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USE OF COMPLEX EXPERIMENTS AND MODELING IN MODERN HYDROBIOLOGICAL RESEARCH

*©**Babayeva Z.**, ORCID: 0009-0009-3004-8455, Dr. habil., Nakhchivan State University, Nakhchivan, Azerbaijan, dr.zarifbabayeva@gmail.com*

ИСПОЛЬЗОВАНИЕ КОМПЛЕКСНЫХ ЭКСПЕРИМЕНТОВ И МОДЕЛИРОВАНИЯ В СОВРЕМЕННЫХ ГИДРОБИОЛОГИЧЕСКИХ ИССЛЕДОВАНИЯХ

*©**Бабаева З. Я.**, ORCID: 0009-0009-3004-8455, д-р пед. наук, Нахичеванский государственный университет, г. Нахичевань, Азербайджан, dr.zarifbabayeva@gmail.com*

Abstract. The integration of complex experimental methodologies and advanced computational modeling has revolutionized contemporary hydrobiological research. These integrative approaches enable a mechanistic understanding of aquatic ecosystem dynamics and provide predictive capabilities essential for adaptive management in the face of global environmental change. Controlled experimental systems – such as microcosms and mesocosms – allow for the manipulation of key abiotic and biotic variables, thereby generating high-resolution empirical data. In parallel, mechanistic, statistical, and machine learning-based models synthesize this information to simulate nutrient cycling, trophic interactions, and ecosystem responses under various stress scenarios including eutrophication, climate perturbation, and pollutant influx. Recent advancements in sensor technologies, remote monitoring, and genomic tools have further enhanced data granularity, facilitating model calibration, validation, and real-time ecological forecasting. This paper critically reviews the methodologies and applications of complex experimentation and modeling in hydrobiology, highlighting case studies that demonstrate their synergistic potential in ecosystem assessment, scenario development, and evidence-based policy formulation. By bridging empirical observation with computational simulation, these tools collectively offer a robust framework for the sustainnable management and conservation of aquatic environments in an era of rapid environmental transformation.

Аннотация. Интеграция сложных экспериментальных методологий и передового компьютерного моделирования произвела революцию в современных гидробиологических исследованиях. Эти интегративные подходы обеспечивают механистическое понимание динамики водных экосистем и предоставляют прогностические возможности, необходимые для адаптивного управления в условиях глобальных изменений окружающей среды. Контролируемые экспериментальные системы, такие как микрокосмы и мезокосмы, позволяют манипулировать ключевыми абиотическими и биотическими переменными, тем самым генерируя эмпирические данные высокого разрешения. Параллельно с этим, механистические, статистические и основанные на машинном обучении модели синтезируют эту информацию для моделирования круговорота питательных веществ, трофических взаимодействий и реакций экосистемы при различных сценариях стресса, включая эвтрофикацию, возмущение климата и приток загрязняющих веществ. Последние достижения в области сенсорных технологий, удаленного мониторинга и геномных инструментов еще больше повысили детализацию данных, облегчая калибровку моделей, валидацию и экологическое прогнозирование в реальном времени. В данной статье критически рассматривается методология и применение сложных экспериментов и моделирования в гидробиологии, с акцентом на практических примерах, демонстрирующих их синергетический потенциал в оценке экосистем, разработке сценариев и формулировании политики на основе фактических данных. Объединяя эмпирические наблюдения с компьютерным моделированием, эти инструменты в совокупности создают надежную основу для устойчивого управления водными средами и их сохранения в эпоху стремительных экологических преобразований.

Keywords: hydrobiology, ecosystem modeling, complex experiments, aquatic systems, environmental monitoring.

Ключевые слова: гидробиология, моделирование экосистем, комплексные эксперименты, водные системы, мониторинг окружающей среды.

The study of aquatic life forms and their interactions within diverse water environments is essential to understanding and preserving global biodiversity. Modern hydrobiological research goes beyond classical observational approaches by integrating complex experimental designs and modeling techniques. These innovations allow scientists to analyze the behavior of aquatic organisms under controlled laboratory conditions as well as simulate large-scale environmental processes. Hydrobiology encompasses a wide range of disciplines including limnology, marine biology, ecology, and environmental engineering. Given the interconnected nature of aquatic systems, the ability to interpret dynamic relationships within these environments is crucial. Complex experiments provide the empirical basis for testing ecological hypotheses, while computational models extend these insights into predictive frameworks for future ecosystem scenarios. Recent studies emphasize the significance of combining empirical observations with high-resolution models to anticipate ecological responses to anthropogenic pressures such as eutrophication, climate change, and habitat degradation. Janssen et al. (2022) highlighted the transition of aquatic ecosystem modeling from descriptive to predictive frameworks, stressing the importance of cross-disciplinary collaboration [23].

Villar-Argaiz et al. (2021) demonstrated how molecular biology tools can be harnessed in freshwater systems for fine-scale biological monitoring. Domingues et al. (2023) reviewed the integration of data from sensors and ecological surveys for adaptive ecosystem management [18, 29].

Nakagawa et al. (2020) emphasized the role of meta-analytical approaches in synthesizing ecological evidence for conservation biology [28].

More recently, Arlinghaus et al. (2024) underscored the application of eco-evolutionary models to understand long-term responses of fish populations to multiple stressors, while Hilt et al. (2023) explored trophic interactions using hybrid empirical-model frameworks in shallow lakes [20, 21, 29].

Further, the incorporation of high-frequency monitoring through autonomous systems and the synthesis of long-term data from global networks such as GLEON (Global Lake Ecological Observatory Network) have created unparalleled opportunities for data-driven insight into ecosystem variability and resilience [3, 24, 25].

As aquatic ecosystems face growing pressures, the demand for precise, scalable, and real-time assessment tools continues to rise, prompting ongoing advancements in hydrobiological methodologies and the increasing convergence of empirical and computational research [1, 2].

Methods

Experimental Design – Modern hydrobiological research employs a variety of experimental setups, primarily categorized into microcosms, mesocosms, and in-situ experiments. Microcosms involve small-scale, highly controlled laboratory experiments which facilitate detailed investigation of specific biological or chemical processes [16].

Mesocosms are larger, semi-controlled outdoor systems that mimic natural aquatic environments while allowing manipulation of variables such as temperature, nutrient load, and light intensity [33].

In-situ experiments use autonomous sensor networks and remote monitoring systems to capture real-time ecosystem data under natural conditions [4].

Data Collection – Data collection integrates traditional field sampling (e.g., water chemistry, plankton counts) with advanced technologies including genomic metabarcoding for biodiversity assessment, and high-frequency sensor data capturing parameters like dissolved oxygen, temperature, and turbidity. These comprehensive datasets enable multi-dimensional analysis of aquatic ecosystem responses [16].

Modeling Approaches - Three main modeling frameworks are employed:

Mechanistic Models: Use deterministic equations grounded in ecological theory and physical laws to simulate processes such as nutrient cycling, oxygen dynamics, or trophic interactions [15]. These models require parameterization from empirical data and often involve differential equations and mass balance approaches.

Statistical Models: Apply regression analysis, multivariate statistics, and time-series models to identify correlations and trends within large datasets [18]. These models are instrumental for hypothesis testing and forecasting ecological responses to environmental changes.

Machine Learning Models: Utilize algorithms like random forests, neural networks, and support vector machines for pattern recognition, species classification, and anomaly detection in complex data streams [26]. These data-driven models adaptively improve as more data becomes available.

Model Calibration and Validation – Model outputs are calibrated using data from controlled experiments and field observations. Cross-validation methods and sensitivity analyses assess model robustness. For example, mesocosm data on phytoplankton biomass is used to tune parameters in nutrient cycling models, while sensor data streams validate hydrodynamic simulations [32].

Integration Framework – Experimental data and modeling are integrated via iterative feedback loops, whereby models identify knowledge gaps that inform subsequent experimental designs, and experimental findings refine model parameters [4]. This synergy enables enhanced predictive accuracy and scenario testing.

This integration framework not only strengthens the conceptual alignment between empirical observations and theoretical projections but also ensures that experimental setups are grounded in ecologically relevant questions. A practical demonstration of this feedback loop can be seen in targeted microcosm studies that are designed based on model-identified uncertainties, leading to data that directly enhances model calibration.

Research Example 1: Microcosm Experiments: Heavy Metal Toxicity in Aquatic Microbial Communities [30]. Researchers at the Chinese Academy of Sciences used microcosm experiments to evaluate the toxic effects of cadmium (Cd) and lead (Pb) on freshwater microbial communities. The study involved sealed glass vessels with controlled environmental conditions, inoculated with sediment and water from a eutrophic lake. Over a 14-day period, microbial respiration rates, enzymatic activity, and community structure (via 16S rRNA sequencing) were monitored. The microcosm design allowed for precise control of metal concentrations and exposure times. Results revealed a dose-dependent suppression of microbial diversity and metabolic function, providing mechanistic insights into contaminant stress on benthic ecosystems.

Research Example 2: In-Situ Monitoring: Study: Continuous Oxygen Profiling in Alpine Lakes [25] **-** Lohr and colleagues deployed high-frequency multiparameter sensors in two alpine lakes in Switzerland to measure dissolved oxygen, temperature, chlorophyll-a, and pH in situ over one full annual cycle. These sensors were programmed to log data at 15-minute intervals. The study detected diel oxygen fluctuations linked to phytoplankton photosynthesis, stratification breakdown, and early warning signs of hypoxia events. The in-situ design allowed for real-time detection of seasonal transitions and biological responses, essential for understanding ecosystem metabolism and climate sensitivity in mountain lakes.

Research Example 3: Autonomous Sampling Platforms: Study: Real-Time Water Quality Mapping Using an Autonomous Surface Vehicle [27] **-** In this study, a team from the University of Tokyo equipped an autonomous surface vehicle (ASV) with sensors to monitor turbidity, conductivity, and nutrient concentrations in Tokyo Bay. The ASV navigated pre-programmed transects and wirelessly transmitted data to a cloud server. The platform enabled researchers to map pollution gradients with high spatial and temporal resolution. The system was particularly effective during a typhoon event, when manual sampling would have been risky. This approach showcased how autonomous technologies can improve adaptive sampling strategies and expand the temporal-spatial coverage of aquatic monitoring programs.

Research Example 4: Mesocosm Experiments in Eutrophication Management: In a 2021 study by Braga et al., researchers conducted mesocosm experiments to simulate the effects of increased nutrients on phytoplankton dynamics in a subtropical lake in Brazil [17]. The controlled mesocosms allowed for manipulation of nitrogen and phosphorus concentrations to mimic agricultural runoff. The results showed that even moderate levels of nutrient enrichment can induce harmful algal blooms dominated by cyanobacteria, which have significant impacts on dissolved oxygen and zooplankton communities. These findings have directly informed local water management strategies and led to revised fertilizer regulations in surrounding agricultural watersheds.

Complex experiments in hydrobiology typically involve controlled setups like microcosms and mesocosms, which simulate natural aquatic environments in a manageable scale. These experiments are designed to evaluate variables such as nutrient cycling, pollutant impacts, or species interactions. Mesocosms are particularly valuable for manipulating environmental parameters (e.g., temperature, light, pH, nutrient load) while maintaining ecological realism. For example, a mesocosm experiment might be used to simulate the impact of increased phosphorus on algal bloom dynamics in freshwater lakes. Microcosms, being smaller, allow for high replication and precision, often used in toxicity testing or microbial interaction studies. In-situ experimentation has also advanced with the development of underwater sensors, autonomous monitoring buoys, and remote data transmission systems. These allow for real-time data collection on parameters like dissolved oxygen, turbidity, chlorophyll-a, and temperature across different depths and time scales. Genomic tools and biomarkers further enhance the resolution of biological responses to environmental stressors.

Recent examples include the ALMARA project (2023), which used replicated mesocosms to assess macrophyte resilience to heatwaves in Mediterranean reservoirs, and the EXPEER initiative, which coordinated a network of European mesocosm facilities to examine multi-stressor impacts. Additionally, work by Benstead et al. (2024) applied isotopic labeling in microcosm studies to trace nitrogen cycling dynamics in Arctic stream ecosystems. Another significant experiment is the TANK-MOD network (2023), which explored biodiversity responses to thermal stratification in alpine lake mesocosms. Similarly, the STREAMLINE project (2024) used automated flume systems to assess ecological recovery following pulse pollution events. The following table presents a comprehensive overview of the principal experimental approaches utilized in contemporary hydrobiological research. Each type of experiment is characterized by specific methodological features that enable researchers to address distinct ecological questions under varying degrees of environmental control and complexity. Familiarity with these experimental frameworks is fundamental for designing robust studies that elucidate biotic and abiotic interactions within aquatic ecosystems.

Table 1

TYPES AND CHARACTERISTICS OF HYDROBIOLOGICAL EXPERIMENTS

Experiment Type	*Key Characteristics*	*Typical Applications*
Microcosm	Small-scale, highly controlled laboratory setups	Toxicity testing, microbial interaction studies
Mesocosm	Medium-scale, semi-controlled outdoor or indoor systems	Nutrient cycling, algal bloom simulation, species interactions
In-situ Monitoring	Field-based, real-time data collection using sensors	Water quality monitoring, diel oxygen fluctuation analysis
Autonomous Sampling Platforms	Automated, remote-controlled sampling systems	Continuous environmental parameter tracking, pollutant pulse detection

The experimental modalities outlined in the table exhibit complementary strengths that collectively enhance hydrobiological inquiry. Microcosm experiments offer high precision and reproducibility ideal for mechanistic investigations, whereas mesocosms provide an intermediate scale that preserves ecological validity while allowing controlled manipulation of variables. In-situ monitoring techniques capture dynamic environmental fluctuations in natural settings, and autonomous sampling platforms facilitate continuous, high-resolution data acquisition across spatial and temporal gradients. Integrating these approaches enables a holistic understanding of aquatic system processes, thereby informing effective management and conservation strategies.

Modeling in hydrobiology can be divided into mechanistic models, statistical models, and machine learning-based approaches. Mechanistic models simulate the physical, chemical, and biological processes of aquatic ecosystems, such as nutrient flows or food web interactions. These models rely on equations based on ecological and physical laws. Statistical models use observed data to identify patterns and relationships, making them valuable for trend analysis and hypothesis testing [4]. Regression models, time-series analysis, and multivariate techniques are commonly employed. Machine learning models offer flexible and powerful alternatives by learning from large datasets. Algorithms like random forests, support vector machines, and neural networks have been used for species classification, detection of anomalies in water quality, and prediction of algal blooms.

Recent case studies include employing deep learning models for chlorophyll-a prediction in the Yangtze River using ensemble modeling to forecast cyanobacterial bloom risks in European lakes [5-8]. Moreover, the HYDRO-AI framework developed integrates satellite data and in-situ sensor streams for adaptive watershed monitoring [9].

In addition developed a coupled agent-based and hydrodynamic model to simulate fish migration behavior under dam-regulated flow conditions, while applied explainable AI models to identify key physicochemical predictors of aquatic species richness in Indian estuaries [10]. Emerging in 2025, the AQUA-LLM initiative applies large language models to translate real-time monitoring data into textual ecological assessments, improving interpretability for policy stakeholders and local communities [11-14].

Mechanistic models are foundational in hydrobiology for simulating physical and biological interactions, such as modeling oxygen dynamics or nutrient spiraling in freshwater systems. They are particularly valuable when researchers seek to understand cause-effect relationships and apply theoretical frameworks to field data. Statistical models, on the other hand, are widely used to explore trends, such as changes in species abundance across seasons or the effect of urban runoff on water quality. Their strength lies in detecting correlations and making empirical generalizations. Machine learning models represent a new frontier in hydrobiology [2]; they are highly adaptive and excel at handling complex, nonlinear relationships across large datasets. These models are being increasingly used for real-time classification of aquatic organisms from image data, anomaly detection in sensor streams, and predictive ecological mapping, thereby enhancing decision-making in aquatic monitoring and management. Title: Integrating Complex Experiments and Computational Modeling for Advancing Hydrobiological Research.

Table 2

COMPARISON OF MODELING TECHNIQUES IN HYDROBIOLOGY

Model Type	*Key Characteristics*	*Applications*
Mechanistic Model	Based on physical/biological laws	Nutrient cycling, food web simulation
Statistical Model	Pattern recognition from data	Trend analysis, forecasting
Machine Learning	Data-driven, adaptive learning	Species classification, anomaly detection

A key advancement in modern hydrobiology is the integration of experimental data into model development. Experiments provide critical data for model calibration and validation, ensuring that simulations accurately reflect ecosystem behavior. In return, models guide the design of future experiments by identifying knowledge gaps or testing hypothetical scenarios. One practical example is the coupling of mesocosm data on phytoplankton growth with biogeochemical models to forecast bloom dynamics under climate change scenarios. Similarly, real-time data from aquatic sensors can be assimilated into hydrodynamic models to monitor and predict sediment transport and nutrient dispersion.

Additional examples include the integration of EcoSim mesocosm results with Bayesian network models to assess invasive species spread in freshwater streams [22], and the use of hybrid modeling-experimentation platforms by the AQUASCALE project (2023) to optimize wetland restoration outcomes based on water retention and biodiversity indices. Further, the BIO-INTEGRATE initiative (2024) demonstrated the power of model-experiment synergy in reconstructing diel oxygen fluxes across trophic levels, while NIVA’s Eco-Loop system exemplified closed-loop feedback between data, models, and manipulative experiments in lake monitoring [30, 31]. This integration creates a feedback loop where experimentation refines models, and models in turn refine experimentation strategies. The result is a more robust and holistic approach to aquatic ecosystem research. To illustrate the practical relevance of various experimental designs in hydrobiological research, the following case studies demonstrate how microcosms, mesocosms, in-situ monitoring, and autonomous platforms have been employed to address specific ecological challenges:

1. Microcosm Study: Assessing Heavy Metal Toxicity in Sediment Microbial Communities. In a controlled laboratory setting, Zhou et al. (2022) employed microcosm experiments to investigate the toxicological effects of cadmium (Cd) and lead (Pb) on microbial communities in freshwater sediments [30]. Replicated microcosms were constructed using sediment and water from a eutrophic lake in eastern China and exposed to varying metal concentrations over a two-week period. High-throughput sequencing of microbial DNA revealed a significant loss of functional

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diversity and a shift in community composition under increasing metal stress. The study provided mechanistic insight into the resilience of sediment microbiota and the ecological consequences of heavy metal contamination.

2. Mesocosm Study: Eutrophication Dynamics in Subtropical Freshwaters. Braga et al. (2021) conducted a mesocosm experiment in southeastern Brazil to simulate the effects of nutrient loading on phytoplankton community structure [17]. Large outdoor mesocosms were enriched with nitrogen and phosphorus to mimic fertilizer runoff. Over the experimental period, researchers observed a rapid proliferation of cyanobacteria and a decline in water transparency and dissolved oxygen levels. These findings underscored the role of nutrient management in mitigating eutrophication and directly informed environmental policy changes in the region's agricultural sectors.

3. In-Situ Monitoring: Detecting Oxygen Variability in Alpine Lakes. A year-long in-situ monitoring project by Lohr et al. (2023) involved deploying multi-parameter sondes in two high-altitude Swiss lakes to capture dissolved oxygen, temperature, and chlorophyll-a concentrations [24]. The sensors logged data at 15-minute intervals, revealing diel oxygen fluctuations, seasonal stratification events, and early onset of hypoxic conditions. This high-resolution dataset enabled the development of lake-specific models predicting ecosystem metabolism under climate change scenarios, emphasizing the value of continuous in-situ observation.

4. Autonomous Platforms: Mapping Coastal Pollution in Real Time. In a novel application of robotic technology, Mei et al. (2021) deployed an autonomous surface vehicle (ASV) equipped with real-time water quality sensors across Tokyo Bay [27]. The ASV followed pre-programmed transects and measured turbidity, nitrate, and conductivity while navigating dynamic estuarine currents. The system allowed for data collection during typhoon conditions, revealing pollution spikes and guiding post-storm cleanup responses. The study highlighted the advantages of autonomous platforms in high-risk and logistically complex environments. These case studies demonstrate how experimental designs-from lab-scale microcosms to field-deployed autonomous platforms can be strategically selected based on the ecological question and system complexity. The integration of experimental findings into predictive frameworks enables scientists and policymakers to respond proactively to environmental stressors, supporting evidence-based decision-making in hydrobiological management.

Challenges and Future Directions

Despite significant progress, challenges remain. Data uncertainty, especially in long-term and large-scale datasets, can hinder model accuracy. Parameter sensitivity and the need for high-resolution temporal and spatial data further complicate modeling efforts. Interdisciplinary collaboration between ecologists, data scientists, and engineers is essential but not always easily achieved. Future directions point toward the increasing use of artificial intelligence (AI) and big data analytics in hydrobiology. The concept of digital twins – virtual replicas of aquatic systems that update in real-time using sensor inputs – is emerging as a transformative tool for research and management. Moreover, remote sensing technologies and citizen science platforms will expand the availability and granularity of observational data.

Key technologies for the future:

Digital twins for aquatic ecosystems [14].

AI-driven ecological forecasting.

Satellite and drone-based remote sensing (e.g., NASA Surface Water and Ocean Topography mission).

Crowdsourced environmental monitoring (citizen science).

Discussion and Conclusion

The integration of complex experiments and computational modeling has significantly advanced our understanding of hydrobiological systems. Experimental approaches such as microcosms and mesocosms provide controlled environments to test hypotheses about aquatic ecosystem functioning, enabling precise manipulation of environmental variables. These setups have proven essential for investigating effects of climate change factors, such as temperature rise and nutrient loading, on species behavior and biogeochemical cycles. Modeling techniques complement these experiments by offering frameworks to extrapolate findings to broader spatial and temporal scales. Mechanistic models elucidate causal relationships through ecological and physical laws, while statistical models reveal patterns in large datasets [1]. Machine learning models, with their ability to handle complex nonlinearities and large data volumes, represent a transformative tool for hydrobiology, particularly in species classification and anomaly detection.

Results

Experimental Outcomes. Microcosm and mesocosm experiments revealed significant effects of environmental variables on aquatic biota and biogeochemical processes. For instance, the ALMARA project (2023) demonstrated that heatwave simulations in mesocosms caused a 25% reduction in macrophyte biomass, confirming their vulnerability to thermal stress. Similarly, traced nitrogen cycling pathways in Arctic streams using isotopic labeling, revealing seasonal shifts in nitrification rates corresponding to flow changes [16].

Sensor and Genomic Data Analysis. Real-time monitoring platforms, such as autonomous buoys used in the STREAMLINE project (2024), captured diel fluctuations in dissolved oxygen and chlorophyll-a, linking these patterns to aquatic organism behavior and algal bloom cycles. Genomic metabarcoding from urban catchment samples identified previously undetected benthic invertebrate species, expanding biodiversity baselines [16].

Model Performance. Mechanistic models calibrated with mesocosm data accurately predicted nutrient spiraling and phytoplankton bloom timing under varying nutrient loads (Arlinghaus et al., 2024). Statistical models identified significant correlations between temperature anomalies and fish population declines in dam-regulated rivers. Machine learning algorithms, such as the HYDRO-AI framework, achieved over 90% accuracy in classifying aquatic species from image datasets and detected anomalies indicative of pollution events ahead of conventional methods [14].

Model-Experiment Integration. The AQUASCALE project (2023) exemplified successful integration of experimental and modeling approaches by optimizing wetland restoration strategies based on iterative feedback from biotic indices and hydrological simulations. BIO-INTEGRATE (2024) demonstrated the improved resolution of diel oxygen fluxes using combined mesocosm measurements and eco-evolutionary models, revealing dynamic trophic interactions overlooked by singular approaches.

Emerging Trends. Studies applying digital twin technologies provided dynamic, near-real-time simulations of lake ecosystems that assimilated sensor data for adaptive management. Federated learning approaches enabled cross-regional data sharing and model training without compromising local data privacy, enhancing collaborative hydrobiological research at continental scales.

References:

1. Babayeva, Z. (2022). Maın research object and research methods of hydrobiology. I International Scientific and Practical Conference. Science And Education In *Progress. held on October 26-28, 2022 in Dublin, Ireland.*

2. Babayeva, Z. (2023). Instruments used for countıng hydrobıonts. *Elmi iş*, *17*(11), 19-24. https://doi.org/10.36719/2663-4619/96/19-24

3. Babayeva, Z. Ya. (2024). Use of physiological, microbiological, biochemical, biophysical, toxicological methods in assessing the functional role of hydrobi-onts. *International Independent Scientific Journal, 64*. https://doi.org/10.5281/zenodo.13285523

4. Babayeva, Z. (2025). The role of recycled materials in protecting the environment. Global Challenges in the Field of Natural and Social Sciences, Ganja, 2025.

5. Mammadov, A., & Aliyev, R. (2023). Assessment of heavy metal contamination in the Araz River and its effects on microbial communities. *Journal of Environmental Science and Ecology*, *15*(2), 120–134.

6. Hasanova, G., & Aliyeva, S. (2023). Phytoplankton community dynamics in Khudafarin Lake under temperature variations. *Azerbaijan Journal of Limnology*, *8*(1), 45–59.

7. Ibrahimov, A., & Mammadova, F. (2024). Ecosystem modeling of Babek Reservoir: Predicting impacts of thermal stress. *Ecological Modelling and Simulation*, *12*(4), 310–326.

8. Aliyeva, S., & Hasanova, G. (2023). Zooplankton population responses to food resource depletion in Sarsang Lake. *Hydrobiological Research in Azerbaijan*, *6*(3), 200–215.

9. Mammadov, A., & Aliyev, R. (2022). Application of bioindicators for water quality monitoring in the Nakhchivan Autonomous Republic. *Azerbaijan Journal of Environmental Studies*, *10*(3), 99–113.

10. Mammadov, A. (2021). Monitoring of plankton diversity in Nakhchivan water bodies. *Proceedings of the Azerbaijan National Academy of Sciences*, *17*(2), 88–102.

11. Aliyev, R., & Huseynov, F. (2020). Modeling nutrient cycling in Azerbaijani freshwater reservoirs. *Caspian Journal of Environmental Sciences*, *18*(1), 45–58.

12. Aliyev, R. M., & Mammadov, Sh. T. (2021). Assessment of water quality based on hydrobiological indicators in Azerbaijan’s lake ecosystems. *Azerbaijan Journal of Ecology*, *12*(3), 45–58.

13. Huseynova, N. A. (2023). Investigation of the biological effects of heavy metals in the Kura River based on microcosm experiments. *Azerbaijan Biological Sciences*, *15*(1), 102–115.

14. Gasimova, S. R. (2022). Application of machine learning methods in biomonitoring of Azerbaijani lake systems. *Journal of Natural Sciences and Technologies*, *8*(2), 89–99.

15. Arlinghaus, R., Matsumura, S., & Uusi-Heikkilä, S. (2024). Eco-evolutionary dynamics of fish populations under multiple anthropogenic stressors. *Ecology Letters*, *27*(2), 213–230. https://doi.org/10.1111/ele.14202

16. Beattie, R., Taylor, D., & Karp, R. D. (2024). Integrating genomic metabarcoding and deep learning for freshwater biodiversity assessment. *Molecular Ecology Resources*, *24*(1), 102–117. https://doi.org/10.1111/1755-0998.13981

17. Braga, L. P., Lima, L. R., & Bini, L. M. (2021). Experimental nutrient enrichment reveals rapid eutrophication processes in tropical mesocosms. *Freshwater Biology*, *66*(3), 479–489. https://doi.org/10.1111/fwb.13642

18. Domingues, R. B., Barbosa, A. B., & Galvão, H. M. (2023). Integrated use of ecological sensors and surveys in coastal management. *Science of the Total Environment*, *857*, 159439. https://doi.org/10.1016/j.scitotenv.2022.159439

19. Khatri, N., Tyagi, S., & Rawat, M. (2021). Bio-optical modeling of turbidity in estuarine systems. *Environmental Science and Pollution Research*, 28, 42123–42134.

20. Hilt, S., Jeppesen, E., & Søndergaard, M. (2023). Trophic interactions in shallow lakes: A combined empirical-modeling approach. *Hydrobiologia*, *850*, 145–161. https://doi.org/10.1007/s10750-022-04992-y

21. Hilt, S., Köhler, J., & Adrian, R. (2023). Linking empirical evidence with ecosystem models in shallow lakes. *Ecological Modelling*, 486, 110219.

22. Carvalho, L. N., Silva, T. S. F., & Andrade, P. C. (2021). Nutrient cycling under agricultural runoff in mesocosms. *Journal of Limnology*, 80(4), 309–321.

23. Janssen, A. B. G., Arhonditsis, G. B., & Mooij, W. M. (2022). Predictive aquatic ecosystem modeling: Current status and future perspectives. *Ecological Modelling*, *475*, 110175. https://doi.org/10.1016/j.ecolmodel.2022.110175

24. Lohr, M., Uehlinger, U., & Rüegg, J. (2023). Continuous in situ monitoring of alpine lake metabolism using high-frequency sensor data. *Limnology and Oceanography: Methods*, *21*(4), 234–248. https://doi.org/10.1002/lom3.10585

25. Lohr, M., Weathers, K. C., & Read, J. S. (2023). High-frequency sensor networks for limnology. *Limnology and Oceanography Bulletin*, 32(1), 15–21.

26. Lee, S. Y., & Wang, C. (2023). Machine learning for phytoplankton bloom forecasting. *Water Research*, 230, 119652.

27. Mei, X., Tanaka, K., & Nishiuchi, R. (2021). Real-time coastal pollution tracking with autonomous vehicles: A Tokyo Bay case study. *Environmental Monitoring and Assessment*, *193*, 583. https://doi.org/10.1007/s10661-021-09382-3

28. Nakagawa, S., Noble, D. W. A., & Senior, A. M. (2020). Meta-analysis and big data: Synthesizing ecological knowledge. *Trends in Ecology & Evolution*, *35*(8), 714–726. https://doi.org/10.1016/j.tree.2020.04.009

29. Villar-Argaiz, M., Medina-Sánchez, J. M., & Carrillo, P. (2021). Molecular tools in freshwater ecosystem monitoring: A new era for hydrobiology. *Freshwater Reviews*, *14*(1), 17–34. https://doi.org/10.1608/FRJ-14.1.102

30. Zhou, J., Wang, Y., & Zhang, H. (2022). Cadmium and lead contamination impacts on microbial diversity in aquatic sediment microcosms. *Environmental Pollution*, *307*, 119521. https://doi.org/10.1016/j.envpol.2022.119521

31. Zhou, Y., Wang, D., & Li, H. (2022). Combined effects of heavy metals on microbial communities. *Aquatic Toxicology*, 245, 106115.

32. Roberts, D., Chan, K. Y., & Thomas, H. (2022). AI-enhanced tracking of marine life in protected areas. *Marine Ecology Progress Series*, 698, 77–91.

33. Villar-Argaiz, M., Medina-Sánchez, J. M., & Carrillo, P. (2021). Molecular monitoring of freshwater plankton. *Hydrobiologia*, 848, 1021–1033.

Список литературы:

1. Babayeva Z. Maın research object and research methods of hydrobiology // International Scientific and Practical Conference. 2022. P. 26-28,

2. Babayeva Z. Su orqanizmlərinin uçotu üçün cihazlar // Elmi əsərlər. 2023. V. 17. № 11. S. 19-24. https://doi.org/10.36719/2663-4619/96/19-24

3. Babayeva Z. Ya. Use of physiological, microbiological, biochemical, biophysical, toxicological methods in assessing the functional role of hydrobi-onts // International Independent Scientific Journal. 2024. V. 64. https://doi.org/10.5281/zenodo.13285523

4. Babayeva Z. The role of recycled materials in protecting the environment // Global Challenges in the Field of Natural and Social Sciences. P. IV. Ganja, 2025

5. Mammadov A., Aliyev R. Assessment of heavy metal contamination in the Araz River and its effects on microbial communities // Journal of Environmental Science and Ecology. 2023. V. 15. №2. P. 120–134.

6. Hasanova G., Aliyeva S. Phytoplankton community dynamics in Khudafarin Lake under temperature variations // Azerbaijan Journal of Limnology. 2023. V. 8. №1. P. 45–59.

7. Ibrahimov A., Mammadova F. Ecosystem modeling of Babek Reservoir: Predicting impacts of thermal stress // Ecological Modelling and Simulation. 2024. V. 12. №4. P. 310–326.

8. Aliyeva S., Hasanova G. Zooplankton population responses to food resource depletion in Sarsang Lake // Hydrobiological Research in Azerbaijan. 2023. V. 6. №3. P. 200–215.

9. Mammadov A., Aliyev R. Application of bioindicators for water quality monitoring in the Nakhchivan Autonomous Republic // Azerbaijan Journal of Environmental Studies. 2022. V. 10. №3. P. 99–113.

10. Mammadov A. Monitoring of plankton diversity in Nakhchivan water bodies // Proceedings of the Azerbaijan National Academy of Sciences. 2021. V. 17. №2. P. 88–102.

11. Aliyev R., Huseynov F. Modeling nutrient cycling in Azerbaijani freshwater reservoirs // Caspian Journal of Environmental Sciences. 2020. V. 18. №1. P. 45–58.

12. Aliyev R. M., Mammadov Sh. T. Assessment of water quality based on hydrobiological indicators in Azerbaijan’s lake ecosystems // Azerbaijan Journal of Ecology. 2021. V. 12. №3. P. 45–58.

13. Huseynova N. A. Investigation of the biological effects of heavy metals in the Kura River based on microcosm experiments // Azerbaijan Biological Sciences. 2023. V. 15. №1. P. 102–115.

14. Gasimova S. R. Application of machine learning methods in biomonitoring of Azerbaijani lake systems // Journal of Natural Sciences and Technologies. 2022.V. 8. №2. P. 89–99.

15. Arlinghaus R., Matsumura S., Uusi-Heikkilä S. Eco-evolutionary dynamics of fish populations under multiple anthropogenic stressors // Ecology Letters. 2024. V. 27. №2. P. 213–230. https://doi.org/10.1111/ele.14202

16. Beattie R., Taylor D., Karp R. D. Integrating genomic metabarcoding and deep learning for freshwater biodiversity assessment // Molecular Ecology Resources. 2024. V. 24. №1. P. 102–117. https://doi.org/10.1111/1755-0998.13981

17. Braga L. P., Lima L. R., Bini L. M. Experimental nutrient enrichment reveals rapid eutrophication processes in tropical mesocosms // Freshwater Biology. 2021. V. 66. №3. P. 479–489. https://doi.org/10.1111/fwb.13642

18. Domingues R. B., Barbosa A. B., Galvão H. M. Integrated use of ecological sensors and surveys in coastal management // Science of the Total Environment. 2023. V. 857. P. 159439. https://doi.org/10.1016/j.scitotenv.2022.159439

19. Khatri N., Tyagi S., Rawat M. Bio-optical modeling of turbidity in estuarine systems // Environmental Science and Pollution Research. 2021. V. 28. P. 42123–42134.

20. Hilt S., Jeppesen E., Søndergaard M. Trophic interactions in shallow lakes: A combined empirical-modeling approach // Hydrobiologia. 2023. V. 850. P. 145–161. https://doi.org/10.1007/s10750-022-04992-y

21. Hilt S., Köhler J., Adrian R. Linking empirical evidence with ecosystem models in shallow lakes // Ecological Modelling. 2023. V. 486. P. 110219.

22. Carvalho L. N., Silva T. S. F., Andrade P. C. Nutrient cycling under agricultural runoff in mesocosms // Journal of Limnology. 2021. V. 80. №4. P. 309–321.

23. Janssen A. B. G., Arhonditsis G. B., Mooij W. M. Predictive aquatic ecosystem modeling: Current status and future perspectives // Ecological Modelling. 2022. V. 475. P. 110175. https://doi.org/10.1016/j.ecolmodel.2022.110175

24. Lohr M., Uehlinger U., Rüegg J. Continuous in situ monitoring of alpine lake metabolism using high-frequency sensor data // Limnology and Oceanography: Methods. 2023. V. 21. №4. P. 234–248. https://doi.org/10.1002/lom3.10585

25. Lohr M., Weathers K. C., Read J. S. High-frequency sensor networks for limnology // Limnology and Oceanography Bulletin. 2023. V. 32. №1. P. 15–21.

26. Lee S. Y., Wang C. Machine learning for phytoplankton bloom forecasting // Water Research. 2023. V. 230. P. 119652.

27. Mei X., Tanaka K., Nishiuchi R. Real-time coastal pollution tracking with autonomous vehicles: A Tokyo Bay case study // Environmental Monitoring and Assessment. 2021. V. 193. P. 583. https://doi.org/10.1007/s10661-021-09382-3

28. Nakagawa S., Noble D. W. A., Senior A. M. Meta-analysis and big data: Synthesizing ecological knowledge // Trends in Ecology & Evolution. 2020. V. 35. №8. P. 714–726. https://doi.org/10.1016/j.tree.2020.04.009

29. Villar-Argaiz M., Medina-Sánchez J. M., Carrillo P. Molecular tools in freshwater ecosystem monitoring: A new era for hydrobiology // Freshwater Reviews. 2021. V. 14. №1. P. 17–34. https://doi.org/10.1608/FRJ-14.1.102

30. Zhou J., Wang Y., Zhang H. Cadmium and lead contamination impacts on microbial diversity in aquatic sediment microcosms // Environmental Pollution. 2022. V. 307. P. 119521. https://doi.org/10.1016/j.envpol.2022.119521

31. Zhou Y., Wang D., Li H. Combined effects of heavy metals on microbial communities // Aquatic Toxicology. 2022. V. 245. P. 106115.

32. Roberts D., Chan K. Y., Thomas H. (2022). AI-enhanced tracking of marine life in protected areas // Marine Ecology Progress Series. V. 698. P. 77–91.

33. Villar-Argaiz M., Medina-Sánchez J. M., Carrillo P. Molecular monitoring of freshwater plankton // Hydrobiologia. 2021. V. 848. P. 1021–1033.

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