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# Artificial intelligence and modelling in hydrobiological research

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**ABSTRACT.** Information technology is essential for the advancement of science. Every day, scientists across all fields face overwhelming data volumes that exceed manual processing capabilities. Mathematical models and artificial intelligence (AI) are introduced as a necessary component for processing environmental information. Environmental AI is used mainly for environmental monitoring, hazard toxicology forecasting, and robotic systems aimed at high sampling depth accuracy. A comparative analysis of convolution neural network (CNN) models shows their potential for successful identification of algal species with sufficient illustrative data for successful machine learning. We systematized the application of modern research methods using AI and mathematical modeling in hydrobiology.

***Keywords:*** machine learning, microalgae classification, artificial intelligence (AI), mathematical model of hydrobiology, convolution neural network (CNN)

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## 1. Introduction

Environmental problems are of special attention in the general list of urgent tasks addressed through mathematical modeling. The heavy exploitation of natural resources causes an increase in anthropogenic impact on the environment. Material production processes lead to a violation of the ecological balance both locally in certain areas and globally. The need to combat anthropogenic eutrophication of reservoirs and their global pollution has stimulated a wide range of research in limnology, mathematical modeling, and economics concerning the problems of conservation, restoration, and efficient use of natural resources of lakes and artificial reservoirs. Studies today inherently require mathematical processing of their findings. This entails calculating the volumes of the investigated objects, statistically analyzing the results, and creating predictive or simulation models to understand the dynamics of the phenomena. Hydrobiologist A.I. Bakanov compiled a bibliographic list of authors who employ quantitative methods in ecology and hydrobiology, including 4460 references (Quantitative methods, 2005). In 2003, Shitikov et al. postulated that AI application methods are a necessary component of environmental data processing. The extensive use of AI capabilities substantially facilitates the selection of hydrobiological samples from different-sized water bodies and improves mathematical models for predicting ecological processes, which is increasingly relevant as anthropogenic pressures on the environment intensify (Glushchenko and Piguz, 2011). Main research involving AI techniques focuses on environmental monitoring, robotic systems, mathematical modeling of natural processes, and man-made disasters, which are virtually impossible to predict.

The aim of this study is to systematize the directions of the application of modern research methods involving AI and mathematical modeling in hydrobiology.

## 2. Materials and methods

In order to organize the main areas of hydrobiological research, where methods of mathematical modeling and artificial intelligence are most actively applied, a search for scientific articles was conducted. Keywords such as ‘artificial intelligence in hydrobiol-

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ogy' and 'methods of artificial intelligence in hydrobiology' were searched in major scientific databases, including scholar.google.com, scopus.com, and sciencedirect.com. The found documents were grouped into several areas, focusing on the following issues: classification of species of algae, ecological monitoring, and mathematical modeling of hydrobionic development.

AI techniques such as machine learning, deep learning, and vision transformers are employed for addressing crucial environmental challenges, including species identification, habitat modeling, environmental risk assessment, remote sensing analysis, and biodiversity conservation (Miller et al., 2025).

The main neural network architectures used in hydrobiology, depending on the tasks, were grouped as follows (Table 1).

As shown in Table 1, CNN is the main architecture used in different fields of hydrobiology. A convolutional neural network (CNN) is a type of feedforward neural network that learns features via filter (or kernel) optimization. This type of deep learning network was used to process and make predictions for various types of data, including text, images, and audio (LeCun et al., 2015).

Over the past 20 years, artificial intelligence (AI) applications in hydrobiology have transformed from single experiments to a fundamental tool. The number of relevant scientific publications has increased significantly since 2000, including research using machine learning algorithms.

## 3. Results and discussion

In hydrobiology, mathematical models and artificial intelligence (AI) are introduced as a necessary component for processing environmental information. According to some authors, the main AI areas in ecology are environmental monitoring, forecasting hazardous toxicological processes, and robotic systems aimed at sampling depths with high accuracy. Analysis of the history of models in aquatic ecosystems demonstrates continuous improvement of the mathematical apparatus used in hydroecological studies, thanks to the development of modern computing technology, which allows reducing errors in calculations. The use of AI in hydrobiology covers marine and freshwater ecosystems, from simple data processing to complex forecasting (Table 2).

Neuronetworks (e.g. LSTM models) in freshwater ecosystems can analyze temperature, phosphorus, and nitrogen levels to predict an outbreak of blue-green algae (cyanobacteria) that emit dangerous toxins within 7-14 days. Computer vision models allow the sorting and determination of riverine invertebrates (spring larvae) to calculate environmental quality indices. Machine learning algorithms can process environmental DNA (eDNA) samples of rivers to identify invasive species at the early penetration stage.

In marine ecosystems, AI is being trained to process multispectral satellite imagery (Sentinel, Landsat) to assess chlorophyll concentration and to map ice fields and ocean-scale macroalgae dynamics. The CNN can continuously analyze audio signal flows from hydrophones. They separate the ships' noises from the sound-sounding whales, orcas, and dolphins that can be used during the migration of rare animals. AI integrated into the on-board submarine drone computers (ANPA) allows for scanning coral reefs and automatically detecting coral bleaching zones or outbreaks of predators (such as crown-of-thorns starfish).

AI in hydrobiology is shifting from point studies to global ecosystem monitoring. Neural networks automate species recognition, predict algal blooms, and associate bioindicators with water quality. Convolutional neural networks (CNNs) are used to recognize plankton, benthos, and fish in underwater photographic and video materials, as well as in the analysis of hydroacoustic data. Machine learning is used to analyze eDNA. Models compare genetic data with arrays of biological sequences for rapid biodiversity assessment. AI based on satellite imagery and sensor data (IoT) predicts the spread of harmful algae. Such systems can function as an early warning system for environmental threats. Hybrid models estimate the anthropogenic load on water bodies by modeling the impact of pollution on trophic structures. The concepts of digital water bodies are being developed, where hydrobiological data is combined with physical models of the aquatic environment (flow velocity and temperature). Although these approaches substantially accelerate data processing, they are limited by the absence of standardized sample sizes and regional data differences.

According to analysis using the ScienceDirect search engine, the number of publications covering AI applications in hydrobiology has increased significantly in recent years (Fig. 1a).

**Table 1.** Neural network architecture in hydrobiology

| Task | Architecture |
|---|---|
| Plankton classification | CNN (ResNet, VGG, AlexNet), Vision Transformers, MobileNet |
| Fish and invertebrate dentification | YOLO, Faster R-CNN, ResNet, SE-ResNet, CNN + Transfer Learning |
| Water plant recognition | YOLOv8, DenseNet, Faster R-CNN |
| HAB prognosis | CNN, LSTM, GRU, ConvLSTM, Transformers |
| Water quality | ANN (MLP), CNN, LSTM |
| Toxicology | CNN (video), RNN/LSTM (time-series) |
| Bioacoustics | CNN (spectrogram), RNN |
| Habitat modeling | CNN, Random Forest, Reinforcement Learning |
| Hydrological modelling | LSTM, GRU, Graph Neural Networks, STGNN |

**Table 2.** AI methods in ecosystem research

| Application scope | Freshwater ecosystems | Marine ecosystems |
|---|---|---|
| Sources | IoT sensors and UAV eDNA | Satellites, hydroacoustic buoys, underwater ANPA |
| Bloom monitoring | Forecasting cyanobacterial development | Monitoring of the «red tides» |
| Biodiversity analysis | Classification of river fauna and water purity indicators | Recognition of cetaceans by sound, mapping coral reefs |
| Anthropogenic load | Detection of point-to-point wastewater discharges and field | Run-off Illegal Catch Control (IUU), tracking plastic debris |

The main research areas that most actively use AI methods include ecological monitoring, mathematical modeling of hydrobiological processes, classification of species of algae and other hydrobionts, detection of algae bloom spots, and analysis of environmental microplastic pollution. Below, we describe the development of these areas in more detail.

## 3.1. Monitoring

The application of AI for environmental monitoring can provide a continuous analysis of water quality, detection of spills of polluting chemicals, and prediction of floods or other environmentally damaging phenomena. The sustainable management of water cycles is crucial in terms of climate change and global warming. It involves managing global, regional, and local water cycles, as well as urban, agricultural, and industrial water cycles, to conserve water resources and their relationships with energy, food, microclimates, biodiversity, ecosystem functioning, and anthropogenic activities. Quantitative estimation is a key and challenging issue in water quality monitoring. Sun et al. (2024) stated that AI, with its powerful autonomous learning capabilities and ability to solve complex problems, can deal with the nonlinear relationships between different spectral bands' apparent optical properties and various water quality parameter concentrations. Exploring more water quality parameters with remote sensing technology and AI, intensifying the monitoring of special types of water bodies, and expanding to larger scales remain key focuses of current intelligent water quality monitoring. AI approaches have proven to be powerful tools for accurately modeling complex, non-linear hydrological processes and effectively employing various digital and imaging data sources (Chang et al., 2023).

Shiryaeva and Pushkareva (2026) developed a hybrid neural network model to forecast water quality parameters based on the Python platform and machine learning libraries (TensorFlow Keras, Scikit-learn, and Pandas). The model showed unprecedented forecasting accuracy with a coefficient of determination $R2 > 0.995$ for key water quality parameters. Mitrofanov et al. (2024) demonstrated that AI offers advantages over traditional methods, such as handling vast datasets, improving measurement accuracy, and enabling real-time analysis. The mathematical models and algorithms used for data processing and forecasting were discussed, including regression models, convolutional and recurrent neural networks, time series methods, and Kalman filters (Mitrofanov et al., 2024). Pikunov et al. (2025) indicated that AI is being actively implemented in the field of water quality monitoring. Sensor complexes such as YSI EXO and Eijkelkamp are used to record pH, oxygen concentration, turbidity, and nitrate content. These indicators are compared with satellite images after CNN analysis (U-Net and ResNet). Such networks identify areas of saturation of water bodies with nutrients such as nitrogen and phosphorus, leading to an exuberant growth of algae and a decrease in water quality, and other anomalies. The Google Earth Engine platform processes a huge number of images, calculates water quality indices, and generates thematic maps. The ENVI software package provides analysis of the spectral characteristics of water reflection, which determines the concentration of chlorophyll and the density of algae (Pikunov et al., 2025). Biological early warning systems (BEWS), in which living organisms are used as biosensors, allow for a comprehensive assessment of the aquatic environment's state and a timely response in the event of an emergency. Grekov et al. (2024) examined three machine learning algorithms (Theta, Croston, and Prophet) to forecast bivalves' activity data from the BEWS developed by the authors. An algorithm for anomaly detection in bivalves' activity data was developed.

Lavrova et al. (2014) concluded that the Landsat data are best suited for the detection of cyanobacterial blooms, while SAR data better reveal areas of intense diatom blooms. From Envisat MERIS data, chlorophyll-a concentration and total suspended matter maps were compiled to estimate the algae biomass. In cases of intense cyanobacterial blooms, when algae form

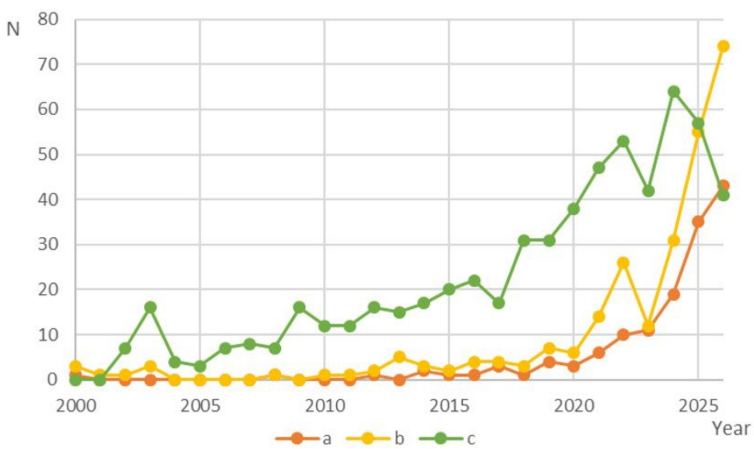


**Fig.1.** Number of publications based on the following ScienceDirect search: "Artificial Intelligence in hydrobiology" (line a), "AI for environmental monitoring in hydrobiology" (line b), and "Mathematical modeling in hydrobiology" (line c), from 2000 to 2026.

dense clumps on the water surface, standard algorithms developed by NASA for Envisat MERIS data showed significant limitations. Frincu (2025) studied how AI techniques could be applied in water quality monitoring. It was found that the most recent interest is among researchers from India, Pakistan, and China. More than half of the studies concern surface water monitoring, 34%–groundwater and to a lesser extent–drinking and irrigation water-related observations. Although almost all research is aimed at obtaining identical types of monitoring data, the procedure for data selection and analysis has not yet been standardized on a global scale (Frincu, 2025). ANN and LSTM neural networks, as well as RF and XGBoost methods, are considered the most suitable for monitoring aquatic ecosystems. Recently, AI techniques have been successfully applied to the prediction of extreme weather events such as floods (Haider et al., 2024) and in groundwater monitoring in regions with limited water resources (Morante-Carballo et al., 2025). Kurzenkov et al. (2025) proposed methods that allow the implementation of a systematic approach to the automated detection and monitoring of phytoplankton blooms in water bodies based on Earth remote sensing data. AI techniques in water resource management have the potential to improve the efficiency and accuracy of various tasks (Toryila et al., 2023). The advantage of AI in monitoring lies in its ability to quickly process large datasets, including through remote sensing systems.

Fig. 1b shows an increasing trend in the number of publications on ecosystem monitoring via IA data. Obviously, the number of references to AI applications in monitoring aquatic ecosystems has risen significantly since 2020.

## 3.2. Mathematical modeling

The mathematical modeling apparatus is currently represented in various directions, among which modeling of eutrophication processes (Sukhinov et al., 2022) and use of remote sensing data are priorities. Mathematical models and methods are widely used to study hydrological and hydrobiological processes, replacing more expensive field experiments. Hydrological modelling plays a crucial role in managing water resources in arid and semiarid regions (Kambarbekov and Baimaganbetov, 2024). Mathematical modeling in hydrobiology is the most developed among environmental fields, as noted by Kalaida and Galeeva (2010). Over 4,000 models are currently being developed using a particular mathematical apparatus, such as balance-energy principal models, water basin eutrophication models, and GIS-based models. The data assimilation methods can provide mathematical models with input data and parameter values. Hydrodynamics of lakes results from numerous processes that have a wide range of spatio-temporal scales. Understanding the patterns of currents and water circulation in lakes is important for assessing transport and transformation, as well as for predicting changes in aquatic ecosystems with various anthropogenic and climatic changes. Knowledge of seasonal and multi-year water circulation is used in the construction of ecosystem models for rational use, lake conservation, and water management.

The communities of phytoplankton and phytoperiphyton have been subject to mathematical modeling for a long time. For example, we developed a universal periphyton simulation model based on the individual examination of each species of the phytoperiphyton community throughout the development period (Sysova, 2008). The formation of a direct gradient of fouling on a substratum surface is due to the current in a boundary layer. The developed two-parametric model of algal cell reduplication adequately describes an exponential stage of periphyton development, and the three-parametric model can be used during any stage of the succession process. Filatov et al. (2017) proposed a mathematical model for plankton population dynamics that includes a system of convection-diffusion-reaction equations with nonlinear components, allowing for the study of the mechanism of external hormonal regulation based on the scenario approach. This model includes a nonlinear dependence to describe the growth rate of algal cells on the concentration of the metabolite, which enabled the description of the ability of algal excretion products to control their growth even under conditions of massive influx of pollutants.

Belova and Nikitina (2024) predicted the development of complex natural systems under pollution conditions using mathematical modeling techniques. The software based on mathematical models enables the creation of short- and medium-term forecasts for the spread of harmful substances, assessment of their impact on the growth of major phytoplankton species in the Azov Sea, and determination of management strategies for sustainable development (Belova and Nikitina, 2024).

Point and one-dimensional mathematical models of aquatic ecosystems, constructed by Petrov and Raspopov (2010), include ten differential equations. These models allow the identification of the dynamics of processes in a complex ecological water system and predict its state in time and space.

Abakumov and Izrailsky (2021) developed a of phytoplankton development dynamics based on the change in chlorophyll concentration under changing environmental conditions. The model takes into account mineral nutrients, water temperature, and illumination.

Nutrient transport has been regarded as a model for several decades. Model simulation of potassium distribution was developed by Kalinkina and Korosov (2015) for the River Kenti and adjacent lakes. Model and empirical data on the role of N/P relationships for species and dimension structures in phytoplankton communities enabled the formulation of a concept of targeted regulation of water-body bloom types through biogenic manipulation (Levich, 2000). Abakumov et al. (2013), within the framework of multi-model approach to the study of natural biological systems, offered four options that describe the dynamics of phytoplankton biomass in the aquatic environment: to examine the closed and open models, taking into account the internal condition of the body and ignoring it. Rusakov and Samokhin (2018) developed a pattern of oxygen formation in the bottom layer of the water basin.

Despite the great diversity of areas and numerous models concerning narrow mechanisms, scientists need to make considerable efforts to develop integrated models that can predict the development of ecosystems as a whole.

In addition to mathematical modeling, which describes various processes through differential or any other equations, for over 20 years, developments have appeared, which describe processes through trained neural networks. Back in 2000, Lyakh attempted to describe the phytoplankton production in the Black Sea using a neural network. He analyzed the relationship between phytoplankton primary production, chlorophyll a concentration, temperature, and water transparency. He revealed that the neural network is a powerful tool for estimation these parameters (Lyakh, 2000). The successful deployment of CNN could significantly enhance the understanding of algae species distribution (Pardeshi, 2023). On the contrary, Lakra et al. (2026) found that UNet adeptly navigates the complex phytoplankton dynamics better than CNN, ConnLSTM, and FourcastNet.

Interest in mathematical modeling in hydrobiology has been growing steadily over the past 25 years (Fig. 1c). This direction is developing gradually, together with the development of computer technology.

In summary, despite the widespread use of AI techniques in monitoring, there is still no common understanding. Efforts should be made by scientists to standardize approaches in order to facilitate the use of data obtained by researchers in other studies. The most suitable AI techniques for modeling complex hydrobiological ecosystem dynamics have yet to be identified.

## 3.3. Algal classification

Marine and freshwater microalgae belong to taxonomically and morphologically diverse groups of organisms spanning many phyla with thousands of species. These organisms play an important role as indicators of water ecosystem conditions, since they react quickly and predictably to a broad range of environmental stressors, thus providing early signals of dangerous changes. Conventionally, microscopic analysis was used to identify and enumerate different organisms within a given environment at a given point in time.

Barsanti et al. (2021) indicated four different methodologies to implement systems of automated and real-time analysis of microalgae. They include flow cytometry, metagenomic analysis, remote sensing, and digital microscopy.

In recent decades, computer visualization systems have been used for species classification (Pardeshi, 2023). Support vector machine methods qualified members of the genus *Scenedesmus* (Pardeshi, 2021). Kaya et al. (2023) used MobileNetV3small and Mobile NetV3large methods to classify such virtues as *Anabaena, Aphanizomenon, Gymnodinium, Karenia, Microcystis, Noctiluca, Nostoc, Oscillatoria, Proracentrum*, and *Sceletonema*. Barsanti et al. (2021) presented 13 most representative automated systems that can recognize microbiota by morphological traits. The authors generalized that recognition basically consists of five steps: sampling, obtaining high-quality images, and image processing, which in turn includes denoising, thresholding, segmentation, and contour detection. The fourth step is feature extraction and selection. Different features that describe microalgae characteristics are calculated for each image (Baltsevich and Shevyaleva, 2022). The fifth step is the identification of the objects recognized as microalgae. Automatic microalgae classification systems use CNN. The time necessary for scanning a slide and building the input dataset is ~45 minutes.

Teng et al. (2020) demonstrated that computer vision and ML algorithms allow for accurate strain species screening and classification, making high-quality microalgae images useful for further analysis. Gaur et al. (2021) used a deep learning-based algorithm to design a CNN based on the auto-classifier for *Pediastrum* identification and classification to decrease time and reliance on an algal specialist by modifying the topology of AlexNet CNN. The results of the proposed model are rather high on the augmented dataset. The efficacy of the proposed model is determined by a high training accuracy, validation accuracy, and F1-score, accounting for 100%, 99.54% and 99.99%, respectively. Shapovich (2020) using a CNN with one input layer, two convolutional, and two sub-discretionary layers, implemented an algorithm for recognizing 10 types of diatoms.

Hybrid deep learning and machine learning methods showed a significant increase in classification success rates rather than using them separately.

Due to the laboriousness of species definition under a microscope, researchers' interest in using neural networks to facilitate this process is obvious (Fig. 2).

During a period of intense development of machine learning techniques that use enough images to pretrain neural networks to identify species of algae, the number of publications of this kind has increased greatly (see Fig. 4).

Despite numerous attempts by researchers to use AI in determining species of algae, the question remains open. Researchers should focus on building a common database of algal species that includes high-quality images for successful neural network training.

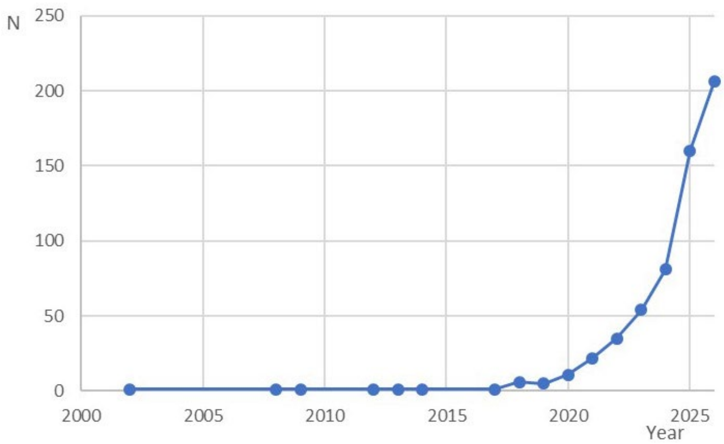


**Fig.2.** Numbers of publications based on ScienceDirect search "CNN in algal species classification", from 2000 to 2026.

### 3.4. AI-based algorithms for detection of harmful bloom-forming algae

The applications of deep learning in image recognition and classification of the bloom-forming algae, a major cause of water pollution, will be on the front line in the new innovative products, technologies, and ideas that can improve our environment. For the categorization of 15 bloom-forming algae, the MobileNet V-2, Visual Geometry Group-16 (VGG-16), AlexNet, and ResNeXt-50 models were tested with the goal of identifying or developing the best-suited convolution neural network (CNN) model for effective monitoring of bloom-forming algae. VGG-16 and Alex Net may appear to be good at first glance, with 96 and 98% accuracy, respectively, but another well-known algal-classifier model, ResNeXt-50, outperformed these two with 99% classification accuracy (Gaur et al., 2023). Qi et al. (2026) were analyzed 1.2 million satellite images with computer artificial intelligence to quantify macroalgal mats and microalgal scums in global oceans between 2003 and 2022. With a total cumulative realized niche area of 43.8 million km$^2$, macroalgae blooms in the tropical Atlantic and western Pacific both expanded at unprecedented rates since the 2010s. They found that he annual expansion rate of microalgae scums is also statistically significant (1.0% per year since 2003).

Because the problem of water blooms is so relevant in today's world, especially due to the possibility of toxic pollution of water bodies, this direction is one of the most studied in the scientific world (Fig. 3).

Similar to the above problem, references to machine learning techniques for detecting water blooms have shown a more than nine-fold increase in the past five years (see Fig. 3).

### 3.5. Microplastic pollution

The rising infiltration of microplastics (MPs) into aquatic environments is a complex threat encompassing marine biodiversity and destabilizing entire ecosystems. Traditional methods for identifying and characterizing microplastics are often manual, requiring significant time and effort due to the small size and varying sources of microplastics. Machine learning techniques can detect microplastics in aquatic ecosystems, one of the most acute challenges facing the world today. The floating giant garbage islands pollute the biosphere, causing irreparable harm to aquatic dwellers. In addition to the mechanical damage associated with the entanglement of animals in plastic packaging, micro-quantities of destructive material are introduced into food webs, being mixed with plankton, which is the basis of various organisms' diets. Manual detection and quality composition determination for time-consuming compounds require significant labor.

Nagpal et al. (2025) identified three main areas of AI application in the microplastic issue: collection and sorting, identification and definition of structures using computerized visualization systems, and modeling and monitoring of plastic decomposition in the environment. For microplastic detection and calculation, AI-integrated equipment with sensors to calculate particles in real time using DNNs is recommended, which will avoid manual counting errors. Equipment with embedded SVMs, which distinguish holographic characteristics, allows distinguishing plastic from diatoms, while this group causes the most difficulty in its detection.

Since the use of machine learning techniques, robotic machines have been able to distinguish plastics by shape, size, texture, and even color. U-Net and MultiResUNet deep learning models can detect dissimilar plastic particles in flowing waters with different flow rates (from 1 to 50 cm/s) (Nagpal et al., 2025). The YOLOv5 system can recognize transparent plastic inserts from 1 to 7 mm in images, each of which takes about 30 ms (Han et al., 2023). AI in FTIR spectroscopy significantly enhances the detection efficiency of microplastics of different configurations in marine ecosystems. Among the areas related to modeling microplastic degradation, there are models of degradation by bacteria, such as the MPL-ANN model based on calculations of bacterial colonies associated with plastic particles (Sun et al., 2019). Moreover, some models predict thermal decomposition (Nagpal et al., 2025). Large-scale projects were developed to control the amount of microplastics in oceans, such as Precision Plastic Waste Cleanup and Monitoring by Columbia Engineering, USA, a project by Japan Agency for Marine-Earth Science and Technology (JAMSTEC), and the Ocean Cleanup, a nonprofit from the Netherlands. In Hong Kong, Open Ocean Engineering created Clearbot Neo, an autonomous robotic boat using AI to identify and collect floating plastic waste in waterways, preventing it from entering the ocean (Deayton, 2022). The AI model for detecting and analyzing marine pollution, including plastic waste and oil spills, through remote sensing along India's coastline was created in India (The Hindu, 2024). These technologies aim to accelerate cleanup efforts and mitigate the impact of plastic pollution on marine ecosystems (Nagpal et al., 2025).

The problem of modeling microplastic transformation has appeared in the past decade and is of constant interest among scientists (Fig. 4).

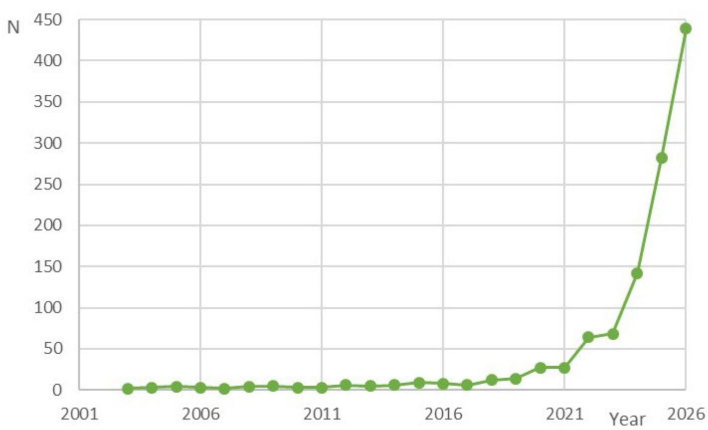


**Fig.3.** Number of publications, based on ScienceDirect search "AI in algal bloom classification" since 200 to 2026 years.

### 3.6. Investigation periods

The exact number of publications on AI applications in hydrobiology depends on the coverage of databases and search keywords because hydrobiology is an interdisciplinary science that overlaps with ecology, hydrology, bioinformatics, and oceanography. In the Web of Science and Scopus databases, the total number of peer-reviewed scientific articles on this topic over the past 20 years is estimated as 1,500 to 2,500 publications.

The dynamics of publication activity based on requests in ScienceDirect can be divided into three stages (Fig. 5).

1. Initial development stage of AI technologies in hydrobiological research (2000-2015) (see Fig. 5). In this period, researchers used simple architectures–classical artificial neural networks (ANN) like the multilayer perceptron (MLP) or the support vector method (SVM). AI was employed to model chlorophyll biomass or for a basic assessment of water quality by chemical indicators.

2. Growing interest in AI applications by researchers (2016-2020) coincides with the "deep learning revolution" and the development of CNN: the first major studies on the automatic recognition of plankton by photography, classification of fish stocks, and analysis of cetacean voices.

3. Exponential growth in the number of publications (2020-2026). This period accounts for a large share of all existing articles (from 50 to 98% of all publication volumes). This is due to the availability of pre-trained computer vision models (YOLO and transformer architectures), the development of eDNA technologies, and the launch of free high-resolution satellite archives (Sentinel, Landsat).

Among types of publications, research articles are the main source (Fig. 6).

Obviously, mathematical modeling and harmful blooms in water bodies are the most urgent issues (see Fig. 6). The largest number of reviews focused on microplastic pollution problems.

The main drivers of scientific AI productivity for hydrobiology are China (50-70% of publications on freshwater systems and water quality forecasting) and the United States (leading in global ocean monitoring and marine mammal bioacoustics). The EU countries (Germany and France), India, and Australia follow with a slight margin, which Yang et al. (2025) confirm. Interest in applying AI techniques to hydrobiology is likely to increase in the near future.

## 4. Conclusions

Machine learning-based models, including artificial neural networks, genetic algorithms, and support vector machines, are considered practical tools in ecological restoration and water quality prediction. Future research should focus on developing more transparent and interpretable models that can handle biases and low-quality data. The impact of AI application in water quality prediction, hydrological and hydrobiological modelling, algae classifications and monitoring, and optimization of ecological restoration strategies should be spread by addressing existing gaps through future research focused on improving the interpretation of AI models, combining AI with nature-based approaches.

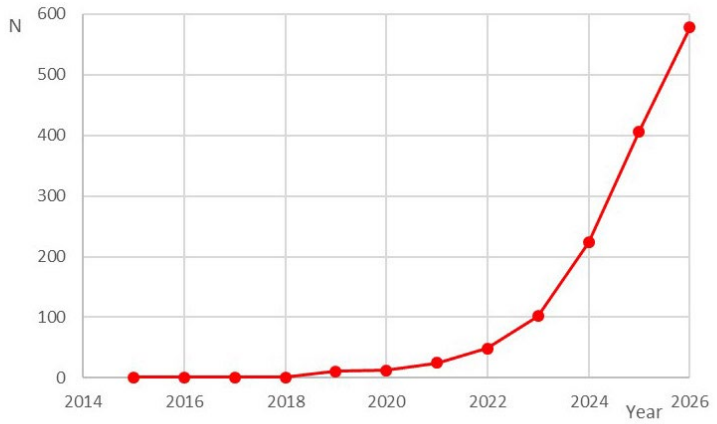


**Fig.4.** Number of publications based on ScienceDirect search "Artificial intelligence for modeling microplastic pollution in aquatic environment" from 2000 to 2026.

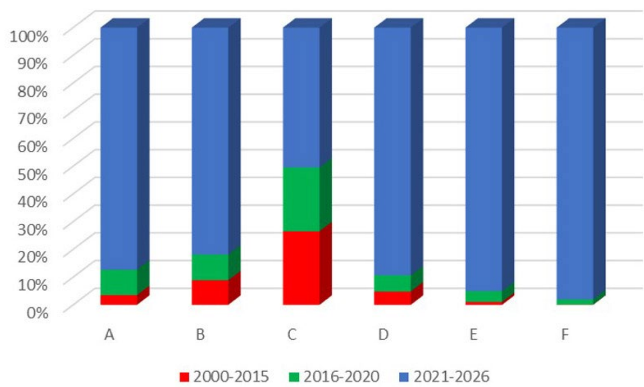


**Fig.5.** Publication dynamics from 2000 to 2026 in different fields of investigations (A–AI in hydrobiology; B–AI for environmental monitoring in hydrobiology; C–mathematical modeling in hydrobiology; D–AI in algal bloom classification; E–CNN in algal species classification; F–AI for modeling microplastic pollution in the aquatic environment).

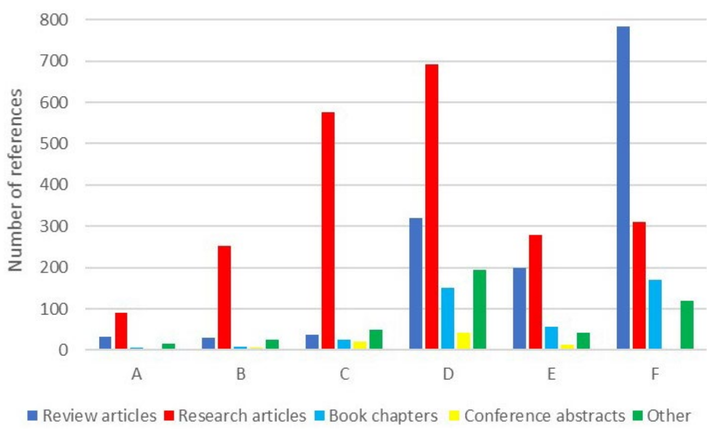


**Fig.6.** Types of publications from 2000 to 2026 in different fields of investigations (A–AI in hydrobiology; B–AI for environmental monitoring in hydrobiology; C–mathematical modeling in hydrobiology; D–AI in algal bloom classification; E–CNN in algal species classification; F–AI for modeling microplastic pollution in aquatic environment).

As AI techniques continue to rapidly evolve across the globe, future research should focus on developing AI techniques and methodologies, integrating advanced hydrobiological monitoring devices with varying spatial and temporal scales. AI is used in various scientific fields. It is most often used to analyze data that are difficult to process manually for a variety of reasons, from the vast volume of information to the inaccessibility of research objects. Machine learning algorithms are used to predict the bloom of toxic algae. AI allows automatic processing of satellite images.

A comparative analysis of CNN models shows their potential to successfully identify algal species with sufficient illustrative data for successful machine learning. Hybrid deep learning and machine learning methods have proven to be most effective in recognizing algae species. The application of UNet's deep learning architecture allows forecasting seasonal and multiyear dynamics of phytoplankton biomass development in oceans. The development of such models will lead to a qualitatively higher level of research on production processes in water bodies. Neural networks combined with databases of algological studies will contribute to a deeper understanding of the role of microalgae in ecosystems.

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## Conflict of interests

The author declares no conflicts of interest.

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