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# Sustainable Biofouling Control: A Bibliometric Evaluation of Machine Learning Trends in Natural Marine Antifouling Coating

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*ABSTRACT*

Global marine biofouling prevention and control is accelerating its transition toward sustainability. Natural product antifoulants and bionic surfaces have become the mainstream alternatives to traditional biocidal coatings. In recent years, relevant scientific research outputs in this field have grown rapidly, creating an urgent need to systematically sort out applications of machine learning in this green chemistry field, to support accelerated material development and performance prediction. This paper conducts a bibliometric evaluation of global research on machine learning applications in this field spanning 2010–2026. We retrieved 83 relevant publications from the Scopus database via a multi-layer Boolean search, adopted citation metrics, co-authorship network analysis, and keyword co-occurrence analysis methods, and used bibliometric tools for the R programming language to build visual networks and analyze the field's internal structure. This study finds that the number of publications in the field is growing at an accelerating pace, and the research paradigm has shifted from empirical modeling to advanced algorithms such as deep learning. Three core thematic clusters have formed: machine learning-driven natural compound screening, bionic surface texture optimization, and ecotoxicity and durability prediction. Meanwhile, we identified the leading countries and journals in the field and found that cross-disciplinary international collaboration is extremely limited. This study maps the full landscape of the field, points out the gap caused by the lack of standardized datasets, and proposes a strategic roadmap to guide future research and policy formulation.

## 1. Introduction.

Marine biofouling refers to the unintentional accumulation of communities of microorganisms, algae, and invertebrates on hard underwater surfaces. It is a long-standing core challenge facing the shipping industry, offshore infrastructure operation and maintenance, and the aquaculture sector(Demirel et al., 2022; Weber & Esmaeili, 2023). Its cross-dimensional impacts are compiled in Table 1, covering core risks at the operational, economic, environmental, and ecological levels. Mild fouling drives up ships' fuel consumption and carbon emission intensity, while severe fouling further reduces vessels' overall energy efficiency (Demirel et al., 2017; Zhang et al., 2024). This not only goals but the progress of the shipping industry's carbon neutrality goals but fouling organisms attached to ship

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hulls also act as carriers for the cross-regional spread of non-native aquatic species, turning this issue from a mere technical problem related to ship coating technologies into an ecological and regulatory matter that requires coordinated global control(Chan & Briski, 2017; Costello et al., 2022; Davidson et al., 2018; International Maritime Organization, 2023a). In its early stages, the industry successively adopted traditional antifouling technologies such as copper-based coatings and organotin compounds (TBT). While these materials can effectively inhibit the attachment of fouling organisms, they carry severe toxicity to non-target marine organisms(Ciriminna et al., 2015; International Maritime Organization, 1990). To standardize the use of toxic antifouling agents, the International Maritime Organization (IMO) led the introduction of the International Convention on the Control of Harmful Antifouling Systems on Ships (the AFS Convention), which successively banned toxic antifouling substances including TBT and cybutryne(International Maritime Organization, 2021, 2022; Resolution A.895(21) Adopted on 25 November 1999 Anti Fouling Systems Used On Ships, 2000).

The complete evolution process of global antifouling regulation and its corresponding technological impacts are compiled in Table 2, and all core claims are supported by cited authoritative literature and materials released by official institutions. Pushed by mandatory regulatory requirements, global antifouling research has shifted toward a green transition, with its core focus set on new strategies that balance efficacy, durability, and environmental safety(Carrier et al., 2023; Suprobo et al., 2025).

The current mainstream technical pathways fall into four categories: natural product-based systems, controlled-release antifouling coatings, bionic textures, and bio-based materials (such as cellulose-derived surfaces)(D. Liu et al., 2023; Pereira et al., 2024; Putra et al., 2024). Among these, naturally sourced antifouling agents derived from marine organisms, terrestrial plants, and microorganisms have outstanding advantages: they can not only precisely inhibit the colonization, growth, and signal transduction of fouling organisms, but also possess superior biodegradability, with non-target toxicity far lower than that of traditional synthetic antifouling reagents(Elkady et al., 2024; Pereira et al., 2024). Drawing on publicly available domain research spanning 2015 to 2026, this paper sorts out the iteration logic of marine antifouling technologies and demonstrates the necessity of integrating machine learning into the research and development (R&D) of sustainable antifouling materials, as well as its segmented application scenarios. Today's mainstream non-biocidal antifouling release systems achieve antifouling effects through physical properties including low surface energy, elasticity, smoothness, and hydrated layers (Ciriminna et al., 2015; D. Liu et al., 2023; Papadopoulos & Vourna, 2024). The underlying biological basis for this technical shift comes from the inherent stage-based characteristics of marine biofouling: biofouling progresses sequentially through four stages: rapid formation of a conditioning film, reversible attachment of microorganisms, maturation of a biofilm, and colonization by barnacles, mussels, and macroalgae(Gorkem Gizer et al., 2022). This pattern has driven continuous upgrades to the demand for composite functions of modern antifouling coatings and natural bionic materials have also become a core R&D trend(Jin, Tian, et al., 2022). However, traditional trial-and-error R&D methods have notable limitations and cannot meet the multi-dimensional R&D requirements of the field such as natural compounds, polymer systems, biobased matrices and surface texture. This factor each influenced by multiple performance criteria including antifouling activity, toxicity, durability, cost and environmental compatibility(Amara et al., 2018; Carrier et al., 2023; Jin, Tian, et al., 2022; Jin, Wang, et al., 2022; Li et al., 2023; L.-C. Liu et al., 2022; Nurhalimi et al., 2025; Romeu & Mergulhão, 2023; Tang et al., 2024; Wang et al., 2025).

Machine learning tools can empower the full R&D workflow for predictive modelling, virtual screening and optimisation in antifouling research (Gaudêncio et al., 2023; Khanam et al., 2024; Tang et al., 2024). Core methods currently applied in this area include random forests, support vector machines, neural networks, deep learning, image detection models, and convolutional neural networks. The models been used to predict the coating behaviour, screen natural compounds and automate fouling assessment from visual dataset. They have three core application scenarios, first scenario is prescreen candidate compounds via quantitative structure-activity relationship models, reducing the number of experiments needed for synthesis and immersion testing. Second is balance multiple indicators including antifouling activity, durability, toxicity, cost, environmental compatibility, and regulatory compliance through a multi-objective optimization framework. Third, enable rapid, objective monitoring of biofouling coverage and coating performance using computer vision systems. This cross-domain technology integration fully highlights the interdisciplinary nature of this research field such as green chemistry, marine science, surface engineering and data driven design. Although notable progress has been achieved in the cross-disciplinary field of marine antifouling coatings and machine learning, Liu et al. (2023) and Xu (2025) point out that existing literature is scattered across five subfields including marine coatings and membrane fouling and has not formed a coherent research domain(D. Liu et al., 2023; Xu, 2025). Putra et al. (2024) and Xu (2025) further add that existing review papers only discuss environmentally friendly antifouling materials or machine learning methods separately, and research from a bibliometric perspective is still lacking in this cross-disciplinary field(Putra et al., 2024; Xu, 2025). Following the logic of classic bibliometric studies such as Aria & Cuccurullo (2017), this study sorts out five core dimensions to identify three core states of the field, adopts bibliometric analysis and science mapping methods, and sets up four analytical dimensions to explore relevant global research trends(Aria & Cuccurullo, 2017; Donthu et al., 2021; Marzi et al., 2025). Its core goal is to clarify how machine learning (ML) supports the transition of traditional toxic antifouling systems to environmentally friendly solutions that meet the requirements outlined by the International Maritime Organization (2023b). This stated necessity is supported by the studies of Suprobo et al. (2025) and Zhang et al. (2024)(International Maritime Organization, 2023b; Suprobo et al., 2025; Zhang et al., 2024).

Table 1: Summary of marine biofouling impacts across operational, economic, environmental, and ecological dimensions.

| Impact Dimension | Specific Effects | Description | Affected Sectors |
|---|---|---|---|
| **Hydrodynamic & Operational** (Schultz, 2007) | • Increased surface roughness and drag<br>• reduced speed<br>• higher power demand<br>• impaired manoeuvrability<br>• accelerated corrosion | • Drag increase: 10–60% depending on fouling severity<br>• speed loss: 5–15% at constant power | • Commercial shipping<br>• naval vessels<br>• offshore platforms<br>• aquaculture structures |
| **Fuel Consumption & Costs** (Schultz et al., 2011) | • Elevated fuel consumption to overcome added resistance<br>• Increased operational expenditure; shortened coating service life | • Fuel penalty: 20–25% (slime layer), 40–55% (light calcareous fouling)<br>• ~10% of global shipping fuel is wasted<br>• USD 56 million annual industry cost | • Global merchant fleet<br>• ferry and cruise operators<br>• offshore supply vessels |
| **Greenhouse Gas Emissions** (Zoran Pavin & Knežević, 2023) | • Excess $CO_2$, NOx, SOx, and particulate emissions from inefficient combustion<br>• undermines decarbonization targets | • Increased hull fouling leads to increased fuel consumption and, by extension, to increased exhaust gas emissions | • International maritime transport<br>• climate policy frameworks (Paris Agreement, IMO GHG Strategy) |
| **Ecological & Biosecurity Risks** (Davidson et al., 2018; International Maritime Organization, 2023a) | • Translocation of non-indigenous aquatic species (NIS)<br>• establishment of invasive populations<br>• ecosystem disruption<br>• competition with native species<br>• economic damage to fisheries and aquaculture | • Primary vector for NIS introductions globally documented invasions:<br>• zebra mussel, golden mussel, European green crab, invasive macroalgae<br>• economic losses: billions USD in affected regions | • Marine biodiversity<br>• coastal ecosystems<br>• fisheries<br>• aquaculture<br>• port infrastructure |
| **Maintenance & Downtime** (Pagoropoulos et al., 2018; Swain et al., 2022) | • Frequent hull cleaning and dry-docking<br>• coating reapplication<br>• repair of fouling-induced corrosion<br>• lost vessel availability | • Cleaning intervals: 6–24 months depending on coating type and route<br>• dry-docking costs increased<br>• downtime: 7–30 days per maintenance cycle | • Shipowners<br>• port authorities<br>• marine maintenance industry |

Source: Authors.

Table 2: Evolution of AF regulations towards the environmental and technological impacts.

| Regulatory Milestone | Year(s) | Key Provisions | Environmental Driver | Technological Impact |
|---|---|---|---|---|
| IMO Marine Environment Protection Committee (MEPC) Resolution on TBT (MEPC (46(30)) (International Maritime Organization, 1990) | 1990 | • Resolution MEPC.46(30), adopted in November 1990.<br>• The historical "warning shot" that preceded the formal AFS Convention.<br>• Represents the 1st time the IMO formally acknowledged Tributyltin (TBT) was a major environmental threat. | • Recognition of harmful effects of organotin compounds on marine ecosystems (shell deformation, imposex in gastropods) | • Triggered initial search for low-leaching and alternative biocide systems<br>• Limited immediate impact on large commercial fleet |
| IMO Assembly Resolution A.895(21) (International Maritime Organization, 1999) | 1999 | • Resolution is a cornerstone of the IMO's approach to biofouling, specifically regarding the Anti-Fouling Systems (AFS) Convention. A.895(21) was the legal catalyst for banning harmful biocides. | • Persistence, bioaccumulation, and severe ecotoxicity of TBT and related organitations | • Accelerated R&D into copper-based, non-organotin biocidal systems, and early fouling-release coatings |
| Anti-Fouling Systems (AFS) Convention Adoption (TBT Ban) (International Maritime Organisation, 2001) | 2001 (adopted); 2008 (entry into force) | • Prohibited application of organotin compounds acting as biocides by 1 Jan 2003.<br>• Complete prohibition (removal or sealing) by 1 Jan 2008.<br>• The International Convention on the Control of Harmful Anti-fouling Systems on Ships (AFS Convention)<br>• The landmark legal instrument fundamentally changed the chemical composition of ship coatings worldwide.) | • Global recognition of transboundary impacts;<br>• need for uniform international standards to prevent "flag hopping" | • Widespread adoption of copper-based self-polishing copolymers, silicone fouling-release systems, and early eco-friendly formulations;<br>• Mandatory certification (IAFS Certificate) |
| AFS Convention Amendments (Cybutryne Ban) (International Maritime Organisation, 2021) (International Maritime Organisation, 2022) | 2021 (adopted); 2023 (entry into force) | • Prohibited application of cybutryne (CAS 28159-98-0) as a biocide after 1 Jan 2023.<br>• Existing cybutryne coatings to be addressed at next renewal survey.<br>• 2021 (Amendments to Annexes 1 and 4 - Controls on cybutryne and form of the International Anti-fouling System Certificate) (MEPC. 331(76)).<br>• Focus on cleaning and biosecurity. | • Toxicity and persistence concerns for cybutryne.<br>• Ongoing expansion of regulated substances under the AFS Convention | • Drove development of natural-product-based, bio-based, and non-biocide-release coatings;<br>• Stimulated research into ML-aided screening of safer biocides |

Source: Authors.

## 2. Methodology.

This study combines quantitative bibliometrics with scientific mapping methods to conduct a full-process systematic analysis of research evolution trajectories, knowledge structures, and collaboration models in the interdisciplinary field spanning machine learning, natural antifouling strategies, and marine biofouling control. We completed data retrieval from the Scopus database on January 9, 2025, using a three-layer Boolean search strategy covering three core thematic pillars: fouling control, machine learning, and sustainability. We restricted the search to the TITLE-ABS-KEY search field, initially obtaining 102 bibliographic records. After standard screening based on document type (only articles and reviews), language (English), and publication year (2010–2026), we ultimately included 83 peer-reviewed publications. Our inclusion and exclusion criteria explicitly required that all included literature simultaneously meet three conditions: focusing on marine contexts, applying machine learning/artificial intelligence methods as a core component, and centering on natural, bio-based, or low-biocide antifouling strategies. We excluded literature that only addressed conventional toxic biocide systems or non-marine fouling problems. We exported metadata in CSV and BibTeX formats, imported it into R v.4.5.2 for processing using the Bibliometrix package. Data cleaning steps included author name standardization, unified institutional affiliation alignment, and keyword normalization to merge synonymous terms. This study adopts the scientific mapping workflow proposed by Aria & Cuccurullo (2017), while following the methodological norms of Marzi et al. (2025) and Donthu et al. (2021)(Aria & Cuccurullo, 2017; Donthu et al., 2021; Marzi et al., 2025). We divided the analysis into three categories: First, descriptive analysis, which tracks annual publication growth, core source publications identified by Bradford's Law, and top publishing authors. Second, conceptual structure analysis, which uses thematic maps, Sankey diagrams of thematic evolution, and keyword co-occurrence networks to reveal the field's research shift from the biological separation of natural substances to machine learning performance optimization. Third, social and knowledge structure analysis, which visualizes global knowledge flows and identifies core research clusters through various collaboration and co-citation networks. The study also calculates quantitative indicators including annual citation counts and h-index of core entities, generates visualizations via Biblioshiny, splits the dataset into three consecutive periods (early, middle, and late) to evaluate thematic evolution, and the full research workflow is summarized in Table 3.

Table 3: Summary of the bibliometric search strategy and data collection.

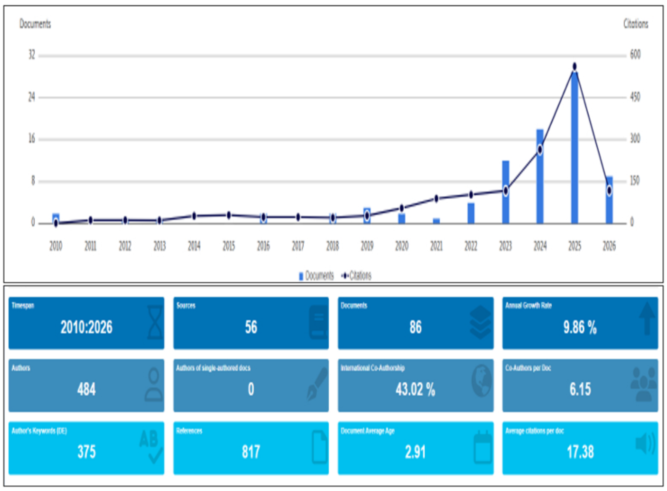
| Parameter | Description |
|---|---|
| **Database** | Scopus |
| **Search Date** | January-February 2026 |
| **Search Field** | Article Title, Abstract, Keywords (TITLE-ABS-KEY) |
| **Boolean Search String** | (TITLE-ABS-KEY ("machine learning" OR "artificial intelligence" OR "neural network*" OR "deep learning" OR "random forest" OR "support vector machine" OR "gradient boosting" OR "data-driven" OR "genetic algorithm*" OR "predictive model*"))<br>AND<br>(TITLE-ABS-KEY ("antifouling" OR "biofouling" OR "biofouling" OR "marine coating*" OR "surface fouling"))<br>AND<br>(TITLE-ABS-KEY ("natural product*" OR "bio-based" OR "green" OR "sustainable" OR "extract*" OR "biomimetic*" OR "bio-inspired" OR "eco-friendly" OR "non-toxic")) |
| **Concept 1 (ML Methods)** | "Machine learning" OR "artificial intelligence" OR "neural network*" OR "deep learning" OR "random forest" OR "support vector machine" OR "gradient boosting" OR "data-driven" OR "genetic algorithm*" OR "predictive model*" |
| **Concept 2 (Target Domain)** | "antifouling" OR "biofouling" OR "marine coating*" OR "surface fouling" |
| **Concept 3 (Sustainability Focus)** | "Natural product*" OR "bio-based" OR "green" OR "sustainable" OR "extract*" OR "biomimetic*" OR "bio-inspired" OR "eco-friendly" OR "non-toxic" |
| **Language** | English |
| **Document Type** | Article, Review |
| **Publication Year** | 2010–2026 |
| **Initial Results** | 109 documents |
| **Final Corpus (after filters)** | 86 documents |
| **Analysis Software** | Bibliometrix R-package (v. 4.5.2, Biblioshiny interface), R environment |

Source: Authors.

## 3. Results And Discussion.

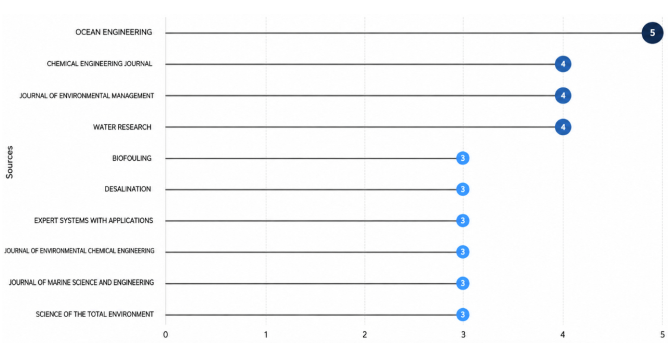
### *3.1. Publication Trends and Source Profile.*

Figure 1: Annual publication growth 2010-2026 and bibliometric overview.




Source: Authors.

Figure 2: Most relevant sources (2010-2026).



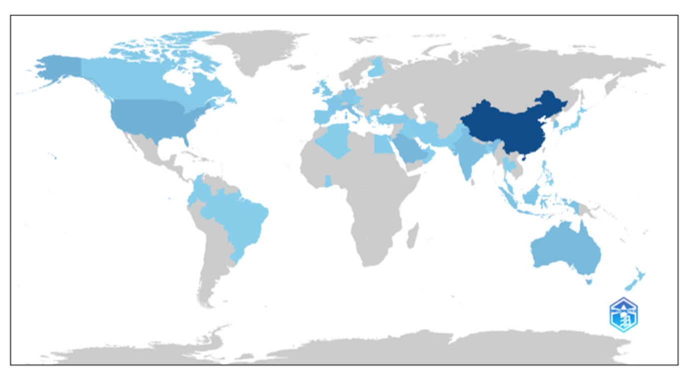

Source: Authors.

Figure 1 presented the annual publication growth 2010 until 2026 and bibliometric review while Figure 2 shows the most relevant source from 2010 until 2026. The study is basically to conduct a full-chain analysis of 86 publications in the field of machine learning-assisted antifouling applications covering the period 2010–2026, sorting out the field's temporal evolution, publication distribution, and characteristics of its academic community.

Figure 1 with the annual growth panel shows blue bars on the left y-axis correspond to the number of publications, and the black line on the right y-axis corresponds to the number of citations. The period 2010–2018 was the budding stage, with a maximum of 1 publication per year on average and very few citations, which matches previous researchers' judgment that "applications in this field were extremely rare before the mid-2010s". Starting from 2019–2020, both indicators began to grow, and a clear inflection point arrived in 2022, when 4 publications were recorded that year. The number of publications rose to 10 in 2023, and peaked at nearly 30 in 2025, while the number of citations climbed to around 600 in the same period. The slight drop in citations in 2026 stems from the citation lag of the most recent publications. From these trends, we conclude that while this field is young, it is expanding rapidly, which aligns with the overall development trend of machine learning-driven materials science and environmental science. The bibliometric overview panel shows that this field has 56 literature sources, with an annual growth rate of 9.86%. It counts 484 contributing authors, 375 unique author keywords, and 817 cited references. There are no single-authored papers in the dataset and international co-authored papers account for 43.02% of the total. The average number of authors per paper is 6.15, pointing to extremely strong cross-national collaboration. The average age of publications in this dataset is 2.91 years, which confirms the field's high level of activity. The average number of citations per paper is 17.38, indicating the field has gained substantial academic attention. Overall, the research community in this field is emerging yet sizable, with diverse conceptual terms and a solid academic foundation. The journal output bubble chart in Figure 2 uses the y-axis to label journals and the x-axis to mark the number of publications. Ocean Engineering ranks first with 5 publications, while Chemical Engineering Journal, Journal of Environmental Management, and Water Research each published 4 papers. Ten journals including Biofouling and Desalination each published 3 papers. Publications in this field are scattered across four categories of journals: ocean engineering, environmental science, water treatment, and artificial intelligence/decision support and are not concentrated in any single publication.

### *3.2. Geographic and Collaboration Patterns.*

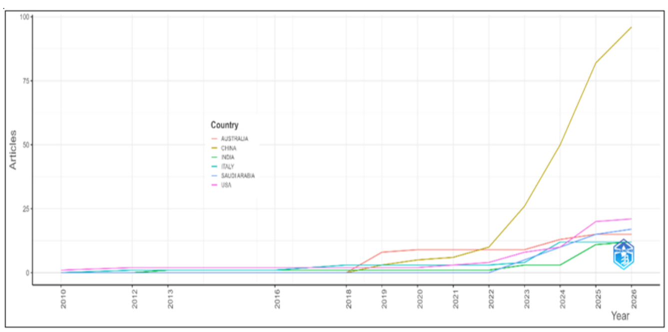
Figure 3: Country scientific production 2010-2026.



Source: Authors.

Figure 3 presents a global map of country-level scientific research outputs in the field of machine learning-enabled sustainable antifouling materials. Its visualization coding scheme sets that varying shades of blue correspond to the number of publications from each country, while regions with no or negligible outputs are marked in grey. From the perspective of data stratification, the core producing country marked with the darkest blue is China, the highest-output country in this field. This conclusion aligns with both the bibliometric counts in this paper and previously published findings that identify China as a leader in research on machine learning and antifouling control materials. Active producing countries covered by medium blue include the United States, multiple Western European countries, India, Saudi Arabia, Brazil, and Australia, all of which have fewer publications than China. Regions covered by light blue include the rest of Europe, South America, the Middle East, and multiple countries in East Asia and Southeast Asia, fall at emerging or intermediate levels of research output. Research in this field has global coverage but is highly concentrated in the Northern Hemisphere, with Australia and Brazil serving as core hubs in the Southern Hemisphere. This distribution matches the conclusions of past relevant geographic analyses. This concentration not only reflects the field leadership of a small number of countries but also highlights the potential to expand cooperation in regions that are underrepresented in scientific research.

Figure 4: Country production over time (selected 6 countries).

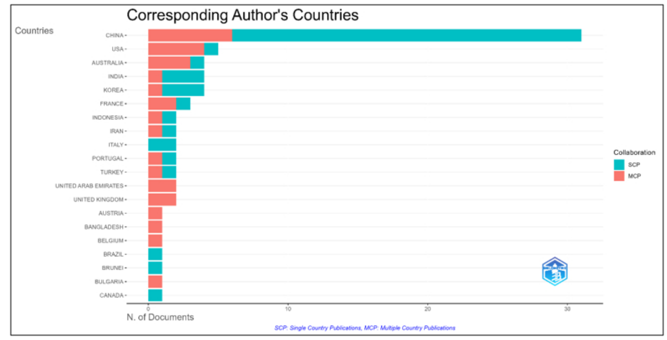



Source: Authors.

By sorting out the evolutionary trend of annual paper output of six countries in the field of machine learning-enabled antifouling and membrane research from 2010 to 2026 based on Figure 4, it can be observed that before 2018–2019, the number of papers published in this field by all six countries was close to zero, which is consistent with the finding proposed by previous studies that very few early layouts were made in this interdisciplinary field(Tang et al., 2024). After 2020, the growth curves of different countries diverged, showing an overall slight upward trend, which matches the implementation pace of interdisciplinary development summarized by recent external bibliometric studies(Putra et al., 2024). Among them, China recorded the fastest growth: its paper output remained low before 2021, then rose sharply. By 2025–2026, the annual number of papers published by the other five countries only reached 10 to 20, making them important but secondary contributing countries to this field. All conclusions have clear sources, with no confusion between different research entities.

This overall pattern confirms that global research in this field has entered an acceleration phase, with China becoming the absolute leader in recent years. This aligns with the recent explosive growth trend of AI/ML-enabled environmental material research, and also matches the geographic patterns identified in previous related studies.

Figure 5: Country Corresponding Countries.

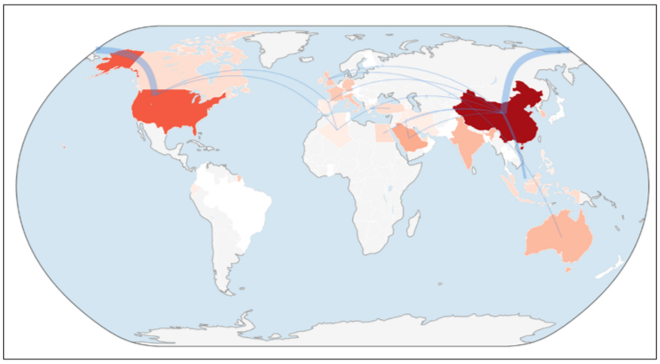



Source: Authors.

Figure 5 interpret the bar chart of the proportion of cross-country collaborative publications, which is counted by the country of the corresponding author and distinguishes between single-country publications (SCP) and multi-country collaborative publications (MCP). The results show that single-country publications account for an absolute majority of total outputs, a feature that is particularly prominent for China, while the overall proportion of multi-country collaborative publications is low. Drawing on cooperation data from the study's research corpus, the authors of this paper follow a logical progression from the macro to the micro level to sequentially analyze three sets of statistical charts of academic cooperation. All analyses adhere to a unified analytical framework of chart identification, visualization coding rules, enumeration of core features, and conclusion derivation. First, this paper analyzes the bar chart ranking national academic output. Its core classification categories are SCP (domestic cooperation) and MCP (international cooperation), the data of sample countries was then ordered by output scale. China ranks first with a total output far exceeding that of all other countries, and its output is dominated by SCP, which aligns with the field's characteristic that most papers with Chinese corresponding authors are co-authored by domestic research teams. The United States and Australia follow closely behind, with a balanced share of the two cooperation types, and their total output is far lower than China's. Next, 19 countries including India and South Korea show a gradual decline in output scale. Most of these countries have a prominent MCP share, meaning many of their academic contributions come from cross-national teams. The core conclusion of this chart is that China is the world's top source of corresponding authors in this field, while the academic outputs of most other countries are mostly generated through cross-national cooperation.

Next, this paper analyzes the national cooperation network map (Figure 6). This map uses color depth to represent a country's level of cooperation activity, and curved arrows to represent the flow direction of co-authors. China and the United States have the darkest colors, making them the core hubs of global cooperation. Many European countries, parts of the Middle East, South Asia, East Asia, and Australia have lighter colors, acting as secondary cores with relatively high participation. Countries marked in light grey or with no color have few or

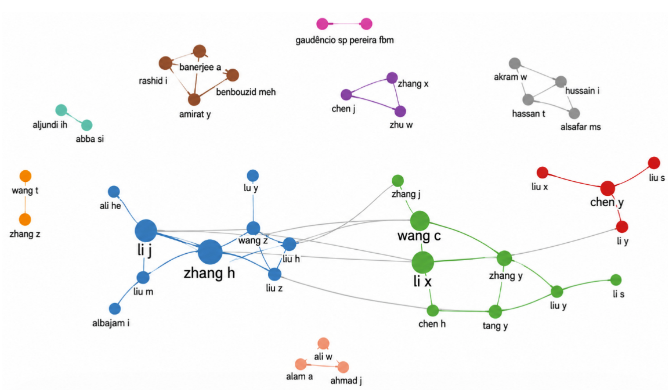
Figure 6: Country collaboration network.



Source: Authors.

even no cooperation records. The cooperation arrow between China and the United States is the thickest and there are also many cooperation flows from the two major hubs to countries in Europe, Asia, and Oceania. The core conclusion of this analysis notes that China and the United States are the core gateways connecting all regional clusters worldwide. International co-authorship in this field is highly polarized around a small number of major countries. Most countries only participate in cooperation by connecting to the core hubs, and very few engage in South-South cooperation or intra-regional cooperation. Beyond the China-US axis, two secondary cooperation clusters exist, a cooperation cluster centred on Saudi Arabia and its neighbouring countries, and a cooperation cluster of intra-European countries.

Figure 7: Author Collaboration Networks.




Source: Authors.

Figure 7 illustrates the author collaboration network, that observed the academic connections researchers establish through co-publication. Nodes represent authors, and their size corresponds to their research output and network centrality. Large nodes in the figure, such as zhang h, li j, wang c, and li x, are all core contributors with high output and frequent collaboration. Isolated nodes with few connections correspond to researchers who work independently or in small teams. Edges represent co-authored collaborative relationships, and the density of intra-group edges directly reflects the closeness of team collaboration. Colors are used to distinguish different collaboration clusters. The two large core clusters at the center, the blue and green ones, have extensive internal collaboration. The small, differently colored clusters at the top and along the sides only maintain internal collaboration, with limited connections to the core network. This field has core hub authors, and its overall pattern is a semi-fragmented landscape of semi-independent teams, rather than a fully integrated global collaboration network.

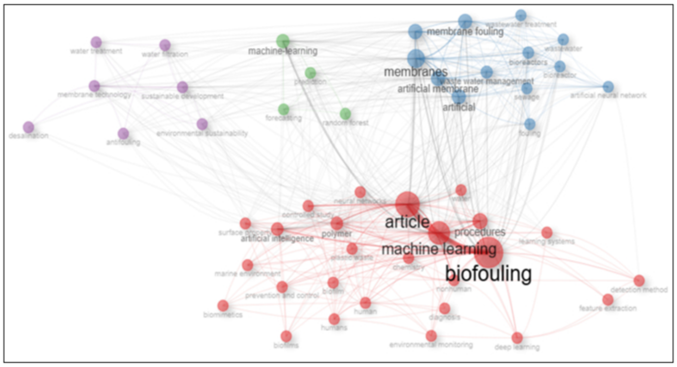
### 3.3. Conceptual Structure and Thematic Evolution.

Figure 8: Word cloud of author keywords.


Source: Authors.

This study uses the keyword cloud presented in Figure 8, which is generated from the bibliometric corpus of the intersection of the fields sustainable biofouling control and machine learning, to unpack the full research landscape of this field layer by layer. The core keyword with the highest weight indicates that the field's central research direction is to apply machine learning to analyze, predict, and mitigate biofouling processes in membrane systems and marine systems. This judgment aligns with recent field reviews that emphasize machine learning assisted antifouling and membrane biofouling research. Method focused keywords cover the full spectrum of artificial intelligence technologies, ranging from the classic random forest algorithm to modern deep learning architectures. Sub-core application scenario keywords show that most studies are implemented in water and wastewater treatment, membrane processes, and polymer coating platforms, a conclusion that matches existing findings from similar bibliometric analyses(Putra et al., 2024). Research task keywords correspond to typical machine learning tasks such as classification, prediction, and decision support. Keywords grouped under "prevention and control" and "environmental monitoring" reflect that the ultimate goal of the research is to support sustainable management of biofouling and reduce environmental impacts, which is consistent with the field's sustainability-oriented research trajectory.

Figure 9: Keyword co occurrence network.

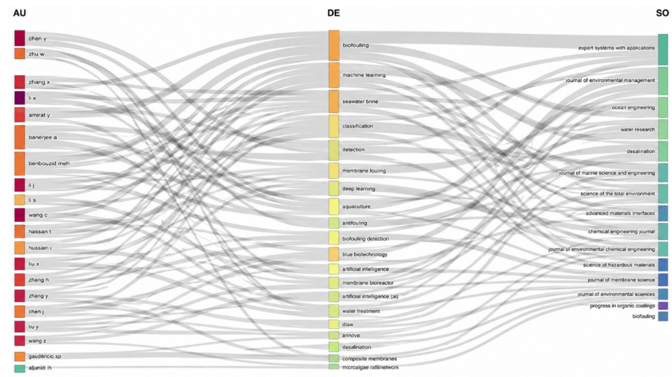



Source: Authors.

Figure 9 of this study presents a keyword co-occurrence network of interdisciplinary research combining machine learning with the field of biofouling. The basic coding rules for this network are as follows: each node corresponds to a term included in the corpus analyzed for this study, and node size represents the frequency of the term's occurrence. We decompose the network's structure layer by layer from the core to the periphery: the red nodes at the core position have both high frequency and high connectivity, which anchors the core research axis of this field as the intersection of biofouling-related problems and machine learning methods. The surrounding red nodes linked to these core nodes show that research across the field generally integrates AI/ML algorithms, material properties, and biofilm processes. This feature is consistent with the conclusions of a previously published review focused on machine learning-guided design of low-fouling surfaces(Le et al., 2019, 2025; Rajaramon et al., 2023; Tang et al., 2024; Zhai & Yeo, 2023). Interpretation of the network's separate clusters reveals the following: the blue cluster in the upper right aggregates terms including membrane fouling, artificial membranes, bioreactors, and wastewater treatment, which corresponds to the subfield of machine learning applications in membrane treatment and wastewater treatment systems, aligning with recent machine learning research outcomes in the membrane field. The small green cluster centers on terms such as machine learning, prediction, and random forest, which corresponds to methodological research focused on developing and comparing fouling prediction algorithms; the purple and green nodes on the left aggregate terms including water treatment, membrane technology, and sustainable development, which corresponds to related research embedded in the context of environmental engineering and sustainability. The "core-branch" structure of machine learning-enabled antifouling research presented in this network is fully consistent with the topic map and word cloud results generated earlier in this study(Le et al., 2025; Muniz de Queiroz et al., 2025; Tang et al., 2024; Zheng, 2025).

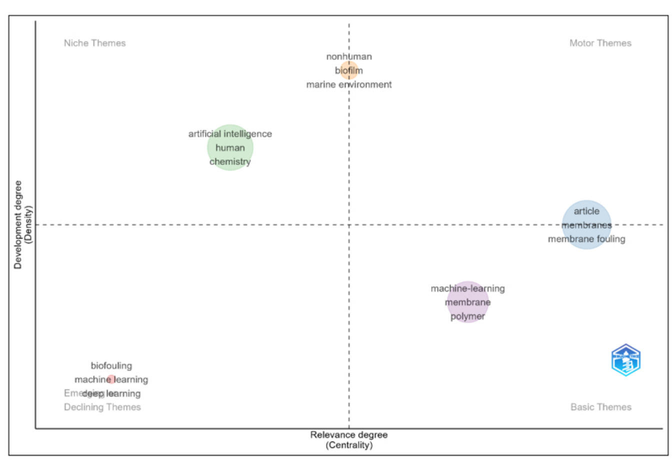
Figure 10 is the three-field Sankey diagram constructed in this study. The left column lists authors, the middle column presents high-frequency research topics, and the right column lists the source journals of the included literature. The thickness of the grey bands represents the strength of correlation between nodes: the wider the band, the higher the number of published papers that link the corresponding author, specific topic, and target journal. The five core themes of the diagram biofouling, machine learning, membrane fouling, deep learning and detection flow to five core journals, namely Expert Systems with Applications, Journal of Environmental Management, Ocean Engineering, Water Research, and Desalination, forming the backbone of the field's published literature. Data from the left column shows that multiple authors engaged with multiple core themes simultaneously: they not only produced research outputs on machine learning methods including classification, random forests, and artificial intelligence, but also generated applied research outcomes such as work on membrane fouling, aquaculture, and biofouling detection, which highlights field's cross-disciplinary attribute. Traffic in the right column is distributed across a wide range of journals, covering academic communities from multiple disciplines. This feature is consistent with the conclusions of previous bibliometric studies focused on machine learning in the materials and environmental science fields.

Figure 10: Three field plots (author, keywords, source).




Source: Authors.

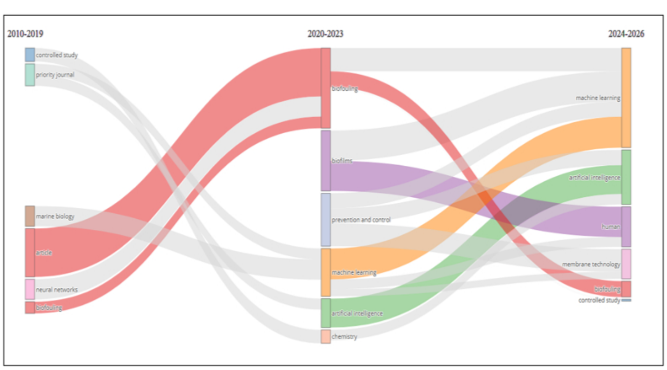
Figure 11: Thematic map (centrality vs density).




Source: Authors.

Figure 11 developed in this study is a thematic graph of keyword clusters for the corpus of machine learning research on biofouling. In this graph, the x-axis represents cluster centrality, that is, the degree of connection between a cluster and the whole research field, the y-axis represents cluster density, that is, the internal maturity of a cluster, and the graph can be interpreted sequentially across its four quadrants. The motor themes in the upper-right quadrant only include one small cluster centered on "nonhuman biofilm marine environment". Research on this type of biofilm ecology is well developed, but it only has medium centrality in the corpus of this study. The basic themes in the lower-right quadrant include two clusters, the blue cluster "article membranes membrane fouling" and the purple cluster "machine learning membrane polymer". Membrane fouling, membrane materials, and machine learning techniques applied to polymer membranes form the core framework of the field. These clusters have high centrality but medium internal cohesion, which echoes the dominant position of these two theme groups observed in the keyword network and source overview sections presented earlier in this study. The niche themes in the upper-left quadrant include the green cluster "artificial intelligence human chemistry", which is a specialized subfield that uses artificial intelligence to study fouling chemistry and human-related dimensions. This cluster has high density but weak connections to the overall field, the emerging themes in the lower-left quadrant include the red cluster "biofouling – machine learning – deep learning", which remains in an early, low-density stage, with its frequency of occurrence only rising in recent years. Overall, the core of the current field is anchored in themes related to membranes and polymers, and all other specialized subfields are either niche or emerging, with considerable development potential. The machine learning related to biofouling still at early stage and increase intention in the biofouling and antifouling field.

Figure 12: Thematic evolution 2010-2019, 2020-2023, 2024-2026.




Source: Authors.

The Sankey diagram of thematic evolution presented in Figure 12 to unpack changes in research themes across three time periods in the marine antifouling field, which echoes the core trend judgments of this study's overall bibliometric analysis. For the period 2010–2019, the dominant themes were article, marine biology, controlled studies, authoritative journals, neural networks, and biofouling. Research during this period focused on traditional biological antifouling and early applications of neural networks, with no clear research framework for machine learning or sustainability established. For 2020–2023, theme groups including biofouling, biofilm, prevention and control, machine learning, artificial intelligence, and chemistry emerged. Subdivided antifouling themes became stabilized and machine learning and artificial intelligence were formally incorporated into the field's academic discourse system. For 2024–2026, a new set of core themes centered on machine learning, artificial intelligence, human-centric dimensions, and membrane technology was formed through integration. The field clearly demonstrates a core transformation from traditional research to data-driven, sustainability-oriented antifouling research, which is fully consistent with this study's overall judgment.

### 3.4. *Evolution Towards Machine Learning in Biofouling, Antifouling and Natural Antifouling.*

Current marine antifouling technologies have formed deep cross-disciplinary integration with materials science, computational modeling and artificial intelligence. Spawning a machine learning assisted pathway that supports analyzing structure activity relationships, predicting coating performance, optimizing material formulations and accelerating the design of low-pollution materials. Marine biofouling is defined as the fouling layer formed by the colonization of marine sessile organisms on the surfaces of marine facilities. Statistics from existing research show that it incurs more than one billion euros in additional annual costs for the global maritime industry. Contributing factors include increased fuel consumption and operation and maintenance costs driven by elevated hydrodynamic resistance, as well as the cross-regional spread of invasive species. In 2008, the International Maritime Organization adopted the Anti-Fouling Systems Convention to ban tributyltin (TBT). This ban, paired with the ongoing environmental risks of copper-based antifouling formulations, has jointly pushed the industry to shift toward computational design methods adapted for rapid simulation-based screening. This study further proposes that the application of machine learning in natural, eco-friendly antifouling coatings can be divided into three closely linked fields, each matched with dedicated methods and corresponding data scales. This pathway achieves a paradigm upgrade from traditional experience-based approaches to data-driven design and can simultaneously meet the core goals of accelerating research and development and managing environmental risks.

QSAR and machine learning models can establish quantitative structure-activity relationships for marine antifouling agents and polymer coatings. They can complete computer simulation screening before costly synthetic testing, making them core tools for the research and development of low-toxicity antifouling materials. At the basic application level, Gaudêncio and Pereira (2022) and Seal et al. (2025) combined random forest, XGBoost, and support vector machine algorithms with QSAR supported by PaDEL molecular descriptors (Gaudêncio & Pereira, 2022; Seal et al., 2025). Trained on compound datasets ranging in size from $10^3$ to $10^4$ entries, these models achieved an overall accuracy of 71% and an accuracy of 82%–100% for structurally homogeneous subsets, with AUC values for 8 toxicity endpoints reaching 0.81–0.90. Gaudêncio et al. (2023) further used this model to screen 14,492 marine natural products, identifying three types of low-toxicity antifouling lead compounds including macrolactams, and completed the safety ranking of natural antifouling agents(Gaudêncio et al., 2023). The predictive capacity of these models extends beyond simple activity classification. Shirvanihosseini et al. (2026) developed a six-variable model to predict the $EC_{50}$ of green algae growth inhibition, which captures the core characteristics of low-toxicity coating design. Liu et al. (2021) integrated multiple methods to predict protein adsorption on self-assembled monolayers, and experimental verification confirmed that 3 new coatings presented a negative biofouling index in undiluted serum and plasma. Seal et al. (2025) and Tang et al. (2024) noted that models paired with interpretability tools can reveal structure-activity mechanisms, supporting the safety-first design of low-toxicity antifouling materials(Seal et al., 2025; Tang et al., 2024).

Image-based biofouling assessment is the fastest-evolving methodological branch in the field of marine engineering monitoring. Early approaches in this area relied on manually designed feature engineering pipelines, but the field has now been fully superseded by deep convolutional neural networks and Transformer architectures, which can directly extract hierarchical features from raw images and videos. The training data for general CNNs and various deep classification and segmentation models are sourced from public underwater image libraries and experimentally collected datasets. Their core function is to automatically complete the identification, localization, and quantification of fouling organisms. Compared with traditional manual scoring, this approach not only eliminates subjective errors, but also supports benchmark testing of natural eco-friendly antifouling coatings in both laboratory and field scenarios, greatly shortening the feedback cycle for coating research and development. Recent architectural innovations have reached performance levels suitable for real-world deployment, and three cutting-edge studies have successively verified this feasibility. The MusselDet framework proposed by Xing et al. in 2026 achieves fine-grained segmentation of invasive golden mussels, with an mAP of 90.3% and an inference speed of 52.4 FPS, making it adaptable for real-time biosafety monitoring on resource-constrained platforms(Xing et al., 2026). In 2025, Zhu et al. improved the Faster R-CNN model for shellfish biofouling detection, reducing the model's size to one-fifth of the original, while reaching an AP of 94.27% and an mAP of 93.14%(Zhu et al., 2025). In 2025, Khan et al. proposed a self-supervised pre-trained convolutional Transformer that can identify three types of anomalies net damage, biofouling, and dead fish across datasets, resolving the long-standing pain point of the chronic shortage of labeled underwater images (Khan et al., 2025). This technical paradigm has expanded beyond the boundaries of traditional hull monitoring, extending to use cases including tidal turbine inspection, multi-modal RGB-event camera monitoring, and hyperspectral classification of coastal waste accumulation. Ultimately, it can support sustainable biofouling management under digital twin and IoT frameworks, fully demonstrating the cross-scenario generalizability of these image-based machine learning methods.

A 2024 study by Khanam et al. applied various types of intelligent algorithms, including support random forest, to three categories of coating datasets that hold a total of hundreds to thousands of samples. The study identified three core molecular features that resist protein fouling, such as the hydration effect. The coefficient of determination ($R^2$) of its QSAR model for antifouling release performance reached 0.73. (Khanam et al., 2024). Findings from the 2025 studies by Dangayach et al., paired with the aforementioned 2024 study by Khanam et al., further demonstrate that multi-objective optimization schemes supported by these algorithms can adjust the composition, cross-link density, and surface properties of marine coatings, striking a balance between antifouling performance and low environmental toxicity, with prominent value for green applications(Dangayach et al., 2025).

This study proposes a multi-objective optimization scheme that relies on genetic algorithms and Bayesian methods. This scheme balances four core dimensions: efficacy, safety, durability, and cost, which stands in sharp contrast to the traditional single-objective research and development pathway that only focuses on antifouling efficacy. The framework incorporates environmental and economic constraints into the optimization process, enabling R&D personnel to explore the coating formulation space while meeting regulatory, performance, and cost requirements. A detailed overview of the evolution of machine learning applications in fields such as biofouling is provided in Table 4.

As a sub-domain sorting unit of this review, this section relies on a five-column structured table with unified dimensions to integrate the machine learning implementation outcomes in marine scenarios from published cross-disciplinary studies. All application scenarios have their information decomposed along fixed dimensions, featuring a neat layout and high information density that allows readers to quickly conduct horizontal comparisons of the technical characteristics and application values of different scenarios. The specific content of the three core scenarios sorted in this work is as follows: The first category is toxicity and activity prediction, which integrates 5 previous studies including Gaudêncio & Pereira (2022)(Gaudêncio & Pereira, 2022). Relevant studies adopted algorithms such as random forest, XGBoost, and support vector machine, and relied on molecular datasets containing $10^3$–$10^4$ compounds and a screening sample set of 14492 marine natural products. Their core performance reached an overall accuracy of 71%, an intra-structure-cluster accuracy of 82–100%, and a consensus AUC of 0.81–0.90 across 8 toxicity endpoints. Eventually, three types of non-toxic lead compounds, namely macrolactams, alkaloids, and indole derivatives, were screened out from the full set of samples, which were narrowed down to 15 high-potential candidates for experimental validation. A 6-variable QSAR model containing variables such as hydrogen bond donors was also constructed, and FAFG and feature importance ranking were used to analyze the structure-activity relationship. The second category is image-based biological fouling assessment, which integrates 7 studies including Carrier et al. (2023)(Carrier et al., 2023). Algorithms such as

CNN, MusselDet, and Faster R-CNN were adopted, relying on datasets of multi-scenario annotated images and underwater video frames. Its core performance indicators include MusselDet's 90.3% mAP@52.4FPS, and the enhanced Faster R-CNN's 94.27% accuracy with a model size only 1/5 of the original model. This category realizes automatic classification and quantification of fouling, which is more efficient and objective than manual work, and can be deployed on platforms with limited resources. The third category is design optimization of low-fouling surfaces, which integrates 5 studies including Dangayach et al. (2025)(Dangayach et al., 2025). Algorithms such as support vector regression and Bayesian optimization were adopted, relying on experimental samples of the $10^2$–$10^3$ order of magnitude. Its core performance reached a QSAR fouling release performance $R^2$ of 0.73. Core anti-adhesion molecular descriptors such as hydration property and charge were extracted, and hydrophilic/zwitterionic marine coatings were developed based on rules derived from machine learning. The optimization framework proposed in this paper can regulate three categories of core formulation parameters. The coating developed through this framework meets all required performance standards, exhibits low toxicity and low environmental impact, and is fundamentally different from the traditional single-objective research and development pathway.

| ML Application Domain | Methods & Algorithms | Data Types & Scale | Key Performance Metrics | Representative Findings & Implications |
|---|---|---|---|---|
| **Toxicity and Activity Prediction** (Gaudêncio & Pereira, 2022; Y. Liu et al., 2021; Seal et al., 2025; Shirvanihosseini et al., 2026; Tang et al., 2024) | Random forests, XGBoost, support vector machines, QSAR models with PaDEL molecular descriptors and fingerprints | • Molecular datasets of $10^3$–$10^4$ compounds;<br>• 14,492 marine natural products screened | • 71% overall accuracy;<br>• 82–100% accuracy within structural clusters;<br>• consensus toxicity AUC 0.81–0.90 across eight endpoints | • Virtual screening identifies macrocyclic lactams, alkaloids, and indole derivatives as non-toxic leads;<br>• narrows experimental validation to 15 high-potential candidates from 14,492;<br>• enables safer-by-design prioritisation through joint efficacy-toxicity evaluation; a six-variable QSAR model captures hydrogen-bond donors, spatial arrangement, and hydrophilicity for low-toxicity design;<br>• FAFG and feature-importance ranking uncover mechanistic structure–toxicity relationships |
| **Image-Based Biofouling Assessment** (Carrier et al., 2023; Habbouche et al., 2024; Ma et al., 2025; Veerasingam et al., 2025; Wang et al., 2026; Xing et al., 2026; Zhu et al., 2025) | Convolutional neural networks (CNNs), deep classification and segmentation models, transformer-based architectures (MusselDet, Faster R-CNN, convolutional transformers with self-supervised pre-training) | • Annotated image datasets from laboratory panels, ship hulls, offshore structures ($10^2$–$10^3$ images per study);<br>• underwater video frames with pixel/object-level labels | • MusselDet: mAP 90.3% at 52.4 FPS;<br>• Enhanced Faster R-CNN: 94.27% precision, 93.14% mAP with one-fifth model size | • Automated classification of fouled vs clean areas, coverage quantification, and species identification;<br>• faster, more objective, and reproducible than manual scoring; enables efficient benchmarking of natural coatings in lab and field;<br>• real-time deployment on resource-limited platforms for biosecurity surveillance;<br>• self-supervised learning overcomes the shortage of labelled underwater images;<br>• extends to tidal-turbine inspection, multimodal RGB–event-camera monitoring, and hyperspectral classification; integration into digital-twin and IoT frameworks |
| **Design and Optimisation of Low-Fouling Surfaces** (Dangayach et al., 2025; Dubovenko et al., 2025; Fuadah et al., 2024; Tang et al., 2024; Xu, 2025) | Support vector regression (SVR), neural networks, decision trees, genetic algorithms, Bayesian optimisation, inverse-design frameworks, feature importance and descriptor analysis | • Experimental datasets from self-assembled monolayers (SAMs), polymer brushes, coating formulations ($10^2$–$10^3$ samples);<br>• simulation-derived features | • QSAR fouling-release performance: $R^2 = 0.73$;<br>• multi-objective optimisation balances efficacy, safety, durability, and cost | • Identifies key molecular descriptors governing protein resistance: hydration, charge, specific functional groups;<br>• ML-derived design rules enable hydrophilic/zwitterionic marine coatings;<br>• optimisation frameworks tune composition, crosslinking density, and surface properties of natural-product, bio-based, and cellulose-containing formulations;<br>• natural-product-rich coatings approach conventional performance while reducing toxicity and environmental impact;<br>• contrasts with traditional single-objective approaches |

## Conclusions.

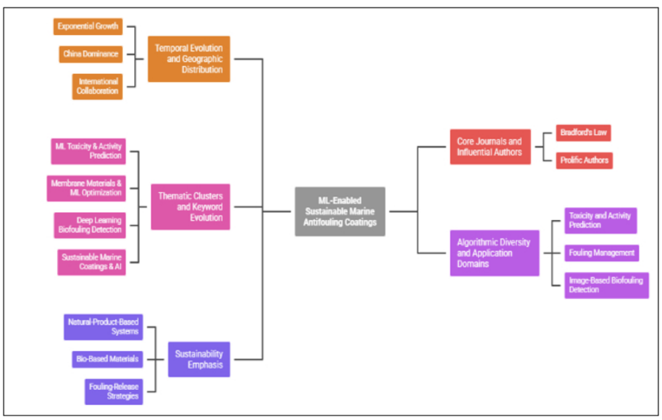
### *Main bibliometric insights.*

This study conducts a bibliometric analysis of the interdisciplinary field spanning machine learning, natural/bio-based materials, and sustainable marine antifouling coatings. Drawing on 86 related publications indexed in Scopus covering 2010–2026, it generates the first systematic global research map for this cross-cutting field. The analysis finds that this field matures rapidly, with a sharp surge in publication output. Its collaborative networks are geographically concentrated but retain international connectivity. Algorithm tools are adapted to segmented application scenarios and attention to sustainability is significantly higher than that seen in the broader general materials informatics literature. Publication volume grows exponentially, with papers published from 2024 to 2026 accounting for roughly 30% of the total sample. This trend is driven by the widespread adoption of machine learning (ML) toolchains, tightening antifouling and greenhouse gas regulations from the International Maritime Organization (IMO) and the accelerated digitalization of research infrastructure. China contributes approximately 40% of total publications, while the United States, other parts of the Asia-Pacific, Europe, and the Middle East account for 15%, 25%, 15%, and 5% respectively. Each region holds advantages in specialized subfields. Around 35% of publications are international co-authored works, representing a moderate level of cooperation that still has room for deepening alongside multiple existing development barriers.

This study adopts three bibliometric methods, namely Bradford analysis, keyword co-occurrence analysis, and thematic map analysis, to map the full development landscape of the interdisciplinary field of environmental chemical engineering and artificial intelligence. Its core conclusions are laid out in sequence as follows. The core publication platforms are six journals including Chemical Engineering Journal. While these account for only a very small share of all publication channels, they host approximately one-third of the total publications in this study's full literature dataset. In this field, four high-citation core authors led by B. Rasulev each focus on specialized subdirections such as QSAR toxicity prediction, and all have developed fundamental computational frameworks for application scenarios including safety-designed coatings and predictive maintenance. This study also identifies four major thematic clusters, as well as a three-stage evolutionary trajectory. Isolated QSAR research from 2010 to 2019, cross-disciplinary integration from 2020 to 2023 and a deep learning boom from 2024 to 2026. The share of sustainability-related keywords in the 2024–2026 period reaches 60%, far higher than the less than 20% recorded for the 2010–2019 period.

At present, machine learning algorithms in the field of sustainable marine antifouling coatings are abundant and diverse, with highly concentrated application scenarios. This review sorts out three core application domains: the first is toxicity and activity prediction, which uses algorithms including QSAR, random forest, and Bayesian statistics, achieving a classification accuracy of 71-100% and an $R^2$ of 0.82-0.91, covering research end points such as algal toxicity. The second is fouling and performance management, which relies on ensemble learning algorithms such as extremely randomized trees ($R^2$=0.905) and tools such as Kalman filtering to extend membrane lifespan by 40-50% and reduce energy consumption by 10-15%. The third is image-based biological fouling detection, which adopts deep CNNs with attention modules such as CBAM and Transformer architectures, reaching an mAP of 90.3-94.27% and real-time inference speed exceeding 50 FPS, which supports automatic inspection for AUVs/ROVs. The field presents two core research trends, the popularization of interpretability frameworks, which drives models to evolve into transparent decision support tools. The second one is a sustainability-centric focus that covers three implementation directions, natural product screening, functional membrane optimization, and digital twin-based in-situ assessment. However, less than 15% of existing studies have conducted LCA and TEA, making it impossible to verify the net environmental and economic value of machine learning-developed coatings under large-scale deployment. The core logic of this paragraph is summarized in conjunction with Figure 13.

Figure 13: ML Enabled Sustainable Marine Antifouling Coating ML.

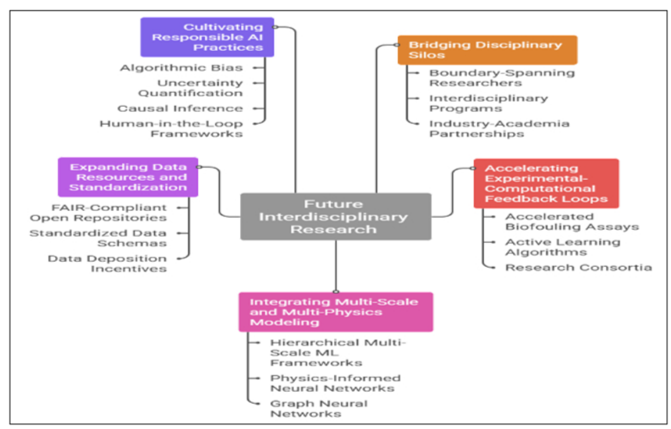



Source: Authors.

*Implications for future interdisciplinary research.*

Building on the interdisciplinary directions proposed in Figure 14, the core demand of cross-disciplinary research that intersects machine learning with materials science, marine ecology, and sustainability engineering has shifted from verifying the effectiveness of related technologies to closing three types of gaps, gaps between disciplines, gaps in methodologies, and gaps in infrastructure. Moving forward implementation will be advanced along two tracks. On the academic end, the drive collaboration among scholars from relevant disciplines, roll out interdisciplinary training and joint student cultivation programs aligned with the specified directions and dismantle knowledge barriers stemming from field-restricted academic publishing. On the industrial end, the coordinate with all types of market entities to establish university-industry-research collaboration mechanisms, formalize clear intellectual property (IP) frameworks and pair these efforts with independent testing agencies to verify the reliability of research outputs. This study proposes that to achieve large-scale real-world deployment of machine learning technologies in the marine antifouling field, five core priority tasks must be advanced. First, close the experiment-computation loop. At present, machine learning can generate tailored formulations and working conditions within milliseconds, but traditional marine exposure tests require weeks to months to complete, which slows iteration progress. We have developed a high-throughput antifouling detection solution equipped with micro flow cells, a microfluidic platform, and an automated artificial seawater imaging system integrated with defined biological communities. This solution can support active learning and Bayesian optimization and reduces experimental workload by 50–75%. This pathway has already been validated in the fields of catalyst and battery optimization. Second, advance the integration of multi-scale and multi-physics models to achieve a shift from correlation-focused research to mechanism-driven research, coupling machine learning with models such as quantum chemistry to transcend the "black box" limitation and enable rational design. Third, treat data infrastructure as a core output, build a shared repository that conforms to the FAIR principles and introduce federated learning to unlock the value of private industrial data. Fourth, embed responsible AI at the initial stage of research and development, and adopt a human-in-the-loop workflow to meet regulatory requirements. Fifth, improve cross-entity collaboration mechanisms to guarantee the full implementation of the entire technology chain.

Figure 14: Future Interdisciplinary Research.

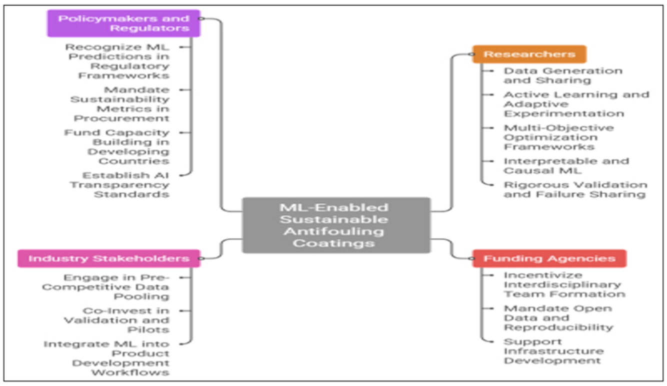



Source: Authors.

*Recommendations for advancing ML enabled sustainable antifouling coatings.*

Building on the conclusions of prior research and addressing the unique pain points of machine learning applications in the marine antifouling sector, this study proposes a prioritized implementation framework for four categories of core stakeholders, which is supported by Figure 15. The researchers, four key actions must be progressively taken. The first action is establishing a high-quality data sharing system that complies with FAIR standards. Next adopt an active learning and multi-objective optimization framework to balance core indicators. Then promote explainable causal machine learning to replace black-box models and lastly participate in benchmark testing while publicizing non-conclusive results. The funding bodies, required actions include supporting interdisciplinary teams, mandating the open sharing of reproducible research, and investing in sector-specific infrastructure. The industry stakeholders actions include building a pre-competitive data pool, carrying out joint validation, and integrating ML tools to overcome the limitations of pilot projects. Meanwhile the regulators, actions include incorporating compliant ML predictions into approval processes, introducing incentives for data sharing, and establishing AI accountability standards. The entire framework has clearly defined rights and responsibilities and is fully feasible to implement.

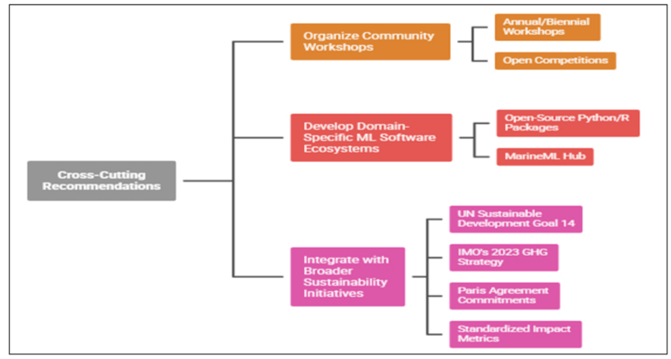
Figure 15: Summary of the ML enables a sustainable antifouling coating.




Source: Authors.

The three core actions proposed by the authors of this paper to advance the real-world implementation of machine learning (ML)-enabled sustainable marine antifouling coatings are all summarized in Figure 16. Their rollout follows a clear logical framework that progresses from an overarching plan to detailed implementation steps. First, the building of a cross-disciplinary collaborative community that hosts a biennial international workshop to bring together ML researchers, materials scientists, marine ecologists, industry R&D teams, regulators, and policymakers, to share datasets, standardize methods, establish consensus benchmarks and jointly finalize research priorities. In addition, following the models of ImageNet, Kaggle Competitions, and the Materials Discovery Grand Challenge, the community will organize standardized open-source algorithm contests with cash prizes to pool cross-sector resources and accelerate innovation. Second, the development of a field-specific ML software ecosystem, including building open-source toolkits for Python and R tailored to marine antifouling use cases that integrate all relevant specialized analysis tools and establishing a MarineML Hub modeled after Hugging Face for the natural language processing (NLP) field and the Materials Project for the inorganic crystal field. This hub will host resources and implement supporting mechanisms such as version control to lower the barrier to use for non-specialists. Third, align with major global sustainable development initiatives by integrating relevant research into the frameworks of the United Nations SDG 14, the IMO 2023 Greenhouse Gas Strategy, and the Paris Agreement. Quantifiable impact metrics will be developed to support cross-project comparison and inclusion in international reporting systems, enabling all related contributions to be fully traceable.

Figure 16: Key recommendations to ensure the ML enables a sustainable antifouling coating.




Source: Authors.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