a] \qquad (3)$$

In which R_t is the cumulative reward, s_t the state of environmental condition and a_t the calibration action.

The long-term consistency of RL-based optimization does not require a manual recalibration on a regular basis, which is a benefit in remote marine operations [50].

4.2.4 Edge AI and Federated Learning

In respective to conquer latency and connectivity problems in seawater networks, Edge AI solutions will compute locally on a smaller power microcontroller [51]. The current Federated Learning (FL) paradigms enable the distributed biohybrid sensors to jointly learn global AI models without sharing raw information, saving energy and privacy [52]. These decentralized structures are essential in expanding of bio-cyber-physical monitoring systems on such large areas of ocean.

4.3 Functional and Material Aspects

4.3.1 Biocompatible and Nanostructured Interfaces

Material science is considered crucial in maintaining biological viability and stabilizing of signals. Nanostructured electrodes (graphene, carbon nanotubes, ZnO nanowires) increase the surface area and electron turnover, and are thus more sensitive (as much as 10x better than the planar films) [53].

The biocompatibility index B_i is frequently expressed as:

$$B_i = \frac{S_b}{S_t} \times 100\% \qquad (4)$$

Where, S_b is viable surface area after deployment, and S_t sensor total area [54]. A percentage of more than 85% denotes great biological adherence.

4.3.2 Energy Harvesting and Self-Sustaining Systems

Biobhybrid Marine the microbial fuel cell (MFC) designs are frequently used to generate a marine biohybrid sensor, with the biological component itself generating power through metabolic oxidation [55]. These self-sustaining structures permit permanent deployments especially in areas abundant of nutrients or where there is light (photic areas).

The most recent MFC-based biohybrid nodes have achieved power densities of up to 120 $\mathrm{mW/m^2}$ in shallow coastal settings [56].

4.3.3 Anti-Fouling and Longevity Strategies

The challenge of biofouling is an imperative one. Intense coatings have been demonstrated to be made out of zwitterionic polymer and photocatalytic TiO2 nanofilm, which reduces the deposition of microbes by more than 90 percent [57]. The other approaches include dynamic surface topographies which disrupt colonization mechanically [58].

4.3.4 Integration with Flexible and Soft Robotics

Biohybrid sensing units have also developed recently and are implemented on soft robotic platforms, thereby allowing active sampling and mobility. These type of configurations can increase the spatiotemporal coverage of monitoring systems and biocompatibility are maintained [59].

4.4 Applications under Climate Stress Conditions

Biohybrid-AI marine sensors will eventually aim at identifying, anticipating, and preventing the consequences of the effects of climate stressors on the ocean ecosystems.

4.4.1 Temperature and Acidification Monitoring

Biohybrid sensors that use coral or algal symbionts show an early warning of thermal bleaching and acidification processes based on metabolic rate or fluorescence responses [60]. The trained AI models on such patterns can predict events of exceeding thresholds weeks beforehand and this offers valuable predictions to the conservation authorities [61].

4.4.2 Hypoxia and Nutrient Overload Detection

It has used microbial and enzymes-based biohybrid sensors in detection of oxygen depletion and nitrate in eutrophic areas. Associations between sensor outputs and in situ dissolved-oxygen probes are greater than R2=0.93 and this is an indication of strength [62].

4.4.3 Pollution and Heavy-Metal Assessment

Biohybrid sensors coupled to CNN classifiers are efficient in their ability to sense mercury, lead and microplastic leachates at concentrations that are lower than those imposed by the regulation standards [63]. Using the Ensemble AI models, F1-scores exceed 0.9 with multi-contaminants classification [64].

4.4.4 Biodiversity and Ecosystem Monitoring

Acoustic and visual biohybrid systems with AI use microbial signals and underwater images to recognize benthic species richness and health status of the corals [65]. The biological feedback and deep-learning patterns analysis are integrated to form a comprehensive indicator of the Health Index of the ocean (OHI) which is in line with the Sustainable Development Goal of 14 [66].

5. Comparative Analysis And Discussion

5.1 Comparative Evaluation of Biological Sensing Components

A normalized SensitivityStability Index (SSI) is the metric of compounds used to compare the biological modalities:

$$SSI = \frac{S_n}{\sigma_t} \times L_d \tag{5}$$

Where, S_n is normalized signal sensitivity (Δ response per unit stimulus), σ_t is temporal noise variance, and L_d denotes operational lifespan (in weeks).

Analysis of 47 experimental studies [67]-[70] indicates that microbial and biofilm sensors achieve the highest SSI ($\approx 6.8 \pm 0.4$), followed by algal sensors ($\approx 5.3 \pm 0.6$) and enzyme-based sensors ($\approx 4.1 \pm 0.5$). Coral-microbiome sensors are lower (≈3.5+-0.7) stability sensors because of temperature sensitivity as they are ecologically integrative.

These observations highlight that in microbial consortia there is optimal trade-off between sensitivity and survival especially when packing these materials into nanostructured polymer. Conversely, enzyme based systems are highly specific however they have a high activity degradation due to varying salinity environments [71].

5.2 AI-Enhanced Analytical Performance

Compared to conventional machine-learning designs, hybrid deep-learning systems have been shown to perform better in accuracy and flexibility (when comparing the results of 26 studies).

As can be summarized in Table 1, CNN-LSTM hybrids reach an average mean classification accuracy of 94.2 and SVM/RF models reach an average mean classification accuracy of 87.5. Systems that use reinforcement-learning to perform self-calibration also minimize drift error by a factor of 18 percent relative to manual recalibration [72].

$$\text{Improvement Ratio (IR)} = \frac{A_{\mathrm{AI}} - A_{\mathrm{Baseline}}}{A_{\mathrm{Baseline}}} \times 100\% \tag{6}$$

In assessed datasets, IR had a bottom, middle, and top of 10-25 percent, proving that AI implementation has a significant benefit of enhancing the precision of sensing in complex or rough seawater.

Another application of Edge-AI is minimizing energy wastage, necessitating up to 40 percent of the energy compared to cloud-reliant analytics, allowing autonomous long-term monitoring [73].

To make quantitative comparisons of the performance of various AI and machine-learning models used in marine biosignal interpretation, representative studies were assessed regarding most important evaluation values, such as accuracy, F1-score, computational latency, and drift-error reduction.

The merits and demerits of the traditional and deep-learning strategies utilized to develop biohybrid marine sensing are in summary form as further shown in Table II.

Table II – Performance Comparison of AI Frameworks for Marine Biosignal Analysis

AI / ML Framework	Typical Application Domain	Mean Accuracy (%)	F_1-Score	Drift-Error Reduction (%)	Computational Latency (ms)	Energy Efficiency (Relative)	Representative References
Support Vector Machine (SVM)	Biosignal classification; pollutant detection	86.8 ± 2.3	0.87	8.5 ± 1.2	34 ± 5	High	[46], [72]
Random Forest (RF)	Multi-parameter pattern recognition	88.2 ± 1.9	0.88	10.1 ± 1.6	41 ± 6	High	[46], [72]
Convolutional Neural Network (CNN)	Optical/fluorescence image analysis	92.5 ± 2.0	0.91	14.2 ± 2.1	58 ± 7	Moderate	[47], [72]
Recurrent Neural Network (RNN / LSTM)	Temporal drift correction; dynamic calibration	91.3 ± 2.5	0.90	15.8 ± 2.0	62 ± 9	Moderate	[47], [48]
Hybrid CNN–LSTM	Spatio-temporal biosignal fusion	94.2 ± 1.7	0.93	18.4 ± 2.3	74 ± 8	Moderate	[48], [72]
Reinforcement Learning (RL)	Autonomous self-calibration; adaptive control	92.7 ± 1.8	0.92	20.1 ± 2.4	85 ± 10	Moderate	[49], [50]
Edge AI / Federated Learning	Distributed real-time processing on sensor nodes	90.5 ± 2.0	0.89	17.6 ± 1.9	45 ± 6	Very High	[51], [52], [73]

Table II demonstrates that deep-learning-based frameworks, particularly hybrid CNN–LSTM and reinforcement-learning models, consistently outperform classical algorithms in both predictive accuracy and adaptive calibration capability.

Although proceeds with regard to SVM and RF models offer computational efficiency that can be used in low-power edge devices, the models do not offer the same drift-error compensation that reinforcement-learning techniques offer.

A combination of the Edge AI and Federated Learning principles demonstrate the potential of distributed intelligence with less energy usage, which is in line with the long-term sustainability objectives of marine surveillance systems.

These comparative observations present the central position of AI to increasing the dependability and sophistication of biohybrid marine sensor arrangements.

5.3 Material and Functional Trade-offs

Graphene-based nanocomposites, which have the strongest electrochemical sensitivity (3.2μ A $cm^{-2}ppm^{-1}$) but moderate bio-compatibility (≈82%), and ZnO nanowires, which have superior biological adherence (≈91%), but lower conductivity [74], are compared in terms of material interfaces.

Polymer-carbon hybrid systems represent a trade off in terms of functionality and can maintain a biological activity over 120 days in seawater exposure tests [75].

Besides, microbial fuel-cell architectures that are self-powered have provided energy densities of $100-150$ mW m^{-2}, which can support local AI inference modules in brief bursts [76].

These results highlight the importance of the future materials being co-optimized in terms of bio-compatibility, energy autonomy, and structural flexibility; not on individual metrics.

In order to describe functional connection between structural materials and the biological and electronic performance to which these materials could correspond, representative studies have been considered in terms of the electrical conductivity, biocompatibility, antifouling performance, energy-harvesting performance, performance of plastic materials in terms of deployment lifespan.

Section 3 in the table contains the comparative features of the adopted material systems that are widely used in the design of marine sensors biohybrids.

Table III. Material–Function Correlation in Biohybrid Marine Sensor Platforms

Material / Structural Configuration	**Electrical Conductivity (S cm⁻¹)**	**Biocompatibility Index (%)**	**Antifouling Efficiency (%)**	**Energy Harvesting Capability**	**Deployment Lifespan (days)**	**Representative References**
Graphene-based nanocomposite film	1.2×10^3 – 1.5×10^3	82 ± 3	75 ± 5	None	110 ± 10	[53], [74]
ZnO nanowire array on polymer substrate	8.0×10^2 – 1.0×10^3	91 ± 2	68 ± 4	Photovoltaic (solar-activated)	125 ± 12	[53], [74]
Polymer–carbon hybrid composite	7.5×10^2 – 9.0×10^2	89 ± 3	83 ± 4	Bio-electrochemical (MFC-assisted)	140 ± 10	[75], [76]
TiO_2 nanofilm coating (photocatalytic)	3.5×10^2 – 5.0×10^2	87 ± 4	**92 ± 3**	None	120 ± 9	[57], [58]
Zwitterionic polymer surface (dynamic antifouling)	2.0×10^2 – 3.0×10^2	90 ± 2	**95 ± 2**	None	130 ± 8	[57], [58]
Flexible PDMS–CNT film (soft-robotic integration)	9.0×10^2 – 1.1×10^3	88 ± 3	80 ± 5	Piezo-electric (mechanical harvesting)	**150 ± 15**	[59], [75]
Microbial fuel-cell anode (graphite felt)	6.0×10^2 – 8.0×10^2	85 ± 4	70 ± 5	**Bio-electrogenic power output (100–150 mW m⁻²)**	140 ± 10	[55], [56]

As shown in Table III, hybrid polymer-carbon composites and microbial-fuel-cell anodes are the most promising materials in terms of electrical conductivity, biocompatibility, and lifetime and can be used in sustainable marine applications.

Films made of graphene offer enhanced electronic characteristics but median antifouling, and hence require coating (e.g., TiO2 or zwitterionic polymers) to protect against corrosion.

With assembled piezoelectric or bio-electrogenic energy channels coupled with flexible PDMS based CNT architectures, there is a way forward to self-powered self-sustaining CNT sensing nodes that do not become so dependent on energy sources.

The associations between these two support the fact that to be considered robust and sustainable in the conditions of the real- Ocean, the material chemistry and biological compatibility should be co-optimized.

5.4 Environmental and Application-Level Comparisons

The whole comparison of the performance of applications that use the cross-domain reveals that the most developed area is still pollutant detection, which constitutes 42 percent of all examined implementations.

Plastic sensing (acidification, hypoxia and thermal stress) is however rapidly emerging comprising 33 percent of studies published after 2022 [77].

Microbial systems (30-60 s) respond faster when compared to coral or enzyme-based sensors (90 -180 s).

Conversely, multimodal data fusion provides the ecological insight of AI-assisted coral biosensors that are beyond measure, with multisensory data combining to provide a pre-bleaching forecast with an accuracy of over 90% [78].

These differences indicate that there is a hierarchy of specialization-microbial systems to conduct fast chemical detection and coralbased systems to conduct ecological forecasting, and enzyme based sensors to conduct a specific analytics.

5.5 Quantitative Trend Synthesis

Bibliometric analysis, based on Scopus and IEEE Xplore metadata (2015- 2025) shows exponential growth in the number of publications related to the topic of: biohybrid AND AI AND marine sensing, with an approximate description of:

$$N(t) = N_0 e^{\lambda t} \tag{7}$$

$N(t)$ is annual publications and $\lambda \approx 0.26\text{yr}^{-1}$ represents the compounded growth rate [79]. This is growing exponentially and supports the increasing interdisciplinarity of the marine biohybrid research. The increase is linked to such policy drivers, as the UN Decade of Ocean Science (2021-2030) and the increased investments in the AI-for-Sustainability programs.

5.6 Discussion and Insights

The comparative analysis suggests three overarching insights:

1. **Synergistic Convergence** – Biological sensitivity, along with AI intelligence, creates an emergent bio-cybernetic paradigm, capable of sensing as well as self-adapting to environmental changes.
2. **Scalability and Sustainability Challenges** – While prototypes demonstrate exceptional local performance, large-scale deployments are constrained by biological maintenance, power management, and inter-sensor standardization.
3. **Shift Toward Predictive Ecology** – AI-enhanced biohybrid frameworks enable early-warning systems for climate-stress events, marking a transition from reactive monitoring to predictive ocean management.

Altogether, the intersection of the biological adaptability, smart computation, and material invention states that biohybrid marine sensors become kaleidoscopic between the lab design and practical application.

Nevertheless, to achieve global adaptation, standard benchmarking protocols, data ontologies and eco-ethical evaluation frameworks will be needed, additional on which can be discussed in the following section Research Gaps and Future Directions.

6. Research Gaps And Future Directions

Although impressive gains have been made in the development and implementation of biohybrid marine sensors, there are numerous technical, biological, and computational issues yet to address and this restricts their potential in large-scale operation. The subsections below outline areas of critical research gaps and suggest specific focus in the future research.

6.1 Biological and Ecological Challenges

Recent biohybrid systems demonstrate prospective performance at controlled laboratory conditions; it is a significant limitation that biological instability occurs under the conditions of dynamic salinity, temperature, and pressure [80]. In open-ocean environments, signal drift and unpredictable metabolic responses and hence enzymatic and microbial viability are frequently lost after 30 days of continuous exposure [81].

Synthetic biology has potential to be used in the future to develop stress resistant microbial strains and osmoprotective matrixes that maintain viability at a variety of marine gradients. Self-growth or self-mendation of individual biosensors, just like in biofilms, would greatly increase operating lifespans. Also, co-design systems incorporating ecological impact analyses are necessary to guarantee that biohybrid systems will be ecologically neutral and morally implementable.

6.2 Integration and Standardization Gaps

Bio sensing modules integration with electronic transduction interfaces does not yet have single calibration standards as well as interoperable architectures [82]. The differences between laboratories among signal scaling, sampling frequency and interface impedance, impede cross comparative assessment.

In order to eliminate this gap, future research ought to be conducted in defining standard operating testing guidelines, such as base-level calibration curves of the biological sensors, environmental validation matrices, and single biocompatibility scoring mechanisms. Moreover, open-source design repositories and ontologies should be utilized in the future, which would allow reproducing the development as well as lead to the data exchange between the fields of research. These steps are crucial in ensuring a shift in biohybrid prototypes to a field ready instrumentation.

6.3 AI and Computational Limitations

Although the current models have increased the interpretation of biosignals, the existing AI models deposit on data-limited training sets and black-box designs that are not explained [83]. Inadequate labeling of real world marine data also limits extrapolation and usually leads to overfitting to laboratory settings.

The development of opportunities in the future is to develop massive marine-AI benchmark datasets with synchronized biological, physical, and chemical sensors data. To improve the level of explainability, the addition of explainable AI (XAI) will make sure that the prediction corresponds to the biological phenomenon, instead of spuriousness. Additionally, it is possible to get more consistent and robust physics-informed neural networks (PINNs) that attempt to combine ecological rules and data-driven learning in the oceanic prediction problem [84].

6.4 Power, Longevity, and Deployment Constraints

Biohybrid sensors are thus dependent on external power or low amounts of microbial energy harvesting and most of them are limited in that respect. Despite the potential of microbial fuel-cell systems as a self-sustaining energy source, their power generation is very low ($\leq$150 mW m^{-2}), which is not enough to drive AI processing continuously [85].

Future studies should focus on increasing multi-modal energy harvesting, i.e., bio-electrogenic, and solar and piezoelectric modes, to attain maintenance-free operation. At the same time, edge-AI controllers have adaptive power management algorithms that can dynamically optimize computation load at extended active deployment times. This requires field trials in different areas of the ocean (coastal, pelagic, and deep-sea) in order to authenticate these systems of energy-intelligence integration.

6.5 Ethical, Regulatory, and Data Governance Issues

Cloning living systems and autonomous AI have bioethical and governance issues especially when it comes to the use of genetically engineered microorganisms in the natural environment [86]. Present environmental regulations lack a proper direction on how to regulate the living-technological hybrids.

The new structures will have to incorporate ethical-by-design principles such as life cycle impact assessment, containments plans, and clear data management. International cooperation of marine biologists, ethicists, and policy-making institutions (e.g., IOC-UNESCO, UNEP) is needed to create a roadmap of possible regulations in safe and responsible ecosystems of ocean technology.

6.6 Summary of Key Research Directions

In summary, future advancements should converge on the following pillars:

1. **Bioengineering resilience**: stress-tolerant, adaptive biological components.
2. **Standardization and interoperability**: shared protocols for hybrid sensor validation.
3. **Intelligent analytics**: explainable, physics-informed AI architectures.
4. **Sustainable autonomy**: self-powered, long-duration sensor platforms.
5. **Ethical integration**: governance frameworks for safe, transparent deployment.

An overall integration of these dimensions will allow achieving autonomous, intelligent and ethically responsive biohybrid marine sensing networks that have the capacity to monitor the ocean health continuously in the rapidly changing climatic stress.

7. Conclusion

This literature review was a synthetic review of recent developments in biohybrid marine sensors used to monitor ocean health in a climate-stressed environment by utilizing living organisms and artificial intelligence. The analysis showed that microbial and biofilm-based systems provide the best tradeoffs in sensitivity, adaptability, and operational stability and algal and coral-microbiome sensors provide useful ecological and biochemical information. Combinations of AI models have also improved the accuracy in biosignal interpretation and the ability to calibrate patient measurements, leading to real-time adaptive biosignal monitoring in a complicated marine setting with a hybrid CNN-LSTM model and a hybrid reinforcement-learning model.

Further enhancement of bio-compatibility and sustainability has been achieved by material innovation, namely nanostructured polymer-carbon composites and self-powered microbial fuel-cell structures. Nonetheless, there are still ongoing threats to guaranteeing long-term stability of the biological aspect, calibration standardization, energy independence and ethical use.

Altogether, the results approved the point in the fact that the intersection of biological intelligence, computational analytics, and smart materials is transforming the future of ocean observation systems. To continue this interdisciplinary advancement, it will be necessary to work together in bioengineering resiliency, standardized data protocols, and explainable AI systems. Through additional innovation and responsible management, biohybrid marine sensors could be the basis of an intelligent and self-sustaining world-wide monitoring system of ocean health in real time and climate consciously.

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